Computational Trust in Multiplayer Online Games

A DISSERTATION
SUBMITTED TO THE FACULTY OF THE GRADUATE SCHOOL
OF THE UNIVERSITY OF MINNESOTA
BY

Muhammad Aurangzeb Ahmad

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
Doctor of Philosophy

Jaideep Srivastava

May, 2012

Acknowledgements

There are a number of people and organizations that I would like to thank without whose help the current endeavor would not have been possible. I would like to thank my advisor and mentor Professor Jaideep Srivastava for his guidance in the academic as well as in the non-academic arena. I have learned many vaulable life long lessons while working with Professor Srivastava. I would also like to thank all of my labmates for their collaborative efforts and their support. In particular I would like to thank the following individuals in the lab, in alphabetical order: Zoheb Borbora, David Kuo-Wei Hsu, Xia Hu, Young Ae Kim, Komal Kapoor, Amogh Mahapatra, Nishith Pathak, Kyong Jin Shim and Nisheeth Srivastava.

Outside of University of Minnesota, I would like to acknowledge my collaborators at the Virtual Worlds Observatory Project. Firstly I want to acknowledge the faculty in the project Professor Noshir Contractor, Professor Dmitri Williams and Professor Marshall Scott Poole, all of whom were also instrumental in broadening my horizons given the inter-disciplinary nature of this project. Amongst the students in this project I would like to thank the following individuals: David Huffaker, Brian Keegan, Cuihua Shen, Jeffrey Treen and Jing 'Annie' Wang. I would also like to thank the committe members Professor Abhishek Chandra, Professor David Knoke and Professor John Riedl in addition to my adviser for agreeing to be part of the committee. Last but not least I would like to thank my family, my parents (Mushtaq Ahmad Mirza, Khalida Parveen), my brothers (Muhammad Farooq Ahmad, Muhammad Maqsood Ahmed, Muhammad Abubakar Ahmad), my sister in laws (Zoonaz Murad, Rabia Haneef, Shawana Afzal) for the love and support all these years.

Dedication

This thesis is dedicated to my parents: My father, Mushtaq Ahmad Mirza who taught me the meaning of patience without ever uttering a single word about patience and my mother Khalida Parveen who is the person who not just gave me more love than any person in the universe but also more than what any person can in the universe.

اوّل حمد خدا دا ورد کیجے، عشق کیتا سو جگ دا مول میاں
پہلے آپ ہی رب نے عشق کیتا، معشوق ہے نبی رسول میاں
عشق پیر فقیر دا مرتبہ ہے، مرد عشق دا بھلا رنجول میاں
کھلے تنہا ندے باغ قلوب اندر، جنہاں کیتا ہے عشق قبول میاں

- Waris Shah [1] (1722-1798)

[1] Hazrat Waris Shah is considered to be the greatest poet of the Punjabi langauge. His Magnus Opus *Heer Ranjha* is considered to be the crowning achievement of the Punjabi literature.

Abstract

Trust is a ubiquitous phenomenon in human societies. Computational trust refers to the mediation of trust via a computational infrastructure. It has been studied in a variety of contexts e.g., peer-to-peer systems, multi-agent systems, recommendation systems etc. While this is an active area of research, the types of questions that have been explored in this field has been limited mainly because of limitations in the types of datasets which are available to researchers. In this thesis questions related to trust in complex social environments represented by Massively Multiplayer Online Games (MMOGs) are explored. The main emphasis is that trust is a multi-level phenomenon both in terms of how it operates at multiple levels of network granularities and how trust relates to other social phenomenon like homophily, expertise, mentoring, clandestine behaviors etc. Social contexts and social environments affect not just the qualitative aspects of trust but this phenomenon is also manifested with respect to the network and structural signatures of trust network

Additionally trust is also explored in the context of predictive tasks: Previously described prediction tasks like link prediction are studied in the context of trust within the context of the link prediction family of problems: Link formation, link breakage, change in links etc. Additionally we define and explore new trust-related prediction problems i.e., trust propensity prediction, trust prediction across networks which can be generalized to the inter-network link prediction problem and success prediction based on using network measures of a person's social capital as a proxy.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

”You must trust and believe in people or life becomes impossible.”
- Anton Chekhov

1.1 Introduction

Trust is a ubiquitous social phenomenon, it is observed in almost all human relationships wherever there is uncertainty involved or there is prolonged social interaction [126]. It has even been described as the lubricant of the human society. The literature on trust is vast both in terms of breath (spanning many disciplines) and depth (multitudes of concepts being discussed). Thus there are treatments of trust from a philosophical [127], sociological [61], neurological [105], cognitive [69] and computational perspective [67] and many additional treatments within each discipline. The current discourse is confined to the network aspects of trust within the context of computational social trust with special reference to the socio-cognitive and psychological aspects of trust. Within the field of computing trust has been studied in a variety of contexts e.g., trust in recommendation systems [178], trust in P2P systems [161], trust in security and encryption [1], trust in computationally mediated social systems [69]. It is the last environment that we are primarily interested in for this chapter and restrict our scope to this domain.

The notion of Trust has also been tied to Epistemology and the society’s need to believe in the truth claims made by experts. On the other hand some philosophers have gone as far to say that even the notion of objectivity is rooted in the concept of trust [156]. The current endeavor can be described as part of a larger endeavor to situate trust at the center of human behavior. Trust is a polysemic word with the various semantics trust occupying an overlapping concept space. One consequence of this semantic ambiguity is that the concepts which are derived from trust also exhibit this extension in semantic space. Thus one such concept of interest is the concept of breach of trust which can only be described with respect to trust. Given the varied and often conflicting yet intersecting definitions of trust it is not possible to cover all aspects of trust in a single thesis or even in a several thesis, the discourse on trust in the current thesis is thus restricted to a particular notion of trust and the sematics associated with this notion. The current chapter thus elucidates this particular notion of trust.

Computing with social trust refers to trust between people in environments where the interaction between them is being mediated through a computer and there is an element of some form of socialization involved e.g., online social networks, recommendation websites, blogs and microblogs, online games with social elements etc. The vast majority of the literature in this area deals with trust at the dyadic level i.e., between two entities [69] and some work on trust as a global phenomenon. Literature on trust at intermediate levels of network structures is conspicuously missing in this field. Thus the sociology literature [131] talks about network structures at the intermediate levels of organization which are explained in terms of socio-cognitive and psychological processes. The aim of the current chapter is thus two fold: (i) To describe a network based view of trust that integrates multiple views of trust. (ii) To link the afore mentioned network view of trust with a socio-cognitive framework in a similar vein to the MTML framework of Monge and Contractor [131].

1.2 Representing Trust

Trust can be represented in different ways [69] and the choice of representation mainly depends upon the application domain. The choice of representation usually depends upon the application domain. Thus trust can be represented as categorical or numerical. In the case where trust is categorical, trust is usually expressed on an ordered scale (trust a lot, trust somewhat, neutral, do not trust). Other categorical scales are also possible e.g., (trust vs. distrust), (trust, neutral, distrust) etc. There are also multiple schemes for representing trust as a numerical value: binary trust $\{0, 1\}$, ternary trust $\{-1, 0, 1\}$, ranged trust $\{1, 2, ..., k\}$ where $k \geq 3$ [69]. Other, albeit less often used schemes for representing trust allows the users to give numerical values within a range e.g,, $t \in (1, 10)$.

1.3 Trust as a Network Phenomenon

Since trust can be described as a social relation (or disposition) between two entities, given all such relationships amongst a group of entities, it is possible to represent the aggregates of these relationships as a graph or a social network. A graph thus describes a set of relationships (links or edges) between a set of entities (nodes or vertices) [53]. In our present context the nodes are the entities (people, organizations, groups) and the edges between them represent trust. The trust values between the nodes correspond to edge weights which can be directed or undirected, depending upon the context and application. We also note that trust is not always one dimensional i.e., trust can be described in various contexts e.g., a person may trust his mother's opinion on cooking but he may not trust her opinion on recommendation on data mining. In such multi-context settings trust can be conceived of as a vector and the trust graph thus becomes a multi- graph.

While the basic unit of analysis in a network is a dyad, we note that other levels of network organization like triads (relationships involving three entities), trust within and across groups etc offer us a fundamentally different way to study trust e.g., triadic structures can be used to study balance [82]. Of course one could also argue that triads are nothing but an agglomeration of three dyads, and the same can be said of larger structures like communities in social networks. However this criticism would miss the point of the reality of such social structures as criticism of biology as a redundant science since all biology is essentially chemistry would miss the point of the reality of biological processes and biological categories. Additionally trust manifests in different ways at different levels of granularity e.g., perception of other's views about oneself are likely to influence how one trust other people which may in turn depend upon whether the trustee are part of one's group or are outside of one's group. Analysis of trust at the global network level can yield insights about the environment in which the network is embedded e.g., cross network comparisons can tell us whether trust is prevalent in one network vs. another network.

While the analysis of trust at various network granularities can yield interesting insights regarding trust, an additional orthogonal dimension of social science theories has to be added to the analysis in order to make sense of not just how trust operates in social networks but also why trust relationships form and evolve over time. In order to address this question we integrate the MTML framework of Monge and Contractor [131] to the network based trust framework that we just described. As stated previously, the MTML framework is a framework that combines various theories about how social and communication networks evolve and gives descriptions of why people form links with one another. Thus Table 1.1 describes trust as a network phenomenon and map the corresponding social science theories from the MTML framework. We refer the reader to the text by Monge and Contractor [131], a brief description of these is given as follows:

- **Theories of Self-Interest:** Describes linkages in terms of a person's self-interest and desires. The main theories are the theory of social capital and the theory of transaction cost economics.

- **Theories of Collective Action:** Mainly examines how coordinated activity can produce outcomes which cannot really come about with individual action. Representative theories are public goods theories and critical mass theories.

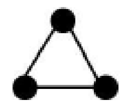
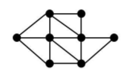
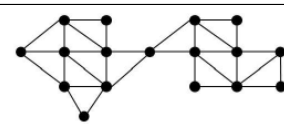
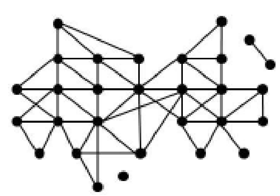
- **Theories of Contagion:** Addresses the issues related to the spread of ideas, beliefs and influences in the social network. Contagion spread can be by cohesion or by structural equivalence.

- **Theories of Cognition:** Describes the role of knowledge and perception in social network. Represent theories include the Theory of Balance and and theories regarding Cognitive Communication structures.

- **Theories of Exchange:** Describes the emergence of social networks in terms of distribution of resources and how these change hands in social networks

- **Theories of Homophily:** Explains the role of similarity between the members of the network in the formation and evolution of the network.

Table 1.1: Trust at Multiple Network Resolutions

Network Level	**Explanation**	**Example**	**Key Theories**
Dyadic Trust	Trust Between two entities		Theory of Contagion Theory of Cognition
Triadic Trust	Trust between three entities		Theory of Balance Theory of Proximity Theory of Cognition
Intra-Group Trust	Trust within entities in a group		Theories of Self-Interest Theories of Exchange Theory of Cognition
Trust Inter-Group	Trust between and across groups		Theories of Collective Action Coevolutionary Theories Theories of Exchange Theory of Cognition
Trust Network Level	Trust at the global level		Theories of Collective Action Coevolutionary Theories Theories of Exchange Theory of Cognition Theory of Contagion

- **Theories of Proximity:** Based on the idea that people are more likely to interact with other people who are closet to them in physical proximity,
- **Coevolutionary Theories:** Describes the formation of links on the basis of fitness functions i.e., in order to survive organizations and groups must adopt to the surroundings.

1.3.1 Trust as a Multi-Level Phenomenon

We now describe trust at various network levels and the what kind of phenomenon are associated with trust at these levels and how they relate to one another.

- **Intrinsic/Psychological:** These refer to the intrinsic or psychological make up of a person e.g., some people have a greater propensity of trust as compared to others. Additionally this propensity may vary from context to context. A person's propensity to trust either be measured by directly eliciting how much they trust others or indirectly measuring how much they trust other people. A person's propensity to trust will also be reflected in the immediate social neighborhood of their trust network.

- **Dyadic Trust:** This level of trust refers to trust between two different entities which could be people, organizations, groups etc or a combination of these e.g., trust can be described between two people, it can be from one person to a group or vice versa. Dyadic trust is how trust is usually conceptualized in the context of Social Trust [69]. It is usually represented as an edge between two nodes. Dyadic Trust can be said to be the most fundamental way of conceptualizing trust [69].

- **Triadic Trust:** While trust at the dyadic level is between two entities, at the triadic level trust is described between three entities. The relationships between these entities may be directed or undirected, signed or unsigned, weighted or unweighted. This implies that there can be may such possible relationships even when three entities are involved. Thus even in the case of unsigned unweighted directed networks there are at least 16 possible relationships between the nodes [181]. In case of signed edges, it is also possible to predict the sign of the edges given the configuration and signs of the edges which are already present. In other words even trust at the dyadic level has to be evaluated in the context of triads since trust relationships at the dyadic level is not really independent of other dyads.

- **Intra-Group Trust:** As the name implies, intra-group trust refers to trust within a group. Trust within groups and trust outside of groups operates in different ways. Thus trust is supposed to be stronger within groups as opposed to trust outside groups. Trust within groups gives rise to the concept of bonding social capital [35].

- **Inter-Group trust:** Trust between groups can be described into different ways depending upon how groups are defined. Thus groups can be defined in terms of graph theoretic structures [181] or they can be described in terms of some hierarchical or organizational partition [181]. Trust edges between individual across groups gives rise to bridging social capital [35].

- **Trust as a Network Phenomenon:** Trust can also be studied as a network phenomenon where the main distinguishing feature of the network is that the edges in the network represent trust. The main research in this area has focused on inference algorithms to determine the most trustworthy nodes in a network [69], determining recommendations [178] etc. We note that other traditional questions associated with networks like network characteristics of such networks [181] and the evolution of such networks [116] has not really been addressed in detail and thus represents a gap which should be addressed in the literature.

1.3.2 Trust-related Concepts in Network Terms

In this section we describe how concepts related to trust can be described in terms of network structure even though traditionally that is not how they are described. Ahmad et al [10] take the Hubs and Authorities paradigm of Kleinberg [104] and apply it to the trust related concepts.

Trustworthy Person

In the HITS Algorithm an authority is defined as a node which is pointed at by many Hubs and a Hub is defined as a node which is pointed out by many Authorities. Intuitively an Authority is a node which is pointed to by many other nodes implying that they consider it an authority with respect to a particular topic. Hubs intuitively refer to nodes which point to many other nodes, ideally these nodes are authorities. We map the people with high trust propensity to Authorities in the HITS framework while at the same time we note that Hubs are not analogous to people who are opposite to people who have high trust propensity. A trustworthy person is thus one who is trusted by many people who are in general less likely to trust others.

Trusting Person

In the same analogy described above, a better analogy for describing a person who is less likely to trust other people in general would be someone who is cautious χ and being trusting can thus be describes as

Co-Trust

The concept of Co-Trust takes its inspiration from the idea of co-citation [135]. The original concept of co-citation states that given a corpus of documents or research chapters, the co-citation relationship is defined if the same document or chapter is cited by two or more chapters then the co-citation relation is formed between the chapters to cite that chapter. In the context of trust Kim et al [102] describe co-trust as the relationship which is formed when one or more people trust the same person.

Expertise

There are multiple ways to describe expertise e.g., expertise can be described in terms of a person's knowledge, perceived knowledge, interaction history with others etc. Especially in contexts where trust is described with respect to a person's knowledge in a certain field then expertise can also be described with respect to how much that person is trusted in the network. In this case standard prestige based metrics can be used to compute expertise based on the trust links in the network [181]. This is the approach which is adopted by Kim et al [102].

1.3.3 Trust at Multiple-Temporal Resolutions

Complementary to the idea of analyzing trust at multiple network resolutions is to analyze trust at multiple temporal resolutions. The behavioral view of trust [69] implies that interactions between different entities lead to changes in the trust between them and also that the change in trust can result in the amount and type of interaction between the nodes. We note that this is also a somewhat neglected area of study mainly because of the fact that the datasets with enough temporal information are usually not available. Additionally trust operates differently with respect to the length and duration of transactions that involve trust. Thus consider the case where trust involves short term interaction or interaction which is limited number of times. In this case, an external guarantees may have to be provided to ensure that trust is not breached especially if a valuable commodity is involved.

1.4 Virtual Worlds as Testbeds for a Multi-Level Exploration of Trust

Virtual Worlds include open ended environments like SecondLife or more structured environments like MMORPGs (Massively Multiplayer Online Role Playing Games). One of the issues with lack of studies which address the questions described in this manuscript is because of unavailability of datasets in the past which can be used to address such questions. Given the constraints described above, we note that a dataset with the following characteristics would constitute the minimum threshold of the type of data that would be required to address such questions:

- A large number of users or participants to allow for sufficient detail for multi-resolution analysis.
- Temporal information so that it is possible to study how trust relationships and the network as a whole is evolving over time.
- Attributes of the users e.g., demographics or other ascribed characteristics and acquired characteristics.
- Social interaction information in addition to trust.
- Affiliation or group membership information.

Given the issues and difficulties associated with collecting datasets that satisfy all these constraints, historically speaking it was not possibly to collect datasets which satisfy all these conditions. With the proliferation of information rich environments on the Internet like Facebook, SecondLife, World of Warcraft etc it is possible to collect data which has all the aforementioned characteristics. To illustrate the usefulness and viability of the multi-resolution and the multi-level framework described here we use data from an MMORPG called EverQuest II (EQ2) to gain some insights into the phenomenon of

Table 1.2: Trust in MMORPGs

Network Level	Key Observations
Psychological Personal	Factors associated with trust in MMOGs The Trust Propensity Prediction Problem
Dyadic Trust	The Trust Prediction Family of Problems Trusting and Trustworthiness as Network Concepts Link prediction across social networks
Triadic Trust	Triadic structure are manifested differently in different social environments
Intra-Group Trust	Structural signatures of Clandestine vs. other actors in a network are different Use of hypergraphs to represent trust Rethinking models of team formation by augmenting trust Comparison of trust vs. other networks fir recommendations
Inter-Group Trust	Social Capital inspired methods to predict trust
Network Level Trust	Social Environment effect social structures Feature-selection and generalization should take into account social environments in prediction tasks Integration of the MTML framework with Trust

trust in a complex information rich environment. MMORPGs are analogous to online persistent shared worlds where millions of players can interact with one another in real time. There is a multiplicity of activities in the game e.g., trading, raiding, exploring, questing etc and also multitude of social interactions e.g., grouping, mentoring, chatting etc. It is also possible to explicitly describe trust in the game. Trust in EQ2 is described in terms of access to a resource i.e., a house and players can grant access to their house to other players. There are four levels of trust in EQ2: Trustee, Friend, Visitor and None. Risk is however only associated with Trustee. Table 1.2 gives a summary of our work on studying trust in EQ2 and how does it relate to the overall framework that we just described.

1.4.1 Psychological Factors

Ratan et al [146] examined how trust is related to online social institutions, self-disclosure, mode of communication, and message privacy. They observed that trust was higher within closer social circles: trust was highest in teammates, followed other players across the game, followed by others online. Ahmad et al [10] explore the relationship between network structures and a person's propensity to trust. The trust propensity data consists of survey data of players from the game where they specify how much they trust other people in various contexts. The data that are used in these studies consist of self-reported data about how much people trust others in general in addition to trust which is explicitly specified of other people. The propensity to trust of a person captures how much they trust others in general. It has been argued that propensity to trust [10] is a psychological trait associated with a person and is manifested in the network structures themselves in terms of patterns of trustingness.

1.4.2 Trust between two People (Dyadic Trust)

As described previously dyadic trust is trust between two entities (people, organization, groups etc). In our previous work we have explored a number of issues related to dyadic trust e.g., reciprocity [13], trust prediction problems with respect to the predict of formation [10][28], trust breakage [10], change in trust [10] and trust across social networks [10][28] in terms of social structures [10] as well as socio- psychological theories [10][28], the operationalization of the concept of a trustworthy individual and a trusting individual as network concepts [10].

1.4.3 Trust in Triads

We have explored the issue of triads in trust networks in MMOs in the context of balance and how the distribution of triadic structures should be different in different social environments [10]. The main result from this study is that the triadic census in cooperative environments is similar to other cooperative environments and the same can be said of adversarial environments and that these are different *across* environments.

1.4.4 Intra-Group Trust

While there is some previous work on the analysis of trust in criminal networks [176], in [8] we looked at the network structure associated with the trust networks of gold farmers (a form of deviant behavior in MMOs) [15], their affiliates and other people in general in MMOs and discovered that the structures (hypergraphs) which are associated with deviants in MMOs are usually sparse and can be used to distinguish between deviants and non-deviants. Additionally it was observed that in general gold farmers do not trust one another. In another body of work [5] we observed that earlier models of team formation in the online and the offline worlds [95] do not generalize to other MMOs and thus raise an important point with respect to generalization of results in MMOs. Relationships from the trust network is introduced in these models to determine the effect of trust in the network formation models. In [9] we observed that contrary to expectation that trust and other positive social relationship networks, it is actually information from adversarial networks which are most effective in making predictions about recommendations.

1.4.5 Inter-Group Trust

Trust across groups is already covered in the rubric of trust amongst gold farmers [8], in the current context we note that the affiliates of the gold farmers usually serve as bridges between the gold farmers and the rest of the population in the trust network. This allows the gold farmers to conceal their structural signatures in the social network. In [6] social capital is operationalized by using Ron Burt's notion of Structural Holes [35] with the main idea being that the network structures of people can be more effective in predicting how successful they will be as compared to using the standard way of using their past performance to predict future performance.

1.4.6 Trust as a Global Network Phenomenon

Studying trust based networks in MMOs at the global level requires us to take into account a number of issues into account and address the following questions: Are social networks in MMOs similar or fundamentally different from social networks in other domains? Do the social environments in MMOGs effect the evolution of network structures. We addressed these question in the context of both descriptive [10] as well as predictive [6][12] analysis. In the context of link prediction tasks, it is observed that the results of such tasks do not generalize across different types of social environments but do generalize within the same environments.

1.5 Modeling Issues

The discussion on trust up to this point is from a network perspective of trust where it is assumed that trust is social networks can be modeled as a graph. We however note that there may be cases where the either the domain or the application may have certain constraints so that the problem may not be amenable to simple graph representations. Consider the scenario given by Ahmad et al [8] who model trust networks in MMOs as hypergraphs instead of graphs. They describe a setting where multiple identities can be associated with the same person and trust is described in terms of trust with respect to multiple resources. Consequently a graph based representation is not appropriate for this setting and a hypergraph representation is used.

We note that the hypergraph approach can be extended to other domains as well e.g., the vast majority of the models assume that the trust between two people is with respect to a certain context but these models do not elucidate the context in more detail [8]. This assumption suffices in most cases but it can break down in some scenarios. Thus Kim et al [102] argue that in Epinions (a recommendation system with a trust based social network), it is assumed that the user-specified trust is a general type of trust but that is not necessarily the cases because even though the users specify one value of trust they interact in a limited number of categories so that the trust between them is likely to be with respect to those categories and not a general form of trust. This scenario is quite suitable to be modeled as a hypergraph.

Another modeling issue is with respect to a person's specified trust and trust which can be inferred based on their actions. Thus consider the trust propensity dataset used by Ahmad et al [10]. In the chapter they assume the user specified propensity values as ground truth. An alternative way to look at this problem would be to compare the reported trust with the observed trust and determine trust values based on what is actually observed as opposed to taking the reported values as ground truth.

Over the course of the last decade a number of studies [116][125][117] on the evolution of social networks have observed a large number of similarities between in a large number of datasets, to the effect that researchers have identified a number of network features which are observed in a large class of social networks [116][125][117]. While the later studies tend to assume that social networks in general do exhibit such traits, it remains to be seen that this is the case for trust based social networks in general or not. We note that in case of trust networks in MMOGs, some of these observations hold in certain cases but not in others[14]. Another unexplored question is how the social context effects network structure.

A meta-level modeling issue that is relevant to almost all studies of trust related studies is generalizability. Studies on computational trust either involve simulations or use datasets from just one source [69]. This limitation is mainly because of difficulties related to obtaining datasets related to trust and privacy issues which limit not just the release of data in the public domain but also the sharing of data between different researchers [69]. Thus it is quite possible to run into situations where the earlier results are not generalizable or generalizability is limited [95].

1.6 An MTML Theory of Trust?

Monge and Contractor [131] created the MTML framework to describe the evolution of communication and social networks by linking together various network theories with network structures. We note that the MTML framework was not developed with trust explicitly in mind but trust can be readily incorporated into the framework. In the current piece we expand the scope of the trust related network phenomenon and link them to one another and to the MTML framework. Thus the current framework can also be thought of as an attempt to give an MTML formulation of Trust networks.

1.7 Conclusion

The literature on social trust abounds with respect to both breadth and depth of issues discussed regarding trust but a unifying framework linking various network level phenomenon to each other and to socio-cognitive theories of trust is missing. In the current manuscript we have tried to bridge this gap by describing trust as a network phenomenon and then describing trust at various levels of network granularity. Additionally we have tried to link the various socio-cognitive theories from the MTML framework. believe that this framework not only helps unify many of the strands which have already been explored in the literature but it can also be use as a guide to future research.

Chapter 2

Trust and Socialization in MMOs

”Love all, trust a few, do wrong to none.”
- William Shakespeare

2.1 Introduction

Human are social creatures, even the most defininig characteristics of humans i.e., intelligence is a fundamentally social phenomenon in the sense that it is always emergent in a social strata. Given that survial in any environment requires proficieny in a multitude of skills and abilities which cannot be mastered by a single person people have to depend upon others for not just cooperation but about beliefs with regards to the state of the environment. This is where the concept of trust becomes paramount, it is mainly because of this limitation of resources in terms of time and space that people have to trust on one another. As described in the introduction, trust in not an all purpose general concept but is determined by multiple factors, the two most important of which are context and duration.

To illustrate the effect of these two orthogonal factor consider the following examples: The fact that one person trusts another person in one context this does not imply that she may also trust the other person in all contexts e.g., a person may trust his mothers opinion on cooking but he may not trust her opinion on books on Quantum Mechanics unless she is also a Physics professor. An additional constraint that may affect a persons behavior with respect to trusting others is the environment in which she has to make decisions about trusting others. Thus if it is a cooperative environment then a person may behave differently as opposed to if it is an adversarial environment e.g., trust can manifest in the form of alliances between people when they are faced with an outside threat. Alternatively working towards a common goal can be the source of positive interactions between people which in turn can lead to the formation of trust relationships between them.

In most contexts however trust is not an isolated relationship but rather there are multiple types of social interactions which may affect trust and are in turn affected by it. Thus for example one may have trade relationship, mentor-apprentice relationship, acquaintance relationship etc. One possible issue with studying trust with these types of social relationships is that they also have some component of trust associated with them. However if we consider adversarial relationship then the overlap is minimal if not complete lack of overlap. The theory of balance [82] suggests that when the presence of cooperative and adversarial relationships within the same social networks allow only certain type of social structures to be present because people try to minimize tensions in their social networks. However because of extreme difficulty in collecting data where such comparisons can be made, problems related to comparative analysis of social networks based on trust have not been done in detail before. Online and virtual environments offer us an avenue where the issues of data collection and analysis can be overcome. In this chapter the questions related to trust in cooperative vs. adversarial settings are explored. Namely the differences between the network structures in trust in cooperative environments vs. adversarial environments is explored. In the adversarial environment it is also possible to obtain data regarding adversarial relationships between people and thus one can complement the trust data with adversarial relationships to study how these affect one another.

2.2 Related Work

While there is a large body of work on trust in Online Social Networks [69], almost all of that work deals with trust in recommendation systems or web based social networks, the literature on trust in adversarial setting or environments is somewhat scarce. One exception to this is the literature in sensor networks [187] however the trust in sensor networks is not social trust and thus it is not really relevant to the current discussion. Another notable exception is the game theoretic aspects of trust in social games [Camerer]. However in this chapter we limit ourselves to social trust in online settings where thousands of people may be involved. The issue of trust in MMOGs has been addressed with respect to a number of research questions. Ratan et al 2010 discovered that that social structures and communication processes contribute to trust development in MMOGs. Ahmad et al [8] address the problem of trust amongst deviants in this context and discovered that deviants tend to express trust for trustworthy individuals [146]. The work of Ahmad et al [13] with respect to comparing network exchange in different trust networks is also relevant work to the current chapter. They discovered that different trust networks in different social settings have different structural signatures. However they did not explore the temporal nature of these networks in detail. A number of prediction tasks have also been addressed in this context. Thus Ahmad et al [12] study the problem of link prediction within trust networks and also introduce the problem of link prediction across social networks including trust networks.

2.3 Dataset

Data are taken from two servers: a player vs. player server (Nagafen) and a player vs. environment server (Guk). These servers are selected because the PvE server represent a cooperative social environment where other players do not pose a threat from another player, while the PvP server represents an adversarial social environment because other players can directly confront one in combat. Both servers are designed to accommodate players located in North America. Data from January 1, 2006 to August 31, 2006 were used in the study. In addition to the trust networks we also used data for an adversarial network from EQ2. An edge is constructed between two player characters if they have played against one another in the game. There are two variations of this network the undirected combat network which only denotes if two characters have played against one another and the directed kills network where an edge exists from the player character that kills to the player character who was killed.

The network characteristics of the trust networks from the two servers as well the combat network are given in Table 2.1. The trust network from Guk is visualized in

Figure 2.1 which shows the presence of one large connected component as well as the presence of a large number of smaller components. It is also clear that a huge subset of the components is just dyads and triads. The same phenomenon is observed for the other server, Nagafen. From Table 2.1 it is clear that there are vast differences between the trust network and the combat network. Not only are there more than three times as many nodes which participate in the combat network as opposed to the trust network but it is also the case that combat network is vastly more dense as opposed to the trust network. Another remarkable difference between these two networks is the presence of a large number of connected components in the trust network but not in the combat network. In the combat network almost all of the players belong to the largest connected component where LLC1, LCC2 and LCC3 in Table 2.1 refer to the largest, the second largest and the third largest connected components respectively and NComp refers to the number of connected components.

The Jacquards coefficient between the nodes and the edges of the combat network and the trust network is 0.178 and 1x10^{-5} respectively. This shows us that even though there is non-trivial overlap between the trust and the combat network it is the case that almost all the player who trust another player do not take part in combat activities against the other player which is not surprising. However given the massive difference in sizes between the combat network and the trust network we recomputed the network characteristics of these networks based on the subgraphs which are induced by considering the intersection of the nodes between the two networks. Another major difference between the two networks is the distribution of node and edge degrees in the two networks as given in Figure 2.1, which basically show that while on average the nodes in the combat network are connected to many more nodes and the same is true for edges as well.

Table 2.1: Characteristics of the Trust and the Combat Networks

Network	Nodes	Edges	Comp	$< Deg >$	LCC1	LCC2	LCC3	d
T_N	13,184	15,945	2,237	2.42	4,648	58	48	27
C_N	59,468	3,767,395	32	126.70	59,400	3	3	≤ 25

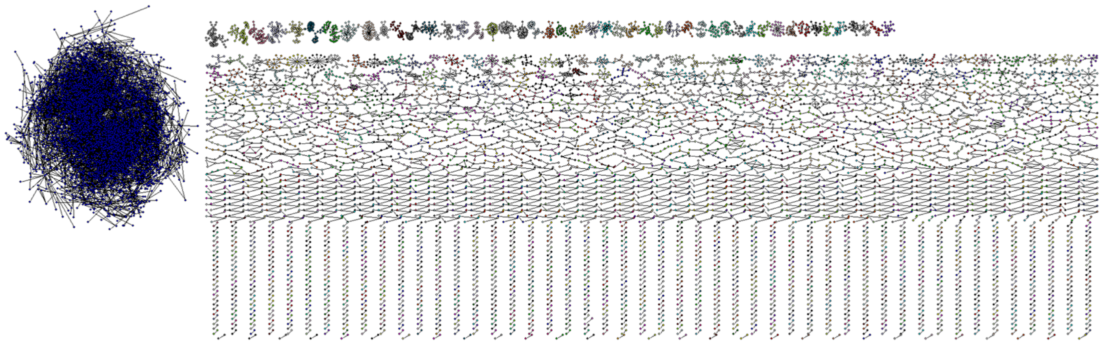


Figure 2.1: The Trust Network in August 31, 2006 (Guk)

2.4 Temporal Characteristics of Trust Networks in MMOGs

For any given social system network models only consider the nodes which participate in the network; however there are many situations where only a subset of the people may choose to participate in the social network while the rest of the nodes can either be treated as isolates or not considered part of the network at all. The dataset that we have also includes characters which did not take part in the either of these two networks under consideration. In Figure 4 we give the number of nodes in these networks on a weekly basis for the course of 8 months and we also show the total number of player characters which are present in the game. Similarly Figure 5 shows the distribution of edges over the same period of time. Another unique feature of this dataset is that it is also possible to record the death of nodes i.e., player characters who leave the game essentially leave the social network of the game.

2.5 Trust in Social Networks: Adversarial vs. Cooperative Settings

2.5.1 ERGM/p* Models

To explore the network level differences between the trust network in the adversarial environment vs. the cooperative environment we employed the Exponential Random

Graph Models (ERGM), also called p* family of models. The main idea behind ERGM models is to study local network processes which may lead to certain global structures in social networks. Consider a Social Network G with n nodes and let Y be the adjacency matrix of A i.e., $Adj(A) = Y$. If θ is the set of all possible network with nodes n i.e., it is the set of all obtainable networks. The distribution of Y can be parameterized as follows:

$$P_{\Theta,y}(Y = y) = \frac{exp\{\Theta^T g(y))\}}{\kappa(\Theta, y)}, y \in \nu \tag{2.1}$$

where is the vector of model coefficients and g(y) is a q-vector of statistics based on the adjacency matrix y. We can expand this model by replacing g(y) with g(y;X) to allow for additional covariate information X about the network as follows:

$$\kappa(\Theta, \nu) = \sum_{z \in \nu} exp\{\Theta^T g(z)\} \tag{2.2}$$

Which is the normalizing factor that ensures that equation 2.1 corresponds to a legitimate probability distribution. The maximum value for v can be $N = 2n(n-1)$ which implies that the model can easily run into scalability issues even for small values of n. Thus given a network and a model with statistics of interest the goal is thus to find maximum likelihood estimates of the coefficients for that model which gives one an idea about the relevance of those statistics in generating a network which corresponds to the model under consideration.

2.5.2 ERGM/p* Models for Trust Networks

Two p*/ERGM model were estimated, with Model 1 including edges and reciprocity, and Model 2 adding transitivity and generalized reciprocity. In both trust networks, Model 2 exhibits a better fit, as evidenced in both MLE likelihood and Akaike information criterion (see Table 2.2). Therefore, the following results and discussion are based on Model 2 only (see Table 2.3). As shown in Table 1, the trust network on PvE has 10527 nodes and 20576 connections (excluding self-trust), while the trust network on PvP server has 10058 nodes and 16245 connections (excluding self-trust). Both networks are notably sparse, as evidenced in the low density and the negative estimate for edges (Table 2). The ERGM estimation further showed that the PvP trust network (coefficient = -9.62669, p .001) is sparser than the PvP network (coefficient = -9.30390, p

.001), suggesting that people are even more selective in forming trust ties in adversarial setting.

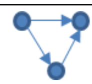
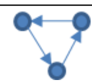
The PvE network did not display a structural tendency to reciprocate trust ties (coefficient = 7.51296, n.s.), while the PvP trust network shows a positive and significant tendency to do so (coefficient = 7.48238, p.001). This suggests that trust ties tend to be one-sided on PvE and bidirectional on PvP. It is possible that in a cooperative setting (PvE), a non-reciprocated trust tie is quite acceptable, while adversarial setting demands reciprocated trust relationship. The social context thus determines the norms associated with trust. Both PvE and PvP trust network have a significant and positive tendency to form transitive triads (A trusts B, B trusts C, and A trusts C). The PvP trust network also has a significant and negative tendency to form cycles (A trusts B, B trusts C, and C trusts A) but the PvE network does not have such a tendency. Taken together, it suggests that, compared with trust network in cooperative settings, trust network in adversarial settings shows a strong pattern to favor specific reciprocity (A trusts B, B trusts A) and to discourage generalized reciprocity (A trusts B, B trusts C, C trusts A). This finding suggests that trust network on PvP tends to be highly selective and specific. Trust is not given to just anyone in an adversarial setting. It demands reciprocation (in other words, trust is earned or exchanged). In addition, the mutual trust between two players is not easily transferred to affiliates. Only in specific circumstances (transitive triads, where A trusts B, and A also trusts Bs trustee), trust could be extended beyond dyads.

Table 2.2: Comparison of Trust Networks

Variable of Interest	**Trust Network on PvE**	**Trust Network on PvP**
Nodes	10,527	10,058
Edges	20,576	16,245
Density	1856919 x 10^{-4}	160597 x 10^{-4}
% Dyadic Reciprocity	0.538893	0.5575264
Model 1 (Edges + Reciprocity)	-144981.3 (289967)	-114706.1 (229416)
Model 2 (Model 1 + Transitivity +	-140269 (280546)	-110793.3 (221595)

Generalized Reciprocity)		

Table 2.3: Parameter estimates, standard errors, and significance

Parameters	**Network Structures**	**Trust Network in PvE** Coefficient	S.E	**Trust Network in PvP** Coefficient	S.E.
Edges		-9.30390***	0.06746	-9.62669***	0.03341
Reciprocity (Mutual)		7.51296	8.73223	7.48238***	0.44729
Transitivity (Ttriple)		1.59941***	0.32863	2.48497***	0.05356
Generalized Reciprocity (Ctriple)		-2.16273	1.18803	-2.99752***	0.73358

*** p 0.001; ** p 0.01; * p 0.05

2.6 Conclusion

While there has been a quite some work on social trust in online networks, trust in social networks has only recently been explored in any detail. In the current chapter some questions related to trust in cooperative as well as adversarial settings were addressed using exponential random graph models. The main takeaway from this chapter is that trust is manifested is differrent ways in different social setting i.e., adversarial vs. cooperative environment and the such differences can be captured by the differences in the social structure as manifested in the network signatures of the respective networks.

Chapter 3

Trust in Social Contexts

"You must trust and believe in people or life becomes impossible."
- Anton Chekhov

3.1 Introduction

As the World-Wide-Web has grown the number of possible ways in which people can interact with one another on the web has also grown tremendously. One way to facilitate interaction between people is through trust. Thus in many contexts and settings on the web people can express trust about one another [102] which facilitates future interaction between them. While there is an extensive body of literature on trust, it has also been noted that people may refer to slightly different concepts when they refer to trust [67]. Additionally in different types of contexts trust is operationalized differently, trusting other people in computer mediated communication or interaction environments usually refer to Social Trust [102]. In this chapter we limit our analysis to networks with Social Trust. It should be noted that even in the case of social trust, trust may mean different things in different context e.g., in Trust based recommendation networks like FilmTrust [67] and Epinions [124] trust is with respect to recommendation, in online virtual worlds like EverQuest II (EQ2) trust is defined in terms of access to a commodity like a virtual house. The phenomenon of trust in social networks has been studied in various contexts e.g., making recommendations [124], access control [22], spam filtering [66] etc. However Golbeck [102] notes that almost all of the studies of trust in social networks have used a single social network for analysis and the results may not be generalizable. Thus it is not clear if the characteristics of trust networks across different domains or even within the same domain like recommendations are sufficiently similar. Thus a first step towards addressing these issues is to analyze these networks and determine how similar these networks are and determine if there is an underlying generative process across multiple trust based social networks. In this chapter we address this problem by analyzing network properties of various trust networks, especially exchange. It should be noted that while many of the global properties of the trust networks are similar to what have been observed in many real world networks [125], it is the local properties of these networks that distinguish them from one another and these properties can be linked back to social processes which are prevalent in these networks. While there is an extensive body of literature on social networks [167], we limit our analysis to properties related to Social Exchange like reciprocity, triads and other motifs. The contributions of this chapter can be summarized as follows:

- Comparison of Network Exchange related properties of trust based social networks and other networks.
- Discovery of similar triadic distributions for trust networks.
- Analysis of how operationalization of networks affects measurement of exchange.
- Methodology for measuring Generalized Exchange in social networks.

3.2 Related Work

One of the earliest studies on trust based social networks was on the FilmTrust dataset by Jennifer Golbeck [67] who studied the problem of trust-based recommendations and the use of trust networks to create an e-mail filtering application [66]. There have been numerous studies on propagating Trust in social networks e.g., Guha et al [74] proposed a method to infer trust in cases where there is no direct interaction between users, other trust propagation techniques have been proposed in [96]. There is another body of literature on trust in P2P Networks [97] and trust in multi-agent systems [143]. A comprehensive survey of trust in various fields in computer science is given by Artz and Gil [22].

There are a number of generative models of social networks like the Preferential Attachment Model [24], the Small World model [183], Forest-Fire model [118], Butterfly model [125], RTG etc. Most of these models however concentrate on replicating the global properties of these networks. On the other hand statistical models of evolution of networks like ERGM or $p*$ family of models use small network structures or motifs to study social processes in the evolution of social networks [167]. Similarly the MTML framework of Monge and Contractor [131] describes various social processes in terms of network motifs.

This implies that models of social networks should take into account the presence of various types of network motifs. Network motifs have been studied in various domains like biological networks, the World Wide Web and social networks. [129]. It has been observed that the network motifs in one class of networks e.g., brain network of worms are different from those observed in engineering networks [129]. It should also be noted that while domain independent models of network evolution offer insights about generalities across domains there may also be cases where the social networks in certain contexts do not behave like other common networks e.g., mentoring networks [15].

3.3 Network Datasets

We use a total of 13 networks for a comparative analysis, 7 of these were trust networks from four different datasets. Table 3.2 gives the various characteristics of these networks.

Table 3.1: Server Types in EQ2

Server Name	**Server Type**
Antonica	Role-Playing Server
Bazaar	Player vs. Environment Server with Allows real money Transactions
Guk	Player vs. Environment Server
Nagafen	Player vs. Player Server

3.3.1 Trust Based Social Networks

The operationalization of trust in these various networks is different but the semantics of the trust relationship sufficiently overlap so that a cross comparison can be made. The various trust networks that we use in our study are as follows:

- Epinions: Trust in Epinions [124] is defined in terms of trusting another persons recommendations with respect to products. Distrust is defined in an analogous manner.

- FilmTrust: Trust in FilmTrust [67] is defined in a manner very similar to Epinions but with the difference that the space of trust values does not include distrust.

- Slashdot Zoo: In Slashdot Zoo users can specify other users as Friend or Foe [108], these can considered as proxies for trust and distrust since the friends and the foes are usually described in terms of reactions of users to others postings.

- EverQuest II: The trust network in EQ2 is access based with respect to a virtual house that a player character can own in the game. The level of access that a player character grants to another character defines the trust between them. Data from four different servers is available, each of which represent different types of gameplay as given in Table tab:server$_{t}$*ypes*.

3.3.2 Additional Networks

In order to do a fair comparison we compared the trust networks with other non-Trust related networks. These Networks included Mentoring Network from EQ2 [14], Chat Network from EQ2 [88], Trade Network from EQ2 [15] Biological Networks (Protein-Protein Interaction Networks [143]), e-mail Networks (Univeristy Rovira-i-Virgili e-mail Network [75]), and the World Wide Web [24]).

Table 3.2: Network Characteristics of Various Networks

Type	**Network**	**Nodes**	**Edges**	**d**	{bfseries ρ
Trust	EQ2 (Guk)	15,465	30,991	37	0.2840
Trust	EQ2 (Antonica)	23,292	53,584	24	0.3513

Trust	EQ2 (Nagafen)	13,184	20,873	24	0.3090
Trust	EQ2 (Bazaar)	14,513	35,117	26	0.3676
Trust	FilmTrust	571	1,289	10	0.1791
Trust	Epinions	131,828	841,372	16	0.3310
Trust	Slashdot Zoo	79,120	515,581	15	0.1017
Bio	Protein-Interaction	2,361	7,182	11	-0.0012
Chat	EQ2 Chat	5,629	30,209	15	0.803
Mentor	EQ2 Mentoring	23,207	92,079	39	0.0085
Trade	EQ2 Trade	31,900	1,796,438	<30	0.4333
e-mail	Virgili e-mail	1,134	10,903	1	1
WWW	Norte Dame	325,729	1,497,135	19	0.3481

3.4 Exchange in Trust Networks

Exchange refers to the movement of information or resources from one entity to another entity. The form of exchange that may occur in a network is dependent upon the topology of the network. Two main types of exchange processes have been recognized: Generalized Exchange and Specialized (or Restricted) Exchange [59].

Generalized exchange is organized around a community whose members are linked "in an integrated transaction in which reciprocations are indirect, not mutual" [59]. Triads, n- Rings and other more complicated sub-graphs or motifs can be used as proxies generalized exchange. A general agreed upon objective measurement for generalized exchange does exist. Specialized exchange is organized around exchanges between two parties, each of whom benefits directly from interactions and transactions with the other.

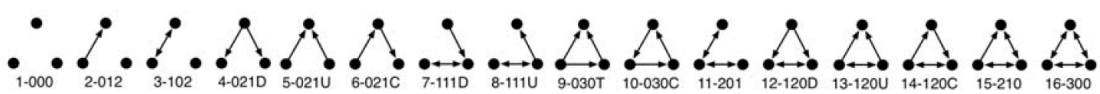


Figure 3.1: Structure of 16 possible triads

3.4.1 Specialized Exchange in Trust networks

Thus specialized exchange can be studied in terms of reciprocity. If $L^{\leftrightarrow}$is the number of edges in either direction, and L is the total number of links then reciprocity is traditionally [167] defined as:

$$r \equiv \frac{L^{\leftrightarrow}}{L} \tag{3.1}$$

Garlaschelli and Loffredo [62] note that there a number of problems with this measure of reciprocity e.g., it does not take into account the presence of reciprocity because of some generative process within the network as compared to reciprocity in random networks and it also does not give a relative ordering of reciprocity which can be compared across networks. To address these issues they define reciprocity as the correlation coefficient between the entries of the adjacency matrix of a directed graph, if N is the total number of nodes and

$$\overline{a} = \frac{\Sigma_{i \neq j} a_{ij}}{N(N-1)} \tag{3.2}$$

The correlation coefficient for reciprocity, as defined by Garlaschelli and Loffredo [62] can be given as follows:

$$\rho = \frac{L^{\leftrightarrow}/(L-\overline{a})}{1-\overline{a}} = \frac{r-\overline{a}}{1-\overline{a}} \tag{3.3}$$

It should be noted that $\rho = 0$ implies an areciprocal network while $\rho = 1$ implies a network with perfect reciprocity. Garlaschelli and Loffredo [62] also observed that similar types of networks like e-mail networks, biological networks, trade networks etc have similar values for reciprocity. In the various trust networks we are observe a similar phenomenon. The values of reciprocity for the trust networks in EQ2 are close to one another. Thus consider the values for reciprocity for various networks given in Table 3.2. The values for reciprocity for the various trust networks in EQ2 are within a narrow range for reciprocity, while Slashdot Zoo and FilmTrust exhibit very different value for trust. We should note that both Slashdot Zoo and Epinions allow negative values for edges, which correspond to distrusted individuals or foes. Interestingly the values for reciprocity for Epinons are closer to those for the EQ2 networks. At first glance one would expect Epinions and FilmTrust to have similar values for reciprocity since both of these trust networks are about recommendations. There is however one subtle but important difference here, in FilmTrust there is only one type of category for recommendation i.e., movies but in case of Epinions there are hundreds of categories

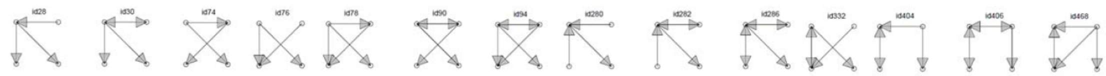


Figure 3.2: Structure of the various trust motifs

where people can recommend products to one another. Thus the judgment to trust or not trust another person in Epinions is with respect to a set of products and product category and is a more general type of trust in the context of recommendations. An ever lower level of reciprocity is exhibited in case of Slashdot Zoo. This could be because in addition to normal users there are also a number of 'trolls' [108] present in the Slashdot Zoo network which skews the distribution of trust and distrust. Two different graphs with the same number of nodes but with a different topology can still have the same value for reciprocity. B. Generalized Exchange in Trust Networks While there have been a number of studies on generalized exchange [59], to the best of our knowledge, a quantitative measurement of the generalized has not been proposed. We address this deficiency by proposing such a measure based on the clustering coefficient. We however note there are multiple definitions of the Clustering coefficient [143], here we use the following definition where the Generalized clustering coefficient of a graph G is defined as follows:

$$C(k) = \frac{\delta(k)}{p(k)} \tag{3.4}$$

Where $\delta(k)$ is the number of cycles of length k in the graph and $p(k)$ is the number of paths of length k in the network. If C_r is the clustering coefficient of a random graph with the same number of nodes and edges as G, we define the Generalized Exchange Ratio as:

$$\gamma(k) = \frac{C(k)}{C_r(k)} \tag{3.5}$$

Note that $\gamma(k)$ is a relative measure of Generalized Exchange, given graphs G_i and G_j if $\gamma i(k) > \gamma j(k)$then one can say that generalized exchange is more prominent in G_i as compared to G_j. If $\gamma(k) < 1$ then that means that generalized exchange is not being observed in the network while $\gamma(k) < 1$ implies that some form of network exchange is observed in the network. There are however two issues that should be addressed here and require the formula to be modified. Firstly, it is possible that the denominator in the last equation is extremely small or zero e.g., consider a graph $G_i(n = 10,000)$ which consists of a cycle of length n. In this case $C_i(K) = 1$ but $C_i(K) = 0$. In this case the Generalized Exchange Ratio would be undefined, alternatively if we take the expected value of the formation of a cycle of length n in a random network then $C_i(K) = \epsilon$, where ϵ is an extremely small number $\epsilon > 0 and \gamma j(k)$ would be an extremely large number. Secondly one can get very different values for $\gamma(k)$ for different values of k. A single measure of Generalized Exchange should take into account cycles of different length based on the domain. We thus propose the following generalization of the Generalized Exchange Ratio as follows:

$$\gamma(k) = \sum_{j \in N} \alpha_j \frac{C(j)}{C_r(j)}, where \quad \sum_{j \in N} \alpha_j = 1 \tag{3.6}$$

Where α_j gives the relative importance of Generalized Exchange ratio for length j where j is always greater than 2. We note that the choice of the set of values for N and α_j would be domain dependent. We use this formula to compute the generalized exchange ratio for the various Trust Networks for $N = 3, 4, 5, 6$ and we set the quantity equal to $1/|N|$ or 0.25. The values for the Generalized Exchange ratio as well as reciprocity which measure Specialized Exchange is given in Table 3.3. As expected the Trust networks in EQ2 exhibit higher values for Generalized Exchange as compared to other networks except Epinions. Within the EQ2 networks Bazaar has a higher value for Generalized Exchange as compared to the other networks. This is to be expected since the Trust network in Bazaar is a market related trust network and the literature indicates [59] that Generalized Exchange is more likely in trade based networks. Interestingly Epinions and FilmTrust have divergent values for Generalized Exchange even though both of these are trust networks in a recommendation based setting. One possible explanation could be that Epinions involves single individuals rating products and so contributing to a community, whereas FilmTrust combines ratings with social networking, thus establishing reciprocal ties among members and fostering restricted exchanges. This underscores the importance of considering which type of exchange corresponds to the mechanisms on the sites and not assuming simple restricted exchange is sufficient.

Table 3.3: Generalized Exchange Ratio for Trust Networks

Network	$\gamma(k)$	ρ
EQ2 (Guk)	5.19	0.28
EQ2 (Antonica)	5.17	0.35
EQ2 (Nagafen)	5.23	0.31
EQ2 (Bazaar)	7.67	0.37
FilmTrust	1.14	0.18
Epinions	7.71	0.33
Slashdot Zoo	2.18	0.10

3.5 Network Motifs

Network motifs have been identified as important network attributes to characterize different types of networks[129]. In this section we use and extend this idea to differentiate various types of networks and argue that a set of motifs can be used to differentiate various types of trust networks and study exchange. In this chapter we limit our study to motifs of size 3 (triads) and 4. Figure 3.1 enumerates all the possible triads [143] and Figure 3.5 gives the distribution of all these triads in the trust networks. The x-axis gives the id of the triad which corresponds to triads from Figure 3.1 and the y-axis gives the log of the value for the relative importance of each type of triad in a network computed in Pajek [140] as follows:

$$\tau = \frac{n_i - e_i}{e_i} \tag{3.7}$$

Where n_i is the number of triads and e_i is the number of expected triads in a random network. It is interesting to note that the distributions of various trust networks are similar to one another which also indicate that the triadic census is not sufficient to distinguish these trust networks from one another. For the same types of networks the distributions for the triadic census are quite similar. This indicates that there is a fundamental difference between these networks even at the local level and it can be gauged from the triadic census. To characterize differences between these networks at a finer grained level we give a summary of the trust networks in terms subgraph concentration for sub-graphs of size 4, which can be defined as follows:

Subgraph Concentration: Given a graph G and a subgraph g_i of n-nodes, the subgraph concentration [140] of g_i is defined as the ratio of number of times N_i graph g_i appears in graph G there are k such graphs then the subgraph concentration is as follows:

$$C_i = \frac{N_i}{\Sigma_{j=1}^{k} N_j} \tag{3.8}$$

For computing the number of subgraphs in a network we used MFinder program [140]

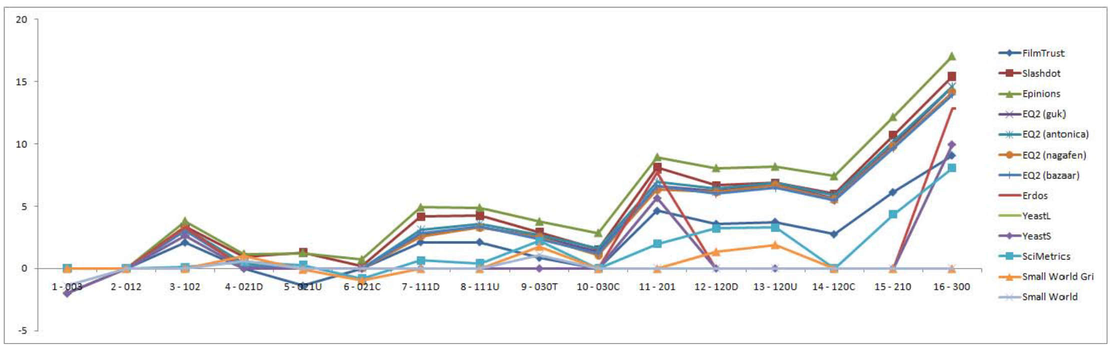


Figure 3.3: Triadic Census for all the Triadic motifs for the various Networks

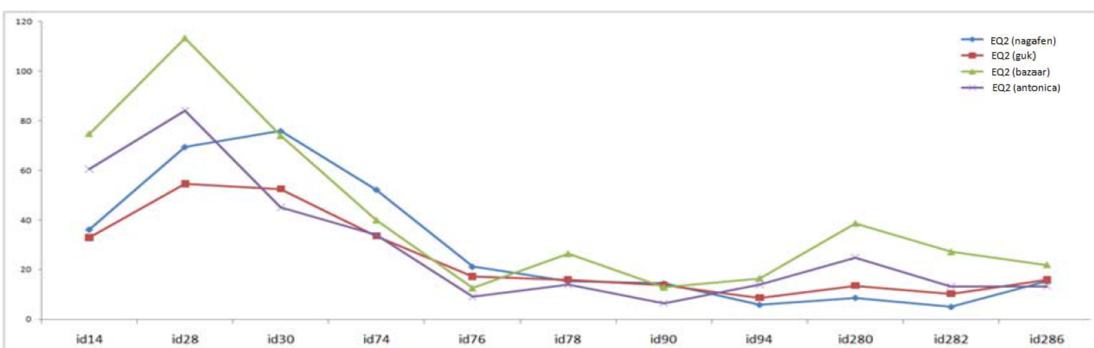


Figure 3.4: Distribution of values of Sub-graph concentration for 4-motifs in the Trust Networks

which employs the sub-graph enumeration algorithms described in [129]. For each of the four networks from EQ2, top k=7 motifs were taken and the union of motifs from these networks resulted in 14 motifs 3.2. The distribution of these motifs are given in Figure 3.3 for the Trust Networks in EQ2. From this figure it is evident that Bazaar and Antonia Bayle exhibit similar distributions while Guk and Nagafen exhibit similar distributions. Guk and Nagafen are more similar to each other because in these servers the focus is on the core game mechanics of fighting, questing, raiding and PvP, while on the Bazaar and Antonia Bayle, that focus is shared with the other goals of role playing and real-money trading, which are more likely to result in community level exchange. In terms of the meanings of the networks, the triadic census indicates that all these networks are driven primarily by restricted exchange with small elements of generalized exchange indicated in triads 12 and 13. When we get to the four node motifs, there is more evidence for generalized exchange, which would make sense since most of Levi-Strausss generalized exchange patterns had four actors [59]. The graphs suggest that all four worlds have strong elements of generalized exchange, with restricted exchange showing up in id30. Bazaar is the strongest in terms of generalized exchange. This makes sense since selling or trading is likely to be not as reciprocated as trust is in grouping activities. Here we limit our analysis to the networks in EQ2 since temporal information is only available for these networks.

3.6 Exchange in Trust Networks with Birth and Death of Nodes

Most models of network generation and evolution assume that once a node is part of a network it will continue to be part of the network. This is however not always true since in social networks people may decide to leave a social network after some time. However most of the trust datasets which are available have information only about node arrival but do not have any information about node departure from the social network. The EQ2 trust networks are an exception since they have information for node arrival and node departure from the network. In other networks it is not always possible to determine if a node has left the network because of lack of activity does not necessarily imply node departure. In case of EQ2 network it is possible to determine the date of departure as account cancellation information for the corresponding node is available.

Since this information is available for the EQ2 Trust networks, we use it to construct these networks with only the nodes which are active and compare it to previous results. Unsurprisingly the distributions of the motifs at the triadic level remain almost unchanged but the values of sub-graph concentration change. The change is not substantial so that the overall distributions of the various 4-motifs are similar. Figure 3.4 gives the distributions of the various graph concentrations, with and without considering the active nodes. The results imply that the overall interpretation of similarities or differences between the graphs still holds, additionally the behavior of the graph at the aggregate level as well as level of active nodes is similar.

Table 3.4: Exchange in Trust Networks

Network	$\gamma(k)$ **Accumulative**	$\gamma(k)$ **Active**
EQ2 (Guk)	5.19	2.89
EQ2 (Antonica)	5.17	4.80
EQ2 (Nagafen)	5.23	3.07
EQ2 (Bazaar)	7.67	6.01
FilmTrust	1.14	-
Epinions	7.71	-
Slashdot Zoo	2.18	-

However one major difference which is observed is that the value for the Generalized exchange ratio greatly changes for all the networks where temporal information is available as shown in Table 3.3. In all the four trust networks from EQ2 the value for Generalized Exchange for these networks decreases and while the ordering remains more or less the same, change in the differences between the two cases changes the interpretation of the results. If we take the values for the Generalized Exchange ratio for the accumulative network then the values for all the networks except Bazaar are fairly close to one another but in the case of the active network the values vary greatly 3.5, 3.6. This would imply that the previous conclusion based on the accumulative network that these networks have similar types of generalized exchange is no longer valid. A marked difference is also seen in the case of Antonica versus others. Table 3.4 also seems to indicate that the new values for Bazaar and Antonica are similar to one another which is consistent with the previous results. These observations seem to indicate that while the operationalization of the network may not have a significant impact on some measurements of exchange like triads and 4-motifs, it does impact the measurement of Generalized exchange. Thus for future studies these factors should be taken into account.

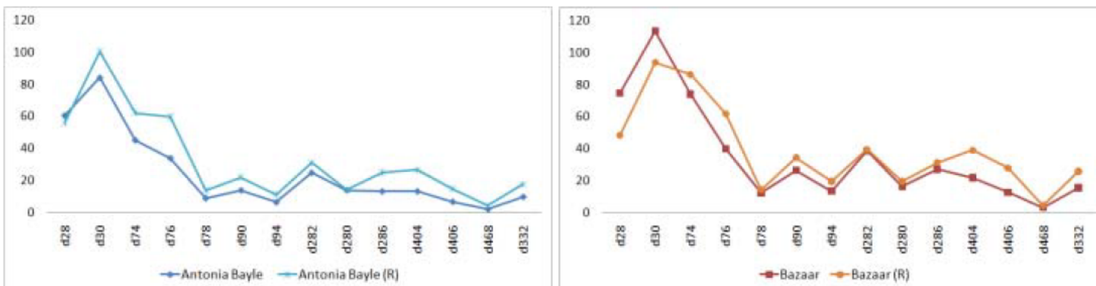


Figure 3.5: Comparison of distributions of Prominent Motifs for the various servers with and all the nodes and with only active nodes (i)

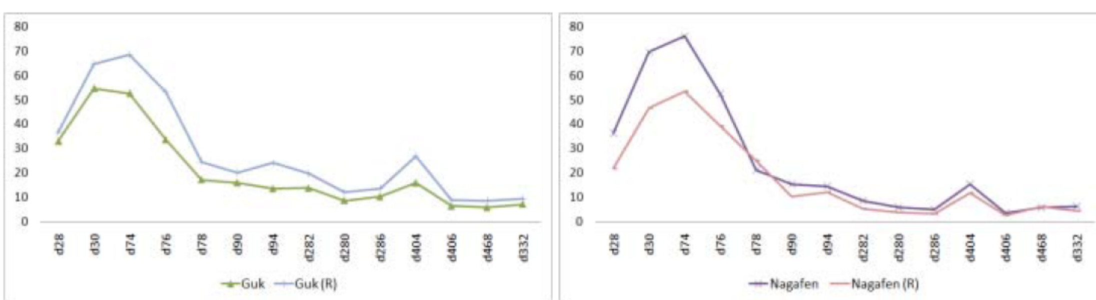


Figure 3.6: Comparison of distributions of Prominent Motifs for the various servers with and all the nodes and with only active nodes (ii)

3.7 Conclusion

Trust is an important element of social interactions. While a number of studies have been done on trust in social networks, comparative studies of such networks are somewhat rare. In this chapter we studied exchange in various trust networks in terms of reciprocity, triads and 4-motifs. Given that there is not an objective metric for Generalized Exchange we also introduced a metric to measure Generalized Exchange. Reciprocity for various networks was computed and it was observed that a class of trust networks has similar values for Trust. Even though some trust networks have different values for reciprocity, the distribution of the various structures in the triadic census for the trust networks is quite similar while it is quite different from non-Trust related networks. This leads us to conjecture that there is a common mechanism driving the evolution of trust networks. Additionally we proposed the use of motifs of size 4 to separate out various trust networks. Even in this case, some networks exhibit similar distributions for the most prominent motifs, again pointing to similarities in structure and process. In order to illustrate how reciprocity and the distribution of triads may be related, using the underlying network from the FilmTrust network. The results from the triadic and four-node motif analyses indicate that trust networks are generated by both restricted and generalized exchange processes, though the relative influence of the two mechanisms may differ across networks. To the best of our knowledge it is the first comparison of multiple trust networks.

Chapter 4

Trust, Expertise and Homophily

"Do not trust all men, but trust men of worth; the former course is silly, the latter a mark of prudence."
- Democritus

4.1 Introduction

The Homophily principle argues that there is a strong relationship between association and similarity, thus, people with similar characteristics get along with more ease as compared to people who are different. The similarity-attraction hypothesis [58] and the theory of self-categorization [131] are usually given as the basic arguments behind homophily principle [154]. The similarity-attraction hypothesis posits that people who share similar traits are likely to interact at a higher rate. The theory of self-categorization argues that people have a tendency to categorize themselves and others in terms of observed socio-demographic factors. This categorization helps people to differentiate between us and them which act as a relational filter [111]. Existing research on homophily has firmly established strong homophilous behavioral association patterns influenced by race, ethnicity and attitudinal prejudice. Age was found to be an individual as well as mediating factor that determines the strength of other factors influence [131]. Lazarsfeld and Merton [111] distinguished status and value as two types of homophily. Status homophily includes similarities based on informal and formal socio-cultural and economic dimensions that stratify society (i.e., race, ethnicity, gender, age, etc.) or ascribed and acquired status (i.e., profession, education, behavioral characteristics, etc.) of an individual. Value homophily is based on values, attitudes, and beliefs [128].

Homophily in the network perspective implies that distributed team members have a higher probability to form task-related ties with people of racial and gender similarity [111]. These kinds of ties are known as instrumental network ties. People develop such ties to exchange information or resources required for task completion [111]. Homophily in task environments, therefore, could be a factor with a positive influence as similar people could understand each other better. A better understanding, then, leads to conflict resolution and trust development. Empirical studies have already established conflict as negative factor for team performance and satisfaction. Conflict produces tension and antagonism that distracts team members from performing the task effectively [64][154][177]. On the other hand, majority of the trust-related research support trust as a positive factor for group process and performance [58]. Although trust can be viewed as a rational or social perspective, majority of the perspectives view trust as a rational one. From a rational perspective, trust is based on the expectation that other will behave as anticipated, whereas from social perspective it is a moral duty to trust specific people, idea, or action. The idea of trust, therefore, leads one to believe in a strong relationship between homophily and trust.

The tendency of people to trust people who are similar has also been noted in the social computing literature [69]. The identification of experts based on their activities and trust based social networks has been demonstrated in many systems [16]. Monge et al relate these two in the context of the MTML framework [131]. While there is a vast body of literature on trust in social networks especially with respect to recommendations, trust inference and propagation etc. [69], the focus of this chapter is on the social and computational modeling related aspects of trust in MMOs. The issue of trust in MMOs has been addressed before. Thus Ahmad et al [13] described the network characteristics of various trust networks including four trust networks in EQ2 for comparative purposes and observed that trust network which are generated by similar social processes have similar network characteristics as well. They also address the problem of trust prediction in the context of MMOs [9]. Lastly the problem of structural signatures of subpopulations within trust networks in MMOs has been explored within the context of clandestine networks [8].

Massively Multiplayer Online Games (MMOs) are online games where hundreds of thousands and even millions of players can simultaneously share a persistent virtual world and interact with one another. We use data from a well-known MMO called EverQuest II (EQ2) in this chapter to study the phenomenon of interest. Previous work on the similarity and differences between social phenomenon in online virtual worlds and the offline world has established sufficient mapping [199] between the two that it is possible to make inference about the later based on the former.

Trust in EQ2 is defined in terms of access to the house i.e., a player can give access to other players by explicitly specifying how much she trusts them. There are many different ways in which homophily can be defined in EQ2. In this section we create a topology of factors, based on that literature discussed earlier, directly related to homophily in not just EQ2 but to MMOs in general. These factors are given in Figure 4.4. As described previously, the literature describes two types of homophilies which can be mapped to our present context: Status homophily and Value homophily. Status Homophily consists of two types of characteristics: Ascribed and Acquired characteristics. Ascribed characteristics refer to the characteristics of a person which they have by the virtue of their background e.g., gender (biology) or race (biology and society). Acquired characteristics on the other hand refer to the characteristics which people can acquire over the course of time e.g., skills, character attributes etc as given in Table 4.4. Value Homophily is described in terms of similarity of values that people hold. While value homophily can be described in multiple ways in the offline world, in a game setting there are since the only data which is available is behavioral data, it has to be inferred indirectly. Here we describe value homophily in terms of similarity defined in terms of how players respond to challenge i.e., do they actively seek tasks that require challenge or just play average quests and engage mostly in mundane tasks. There are multiple ways to define expertise in MMOs. Huffaker et al [88] note that there are two main aspects of expertise in MMOs: Achievement and Performance. It is their definition of Expertise that we use here.

Homophily Types	Sub-category	Variables	Description
Status	Ascribed characteristics	gender	Player gender
		age	Player age
	Acquired characteristics	Class*	MMO professional class
		Guild membership	
		Location	
		Player level	
		Race*	Character race
		* Though class and race are ascribed characteristics in the real world, it is a matter of choice in MMOs – therefore, labeled as acquired characteristics.	
Value		Time needed for level change	Average time of a player to climb up “Player level” - support “aspiration” idea of value Homophily – hypothesis is that players will like to see similarity in climbing up levels among their peers (mentor- mentee relationships as exceptions)
		Quest difficulty level	Explain the idea of “challenge” a person like to take in the game – hypothesis is that players like challenge are more likely to group together.

Figure 4.1: The Space of Homophilies in MMOGs

4.2 Dataset

For studying the characteristics of trust in EQ2, we use data from one of the servers (Guk) spanning from January 1, 2006 to August 31, 2006. The dataset contains 15,237 player characters. A player account can have multiple characters associated with it and thus the data can be analyzed at either the character or the account level. Following the approach used in previous research on EQ2, [8][13] [9] [8] [11] [14] [88] we take the player characters as the unit of analysis. Trust Networks in MMOs.

A trust based social network can be constructed on the basis of who gives trust access to whom within the game. Based on this scheme we construct a trust network of players in EQ2. The network consists of 15,237 nodes, 30,686 edges and 1,476 connected components. This implies that the nodes have an average degree of 4.03. The size of the three largest connected components are as follows: 9,039, 51 and 49. The largest connected component accounts for 59

Figure 4.2 and 4.3 show the growth of the number of node and edges over time. Figure 4.4 shows the sizes of the three largest connected components as percentage of

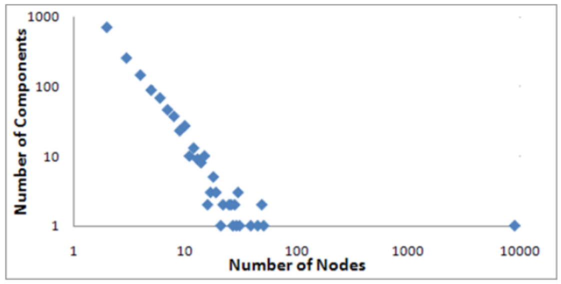


Figure 4.2: Distribution of Component Sizes

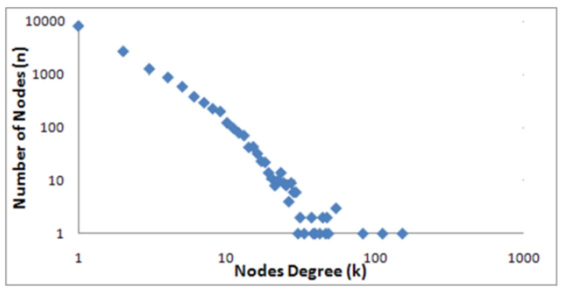


Figure 4.3: Distribution of Node Degrees

the total nodes in the network. LCC1, LCC2 and LCC3 correspond to the largest, the second largest and the third largest connected component respectively. There are a few things to note here that present which are not observed in most other social networks [14] [116] [117] [125] [183]. Thus, for example a difference between this network and social networks which have been observed in a large number of other domains is that the diameter of the network does not monotonically decrease over time [125]. In the case of the trust network, the diameter fluctuates and then somewhat stabilizes after week 10 as shown in Figure 4.4. Another common observation in the literature in social networks [117] [125] is that there is usually a gelling point after which the largest connected component accounts for the majority of the nodes in the network. We observe a similar phenomenon in our network, however one major difference is that at the gelling point 4.4, the largest connected component accounts for around 20 percent of all the nodes by mid-February and it grows much slowly so that by the end of March it accounts for close to 40 percent of all the nodes and around 60 percent of the nodes by the end of August. In terms of percentage, the amount of time that it takes for the network to gain the proportion of the network grows longer and longer.

An interesting thing to notice here which is not seen in many other networks [125] is that in addition to the presence of a large connected component and a few smaller ones, there are a large number of components which are very small in size and which are effectively isolates. Thus out of the 1476 components there are 1,455 components which have 20 nodes or less. Again this observation is in contrast to most other social networks [117] [125]. In terms of game dynamics the reason why this is observed is because there are many players who frequently play with a small group of other players without much interaction with others.

From these figures it is evident that the evolution of the network in terms of the increase in the number of nodes, edges and the components is very similar to what has been reported for social networks in general but not in some respects. McGolohan et al [125] observed that in many social networks the size of the second and the third largest connected components remains constant after the gelling point even though the identity of these networks changes. We observe a similar phenomenon in Figure fig:homophily1. However consider (e) in Figure fig:homophily1 which shows the ratio between the sizes of the second and the first largest connected component. By February 8 the largest connected component is already five times the sizes of the second largest one and by the end of March the relative size of other components is negligible as compared to the largest connected component. Based on these observations one can say that there are certain characteristics of trust networks in MMOs which set them apart from social networks observed in other domains. One possibility is that this could be because of the peculiar nature of MMOs, as has been observed for mentoring networks in MMOs [11][14]. The differences between the trust network in MMOs and other social networks in general can be summarized as follows: (i) Non-monotonic change in the diameter of the network. (ii) A large percentage of the nodes as being part of components other than the largest connected component. (iii) At the gelling point and even a long time after it, the majority of the nodes are not part of the largest connected component. (iv) Presence of a large number of components which increase monotonically over time. It should be noted that while it possible that these properties may be peculiar to not just trust networks in MMOs but other networks as well. We can however rule out this possibility because previous literature on the subject shows that this is not the case [9] [14].

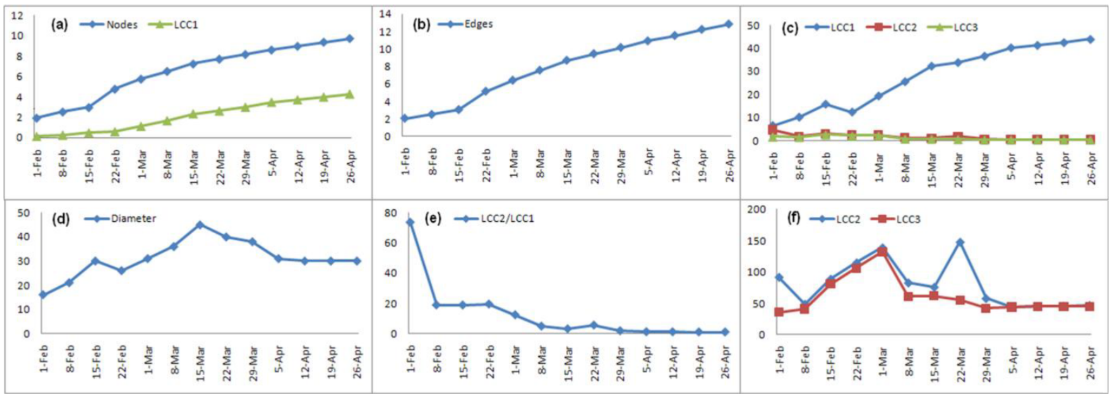


Figure 4.4: The Characteristics of the Trust Ntework

4.3 Trust And Homophily in MMOs

In this section we describe and try to find support for some hypothesis regarding trust. The homophily related hypotheses are derived from the topology described in Table 4.4, quest difficulty level and location are not included from Table 4.4 as the data for these was not available.

- **H1 (Gender Homophily):** Players trust other players who have the same gender: Table 4.2 gives the distribution of various types of edges in the data and how players of one gender trust players from the same or different gender. The table indicates support for the gender homophily hypothesis since the majority of the trust relationships are between people who are of the same gender.

- **H2 (Age Homophily):** Players trust other players who are of the same age cohorts: Table 4.3 shows the average age difference between players for the various age types. Here we see a significant difference between the Trustee type of relationship and other trust relationship. We note that trustee is the only trust relationship in EQ2 where a significant risk is involved in the relationship and here we do observe that the age difference is much less as compared to the other types of relationships. This provides some evidence that players trust each who are in the same age cohorts. The table also indicates that the stronger the trust type the lesser is the age difference.

- **H3 (Class Homophily):** Players trust other players who are of the same class: As noted previously, class in MMOs is acquired characteristics unlike the offline world where it is mostly an ascribed characteristic. Table 4.3 shows the distribution of instances where the players have the same and different class. In contrast to the offline world where class homophily is observed, strong support is observed for the opposite hypothesis i.e., players do not tend to trust or associate with players who have the same class. In MMOs this difference can be readily explained since the game is designed such that in order for large quests or tasks to be successful players with different skillsets and thus different classes have to group together. Age Homophily in the Trust Network

- **H4 (Race Homophily):** Players trust other players who are of the same race: The distribution of trust relationships between different and same race players is given in Table 4.4 and the results are similar to what was observed for Class Homophily. We note that the race in this case is the race of the virtual character and not the race of the player. The prevalence of majority of the edges between players of different races is observed for the same reason that the game is designed such that success hinges upon making relations with players of a different race.

- **H5 (Guild Homophily):** Players trust other players who are of the same guild: Guilds in MMOs are analogous to organizations or membership clubs in the offline world. Since only a subset of the players ever join a guild, we restrict or analysis to only such players. The distribution of trust relationships in Table 4.5 does not give credence to this hypothesis since the majority of these relationships are outside the guilds. This is a somewhat surprising result since guilds can are usually a strong form of socialization [190].

- **H6 (Level Homophily):** Players trust other players who are at a similar level: In Table 4.6 we compute the level difference between the players at the time when a trust edge is formed between them and it does not reveal any significant differences. However if we break down the relationship further in terms of what was the level difference when the trust relationship was formed then another pattern emerges. Table 4.6 shows the relative levels of players when the edge was formed and the percentage of edges of the total for which the relative levels were observed: In the case of the Trustee relationship the majority of the access grants are associated from the lower to the higher levels while in the case of friend relationship the opposite is true. A possible explanation is that risky behavior is associated with lower level players with respect to the higher level players but not vice versa. Thus it can be concluded that support for level homophily is not observed.

- **H7 (Challenge Homophily):** Players trust other players who have similar values: It is not possible to get the data regarding what kind of values do people have. The closest substitute is how player play the game i.e., in terms of challenge which can be measured in terms of rate of leveling i.e., the number of levels passed divided by time (in minutes). Thus Table 4.7 gives the average difference between the players in the network for this metric. In this case as well there is no discernable pattern in how the players trust one another and the difference between them is sufficiently great such that homophily can be ruled out for trusting one another.

Table 4.1: Gender Homophily in the Trust Network

Trust Type	**Total Edges**	**Same Gender**	**Diff. Gender**	**% Same Gender**
Trustee	17,074	13,056	4,018	76.47
Friend	5,758	3,750	2,008	65.13
Visitor	1,523	983	540	64.54

Table 4.2: Age Homophily in the Trust Network

Trust Type	Total Edges	$< A_i - A_j >$
Trustee	17,157	4.04
Friend	5,794	8.43
Visitor	1,546	9.37

Table 4.3: Class Homophily in the Trust Network

Trust Type	Total Edges	Same Class	Different Class	% Same Class
Trustee	2,774	49	2,725	1.74
Friend	1,367	32	1,335	2.29
Visitor	422	18	404	4.09

Table 4.4: Race Homophily in the Trust Network

Trust Type	Total Edges	Same Race	Different Race	% Same Race
Trustee	2,774	174	405	5.90
Friend	1,367	118	1,249	7.95
Visitor	422	43	379	9.25

Table 4.5: Guild Homophily in the Trust Network

Trust Type	Total Edges	Same Guild	Different Guild	% Same Guild
Trustee	8,979	7,848	1,131	46.64
Friend	2,889	1,962	927	40.45
Visitor	728	408	320	35.92

Table 4.6: Level Homophily in the Trust Network

Trust Type	Total Edges	$< L_i - L_j >$
Trustee	16,826	21.92
Friend	5,756	16.69

Visitor	1,538	17.14

Table 4.7: Value Homophily in the Trust Network

Trust Type	**Total Edges**	$< L_{Ti} - L_{Tj} >$
Trustee	16,826	879.55
Friend	5,756	781.57
Visitor	1,538	800.00

Generative Models for Trust in Social Networks in MMOs In the previous sections we have described the various aspects of trust formation in EQ2 with respect to homophily and expertise. It should be noted that the current models for graph generators [95][14][24][116][117][125] do not incorporate the peculiar network properties that we described in section IV. We refer the reader to the relevant literature for the corresponding network properties of the network genertors [116][117][125] because of limitayons in space. We employ the Preferential Attachment model [24] as our starting point. Given a initial set of m_0 nodes such that $m_0 > 1$ and the degree of the nodes also greater than one, new nodes are added to the network with a probability proportional to the number of links that an existing node n_i already have and is given as follows:

$$p_i = \frac{k_i}{\Sigma_j k_j} \tag{4.1}$$

Where ki is the node degree of the node ni. This model is basically the rich get richer model. We note that in our data there seems to be an upper bound with respect to trustees in the data. This is not a theortical bound or even a constraint within the game but rather an observational bound. Thus we modify equation 4.1 so that the edge formation is bound by the lifetime of the nodes.

$$p_i = \frac{t_{init} - t_x}{t_{init}} . \frac{k_i}{\Sigma_j k_j} \tag{4.2}$$

Where tx is the current iteration and the tinit is iteraton at which the current node was added to the network. The formula imples that it is more likely for a node with high degree and which is itself a more recent arrival in the network as compared to a node which has the same degree but which has been in the network for a much longer time. We note that this equation is similar to the model given by [14]. Another observation that has to be replicated is the presence of a large number of small components (auxiolary components) which actually consist of people who form edges with one another at the same time but do not interact with the rest of the population. Since these seldom form new edges after the intial burst of activity, if at all, these components can be described in terms of a generator function.

$$g(s_i) = \frac{1}{n}.\frac{min(e_i)}{E_i}, n \geq 2, s_i \in s_1, s_2, ..., s_m \tag{4.3}$$

Where s_i corresponds to the set of all the graphs which are of size i, E_i is the number of edges is the complete graph of size i and $min(e_i)$ is the number of edges in the smallest graph of size ei which is a connected graph. The function states that the probability that a probabilty that a graph will be selected for generation depends upon the size of the graph and the number of edges between them. The smaller the graph and less connected it is, the more likely it will be chosen to be generated. A peculiar aspects of this network is the non-monotnic change in the diameter of LCC1. It is possible to get this behavior if we treat various communities of player. This condition can be actualized by stating that nodes have a certain lifetime after which they cannot form new edges in the network. This is actually true in the conext of MMOs since many of the players leave the gaem after acertain amount of time. Ahmad et al [11] discuss the lifetime of nodes in EQ2 in the context of mentoring networks and their observations are valid in this context as well. Thus:

$$p_i = \begin{cases} \frac{(t_{init}-t_x)}{t_{init}} & , t_{init} - t_x \leq l(n_i) \\ 0 & , t_{init} - t_x > l(n_i) \end{cases} \tag{4.4}$$

Where l(ni) is the lifetime of the node ni. For replicting the homophily related dynamics we represent the attributes or characteristics of the players as a vector ai = a1,a2, ..., an. When a new node joins the network, its probability of joining with an existing node is that dependent upon not just the degree distributions as given in equation 2 but also upon how similar or different the attributes are from the existing nodes. We employ the approach used by Johnson et al [95] for representation of characteristics. Thus the connectivity equation becomes.

$$p_i = f(A).\begin{cases} \frac{(t_{init}-t_x)}{t_{init}} & , t_{init} - t_x \leq l(n_i) \\ 0 & , t_{init} - t_x > l(n_i) \end{cases} \tag{4.5}$$

Where the function f(A) describes the simiarlity or differences between the attributes of interest and captures homophily. Thus if $a_i \in A$ is a categorical attribute then f(A) is given as an indicatior function as follows:

$$f(a_{i \neq j}) = \begin{cases} 1 & , a_i = a_j \\ 0 & , a_i \neq a_j \end{cases} \tag{4.6}$$

In the case where the attribute has a numerical value then f(a) is given as the difference between the values of the attributes as follows:

$$f(a) = |a_i - a_j|, a_{ij} \tag{4.7}$$

The function f(A) is thus the summation of the functions for the individual functions for each of the characteristics if homophily in connections is desired and one minus summation is hetrophily is desired. Thus the idea is that a node is likely to connect to other nodes if they have similar or different nodes.

4.4 Conclusion

Trust, expertise and homophily are inexorably linked in social networks. Based on the literature on homophily we explored various hypothesis regarding trust, expertise and homophily. It was discovered that given the constraints in the virtual environments the mapping between the offline and the online aspects of homophily is only partial. Additionally we also explored the relationship between expertise and trust in the gaming environment. It was observed that it is only in the case of ascribed homophily that people trust one another, in all the other contexts hetrophily was observed. In future work we plan to extend the current work by using ERGM/p* models [92] to explore in greater length the structural signature as well as expert characteristics associated with the evolution of trust based network.

Chapter 5

Trust and Clandestine Behaviors

"Tie your camel first, then put your trust in God."
(Al-Tirmidhi).

As information communication technologies have grown more pervasive in social and cultural life, deviant and criminal uses have attracted increasing attention from scholars [84], [63]. Virtual communities in massively-multiplayer online games (MMOGs) such as World of Warcraft and EverQuest II have millions of players engaging in co-operative team behaviors, barter and trade, and communication via multiple modes of communication. Many of these games primarily operate on a monthly subscription basis and as described in Chapter 1 they have over 45 million subscriptions among Western countries alone, and perhaps double that number in Asia [184]. While the in-game economies exhibit characteristics observed in real-world economies [41], a grey market of illicit transactions also exists at the margins. Virtual goods like in-game currency, scarce commodities, and powerful weapons require substantial investments of time to accumulate, but these can also be obtained from other players within the game through trade and exchange. This gives rise to the phenomenon of illicit trade activity within these game. It is in this murky and grey area that the problem of trust in clandestine behaviors arises.

The current chapter is organized into three main sub-parts: Part 1 is mainly about describing and delineating the scope of the problem of gold farming in the context of trust and how machine learning classification models can be used to detetct gold farmers. Part 2 mainly deals with the trust based social networks of gold farmers and how these social networks contrast with the social networks of other types of players. Part 3 extends the techniques described in Part 2 for other types of social networks and shows how network based methods can be used to dramatically improve gold farmer detection.

Detection of Clandestine Behaviors

5.1 Introduction

Gold farming or real-money trading refers to a body of practices that involve the sale of virtual in-game resources for real-world money. The name gold farming stems from a variety of repetitive practices ("farming" to accumulate virtual wealth ("gold" which farmers illicitly sell to other players who lack the time or desire to accumulate their own in-game capital. By repeatedly killing non-player characters (NPCs) and looting the currency they carry, farmers accumulate currency, experience, or other forms of virtual capital which they exchange with other players for real money via transactions outside of the game. Gold buyers then employ the purchased virtual resource to obtain more powerful weapons, armor, and abilities for their avatars, accelerating them to higher levels, and allowing them to explore and confront more interesting and challenging enemies [39].

Game developers do not view gold farmers benignly and have actively cracked down on the practice by banning farmers' accounts [173],[33]. In-game economies are designed with activities and products that serve as sinks to remove money from circulation and prevent inflation. Farmers and goldbuyers inject money into the system disrupting the economic equilibrium and creating inflationary pressures within the game economy. In addition, farmers' activities often exclude other players from shared game environments, employing computer subprograms to automate the farming process, and engaging in theft of account and financial information [109]. Game companies are also motivated to ban farmers to ensure that the game fulfills its role as a meritocratic fantasy space apart from the real world [169]. Because gold farmers are motivated only to accumulate wealth by the repetitive killing of NPCs, they detract from other players game experience and may drive legitimate players away [122].

While the earliest instances of real money trade can be traced back to the terminal-based multi-user dungeons (MUDs) of the 1970s and 1980s [91], formal gold farming operations originated in an early massively multiplayer online role-playing game, Ultima Online, in 1997. An informal cottage industry of inconsequential scale and scope at first, the practice grew rapidly with the parallel development of an ecommerce infrastructure in the late 1990s [56], [57]. The complexity of gold trading organizations continued to grow as indigenously-developed massively multiplayer games as well as Western-developed games were released into East Asian markets like Japan, South Korea, and China [89], [42]. Gold farming operations now appear to be concentrated in China where the combination of high-speed internet penetration and low labor costs has facilitated the development of the trade [57], [25], [54]. The scale of real money trading has been estimated to be no less than \$100 million and upwards of \$1 billion annually [56], [115], [41], and the phenomenon has begun to capture popular attention [25], [42].

5.2 Related Work

Previous studies of virtual property have focused on the economic impacts [40], user rights and governance [73], [109] and legal vagaries [23], [93] rather than the behaviors of the farmers themselves. Surveys of players have measured the extent to which the purchase of farmed gold occurs and how players perceive both producers and consumers of farmed gold [195], [197]. Other research has imputed the scale of the activity based upon proxy measures of price level stabilization and price similarity across agents [114], [115]. No fieldwork beyond journalistic interviews has been done in this domain because of a confluence of factors. Secrecy is highly valued, given the prevalence of competitors as well as the negative repercussions of being discovered [113], [94]. The popular perception of gold farming as an abstract novelty, the rapid pace of innovation and adaption in organizations and technology, the significant language barriers, and the geographic distance likewise conspire against thorough observation or systematic examination [80]. Yet perhaps the largest barrier has been the lack of availability of data from the game makers themselves.

If the data were present, data mining and machine learning techniques exist to explore the phenomenon. These have received considerable attention in the context of detecting and combating cybercrime [170], [47]. Other studies employing social network analysis, entity detection, and anomaly detection techniques have been used extensively in this context [110], [46]. The current research is the first to take advantage of these techniques by virtue of cooperation with a major game developer, Sony Online Entertainment. As outlined below, the current research is the first scholarly attempt to employ data mining and machine learning to detect and identify gold farmers in a data corpus drawn from a live MMOG.

5.3 Background

5.3.1 Game Mechanics

The study uses anonymized data archived from the massively-multiplayer online game Everquest II. In this fantasy role-playing world, a user controls a character to interact with other players in the game world as well as non-player characters (NPCs) controlled by the code of the software. Users complete quests, slay NPCs, and explore new areas of the game to earn experience points as well as currency that allows them to purchase more powerful equipment. The experience required to advance one additional level increases exponentially and more powerful weapons, armor, and spells likewise become more expensive and difficult to acquire at higher levels. Players can shortcut to more exciting content by purchasing the requisite weapons, armor, and skills rather than engaging in the more tedious aspects of accumulating the resources to sell or exchange for these items. Because players can exchanges goods and currency within the game, being able to obtain a large reserve of game currency from another character reduces the time investment necessary to progress.

5.3.2 Gold Farming

As previously discussed, gold farmers repeatedly kill ingame NPCs and collect the currency they carry. The tedious nature of this activity is somewhat lessened by the use of automated programs called bots which simulate user input to the game. While the size of the market for virtual ”gold” has created intense competition within the gold farming industry, the ability for the game company to ban these accounts and effectively destroy the value they have accumulated likewise introduces a substantial amount of uncertainty into farmers operations. These operators have adapted to the environment by employing a highly-specialized value chain that both minimizes the amount of effort and time required to procure gold as well as reducing the likelihood of being detected and attendant issues of losing inventory. Discussions with game administrators have revealed that accounts engaged in gold farming operations within the game fulfill five possible archetypes [185]:

- Gatherers: Accounts accumulating gold or other resources.
- Bankers: Distributed, low-activity accounts that hold some gold in reserve in the event that any one gatherer or other banker is banned.
- Mules and dealers: One-time characters that interact with the customer, act as a chain to distance the customer from the operation, and complicate administrator back-tracing.
- Marketers: One-time accounts that are barkers, peddlers, or spammers of the companys services.

The roles are not necessarily exclusive nor proscriptive, but these descriptions of behavioral signatures will inform subsequent methods. The highly specialized roles of gold farmers also suggests that they differ from typical players along several potential salient and latent dimensions. Where players are largely motivated to explore the game and storyline as they gain experience and level up, gold farmers may follow highly optimized paths that allow them to level quickly without engaging in these sideshows. Currently gold farmers are caught in a number of ways such as heuristicbased methods which would indicate illegitimate activity in the game, reporting of gold farmers by other players, peculiar behavior of players like making a large number of transactions over a very short span of time, and stingoperations. In all the above cases after being potentially flagged as a gold farmer the activities of the player in the past, present and the future have to be analyzed by a human expert before it can be ascertained that the player is indeed a gold farmer and not a legitimate player. These administrators are the ultimate arbiters of which users are banned.

5.4 Dataset

Anonymized EverQuest II database dumps were collected from Sony Online Entertainment. Five distinct types of data were extracted for analysis: experience logs, transaction logs, character attributes, demographic attributes, and cancelled accounts.

- Demographic information of player: Demographic information about the player in the real-world. This is already anonymized so that it is not possible to link the player back to a real-world person.
- Character game statistics of players: These characteristics are of two types. Demographiccharacteristics of the character like race (human, orc, elf etc), character sex, etc.; Cumulative statistics like total number of experience points earned, or number of monsters killed.
- Anonymized player-player social interaction information: This information is available in the form of messages sent from one player to another over a given period of time. It should be noted that the content of the messages themselves was not recorded.
- Player activity sequence: Players can perform a wide range of activities within the game. The sequences of activities include but are not limited to mentoring other players, leveling up, killing monsters, completing a recipe for a potion, fighting other players, etc.
- Player-Player economic information: This information is in the form of number of items sold or traded by one player to another player.

The cancelled accounts contained dates, account IDs, and rationales for an administrator cancelling an account including abusive language, credit card fraud, and gold farming. These players were either caught by the game developers staff or were identified for investigation by other players. Players and developers recognize that is by no means a comprehensive list, and some unknown gold farmers elude capture. However, our starting point was a simple list of those who were captured. The rationales were manually parsed to identify cases with rationales pertaining to gold farming and real money trade and extracted to generate a master list of accounts banned for gold farming. There were a total of 2,122,600 unique characters out of which 9,179 were gold farmers, or 0.43% of the population. Character attributes are the stored attributes of every character at their most recent log-out such as level, experience, class type, damage resistance, and so forth. The player demographic table included self-reported characteristics such as player birthday, account creation date, country, state, ZIP code, language, and gender. The popular stereotype of gold farmers being Chinese men appears to be borne out in the descriptive analysis as 77.6% of players banned for gold farming speak Chinese while only 16.8been banned for farming. In the game, women make up 13.5of the population, the average player is 31.6 years old, the average account is 3.7 years old, and the most commonlyspoken languages are English (80%), German (2.4%), Chinese (2.08%), French (1.57%), and Swedish (1.29%). The experience and transaction tables are longitudinal records of every event in the game that awards experience points to a player or results in an item being exchanged between players, respectively. Given the large size of these datasets, the analysis was limited to the month of June 2006 and contains 24,328,017 records related to experience and 10,085,943 records related to user transactions. Out of the 23,444 players with behavioral data for June 2006, only 147 were subsequently identified as gold farmers.

5.5 Methods

One of the most important tasks in data mining and machine learning is selecting the features to be used in the classifier. This approach uses data mining and machine learning to identify gold farmers by using an analysis in two phases. The first phase is a deductive logistic multiple regression model that describes the characteristics of gold farmers that differentiate them from a random sample of the population. The second phase is inductive and evaluates a cross-section of well-known binary classifiers like Naive-Bayes, KNN, Bayesian Networks, Decision Trees (J48) to correctly identify gold farmers. We propose to study the problem of identifying gold farming as a binary classification problem. One of the motivations for doing so was that class labels for gold farmers were readily available. It should be noted that the two methods are complimentary to each other, the inductive method can be used to describe characteristics that can differentiate gold farmers from nongold farmers. The data mining based method can be used to make preictions about particular players if they are gold farmers or not.

5.5.1 Phase I: Deductive logit model

Because a single account can potentially control several characters, the master list of banned characters was collapsed by character level to generate a list of the highest-level character on 12,134 banned accounts. The banned table was joined with the character and demographic attribute tables by account number. A random sample of non-banned accounts matched by sever population was added as a control. The total sample was 24,267 unique account-characters. Based upon previous accounts of the behavior of gold farmers, we identified sets of demographic and character attributes to use as independent variables and controls in the sequential logistic regression against the binary banned/notbanned outcome.

- Player demographics (Model 1): Player demographics (Model 1): Players banned for gold farming should be younger, more male, speak more Chinese, and have more recently-established accounts than typical players.

- Salient gold farming behavioral characteristics (Model 2): Players banned for gold farming should play for more extended periods of time, have more recorded adventuring time, a greater number of NPC kills, and greater overall wealth than typical players.

- Non-salient gold farming behavioral characteristics (Model 3): Players banned for gold farming should have lower levels of quests completed, active quests, tradeskill knowledge, tradeskill manufacturing, and deaths than typical players.

- Model 4 integrates the explanatory variables of models 2 and 3 to analyze identified behavioral characteristics and model 5 integrates model 1 and model 4 to control and analyze for both demographic and behavioral variables. The complete model (5) has a very good fit to the observed data (r2 = 0.677) and logistic regression diagnostics indicate no substantial multicollinearity or specification errors. With respect to other behavioral characteristics, the large standardized coefficients for character age, number of NPCs killed, number of deaths, and experience gained from completing quests suggest these be employed for classification.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Player age	0.097*(-2.54)				-0.174*** (-3.78)
Account age	-1.713*** (-25.81)				-0.747***(-10.83)
Chinese	4.410***(-64.06)				3.846***(-48.23)
Female	0.028(-0.65)				-0.102(-1.95)
Character age		1.481***(-17.69)		3.585***(-28.46)	3.405***(-23.39)
Time adventuring		3.031***(-53.69)		1.326***(-20.17)	0.553***(-7.01)
NPC kills		-1.792***(-24.22)		-3.011***(-20.67)	-3.759***(-20.89)
Bank wealth		-0.175***(-5.36)		-0.025(-0.50)	-0.008(-0.13)
Personal wealth		0.095**(-2.89)		0.488***(-9.57)	0.763***(-12.73)
Rare items collected		-0.615***(-16.98)		0.882***(-12.88)	0.868***(-9.3)
Quests completed			-5.375***(-54.71)	-5.352***(-45.52)	-3.045***(-20.72)
Quests active			-0.566***(-6.62)	-0.424***(-4.59)	-0.162(-1.37)
Recipes known			-1.337***(-15.46)	-1.366***(-14.83)	-0.752***(-6.31)
Items crafted			1.454***(-19.27)	0.312***(-3.87)	0.267**(-2.65)
Total deaths			6.644***(-69.92)	4.983***(-34.74)	3.359***(-19.14)
Total PVP deaths			-0.289***(-6.31)	-0.318***(-5.94)	-0.447***(-6.14)
Psuedo-R^2	0.550	0.214	0.430	0.530	0.677

Figure 5.1: Standardized Beta Coefficients; T Statistics in Paranthesis $*P < .05, **P < .01, ***P < .001, N = 24,267$

5.5.2 Phase II: Inductive machine learning models

Each set of features can be used separately to build classifiers or alternatively different types of features can be combined in the same classifier. We identify 22 unique types of activities in the data that form the basis of regular expression alphabets for analysis. It should be noted that some of these activities could also be divided into many sub-activities e.g., one activity that we identify is killing a monster, which can be divided in terms of killing a monster of level 5 versus killing a monster of level 10 since the nature of the encounter in both cases is significantly different.

After identifying and extracting the features, the main intuition behind posing this problem as a classification problem is that gold farmers possess certain demographic and behavioral characteristics that can be exploited. For the features about the distribution of activities, we extracted Activity Sequence Features which are the number of times the player was engaged in that activity e.g., the number of monsters killed, the number of potion recipes completed, number of times the player was killed, etc. In addition to the features that were available to us directly from the dataset we constructed another set of features based on the sequences of activities performed by the players.

Table 5.1: Feature Space for various types of Features

Feature Type	**Features**
Demographic	Gender, Language, Country, State.
Character Stats	Character Race, Character Gender, Character Class, Accumulated Experience, Platinum, Gold, Silver, Guild Rank, Character age, Total Deaths, City Alignment, PVP Title Rank, Achievement Experience, Achievement, Points, PVP Deaths, PVP Kills, Copper.
Economic Features	Number of Transactions as Seller, Number of Transactions as Buyer.
Annonymized Social Interaction	Indegree, Outdegree.

The behavioral data of any given player can be captured by looking into the sequence of activities performed by a player in a given session. A session is defined as a chunk of time in which the player was continuously playing the game e.g., if a player played the game for two hours in the morning and one hour in the evening on the same day then the game play for that day is said to constitute two different sessions of game. In order to reconstruct session we look at the ordered lists of all the activities in terms and a set of k activities is said to belong to the same session if the time difference between any two adjacent activities is less than 30 minutes. Thus consider the following example of a sequence in a session: KKKDdKdEKdKD where K is killed a monster, D is player died, d is damage points and E is points earned. This sequence implies that the player killed three monsters before being killed, after resurrection the player suffered some damage followed by killing the monster but sustained further damage, and so on. The sequences for three different players can be visually illustrated by the sequences in Figure 5.5.2

Figure 5.2: Visual Representation of Activity Patterns for three different players

Table 5.2: Sequence Patterns for Player Activities

Sequence	**Explanation**
KKKKKKKKKK+	10 or more kills in a row
d+K+	One or more damage followed by one or more kills
d+[a-z,A-Z]*K+	Damage followed by other activities and then by one or more kills
E+[a-z,A-Z]*K+	Earned payment followed by other activities and then by one or more kills
M+S+	One or more mentoring instances followed by successful completion of recipes
M+[a-z,A-Z]*K+	Damage followed by other activities and then by kills
K+D	One or more kills followed by the death of the character
E+D	One or more earned payments followed by the death of the character
M+[a-z,A-Z]*q	Mentoring followed by other activities and then by quest points
M+[a-z,A-Z]*K+	Mentoring followed by other activities and then by one or more kills
M+E+	One or more instances of mentoring followed by one or more instances of earned payments
MMMMMMMMMM+	Ten mentoring instances in a row

The experiments were performed on the open source Data Mining software Weka which has implementations of many well-known data mining algorithms [186]. Results from different sets of features are given in a series of tables below. Since the current problem is a rare class problem we only report the classification results for the rare class as the precision and recall for the dominant class is more than 99% in almost all the cases. It would have been helpful if there was a baseline model for comparing the result of these classification models, however catching gold farmers is currently a given, but the most relevant to choose a classifier is precision vs. recall. From the domain experts point of view the goal of any gold farmer-detecting technique should be to increase the number of true positives (correctly identified gold farmers) while at the same time decreasing the number of false positives (legitimate players labeled as gold farmers). It is essential for these classifications to have high precision to minimize the number of false positive since any positive match has to be investigated by an administrator. Recall captures the other aspect of performance i.e., capturing as many gold farmers as possible but requires the actual number of positives in the dataset. While the records in the data are all labeled as gold farmers and are assumed to certain gold farmers, there are likely to be players in the dataset who are gold farmers but were not identified or banned.

5.6 Results

5.6.1 Phase I: Deductive logit model

The analysis from Phase I demonstrated that non-salient behavioral characteristics (model 3) accounted for substantially more variance than the salient behavioral characteristics (model 2). This suggests that along these salient characteristics (wealth, time played, rare items acquired), gold farmers may not differ substantially from other (elite) players but are significantly different along more latent characteristics such as how many quests they complete, how often they die, and their tradeskill expertise. It is likewise telling that even with 12 distinct predictive variables of gold farming activity in model 4, the 4-variable demographic-only model (model 1) still accounted for more of the variance among players identified as gold farmers. The analysis also bears out the intuition that players with old and well-established accounts are not as likely to be gold farmers.

Other than Chinese language (a dummy variable), player demographic attributes have a small effect compared to other variables. High levels of NPC kills, quests completed, and tradeskill recipe knowledge all strongly decreased the likelihood of being identified as a gold farmer in the model. This combination of variables suggests that farmers exhibit low levels of expertise across a variety of metrics. High levels of time played, time spent adventuring, and high total deaths are all factors associated with gold farming activity which also implies a low level of expertise within the game itself. While the accumulation of wealth in a bank was not significantly associated with gold farming activity which suggests that farmers have possibly adapted their behavior on this count to avoid detection the model does predict that gold farmers carry more coins on their character.

5.6.2 B. Phase II: Inductive machine learning models

Using only the players self-reported demographic characteristics for classification should have strongly predicted the identification of gold farmers given their skewed language distribution, but as seen in Model 1, two classifiers (JRIP and J48) misclassified every instance of the farmerclass. By Fscore, the KNN algorithm is the best metric for demographic features. Examining only features of the character played within the game, model 2 reveals that the algorithms identify gold farmers with much lower precision and recall than the demographic model alone. The findings for activity distribution in model 3 are marginally better than the previous model employing character features classifiers but the KNN algorithm has markedly inferior precision and recall as compared to the demographic model. These predictive machine learning findings corroborate our earlier descriptive regression results that the salient behavioral characteristics on which we expect gold farmers to be differentiated from other players (wealth, time played, etc.) are not reliable features. The inability to distinguish farmers suggests that they are able to cloak their behavior given their similarity to highly-skilled players along the variables included in these models.

Table 5.3: Description of Models

Model name	**Classifier features**
Model 1	Demographic features only
Model 2	Character features only
Model 3	Activity distribution features
Model 4	Demographic and accumulation features
Model 5	Sequence activity features
Model 6	Activity distribution features and economic transactions

Model 7	Activity distribution features for gold farmer sub-class

Next, we incorporated both the previous demographic features with cumulative statistics of how much experience and money characters had. As shown in Figure 5.1, the performance of all algorithms increased substantially across the board with the BayesNet exhibiting the strongest recall performance and KNN being an accurate predictor of gold farming activity. We next used our alphabet of 22 activities captured in the experience and transaction logs to perform two analyses incorporating activity sequences alone and the distribution of activity with economic transactions. We define a set of 10 patterns in Table 5.2 to measure whether the sequences of activities were predictive. As seen in Table 5.5, this sequence approach alone has poor precision and recall across all algorithms compared to previous methods. Table 5.6 describes the results for activity distribution as well as character and demographic features. The low discriminatory power of this sequence method implies that, again, farmers and non-farmers do not differ substantially along the sequences we have specified.

A close analysis of gold farmers indicate that the number of tasks performed by the gold farmers vary greatly. This can potentially be the source of confusion for the classifiers when instances of the same class exhibit a wide range of characteristics and thus are not discriminatory enough. To address this issue we removed all such instances from the dataset. When we removed all instances where the number of activities associated with gold farmers was less than six, the number of gold farmers was reduced to 83. We then reran the same set of classifier for this new dataset for the activity distribution features, the results of which are given in table 5.7. It should be noted that the performance of most of the classifiers improves in terms of both precision and recall. This confirms our earlier hypothesis that the various subclasses within the gold farmer class could be a source of confusion for the classifiers.

Table 5.4: Classifier Performance for Gold Farmer Sub-Classes (Activity Distribution Features)

Classifier	**TPR**	**FPR**	**Prec.**	**Recall**	**F-Score**	**ROC**
BayesNet	0.265	0.008	0.109	0.265	0.155	0.644

NaiveBayes	0.313	0.028	0.038	0.313	0.068	0.724
Logistic Reg.	0.036	0	0.273	0.036	0.064	0.697
AdaBoost	0.313	0.028	0.038	0.313	0.068	0.690
J48	0.036	0	0.300	0.036	0.065	0.596
JRIP	0.060	0.001	0.250	0.060	0.097	0.519
KNN	0.157	0.003	0.176	0.157	0.166	0.577

Classifier	Measure	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
BayesNet	Prec.	0.208	0.033	.0125	0.291	.131	0.134	0.109
	Recall	0.225	0.186	0.102	0.513	0.131	0.102	0.265
	F-Score	0.216	0.057	0.112	0.371	0.131	0.116	0.155
NaiveBayes	Prec.	0.211	0.051	0.042	0.204	0.052	0.037	0.038
	Recall	0.223	0.136	0.19	0.223	0.293	0.19	0.313
	F-Score	0.216	0.074	0.069	0.213	0.088	0.061	0.068
LogisticReg.	Prec.	0.636	0.182	0.333	0.630	0.091	0.300	0.273
	Recall	0.192	0.017	0.020	0.192	0.010	0.020	0.036
	F-Score	0.294	0.031	0.038	0.294	0.018	0.038	0.064
AdaBoost	Prec.	0.412	0.051	0.042	0.271	0.052	0.037	0.038
	Recall	0.138	0.136	0.190	0.183	0.293	0.190	0.313
	F-Score	0.207	0.074	0.069	0.218	0.088	0.061	0.068
J48	Prec.	0	0.75	0.286	0	0.143	0.353	0.300
	Recall	0	0.025	0.027	0	0.010	0.041	0.036
	F-Score	0	0.049	0.050	0	0.019	0.073	0.065
JRIP	Prec.	0	0.333	0.286	0.526	0.250	0	0.250
	Recall	0	0.068	0.014	0.056	0.020	0	0.060
	F-Score	0	0.113	0.026	0.102	0.037	0	0.097
KNN	Prec.	0.493	0.050	0.086	0.345	0.112	0.122	0.176
	Recall	0.304	0.017	0.061	0.361	0.111	0.082	0.157
	F-Score	0.376	0.025	0.071	0.353	0.112	0.098	0.166

Figure 5.3: Classifier Performance for all Gold Farmers (By Model)

Table 5.5: F-Measures for all Gold Farmers (Demographic and Statistics Features)

Classifier	**F_1-Score**	**$F_{0.8}$-Score**	**F_2-Score**	**$F_{0.5}$-Score**
BayesNet	**0.371**	0.350	**0.445**	0.318
NaiveBayes	0.213	0.211	0.218	0.207
Logistic Reg.	0.294	0.333	0.223	**0.432**

AdaBoost	0.218	0.228	0.195	0.247
J48	0	0	0	0
JRIP	0.102	0.123	0.068	0.196
KNN	0.353	**0.351**	0.357	0.348

Table 5.6: Classifier Performance for all Gold Farmers (Activity Distribution Features)

Classifier	**TPR**	**FPR**	**Prec.**	**Recall**	**F-Score**	**ROC**
BayesNet	0.102	0.005	0.125	0.102	0.112	0.797
NaiveBayes	0.190	0.027	0.042	0.190	0.069	0.632
Logistic Reg.	0.020	0	0.333	0.020	0.038	0.661
AdaBoost	0.190	0.027	0.042	0.190	0.069	0.629
J48	0.027	0	0.286	0.027	0.050	0.535
JRIP	0.014	0	0.286	0.014	0.026	0.512
KNN	0.061	0.004	0.086	0.061	0.071	0.529

Table 5.7: Classifier Performance for all Gold Farmers (Activity Distribution Features and Economic Transactions)

Classifier	**TPR**	**FPR**	**Prec.**	**Recall**	**F-Score**	**ROC**
BayesNet	0.102	0.004	0.134	0.102	0.112	0.812
NaiveBayes	0.190	0.032	0.037	0.190	0.069	0.628
Logistic Reg.	0.020	0	0.300	0.020	0.038	0.685
AdaBoost	0.190	0.032	0.037	0.190	0.069	0.628
J48	0.041	0	0.353	0.041	0.050	0.523
JRIP	0	0	0	0	0	0.502
KNN	0.082	0.004	0.122	0.082	0.098	0.539

5.7 Classifier Selection

Given that the range of values for precision and recall are observed for the various classifiers that we described, we would suggest a classifier that consistently outperformed all other classifiers in terms of precision and recall. However this is not the case as trade-offs between precision and recall are to be expected. The best F-Score was obtained by using demographic features with KNN, yet BayesNet gives the highest value for recall if both the demographic and the character statistics are used. This can be further illustrated by the precision vs. recall graph for the demographic features as illustrated in Figure 5.7; while KNN has the best precision, logistic regression has better recall. An alternative would be to use the ROC curve to decide which classifier to use. However, this cannot be used in our case since the false positive rate is extremely low for all the cases of classifiers and features that we have investigated. This can be illustrated by Figure 5.5 where all the data points are aligned almost to the y-axis. Using information about the relative proportion of false positives and true positives is not available in this case.

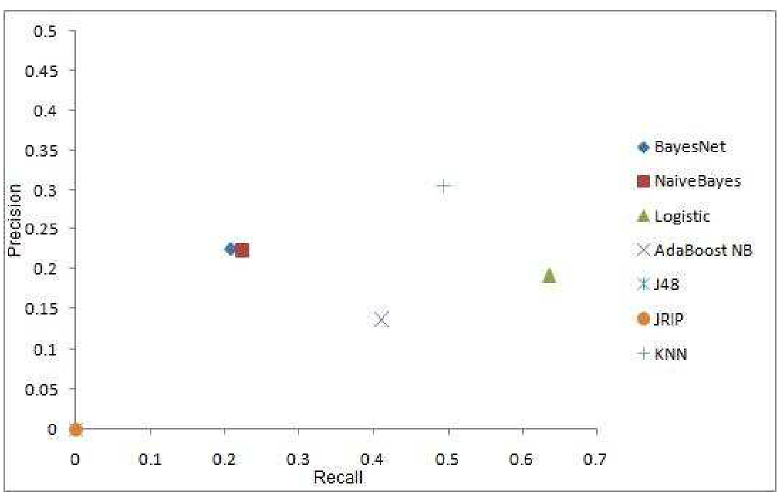


Figure 5.4: Precision vs. Recall for Demographic Features

However, we can address the problem of selecting a consistent classifier by referring to the domain. As described previously, there are two main constraints that we are trying to satisfy: increasing the number of gold farmers who are caught by an algorithm

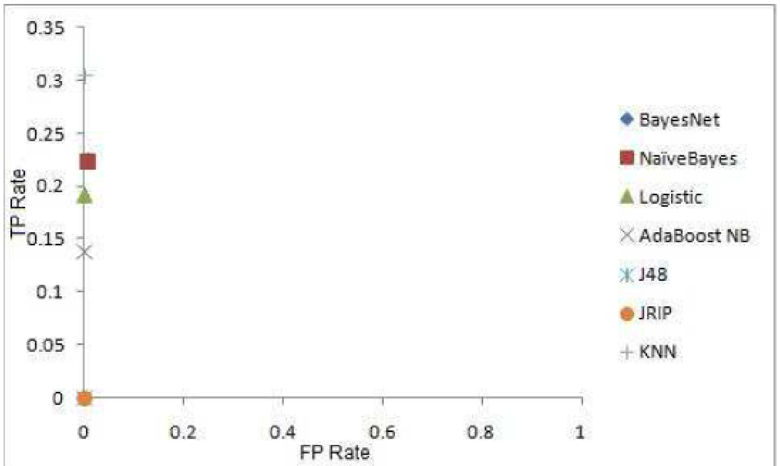


Figure 5.5: ROC for Demographic Features

and reducing the number of false positives as this would translate into work that has to be done by humans. Thus, given scarce human resources, precision should be given a high priority. One the other hand, if enough human resources are available, then more false positives can be tolerated if the number of true positives are likely to increase. This tradeoff can be captured by using the generalized version of van Rijsbergens [174] F-measure as the metric for decision making. It can be described as follows:

$$F_\beta = (1 + \beta^2) \cdot \frac{(precision \cdot recall)}{(\beta^2 \cdot precision + recall)} \tag{5.1}$$

where β is a scaling factor that describes the relative importance of recall with respect to precision. This criteria can be illustrated as follows. Consider the results of various algorithms from Table 5.5. If equal weight is given to both precision and recall then Bayes not should be used as the classifier of choice. The same would occur if recall is given twice as importance as precision. However if precision is given twice as importance as recall then Logistic Regression will be chosen, similarly if recall is said to be only 80as precision then KNN would be chosen. The choice of values for β would depend upon the domain expert while taking into account the resources available.

5.8 Conclusion

Using an anonymized dataset extracted from the massively multiplayer online game EverQuest II, we used several machine learning binary classification techniques to identify gold farmers within the game world. A number of feature types were explored for classification and various combinations of classifiers and features gave a wide range of results in terms of precision and recall. Despite the strong, significant effects observed across five logistic regression models for exploratory analysis, classifier algorithms operating on seven different combinations of behavioral data were not able to precisely identify gold farmers. We attribute the difficulty in discriminating between gold farmers and legitimate players to farmers specialization into distinct roles that exhibit very different behavioral signatures. From a domain expertise point of view, given the trade-off between identifying gold farmers and amount of effort required in investigating we proposed that the generalized F-Measure should be used to select which classifier and feature set combination should be used in which context. We note, however, that our evaluation is likely to be conservative. Since we cannot know the true number and identity of gold farmers within the data, it is possibleperhaps likelythat a number of our false positives were farmers who had yet to be caught. Thus the precision rates here should be seen as a minimum baseline. If these cases could be investigated more closely, some may translate into true positives, further validating the approach. Our future work will explore how to incorporate the behavioral signatures of each distinct gold farming role. Thesebehavioral signatures will inform the development of different hierarchical regression models as well as building different classifiers. In this chapter we have simply looked at the overall performance of the classifiers in detecting gold farmers. It could be the case that some classifiers are much better in classifying certain types of gold farmers.

Future research should also seek to develop a more systematic approach to determine sequences of patterns of activities that can be used to identify gold farmers as well as longitudinal analyses of how these behavioral signatures change over time. Given the applicability of this line of research to identifying other forms of cybercrime such as credit card fraud and money laundering as well as national security applications, we anticipate that the methods we develop for detecting gold farming could potentially be applied to these other datasets for validation. Before exploring this line of reasoning we first analyze the trust networks of gold farmers in the next section by applying frequent patternset minning to hypergraphs of gold farmers and other typoes of players.

Trust Networks of Clandestine Actors

"A plague upont when thieves cannot be true one to another!"
– Falstaff, Henry IV, Part 1, II.ii

5.9 Introduction

The previous section described the problem of gold farmer detection and why it is a cause of concern for game developers and administrators. This problem can be mapped onto its counterpart in the offline world as well. The type of exchanges that take place amongst the gold farmers and their clients undermine meritocratic norms, upset in-game economic equilibria, and raise complicated legal questions about property, taxes, torts, and labor [56]. Because of these reasons, game administrators attempt to ban gold farmers by observing unusual game activity or investigating reports from other players. However, these detection methods are ad-hoc and 'as with criminals in the offline world' many gold farmers escape detection. But the ability to collect exhaustive longitudinal digital trace data on organizations operating under similar motivations and constraints as offline clandestine organization suggests that social behavior in MMOGs can also potentially be mapped back to test and inform theories clandestine social behavior and organization in offline contexts [191].

In this part of the chapter the analysis and techniques for gold farmer detection are extended to longitudinal as well as network data and the focus is specifically on occurrence of frequent patterns in trust networks in MMOGs. There are multiple ways to describe trust in MMOGs the most explicit and the strongest indicator in terms of in-game features to specify trust in EQ2: The ability for players to grant other players permission to enter their in-game houses, move objects around in them, or even remove objects from the house is a ready proxy for the level of trust amongst characters. However, these permissions require modeling the relationships among houses, in-game characters, and the user accounts which own each. To capture these complex inter-dependencies, we employ a hypergraph to model triparite relational structures. A variety of hypergraph projections for network analysis are defined, extracted from the network and then the graph structures of farmers are compared to typical players and unidentified gold farmers. Additionally a label propagation approach based on insights by [100] to compare the trust network structures of gold farmers, their undetected affiliates, and normal players are employed. The findings demonstrate that gold farmers housing permission behavior has distinct patterns when compared to the general player population as well as farmers who have yet to be detected by the game operator. The implications of the findings have for augmenting detection methods in MMOGs and evaluating theories of clandestine organization are finally described at the end.

5.10 Motivation and Background

Traditional analyses of trust networks have mainly focused on trust between people who come together in a certain context to achieve a certain goal or to connect with other people such as recommendation systems, friendship, and resource sharing [69]. In trust-based recommendation networks like FilmTrust [67] and Epinions

5.11 Housing Permissions as Trust in EverQuest II

Data from EQ2 is used for these set of experiments as well. It is important to make distinction between accounts, characters, and houses. Each account can create several characters, but these cannot be played simultaneously. Each character has the option to buy a virtual house in the game. Thus houses are connected to players which are in turn embedded within accounts. Players can use their houses for a variety of purposes such as displaying valuable items, storing excess inventory, and selling crafted goods. By default, only the character who buys the house has access to the house. However, a character may grant different levels of access to other characters in the game. In EQII the following access levels, in ascending order of trusted access, are defined:

- None: Has no access and cannot enter the house.
- Visitor: Can enter the house and can interact with objects in the house.
- Friend: Has all the privileges of the Visitor and can move things around the house.
- Trustee: Has all the privileges of the Friend and can add and remove objects in the house. A Trustee can also pay the rent of the house on the behalf of the owner of the house.

From a security perspective, all the access levels except trustee are functionally equivalent because characters who are given that type of access cannot make any change to the value of the house while a character with trustee privileges can make such a change. To simplify our analysis along these functional lines, we dichotomize these three potential types of relations into trustee and non-trustee (visitor and friend). Hypergraph Model of Housing-Trust Network The housing-trust network can be modeled in different ways. Previous research using housing-trust networks has looked at the structure of the housing network in terms of access-grants while ignoring the presences of houses or even permissions for multiple characters [13]. While these models are sufficient for studying the social networks amongst the gold farmers, they limit the types of inferences that can be made about the larger trust-based social structures and the use of such structures for making inferences about gold farmers. Our approach follows previous work using hypergraphs to model tagging systems where there is a natural distinction between three types of nodes in the networks such as person, tag and object. We also adopt a hypergraph model to describe the three types of nodes in our data: player account, player character, character house. Multiple models of hypergraphs exist which describe the evolution and generation of such hypergraphs [65]. The complex game mechanics of EQII which cannot be captured by a traditional graph representation are another motivation for using hypergraphs to model trust relationships. Players at each level not only have these privileges associated with that level, they also have the privilege to grant the same or lesser level of access to other people. Thus consider the situation in Figure 5.6 which ignores the player accounts for simplification purposes. In the first case character $c_{a11} trusts c_{a22}$ and c_{a31} trusts. From this representation it is not clear if there is a trust relationship between c_{a11} and c_{a31}. While it could be the case that c_{a11} also trusts c_{a31} but since c_{a22} has already granted permissions to c_a11 it is not necessary for c_{a11} to grant permissions to c_{a31}. However given that there is still a possibility that c_{a11} instructed c_{a22} to grant access to $c_{a31} e.g.,$c$_{a11}$ is a superior officer of c_{a22}, an important piece of information is lost. One way to remedy would be to add an edge between c_{a11} and c_{a31} but even in this case we will lose information about which players are connected with each other by which house. We use the alternative projection in Figure {fig:hyper2 wherein player nodes are connected by access ties to house nodes. Even in this case some information is also lost such as how the access grants were given but since we are interested in the relationship between houses, players and characters this can be overlooked. A hypergraph is a generalization of a graph [53] and can be defined as follows:

Tripartite Hypergraph: A tripartite hypergraph $G = (V, H)$consists of a set of nodes V and a set of hyperedges V such that the following conditions are satisfied.

1. $V = \{V_h, V_c, V_a | V_i \cap V_j = \phi\}$

2. $H \in \{(v_h \in V_h, v_c \in V_c, v_a \in V_a)\}$

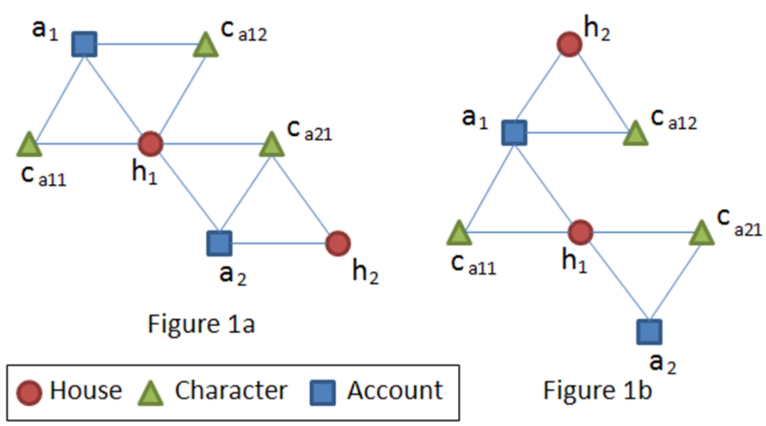


Figure 5.6: Different scenarios for housing access for characters associated with (a) the same account and (b) with different account

Figure 5.6 shows a hypergraph which contains hyperedges (a_1, c_{a11}, h_1), (a_1, c_{a11}, h_1), (a_1, c_{a11}, h_1) and (a_1, c_{a11}, h_1). **Node Degree:** The degree of the nodes can be defined in a umber of ways. One can define it in terms of how many other nodes is a node connected to. However in this case no distinction is being made between the various types of nodes that may be present in the hypergraph and in the current domain the semantics of the graph will be lost if such an approach is used. Another approach which is more suited to our present context is to define node degree in terms of the hyperedges that are connected to a node. Thus in Figure 5.6 the degree of h_1 is 3 and the degree of h_2 is 1. **Edge Degree:** In addition to the node degree, it is also possible to describe the edge degree in the hypergraph [200]. The edge degree is defined

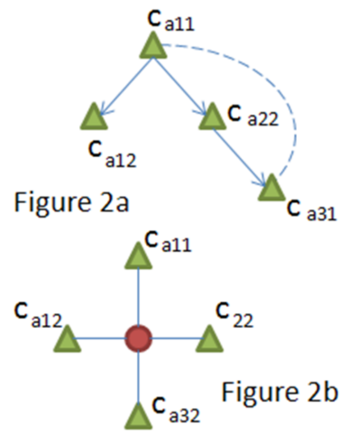


Figure 5.7: Alternative ways to represent the housing-trust network

as the number of hyperedges in which the edge participates in. Consider edge (a_1, h_1) in Figure 5.6, it has edge degree two because it participates in two different hyperedges (a_1, c_{a11}, h_1) and (a_1, c_{a11}, h_1). Projections of a Hypergraph: There are multiple ways in which hypergraph projections can be formed e.g., one way to create a projection would be to create an edge between two nodes if they share a house, another way to project would to create a node if they share an account. It is also possible to create a double projection by projecting onto a projection.

In order to distinguish between the characteristics of gold farmers and legitimate players we consider the frequent subgraph patterns which are associated with different types of players. We now describe various terms which would be helpful in finding such patterns. **Frequent Tripartite Hypergraph Pattern:** Given a tripartite graph H with nodeset N and an edgeset E, a frequent tripartite hypergraph patterns is a sub-hypergraph sub of graph H such that it occurs frequently in H with a support S, confidence C and at least one of the nodes containing a label P. Since the dataset that we are dealing with is not a transaction dataset the definitions of support and confidence are modified accordingly. The support and confidence are defined as follows: **Support of a Hyper-subgraph:** Given a sub-hypergraph of size k, subP is the pattern of interest containing the label P, shP is a pattern of the same size as subP and contains the label P, the support is defined as follows:

$$S = \frac{|sub_P}{|\{sh_P|sh_P \subseteq H, |sh_P| = k\}|} \tag{5.2}$$

Confidence of a Hyper-Subgraph: Given a sub-hypergraph of size k, subP is the pattern of interest containing the label P, subG is a pattern which is structurally equivalent but which does not contain the label P, the confidence is defined as follows:

$$S = \frac{|sub_P}{|\{sub_G|sub_G \subseteq H, |S| = k\}|} \tag{5.3}$$

Frequent Tripartite Hypergraph Pattern Mining: We now describe a technique which can be used to extract frequent tripartite hypergraph patterns, with and without constraints, from our data. Consider the hypergraphs in Figure 5.6; it is clear that a hypergraph can be visualized as a graph with a larger number of triads. This implies that there is already implicit structure in the data which can be exploited for pattern mining. The task of mining such patterns can thus be formulated as discovering triads in a 3-Regular graph with certain constraints.

The problem of discovering the frequent patterns described in the previous discussion can be formalized as follows:. Consider the hypergraph in Figure 5.6, if we consider the triads which are connected to h1 then these are (a_1, c_{a11}, h_1), (a_1, c_{a12}, h_1) and (c_{a21}, a_2, h_1). Given that it can be treated as a 3-Regular graph, we know can describe the structure of the neighborhood of h1 in terms of connectivity of the accounts. For example, account a1 is connected to h_1 with two characters, account a_2 is connected to h_1 with one character. We can represent the neighborhood of h_1 as $(2CH0, 1CH1)$ where A and C signify accounts and characters respectively. The representation can be further extended by considering the other houses to which a node may have access to. Thus in Figure 5.7 the neighborhood of h_1 would be represented as (C2H1, C1H0) which show that the representation of the neighborhood of h_2 would be $(C2H0)$. Even with this representation there can be multiple ways to represent the same graph since there are multiple ways to traverse a graph. To address this issue we represent the subgraphs in the DFS Lexicographical order [194]. Of course in this type of representation some information is lost. However with this representation standard association rule mining techniques can be applied to discover useful discriminative patterns in the data as we demonstrate in the analysis section.

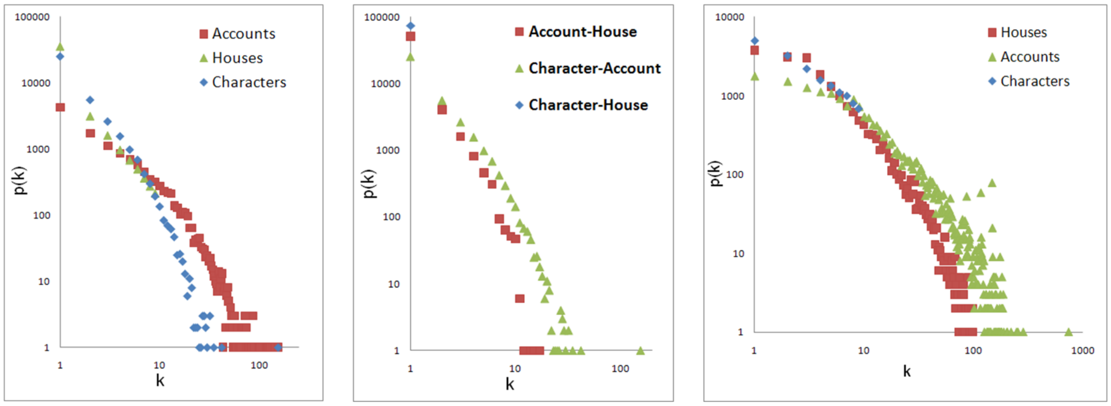


Figure 5.8: (a) Distribution of node degree for the trust hyper graph. (b) Distribution of edge degree for the trust hypergraph (c) Distribution of the projection networks

5.12 Dataset

The same dataset from EverQuest II us sed for these set of experiments as well. The dataset contains 38,217 characters associated with 12,667 accounts, with 43,548 houses and a total of 3,013,741 hyperedges between them. 151 of these accounts were banned by SOE administrators for reasons related to gold farming. A small number of records (105 accounts, 482 characters) were discarded because of incomplete transcription of data. However none of the houses were discarded in this case. The Trustee access was granted 20,029 times, the Friend access was granted 32,711 times and the Visitor access was granted 273,355 times for all the players in the network. Additionally there were 8,295 instances where the trust privileges were revoked. We note that these counts sum up to be greater than the number of edges in the network because there were many redundant instances where the same access was granted to the same person on the same house multiple times. Figure 5.8 gives the node degree distribution of the various types of nodes on a log scale. It is clear from the figure that the majority of the accounts have fewer than four houses and character pairs associated with them. Similarly, the same applies for the characters as well. While the distributions for the accounts and the characters follow a long-tail distribution, the distribution for the houses is linear with a maximum of 8 character-account ties. We note that this is not a constraint in the game. Similarly Figure 5.8 gives the edge degree distributions for the various edge types. In this case also the account-house and the character-house distributions follow a power law more or less. The character-house edges always have a degree of one because there is a unique mapping from a character to an account in the game.

5.13 Analysis of the Housing-Trust Network

Using a label propagation technique derived from Keegan, Ahmad, et al. [100], it is possible to distinguish between three types of players based on their relationship with identified gold farmers in the housing-trust network.

- Gold farmers: These are characters who are explicitly labeled as gold farmers in the data.
- Gold farmer affiliates: These are characters who have interacted with the gold farmers by either extending housing permissions to gold farmers or are trusted by other gold farmers but they are not labeled as gold farmers themselves. Using our guilt-by-association label propagation technique, we assume these characters have a much higher likelihood of being unidentified gold farmers.
- Non-affiliates: The rest of the characters who are neither gold farmer nor affiliates.

Table 5.8 reports the average neighbor connectivity of the three types of players. Here n refers to all the neighbors regardless of farmer/affiliate attribute, ni refers to neighbors with incoming edges and no refers to neighbors with outgoing edges. From the table it is clear that gold farmers grant or receive permission from fewer players (1.82) than their affiliates (4.03). The second column nGF refers to neighbors who are gold farmers. In this case gold farmers also have very low tendency to grant other gold farmers permission (0.29). nAff refers to the neighbors of affiliates. Here the connectivity patterns of affiliates stand out markedly; on average, non-affiliates have granted housing permission to 7.77 affiliates even though affiliates intra-class connectivity (0.70) suggests they are unlikely to give other affiliates housing permissions.

On average non-affiliates give 5.98 affiliates housing permission while affiliates only reciprocate by giving permissions to 2.34 affiliates on average. We also see that although gold farmers have relatively low base rates for granting housing permissions to other players, they appear to be strongly averse to granting other gold farmers access. Instead, gold farmers appear to both grant (0.89) and receive (1.07) permissions at a substantially higher rate than they are granted (0.29) or received (0.29) from other gold farmers. As the title of the chapter indicates, there appears to be little honor among thieves. These

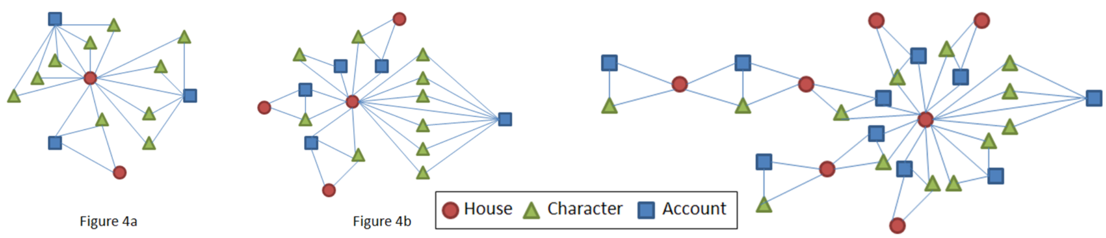


Figure 5.9: (a) Gold Farmer Hypergraph Pattern: Support = 0.33, Confidence = 1. (b) Gold Farmer Hypergraph Pattern: Support = 0.50, Confidence = 1. (c) Gold Farmer Affiliate Hypergraph Pattern: Support = 0.50, Confidence = 1

findings have several important implications. First, housing access appears to serve a non-trivial role in enabling gold farming operations as affiliates and farmers alike avoid granting permissions to characters of the same type. Second, the affiliate players whom gold farmers grant permissions are also players who themselves have high connectivity with the rest of the network. Third, farmers do not grant housing permissions at all to non-affiliates. Clearly the affiliates play a crucial and trusted role in brokering between identified farmers and the general population while isolating themselves from the general player populations. This corroborates previous findings by Keegan, Ahmad, et al. [100] about differences in centrality between character classes in the trade network. A possible explanation is that these affiliates are gold farmers themselves but they have not been caught by the game administrators and thus the data does not label them as such. However given that affiliates are so strongly trusted by farmers, it could be the case that the gold farmers grant this access as a conduit for distributing their goods via trusted channels. In either case, there is a clear implication that affiliates are an integral part of the gold farming supply chain.

To explore the connectivity of gold farmers in the data, we extracted tripartite hypergraph patterns occurring frequently in the data for the three types of players using standard pattern mining techniques [4]. Most of the patterns which were obtained for gold farmers had a very low support and confidence and only 8 patterns had support and confidence greater than a standard 0.1 threshold. Because of the limitation of space only two most frequently occurring patterns are shown in Figure 5.9. Part (a) of Figure 5.9 refers to a pattern where a house is shared by three players two of whom have many characters associated with their respective accounts and the third player has access to another house. Part (b) of Figure 5.9 on the other hand shows a situation where a player has many characters and all the characters have access to the house but at the at the same time there are other players who have access to that house but they only have one character and also have access to another house. Both evoke a house being used as a shared, central safehouse shared by many farming character-accounts but also with connections to affiliate character-accounts with access to other houses.

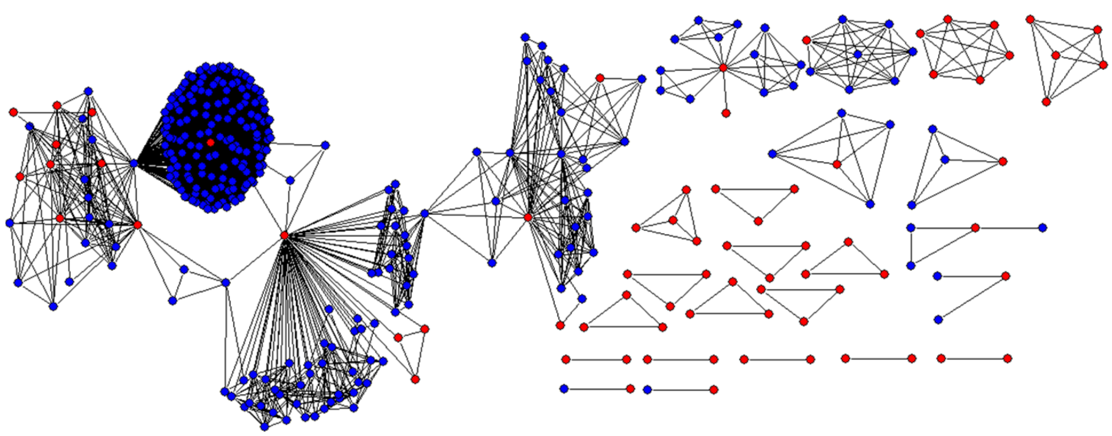


Figure 5.10: The house projection displaying houses associated with gold farmers (in red) and houses associated with affiliates (in blue). The network is obtained by the projection of the Hypergraph H

We also extracted the patterns which were associated with the various affiliates and surprisingly a third (15/44) of the sequence patterns with more than 10 nodes were associated with affiliates. We note that these patterns are too long to visualize here, an example of a smaller pattern is given in Part (*c*) of Figure 5.9. Like part (*a*) and (*b*) of Figure 5.9, there is a clear star-like structure with several affiliate character-accounts sharing a house, but select few having access to other houses as well. The earlier observation that gold farmer affiliates are highly connected players is borne out here as gold farmers connect to trustworthy affiliates but avoid directly granting trust to each other.

Table 5.8: Average neighbor connectivity for gold farmers, affiliates and non-affiliates.

	Neighbors' total degree			Neighbors' in-degree			Neighbors' out-degree		
	(n)	(n_{GF})	(n_{Aff})	(n_i)	$(n_{i,GF})$	$(n_{i,Aff})$	(n_o)	$(n_{o,GF})$	$(n_{o,Aff})$
Farmr.	1.82	0.29	1.82	0.89	0.29	0.89	1.07	0.29	1.07
Affs	4.03	1.28	0.70	1.55	0.75	0.70	2.88	0.625	0.70
Non-Aff.	2.73	-	7.77	1.57	-	5.98	1.56	-	2.34

Table 5.9: Global Characteristics of the Projection Networks of the Hypergraph H

Network Projection	**Nodes**	**Edges**	**NCC**	**LCC**	**% LCC**
Account	18,231	159,676	1,015	14,431	79.16
Character	16,878	119,757	1,070	13,111	77.68
House	19,832	83,715	1,764	14,801	74.63

Hypergraph Projection for the Network of Accounts: As noted earlier, it is possible to create projections of the hypergraph for different node types in the network and determine the prevalence of gold farmers in each network. The characteristics of the various projections are given in Table 5.9. Here NCC refers to the number of connected components, LCC refers to the size of the largest connected component and %LCC refers to the percentage of the total nodes which are part of LCC. We now describe the various projections of the hypergraph H. The node-degree distributions of these graphs are given in Figure 5.8.

If we consider the subgraph which consists of the gold farmers, their affiliates and the neighbors of the affiliates then we observe that the majority (79%) of these accounts are isolates. There are a large number of instances of gold farmers where the gold farmer have exclusive access to the houses without giving access to other players including other gold farmers. On the other hand if we consider the affiliates then again they have a very high connectivity 8.89 as compared to both the gold farmers 0.31 as well as the non-affiliates 3.47. This again reinforces the observation that gold farmers do not trust one another but they trust other people who are trusted by the population in general.

Hypergraph Projection for the Network of Characters: The projection of characters is the projection of the accounts and the houses in the networks. The same phenomenon of gold farmers not connecting to other gold farmers is also observed which a large percentage (84%) of gold farmer nodes being isolates. In both the cases of the projection of the accounts as well as the projection of the characters, the degree to which gold farmers are connected to one another is quite low which reinforces the conclusion that sharing houses and thus trust across gold farmers is not very common. The affiliates again have a very high connectivity (10.42) as compared to the rest of the population (3.23). Hypergraph Projection for the Network of Houses: Another way to project the hypergraph H is to project the accounts and the characters so that we get a projection of the houses in the network. In the projected House network there are 43,548 nodes and 83,715 edges. There are 521 gold farmer houses which we define to be a house having a direct connection with a gold farmer. However many houses associated with gold farmers are isolated nodes. Table 5.9 shows that there are a large number of components (1,764) but a single giant component contains three-quarters of the nodes. The rest of the components are relatively small the second largest connected component has 30 nodes. Thus the smaller components in Figure fig:hyper5 are indeed isolated components and the large component is part of the largest connected from the original component. It is clear that there are many cases where the gold farmerss houses form isolated groups. The most prominent examples are the two components in the upper right side of Figure fig:hyper5 with farmers houses having access to other farmers houses. In the larger component, at least four main clusters are easily identifiable. In there are cases where the gold farmers houses are almost at the site of cut vertices and join a large number of other houses on the either side. These are promising candidates for gold farming distribution centers. In terms of connectivity the house projection network is much more highly connected. The average connectivity for gold farmers is 7.56, non-affiliates is 7.09 and for affiliates it is extremely high: 84.02. This implies affiliates houses are connected to a large number of other houses. On average gold farmer houses are connected to 5.86 other gold farmer houses but the average connectivity with non-affiliates is 21.88. This again reinforces the idea that gold farmers tend to trust only the individuals who are trusted in general but not other gold farmers.

5.14 Discussion

Our results provide novel insights into the trust networks which exist among players engaged in clandestine behavior in an online game. Using a hypergraph model to capture the complex dependencies and relationships between accounts, characters, and houses, we performed network analyses on projections of this hypergraphs to identify behavioral patterns of granting and receiving trusted access among farmers, affiliates, and general player population. We showed that the distribution of links in the hypergraph is very heterogeneous and follows a long-tailed distribution such that most of links in the housing network are concentrated in a few nodes. These distributions arise in a variety of other complex networks and suggest an underlying preferential attachment process [137]. Examining this topology based upon the types of accounts, characters, and houses, we found that gold farmers preferentially grant trusted housing access to affiliates who remain undetected rather than to other farmers. These affiliates, in turn, are strongly connected to the rest of the network. The strong disparities between farmers and affiliates housing permissions behavior compared with the general player population suggests these selective patterns capture trust-based relationships. Permissions appear to serve an instrumental purpose in enabling farming operations and avoiding detection. Using frequent subgraph mining techniques, we also identified structural patterns in the hypergraph associated with farmers To the extent that they capture underlying trust among members of these clandestine organization, these frequent subgraphs reveal the strategies adopted to conceal their operations. It may be possible to develop detection algorithms to identify these patterns and improve predictive models. To Sir Falstaffs lament referenced in the introduction, because gold farmers avoid granting trust permissions to other gold farmers, our results seem to suggest that our thieves are in fact rogues among themselves. However the absence of trust ties among these players may not reflect amoral opportunism on the part of this type of players but rather a principled survival instinct evolved and honed from prior encounters with authorities. Or, it could be a combination of both. Nevertheless, gold farmers do not represent a monolithic behavioral class of players; like other criminal organizations, the dividends of comparative advantage lead to a division of labor and skill specialization. We expect that gold farming operations should in many ways resemble drug trafficking operation which need farmers to generate the raw material, distributors to package and deliver the goods, and dealers to interact with customers. Farming operations may exploit administrator heuristicswhich only detect certain behaviorsto concentrate essential but easily-identified behavior into expendable characters. These identified farmers may be sacrificial lambs serving an instrumental but easily replaced role in the operation as well as distracting administrators from identifying the latent organizational patterns we observed. The dissortative or heterophilic mixing we observed among player types could be a strategy employed by farmers to increase survivability of the organization by routing goods and services produced by farmers through complex relationships with other co-conspirators whom they trust will remain unidentified. The generalizability of our findings and the extent to which they map to offline clandestine contexts crucially depends on the extent to which both contexts share the same affordances and constraints. On one hand, the costs of identification for gold farmers are largely pecuniary (re-creating a character) rather than physical (violent reprisal, imprisonment, etc.). On the other hand, previous work (e.g., Keegan, Ahmad et al, [100]) has established striking similarities between online and offline clandestine networks which suggests the need for further comparative and situated research on how gold farmers operate. Future research examining trust networks among clandestine organizations in MMOGs should emphasize generative rather than the descriptive models of behavior we employed. Agent based models, exponential random graph approaches, and stochastic actor-oriented models are all methods for generating graph structures based on local behavioral properties. Future work employing these methods permit the statistical testing of multilevel, multitheoretical hypotheses about processes governing the evolution of networks [131].

Network Analysis Based Methods for Clandestine Behaviors

5.15 Introduction

Contraband are illegally obtained items constituting a parallel or shadow economy which evade regulation or taxation. Although governments have a compelling interest to interrupt these exchanges, especially when they involve dangerous or harmful items like weapons or drugs, knowledge about how trafficking rings are structured or evolve is often ad hoc and anecdotal because it is necessarily difficult to collect information about clandestine organizations. Just as the smuggling of contraband has plagued governments since time immemorial, contraband has likewise appeared within socio-technical systems like virtual worlds such as massively multiplayer online games (MMOGs) in the form of illicitly exchanges of virtual wealth and items for real, offline currency.

If the organization of contraband trafficking operations follow similar demands and constraints online as they do offline, analyzing the structures and dynamics in one context can be mapped to other contexts [191]. Given the difficulties of obtaining data about traditional clandestine organizations, we use anonymized digital trace behavioral data from an MMOG to analyze the in-game items traded by users engaged in illicit activity. This exhaustive data, the unobtrusive way in which it was obtained, and the extent to which online behaviors are similarly motivated and constrained suggests using MMOGs can provide a test bed for both empirically testing theories about social and organizational behavior and developing methods such as improving the detection of clandestine activity. Previous work has suggested that the properties of clandestine networks in a MMOG are created by processes that are similar to those exhibited by drug trafficking networks [100][101].

The exchange of contraband items between game users can be modeled as networks of the items and actors. First, we recognize that multiple types of actors exist as well as multiple dimensions of interactions which bind actors together; second, that these networks are structured by processes occurring at multiple levels of analysis; and third, that these processes and networks can change over time [131][166][52]. Next, we employ network analytic metrics of the relationships among contraband items as predictive features for machine learning methods. These behavioral models of contraband item use and exchange are associated with individuals engaged in clandestine activity. Finally, we integrate these contraband item models with other behavioral features to improve upon existing prediction approaches [15]. Finally the implications this approach has for understanding the general processes which support clandestine organizations is discussed at the end along with the directions for future methodological development and research.

5.16 Related Work

The problem of smuggling and contraband is as old as the establishment of formal trade relationships between nations. It plagued England after the establishment of a national customs collection system in 1275 [72]. Williams [189] gives a historical overview of the problem of smuggling and contraband and notes that in the medieval era smuggling was mainly focused on highly taxed and sought-after export goods. Interestingly, we observe a similar phenomenon in the massively multiplayer online game EverQuest II (EQII), as described in Section IV. A comprehensive historical survey of smuggling and contrabands by Karras [98] describes the relationship between the recognized trade and the shadow economy which constitutes smuggling. Karras finds also that the combination of corrupt officials and smugglers in some cases actually eased the life of local residents in different countries during the imperial era.

The inherent obstacle in studying smuggling is the extreme difficulty in collecting data in this domain, and thus there are not many such studies which use empirical data. There are, however, a few notable examples e.g., Von Lampe [175], who assessed the black market of cigarettes in Europe based on the open source data available on the subject, and the Caviar network data of Morselli [133]. The literature on contraband also notes that, while generally only one type of contraband item is transported at a time, there is mounting evidence that a large volume of contraband follows the Multiple Consignment Contraband (MCC) method which is based on the idea that multiple contrabands are shipped together in consignments. Within the computer science domain, the literature about contraband is mainly focused on using computing techniques for enabling the discovery of contraband in the real world or in contraband digital files.

Shrader et al [158] describe a digital forensic tool for the identification and tracking of contraband digital files shared via the BitTorrent protocol.

An important component of studying illicit trade and contraband in any domain is the study of the social networks of the smugglers and the clandestine actors themselves. Ahmad et al [15] describe the use of machine learning approaches for identifying gold farmers, the players who stockpile in-game wealth and goods in order to sell them to other players for real money. Keegan et al [100] and Ahmad et al [8] studied the clandestine trade and trust networks of gold farmers respectively and described how the gold farmers try to obfuscate their interaction patterns in these networks to evade detection. Also relevant is the study of recommendations in co-extensive networks in MMOGs by Ahmad et al [9] which describes the relationship between item trade and social relationships in MMOGs. Lastly, Keegan et al [101] discuss the usefulness of studying clandestine networks in virtual worlds and their applications to studying their counterparts in the offline world.

5.17 Legal vs. Illicit Trade Activity in MMOGs

Trade is an important an integral activity in most MMOGs and serves a variety of purposes e.g., buying new items to improve ones character, raw materials to craft new items, materials to repair equipment etc. We use data from one PVE (Player vs. Environment) server in EQII called the Guk server. The data that we use spans from January 1 to June 11, 2006. We only consider the players who were involved in trade activities in this period which contains 7,652 players and out of these 251 are gold farmers. We note, however, that the number of active gold farmers changes over time partially because the identification of these players as gold farmers resulted in the removal of these accounts from the game. We define an item to be contraband not by an intrinsic property of the item but rather if the item was sold by a player identified as a gold farmer. Gold farming activity and consequently contraband sold either varies over the course of time or eludes detection after a certain point in time. Figure 5.11 shows the volume of trading activity as measured by the number of transactions over time on a weekly basis. It is clear that gold farmer trading activity is a significant fraction of the trading activity for the first two months and then significantly declines. There are several possible

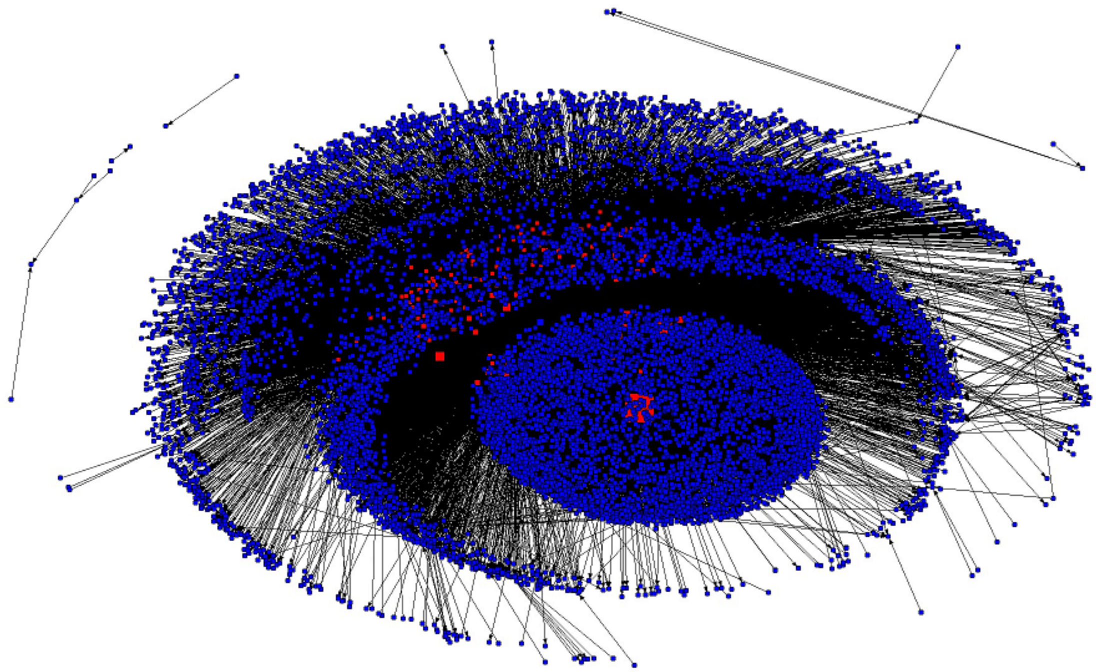


Figure 5.11: Gold Farmers in the Trade Network

explanations for this: Gold farming activity declined within this server as a result of changes in market demand, administrator enforcement, or practices employed by the gold farmers to evade detection[100]. There is however insufficient data to decide which possibility is the correct one. Also noteworthy is the overall trading activity exhibits regular periodicity beginning in March. The peaks correspond to increases in trading activity on weekends over weekday activity.

Since the main revenue generation activity of gold famers is by selling their loot or the result of their efforts to other players, we also compared how the buying activity of gold farmers compares with selling activity as given in Figure 5.12. Surprisingly, a larger volume of trading activity of gold farmers is for buying items instead of selling them. This implies that gold farmers may be buying items for some other purpose. We explore this in more detail in the next section. Previous work on gold farming [100] has indicated that the gold farmers may be trading with one another in order to confuse the game administrators and evade detection. To explore this further we plotted the volume of trade between gold farmers as given in Figure 5.13. Here we do not see any discernable patterns but the trade volume declines to nearly zero after March and is never a significant proportion of the total gold farmer trading activity.

The trading volume measured in terms of transactions declines over time and becomes increasingly periodic; however, the number of items which are traded, as shown in Figure 5.14, indicates a different type of behavior when it comes to gold farmers. The number of unique items sold shows periodic behavior for most of the span of the data, with the exception of a phase shift in February. Interestingly, even though the trade volume of items sold by gold farmers changes over time, the number of items remains more or less constant. This implies gold farmers are interested in certain types of unique items, a phenomenon which is discussed in more detail in the next section. Figure 5.15 gives a more detailed breakdown of gold farmer items. There are some major differences with respect to the number of unique items which are bought or sold by gold farmers e.g., the number of unique items which are sold by gold farmers, or contraband, are more than the number of items which are bought by gold farmers even though the reverse is observed when we look at the trade volume for the gold farmers. This implies that the gold farmers are buying many items in bulk but sell items to other players in smaller portions.

5.18 Clandestine Social Networks & Illicit Trade in MMOGs

Previous work on the trade networks of gold farmers [100] has concentrated on only the transaction networks without considering the items that are traded. Here we extend the previous work on this area by concentrating on the contraband items in the data.

5.18.1 Item Projection Networks

Consider the bipartite (two-mode) network consisting of the social network of market actors (buyers and sellers) in one mode and the items that they trade in the second mode. We project this network into a unipartite (one-mode) space of relationships connecting items only if they have been traded by the same person. This network reveals whether pairs of items are regularly exchanged by many players.

Table 5.10: Characteristics of the item network over time

Mon.	**Edges**	**Nodes**	**d**	**Edges$_{GF}$**	**Nodes$_{GF}$**	**d$_{GF}$**
Jan	3,489,037	13,009	0.041	76,559	1,874	0.044
Feb	4,392,985	16,543	0.032	83,998	2,432	0.028
Mar	7,539,607	29,998	0.017	180,348	3,369	0.032
Apr	7,033,935	18,568	0.041	77,428	2,011	0.038
May	7,755,564	19,012	0.043	81,758	1,436	0.079

Table 5.10 gives the summary of the item network over the course of five months. We also consider a gold farmer (GF) subnetwork of items which are traded by gold farmers. Since there are a large number of items which can be traded by a player, the item network can be very dense. Comparing the general item network to the gold farmer network, we see that both networks have similar densities. While this suggests that gold farming activity is difficult to discern from licit in-game economic, we also note that gold farmers trade in a relatively small number of items as compared to the rest of the population. As shown in Figure 5.16, total activity for all items in the network follows a long-tailed distribution with most items being exchanged few times but a few items constituting the vast majority of trading activity.

Table 5.11: The top 5 items, bought by gold farmers

Item Name	**Number of Transactions**	**Support**
Repair materials	3,898	0.81
Aerated mineral water	3,611	0.99
Mulberry	2,273	0.53
Bees wax candle	1,173	1.0
Crude solidified Enneanoid Loam	201	1.0

Table 5.12: The top 5 contraband items, sold by gold farmers

Item Name	**Number of Transactions**	**Support**

Ebon Relic	6,417	0.70
Star Sapphire Amulet	5,478	0.68
Indicolite Relic	5,000	0.67
Star Sapphire Scrying Stone	4,971	0.70
Bayberry Sealed Document	3,964	0.71

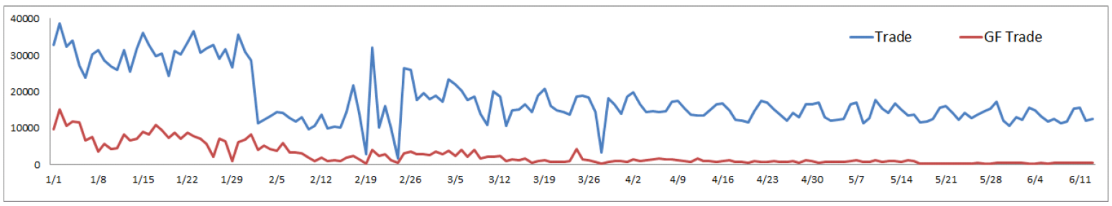


Figure 5.12: Weekly trade volume for all players and gold farmers

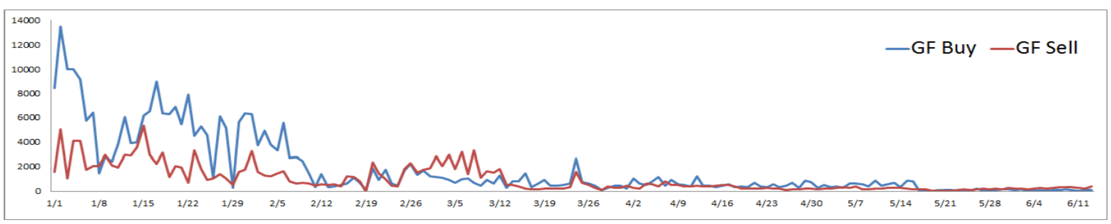


Figure 5.13: Weekly buying and selling trade volume for gold farmers

Now, we consider the items which are sold or bought more often by gold farmers than the rest of the players. We examine items which are not only frequently sold but also frequently bought by gold farmers. Tables 5.11 and 5.12 respectively report a list of the top 5 items frequently bought and sold by gold farmers. We define Support of an item X as the number of transactions where the item occurs divided by the total number of transactions. One interesting characteristic of the items frequently bought by gold farmers is that these are usually low-end items, i.e. items that are cheap to

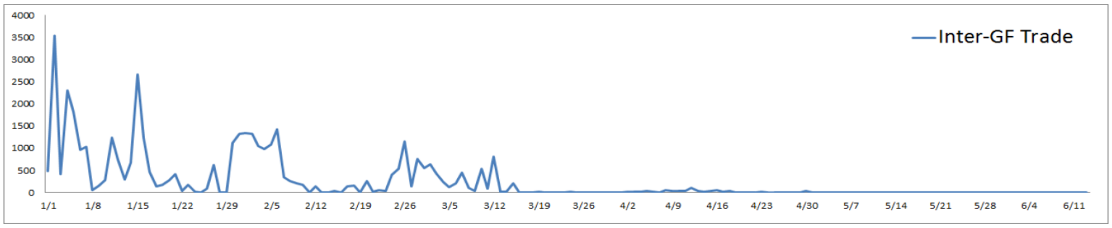


Figure 5.14: Volume of trade between gold farmers

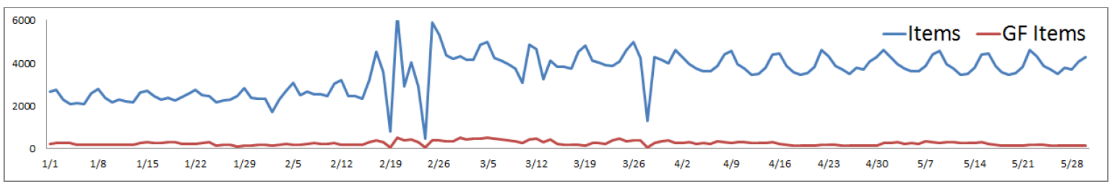


Figure 5.15: Weekly number of unique items sold over time

buy and, in many instances, used for crafting other items. Gold farmers could also be using these items to craft more complex items to be sold later. One possible explanation for this phenomenon is that gold farmers may be hoarding some materials in order to monopolize the production of certain items in the game. On the other hand, the items which are sold almost exclusively by gold farmers have a very different characteristic: these are almost always high-end items which require a lot of in-game effort to obtain or craft. This makes sense from the domain perspective since the gold farmers would mainly be interested in selling items which are likely to yield a higher payoff as compared to more generic items within the game.

5.18.2 Frequent pattern mining analysis

We improve upon this analysis by doing frequent pattern mining analysis to determine what items are sold together by gold farmers, using an adaption of the Association Rule Mining framework [4]. The concept of Support as described previously is useful here since we are only interested in the items that are sold almost solely by gold farmers, the

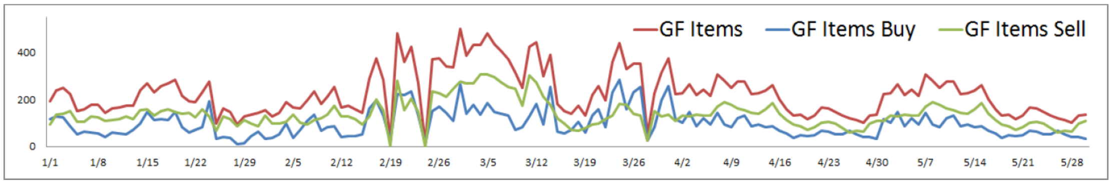


Figure 5.16: Weekly number of unique items, bought and sold over time by gold farmers

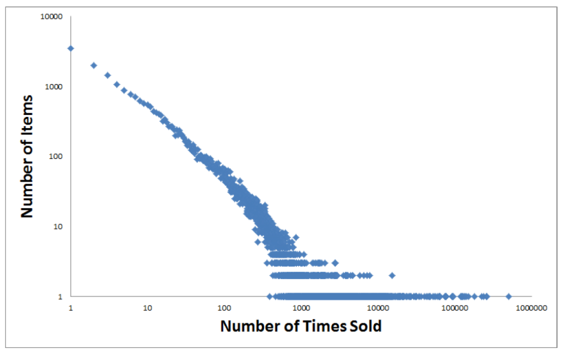


Figure 5.17: Dist. of items sold over the course of 5 months

Confidence of an item, from the frequent mining paradigm [4], is a less useful concept since there are a large number of items which have extremely low support, e.g. only ten transactions out of 28 million. The inclusion of such items in the analysis is important since such items are usually high end items as described previously and thus require some time to accumulate. We can, however, specify a threshold in terms of the least number of transactions ? that must be present in dataset. Once we have identified the items which have high Support amongst gold farmers these can be used as features to predict gold farmers as we demonstrate in section 5. Since we are only interested in the item sets which have high support amongst the gold famers, item set generation can take this into account by only generating the frequent item sets which have a minimum support amongst the gold farmers. It should be noted that there is one shortcoming that must be addressed in the interpretation of these results. Since the gold farmers studied are only the ones who were identified, there are certainly players who are gold farmers but had not been identified [15]. Consequently, this affects the support of the item sets bought or sold by the gold farmers. Previous work [100] has established that a substantial subset of the people who trade with gold farmers, called gold farmer affiliates, may be gold famers themselves. We thus refine the support metric to include the cases where the items were bought or sold by gold farmers. Thus the Auxiliary Support of an item is defined as the proportions of items which are sold by gold farmers and the gold farmer affiliates with respect to the total number of transactions involving that item. This, however, dramatically changes the number of items under consideration since many of the gold farmer affiliates are prolific buyers and sellers. Thus in January there are 1,874 items associated with gold farmers but 3,998 (more than twice as many) items associated with the affiliates. An analysis of the types of items associated with the affiliates paints a more complex picture the gold farmer in-affiliates i.e., players who buy items from gold farmers, usually buy high-end expensive items from them while the gold farmer out-affiliates usually buy a combination of all types of items so that it is difficult to categorize them.

5.18.3 Frequent-Networks of Contraband in MMOGs

Just as there are certain items which are frequently associated with gold farmers, there are also certain groups of items which are almost always sold by some gold farmers but not at the same time e.g., consider items A and B which are sold together by gold farmers and item C which is also sold by the same gold farmers but at a later time. While market basket analysis can be used to determine the groupings of items which are sold together frequently, the traditional framework of market basket has to be modified in order to discover grouping of items which are separated across time but which are nonetheless sold by gold famers. It should be noted that this problem is different from sequential pattern mining because we are not interested in the sequence or the order in which the item is sold or bought but if certain items are likely to be bought or sold by the same group of people over the course of many transactions. Thus, it is possible to construct a network of such items, which we call the frequent-network of contraband in MMOGs. Raeder et al [148] introduce the concept of market basket analysis with network data. We use a different framework from that used by Raeder et al [148] since the purpose of our analysis is not to discover network based association rules for all the transactions but to discover frequent patterns of networks of items which are associated with gold farmers or their affiliates. An example of the network of items [9] with the largest support is given in Figure 5.18.

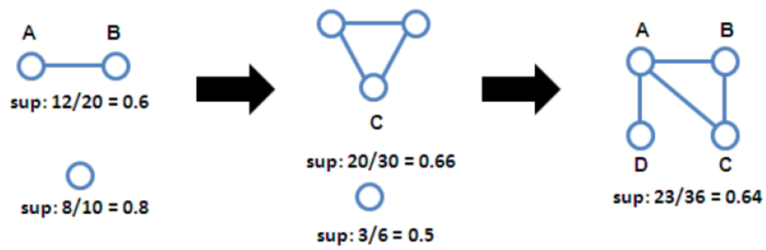


Figure 5.18: Constructing frequent-networks of contraband items

We used the association rule mining framework for this task as well; the algorithm given below describes the candidate generation and evaluation task. First only the items which have the minimum Support amongst the gold farmer class are generated. Once such item sets have been generated, a levelwise generation of more candidate sets can be done in a manner similar to the Apriori algorithm [4] by generating new item sets by concatenating the item for an item set by an item set of size one but for only those cases where the support is greater than or equal to the minimum support. Once all such itemsets have been generated, the network of itemsets can now be generated. Since the networks of items that we want to extract are not necessarily present in the same set of transactions, we have to define the concept of support in a different manner. Given an itemset consisting of k items we represent it as a k-complete graph NS. Now consider the social network of people who have traded with this item, for all the frequent items associated with these people we generate new itemsets by the union of the previous graph NS and itemsets which have at least one element common with NS. The support for the network graphs is defined differently because of the network effect. Additionally we introduce the idea of background support - the proportion of people who are common to both itemsets i.e., the number of people who have either bought or sold that item. Thus given two item- networks represented as graphs NA and NB having one or more elements (represented by set NC) common between them, the support of the two elements is the number of transactions where either of these two itemsets are observed with the class of interest (gold farmers in the current domain) in the dataset divided by the total number of transactions where these instances are observed. This can be illustrated by considering graph GAB in Figure 5.18, itemset C is associated with a subset of the same people who are associated with G_{AB}.

Algorithm 1 Generating the frequent Item Network

Given: Transaction database T,
Minimum Support $minSupp$
Maximum size of the graph $G, maxNetSize$
The background support $backSupI(j)$
itemset at level j
for $i = 1 \rightarrow size(T)$ **do**
  Save counts C_j and counts C_{jGF}
  for $j = 1 \rightarrow size(I(l))$ **do**
    Save the itemsets I_j where $C_j / C_{jGF} \geq minSupp$
  end for
end forset: j = 1
while $supGF(I(j)) \geq minSupp$ **do**
  Generate $I(j+1) = I(j) + I(1), j = j+1$
end whileset: N(1) = I(1)
while $sup(N(j)) \geq minSuppandj < maxNetSize$ **do**
  Generate $N(j+1) = N(j) + N(j-1), j = j+1$
  $sup(N(j+1)) = (C_{GF}(j) + \frac{C_{GF}(j+1))}{(C(j)+C(j+1))}$
end while

The main idea behind the approach of using not only item sets but also networks of item sets is that if one can discover such groups of items then they can be used to enhance gold farmer prediction methods. In this case, a feature would constitute a graph of frequently sold items instead of features which are just counts of scalars using the count of items themselves. Figure 5.19 illustrates this approach where the feature sets consist of a network of frequently occurring items.

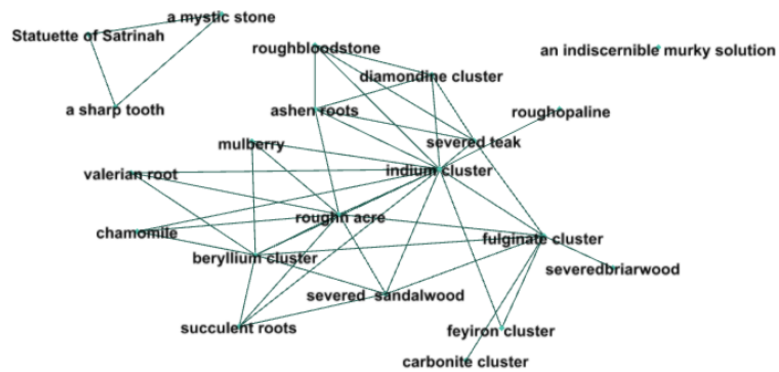


Figure 5.19: Network of Items with more than half a million transactions

5.19 Contraband Based Prediction in Clandestine Networks

We now demonstrate the utility of using contraband and contraband-networks as features in machine learning models for predicting if a player is a gold farmer or not.

5.19.1 Datset

The timespan that we consider is five and a half months as described previously. We limit the set of players under consideration to those who have traded at least once and exclude players who have engaged in other forms of trade like gifting or bartering. Thus there are 9,383 players, and out of these, there are 331 are gold farmers. There are also 5,650 gold farmer affiliates, i.e. players that gold farmers have traded with. 4,497 players sold items to gold farmers and 4,136 players bought items from gold farmers. This implies not only that the gold farmers are prolific traders but also that the gold farmers trade with a large set of same traders.

5.19.2 Model Descriptions

Using the consignment trade data, we constructed a set of machine learning models using the item sets, their networks, player demographics and in-game characteristics as features. The last two feature sets correspond to the features used in the previously reported results on gold farmer detection [15]. Using a combination of these features and also considering them in isolation, we describe the following four models which were to address the current classification problem:

- Model 1 (Player Attribute Based Features): These features are based on the attributes of the players character in the game e.g., character race, character gender, distribution of gaming activities etc. These are the same features which were used by Ahmad et al [15].

- Model 2 (Item Based Features): These are the features which are derived from items bought and sold from the consignment network. These features are based on the frequency of the frequent items sold or bought by gold farmers.

- Model 3 (Player Attribute Item Based Features): All the attributes from the previous two models.

- Model 4 (Item Network Based Features): Features which are derived from the item network in a manner analogous to Model 2.

- Model 5 (Player Attribute Item-Network Based Features): A combination of features from Model 1 and Model 4.

- Model 6 (Item Network Item-Network Based Features): A combination of features from Model 2 and Model 4.

- Model 7 (Player Attribute, Item Item-Network Based Features): Union of all the features described above.

5.19.3 Experiments and Results

We used a set of standard classifiers for the classification task using the Machine Learning package Weka [78]. The classifiers that we used are as follows: Naive Bayes, Bayes Net, Logistic Regression, KNN, J48, JRip, AdaBoost and SMO. The results of the predictions from the various models are given in Table 5.13 where the models correspond to the models described in the previous section. We only report results from the best classifier for each model instead of giving results for all the classifiers mainly because of space constraints. Model 1 corresponds to the model used by Ahmad et al [15]. From Table 5.13 it is clear that the results vastly improve upon the previous reported results for gold farmer detection.

The best overall results are obtained from Model 6 which corresponds to the model which is constructed by combining the item based features with the item-network features. Model 3 also gives a relatively high value for recall but the value for precision and F-Score is much less that that of the combined model. Interestingly Model 7 which corresponds to the combined model and which uses features from all the previous models does not perform as well but it still performs better than the baseline model. Also noteworthy, is that Model 2 and Model 4 have similar F-Score but the trade off between precision and recall for each is observed.

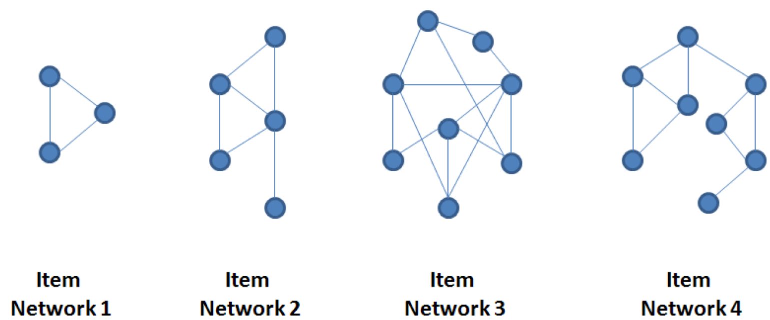


Figure 5.20: Examples of Network Features

Table 5.13: Prediction Results

Model	Precision	Recall	F-Score
Model 1	0.721	0.657	0.687
Model 2	0.747	0.873	0.805
Model 3	0.723	0.694	0.708
Model 4	0.866	0.749	0.803
Model 5	0.703	0.716	0.709
Model 6	0.943	0.729	0.822
Model 7	0.728	0.683	0.705

Thus, for model selection, the main criteria that one has to address in this domain is not just the performance in terms of these metrics but also the human effort is required to determine if the person who is flagged is indeed a gold farmer or not. This is so because in some contexts there is a high cost associated with flagging gold farmers incorrectly. In such contexts a model with high precision is highly desired. In other contexts where gold farming related activities have a high volume and there are a high number of gold farmers within the game, recall is a more important metric. The choice between these two models will thus depend upon the requirements of the domain.

5.20 Summary

Trade is an important aspect of gaming in MMOGs. Previous work on the economies of MMOGs has demonstrated that many real-world phenomena can be mapped onto virtual worlds [191]. Because of challenges related to data collection in the offline world, it is not possible to study certain types of phenomenon in sufficient detail, especially phenomenon related to the study of clandestine activities and their associated networks [101]. Thus, virtual worlds offer an opportunity to bridge this gap and study such phenomena in much more detail than is possible in the offline world. The insights gained from studying virtual worlds can be applied to the real world if sufficient mapping can be established between them. One such problem that we addressed in this chapter is that of trade associated with contraband and their item networks. After discovering a set of items which were most often associated with gold farmers, we used those items as well as the networks between them as feature sets in machine learning models to predict who the gold farmers are. The improvement of results demonstrated the viability of this approach.

5.21 Conclusion and Future Work

The availability of datasets which contains information about clandestine activities opens new avenues of research for studying such activities. In this chapter, we analyzed contraband trading activity and contraband networks in MMOGs. It was discovered that gold farmers sell certain items more than other players, and there are certain items they also buy more often. The items that gold farmers sell more often as compared to normal players are high end items that likely fetch more money. On the other hand, the items that the gold farmers are inclined to buy more often are the low end items. There are two possible explanations of why these patterns appear. One possibility is that they do so in order to corner the market and create an artificial monopoly over that resource. The alterative is that they do so in order to use them in crafting other items. In our future work we seek to address this issue. Using insights gained from the analysis of contraband networks in MMOGs, we addressed the challenge of gold farming detection. While the difficulty of gold farmer detection has been addressed before [15], in this chapter we extend the previous results by adding information from contraband networks as feature sets to enhance the prediction task. The approach that combined features from both the list of items and item-networks associated with gold farmers yielded the best results. In future work, we plan to expand the current analysis from contraband networks to a multi-network analysis which includes other networks in MMOs like the trust network [8], mentoring networks, chat networks and other trade networks.

Chapter 6

Trust and Mentoring

”He who does not trust enough, Will not be trusted.”
– Lao Tzu

The previous chapters mainly focused on the explicitly defined trust networks. As described in the introduction chapter there are multiple ways to define trust and thus trust networks. The current chapter addresses the issue of using other proxies of trust in addition to explicitly defined trust. After explicitly defined trust the strongest proxy of trust in MMOs is mentoring. In EQ2, character levels range from 1 to 70 and higher level players can select a lower-level player and enter in a mentoring relation, in which their level is lowered to match their apprentice. This allows apprentices to benefit from the experience and abilities of their mentors when fighting monsters or completing quests. It also allows friends to play together regardless of level differences, or players in the same guild to help guild-mates complete difficult encounters or level-up in order to tackle high-level raid encounters. In addition, mentoring offers bonus points for both mentors and apprentices, which expands their overall achievement in the game. This suggests that mentoring in EQ2 also serves both social and performance-enhancing functions. Though mentoring can be established, maintained, or dissolved for a variety of reasons, at the foundation of these interactions is some type of exchange among individuals [198]. Treating mentoring as an exchange relationship allows us to consider the dynamic and interdependent nature of mentoring in organizational settings.

Models of Mentoring Networks

6.1 Introduction

There is a large body of literature on analysis of complex networks in the real world [181]. Empirical work suggests that there are many commonalities among these networks such as a shrinking diameter [19] or power law distributions [24]. Given such common characteristics researchers have proposed several graph generating mechanisms for these networks [125], [17], [18]. While a wide range of networks including blogs, patents, and scientific citations have been studied, rarely if ever have scholars examined networks consisting of mentor-apprentice dyads. In this chapter, the analysis is extended to mentoring networks and it is shown that these networks do not share many of the characteristics of 'regular' networks. This network is conceptualized in terms of exchange theory and then a generative model is developed that best simulates it. Data from EverQuest II (EQ2) is used in the present case as well. Many of these game activities require players to collaborate and team up in order to be successful.

The main inquiry in this chapter is with respect to the nature of mentoring in large-scale virtual worlds. Is it primarily a one-on-one phenomenon, in which mentor and apprentice form a strong mutual relationship? This is how it is portrayed in much of the literature. However, recent research on networks suggests that many phenomena previously regarded as primarily individual-level exchanges are in fact more complex. Rather than being a one-to-one relationship, mentoring may be more communal in nature. With this view mentoring is conducted by a larger community which gives the apprentice coaching, and the apprentice is embedded in a mentoring community rather than connected to a single mentor. In order to answer this question, we rely on a temporal data-set of a social network of mentoring links between all players over an eight-month period.

This analysis enables one to gain insights into mentoring in online games and, it can be argued, more generally. The analysis points to some key problems with widely accepted network models for complex relationships such as mentoring. These models have been developed primarily on relatively simple relationships, such as internet connectivity or small world phenomena. Mentoring is a more complex relationship than these graphs represent and thus represents an excellent context for inquiry into fundamental properties of networks. We present a generative model GTPA (Generative Temporal Preferential Attachment) which can recreate a set of desired features that are observed in mentoring networks, which can not be explained by other models such as Preferential Attachment, Forest Fire, Butterfly, RTM. The models employ in this analysis are centered on exchange relationships, which may be multitiered and multi-level. Prior to developing the models we will consider how mentoring can be conceptualized as 'exchange.' Two fundamentally different models of exchange are then considered that provide basic frameworks for dynamic modeling of mentoring networks. Mentoring in Virtual Worlds as Exchange Definitions of mentoring range from basic aide to formalized organizational arrangements [43], and instances of mentoring have been found in a variety of educational, organizational, and social settings. Research on mentoring has predominantly focused on the respective costs and benefits for both mentors and apprentices. For example, [90] discuss how mentoring in organizational settings can increase work competence -individual salary and job satisfaction, while [106] finds that mentoring also serves psychosocial functions including providing friendship and counseling.

There is reason to believe that many real-world phenomena such as mentoring may occur in much the same way in virtual worlds. Studies of socializing, trust, and expertise in virtual worlds suggest that causality in virtual worlds is similar to that in the real world [190], [180]. This is coupled with the fact that EQ2 has an explicit design feature which encourages mentoring relationships.

6.2 Exchange as a Basis for Network Generation

Monge and Contractor [131] review much of the literature on exchange theory as a theory of networking. They note that while a great deal of work has been done on exchange relationships between individuals and among groups, larger networks are generally assumed to simply be the sum of dyadic relationships. This assumes that exchange operates primarily at the micro-level and that resulting networks will be extensions and complexities of micro-level relationships. As such, this approach relies heavily on discrete exchanges and does not reflect all of the ways exchange networks may evolve over time Ekeh [59] distinguishes two versions of social exchange models that trace back to individualistic and collectivistic traditions in social theory. Restricted exchange is f around exchanges between two parties, each of whom benefits directly from interactions and transactions with the other. In restricted exchange, there is a high degree of accountability on the part of both parties. Each knows what he or she is getting from the other and can call the other to account if the relationship is not satisfactory. Second, they tend to involve quid pro quo relationships between the parties that become very specialized.

Generalized exchange, on the other hand, is organized around a community where members are link "in an integrated transaction in which reciprocations are indirect, [59]. Exchange occurs among members of a community rather than between two individuals. Ekeh notes that this might occur in a chain of exchange, where A gives to B who gives to C who gives to D, etc. It may also occur when a group joins together to give an individual value that no single member could, that when A, B, C, and D jointly give to E (a bridal shower where a group of friends give gifts to the bride and convey community approval on her marriage is one example of this). Finally, generalized exchange may occur when individuals "successfully give to a group as a unit and then gain back as part of the group from each of the unit members" [59]. Each of these patterns represents exchange across a more complex network.

Considering mentoring, both types of exchange seem possible. Restricted exchange would occur when friends or regular partners mentor one another. Chat sites for EQ2, exhibit numerous stories about mentoring that reflect this. Friends mentor friends to help them advance, and in return receive thanks and the satisfaction of helping those close to them. Generalized exchanges of at least two types seem likely to occur. First, some members may seek to build the community in the game by mentoring others, helping them "learn the ropes" and advance. Second, multiple mentors may help a single individual to gain by helping them, which represents the final type of generalized exchange discussed by Ekeh.

If restricted exchange holds, then the primary generative mechanism behind the network will be reciprocation of ties, once a single tie is formed. This will tend to generate particular triadic structures such 3, 7, 11, 12, 13, 14, 15, and 16 seen in Figure 3.1, and these should be more common than expected by chance in the network. On the other hand, if generalized exchange holds, then chains and lengthy cycles of links might hold, as well as it should favor triads 4, 5, 6, and 10, which should be more common than expected by chance. Triad 8 is likely to occur when both types of exchange occur [59].

6.3 Data Description and Observations

Although we have data available from multiple servers, in this chapter we report the results of experiments from only one of the servers. However we note that the results are generalizable to other servers as well (similar results were obtained on those servers). The network data is available at the granularity level of seconds. We analyzed the data at various levels of temporal granularity and observed that the network behaves in a similar manner at various though not all levels of granularity. Figure 6.3 gives the visualization of the mentoring network at hourly, daily, weekly and monthly levels of granularity.

Figure 6.3 summarizes many commonly used graph characteristics. Part (a) through (d) of 6.3 illustrates that the number of nodes, number of edges, number of components and the diameter of the mentoring network increases over time. Power law distributions of both in-degree and outdegree are observed here as in many real world networks, along with a long tail. Figure 4 gives the size of the Largest Connected Component (LCC1), the second and the third largest connected components (LCC2, LCC3) over time. From Figure 6.3 and Figure 6.4, it is apparent that the overwhelming majority of the nodes belong to the largest connected component.

It should be noted that Pearson's Correlation cannot be used to study how much overlap there is between two successive iterations in the network. This is because if the graph is sparse and thus most entries are zero, would create a very large and misleading correlation value. Instead, we use the Adjacency Correlation $Adjj$ as defined by Clauset and Eagle [49]:

$$\gamma_j = \frac{\sum_{i \in N_j} A_{i,j}^{(x)} A_{i,j}^{(y)}}{\sqrt{(\sum_{i \in N_j} A_{i,j}^{(x)})(\sum_{i \in N_j} A_{i,j}^{(y)})}} \tag{6.1}$$

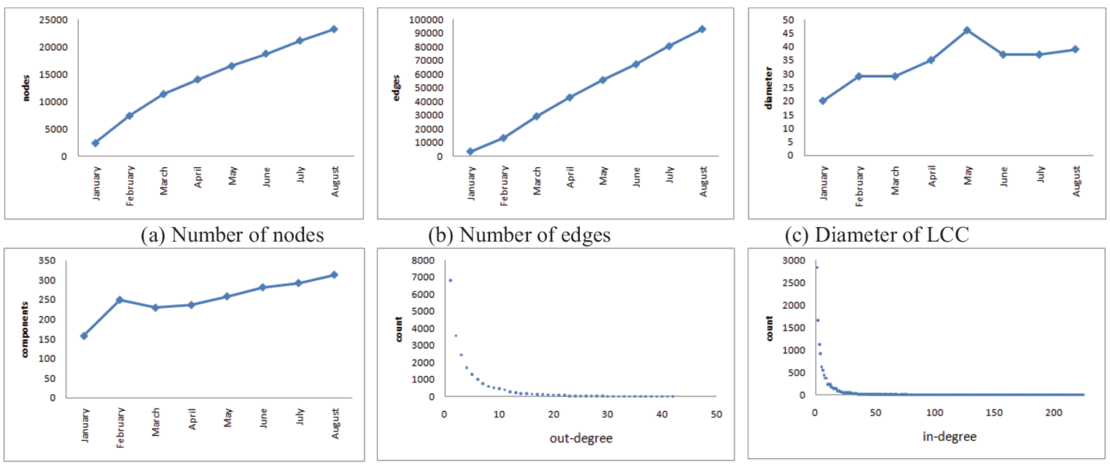
Table 6.1: Adjacency Correlation for the Mentoring Network over the course of 8 months in 2006

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
Jan								
Feb	0.12							
Mar	0.09	0.12						
Apr	0.06	0.07	0.12					
May	0.05	0.08	0.09	0.13				
Jun	0.05	0.06	0.07	0.08	0.13			
Jul	0.04	0.05	0.05	0.06	0.08	0.14		
Aug	0.05	0.05	0.06	0.06	0.07	0.10	0.13	

In 6.1, $A(x)$ and $A(y)$ are the adjacency matrices of the graph at Time x and at Time y. $N(j)$ is the union of row elements which are non-zero in at least one of the two matrices, γ is the correlation for the row for the two graphs. The adjacency correlation for the network is defined as the average of the adjacency correlation for all the rows in the adjacency matrix. The results for adjacency correlation for the mentoring network for eight months are given in Table 6.1. It is interesting to note that the adjacency correlation between a month and the next month is often close to 0.12 and drops thereafter. This demonstrates that while there is overlap between the networks, the overlap in successive months is not very large, implying that between any two time slices only a certain subset of the network is active (i.e., participants in the growth of the network). We refer to this subgraph as the Active Graph. Given the 16 types of possible triads as described above, the following quantity computed via Pajek [140] is a standard measure of determining the relative importance of each type of triad in a network:

$$\tau = \frac{n_i - e_i}{e_i} \tag{6.2}$$

In 6.2 n_i is the number of triads and e_i is the number of expected triads in a random network. Figure 6.4 gives the value of for each of the 16 types of triads. The results show that the types of triads that were most common were consistent with specialized exchange rather than generalized exchange (as defined in the previous section on exchange). These include Triads 11, 12, 13, 14, and 16.



(a) Number of nodes (b) Number of edges (c) Diameter of LCC

(d) Number of components (e) Out-degree (f) In-degree

Figure 6.1: Various Network Characteristics of the Mentoring Network over time

6.4 Graph Laws in the Mentoring Network

Akoglu et al., [18] observed that a number of laws or observed patterns are found in a large number of real world networks. Based on their observations, they develop a set of 11 laws and an RTG generator for realistic graphs. In the mentoring dataset we observe that several of these laws do not hold:

1. **Small and shrinking diameter:** the (effective) diameter of the graph should be small with a possible spike at the 'gelling point'. It should also shrink over time [116]. However, our analysis shows that the diameter of the mentoring network increases over time but not in a manner predicted by scale-free networks [20].

2. **Constant size secondary and tertiary connected components:** Even though the 'largest connected component' continues to grow, the secondary and tertiary connected components tend to remain constant in size with small oscillations. In our data set, the majority of the nodes belong to LCC1 (Figure 6.4) even though there is more than one component. This contrasts with the preferential attachment model [19].

3. **Bursty/self-similar edge/weight additions:** Edge (weight) additions to the graph over time should be self-similar and bursty rather than uniform with possible spikes. The last law is only partially violated as self-similar behavior is indeed observed at the monthly as well as the weekly level. The growth of the network is different on different days of the week because of differences in playing activity for different days (i.e., players tend to play more on weekdays). The same effect is observed on holidays.

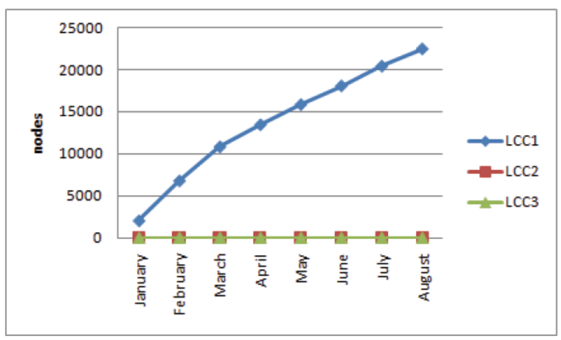


Figure 6.2: Components of the Mentoring Netwok over time

6.5 GTPA Graph Generative Model

Based on the observations described in the previous section we propose the following criteria that a generative model for mentor networks should satisfy:

1. The diameter of the network increases over time.

2. The number of components increases over time.

Triads	January	February	March	April	May	June	July	August
1 - 003	0	0	0	0	0	0	0	0
2 - 012	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-0.02
3 - 102	11.34	32	42.08	51.73	63.4	76.46	87.31	98.78
4 - 021D	2.33	5.06	5.1	4.96	5.08	5.16	5.21	5.26
5 - 021U	0.26	0.4	0.64	0.77	0.82	0.84	0.86	0.87
6 - 021C	-0.19	0.03	0.37	0.53	0.66	0.73	0.79	0.83
7 - 111D	6.6	45.61	65.26	89.33	114.5	136.38	159.48	177.07
8 - 111U	15.88	88.28	146.56	183.86	228.72	283.53	332.94	389.6
9 - 030T	139.12	320.61	371.7	375.47	392.8	406.99	419.73	431.53
10 - 030C	-1	1.15	2.24	2.99	3.28	4.52	5.44	5.74
11 - 201	1523.24	2989.24	4789.53	9944.71	12660.17	18275.82	24179.46	24567.75
12 - 120D	35056.47	101667.2	102729.2	131859.9	164847.4	193823.6	237207.36	270255.2
13 - 120U	7620.19	113628.17	159150.9	205650.6	277531.8	335976.6	383489.18	461066.5
14 - 120C	761.12	5979.48	6918.65	10265.54	13419.84	18388.64	22580.76	25733.42
15 - 210	-1	6234638.77	23645474	32352174	47536672	72387840	99573627.01	1.31E+08
16 - 300	14910406189	2.33986E+11	2.21E+11	3.03E+11	3.61E+11	6.45E+11	1.06579E+12	1.46E+12

Figure 6.3: Triadic census of the mentoring network over time

3. Bursty behavior is observed at certain levels in the network while periodic behavior at others levels of granularity.

4. The size of the active sub-graph remains more or less the same.

5. The overlap between the graphs between successive iterations is small.

6. Generate sub-structures that favor specialized exchange.

We describe this model by modifying the preferential attachment model in the following way:

1. Consider a set of initially connected nodes n0.

2. Consider another set of n_1 nodes ($|n_1| > 2$) which have to be added to the network. We add these nodes one by one. When adding a new node we randomly select them and connect to one another. This ensures that there is more than one component.

3. From the second iteration onwards randomly select a set of ns nodes from the graph from the previous iteration. These nodes and the edges between them form a new graph GN. Connect all the new incoming nodes to one another according to the scheme described in (ii) and connect them to ns according to (iv).

4. Temporal Preferential attachment: When choosing the nodes to which a new node connects, assume that the probability that an edge will be created from new node j to an existing node i is given as follows:

$$\rho = \frac{k_i}{\sum_j k_j} \cdot \left(1 - \frac{t(i))}{max(t(j))}\right) \tag{6.3}$$

In this equation, k_i is the connectivity of the node and $\sum jk_j$ is the total number of nodes in the network, $t(i)$ is the age of the node and $max(t(j))$ is the maximum age of any node in the network and thus gives the age the network.

In step (iv) the choice of having a new node more likely to connect to an already present node which is younger as compared to an older node seems to be counter-intuitive at first since one would expect people would prefer to be mentored by people who are more established. However we note that the number of player that a player knows is limited and it is usually in a small window of opportunity that a mentor mentors another player.

6.6 Properties

We assume that the graph and its subgraphs being considered are connected.

Lemma: The diameter of the network generated by GTPA will either remain constant or increase over time.

Proof: Suppose the diameter of the network G_0 initially is d_0 then the diameters of a subgraph (Active Graph) G_{0S} of G_0, is given by $d_{0S} \leq d_0$. At the end of the first iteration the diameter of the active graph and its union with the graph consisting of the new nodes is given by:
$d_{0U} = d_0 \pm \tau$, where $\tau << d_0$
This is so because G_1 is generated by the same mechanism that generated G_0 and has (roughly) the same number of nodes and edges. Here τ is the uncertainty in the diameter. The network at the end of the iteration is given by
$G_1 = G_{0U} + G_{0L}$.
The diameter of this graph is given by:
$d_1 = d_{0U} \pm \tau + r$
The maximum value of r is when d_0L is equal to $(n-1)$ nodes and the minimum value is

obtained when r is zero i.e., $d_1 = d_{0U} \pm \tau$ diameter remains constant while the diameter increases in all the other cases.

Periodicity: Periodicity in the model can be introduced by adding new nodes and edges to the graph based on a regular intervals such that the net effect of such an addition of a constant addition.

6.7 Experiments

The main question that we want to address here is to see if the proposed model can generate the desirable features of the mentoring network. Our model has three free parameters: τ, N_s and β. We used the grid search method [85] to determine the most suitable set of values for these parameters. The main idea behind grid search is that given a parameter space it ties a whole range of values in geometric steps. If the model fit improves then the search moves to the next value, if not then it reduces the step size until the step size is smaller than a prespecified threshold.

Although we have only given the results at the monthly level of analysis we ran the experiment for the monthly, weekly and the daily levels as well. The best results obtained through grid search are given in Figure 6.7, which are plotted alongside the observed characteristics of the mentoring dataset. Part (a) and (b) of this figure show that the diameter and the number of components increases over time. Part (c) shows that the size of the largest connected component for both the real network and the generated network. One noticeable difference between the two is that the diameter and the number of components from the generative model are monotonically increasing while in the observed network these quantities increases but with some oscillations.

Figure 6.7 gives the values of log of the mentoring network, the scale-free network and the GTPA network. It should be noted that the values log very close to one another indicating that the triadic substructures have been recreated at the global level and thus similar types of exchanges are going on in the observed and the generated network.

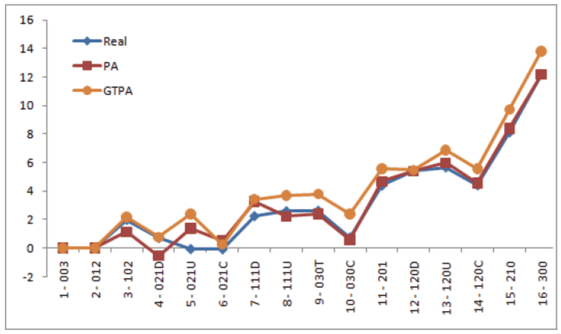


Figure 6.4: Triadic Census of the various Networks

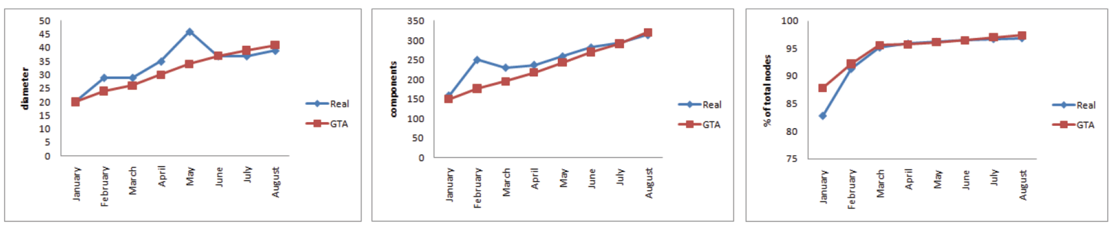


Figure 6.5: Network characteristics of the real and the simulated network

6.8 Conclusion

In this chapter we analyzed a special type of network formed by mentor-apprentice relationships. Many of the characteristics that are observed in this network are not observed in many other real world networks e.g., the diameter and the number of components of the network increase over time. We also explored the relationship of types of exchanges to mentoring networks (i.e., mentoring networks are characterized primarily, but not exclusively by restricted exchange). Thus, because any of the wellknown graph generator models cannot be applied to this data, we presented a new model GTPA for generating networks which have characteristics similar to the mentoring networks.

Our chapter also demonstrates how mentoring exchange emerges in MMORPG environment, and provides some insight into how mentoring mechanisms might emerge when introduced in other virtual worlds. For example, our finding that specialized exchange occurs more often contrasts with our intuitions that a virtual community would demonstrate complete egalitarian or equitable behavior. Instead one observes preferential attachment, reciprocity and stronger ties between specific dyads. Admittedly, these network structures may be in part a function of the specific features of this game. However, several of the known motivations for mentoring discussed earlier playing with friends, replaying levels appear in line with our findings. This suggests that mentoring may be difficult to coordinate among multiple people over time. We might expect to find more generalized exchange patterns in more simplistic help-giving interactions online such as discussion groups or message boards. Still, our results are quite relevant for other game developers and virtual world creators where players are both permitted and encouraged to interact and collaborate. Our results point to the value of treating mentoring as an exchange relationship that is interdependent with ones goals, and the affordances of the network at the time. Therefore, designers hoping to use mentoring to create a more communal environment will likely need to alter the incentive scheme to support this behavior.

Elements of Mentoring

6.9 Introduction

Answering questions and sharing expertise in online communities is commonplace, but it is unclear what motivates users to help one another, or what the actual social processes resemble. While researchers hail the benefits of mentoring in online settings [60], we know little about how often it occurs or what motivates users to act as mentors. People can have a variety of reasons for mentoring; however the main goal of mentoring is usually the advancement of the apprenticeIn this chapter, we examine the extent to which players of massive multiplayer online games such as World of Warcraft, Final Fantasy, Eve or EverQuest spend time mentoring other players. Given the fact that it is often tedious to collect data about mentor-apprentice relationships in the real world, these virtual world offer an excellent venue to study this phenomenon. We identify several motivations for engaging in a mentoring relationship, including those that focus on mentoring friends or guildmates, or those who focus on their own advancement. We also measure the social networks of mentors and apprentices across multiple levels, and develop models that study mentorship exchange in MMORPGs. This work contributes to our understanding of knowledgesharing and mentorship in large-scale organizations or online settings, and demonstrates the importance of modeling social behavior at multiple levels. This is one of the first studies of the phenomenon of mentoring and the characteristics of mentoring in MMORPGs. Observation and insights gained from this study can be used to improve mentoring systems in online games, improve user experience and understand how mentoring in online gaming contrasts with mentoring in the offline world.

6.10 Related Work

Literature on mentoring finds the relationship present in a variety of contexts [43, 44] including studies in organizations [107], educational settings [150], and in close impersonal relationships. These mentoring relationships often facilitate the professional advancement of protgs or provide desired emotional support [107]. Furthermore, they can be expressed through formal relationships or informal linkages [145]. The diversity of potential mentoring relationships poses a challenge for researchers aiming to predict th200e development of mentor pairs among a heterogeneous population. The problem of analyzing mentoring in MMORPGs is related to the problem of socialization in such games namely each construct is driven by different motivations and produces varied outcomes. Shim et al [160] discuss the problem of inferring performance of players in games, Huffaker et al [88] studied expert behavior. Earlier studies of networks in MMORPGs have also looked at Trade [15], how can MMORPGs be used to foster learning [165], hence the connection with mentoring. The work that is most relevant to the current chapter is a study on a generative model of a mentoring network in MMORPGs [14] which shows that such mentoring networks have certain characteristics which are not present in many other social networks.

6.11 Mentoring in EverQuest II

In EverQuest II, while there are a large number of activities that players can be involved in, we concentrate on mentoring in this chapter. Just like many other games the characters in EQ2 have various levels, and when a player mentors another player the effective level of the mentor becomes equals to the level of the apprentice [163]. The mentoring player is always the more experienced player with respect to the apprentice. The game is designed such that player who is being mentored 'levels' up faster as a result of mentoring. In EQ2 a player can mentor another player by clicking on the other player and then agreeing in a dialog box that their effective level will be lowered.

The mentoring network can be constructed by considering the mentoring apprentice pairs. Thus a directed edge in the network represents a relationship from the mentor to the apprentice. The mentoring network that we use in this chapter is from one of the servers (guk) from EQ2 and consists of 23,207 nodes, 93,079 edges, 4,935,602 instances of mentoring, 11,632 mentors and 21,256 apprentices. Notice that there is an overlap between the players who are mentors and who are also apprentices at some period of time. While the same player can have multiple characters, it is not possible for the same player to mentor another character that he or she has using the same account.

The majority of the players, more than 97 percent are part of the largest connected component (LCC) even though there are a total of 316 components in the networks. The second largest connected component has only 6 nodes.

The plots in Figure 6.11 give two characteristics of the network and player activities. Part (a) of 6.11 plots total number of activities versus total number of mentoring activates. The figure shows that for the majority of the players mentoring activities are a small percentage of the total number of activities that they perform. Part (b) of 6.11 gives the distributions for time span for the difference as defined by the time between the first game activity and the last game activity recorded for a player and the corresponding difference for mentoring activities. The main thing to notice here is that the observed data points cover almost all of the possible data points in the curve. The main implication here is that the player exhibit a wide range of behaviors in terms of time allocated for mentoring.

While it is possible for a player A who was mentored by another player B to later on mentor B, it is quite rare as the level difference between the players usually persist over time. Thus out of the total of 93,079 edges only 804 edges are reciprocated which implies that the network is nonreciprocal. Just like in the real world, mentors have different motivations for mentoring. Based on extensive experience with game play in EQ, we suspect that the various categories for mentoring which have been identified in the offline world are also applicable to the online world of EQ2. These are also borne out by various clusters of mentors that we obtained based on the mentoring data. Players can have the following motivations for mentoring in EQ2:

- Instrumental: A player may mentor another player in order to gain achievement points.

- Friend-Focused: A player may mentor another player in order to help his or her friend quickly gain in level.

- Guild-Focused: A player may mentor another player in his or her guild as an obligation to help other guild members and foster stronger relations.

- Veteran (Low Participation): There may be many instances of mentoring where a player tries mentoring but after only a few instances decide not to pursue mentoring.

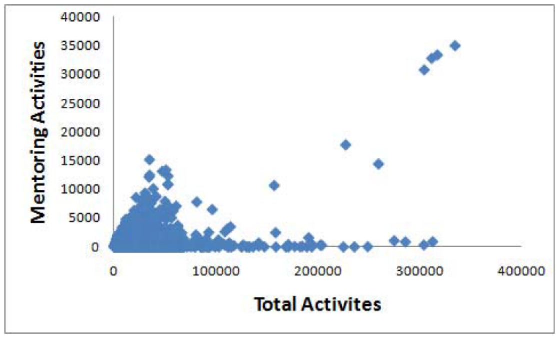


Figure 6.6: Ratio of Mentoring Activities

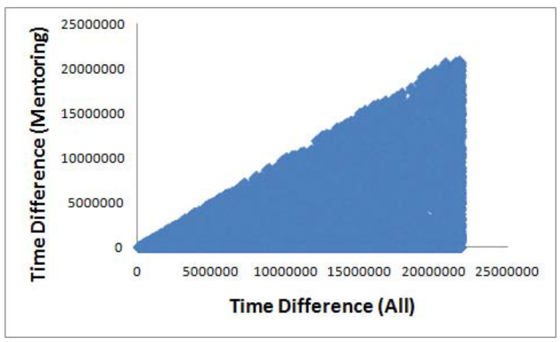


Figure 6.7: Playtime with respect to total activites and with respecting to mentoring activities

Table 6.2: Means of Mentor Clustering Variables

Attribute	**Instr.**	**Friend-Focused**	**Guild-Focused**	**Veteran (Low)**
Cluster Size	1,685	2,985	5,354	1,608
Num. Mentored	13.49	5.18	21.54	1.26
Play Concen.	0.19	0.33	0.34	0.004
Num. Guild. Mnt.	3.77	0.34	4.33	0.26
Guild Play Concen.	0.13	0	0.37	0
Mentoring Instances	659.55	205.39	1439.083	343.43
Avg. Level Diff.	12.13	10.71	13.14	6.26

It should be noted that in some cases there may be overlap between the various groups or reasoning for mentoring e.g., a player may be mentoring because of helping her friend and also for gaining achievement points.

6.12 Mentoring Clusters

As described in the previous sections, people have different motivations for mentoring and these should be mirrored in partitions or clustering of the mentoring data. We applied the Weka [78] implementation of the EM clustering algorithm to discover the clusters. The characteristics of the individual clusters discovered are similar to the mentoring archetypes described before. The variables for clustering were selected based on domain knowledge of the game and the familiarity of the authors with the game play. The list of the variables which were used for clustering are given as follows:

1. Number of Characters Mentored: The number of characters that this character has mentored over the course of the time span under consideration.

2. Number of Mentor Instances: The number of unique instances of mentoring, where an instance is defined as gaining experience points in the game. Thus a same character can mentor another character over hundreds of instances. We used number of mentoring records instead of time spent on mentoring because that the information about time spent on mentoring is not available from the game logs.

3. Play Concentration: This quantity is defined as the Gini Coefficient of a mentor as computed with respect to the number of mentoring instances for all the other players that he or she has mentored. Given a variable $X = x_1, x_2, .., x_n$, the Gini Coefficient can be computed as follows:

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j|}{2n^2\mu} \tag{6.4}$$

4. Number of Guild-mates Mentored: The number of characters that this character has mentored in his or her guild over the course of the timespan under consideration.

5. Guild Play Concentration: This quantity is defined in an analogous manner to Play Concentration but with it is computed with respect to only players within the guild.

6. Average Diff Level: This is the average level difference between a mentor and all of its apprentices, averaged over the number of instances of mentoring. The four clusters of mentors and the corresponding characteristics of these clusters are given in Table 6.2. While there is some overlap between the characteristics of the various clusters, some differences stand out more than others so that they can said to belong to different clusters e.g., both Instrumental and the Guild-Focused clusters have higher values for number of guildmates mentored, the guild focused cluster has a much higher value for guild play concentration.

6.12.1 Social Characteristics of Mentors

After the four types of mentors are identified, it allowed us to see how they might differ in terms of social networks, especially since some mentors might be altruistic while others are self-serving. We investigated these social networks at multiple levels between the mentor-apprentice dyads and more complex grouping such as triads.

We began with three popular individual-level measures of social capital within the mentor-apprentice networks. These include: (a) closeness centrality, which measures how close mentors are to all other players in the network based on their direct and indirect ties; (b) structural holes, which measures the extent to which a mentor connects with two players who don't connect with each other; and (c) clustering coefficient, which measures how often a player creates cliques or clusters with other players.

Table 6.3: Means and Standard Deviations of Social Network Measures for the Four Types of Mentors. (i)

Attribute	**Instr.**	**Friend-Focused**	**Guild-Focused**	**Veteran (Low)**
Closeness Centrality	.24(.02)	.22(.03)	.21(.05)	.23(.03)
Structural Holes	.10(.10)	.17(.13)	.30(.30)	.15(.20)
Clustering Coefficient	.09(.11)	.07(.12)	.09(.17)	.06(.10)

Table 6.4: Means and Standard Deviations of Social Network Measures for the Four Types of Mentors. (ii)

Attribute	**Instr.**	**Friend-Focused**	**Guild-Focused**	**Veteran (Low)**
Indegree Edges	4863	6471	10824	3134
Outdegree Edges	11760	7703	9587	9937
Ind/Outd Ratio	0.41	0.84	1.13	0.32
Homophilous Dyads	1712	1224	2675	985
Homophilous Transitive Triads	101	36	59	35

As shown in Table 6.3, we found that instrumental players demonstrate the highest closeness centrality, followed by veterans, friend-focused and guild-focused mentors using oneway analysis of variance, F(3,10563) = 288.29, p¡.001. Tukeys HSD revealed significant differences across all four types, p¡.001. We also found that guild-focused mentors demonstrated the highest structural holes, followed by friend- focused, veterans and instrumental, F(3,10563) = 444.62, p¡.001. Tukey's HSD post-hoc tests revealed significant differences across all four types (p¡.001), except in the mean difference between friend-focused and veteran mentors (p = .07). Finally, guild-focused mentors showed the highest clustering coefficient, followed by instrumental, friendfocused and veteran mentors, $F(3, 10563) = 25.29, p < .001$. Tukeys HSD revealed significant differences across all four types ($p < .001$), except in the mean difference between guildbased and instrumental mentors (p = .83).

It is interesting that instrumental players or veteran players (who rarely enter into mentoring exchanges) show the highest closeness centralitya popular measure of overall influence in a network. One explanation is that because instrumental and veteran players are more focused on their own achievement and don't confine themselves to a particular guild or small friendship circle, which allows them to spread out throughout the network.

The finding that these mentors bridge structural holes is not surprising if we think about them in terms of a teacher within a group that helps various pupils who are not ready to help each other yet. In other words, these mentors are spreading their time among several other guilds that are likely at small levels and not ready to serve as mentors in their own capacity. A second explanation is that guild-focused mentors might occasionally branch out to help players in other guilds who would not interact with players in the mentor's guild. The finding that both guild-focused and instrumental mentors show higher values in the clustering coefficient suggests that these types of mentors are forming their own smaller networks, whether it is reflective of the guild or of a selection of teams. These more complex network structures are discussed in more detail below.

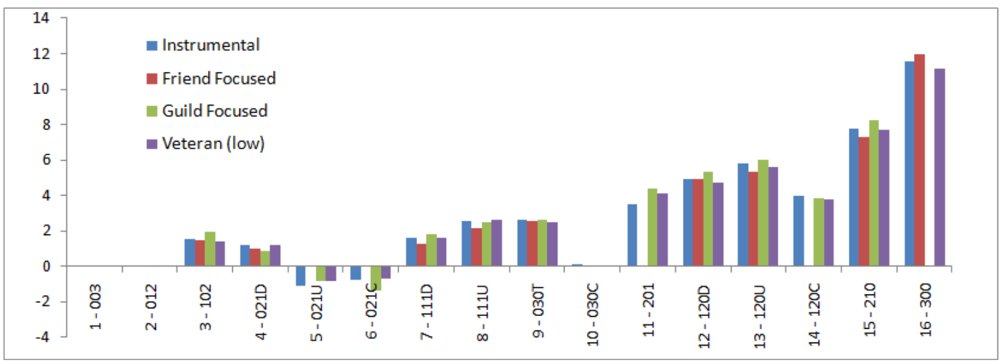


Figure 6.8: The Triadic Census of Various Triads in the Mentor Clusters

In order to gain further insight into the individual-level network measures, we can examine the presence of dyadic relationships. The closeness centrality of instrumental and veteran players is supported by their low ratio of indegree to outdegree relative to the other groups. Since outdegree in this network indicates mentor-to-apprentice relations this indicates players in these groups wield influential network positions. Oddly, the reverse pattern may explain why the guildfocused and friend focused clusters are highest in structural holes. As frequent apprentices, these individuals may serve as brokers to parts of the network that would be redundant ties for more focused instrument and veteran players. Additionally, the presence of cliques among guild-focused and instrumental players is further suggested by the high number of homophilous dyadic and triadic relations in the two groups,

In addition to the individual-level, and dyadic network measures, we were interested in more complex structures such as triads. A triad is a graph consisting of 3 nodes, which can create up to sixteen configurations (the set of all possible Triads on a directed graph are given in Figure 6.12.1). The differences between the network structures of the various clusters that constitute the mentoring network can be gauged by looking at the logarithm of triadic census of the triads given in Figure 6.12.1. The x-axis in the figure corresponds to the various triads given in Figure 6.12.1. The distributions of the triads for the clusters are similar except the case of Friend-focused clusters, which demonstrate less of 11 and 14. Interestingly Triad is also observed to a lesser extent in the case of Guild-Focused clusters. Intensity of Mentor Exchange.

Table 6.5: Overlap between clusters

	Inst.(A)	**Friend(A)**	**Guild(A)**	**Veteran(A)**	**Total**
I(M)	72.45	8.38	12.9	6.19	100
F(M)	16.94	25.88	41.42	15.74	100
G(M)	18.15	25.32	41.43	15.08	100
V(M)	19.93	24.24	38.45	17.37	100

Table 6.6: Cluster overlap from the model

	Inst.(A)	**Friend(A)**	**Guild(A)**	**Veteran(A)**	**Total**
I(M)	77	11	5	7	100
F(M)	15	26	41	18	100
G(M)	14	25	44	17	100
V(M)	17	26	42	15	100

6.12.2 Behavioral Signatures of Mentors

In this section we describe a novel way to visualize the various mentoring clusters. Given that the corresponding temporal data is available for all the mentors, we can visualize each cluster by graphing the average intensity of mentoring activity in the span of a day. Thus consider the visualizations in Figure 6.12.2 where the rectangular plotting area is divided into 24 hours and the colors represent the intensity of mentoring. Here the intensity of mentoring is plotted based on the visible color spectrum from blue to red i.e., blue represents low levels of intensity, red represents higher levels of intensity and the composite colors in between represent intermediate levels of intensity.

From Figure 6.12.2 it is possible to see the differences in the various mentor clusters just by looking at the levels of intensity of mentoring at various time periods during the day. Thus mentoring activity is more spread out during the day in the case of friend-focused cluster and it is most concentrated in the case of Guild focused cluster. It is also evident that in general mentors are less active earlier in the day as compared to the later in the day. The key insight from these visualizations is that it is not just the individual level attributes of the mentor clusters which distinguish them from one another but the spread of activity throughout the day is also a distinguishing factor between the mentoring clusters.

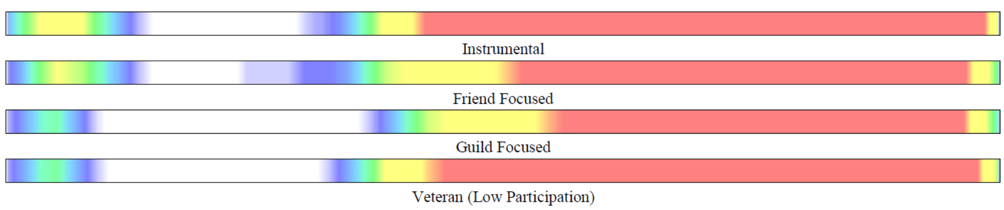


Figure 6.9: Behavioral Signatures of Mentoring Clusters

6.12.3 Life Cycle of Mentorship

From the perspective of the apprentice the primary goal of mentoring is to increase the level of the apprentice. A soon as the level of the mentor equals to the level of the mentor then it is no possible for the mentor to mentor the apprentice. Thus there is a limit to when a mentor can mentor an apprentice in EQ2. However the same mentor may mentor other people who are at a level lesser than her level. An additional constraint in the game is that a player can be mentored by up to four players simultaneously but a player cannot mentor multiple players at the same time. Since for most player mentoring instances are only a small fraction of total activities performed, mentoring instances are spread out over time. Additionally the overlap between active nodes in the mentoring network is relatively large as compared to the overlap in edges. A comparison of Adjacency Correlation and the Jaccards Coefficient for the nodes over time reveals this difference clearly [14].

Thus it is the case that while the same mentors mentor over a span of time, they are less likely to mentor the same people after a certain amount of time. One possible factor could be because the apprentices advance to greater levels and thus have a less need for mentoring. Many of the apprentices in turn mentor other players. Table 6.5 shows the percentage of players that a player from one cluster mentors in another cluster. The table shows that instrumentals are more likely to help other instrumentals while the distributions for all the other classes are similar but everyone is more likely to mentor players in guilds. While the number or the percentage of apprentices from one cluster to another cluster appears to be the same the intensity of mentoring is not the same. Thus consider the case of veteran players who mentor less than all the other clusters but their percentages of mentoring are comparable.

6.13 A Network Model of Mentoring

Based on the observations and the discussion in the previous section, we propose that a model for the formation and evolution of the mentoring network in the current setting should satisfy the following characteristics:

1. Lifespan of nodes i.e., after the lifespan of the nodes has expired they can no longer participate in the network.

2. The propensity of nodes to be active at a certain time period.

3. The global network characteristics of inter-cluster and intra-clusters for the various mentoring archetypes.

4. External constraints in the environment i.e., limit on the maximum number of mentors and apprentices at any given time.

The first and the second criteria in the model are based on observations reported by Ahmad et al [14] regarding mentoring networks in MMOs where only certain parts of the network were active at any given time. An additional reason is that players are not active in mentoring all the time but rather mentoring is a subset of activities performed by the players as described in section 3. It should be noted that the clusters described here are the clusters based on the player characteristics and not on the characteristics of the graph structure of the network More than 98 percent of all the nodes in the network belong to the same largest connected component and given the density of the network a criteria like modularity [138] would reveal one large graph based community. Thus based on the criteria just described and empirical observations described in the previous section, we describe the following model for the phenomenon of mentoring and the characteristics of the various associated clusters observed for mentors.

1. The model is initialized with a set of n0 nodes each of which belongs to one of the four archetypes or none at all which are assigned uniformly at random. Each node is additionally assigned a guild id uniformly at random or none at all.

2. At each instance a node is chosen for mentoring from the nodes already present in the network. A node can only be selected if it is not already mentoring.

3. When a new node arrives it is assigned at random one of four archetypes of mentoring behaviors or none at all.

4. Associated with each archetype is a bimodal distribution for its lifetime. The newly arrived node samples its lifetime from the corresponding bimodal distributions dlc depending upon its archetype. Each node is assigned a guild id uniformly at random or none at all.

5. If l(.) is the function which describes the label of the node as one of the four clusters then the mentoring node and the apprentice node establish their relationship based on the following probabilities:
   $p(m \leftarrow a) = 0.75, l(m) = l(a) = Inst.\}$
   $p(m \leftarrow a) = 0.4, l(a) = \{GuildBased\}, = l(m) \neq \{Inst.\}$
   $p(m \leftarrow a) = 0.25, l(a) = \{FriendBased\}, = l(m) \neq \{Inst.\}$
   $p(m \leftarrow a) = 0.15, l(a) = \{VeteranBased\}, = l(m) \neq \{Inst.\}$
   $p(m \leftarrow a) = 0.15, l(a) = \{Inst\}, = l(m) \neq \{Inst.\}$

6. The mentor node then samples the lifetime of its mentoring relationship with the apprentice node from the distribution dm.

7. Repeat Steps 2-5 by selecting a node from the set already present instead of newly arrived nodes. Since the lifetime of the nodes are chosen based on the distributions obtained from the data it ensures that the first two requirements of the model are met i.e., the lifetime of the number of nodes are active. Additionally the cluster overlap for model is given in Table 6.6 which agrees with the observations from the data given in Table 6.5 since the probabilities of connectivity are based on the observed data.

6.14 Discussion

In this chapter we analyzed various aspects of mentoring in a large scale MMORPG called EverQuest II. We found that mentors have different motivations for helping others: some are focused on helping friends and guildmates, while others use mentoring as a way to receive additional rewards and achievement in the game. Using cluster analysis, we were able to disentangle the various types of mentors based on play behaviors such as the amount and diversity of mentoring exchanges. We then examined social network measures between dyadic mentor-apprentice relationships, as well as more complex triadic exchanges. We found that these clusters differ in social network behaviors. Guild-focused mentors show higher brokering positions, while instrumental mentors show more centrality in the network. We argue that this is because those focused on their own achievement tend to be diverse in their connections, and thus have more opportunities to influence others, while those focused on helping their guildmates tend to form repeated clusters.

Second, the network formed by the mentoring relationship in itself is a novel network. In this regard the current chapter extends the work by Ahmad et al [14] by proposing a network model that explains how mentoring emerges and evolves. By taking into account the lifespan and intensity of mentoring exchanges, we are able to highlight the uniqueness of this type of model. Future studies of mentoring in games and organizations can take these rules into account when modeling social behavior. To the best of our knowledge this is the first work on the social aspects of mentoring in MMORPGs. Overall, our chapter contributes to computational social science by distinguishing several types of mentoring motivation and showing important differences in the social networking behaviors.

Chapter 7

Trust Prediction Family of Problems

"All models are false but some models are useful."
- George Box

Trust is almost ubiquitous in human interactions and social settings. Computational Trust refers to the operationalization of trust in settings where interaction between people are mediated via a computer or computing infrastructure. The problem of computational trust has been extensively studied in the literature, especially the problems of trust inference and trust propagation [69]. Over the last two decades the Internet has grown exponentially and with the advent of Web 2.0 and other Internet technologies the number of possible ways in which people can interact with one another has also grown exponentially. Consequently a need to determine what are the sources of information and people that can be trusted and in which types of environments one should trust them has arisen. There are now many environments on the web where people can explicitly specify trust in other people [124, 69]. In order to manage trust in different types of environments, computational models of trust have been proposed and studied in a number of domains. These models range from trust models for multi-agent systems to models of trust for recommendation systems. Web 2.0 and other newer technologies have not only expanded the types of interactions but also the complexity of interaction between people and thus many of the previous models for studying trust may not be adequate for studying trust in more complex environments. The current chapter is divided into two parts: Part 1 is mainly focused on the problem of trust prediction and Part 2 mainly extends the analysis to link it to various social science theories.

Trust Prediction Problems

7.1 Introduction

Most of the earlier studies on trust were limited by the type of datasets which were available to study trust *e.g.,* multi-relational data for studying trust was not available to study trust in previous settings [69]. Thus consider the most widely used datasets for studying trust like FilmTrust[68], epinions [124] etc, where the main type of information which is available is trust edge information in addition to some limited interactions between people *e.g.,* rating information in case of FilmTrust. These datasets have primarily been used to study problems like predicting trust between users or making recommendations, more complex problems like what factors affect the formation of trust or how and why does trust change over time may not be amenable to a solution using these types of datasets. The availability of more complex datasets e.g., virtual world like SecondLife, World of Warcraft, EverQuest II etc opens up new horizons for studying such problems and in new contexts. With these types of datasets it is possible to study things like the factors that lead to formation of trust and change in trust, how does trust affect other types of social relationships etc.

In this chapter we first address the traditionally studied problem of trust formation and breakage and also address the problem of trust change prediction. Additionally we describe a new problem for predicting trust - the problem of trust propensity prediction where the objective is to predict how much a person trusts others in general when this information is explicitly available. We also describe a number of techniques to address this issue. We use data from a Massively Multiplayer Online Role Playing Game (MMORPG) called EverQuest II (EQ2)[1] . The rest of the chapter is organized as follows: In section 7.2 we describe related work, in section 7.3 we describe the set of

[1] EverQuest II Official Site: http://everquest2.com/

trust related problems that we are addressing, in section 7.4 we describe the data 7.4, in section 7.5 we describe the experiments and results and the conclusion in described in section 7.7.

7.2 Related Work

Marsh [123] was the first person to describe a computational model of trust. A number of trust models have been proposed since then and the phenomenon of trust in social networks has been studied in numerous goals in mind *e.g.,* making recommendations [124], access control [21], spam filtering [66], inferring trust in social networks [68] etc. There have also been numerous studies on propagating Trust in social networks e.g., Guha et al [74] proposed a method to infer trust in cases where there is no direct interaction between users, other trust propagation techniques have been proposed in [69, 97, 102, 143]. There is another body of literature on trust in P2P Networks [96] and trust in multi-actor systems[179]. A comprehensive survey of trust in various fields in computer science is given by Arts and Gil [22]. Homophily is also observed in trust networks [68], people who trust one another are likely to be similar to one another as compare to others. Additional problems for trust prediction have also been addressed before, thus Ahmad et al [12] proposed the problem of inter-network link prediction in the context of trust where the task is to predict trust based of network characteristics in a coextensive network setting.

While there is a vast literature on trust in social network, Golbeck [69] notes that work comparing different networks in the same study are relatively rare. Ahmad et al [13] described the network characteristics of various trust networks for comparative purposes and observed that trust network which are generated by similar social processes have similar network characteristics as well. In trust based recommendation networks like FilmTrust [68] and Epinions [124] trust is with respect to recommendation, in online virtual worlds like EverQuest II (EQ2) trust is defined in terms of access to a commodity like a virtual house [13]. Statistical models of evolution of networks like ERGM or p* family of models use small network structures or motifs to study social processes in the evolution of social networks [181]. Similarly the MTML framework of Monge and Contractor [131] describes various social processes in terms of network motifs.

The availability of detailed behavioral data in virtual worlds point to the fact that it is possible to study such phenomenon in such detail which may not be possible in the offline world e.g., studies of mentoring behavior in MMOs reveal multiple motivations for mentoring [11], clandestine social networks in MMOs show similar structural features to that of corresponding offline networks [100], some social networks in MMOs behave in a manner different from what is observed in many real world social networks [14], analysis of network structure of trust based social networks reveal that their structure varies based on the social settings in which they are generated [13].

7.3 Trust Prediction Problems

Trust prediction consists of a family of problems. In this chapter a subset of such problems are addressed and a new problem for trust prediction is also described. The set of problems that are addressed here are as follows: Trust Formation Prediction Problem, Trust Change Prediction Problem, Trust Break Prediction Problem and the Trust Propensity Prediction Problem.

7.3.1 Trust Edge Formation Prediction

There are multiple versions of the trust formation problem, the simplest version of this problem is the problem of predicting the formation of trust relationship between two nodes in the future. The data for studying this problem is temporal in nature and is divided into a training period and a test period which reflects the presence or absence of edges. **Problem:** *Given a graph G and pair of nodes n_i and n_j the problem of trust formation prediction is to predict if a link will be formed between the nodes.* $e(n_i, n_j)$

Notice that this problem is very similar to the link prediction problem and in fact can be described in terms of link prediction. One can thus formulate this problem as a binary classification problem using a scheme similar to Hasan et al [79]. One can divide the dataset into training period and test period where a positive example consists of examples where an edge was not present between the nodes in the training period but was present in the test period and a negative example is where an edge was not observed in either of the two periods.

7.3.2 Trust Change Prediction

Trust between two entities can change over time. In the EverQuest II dataset that is being used here, the players with in this game have the option to not only specify trust but also change trust. Change in trust can happen because of different reasons, trust between two players can increase because of positive experiences between them and it can decrease as a consequence of negative experiences. The task of trust change prediction can be formally described as follows:

Definition: Given that τ_{ijk} is the trust between a node n_i and another node n_j at time k then the task of Trust Change Prediction is predicting if the trust between n_i and n_j is going to change at time $l, k < l$.

7.3.3 Trust Breakage Prediction

Trust between two entities can not only change over time but it can disappear altogether. The task of trust change prediction can be formally described as follows:

Definition: Given that τ_{ijk} is the trust between a node n_i and another node n_j at time k then the task of Trust Breakage Prediction is predicting if the trust edge τ_{ijk} between nodes n_i and n_j at time $l, k < l$ will disappear or not.

7.3.4 Trust Propensity Prediction

The problem of trust propensity prediction is to predict the likelihood of a person trusting other people i.e., is it the case that they trust or do not trust other people in general.

Definition: Given a set of observations $O(V)$ about the trusting behavior of a set of nodes V, predict trust propensity τ of a node $v_i \in V$ based on the observations $O(V)$. Thus $F(O(V)) \longrightarrow \tau_i$.

The problem of Trust Propensity Prediction can be addressed in a number of ways. It can be described as a classification problem where the prediction classes correspond to the various levels of trust propensity. It can also be defined as the problem of prediction based on one's similarity with respect to other people in the population. In this formulation the problem is similar to the Collaborative Filtering Problem [70]. Yet another way could be to use the structural properties of the social network to make the predictions about trust propensity. The last two approaches are taken in this chapter. Additionally one can also take into account the network structure for prediction in some cases. These similarity function based approaches work as follows: Given a vector of attributes $A = a_1, a_2, ..., a_n$ determine the k most similar nodes V_S based on a distance function and predict the propensity to trust as the average propensity value from the set N_S.

$$\tau_i = \sum_{j \in V_s} \frac{\tau_j}{|V_S|}, V_s = \{v_j \| v_j \in V, min(dist(v_i, v_j))\} \tag{7.1}$$

One can now describe the various approaches that can be used to predict the propensity to trust.

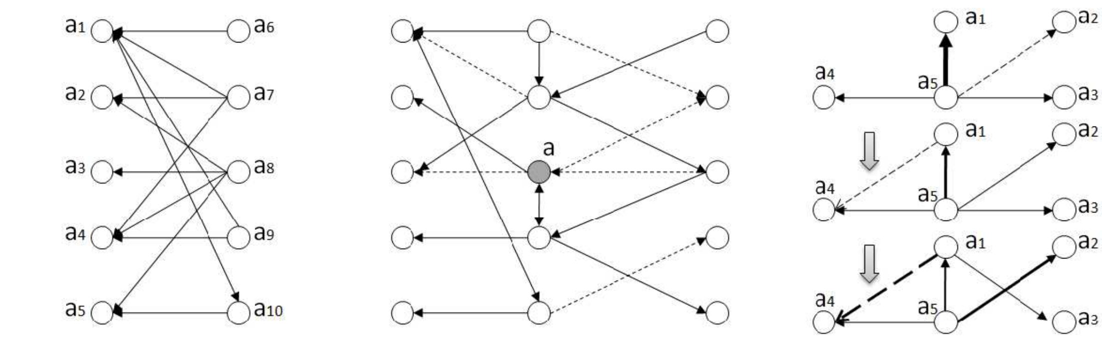
Baseline Approaches

To compare the results from the proposed approaches with baseline models one can describe a number of simple models which can be used as baselines as follows: *Random* predicts the trust propensity randomly within the range of values, *Mid-value* always predicts the value to be the median value, *Max* always returns the maximum value and *Avg* always returns the average value as the predicted value.

HITS Based Approach

One can adopt the analogy of Hubs and Authorities scheme introduced by Kleinberg in the HITS Algorithm[104] to the trust domain. In the HITS Algorithm an authority is defined as a node which is pointed at by many Hubs and a Hub is defined as a node which is pointed out by many Authorities. Intuitively an Authority is a node which is pointed to by many other nodes implying that they consider it an authority with respect to a particular topic. Hubs intuitively refer to nodes which point to many other nodes, ideally these nodes are authorities. One can map the people with high trust propensity to Authorities in the HITS framework while at the same time we not that Hubs are not analogous to people who are opposite to people who have high trust propensity.

We note that in the HITS framework while computing Trustingness one must not only consider the links in the trust network but also other types of non-trust related links which may be present e.g., in the case of the EQ2 dataset other types of interactions like mentoring, grouping, trade etc are observed. We assume that a person is more likely to be trusting if he or she trusts more people that he or she interacts with as compared to trusting a smaller fraction. Consequently this will affect how Trustingness is computed. Consider actor a in Figure 7.3.4 (b), both the Hub score and the authority score of this node would be different if we include only the trust network represented by solid nodes as opposed to the complete social network which consists of both the trust links as well as links from other types of social interactions represented by dotted lines. If we consider the larger network then both the indegree and the outdegree will be half of if we consider the trust network. Based on these observations we can now describe the TrustHits algorithm for computing trust propensity.



(a) Hubs and Authorities Analogy (b) Trustingness In a Network (c) Factors Affecting Trust

Figure 7.1: Analogues for TrustHITS

It should be noted that the initializing of the weights in TrustHITS explicitly takes into account the larger social network of the node. The normalized edge weights of the outlinks are also considered since in this dataset explicit information about edgeweights is present in the form of explicit ratings for trust and number of times interacted in the case of other trade an mentoring relationships. The final value for Trust Propensity is computed after the algorithm has converged.

Structural Holes Based Approaches

There are many social science theories which describe how social communication networks evolve over time and how do people form relationships [131] e.g., Theories of

Homophily predict that people are likely to form edges with other people who are most similar to them. Similarly Theories of Balance predict that people form relationships in order to minimize conflict and to balance their relationships. These theories can thus be used to get an idea about trust propensity in a social network. Thus trust is likely to be high in a tightly knit group which implies that a person who is part of that group is not necessarily trusting even though she trusts a lot of people. This observation is virtue of the fact that the group has a high social capital. Thus social theory points us to the observation that if a person trusts people outside of a tightly knit group then she is more like to be more trusting as compared to trusting people with the same tightly knit group. While it is not possible to get information about the strength of relationship between the nodes in the network it is possible to use the type of trust edges in the network, the density and the redundancy of edges in the network to indirectly capture this. These properties can be captured by the Network Constraint Index (NCI) [35] which can be given as:

$$C_i = \sum_j (p_{ij} + \sum_q p_{iq} p_{qj})^2, q \neq i \tag{7.2}$$

where p_{ij} are the proportion of i's relations invested in contact j. The quantity in the parenthesis thus represents the proportion of i's relations invested in contact j [35]. In the cases where it is not possible to determine this metric e.g., when the node is an isolate then we take its value to be zero. We use a similarity based approach for determining propensity based on the network constraint index. We predict the propensity to trust of an agent as the average value of propensity for all the nodes which are most similar to it in terms of the network constraint index.

Characteristics Based Approaches

The characteristics based approaches are similarity function based approaches and use the characteristics of the players to make predictions about propensity to trust. The characteristics of the player can be of three types: In-game attributes, in-game behaviors and demographic attributes. In-game attributes refer to the attributes of the avatar of the player e.g., what in the in-game race, in-game gender, in-game class, in-game character abilities etc. In-game behaviors refer to attributes which are derived based on the behavior of the players within the game e.g., number of monsters killed, number of quests completed, number of spells learned etc. The demographic characteristics of the player are age, gender, location etc.

Structure Based Approaches

The structure based approaches are also similarity function based approaches and also look at the structure of the social networks and makes prediction on the basis of the similarity between the neighborhoods social networks of the nodes of interest. These approaches are graphically represented in Figure 7.3.4. The first three approaches referred to as *in-degree, out-degree* and *degree* look at the trust propensity of nodes which have similar in-degress, out-degrees and total degree as compared to the node for which we have to make the trust propensity prediction. The *neighborhood* approach looks at the immediate neighborhood of the nodes i.e., nodes who are connected to the node of interest. The distance function from Equation 1 thus becomes the Edit distance in this case. The *Network-Trans* approach looks at the change in the network structure over time. Thus the Edit distance for this case is computed as the edit distance between the corresponding graphs at each instance and taking the average distance.

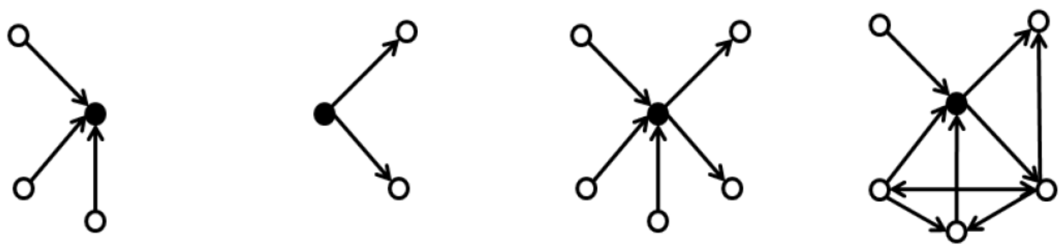


Figure 7.2: Various Structure based approaches for predicting Trustingness (a-d)

7.4 Dataset

The data that we use for experiments comes from an MMORPG called EverQuest II. The data consists of in-game data about the attributes and the behaviors of the avatars of the players in the form of Game logs as well as offline data about demographic

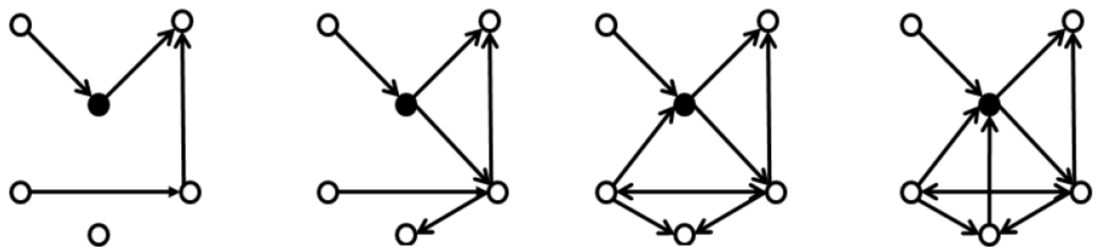


Figure 7.3: Various Structure based approaches for predicting Trustingness (e)

characteristics of the player. We note that the data is annonymized so that it is not possible to link a player with the identity of a person in the offline world. In addition to the in-game behavioral data we also have additional information about the players from an in-game survey. The in-game behavioral data consists of information about more than 2 million players while the survey data contains contains survey information from 7,129 players. People's propensity to trust can be guaged by responses to four survey questions which are as follows:

- **Trust 1:** Generally speaking, would you say that most people in everyday life can be trusted or that you can't be too careful in dealing with people?
- **Trust 2:** What about the people online?
- **Trust 3:** What about other players in this game in general?
- **Trust 4:** What about other players in your guild? If you aren't in a guild, just leave this blank.

There are four options to reply to these questions. These options are given in table 7.1. From the game logs we have information about the trusting behavior of players i.e., who trusts whom and to what extent. In EQ2 trust is defined in terms of access to an in-game commodity (a virtual house). Thus players can specify how much they trust other players with respect to how the other players can interact with their house. The various levels of trust in EQ2 can be given as follows.

Table 7.1: Trust Responses and Corresponding Code

Trust Response	**Code**
Trust them a lot	4
Trust them some	3
Trust them only a little	2
Trust them not at all	2

- **Trustee:** Can add, remove and move objects with in the house and even pay rent. Everything owner does except picking owner rewards.
- **Friend:** Interact and move objects but cannot add/remove in the house.
- **Visitor:** Interact with objects but cannot move objects in the house.
- **None:** Cannot even enter the house and has no-privileges.

These trust links can be used to construct the trust network which in turn can be used to make predictions about trust propensity. In addition to the questions about trust the survey also included information about the age and gender of the player. Since this information is also available from the time when the players actually signed up for the game, it is possible to cross-check the information that they provide. Thus there are cases where the information in the survey is different from the information in game logs. This could be either because the player deliberately gave incorrect responses to the survey or it could be because the players randomly answered the question in order to get the survey done as early as possible in order to get the special in-game item. Such cases were removed from the dataset in order to reduce the bias in the data. We note that there are additional discrepancies in the data since the four questions on the trust survey can also be thought of as questions on the Guttman Scale [76]. The idea behind the Guttman Scale is that given a set of related questions the responses to one of the questions may actually encompass response to other questions e.g., consider the first question *Do you trust people in General?*. If the answer this question is 'Not at all.' but the answer to the second question *Do you trust people online?* is 'Trust a lot' then that would imply inconsistency. Such inconsistencies can be overcome if we readjust the responses and discard such cases where there are inconsistencies.

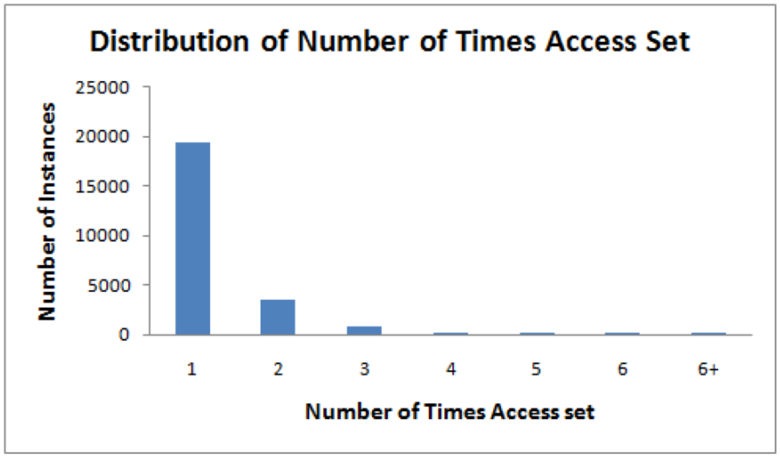


Figure 7.4: Distribution of Access Grants in EQ2

7.5 Experiments

We first describe the results for predicting the formation of a trust edge. We used the set of standard classifiers from Weka [78] for classification purposes. Here we only give the best results from classification. Ten fold cross validation for 30,000 instances was performed. The results of the experiments are given in Table 7.2. Random refers to randomly predicting the formation of trust, In-game refers to using the in-game characteristics of the players to predict trust formation, offline refers to using offline characteristics of the players e.g., demographic characters like gender, age, location etc and TRUCE (TRUst in Complex environments) refers to using features from our framework (Trustworthiness, Trustingness, Distance between the nodes, strength of interaction) to predict trust formation. The results reveal that features constructed by using the proposed framework outperform the other features.

We now describe the results for change in trust prediction. Since the number of cases where trust changed is somewhat limited, we use all the examples of such change for the experiments. The positive and the negative example for the classifiers are constructed in a manner similar to what was described for Problem 1 i.e., a positive example is when a link is not present between the two nodes in the training period but is present in the test period. A negative example is when the edge is not present in either of the

Table 7.2: Results for Trust Formation Prediction

Technique	Precision	Recall	F-Score
Random	0.23	0.27	0.25
In-Game	0.85	0.66	0.75
Offline	0.29	0.22	0.25
TRUCE	0.78	0.68	0.73

Table 7.3: Results for Trust Change Prediction

Technique	Precision	Recall	F-Score
Random	0.09	0.27	0.14
In-Game	0.19	0.25	0.22
Offline	0.26	0.34	0.29
TRUCE	0.39	0.42	0.40

two periods. The results for these experiments are given in Table 7.3. Ten fold cross validation with 30,000 instances was used. The corresponding techniques and their features are similar to what was described for Problem 1. Since the majority of the cases are negative examples we only give the results for the performance for negative samples since reporting the results for both would make the results appear better than they actually are. Table 7.3 reveals that overall the predictors do not perform that well but the proposed approach does better than others.

A similar setting was used to study the problem of breakage of trust. However there some practical issues with respect to using the dataset for studying breakage: A trust edge is considered to be broken if the trustor explicitly changes the trust permission to 'None.' However the change in trust to 'None' are relatively rare. Additionally there are many such instances of changes in trust which are reversed after a few seconds. Given the game mechanics the most likely explanation for this is that the player accidentally changed the trust level within the game and then reverted it back to the previous. We thus ignore such cases. After removing such instances, there are only 212 cases left where this is the case. For these set of experiments, 10,000 instances were used of which 212 were positive examples of link breakage. The results are given in Figure 7.4 which shows that the overall performance of all the techniques is quite abysmal. The technique

Table 7.4: Results for Trust Breakage Prediction

Technique	Precision	Recall	F-Score
Random	0.02	0.50	0.04
In-Game	0.10	0.26	0.15
Offline	0.02	0.11	0.04
TRUCE	0.06	0.09	0.08

using offline features actually does worse than random in this case. Our hypothesis is that the reason that all of these techniques do quite bad is because the featuresets which are used is not rich enough to capture the differences between the people who break trust relationships and the people who retain this relationship which actually constitute the majority of the players in the game. It is only under extreme circumstances that people break the trust relationship within the game and thus this problem needs to be explored further to obtain better results.

We used the techniques described in section 7.3.4 to predict the propensity to trust. Since there are four types of questions regarding trust we report the results separately for each of the trust types. Additionally we report the results for the Gutmann Scale. Thus Table 7.5 gives the results for the four questions as the average of the difference between the predicted value and the real value. From the table it is clear that the best results are obtained for the Structural Hole Based approaches (Network Constraint Index) and the trust HITS based approaches. However given the nature of the questions it is not clear why one approach performs better in one case as compared to the other. It should be noted that the results obtained from just using simple structure based approaches like in-degree ,k out-degree etc are very close to the values obtained from the random approach, although in most cases the results for the Median as well as the Average approach are much better.

Similarly we also replicated the results for the Guttman Scale version of Trust values as well. These are given in Table 7.6. Again in this case it is observed that the best results are obtained for the Structural Hole Based Approaches (Network Constraint Index) and the trust HITS based approaches. Interestingly the structural holes based approach performs better in three of the four cases of trust as compared to the trust HITS approach.

Table 7.5: Trust Propensity Prediction Results $\leq \tau_{pred}\tau_{real} \geq$

Technique	**Trust 1**	**Trust 2**	**Trust 3**	**Trust 4**
Random	1.80	1.75	1.80	1.76
In-Degree	1.69	1.73	1.74	1.78
Out-Degree	1.73	1.77	1.80	1.83
Degree	2.37	2.73	2.36	2.39
Max	2.07	2.06	2.07	1.76
Median	1.47	1.47	1.47	1.47
Average	1.56	1.55	1.55	1.56
Char Based	1.91	1.98	1.79	1.10
Behavior	1.45	1.49	1.40	1.46
Demographic	1.51	1.65	1.90	1.86
Neighborhood	1.36	1.57	1.41	1.67
Network Trans	1.78	1.79	1.31	1.72
Struct. Holes	1.21	1.17	1.31	0.98
tHITS	1.33	1.67	1.05	1.01

Table 7.6: Trust Propensity Prediction $\leq \tau_{pred}\tau_{real} \geq$ (Guttman Scale)

Technique	**Trust**
Random	1.74
In-Degree	1.80
Out-Degree	1.74
Degree	2.03
Max	1.89
Median	1.57
Average	1.55
Char Based	1.91
Behavior	1.80
Demographic	1.99
Neighborhood	1.71
Network Trans	1.58
Struct. Holes	1.52
tHITS	1.44

7.6 Discussion

In this chapter we have considered the problem of trust prediction and specifically addressed the problem of trust formation, change in trust and trust propensity prediction. While the proposed approach performed better than the other techniques, there was still a great deal of discrepancy between the predicted values and the ground truth. This result can be interpreted in two different ways. One possibility is that none of the techniques used, including the baselines and the proposed approaches capture the structure and the properties of the trusting behavior of the players and thus do not perform as well in prediction. The other possibility is that a person's propensity to trust in the offline world is not the same that person's propensity to trust in the online game setting. This is a problem which has to be explored further. In our future work we plan to address this issue by taking a different approach. Instead of taking the person's reported propensity to trust, we will use a data driven observational approach to determine a person's propensity to trust and then compare it with the reported propensity to trust.

7.7 Conclusions

The problem of trust prediction has been studied in many domains and large number of models have been proposed to study this problem. In this chapter we studied three classical problems of trust prediction and also proposed a new problem for trust prediction - the problem of trust propensity prediction where the task is to predict how much does a person trust other people in general. We used data from an MMORPG for this prediction task by using in-game features, as well as demographic features of the players. The proposed approach used a modified version of the HITS algorithm to describe the concept of trustingness and trustworthiness in a network setting. Additionally we used network features and features derived from these networks in order to predict trust propensity. We used a number of baseline models for prediction and the proposed approach except in the case of breakage of trust. In the future we plan to explore the feature space further to improve the results of prediction for the various tasks, especially for the newly proposed prediction task.

Algorithm 2 The TrustHITS Algorithm

Given: Graph G_S, Trust subgraph $G \in G_S$
for $i = 1 \rightarrow size(N)$ **do**
  $n_i(\xi) = Wt(OutNebs(n_i, G))/Wt(OutNebs(n_i, G_S))$
  $n_i(\omega) = 1$
end for
ComputeTrust—(G)—
for $i = 1 \rightarrow convergence$ **do**
  for $j = 1 \rightarrow size(N)$ **do**
    for $j = 1 \rightarrow size(InNebs(n_i, G))$ **do**
      $n_j(\omega) = n_j(\omega) + n_k(\xi)$
    end for
  end for
  for $j = 1 \rightarrow size(N)$ **do**
    for $k = 1 \rightarrow size(OutNebs(n_i, G))$ **do**
      $n_j(\xi) = n_j(\xi) + n_k(\omega)$
    end for
    for $k = 1 \rightarrow size(N)$ **do**
      $n_j(\omega) = n_j(\omega)/sum(N(\omega))n_j(\xi) = n_j(\xi)/sum(N(\xi))$
    end for
  end for
  for $j = 1 \rightarrow size(N)$ **do**
    $n_j(\mu) = 1 - n_j(\xi)$
  end for
end for

Trust Prediction and Social Science Theories

7.8 Introduction

One of the seminal events of the last decade has been the explosion of myriad arrays of various form of social media which generate gigabytes of data every hour and thus provide an unprecedented opportunity to analyze human behavior on a massive scale. Mainly because of this data revolution it is now possible to not just build better theories regarding human behavior but also move from a descriptive analysis of social data to a predictive analysis. One issue which is usually coterminous with predictive modeling is that it is often the case that the models do not explain the psychological and social reasons behind *why* the model is successful in predictive analysis and thus essentially a black box. We consider these issues in the context of the link prediction problem.

While the problem of link prediction has been studied before in a number of contexts in social networks, we note that this problem has not been addressed with respect to the role of social science theories to explain the efficacy of featuresets in prediction tasks. One step in that direction is work by Ahmad et al [12] who try to incorporate Monge and Contractor's Multi-Theoretical Multi-Level framework [131] in the link prediction tasks. We take their work one step further by linking the feature space to theory space and additionally describe how the results of prediction tasks can be interpreted in terms of social science theories.

7.9 Background

The link prediction problem consists of a family of prediction problems which may range from predicting the formation [119], breakage [159], change of links to recurrence in the edge formation [172]. The link prediction problem was first described by Liben-Nowell and Kleinberg [119] and the Inter-Network Link Prediction Problem was first described by Ahmad et al [12] who also proposed a social science theory based approach to address that problems. In a follow up work Borbora et al [28] explored the problem of efficacy of feature space associated with link prediction to determine a robust set of features for link prediction.

Model based explanations for predictive modeling can be divided into three main types: (i) Explanations regarding how the algorithm works (ii) Explanations regarding how the model explains the phenomenon, such explanations are usually absent from black box models e.g, Neural Nets. (iii) In social, psychological and cognitive domains explanations that link the model to motivations that can be ascribed to intentional agents (people) or groups of such agents (society). In recent years there has been a move towards linking prediction algorithms, models and feature spaces to explanations in terms of social and psychological theories when these involve social phenomenon. That is mainly because an explanation agnostic model would not gain much currency in the social science domain where the primary goal is to not just study these phenomenon but also provide explanations with respect to why things happen. Borbora et al [29] thus note the distinction between theory driven and data driven models and how one can inform the other in creating better predictive models.

7.10 MMOGs as Testbeds of Human Societies

While the natural science have had a long tradition of predictive analytics and precision in analysis, social sciences in general have been farther behind in catching up with respect to these metrics. This is mainly because of the difficulty in collecting sufficiently large amounts of data with respect to human behavior as compared to collecting the same type of data for physical systems [164]. Additionally the phenomenon that is being studied in the social sciences is much more complex. The availability of massive amounts of social data offers a possibility to bridge this divide. Social data is available in a large number of settings, ranging from micro-blogging twitter data, online social networks, location-based socialization, online virtual worlds like SecondLife, World of Warcraft etc. Out of all of these MMOGs are the most complex forms of social medium where potentially millions of players can share a persistent online world. Many of the affordances that one sees in the offline world are also present in the offline world. Thus if sufficient mapping can be done from the MMO domain to the offline world in terms of affordances and contexts then it is possible to make inferences about the offline world from their online counterparts [192]. This opens up a viable channel to study social phenomenon which was not hitherto possible to do so because of lack of data. A similar argument is made by Keegan et al [101] regarding the analysis of criminal behaviors in the offline world. To conclude, MMOGs thus provide excellent testbeds to study human societies given the right kind of affordances.

7.11 A Psycho-Social Framework for Link Prediction

The MTML framework [131] describes the creation, maintenance and development of linkages in social networks in organizational and inter-organizational contexts and links together various theories in the sociology literature which also harkens to psychological motivations regarding why people form relationships with one another. The main theories and their corresponding applications can be summarized as follows:

- **Theories of Self-Interest:** Describes linkages in terms of a person's self-interest and desires. The main theories are the theory of social capital and the theory of transaction cost economics.

- **Theories of Collective Action:** Mainly examines how coordinated activity can produce outcomes which cannot really come about with individual action. Representative theories are public goods theories and critical mass theories.

- **Theories of Contagion:** Addresses the issues related to the spread of ideas, beliefs and influences in the social network. Contagion spread can be by cohesion or by structural equivalence.

- **Theories of Cognition:** Describes the role of knowledge and perception in social network. Represent theories include the Theory of Balance and and theories regarding Cognitive Communication structures.

- **Theories of Exchange:** Describes the emergence of social networks in terms of distribution of resources and how these change hands in social networks

- **Theories of Homophily:** Explains the role of similarity between the members of the network in the formation and evolution of the network.

- **Theories of Proximity:** Based on the idea that people are more likely to interact with other people who are closet to them in physical proximity,
- **Coevolutionary Theories:** Describes the formation of links on the basis of fitness functions i.e., in order to survive organizations and groups must adopt to the surroundings.

Table 7.7: Mapping Between Feature-sets and Theories in the MTML Framework (i)

	Self-Intr.	Cognition	Evol.	Exch.	Contag.	Homo.	Prox.
Ascribed							
Human Gender						X	
Avatar Gender						X	
Avatar Race						X	
Country						X	X
Σ Human Age						X	
ΣAvatar Age						X	
Human Age Diff.						X	
Avatar Age Diff.						X	
ΣJoining Age	X						X
Joining Age Diff.	X						X

Table 7.8: Mapping Between Feature-sets and Theories in the MTML Framework (ii)

	Self-Intr.	Cognition	Evol.	Exch.	Contag.	Homo.	Prox.
Acquired							
Char Class Ind.	X						
Char Level Sum		X					
Char Level Diff.		X					
Guild Indicator		X			X		X
Guild Rank Sum	X	X					X

Guild Rank Diff.	X	X					

We take these theories as starting point in feature set construction and also the partition of the feature space based on the appropriate features. We use the feature-set scheme used by Hasan et al [79] and modified by Ahmad et al [12] as our starting point but we expand it to include additional features which are more appropriate for a larger social space. They divide their feature space into three sets of features as follows: (i) Proximity Features (ii) Aggregated Features (iii) Topological Features. We note that this classification scheme is based on how the featuresets are constructed with minimal or no regard to their relationship to motivations with respect to why people form links. We expand their scheme and extend the set of features and first divide them based on how they are described in the sociology literature. Thus the Proximity features can be mapped to Ascribed (attributes based on some intrinsic node characteristics) and Acquired characteristics (node characteristics which can change in time). The topological features mostly map onto the social neighborhood based characteristics. Additionally we introduce a new class of characteristics i.e., trans-social characteristics which span multiple social networks and are defined as indicator functions i.e., if the node n belongs to the network A then the value of the function is 1. The mappings between the theories and the featuresets is given in Tables 7.7 and 7.8.

Table 7.9: Mapping Between Feature-sets and Theories in the MTML Framework (iii)

	Self-Intr.	Cognition	Evol.	Exch.	Contag.	Homo.	Prox.
Soc. Neighb.							
Degree Cent. Diff	X		X				
Betwn. Cent. Diff	X		X				
Σ Degree			X			X	X
Degree Diff.			X			X	X
Shortest distance					X		
Σ Clustering Ind.	X		X	X			
Common Neighbors				X			
Salton Index	X	X	X				

Jaccard Index	X	X	X				
Sorensen Index	X	X	X				
Adar-Adamic Index	X	X	X				
Resource Alloc. Index	X	X	X				

Table 7.10: Mapping Between Feature-sets and Theories in the MTML Framework (iv)

	Self-Intr.	Cognition	Evol.	Exch.	Contag.	Homo.	Prox.
Trans-Social							
Trust Link		X	X	X			
Mentor Link		X	X	X			
Trade Link		X	X	X			
Group Link		X	X	X			
Combat Link		X	X				X

7.12 Experiments

We use dataset from a massively multiplayer online game called EverQuest II (EQ2) where players can interact with one another in multiple ways and there are many avenues of socialization so that it is possible to construct multiple coextensive social networks between them. To check how well the classification tasks do in different social environments, we use data from two different servers or social environments in EQ2. One of the servers (called guk) represents a cooperative or neutral environment, called Player vs. Environment (PvE). The other server (called Nagafen) represents an adversarial environment, Player vs. Player (PvP). Our main motivation behind using different social environments was that the social relationships would form differently in the two networks and thus that would be reflected in the efficacy of the prediction algorithms even though the same feature sets are used in the feature space. The network characteristics of these networks are given in Table 7.11 where NCC refers to the number of connected components. We use a binary classification approach for link prediction as proposed by Hasan et al [79] for link prediction within and across social networks [12]. The dataset is divided into training period and test period. For each of the tasks 60,000 instances are prepared for prediction. A positive example is when the edge does not exist in the training period but exists in the test period. In the case of the negative example the edge does not exist in either periods. We used a standard set of classifiers (Naive Bayes, Bayes Net, KNN, SVM, JRip, J48, Adaboost) for our experiments and report for best results for each classification task.

Table 7.11: Network Statistics for all the networks used

Type	Network	Nodes	Edges	Diameter	NCC
PvE	Trust	15,465	23,145	37	1,488
PvP	Trust	13,184	15,945	27	2,237
PvE	Mentor	23,207	93,079	39	316
PvP	Mentor	36,973	187,452	≤ 27	97
PvE	Trade	31,900	1,796,438	≤ 24	11
PvP	Trade	49,132	2,142,832	≤ 24	20
PvP	Combat	59,468	3,767,395	≤ 24	32

The results of the experiments for the two networks are given in Table 7.12. The source network refers to the network which is used to construct the training examples and the destination network is the network for whom the prediction has to be made and is from the test period. The main thing to note here is that while the results for many of the prediction tasks remain more or less the same, in a subset of the cases there is a marked difference between the results that we get for the adversarial environment vs. the cooperative environment. The cases which are markedly different for the two environments are highlighted in a different color in Table 7.12. Thus consider the prediction results for the mentoring network, as noted in previous work [12] and [28] the prediction performance for the mentoring network is relatively low as compared to the other networks. However the results for the same prediction task but in the adversarial network are much better. This difference can be attributed to the fact that just as the adversarial environment results in greater competition between players who are in opposing teams and thus adversaries, the opposite is also true for people in the same teams i.e., one would expect greater loyalty for players in the same teams in adversarial environments as compared to people who are in cooperative environments. This results in overall better prediction results for the mentoring network prediction task. A similar difference is noted for the prediction tasks from mentoring to trade as well as from the trade to the mentoring network. Again, in both the cases the results for the adverbial environment are better as compared to the cooperative environment. The main take away from these observations is that the mentoring network is a better predictor for links in the trade network and vice versa in the adversarial environment as compared to the cooperative environment and for the same reasons.

Table 7.12: Results for Link Prediction in Adversarial vs. Cooperative Environments

Networks		Cooperative			Adversarial		
Source	Destination	Precision	Recall	F-Score	Precision	Recall	F-Score
Trust	Trust	0.79	0.69	0.74	0.79	0.66	0.72
Mentor	Mentor	0.63	0.48	0.54	0.77	0.71	0.74
Trade	Trade	0.80	0.78	0.79	0.86	0.85	0.86
Trust	Mentor	0.67	0.43	0.52	0.64	0.47	0.54
Trust	Trade	0.75	0.73	0.74	0.78	0.79	0.78
Mentor	Trust	0.88	0.76	0.82	0.85	0.67	0.75
Mentor	Trade	0.74	0.74	0.74	0.84	0.85	0.84
Trade	Trust	0.89	0.83	0.86	0.88	0.75	0.81
Trade	Mentor	0.67	0.55	0.60	0.81	0.75	0.78

While the mentoring and trade results are commutative in this case, this is not true for the prediction tasks for the trade and trust networks i.e., there is a marked difference in the prediction results for trade to trust and not vice versa for the two environments. The main reason for this result is that a trade edge has a low transaction cost associated with it as compared to a trust edge which has a high cost associated with it. Thus a trust relationship is likely to have a corresponding trade relationship associated with it but not vice versa. Theories of co-evolution [131] would imply that in cooperative environments neutral and positive interactions (trade and trust respectively) are likely to percolate from one dimension to another but this is less likely in adversarial environments which explains the results.

We note that given the nature of the two environments the Combat network is not present in the PvE server. Additionally we have access to another network in the PvE environment, called the grouping network, which was not extracted for the PvP environment at the time of these experiments. The group network refers to an ingame network formed by players who group together to complete quests. These are analogous to military missions or other logistical missions in the offline world. The results for the Combat network in the adversarial environment and the results for the Grouping network in the cooperative environment are given in Table 7.13. Over all the results for the combat network as well as the grouping network are quite good even when compared against other prediction tasks. The main exception in this case is again the mentoring network where the prediction results for grouping to mentoring network are not as good as the other prediction results. The main reason for this observation is that while a large number of mentoring instances co-occur with the grouping instances i.e., mentoring occurs in the context of grouping in such cases but the opposite is not necessarily true i.e., grouping usually does not co-occur with mentoring [11].

Table 7.13: Results for Link Prediction for the Group Networks

Networks		Adversarial		
Source	Destination	Precision	Recall	F-Score
Group	Group	0.88	0.90	0.89
Trust	Group	0.88	0.90	0.89
Mentor	Group	0.85	0.83	0.84
Trade	Group	0.86	0.86	0.86
Group	Trust	0.87	0.75	0.80
Group	Mentor	0.61	0.47	0.53
Group	Trade	0.81	0.83	0.82

7.13 Interpretation and Methodological Issues

We have considered the problem of link prediction in the context of two different social environment and a feature space mapped onto different social science theories. Our main motivation for using two different social environments is to highlight the hazards of generalization without considering the social environments associated with the prediction task. Thus consider previous results reported by Hasan et al [79], Ahmad et al [12] and Borbora [28] using similar techniques and link prediction tasks in general, the generalizability of the feature space is assumed without the social context. Theories in the social sciences e.g., the MTML framework [131] imply that social networks in different social environments evolve different which is in turn reflected in their network structure. The differences in the network structures are also likely to effect prediction that and this is in line with some of the observations that we made in the results.

There are additional methodological issues with respect to generalizing across MMOG environments. Thus consider the case of modeling of team formation dynamics in the online world by Johnson et al [95] who show that the same generative models can be used to explain guild formation in World of Warcraft and street gangs in Los Angeles. Based on their observations they generalize that there must be some common generative mechanism for team formation in online guilds and offline street gangs. Ahmad et al [5] replicated their results in EQ2 and discovered that the generalization does not carry over to EQ2. More research is required to settle this issue conclusively but both these cases highlight the fact that generalizations are unwarranted especially in contexts where social contexts are not taken into account.

Table 7.14: Results for Link Prediction for the Combat Networks

Networks		Cooperative		
Source	Destination	Precision	Recall	F-Score
Trust	Combat	0.88	0.91	0.89
Mentor	Combat	0.84	0.85	0.84
Trade	Combat	0.88	0.90	0.89
Combat	Combat	0.89	0.91	0.90

Combat	Trust	0.88	0.74	0.80
Combat	Mentor	0.83	0.78	0.81
Combat	Trade	0.86	0.88	0.87

7.14 Conclusion

Predictive analysis, especially classification, is an important aspect of data mining and while the internal mechanism of most classification algorithms are well understood, a mapping of feature spaces to social and psychological theories is not well understood. In this chapter we considered such a mapping and used two datasets representing two social environments in an MMOG. The results showed that for a subset of the prediction tasks the prediction models perform different using the same feature set. This implies that it is also the network structures associated with the adversarial as well as the cooperative environments are different and should inform the selection of features for future work.

Chapter 8

Trust Prediction Across Networks

"I'm not upset that you lied to me, I'm upset that from now on I can't believe you."
- Friedrich Nietzsche

8.1 Introduction

Humans are social creatures and interact with one another in a variety of manners such that human social networks are ubiquitous in nature. Such social networks can range from offline networks based on friendship or kinship ties to online networks in social networking websites like Facebook, LinkedIn, MySpace etc. Social Networks are most often represented as graphs or hypergraphs and there is an extensive body of literature on social networks[181]. Various predictive problems have been proposed for social networks, the link prediction problem is the problem of predicting links in a network which may form in the future between the nodes in the network. The link prediction problem was first proposed by Liben-Nowell and Kleinberg [119] and has been studied extensively since then. The link prediction actually consists of a family or subproblem e.g., predicting the existence of the link, type of the link, the strength of the link etc.

While the link prediction problem has been applied in many domains like social networks, protein-protein interaction, record linkage problem, web-link prediction etc, we restrict ourselves to application of link prediction in social networks although our technique can be applied in other domains as well. The link prediction problem has a wide range of applications in addition to the well known example of e.g., recommendation systems [87], making recommendation to create mutually beneficial professional links [178], improve navigational efficiency of websites[178] etc.

For experiments and validation, data from an Massively Multiplayer Online Role Playing Game (MMO) EverQuest II (EQ2) is used for multiple types of networks were extracted from the game for the link prediction tasks. These networks form because of different types of social processes and represent networks of different nature. Most of the previous work on link prediction has used data from citation or collaboration [119] networks for link prediction. The link prediction problem is well studied in such types of datasets. Here we concentrate on networks which form as a result of different social processes. Previous studies of socializing [190] in virtual worlds suggest that causality in virtual worlds is similar to that in the real world. Consequently results in insights from studying virtual world may be applied to the offline world in some contexts.

The problem of link prediction actually consists of a family of prediction problems. To the best of our knowledge the previous literature on link prediction is restricted to link prediction within the same network. In this paper we propose a new problem, inter-network link prediction (INLP), which is the problem of predicting the formation of links across networks i.e., given networks G_1 and G_2 the task is to use information from G_1 to make predictions about G_2 and vice versa. Link prediction techniques exploit various techniques like the attributes of the nodes, topological features of the graph or aggregate features of the nodes to make predictions about the links. The performance of some of these techniques can be enhanced by adding domain knowledge to these techniques. An oft neglected source of domain knowledge is social science theories which link back to network processes that may be going on in various social networks. In this paper we seek to employ insights from theories of social communication to enhance the internetwork link prediction task. Many of these theories propose the existence of Structural Signatures (expected subgraphs) which are likely to be present in certain types of networks. To the best of our knowledge social science theories have not been applied before in improving link prediction. The closest example that is work by Lu and Zhou [121] who used weighted versions of many well known local topological measures to make predictions and discovered that weighted versions perform worse than their unweighted counterparts. The implication being that the weak ties in the network play a significant role in link prediction. There are multiple theories about how social communication networks evolve over time. Monge and Contractor [131] developed the Multi-Theoretical Multi-Level (MTML) Framework which synthesized insights from various theories of social communication and also identified a set of structural signatures associated with each type of theory. Insights from MTML are used to propose a model for predicting links across networks. The link prediction family of problems can be addressed through different frameworks, in this however paper we focus on the predictive power of topological features and use a machine learning approach similar to that of Hasan et al [79]. The contributions of this paper can be summarized as follows:

- Define a new link prediction problem, the inter-network link prediction problem, and propose a solution to the problem.
- Use of insights from social science theories to augment the process of link prediction and improve the results of link prediction.
- Define and address the problem of inter-network link prediction where network information from one network can be used to make link predictions in another network.

The rest of the chapter is organized as follows: In section 8.2 we describe related work in the domain of link prediction and background from theories of social communication networks, in section 8.3 we describe our proposed approach and in section 8.4 we describe the inter-network link prediction task. The dataset, experiments and results are described in section 8.5 and the conclusion is in section 8.6.

8.2 Related Work

8.2.1 The Family of Link Prediction Problems

The link prediction problem was first proposed by Liben- Nowell and Kleinberg [119] who used various graph proximity measures to make predictions about co-authorship networks in Physics. Rattigan et al [147] defined the problem of anomalous link discovery where the task is to discover links which may be 'surprising' as compared to other links in the network. The motivation being that since the number of dyads that have to be evaluated for link prediction grows combinatorially as the network size grows it is more useful to concentrate on the surprising links. The link prediction problem consists of a family of prediction problems. While most classifications of the link prediction problem sub-divide it into two or three sub-problems [193], we give a more comprehensive classification of the problem as follows:

- Link Formation Prediction. (Does a link exist?) [119][79]
- Link Disappearance Prediction. (Will a current link disappear?) [159]
- Link Classification. (What is the nature of the link?)[178]
- Anomalous Link Discovery. (What are the unexpected links?) [147]
- Link Weight Prediction (Predict the change in the weight of link) [193]
- Time Series Link Prediction (Prediction which links will reoccur over time)[172]
- Link Regression. (How does a user rate an item?)[86]

A number of topology based measures have been used for the link prediction tasks, these include Newman's common neighbors [136], Jaccards Index, Adamic/Adar metric [2] etc. Murata and Moriyasu [134] extend these metrics for weighted graphs and use for link prediction in a QA system. Huang [86] proposed a graph topology based method which generalizes the clustering coefficient and defines the problem of link prediction as that of cycle completion in graphs. It should also be noted that the topology based formulation of the problem can also be described as the problem of matrix completion which can be accomplished by matrix factorization [112]. Topology based temporal metrics were employed by Potgieter et al [141] to increase the performance of link prediction techniques.

Clauset et al [50] describe a maximum likelihood based approach combined with Monte-Carlo Algorithm and fit a hierarchical model on a network graph to make link predictions. Kunegis and Lommatzsch [108] describe a framework for link prediction based on transformation of a graphs algebraic spectrum. Their approach generalizes many previous graph kernel based approaches for link prediction. Sharan et al [159] describe a method based on graph summary which can predict both link formation and disappearance. For a more detailed review of link prediction literature we refer the reader to a survey on link prediction by Xiang [193]. B. Theories of Social Communication Networks In this section we adopt the word communication as used in the context of social networks and is defined in terms of flow of ideas, commodities, influence etc in a social networks [131]. There are many theories which describe how social communication networks evolve over time and how links form in these networks. The salient features of the most prominent theories are given below. These theories are based on hundreds of empirical studies in social science and have a solid empirical and theoretical grounding. We refer the reader to the text by Monge and Contractor [131] for a more detailed description of these theories.

These theories describe a different aspect of communication networks. In some social network some of the theories are more applicable than others e.g., theories of balance may explain friendship networks better than say theories of contagion. Monge and Contractor [131] developed the Multi-Theoretical Multi-Level Framework which synthesized insights from the theories described above. There are certain archetypical behaviors which are found in many human networks which are expected to occur in networks where one type of social theory is at play versus another type of theory. These behaviors are: Exploring, Exploiting, Mobilizing, Bonding and Swarming.

The corresponding social theories for these are given in Table 8.1. Based on these behaviors and theories they also identified network substructures or subgraphs that are likely to be associated with each type of theory. The corresponding structural signatures for these theories is given in Figure 8.2.1. The MTML framework has been adopted to determine the applicability of each type of these theories in various networks [131]. The models which are most commonly used for this purpose are the Exponential Random Graph Models (ERGM) or the p* family of models [181]. The main idea behind the ERGM model is that given a network and an expected set of structures (subgraphs) we determine that in the space of all possible graphs with the same number of nodes how likely is the observed network given the distribution of the expected substructures over all possible such graphs.

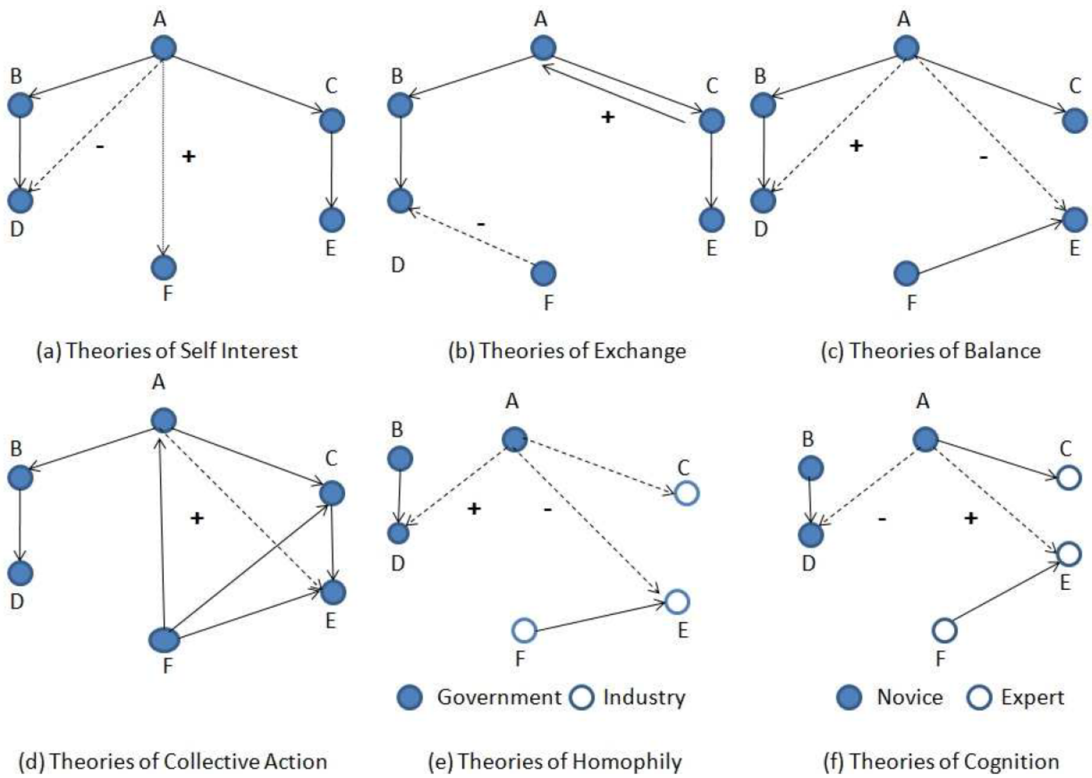


Figure 8.1: Structural Signatures from MTML

8.3 Inter-Network Link Prediction

In this section we describe inter-network link prediction problem (INLP). **Definition:** Given two graphs G_A and G_B with set of nodes $n_A \in N_A$ and $n_B \in N_B$, if $N_C = N_A \cup N_B$ and $N_A \cap N_B \neq phi$, if $e_{Aij} \in E_A$ is the set of edges observed in the graph G_A then the task of inter-network link prediction is to predict $e_{Bij} \in E_B$ by using only the node $n_A \in N_A, e_{Aij} \in E_A$ or attribute $v(N_A)$ information from graph G_A.

As a practical example consider a case where network data is available from a social network amongst people who play golf together and additional information like demographics, profession, frequency of interaction etc is also available. There is also membership information available from another dataset for a subset of the people regarding trade but the edges in the trade network are not available. The task in this case would be to use the golf network and the additional available information to make predictions about the edges in the trade network. This type of information can also have practical applications like using it for marketing purposes etc.

8.4 A Structural Signatures Based Approach

We now describe a structural signatures based approach for the link prediction problem. The main idea is to identify a set of substructures or subgraphs which are likely to be present in certain types of graphs which are known to be generated by certain social processes. We propose an algorithm, MTML Inter NeTwork Predictor (MINTP), for predicting link across networks. Before describing the algorithm in detail we first describe some background and motivations for this approach.

The MTML theory predicts the existence of certain substructures in networks which are driven by certain social processes. For a more detail exposition of this idea and the MTML theory we refer the reader to [131]. It should also be noted that the existence of these sub-structures are not independent from one another e.g., if we are considering only one type of network then certain types of structures are likely to occur in these networks.

On the other hand if we use information from multiple interacting networks then we would end up with different structures. The MTML theory also implies he transformation of certain types of sub-structures to other types. This information can be used for predictive purposes e.g., it could be the case that these transformations correspond to presence or absence of link formation that we are likely to see in the network. The following example can be used to illustrate this.

Consider Figure 2 which shows the evolution of graph G_i at time t_1, t_2, t_3, t_4. The subgraphs g_1 through g_n are the various subgraphs that are observed in the graph Gi. The notation $g_i \rightarrow g_j$ denotes that graph g_i gets transformed into graph g_j. It is clear from the figure that certain types of subgraph are being transformed into other types e.g., $g1 \rightarrow g_5$ in $(t_1, t_2), g_2 \rightarrow g_7$ in (t_1, t_2) and $(t_3, t_4), g_3 \rightarrow g_8$ in $(t_1, t_2), (t_2, t_3)$ and (t_3, t_4). These can also be automatically discovered by sequential pattern mining

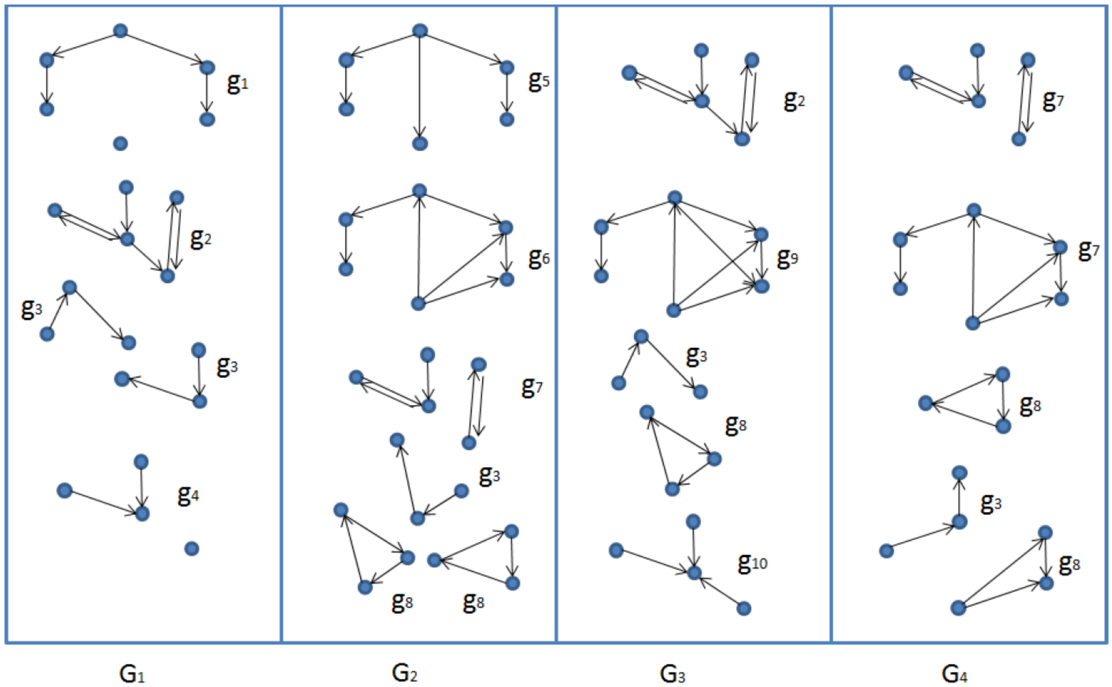


Figure 8.2: Examples of subgraph transformations

but since we are assuming that information about one network is not available we cannot apply sequential pattern mining. As a substitute however we are interested in the subgraphs which are predicted by the various social science theories and the transformation of these subgraphs into other subgraphs. The problem of finding such transformation can be represented as follows:

$$G_{t,t_{\Delta+t}} = \{g_i \rightarrow g_i || g_i \in G_t \wedge g_i \in G_{t_{\Delta+t}}\} \tag{8.1}$$

The task of making predictions can thus be defined in terms of determining how many such transformations $g_i \rightarrow g_j$ will result in transformation into cases where the link is formed between two nodes. To illustrate this again consider graphs g_6 and g_9 in Figure 2. From t_2 to t_3 an additional link is formed in the graph when $g_6 \rightarrow g_9$. If we see the same transformation occurring in sufficiently large number of cases, as compared to such a transformation occurring in purely random graphs, then we can predict that this link is likely to form. We note that an alternative method would be to use graph generators to generate the underlying networks for comparison.

The outline of the algorithm is given below. The main idea is as follows: Given a graph G_A which contains the edge information and the node attribute information and another graph G_B which only contains the node information but no edge information, take the union of the graphs. It should be noted that the union does not include any edge information from G_B. Rewire the edges until the stopping criteria of adjacency correlation, details are given in the experiments section, is met. For the next k iterations perform the following procedure. Save the nodes in the graph in a lexicographical order and the randomize the ordering. Create or delete edges based on their likelihood of presence or absence according to their likelihood as described by MTML. The final predictions are based on taking the average of the network by running this procedure z times. We note that in this algorithm k and z are the free parameters which describes the number of times these graphs have to be generated. For our experiments we used $k, z = 10,000$. If T represents the set of theories which are applicable to a particular domain then the MINTP Algorithm can be described in the figure below. The notation $e_{Aij} = (n_i \rightarrow n_j)$ implies that the edge e_{Aij} exists between nodes n_i and n_j in Graph A.

One of the most important elements of the MINTP algorithm is to determine the conditions on which the conditional probabilities for the existence or the non-existence of an edge must be predicted. It should be noted that this is a very domain dependent task and would vary across networks and domains. In the experiments section we describe six combinations of networks for link prediction across networks. Due to limitations in space we describe the procedure for determining the conditions for just one of the cases. Edges in the housing network in EQ2 can be of different types depending upon the type of relationship, corresponding to edge weight, that two players have with one another [13]. The strongest form of relationship is the Trustee relationship between two nodes in the trust network and while the other types of relationship represent some form of linkage between two people, the relationship is not as strong. Given the nature of the housing network one would expect the Theory of Balance and the Theory of Homophily to play the most important part in explaining behavior in the housing network. While in the mentoring network the Theory of Cognition and the Theory of Self Interest would be the most prominent.

Thus one would expect the corresponding structures from Figure 1 to figure prominently in these networks. We get a more complex picture if we take all these factors together e.g., Theory of Homophily would predict that the links would be formed between nodes which are topologically closer together and have similar characteristics in the same network. The Theory of Self-Interest on the other hand implies that such structures are not going to be common. Taken together these observations imply that if a triangle is observed between these nodes in the housing network, it is unlikely to be present in the mentoring network between the same nodes. Another observation is the likelihood of formation of edges between nodes which are different with respect to expertise in the game. In the mentoring network this is going to be the case since mentoring relationship is established between actors if there is a difference in expertise between them. In the context of EQ2 this can be translated as the level of the player. However it is not possible to mentor any character in the game, they have to be in the same location at the same time.

Theory of Balance also implies that the more common neighbors that player have in a network, the more likely that they will form an edge. Additionally if the players have some other common identification e.g., guild membership then they are likely to form edges between themselves in case of the trust network and also mentor mentor other players in the guild if their level difference is sufficiently high.

Table 8.1: The MTML Framework: Social Drivers for Creating and Sustaining Communities

Theories	**Exploring**	**Exploiting**	**Mobilizing**	**Bonding**	**Swarming**
Self Interest	+		-		
Cognition		+	+		+
Balance	-		+	+	
Exchange		+		+	
Contagion	+		+		
Homophily	-			+	
Proximity	-			+	+

Table 8.2: Network Characteristics of EQ2 Networks

Net	N	E	d	NC	CC_1	CC_2
M	23,207	93,079	39	316	22,477	6
H	15,465	23,145	37	1,488	9,152	52
T	31,900	1,796,438	< 28	11	31,858	10

8.5 Experiments

8.5.1 Dataset

Data from EQ2, a fantasy based MMORPG where thousands of players can simultaneously engage in many different types of activities like fighting non-player characters (NPCs), engaging in trade with other players, helping out other players, going on quests, exploring the landscape etc. Thus it is possible to construct multiple networks of players from this dataset. The game is played on multiple servers which can be thought of as parallel worlds. Data from one of the servers guk is used for experiments. We only consider the nodes in the largest connected component for our analysis. The following three networks are constructed from the game data:

Housing-Trust Network: Player can then give access network is contructed on the basis of access ties.

Mentoring Network: Players who are at a higher level can mentor players who are at a lower level and a social network is constructed based on this information.

Trade Network: The social network constructed by creating an edge between two players if they engage in trade between one another.
We use data from the game starting from January 1st, 2006 to September 11th, 2006. The global characteristics of these networks are given in Table 8.2 where N is the number of nodes, E is the number of edges, d is the diameter of the network and NC is the number of components. CC1 and CC2 are the largest and the second largest connected components respectively. M, H and T refer to the mentoring, housing and the trade network respectively. We now describe the feature set which is used in the

experiments. While the main focus of the paper is on topological features, we also include other types of features for comparison. Following is the list of features that we use in our experiments. Proximity features: These are features that represent some form of proximity between a pair of nodes e.g., two game characters may belong to the same guild/clan. The proximity features that are used here are defined in terms of indicator functions. If ax is an attribute of node nx then the indicator function can be given as:

$$s_{ij} = \begin{cases} 1, & if \quad a_i = a_j \\ 0, & if \quad a_i \neq a_j \end{cases} \tag{8.2}$$

The following indicator functions are used for the proximity featres: Real Gender Indicator, Real country indicator, Character class indicator, Character gender indicator, Character race indicator. Aggregated features: These are combination of individual attributes of the node pair. The individual attribute can provide information which can help in the link prediction task e.g., The higher the character level of a player, the more likely it is that it will interact with another character in some manner. Thus sum of character levels of a character pair can be a good aggregated feature. The following aggreated features are used: Sum of neighbors, Sum of actual age in 2006, Sum of joining age, Sum of character levels and Sum of character levels of the two game players. Topological features: These are based on network topology. e.g, shortest distance between the pair of nodes. These are given below. The parametric versions of the common neighbors, Adar-Adamic Index and Resource Allocation Index were given by [121]. Given nodes n_i and n_j , these features are defined as follows:

- **Common Neighbors** If $\Gamma(x)$ represents the neighbors of x then:

$$s_{ij} = \Gamma(i) \cap \Gamma(j) \tag{8.3}$$

- **Shortest distance:** The shortest distance between the pair of nodes in the network.

- **Clustering Coefficient:** This is a measure of localized density and measures the participation of the nodes in triads.

- **Adar Adamic Index:** This metric improves on the common neighbors metric by giving more weight to the neighbors who are lower connecting nodes. If $f(k) =$

$\Gamma(k)$:

$$s_{ij} = \sum_{k \in \Gamma(i) \cap \Gamma(j)} \frac{1}{log f(k)} \tag{8.4}$$

- **Resource Allocation Index:** This metric is a modified form of the Adar-Adamic Index.

$$s_{ij} = \sum_{k \in \Gamma(i) \cap \Gamma(j)} \frac{1}{f(k)} \tag{8.5}$$

- **Parametric Weighted Common Neighbors:** If $w(i, j) = w(j, i)$ is the weight of the links between nodes n_i and n_j then this metric is defined as follows. Note that if $\alpha = 0$ then the metric is equivalent is to the common neighbors metric and if $\alpha = 1$ then the metric is equal to taking the weights of the neighbors.

$$s_{ij} = \sum_{k \in \Gamma(i) \cap \Gamma(j)} w(i, k)^{\alpha} + w(k, j)^{\alpha} \tag{8.6}$$

- **Parametric Adar Adamic:** In this version of the Adar Adamic metric, 1 is added to $log(k)$ because the value of $s(k)$ may be less than 1 which may lead to negative values. The metric is given as follows:

$$s_{ij} = \sum_{k \in \Gamma(i) \cap \Gamma(j)} \frac{w(i, k)^{\alpha} + w(k, j)^{\alpha}}{log(1 + s(k))} \tag{8.7}$$

- **Parametric Resource Allocation:** The metric is given as follows:

$$s_{ij} = \sum_{k \in \Gamma(i) \cap \Gamma(j)} \frac{w(i, k)^{\alpha} + w(k, j)^{\alpha}}{s(k)} \tag{8.8}$$

While generalizations of the clustering coefficient exists, it has been noted [86] that the higher level analogues of the clustering coefficient are not really helpful in prediction.

8.5.2 Results

Given that there are thousands of nodes present in each network and thus millions of possible links between them, a prediction scheme which always predicts the non-existence of a link will get high precision and recall. To avoid this problem we randomly sample from the pairs of instances of nodes for positive and negative samples until we have the required number of examples, 60,000 in our case. We divide our data set into a training period spanning from January 2006 to June 2006 and test period spanning from July 2006 to September 2006. Following [79] the link prediction task in these experiments is defined as a machine learning problem where the binary classes are form-link and do-not-form link. A positive example is an edge in the test period which does not appear in the training period. A negative sample is an edge (with both of its nodes present in the training period) which is present neither in the training period nor in the test period. We used a total of 60,000 samples - with a maximum of 30,000 positive samples and the negative samples making up the rest. For validation and comparison with our technique we used six standard classification algorithms available in the popular machine learning library WEKA [78]. The algorithms that were used are J48, JRip, AdaBoost, Bayes Network, Nave Bayes and k-nearest neighbor, and 10-fold cross validation was used. The problem of predicting across networks is non-trivial because participation of nodes in graph does not imply that these node are going to participate in other networks. This can be done by determining how much overlap there is between the various networks. For this purpose we computed the Adjacency Correlation, as defined by Clauset and Eagle [49] which determine the correlation between the adjacency matrices of two graphs.

$$\gamma_j = \frac{\sum_{i \in N_j} A_{i,j}^{(x)} A_{i,j}^{(y)}}{\sqrt{(\sum_{i \in N_j} A_{i,j}^{(x)})(\sum_{i \in N_j} A_{i,j}^{(y)})}} \tag{8.9}$$

Where A(x) and A(y) are the adjacency matrices of the graph at Time x and at time y,N(j) is the union of row elements which are non-zero in at least one of the two matrices, j is the correlation for the row for the two graphs. The adjacency correlation for the network is defined as the average of the adjacency correlation for all the rows in the adjacency matrix. The adjacency correlation between the three networks is given in Table 8.3. The table indicates that there is very small overlap between the three networks which could partially explain why we are getting poor results for our predictors.

Table 8.3: Adjacency Correlation for the Networks

	Housing	Mentoring	Trade
Housing	1	0.10056	0.00669
Mentoring		1	0.00492
Trade			1

Table 8.4: Jaccard's Index for the Networks

	Housing	Mentoring	Trade
Housing	1	0.34296	0.35019
Mentoring		1	0.55459
Trade			1

The adjacency correlation values from table 8.3 would seem to indicate that there is very little overlap between the various networks in terms of participation of nodes from one network to another network. The relationship between the networks is however more complex than this. To illustrate this we computed the Jaccards Index for only the nodes in the networks without considering the edges. The Jaccards index for the three networks is given in Table 8.4. From the table it is clear that there is a high degree of overlap between the networks especially in case of the trade and the mentoring network but from Table 8.3 we know that the adjacency correlation between these networks is low which would imply that although the same types of nodes are participating in these networks but in general they are not forming the same type of ties. This type of information should be included in future approaches to this problem in order to improve the results.

Results from Table 8.5 to 8.10 reveal that the proposed approach consistently performs better than the other approaches. The two instances where the performance of other approaches is comparable to the proposed approach is in the case where prediction has to be done on the Trade network. The reason for this is that the trade network is a very dense network which is evident from Table II which shows that there are more than 1.7 million edges in the trade network, while in the other networks the number of links are less than a hundred thousand. Thus many nodes which are picked at random are likely to form an edge if they are sufficiently close to one another. In the other instances the proposed approach performs much better than other techniques.

Table 8.5: Housing to Mentoring

Technique	**Positive**	**Negative**	**Precision**	**Recall**	**F-Score**
J48	4108	55892	0.741	0.225	0.345
JRip	4108	55892	0.751	0.167	0.273
AdaBoost	4108	55892	0.834	0.162	0.271
NaiveBayes	4108	55892	0.248	0.343	0.288
BayesNet	4108	55892	0.354	0.426	0.387
KNN	4108	55892	0.288	0.146	0.193
MINTP	4108	55892	0.458	0.398	0.426

Table 8.6: Mentoring to Housing

Technique	**Positive**	**Negative**	**Precision**	**Recall**	**F-Score**
J48	2528	57472	0.696	0.284	0.404
JRip	2528	57472	0.667	0.313	0.426
AdaBoost	2528	57472	0.173	0.257	0.207
NaiveBayes	2528	57472	0.278	0.464	0.348
BayesNet	2528	57472	0.680	0.308	0.424
KNN	2528	57472	0.273	0.098	0.144
MINTP	2528	57472	0.581	0.398	0.472

Table 8.7: Mentoring to Trading

Technique	**Positive**	**Negative**	**Precision**	**Recall**	**F-Score**
J48	30001	29999	0.766	0.789	0.777
JRip	30001	29999	0.776	0.790	0.783
NaiveBayes	30001	29999	0.669	0.915	0.773
BayesNet	30001	29999	0.720	0.838	0.774
AdaBoost	30001	29999	0.790	0.746	0.767

KNN	30001	29999	0.736	0.748	0.742
MINTP	30001	29999	0.767	0.790	0.778

Table 8.8: Trading to Mentoring

Technique	**Positive**	**Negative**	**Precision**	**Recall**	**F-Score**
J48	12740	47260	0.619	0.509	0.559
JRip	12740	47260	0.627	0.551	0.586
NaiveBayes	12740	47260	0.441	0.743	0.553
BayesNet	12740	47260	0.436	0.755	0.553
AdaBoost	12740	47260	0.593	0.563	0.578
KNN	12740	47260	0.545	0.483	0.512
MINTP	12740	47260	0.666	0.592	0.627

Table 8.9: Hosuing to Trade

Technique	**Positive**	**Negative**	**Precision**	**Recall**	**F-Score**
J48	30001	29999	0.790	0.821	0.805
NaiveBayes	30001	29999	0.743	0.874	0.803
BayesNet	30001	29999	0.737	0.865	0.796
AdaBoost	30001	29999	0.809	0.788	0.798
KNN	30001	29999	0.769	0.785	0.777
MINTP	30001	29999	0.785	0.796	0.790

Table 8.10: Tradign to Housing

Technique	**Positive**	**Negative**	**Precision**	**Recall**	**F-Score**
J48	2869	57131	0.587	0.137	0.222
JRip	2869	57131	0.538	0.131	0.211
NaiveBayes	2869	57131	0.205	0.453	0.282
BayesNet	2869	57131	0.202	0.628	0.306
AdaBoost	2869	57131	0.538	0.005	0.010

KNN	2869	57131	0.363	0.163	0.225
MINTP	2869	57131	0.784	0.239	0.366

8.6 Conclusion

In this chapter a new link prediction problem, inter-network link prediction, was proposed where the goal is to predict which links across multiple network are likely to form. Thus if information is available about node attributes and edge information from one network then one predict edges in another network where there is an overlap in membership between the two networks. While there are a large number of techniques for link prediction, these techniques seldom use knowledge from social science theories on network evolution. Data from a Massively Multiplayer Online Role Playing Game (MMORPG) EQ2 was used for experiments and validation. These networks are formed by different social processes and thus different feature set are helpful in making predictions in these networks. We then described a new technique which can be used for link prediction across networks which employs insights from social science theories to make predictions about links across networks. Specifically the MTML theory of Monge and Contractor [131] was employed to make predictions about the existence or non-existence of edges. Future work would involve extending the inter-network link prediction problem to include other characteristics of network and employ other datasets to test the generalizability of the proposed approaches.

Algorithm 3 MINTP Algorithm

Given: G_A with edgeset E_A and nodeset N_A, Graph G_B with nodeset N_A.
Task: Predict edges $e_{Bi} \in E_B, G_A \xrightarrow{E_A} E_B$.
$T \Rightarrow S = \{g_1, g_2, ..., g_n\}$ (Substructures associated with T)
begin: $GP := (N_P = N_A N_B, E_P = E_A)$
while $A(G_P, G_B) \leq A(G_P, G_A)$ **do**
  remove:
  $e_{Pij} := rand(EP)$,
  $e_{Pij} = (n_i \rightarrow n_j), \exists e_{Aij} = (n_i \rightarrow nj_{)} \in E_A$
  add :
  $e_{Pij} = (n_i \rightarrow n_j), n_i \in N_A, n_j \in N_B$
end while
for $i = 1 \rightarrow k$ **do**
  $n_i = rand(N_P)$
  $n_j = rand(N_P)$
  $P = p(e_{Pij} || c_1, c_2, ..., c_n)$
  if $\exists e_{pij}$ **then**
    if $P < \tau$ **then**
    remove: e$_{Pij}$
    end if
    if $P < \tau$ **then**
    add: e$_{Pij}$
    end if
  end if
end for

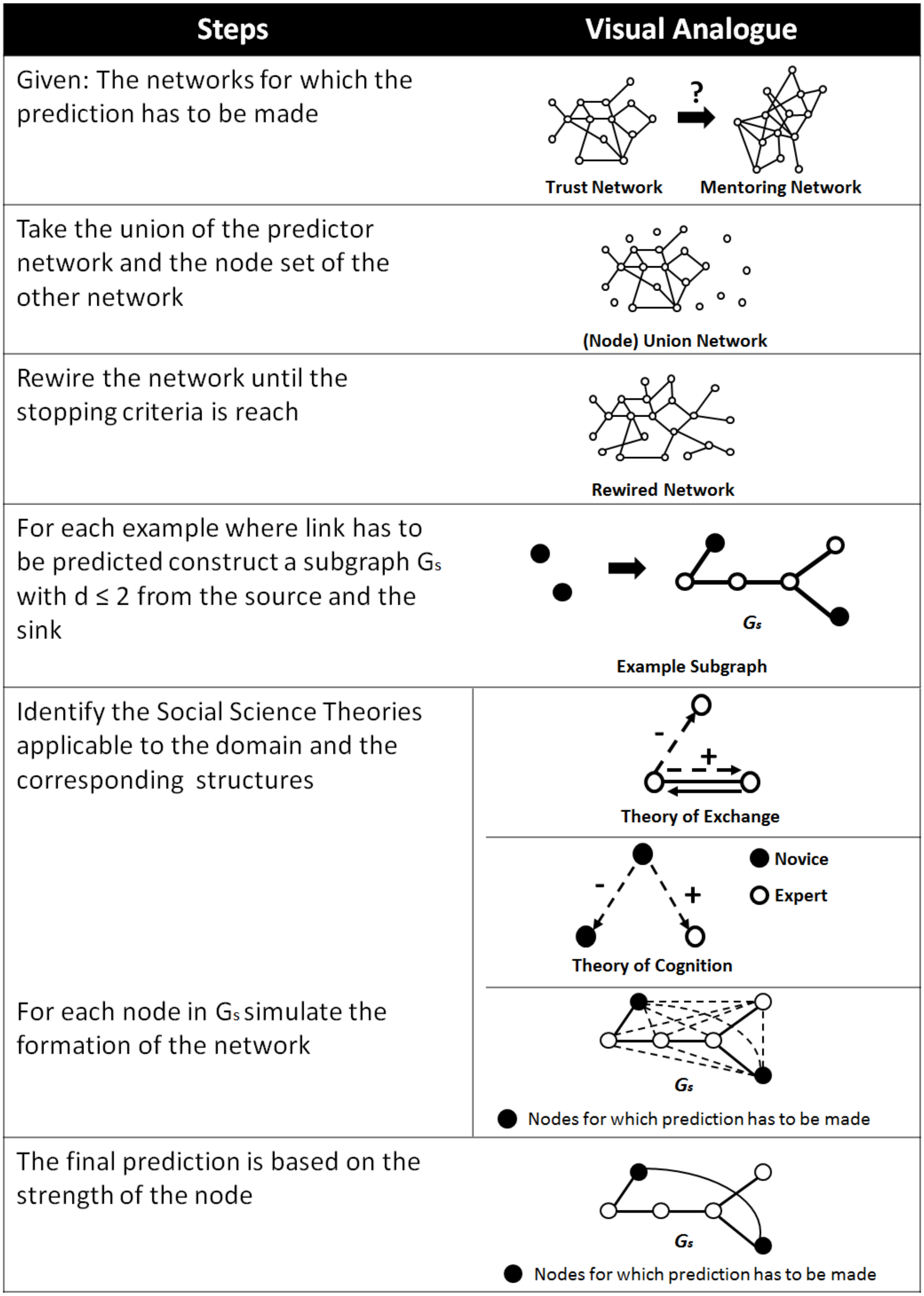


Figure 8.3: Summary of MINTP

Chapter 9

Trust and Item Recommendation

"The best way to find out if you can trust somebody is to trust them."
- Ernest Hemmingway

9.1 Introduction

Recommendation of items and products is a well-studied problem [3]. Such recommendations are usually made based on similarities between people for whom the recommendation has to be made. Similarity can be computed in terms of the characteristics, past preferences as well as the social networks of the people in the recommendation system. With the rise of e-commerce in the last decade or so, recommendation systems have become almost ubiquitous on e-commerce website. Notable examples of recommendations or recommendation systems integrated in well known websites include Amazon, Epinions, Shoppero etc. Since many of these websites lack information about the social network between the users they employ similarity information between the users to make recommendations. In social networking websites like Facebook, recommendations can be indirectly made by showing the users what their friends have liked or making 'suggestions' based on what their friends have liked. Even Twitter has a recommendation feature to recommend what people to follow on twitter.

The problem of using social network information for making recommendations has also been addressed in many contexts before [178], [55]. The main advantage of using the social network for recommendations is that not only does it reduce the search space for users for which one has to compute similarity in order to make recommendations but the people who are friends with one another are likely to have similar tastes in products or services because of homophily in social networks [128]. Thus social network based approach not only reduce the computation time but are also likely to improve the results of prediction.

While collaborative filtering and many social network based methods have been employed in the past for successful prediction of recommendations, to the best of our knowledge the problem of recommendation in multiple overlapping social networks (co-extensive networks) has not been addressed to date. This problem can be described as follows: Consider a scenario where a person participates in multiple social networks. This is also reflective of human societies where any given person is usually part of multiple social networks e.g., a person's social network may consist of her family, her friends, her co-workers, people with similar interests etc. If data about such multiple social networks is available then these different social networks can be used to make recommendations to the people in these networks. Given that different people have different interests, the effectiveness of recommendations will depend upon the network used.

In this chapter we thus address the problem of making recommendations in coextensive social networks. We use data from a Massively Multiplayer Online Game (MMOG) called EverQuest II to address this problem. MMOGs are virtual environments where millions of players can simultaneously interact with one another. Well known examples of MMOGs include World of Warcraft, Eve Online, Runescape, EverQuest etc. In such games players can engage in various types of social activities e.g., players can group together to accomplish tasks and missions, trade with one another, become part of a virtual organization, explicitly specify trust for one another etc. The main contributions and the goals of this chapter are two-fold: (i) Describe and study the problem of item recommendations in a coextensive network setting. (ii) Given multiple social networks determine information from which social networks are more effective for recommendations.

The rest of the chapter is organized as follows: In section 9.2 we discuss related work, in section 9.3 we describe the various coextensive networks in MMOGs in general and specifically in our data, section 9.4 discusses issues related to recommendations in coextensive networks, a detailed description of the dataset and the results is given in section 9.5, finally section 9.6 discuss the interpretation of the results, conclusion and future work is given in section 9.7.

9.2 Related Work

There is a large body of literature on recommendation systems and making recommendations of items. Similarity based methods which look at similarities between participants in the recommendation systems form the basis of some of the most common techniques for making recommendation. The two most common techniques are k-nearest neighbors [155] and collaborative filtering [151]. The main idea behind collaborative filtering is to make predictions regarding the interests of users given the likings of a large number of other users. Social network information has also be used to make recommendation [99], trust based networks have also been used [68],[178]. The Netflix Prize [26] has also spurred progress in this field by offering a prize of one million to a research team who could improve upon Netflix's own algorithm for predicting movie ratings by 10

Recommendation in recommendation systems are done on the basis of general opinion and similarity between users. In other contexts, it may be necessary to give a recommendation based on the opinion of an expert. SNA techniques have been extensively used [181] to identify people of influence who can provide the required expertise to a person who seeks such an opinion [103]. Combinations of social and information networks have also been employed in this context to identify experts for recommendation purposes[130]. An important issue in recommendations is evaluating the performance of recommendation algorithms since in many contexts only a small number of recommendations may translate into actual transactions. A detailed survey of the evaluation literature is given by Herlocker et al [83]. Lastly scalability issue feature prominently in recommendation systems especially in cases where there may be millions of people in the recommendation systems and hundreds of thousands of products to recommend [168].

Study of problem applications related Co-extensive Networks is relatively new [12] mainly because of the unavailability of datasets in the past. Thus Ahmad et al [10] explore the problem of predicting links from one social network given information about

Table 9.1: Network characteristics of the coextensive networks in EQ2

Network	N	E	Avg. Deg.	NCC	LCC1	LCC2	LCC3	diam.
Mentoring	32886	168416	10.242	83	32687	6	5	$10 \leq d \leq 30$
Adversarial	44233	44233	127.159	23	44184	3	3	$7 \leq d \leq 20$
Trade	31285	1125362	71.943	16	36402	12	7	$15 \leq d \leq 30$
Housing-Trust	9834	11399	2.318	1851	2700	50	48	27

another social network in a Co-extensive network setting. The work of Huang and Contractor [87] is most directly relevant our current work. While they do not have coextensive networks in the same sense as in our datasets, they do construct the networks in their study based on different types of social interactions and knowledge networks. Additionally they link their observations and recommendation models to various social science theories.

9.3 Coextensive Networks in MMOs

We use data from a massively multiplayer online game (MMO) called EverQuest II (EQ2) developed by SOE which contains social network information about different types of social relationships between the players. Each of these relationships is used to build social networks which have overlapping node membership and overlapping edges. Co-extensive networks can be represented in different ways e.g., they can be represented in the form of a Multi-graph or alternatively as separate graphs with overlapping membership.

Additionally trade information in the form of what items were bought by which players and from which sellers is also available. Two types of trade information is available, one in the form of direct trade where players sell the items to one another "directly" and another types of network where the players trade the items through auction or from fixed vending locations (player houses) in the form of consignments. These networks will be referred to as the Trade network and the Consignment network respectively. We use the consignment network for prediction purposes. These various types of social interactions which are used to construct the social networks within the game are described as follows:

- **Trust:** Trust is described in terms of explicitly granting trust access to another player within the game to one's virtual house within the game.
- **Trade:** Trade corresponds to virtual face to face trade between characters with in the game. It should be emphasized that trade is not the same as consignment within the game, although there is a large overlap in terms of players using both the trade and the consignment mechanism to acquire items.
- **Mentoring:** A mentoring relationship is established within the game when a player explicitly mentors another player within the game. Mentoring is a build-in feature of the game and all mentor-apprentice instances are recorded in the game.
- **Adversarial:** An adversarial relationship refers to player vs. player combat within the game which results in the death of one of the players. A social network can thus e build based on 'who killed who.'
- **Consignment:** Indirect trade between the players which corresponds to the consignment of items. The main difference between trade and consignment is that while consignment can be done without direct interaction between the players, trade in EQ2 requires face to face interaction as illustrated in Figure 9.3.

Figure 9.1: The Trade Feature in EverQuest II

We also note that even though these networks have overlapping membership the overlap between the edges is not very substantial Ahmad et al [10]. The manner in which these networks evolve is also substantially different. Given the limitations in space, we only show the visualizations for the evolution of two of the social networks, one positive (Mentoring Network) in Figure 9.3 and one negative in Figure 9.3.

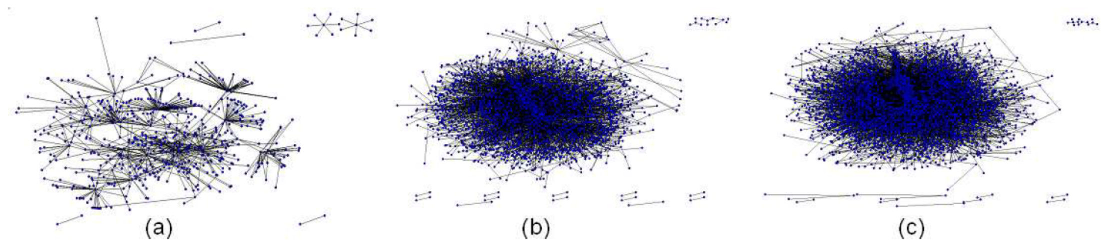


Figure 9.2: The Evolution of the Mentoring network over the course of 3 days; (a) Feb 21 (b) Feb 22 (c) Feb 23

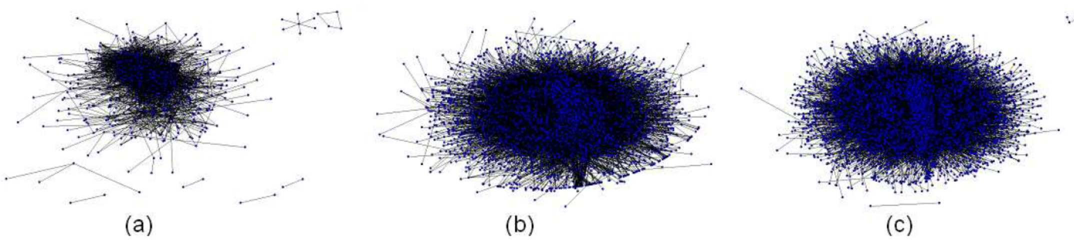


Figure 9.3: The Evolution of the PvP network over the course of 3 days; (a) Feb 21 (b) Feb 22 (c) Feb 23

9.4 Recommendation in Coextensive Networks

The main advantage of using social networks for making recommendations is that it greatly reduces the search space for which similar users have to be discovered in order to make recommendations and it also mitigates the problem of cold start recommendations. The MMOG setting is however unique because unlike traditional settings e.g., FilmTrust or ePinions where the edges between the nodes correspond to some sort of trust between them with respect to the quantity of interest, this is not the case in EQ2 since the various types of interactions do not necessarily map onto the quantity of interest. We use the consignment network instead of the trade network for prediction because while the trade network can be described as a proper social network because there is face to face interaction between the players in the trade network but this is not necessarily the case for the consignment network. Thus we ignore the social network in the consignment network and do not use it for prediction purposes.

The main advantage of using social networks for making recommendations is that it greatly reduces the search space for which similar users have to be discovered in order to make recommendations and it also mitigates the problem of cold start recommendations. The MMOG setting is however unique because unlike traditional settings e.g., FilmTrust or ePinions where the edges between the nodes correspond to some sort of trust between them with respect to the quantity of interest, this is not the case in EQ2 since the various types of interactions do not necessarily map onto the quantity of interest. We use the consignment network instead of the trade network for prediction because while the trade network can be described as a proper social network because there is face to face interaction between the players in the trade network but this is not necessarily the case for the consignment network. Thus we ignore the social network in the consignment network and do not use it for prediction purposes.

9.5 Experiments

9.5.1 Dataset

As described previously we used data from Everquest II (EQ2) for our experiments. In contrast to earlier studies on EverQuest II [8, 100, 10] which used data from a Player vs. Environment (PvE) server called 'guk', we use data from a Player vs. Player server called 'Nagafen' for these experiments. We use data from from February 2006 to June 2006 since this server became operational in February 2006.

The characteristics of the various networks are given in Table 9.1. In the table N refers to the number of nodes, E refers to the number of edges, NCC is the number of components, $LCC1, LCC2, LCC3$ refer to the first, second and the third largest connected components respectively. The table shows that some networks like the trade and the adversarial network are highly dense as compared to the mentoring and the trust network even though the network participation in terms of the nodes being part of these networks is much less. Another thing to notice is that the overwhelming majority ($> 99\%$) of the nodes belong to the largest connected component in the case of the largest networks.

There are also a number of issues with respect to data cleaning within the dataset and many consignment transaction instances had to be removed. We remove all such instances where it was not possible to link a player account with the corresponding player character. Additionally we removed all cases where either the source or the destination information for transactions was missing. Also all such cases where the buyer was a gold farmer[15, 100] were removed.[1] After all of these data cleaning steps we end up with 25,870,200 unique consignment based transactions between the players.

We adopt a classification approach for making recommendations in our framework, instead of using the more traditional approach where the predictions are made based on collaborative filtering and the top items obtained from using similarity measures. We divided our dataset into training period of February 2006 to May 2006 and test period of June 2006. Given a randomly sampled item, a positive example is when a player who had not bought the item in the training period bought the item in the test period. The reason for this is that since we are interested in determining how the social network of a player affects her decision to purchase an item, we do not consider the items which were bought by the player previously. A negative example is when the item was not bought by the player at all.

It should also be noted that there are certain items in the game which have a high trading volume and which are traded frequently between the players. Interestingly some of these items have a really high volume of being traded together or by the same set of players over a short span of time. These items may bias the results of the predictions and are thus removed from the dataset. An example of such a network of such items is given in Figure 9.5.1. In the figure an edge exists between two nodes if they trade by two people. Thus this is a subset of the projection network[45] of the consignment

[1] Gold farmers correspond to deviant players in MMORPGs who perform clandestine activities within the game.

Figure 9.4: Network of frequently traded items

network.

9.5.2 Featureset

The featureset that we use can be divided into three types of features: Ascribed Features (Offline), Acquired Features (In-game) and Network based Features. These can be described as follows:

Ascribed Features

These are the features that are derived from the characteristics of the player in the real/offline world. These include age, gender, location and a counting function for each of these features. If S_i the set of most similar players to the player s_i and a_i is an attribute of the player under consideration then the counting function can be defined as follows:

$$\phi(a_i) = \Sigma_j^m b(s_j), s_j \in S_i \tag{9.1}$$

In a similar manner we also define an indicator function where the value of the function is one if any of the similar players to that player has bought that item.

$$\phi(a_o) = \begin{Bmatrix} 1, \exists b(s_j) = 1, s_j \in S_i \\ 0, otherwise \end{Bmatrix} \tag{9.2}$$

Acquired Characteristics Features:

These are the features that correspond to the in-game characteristics of the player character. These are age of the character, gender of the character, level of the character, activities count i.e., number of activities of a certain kind performed, number of monsters killed, counting and the indicator function number of the items bought for the players which have similar characteristics.

Network Based Features:

The network based featured are the features which are based on information from the coextensive networks. These include number of friends in the network who bought the

Table 9.2: Prediction results when all items are used

Approach	**Network**	**Precision**	**Recall**	**F-Score**
Random	N	0.50	0.50	**0.50**
Ascribed	N	0.27	0.06	0.09
Acquired	N	0.80	0.40	**0.53**
Trust	Y	0.43	0.19	0.26
Mentoring	Y	0.41	0.20	0.27
Trade	Y	0.66	0.29	0.40
Adversarial	Y	0.83	0.40	**0.54**
Multi-Net	Y	0.22	0.10	0.13

item, given the item of interest $it(k)$ the fraction of total items bought by friends of the person for whom the prediction has to be made, corresponding counting and the indicator functions are also defined for this feature. Additionally the corresponding functions are defined for FoAF (friend of a friend) of the player under consideration.

9.5.3 Results

For the prediction task 10,000 instances of recommendations for player-player-item instances are constructed with equal number of positive and negative examples. We use a set of standard classifiers (JRip, NaiveBayes, BayesNet, J48, Logistical Regression, IBk, SMO, AdaBoost with J48) from the machine learning software package Weka [78] for the classification task. The results of the experiments for the best classifiers for the various approaches are given in Table 9.1.

The top three results are highlighted in the table which correspond to the Acquired characteristics, Adversarial network characteristics and Random in that order. All the techniques except the top three are network based. The results show that predictions based on ascribed (real world) characteristics do quite poorly for the prediction task. This is the case because there are a large number of players which may have similar real world characteristics e.g., age, gender etc but their in-game characteristics may be different. Additionally the network based approaches do not perform well and in fact most of them perform worse than random. This was a surprising result as one of our initial hypothesis was that the network based approaches will perform well as they are known to perform well in other domains.

Given the fact that the nature of interaction in the different networks is vastly different from one another, a possible explanation is the poor results are indicative of the fact that a *friendship* in one type of social interactions is not an indicative of trade in another network. A surprising result is that the predictions based on the adversarial network gives the best performance. In the context of the game dynamics the results become less surprising because the players who are adversaries of one another are likely to buy similar items e.g., in order to keep up with one another and to ensure that they do not get left behind in an *arms race* between the players. These observations point to the fact that a combination of acquired characteristic based and an adversarial network based approach may obtain superior results.

We also make a distinction between frequently bought low-end items and between rare items which have a low frequency of being bought. In reality there is a continuum of items from the low end items to the high end items but for the sake of illustration of different dynamics within the consignment network we use less frequently sold items by gold farmers and consider them as high end items. We randomly cross checked a list of such items with the official list of rare items from the EverQuest II Wiki[2] and these items were found to be rare items. However we note that an exhaustive test to determine if such items are rare or not was not performed given the resource constraints. For determining the list of low end items we used the list of items which are associated with crafting and do not require the use of Platinum or Gold[3] within the game but only required Silver.

We thus replicate the results from the previous set of experiments with the same experimental set up but with the difference that we only consider the low-end items in constructing our dataset for both the training and the test period. For these set of experiments 3,000 instances were construed and the results are given in Table 9.2. The results indicate that the network based approaches perform much better as compared to the general case. The ascribed characteristics based approach again does poorly however. This improvement in results is possibly because pf the fact that if a friend

[2] http://eq2.wikia.com/

[3] Platinum, Gold and Silver correspond to in-game virtual currencies such that 10 Platinum = 100 Gold and 1 Gold = 100 Silver

Table 9.3: Prediction results when only low-end items are used

Approach	**Network**	**Precision**	**Recall**	**F-Score**
Random	N	0.50	0.50	0.50
Acscribed	N	0.07	0.12	0.08
Acquired	N	0.45	0.80	**0.57**
Trust	Y	0.40	0.67	**0.50**
Mentoring	Y	0.37	0.65	**0.47**
Trade	Y	0.24	0.38	0.20
Adversarial	Y	0.38	0.53	0.44
Multi-Net	Y	0.47	0.49	0.53

buys a high end item item then that is a strong indicator that the person also buy it. However the same applies for a foe since the predictions based on the adversarial network also performs well. Another possibility is that there may be some leveling effect in terms of a player's friends being at a similar level and thus likely to be interested in similar items. The Trade network based approach performs the worst however which is surprising. We hypothesize that this is so because the kind of items which are being in the consignment and the trade network may be different.

The experimental set up for the low-end items was similar to the experimental set up for the previous two cases. For these experiments 3,000 instances were constructed which were equally divided between positive and negative examples. In this case all of the techniques significant improvement in results is obtained as compared to the previous instances. The Trade network based approach performs the best in this case. The hypothesis about different trading types from the low-end items thus makes sense. Additionally there are many low-end items which are likely to be bought by a large group of people especially who are involved in crafting activities[4] and others which are less likely so, this could be one of the reasons why all these techniques seem to be doing well.

[4] Crafting refers to a set of in-game activities in MMORPGs where the players collect *raw* items or materials to create more advanced materials.

Table 9.4: Prediction results when only high-end items are used

Approach	**Network**	**Precision**	**Recall**	**F-Score**
Random	N	0.50	0.50	0.50
Acscribed	N	0.50	0.59	0.54
Acquired	N	0.62	0.67	0.65
Trust	Y	0.55	0.63	0.58
Mentoring	Y	0.64	0.74	**0.69**
Trade	Y	0.67	0.80	**0.73**
Adversarial	Y	0.65	0.76	**0.70**
Multi-Net	Y	0.59	0.67	0.63

9.6 Discussion

The results of recommendation based on the various recommendation techniques indicates that certain types of networks i.e., the trade network is more accurate in prediction and recommendation of high priced valuable items while other networks like the mentoring network are more accurate in terms of predicting low priced items. Another surprising result is that the adversarial networks are in fact more useful in predicting and recommending items as compared to friendly networks like the trust network or the mentorig network. In the general case for prediction overall poor performance is observed when predicting items.

The Adversarial network is surprisingly a good predictor for overall prediction as well as for high end items but not for low end items. We think this is the case because adversaries may buy similar items in order to keep up with one another in an arms race. The trust network which represents the strongest type of friendship in the coextensive networks but it is not as useful for prediction as one may expect beforehand. In other domains one may expect to see the adversarial and the trust network to exhibit opposite behaviors but this is not he case here. Given the encouraging results from the use of the adversarial network, we note that a natural partitioning for the prediction of items would be to divide them by player levels associated with the items since players at certain levels within the game are more likely to buy and sell certain items as compared to players at the other levels.

9.7 Conclusions

The problem of recommendation has been addressed in a variety of contexts, in this chapter we addressed this problem in the context of coextensive social networks which are multiple social networks which have overlapping membership and are evolving in time. In contrast to previous studies on EverQuest II we used data from an adversarial environment or server (Player vs. Player) for our experiments since anecdotal evidence from game play pointed us to the fact that players who are opponents may be biased in terms of buying similar items to keep up with one another. The experimental results in this chapter confirmed this observation.

Thus we considered the problem of recommendations in coextensive social networks and compared the efficacy of different networks in the prediction task. The main result was that the choice of network for prediction depends upon what type of items one has to predict. In the general prediction task the various networks used were not very successful in the prediction tasks but the in-game similarity based approach and the adversarial network based approach seemed to perform better than the other approaches. Future work involves replicating these results in different servers since those servers have a different social environment. Additionally replicate results in the trade network as well.

In the future we plan to replicate the results in this study for other servers within EverQuest II. Our hypothesis is that given that different servers correspond to different social environments, trade patterns and consequently recommendation patterns will vary as well. Additionally we also plan to link the performance of the various networks for the recommendation tasks with various social science theories. The work of Huang and Contractor [87] is the most relevant in this regard. In this chapter we have used each network separately for our prediction purposes. We also plan to use various combinations of these coextensive networks and determine which of these combinations are best in the prediction tasks. Another unexplored area for future research is the cold start problem for recommendations.

Chapter 10

Trust, Social Capital and Success Prediction

”But it does not seem that I can trust anyone,’ said Frodo. Sam looked at him unhappily. ’It all depends on what you want,’ put in Merry. ’You can trust us to stick with you through thick and thin–to the bitter end. And you can trust us to keep any secret of yours–closer than you keep it yourself. But you cannot trust us to let you face trouble alone, and go off without a word. We are your friends, Frodo.” - J.R.R. Tolkien

10.1 Introduction

The main idea behind the theory of Social Capital is that social networks have value by the virtue of a person’s position in the network. Given a social network consisting of multiple actors, some actors can acquire certain advantages over other just because of their position within a social network. Thus consider two social networks, one consisting of people who are graphic artists and another group consisting of game developers. If there is minimal overlap between the two groups i.e., one person overlap between these two group then it is highly likely that that person and her immediate contacts would be sites in the network where new innovations take place by virtue of the fact that she controls the flow of information between the two groups.

There is a vast amount of literature in the social sciences which deals with the success of people based on their social capital [34]. The main problem in creating predictive models of social capital is that not only is it difficult to operationalize social capital but there are inherent difficulties in evaluating success in social settings. The domain of gaming is one such domain where there are well defined methods for computing success. We use data from a Massively Multiplayer Online (MMO) game called EverQuest II for the experiments. The advantage of using an MMO for analysis is that it offers a ready made way to compute success as compared to many offline studies where it is sometimes difficult to compare given multiple measures and metrics of success. Prediction of success in games and other competitive environments has mainly focused on the behavioral as well as the performance data of the participants.

There are multiple ways to describe expertise and competence in such environments, we use the approach adopted by [88]. In this chapter we take a novel approach where instead of using a person's previous performance or behavioral data we only use the social network information to predict the relative success and failure of players. As a baseline, we do use these two types of data for comparison in addition to using the player characteristics for prediction. Additionally we use Ron Burt's Network Constraint Index (NCI) and modify it to include temporal constraints with respect to the changing network structure and modify it to describe how social ties can actually form in bursts. Multiple social networks from the MMO are employed for analysis i.e., trust network, mentoring network, trade network and the adversarial network. The results from experiments show that the success of players and their leveling behavior can be predicted with a high level of accuracy by using only the social network of the players with the social capital inspired technique.

10.2 Related Work

There is an extensive body of work on social capital [34]. Study of the relationship between associational life and connectedness has a long history and the idea of community governance goes back all the way to at least Aristotle [32]. The work of Bourdieu [31], Coleman[51] and Putnam [142] conceptualize three different but overlapping views of social capital and their work is considered to be seminal in the field. Depending upon which view of social capital is taken, social capital is operationalized differently. Borgatti et al [30] give an overview of various metrics which have been used to measure social capital and it represents the state of the art in the subject. Even though social capital talks about competitive advantage for the person who has high social capital, to the best of our knowledge the theory of social capital has not really been used for predictive modeling. [120] is an exception in this regard but even in that case the authors use it to predict event participation. They use various centrality measures as proxies for social capital and use it to predict participation in future conferences. Since the data for multiple submissions to the same conference which may have been rejected or data about submissions to other conferences is not available it is difficult to ascertain the relative success or failure of people.

Since the main goal of this chapter is to use social capital for predictive analysis, it is also important to describe how success is measured in the relevant domain. Since MMOs are goal oriented environments, the success in such environments is described in terms of how well a player does within the game. Players progress in such games by accumulating experience and thus progress in the game can be measured in terms of levels within the game. Huffaker et al [88] propose two metrics for measuring success: *Achievement* and *Performance*. The leveling aspects of the game are captured by achievement and the performance aspects are captured by the player's efficiency. In general excellence in performance is demonstrated by a superior ability to complete a set of tasks [162].

10.3 Theory of Social Capital

Even though there is a massive literature on Social Capital in the Social Sciences [35][36], there is not a single metric or even a set of standard agreed upon metrics which are used across multiple domains and even multiple problems [36]. In most instances only proxies are used for measuring social capital. In many cases, standard graph theoretic metrics are used for measuring social capital [30] and the use of these metrics is usually problem specific. The literature also identifies multiple ways to conceptualize different types of social capital. In the network view of social capital two main types are recognized (i) Bridging Social Capital (ii) Bonding Social Capital. The bridging social capital refers to social capital accumulated by the virtue of such a position in a social network that she acts a locus of connection between two or more parts of a social network. Bonding social capital on the other hand refers to social capital which is gained by the virtue of being part of a tightly knit group where members of the group are strongly connected with one another but weakly connected with people outside of the group.

10.3.1 Measuring Social Capital

As described previously there are multiple ways to measure social capital but we use the Structural Holes framework of Ron Burt [36] to operationalize Social Capital by using the Network Constraint Index. Given a node n_i and n_j, the network constraint value of n_i with respect to n_j is given as follows.

$$c_{ij} = (p_{ij}\Sigma_q p_{iq} p_{qj})^2 \tag{10.1}$$

where $q \neq i, j$, $p_{ij} = z_{ij}/\Sigma_q z_{iq}$, z_{ij} =the strength of the connection between n_i and n_j. If N_i is the nodeset which consists of the neighbors of the node n_i then the overall network constraint index value for n_i can be given as follows;

$$c_i = \Sigma_{j=1}^{m}, m = |N_i| \tag{10.2}$$

The other aspect of measurement within the game is to have a standard metric to assess the success of players. MMOs are goal oriented games where the goal can be described in terms of leveling up, achieving some goals or finishing some tasks [196]. Success is defined in terms of how well a player does within the game and defined as the number of levels completed divided by the length of the sessions of game.

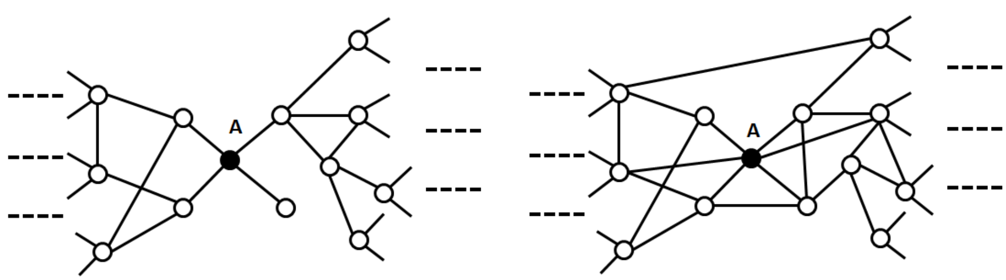


Figure 10.1: Change in the value of Network Constraint Index in the Mentoring Network

10.3.2 Temporal Aspects of Social Capital

Since the structure of social networks changes over time a person who may have some social advantage one point in time may no longer have that advantage some time in the future. The network constraint index is however a static measure and thus a person who may have an advantage over others at a particular point in time as measured by NCI may no longer have the same advantage as new edges form in the network. This can be illustrated by Figure 10.3.1, where node A on the left side of the evolving graph is in a advantageous position with respect to other nodes in the network and serves as a broker between two parts of the social network. Thus information from either side of the networks must pass through this node. According to Equation 10.1, this node has a low value for the Network Constraint Index. Now consider the same graph at the right side after some time where many more edges have been formed in the network and the node A is no longer in the advantageous position that it was in previously. Node A will have a much higher value for the Network Constraint Index and no longer enjoys the advantages that it enjoyed previously. Thus the time at which social capital is measured will be biased with respect to the current state of the network since the temporal information regarding the structure of the network in its history is lost.Thus a metric for measuring social capital should take into account how the network is changing over time or the manner in which the network is constructed should be modified.

Another factor that must be taken into account is the fact that social ties may decay over time. To illustrate that the value of the Network Constraint Index changes over time, we propose a novel visualization technique for representing the Network Constraint Index over time. Thus consider Figure 10.3.2 which gives the visualization of the values for the network constraint index for the entirety of the dataset and on a weekly basis. Each entry or row on the y-axis corresponds to a player character and the y-axis represents time. The colors in the visualization represent the value of the network constraint index, the color spectrum from red to blue corresponds to high values to low values. Thus red color corresponds to high values and blue colors represent low values. Each row in the visualization is thus a time series of the network constraint index of a player character.

If we cluster the time series together then we get four distinct groups of time series which correspond to four distinct types of how the network constraint indices evolve over time. This also implies that the manner in which the social capital evolves over time is similar for a subsets of population in the network. This observation can be tied to how groups of players may enjoy advantages within the game but also that these advantages may increase or diminish similarly over the course of time for many of the players. We use this observation as a basis to predict the success of the players. The idea is that players with similar values for the network constraint indices with have similar success rates over the course of time.

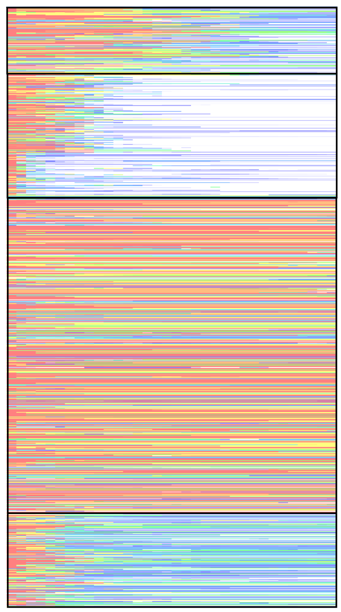


Figure 10.2: Decrease in the Brokerage value over time

Thus we modify how the network is constructed over time by introducing a decay factor with respect to the edge weight. Thus if $e_{ij}(k)$ is an edge between a node n_i and n_j at time k, the strength of the edge may decay by a factor α if it is not reinforced during an iteration then the edge strength at time t_k can be given as the function of the edge strength in the previous iteration i.e., $e_{ij}(k) = \alpha e_{ij}(k-1)$ and in the penultimate iteration the edge strength is a function of the edge strength in the iteration previous to that i.e., $e_{ij}(k-1) = \alpha e_{ij}(k-2)$ and so on and so forth. Combining the previous two equations we get $e_{ij}(k) = \alpha^2 e_{ij}(k-2)$. This can be generalized as follows:

$$e_{ij}(k) = \alpha^m \cdot e_{ij}(k-m) \tag{10.3}$$

However since the edge may actually be strengthened because of an interaction between the two nodes, we also have to take into account the fact that a positive interaction will reinforce the relationship between them. Thus Equation 10.2 can be modified as follows:

$$e_{ij}(k) = \alpha^p \cdot e_{ij}(k-p), k-1 \leq p \leq 0 \tag{10.4}$$

10.4 Experiments and Results

As described previously we use data from an MMOG called EverQuest II (EQ2) for our experiments. We use coextensive social networks from this dataset. Coextensive networks refer to social networks which have overlapping membership and are evolving in time.We compute the metrics and indices described in the previous section on these various networks in EQ2. The dataset that we use spans from February 2006 to April 2006. In this span of time there are 29,910 player characters who participated in the network. The network characteristics of the various networks used are given in Table 10.1. Each of the networks corresponds to a different type of social relationship within the game: Trust, Mentoring, Trade, Grouping and Consignment. The last entry in the table *i.e.*, Multi-Net refers to the union of all five networks above it. Previous work on multiple networks in MMOG has shown that even though players may partake in overlapping social networks, they usually do not form the same types of social relationships with other players [10]. Thus for each network in isolation the values for social capital would be different in different networks.

The metric for evaluating the performance is the average difference in the predicted time and the observed time for a player leveling from level j to level $j+1$. For comparison, we employ a number of methods which mainly look at the performance data without considering the network data . Thus consider Table 10.2 where Random predicts the time as a random interval between the minimum and the maximum time observed for leveling for the subset of the population on which the prediction is based. This subset would be different if the players in the Trust network are used vs using

Table 10.1: Networks from EQ2

Network	**N**	**E**	**Comps**	**LCC**
Trust	8,774	11,467	1,140	3,726
Mentoring	13,090	39,936	213	12,572
Trade	18,5571	680,425	8	18,536
Grouping	23,838	1,094,935	1,131	21,184
Consignment	18,561	681,094	9	18,539
Multi-Net	29,910	1,773,318	838	27,999

Table 10.2: Prediction Results from the various techniques and networks

Technique	**Trust**	**Mentor.**	**Trade**	**Group.**	**Consign.**	**Multi-Net**
Random	138.64	132.16	138.13	169.24	146.56	**130.01**
Average	149.88	**133.44**	167.57	161.08	139.27	137.51
Class Average	170.13	164.20	**140.18**	141.77	145.45	150.52
k-Most Similar	131.13	**98.72**	123.93	118.19	123.93	101.81
NCI Similar	121.70	**94.41**	131.74	129.25	131.01	103.42
NCI Decay Similar	138.09	**95.94**	123.03	130.79	123.03	99.00
Cascade	132.49	**91.16**	122.07	112.30	111.89	97.54

players in the Mentoring Network. Average refers to predicting the average time for the players in that particular level as the predicted time. Class Average refers to predicting the leveling time as the average time for the character class to which that particular player character belongs to. $K-$most similar refers to the set of k most similar players for which the prediction has to be made. NCI similar makes the prediction based on the similarity with players who have similar values for the network constraint index, the same applies for the network constraint index as described in section 10.2. The Cascade technique combines the NCI based techniques with the characteristics based techniques to determine similarity.

The entries in Table 10.2 correspond to the average time difference given in minutes for leveling from level 1 to level 70 for the cases wherever the data was available for prediction. The main thing to note here is that the techniques that seem to perform well in most of the cases are the ones which are associated with the mentoring network. The best results are the ones which are obtained by using the Cascade approach and with the mentoring network. The results obtained for the Trade network and the consignment network are similar. That is mainly because there is a high degree of overlap between these two networks. Thus after computing similarity, the set of players which are returned for many of these techniques have a high degree of overlap in their membership as well. While the various techniques when combined with Multi-Net do not perform the best with NCI, at least for NCI and $k-$ most similar, second best results are obtained. Based on this observation we conjecture that if better ways of combining these networks are devised then the results can be improved further.

10.5 Conclusions

In this chapter we have considered the problem of computing social capital on different co-extensive social networks. We used data from an MMO where it is possible to unambiguously quantify success and compared network based methods with characteristic similarity based methods for predicting success. The surprising result was that the network based methods performed better than the other techniques. An unsolved problem in this area is to combine information from different types of edges to get an overall metric for social capital. Alternatively this problem can be formulated as the problem of computing social capital in multi-graphs. We seek to address these problems in our future work. The current work shows thats it is possible to predict the success of players based on social based network indices, Such techniques can perform better than the more traditionally used player attributes based techniques. Future work involves refining the network based indices for prediction and incorporating ideas related to calculating network constraint in coextensive social networks.

Chapter 11

Conclusion

The literature on social trust abounds with respect to both breadth and depth of issues discussed regarding trust but a unifying framework linking various network level phenomenon to each other and to socio-cognitive theories of trust is missing. In the current manuscript we have tried to bridge this gap by describing trust as a network phenomenon and then describing trust at various levels of network granularity. Additionally we have tried to link the various socio-cognitive theories from the MTML framework. We believe that this framework not only helps unify many of the strands which have already been explored in the literature but it can also be use as a guide to future research.

A number of related problems were explored in this thesis, the underlying theme with respect to these problems is examining trust as a multi-level network phenomenon in the context of different social environments and with respect to different social interactions e.g., mentoring, trade, clandestine behaviors etc. Trust in complex environments is a phenomenon which is just beginning to be explored. The main reason for this is that the datasets which could be used to answer this question are only now beginning to be available to researchers. Thus it is hoped that further research in this area will be able to elucidate some of the questions that were raised in this thesis and will be able to answer them to a greater extent.

References

[1] Alfarez Abdul-Rahman *The PGP Trust Model* EDI-Forum, April 1997

[2] Adamic, L. A., Adar, E., *Friends and Neighbors on the Web*, Social Networks, Vol.25, No.3, pp.211-230, 2003.

[3] G. Adomavicius, and A. Tuzhilin *Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions.* In IEEE Transactions on Knowledge And Data Engineering, Vol 17, No. 6, June 2005

[4] Agrawal, R. Srikant. 1994. *Fast algorithms for mining association rules in large databases.* In Proc. VLDB94 Santiago, Chile: 487-499.

[5] Muhammad Aurangzeb Ahmad, Zoheb Borbora, Cuihua Shen, Jaideep Srivastava, Dmitri Wiliams Guilds Play in MMOs: Rethinking Common Group Dynamics Models SofInfo 2011 October 6-8, 2011

[6] Muhammad Aurangzeb Ahmad, Jaideep Srivastava *Models of Social Capital for Predicting Success in MMOs* The Third ACM WebSci Conference, Koblenz, Germany June 14-17, 2011

[7] Muhammad Aurangzeb Ahmad, Iftekhar Ahmad, Jaideep Srivastava, Marshall Poole *Trust me, I m an Expert: Trust, Homophily and Expertise in MMOs* IEEE SocialCom 2011 Boston, MA October 9-11, 2011

[8] Muhammad Aurangzeb Ahmad, Brian Keegan, Dmitri Williams, Jaideep Srivastava, Noshir Contractor *Trust Amongst Rogues? A Hypergraph Approach for Comparing Clandestine Trust Networks in MMOGs* 5th International AAAI Conference on Weblogs and Social Media (ICWSM 2011), July 17-21, 2011

[9] Muhammad Aurangzeb Ahmad, Jaideep Srivastava *Item Recommendations in Multiple Overlapping Social Networks in MMOs* The Third ACM WebSci Conference, Koblenz, Germany June 14-17, 2011

[10] Muhammad Aurangzeb Ahmad, Marshall Scott Poole, Jaideep Srivastava *The Trust Propensity Prediction Problem* The Third ACM WebSci Conference, Koblenz, Germany June 14-17, 2011

[11] Muhammad Aurangzeb Ahmad, David Huffaker, Jing Wang, Jeff Treem, Dinesh Kumar, Marshall Scott Poole, Jaideep Srivastava *The Many Faces of Mentoring in an MMORPGs* IEEE Social Computing (SocialCom-10). Workshop on Social Intelligence in Applied Gaming. Minneapolis, MN, USA, August 20-22, 2010.

[12] Muhammad Aurangzeb Ahmad, Zoheb Borbora, Jaideep Srivastava, Noshir Contractor *Link Prediction Across Multiple Social Networks* Domain Driven Data Mining Workshop (DDDM2010), ICDM 2010 Sydney, Australia.

[13] Muhammad Aurangzeb Ahmad, Marshall Scott Poole, Jaideep Srivastava, *Network Exchange in Trust Networks* IEEE Social Computing (SocialCom-10). Workshop on Social Intelligence in Applied Gaming. Minneapolis, MN, USA, August 20-22, 2010.

[14] Muhammad Aurangzeb Ahmad, David Huffakar, Annie Wang, Jeff Treem, Scott Poole, Jaideep Srivastava *GTPA: A Generative Model for Online Mentor-Apprentice Networks* Twenty-Fourth AAAI Conference on Artificial Intelligence Atlanta, Georgia July 11-15, 2010

[15] Muhammad Aurangzeb Ahmad, Brain Keegan, Jaideep Srivastava, Dmitri Williams, Noshir Contractor, *Mining for Gold Farmers: Automatic Detection of Deviant Players in MMOGS* Proceedings of the 2009 IEEE Social Computing (SocialCom-09). Symposium on Social Intelligence and Networking (SIN-09). Vancouver, Canada, August 29-31, 2009.

[16] Muhammad Aurangzeb Ahmad, Xin Zhao *COLBERT: A Scoring Based Graphical Model For Expert Identification* 2010 International Conference on Social Computing, Behavioral Modeling and Prediction (SBP10) March 29 - April 1, 2010 Bethesda, MD.

[17] L. Akoglu, M. McGlohon, C. Faloutsos. *RTM : Laws and a Recursive Generator for Weighted Time-Evolving Graphs*. ICDM Pisa. 2008.

[18] L. Akoglu, C. Faloutsos. (2009) *RTG: A Recursive Realistic Graph Generator using Random Typing*. ECML PKDD, Bled, Slovenia.

[19] R. Albert, H. Jeong, A.-L. Barabasi. *Diameter of the World Wide Web*. Nature, 401:130 131, 1999.

[20] R. Albert; A.-L. Barabsi (2002). *Statistical mechanics of complex networks*. Reviews of Modern Physics 74: 47 97.

[21] Bader Ali, Wilfred Villegas, Muthucumaru Maheswaran *A trust based approach for protecting user data in social networks*. CASCON 2007

[22] Artz, D., Gil, Y. *A survey of trust in computer science and the Semantic Web*. Journal of Web Semantics 5, 58-71 (2007)

[23] J. Balkin, *Virtual Liberty: Freedom to Design and Freedom to Play in Virtual Worlds.*, Virginia Law Review, vol. 90, no. 8, 2004.

[24] Barabsi, A.-L.; R. Albert (1999). *Emergence of scaling in random networks*. Science 286: 509-512.

[25] D. Barboza, *Ogre to Slay? Outsource It to Chinese, Book Ogre to Slay? Outsource It to Chinese, Series Ogre to Slay? Outsource It to Chinese*, ed., Editor ed. eds., 2005,

[26] Robert M, Bell, Yehuda Koren, Chris Volinsky (2007). *The BellKor solution to the Netflix Prize*

[27] Robert M. Bell, Jim Bennett, Yehuda Koren, Chris Volinsky (May 2009). *The Million Dollar Programming Prize*. IEEE Spectrum.

[28] Zoheb H Borbora, Muhammad Aurangzeb Ahmad, Karen Zita Haigh, Jaideep Srivastava, Zhen Wen *Exploration of robust features of trust across multiple social networks* Fifth IEEE Conference on Self-Adaptive and Self-Organizing Systems Workshops (SASOW 2011) 3-7 October 2011 Ann Arbor, Michigan, USA

[29] Zoheb Borbora, Kuo-Wei Hsu, Jaideep Srivastava, Dmitri Williams. *Churn Prediction in MMORPGs using player motivation theories and ensemble approach*, Third IEEE International Conference on Social Computing, MIT, Boston, 2011

[30] Borgatti, S.P., Jones, C. and Everett, M.G. 1998. *Network measures of social capital.* Connections 21(2):-36

[31] Pierre Bourdieu. (1972) *Outline of a Theory of Practice* Cambridge University Press 1977.

[32] Bowles, S. and Gintis S. (2002) *Social Capital and Community Governance].* The Economic Journal, 112: 419-436

[33] T. Bramwell, *World of Warcraft players banned for selling gold, Book World of Warcraft players banned for selling gold, Series World of Warcraft players banned for selling gold* Editor, 2005

[34] Ronald S. Burt. *Structural Holes: The Social Structure of Competition.* Harvard University Press, Cambridge, MA, 1992.

[35] Ronald S. Burt Bridge *Decay. Social Networks*, 2002, 24(4), pp. 333-63.

[36] Ronald S. Burt *The Social Capital of Structural Holes*, in M. F. Guilln: The New Economic Sociology : Developments in an Emerging Field. New York: Russell Sage Foundation, 2002, pp. 148-90

[37] Byrne, D. (1971). *The Attraction Paradigm.* Orlando, FL: Academic Press.

[38] Camerer, Colin (2003), *Behavioral Game Theory: Experiments in Strategic Interaction*, Russell Sage Foundation

[39] Castronova, E. (2005) *Synthetic worlds: The business and culture of online games.* Chicago: University of Chicago Press.

[40] Castronova, E. (2006) *A cost-benefit analysis of real-money trade in the products of synthetic economies*, Info, 8(6), 51-68

[41] Castronova, T., D. Williams, C. Shen, Y. Huang, B. Keegan, L. Xiong, R. Ratan (2009), *As real as real? Macroeconomic behavior in a large-scale virtual world.* New Media and Society.

[42] D. Chan, *Negotiating intra-Asian games networks: on cultural proximity, East Asian games design, and Chinese farmers*, Fibre Culture, vol. 8, 2006.

[43] Chao, G. T., Walz, M., Gardner, D. (1992). *Formal and informal mentorships: A comparison on mentoring functions and contrast with non-mentored counterparts.* Personnel Psychology, 45, 619-636.

[44] Chao, G. T. (1997). *Organizational socialization: Mentoring phases and outcomes.* Journal of Vocational Behavior, 51, 15-28.

[45] Gary Chartrand, *Introductory Graph Theory*, (1985), Dover.

[46] H. Chen, R. V. Hauck, H. Atabakhsh, H. Gupta, C. Boarmana, J Schroeder, L. Ridgeway, *COPLINK*: Information and Knowledge Management for Law Enforcement.* Photonics East Conference, SPIE, Technologies for Law Enforcement; Boston Nov. 5-8, 2000.

[47] H. Chen, W. Chung, J.J. Xu, G. Wang, Y. Qin, M. Chau, *Crime Data Mining: A General Framework and Some Examples*, Computers and Security, vol. 37, no. 4, 2004, pp. 50-56.

[48] A. Clauset, M.E.J. Newman and C. Moore, *Finding community structure in very large networks.* Phys. Rev. E 70, 066111 (2004).

[49] A. Clauset and N. Eagle (2007), *Persistence and periodicity in a dynamic proximity network*, DIMACS.

[50] Clauset, A., Moore, C., Newman, M. *Hierarchical structure and the prediction of missing links in networks*, Nature 453, 98-101 (2008).

[51] Coleman, James. (1988). *Social Capital in the Creation of Human Capitals.* American Journal of Sociology Supplement 94: S95-S120.

[52] N. Contractor, *The emergence of multidimensional networks*, Journal of Computer-Mediated Communication, vol. 14, pp. 743-747, 2010.

[53] Dauber, E. 1969. *Graph theory*, ed. F. Harary. Addison Wesley

[54] R. Davis, *Welcome to the new gold mines*, The Guardian, 2009.

[55] Frank Edward Walter, Stefano Battiston, Frank Schweitzer *A model of a trust-based recommendation system on a social network.* Autonomous Agents and Multi-Agent Systems 16(1): 57-74 (2008)

[56] J. Dibbell, *Play Money: Or, How I Quit My Day Job and Made Millions Trading Virtual Loot*, Basic Books, 2006.

[57] J. Dibbell, *The Life of a Chinese gold farmer, Book The Life of a Chinese gold farmer, Series The Life of a Chinese gold farmer* Editor 2007

[58] Dirks, K. T. (1999). *The Effects of Interpersonal Trust on Work Group Performance.* Journal of Applied Psychology, 84, 445-455

[59] P. P. Ekeh (1974). *Social exchange theory: The two traditions.* Cambridge, MA: Harvard University Press.

[60] Ensher, E.A., Heun, C. Blanchard, A. *Online mentoring and computer-mediated communication: New directions in research?* Journal of Vocational Behavior, vol. 63, p. 264, 2003.

[61] Fukuyama, F. (1996) *Trust: The Social Virtues and the Creation of Prosperity*, Touchstone Books.

[62] D. Garlaschelli, M.I. Loffredo, *Patterns of link reciprocity in directed networks*, Phys. Rev. Lett. 93 (2004) 268701.

[63] D. Geer, *The Physics of Digital Law: Searching for Counterintuitive Analogies, Cybercrime: Digital Cops in a Networked Environment*, J.M. Balkin, G. Grimmelmann, E. Katz, N. Kozlovski, S. Wagman, and T. Karzky eds., New York University Press, 2007.

[64] Gladstein, D.L. 1984. *Groups in context: A model of task group effectiveness.* Administrative Science Quarterly, 29: 499-517.

[65] Ghoshal, G.; Zlatic, V.; Caldarelli, G.; M.E.J. Newman. *Random hypergraphs and their applications.* Physical Review E, 79:066118, 2009.

[66] Jennifer Golbeck, James Hendler, *Reputation Network Analysis for Email Filtering.* Proceedings of the First Conference on Email and Anti-Spam, July 30-31, 2004 Mountain View, California.

[67] J. Golbeck. *Filmtrust: Movie recommendations using trust in web-based social networks.* Consumer Comm. and Networking Conf., 2006.

[68] Golbeck, J. Hendler, J. 2006. *Inferring binary trust relationships in web-based social networks.* ACM Trans. Internet Technology, 6:497-529.

[69] Golbeck, J. 2009. *Computing with Social Trust.* Springer.

[70] Goldberg, David; David Nichols, Brain M. Oki, Douglas Terry (1992). *Using collaborative filtering to weave an information tapestry.* Communications of the ACM 35 (12): 61-70.

[71] S. M. Goodreau, M. S. Hancock, D. R. Hunter, C. T. Butts, M. Morris, *A statnet tutorial*, Journal of Statistical Software, vol. 24,. 1-26, 2008

[72] N.S.B. Gras, *The early English customs system: a documentary study of the institutional and economic history of the customs from the thirteenth to the sixteenth century.* Cambridge: Harvard University Press, 1918.

[73] Grimmelmann, J. (2006). *Virtual Power Politics. The State of Play: Law, Games, and Virtual Worlds.* J. M. Balkin and B. S. Noveck. New York, New York University Press.

[74] R. Guha, R. Kumar, P. Raghavan, A. Tomkins. *Propagation of trust and distrust.* In Proc. of WWW, pages 403-412, NY, USA, May 2004.

[75] R. Guimera, L. Danon, A. Diaz-Guilera, F. Giralt and A. Arenas, Physical Review E , vol. 68, 065103(R), (2003).

[76] Guttman, L. (1950). *The basis for scalogram analysis.* In Stouffer et al. Measurement and Prediction. The American Soldier Vol. IV. New York: Wiley

[77] M. S. Handcock, D. R. Hunter, C. T. Butts, S. M. Goodreau, M. Morris, *Statnet: Software tools for the representation, visualization, analysis and simulation of social network data*, Journal of Statistical Software, vol. 24, p. 11, 2008.

[78] Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, Ian H. Witten (2009); *The WEKA Data Mining Software: An Update*; SIGKDD Explorations, Volume 11, Issue 1.

[79] Al Hasan, M., Chaoji, V., Salem, S., Zaki, M. *Link prediction using supervised learning Workshop on Link Counter-terrorism and Security*, SIAM, 2006.

[80] Heeks, Richard *Analysis Current Analysis and Future Research Agenda on 'gold farming': Real-World Production in Developing Countries for the Virtual Economies of Online Games Development* Informatics Group IDPM, SED, University of Manchester, UK - 2008

[81] Heider, F. (1946). *Attitudes and cognitive organization.* Journal of Psychology. 21, 107-112.

[82] Heider, F. (1958). *The psychology of interpersonal relations.* New York: John Wiley and Sons.

[83] Herlocker, J. L.; Konstan, J. A.; Terveen, L. G.; Riedl, J. T. (January 2004), *Evaluating collaborative filtering recommender systems*, ACM Trans. Inf. Syst. 22 (1): 5-53

[84] B. Howell, *Real World Problems of Virtual Crime, Cybercrime: Digital Cops in a Networked Environment*, J.M. Balkin, G. Grimmelmann, E. Katz, M. Kozlovski, S.Wagman, and T. Karzky eds., New York University Press, 2007.

[85] C.W. Hsu, C.C. Chang, C.J. Lin. *A practical guide to support vector classification.* Tech. report, Dept of Comp. Science, National Taiwan University. July, 2003.

[86] Huang, Z., *Link Prediction Based on Graph Topology: The Predictive Value of the Generalized Clustering Coefficient, Workshop on Link Analysis: Dynamics and Static of Large Networks*, the 12th ACM SIGKDD , Philadelphia, PA, 2006.

[87] Yun Huang, Noshir Contractor, Y. Yao, Y. (2008). *Recommendation based on Social Networks*, Proceedings of DG.O 2009 annual conference for Digital Government, Montreal, Canada.

[88] David Huffaker, Annie Wang, Jeff Treem, Muhammad Aurangzeb Ahmad, Lindsay Fullerton, Dmitri Williams, Scott Poole, Noshir Contractor. *The Social Behaviors of Experts in Massive Multiplayer Online Role-playing Games*. 2009 IEEE Social Computing (SocialCom-09).

[89] J.-S. Huhh, *Culture and Business of PC Bangs in Korea, Games and Culture*, vol. 3, no. 1, 2008, pp. 26.

[90] Hunt, D. M., Michael, C. (1983). *Mentorship: A Career Training and Development Tool*. The Academy of Management Review, 8(3), 475-485.

[91] Hunter, D. *The early history of real money trades*, TerraNova, 13 January, 2006 http://terranova.blogs.com/terra nova/2006/01/the early histo.html

[92] Hunter, D. R., Handcock, M. S., Butts, C. T., Goodreau, S. M. and Morris, M. *ergm: A package to fit, simulate and diagnose exponential-family models for networks*. Journal of Statistical Software, 24, 3 (2008).

[93] A.E. Jankowich, *Property and Democracy in Virtual Worlds*, Boston University Journal of Science and Technology, vol. 11, no. 2, 2005.

[94] G. Jin, *Chinese Gold Farmers in the Game World, Consumers, Commodities, and Consumption*, vol. 7, no. 2, 2006.

[95] Johnson, N. F., Xu, C., Zhao, Z., Ducheneaut, N., Yee, N.,Tita, G., et al. (2009). *Human group formation in online guilds and offline gangs driven by a common team dynamic*. Physical Review E, 79(6), 066117.

[96] A. Josang, R. Ismail, C. Boyd. *A survey of trust and reputation systems for online service provision*. Decision Support Sys. 43:618-644, 2007.

[97] S. D. Kamvar, M. T. Schlosser, and H. Garcia-Molina. *The eigentrust algorithm for reputaion management in p2p networks.* In Proc. of WWW, pages 640-651, Budapest, Hungary, May 2003.

[98] A. L. Karras *Smuggling Contraband and Corruption in World History.* Lanham: Rowman and Littlefield Pub. Group, 2009.

[99] Kautz H, Selman B, Shah M *Referral web: Combining social networks and collaborative filtering* CACM 40: (3) 63-65, 1997

[100] Brian Keegan, Muhammad Aurangzeb Ahmad, Dmitri Williams, Jaideep Srivastava, Noshir Contractor, *Dark Gold: Statistical Properties of Clandestine Networks in Massively-Muliplayer Online Games* IEEE Social Computing Conference (SocialCom-10) Minneapolis, MN, USA, August 20-22, 2010.

[101] Brian Keegan, Muhammad Aurangzeb Ahmad, Dmitri Williams, Jaideep Srivastava, Noshir Contractor. *Sic Transit Gloria Mundi Virtuali? Promise and Peril at the Intersection of Computational Social Science and Online Clandestine Organizations* The Third ACM WebSci Conference, Koblenz, Germany June 14-17, 2011

[102] Young Ae Kim, Muhammad Aurangzeb Ahmad, Jaideep Srivastava, Soung Hie Kim, *Role of Computational Trust Models in Service Science* (January, 05 2009) KAIST Business School Working Paper No. 2009-002.

[103] Kirchhoff, L, Stanoevska-Slabeva, K.. Nicolai, T., Fleck, M. *Using Social Network Analysis to Enhance Information Retrieval Systems.* Proceedings of the 5th Conference on Applications of Social Network Analysis (2008).

[104] Jon Kleinberg (1999). *Authoritative sources in a hyperlinked environment.* Journal of the ACM 46 (5): 604-632.

[105] Kosfeld, M., Heinrichs M., Zak, P. J., Fischbacher, U., and Fehr, E. (2005) *Oxytocin increases trust in humans.* Nature 435, 2005, 673-676.

[106] Kram, K. E. (1983). *Phases of the Mentor Relationship.* The Academy of Management Journal, 26(4), 608-625.

[107] Kram, Kathy. (1985). *Mentoring at Work: Developmental Relationships in Organizational Life*. Scott, Foresman.

[108] J. Kunegis, A. Lommatzsch, C. Bauckhage. *The Slashdot Zoo: Mining a social network with negative edges*. Proc. WWW, 2009.

[109] G. Lastowka, *ID theft, RMT and Lineage, Terra Nova* 2006; http://terranova.blogs.com/terra nova/2006/07/id theft rmt nc.html.

[110] Aleksandar Lazarevic, Levent Ertz, Vipin Kumar, Aysel Ozgur, Jaideep Srivastava *A Comparative Study of Anomaly Detection Schemes in Network Intrusion Detection*. SDM 2003

[111] Lazarsfeld PF, Merton RK. 1954. *Friendship as a social process: a substantive and methodological analysis*. In Freedom and Control in Modern Society, ed. M Berger, pp. 18-66. New York: Van Nostrand

[112] Lee, D., Seung, H., *Algorithms for non-negative matrix factorization*. NIPS 13, 2001.

[113] J. Lee, *Wage slaves, Book Wage slaves, Series Wage slaves* July/August, ed., Editor ed. eds., 2005, pp. 20-23.

[114] V. Lehdonvirta, *Virtual economics: applying economics to the study of game worlds*, Virtual Economy Research Network, 2005.

[115] T. Lehtiniemi, *How big is the RMT market anyway*, Virtual Economy Research Network, no. March 2, 2007.

[116] Jure Leskovec, Jon Kleinberg, Christos Faloutsos *Graphs over Time: Densification Laws, Shrinking Diameters and Possible Explanations* ACM SIGKDD International Conf. on Know. Disc. and Data Mining, 2005

[117] Jure Leskovec, Deepayan Chakrabarti, Jon Kleinberg, Christos Faloutsos *Realistic, Mathematically Tractable Graph Generation and Evolution, Using Kronecker Multiplication* European Conf. on Principles and Practice of Know. Dis. in Databases (ECML/PKDD), 2005.

[118] Jure Leskovec, Jon M. Kleinberg, Christos Faloutsos *Graph evolution: Densification and shrinking diameters.* TKDD 1(1): (2007)

[119] David Liben-Nowell, Jon M. Kleinberg *The link prediction problem for social networks.* CIKM 2003

[120] Louis Licamele, Lise Getoor *Social Capital in Friendship-Event Networks.* ICDM 2006: 959-964

[121] Lu, L., Zhou, T *Role of weak ties in link prediction of complex networks.* CIKM-CNIKM 2009: 55-58

[122] T. M. Malaby, *Anthropology and Play: The Contours of Playful Experience*, SSRN, 2008.

[123] S. Marsh *Formalizing Trust as a Computational Concept.* PhD thesis, University of Stirling, Department of Computer Science and Mathematics..

[124] Paolo Massa, Paolo Avesani *Controversial Users Demand Local Trust Metrics: An Experimental Study on Epinions.com Community.* AAAI 2005: 121-126

[125] M. McGlohon, L. Akoglu, C. Faloutsos *Weighted Graphs and Disconnected Components: Patterns and a Generator* ACM Special Interest Group on Knowledge Discovery and Data Mining (KDD08) 2008.

[126] McKnight, D. H., and Chervany, N. L. (1996) *The Meanings of Trust* [http://www.misrc.umn.edu/wpaper/wp96-04.htm Scientific report, University of Minnesota.

[127] McLeod, Carolyn (2006). *Trust.* The Stanford Encyclopedia of Philosophy. http://plato.stanford.edu/entries/trust (Retrieved 11/11/2011)

[128] McPherson, M., Smith-Lovin, L., Cook, J.M. (2001). *Birds of a Feather: Homophily in Social Networks.* Annual Review of Sociology. 27:415-44.

[129] Milo, R., S. Shen-Orr, S. Itzkovitz, N. Kashtan, D. Chklovskii, U. Alon, *Network motifs: simple building blocks of complex networks.* Science, 2002. 298(5594): p. 824-7.

[130] Peter Monge, Noshir Contractor, *Managing knowledge networks*, Management Communication Quarterly, 16: 2 (November 1, 2002), 249-258.

[131] Peter Monge, Noshir Contractor *Theories of Communication Networks.* Cambridge: Oxford University Press (2003).

[132] Morselli, C.; Giguere, C.; and Petit, K. 2007. *The efficiency/security trade-off in criminal networks.* Social Networks, 29(1): 143-153.

[133] C. Morselli, *Inside Criminal Networks.* New York: Springer, 2009.

[134] Murata, Tsuyoshi., Moriyasu, Sakiko., *Link Prediction of Social Networks Based on Weighted Proximity Measures.* Web Intelligence 2007: 85-88

[135] V. V. Nalimov, *The Application of Mathematical Statistics to Chemical Analysis*, Fizmatgiz, Moscow, 1960. [In English-Oxford: Pergamon Press, 1963.]

[136] Newman, M. E., *Clustering and Preferential Attachment in Growing Networks*, Physical Review Letters E, Vol.64 (025102), 2001.

[137] Newman, M.E.J. 2003. *Structure and function of complex networks.* SIAM Review, 45: 167-256.

[138] M. E. J. Newman (2006). *Modularity and community structure in networks.* Proc. Natl. Acad. Sci. USA 103: 8577-8582.

[139] Nilsson, N. J. (1998). *Introduction to Machine Learning.* Course Publication, Stanford University. Retrieved from: http://ai.stanford.edu/ nilsson/MLBOOK.pdf

[140] W. de Nooy, A. Mrvar, V. Batagelj *Exploratory Social Network Analysiswith Pajek, Structural Analysis in the Social Sciences* 27, Cambridge University Press, 2005.

[141] A. Potgieter, K. April, R. Cooke, I. O. Osunmakinde, *Temporality in Link Prediction: Understanding Social Complexity*, Journal of Trans. on Eng. Management, (2006).

[142] Robert Putnam. (2000), *Bowling Alone: The Collapse and Revival of American Community* (Simon and Schuster).

[143] D. Quercia, S. Hailes, and C. Licia. *Lightweight distributed trust propagation.* In Proc. of IEEE ICDM, Omaha, USA, October 2007.

[144] T. Raeder, and N. V. Chawla, *Market basket analysis with networks*, Social Network Analysis and Mining, vol. 1, pp. 97 - 113, 2011.

[145] Ragins, B. R., Cotton, J. L. (1999). *Mentor Functions and Outcomes: A Comparison of Men and Women in Formal and Informal Mentoring Relationships.* Journal of Applied Psychology, 84(4), 529-550.

[146] Ratan, R., Chung, J.E., Shen, C., Williams, D., Foucault, B., Poole, M.S. *Schmoozing and Smiting: Trust and Communication Patterns in an MMO.* Communication and Technology Commission of the International Communication Association, Chicago, USA.

[147] Rattigan, Jensen. *The case for anomalous link discovery.* ACM SIGKDD, 2005.

[148] Troy Raeder, Nitesh V. Chawla

[149] . Social Netw. Analys. Mining 1(2): 97-113 (2011)

[150] Redmond, S.P. (1990). *Mentoring and Cultural Diversity in Academic Settings.* The American Behaviorial Scientist, 34(2), 188-201.

[151] Resnick, Paul; Iacovou, Neophytos; Suchak, Mitesh; Bergstrom, Peter; Riedl, John (1994). *GroupLens: an open architecture for collaborative filtering of netnews.* Proceedings of the 1994 International ACM Conference on Computer Supported Cooperative Work. Computer Supported Cooperative Work. ACM Press. pp. 175-186

[152] Robins, G., Snijders, T., Wang, P., Handcock, M., Pattison, P. (2007). *Recent developments in exponential random graph (p*) models for social networks.* Social Networks, 29(2), 192-215.

[153] Schiesel, S. (2007). *Game on: Hero returns to slay his dragons.* New York Times, p. 1.

[154] Saavedra, R, Earley, P. C., Van Dyne, L. (1993). *Complex interdependence in task-performing groups.* Journal of Applied Psychology, Vol 78(1), Feb 1993, 61-72

[155] Sarwar, B.; Karypis, G.; Konstan, J.; Riedl, J. (2000), *Application of Dimensionality Reduction in Recommender System A Case Study.*

[156] Naomi Scheman, *Epistemology Resuscitated: Objectivity as Trustworthiness*, in(En)Gendering Rationalities, ed. Sandra Morgen and Nancy Tuana, SUNY Press, 2001

[157] S. Schiesel, *Virtual Achievement for Hire: Its Only Wrong if You Get Caught*, Book December 9, 2005 ed., Editor.

[158] K. Schrader, B. Mullins, G. Peterson R. Mills, *Tracking contraband files transmitted using BitTorrent*, in Advances in Digital Forensics V: Fifth IFIP WG 11.9 International Conference on Digital Forensics, Orlando, Florida, USA, January 26-28. 2009, Revised Selected Papers, G. Peterson and S. Shenoi, Eds., ed New York: Springer, 2009, pp. 159 - 173.

[159] Sharan, U., Neville, J., *Exploiting Time-Varying Relationships in Statistical Relational Models.* SNA-KDD 2007.

[160] Kyong Jin Shim, Muhammad Aurangzeb Ahmad, Nishith Pathak, Jaideep Srivastava, *Inferring Player Rating from Performance Data in Massively Multiplayer Online Role-Playing Games (MMOs)*, CSE, vol. 4, pp.1199-1204, 2009 Inernational Conference on Computer Science and Engineering, 2009.

[161] A. Singh and L. Liu, *TrustMe: Anonymous Management of Trust Relationships in Decentralized P2P Systems*, IEEE Intl. Conf. on Peer-to-Peer Computing, Sep. 2003.

[162] S. Sonnentag, *Expertise at work: Experience and excellent performance*, International Review of Industrial and Organizational Psychology, vol. 15, pp. 223-264, 2000.

[163] SONY Station: New Mentoring System http://everquest2.station.sony.com/ news $_{a}rchive_{c}ontent.vmmonth = 032005\&id = 396(RetrievedApril23, 2010)$

[164] Jaideep Srivastava *Data Mining as a Key Enabler of Computational Social Science.* SocInfo 2011: 4

[165] Steinkuehler, C. A. (2004). *Learning in massively multiplayer online games.* In Y. B. Kafai, W. A. Sandoval, N. Enyedy, A. S. Nixon, F. Herrera (Eds.), Proc. of the 6th ICLS (521-528). Mahwah, NJ: Erlbaum.

[166] C. Stohl and M. Stohl, *Networks of terror: theoretical assumptions and pragmatic consequences*, Communication Theory, vol. 17, pp. 93-124, 2007.

[167] S. Sun, L. Ling, N. Zhang, G. Li, R. Chen *Topological structure analysis of the protein-protein interaction network in budding yeast.* Nucleic Acids Research, 2003, Vol. 31, No. 9 2443-2450

[168] Takcs, G.; Pilszy, I.; Nmeth, B.; Tikk, D. (March 2009), *Scalable Collaborative Filtering Approaches for Large Recommender Systems*, Journal of Machine Learning Research 10: 623-656

[169] T. Taylor, *Play between worlds: Exploring online game culture*, MIT Press, 2006.

[170] K. Taipale, *How Technology, Security, and Privacy Can Coexist in the Digital Age, Cybercrime: Digital Cops in a Networked Environment*, J.M. Balkin, G. Grimmelmann, E. Katz, N. Kozlovski, S. Wagman, and T. Karzky eds., New York University Press, 2007.

[171] Turner, J. C. (1987). *Rediscovering the Social Group: A Self-Categorization Theory.* Oxford: Basil Blackwell.

[172] Tylenda, T., Angelova, R., Bedathur, S., *Towards Time-aware Link Prediction in Evolving Social Networks*, KDD-SNA 2009

[173] Tyren, *World of Warcraft Accounts Closed Worldwide*, 2006; http://forums.worldofwarcraft.com/thread.html?topicId=59377507.

[174] van Rijsbergen, C. J. (1979). *Information Retrieval.* Butterworths, London

[175] von Lampe, K. and Johansen, P.O. 2004. *On the conceptualization and empirical relevance of trust in the context of criminal networks.* Global Crime, 6(2).

[176] K. von Lampe, *Explaining the emergence of the cigarette black market in Germany*, in The Organised Crime Economy: Managing Crime Markets in Europe, P. C. van

Duyne, et al., Eds., ed Nijmegen, The Netherlands: Wolf Legal Publishers, 2005, pp. 209 - 229.

[177] Wall, Jr., V. D. Nolan, L. L. (1986). *Perceptions of Inequity, Satisfaction, and Conflict in Task-Oriented Groups*. Human Relations, vol. 39 no. 11, 1033-1051

[178] Walter, Frank Edward, Battiston, Stefano, Schweitzer, Frank *A Model of a Trust-Based Recommendation System on a Social Network, in: Journal of Autonomous Agents and Multi-Agent Systems*, vol. 16, no. 1 (2008), pp. 57-74

[179] Y. Wang and F.-R. Lin. *Trust and risk evaluation of transactions with different amounts in peer-to-peer e-commerce environments*. In Proc. of IEEE Int'l Conference on e-Business Engineering, pages 102-109, Shanghai, China, October 2006.

[180] Wang, J., Huffaker, D. Treem, J. W., Fullerton, L., Ahmad, M. A., Poole, M. S., Contractor, N. *Focusing on the prize: Characteristics of experts in virtual worlds?* ICA Convention, Chicago, IL 2009

[181] Wasserman, Stanley, Faust, Katherine. (1994). *Social Networks Analysis*. Cambridge University Press.

[182] Wasserman, S., Pattison, P. E. (1996). *Logic models and logistic regressions for social networks: I. An introduction to Markov graphs and p**. Psychometrika, 61, 401-425.

[183] Watts, Duncan J.; Strogatz, Steven H. (June 1998). *Collective dynamics of 'small-world' networks*. Nature 393 (6684): 440-442

[184] White, P. (2008). *MMOGData: Charts*. Gloucester, United Kingdom. http://mmogdata.voig.com/

[185] Brian Wilcox Sony Online Entertainment *Personal Communication* (2007).

[186] Ian H. Witten and Eibe Frank (2005) *Data Mining: Practical machine learning tools and techniques*, 2nd Edition, Morgan Kaufmann, San Francisco, 2005.

[187] A. D. Wood, J. A. Stankovic *Denial of service in sensor networks* Computer, Vol. 35, No. 10. (2002) pp.54-62

[188] Woodcock, B. S. (2008, April 9). *MMOG Subscriptions Market Share* - April 2008. Retrieved October 28, 2009, from http://www.mmogchart.com/Chart7.html

[189] N. J. Williams, *Contraband Cargoes: Seven centuries of smuggling*. London: Longmans Green and Co, 1959.

[190] Dmitri Williams. *From Tree House to Barracks: The Social Life of Guilds in World of Warcraft*. Games and Culture. 2006;1(4):338-361.

[191] Dmitri Williams, (2010). *The mapping principle, and a research framework for virtual worlds*. Communication Theory.

[192] Dmitri Williams, *The Mapping Principle and a Research Framework for Virtual Worlds*. Communication Theory, 20(4): 451-470.

[193] Xiang, Evan W., *A Survey on Link Prediction Models for Social Network Data* PhD Qualifying Exam (2008).

[194] Yan, X., Han, J. 2002. *gspan: Graph-based substructure pattern mining*. In Proc. ICDM02, Maebashi City, Japan. IEEE: 721-724.

[195] N. Yee, *Buying gold, Daedalus Project* 2005; http://www.nickyee.com/daedalus/archives/pdf/3-5.pdf.

[196] Nic Yee (2006). *Motivations of Play in Online Games*. Cyber Psychology and Behavior, 9, 772-775

[197] N. Yee, *The labor of fun: how video games blur the boundaries of work and play*, Games and Culture, vol. 1, no. 1, 2006, pp. 68-71.

[198] Young, A. M., Perrew, P. L. (2000). *The exchange relationships between mentors and proteges: The development of a framework*. Human Resource Management Review, 1-0(2), 177-209.

[199] Yuan, Y. C., Gay, G. (2006). *Homophily of network ties and bonding and bridging social capital in computer-mediated distributed teams*. Journal of Computer-Mediated Communication, 11(4), article 9.

[200] Zlatic, V.; Ghoshal, G.; and Caldarelli. G. 2009. *Hypergraph topological quantities for tagged social networks*. Phys. Rev. E 80:036118, 2009.