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Trust me, I ‘m an Expert: Trust, Homophily and Expertise in MMOs

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Abstract— Trust is a ubiquitous phenomenon in social networks and people trust one another for a variety of reasons. In this paper we study the problem of trust in massively multiplayer online games (MMOs) with respect to homophily and expertise. We propose a topology of homophily in MMOs based on the literature on homophily and domain knowledge of MMOs. Our results show that while there is some mapping between homophily in MMOs and the theories of homophily in the offline world, the mapping is not complete. Only ascribed homophily and value homophily is observed in the trust network, while other types of homophilies are conspicuously absent. We observed that the trust network exhibits many properties which are not observed in most other social networks. Based on our observations we propose a generative model for trust networks in MMOs.

Keywords-Trust in Social Networks, Homophily, Experts.

I. 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 [9] and the theory of self-categorization [23] are usually given as the basic arguments behind homophily principle [21], [2003]. 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 [29]. 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 [20]. Lazarsfeld and Merton [16] 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 [20].

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 [28]. These kinds of ties are known as instrumental network ties. People develop such ties to exchange information or resources required for task completion [28]. 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 [11] [22] [24]. On the other hand, majority of the trust-related research support trust as a positive factor for group process and performance [10]. 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 [14]. The identification of experts based on their activities and trust based social networks has been demonstrated in many systems [1]. Monge et al relate these two in the context of the MTML framework [21]. While there is a vast body of literature on trust in social networks especially with respect to recommendations, trust inference and propagation etc. [14], the focus of this paper is on the social and computational modeling related aspects of trust in MMOs. The issue of trust in MMOs has been addressed

TABLE I THE TOPOLOGY OF HOMOPHILY IN MMOS

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.

before. Thus Ahmad et al [2] 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 [3]. Lastly the problem of structural signatures of subpopulations within trust networks in MMOs has been explored within the context of clandestine networks [5].

II. BACKGROUND: SOCIAL DYNAMICS OF MMOS

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 paper 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 [27] 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 Table 1. As described in section I, 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 1. 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 [12] note that there are two main aspects of expertise in MMOs: *Achievement* and *Performance*. It is their definition of Expertise that we use here.

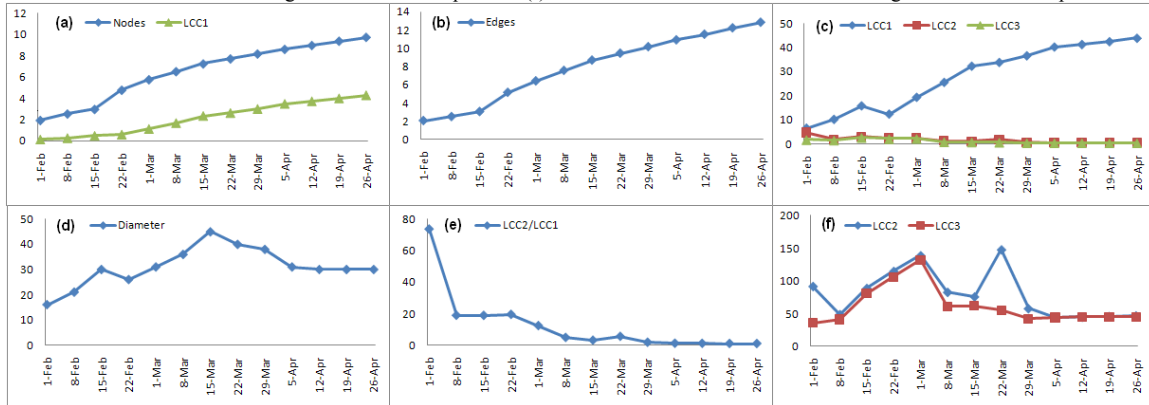
III. DATASET

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, [2] [3] [4] [5] [6] [7] [12] we take the player characters as the unit of analysis.

IV. 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% of all the nodes in the

Figure 1: Temporal properties of the Trust Network: (a) Total number of nodes in the network and in the largest connected components (in thousands) (b) Total number of edges (in thousands) (c) The size of the three largest connected components as percentage of the total (d) The diameter of the network (e) The ratio of the first and the second largest connected components (f) The sizes of the second and the third largest connected components



network. While we used 8 months' worth of data, the temporal characteristics the network for only 13 weeks are given in Figures I mainly because of space constraints.

Figure 1(a) and 1(b) show the growth of the number of node and edges over time. Figure 1(c) shows the sizes of the three largest connected components as percentage of 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 [7] [17] [18] [19] [25]. 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 [19]. In the case of the trust network, the diameter fluctuates and then somewhat stabilizes after week 10 as shown in Figure 1(d). Another common observation in the literature in social networks [18] [19] 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 (Figure 1a and 1c), 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 [19] 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 [18] [19]. 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 [19] 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 I(f). However consider Figure I(e) 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 [6][7]. 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 [3] [7].

TABLE II. GENDER HOMOPHILY IN THE TRUST NETWORK

Trust Type	Total Edges	Same Gender	Different 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

V. 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 I, quest difficulty level and location are not included from Table I as the data for these was not available.

H1 (Gender Homophily): Players trust other players who have the same gender: Table II 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 III 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 IV 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

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

TABLE III. 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 IV. 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 V. 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 VI. LEVEL HOMOPHILY IN THE TRUST NETWORK

Trust Type	Total Edges	$\langle L_i - L_j \rangle$
Trustee	16,826	21.92
Friend	5,756	16.69
Visitor	1,538	17.14

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 V 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 VI 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 [26].

H6 (Level Homophily): Players trust other players who are at a similar level: In Table VII 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 VIII 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.

H6 (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 IX 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 IX. VALUE HOMOPHILY IN THE TRUST NETWORK

Trust Type	Total Edges	$\langle \text{LT}_i - \text{LT}_i \rangle$
Trustee	16,826	879.55
Friend	5,756	781.57
Visitor	1,538	800.00

VI. 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 [7][8][15][17][18][19] 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 generators [17][18][19] because of limitations in space. We employ the Preferential Attachment model [8] as our starting point. Given an 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:

$$p_i = \frac{k_i}{\sum_j k_j}$$

Where k_i is the node degree of the node n_i . 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 theoretical bound or even a constraint within the game but rather an observational bound. Thus we modify equation (1) so that the edge formation is bound by the lifetime of the nodes.

$$p_i = \frac{t_{init} - t_x}{t_{init}} \cdot \frac{k_i}{\sum_j k_j}$$

Where t_x is the current iteration and the t_{init} is iteration at which the current node was added to the network. The formula implies 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 [7]. Another observation that has to be replicated is the presence of a large number of small components (auxiliary 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 initial burst of activity, if at all, these components can be described in terms of a generator function.

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

Where s_i corresponds to the set of all the graphs which are of size i , E_i is the number of edges in the complete graph of size i and $\min(e_i)$ is the number of edges in the smallest graph of size e_i which is a connected graph. The function states that the probability 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 aspect of this network is the non-monotonic 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 context of MMOs since many of the players leave the game after a certain amount of time. Ahmad et al [6] discuss the lifetime of nodes in EQ2 in the context of mentoring networks and their observations are valid in this context as well. Thus:

$$p_i = \begin{cases} \frac{t_{init} - t_x}{t_{init}} \cdot \frac{k_i}{\sum_j k_j}, & t_{init} - t_x \leq l(n_i) \\ 0, & t_{init} - t_x > l(n_i) \end{cases}$$

Where $l(n_i)$ is the lifetime of the node n_i . For replicating the homophily related dynamics we represent the attributes or characteristics of the players as a vector $a_i = \{a_1, a_2, \dots, a_n\}$. 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 [15] for representation of characteristics. Thus the connectivity equation becomes.

$$p_i = f(A) \cdot \begin{cases} \frac{t_{init} - t_x}{t_{init}} \cdot \frac{k_i}{\sum_j k_j}, & t_{init} - t_x \leq l(n_i) \\ 0, & t_{init} - t_x > l(n_i) \end{cases}$$

Where the function $f(A)$ describes the similarity 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

TABLE VIII. BREAKDOWN OF THE TRUST RELATIONSHIP BY LEVELS

Relative Levels of Players at Trust Formation	Trustee		Friend		Visitor	
	E	% E	E	% E	E	% E
Higher Level to Lower Level	5,564	33.07	2,037	49.68	565	36.74
Same Level	1,498	8.90	1,498	36.54	221	14.37
Lower Level to Higher Level	9,764	58.03	565	13.78	752	48.89

an indicator function as follows:

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

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:

$$f(a) = |a_i - a_j|, a_i \neq a_j$$

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 heterophily is desired. Thus the idea is that a node is likely to connect to other nodes if they have similar or different nodes.

VII. 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 heterophily was observed. In future work we plan to extend the current work by using ERGM/p* models [13] to explore in greater length the structural signature as well as expert characteristics associated with the evolution of trust based network.

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REFERENCES

- [1] Muhammad Aurangzeb Ahmad, Xin Zhao *COLBERT: A Scoring Based Graphical Model For Expert Identification* 2010 International Conference on Social Computing, Behavioral Modeling, & Prediction (SBP10) March 29 - April 1, 2010 Bethesda, MD
- [2] Muhammad Aurangzeb Ahmad, Marshall Scott Poole, Jaideep Srivastava, *Network Exchange in Trust Networks* IEEE Social Computing (SocialCom-10). Muhammad Aurangzeb Ahmad, Marshall Scott Poole, Jaideep Srivastava *The Trust Propensity Prediction Problem* The 3rd ACM WebSci Conference, Koblenz, Germany June 14-17, 2011
- [3] Muhammad Aurangzeb Ahmad, Jaideep Srivastava *Item Recommendations in Multiple Overlapping Social Networks in MMOs* The 3rd ACM WebSci Conference, Koblenz, Germany June 14-17, 2011
- [4] Muhammad Aurangzeb Ahmad, Brian Keegan, Dmitri Williams, Jaideep Srivastava, Noshir Contractor *Trust Amongst Rogues? A*

- Hypergraph Approach for Comparing Clandestine Trust Networks in MMOs* 5th International AAAI Conference on Weblogs and Social Media (ICWSM 2011), July 17-21, 2011
- [5] Muhammad Aurangzeb Ahmad, David Huffaker, Jing Wang, Jeff Treem, Dinesh Kumar, Marshall Scott Poole, Jaideep Srivastava, *The Many Faces of Mentoring in an MMORPG* IEEE Social Computing (SocialCom-10).
- [6] Muhammad Aurangzeb Ahmad, David Huffaker, 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
- [7] Barabási, A.-L.; R. Albert (1999). *Emergence of scaling in random networks* Science 286 (5439): 509–512.
- [8] Byrne, D. (1971). *The Attraction Paradigm*. Orlando, FL: Academic Press.
- [9] Dirks, K. T. (1999). *The Effects of Interpersonal Trust on Work Group Performance*. Journal of Applied Psychology, 84, 445-455
- [10] Gladstein, D.L. 1984. *Groups in context: A model of task group effectiveness*. Administrative Science Quarterly, 29: 499-517.
- [11] 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).
- [12] 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).
- [13] J. Golbeck: *Computing with Social Trust*. Springer, London (2009)
- [14] Johnson, N., Xu, C., Zhao, Z., Ducheneaut, N., Yee, N., Tita, G., & Hui, P. (2009). *Human group formation in online guilds and offline gangs driven by a common team dynamic*. Physical Review E, 79, 066117.
- [15] 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
- [16] Jure Leskovec, Deepayan Chakrabarti, Jon Kleinberg, Christos Faloutsos. *Realistic, Mathematically Tractable Graph Generation and Evolution, Using Kronecker Multiplication* European Conf. on Principles & Practice of Know. Dis. in Databases (ECML/PKDD), 2005.
- [17] Jure Leskovec, Jon Kleinberg, Christos Faloutsos *Graphs over Time: Densification Laws, Shrinking Diameters and Possible Explanations* ACM SIGKDD Int'l Conf. on Know. Disc. and Data Mining, 2005.
- [18] M. McGlohon, L. Akoglu, C. Faloutsos. *Weighted Graphs and Disconnected Components: Patterns and a Generator*. ACM Special Interest Group on Knowledge Discovery & Data Mining (KDD08) 2008.
- [19] McPherson, J., Smith-Lovin, L., Coe, J. M. (2001). *Birds of a feather: Homophily in social networks*. A. Rev. of Sociology, 27, 415–44.
- [20] Monge, P. R., & Contractor, N. (2003). *Theories of Communication Networks*. Oxford: Oxford University Press.
- [21] 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
- [22] Turner, J. C. (1987). *Rediscovering the Social Group: A Self-Categorization Theory*. Oxford: Basil Blackwell.
- [23] 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
- [24] Watts, Duncan J.; Strogatz, Steven H. (June 1998). *Collective dynamics of 'small-world' networks*. Nature 393 (6684): 440–442
- [25] Dmitri Williams. *From Tree House to Barracks: The Social Life of Guilds in World of Warcraft*. Games and Culture. 2006;1(4):338-361.
- [26] Dmitri Williams, (2010). *The mapping principle, and a research framework for virtual worlds*. Communication Theory.
- [27] Yuan, Y. C., Gay, G. (2006). *Homophily of network ties and bonding and bridging social capital in computer-mediated distributed teams*. J. Computer-Mediated Communication, 11(4), article 9.