Exploration of robust features of trust across multiple social networks

Zoheb H Borbora*, Muhammad Aurangzeb Ahmad*, Karen Zita Haigh†, Jaideep Srivastava* and Zhen Wen‡
*Dept. of Computer Science, University of Minnesota, Minneapolis, Minnesota-55455
borbo001@umn.edu, mahmad@cs.umn.edu, srivasta@cs.umn.edu
†Raytheon BBN Technologies, 5775 Wayzata Blvd, St. Louis Park, MN 55416. khaigh@bbn.com
‡Thomas J. Watson Research Center, Hawthorne, NY. zhenwen@us.ibm.com

***Abstract*—In this paper, we investigate the problem of trust formation in virtual world interaction networks. The problem is formulated as one of link prediction, intranetwork and internetwork, in social networks. We use two datasets to study the problem - SOE's Everquest II MMO game dataset and IBM's SmallBlue sentiments dataset. We explore features based on the node's individual properties as well as based on the node's location within the network. In addition, we take into account the node's participation in other social networks within a specific prediction task. Different machine learning models built on the features are evaluated with the goal of finding a common set of features which are both robust and discriminating across the two datasets. Shortest Distance and Sum of Degree are found to be robust, discriminating features across the two datasets. Finally, based on experiment results and observations, we provide insights into the underlying online social processes. These insights can be extended to models for online social trust.**

I. Introduction

Trust is a ubiquitous phenomenon in social networks, people trust one another for different reasons in a vary of social contexts. A person may trust another person because of homophily, the other person's expertise in an area or because other people in her network may already trust that person. Previous research on trust in social networks has shown that homophily is observed between people who trust one another but it may not be necessarily be the case that homophily leads to trust [6]. There may be additional factors which may affect a person's decision to trust another person e.g., how people socialize in other contexts. Thus it may be the case that having trade relationships with another person may affect how a person trusts another person or being an apprentice to another person would positively affect a person's decision to trust them. Given the wide variety of contexts and disparities with respect to why people trust others, the decision to trust may be context specific or there may be a set of context independent reasons applicable across multiple domains which may determine why people trust one another. In this paper we address this problem by operationalizing it in the context of link prediction in trust based social networks and extend it to other social networks.

To the best of our knowledge, no prior work has done a comprehensive study of a set of features that can be used for the prediction of trust in social networks. The utility of such a study not only lies in a set of features that can be used for prediction in trust networks and other social networks, but also the discovery of a set of common features that are robust across many domains. Such robust predictors of trust can also be useful in the inter-component interactions of self-organizaing systems. In this paper we use two different datasets for studying link prediction problems: Sony Onile Entertainment's (SOE) *Everquest II* MMO game dataset and IBM's *SmallBlue* sentiments dataset. We emphasize that both of these datasets are annonymized so that it is not possible to link back an account in either EQII or IBM SmallBlue back to the corresponding person in the offline world.

II. Related Work

Trust has been a well-studied problem in computer science across diverse areas such as computer networks, distributed systems, game theory and agent systems and has gained importance in Web related research regarding reliability of web sites and resources [4]. Trust propagation models are an important part of computing with social trust and such models have been proposed in [7], [18] and [12]. While [7] uses small world concepts to optimize formation and propagation of trust, [18] and [12] use local group trust metrics in social networks. [6] provides a survey of important research in computing with social trust and includes models, metrics and applications of social trust. This list of features analyzed in this paper is far more comprehensive than previously examined.

III. Methodology and Data description

In this paper, the problem of trust formation in social networks is formulated as one of predicting formation of links/ties. We use a supervised learning approach to link prediction adopting the framework developed by Hasan et al [10]. The dataset is divided into training and test period. In this binary classification setup, a positive instance is a node-pair which has no edge in the training period, but has an edge in the test period. A negative instance is a node-pair for which no edge exists either in the training or the test period. In addition to predicting link formation within the same network, we also address the problem of prediction across social networks [2].

The EQII dataset consists of network data from four different social networks within the game. Each of these networks represent different types of socialization in EQII and can be described as follows:

- Housing-Trust: A housing-trust edge is constructed when one player grants trust access to another player to his or her house within the game.
- Mentoring: Players have the option to mentor other players within the game. A mentor helps the apprentice in level up in the game.
- Trade: Players can trade virtual items with one another. An edge is formed between two players if they trade an item with one another.
- Grouping: The completion of certain tasks requires players to group together. The size of the groups can range from groups of size 2 to groups of size 24.

The training period for the EQII dataset is from February 2006 to June 2006 and the test period is from July 2006 to August 2006.

The SmallBlue dataset is constructed from IBM internal communications. Each communication is labelled as *positive* or *negative* based on the sentiment contained in the communication. This gives us two networks for our link/sentiment prediction task. The training period for the SmallBlue dataset is from January 2008 to August 2008 and the test period is from September 2008 to December 2008.

Within each dataset, we consider all combinations of networks in the training and test periods. Each such combination becomes a *prediction task*, yielding 16 prediction tasks for the EQII dataset and 4 prediction tasks for the SmallBlue dataset (as shown in the columns of figures 1 and 2). Each of the prediction task uses 60000 samples.

IV. FEATURES DESCRIPTION

We investigate three broad categories of features for the problem as outlined in the following sub-sections. Each feature is computed for a pair of nodes i,j in the training network.

$$indicator(i,j) = \begin{cases} 1, & \text{if } \phi(i) = \phi(j) \\ 0, & \text{otherwise} \end{cases} \tag{i}$$

$$sum(\phi_{i,j}) = \phi(i) + \phi(j) \tag{ii}$$

$$diff(\phi_{i,j}) = |\phi(i) - \phi(j)| \tag{iii}$$

where, $\phi(x)$ is a feature calculated for node x.

A. Features derived from node properties

The following 16 features capture node properties, and are computed using Equations i, ii or iii. In a social network, these include demographics; communications networks might describe what kind of hardware is being used or the protocols required for communication; information networks might describe the algorithms for sensor fusion or the databases.

- Human *Gender* and *Country* Indicators. (1, 2)
- Avatar *Gender* and *Country* Indicators. (3, 4)
- Avatar *Class* and *Guild Indicators*. These features capture memberships and interests. (5, 6)
- *Sum and Difference of Human Age*. (7, 8)
- *Sum and Difference of Avatar Age.*[1] These features capture activity levels. (9, 10)
- *Sum and Difference of Joining Age.* The ages of the players when they joined the game. (11, 12)
- *Sum and Difference of Character Level* at end of the training period. These features capture expertise. (13, 14)
- *Sum and Difference of Guild Rank* at the end of the training period. These features capture seniority. (15, 16)

B. Topological features

Topological features are derived from the node's location in its network, including its relationships to its neighbors and how well connected it is. For this discussion, let $\mathbb{G}(i)$ be the set of i's neighbors.

- *Difference in Relative Degree centrality*: Degree centrality is based on the number of edges incident upon the node (i.e., the number of ties that a node has) [14]; the relative degree centrality of a node i is:

$$C_D(i) = \frac{deg(i)}{n-1} \tag{17}$$

- *Difference in Relative Betweenness centrality*: Betweenness centrality of a node is a measure based on the number of shortest paths that a vertex lies in [5]:

$$C_B(i) = \sum_{s \neq i \neq t \in V} \frac{\sigma_{st}(i)}{\sigma_{st}}$$

  where σ_{st} is the number of shortest paths from s to t and $\sigma_{st}(i)$ is the number of shortest paths from s to t that pass through vertex i. Relative betweenness centrality is given by

$$C'_B(i) = \frac{C_B(i)}{n(n-1)/2} \tag{18}$$

- *Sum and Difference of Node degree* (19, 20)
- *Shortest distance* between the two nodes (21)
- *Sum of Clustering Index*: Clustering index is the fraction of pairs of a person's collaborators who have also collaborated with one another [13].

$$C(i) = \frac{3 \times \textit{number of triangles}}{\textit{number of connected triples}} \tag{22}$$

[1] We use player sums of session lengths (in minutes) to approximate avatar age. A player session is defined as a contiguous period of player activity. Since the activity logs in EQII only record player actions, we used a a simple heuristic to define player session. A session consists of sets of activities which are separated by no more than 30 minutes.

- *Number of Common neighbors*: as given by

$$n(i,j) = |\mathbb{G}(i) \cap \mathbb{G}(j)| \tag{23}$$

- *Salton index* [15]: one of many metrics that seek to reduce the influence of heavily-connected nodes.

$$\zeta(i,j) = \frac{|\mathbb{G}(i) \cap \mathbb{G}(j)|}{\sqrt{|\mathbb{G}(i)| \times |\mathbb{G}(j)|}} \tag{24}$$

- *Jaccard Index* [11]: a statistic used for comparing the similarity and diversity of sets.

$$\gamma(i,j) = \frac{|\mathbb{G}(i) \cap \mathbb{G}(j)|}{|\mathbb{G}(i) \cup \mathbb{G}(j)|} \tag{25}$$

- *Sorensen index* [16]: a measure of the similarity of two samples that retains sensitivity in more heterogeneous data sets and gives less weight to outliers:

$$f_{ij} = \frac{2 \times |\mathbb{G}(i) \cap \mathbb{G}(j)|}{|\mathbb{G}(i)| + |\mathbb{G}(j)|} \tag{26}$$

- *Adar-adamic index*: Neighbours with few connections have more weight in capturing the similarity of nodes i and j [1].

$$\alpha(i,j) = \sum_{k \in \mathbb{G}(i) \cap \mathbb{G}(j)} \frac{1}{\log(|\mathbb{G}(k)|)} \tag{27}$$

- *Resource allocation index* [17]: Each neighbor will averagely distribute a resource to its neighbors.

$$\beta(i,j) = \sum_{k \in \mathbb{G}(i) \cap \mathbb{G}(j)} \frac{1}{|\mathbb{G}(k)|} \tag{28}$$

C. Cross-network features

These features indicate the presence or absence of other social relationships during the training period within a prediction task and is given by:

$$cn(\bar{X}_{i,j}) = \begin{cases} 1, & \text{if a link exists between } i,j \text{ in network } \bar{X} \\ & \text{ for the prediction task } X \to Y \\ 0, & \text{otherwise} \end{cases} \tag{29, 30, 31, 32}$$

where $X, Y \in$ Housing, Mentoring, Trade, Group for EQII dataset, and $X, Y \in$ POS,NEG for SmallBlue dataset; and, $\bar{X}$ is a network which is not X. As an example, for the prediction task Housing-Housing, the cross-network feature $cn(\mathit{Mentoring}_{i,j})$ would indicate whether a mentoring relationship existed between i and j during the training period.

V. Experimental results and Analysis

We perform experiments to analyze the feature space of the problem, evaluate different machine learning models built with those features and look for robust features across the datasets. For each experiment, we have listed some key observations from the results. Later in the discussion section, we give potential social explanations for these observations.

A. Experiment 1

The purpose of this experiment is to analyze and compare the performance of the features across the two datasets and for all prediction tasks, using a measure of the feature's *information gain*. Information gain measures how well a given attribute separates the training examples according to the target classification and is given by the expected reduction in entropy caused by partitioning the examples according to the attribute. Additionally, we use a Correlation based Feature Selection (CFS) technique [9] to identify the subset of features which are highly correlated with the class while having low intercorrelation. We used the Weka machine learning tool to perform the experiments [8]. Figures 1 and 2 show the info-gain matrices for the prediction tasks in the two datasets. The top-10 most discriminating features are highlighted with a darker background. Boldface indicates discriminating features not correlated with others (CFS). The last two columns give the average info-gain value and ranking for the feature.

1) Feature analysis for the EQII dataset: A few key observations from Figure 1 are

- For predicting group and trade links, the node-based features *Char Level Sum* and *Avatar Age Sum* are both highly discriminating and uncorrelated.
- The topological features are generally good predictors, with the notable exceptions of *Jaccard Index* and *Sorensen Index*. *Shortest Distance* is a consistently good predictor across all networks whereas *Sum of Degree* has good predictive power for all but housing links. *Common Neighbors*, *Salton Index*, *Adar Adamic Index* and *Resource Allocation Index* have good predictive power for housing or mentoring links.
- Among the cross-network features, we find that if a node-pair has a housing or group relationship during the training period, this is a good indicator of a housing link being formed in the test period. Similarly, presence of a mentoring or group relationship during the training period is a good indicator for formation of a mentoring link. However, the cross-network features are not useful at all for predicting group or trade ties.

2) Feature analysis for the SmallBlue dataset: For privacy reasons, we did not have node-based features for the SmallBlue dataset, but all of the topological features were easily computable. Key observations from Figure 2 include:

- *Sum of degree* is the most discriminating feature across all prediction tasks as per the info-gain metric. This feature is also not correlated with others.
- As in the EQII dataset, the *Jaccard Index* and *Sorensen Index* are very poor predictors.
- Cross-sentiment features have poor predictive power, the only exception being the presence/absence of a positive link in the NP prediction task.

	Prediction tasks (Training Period: FEB-JUN, Test Period: JUL-AUG)																	
	Networks: **H**=Housing-trust, **M**=mentoring, **T**=Trade, **G**=Group																	
Category	**Feature Name**	**HH**	**MH**	**TH**	**GH**	**HM**	**MM**	**TM**	**GM**	**HG**	**MG**	**TG**	**GG**	**HT**	**MT**	**TT**	**GT**	**Averag**	**Rank**
Node	Human Gender Indicator	0	0	0	5E-05	0	0	0.0001	7E-05	0.002	**6E-04**	0.0007	0.0003	0	0.0006	0.0007	0.0008	0.0004	31
Node	Avatar Gender Indicator	0	0	0	0.0002	6E-05	0	8E-05	0	0.0004	0.0002	0.0005	0.0003	0	0	0	8E-05	0.0001	32
Node	Avatar Race Indicator	0.0004	**8E-04**	**0.001**	0.0005	6E-05	0	0.0002	0	0	1E-04	0.0002	9E-05	0.0017	0.0013	0.0016	0.0013	0.0006	30
Node	Country Indicator	**0.002**	**0.004**	**0.007**	**0.004**	**0.003**	**0.004**	**0.006**	**0.002**	**0.001**	0.0011	0.0013	**8E-04**	0.0011	9E-05	0.0002	0	0.0023	26
Node	Human Age Sum	0.0034	0.0049	0.0052	0.0039	0.0011	0.0015	0.0014	0.0032	**0.007**	0.0007	**0.003**	0.0006	0.0023	0.0038	0.0016	0.0133	0.0035	25
Node	Avatar Age Sum	0.0055	0.0099	0.0187	0.0093	**0.022**	0.0261	**0.06**	**0.049**	**0.326**	**0.203**	**0.24**	**0.291**	**0.217**	**0.191**	**0.175**	**0.309**	0.1344	2
Node	Human Age Difference	0.0129	**0.032**	**0.047**	**0.036**	0.0007	0.0005	0.0028	0.0007	0.0015	**8E-04**	0.0014	0.001	0	0.0002	0.0002	0.0004	0.0086	22
Node	Avatar Age Difference	0	0.0013	0.0029	0.0018	0.0043	0.005	0.0104	0.0102	0.0247	0.014	0.0288	0.0403	0.0376	0.0353	0.0499	0.073	0.0212	16
Node	Joining Age Sum	0.0031	**0.005**	0.0048	0.0063	**0.001**	**0.002**	0.0017	**0.004**	0.0034	0	0.0011	0.0017	**0.003**	**0.006**	0.0033	**0.016**	0.0039	24
Node	Joining Age Difference	0.0094	0.0261	0.0372	0.0323	0.0003	0.0003	0.0012	0	0.0015	0.0008	0.0013	0.0008	0	0.0002	**2E-04**	0.0004	0.007	23
Node	Character Class indicator	0	0	0	0	8E-05	0	**1E-04**	0	**7E-04**	**4E-04**	**7E-04**	0.0004	**0.002**	**0.002**	**0.002**	**0.002**	0.0006	29
Node	Char Level Sum	0.0063	0.0145	0.0227	0.0113	0.025	0.0205	0.0511	**0.055**	**0.443**	**0.275**	**0.321**	**0.398**	**0.21**	**0.175**	0.1443	**0.328**	0.1563	1
Node	Char Level Difference	0.0042	0.005	0.0074	0.0018	0.0238	**0.025**	**0.039**	**0.03**	**0.356**	**0.255**	**0.267**	**0.298**	0.0421	0.0247	0.0103	0.0558	0.0903	4
Node	Guild Indicator	**0.033**	**0.052**	**0.067**	**0.029**	**0.031**	**0.042**	**0.053**	**0.019**	**0.065**	**0.046**	0.0378	0.0106	**0.01**	**0.01**	**0.014**	**0.029**	0.0342	14
Node	Guild Rank Sum	0.001	0.0018	0.0021	0.0022	0.0034	0.0069	0.0128	0.0135	**0.032**	0.0288	0.0421	**0.062**	0.0167	0.0184	0.0172	0.0356	0.0185	17
Node	Guild Rank Difference	0.0022	0.0032	0.005	0.002	0.0029	0.0053	0.0096	0.0093	0.0238	0.024	0.0275	0.0404	0.0149	0.0189	0.0202	0.0359	0.0153	18
Topo	Degree centrality (difference)	0.0029	0.0017	0.008	0.0021	0.0014	0.0346	0.0066	0.0257	0.0268	0.0373	0.0389	0.096	0.0469	0.0317	0.1397	0.0852	0.0366	13
Topo	Betweenness centrality (difference)	0.004	0.003	0.0113	0.0013	0.0026	0.0483	0.0153	**0.027**	0.0832	0.061	0.0694	0.0864	0.0723	0.0452	**0.195**	0.0447	0.0481	11
Topo	Degree Sum	**0.009**	0.007	0.0216	0.0043	0.0033	**0.082**	0.0249	0.0404	0.0596	0.1164	0.1494	0.2627	**0.089**	0.0849	**0.287**	0.1574	0.0874	5
Topo	Degree Difference	0.0029	0.0017	0.008	0.0021	0.0014	0.0346	0.0066	0.0257	0.0272	0.0373	0.0389	0.096	0.0472	0.0317	0.1397	0.0852	0.0366	12
Topo	Shortest distance	0.0393	0.0343	0.0244	0.021	0.0413	**0.082**	0.0333	**0.054**	0.0614	**0.144**	0.1704	**0.367**	0.0121	**0.066**	**0.238**	**0.169**	0.0973	3
Topo	Sum clustering index	0.0044	0.0022	0.0235	0.0023	0.0047	0.0298	0.0229	**0.034**	0.0374	0.0414	0.1736	0.1135	0.048	0.0352	0.2769	0.0627	0.057	10
Topo	Common neighbors	**0.055**	0.0305	0.0372	0.0194	0.0266	**0.037**	0.0332	0.0351	0.0173	0.0271	0.2183	0.3101	0.0002	0.0044	0.3126	0.0994	0.079	6
Topo	Salton Index	**0.055**	0.0299	0.0383	0.023	0.0267	0.0358	0.0312	**0.034**	0.0175	0.0264	0.1942	**0.298**	0.0006	0.0052	**0.277**	**0.094**	0.0742	9
Topo	Jaccard Index	0.0095	0.0009	**4E-04**	**5E-04**	0.0046	0.0003	0	0	0.0011	0.0001	0	5E-05	0	0.0001	0	0	0.0011	27
Topo	Sorensen Index	0.0095	0.0009	0.0004	0.0005	0.0046	0.0003	0	0	0.0011	0.0001	0	5E-05	0	0.0001	0	0	0.0011	27
Topo	Adar-Adamic Index	**0.056**	**0.033**	0.0375	0.021	0.0269	**0.038**	0.0342	**0.037**	0.0171	0.0268	0.217	0.3032	0.0004	0.0042	**0.315**	0.0967	0.079	7
Topo	Resource Allocation Index	**0.056**	0.0325	**0.037**	**0.024**	**0.027**	0.038	0.0357	**0.035**	0.017	0.0268	0.2096	**0.3**	0.0004	0.0042	**0.316**	0.0943	0.0783	8
XN	Has link in housing network?	0	**0.042**	**0.061**	**0.031**	0	0.004	0.0123	0.0026	0	0.0028	0.0044	0.0007	0	0	0.0002	8E-05	0.0101	21
XN	Has link in mentoring network?	0.0124	0	0.031	0.0023	**0.032**	0	**0.053**	**0.012**	0.0136	0	0.0126	**0.002**	0.0005	0	0.0003	0.0004	0.0108	20
XN	Has link in trade network?	0.0008	0.002	0	**0.001**	0.0004	0.0005	0	0.0009	**0.016**	0.0101	0	**0.011**	**0.058**	**0.046**	0	0.057	0.0128	19
XN	Has link in group network?	**0.017**	**0.023**	**0.046**	0	**0.024**	**0.012**	**0.046**	0	**0.107**	**0.064**	0.0768	0	0.0054	0.0032	0.0027	0	0.0268	15

Figure 1. Information gain values for features in the EQII dataset show that certain features are rarely helpful (in lighter background) while others are consistently helpful (in darker background). Certain features, like *shortest distance* are useful in almost every prediction task.

B. Experiment 2

In this experiment, we investigate the performance of different machine learning models across the prediction tasks. Figure 3 lists the F-measure results for the positive class (link is formed) using 6 classifiers: J48, JRip, NaiveBayes, BayesNet, AdaBoost and ibk. A few key observations are:

- JRip is the best classifier for predicting housing, trade and group links with average F-measures of 0.8196, 0.7799 and 0.8679 respectively.
- None of the classifiers do well predicting mentoring links: the average best is only 0.5498 using J48.
- For the SmallBlue dataset, J48 gives the best performance for predicting both positive and negative links with average F-measures of 0.8411 and 0.6894 respectively.

C. Experiment 3

This experiment explores the feature space to find robust features that are good discriminators *across* the two datasets. For each prediction task, we sort the features in decreasing order of their info-gain value and look at the performance of the classifier using the top-k attributes in an ablation study. We repeat the process using the same classifier but the top-k *average*-ranked attributes for the dataset (refer to the last column, *Rank* of Figure 1). Based on the results from Experiment 2, JRip is used as the classifier for the EQII dataset and J48 for the SmallBlue dataset.

The process is illustrated in Figure 4 for the Housing-Housing prediction task where we compare the F-measure scores of the dataset-specific attributes model against the average-ranked attributes model. In this case, we observe that the JRip classifier performs very poorly with just the top two average-ranked attributes: *Char Level Sum* and *Avatar Age Sum*. This is because these two attributes have little discriminating power for the housing-housing prediction task (refer to column *HH* in Figure 1) and the classifier does not use them. Instead, it just predicts none of the node-pairs form a link. However, the third best average-ranked attribute *Shortest Distance* is discriminating for the HH prediction task, and so we see a drastic improvement in the results for top-k = 3. Observe that for $k \geq 2$ the difference in F-measure scores of the two models is less than 0.06.

	Prediction tasks (Training Period: JAN-AUG, Test Period: SEP-DEC)						
	Networks: P=SB Positive, N=SB Negative						
Category	**Feature Name**	**PP**	**NP**	**PN**	**NN**	**Averag**	**Rank**
Topo	Degree centrality (difference)	0.3985	0.3026	0.2335	0.1068	0.2603	2
Topo	Betweenness centrality (difference)	**0.367**	0.2584	0.2105	**0.095**	0.2326	5
Topo	Degree Sum	**0.448**	**0.352**	**0.272**	**0.122**	0.2986	1
Topo	Degree Difference	0.3985	0.3026	0.2335	0.1068	0.2603	2
Topo	Shortest distance	**0.386**	0.2216	**0.249**	**0.084**	0.2351	4
Topo	Sum clustering index	**0.274**	0.1052	0.1587	**0.059**	0.1492	6
Topo	Common neighbors	**0.146**	0.0794	0.1099	0.0308	0.0914	8
Topo	Salton Index	**0.149**	**0.084**	**0.115**	**0.035**	0.0958	7
Topo	Jaccard Index	0	9E-05	0.0001	0	6E-05	13
Topo	Sorensen Index	0	9E-05	0.0001	0	6E-05	13
Topo	Adar-Adamic Index	0.1429	0.0804	0.1098	**0.031**	0.0911	9
Topo	Resource Allocation Index	0.1427	0.0801	0.1096	**0.031**	0.0908	10
XN	Has link in positive?	0	**0.302**	0	0	0.0756	11
XN	Has link in negative?	0	0	**0.129**	0	0.0322	12

Figure 2. The info-gain matrix for SmallBlue predictive tasks shows that the topological features have similar utility as for EQII predictive tasks.

Figure 5 shows results of the ablation study for all of the 16 EQII prediction tasks using the average-ranked attributes. Each line in the plot depicts how the performance of the

Classifier	HH	MH	TH	GH	HM	MM	TM	GM	HT	MT	TT	GT	HG	MG	TG	GG		PP	NP	PN	NN
J48	0.7913	0.8166	0.8553	0.7979	0.5194	0.5417	0.6044	0.5337	0.7338	0.7086	0.7632	0.7909	0.8812	0.8211	0.8389	0.8741		0.8532	0.8289	0.8026	0.5762
JRip	0.8038	0.8138	0.8566	0.8043	0.4866	0.4657	0.5864	0.4947	0.767	0.7402	0.7924	0.82	0.8921	0.8352	0.8549	0.8893		0.8448	0.8079	0.8015	0.5838
NaiveBayes	0.5463	0.376	0.3579	0.3101	0.2997	0.3226	0.3908	0.475	0.6222	0.7037	0.6564	0.6431	0.7053	0.5865	0.6913	0.7251		0.7284	0.4399	0.6244	0.4581
BayesNet	0.7358	0.5916	0.3579	0.2795	0.4574	0.4869	0.4728	0.4553	0.7355	0.7199	0.7893	0.7593	0.8466	0.7966	0.7706	0.8168		0.822	0.7676	0.7092	0.4556
AdaBoostM1	0.7238	0.3552	0.4093	0.3904	0.3139	0.3069	0.3902	0.3152	0.7377	0.7209	0.7778	0.7927	0.8595	0.8206	0.8271	0.8623		0.8048	0.8079	0.7812	0.5296
IBk	0.7262	0.749	0.8093	0.7204	0.4763	0.4877	0.5469	0.494	0.7113	0.6906	0.725	0.775	0.8714	0.8141	0.8339	0.8685		0.8461	0.8304	0.7978	0.55
Avg Best	JRip<0.8196>				J48<0.5498>				JRip<0.7799>				JRip<0.8679>					J48<0.8411>		J48<0.6894>	

Figure 3. The F-measure for the different prediction tasks across the two datasets shows that JRip performs well for EQII and J48 for SmallBlue.

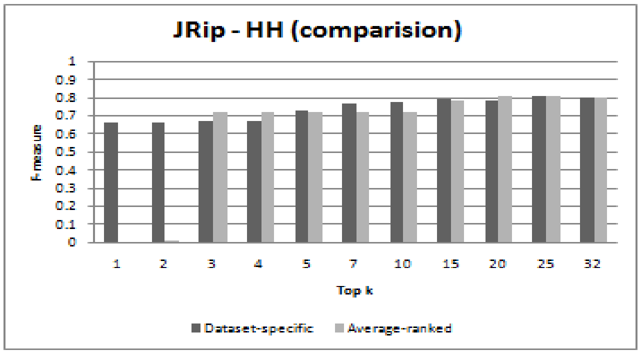

Figure 4. The top-3 average-ranked features provide almost as much predictive accuracy as the top-3 dataset-specific features (JRip for Housing-Housing prediction). The X-axis represents how many features were used, and the Y-axis represents accuracy from 0.0 to 1.0.

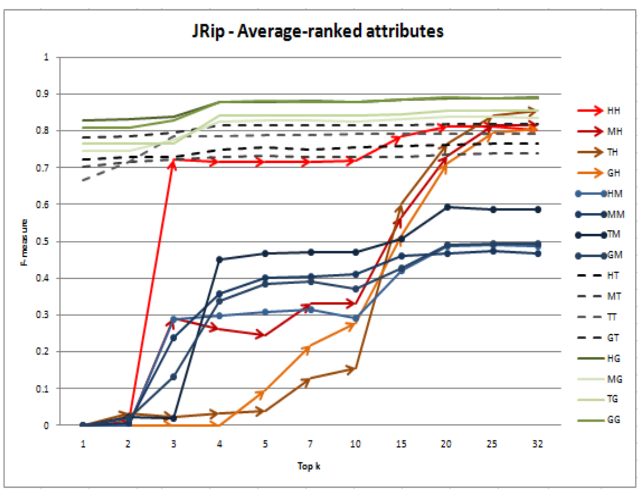

Figure 5. Predictive accuracy for EQII (JRip) using top-k average-ranked attributes. Line styles identify whether we are predicting Housing(arrow), Mentoring(circle), Group(solid) or Trade(dashed). On average, for $k > 10$, the difference is less than 12% of the best F-measure.

JRip classifier changes as we gradually increase the number of average-ranked attributes in the model.

The results point towards certain distinct patterns based on the type of social relationship being predicted. We observe that if we are trying to predict Group or Trade links, for $k \geq 4$ the performance is very close to the best F-measure that we can get using all 32 attributes. This implies that the attributes *Char Level Sum*, *Avatar Age Sum*, *Shortest Distance* and *Char Level Difference* can predict Group or

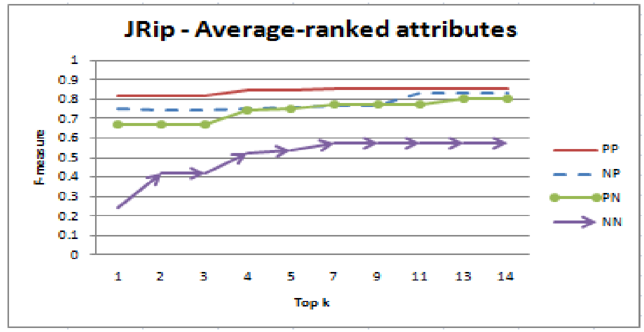

Figure 6. Predictive Accuracy for SmallBlue (JRip) using top-k average-ranked attributes.

Trade ties with a high degree of accuracy.

When predicting Mentoring and Housing links, we observe that we need more than 4 average-ranked attributes to converge towards the best results. For Mentoring link prediction convergence happens at k = 15 whereas for Housing link prediction convergence requires an even larger k (between 20 and 25). An exception for Housing link prediction is the Housing-Housing prediction task, where we observe that we get very good results as soon as we get to top-k = 3 i.e., we use *Shortest Distance*. If we observe the average across the 16 prediction tasks, we find that for $k \geq 4$, the difference is less than 20%, and for $k > 10$, the difference is less than 12% of the best F-measure.

For the SmallBlue prediction tasks (Figure 6), we observe that with just the top average-ranked attribute (*Sum of Degree*), the prediction accuracy is very near the best for PP, NP and PN. However, for the NN prediction task, convergence happens around k = 4.

VI. Discussion

Experiment 1 results showed *Shortest Distance* to be a very good predictor. This can be attributed to the fact that a person is more likely to trust someone who is friend of a friend. We observe that if we are predicting a housing tie, having a housing or group relationship (cross-network feature) is helpful. This is because both of these are positive relationships and thus, having a grouping or housing relationship can lead to formation of trust in the future. For the same reason, if we are a predicting mentoring tie, having a mentoring or group relationship (cross-network feature) is helpful. Cross-network features are not good for trade ties because trade is a neutral type of relationship. In the SmallBlue dataset, we observe that mixed sentiments between two people during the training period are likely to develop into positive sentiments in the test period. This agrees with another study on the dataset, which shows sentiments between employees in the organization tend to improve over time. That means employees' relationship with their colleagues will improve in general, as they get to know each other better.

Experiment 2 showed that a rule-based classifier can achieve high degree of accuracy in predicting all types of ties except in the case of Mentoring links. This is because even though on surface, mentoring in MMOs may appear to be a singular social phenomenon, but previous research [3] has shown that people mentor for four primary reasons that are manifested in the different characteristics of mentor-apprentice pairs. The classifier is trying to fit a single model to four different processes and hence it is performing poorly.

Experiment 3 results indicate that *Char Level Sum* and *Avatar Age Sum* are top two attributes across all EQII prediction tasks. This can be explained for mentoring relationship because by nature this kind relationship is allowed only if there is sufficient difference in level and hence age. Also, for networks where the cost of forming a link is low, we find *Sum of Degree* to be an important variable (e.g: Smallblue, Grouping and Trade). This is because people who have higher degree tend to form more links within that network/relationship.

VII. Conclusion

We have done a detailed exploration of a set of 32 features that can be used to predict trust in social networks. As part of this study, we performed link prediction experiments using two very different datasets: SOE's Everquest II MMORPG game dataset and IBM's SmallBlue sentiments dataset. Prior work did not cover as many features nor multiple datasets. Our experiment results show that JRip rule-based classifier performs consistently well for the EQII dataset and J48 decision tree does well for the SmallBlue dataset. Shortest Distance and Sum of Degree are found to be robust, discriminating features across multiple prediciton tasks for the two datasets. Finally, based on experiment results and observations, we have provided insights into the underlying online social processes. The features analyzed in this paper are generic in nature - the node properties capture aspects such as node age and seniority, the topological features are based on the network structure and the cross-network features can be interpreted as inter-network influence on trust. So, appropriate versions of these features can be used in other social networks for predicting trust formation.

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References

[1] Lada A. Adamic and Eytan Adar. Friends and neighbors on the web. *Social Networks*, 25(3):211–230, July 2003.

[2] M. A. Ahmad, Z. Borbora, J. Srivastava, and N. Contractor. Link prediction across multiple social networks. *ICDM Workshops*, pages 911–918, 2010.

[3] M.A. Ahmad, D. Huffaker, Jing Wang, J. Treem, D. Kumar, M.S. Poole, and J. Srivastava. The many faces of mentoring in an mmorpg. In *Social Computing (SocialCom), 2010 IEEE Second International Conference on*, pages 270 –275, aug. 2010.

[4] Donovan Artz and Yolanda Gil. A survey of trust in computer science and the semantic web. *Web Semantics: Science, Services and Agents on the World Wide Web*, 5(2):58 – 71, 2007. Software Engineering and the Semantic Web.

[5] L. Freeman. A set of measures of centrality based upon betweenness. *Sociometry*, pages 35–41, 1977.

[6] Jennifer Golbeck. *Computing with Social Trust*. Springer Publishing Company, Incorporated, 1st edition, 2008.

[7] Elizabeth Gray, Jean-Marc Seigneur, Yong Chen, and Christian Jensen. Trust propagation in small worlds. In Paddy Nixon and Sotirios Terzis, editors, *Trust Management*, volume 2692 of *Lecture Notes in Computer Science*, pages 1072–1072. Springer Berlin / Heidelberg, 2003.

[8] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten. The weka data mining software: An update. *SIGKDD Explorations*, 11(1), 2009.

[9] M. A. Hall. Correlation-based feature selection for discrete and numeric class machine learning. In *Proc. 17th Intl. Conf. Machine Learning*, pages 359–366, 2000.

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

[11] Paul Jaccard. Distribution de la flore alpine dans le bassin des dranses et dans quelques régions voisines. *Bulletin de la Société Vaudoise des Sciences Naturelles*, 37:241–272, 1901.

[12] Raph Levien. Attack-resistant trust metrics. In Jennifer Golbeck, editor, *Computing with Social Trust*, Human-Computer Interaction Series, pages 121–132. Springer London, 2009.

[13] M. E. J. Newman. The structure of scientific collaboration networks. *Proceedings of the National Academy of Sciences*, 98(2):404–409, 2001.

[14] J. Nieminen. On the centrality in a graph. *Scandinavian Journal of Psychology*, 15:332–336, 1974.

[15] G. Salton and M. J. McGill. *Introduction to Modern Information Retrieval*. (New York, NY: McGraw-Hill), 1983.

[16] T. Sørensen. A method of establishing groups of equal amplitude in plant sociology based on similarity of species content and its application to analyses of the vegetation on danish commons. *Biologiske Skrifter / udg. af det Kgl. Danske Videnskabernes Selskab*, pages 1–34, 1948.

[17] Tao Zhou, Linyuan Lü, and Yi-Cheng Zhang. Predicting missing links via local information. *The European Physical Journal B - Condensed Matter and Complex Systems*, 71(4):623–630, 2009.

[18] Cai-Nicolas Ziegler and Georg Lausen. Propagation models for trust and distrust in social networks. *Information Systems Frontiers*, 7:337–358, 2005.