Is Distrust the Negation of Trust? The Value of Distrust in Social Media

Jiliang Tang, Xia Hu and Huan Liu
Computer Science and Engineering
Arizona State University
Tempe, AZ, USA
{Jiliang.Tang, Xia.Hu, Huan.Liu}@asu.edu

ABSTRACT

Trust plays an important role in helping online users collect reliable information, and has attracted increasing attention in recent years. We learn from social sciences that, as the conceptual counterpart of trust, distrust could be as important as trust. However, little work exists in studying distrust in social media. What is the relationship between trust and distrust? Can we directly apply methodologies from social sciences to study distrust in social media? In this paper, we design two computational tasks by leveraging data mining and machine learning techniques to enable the computational understanding of distrust with social media data. The first task is to predict distrust from only trust, and the second task is to predict trust with distrust. We conduct experiments in real-world social media data. The empirical results of the first task provide concrete evidence to answer the question, "is distrust the negation of trust?" while the results of the second task help us figure out how valuable the use of distrust in trust prediction.

Categories and Subject Descriptors

H3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval—*Information filtering*

General Terms

Algorithms; Design; Experimentation

Keywords

Distrust; The Negation of Trust; A New Dimension of Trust; Added Value of Distrust

1. INTRODUCTION

The pervasion of social media produces a large amount of user generated data, which exacerbates the information overload problem. Trust, which provides information about from whom we should accept information and with whom we should share information [8], plays an important role in helping online users collect reliable information. Therefore trust is extensively studied in social media [36], which encourages many trust related applications such as trust-aware recommendation systems [8, 23], finding high-quality user generated content [21], and viral marketing [30].

Social scientists notice that distrust, the conceptual counterpart of trust, could be as important as trust [31, 18, 3]. For example, both trust and distrust help a decision maker reduce the uncertainty and vulnerability (i.e., risk) associated with decision consequences [3], and distrust may exert a more critical role than trust in consumer decisions [32, 27]. A fundamental problem about distrust is what the relation between trust and distrust is. Some social scientists suggest that distrust is the negation of trust and they are two ends of the same conceptual spectrum [31, 1, 13]. Their theories indicate that low trust is equivalent to high distrust; likewise, the absence of distrust means high trust, and outcomes of high (or low) trust would be identical to those of low (or high) distrust. An alternative understanding is that distrust is a new dimension of trust [18, 15]. There is no consensus answer about the question, which is still considered as the "darker" side of trust by some social scientists [24].

Distrust has attracted increasing attention from social sciences and social scientists investigate distrust from the perspectives of formation mechanisms and constructs [18, 3]. While little work exists in studying distrust in social media and understanding distrust with social media data faces unique challenges. Social media does not provide the necessary information for these perspectives sociologists ascribe in studying distrust, because more often than not, available social media data is from passive observation. This property of social media data not only determines that it is difficult to directly apply methodologies from social sciences but also suggests that we should understand distrust in social media from a new perspective.

In this paper, we study distrust in social media from the computational perspective. The significance of this study is two-fold. First, our work provides the first systematical understanding of distrust in social media. Second, we provide results in social media from the computational perspective, which is complementary to those from social sciences. We first investigate the properties of distrust, and then design two computational tasks by leveraging data mining and machine learning techniques to enable the understanding of distrust with social media data.

- *Task 1:* Predicting distrust from only trust, which is designed to seek an answer for the question of "is dis-

HT'14, September 1–4, 2014, Santiago, Chile.
Copyright 2014 ACM 978-1-4503-2954-5/14/09 ...$15.00.
http://dx.doi.org/10.1145/2631775.2631793 .

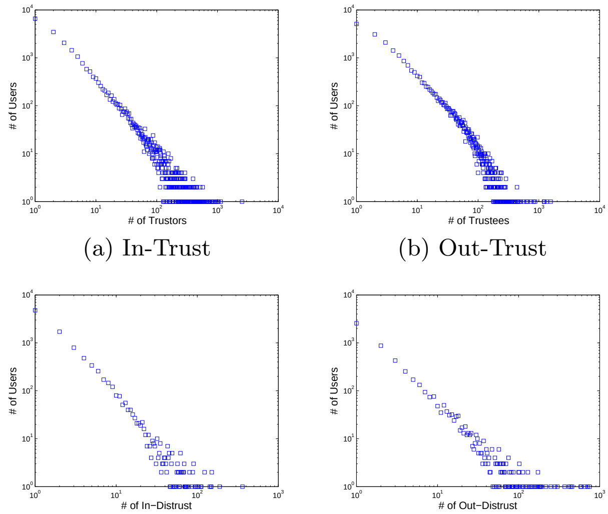
Table 1: Statistics of the Epinions.

# of Users	30,455
# of Trust Relations	363,773
# of Distrust Relations	46,196
# of Users Receiving Distrust	9,513
# of Users Creating Distrust	5,324
# of Items	89,270
# of Ratings	562,355
Avg of Rating Score	3.9053

trust the negation of trust?" The intuition of *Task 1* is if distrust is the negation of trust, evidence of low trust can indicate that of distrust, hence, distrust could be predicted by trust.

- *Task 2:* Predicting trust with distrust, which is designed to measure the value of distrust. The intuition of *Task 2* is if distrust has added value over trust, we can potentially predict trust better with distrust.

The rest of paper is organized as follows. Section 2 describes the dataset used in this study and investigates the properties of distrust. Section 3 introduces the details about the first task. We introduce the second task in Section 4. Section 5 presents experimental results and our observations. Section 6 briefly reviews related work. Section 7 concludes this study with future work.



(a) In-Trust (b) Out-Trust (c) In-Distrust (d) Out-Distrust

Figure 1: The Distributions of Trust and Distrust. Note that "In-Trust", "Out-Trust", "In-Distrust" and "Out-Distrust" in the figure denote trust receiving, trust creating, distrust receiving and distrust creating, respectively.

2. PROPERTIES OF DISTRUST

The properties of trust are systematically and extensively studied, and some important properties include transitivity, asymmetry and correlation with similarity [6]. However, the properties of distrust are seldom studied in social media. Can we equally and conversely extend the properties of trust to distrust? In this section, we investigate the properties of distrust analogy to those of trust with real-world social media data.

Before investigations, we first introduce the dataset we used in this work. We collect a dataset from an online social media website Epinions [1] to study distrust. Epinions is a product review site where online users can rate various products with reviews, and establish both trust and distrust relations with other users. We preprocess the data by filtering users without any trust and distrust relations, and the statistics of the dataset are shown in Table 1.

We compute the number of trust and distrust relations each user receives and creates, and these distributions are shown in Figure 1. Note that "In-Trust", "Out-Trust", "In-Distrust" and "Out-Distrust" in the figure denote trust receiving, trust creating, distrust receiving and distrust creating, respectively. The distributions for both trust and distrust suggest a power-law-like distribution that is typical in social networks. With this dataset, we study the properties of distrust in the following subsections.

2.1 Transitivity

Transitivity is a primary property of trust and it describes that trust can be passed between people [13, 6]. For example, if user u_i trusts user u_j, and user u_j trusts user u_k, then transitivity indicates that with a high probability, user u_i will trust user u_k. In this subsection, we study the property of distrust with respect to transitivity. Note that in this paper, we use x+y, x-y, and x?y to denote the observations of a trust, a distrust and a missing relation from user x to user y, respectively.

To investigate the transitivity property of distrust, we first find all pairs of relations $\langle u_i$-u_j,u_j-$u_k\rangle$, and check whether u_i and u_k are with a trust (u_i+u_k), a distrust (u_i-u_k), or a missing relation (u_i?u_k). We conduct a similar process for trust, and the results are demonstrated in Table 3. For the first calculation, we consider all $\langle u_i$,$u_k\rangle$ pairs (i.e., u_i+u_k, u_i-u_k, and u_i?u_k) and use "P1" to denote the percentage of pairs of $\langle$ u_i,$u_k\rangle$ with a trust, a distrust or a missing relation over all pairs. For the second calculation, we only consider$\langle u_i$,$u_k\rangle$ pairs with observed relations (i.e., trust u_i+u_k and distrust u_i-u_k), and adopt "P2" to represent the percentage of $\langle$ u_i,$u_k\rangle$ with a trust or a distrust relation over pairs with observed relations (i.e., u_i+u_k and u_i-u_k). The results are shown in Table 3.

Golbeck suggests that trust is not perfectly transitive in the mathematical sense and is conditionally transitive [6], which is consistent with our observations - a trust relation u_i+u_k only takes 11.46% (P1) of all pairs of $\langle u_i$,u_k $\rangle$ for trust. However, among pairs with observed relations, u_i+u_k takes as high as 97.75% (P2), which suggests the transitivity property for trust - if u_i establishes a relation with u_k, it is likely to be a trust relation. For distrust, the percentages of u_i-u_k and u_i+u_k are comparable. u_i-u_k suggests transitivity, while u_i+u_k can be explained by balance theory [2, 12] as "the enemy of your enemy is your friend." These observations are consistent with two possible relations between u_i and u_k suggested by [10]. First, perhaps u_i has concluded that u_j's judgments are simply inferior to u_i's own, and u_j has concluded the same about u_k, therefore u_i

[1]http://www.epinions.com/

Table 2: Transitivity of Trust and Distrust.

Types	Number	P1	P2
Trust			
$\langle u_i$+u_j,u_j+$u_k\rangle$, $u_i?u_k$	25,584,525	88.34%	N.A
$\langle u_i$+u_j,u_j+$u_k\rangle$, u_i+u_k	3,320,991	11.46%	97.75%
$\langle u_i$+u_j,u_j+$u_k\rangle$, u_i-u_k	76,613	0.2%	2.25%
Distrust			
Types	Number	P1	P2
$\langle u_i$-u_j,u_j-$u_k\rangle$, $u_i?u_k$	716,340	91.70%	N.A
$\langle u_i$-u_j,u_j-$u_k\rangle$, u_i+u_k	38,729	4.96%	59.73%
$\langle u_i$-u_j,u_j-$u_k\rangle$, u_i-u_k	26,114	3.34%	40.27%

Table 3: Asymmetry of Trust and Distrust.

	u_j+u_i(%)	u_j-u_i(%)	$u_j?u_i$(%)
u_i+u_j	136,806(37.61)	967(0.27)	226,000(62.13)
u_i-u_j	967(2.09)	2,623(5.86)	42,606(92.23)

should strongly distrust u_k as u_i-u_k. Second perhaps u_i is expressing the view that u_j's entire value model is so misaligned with u_i's that anyone u_j distrusts is more likely to be trusted by u_i as u_i+u_k.

2.2 Asymmetry

The asymmetry of trust is also important and suggests that for two people involved in a relation, trust is not necessarily identical in both directions [7]. For example, if u_i trusts u_j, one cannot infer that u_j trusts u_i. In this subsection, we examine the property of distrust in term of asymmetry.

For each trust relation u_i+u_j (or each distrust relation u_i-u_j), we check the possible relations between u_j and u_i, and the results are shown in Table 3. Note that in Table 3 the numbers in parentheses are the percentages of the corresponding relations over all possible relations. We observe 37.71% mutual trust relations, but only 5.86% mutual distrust relations. These results suggest that trust is asymmetric, and distrust is even more asymmetric.

2.3 Correlation with Similarity

Siegler et al. pointed out that there is a strong and significant correlation between trust and similarity [40], and users with trust relations are more similar than those without. In this subsection, we study the similarities of pairs of users with distrust relations. In the context of Epinions, the similarity is calculated as the rating similarity and in this paper we calculate the similarity between u_i and u_j as the number of common items rated by both u_i and u_j. The average similarities for pairs with trust, pairs with distrust and randomly selected pairs are 0.6792, 0.4994 and 0.1247, respectively. Pairs with distrust relations are much more similar than randomly selected pairs, which suggests that distrust may be not a dissimilarity measurement. However, they have much low similarities than pairs with trust relations, which indicates that distrust may not be a similarity measurement as trust.

2.4 Discussion

Through this comparative study of properties of trust and distrust with respect to transitivity, asymmetry and correlation with similarity, we can conclude that the properties of trust cannot be both equally and conversely extended to distrust. In the following two sections, we leverage data mining and machine learning techniques to design two tasks to enable the computational understanding of distrust with social media data. Before going to the following sections, we would like to first introduce notations used in this paper. Let $\mathcal{U} = \{u_1, u_2, \ldots, u_n\}$ be the user set where n is the number of users. We use $\mathbf{T} \in \mathbb{R}^{n\times n}$ to represent use-user trust relations where $\mathbf{T}_{ij} = 1$ if u_i trusts u_j, zero otherwise. Similarly, we use $\mathbf{D} \in \mathbb{R}^{n\times n}$ to denote user-user distrust relations where $\mathbf{D}_{ij} = 1$ if u_i distrusts u_j, zero otherwise.

3. DISTRUST PREDICTION WITH ONLY TRUST INFORMATION

Some social scientists, who believe distrust as the negation of trust, support that trust and distrust are two ends of the same conceptual spectrum, and distrust can be suggested by low trust [31, 1], which motivates us to design the first task of predicting distrust from only trust. The intuition behind this task is if distrust is the negation of trust, distrust can be suggested for pairs of users with low trust scores. Therefore *distrust prediction problem with only trust information boils down to the problem of predicting low trust with trust information.* Given the propagation of trust, the task of trust prediction is proposed to compute trust scores for any pairs of users in the same trust network [25]. Therefore trust scores of pairs of users in the same trust network can be obtained via trust prediction. For n users, there are totally n^2 pairs of users. Assume that N pairs of users have trust relations; while M pairs of users have distrust relations. The problem of *task 1* is formally stated as:

Given N pairs of users with trust relations, and a trust predictor f, we aim to predict M pairs of users with distrust relations from $n^2 - N$ pairs of users via low trust scores suggested by the trust predictor f.

If distrust is the negation of trust, pairs of users have distrust relations should have low trust among $n^2 - N$ pairs of users; otherwise, distrust is not the negation of trust. The framework of the first task *Task 1* is shown in Algorithm 1. Next we briefly review Algorithm 1. We first choose a trust prediction algorithm f to calculate trust scores for pairs of users without trust relations, and then suggest pairs with low trust scores to distrust. In this paper, we choose two representative trust prediction algorithms - trust propagation [10] and a matrix factorization based method [34] to calculate trust scores.

Algorithm 1 The framework of *Task 1* to predict distrust from only trust

Input: User-user trust relation matrix $\mathbf{T}$, a trust prediction algorithm f
Output: Ranking list of pairs of users

```
for Each pair of users without trust relations ⟨u_i, u_j⟩ do
    Calculate the score of T̃_ij that u_i trusts u_j by f
end for
Ranking pairs of users (e.g., ⟨u_i, u_j⟩) according to T̃_ij in an ascending order.
```

3.1 Trust propagation

In [10], a trust propagation framework is proposed with four atomic propagations - direct propagation, co-citation, transpose trust, and trust coupling as:

- if u_i trusts u_j, and u_j trusts u_k, direct propagation allows us to infer that u_i trusts u_k, and its corresponding operator is $\mathbf{T}$;
- co-citation propagation concludes that u_ℓ should trust u_j if u_i trusts u_j and u_k, and u_ℓ trusts u_k. $\mathbf{T}^\top\mathbf{T}$ is the operator of co-citation propagation;
- in transpose trust, u_i's trust of u_j causes u_j to develop some level of trust towards u_i, and its operator is $\mathbf{T}^\top$;
- trust coupling suggests that u_i and u_j trust u_k, so trusting u_i should imply trusting u_j. $\mathbf{T}\mathbf{T}^\top$ is its operator.

$\mathbf{C}$ is defined as a single combined matrix of all four atomic propagations,

$$\mathbf{C} = \alpha_1\mathbf{T} + \alpha_2\mathbf{T}^\top\mathbf{T} + \alpha_3\mathbf{T}^\top + \alpha_4\mathbf{T}\mathbf{T}^\top, \tag{1}$$

where α_1, α_2, α_3, and α_4 control contributions from direct propagation, co-citation, transpose trust and trust coupling, respectively.

Let $\mathbf{C}^k$ be a matrix where $\mathbf{C}^k_{ij}$ denotes the propagation from u_i to u_j after k atomic propagations, and the final estimated matrix representation of the user-user trust relation $\tilde{\mathbf{T}}$ is given by [10],

$$\tilde{\mathbf{T}} = \sum_{k=1}^{K} \gamma^k \mathbf{C}^k \tag{2}$$

where K is the number of steps of propagation and γ^k is a discount factor to penalize lengthy propagation steps.

3.2 Matrix factorization based method

The low-rank matrix factorization method is widely employed in various applications such as collective filtering [14, 35] and document clustering [39, 5]. A few factors can influence the establishment of trust relations and a user usually establishes trust relations with a small proportion of $\mathcal{U}$, resulting in very sparse and low-rank $\mathbf{T}$; hence, users can have a more compact but accurate representation in a low-rank space [34]. The matrix factorization model seeks a low-rank representation $\mathbf{U} \in \mathbb{R}^{n\times d}$ with $d \ll n$ for $\mathcal{U}$ via solving the following optimization problem,

$$\min_{\mathbf{U},\mathbf{V}} \quad \|\mathbf{T} - \mathbf{U}\mathbf{V}\mathbf{U}^\top\|_F^2, \tag{3}$$

where $\|\cdot\|_F$ is the Frobenius norm of a matrix and $\mathbf{V} \in \mathbb{R}^{d\times d}$ captures the correlations among their low-rank representations such as $\mathbf{T}_{ij} = \mathbf{U}_i\mathbf{V}\mathbf{U}_j^\top$. It is easy to verify that Eq. (3) can model the properties of trust such as transitivity and asymmetry [34]. For example, the learned $\mathbf{V}$ is asymmetric, therefore $\mathbf{T}_{ij} = \mathbf{U}_i\mathbf{V}\mathbf{U}_j^\top$ could be unequal to $\mathbf{T}_{ji} = \mathbf{U}_j\mathbf{V}\mathbf{U}_i^\top$.

To avoid over-fitting, we add two smoothness regularizations on $\mathbf{U}$ and $\mathbf{V}$, respectively, into Eq. (3), and then we have,

$$\min_{\mathbf{U},\mathbf{V}} \quad \|\mathbf{T} - \mathbf{U}\mathbf{V}\mathbf{U}^\top\|_F^2 + \alpha\|\mathbf{U}\|_F^2 + \beta\|\mathbf{V}\|_F^2, \tag{4}$$

where α and β are non-negative, and are introduced to control the capability of $\mathbf{U}$ and $\mathbf{V}$, respectively. With the learned $\mathbf{U}$ and $\mathbf{V}$, the estimated matrix representation of the user-user trust relation $\tilde{\mathbf{T}}$ is obtained as $\tilde{\mathbf{T}} = \mathbf{U}\mathbf{V}\mathbf{U}^\top$.

4. TRUST PREDICTION WITH DISTRUST INFORMATION

An alternative understanding is that distrust is a new dimension of trust rather than the negation of trust [18, 15]. If distrust is a new dimension of trust, distrust should provide extra information about users, and have potentially added value beyond trust. This intuition motivates us to design the second task to measure the value of distrust. The second task *Task 2* is to predict trust relations among users with distrust information. If distrust has added value over trust, we should predict trust better with distrust information. Assume that $\mathcal{E}$ is the set of pairs of users creating new trust relations after N pairs of users, and then *task 2* is formally stated as,

Given N pairs of users with trust relations, and M pairs of users with distrust relations, we aim to suggest new trust relations to $|\mathcal{E}|$ pairs of users by using information of both N trust relations and M distrust relations.

If distrust is a new dimension of trust and has added value about users beyond trust, using both N trust relations and M distrust relations should obtain better performance than only using N trust relations. Next we will investigate how to exploit distrust in the previously mentioned trust prediction algorithms - trust propagation and the matrix factorization based method.

4.1 Trust propagation with distrust information

The propagation of distrust has attracted increasing attention recently, and two distrust propagation mechanisms are widely investigated [42, 10]. One mechanism assumes that trust and distrust both propagate together, and the single combined matrix of all atomic propagations is defined as,

$$\mathbf{E} = \alpha_1\mathbf{F} + \alpha_2\mathbf{F}^\top\mathbf{F} + \alpha_3\mathbf{F}^\top + \alpha_4\mathbf{F}\mathbf{F}^\top, \tag{5}$$

where $\mathbf{F} = \mathbf{T} - \mathbf{D}$ and the estimated user-user trust matrix $\tilde{\mathbf{G}}$ is obtained similarly to Eq. (2) as,

$$\tilde{\mathbf{G}} = \sum_{k=1}^{K} \gamma^k \mathbf{E}^k. \tag{6}$$

The other assumes if u_i distrusts u_j, u_i will discount all judgments made by u_j, hence, distrust propagates only a single step instead of propagating repeatedly as trust. Under this mechanism, the estimated user-user trust matrix $\tilde{\mathbf{G}}$ is computed as [10],

$$\tilde{\mathbf{G}} = \sum_{k=1}^{K} \gamma^k \mathbf{C}^k(\mathbf{T} - \mathbf{D}) \tag{7}$$

4.2 The matrix factorization based method with distrust information

A straightforward way to incorporate distrust into the matrix factorization based method is to replace $\mathbf{T}$ in Eq. (4)

which exploits balance theory under the matrix factorization framework. The parameter λ is introduced to control the contributions from balance theory.

The proposed framework disMF is to solve the following optimization problem,

$$\min_{\mathbf{U},\mathbf{V},\mathbf{r}} \|\mathbf{F} - \mathbf{U}\mathbf{V}\mathbf{U}^\top - \lambda\mathbf{r}\mathbf{r}^\top\|_F^2 + \alpha\|\mathbf{U}\|_F^2 + \beta\|\mathbf{V}\|_F^2 + \eta\|\mathbf{r}\|_2^2, \quad (12)$$

where $\mathbf{r} = [r_1, r_2, \ldots, r_n]^\top$ and the term $\|\mathbf{r}\|_2^2$ is introduced to avoid overfitting. A local minimum of Eq. (12) can be obtained through a gradient decent optimization method.

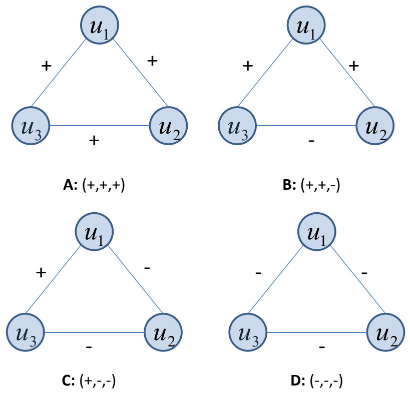


Figure 2: An Illustration of Balance Theory.

with $\mathbf{F} = \mathbf{T} - \mathbf{D}$ as,

$$\min_{\mathbf{U},\mathbf{V}} \quad \|\mathbf{F} - \mathbf{U}\mathbf{V}\mathbf{U}^\top\|_F^2 + \alpha\|\mathbf{U}\|_F^2 + \beta\|\mathbf{V}\|_F^2, \quad (8)$$

where $\mathbf{F}_{ij}$ is modeled as

$$\mathbf{F}_{ij} = \mathbf{U}_i\mathbf{V}\mathbf{U}_j^\top. \quad (9)$$

As mentioned above, balance theory paves a way to understand the formation of trust and distrust, and prediction accuracy may be improved by exploiting balance theory. For example, in [17], local-topology-based features based on balance theory are extracted to improve the performance of a logistic regression classifier in signed relation prediction. Next we will investigate how to exploit balance theory under the matrix factorization framework. Note that balance theory is proposed for undirected networks and following a common practice [17], we ignore the directions of relations, and only consider the signs of relations (i.e., trust and distrust) when modeling balance theory.

We use s_{ij} to denote the sign of the relation between u_i and u_j where $s_{ij} = 1$ (or $s_{ij} = -1$) if we observe a trust relation (or a distrust relation) between u_i and u_j. With these notations, balance theory suggests that a triad $\langle u_i, u_j, u_k\rangle$ is balanced if

- $s_{ij} = 1$ and $s_{jk} = 1$, then $s_{ik} = 1$; or
- $s_{ij} = -1$ and $s_{jk} = -1$, then $s_{ik} = 1$.

For a triad $\langle u_i, u_j, u_k\rangle$, there are four possible sign combinations **A**(+,+,+), **B**(+,+,-) **C**(+,-,-) and **D**(-,-,-) as shown in Figure 2. According to balance theory, only **A**(+,+,+) and **C**(+,-,-) are balanced.

There are three major ways to exploit social theories in social media mining including feature engineering, constraint generating, and objective defining [33]. In this work, we choose objective defining to model balance theory. For each user u_i, we introduce a one-dimensional latent factor r_i and we further assume that the trust relation between u_i and u_j due to the effect of balance theory is captured as [37],

$$\mathbf{F}_{ij} = r_i r_j, \quad (10)$$

It is easy to verify that Eq. (10) can capture balance theory.

Combining Eq. (9) and Eq. (10), $\mathbf{F}_{ij}$ can be modeled as

$$\mathbf{F}_{ij} = \mathbf{U}_i\mathbf{V}\mathbf{U}_j^\top + \lambda r_i r_j, \quad (11)$$

5. EXPERIMENTS

In this section, we conduct experiments to answer the following questions - (1) is distrust the negation of trust? and (2) does distrust have added value in trust prediction? To answer the first question, we check how accurately we can predict distrust from only trust by evaluating *Task 1*. To answer the second question, we examine whether the performance of trust prediction is improved by exploiting distrust by evaluating *Task 2*. Finally we further probe the effects of distrust in disMF to seek a deep understanding of the value of distrust in trust prediction. Since most of trust prediction algorithms such as trust prediction and matrix factorization methods cannot work well with users with very few trust relations, we further filter users with less than three trust relations and finally we obtain a dataset with $12,353$ users, $322,040$ trust relations and $41,253$ distrust relations for the following evaluations.

5.1 Evaluation of *Task 1*

We first introduce the experimental setting for this evaluation. $\mathcal{A}_T = \{\langle u_i, u_j\rangle | \mathbf{T}_{ij} = 1\}$ is the set of pairs of users with trust relations, and $\mathcal{A}_D = \{\langle u_i, u_j\rangle | \mathbf{D}_{ij} = 1\}$ is the set of pairs of users with distrust relations. The pairs in both $\mathcal{A}_T$ and $\mathcal{A}_D$ are sorted in chronological order in terms of the time when they established relations. We assume that until time t, x% of pairs in $\mathcal{A}_T$ establish trust relations, denoted as $\mathcal{A}_T^x$, and we use $\mathcal{A}_D^x$ to denote pairs of users in $\mathcal{A}_D$ establishing distrust until time t. x is varied as $\{50, 55, 60, 65, 70, 80, 90, 100\}$. For each x, we repeat the experiments for 10 times and report the average performance since most of predictors can only obtain local optimal solutions. The experimental setting is demonstrated in Figure 3 where N_T^x denotes the set of pairs without trust relations at the time t.

For each x, *Task 1* is to use $\mathcal{A}_T^x$ to predict $\mathcal{A}_D^x$ from N_T^x. We follow the common metric for trust evaluation in [19, 34] to assess the prediction performance. In detail, each predictor ranks pairs in N_T^x in **ascending** order of confidence and we take the first $|\mathcal{A}_D^x|$ pairs as the set of predicted distrust relations, denoting $\mathcal{A}_D^p$. Then the performance of *Task 1* is computed as,

$$M_1 = \frac{|\mathcal{A}_D^x \cap \mathcal{A}_D^p|}{|\mathcal{A}_D^x|} \quad (13)$$

where $|\cdot|$ denotes the size of a set. The results are shown in the Table 4. "dTP", "dMF", and "dTP-MF" and "Random" in the table are defined as follows:

- *dTP:* this distrust predictor uses the trust propagation algorithm to obtain trust scores for pairs of users and

Table 4: **Performance of Different Predictors for *Task 1*. The magnitude of all numbers in the table is 10^{-5}.**

x (%)	dTP ($\times 10^{-5}$)	dMF($\times 10^{-5}$)	dTP-MF($\times 10^{-5}$)	Random($\times 10^{-5}$)
50	4.8941	4.8941	4.8941	5.6824
55	5.6236	5.6236	5.6236	8.1182
60	7.1885	7.1885	7.1885	15.814
65	11.985	11.985	11.985	19.717
70	13.532	13.532	13.532	18.826
80	10.844	10.844	10.844	16.266
90	12.720	12.720	12.720	25.457
100	14.237	14.237	14.237	29.904

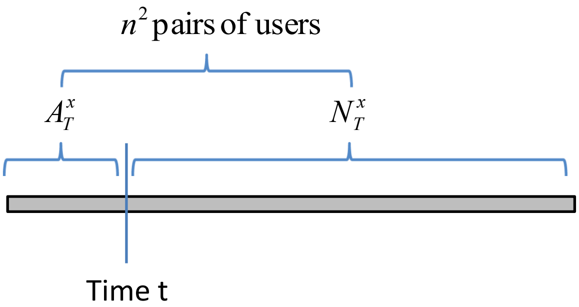


Figure 3: Experimental Settings for the Evaluation of *Task 1*.

then suggests distrust relations for pairs with low trust scores;

- *dMF:* this distrust predictor adopts the matrix factorization algorithm to compute trust scores for pairs of users and then predict pairs with low trust scores as distrust relations;
- *dTP-MF:* this distrust predictor combines trust scores inferred by dTP and dMF to infer distrust relations; and
- *Random:* this distrust predictor randomly guesses pairs of users with distrust relations.

All parameters in above predictors are determined through cross-validation and the magnitude of all numbers in the table is 10^{-5}.

If distrust is the negation of trust, low trust scores should accurately indicate distrust. However, we observe that the performance of dTP, dMF and dTP-MF is consistently worse than that of the randomly guessing (Random). These results suggest that low trust scores cannot be used to predict distrust; hence distrust is not the negation of trust. Social scientists, who support distrust as a new dimension of trust, argue that pairs of users with untrust can have very low trust scores [24, 9]. This phenomenon is especially true with social media data since users in social media are world-widely distributed and many pairs of users in the trust network do not know each other. As mentioned above, $\mathcal{A}_D^x$ is the set of pairs of users who have distrust relations as ground truth, while $\mathcal{A}_D^p$ is the set of pairs who are predicted with distrust relations (or with low trust scores). The low accuracies in Table 4 also suggest that pairs of users in $\mathcal{A}_D^p$ may also have low distrust.

Let us further examine trust scores for users in $\mathcal{A}_D^x$ and $\mathcal{A}_D^p$ when $x = 70$, since we have similar observations for other values of x. We use $\mathbf{t}_x$ and $\mathbf{t}_p$ to represent the trust score vectors of $\mathcal{A}_D^x$ and $\mathcal{A}_D^p$, respectively. We find that the mean of $\mathbf{t}_x$ 0.0149 is much larger than that of $\mathbf{t}_p$ 5.8634e-7 and its significance is also confirmed by the t-test. These results suggest that pairs of users with distrust relations (or in $\mathcal{A}_D^x$) are unnecessary to have low trust scores.

To sum up, pairs of users with distrust relations are not necessary to have low trust scores and pairs with low trust are not necessary to have distrust relations. These results show strong evidence that using low trust scores fails to predict distrust, and suggest that distrust is not the negation of trust in social media, which correspondingly answer the first question.

5.2 Evaluation of *Task 2*

Before going to the detailed evaluation, we first introduce the experimental setting for this evaluation. We use $\mathcal{O} = \{\langle u_i, u_j\rangle | \mathbf{T}_{ij} \neq 1\}$ to denote the set of pairs of users without trust relations. We choose $x\%$ of $\mathcal{A}_T$ as old trust relations $\mathcal{A}_T^x$, and the remaining $1 - x\%$ as new trust relations $\mathcal{A}_T^n$ to predict. We assume that the last pair of users establishes a trust relation at time t, and we use $\mathcal{A}_D^x$ to denote pairs of users in $\mathcal{A}_D$ establishing distrust until time t. In this paper, we vary x as $\{50, 55, 60, 65, 70, 80, 90\}$. For each x, we also repeat the experiments 10 times and report the average performance. The experimental setting is illustrated in Figure 5 where N_T^x denotes the set of pairs without trust relations at time t.

For each x, *Task 2* uses old trust relations $\mathcal{A}_T^x$ and distrust relations $\mathcal{A}_D^x$ to predict new trust relations $\mathcal{A}_T^n$. We follow a similar evaluation metric for *Task 1* to assess *Task 2*. In particular, each predictor ranks pairs in N_T^x in **decreasing** order of confidence and we take the first $|\mathcal{A}_T^n|$ pairs as the set of predicted trust relations, denoting as $\mathcal{A}_T^p$. Then the performance of *Task 2* is computed as,

$$M_2 = \frac{|\mathcal{A}_T^n \cap \mathcal{A}_T^p|}{|\mathcal{A}_T^n|} \tag{14}$$

We use disTP-m and disTP-s to denote performing multiple steps and a single step distrust propagation in trust propagation (TP), and their comparison results are shown in Figure 4. disMF incorporates distrust into the matrix factorization method (MF) framework, and their comparison results are demonstrated in Figure 6. Parameters for all methods are determined via cross validation. Note that "Random" in figures denotes the performance of randomly guessing.

	50%	55%	60%	65%	70%	80%	90%
TP	**0.1376**	0.1354	0.1293	0.1264	0.1201	0.1156	0.1098
disTP-s	**0.1435**	0.1418	0.1372	0.1359	0.1296	0.1207	0.1176
disTP-m	**0.1422**	0.1398	0.1359	0.1355	0.1279	0.1207	0.1173
Random	**0.0023**	0.0023	0.0020	0.0019	0.0018	0.0015	0.0013

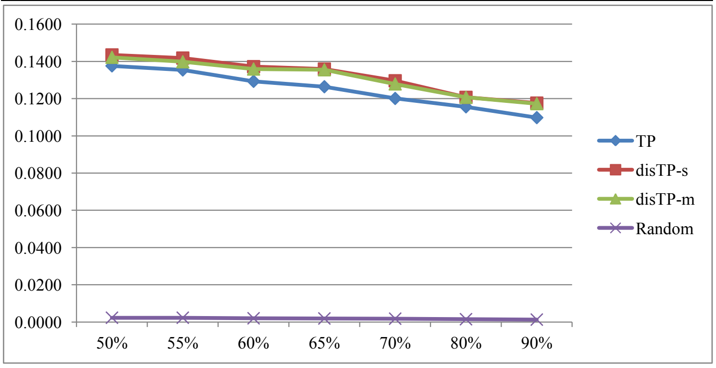


Figure 4: Performance Comparison for Trust Propagation without and with Distrust. The prediction problem becomes more difficult from 50% to 90%.

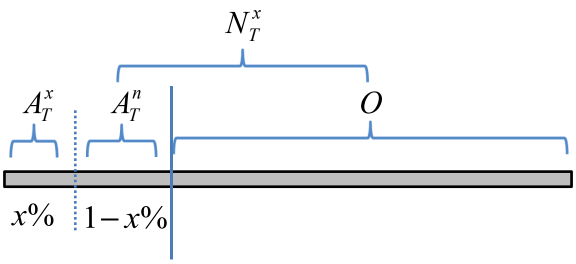


Figure 5: Experimental Setting for the Evaluation of *Task 2*.

Let us first examine the performance comparisons when $x = 50$, which are highlighted in Figure 4 and Figure 6. We make the following observations:

- For the first column results in Figure 4, both disTP-s and disTP-m outperform TP. For example, disTP-s obtains 4.28% relative improvement compared to TP. disTP-s and disTP-m incorporate distrust propagation in the trust propagation, and the improvement is from the distrust propagation. These results support that distrust can improve trust propagation and leads to the performance gain in trust prediction. We also note that most of the time, disTP-s with one-step distrust propagation outperforms disTP-m with multiple step distrust propagation.
- For the first column results in Figure 6, disMF obtains better performance than MF, and gains 8.55% relative improvement over MF. There are two major contributors - (1) factorizing both trust and distrust instead of only trust as MF; and (2) modeling balance theory. We will further investigate the effects of distrust in disMF in the following subsection.

For other values of x, we can have similar observations - distrust can improve the performance of trust prediction. For example, on average, disTP-s and disMF obtain 6.01% and 10.78% relative improvement over TP and MF, respectively. We also note that with the increase x, the performance of all methods reduces. With the increase of x, the size of $\mathcal{A}_T^n$ $1 - x\%$ decreases. Since the size of $\mathcal{O}$ is fixed, it becomes more and more difficult to predict $\mathcal{A}_T^n$, which is buried in $\mathcal{O}$. This observation is consistent with that in [34].

We perform t-test on all improvement above and the t-test results suggest that all improvement is significant. With the help of distrust, *Task 2* can significantly improve the performance of trust prediction, which supports a positive answer to the second question - distrust has added value over trust. For disTP-s and disTP-m, the improvement is from integrating distrust propagation into trust propagation. While for disMF, there are major two contributors to the improvement - (1) incorporating distrust into trust during the factorization process; (2) capturing balance theory. In the following subsection, we will investigate the effects of these two components on disMF.

5.3 Effects of Distrust in disMF

There are two components in disMF to exploit distrust for disMF. The parameter λ controls their contributions. For example, we can eliminate the effect for the component of balance theory by setting $\lambda = 0$. Therefore we investigate the effects of distrust in disMF by analyzing how the changes of λ affect the performance of disMF. The value of λ is varied as $\{0, 0.001, 0.01, 0.1, 0.5, 1, 5, 10, 100\}$, and the results are depicted in Figure 7. In general, the performance first increases, and then degrades rapidly. In particular, it can be observed,

- when λ is equal to 0, we eliminate the effect of the component of balance theory, and then the only difference between MF and disMF is that disMF is also factorized with distrust in addition to trust. The performance comparison of MF and disMF with $\lambda = 0$ is shown in Table 5. Note that "Imp" denotes the relative performance improvement of disMF with different values of λ compared to "MF". disMF can significantly

	50%	55%	60%	65%	70%	80%	90%
MF	**0.1531**	0.1502	0.1489	0.1444	0.1391	0.1332	0.1277
disMF	**0.1665**	0.1654	0.1639	0.1601	0.1563	0.1498	0.1415
Random	**0.0023**	0.0023	0.0020	0.0019	0.0018	0.0015	0.0013

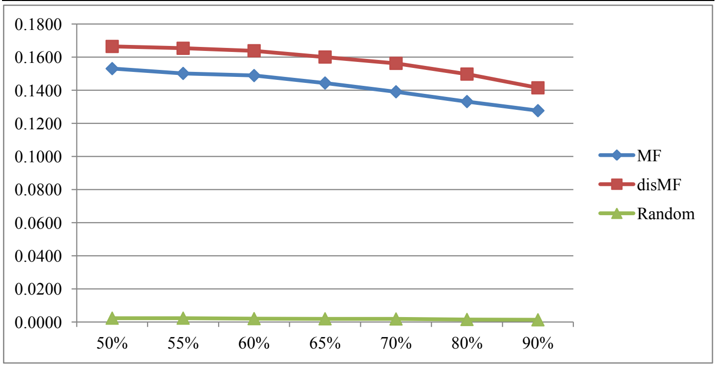


Figure 6: Performance Comparison for the Matrix Factorization based Method without and with Distrust. The prediction problem becomes more difficult from 50% to 90%.

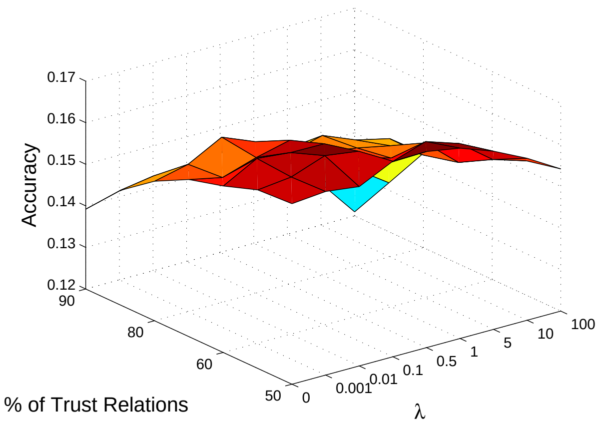


Figure 7: The Effects of Distrust in disMF.

improve the performance of MF by performing factorization on both trust and distrust.

- when λ is increased from 0 to 0.1, the performance improves and details are shown in Table 5, suggesting that the balance theory component for distrust can also improve the performance of trust prediction.
- from $\lambda = 5$ to $\lambda = 100$, the performance decreases rapidly. When λ is very large, balance theory dominates, which will lead to inaccurate estimations of parameters.

In conclusion, by simply adding distrust in the factorization process, disMF ($\lambda = 0$) significantly improves the performance of MF, which can be further improved by modeling balance theory for distrust.

6. RELATED WORK

In social sciences, the conceptual counterpart of trust, distrust, is considered as important and complex as trust [27, 16, 11, 4]. For example, [32, 3] claim that trust and distrust help a decision maker reduce uncertainty and vulnerability (i.e., risk) associated with decision consequences; and [4] indicates that only distrust can irrevocably exclude services from being selected at all. There is an enduring problem about distrust - what is the relation between trust and distrust. Answering this question has its significance. If trust and distrust are the same, lack of distrust research matters little; however, if they are different, the lack of distrust research could be problematic because distrust may have unique impact. Some researchers believe distrust simply means a low level of trust, hence evidence of high trust was always regarded as being that of low distrust, and outcomes of high trust would be identical to those of low distrust [31, 1, 13]. Others believe distrust is a concept entirely separate from trust [18, 15]. Therefore distrust and trust can coexist, and they have different antecedents and consequents [28]. For example, in [18], three reasons are proposed to prove that trust and distrust are separate - (1) they separate empirically; (2) they coexist; and (3) they have different antecedents and consequents. There is still no consensus answer about this problem, and some social scientists consider distrust as the "darker" side of trust [24].

The notion of trust is extensively studied in the online world [36]. The connection between user similarity (such as ratings of movies) and trust is investigated in [40]. A strong and significant correlation is suggested between trust and similarity. The more similar two people are, the greater the trust between them is. A formal framework of trust propagation schemes is developed [10]. By separating trust and distrust matrix, the framework performs operations on them to obtain the transitive trust between two nodes. [29] proposes a method to model and compute the bias or the truthfulness of a user in trust networks, and shows that there are users who have a propensity to trust/distrust other users. In [20], a classification approach is proposed to predict if a user trusts another user using features derived from his/her

Table 5: Performance Comparison. Note that "Imp" denotes the relative performance improvement of disMF with different values of λ compared to "MF".

x (%)	MF (Imp)	disMF ($\lambda = 0$)(Imp)	disMF($\lambda = 0.1$) (Imp)
50	0.1531	0.1614 (+5.42%)	0.1665 (+8.75%)
55	0.1502	0.1610 (+7.19%)	0.1654 (+10.12%)
60	0.1489	0.1600 (+7.45%)	0.1639 (+10.07%)
65	0.1444	0.1557 (+7.83%)	0.1601 (+10.87%)
70	0.1391	0.1525 (+9.63%)	0.1563 (+12.37%)
80	0.1332	0.1465 (+9.98%)	0.1498 (+12.46%)
90	0.1277	0.1381 (+8.14%)	0.1415 (+10.81%)

interactions with the latter as well as from the interactions with other users. The development of trust in social media also encourages many trust online applications. In [22], several approaches are studied to exploit trust networks in recommender systems. The bidirectional effects between trust relations and product ratings are investigated and modeled in [26]. Trust relations are also modeled to help review quality prediction [21].

7. CONCLUSION

As informed by social sciences, distrust could be as important as trust. A fundamental problem about distrust is what the relation between trust and distrust is. Passive observation is the modus operandi to obtain social media data, which lacks necessary information to apply methodologies from social sciences to understand distrust. However, an understanding of distrust with social media data is necessary because if distrust is the negation of trust, lacking distrust study matters little; while if distrust is a new dimension of trust, ignoring distrust in trust study may yield an incomplete and biased estimate of the effects of trust. In this paper, we first investigate the properties of distrust and find that we cannot equally and conversely extend the properties of trust to distrust. Then we then design two tasks by leveraging data mining and machine learning techniques to enable a computational understanding of distrust with social media data. The first task is to predict distrust with only trust information, and the second task is to predict trust with distrust information. We conduct experiments in real-world social media data. The evaluations of the first task suggests that distrust is not the negation of trust, while the results of the second task reveal that distrust has added value over trust.

The computational understanding of distrust in this paper suggests that it is necessary to study distrust in social media and more investigations are needed. First, as suggested by psychology, distrust is an "unwanted" property for online communities and distrust mechanism is rarely implemented by social media services, therefore distrust information is publicly unavailable and we would like to address the data challenge for distrust study. Second, the major computational tasks for trust are well defined including representing trust, measuring trust and applying trust, however, we lack systematical definitions of computational tasks for distrust in social media, and hence we will formally define major computational tasks for distrust. Finally trust information is widely exploited to improve various online applications such as recommender systems, spammer detection, finding high-quality user generated content and viral marketing and distrust has added value on trust, therefore we will investigate how to exploit distrust to facilitate these applications.

Acknowledgments

The work is, in part, supported by Army Research Office (#025071) and The Office of Naval Research (N000141410095).

8. REFERENCES

[1] B. Barber. *The logic and limits of trust.* Rutgers University Press New Brunswick, NJ, 1983.

[2] D. Cartwright and F. Harary. Structural balance: a generalization of heider's theory. *Psychological Review*, 63(5):277, 1956.

[3] J. Cho. The mechanism of trust and distrust formation and their relational outcomes. *Journal of Retailing*, 82(1):25–35, 2006.

[4] P. Cofta. Distrust. In *ICEC*. ACM, 2006.

[5] C. Ding, T. Li, and M. Jordan. Nonnegative matrix factorization for combinatorial optimization: Spectral clustering, graph matching, and clique finding. In *Data Mining, 2008. ICDM'08. Eighth IEEE International Conference on*, pages 183–192. Ieee, 2008.

[6] J. Golbeck. Computing and applying trust in web-based social networks. *Ph.D. dissertation*, 2005.

[7] J. Golbeck. *Computing with social trust.* Springer Publishing Company, Incorporated, 2008.

[8] J. Golbeck. Trust and nuanced profile similarity in online social networks. *ACM Transactions on the Web*, 3(4):1–33, 2009.

[9] N. Griffiths. A fuzzy approach to reasoning with trust, distrust and insufficient trust. In *Cooperative Information Agents X*, pages 360–374. Springer, 2006.

[10] R. Guha, R. Kumar, P. Raghavan, and A. Tomkins. Propagation of trust and distrust. In *Proceedings of the 13th international conference on World Wide Web*, pages 403–412. ACM, 2004.

[11] R. Hardin. *Distrust: Manifestations and management.* Russell Sage Foundation, 2004.

[12] F. Heider. Attitudes and cognitive organization. *The Journal of psychology*, 1946.

[13] A. Josang, E. Gray, and M. Kinateder. Analysing topologies of transitive trust. In *Proc. of the 1st workshop on Formal Aspects in Security and Trust (FAST2003)*, 2003.

[14] Y. Koren. Factorization meets the neighborhood: a multifaceted collaborative filtering model. In *Proceeding of the 14th ACM SIGKDD international*

conference on Knowledge discovery and data mining, pages 426–434. ACM, 2008.

[15] R. M. Kramer. Trust and distrust in organizations: Emerging perspectives, enduring questions. *Annual review of psychology*, 50(1):569–598, 1999.

[16] D. W. Larson and R. Hardin. Distrust: Prudent, if not always wise. *Distrust*, pages 34–59, 2004.

[17] J. Leskovec, D. Huttenlocher, and J. Kleinberg. Predicting positive and negative links in online social networks. In *Proceedings of the 19th international conference on World wide web*, 2010.

[18] R. J. Lewicki, D. J. McAllister, and R. J. Bies. Trust and distrust: New relationships and realities. *Academy of management Review*, 23(3):438–458, 1998.

[19] D. Liben-Nowell and J. Kleinberg. The link-prediction problem for social networks. *Journal of the American society for information science and technology*, 58(7):1019–1031, 2007.

[20] H. Liu, E. Lim, H. Lauw, M. Le, A. Sun, J. Srivastava, and Y. Kim. Predicting trusts among users of online communities: an epinions case study. In *Proceedings of the 9th ACM Conference on Electronic Commerce*, pages 310–319. ACM, 2008.

[21] Y. Lu, P. Tsaparas, A. Ntoulas, and L. Polanyi. Exploiting social context for review quality prediction. In *Proceedings of the 19th international conference on World wide web*, pages 691–700. ACM, 2010.

[22] H. Ma, H. Yang, M. Lyu, and I. King. Sorec: social recommendation using probabilistic matrix factorization. In *Proceeding of the 17th ACM conference on Information and knowledge management*, pages 931–940. ACM, 2008.

[23] H. Ma, D. Zhou, C. Liu, M. Lyu, and I. King. Recommender systems with social regularization. In *Proceedings of the fourth ACM international conference on Web search and data mining*, pages 287–296. ACM, 2011.

[24] S. Marsh and M. R. Dibben. Trust, untrust, distrust and mistrust–an exploration of the dark (er) side. In *Trust Management*, pages 17–33. Springer, 2005.

[25] P. Massa and P. Avesani. Controversial users demand local trust metrics: An experimental study on epinions. com community. In *Proceedings of the National Conference on artificial Intelligence*, volume 20, page 121. Menlo Park, CA; Cambridge, MA; London; AAAI Press; MIT Press; 1999, 2005.

[26] Y. Matsuo and H. Yamamoto. Community gravity: measuring bidirectional effects by trust and rating on online social networks. In *Proceedings of the 18th international conference on World wide web*, pages 751–760. ACM, 2009.

[27] D. H. McKnight and N. L. Chervany. Trust and distrust definitions: One bite at a time. In *Trust in Cyber-societies*, pages 27–54. Springer, 2001.

[28] D. H. McKnight and V. Choudhury. Distrust and trust in b2c e-commerce: Do they differ? In *ICEC*, pages 482–491. ACM, 2006.

[29] A. Mishra and A. Bhattacharya. Finding the bias and prestige of nodes in networks based on trust scores. In *Proceedings of the 20th international conference on World wide web*, pages 567–576. ACM, 2011.

[30] M. Richardson and P. Domingos. Mining knowledge-sharing sites for viral marketing. In *Proceedings of the eighth ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 61–70. ACM, 2002.

[31] J. B. Rotter. Interpersonal trust, trustworthiness, and gullibility. *American psychologist*, 35(1):1, 1980.

[32] J. Singh and D. Sirdeshmukh. Agency and trust mechanisms in consumer satisfaction and loyalty judgments. *Journal of the Academy of Marketing Science*, 28(1):150–167, 2000.

[33] J. Tang, Y. Chang, and H. Liu. Mining social media with social theories: A survey. *SIGKDD Explorations*, 2014.

[34] J. Tang, H. Gao, X. Hu, and H. Liu. Exploiting homophily effect for trust prediction. In *Proceedings of the sixth ACM international conference on Web search and data mining*, pages 53–62. ACM, 2013.

[35] J. Tang, H. Gao, and H. Liu. mtrust: Discerning multi-faceted trust in a connected world. In *the 5th ACM International Conference on Web Search and Data Mining*, 2012.

[36] J. Tang and H. Liu. Trust in social computing. In *Proceedings of the companion publication of the 23rd international conference on World wide web companion*, pages 207–208, 2014.

[37] S.-H. Yang, A. J. Smola, B. Long, H. Zha, and Y. Chang. Friend or frenemy?: predicting signed ties in social networks. In *Proceedings of the 35th international ACM SIGIR conference on Research and development in information retrieval*, pages 555–564. ACM, 2012.

[38] S. Chang, G. Qi, J. Tang, Q. Tian, Y. Rui and T. Huang. Multimedia LEGO: LEarning structured model by probabilistic loGic Ontology tree. In *IEEE 13th International Conference on Data Mining*, 2013.

[39] S. Zhu, K. Yu, Y. Chi, and Y. Gong. Combining content and link for classification using matrix factorization. In *Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval*, pages 487–494. ACM, 2007.

[40] C. Ziegler and J. Golbeck. Investigating interactions of trust and interest similarity. *Decision Support Systems*, 43(2):460–475, 2007.

[41] Z. Li, S. Chang, F. Liang, T. Huang, L. Cao and J. Smith. Learning Locally-Adaptive Decision Functions for Person Verification. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2013.

[42] C.-N. Ziegler and G. Lausen. Propagation models for trust and distrust in social networks. *Information Systems Frontiers*, 7(4-5):337–358, 2005.