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MODELING PERSONALITY EFFECT IN TRUST PREDICTION

SEYED MOHSSEN GHAFARI
Macquarie University
Sydney, Australia
seyed-mohssen.ghafari@hdr.mq.edu.au

AMIN BEHESHTI
Macquarie University
Sydney, Australia
amin.beheshti@mq.edu.au

ADITYA JOSHI
Seek Limited Company
Australia
ajoshi@seek..com.au

CECILE PARIS
CSIRO Data61, Marsfield
Sydney, Australia
cecile.paris@data61.csiro.au and cecile.paris@mq.edu.au

SHAHPAR YAKHCHI
Macquarie University
Sydney, Australia
shahpar.yakhchi@hdr.mq.edu.au

MEHMET A ORGUN
Macquarie University
Sydney, Australia
mehmet.orgun@mq.edu.au

ALIREZA JOLFAEI
Macquarie University
Sydney, Australia
alireza.jolfaei@mq.edu.au

QUAN Z. SHENG
Macquarie University
Sydney, Australia
michael.sheng@mq.edu.au

Trust among users in online social networks is a key factor in determining the amount of information that is perceived as reliable. Compared to the number of users in online social networks, user-specified trust relations are very sparse. This makes the pair-wise trust prediction a challenging task. Social studies have investigated trust and why people trust each other. The relation between trust and personality traits of people who established those relations, has been proved by social theories. In this work, we attempt to alleviate the effect of the sparsity of trust relations by extracting implicit information from the users, in particular, by focusing on users' personality traits and seeking a low-rank representation of users. We investigate the potential impact on the prediction of trust relations, by incorporating users' personality traits based on the Big Five factor personality model. We evaluate the impact of similarities of users' personality traits and the effect of each personality trait on pair-wise trust relations. Next, we formulate a new unsupervised trust prediction model based on tensor decomposition. Finally, we empirically evaluate this model using two real-world datasets. Our extensive experiments confirm the superior performance of our model compared to the state-of-the-art approaches.

Keywords: Trust Prediction, Personality Traits, Online Social Networks

1. Introduction

Online Social Networks (OSNs) enable users to connect with others, expand their social networks, share multimedia content and write reviews on specific items. However, users in OSNs are bombarded with a huge amount of information, i.e., the information overload problem [29]. To find relevant and reliable sources of information trust plays a vital role [37]. Trust "provides information about with whom we should share information, from whom we should accept information and what considerations to give to information from people when aggregating or filtering data" [16].

There are many applications for trust in social media analytics, including: fake news detection [10] [13], retweet behavior detection [4] [1] and recommender systems [22] [43] [41] [39]. For all of these applications, trust relations between users need to be predicted. Trust prediction is defined as "the process of estimating a new pair-wise trust relation between two users who are not directly connected based on existing observations" [45]. However, the trust relations in OSNs follow the rules of the power law distribution [29]: many of the trust relations can be accounted for a small number of users and a large number of users participate in a few trust relations. Hence, on OSNs, the explicit trust relations are very sparse [37]. As a result, a solution for the trust prediction problem, which enables predicting unknown trust relations [29], needs to deal with the problem of sparsity.

The literature on trust prediction can be divided into two main categories [29] [8]: supervised approaches and unsupervised approaches. Supervised trust prediction approaches treat the trust prediction problem as a classification problem (just like any other supervised approach [42] [14]). They create a feature set for their classifiers. They also consider the existence of trust as labels to train a binary classifier [29]. The shortcoming of these approaches is that they face an imbalance classification problem [29] due to the data sparsity problem. Associated with them, unsupervised approaches can identify the trust relations among users, even if they are not directly connected. These approaches use methods like trust propagation or low-rank representation [37]. However, their performance may also be limited due to the lack of sufficient trust relations [37]. To overcome the problem of sparsity of trust relations, some of the unsupervised trust prediction approaches incorporate *implicit or additional infor-*

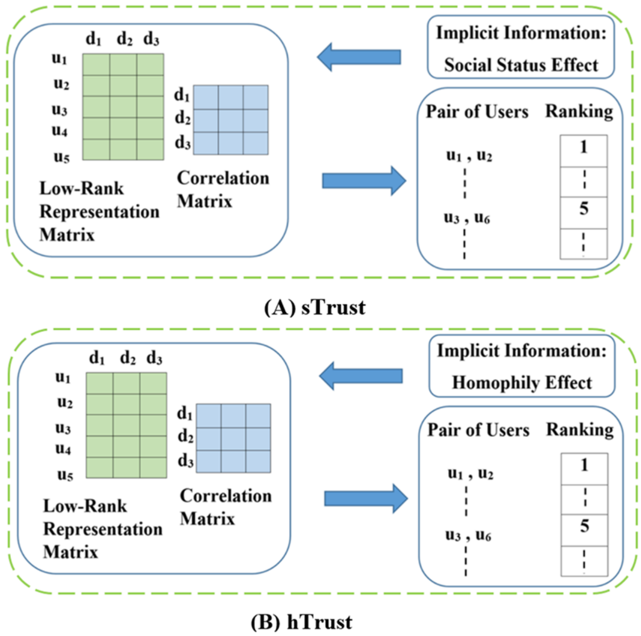

Fig. 1. Low-rank representation of trust relations: (A) sTrust and (B) hTrust

mation (users' rating similarities [29] or users' social status [37]) to alleviate the data sparsity problem (as shown in Figure 1-A,B).

Many social studies have attempted to explore the reasons behind establishing trust relations among people. Although many of them consider trust as a situational construct, some investigate individual characteristics in their trusting behavior predictions [6]. One of these characteristics is people's personality. Alarcon et al. [5] stated that "personality can assist researchers in understanding the processes underlying trust interactions". The studies in social science consider people's personality as a part of developing trust relations in their face-to-face interactions. However, this important attribute remains unexplored for pair-wise trust relations prediction in OSNs. Based on one of the well-known psychology theories, the Big Five Personality model [27], people's personality can be characterized by five personality traits: Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism. Augmenting these personality traits (as *implicit or additional information*) incorporated with proposing a low-rank representation of users in our unsupervised trust prediction approach can help us to alleviate the data sparsity problem.

In our previous work [9], we investigated whether there is any relationship between users' emotions and their trust relations and how this relationship can be used to dynamically predict trust relations. In this paper, we aim to extend that work by exploiting the impact of other users' characteristics, e.g., personality traits, on trust relations. We investigate: (i) the relations between users' personality traits and their trust relations; and (ii) how to make use of personality traits in our trust prediction approach. Our solutions for these questions are resulting in a novel trust prediction model, namely Personality-Aware Trust prediction (PAT) approach. PAT is an unsupervised model which seeks for a low-rank tensor representation of users while investigate the effects of users' personality traits on their trust relations. Our main contributions are as follows:

- We demonstrate the effects of users' personality traits on pair-wise trust relations. Users who have established trust relations are likely to have similar personality traits.
- We demonstrate the impact of personality traits of users on pair-wise trust relations. The impact of Extraversion and Conscientiousness personality traits is significant on pair-wise trust relations.
- We propose an unsupervised method based on tensor decomposition for the trust prediction problem by making use of users' personality.

The rest of the paper is organized as follows: Section provides a background and overview of the related works. Section discusses the proposed method. We present the experimental results in Section . Section concludes the paper.

2. Background and Related Work

Personality refers to 'the characteristic set of behaviour, cognition and emotional patterns that evolve from biological and environmental factors' [23]. Users' personality traits can be either identified 'explicitly by filling a questionnaire or implicitly through observing users' behavioural patterns' [38]. Among several personality trait detection models, the Big Five model is one of the most studied in psychology. It characterizes five personality traits [27]: openness, conscientiousness, extraversion, agreeableness, and neuroticism.

To identify the personality traits of users, we first gather all the users' reviews/tweets /posts. We then analyze the textual content of these reviews/tweets/posts using the Linguistic Inquiry and Word Count (LIWC). LIWC is a standard text analysis tool [3] [38] [2] to identify personality traits from text. This tool categorises words into more than 88 categories (such as 'word count', 'negative emotion', 'anxiety' and 'anger'). Next, inspired by Yakhchi et al. [38] [40], we use a linear regression model to calculate the users' personality trait values as follows:

$$Openness = w_1 \times X_1 + w_2 \times X_2 + w_3 \times X_3 + \dots, \tag{1}$$

where X_t denotes the categories of LIWC for $t = \{1, 2, 3, ..., b\}$, and b is the number of these categories. Out of more than 88 linguistic categories of LIWC, we only consider those related to the Big Five personality traits (e.g., Affect Words, Anger and Anxiety, according to Table 1). In Table 1, the personality traits are listed in no particular order and they are based on the analysis from Pennebaker and King [26]. Moreover, w_c represents the d^{th} weight, where $c = \{1, 2, 3, ..., d\}$ and d is the number of categories of LIWC related to a particular personality trait. This is based on the extracted weights by Mairesse et al. [23]. Table 1 shows the relationships between the LIWC categories and the personality traits. The procedure for calculating the values of the other four personality traits is the same. The Linguistic Inquiry and Word Count (LIWC) categorises words into more than 88 categories. The categories of LIWC are related to Big Five personality traits.

2.1. *Supervised Trust Prediction Approaches*

Table 1. The relation between the Big Five personality traits and different LIWC categories.

Openness	**Conscientiousness**	**Extraversion**	**Agreeableness**	**Neuroticism**
Punctuation	Affect Words	Total pronouns	Exclamation marks	Friends
Affect Words	Death	Parentheses	Dictionary words	Anger
Apostrophes	Future	Article	Feel	Anxiety
Achievement	Home	Friends	Home	Article
Anger	Prepositions	Periods	Singular Pronoun	Feel
Home	Anger	Pronoun	Anger	Leisure
Article	Body	Body	Negative emotion	Music
Assent	Hear	Family	Positive emotion	Number

Liu et al. [20] developed a supervised trust prediction model and developed a classifier which works with a set of users' features and users' interactions. Ma et al. [21] proposed a personalized and cluster-based classification trust prediction. It creates user clusters and then trains a classifier for user clusters [21]. Matsuo et al. [24] focused on a Japanese E-commerce website called @cosme. They first explained the Community Gravity concept, which is a two-way effect of trust and rating. Then, they introduced a model to formulate the trust prediction and rating prediction problems. Finally, in our previous work, we proposed a deep learning-based graph analytics model called DCAT [11] to predict trust relations in OSNs. We leveraged and extended GraphSAGE, a method for computing node representations in an inductive manner, to develop a deep classifier.

2.2. *Unsupervised Trust Prediction Approaches*

Tang et al. [29] proposed an unsupervised trust prediction model called hTrust. It exploits the impact of homophily effect on trust prediction procedure by focusing on similar users. Wang et al. [37] developed an unsupervised model using the Social Status Theory and PageRank algorithm [25]. Ghafari et al. [10] proposed a trust prediction model called TDTrust. It uses tensor decomposition and a set of context factors where context here refers to "any knowledge to specify the condition of an entity" [44], to predict trust relations in different contexts. Ghafari et al. [12] proposed another unsupervised approach, SETTrust, which incorporates the Social Exchange Theory and suggests that a trust relation can be established if the cost of that relation is less than its benefit. Guha and Kumar [17] developed a trust prediction model based on propagating trust using users that have trust or distrust relations with others. Golbeck [15] proposed a website called FilmTrust which employs trust to produce movie recommendations. Wang et al. [34] proposed a trust prediction approach that in addition to learn low-rank representation of users, it also learns sparse component of the trust network [34]. Zheng et al. [44] proposed an unsupervised trust prediction based on a concept, named trust transference, to transfer trust between different contexts [44]. Wang et al. [36] introduced an unsupervised trust prediction model to infer trust between users who have an indirect connection. Liu et al. [19] proposed a trust inference model but they incorporated different factors, such as Residential Location and Outdegree. Liu and Datta [35] proposed a novel trust prediction model for auction websites using Hidden Markov Models. Finally, in our previous work [9] we proposed a dynamic deep trust prediction model to investigate the

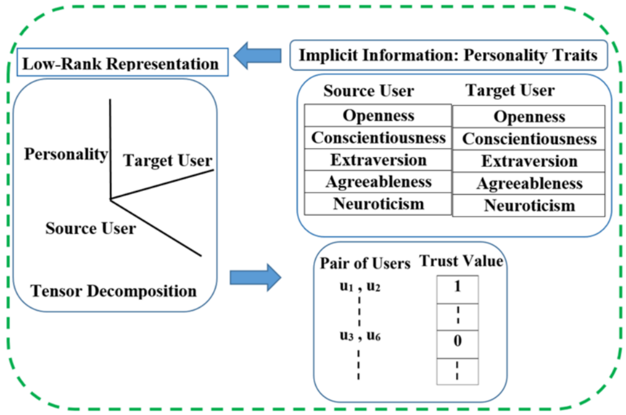

Fig. 2. Our Proposed Trust Prediction Approach (PAT)

impact of incidental emotions on trust. We designed a a novel deep structure to incorporate users' emotions and their textual contents to predict pair-wise trust relations.

2.3. *Personality and Trust*

Alarcon et al. [5] investigated the relation between personality and trust. Thielmann et al [31] researched on the impact of another trait-based personality mechanism called HEXACON on trustworthiness. Another study by Evans and Revelle [6], considered the trust inventory and personality traits, and validated this inventory by an economic task. They discovered that trust can be related to the Extravesion personality trait. Sicora [28] focused on trust among coworkers and workplace leaders and its relation with two personality models. Finally, Gerris et al. [7] studied the impacts of the Big Five personality traits of couples on their marriages.

The above mentioned studies are based on information systems, typically conducted by designing questionnaire, handing out questionnaires to subjects and analyzing their answers. However, our model analyzes the digital footprints of people in OSNs, and, to the best of our knowledge, it is the first unsupervised approach that incorporates the personality traits of users to design a trust prediction model in OSNs.

3. Proposed Model

Our proposed method is an unsupervised trust prediction approach that incorporates users' personality traits, as implicit information, and use tensor decomposition for low-rank representation of trust relations (Figure 2). First, we discuss the problem statement. Next, we formulate the personality traits of users. Finally, we exploit them in our trust prediction model.

3.1. *Problem Statement*

With n users $U = \{u_1, u_2, ..., u_n\}$ and H_p as their personality traits, p is their five personality traits $p = \{1, 2, ..., 5\}$, G is a three-way trust tensor that represents trust relations among users together with their personality traits, where $G \in R^{n \times n \times p}$. Considering the personality traits of u_i and u_j, if u_i trusts u_j, this can be shown as $G(i,j,p)=1$. Conversely, $G(i,j,p)=0$ indicates the lack of a trust relation between them. Since G is very sparse [10], we are looking for a low-rank representation. Hence, we model our trust prediction approach on tensor decomposition, following the approach proposed by Wang et al. [32] and the CPD/Parafac model, to learn three f-dimensional matrices: $U \in R^{n\times f}$, $U' \in R^{n\times f}$ and $H \in R^{p\times f}$, where U and U' indicate the source and target users, respectively. Finally, the sum of the inner product of these matrices creates the trust prediction tensor.

3.2. *Personality-Awareness*

In this section, we identify user's personality traits. Each user has five personality trait values, V_{ip}, with i indicating the i^{th} user and p indicates p^{th} personality trait, where $p=\{1,...,5\}$. We consider the order of the personality traits as Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism. Hence, V_{i2} refers to the Conscientiousness personality trait value of the i^{th} user. Thus, $V_{ijp}=\sum_{p=1}^{5} V_{ip}+V_{jp}$ captures the effects of the five personality traits of the i^{th} and j^{th} users on their trust relation. In addition, $SV_{i,j}$, which captures the similarity of the personality trait values of the source and target users, can be calculated by the cosine similarity metric as follows:

$$SV_{i,j} = \frac{\sum_{p=1}^{5}(V_{ip}\times V_{jp})}{\sqrt{\sum_{p=1}^{5} V_{ip}^2}\times\sqrt{\sum_{p=1}^{5} V_{jp}^2}}, \tag{2}$$

where $SV_{i,j}\in R^{n\times n}$ captures the similarity of personality traits of u_i and u_j.

3.3. *The Personality-Aware Trust Prediction Approach*

We use the following regularization to incorporate the personality traits and the impact of their similarities:

$$\beta\times\sum_{i}^{n}\sum_{j\neq i}^{n}\sum_{p=1}^{5}(min\{0,f((V_{ijp})(SV_{i,j})((H\odot U')U^T)\}))^2, \tag{3}$$

where $f(y)$ is a function that has the same sign as y. U dimension is fixed to overcome the non-convex problem and to turn this problem into a linear one. U^T indicates the transpose of U, 5 is the number of users' personality traits (five), and β is a controlling parameter for the effect of this regularization. In addition, $\odot$ is the Hadamard product. We follow the same procedure for fixing H and U'. With the definition of the above regularisation, PAT is based on a tensor decomposition while exploiting the effect of users' personality traits:

$$\begin{aligned}&min_{U,H,U'}\|G-(H\odot U')U^T\|_F^2+\\&\beta\times\sum_{i}^{n}\sum_{j\neq i}^{n}\sum_{p=1}^{5}(min\{0,f((V_{ijp})(SV_{i,j})((H\odot U_i')U^T)\}))^2+\\&\alpha\times(\|U\|_F^2+\|H\|_F^2+\|U'\|_F^2)U\geq 0, U'\geq 0, H\geq 0,\end{aligned} \tag{4}$$

where α controls U, H and U', and '$\|_F$' is the Frobenius norm. Further, after applying the

Algorithm 1 Trust prediction with PAT

Input: G, β, α, n, z
Output: $\tilde{G}$ which is a low-rank representation of G
Calculate the personality trait values
Calculate the similarities in the source and target users' personality traits
Randomly initialise U, U', and H
while It is not the convergent state **do**
    $A = -2G^T(H \odot U')$
    $B = (H \odot U')U(H \odot U') + (H \odot U')^T U(H \odot U') + \beta \times VSV(H \odot U')UVSV(H \odot U') + \beta \times V^T SV^T (H \odot U')^T UVSV(H \odot U') + 2\alpha U$
    for $j = 1$ to n do
        for $j = 1$ to n do
            for $r = 1$ to 5 do
                $U \longleftarrow U \bullet (\frac{A_{ijr}}{B_{ijr}})$
            end for
        end for
    end for
    Repeat the same procedure for updating H and U'
end while
return U, H, U'

Lagrangian function, we have:

$$\begin{aligned}
&L(G; U, H, U') = \\
&Tr((G - (H \odot U')U^T)(G - (H \odot U')U^T)^T) + \\
&\beta \times (Tr((VSV)(H \odot U')U^T)(VSV(H \odot U')U^T)^T) + \\
&\alpha \times Tr(UU^T)) + \alpha \times Tr(HH^T) + \alpha \times Tr(U'U'^T),
\end{aligned} \tag{5}$$

where Tr indicates the trace of a matrix in linear algebra. The procedure is the same when we fix H and U'. Now, we use the alternating least squares algorithm and the updating rule presented by Krompaas et al. [18] to update U, U' and H as follows:

$$\Theta_i = \Theta_i \left(\frac{\frac{\partial C(\Theta)^-}{\partial \Theta_i}}{\frac{\partial C(\Theta)^+}{\partial \Theta_i}} \right)^a, \tag{6}$$

where Θ is a non-negative variable, and $C(\Theta)$ is the negative part of the derivation. We use two element-wise operations for multiplication and division as $\bullet$ and $/$, respectively. Then, we calculate the partial derivative of Equation 5 with respect to U, H and U' and make them equal to zero. Next, based on Karush Kuhn Tucker complementary condition and the approach presented by Tang et al. [29], we have the updating rule as follows:

$$\begin{aligned}
&U \longleftarrow U \bullet \left((2G^T(H \odot U')) \Big/ ((H \odot U')U(H \odot U') + \right. \\
&(H \odot U')^T U(H \odot U') + \beta \times VSV(H \odot U')UVSV(H \odot U') \\
&\left. + \beta \times V^T SV^T (H \odot U')^T UVSV(H \odot U') + 2\alpha U) \right).
\end{aligned} \tag{7}$$

We can also follow the same updating approach for H and U' (Algorithm 1).

4. Experimental Setup

To evaluate the trust prediction approach, we use two benchmark datasets from real-world websites: Epinions (with 1050 users, trust network density of 0.0093, number of trust relations 10264, and Minimum number of reviews per users 3) and Ciao (with 1000 users, trust network density of 0.0087, number of trust relations 8726, and Minimum number of reviews per users 3) [30]. These are review websites, frequently used by trust prediction studies [37] [29], which contain users' ratings, reviews and trust relations.

The trust network density in the mentioned datasets refers to the proportion of known trust relations compared to the potential trust relations among users. For example, the Epinions dataset has the potential for around one million trust relations among all its users (the number of users $\times$ the number of users). However, it has only 10264 known trust relations, making the trust network density 0.0093. Thus, in this dataset, the users' specified trust relations network is very sparse. This is also the case in the Ciao dataset (trust network density is 0.0087).

We use a four-fold cross-validation method and consider the average performance of all folds as the final performance value. The trust labels already provided in these datasets are used as the ground truth. The controlling parameters of our model were defined by applying cross-validation, and it reached its best performance when: $\beta = 0.5$, $\alpha = 0.1$ and $f = 100$.

5. Experiments

5.1. *Impact of Similarity of Personality Traits*

In this section, we investigate the question of *do users who bear a trust relation between them have similar personality traits?* We explore the impact on PAT of considering the similarity of source and target users' personality traits. We remove the similarity metric $SV_{i,j}$, proposed in Equations 2 and 3, from our model, to observe the performance of PAT when it does not consider the similarity of the personality traits of users. This new version of PAT is given the name PAT_{+}. Figure 3 compares the performance of PAT and PAT_{+} on the Ciao and Epinions datasets (Presented in Section 3) with respect to the mean absolute error (MAE) and root mean squared error (RMSE) metrics. It demonstrates that adding $SV_{i,j}$ to PAT (when PAT considers the similarity of users' personality traits) significantly improves the model's performance. PAT has around 32% and around 24% lower MAE and RMSE compared to PAT_{+}. Hence, considering the similarity of the source and target users' personality traits can significantly improve the performance of our trust prediction approach (PAT).

5.2. *Performance of the Personality-Aware Trust Prediction*

Tables 2 and 3 show the trust relation prediction performance of PAT in response to the following three questions:

- What is the performance of PAT if only the personality traits of source users or V_{ip} are considered (Scenario 1, Tables 2 and 3)?
- What is the performance of PAT if only the personality traits of target users or V_{jp} are considered (Scenario 2, Tables 2 and 3)?

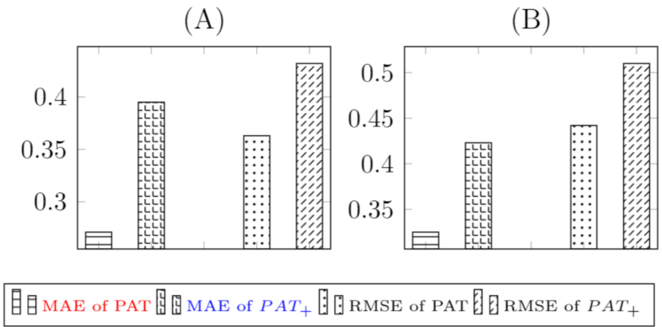

Fig. 3. Comparison of the performance of PAT and PAT_+ using MAE and RMSE.

Table 2. Comparison of the trust relation prediction performance of PAT using the MAE metric.

The Personality Trait of	**Ciao**	**Epinions**
Source Users (Scenario 1)	0.271	0.325
Target Users (Scenario 2)	0.321	0.363
Both Users (Scenario 3)	0.348	0.395

- What is the performance of PAT if the personality traits of source users and target users or V_{ijp} are considered simultaneously (Scenario 3, Tables 2, 3)?

To answer the first two questions, we replace V_{ijp} in Equation 3 with the personality traits of the source users, V_{ip}, and target users, V_{jp}, respectively. For answering the third question, there is no need to modify Formula 3, as it already considers the personality traits of the source and target users. It should be noted that for answering these questions, we only modify V_{ijp} in Equation 3, which contains the personality trait values of source or target users; the similarity metric of SV_{ij} remains unchanged. This similarity metric is the similarity of the personality trait values of the source or the target users.

As seen in Tables 2 and 3, PAT in Scenario 1 has the lowest MAE and RMSE compared to scenarios 2 and 3 for both datasets. In the Ciao dataset, it has about 15% and 23% lower MAE in Scenario 1 compared to scenarios 2 and 3, respectively. In the Epinions dataset, it has approximately 11% and 18% lower MAE in Scenario 1 compared to scenarios 2 and 3, respectively. This superior performance can also be seen in Table 3, with respect to the RMSE metric.

In summary, the best performance of PAT is achieved in both the CIao and Epinions datasets when it only considers the personality trait values of source users. We conclude that considering the personality trait values of source users and the similarity value of source and target users simultaneously (as two separate factors) can improve the performance of PAT. These results demonstrate that, in addition to considering the similarity of both users, focusing on the personality trait values of the source user may be an important indicator for trust prediction approaches. In the following experiments, we only consider the personality traits of the source users or V_{ip}, in Equation 3 of our model.

5.3. *Comparison of Different Trust Prediction Approaches*

Table 3. Comparison of the trust relation prediction performance of PAT using the RMSE metric.

The Personality Trait of	Ciao	Epinions
Source Users (Scenario 1)	0.363	0.442
Target Users (Scenario 2)	0.401	0.472
Both Users (Scenario 3)	0.419	0.498

Table 4. Comparison of PAT with other baseline approaches using MAE and RMSE.

Metric	Dataset	Random	RS	MF	sTrust	hTrust	PAT
MAE	Ciao	5.63	3.1	1.95	1.8	1.17	**0.27**
	Epinions	5.98	3.19	2.05	1.47	1.36	**0.32**
RMSE	Ciao	6.65	3.11	2.09	1.93	1.32	**0.36**
	Epinions	6.85	3.29	2.16	2.15	1.56	**0.442**

In this section, we compare PAT with various **baseline approaches** as: **1)** hTrust [29]: it exploits homophily effect on trust relations. hTrust investigate the effect of similarities between users (particularly their ratings similarities) on their trust relations. **2)** sTrust [37]: it investigates the relation between the status of users in OSNs, in which the users' status is identified by PageRank algorithm, and their trust relations. **3)** Matrix Factorization (MF) [29]: This approach is based on a link matrix factorization model. **4)** Rating Similarity (RS) [29]: It captures different users' tastes to find the most similar users (the similar users are more willing to trust to each other). **5)** Random: it randomly assigns a trust value to a pair of users (Random).

Table 4 compares the performance of PAT and other pair-wise trust prediction approaches with respect to MAE and RMSE metrics in the Ciao and Epinions datasets. We see that PAT has the lowest MAE and RMSE in both datasets. In the Ciao dataset, the MAE of PAT is about 4, 7, 7, 11 and 21 times less than for $hTrust$, $sTrust$, MF, *RS* and *Random*, respectively. Likewise, in the Ciao dataset, the RMSE of PAT is approximately 4, 5, 6, 9 and 18 times less than for $hTrust$, $sTrust$, MF, *RS* and *Random*, respectively. Similar superior performance for PAT can be observed on the Epinions dataset (Table 4).

In summary, PAT outperforms the baseline trust prediction approaches with respect to the MAE and RMSE metrics on the Ciao and Epinions datasets.

5.4. *Impact of Each Personality Trait*

Table 5. Impact evaluation of personality traits on PAT using the Ciao dataset.

Approach	MAE-Ciao	Δ_{MAE}	RMSE-Ciao	Δ_{RMSE}
PAT	0.271	-	0.363	-
PAT-Openness	0.346	0.075	0.426	0.063
PAT-Conscientiousness	0.393	**0.122**	0.465	**0.102**
PAT-Extraversion	0.395	**0.124**	0.482	**0.119**
PAT-Agreeableness	0.308	0.037	0.398	0.035
PAT-Neuroticism	0.309	0.038	0.391	0.028

Table 6. The impacts of each personality trait on PAT using MAE and RMSE metrics on the Epinions dataset.

Approach	**MAE-Epinions**	Δ_{MAE}	**RMSE-Epinions**	Δ_{RMSE}
PAT	0.325	-	0.442	-
PAT-Openness	0.362	0.037	0.481	0.039
PAT-Conscientiousness	0.408	**0.083**	0.509	**0.067**
PAT-Extraversion	0.412	**0.087**	0.513	**0.071**
PAT-Agreeableness	0.328	0.003	0.472	0.03
PAT-Neuroticism	0.331	0.006	0.468	0.026

To investigate the question of *what is the relationship between personality trait and trust relations?* In this section, we explore the effect of each personality trait on the performance of PAT. To do so, we remove the personality trait values one by one from the V_{ijp} in Equation 3 of our model and evaluate the performance. In other words, in each iteration, we only consider four of the users' personality trait values in our model, calling this the new version of PAT (i.e., PAT_{new}). In this way, we can investigate the following question: *Ignoring which personality trait can have a higher negative impact on the performance of PAT?* We define two metrics named Δ_{MAE} and Δ_{RMSE}, where Δ_{MAE} and Δ_{RMSE} represent the differences between the performance of PAT, when it includes all of the Big Five personality traits, and PAT_{new}, when it excludes a particular personality trait value with respect to the MAE and RMSE metrics, respectively. Tables 5 and 6 show the results on the Ciao and Epinions datasets, respectively. We see that when we remove the Extraversion trait from the personality vector in the Ciao dataset, the MAE increases to 0.395 from 0.271. Hence, $\Delta_{MAE} = 0.124$. We should consider the fact that higher Δ_{MAE} and Δ_{RMSE} indicate a greater negative impact on PAT's performance of ignoring a particular personality trait. Accordingly, we can identify the most important personality traits for the trust relation prediction procedure.

Tables 5 and 6 show the impacts of each personality trait on PAT. In these tables, Δ_{MAE} and Δ_{RMSE} represent the difference between the performance of PAT, when it includes all the personality traits, and PAT_{new}, when it excludes a particular personality trait value, with respect to the MAE and RMSE, respectively. As illustrated in Tables 5 and 6, removing the Extraversion or Conscientiousness traits from our model increases the MAE and RMSE of PAT significantly. The Δ_{MAE} and Δ_{RMSE} for these cases are more than 0.1 in the Ciao dataset. Ignoring Agreeableness or Neuroticism does not lead to significant changes in the MAE or RMSE, indicating the low negative impact of ignoring Agreeableness or Neuroticism.

5.5. *Impact of Data Sparsity Degree*

Finally, we investigate the impact of the degree of data sparsity on PAT. According to Wang et al. [33], the data sparsity $Degree$ (how sparse a dataset is [33]) is:

$$Degree = \frac{NT}{n^2}, \tag{8}$$

where NT is the number of existing trust relations, and n is the number of users. A smaller $Degree$ indicates a sparser dataset. We follow the same approach proposed by Wang et al. [33] and evaluate PAT on the Epinions and Ciao datasets with different $Degrees$ of

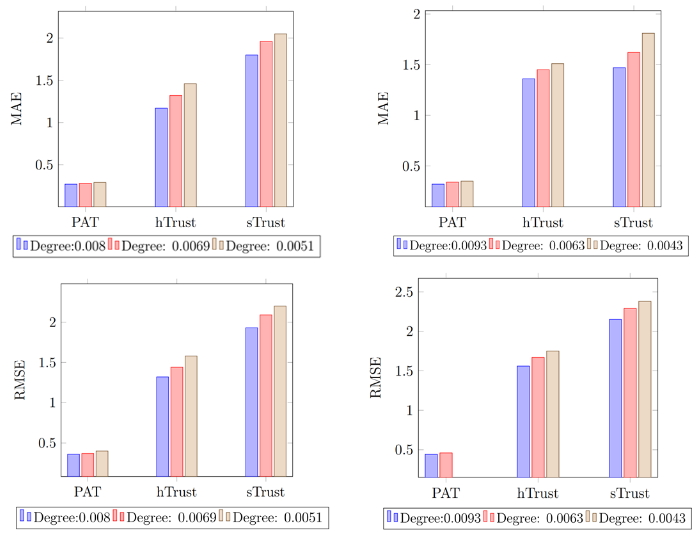

Fig. 4. The impact of degree of sparsity on the performance of trust prediction models.

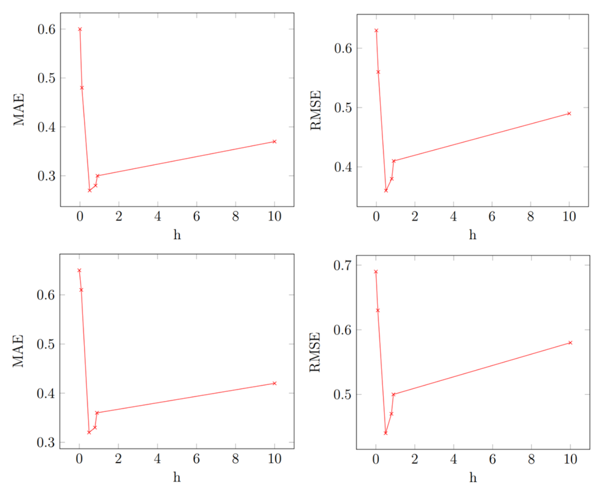

Fig. 5. PAT regularization effects using MAE and RMSE on the Ciao (the upper images) and Epinions (the lower images) datasets.

0.0093, 0.0063, and 0.0043, and 0.008, 0.0069 and 0.0051, respectively. Figure 4 shows the impact of degree of sparsity on the performance of trust prediction approaches. The left images illustrate the performance of trust prediction approaches using MAE and RMSE in the Ciao dataset. The right images demonstrate the performance of these approaches using the MAE and RMSE in the Epinions dataset. Figure 4 demonstrates that unlike the two state-of-the-art trust prediction approaches to which it is compared in the figure, PAT is insensitive to the sparsity degree of the trust relations. PAT has a close to stable prediction performance in the presence of different degrees of sparsity, whereas $hTrust$ and $sTrust$ are negatively affected by increasing the degree of sparsity of the datasets.

5.6. *The PAT regularization Effects*

In our experiment, we used $\beta = \{0, 0.1, 0.5, 0.8, 0.9, 10\}$ and identified that the best performance of **PAT** is achieved by $\beta = 0.5$ (Figure 5). The performance of **PAT** is increased by increasing β from 0 to 0.5. However, when $\beta > 0.5$, the performance decreases.

6. Conclusion

In this paper, we have proposed a novel unsupervised trust prediction model named Personality-Aware Trust (PAT) prediction approach that incorporates users' personality traits. We first analyzed the relation between trust and similarity of personality traits of the source and the target users and also the impact of each personality trait on the trust relations. Then, we proposed a new trust prediction model, incorporating users' personality traits, based on tensor decomposition, for predicting pair-wise trust relations in Online Social Networks. The experimental results demonstrate the effectiveness of our approach compared to the state-of-the-art approaches. As trust is not a fixed value and can be changed during the time, PAT should also detect trust relations during different time windows and should update its predictions after a fraction of time. Thus, the time factor and converting PAT to a time-aware trust prediction approach need to be further explored in future work.

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