Knowledge-Based Systems 182 (2019) 104803

Contents lists available at ScienceDirect

Knowledge-Based Systems

journal homepage: www.elsevier.com/locate/knosys

Identifying top persuaders in mixed trust networks for electronic marketing based on word-of-mouth[☆]

Xiaojing Hu [a], Shixi Liu [a,b,*], Yudong Zhang [b], Guozhu Zhao [a], Cuiqing Jiang [c]

[a] School of Computer and Information Engineering, Chuzhou University, Chuzhou, Anhui 239000, China
[b] Department of Informatics, University of Leicester, Leicester, LE1 7RH, United Kingdom
[c] School of Management, Hefei University of Technology, Hefei, Anhui 230009, China

ARTICLE INFO

Article history:
Received 9 December 2018
Received in revised form 9 June 2019
Accepted 10 June 2019
Available online 21 June 2019

Keywords:
Trust
Distrust
Top persuaders
Social network
e-commerce
Word-of-mouth marketing

ABSTRACT

The identification of top persuaders from social networking websites is increasingly attracting attention because they can significantly affect consumers' purchasing decisions in electronic word-of-mouth (eWOM) marketing. Existing studies on the identification of top persuaders have mainly focused on the idea of trust and have not considered distrust. However, this omission may lead to a high negative impact of the top persuaders identified from trust networks. To address this issue in the context of mixed trust networks, this study formulates the top persuader identification problem and develops a novel approach to identifying top persuaders. The structural properties of mixed trust networks are investigated through four measures: the degree of distribution, the correlation coefficient of trust and distrust, the cumulative distribution of the ratio between the degree of distrust and the degree of trust, and the mix pattern. To adapt to the context of mixed trust networks, a mixed trust PageRank (MTPR) index is conceived to evaluate the influential power of a top persuader. Reinforced by the dimensions of trust and distrust, the MTPR-based approach is proposed to identify top persuaders in mixed trust networks. The experimental results using real-world data collected from Epinions show that the proposed approach outperforms the degree centrality approach and the PageRank approach.

1. Introduction

In the digital era, Internet-based social communication services (e.g., Twitter, MySpace, Facebook, and LinkedIn) have resulted in the emergence of social persuasion as a complex force that governs the propagation of influence in online social networks (OSNs) [1–3]. Social persuasion is closely related to social contagion and network diffusion, by which a consumer's attitude, belief, or behavior is influenced by other consumers in an OSN [4]. This phenomenon has allowed various companies to identify top persuaders who can propagate social influence through their high network status in OSNs and who have the ability to affect the behavior and attitudes of other consumers [5–7]. Therefore, the ability to discover top persuaders in an OSN has become critical to companies in electronic word-of-mouth (eWOM) marketing [8–10]. In this context, marketing information can be diffused faster and be promoted better by top persuaders to their followers in OSNs via word of mouth.

Through their social reach, original content, and consumer trust, top persuaders play an important role in eWOM marketing campaigns. In particular, trust plays a critical role in consumers' decisions, especially when the participants are anonymous and do not engage in direct face-to-face interactions [11,12]. As the counterpart of trust, distrust can be simultaneously present in consumers' sentiments [13,14]. Users in some OSNs, such as Slashdot, Essembly, and Epinions, are allowed to directly express whom they trust and distrust based on their previous interaction experience [15]. Thus, both trust and distrust build a strong eWOM foundation in the digital world. However, eWOM communication involves positive or negative statements of trust or distrust information made in OSNs [16,17]. Trust information delivers a positive signal of product popularity, whereas distrust information delivers a negative signal. Therefore, a top persuader who may be trusted or distrusted by his/her peers will exert either a positive or negative influence on product popularity [18,19].

Prior approaches to identifying top persuaders have mainly focused on the idea of trust [9,16,20]. Liu et al. developed a research framework for identifying top persuaders from trust networks composed of trust relationships, ignoring the distrust relationships among users [9]. Although Kim et al. [20] investigated

☆ No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to https://doi.org/10.1016/j.knosys.2019.06.011.

* Corresponding author.
E-mail address: liusxchuz@163.com (S. Liu).

https://doi.org/10.1016/j.knosys.2019.06.011
0950-7051/

the effect of distrust on top persuaders, they did not simultaneously consider the effect of trust and distrust on top persuader identification; however, a top persuader with a highly negative impact could be identified, and trust and distrust were separately considered [16]. In the context of mixed trust networks, a user not only obtains an approval ticket (trust relationship) from his/her peers but also may obtain a disapproval ticket (distrust relationship). For example, in Fig. 1, Alice receives 4 trust relationships and 1 distrust relationships from her followers, while Bob receives 4 trust relationships and 2 distrust relationships. As a top persuader, Alice is more promising than Bob in regard to eWOM marketing because she has a higher degree of trust and maintains a lower degree of distrust in mixed trust networks. However, a top persuader with a higher degree of distrust in mixed trust networks, such as Bob, is often identified by traditional approaches, such as degree centrality and the PageRank approach. Therefore, a top persuader with negative eWOM identified by traditional approaches poses problems for most marketers. The goal of this study is to develop an innovative scheme to identify top persuaders in mixed trust networks.

This study focuses on identifying top persuaders in mixed trust networks by combining the trust and distrust relationships among users. Mixed trust networks provide corporations with an opportunity where the network structure acts as an eWOM marketing and promotion medium. Top persuaders often take advantage of the network structure of OSNs to propagate their influence by relying on their high network status [21]. Thus, the structural properties of mixed trust networks are first investigated using four measures: the degree of distribution, the correlation coefficient of trust and distrust, the cumulative distribution of the ratio between the degree of distrust and the degree of trust, and the mix pattern. Then, we design a new index called the mixed trust PageRank (MTPR) index to evaluate the influential power of a top persuader in mixed trust networks. Finally, reinforced by the dimensions of trust and distrust, a novel approach is proposed to identify top persuaders in mixed trust networks. The proposed MTPR-based approach can help marketers identify top persuaders who have a lower degree of distrust and maintain a higher degree of trust in mixed trust networks. The experimental results from real-world social network data show that our approach substantially outperforms traditional approaches from representative prior research.

The principal contributions of our work can be summarized as follows: (1) The structural properties of mixed trust networks are investigated in terms of four measures; (2) a new MTPR index is conceived to evaluate the influential power of a top persuader in mixed trust networks; (3) reinforced by the dimensions of trust and distrust, a novel MTPR-based approach is proposed to identify top persuaders in mixed trust networks; and (4) the experimental results using real-world data collected from Epinions show that our approach outperforms the degree centrality approach and the PageRank approach using the positive–negative influence (PNI) measure.

The remainder of this paper is organized as follows. Section 2 introduces the related works. Then, the methodology and problem formalization are proposed in Section 3. Section 4 presents the empirical work and reports the evaluation results. The last section concludes the paper by summarizing the most important features of the proposed approach and suggesting future research directions.

2. Related works

There has been a rich body of literature that examines top persuader identification via trust in OSNs. The studies within this literature were principally conducted based on three aspects: theory, methods, and techniques. More specifically, they relied on social trust and distrust, investigations of the structural properties of social networks, and the identification of top persuaders.

2.1. Definitions: social trust and distrust

Studies on trust and distrust from different disciplines have different definitions. In psychology, psychologists regard trust/distrust as personal psychological events [22–24]. They focus only on the cognitive content and behavior of trust and distrust and do not consider the influence of the social environment. In sociology, sociologists believe that trust and distrust are equally important concepts in social relations and that they are social phenomena associated with the social structure and cultural norms [25–27]. They investigate not only the trust and distrust among individuals but also the trust and distrust among large social groups. Management scholars believe that trust and distrust are the result of behavioral expectations and interactions between individuals or between individuals and organizations [28,29]. The relationship between trust and distrust in different disciplines is shown in Table 1. Following Lewicki's definition [30], in this study, trust is conceptualized as "a consumer's positive expectations regarding an e-vendor's conduct, characterized as faith, confidence, and assurance"; additionally, distrust is defined as "a consumer's negative expectations regarding an e-vendor's conduct, characterized as suspicion, wariness, and fear of transactions". Because of the simultaneous coexistence of trust and distrust in OSNs, we simultaneously consider the effect of trust and distrust on top persuader identification.

2.2. Investigation of the structural properties of trust networks

Productive efforts have been made to understand trust networks by exploring their structural properties. Based on graph theory, a trust network can be abstracted as a graph, where users can be viewed as nodes and the trust relationships among them can be considered edges [31]. Because top persuaders propagate social influence by their high network status and reach target users via network breadth [32], better understanding the structural properties of trust networks will provide an intuitive identification of top persuaders [33]. Extant studies focus on the robustness of a graph and the properties of a trust network structure [11,34,35]. Meo et al. investigated graph robustness using the Randic index, which is a parameter introduced in chemistry to study organic compounds [34]. Jiang et al. adopted graph theory to model trust networks and to then investigate their structural properties [35]. Because the imbalanced data issue is a common phenomenon in trust network extraction, Bi et al. proposed a new imbalance learning method that can be used to improve the imbalanced data classification [36]. Nevertheless, to characterize the enriched features of trust networks, a basic trust network structure with single trust relationships between users is insufficient because distrust inheres in mixed trust networks. To understand the trust and distrust behavior among users, our study attempts to investigate the structural properties of mixed trust networks through four measures.

2.3. Identification of top persuaders

Because eWOM websites can provide tools for consumers to discuss products and consult information from peers with high online status, the identification of top persuaders is vital to increasing the efficiency of eWOM marketing [6,37]. Existing approaches to identifying top persuaders in OSNs mainly include centrality-based approaches [33,38,39], PageRank-based

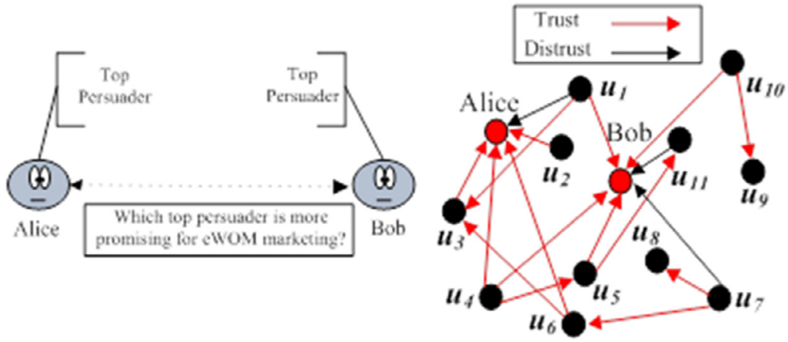

Fig. 1. A scenario of top persuaders in mixed trust networks.

Table 1
Studies on the relationship between trust and distrust in different disciplines.

Displine	Psychology	Sociology	Management
Author (Year)	Lewicki and Bunker [30] (1995)	LuhMann [27] (2000)	Cho [28] (2006)
Representative viewpoints	The conflict psychological state characterized by trust and distrust is unstable and transient in nature.	Trust and distrust are equally important as mechanisms to reduce social complexity and uncertainty.	The negative influence of distrust on individuals' willingness to disclose personal information is greater than that of trust in revealing personal information.

approaches [40,41], and TwitterRank approaches [42]. Centrality-based approaches rank users in a social network using a centrality measure and regard users with high centrality scores as top persuaders. Lu et al. developed a graph-based action network framework to identify top persuaders according to degree centrality measures [33]. In [39], the authors utilized centrality measures to compute user reputation scores in trust networks. Bodendorf et al. proposed a novel approach to identifying top persuaders in forums via centrality indicators that include degree centrality, closeness centrality and betweenness centrality [43]. PageRank approaches rank users by analyzing the weights of relationships through the lens of social influence and then leveraging such weights to discover top persuaders [41]. Saez et al. proposed a methodology that combines the temporal attributes of the nodes and edges of a network with a PageRank-based algorithm to identify the top persuaders in a given topic [38]. TwitterRank is an extension of PageRank that is utilized to measure the influence of Twitter users. For example, Weng et al. proposed a TwitterRank approach to measure the influence of Twitter users and to identify top persuaders by taking both topical similarity and the link structure of users into account [42].

In summary, a series of major studies have proposed various approaches to identifying top persuaders. However, in the context of mixed trust networks, many OSN users who could be defined as top persuaders in these previous approaches may have a high negative influence on eWOM marketing. Our study attempts to identify top persuaders who have a higher positive influence and a lower negative influence. The crucial differences between the proposed approach and the relevant literature are compared and shown in Table 2.

3. Problem formulation and methodology

3.1. Problem formulation

This section introduces the problem of top persuader identification in mixed trust networks. Mixed trust networks are composed of user trust networks and user distrust networks. We first propose the formal descriptions of user trust networks, user distrust networks, and mixed trust networks as follows.

Definition 1 (*User Trust Networks*)**.** ***UTN*** $= (V^T, T, W_t)$ is a triple, where V^T denotes the node set of a trust network; $T = \{(u_i, u_j, \omega_t) | u_i \in V^T \wedge u_j \in V^T \wedge \omega_t \in W_t\}$ denotes the set of trust relationships between nodes in the trust network. $u_i\ T\ u_j$ denotes that node u_i trusts node u_j, and W_t denotes the trust strength between nodes.

Definition 2 (*User Distrust Networks*)**.** ***DTN*** $= (V^D, D, W_d)$ is a triple, where V^D denotes the node set of a distrust network; $D = \{(u_i, u_j, \omega_d) \mid u_i \in V^D \wedge u_j \in V^D \wedge \omega_d \in W_d\}$ denotes the set of distrust relationships between nodes in the distrust network. $u_i\ D\ u_j$ denotes that node u_i distrusts node u_j, and W_d denotes the distrust strength between nodes.

Definition 3 (*Mixed Trust Networks*)**.** ***MTN*** $= (V, T, D, W_t, W_d)$ is a 5-tuple, where V denotes the node set of a mixed trust network; $T = \{(u_i, u_j) \mid u_i \in V \wedge u_j \in V\}$ denotes the set of trust relationships between nodes in the mixed trust network. $u_i\ T\ u_j$ denotes that node u_i trusts node u_j. $D = \{(u_i, u_j) \mid u_i \in V \wedge u_j \in V\}$ denotes the distrust relationship between nodes in the mixed trust network. $u_i\ D\ u_j$ denotes that node u_i distrusts node u_j. W_t and W_d denote the trust strength and distrust strength between nodes, respectively. The trust network and the user distrust network are subnets of the mixed trust network, i.e., *UTN*⊆*MTN* and *DTN*⊆*MTN*.

Based on the above definitions, the top persuader identification problem in a mixed trust network is formulated as follows. Assume that $MTN = (V, T, D, W_t, W_d)$ denotes a mixed trust network that includes trust and distrust relationships among users. $u_1, u_2, \ldots, u_n \in V$ denote the users in the mixed trust network. The task is to discover top k top persuaders $\{I_1, I_2, \ldots, I_k\}$ from $\{u_1, u_2, \ldots, u_n\}$, satisfying the condition of $Inf_1 > Inf_2 > \ldots > Inf_k$, where Inf_j denotes the influential power of top persuader I_j in the mixed trust network and $j \in \{1, 2, \ldots, k\}$.

3.2. Investigation of the structural properties of mixed trust networks

To identify top persuaders in mixed trust networks, we investigate the structural properties of mixed trust networks. Based on social network analysis theory, we explore four measures to investigate the structural properties of mixed trust networks: the

Table 2
Summary of top persuaders identification and relevant literature.

Work	Trust relationship	Distrust relationship	Focus	Limits
Li and Lin [37] (2010)	√		Identifying top persuaders by an artificial neural network and a trust mechanism.	Overlooking the distrust relationships among users for the trust mechanism.
D. Lu et al. [33] (2012)			Prestigious members on camera domain through member's prestige evolution.	Overlooking the trust and distrust relationships of top persuaders.
Saez-Trumper [38] (2012)			Finding top persuaders by combining the temporal attributes of nodes and edges of a network with a PageRank-based algorithm.	Overlooking the negative influence of trendsetters in online social networks.
Kim and Tran [20] (2013)	√	√	Assessing ripple effects of top persuaders using three topological measures.	Separating the trust and distrust while identifying top persuaders.
Shixi Liu et al. [9] (2015)	√		Identifying top persuaders based on trust relationship and domain for eWOM.	Overlooking the distrust relationships of top persuaders in trust networks.
This paper	√	√	Identifying top persuaders in mixed trust networks by dimensions of trust and distrust.	How to build the mixed trust networks for an OSN without web of trust.

degree distribution of a mixed trust network [44], the correlation coefficient of trust and distrust [33], the cumulative distribution of the ratio between the degree of distrust and the degree of trust [11], and the mix pattern [45,46].

3.2.1. The degree distribution of a mixed trust network

The degree distribution of a mixed trust network includes the trust degree distribution and the distrust degree distribution; the formal descriptions are shown in Eqs. (1) and (2) [44], respectively.

$$trustDegree(u) = \sum trustee(u) \tag{1}$$

where *trustee(u)* denotes the trust frequency of a trustee who is trusted by his/her peers.

$$distrustDegree(u) = \sum distrustee(u) \tag{2}$$

where *distrustee(u)* represents the distrust frequency of a distrustee who is distrusted by his/her peers.

3.2.2. The correlation coefficient of trust and distrust

The relation strength between the trust and distrust of a user in a mixed trust network can be calculated through the correlation coefficient of trust and distrust, denoted by Eq. (3) [33].

$$corr = \frac{\sum_{i=1}^{n}(k_t^i - \overline{k_t})(k_d^i - \overline{k_d})}{\sqrt{\sum_{i=1}^{n}(k_t^i - \overline{k_t})^2}\sqrt{\sum_{i=1}^{n}(k_d^i - \overline{k_d})^2}} \tag{3}$$

where *corr* denotes the correlation coefficient, k_t^i denotes the degree of trust of user u_i, $\overline{k_t}$ denotes the average value of the degree of trust of a user, ${k_d}^i$ denotes the degree of distrust of user u_i, and $\overline{k_d}$ denotes the average value of the degree of distrust of user u_i.

3.2.3. The cumulative distribution of the ratio between the degree of trust and the degree of distrust

To further investigate the correlation between trust and distrust in a mixed trust network, we calculate the cumulative distribution of the ratio between the degree of trust and the degree of distrust, denoted by Eq. (4) [11]. $R(\rho)$ denotes the cumulative distribution of the ratio between the degree of trust and the degree of distrust, k_t denotes the degree of trust, and k_d denotes the degree of distrust.

$$R(\rho) = \frac{k_t}{k_d} > \rho \tag{4}$$

According to Eqs. (3) and (4), if users' trust and distrust are weakly correlated and most users' degree of trust is larger than their degree of distrust, then users are more likely to trust trustees with a higher degree of trust.

3.2.4. Mix pattern

The mix pattern is used to measure the probability that a user with a k_t degree of trust is connected to a user with a k_d degree of distrust. It includes the correlation function K_{nn} and the assortativity coefficient. The correlation function K_{nn} of the degree of trust and the degree of distrust is a measure of the mapping between the degree of trust and the average degree of distrust of all nodes linked from the nodes of that degree of trust, denoted by Eq. (5) [46].

$$K_{nn}(k_{out}) = \frac{1}{|u|k_u = k_{out}|} \sum_{u|k_u=k_{out}} \frac{1}{|v|(u,v)\in A|} \sum_{v|(u,v)\in A} k_{in}^{v} \tag{5}$$

Additionally, the assortativity coefficient is defined as the Pearson correlation coefficient of the degrees between pairs of linked nodes, denoted by Eq. (6), where j_i and k_i are the degrees (degree of trust and degree of distrust) of nodes at the ends of the *i*th edge, with $i = 1, \ldots, M$.

$$r = \frac{\frac{1}{M}\sum_{i=1}^{n} j_i \times k_i - [\frac{1}{M}\sum_{i=1}^{n}\frac{1}{2}(j_i + k_i)]^2}{\frac{1}{M}\sum_{i=1}^{n}\frac{1}{2}(j_i^2 + k_i^2) - [\frac{1}{M}\sum_{i=1}^{n}\frac{1}{2}(j_i + k_i)]^2} \tag{6}$$

According to Eq. (5), if K_{nn} is an increasing trend, then there is a central authoritative node in the mixed trust network. According to Eq. (6), a positive assortativity coefficient value shows that users with a high degree of trust prefer to connect to each other. However, a negative assortativity coefficient value shows that users with a small degree of trust tend to connect to users with a high degree of trust.

3.3. Methodology

3.3.1. The influential power metric of top persuaders in a mixed trust network

The influential power metric is a measure used to evaluate the influential power of a top persuader in a social network. However, existing metrics, such as degree centrality, take into account only the homogeneous relationships between users, ignoring heterogeneous relationships. For example, a mixed trust network includes both trust relationships and distrust relationships. Therefore, it is imperative to design a new metric to measure the influential power of a top persuader in a mixed trust network.

The PageRank algorithm is mainly used to measure the importance of a specific web page on the Internet relative to other web pages in a search engine [41]. The algorithm is also widely used to assess the importance of a user in OSNs [38]. The PageRank value of a web page (that is, the number of tickets) is derived from the recursive algorithm for the importance of all links to its web pages. However, in a mixed trust network, most users have both trust relationships and distrust relationships. It is assumed that

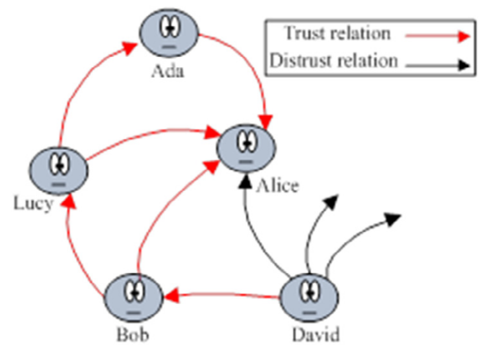

Fig. 2. A toy for mixed trust PageRank metric . (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

a trust relationship indicates a positive vote and that a distrust relationship indicates a negative vote. In this case, the PageRank algorithm cannot be directly used to measure the importance of the influence of a user in a mixed trust network. Therefore, based on the PageRank algorithm, we present a novel metric called the MTPR to measure the importance of a user in a mixed trust network. The MTPR is denoted by Eq. (7).

$$MTPR(u_i) = \sum_{u_j \in T_i} \frac{MTPR(u_j)}{trustDegree_j} - \sum_{u_k \in D_i} \frac{MTPR(u_k)}{distrustDegree_k} \tag{7}$$

where $MTPR(u_i)$ denotes the mixed trust PageRank value of user u_i and $trustDegree_j$ and $distrustDegree_k$ denote the degree of trust of user u_j and the degree of distrust of user u_k, respectively. T_i denotes the set of users who trust user u_i, and D_i denotes the set of users who distrust user u_i.

To illustrate the MTPR metric in a mixed trust network, a toy is shown in Fig. 2. Suppose that there is a social network that includes both trust relationships and distrust relationships among users. The red arrows and black arrows denote the trust relationships and distrust relationships, respectively. Taking Alice as an example, we introduce the calculation method of the MTPR value as follows.

Alice obtained three trust relationships from Lucy, Ada, and Bob and obtained a distrust relationship from David. According to Eq. (7), the *MTPR* value can be calculated via Eq. (8).

$$\begin{aligned} MTPR(\text{Alice}) = {} & MTPR(\text{Ada}) + MTPR(\text{Lucy})/2 \\ & + MTPR(\text{Bob})/2 - MTPR(\text{David})/3 \end{aligned} \tag{8}$$

3.3.2. The novel top persuader identification approach based on MTPR

Prior approaches to identifying top persuaders considered only trust relationships and ignored distrust relationships [9,47], which led to the identification of top persuaders with a high negative impact. Since there are both trust relationships and distrust relationships between users in a user trust network, it is necessary to propose a novel approach to identifying top persuaders. Therefore, based on the *MTPR* metric, the top persuader identification approach is proposed; it adapts to mixed trust networks by improving the traditional PageRank algorithm. The detailed approach is shown in Algorithm 1.

Algorithm 1 The top persuader identification algorithm based on *MTPR*

Input: User trust list sets (Trust-list) and user distrust list sets (Distrust-list)

Output: The influential power rank of top persuaders.

Variable: The number k of top persuaders

1. $\boldsymbol{T}_{N\times N}$, $\boldsymbol{D}_{N\times N}$ and $\boldsymbol{G}_{N\times N}$ are adjacency matrices used to store trust networks, distrust networks and mixed trust networks respectively, where N represents the number of users in mixed trust networks.
2. **for** i=1 **to** N **do**
3. **for** j=1 **to** N **do**
4. **if** $(u_i, u_j) \in$ Trust-list
5. t_{ij}=1;
6. **else** t_{ij}=0;
7. **if** $(u_i, u_j) \in$ Distrust-list
8. d_{ij}=1;
9. **else** t_{ij}=0;
10. **end for**
11. **for** i=1 **to** N **do**
12. **for** j=1 **to** N **do**
13. $g_{ij}= t_{ij}- d_{ij}$ // Calculate the adjacency matrix of the mixed trust network
14. **end for**
15. **for** i=1 **to** N **do**
16. **for** j=1 **to** N **do**
17. $c[i]= c[i]+g[i][j]$; // Calculate the column sum of the adjacency matrix
18. $r[i]= r[i]+g[j][i]$; // Calculate the row sum of the adjacency matrix
19. **end for**
20. **for** i=1 **to** N **do**
21. **for** j=1 **to** N **do**
22. $\delta_{ij}=g_{ij}$ ***div*** c[i]; // Obtain the Markov state transition matrix
23. **end for**
24. Solve equation $\alpha=(x_1, x_2, ..., x_N)^T$, $A\alpha = \alpha$ // α represents the steady-state probability, which is defined as the *MTPR* vector under the mixed trust network, and x_i represents the influential power of the ith user.
25. Descend the order for α , and output Top K top persuaders.

The algorithm tries to identify top persuaders in mixed trust networks based on the MTPR index. Mixed trust networks are represented by a directed graph, where each user represents a node of the directed graph and a directed edge of the directed graph represents the trust/distrust relationship between users. Suppose that the process of a user who selects to trust/distrust the next user is independent of his/her past trusted/distrusted users and depends only on that user's current trusted/distrusted users. Therefore, the user selection process in a mixed trust network can be regarded as a finite state discrete time stochastic process, and its state transition process can be described by a Markov chain [48]. The MTPR value of each user in a mixed trust network is calculated through step 24 in Algorithm 1. The time complexity of Algorithm 1 is $O(N^2)$.

4. Empirical study

4.1. Datasets

This study utilized public datasets crawled by Paolo Massa from Epinions.com [49]. The datasets contain not only the trust

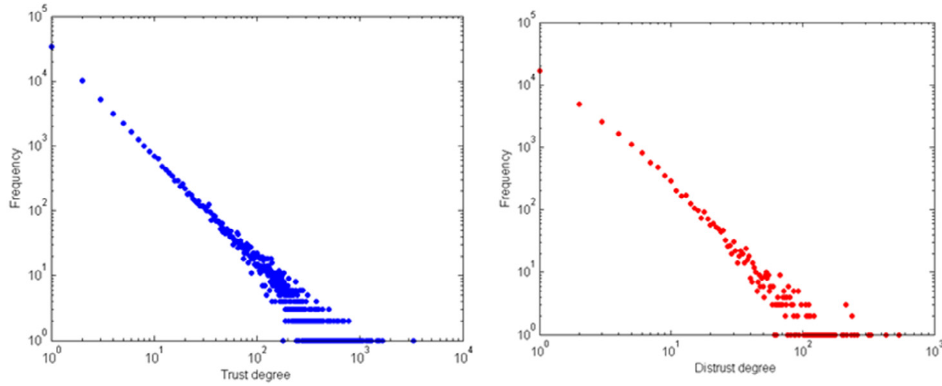

Fig. 3. The degree distribution of mixed trust networks.

relationships but also the distrust relationships between users. They provide a data basis for studying the structural properties of mixed trust networks and top persuader identification in a mixed trust network. The statistical characteristics of the datasets have been studied, and the validity of the datasets as a sample of the Epinions.com social network has been verified. The datasets contain 131,829 users and 841,372 trust/distrust relationships, where the number of trust relationships is 717,667 and the number of distrust relationships is 123,705. There are 85,000 users who obtained at least one trust/distrust relationship, 1,560,144 reviews, and 13,668,319 review ratings.

4.2. The positive and negative influence evaluation metric

To compare the top persuader identification approaches by considering positive and negative influence, the PNI measure is applied to determine the influence of a top persuader in an OSN [50]. The value of the PNI can be regarded as an influence rate that describes how the audience of a top persuader is positively or negatively influenced. We first introduce the positive–negative ratio (PN ratio) for a top persuader. The PN ratio for a top persuader is defined as the number of trusted users from the audience divided by the number of distrusted users from the audience. The PN ratio is defined by Eq. (9).

$$\rho(\mathrm{u_i}) = \frac{count_i(\text{trusted users of audience of top persuader } \mathrm{u_i})}{count_i(\text{distrusted users of audience of top persuader } \mathrm{u_i})} \tag{9}$$

where $\rho(u_i)$ denotes the PN ratio of top persuader u_i, $count_i$ (trusted users in the audience of top persuader u_i) denotes the number of trusted users who trust top persuader u_i, and $count_i$ (distrusted users in the audience of top persuader u_i) denotes the number of distrusted users who distrust top persuader u_i. Based on the PN ratio, the PNI measure is defined by Eq. (10) [50].

$$PNI = \left[\sum trustee(u_i) + \sum distrustee(u_i)\right] \times \rho(u_i) \tag{10}$$

where PNI denotes the positive–negative influence value of top persuader u_i, $\rho(u_i)$ denotes the PN ratio, and $\sum trustee(u_i) + \sum distrustee(u_i)$ represents the entire audience of top persuader u_i. Based on the PNI measure, different top persuader identification approaches can be tested by considering positive and negative influence in a social network.

4.3. Experimental results

4.3.1. Analytical results of the structural properties of mixed trust networks

Analysis is conducted to investigate the potential structural properties of mixed trust networks using the four measures introduced in Section 3.2, i.e., the degree distribution, the correlation coefficient of trust and distrust, the cumulative distribution of the ratio between the degree of trust and the degree of distrust, and the mix pattern.

Fig. 3 illustrates the distributions of probability when finding a user with a degree of trust and a degree of distrust in mixed trust networks. The results show that both the user's degree of trust and degree of distrust obey the power law distribution, which is consistent with the results from the literature [51]. Furthermore, the observation that these distributions are broad indicates that both trust and distrust degree patterns of users are highly heterogeneous in mixed trust networks. The mean value and variance of the degree of trust of uses are 5.444 and 1045.772, respectively; in addition, the mean value and variance of the degree of distrust of users are 0.9383 and 30.1014, respectively. These characteristics show that mixed trust networks tend to contain centrally located users and that the distrust relationships among users are also widely distributed in a user trust network. The user behavior properties confirm the identification of top persuaders and their influence in distrust relationships on information diffusion.

According to Eq. (3), the correlation coefficient between trust relationships and distrust relationships is 0.3704 (p-value $<$ 0.001). These results show that users' trust relationships are not strong enough to be correlated with their distrust relationships in the context of mixed trust networks. In addition, Fig. 4 shows the cumulative distribution of the ratio between users' degree of trust and degree of distrust. When the ratio between the degree of trust and the degree of distrust is 0.001, 0.01, 0.1 and 1, the cumulative distribution function values are 46.24%, 46.26%, 52.88% and 63.46%, respectively. These results show that most users' degree of distrust is higher than their degree of trust, while for only a small number of users is their degree of trust higher than their degree of distrust. The findings of this study indicate that it is difficult for users with a lower degree of trust to obtain trust from other users and that most users are more likely to be biased toward users with a higher degree of trust than toward those with a high degree of distrust in mixed trust networks. To further confirm this observation, we study the mix pattern of mixed trust networks.

Figs. 5 and 6 provide the results of the correlation function K_{nn} of the user degree of trust and degree of distrust in mixed trust networks, respectively. Fig. 5 shows the mapping between the degree of trust and the average degree of distrust of all nodes with that degree of trust. In Fig. 5, the X-axis denotes the degree of trust, whereas the Y-axis denotes the average degree of distrust. This finding indicates that for users with a low degree of trust, their degree of distrust is also low; however, users with a high degree of trust still maintain a low degree of distrust. In addition, Fig. 6 shows the mapping between the degree of distrust and the average degree of trust of all nodes with that degree

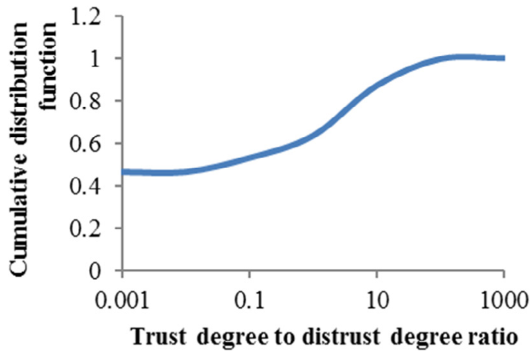

Fig. 4. The cumulative distribution of trust degree to distrust degree ratio.

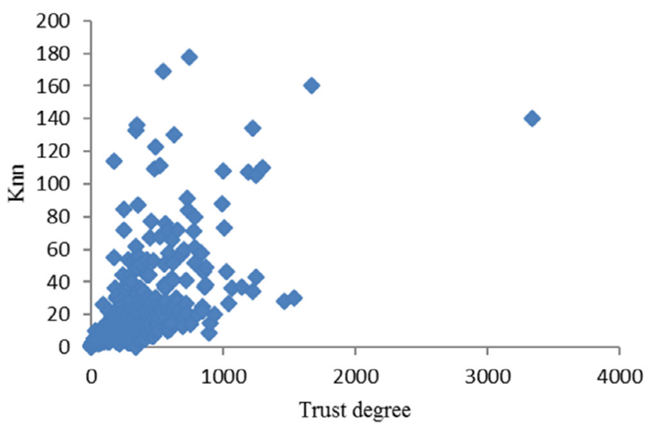

Fig. 5. Log–log plot of K_{nn} values over trust degree.

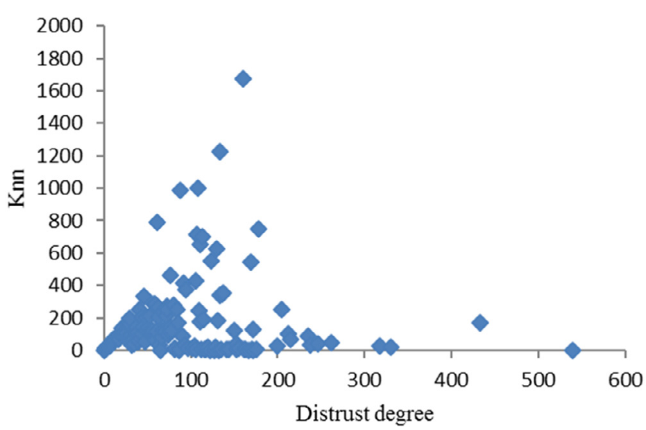

Fig. 6. Log–log plot of K_{nn} values over distrust degree.

of distrust. Similarly, in Fig. 6, the X-axis denotes the degree of distrust, and the Y-axis denotes the average degree of trust. This result shows that users with a high degree of distrust have a low degree of trust; as their degree of distrust increases, their average degree of trust will gradually decrease. The findings from Figs. 5 and 6 indicate that users are more likely to trust their peers with a high degree of trust than those with a high degree of distrust.

If the relationships of trust and distrust in a mixed trust network are both regarded as a relationship between users, then the assortativity coefficient of the mixed trust network is calculated as -0.01725 according to Eq. (6). This negative correlation shows that nodes with small degree values in a mixed trust network tend to connect to nodes with high degree values. In other words, the mixed trust networks in this experiment have disassortativity. On the one hand, the virtual relationships formed in a mixed trust network make it easier for ordinary people to connect with the top persuader, and they tend to be willing to accept connections from others in the network. On the other hand, the top persuader also needs support from the virtual world to achieve his/her real-world performance or to maintain his/her network status. Because the virtual relationship does not require enormous costs (such as time, money, and energy) to maintain interpersonal relationships in real life, it leads to disassortativity, i.e., in a mixed trust network, nodes with small degree values tend to connect to nodes with high degree values.

4.3.2. Top persuader identification and evaluation in a mixed trust network

To validate our MTPR-based top persuader identification approach, this study selects existing algorithms based on the degree centrality algorithm [9] and the PageRank algorithm [41] as benchmark methods. The degree centrality algorithm uses the degree centrality index to express users' influential power, the PageRank algorithm utilizes the PageRank value to measure users' influential power, and our proposed algorithm uses the MTPR index to measure users' influential power. These three algorithms are evaluated based on positive and negative influence in mixed trust networks in terms of the PNI measure [50].

Table 3 shows the top 20 persuaders identified by the three algorithms mentioned above. In this table, the user ID indicates a top persuader's identification number in the mixed trust network, and the user's influential power is calculated by the three algorithms. First, the top persuader rankings are significantly differentiated. For example, user #200118 is ranked no. 2 by the MTPR-based algorithm, but he/she is ranked no. 3 and no. 11 by the degree centrality algorithm and the PageRank algorithm, respectively. In addition, from the perspective of positive influence, the MTPR-based algorithm can identify a top persuader with the highest degree of trust (e.g., user #210284), which is similar to the other algorithms. However, from the perspective of negative influence, the MTPR-based algorithm can identify top persuaders who have a lower degree of distrust and maintain a higher degree of trust. For example, users #200118, #205639, and #480385 are ranked no. 2 by the MTPR, degree centrality, and PageRank algorithms, respectively. User #200118, discovered by the MTPR algorithm, has a higher degree of trust, 1535, and a lower degree of distrust, 30. Although user #480385, discovered by the PageRank algorithm, has the lowest degree of distrust, 9, he/she has the lowest degree of trust, 890. However, user #205639, discovered by the degree centrality algorithm, has the highest degree of distrust, 160, among these three top persuaders.

To further validate the proposed MTPR approach by considering positive and negative influence, the PNI measure is utilized to evaluate the influence of a top persuader in mixed trust networks discovered by the above three approaches. Table 4 shows the PN ratio values and negative influence (distrusted) user percentages of the top 20 persuaders in descending order by the PN ratio. The results indicate that the PN ratio values are inversely proportional to the distrusted user percentages. That is, the larger the PN ratio value is, the smaller the negative influence user percentage of a top persuader. Among the top 20 persuaders, the largest negative influence user percentage of the top persuader discovered by the MTPR algorithm is 8.47%, which is less than percentages of 9.88% and 11.545% of the degree centrality and PageRank algorithms, respectively. In addition, there are 806 distrusted users among the top 20 persuaders discovered by the MTPR algorithm, which is less than the 1259 and 1221 distrusted users discovered by the degree centrality and PageRank algorithms. Overall, the percentage of distrusted users of top persuaders discovered by the MTPR algorithm is less than those of the degree centrality and PageRank algorithms.

Table 3
The rank of top 20 persuaders identified by three algorithms.

Rank	Degree centrality		PageRank		MTPR	
	User ID	Influential power	User ID	Influential power	User ID	Influential power
1	210 284	3338	210 284	99.4711	210 284	124.0093
2	205 639	1673	480 385	91.0574	200 118	107.0046
3	200 118	1536	346 777	83.1920	232 924	88.5378
4	252 420	1464	295 491	75.1894	233 969	87.1540
5	253 067	1295	335 034	73.0939	243 427	83.3482
6	200 338	1252	252 420	70.6929	232 734	83.3007
7	295 491	1246	405 503	68.4578	279 675	80.9240
8	223 677	1225	306 614	67.2847	252 420	77.8755
9	204 418	1222	515 078	66.2365	249 990	74.1532
10	346 777	1190	394 804	65.0787	276 559	74.0456
11	243 427	1139	200 118	61.1328	245 622	74.0311
12	204 441	1067	304 270	58.7504	209 674	73.0211
13	209 674	1040	3 239 350 148	58.6572	272 981	72.4651
14	355 176	1027	205 639	57.4927	223 677	72.4286
15	234 885	1010	471 240 580	56.2635	247 911	72.2125
16	207 186	1001	253 067	56.0373	200 396	68.9521
17	335 034	989	302 444	55.8239	480 385	66.8637
18	200 500	936	293 976	55.6868	471 240 580	66.1876
19	262 868	899	321 708	55.3192	229 318	64.6661
20	480 385	890	372 200	55.0637	253 067	64.3424

Table 5 shows the PNI values of the top 20 persuaders in descending order by the PNI measure and identified by the three algorithms. Apparently, the PNI values of the top persuaders identified by the MTPR algorithm are greater than or equal to those of the degree centrality and the PageRank algorithms. The PNI values of the top 5 persuaders discovered by the MTPR algorithm are the same as those of the PageRank algorithm. However, the PNI values for the MTPR-based algorithm are larger than those of the PageRank algorithm from the 6th to the 20th top persuader. Similarly, the PNI values for the MTPR-based algorithm are basically greater than or equal to that of the degree centrality algorithm. These results indicate that by considering both positive and negative influences in mixed trust networks, the proposed MTPR-based approach is better than the degree centrality approach and the PageRank approach. The main reason is that the MTPR-based approach takes into account both trust relationships and distrust relationships, which makes it possible to identify top persuaders who have the lowest degree of distrust and maintain a higher degree of trust.

4.3.3. Discussion

We investigated the structural properties of mixed trust networks through four measures and compared the proposed MTPR-based approach with benchmark approaches, i.e., the degree centrality and PageRank approaches, in terms of the PNI measure. In mixed trust networks, most users' degree of distrust is higher than their degree of trust, and for only a small number of users is their degree of trust higher than their degree of distrust. Users with a higher degree of distrust have a lower degree of trust because users are more likely to trust their peers with a higher degree of trust than those with a higher degree of distrust. This investigation is meaningful because the positive and negative influence of top persuaders can be both propagated and promoted via the recommendations of users to their followers and peers in OSNs. It would be reasonable for marketers to employ top persuaders with a higher positive influence and a lower negative influence. The proposed MTPR-based approach can identify top persuaders who have a lower degree of distrust and maintain a higher degree of trust in mixed trust networks. By employing these top persuaders discovered by the MTPR-based approach, eWOM marketing campaigns that efficiently utilize mixed trust network resources can not only reach more customers in mixed trust networks but also decrease the negative influence. There are limits to how the proposed approach can be generalized to an OSN without a web of trust because most users in an OSN are reticent in regard to expressing values of trust and distrust.

5. Conclusions

Top persuaders play a critical role in eWOM marketing campaigns, and identifying them with respect to trust in a social network has become valuable to corporations. This study formulates the top persuader identification problem and proposes a novel approach to identifying top persuaders in mixed trust networks. The structural properties of mixed trust network are investigated by four measures: the degree distribution, the correlation coefficient of trust and distrust, the cumulative distribution of the ratio between the degree of distrust and the degree of trust, and the mix pattern. The MTPR index is then designed to evaluate the influential power of a top persuader in the context of a mixed trust network. Reinforced by the dimensions of trust and distrust, an innovative approach is proposed to identify top persuaders in mixed trust networks. The experimental results from real-world social network data show that our approach substantially outperforms traditional approaches in terms of the PNI measure.

This study contributes to the extant literature in several ways. First, based on social network analysis theory, four measures are explored to investigate the trust and distrust behaviors of users in mixed trust networks. Better understanding these behaviors will provide an intuitive identification of top persuaders. Our findings reveal that it is difficult for users with a low degree of trust to obtain trust from other users, i.e., most users are more likely to be biased toward users with a higher degree of trust than those with a high degree of distrust. In addition, mixed trust networks have disassortativity, which indicates that nodes with smaller degree values tend to connect to other nodes with high degree values. Second, our approach to identifying top persuaders simultaneously considers trust relationships and distrust relationships in the context of mixed trust networks; in contrast, most existing approaches focus only on trust relationships. The experimental results indicate that the top persuaders identified by our proposed approach have a higher degree of trust and maintain a lower degree of distrust in mixed trust networks. Finally, from the perspective of eWOM marketing practices, enterprises should not only pay attention to the positive influence of the trust of top persuaders but also make efforts to reduce the negative influence of their distrust on consumers. The proposed approach used in this research can offer a list of effective top persuaders so that corporations can reach more customers in mixed trust networks and then increase their response rate accordingly.

However, this study is limited and must be further expanded. First, mixed trust networks are not always available in all types

Table 4
The percentage of negative (distrusted) users descending by PN ratio.

No.	Degree centrality			PageRank			MTPR		
	Number of audience	PN ratio (ρ)	Negative users (%)	Number of audience	PN ratio (ρ)	Negative users (%)	Number of audience	PN ratio (ρ)	Negative users (%)
1	899	98.89	1.00%	899	98.89	1.00%	899	98.89	1.00%
2	914	59.93	1.64%	593	58.30	1.69%	1492	52.29	1.88%
3	1492	52.29	1.88%	608	54.27	1.81%	1566	51.20	1.92%
4	1566	51.20	1.92%	709	53.54	1.83%	586	44.08	2.22%
5	956	46.80	2.09%	1492	52.29	1.88%	1067	38.52	2.53%
6	1067	38.52	2.53%	1566	51.20	1.92%	868	38.45	2.53%
7	1259	36.03	2.70%	605	45.54	2.15%	726	37.21	2.62%
8	1176	30.78	3.15%	1176	30.78	3.15%	1259	36.03	2.70%
9	1103	29.64	3.26%	1289	28.98	3.34%	1176	30.78	3.15%
10	1289	28.98	3.34%	644	27.00	3.57%	644	27.00	3.57%
11	1073	22.33	4.29%	699	26.96	3.58%	750	26.78	3.60%
12	921	17.80	5.32%	3478	23.84	4.03%	614	25.70	3.75%
13	1083	13.84	6.74%	847	12.89	7.20%	666	24.62	3.90%
14	1357	11.92	7.74%	676	12.00	7.69%	553	24.14	3.98%
15	1405	11.77	7.83%	1405	11.77	7.83%	3478	23.84	4.03%
16	1077	11.24	8.17%	1077	11.24	8.17%	897	18.50	5.13%
17	1297	11.12	8.25%	1297	11.12	8.25%	893	14.40	6.49%
18	1833	10.46	8.73%	1833	10.46	8.73%	847	12.89	7.20%
19	1109	9.27	9.74%	870	9.88	9.20%	1405	11.77	7.83%
20	1356	9.12	9.88%	589	7.66	11.54%	602	10.80	8.47%

Table 5
The positive and negative influence comparison of top 20 persuaders using PNI measure.

Rank	Degree centrality		PageRank		MTPR	
	User ID	PNI	UserID	PNI	User ID	PNI
1	480 385	88 901.11	480 385	88 901.11	480 385	88 901.11
2	210 284	82 925.46	210 284	82 925.46	210 284	82 925.46
3	200 118	80 179.20	200 118	80 179.20	200 118	80 179.20
4	252 420	78 010.29	252 420	78 010.29	252 420	78 010.29
5	262 868	54 779.07	372 200	70 901.14	372 200	70 901.14
6	223 677	45 361.03	304 270	37 958.77	223 677	45 361.03
7	200 500	44 740.80	295 491	37 351.02	209 674	41 099.26
8	209 674	41 099.26	243 427	36 201.73	304 270	37 958.77
9	295 491	37 351.02	405 503	34 571.90	295 491	37 351.02
10	243 427	36 201.73	496 579	32 997.82	243 427	36 201.73
11	204 441	32 691.69	394 804	27 550.76	667 808	35 279.11
12	355 176	23 955.89	3 239 350 148	26 082.00	405 503	34 571.90
13	205 639	19 166.31	205 639	19 166.31	232 924	33 378.55
14	253 067	16 540.68	302 444	18 845.04	496 579	32 997.82
15	372 535	16 390.04	471 240 580	17 388.00	257 170	29 200.56
16	200 338	16 180.61	253 067	16 540.68	394 804	27 550.77
17	234 885	14 983.97	346 777	14 424.58	3 239 350 148	26 082.00
18	346 777	14 424.58	335 034	12 104.01	562 458	24 681.07
19	204 418	12 365.91	249 990	10 913.80	205 639	19 166.31
20	335 034	12 104.01	321 708	8591.25	302 444	18 845.04

of OSNs, such as MySpace and Facebook. Since most users in an OSN are reticent in regard to expressing values of trust and distrust, the proposed approach does not always work effectively. Therefore, the issues of how to evaluate the trust and distrust between users in these types of OSNs and how to build mixed trust networks based on them constitute an interesting problem that will be investigated in our future research. Second, there is massive unstructured information (such as user reviews) available in OSNs that can be utilized for more fine-grained and accurate trust and distrust evaluations. In this context, the methods of sentimental analysis and deep learning could be leveraged to improve the performance of our proposed MTPR approach. Third, there are a great number of isolated users who have no connections with other users in OSNs. The question of how the marketing information of top persuaders reaches these isolated users through their social channels or social reach will be further studied in future work.

Acknowledgments

The authors would like to thank the anonymous reviewers and the editor for their valuable comments and helpful suggestions. This work was partially supported by a grant from the National Natural Science Foundation of China (nos. 71731005 and 61702068), the Natural Science Fund Project of Anhui province, China (nos. 1808085MF170 and KJ2017B16), the Excellent Young Talents Fund Program of Higher Education Institutions of Anhui Province, China (no. gxgwfx2019059), the Education Research Project of Anhui province, China (no. 2017jyxm1240) and the Scientific Research Startup Fund Project of Chuzhou University, China (no. 2016qd10).

References

[1] X. Zhao, J. Yuan, G. Li, X. Chen, Z. Li, Relationship strength estimation for online social networks with the study on facebook, Neurocomputing 95 (14) (2012) 89–97.
[2] T. Leung, F.L. Chung, Persuasion driven influence propagation in social networks, in: 2014 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, IEEE Press, 2014, pp. 548–554.

[3] Feng Wang, Wenjun Jiang, Xiaolin Li, Guojun Wang, Maximizing positive influence spread in online social networks via fluid dynamics, Future Gener. Comput. Syst. 86 (2018) 1491–1502.
[4] L. Corazzini, F. Pavesi, B. Petrovich, L. Stanca, Influential listeners: an experiment on persuasion bias in social networks, Eur. Econ. Rev. 56 (2012) 1276–1288.
[5] Z. Zengin Alp, S. Gündüz Ögüdücü, Identifying topical influencers on twitter based on user behavior and network topology, Knowl.-Based Syst. 141 (3) (2018) 211–221.
[6] X. Fang, P.J. Hu, Top persuader prediction for social networks, Soc. Sci. Electron. Publ. 42 (1) (2018) 63–82.
[7] V. Arnaboldi, M. Conti, A. Passarella, R.I. Dunbar, Online social networks and information diffusion: The role of ego networks, Online Soc. Netw. Media (1) (2017) 44–55.
[8] S. Jendoubi, A. Martin, Liétard Ludovic, H.B. Hadji, B.B. Yaghlane, Two evidential data based models for influence maximization in twitter, Knowl.-Based Syst. 121 (2017) 58–70.
[9] S.X. Liu, C.Q. Jiang, Z.X. Lin, Y. Ding, R. Duan, Z.C. Xu, Identifying effective influencers based on trust for electronic word-of-mouth marketing, Inform. Sci. 306 (2015) 34–52.
[10] S. Jendoubi, Influencers Characterization in a Social Network for Viral Marketing Perspectives (Ph.D. Thesis), University of Rennes, 2016, 1.
[11] C.Q. Jiang, S.X. Liu, Z.X. Lin, G.Z. Zhao, R. Duan, K. Liang, Domain-aware trust network extraction for trust propagation in large-scale heterogeneous trust networks, Knowl.-Based Syst. 111 (2016) 237–247.
[12] N.K. Lankton, D.H. McKnight, J. Tripp, Technology, humanness, and trust: re-thinking trust in technology, J. Assoc. Inf. Syst. 16 (2015) 880–918.
[13] C.X. Ou, C.L. Sia, Consumer trust and distrust: an issue of website design, Int. J. Human-Comput. Stud. 68 (12) (2010) 913–934.
[14] G.D. Moody, D.F. Galletta, P.B. Lowry, When trust and distrust collide online: the engenderment and role of consumer ambivalence in online consumer behavior, Electron. Commer. Res. Appl. 13 (4) (2014) 266–282.
[15] Y.A. Kim, A trust prediction framework in rating-based experience sharing social networks without a web of trust, Inform. Sci. 191 (9) (2012) 128–145.
[16] M. Olmedilla, F.J. Arenas-Márquez, M.R. Martinez-Torres, S.L. Toral, Identification of influencers in eWord-of-Mouth communities using their online participation features, in: 1st International Conference on Advanced Research Methods and Analytics, Editorial Universitat Politècnica de València, Spain, 2016, pp. 38–45.
[17] C. Yi, Y. Bao, J. Jiang, Y. Xue, Modeling cascading failures with the crisis of trust in social networks, Physica A 436 (2015) 256–271.
[18] W. Chen, A. Collins, R. Cummings, T. Ke, Z. Liu, D. Rincon, X. Sun, Y. Wang, W. Wei, Y. Yuan, Influence maximization in social networks when negative opinions may emerge and propagate, in: Proceedings of SIAM International Conference on Data Mining (SDM), 2011, pp. 379–390.
[19] C.M. Cheung, M.K. Lee, Online consumer reviews: Does negative electronic word-of-mouth hurt more?, in: Proceedings of the Fourteenth Americas Conference on Information Systems, Toronto, Canada, 2008, pp. 1–10.
[20] Y.S. Kim, V.L. Tran, Assessing the ripple effects of online opinion leaders with trust and distrust metrics, Expert Syst. Appl. 40 (9) (2013) 3500–3511.
[21] Y.M. Li, C.Y. Lai, C.W. Chen, Discovering influencers for marketing in the blogosphere, Inform. Sci. 181 (23) (2011) 5143–5157.
[22] W. Sherchan, S. Nepal, C. Paris, A survey of trust in social networks, ACM Comput. Surv. 45 (2013) 115–123.
[23] D.E. Zand, The Leadership Triad: Knowledge, Trust, and Power, Oxford University Press, 1997.
[24] P. Dasgupta, Trust as a commodity, Trust Mak. Breaking Coop. Relations 4 (2000) 49–72.
[25] M. Deutsch, Trust and suspicion, J. Conflict Resolution 2 (4) (1958) 265–279.
[26] L.T. Hosmer, Trust: The connecting link between organizational theory and philosophical ethics, Acad. Manag. Rev. 20 (2) (1995) 379–403.
[27] N. Luhmann, Familiarity, confidence, trust: Problems and alternatives, Trust Mak. Reaking Coop. Relations 6 (2000) 94–107.
[28] J. Cho, The mechanism of trust and distrust formation and their relational outcomes, J. Retailing 82 (1) (2006) 25–35.
[29] D.H. McKnight, V. Choudhury, Distrust and trust in B2C e-commerce: Do they differ?, in: Proceedings of the 8th International Conference on Electronic Commerce: The New E-Commerce: Innovations for Conquering Current Barriers, Obstacles and Limitations To Conducting Successful Business on the Internet, Fredericton, ACM, Press, New York, NY, USA, 2006, pp. 482–491.
[30] R.J. Lewicki, B.B. Bunker, Trust in Relationships: A Model of Development and Decline, Jossey-Bass Press, 1995.
[31] P.J. Carrington, J. Scott, S. Wasserman, Models and Methods in Social Network Analysis, Cambridge University Press, UK, 2005.
[32] I. Roelens, P. Baecke, D.F. Benoit, Identifying influencers in a social network: The value of real referral data, Decis. Support Syst. 91 (2016) 25–36.
[33] D.Y. Lu, Q. Li, S.S. Liao, A graph-based action network framework to identify prestigious members through member's prestige evolution, Decis. Support Syst. 53 (1) (2012) 44–54.
[34] P.D. Meo, F. Messina, G.M.L. Sarnè, A.V. Vasilakos, Estimating graph robustness through the randic index, IEEE Trans. Cybern. 48 (11) (2018) 3232–3242.
[35] W.J. Jiang, G.J. Wang, J. Wu, Generating trusted graphs for trust evaluation in online social networks, Future Gener. Comput. Syst. 31 (2014) 48–58.
[36] Jingjun Bi, Chongsheng Zhanga, An empirical comparison on state-of-the-art multi-class imbalance learning algorithms and a new diversified ensemble learning scheme, Knowl.-Based Syst. 158 (2018) 81–93.
[37] Y.M. Li, C.H. Lin, C.Y. Lai, Identifying influential reviewers for word-of-mouth marketing, Electron. Commer. Res. Appl. 9 (2010) 294–304.
[38] D. Saez-Trumper, G. Comarela, Finding trendsetters in information networks, in: Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, ACM, Press, New York, NY, USA, 2012, pp. 1014–1022.
[39] P.D. Meo, K. Musial-Gabrys, D. Rosaci, G.M.L. Sarnè, L. Aroyo, Using centrality measures to predict helpfulness-based reputation in trust networks, ACM Trans. Internet Technol. 17 (1) (2017) 1–20.
[40] Z.A. Zeynep, Gündüz. Öğüdücü Şule, Identifying topical influencers on twitter based on user behavior and network topology, Knowl.-Based Syst. 141 (2018) 232–238.
[41] D. Fiala, L. Šubelj, S. Žitnik, M. Bajec, Do pagerank-based author rankings outperform simple citation counts?, J. Inform. 9 (2015) 334–348.
[42] J. Weng, E.P. Lim, J. Jiang, Q. He, TwitterRank: finding topic-sensitive influential twitterers, in: Proceedings of the Third ACM International Conference on Web Search and Data Mining, ACM, Press, New York, NY, USA, 2010, pp. 261–270.
[43] F. Bodendorf, C. Kaiser, Detecting opinion leaders and trends in online social networks, in: Proceeding of the 2nd ACM Workshop on Social Web Search and Mining, ACM, Press, New York, NY, USA, 2009, pp. 65–68.
[44] A. Mislove, M. Marcon, K.P. Gummadi, P. Druschel, B. Bhattacharjee, Measurement and analysis of online social networks, in: Proceedings of the 7th ACM SIGCOMM Conference on Internet Measurement, ACM, Press, New York, NY, USA, 2007, pp. 29–42.
[45] M.E. Newman, Assortative mixing in networks, Phys. Rev. Lett. 89 (20) (2002) 208701.
[46] M.E. Newman, Mixing patterns in networks, Phys. Rev. E 67 (2) (2003) 026126.
[47] Z. Zhu, Discovering the influential users oriented to viral marketing based on online social networks, Physica A 392 (16) (2013) 3459–3469.
[48] K.W. Khong, N.C. Onyemeh, Y.L. Chong, Bsem estimation of network effect and customer orientation empowerment on trust in social media and network environment, Expert Syst. Appl. 40 (12) (2013) 4858–4870.
[49] P. Massa, P. Avesani, Trust-aware recommender systems, in: Proceedings of the 2007 ACM Conference on Recommender Systems, ACM, Press, New York, NY, USA, 2007, pp. 17–24.
[50] Y. Bae, H. Lee, Sentiment analysis of twitter audiences: measuring the positive or negative influence of popular twitterers, J. Am. Soc. Inf. Sci. Technol. 63 (12) (2012) 2521–2535.
[51] W. Yuan, D. Guan, Y.K. Lee, S. Lee, S.J. Hur, Improved trust-aware recommender system using small-worldness of trust networks, Knowl.-Based Syst. 23 (2010) 232–238.