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A trust prediction framework in rating-based experience sharing social networks without a Web of Trust

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ABSTRACT

As online experience sharing sites have become one of the popular collaborative online communities, people are easily able to share their good and bad experiences on various products and services with a large number of unknown people as well as their friends. These experience sharing communities try to encourage social interaction among people and facilitate experience sharing and dissemination with satisfaction. The social interactions among users in such online communities are constructed based on trust that is established from each user's subjective perspective on the experiences in the community. Since a robust trust system is vital in experience sharing online communities, we therefore propose a computational trust framework for predicting a degree of trust or trust-connection between a pair of users. The Web of Trust, which consists of explicit trust rating among users, is not always available and is typically sparse, so the proposed framework does not rely on a Web of Trust. The proposed trust system measures a degree of trust based on users' expertise and preferences regarding topics (i.e. categories), using users feedback rating data which are available and much denser than a Web of Trust. In order to derive a more personalized degree of trust, the expertise- and preference-based trust is refined with each user's subjective and direct experiences with community members as well as a target user. The empirical experiments show that our proposed trust framework is quite promising in ratings-based online experience sharing communities, even when there are not enough user feedback ratings to predict a degree of trust.

1. Introduction

Users frequently share with their friends their good and bad experiences with all aspects of commerce, such as products, paid services, advice, transaction experiences with a vendor, etc. The information about a user's experiences often flows through social relations and strongly influences other people's future experiences including purchasing decisions. An online experience sharing community, which is one of the popular collaborative online communities, facilitates knowledge and experience sharing among users through user-generated content such as reviews, reports, videos or photos. These experience sharing communities also encourage large-scale social relationships among community users to enhance the quality of information discovery and dissemination through social networks [3]. For example, Epinions.com (an online product review sharing community) allows users to express their opinions regarding who to trust or distrust, and then maintains a trust network called 'a Web of Trust' consisting of 1 (trust), −1 (distrust), or 0 (non-trust) between users. In order to

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leverage social connections between users, trust values in 'a Web of Trust' can be used for personalized recommendations of reviews or users that may interest another user.

In terms of personal knowledge and experience sharing, social interactions among users are constructed based on trust that is established from each user's subjective perspective. Some users trust certain other users very strongly, and then are more influenced by their opinions. Even though a certain user is very reputable in a whole network, some users may not trust him/her. This phenomenon is explained by the subjective property of trust [8]. Since trust is a subjective degree of belief about a user, the global approach, such as the average opinion about the person's trustworthiness, may not be effective for capturing trustworthy social relations for each user. Therefore, the goal of trust systems in users' experience sharing online communities is for each user to predict a subjective degree of trust, and then personalize a large-scale online community using reliable content of each user's trustworthy users. Then, a satisfactory and robust trust system will allow evaluation of neighbors, reduce uncertainty regarding trustworthiness of unknown users in a community and reach out to the rest of the community through social connections [3].

Recently, a large amount of study on online social networks has focused on developing a trust inference model [1]. One significant proposed approach on trust prediction involves constructing a Web of Trust (i.e. a network of pair-wise trust relationships) by asking users to explicitly express whom they trust and how much they trust them. In return, this is applied to the entire network of relationships through a chain of trust relationship using trust propagation, link prediction or various classification models with network topological features [6,8,10,16,18–20]. However, these approaches strongly rely on the availability of a Web of Trust. In practice, a Web of Trust is not always available for all online experience sharing communities. In the few cases that it is available, such as Epinions, it does not work effectively since most users in online experience sharing communities are very reticent to express trust values. The sparseness of a Web of Trust strongly affects the quality of trust prediction because many users are not connected to a trust network and most of the user pairs fail to find paths from a source user to a target.

In the context of such an experience sharing community, it is more beneficial and promising to propose a trust system which is not affected by the density and availability issues of a Web of Trust. Therefore, in this paper, we propose a trust framework for predicting a degree of trust without a Web of Trust. The framework can be generally applicable to most of the rating-based experience sharing online communities where users evaluate individual user-generated content with numerical ratings. For example, Fig. 1 illustrates how a content provider is connected to content users (i.e. content consumers) based on his/her content (i.e. a product review) in Epinons.com, one of the popular ratings-based experience sharing communities. In Fig. 1, user A writes some review content Rk as a content provider and users B, C, and D, as content users/consumers, evaluate part of the review content Rk with numerical ratings. The numerical feedback ratings data on user-generated content is easily collected in online experience sharing communities and is much more frequently expressed by users compared to trust values within a Web of Trust. However, predicting a degree of trust with such numerical feedback

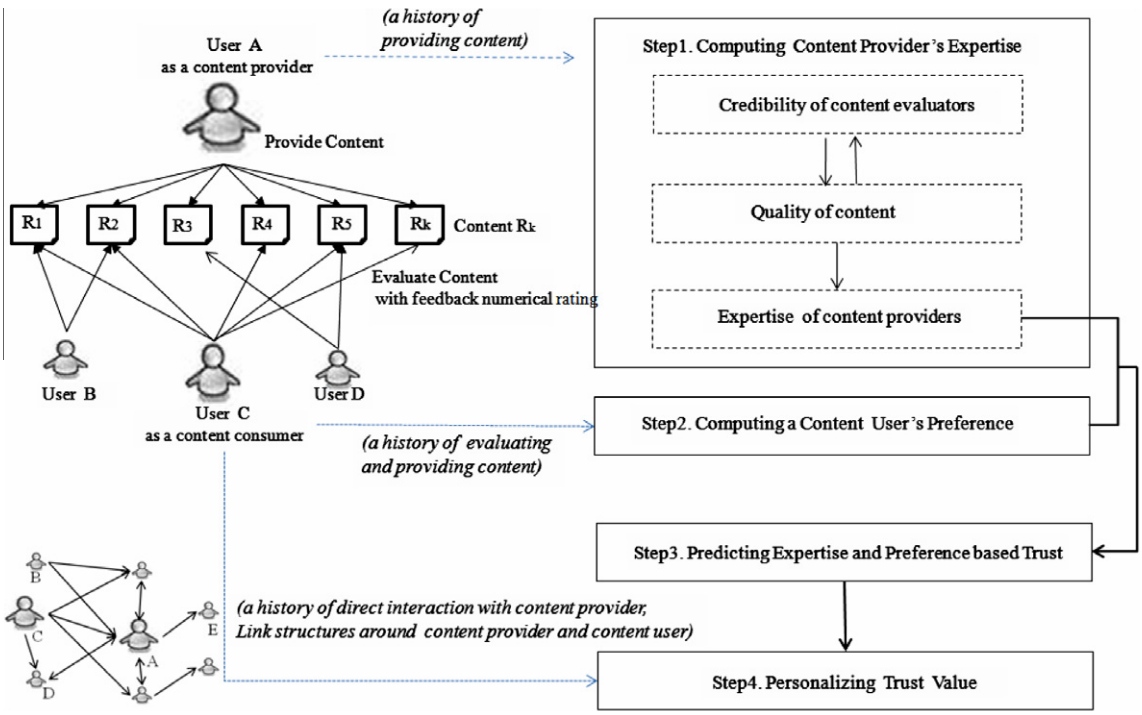

Fig. 1. A trust prediction framework.

ratings on content is also challenging because of the introversive behavior of content users. For example, when a content user has to make a trust decision on a certain content provider whose content is of interest to the content user, s/he may read all or most of the content of this provider but *may not explicitly evaluate all reviews with numerical ratings*. This introversive behavior regarding a trust connection may be confused with a non-trust relationship. A non-trust relationship is defined as a loosely affiliated connection with a content provider, of which status remains until the content user is fully confident about the content provider's trustworthiness. In reality, much of the explicit trust in Epinions' Web of Trust is established after providing only 1 or 2 positive numerical feedbacks on a content provider's review content. Also, a large percentage of non-trust connections in a Web of Trust exists based on 1 or 2 positive numerical feedback ratings on a content provider's content. For example, say user B and user C explicitly evaluate one review of user A as 'most helpful' and then user B expresses 'trust' for user A, but user C does not. Judging by introversive behavior, we could expect that user B may read many reviews to establish a trust decision, but not explicitly evaluate all of the reviews with numerical ratings. In the case of user D, s/he did not fully trust user A after reading a single review and hence is loosely affiliated with user A. Without explicit trust information (i.e. a Web of Trust), it is challenging to distinguish the trust connection based on introversive behavior, such as the relationship between user B and user A, from the non-trust connection of a loosely affiliated relationship, such as the one between user C and user A.

In order to overcome the lack of direct interaction such as explicit numerical feedback rating between a content user and a content provider, we start with a content provider's expertise (i.e. reputation) and a content user's preference (i.e. interests). These become the principal factors in deriving trust connectivity. The key idea is that a user would trust an expert in an area of great interest to the user. For example, say user B is mostly interested in electronic products, according to his/her history of activity in Epinions, while user A has developed a good reputation on movie and electronic products recommendations by writing many helpful reviews. In this situation, we can expect that user B will trust user A to some degree and user B's trust for user A comes from the electronic products category, not the movie category. Since the degree of trust is a function of the expertise (i.e. reputation) of a content provider and the preference (i.e. interests) of a content user, the degree of trust will be zero if no overlap is present between their categories. Users' expertise and preferences on specific categories can be easily calculated even though an individual interaction between a content user and a content provider is established with a few direct feedbacks. However, this expertise- and preference-based trust is similar to reputation-based trust (i.e. global trust) and provides a less personalized value. Although introversive behavior in explicitly expressing numerical ratings on content poses an important challenge to achieving sufficient feedback ratings between two users, trust connections (which are primarily subjective) should be constructed and predicted with a personalized feedback mechanism. Therefore, we refine the trust value with given limited direct interactions, such as user-to-content and user-to-user interactions, in order to raise the level of personalized trust estimates between each pair of users. Even for introversive users who barely provide explicit feedback rating, a small number of feedback ratings with a content provider and interactions with other community members are useful for personalizing trust value and will positively affect the prediction accuracy.

In this paper, we propose a computational social trust framework for predicting trust connectivity between a pair of users based on users' expertise and preferences regarding specific topics and a small number of direct interactions. Our algorithm uses only user feedback rating data on content, even without the existence of a Web of Trust. Extensive experiments with datasets from Epinions show that our framework successfully works in online experience sharing communities where many of the users show introversive behavior and lack direct interactions to be used in developing accurate trust estimates. It is also quite promising to apply our trust framework to E-commerce websites such as Amazon.com or Netflix.com, which allow users to write reviews for various products and to evaluate other user's reviews with numerical ratings for assisting their potential consumer purchasing decision.

The remainder of the paper is organized as follows. In Section 2, we provide an overview of the related work on trust prediction models. Section 3 describes our proposed trust framework and Section 4 presents the experimental results. In Section 5, we conclude with the discussions and contributions of this study.

2. Related work

Drawing from theoretical and empirical studies on trust, social interactions or transactions in an online context are conducted based on trust and reputation of a participant or online environment itself [12,31]. Then, it is necessary to provide a robust trust mechanism which can predict trust with other participants and recommend trustworthy participants in order to facilitate social interactions among them. Regarding this objective, technical and computational trust models are suggested in various online environments.

One of the major approaches to predicting trust is to develop 'global trust models' such as the reputation model in e-Bay (www.eBay.com). Global trust models compute a universal measure of trust for an individual user using either feedback from all witnesses or a link structure in the online communities. Kamvar et al. [13] provide the EigenTrust algorithm to calculate a unique global trust value for each peer in a peer-to-peer file sharing network based on a history of each peer's file uploading. It aggregates the local trust assessments of all peers with a variation of the PageRank model. However, many of the EigenTrust-based approaches generate a ranking of the trustworthiness among network users, but cannot produce trust values with the same scale employed by users to assign ratings. Chen and Singh [4] develop a rating aggregation system for the rating-based online communities to measure a reputation value for raters and generate high quality information about rated objects. The global trust value (i.e. reputation) or ranks are assigned to each peer in a network and quantify the amount of trust the system as a whole places in each peer. The global trust value can clearly reflect the general agreement regarding a user. However, it would meet a challenge when predicting a trust value on users who received a variety of high and low scores, reflecting disagreement on trust ratings.

The other approach is 'local trust models,' sometimes called a private reputation, which calculates a personalized trust value from each user's subjective view of the network. Some researchers consider only 'local trust' as true 'trust metrics' and distinguish 'global trust' from these true 'trust' metrics. They claim to define 'local trust' as trust and 'global trust' as reputation. With the assumption that each user first explicitly specifies a small set of users whom s/he trusts and then defines a personalized Web of Trust (if available), the trust value from one user to an unknown user is measured based on the set of direct trust relationships around a user and the set of indirect trust relationships reachable by passing through the trust chains.

Richardson et al. [26] and Golbeck [8] propose trust propagation-based trust prediction mechanisms given a Web of Trust consisting of continuous trust values. The trust value from a source user to a target user is computed by propagating trust through the source user's trustworthy network until it reaches a target user. Guha et al. [10] develop a framework of trust propagation schemes which reduce the sparsity of a Web of Trust by introducing the concepts of co-citation, transpose trust and trust coupling, and then propagate trust and distrust. The performance of these trust propagation approaches cannot help being affected by the density of a Web of Trust. If a Web of Trust is too sparse, it is difficult to find trustworthy paths from a source user to a target. In addition, aggregation functions along each possible chain of trust from the source user to a target user affect the prediction accuracy. The computational complexity of aggregation in the trust propagation approach exponentially increases as there may be larger numbers of reachable users and many different paths of various lengths.

Matsuo and Yamamoto [20] empirically measure bidirectional effects of trust and the similarity of product ratings in a Japanese cosmetic review sharing community. In this study, by developing a trust prediction model of SVM classifier, they identify the positive features in the trust prediction model, such as the common trust neighbors and the similarity of common product ratings between two users. Zolfaghar and Aghaieb [40] proposed a time-aware trust prediction approach which incorporates the temporal evolution of trust networks to predict future trust relations (or links) with a supervised learning method. While most of the current studies on trust prediction use a trust graph structure at a single snapshot of time, the time-aware trust prediction considers the impact of the dynamics of trust networks and then improves the prediction accuracy of future trust links. In the classification or the supervised model, the explicit trust value in a Web of Trust is necessary and critical to train the trust prediction model as an output variable.

The growing research on trust in social networks, as well as the popularity of online social networks, has also generated a rising interest in trust-based or trust-enhanced recommender systems. Such systems incorporate trust relations among users into their recommendation algorithms where trust information is used as a sophisticated filter to find a fitting (i.e. similar and trustworthy) neighborhood. One of the very important features of the trust-enhanced recommender systems is the mechanism of trust propagation. Compared to traditional recommender systems employing Collaborative Filtering (i.e. CF), it improves the performance of recommendation, especially for cold start users, in both prediction accuracy and coverage using a trust propagation approach. Pitsilis and Chia [25] explored whether explicit trust relations are able to improve the performance of recommendation in conjunction with users' similarity or usage experience. They found that using explicit trust to select the best neighborhood is more useful to the least active users who are less experienced than to the active users within the Epinions dataset. Yuan et al. [37] identified the existence of small-world properties in explicit trust networks and then made use of the features to improve the trust-based recommender systems. The trust-based recommender system is not directly related to our research objective. However, since such system highly relies on explicit trust information, it will benefit from a trust prediction model like our study which provides a denser Web of Trust for recommendation.

Instead of using explicit trust information for a trust-based recommender system, O'Donovan and Smyth [24] and Victor et al. [33] focus on simple but useful approaches to integrating trust into a standard recommendation algorithm where trust or the level of influence is simply measured with ratings on items/reviews. O'Donovan and Smyth [24] measured user trust based on a history of rating errors in contribution to recommendations. However, the error-based trust model produces a global trust reflecting the general contribution over all users, not a local trust (i.e. private trust). Victor et al. [33] simply defined key figures such as mavens, frequent raters, connectors based on the number of reviews written or rated. These selected key figures are globally reputable users who wrote or rated many items/reviews and then contribute to a cold start user's recommendation on the whole. However as Victor et al. [33] mentioned, the global trust may help a cold start user connect a large number of influential users, but will fail to provide a personalized recommendation for users having different preference from the general agreement.

In summary, a small number of explicit binary or continuous trust values given by each user and leading to a Web of Trust play an important role in modeling a robust social trust system. Many studies have been done on local and global trust models by relying on a Web of Trust. However, these models cannot be directly applied to general rating-based experience sharing online communities where users are asked to evaluate individual objects (i.e. reviews, comments or knowledge shared by others), rather than to evaluate an individual user's trustworthiness. Therefore, the research contribution and purpose of this study is twofold. First, we predict a trust rating value without the use of explicit trust ratings which are not always available and are difficult to collect in sufficient quantities for trust prediction. Second, the trust value generated by the model uses the same scale employed by users to assign ratings, not a ranking or relative score (i.e. the ratio of positive experience over negative experience). Then, the predicted trust score can be incorporated with explicit trust scores when they are available to improve the density of a Web of Trust. The denser Web of Trust will open opportunities to obtain improvement in some applications, such as a trust-enhanced recommender system or trust propagation for long-distance connected users' trust value.

3. The framework for deriving trust

In this section, we describe a framework for deriving a degree of user trust in experience sharing online communities. As shown in Fig. 1, users participate in experiences sharing and dissemination by providing own user-generated content or evaluating other user's content with numerical ratings. Then, a content user (i.e. consumer) can be directly connected to a content provider based on common content that the provider generates in an online community. The proposed framework estimates a degree of trust from a content user to a content provider based on a content user's preference, a content provider's expertise and a small number of direct interactions between them. The first step is to compute the expertise of a content provider for each category based on a history of providing content about the category. The second step is to compute the preference of a content user for each category, which captures his/her interest in and affinity with the category based on various participation activities in that category. In the third step, a degree of trust is predicted by combining a content provider's expertise and a content user's preference over all categories. In the last step, the derived trust is refined by direct interactions and the link structure around the two users in order to achieve a trust value from a content user's more subjective point of view toward a content provider.

3.1. Step1. Computing a content provider's expertise on a category

While trust is a subjective degree of belief that a user has toward a certain other user, reputation represents the objective views of the certain user's expertise from the whole of online community members [39]. In the rest of the paper, we will use "expertise" of a content provider instead of "reputation" since the term is more specific for our study. Users' expertise as a content provider usually varies across knowledge contexts or topics which are often arranged by categories in online communities [4,27]; hence, a content provider's expertise should be calculated by the categories in an online community. In our context, "category", "context", and "topic" are used interchangeably.

The general idea of the computation of a content provider's expertise on a category is as follows:

- The good content providers are those who provide *many high quality content reviews* for a specific category (i.e. context or topic).
- High quality content are those which receive *high ratings* from *more reliable content users*.
- Reliable content users (i.e. evaluator) are those who *consistently evaluate many content ratings* near *the ultimate consensus of the quality of content* in a specific category.

As shown in step 1 of Fig. 1, first the quality of content and credibility (i.e. reliability) of a content user in a category will be measured simultaneously, then the expertise of a content provider is computed as a function of the quality of content in a category.

3.1.1. The quality of content and the credibility of a content user in a category

The quality of content is a weighted average of received feedback from all content users in the content category. The rating value from a more credible user is weighted more than from a less credible user as follows:

$$\boldsymbol{q}_j = \frac{\sum_{i\in U(q_j)} \boldsymbol{u}_i^c \cdot \boldsymbol{r}_{ij}}{\sum_{i\in U(q_j)} \boldsymbol{u}_i^c} (0 \leqslant \boldsymbol{q}_j \leqslant 1) \tag{1}$$

where q_j: the quality of content j, $U(q_j)$: the set of users that evaluate content j, $\boldsymbol{r}_{ij}$: a feedback rating value that user $i(u_i)$ gives to content $j(0 \leqslant \boldsymbol{r}_{ij} \leqslant 1)$ and $\boldsymbol{u}_i^c$: a credibility of content user i on the content j's category.

$$\boldsymbol{u}_i^c = \left(1 - \frac{1}{|N(\boldsymbol{u}_i^c)| + 1}\right) \times \frac{\sum_{j\in N(\boldsymbol{u}_i^c)} 1 - |q_j - r_{ij}|}{|N(\boldsymbol{u}_i^c)|} (0 \leqslant \boldsymbol{u}_i^c \leqslant 1) \tag{2}$$

where $\boldsymbol{u}_i^c$: the credibility of content user i on a category and $N(\boldsymbol{u}_i^c)$: the set of content evaluated by user $i(\boldsymbol{u}_i)$ in a category.

As shown in Eq. (2), the credibility of a content user as an evaluator considers the number of content evaluated by the user in a category as well as an average difference between ultimate quality of content and the user's explicit rating. If a user has rated one content category close to the ultimate quality of content, it is difficult to conclude whether the user is a reliable evaluator. Then, this model compensates for less experience evaluating content by discounting the number of evaluated content as:

$$\left(1-\frac{1}{|N(u_i^c)|+1}\right)\ [15,27].$$

In each category, all of the content and content users who evaluate at least one content in a category are simultaneously calculated until their convergence is reached and periodically updated.

3.1.2. The expertise of a content provider with a category

Given the quality of content in a category, the expertise of a content provider within a category is computed by an average of the quality of all content that a content provider has input into a category. In order to discount less experience with providing content in a category, we also consider the number of content provided by a content provider as follows:

$$\boldsymbol{u}_i^e=\left(1-\frac{1}{|N(\boldsymbol{u}_i^e)|+1}\right)\times\frac{\sum_{j\in N(u_i^e)}\boldsymbol{q}_j}{|N(\boldsymbol{u}_i^e)|}\left(0\ \leqslant\ \boldsymbol{u}_i^e\ \leqslant\ 1\right) \tag{3}$$

where $\boldsymbol{u}_i^e$: the expertise of content provider $i(u_i)$ in a category and $N(u_i^e)$: the set of content that content provider $i(u_i)$ provides in a category.

The more high quality content a content provider shares, the more visible s/he is to the people who are interested in the category. Moreover, the content provider with a high expertise value will become popular with the direct evaluators' surrounding neighbors who are also interested in the category through word-of-mouth effects; this leads to a high reputation with many trust in-links.

3.2. Step2. Computing a content user's preference for a category

User preference modeling has been employed to improve the representation of a user's purchasing or information needs in recommender systems [5] and information filtering systems [14,22]. The User preference can be inferred by observing a user's explicit or implicit web usage actions, such as click-through, reading time of a page, basket placement of products and the like, on a Web site, or actual consumption patterns [14,22]. Cho et al. [5] proposed a customer preference model for recommender systems, which counts the number of occurrences of three web usage actions: 'clicking on a product webpage,' 'placing a product in a basket,' and 'purchasing a product.' They measured the numbers of each action in a product category and combined them as a product category preference measure. In this section, we adopted and extended the basic approach of Cho et al.'s user preference model by considering a user's general activities in online social networks.

3.2.1. A content user preference analysis

The preference of a content user can be captured based on the user's participation activities, such as providing content or evaluating other users' content about topics in which s/he is interested. In multi-topic online communities, users may be involved in various topics (i.e. categories), but may not necessarily have the same level of preference, affinity or interest in all topics. If a user participated in a certain category more frequently as either a content provider or a content user, this category will be more important for the user as far as finding trustworthy content providers.

For this reason, a content user's preference for a category is measured by counting the number of content evaluated and the number of content provided in a category. In general, the occurrence of providing content is rarer than that of evaluating content. For example, the number of reviews evaluated in Epinions.com is much larger than the number of reviews written by each user, since a user is able to evaluate multiple reviews of a product, but often allowed to write only one review of the same product. Also, writing a review involves more active participation and effort than reading and evaluating others' reviews. Hence, we extract the affinity level as a content provider and the affinity level as a content user separately, and then combine them later after normalization.

From the above discussions, we develop User_Category Preference matrixes for content evaluating behavior (i.e. $\mathbf{P^e}$) and content providing behavior (i.e. $\mathbf{P^p}$) separately as follows:

Let $\mathbf{P^e}$ be User_Category Preference$^{\text{evaluating content}}$ matrix.

$\mathbf{P^e}=(p_{ik}^e),\ i=1,\ \ldots,\ N$ (total number of users), $k = 1, \ldots, M$ (total number of analysis-level categories)

$$p_{ik}^e=\frac{n_{ik}^e}{\sum_{k=1}^M n_{ik}^e},\qquad \left(0\ \leqslant\ p_{ik}^e\ \leqslant\ 1,\sum_{k=1}^M p_{ik}^e=1\right) \tag{4}$$

where p_{ik}^e: the (i,k) element of matrix $\mathbf{P^e}$ and n_{ik}^e: the total number of evaluating content by user i in category k.

Let $\mathbf{P^p}$ be User_Category Preference$^{\text{providing content}}$ matrix.

$\mathbf{P^p}=(p_{ik}^p),\ i=1,\ \ldots,\ N$ (total number of users), $k = 1, \ldots, M$ (total number of analysis-level categories)

$$p_{ik}^p=\frac{n_{ik}^p}{\sum_{k=1}^M n_{ik}^p},\left(0\ \leqslant\ p_{ik}^p\ \leqslant\ 1,\sum_{k=1}^M p_{ik}^p=1\right) \tag{5}$$

where p_{ik}^p: the (i,k) element of matrix $\mathbf{P^p}$ and n_{ik}^p: the total number of providing content by user i in category k.

Table 1
Examples of a content user's preference analysis.

(a) Example of User_Category Preference$^{\text{evaluating content}}$ matrix $\mathbf{P^e}$

	C1	C2	C3	C4
U1	0.8	0.2	0	0
U2	0.5	0	0.5	0
U3	0.2	0.3	0.4	0.1
⋮	⋮	⋮	⋮	⋮
Un	0	0.3	0	0.7

(b) Example of a transaction database from $\mathbf{P^e}$

Transaction ID	Items/categories
U1	{C1,C2}
U2	{C1,C3}
U3	{C1,C2,C3,C4}
⋮	⋮
Un	{C2,C4}

(c) Example of a Category_Association$^{\text{evaluating content}}$ matrix $\mathbf{A^e}$

	C1	C2	C3	C4
C1	1	0.75	0.75	0
C2	0.7	1	0	0.8
C3	0.8	0	1	0
C4	0	0.9	0	1

(d) Example of User_Extended Category Preference matrix $\mathbf{P^{e^*}} (= \mathbf{P^e} \cdot \mathbf{A^e})$

	C1	C2	C3	C4
U1	0.94	0.8	0.6	0.16
U2	0.9	0.375	0.875	0
U3	0.73	0.54	0.55	0.34
⋮	⋮	⋮	⋮	⋮
Un	0.21	0.93	0	0.94

Given the number of content evaluated by user i over all categories k (i.e. n^e_{ik}), each user i (i.e. row i) is normalized so that every row of sums should be 1, as the Example in Table 1a. The (i,k) element p^e_{ik} in matrix $\mathbf{P^e}$ represents user i's relative affinity or interest level in category k compared to other categories. Similarly, the matrix $\mathbf{P^p}$ is obtained from the number of content provided by users (n^p_{ik}).

3.2.2. A category association analysis

In order to capture online users' implicit interest or potential preferences across categories, we search for meaningful associations among a user's categories. We explore association rules among categories from User_Category Preference matrixes $\mathbf{P^e}$ and $\mathbf{P^p}$ respectively. The revealed meaningful rules will be used to predict both implicit interest in categories that are difficult to capture because of introversive behavior by users and potential interest in categories in which users are not currently interested but may show interest if a highly reputable content provider is recommended.

Given User_Category Preference matrix $\mathbf{P^e}$ (or $\mathbf{P^p}$) such as the Example in Table 1a, the mining steps for association rules among categories in terms of content evaluating (or providing) behavior are as follows:

Step1. Transform the matrix $\mathbf{P^e}$ into a transaction database: Each ith row user in $\mathbf{P^e}$ corresponds to a single transaction as $\langle u_i$, {a set of categories k}$\rangle$ where category k refers to the category in which user u_i explicitly show interest (i.e. $p^e_{ik} > 0$). Table 1b demonstrates a corresponding transaction database transformed from Table 1a.

Step2. Set minimum support and confidence for association rule mining: The problem of determining appropriate minimum support and confidence is always difficult in association rule mining. When the distribution of target classes is extremely imbalanced, it is not appropriate to use a single minimum support such as in traditional association rule mining [17]. Using Epinions.com as an example, a category refers to a target class when mining association rules are in the form of rule $\langle$categories $k_i \rightarrow$ categories $k_j\rangle$ and some categories are more popular than others (e.g. movie vs. car or comedy movies vs. religious movies). Hence, we set a minimum support for each category according to the category frequency over all transactions which is proposed by Lui et al. [17] as follows:
For the minimum support for category k,

$$minsup(Category_k) = global\_minsup \times \frac{frequency(Category_k)}{|D|} \tag{6}$$

where *global_minsup*: the global minimum support, *frequency*($Category_k$): the number of transactions (cases) including $Category_k$ in transaction DB and $|D|$: the total number of transactions in transaction DB.

In Eq. (6), we provide a global minimum support and frequency for each category in a transaction database. Then, this Equation generates high minimum support for rules with frequent categories and low minimum support for rules with infrequent categories.

In terms of the minimum confidence, we recommend providing a single confidence (i.e. *minconf*) high enough to find meaningful rules regardless of a distribution of classes.

Step3. Explore all frequent itemsets (category sets) of size 2 and generate association rules in the form of ⟨category $k_i \rightarrow$ category k_j⟩, which satisfy the minimum support and confidence

Step4. With meaningful association rules discovered from Step 1 to 3, construct Category_Association$^{\text{evaluating content}}$ matrix $\mathbf{A^e}$ (or $\mathbf{A^p}$) for content evaluating (or providing) behavior such as the Example in Table 1c:

$\mathbf{A^e} = \left(a^e_{ij}\right),\ i = 1,\ \ldots,\ M$ (total number of categories), $j = 1, \ldots, M$

$$a^e_{ij} = \begin{cases} 1 & \text{if } i = j \\ conf(i,j) & \text{if } conf(i,j) \geqslant minconf \\ 0 & \text{others} \end{cases} \tag{7}$$

where)(a^e_{ij}: the (i,j) element of matrix $\mathbf{A^e}$ and $conf(i,j)$: confidence of discovered rule ⟨category $k_i \rightarrow$ category k_j⟩.

It is noted again that Category_Association matrix $\mathbf{A^e}$ and $\mathbf{A^p}$should be derived respectively from each transaction database of content evaluating behavior and content providing behavior.

3.2.3. The preference of a content user for a category

With User_Category Preference matrixes $\mathbf{P^e}$ and $\mathbf{P^p}$ and Category_Association matrixes $\mathbf{A^e}$ and $\mathbf{A^p}$, we build User_Extended Category Preference matrixes $\mathbf{P^{e^*}}$ and $\mathbf{P^{p^*}}$. Then, we combine two extended preference values from each user i in $\mathbf{P^{e^*}}$ and $\mathbf{P^{p^*}}$ to achieve the final User_Category Preference matrix $\mathbf{P}$.

The User_Extended Category Preference matrix $\mathbf{P^{e^*}}$ (or $\mathbf{P^{p^*}}$) is derived by matrix multiplication of $\mathbf{P^e} \cdot \mathbf{A^e}$. Table 1d shows the example of User_Extended Category Preference matrix $\mathbf{P^{e^*}}$ which is derived by multiplying $\mathbf{P^e}$ in Table 1a and $\mathbf{A^e}$ in Table 1c.

Then, with two prepared matrixes $\mathbf{P^{e^*}}$ and $\mathbf{P^{p^*}}$, the final User_Category Preference matrix $\mathbf{P}$ is computed by the simple average of two preference values in $\mathbf{P^{e^*}}$ and $\mathbf{P^{p^*}}$ as follows:

$$\mathbf{P} = \frac{1}{2}\mathbf{P^{e^*}} + \frac{1}{2}\mathbf{P^{p^*}} \tag{8}$$

where p_{ik}: the (i,k) element of matrix $\mathbf{P}$, the preference level of user i on category $k(0 \leqslant p_{ik} \leqslant 1)$.

The p_{ik} value in final User_Category Preference matrix $\mathbf{P}$ reflects the individual user's explicit, implicit or potential interest over categories. It is meaningful to see which category matters more than others for each user i when finding trustworthy content providers.

3.3. Step3. Predicting expertise and preference based trust

The content providers with high expertise are those who want to share their wisdom and experiences through high quality content for many users. Then they become more visible than others and have an influence on many content users who would put them in their Web of Trust with high probability. In the process of determining trust beliefs in a content provider, the context-dependency of trust is one of the basic properties that we need to consider, as well as the expertise of a content provider [8,38]. For example, say user B is interested in electronic products according to her history of activity, and user A has developed a good reputation (i.e. expertise value) on movie and electronic recommendations by writing many helpful reviews. In this situation, we can expect that user B will trust user A to some degree and user B's trust for user A comes from the electronic category and not the movie product context. Therefore, in this step, we derive a degree of trust as a weighted average of a content provider's expertise for all categories. The value of expertise for a category which is more highly preferred by a content user is weighted to show the content user's preference for the category.

Let $EPTr_{ij}$ be the expertise- and preference-based trust from content user i toward content provider j

$$EPTr_{ij} = \frac{\sum_{k=1}^{M} p_{ik} \cdot u^e_{jk}}{\sum_{k=1}^{M} p_{ik}} \tag{9}$$

where $p_{ik}(0 \leqslant p_{ik} \leqslant 1)$: the preference level of user i on category k in $\mathbf{P}$, $u^e_{jk}\left(0\ \leqslant\ u^e_{jk}\ \leqslant\ 1\right)$: the expertise of content provider $j(u_j)$ on category k and M: the total number of categories.

3.4. Step4. Personalizing trust value

Based on our approach using the expertise- and preference-based trust value $EPTr_{ij}$, we can predict a degree of trust from content user i to content provider j even though there is no direct interaction or no trust path from user i to user j. This is beneficial in creating a large number of trustworthy content providers for content users in order to encourage many new interactions with potential trust providers. However, the expertise- and preference-based trust needs to be more refined for content user i's personalized trust network. In this section, we develop the more personalized trust value from content provider i to content provider j who has at least one previous direct interaction on content.

3.4.1. Personalization with direct interaction feedbacks

Under a circumstance that content user i has direct experiences of content provided by content provider j and explicitly gives at least one numerical feedback rating, we aggregate the personal feedback ratings on content as a direct experience-based trust and combine it with the expertise- and preference-based trust value as follows:

Let $\overline{Tr_{ij}}$ be the personalized trust value from content user i toward content provider j

$$\overline{Tr_{ij}} = \alpha Dt_{ij} + (1 - \alpha) EPTr_{ij} \tag{10}$$

Let Dt_{ij} be a direct experience-based trust from user i toward user j

$$Dt_{ij} = \frac{\sum_{r_{ij} \in R_{ij}} r_{ij}}{|R_{ij}|} \quad (0 \leqslant Dt_{ij} \leqslant 1) \tag{11}$$

where $R_{ij} = \{r_{ij_1}, r_{ij_2}, \ldots, r_{ij_m}\}$: a set of all feedback ratings that user i gives user j's content.

Please note that Dt_{ij} computed using ratings of user j's individual content (e.g. review), not the explicit trust rating of user j.

Since trust building is a social process highly dependent on the past interactions between two users [38], the subjective numerical feedback ratings on content are the most important evidence for influencing trusting beliefs in the content provider. However, if a content user has little personal knowledge (i.e. limited direct experience) with a target content provider, s/he will attempt to get more information from witness testimonies to reduce uncertainty about the content provider. The general idea of combining two trust values Dt_{ij} and $EPTr_{ij}$ adopts the content user's decision-making mechanism regarding a content provider. If a content user has a sufficient number of direct interactions with a content provider, the direct experience-based trust Dt_{ij} is reliable enough for the evidence of trust evaluation $\overline{Tr_{ij}}$ so then the weight α for the direct experience based-trust value in Eq. (10) is increased. On the contrary, if a content user has a small number of direct interactions, the direct experience-based trust value Dt_{ij} is not enough to make a reliable evaluation for trust value $\overline{Tr_{ij}}$. Then, the combination mechanism reduces the weight α for Dt_{ij} and increases the importance of the expertise- and preference-based trust value $EPTr_{ij}$ which helps complement the uncertainty from the lack of direct feedback. The weight α for the direct experience-based trust value Dt_{ij} is determined by the reliability of the estimated direct experience-based trust value Dt_{ij}. We adopt the following reliability function proposed by Sabater and Sierra [28,29] and Xu et al. [35].

Let α_{ij} be the reliability (weight) of a direct experienced-based trust value Dt_{ij}

$$\alpha_{ij} = \begin{cases} \sin\left(\frac{\pi}{2} \cdot \frac{|R_{ij}|}{N_{\min}}\right) & |R_{ij}| \in [0, N_{\min}] \\ 1 & \text{otherwise} \end{cases} \tag{12}$$

where $N_{\min}$: the minimum number of numerical feedback ratings that user i gives on user j's content, for a direct experience-based trust to be confident.

The above method of investigating reliability has been used by Sabater and Sierra in their reputation model [28,29] in multi-agent systems and by Xu et al. in their Swift Trust model in a virtual temporary system [35]; these experiments' results found it reasonable. The intuition behind the minimum number of direct feedback ratings for trust is that an isolated experience is not enough to make a correct trust decision about someone. In order to have full confidence on Dt_{ij}, a certain number of direct feedback ratings is needed. As the number of direct feedback ratings (i.e. $|R_{ij}|$) increases, the amount of confidence (i.e. reliability) increases until it reaches a point which signifies a close relationship between two users. From a social point of view, $N_{\min}$ is the minimum number of direct interactions (i.e. $N_{\min}$) for a close relationship to be constructed. The number of direct feedback ratings higher than $N_{\min}$ will not increase the reliability of Dt_{ij}. As noted in previous researches, a sine function is appropriate to the process of building up and managing the reliability of trust based on intuition.

In some online communities, users need a large number of direct interactions before a final trust decision is made with high confidence while, in other cases, they do not. The minimum number of direct feedback ratings varies in online communities and depends on the direct interaction frequency of content users in the online community [28].

Therefore, we propose to determine the minimum number of direct feedback ratings $N_{\min}$ based on the distribution of the number of direct feedback ratings between all content users and all content providers. When we draw the distribution of the number of direct feedback ratings between content user i and content provider j, the distribution graph (x-axis: the value of $|R_{ij}|$, y-axis: frequency/number of cases) in general will follow the power law distribution (see example of Epinions dataset in our experiments in Fig. 2). Users in online communities will not have a high number of direct interactions and give explicit feedback rating without a strong interest or trust belief. Furthermore, once trust is constructed between a content user and a content provider, the content user keeps interacting with the trustworthy content provider and then the number of interactions will increase. Therefore, as the number of feedback ratings $|R_{ij}|$ increases, there is a high chance that a trust

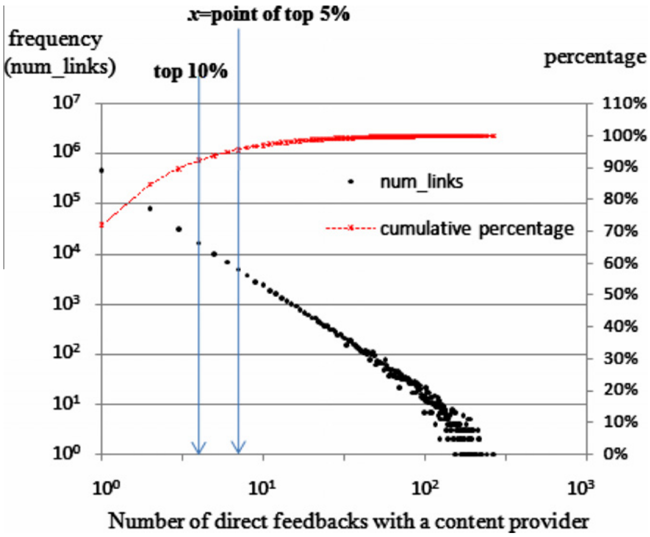

Fig. 2. Distribution of number of feedback ratings on a link between a content user and a content provider.

relationship is established between the two users. Hence, we assume that the top k % ranked user connections in Fig. 2 are built as strong trust connections. In other words, the minimum number of direct feedback ratings of the top k % ranked relations is required for confident trust decisions by individual content users. Then, we set $N_{\min}$ by the number of direct interactions in the top k % rank. In our experiments, we set $N_{\min}$ from the top 5% rank and top 10% rank.

3.4.2. Personalization with network influence

In addition to the direct interaction with content provider j, content user i may maintain direct experiences with a small fraction of other community members. The information on content user i's connections with other community members in a network is useful to view the whole network from content user i's subjective perspective. In particular, the value of $EPTr_{ij}$ in which content provider j's expertise is estimated based on the combined opinion of all network members can be more personalized by using the established connections of content user i with other community members:

$$\overline{Tr_{ij}} = \alpha \cdot Dt_{ij} + (1 - \alpha) \cdot EPTr_{ij} \cdot St_{ij} \tag{13}$$

where St_{ij}: strength of link connection from user i to user j.

As shown in Eq. (13), we propose to discount the expertise- and preference-based trust value $EPTr_{ij}$ with the strength of the link connection from user i to user j. The assumption underlying this discounting approach is that the full potential influence of a highly reputable content provider's expertise can be realized through network influence by trustworthy network neighbors between a content user and a content provider. If there is no or only a weak network connection through users' network friends, it is hard to assume that the trust value $EPTr_{ij}$ influences a content user's subjective trusting beliefs. So, we measure how strongly the link connection is established through a content user and a content provider's trustworthy network neighbors. In this paper, we consider the trust transitivity property and homophily in social ties for the strength of the link connection.

(a) Trust transitivity property

The first metric for the strength of the link connection St_{ij} is derived based on trust transitivity property: Trust is propagated through trusted friends (friends-of-friends network) [8,11]. If content user i has no knowledge about content provider j, content user i will ask his/her trustworthy friends' opinions about content provider j. Studies regarding the social comparison theory have also demonstrated that people have a tendency to evaluate themselves by comparing their opinions with others who are similar and close in their social network, and are then influenced by others' opinions in support of their position [7,32]. Online social networks make it much easier and highly encouraging for people to seek out and share opinions with others who have similar attributes (i.e. interest, value, abilities). Then, social influence by social comparison is a stronger influence on people's trust opinion of a person in online communities compared to traditional networks [30]. The more friends who trust and recommend content provider j, the stronger is the trusting belief conveyed to content user i through his/her friends who also trust content provider j [8,11].

The strength of the link connection based on trust transitivity is measured as follows:

$$St_{ij} = \frac{|Out_i \cap In_j|}{|Out_i|} \tag{14}$$

where Out_i: a set of out-link from user i and In_j: a set of in-link to user j.

In this metric, the strength of link connection St_{ij} represents the level of influence realized from trust transitivity compared to the full potential influence that user i can achieve from his/her direct neighbors. The higher the percentage of content user i's friends who also trust content provider j, the larger the effect of transitivity realized through content user i's friends.

(b) The theory of homophily The other metric for the strength of link-connection St_{ij} is derived based on the theory of homophily: Users are more likely to interact with those who are similar to themselves in respect to a variety of qualities and characteristics [21]. In particular, we consider homophily in social ties (i.e. connections) with community members. If the homophily in social ties between two users is high, there is a high chance that the two users share mutual trust in the homophily effective community.

$$St_{ij} = \frac{|Out_i \cap Out_j|}{|Out_i|} \tag{15}$$

The more common neighbors that two users share, the larger the homophily effect increases. In this metric, we normalize the number of common neighbors by user i's all trust out-links neighbors and then the strength of link connection St_{ij} represents the level of homophily in social ties from user i's perspective. It is noted that the strength of link connection (i.e. both (a) and (b)) is asymmetric such as a trust relationship.

In the metrics of the strength of link-connection St_{ij}, we stress trust transitivity from *trustworthy* neighbors and homophily in *trustworthy* social ties. Since we assume that a Web of Trust (i.e. binary or continuous trust value directly collected from users) is not available in this paper, "the trustworthy link-connection" needs to be defined in order to compute the strength of link connection.

Then, we define "the trustworthy link-connection" for measuring St_{ij} in two ways as follows:

$$\begin{array}{l} \text{If } Dt_{ij} = 1 \text{ and } \alpha_{ij} = 1, \quad Trust - Link_{ij} = 1 \\ \text{else } Trust - Link_{ij} = 0 \end{array} \tag{16-1}$$

$$\begin{array}{l} \text{If } Dt_{ij} = 1, \quad Trust - Link_{ij} = 1 \\ \text{else } Trust - Link_{ij} = 0 \end{array} \tag{16-2}$$

First, Eq. (16-1) adopts our trust prediction mechanism. According to Eqs. (10)–(12), if the total number of direct interactions is larger than or equal to the minimum number of direct feedback ratings $N_{\min}$, our proposed trust metric will be confident about the direct experience-based trust value Dt_{ij} and then estimate $Tr_{ij} = Dt_{ij}$ (where $\alpha_{ij} = 1$) without the expertise- and preference-based trust $EPTr_{ij}$. Therefore, we assume that if and only if a content user is *perfectly satisfied with enough number of content* by a content provider, a trustworthy link-connection is established. The trust connection from this definition is very sound, but the derived link-connections will be very small compared to all established link-connections. In other words, if trust transitivity or homophily in link-connection (i.e. social ties) can be measured with this very rare trust-connection, the connection between two users is very strong and meaningful.

Second, in Eq. (16-2), we consider the quality of direction interactions without its reliability in order to derive more connections for introversive behavior. All of the link-connections derived from Eq. (16-2) may not be strongly trustworthy, but it is helpful to increase the cases for computation. Then if the strength of link-connection is computed based on a large number of link-connections, it is also meaningful.

Even though the trust network based on a direct experience-based trust value and its reliability, as shown in Eq. (16), has a limitation of not being able to fully and correctly extract a Web of Trust, this trust network is stronger than the entire network which consists of all link-connections regardless of the quality of direct interactions and their reliability. In our experiments, we compare the strength of the link connection from Eqs. (16-1) and (16-2) in terms of trust prediction accuracy.

4. Evaluation

In this section, we evaluate the proposed trust prediction framework for rating-based experience sharing communities with real social network data. We also investigate the level of introversive behavior of a user on trust-connection with the dataset. Then, we conduct the experiments on the dataset to evaluate trust prediction accuracy of the proposed framework under a variety of parameter settings. In addition, we evaluate the effectiveness of the trust framework on link-connections established under a severe level of introversive behavior.

4.1. Dataset and pre-processing

The data for our experiments was obtained from Epinions.com (http://www.epinions.com). Epinions is an online community website where users can write reviews of products and services and also rate other users' reviews on a numerical scale. A review in this context can be seen as content, and a review writer is a content provider who wants to share his/her product experiences with community members. The ratings for reviews are given by review raters who have read the reviews and evaluated the degree of helpfulness of the reviews. Then, review raters can be seen as content users. The rating for reviews is assigned using a scale of 1–5 (i.e. not helpful:1, most helpful:5) which is normalized, ranging from 0.2 (not helpful:1) to 1(most helpful:5) for our experiments.

The range of products or services that users review is quite large, including books, movies, computers & software, travels, and so on. The products are classified under different categories and sub-categories in Epinions. Given the computational cost and runtime, we select one category, Video & DVD, for our data collection and experiments. The Video & DVD category is further subdivided into 12 sub-categories where sub-category represents a movie genre from Action/Adventure to Westerns. We think that the Video & DVD category alone is appropriate for evaluating our framework since it has multiple sub-categories with significant size of data. In this category, a single user could watch many movies and then rate a large number of reviews or write reviews for various movies, as compared to other categories such as computer & software or travels. In our experiments, we consider 12 sub-categories as analysis unit categories and then calculate a content provider's (i.e. a review writer) expertise and a content user's (i.e. a review rater) preference at a sub-category level.

In order to collect all related data on the Video & DVD category, we first crawled all the reviews in all 12 sub-categories of Video & DVD. From those collected reviews, we extracted all the users who had either written at least 1 review or evaluated at least 1 review in the Video & DVD category. From the user information, we proceeded to crawl all of the users' profiles to extract their Web of Trust. Epinions provides a Web of Trust by allowing a user to express an explicit trust link with a review writer. Then, if a user has found a certain user's reviews consistently valuable, the user adds the review writer to his/her Web of Trust (i.e. a binary trust (1: trust, 0: not decided)).

The final dataset has 44,197 users who either wrote at least 1 review or rated at least 1 review in any sub-category. The total number of written reviews is 80,139 and the average of a sub-category is 6678. The total number of ratings for all reviews is 1,533,163 and the average number of ratings in a sub-category is 127,764. From these reviews and ratings, a direct interaction from review rater *i* to review writer *j* is established if review rater *i* evaluates at least one review of review writer *j*. The final dataset has 644,992 unique direct interactions (i,j).

Among these interactions, some interactions are expressed as "trust" connectivity in a Web of Trust. The collected data has 429,955 trust connectivity interactions among 44,197 users. Since Epinions maintains a single Web of Trust regardless of categories, we do pre-processing to remove trust connectivity not related to the Video & DVD category. Then, among all 429,955 collected trust connectivity interactions, we remove trust connectivity (i,j) if review rater *i* has no direct interaction with review writer *j* in the Movie & DVD category. We assume that the trust connectivity (i,j) with no direct interaction in the Movie & DVD category is established based on interactions outside of the Movie & DVD category. After the pre-processing for trust connectivity, 99,495 trust connectivity interactions are collected for the Movie & DVD category. As expected, the Web of Trust (i.e. a trust matrix (user by user)) in the Movie & DVD category is very sparse. The density of the Web of Trust is only 0.0051%. In graph theory, graph density is defined as the ratio of the number of edges present in the graph to the number of possible edges in a completely connected graph with the same size or number of nodes. Among all direct interactions of 644,992, 15% of them are established as trust connectivity by users.

4.2. Introversive behavior in Epinions.com

In the beginning of this study, we explain that predicting trust connectivity or a degree of trust without a Web of Trust (i.e. explicit trust) but rather by using direct interactions and its feedback ratings is challenging because of users' introversive behavior in terms of expressing explicit feedback rating on individual direct interaction (i.e. content). With the Epinions dataset, we explore users' introversive behavior on trust link-connections. Fig. 3 describes the percentage of links with a certain number of feedback ratings. Out of 99,495 trust connectivity interactions in the Movie & DVD category, 44% trust connectivity is established with 1 explicit feedback rating and 16.7% is established with 2 feedback ratings. Compared to trust connectivity, 75% of the 571,222 non-trust connectivity links has 1 explicit feedback rating. In non-trust connectivity, it is a natural behavior to have few direct interactions with a content provider whom a content user trusts. As shown in Fig. 3, the number of direct interactions follows the power law distribution in both trust connectivity and non-trust connectivity. But, as the number of direct interaction increases, the percentage of trust-links is higher than that of non-trust links. Since a large percentage of trust connectivity is constructed under introversive behavior (i.e. 1 or 2 feedback ratings), it is important to distinguish the trust connectivity with few direct interactions from non-trust connectivity.

4.3. Experimental setup and evaluation metrics

Based on the trust framework proposed in Section 3, the framework needs the following parameters to be determined, depending on applied online social networks:

- The global minimum support, *global_minsup* and minimum confidence, *minconf* to mine association rules among categories for both Category_Association$^{\text{evaluating content}}$ matrix $\mathbf{A^e}$ and Category_ Association$^{\text{providing content}}\mathbf{A^p}$ (see Section 3.2.2): In this experiment, we set *global_minsup* = 0.5 and *minconf* = 0.65.
- The minimum number of direct feedback ratings $N_{\min}$ for the reliability of a direct experienced-based trust evaluation (see Eq. (13)): Based on the distribution of the number of direct feedback ratings between a content user and a content provider (such as in Fig. 2 in our dataset), we set $N_{\min}$ as 4 from the top 10% ranked point and 7 from the top 5% ranked point. For the rest of this paper, we call 'top5%-reliability-trust model' and 'top10%-reliability-trust model' for each trust model with respective $N_{\min}$ value. We compare the experiment results of the 'top5%-reliability-trust model' and 'top10%-reliability-trust model' to note the effects of the level of $N_{\min}$ (i.e. reliability setting) on the performance of trust prediction.

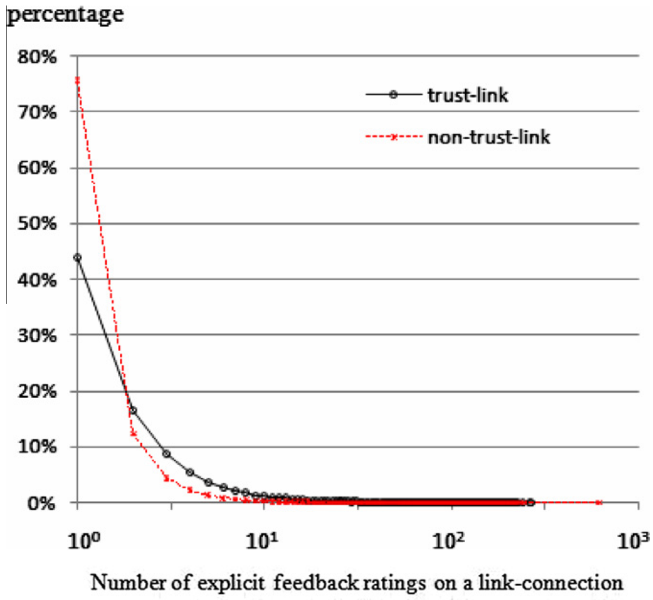

Fig. 3. Introversive behavior on trust-link connections: the percentage of links with a certain number of feedback ratings in Epinions.

For comparison of our proposed approach, a trust prediction framework without a Web of Trust, we consider two baseline models. The first baseline is a combination of direct experience-based trust evaluation and local witness evaluation as follows:

$$\overline{Tr_{ij}} = \beta \cdot Dt_{ij} + (1-\beta) \cdot \frac{\sum_{k\in\{Out_i \cap In_j\}} Dt_{ik} \cdot Dt_{kj}}{\sum_{k\in Out_i} Dt_{ik}} \tag{17}$$

where Out_i: a set of out-link from user i and In_j: a set of in-link to user j.

There are no universal trust prediction metrics available for online social communities, and most of the proposed trust models require a Web of Trust. Even though that, evaluating trusting beliefs of a participant based on direct experiences and witness testimonies is a well-known approach [3,36]. In particular, if a content user has few direct experiences with a target content provider or no direct experience, a content user will collect testimonies from local witnesses. If the witness is one of a content user's close trustworthy neighbors, his/her opinion influences the content user's trusting belief more than others, as noted in Eq. (17). The second term in Eq. (17) also represents the transitive trust which is the influence from neighbors at distance two, following the formulation in [9,20]. Here we simply set the weight factor β at 0.5.

The second baseline is a reputation-based trust model which aggregates all of the feedback ratings from all community members to a content provider's content. As a simple reputation model, we can compute the expertise value regardless of categories for content providers and then simply recommend top-k experts to all users. The mechanism of the expertise labeling in Eq. (3) (i.e. u^{e}_{ik}) is adopted in the previous study [15] and shows high performance in identifying reputable users, called "Top reviewers" in Epinions. Then, it is reasonable to use the expertise metric as a reputation in a simple reputation model. For a more sophisticated reputation-based trust model, however we consider our expertise- and preference-trust model $EPTr_{ij}$, which combines the expertise of a content provider and the preference of a content user over categories (see Eq. (9)), as a second baseline model.

As a result of our proposed trust framework as well as baseline models, it provides a continuous-valued trust between 0 and 1. Since Epinions maintains a discrete-valued trust in a Web of Trust such as trust or non-trust (i.e. 1 or 0), we need to convert degree of trust to discrete ones (1 or 0) for validation. Given the predicted degree of trust from content user i to content user j, we judge that content user i trusts j if the degree of trust is higher than rounding threshold θ. In the next section, we will explain the method for determining the rounding threshold θ in our experiments for achieving the best performance.

4.4. Results and discussion

For validation of our proposed trust framework with some variations on parameters, first we randomly choose 1,000 pairs of users with explicit trust connections and 1,000 pairs of users with non-trust connections from 644,992 unique interactions (i,j). We measure precision and recall for trust prediction with various rounding thresholds θ. Then, we compare our proposed various trust models and baseline models.

Table 2 shows the performance of trust prediction on various trust models. Our proposed trust framework combines Dt_{ij} and $EPTr_{ij}$ according to a reliability of Dt_{ij} (i.e. parameter α_{ij} in Eq. (12)). Table 2 describes nine different combination models

Table 2
Performance of trust prediction.

N_{min} for reliability	Trust model and description		Precision	Recall	F1	Top 1000-precision
	Baseline 1	*Dt + local neighbors'testimonies(Dts)*	0.7068	0.4170	0.5245	0.6650
	Baseline 2	*EPTr*	0.5523	0.6390	0.5925	0.5650
5%-reliability-network: from top 5% rank	Reliability based combination	1. *Dt* + *EPTr*	0.5957	0.7250	0.6540	0.6160
	Reliability based combination & combination of *St*	2. *Dt* + *St*(transitivity on 5%-rel-network)	0.7353	0.4500	0.5583	0.6659
		3. *Dt* + *St*(transitivity on simple-avg-network)	0.7390	0.5520	0.6319	0.6850
		4. *Dt* + *St*(homophily on 5%-rel-network)	0.7597	0.5310	0.6251	0.6861
		5. *Dt* + *St*(homophily on simple-avg-network)	0.7516	0.6050	0.6704	0.7210
	Reliability based combination & combination of personalized *EPTr* with *St*	6. *Dt* + *EPTr***St*(transitivity on 5%-rel-network)	0.7234	0.5650	0.6345	0.6659
		7. *Dt* + *EPTr***St*(transitivity on simple-avg-network)	0.7370	0.6080	0.6663	0.6680
		8. *Dt* + *EPTr***St*(homophily on 5%-rel-network)	0.6908	0.6590	0.6745	0.6820
		9. *Dt* + *EPTr***St*(homophily on simple-avg-network)	0.7286	0.6470	0.6854	0.7050
10%-reliability-network: from top 10% rank	Reliability based combination	1. *Dt* + *EPTr*	0.6264	0.6690	0.6470	0.6380
	Reliability based combination & combination of *St*	2. *Dt* + *St*(transitivity on 10%-rel-network)	0.7167	0.5920	0.6484	0.7367
		3. *Dt* + *St*(transitivity on simple-avg-network)	0.7145	0.6130	0.6598	0.6770
		4. *Dt* + *St*(homophily on 10%-rel-network)	0.7294	0.6470	0.6857	0.7037
		5. *Dt* + *St*(homophily on simple-avg-network)	**0.7254**	**0.6630**	**0.6928**	**0.7090**
	Reliability based combination & combination of personalized *EPTr* with *St*	6. *Dt* + *EPTr***St*(transitivity on 10%-rel-network)	0.6985	0.6070	0.6495	0.6450
		7. *Dt* + *EPTr***St*(transitivity on simple-avg-network)	0.6857	0.6350	0.6594	0.6660
		8. *Dt* + *EPTr***St*(homophily on 10%-rel-network)	0.7166	0.6650	0.6898	0.6930
		9. *Dt* + *EPTr***St*(homophily on simple-avg-network)	**0.7082**	**0.6870**	**0.6975**	**0.6980**

Note: Model 1: a simple reliability based combination of Dt_{ij} and $EPTr_{ij}$ (see Eq. (10)).
Models 2 and 3: a reliability based combination of Dt_{ij} and trust transitivity based strength of link-connections St_{ij}.
Models 4 and 5: a reliability based combination of Dt_{ij} and homophily based strength of link-connections St_{ij}.
Models 6 and 7: $EPTr_{ij}$ is personalized by trust transitivity based strength of link-connections (see Eqs. (13) and (14)).
Models 8 and 9: $EPTr_{ij}$ is personalized by homophiliy in social ties based strength of link-connections (see Eqs. (13) and (15)).
Models 2, 4, 6 and 8 compute St_{ij} with the link-connection which is defined if and only if $Dt_{ij} = 1$ and $\alpha_{ij} = 1$ on 5% (or 10%)-reliability-network by Eq. (16-1).
Models 3, 5, 7 and 9 compute St_{ij} with the link-connection which is defined if and only if $Dt_{ij} = 1$ (i.e. simple-average-network) by Eq. (16-2).

Table 3
Performance of Model 9 in 5%-reliability-network with various thresholds of θ.

Threshold	Precision	Recall
0.9	0.8388	0.2810
0.8	0.8255	0.3170
0.7	0.8078	0.3740
0.6	0.7835	0.4450
0.5	0.7514	0.5200
0.4	**0.7286**	**0.6470**
0.3	0.6697	0.7440
0.2	0.5712	0.9710
0.1	0.5038	1.0000
0	0.5000	1.0000

Note: the average of $\overline{Tr_{ij}}$ in model 9 is 0.46, trust decision rule: if $\overline{Tr_{ij}} > \theta,\ \textit{trust-connection}(i,j) = 1$.

in a 5%-reliability-network (α_{ij} with $N_{\min} = 7$) and in a 10%-reliability-network (α_{ij} with $N_{\min} = 7$) respectively. Please see the description of each model in Table 2. Precision, recall and F1 score on each trust model as well as baseline models show the best performance results obtained at each optimal rounding threshold θ^*.

Before we discuss the performance results in Table 2, we briefly describe how precision and recall are changed as varying rounding threshold θ and how the optimal rounding threshold θ^* can be decided for each trust model. Table 3 shows the performance of our proposed trust model 9. Trust model 9 represents a combination model of Dt_{ij} and $EPTr_{ij}$ where $EPTr_{ij}$ is personalized by homophily based strength of link-connection and link-connection is defined if and only if $Dt_{ij} = 1$. As the rounding threshold changes from 0.9, 0.8, ..., 0, precision decreases from 0.8388 to 0.5 and recall increases from 0.2810 to 1. In more detail, the precision gradually changes until threshold 0.4 but, after that, the precision considerably drops and the recall largely increases. In all proposed trust models and baseline models, we found that the threshold that made the most significant change in precision and recall is always around the average of $\overline{Tr_{ij}}$ for each model.

In trust model 9, the average of predicted trust value $\overline{Tr_{ij}}$ is 0.46. Then, if we change the rounding threshold θ by *throwing the average off* to 1 decimal place which is $\theta = 0.4$, we can achieve precision of 0.7286 and recall of 0.647. If we set the rounding threshold θ by *rounding the average off* to 1 which is $\theta = 0.5$, we can achieve higher precision 0.7514 but lower recall 0.52 compared to $\theta = 0.4$. The threshold derived from throwing off the average will provide higher recall and lower precision and the threshold from rounding off the average achieves the opposite. But, in most proposed trust models, the threshold from throwing off the average achieves better performance in general, because the increase in recall (from 0.52 to 0.647) is much larger than the decrease in precision (from 0.7514 to 0.7286). We can observe this phenomenon over all proposed trust models. Based on this observation, we then decide the optimal rounding threshold θ^* for trust decision is the threshold throwing off the average of predicted trust value $\overline{Tr_{ij}}$. However, we also suggest that the optimal rounding threshold can be determined by domain experts' opinion or the purpose of trust prediction in an application (e.g. which factor is more important between precision and recall in an application? or Select top-*k* % of a pair of users). Otherwise, since continuous-valued trust is mathematically clean rather than discrete-valued trust [10], it is also useful to provide each user with a predicted degree of trust with reasoning behind the computation. It will help users make a decision about future interactions including trust-connections with recommended targets.

Table 2 shows the best performance (precision, recall and F1 score) of trust prediction with each optimal rounding threshold θ^* which is obtained by throwing off average of $\overline{Tr_{ij}}$ to 1 decimal place for each trust model. In addition, we also measure the top1000-precision by selecting the top 1000 connections as trust-connections based on a degree of predicted trust value $\overline{Tr_{ij}}$.

As we expected, baseline model 2, the expertise- and preference-based model (i.e. $EPTr_{ij}$), provides global trust and then recommends all high reputable users to a large percentage of users. Therefore, it achieves lower precision and higher recall compared to baseline model 1. Baseline model 1 achieves high precision by combining local neighbors' direct evaluations of a target as well as a user's direct trust evaluation, but fails at high recall. On the other hand, our proposed trust models 6, 7, 8 and 9 achieve both higher precision and recall in both 5%-reliability-network and 10%-reliability network by combining Dt_{ij} and $EPTr_{ij}$ which is personalized with the strength of connection St_{ij}. In comparison, trust models 2, 3, 4 and 5, which do not consider $EPTr_{ij}$, show slightly lower performance in the 5%-reliability-network, but they achieve similar good performance with our proposed models in the 10%-reliability-network. In addition, we observe that trust models 4, 5, 8 and 9, which adopt homophily-based St_{ij}, show better performance (i.e. higher F1 and Top1000-precision) than trust models 2, 3, 6 and 7, which adopt trust transitivity-based St_{ij}. However, we could not find a distinctive difference in performance between the trust models 2, 3, 4 and 5 and the proposed trust models 6, 7, 8 and 9.

Then, we validate the trust models with trust connection established under introversive behavior to see how well our proposed trust models work. As we investigate the level of introversive behavior in the Epinions dataset in Section 4.2 (see Fig. 3), 60% trust connectivity is established with 1 or 2 explicit feedback ratings. Also, 88% of non-trust connectivity has 1 or 2 explicit feedbacks. For validation, we then randomly choose 1,000 pairs of users with explicit trust and 1,000 pairs of users with non-trust connections among all direct interactions with less than or equal to 2 feedback ratings.

As shown in Table 4, the overall performance in precision, recall and top1000-precision is lower than the performance in Table 2. This demonstrates the difficulty of predicting trust with the lack of direct feedback ratings. In this experiment, we

Table 4
Performance of trust prediction on trust-link connections under introversive behavior.

N_{min} for reliability	Trust model and description		Precision	Recall	F1	Top 1000-precision
	Baseline 1	*Dt + local neighbors'testimonies(Dts)*	0.6712	0.2940	0.4089	0.6480
	Baseline 2	*EPTr*	0.5184	0.7060	0.5978	0.5180
5%-reliability-network: from top 5% rank	Reliability based combination	1. *Dt* + *EPTr*	0.5516	0.8290	0.6624	0.5600
	Reliability based combination & combination of *St*	2. *Dt* + *St*(transitivity on 5%-rel-network)	0.7157	0.2920	0.4148	0.6370
		3. *Dt* + *St*(transitivity on simple-avg-network)	0.6941	0.4220	0.5249	0.6430
		4. *Dt* + *St*(homophily on 5%-rel-network)	0.7505	0.3910	0.5141	0.6729
		5. *Dt* + *St*(homophily on simple-avg-network)	0.7814	0.3360	0.4699	0.6790
	Reliability based combination & combination of personalized *EPTr* with *St*	6. *Dt* + *EPTr***St*(transitivity on 5%-rel-network)	0.6627	0.3320	0.4424	0.6370
		7. *Dt* + *EPTr***St*(transitivity on simple-avg-network)	0.6454	0.5150	0.5729	0.6270
		8. *Dt* + *EPTr***St*(homophily on 5%-rel-network)	0.6912	0.4320	0.5317	0.6739
		9. *Dt* + *EPTr***St*(homophily on simple-avg-network)	**0.6841**	**0.5890**	**0.6330**	**0.6720**
10%-reliability-network: from top 10% rank	Reliability based combination	1. *Dt* + *EPTr*	0.5654	0.6790	0.6170	0.5730
	Reliability based combination & combination of *St*	2.*Dt* + *St*(transitivity on 10%-rel-network)	0.7073	0.3190	0.4397	0.6117
		3. *Dt* + *St*(transitivity on simple-avg-network)	0.6770	0.4800	0.5617	0.6430
		4. *Dt* + *St*(homophily on 10%-rel-network)	0.7477	0.4090	0.5288	0.6567
		5. *Dt* + *St*(homophily on simple-avg-network)	0.7440	0.4360	0.5498	0.6780
	Reliability based combination & combination of personalized *EPTr* with *St*	6. *Dt* + *EPTr***St*(transitivity on 10%-rel-network)	0.6319	0.4120	0.4988	0.6122
		7. *Dt* + *EPTr***St*(transitivity on simple-avg-network)	0.6841	0.5890	0.6330	0.6290
		8. *Dt* + *EPTr***St*(homophily on 10%-rel-network)	0.6821	0.5600	0.6150	0.6584
		9. *Dt* + *EPTr***St*(homophily on simple-avg-network)	**0.6606**	**0.7320**	**0.6945**	**0.6700**

can see that our proposed trust models 6, 7, 8 and 9 considerably outperform trust models 2, 3, 4 and 5, as well as the baseline models. In the previous experiment, trust models 2, 3, 4 and 5 show similar good performance in precision and recall with trust models 6, 7, 8 and 9. But, in this experiment, our proposed trust models combining Dt_{ij} and personalized $EPTr_{ij}$ achieve much higher recall with only a slight reduction in precision compared to the trust models combining Dt_{ij} and St_{ij}; our proposed trust models ultimately have the better F1 score. Among trust models 6, 7, 8 and 9, trust models 8 and 9, which adopt homophily-based St_{ij}, still outperform trust models 6 and 7 that adopt trust transitivity-based St_{ij}. In particular, trust model 9 achieves the best performance in predicting trust connections established under introversive behavior. Since trust model 8 generates a lower-density connected network for the strength of link-connection St_{ij} computation, many trust connections established under introversive behavior maybe suffer from finding link-connections for St_{ij} computation.

In summary, most of the ratings-based experience sharing social networks suffer from users' severe introversive behavior, so a trust prediction model must be designed to overcome this challenge. Based on the first and second experiments, we recommend trust model 9 which will perform well and be less affected by the level of introversive behavior compared to other combination models.

5. Conclusions

In this study, we have presented a computational framework for predicting a degree of trust between a pair of users in rating-based experience sharing online communities without a Web of Trust. In most of the previous trust approaches, a Web of Trust consisting of explicit trust from users plays a critical role in predicting trust with high accuracy, but it is not always available and can be very sparse. The proposed framework starts with developing content providers' expertise (i.e. reputation) and content users' preference (i.e. affinity) based trust from all feedback ratings on content in order to overcome the lack of direct interactions between a content consumer and a content provider. For a more personalized trust evaluation, the framework discounts the expertise- and preference-based trust with the strength of connection between two users. It also combines direct experience- based trust from a content user to a content provider. The feedback ratings on content necessary for our trust framework are easily collected and much more frequently expressed by users than is explicit trust. Our research addresses the challenge of predicting trust without a Web of Trust due to the introversive behavior of users. The empirical experiments with the Epinions dataset show that our proposed framework can be used in most ratings-based experience (i.e. content) sharing communities where users provide, share or evaluate content using numerical ratings for each other, even where introversive behavior prevails over trust connections.

This study has some limitations, which will inform future research studies. First, we adopted Rigg's algorithm [27] to compute the quality of content and the credibility of a content user in step 1. The iterative algorithm is designed to keep a content user from benefitting from giving a simple average, but to benefit from giving an ultimate average of ratings, that is a weighted average. Even with that, a content user could be influenced by earlier major ratings and then eventually obtain high reliability. In other words, a malicious user can always wait until a major consensus of ratings is collected and then insert a major rating to gain higher credibility. In order to alleviate this kind of vulnerability, one can consider the time when a content user gives rating. Riggs' algorithm gives less credit to a later review rater than an earlier review rater using the rank order of the reviewer's ratings on an item. In future research, we will use an enhanced algorithm that considers the time factor and validate the success of the algorithm in protecting from malicious users.

Second, we provided a user preference model with various kinds of explicit behavior data such as users' content rating and content writing behavior. We admit that the user preference model could be much improved if it could capture users' implicit behavior on online social network sites. In the implicit approach, user preferences can be inferred from browsing behavior such as clicking a review page and spending time reading a review. Because of the limitations of an actual web log, we could not collect such implicit feedback for this paper. In future research, we will collaborate with a company owning an online social network platform and evaluate both the explicit and implicit feedback effects on a user preference model in terms of predicting trust relations.

As ideas for other future research, we can validate our trust framework on trust-based recommendations to determine if the predicted trust links are better than a sparse Web of trust and, if not, how the trust-based recommendation can be improved by combining two trust links (i.e. our predicted links and explicit trust links). In addition, if distrust links are given, such as Epinions, another interesting problem will be to develop a new model of trust- and distrust-based recommendations [34] enhanced by implicit trust links. Last, in future research, we will consider the reciprocity property on rating and link behavior to enhance personalized prediction in our trust framework. While a few researchers [2,23] empirically showed that reciprocity behavior and trust can reinforce each other, reciprocity in trust modeling needs improvement in respect to its modeling and its combination with trust modeling.

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