

Trust-Based Rating Prediction for Recommendation in Web 2.0 Collaborative Learning Social Software

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Abstract—Benefiting from the advent of social software, information sharing becomes pervasive. Personalized rating systems have emerged to evaluate the quality of user-generated content in open environment and provide recommendation based on users' past experience. In this paper, a trust-based rating prediction approach for recommendation in Web 2.0 collaborative learning social software is proposed. Trust network is exploited in the rating prediction scheme and a multi-relational trust metric is developed in an implicit way. Finally the evaluation of the approach is performed using the dataset of collaborative learning social software, namely *Remashed*.

Keywords—collaborative learning, trust, reputation, rating, social software

I. INTRODUCTION

As the interactive information sharing becomes pervasive in Web 2.0 social software, the challenge is no longer the lack of resources but the selection of useful resources from massive user-generated content. Especially in collaborative learning social software where learners exchange knowledge, skills and competences, it's an important issue to filter helpful learning resources, peers and group activities depending on individual users. Therefore, rating systems have emerged for the purpose of evaluating the quality of the content in open environment, and providing recommendation for different users.

In order to make personalized recommendation and guidance, a trust-based rating prediction approach is presented in this paper. It relies on the 3A interaction model [1] dedicated to describe collaborative learning social software. Rating scores of items associated to a community are predicted using the implicit trust network of a particular user. A multi-relational trust metric is proposed, aiming at measuring the trust relationship between the target user and people in his/her trust network.

The rest of the paper is organized as follows. In section II, current trust and rating models are investigated both on application and academic research levels. Section III presents the particular requirements in the domain of collaborative learning. Trust-based rating prediction approach is addressed in section IV. In section V, the model evaluation is performed on the dataset of collaborative learning social software *Remashed* and evaluation results are discussed. Section VI concludes the paper and discusses the future work.

II. RELATED WORK

As a complex social concept, trust can be influenced by many factors, such as social rules, human relationships, or past experience. Thus trust is difficult to quantify and measure. A number of attempts have been made to develop different trust models and trust metrics. On the application level, most social software uses reputation as the main input to trust evaluation. Investigation of trust metrics was conducted for product review sites, professional communities and general knowledge base sites where trust measurement plays an important role in Web-based interaction. Afterwards, the models are extended to comply with collaborative learning requirements in section IV.

The product review site “*epinions*” (<http://www.epinions.com>) uses a reputation system that applies to products, shops and reviewers themselves. Members of “*epinions*” give quantitative ratings from 1 to 5 stars for a set of aspects such as Ease of Ordering, Customer Service, and On-Time Delivery, to shops and products. Members themselves obtain different status like Advisor, Top Reviewer and Category Lead, according to the ratings on the reviews they have written.

The “*ePractice.eu*” (<http://www.epractice.eu>) is an online professional community in the domain of eGovernment, eInclusion and eHealth. It uses “*Kudos*” as a way to acknowledge the activity and reliability of registered members. Each activity a user performs on the portal is awarded a numerical value that is associated to the user's profile. The higher the total number of Kudos a user has, the more active he/she is.

“*Everything2*” (<http://www.everything2.com>) is a general knowledge base site composed of user-generated content. Users submit various kinds of articles, which can be voted as “positive” or “negative” by other users. The article keeps track of its total voting scores (reputation number) that can be viewed by the author and all the voters. “*Everything2*” also maintains users' ranking based on the quantity of the users' articles and the average voting score of their articles.

It's easy to discover that, most of current trust and reputation systems consider reputation as a global property and use it as the measurement of trust, which makes trust value static even from different people's point of views. However, people's trust opinions about a certain party vary because of various personal experiences. In an attempt to solve this problem, many efforts have been made on the academic research level. The representatives of personalized trust models

are TidalTrust [2], MoleTrust [3] and @cosme [4]. All of them exploit the trust network for a particular user and thus make personalized rating prediction by emphasizing rating opinions provided by trusted users and ignoring those provided by unreliable ones. However, those trust systems without exception need users to specify explicitly whom they trust and how much they trust each other.

TidalTrust builds a trust network by asking user to assign a trust value to another user when the former adds the latter as a friend. A modified breadth first search is performed in the trust network in order to find all raters with the shortest path distance from the source user. Then a rating score for a particular item is predicted by aggregating all those ratings weighted by the trust value of the raters. Finally items with high predicted rating scores are recommended. Similarly, MoleTrust asks user to express how much he/she trust others and therefore constructs the trust network. While in @cosme, users' personalized trust opinions are acquired in the form of bookmarking their trusted users.

III. COLLABORATIVE LEARNING DOMAIN

Lessons learned from e-commerce and review sites can be summarized as follows. Firstly, most of current production-level trust models adopt global trust metrics, which is unilateral since trust is more of a personalized concept greatly depending on personal experience. Secondly, the performance of those personalized trust models largely relies on users' input of their trust opinions because they need users to specify explicitly who and how much they trust.

The issues above should be taken into account when designing the trust metrics in collaborative learning social software. Moreover, the domain of collaborative learning is somehow different from the e-commerce and review sites scenarios. Unlike the communities of market economy, collaborative learning is a community of "gift economy", where resources and services are regularly given without any explicit agreement for immediate or future rewards. In collaborative learning environments, trust means that one party thinks another party is reliable that the former would like to perform some transactions with the latter, such as cooperation, discussion, or download. It is usually presented in the form of rating; that is to say, giving high rating indicates strong trust opinion. From this point of view, rating score is representative of quality. Using rating systems in collaborative learning environments facilitates evaluating the quality of user-generated content and identifying useful learning resources, peers and group activities.

In section IV, a trust-based approach is addressed, which personalizes the rating prediction from the standpoint of a particular user using his/her implicit trust network. The basic idea is that what influences rating prediction lies in two aspects: similarity and familiarity. It's similarity because people tend to trust the rating opinions of those who have similar interests and tastes. For instance, Alice would probably believe Bob's rating opinions to an item relevant to computer science because Alice and Bob have both joined a computer science club. It's also about familiarity because of the real-life intuition that people usually prefer to rely on opinions of acquaintance rather than strangers.

It's worth mentioning that in comparison with some rating systems like eBay, only positive rating scores are used in our model. As a result, the rating score of a new user is always the lowest, which avoids the situation that some users get very low rating scores due to their bad behaviors, and then decide to create a new account identifying themselves in a community to hide their bad reputation.

IV. PROPOSED APPROACH

A. The 3A Interaction Model

The trust-based rating prediction approach proposed relies on the 3A interaction model, which is particularly intended for designing and describing social and collaborative learning environments. It consists of three main constructs referred hereafter as entities: **Actors** represent entities capable of initiating an event in a collaborative environment, such as regular users or agents. Group **Activities** is the formalization of a common objective to be achieved by a group of actors. **Assets** represent artifacts produced, edited, shared and annotated by actors in order to mediate collaboration and meet objectives of group activities. They can consist for example of simple text files, RSS feeds, content of wikis, as well as video and audio files. There are three types of asset access rights: ownership, editorship and read-only. A role consists of a label and an associated set of rights granted to an actor within an activity. Furthermore, the latter can possibly have a well-defined planning of expected assets with concrete submission and evaluation deadlines, predefined evaluators and submitters. This is particularly useful in project management communities and online educational environments. The model accounts for Web 2.0 features: entities can be tagged, shared and rated. Moreover, actors can define any type of bidirectional and unidirectional semantic links between entities of the same type. For instance, an actor can be a "co-worker" of another actor and a group activity can consist of a "sub-activity" of another one.

B. Trust Inference

In the 3A interaction model, actions performed by actors result in heterogeneous types of relationships like tag, link, authorship, membership, comment, or rate. Those relationships somehow represent different amount of potential trustworthiness depending on the importance of that particular type of relationship. For instance, the action of Alice joining a group activity called "Advanced Algorithms" indicates that Alice holds a certain amount of trust regarding to the "Advanced Algorithms" group activity. Instead of asking users express trustworthiness directly, the trust relationship is dealt with in an implicit way. Considering the 3A entities as nodes and relationships as edges between them, a weighted trust network is constructed, taking into account the importance of relationships.

Deriving from the 3A trust network in the collaborative learning environment, a so-called "Web of Trust" for a particular user is built. The idea is to mimic real life situation where trust can be inherited, while not being completely transitive from a mathematic point of view. In real life, if Alice trusts Bob and Bob trust Clark, Alice may have certain amount of trust to Clark. However, trust relationship could not

completely transfer without decay through distance. These natural social observations argue for transitive trust evaluation frameworks as in [5].

Based on the intuition that trust is transitive but can also decay during the transfer, a trust propagation distance is introduced to constrain the range that trust is able to propagate (i.e. trust relationship is unable to extend beyond that distance). Within the trust propagation distance of a particular user, direct trust relationship and indirect trust relationship is inferred between the target user and all his/her trusted users, which leads to his/her “Web of Trust” accordingly.

In an attempt to construct a user’s “Web of Trust”, a random walk is performed starting from this target user and ending until reaching the trust propagation distance. During the random walk, direct trust value and indirect trust value are inferred respectively. Direct trust value is derived from a particular type of relationship, say R_i . Supposing that there exists a relationship R_i between node s and node t , $W(R_i)$ denotes the weight of R_i and $N(s,i)$ denotes the number of outgoing edges from s with the type R_i , then the direct trust value $DT(s,t)$ is inferred as in (1):

$$DT(s,t) = \frac{W(R_i)}{N(s,i)} \quad (1)$$

Let’s take the example of Alice joining the “Advanced Algorithms” group activity (i.e. AAG). $N(Alice, Membership)$ denotes the number of group activities Alice joins and $W(Membership)$ denotes the weight of membership. The direct trust value is calculated as in (2):

$$DT(Alice, AAG) = \frac{W(Membership)}{N(Alice, Membership)} \quad (2)$$

In addition, each particular type of relationship between two entities results in two different trust values from two opposite directions. Taking the example of a user using a tag, the trust value from the user to the tag is the times of the user using this tag divided by the total times of the user using all the tags. Similarly, the trust value from the tag to the user is the times of the tag being used by this user divided by the total occurrence number of this tag.

Besides the direct trust, trust also propagates along the relationship path starting from the target user. As shown in Fig. 1, the target user namely Alice, rated an item “Article” created by another user Bob. It indicates implicitly that trust propagates from Alice to Bob through item “Article”. In this way, Alice’s trust relationships propagate through different assets, activities and other actors, forming her own trust network accordingly.

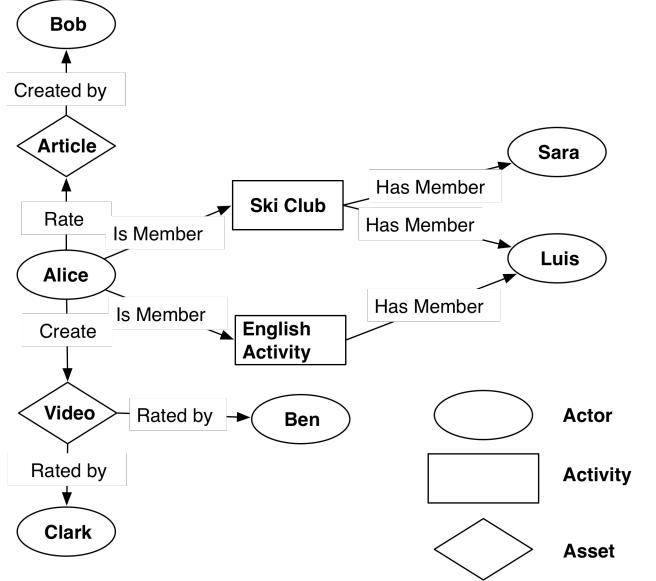


Figure 1. Alice’s Trust Network

Using the direct trust value between each pair of entities, indirect trust value can be inferred by extending the “Web of Trust” layer by layer, centered on the target user. The trust values of the user’s direct neighbors are computed first, followed by computing the items at distance 2. The trust inference process is continuously performed until it reaches the predefined trust propagation distance. The inferred trust value for an item at a certain distance is the average of all the incoming trust edge values, weighted by the trust value of the corresponding node, which the trust edge is derived from. Let s denote the target user which lies at the center of the trust network, and t denote a node at a certain distance in s ’ trust network. E is the set of all the nodes e_j which has a direct trust edge to t . $T(e_j, t)$ denotes the trust value from e_j to t , and $T(s, e_j)$ denotes the trust value from s to e_j . Then the indirect trust value from s to t , $IT(s, t)$, is inferred as in (3) :

$$IT(s, t) = \frac{\sum_{e_j \in E} T(e_j, t) T(s, e_j)}{\sum_{e_j \in E} T(s, e_j)} \quad (3)$$

As shown in Fig. 2, Jack is an actor in Alice’s trust network. The trust relationships from Alice propagate layer by layer and finally reach Jack through three other nodes A, B and C. In this case, for Jack, there are three incoming edges, therefore the indirect trust value from Alice to Jack is computed as in (4) :

$$IT(Alice, Jack) = \frac{T(A, Jack)T(Alice, A) + T(B, Jack)T(Alice, B) + T(C, Jack)T(Alice, C)}{T(Alice, A) + T(Alice, B) + T(Alice, C)} \quad (4)$$

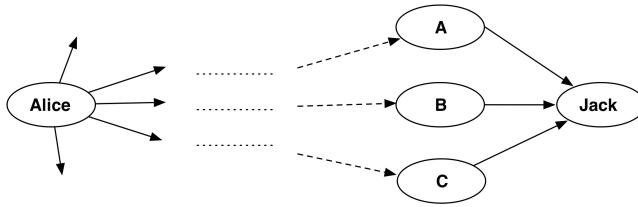


Figure 2. Indirect Trust Relationship from Alice to Jack

At the end of the random walk, a “Web of Trust” of the target user is formed, which consists of his/her trustable people. Thanks to the trust propagation distance, it’s not necessary to reach every entity in the social network when computing the trust value, which reduces computation complexity. In the “Web of Trust”, in order to eliminate those people who have little trust relationship with the target user, a trust value barrier is defined. The people with trust value lower than the barrier are seen as distrusted and thus are excluded from the “Web of Trust”.

C. Rating Prediction for Recommendation

For a particular item in the collaborative learning environment, instead of giving a static rating score, a personalized rating score is predicted from the standpoint of the target user using his/her “Web of Trust”. The predicted rating score to the item is the average of all the ratings given by the trustable people, weighted by the trust value of those people. Only the rating opinions provided by trustable people of the target user are taken into account, which eliminates the unreliable rating information, improves the quality of rating prediction, and therefore facilitates providing better recommendation and guidance for identifying useful learning resources, peers and group activities. Considering the timeliness of rating, a time decay function is adopted to all the rating scores, giving higher weight to more recent ones.

V. MODEL EVALUATION

For the purpose of evaluating trust-based rating prediction approach, the proposed model is applied on the dataset of Web 2.0 collaborative learning social software, namely *Remashed* (remashed.ou.nl) [6]. *Remashed* is an informal learning environment that gathers the public items of users’ Web 2.0 services such as SlideShare, Delicious, Flickr, or Twitter. The posted items can be tagged and rated. The *Remashed* dataset contains 50 users, more than 6000 contributed items, more than 3000 tags and approximately 450 ratings.

A. Mapping Remashed to 3A Model

In order to conduct the evaluation, *Remashed* dataset is first mapped to the 3A interaction model. The structure of *Remashed* dataset is relatively simple, composed of two entities: user and posted item. Posted items, which can be tagged and rated, are gathered from users’ Web 2.0 services. User can obviously be mapped to actor in the 3A model, and posted item can be mapped to asset. However, activity in the 3A model is omitted here since *Remashed* dataset doesn’t contain such a structural entity. Based on the user actions in *Remashed* system, there are three types of relationship between users and items:

authorship, rating and tagging. Each type of relationship represents a certain amount of trust value and thus will be given different weights when inferring trust.

B. Evaluation Setups

A target user’s trust network is constructed based on the relationships of authorship, tagging and rating. A typical evaluation method for recommender systems, “leave-one-out” [7], is used to perform the evaluation experiment. The basic idea of this method is to withhold a rating given by a user to an item and then try to predict it using the remaining trust network of this user. Then the predicted rating score can be compared with the actual rating score specified by the user. The difference will be considered as prediction error.

Mean Absolute Error (MAE) [8] is adopted to measure the deviation of a predicted rating score from its actual rating score. Let S denote the size of the test set, pr_i denote the predicted rating score and ar_i denote the actual rating score, then MAE is calculated as in (5):

$$MAE = \frac{\sum_{i=1}^S |pr_i - ar_i|}{S} \quad (5)$$

C. Evaluation Results

In *Remashed* dataset, 12 out of 450 rating records are used as test set, because only a small number of posted items have multiple ratings. During the evaluation, different trust weights are given to three types of relationships in *Remashed* dataset separately. Fig. 3 illustrates the deviation of trust-based predicted rating score from the actual rating score, compared to the deviation of simple average rating score. In this case, authorship, rating and tagging are given the weights of 1.0, 0.6 and 0.6 respectively. Maximal trust propagate distance is predefined as 3.

As shown in Fig. 3, trust-based rating prediction obviously reduces the deviation from the actual rating score. MAE of trust-based rating prediction approach is 0.823, while MAE of average rating score is 0.985 with the rating scale of 5.

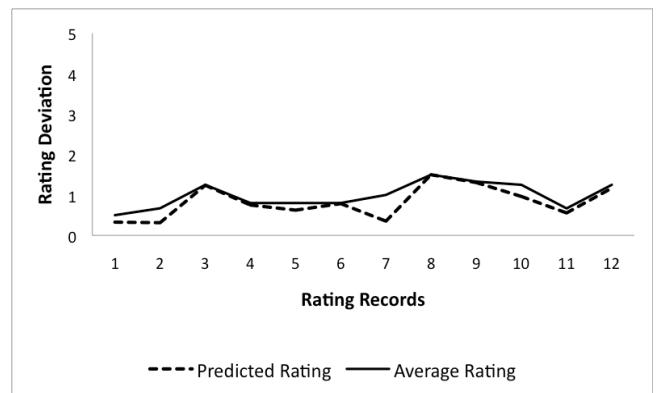


Figure 3. Deviation Comparison between Trust-Based Prediction and Simple Average

Different propagate distances and trust weight settings are chosen for evaluation. Table I, in which WS denotes weight setting, illustrates the trust weight settings for authorship, rating and tagging. The MAE results are presented in Table II, in which PD denotes propagate distance. The evaluation results show that, the trust-based rating prediction approach has much smaller prediction error than the simple average rating. On this test set, the change of trust weights for relationships doesn't make a significant difference in the results of rating prediction, and trust propagate distance of 2 is the optimal value in general. It indicates that, instead of improving the prediction results, increasing the size of trust network might add noise, which might lead to bigger prediction error.

TABLE I. TRUST WEIGHT SETTINGS FOR DIFFERENT RELATIONSHIPS

Weight Settings	Authorship	Rating	Tagging
WS 1	1.0	0.6	0.6
WS 2	1.0	0.6	0.8
WS 3	1.0	0.8	0.6
WS 4	1.0	0.8	0.1

TABLE II. MAE OF DIFFERENT PARAMETER SETTINGS

Parameter Settings	WS1	WS2	WS3	WS4
PD = 2	0.756	0.762	0.784	0.802
PD = 3	0.823	0.830	0.830	0.799
PD = 4	0.797	0.805	0.783	0.824
Average Rating	0.985			

Through the evaluation, several exceptions occur when user has a distinctive rating opinion, totally different from the opinions of people in his/her trust network. In this case, the

prediction error is relatively big since rating score is inferred based on the opinions of people he/she trusts. However, the proportion of such exceptions is quite small, which proves that mostly, people tend to have similar rating opinions with the people they trust.

VI. CONCLUSION AND FUTURE WORK

The paper proposes a trust-based rating prediction approach for recommendation in collaborative learning social software. A multi-relational trust metric is presented, dealing with the trust relationship in an implicit way. The proposed approach aims at quality evaluation of user-generated content in the open learning environment, and therefore facilitates providing personalized recommendation and guidance. Finally the model evaluation is performed on *Remashed* dataset and the evaluation results are discussed afterwards. In the future, the trust-based rating prediction approach will be deployed and evaluated in a collaborative learning platform namely *Graasp* (graaasp.epfl.ch).

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