Trust Modeling and Evaluation in Collaborative Learning Social Software

Na Li

I&C, EPFL

***Abstract*—The design of effective trust and reputation mechanisms for personal and collaborative learning environments is believed to be a promising research direction. We propose to investigate contextualized and personalized trust and reputation models, aiming at agile recommendation of trusty people and services to support self-directed learning activities. In this proposal, existing trust and reputation systems are discussed and the particular requirements of social learning environments are analyzed as well. Finally, our preliminary research work is addressed with some encouraging results.**

***Index Terms*—trust, reputation, collaborative learning, social media**

I. Introduction

BENEFITING from the popularity of Web 2.0 social software, interactive information sharing becomes pervasive. For users surrounded by an abundance of information, the challenge now is how to determine which resources can be relied upon and whom is reliable enough to interact with. For the purpose of solving this problem, a number of trust and reputation systems have been developed in various platforms, including e-commercial sites, product review systems, and professional communities. As indicated in [1], trust and reputation measures can assist other parties in deciding whether or not to transact with a given party in the future, and whether it is safe to depend on a given resource. This represents an incentive for good behavior, which thereby tends to have a positive effect on the quality of interaction in online communities.

Proposal submitted to committee: July 10th, 2010; Candidacy exam date: August 26th, 2010; Candidacy exam committee: Prof. Pierre Dillenbourg, Prof. Denis Gillet, Prof. Boi Faltings.

This research plan has been approved:

Date: ____________________

Doctoral candidate: ____________________
(name and signature)

Thesis director: ____________________
(name and signature)

Thesis co-director: ____________________
(if applicable) (name and signature)

Doct. prog. director: ____________________
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As a particular type of online communities, social media exploited as personal and collaborative learning platforms support learners to exchange knowledge, skills and competences. It is intended to sustain the new learning mode of "Digital Native" or "Net Generation" [2], who are intuitively tech-competent and highly involved in online social communications. Web 2.0 solutions like blogging, tagging, rating and commenting are gradually incorporated into learners' overall learning ecology, which is believed to increase new learners' learning incentives and enhance their learning experience [3]. On one hand, these Web 2.0 features enable users to express opinions easily and facilitate accumulating domain knowledge. On the other hand, users' active contributions produce a large amount of user-generated content, which may lead to information overflow. In such an open learning environment, it's not easy for learners to find suitable people to learn from or to collaborate with. Moreover, the flood of data might bring about the challenge of selecting useful learning resources depending on personal learning goals. Therefore, research efforts are needed to design appropriate trust and reputation mechanisms for personal and collaborative learning environments, aiming at expertise assessment and quality assurance.

The notion of trust is a complex social concept, which reflects the subjective perception one party holds about another party. It's asymmetrical, transferable, dynamic, context-dependent and can be influenced by various factors, such as social rules, personal experiences, rumors, and human relationships [4]. Compared to trust, reputation is a shared, aggregated belief a group holds about a particular entity. It can be considered as a collective measure of trustworthiness based on the referrals or ratings from members in a community [1]. In order to develop effective trust and reputation schemes, a number of attempts have been made in both literature and practice. On production level like Epinions (http://www.epinions.com), eBay (http://www.ebay.com/) and Everything2 (http://www.everything2.com), most trust models adopt global trust metrics, which is unilateral since trust is more of a personalized concept greatly depending on personal experience. Some personalized trust models have also been proposed on academic research level, including TidalTrust

[5] and MoleTrust [6]. However, those trust systems without exception need users to specify explicitly whom they trust and how much they trust each other, which greatly relies their performance on users' input of their trust opinions. It's also worth mentioning that most of the existing trust models don't take "context" into account, probably due to the difficulty of specification and integration. The investigation of current trust and reputation systems will be detailed in section II.

In short, the objective of our research is to investigate trust models and adapt them to the personal and collaborative learning requirements in social media, aiming at offering guidance for learners on selecting trusty people and services, as well as providing collaborative sanctioning mechanisms to construct reliable learning environment. Ongoing research is being conducted, and preliminary results have been obtained. A multi-relational trust metric is proposed, using the implicit trust network of users in the community. An evaluation has been performed using the dataset of a collaborative learning platform, namely *Remashed* (remashed.ou.nl) [7]. The rest of the paper is organized as follows. Three papers relevant to our research topic are described in Section II. Section III illustrates the current progress of the research work. Section IV addresses the future research directions. Finally, section V concludes the paper and discusses the future work.

II. Survey of the Selected Papers

In this section, existing trust and reputation metrics are investigated, as well as live reputation systems. Numerous problems in current practical and academic reputation systems are also analyzed [8]. Afterwards, a recent study on how profile similarity relates to trust is addressed, based on a controlled experiment on a movie rating dataset [9]. Finally, the role of trust and reputation systems in social learning environments are discussed, including supporting learners to find helpful resources as well as people, and motivating learners [10].

A. Survey of Trust and Reputation Systems

An overview of existing trust and reputation systems is introduced by A. Josang, R. Ismail and C. Boyd in [8]. As indicated by the authors, in real life, the trust relationship between two parties (i.e. trustor and trustee) formed naturally through a variety of social interactions, including personal experience and second hand referrals from others. From the online system point of view, trust means that the trustor thinks the trustee is reliable in a particular context so that the former would like to perform some transactions with the latter, such as cooperation, discussion and download.

Moving from social trust to digital trust, there are two crucial issues which should be tackled. Firstly, the real-life evidences which are used to determine trust and reputation are missing in online environments. Therefore, adequate electronic substitutes for the traditional cues to trust and reputation need to be exploited. Secondly, in the physical world, exchanging information related to trust and reputation is usually constrained to local communities, while online environments allow people to share and collect such information on a global scale. Online trust and reputation systems should be able to take the advantage to derive efficient measures using data from heterogeneous sources.

Motivated by this basic observation, various principles for computing reputation and trust measures have been proposed, such as simple average of ratings, Bayesian systems, belief models, and flow models. The detailed metrics of these principles are described hereafter.

Simple average of ratings is the reputation scheme used in eBay, Epinions and Amazon. Reputation scores are computed either by keeping a total score as the number of positive ratings minus that of negative ratings, or by making an average of all ratings. Some improvements are also made by computing a weighted average of all the ratings, where the rating weight can be determined by factors such as rater reputation, distance between rating and current score, and age of the rating. The advantage of this scheme is that it's easy for users to understand, the disadvantage is that it is primitive and therefore gives a poor picture on participants' reputation score.

Bayesian systems take binary ratings as input (i.e. positive or negative), and compute reputation scores by statistical updating of beta probability density functions. The updated reputation score is generated by combining the previous reputation score with the new rating, accompanied with the variance or a confidence parameter. Trust metrics based on Bayesian theory provide a theoretically sound basis for computing reputation scores, but it's too complex for average users to understand.

A representative of **belief models** is proposed in [11], where the author introduced a trust metric called *opinion* denoted by $\omega_x^A = (b, d, u, a)$. Here ω_x^A expresses the relying party A's belief in the truth of statement x. The parameters b, d, and u represent belief, disbelief and uncertainty respectively, where $b, d, u \in [0, 1]$ and $b + d + u = 1$. The parameter $a \in [0, 1]$, which is called the relative atomicity, denotes the base rate probability in the absence of evidence. If the statement says "David is honest and reliable", then the belief can be interpreted as the relying party A's trust perception in David. The trust measures can be illustrated by the following example. As shown in Fig. 1, Alice is looking for a good car mechanic, so she asks Bob and Claire for recommendation. Bob and Claire both recommend David, but with different degrees of trust. Each of the two transitive trust paths "$Alice \rightarrow Bob \rightarrow David$" and "$Alice \rightarrow Claire \rightarrow David$" is computed with the *Discounting Operator*, where the idea is that the referrals from Bob and Claire are discounted using a function of Alice's trust in Bob and Claire respectively. Finally the derived trust value from Alice to David is computed by *Consensus Operator*, which combines the trust values of the two paths.

Flow models are the ones that compute trust or reputation by transitive iteration through looped or arbitrarily long chains. Google's PageRank [12], Advogato's reputation scheme [13], and EigenTrust model [14] belong to this category. Some flow models assume a constant trust or reputation value for the whole community, and this value is distributed among the members of the community. The trust or reputation score of a member can only increase at the cost of others. In short, a participant's trust or reputation score increases as a function of

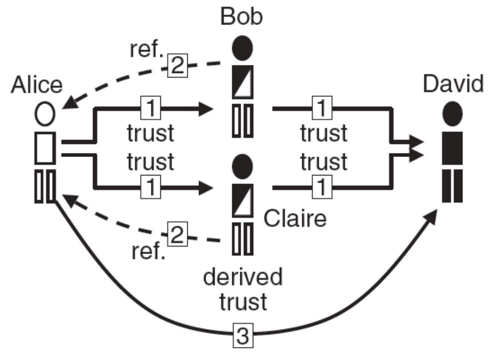

Fig. 1. Deriving Trust from Parallel Transitive Chains

incoming flow, and decreases as a function of outgoing flow.

A number of these proposed trust metrics have been adopted in a variety of online communities, such as commercial sites, expert communities, product review platforms, discussion forums and web search engines. Several well known applications of online reputation systems are discussed hereafter.

The popular auction site **eBay** uses a centralized reputation system, where buyers and sellers are given the opportunity to rate each other as positive, neutral or negative after every transaction. The total reputation score of each participant is the sum of positive ratings minus the sum of negative ratings. In order to provide information about a participant's more recent behavior, reputation scores of three different time windows (i.e. past six months, past month, and past seven days) are all displayed. The drawback of this reputation scheme is that it can be misleading. As an example, a participant with 100 positive and 10 negative ratings should intuitively appear less reputable than a participant with 90 positive and no negative ratings. While in eBay, they have the same reputation score.

AllExperts (www.allexperts.com) is a community which provides free question and answer service. Its reputation system is dedicated to evaluate the expertise of community members. According to their answers, experts can be rated as an interval between 1 and 10 in the following aspects: *Knowledgeable*, *Clarity of Response*, *Timeliness* and *Politeness*. The score in each aspect is simply the numerical average of ratings received. A *General Prestige* score, which is the sum of all average ratings an expert has received, is displayed as well as the number of questions the expert has answered.

As a product review site, **Epinions** has a pool of individuals providing product and shop reviews. Epinions allows its members to rate the products and shops in the form of five stars for a set of aspects, such as *Ease of Use* and *Battery Life* in the case of products, and *Ease of Ordering*, *Customer Service*, *On-Time Delivery* and *Selection* in case of shops. The review itself can be rated by other members as *Not Helpful*, *Somewhat Helpful*, *Helpful* and *Very Helpful*. According to the overall quality of his or her reviews, a member can obtain the status like *Advisor*, *Top Reviewer* or *Category Lead*. The concept of "Web of Trust" is also introduced in Epinions' reputation mechanism, where members are able to decide to either trust or block another member. The number of trust relationship received by a member will also have an influence on his or her status.

Google adopts **PageRank** algorithm to rank the best search results based on a page's reputation. A hyperlink can be seen as a positive referral of the page it points to. Roughly speaking, PageRank ranks a page according to how many other pages are pointing to it. Let P be a set of hyperlinked web pages, and let u and v denote web pages in P. Let $N^-(u)$ denote the set of web pages pointing to u and let $N^+(v)$ denote the set of web pages that v points to. Let E be some vector over P corresponding to a source of rank. Then the PageRank $R(u)$ of a web page u is defined as follows:

$$R(u) = cE(u) + c \sum_{v \in N^-(u)} \frac{R(v)}{|N^+(v)|} \tag{1}$$

In Eq. (1), c is chosen such that $\sum_{u \in P} R(u) = 1$. The first term $cE(u)$ gives rank value based on initial rank. The second term c $\sum_{v \in N^-(u)} \frac{R(v)}{|N^+(v)|}$ gives rank value as a function of hyperlinks pointing at u. Before Google's PageRank algorithm entered the search engine market, some web masters used to promote their websites by filling web pages with commonly used search keywords, in order to have a high probability of being picked up by a search engine. Google's PageRank makes it difficult or expensive to influence web pages' rankings in that a high PageRank is also needed besides keywords matching.

Along with the rapid development of various trust and reputation systems in both literature and practice, a number of problems also arise and some solutions have been proposed accordingly. A few main problems are addressed as follows.

1) Low Incentive for Providing Rating: Lack of incentives for providing ratings is a general problem in most systems, since a rater doesn't benefit directly from it. Effective incentive mechanisms are required, for trust and reputation metrics usually rely their performance on users' active input. To solve this problem, some incentive schemes based on payments have been proposed [15].

2) Bias toward Positive Rating: It's discovered that there is often a positive bias of ratings in most reputation systems. The reason why people tend to give positive rating is probably that they hope to get a positive rating in return or alternatively they want to avoid retaliation from others. A conspicuous solution to this problem is to allow anonymous ratings.

3) Unfair Ratings: Since ratings are given based on subjective opinions, unfair ratings seem to be unavoidable. It's evident that unfair ratings will have a negative impact on the accuracy of reputation computation. Some attempts have been made to exclude or give low weight to presumed unfair ratings, using statistical analysis. Others methods determine the weight given to ratings by the reputation score of the rater.

4) Change of Identities: For some participants with low reputation scores, they might change their identities and enter the community as newcomers. From the whole community point of view, this behavior should be prevented. Some methods have been proposed to give extremely low reputation score to newcomers, in order to discourage users from changing identities.

The state of the art in trust and reputation systems has been addressed so far. How to extend and improve the existing models in order to comply with personal and collaborative learning requirements is the main focus of our research. Unlike the communities of market economy which concentrate on particular domains, learning communities are multi-disciplinary and multi-dimensional platforms where resources and services are aggregated from heterogeneous sources. It's essential to evaluate the quality of user-generated content and expertise of unknown parties in given learning context and for particular learning goals. Therefore we propose to design effective and robust trust and reputation mechanisms, facilitating constructing personalized and contextualized learning environment, as well as providing an incentive for good behavior in the learning community.

B. Trust and Nuanced Profile Similarity in Online Social Networks

The correlation of trust and profile similarity in online social networks is investigated in detail by J. Golbeck in [9]. Instead of investigating overall similarity, the influence of several facets of profile similarity on trust is examined, through a controlled experiment on a movie review dataset.

The platform used in the experiment is FilmTrust (trust.mindswap.org/FilmTrust), which is a trust-based social networking website allowing users to rate and review movies. Users in FilmTrust maintain lists of their friends and are also required to assign a trust rating to each friend that indicates how much they trust that person's opinions about movies. A trust network is then constructed using the trust value provided by users. The system produces predictive movie ratings by computing a weighted average of the ratings assigned to a movie, using trust as a weight. Without going into detail, 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 movie is predicted by aggregating all those ratings weighted by the trust value of the raters.

The evaluation of the algorithm suggests that when users assign trust ratings, they are capturing more than simply how similar their taste are to others'. In order to further understand how similarity on different profile attributes affect the trust people assign to one another, a survey-based experiment is conducted. Subjects begin by rating a large number of movies, where ratings are on a 1-10 scale (1 for bad movies, and 10 for good ones). Profiles of hypothetical users that include ten to twenty movies are generated so that these profiles represent people with different movie preferences. Each subject is shown the hypothetical user's rating for each movie, along with the subject's own rating and the average rating. Subjects are then asked to express how much they would trust this hypothetical user in his or her movie taste based on the profile.

To measure how trust correlates to similarity on certain profile features, the experiment is conducted in two phases, using different sets of hypothetical user profiles. Let r_{si} and r_{pi} denote the subject's and hypothetical user's rating for movie i. Let $\Delta_{r_{si},r_{pi}}$ denote the absolute difference between these two ratings, and σ denote the standard deviation on a hypothetical profile. Let $\overline{\Theta}$ denote the average difference between subjects' and hypothetical profiles' ratings.

TABLE I
SINGLE MAXIMUM DIFFERENCE - TRUST RELATIONSHIP WHEN $(\sigma, \overline{\Theta}) = ([0, 1), [0, 1))$

∇ Value	0-1	1-2	2-3	3-4
Average Trust Value	9.11	8.58	8.16	7.52

TABLE II
SINGLE MAXIMUM DIFFERENCE - TRUST RELATIONSHIP WHEN $(\sigma, \overline{\Theta}) = ([1, 2), [1, 2))$

∇ Value	2-3	3-4	4-5	5-6
Average Trust Value	7.30	6.61	6.22	5.49

In **phase one**, two steps are carried out as follows.

Step #1: The agreement on movies where the user has assigned **extreme** ratings ($r_{si} \leq 2$ or $r_{si} \geq 9$) is examined. The idea is to hold overall average difference between subjects and hypothetical users constant, and then check the correlation between trust and agreement on extreme ratings. In this case, if agreement on extreme ratings increases, then agreement on nonextreme ratings ($3 \leq r_{si} \leq 8$) must decrease. The results show that, when holding the overall average difference constant, as agreement on extremes increases, trust increases. This initially would indicate that, trust is tied, in part, to agreement on extremes. However, when holding the overall average difference constant and increasing agreement on nonextremes (and thus agreement on extremes decreases), trust also increases. This suggests that some factor other than extremes or nonextremes is involved and will affects the trust values.

Step #2: The correlation of trust with the maximum $\Delta_{r_{si},r_{pi}}$ on a given profile is tested, where the maximum $\Delta_{r_{si},r_{pi}}$ is called **single maximum difference**, denoted by ∇. As the single maximum difference ∇ increases, standard deviation σ will also increase. To the see the effect of the single maximum difference independent of the standard deviation, standard deviation and overall average difference are held in fixed ranges. If ∇ is a factor in how users assign trust, there will be significant changes in trust when ∇ increases while σ and $\overline{\Theta}$ are held constant. A statistical analysis of the single maximum difference - trust relationship on two $(\sigma, \overline{\Theta})$ pairs is performed, where $(\sigma, \overline{\Theta}) = ([0, 1), [0, 1))$ and $(\sigma, \overline{\Theta}) = ([1, 2), [1, 2))$ respectively. In both cases, which together cover approximately 65% of all the trust ratings given in phase one, a clear relationship between the single maximum difference and trust is shown. Table I and II illustrate that, the average trust rating decreases as the single maximum difference increases. This result suggests that the maximum difference between the user's rating and profile's rating of a given movie, is a significant factor in how users assign trust. Specifically, for the movie with the maximum difference, as the difference grows, trust decreases. This is true even with overall agreement and standard deviation kept constant.

In **phase two**, the profiles are more controlled and two steps are tested as well.

Step #1: A further investigation of the relationship between

extreme ratings and trust is conducted, in that this point cannot be clearly observed in phase one. In this step, the average difference $\overline{\Theta}$, single maximum difference ∇, and standard deviation σ are all held constant, the only variable is the difference on extreme and nonextreme movies. The result shows that when high difference is assigned to movies with extreme ratings, the average trust value for the profile is over 0.5 lower than when low difference is assigned to those movies. So the conclusion is that agreement on movies to which the subject has assigned extreme ratings affects trust, independently of overall agreement. When agreement is closer on these movies, trust is higher.

Step #2: The **trusting degree** of the users is estimated in this step, that is how ”trusting” the users are. The profiles are carefully controlled, so that profiles rated by each subject all varied from the user in the same way. Thus, the average trust value assigned by user s (call this τ_s) represents the trusting degree of this user. As indicated in the results, the distribution of trust ratings given by users varies greatly from user to user. The average trust rating τ_s ranges from as low as 3.73 up to 8.48. This range of τ_s among users suggests that, some subjects are more trusting than others, or that subjects interpret the scale of trust values differently.

From all the experiments conducted so far, the results indicate that, besides overall agreement, the maximum single difference in movie ratings, difference on movies to which the user assigned extreme ratings, and the average trust value assigned by the user are all factors in how users assign trust. Based on this conclusion, the author of [9] proposes to predict trust using all these aspects of profile similarity that correlate with trust. The objective is to solve the problem that, in many Web-based social networks, a significant percentage of users are completely isolated from most others, thus the social network-based trust measures are not applicable. However, those isolated users are usually inactive ones who rarely contribute to the system and hence provide few ratings. Lack of ratings would probably be a problem for trust metrics relying on rating similarity. Despite the drawback, the interesting experimental results still provide some insight in how to normalize rating and how trust correlates with similarity, which might be useful in our future research work.

C. Toward Social Learning Environments

The recent trend and particular requirements in social learning environments is discussed by J. Vassileva in [10]. As stated by the author, Web 2.0 emphasizes supporting users in connecting, communicating, and collaborating with each other and deriving value from this. The user is no longer a viewer, a recipient, or a consumer; the user is now a collaborative contributor. Along with the evolution of online environments, a new generation of learners arise, who are tech-competent, exploring and trying things out. Multitasking allows them to instantly gratify themselves and put off long-term goals. Generally speaking, the motivation for the new mode of learning is to satisfy a short-term goal; it is ”solution-driven” rather than ”learning on principle”. The social learning environments allow a mode of learning that is well suited to the learning needs of the new learners. They are no longer isolated systems that ”teach” the user. Instead, they connect existing resources, content and people, to offer learners purpose-driven, self-centered environments.

The evolution of social learning facilitates easily opinion expression and encourages free contributions. Unfortunately, relying on volunteer contributors without credentials may lead to content that is contentious or simply false. This makes participatory media, like Wikipedia, somewhat problematic as an educational resource because a recent study has found that young people have difficulty in assessing the quality of information sources they find on the Web [18].

Based on the previous analysis, the social learning environments should be able to:

1) Help the learners find the ”right content” to learn,
2) Help the learners find the ”right people” to collaborate or to learn from,
3) Make learning gratifying and motivation participation.

The ”right” here suggests multi-demensional meanings, including the particular learner (personalization), the context (related to the particular purpose, task, or query) and the pedagogy (the sequence of content, the sequence of activities, and the difficulty level). For the purpose of finding the ”right content” and ”right people”, a handful of solutions have been proposed.

1) Ontology-Based Approach: To be able to find the ”right content”, it is necessary to be able to distinguish between different aspect, characteristics of content, context, learner, and pedagogy. For this, ontology-based approaches are proposed, which allow complex objects and relationships to be represented, and thus provide reasoning, recommendation, and adaptation mechanisms. The problem is that ontologies are very difficult for experts to agree on in that different communities use different naming standards and interpret entities in different ways. Even if there is agreement among designers about using a particular simple ontology, from a user’s point of view, it imposes an inconvenient way of organizing or finding content.

2) Folksonomy-Based Approach: Compared to the predefined ontologies, tags allow users to annotate content with whatever words they find personally useful. With many users tagging the same documents, the pool of tags will capture some essential characteristics of the documents. Therefore, ”folksonomies” emerge, developed by collaborative tagging of community users. Tags can express a variety of semantic dimensions, such as content, context, pedagogical characteristics, learner, and media. For a person searching for something, the abundance of tags guarantees that there will be something found that is suitable. However, tags in a folksonomy are not machine-understandable, since they are discrete labels with no relationship among them. It’s difficult to use tags for inference or reasoning.

3) Recommender Systems: Recommender systems have evolved as a practical approach for providing recommendations without the need for understanding the semantics of the content. Recommender systems based on collaborative filtering algorithms compute the correlation between users using their past choices. The problem is that, if there are not enough users and ratings in the system, the accuracy of prediction goes down dramatically. In addition, the idea of recommender systems is to ”follow people similar to you”. However, in education, it is desirable no to follow people similar to oneself, but to follow people one strives to become similar to, such as supervisors, experts, and teachers. Approaches which take pedagogical requirements into account still need to be developed.

4) Trust and Reputation Systems: Trust and reputation mechanisms can be used to dynamically form communities of like-minded users without any centralized authority. By gossiping and maintaining individual reputation, a community of completely autonomous and self-interested users can collectively self-organize to create a semicentralized reputation management systems that helps to quickly find good resources and people in the community. Yet, to make the mechanism work effectively, it's necessary that each user contributes actively his or her personal trust perception for trust computing in the overall community, even if there may be not immediate payoff for this. As mentioned previously, designing effective incentive mechanisms to motivate participation is a big challenge faced by social learning environments.

III. Preliminary Work

Despite the fact that there is a rapidly growing literature around trust and reputation systems, the design of effective trust and reputation mechanisms dedicated for personal and collaborative learning environments has still not been extensively exploited. The objective of our research is to investigate the opportunity of using trust and reputation systems in personal and collaborative learning environments, aiming at supporting evaluating the quality of user-generated content and the expertise of members in the learning community, therefore facilitate selecting reliable and useful learning resources and peers depending on personal learning goals. Lessons learned from the prior work should be taken into account, special attention should also be paid to the particular requirements of collaborative learning domain. In this section, the preliminary work is addressed and some encouraging results are shown as well.

In our previous work, a trust-based rating prediction approach is proposed [19]. It relies on the 3A interaction model [20] that is particularly focused on describing and designing social and collaborative environments. A multi-relational trust metric is designed, aiming at measuring the trust relationship between the target user and people in his or her trust network. Rating scores of items associated to a community are predicted using the implicit trust network of a particular user. An evaluation of the approach has been conducted using the dataset of a collaborative learning platform, namely *Remashed*.

A. Proposed Approach

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. The model accounts for Web 2.0 features: entities can be tagged, shared and rated.

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.

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 or her trusted users, which leads to his or 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 Eq. (2):

$$DT(s,t) = \frac{W(R_i)}{N(s,i)} \tag{2}$$

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 (i.e. indirect trust). 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 Eq. (3):

$$IT(s,t) = \frac{\sum\limits_{e_j \in E} T(e_j, t) T(s, e_j)}{\sum\limits_{e_j \in E} T(s, e_j)} \tag{3}$$

At the end of the random walk, a Web of Trust of the target user is formed, which consists of his or 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.

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 or 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.

B. Model Evaluation

For the purpose of evaluating trust-based rating prediction approach, the proposed model is applied on the dataset of the learning platform, *Remashed*. *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.

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. 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.

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 [21], 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) [22] 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 Eq. (4):

$$MAE = \frac{\sum\limits_{i=1}^{S} |pr_i - ar_i|}{S} \tag{4}$$

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. 2 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. 2, 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.

Different propagate distances and trust weight settings are chosen for evaluation. 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.

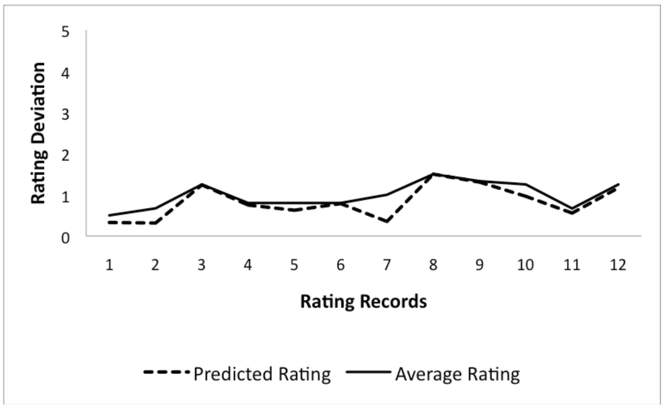

Fig. 2. Deviation Comparison between Trust-Based Prediction and Simple Average

IV. RESEARCH PROPOSAL

The proposed research will be carried out in the framework of the ROLE European project (Responsive Open Learning Environment), which aims at supporting self-directed learning thanks to innovative Web-based personal learning environments. In this section, the future research directions for the PhD thesis are briefly described.

As mentioned previously, trust and reputation models proposed in prior research mostly adopt global trust metrics based on users' past performance or interactive feedback. However, in personal learning environments, trust models are required to be contextual, personalized and evolutive. We will investigate context-dependent trust and reputation models. The objective is to enable agile recommendation of trusty people and services associated with various online communities and open repositories to support self-directed learning activities.

Although sharing information is one of the major benefits in social learning environments, not everything is to be shared with everyone. Adequate privacy mechanisms should be defined so that data is only shared among trusty entities depending on specific context. We will enhance trust and reputation models to enforce privacy based on learners' implicit and explicit privacy preferences, ensuring reliable access control in given situations.

V. CONCLUSION

The design of effective trust and reputation mechanisms for personal and collaborative learning environments is believed to be a promising research direction. In this proposal, prior work in trust and reputation systems are discussed, and the particular requirements for social learning environments are also analyzed. Finally, our preliminary work is addressed and the first-step evaluation produces some encouraging results. In the future, we will continue to investigate context-dependent trust and reputation models and deploy them in a real system. Trust-based privacy management will be tackled as well.

REFERENCES

[1] A. Josang, "Trust and Reputation Systems", *Lecture Notes in Computer Science*, Volume 4677: 209-245, 2007.

[2] D. Tapscott, "Grown up Digital: How the Net Generation is Changing Your World", McGraw-Hill, New York, 2009.

[3] G. Heiberger, R. Harper, "Have You Facebooked Astin Lately? Using Technology to Increase Student Involvement", *New Directions for Student Services*, Volume 124: 19-35, 2008.

[4] Z. Yan, S. Holtmanns, "Trust Modeling and Management: from Social Trust to Digital Trust", *Computer Security, Privacy and Politics: Current Issues, Challenges and Solutions*, IGI Global, 2008.

[5] J. Golbeck, J. Hendler, "Film Trust: Movie Recommendations using Trust in Web-based Social Networks", *Consumer Communication and Networking Conference*, Volume 1: 282-286, 2006.

[6] P. Massa,P. Avesani, "Trust-aware Recommender Systems", *ACM Conference on Recommender Systems*, 17-24, 2007.

[7] H. Drachsler, D. Pecceu, T. Arts, et al., "Remashed - Recommendations for Mash-Up Personal Learning Environments", *Lecture Notes in Computer Science*, Volume 5794/2009: 788-793, 2009.

[8] A. Josang, R. Ismail, C. Boyd, "A Survey of Trust and Reputation Systems for Online Service Provision", *Decision Support Systems*, Volume 43: 618-644, 2007.

[9] J. Golbeck, "Trust and Nuanced Profile Similarity in Online Social Networks", *ACM Transactions on the Web*, Volume 3(4), 2009.

[10] J. Vassileva, "Toward Social Learning Environments", *IEEE Transactions on Learning Technologies*, Volume 1(4): 199-241, 2008.

[11] A. Josang, "A Logic for Uncertain Probabilities", *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, Volume 9 (3): 279-311, 2001.

[12] L. Page, S. Brin, R. Motwani, "The PageRank Citation Ranking: Bringing Order to the Web", Technical Report, Standford Digital Library Technologies Project, 1998.

[13] R. Levien, "Attack Resistant Trust Metrics", PhD thesis, University of California at Berkeley, 1998.

[14] S.D. Kamvar, M.T. Schlosser, H. Garcia-Molina, "The EigenTrust Algorithm for Reputation Management in P2P Networks", *12th International World Wide Web Conference*, 640-651, 2003.

[15] R. Jurca, B. Faltings, "An Incentive Compatible Reputation Mechanism", *6th International Workshop on Deception Fraud and Trust in Agent Societies*, ACM, 2003.

[16] R. Sinha, K. Swearingen, "Comparing Recommendations Made by Online Systems and Friends", *DELOS-NSF Workshop on Personalization and Recommender Systems in Digital Libraries*, 2001.

[17] C.N. Ziegler, J. Golbeck, "Investigating Correlations of Trust and Interest Similarity", *Decision Support Services*, 2006.

[18] A. Forte, A. Brukman, "Information Literacy in the Age of Wikipedia", *International Conference of Learning Sciences*, 2008.

[19] N. Li, S. El Helou, D. Gillet, "Trust-Based Rating Prediction for Recommendation in Web 2.0 Collaborative Learning Social Software", *9th International Conference on Information Technology Based Higher Education and Training*, 208-212, 2010.

[20] S. El Helou, N. Li, D. Gillet, "The 3A Interaction Model: Towards Bridging the Gap between Formal and Informal Learning", *3rd International Conference on Advances in Computer-Human Interactions*, 179-184, 2009.

[21] J. Golbeck, "Generating Predictive Movie Recommendations from Trust in Social Networks", *4th International Conference on Trust Management*, 93-104, 2006.

[22] S. Moghaddam, M. Jamali, M. Ester, "Feedback Trust: Using Feedback Effects in Trust-Based Recommendation Systems", *3rd ACM Conference on Recommendation Systems*, 269-272, 2009.