# Generating Trust-Based Recommendations for Social Networks organized by Groups

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***Abstract*—Evidence suggests that people often waver to buy from online vendors because of uncertainty about vendor behavior or the risk of having wrong information about the products. Trust plays a central role in helping consumers overcome perceptions of risk. Moreover, thematic groups are gaining a lot of attention and high centrality in online community, as users share opinions and/or mutually collaborate for reaching their targets. The users can be helped by personal software agents able to perform activities aimed at supporting the purchase of products. This paper proposes a new trust measure in social networks organized by groups. In particular, we present a model to represent this scenario, and we introduce an algorithm for detecting trust recommendations in virtual communities in presence of groups. We technically formalize our idea and show a complete example of how our approach works.**

***Index Terms*—Recommendation, Online Communities, Trust, Group.**

## I. INTRODUCTION

An important issue in Online Social Networks (OSNs) is that of designing recommender systems capable to provide OSN users with useful suggestions regarding other potentially promising OSN users to contact as interlocutors or interesting content to access. Such an issue leads to the necessity of considering the opinions that different users express about other users or OSN content [1]–[3]. However, recommender systems have to face with the general problem of malicious or even fraudulent behaviors of some users, that results in unreliable opinions which can negatively affect the effectiveness of the generated recommendations.

The issue of trusting own interlocutors widely emerged in large online e-Commerce communities as, for instance eBay, and now it is largely discussed in many OSNs which allow their users to create and share contents with other users as well as opinions. This is the case, for example, of well-focused OSNs like EPINIONS[1] and CIAO[2], in which users provide reviews concerning commercial products falling in different categories. Almost all of these platforms face this issue by adopting a reputation system. Reputation is a form of indirect trust, where a user takes advantage from the opinions coming from other users for evaluating the probable trustworthiness of an interlocutor. Commonly, in the traditional OSN contexts, the reputation of a user is evaluated by averaging feedbacks provided by all the other users belonging to the same community. In the past literature, a common approach for predicting trust is represented by a number of models that rely on global reputation [4]–[6]: they are based on the evaluation of the behaviors of the users, that is shared across the entire community. These models, however, show an evident limitation due to the difficulty of taking the effects of malicious or fraudulent behaviors into account, thus making the feedback themselves. Other approaches, that consider also a local perspective of the trust, are limited by the fact they are supervised, i.e. they need a training phase in generating recommendations. In [7], we proposed to integrate the traditional use of the global reputation with the local reputation, that is based on the recommendations coming by the entourage of the user (friends, friends of friends and so on). But this proposal was limited because it does not consider a group-based structure [8]–[10].

In this paper, we define a new model to represent the groups of users linked by trust relationships. Such a model depends on three main parameters: the relevance given to the reliability with respect to the reputation, the threshold of recommendation under which a product can be considered as not interesting and the number of the groups in online communities. We propose an algorithm for detecting trust recommendations for a user considering the recommendations that come from users within his own group and those of other groups weighted with the global reputation. We technically formalize our idea and algorithm, and we present a complete example of how our approach works. The paper is organized as follows: in Section II we deal with some related work. Section III provides technical details about our approach for finding trust recommendations about products, while Section IV describes a concrete example of application. Finally, in Section V we draw our conclusions and illustrate some possible future works.

## II. RELATED WORK

A large number of papers in the literature investigated on the topic we deal with here, therefore, in this section we cite only those approaches which we consider comparable with that discussed in this paper.

Concerning the concept of trust, there exist in the literature several proposals. Sherchan et al. [11] present an important review of trust, in which they comprehensively examine trust definitions and measurements, from multiple fields including sociology, psychology, and computer science. Trust models [12]–[15] allow to exploit information derived by direct experiences and/or opinions of others to trust potential partners by

[1]www.epinions.com
[2]www.ciao.it

means of a single measure [16], [17]. Xia et al. [18] build a subjective trust management model AFStrust, which considers multiple factors including direct trust, recommendation trust, incentive function and active degree, and treats those factors based on the analytic hierarchy process (AHP) theory and the fuzzy logic rule. [19] describes how to build robust reputation systems using machine learning techniques, and defines a framework for translating a trust modeling problem into a learning problem.

In many disciplines, there is a population of people which should be optimally divided into multiple groups based on certain attributes to collaboratively perform a particular task [20], [21]. The problem becomes more complex when some other requirements are also added: homogeneity, heterogeneity or a mixture of teams, amount of consideration to the preferences of individuals, variability or invariability of group size, having moderators, aggregation or distribution of persons, overlapping level of teams, and so forth [5], [22]–[25]. Basu et al. [26] consider the problem of how to form groups such that the users in the formed groups are most satisfied with the suggested top-k recommendations. They assume that the recommendations will be generated according to one of the two group recommendation semantics, called Least Misery and Aggregate Voting. Rather than assuming groups are given, or rely on ad hoc group formation dynamics, their framework allows a strategic approach for forming groups of users in order to maximize satisfaction. In [27], the authors reveal how these problems can be mathematically formulated through a binary integer programming approach to construct an effective model which is solvable by exact methods in an acceptable time.

## III. Our Scenario

Our scenario is represented by a virtual community $\mathcal{S}$, formally denoted as $\mathcal{S} = \langle \mathcal{A}, \mathcal{G} \rangle$, where $\mathcal{A}$ is the set of *agents* joined with $\mathcal{S}$ and $\mathcal{G}$ is the set of *groups* contained in $\mathcal{S}$. We also assume that each group $g$ is managed by an administrator agent $a_g$. Generally, all such communities are organized in social structures based on social relationship (like, Facebook [28], [29] or Twitter [30]). The formation of a group is a process based on two main events: a user asks for joining with a group and the administrator of the group accepts or refuses the request.

### A. Trust

The trust measure $t_{u,v}$ is a mapping that receives as input two agents $u$ and $v$ and yields as output a boolean value representing the degree of trust between two agents $u$ and $v$: $t_{u,v}$ = 0 (resp. $t_{u,v}$ = 1) means that $u$ assigns the minimum (resp. maximum) trustworthiness to $v$. The trust measure is asymmetric, in the sense that we do not automatically expect that $v$ trusts $u$ at the same level.

As a theoretical proposal, we had introduced a more general trust measure, by combining two components $rel_{u,v}$ and $rep_u$, where *(i)* $rel_{u,v}$ is the direct reliability of $u$, i.e. the trustworthiness that $v$ has in $u$ based on the past interactions between $u$ and $v$ while *(ii)* $rep_u$ is the global reputation of $u$, i.e. the trustworthiness that all the community has in $u$. The reason of this choice, was due to the necessity, when $v$ does not have a sufficient direct knowledge of $u$, to use the recommendations coming from the other agents of the community.

*1) Reliability:* As for the reliability, we denote it by the mapping $rel_{u,v}$, assuming values ranging in the domain $[0 \cdots 1] \bigcup NULL$, while $rel_{u,v}$ = NULL means that $v$ did not have past interactions with $u$ and thus it is not able to evaluate $u$'s trustworthiness.

*2) Reputation:* As for the reputation of $u$, we denote it by $rep_u$ in the interval $[0 \cdots 1] \epsilon \mathbb{R}$. In order to compute the reputation, we adopt the notion of

$$rep_u = \frac{1}{h_{max}|REV_u|} \sum_{\rho \in REV_u} h_\rho \tag{1}$$

where $|REV_u|$ is the set of the reviews made by the user $u$ and $h$ is the helpfulness, i.e., it is associated with each review that represents the level of satisfaction of the other users for that review. To normalize $rep_u$, we divide it by the maximum value of the helpfulness $h_{max}$.

The two trust components reliability and reputation are integrated in a unique value to compute the mapping trust $t_{u,v}$ of $u$ about $v$, producing a input ranging in $[0 \cdots 1]$ as follows:

$$t_{u,v} = \alpha \cdot rel_{u,v} + (1 - \alpha) \cdot rep_v \tag{2}$$

where $\alpha$ is a real number, ranging in $[0...1]$, which is set by $u$ to weight the relevance he/she assigns to the reliability with respect to the reputation.

### B. Product recommendation

The user receives, at the current step, some recommendations about the products present in the community. In other words, $rec_u^p$ is the recommendation that the user $u$ receives about the product $p$. It is calculated as follows:

$$rec_u^p = \frac{\sum_{v \in \rho, v \neq u} t_{u,v} \cdot rate_v^p}{\sum_{v \in \rho, v \neq u} t_{u,v}} \tag{3}$$

where $rate_v^p$ is the review of the the user $v$ about the product $p$ (a number between 1 and 6), weighed by the trust of $v$. This means that his/her opinion about a product is taken into account if his/her trustworthiness is high. The weighted average allows us to identify an average value in which the starting numerical values have their own importance, specified by its weight. In particular, we can identify the center of gravity of the rate. In this way, we give more importance to the rate from users that the user $u$ trusts. With a normal mean we would lose significant information.

### C. Groups

At this point, we introduce the group's concept in the community. In this context, we define trust $t^*_{u,v}$ in two different ways. We suppose that the trust perceived by an agent $u$ with respect to the component of his/her group is equal to 1 (i.e,

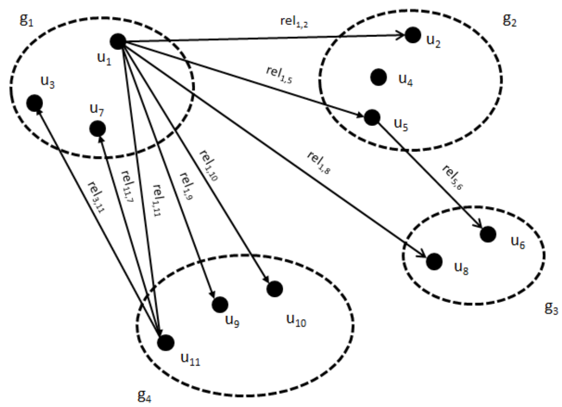


Fig. 1. A community associated to the online e-Commerce.

$t^*_{u,v}$=1), instead the agent $u$ considers the trust that user has in the whole community (see Equation 2). In this way, we define $rec_g^{*p}$ that is the recommendation that the user $u$ receives about the product $p$ in presence of the groups:

$$rec_u^{*p} = \frac{\sum_{v \in g_u} rate_v^p + \sum_{v \notin g_u} t_{u,v} \cdot rate_v^p}{\sum_{v \in |REV_p|} t^*_{u,v}} \tag{4}$$

where $g_u$ is the group to which the agent $u$ belongs and $|REV_p|$ is the set of the agents who have purchased the product $p$. It is calculated as the combination of two contribution: the average rating of the users that belong to the group of the user $u$ and the score that the other groups give to the product multiplied by the trust that $u$ assign to its agents.

## IV. An example of scenario: e-Commerce

Now, we explain how it is possible to use groups to generate the recommendations of products for the users inserted into an online e-Commerce communities. As an example, we propose to model each user by a node (see Figure 1).

We assume that all the elements of a group are trust-related, a trust group $g$ determined into $G$ represents a mutual trust relationship between its elements. In our case, there are four groups of users called $g_1$, $g_2$, $g_3$ and $g_4$. All the users in the same group are mutually linked by a trust relationship with the value 1; while the values of the reliability are shown in the Table I.

| $u$ | $v$ | $rel_{uv}$ |
|---|---|---|
| 1 | 2 | 0.7 |
| 1 | 5 | 1 |
| 1 | 8 | 0.3 |
| 1 | 9 | 0.2 |
| 1 | 11 | 0.1 |
| 3 | 11 | 0.8 |
| 5 | 6 | 0.1 |
| 11 | 7 | 0.2 |

TABLE I
SIMULATION PARAMETERS

In particular, in our example, there are nine products that are divided in three main categories called Electronics, Informatics and Software (see Table II). In the Table III, we show an example of datasets.

| productID | name | categoryID |
|---|---|---|
| 1 | Car TomTom, Display 5” | Electronics |
| 2 | Smartphone Android 5.1 | Electronics |
| 3 | TV HD Ready 15,6” Format 16:9 | Electronics |
| 4 | Notebook 15” i7, RAM 8 GB, HDD 500GB | Informatics |
| 5 | Black and white laser printer | Informatics |
| 6 | Tablet 7”, Wi-Fi, 8 GB | Informatics |
| 7 | Microsoft Windows 7 PRO SP1 32/64-bit | Software |
| 8 | Microsoft Office 365 Personal - 32/64 Bit | Software |
| 9 | Nuance Power PDF Standard | Software |

TABLE II
LIST OF PRODUCTS

| userID | productID | categoryID | rating | helpfulness |
|---|---|---|---|---|
| 1 | 9 | 3 | 5 | 6 |
| 1 | 5 | 2 | 3 | 5 |
| 1 | 6 | 2 | 5 | 2 |
| 1 | 7 | 3 | 1 | 6 |
| 1 | 8 | 3 | 5 | 6 |
| 2 | 1 | 1 | 3 | 5 |
| 2 | 2 | 1 | 4 | 6 |
| 2 | 5 | 2 | 4 | 5 |
| 2 | 8 | 3 | 5 | 2 |
| 3 | 1 | 1 | 4 | 2 |
| 3 | 8 | 3 | 5 | 3 |
| 3 | 2 | 2 | 3 | 5 |
| 3 | 4 | 2 | 5 | 6 |
| 4 | 1 | 1 | 5 | 1 |
| 4 | 3 | 1 | 5 | 2 |
| 4 | 6 | 2 | 3 | 6 |
| 4 | 9 | 3 | 2 | 1 |
| 5 | 1 | 1 | 2 | 6 |
| 5 | 3 | 1 | 2 | 6 |
| 5 | 6 | 2 | 6 | 6 |
| 5 | 9 | 3 | 6 | 6 |
| 6 | 6 | 2 | 2 | 6 |
| 6 | 5 | 2 | 4 | 2 |
| 6 | 7 | 3 | 1 | 4 |
| 6 | 8 | 3 | 0 | 3 |
| 7 | 1 | 1 | 4 | 0 |
| 7 | 9 | 3 | 2 | 6 |
| 7 | 5 | 2 | 5 | 3 |
| 7 | 8 | 3 | 4 | 2 |
| 8 | 1 | 1 | 5 | 2 |
| 8 | 3 | 1 | 5 | 0 |
| 8 | 6 | 2 | 2 | 5 |
| 8 | 9 | 3 | 3 | 5 |
| 9 | 2 | 1 | 4 | 4 |
| 9 | 6 | 2 | 2 | 5 |
| 9 | 9 | 3 | 3 | 5 |
| 11 | 1 | 1 | 5 | 3 |
| 11 | 3 | 1 | 3 | 3 |
| 11 | 2 | 2 | 4 | 3 |
| 11 | 9 | 3 | 4 | 5 |

TABLE III
AN EXAMPLE OF DATABASE

In our model, we have associated with each agent a profile contained, as unique feature, the reputation to review the products. This reputation has been computed by averaging, on all the reviews posted by the agent, the helpfulness associated with each review, where the helpfulness is an information available on the dataset and obtained by the opinions expressed by the users of the community. We obtain that the reputation values (see Equation 1) of the agents belonging to our scenario are as follows: $rep_1$=0.83; $rep_2$=0.75; $rep_3$=0.66; $rep_4$=0.41; $rep_5$=1; $rep_6$=0.62; $rep_7$=0.45; $rep_8$=0.5; $rep_9$=0.79; $rep_{10}$=0 and $rep_{11}$=0.58. At this point, we introduce a new value of trust

$t_{u,v}$ that is the combination of the reliability and the reputation. Fixed the agent $a_1$, we compute the opinion (i.e., trust) that $a_1$ has with regard to other agents. Recall that this value changes with $\alpha$. We consider three values of $\alpha$. In particular, $\alpha$=1 means that the agent $a_1$ considers only the opinions of the agents with whom he/she interacted in the past (contrariwise, $\alpha$=0). Finally, $\alpha$=0.5 means that the agent $a_1$ considers in the same way both the opinions of the agents with whom he/she interacted both others. For detail, see Tables V-VII. Let $\xi$ be a threshold fixed by the agent $a_1$, we suggest only those products that have $rec_u^p$ greater than $\xi$ (in our case, we fix $\xi > 4$). In particular, we note that the agent $a_5$ that has a high value of reliability for the agent $a_1$ buys the products $p_8$ and $p_9$. Also, $u_5$ assigns to them a high rate while the rest of the community gives a very low rate. Surely $a_1$ would be very interested in these products, because he/she trusts $a_5$ with a high value. At this point, we see how the algorithm behaves. The agent $a_1$ receives, at the current step, some recommendations by the other agents, in response to previous recommendation requests (see Table IV). If $\alpha$=1, we suggest to $a_1$ the products $p_6$, $p_8$ and $p_9$. In this case, we consider the recommendations that come from agents that have a high reliability. In fact, these products were acquired and evaluated good by agents $a_5$ and $a_2$. Comparing these results with truly user-purchased products, it is visible that three out of three products were actually purchased by $u_1$. If $\alpha$=0, we suggest to $a_1$ the products $p_1$, $p_4$ and $p_5$. This is correct because they are products purchased by agents who have a high reputation in the community. But, these agents did not interact directly with $a_1$ therefore they do not know his/her preferences. Indeed, only the product $p_1$ is of interest to $a_1$. If $\alpha$=0.5, we suggest to $a_1$ the products $p_4$, $p_5$, $p_8$ and $p_9$. This choice is a good compromise, since three of the four products are of liking for the agent $a_1$.

| $\alpha$ | $p_1$ | $p_2$ | $p_3$ | $p_4$ | $p_5$ | $p_6$ | $p_7$ | $p_8$ | $p_9$ |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 4.35 | 3.2 | 3.3 | 5 | 4.26 | 3.32 | 1 | 3.56 | 3.72 |
| 0.5 | 3.48 | 3.26 | 3.10 | 5 | 4.2 | 3.75 | 1 | 4.01 | 4.10 |
| 1 | 3.11 | 3.4 | 2.71 | 0 | 4 | 4.66 | 0 | 5 | 4.93 |

TABLE IV
THE RECOMMENDATIONS TO THE AGENT $a_1$

| $u$ | $v$ | $t_{uv}$ |
|---|---|---|
| 1 | 2 | 0.75 |
| 1 | 3 | 0.66 |
| 1 | 4 | 0.41 |
| 1 | 5 | 1 |
| 1 | 6 | 0.62 |
| 1 | 7 | 0.45 |
| 1 | 8 | 0.5 |
| 1 | 9 | 0.79 |
| 1 | 10 | 0 |
| 1 | 11 | 0.58 |

TABLE V
SIMULATION PARAMETERS FOR $\alpha$=0

With the introduction of the groups in the community, we can consider the assumption made in the Section III. Recall that, for the agents that are in the same group, the trust is equal to 1. In our case, $a_1$ is in the group $g_1$ with the agents $a_3$ and $a_7$, therefore $t^*_{13}$ and $t^*_{17}$ are always equal to 1. Now, we can calculate the recommendations (see Equation 4) to the agent $a_1$ for all the products in the community in presence of the groups. The table VIII shows the results obtained.

| $u$ | $v$ | $t_{uv}$ |
|---|---|---|
| 1 | 2 | 0.72 |
| 1 | 3 | 0.83 |
| 1 | 4 | 0.20 |
| 1 | 5 | 1 |
| 1 | 6 | 0.31 |
| 1 | 7 | 0.22 |
| 1 | 8 | 0.4 |
| 1 | 9 | 0.49 |
| 1 | 10 | 0 |
| 1 | 11 | 0.34 |

TABLE VI
SIMULATION PARAMETERS FOR $\alpha$=0.5

| $u$ | $v$ | $t_{uv}$ |
|---|---|---|
| 1 | 2 | 0.7 |
| 1 | 3 | 1 |
| 1 | 4 | 0 |
| 1 | 5 | 1 |
| 1 | 6 | 0 |
| 1 | 7 | 0 |
| 1 | 8 | 0.3 |
| 1 | 9 | 0.2 |
| 1 | 10 | 0 |
| 1 | 11 | 0.1 |

TABLE VII
SIMULATION PARAMETERS FOR $\alpha$=1

| $\alpha$ | $p_1$ | $p_2$ | $p_3$ | $p_4$ | $p_5$ | $p_6$ | $p_7$ | $p_8$ | $p_9$ |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 3.75 | 3.68 | 3.3 | 5 | 4.42 | 3.75 | 1 | 3.79 | 3.31 |
| 0.5 | 3.61 | 3.6 | 3.10 | 5 | 4.49 | 3.75 | 1 | 4.15 | 3.49 |
| 1 | 3.43 | 3.5 | 2.71 | 0 | 4.59 | 4.66 | 0 | 5.18 | 4.57 |

TABLE VIII
THE RECOMMENDATIONS TO THE AGENT $a_1$ IN THE PRESENCE OF GROUPS

The results in the presence of the groups are best, because $a_3$ and $a_7$ know better $a_1$ and consequently are able to make targeted recommendations.

### A. The Performance Recommendation Measure

In order to model the process of evaluating the performance of recommendation provided by learning agents, we defined two indexes. Let be $R_i$ the set of recommendations provided to the agents $a_i$, and $\overline{R_i} \subset R_i$ the set of recommendations relating to the products which $a_i$ purchased. Besides, let be $\Gamma_i^*$ the set of purchases made by $a_i$, where $\Gamma_i$ is the set of all actions executed within the context of agent $a_i$.

To provide a performance measure we defined two indexes, called Precision and Recall, as follows:

$$Pre(R_i) = \frac{|\Gamma_i^* \bigcap \overline{R_i}|}{|\overline{R_i}|} \tag{5}$$

$$Rec(R_i) = \frac{|\Gamma_i^* \bigcap \overline{R_i}|}{|\Gamma_i^*|} \tag{6}$$

By the definition of $Pre(R_i)$, it follows that a high value does not mean to be a good recommender agent. Indeed, it is possible that the overall performances of provided recommendations are not the greatest possible. $Rec(R_i)$, which is the fraction of recommendations successfully suggested by the agent $a_i$, allows us to consider the aspect above. In our case, we have different values of Precision and Recall to vary by $\alpha$ (see Table IX). It is clear that when $a_i$ takes into account only the opinion of the whole community, we have relatively low performances. Instead, combining the opinion of the whole community with that of the agents who had direct interactions with $a_i$, we obtain high values of Precision and Recall. In particular, when $\alpha$=0.5 in the absence of the groups we have a higher value of Recall because the agents who belong to the community but had no interactions with $a_i$ bought many products and then their evaluations are appreciated in the community. This situation allows to advise the products that are of interest for $a_i$. However, when $\alpha$=1 in the presence of the groups, we obtain $Rec(R_i)$=0.8 that is the highest value. This means that the recommendations of agents within the group joined to those of the agents with which $a_i$ has interacted in the past, allow us to suggest the products of his/her interest with very high accuracy (88%).

| $\alpha$ | $Pre(R_i)$ | $Rec(R_i)$ |
|---|---|---|
| 0 | 0.33 | 0.2 |
| 0.5 | 0.75 | 0.6 |
| 1 | 1 | 0.6 |

TABLE IX
PRECISION AND RECALL IN OUR EXAMPLE TO VARY BY $\alpha$

| $\alpha$ | $Pre(R_i)$ | $Rec(R_i)$ |
|---|---|---|
| 0 | 0.33 | 0.2 |
| 0.5 | 0.66 | 0.4 |
| 1 | 1 | 0.8 |

TABLE X
PRECISION AND RECALL IN OUR EXAMPLE WITH GROUPS

## V. CONCLUSION

In this paper, we propose a model capable to integrate reliability and reputation in an OSN organized by groups. In particular, we considered three important parameters in order to characterize the model: the relevance given to the reliability with respect to the reputation, the threshold of recommendation under which a product can be considered as not interesting and the number of the groups. We have presented a realistic example and the results have shown that when the agent takes into account only the reputation, we have low performances. Instead, combining the opinion of the whole community (reputation) with that of the agents who had direct interactions with her/him (reliability), we obtain high values of Precision and Recall. However, in the presence of the groups, we obtain that Recall has the highest value. In other words, in this letter case, our model allows to suggest the products with very high accuracy (88%). In this paper, we limited ourselves to introduce and formalize the idea, and we present an example of how the presented approach can found product recommendations in an online e-Commerce communities. Our ongoing research is currently devoted to apply the approach to real social networks, in which the advantages and limitations introduced by our proposal can be quantitatively and effectively evaluated.

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