Evaluating Group Formation in Virtual Communities

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***Abstract*—In this paper, we are interested in answering the following research question: "Is it possible to form effective groups in virtual communities by exploiting trust information without significant overhead, similarly to real user communities?" In order to answer this question, instead of adopting the largely used approach of exploiting the opinions provided by *all* the users of the community (called *global reputation*), we propose to use a particular form of reputation, called *local reputation*. We also propose an algorithm for group formation able to implement the proposed procedure to form effective groups in virtual communities. Another interesting question is how to measure the effectiveness of groups in virtual communities. To this aim we introduce the G_k *index* in a measure of the effectiveness of the group formation. We tested our algorithm by realizing some experimental trials on real data from the real world EPINIONS and CIAO communities, showing the significant advantages of our procedure w.r.t. another prominent approach based on traditional global reputation.**

***Index Terms*—Group formation, Helpfulness, Online Social Communities, Reputation, Trust**

I. Introduction

Virtual communities consist of social entities, users and/or agents, interested to mutually interact on a technical platform for reaching specific (individual or collective) goals. These communities usually exhibit complex social structures, emerging by some kind of social relationships, within a multidimensional scenario involving, for instance, social, physiological and computer science issues, to mention but a few. For example, online communities such as Facebook[1] and Twitter[2], that account for hundreds of millions of in subscribers (in 2019, Facebook has reached 2.4 billion active users and Twitter surpassed 300 million users), allow the formation of thematic *groups*. In fact, more than 1 billion groups have been formed in the last 5 years on Facebook.

Given their relevance, dynamics of virtual communities have been subject to a great number of studies [1]. Indeed, group formation in a community is often triggered by individual initiatives and evolves by means of well-defined social activities. For instance, a community member may ask to join an existing group for diverse reasons. One may be the similarity with certain attributes of the existing members (e.g., age, interests, and so on). In this case the group administrator may accept or refuse the request of the new member by evaluating a few important concerns. In this process, the group administrator may also want to involve group members in deciding whether the newcomer may join the group. We remark that this kind of scenario involves two different goals: i) the user wants to obtain a kind of "utility" by joining the group (e.g. for gaining knowledge); ii) the administrator wants to improve the "assessment" of the group itself, on the basis of some criteria.

The two activities above bring to a new member affiliation only when the sub-community representing the group gives a positive assessment to the new member. Differently, if the member joins the group without a positive assessment of his/her own social attitudes, there is a high probability that he/she will exit the group within a short timeframe. In other cases, his/her contribution to the social activities of the group will be very poor, and he/she will be classified as an "outsider". In general, the ability of the members of the same groups to have positive interactions will improve the social capital (or simply the effectiveness) of the community which represents the group itself [2].

In this work we address the general problem of forming effective groups. In particular, we are interested in three specific aspects related to the scenario described in the previous paragraph. The first aspect is related to the measurements of the overall effectiveness of a group, which is strictly related to the group composition, i.e., how the group component have been selected, and to the context variables, e.g., the group topics. The second aspect is related to the group formation, i.e., the strategy applied by the community and/or by the group administrator to form groups. Last but not least, group formation is based on the computation of proper information about existing members and newcomers which is the third concern of our interest.

Note that our method performs a group formation, not a community detection. In fact, in our framework, agents are free to join with a group, and each group is free to accept or refuse a request. Our algorithm guides the agents to make the most rational choices, but it is not an automatic detection of sub-structures in the community, as for a clustering method, since it is necessary the willing of the actors for forming the groups, and also the values of reputations derive from the free behaviours of the actors.

A. Main contributions

The contributions provided by this paper are as follows: (*i*) the introduction of the G_k index associated with a set of groups in a virtual community, as a measure of effectiveness of the group formation activity; (*ii*) the computation of individual trust, by combining reliability and local reputation

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[1]www.facebook.com

[2]www.twitter.com

information; (*iii*) the adoption of a suitable voting mechanism, tested by means of a general-purpose distributed algorithm (referred to as *GF*, for Group Formation), to take decisions about newcomer affiliations. As we will discuss later in this paper, we will call TV (*Trust-Voting*) the particular version of GF that makes use of the voting mechanism.

In order to test the approach described in this paper, we performed a number of experimental trials on the real data derived from the EPINIONS [3] and CIAO [4], communities. These include users' reviews concerning commercial products falling under different categories. These datasets have been largely used to perform study concerning trust, recommendation and social networks [5]. Our experimental results show that the choice of combining reliability and local reputation, along with a voting mechanism, produces better results, in terms of the G_k index ($k = 10$), compared to other existing solutions that did not use local reputation and voting mechanisms.

It is important to highlight that we have obtained these results on real datasets that are representative enough of common virtual communities, as the most known social networks, in terms of network topology and behaviour of the users. However, if data change, and for instance we have to face a community with a particularly high number of low-reputation users, the results could vary, and other investigations should be realized in the future for these particular situations.

The rest of the paper is organized as follows. Section II discusses the details of the approach, while Section III describes the trust measures and the voting mechanism adopted in the proposed scenario. Section IV discusses the two parts of the GF algorithm, while Section V presents the experimental trials we carried out. In Section VI our work is compared to related literature, while in Section VII we present our conclusions and anticipate possible further works.

II. Overall Approach

In this section we provide the details of the three research questions mentioned in the introductory section, as well as our approach for effective group formation.

A. Measuring the effectiveness of a group

To clearly explain our first research question, let us suppose that each user belonging to the virtual community is characterized by a *social value*, v that quantitatively represents his/her utility for the whole community. For example, in the social communities CIAO[3] and EPINIONS[4], in which users can publish reviews about products, the social utility of a review is represented by a value called *helpfulness* [6], computed by the feedbacks provided by the users about that review. In this context, the social utility v, of a user u, could be reasonably considered as equal to the average of the helpfulness values associated with all the reviews published by u.

Now, let us suppose to classify the users belonging to a virtual community in n classes of social relevance, based on their social value. Just as an example, we could assume to have three classes (i.e., $n = 3$): the class C_1 of the *bad users*, having social value $v \leq v_1$; the class C_2 of the *medium users*, having $v_1 < v \leq v_2$ and the class C_3 of the *good users*, having $v > v_2$, where v_1 and v_2 are specific social values such that $v_1 < v_2$. In general, the number n of classes can be arbitrarily fixed by the social analysts.

From a social viewpoint, i.e., from a perspective in which the satisfaction of the whole community is the ultimate goal, the desired ideal configuration of the groups does not require to be composed only by the good users. Depending on the context, i.e., on the particular nature of the involved social network, the possibility could arise to have groups whose composition involves also bad and medium users (that are themselves members of the network and, in such a way, have a social value and their own expectancy).

Then, let us suppose that we wish to obtain groups having a particular distribution of the social values, i.e., a percentage $p1$ of users of class $C1$ exactly equal to π_1, a percentage $p2$ of users of class $C2$ exactly equal to π_2, and so on until to a percentage p_n of users of class C_n exactly equal to π_n (obviously, $p1 + p2 + ... + pn = 1$); where $p1, p2, \ldots, pn$ are percentage values chosen by the group administrator.

For example, in the case of the CIAO and EPINIONS opinion networks, let us consider the three classes of bad, medium and good users, respectively, and let us suppose that it is socially desirable that all users have the same opportunity to find effective members into the groups that they have joined. The ideal goal of the whole community could reasonably be to achieve groups with an equipartition of the users in the three classes (i.e., $p1 = p2 = p3 = 1/3$), since any other distribution would assign some social disadvantage to the users of some classes with respect to the users of other ones.

More formally, we can denote by $V = \{V_1, V_2, \ldots, V_n\}$ a set of requirements on group formation, where V_i represent the *ith* requirement. For example we may denote as $V = \{V_1 = \{p_1 = 33.3\%\}, V_2 = \{p_2 = 33.3\%\}, V_1 = \{p_3 = 33.3\%\}\}$, the simple requirements for group formation in the previous example, where p_i represents the desired percentage of users of class c_i in every group.

Also in the case of an e-Learning social community, where users are students with different levels of expertise, the equipartition appears the best choice, if the goal is to offer equal opportunities to all students (in an equi-partitioned solution, each group is formed by individuals of the same class, so that the learning process does not need to be adapted to students of different levels). However, in other situations, the equipartition of the users in the available classes may not be the best choice. For example, in an e-Commerce scenario such as in the case of eBay, where the social value of a user is given by the feedback score representing his/her reliability, it is probable that the best distribution is that of groups containing only users having high feedback scores, admitting only a few users that have medium feedback score (so as to give them some sort of second chance) and tending to exclude users having low feedback scores. In such a situation, depending on the tolerance degree of the network administrator for the medium users, we will have distributions with high value of

[3] www.ciao.com
[4] www.epinions.com

$p1$, low value of $p2$ and a value 0 for $p3$.

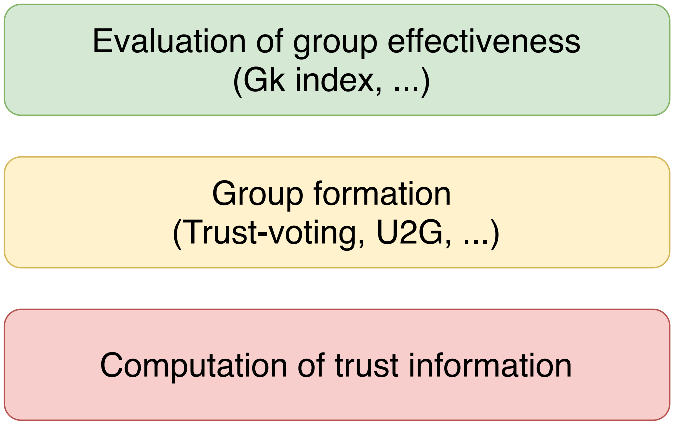

Fig. 1. The conceptual framework about group formation and evaluation

If the group configuration chosen by the administrator is the goal of our group formation, it is a matter of fact that a group differing from such a configuration will generate a *social disadvantage*. For example, if the percentage $p1$, instead of being equal to π_1, will be equal to π_1^*, the social disadvantage derived from this situation (in absolute value) will be $|\pi_1 - \pi_1^*|$. Then, the social disadvantage D, associated with the n components of the g group, will be on average $1/n \sum_{i=1}^{n} |\pi_i - \pi_i^*|$ and will vary from 0 (when the group coincides perfectly with the ideal one) to 1 (when the group is totally different from the ideal one).

More formally, we can give the following simple definition.

Definition 1 *The social disadvantage is defined as a function $D^V(g)$ to measure the social disadvantage of a group g w.r.t. a given set of requirement V.*

We observe that, if we have formed m groups, we would like to have a high percentage of groups having a low social disadvantage. Basing on this simple observation, we can give the following definition.

Definition 2 *The G_k index associated with a set of groups g and a set of requirements V in a given virtual community is defined as the percentage of the groups whose social disadvantage $D^V(g)$ is less than or equal to $k/100$.*

We remark that group formation is not an optimization problem "driven" by the social values. Indeed, the social values of the users (i.e., the helpfulness values in the case of CIAO and EPINIONS) are not perfectly known *a priori*, when forming the groups. Conversely, these social values emerge and are consolidated in time, and are often unknown when a user (who could be even a newcomer) requests to join a group. Such social values can be evaluated only at a global level, by taking into account the opinions of all the users of the social community. In other words, the G_k index can only be used as a measure for the *a posteriori* evaluation of the effectiveness of a group formation algorithm, and not as key information for leading the formation itself. Indeed, each algorithm of group formation can be viewed as a heuristic method trying to produce, based on some information available into the community, a set of groups having a high value of G_k index.

Thus, a specific choice for k represents a simple criterion to evaluate some group formation algorithms. In particular, the higher the value of k, the higher the average evaluation for the group formation algorithms, because a high value of k represents a bland requirement in terms of group composition. On the contrary, the lower the value of k, the lower the average evaluation of the tested algorithms, because a small value of k represents a strict requirement in terms of group composition.

In order to clarify this important concept, let us suppose to evaluate three algorithms for group formation – A, B and C – with different behaviours. Let us suppose, for convenience, that we test the three algorithms in order to produce 5 groups g_1, g_2, g_3, g_4, g_5 with specific requirements, and that we are able to measure the resulting social disadvantage in every group. The first algorithm, A, is able to form 5 groups with social disadvantages $D_1 = 0.015$, $D_2 = 0.011$, $D_3 = 0.025$, $D_4 = 0.11$, $D_5 = 0.02$; the second algorithm, B, is able to form 5 groups with social disadvantages $D_1 = 0.23$, $D_2 = 0.11$, $D_3 = 0.025$, $D_4 = 0.01$, $D_5 = 0.018$; finally, the third algorithm, C, is able to form 5 groups with social disadvantages $D_1 = 0.3$, $D_2 = 0.18$, $D_3 = 0.12$, $D_4 = 0.07$, $D_5 = 0.09$; The choice of k of the G_k index plays an important role. Indeed, if we choose a value $k = 10$, then, we will have $G_{10}(A) = 4/5 = 80\%$, $G_{10}(B) = 3/5 = 60\%$, and $G_{10}(C) = 2/5 = 40\%$. Nevertheless, if we choose a value $k = 20$, we will have $G_{20}(A) = 5/5 = 100\%$, $G_{20}(B) = 4/5 = 80\%$, and $G_{20}(C) = 4/5 = 80\%$. Therefore, as expected, the higher the value of k, the higher the average evaluation of the tested algorithm.

The introduction of the G_k index for evaluating the effectiveness of a group formation activity, from the viewpoint of the desired group composition, represents the first contribution we provide in this work. To the best of our knowledge, no other proposals have been previously presented in the literature to this purpose. However, we also highlight that this contribution is functional to support another goal of our research, that is related to the possibility of forming effective groups, as we will explain in Section II-C.

As already discussed, it is reasonable that the value of k is chosen to be sufficiently small; therefore, in the experiments performed in this paper (relating to virtual communities of product reviewers) we will use the G_{10} index, considering that a difference of 10 percent between the obtained configuration of a group and the desired one to be a "small enough" value. This choice strictly depends on the particular application domain and on the goals of the analyst.

B. Computing information to form effective groups

In the overall aforementioned scenario, we are interested in answering to the following research question: "Is it possible to form effective groups in virtual communities (where the effectiveness is determined by an objective measure, as discussed in subsection II-A) by exploiting trust information in a simple way, similarly to real user communities?"

To answer this question, in this paper we propose to use a particular form of reputation, referred to as *local reputation* [7], using it instead of the *global reputation*. Specifically, the local reputation is based on opinions that come from the users' *entourage*, i.e., 1st level connections (friends), 2nd level connections (friends of friends), and so on [8]. This tends to be more reliable than using completely unreferenced recommendations. Therefore, similarly to real communities, when a user's experience is insufficient to trust another user, the usual process will be to require an opinion from the user's own network of friends.

A further level of connections should be taken into account when the number of user's friends is insufficient to achieve a statistically significant number of recommendations (friends of friends and so on). But in this case we still need to decide how to weight their trustworthiness.

This approach has the additional advantage of fitting well with the distributed architecture that is often adopted by virtual communities, on which the local reputation is locally managed by each member by involving a generally very small number of members having a limited consumption of computational and communication resources. This (desirable) property cannot be satisfied when global information must be stored, accessed and processed by all the members of vast communities.

C. Forming effective groups

The problem of forming effective groups is based on the following premises, discussed in the previous sections:

- a set of requirements $V = \{V_1, V_2, \ldots, V_k\}$ concerning the desired composition of the groups;
- a given function $D^V(g)$, to measure the social disadvantage of a group g w.r.t. the given set of requirement V;
- a function G_k (see Definition 2), along with a fixed value of k, to evaluate the effectiveness of the group formation on the basis of the given function $D(V)_g$.

Therefore, given a set of algorithms for group formation, the "best" algorithm can be chosen as that maximizing the value G_k.

To this purpose, trust values must be appropriately combined and evaluated within each community [9] in order to assume the best decision as possible about potential newcomers. Sometimes, trust information may be available in a binary form, by which it is possible to represent only a full trust or distrust, and a fine grain evaluation is impossible to have. Then some kind of aggregation of the individual expressions of trust about a target (e.g., by adding their values, by using a function or by exploiting a linear system [10]) is adopted in order to achieve a synthetic value which is suitable for making a decision. However, all these modalities deeply differ from the processes that typically take place in human societies whereby decisions are based on some form of voting mechanism. This is one of the most important forms of social choice, allowing the community members to manifest their individual preferences.

In particular, the voting mechanism is largely used in the context of coordination activities, auctions, negotiation and also team formation [11]. However, while voting comes with all the advantages deriving from democratic processes, it also presents manipulation risks. These are intrinsic in the voting itself, for instance due to strategic voting [12]. Therefore, a great attention is commonly paid to adopting a voting strategy that is both resilient to manipulation and correct (in terms of outcomes). Specificaly, with respect to our research question, we consider the first issue as an orthogonal problem, which will therefore not be examined in this paper. On the contrary, the second issue is more interesting for us because our goal is to form groups in a simple way and in accordance to the adopted group formation strategy.

The analysis above lead us to propose a strategy to form groups in virtual communities based on a combination of trust (obtained as a combination of reliability and local reputation) and a suitable *vote* given by every member of the group itself. In turn, this is based on the local trust of the user w.r.t. the requester.

III. Local and global trust, similarity

Let us denote the user community as U and a relationship taking place therein by using a directed unlabeled graph $G = \langle N, A \rangle$, where N is a set of nodes ($n \in N$ represents the user $u_n \in U$) and A is a set of arcs, where $a \in A$ is a pair (i, j) representing a trust relationship among the users u_i and u_j. From this point, we will denote either a node $n \in N$ or a user $u_n \in U$ to represent the same entity.

In the following we provide a few preliminary definitions. To this end, the main symbols used in this paper are grouped in Table I.

A. Trust

The *trust* relationship between users is defined as a relation $\hat{\tau} : U \times U \rightarrow [0, 1]$, where 0 (resp., 1) represents the minimum (resp., maximum) level of trust. In our previous research [13], these two different trust measures were combined to obtain a final trust measure between two users. The *reliability* $\rho_{n,k}$ is a measure of direct trust that n has in k based on his/her direct past experiences occurred with k. The *global reputation* ω_k represents the global measure of trust that the whole community perceives about a node $k \in N$. The global reputation ω_k is simply obtained by averaging all the reliability values $\rho_{x,k}$, for each $x \in N$. Therefore, each node $n \in N$ will derive a synthetic measure of the trust about the other node k by integrating reliability and global reputation by assigning to them proper weights. Global trust $\hat{\tau}_{n,k}$ is then defined as:

$$\hat{\tau}_{n,k} = \alpha \cdot \rho_{n,k} + (1 - \alpha) \cdot \omega_k \quad (1)$$

where $\alpha \in [0, 1] \subset \mathbb{R}$ is a parameter weighting the relevance of the reliability with that of the reputation.

Based on this definition, trust is an asymmetric measure because it takes into account reliability. Moreover, this trust measure can be exploited to derive a measure $\hat{\tau}_{n,g}$, where $g \subset N$ is a group of users, to determine the "trustworthiness" of a group g as perceived by n. As we explain later, in our model this last measure affects the "probability" that a user will ask to join a certain group: the higher the level of trust w.r.t. a certain group, the higher the probability that the user will wish to join the group itself. In this work we compute it as the average of all the values $\hat{\tau}_{n,k}$ for all the users k belonging to g. However, this measure can be computed in several different manners. Similarly, the measure $\hat{\tau}_{g,n}$ represents a synthetic evaluation of the trust that the whole group g perceives about user n. This can be computed by averaging all the trust values $\hat{\tau}_{k,n}$, where k is any member of g. Formally, $\hat{\tau}_{g,n} = 1/|g| \sum_{k \in g} \hat{\tau}_{k,n}$, where $|g|$ represents the number of members of the group g.

B. Similarity and Compactness

The *compactness* combines the *similarity degree* between two users or a user and a group, as well as their associated *trust level* [13]. Overall, the similarity $\sigma_{n,k}$ is computed by combining a subset of the "features" of the n and k users' profile (e.g., interests, age, gender, categories of items recently bought, and so on). The similarity $\sigma_{n,g}$ between a user n and a group g can be computed by weighting the similarities between n and all the users of group g. Finally, the compactness $\eta_{n,k}$ between a user n and a user k is computed by combining trust and similarity by means of a number $\gamma \in [0, 1]$:

$$\eta_{n,k} = \gamma \cdot \sigma_{n,k} + (1 - \gamma) \cdot \hat{\tau}_{n,k} \tag{2}$$

while $\eta_{n,g}$ between a user n and a group g is obtained as:

$$\eta_{n,g} = \gamma \cdot \sigma_{n,g} + (1 - \gamma) \cdot \hat{\tau}_{n,g} \tag{3}$$

and $\eta_{g,n}$ between a group g and a user n is defined as:

$$\eta_{g,n} = \gamma \cdot \sigma_{g,n} + (1 - \gamma) \cdot \hat{\tau}_{g,n} \tag{4}$$

where γ is used to weight the relevance between similarity and trust. The higher the γ, the greater the relevance of the similarity σ, the $smaller$ the relevance of the global trust $\hat{\tau}$.

As we will discuss later in section IV, the measure $\eta_{n,g}$ can be conveniently exploited by any user to evaluate how good it would be to join a given group g; whereas the measure $\eta_{g,n}$ can be used by a group administrator to evaluate the *convenience* to admit a given user n in group g. Moreover, in subsection III-C, we will give the important definition of *local trust*, which is exploited to perform a trust-based voting mechanism, to be adopted in place of the evaluation of the compactness measure η.

C. Local trust

As for the global trust $\hat{\tau}$, the *local trust* is a relationship between users defined as $\tau : U \times U \rightarrow [0, 1]$, where 0 (1) represents the minimum (maximum) level of trust. The definition of local trust relies on the common definition of ego-network for any user $u_n \in U$.

This ego network simply represents the portion of the network that is connected with u_n, composed by all the nodes that can be reached from u_n and all the edges necessary for going to these nodes by originating from u_n.

Formally, it is represented by the sub-graph $G_n \in G$, where $G_n = \langle T, P \rangle$ consists of a set $T \in N$ of nodes containing n and of all the nodes k connected to n by a path $(n, \dots, k)$, while $P \in A$ includes all the arcs belonging to the oriented paths between n and all the nodes $k \in T$.

For each pair of nodes $n, k \in G$ the local trust that n has about k (i.e., $\tau_{n,k}$) is given by the combination of the reliability $\rho_{n,k}$ previously defined and a *local reputation* denoted as $\omega_{n,k}$. In particular, the local reputation is defined as the (normalized) measure of indirect trust computed by summing the contributions (in terms of trust in k) of how much the users, belonging to the ego-network G_n, trust k.

Let $L(n, k) = \{h \in G_n : \exists (h, k) \in G_n\}$ be the set of nodes belonging to the ego-network of n directly connected with the node k. Moreover, let $l_{(n,k)}$ be the shortest path between n and k. Then, we consider the sum of the contributions, in term of the indirect trust, given by the nodes $h \in L(n, k)$; finally, we define the (normalized) local reputation $\omega_{n,k}$ as:

$$\omega_{n,k} = \frac{\sum_{h \in L(n,k), h \neq n,k} \frac{1}{2^{(l_{(n,h)}-1)}} \cdot \tau_{h,k}}{\sum_{h \in L(n,k), k \neq n,k} \frac{1}{2^{(l_{(n,h)}-1)}}} \tag{5}$$

According to (5), the contribution provided by h to the local reputation computed by n for k is multiplied by the exponential weight $1/2^{(l_{(n,h)}-1)}$. Thus, less importance is given to those trust relationships (h, k) that are "far" from n.

Finally, the value of the local trust $\tau_{n,k}$ is given by combining reliability and local reputation:

$$\tau_{n,k} = \alpha \cdot \rho_{n,k} + (1 - \alpha) \cdot \beta \cdot \omega_{n,k} \tag{6}$$

where the parameters α and β are two real values ranging in $[0, 1]$. The former parameter (i.e., α) provides a simple way to weight reliability and local reputation for giving more or less relevance to one or the other. The parameter β is instead computed as:

$$\beta_{u,x} = \begin{cases} \frac{\|L(u,x)\|}{N} & \textit{if } \|L(u,x)\| < N \\ 1.0 & \textit{if } \|L(u,x)\| \geq N \end{cases} \tag{7}$$

where N is a system threshold denoting the number of nodes, belonging to an ego-network, considered as sufficient to obtain an effective value of the local reputation. The parameter β takes into account the dependability of $\omega_{n,k}$ which is based on the number of nodes belonging to $L(n, k)$ that contributed in computing $\omega_{n,k}$. In fact, if the number of nodes $\|L(n, k)\|$ is very small, this means that n will not receive sufficient information about k from his ego-network and, therefore, the local reputation measure will assume a low relevance.

We observe that several authors proposed to weight the opinion provided by each user to the truster by the same trust that the truster has in them. As the same time, authors of [14] correctly highlighted that the capability to provide reliable opinions is unrelated to other aspects and, therefore, it needs a specific trust/reputation measure. For example, whenever a trust/reputation measure is computed w.r.t. the honesty in a commercial transaction, using this type of measure to weight the opinions provided by the users may give unreliable results. For this reason, in computing our local reputation we prefer to tune its relevance in Equation 7 by means of simple parameters like α and β, as defined above.

D. The Voting Mechanism based on the local trust computation

Voting represents a fundamental mechanism to take social decision in deliberative assemblies, and it is used for a large variety of purposes [15]. The voting approach discussed here is designed in order to exploit the computation of local trust, as defined above, to decide whether a user of the virtual community U can join a group. To this end, once a joining request is presented to a group, its members will give a vote based on the local trust measures w.r.t. the applicant.

The voting mechanism can use the value of the trust relationship between the user $n \in g$ (where g is an established group of the community G) and the user $k \in G$, who asks to join group g. For instance, user n may express a preference (i.e., a vote) $v_{n,k} \in 0, 1$ to either accept or not the requester in the group g (e.g., 0 means "prefer to not accept" and vice versa for 1). In particular, any user n will check whether the local trust measure $\tau_{n,k}$ is greater than or equal to a threshold $T_n \in [0, 1]$. In the former case, $v_{n,k} = 1$, otherwise it is set to 0. More formally:

$$v_{n,k} = \begin{cases} 0 & \textit{if } \tau_{n,k} < T_n \\ 1 & \textit{if } \tau_{n,k} \geq T_n \end{cases} \tag{8}$$

For convenience, we can denote the result of the voting process on a group g for a potential new member k and a particular voting criterion v (like that defined in formula 8), as the output of a function $V(v, g, k)$. As a possible example, the requester may be accepted in the group only if the most part of its members has voted for his/her acceptance.

E. Discussion

Here we provide a simple example in order to illustrate the computation of the local trust and the voting procedure. Figure 2-A shows a user community made by 8 nodes, while Figure 2-B represents a group of users belonging to this community. Let us suppose that nodes b and d ask to join the group of Figure 2-B. Based on the simple voting mechanism described above, all the members of the group must be aware of the their local trust w.r.t. b and d. To this end, Figure 2-C shows the ego-network for user a. In this case we observe that $\rho_{a,b} = 1$ and $\rho_{a,d} = 0$, because there is no edge between a and d. Moreover, Figure 2-D represents the set of nodes that give a contribution to the local reputation measures $\omega_{a,b}$ and $\omega_{a,d}$: *i*) the nodes contributing to the local reputations are respectively $\langle g, c, h\rangle$ and $\langle c, e\rangle$ and *ii*) their trust values about b and e. In particular, in computing $\omega_{a,b}$, the contributions of g and c to the sum weight 1, because g and c are directly connected with a, while the contribution of h weights $1/2$ since the length of the shortest path between a and h is 2. As a consequence, $\omega_{a,b} = (1 \cdot 0.75 + 1 \cdot 0.75 + 0.5 \cdot 0.5)/(1 + 1 + 0.5) = 0.6$. Instead, in computing $\omega_{a,d}$ both the contributions of c and e weight 1 due to their direct connections with a and in this way $\omega_{a,d} = (0.5 \cdot 1 + 0.5 \cdot 0.25)/(0.5 + 0.5) = 0.625$. Then, by assuming for b and d the same values of the parameters α and β (i.e., $\alpha = 0.5$ and $\beta = 1$), the two measures of the local trust $\tau_{a,b}$ and $\tau_{a,d}$ will be respectively $\tau_{a,b} = 0.5 \cdot 1 + (1 - 0.5) \cdot 1 \cdot 0.6 = 0.8$ and $\tau_{a,d} = 0.5 \cdot 0 + (1 - 0.5) \cdot 1 \cdot 0.625 = 0.31$. If we give $T_g = 0.5$, a will vote YES to the admission of b (i.e., $v_{a,b} = 1$) while will vote NO for the admission of d (i.e., $v_{a,d} = 0$).

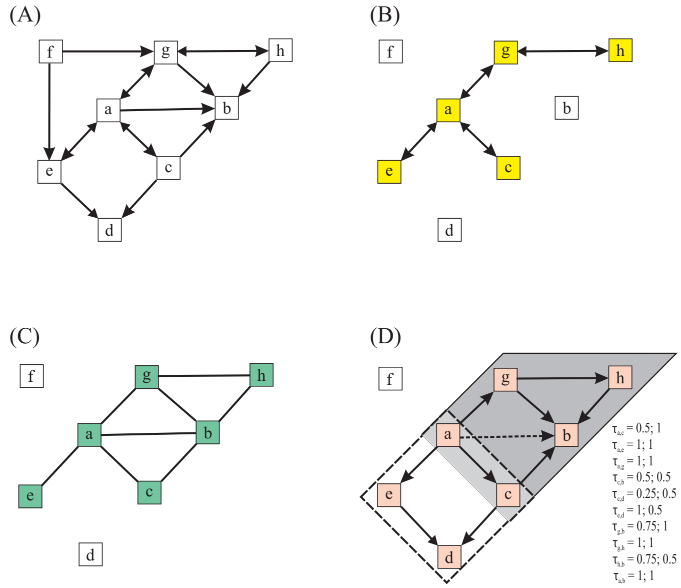

Fig. 2. A) - An example of virtual community; B) - An example of group: C) - The ego-network of node a; D) - The nodes involving in the computation of $\tau(a, b)$ and $\tau(a, d)$ – the label on the links report the -trust; reliability-values and the weights of the contributions.

IV. The distributed procedure for Group Formation

Here we describe the simple distributed algorithm (for short, GF) for group formation which is used for the experiments presented in section V, where the main symbols used in the algorithms are resumed in table I. The algorithm includes various selection criteria for group formation (e.g., voting vs compactness), and it has been used to address the research question outlined in section I. It can be assumed that the algorithms are executed by software agents that operate on behalf of their users, without loss of generality. Therefore, in the following we will denote agents and users interchangeably. The algorithm is composed by two parts. The former is designed to be executed on the user-side, while the latter will be executed by the *administrator* of the group to decide whether or not to admit the user into the group.

Moreover, the procedure executed by the administrator may rely on different mechanisms and measures to drive the user-admission decision. This leads to two different versions of the GF algorithm, as we detail later in this section: the former takes into account only the compactness measure in order to decide whether to admit a user into a group, and it is dubbed $U2G$. In particular, $U2G$ has been already used in our previous work [16], where we defined the compactness measure. The latter version is dubbed TV (Trust-Voting), as it relies on the voting mechanism and the computation of the local trust (as described in section III-E and III-D). We observe that, since any node can join more than one group, groups may overlap. Moreover, there is no restriction in the GF procedure executed by the administrator on group overlapping.

A. The GF procedure performed by the user agents

The GF procedure performed by the user agents is represented by the pseudocode listed in Algorithm 1, whereby X_n is the set of the groups to which the node n is affiliated to, and N_{MAX} is a parameter representing the maximum number of groups that a node is capable to analyze. It is assumed that $N_{MAX} \geq |X_n|$. Furthermore, we suppose that the generic user a_n stores into a cache the group profile of each group g_j contacted in the past and the time elapsed d_j from the last execution of the GF procedure for that group. Finally, let ξ_n be a timestamp threshold and $\chi_n \in [0, 1]$ be a threshold fixed by the node n. The ratio behind the procedure executed by node n is represented by his attempt to improve the overall social advantages of joining a specific set of group. For this aim, first of all, the values of compactness η (section III-B) are recalculated if they are older than the fixed threshold ξ_i (lines 1-4). Then, candidate groups are sorted in a decreasing order with respect to the compactness η.

The loop in lines 7-17 represents the core of the procedure, on which a number of N_{Max} groups are selected. If some groups in the set L_{good} are not in the set X_n, then node n can potentially improve the overall compactness by joining with those groups. The only constraint of the algorithm is the maximum number of groups that the user can join. In the algorithm 1, parameter m is useful to count the number of new groups the user agent can join. As a consequence, the agent will leave the same number of groups which are in the set X_i but not in the set L_{good}.

Algorithm 1 GF Procedure executed by every user agernt

Input:
$X_n, N_{MAX}, \xi_n, \chi_n$;
$Y = \{g \in G\}$ a set of groups randomly selected : $|Y| \leq N_{MAX}$, $X_n \bigcap Y = \{0\}$, $Z = (X_n \bigcup Y)$

1: **for** $g_j \in Z : d_g > \xi_i$ **do**
2: Send a message to A_j to retrieve the profile P_j.
3: Compute η_{i,g_j}
4: **end for**
5: Let be $L_{good} = \{g \in Z : \mu_{n,g_j} \geq \chi_n\}$, with $|L_{good}| = N_{MAX}$
6: $m \leftarrow 0$
7: **for** $g_j \in L_{good} \wedge g_j \notin X_i$ **do**
8: send a join request to A_j
9: **if** A_j accepts the request **then**
10: $m \leftarrow m+1$
11: **end if**
12: **end for**
13: **for** $g_j \in \{X_i - L_{good}\} \wedge m > 0$ **do**
14: Sends a leave message to g_j
15: $m \leftarrow m-1$
16: **end for**

Algorithm 2 GF Procedure, executed by every group admin g_i

Input: $K_j, K_{MAX}, n, \omega_j, Z = K_j \bigcup \{n\}$, M;

for $m \in K_j$ **do**
  if $d_i \geq \omega_j$ **then**
    ask to m its updated profile
  end if
end for
if $(M == TV \wedge V(v, g_j, n) == 0)$ **then** $\triangleright$ only TV
  Send a reject message to n
  return
else $\triangleright$ TV or $U2G$
  if $|Z| \leq K_{MAX}$ **then**
    Send an accept message to n
    return
  else
    for $m \in Z$ **do**
      compute $\eta_{g_j - \{m\}, m}$
    end for
    Let $S = \{s_1, s_2, \ldots, s_{K_{MAX}+1}\}$, with $s_i \in Z$ and $\eta_{g_j - \{s_i\}} \leq \eta_{g_j - \{s_k\}}$ iff $i \geq k$
    if $S[K_{MAX} + 1] == n$ **then**
      Send a reject message to n
    else
      Send a leave message to the node $S[K_{MAX} + 1]$
      Send an accept message to n
    end if
  end if
end if

B. The GF procedure performed by the group agent

he GF procedure performed by the group agent is represented by the pseudocode in 2. Let K_j be the set of nodes affiliated to group g_j, where $||K_j|| \leq K_{MAX}$, being K_{MAX} the maximum number of users allowed to be within group g_j. Suppose that the group administrator A_j stores into its cache the profile P_i of each user node i and the timestamp d_i of its retrieval. Moreover, let ω_j be a time threshold fixed by agent A_j. The procedure performed by the group agent A_j is triggered whenever a join request by the user agent n (along with its profile P_n) is received by A_j. Parameter M can assume two values, TV (Trust-Voting) or $U2G$. Before of discussing the algorithm in detail, we remark that parameter M represents a simple setting of the group administrator in order to switch to the TV algorithm – which relies on the computation of the local trust – or to the U2G algorithm – which relies on the computation of the compactness which, in turns, includes the computation of the global trust. The difference between the U2G and TV is very simple, although relevant. The U2G algorithm tries to maximize the compactness of the member of the group; instead the TV algorithm relies on the vote of every group component – which relies, in turn, to the evaluation of the local trust – in order to decide whether to admit the new member into the group.

By lines $1-5$ the group agent asks the updated profile of the components of the group itself. By line 6 of the algorithm, all the users of group g_j are asked to express a preference (i.e., a vote) about the possible joining of user n in group g_j only if the parameter M is set to TV. This represent the TV variant of algorithm GF, which, for brevity, we refer to as TV in Section V. Here we use the function $V(\cdot)$ as defined in section III-D.

From line 7 of the algorithm, there are several different options, which are listed below, along with the correspondent lines of code:

- the users of the group did not accept user n (i.e., the voting has given a negative result); in this case the procedure will end and n will not join group g_j (line 7);
- the number of users in the group plus n is not larger than K_{MAX}; then user n will join the group (line $8-10$);
- the number of nodes in the group is equal to K_{MAX}: a set $S = \{K_j \bigcup n\}$ is built and it is sorted on the basis of the compactness $\eta_{g_j - \{x\},x}$, computed for all $x \in S$ (line 15); in order to compute the compactness for all the nodes, the user profiles are updated in lines $12-14$. Then, by looking at the last node in the list (i.e., the one having the worst value of η – line 16), say m:
  - if m is the same node n that asked to join the group, it is not admitted in the group itself (line 17);
  - if $m \in K_j$, then the group agent A_j will send to the node m a *leave* message, and will admit node n in the group g_j (lines 19 and 20).

In the next section V, we will refer to the approach based on voting ($M == TV$) simply as TV, while the second approach ($M == U2G$) will be referred to as $U2G$.

V. Experiments

In this section we discuss a number of experimental results obtained by comparing the proposed TV approach with the past U2G approach, on two different datasets[5] extracted from the social networks CIAO and EPINIONS. Both these datasets have been crawled by some researchers in order to carry out the study described in [17]. They are widely used to investigate on trust evaluation and trust-based recommendations because they store information on *i*) user trust relationships and *ii*) user-item ratings. In particular, EPINIONS and CIAO users review items, assign them numeric ratings and can also build their own trust network by adding the people whose reviews they think are valuable. Moreover, in EPINIONS and CIAO datasets timestamps inform about when the reviews have been published. Data extracted from EPINIONS and CIAO represent interactions of the users in the whole community, i.e, they are not aware of belonging to a particular sub-community or group. This aspect is quite useful for our research. Indeed, users interact with each other (i.e. they produce and rate reviews) without any influence or constraint related to the communities to which they belong, which is important to test algorithms for group formation.

[5]Data used in our experiments are publicly available at http://www.cse.msu.edu/~tangjili/trust.html

TABLE I
SymbolTable

Trust model	
U	The virtual community
N	The number of users of the community
α	Weight used for reliability and reputation in the computation of trust
γ	Weight used for trust and similarity in the computation of the compactness
β	Scaling factor for the local reputation. Defined by expression 7
$L(n,k)$	Local network of the user n w.r.t. the user k
$\omega_{n,k}$	Local reputation of the user n in the local network $L(n,k)$.
$\tau_{n,k}$	Local trust of the user n to the user k
$\hat{\tau}_{n,k}$	Global trust of the user n to the user k
$\eta_{n,k}$	Compactness computed on the users n and k
$\eta_{n,g}$	Compactness computed on the user n and group g
$\eta_{g,n}$	Compactness computed on the group g and the user n
Group formation	
N_{max}	Maximum number of users a group is able to host
K_{max}	Maximum number of groups a user can join with
C_1	Class of bad users, $v \leq 2$
C_2	Class of medium users $2 < v \leq 3$
C_3	Class of good users $v > 3$
T_g	Trust threshold for the voting mechanisms
$\{p_1, p_2, p_3\}$	Probability that a user of class $\{C_1, C_2, C_3\}$ will join a group

EPINIONS and CIAO dataset store data of $22,166$ and $12,375$ users, respectively. Both datasets consist of a pair of matrices (EM, TM). In the specific case, rows of EM have the form of $\{$*userID, productID, categoryID, rating*, *helpfulness*, *timestamp*$\}$. More in detail, *categoryID* represents the commercial product category identified by *productID* which received the rating by the user identified by *userID*, and *helpfulness* is the level of satisfaction of the other user for that *rating* (the latter – timestamp – is unused in our experiments). In particular, the helpfulness can assume values between 0 and 5. The matrix TM is instead composed by the numbers representing the trust relations between the different users (the "trust matrix"). This matrix is used to compute the local as well as the global reputation.

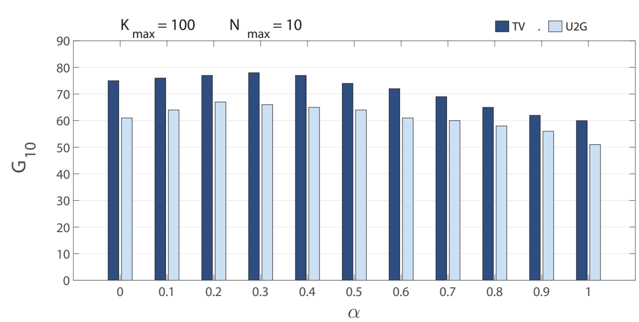

Fig. 3. TV vs U2G-comp on EPINIONS for configuration S_1 ($p_1 = p_2 = p_3 = 0.33$) with $N_{max} = 10$, and $K_{max} = 100$

A. Experimental settings and software

In our experiments we have considered helpfulness to be reflecting a social value. The goal of our activity of group formation is to obtain several different group configurations

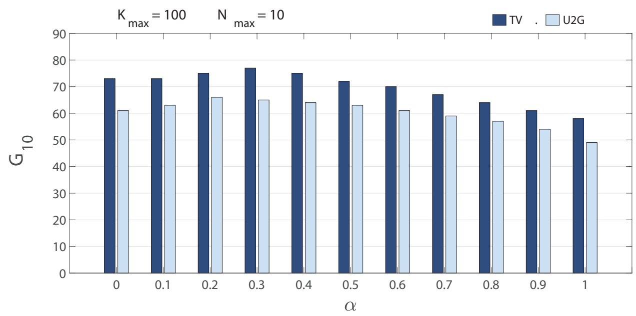

Fig. 4. TV vs U2G-comp on CIAO for configuration S_1 ($p_1 = p_2 = p_3 = 0.33$) with $N_{max} = 10$, and $K_{max} = 100$

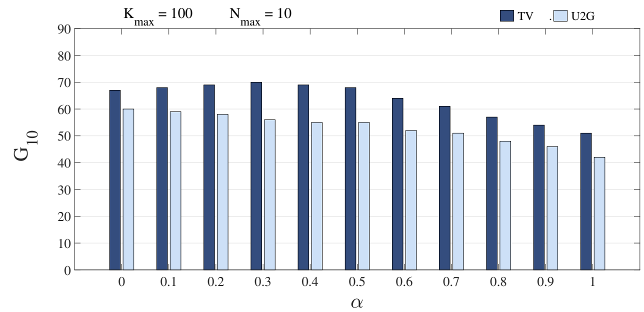

Fig. 7. TV vs U2G-comp on EPINIONS for configuration S_2 ($p_1 = 0.1$, $p_2 = 0.3$, $p_3 = 0.6$) with $N_{max} = 10$, and $K_{max} = 100$

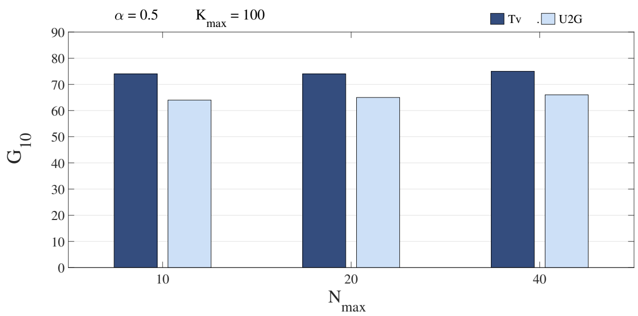

Fig. 5. TV vs U2G-comp on EPINIONS for configuration S_1 ($p_1 = p_2 = p_3 = 0.33$) with $K_{max} = 100$, and $\alpha = 0.5$

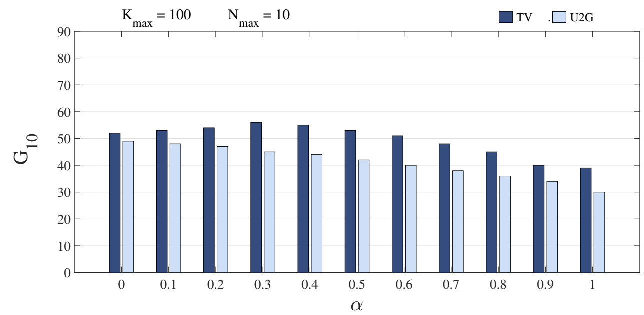

Fig. 8. TV vs U2G-comp on EPINIONS for configuration S_3 ($p_1 = p_2 = 0$, $p_3 = 1$) with $N_{max} = 10$, and $K_{max} = 100$

in terms of distribution of social values. We categorized the users of the communities into three classes, C_1, C_2 and C_3: C_1 as the class of *bad users*, having helpfulness $h \leq 2$; class C_2 is that of the *medium users*, having $2 < h \leq 3$; and, finally, class C_3 includes the *good users*, having $h > 3$. Then, we tested three different configurations, as follows:

- S_1: the ratio of users in each of the three classes are $p_1 = p_2 = p_3 = 0.33$, i.e., the users of each class are *equally distributed into the groups*;
- S_2: the ratio of users in each of the three classes are $p_1 = 0.1$, $p_2 = 0.3$, $p_3 = 0.6$, i.e., groups should have *many good users, a few medium users, and a very low percentage of bad users*;
- S_3: the ratio of users in each of the three classes are $p_1 = p_2 = 0$, $p_3 = 1$, i.e., groups should be formed by *only good users*.

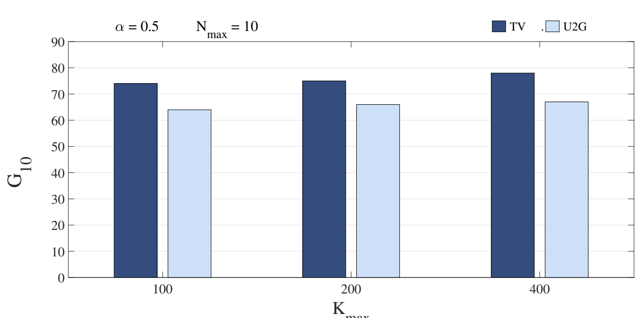

Fig. 6. TV vs U2G-comp on EPINIONS for configuration S_1 ($p_1 = p_2 = p_3 = 0.33$) with $N_{max} = 10$, and $\alpha = 0.5$

Let us remind that we defined the G_k *index* associated with a set of groups in a virtual community as the percentage of the groups having a social disadvantage less than or equal to $k/100$. Therefore, we show the results only in terms of impact on the G_k index, as the G_k index is directly dependent on the values of social advantage.

We set $k = 10$, thus we compare, in term of the G_{10} index, the TV and U2G algorithms for different values of α, N_{max}, and K_{max}.

We highlight the following important issues:

1) In our experiments, we have used the version U2G-comp of our algorithm, instead of U2G-diff that does not take into account the trust component of the compactness, giving importance only to the similarity between users' profiles. In our previous research [18], we have already compared U2G-comp and U2G-diff, showing that the performances of the first method is always better than the second one, and thus highlighting that the use of trust is essential to obtain significant improvements of the group compactness.
2) We have reported the results corresponding to G_k only for $k = 10$, since this value of k represents a very strict requirement in terms of group composition (corresponding to obtain a social disadvantage less than or equal to 10%). We have verified by an exhaustive campaign of experiments that the results for values of k greater than 10 are always favourable for our approach (with and advantage that is increasing with k) with respect to U2G, while values smaller than 10 represents too strict requirements that are not practically significant.

Note that all the settings used for the involved parameters must be considered as examples of possible realistic configurations. More specifically:

- **A**) - Figure 3 shows the results obtained by applying TV and U2G in the configuration S_1 to EPINIONS, for different values of α, fixed $N_{max} = 10$ and $K_{max} = 100$. We note that TV always outperforms U2G with an advantage in term of G_{10} ranging from a minimum of 11% to a maximum of 23%. An analogous result has been obtained on the dataset CIAO (Figure 4) where the advantage of TV vs U2G ranges from a minimum of 13% to a maximum of 20%.
- **B**) - Figure 5 shows the comparison between TV and U2G on EPINIONS for different values of N_{max}, fixed $\alpha = 0.5$ and $K_{max} = 100$. We see that also with respect to this dimension of the analysis, TV is better than U2G by about 16%.
- **C**) - Finally, Figure 6 presents the comparison TV vs U2G on EPINIONS for different values of K_{max}, fixed $\alpha = 0.5$ and $N_{max} = 10$. Also in this situation, we remark that TV performs better than U2G by about 16%.

We repeated the experiments B and C also on CIAO by obtaining an advantage of about 14% and 15%, respectively. The experiments show also that values of α higher than 0.3 lead to a reduction of G_{10} (Figures 3 and 4). This underlines that, in a group scenario, reliability should be considered as less important than reputation.

The influence of the values of both N_{max} and K_{max} on G_{10} is modest (Figures 5 and 6), although little improvements are obtained for high values of both parameters; that is a statistical consequence of having set fewer constraints in the group formation algorithms. In any cases, TV shows significantly better results than $U2G$, highlighting the importance of using the notion of local reputation in the mechanism of voting the acceptance of a newcomer in the group.

A further confirmation on the advantage introduced by TV with respect to U2G comes from the experiments on the configurations S_2 and S_3, for which we report in Figures 7 and 8 the values of G_{10}, for different values of α on EPINIONS. We see that the performances of both algorithms (TV and U2G) decreases with respect to the configuration S_1, which highlights the increased difficulty in obtaining the desired configurations with respect to the case of equipartition of the classes. However, also in both these situations, TV performs better than U2G, with advantages ranging in 12-25% (on the S_1 configuration) and 10-30% (in S_2). Similar results have been found on the CIAO dataset. Also the results achieved by varying N_{max} and K_{max} (not reported due to space limitations) completely confirm the trend shown in the analogous results obtained for the S_1 configuration.

VI. Related Work

To form groups within social communities, a large number of proposals in the literature exploit a *matching* approach between user's requirements and group's characteristics. These similarity measures are derived from personal profiles which are built by the users' behaviors [19], [20].

A "similarity" metric can be considered as the most natural way to measure how much the group members are close to each other based on specific interests. However, the similarity criterion will neither ensure that group components will actually be engaged in the group interactions nor guarantee a minimum level of quality for such interactions. Nevertheless, recent studies [21] report that the level of mutual trust is tightly related to both the number and the quality of members' interactions (which can even occur through different channels [22]), as well as to the formation of thematic groups [1], [23]. Therefore, we can argue that the larger is the level of reciprocal trust among members, the larger their interest in engaging in mutual interactions [24], [25].

To solve this later issue, and for improving the group effectiveness, a common solution chooses to refine the group formation processes by combining similarity and trust measures. As an example, in [13] similarity and trust measures are combined together to represent both the individual and the global satisfaction, as respectively perceived by a user and by all the members of a group of a virtual community. However, the computation of similarity measures in large communities could imply the need to explore the whole member space [26], [27]. This may become impracticable, and the matching may not be reliable due to a lack of information, or due to imprecise or fraudulent data [28].

Trust approaches have been widely used in several different fields, as Vehicular social network, social media transportation, and Cloud Computing [29]–[32]. In the specific case of communities, recent contributions in the group formation area give relevance only to trust measures [33]. In particular, a complete and useful representation of trust within a given community through direct knowledge (referred to as reliability), would require community users to directly interact with each other. Yet, the usual approach is to exploit also the information deriving by other members of the community, referred to as reputation.

In computing reputation, an approach largely used is to gather the recommendations provided by *all* the members of the community, which is known as *global reputation* [34], [35]. Also, in this case a large number of members would make it difficult to compute this global information about the users. In fact, in similar contexts unreliable recommendations may lead to misleading estimations in trustworthiness, particularly for the unknown community members. This is often due to malicious behaviours aimed at gaining undeserved benefits [14]. Therefore, reliable reputation measures require to evaluate the trustworthiness of the recommenders. To address this critical issue, researchers have developed complex, sophisticated and also computationally expensive techniques, often involving significant communication overloads [10]. Thus, forming groups within virtual communities on the basis of a trust criterion bears the risk to realize processes dissimilar and more complex than those implemented in real user communities.

An interesting problem related to our work is that of team performance modeling and prediction, in order to drive team formation and to maximize the performance of the team itself. In [36], the authors analyze the problem team performance prediction and modeling and propose an novel way to model and predict the performance of a team/group. The model is named "E-CARGO" and includes a few algorithms which have been verified by a case study to demonstrate the practicability of the proposed method.

Role assignment is a critical task in role-based collaboration. The authors of [37] have performed a study related to group role assignment problem (GRAP). Moreover they described a general assignment problem (GAP), converts a GRAP to a GAP and, finally, they proposed an efficient algorithm based on the Kuhn-Munkres (K-M) algorithm along with numerical experiments. From the analysis of the results the authors show that the proposed algorithm significantly improves the algorithm based on exhaustive search. In particular, the authors has contributed to expand the application scope of the K-M algorithm, by offering an efficient solution based on the K-M algorithm.

In this scenario, another main question is how to aggregate such trust information to form groups in a simple way. To this aim, voting is one of the most popular techniques, both in real and virtual communities, to aggregate individual preferences [38] by giving equal decisional weight to everyone, specifically when a common members' decision has to be made in face of different alternatives [39]. Voting outcome is a mediation among different members' opinions and interests and, for this reason, it is effective when conflicts must be reduced [40], as well as when the social utility has to be maximized [41].

In the literature, different voting procedures have been designed by adopting either a global or a local approach. In the presence of very large communities, global procedures are inefficient or unfeasible (high computational complexity, absence of stable communications, and so on); local voting procedures – i.e., decomposing the vote in more local votes and then gathering them together – generally represents a better choice [42].

Another aspect is represented by the possible attempt of manipulating the voting result. The literature includes several techniques useful to manipulate the outcome by strategic voting [43], [44]. For example, selfish behaviors can address one or more community members to release a vote which is not in accordance with their true preferences but, in an egocentric vision, is aimed at obtaining as many individual benefits as possible in that specific scenario [45], [46]. In particular, software agent societies are more exposed to voting manipulations than human societies because agents decide their vote based on coded algorithms and can easily explore a wide range of manipulation opportunities [47]. Therefore, the challenge of designing voting mechanisms that show robustness is addressed in several works [48], [49].

However, the issue above can be considered orthogonal with respect to the focus of our proposal. In a very similar view, trust can assist voting mechanisms in virtual communities. Trust is a major asset of both human and virtual societies which arise from the inability of a (real or virtual) entity to suitably monitor or control its environment and relationships. Given its relevance and multidisciplinarity, trust is largely studied in many disciplines under different perspectives (e.g., sociology [50], economics [51], computer science [52] and so on). Sociologically, trust can be assumed as the expectation that one or more entities have about the fulfillment of one or more events or behaviors [53], [54]. In other words, trust is a bet a trustor places on a trustee about a future event [55] in order to receive either an individual or a collective benefit [56].

Conceptually, a vote is not dissimilar from trust, because voters place their own expectations on some other actor (or in a future event) similarly to a trustee. Indeed, based on cognitive and emotional dimensions, voters expect to receive some form of benefit arising from their vote. Benefits may be individual, when the voters are driven by selfish targets, or social, for instance when they aim at improving the social capital of a group [13]. On the contrary, voting and trust hold different properties and adopt different models among them.

As stated before, approaches relying on local trust and local voting are preferred to realize reliable relationships and quick decisions in all those contexts denoted by a great population, mobility, lack in infrastructure and/or communications, as well as in presence of limited computational and/or storage capabilities. To this regard, a trust-based voting strategy is described in [57], where a local voting mechanism is applied in a mobile wireless network context for establishing whether or not a node should be included in a transmission path. The evaluation is based on trustworthiness, as it is perceived by the other nodes. The theory of semi-rings is used in [58] to model trust in Ad-Hoc Networks by a graph where links represent trust relationships. Users form their trust opinions about the other nodes by also using second-hand information, even though this information is weighted differently from that derived by direct experiences. By using a modified Mohri [59] iterative algorithm, the trustworthy nodes are identified on the basis of a voting process performed only by those nodes that have a trust value higher than a suitable threshold. Even though this algorithm currently implements a global approach, it could be easily converted in a local strategy. The authors of [60] discuss a group affiliation procedure where any group-joining request is evaluated by means of a democratic group voting mechanism. In particular, each vote is driven by trust because each group member evaluates if the requirements for joining the group are satisfied by means of a local trust-engine.

VII. Discussion and Conclusions

Group formation is a key issue in social communities, due to the importance of establishing an effective organization in which users perform actions that could benefit from collaboration and mutual social interactions. In this context, the necessity of determining the levels of trustworthiness between users naturally arises as well as the possibility of associating a reputation to each user. From this viewpoint, the question arises about which possible definition of effectiveness for a group should be adopted. In fact, the desired ideal configuration of the groups is not necessarily the one composed only by the highly reputable users. Depending on the context, the possibility could arise to have groups whose composition involves also bad and medium reputable users, which are themselves members of the network and, thus, have a social value and bring their own expectations.

Although an overwhelming amount of proposals exist in the literature about the problem of trust-base group formation, to the best of our knowledge nobody has yet proposed an objective metric for measuring the effectiveness of the groups, specifically from the viewpoint of their desired composition. In this paper, we propose to use a novel measure, dubbed G_k index, to face this issue in a natural and objective way. Starting from the goal of improving the effectiveness of the group formation activity in terms of G_k index, we then proposed, as the core contribution of the paper, a strategy to form groups in virtual communities based on a weighted voting mechanism, whereby each vote is represented by a trust value obtained by a suitable combination of reliability and local reputation. This latter is a form of reputation that is based on opinions only coming from the entourage of the user (i.e, friends, friends of friends and so on) that appears as more reliable than using completely unreferenced recommendations.

Therefore, similarly to real communities, when the user's experience is inadequate to trust another user, the usual process is to require an opinion to his/her network of friends. We have implemented this strategy by the TV algorithm, an evolution of the U2G algorithm, which uses the local reputation instead of the global one and integrates a voting mechanism. Experiments performed on the real social networks CIAO and EPINIONS show that our proposed strategy significantly improves the results obtained by U2G in terms of G_k index. While the presented experiments are limited to the presence of three classes of users, our ongoing research is now devoted to studying the behavior of TV in the presence of even more complex configurations of the groups, in cases in which many different classes of users exist.

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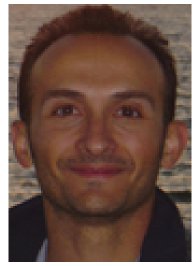

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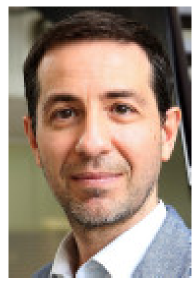

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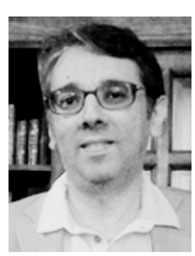

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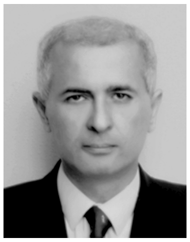

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