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Forming Time-Stable Homogeneous Groups into Online Social Networks

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Abstract

In this work we investigate on the time-stability of the homogeneity — in terms of mutual users' similarity within groups — into real Online Social Networks by taking into account users' behavioral information as personal interests. To this purpose, we introduce a conceptual framework to represents the time evolution of the group formation in an OSN. The framework includes a specific experimental approach that have been adopted along with a flexible, distributed algorithm (U2G) designed to drive group formation by weighting two different measures, mutual trust relationships and similarity, denoted by compactness. An experimental campaign has been carried out on datasets extracted from two social networks, CIAO and EPINIONS. Results show that the time-stability of similarity measure for groups formed by the algorithm U2G based on the sole similarity criterion is lower than that of groups formed by considering similarity and trust together, even when the weight assigned to the trust component is low. Experimental trials have shown that compactness-driven group formation will give groups showing a time-homogeneous behavior even when uncorrelated behavioral components (i.e., aspects of the user behavior that are mostly random, as preferences with respect to group privacy rules, level of participation in group activities, etc.) included in the computation of similarity assume a relevant weight.

Keywords: Online Social Network, Similarity, Homogeneity, Reputation, Trust.

1. Introduction

Most of the existing Online Social Networks (OSNs) platforms target at connecting as many people as they can and it is not surprising that OSNs are became mainstream communication medium. Indeed, everyday an overwhelming amount of users share their interests, objectives, opinions, posts and contents with other OSN users[1].

In order to increase the fruition of the social platforms, OSNs allow the creation of thematic *groups* (e.g. more than 100,000 groups per day only on Facebook [14]). Group formation, as well as their evolution, encompasses the dynamics underlying human interactions in forming and spreading opinions and decisions [4]. Researchers of several communities have been studying users' motivations to join with a group [11] and their impact on the groups growth [4, 13] and failure [14]. A key issue widely investigated in the latest years is that of forming "homogeneous" groups in OSNs and, consequently, selecting the best groups a user could join with [7, 10, 28]. Indeed, users basically need to look for those groups which are potentially able to best satisfy the expectations of a user, as well as the utilities that the other groups members can receive in accepting him/her into a group.

A considerable number of works focused on understanding the driving forces modeling group formation and their evolution, to design effective algorithms to find right groups. Some of these studies [4, 13] relates Complex Networks to OSNs, use diffusion processes to model formation and evolu-

[1]Almost a billion of daily active users on average on June 2015 on the sole Facebook. http://newsroom.fb.com/company-info/

tion of OSNs groups or highlight as some topological network properties, are reliable indicators to predict if a user will join with a group or if a group will survive in a particular time frame. Interestingly, a lot of work aimed at designing algorithms and heuristics able to drive group formation rely on the assumption that groups should be formed by like-minded people. Therefore, there is a great interest to identify like-minded people due to the idea that higher the similarity degree among users (or a user and a group), the higher the chance that quality of interactions among people will increase.

Several different *similarity measures* have been proposed in the literature to assess the similarity degree existing among individuals within a group [2, 7, 10, 26, 28]. Among the parameters taken into account we mention the number of groups two users are jointly affiliated [28], user/group interests [7], as well as personal preferences [10]. From this point of view, the compulsive growth of OSNs users and groups implies the necessity of adopting scalable algorithms to efficiently process large amounts of user- and group-related data. In addition, restrictions imposed by group administrators may deny the access to the data characterizing OSN groups to a user and, in this way, it is made impossible for him/her to adopt a brute-force approach to find the best groups fitting his/her needs.

1.1. Main motivations underlying our proposal

A crucial problem in the study of group formation and evolution is *time stability* [5, 17], i.e. the *aptitude of a group to retain its members.*

It is easy to realize that time-stability constitutes a major factor in decreeing the success (and, then, the survival) of a group or, vice versa, its failure (and, then, its extinction). Some concrete examples, in fact, shed light on the importance of building up time-stable groups: let us consider, for instance, co-citation or patent networks in which nodes represent scientists (resp., patents) and edges encode co-authorship relationships (resp., citation between patents). In this setting, time-stable groups coincide with research teams displaying a long-term interest in solving related research problems. Collaboration among research teams is often an essential ingredient to accelerate scientific progress and to foster research in a given field. If a group would dissolve into many non-communicating sub-groups, we would lose the wealth of scientific and technological achievements in the field of that group.

Due to its practical relevance, it is not surprising that several researchers were interested in studying the evolution of OSN groups in order to understand the mechanisms driving their growth [3, 16, 19]. Asur et al. [3] proposed an intuitive approach to investigate the evolution of real OSN groups across time frames, by computing group sizes and the degree of overlapping of all possible pairs of groups in consecutive time frames. In [16], user-to-user similarity is considered as the only criterion leading to group formation. The authors of [19] identified the member diversity and the group activities as critical factors for the stability of a group along with the presence of highly dynamic group members.

Nevertheless, none of the aforementioned approaches investigates the limitations of using user-to-user similarity alone in the process of forming groups. To illustrate these limitations and their practical impact, let us consider the problem of recommending groups to user. If we would rely only on similarity, we should consider user personality traits, features and behaviors at the time instant t to calculate to what extent user features match the overall interests of a group. We would recommend our target user to join the group $g^\star$ if $g^\star$ best fits the interests of our target user.

However, user behavior and preferences may rapidly vary in relatively short time frames and, thus, we are no longer confident that $g^\star$ is still the best option for our target user at the time instant $t + \Delta t$. Our paper aims at addressing the limitations above: in detail, we target at studying techniques to form time-stable groups and, to this extent, we suggest that user-to-user similarity alone is not enough to ensure time stability.

1.2. Our Contribution

In this paper we present the results of an experimental campaign aimed at understanding the main factors affecting the time-stability of OSN group homogeneity, in terms of internal similarity between the members of the group. Below we describe the main contributions that our work provides.

1. Our first contribution is providing an answer to the following question: "How much time-stable is the homogeneity of those OSNs groups formed on the basis of the users' similarities?" By using the data of two real OSNs, i.e., EPINIONS and CIAO [27], we had the opportunity to verify, in different time frames, the time-stability of the homogeneity of the groups formed within the OSN basing on the similarity. As we discuss in Sections 7 and 8, the experimental results have shown that group formation driven by similarity does not guarantee a time-stability of the homogeneity, especially when uncorrelated users behavioral components, i.e. aspects of the user behavior that can be considered mostly random, as preferences with respect to group privacy rules, level of

participation in group activities, etc., included in the computation of similarity, assume a relevant weight. In other words, the sole similarity criterion seems not sufficient to form OSN groups which will eventually assume a stable homogeneity, in terms of similarity.

2. Given the aforementioned results, our second contribution consisted of solving also another question, namely: "Is it possible to improve the time-stability of the homogeneity in terms of similarity into OSNs groups?" In this respect, we acknowledge that recent studies on group formation processes did not consider the similarity as the sole key criterion to form groups. In fact, frequently an increasing relevance is given also to the *trust* as a crucial factor to keep the level of user's engagement into a group high enough over time and prevent group failures [25]. Here we use the term *trust* that a user a has in another user b in the following, classical meaning: a trusts b if a commits to an action based on a belief that b's future actions will lead to a good outcome [9].

   This notion of trust is very different from the concept of *similarity* between a and b, that considers what aspects are similar in a's and b's profiles (preferences, tastes etc.) Obviously, a can trust b also if b has a very different profile from that of a, simply based on the a's opinion that the actions of b will produce a good income. This leads to observe that trust is not a symmetric relationship, differently from similarity.

   It is not surprising the importance of trust in social networks, because we can note as OSNs users are more motivated to stay in groups with members they trust, likely we observe in other social contexts as, for instance, the multi-agent communities [24, 23].

1.3. Differences and novelty with the state of the art and our previous work

With respect to the two research questions defined above, we observe that approaches reviewed in [25] highlight the importance of using trust measures in forming groups. These approaches, however, do not face the problem of combining trust with similarity. In a previous work we proposed an approach for integrating similarity and trust in a unique measure to form groups and finding those most suitable a user can join with [8]. Our approach is rooted in the *Social Capital* theory [25] as expression of the concrete advantage a user can get from interacting with both trusted and like-minded users. However, in [8] we did not consider changes in user similarity occurring over time and, as such, we did not consider how changes in user similarity impact on the formation of groups.

In this paper, we extend our previous work by introducing a conceptual framework to represent the time evolution of the group formation in an OSN. Our approach takes both similarity and trust measures into account in forming groups, and, unlike existing approaches, it also considers the changes that these measures undergo over time. We expect that our choice does not produce a starting group formation representing the best clustering of the users, since the goal of the actual objective function is to maximize the overall internal similarity of the groups, while in our approach we will form the group by exploiting an objective function which combines similarity and trust.

Then, we have used the new conceptual framework that we have introduced for performing an extensive set of experiments on real data coming from the social networks CIAO and EPINIONS. Our main research result is that groups formed by considering both similarity and trust show a time-stable homogeneity — in term of similarity — which is higher than that of the groups formed by considering the similarity criterion alone.

This phenomenon is remarkable even when the weight assigned to the trust component is low. Interestingly, experimental trials have shown that compactness-driven group formation will give groups showing a time-stable behavior even when random components of user behavior included in the computation of similarity assume a relevant weight. We consider *random components* as those components included in the computation of the similarity which appear as "uncorrelated", i.e. as not having a strict relationship, with the others.

Furthermore, successive experiments identify also the most suitable ratio between uncorrelated components, included in computing similarity, and the other components. These results can be explained as follows.

From one hand, our approach yields more robust results because potential errors due to the similarity measures may be balanced by the trust contribution. On the other hand, this aggregation measure does not strictly depend on the choice of the aggregating function. In principle, we could to consider complex strategies to aggregate similarity and trust values, as well as to manage further criteria in the group formation but, as in [8], we aggregated similarity and trust by simply computing their weighted sum. This choice has been due to the necessity of achieving a good trade-off between the need of producing accurate results and the need of having a model of easy interpretation.

1.4. Plan of the paper

The remaining of the paper is structured as follows: in Section 2 we compare our work with related literature, Section 3 introduces the adopted reference scenario, while Section 4 deals with the computation of the similarity and trust measures. Sections 5 illustrates the U2G algorithm. In Section 6 we present the conceptual framework we have introduced for supporting our time-stability analysis of the group homogeneity. Then, Section 7 provides all the details of the experimental campaign, i.e. experimental approach, software, parameters, and results, and Section 8 provides a detailed discussion of the experimental results. Finally, in Section 9 we draw our conclusions and also some possible future works.

2. Related Work

In this section we compare our work with related literature. In detail, we review studies first on the formation and evolution of groups (see Section 2.1) and, subsequently, on the group time-homogeneity over time (see Section 2.2).

2.1. Group Formation and Evolution

The study of mechanisms regulating group formation and growth has a long tradition in Social Sciences and, more recently, in Computer Science [4].

One of the early (and most popular) theory about the formation of groups is known as *common identity and common bond* [21]. It identifies two main mechanisms driving people to join with groups: on one hand, strong personal ties with other group members may persuade a user to join with a group; on the other hand, individuals are likely to join with a group based on shared interests with other group members. In real scenarios, according to the prevalent reasons drifting an individual to join with a group, we can classify groups into *social* and *topical*. Authors of [11] suggested to apply community detection algorithms to identify clusters in an OSN and to compare the structural features of these graphs with user-defined communities. In Computer Science field, one of the first studies devoted to clarify the mechanisms leading a user to become member of a group and explaining the growth over time of a group is due to [4]. In this paper, the authors focused on the LiveJournal friendship network and on the DBLP co-authorship network. They observed as the act of joining with a group can be modeled in terms of the spread of new ideas. Surprisingly enough, most of the findings discovered for the LiveJournal dataset were also true for DBLP dataset, despite groups have a very different meaning in each of the two datasets.

Kairam *et al.* [13] considered diffusion growth processes (i.e., processes in which groups attract new members by means of social ties binding new members to existing ones) and *non-diffusion growth*, in which individuals with no prior social ties to any group members decide to join with the group. In this case, the main finding is that if a group is highly clustered, then it is more likely to grow due to diffusion processes; however, those groups are usually smaller than other groups.

The result of [13] is consistent with the results presented in [14]: the authors monitored for a 3 month period almost half a million of Facebook groups that were created in an 8-day period in 2013. It has been found that about 57% of these groups stopped from creating new content by the end of the 3-month of observation. Nevertheless, some of these groups were fictitiously formed, indeed, in other cases, group members continued to communicate in person or by means of other electronic means (e.g., e-mail) but they abandoned their own group. Despite these caveats, true failure of Facebook groups occurred very frequently. The analysis of [14] highlighted that group survival depends on the social capital brought by group founders and on their behavior. The papers above considered formation and evolution of OSN groups but any of them explored the homogeneity of such group in different frame time. On the contrary, we do not simply study the mechanisms of formation and growth of groups but we aim at exploring to form groups which result time-stable homogeneous in terms of similarity.

2.2. Time-Stable Homogeneous Groups

Homogeneous processes are defined as those processes whose parameters do not change over time or, in other words, they are time-stable with respect to some measure. Usual group formation processes consider one or more properties (e.g. similarity, social identity, etc.), also in a combined fashion, but without to assure that group evolution will preserve them over time. Conversely, different formation processes are specifically aimed to drive OSN group formation with the aim of preserving the considered properties over time. Therefore, a specific declination of the more general problem known as *affiliation recommendation* [28] consists of selecting those suggestions about groups to be recommended to users, and vice versa, which give a reasonable probability to form time-stable groups.

In [22] the role played by the *Social Identity* and *Cohesion* theories in the stability of OSN groups has been investigated together with other approaches based on properties, such as group size, in a large scale experimentation involving diverse sets of real-world events by using data extracted from Twitter. Authors found, as in presence of transient events, that group cohesion stability over time is critical when compared with those groups formed on the users' social identity when the group members are interested in a great variety of different topics. To this purpose, for measuring *Social Group Sustainability* and *Membership Stability* two different measures have been proposed. The first one incorporating the notion of group discussion divergence and the other reflecting the membership stability. Some experiments tested the effectiveness of such measures by correlating them with the size of the groups and other measures of sustainability referred to different types of statistical and entropic structural cohesions.

The temporal evolution of scientific collaboration is the focus of two methods proposed in [12]. Authors applied these methods to analyze a co-authorship network constructed with data related to conference contexts. In [10] is provided a flexible framework in which group affiliation is treated as an event capable of impacting on user's preferences. To this purpose, a probabilistic framework capable of modeling the preferences that arise in an individual when he/she joins with a group is proposed and experimentally validated. In other words, it implies to consider the affiliation to a group of those users who maintain a high similarity level into the group over time and keep homogeneous the group under this point of view.

In this scenario, we note as friendships and their relationships strictly depend by the mutual trust occurring among individuals which, consequently, affects the time-homogeneity of OSN communities.

In the literature, the most part of the papers dealt with the problem of forming time-stable groups by considering it as a problem essentially involving the affiliation into a group of those users which appear mutually similar under some aspect. This reflects the idea that the resulting groups will be more stable over time. Conversely, we have shown as an approach only based on a similarity criterion could not be the best choice to form time-stable homogeneous OSN groups and that, in this context, the contribute due to the trust plays a fundamental role. Among the cited contributions, only [5] indirectly refers to trust, in the mean derived by the social theories [18], while the other only consider some form of similarity as the unique criteria to forming possible time-stable homogeneous OSN groups.

3. The Reference Scenario

Our framework is applied to an OSN $\mathcal{S}$, represented by a tuple $\mathcal{S} = \langle \mathcal{U}, \mathcal{G} \rangle$, where $\mathcal{U}$ is the set of *users* affiliated with $\mathcal{S}$ and $\mathcal{G}$ is the set of *groups* active in $\mathcal{S}$. Let's assume also to have a set $\mathcal{I}$ of available *items* which can be rated by the users of the OSN. They can belong, without any restriction, to a specific category $c \in \mathcal{C}$. An example of this scenario is represented by those social networks, as CIAO or EPINIONS, in which items are products belonging to commercial categories (e.g. software, hardware, books, etc.).

As already stated, it is assumed that, in $\mathcal{S}$, each user $u \in \mathcal{U}$ is allowed to *review* an item. Let $\mathbf{r}_{u,i}$ be the generic *review* of an item $i \in \mathcal{I}$ released by u. A review $\mathbf{r}_{u,i}$ has a suitable form which specifies the following information:

- a rating assigned to i by u that we assume to be an integer varying from 0 to 5;

- a category $c \in \mathcal{C}$ associated with i, where $\mathcal{C}$ is the set of categories;
- a numerical score specifying the helpfulness of $\mathbf{r}(u, i)$;
- a timestamp.

As helpfulness we mean a measure of how many the rating associated with a review is valuable to make a decision. To this purpose, we assumed that each user can rate each review posted by other users. By collecting the scores assigned by all the users to a particular review its helpfulness is computed as the average of the scores. The field category is a bit harder to manage. In fact, in case of product review systems like EPINIONS and CIAO the categories are directly available and corresponding to commercial categories, e.g. *Music* or *Books*. In other types of OSNs, the identification of categories is sometimes, feasible as, for instance, when it is allowed members of OSNs to apply tags to classify objects. Techniques like Latent Dirichlet Allocation [6] might map users' tags onto *topics*, which allow to partition the space of available items into classes (each one associated with a category, while the label associated with each class corresponds to the tag associated with that topic).

Finally, we denote by $\overline{\mathbf{r}}_u$ the set of reviews associated with u, called *review history*, and by $\mathcal{R}$ the set of all the review history in $\mathcal{S}$.

In the aforementioned scenario, we assume to adopt a multi-agent platform to manage users and groups. In detail, each user u is assisted by his/her personal agent a_u, whereas each group g is assisted by an administrator agent a_g. The agents knowledge representation, the agent tasks and our definitions of similarity and trust will be introduced below.

To characterize the interests and the preferences of the generic user $u \in \mathcal{U}$ it is assumed that a *profile* p_u is associated with him, and to characterize those of each group $g \in \mathcal{G}$, a similar *profile* p_g is obtained by aggregating the profiles of its members. In particular, the profile p_u stores a tuple containing (i) interests, (ii) behaviors, (iii) preferred access modes and (iv) trust levels, as follows:

- **Interests**: Let $u \in \mathcal{U}$ be a user and let $c \in \mathcal{C}$ be a category. The interest of u in c is a function $I_u(c) : \mathcal{U} \times \mathcal{C} \rightarrow [0, 1]$ computed as the overall ratio of reviews for items belonging to c. More formally, $I_u(c)$ is expressed by:

$$I_u(c) = \frac{|\{r_{u,i} : i \in c\}|}{|\overline{\mathbf{r}}_u|} \tag{1}$$

  where $\overline{\mathbf{r}}_u$ is the review history of u, and we denote by $r_{u,i}$ each review contained in $\overline{\mathbf{r}}_u$ and referred to an item i.

- **Behaviors**: The behavior field informs us if a past user's activity is (or is not) tolerated within a group. It is assumed to be a statement of the form "The average rating of items is greater than 3.0" or "The helpfulness of a review is less than 2.5". Other examples may regard the length of the longest posted message or their frequency.

  The choice of relevant behavior is made by the social network analyst, interested to study some properties of the network. The analyst, depending from the particular social network and the particular goals of the analysis chooses the behavioral aspects that he/she judges most significant (e.g., average rating, frequency of posts, etc.) as well as the thresholds for discriminating the two possible boolean values that each behavior can assume.

Let b be a behavior and let $\mathcal{B} = \{b_1, b_2, \ldots, b_p\}$ be a given a set of behaviors. We assume to dispose of a function $\zeta_u(b) : \mathcal{U} \times \mathcal{B} \rightarrow \{\texttt{True}, \texttt{False}\}$ which takes a user $u \in \mathcal{U}$ and a behavior $b \in \mathcal{B}$ and checks whether the behavior b matches with the u's past behaviors. So, for instance, if b is "The average rating of items is greater than 3.0" and the average rating associated with u is 2.7; then the $\zeta_u(b)$ is equal to `False`. The set of behaviors associated with a user u will be defined as B_u, i.e., we set $B_u = \{\zeta_u(b) | \quad b \in \mathcal{B}\}$.

The behaviors tolerated within a group g can be modeled in a similar way, e.g. by a function $\zeta_g(b) : \mathcal{G} \times \mathcal{B} \rightarrow \{\texttt{True}, \texttt{False}\}$; for each behavior $b \in \mathcal{B}$ and each group g, it returns `True` if and only if the behavior b belongs to the set B_g of behaviors tolerated within g.

- **Access modes**: An access mode identifies a different modality to access a group, like to *open*, *closed* or *secret*, and let L be a list specifying such accessing modes. In fact, some groups can be open, when any user can freely access the content available in the group, or closed if its contents are visible only to group members, etc. More in general, we supposed that a function $A : \mathcal{U} \rightarrow L$ is available to associate a user $u \in \mathcal{U}$ with a mode $l \in L$ for accessing to a group. For instance, the user a could be associated with the access mode *secret*, meaning that

a usually prefers to join with groups that have set their access mode on *secret*. We highlight that the choice of an access mode for a group is arbitrarily made by the group administrator, as well as each user arbitrarily sets his/her particular preference for an access mode. This components of the user profiles can be considered as fully random, and not correlated with the other components.

- **Trust levels**: We suppose that a *trust function* returning how much a user u perceives another user v as trustworthy is available. This function is *asymmetric*, in the sense that if u trusts v it does not imply that v trusts u too but, in general, $t_{u \to v} \neq t_{v \to u}$ Therefore, let $t_{u \to v}$ be the level of trust of a user u with respect to the members of the OSN. Trust levels are generally assigned directly by the users during their interactions, in a way that depends on the specific social network. For instance, in CIAO and EPINIONS a user a can explicitly declare if he/she trusts or not in another user b (in this particular case, we have a binary value for the trust level). Similarly, the trust perceived by a user u with respect to a set g of group members can be defined as:

$$t_{u \to g} = \frac{\sum_{v \in g} t_{u \to v}}{|g|} \tag{2}$$

For each set of group members $g \in \mathcal{G}$, the profile p_g associated with g is specularly defined as follows. The interest $I_g(c)$ of g to a category c is defined as the average of the interests of the users of g to c, where the interests are computed as described for the user profile. Moreover, we suppose that the administrator g is in charge of establishing the behaviors admitted into the group and a mode to access g (denoted as A_g). A group profile also stores how the members of g perceive as trustworthy a user u, as follows:

$$t_{g \to u} = \frac{\sum_{v \in g} t_{v \to u}}{|g|} \tag{3}$$

3.2. The agents' tasks

According to the profiles and the properties already defined, each time u (resp., a user of g) performs an action involving any information represented in p_u (resp., p_g) it is automatically updated by the associated agent a_u (resp., a_g) as follows:

- When u performs an action (e.g., rating an item) his/her agent a_u analyses the action and properly updates the user's interests and the boolean values of the variables contained in B_u. Similarly, the agent a_g updates the variables stored in B_g every time the administrator of g changes the corresponding rules. Furthermore, if u (resp., the administrator of g) decides to change his/her preferences with respect to the access mode, then the agent a_u (resp. a_g) properly updates A_u (resp. A_g).

- When u expresses his/her evaluation about a post authored by another user v, then the agent a_u updates the trust measure $t_{u \to v}$ as described in Section 4.

We also assume that a *Distributed Directory Facilitator* agent (DDF) will support user and group agents in the whole OSN, providing an *Agent Indexing Service*, and a *Communication Layer* allows each agent to send to each other agent a message by using its name in the *receiver* field of the message.

4. Similarity and Trust

As previously stated, our goal is studying the time-stability of groups, in terms of similarity, in the OSN model presented in the previous section. For this aim we consider users' similarities and trust relationships, which are defined in the following of this section.

4.1. Similarity measure

Let $s_{u,v}$ be the measure of similarity between the profiles of users u and v computed as a weighted mean of the contributions due to the interests (c_I), the behaviors (c_B) and the access modes (c_A) normalized in the range $[0, 1]$ in order to make them comparable. More formally, the similarity $s_{u,v}$ is computed as:

$$s_{u,v} = \frac{w_I \cdot c_I + w_B \cdot c_B + w_A \cdot c_A}{w_I + w_B + w_A} \tag{4}$$

where the weight w_I, w_B and w_A are real system coefficients belonging to $[0, 1]$ which suitably weight the contributes c_I, c_B and c_A that, in turn, are computed as follows:

- c_I is based on the average difference between the interest values of u and v for the all available categories into the OSN:

$$c_I = 1 - \frac{\sum_{c \in C} |I_u(c) - I_v(c)|}{|C|} \tag{5}$$

- c_B is based on the average difference between the boolean variables contained in B_u and B_v. This difference is 0 (resp., 1) if the two corresponding variables are equal (resp., different).

- c_A is set to 1 (resp., 0) if A_u is equal (resp., different) to A_v.

The similarity $s_{u,g}$ between a user u and a group g is computed in the same manner described above, simply by substituting the user v with the group g.

4.2. Trust measure

In our model, the trust is viewed as the sum of (i) a *local* term, which specifies how much a user trusts another user, and (ii) a *global* term, to express how much the whole OSN perceives a user as trustworthy.

For the local component, we observed that some OSNs allow their members to directly specify if they trust (or distrust) another member of the platform. This is, for instance, the case of platforms like EPINIONS and CIAO we consider in this paper [27]. A more common (but harder to manage) configuration arises when users can interact in pairs (e.g., a user can review/comment the reviews or ratings provided by other users) but they are not able to provide trust values. In this case user's behaviors has to be analyzed to infer trust relationships. Usually, a *feedback mechanism* exists, allowing each user to record if he/she is satisfied by his/her interactions with other users (e.g., in Facebook a user can click on the button "`I Like It`"). Such positive/negative users' interactions are a useful information sources to compute the trust between users themselves [9, 15] on the basis of the concept of social capital [1]. In fact, a high rate of positive interactions means that a user u can get a concrete advantage to interact with a user v and, therefore, trust should increase (resp., decrease) in presence of positive (resp., negative) interactions

In compliance with terminology adopted in *trust theory*, the first component to compute trust is represented by the satisfaction of u about v as *reliability* and it is denoted by $rel_{u \rightarrow v}$. We highlight that generally reliability can indicate several types of trust relationships between two users, as, for instance, the *honesty* that u perceives in v or the *dependability* that u has with respect to the v's behavior. In this work we use the term meaning how much u is satisfied by the services provided by v. For example, in our experiments with the social networks CIAO and EPINIONS, the users provide reviews on commercial products, and the reliability that u has in v represents how much u is satisfied by the reviews provided by v. Usually, reliability can assume values ranging in the interval $[0..1] \in \mathbb{R}$ and the higher $rel_{u \rightarrow v}$, the higher the perception of the reliability of v by u. Note that reliability is an asymmetric measure: this implies that $rel_{u \rightarrow v} \neq rel_{v \rightarrow u}$.

The second trust component is a global measure of the trust perceived by the whole OSN about each other user v. We call this measure *reputation* of v and denoted it by rep_v in the interval $[0..1] \in \mathbb{R}$. The reputation is computed by averaging all the reliability values $rel_{u \rightarrow v}$ for each $v \in \mathcal{U}$.

The two trust components are joined in a unique value to compute the *trust* $t_{u \rightarrow v}$ of u about v as:

$$t_{u \rightarrow v} = \alpha_u \cdot rel_{u \rightarrow v} + (1 - \alpha_u) \cdot rep_v \tag{6}$$

where α_u is a real coefficient belonging to $[0..1]$ which is set by u to weight the relevance he/she assigns to the first trust term with respect to the second one. Trust is an asymmetric measure because in its formulation it accounts for reliability, which is updated by a_u each time u provides a feedback on v. Besides, each time a reliability value is updated by a_u, it sends the new value to the DF that, in turn, returns a reputation value to a_u when it needs to compute a trust measure.

4.3. Compactness: joining similarity and trust measures

As defined in [8], compactness is a measure obtained by combining trust and similarity in a unique measure, say $\gamma_{u \to v}$. By means of compactness we are able to exploit importance users gives to the mutual similarity with respect to the mutual trust. We model the level of importance given to the similarity by a real coefficient Ws, ranging in [0..1], and, consequently, we define $\gamma_{u \to v}$ as follows:

$$\gamma_{u \to v} = Ws \cdot s_{u,v} + (1 - Ws) \cdot t_{u \to v} \tag{7}$$

Since trust is an asymmetric measure, $\gamma_{u \to v}$ is asymmetric, i.e., in general $\gamma_{u \to v} \neq \gamma_{v \to u}$.

Symbol	**Meaning**
$\mathcal{S}$	Social Network
$\mathcal{G}$	Set of groups
$\mathcal{U}$	Set of users
$\mathcal{C}$	Set of categories
$\mathcal{I}$	Set of items
$\mathbf{r}_{u,i}$	review of the user u for the item i
a_u	agent of the user u

a_g	agent of the group g
p_u	profile of the user u
p_g	profile of the group g
$I_u(c)$	interest value of the user u for the category c
$I_g(c)$	interest value of the group g for the category c
B_u	set of behaviors associated with the user u
A_u	access mode preferred by the user u
A_g	access mode set by the group g
$t_{u \to v}$	level of trust perceived by the user u with respect to the user v
$t_{u \to g}$	level of trust perceived by user u with respect to the group g
$t_{g \to u}$	level of trust perceived by the group g with respect to the user u
$s_{u,v}$	similarity between users u and v
$s_{u,g}$	similarity between the user u and the group g
$rel_{u \to v}$	reliability perceived by the user u with respect to the user v
rep_u	reputation of the user u
α_u	weight the user u assigns to the reliability with respect to the reputation
$\gamma_{u \to v}$	compactness perceived by the user u with respect to the user v
Ws_u	weight the user u assigns to the similarity with respect to the trust

W_I	weights the contribution of the interest (I_c) into the computation of the similarity $s_{u,v}$
W_B	weights the contribution of the behavior (I_B) in the computation of the similarity $s_{u,v}$
W_A	weights the contribution of the access mode in the computation of the similarity $s_{u,v}$

Table 1: Main symbols used in the paper, and their meaning.

In Table 1 we reported the meaning of all the symbols used by our notation.

In the next section we discuss the algorithm $U2G$, which is designed to drive OSN group formation, and has been exploited to perform the experimental campaign discussed in Section 7.

5. U2G: Matching users with Groups

In this section we summarize the design of the algorithm User-To-Group (*U2G*), which enables user agents to select the groups to join with by maximizing the values of compactness, defined in Section 4.3.

Let $\mathcal{G} = \{g_1, g_2, \ldots, g_n\}$ be the OSN groups, with $|\mathcal{G}| = n$. Moreover, let $k^u_{\mathtt{MAX}}$ be a threshold ranging in $[0, n]$ which specifies the upper bound on the number of groups u desires to join with, i.e. from any group to all available groups in the OSN but, reasonably, it will be $k_{\mathtt{MAX}^u} << n$. In the following, for convenience, the notation $k_{\mathtt{MAX}}$ will be used instead of $k^u_{\mathtt{MAX}}$.

Algorithm U2G has been designed to select $k_{\mathtt{MAX}}$ groups yielding the largest value of compactness of u vs the joined groups. We assume that as u joins

Data: u: a user, X: a set of groups, m: an integer in $[0, n]$, $k_{\texttt{MAX}}$: the number of groups u can join with

Result: A set Z of groups

Let Y be a set of m random groups extracted from DF;

Let $Z = X \bigcup Y$;

for $g \in Y$ **do**

  a_u sends a message to a_g associated with the group g and let p_g be the profile associated with g ;

end

Let $\mathcal{S}$ be the set of $k_{\texttt{MAX}}$ groups of Z having the highest values of compactness;

for $g \in \mathcal{S}$ **do**

  if $g \notin X$ **then**

    a_u sends a join request to the agent a_g that also contains the profile p_u of u;

    else

      a_u deletes u from g;

    end

  end

end

return Z

Algorithm 1: The U2G algorithm – User Agent Task

with more than one group then each of them still continues to give the whole benefit to u, so that the overall benefit, in term of compactness, received by u is equal to the sum of each contribution. Therefore, in presence of

Data: u: a user, X: a set of groups associated with U,

Result: A set of groups

for $u \in K$ **do**

  a_g sends a message to a_u;

end

for $u \in K \bigcup \{r\}$ **do**

  Compute $\gamma_{g \rightarrow u}$

end

Let $\pi = \frac{\sum_{u_i \in g} \sum_{u_j \in g} \gamma_{u_i \rightarrow u_j}}{|g|^2} \quad \forall \langle u_i, u_j \rangle \in g$;

Let $\mathcal{S} = \varnothing$;

for $u \in K \bigcup \{r\}$ **do**

  if $\gamma_{g \rightarrow u} \geq \pi$ **then**

    $\mathcal{S} = \mathcal{S} \bigcup \{u\}$;

  end

end

Let $\mathtt{Top}_{\mathcal{S}}$ be the set of top-$n_{\mathtt{MAX}}$ users in $\mathcal{S}$;

if $r \in \mathcal{S}$ **then**

  a_g accepts the join request of r;

end

for $u \in K \wedge u \notin \mathcal{S}$ **do**

  a_g deletes u from g;

end

Algorithm 2: U2G – Group Agent Task

an arbitrary number of groups $\mathcal{K} \subseteq \mathcal{G}$, the benefit gained by u in joining with all the groups in $\mathcal{K}$ is given by $\sum_{g_i \in \mathcal{K}} \gamma_{u \to g_i}$. The question of finding the subset $\mathcal{K}^\star \subseteq \mathcal{G}$ producing the best benefit for u under the constraint $|\mathcal{K}^\star| = k^u_{\mathtt{MAX}}$ is equivalent to solve an optimization problem. While we analyzed the theoretical foundation of the problem above in a previous work [8], in this work it is enough to assume that each user agent a_u is not able to know, in advance, the compactness of all groups in $\mathcal{G}$ versus the associated user u. Furthermore, we assume that:

- a_u is able to sample m random groups from $\mathcal{G}$;
- a_u will record into an internal cache the profiles of the groups u joined in the past; we shall denote this set as X;
- m is the number of the group agents that at each epoch must be contacted by a_u.

Algorithm 1 describes the steps a_u performs to find the $k_{\mathtt{MAX}}$ groups to which u can join with, while the algorithm implemented by the group agent is reported in Algorithm 2. In particular, it is assumed that

- the size of each group $g \in \mathcal{G}$ can not be bigger than a threshold $n_{\mathtt{MAX}}$;
- $n_{\mathtt{MAX}}$ is fixed by the group administrator;
- each agent a_g stores into an internal cache the profiles of the users who joined with g;

In the next Section 7 we discuss a set of experimental results aimed at understanding the stability over time of the homogeneity of groups in OSNs when the formation of groups is driven by the sole similarity criteria or by compactness.

6. A computational framework for analysing time-stability of group homogeneity in OSNs

In this section we introduce the conceptual framework developed for studying how the homogeneity of the OSN groups is stable over time.

In this framework, we associate a given OSN with a temporal dataset of events, consisting of a matrix EM, where each row represents an event containing a timestamp, a user identifiers, and the attributes of the event. Events can be actions performed by users, or external events which change the state of the OSN. In addition, we assume that a (non time-varying) matrix TM of trust relationships is available, where each row is a pair of user IDs (u, v), which represents a trust relationship among user u and user v.

In our framework, we will refer to *U2G-Comp* and *U2G-Sim* as two different versions of the algorithm U2G described in Section 5. The former represents the execution of the U2G algorithm on which the compactness γ (Section 3) is computed by setting $Ws < 1$, i.e. groups formation is driven by similarity and trust, while the latter represents the execution of U2G with $Ws = 1$, i.e. the group formation is driven only by the similarity measure.

The framework provides two weights w_I and Ws, real values in the range $[0 - 1]$, which can influence the results of the execution of U2G algorithm. In particular, w_I impacts on the computation of similarity $s_{u,v}$ (see also

Section 4.1 and Table 1), as it represents the weight assigned to the user interest I, while the remaining value $1 - w_I$, in our experiments, is equally divided among the couple (w_A, w_B), where w_B represents the weight assigned to the behavior of the users (the corresponding value c_B is inferred from the analysis of events in the dataset), while the value c_A was set as *random* (it is not in the original dataset). The lower the value of w_I, the higher the incidence of the component c_A in the computation of similarity. We say that c_A is the "uncorrelated component" in our analysis. Furthermore, the higher the value of Ws, the lower the impact of the trust relationship in the computation of the compactness γ (see Section 4.3).

In this perspective, we define below the following measures, that can be used when performing experiments, in dependence of framework parameters w_I and Ws.

6.1. Average similarity and compactness

We define MAC (Mean Average Compactness) and MAS (Mean Average Similarity), as follows:

$$MAC(w_I, Ws) = \frac{\sum_{g \in G} AC_g}{|G|} \qquad AC_g = \frac{\sum_{x,y \in g, x \neq y} \gamma_{x \to y}}{|g|}. \tag{8}$$

$$MAS(w_I, Ws) = \frac{\sum_{g \in G} AS_g}{|G|} \qquad AS_g = \frac{\sum_{x,y \in g, x \neq y} s_{x \to y}}{|g|}. \tag{9}$$

In particular, AC_g (resp., AS_g) is defined as the *Average Compactness* (resp., *Average Similarity*), similarly to the average dissimilarity commonly exploited in Clustering Analysis [20], since a group g can be viewed as a cluster of users. As described in the following of this section, MAC is computed during the training phase of the U2G-Comp algorithm, i.e. it is only used to drive group formation, while MAS is computed during the *test* phase. Therefore measuring the variation of MAS can be useful to verify the homogeneity, in terms of similarity, of the groups formed in the training phase.

6.2. Experimental approach and main parameters

In our framework, we measure and compare the time-variation of the average similarity of the groups in two different cases:

Comp Groups formed by the algorithm *U2G-Comp*, the U2G algorithm is driven by compactness ($Ws < 1$).

Sim Groups formed by the *U2G-Sim*, i.e. the U2G algorithm is driven by the sole similarity criterion ($Ws = 1$).

The computation of the measures are performed following the steps described below:

1. Rows of the matrix EM are *arranged in an increasing order*, basing on the timestamp found on the sixth column.

2. The matrix EM is divided into a *number of time-windows* of equal size. The first time-window will be used as training set and the remaining for the subsequent tests.

3. The *trust network* is constructed by loading the matrix TM and for all.

4. The *training* is performed by executing the algorithm *U2G-Comp* (resp. *U2G-Sim*) on the first time-window, in order to form groups of users.

5. The training is stopped once the value of MAC for *U2G-Comp* (MAS for *U2G-Sim*) is "stable", i.e. the difference between the value measured after the previous execution and the current value is less than a given threshold (in our case it was 5%).

6. Data of the remaining time-windows is loaded, one after another and, for each of them, MAS is computed without executing the algorithm U2G, such that group composition remains the same as in the end of the training phase. This technique allows us to study the variation of MAS due to the addition of events, which represent the execution of some further actions by the users.

7. Experiments

In this section we discuss some experimental results obtained by applying the computational framework described in the previous section on two different datasets extracted from social networks CIAO and EPINIONS. Both datasets have been crawled by some researchers in order to carry out the research described in [27][2].

We have chosen as datasets for our experiments EPINIONS and CIAO since they are two good testbeds that are widely used in the research of trust evaluation and trust-based recommendations, because they have both the information of user trust relationships and user-item ratings. Users can review items and assign them numeric ratings. They can also build their own

[2]Data used in our experiments are publicly available at `http://www.public.asu.edu/~jtang20/datasetcode/truststudy.htm`

trust network by adding the people whose reviews they think are valuable. Moreover, in EPINIONS and CIAO datasets time stamps information of the reviews have been published, and this information is crucial for our study on time-stability of the homogeneity.

EPINIONS consists of $22,166$ users, while CIAO contains $12,375$ users. Both datasets consist of a pair of matrices (EM, TM), as described in Section 6. In the specific case, rows of matrix EM have the form {*userID, productID, categoryID, rating*, *helpfulness*, *timestamp*}. More in detail, *categoryID* represents the commercial category of the product identified by *productID* which received the rating by the user identified by *userID*, and *helpfulness* represents the level of satisfaction of the other user for that *rating* (the latter has not been used in our experiments).

7.1. Experimental settings and software

Table 7.1 contains the parameters used to carry out the experiments for both datasets, CIAO and EPINIONS. The size of the training set, as well as the remaining data used for test are reported in the last two rows. In case of EPINIONS, the training set is represented by the $100k$ events, while in the case of CIAO the training set is made by the first $10k$ events.

The software used for the experiments is an extension of the previous one, which has been implemented in Java, and was used to prove the convergence of the algorithm U2G [8]. The used software, as well as the entire set of configurations, experimental results and scripts to process and plot results can be downloaded at `https://github.com/fmes/simU2G`.

Table 2: Parameters used in experiments on the EPINIONS and CIAO dataset.

EPINIONS		CIAO	
Parameter	Value	Parameter	Value
Number of Groups	100	Number of Groups	50
$k_{\mathtt{MIN}}$	0	$k_{\mathtt{MIN}}$	0
$k_{\mathtt{MAX}}$	50	$k_{\mathtt{MAX}}$	50
$n_{\mathtt{MIN}}$	0	$n_{\mathtt{MIN}}$	0
$n_{\mathtt{MAX}}$	30	$k_{\mathtt{MAX}}$	10
N_{REQ}	5	N_{REQ}	5
Size of the Training Set	100, 000	Size of the Training Set	10, 000
Size of the Test Set	822, 267	Size of the Test Set	26, 065

7.2. Results

Experiments were performed by varying weights w_I and Ws in the range $[0.1 - 0.9]$.

Figures 1-2 represent the results for the CIAO network, as five-number summary, i.e. 1st, 2nd, and 3rd quartile, minimum and maximum values (bottom and top whiskers) of MAS computed after the training, for all the remaining time windows. In particular, Figure 1 shows the overall behavior of the algorithm *U2G-Sim* for different values of w_I, while Figure 2 represents the different values of computed MAS for the algorithm U2G-Comp. In this last case, the value of Ws was fixed as 0.5. By comparing figures 1 and 2, it can be observed that the lower the value of w_I, the lower the value of overall similarity obtained at the end of the test for U2G-Sim (Figure 1), while the results obtained for the groups formed by the algorithm *U2G-Comp* show higher values of MAS, in the order of about 10%. This first set of results say us that driving groups formation by compactness (i.e., mixing trust with similarity) – when the weight w_A of the uncorrelated component A has an incidence in the order of at least 25% (i.e., $w_A + w_B > 0.5$) – will results in a set of groups that best preserve their internal similarity over time, i.e. the groups result time-stable in homogeneity with respect to the average similarity.

A further set of results is shown into Figures 3 and 4, to report the execution of the algorithm *U2G-Comp* for Ws in the range $[0.1 - 0.9]$, $w_I = 0.1$ and $w_I = 0.5$ respectively. In the case $w_I = 0.1$ (Figure 3) the leverage of the couple (w_A, w_B) is the highest, and even in the case the weight of the trust component is low (i.e., Ws assume values larger than 0.5), values of MAS assume values which are larger than 0.8 (e.g., median is 0.82 for $Ws = 0.8$), showing a good resilience – in terms of time-stability – with respect to the results of *U2G-Sim* (compare with Figure 1, $w_I = 0.1$). Nevertheless, the slight variability of the five-number summary shown in Figure 3 disappears as w_I is set to 0.5, as shown into Figure 4, which is the expected behavior, as the uncorrelated component starts to assume a less significant weight.

Figures 5 and 6 show the results related to the execution of the algorithm *U2G-Comp* and *U2G-Sim* for CIAO dataset in the cases $[Ws = 0.5, w_I = 0.1]$, and $[Ws = 0.5, w_I = 0.9]$ respectively, on which x-axis represents the number of the time-window which is loaded before the computation of MAS. By our analysis, these cases "lie at the borders": in the former the average similarity of the groups formed by the algorithm *U2G-Comp* is higher than the similarity of the groups formed by the algorithm *U2G-Sim*, while in the

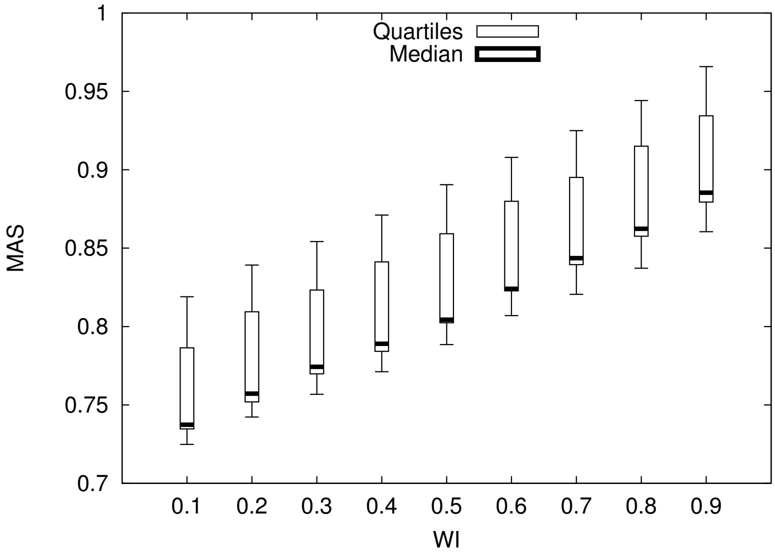

Figure 1: CIAO - MAS vs parameter w_I achieved by the U2G-Sim.

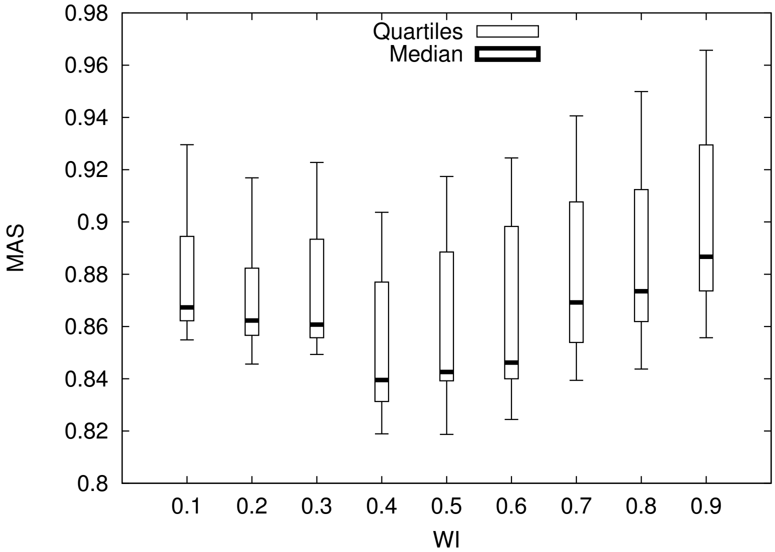

Figure 2: CIAO - MAS vs. parameter w_I achieved by the U2G-Comp with $Ws = 0.5$.

latter we observe almost no difference.

Figures 7 and 8 represents the reduction ratio – i.e., the ratio between the

MAS measured at the end of the training and the MAS measured at the end of the test – for the CIAO dataset. Results shown in Figure 7 confirm that the

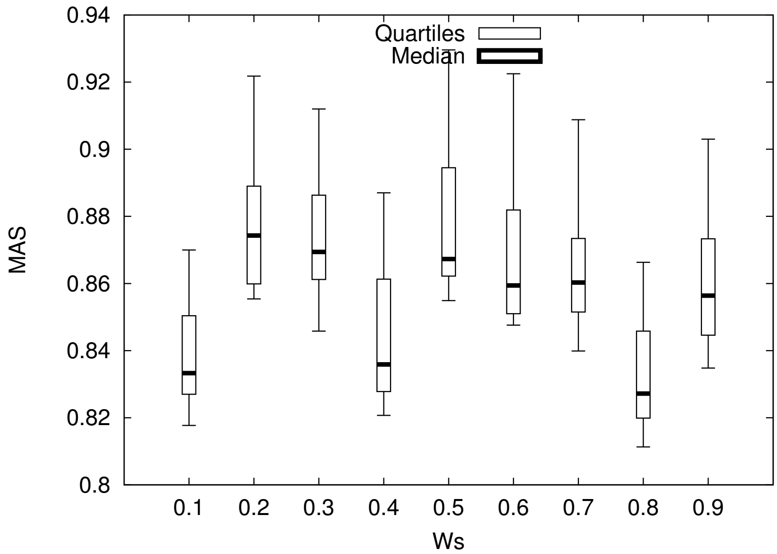

Figure 3: CIAO - MAS vs parameter Ws achieved by the U2G-Comp. ($w_I = 0.1$).

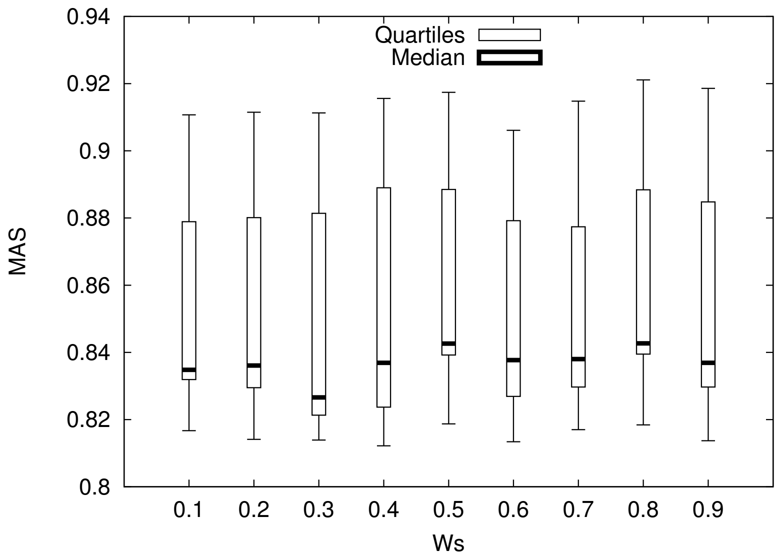

Figure 4: CIAO - MAS vs parameter Ws achieved by the U2G-Comp ($w_I = 0.5$).

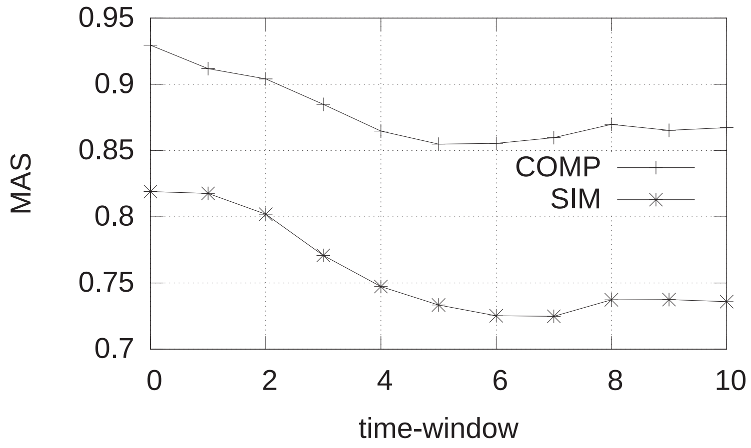

Figure 5: CIAO - MAS measured over 10 time-windows for *U2G-Sim* ($Ws = 0.5, w_I = 0.1$), and *U2G-Comp*, $w_I = 0.1$.

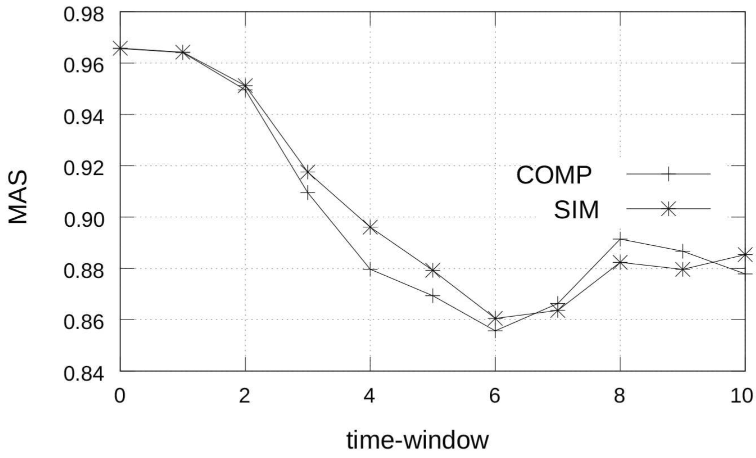

Figure 6: CIAO - MAS measured over 10 time-windows for $U2G - Sim$ ($Ws = 0.5, w_I = 0.9$), and $U2G - Comp$, $w_I = 0.9$.

average similarity inside groups is stable until $w_I = 0.4$, while starting from $w_I = 0.5$ MAS reduction becomes relevant. Nevertheless, we remark that the five-summary of Figure 2 shows values of MAS for U2G-Comp which are higher than those reached by U2G-Sim until $w_I = 0.6$. Figure 8 reports the reduction ratio of MAS for $w_I = 0.1$. The value reported for Ws is related to the setting of U2G-Comp (indeed, in the case of U2G-Sim, $Ws = 1$). However, for U2G-Sim we reported, for convenience, the measure of MAS next to the value obtained with U2G-Comp, by observing that the reduction ratio in the case of U2G-Comp is always lower than that of U2G-Sim, and does not increase as parameter Ws increase.

A further set of results is reported for EPINIONS into Figures 9-12. In this case, we observed almost the same behavior reported in the case of CIAO. In particular, the five-number summary shown into Figures 9 and 10 denotes an interquartile range which is lower then that shown for CIAO (compare with Figures 1 and 2). This is due to the fact that EPINIONS dataset is larger than CIAO by an order of magnitude, therefore results show a less variability, i.e. more accurate that those obtained for CIAO dataset. Furthermore, we compared results reported into Figures 5-6 with those of Figures 11 and 12: while the overall behavior of the former (Figures 5 and 6) is quite confirmed by the latter, observed that, for $w_I = 0.1$ the gap between the two approaches – in terms of similarity – shown in Figure 11, is larger than that shown into Figure 5. These results seems once again consistent with the fact that EPINIONS dataset is made by about 1 million events (CIAO about 36000 – see Table 7.1), as remarked before.

We further discuss the experimental results shown in this section in section 9.

8. Discussion

In this section we summarize and discuss the background and the main findings of the experiments presented in the previous section.

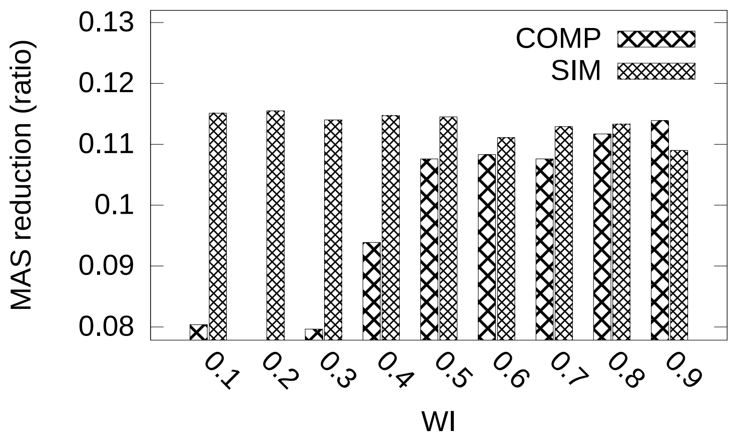

Figure 7: CIAO - MAS reduction vs parameter WI, U2G-Comp and U2G-Sim ($Ws = 0.5$) .

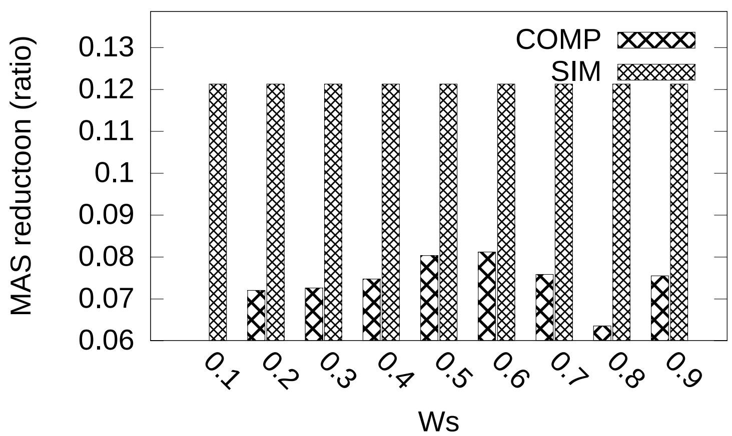

Figure 8: CIAO - MAS reduction (ratio) vs parameter Ws U2G-Comp and U2G-Sim ($WI = 0.1$) .

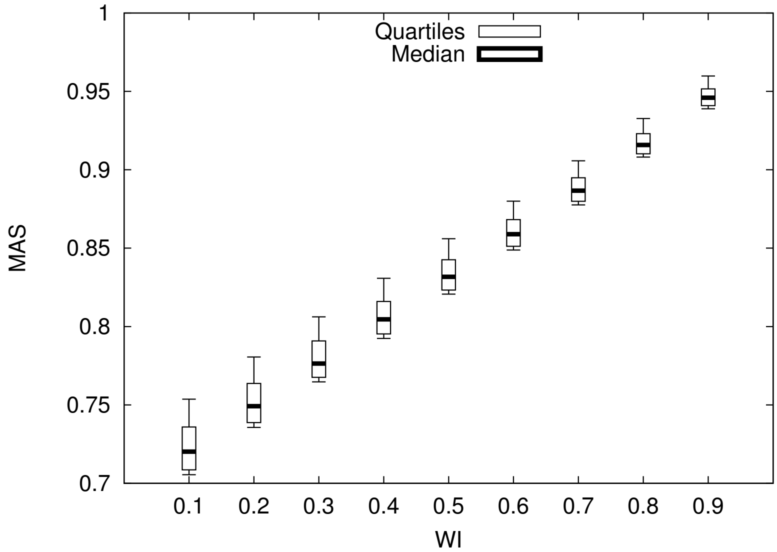

Figure 9: EPINIONS - MAS vs parameter w_I achieved by the U2G-Sim

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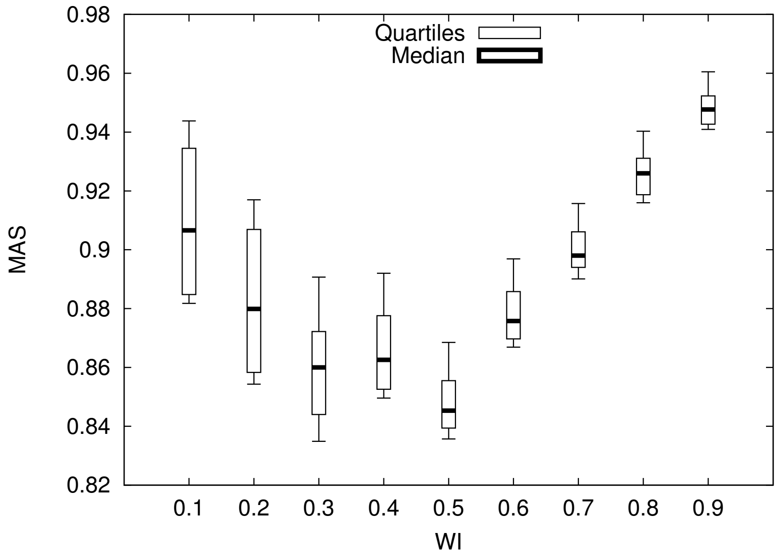

Figure 10: EPINIONS - MAS vs. parameter w_I achieved by the U2G-Comp with $Ws = 0.5$.

The U2G algorithm presented in Section 3 is flexible, i.e. it is able to drive the group formation by considering different combinations of several cost functions, as specified in the experimental approach discussed in subsection 6. In particular, we have carried out some experiments in order to verify whether (and how much) groups formed by considering a non-trivial combination

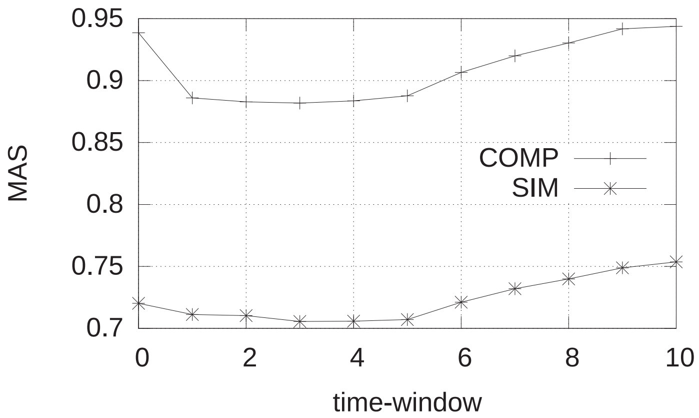

Figure 11: EPINIONS - MAS measured over 10 time-windows for *U2G-Sim* ($Ws = 0.5, w_I = 0.1$), and *U2G-Comp*, $w_I = 0.1$.

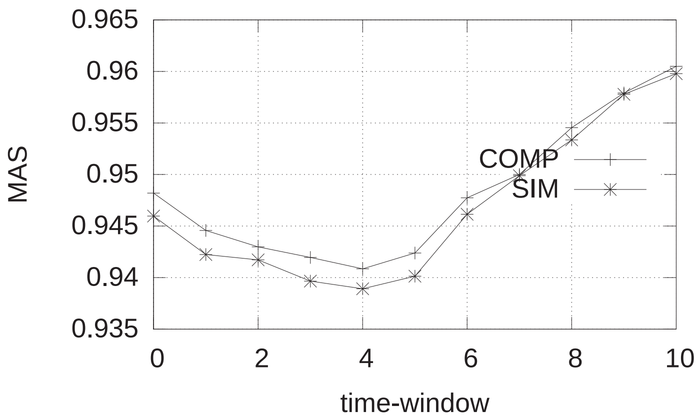

Figure 12: EPINIONS - MAS measured over 10 time-windows for $U2G - Sim$ ($Ws = 0.5, w_I = 0.9$), and $U2G - Comp$, $w_I = 0.9$.

of trust and similarity ($0 < Ws < 1$) are time-stable homogeneous with respect to users similarity, with respect to group formation driven by the sole similarity.

Experiments show that forming groups on the base of users similarity (i.e. U2G with $Ws = 1$) will lead to form "time-stable homogeneous" groups if the *uncorrelated components* included in the computation of similarity assume a weight which is not significant. In this case we verified that, as $W_A + W_B < 0.5$ (i.e. $W_I > 0.5$), the similarity of the resulting groups over time is not affected by a significant degradation.

Nevertheless, when group formation is driven by compactness (i.e. combining similarity and trust by setting $Ws < 1 \wedge Ws > 0$), groups will result in a time-stable homogeneous behavior even if uncorrelated behavioral components included in the computation of similarity assume a significant weight ($W_A + W_B > 0.5$, i.e. $W_I > 0.5$). The result above says us that trust relationships will help to improve the level of resilience, in terms of similarity, also in presence of behavioral components which are not strongly linked with the others. In other words, mixing trust and similarity to aggregate users into groups yields more robust results because potential errors due to the similarity measures may be balanced by the contribution due to the trust.

Interestingly, experiments show that there is no tight relationship between the results reported in the previous paragraph and the weight assigned to the trust component ($1 - Ws$) in the computation of compactness. In other words, even when the weight assigned to the trust relationship in the computation of compactness is very low (i.e., $1 - Ws = 0.1$), groups formed by the algorithm *U2G* show a higher level of time-stability with respect the similarity measure.

Finally, it is important to highlight that, in our paper, we discuss how the effectiveness of the group formation, in terms of MAS, tightly depends on the parameters named W_s and W_I. The other parameters, that we have reported in Table I, do not have a particular impact on this study, unless we choose unreasonable value for them. We have performed a sensibility analysis, varying these parameters in their space of admissibility, without observing any significant variation of the effectiveness of the group formation. We also remark that the only parameters that affect the results are the size of the training and the test set. However, the issue of how the size of training and test set influence the ability of the algorithm to form good groups is orthogonal to the issues of how W_s and W_I impact on the group formation. Our paper is devoted to treat only these two latter issues.

9. Conclusions

In this work we discussed the results of an experimental campaign aimed at studying the time-stability of OSN group homogeneity in terms of similarity. In order to carry out this study, we have introduced a conceptual framework which takes into account temporal dataset of events – which represents the evolution of the social network – and a (non time-varying) matrix of trust relationships. The framework introduced several different weights that allowed us to characterize the impact of the user similarity compared to the component said "uncorrelated", i.e. that are not in the original dataset, as well as the impact of the weight on the trust relationships.

The experimental study has been conducted with a distributed algorithm for OSN groups formation, named U2G, which exploits the compactness measure, i.e. a combination of similarity and trust, on two different OSN datasets, CIAO and EPINIONS. As algorithm U2G is provided with the flexibility needed to implement the experimental approach of the conceptual framework, it permits to employ different combination of similarity and trust, e.g. to set the weight of the trust as zero and study the similarity-driven group formation.

Obtained results have shown that forming groups on the base of users similarity will lead to form time-stable homogeneous groups if the weight of the uncorrelated components is not significant. Nevertheless, when group formation is driven by compactness, i.e., by combining similarity and trust, groups will result in a time-stable homogeneous behavior even if uncorrelated behavioral components included in the computation of similarity assumes a significant weight. Therefore, trust relationships will help to improve the level of resilience, in terms of similarity, also in presence of behavioral components which are not strongly linked with the others.

Interestingly, even when the weight assigned to the trust relationship in the computation of compactness is very low, group formation driven by compactness will lead to a number of groups having a higher level of time-stability with respect the similarity measure.

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