Analyzing Two Participation Strategies in an Undergraduate Course Community

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Abstract. Nowadays, information systems, and more particularly, learning support systems, tend to include social interaction features in their design. These features generally aim to sustain the activities of partially virtual communities and help extend the physical presence of the community in the virtual space. In order to achieve a sustainable community, it is important to understand how the strategies used to promote participation influence the way in which community members interact and relate with each other. This article reports a comparative study on two different student participation strategies mediated by a learning support system. The first strategy stressed the quantity of contributions, and the second one promoted both quantity and quality of contributions. By analyzing the resulting interaction networks, we could better understand the interaction patterns among students in their respective communities and conclude ways to monitor interaction and help maintain the community sustainability in time.

Keywords: Interaction patterns, participation, community structure, socio-technical analysis, monitoring, partially virtual communities.

1 Introduction

Social computing has become an important field in the research agenda of the groupware community. In fact, since its 16^{th} edition in 2013, the ACM CSCW conference (one of the most competitive and cited in the field) changed its name to: "ACM Conference on Computer Supported Cooperative Work and Social Computing", thus reflecting a particular interest on socio-technical issues.

Online communities are changing the fundamental way in which people share information and communicate among them. This is affecting the global economy, social interaction, and every aspect of our lives [25]. This paradigm shift changes the main issues involved in the design and development of collaborative systems. It raises a number of questions linking social sciences and human-computer interaction,

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such as stating the relationships between software, social groups, and individuals; managing privacy and security concerns; and also establishing relevant criteria for measuring the success of online and partially virtual communities.

Interaction in these communities can be found in several situations. For example, it can be completely based in the virtual space (e.g. gaming communities), or it may lead to extend the physical presence toward a virtual scenario (e.g. students using an online discussion board outside their class hours) and, conversely, augment the physical space with information brought from the virtual space (e.g. a *Facebook* notification system triggering an alert in a mobile phone when a contact becomes available). Since most physical communities may benefit from extending their presence into an online environment, we are interested in studying in more depth, the dynamics of what Gutierrez et al. refer to as partially virtual communities [8]. In these communities, members have the opportunity to interact through both, a virtual and a physical space. Their members know each other, and this mutual information is useful to understanding the context of the contributions of others.

In fact, when we consider learning communities, today various universities use learning platforms that support interaction among students and instructors, mainly in the form of online asynchronous discussion boards. This form of social interaction is broadly accepted as a way to support different courses, for both instructors and students, [17] and it has led to an understanding of how these tools are used [19].

These communities usually suffer from a lack of user participation at their initial stages of their life cycle. Therefore, it turns out necessary to motivate people to contribute using different strategies that may help the community reach a minimum number of users and content, in order to ensure its sustainability over time [3]. This situation raises a couple of questions: (1) *how do users react to different participation strategies when they get exposed to generate new content?*, and (2) *how do these strategies impact the structure of the community?*.

This article reports the results of a comparative study, where two homogeneous groups of university students were exposed (through the use of a learning platform) to two different participation strategies. The first strategy enhanced the quantity of students' contributions, and the second one enhanced the quantity of contributions, as well as the perceived quality of them by others.

Each group was assigned to a dedicated online discussion board that supported their activities as a partially virtual community, and we gathered data in a monthly basis over a period of 15 weeks, concerning the number of published articles for all users and the number of replies given to the published articles. Afterwards, we built the interaction network for each group, and we analyzed how it evolved over time. The analysis of the results indicates that the participation strategy used to motivate contributions in the community indeed marked a difference on the interaction patterns of their members, and that by performing such an analysis it is possible to monitor the evolution of the community over its life cycle.

Next section reviews participation strategies in online communities, as well as interaction patterns in social networks. Section 3 describes the case study, the participation strategies used, and the metrics used to analyze the community structure. Section 4 shows and discusses the obtained results. Section 5 presents the conclusions and further work.

2 Related Work

This section first introduces reported strategies for fostering participation in online and partially virtual communities. We then present some of the most well known methods, used in Social Network Analysis, for quantifying and analyzing interaction patterns among members of a social group.

2.1 Participation in Online Communities

The problem of improving participation in online communities has been tackled by considering theories derived mainly from social psychology. For example, Cheng and Vassileva proposed a motivation strategy based on persuasion, in order to reinforce the value of quantity and quality in user contributions [2]. Harper et al. studied the effects of social comparisons (i.e., displaying how community members can compare to others in the system, e.g. in terms of performance, participation and interaction) [10]. Janzik and Herstatt proposed a set of incentives to motivate community members (using peer recognition, status, reputation, and identification) [12].

Preece and Shneiderman followed users' life cycles through their evolution in a community and listed strategies for motivating their participation according to their evolving role within the group [20]. Gutierrez et al. proposed a framework for motivating user participation based on intrinsic motivation, which included several strategies such as displaying rankings, proposing challenges, and displaying feedback [7]. In the case of physical and partially virtual communities, Westerlund et al. found out that trust and commitment are multi-dimensional constructs, where their evolution in a social network is dynamic and complex. Typically, trust precedes commitment [28].

Several authors claim that communities have to achieve a certain critical mass, i.e., a minimum number of users in order to sustain activity and information exchanges within the group [1, 14, 21]. Dabbish et al. studied the effects of turnover in online communities, i.e., the dynamics of user entrance and exiting in a particular group. In online communities, both participation and member commitment tend to increase when there is a noticeable turnover. This is understood by the group members as a dynamic evidence of the community activity and it is consequently perceived by them. Therefore, turnover may dramatically impact information exchange and content generation within the group. It turns out to be more important for the sustainability of a community to achieve a critical mass of contributions rather than a critical mass of users [4].

According to Cheng and Vassileva, regulating the quality and the quantity of user contributions, therefore ensuring a sustainable level of user participation in an online community, requires an adaptation of the participant rewards for particular forms of participation, depending on the user reputation and the current needs of the community. Their proposed methodology is to measure and reward the desirable user activities by computing a user participation measure (in order to enhance quantity and quality of contributions), and then clustering users according to this value [3].

2.2 Social Network Analysis

Discussion boards (i.e. a space where users can interact through posted messages, mainly in an asynchronous way) are broadly accepted as a tool for supporting user interaction in online communities. In fact, among all the different forms of computer-mediated communication used to support learning and teaching processes, asynchronous discussion boards are the most frequently used [9].

Researchers and instructors claim that discussion boards reinforce the learning experience by increasing student commitment in their courses, resulting therefore in significantly better results [17]. However, participation and interaction in online discussion boards does not necessarily translate to higher grades at the end of an academic period [6, 19]. In terms of platform support, Vonderwell and Zachariah found that technology, user interface design, content-area experience, student roles and tasks, and information overload, influence online learner participation and their interaction patterns [24].

For better understanding the underlying interaction patterns that emerge in a particular kind of human group, social scientists have historically used techniques from social network analysis [26]. In formal terms, social network analysts work at describing underlying patterns of social structure (based on people interactions), explaining the impact of such social structures on other variables [27]. Since the 1970s, the empirical study of social networks has played a central role in social science, and many of the mathematical and statistical tools used for studying these networks have been first developed in sociology [18].

Social network analysis manages social relationships in terms of network theory. It models individual actors within the network as *nodes*, and the relationships between them as *ties*. For example, Alice and Bob are friends in real life, and they declare this relationship in *Facebook*. This representation is modeled as Alice and Bob as nodes in the network, and they are tied by a relationship that reflects their friendship.

Several approaches for social network analysis have been successfully used in CSCL scenarios to understand participation and interaction aspects during learning processes [11, 15, 16, 22]. Course communities can be understood as graphs where the students represent the nodes and the edges indicate the relationship among nodes. Therefore, social network analysis techniques are mainly expressed in terms of graph theory. Among the main metrics used to characterize and study social networks, we identify: degrees, centrality, density, clustering, cliques, and cohesion [23]. Finally, a visual representation of social networks is important to understand the network data and convey the result of the analysis [5].

Since social networks can be represented as graphs, it is natural to assume that it can be composed by a wide variety of sub-graphs. One important local property of these networks is the so-called *network motifs*, which is defined as recurrent and statistically significant sub-graphs (or patterns) that are present in the network. Although network motifs may provide a deep insight into the network functional abilities, their detection is computationally challenging [13].

3 Case Study Scenario

This section describes the global scenario used for studying the effects of two different participation strategies and how they affect the interaction patterns among its group members. Later, we identify and discuss the key metrics to quantify in our analysis.

3.1 Settings

We worked with two groups of students (30 and 48 people respectively) enrolled in the course *Information Technology* from the Business School at the University of Chile. The first group was composed of 30 students (16 men and 14 women), and they participated in this study between March and June 2012. The second group involved 48 students (19 men and 29 women) that participated between August and November 2012. None of the students was in both groups simultaneously.

Within each group, we put two versions of an online discussion board in service, which runs on the learning platform that students regularly use to support their activities. Both discussion boards offered exactly the same services (e.g. publication of new topics, possibility of replying to others' contributions, notifications concerning user availability and recent activity), except that they used different algorithms to calculate the users' participation. This metric was visible in the user interface of the tool, and it was also used to rank the students according to their participation.

The course lecturer and teaching assistants had also access to the platform, but they had no privileges to moderate content, nor were identified as having a different role. This reduces the pressure on community members and allows them to express themselves. Thus, it was possible to properly identify their interaction patterns.

As part of their mandatory assignments for completing the course, students had to perform three short projects, pass three exams and regularly contribute in the discussion board by including recent news found in diverse media related to the different topics covered in the lecture sessions. In order to make a contribution, students had to select news, cite their respective sources (e.g. a link to the original article found on the Web), and write a short personal opinion on it. Once this contribution is made available in the software platform, other students had the chance to rate the article (according to their own perception on quality and pertinence) and comment on the contribution. It is important to note that ratings could only be made after a student commented on the contribution in order to address the typical free riding situations.

The user interface is divided into two modules: (1) a main page where users can read the different contributions published in the site, and (2) a detailed view of one of these contributions. The first module displays a list of the 10 most recent contributions, a tag cloud and a panel of links pointing to other articles classified by categories and relevant tags (Fig. 1). This element, alongside with the search bar, helps users identify and find relevant documents, facilitating thus the interaction between the author and the reader. Users can access to the detailed view of any contribution by either clicking on its title, content, or dedicated icon at the bottom of the box. Other articles can be found by navigating through different pages at the bottom of the site.

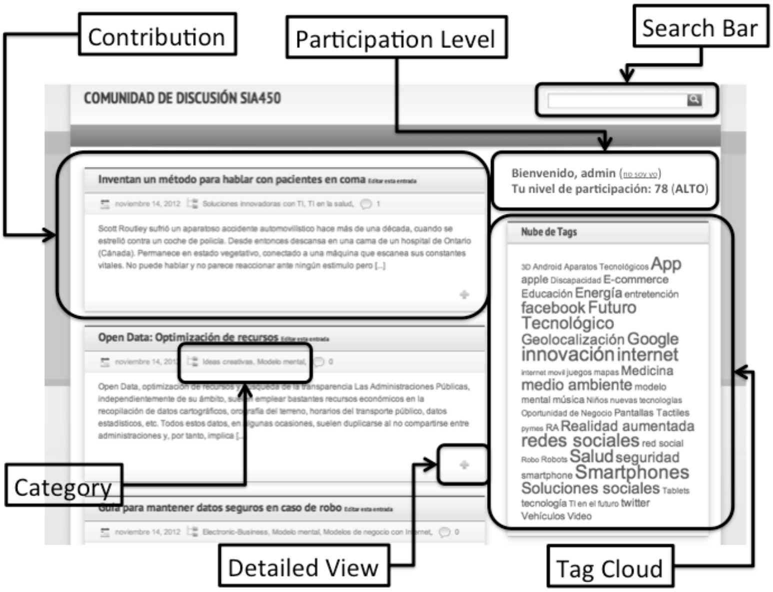

Fig. 1. General user interface of the online discussion board

The detailed view of each contribution displays the complete text (citing the source from where it was taken), the personal opinion of the author regarding the content of the article, and a list of reactions made to the contribution by other students (Fig. 2). Once a student publishes a comment linked to a particular contribution, the system proposes a rating system for grading the perceived quality of the article on a scale of one to seven stars. We chose to set this metaphor, since students are graded in a similar way in their regular courses at the University.

The platform was in service for both groups over 15 weeks. We established three milestones where we gathered the traffic data from the site, and afterwards reinitialized the counters. These milestones were roughly placed every five weeks, in order to make results comparable not only between groups, but also to analyze the evolution of the interaction patterns over time.

In each milestone, we identified: (1) the number of published contributions of each student; (2) the perceived quality of the contributions by other students; (3) the number of comments to other articles made by each student; and (4) the number of comments received by the other students. With these values, we computed a participation metric for each student, according to the strategy used in each situation. Moreover, each student could see his/her participation value in the home page of the platform every time s/he logged in. In this section of the home page, the students could get the computed value for their participation, and a label that situated them within the group. We classified students in three categories: “high participation” (top 20% of the whole group), “low participation” (bottom 20% of the group), and “medium participation”.

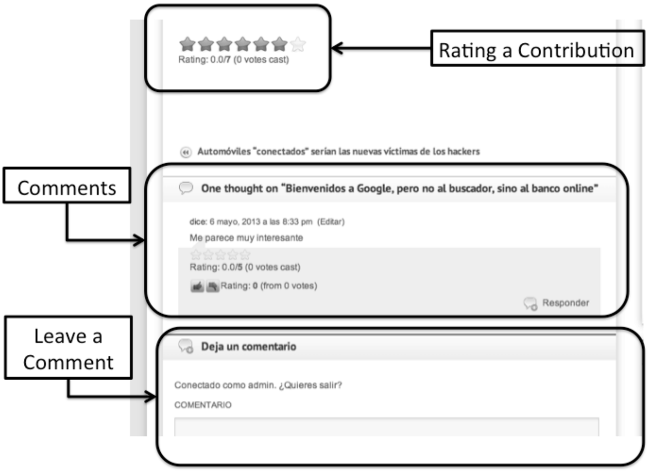

Fig. 2. Detailed user interface for the comments

The maximum and minimum values to set up the three categories were calculated in real time. At each milestone, we published the participation values for all students and we reinitialized the counters for all metrics.

3.2 Measuring User Participation

Every group involved in this study used a particular participation strategy to motivate contributions. We computed the participation function with the values gathered in each milestone, considering the number of published articles (A), perceived quality of the contributions (Q), number of published comments to other students (PC), and number of received comments from other students (RC).

In the first scenario (i.e. the first group), we highlighted the quantity of contributions rather than the quality of them. With this strategy, our aim was for students to increase the number of contributions in time. Considering the four metrics, we computed the value of participation (P) for the first group as follows:

$$P = A + PC . \tag{1}$$

The participation value is in this case a function of the number of published articles and the published comments to other students. We purposely did not consider in Eq. 1 the value of received comments and the perceived quality of the contributions by other students.

On the other hand, the second scenario (i.e. the second group) also included quality as a dimension of how participation is measured. With this strategy, we also aimed to increase the number of contributions, but also to improve the perceived quality of them by the other students of the group. In this case, we computed the value of participation (P) as follows:

$$P = A \times Q / 2 + RC . \tag{2}$$

In this case, the participation value stresses the quality of the contributions, since those that are perceived as more "useful" or "pertinent" by other members, will weigh more in the participation value of a student. The students were pushed to write personal opinions with a minimum length (300 words) before publishing the article, in order to ensure a certain level of quality.

In Eq. 2 we have also considered the number of received comments instead of the published ones. This was done for two reasons: (1) students will tend to comment on those articles that they find interesting or useful, therefore they might be of better quality; and (2) when a student posts a comment on the contribution of another student, s/he helps increase the other's participation value instead of his/her own.

3.3 Relevant Metrics to Analyze

We modeled the interaction network as a weighted directed graph, where the nodes are the students and the edges between nodes represent the number and direction of comments that one student published to another. Figure 3 shows an example of the representation of the network: Alice, Bob and Charlie are students in the course and published at least one article; Alice posted three comments to Bob, Bob commented four articles written by Charlie, but Charlie only returned one comment to Bob.

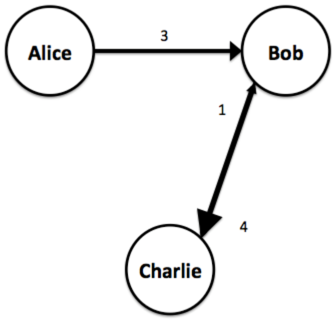

Fig. 3. Example of the interaction network

In order to understand the interaction network, we analyzed these interactions considering the following metrics:

- *Indegree*: This metric represents the number of edges that arrive to a given node. It can be understood as the number of students who write to a particular node.
- *Weighted indegree*: This indicates the number of edges that arrive to a given node, weighted by the number of comments. This metric can be understood as the number of comments that a given student receives.
- *Outdegree*: This metric shows the number of edges that emerge from a given node. It can be understood as the number of students that a particular node is writing to.

- *Weighted outdegree*: This is the number of edges that emerge from a given node, weighted by the number of comments. It represents the number of comments that a student posts in the community.
- *Modularity*: This is a factor between -0.5 and 1.0 that reflects the division of the network into groups within which the network connections are dense, but between which they are sparser. If this value is positive, the number of edges within groups exceeds the number expected on the basis of chance. When this value approaches 1, it means the strength of division of a graph structure is high (e.g. clear and distinct groups within the community).

Finally, we will analyze the different triads that coexist within the network in the form of 3-node motifs. There are 13 different isomorphic 3-node motifs, and they are presented in Figure 4. It is worth pointing out that among these motifs, seven of them are complete (or partially complete), since they tend to form 3-cliques (i.e. a subset of three nodes in a graph, such that every two nodes in the subset are connected by an edge). On the other hand, six of the motifs are partially incomplete, since they represent the interaction between only two out of the three nodes in the triad.

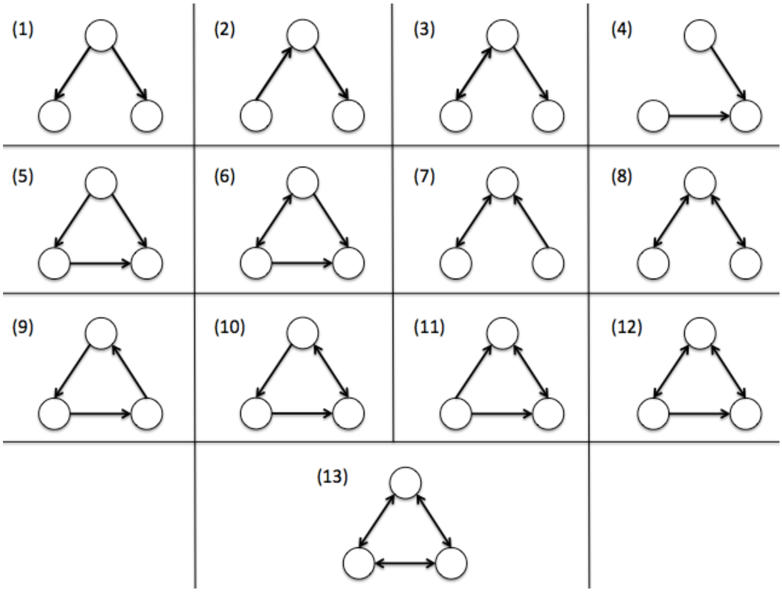

Fig. 4. Isomorphic 3-node motifs

4 Analysis of the Results

This section reports the main results obtained by analyzing participation metrics and the graph structure of the two networks used in the study. For analyzing and visualizing the networks, we used the software Gephi v.0.8.

We first analyze the main participation metrics defined in section 3, and then we show the main structural metrics of the graph. Later, we identify and quantify the different 3-node motifs that compose the structure of each network. Finally, we comparatively discuss these results between both scenarios in order to better understand how the different participation strategies affect both interaction networks (and hence, the interaction patterns among students in their respective communities).

4.1 Participation Metrics

Table 1 presents the mean values obtained for the participation metrics (i.e. number of published articles, perceived quality of contributions, and number of comments) in each scenario. It is worth pointing out that after each milestone, we reinitialized all counters.

Table 1. Participation Metrics (Mean Value)

Scenario 1	Weeks 1 – 5	Weeks 6 – 10	Weeks 11 – 15
Number of articles	11.31	6.41	12.17
Perceived quality	5.89 / 7.00	5.92 / 7.00	5.95 / 7.00
Comments	28.97	13.00	31.97

Scenario 2	Weeks 1 – 5	Weeks 6 – 10	Weeks 11 – 15
Number of articles	3.20	7.15	12.41
Perceived quality	6.22 / 7.00	6.45 / 7.00	6.27 / 7.00
Comments	14.00	23.35	20.15

The results show that the perceived quality of contributions was better in the second scenario than in the first one. This can be a positive response to the participation strategy motivating quality. However, the number of published articles in the second scenario was lower than in the first one, even if there were more students in the second group. This can be explained since in the second scenario it was mandatory for students to submit a personal opinion of at least 300 words before publishing the contribution in the platform. Finally, the mean number of comments per article significantly increased in the second case (3.09) with respect to the first one (2.12). This can be explained because we induced a quality factor in the participation strategy, and this could have triggered more interest to generate better and more appealing contributions. Nevertheless, in order to properly conclude this fact, we need to carry on further research regarding this situation.

4.2 Network Analysis

After building the interaction graph (in each milestone), we quantified the metrics presented in section 3.3 in order to analyze the structure of the community in time. Table 2 presents these results for each study scenario.

Table 2. Network Metrics

Scenario 1 (30 nodes)	Weeks 1 – 5	Weeks 6 – 10	Weeks 11 – 15
Edges	292	282	321
Average degree	9.73	9.40	10.70
Average weighted degree	17.03	25.13	34.53
Modularity	0.12	0.12	0.14

Scenario 2 (48 nodes)	Weeks 1 – 5	Weeks 6 – 10	Weeks 11 – 15
Edges	436	662	429
Average degree	9.08	13.79	8.94
Average weighted degree	13.42	22.38	19.31
Modularity	0.28	0.19	0.40

Despite the differences in the number of nodes (and hence, the number of edges) in these situations, both the average degree (i.e. the mean number of students that are connected through comments) and the average weighted degree (i.e. the mean number of published comments in the platform) remain similar. However, there is a noticeable difference in both scenarios concerning what happened during the last five weeks: the average weighted degree is significantly greater in the first scenario, and the modularity is significantly greater in the second scenario.

Regarding the first situation, this might be a consequence of a "snowball effect", since the goal of the participation strategy was merely to increase the number of contributions in the community. Therefore, the perceived metric of success is linked to the number of contributions published by the students. In fact, since posting a comment requires less effort than selecting and publishing a new article. This can be a plausible explanation for this particular difference. Moreover, this is linked to the participation metrics for the third period, presented in table 1.

Concerning the second situation, the higher value of modularity is opposed to the closed and homogeneous structure of the community during the whole observation period in the first scenario (when the participation was motivated uniquely through quantity of contributions). It is worth pointing out that greater values of modularity are correlated to the formation of subgroups within the community.

In order to have a closer look at what happened in this situation, Figures 5 and 6 show a visualization of each interaction network at the end of third milestone (i.e. covering weeks 11 through 15). The size of nodes represents the value of the weighted indegree, the colors represent the different modularity classes, and the thickness of the edges represents the number of comments that are posted in that particular sense.

In the interaction network of the second scenario (Figure 6), we can identify a clear subgroup in the community (i.e. black nodes). This subgroup consists of 12 nodes (25% of the network), it has a noticeable central leader (the biggest node in the group), and also a small node that is in between both subgroups. On the other hand, the interaction network in the first scenario (Figure 5) does not display a clear leader within the community, but rather a set of central nodes that gather the attention and drive the interaction of the other students. The structure in this case is rather closed and it does not display clear subgroups.

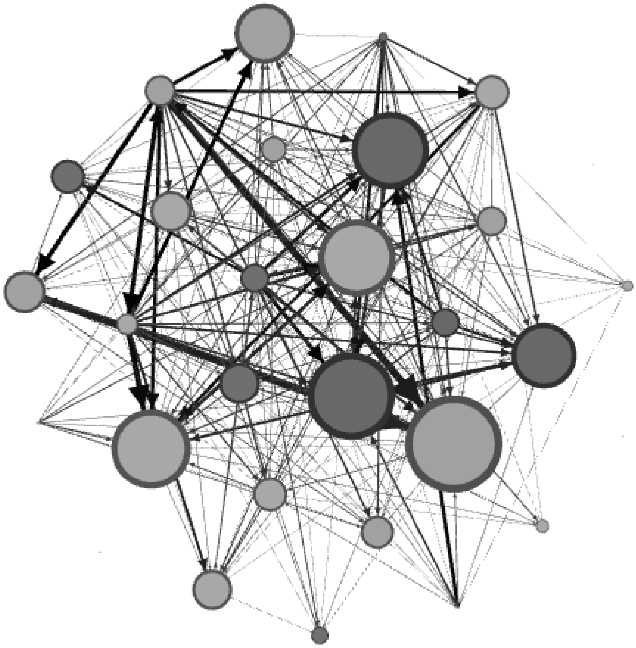

Fig. 5. Interaction network: Scenario 1 – Weeks 11 through 15

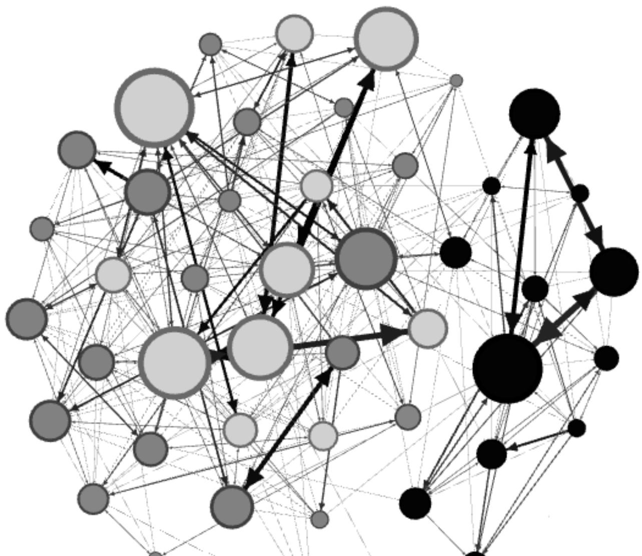

Fig. 6. Interaction network: Scenario 2 – Weeks 11 through 15

At this point, it turns out relevant to analyze if it is worth considering a community structure that is composed of two or more independent subgroups, or if it is better to have a closed and tightly connected group. Both situations have their own pros and cons, and the answer to this dilemma is rather unclear since the answer depends on the context where the community is going to be established. In this case, since we are supporting a small partially virtual community, we would like to benefit from having discussions in small groups. However, to some extent we do have to maintain the size of these subgroups, avoiding that they become independent and generate traffic that will be eventually irrelevant to the rest of the community. Therefore, having a visualization that displays the dynamics of group generation over time would give signs of how the community is evolving, and also if it turns out to be necessary to put some control mechanisms in order to prevent the community break into independent subgroups. In other terms, this kind of analysis can be used for designing strategies for monitoring in real-time the dynamics of a community alongside its life cycle. In relation to this proposition, one way to affect the interaction patterns in the community would be to influence central nodes in the network (e.g. those that gather interest from other members and generate relevant and important traffic). In terms of affecting the participation strategy, this would be related to motivating the activity, aiming to integrate the different groups that appear to be in different modularity classes.

4.3 Identifying and Quantifying Motifs

Figure 7 shows a histogram representing the different isomorphic 3-node motifs in a directed network (as shown in Figure 4). By identifying the different 3-node motifs we can structurally analyze the network representing the community in more depth. In the case of Figure 7, we can see that it supports the results found when analyzing the modularity of the community.

In the first scenario (i.e. where participation was stressed in terms of quantity), the interaction patterns tended to close the group. Thus, the possibility of completing 3-cliques is higher. In this group, motifs 12 and 13 count for about 50% of the total, and they are almost-fully connected (12) and fully connected (13) 3-cliques. Therefore, this is an alternative way to conclude that the community was tightly closed.

Regarding the second scenario, the motifs 3, 7 and 8 count for about 50% of the total, and they all correspond to disconnected 3-motifs. This fact indicates that the community is partially connected (as opposed to what happened in the first scenario), and community managers could take some actions into identifying why this is happening. Eventually they can try to integrate the community, if desired.

In summary, by analyzing the histogram of 3-node motifs, community managers can get an overview of how connected is the community, and how the different interaction patterns are distributed in the whole group. In other words, this technique can be used as an alternative tool for monitoring the evolution of the community alongside its life cycle.

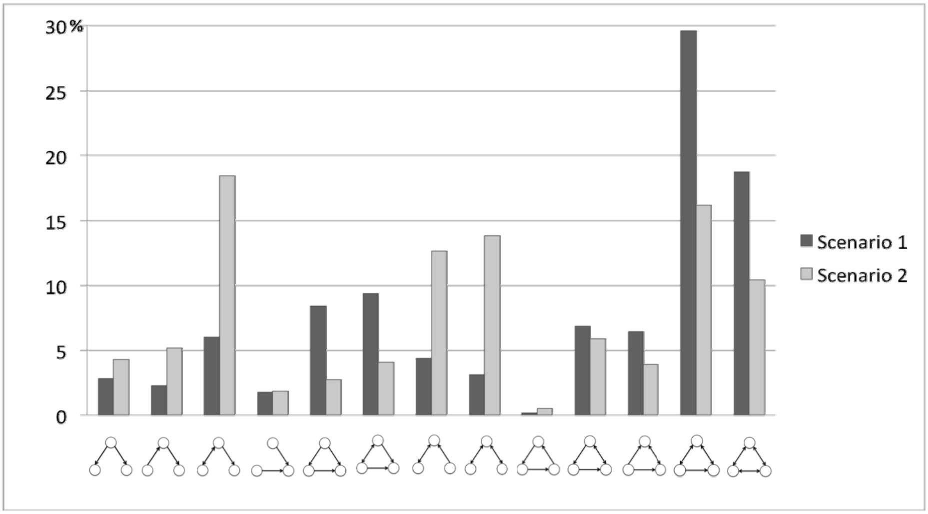

Fig. 7. Three-node motifs found in each interaction network

5 Conclusions and Future Work

This article reports the effects of exposing two homogeneous groups of university students to two different participation strategies in a partially virtual community over a period of 15 weeks. We aimed to motivate contributions in the first scenario by stressing the value of the quantity of contributions, and enhancing the quality of the contributions in the second scenario. We comparatively analyzed the activity within both groups in terms of: (1) participation metrics, (2) structural network metrics, and (3) 3-node motifs that reflect the interaction among members.

Even if we got some relevant observations regarding how participation can be triggered in terms of quantity and quality, it is worth recognizing that neither of both strategies was perfect. In the case of the first scenario, the group tended to follow a snowball effect, where publishing new contributions and generating traffic became the center of the community, rather than the interaction itself. In the second case, the community tended to split into two subgroups that interacted independently. Considering these results, we can say that the participation strategy clearly affected the community structure and the interaction patterns among its members.

By analyzing the different structural network metrics, and more precisely, by having a visualization that displays the dynamics of group generation over time, we can get a first idea on how the community evolves, and also if it is necessary to install some control mechanisms to prevent the community from breaking into independent subgroups. In other terms, this kind of analysis can be used for designing strategies to monitor (in real-time) the dynamics of a community alongside its life cycle. Another alternative for monitoring the activity in the community is analyzing how the community is structured in terms of motifs, which reflect the inner interaction patterns within the group.

There are two major limitations in this study. First, we modeled the interaction network as a directed weighted graph. However, the presented motif classes are based on directed unweighted graphs. Therefore, in the case of detecting weighted edges that outnumber the frequency of a particular motif class, we would need to analyze further in detail the resulting patterns and eventually decide if they need to be considered as independent objects. Thus, the global motif distribution of the network would be altered. Second, some of the presented observations might be due to the differences in the two even homogeneous groups of students. These limitations will be further analyzed in a second stage of this study.

As future work, we are currently studying how we can refine the second participation strategy, in order to better understand the interaction patterns within the community when quality becomes a structural issue in the group activity. In addition, we will carry further experimentation in order to understand how the different triads can be understood as a measure of social cohesion within the network. Finally, we are analyzing which are the correct metrics to consider when monitoring the evolution of a community alongside its life cycle, and how to design visualizations aiming to help community managers understand the dynamics of an online community in real-time.

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