Analyse Social Influence on Student Motivation based on Social Activity Network

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***Abstract*—Student motivation is one of the most important individual characters for explaining student performance in class. Existing researches show that it can be affected largely by social-contextual factors. Rather than focusing on social relationship, in this paper we construct social activity networks for analyzing the impact of collective behaviors on student motivation. We conduct field experiments to compare social activity networks with relationship networks by analyzing the structural characteristics. We also investigate the dynamic of social activities, and validate the effectiveness of social activity network in reflecting social influence on student motivation. Our results show that social activities are important factors affecting student motivation.**

Keywords: student motivation, collective behaviour, social network analysis, online course.

I. Introduction

Student motivation is a complex part of students' psychology and behaviour explaining goal-directed activity related to learning such as school task engagement [1]. Considerable researches have focused on how to affect student motivation, and social influence has been considered as a powerful method to improve student motivation[2].

Recently, with the rapid development of the Internet and social network softwares there are growing interests for online courses and utilizing social networks in college classrooms for educational purpose. As a Cyber-Physical-Social system (CPSS) [3], online course websites make it possible for tracking students' learning behavior to infer the latent student motivation, and adjusting teaching strategies. Social networking services (SNS) have the potential to raise the quality of education, because of their ability to show social context, which may influence individual motivation such as students' willingness to engage in course tasks and their level of effort [4, 6–8].

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A social relation is any relationship described by law, custom and tradition, which means regular interactions between individuals. And a social activity is an action or behavior which addresses (directly or indirectly) other people and solicit a response from them. Social relationships are almost unchanged in a college class with more than hundreds of students, since most students may not know each other and keep strange until the class is over. Hence, we suggest to understand social influence by social activities that are happening frequently.

The contributions of this work can be summarized as follows: 1) We build social activity networks based on real-world data and analyze the dynamics; 2) Field experiments are conducted to statistically analyze social effects on social motivations and conclude that social activities are important factors affecting social motivations. 3) A four-layer maxout neural network is built to validate the effectiveness of social activities in describing variations of student motivations.

The rest of this paper is arranged as follows. Next section reviews related works on social networks, their influence on student motivation, and methods of analyzing social networks. Section III analyzes social motivation, describes social activity networks and gives preliminary analysis. Then, we compare our social activity network with the social relationship network in Section IV. Section V analyzes the dynamics of social activities. Section VI conducts experiments to predict student motivation utilizing the proposed social activity network model. Lastly, we conclude our work in Section VII.

II. Related Works

A. Social influence

Generally, a social network is a social structure of nodes that represent individuals and the relationships between them within a certain domain[4]. Over the last decades, online social networks have been increasingly used for educational purpose. Considerable empirical researches on using social networks as either formal [6] or informal learning environment[7][8] shows social networks take advantage of facilitating interaction, communication, and collaboration for students and teachers so as to help with learning-related tasks. Researchers focus on investigating the link between social relationships and students' performances, regarding social networks as effective platforms that positively affecting social relationships.

The importance and influence of online social networks on education has received attention in the literature, but there rarely has been an explicit interest in linking student motivation and social activities. Research on social influence shows individual preferences can be adapted as a result of collective behaviours[9–11]. From the social-cognitive perspective, social motivation is also believed to emerge from the social interactions between individuals[2]. Hence student motivation with individual differences may be influenced by social activities generated by teachers, friends, and non-friend classmates.

B. Social network analysis

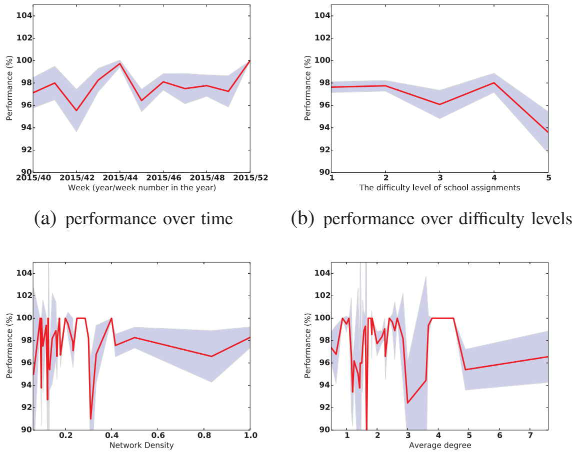
Social network analysis has been applied for individual and collective behavior in the recent past[12]. It makes use of mathematical tools and concepts that belong to graph theory and has emerged a set of methods for the analysis of social structures[13], such as link symmetry, power-law node degrees, correlation of in-degree and out-degree, and so on[14]. In this paper, we focus attention on small-scale social networks, specifically online chat group. In contrast to large-scale ones like Facebook, Online chat group is an extension of the social group on online social networks and related research presents that the group owners and members are obviously concerning social activities which includes discussions and information exchanging between group members[15].

III. Student Motivation and Data Description

A. Student motivation

In order to analyze factors affecting student motivation, we develop a website for course management service which enables students to study with it and record learning behaviors of students on the websites. The more student motivation is, the better students perform in school tasks. Therefore we consider the learning performance, specifically the accuracy rate ($score/total\ score$) of student assignments, is an important index to indicate student motivation.

Each time a student received a score on an assigned problem, we made a record with features including the score, the total score, the difficulty level which values from 1 to 5, the completion time, and the temporal social activities collected from social networking tools. We divided those records into groups by features and made some statistical analysis.



(a) performance over time (b) performance over difficulty levels

(c) performance over network density (d) performance over average degree

Fig. 1. Variation of student motivation indicated by performance

A simple depiction on the variation of student motivation is shown in Figure 1, presented as mean and 95% confidence intervals (CI) of accuracies in each group. Note that CI are represented as shaded areas and mean values are dots connected by lines in the middle of those shaded areas. Statistically significant differences were small between groups over time or over difficulty levels, while there were outstanding significant differences when comparisons were made between those under different network densities or average degrees of social activity networks defined in section V . The maximum differences were in turn 4.46%, 4.43%, 9.0% and 10.0%. The latter two are obviously higher than the previous two. Consequently we found the significant effect of social activities on student motivation in our study, which motivated us to analyze social activities in the following sections.

B. Social activity networks

To investigate the impact of collective behavior on student motivation, we built social activity networks centered on reflecting collective behaviours.

A social activity network is denoted as (V_a, E_a), where V_a is the set of all the persons involve in the network, an arc $e_a \in E_a$ connects A to B if and only if

A has perform some social activity on B, e.g. A ask a question to B.

We construct a specific environment convenient for observing social activities. We create a chat group for the course with WeChat [1], a leading social network software in China. All the students are asked to join this group. Besides, two course projects are posted to students, which require students arrange themselves into several teams that contains no more than 5 members.

Social activity networks are instantiated based on (1) the chat messages, with which the sender is connected to the receiver(s) and (2) the team member list, with which team members are interconnected with each other. We label the sender and the receiver(s) of each chat message via @- messaging or contextual semantic. Some chat messages are labeled as no receiver, because they are send to all group members or non-specific receiver, e.g. questions and festival greetings.

C. Dataset

The data we used in this paper is related to the Optimal Control course in University of Chinese Academy of Sciences throughout the semester from September 2015 to February 2016. We collect data from the corresponding course website[2] and the course chat group in WeChat . During this time, there are 94 students from 22 colleges participating in the course. 17 class assignments and 2 course projects were posted. There are 2913 chat messages in total and 325 of them are labeled as no receiver.

IV. Social Activity and Social Relationship

In this section, we construct a social activity network based on cumulative social activities and compare the structural characteristics with a friendship-driven social network centered on building social relationships, namely social relationship network. The social relationship network is built using the college information and the invitation records.

A. Reciprocity

As for the social relationship network, reciprocity is used to reflect the pairwise bidirectional relationship between two nodes. In the social activity network, reciprocity is considered as a good measure of the social pressure of people to return the favor to those who have performed actions on them. For example, students may reply to those who have answered their questions.

We measured reciprocity rate defined as the number of reciprocity links over all links of all users. The reciprocity rate of the social activity network is 49.3% while the social relationship network is 89.3%. According to the results, almost half of the time, user A has responses to user B who has send messages to him/her. Although the actual user behavior has a quite high link symmetry, it is much lower than the established social relationship. This result conforms to a phenomenon in the social activity network, in which user A may build or accept the friendship establishment with user B but does not have actual online interactions with B.

B. Degrees Distribution

We draw the complementary cumulative distribution functions (CCDF) of the in-degree and out-degree of each user in Figure 2 and Figure 3. The figures show that both in-degree and out-degree in the social activity network and social relationship network approximately conform to the power-law distribution, which is indicated by the fact that most nodes have small degrees while a small portion of nodes have much larger degrees. Actually in both social activity network and social relationship network, the node with the highest in-degree and out-degree is a teacher so that the teacher plays an important role both for building relationships and performing activities. The power of in-degree distribution and out-degree distribution in the social activity network is 2.27 and 2.52. And the power of in-degree distribution and out-degree distribution in the social relationship network is 5.7 and 6.15. The results indicates that most relationships are related to a much smaller group of nodes than activities.

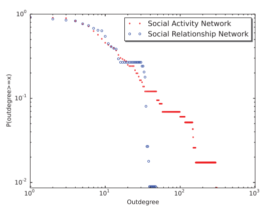


Fig. 2. Out-degree

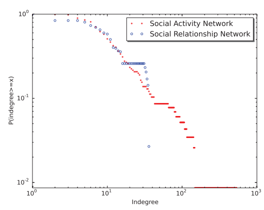


Fig. 3. In-degree

C. Correlation between In-degree and Out-degree

We separately generated two ranked lists of nodes by each node's in-degree and out-degree for both the two networks. The overlap percent is defined as $\frac{l_{in} \cap l_{out}}{l_{in} \cup l_{out}}$,

[1]WeChat , http://www.wechat.com is a mobile social network software by Tencent Ltd.

[2]Feiyue Optimal Control, http://www.parallelcontrol.com

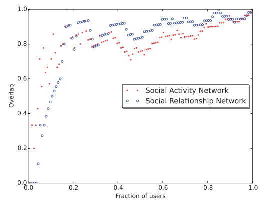


Fig. 4. Overlap of two node lists ranked by in-degree and out-degree

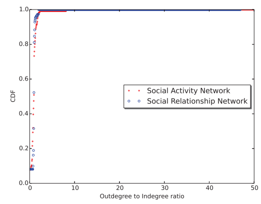


Fig. 5. Correlation between in-degree and out-degree

where l_{in} and l_{out} denote the groups of the top x% of nodes in the two ranked lists. Figure 4 shows the variation of the overlap percent. Obviously the overlap percent of social activity network starts to change much strongly. When the fraction of users is raised to 20%, the overlap percent of social activity network is about 84% while social relationship network is about 46.7%. The result denotes nodes in social activity network with much higher in-degree or out-degree have a high probability of higher out-degree or in-degree than other nodes, reflecting active students in social activity network may be active in both action and reaction, which is different from the social relationship network.

In Figure 5, we draw the CDF of the out-degree to in-degree ratio to explore the relationship between the in-degree and out-degree of individuals. Both in social activity network and social relationship network, less than 2% of nodes have an ratio below 0.5, about 10% of nodes have an ratio above 2.0, and about 30% of nodes in have an ratio around 1 (from 0.9 to 1.1). These indicates students are mostly neither selfless nor selfish, that is, they tend to react to persons who have reacted to them and they are willing to make friends to persons who have show friendships to them.

D. Summary

According to above sections, the social activity network has similar structural characteristics with the social relationship network. That is, some aggressive nodes in performing social activities are also active in building social relationships. However, the social activity network differs from the social relationship network in several ways: 1) The link reciprocity of the social activity network is much lower than the social relationship network, which means that people may build friendship with another one, but does not have actual online interactions with him/her; 2) The power of in-degree distribution and out-degree distribution in social activity network is lower than social relationship network, indicating that most relationships are related to a much smaller group of nodes than activities; 3) Nodes in social activity network with much higher in-degree or out-degree have a high probability of higher out-degree or in-degree than other nodes, reflecting active students in social activity network may be active in both action and reaction, which is different from the social relationship network.

V. The Dynamics of Social Activity

In this section, we analyze the dynamics of cumulative social activity by tracking the variation of topological properties of the social activity network over time. Specifically, we put social activity data into chronological order, step by step construct the social activity network using these data, and make social network analysis on the network by date.

A. Comparison of the initial and the final state of social activity network

Table I shows several topological properties of the initial and the final version of the social activity network. The meaning of measures are listed as follows: 1) N is the number of nodes; 2) M is the number of links; 3) w is the sum of link weights, which is $\sum_{e_a \in E_a} weight(e_a)$; 4) Δ is the network density, which is $\frac{M}{N*(N-1)}$; 5) N_c is the number of strongly connected components[16]; 6) N_g is the number of nodes in the giant strongly connected components; 7) $< d >$ is the average degree over all nodes.

TABLE I
THE TOPOLOGICAL PROPERTIES OF THE INITIAL AND THE FINAL SOCIAL ACTIVITY NETWORK

Measure	Initial	Final
N	64	116
M	8	670
w	8.0	1353.0
Δ	0.002	0.05
N_c	61	43
$N_g(\%)$	3(4.69%)	74(63.79%)
$< d >$	0.125	11.664

As shown in Table I, N is initially more than half of the final version, which indicates most students have been invited to join the chat group in the beginning. In the contrast, there is an appreciable increase in M, w, Δ, N_g, and $< d >$, illustrating great improvement in students interactions during the course. Although N_c also decreases relatively, the number is still high, which means some students remain inactive throughout the semester.

B. The dynamics of the social activity network

To display the dynamics of the social activity network, we depict the variation of topological properties mentioned in previous section via a series of figures, including Figure 6, Figure 7, Figure 8, Figure 9, Figure 10, and Figure 11.

As shown in these figures, most students join the social activity network in the early few days and the number N almost keeps unchanged until 2015-10-13, the day when the first course project was posted, and 2015-11-19, the day of mid-term examination. Besides, the numbers M, w, Δ, and $< d >$ increase significantly at 2016-01-06 and 2016-01-07, while a number of students were discussing questions as the latter date is the day of final examination. One of the most popular topic at that day attracted 20 students to make 124 chats. Hence it is inferred that course projects and examinations can promote the development of social activity network and raise social activities. The number N_g steadily increase which indicates most nodes has joined the giant component in which nodes are strongly connected with each other, while the number N_c keeps a sustained downward trend except when a group of new nodes join in the social activity network.

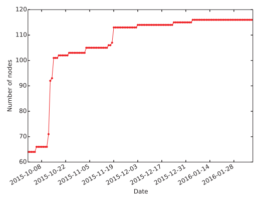


Fig. 6. Number of nodes

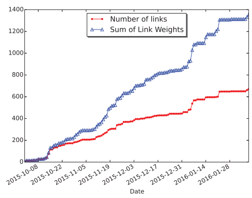


Fig. 7. Weighted links

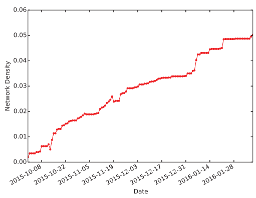


Fig. 8. Network density

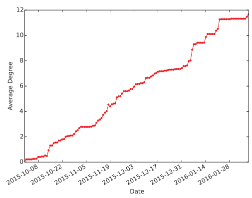


Fig. 9. Average degree

VI. The Effect of Social Activities on Student Motivation

A. Statistical analysis

In Figure 1, we have depicted variations of student motivation over several factors. And variations over

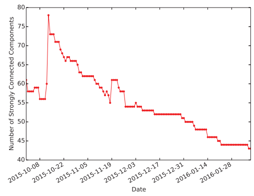


Fig. 10. Number of strongly connected components

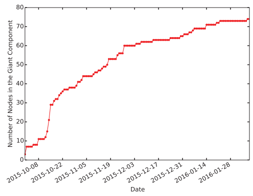


Fig. 11. Number of Nodes in the Giant Component

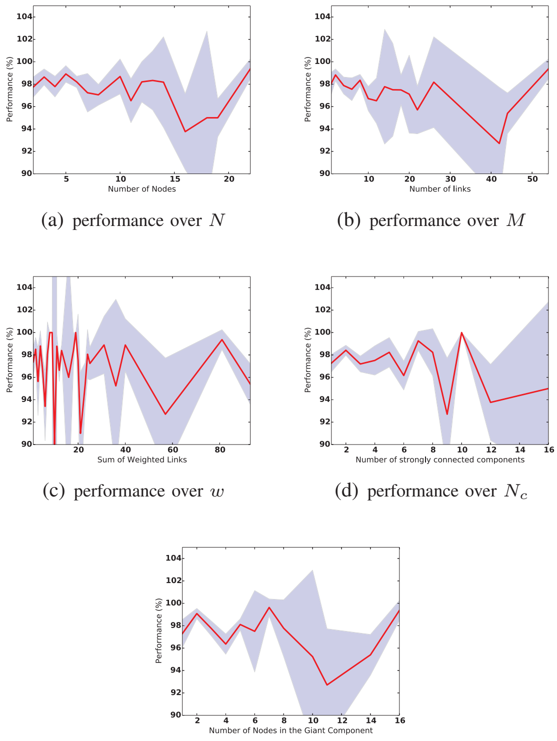
the remained topological properties of social activity networks are shown in Figure 12. Significant differences also exist between groups divided by these features. The maximum differences over N, M, w, N_c, N_g were in turn 5.6%, 6.65%, 10.0%, 7.29% and 6.92%.

There are some similarities in these figures. Firstly, the performance fluctuates drastically in the beginning, when the values of these features are small. This is probably because performance is mainly influenced by other factors since social effects are small. Secondly, as the values increases, the performance tends to be steady and every upper bounds of CI has a rising trend, which suggests positive impacts of social activities to a certain extent. Finally, the mean of performance has a sudden drop and the range of CI becomes larger when the values increase to a relative big number. This may be due to a two-sided social effect, which means active social activities could either positively or negatively affect student motivation. We consider one of key point is the temporal topic of social activities.

Based on the above analysis, we conclude that these topological properties of structural of social activity networks are important factors affecting student motivation. However, social activities have nonlinear effects on student motivation, which is hard to be analyzed through linear methods. As neural network models are considered to be effective to model nonlinear relationships, we utilize a neural network to explain variations of student motivation.

B. Neural network approach

The general idea of utilizing neural networks in this section is to fit student motivation using only current state of the students, the teachers and the temporal social activities. The information consists of : 1) the seven topological properties of the temporal social activity network; 2) the seven topological properties of the cumulative social activity network; 3) the homework assignment information including total score and difficulty level;



(a) performance over N

(b) performance over M

(c) performance over w

(d) performance over N_c

(e) performance over N_g

Fig. 12. Variation of student motivation indicated by performance: II

4) the factors indicating a student's previous state, such as the previous accuracy rate; 5) the week in the year.

We use the data to predict current accuracy rate of students. We collect a dataset with 94 students during 117 days, and use 80% as the training set and the remaining 20% as the test set. We use the mean squared error as the loss function, and build a four-layer maxout neural network ([17]) optimized by the stochastic gradient descent method. The experiment results shows the loss on test set is 0.009 and the accuracy is 88.9%. It suggests that social activities are effective in describing social influence of collective behavior on student motivation.

VII. Conclusion

In this paper, we construct social activity networks for analyzing the impact of collective behaviors on student motivation. Field experiments show that social activity networks is quite different from relationship networks. It can better interpret the dynamic nature of social activities. We statistically analyze the social effects on student motivation based social activity networks and conclude that features of social activity network are important factors affecting student motivation. Finally, we build a neural network to validate the effectiveness of social activities.

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