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Research paper

Social Network Accelerates to Strengthen the Relationship between Teachers and Their Students

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Abstract

To make sure that relationship can play an important role in building community as well as knowledge; this article is going to highlight the relationship between teacher-students, teacher-teachers, and student-students by using communities' detection in social network, and this is done by calculating betweenness for all edges and applying the edge removal approach. This paper will make a bridge between the students and the teachers to decide whether this interaction helps to encourage and increase the level of students as well as the teacher performance.

Keywords:*Social network, relationship, community, betweenness, edge removal approach.*

1. Introduction

Social media are affecting the way people communicate, develop relationships and build trust in home and work settings [1]. What began as a set of tools for friends to stay connected has evolved into a means for businesses to communicate internally and externally. Although social media channels are used in a variety of contexts, this paper focuses on the emerging trend of its application to support relationship between teachers and their student. There are millions of people using Facebook, Twitter and Skype. These online fashions produce the large amount of data that are arriving in the form of a data stream. Users post a variety of data online on Facebook, such as text, images, videos, and so on. Similarly, Twitter has short text messages. The data is high volume and arrives with high velocity at the Facebook/Twitter servers. Users may be tagged by their location using GPS coordinates. These coordinates are usually imprecise leading to veracity of the data [2]. Skype also offers various types of communication: text, voice call, and video call. It is possible to send various different types of data into the text messages (Pdf files, images, videos, and so on). At any given moment millions of users from various locations around the world can be using Skype. Doing so, they produce a high volume of data that is arriving at the Skype server rapidly. This data has a high variety in terms of the different forms used for communication.

2. Social network

Social network analysis focuses on patterns of relationships between actors and examines the availability of resources and the exchange of resources between these actors [3].Some of the best examples of social networks are the 'friend' relations found on social media sites, such as Facebook [4], Instagram and Twitter. There is a lot of information that we can gain from analysing big data sets found in social networks. When working with big data, we generally want to analyses relationships and information which links the nodes in a social network. If we use Facebook as an example, the nodes within the network are individuals - each person has created an account. The links between the nodes are friendships [5].

An important thing to be able to identify in social networks is common groups [6]. A common group is a subset of nodes within the network with unusually strong connections. They generally do not divide a population; that is, we would not get a social network that looks like Figure 1:

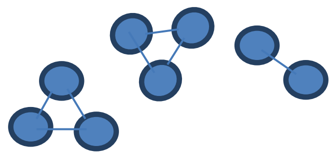

Fig.1: Social network with no overlaps between common groups

Generally, a social network has are overlaps between common groups, which would look like this:

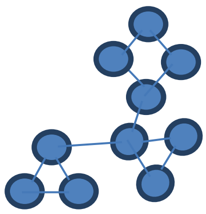

Fig 2: Social network with overlaps between common groups

Let us consider the example of Facebook; it is a network of friends, where people are nodes and the edges between people indicate friendships between those two people. We know that two people can exist without being friends, but this is not that interesting, so we want to find common groups. For Facebook, the common groups are people who are friends - friendship is what indicates a strong connection [7]. For all these reasons, there are several characteristics that can help to define what a social network is. While these characteristics are not the definitive list of what defines a social network, they help identify possible social networks.There is a collection of entities in the network. Using Facebook as an example, the entities could be people. However, entities for different networks can mean anything.There is at least one relationship between entities of the network. Typically, there will be many relationships, and one entity may have multiple relationships within the network. Furthermore, some networks keep track of additional information about relationships. It could be discrete (for example, number of common friends) or a continuous number (such as distance from each other).There is an assumption of non-randomness or locality. This is the condition that relationships tend to cluster. That is, if the entity A is related to entities B and C, then it's likely that B is also related to C.

Varieties of Social Networks.There are many different social network types. In a telephone network, telephone numbers represent individual nodes, which are similar to individuals, as typically an individual has a phone number. If there has been a call between them within a fixed period, the period for recording edges varies [8]; it could be a week, a month, or forever. Edges just can be weighted based on the number of calls between the nodes. In this way, telephone networks are undirected and weighted graphs.The locality of relationship forms between people that communicate frequently, which could be groups of friends or people working together [9].

In an e-mail network, e-mail addresses represent nodes. This is essentially an individual. An edge exists between two nodes if at least one e-mail is sent in at least one direction. Unlike the telephone network, we can classify the relationships here differently. For example, this could be undirected relationships. That is, an e-mail does not require a reply to be considered an edge, and these edges can have weighting based on the number of e-mails sent [10].Alternatively, edges could be weighted as weak or strong to represent one-way or two-way communication. Locality of relationship forms in a similar way to a telephone network. That is, it forms between friends or colleagues. Collaboration networks represent publishers as nodes, and edges are between individuals who have published a paper together or contributed to the same document. Edge weighting can be based on the number of shared collaborations. There are many other ways of looking at a collaboration network [11]. One is where each published paper is a node, and the edges between papers are based on references. If one paper references another, then there is an edge between them. These kinds of networks are specifically prevalent in research communities, where locality of relationship forms between colleagues. There are many other types of social networks other mentioned early. These usually relate to an existing and real world network. Additionally, there are networks that do not fall easily into any category and are unique.

3. Power Law Degree Distribution

One of the most documented aggregate network properties is the so-called "scale free" property, which is satisfied when vertices' numbers of edges (degrees) are power-law distributed, resulting in few vertices having many edges and many vertices having few edges [12].

Social networks are usually modelled as graphs. In social networks like Facebook, there are usually a small number of people with an extremely large number of friends whereas most people have a relatively small number of friends. This type of relationship can be modelled by a power law distribution. For a fixed γ (usually a real value between 2 and 3) the fraction of nodes, P(k), which have k connections to other nodes is :

$$P(k) \sim k^{-\gamma} \tag{1}$$

If *k* is sufficiently large.

If our social network follows a power law distribution, so we can choose γ to model how quickly the fraction of nodes of degree k is declining when increasing this value.

4. Dealing with Graphs

In computer science, the term graph holds special significance. A graph is a data structure consisting of a collection of nodes, and these nodes can be connected together by edges. Each node contains data, and a node can have any number of edges. Each edge represents a link between these two nodes. That is, an edge represents a relationship between two pieces of data.

Social Networks as Graphs. While a social network is a structure made up of social actors (individuals or organizations that interact), and sets of ties between actors [13], this concept of actors and ties can naturally be modelled as a graph in programs. These are sometimes called social graphs.

In Computer Science, the term "graph" has special significance. It represents a data structure which is comprised of Nodes and Edges.

When representing a social network as a social graph [14], the actors are the nodes and the ties are the edges. When drawing social graphs, we can use circles to represent nodes, and lines to represent edges.An example for a mixed graph with bidirectional and unidirectional edges is a road network. In such an instance, edges are streets, and nodes are intersections of streets. One-way streets can only be followed along the assigned direction (unidirectional). Most streets, however, are bidirectional and drivers are allowed to drive along a street in either direction.

The Implementation of Graphs. There is a lot of material online that we can use to understand and create our own implementation of the graph data structure. Graphs give us a convenient way of visualizing and representing data, and the relationships it has with other data [15]. A common set of nomenclature (or the way we describe or refer to something) is used to discuss graphs because it enables us to understand what is being represented without lengthy explanations. There are two different ways that we can implement graphs as an adjacency matrix, or an adjacency list.

An adjacency matrix [16] is an easy way to store the connectivity information of a graph and is very fast at checking if two nodes are directly connected.Make an $n \times n$ matrix A, where n is the number of nodes in the array. In this matrix; row i and column j is equal to 1 if there is an edge from the node i to the node j. Otherwise, the value is 0, which means there is no connection between the node at row i and column j [17]. For example, if we had this undirected graph:

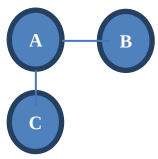

Fig 3: Undirected graph

The adjacency matrix for this would look like this:

Table 1: The adjacency matrix

	A	B	C
A	0	1	1
B	1	0	0
C	1	0	0

An adjacency list is a bit more complicated to program. However, it is easyto iterate over the edges belonging to a certain node. There are several methods of implementing this structure.

One way is to use linked lists. However, this has a lot of overhead. Another is to create an array of vectors, which is slightly more efficient, but can be slow for large lists. Another solution uses arrays, and assumes that the total number of edges is known. Using the example from above, the adjacency list will be like this:

Table 2: The adjacency list

From	To	
A	B	C
B	A	
C	A	

Graphs with several node types: In some networks, it is more practical to have multiple types ofnodes. These cases arise when there are different types of entities within the same network. A simple example of this is collaboration networks. Rather than having a network of just teachers or just students, we can combine these into one network. In this network, students are related to teachers, and teachers are related to students. This becomes an apprenticeship network.

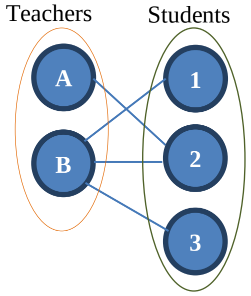

Fig.4: Apprenticeship network

This will look similar to the bipartite graph. In this example, there are two teachers, A and B, in set K, where teacher A had taught the student 2, and teacher B had taught students 1, 2, and 3. In this instance, teachers A and B have co-taught student 2.

5. Community Detection in Social Networks

In graph theory, the betweennessis used to measure the centrality of agraph based on the shortest paths in it. A shortest path is defined as a path between two vertices which has the shortest length in the graph. There can be more than one shortest path in a graph.

The betweenness of a node in the graph G= (V, E)[18] canbe calculated as:

1. *For each pair of nodes s, t where both nodes are not v, find the number Nst of shortest paths between them.*
2. *For each pair of nodes s, t, find the number nst of shortest paths that pass through node v.*
3. *Sum up nst/Nst over all possible combinations of s and t.*

The betweenness can be normalised by dividing the number of node pairs excluding node v.

A vertex with a high probability to occur on a randomly chosen shortest path between two randomly chosen vertices has a high betweenness.

The edge betweenness centrality is defined as the number of shortest paths that go through an edge in a graph or network [19]

So we have searching for communities by partitioning all individuals in a social network.

One way of finding communities or clusters in a social network graph is through a process called edge removal.

Edge removal:In the approach of edge removal, we are trying to remove the edges that carry themost 'traffic' in the network.

The Girvan-Newman algorithm detects communities by progressively removing highly used edges from the network by:

1. *Calculating the betweenness for all existing edges in the network.*
2. *Finding the edges with highest betweenness and removing them from the graph.*
3. *Re-calculating the betweenness of all edges affected by the removal.*
4. *Repeating steps 2 and 3.*

6. ASTEMOI Discussion Forum

In our platform (ASTEMOI) [20][21], we will have a discussion forum in each part of the course where each student has the opportunity to discuss with his colleagues and his teachers, and share their knowledge.We also offer practical ideas to help students use social media for more personalized and collaborative studies.It is common for many students to be confronted with the same learning concept or course assignment. Social media can help centralize the collective knowledge of a group of students to make learning and communication more effective for everyone by:

- *Create a list of contacts or a group so that the class can collaborate and share study tips.*
- *Invite teachers to follow the group conversation or join in discussions.*

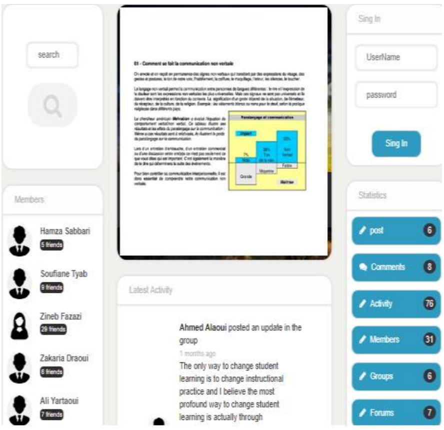

Fig.5: Screenshot of ASTEMOI platform discussion forum

The information drawn from these discussions will be used to group the discussants into several groups, including their interferences.

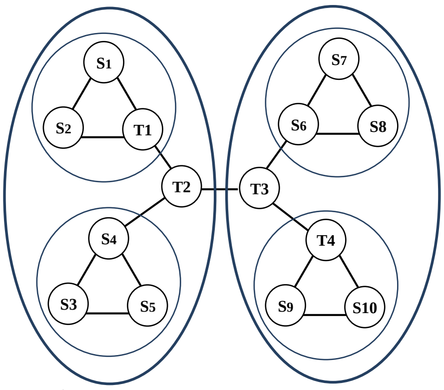

Fig.6: Example of social graph representing the communities created in the ASTEMOI forum between ten students and four teachers.

Graph utilises student data related to the level of engagement in the learning activities conducted within a forum, by representing students and teachers as nodes and connecting them with edges.

In the above graph, the edge connecting T2 and T3 has the highest betweenness. This edge will be removed in the first stage. After the removal, there are two separate sets of nodes in the network and the betweenness needs to be re-calculated for the next phase.

So the approach of edge removal can identify different levels of clusters. When we get at least two isolated partitions of nodes, these could be clusters of some degree.

7. Conclusion

Several recent studies have found that most students believe that the technology they use to study should be as relevant to their needs as social media. We are still working to achieve this with important updates on our ASTEMOI adaptive learning platform.

In this paper, we have been able to separate the social network into communities composed of students and teachers, which makes it possible to focus on the needs of each one of these communities since its components have many properties in common.

Separating students into groups and offering them support can help improve their levels of study.Studies have shown that students are more likely to succeed in training when they believe that the teacher supports them, cares about students' success, and honestly assesses their weaknesses and strengths.it is easier to maintain the motivation of the student if during the discussions he receives honest answers and helps to improve his weak points.

Improving student behaviour is part of the teacher's job. By taking measures to support students, offering different teaching strategies and focusing on rigorous educational standards, teachers keep students motivated and encourage better academic performance.

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