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Exploring the Properties and Growth of Student Interaction Networks on Twitter: Insights on STEM Learning and Engagement

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1. INTRODUCTION AND MOTIVATION

Network science is becoming emergent to quantify different aspects of various physical and social networks. By implementing experiments on large-scale, real networks, many new network concepts, properties, and measures have been developed. Such experiments have identified several statistical properties and unifying principles of the real networks. Significant research efforts have helped develop new network modeling tools, replicate the structural properties observed from empirical network data and build these networks effectively to acquire more advanced knowledge of evolutionary network growth mechanisms [1]. Most of the real networks have interesting properties[2], unlike random graphs that show possible mechanisms that direct network building and ways to manipulate network structure with specific goals [3].

Social network analysis (SNA) is used to explore an individuals' social ties, network density, and strength [2]. The study of the Social Network (SNA) helps to analyze relevant data which are interconnected in nature. SNA can be effective to analyze students' community interactions to measure student relations. SNA allows students to examine how they participate in an informal atmosphere by equal participation [4]. Bruun et al. explored how self-reported student interactions can be viewed as meaning-making processes and use this to understand how quantitative measures that describe the position in a network, called centrality measures, can be understood in terms of the interactions that occur in the context of a university physics course [5]. Applying social network analysis (SNA) to measure student experiences, Dou et al. found a correlation between the role of the students in their social network classroom and enhanced production of self-efficacy [6].

Social media has been an immense influencer for making decisions nowadays [7], [8]. People are not only being connected but also making their career progress through it and the networks of relevant people are powerful [9]. Recent studies show that social media plays a vital role in effective information dissemination even in extreme situations for a particular group of people [10]. The degree of influence of a particular student group and other people connected with these student's activities were monitored and found a positive impact of connectivity of the group themselves and with the practicing professionals too. The engagement of STEM learning students can greatly increase the number of STEM enrollment. The development of society and progression greatly depends on STEM knowledge and empowerment. One of the greatest challenges of the University has been keeping the attraction of students in a particular course and their persistence [11].

This research is focused on the importance of social impact while considering STEM learning. Students are encouraged to engage in social media activities related to the topics covered in particular STEM courses and interact with students in class as well as out-of-class peers (senior students, alumni, practitioners, subject matter experts among others) [12]. Along these lines of research, studies have shown that similar activities led to an increment in the number of physics majors by a factor of 400% [13], [14], which is indicative of the inefficacy of classroom-based methods to address such increments. The advancement of society greatly depends on the number of experts in science, technology, and math (STEM). But surprisingly in four years of college, more than thirty percent of students failed to graduate with a STEM degree [15]. To observe and measure the social interactions of a fully online class of BCN2210- Construction Materials and Methods at the Florida International University in Spring 2020, a task was given to post any information of their choice relating to the construction and also comment on at least two other student's posts. This also gauged interests of social media participants with similar backgrounds like alumni, faculty, senior students, etc. who observed such activities and reacted to these posts.

The goal of this study is to explore student's social media communication patterns on Twitter involving both in-class interactions as well as the ones from out-of-class social media followers. Twitter was used in particular since it is a public social media platform and people with similar interests can connect, interact and engage. The dynamics and growth of student social media interaction networks were explained using network science theories and principles. Specific research questions of this study include:

- How to systematically integrate social media activities in a STEM course?
- How students' social media interactions in a STEM class grow over time?
- How to quantify social media interactions using key network metrics such as degree, density, centrality, clustering among others?
- Are there unifying characteristics of social interaction networks of STEM students?
- How are student's networks influenced by their followers from both in-class and out-of-class members?

To answer these questions, student's Twitter data regarding their online participation as well as information about their followers (publicly available) were collected using Twitter streaming Application Programming Interface (API)[16]–[18]. Such data have been used to conduct network visualization and analysis to obtain meaningful insights regarding student interactions.

In Figure 1, a hypothetical network figure is created to introduce the network concepts and metrics such as degree (number of followers), density, centrality, among others. There are nine nodes drawn in a green circle and the nodes are connected by straight lines. Node 9 is the most central in the figure and it is connected with 4 other nodes. As it is connected with four nodes, we say node 9 has a degree of four. Then, nodes 1, 3, 5, and 7 are each connected with two other nodes, as such, each of these nodes has a degree of two. Similarly, nodes 2, 4, 6, and 8 have a degree of three. Again, node 9 having more connectivity than other nodes it has a more closeness centrality value of 0.381.

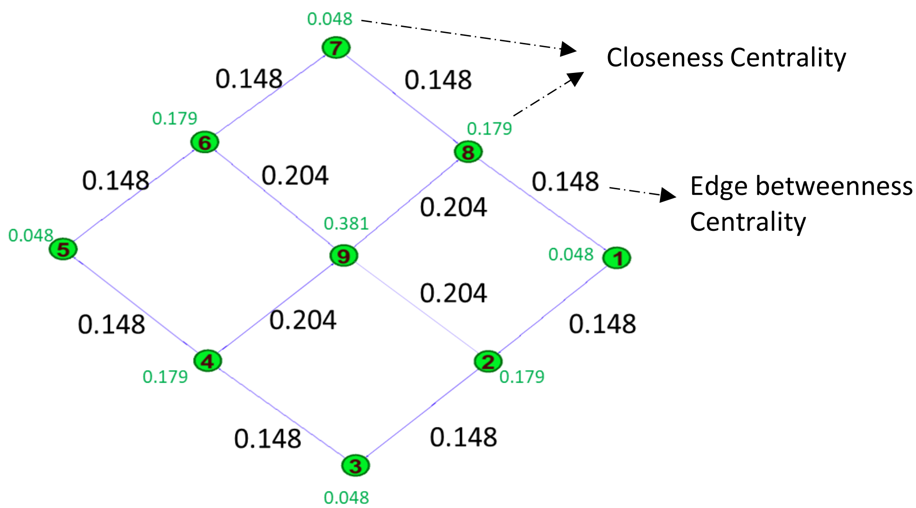

Figure 1: Simple network

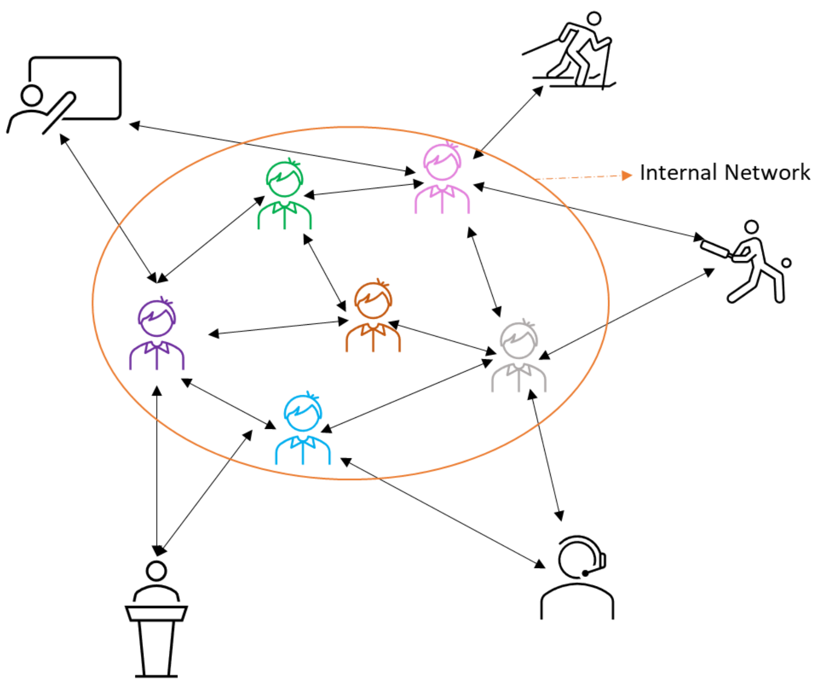

Figure 2: Social network of student's

Through online social media (Twitter or Facebook), in-class students can be connected with other students as well as some other external people such as alumni, faculty members, supervisors (Figure 2). All the influential students are situated in a central position of the circle or class and connected with most of the other students of the class. That's how social media could provide a great opportunity to expose to a larger learning and engagement network environment by establishing new connections with both internal and external members of a STEM course.

2. BACKGROUND AND RELATED WORK

Existing literature explored the influence of social media on the different communities in various scenarios. Malik et al. (2018) explored social media (Twitter) based activism campaigns to examine engineering diversity factors, whereas conventional methods to increase diversity within the engineering domain failed to achieve desired results. Authors claimed that information from social media can also be used for better understanding and developing the diversity of engineering. They presented findings from #ILookLikeAnEngineer campaign using Twitter data, which aimed at increasing gender diversity in the engineering work as a case study to illustrate the viability of the approach. The campaign provided continuous momentum to the complete effort to increase diversity and new ways to connect with the relevant audience. The analysis displayed that STEM-related diversity programs may draw attention from different communities, including individuals, large organizations, media channels, and community interest groups [19].

Trustworthy user identification on social media for emergency management organizations is performed by Pandey et al. (2018) using artificial intelligence and machine learning. Twitter data is also used here for a fine-grained understanding of credible sources to develop trusted user-specific (organizations, individuals both affiliated and non-affiliated with organizations) networks during three types of humanitarian or disaster events. Using a diverse set of social, event, and concise representation features derived from user profile metadata, the authors proposed a reliable user classification method. The detailed experiments showed a contrasting user identity participation behavior in their ways of communication; for example, the use by an organization and organization-affiliated users of lower authoritative information sharing. This study provides recommendations for the development of reliable content analysis systems for humanitarian organizations and disaster response agencies in real-time [20].

Intersectional self-expressions in Twitter are examined by Johri et al. (2018) during a hashtag activism campaign for engineering diversity. Authors analyzed the self-expressions of participants on a project to increase engineering diversity (# ILookLikeanEngineer) and found that, consistent with the viewpoint of intersectionality, in addition to their identification as an engineer, participants opted to extend and clarify their engineering identity; express their association with an organization or company and also the individual aspects of their personality (family or hobbies). Besides, conveying support for someone they met who was an engineer; articulating solidarity with other diversity-related social causes; and expressing excitement for or humorously referencing the movement are also found as significant. This research illustrates the inherent difficulty of identifying people as they self-express [19].

Le et al. (2019) developed a framework to use social media data for workplace learning by analyzing cybersecurity-related tweets. The research provided a structure that describes how data can be developed by using descriptive, material, and network analysis to explore how professionals learn. Findings depicted that most of the tweets covered multiple subjects and used three or more hashtags; the popular users were not automatically the most powerful (based on retweets); companies and other organizations had the highest number of followers, but the most retweeted were the individual users who were the experts in their field. Besides, infographics were the main content of popular tweets, and the overall sentiment of cybersecurity-related tweets was found negative as many hashtags tweet represented current threats [21].

A thorough small-scale review of the research study was presented by Toole (2019) on networked learning teacher communities for Continuous Professional Development (CPD) by using a Virtual Learning Environment (VLE). Findings of this study indicate that while networked learning environments have positive CPD impacts including improved social learning mechanisms, increased use of formal and informal training, learning across time and space barriers, and increased levels of engagement, challenges remain that may impede continued professional development. This suggests that it is possible to test a networked learning community at a chosen HEI with a subgroup of VLE teachers and that further qualitative and quantitative research could be carried out [22].

“National Engineering Week” was monitored by Malik et al. (2018) using Twitter data to understand the engineering community engagement. The authors used three quantitative methods to study the effect of the outreach: qualitative analysis, content analysis, and analysis of the network. It was noticed that engineering firms and individual users dominated the involvement of the Twitter campaign, accompanied by small participation by educational institutions, professional engineering associations, and non-profits. Besides, not a single news media outlet had been listed as a participating client suggesting the campaign's lower media-driven public reach. The tweets could be classified as event promotion from a content perspective, highlighting engineering company employees, or encouraging and inspiring the public (especially women and children) to be an engineer [23].

Johri et al. (2018) also examined how different users and activities initiate connectivity over Twitter. Authors explored here how a campaign (#ILookLikeAnEngineer) of social media activism aimed at enhancing the diversity of gender within technology gained momentum in its early period. The results showed that varied engagement–of user types–increased activity at crucial moments. These causes are classified into four types: a) Event-based: the arrangement of the project with the issue-related offline incidents (SFO diversity, disruption, etc.); b) Media based: news coverage of media events (CNN, BBC, etc.); c) Industry based: the web involvement of large organizations (Microsoft, Tesla, Google, Cisco, etc.) in the campaign; and d) Personality based: association of events with famous and/or established personalities [24].

For analyzing diverse complex systems from natural, social, and technological domains use of networks can be helpful [25] and even in the safety of traffic engineering by detecting traffic accidents rapidly [26]. A small world property is also found in the transportation network [27], [28] and analysis of such network can help to attract people to public transit [29]. Apart from that, the online social network interaction can be analyzed to better design and implement guidelines during crisis moments [30]–[33]. It is challenging to devise an effective qualitative method for the comparison of networks as the data grows remarkably [34]. Concept inventory is used to assess students' conceptual understanding in the specific domain with the help of multiple-choice questions [35], [36]. Using an informal environment for educational experimentation may help integrating STEM formal learning environments [12]. Again, peer influence can greatly enhance STEM learning which can be achieved through social media [37].

From the above literature, it can be summarized that researchers explored the potential of social media data (Twitter) to solve a variety of problems. Among these, very few studies investigated how social media can benefit the STEM learning environment and engagement. Moreover, the empirical literature is inconclusive on how to systematically integrate social media in a STEM course and observe students' social media interactions and peer influence on learning, which is the key contribution of this study.

3. METHODOLOGY AND DATA COLLECTION

Social networks have interesting properties, unlike random graphs that suggest possible mechanisms to direct network creation and ways to manipulate network structure with specific goals. To achieve the goal and objectives of the study and to explore the properties of student interaction networks both in-class and outside members, key network metrics used in this study are explained below. These definitions and explanations can support the interpretation of the findings presented in the result analysis section.

Degree- A node degree is the number of direct links in a graph to other nodes [17]. The degree distribution in real networks (probability of a randomly selected node has a degree of n, where n is a positive integer) is significantly different from the Poisson distribution, usually assumed in random graph modeling.

Density- The density is the ratio of edges to nodes [38], for undirected graphs is $d = 2m/n(n-1)$ and for directed graphs is $d = m/n(n-1)$. where (n) is the number of nodes and (m) is the number of edges in the network graph.

Betweenness Centrality- The betweenness centrality of a node is the sum of the fraction of all-pairs shortest paths that pass through it [39], [40]. It computes the shortest-path betweenness centrality for nodes.

Closeness Centrality- Closeness centrality of a node is the reciprocal of the average shortest path distance to overall reachable nodes. It means the distance of two points of a graph is the shortest-path distance between these and n number of nodes that can reach each point [41].

Clustering Coefficient- For unweighted graphs, the clustering coefficient is a measure of the degree to which nodes in a graph tend to cluster together, which is the ability of a given node to cluster with other nodes [42].

Then, Twitter data was collected using Twitter streaming API in python codes. Using the Twitter ID provided by the students' historical tweets were extracted [7], [31], [43], [44]. The collected specific tweets were filtered from 5th January 2019 to 11th April 2019. Each of the user IDs was assigned a unique label to keep the identity secured. Out of sixty-five in-class students, forty-nine students were found active on Twitter with tweets and re-tweets. Then, the followers' list of these forty-nine students was collected separately using the student’s username on Twitter. Here, four students had more than 90 plus followers and 24 students with no followers. The rest of the students was found with a smaller number of followers on Twitter. For all the forty-nine students, 69 external mentions were found [2], [18].

4. DISCUSSION OF FINDINGS

From the collected Twitter data, the student’s user mentions’ networks of BCN2210 course from the Spring 2020 semester are created for different network measures; such as degree, density, clustering coefficient, and closeness centrality (Table 2).

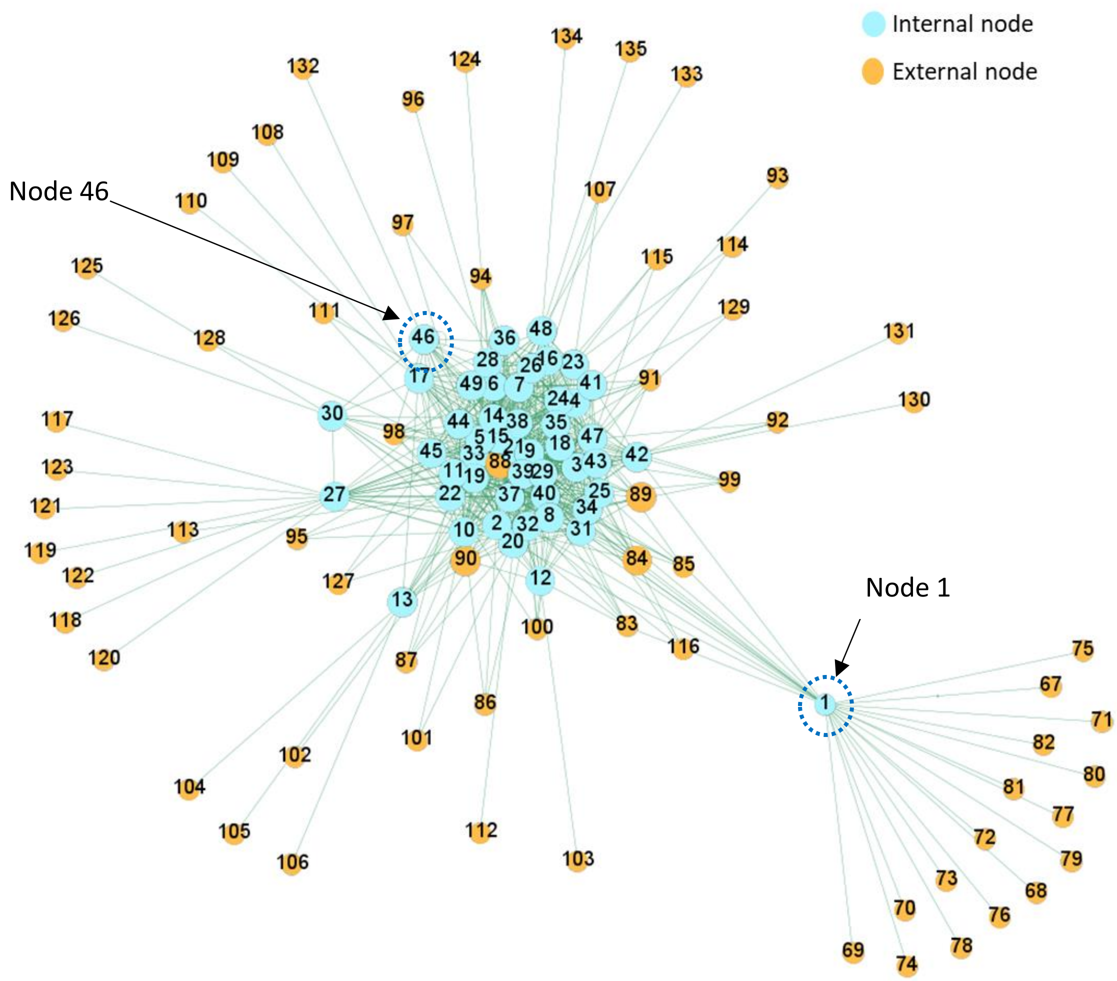

Figure 3: Student's connectivity with internal and external nodes during Spring 2020

Table 1: Network-level properties

Events	*Counts*
Number of total tweets	1,325
Tweets without mentions	254
Number of nodes	118
Number of edges	1,070
Number of directed edges	831
Number of unique edges	770
Clustering coefficient	0.176
Average degree	13.05

In Figure 3, the network is having 118 nodes out of which 49 nodes are from the BCN2210 course. The whole network is plotted in Figure 3 where node level 1 to 49 is assigned to student id (pseudo labels as previously explained) and the rest of the labels are assigned for other nodes. The internal nodes are mostly connected with each other and very few nodes have more external node connection than the internal node connection. For example, node 1 has a good amount of external node connectivity along with internal nodes. On the other hand, node 46 has very limited external connectivity. The network has 1,070 edges which included repeated user mentions and 770 unique edges (i.e. without repetitions) which are developed over the Spring 2020 semester.

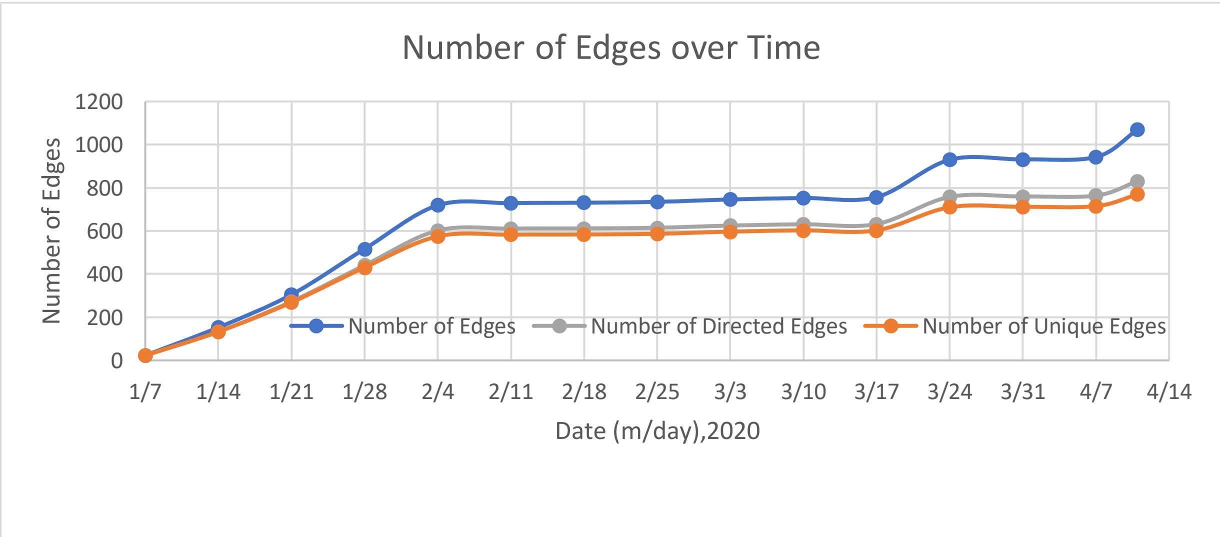

Figure 4: Number of Edges over Time.

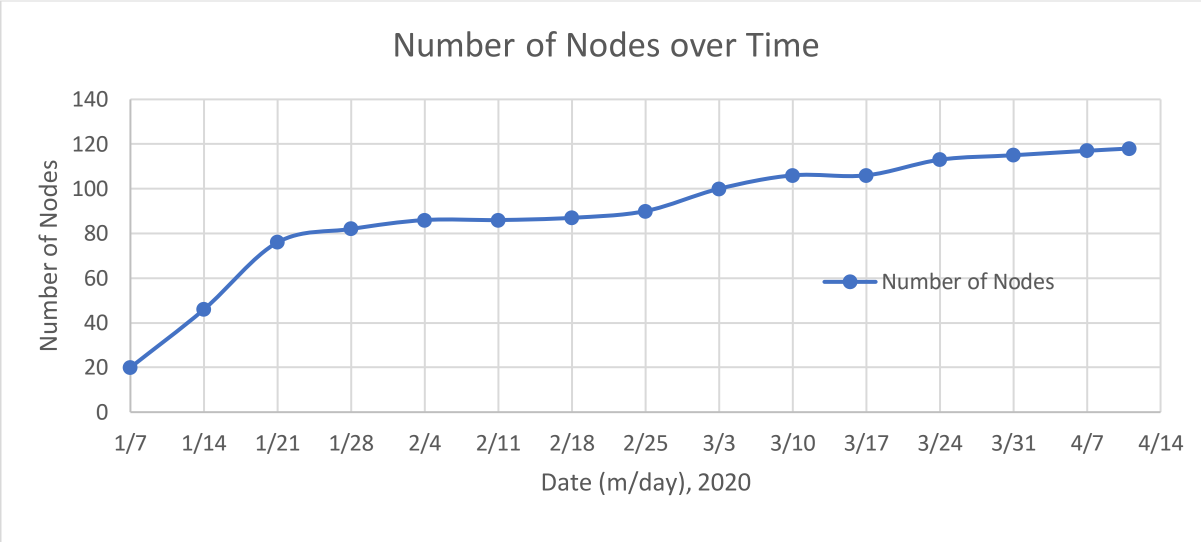

Figure 5: Number of Nodes over Time.

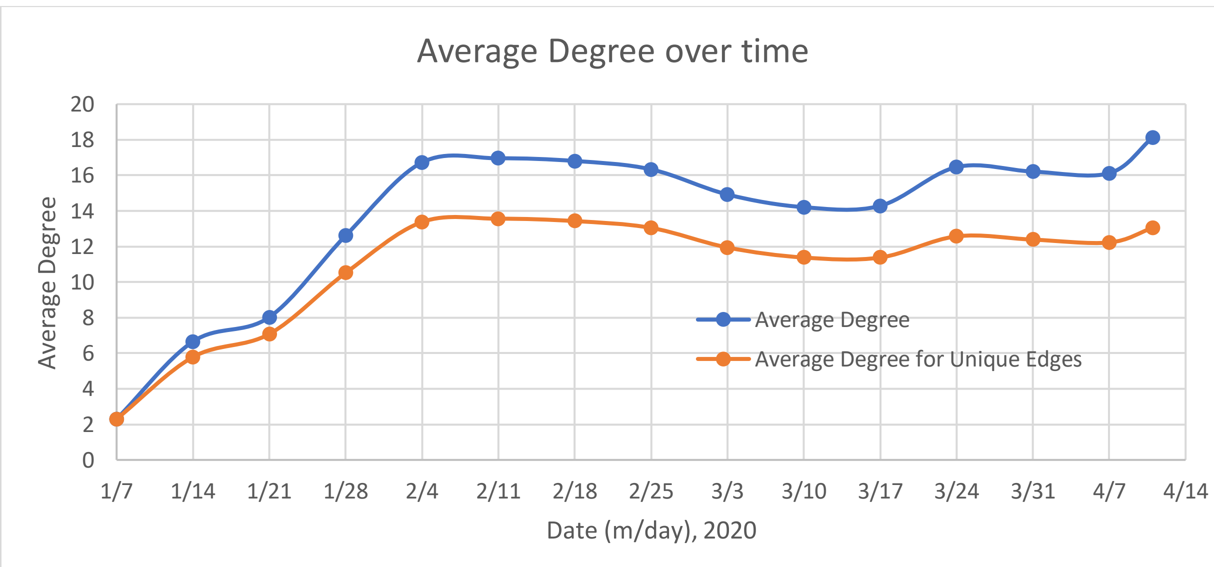

Figure 6: Average Degree over Time.

From the graphical representation in Figure 4,5 and 6 followings are the key insights:

- The number of edges represents the users' mentions (students who are trying to attract based on their interests) which includes repeating user mentions (shown in Figure 4). For example, students notify others by mentioning them through social media on a given STEM topic or ideas they are posting. This allows students to interact and identify other online peers having similar interests.
- The number of unique edges represents the unique user mention where repeating mentions were discarded (shown in Figure 4). Students connecting with new participants create unique edges and grow their network with more participants. The difference between the number of unique edges and the number of total edges (with repeating

mentions) is insignificant which indicates that students are more likely to find newer connections (i.e. user mentions) compared to the connections they already established.

- The network growth was prominent for the first few weeks and the network hardly increased for the next few weeks. It was found that the class had no deliverables from February 2nd to March 8th, 2020 which resulted in less activity in the network. It shows that the timing of social media deliverables strongly influences network growth.
  The average degree indicates how many other students for a given student are connected or influenced on average. Within the first 25 days, the average degree of the students' network increased from 2.29 to 12.92. Although the number of participants increased over time, the average degree of the students' network drops down after a certain point for having fewer active participants. After a few weeks of no deliverables when the deliverables were assigned again the average connectivity of the students increased again. This means the quiet participants' activity has increased with new deliverables.

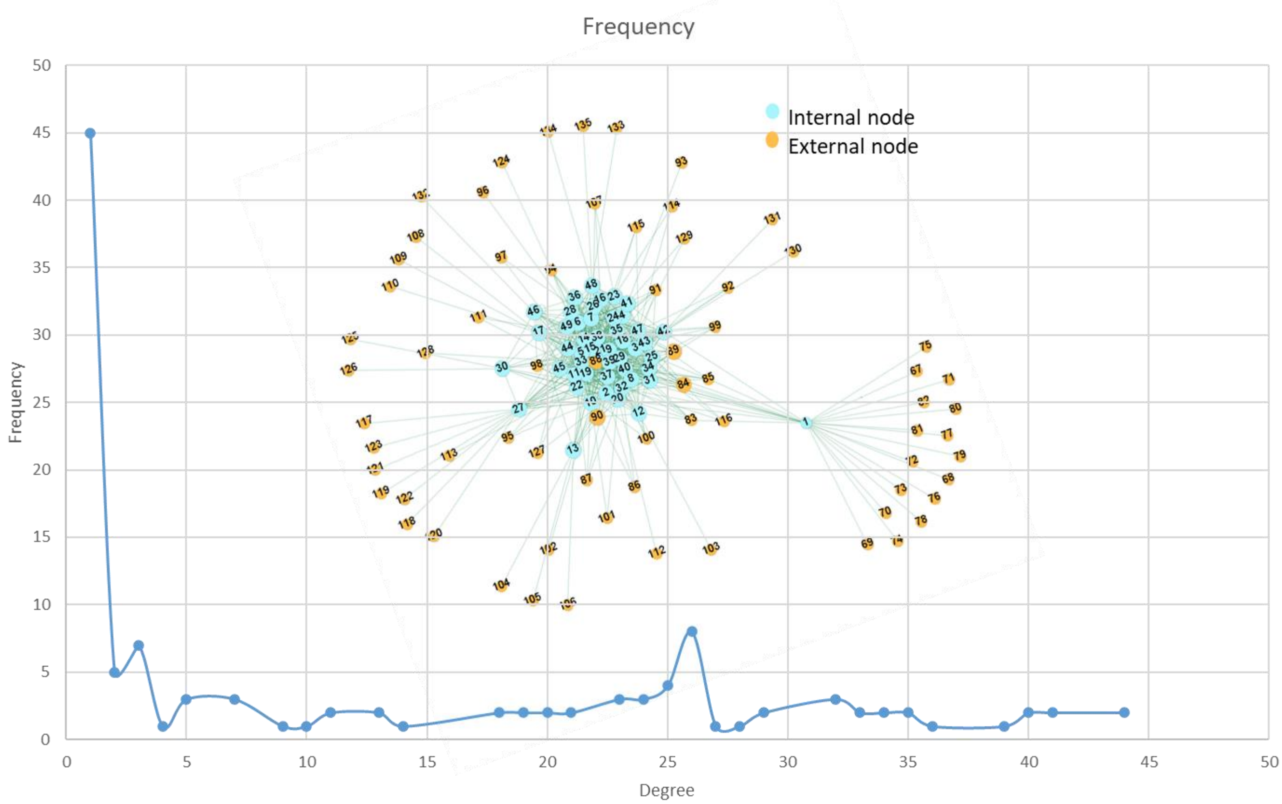

Figure 7: Degree of all nodes (internal and external)

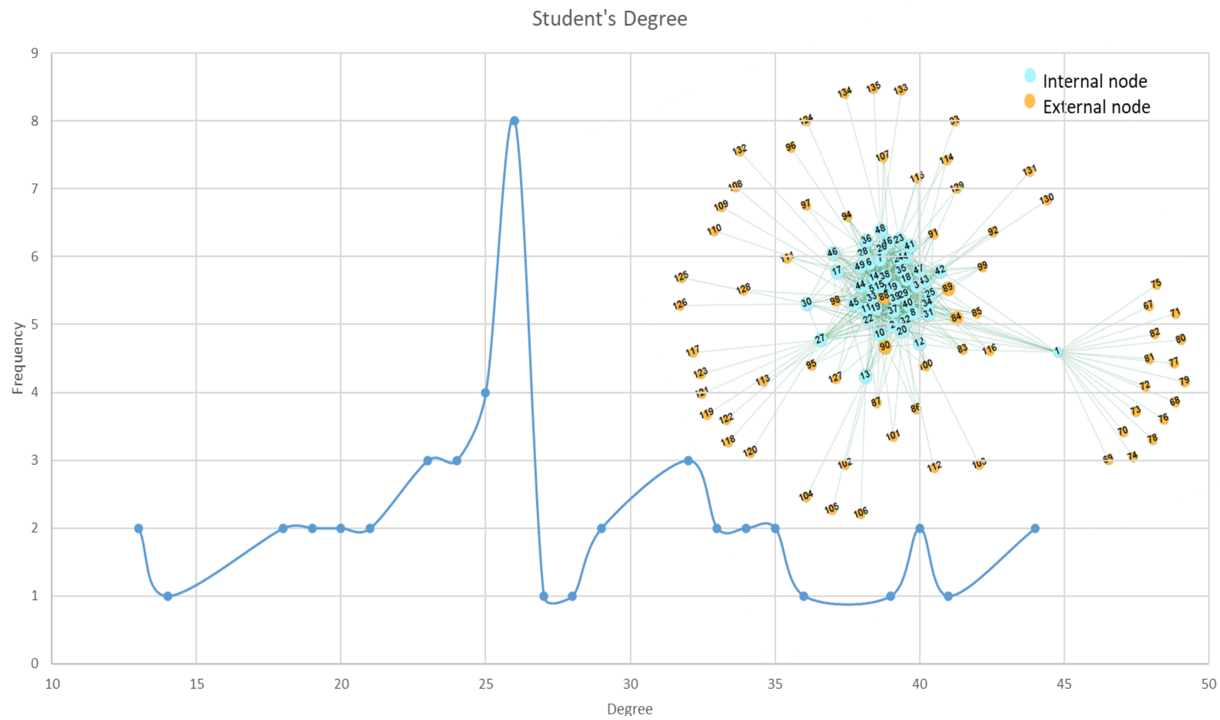

Figure 8: Degree of internal nodes

From the graphical representation in Figures 7-9, below are the key insights:

- The network degree distributions of the nodes follow the power law [45] (shown in Figure 7). Which means most of the node having a very low degree, whereas only a few nodes having a very large degree.
- The degree distribution of the students (internal nodes) does not follow the power law. The students' connectivity was found to be 13 to 44 with other participants (shown in Figure 8). Most of the students have a degree of 26. From Table 3, statistical properties of students (internal nodes), we can see the median, mode and average degree are close to 26.
- While closeness centrality indicates the reachability of a given node from all other nodes in that network, the average closeness centrality of the student networks seemed to have increased initially, reaching the peak of 0.45 in the middle of the semester. This is indicative of students who took part in social media activities held an equivalent central position in the network. However, it dropped later in the semester since, as more new students participated in social media posting, they did not mention as many other nodes as was expected.
- In contrast, betweenness centrality indicates how many times a given node falls under the shortest path of any two other nodes in the network. Figure 9 indicates that such centralities in the student interaction network drop-down fast at the beginning of the semester and continues to be close to zero throughout the semester.

Table 2: Statistical properties of internal nodes

Statistical Properties	*Value*
Number of Nodes	49
Sum of Degrees	1342
Mean (Average) Degree	27.388
Median Degree	26
Degree Mode	26, appeared 8 times
Largest Degree	44
Smallest Degree	13

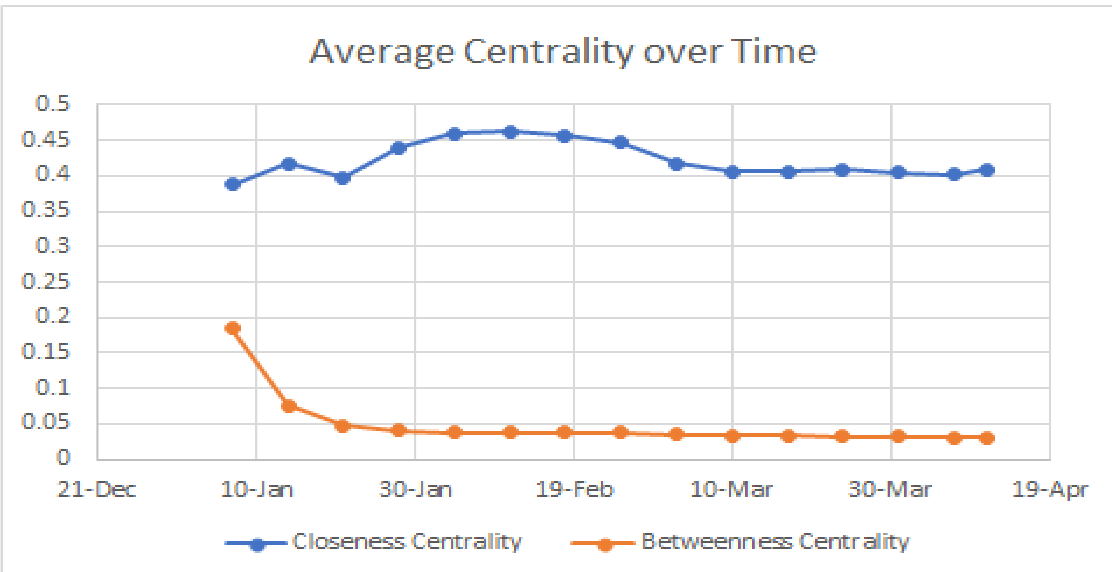

Figure 9: Average Centrality over time

6. CONCLUSIONS

The objective of this research is to promote student engagement in STEM learning and demonstrating an opportunity for leveraging social media as a pedagogical platform. As such, the study utilizes social media interactions on Twitter from students in an online class of Construction Materials and Methods during Spring 2020. Traditional datasets have limited capacity to capture online information sharing and interactions of students and external peers in a STEM class with such details and coverage. The fully online class consisted of 66 students enrolled in the fully online class and 49 of them provided Twitter handle through an end-of-semester survey. Twitter Application Programming Interface (API) was used to retrieve students' online interactions in five consecutive deliverables during the semester. These deliverables included student social media interactions on several topics covered in class such as (i) construction; (ii) delivery methods, drawings and specifications, zoning regulations, building codes, construction standards; (iii) soil types, properties, gradation, testing, and exploration; (iv) concrete ingredients, making, placing and reinforcing concrete, sitecast and precast concrete, wood products, masonry; and (v) steel construction. The requirement was to post any information of their choice (photo, video, text, website link, or anything relevant) already covered in the class and comment to at least five other students. To maximize peer influence, students used several keywords (such as #course number, #university name, #construction) as hashtags and mentions. Interactions from external peers such as experts, alumni faculty, senior students among others were also observed. A few of the posts from the students' social network are shown below:

- *"I can't wait to see how the Inter Miami stadium turns out. Its construction is scheduled to be done by March".*
- *"Steel comes with very distinct qualities that make it the material of choice among construction professionals".*
- *Wooden construction isn't as popular as it is up north, but the energy efficiency is extremely significant compared to others.*

Analyses of such interaction networks showed significant growth of students' social media activity and connectivity over time i.e. the number of network agents and their connectivity increased significantly from the first deliverable to the final deliverable. These also exhibit small-world properties that are evident in many real networks. For example, within the first 25 days of assigning the initial deliverable, five times more participants and twenty-seven times more interactions were observed. We also observed that the degree (i.e. number of immediate neighbors) distribution follows power-law which means many nodes with less interaction and very few in the network are having most of the interactions. Within the first 25 days, the average degree of the participants increased from 2.29 to 12.92. Social media engagement of the students can be monitored following the slope of network growth over time. For example, network growth was observed to be the least since no social media participation deliverable was assigned in February. Most of the external nodes which have greater connectivity with other nodes in the network are user mentions such as @ FIU_Mossschool, which can serve as an information hub to influence internal as well as external peers. Through network analysis, influential and non-influential students can be identified which could help instructors and educators to prepare a better strategy to increase the students' engagement in any particular course. Some of the key insights of this study include: (i) *students who are highly active on social media, are also likely to engage with students with similar activity level; (ii) students are more likely to find newer connections (i.e. user mentions) compared to the connections they already established; (iii) the timing of social media participation deliverables increases the likelihood students' interaction activities in the network. The absence of such deliverables slowed down the network growth and resulted in reduced average connectivity of the students' network.*

The insights of this study can be useful in facilitating STEM learning and engagement with more efficient peer influence. The findings of this research will help to craft targeted information-sharing strategies for various student groups based on their interaction, activities, and characteristics on how students react to what others post on social media on a related STEM topic. Although the findings of this study are obtained by applying network science theories in STEM learning, this study has some limitations and could be improved in future research. The data was collected only for 49 students who were enrolled in Spring 2020. In future studies, by conducting similar experiments, more data can be collected to perform a comparative analysis of network growth. The study also did not consider the emerging discussion topics that may exist in the tweeting activities of the students as well as external peers. The study is limited to exploring network growth within a semester, however, future studies may uncover whether such network connectivity sustains even after the end of the semester. The study is also inconclusive on how social media interactions on a STEM topic may influence knowledge building. The study was limited to the class of Construction Material and Methods; more efforts are needed to find out whether such network growth patterns exist in different STEM courses.

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