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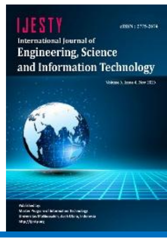

Hybrid Graph Attention Networks for Influencer Ranking in Student Activity Networks

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Abstract

Detecting influencers in a social network of massive student activities is vital for universities because it will help them understand potential leaders and social behavior. This paper mitigates the issues of classical topology-based metrics by presenting volume calculation through Graph Attention Networks (GATs) applied to a real network with 2,520 students and about 282,000 interactions. A new hybrid method of influencer ranking proposed, which combines the node embeddings obtained by GAT with a structural influence signal from PageRank. The evaluation system includes two main parts. First, qualitative evaluation of the hybrid ranking method against PageRank-only. This assessment learns from a ground truth dataset of 993 formal leaders. Second, evaluate the communities found by GNNs against those discovered by classical methods using internal quality criteria, including modularity and conductance. From the observation, PageRank baseline does slightly better than the hybrid method in ranking and both methods are significantly better from a random rank with their Spearman's Rank Correlation equal to 0.513 for PageRank based and 0.451 of the hybrid variant, respectively. Yet, in the task of community detection, GNNs have greater representational capacity. Even though the resulting modularity score was also very competitive, communities had much lower (and hence better) average conductance than Louvain and Walktrap methods (0.137 vs 0.198 and 0.302). These paired results shows that: the success of a PageRank baseline is tied to our formal-role-based ground truth which is structural. The GNN's increased ability to discriminate such well-delineated, socially close communities implies that the embeddings it learns better represent the network's true social structure. In conclusion, while PageRank effectively reveals the formal leaders in a community, our hybrid GAT technique acts as complement to shed light on emerging influencers.

Keywords: *Influencer Ranking, Community Detection, Graph Attention Network, Social Network Analysis, Student Activities.*

1. Introduction

In the context of institutions of higher education, non-academic student affairs offer critical opportunities for the development of soft skills, collaboration and an enriching college experience [1]. The activity interactions would naturally lead to the creation of a complex social network, which can be analyzed for useful insights such as influential individuals or "influencers" [2]. And these opinion leaders are frequently the conduit of important information, and also potential future leaders, so the identification of such personalities has strategic value for organisational planning and change [3].

Conventionally, identify influencers led to classic centrality measures for network topology[4]. Our previous research, measured centrality based on the correlations with academic performance and applied the methods to a comparable dataset such as heuristic algorithms e.g., Fast Greedy, Walktrap for community detection [5]. Yet that paper also raised a major issue: classical methods pay more attention to the network structure, and do not fully utilize the heterogeneous attributes of each node, such as past leading experience or wide range involved in activities, which are also important factors affecting someone's influential power.

To fill this gap, in this research, deep learning model on graphs is used instead of classical methods. Graph Neural Networks (GNNs), such as sophisticated architectures including the Graph Attention Network (GAT) [6], enable the learning of context-rich representations (embeddings) for each student by capturing both structural and feature-based information [7]. This makes it possible for the GNN to "grasp" the network in a more complete sense.

Accordingly, this work presents a hybrid approach to enhance the accuracy of influencer ranking. To this end, this work leverage the best of both worlds by: (1) training GAT to generate embeddings that capture student profiles and (2) using classical PageRank as a metric for structural influence [8]. The key contribution of this study is the design and systematic validation of a hybrid approach on a student activity dataset for the first time, along with a comparison between GNN-derived communities and several classical algorithms.

2. Literature Review

2.1. Classic Approaches to Influencer Detection and Community Detection

Classical methods are the basis of computation to measure the strategic position of a node degree, betweenness and closeness centrality[4]. PageRank, first proposed for web page ranking purposes, has been applied as a strong indicator of influence on a wide range of social networks [8]. At the same time, detecting tight groups of individuals, communities, still occupies a predominant place in social network analysis [9][10]. Several algorithms have been developed for solving this problem. The Fast Greedy algorithm, for instance, greedily integrates communities according to the optimal quality function called modularity [11]. The Walktrap algorithm is based in the fact that short random walks are likely to be 'trapped' within highly connected portions of the network which can be related to communities [12]. Another well-known efficient modularity-maximization algorithm is the Louvain method, known for its scalability to big networks [13]. However, the classical methods can only use the topological information and are not applicable to real-world networks. This finding was supported by our previous work, which demonstrated a low correlation between student centrality and GPA, indicating the importance for models that exploit additional information [5].

2.2. Modern Approaches with Graph Neural Networks

Representation learning on graphs, initiated by methods like DeepWalk [14] and node2vec [15], makes representation the first-class citizen. These approaches generate low-rank embeddings which retain well the underlying network structure. Graph Neural Networks (GNN) extended this idea by working directly with graph structures and incorporating node feature. As extensively discussed by Wu and colleagues [7], GNNs and their variations, e.g., Graph Convolutional Networks (GCN)[16] and GraphSAGE [17], learn embeddings that capture the information of both network structure and node features; which makes them especially suitable for sophisticated analysis.
GNNs have recently been applied toward influencer and community analysis. Chen[18] used GCN models to predict KOLs dynamically, and Kanavos et al. [19] studied influencer analysis in multidimensional social networks. Zhou et al.[20] employed GNNs for community detection and influencer finding in precision marketing. However, one research gap remains when considering hybrid methods that directly combine the learned features from GNNs and the well-known robustness of classic centrality measures as well as in investigating in a systematic way to which extent GNN-based communities can compete with classical algorithms over multiple community evaluation measures. The intention of this study is to fill that gap.

3. Methods

3.1. Dataset and Pre-processing

The main data used in this study is student activity database from Institut Sains dan Teknologi Terpadu Surabaya (ISTTS) which is originally consisted of 23,267 records of students participating on any events and organizations. Among the initial data processing steps were: (1) converting column with date to standardized datetime format for easier duration calculation; (2) cleaning the dataset by deleting rows that had missing values in some essential identifier fields, such as student id (mhs_nrp) and organization code (org_kode); and (3) changing types. This detailed cleaning left us finally with dataset from which 2,520 students identified as the nodes of this study.

3.2. Weighted Graph Construction

After pre-processing data is complete, an undirected graph G = (V, E) created, where each edge(v,u) indicates that two students had at least one student's activity together. To make sure this connection have more meaning, a weighted graph created where the weight (w_{uw}) associated with each edge represents how strong is the interaction. This weight is calculated from two most important things: interaction duration and student's role in those activities like chairperson.

$$w_{uw} = duration\_weight \times role\_weight \quad \ldots(1)$$

1. Duration _Weight: This represents the how long that student involved in one activity, the longer one student involved in one activity with another student, more likely that student interact with each other. For example, being part of the same student organization over a year will more likely give a stronger social connection than only going to the same one-day workshop. To express this, a scale was used and a log transformation was applied to the duration (in days). The logarithm (log1p) is used to avoid overly penalizing extremely long duration when calculating the edge weight and at the same time maintaining the order-of-magnitude difference in commitment.
2. Role Weight: This represents what role that student has in one student activities. Two students with high role or position in one organization, such as between chairperson with vice chairperson, will more likely make a stronger connection between those students, compared to two students with low role or position like participant. Table 1 shows point-based method to measure importance of formal roles. The combined significance of a high-level interaction is represented by the product of the two roles score for interacting students. For instance, the role weight will be (6 x 4 = 24) if a role of Chair (6 points) and another typer of Coordinator (4 points) interact.

Table 1. Point Allocation Scheme For Student Roles

Tier	Role Title (Example)	Points
Top Leadership	Chairperson	6
	Vice Chairperson	6
Core Committee	Treasurer	5
	Secretary	5
Coodinator Level	Coordinator	4
Active Member	Committee Member	3
	Member	3
Other Roles	E.g., Master of Ceremony	2
Default	Any other role	1

3.3. Node Feature Engineering

One important feature for Graph Neural Networks (GNNs) is the transfer of properties from nodes to edges, which does not pass on features from GNNs. We construct an extensive 31-dimensional feature vector for each student in order to furnish the model with a detailed profile that goes beyond their network placement. These features, described in Table 2, were chosen to represent different aspects of a student's academic and non-academic life.

Table 2. Summary of Engineered Node Features

Category	Feature Name	Description
Activity	total_activities	Total count of unique activities
	leadership_score	Cumulative sum of role points from Table 1
Academic	student_gpa	The student's Grade Point Average.
Demographic	major_name	The student's academic major
	cohort_year	The year the student enrolled

Categorical variables (major_name, cohort_year) were converted to numerical values with one-hot encoding to avoid introducing a false order. Then, all the numerical features were normalized by a Min\xa0-Max Scaler to be scaled on an interval of [0, 1], such that no single feature would dominate the learning process of GNN.

3.4. Representation Learning with GAT

Graph Attention Network (GAT) [6] is used for learning node representations. Contrary to GCN and GraphSAGE which adopts a hard-(e.g., mean) wired aggregation weight, GAT's main power comes from its attention mechanism. It allows the model to give different importance (attention) weights to nodes by aggregating information, which makes its power of capturing complex relational dynamics improved.

Our architecture consists of two GAT convolutional layers. The first layer reduces input features of 31 dimensions to a 64-dimensional hidden space using eight attention heads. The second layer then projects this representation into a 16-dimensional embedding vector for students.

An unsupervised model was trained using link prediction task. In this setting the model needs to discriminate between real edges (positive samples) and non-edges (negative samples) in the graph. By learning to solve this task, the GNN is forced learn how to yield robust embeddings that those should capture the underlying principles of how nodes form a network, even without having explicit supervision for the structure of individual nodes.

3.5. Hybrid Method for Influencer Ranking

In this paper, a novel hybrid approach used which combines two types of influence, the first one is feature-based strength and the second one is structural importance, to compute the final influencer score (Sfinal).

$$S_{final} = Norm(||z||_2) \times Norm(PageRank) \quad \text{.....(2)}$$

1. GAT Profile Strength ($||z||_2$): The L2-norm of the embedding vector z generated by GAT indicates the "magnitude" or "strength" of a student's profile within its learned multidimensional space. A large norm means that the GNN has recognized this student to own a peculiar and important set of features and relationships.
2. Structural Influence (PageRank): The well-known PageRank algorithm[8] used on our weighted graph to measure a student's "reputational" influence. High PageRank means that node is followed by other important nodes. The multiplicative product of their combination serves as a logical AND gate, requiring top-ranked influencers to have both strength - realizing a feature-rich profile (i.e. high L2-norm) AND strategic placement in the network structure (i.e. high PageRank).

3.6. Evaluation Framework

For the evaluation, two evaluation paradigms used: 1) the main task of influencer ranking; and 2) community detection as a secondary task, which verifies the representative capability of GNN.

First, in terms of influencer ranking, hybrid approach compared to a simple weighted PageRank approach. For this quantitative analysis, ground truth developed, which is a dataset of 993 students who were recognized as formal leaders. The records in this directory were assembled by examining the institution's student activities database, which includes files for both chartered student organizations and ad-hoc event committees. The curation was conditioned by some constraints tailored to exclude the students who were not taking action but played merely managerial or organisational roles.

The key filtering criteria were as follows: first, only students record from the 2010 cohort to data updating time, in order for recent and valid information. Most importantly, roles like 'Participant', or 'Winner', or other similar and prize-related ones have been explicitly excluded: Hence, the main focus is on the organizers and committee members themselves who directly influence activities. Furthermore, records filtered with a certain invalid date (e.g.'0000-00-00') as in closing_date and activity around some 'weird' category values (e.g. 'HON') that would not meet our data quality or temporal clean-up requirements in mind. The resulting list of 993 individuals provides a strong ground truth setup of formal student leaders for us to compare against, via two standard metrics: F1-Score@K — measuring the level of overlap in top-K rankings, and Spearman's Rank Correlation — assessing the correctness of rank order.

Second, to verify the quality of learned representation by GNN for a primary network task, GNN also used it in community detection. These communities, obtained by clustering the GNN embeddings, were exhaustively compared against three standard partitioning methods (Fast Greedy [11], Walktrap [12], Louvain [13]) on some quality measures: Modularity (a coverage-based community density function [10]), Conductance (an operational measure of community well-knittedness [21]) and computational time.

4. Results and Discussion

4.1. Network Characteristics and Visualization

The resulting graph consists of 2520 nodes and 282,824 weighted edges. Figure 1 contains a visualisation of the whole network, with nodes coloured according to academic major. This visualization shows a dense core of students who are densely connected, mainly students from the large departments and then there is clustering around academic major. However, many between-major connections itself illustrates the complex social organization cutting across the departments, indicating difficulty of finding global influencers.

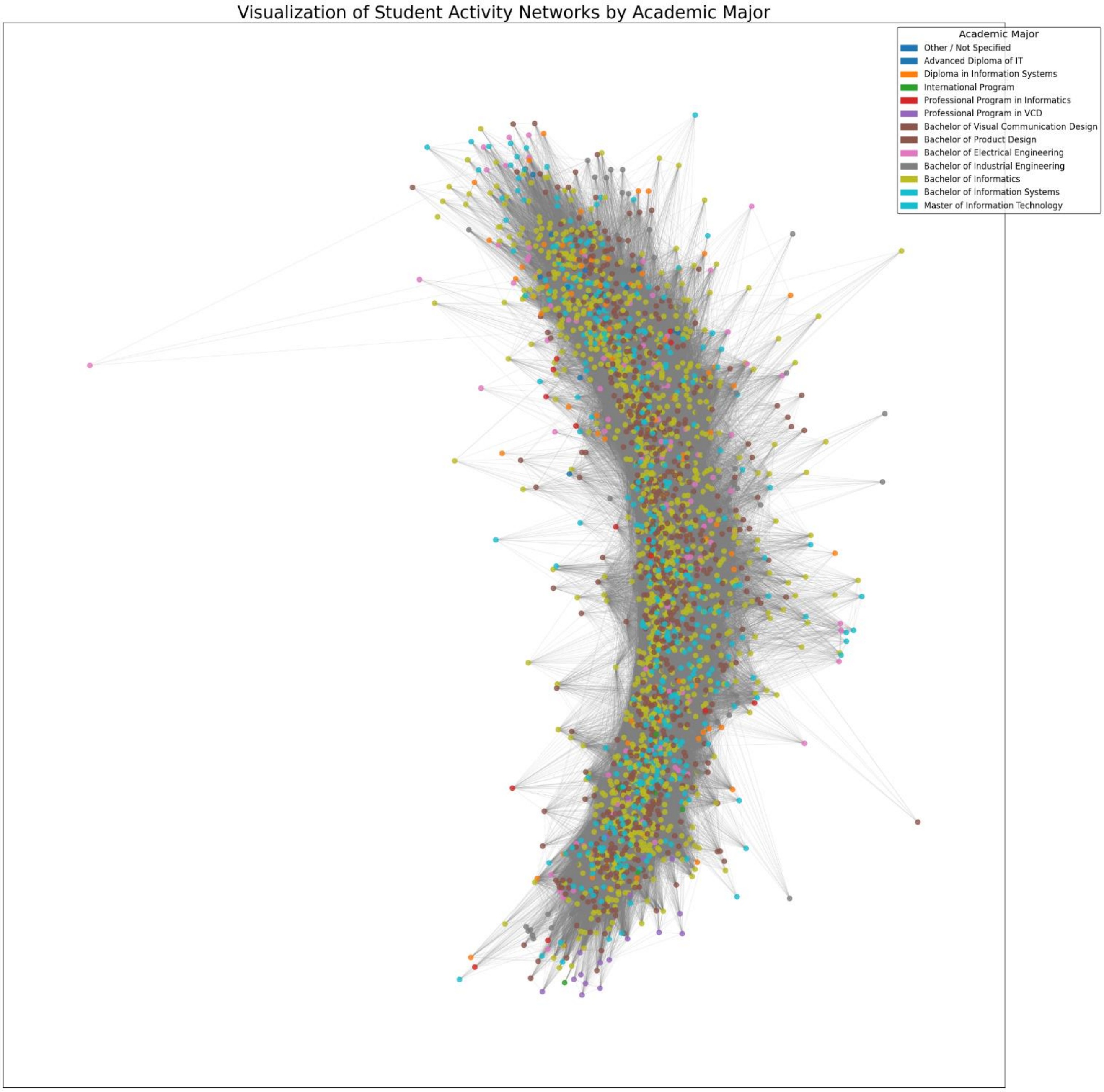

Fig 1. Visualization of the student activity network. Nodes are colored by academic major, revealing dense clusters and inter-cluster links.

4.2. GNN-based Community and Influencer Visualization

Prior to partitioning the network, the best number of communities determined by examining its Silhouette Score in various numbers of clusters (k). As illustrated in Figure 2, the score is maximized at k = 3 which means that this number of communities is most statistically significant for our dataset. As a result, the graph divided into three groups based on the learned GAT embeddings. The resultant structure is shown in Figure 3. This visualization nicely shows the three social clusters (dark red, dark blue and light green) as the main result, while also showing that top-ranked global (though biased by a huge focusing factor due to their low degree in real terms) influencers detected using our hybrid approach. Significantly, the major communities are often centered on their intersections where key influencers become essential messengers of information. Other than community visualization, the result also shows Top 20 global influencer identified by Hybrid GAT method.

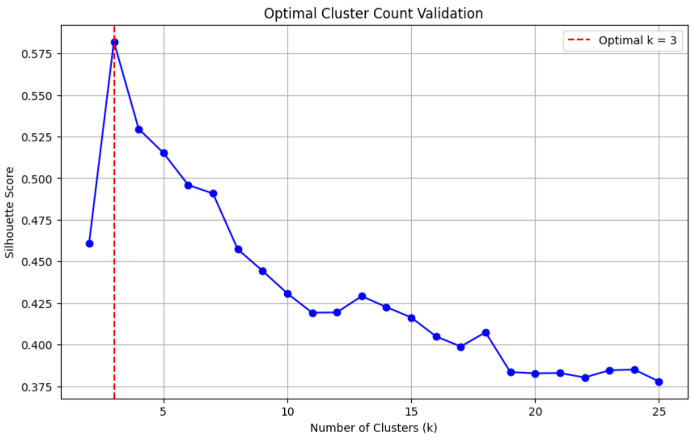

Fig 2. Optimal cluster count validation using the Silhouette Score, which peaks at k=3.

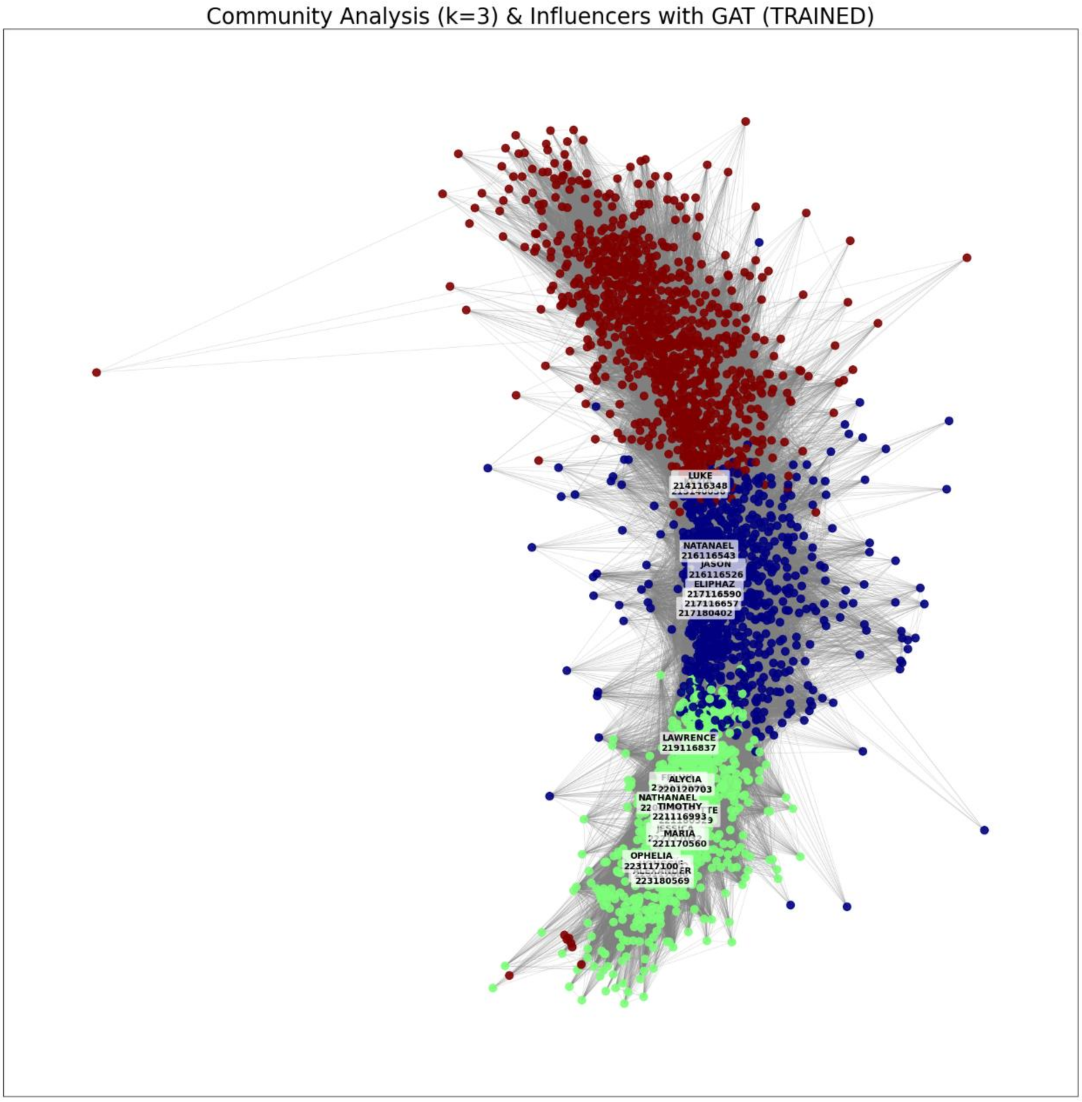

Fig 3. Main visualization of the network partitioned into three communities (k=3) based on GAT embeddings. Labels highlight the top-20 global influencers identified by our hybrid method.

The output of our hybrid method also gives a ranked list of students based on their influence scores. Table 3 displays examples for the Top-10 global influencers identified. A qualitative analysis of the Top-20 list confirms the method's validity. The results show a diverse distribution across cohorts and academic majors, with a majority (12 out of 20) from the large Informatics Engineering department. Crucially, a detailed role analysis reveals that a vast majority of these individuals have held formal leadership positions, indicating that the results are contextually relevant.

Table 3. Top-10 Global Influencers Identified by the Hybrid GAT Method

Rank	Student Name (ID)	Hybrid Score
1	JENNY ELIZABETH ALIM (223117090)	0.5882
2	JESSICA WAHYUDI (222117032)	0.5044
3	ADELTRUDO DONAL (223117071)	0.4457
4	BERNADETTE GRACIELA S. (221180529)	0.4384
5	KEZIA VIVIAN (215140056)	0.4201
6	FELLYA RUTH TANJAYA (220170500)	0.4194
7	MARIA ANGELINA EMMANUELA (221170560)	0.4161
8	JASON MARCELLINO (216116526)	0.4135
9	ALYCIA LAUREN (220120703)	0.4040
10	ONG, HANSEL SANTOSO (217180402)	0.4034

4.3. Quantitative Performance of Influencer Ranking

To evaluate the performance of our method quantitatively, experiments conducted by comparing our approach with PageRank only. Our hybrid GAT model achieved token-level Spearman's Rank Correlation score of 0.451, while the PageRank baseline got a score of 0.513, which can be referred in Figure 4. The scatter diagram in Figure 5, shows that a positive correlation exists, many nodes deviate from the ideal "Perfect Ranking" line. Table 4 lists the result of the unranked evaluation, and indicates such pattern: only that baseline features slight advantage.

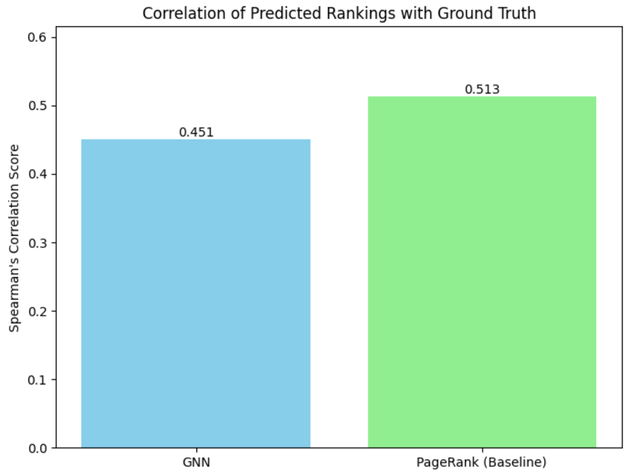

Fig 4. Comparison of Spearman's Correlation Score between the GNN hybrid method and the PageRank baseline

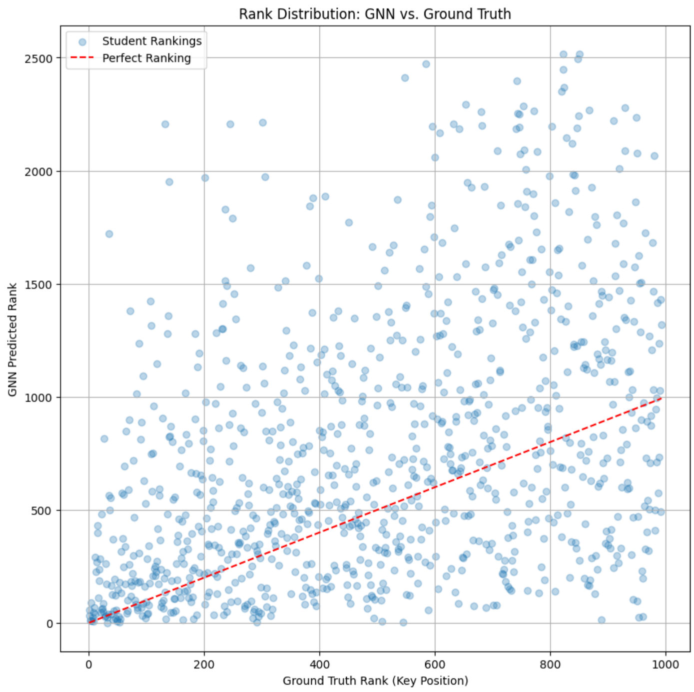

Fig 5. Scatter plot of GNN-predicted rank vs. ground-truth rank.

Table 4. Detailed Unranked Evaluation Metrics Comparison (F1-Score)

K	Student Name (ID)	Precision	Recall	F1-Score
50	GNN (Hybrid)	0.9600	0.0483	0.0920
	PageRank Only	0.9600	0.0483	0.0920
100	GNN (Hybrid)	0.9660	0.0967	0.1757
	PageRank Only	0.9500	0.0957	0.1738
200	GNN (Hybrid)	0.9150	0.1843	0.3068
	PageRank Only	0.9400	0.1893	0.3152
300	GNN (Hybrid)	0.8867	0.2679	0.4114
	PageRank Only	0.9000	0.2719	0.4176
993	GNN (Hybrid)	0.7009	0.7009	0.7009
	PageRank Only	0.7150	0.7150	0.7150

4.4. Comparative Analysis of Community Detection Methods

To further validate the GNN's representations, a comprehensive evaluation conducted of its community detection performance against classical algorithms. The results, summarized in Table 5 and visualized in Figure 6, present a nuanced trade-off between quality and performance.

Trade-offs are also evident in the results of Table 5. Although Louvain achieves the highest modularity score, our GNN-based method is highly competitive with it and produces much higher quality communities with an average conductance of 0.1368 (vs 0.1980 for Louvain) and performed much better than Walktrap, whose average conductance is as high as 0.3022. This suggests that the clusters found by our method are more stable.

But most imperative is the difference in computational throughput. For classical algorithms like Louvain and Walktrap record high time efficiency, performing their single-pass runs in less than 10 seconds. In comparison, our GNN method requires an large upfront computational cost (600 seconds). It is important to understand, that 600 seconds not spent on the clustering task itself, which is almost instant, but rather to the full model unsupervised training.

This investment leads to an influential and flexible resource: a collection of high-quality node embeddings. In contrast to classical algorithms, which has a single-purpose output that only returns community partition, these embeddings can be used for a wide-range of different tasks at the same time (e.g., evaluating the primary influencer ranking task considered in this paper). As a result, the method makes a clear compromise: efficiency for analysis on-the-fly versus learning to represent deep, reusable networks.

Table 5. Comprehensive Comparison of Community Detection Methods

Method	Modularity	Conductance	Communities	Time (s)
Louvain	0.5486	0.1980	4	7.17
GNN (Trained)	0.5255	0.1368	3	600.04
Walktrap	0.5242	0.3022	6	8.81
Fast Greedy	0.5142	0.1244	3	42.72

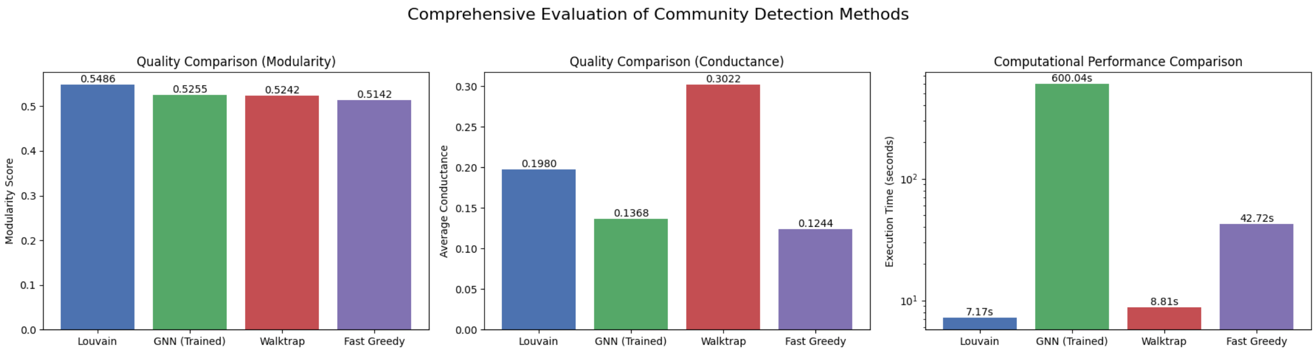

Fig 6. Evaluation of community detection methods across three dimensions: Modularity, Conductance, and Computational Performance.

4.5. Overall Interpretation and Broader Implications

The quantitative results demonstrate an interesting and somewhat counterintuitive result: the architecturally simpler PageRank baseline slightly outperformed our hybrid Graph Attention Network (GAT) method in terms of all primary ranking metrics. Although this result may not necessarily reflect a weakness of the GNN, it raises interesting observations regarding our methodological approach and the intricate definition of influence.

The effectiveness of PageRank is easy to be understood, being attributed to our ground-truth data collected from formal leadership titles as explained before. At a more abstract level, the PageRank algorithm is best understood as a mathematical measure of structural and reputational importance—a proxy that trivializes with hierarchical organization, for it's hard to think of a hierarchy in which those known statistics muted capacity instead of magnified it. This alignment is demonstrated by its higher Spearman's Rank Correlation of 0.513 than the hybrid method with 0.451, shown in Figure 4, and its stable edge in F1-Score, shown in Table 4.

On the other hand, GAT model learns a more context-dependent definition of "influence". It may simply be that our hybrid approach captures a different — but equally valid type of influencer: the informal/emergent leader. Their influence, as encoded in the GNN's embeddings, is not present in our formal-role-based ground truth.

For its superior performance in the community detection task shown in Figure 6. Communities were the of lowest average conductance (0.1368) produced by GNN among high-modular methods, showing that its embeddings are very effective in grasping true distinct and crisp structures between social clusters. These results support the stance that the GNN is not a bad model but in practice can effectively learn good representation of network's social status.

Thus, the 2 approaches can be regarded as analytical complements. PageRank performs well in the timely and efficient discovery of the formal established leadership structure.On the other hand, the more computationally demanding hybrid GAT method can be considered as network's "talent scouting", identifying that special individuals who leave their impact felt through diverse manners among university social membership practices—"hidden gems" whose interest is also noticeable from their (rich) multidimensional activity within the university's life.

5. Conclusion

In this study, we propose a new hybrid algorithm for influencer ranking in a student activity social network, which combines representations learned by Graph Attention Network (GAT) with PageRank centrality. In our quantitative validation using a formalized role-based ground truth, however, PageRank-only produces only a slightly better performance – Spearman's correlation = 0.513 compared to the hybrid's 0.451. We believe that this arises because our ground truth corresponds to the structural nature of PageRank.

Nevertheless, the study results in three major findings. Primarily, Graph Neural Network (GNN) showed representations are powerful for a classic problem on networks: GNN embeddings generate, in a fundamental network task, communities with clearly better structural quality (with a low conductance score of 0.1368), when compared to many classical and state-of-the-art algorithms. Second, contributed to a data-driven discussion of the many aspects of influence that there are, suggesting that our approach based on GNNs is able to reveal informal influencers which go unnoticed by purely structural metrics. Third, proposed an end-to-end full pipeline to apply the GNNs to real-world student activity data including weighted graph construction and multifaceted evaluation.

Future work should focus on validating this method with a more nuanced ground-truth dataset that includes peer-nominated informal leaders. Such a dataset would allow for a more direct evaluation of the hybrid method's unique strength in discovering latent influential figures within the academic community.

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