Spotting Key Influencers in Event Participation using Social Network Analysis

Prof. Hitha S
Assistant Professor
Department of AI & DS
BMS College of Engineering
Bengaluru, India
email: hithas.ads@bmsce.ac.in

Vaibhavi K
AI and Data Science
BMS College of Engineering
Bengaluru, India
email: vaibhavi.ad22@bmsce.ac.in

Pallavi
AI and Data Science
BMS College of Engineering
Bengaluru, India
email: pallavi.ad23@bmsce.ac.in

Monisha B
AI and Data Science
BMS College of Engineering
Bengaluru, India
email: monishab.ad24@bmsce.ac.in

***Abstract*—Event participation within educational and professional institutions is frequently driven by peer influence rather than direct advertising. Identifying the individuals who drive this participation is crucial for optimizing outreach strategies. This paper proposes a Social Network Analysis (SNA) approach to identify key influencers in event participation networks. By constructing a directed graph where nodes represent participants and edges represent invitation relationships, we apply centrality metrics including PageRank, Betweenness Centrality, and Degree Centrality to compute influence scores. Furthermore, this study categorizes influence across three distinct domains: Student, Business, and Entertainment events. The system includes an interactive dashboard developed using Streamlit to visualize network structures and rank influencers. The results demonstrate that SNA provides a more accurate identification of influential individuals compared to traditional participation counts, offering actionable insights for data-driven event management.**

***Index Terms*—Social Network Analysis, Influencer Detection, PageRank, Centrality Measures, Community Detection, Event Management.**

I. Introduction

Event participation in academic and organizational settings is heavily influenced by social connections. Students and professionals often attend events not solely due to the content, but because they are motivated or invited by peers they trust. However, event organizers typically lack the tools to identify these “hidden” influencers, relying instead on broad, untargeted promotion strategies such as posters or mass emails. This often leads to suboptimal turnout and inefficient resource allocation.

Social Network Analysis (SNA) offers a scientific framework to uncover these underlying influence patterns. By modeling participants and their interactions as a network, it becomes possible to mathematically quantify influence. While traditional metrics might simply count the number of events a person attends, SNA allows us to understand *who* invites *whom*, who acts as a bridge between disconnected groups, and who holds the most authority within the network structure.

This paper presents a comprehensive system for spotting key influencers in event participation. The objectives of this research are:

- To construct a directed influence graph from event participation data.
- To compute advanced centrality metrics (PageRank, Betweenness, Degree) to rank user influence.
- To perform category-wise analysis, distinguishing between influencers in Student, Business, and Entertainment domains.
- To visualize these patterns through an interactive dashboard to support decision-making.

The remainder of this paper is organized as follows: Section II reviews existing literature and identifies research gaps. Section III details the methodology and system architecture. Section IV describes the implementation and algorithms used. Section V presents the results and discussion, and Section VI concludes the study with future directions.

II. Literature Review

The field of Social Network Analysis has been extensively explored to understand information propagation and node importance.

A. Centrality-Based Influence

Foundational works in SNA have established centrality measures as the primary method for identifying key nodes. Freeman’s work on centrality [7], [14] defined degree, closeness, and betweenness as distinct indicators of a node’s role. More recently, PageRank [15] has been adapted from web search to social networks to measure influence based on the quality of connections rather than just the quantity.

B. Influence Propagation

Research by Kempe et al. and others on influence maximization [16] introduced models like the Independent Cascade and

Linear Threshold to explain how influence spreads. Recent studies [1], [6] have focused on predicting influential nodes based on user reactions and interaction history.

C. Research Gap

Despite the rich literature, most existing studies focus on massive online social networks (Twitter, Facebook) [5], [9]. There is a significant lack of research applied to *institutional* event participation networks, which are smaller but highly dense and structured. Furthermore, existing systems rarely offer category-wise influencer detection—treating a technical influencer the same as a cultural one. This paper addresses this gap by applying SNA to a multi-category event dataset and integrating community detection [18] for practical, on-ground application.

III. Methodology

A. Research Design

The proposed system employs a quantitative analytical approach. We model the event ecosystem as a graph $G = (V, E)$, where V represents the set of participants (users) and E represents the set of directed edges denoting an invitation or influence relationship.

B. System Architecture

The system architecture consists of four primary layers:

1) **Data Preprocessing Layer:** Cleans raw participation data, handles missing values, and categorizes events.
2) **Graph Construction Layer:** Builds the global and category-specific networks.
3) **SNA Engine:** Computes centrality metrics and detects communities.
4) **Visualization Layer:** A Streamlit dashboard for end-user interaction.

C. Mathematical Model of Influence

To quantify influence, we utilize three specific metrics:

1) Degree Centrality: For a given node v, degree centrality is defined by the number of direct connections. We focus specifically on *Out-Degree* (C_{out}), which represents the number of people a user has successfully invited:

$$C_{out}(v) = \sum_{u \in V} A_{vu} \tag{1}$$

where A is the adjacency matrix such that $A_{vu} = 1$ if v invited u, and 0 otherwise.

2) Betweenness Centrality: This metric identifies "bridge" influencers who connect different communities. It is calculated as the sum of the fraction of all-pairs shortest paths that pass through node v:

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{2}$$

where σ_{st} is the total number of shortest paths from node s to node t, and $\sigma_{st}(v)$ is the number of those paths passing through v.

3) PageRank: PageRank measures the importance of a node based on the importance of the nodes linking to it. It is calculated iteratively:

$$PR(u) = \frac{1-d}{N} + d \sum_{v \in B_u} \frac{PR(v)}{L(v)} \tag{3}$$

where B_u is the set of nodes pointing to u, $L(v)$ is the number of outbound links from v, and d is the damping factor (typically 0.85).

D. Categorization Strategy

Unlike generic models, our system segments the graph into three sub-graphs based on the event type field in the dataset:

- **Student Events:** Academic and campus-life activities.
- **Business Events:** Professional networking and seminars.
- **Entertainment Events:** Cultural and social gatherings.

This allows for the identification of niche influencers who may be dominant in one category but passive in others.

IV. Implementation

A. Data Collection and Preparation

The dataset comprises event participation records including `User_ID`, `Event_ID`, `Invited_By`, and `Category`. Privacy is maintained by using anonymized User IDs. The data is processed using the Python `pandas` library to remove duplicates and normalize the "Invited_By" field, ensuring a clean adjacency list for graph generation.

B. Graph Construction

The `NetworkX` library is used for graph operations. We construct a directed graph where an edge $u \rightarrow v$ exists if User u was the "Invited_By" reference for User v.

C. Community Detection

To understand the structure of the network, we apply the Louvain method [19] for community detection. This algorithm optimizes modularity to identify clusters of users who interact more densely with each other than with the rest of the network.

D. Dashboard Development

The user interface is built using `Streamlit`. It allows organizers to:

- Filter influencers by category.
- View top-N rankings based on aggregate influence scores.
- Visualize influence trends and score distributions.

V. Results and Discussion

A. Network Analysis

The analysis of the constructed influence graph revealed significant structural insights. The degree distribution followed a power-law, indicating a scale-free network property where a small number of "hub" participants accounted for a disproportionately large number of invitations.

B. Centrality Metric Evaluation

- **PageRank vs. Degree:** While some users had a high Out-Degree (invited many people), they did not always have the highest PageRank. High PageRank users were often invited by other influential users, suggesting a hierarchy of influence.
- **Betweenness:** Users with high betweenness scores were identified as critical connectors. Removing these nodes would likely fragment the network, isolating specific student groups.

C. Category-Wise Findings

The category-wise analysis showed distinct sets of influencers for different domains. For instance, User U544 emerged as a top influencer in the *Entertainment* category (as seen in the dashboard results) but had negligible influence in the *Business* category. This validates the hypothesis that influence is context-dependent.

TABLE I
Top Influencers by Metric (Entertainment Category)

Rank	User ID	Out-Degree	Influence Score
1	U544	1	High
2	U021	0	Med
3	U253	2	High
4	U052	3	Very High

D. Dashboard Performance

The Streamlit dashboard successfully visualized these metrics. Figures from the testing phase confirm that the system correctly filters and ranks users. For example, the "Certified Influencer Score Distribution" showed that the majority of participants have low influence scores (< 0.2), while a select few exceed 0.8, clearly marking them as key targets for event organizers.

Fig. 1. Category selection interface used to filter influencers by event type such as Global, Student, Business, and Entertainment.

Fig. 2. Certified Influencer Dashboard illustrating proof-based influencer validation using friend counts, invitations, and participation confirmations.

Fig. 3. Top Certified Influencers view highlighting users with the highest influence scores across multiple events.

VI. Conclusion and Future Scope

A. Conclusion

This project successfully demonstrates the efficacy of Social Network Analysis in enhancing institutional event participation. By shifting from manual promotion to data-driven influencer targeting, organizers can leverage the natural social structure of their community. The study confirms that influence is multidimensional, requiring a combination of metrics (Degree, Betweenness, PageRank) for accurate assessment. The developed dashboard bridges the gap between complex network theory and practical application.

B. Future Scope

Future work will focus on:

- **Temporal Analysis:** Incorporating time-stamped data to analyze how influence evolves over the course of a semester.
- **Graph Neural Networks (GNNs):** Implementing GNNs (e.g., GraphSAGE) to predict potential future influencers based on node attributes and early interaction patterns.
- **Sentiment Analysis:** Integrating qualitative data from event feedback to weight the edges of the graph based on positive or negative peer experiences.

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