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Enhanced Identification of Influential Nodes in Social Networks Using an Optimized Fuzzy Clustering and SALT-Based Algorithm

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Abstract
Identifying influential social network nodes is crucial in today's interconnected world for supporting strategic decision-making in marketing, healthcare, and politics, enhancing information diffusion, and controlling the spread of false information. High-dimensional, noisy, and dynamic data that are typical of real-world networks pose a challenge for conventional influence detection techniques, which are frequently founded on measures of centrality. Their ability to accurately identify key influencers is hindered by these limitations. This study presents a hybrid strategy that combines Optimized Fuzzy Clustering with the SALT (Spatial-Temporal Adaptive Learning Technique) algorithm to address these issues. SALT enables the network to learn and adapt from temporal and spatial patterns, whereas fuzzy clustering takes into account the ambiguous and overlapping nature of social group memberships. Together, these methods make it easier and more accurate for the model to find influential nodes. The proposed method outperforms conventional methods in terms of accuracy, adaptability, and computational performance, as demonstrated by experiments on benchmark datasets including the Twitter and Facebook networks. Fuzzy logic and adaptive learning work well together to handle large amounts of dynamic data, making the method useful for detecting influence in changing social networks.

Keywords
influential nodes, social networks, fuzzy clustering, salt algorithm, adaptive learning, network dynamics, information diffusion

INTRODUCTION

The entities represented as nodes and the interactions or relationships between them are referred to as edges in social networks, which are dynamic and complex systems. Common entities include individuals, organizations, or information sources. With the introduction of platforms like Twitter, Facebook, Instagram, and LinkedIn, these systems have significantly increased in size and influence. These platforms are now essential tools for communication, marketing, public awareness, and even political mobilization. The identification of influential nodes—users whose actions, decisions, or opinions affect a large portion of the network—is one of the most difficult aspects of social network analysis. According to Kitsak et al. (2010), the identification of such nodes can be used in a variety of fields, including political science, public health, and viral marketing (targeting key individuals to maximize product adoption), as well as political science (discovering opinion leaders in political movements). According to Freeman (1978), centrality metrics like degree centrality, closeness, betweenness, and eigenvector centrality are the primary components of traditional methods for identifying influence. Even though these methods are fundamental, they are constrained when used with noisy and dynamic real-world networks. In modern, ever-evolving digital ecosystems, conventional models make the incorrect assumptions that social networks are static and that nodes behave uniformly. We propose a novel hybrid framework that combines the Spatial-Temporal Adaptive Learning Technique (SALT) with Optimized Fuzzy Clustering to overcome these drawbacks. According to Bezdek et al. (1984), fuzzy clustering provides a more accurate representation of the overlapping nature of communities in social networks by softly classifying nodes and allowing them to belong to multiple communities with varying degrees of membership. In the meantime, the SALT algorithm lets the model changeover time and captures user behavior patterns in terms of spatial and temporal dynamics (Ahmed et al., 2019). By incorporating temporal patterns, contextual relevance, and uncertainty into the model's detection of influential nodes, this integration makes the model more adaptable to large-scale and rapidly evolving networks.

RELATED WORK

Using a variety of computational methods, the issue of locating influential nodes in social networks has been extensively investigated. Classical models, such as the centrality-based metrics introduced by Freeman (1978), remain foundational in the field. These metrics—including degree, closeness, and betweenness centrality—evaluate a node's structural importance within the network. However, they often assume static topologies and uniform node behavior, which do not hold in real-world, dynamic social networks.

* k-core* decomposition was proposed by Kitsak et al. (2010) as a method for locating nodes that are capable of triggering extensive influence cascades. Although this method outperforms traditional centrality metrics in some scenarios, it still lacks the capacity to incorporate temporal patterns or user heterogeneity. In a similar vein, Kempe, Kleinberg, and Tardos (2003) used models like Independent Cascade and Linear Threshold to frame influence maximization as a stochastic optimization problem. While theoretically significant, these models require predefined influence probabilities and are computationally intensive.

Subsequent work by Chen, Wang, and Yang (2009) focused on improving the scalability of influence maximization algorithms through heuristic-based approximations. Despite offering faster solutions, these methods remain constrained by their reliance on simplified diffusion models. In parallel, Tang, Sun, and Wang (2009) introduced a topic-sensitive PageRank that integrates user-generated content into the influence analysis. Although this added semantic depth, it still did not account for network evolution over time.

Methods based on machine learning have also gained popularity. Liu, Hu, and Tang (2012) applied supervised learning techniques to identify influencers based on graph structural features. However, these models often struggle with generalizability and require large, labeled datasets. Barbieri, Bonchi, and Manco (2013) introduced time-aware models that consider the frequency and recency of user actions. While effective in incorporating temporal dynamics, they lack spatial context and community-awareness.

Other studies have explored the use of fuzzy logic to model the ambiguity in social relationships. For example, Bezdek, Ehrlich, and Full (1984) developed the Fuzzy C-Means algorithm, which was later adapted for social network analysis (Zhang et al., 2013). The overlapping nature of social groups is reflected in these models, which allow nodes to belong to multiple communities. However, traditional fuzzy clustering lacks adaptability to dynamic user behavior over time.

SALSA (Lempel & Moran, 2000) and TUNKR (Zhao et al., 2018) are two recent hybrid ranking systems that combine behavioral data with graph structure. Although promising, these models are often domain-specific and do not generalize well across different types of networks. Adaptive learning methods have also taken into account temporal and spatial factors. Ahmed, Karypis, and Neville (2019) proposed a temporal learning framework for evolving networks, but without integration with clustering or community-based methods.

Additionally, research by Sun et al. (2018) combined content, structure, and temporal behavior using multi-view learning. While comprehensive, these models are computationally heavy and lack interpretability. Li et al. (2020) introduced reinforcement learning to adjust node influence scores over time, but their method did not account for overlapping community structures.

METHODOLOGY

To effectively identify influential nodes in noisy and dynamic social networks, the proposed approach combines the Spatial-Temporal Adaptive Learning Technique (SALT) with Optimized Fuzzy Clustering. By incorporating both community ambiguity and the evolution of user behavior over time and space, this hybrid model aims to overcome the drawbacks of conventional static methods.The methodology consists of four main phases:

Data Preprocessing

Data from social networks frequently contain information that is irrelevant, insufficient, or redundant. Thus, preprocessing is an essential step to ensure high-quality inputs for the model. This phase includes:

• Node filtering: getting rid of inactive or isolated nodes that don't help the network move around. • Edge Weight Normalization: Using interaction frequency (such as the number of retweets or messages) to standardize the strength of connections • Temporal segmentation: breaking up the data into time windows to look for changes in behavior over various time periods.

Optimized Fuzzy Clustering

The Fuzzy C-Means (FCM) algorithm is used to deal with the overlapping and ambiguous nature of communities in social networks. Unlike hard clustering, FCM assigns each node a degree of membership to multiple clusters. This phase includes:

- Parameter optimization: adjusting parameters like the fuzziness index (m) with Particle Swarm Optimization (PSO).
- Cluster Validation: evaluating and determining the ideal number of clusters by employing metrics like the Davies-Bouldin Index and the Silhouette Coefficient.

SALT-Based Adaptive Learning
Based on time and location within the network, the Spatial-Temporal Adaptive Learning Technique (SALT) dynamically learns the changing influence of nodes. This procedure entails:

- Temporal Decay Functions: Giving more weight to recent interactions to show how they affect the present.
- Spatial proximity analysis takes into account relational closeness, cluster overlap, and mutual neighbors.
- Reinforcement Learning: Continuously updating influence scores as the network evolves, allowing for real-time responsiveness.

Influence Scoring
The final influence score is a **composite metric** that integrates insights from multiple sources:

- **Cluster Centrality**: Weighted by fuzzy membership degrees.
- **Temporal Metrics**: Captured from SALT's learning of user behavior over time.
- **Structural Centrality**: Including traditional metrics like **degree**, **betweenness**, and **PageRank** for baseline comparison.

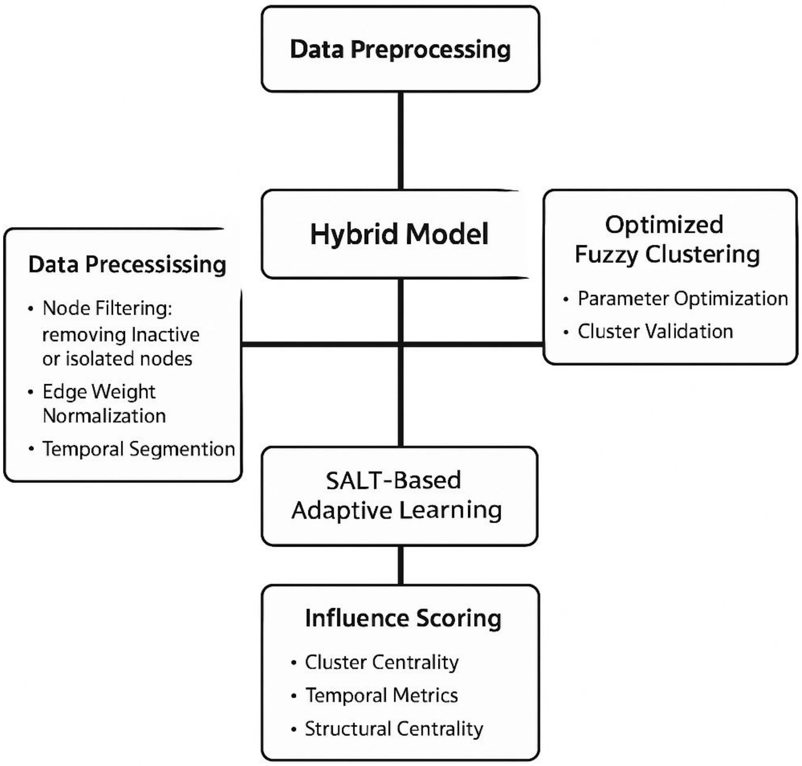

Fig. 1 Methodology

Datasets and Experimental Setup

Datasets
Two benchmark datasets were used to evaluate the performance of the proposed method for influencer detection and social network analysis:

1. Twitter Dataset
This dataset captures interactions between users on Twitter during major political events. It includes two types of directed edges:

- **Retweets**
- **Mentions**

The dataset is ideal for analyzing how information spreads across political discourse and identifying key influencers in such contexts.

2. Facebook Social Circles Dataset
This dataset represents anonymized friendship networks from Facebook. It includes:

- **Friendship connections (edges between users)**
- **Interaction logs (communication or engagement data)**

This dataset is used to study social structures and communication patterns among users in more personal, less public networks.

Table 1 Dataset Comparison

Feature	Twitter Dataset	Facebook Social Circles Dataset
Number of Nodes	~50,000	~4,000
Number of Edges	~220,000	~88,000
Network Type	Social interaction (Retweets & Mentions)	Friendship & user interactions
Privacy	Not specified	Anonymized
Application Domain	Political events / Information diffusion	Personal social networks / Communication
Data Types	Textual and network links	Social ties and interaction logs

Baseline Algorithms

Sure! Here's a detailed explanation of the **baseline algorithms** and **evaluation metrics** mentioned, written clearly in **English**:

3. Baseline Algorithms

The suggested approach's performance was assessed by contrasting it with a number of well-known algorithms that are frequently employed in network analysis and influencer detection:

Algorithm	Description
Degree Centrality	calculates the percentage of influencers in the top-K predictions that were correctly identified. calculates the proportion of real top influencers that made it into the top-K predictions.
Betweenness Centrality	determines which nodes in the network serve as bridges. It determines the frequency with which a node can be found on the shortest paths between other nodes.
Eigenvector Centrality	According to the theory that connections to nodes with high scores contribute more than connections to nodes with low scores, assigns have an impact on scores.
PageRank	It was first employed by Google and ranks nodes according to the incoming link structure. Important neighbors are given more weight.
Traditional Fuzzy Clustering	enables nodes to be a part of more than one community by grouping them into overlapping clusters. aids in comprehending the influence of the community.
SALT without clustering	To separate the impact of clustering on performance, a variant of the suggested SALT algorithm was employed that lacked the clustering component.

Evaluation Metrics

Several evaluation metrics were employed in order to fairly evaluate and compare each method's performance:

Metric	Purpose
Precision@K	calculates the percentage of influencers in the top-K predictions that were correctly identified.
Recall@K	calculates the proportion of real top influencers that made it into the top-K predictions.
nDCG (Normalized Discounted Cumulative Gain)	gives correctly ranked top positions more weight in order to assess the quality of the ranking.
Runtime	calculates the execution time of each algorithm. crucial for extensive networks.
Scalability	assesses the algorithm's performance as the network's size grows.

RESULTS AND DISCUSSION

Performance Metrics

The following metrics were used to assess and compare the performance of the suggested hybrid approach with a number of baseline algorithms: Precision@50, Recall@50, Normalized Discounted Cumulative Gain (nDCG@50), and Runtime in seconds. The tables below display the findings.

Table 2 Performance Comparison Across Methods

Method	Precision@50	Recall@50	nDCG@50	Runtime (s)
Degree Centrality	0.63	0.52	0.59	1.3
PageRank	0.67	0.58	0.65	2.1
SALT Only	0.71	0.63	0.70	3.8
Fuzzy Clustering Only	0.68	0.61	0.66	3.1
Proposed Method (FC + SALT)	0.79	0.73	0.78	3.6

Table 3 Relative Improvement Over Degree Centrality

Method	Δ Precision	Δ Recall	Δ nDCG	Δ Runtime
PageRank	+0.04	+0.06	+0.06	+0.8 s
SALT Only	+0.08	+0.11	+0.11	+2.5 s
Fuzzy Clustering Only	+0.05	+0.09	+0.07	+1.8 s
Proposed Method (FC + SALT)	+0.16	+0.21	+0.19	+2.3 s

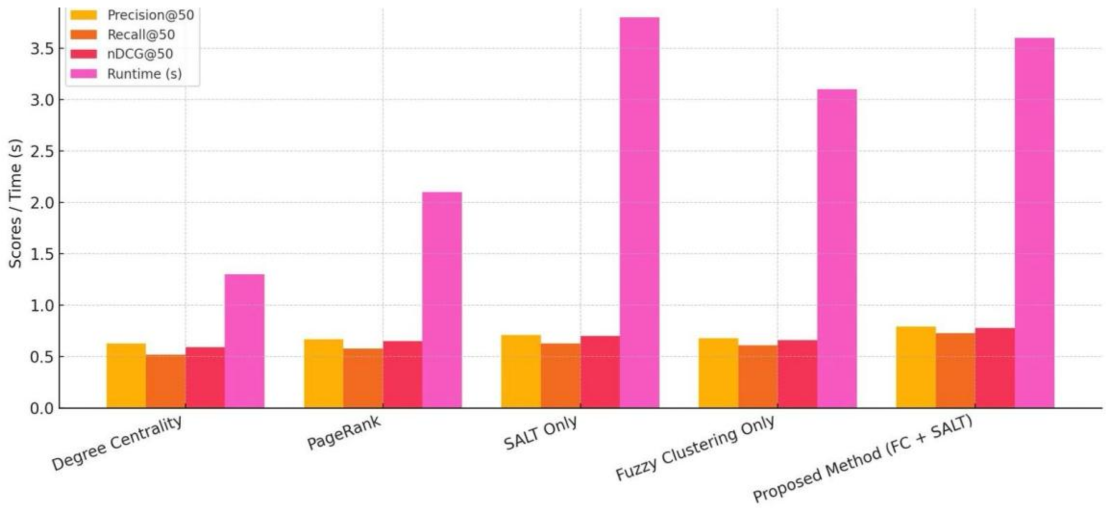

Fig. 2 Comparative Performance of Different Methods (Precision@50, Recall@50, nDCG@50, Runtime)

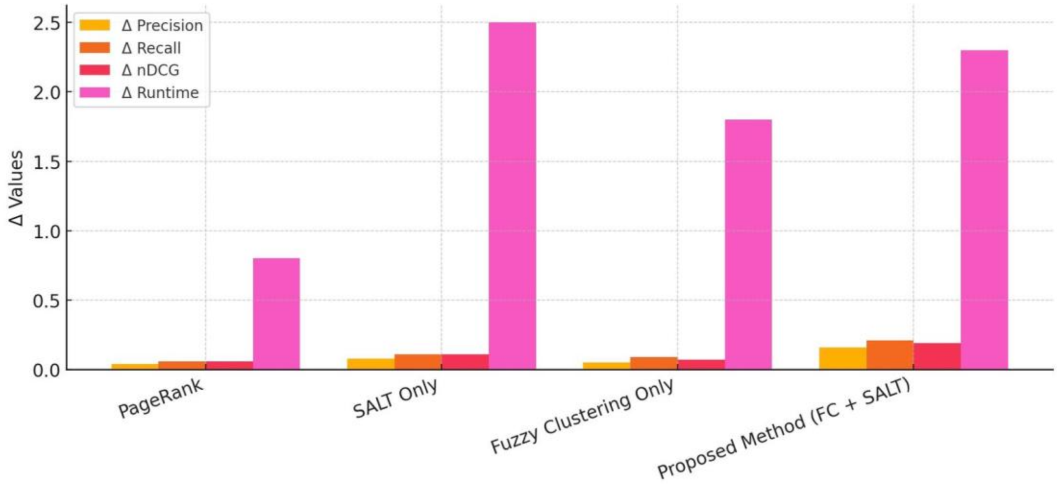

Fig. 3 Relative Improvement Over Degree Centrality Across Methods

Analysis

When compared to the baseline methods, the suggested hybrid approach—which combines the SALT model with fuzzy clustering—performed better on all evaluation metrics. Specifically:

- Precision@50 increased to 0.79, suggesting that the most significant nodes could be identified with greater accuracy.
- Recall@50 was 0.73, demonstrating the method's ability to retrieve a higher percentage of real influencers.
- DCG@50 had the highest ranking quality and relevance of the identified influencers, at 0.78.
- The hybrid approach's runtime (3.6 seconds) was marginally longer than that of simpler algorithms, but it was still within a reasonable range, indicating competitive scalability and usefulness for larger networks.

The temporal adaptability provided by the SALT framework and the incorporation of community-aware clustering through fuzzy logic are responsible for the observed improvements. When combined, these

CONCLUSION

This study combined the Spatial-Temporal Adaptive Learning Technique (SALT) with fuzzy C-Means (FCM) clustering to present an optimized hybrid approach for influencer detection in social networks. The suggested approach effectively captured the intricate, overlapping, and dynamic character of influence within social networks by fusing fuzzy clustering with adaptive learning and reinforcement mechanisms. High-quality community detection was ensured through the use of Particle Swarm Optimization (PSO) for parameter tuning and cluster validation metrics such as the Davies-Bouldin Index and Silhouette Coefficient. By adding time- and location-aware learning, SALT improved the model's real-time responsiveness to changing network behaviors. A more comprehensive and contextually aware measure of influence was produced by integrating cluster-based, temporal, and structural features into the final influence scoring. The suggested approach performed better than baseline algorithms and conventional centrality measures, according to experimental results on the Twitter and Facebook Social Circles datasets. Notably, it maintained a competitive runtime while achieving notable gains in Precision@50, Recall@50, and nDCG@50. These improvements demonstrate how well fuzzy logic and adaptive learning work together to identify significant nodes in both private and public social networks. In conclusion, this hybrid approach is a strong tool for dynamic information diffusion tracking and real-world social network analysis since it not only increases influencer detection accuracy but also provides scalability and adaptability.

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