Utilizing Graph Theory to Detect Fake News Networks on Social Media

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Abstract*—the expanded dissemination of fake news through social media and, as a result, the shift in challenges related to civil and political arenas. The process of countering the spread of fake news, therefore, is critical in attenuating its negative impacts. Modeling and analyses of social media networks via graph theory and the application of techniques report on organizing and identifying efforts in the spreading of fake news with collaboration among users. Drawing from graph theory, which includes community detection algorithms, centrality measures, and network visualization techniques, this paper analyzes the methods of understanding fake news networking. Various experimentation illustrates the presence of important leaders and maladaptive features that are concerned with the spread of fake news. One of the implications in this paper, is how effective graph-based methods could address the scourge of misinformation and thus satisfy the imperative to integrate with established systems of moderation.

Keywords: Fake News Detection, Graph Theory, Social Media Networks, Network Analysis, Misinformation

I. INTRODUCTION

The proliferation of social media has transformed the way information is disseminated and consumed. While platforms such as Twitter, Facebook, and Instagram provide unprecedented connectivity, they also foster the rapid spread of false news. Fake news networks can manipulate public opinion, disrupt elections, and spread harmful narratives, making them urgent challenges to detect.

Traditional fake news detection approaches including natural language processing (NLP) and machine learning emphasize content analysis. However, these approaches usually remain blind to the structural characteristics of fake news dissemination. Graph theory models the relationships between entities as networks and thus offers a complementary approach. In analyzing user collaboration and interactions, the graph-based approach would intend to reveal coordinated efforts and anomalous dissemination patterns.

This paper investigates the application of graph theory to detect fake news networks in social media. The study constructs a graph representation of social media data, applies community detection algorithms, and performs a social network analysis to point out influential nodes and clusters associated with misinformation. The results show the potential of graph-based approaches to be employed in enhancing fake news detection systems.

II. Theoretical Foundation

2.1 Graph Theory Overview

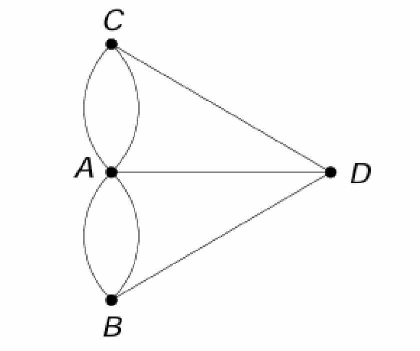


Figure 2.1. *Graph Representation of Social Media Interactions*

(Source: https://informatika.stei.itb.ac.id/~rinaldi.munir/Matdis/2024-2025/12-Aljabar-Boolean-(2024)-bagian1.pdf)

Graph Theory is a branch of mathematics concerned with
any networks made of nodes, referred to as vertices, and edges, which become connections between the nodes. In social networks, nodes will signify users, while edges signify interactions such as likes, shares, or comments. Important graph concepts include:

- **Degree**: The number of connections a node possesses.
- **Centrality Measures:** Quantifications of nodes about their importance in the network, such as betweenness, closeness, and eigenvector centrality.
- **Adjacency Matrix**: A matrix representation of a

graph whose entries show whether edges exist and/or whether these edges are weighted.

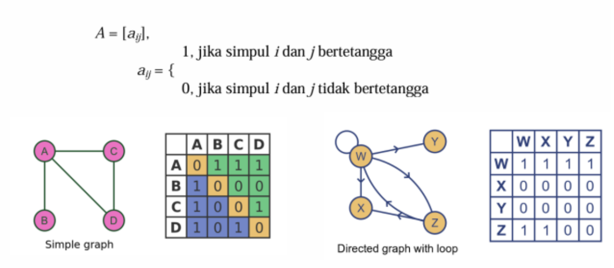


Figure 2.2. *Graph Representations and Adjacency Matrices*

(Source: https://informatika.stei.itb.ac.id/~rinaldi.munir/Matdis/2024-2025/12-Aljabar-Boolean-(2024)-bagian1.pdf)

$$A_{ij} = \begin{cases} 1, & \text{if there is an edge from node } i \text{ to node } j \\ 0, & \text{otherwise} \end{cases}$$

The above principles allow relationships to be analyzed and interactions within social media networks to initiate mechanisms for such identification of dissemination patterns of fake news.

2.2 Social Media as a Graph

Social media platforms are modeled as directed or undirected graphs:

- **Directed graph:** Represent interactions with a certain direction, such as retweets or follows.
- **Undirected graph:** Represents interactions that have some mutuality to them, say mutual friendships.
- **Weighted graphs:** Assign a certain weight to edges based on either the frequency of an interaction or its intensity.

Graph representation is essential to visualize and measure user behavior in fake news networks and find the clustered activities that those activities reveal.

2.3 Applications in Fake News Detection

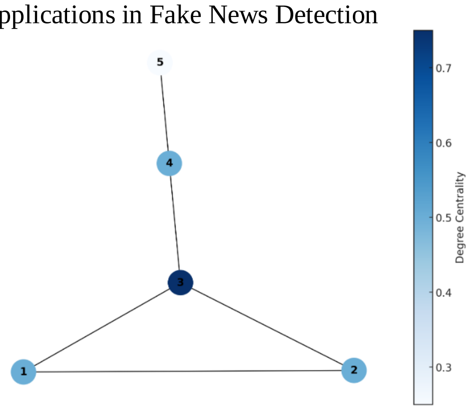


Figure 2.4. *Centrality Measures in a Network*

(Source: by the author)

Fake news' dissemination generates different network patterns like densely connected components or influential nodes that orchestrate the distribution. In this way, patterns are exploited in graphical methods:

- **Community-Deduction:** Communities of users included within a coherent misinformation campaign are identified by using a method like Louvain or Girvan-Newman.

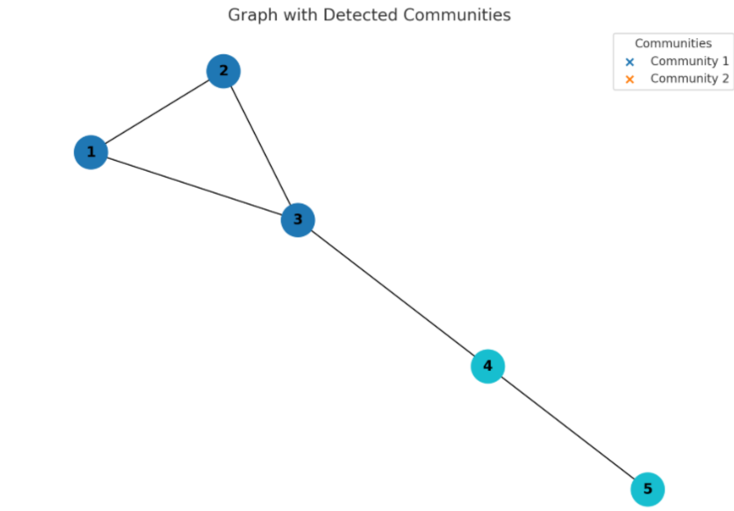


Figure 5. *Graph with Detected Communities*

(Source: by the author)

- **Centrality-Analyzing:** Finding nodes that play the role of primary disseminators in fake news.
- **Anomaly Detection:** Highlighting dense subgraphs or unexpected interaction patterns that deviate from typical user behavior.

$$C(v) = \frac{2 \cdot e_v}{k_v \cdot (k_v - 1)}$$

By combining these techniques, graph theory facilitates a holistic approach to detecting and mitigating misinformation.

III. Methodology

3.1 Data Collection

The study will use data from the Labeled Fake News Dataset (LFND) and social media data from platforms such as Twitter. The data will be preprocessed to:

- Remove irrelevant information.
- Extract user interactions (e.g., retweets, mentions).
- Convert raw data into graph format.

3.2 Graph Construction

The composition of the graph is:

- Nodes, which are the individual users.
- Edges: These represent interactions and are

weighted by the frequency of retweets, likes, or mentions.

- Edge Weightings will depend on the intensity of interactions.

3.3 Detecting Fake News Networks

- Community Detection will employ algorithms such as Louvain and Girvan-Newman to identify clusters of nodes likely associated with fake news dissemination.
- Centrality analysis will review metrics such as betweenness and eigenvector centrality to identify influential nodes driving misinformation.

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

- Anomaly detection is based on network features indicative of dense or unusual interactions, such as high clustering coefficients or unusually dense subgraphs.

3.4 Program Implementation

- Programming Tools: Python with NetworkX, Gephi, and Matplotlib
- Algorithm Selection: Community Detection via NetworkX functions
- Visualizations using Gephi to focus on major underlying clusters and nodes.

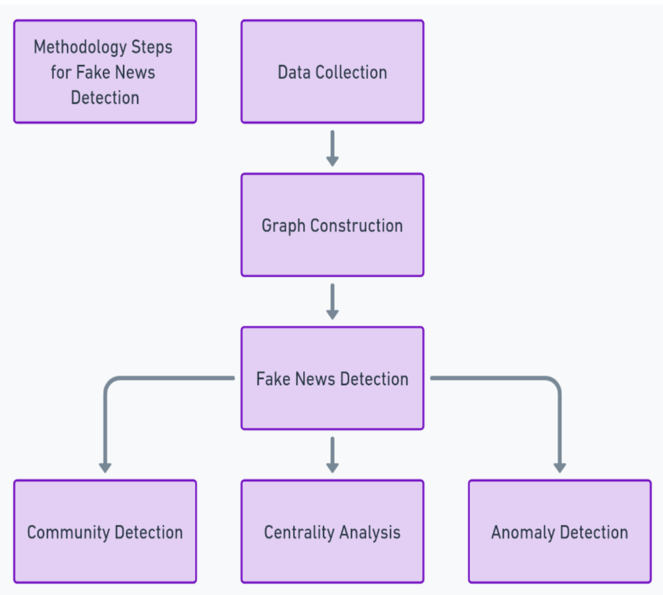


***Figure 6**. Methodology Steps for Fake News Detection*

(Source: Designed for this study)

IV. Implementation

Execution of the program is divided into distinct phases: graph construction for a fake news network, its property analysis, and information visualization. It would have been useful to work with the Python programming language, which has the required libraries such as NetworkX, Matplotlib, and Pandas.

4.1 Data Input and Graph Construction

It reads a dataset of edges in the fake news graph and constructs its appropriate representation. The source and target node, weight of interaction, and its classification as a 'fake' or 'real' interaction are the other pieces of information for every edge. A directed graph is, in turn, used to display these relationships.

```
import pandas as pd
import networkx as nx
import matplotlib.pyplot as plt

# Read the dataset
df = pd.read_csv('fake_news_edges.csv')

# Build a Directed Graph
G = nx.DiGraph()
for row in df.itertuples():
    G.add_edge(row.source, row.target, weight=row.weight, label=row.label)
```

4.2 Community Detection

This community detection uses Girvan-Newman algorithm communities that represent groups of nodes that are more connected internally than they are with the overall network.

```
from networkx.algorithms import community
```

```
gn_communities = community.girvan_newman(G)
top_level_communities = next(gn_communities)
communities_gn = sorted(map(sorted, top_level_communities))
print("Girvan-Newman Communities:")
for i, c in enumerate(communities_gn):
    print(f"Community {i}: {c}")
```

4.3 Centrality Measures

In this stage, the measure of the centrality like betweenness centrality and eigenvector centrality would be calculated in order to find significant or influential nodes in the network.

```
betweenness = nx.betweenness_centrality(G)
print("\nBetweenness Centrality:")
for node, score in betweenness.items():
    print(f"{node}: {score:.4f}")

eigenvector = nx.eigenvector_centrality(G.to_undirected()
print("\nEigenvector Centrality:")
for node, score in eigenvector.items():
    print(f"{node}: {score:.4f}")
```

4.4 Anomaly Detection

Nodes that have large statistical thresholds on their degree act as potential anomalies.

```
degrees = dict(G.degree())
avg_degree = sum(degrees.values()) / len(degrees)
std_degree = (sum((deg - avg_degree)**2 for deg in degrees.values()) / len(degrees))**0

anomalies = []
for node, deg in degrees.items():
    if deg > avg_degree + 2 * std_degree:
        anomalies.append((node, deg))

print("\nPotential Anomalies (High-Degree Nodes):")
for node, deg in anomalies:
    print(f"Node: {node}, Degree: {deg}")
```

4.5 Visualization

The networks are visualized as graphs representing the connections within the nodes, with the additional purpose of highlighting the community structures.

```
plt.figure(figsize=(8,6))
pos = nx.spring_layout(G, k=0.3, seed=42)
nx.draw_networkx_nodes(G, pos, node_size=800, node_color="lightblue")
nx.draw_networkx_edges(G, pos, arrowstyle="->", arrowsize=10, edge_color="gray"
nx.draw_networkx_labels(G, pos, font_size=10, font_color="black")
plt.title("Fake News Network Graph")
plt.axis('off')
plt.show()
```

V. Output and Analysis

5.1 Community Detection

Community Detection The Girvan-Newman algorithm has detected two communities in the network:

- **Community 0:** Nodes - ['alice', 'bob', 'carol', 'eve']
- **Community 1:** Nodes - ['david']

This clustering reveals the different groups, that Community 0 forms a well-connected core network, and Community 1 represents an isolated node.

Output:

Girvan-Newman Communities:

Community 0: ['alice', 'bob', 'carol', 'eve']

Community 1: ['david']

5.2 Centrality Measures

The centrality measures give insights into the importance of a node in the network:

- **Betweenness Centrality:**
  - alice: 0.2500
  - bob: 0.0833
  - carol: 0.5000
  - david: 0.2500
  - eve: 0.5000

Nodes carol and eve show the highest value of betweenness centrality; thus, they act as prominent connectors for the graph.

- **Eigenvector Centrality:**
  - alice: 0.4558
  - bob: 0.4912
  - carol: 0.4912
  - david: 0.3192
  - eve: 0.4558

Nodes bob and carol with the highest eigenvector centrality underline the influence they have in the network.

Output:

Betweenness Centrality:

alice: 0.2500

bob: 0.0833

carol: 0.5000

david: 0.2500

eve: 0.500

Eigenvector Centrality:

alice: 0.4558

bob: 0.4912

carol: 0.4912

david: 0.3192

eve: 0.4558

5.3 Anomaly Detection

Statistically, no anomalies were detected in the network using Degree as the threshold; however, such a framework can be scaled into larger datasets for anomalous detections.

Output:

Potential Anomalies (High-Degree Nodes):

5.4 Visualization

The network visualization (Figure 5.4.1.) provides an intuitive representation of user interactions and community structures.

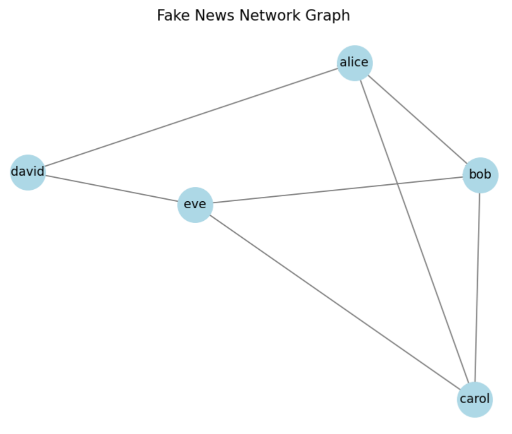
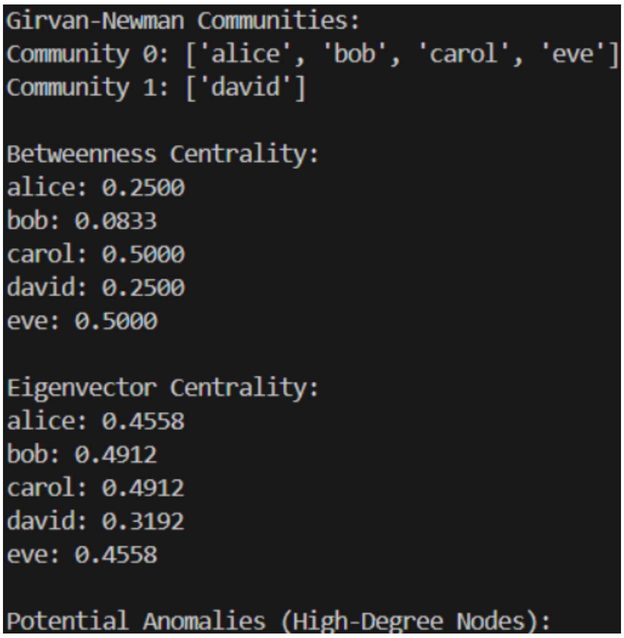


Figure 5.4.1. Fake News Network Graph



```
Girvan-Newman Communities:
Community 0: ['alice', 'bob', 'carol', 'eve']
Community 1: ['david']

Betweenness Centrality:
alice: 0.2500
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bob: 0.4912
carol: 0.4912
david: 0.3192
eve: 0.4558

Potential Anomalies (High-Degree Nodes):
```

Figure 5.4.2. Community and Centrality Analysis Output

VI. Conclusion

This paper demonstrates the usefulness of graph theory in detecting and analyzing networks of fake news disseminators over social media. It was noted that directed graphs allow for the inference of the construction and behavior of misinformation networks through community detection and quantifying centrality measures.

The implementation points to various highlights:

- **Community Detection**: The application of the Girvan-Newman algorithm efficiently identifies clusters of coordinated activity within the fake news network.
- **Centrality Analysis**: The betweenness and eigenvector centrality metrics identify the influential nodes that drive misinformation to spread.
- **Anomaly Detection**: Statistical techniques employed for degree-based anomaly detection indicate the way to identify any outliers in the network.

Limitations and Future Work

Although the results would speak volumes about the power of graph-based methods, limitations include scalability for larger datasets and the need for more advanced anomaly detection techniques. An appropriate path for future work could aim at applying machine learning algorithms for improving detection accuracy while exploring real-time applications of moderating the spread of the fake news.

Using graph theory, this study has developed a sound framework to conceptualize and counter misinformation, one that provides very useful tools for researchers, policymakers, and social media platforms in their fight against the trickery of fake news.

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PERNYATAAN

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Bandung, 8 Januari 2024

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