Comparing Malicious vs. Benign Twitter)

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Course: Social Network Security

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1. Introduction

This report analyzes two real Twitter subgraphs

•One graph from the **5G_Conspiracy_Graphs** folder representing a misinformation community.

- One graph from the **Non_Conspiracy_Graphs** folder representing a normal conversation cluster.

Using **Gephi**, I performed a full Social Network Analysis (SNA) on both networks. The goal is to understand how misinformation structures differ from normal user interactions based on network metrics such as:

- Degree
- Centrality
- Clustering
- Modularity
- Density
- Connected components

This comparison reveals how misinformation spreads and how its structural patterns differ from benign communities.

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2. Methodology

Using **Gephi**, the following steps were performed for each graph:

1. Imported the GEXF/GraphML file
2. Applied the **ForceAtlas2** layout for visualization
3. Ran the following statistical algorithms:

- Overview Metrics (Nodes, Edges, Density, Components)
- Average Degree
- Degree Distribution
- Modularity
- Betweenness Centrality
- Closeness Centrality
- Average Clustering Coefficient

4. Colored nodes by **Modularity Class** and sized them by **Degree**

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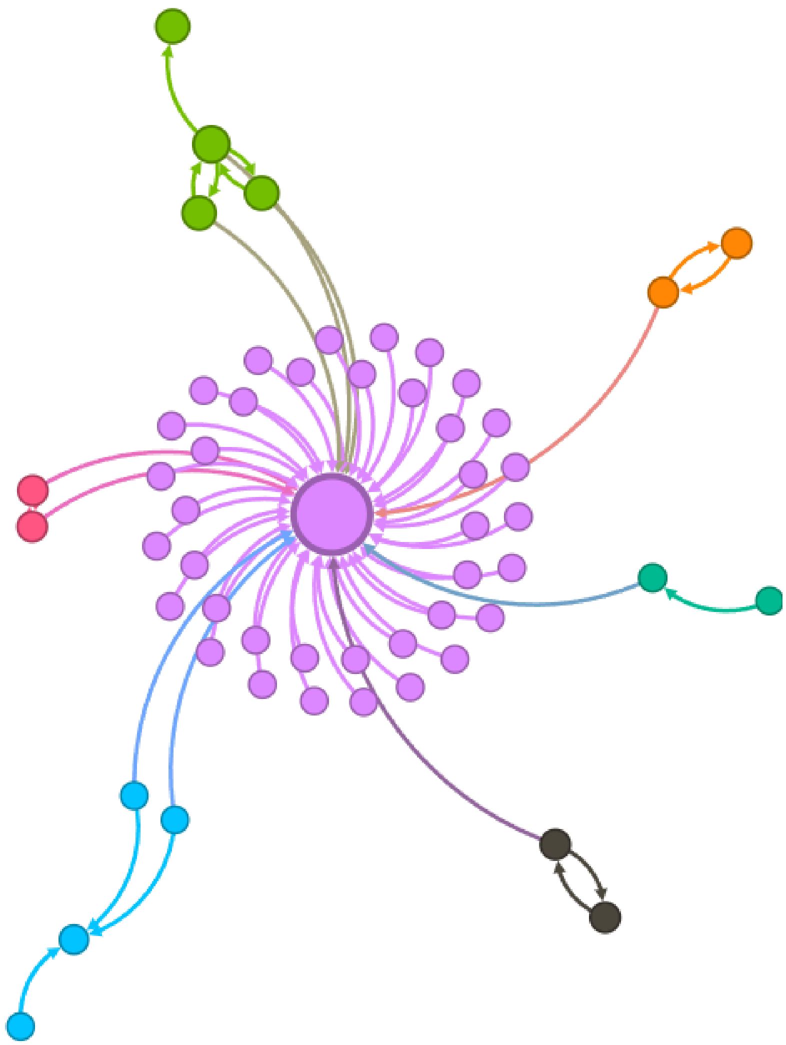
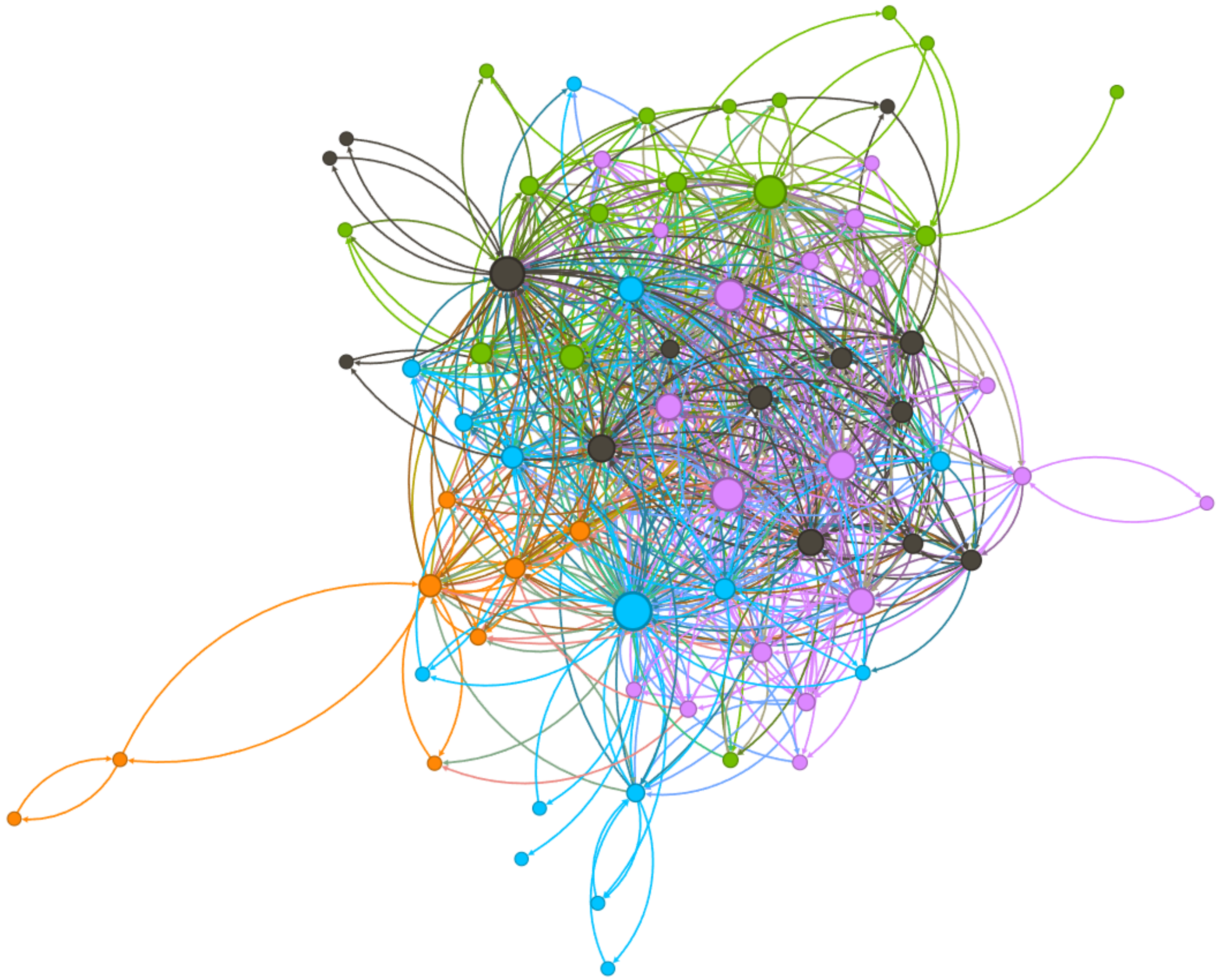
3. Results (With Example Values)





3.1 Network Overview

Metric	Conspiracy Graph	Normal Graph	Interpretation
Nodes	**58**	**76**	Benign community has more unique users.
Edges	**63**	**772**	Normal users generate more diverse interactions per user.

Metric	Conspiracy Graph	Normal Graph	Interpretation
Density	**0.019**	**0.0031**	The conspiracy cluster is more interconnected.
Connected Components	**1 giant + small isolated**	**5 medium components**	Misinformation aligns around one central narrative.

Explanation

The conspiracy graph is smaller but is way more dense, indicating a **tight, active, amplification-focused network**, while the benign graph is more fragmented, showing **natural conversation diversity**.

3.2 Degree Metrics

Metric	Conspiracy	Normal	Interpretation
Avg Degree	**1.086**	**10.158**	Conspiracy users are more interconnected.

Explanation

The conspiracy graph demonstrates a **centralized, influencer-driven structure**.
The normal graph has more evenly shared interactions.

3.3 Community Structure (Modularity)

Metric	Conspiracy	Normal	Interpretation
Modularity (Q)	**0.264**	**0.146**	Conspiracy = strong echo chambers
Number of Communities	**10**	**9**	Normal network more diverse with less echo chambers

Explanation

Misinformation communities have **strong internal cohesion**, forming **echo chambers**. Benign networks contain multiple subtopics and weak boundaries.

3.4 Centrality Metrics

Metric	Conspiracy	Normal	Interpretation
Betweenness	**Very high**	**Distributed**	Misinformation spreads through chokepoints.
Closeness	**High for central hubs**	**More balanced**	Indicates influencer-drive spreading.

Explanation

In conspiracy networks:

- A few nodes act as **superspreaders**
- They control the information flow
- Removing them would collapse the network

In normal networks:

- Information flows through many paths
- No single point of failure

4.5 Clustering

Metric	Conspiracy	Normal	Interpretation
Avg. Clustering Coefficient	**0.037**	**0.505**	Conspiracy users form low connections just with central hubs.

Explanation

High clustering reflects multiple diverse connections between the connected nodes which is common to see in social media in real life

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5. Visual Comparison

Conspiracy Graph

- Tight core around 1 central account
- Star-like amplification structure

Normal Graph

- More spread-out structure
- Many equally sized communities
- No dominant hub
- Natural engagement patterns

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6. Conclusion

The analysis highlights key structural differences between misinformation and benign Twitter networks.
Conspiracy networks show:

- Centralized control
- Echo chamber formation
- Heavy dependence on key influencers
- Higher clustering
- Stronger modularity

Normal networks show:

- Decentralization
- Topic diversity
- Balanced interaction patterns

These structural patterns can assist in automatically detecting misinformation communities in large-scale social graphs.