

# CS 429

## Project Presentation

**Identifying Malicious Networks and Individuals  
on Twitter by Misinformation Classification and  
Network Analysis**

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# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

- Spread of false information
- Technological advancements
  - Social media
- Individual Level
- Community Level
  - Business
  - Healthcare
  - Economy

# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

- Covid-19
  - Contagion Ways
  - Vaccines

Misperceptions about doctors' trust in Covid-19 vaccines influence vaccination rate

Informing people about the strong positive consensus among doctors persistently leads to increases in Covid-19 vaccinations

JUNE 01, 2022

Corona Social Sciences

# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

- Covid-19
  - Contagion Ways
  - Vaccines



Rep Andy Biggs  
@RepAndyBiggsAZ

In 2021, the nine most terrifying words in the English language:

"I'm from the government, have you been vaccinated yet?"

1:55 PM · Jul 7, 2021 · Twitter Web App

- In order to minimize negative effects,
  - SNA

A screenshot of a Twitter post. The user is tokidoki340 (@shiroi115). The tweet reads: "Experts all agree that the Covid-19 vaccine is not a vaccine. It was designed to make you sick with multiple diseases, including Cancer, Alzheimer's. This shot is a synthetic pathogen that is injecting the disease into your cells and it cannot be removed." The timestamp is 12:13 AM · Jul 14, 2021 · Twitter for iPhone.

Brains behind new **5G** data communications networks described below! New Bill Gates sponsored **corona virus** vaccine, w/nano tech, will run everything and control everyone who are still necessary, like bots to serve the elite? Get your vaccine now?

⚠️ Get the facts about COVID-19

A screenshot of a Twitter post. The user is berg (@berg). The tweet includes a video thumbnail showing three stylized figures. The caption reads: "The Rise of AI" and "There's an AI revolution sweeping across the world. Yet few people know the real story about where thi...". Below the link is a small note: "🔗 youtube.com". The interface shows standard Twitter interaction icons at the bottom.

# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

- Social Network Analysis
  - Influential People
  - Scale of Misinformation
- Algorithm Based Techniques
  - Insufficient Level
- Government

# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

- Contents of Tweets
  - Polarity Analysis
  - Subjectivity Analysis
  - ML and AI methods
- Compare Results with Datasets
- Measure Metrics
  - Node Level
  - Network Level
- Collect Tweets with Python Code

# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

## Background

- No universal algorithm to decide a tweet is fake news or not.
  - Polarity & Subjectivity
  - Assumptions:  
“If X% of a user’s tweets are in this category, he spreads misinformation”
- Eigenvector centrality
- Page Rank

# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

## Background (Cont'd)

- Analyzing
  - Homogeneous Networks
  - Heterogeneous Networks
- Louvain Method
- Cohesive Groups

# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

## Methodology

- Gathering Data
  - Python Libraries / APIs
- Identifying Misinformation
  - ML and AI methods
- Network Creation
  - Retweets
- Identifying Malicious Groups and Individuals in Network
  - Network Analysis

# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

## Gathering Data

- Twitter API permission rejected
- Snscreape library
  - a scraping tool for social networking services
  - Has subject, date, language, etc. parameters
  - Cannot access followers directly but can get follower number

```
query = "covid vaccine lang:en until:2021-01-01 since:2020-01-01"
```

	Date	User	Followers	Retweets	...
0	2020-12-31 23:59:56+00:00	dcsdirt	278	0	...
1	2020-12-31 23:59:48+00:00	kimberlyanndon0	982	0	...
2	2020-12-31 23:59:43+00:00	VeritasEver	4378	0	...
3	2020-12-31 23:59:33+00:00	BenBlankley	1539	0	...
4	2020-12-31 23:59:21+00:00	PittsburghNerd	9225	1	...
5	2020-12-31 23:59:15+00:00	zsheinberg28	515	0	...
6	2020-12-31 23:59:00+00:00	Skorp_17	134	0	...
7	2020-12-31 23:58:50+00:00	justin_indyk	306	3	...
8	2020-12-31 23:58:49+00:00	CesarTrevino11	937	0	...
9	2020-12-31 23:58:30+00:00	SocialAisha	557	0	...

# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

## Identifying Misinformation

- Biggest challenge is identifying intent
- First model
  - Polarity + Subjectivity
  - We make the assumption that highly polarized and subjective tweets are more likely to be misinformation/fake news/clickbait

	precision	recall	f1-score	support
False	0.47	0.37	0.41	171
True	0.53	0.63	0.57	190
accuracy			0.51	361
macro avg	0.50	0.50	0.49	361
weighted avg	0.50	0.51	0.50	361

# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

## Identifying Misinformation

- Final model
  - Fine-tuned BERT(Trained on a set of 6735)

	precision	recall	f1-score	support
0	0.84	0.92	0.88	3213
1	0.92	0.84	0.88	3522
accuracy			0.88	6735
macro avg	0.88	0.88	0.88	6735
weighted avg	0.88	0.88	0.88	6735

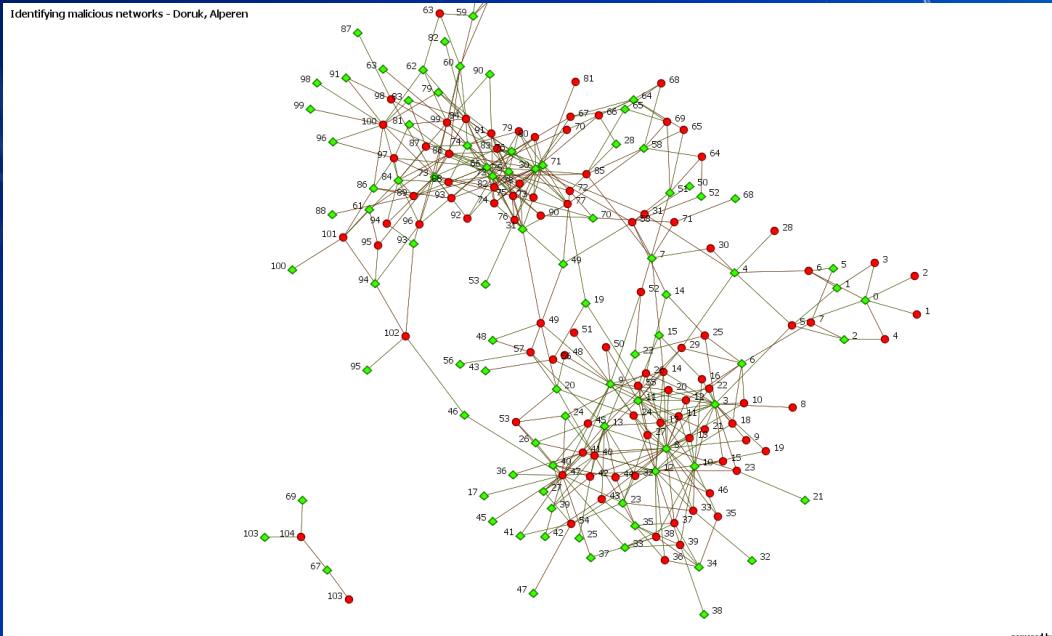
# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

## Network Creation

- Bipartite Network of Tweets and Users
- Relations Between Tweets and Users are Retweets
- Only Misinformation tweets are kept in Network
- Tweet x User Network turned into User x User

# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

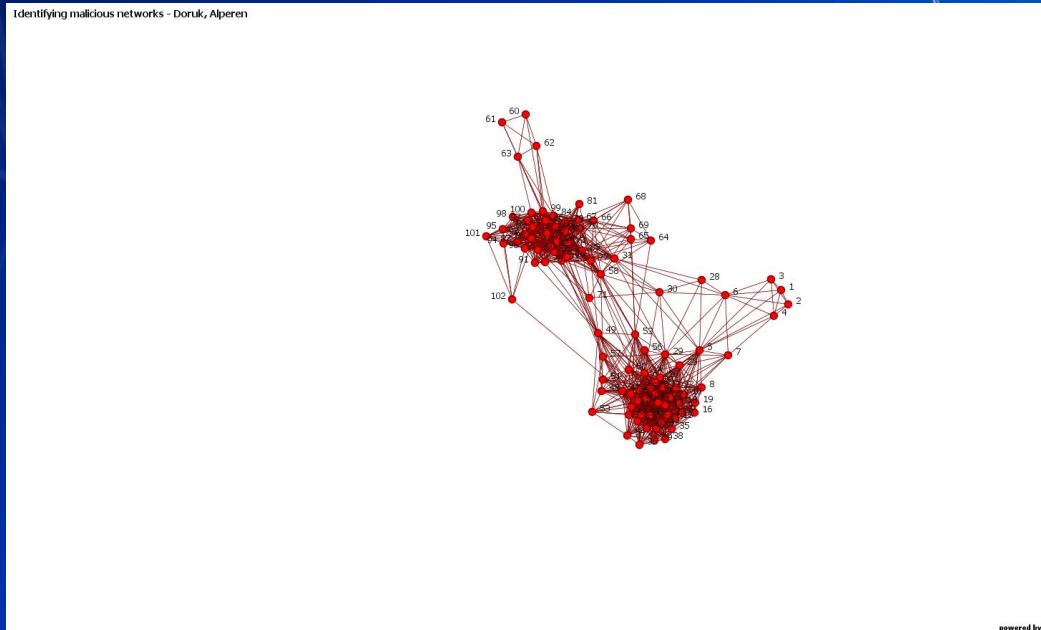
## Network Creation



Users X Tweets

# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

## Network Creation



Users X Users

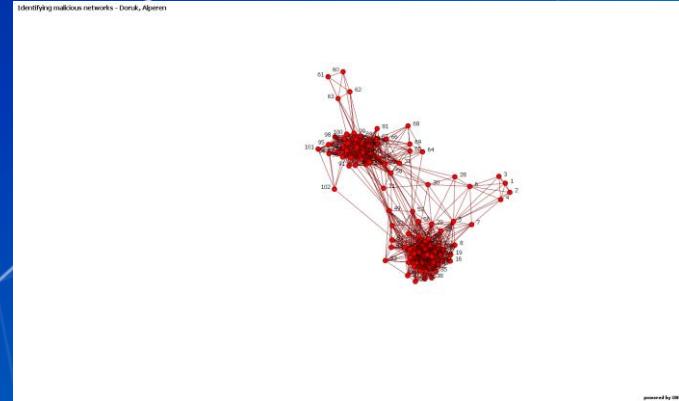
# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

## Network Analysis

- **Degree Centrality**

Measure of influence and importance

Nodes with high degree centrality have the opportunity to influence and be influenced directly.



Rank	Agent	Value	Unscaled
1	84	0,065	112
2	14	0,056	97
3	47	0,055	96
4	82	0,055	96
5	86	0,055	95
6	12	0,053	92
7	99	0,053	92
8	74	0,052	90
9	76	0,051	88
10	75	0,050	86

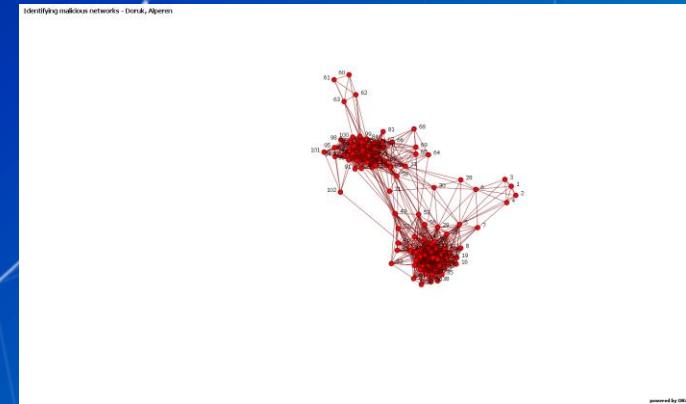
# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

## Network Analysis

- **Betweenness Centrality**

Related to how often a node lies along the shortest path between two other nodes

Gate-keeping, brokering, bridges, controlling the flow



Rank	Agent	Value	Unscaled
1	58	0,110	557,171
2	31	0,100	505,681
3	49	0,093	467,857
4	5	0,080	404,380
5	14	0,074	375,466
6	77	0,054	272,620
7	99	0,047	238,322
8	85	0,044	220,764
9	57	0,037	187,761
10	29	0,037	187,333

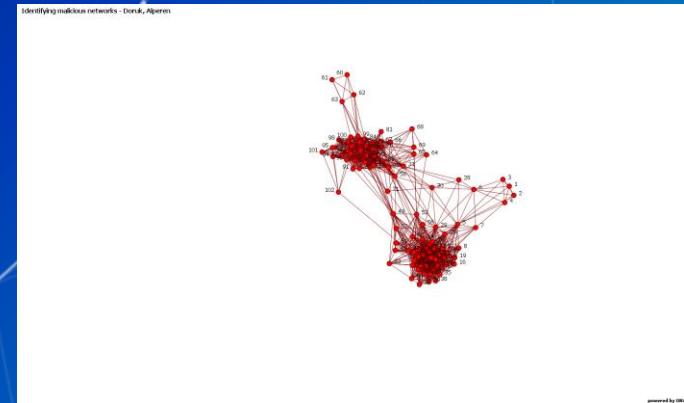
# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

## Network Analysis

- Closeness Centrality

About the nodes which is usually in the middle of the network by being close to many nodes.

The node with high closeness hears first, reaches out everyone quickly.



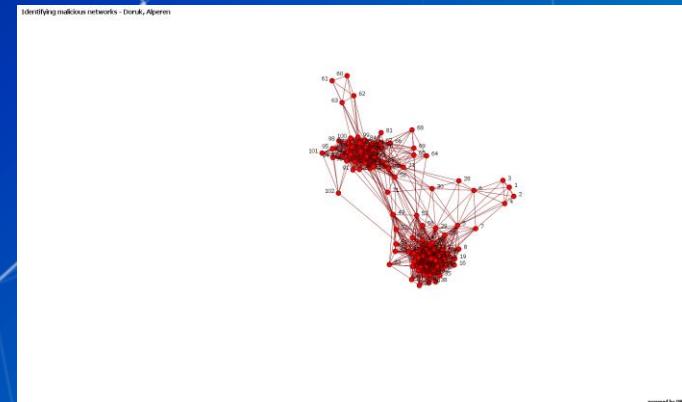
Rank	Agent	Value	Unscaled
1	58	0,028	2,743e-04
2	14	0,028	2,734e-04
3	31	0,028	2,734e-04
4	49	0,028	2,732e-04
5	5	0,028	2,729e-04
6	29	0,028	2,727e-04
7	77	0,028	2,727e-04
8	25	0,028	2,726e-04
9	26	0,028	2,724e-04
10	52	0,028	2,724e-04

# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

## Network Analysis

- **Page Rank**

Influence of a node depends on the influence of its neighbors.



Rank	Agent	Value
1	84	0.024
2	14	0.022
3	82	0.021
4	86	0.021
5	12	0.021
6	74	0.020
7	99	0.020
8	76	0.019
9	75	0.019
10	47	0.019

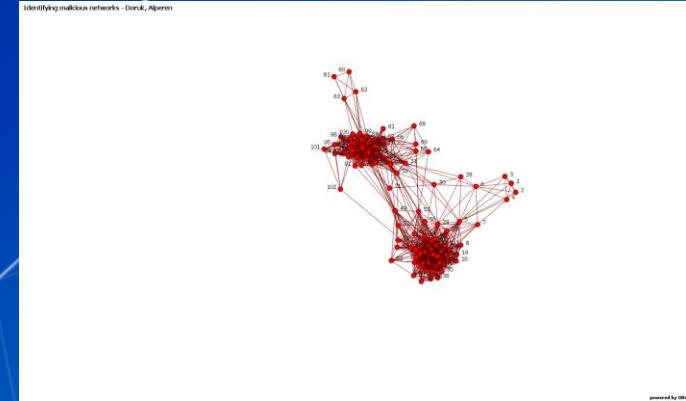
# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

## Network Analysis

- Eigenvector

It shows a node is connected to nodes who themselves have high scores.

Effective way to find the leader, strongest person, etc.



Rank	Agent	Value	Unscaled
1	84	0,462	0,327
2	82	0,395	0,279
3	86	0,370	0,262
4	74	0,356	0,252
5	76	0,348	0,246
6	75	0,340	0,240
7	99	0,335	0,237
8	73	0,295	0,208
9	79	0,270	0,191
10	80	0,257	0,182

# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

## Network Analysis

- **Conclusion for Node Level Metrics**

Degree centrality: 84, 14, 47, 82, 86, 12, 99, 74, 76, 75

Betweenness centrality: 58, 31, 49, 5, 14, 77, 99, 85, 57, 29

Closeness centrality: 58, 14, 31, 49, 5, 29, 77, 25, 26, 52

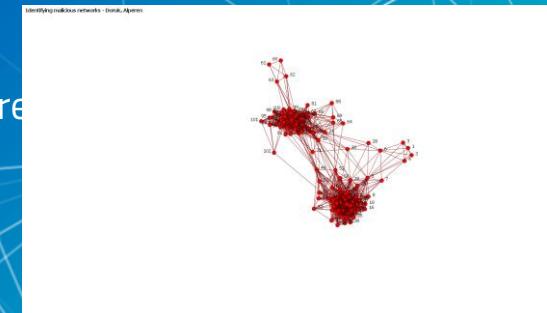
Page rank: 84, 14, 82, 86, 12, 74, 99, 76, 75, 47

Eigenvector: 84, 82, 86, 74, 76, 75, 99, 73, 79, 80

Different centralities yield in similar results.

Most influential Twitter users spreading misinformation are  
84, 14, 82, 86

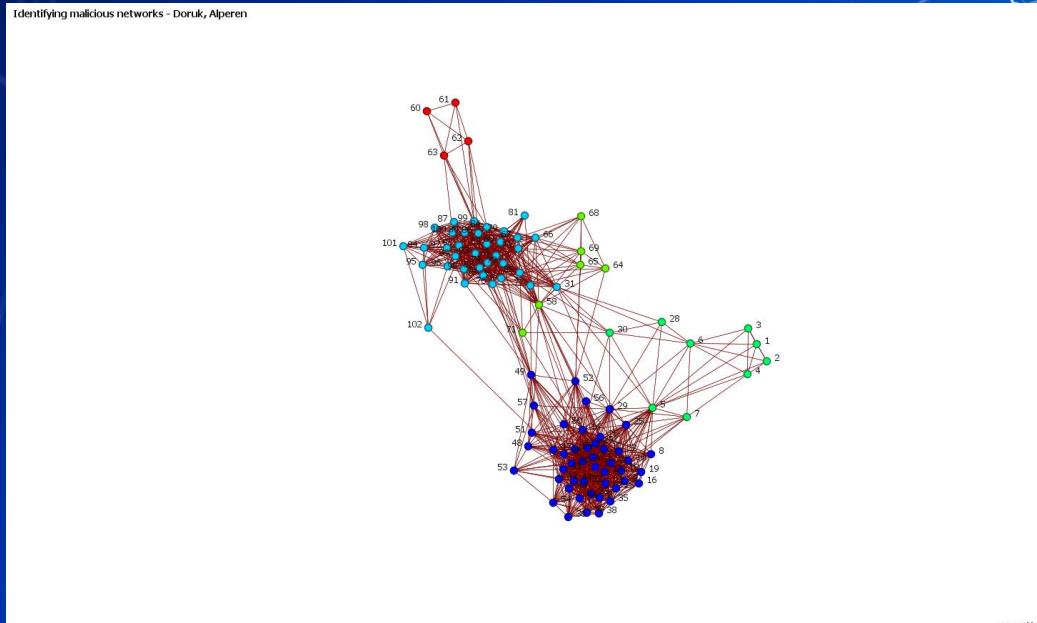
The ones who are bridges and reaching out other first are  
58, 49, 14

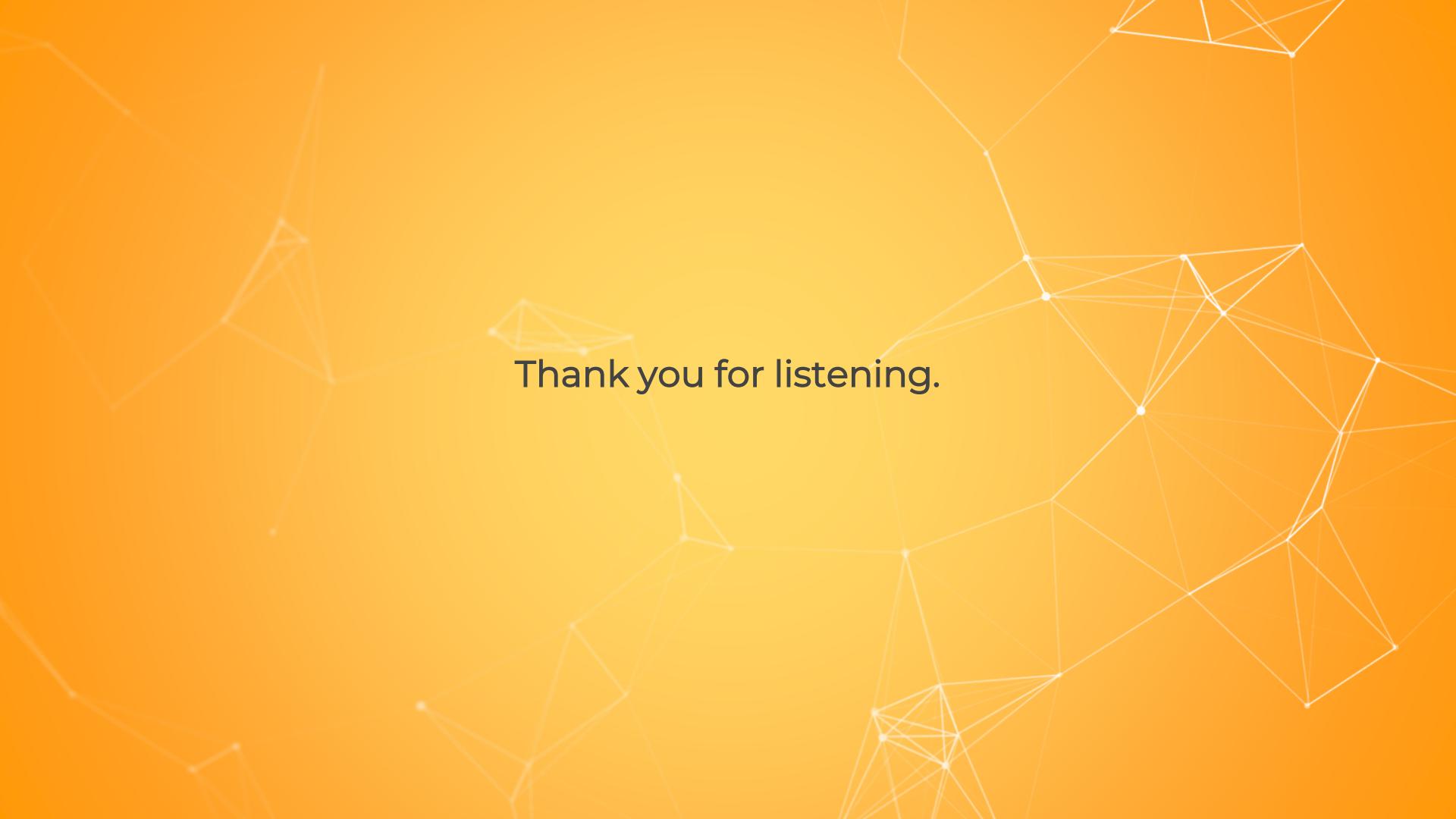


# Identifying Malicious Networks and Individuals on Twitter by Misinformation Classification and Network Analysis

## Network Analysis

- Louvain Grouping



The background of the slide features a complex, abstract network structure composed of numerous small, semi-transparent white triangles and dots on a solid orange background. This visual metaphor represents connectivity, data flow, or a social network.

Thank you for listening.