

## Project Overview

We collected social media data using web scraping to find insights in the social media campaigns of Central Insurance Company (CI). We analyzed comment and reaction rates of competitors on Facebook, Instagram, LinkedIn, and Twitter, and developed networks to evaluate Central's outreach.

### Data Acquisition

Web Scraping | Automated API Pipeline

### Data Preprocessing

Exploratory Data Analysis | Python Scripts

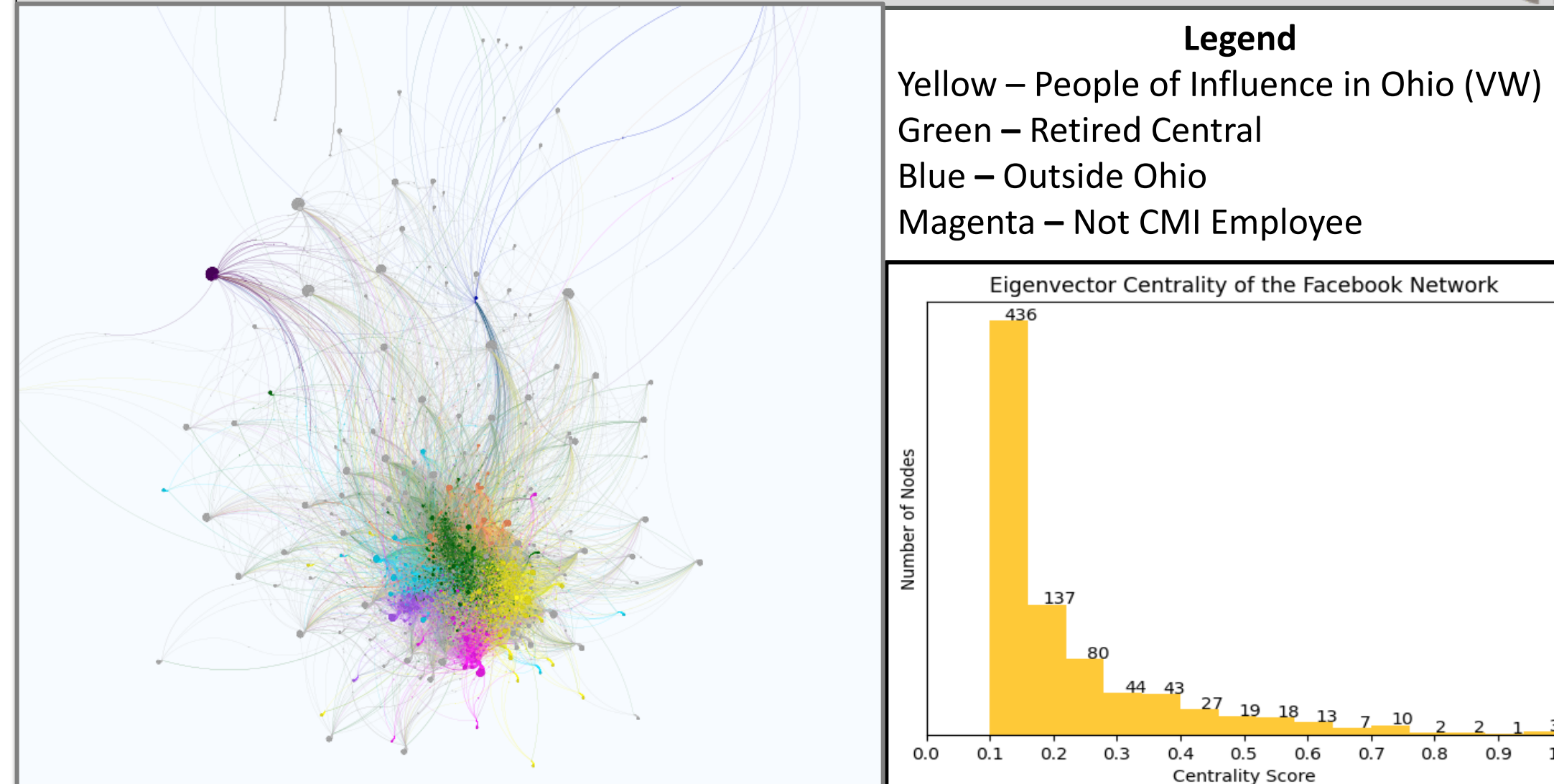
### Data Analysis

Competitor Analysis | Graph Network Analysis

## Definitions

- Web Scraping** – The process of extracting data from web pages.
- Network Science** – Extension of graph theory that studies networks (graphs) that represent biological, physical, and social relations.
- Eigenvector Centrality** – The ranking of each node of a network based on the eigenvector centrality scores of its neighbors.
- Modularity** – Measures the strength of divisions in a graph.

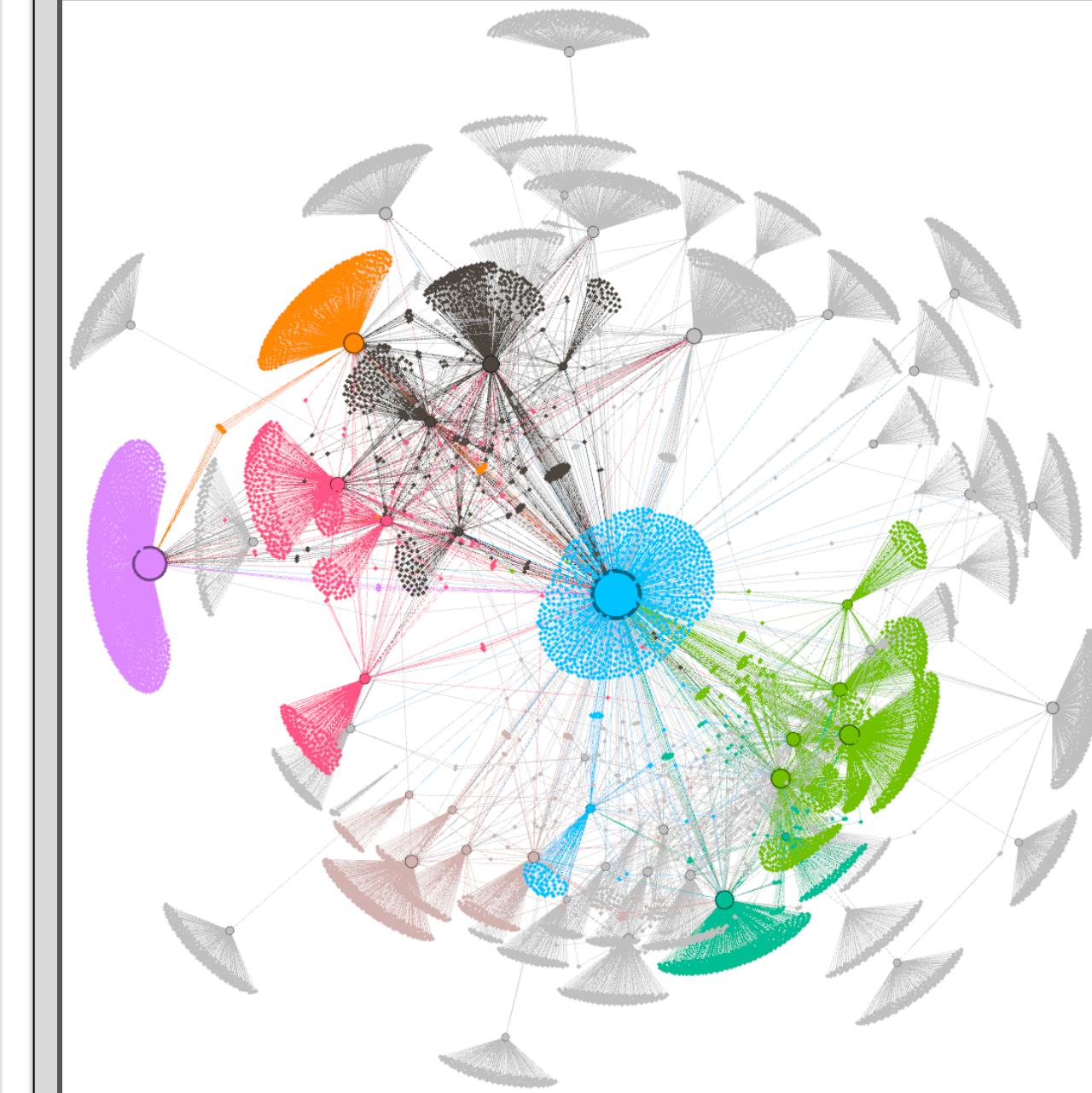
## Facebook



### Page/Network Information

- 4.3K Followers
- 202 Post
- 1287 Unique Reactors
- 6170 Reactions
- 83K Nodes
- 116K Edges
- Colored by Community
- Sized by Degree Centrality
- 76k Communities
- Modularity 0.794
- An important reactor may not need lots of followers to impact a community.
- Central Mutual Insurance should encourage employees to react to post.

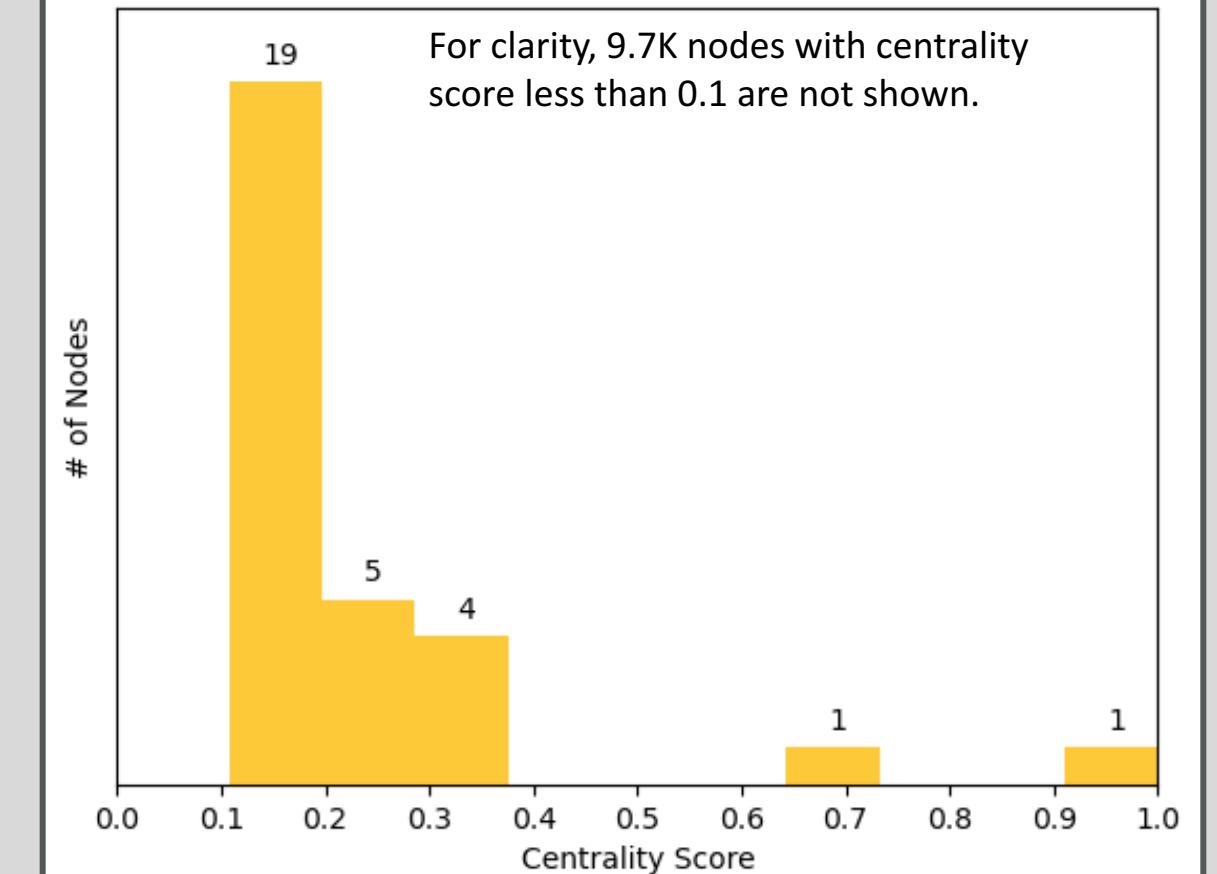
## Instagram



### Legend

Blue – Central Insurance  
 Light Green – Career Opportunities  
 Grey – Individual Accounts  
 Other colors – Competitors

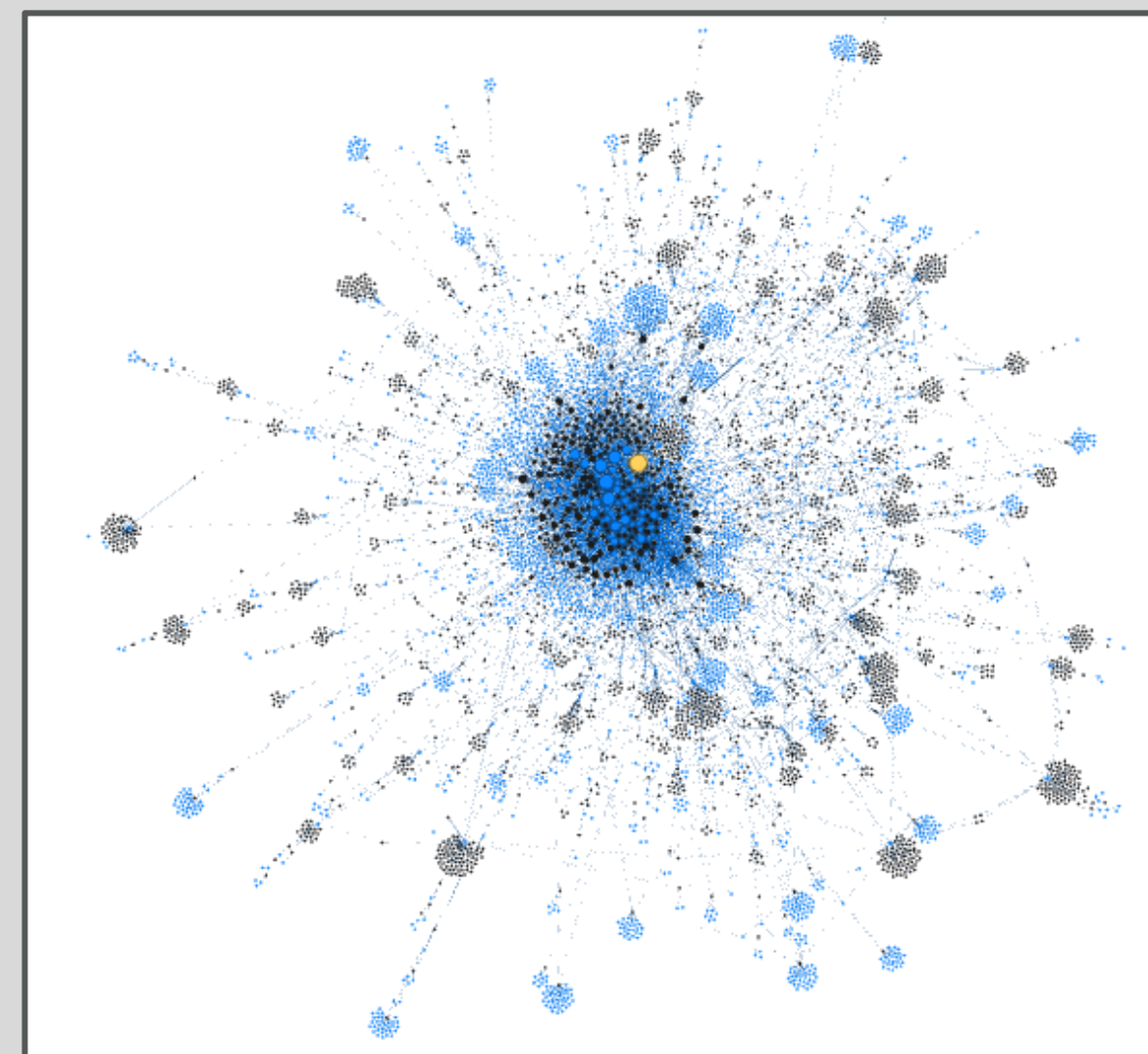
### Eigenvector Centrality of the Instagram Network



### Community Detection

- 7 distinct communities
- Modularity of 0.842
- Eigenvector Centrality**
- All but 30 accounts < 0.1
- 10 influential accounts

## LinkedIn



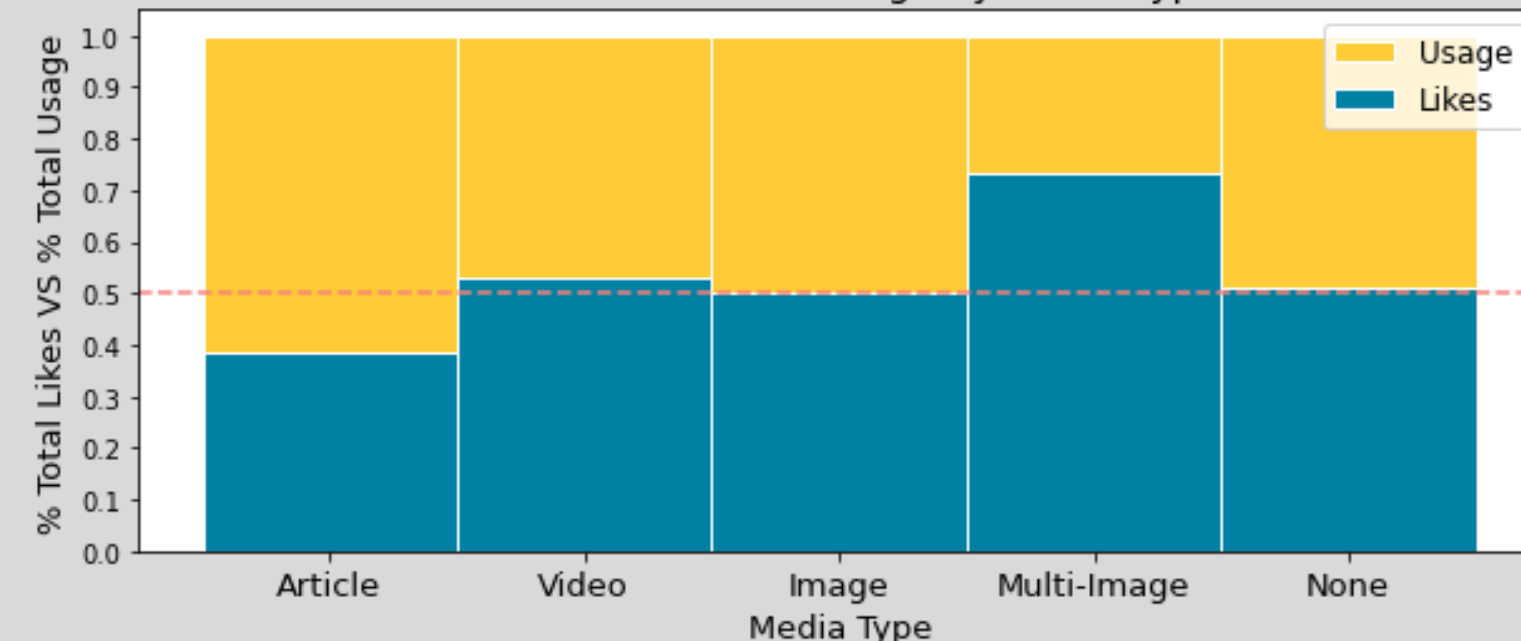
### Graph Statistics

- 11,000 Edges
- 7,400 Likes
- 1,500 Comments
- 400 Empathies
- 5,000 Nodes
- 3,000 Posts
- 1,500 Users
- Eigenvector Centrality**
- Central Insurance has Centrality 1
- Next 11 Highest are Users
- Centralities from 0.812 to 0.315

### Modularity

- At Resolution 1, 111 Groups form.
- Center split between groups 0 and 1.
  - Group 0 is largest; CI is in Group 1.
  - Most groups formed in branches on outside of graph model.
- At higher resolutions, center group unifies, and branches remain independent.
- Note:** Resolution determines group size.
- Higher Resolution = Fewer Groups
- Lower Resolution = More Groups

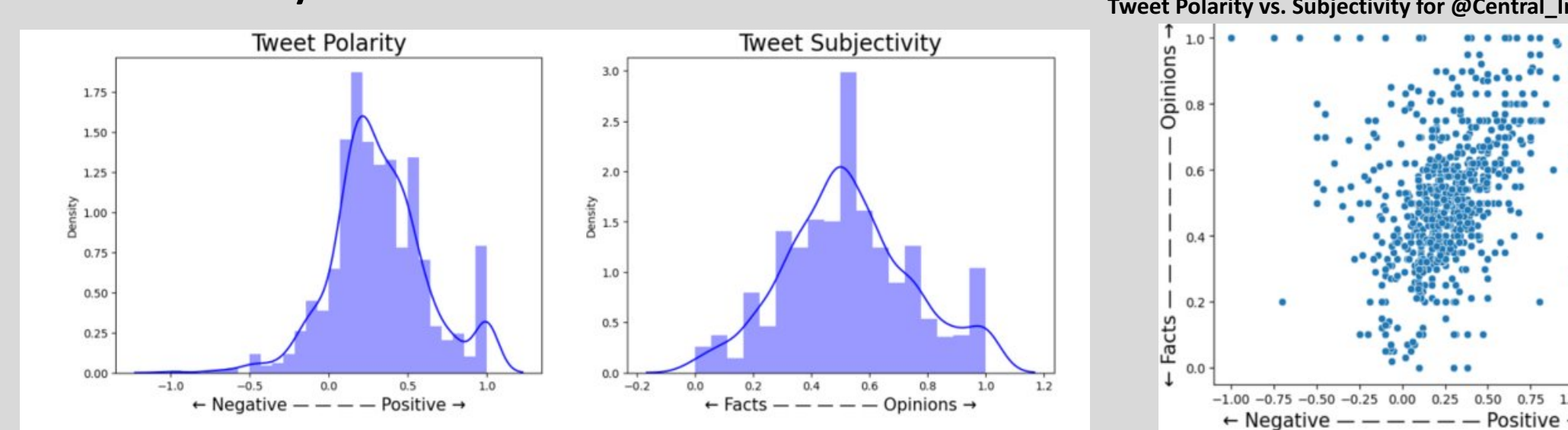
### LinkedIn - Like v.s. Usage By Media Type



- Data collected from 5 companies' pages.
- Articles perform worst
- Overused
- Multi-Image perform best
- Underused

## Twitter

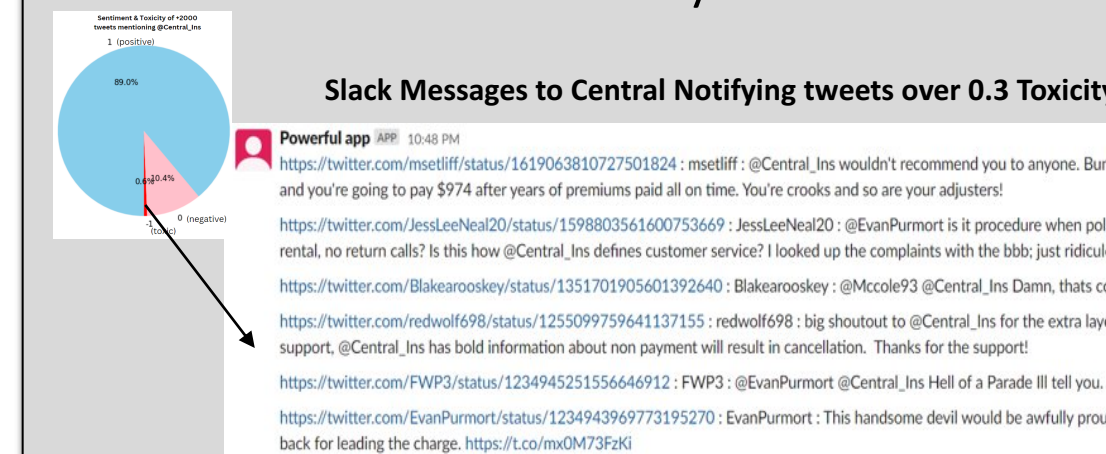
### Sentiment Analysis



- Web scraped data of over 2000 tweets mentioning @Central\_Ins over the past 3 years
- Polarity: Sentiment score of positive, neutral, or negative on a scale of 1 to -1
- Subjectivity: Sentiment score of opinion or fact on a scale of 1 to 0

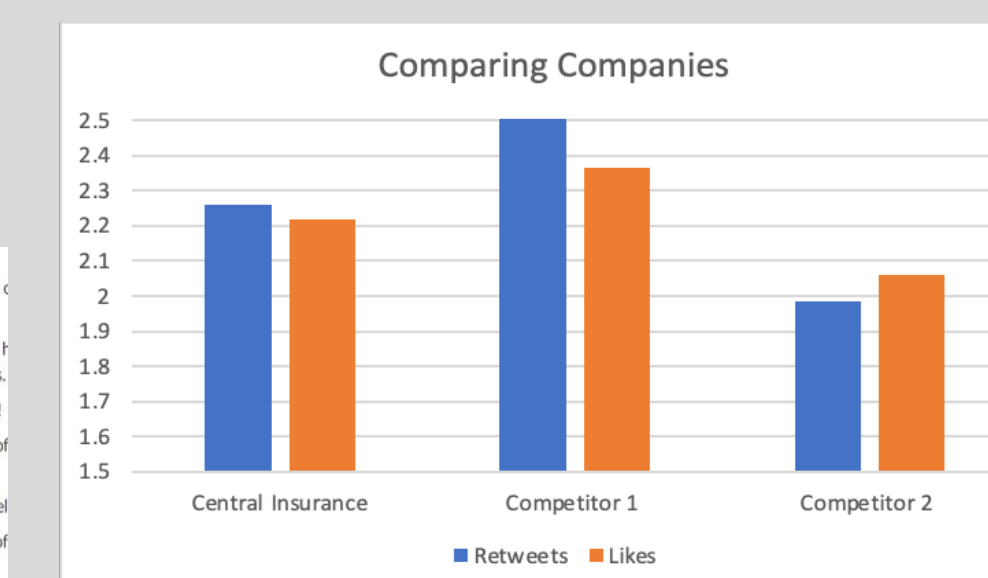
### Toxicity Analysis

- Periodic toxicity scoring of tweets mentioning CI using Perspective API
- Tweets scoring over 0.3 are sent to CI's Slack Channel for timely reaction



### Competitor Analysis

- Determined comparative competitor analytics and presence boosting strategies



## Conclusions

Using various forms of web scraping, we created graph models that represent Central Insurance's presence on four social media platforms. Our insights included:

- Community Detection** in user groups interacting with Central Insurance.
- Influential Users** related to Central Insurance's social media activity.
- Full map of **Second-Degree Connections** for Central on Instagram, Facebook and LinkedIn.
- Sentiment Scores** for user reviews on Twitter.
- Media-Type Effectiveness** for posts on LinkedIn.

Our efforts have paved the way for further graph construction. Future research could define common factors in groups identified here and explore post effectiveness.

## Acknowledgements

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