



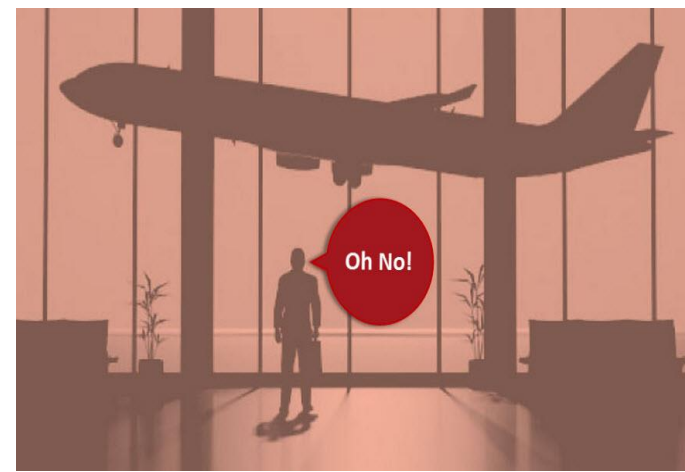
# How Gullible Are you? Predicting Susceptibility to Fake News



Tracy Shen  
jq5443@psu.edu Penn State University

## Introduction

### Research Problem:



← Conventional Fake News Detection

Proposed Detection Method →



### Research Questions:

- How to define susceptibility and what impacts users' susceptibility?
  - Five levels of susceptibility:**
    - Highly susceptible (strong agreement)
    - Slightly susceptible (weak agreement)
    - Neutral
    - Not-quite susceptible (weak disagreement)
    - Not-at-all susceptible (strong disagreement)
- Can we build an accurate prediction model to detect susceptibility?

### Planned Future Steps:

- Figure out if susceptibility is the same for the same person facing different fake news scenarios
- Develop a susceptibility score tool enabling users to measure their susceptibility themselves



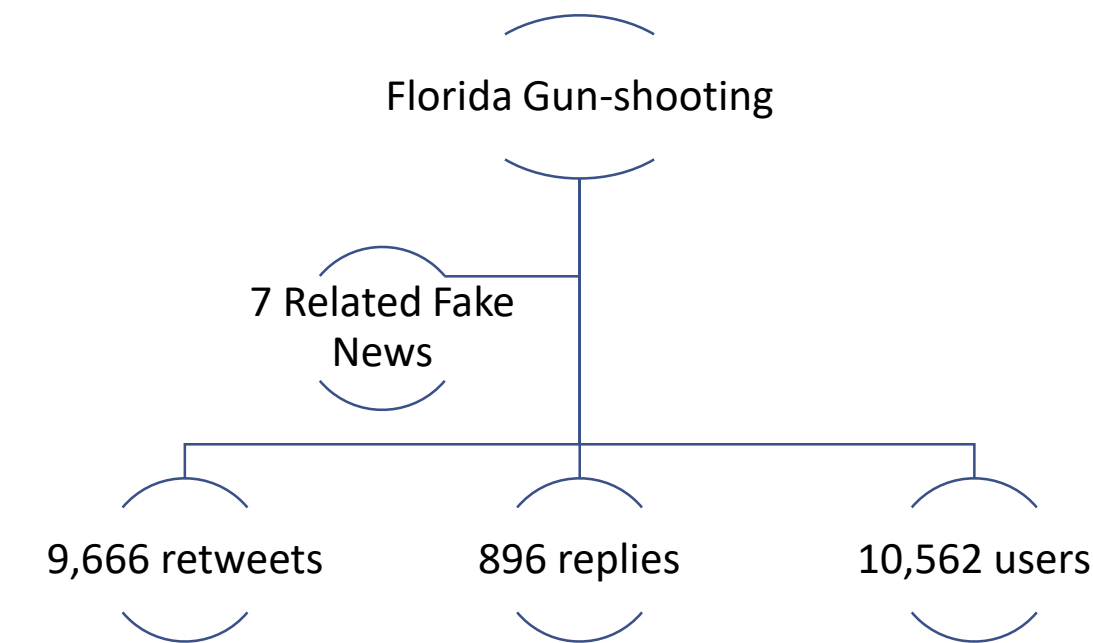
Example Fake News: claiming Soros is the backer of anti-gun shooting student activists

Class	Example Tweet
Strong Agreement	Always knew these kids had ties to #Soros . The parents need to have a Mental background check.
Weak Agreement	Florida is his home base! He found more Useful Idiots!
Neutral	Good lord.
Weak Disagreement	Youre a con man too.
Strong Disagreement	Wow. Imagine being a bad enough human to attack teenagers who just survived a mass shooting.

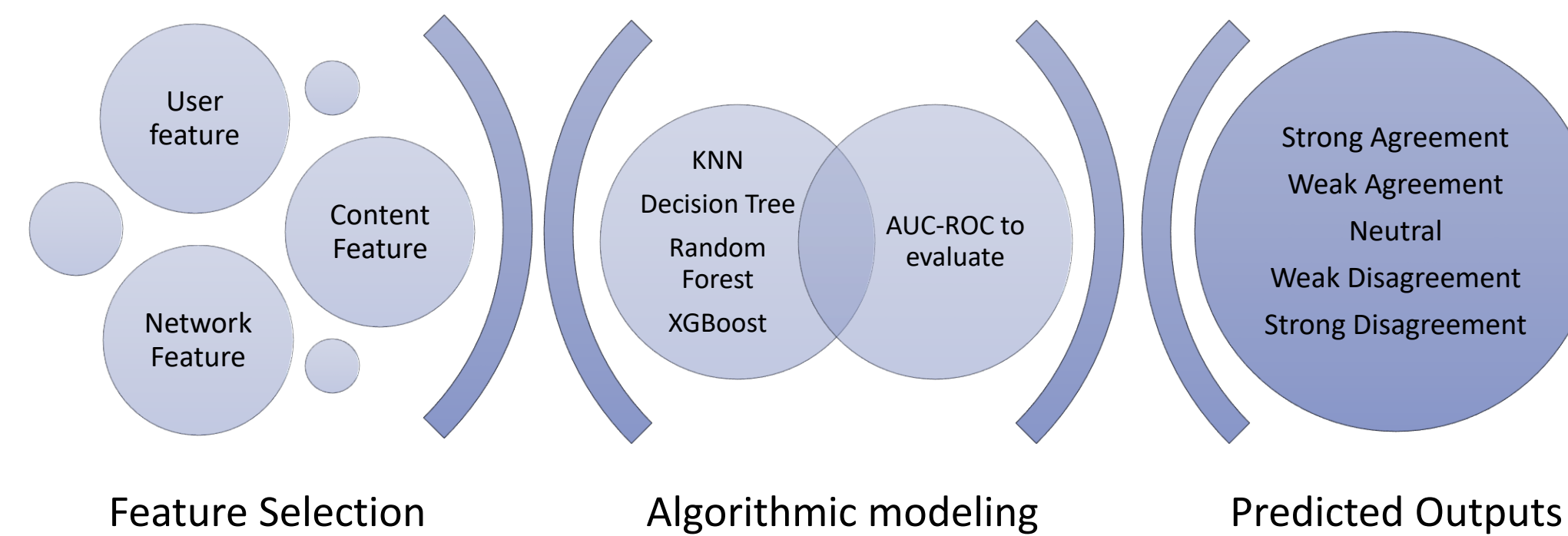
Example for Five Levels of Susceptibility

## Data and Methods

### Data:



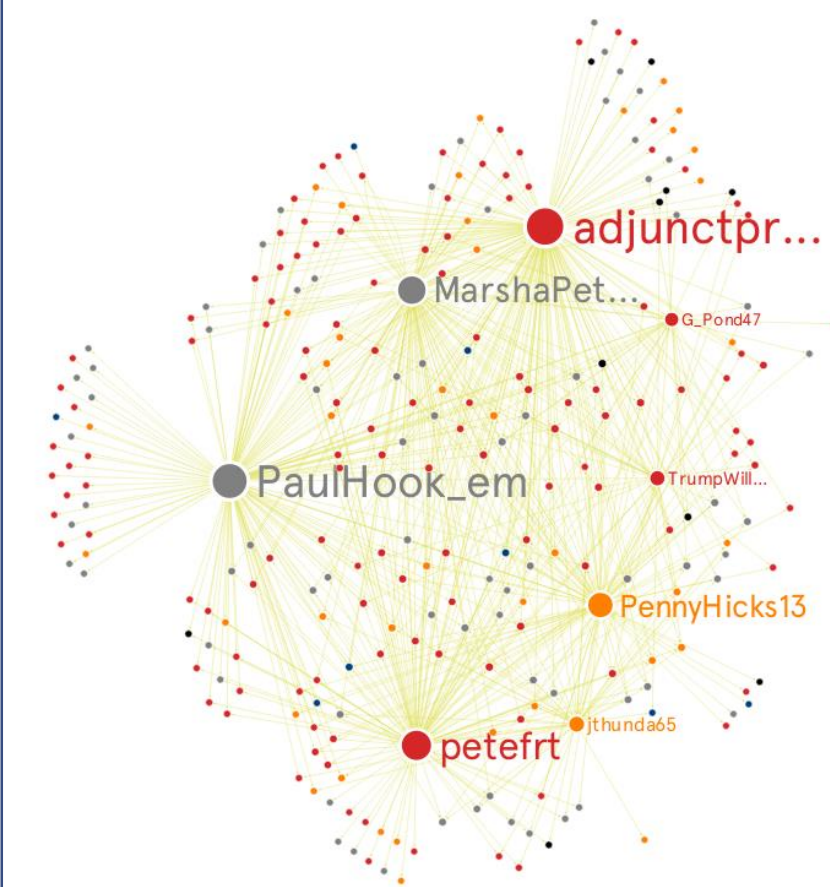
### Methods:



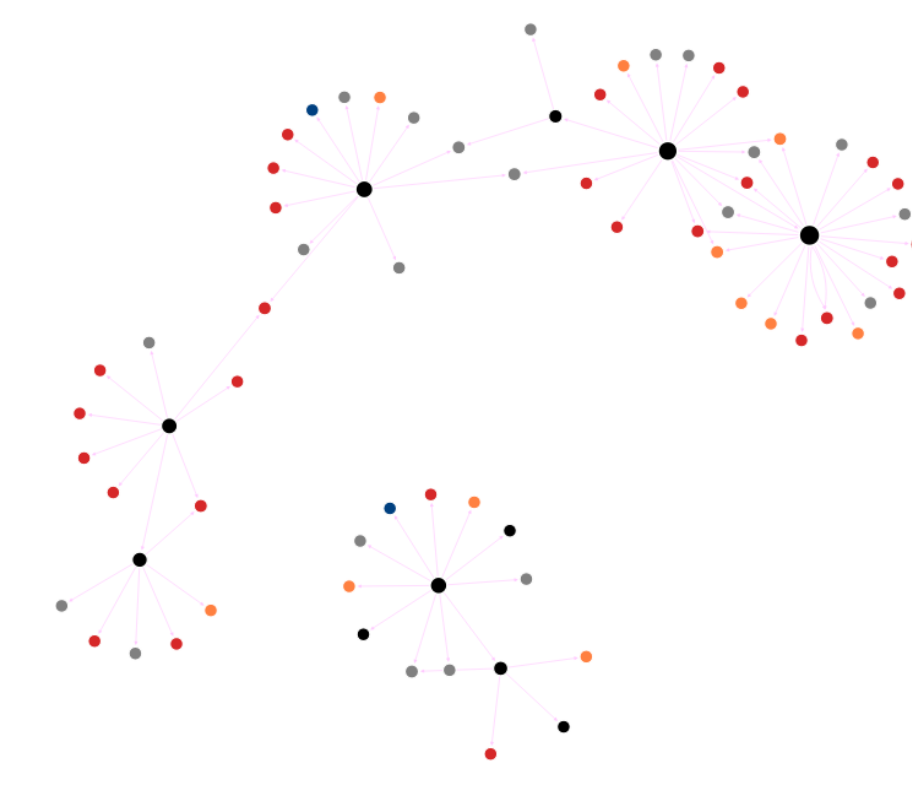
## Results

### Preliminary Analysis:

- Majority of the network center nodes are found to be highly susceptible, aligning with the entire network susceptibility (see below left)
- Non-susceptible users remain non-susceptible regardless they are mainly surrounded by highly susceptible users (see below right)



Network susceptibility: red-highly susceptible, orange-slightly susceptible, grey-neutral, green-not quite susceptible, black-not at all susceptible



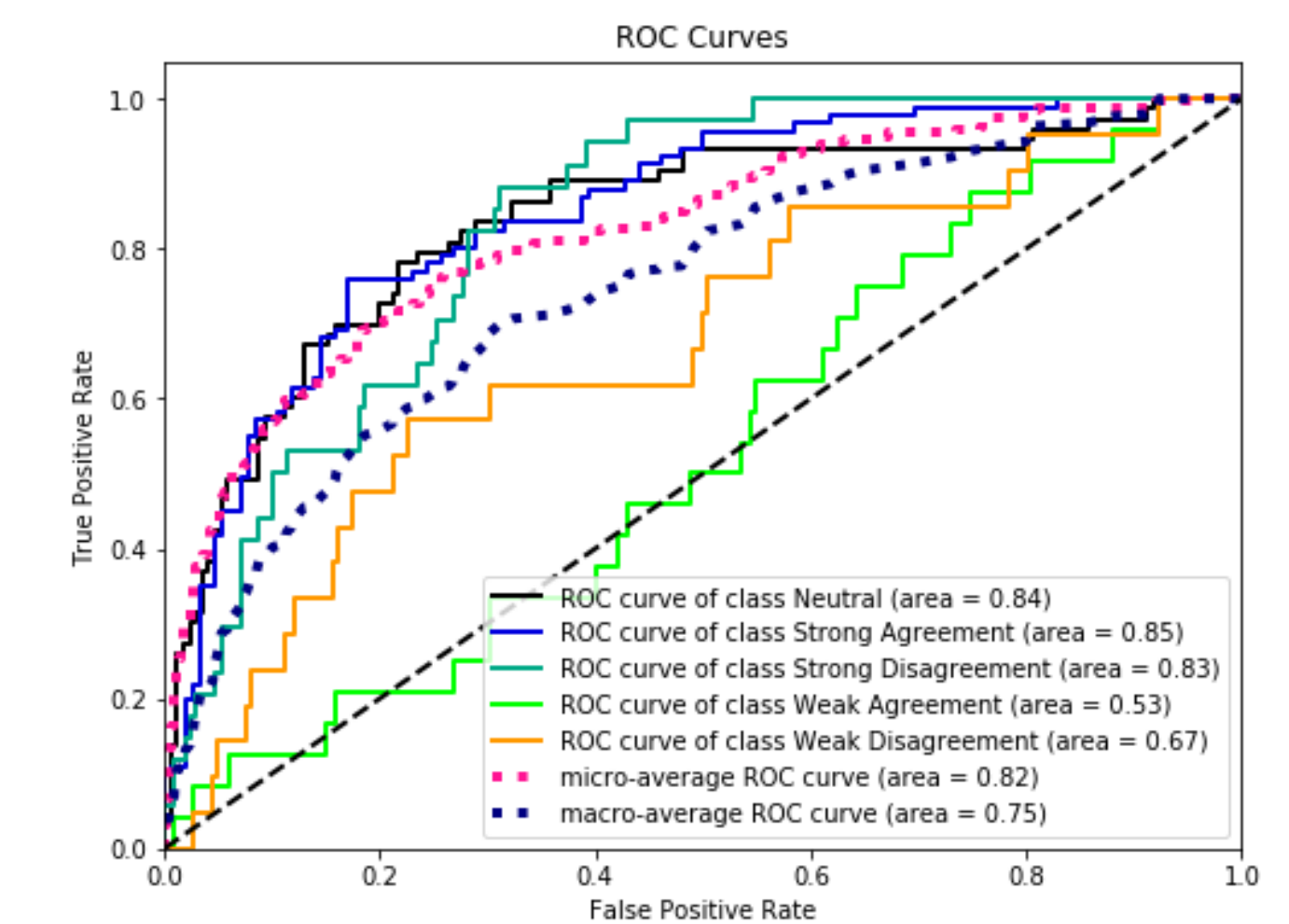
Not-at-all susceptible Nodes (in black) Zoom-in, mainly surrounded by highly susceptible nodes (in red)

## Results

### Modeling Results:

- Best performance was achieved by XGBoost algorithm with all features in which gained 0.82 average AUC-ROC (see below table)
- The best model well predicts highly and not-at-all susceptible classes for 0.84 and 0.83 AUC-ROC (see below figure)

	KNN	Decision Tree	Random Forest	XGBoost
Content Alone	0.60	0.54	0.66	0.69
User Alone	0.59	0.62	0.74	0.76
Network Alone	0.63	0.56	0.68	0.68
Content +User	0.65	0.68	0.71	0.80
Content + Network	0.68	0.57	0.68	0.75
User+ Network	0.61	0.64	0.73	0.77
<b>All Features</b>	<b>0.62</b>	<b>0.65</b>	<b>0.77</b>	<b>0.82</b>



## Conclusion

**To sum up**, we studied on the problem of user susceptibility to fake news, and aimed to answer two research questions: characterizing and predicting susceptible users. First, among other findings, we found that susceptible users are more likely to be connected with other susceptible users, especially when majority of center nodes are highly susceptible, but the same observation did not occur for non-susceptible users. Second, we demonstrated that it is possible to predict one of five susceptibility levels of users using various features trained in XGBoost model, achieving 0.82 in average AUC-ROC.

## Collaborators

Robert Cowell, Aditi Gupta, Amulya Yadav, Dongwon Lee (PI)  
College of Information Sciences and Technology, Penn State University  
Westgate Building, University Park, PA 16802

## References

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