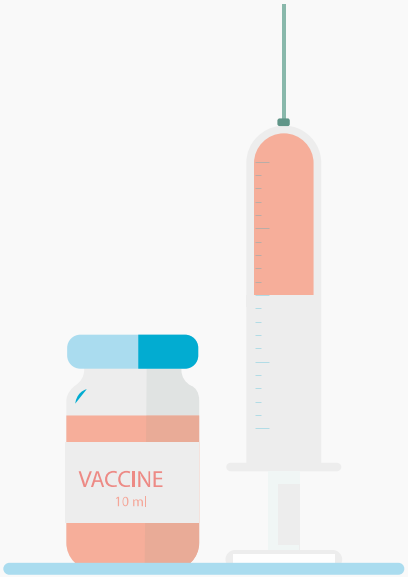
PennState
Donald P. Bellisario
College of Communications

# The Infinity Vaccine War:

## linguistic regularities, audience engagement, and community network of vaccine debate on Twitter

Rachel Peng

Ryan Wang




# Introduction

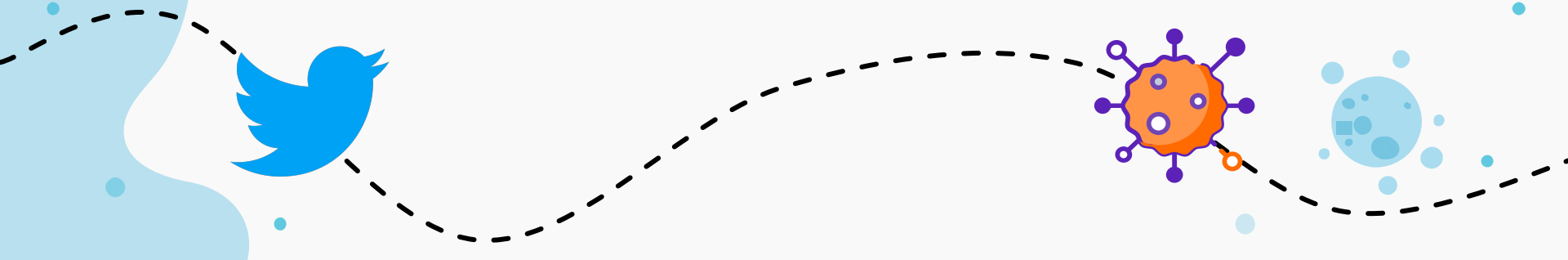
Vaccines at the center of controversy

# Introduction

- Vaccines have made huge contributions to the decrease of the mortality from infectious diseases since late 1990s.

- Anti-vaxxers' ability to reach large audiences with their messages has increased with the advent of the social media.

- Twitter, a social media platform, allows personal expression and encourage individuals to build, maintain, and exhibit wide social networking and information sharing.



**Pro-vaxxer**

Vaccine advocacy

**Anti-vaxxer**

Vaccine denialism

We decide to focus on the textual and relation data on Twitter which constitute the language and network of entities from both pro- and anti-vaxxers. In study 1, we will compare sentiments, topics and audiences' engagement between tweets sent by two communities, the so-called pro- and anti-vaxxers. We also aim to examine whether content features as the occurrence of emotion words and topics can be leveraged to improve audiences' engagement.

In study 2, we are focusing on the following network within these two communities. And we try to focus on systematically identifying the structural distinctions between the pro- and anti-vaxxers' online networks.

## Study 1:

RQ1: Which emotions(a) and sentiments(b), and topics(c) are dominant in tweets of pro- and anti-vaxxers, respectively?

RQ2: How does the emotions(a) and sentiments(b), and topics(c) change during COVID-19 pandemic?

**RQ3: What are the associations between emotional words(a), sentiment words(b), topic(c) and the engagement of tweets?**

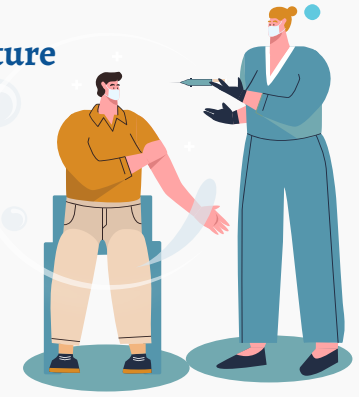
## Study 2:

RQ1: Does the network structure of anti-vaxxers differ than the network structure of pro-vaxxers?

RQ2: How does the network structure of anti-vaxxers differ than the network structure of pro-vaxxers in terms of network characteristics on nodal level and dyadic level?

**RQ3: How does the role of the following attributes in anti-vaxxer's network structure differ than the ones in pro-vaxxer's network structure on nodal level and dyadic level?**

**(1) Account type; (2) Group; (3) Sentiment; (4) Influence**



# Method

Data collection
Study 1: Hurdle negative binomial model
Study 2: Exponential Random Graph Modeling

# Data collection

## Sample

100 Pro-vaxxers
267,260 tweets

173,612 original tweets
and 93,648 retweets
(2009-2020)

100 Anti-vaxxers
248,425 tweets

158,199 original tweets
and 90,226 retweets
(2009-2020)

## Snowball sampling approach

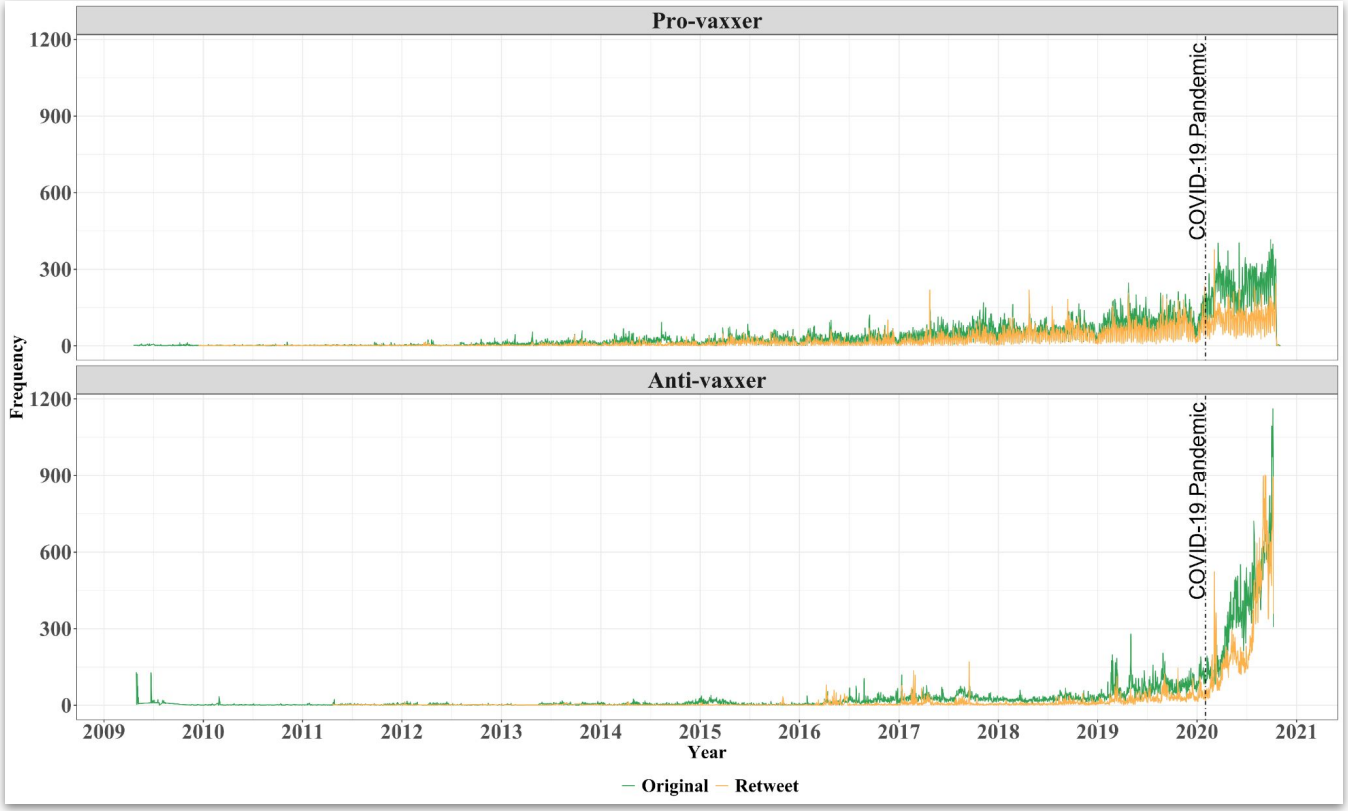
We started with one of the most active pro- or anti-vaxxers on Twitter, then we searched for another pro- or anti-vaxxer based on his/her/its following list.

Criteria:
(1) their profile shows clearly positive or negative attitude towards vaccine; and
(2) their first page has more than 10 tweets about vaccine

Study 1: The historical tweet data of each account (up tp 3200 tweets across the timelines)
We scraped the historical tweet data of these accounts through Twitter API via “rtweet” R package.

Study 2: The following list of each pro-/anti-vaxxer (excluding those not in our targets)

# DATA COLLECTION



# Study 1

What are the associations between emotional words(a), sentiment words(b), topic(c) and the engagement of tweets?

# Measures

Annotated eight basic emotions: Anger, Anticipation, Disgust, Fear, Joy, Surprise, Sadness, and Trust (Plutchik, 2001), and the negated sentiment on tweet-level with the “sentimentr” package

## (Lexicon-based) Sentiment analysis

Analyze the words to uncover the underlying themes, with the “stm” package

## Structural topic modeling

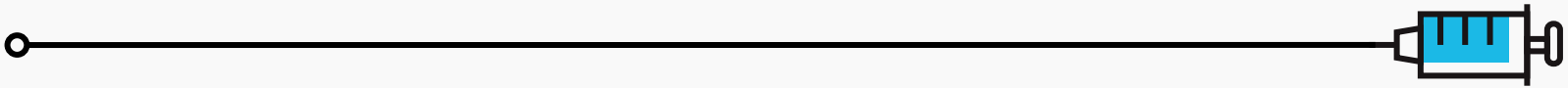
The count of retweets (diffusion) and likes (endorsement)

## Engagement

# Results

## Sentiment and emotions:

- Trust was the predominant emotion encouraging retweet across pro- and anti-vaccine corpus, thus tweets with cue of Trust have bigger impact and greater spreading in general.
- Tweets amplifying the emotion of Anger capture are more attention-grabbing and getting more like among anti-vaxxers.



## Topics:

- Pro-vaxxers: Tweets discussing “Child protection”, “COVID-19 situation” are linked with more retweet counts as well as like counts.
- Anti-vaxxers: Tweets talking about “Supporting Trump”, “Injured children”, “COVID-19 situation”, “Media propaganda”, and “Community building” are associated with more retweet counts and like counts.

# Study 2

How does the role of the following attributes in anti-vaxxer's following network structure differ than the ones in pro-vaxxer's network structure on nodal level and dyadic level?

1. Account type;
2. Group;
3. Sentiment;
4. Influence

# Measures

Average negated sentiment of the tweets (with lexicon-based approach) on each account

## Sentiment

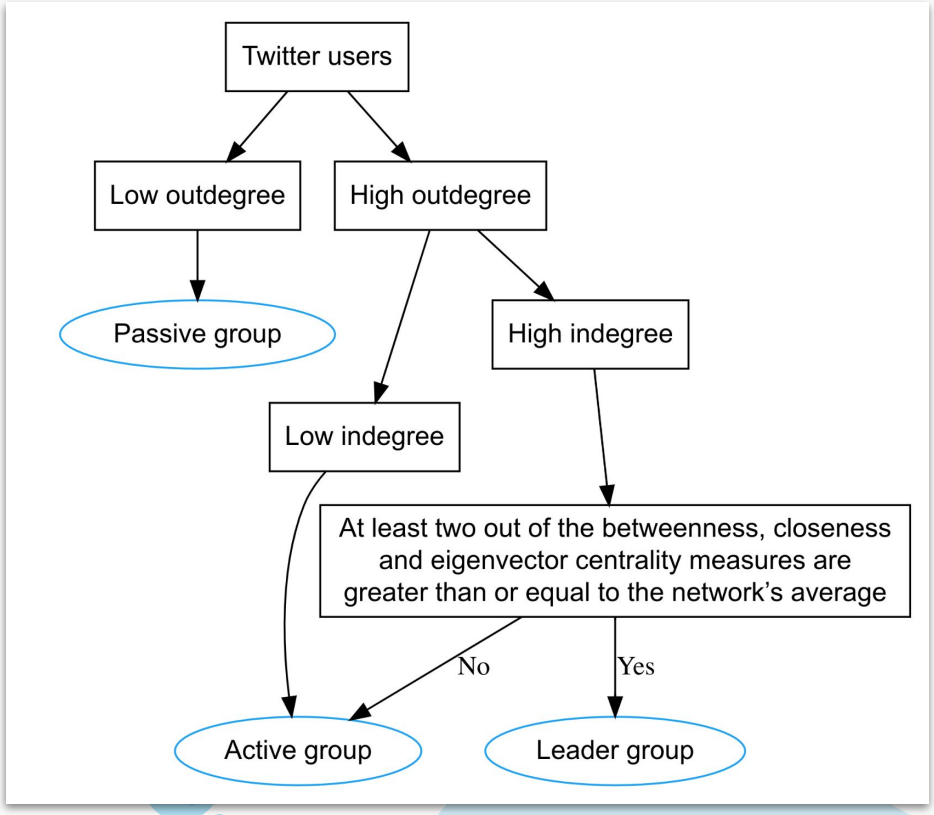
The outdegree of each node in the retweeting network

## Influence

Classified based on outdegree, indegree, betweenness, closeness and eigenvector centrality in the retweeting network

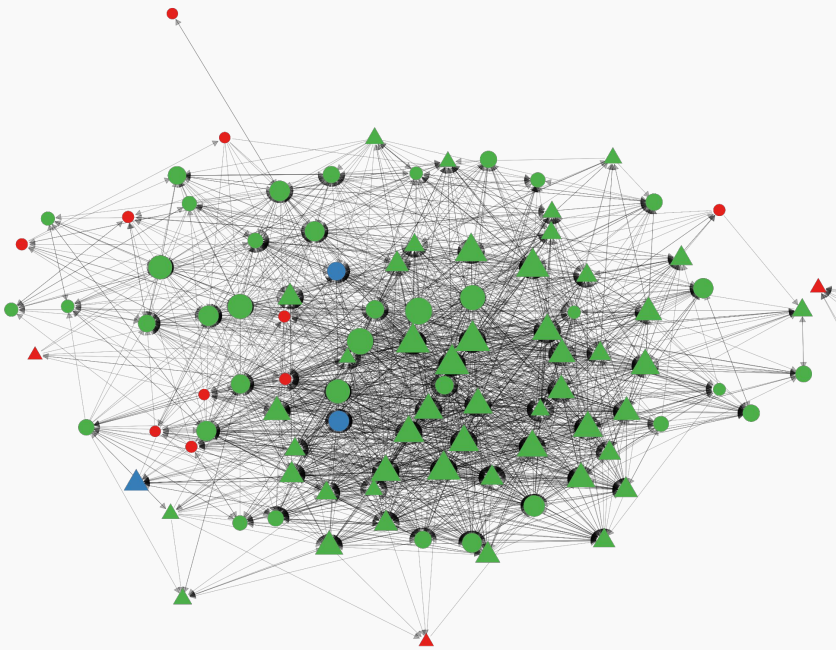
## Group

# Users Classification (Bartal et al., 2019)

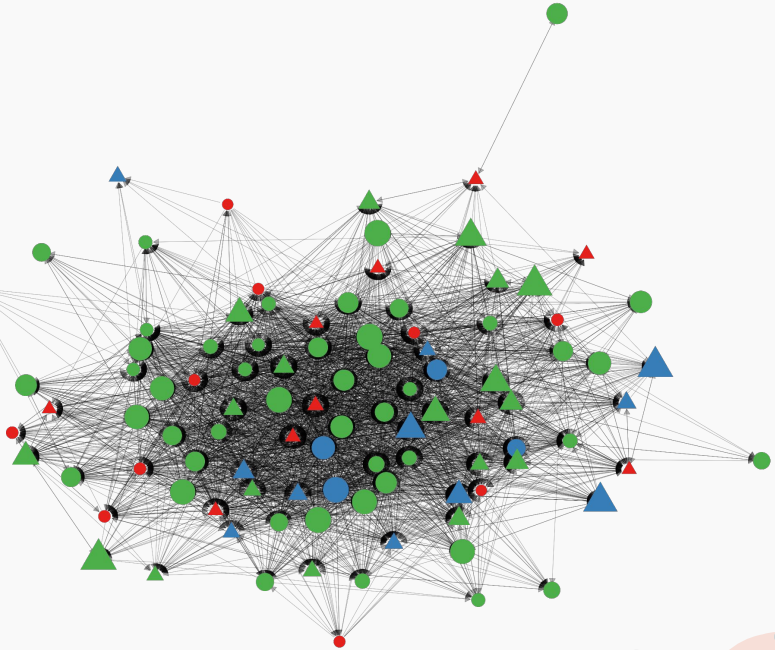


# Network visualization

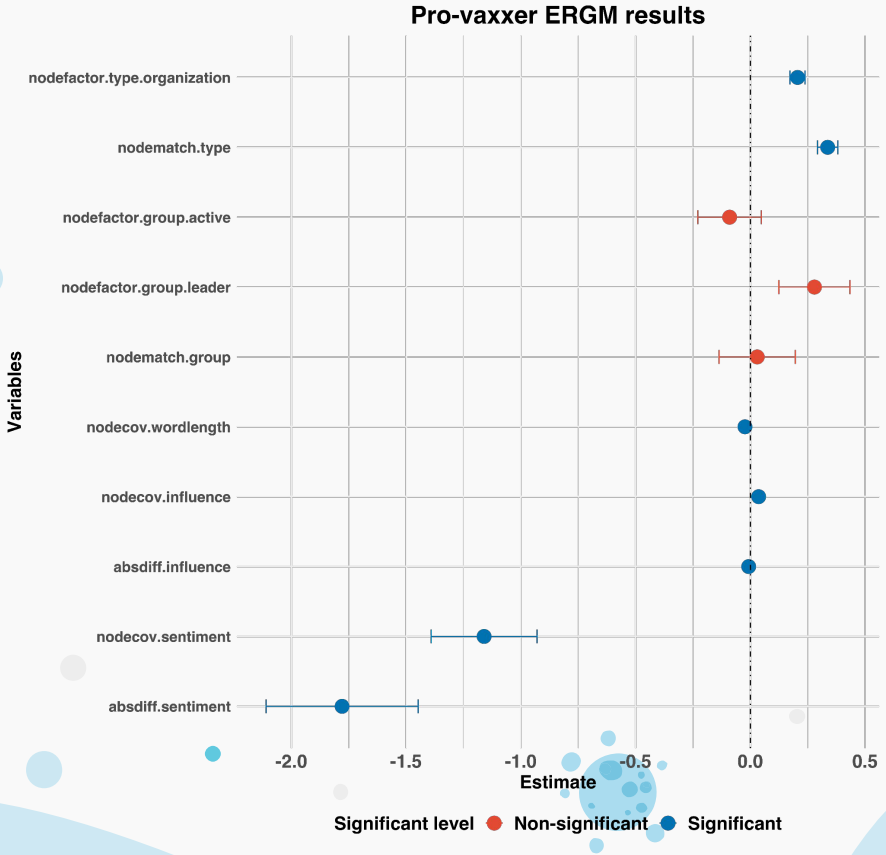
Pro-vaxxer following network

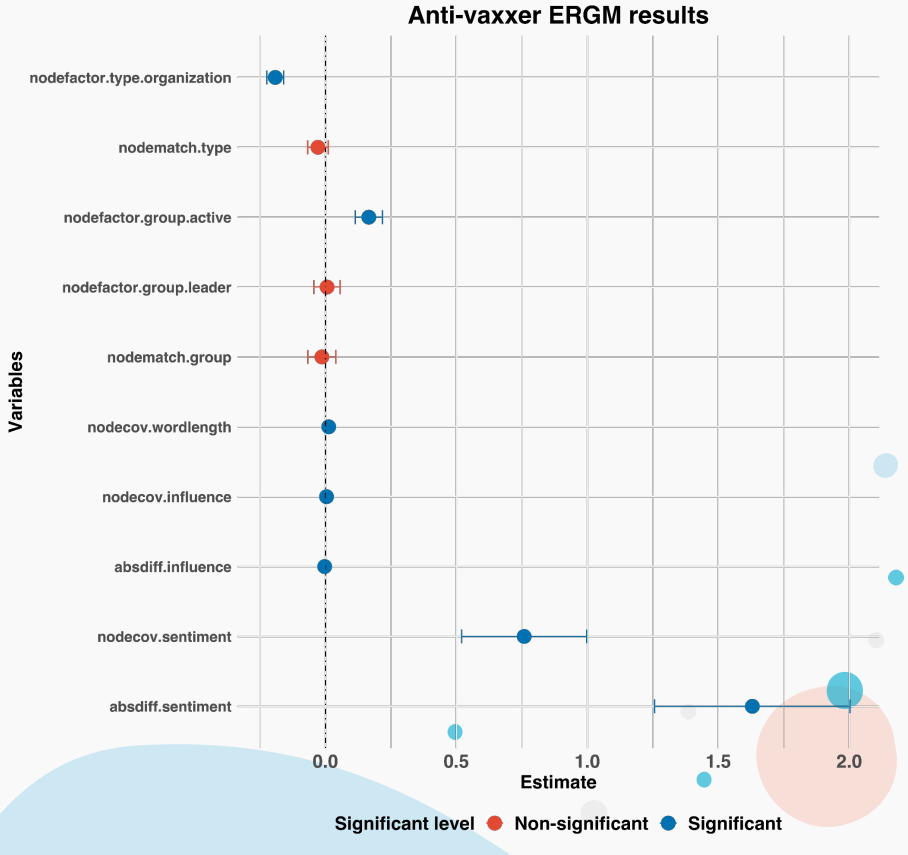



Anti-vaxxer following network



# ERGM Result


Pro-vaxxer ERGM results
nodefactor.type.organization
nodematch.type
nodefactor.group.active
nodefactor.group.leader
nodematch.group
nodecov.wordlength
nodecov.influence
absdiff.influence
nodecov.sentiment
absdiff.sentiment
Variables
-2.0
-1.5
-1.0
-0.5
0.0
0.5
Estimate
Significant level
Non-significant
Significant


Anti-vaxxer ERGM results
nodefactor.type.organization
nodematch.type
nodefactor.group.active
nodefactor.group.leader
nodematch.group
nodecov.wordlength
nodecov.influence
absdiff.influence
nodecov.sentiment
absdiff.sentiment
Variables
0.0
0.5
1.0
1.5
2.0
Estimate
Significant level
Non-significant
Significant

# Discussion

# Thank you!

## Do you have any questions?


rachelxpeng@psu.edu

ryanwang@psu.edu