Pro or Anti? A Social Influence Model to Stance Flipping Predictions of Coronavirus Vaccine

Lynnette Ng

Social Influence

- Social Influence = change of opinions in a complex social environment
- Incorporates individual past stances & impact of interpersonal influence

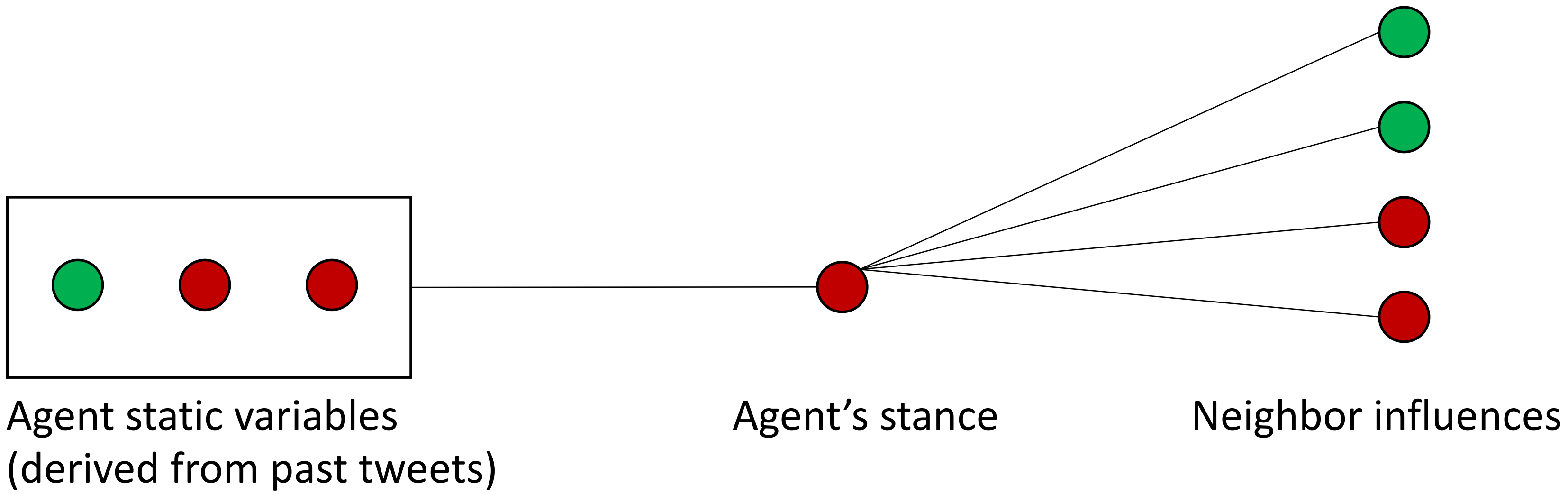
- Examine COVID vaccine stance behavior from April 2020 to May 2021
- Considers agent's past tweets and overall network structure towards a stance score
- Model for prediction of stance flipping behavior achieves 86% accuracy

Data

- Collected Twitter data using the hashtag #coronavirus from April 2020 to May 2021
- Bot Annotation: bot-probability annotation using the BotHunter algorithm at the 0.70 threshold level
- Stance Labelling: Manually inspected hashtags and classified them into pro/con; used network-based stance propagation algorithm to label
- Linguistic Annotation: characterized thoughts and emotions through key lexical categories (positive, negative terms, 1st person pronouns)…
- Network annotation: characterized influence of agent in a network (centrality values)

Social Influence on Vaccine Stance

- Describe the formation of a stance towards the coronavirus vaccine with:
  - Agent static variables – linguistic cues, number of tweets, number of followers…
  - Interpersonal influences from the network – neighbor's factors



Carnegie Mellon University

Predicting Stance Flips with a Social Influence Model

- Describe the formation of a stance towards the coronavirus vaccine with:
  - Agent static variables – linguistic cues, number of tweets, number of followers…
  - Interpersonal influences from the network – neighbor's factors

Agent stance value $$Y_{\{agent\}} = \gamma C X_* B_*$$

Stance Strength (Conviction of agent)

Connection (Proportion of neighbors that support agent's stance)

Variables (linguistic & network)

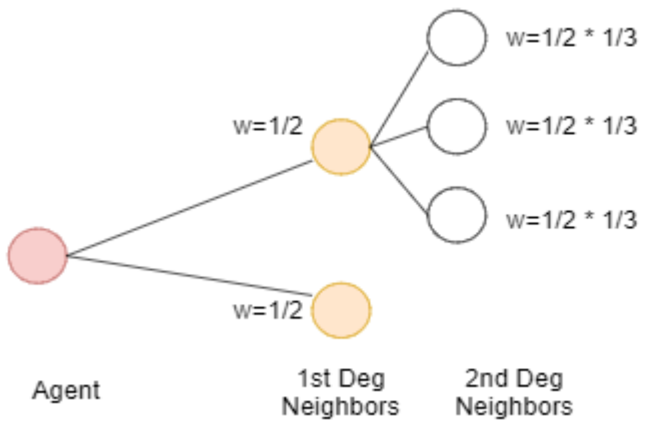
Coefficients (eg weights)

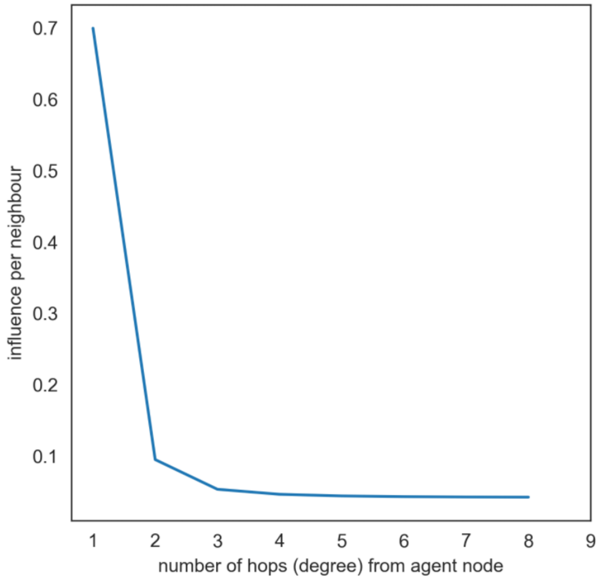
Neighbor stance value $$Y_{\{neighbor\}} = \gamma C X_* B_* + R$$

Reciprocity (Two way interaction between agents)

Predicting Stance Flips with a Social Influence Model

- ❑ We only consider neighbors that are one and two hops away
- ❑ Influence weight of each neighbor tends to 0 as number of hops of agents increases





Predicting Stance Flips with a Social Influence Model

- We only consider neighbors that are one and two hops away
- Influence weight of each neighbor tends to 0 as number of hops of agents increases

$$Y_{\{agent\}} = \gamma C X_* B_*$$

$$Y_{\{neighbor\}} = \gamma C X_* B_* + R$$

Influence on an agent

$$I = \alpha[\underbrace{\sum_{i=0}^{n} Y_{\{1st\deg neighbors\}}}_{\text{Influence from 1st degree neighbors (1 hop away)}} + \underbrace{\sum_{i=0}^{n}\sum_{j=0}^{m} \beta Y_{\{2nd\deg neighbors\}}}_{\text{Influence from 2nd degree neighbors (2 hops away)}}], \alpha = \frac{1}{n}, \beta = \frac{1}{m}$$

Carnegie Mellon University

Determining Variable Importance

- Performed a binary classification task with a decision tree model
- Most important features:
  - Linguistic variables: number of tweets, avg word/sentence length, reading difficulty, type of pronouns
  - Network variables: num of followers, eigenvector centrality, betweenness centrality

Predicting Stance Flips with a Social Influence Model

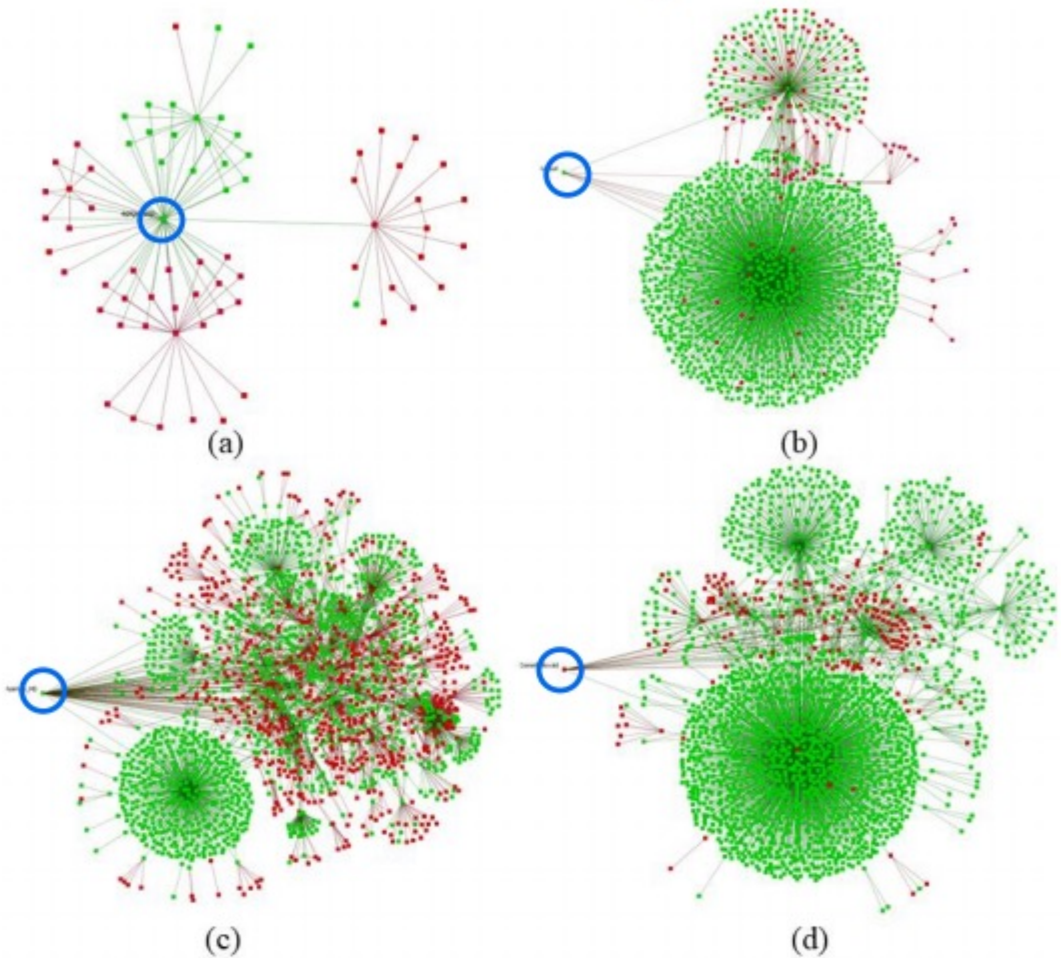
- Both linguistic + network factors are important to the influence of agent stances
- Accuracy (F1-score) increases drastically upon the reciprocal ties

Model #	Model	Accuracy
Baseline	Decision Tree	0.53
Base - network	Base social influence model without network variables	0.47
Base - linguistic	Base social influence model without linguistic variables	0.55
Base Model 1	Base social influence model	0.50
Model 2	Model 1 + 2nd deg neighbor information	0.59
Model 3	Model 2 + stance strength	0.72
Model 4	Model 3 + connection	0.73
Model 5	Model 4 + reciprocity	0.86

Table 2: Results of Social Influence Models. The base social influence model is agent stance with 1st degree neighbor information.

Predicting Stance Flips with a Social Influence Model

- ❑ Model accurately predicts 86% of the stance flips
- ❑ Positive examples:

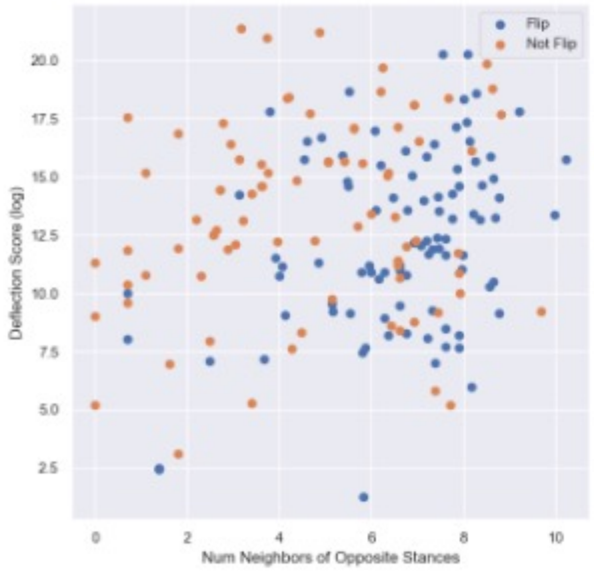


Green: provax
Red: antivax

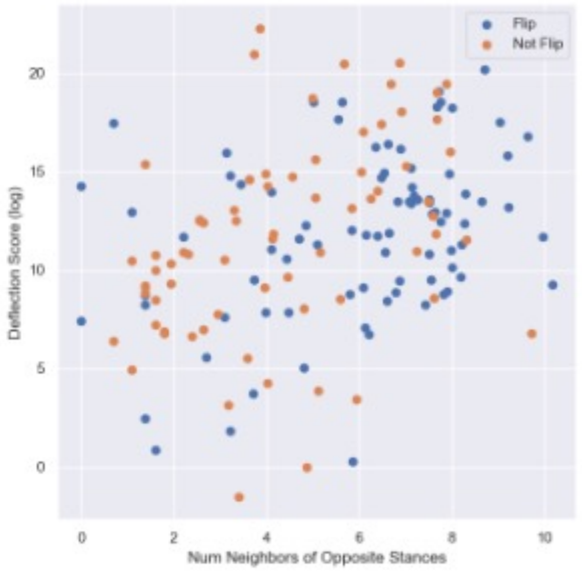
Circle: Agent in focus
Stance of agent depicted before flip

Bot vs Non-bot agents

- 53.7% of the population are bots
- 6.6% of the overall population flip, while only 2.7% of non-bot agents flip
- Bot population have lower deflection score and overall population averages; form more interactions; more convicted



(a) Bots stances



(b) Non-Bots stances

Carnegie Mellon University

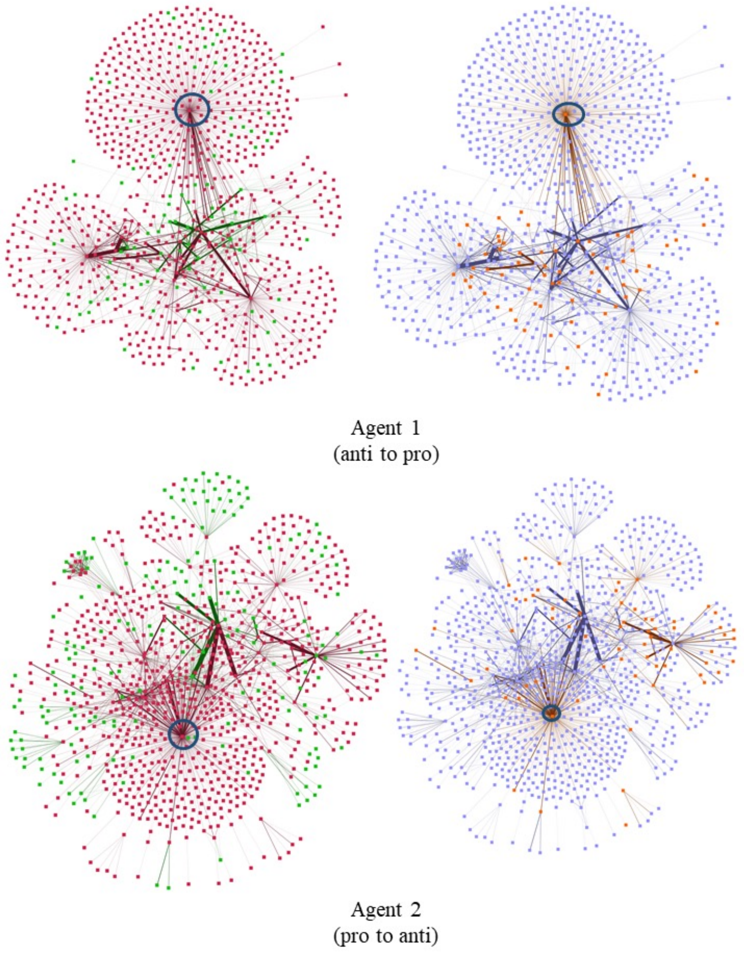
Collective Expression of Agents

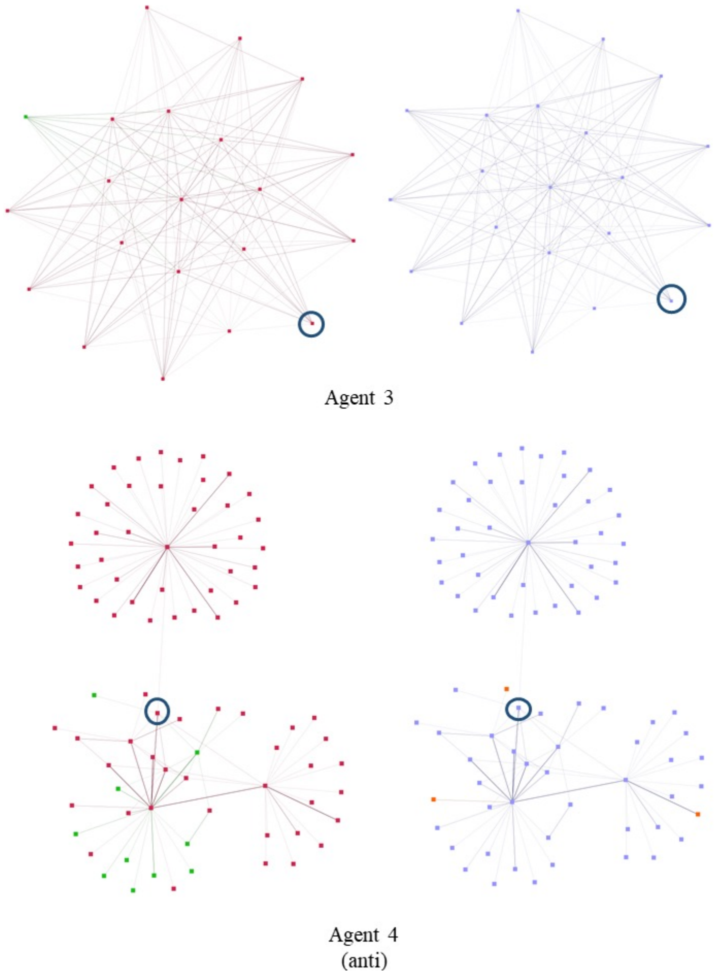
- Idea is derived from "coordinated activity" in social media
- Identify posting of hashtags synchronized in time
  - Removed common words (e.g. #covid, #vaccine)
  - Identify pairs of agents that post a lot of the same hashtags within a 5-min time window
- For agents that flip, larger proportion of neighbors are of opposite stance & participate in collective expression
  - Floods news feeds, illusion that neighbors are all of the opposite expression

	Agents that flip stances	Agents that do not flip stances	p-value
Proportion of bots	0.452	0.293	2.14e-13*
Percentage of neighbors that are bots	0.352 ± 0.372	0.358 ± 0.280	0.051
Proportion of neighbors of the opposite stance	0.409 ± 0.443	0.196 ± 0.271	0.011*
Proportion of neighbors participating in collective expression	0.0389 ± 0.068	0.0302 ± 0.115	0.027*
Proportion of neighbors participating in collective expression and are of opposite stance	0.0207 ± 0.0996	0.0136 ± 0.0350	0.0078*

TABLE 4: Comparison of actors that flip stances and do not flip stances with respect to their 2-degree neighborhood. A * denotes a p-value that is significant at the 0.05 significance level.

Collective Expression of Agents





Stance network Expression network

Stance network Expression network

Carnegie Mellon University

References/ Contact

- Lynnette Ng and lynnetteng@cmu.edu
- L. H. X. Ng and K. M. Carley, "Pro or Anti? a Social Influence Model of Online Stance Flipping," in *IEEE Transactions on Network Science and Engineering*, 2022, doi: 10.1109/TNSE.2022.3185785.

Carnegie Mellon University