An exploration of emotional contagion among #immigration tweets

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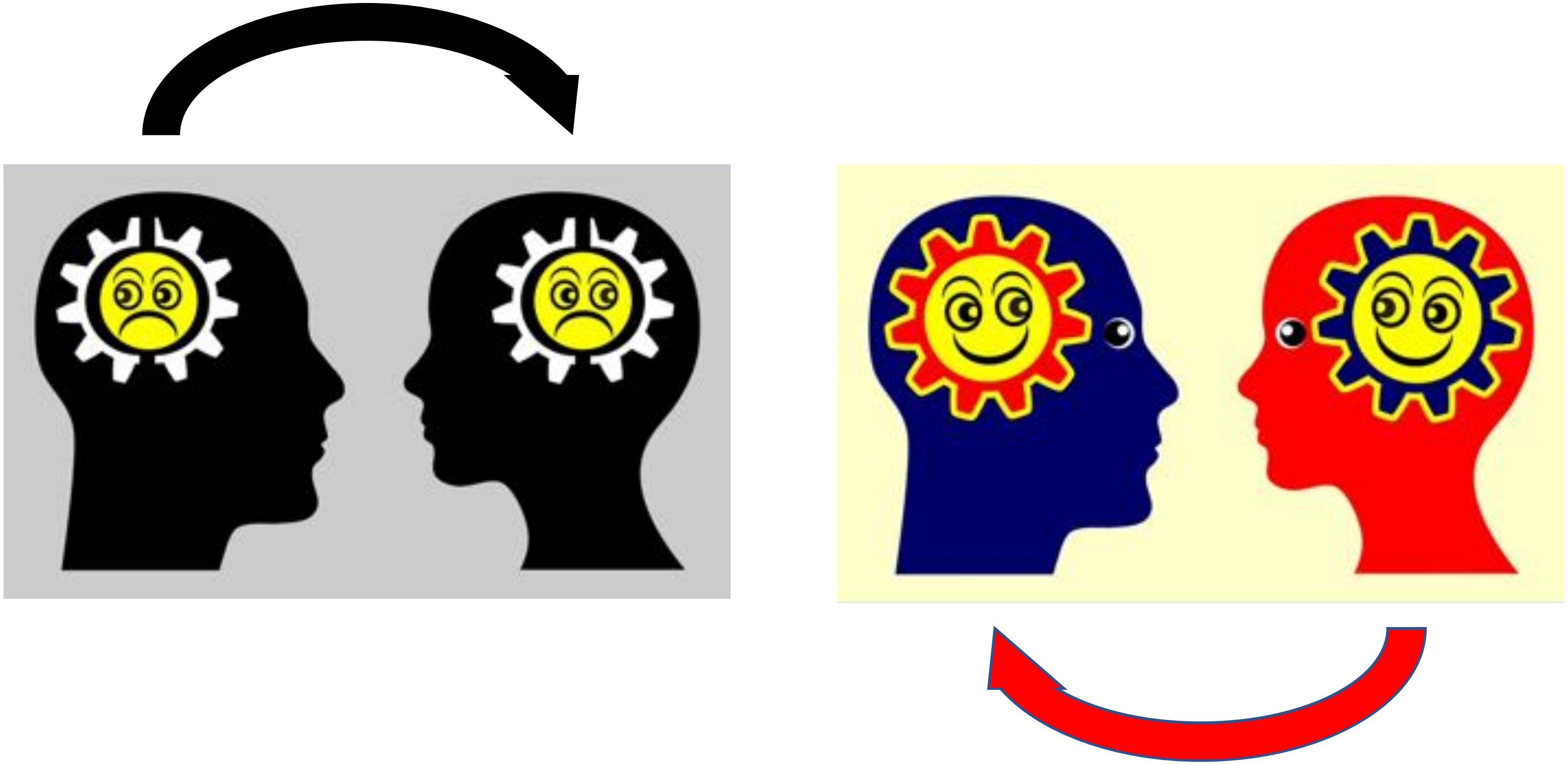
Introduction

- Central issue: How does the content produced and consumed on social media affect an individual's emotional states and behaviors?

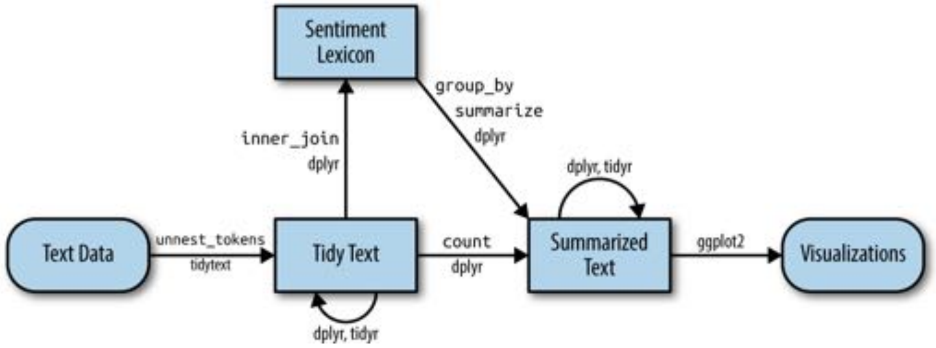


Literature Review

- 20-year longitudinal study suggests that emotions can be passed via social networks and have long term effects (Fowler et al., 2008)
- Facebook study proposes that emotional contagion occurs online even in absence of non-verbal cues (Harris & Paradice, 2007)
  - Manipulated timeline content

Ethical concerns?

Sentiment Analysis



- Analysis of a piece of text's emotional valence
- R function "sentiment.score" function (tidyr, dplyr and stringr packages)
- **FLAWED!**

	A
1	2-faced
2	2-faces
3	abnormal
4	abolish
5	abominable
6	abominably
7	abominate
8	abomination
9	abort
10	aborted
11	aborts

+1 **-1** **0**

	A
1	a+
2	abound
3	abounds
4	abundance
5	abundant
6	accessable
7	accessible
8	acclaim
9	acclaimed
10	acclamation
11	accolade

Data

- Goal: Establish a relationship between the sentiment of a tweet and that of the the tweets its author may have been exposed to prior to posting

Variable	Description
U	sample of users who posted at least one tweet with the hashtag "immigration" in the second week of July 2018 (3,800 users)
F	the set of followees of all users in ***U***
h_t	the set of tweets produced by any of ***u***'s followees in a time span of one hour preceding the posting of each tweet ***t***

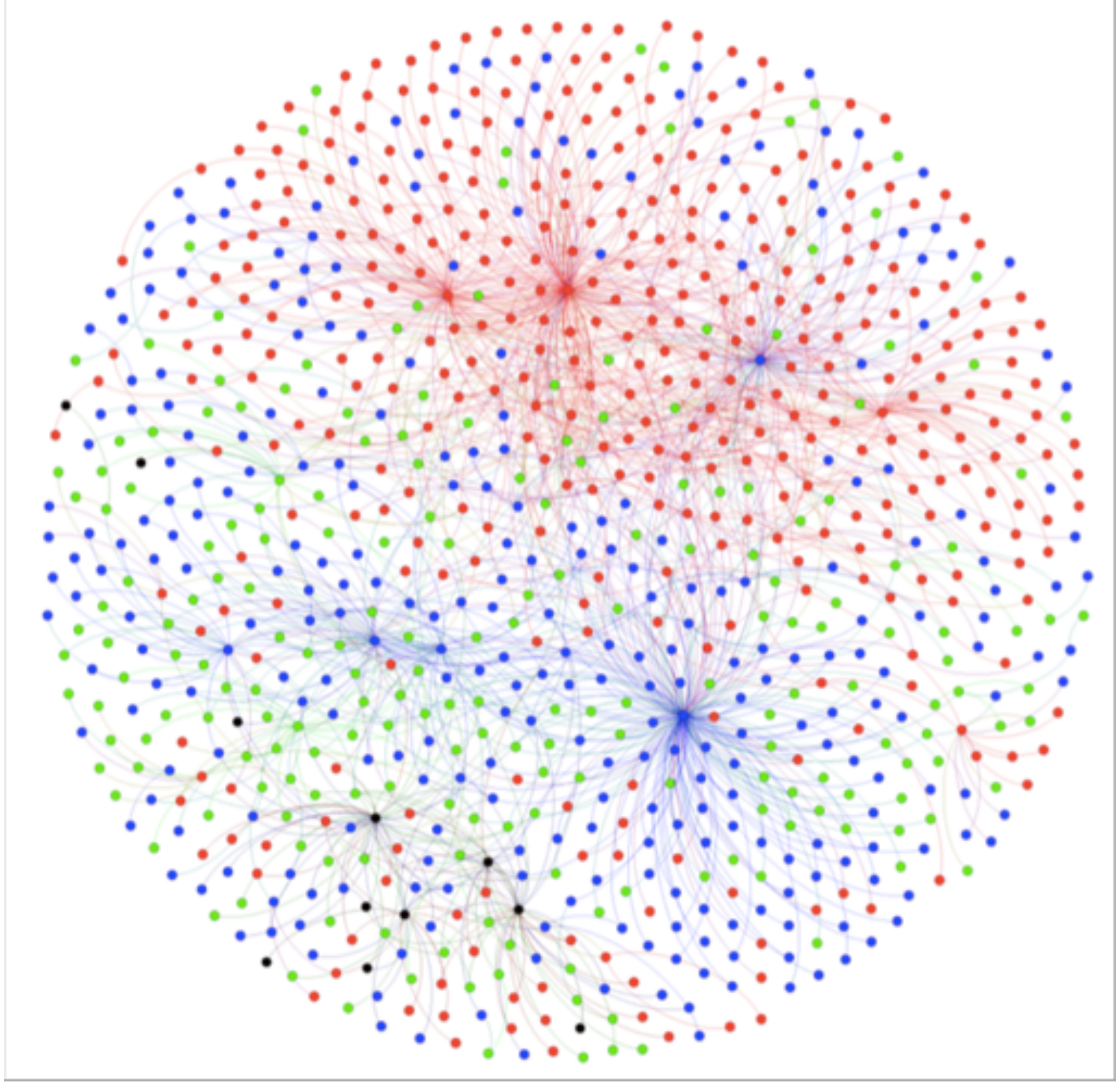


Fig 1. Emotionally-valenced network structure.

Effect of Emotional Contagion

- $\boldsymbol{H_i}$: The average sentiments of tweets preceding a positive, negative, or neutral tweet are significantly different
- Reshuffling strategy –> baseline (null) model
- Divided tweets into sentiment categories
- Generated the distribution of positive, negative, and neutral sentiments observed in the stimuli prior to the posting of each $\boldsymbol{t_u}$

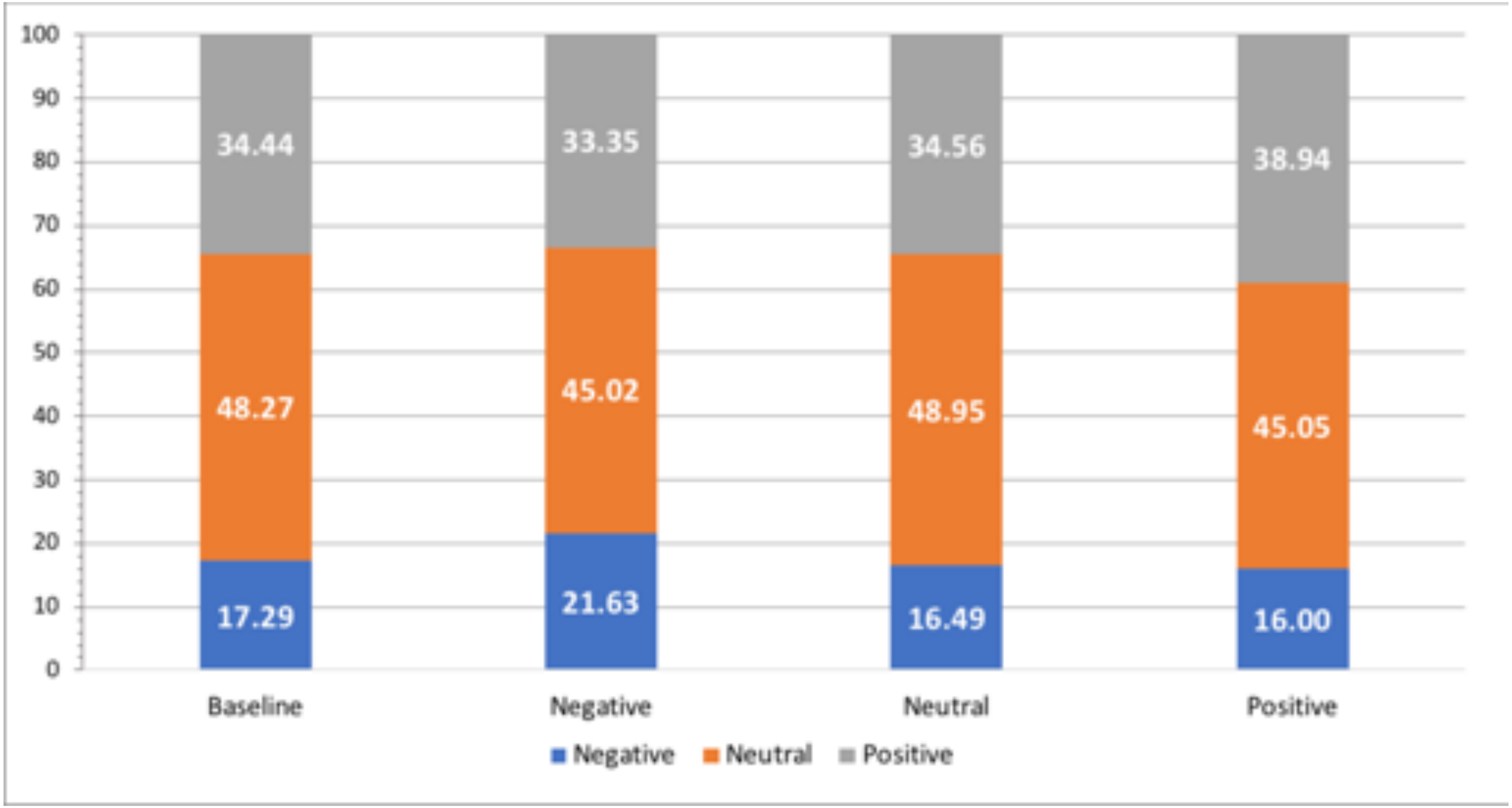


Fig 2. Average proportions of positive, neutral, and negative emotions prior to each observed tweet.

Fig 3. Distributions of positive and negative stimuli before positive and negative responses.

Individual Susceptibility

- ***H_{ii}***: Different Twitter users are differentially susceptible to the effects of emotional contagion
- Baseline model reutilized
- Calculated the smallest Euclidean distance among distances between the observed distribution and any of the three baseline sentiment proportions
- Characterized each user ***u*** with a fraction summarizing the proportion of tweets affected by emotional contagion

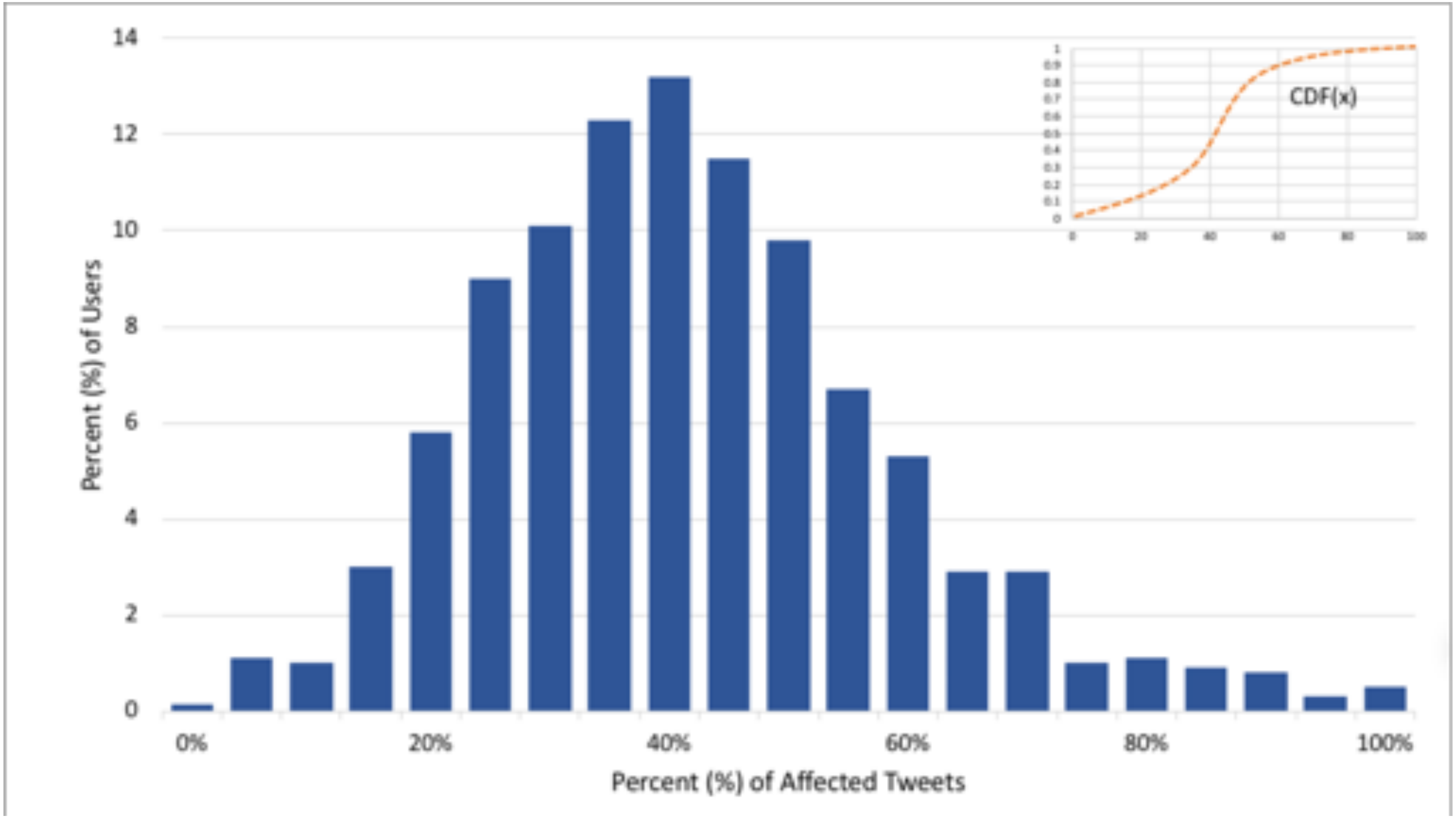


Fig 4. Measurement of emotional contagion on users' content posted on Twitter.

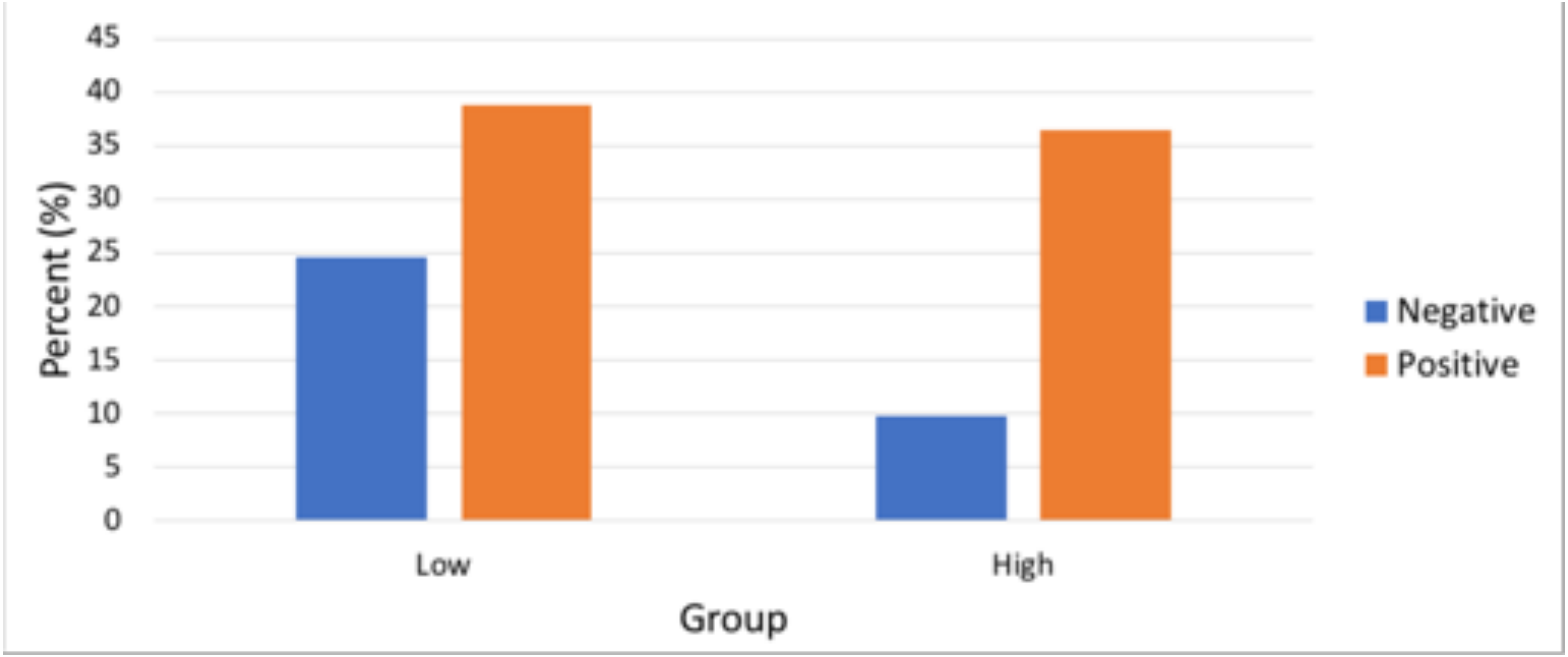


Fig 5. Different extent of emotional contagion on the two groups of scarcely and highly susceptible users.

Limitations

- Emotional contagion may co-occur with network effects like homophily
- Difference between contagion and empathy?
- Sentiment analysis
  - Fails to capture sarcasm and irony
  - Noisy outputs
  - Attribution of equal weights to all emotions
- Twitter data = limited sample
- Relies on assumption that each user scrolls through timeline prior to posting

Conclusion

- Observational analysis of patterns of emotional contagion on sample of #immigration Twitter users
- We can hypothesize the effects of this phenomenon without experimental manipulation
- On average, a **negative tweet** follows an over-exposure to **4.34%** more negative stimuli, whereas a **positive one** follows an over-exposure to **4.50%** more positive tweets
- In general, positive emotions are more prone to contagion, and highly-susceptible users are significantly more inclined to adopt positive emotions

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