Replication Exercise:
“Out-group animosity drives engagement on social media”

Introduction

animosity towards political “out-groups”

user engagement on social media platforms (e.g. Facebook and Twitter)

Keywords:

Political polarization

Divisive content

“High-arousal emotions”

“Dark Energy”

Political sensationalism

Negativity bias

Method of Analysis

The study analyzed over **2.7 million posts** from news media accounts and **US congressional members** on **Facebook** and **Twitter**.

For this replication: 1.2M tweets from Congresspeople (2008 - 2017).

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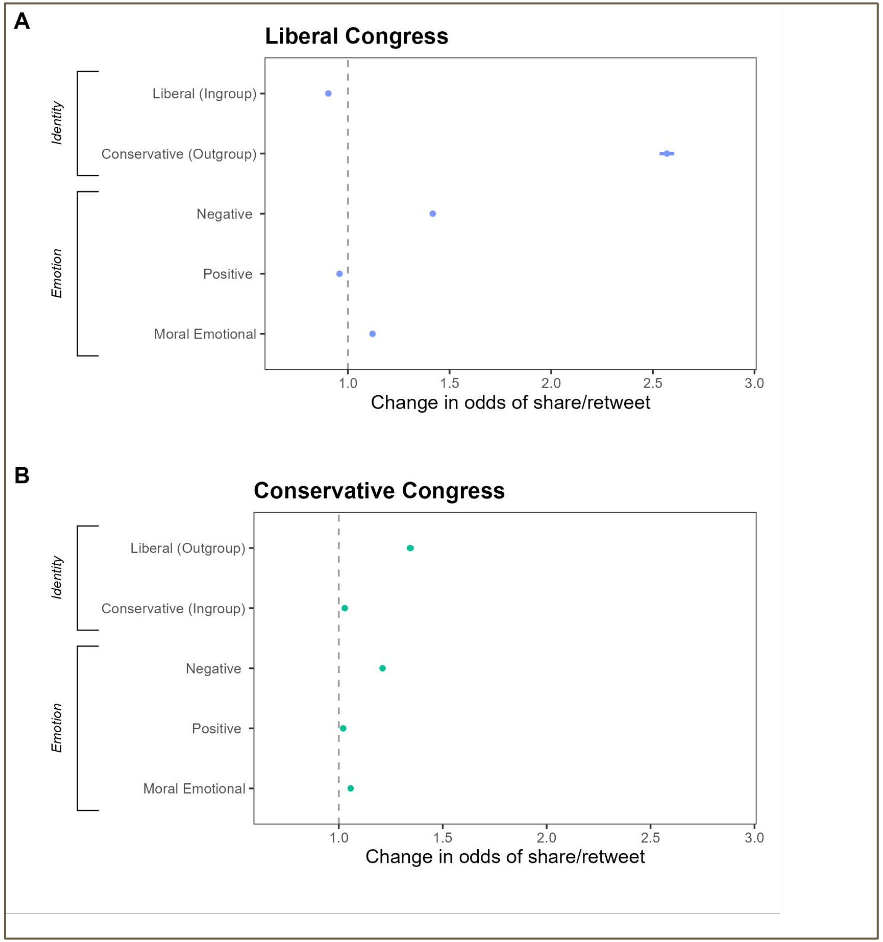
Out-group references in a post >< the post's likelihood of being retweeted

- Out-group language was quantified based on references to political opponents, including specific terms referring to opposing political figures and groups, (e.g. "MAGA", "woke", "progressive", ..)
- The study also controlled for factors like the presence of URLs, media, the followers count, and emotional language to isolate the effect of out-group language.

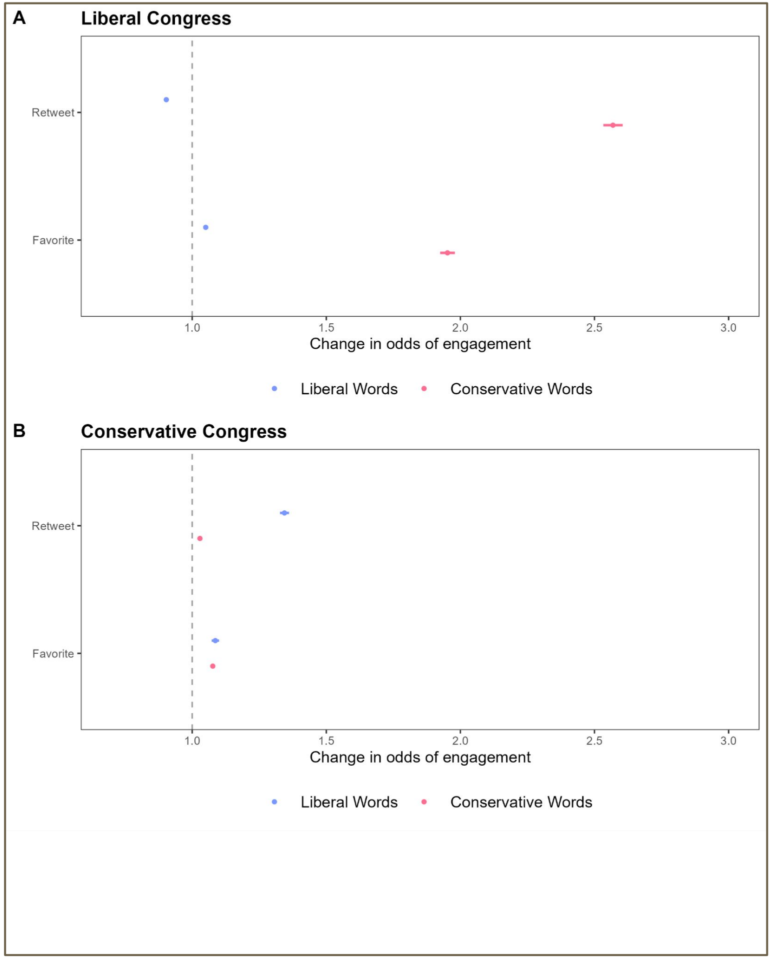
Similarities & Differences

- **[S]** Political *out-group* words were the strongest predictors of retweets from both liberal and conservative congress member accounts on Twitter. Similarly, albeit weaker, *negative affect* was also a significant predictor of retweet possibility.
- **[S]** Removing the controls, both the study and the replication arrived at similar sets of findings.
- **[D]** In this replication exercise, an *additional out-group* word can lead to an increase in 34% of *possibility of retweet* for conservatives, and 157% for liberals. In comparison, the original study showed 180% and 113%, respectively.



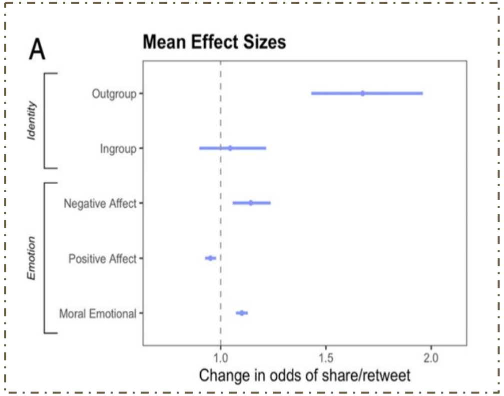
Similarities & Differences

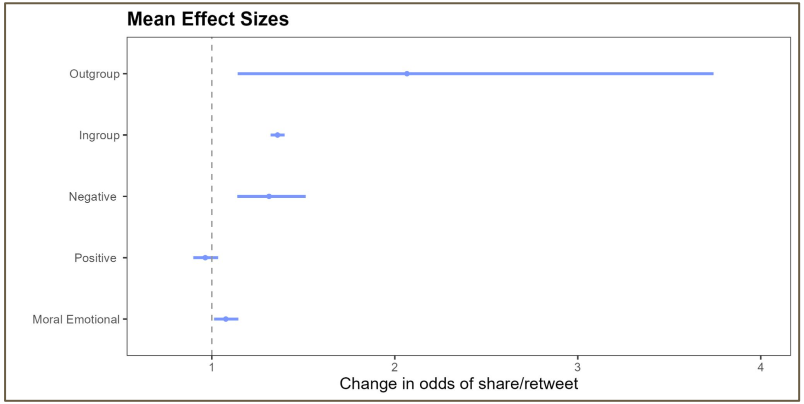
- [S] Political *out-group* words positively predict both the odds of retweet and of favorite, with the former stronger than the latter.
- [D] In this replication, the *liberals are more sensitive* to out-group words than the conservatives are, based on their greater odds of engagement. In the original study, the opposite was observed.



Similarities & Differences

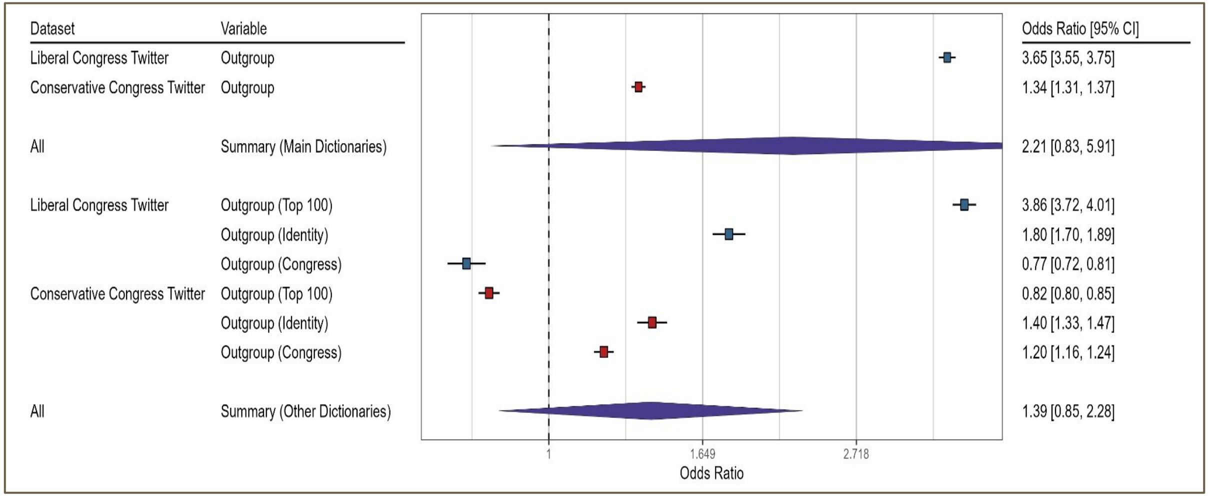
➢ **[S]** Combining both sides of the aisle, overall, outgroup language continues to be the strongest predictor of tweet engagements. Following is the measure of negative sentiment, which also shows a significantly positive correlation.





Similarities & Differences

➢ **[D]** To validate that this phenomenon is not dependent on anyone specific dictionary and is robust across specifications, the study shows that the top100 dictionary, the identity dictionary, and the Congress dictionary, all showed positive correlation with the rate of engagement. In this replication below, we only found such positive correlations with some of the dictionaries, indicating some dictionary dependency.



Autopsy

- For reading large json files, Python performs **~60 times faster** than R.
- The study used a lot of proprietary, 'mysterious' data. Facebook data was not available so the reaction analysis was missing 😞
- Publicly available data is limited and flawed!!!

  ⇒ I had to write separate script to verify the Twitter profile data..
- Still, very grateful for Kaggle.
- LIWC was not available so VADER was chosen.
- Nevertheless, the replication works and points to roughly similar conclusions to those of the original study.

Extension

- ➢ More data. Better updated, better cleaned.
- ➢ Updated dictionaries with more nuanced and more recent colloquials to better capture the discourse.
- ➢ Additional analysis with the time dimension.

  ⇒ Look into the change in the observed animosity before and after the company's rebranding in 2022.