Analyzing Polarization in Social Media: Method and Application to Tweets on 21 Mass Shootings

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Demszky et al. (2019)
Presented by Peter Sullivan

Purpose

- Develops tools for analyzing how group division manifests in language & computational methods for studying them.

- TLDR: Shows validation for NLP methods for evaluating these aspects. Results are in line with literature.

What?

- Use NLP approach to analyze four linguistic dimensions of tweets sent in the wake of mass shootings.
    - Topic Choice
    - Framing
        - Grounding/Affect
    - Illocutionary Force
- Quantify these dimensions
- Cluster based on the dimensions
    - Show that this works better than LDA
- Finds that framing is the biggest dimension partisan difference.

How?

- Collected tweets 2 weeks following major shootings based on keywords.
    - Filtered down to keep 21 events with 10k relevant tweets.
- Identified Partisan ship using network model (Volkova et al. 2014)
    - Use public politician twitter accounts to decide whether a given user is R or D (covers 51-72% of users for each event)
- Quantified “polarization”
    - Build vocabulary for each event for uni/bigrams (n > 50) taken from stemmed set of words.
    - Estimate polarization using Leave-out-method.
- Analyze linguistic dimensions (Topic, Framing, Affect, Illocutionary Force)

Partisanship Affiliation Method (Volkova 2014)

Summary of Volkova 2014:

- Neighborhoods work very well in terms of predicting political alignment
- It is better to sample from a broader neighborhood than sample deeply (same n, just spread out over more neighbors)
- Retweets, user mentions, and friends are all better than just followers for creating the neighborhood.

So... look at which users follow which political figures and base their partisanship on this.

Validate by comparing with state-by-state political makeup

Polarization Estimation

Use leave out method, basic idea: Would a viewer predict the user to be a R/D based on seeing some random token?

$$\pi^{LO} = \frac{1}{2}\left(\frac{1}{|D|}\sum_{i\in D}\hat{\mathbf{q}}_i\cdot\hat{\boldsymbol{\rho}}_{-i}+\frac{1}{|R|}\sum_{i\in R}\hat{\mathbf{q}}_i\cdot(1-\hat{\boldsymbol{\rho}}_{-i})\right)$$

$$\rho_{-i} = (\hat{\mathbf{q}}^{D\setminus i} \oslash (\hat{\mathbf{q}}^{D\setminus i} + \hat{\mathbf{q}}^{R\setminus i}))$$

Topic Choice and Framing

- Preprocess your total set of tweets (*T*)
  - Sample 10k tweets from each event (generalize+compare across event sz) (*S*)
  - Create a vocab (*V*) by stemming words in *S* that occur 10+ times in 3+ events.
  - Remove all stems from *T* that are not in *V*
- Create Embeddings
  - Train GloVe (word vector model) on V based on 11-50k random tweets per event.
  - Do the same for MALLET and BTM (LDA approaches) as comparisons
  - Filter out tricky tweets (based on ratio between two highest topics)
- Cluster
  - K-means cosine distance
  - Assign tweet embedding to closest cluster centroid
- Analyze w.r.t. Polarization
  - Within Topic vs. Between Topic

Topic Clustering

Topic	10 Nearest Stems
news (19%)	break, custodi, #breakingnew, #updat, confirm, fatal, multipl, updat, unconfirm, sever
investigation (9%)	suspect, arrest, alleg, apprehend, custodi, charg, accus, prosecutor, #break, ap
shooter's identity & ideology (11%)	extremist, radic, racist, ideolog, label, rhetor, wing, blm, islamist, christian
victims & location (4%)	bar, thousand, california, calif, among, los, southern, veteran, angel, via
laws & policy (14%)	sensibl, regul, requir, access, abid, #gunreformnow, legisl, argument, allow, #guncontolnow
solidarity (13%)	affect, senseless, ach, heart, heartbroken, sadden, faculti, pray, #prayer, deepest
remembrance (6%)	honor, memori, tuesday, candlelight, flown, vigil, gather, observ, honour, capitol
other (23%)	dude, yeah, eat, huh, gonna, ain, shit, ass, damn, guess

Partisanship vs Topic

- Within Topic Partisanship
  - Use Leave-out estimator looking at all the tweets assigned a topic, then use a weighted mean for topics for a given event, w.r.t. how frequent that topic was in the event.
- Between Topic Partisanship
  - Posterior assigned by user asked to estimate party based on the topic (but not content) of tweet

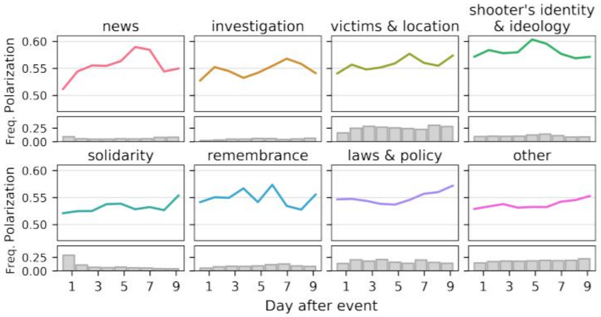

Figure 6: Las Vegas within-topic polarization in the days after the event. The bar charts show the proportion of each topic in the data at a given time.

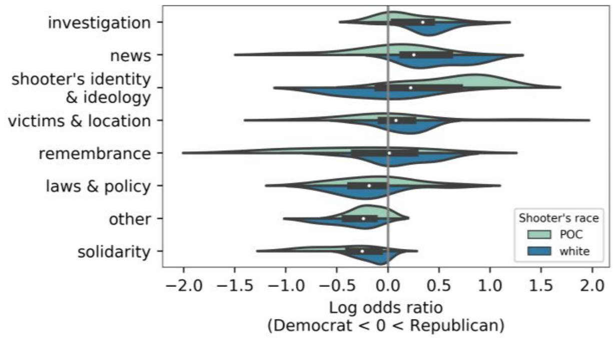

Figure 7: The plot shows the kernel density of the partisan log odds ratios of each topic (one observation per event). The white points show the median and the black rectangles the interquartile range across events.

Framing Devices

- Estimate partisanship of tokens
- Grounding
  - Create set of words to describe different prior events (other shootings)
  - Focus on “crazy” and “terrorist” and look at race
  - Find that:
    - Race has a major impact
    - 9/11 vs Sandy Hook as exemplar grounding incidents
- Affect
  - Emotion based approach (disgust, fear, trust, anger, and sadness) with +/- valence
  - Tailor NRC Emotion Lexicon to domain through label prop (use GloVe to find relevant in domain stems)
  - Find that:
    - Democrats focus on + sent, Sadness and Trust, Rs focus on Disgust and Fear (esp. w/race)

Modality/ Illocutionary Force

- Use 4 most frequent modals (Should, Have, Must, Need to)
    - Annotate a random set (200) to see call for change (78%) or mental state (40%)
    - Evaluate representativeness of modals for a given topic $(f_x^m / \sum_{x' \in X} f_{x'}^m)/(f_x / \sum_{x' \in X} f_{x'})$
        - Over represented in Law and Policy
        - Democrats more likely to call for change

Demszky, D., Garg, N., Voigt, R., Zou, J., Gentzkow, M., Shapiro, J., & Jurafsky, D. (2019). Analyzing Polarization in Social Media: Method and Application to Tweets on 21 Mass Shootings. arXiv preprint arXiv:1904.01596.

Volkova, S., Coppersmith, G., & Van Durme, B. (2014, June). Inferring user political preferences from streaming communications. In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers) (pp. 186-196).