ABSTRACT

People tend to perceive information so it confirms their existing beliefs, a phenomenon called confirmation bias. One countermeasure to confirmation bias is to give more prominence to opposing views. We propose a content-based recommendation approach to increase exposure to opposing beliefs and opinions. Our aim is to help provide users with more diverse viewpoints on issues, which are discussed in partisan groups from different perspectives.

DATASET GENERATION

- Set of manually selected hashtags to crawl initial dataset
  - **Pro-Trump**: #maga, #tcot, #americafirst, #trumptrain, #presidenttrump, #draintheswamp, #fakenews, #potus, #buildthewall, #presidentelect-trump.
  - **Contra-Trump**: #impeachtrump, #theresistance, #nobannowall, #resist, #trumprussia, #impeach45, #notetheenemy, #resistance, #notmypresident, #iamamuslimtoo, #nobannowallnoraid, #fakenews, #presidenttrump, #dumptrump, #trumplies

- Create pro-Trump and contra-Trump issue stance vectors: concatenate all tweets of users from stance, normalize, tokenize and stem them & extract trigrams using TF-IDF
- Create user stances: concatenate user tweets & TF-IDF to extract their trigrams
- Cosine similarity between issue stance vectors & user vectors to verify if user actually belongs to issue stance
- Removed accounts that used hashtags from both stances
- In total: 2,150 pro-Trump users with 2,615,140 pro-Trump tweets and 3,522 contra-Trump users with 3,852,895 contra-Trump tweets

EVALUATION MEASURES

- **Beyond accuracy** metrics of recommender systems research:
  - **Diversity**: intra-list similarity. Sums all pairwise cosine similarities of the items in a given set and calculates the average of the sum. High if a set has many similar items, low otherwise
  - **Serendipity**: measures how surprising recommendations for a user are. Distance between recommended items and their expected content
- Plus: **average topic similarity** (i.e., pairwise cosine similarity between all users of an issue stance) to understand how diverse partisan groups are per se

RESULTS

<table>
<thead>
<tr>
<th>Issue stance</th>
<th>Recommendation variant</th>
<th>Serendipity</th>
<th>Diversity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pro-Trump</td>
<td>Standard</td>
<td>.935</td>
<td>.560</td>
</tr>
<tr>
<td></td>
<td>Pro-Trump</td>
<td>.943</td>
<td>.630</td>
</tr>
<tr>
<td></td>
<td>Contra-Trump</td>
<td>.951</td>
<td>.695</td>
</tr>
<tr>
<td></td>
<td>Hybrid</td>
<td>.946</td>
<td>.728</td>
</tr>
<tr>
<td>Contra-Trump</td>
<td>Standard</td>
<td>.924</td>
<td>.441</td>
</tr>
<tr>
<td></td>
<td>Pro-Trump</td>
<td>.957</td>
<td>.728</td>
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<tr>
<td></td>
<td>Contra-Trump</td>
<td>.925</td>
<td>.487</td>
</tr>
<tr>
<td></td>
<td>Hybrid</td>
<td>.940</td>
<td>.701</td>
</tr>
</tbody>
</table>

- **Serendipity**: best results when recommending tweets from opposing view
- **Diversity**: best results in pro-Trump setting, hybrid wins
- **However**: in contra-Trump setting, hybrid wins wrt diversity - why?
  - **Higher average topic similarity of contra-Trump users (44.6%) versus 27.7% for pro-Trump users** in our dataset
  - Diversity lower if many tweets from a low diversity group mixed into the recommendations
  - Better diversity results: recommend fewer of the more similar contra-Trump tweets and more of the diverse pro-Trump tweets

RECOMMENDER APPROACH

- Content-based filtering: Apache Solr®
- **15 most common trigrams** of user as proxy for personal preference
  - Example account “FxgFx”
  - Recommend similar tweets

REFERENCES