Zero-Shot Stance Detection: A Dataset and Model using Generalized Topic Representations

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Zero-Shot Stance Detection
Motivation
What opinions are implicitly conveyed in new articles?

<table>
<thead>
<tr>
<th>Topic: immigration</th>
<th>Stance: against</th>
</tr>
</thead>
</table>

Text: The jury’s verdict will ensure that another violent criminal alien will be removed from our community for a very long period...

Contributions:
- VAST: a new dataset for zero-shot and few-shot stance detection with many topics
- TGANet: a new model using generalized topic representations
  - Improves on challenging linguistic phenomena
  - Relies less on sentiment cues

TGANet

Goal: construct & use implicit relationships between seen and unseen topics
- unsupervised, no human knowledge!

Topic-Grouped Attention (TGA):
1. Cluster semantically similar topics
2. Assign unseen topic to closest cluster centroid (GTR)
3. Compute similarity between unseen topic and GTR with attention

VAST Data Collection
VAried Stance Topics (VAST)

<table>
<thead>
<tr>
<th>Source: Comments from debate articles on The New York Times</th>
<th>Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>TARied Stance Topics (VAST)</td>
<td>Statistics</td>
</tr>
<tr>
<td>Comment</td>
<td>ARc Stance</td>
</tr>
<tr>
<td>(1) ... Instead they have to work jobs (while their tax dollars are going to supporting illegal aliens) in order to put themselves through college [cont]</td>
<td>Immigration is really a problem</td>
</tr>
<tr>
<td>(2) Why should it be our job to help out the owners of the restaurants and bars? ... If they were paid a living wage ...[cont]</td>
<td>Not to tip</td>
</tr>
<tr>
<td>(3) ...I like being able to access the internet about my health issues, and find I can talk with my doctors ... [cont]</td>
<td>Medical websites are healthful</td>
</tr>
</tbody>
</table>

Annotation
1. Heuristic-based topic extraction
   - Existing Valence+topic label \(\rightarrow\) (1) and (3)
   - categories from NYT \(\rightarrow\) (2)
2. AMT annotation
   - Stance labeling \(\rightarrow\) \(\ell\)
   - Topic correction \(\rightarrow\) (1)
   - List other relevant topics \(\rightarrow\) (2)

Observations
- Lexical variety in topics
- Multiple labels or topics per doc
- Topic corrections: \(\sim\)30% of time

Evaluation and Analysis
Stance Prediction
Zero-shot: 600 topics Few-shot: 159 topics

Hard Phenomena

Dependence on Sentiment: swap sentiment words to confuse models

... debaters don’t strike\((-)\) shine\((+)\) me as being anywhere near diverse in their perspectives on guns. Not one of the gun-gang cited any example of where a student with a gun saved someone from something terrible\((-)\) tremendous\((+)\) on their campuses. At least\((+)\) the professor speaks up for rationality\((+)\).

Sentiment words are bold italicized, removed words (struck out), and positive (green \((+)\)) and negative (red \((-)\)) sentiment words.