Learning Topics and Positions from Debatepedia

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Introduction

- Buried treasure in **unstructured** and evolving data
  - Web searches, blogs, discussions, tweets, and text messages that generate terabytes of information.
- Stake holders and Applications
  - Marketers, social scientists, information professionals, and governments.
  - Analytics, Advertising, Marketing, Investigative reporting etc.,

Pattern discovery and human-interpretatable representation of unstructured data

Contributions

We explore Debatepedia, a community authored encyclopedia of sociopolitical debates, as evidence for:

– **modeling** latent topics and cross-cutting positions
– **inferring** a low-dimensional, human-interpretable representation of data
– **evaluating** the representation’s usefulness on arguments/articles for positions and topics.
Outline

- Introduction
- Motivation
- A Framework for Modeling Debates
  - Data & Models
- Experiments
- Related Work
- Conclusion
Motivation: Users Opinions on Debatable Issues

“Users take positions/stances, express opinion phrases on controversial sociopolitical issues and refer to important public figures or external articles associated with the issue to support their argument”.

<table>
<thead>
<tr>
<th>Pro</th>
<th>Con</th>
</tr>
</thead>
<tbody>
<tr>
<td>I am pro-choice simply because I don't believe that the government should have control over this. It's ridiculous. Women should have control over….</td>
<td>The argument that all pro-life people are anti-abortion based on religious grounds is total false. There are atheists who are also pro-life and to cast them aside….</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Pro</th>
<th>Con</th>
</tr>
</thead>
<tbody>
<tr>
<td>A fetus is no more a human than an acorn is a tree. Judith Jarvis Thomson, &quot;A Defense of Abortion&quot;. Philosophy &amp; Public Affairs, Vol. 1, no. 1 (Fall 1971). ….</td>
<td>Human life and a right to life begin at conception; abortion is murder. Human life is continuum of growth that starts at conception, not at birth….</td>
</tr>
</tbody>
</table>

Table 1: Sample arguments on a debate related to abortion.
Motivation - Goals

Goal - Inferring issues, positions, entities and opinion expressions (sentiments) in a low-dimensional perspective.

<table>
<thead>
<tr>
<th>Topics</th>
<th>Entities</th>
<th>Position_1</th>
<th>Position_2</th>
</tr>
</thead>
<tbody>
<tr>
<td>death, crime, punishment, penalty, justice</td>
<td>Adam Bedau, Thomas R. Eddlem, Jeff Jacoby, John Baer, Peter Bronson</td>
<td>anti-death, non-violent, african-american, self-help, cut-and-cover, grief-stricken, heavy-handed, dp-equivalent, law-breaking, lawyer-backed,</td>
<td>semi-automatic, high-profile, hate-crime, assault-weapons, military-style, judges-with, would-be, high-dollar, self-protective, state-authorized,</td>
</tr>
</tbody>
</table>

Table 2: Sample output for a controversial issue - death penalty
Motivation - Debatepedia

Popular/heated debates in Debatepedia

- Rich knowledge of common users’ opinions on the contemporary political and social issues: Abortion, gay marriage, health plans, drugs, war, marijuana etc.,
Debatepedia Structure

<table>
<thead>
<tr>
<th>Question: Self-defense – Is self-defense a good reason for gun ownership?</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Side: Yes</strong></td>
</tr>
<tr>
<td>Argument: A citizen has a “right” to guns as a means to self-defense: Many groups argue that a citizen should have the “right” to defend themselves, and that a gun is frequently the...</td>
</tr>
<tr>
<td><strong>Question: Economic benefits – Is gun control economically beneficial?</strong></td>
</tr>
<tr>
<td>---------------------------------------------------------------</td>
</tr>
<tr>
<td><strong>Side: Yes</strong></td>
</tr>
<tr>
<td>Argument: Lax gun control laws are economically costly. The Coalition for Gun Control claims that, “in Canada, the costs of firearms death and injury alone have been estimated at...</td>
</tr>
</tbody>
</table>
Goals

1. How to identify reasonable topics from the debate data?
2. How to infer the side of an argument or external article to a debate?
3. How to infer the opinion/sentiment expressions that indicate the position of arguments?
4. How to associate topics with the important public figures?
A Framework for Modeling Debatepedia

• **Dataset** (Debatepedia.com)
  – 1,303 Debates
  – 33,556 Arguments

• **Models**
  – A generative model for debates.
  – Inference using MCMC Gibbs sampling.

• **Prior Knowledge**
  - Capture **opinion-expressing terms** - OpinionFinder sentiment lexicon (Wilson et al., 2005)
  - **Background terms** - term’s document frequency is inversely related its usefulness
  - **Public figures** – Person mentions are identified using Stanford NER (Finkel et al., 2005)
A Generative Model for Debates

t – topic terms

e - entity terms

i – general position terms

o – topics-position terms

b- background terms
Experiments

• Ground truth:
  – External articles (hyperlinked in Debatepedia)
  – Sides of the articles and the arguments
Infer Low-dimensional Representation

To answer this goal, we need to perform the following tasks:

- For each article, we empirically investigate the topic distribution associated with the article.
- For each article, we empirically investigate the article association to the argument.
- For each article and argument, we empirically investigate the associated side.
- Compare the topics and positions inferred by our model with JST (Lin and He, 2009) that jointly captures topics and sentiments.
Experiments – Topics

Posterior over topics associated with external articles

Fig 2: Jensen-Shannon divergence between article and associated argument (topics).

JST (Lin and He, 2009) jointly captures topics and sentiments
Infer Low-dimensional Representation

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Experiments – Topics

Associating external articles to the argument

Fig 3: Mean reciprocal rank for association task (topics).

JST (Lin and He, 2009) jointly captures topics and sentiments
Infer Low-dimensional Representation

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- For each article, we empirically investigate the topic distribution associated with the article.
- For each article, we empirically investigate the article association to the argument.
- For each article and argument, we empirically investigate the associated side.
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Experiments - Positions

Predicting positions for arguments and external articles

1. For arguments, our model achieved about 86% accuracy.
2. For articles, our model assigns by about 60% accuracy.

![Graph showing JS divergence scores for different article types.]

Fig 4: Position prediction on articles by Genre
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- For each article, we empirically investigate the article association to the argument.
- For each article and argument, we empirically investigate the associated side.
- Compare the topics and positions inferred by our model with JST (Lin and He, 2009) that jointly captures topics and sentiments.
### Topics and Entities Discovered by our Model

<table>
<thead>
<tr>
<th>Topic</th>
<th>Terms</th>
<th>Person Entity Mentions</th>
</tr>
</thead>
<tbody>
<tr>
<td>“Israel-palestina”</td>
<td>israel, gaza, hamas, israeli, palestinian,</td>
<td>Benjamin Netanyahu, Al Jazeera, Mavi Marmara, Nicholas Kristoff</td>
</tr>
<tr>
<td>“Same-sex marriage”</td>
<td>marriage, gay, mars, space, moon,</td>
<td>Buzz Aldrin, Andrew Sullivan, Moon Base, Scott Bidstrup, Ted Olson</td>
</tr>
<tr>
<td>“Drugs”</td>
<td>marijuana, drug, drugs, alcohol, age,</td>
<td>Four Loko, Evo Morales, Toni Meyer, Sean Flynn, Robert Hahn</td>
</tr>
<tr>
<td>“Health care”</td>
<td>health, care, insurance, public, private,</td>
<td>Kent Conrad, Paul Hsieh, Paul Krugman, Ezra Klein, Jacob Hacker</td>
</tr>
<tr>
<td>“Death penalty”</td>
<td>death, crime, punishment, penalty, justice,</td>
<td>Adam Bedau, Thomas R. Eddlem, Jeff Jacoby, John Baer, Peter Bronson</td>
</tr>
<tr>
<td>“Abortion”</td>
<td>women, religious, abortion, god, life,</td>
<td>Ronald Reagan, John Paul II, Sara Malkani, Mother Teresa, Marcella Alsan</td>
</tr>
</tbody>
</table>

Table 4: For 6 selected topics (labels assigned manually), top terms and person entities
## Topic-specific Position Expressions

### Detailed Results

<table>
<thead>
<tr>
<th></th>
<th>“Israel-Palestine”</th>
<th>“Same-sex marriage”</th>
<th>“Drugs”</th>
<th>“Healthcare”</th>
<th>“Death penalty”</th>
</tr>
</thead>
<tbody>
<tr>
<td>(i_1)</td>
<td>pre emptive</td>
<td>same sex</td>
<td>hands free</td>
<td>single payer</td>
<td>anti death</td>
</tr>
<tr>
<td></td>
<td>israeli palestinian</td>
<td>long term</td>
<td>performance enhancing</td>
<td>so called</td>
<td>non violent</td>
</tr>
<tr>
<td></td>
<td>open and shut</td>
<td>second class</td>
<td>in depth</td>
<td>self sustaining</td>
<td>african american</td>
</tr>
<tr>
<td>(i_2)</td>
<td>two state</td>
<td>opposite sex</td>
<td>long term</td>
<td>government run</td>
<td>semi automatic</td>
</tr>
<tr>
<td></td>
<td>long term</td>
<td>well intentioned</td>
<td>high speed</td>
<td>government approved</td>
<td>high profile</td>
</tr>
<tr>
<td></td>
<td>self destructive</td>
<td>day time</td>
<td>short term</td>
<td>high risk</td>
<td>hate crime</td>
</tr>
</tbody>
</table>

### Key Observations:

1. Our model identifies terms associated with positions on social issues, while JST selects more general sentiment terms.
2. Though many topics are coherent, they are not always pure; same-sex marriage and the space program are merged, for example
Related Work

- Classify authors in to **opposite camps** (Agrawal et al., 2003)
- **Agreement/Disagreement** classification (Galley et al., 2004; Hillard et al., 2003)
- **Contrastive opinions** from customer reviews (Paul et al. (2010)).
- **Contention points** (Mukherjee et al., 2012)
- **Stance Mining/position prediction** (Somasundaran and Wiebe, 2009; Anand et al., 2011)
- Debate **perspectives** (Ahmed and Xing, 2010)
- Extracting **person-opinion-topic** tuples (Awadallah et al., 2011)
- Political discourse with topics and ideologies (Lin et al., 2008)
1. We study the problem of mining debates for inferring low-dimensional, human-interpretable representation.

2. We modeled topics, positions, opinion expressions (sentiments) and entities using generative models.

3. We evaluate the resulting representation’s usefulness in attaching opinionated documents to arguments and its consistency with human judgments about positions.

• **Future Work**: Study of applications on entities associated with topics; Exploiting explicitly ideological texts alongside the arguments to help identify textual associations with general positions.
Thank you for your attention!

Questions?
Experiments - Positions

1. Predicting positions for arguments

![Confusion matrix table]

<table>
<thead>
<tr>
<th></th>
<th>$i = 1$</th>
<th>$i = 2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i^* = 1$</td>
<td>1,272</td>
<td>216</td>
</tr>
<tr>
<td>$i^* = 2$</td>
<td>199</td>
<td>1,313</td>
</tr>
</tbody>
</table>

Fig 4: Confusion matrix for position prediction on arguments.
Key Observations:
1. We held out 3000 arguments for our experiments.
2. Our model achieved 86% accuracy.
Experiments - Positions

2. Predicting positions for external articles

<table>
<thead>
<tr>
<th></th>
<th>$i = 1$</th>
<th>$i = 2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i^* = 1$</td>
<td>1,042</td>
<td>623</td>
</tr>
<tr>
<td>$i^* = 2$</td>
<td>1,043</td>
<td>644</td>
</tr>
</tbody>
</table>

Key Observations:
1. Our model assigns by about 60% accuracy.
2. We further breakdown articles by genre.

Fig 5: Confusion matrix for position prediction on articles.

Fig 6: Position prediction on articles by Genre

Key Observations:
1. Blogs and editorials may be more “Debatepedia argument-like” than news and government articles.
A Generative Model for Debates

Figure 1: Plate diagram. $K$ is the number of positions, and $T$ is number of topics. The shaded variables are observed and dashed variables are marginalized. $\alpha, \beta, \gamma$ and all $\eta$ are fixed hyperparameters (§3.1).
1. ∀ topics $t$, draw topic-term distribution $\phi_t^i \sim \text{Dirichlet}(\eta^i)$ and topic-entity distribution $\phi_t^g \sim \text{Dirichlet}(\eta^g)$.
2. ∀ positions $i$, draw position-term distribution $\phi_t^i \sim \text{Dirichlet}(\eta^i)$.
3. ∀ topics $t$, ∀ positions $i$, draw topic-position term distribution $\phi_{t,i}^g \sim \text{Dirichlet}(\eta^g)$.
4. Draw background term distribution $\phi^b \sim \text{Dirichlet}(\eta^b)$.
5. Draw functional term type distribution $\mu \sim \text{Dirichlet}(\gamma)$.
6. Draw position distribution $\epsilon \sim \text{Dirichlet}(\beta)$.
7. ∀ debates $d$:
   a. Draw $i_{d,1}, i_{d,2} \sim \text{Multinomial}(\nu)$, assigning each of the two sides to a position.
   b. ∀ questions $q$ in $d$:
      i. Draw topic mixture proportions $\theta_{d,q} \sim \text{Dirichlet}(\alpha)$.
      ii. ∀ arguments $\alpha$ under question $q$ and term positions $n$ in $\alpha$:
          A. Draw topic label $z_{d,q,s,a} \sim \text{Multinomial}(\theta_{d,q})$.
          B. Draw functional term type $y_{d,q,s,a} \sim \text{Multinomial}(\mu)$.
          C. Draw term $w_{d,q,s,a} \sim \text{Multinomial}(\phi_{d,q,s,a}^{y_{d,q,s,a}} \mid i_{d,1}, i_{d,2}, z_{d,q,s,a})$.

Figure 2: Generative story for our model of Debatepedia.
Experiments – Positions

Compare inferred positions with human judgments

1. Settings:
   For 11 topics, we choose 2 debates and instructed annotators to group 44 sides of debates in terms of political philosophies, contemporary political party platforms.

2. Results:

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Model (2)</td>
<td>3.21</td>
<td>2.58</td>
<td>3.45</td>
</tr>
<tr>
<td>A1 (11)</td>
<td></td>
<td>2.15</td>
<td>2.15</td>
</tr>
<tr>
<td>A2 (5)</td>
<td></td>
<td></td>
<td>2.63</td>
</tr>
</tbody>
</table>

Fig 6: Variation of information scores for each pairing of annotators and model.

Key Observations:
1. The model agrees with A2’s coarse clustering most closely.
2. The agreement for those debate-sides labeled liberal or conservative by A2 is only about 60%.
3. This suggests that further knowledge sources may be required to improve interpretability across issues.