

Learning Topics and Positions from Debatepedia Supplementary Material

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This document contains information to supplement Gottipati et al. (2013).

A Model

Our model defines a probability distribution over words. Each word occurs in a context defined by the tuple $\langle d, q, s, a \rangle$ (respectively, a *debate*, a *question* within the debate, a *side* within the debate, and an *argument*).

At each level of the hierarchy is a different latent variable:

- Each question q within debate d is associated with a distribution over topics, denoted $\theta_{d,q}$.
- Each side s of the debate d is associated with a position, denoted $i_{d,s}$ and we posit a global distribution ι that cuts across different questions and arguments. In our experiments, there are two positions, and the two sides of a debate are constrained to associate with opposing positions.
- Each word $w_{d,q,s,a,n}$ (n is the position index of the word within an argument) is associated with one of five *functional word types*, denoted $y_{d,q,s,a,n}$. This variable is latent, except when it takes the value “entity” (e) for terms marked as named entity mentions. When it is not an entity, it takes one of the other four values: “general position” (i), “topic-specific position” (o), “topic” (t), or “background” (b). Thus, every word w is drawn from one of these 5 types of bags, and y acts as a switching variable to select the type of bag.
- For some word types (the ones where $y \in \{o, t\}$), each word $w_{d,q,s,a,n}$ is associated with one of T discrete topics, as indexed by $z_{d,q,s,a,n}$.

Figure 1 illustrates the plate diagram for the graphical model underlying our approach.

B Inference

Exact inference of the posterior distribution of the model is intractable. Instead, we approximate it using Gibbs sampling. As we used conjugate priors for our distributions, we can easily integrate out the dotted variables in Figure 1.

We refer the interested reader to Griffiths and Steyvers (2004) for details of using collapsed Gibbs sampling for LDA-like topic models.

For positions, we require that two sides of a debate to be associated with different positions. Hence, we define the joint probability $i_{d,1}, i_{d,2}$ for side 1 and side 2 of a debate as follows:

$$p(i_{d,1} = k, i_{d,2} = k' | \iota) \propto \begin{cases} 0 & \text{if } k = k' \\ p(k | \iota)p(k' | \iota) & \text{if } k \neq k' \end{cases} \quad (1)$$

where k and k' are positions.

To sample $i_{d,s}$ for each debate d , side s , we need to consider those position words and general position words inside. We highlight the associated model parameters that we need to consider when sampling $i_{d,s}$ in Figure 2.

We jointly sample $i_{d,1}$ and $i_{d,2}$ for two sides in debate d according to the following equation:

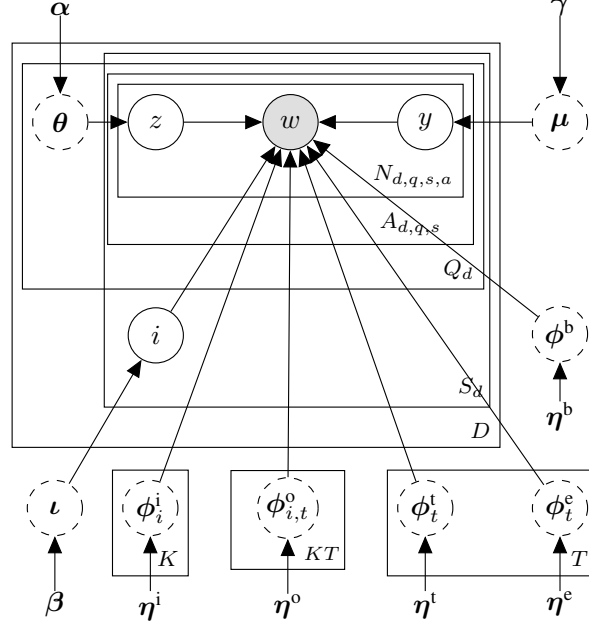


Figure 1: Plate diagram. K is the number of positions, and T is number of topics. The shaded variables are observed and dashed variables are marginalized. α, β, γ and η 's are fixed hyperparameters.

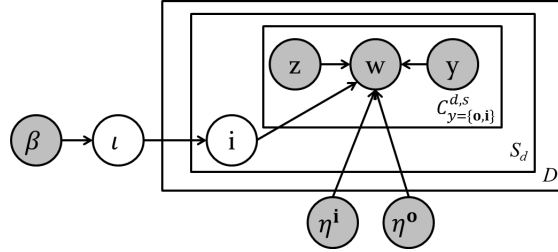


Figure 2: Model parameters associated with position $i_{d,s}$.

$$\begin{aligned}
 p(i_{d,1} = k_1, i_{d,2} = k_2 \mid \mathbf{z}, \mathbf{y}, \mathbf{w}, \mathbf{i}_{-\{d,s\}}, \beta, \boldsymbol{\eta}) \propto & \prod_{s=1}^2 \left(\frac{C_{k_s}^{(\cdot)} + \beta}{\sum_{i=1}^K C_i^{(\cdot)} + K\beta} \cdot \frac{\prod_{w=1}^V \prod_{a=0}^{C_{w,y=i,k_s}^{d,s}-1} (C_{w,y=i,k_s}^{-\{d,s\}} + \eta_w^i + a)}{\prod_{b=0}^{C_{y=i,k_s}^{d,s}-1} (\sum_{w=1}^V (C_{w,y=i,k_s}^{-\{d,s\}} + \eta_w^i) + b)} \right. \\
 & \left. \cdot \prod_{t=1}^T \frac{\prod_{w=1}^V \prod_{a=0}^{C_{w,y=o,k_s,t}^{d,s}-1} (C_{w,y=o,k_s,t}^{-\{d,s\}} + \eta_w^o + a)}{\prod_{b=0}^{C_{y=o,k_s,t}^{d,s}-1} (\sum_{w=1}^V (C_{w,y=o,k_s,t}^{-\{d,s\}} + \eta_w^o) + b)} \right). \quad (2)
 \end{aligned}$$

where $C_i^{(\cdot)}$ denotes the number of times position i appears in arguments, $C_{w,y=i,i_{d,s}}^{-\{d,s\}}$ is the number of times word w is associated with position $i_{d,s}$ without considering words in debated d and side s , and $C_{w,y=o,i_{d,s},t}^{-\{d,s\}}$ is the number of times word w is treated as a opinion word associated with position $i_{d,s}$ and topic t without considering words in debated d and side s .

Let p denotes $\{d, q, s, a, n\}$. For a word w_p in document d , question $q \in \{1, \dots, Q_d\}$, each side $s \in \{1, 2\}$, argument $a \in \{1, \dots, A_{d,q,s}\}$, and position $n \in \{1, \dots, N_{d,q,s,a}\}$, we sample its corresponding topic z_p as follows:

$$p(z_p = t \mid \mathbf{z}_{-p}, \mathbf{y}, \mathbf{w}, \mathbf{i}, \alpha, \boldsymbol{\eta}) \propto \frac{C_t^{d,q} + \alpha}{C_{(\cdot)}^{d,q} + T\alpha} \cdot \left(\frac{C_{w_p}^{y_p,t} + \eta_{w_p}^{y_p}}{C_{(\cdot)}^{y_p,t} + \sum_{w=1}^V \eta_w^{y_p}} \right)^{\mathbb{I}(y_p \in \{\mathbf{e}, \mathbf{t}\})} \cdot \left(\frac{C_{w_p}^{\mathbf{o},t,i_{d,s}} + \eta_{w_p}^{\mathbf{o}}}{C_{(\cdot)}^{\mathbf{o},t,i_{d,s}} + \sum_{w=1}^V \eta_w^{\mathbf{o}}} \right)^{\mathbb{I}(y_p = \mathbf{o})}, \quad (3)$$

where $\mathbb{I}(\cdot)$ is the indicator function.

Similarly, we sample y_p according to the following equation:

$$p(y_p = y \mid \mathbf{z}, \mathbf{y}_{-p}, \mathbf{w}, \mathbf{i}, \gamma, \boldsymbol{\eta}) \propto \frac{C_y^{(\cdot)} + \gamma}{\sum_{y' \in \{\mathbf{b}, \mathbf{a}, \mathbf{o}, \mathbf{i}\}} C_{y'}^{(\cdot)} + 4\gamma} \cdot \left(\frac{C_{w_p}^{\mathbf{b}} + \eta_{w_p}^{\mathbf{b}}}{C_{(\cdot)}^{\mathbf{b}} + \sum_{w=1}^V \eta_w^{\mathbf{b}}} \right)^{\mathbb{I}(y = \mathbf{b})} \cdot \left(\frac{C_{w_p}^{i_{d,s}} + \eta_{w_p}^{\mathbf{i}}}{C_{(\cdot)}^{i_{d,s}} + \sum_{w=1}^V \eta_w^{\mathbf{i}}} \right)^{\mathbb{I}(y = \mathbf{i})} \cdot \left(\frac{C_{w_p}^{\mathbf{t},z_p} + \eta_{w_p}^{\mathbf{t}}}{C_{(\cdot)}^{\mathbf{t},z_p} + \sum_{w=1}^V \eta_w^{\mathbf{t}}} \right)^{\mathbb{I}(y = \mathbf{t})} \cdot \left(\frac{C_{w_p}^{\mathbf{o},z_p,i_{d,s}} + \eta_{w_p}^{\mathbf{o}}}{C_{(\cdot)}^{\mathbf{o},z_p,i_{d,s}} + \sum_{w=1}^V \eta_w^{\mathbf{o}}} \right)^{\mathbb{I}(y = \mathbf{o})}. \quad (4)$$

We do not consider $p(y_p = \mathbf{e} \mid \dots)$ as we assume all the entities are pre-labeled.

Using Gibbs sampler, new values for $i_{d,s}$, $z_{d,q,s,a,n}$ and $y_{d,q,s,a,n}$ are iteratively sampled for each token $w_{d,q,s,a,n}$ from the posterior probability conditioned on the previous state of the sampler.

After sampling the model, we estimate the parameters as follows:

$$\phi_{i,w}^{\mathbf{i}} = \frac{C_w^{\mathbf{i}} + \eta_w^{\mathbf{i}}}{C_{(\cdot)}^{\mathbf{i}} + \sum_{w=1}^V \eta_w^{\mathbf{i}}}. \quad \text{general position word distribution} \quad (5)$$

$$\phi_{t,w}^{\mathbf{t}} = \frac{C_w^{\mathbf{t},t} + \eta_w^{\mathbf{t}}}{C_{(\cdot)}^{\mathbf{t},t} + \sum_{w=1}^V \eta_w^{\mathbf{t}}}. \quad \text{topical word distribution} \quad (6)$$

$$\phi_{t,i,w}^{\mathbf{o}} = \frac{C_w^{\mathbf{o},t,i} + \eta_w^{\mathbf{o}}}{C_{(\cdot)}^{\mathbf{o},t,i} + \sum_{w=1}^V \eta_w^{\mathbf{o}}}. \quad \text{topical-position distribution} \quad (7)$$

$$\phi_{t,w}^{\mathbf{e}} = \frac{C_w^{\mathbf{e}} + \eta_w^{\mathbf{e}}}{C_{(\cdot)}^{\mathbf{e}} + \sum_{w=1}^V \eta_w^{\mathbf{e}}}. \quad \text{topical-entity distribution} \quad (8)$$

C Qualitative Analysis

As a generative modeling approach, our model was designed for the purpose of reducing the dimensionality of the sociopolitical debate space, as evidenced by Debatepedia. 37 out of 40 topics were subjectively judged to be coherent; we manually selected eleven of the most interpretable topics for further analysis here.

Table 1 shows bigrams most strongly associated with general position distributions $\phi^{\mathbf{i}}$ and selected topical-position distributions $\phi^{\mathbf{o}1}$. While these are somewhat internally coherent, we do not observe consistent alignment across topics, and the general distributions $\phi^{\mathbf{i}}$ are not suggestive.

The separation of personal name mentions into their own distributions, shown in Table 2, gives a distinctive characterization of topics based on relevant personalities. Subjectively, the top individuals are relevant

¹For more topics, please refer to the supplementary notes.

to the subject matter associated with each topic (though the topics are not always pure; same-sex marriage and the space program are merged, for example). Our model incorrectly linked some entities (false positives) in the corresponding topic. For example, Ezra Klein is not related to the *food* topic as he is a *Washington Post* journalist specializing in health care and budget policy.

Topic	Terms	Person entity mentions
“Israel-Palestine”	israel, gaza, hamas, israeli, palestinian	Benjamin Netanyahu, Al Jazeera, Mavi Marmara, Nicholas Kristoff, Steven R. David
“Death penalty”	death, crime, punishment, penalty, justice	Adam Bedau, Thomas R. Eddlem, Jeff Jacoby, John Baer, Peter Bronson
“Global warming”	global, emissions, climate, carbon, warming	Alan Robock, Al Gore, Ken Caldeira, Andrew C. Revkin, George Monbiot
“Human rights”	human, rights, animals, life, animal	Tom Regan, Michael Pollan, Peter Singer, Leonardo Da Vinci, Immanuel Kant
“Healthcare”	health, care, insurance, public, private	Kent Conrad, Paul Hsieh, Paul Krugman, Ezra Klein, Jacob Hacker
“Food”	food, consumers, products, calorie, information	Steve Chapman, Jeff Jacoby, David Kiley, Jacob Sullum, Ezra Klein
“Drugs”	marijuana, drug, drugs, alcohol, age	Four Loko, Evo Morales, Toni Meyer, Sean Flynn, Robert Hahn
“Abortion”	women, religious, abortion, god, life	Ronald Reagan, John Paul II, Sara Malkani, Mother Teresa, Marcella Alsan
“Same-sex marriage”	marriage, gay, mars, space, moon	Buzz Aldrin, Andrew Sullivan, Moon Base, Scott Bidstrup, Ted Olson
“American Congress”	president, washington, obama, american, america	Barack Obama, John McCain, Bill Clinton, George W. Bush, Ronald Reagan
“Immigration”	immigration, cameras, police, immigrants, crime	Ken Garcia, Jan Brewer, Kris Kobach, Edwin S. Rubenstein, Jim Gilchrist

Table 2: For 11 selected topics (labels assigned manually), top terms (ϕ^t) and person entities (ϕ^e). Bigrams were included but did not rank in the top five for these topics. The model has conflated debates relating to same-sex marriage with the space program.

References

- Swapna Gottipati, Minghui Qiu, Yanchuan Sim, Jing Jiang, and Noah A. Smith. 2013. Learning topics and positions from Debatepedia. In *Proceedings of EMNLP*.
- Thomas L. Griffiths and Mark Steyvers. 2004. Finding scientific topics. *Proceedings of the National Academy of Sciences*, 101(Suppl. 1):5228–5235.

Topic	$i = 1$	$i = 2$
None (ϕ^1)	vice president, c sections, twenty four, cross pressures, pre dates, anti ballistic, cost effectiveness, anti landmine, court appointed, child poverty	cross examination, under runs, hand outs, half million, non christians, break down, counter argument, seventy five, co workers, run up
“Israel-Palestine”	pre emptive, israeli palestinian, open and shut, first time, hamas controlled, democratically elected, knee jerk	two state, long term, self destructive, secretary general, right wing, all out, near daily, short term, life threatening
“Death penalty”	anti death, non violent, african american, self help, cut and cover, heavy handed, dp equivalent, law breaking	semi automatic, high profile, hate crime, assault weapons, military style, high dollar, self protective, state authorized
“Global warming”	cap and trade, long term, blue ribbon, fossil fuel, sunspot driven, forest based, short lived, anti nuclear	non profit, large scale, half degree, climate change, low carbon, non compliance, human caused, opt in, multi pollutant, inter glacial
“Human rights”	self legislative, life saving, non human, self restricting, auto nomous, self conscious, god given, one another	cost benefit, non animal, cock fighting, bull baiting, self centered, peace loving, non emotional, pan european, state invested, pleasure pain
“Healthcare”	single payer, so called, self sustaining, public private, for profit, long run, high cost, multi payer, government funded	government run, government approved, high risk, two tier, government appointed, low cost, set up, one sixth, draft age
“Food”	health care, health conscious, low cost, point of, reduced fat, time consuming, multi billion, mid range, miracle diet	force fed, trans fat, anti obesity, ill informed, non gm, medium sized, cajun lime, impossible to ignore, well seasoned, fat free
“Drugs”	hands free, performance enhancing, in depth, hand held, best kept, non pharmaceutical, anti marijuana, non toxic, marijuana related	long term, high speed, short term, peer reviewed, alcohol related, mind altering, inner city, long lasting, needle exchange, anti drug
“Abortion”	pro choice, pro life, non muslim, well educated, anti abortion, much needed, church state, birth control, fully informed	would be, full time, late term, judeo christian, life style, day to day, non christian, child bearing, non religious
“Same-sex marriage”	same sex, long term, second class, blankenhorn rauch, wrong headed, self denial, left handed, single parent	opposite sex, well intentioned, day time, planet wide, day night, child rearing, low earth, one way, one third, life bearing
“American Congress”	op ed, state sponsored, fear mongering, on the job, anti earmark, oil rich, lower level, sixty seven, ultra conservative	left wing, smoot hawley, party line, self indulgent, un american, off target, republican controlled, reagan bush
“Immigration”	law abiding, anti social, high profile, american born, one way, hard won, present day, crime solving, high mast	in state, anti crime, low paid, so called, taxpayer funded, out of state, anti immigrant, closed circuit, un american, clear up

Table 1: General position (first row) and topic-specific position bigrams associated with eleven selected topics. Terms are ranked by comparing the log odds conditioned on the position and topic, e.g., $\log \frac{\phi_{i_1,t,w}^o}{\phi_{i_2,t,w}^o}$. We assigned labels manually.