Text-Based Ideal Points

Keyon VafaColumbia University

Joint work with:



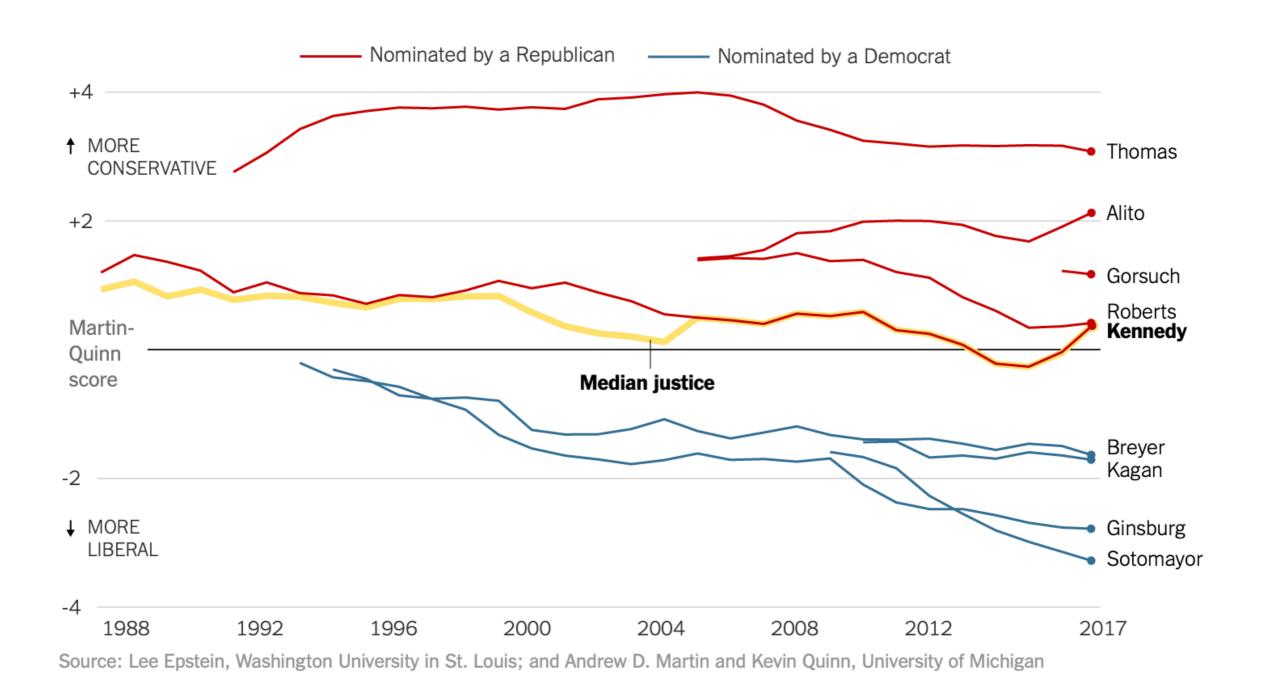
Suresh Naidu
Columbia University



David BleiColumbia University



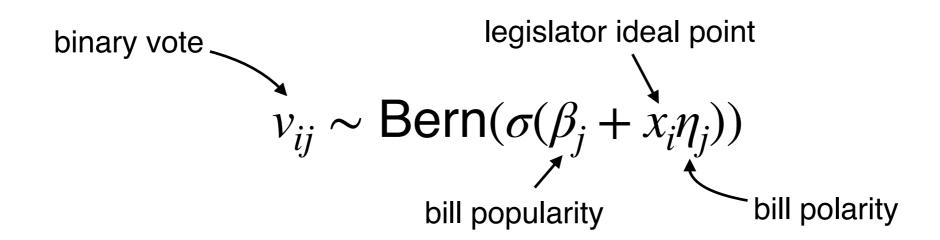
Ideal Points



Ideal Points

Bayesian Ideal Points

- Probabilistic method to measure political positions of legislators
- Based solely on voting record



Vote Ideal Points

Analyze votes on shared bills to infer political positions.

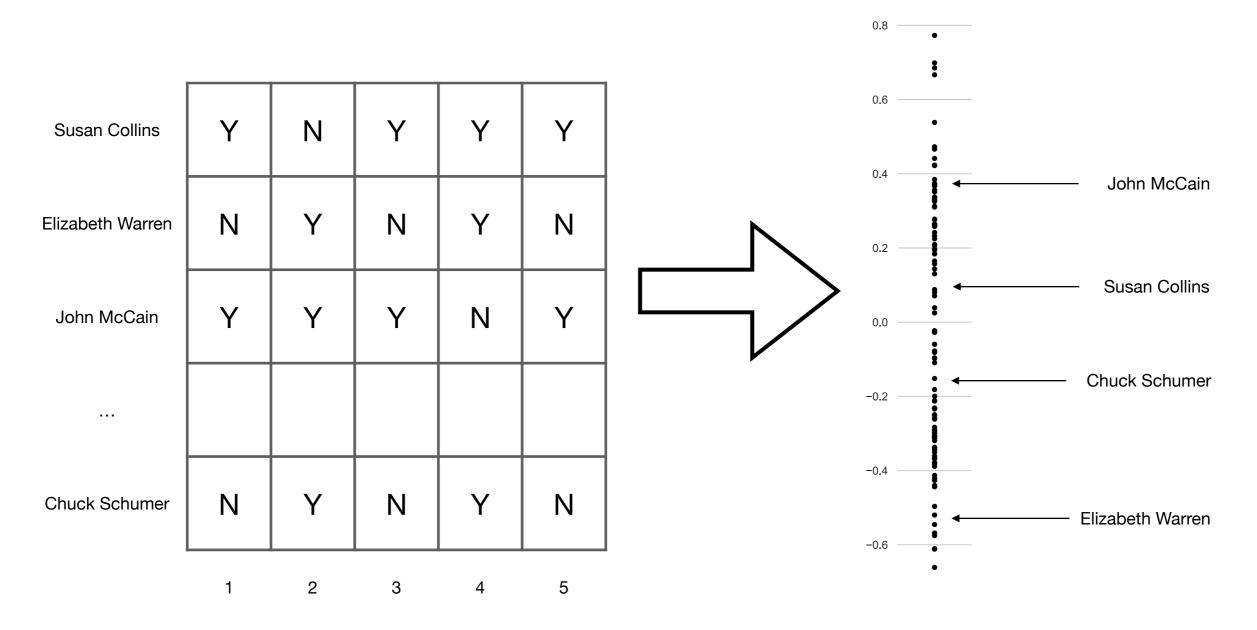
Limitations:

- Cannot compare groups who do not vote together (e.g. judges on different courts).
- Votes on decisions must be available (e.g. cannot extend to presidential candidates).

Solution: Text-based ideal points!

Analyze language of speeches to infer political preferences.

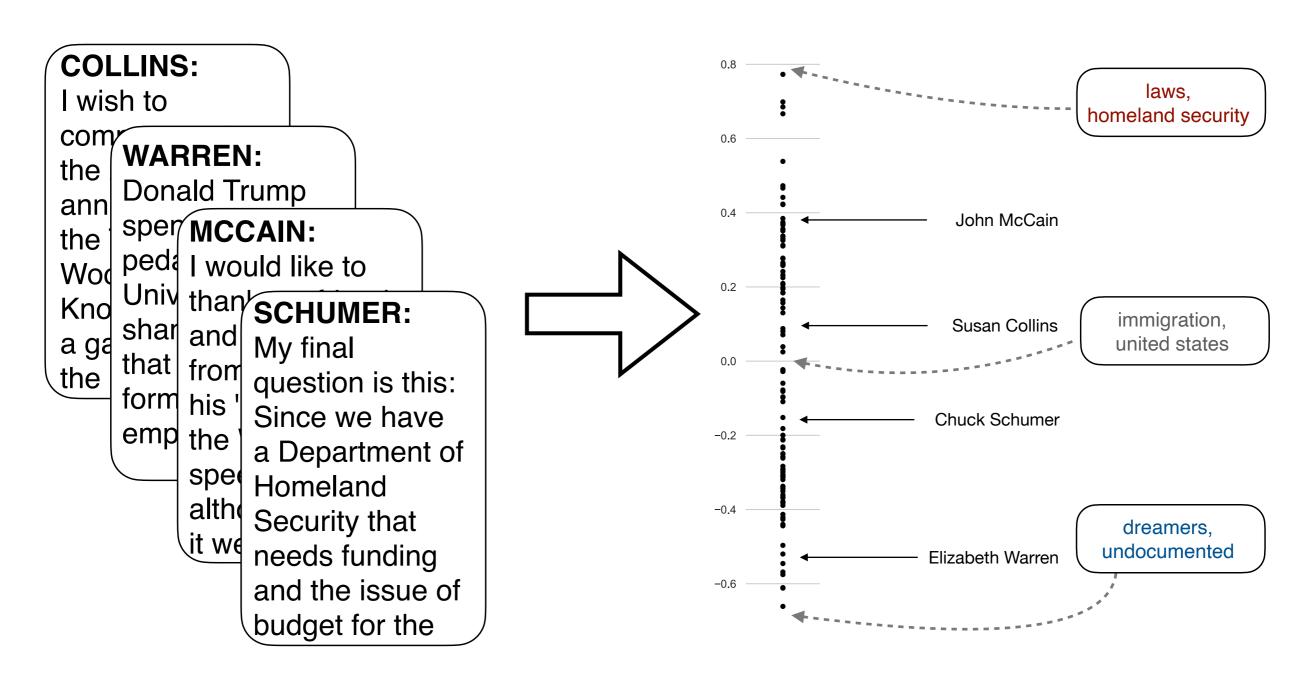
Vote-Based Ideal Points



IN: Voting Record

OUT: Ideal Points

Text-Based Ideal Points



IN: Speeches

OUT: Ideal Points + Ideological Topics

Existing Methods

Existing methods for inferring political positions from text either:

- Use party labels
- Combine text with voting records
- Use hand-labeled political text
- Require grouping of texts into single issues

Text-Based Ideal Points

The Text-Based Ideal Point Model (TBIP) is **completely unsupervised**:

 Does not require party labels, voting records, hand-labeled political text, or grouping of text into single issues

Advantages of being unsupervised:

- Applicable to unlabeled political discourse
- Does not force hard membership into binary groups
- Does not depend on subjectivity of coders

Political Framing

Entman's definition of framing (Entman, 1993):

"[Selecting] some aspects of a perceived reality and [making] them more salient in a communicating text, in such a way as to promote problem definition, causal interpretation, moral evaluation, and/or treatment recommendation for the item described."

Political framing: When discussing a topic, word choice is affected by political message.

Frames for abortion (Boydstun et al., 2014; Johnson et al., 2017):

- "life" and "unborn" invoke morality and religion
- "choice" and "freedom" invoke constitutionality and personal liberty

Text-Based Ideal Points

Vote-based ideal points:

Inferred by vote differences on shared bills.

Text-based ideal points:

Inferred by word choice differences on shared topics.

Model

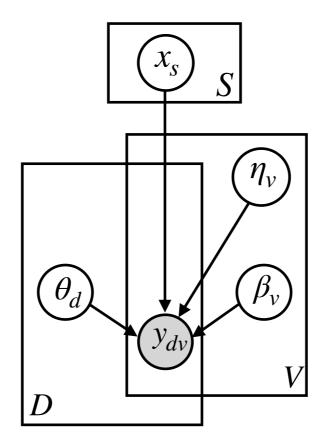
The TBIP is based on **Poisson factorization**:

$$y_{dv} \sim \text{Pois}\left(\sum_{k} \theta_{dk} \beta_{kv}\right)$$
 word counts document intensities topics

We add two terms to the Poisson factorization log-likelihood:

"ideological" topics
$$y_{dv} \sim \text{Pois}\left(\sum_{k} \theta_{dk} \beta_{kv} \exp\{x_{a_d} \eta_{kv}\}\right)$$
 ideal point for author of document d

Inference



Posterior distribution for latent parameters (θ, β, η, x) is approximated with variational inference.

TensorFlow and PyTorch implementations are available at:

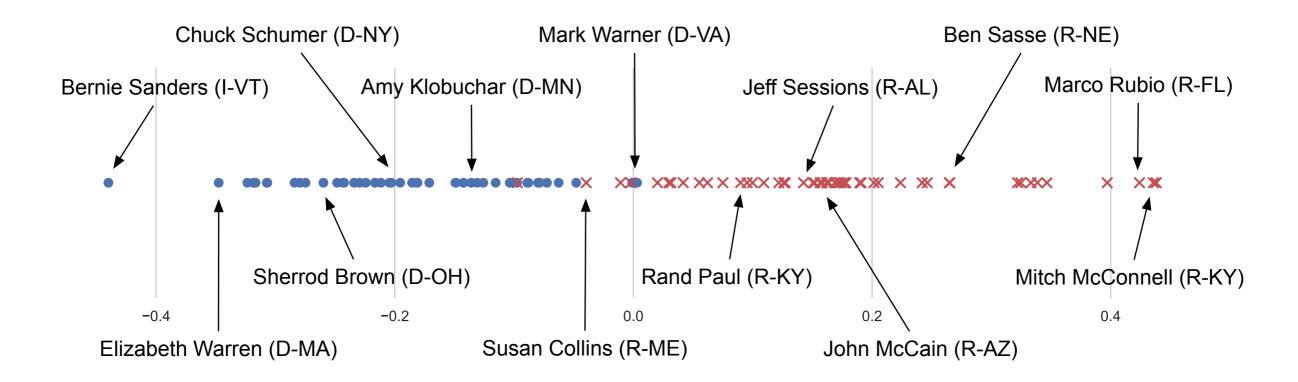
github.com/keyonvafa/tbip



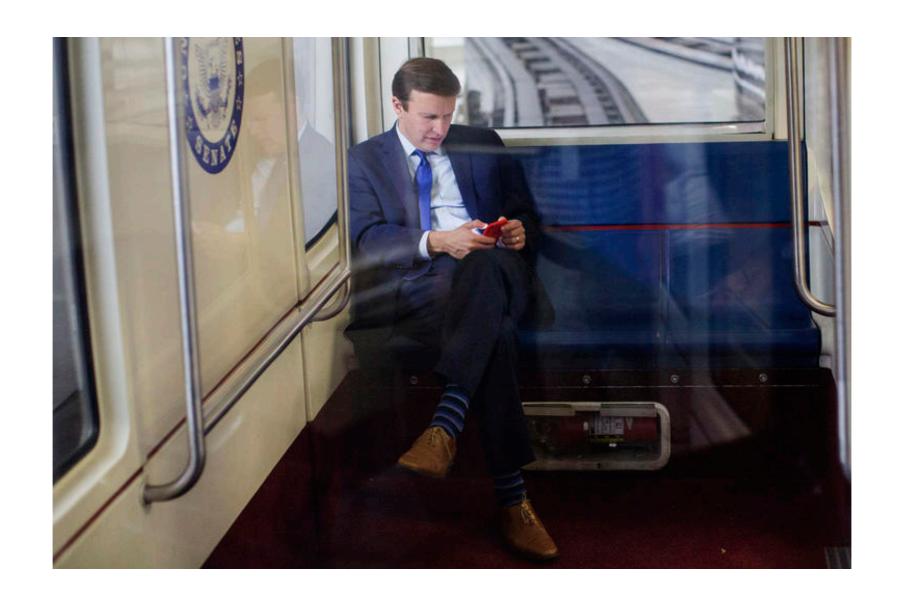
U.S. Senate Speeches



Ideal Points

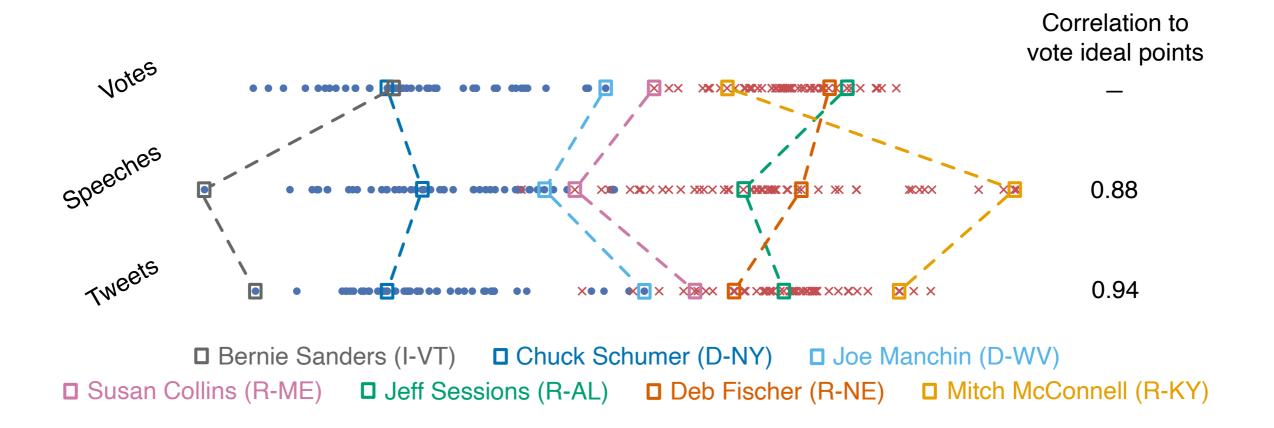


U.S. Senator Tweets



209,779 tweets from senators between 2015-2017

Votes vs Speeches vs Tweets

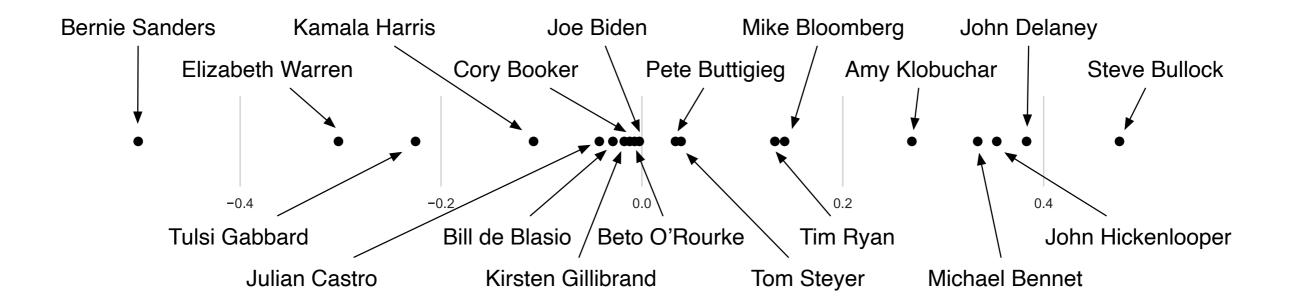


2020 Democratic Presidential Candidate Tweets

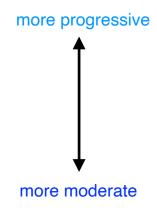


45,927 tweets from 19 candidates between 2019-2020

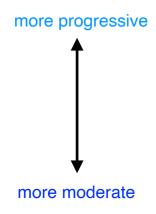
2020 Democratic Candidates



2020 Democratic Candidates



#medicareforall, insurance companies, profit, health care health care, plan, medicare, americans, care, access healthcare, universal healthcare, public option, plan



green new deal, fossil fuel industry, fossil fuel, planet, pass climate change, climate, climate crises, plan, planet, crisis solutions, technology, carbon tax, climate change, challenges

Comparisons

Other methods: Wordfish (Slapin and Proksch, 2008) and

Wordshoal (Lauderdale and Herzog, 2016)

Evaluate each ideal point method by measuring correlation and rank correlation to vote ideal points.

	Speeches 111		Speeches 112		Speeches 113		Tweets 114	
	Corr.	SRC	Corr.	SRC	Corr.	SRC	Corr.	SRC
WORDFISH	0.47	0.45	0.52	0.53	0.69	0.64	0.87	0.80
WORDSHOAL	0.61	0.64	0.60	0.56	0.45	0.44		
TBIP	0.79	0.73	0.86	0.85	0.87	0.84	0.94	0.84

Recap

We develop an unsupervised model to learn ideal points and ideological topics solely from text.

Text-based ideal points can be used to learn political preferences for non-voting entities (e.g. presidential candidates).

We use an efficient variational inference algorithm to apply the model to large datasets.

All code (including Tensorflow and PyTorch implementations) available at:

www.github.com/keyonvafa/tbip

Thank you!



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