Text Based Ideal Point Model

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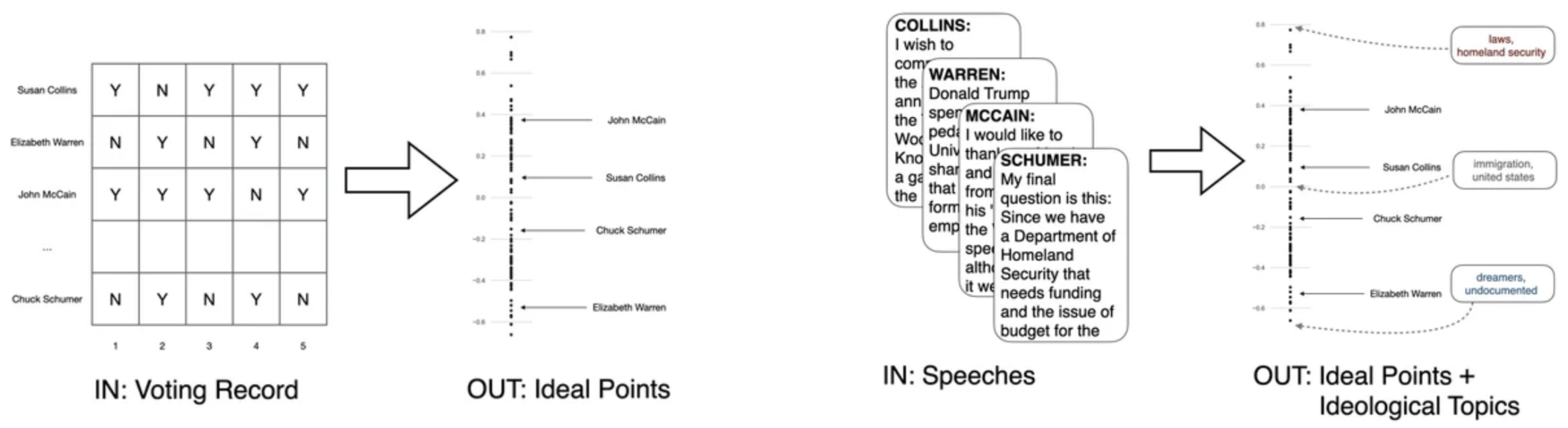
Introduction

Ideal point models are used to predict lawmakers' political preferences by analyzing vote discrepancies on shared bills. The text-based ideal point model (TBIP) [1], initially tested on biparty systems like the US, draws from political speeches to leverage word-choice differences on shared topics to infer estimates of ideal points. This allows for its application to a broader range of individuals who do not vote on legislation. Our aim: Infer ideologies in multi-party contexts, such as the UK's House of Commons.



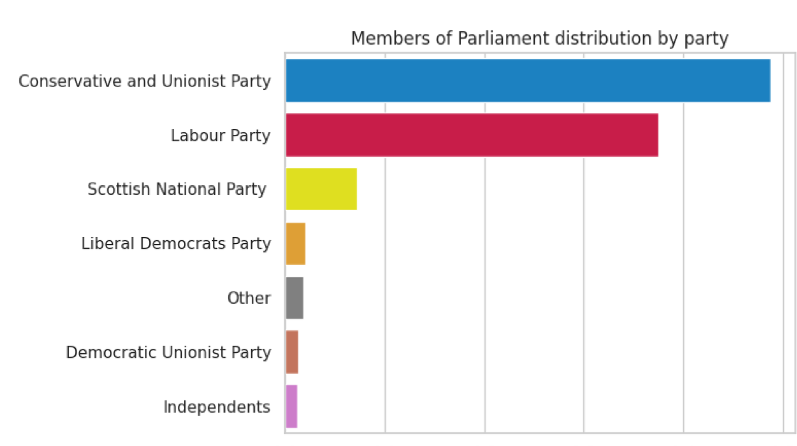
Data

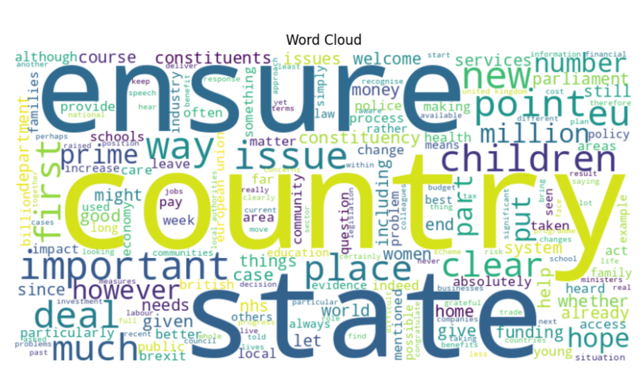
Speeches

- **Source:** Speeches from the House of Commons given between the years 1998 and 2019 [2], including name of speaker and party affiliation.
- **Pre-processing:** Include speeches with over 50 words, MPs with more than 24 speeches, and bigrams spoken by 10 or more authors. Remove stopwords (e.g., UK city names, dates, numbers, and titles), speeches by presiding officers, and nonsubstantive speeches like business of the House and adjournment periods.
- Clean Data: 206,993 speeches from 742 Members of Parliament, and 10,576 words in the vocabulary. From 2016 to 2019.

Votes

- **Source:** Votes of each Member of Parliament from 2016 to 2024 [3]. This data is used to train a traditional ideal point model, as a baseline to evaluate the TBIP.
- Clean Data: 360,137 votes from 972 Members of Parliament on 720 bills. From 2016 to 2019.





References

[1] Keyon Vafa, Suresh Naidu, and David M. Blei. Text-Based Ideal Points, 2020.

[2] Christian Rauh and Jan Schwalbach. The ParlSpeech V2 data set: Full-text corpora of 6.3 million parliamentary speeches in the key legislative chambers of nine representative democracies, 2020.

[3] Developer Hub. Commons Votes API, 2024.

Preliminary models

Bayesian ideal point model

This is a probabilistic model to infer a politician's ideology from votes. For a Member of Parliament i and a bill j, the likelihood of their vote v_{ij} is modeled as:

$$v_{ij} \sim \text{Bernoulli}\Big(\sigma(\alpha_j + x_i\eta_j)\Big)$$

The latent variables are:

- $x_i \sim \mathcal{N}(0,1)$, the ideology of MP i,
- $\alpha_j \sim \mathcal{N}(0,1)$, the popularity of bill j,
- $\eta_j \sim \mathcal{N}(0,1)$, the polarity of bill j.

Poisson factorization topic model

This model factors a word frequency matrix across all documents into matrices of topic intensities per document and topics. It models the count of word v in document d as:

$$y_{dv} \sim \text{Poisson}\Big(\sum_k \theta_{dk}\beta_{kv}\Big)$$

Here, the latent variables are:

- $\theta_{dk} \sim \text{Gamma}(a,b)$, the intensity of topic k in document d,
- $\beta_{kv} \sim \text{Gamma}(a,b)$, the appearance of word v in topic k.

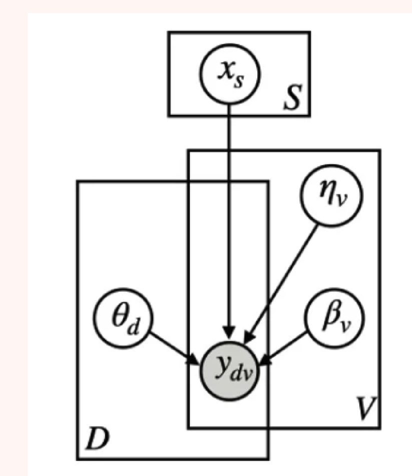
Methodology

Text-based ideal points model (TBIP)

This model combines topic detection in texts with the identification of ideology for each author.

Latent variables:

- Intensity of topic k in document d: $\theta_{dk} \sim \text{Gamma}(a,b)$
- Appearance of word v in neutral topic k: $\beta_{kv} \sim \text{Gamma}(a,b)$
- Ideology of word v in topic k: $\eta_{kv} \sim \mathcal{N}(0,1)$
- Ideal point of author s: $x_s \sim \mathcal{N}(0,1)$



Likelihood: count of word v in speech d

$$y_{dv} \sim \text{Poisson}\Big(\sum_k \theta_{dk}\beta_{kv}\exp(x_{a_d}\eta_{kv})\Big) \quad (1)$$

Once we compute the posterior, we obtain:

- The political position of authors, x_s.
- The latent topics in each document, $\boldsymbol{\theta_d}$.
- The words used for each topic neutrally, those with high β_{kv} and $\eta_{kv} = 0$.
- The words used for each topic with a certain ideology, those with high β_{kv} and $\eta_{kv} > 0$ or $\eta_{kv} < 0$ respectively.

Experimental setup

To examine the performance of the TBIP model in a multi-party context, we utilize our clean UK data and compare the output with a benchmark vote-based ideal point model for the same politicians over the same time period. The evaluation metric is the correlation between the learned ideal points of the two models.

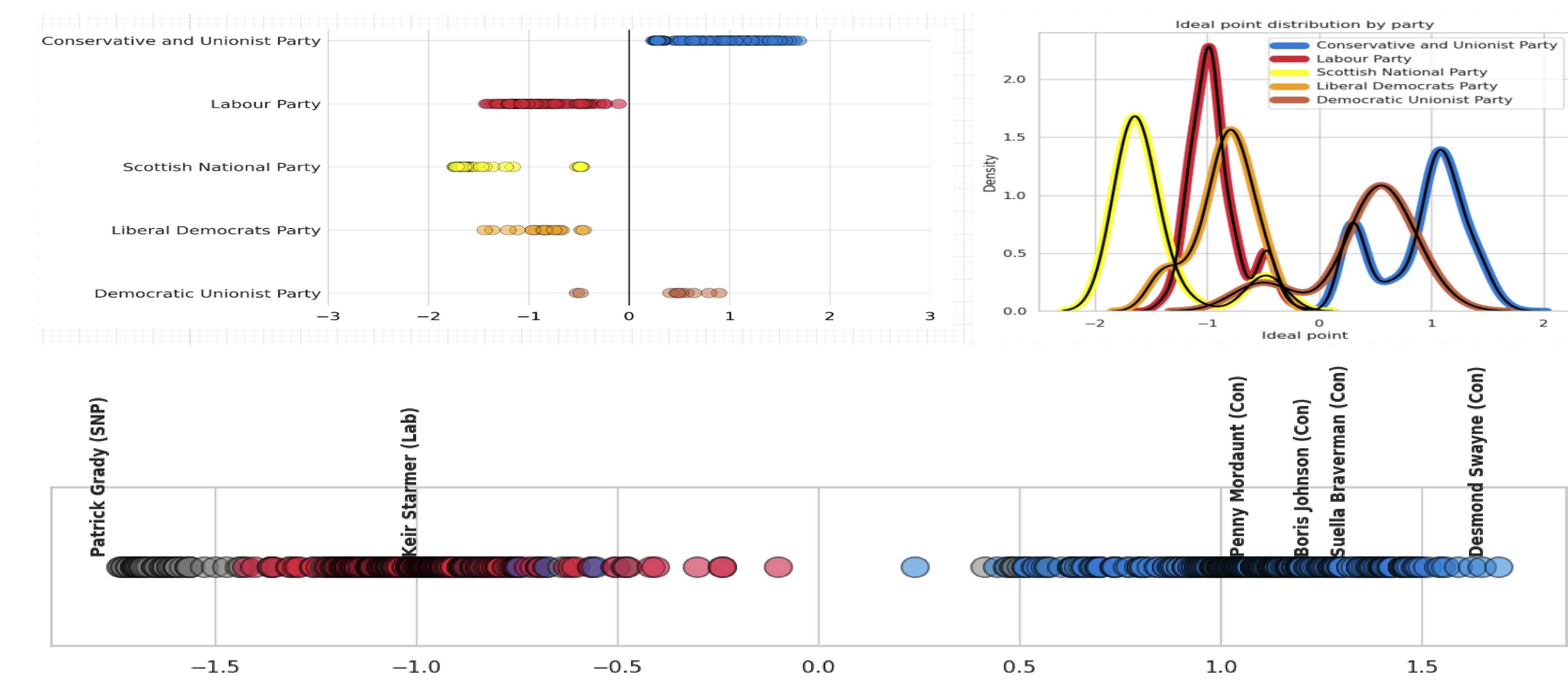
Our TBIP model is trained for 30,000 steps with 512 batch size. Following the original setting, we assume 50 latent topics and the prior distributions as $\theta_{dk}, \beta_{kv} \sim \text{Gamma}(0.3, 0.3)$. Moreover, as the paper suggests, with n_s as the average word count for author s, we apply a weight $w_s = \frac{n_s}{\frac{1}{S}\sum_{s'} n_{s'}}$ to the Poisson rate in equation (1). We find it crucial for better model performance because otherwise, the author's verbosity rather than ideal points will be reflected.

For hyperparameter tuning, the best performance is achieved around 30,000 steps, with diminished performance noted when conducting fewer or greater numbers of steps. Other hyperparameters explored include number of topics, parameters of Gamma prior, learning rate, and batch size. However, none of these have shown a significant impact on our results.

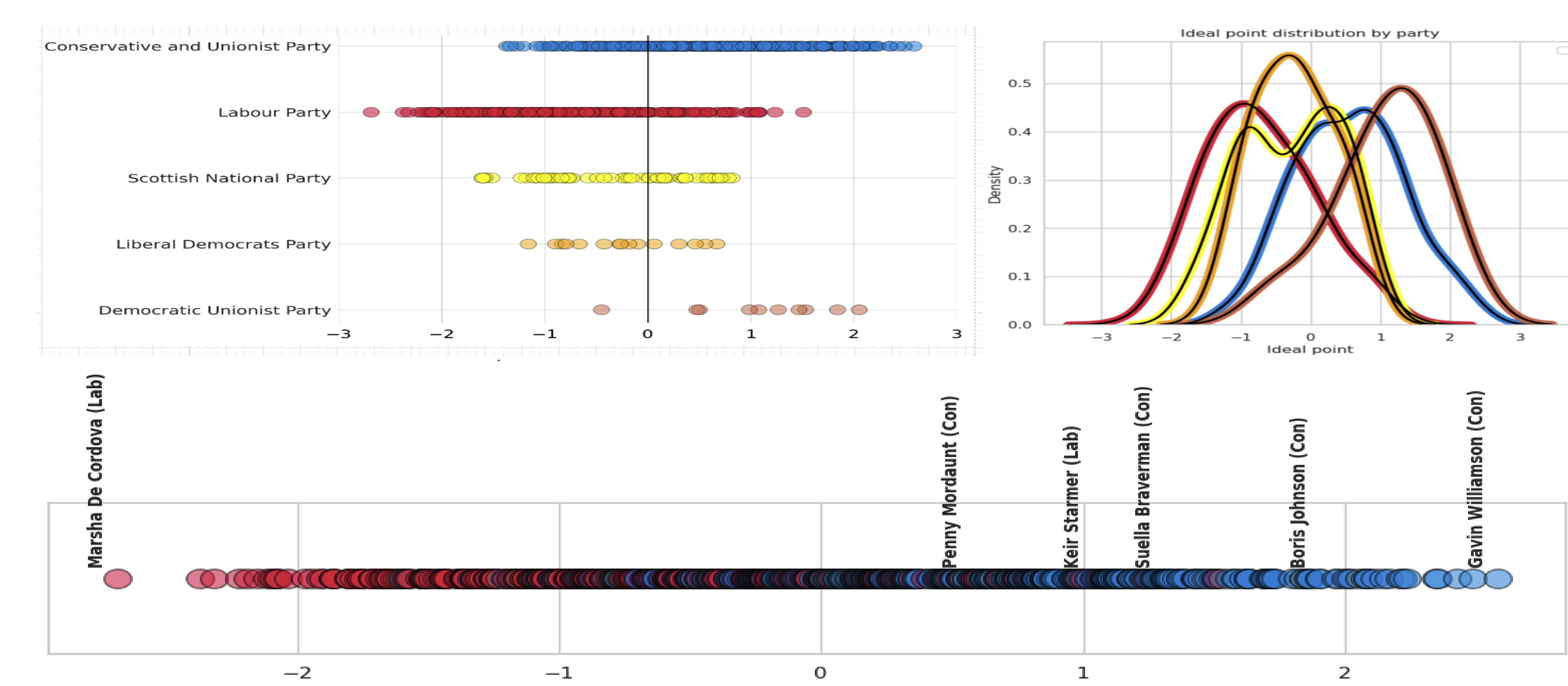
Results and Evaluation

Correlation between TBIP and Bayesian vote-based ideal points: Pearson 0.557, Spearman 0.501. Lower than Vafa et al. (2020) [1] U.S. Senate speech data correlation of 0.88.

Bayesian ideal points – Baseline



TBIP



Topic	Ideology	Top Words
Brexit	Progressive	brexit, prime, deal, country, constituents, eu, jobs, economy, workers rights, deal brexit
	Neutral	deal, eu, prime, brexit, european union, leave, country, voted, referendum, parliament
	Moderate	ensure, european union, relation, deal, eu, united kingdom, negotiations, implementation, leave, clear
Social Programs	Progressive	disabled, social security, universal credit, poverty, cuts, food, million, families, un, sick
	Neutral	universal credit, poverty, benefits, payments, system, benefit, claimants, roll, payment, welfare
	Moderate	workplace, ensure, system, ensuring, important, benefits, payments, point, welfare, course
Foreign Affairs	Progressive	foreign, commonwealth, british, china, world, donald trump, countries, trump, abroad, nazanin
	Neutral	foreign, security, countries, world, international, commonwealth, country, russia, british, china
	Moderate	security, nato, allies, russia, intelligence, international, response, foreign, clear, sanctions

Discussion and Conclusion

1. TBIP model captures some UK MPs' political preferences in multi-party contexts
2. Underperformance due to NLP pre-processing, tailored for US Senate
3. Number of trials impacts model performance
4. Brexit period may have caused larger overlap in party discourse
5. Bayesian ideal point model simpler for voting bodies; TBIP adaptation needed for different countries