The Neural Ideal Point Model

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Measuring Ideology in the Era of Unstructured Data

- Ideal point models position individuals on ideological dimensions based on observed choices.
- Traditionally applied to **structured data**:
  - Voting records in parliaments (Poole and Rosenthal, 1985)
  - Courts (Martin and Quinn, 2002), surveys (Bafumi and Herron, 2010), etc.
- New opportunities arise with **unstructured data**:
  - Manifestos (Slapin and Proksch, 2008), speeches (Lauderdale and Herzog, 2016))
  - *Images, audio, video* → still largely unexplored.
- But unstructured data presents key challenges:
  - **Large** number of observations (**large n**) and high dimensionality (**large p**)
  - **Multimodal** inputs (text + image + audio)
  - Existing methods are often **intractable** for large scale data or not designed for *embeddings*.

→ We propose a deep learning framework to estimate ideal points from unstructured, multimodal data.

The Neural Ideal Point Model

- **Model**
  - Ideal points are drawn from a prior and manifest into response variables.
  - Covariates can affect ideal points.
  - Ideal points can affect outcomes.
  - Allows for multiple modalities.
- **Estimation**
  - Approximate via deep learning the posterior distribution of ideal points conditional on an observed dataset and a researcher prior.
  - Generic, fast, and scalable.
  - Can process and learn embeddings.
- **Simulations & Common Datasets**
  - Good finite sample performance in simulations.
  - Near-identical estimates than other methods on common datasets.
  - Successfully applied to learn ideal points of US politicians from speeches.
  - Flexible framework to derive ideal points from any embeddings — including video.

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A Flexible Model of Latent Ideology

- Notations:
  - Z is a vector of **ideal points**.
  - W_m is a vector of **response variables** for each modality m.
  - Y is a vector of **auxiliary outcomes**.
  - P_Z is a **prior distribution** (modeled as a Generalized Linear Model).
  - X^p, X^c, and X^s are **covariates** that influence the latent, response, or outcome variables.
- We assume that

$$Z \sim P_Z | X^p \quad \text{and} \quad W_m = G_m(Z, X^c) \quad \text{and} \quad Y = F(Z, X^s).$$

- This is a fairly general formulation, as P_Z, G_1,...,G_m, and F are left unspecified (we will parametrize them later for estimation).

Estimation Framework

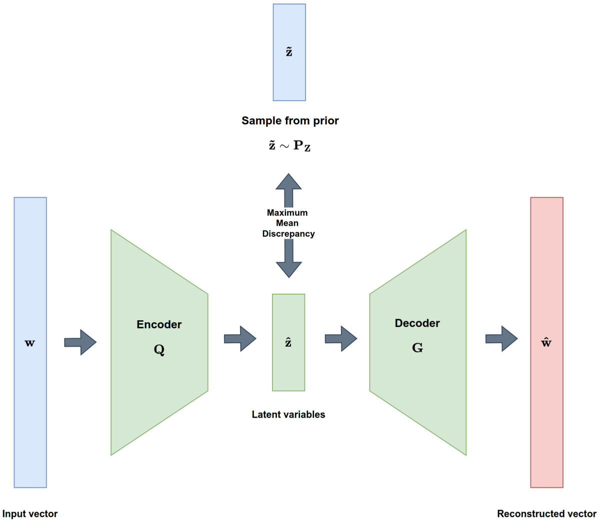
For response variables $\{w_m\} \in \{1, ..., M\}$, outcome y, ideal points z and covariates x^p, x^c, and x^s, we have:

$$P(w_1, ..., w_m, y \mid x^p, x^c, x^s) = \int_{\mathcal{Z}} P(z \mid x^p) P(y \mid z, x^s) \prod_{m=1}^{M} P(w_m \mid z, x^c) dz.$$

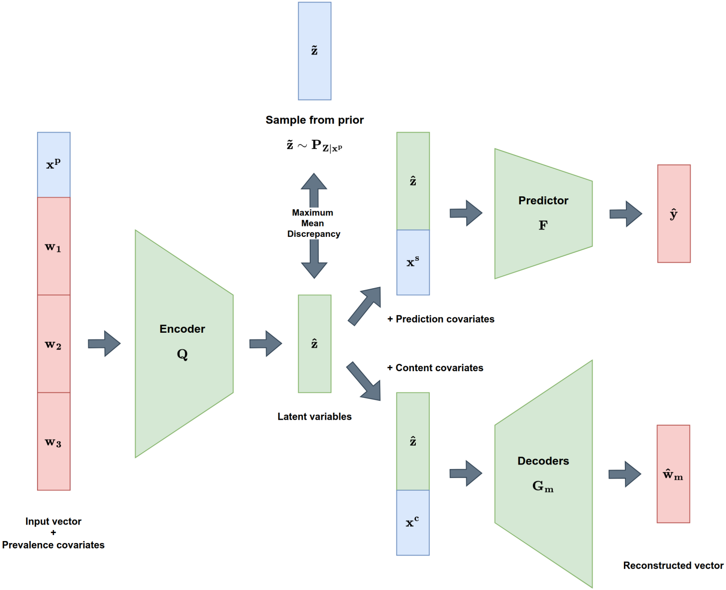
→ **Problem:** The marginal likelihood is *intractable*.

→ **Solution:** Approximate $P(w_1, ..., w_m \mid x^p, x^c)$ as a Wasserstein autoencoder (Tolstikhin et al., 2017):

- The encoder, decoders, and predictor are neural networks.
- Encoder $Q(w_1, ..., w_m, x^p) \approx P(z \mid w_1, ..., w_m, x^p)$
- Decoders $G_m(z, x^c) \approx P(w_m \mid z, x^c)$
- Predictor $F(z, x^s) \approx P(y \mid z, x^s)$
- We nudge $Q(w_1, ..., w_m, x^p)$ to remain close to the prior distribution.



$$\mathbf{TotalLoss} = \mathbf{ReconstructionLoss}(\mathbf{w}, \hat{\mathbf{w}}) + \lambda \widehat{\mathbf{MMD}}_{\mathbf{k}}^{\mathbf{2}}(\hat{\mathbf{z}}, \tilde{\mathbf{z}})$$



$$\mathbf{TotalLoss} = \sum_{\mathbf{m}=1}^{\mathbf{M}} \mathbf{RecLoss}(\mathbf{w}_{\mathbf{m}}, \hat{\mathbf{w}}_{\mathbf{m}}) + \lambda_0 \widehat{\mathbf{MMD}}_{\mathbf{k}}^{\,2}(\hat{\mathbf{z}}, \tilde{\mathbf{z}}) + \lambda_1 \mathbf{PredLoss}(\mathbf{y}, \hat{\mathbf{y}})$$

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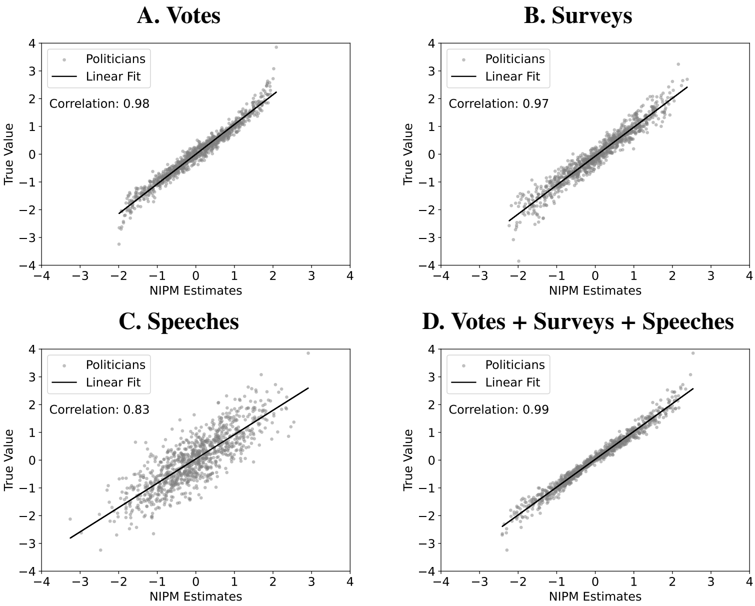
NIPM Recovers Ideal Points Across Modalities



Monte Carlo Simulations: Main Takeaways

1. NIPM recovers true ideal points across modalities.
2. NIPM accurately estimates covariate effects on ideal points. ▸ See Figure
3. NIPM accurately estimates effects of ideal points on outcomes.
4. NIPM is fast and scalable, outperforming MCMC-based approaches. ▸ See Figure
5. Confidence intervals computed using dropout, subsampling, bootstrap. ▸ See Table

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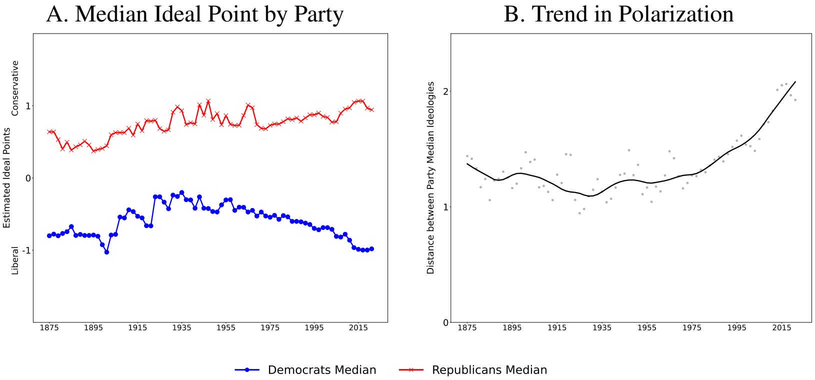
Our model recovers trends in congressional polarization

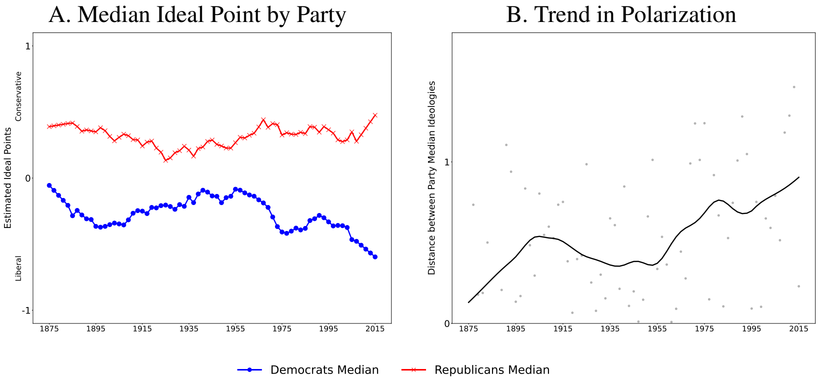
Evolution of Party Ideology in US Senate (Votes)



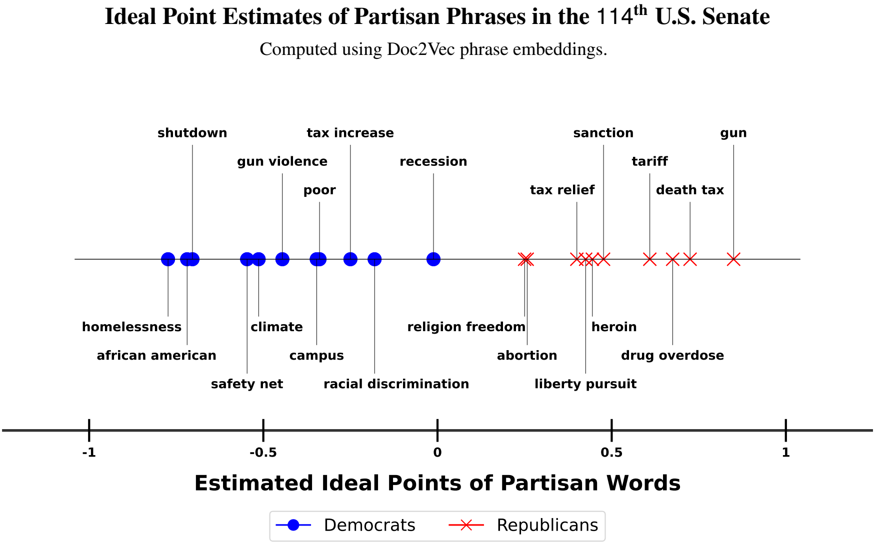
Our model recovers trends in congressional polarization

Evolution of Party Ideology in US Senate (Speeches)

Computed using Doc2Vec phrase embeddings.



Our model interprets partisan language



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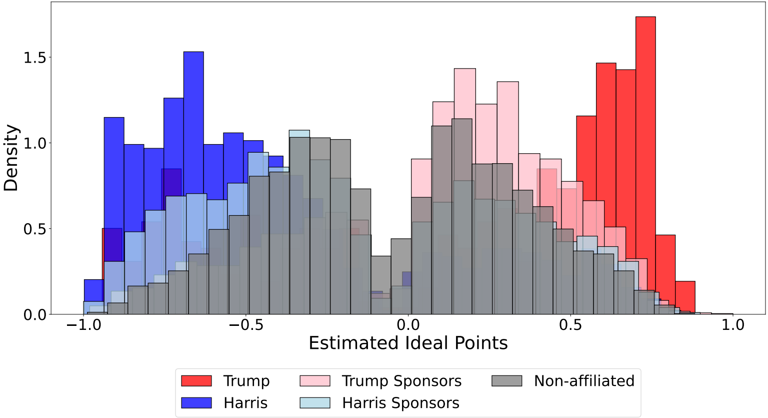
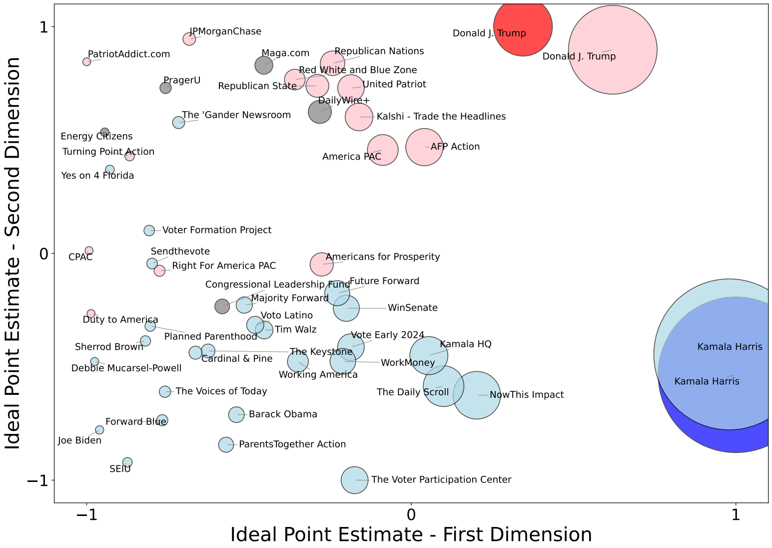
Political Advertisers on Social Media

Distribution of the Median Ideal Point for Political Advertisers

Computed using X-CLIP video embeddings.



Ideal Points of Political Advertisers, US 2024 Election (Weighted by Money)



What kind of content is ideological?

Examples of the most ideologically extreme video descriptions.

Video Description	Ideal Point
A Native American woman is dragged away by police at an oil pipeline protest.	0.4574
A Native elder watches bulldozers destroy sacred burial sites.	0.4279
A migrant caravan marches to the U.S. border, waving foreign flags.	0.3740
A farmer warns that government overreach is hurting small businesses.	0.2536
A crowd of people wearing red hats and caps.	0.1105
A worker on strike holds a sign for higher wages.	-0.2769
A woman gives birth in a car after her hospital closes.	-0.2818
A graduate rips up a student debt statement on stage.	-0.3760
A drag queen reads a storybook to children in a library.	-0.4603
A trans woman, bruised and scared, after being attacked.	-0.4637

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Concluding Remarks

We are preparing an open-source Python package `IdealPointNN` to support future applications

...

and we look forward to your feedback.

Thanks for listening!

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References I

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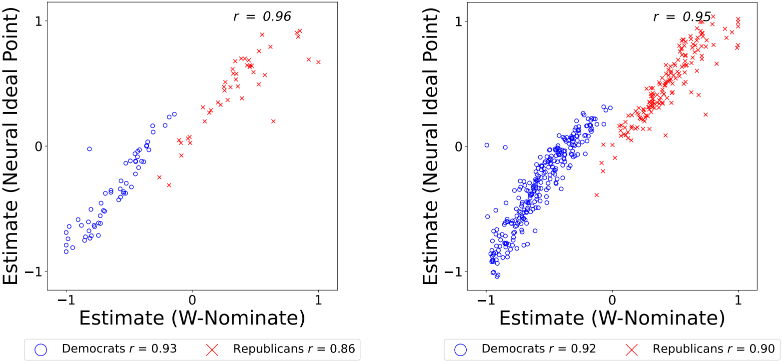
Slapin, J. B. and Proksch, S.-O. (2008). A scaling model for estimating time-series party positions from texts. *American Journal of Political Science*, 52(3):705–722.

Tolstikhin, I., Bousquet, O., Gelly, S., and Schoelkopf, B. (2017). Wasserstein auto-encoders. *arXiv preprint arXiv:1711.01558*.

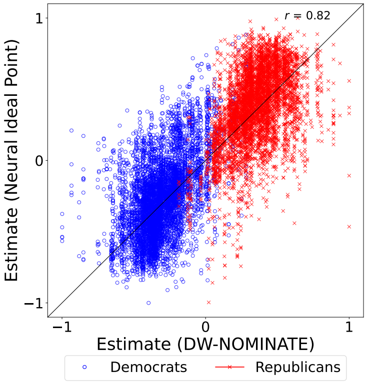
Appendix — W-NOMINATE vs. NIPM (102nd Congress)

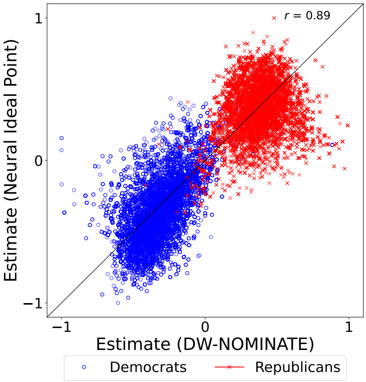
Correlation between W-NOMINATE Estimates and NIPM (102nd Congress)



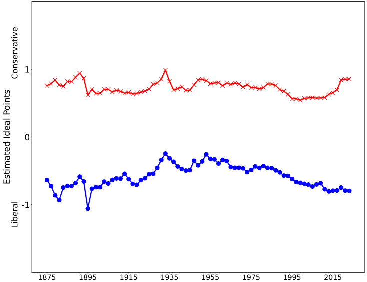
Appendix — W-NOMINATE vs. NIPM (44th–118th Congress)

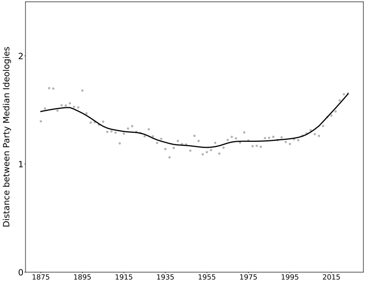
Correlation between W-NOMINATE Estimates and NIPM (44th–118th Congress)



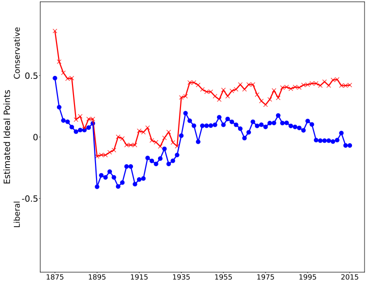


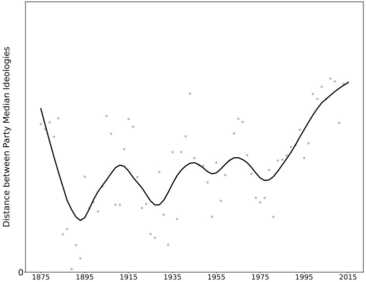
Appendix — Evolution of Party Ideology in US House (Votes)



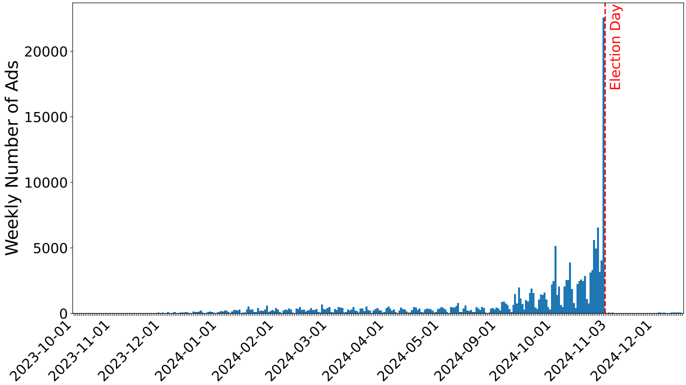


Appendix — Evolution of Party Ideology in US House (Speeches)



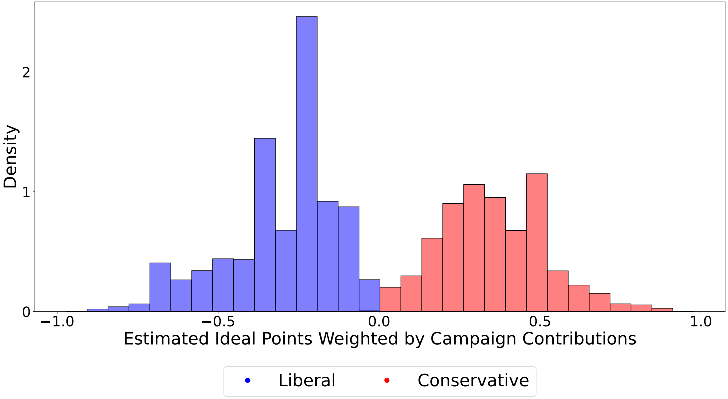


Appendix — Number of Political Ads Over Time



Appendix — Ideal Points Weighted by Money

Distribution of the Median Ideal Point for Political Advertisers (Weighted by Money)



Appendix: Covariate and Outcome Models

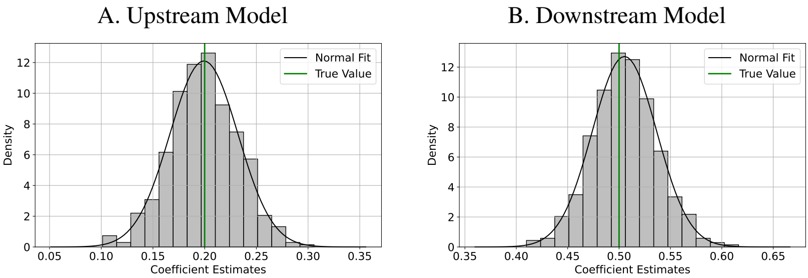


Figure 3. NIPM recovers causal effects well. 500 replications. Vertical green line shows true parameter.

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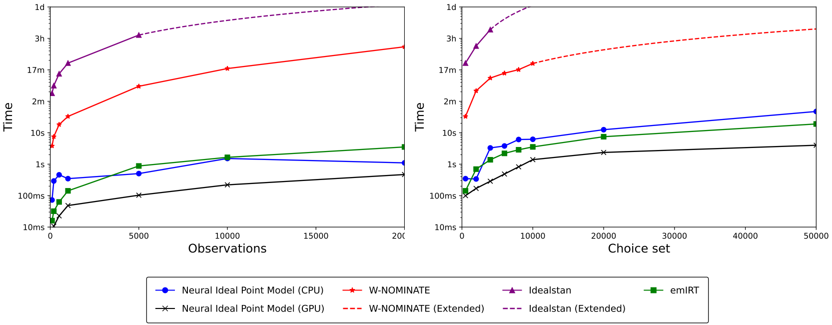
Appendix: Scalability and Speed

Speed and Scalability for Different Dataset Sizes

A. Increasing Number of Politicians

B. Increasing Number of Bills



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Appendix: Uncertainty Estimation

Approach	Mean Std. Error	Coverage (%)	Time
Nonparametric Bootstrap	0.20	90.1	3h
Parametric Bootstrap	0.06	83	3h
Subsampling (5%)	0.06	84.3	30min
MC Dropout (10%)	0.24	93.5	2min
MC Dropout (20%)	0.32	98.4	2min
MC Dropout (30%)	0.36	88.6	2min

Table 1. 95% CI coverage across 1000 simulated politicians. MC Dropout: 500 passes. Bootstrap/subsampling: 200 samples.

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