The Neural Ideal Point Model

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Measuring Ideology: New Opportunities and Challenges

- 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)
- New opportunities arise with **unstructured data**:
  - Manifestos (Slapin and Proksch, 2008), speeches (Lauderdale and Herzog, 2016)
  - Images, audio, and video are still largely unexplored.
- But unstructured data presents **key challenges**:
  - Many observations (large n) and high dimensionality (large p)
  - Multimodal inputs (text + image + audio)
  - Existing methods are often intractable and not designed for *embeddings*.

The Neural Ideal Point Model

We propose a deep learning framework to estimate ideal points from unstructured and multimodal data

...

So how does this work?

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 & Applications**
  - Good finite sample performance in simulations.
  - Near-identical estimates to other methods on common datasets.
  - Estimate ideal points of US politicians from their *votes and speeches*.
  - Estimate ideal points of political advertisers on Meta during the 2024 US election from their *videos*.

Table of Contents

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):

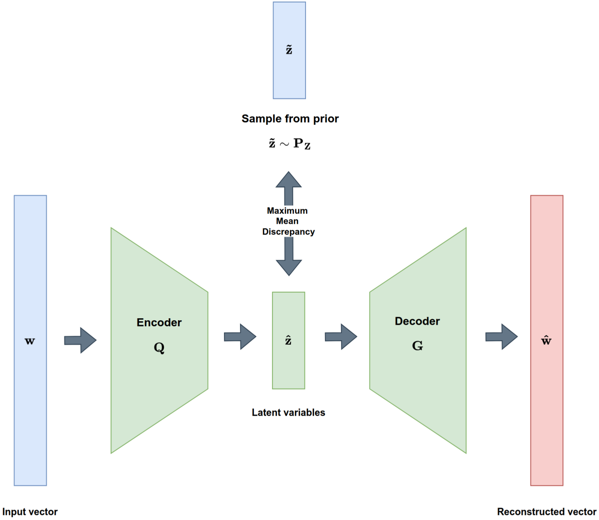
- The encoder, decoders, and predictor are neural networks.

- Encoder $Q(w_1, ..., w_m, x^p) \approx P(z \mid w_1, ..., w_m, x^p)$

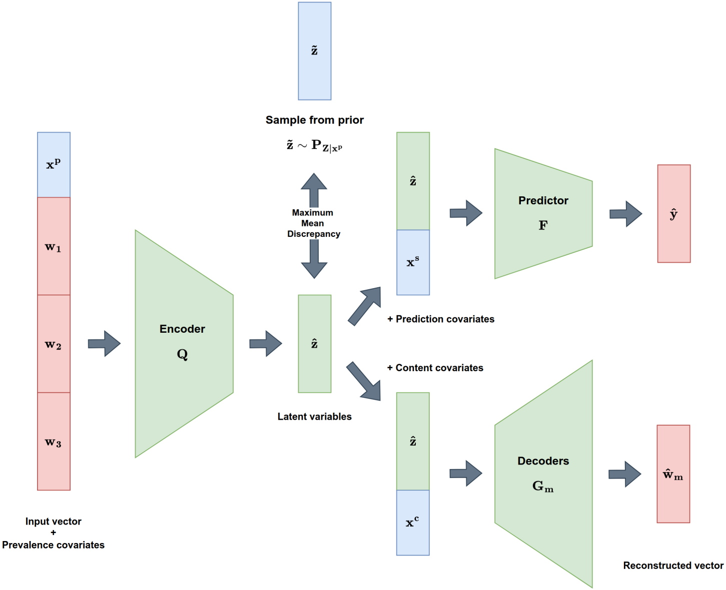
- Decoders $G_m(z, x^c) \approx P(w_m \mid z, x^c)$

- 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.



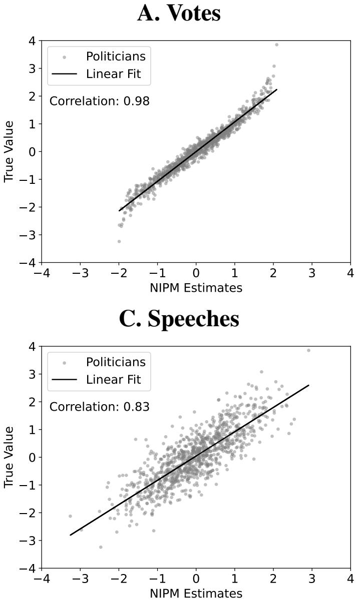
$$\mathbf{TotalLoss} = \mathbf{ReconstructionLoss}(\mathbf{w}, \hat{\mathbf{w}}) + \lambda \widehat{\mathbf{MMD}}_{\mathbf{k}}^{\mathbf{2}}(\hat{\mathbf{z}}, \tilde{\mathbf{z}})$$



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

Table of Contents

NIPM Recovers Ideal Points Across Modalities



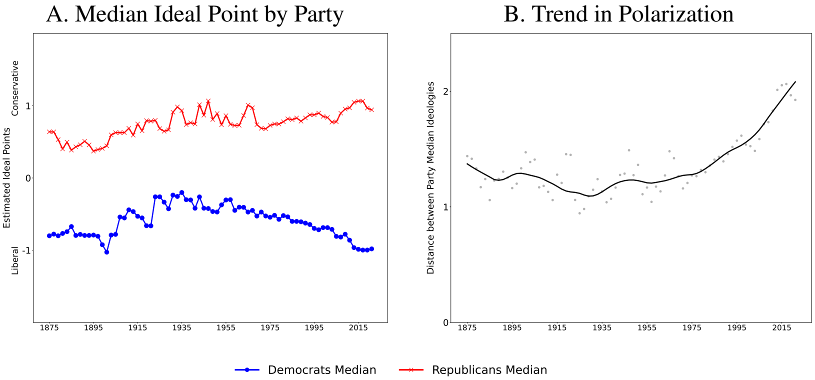
Monte Carlo Simulations: Main Takeaways

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, and bootstrap (*still work in progress*). ▶ See Table

Table of Contents

Our model recovers trends in political polarization.

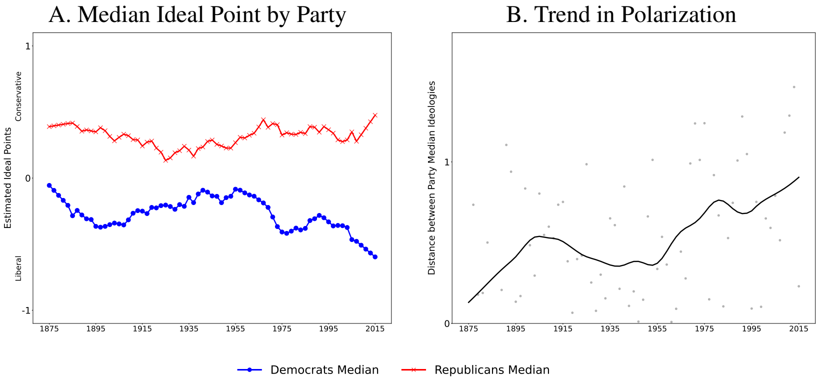
Evolution of Party Ideology in US Senate (Votes)



Our model recovers trends in political polarization.

Evolution of Party Ideology in US Senate (Speeches)

Computed using Doc2Vec phrase embeddings.



Once trained, the model can scale any text snippet instantly.

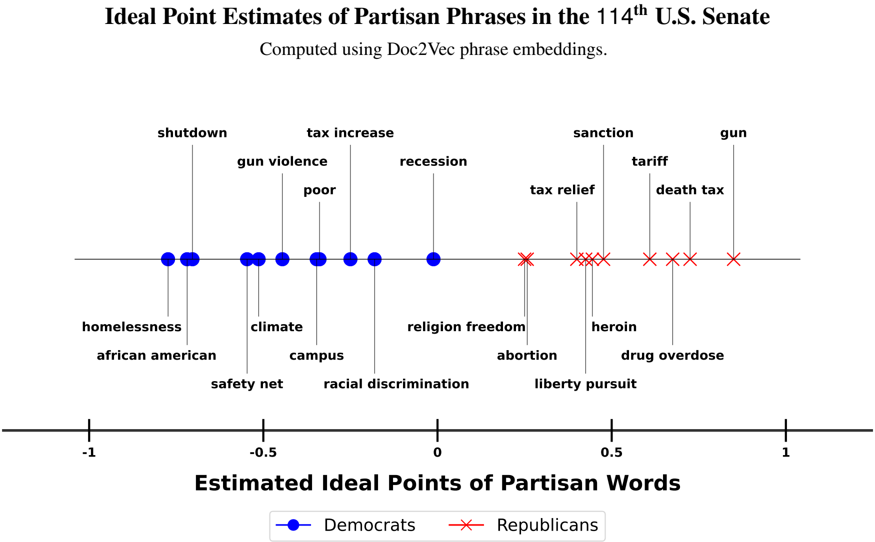


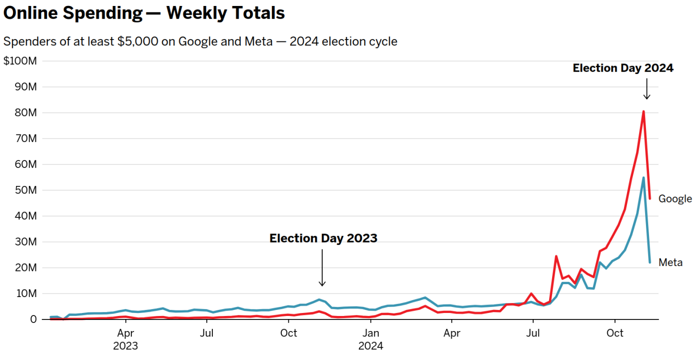
Table of Contents

Political Advertisers on Social Media

Parties spent over 10 billion $ on political ads during the 2024 US election.

Political Advertisers on Social Media

1.35 billion $ were online ads.



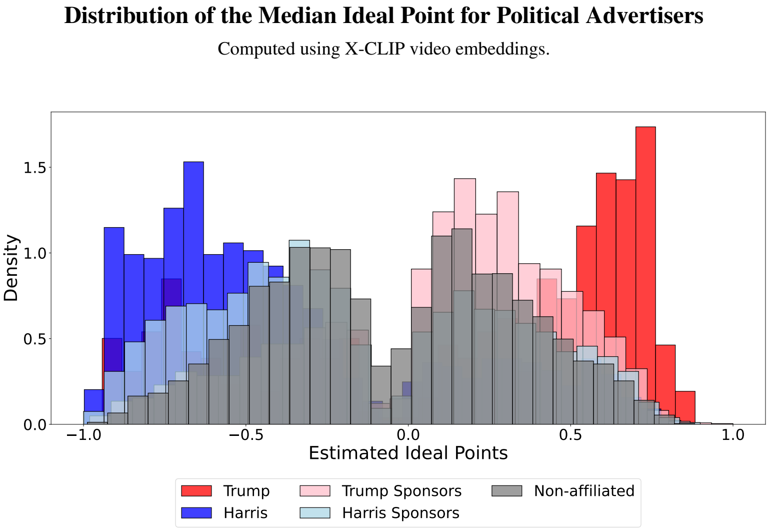
Week of January 1, 2023, through week of November 5, 2024. Analysis by the Brennan Center, OpenSecrets, and Wesleyan Media Project
Source: Google Transparency Reports, Meta Ad Library Reports, FEC, OpenSecrets, and Wesleyan Media Project

Many advertisers are not officially affiliated with a party.

Descriptive Statistics on Political Advertisers Posting Videos on Meta

Party	Amount spent (USD)	%	Number of ads in Library	%
Democrat	129,627,210.05	49.15%	21,508	27.61%
Harris	5,145,304.83	1.95%	725	0.93%
Non-affiliated	65,081,577.69	24.68%	39,533	50.75%
Republican	59,844,786.23	22.69%	15,707	20.16%
Trump	4,013,818.37	1.52%	426	0.55%

Ideal Points of Political Advertisers, US 2024 Election

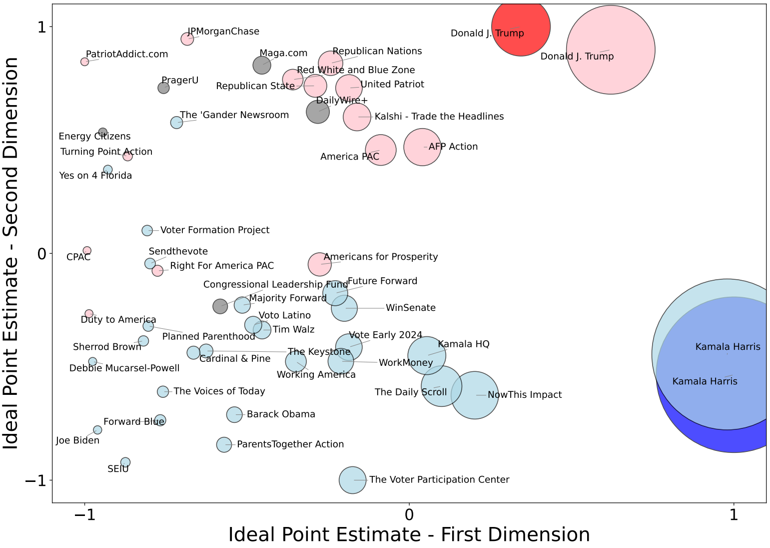


What kind of content is ideological?

Video Descriptions Sorted by Ideal Points

Video Description	Ideal Point
A migrant caravan marches to the U.S. border, waving foreign flags.	0.3740
A family prays at a Thanksgiving dinner table.	0.3001
A farmer warns that government overreach is hurting small businesses.	0.2536
A military parade with soldiers marching, flags waving.	0.1209
A crowd of people wearing red hats and caps.	0.1105
A cowboy on horseback ride across open plains, waving American flags.	0.1015
An activist warns of climate catastrophe through a megaphone.	-0.1472
A woman outside Planned Parenthood shares her abortion rights story.	-0.1956
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 trans woman, bruised and scared, after being attacked.	-0.4637

Relationship with Campaign Contributions



Liberals spent more on Meta platforms.

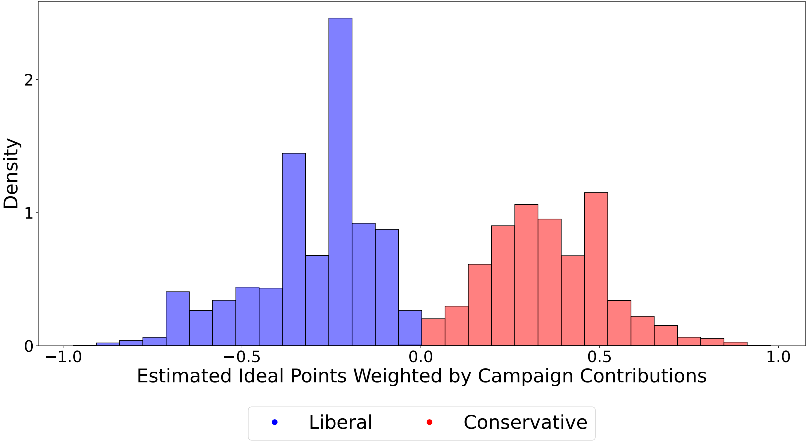


Table of Contents

Concluding Remarks

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

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and we look forward to your feedback.

Thanks for listening!

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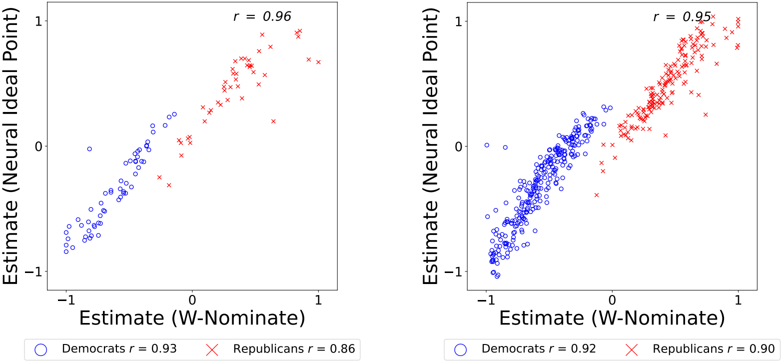
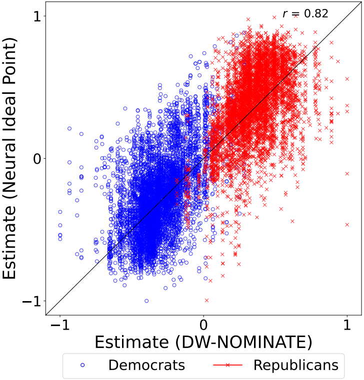
Appendix — W-NOMINATE vs. NIPM (102nd Congress)

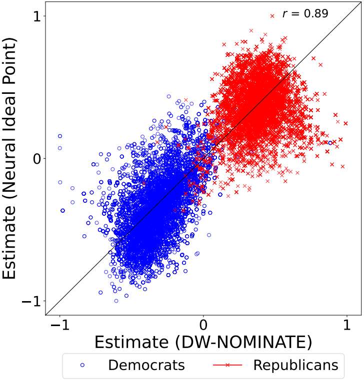
Correlation between W-NOMINATE Estimates and NIPM (102nd Congress)



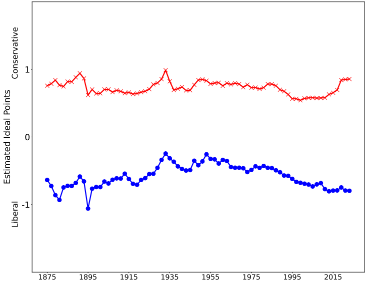
Appendix — W-NOMINATE vs. NIPM (44th–118th Congress)

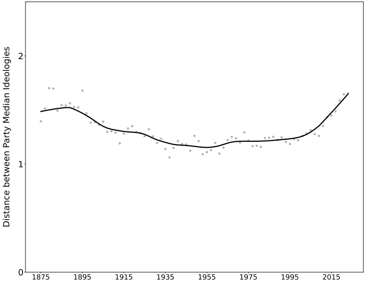
Correlation between W-NOMINATE Estimates and NIPM (44^{th}–118^{th} Congress)



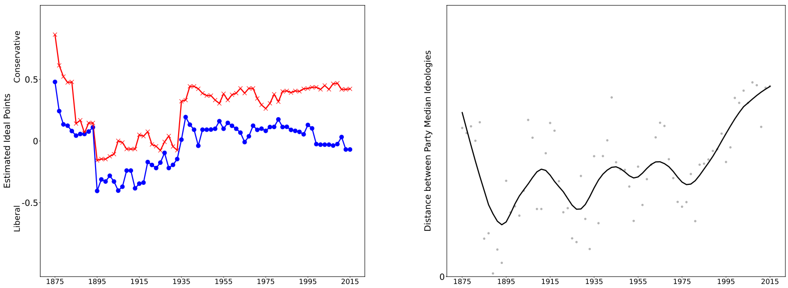


Appendix — Evolution of Party Ideology in US House (Votes)

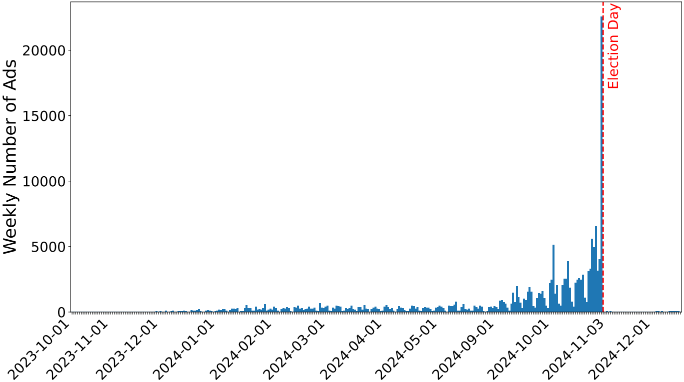




Appendix — Evolution of Party Ideology in US House (Speeches)

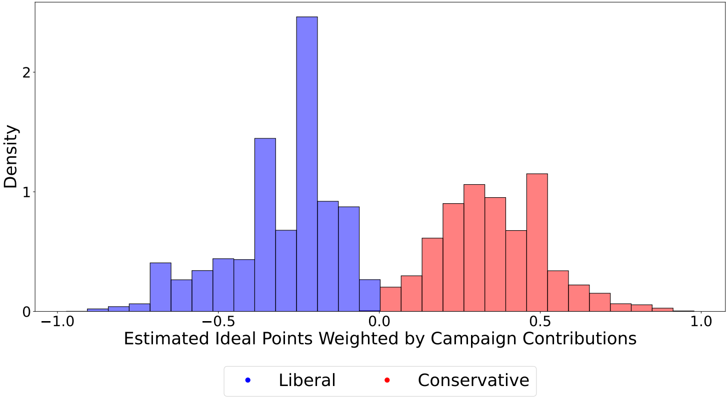


Appendix — Number of Political Ads Over Time



Appendix — Ideal Points Weighted by Money

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



Appendix: Covariate and Outcome Models

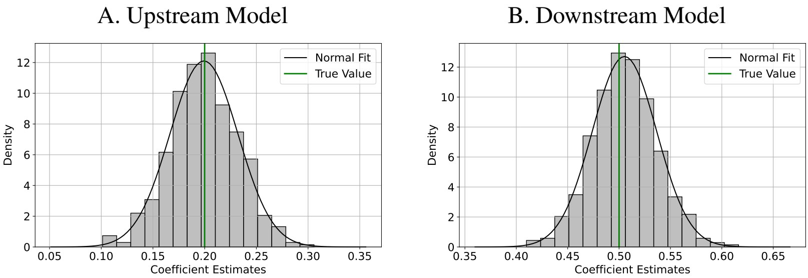
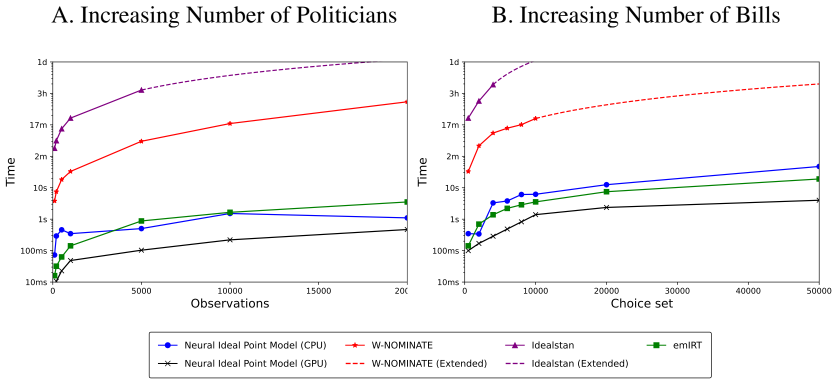


Figure 3. NIPM recovers causal effects well. 500 replications. Vertical green line shows true parameter.

▸ Go back to summary

Appendix: Scalability and Speed

Speed and Scalability for Different Dataset Sizes



Go back to summary

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.

Go back to summary