Revisiting Group Differences in High-Dimensional Choices: Method and Application to Congressional Speech

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Abstract

Gentzkow, Shapiro and Taddy, Econometrica Vol 87, No 4, 2019 (henceforth GST) use a supervised text-based regression model to assess changes in partisanship in U.S. congressional speech over time. Their estimates imply that partisanship is far greater in recent years than in the past, and that it increased sharply in the early 1990s. The paper at hand provides a replication in the wide sense of GST by complementing their analysis in three ways. First, we propose an alternative unsupervised language model, which combines ideas of topic models and ideal point models, to analyze the change in partisanship over time. We apply this model to the Senate speech data used in GST ranging from 1981–2017. Using our model we replicate their results on the specific evolution of partisanship. Second, our model provides additional insights such as the data-driven estimation of evolvement of topical contents over time. Third, we identify key phrases of partisanship on topic level.

Keywords: partisanship, U.S. Senate, text mining, text-based ideal point model, topic model.

1. Introduction

Estimating political positions – so called ideal points – of political key actors has a long tradition in political science (see, e.g., Poole and Rosenthal 1985; McCarty, Poole, and Rosenthal 1997). Gentzkow, Shapiro, and Taddy (2019b) (henceforth GST) contribute to this literature on an aggregate level by proposing a text-based regression model to study to what extent partisanship between political parties, estimated from differences in word usage in speeches, evolves over time. They use transcripts of the speeches given in the U.S. Congress between 1873 and 2016 (Congress Sessions 43 to 114). Their main result is that partisanship in Congress speeches is a relatively recent phenomenon. Its inflection point coincides precisely with innovations in political persuasion in the 1990s formulated under a platform called the Contract with America. Methodologically GST build on Taddy (2013) to learn a predictive model for party given word usage. They also investigate differences in partisanship according to 22 topics which they identified manually based on domain knowledge by assigning key
terms to characterize them.

The paper at hand presents the results obtained with an alternative statistical model to assess the changes in partisanship over time. Our model is a time-varying (TV) extension of the text-based ideal point model (TBIP; Vafa, Naidu, and Blei 2020) (henceforth TV-TBIP). TV-TBIP combines the class of topic models (see Blei, Ng, and Jordan 2003) and text-based ideal point models (see, e.g., Slapin and Proksch 2008; Lauderdale and Herzog 2016). In contrast to the regression-based approach pursued in GST, TV-TBIP is an unsupervised modeling approach where topics are extracted in a data-driven way allowing their evolvement over time.

We apply our model to speeches given in the U.S. Senate in sessions 97–114, i.e., between 1981 and 2017, making use of the speech text data provided as supplementary material by GST\(^1\). Our model estimates for each speaker a session-specific ideological position on a one-dimensional latent scale. This latent scale is shown to primarily capture the party differences. Ideal points capturing the ideological positions thus allow obtaining an aggregate measure of partisanship for each session. In line with GST, we find that Congress Session 105 is the first session where a clear separation between the party-specific distributions of the ideal points is discernible. In contrast to GST, our model provides partisanship estimates on the speaker level and these individual ideological positions allow to infer which speakers are at the extremes of the latent scale or rather centrally located and to track changes of their ideological positions over time. TV-TBIP extends the approach taken in GST by estimating the topics in a data-driven way. In addition, TV-TBIP also allows term compositions of topics to change over time to account for newly emerging or subduing sub-themes within a topic. This is particularly important when analyzing more than 40 years of speeches given in the U.S. Senate.

The paper is organized as follows: Section 2 introduces the time-varying text-based ideal point (TV-TBIP). Section 3 discusses the results and insights gained from fitting the TV-TBIP model and contrasts to them to those in GST. Finally, Section 4 concludes.

2. The Time-Varying Text-Based Ideal Point Model

The TBIP model proposed in Vafa et al. (2020) assumes that documents are composed of a fixed set of topics (latent themes) where ideological differences of the authors influence the term compositions of topics. Considering a corpus of speeches covering an extensive time period of about 40 years, we extend the TBIP model to a time-varying version which allows the term compositions of the topics as well as the individual ideological positions to adapt over time.

2.1. Model Specification

The available data for each session or time point \(t\) consist of the text of the speeches given as well as the information on the speaker giving the speech. Based on the bag-of-words assumption, the speech data are summarized in a document-term matrix \(c_t\). This matrix

\(^1\)GST use hein-daily and hein-bound transcripts (see https://data.stanford.edu/congress_text), where hein-bound covers the time period 1873–2011 and hein-daily 1981–2017. Given the focus on partisanship during the 1990s and later in GST, we make only use of the hein-daily speeches covering 1981–2017 in our analysis.
contains the frequency counts of the terms in each speech at time point $t$ with the number of rows corresponding to the number of speeches and the number of columns to the vocabulary size. The speaker information is combined in the vector $s_t$ with length equal to the number of speeches.

The parameters and latent variables inferred in the TV-TBIP model for each time point $t$ consist of document-specific topic prevalences $\theta^t$, topic-specific term prevalences for neutral speakers $\beta^t$, topic-specific polarity scores for the terms $\eta^t$ and individual ideal points (positions) of the speakers $x^t$. The matrix of topic distributions at time point $t$, $\theta^t$, has dimension number of speeches times number of topics. The matrix $\beta^t$ is of dimension number of topics times number of topics. The matrix $\eta^t$ has the same dimension as $\beta^t$ and the vector of ideal points $x^t$ has the length of the number of speakers at time $t$.

The TV-TBIP model assumes that the observed frequencies of the terms in the speeches are generated independently from a Poisson distribution, i.e., the frequency count $c^t_{iv}$ at time point $t$ for speech $i$ and term $v$ is generated by:

$$c^t_{iv} \sim \text{Pois}(\sum_{k=1}^{K} \theta^t_{ik} \beta^t_{kv} \exp(x^t_s \eta^t_{kv})).$$

The Poisson rates are derived as linear combinations of contributions from the $K$ topics where $\theta^t_{ik}$ is the topic prevalence of topic $k$ in speech $i$ at time point $t$ and $\beta^t_{kv}$ is the term prevalence of term $v$ in topic $k$ at time point $t$ of a neutral speaker, i.e., these term prevalences characterize “neutral topics”.

For each speaker $s$, the ideological position is encapsulated in the ideal point $x^t_s$. For a neutral speaker with $x^t_s = 0$ the model reduces to the simple Poisson factorization topic model (Canny 2004). With ideological positions departing from the neutral one, the Poisson rates of the terms for each of the topics also differ from the neutral one. If the ideal point $x^t_s$ and the prevalence modification $\eta^t_{kv}$ at time point $t$ for term $v$ and topic $k$ have the same sign, a speaker will more often use this term when talking about this topic compared to a neutral speaker. If they have opposite signs, usage of that term for this topic is decreased compared to someone who is neutral. The TV-TBIP model assumes that the polarity of a speaker captured by the ideal points influences their word choice for a specific topic, i.e., the term prevalences of a specific topic differ between a negative, a neutral and a positive speaker. By contrast, the model assumes that ideal points do not impact on the topic prevalences, i.e., a negative, a neutral and a positive speaker talk to a similar extent about each of the topics.

### 2.2. Model Estimation

We estimate the model within a Bayesian framework. The parameters and latent variables are assumed to be independent and identically distributed with the same prior settings used for each time point, speech, term and topic as well as speaker. The priors for the topic and term prevalences $\theta^t_{ik}$ and $\beta^t_{kv}$ are assumed to follow independent Gamma distributions with potentially different hyperparameters for $\theta^t_{ik}$ and $\beta^t_{kv}$, but identical Gamma distributions for all sessions $t$, speeches $i$, terms $v$ and topics $k$:

$$\theta^t_{ik} \sim \text{Gamma}(\alpha_1, \alpha_2), \quad \beta^t_{kv} \sim \text{Gamma}(\gamma_1, \gamma_2).$$

Careful selection of the parameters of the Gamma distributions is required in order to induce a suitable sparsity in the topic prevalences of the speeches and in the term prevalences of
the topics. Sparsity implies that each speech consists of a small number of topics and that each topic is characterized by a few terms with high prevalence values. The choice of these hyperparameters impacts on the specific solution obtained. Here we follow Vafa et al. (2020) and set $\alpha_1 = \alpha_2 = 0.3$ and $\gamma_1 = \gamma_2 = 0.3$. To facilitate interpretability of the topics obtained, such a sparsity characteristic is desirable. In addition, this alleviates the issue of non-identifiability which topic models are known to suffer from and which we would expect to also be an issue for TV-TBIP. For non-identifiable topic models, Ke, Olea, and Nesbit (in press) highlight the importance of selecting suitable priors which support to prefer a specific parameterization among those inducing the same likelihood.

The topic polarity scores and ideal points $\eta_{kv}$ and $x_s$ can take arbitrary values, negative as well as positive. To reflect this unrestricted support, standard normal distributions are imposed as their priors. This means that for all sessions $t$, terms $v$, topics $k$, and speakers $s$, we assume independent distributions given by:

$$\eta_{kv} \sim \text{Normal}(0,1), \quad x_s \sim \text{Normal}(0,1).$$

Restricting the mean values to zero implies that an average speaker in the latent dimension is viewed as a neutral speaker and the average intensities across the latent dimension correspond to the neutral topic intensities. Setting the variance to one improves identifiability of the model, as this fixes the possible within-topic variability due to changes in the polarity of the speaker.

The parameters and latent variables are estimated for each session separately by approximating their posterior distribution given the priors and the observed data. The posterior of interest $p(\theta_t, \beta_t, \eta^t, x^t | c_t, s_t)$ is not available in closed-form and it is also computationally intractable to directly obtain estimates from the posterior. One thus usually resorts to approximation using variational inference (Blei, Kucukelbir, and McAuliffe 2017). Using variational inference, the parameters and latent variables are estimated based on an approximation of the posterior obtained by minimizing the Kullback-Leibler divergence between the posterior and a variational distribution. Point estimates are obtained by considering the posterior means implied for the parameters and latent variables by the fitted variational distributions.

This model specification and estimation scheme enables the derivation of session-specific parameter and latent variable estimates which captures differences and adaptations over time. However, we are also interested in linking topics as well as the latent space over time. This is particularly relevant due to the identifiability issues present for the TBIP model, i.e., neither the topics nor the latent space are identifiable. To obtain a time-varying version of the TBIP model, where the parameters are congruent across time, we make use of a step-wise initialization approach across sessions where the estimates obtained in the previous session are used as initial values in the next session as far as possible when using a general purpose optimizer to minimize the Kullback-Leibler divergence which requires some initial values to be provided anyway.

In the first session, no previous results are available and non-negative matrix factorization (NMF; Lee and Seung 1999) is used to initialize the variational parameters for $\theta^1$ and $\beta^1$. The input to the NMF algorithm is the document-term matrix of the first session (i.e., $c^1$), which is approximated as the product of the topical prevalence matrix $\theta^1$ and topical content matrix $\beta^1$, i.e., $c^1 \simeq \theta^1 \beta^1$. These two matrices obtained with NMF are first ensured to only contain positive entries and then the logarithm is taken. The resulting values are used to
initialize the means of the log-normal distributions used as variational distributions for these parameters.

For each subsequent session with time index $t \geq 2$, the estimated posterior means of the term prevalence vectors of the topics $\beta_{t-1}^k$ are used to initialize the mean parameters of the corresponding variational parameters in the TV-TBIP model. These estimated prevalences are also used as input in the NMF algorithm together with the document-term matrix $c^t$ such that only the initial values for the topic distributions $\theta^t$ of the speeches are determined in this step, i.e., $c^t \simeq \theta^t \beta_{t-1}$ is used for initialization. In addition, the estimated values of $\eta_{t-1}^k$ are put forward as the means of the Gaussian variational family of $\eta_k^t$. Specifying the initial values in this way ensures that the term prevalences of topics and the topic-specific polarity scores are aligned across sessions preventing, for example, label switching of topics and reversing of the latent space\textsuperscript{2}. For more details on the model estimation, we refer to the Online Appendix.

3. 40 Years of Political Discourse in the U.S. Senate

We use the Stanford University Social Science Data Collection database for our analysis (Gentzkow, Shapiro, and Taddy 2018). This database was also used in GST and provides pre-processed text data on the speech level from the United States Congressional Record, covering Congress sessions 97 to 114 (1981–2017). We use all speeches given in the U.S. Senate and implement pre-processing steps similar to GST and Vafa et al. (2020) to obtain session-specific document-term matrices, using bigrams as tokens and retaining only those used by at least 10 speakers per session. We also only retain speakers with at least 24 speeches per session. Our model is fitted using 614,613 speeches given by 355 unique speakers, assuming 25 topics per session. This is in line with GST who manually identified 22 substantive topics based on their knowledge of the database. More details on data pre-processing and implementation of the estimation are given in the Online Appendix.

3.1. Average Partisanship

We inspect the session- and party-specific distributions of the estimated ideal points to assess if the latent scale in fact differentiates between Democrat and Republican speakers for each session. Figure 1 (left) summarizes these ideal point distributions based on box-plots. Note that the ideal points are a-priori assumed to be standard normally distributed with the mean zero indicating a neutral speaker. The values of the estimated ideal points may thus be interpreted as reflecting the degree of partisanship of the speakers with the distance of the ideal point from zero indicating the deviation of the speaker from a neutral speaker in the unit of standard deviations. For each session, a pair of box-plots is displayed for the two parties. This provides a means to compare the party-specific locations based on the medians and assess the overlap based on the boxes. Clearly the boxes overlap strongly in the first sessions, while boxes do not overlap after session 105.

To study the evolvement of average partisanship across Congress sessions, we determine an estimate of the average partisanship between the parties over time by aggregating the point estimates of the ideological positions $\hat{x}_s^t$ of the speakers across parties. For each session, we

\textsuperscript{2}This modeling approach has also been pursued to study central bank communication in the euro area (see Feldkircher, Hofmarcher, and Siklos 2024).
calculate the mean of the estimated ideal points separately for the members of each party and take the difference. I.e., the average session-specific partisanship for session $t$ is determined using

$$\bar{\pi}^t = \left| \frac{1}{N^t_R} \sum_{s \in I^t_R} \hat{x}^t_s - \frac{1}{N^t_D} \sum_{s \in I^t_D} \hat{x}^t_s \right|,$$

(2)

where $N^t_R$ and $N^t_D$ are the number of Republican and Democrat speakers with ideal point estimates available for session $t$ and $I^t_R$ and $I^t_D$ denote the index sets for those speaker groups. This approach neglects the uncertainty of the Bayesian point estimates and treats the estimates of these latent variables as if they were observed. Alternatively, a fully Bayesian approach could also be pursued.

Figure 1 (right) depicts the evolvement of these average partisanship estimates over time and corroborates the key results of GST. The gray shaded area represents the approximate pointwise 95% confidence intervals. These confidence intervals are obtained using $\bar{\pi}^t \pm 1.96 \times \sqrt{\frac{(\hat{\sigma}^t_D)^2}{n^t_D} + \frac{(\hat{\sigma}^t_R)^2}{n^t_R}}$, where $\hat{\sigma}^t_D$ and $\hat{\sigma}^t_R$ are the sample standard deviations of the estimated point estimates for the ideal points for each party. In line with GST, the TV-TBIP model does not detect any noteworthy partisanship in the speeches given in the U.S. Senate before the 1990s. However, at the beginning of the 1990s, the estimated average partisanship between Democrats and Republicans increases rapidly and peaks around 2010. This pattern of evolvement of partisanship closely follow the results obtained using the supervised model proposed in GST (see Gentzkow, Kelly, and Taddy 2019a, Figure 2 on p. 1321). The Online Appendix provides results of a simulation study where the same estimation method is used for analysis. New document-term matrices for each session are generated based on the estimated posterior mean estimates and varying the distribution of ideal points across parties and sessions to induce no, fixed and increasing party differences as well as re-using the estimated ideal points for the speakers across sessions. These results confirm the suitability of the proposed approach to infer the evolvement of partisanship across sessions.

In line with GST, we also validate our aggregate measure of partisanship by comparing it with the first dimension of the DW-Nominate scores estimated from voting data (see, e.g.,
Poole and Rosenthal 1985). In particular, we take the difference between the average DW-Nominate scores of Republicans and Democrats. We find a correlation of 0.77 indicating that our text-based average partisanship measure captures essentially the same effect over time as the vote-based DW-Nominate scores. The Online Appendix provides more details on the timely evolvement of ideological positions on speaker level.

Our model tracks the timely evolvement of ideological positions on individual speaker level. Due to the pronounced partisanship from session 105 onwards, we focus in the following analysis on results from session 105 and later (see also the Online Appendix for more details). We determine the average ideal point score for each speaker across all sessions they were in the Senate during this time period. These results indicate that the most liberal Democrats in this time period are Byron Dorgan, Dale Bumpers, Thomas Harkin, Christopher Murphy and Paul Wellstone. The same analysis for the Republican party shows that TV-TBIP identifies Jesse Helms, a Senator from North Carolina, as the most conservative Republican. This is in line with how this Senator is depicted in the media, e.g., the New York Times (see Holmes 2008) stated that Helms was “bitterly opposed” to federal financing for research and treatment of AIDS which he believed was God’s punishment for homosexuals (see, e.g., Noden 2007). According to the DW-Nominate score, Jesse Helms is also ranked as the most conservative Republican for, e.g., sessions 106 and 107.

3.2. Temporal Change, Drivers of Partisanship and Partisan Phrases

GST requires manual specification of the topics based on domain knowledge. TV-TBIP facilitates the inference of topics in a data-driven manner, thereby enabling an extension where topical content can change over time.

Temporal Change of Topical Content

Topics are usually characterized by their top most frequent terms, and in the following, we refer to the topic-specific term distribution which is used by a neutral speaker, i.e., a speaker with ideal point \( x_t^d = 0 \), as the neutral topic. Table 1 displays the five most frequent terms of the neutral topics for the first and the last session considered. The sessions at both ends of the time frame are shown to highlight the overall evolvement of each of the topics over time.

Table 1 indicates that the first topic is mainly concerned with the United States. This bigram has by far the highest appearance rate (approximately 0.3 for both sessions\(^3\)) across all bigrams in the vocabulary. The additional bigrams listed as having the highest appearance rates for Topic 1 indicate that this topic is about the United States and their concerns with other states such as international trade, foreign relations, trade agreements. Selectively characterizing some other topics, one can discern that Topic 8 is about foreign policies in the Middle East and its most frequent terms changed from saudi arabia, foreign policy to al quaeda, islamic state from the first to the last session; Topic 12 is about taxes in general, but moves from a discussion on tax cuts to focus more on taxation and the middle class from the first to the last session. Of specific interest is also Topic 11, which represents a climate change/public health topic. For this topic, nuclear waste is a prevalent term in session 97, which changes to climate change being a prevalent term in session 114. Figure 2 displays the evolvement of that topic using word clouds across all sessions. It changed from the discussion of nuclear waste over acid rain to climate change and public health related issues.

\(^3\)Indeed, we observe a similarly high value for all sessions.
To assess stability of topic composition in a systematic way, we determine the cosine similarity between the estimated term intensities of the same topic for two consecutive sessions. Figure 3 on the left displays a heat map of these cosine similarities. The topics are sorted by their mean cosine similarity with the most stable one being on the top and the most volatile one at the bottom. For this comparison, the term intensities of the neutral topics were used. On the top, we find Topic 1 (the United States topic) which is the most stable topic over time. Other topics with stable topical content over time are Topic 14, which is concerned with the federal government. In term composition of topics occurs for Topic 23 from session 112 to 113 with still quite a substantial change in term composition to the subsequent session 114. Inspecting the most volatile terms for Topic 23 for sessions 112 and 113 indicates that the term national security is substituted by homeland security and even more important immigration issues started to be also raised in that topic.4

**Topics as Drivers of Partisanship**

In the following we analyze which topics are main drivers of partisanship. We create again a heat map of the cosine similarity matrix, this time comparing the term frequencies of positive and negative topics for each topic and session. The term prevalences of the positive and negative topics are determined using an ideal point of 1 (i.e., liberal) and −1 (conservative). The results are displayed in Figure 3 on the right. Topics are again sorted by their mean cosine similarity with the least polarizing being on the top and the most polarizing one at the bottom.

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4Note that similar observations have also been discussed in https://www.everycrsreport.com.
We find that Topic 1 is the most “neutral”, i.e., the topic where the differences between the terms used by liberal and conservative speakers are smallest. In addition we also observe low discordance for Topic 14 which is about the federal government and Topic 17 which is about war veterans. Topic 11 on climate change/public health is close to the bottom of the heat map in Figure 3 on the right, indicating that there is less congruence in the wording of Democrats and Republican when talking about these issues. The same holds for Topic 21, another energy topic which is ranked as the third least congruent topic. Only Topic 9 (which is about government shutdowns and budget control) and Topic 16 (which appears to be a derivation thereof) have a lower concordance.
Partisan Phrases

GST present estimated partisan phrases for selected periods, i.e., phrases which allow to differentiate most between a Republican and a Democrat speaker (see Table 1 on p. 1325 which provides the 10 most important partisan phrases for every 10th session). In the TV-TBIP model, partisan phrases emerge on the topic level because the term distributions of the topics are influenced by the polarity scores and the ideal points of the speakers. To identify partisan phrases on topic level, we inspect the term compositions of the topics for a liberal speaker with ideal point value 1 and a conservative one with ideal point value −1. More formally, we compare the term distribution $\beta \exp(\eta)$ with $\beta \exp(-\eta)$. Table 2 displays the most frequent terms of each topic for these speakers.

In this analysis, our focus is on session 114, which occurs at the end of the observation period and where the latent dimension distinctly enables discrimination between Republican and Democrat speakers. In line with GST, who identify puerto rico as a partisan phrase, we also see that puerto rico is among the most frequent positive or negative terms for Topics 1, 17 and 24. E.g., for Topic 17 we estimate an appearance rate of 0.049 for Democrats and 0.03 for Republicans. GST find rates of 42 (R) and 79 (D) per 100,000 phrases. Further, also in line with GST, religious freedom appears among the most frequent term only for Republicans. GST find this term to appear 34 times per 100,000 phrases for Republicans and 4 times for Democrats. The TV-TBIP results also highlight the topic where this word appears, i.e., Topic 22.

In addition to GST, e.g., our results indicate that for Topic 21 – which is about natural resources and energy – a speaker with a positive, i.e., a liberal, ideal point uses terms like energy efficiency or clean energy when talking about this topic while a conservative one uses terms like keystone xl (a pipeline project by TC Energy) or energy security. For Topic 5, which is about monetary policy, we find on the liberal side terms like financial crisis and consumer protection but on the conservative side banking housing and monetary policy.
Topic 11, which is about climate change/public health, the term climate change is used three times more often by a speaker with ideal point 1 compared to one with −1. GST also detect climate change as a partisan phrase with 94 (D) and 23 (R) appearances per 100,000 phrases.

4. Conclusion and Discussion

This study replicates GST in a wide sense through an alternative modeling approach, analyzing U.S. Senate speeches from 1981 to 2017. The differences of our approach compared to GST are threefold: Firstly, TV-TBIP combines the class of topic models with ideal point models. Thus, researchers do not have to manually specify topics a-priori using key terms. Secondly, our approach is unsupervised. This implies it can also be used to analyze data for which no information about author positions is known hitherto as pre-labeling is not required (party membership). Thirdly, our model is able to detect the accordance of political parties on topic level through polarity- and topic-specific term distributions in a time-dynamic way.

Our results highlight a sharp rise in partisanship during the 1990s, which aligns with GST’s conclusions. By inspecting individual ideal points, we compare Senators’ positions on a latent scale. We also observe shifts in topic content over time. The climate change/public health topic emerges as a significant driver of partisanship, showing high term discordance between parties, while the natural resources and energy topic also differentiates between speakers across party lines. In contrast, some topics, like war veterans, display similar term compositions across both parties.

This sets the scene for further research which could include, e.g., alternative ways of modeling time variation in this model framework (see Vávra, Grün, and Hofmarcher 2024a) or the incorporation of speaker-specific covariates that influence ideological positions (see Vávra,
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A. More Details on the TV-TBIP Model

A.1. Variational Inference

Performing inference for a Bayesian model such as ours consists of determining the posterior distribution of the parameters and latent variables. Analytical solutions for the posterior distribution are usually only available for very simple models. Alternative approaches rely on computational methods to approximate the posterior distribution. Markov chain Monte Carlo methods enable to sample from the posterior by constructing a Markov chain where the stationary distribution corresponds to the posterior distribution. Due to the computational challenges of Markov chain Monte Carlo methods when used for large latent variable models, variational inference has emerged as the preferred method to approximate the posterior for such models.

Variational inference is a technique that solve the estimation problem by approximating the true posterior distribution with a simpler, more tractable distribution. Instead of relying on sampling such as Markov chain Monte Carlo methods, variational inference recasts the inference problem as an optimization problem. The core aspect in variational inference consists of specifying a family of approximate densities $Q$ for the latent variables. Variational inference aims at determining the density within this family that minimizes the Kullback-Leibler (KL) divergence to the exact posterior. In the following, to simplify notation for describing variational inference, we drop any time indices of our model. Let $q_{\phi}(\vartheta, \theta, \beta, \eta, x) \in Q$ be an approximate density with parameters $\phi$ for the true posterior density $p(\theta, \beta, \eta, x | y)$, with $\theta, \beta, \eta, x$ denoting parameters and latent variables, and $y$ represent the observed data, e.g., consisting of the frequency counts $c$ and the speaker information $s$. In the following to further simplify notation, we use $\vartheta$ to denote the set of all parameters and latent variables, i.e., $\vartheta = \{\theta, \beta, \eta, x\}$.

The goal is to find the best approximation $q_{\phi^*}(\vartheta)$ by optimizing the parameters $\phi$ of the approximate density. This is typically done by minimizing the Kullback-Leibler (KL) divergence between $q_{\phi}(\vartheta)$ and $p(\vartheta | y)$. Formally, the objective function for variational inference can be expressed as:

$$\arg \min_{\phi} \text{KL}(q_{\phi}(\vartheta) || p(\vartheta | y)),$$

where $\text{KL}(\cdot || \cdot)$ denotes the Kullback-Leibler divergence which may also be written as

$$\text{KL}(q_{\phi}(\vartheta) || p(\vartheta | y)) = \mathbb{E}_{q_{\phi}(\vartheta)}(\log(q_{\phi}(\vartheta))) - \mathbb{E}_{q_{\phi}(\vartheta)}(\log(p(\vartheta, y))) + \log(p(y)).$$

The evidence $p(y) = \int p(\vartheta, y) d\vartheta$ is usually unavailable in closed form. However, the evidence also does not depend on $\phi$. Dropping the log evidence and taking the negative results in the Evidence Lower Bound (ELBO) which can thus be maximized to minimize the KL divergence:

$$\text{ELBO}(\phi) = \mathbb{E}_{q_{\phi}(\vartheta)}[\log p(\vartheta, y)] - \mathbb{E}_{q_{\phi}(\vartheta)}[\log q_{\phi}(\vartheta)].$$

For more details we refer to Blei et al. (2017).

A.2. Variational Families for TV-TBIP

The variational family needs to provide sufficient flexibility to be able to closely approximate the posterior. For estimating the TV-TBIP model, a mean-field variational family is used. Let
$q_{\phi^t}(\theta^t, \beta^t, \eta^t, x^t)$ be the variational family for time point $t$, indexed by variational parameters $\phi^t$. Using a mean-field variational family implies that the variational family factorizes over the latent variables, where $i$ indexes speeches, $k$ indexes topics, and $s$ indexes authors:

$$q_{\phi^t}(\theta^t, \beta^t, \eta^t, x^t) = \prod_i q(\theta^t_i) \prod_k q(\beta^t_k) \prod_k q(\eta^t_k) \prod_s q(x^t_s).$$

We use log-normal variational distributions if the variables have positive support and Gaussian variational distributions for variables with unrestricted support:

$$\theta^t_{ik} \sim \text{LogNormal}(\mu_{\theta^t_{ik}}, \sigma_{\theta^t_{ik}}^2), \quad \beta^t_{kv} \sim \text{LogNormal}(\mu_{\beta^t_{kv}}, \sigma_{\beta^t_{kv}}^2),$$

$$\eta^t_{kv} \sim \text{Normal}(\mu_{\eta^t_{kv}}, \sigma_{\eta^t_{kv}}^2), \quad x^t_s \sim \text{Normal}(\mu_{x^t_s}, \sigma_{x^t_s}^2).$$

The complete set of variational parameters is thus given by $\phi^t = \{\mu_{\theta^t_{ik}}, \sigma_{\theta^t_{ik}}^2\}_i, \{\mu_{\beta^t_{kv}}, \sigma_{\beta^t_{kv}}^2\}_k, \{\sigma_{\beta^t_{kv}}^2\}_k, \{\mu_{\eta^t_{kv}}, \sigma_{\eta^t_{kv}}^2\}_k, \{\mu_{x^t_s}, \sigma_{x^t_s}^2\}_s$. These variational parameters are determined by maximizing the Evidence Lower BOund (ELBO) which is equivalent to minimizing the Kullback-Leibler divergence:

$$\mathbb{E}_{q_{\phi^t}}[\log p(\theta^t, \beta^t, \eta^t, x^t) + \log p(c^t, s^t|\theta^t, \beta^t, \eta^t, x^t) - \log q_{\phi^t}(\theta^t, \beta^t, \eta^t, x^t)].$$

Based on the estimated variational parameters, point estimates of the model parameters and latent variables are obtained using the posterior means induced by the estimated $\phi^t$ values. The maximization of the ELBO is performed using a general purpose optimizer, where initial values need to be provided. More details are given in Vafa et al. (2020).

### A.3. Computational Details

The analysis is performed using Python 3.7 (van Rossum et al. 2011), Tensorflow 1.15 GPU (Abadi, Agarwal, Barham, Brevdo, Chen, Citro, Corrado, Davis, Dean, Devin, Ghemawat, Goodfellow, Harp, Irving, Isard, Jia, Jozefowicz, Kaiser, Kudlur, Levenberg, Mané, Monga, Moore, Murray, Olah, Schuster, Shlens, Steiner, Sutskever, Talwar, Tucker, Vanhoucke, Vasudevan, Viégas, Vinyals, Warden, Wattenberg, Wicke, Yu, and Zheng 2015) and scikit-learn 1.0.2 (Pedregosa, Varoquaux, Gramfort, Michel, Thirion, Grisel, Blondel, Prettenhofer, Weiss, Dubourg, Vanderplas, Passos, Cournapeau, Brucher, Perot, and Duchesnay 2011). Running the optimizer with GPU support considerably reduces runtime. For optimizing the ELBO function we make use of the Adam optimizer (Kingma and Ba 2015) using 300,000 iterations per session. Inspection of the ELBO values indicated convergence after about 100,000 iterations.

### B. More Details on Data and Analysis

#### B.1. Data Description and Pre-processing

The Stanford University Social Science Data Collection database (Gentzkow et al. 2018) provides already processed text data from the United States Congressional Record. The speeches given by members of the U.S. Congress have been parsed and are stored as transcripts.
of the full-text speeches together with some related metadata information such as details about the speaker. We use the “daily edition” of the Senate speeches in the database for our analysis which covers sessions 97 to 114 (1981–2017) and provides data on the speech level.

Following GST and Vafa et al. (2020), a number of pre-processing steps were performed to obtain session-specific document-term matrices with an aligned vocabulary from the files containing the transcribed full-text speeches. First, we removed punctuation and numbers, changed the text to lower-case and eliminated stop words. For tokenization, we followed GST and also used bigrams. Gentzkow et al. (2019a) argue that in certain applications such as the analysis of partisan speech, single words are insufficient to capture all important aspects. They point out that at least bigrams are required to capture a limited amount of the dependence between words and they also emphasize that bigrams are better able to gather overtones and ideological phrases. In addition, using bigrams instead of single terms enhances interpretability of the resulting topics when inspecting the topic-specific term prevalences.

For each session, we considered speeches given by Senators as well as external speakers, such as House Representatives. We removed speakers who gave less than 24 speeches in a particular session as well as bigrams which were used by less than 10 speakers in a particular session (cf. Vafa et al. 2020). Finally, speeches resulting in an empty frequency count, i.e., an empty row in the document-term matrix, were omitted from further analysis. The complete vocabulary spanning all the sessions from session 97 to 114 resulting from these pre-processing steps consists of 12,527 unique bigrams.

Prior to these pre-processing steps, the dataset of the Senate speeches contains 1,262,273 speeches given by 1,142 unique speakers. After pre-processing we are left with 614,613 speeches given by 355 unique speakers (including Senators and external speakers) over a period of 18 sessions, i.e., during the years 1981 until 2017. Table 3 displays summary statistics of the original data before pre-processing as well as the data obtained after pre-processing which was then used for estimating the TV-TBIP model.

B.2. Practical Implementation of Model Specification and Estimation

Following GST, we set the number of topics equal to 25 and specify this number to be equal across sessions. We want to emphasize that there is no “true” number of topics (see, e.g., Roberts, Stewart, and Tingley 2019). Estimating only few topics implies that topical content is very “wide”, while a large number of topics might result in very granular and maybe overlapping topics. In contrast to GST, we allow the topical content to change over time with the term distributions of the topics being allowed to be session-specific.

To complete the model specification, we also have to fix the parameters of the prior distributions of the topic prevalences $\theta^t$, the term prevalences $\beta^t$ as well as the polarity scores $\eta^t$ and the ideal points $x^t$. We use standard normal priors for $\eta^t$ and the ideal points $x^t$. Both the topic prevalences as well as the topic-specific term prevalences follow a-priori Gamma priors. Selecting the parameters of these Gamma priors is crucial to induce sparsity in the topic distributions of the speeches as well as the term distributions of the topics. We follow Vafa et al. (2020) for the parameter settings of these priors: We use the same parameter values for both priors, i.e., $\alpha_1 = \gamma_1$ and $\alpha_2 = \gamma_2$. In addition we use the same parameter values for shape and rate of the Gamma distribution, which implies that the prior mean is equal to 1. The specific values selected for the parameters are $\alpha_1 = \alpha_2 = 0.3$, i.e., a value smaller than one is used which is crucial for sparsity and which implies a prior variance of $1 / 0.3$. 
Revisiting Group Differences in High-Dimensional Choices

| Session | Speakers before | Senators before | Speeches before | ∅ Speeches before | Speakers after | Senators after | Speeches after | ∅ Speeches after |
|---------|-----------------|-----------------|-----------------|------------------|----------------|----------------|----------------|------------------|
| 97      | 376             | 118             | 101             | 100              | 110980         | 47088          | 295.16         | 399.05           |
| 98      | 347             | 121             | 101             | 100              | 97755          | 42608          | 281.71         | 352.13           |
| 99      | 304             | 104             | 101             | 100              | 107774         | 49271          | 354.52         | 473.76           |
| 100     | 302             | 105             | 101             | 100              | 108618         | 49707          | 359.66         | 473.40           |
| 101     | 366             | 103             | 103             | 101              | 90024          | 44247          | 245.97         | 429.58           |
| 102     | 334             | 103             | 103             | 101              | 82233          | 42234          | 246.21         | 410.04           |
| 103     | 346             | 103             | 105             | 101              | 83742          | 40957          | 242.03         | 397.64           |
| 104     | 244             | 103             | 102             | 101              | 89763          | 42879          | 367.88         | 416.30           |
| 105     | 191             | 100             | 100             | 100              | 66512          | 33591          | 348.23         | 335.91           |
| 106     | 200             | 101             | 100             | 99               | 66855          | 33833          | 334.28         | 334.98           |
| 107     | 212             | 100             | 101             | 99               | 62267          | 30895          | 293.71         | 308.95           |
| 108     | 150             | 100             | 100             | 99               | 65776          | 33571          | 348.51         | 335.71           |
| 109     | 170             | 101             | 100             | 100              | 53404          | 27842          | 314.14         | 275.66           |
| 110     | 151             | 102             | 102             | 100              | 51919          | 27385          | 343.83         | 268.48           |
| 111     | 208             | 104             | 109             | 100              | 37728          | 20236          | 181.38         | 194.58           |
| 112     | 126             | 100             | 101             | 97               | 32924          | 18421          | 261.30         | 184.21           |
| 113     | 114             | 100             | 105             | 98               | 29721          | 16249          | 260.71         | 162.49           |
| 114     | 111             | 99              | 100             | 97               | 24278          | 13599          | 218.72         | 137.36           |

Table 3: Number of speakers (including Senators and external speakers), number of Senators, number of speeches and average number of speeches per speaker for each session before and after pre-processing.

B.3. Assessing Model Estimation in a Simulation Study

We performed a simulation study to assess the performance of the proposed model estimation scheme. We exploited the fact that TV-TBIP model is a generative model and used the posterior mean estimates of the parameters obtained when applying the estimation scheme to the U.S. Senate data from sessions 97–114 to draw new document-term matrices for each session. To avoid extreme rates for the counts, the estimated topic polarity scores were winsorized to be within $-1$ and $+1$.

We considered four different scenarios which varied in the distribution of the ideal points used across the Democrat and Republican speakers:

1. **No party differences**: The ideal points were identical to zero for all speakers across all sessions.

2. **Fixed party differences**: The ideal points of Democrat speakers were fixed to $-0.5$ and those of the Republican speakers to $+0.5$ for all speakers of the party across all sessions.

3. **Increasing party differences**: The ideal points of Democrat and Republican speakers were set to zero for all speakers until session 100 and starting from session 101 gradually diverged by a linear decrease of 0.05 for each session for Democrats and a linear increase of 0.05 for each session for Republicans inducing an ideal point of $-0.7$ for Democrats and of $+0.7$ for Republicans in the last session.
Figure 4: From top to bottom: no party differences, fixed party differences, increasing party differences, estimated party differences. For each scenario: party- and session-specific ideal point distributions represented as box-plots. Estimated average partisanship over the years together with approximate pointwise 95% confidence intervals (right).
(4) *Estimated party differences*: The estimated ideal points for the Democrat and Republican speakers in the U.S. Senate for each session were used.

We used the same estimation method as for the empirical application on the U.S. Senate data. The results are obtained using a different computing environment than for the empirical application and are based on Python 3.6.13, Tensorflow 1.15 GPU and scikit-learn 0.24.2. The initialization was robustified by winsorizing the estimated polarity scores from the previous session to $-1$ and $+1$.

We performed the same analysis of the results including the visualization of the estimated party- and session-specific ideal point distributions represented as box-plots and the estimated average partisanship over the years together with approximate pointwise 95% confidence intervals. The results for the four scenarios are shown in Figure 4 after re-scaling the newly estimated polarity scores to have the same robust standard deviation (determined based on the inter-quartile range) than those obtained for the original data. The estimation method is able to differentiate well between the scenarios and to identify that there are no party-specific differences in the first scenario, clear differences between the two parties in the second scenario and no difference at the beginning with an increasing difference over session in the third scenario. The results for the forth scenario indicate that the procedure is able to reliably re-estimate the ideal point distributions and the average partisanship.

### C. Additional Results

#### C.1. Party-Specific Ideal Point Distributions Across Sessions

The session- and party-specific ideal point distributions estimated by TV-TBIP are analyzed using box-plots in the main paper. An alternative view is provided in Figure 5 where their kernel density estimates are visualized. The density estimates for each of the two parties for the same session are combined in one panel and the sessions are arranged row-wise across time. Kernel density estimates provide a more flexible and detailed view on the distribution of the ideal points compared to the box-plots. The kernel density estimates indicate that the within party- and session-specific ideal point distributions are approximately unimodal and that the modes between the two parties separate over time, reducing also considerably the overlap of the estimated densities.

#### C.2. Comparison to DW-Nominate Scores

We determine standardized average partisanship estimates across time using the first dimension of the DW-Nominate scores and compare them with the text-based average partisanship estimates from the TV-TBIP model. The session-specific average partisanship based on the DW-Nominate scores is obtained as the difference between the average DW-Nominate scores of Republicans and Democrats for each session.\(^5\)

Figure 6 provides scatter plots of the sessions on the $x$-axis versus the standardized average partisanship estimates for the TV-TBIP model as well as the DW-Nominate scores on the

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\(^5\)The data were downloaded from [https://voteview.com/data](https://voteview.com/data) using Data Type: Congressional Parties, Chamber: Senate Only, Congress: All, with the variable nominate-dim1-mean used for analysis.
Figure 5: Kernel density plots characterizing session- and party-specific ideal point distributions.

Figure 6: Standardized aggregate partisanship estimates on party level based on DW-Nominate scores and the TV-TBIP ideal points across time together with fitted linear regression lines and corresponding 95% confidence intervals for the means. The correlation between these partisanship estimates is 0.77.
Clearly both measures exhibit a similar increase over time. This is also indicated by the overlap of the fitted regression lines and their 95% confidence intervals for the mean which are also included in the plot. This implies that our text-based average partisanship measure captures essentially the same effect over time as the DW-Nominate scores.

### C.3. Ideological Positions on Speaker Level

We further investigate the ideal points estimated by the TV-TBIP for the speakers and in particular their evolvement over time by focusing on speakers who were members of the Senate during the whole analysis period and hence have an ideal point estimated for each session. Figure 7 displays the development of estimated ideal points of the four speakers who were members of the Senate during the whole analysis period. These speakers are three Republicans and one Democrat, namely Thad Cochran (R), Charles Grassley (R), Orrin Hatch (R) and Patrick Leahy (D). Inspection of the evolvement of the ideal points for those four speakers provides the following interesting insights: Firstly, we can discern a drop in the ideal points of all four Senators after the *Contract with America*. The reasons are not obvious and one can only speculate. One possible explanation could be the Congress turnover which took place. At this point in time, it was the first time after 40 years that Republicans had the majority in the Congress. Secondly, Figure 7 confirms that the ideological positions inferred by TV-TBIP are reasonable. Among these four Senators, the most liberal Senator Patrick Leahy (D) clearly has the highest ideal point values for the latter time periods, while the three Republican Senators are after the *Contract with America* consistently positioned on the negative side of the ideological scale. Among the three Republicans displayed in Figure 7, we find Thad Cochran to be the most liberal one. Indeed Thad Cochran is usually considered to be more moderate than most of his Republican colleagues (cf., Enten 2014). For example, the New York Times arranged in 2017 Republican Senators based on ideology and reported

![Figure 7: Development of estimated ideal points over time of those four Senators who were members of the Senate from session 97 to 114.](image-url)
|                  | Min. | 1st Qu. | Median | Mean  | 3rd Qu. | Max. | SD | Sessions (#) |
|------------------|------|---------|--------|-------|---------|------|----|--------------|
| **Most liberal Democrats** |      |         |        |       |         |      |    |              |
| Byron Dorgan (D) | 0.68 | 0.73    | 0.87   | 0.86  | 0.98    | 1.08 | 0.15| 105–111 (7)  |
| Dale Bumpers (D) | 0.68 | 0.68    | 0.68   | 0.68  | 0.68    | 0.68 | 105–105 (1)  |
| Thomas Harkin (D)| 0.21 | 0.48    | 0.57   | 0.63  | 0.66    | 1.14 | 0.27| 105–113 (9)  |
| Christopher Murphy (D) | 0.43 | 0.50    | 0.56   | 0.56  | 0.63    | 0.69 | 0.18| 113–114 (2)  |
| Paul Wellstone (D) | 0.41 | 0.45    | 0.48   | 0.53  | 0.59    | 0.69 | 0.15| 105–107 (3)  |
|                  |      |         |        |       |         |      |    |              |
| **Most conservative Democrats** |      |         |        |       |         |      |    |              |
| Daniel Inouye (D) | −0.56| −0.31   | −0.13  | −0.14 | 0.08    | 0.20 | 0.28| 105–112 (8)  |
| Robert Torricelli (D) | −0.27| −0.20   | −0.13  | −0.16 | −0.10   | −0.06| 0.11| 105–107 (3)  |
| Ben Nelson (D)    | −0.26| −0.24   | −0.19  | −0.17 | −0.14   | −0.01| 0.09| 107–112 (6)  |
| Arlen Specter (D) | −0.29| −0.27   | −0.24  | −0.18 | −0.12   | 0.00 | 0.16| 109–111 (3)  |
| Evan Bayh (D)     | −1.14| −1.07   | −0.52  | −0.49 | 0.06    | 0.22 | 0.65| 106–111 (6)  |
|                  |      |         |        |       |         |      |    |              |
| **Most liberal Republicans** |      |         |        |       |         |      |    |              |
| Ed Bryant (R)     | 0.01 | 0.01    | 0.01   | 0.01  | 0.01    | 0.01 | 106–106 (1)  |
| John Chafee (R)   | 0.09 | 0.09    | 0.09   | 0.09  | 0.09    | 0.09 | 105–105 (1)  |
| Dirk Kempthorne (R)| 0.14 | 0.14    | 0.14   | 0.14  | 0.14    | 0.14 | 105–105 (1)  |
| Phil Gramm (R)    | 0.06 | 0.12    | 0.18   | 0.16  | 0.22    | 0.25 | 0.10| 105–107 (3)  |
| Howard McKeon (R) | 0.21 | 0.21    | 0.21   | 0.21  | 0.21    | 0.21 | 111–111 (1)  |
|                  |      |         |        |       |         |      |    |              |
| **Independent Senators** |      |         |        |       |         |      |    |              |
| James Jeffords (I)| −0.16| −0.16   | −0.15  | −0.15 | −0.14   | −0.14| 0.01| 107–109 (3)  |
| Bernard Sanders (I)| 0.50 | 0.62    | 0.68   | 0.71  | 0.86    | 0.88 | 0.16| 110–114 (5)  |
| Joseph Lieberman (I)| −0.02| 0.01    | 0.05   | 0.05  | 0.08    | 0.12 | 0.07| 110–112 (3)  |
| Angus King (I)    | 0.09 | 0.09    | 0.10   | 0.10  | 0.11    | 0.11 | 0.02| 113–114 (2)  |

Table 4: Overview on the estimated ideal points for the last ten Congress sessions, i.e., starting with session 105, for selected Democrat and Republican speakers. The five most liberal and conservative speakers for each party according to their average ideal point values are included as well as the independent speakers. The estimated ideal points are summarized using descriptive statistics (minimum – Min.; 1st quartile – 1st Qu.; Median; Mean; 3rd quartile – 3rd Qu.; maximum - Max.; standard deviation – SD). The specific sessions (Sessions) when the speaker was a member of the Senate during these last ten Congress sessions are also given together with the number of sessions in parentheses (#).

that Thad Cochran was the fourth most moderate Republican (see Parlapiano and Benzaquen 2017). On the other side of the spectrum we find Orrin Hatch (R), one of the leading figures behind the Senate’s anti-terrorism bill, and a person who is strongly opposed to abortion (see, e.g., Wikipedia 2022b).

Table 4 displays the estimated ideological positions of selected Republican and Democrat speakers for the last 10 sessions, i.e., we consider results from session 105 onwards. For Republicans as well as Democrats, we display the five most liberal and conservative speakers according to their mean ideal point over the last 10 sessions per party. Table 4 indicates that according to TV-TBIP, the most liberal Democrats are Byron Dorgan, Dale Bumpers,
Thomas Harkin, Christopher Murphy and Paul Wellstone.

As a Chairman of the Senate Energy Panel, Dorgan was an early supporter of renewable energy, and in Section 3.2 of the main manuscript we show that the energy topic is very polarizing between the two parties. We also find Paul Wellston among the top five most liberal Democratic Senators. This is completely in line with the DW-Nominate scores. According to these voting-based scores, he is the most liberal Democratic Senator during sessions 105–107. Analyzing the conservative spectrum of Democratic Senators in the Senate, we find that Evan Bayh is most conservative. This is again in line with the DW-Nominate scores, where he is ranked the third most conservative Democrat of session 106.

Proceeding with the Republican party, we find Jesse Helms, a Senator from North Carolina, to be the most conservative Republican. The New York Times (see Holmes 2008) stated that Helms was “bitterly opposed” to federal financing for research and treatment of AIDS which he believed was God’s punishment for homosexuals (see, e.g., Noden 2007). According to the DW-Nominate scores, Jesse Helms is also ranked as the most conservative Republican for, e.g., sessions 106 and 107. Based on the mean ideal point value, the second ranked among the most conservative Republicans is Gordon Smith. This is in line with the following statement: “Smith is often described as politically moderate, but has strong conservative credentials as well” (see Wikipedia 2022a).

On the liberal side of the Republicans, TV-TBIP places the Californian House Representative Howard McKeon, and Senators Phil Gramm, Dirk Kempthorne, John Chafee and Ed Bryant. John Chafee is among the most liberal Republicans according to the DW-Nominate scores which rate him as being more liberal than 96% of Republicans in session 105.

Finally, for independent speakers, the estimated ideal points meet expectations. Bernie Sanders is the most liberal one, also in the Democratic party he would be ranked second. On the other hand, former Democrat Joe Liebermann is categorized as having a slightly liberal position and former Republican Jim Jeffords seems to have a tendency to be on the conservative side.

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