Ideology in Courts: A Textual Analysis of Indian Supreme Court Justices

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May 3, 2024

1 Introduction

The structure of the Indian Supreme Court includes the Chief Justice of India and a maximum of 33 additional judges. These judges form smaller benches known as division benches for routine cases and larger benches, or constitution benches, for fundamental questions of law and constitutional issues. The Chief Justice is nominated by the President of India, who, although a ceremonial head of state, plays a crucial role in this process, influenced heavily by the Prime Minister and the ruling party(Venkatachar, 1971).

Since the BJP, led by Prime Minister Narendra Modi, came to power in 2014, there have been growing concerns about the independence of the Supreme Court. Allegations suggest that the nomination of judges might be increasingly influenced by the BJP's ideological leanings, thereby threatening the court's long-standing reputation for objectivity and reducing its ideological diversity (Dieterich, 2017). Despite the Supreme Court's longstanding reputation of being highly independent of the polity and objective(Jha,2024), similarity of judge ideology can have long term effects on judicial quality such as setting singular precedents, further affecting future judgements via citations, lack of diversity in both legal argumentation and amongst bench members, wherein varying perspectives are key in enhancing deliberation (Orentlicher,2018)

Despite these concerns, the Supreme Court has shown instances of acting against the political interests of the ruling party, such as its decision on the controversial issue of the Ayodhya temple, where it ruled against the demolition of a medieval mosque for a temple, a long-standing BJP agenda (Economic Times, 2019). This decision highlights the court's capacity for independent judgment, critical for maintaining legal integrity in a politically charged environment.

The study proposed here aims to examine the ideological diversity among the justices of the Supreme Court. It analyzes the textual representations of judgment summaries to identify latent semantic attributes that may reflect the justices' ideological leanings. These ideological markers might appear in their arguments and could be influenced by their sympathies or biases towards certain types of case participants or contexts, beyond the direct outcomes of the cases.

The primary research question, therefore, seeks to determine whether ideological alignment exists in the Supreme Court of India, and if so how these alignments have changed before and after the BJP government's rise to power.Unlike the US, there have been no formal attempts to ideologically place supreme court judges on a scale. However for certain popular judges popular perceptions can serve as a method for assessing face validity of our results.

It is important to recognize how ideology is represented in the Supreme Court of India. Historically, the Court strives to ensure that ideology does not influence its decisions, a practice widely regarded as successful. Judges typically avoid discussing ideology or openly supporting political factions during their careers, as such actions could severely impact the public perception of the Supreme Court(The Economist, 2024). Moreover, judgment summaries primarily focus on presenting arguments from involved parties, alongside facts and evidence pertinent to the decision-making process. Only in rare instances involving highly charged constitutional or governmental cases do more philosophical arguments emerge that might reflect a judge's personal beliefs.

2 Data

I utilize the Indian Legal Documents corpus (Malik et al., 2021) which contains judgement summaries for 35000 cases heard by the supreme court between 1958 and 2020. The judgement summaries contain information on the names of the presiding judge and names of the plaintiff and defendant. The dataset is publicly available upon request to the authors. In its raw format the corpus exists in a comma separated value format.

Tokenizing the corpus by extraneous words and characters (detailed in later) sections helps us get a sense of the length of each document. In Figure 1., we see that the maximum length of judgements can be more than 300,000 tokens. Combined with manual review of the document I find that that these are highly detailed complex documents and thus may require more sophisticated methods.

N	34816
Mean	2869
Median	1935
Min	19
Max	302608
Standard Deviation	5406.5

Figure 1: Corpus Summary Statistics

3 Methodology

3.1 Determining Analytic Set and Topic Modelling

Case Selection and Sub-setting:

The cases included in this study span a wide range of topics, including crime, private disputes, business disputes, government disputes, constitutional amendments, and more. To focus our analysis on cases where ideological argumentation is most likely to be present, we need to subset the data to include only governmental cases. Cases where the government is not the plaintiff or defendant are least likely to have ideological argumentation due to heavier focus on objective case facts such as evidence, circumstance and criminal history. The Indian judiciary operates on the principle of constitutional supremacy, with the Supreme Court serving as the final arbiter of disputes involving the government and its agencies. Cases involving the government as a plaintiff or defendant often revolve around constitutional matters, policy decisions, the interpretation of laws, popular perceptions of governmental performance which are more likely to involve ideological considerations and argumentation compared to cases solely between private parties.

Since we do not have explicit information about government involvement in each case in our dataset, we employ topic modeling techniques to identify cases where a government agency or constitutional entity is involved as either the plaintiff or defendant. We experiment with the following topic methodologies:

1. **Structural Topic Modelling (STM)**: STM enhances traditional Latent Dirichlet Allocation by incorporating document-level metadata, allowing the analysis of how topics vary with these covariates. STM employs a logistic normal prior linked to covariates via a generalized linear model, enabling the modeling of both topic prevalence and content based on attributes like authorship or publication date. We can thus observe how topics change across different contexts and also predict topic distributions in new documents based on their metadata

   Input Data Processing

   (a) Remove names of authoring justice from within the text

   (b) Remove Punctuation, stopwords ('a','an','the' etc.), top 10% most common and 5% least common words to remove noise and less informative words from the text data. We are more aggressive in removing commonly occurring words unique to the corpus here due to the high use of procedural words in judicial text.

   (c) Remove tokens of length ≤ 3, digits, alphanumeric tokens: Short tokens, digits, and alphanumeric tokens are removed as they are unlikely to carry significant semantic meaning and can introduce noise into the topic modeling process.

2. **BERT Topic Modelling**: BERT-based topic modeling, specifically employing Maarten Grootendorst's BERTopic implementation in Python (Grootendorst, 2022), utilizes the BERT (Bidirectional Encoder Representations from Transformers) language model to create, contextualized word embeddings. This method clusters these embeddings to identify coherent topics, leveraging BERT's transformer architecture, which analyzes language in both directions of a sentence to capture deep linguistic contexts. This approach significantly enhances topic identification by utilizing the nuanced language patterns captured by BERT, offering a more sophisticated analysis than traditional topic modeling techniques

   Input Data Processing

   (a) Remove names of authoring justice: Similar to the STM approach, removing the names of authoring justices helps to focus the topic modeling on the content of the judgments.

   (b) As per the author's recommendation, we only remove punctuation, numeric and alphanumeric characters to de-noise the data but do not take any pre-processing which may affect the semantic meaning such as removal of stopwords.

3. **Zero-shot Topic Modelling with Chat-GPT (GPT-4-Turbo)**: Zero-shot topic modeling with Chat-GPT - specifically in our case leveraging the GPT-4-Turbo model - employs an advanced transformer architecture to analyze and comprehend text input without prior training specific to topic modeling tasks. Utilizing the model's extensive pre-training on diverse data and a large number of parameters, it generates insightful and contextually relevant topics directly from the input prompt. As a proprietary implementation from OpenAI, we utilize the API and a paid key in GPT to feed the model our texts iteratively, while providing clear instructions in

our prompt for the desired output.
Input Data Processing

(a) Input: A random sample of 2,935 documents is selected, with an approximately equal split between two periods: 2009 to 2013(pre-BJP), and 2014 to 2020 (post-BJP). The first 4000 characters of each judgment are provided as input to the GPT-4-Turbo model. Since our goal is to discern whether a case involves the government or not, manual inspection of the data indicates that this information is contained within the first 4000 characters, further aiding us in reducing monetary costs in addition to sampling, associated with application of the API. No pre-processing is undertaken here.

(b) Prompt:The following prompt is used to guide the GPT-4-Turbo model in identifying the involvement of government agencies or constitutional entities in the judgments:

"In this judgement summary text determine if a government agency or the constitution is involved as either plaintiff or defendant. If the government or constitution is involved, return the response in the following format: (government role):(specific government agency):(broad issue topic). If government is not involved, format your response as: Other: (plaintiff/defendant): (broad issue)."

This prompt instructs the model to analyze the judgment summary text and determine if a government agency or constitutional entity is involved as either the plaintiff or defendant. If the government is involved, the model should return the response in the specified format, indicating the government role, specific government agency, and the broad issue topic. The specified format aids in further pre-processing in later stages.

3.2 Ideological Scaling

With results from topic modeling and thus being able to differentiate which cases involve the government, we only include those cases for our ideological scaling for reasons previously discussed. We experiment with the following methodologies to do this:

3.2.1 Doc2Vec with dimensionality reducition (Rheault and Cochrane, 2019)

First, I adapted the methodology outlined by Rheault and Cochrane (2019) in their study, which investigated the ideological leanings of parliament members in the US, UK, and Canada based on their speeches in parliament, to examine the ideological leanings among justices of the Supreme Court. For pre-processing I follow the authors methodology of removing stopwords, punctuation, digits, alphanumeric characters, tokens 2 characters or less in length and replace their method for manual identification of procedural common words unique to their dataset with removing the 90% most common and 5% rarest words. The steps taken were as follows:

1. **Document Level Embeddings**: We first use Doc2Vec, an extension of the Word2Vec model, that leverages neural network architectures to generate vector representations of documents. This method involves training a neural network to predict words within a context window from the surrounding words and a unique document identifier (a "document token"). The model preserves the word order in a document, employing a sliding context window that predicts a word based on the previous words and the document vector. The input layer represents words, and uniquely in Doc2Vec, the document-level token, or document tag, which as an extra input

to the neural net, distinguishing each document from others in the corpus. Through training, each unique document-level tag's embeddings highlight the overall thematic and semantic patterns associated with the unique document tag. Essentially, these inputs are projected into a dense, continuous vector space via hidden layers, where the learning occurs. The resulting document vectors are akin to the learned representations within the hidden layers, possessing a dimensionality equivalent to that of the hidden layers and encapsulate semantic meanings and relationships, in a lower-dimensional space.

Specifically in our case, a document tag is the *Unique Jutsice Name* associated with a case. Thus the embeddings for a document tag aims to encapsulate the thematic and semantic patterns associated with each justice in a given year taking into consideration all the cases they have presided over. The final parameters in my implementation for Doc2Vec were set as follows:

(a) **Learning rate: 0.05**, experimented with [0.025, 0.05, 0.1, 0.15]

(b) **Epochs: 10**, experimented with [3, 5, 10]

(c) **Hidden layers, i.e. dimensions of embeddings**: **200**, experimented with [200, 300, 400]

(d) **Window size: 10**, experimented with [5, 10, 15, 20]

2. **Dimensionality Reduction**: We can then project the N-dimensional judge embeddings into a substantively meaningful vector space using principal component analysis (PCA) for dimensionality reduction and visualization. To be able interpret the principal components as representative of ideology, we examine the word embeddings associated with each dimension, identifying the concepts most strongly related to each component. By projecting the word embeddings onto the principal components and ranking the words based on their Euclidean distance from the cardinal points (determined by the minimum and maximum party projections on each axis), we characterize the semantic regions of the judge embedding space, providing insights into the latent dimensions that capture the similarities and differences among judges based on their textual data.

3.2.2 PoliticalBias BERT

We also experiment with a pre-trained transformer model called "politicalbiasBert" (Baly et al., 2020) from HuggingFace's library to analyze the political ideology of Indian Supreme Court justices. The model was trained on a dataset of 34,737 news articles in the United States that were manually annotated for political ideology, classified as left, center, or right. Importantly, the test examples used for evaluation come from media sources that were not seen during the model's training, ensuring its ability to generalize to unseen data (Baly et al., 2020). Instead of detecting the explicit political leaning, politicalbiasBert is designed to detect political "bias" in text, which is pertinent to our classification task as Supreme court Justices are indeed more likely to show 'bias' instead of an explicit political leaning, due to the nature of judicial processes and the role of evidence and objectivity.
To apply the model to our dataset, we use the first 512 tokens after the 30th token in each document as input, with input pre-processing remaining the same as in the case of our Doc2vec methodology above. This is due to the model being limited to 512 input tokens, whereas texts in our data can be much higher as seen from table 2. Using tokens only after the 30th token, further ensures that we skip over the 'introductory' section of the judgements and are more likely to include text from the argumentation section, which is most likely to indicate personal beliefs.

The model then outputs logits across three classes of ideology: 0 for Liberal, 1 for Center, and 2 for Conservative. To determine the overall ideology of each justice, we calculate the average of the ideological labels assigned by the model across all cases authored by that justice. In cases where the predicted label with the highest probability is "center" and the difference between the highest and second-highest probability labels is less than 0.1, we use the second-highest label to assign the ideology. This helps us in accurately placing judges as center-left or center-right, which judges are most likely to be according to the content of supreme court judgements. Further This choice is and based on experimentation with model implementations and assessing face validity of results.

4 Results

4.1 Topic Modelling

We begin by comparing the results from our three topic models. It's crucial to note that the objective of our topic modeling involves significantly different and more nuanced tasks than traditional approaches. Specifically, we aim to distinguish between government and non-governmental cases—those where the government is a direct participant in some capacity. The results from the topic modeling with Structural Topic Modeling (STM) and BERT are presented in Figure 1. (a) and (b) respectively.

Topic	Count	Name
-1	11527	-1_appeal_court_prosecution_judge
0	933	0_appellate_assessed_appeal_appeals
1	702	1_admission_qualification_examination_qualifications
2	569	2_tariff_exemption_tribunal_issued
3	524	3_tribunal_arbitration_proceedings_disputes
4	489	4_elections_petitioner_panchayat_constituency
6	313	6_taxation_taxable_tax$_e$*xemption*
7	269	7_eviction_tenant_appeal$_t$*enants*
8	193	8_petition_mining_coal$_l$*td*
9	193	9_constitution_petition_petitions_judicial
10	174	10_detained_detention_magistrate_petitioner
11	166	11_detained_detention_detaining$_d$*etain*

(a) BERT Topic Modelling Results

Topic	Top Words
1	tax, income, assessee, assessment, section
2	evidence, accused, singh, appellant, deceased
3	land, act, section, government, state
4	order, high, respondent, petition, appellant
5	service, government, rules, state, rule
6	section, act, sub, shall, provisions
7	act, state, goods, section, government
8	suit, property, decree, plaintiff, high
9	respondent, companytract, bank, agreement
10	section, criminal, offence, code, accused

(b) Structured Topic Modelling Results

Figure 2: BERT AND STM Topic Results

Our analysis reveals that the optimal STM model, characterized by cohesion and separation, includes 10 topics. However, the compositions of these topics provide little insight into government involvement in cases. For instance, topics 1, 2, and 3 appear to focus on income tax, crime, and land cases, respectively, but they do not clearly indicate whether the government is a party to these cases. In contrast, the BERT topic model, which is more coherent and extracts 198 topics, identifies the first topic with a label of -1, suggesting no specific topic assignment. Despite its detailed topic extraction, BERT similarly struggles to pinpoint government involvement. Although topics 4, 9, and 10 in BERT and topic 5 in STM seem to address government-related cases, there remains significant inaccuracies concerning our specific goal of identifying government participation.

These findings are not surprising, given the lengthy and complex nature of each judgment, which often addresses multiple topics simultaneously, each with distinct word compositions. The specificity of our objective in the context of topic modeling further complicates the task.
Turning to zero-shot modeling with ChatGPT, as detailed in Figure 3, the outcomes are significantly more satisfactory. ChatGPT demonstrates the capability to accurately identify the specific roles of the government, the types of government agencies involved, and the nature of each case. As the most

Label
Government role:Defendant:State Government:Education policy and fee regulation
Other: Cooperative Housing Society: business dispute
Government role:Defendant:Delhi High Court:Compulsory retirement issues
Government role:Defendant:Communal issues
Government role:Defendant:Senior Superintendent of Police, Ferozepur:Crime (murder during panchayat election)
Government role:Other:Defendant:Crime
Plaintiff:State of Uttar Pradesh:Murder investigation and judicial process
Government role:Defendant:Drug enforcement laws
Other: Insurance Company: business/legal compensation issue
Government role:Defendant:Union of India:Contract disputes
Government role:Defendant:Central Government:Promotion procedures in banking sector
Other: (plaintiff/defendant): business
Other: (defacto company/plaintiff): business issue (transaction dispute and alleged theft)

(a) GPT 4.0 Topic Modelling Results

Figure 3: GPT Results

advanced language model currently available, it effectively accomplishes this analysis using just the first 4000 characters of each judgment. Additionally, I observed instances of hallucination in only 3 out of 2935 documents, indicating a high level of reliability. However, there is an important caveat to consider. Due to the substantial monetary costs associated with using the API, I was only able to analyze 2935 cases, with a roughly equal distribution of cases from the five years prior to and following 2014, to facilitate more effective comparisons later. From here we drop, the 25 cases where either hallucination occured or the case was not related to the government.

Subsequently, I have decided to focus on the GPT-based topics to subset my data to only include cases where the government or a government agency is either the defendant or the plaintiff. Thus my scaling analysis is performed on 2910 cases out of the 35000 available.

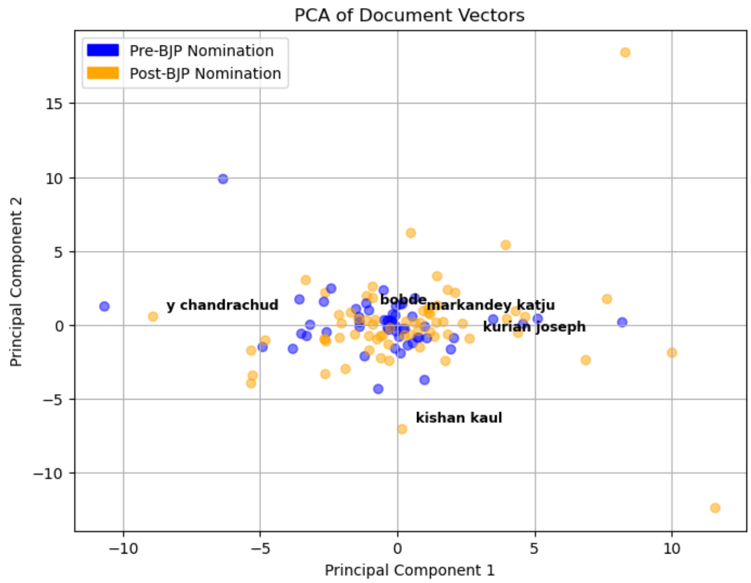
4.2 Ideological Scaling

4.2.1 Doc2Vec with dimension reduction

Figure 4 (a) displays the distribution of the first two principal components (PC1 and PC2) for each unique judge, differentiating judges based on whether they were appointed before or after the BJP government came to power. This visual, in conjunction with Figure 4 (b), which details the words most commonly associated with the extremes of the principal components, helps interpret the axes.

Upon analysis, it becomes evident that the principal components do not capture words that signify political ideology, diverging from findings in studies such as Rheault and Cochrane (2019). From Figure 4 (b), it is apparent that the variation among judges in their document embeddings is more likely derived from the types of cases they adjudicate. For instance, the current Chief Justice Y. Chandrachud frequently handles constitutional cases, among others. Since PC1 and PC2 account for only 10% of the variation in the embeddings, and given the distinct nature of my dataset compared to that used by previous authors, I expanded my analysis to include word associations up to PC6. However, this further analysis confirmed a recurrence of themes across the principal components, predominantly related to different case types.

The inability to achieve our goal of ideologically scaling the judges was anticipated. This outcome likely stems from the fact that variations in judgments written by each judge are minimally influenced by political ideologies. This is reflective of the procedural rigor inherent in the Supreme Court's operations and the nature of the documents in our corpus. The judgments are comprehensive summaries that encompass all aspects of a case, focusing predominantly on outlining the facts, evidence, trial details of the hearings. This comprehensive nature underscores the challenges in deriving ideological leanings from judicial texts, which are primarily focused on legalistic expressions rather than ideological biases



(a) Ideological Placement of Judges with Doc2Vec

Words Associated with Positive Values **(Right)** on First Component	aggrieved, perused, fide, adduced, agricultural, rightly, sufficient, records, prove, false, erred, shop, plaintiff, companyviction, licence, appearing, companytentions, companynsel, companyent, justified
Words Associated with Negative Values (Left) on First Component	day, paragraph, legislative, assembly, areas, results, judges, functions, states, united, drawn, new, election, till, secured, territory, amendment, importance, petitioners, site
Words Associated with Positive Values **(North)** on Second Component	companynsel, advocate, vis, counsel, custody, investigation, reports, sheet, submitted, proposal, crl, companies, petitioner, arrested, pursuant, petitioners, shri, companymit, uttar
Words Associated with Negative Values **(South)** on Second Component	answered, suit, companypensation, workers, employer, finding, revenue, portion, assistant, settlement, damages, deputy, disputes, claims, title, district, landlord, wages, permanent, labour

(b) Words Associated with PCs

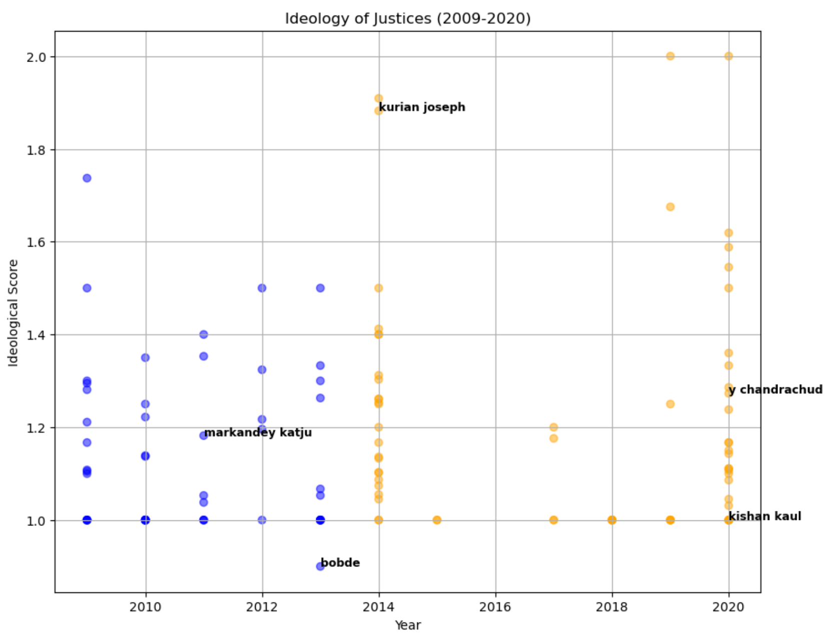
Figure 4: Doc2Vec and PCA Results

4.2.2 PoliticalBias BERT

In Figure 5 (a) and (b), we present the scaling results from the PoliticalBias BERT model, where the ideological values are coded as 0 for Liberal, 1 for Centrist, and 2 for Conservative. As we see in Figure 5 (b), the judges are predominantly scaled as centrists, with little overall variation. However, it is important to note we are unable to conclude the model's success in detecting ideological patterns, as the face validity of these results is questionable. Notably, justices like Y Chandrachud and Kurian Joseph, who are historically considered among the most liberal justices of the Supreme Court, are depicted as more conservative in our results. Conversely, Justices Markandey Katju and

Bobde, known for their conservative stances and current affiliations as BJP members of parliament, do not align with the popular narrative, with Justice Kurian Joseph even labeled as one of the most conservative in our dataset. Nevertheless, I concur with the model's tendency to categorize the majority of judges around the midpoint, or 1, suggesting a centrality in their ideological standings. This finding aligns with our earlier discussions about the commonly accepted narrative of judicial independence from political ideologies, which reflects a broader understanding that, despite variations, the judiciary often operates with a level of autonomy that keeps it insulated from political influences

Additionally, analyzing the ideological spread of judges appointed before and after the BJP government did not reveal any significant trends. This outcome suggests that the political ideologies may not be deeply embedded in the source texts of the judgments. The limitations of the model, which uses only the first 512 tokens from extensive documents and is trained on U.S. news sources—a context markedly different from Supreme Court judgments in India—likely contribute to these discrepancies.



(a) Ideological Placement of Judges with PoliticalBias BERT

Statistic	Value
Judges N	122
Mean	1.8
Median	1.1
Mode	1
Min	0.9
Max	2
Standard Deviation	0.225

(b) Summary Statisics of Ideological Placement

Figure 5: PoliticalBias BERT Results

5 Discussion

In our efforts to ideologically profile the Supreme Court justices of India, the methodologies and datasets employed did not prove to be suitable for precise ideological categorization. The approach to topic modeling was particularly nuanced as it aimed to distinguish cases based on involvement by governmental agencies or the constitution. Given the complexities and length of the judicial documents, only advanced models like ChatGPT were adept at achieving this differentiation. However, dimensionality reduction using Doc2Vec embeddings suggested that ideological leanings are not the primary factors differentiating judges. Instead, the types of cases they handle emerged as the main thematic variations within the principal components analyzed, with no clear ideological distinctions apparent, even with judges appointed before and after the BJP's ascension to power.

The failure of pretrained transformers to yield conclusive ideological scores can be attributed to several factors intrinsic to the nature of the Indian Supreme Court and the limitations of the methodologies employed:

1. Cultural and Training Norms: Supreme Court judges are ingrained with a strong emphasis on political neutrality, a stance that is widely supported by public perception. This institutional culture ensures that judges tend to remain ideologically central, with potential slight leanings toward the center-left or center-right when analyzed through their judgments.

2. Judicial vs. Political Ideology: The ideological framework within the Indian judiciary is distinct from conventional political ideologies, both in thematic substance and linguistic expression. For example, traditional political indicators are unlikely to appear in the Supreme Court's decisions.

3. Differences in Ideological Definitions: The concepts of liberalism and conservatism in India diverge significantly from those in Western contexts. This discrepancy poses a challenge for models like PoliticalBias BERT, which are trained on U.S. media sources and may not accurately reflect the subtleties of Indian judicial proceedings.

4. Judgment Delivery: Judgments are delivered by a bench without a specified author, complicating the attribution of any specific judgment to a single judge's ideology. We use the summary author as a proxy for the ideological stance, but this can be misleading as judgments are collaborative and represent a blend of viewpoints, thus finding an explicit political may be difficult.

5. Language Variability: The language used in judgments, although sometimes sharply critical of parties involved, is not a reliable indicator of a judge's ideological stance. The rhetoric employed may reflect the legal strategies or the nature of the case rather than any personal ideological bias and may lead our embeddings to incorrectly conclude otherwise

6. Currently, there is no clear, validated method to differentiate between judges based on ideologies, akin to DW-Nominate scores used in the U.S. The absence of externally validated data complicates the task, leading to an unguided and ambiguous modeling process without a defined validity goal.

7. Additionally, I lack the necessary depth of legal knowledge required to properly pre-process the documents by filtering out procedural discussions such as evidence presentation and the timeline of case events, which are less relevant for capturing ideological leanings. The use of sophisticated models like ChatGPT for topic modeling faces constraints due to limited sample sizes, introducing sampling bias.

8. The PoliticalBias BERT model is limited by its capacity to process only a small fraction of tokens compared to the full length of judicial documents. Additionally, it was originally trained in a context significantly different from that of Indian judicial proceedings.

Overall for future research avenues, more legally knowledgeable researcher to better process the data and extract relevant texts from the source, end to end use of sophisticated models for chatgpt for the scaling process and maybe a different data source than judgement summaries one which is likely to be more informal and popularly delievered and is not subject to the constraints of judicial processes and standards for a more explicit display of political ideology

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