GEORGETOWN UNIVERSITY | McCourt School of Public Policy

Heard or Halted?

Analyzing the Emotional Tone of Judicial Interruptions

PPOL-6801 Text As Data Tian Tong

Background & Research Motivation

“Let Me Just Interrupt You”: Estimating Gender Effects in Supreme Court Oral Arguments

Erica Cai[1], Ankita Gupta[1], Katherine A. Keith[2], Brendan O’Connor[3] and Douglas Rice[3]

Context: Supreme Court Oral Arguments

Justices and advocates engage in high-stakes, spoken exchanges that shape legal outcomes.

Why study Interruptions?

Female justices and advocates are interrupted more often than their male counterparts.

Institutional power asymmetries and gendered dynamics.

Motivation:

Frequency of interruptions to emotional impact

Research Questions

#1 Semantic Shift

Do interruptions shift the semantic meaning of an advocate's argument during Supreme Court oral arguments?

#2 Gendered Sentiment

Do interruptions directed at female advocates contain more negative sentiment than those directed at male advocates?

Dataset

Supreme Court Oral Argument transcripts from the **ConvoKit Supreme Court Corpus**
Time-range: **2010-2019**
Final Sample set: ***12,663 chunks*** (continuous segments of speech) of advocate speech

Utterance-level Information: Case id/Advocate's name/Speaker type/Actual text etc.
Gender information: **First-name Lookup** from standard U.S. name-based dataset

What does an interruption look like?

> **Advocate (Douglas Laycock):**
> *"Well, some courts have said yes. There's very little in this record about full beards and whether they're safe or whether they're dangerous..."*
>
> **Justice Scalia (Interrupting):**
> *"Mr. Laycock, the problem I have with— with your client's claim..."*

When a speaker is cut off, the transcript will typically show: -- (double dash) and ... (Ellipsis))

Methodology

Pretrained Word Embeddings

GloVe 100d pretrained vectors
Match each token in a chunk to its corresponding vector

Generate Chunk Embeddings

> "Religious belief is personal — but prison policy must be reasonable."

6 words x 100 dimensions matrix
Represents **the semantic meaning** of the entire chunk

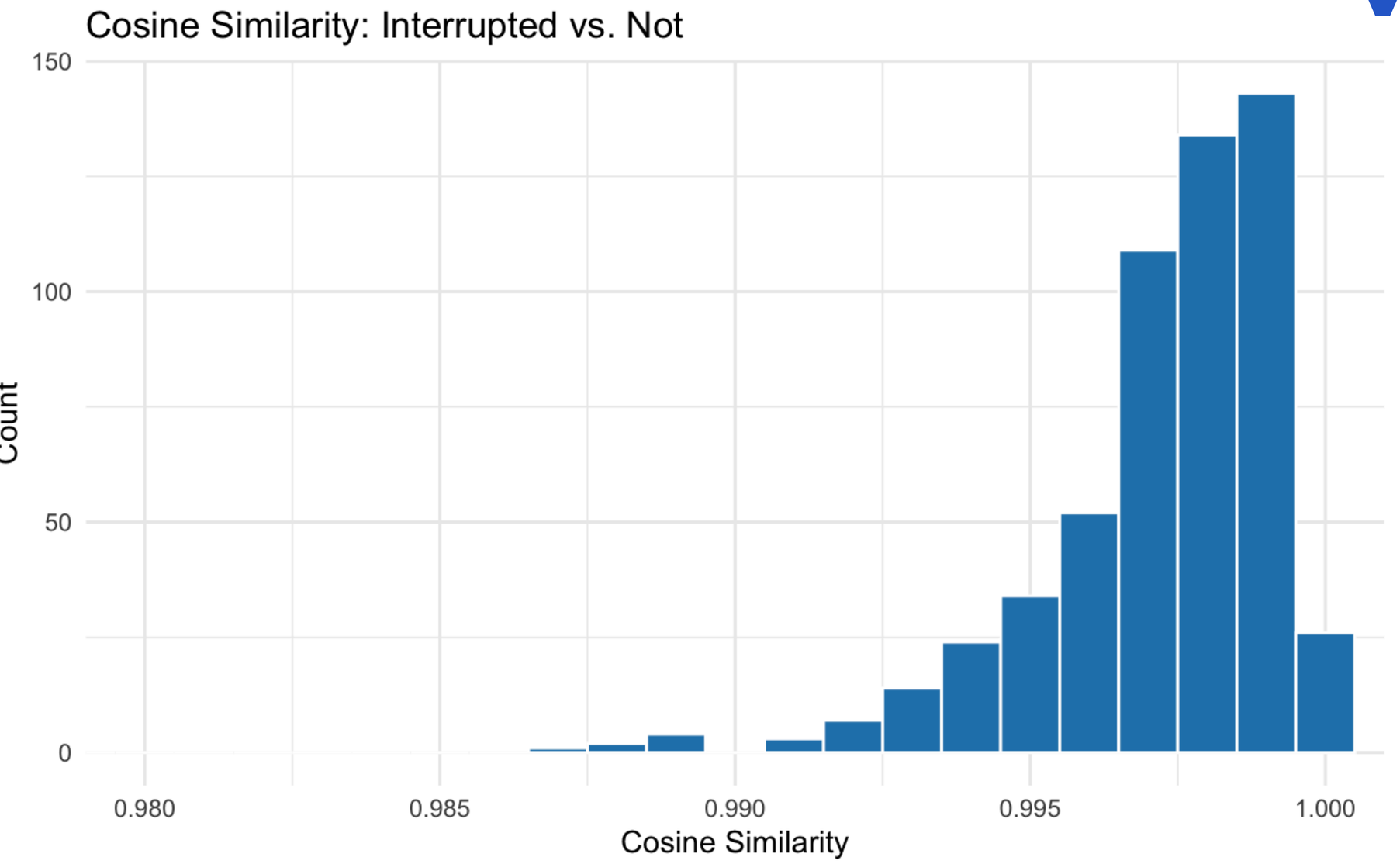
Group by Advocate & Interruption Status

Label: Interrupted or Not Interrupted

Cosine Similarity

Cosine similarity between the two embeddings (per advocate)
Higher similarity(>0.85) → Semantic meaning **preserved**
Lower similarity → Potential semantic **shift**

Visualization




```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  0.8899  0.9965  0.9977  0.9970  0.9986  0.9999      65
```

Semantic content is largely preserved

Power dynamics or interactional dominance

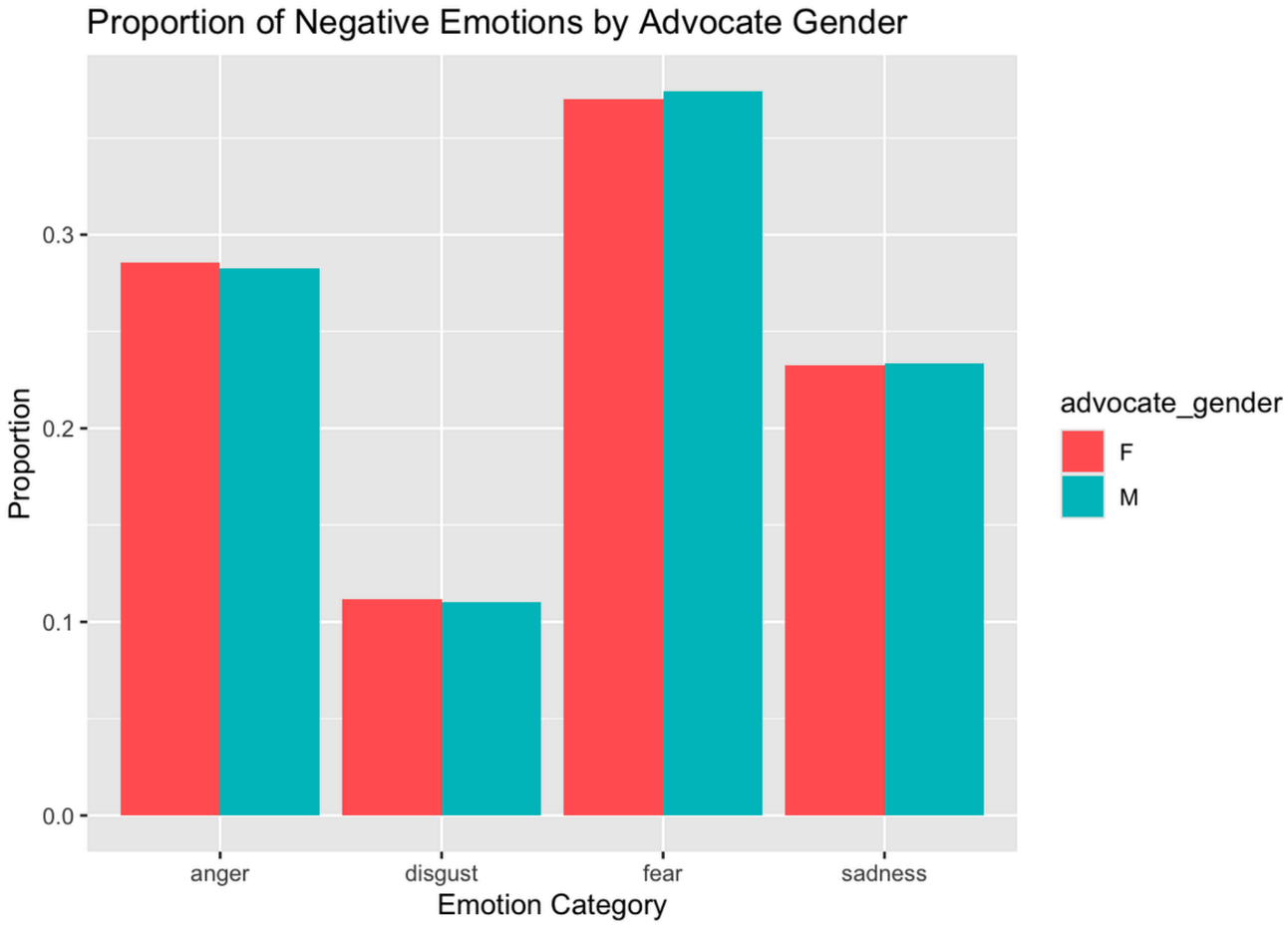
Methodology

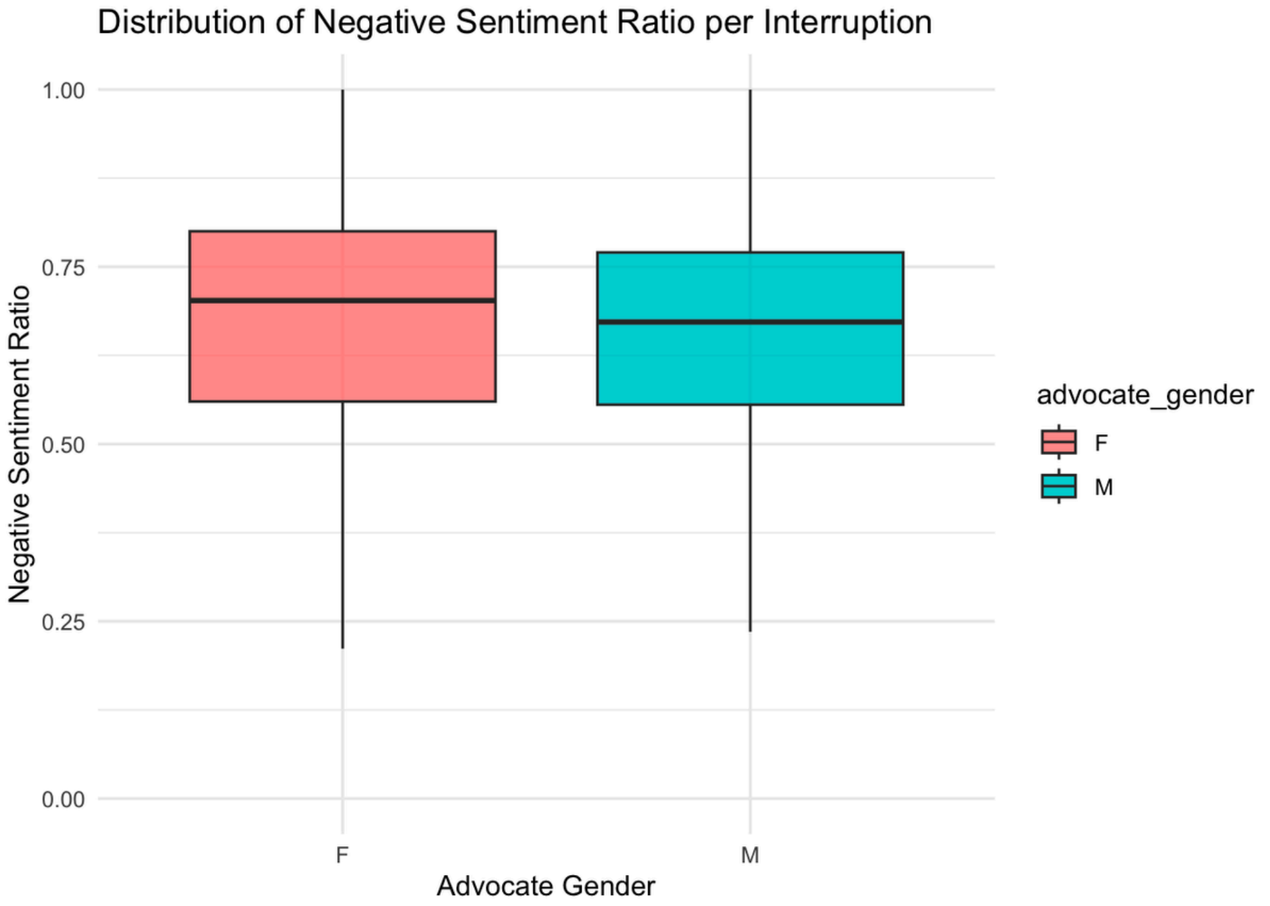
- Filter to inlcude only **interrupted advocate chunks**
- The NRC integration with selected emotions(positive, negative, anger, fear, sadness, and disgust)
- Emtion score aggregation with **Negative Ratio:**

$$\text{neg\_ratio} = \frac{\text{negative} + \text{anger} + \text{fear} + \text{sadness} + \text{disgust}}{\text{total emotion words}}$$

- Gender comparison

Gender Comparison





Gender Comparison

```
t.test(neg_ratio ~ advocate_gender, data = emotion_scores_normalized)
```

```
##
##  Welch Two Sample t-test
##
## data:  neg_ratio by advocate_gender
## t = 2.6623, df = 1729.7, p-value = 0.007834
## alternative hypothesis: true difference in means between group F and group M is not equal to 0
## 95 percent confidence interval:
##  0.003876661 0.025572405
## sample estimates:
## mean in group F mean in group M
##       0.6614017       0.6466771
```

Gender Comparison

Female advocates face more negative interruptions, controlling for case year, experience, and ideological dynamics.

Table 1: Predicting Negative Sentiment Ratio in Interruptions

Variable	Estimate	Std. Error	p-value
(Intercept)	-1.4088	1.2816	0.2717
Advocate gender (Male)	-0.0114*	0.0052	0.0298
Advocate experience (int)	-0.0022***	0.0004	< 0.001
Case year	0.0010	0.0006	0.1064
Female issue[a]	—	—	—
Advocate ideology (Liberal)	0.0061†	0.0035	0.0861
Ideology matches	0.0018	0.0036	0.6196
Residual Std. Error	0.1785 (df = 10291)		
Multiple R^2	0.0041		
Adjusted R^2	0.0036		
F-statistic	8.501 on 5 and 10291 DF, $p < 0.001$		

* $p < 0.05$ *** $p < 0.001$ † $p < 0.1$

[a] *Variable dropped due to collinearity or lack of variance.*

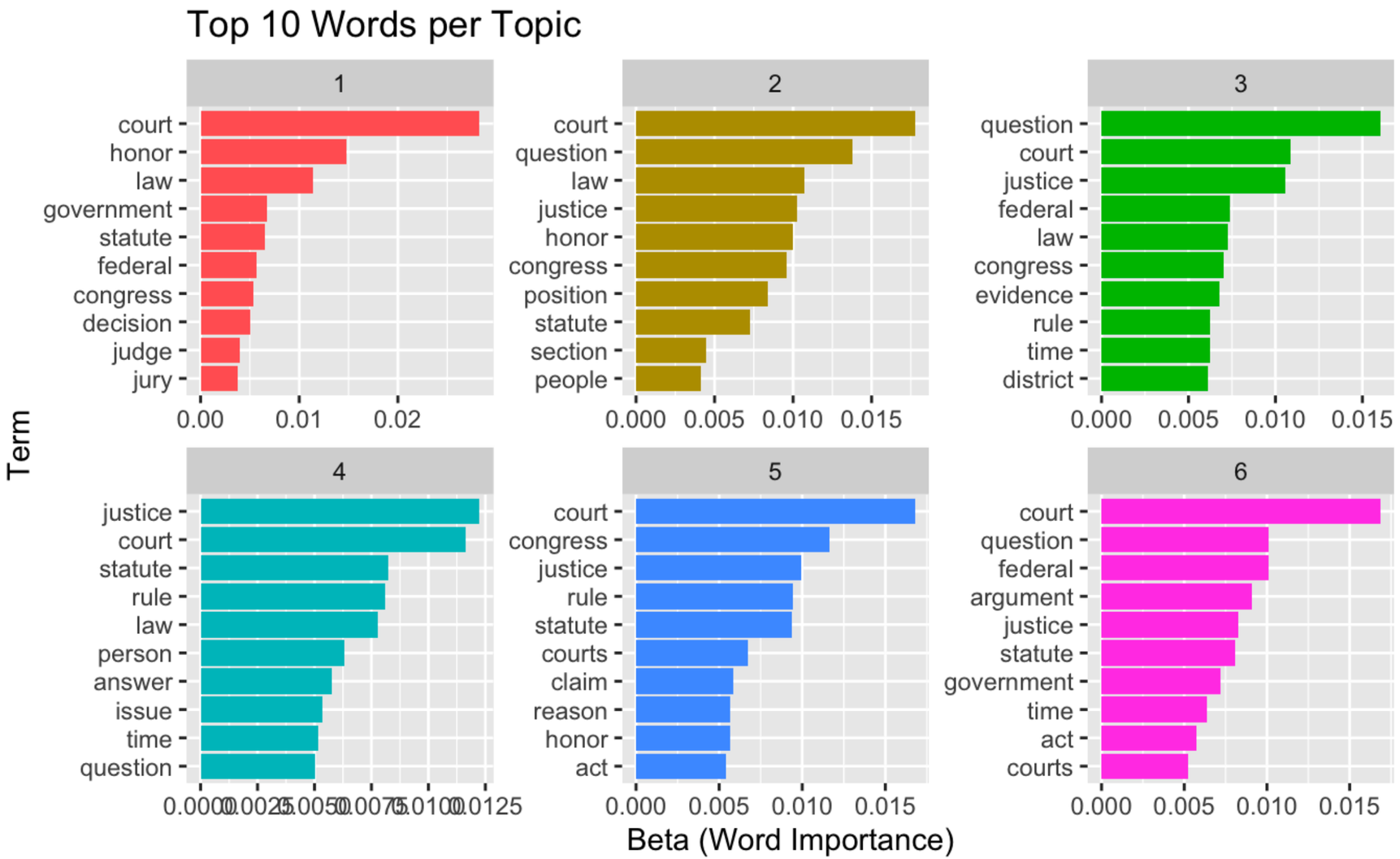
LDA for Topic Modeling

Will advocates be interrupted more under certain topics?
Whether interruptions toward women are more negative with particular areas?

LDA for Topic Modeling

Will advocates be interrupted more under certain topics?

Whether interruptions toward women are more negative with particular areas?



LDA for Topic Modeling

Will advocates be interrupted more under certain topics?
Whether interruptions toward women are more negative with particular areas?

Highly Overlapping Topics	Too similar topics discussed Supreme Court oral arguments are relatively formal and structured
LDA Assumptions Violated	LDA assumes documents are long enough to exhibit **a mixture of multiple topics**
Dominated Vocabulary	Topics offer little analytical value or interpretability Nearly identical top words such as “court” and “justice”
No Clear Thematic Separation	Fail to correspond to clear conceptual or emotional themes variations of ***“court talk”***

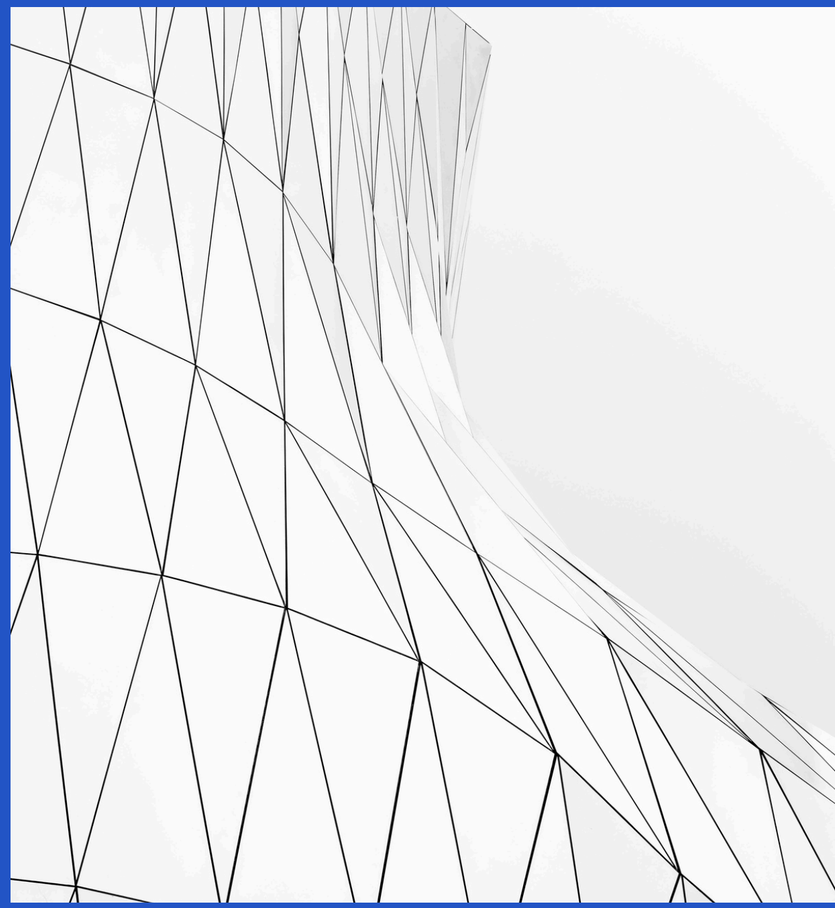
Limitations

- **Semantic Embedding Limitations**
  Miss nuance or context shift? Try BERT or Sentence-BERT for richer sentence representation

- **Domain Specificity**
  Study focuses on U.S. Supreme Court — elite, formal setting

- **Topic Modeling Constraints**

- **Uneven Advocate Distribution**



Future Direction

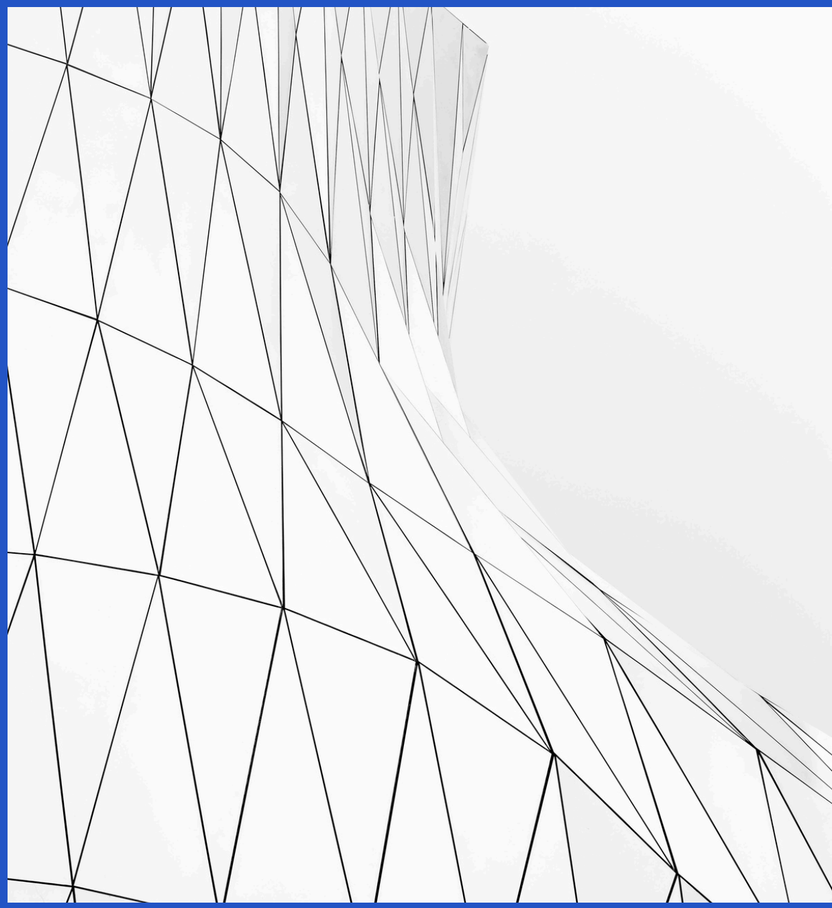
- **Temporal Dynamics of Arguments**
  Analyze changes across time within a case or speaker — e.g., whether tone escalates after interruptions

- **Disentangle Interruption Intent**
  Classify interruptions as supportive vs. opposing using speech acts or dialogue structure

- **Justice-Level Analysis**

- **Cross-Institution Comparison**

- **Incorporate Audio/Behavior Features**



Thank You