



# “We Demand Justice!”: Towards Social Context Grounding of Political Texts

Rajkumar Pujari Chengfei Wu Dan Goldwasser

Purdue University, West Lafayette, USA

{rpujari, wu1491, dgoldwas}@purdue.edu



Department of Computer Science

## Abstract

- ▶ Understanding political discourse on social media fully by reading only the text is difficult. However, knowledge of the social context information makes it easier.
- ▶ We characterize the social context required to understand such ambiguous discourse fully.
- ▶ We propose two datasets that require an understanding of social context and benchmark them using large pre-trained language models and several novel structured models.
- ▶ We show that structured models, explicitly modeling social context, outperform larger models on both tasks, but still lag significantly behind human performance.

## Motivation



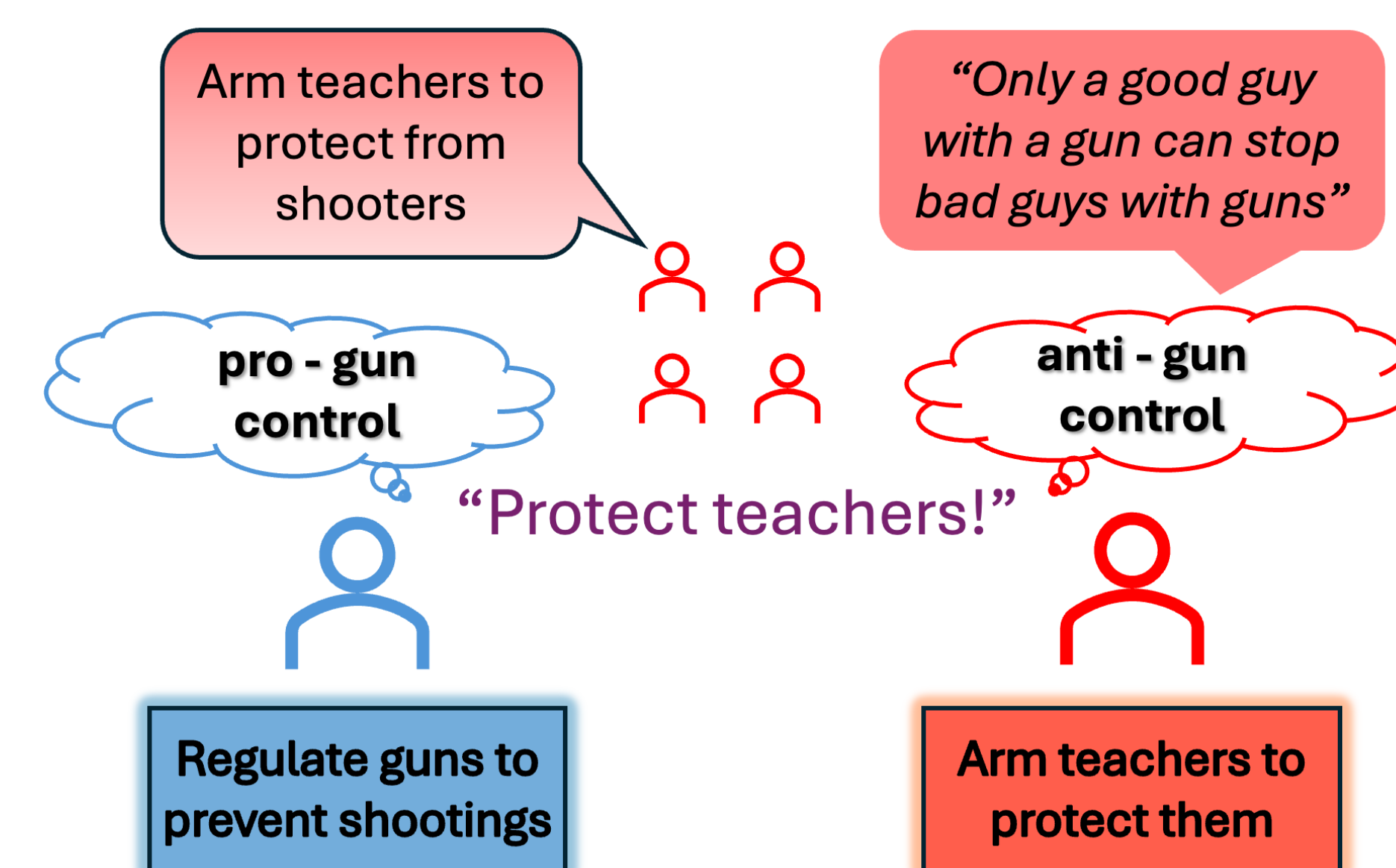
- ▶ Humans familiar with a politician’s stances and, possessing knowledge about the event, can easily understand the *intended meaning*.
- ▶ Our main question is - *Can an NLP model find the right meaning?*

## Dataset Statistics

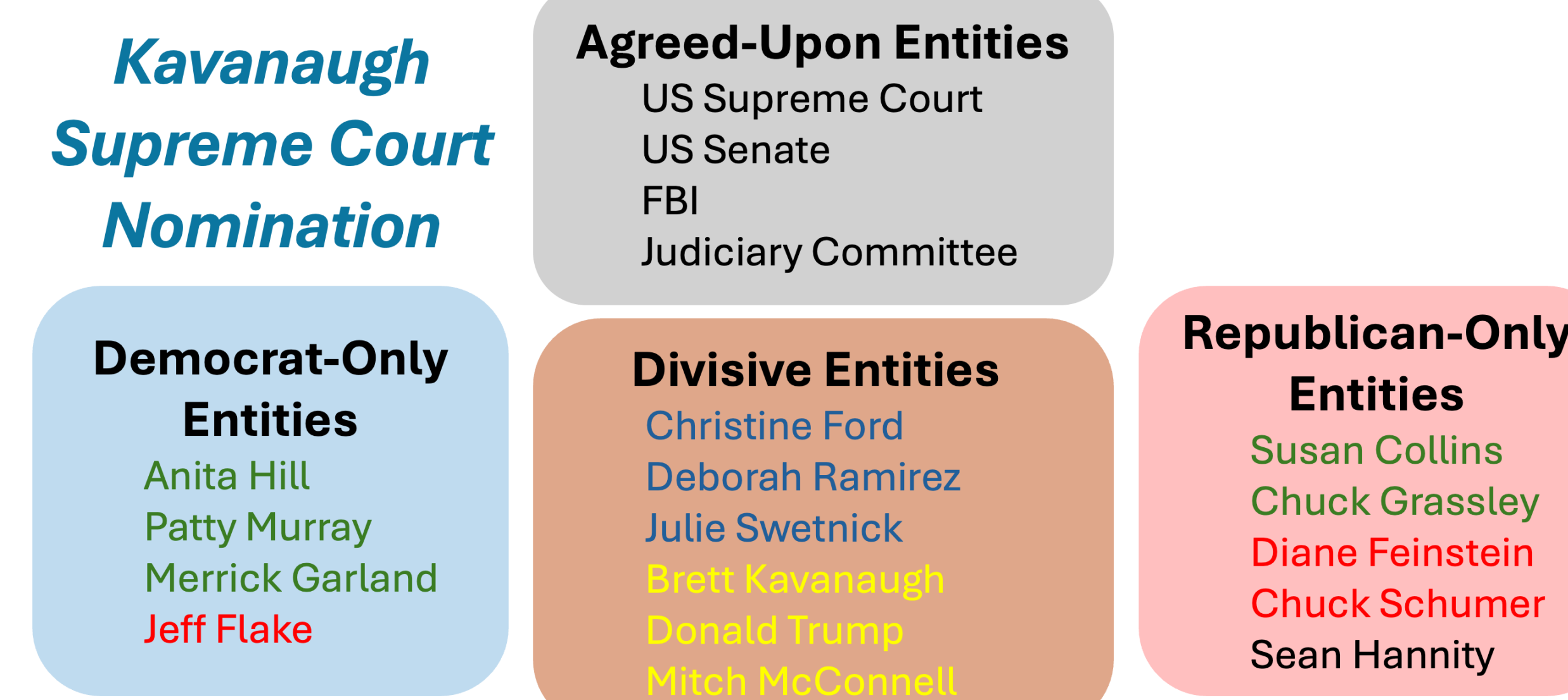
Target Task Data Statistics		Vague Text Data Statistics	
Unique Tweets	865	Unique Vague Texts	93
Positive Targets	1512	Positive Examples	739
Negative Targets	1085	Negative Examples	2217
Neutral Targets	784	Total Examples	2956
Non-Targets	2509	Hard Test Examples	180
Total Data Examples	5891	Number of Events	9
Number of Events	3		

- ▶ We use Amazon Mechanical Turk (AMT), LLMs, and contextual expert annotations to obtain the data.

## Social Commonsense



## Entity-Sentiment Perspective of an Event



## Human Performance Benchmarking

- ▶ Humans familiar with context find the Vague Text Disambiguation task fairly easy. Shows the robustness of the dataset.
- ▶ Current NLP models lag significantly behind humans on the *Vague Text Disambiguation* task

Model	Accuracy
BERT-base + wiki	54.89
BERT-base + DCF-embs	63.38
BERT-base + DCF	64.79
Humans	<b>94.85</b>

## Feature Importance Ablation

- ▶ Ablation of different classes of examples on the Target-Entity task. Shows that no single feature is sufficient for solving the task. A joint understanding of contextual elements is necessary to solve the task.

Data Split	Unseen Party	Unseen Event	Flip Tweet	Flip Event	Flip Party
	Ma-F1	Ma-F1	Acc	Acc	Acc
Random	44.70	29.69	75	75	75
BERT-base +wiki	57.58	39.76	<b>88.14</b>	89.77	<b>87.77</b>
BERT-base +DCF-embs	61.79	<b>47.88</b>	86.10	<b>93.18</b>	84.57
BERT-base +DCF	<b>65.18</b>	45.65	82.03	89.77	84.04

## Proposed Datasets

**Task:** Given an *opinionated tweet* from a politician, identify *intended target entities* and *sentiment* towards them

**Brett Kavanaugh Supreme Court Nomination**

Kavanaugh is not the victim here.

3:27 PM · Sep 27, 2018

343 Reply Copy link Read 18 replies

**Targets:** Brett Kavanaugh (negative), Julie Swetnick (positive), Christine Ford (positive), Deborah Ramirez (positive)

(a) Target-Entity & Sentiment Task

**Task:** Given *party affiliation* and a *vague statement* in context of an *event*, identify a *plausible interpretation* of the text

**Vague statement:** First, but not the last. **Author affiliation:** Republican

**Event:** US withdraws from Paris climate agreement

The withdrawal from the Paris climate agreement is the first of many positive actions for American economy to come for the Trump administration

Trump’s inauguration marks the first day of a new era of progress and prosperity (Incorrect Event)

It’s time for America to move forward & make progress without being held back by a global agreement that doesn’t serve our interests (Doesn’t match vague text)

The Paris Climate Agreement withdrawal is the first of many backward steps Trump administration is sure to take in destroying our environment (Improbable Stance)

(b) Vague Text Disambiguation Task

## Target Entity and Sentiment Results

Model	Target-Entity Task		Target-Sentiment Task		
	Macro-F1	Acc	Macro-F1	Acc	
No-Context Baselines	BERT-large (B-l)	68.83	70.56	58.95	58.37
	RoBERTa-base (R-b)	65.14	66.40	61.36	60.65
Text-Context Baselines	B-l + twitter-bio	69.34	71.66	60.13	59.86
	R-b + twitter-bio	64.79	66.30	59.94	59.46
	B-l + wiki	60.33	61.05	53.9	53.32
	R-b + wiki	68.62	70.27	58.07	58.28
LLMs	GPT-3 zero-shot	69.77	73.78	54.18	56.80
	GPT-3 few-shot	66.45	67.03	55.00	57.15
Contextualized Embeddings	B-l + PAR-embs	60.25	60.56	55.89	55.80
	R-b + PAR-embs	67.67	69.18	55.51	55.40
	B-l + DCF-embs	68.32	69.97	61.22	60.75
	R-b + DCF-embs	<b>73.56</b>	<b>75.82</b>	62.90	63.03
Discourse Contextualized Models	B-l + DCF	71.17	72.94	<b>65.34</b>	<b>65.31</b>
	R-b + DCF	70.39	72.15	63.37	63.23

## Vague Text Results

Model	Vague Text Disambiguation Task	
	Macro-F1	Acc
No-Context Baselines	BERT-large (B-l)	50.28
	BERT-base (B-b)	54.53
Text-Context Baselines	B-l + wiki	66.87
	B-b + wiki	64.36
LLMs	GPT-3 zero-shot	62.58
	GPT-3 few-shot	61.86
Contextualized Embeddings	B-l + PAR-embs	65.53
	B-b + PAR-embs	65.49
	B-l + DCF-embs	67.55
	B-b + DCF-embs	<b>71.71</b>
Discourse Contextualized Models	B-l + DCF	69.94
	B-b + DCF	70.06

## Conclusion

- ▶ We conceptualize and operationalize two holistic social context grounding tasks in English on the US political domain.
- ▶ We evaluate existing state-of-the-art models and humans on these tasks and present interesting observations.
- ▶ Future work directions include building explicit and interpretable models for *Social Context Grounding*, expanding proposed datasets, designing diverse tasks, and other flavors of social context such as cross-cultural understanding, emergency response, etc.

## Resources

<https://github.com/pujari-rajkumar/language-in-context>