Political Ideology Bias Detection with BERT

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Abstract

Abstract: TBD

1 Introduction

Political ideology bias in news sources is a topic of growing concern, not just in the U.S., but across the entire world. As our country grows ever more partisan and misinformation campaigns fuel distrust in mainstream news sources, people have a tendency to turn to alternative news sources which typically reflect the existing ideology bias of the author. This creates echo chambers and reinforces existing partisan ideologies driving the partisan divide ever wider. If biased text could be labeled in a way that informed the reader that the content they were consuming was biased, this could help readers to "take it with a grain of salt" and potentially look for less biased sources. A system like this could also help media sources reduce the amount of bias they include their reporting, using a this tool as a proofreader of sorts which could eventually, hopefully reduce the amount of bias in media and reduce the growing partisan divide.

In this paper, we build off of previous work done by Iyyer et al., etc...

would like to expand this section...

2 Model

Ahsen for BERT model

Need to figure out the document roll up using averaging or L2 norm or something

3 Data

Political bias at the sentence level is a very subjective topic and therefore, there are not many large corpora widely available for use. A large part of this project was devoted to acquiring and preparing a few existing corpora, as well as repurposing a few processing methods on new corpora to develop our own biased sentence corpus. We performed experiments on three separate datasets: Annotated congressional floor debates[3], the Ideological Books Corpus (IBC)[2] as well as the all-the-news dataset from Kaggle user Andrew Thompson. In this section we will describe the content of each dataset and preparations made to each dataset for use in our model.

3.1 Convote

The Convote dataset is a corpus of congressional speeches with each speech treated as a document with automatically derived labels of the speaker's political party (D, for Democrat; R, for Republican; I for Independent) as well as other related extracted information that was not pertinent to our experiments. Since our work attempts to predict ideological bias rather than political party, we relabel each document by mapping Democrat to "liberal", Republican to "conservative" and Independent to "neutral". While the mapping of political party directly to political bias is not always a 1:1 relationship, there is a strong correlation between political party and political ideology. Further, we expect that our method for filtering the dataset for biased sentences will wash out noise that would be seen from speeches made by moderate centrists on either side of the aisle.

3.1.1 Filtering Convote for Bias at the Sentence Level

It would be extremely unreasonable to assume that every sentence spoken by a member of congress during a congressional debate would contain ideological bias. In fact, a large portion of the sentences in the Convote dataset contain no bias at all.[1] Therefore, it is necessary to filter this dataset for sentences that explicitly contain bias.

To select the explicitly biased sentences from the dataset, we used a method inspired by Yano, et al. [5] and shown to be successful as a bias identifier by Iyyer, et al. [2] We started by identifying the most frequently used trigrams and bigrams for each label (liberal and conservative). After removing n-grams that contained stopwords, and English names, we then filtered the bigrams further by requiring that at least one word in the bigram contain an "opinion" defined as a word found in the `opinion_lexicon` corpus from NLTK. We then took the set difference of the resulting top 1000 most frequent liberal and conservative n-grams (i.e. out of the top 1000 liberal bigrams, we only kept those that did not appear in the top 1000 conservative bigrams and vice versa, same for trigrams). This left us with 665 bigrams from each label and 751 trigrams from each label. We kept the top 100 bigrams and top 100 trigrams for each label as our bias indicators. We then filtered sentences such that, if a democratic speaker spoke a sentence that contained one of these top 200 "liberal" n-grams, we labeled that sentence as "liberal" and used the same logic to identify conservative sentences. For this dataset, we identified a neutral sentence as one which was spoken by an independent politician and contained no n-grams from either the liberal or conservative bias indicators. The top 10 n-grams from each label are shown in Table 1.

Table 1: Top 10 n-grams per ideology label - Convote

Liberal		**Conservative**	
Trigrams	Bigrams	Trigrams	Bigrams
social security trust	tax breaks	national electrical contractors	community protection
security trust fund	security trust	electrical contractors association	free market
cbc alternative budget	bad policy	legislative days within	organized crime
black caucus budget	would lose	inner cell mass	bankruptcy relief
estate tax relief	reduce crime	head start program	good news
privatize social security	budget reconciliation	community protection act	relief extension
u.s. trade deficit	ethical standard	million new jobs	delayed notification
republican budget resolution	fiscally irresponsible	death tax repeal	soft money
national wildlife refuge	working poor	9/11 commission report	illegal aliens
guardian ad litem	subpoena power	stem cells without	invasive species

The resulting dataset included 1326 conservative sentences, 1383 liberal sentences and 213 neutral sentences. Example sentences from each ideology label are shown in Table 2.

3.2 IBC

The Ideological Books Corpus was provided to us in a fully processed format, courtesy of Iyyer et al.[2] The original IBC dataset, originally developed by Gross et al.[1] is a collection of books and articles written between 2008 and 2012 by well-known authors with strong political leanings. What Iyyer's team did was to filter this corpus using a similar strategy to the strategy outlined in section 3.1.1. They then crowd-sourced manual ideological bias annotations of the resulting sentences and particular subphrases. We use the data in this processed form as is, with no further processing.

3.3 All-the-news Kaggle corpus

To expand our training data further with a greater diversity of authors, we turned to a Kaggle corpus of 142,570 news articles from 15 different publishers as provided by Andrew Thompson[4]. We assigned each publisher a bias

[1] Many sentences are simply opinion statements on whether or not the speaker agrees with the bill, or parliamentary jargon such as addressing the Speaker of the House, or urging their colleagues to vote a certain way, etc.

Table 2: Sample sentences from each ideology label - Convote

Liberal	**Conservative**	**Neutral**
mr. speaker, during a time of war, in the aftermath of a catastrophic hurricane, with 45 million americans lacking health insurance and skyrocketing home heating costs projected this winter, this majority is proposing to take from those with the least, give to those with the most – and tell our children they will have to pay for it all later.	on both the business records and delayed notification sections of the patriot act (among others), the stance of the american civil liberties union and like-minded critics seems to have an ulterior motive.	let us look at what is going on in america today.
it is clear that there would be plenty of money to deal with the social security trust fund if the president were not using the social security trust fund as a slush fund to give tax cuts to the wealthiest people in america.	that legislation helped to streamline the intelligence community and tightened some asylum rules that allowed potential terrorists to remain in our country.	mr. speaker, parliamentary inquiry.

label, sourced from mediabiasfactcheck.com (MBFC), then we simplified these labels down to the same labels we used in the previous datasets: liberal, conservative and neutral. The labels assigned to each publisher are shown in Table 3.

Table 3: Publisher and bias labels from all-the-news corpus

Publisher	**MBFC Bias Label**	**Simplified Bias Label**
New York Times	left-center	liberal
Breitbart	extreme-right	conservative
CNN	left	liberal
Business Insider	left-center	liberal
Atlantic	left-center	liberal
Fox News	right	conservative
Talking Points Memo	left	liberal
Buzzfeed News	left-center	liberal
National Review	right	conservative
New York Post	right-center	conservative
Guardian	left-center	liberal
NPR	left-center	liberal
Reuters	neutral	neutral
Vox	left	liberal
Washington Post	left-center	liberal

3.3.1 Filtering All-the-news for Bias at the Sentence Level

Because the language used in a congressional debates is quite different than the language typically used in journalism, the bigrams that we found in the Convote dataset don't crossover very well to the all-the-news dataset. Therefore we determine a new set of n-grams for the news article dataset. We applied a similar filtering method to the one explained in section 3.1.1 to filter sentences containing explicit bias.

We first took a subset of publishers with the most extreme MBFC bias labels to determine biased bigrams from. This subset is shown in Table 4.

From this subset, we selected n-grams that indicate bias similarly to the methods applied to the Convote

Table 4: Subset of news publishers for n-gram selection

Publisher	MBFC Bias Label	Simplified Bias Label
Breitbart	extreme-right	conservative
Fox News	right	conservative
National Review	right	conservative
CNN	left	liberal
Talking Points Memo	left	liberal
Vox	left	liberal
Reuters	neutral	neutral

set[2]. The resulting n-grams are shown in Table 5.

Table 5: Top 10 n-grams per ideology label - All-the-news

Liberal		Conservative	
Trigrams	Bigrams	Trigrams	Bigrams
senior administration official	fast facts	battleground prediction map	illegal aliens
green card holders	opioid epidemic	jerusalem bureau chief	illegal alien
greenhouse gas emissions	health reform	popular weekend talk	illegal immigrant
north korean leader	lethal injection	tweetsa question needing	migrant crisis
federal civil rights	budget reconciliation	voter suppression cost	popular weekend
provocative narrative essays	chronic pain	says voter suppression	patriot channel
health care policy	lead poisoning	border patrol agent	hard truths
republican health care	intelligence committees	electionhillary blames america	limited government
gop health care	prison sentences	blames america firsthillary	islamic terror
civil rights laws	rights advocates	america firsthillary says	twin falls

Using these n-grams to select sentences that contained bias led to a dataset which contained

4 Experiments/Results

TBD after we run some experiments

5 Future Research

We will build a HAN model using BERT as our encoder. Will need to find or create better document level

6 Conclusion

TBD

[2]We removed stopwords using a custom stopwords list, removed English names and required bigrams to include one ”opinion” word. This is to remove boilerplate sentences and taglines such as ”associated press”, ”bestselling author”, ”conservative columnist”, etc.

Table 6: Sample sentences from each ideology label - All-the-news

Liberal	**Conservative**	**Neutral**
Here's what you need to know: American divisions are rapidly widening over President Trump's order to close the U. S. to refugees and people from seven predominantly Muslim countries.	And the costs of illegal alien crime continued to mount and a lethal opioid epidemic raged.	Showcasing their attempts to unite with other groups for the election, Islamists campaigned with Awdeh Qawwas, a prominent priest, in the affluent Abdoun district of the capital Amman.
In a video posted on her campaign's Facebook page shortly after Mr. Sanders departed the White House grounds to visit the Capitol, Mr. Obama described Mrs. Clinton as the most qualified candidate to seek the White House, and implored Democrats to come together to elect her after a divisive party primary.	Obama's claim of civic peace is also at odds with the televised evidence: dramatic race riots, cop killings, rapes, murders, illegal alien crimes, and chaos that rippled across the country during the second term of his presidency.	Rousseff's survival hinges on winning over a dwindling number of undecided lawmakers who are also being courted by the man poised to take over if she is ousted, Vice President Michel Temer.

References

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[2] Mohit Iyyer, Peter Enns, Jordan Boyd-Graber, and Philip Resnik. Political ideology detection using recursive neural networks. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1113–1122, Baltimore, Maryland, June 2014. Association for Computational Linguistics.

[3] Matt Thomas, Bo Pang, and Lillian Lee. Get out the vote: Determining support or opposition from congressional floor-debate transcripts. *CoRR*, abs/cs/0607062, 2006.

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