Determining Political Issue Polarity with BERT

Neha Kumar and Sayan Das
W266 Section 5 Saturday 10a PT
Prof. Sid Reddy

Research Goal and NLP

- 2020 Presidential Race saw many different candidates from diverse backgrounds
- Summarize candidates' stances on key issues for the 2020 election with NLP!

Key Issues:
- Pro / anti guns
- Pro / anti Medicare for all
- Pro / anti immigration
- Pro / anti abortion
- Pro / anti military spending
- Pro / anti tax on extreme wealth
- Pro / anti free higher education

Source

Prior Research

Studies classifying political stance

- Classifying politician stance using tweets, by Johnson et al
  - Extracts temporal data
  - Supplemented with party affiliation
  - Bag of words type implementation

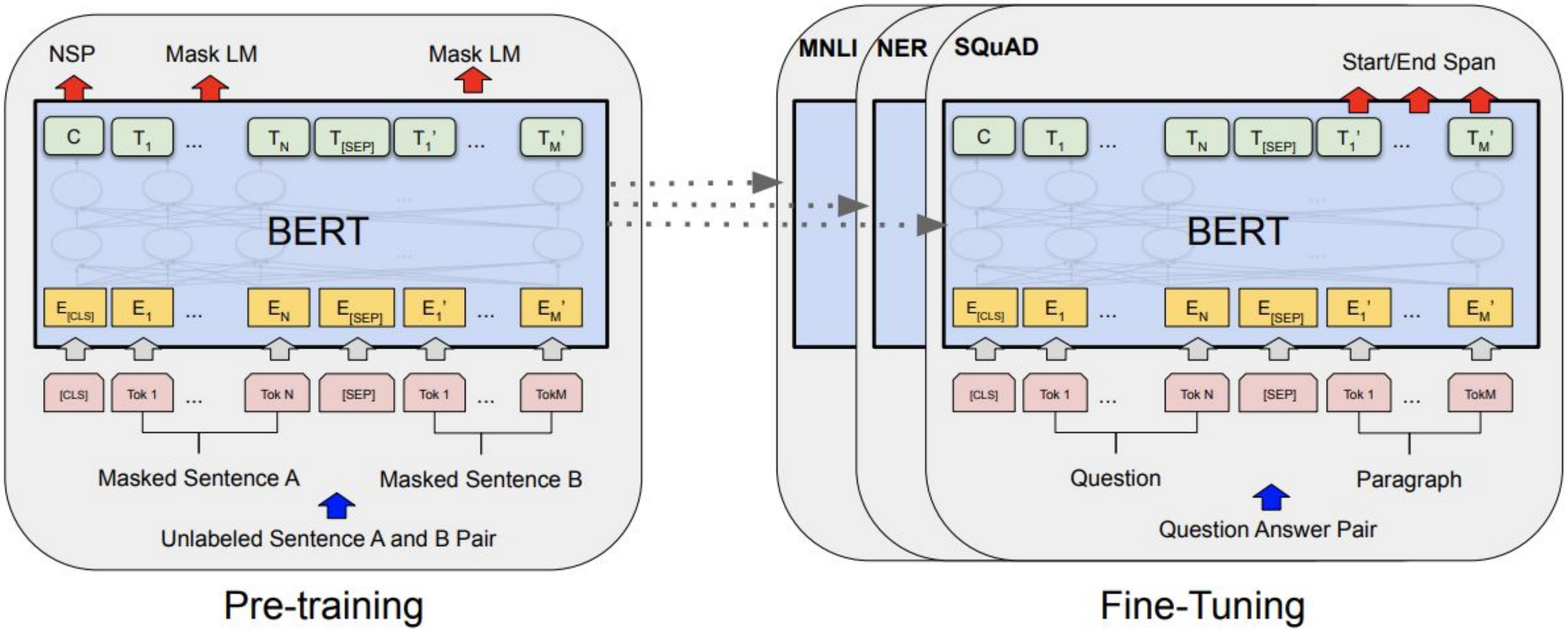
Studies using BERT

- Promising results shown in classifying toxic speech (by d'Sa et al)
- Improving performance with pretraining on unsupervised data (Han et al)
- Some studies found that the LSTM to still be preferable due to the efficiency to train that as opposed to BERT (110M parameters) - Adhikari et al

To the best of our knowledge, there are no studies that apply BERT sequence classification on political text to classify candidate polarity on issues

BERT Architecture

Used: bert-base-uncased
12-layer, 768-hidden, 12-heads, 110M parameters.
Trained on lower-cased English text.



Why BERT?
Current SOTA, better than OpenAI GPT which is only unidirectional

[Source]

Data Collection

Round 1 Unsupervised Pretraining (L1 Data)

Fake News Corpus

Round 2 Unsupervised Pretraining (L2 Data)

We wrote our own scraper to pull articles related to the 7 topics

Labeled Training (L3 Data)

We hand selected articles for and against each issue. We were able to label each sentence with the category since we knew the article it came from

Test Data

We wrote our own scraper to pull text from the Democratic candidates' NYT interviews and campaign websites

Trump tweets corpus

Icons from the noun project

High-Level Workflow

Pretraining

512 word segments

bert-base-uncased

Updated pretrained model

Fine tune bert-base-uncased with 2 levels of unlabeled text data

Training

Sentence 1 | Label

Sentence 2 | Label

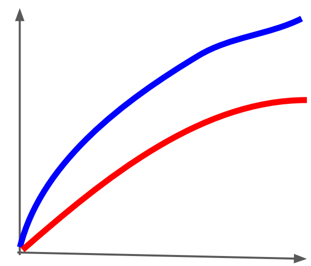
Sentence 3 | Label

Sentence 4 | Label

Sentence 5 | Label

10% of sentences saved for validation

Validation



Assess best hyperparameters

Testing

Sentence 1

Sentence 2

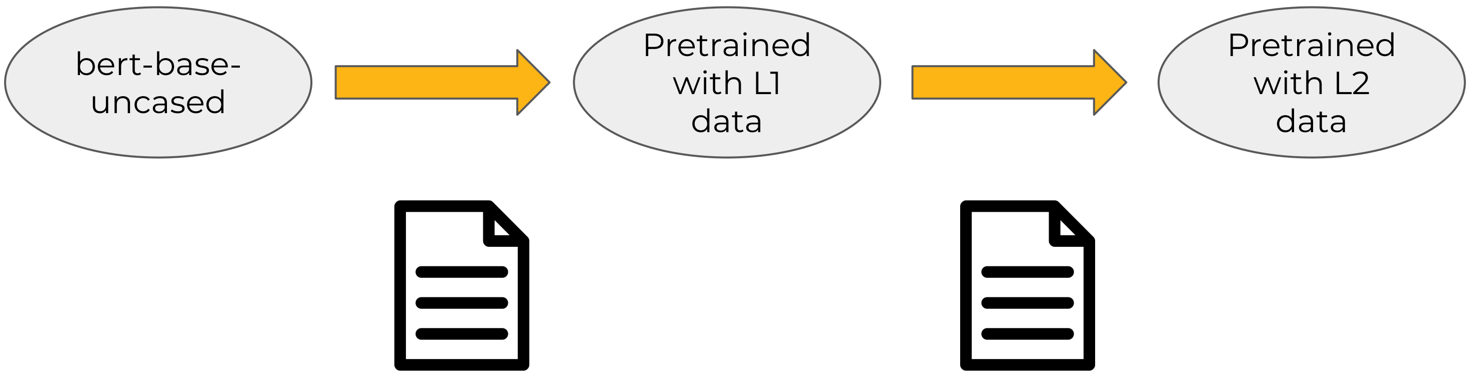
Sentence 3

Sentence 4

Sentence 5

Predict label for candidate statements sentence by sentence and aggregate results per candidate

Closer look at pretraining



L1 data
(48M words)
~1 day of training

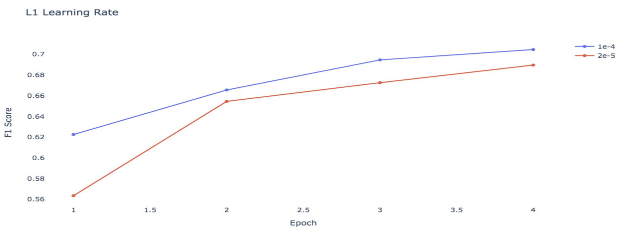
Segmented into
512 word chunks

L2 data
(1M words)
~20 min of training

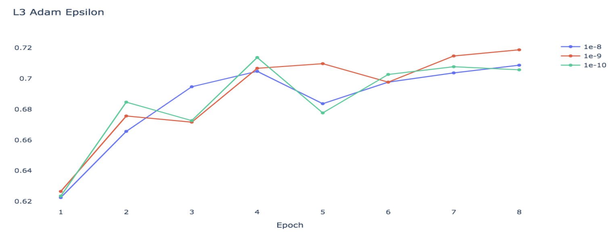
Segmented into
512 word chunks

Hyperparameter tuning, showing F1 Score on Dev data

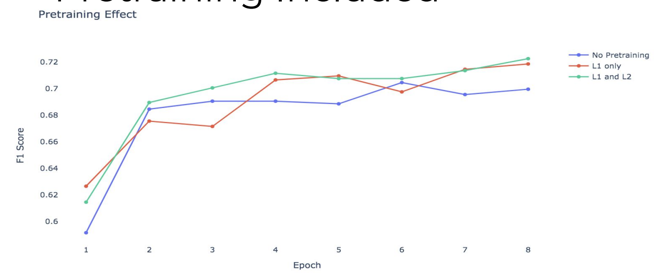
L1 Learning Rate



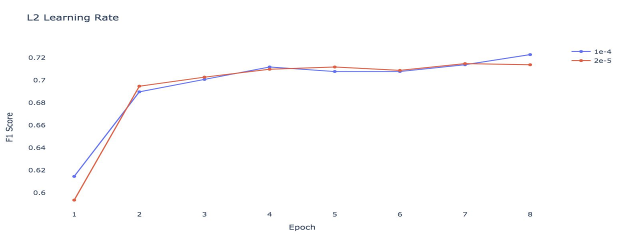
L3 Adam Epsilon



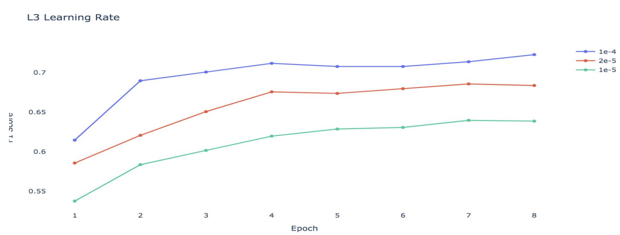
Pretraining Included



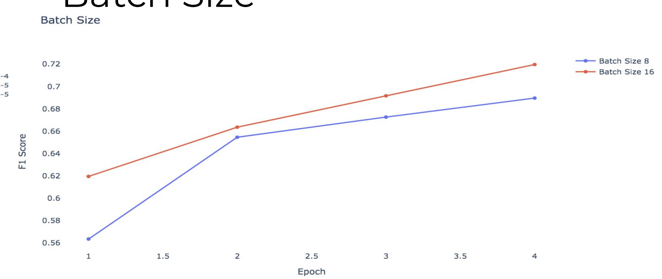
L2 Learning Rate



L3 Learning Rate

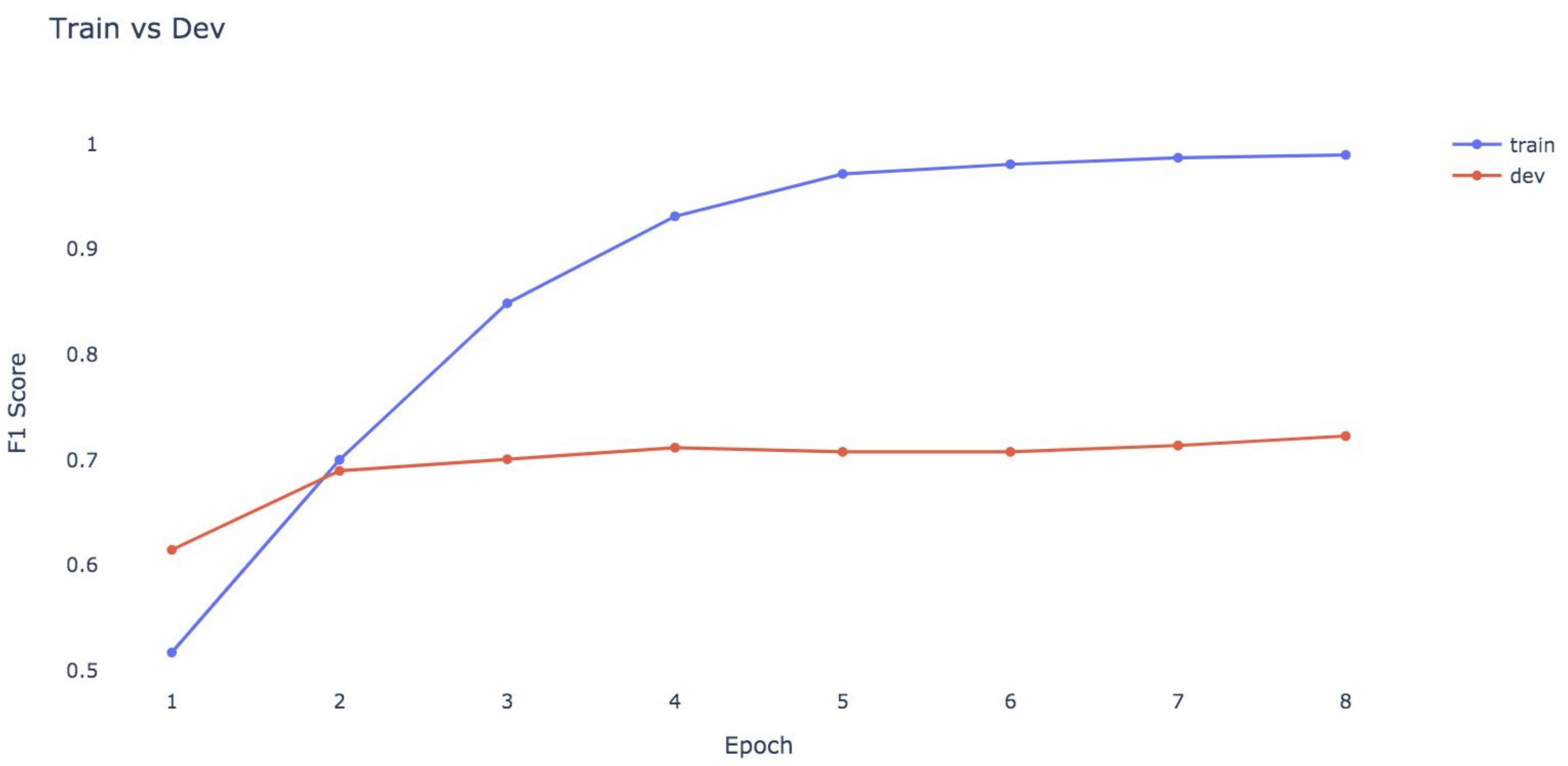


Batch Size



Best Performing Hyperparameters
L1 and L2 Pretraining
Learning rate of 1e-4 for L1 L2 and L3
Adam Epsilon of 1e-9
Batch Size of 8

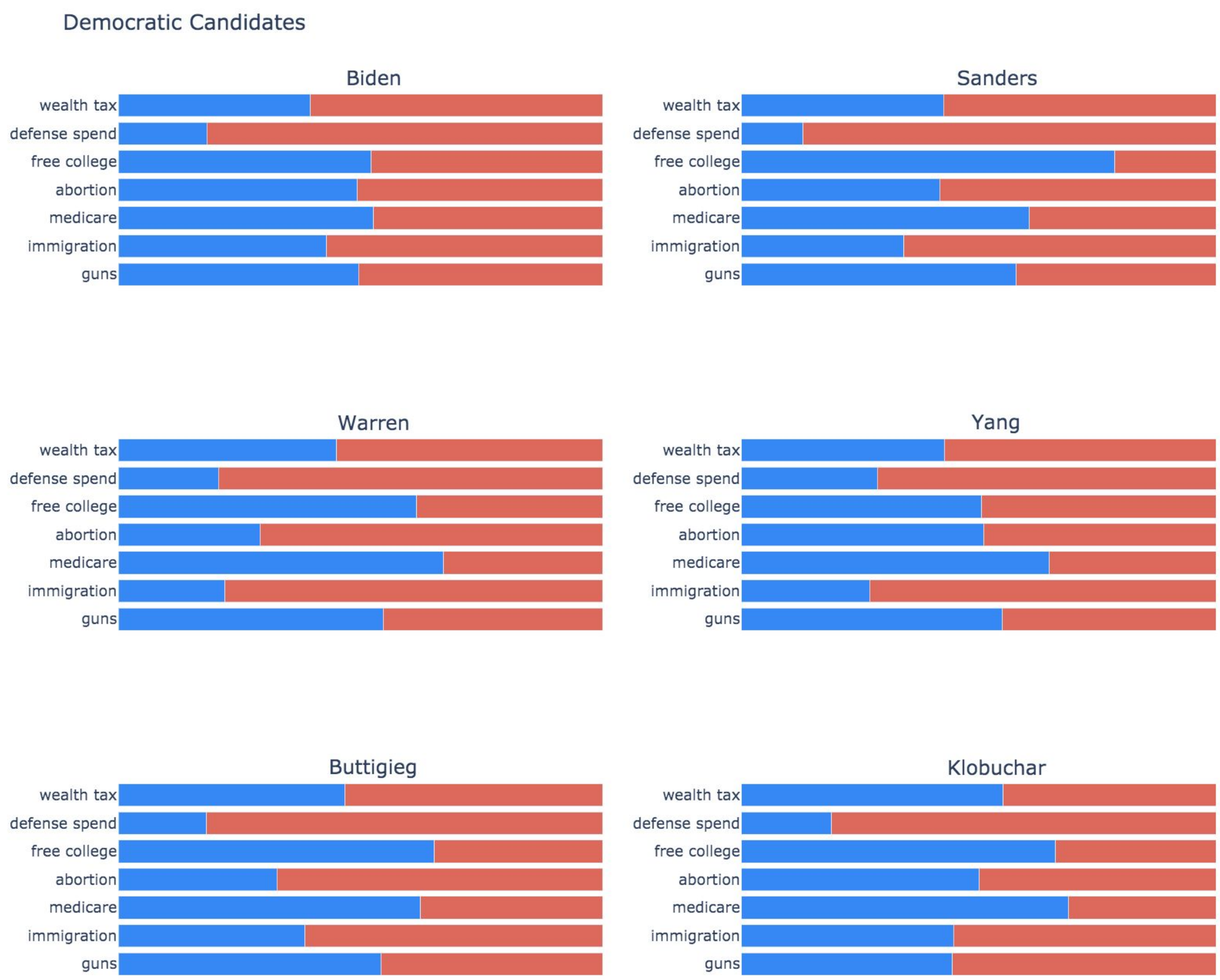
Best Performing Model, Comparing Training and Dev F1



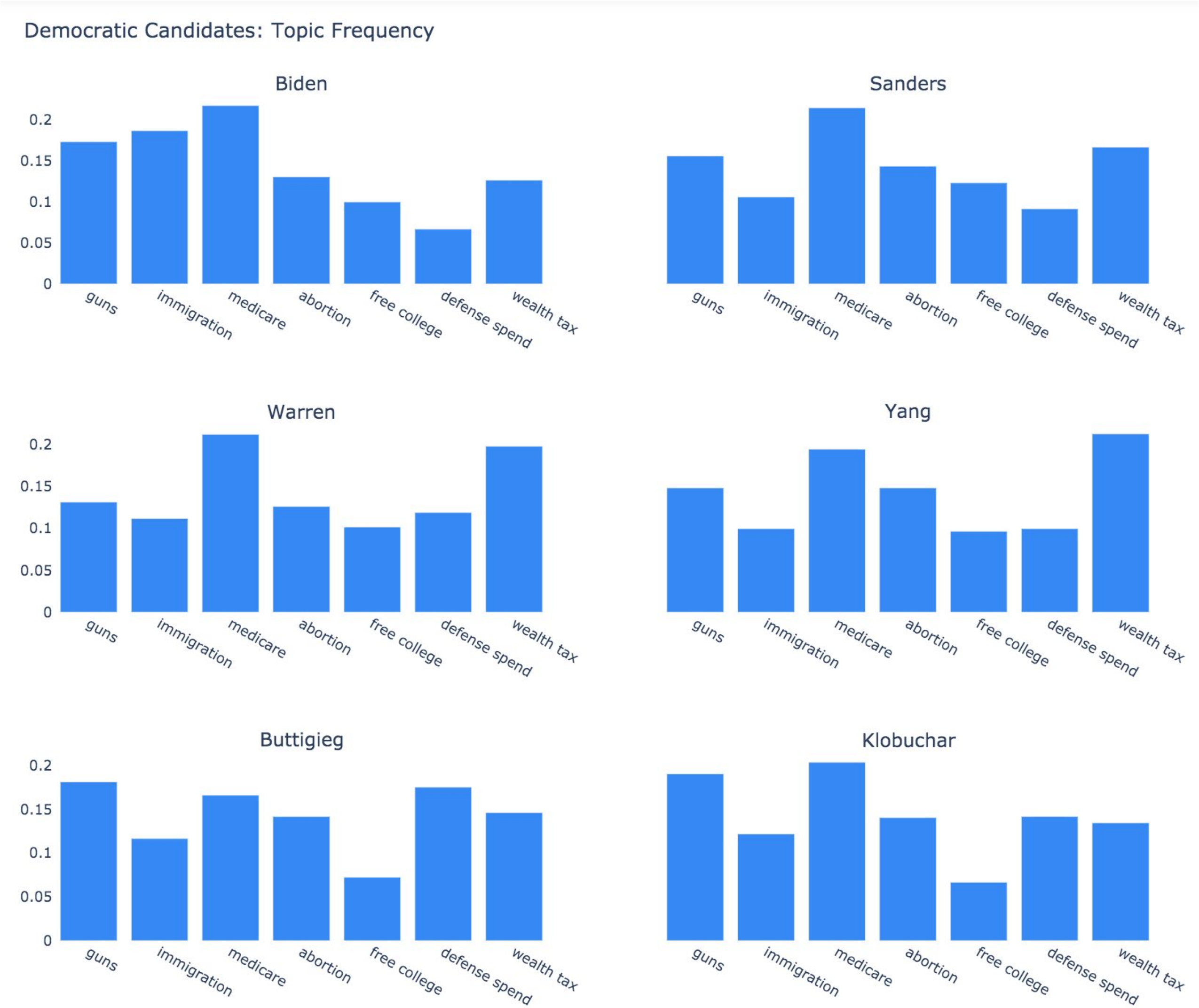
Extremity Score Formula

$$\frac{1}{2} * \frac{sum(Pro) - sum(Anti)}{sum(Pro) + sum(Anti) + 1}$$

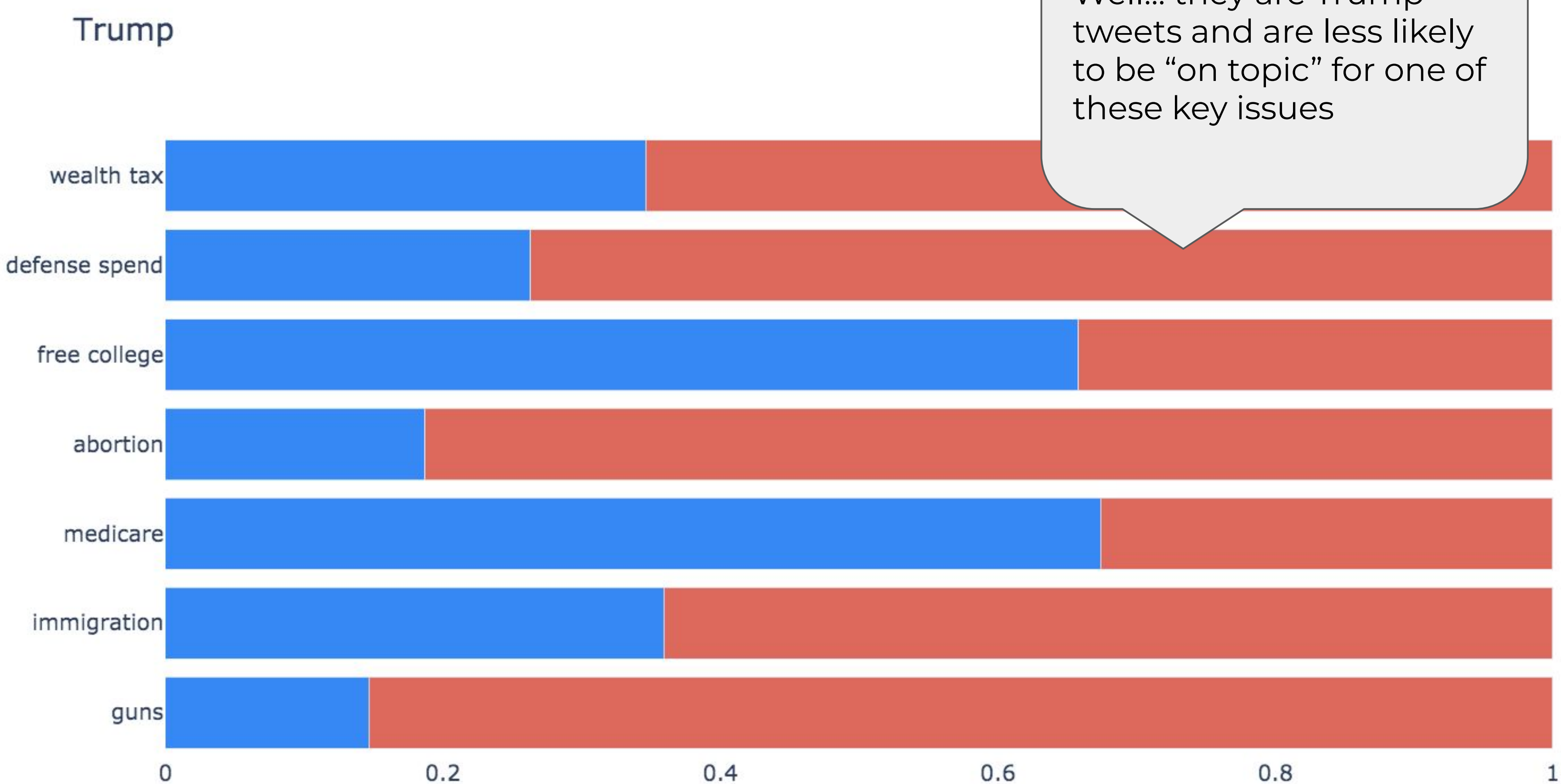
Issue Polarity for Democratic Candidates



Frequency of Statements For and Against each Issue



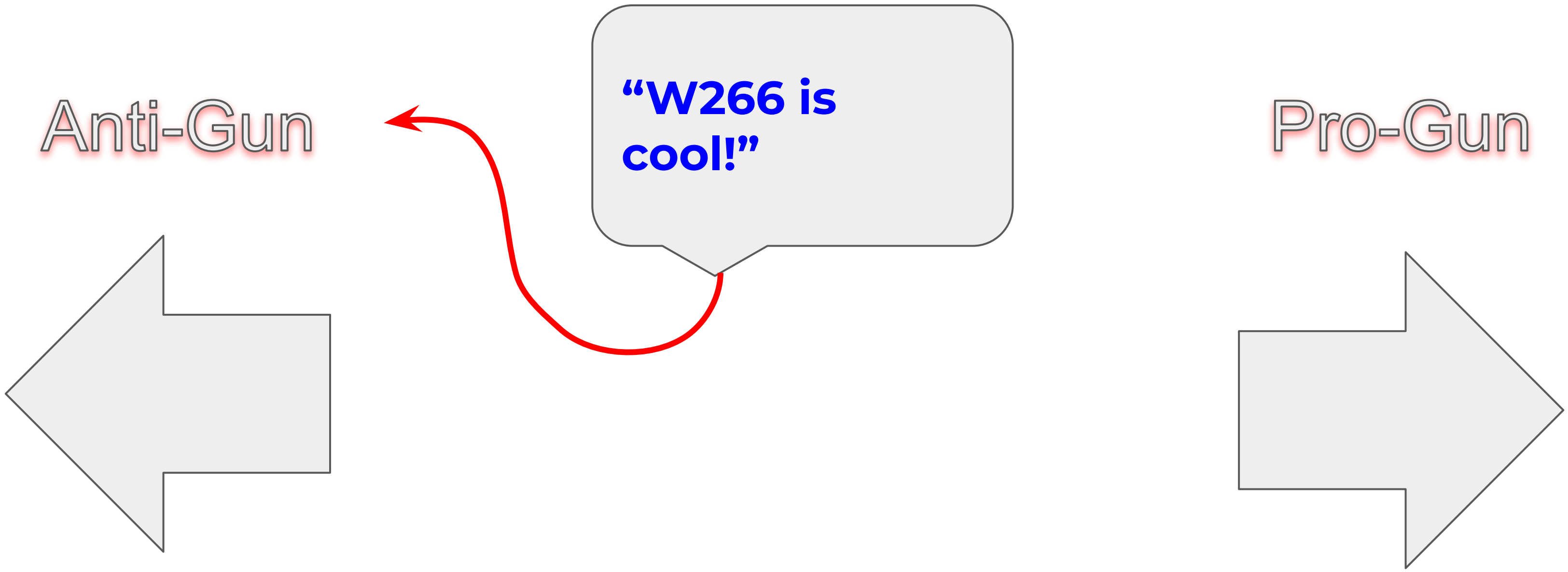
Issue Polarity for Trump



Well... they are Trump tweets and are less likely to be “on topic” for one of these key issues

Next Steps, Further Improvement

- More data! More pretraining!
- Address topic polarization
  - Multiple binary classification models



Literature References

[1] Devlin, Jacob, et al. "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805 (2018).https://www.aclweb.org/anthology/N19-1423.pdf

[2] Sun C., Qiu X., Xu Y., Huang X. (2019) How to Fine-Tune BERT for Text Classification?. In: Sun M., Huang X., Ji H., Liu Z., Liu Y. (eds) Chinese Computational Linguistics. CCL 2019. Lecture Notes in Computer Science, vol 11856. Springer, Cham https://arxiv.org/pdf/1905.05583.pdf

[3] Ashwin Geet d'Sa, Irina Illina, Dominique Fohr. BERT and fastText Embeddings for Automatic Detection of Toxic Speech. SIIE 2020 - Information Systems and Economic Intelligence, Feb 2020, Tunis, Tunisia. Ffhal-02448197 https://hal.inria.fr/hal-02448197/document

[4] Johnson, K., & Goldwasser, D. (2016). Identifying stance by analyzing political discourse on twitter. In Proceedings of the First Workshop on NLP and Computational Social Science. https://www.aclweb.org/anthology/W16-5609.pdf

[5] Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C., Moi, A., ... & Brew, J. (2019). Transformers: State-of-the-art Natural Language Processing. *arXiv preprint arXiv:1910.03771*. https://arxiv.org/pdf/1910.03771.pdf

[6] Ashutosh Adhikari, Achyudh Ram, Raphael Tang, and Jimmy Lin. (2019) DocBERT: BERT for Document Classification. David R. Cheriton School of Computer Science, University of Waterloo. https://arxiv.org/pdf/1904.08398.pdf

[7] Xiaochuang Han, Jacob Eisenstein. (2019). Unsupervised Domain Adaptation of Contextualized Embeddings for Sequence Labeling. Georgia Institute of Technology. https://arxiv.org/pdf/1904.02817.pdf

Coding Resources

- https://github.com/huggingface/transformers
- For LSTM Baseline model: https://github.com/danwild/sagemaker-sentiment-analysis
- Tutorial for preprocessing: https://mccormickml.com/2019/07/22/BERT-fine-tuning/#3-tokenization--input-formatting
- For main training script:
  - https://github.com/huggingface/transformers/blob/master/examples/run_glue.py
  - https://aws.amazon.com/blogs/machine-learning/maximizing-nlp-model-performance-with-automatic-model-tuning-in-amazon-sagemaker/
  - https://github.com/danwild/sagemaker-sentiment-analysis/blob/163913a21837683e7605f6122ad2c10718347f65/train/train.py#L45
  - https://mccormickml.com/2019/07/22/BERT-fine-tuning/#3-tokenization--input-formatting