Offensive Language Detection

Bridget Tyree, Yi-Chien Lin, David Yi, Levon Haroutunian

Outline

- Task description
- System architecture
- Core approach
- Issues and successes
- Related Readings

Task Description

Offensive Language Detection

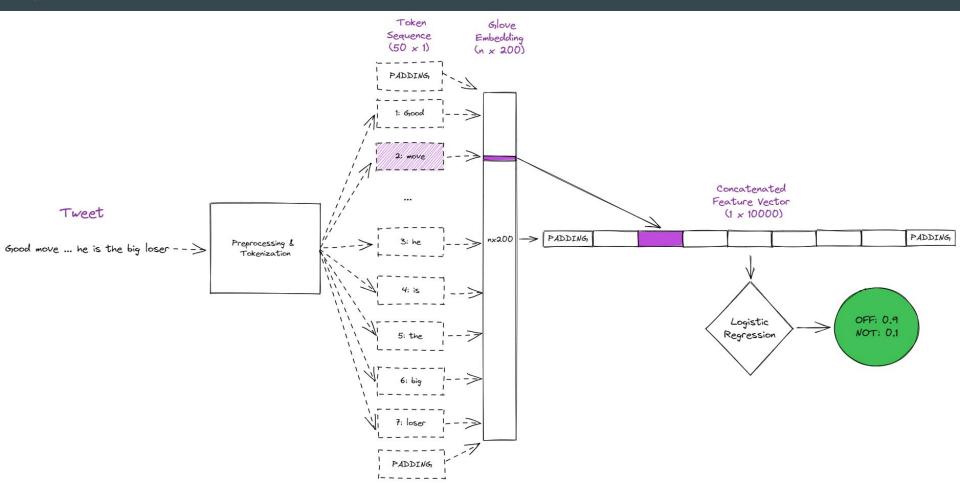
- Primary Task:
 - Subtask A of OffensEval 2019
 - Binary classification: is an English tweet offensive (OFF) or not offensive (NOT)?
 - Data: OLID (Offensive Language Identification Dataset)
 - Total: 13,240 tweets 8,840 NOT & 4,400 OFF tweets
- Adaptation Task:
 - Subtask A of OffenEval 2020
 - Detect offensive tweets in Arabic, Danish, Greek, and Turkish.

Tweet	A	В	C
@USER He is so generous with his offers.	NOT	_	_
IM FREEEEE!!!! WORST EXPERIENCE OF MY FUCKING LIFE	OFF	UNT	
@USER Fuk this fat cock sucker	OFF	TIN	IND
@USER Figures! What is wrong with these idiots? Thank God for @USER	OFF	TIN	GRP
			W

Table 1: Four tweets from the OLID dataset, with their labels for each level of the annotation model.

System Architecture

System Architecture



Core Approach

Featurizing the Tweets

Tokenization: Keras tokenizer that converts tokens to unique integers with minimal preprocessing

- Pad and truncate all sequences to 50 tokens, since our classifier only takes in fixed-length inputs

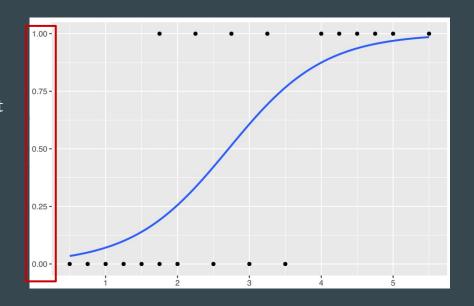
Word Embeddings: 200-dimensional GloVe Embeddings trained on Twitter Corpus

Featurization: Get GloVe embedding for each token in the sequence and stack them horizontally

- Input: Sequence of length 50
- Output: 10000 (50 * 200) dimensional vector

Binary Classification

- Logistic regression
 - Uses logistic function to model a binary output
- Scikit-learn parameters
 - L2 regularization
 - Class weight: balanced
 - Optimization problem: limited-memory BFGS



From Wikipedia

Issues and Successes

Results

Macro F1-Score:

0.5980265654648956

	F1 Score
SVM	0.690
OUR MODEL	0.598
ALL NOT	0.420
ALL OFF	0.220

Confusion Matrix		Predicted label	
		negative	positive
True label	negative	667	210
	positive	254	193

Error Analysis

- Untargeted and targeted offensive tweets were equally likely to be incorrectly classified. This suggests that our model is not making use of word identity.
- Upon looking at the data further, it seems like "controversial" words (like MAGA, antifa, gun control) are not strong indicators.
 - May also be true of negative sentiment more broadly.
- Our model may also be missing helpful information about sequence, which can be useful for determining whether a statement is a threat or insult.

Potential Next Steps (David)

Current System

- Classification: RNNs, (bi)LSTMs
- Emoji Embeddings (emoji2vec)
- Rule-based expansion of acronyms and abbreviations
- Incorporate syntactic or semantic parse trees during preprocessing/tokenization

Major Changes

- Used fine-tuned pretrained Language Model (i.e. RoBERTa) to create contextual word embeddings (Barbieri et al., 2020)
- Classification Ensemble

State of the Art (2019)

Method	F1 Score
BERT (fine-tuned)	0.829
CNN	0.800
BiLSTM	0.750
SVM	0.690
GloVe + Logistic Regression	0.598

SemEval-2019 Task 6: (Zampieri et al., 2019)

Related Reading

References

- SemEval 2019 Report: Zampieri et al., 2019
- TweetEval: <u>Barbieri et al., 2020</u>
- Abusive language overview: <u>Talat et al., 2017</u>
- GloVe Embeddings: <u>Pennington et al., 2014</u>