CS 224n Winter 2019: Toxic Speech Detection

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Introduction

- Rapid growth of online platforms and forums propagates abusive language and toxic speech
- An individual risks being harassed by other users when participating in online discussions
- Problem: deep learning models that detects types of toxic comments (clean, toxic, obscene, insult, identity hate, severe toxic, and threat)

Dataset

- Google Jigsaw's Kaggle dataset: "Toxic Comment Classification Challenge" (published in 2017)
- Separated into train and test sets, both containing approximately 160,000 comments and labels
- Randomly select 20% from test set to be dev. set

Approach

- Existing approaches include "classical methods" such as regression and SVM and deep learning models like CNN and RNN variants
- Text classification problem
- Apply LSTM, GRU, and VDCNN

Conclusion

- Deep learning models are accurate, but have high computational cost
- Adopting a cascading allows us to utilize the efficiency of "classical methods" while drawing from Bi-LSTM model's accuracy when it is needed
- Lack of clean training data and lack of testing on diverse datasets
- Limited computing power for char-based models
- Future work: refining cascading model, combining deep learning architectures, and explore feature extraction mechanisms for SVM

References

- *Google Jigsaw. "Toxic Comment Classification Challenge", 2017.*
- *Conneau, Alexis. "Very Deep Convolutional Networks for Text Classification", 2017.*
- *Zhang, Ziqi. "Hate Speech Detection: A Solved Problem? The Challenging Case of Long Tail on Twitter", 2018.*
- *Vaswani, Ashish. "Attention is All You Need", 2017.*

Experimental Results

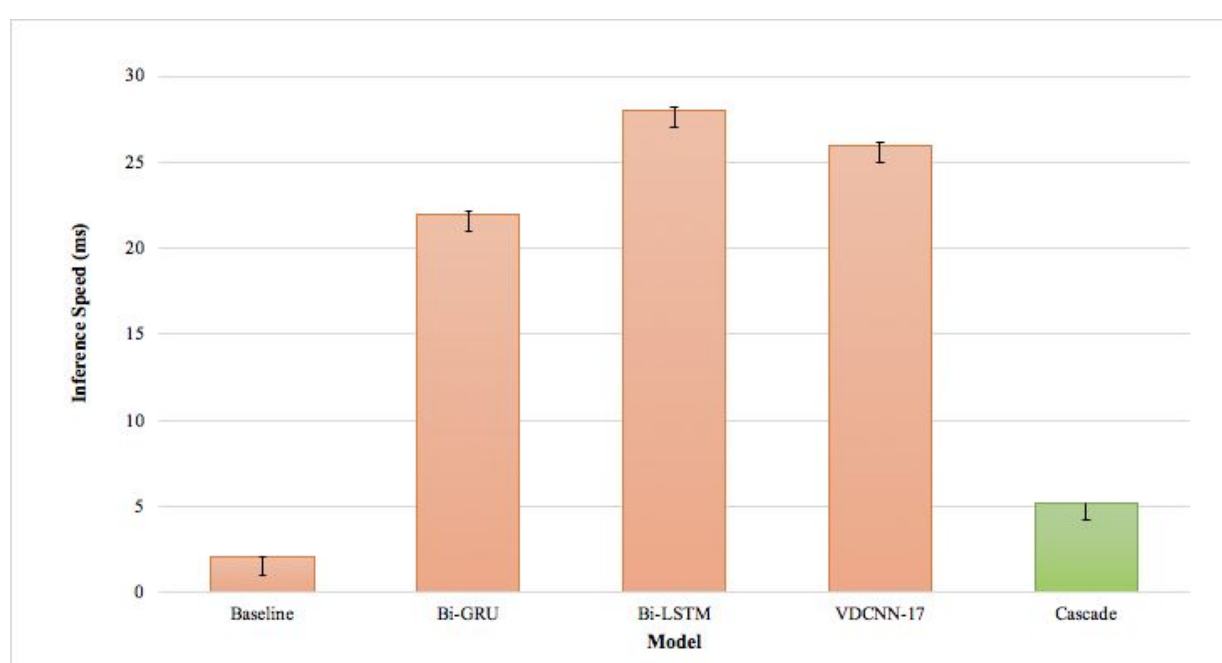
Model	F1 Score	Test Accuracy
Linear regression (Baseline)	0.44	0.967
Bi-GRU	0.57	0.971
Bi-GRU (FastText)	0.61	0.974
Bi-GRU (FastText + Attention)	0.66	0.987
Bi-LSTM	0.60	0.975
Bi-LSTM (FastText)	0.62	0.980
Bi-LSTM (FastText + Attention)	**0.66**	**0.989**
VDCNN-9	0.62	0.975
VDCNN-17	0.62	0.978

- All deep learning models that we tested are able to outperform the baseline
- Bi-LSTM with FastText embeddings and attention produced the highest F1 score and test accuracy
- Using pretrained FastText embeddings leads to a systematic increase in performance, for the following reasons:
  1. FastText is trained on a large corpus (16B tokens), as opposed to our training set (160,000 comments)
  2. FastText generates subword embeddings whereas tokens like "sucklol" would otherwise be treated as unknown
- Using scaled dot product attention also leads to a systematic increase in performance
- Deeper VDCNN appears to produce higher accuracy, but the F1 score remained the same for the two depths

Inference Speed Analysis

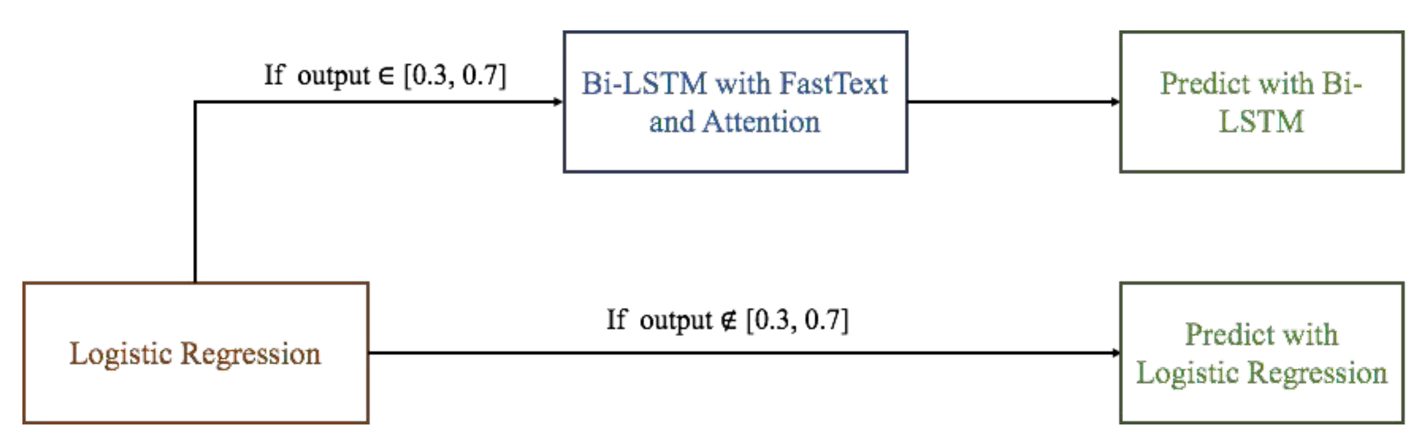
Problem: Computational Inefficiency

- Deep models are expensive
- Thus, they are difficult to use on a large scale
- We evaluate a forward pass with one document for 10 trials of 100,000 runs each and calculate the mean and standard deviation of run time
- Our best model (Bi-LSTM with attention) is 14 times slower than logistic regression
- Since the baseline performs quite well with 96.7% test accuracy, there is less incentive to adopt a deep learning approach



Potential Solution: Cascading Model

- We propose a cascading model which combines a series of models, optimizing for accuracy and speed in average case.
- Use intermediate steps and confidence scores at each step
- Each subsequent step has higher computation cost
- We test a small cascading model composed of a logistic regression as the first step and Bi-LSTM as the second



Performance of Cascading Model:

- Accuracy is 0.973, higher than that of baseline
- Average latency of 5.18 ms, about 2.5 times slower than the baseline but still 6 times faster than Bi-LSTM
- Only 31% of the comments required the use of the Bi-LSTM

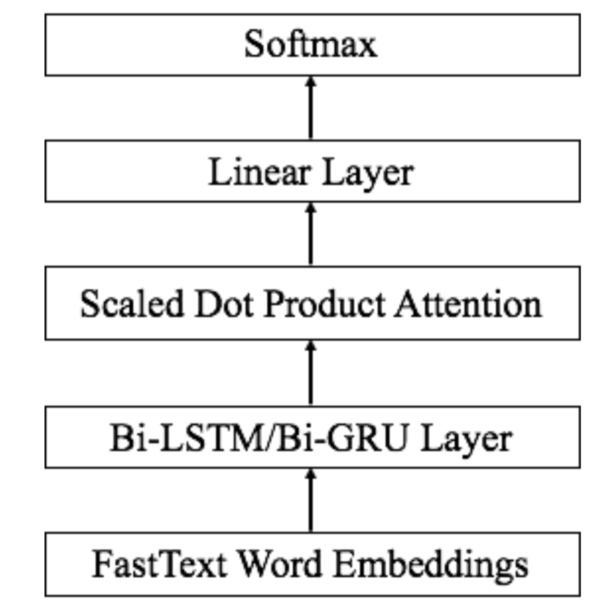
Logistic Regression (Baseline)

- Features include frequencies of word tokens and character n-grams ($2 \leqslant n \leqslant 6$)
- Use stochastic averaging gradient descent

Bi-directional LSTM/GRU

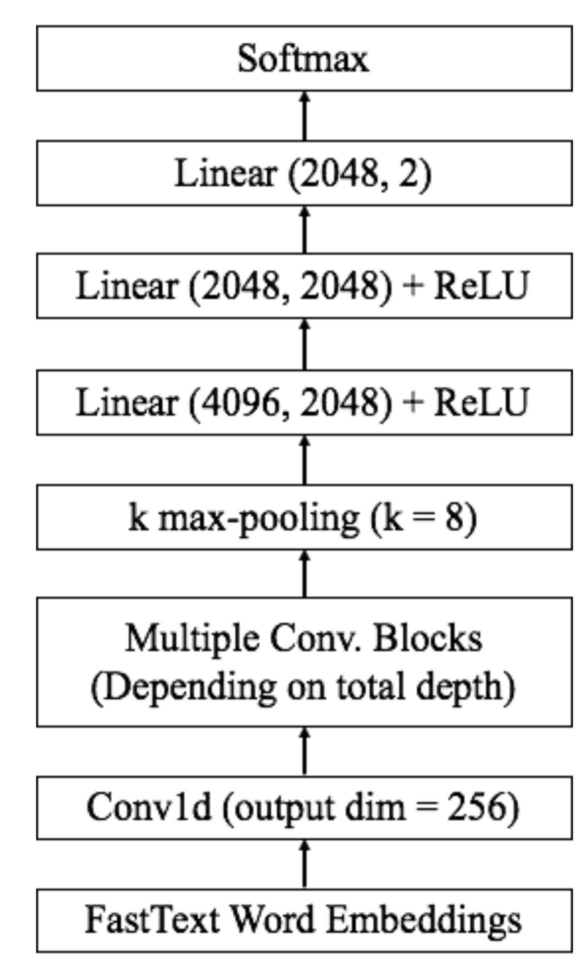
- Pad or truncate each sentence to maximum sentence length
- Start with FastText word embeddings
- Scaled dot product attention score:

$$\frac{q^T k_i}{\sqrt{d_k}}$$

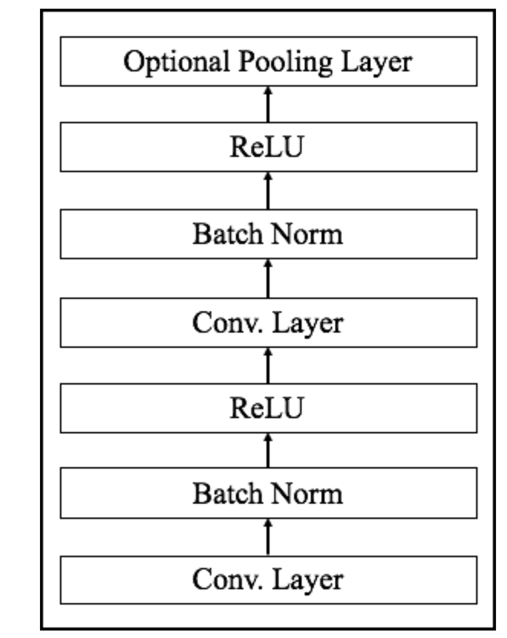


- Batch-size 64; SGD with momentum 0.9 and weight decay 1e-4 with gradient clipping; learning rate 0.001 with decay by factor of 10 on plateaus

VDCNN



- Pad or truncate each sentence to length 256
- Start with FastText word embeddings (300 dim.)
- A convolutional block:



- Apply optional half pooling layer when the output dimension is doubled through convolution to keep memory usage consistent
- Batch-size 128; SGD with momentum 0.9 and weight decay 1e-4; learning rate 0.01, increasing by factor of 10 at epochs 3, 6, 9, 12