Toxic Comment Classification

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TASK AND MOTIVATION

BACKGROUND

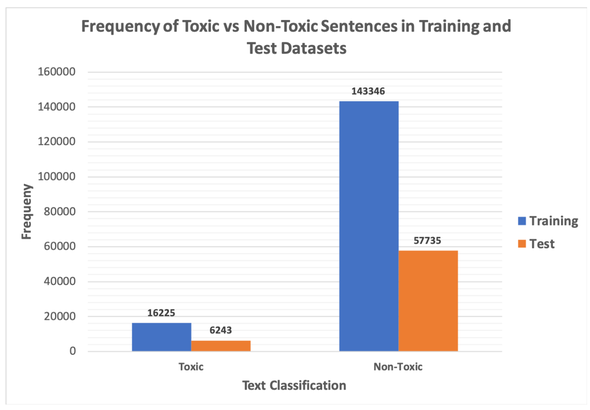
In this day and age, the usage of online human interactions has tremendously increased. Unfortunately, with this increase, online discussion forums have seen a rise in issues of online harassment. Moderators of online forums are not able to control and identify every such negative situation that arises.

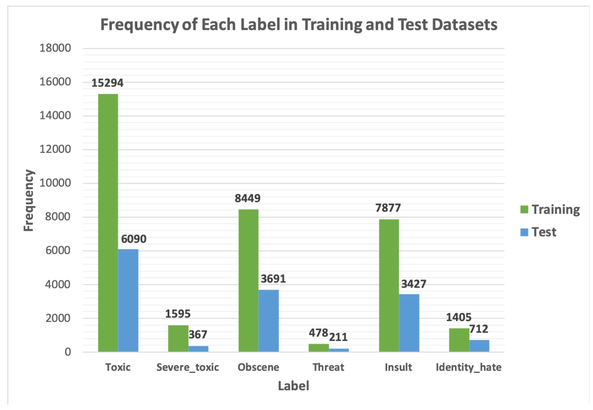
GOAL: Increase accuracy to identify toxic comments in order to improve online conversations by correctly labeling different texts according to their toxicity levels.

- Labels used: toxic, severe_toxic, obscene, threat, insult and identity_hate.

DATASET

- Based on and used datasets provided by Kaggle's "Toxic Comment Classification Challenge" to help identify and classify toxic online comments.
- Training dataset with 159,572 sentences
- Testing dataset with 63,978 sentences
- Pre-trained GloVe vectors from Twitter with 27 billion tokens with 100 and 200 dimensions





PROPOSED METHODS

- **Baseline**
  - SVM model (Khieu and Narwal, 1993)
- **Data Pre-processing** was done for all methods attempted by tokenizing and padding representation
- **LSTM** with 100D embeddings

$$Embeddings \rightarrow LSTM \rightarrow h1 \rightarrow sigmoid$$

- **GRU** with 200D embeddings

$$Embeddings \rightarrow GRU \rightarrow dropout \rightarrow h1 \rightarrow sigmoid$$

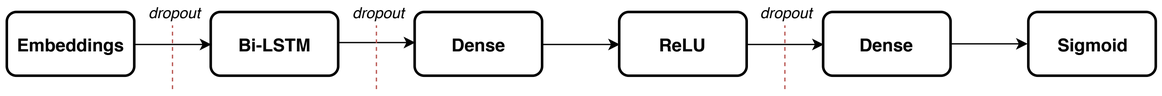
- **Enhanced LSTM** with 200D embeddings

$$Embeddings \rightarrow dropout \rightarrow LSTM \rightarrow dropout \rightarrow ReLU(h1) \rightarrow dropout \rightarrow h2 \rightarrow sigmoid$$

DATA PRE-PROCESSING

1. Delete samples of test data that include -1 in labels
2. Clean up strings
   - "I am 47" → "I am ##"
   - "Aren't" → "Are not"
   - "Hello World!" → "hello world!"
3. Term Frequency Map
   - "Hello hello hello world world the"
     - {"hello" : 1 , "world": 2, "the": 3}
4. Tokenization and Padding of Max Sentence Length (100)
   - "Hello Hello Hello world world the" → [0 0 ... 0 1 1 1 2 2 3]

MODEL ARCHITECTURE



Epochs = 2, Batch Size = 75, Optimizer = Adam, lr = .001, LSTM Hidden = 512, h1= 512, h2 = 256, Dropout = 0.5

EXAMPLE OUTPUT

Comparing two different sentences for each of the six possible types of comment toxicity:

[toxic, severe_toxic, obscene, threat, insult, identity_hate]

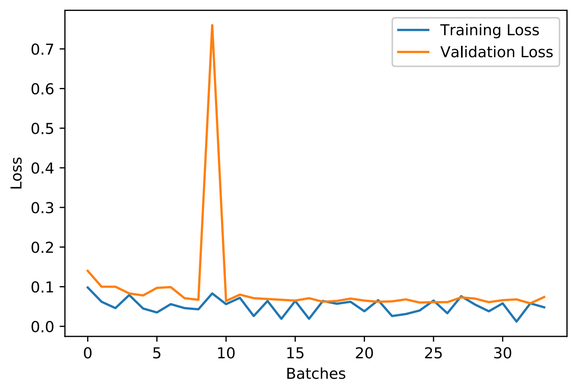
Sentence	Probability for Each Label	Binary Labels
"I hate you. You are stupid"	[.9 .35 .5 .1 .24 .33]	[1 0 1 0 0 0]
"I love you. You are amazing"	[.01 .001 .01 .01 .01 .01]	[0 0 0 0 0 0]

EVALUATION AND ANALYSIS

MODELS STATISTICS:

Method	Accuracy	Correctly Identified Toxic Sentences
LSTM	0.90118	6
GRU	0.84335	1883
Enhanced LSTM	0.8869	2129

LOSS GRAPH FOR ENHANCED LSTM MODEL:



- Baseline SVM model had accuracy of 0.833 (Khieu and Narwal, 1993)
- LSTM model had highest accuracy, but had lowest number of correctly identified toxic sentences
- GRU model had lowest accuracy, but drastically outperformed LSTM in correctly identifying toxic sentences
- Enhanced LSTM had higher accuracy than GRU and had highest number of correctly identified toxic sentences
- Accuracy = $\frac{\#\text{ of correct}}{\#\text{ of sentences}}$

FUTURE WORK

- Implementation of Naive Bayes-SVM(NBSVM)
- NBSVM performs well on snippets and longer documents, for sentiment, topic and subjectivity classification[5]

REFERENCES

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[6] Zheng, Heng. "PyTorch Starter." Kaggle, Kaggle, 14 Dec. 2018, www.kaggle.com/hengzheng/pytorch-starter.