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Leveraging BERT and Convolutional Neural Networks to Aid in Identifying Hate Speech Amongst Online Gaming Communities

Malav Modi - (mhm114)
Shyam Patel - (spp128)
Praveen Sakthivel - (ps931)

Department of Computer Science
Rutgers University

Topic Agenda:

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- I - **Introduction**
- II - **Previous State of Knowledge**
- III - **Challenges**
- IV - **Main**
- V - **Evaluations**
- VI - **Conclusion**

Introduction:

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- Due to the recent pandemic, there has been a massive surge in the number of people who remain active in various online communities
- Hate Speech has been a long standing problem that has plagued the gaming community
- Due to huge imbalances between players and moderator, manual moderation is largely ineffective
- An automatic moderator that can accurately and efficiently detect hate speech would be useful in helping control this issue

Previous State of Knowledge:

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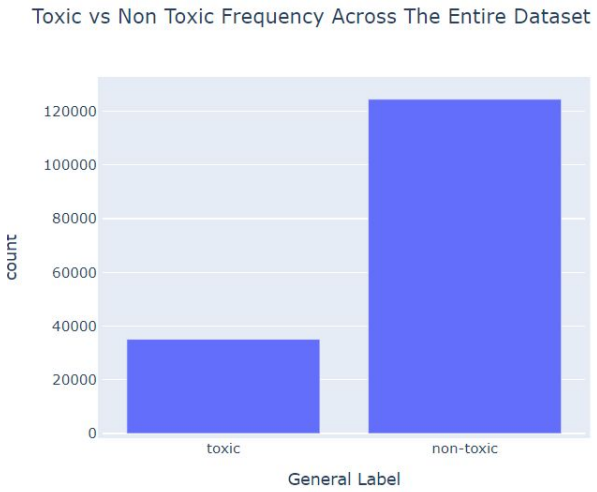
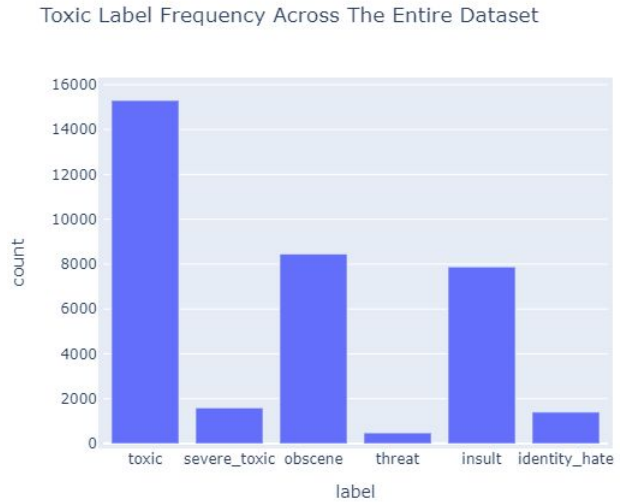
- Kaggle Dataset
- Previous attempts:
  - Naive Bayes + Support Vector Machine
  - Bidirectional LSTM
  - Logistic Regression

Challenges:

- Dataset is skewed
  - Majority of comments are non toxic
  - Not too many examples of toxic comments
- Model overfitting
  - Manipulating hyperparameters
- Capturing subtones and non explicit data





Main: Architecture

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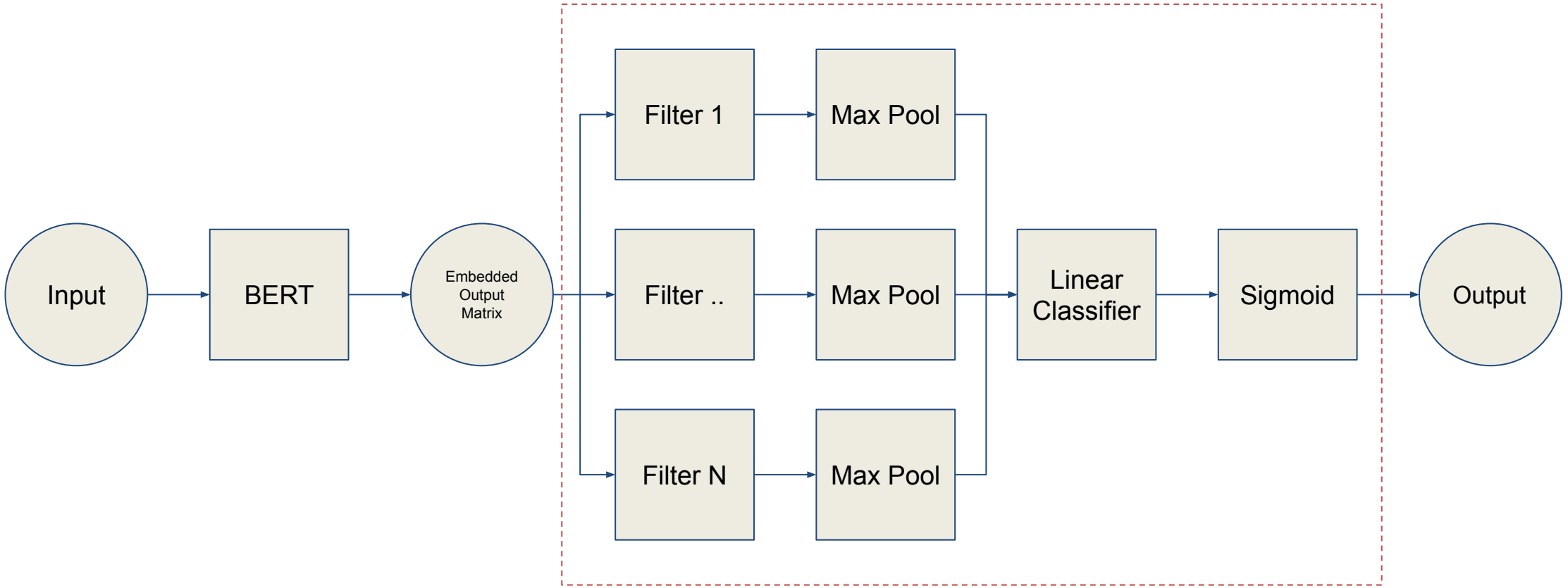

Kim CNN

Encoder: BERT

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- Bidirectional Encoder Transformation from Transformers
- Looks at context of ALL Words not just the preceding ones
- Masked LM
  - Train with entire input, mask 15% of words
  - Mask 80%, Keep 10%, Incorrect 10%
- Next Sentence Prediction
  - Receives 2 sentences, determines if 2nd is subsequent sentence
  - 50% 2nd is subsequent, 50% is a random sentence

Decoder: Kim CNN

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- Embedded Word Vectors have ‘Universal Features”
- Apply multiple filters to the input sequence in parallel
- Max Pool: Extract the highest value feature from each filter
- The max value features are passed into a linear classifier
- Dropout and Sigmoid are applied to produce classifications

Contribution Evaluations:

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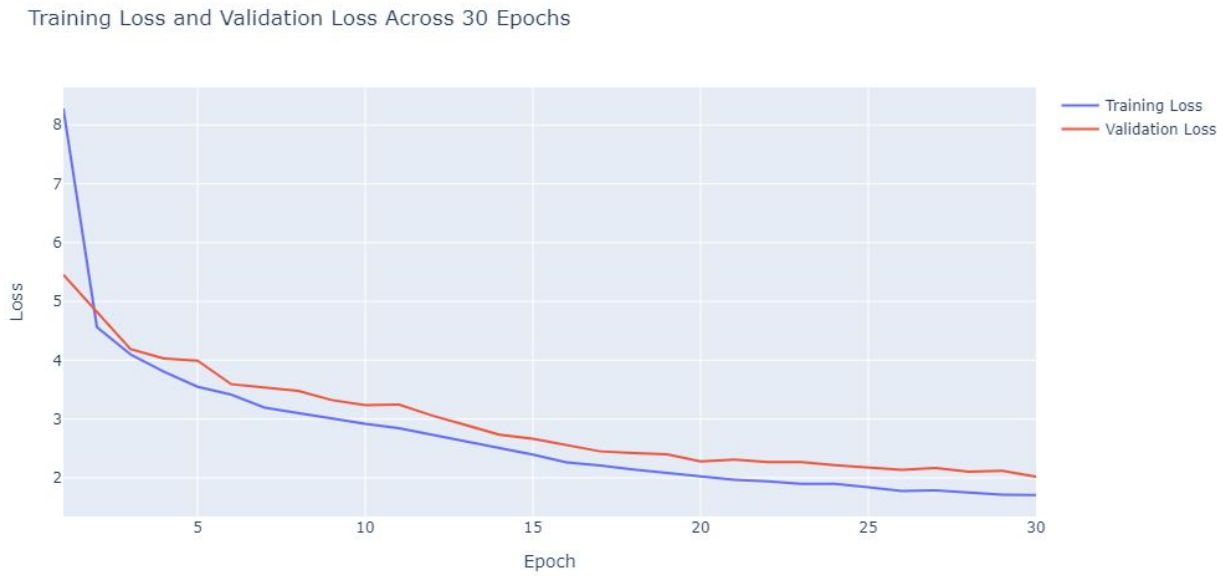
- Our Model was very successful in classifying hate speech
  - 96.7% overall accuracy (test set)
  - Used an ROC-AUC Curve to measure individual label accuracy
    - At least ~94% score across all 6 labels in dataset

label	auc
insult	0.973251
obscene	0.970923
identity_hate	0.960268
toxic	0.957884
threat	0.953939
severe_toxic	0.939353



Conclusion:

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- Our results support Kim's findings that encoders are universal feature extractors (The BERT embedding we used was not trained for hate speech classification)

- Severely Toxic was relatively the most difficult hate speech to detect
  - Most likely because it was one of the labels with the fewest data points

- We found the best learning rate to be 9.625e-6
  - Smaller learning rates prevented overfitting with large number of epochs

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Thank You!

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