

# Hate Speech & Offensive Language Detection Using BERT Transformers

Jose Santiago Campa Morales and Claire Lynch

*CSC 396*

# Motivation

- Detecting harmful speech can help minimize marginalized online groups and is essential for community safety & health
- Context, Intent, Demographics, Ambiguity...  
NOT EASY!

Warning: some of these contain text that may be sensitive to some readers

## Hate Speech

“what's this [ch\*\*\*\*] email? I'm moving to China and slicing his throat”

## Offensive Language

“Wake your [a\*\*] up [h\*\*]”

## Neither

“People who slam on the brakes at yellow lights should not be allowed to drive.”

# Model Explanation

## Transformers.

- Better at understanding context (self-attention), not just keywords
- Pre-training (BERT)
- Reduce false alerts when offensive words appear in jokes or quotes
- Capture subtle tone differences (sarcasm, aggression, harassment)
- BERT has strong generalization since trained on large corpora and has good performance on short texts

# Model Explanation

## Dataset.

- [Hate Speech and Offensive Language Dataset.](#) (Davidson et al., 2017).
- Data split: 77% Offensive Language, 6% Hate Speech, 17% Neither
- Data imbalance.
- Very nuanced language implications and use of characters in posts

# Why Multiclass Classification is Not Viable

- **Goal:** classify data into hate speech, offensive language, or neither
- **Outcome:** transformer slightly overfit + very imbalanced data

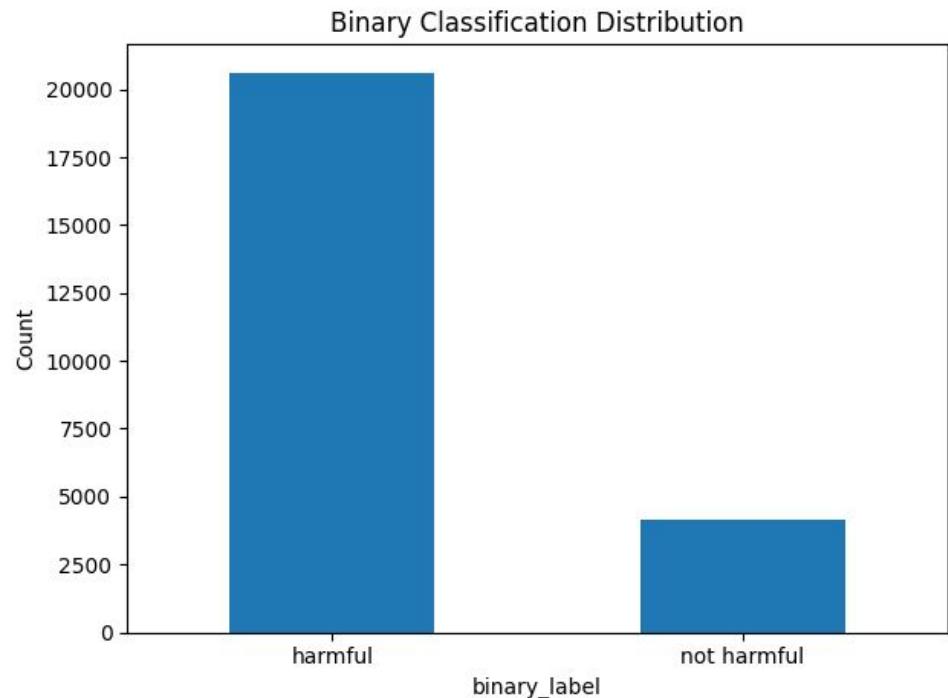
	precision	recall	f1-score
hate_speech	0.58	0.35	0.44
offensive_language	0.94	0.96	0.95
neither	0.89	0.90	0.90



# Solution – Binary Classification

## Harmful Speech vs. Not Harmful Speech.

- Offensive Language & Hate Speech
- 83/17 split
- Predictable
- Applicable
- Removes ambiguity



# Summary – Binary Classification

Epoch	Training Loss	Validation Loss	Accuracy
1	0.087	0.093	0.966
2	0.056	0.119	0.968
3	0.044	0.156	0.964



## Results – Binary Classification

	Precision	Recall	F1	Support
<i>Not Harmful</i>	0.90	0.88	0.89	833
<i>Harmful</i>	0.98	0.98	0.98	4124
<i>Accuracy</i>			0.96	4957
<i>Macro Avg</i>	0.94	0.93	0.94	4957
<i>Weighted Avg</i>	0.96	0.96	0.96	4957

# Binary Confusion Matrix

	precision	recall
<b>non-harmful</b>	<b>0.90</b>	<b>0.88</b>
<b>harmful</b>	<b>0.98</b>	<b>0.98</b>

- More false positives
  - (Predicts safe tweets as harmful)
- Less false negatives
  - (Predicts harmful tweets as safe)



# Baselines

## Random Classifier

- Predicts labels at random
- ~50% accuracy (binary)
- $F1 \approx 0.5$
- Demonstrates how hard the dataset is without learning

## Popularity Classifier

- Predicts all as harmful
- 83% accuracy
- $F1$  (harmful) = 1
- $F1$  (not harmful) = 0
- Misses every safe tweet → useless for real moderation

# Error Analysis

## False Negatives – 80 cases

(Predicts harmful tweets as safe)

- “The Steelers new uniforms look like homosexual bumblebees. #wtf?”
- “I said something to you gorilla, stop listening to monkey music”
- Aggression used without slurs
- Harmful intent was implied or subtle: language is specifically negative

## False Positives – 96 cases

(Predicts safe tweets as harmful)

- “i'd never send my kids to private school because then they would never experience ghetto public school fights”
- “Taco Bell is super trash when you're sober”
- Patterns for posts containing profanity used in non-hostile context or jokingly
- Posts quoting lyrics or offensive memes

Warning: some of these contain text that may be sensitive to some readers

# Observations, Limitations & Biases

- Over-reliant on keywords → **False Positives**
- Class Imbalance → False Negatives
- Length & subtlety bias
- Slang Misclassification & social bias

# Insights, Impact & Conclusion

- Transformers are highly effective for harmful-language detection
- Multiclass labeling suffers from data imbalance
- **Real-world impact:** Small improvements scale to millions of users
- **Not a simple task:** requires careful, ethical deployment

# Self-Evaluation

- 96% accuracy
- Relatively small project leads to meaningful real-world impact
- AI can support safer digital spaces
- Strong technical + ethical awareness

# Future Work

- Larger, more balanced dataset
- Specialized model (HateBERT)
- Thread-level context aware detection
- Better fairness analysis

# Contributions

- Claire
  - Project Idea
  - Dataset Search
  - Model Implementation
  - Baselines
  - Presentation
  - Report
- Jose
  - Dataset Search
  - Data Cleaning
  - Model Implementation
  - Binary Solution
  - Presentation
  - Report

Thank you! Any Questions?