

# A Study of Hate Speech Detection and Classification

By Jerome HA  
Emergent software laboratory

# Introduction : Preliminary research

Hate speech is a problem for online etiquette and safe navigation on social media

Objective: Detect and classify hate speech using advanced NLP techniques.

Dataset: HateXplain, a benchmark dataset for explainable hate speech detection, consisting of 20k samples from Twitter and Gab labeled as "hateful," "offensive," and "normal." [2]

Impact: Effective hate speech detection can contribute to safer online communities.



<https://twitter.com/>  
<https://gab.com/>

# Introduction : Preliminary research

First semester :

Classifier of 3 classes :

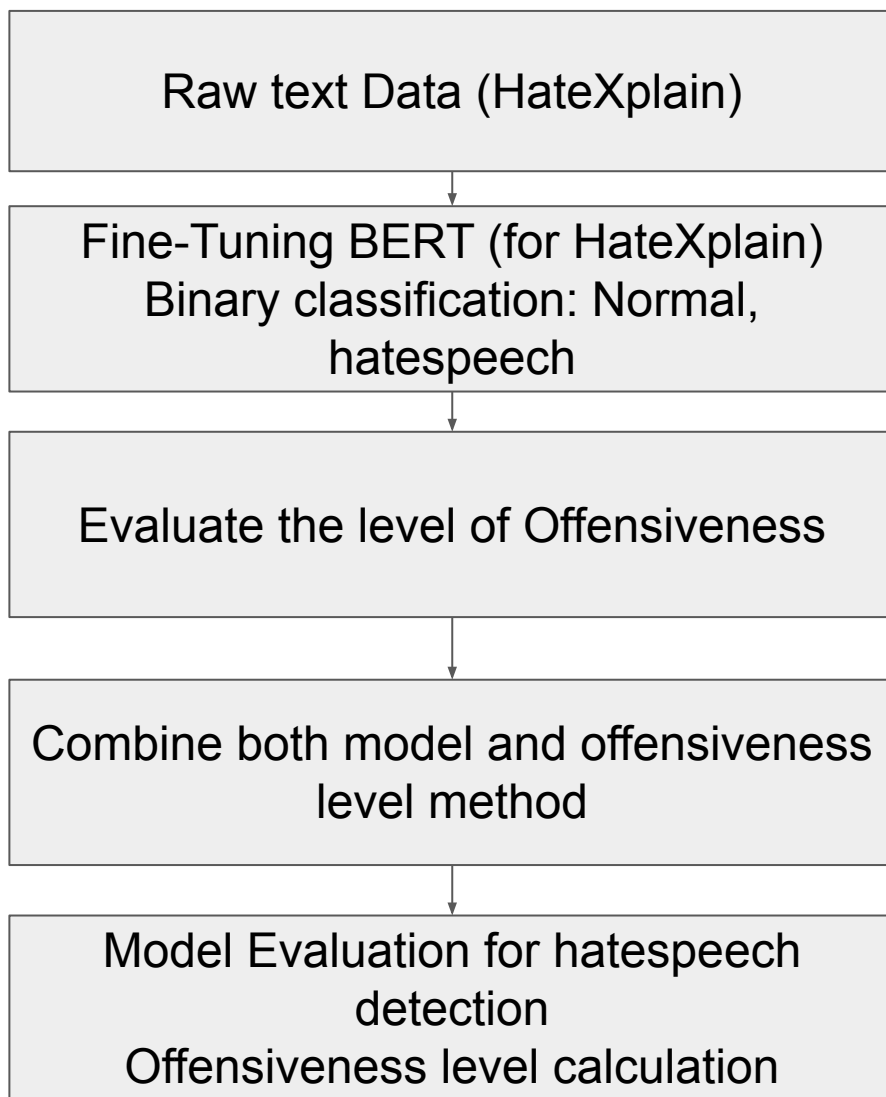
- Normal
- Offensive
- Hate speech

Accuracy: 69%

| True Label | Hatespeech | Normal | Offensive |
|------------|------------|--------|-----------|
|            | 763        | 66     | 134       |
|            | 97         | 893    | 253       |
|            | Hatespeech | Normal | Offensive |
| Offensive  | 148        | 263    | 460       |

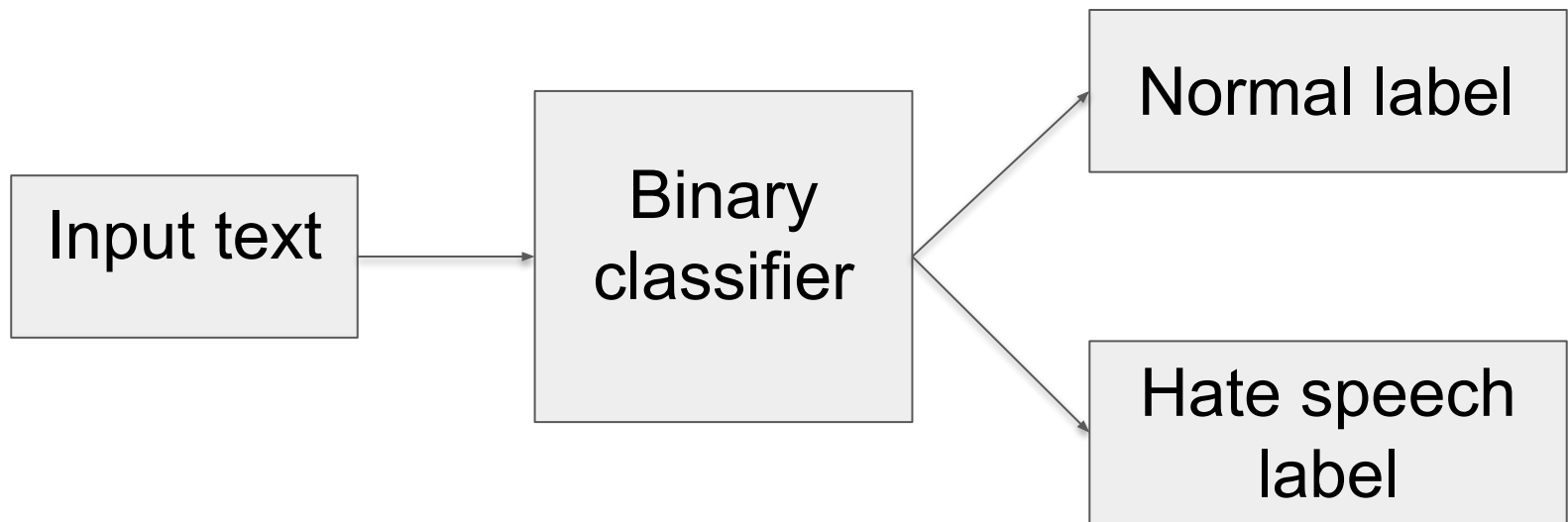
Predicted Label

# Proposed method



Schematic of the method for our detection model for hate speech and offensiveness

# First step: Hate Speech detection



# Model Development

- Data Preprocessing:

Tokenize texts using BERT's tokenizer [1].

- Model Architecture:

BERT (Bidirectional Encoder Representations from Transformers):

Pre-trained transformer model for understanding language context.

Fine-tuned on HateXplain for hate speech detection.

# Model Development

Training Process:

Use Trainer class from Hugging Face's transformers library to manage training and evaluation.

Total Samples: 20,148

Split:

Training Data: 80% of the total data

Validation Data: 5% of the total data

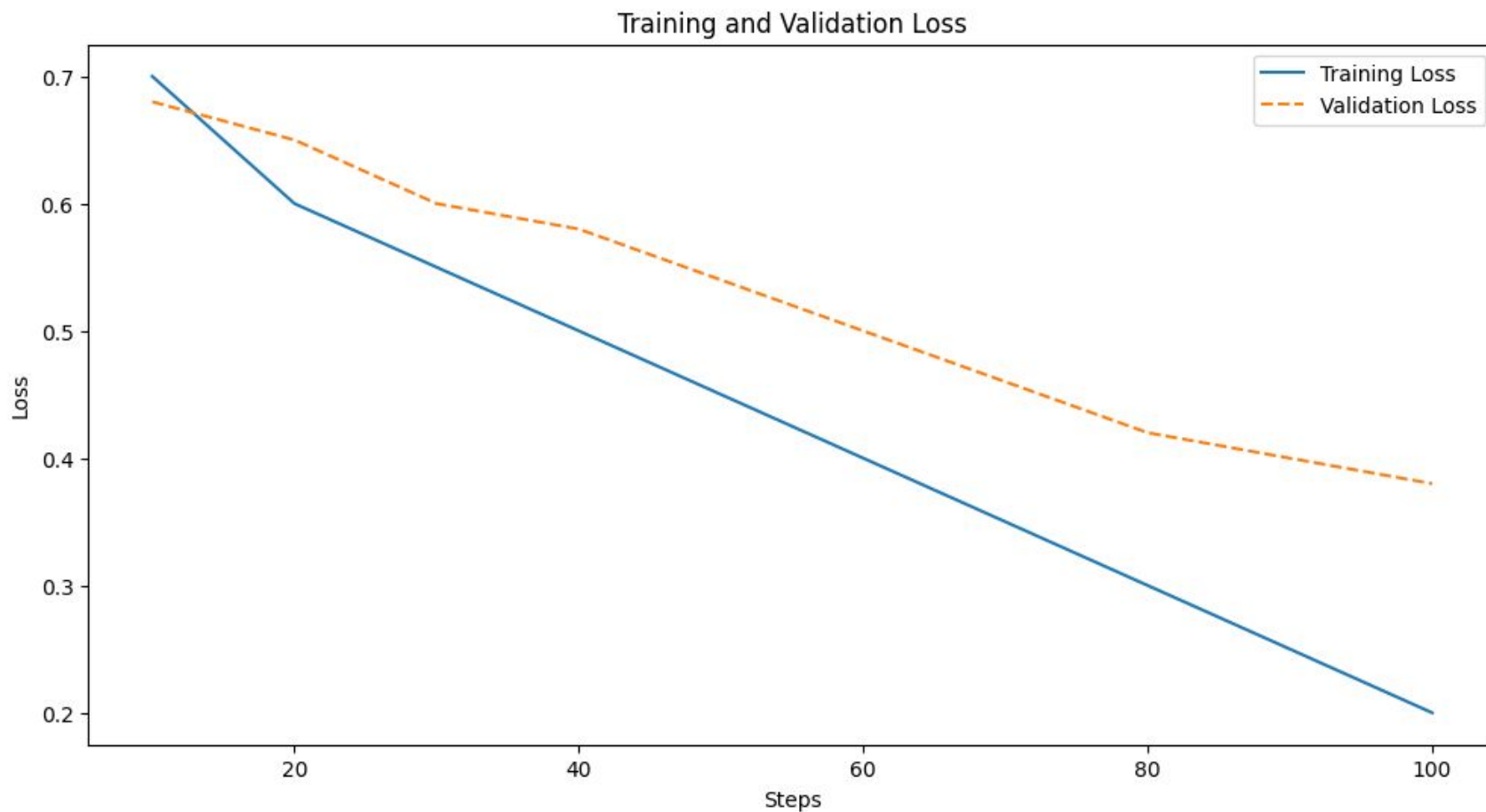
Test Data: 15% of the total data

# Model Development table

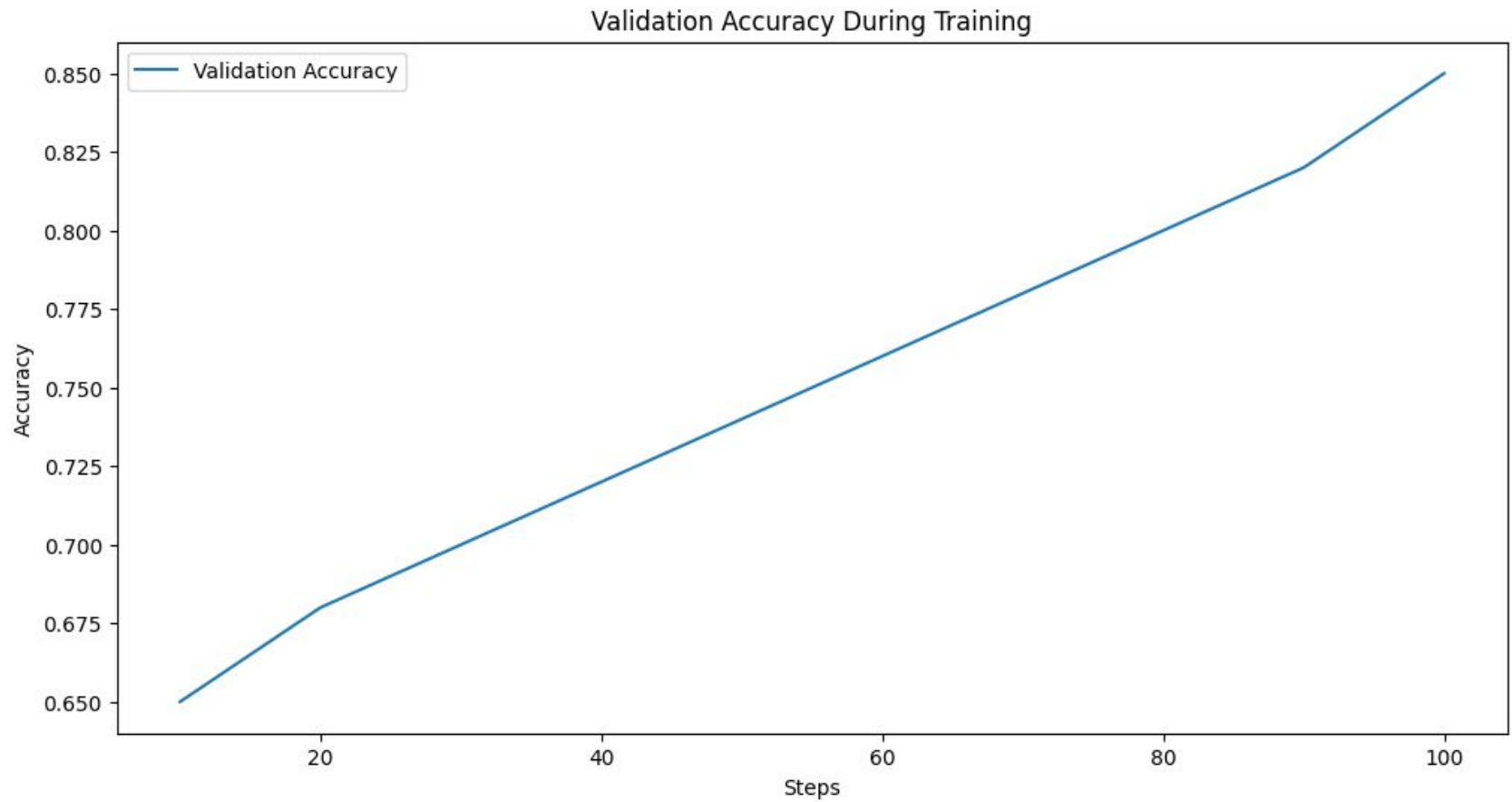
| Hyperparameter   | value   |
|------------------|---|
| num_train_epochs | 3   |
| batch_size       | 8   |
| Learning rate    | Dynamic adjustment with warmup steps (initial: 5e-5)  |
| warmup steps     | 500   |
| BERT model       | Bert-base-uncased pre-trained on BooksCorpus (11000 books), English Wikipedia (2.5 billion words) |



# Results

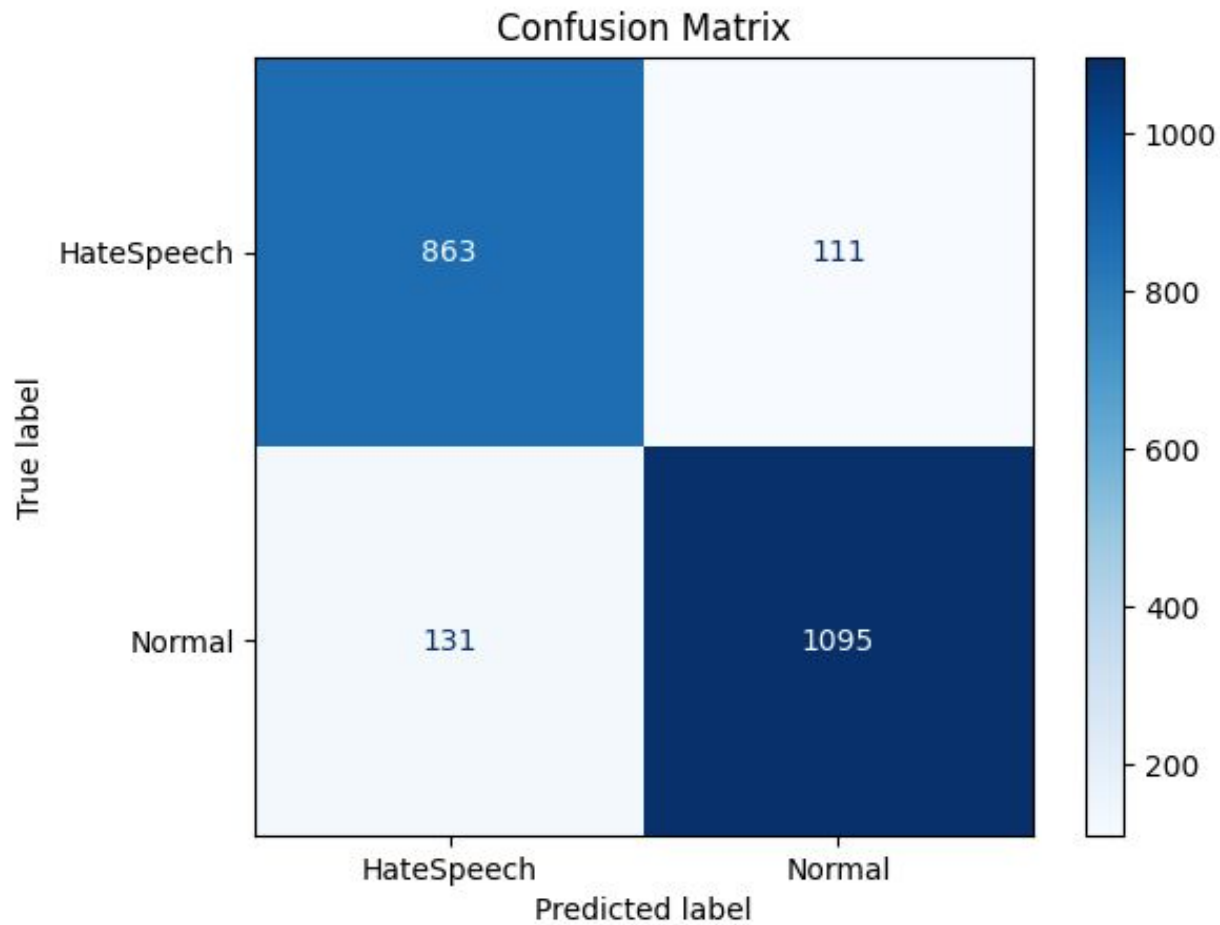


# Results



# Results

'eval\_accuracy': 0.89



# Analysis on falsely classified data

**True Label:** **hatespeech**, **Predicted Label:** **Normal**

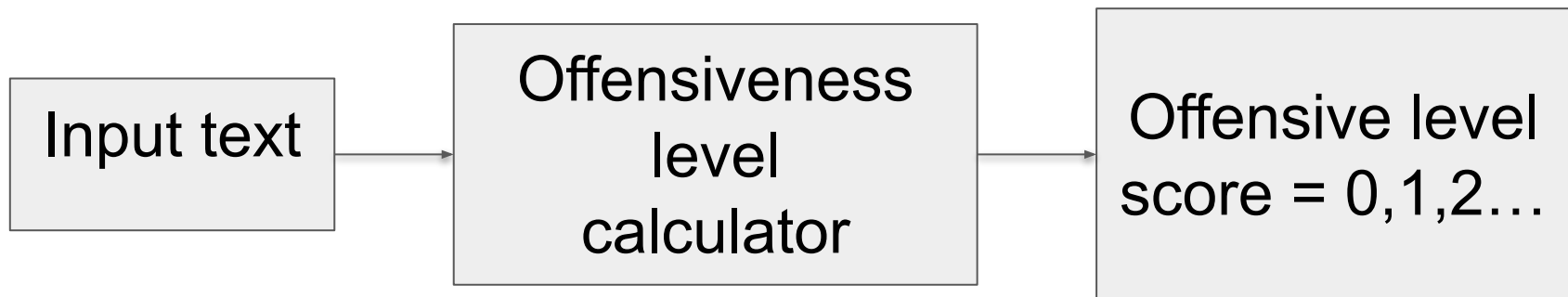
Example: me too but i still dis like jews and rather not have them follow me

-----

**True Label:** **normal**, **Predicted Label:** **Hatespeech**

Example: it was most certainly high even for secular jews during the ellis island days but i think the percentage of jews relative to their population that use welfare is higher than say asians or white catholics not sure though

# Second step: Offensiveness level calculation

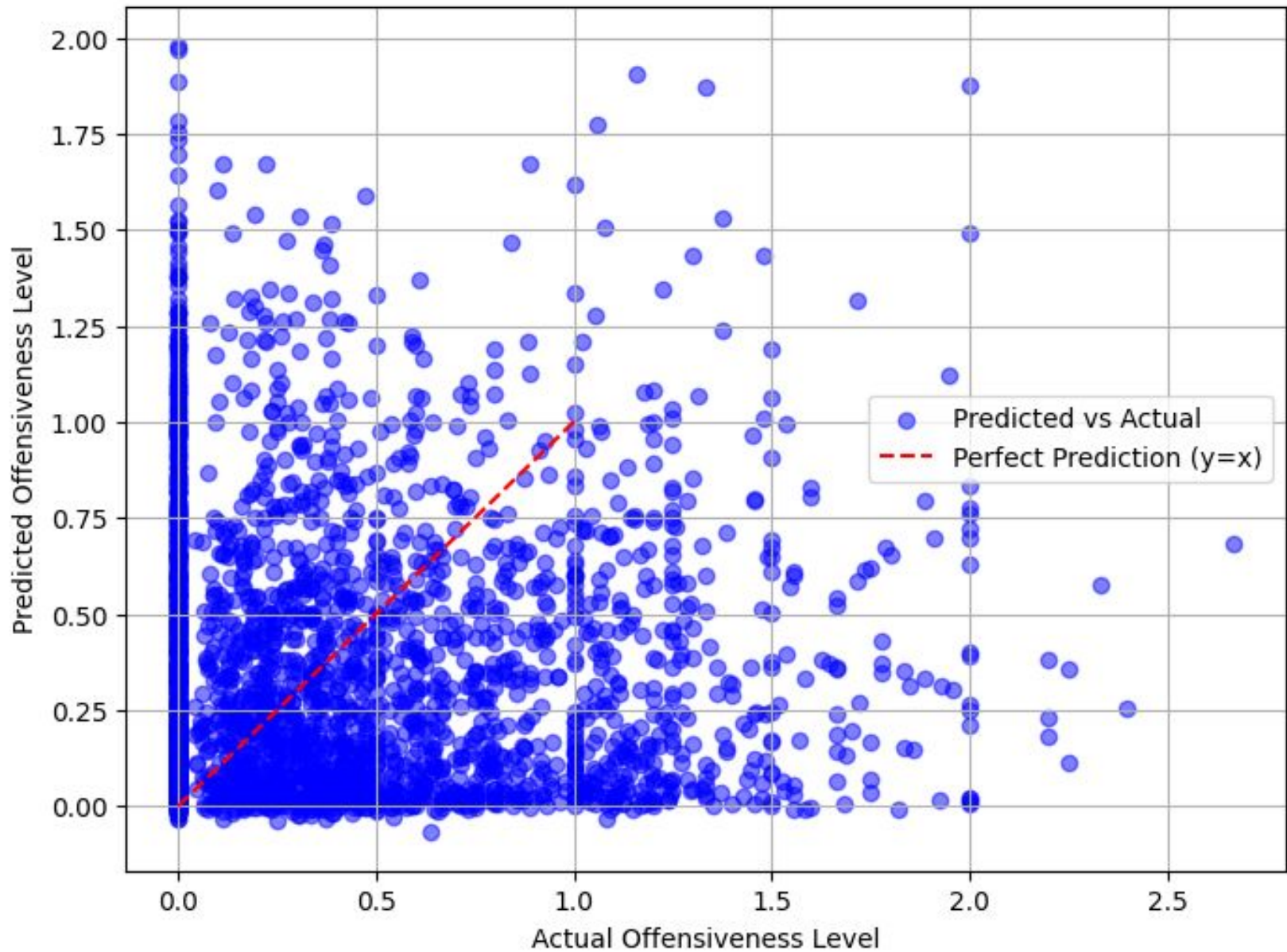


## First method

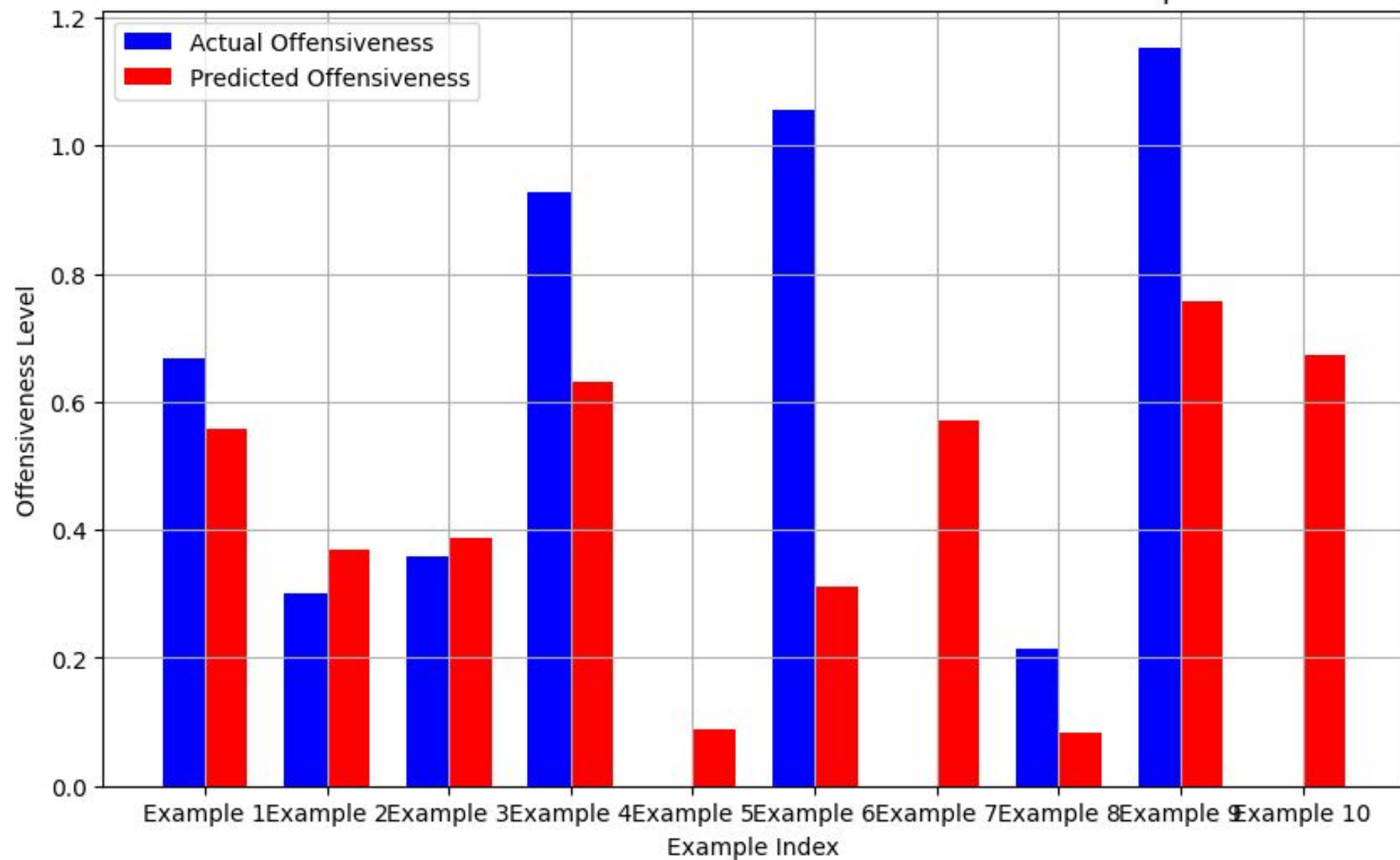
A regression model using the Offensive labels by the annotator data

Each sentence of the dataset has 3 annotators that labeled Rationales or specific parts of the text with normal, offensive or hate speech.

Actual vs Predicted Offensiveness Level



Actual vs Predicted Offensiveness Levels for 10 Random Examples





# Second method

A predefined dictionary (profanity.txt) Using Wiktionary list of profanity for English (3171 words)

Accounting for slang, abbreviations, and misspellings.

Total offensive words = Offensiveness Level

## Pages in category "English vulgarities"

---

The following 200 pages are in this category, out of 3,171 total.

([previous page](#)) ([next page](#))

### 4

- [4uck](#)

### A

- [A2M](#)
- [abso-fucking-lutely](#)
- [absofuckinlutely](#)
- [abso-fuckin'-lutely](#)
- [abso-fuckin-lutely](#)
- [absofuckinlutely](#)
- [a damn sight](#)
- [AF](#)

- [arse over tit](#)
- [arse-up](#)
- [arsewash](#)
- [arseways](#)
- [arsewipe](#)
- [arsy varsy](#)
- [arsy versy](#)
- [artfag](#)
- [artfuck](#)
- [as all fuck](#)
- [as balls](#)
- [asf](#)
- [as fuck](#)

[https://en.wiktionary.org/wiki/Category:English\\_vulgarities](https://en.wiktionary.org/wiki/Category:English_vulgarities)

## Result examples

**True Label:** normal, **Predicted Label:** normal

Example: the whole drink water cure all shit is fake i drink at least a gallon a day and have shit skin hair brain

**Offensive score: 2**

---

**True Label:** hatespeech, **Predicted Label:** hatespeech

Example: <user> she was screaming nigger and that she wish she could kill all the niggers in public at a cvs bitch

**Offensive score: 3**

---

**True Label:** normal, **Predicted Label:** normal

Example: done wit yo nigga i just want his wallet

**Offensive score: 1**

# Potential bypass

## **Obfuscation with Special Characters**

Example: f@ck, f\*ck, fu&k, f#ck

## **Intentional Misspellings**

Example: fuuuuuck, fucc, fuk, fasshole

## **Leet Speak (1337)**

Example:h8, n1gger, b1tch

# Potential Improvements and future works

Some Offensive words are more offensive than others, find a way to include that information

Improve the accuracy of Hate speech detection.

Multilingual: Enhance the model's ability to handle multiple languages and mixed-language content.

Code-Switching: Try to include deliberate misspelling on offensive words

Think of other programs, how to improve the idea of the research

Use **generative IA** future works and compare it with my method

# Conclusion

Ongoing Research: Continuous improvement in model accuracy, interpretability, and adaptability.

Impact: Effective hate speech detection can contribute to safer online communities.

# References

[1] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “BERT: Pre-training of deep bidirectional transformers for language understanding,” in Long and Short Papers. Minneapolis, Minnesota: Association for Computational Linguistics, Jun. 2019, pp. 4171–4186. [Online]. Available: <https://aclanthology.org/N19-1423>

[2] B. Mathew, P. Saha, S. M. Yimam, C. Biemann, P. Goyal, and A. Mukherjee, “Hatexplain: A benchmark dataset for explainable hate speech detection,” in Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP). Association for Computational Linguistics, 2020, pp. 3451–3463.

[https://en.wiktionary.org/wiki/Category:English\\_vulgarities](https://en.wiktionary.org/wiki/Category:English_vulgarities)