# Hate Speech Detection

By Group 2: Still Processing…

Ready? If your view was correct, all strippers would be millionaires.
Reality: Strippers are dirt poor sociopaths.

# Introduction

# Hate Speech

"denial of the values of tolerance, inclusion, diversity and the very essence of the human rights norms and principles"
(UN, Cited May 2022)

"any form of non-acceptable language (profanity) or a targeted offence, which can be veiled or direct. This includes insults, threats, and posts containing profane language or swear words"
(Zampieri et al., 2019a)

"when left unchecked, expressions of hatred can [. . . ] harm social cohesion, peace and development, as it lays the ground for conflicts and tensions, wide scale human rights violations, including atrocity crimes."
(UN, Cited May 2022)

## Traditional Model

Ensemble: SGD + LR + Nu-SVM + C-SVM

## Neural Model

Majority vote: 5 RoBERTas

# Related Research

## Surface Level Features

Bag of Words: frequency dictionary
TF-IDF: term frequency-inverse document frequency

**Word n-grams**
Lose syntactic and semantic context

⇕

**Character n-grams**
Retrieve context
(Burnap and Williams, 2016)

Overcomes typing errors & spelling variations
(Schmidt and Wiegand, 2017; Fortuna and Nunes, 2018; Alorainy et al.) 2018)

Range 1-5
(Alorainy et al., 2018; MacAvaney et al., 2019; Burnap and Williams, 2016)

Related Research

# Surface Level Features Speech

**Capitalisation**
(Burnap and Williams, 2016; MacAvaney et al., 2019)

**Interpunction**
(Alorainy et al., 2018; MacAvaney et al., 2019)

**URL's, @ mention, hashtags**
(Davidson et al., 2017; Gambino and Pirrone, 2020)

**Emojis**

# Linguistic Features

Parts-of-speech
(Markov and Daelemans, 2021; Alorainy et al., 2018)

Custom POS tagger

Lemmatization
(Markov and Daelemans, 2021; Markov et al., 2021; Hee et al., 2018)

# Semantic Feature

**Semantic lexicon**
(Alorainy et al., 2018; Markov and Daelemans, 2021)

**Vader**
(Hutto and Gilbert, 2014)

**AFINN**
(Arup Nielsen, 2011)

## Traditional Model

Stochastic Gradient Descent Model
(Sharif et al., 2020)

Logistic Regression Model
(Alorainy et al., 2018; Davidson et al., 2017)

Support Vector Machine
(Markov and Daelemans, 2021; Burnap and Williams, 2016; MacAvaney et al., 2019)

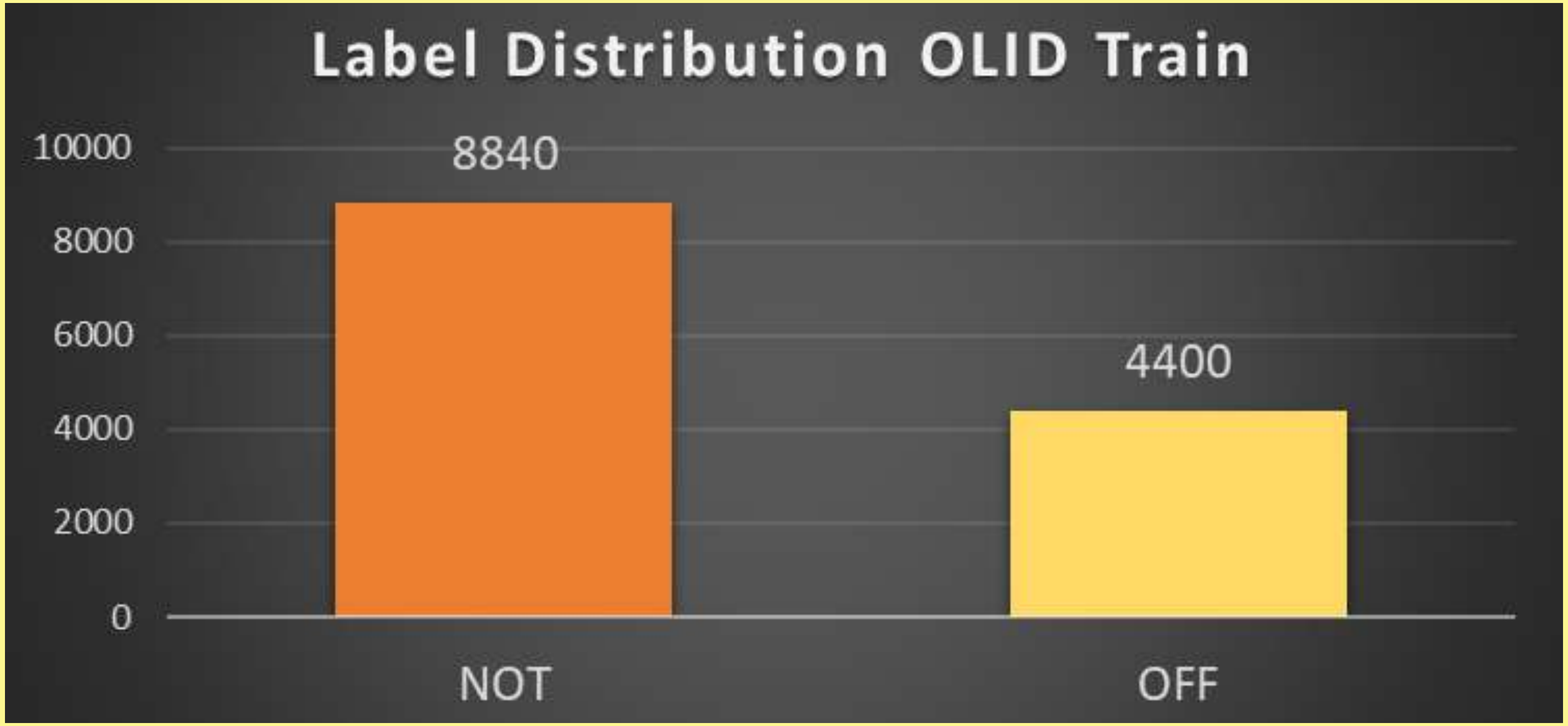
## Neural Model

Hard voting: SVM + BERT + RoBERTa
Markov and Daelemans (2019)

# Methodology

# OLID

English tweets
Two or three annotators
Offensive or not offensive
(Zampieri et al., 2019)

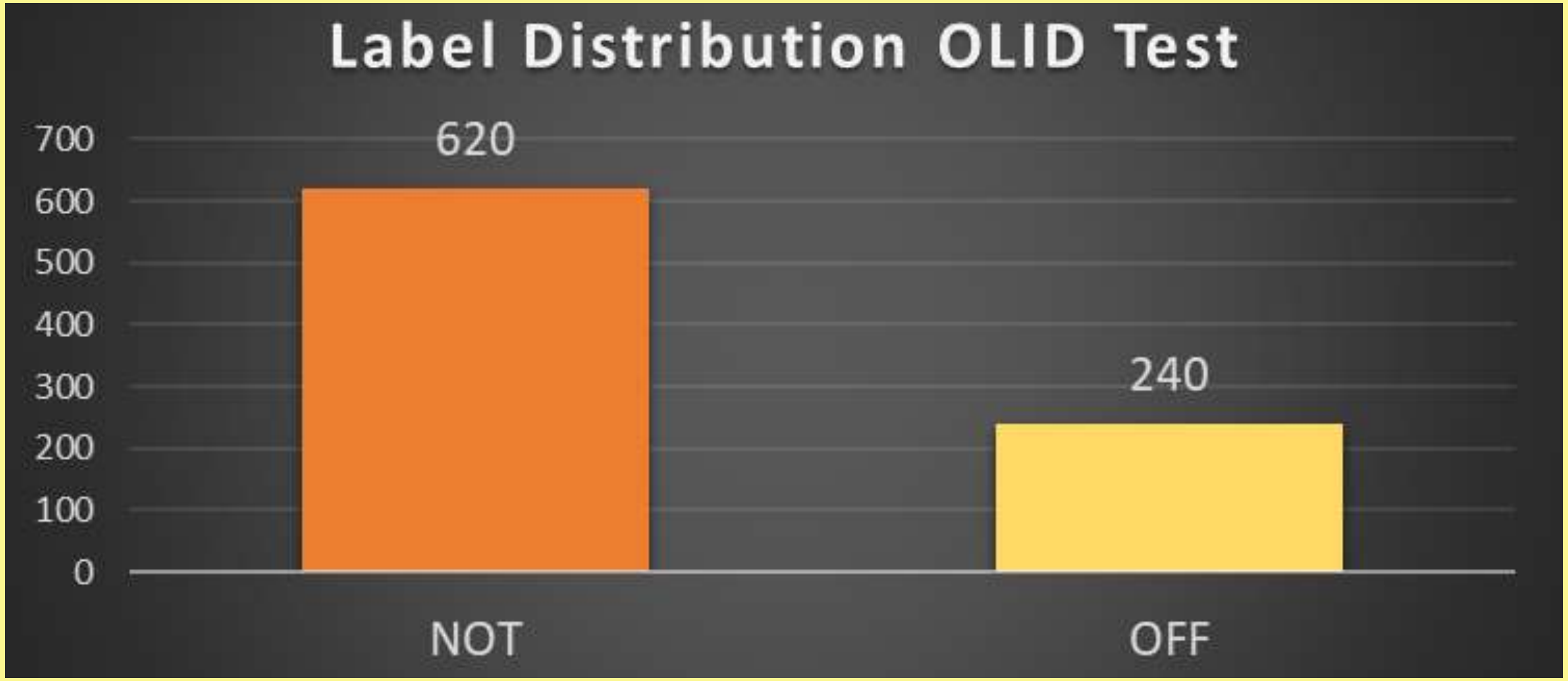


Methodology

Test Data

# OLID

English tweets
Two or three annotators
Offensive or not offensive
(Zampieri et al., 2019)

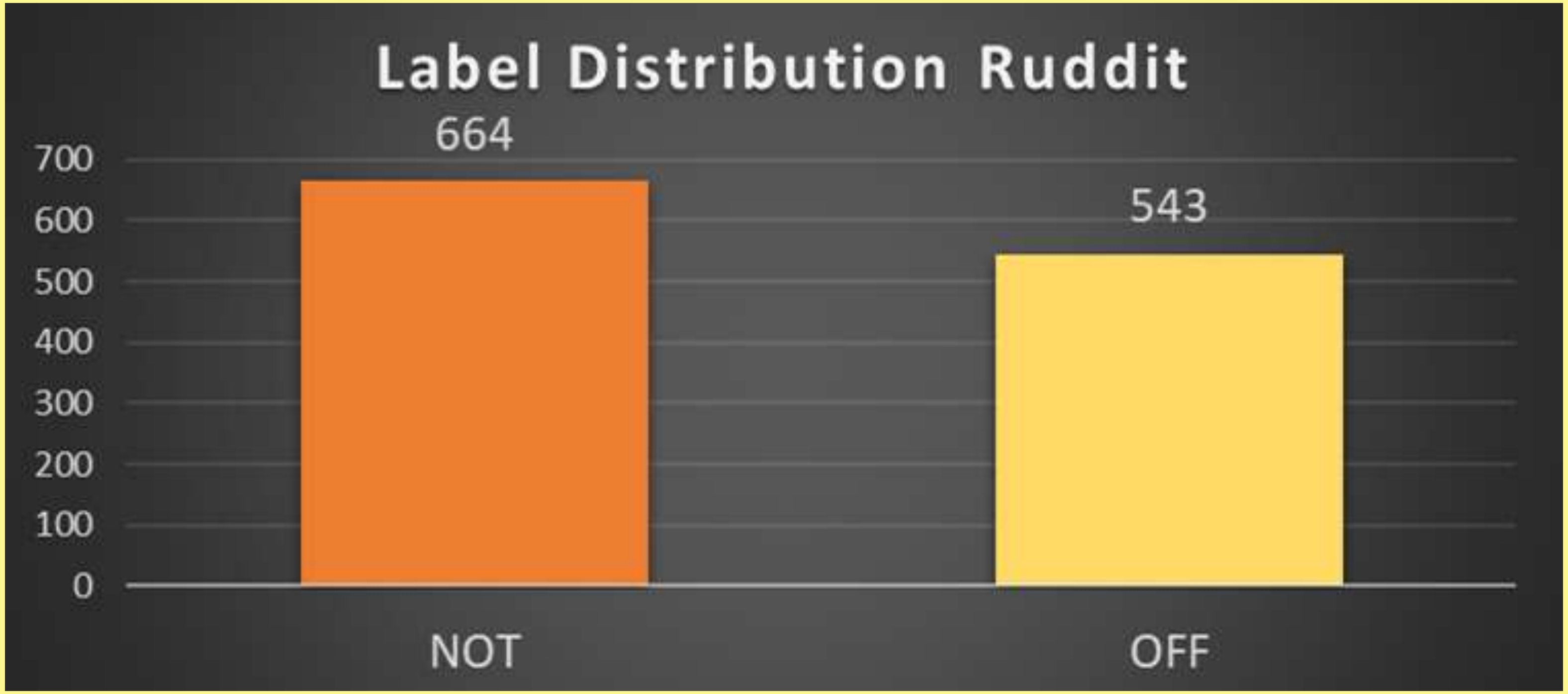


Methodology

Test Data

# Ruddit

English Reddit posts
Best-worst scaling
[-1, 1] → [-0.4, 0.4]
(Hada et al., 2021)

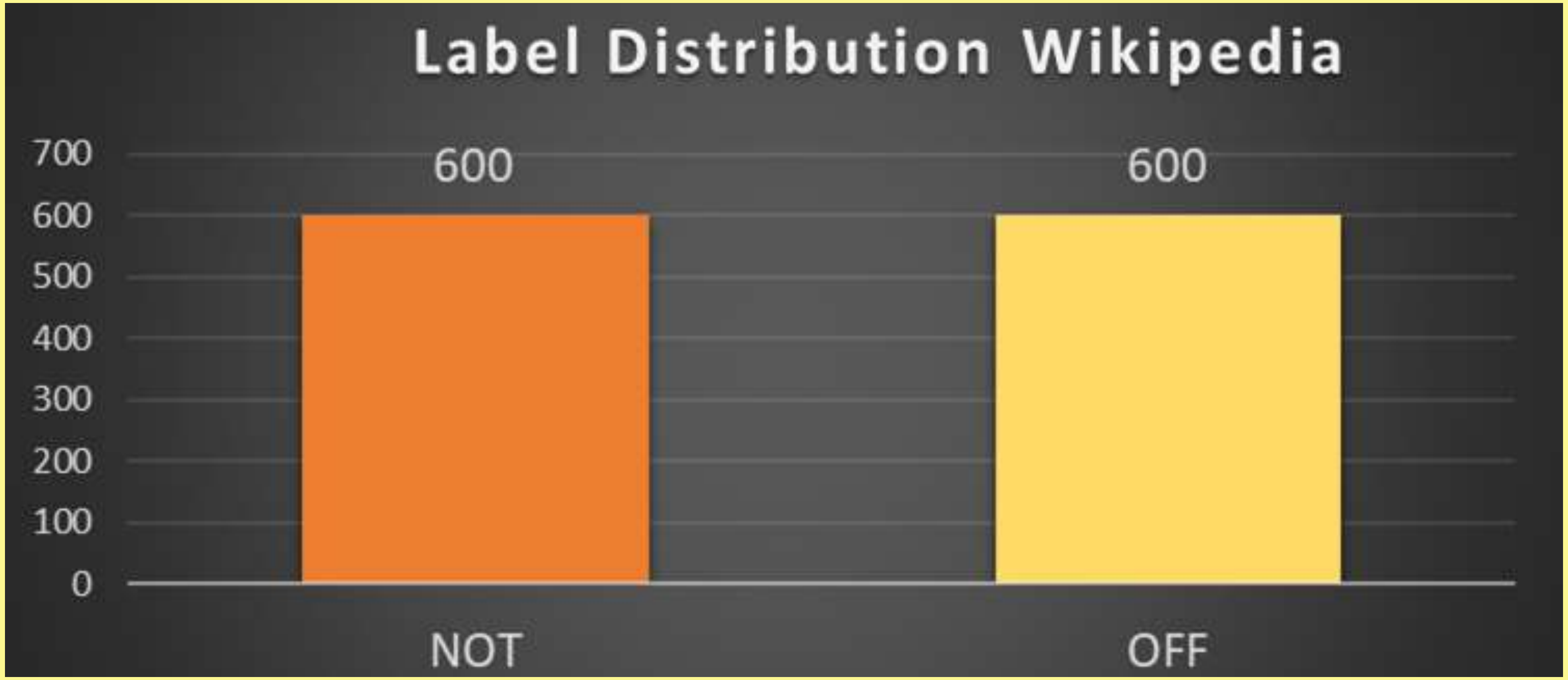


Methodology

Test Data

## Wikipedia

English Wikipedia comments
Manually annotated
Non-toxic, moderately offensive, severely offensive
(AI, 2018)

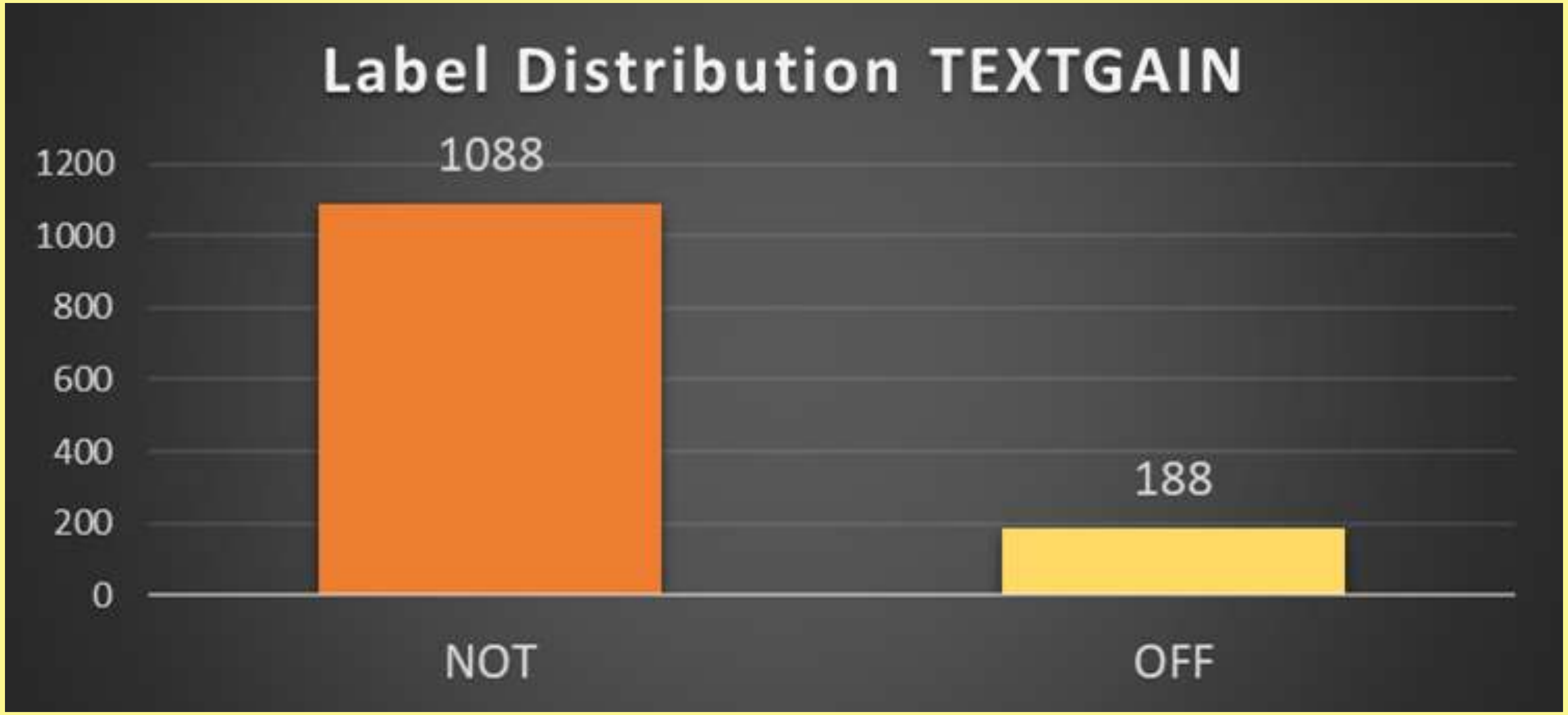


Methodology

Test Data

# TEXTGAIN

English football tweets
Manually labelled as offensive or not offensive



# Baselines

| | OLID | Ruddit | Wikipedia | Total | TEXTGAIN |
|---|---|---|---|---|---|
| **Most Frequent Class** | 0.28 | 0.31 | 0.33 | **0.30** | 0.46 |
| **SpaCy BoW-Model** | 0.70 | 0.66 | 0.86 | **0.73** | 0.54 |
| **Bert** | 0.81 | 0.70 | 0.90 | **0.81** | 0.47 |
| **HateBert** | 0.82 | 0.68 | 0.91 | **0.81** | 0.48 |

# Traditional Classification

## Ensemble Model

Stochastic Gradient Descent Model (SGD)
Logistic Regression Model (LR)
Linear Support Vector Machine 1 (SVM1)
Linear Support Vector Machine (SVM2)

Random state of 42

Class weights are balanced

# SGD Model

SGDClassifier(
random_state=42, class_weight='balanced’,
early_stopping=True, n_iter_no_change=3,
penalty='elasticnet’, loss='log'
alpha=0.001)

Count: Demojised tweet column

Tfidf: POS column (demojised tweets)

Count: Lemma column (demojised tweets)

Afinn

vaderSentiment: ‘pos’, ‘neg’ and ‘compound’

F1 score of 0.71

# LR Model

LogisticRegressionCV(
random_state=42, class_weight='balanced',
cv = 2, scoring='f1_macro’,
penalty = 'l1’, solver = 'saga’,
n_jobs=-1, verbose=2, multi_class='ovr')

Tfidf: Demojised tweet column (without hashtags)

Count: POS column (demojised tweets without punctuation)

Afinn

vaderSentiment: ‘neg’

F1 score of 0.71

# SVM1 Model

```
SVC(
random_state=42, class_weight='balanced’,
kernel='linear', C=0.1, verbose = 2,
probability=True)
```

- Tfidf: Demojised tweet column (without punctuation)
- Tfidf: POS column (basic tweets)
- Afinn
- vaderSentiment: ‘pos’ and ‘compound’
- F1 score of 0.72

# SVM2 Model

```
NuSVC(
random_state=42, class_weight='balanced',
probability=True,
verbose=2)
```

Tfidf: Demojised tweet column (without hashtags)

Tfidf: POS column (basic tweets)

Afinn

vaderSentiment: ‘pos’ and ‘compound’

Macro Average F1 score of 0.72

# Ensemble Model

```
VotingClassifier(
estimators=[
('sgd2', sgd_pipe2), ('log1', log_pipe1),
('svm1', svm_pipe), ('svm2', nu_svm_pipe)
],
verbose= 10, voting='soft’,
weights=[3, 3, 2, 3])
```

Soft Voting

Macro Average F1 score of 0.74

# Neural Classification

5 RoBERTa Models

Hard Majority Vote

Neural Classification

| | # @User | Tokenized | Emoji | Punctuation | Lemmatized |
|---|---|---|---|---|---|
| roberta_tweet | √ | | √ | √ | |
| roberta_hashtag_tweet | | | √ | √ | |
| roberta_token_tweet | | √ | √ | √ | |
| roberta_token_demojize | | √ | | √ | |
| roberta_lemma | √ | | √ | | √ |

# RoBERTa

```
ClassificationModel(
'roberta', 'roberta-base', num_labels=2,
args=model_args, use_cuda=True)
```

```
model_args.num_train_epochs=6
model_args.train_batch_size=64
model_args.learning_rate=1e-5
model_args.max_seq_length=128
```

Early Stopping

Pickle

Neural Classification

# Majority Vote

| | twt | tok_tw | tok_d | lem | hsh | sum | mv |
|---|---|---|---|---|---|---|---|
| 0 | 1 | 1 | 1 | 1 | 1 | 5 | 1 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 1 | 1 | 1 | 1 | 1 | 5 | 1 |
| 6 | 0 | 1 | 1 | 1 | 1 | 4 | 1 |
| 7 | 1 | 1 | 1 | 1 | 1 | 5 | 1 |
| 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Neural Classification

## F1-scores for the best performing RoBERTas + Majority Vote

| | Accuracy | Macro Average |
|---|---|---|
| **roberta_token_demojize** | 0.82 | 0.80 |
| **roberta_token_tweet** | 0.82 | 0.80 |
| **roberta_hashtag_tweet** | 0.81 | 0.79 |
| **roberta_tweet** | 0.81 | 0.79 |
| **roberta_lemma** | 0.80 | 0.78 |
| **majority vote** | 0.82 | 0.80 |

## Precision and recall for the best performing RoBERTas + Majority Vote

| | Precision | | Recall | |
|---|---|---|---|---|
| | OFF | NOT | OFF | NOT |
| **roberta_token_demojize** | 0.77 | 0.85 | 0.69 | 0.89 |
| **roberta_token_tweet** | 0.75 | 0.85 | 0.71 | 0.87 |
| **roberta_hashtag_tweet** | 0.70 | 0.87 | 0.77 | 0.83 |
| **roberta_tweet** | 0.70 | 0.87 | 0.77 | 0.83 |
| **roberta_lemma** | 0.69 | 0.87 | 0.76 | 0.82 |
| **majority vote** | 0.73 | 0.86 | 0.74 | 0.86 |

Neural Classification

# Majority Vote

| | twt | tok_tw | tok_d | lem | hsh | sum | mv |
|---|---|---|---|---|---|---|---|
| 0 | 1 | 1 | 1 | 1 | 1 | 5 | 1 |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 1 | 1 | 1 | 1 | 1 | 5 | 1 |
| 6 | 0 | 1 | 1 | 1 | 1 | 4 | 1 |
| 7 | 1 | 1 | 1 | 1 | 1 | 5 | 1 |
| 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

# Results and Error Analysis

# Results

15 per cent offensive data

| | Ruddit | OLID | Wikipedia | Total | TEXTGAIN |
|---|---|---|---|---|---|
| Traditional Ensemble | 0.661 | 0.753 | 0.874 | 0.76 | 0.434 |
| Neural RoBERTa | 0.713 | 0.803 | 0.912 | 0.808 | 0.504 |

Similar format to train data

Similar format to train data

Clear division between offensive and non-offensive

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# Discussion

## Vectorizers

Tweets, lemmas
POS

## N-grams

Character n-grams
Word n-grams

. . . .

## Linguistic Features

POS
Lemmas

. . . .

## Sentiment Scores

Afinn
Vader

# Conclusion

**NLP_Student42** @NLP_Student42 · 4 s

Wow, the group Still Processing presented so well that I don't have any questions, do you?

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