

# 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)

## Surface Level Features

### 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

(Gambino and Pirrone, 2020)

### Lemmatization

(Markov and Daelemans, 2021; Markov et al., 2021; Van 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

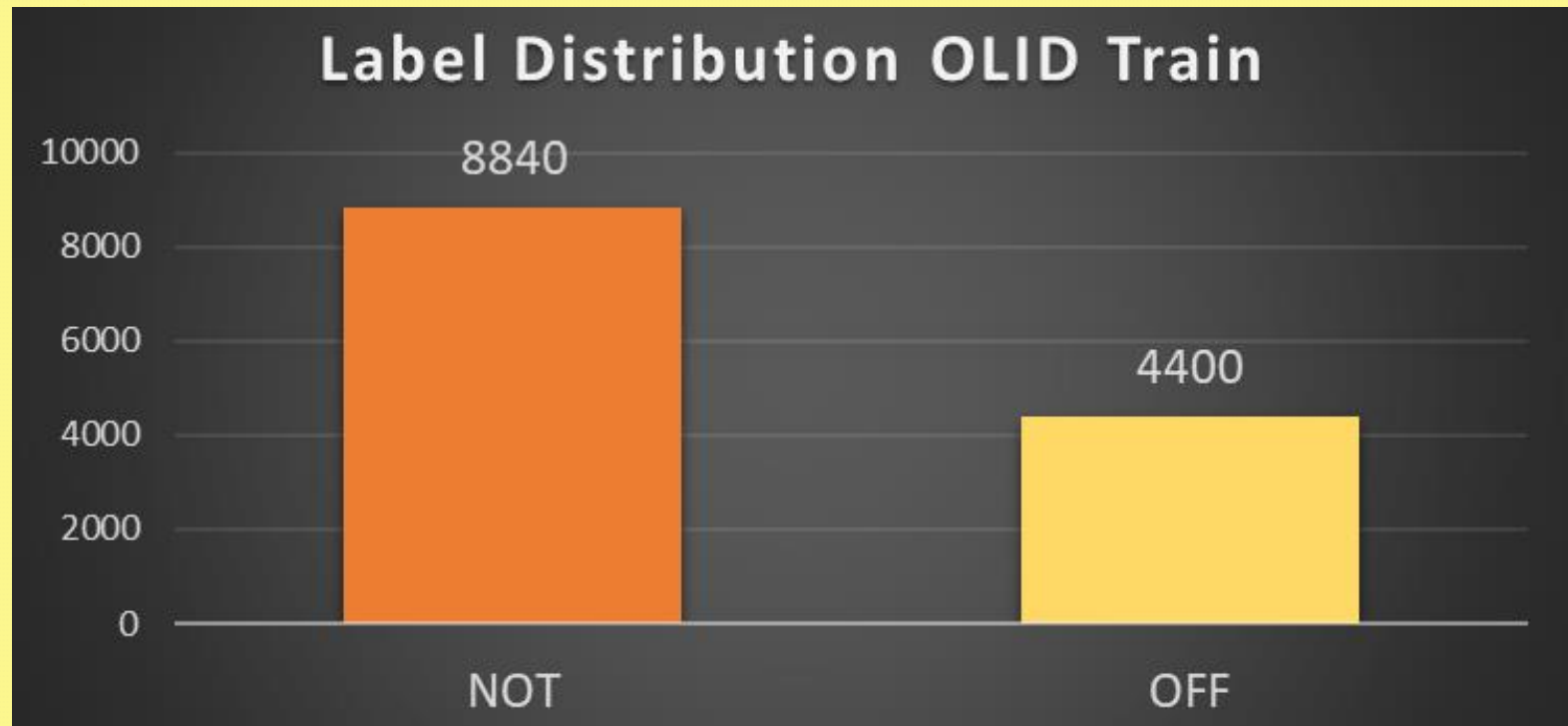
Methodology

Train Data

13

OLID

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





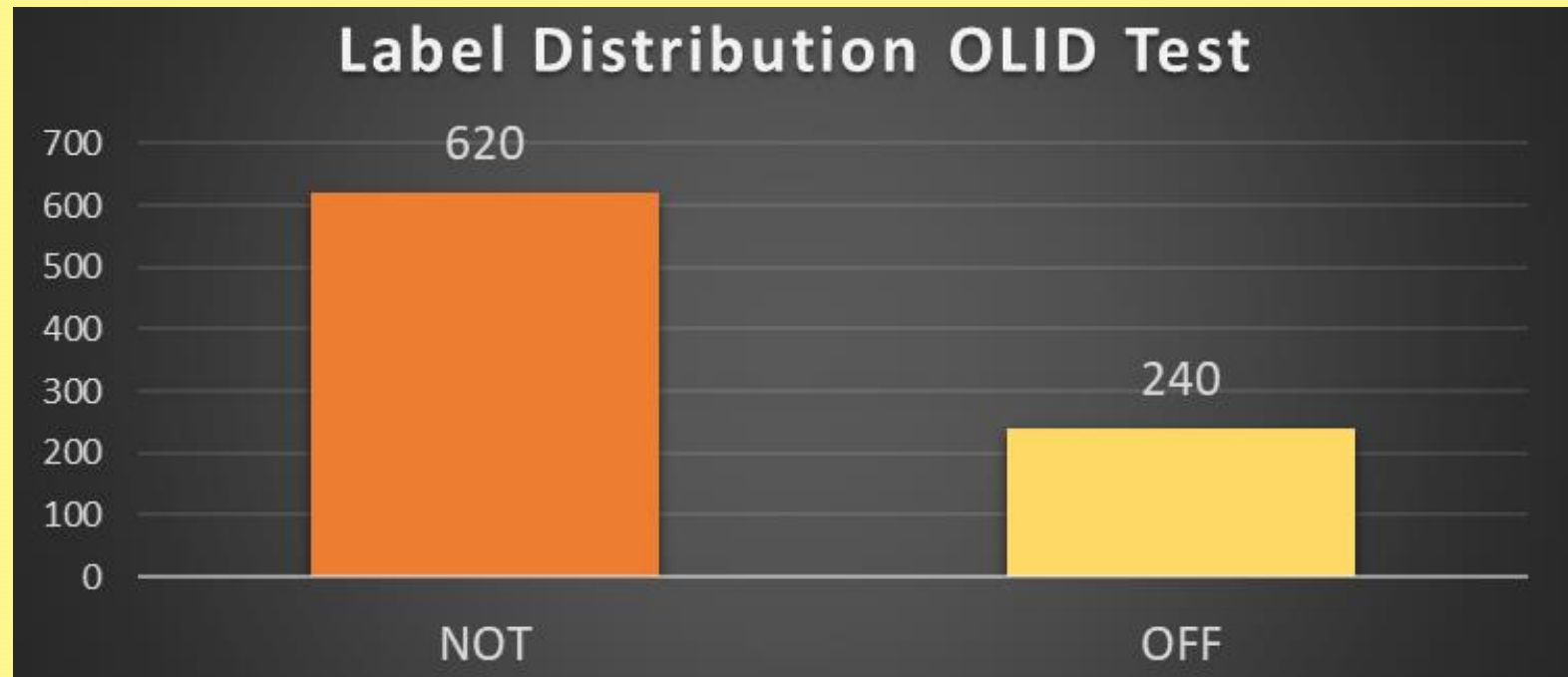
Methodology

Test Data

14

OLID

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



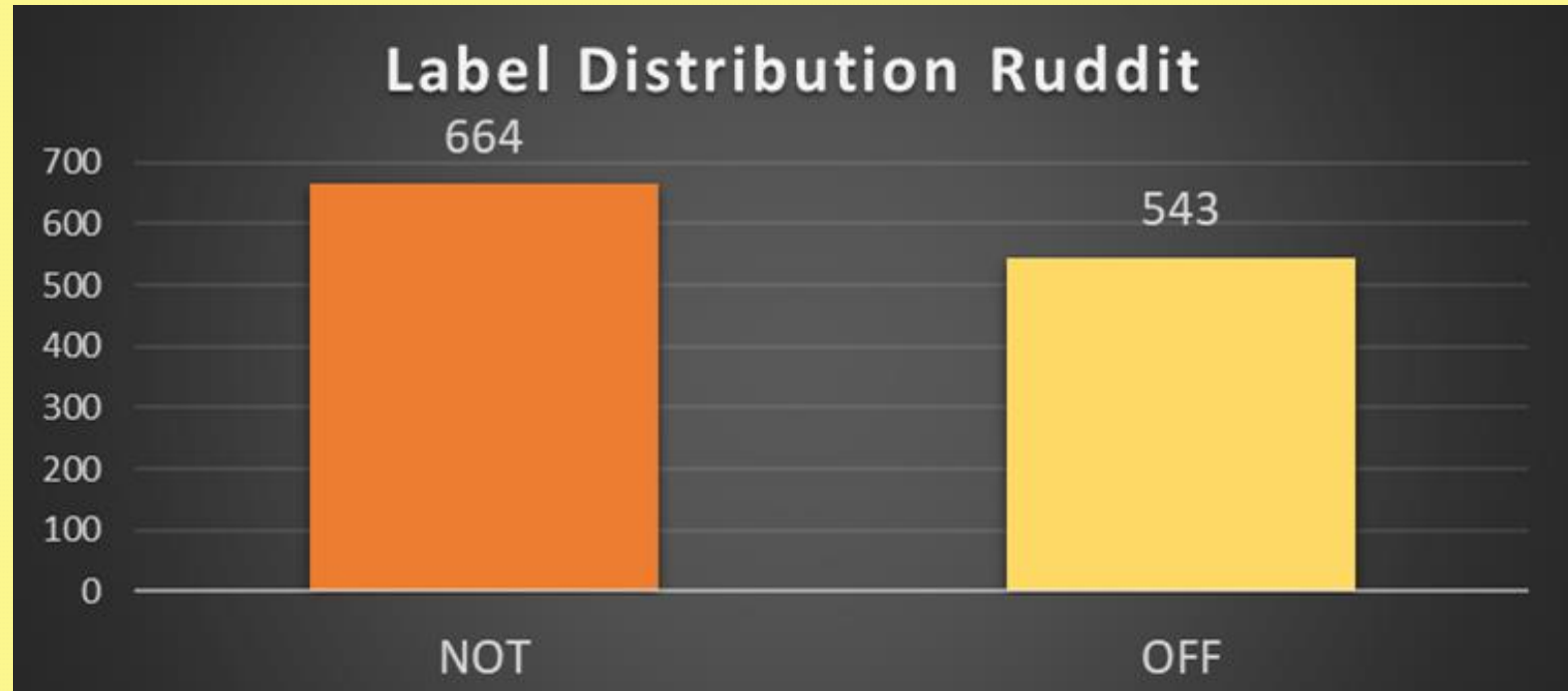
Methodology

Test Data

15

## Ruddit

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



Methodology

Test Data

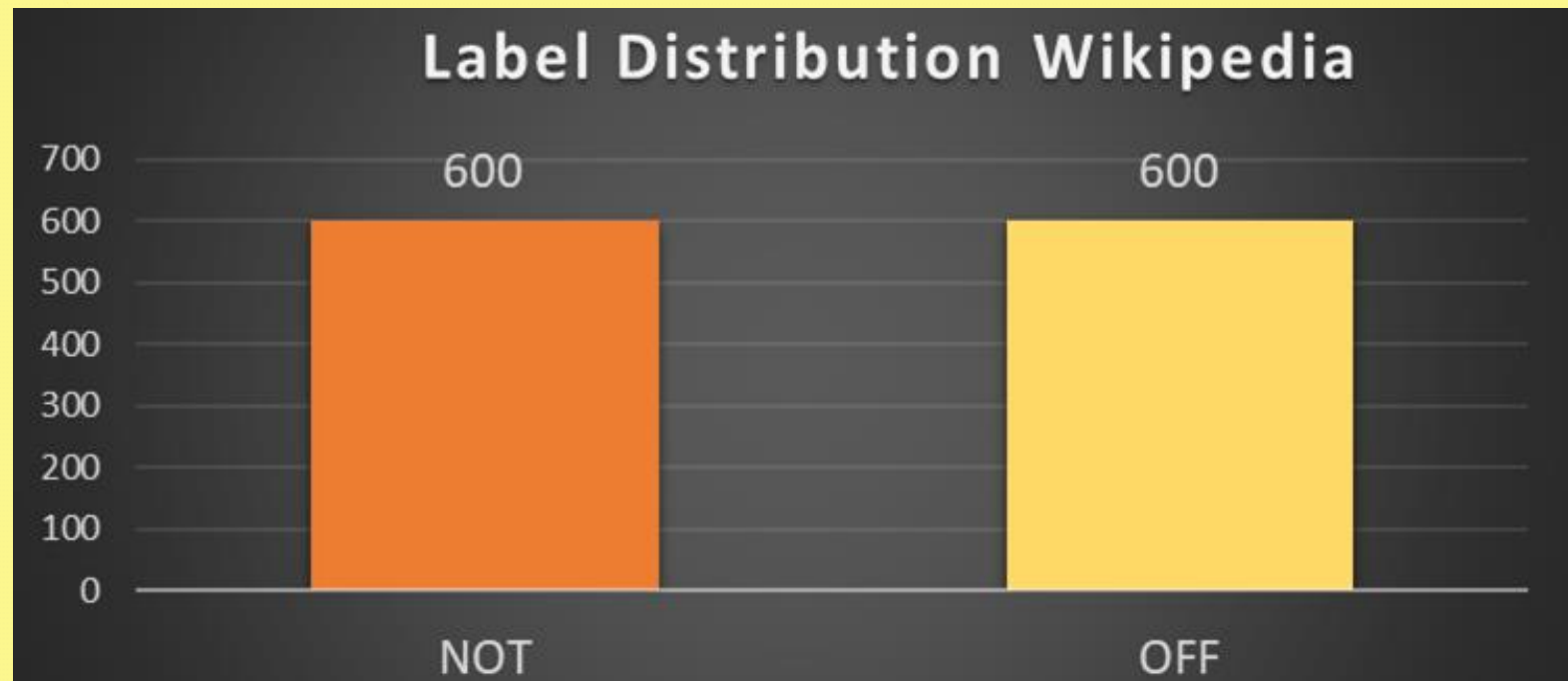
16

## Wikipedia

English Wikipedia comments

Manually annotated

Non-toxic, moderately offensive, severely offensive  
(Al, 2018)





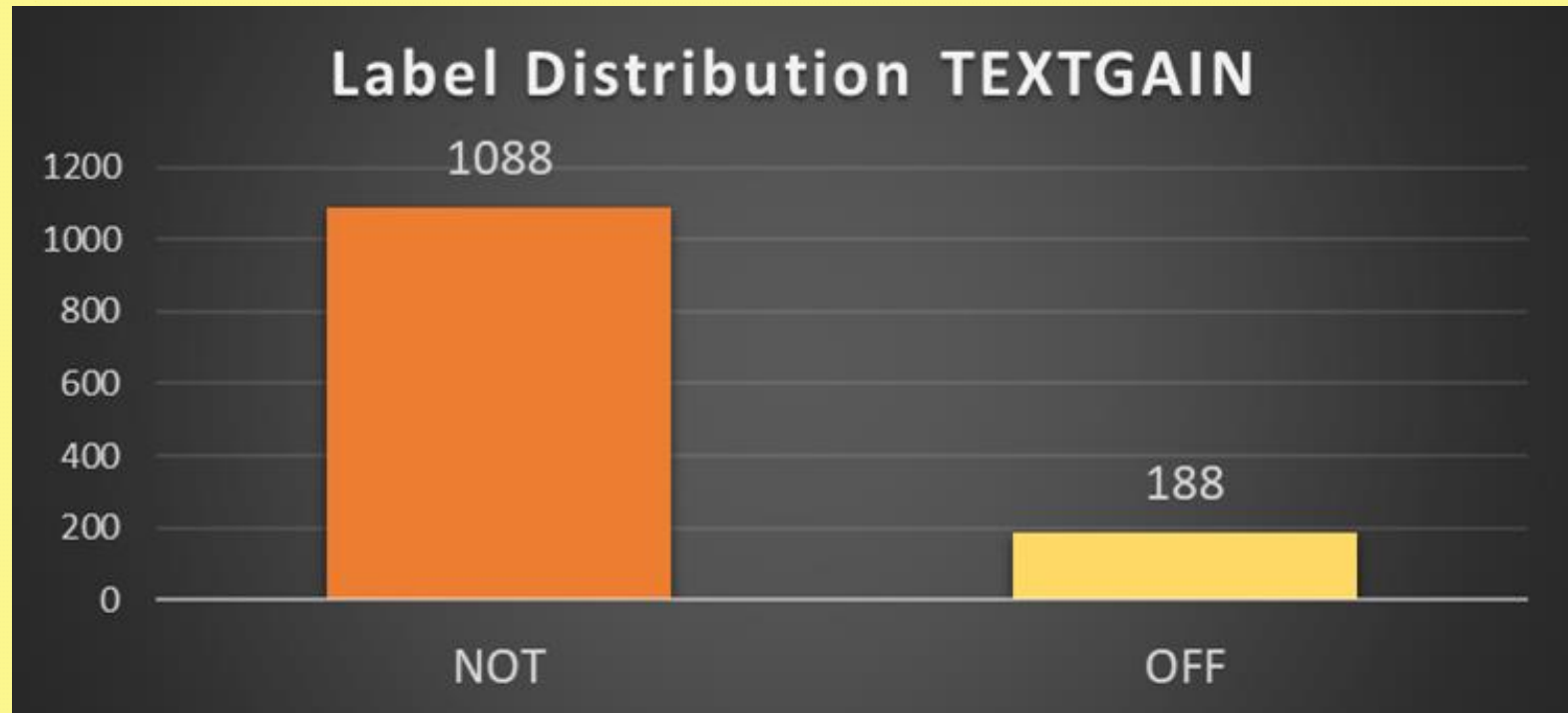
Methodology

Test Data

17

## TEXTGAIN

English football tweets  
Manually labelled as offensive or not offensive



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

# Traditional Classification

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



## Traditional Classification

## 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



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

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
<b>roberta_token_demojize</b>	0.77	0.85	0.69	0.89
<b>roberta_token_tweet</b>	0.75	0.85	0.71	0.87
<b>roberta_hashtag_tweet</b>	0.70	0.87	0.77	0.83
<b>roberta_tweet</b>	0.70	0.87	0.77	0.83
<b>roberta_lemma</b>	0.69	0.87	0.76	0.82
<b>majority vote</b>	0.73	0.86	0.74	0.86



Majority Vote

	twf	tok_tw	tok_d	lem	hsh	sum	mv
0	1	1	1	1	1	5	1
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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 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

Clear division  
between offensive  
and non-offensive

Similar format  
to train data

## Baselines

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## Baselines

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Neural RoBERTa	<b>0.803</b>	<b>0.713</b>	<b>0.912</b>	<b>0.808</b>	<b>0.504</b>

# Discussion



## Vectorizers

Tweets, lemmas  
POS

## N-grams

Character n-grams  
Word n-grams

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## 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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