

The background features a large cyan number '1' in the top left, a red square behind the word 'TOXICITY', and a cyan square behind the word 'DETECTION'. A horizontal black line with a red and cyan dot at its right end is positioned above the title. Various small black squares and red/cyan dot patterns are scattered across the slide.

TOXICITY DETECTION

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01.

The Problem

An overview on the topic

03.

Results

Evaluation of predictions



02.

Modelling Process

Steps in the modeling process and project design



04.

CONCLUSIONS

The takeaway





The Problem


01.





111,350,250

US adults reduced internet usage after receiving abuse.



OVER 1/3

of the US population.

(Johnson, 2021)



■ Related Work



(Davidson, 2017)

**Investigating hate speech
within online comments**

Origin of data set used





(Van Aken, 2018)


Error Analysis of toxic comment
detection systems

Baseline



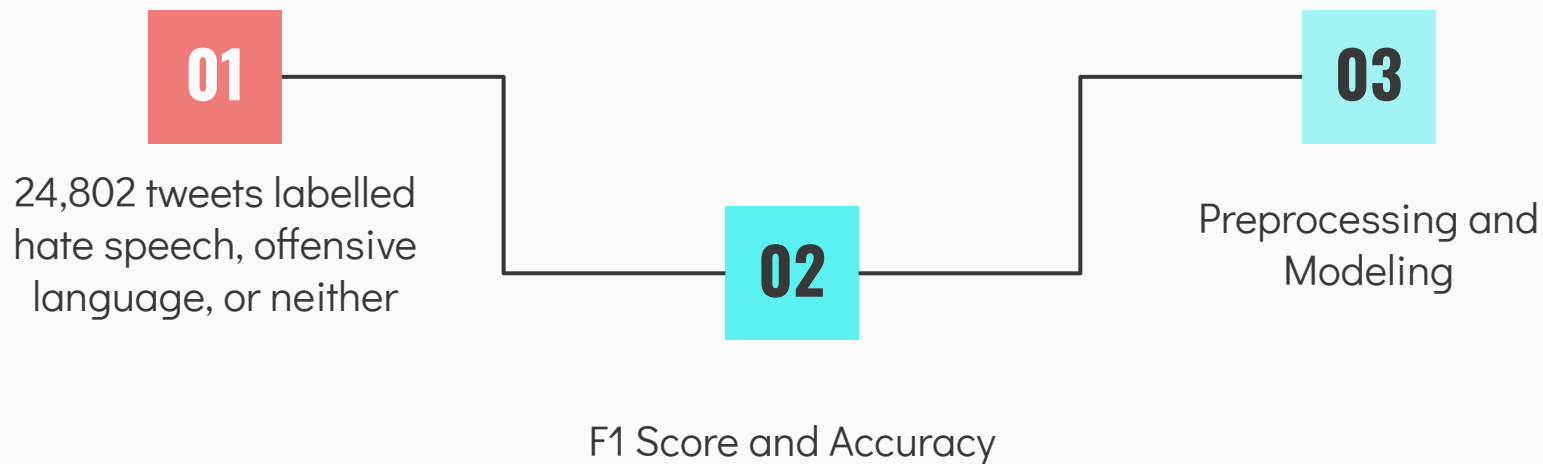


Modelling Process

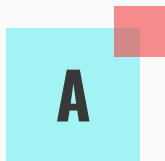


02.

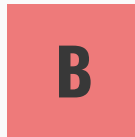
■ Data



■ Preprocessing



Removed usernames



Removed Punctuation



Stemming



Removed Numbers



Tokenization



Bag-of-Words word
embedding



■ Supervised Learning



1

Logistic Regression

Multinomial configuration
of classic logistic function

2

Linear SVC

A support vector
classification model with a
linear kernel

3

Decision Tree Classifier

Tree-like model of outcomes

4

Extra Tree Classifier

Aggregate result of many
de-correlated trees



■ Supervised Learning



5

Random Forest Classifier

Aggregate result of many
de-correlated trees

6

Ridge Classifier

Converts target values
between $[-1,1]$ and treats it
as a regression to predict



7

Gradient Boosting Classifier

Combine weak learning
models together in forward
stage-wise order



■ Deep Learning



8

MLP Classifier

A multi-layer perceptron
from sklearn



9

Neural Network

Embedding Layer, with 2
dense layers with relu
activation function,
dropout , a output dense
layer with a softmax



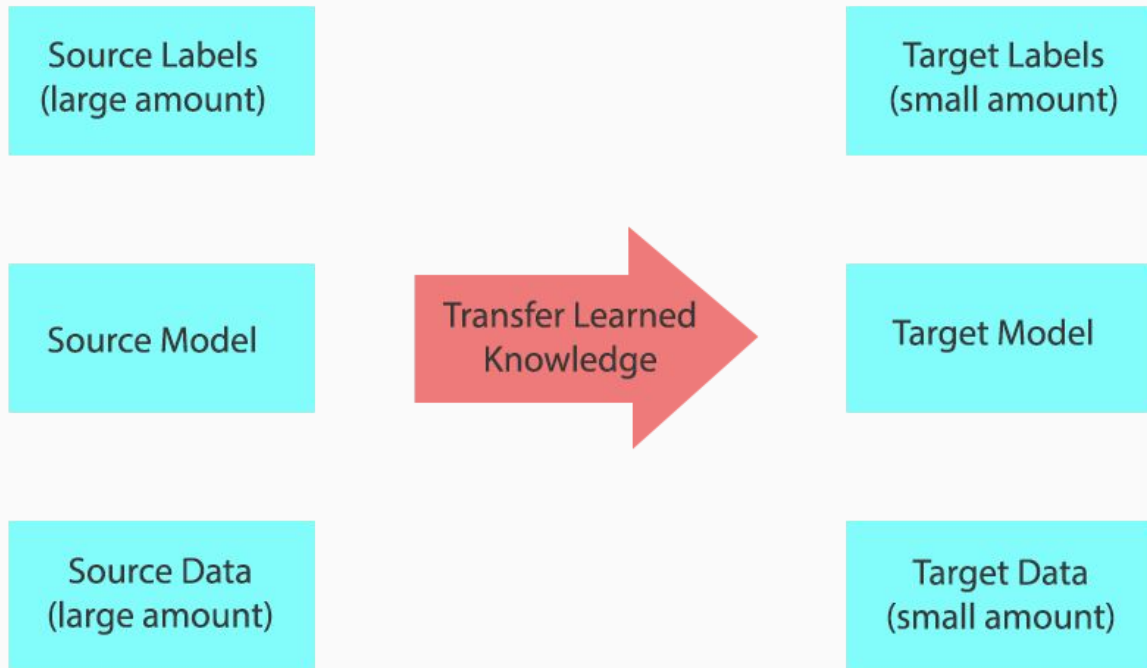
10

FastAi ULMFiT

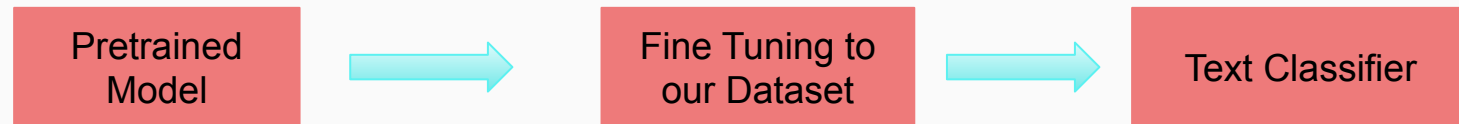
AWD-LSTM



Transfer Learning



FastAi ULMFit





Results



03.

Supervised Modelling Results

Model	Accuracy	F1-Score	Recall	Precision
<i>Logistic Regression</i>	0.90	0.89	0.90	0.89
<i>Linear SVC</i>	0.89	0.88	0.89	0.87
<i>Decision Tree</i>	0.88	0.88	0.88	0.88
<i>Extra Tree</i>	0.83	0.83	0.83	0.83
<i>Random Forest</i>	0.89	0.88	0.88	0.87
<i>Ridge</i>	0.86	0.75	0.74	0.80
<i>Gradient Boosting</i>	0.87	0.76	0.70	0.83

Deep Learning Modelling Results

Model	Accuracy	F1-Score	Recall	Precision
<i>MLP Classifier</i>	0.86	0.77	0.75	0.80
<i>Neural Network</i>	0.81	0.80	0.81	0.80
<i>ULMFiT</i>	0.90	0.90	-	-



Conclusions



04.

CONCLUSIONS

01

The best performing model is FastAI's ULMFiT with a F1 score of 0.8961 and an accuracy score of 0.9029


02

The second best performing model is Logistic Regression with a F1 score of 0.8915 and an accuracy score of 0.9008





■ LIMITATIONS AND FUTURE WORK

LIMITATIONS

- The model is slightly biased to predict hate speech
 - The model might run into problem with new words
- 

FUTURE WORK

- Expand the dataset from different sources and implement more advanced models
 - Explore different ways to vectorize the dataset
 - Attempt stratified k folds for imbalanced label counts
- 
- 





Thank You!

