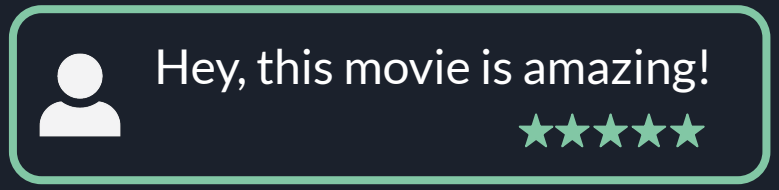
IMDB Movie Reviews

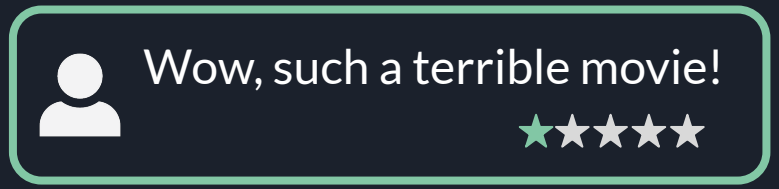
Sentiment Classification

Aleksa Milenovic

Goal of this Project



POSITIVE COMMENT



NEGATIVE COMMENT

~90% Metric

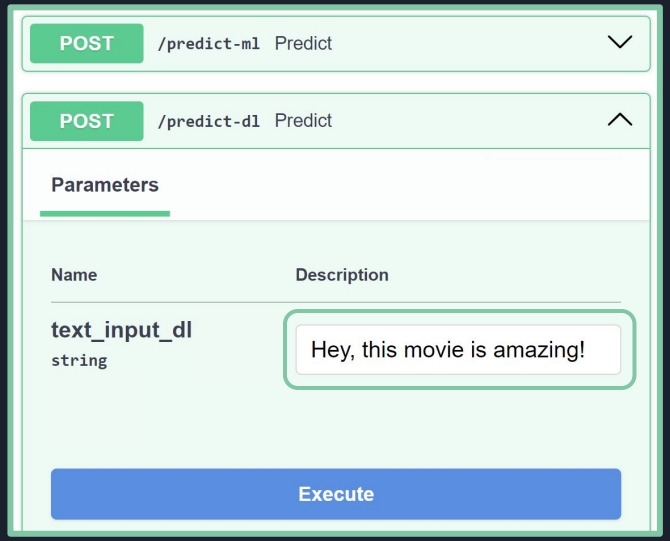
Technologies overview

Preprocessing
Classifier training

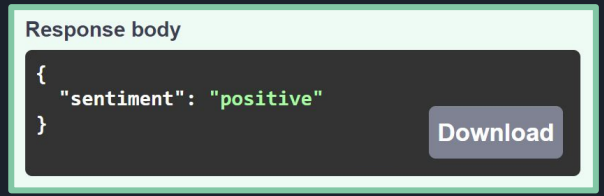
Model Logging

Deployment

Result product



Example sentence on Fast API endpoint



Output Sentiment

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Introduction

NLP

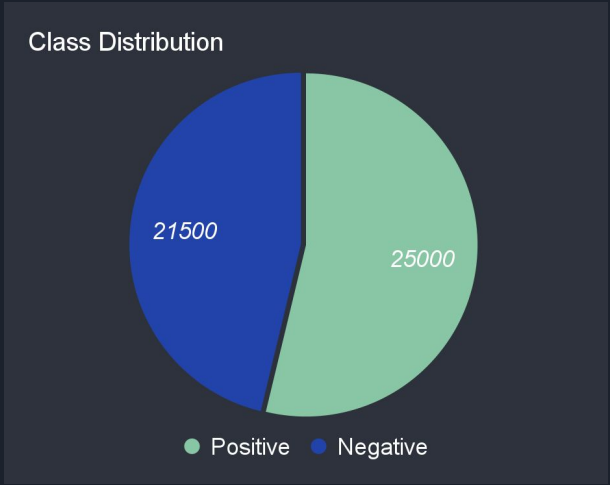
Sentiment Classification

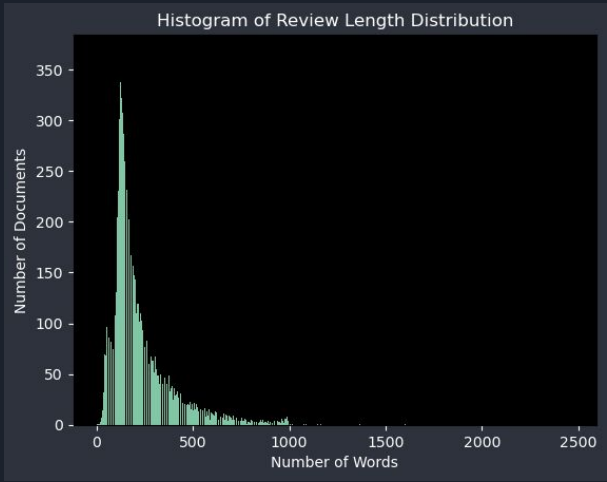
Dataset

This film made John Glover a star. Alan Raimy is one of the most compelling character that I have ever seen on film., positive

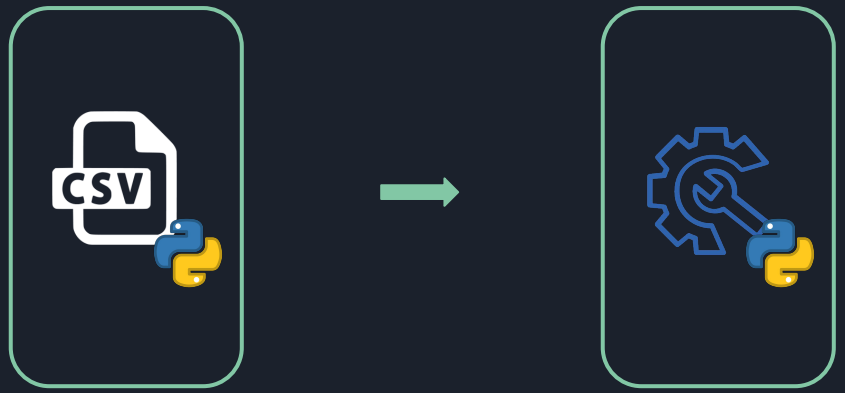
★★★★★

- 46,500 reviews
- 419,475 unique words





Machine Learning approach

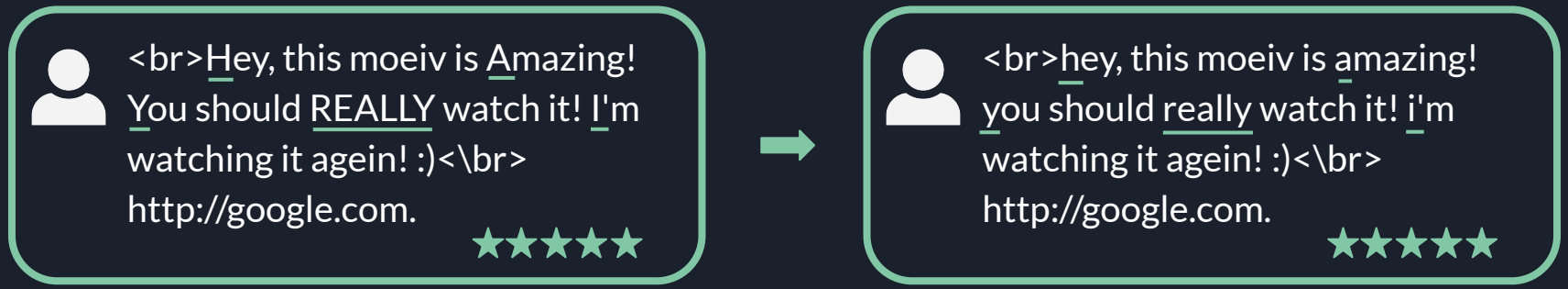


Preprocessing

Training models
(Hyperparameter tuning)

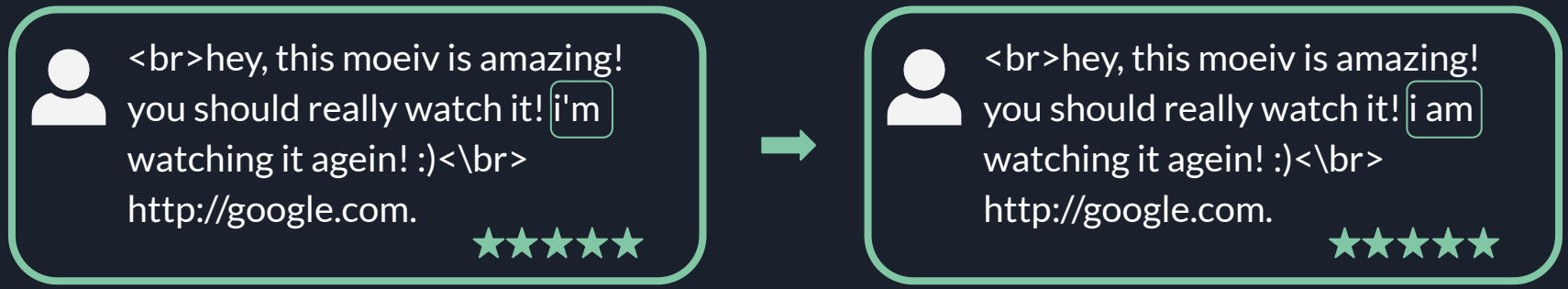
Preprocessing Steps 1/7

- Lowercase text



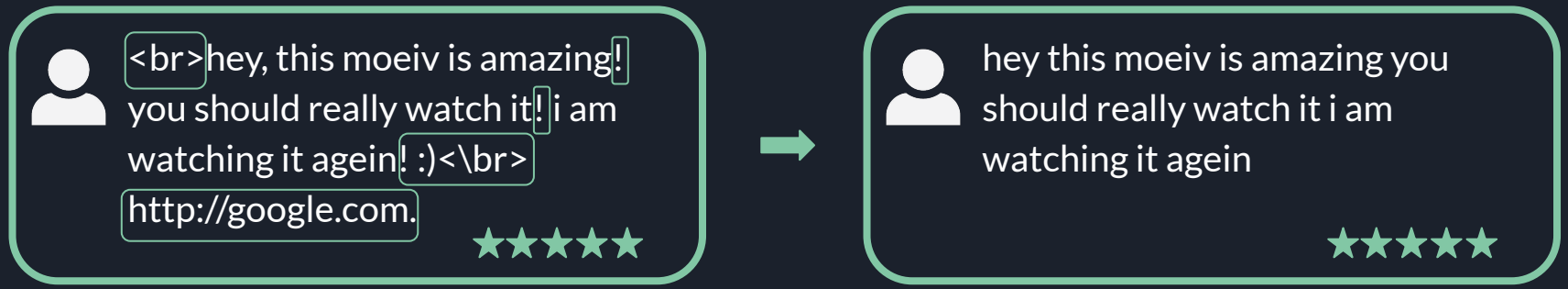
Preprocessing Steps 2/7

- Split contractions *(can't ->can not)*



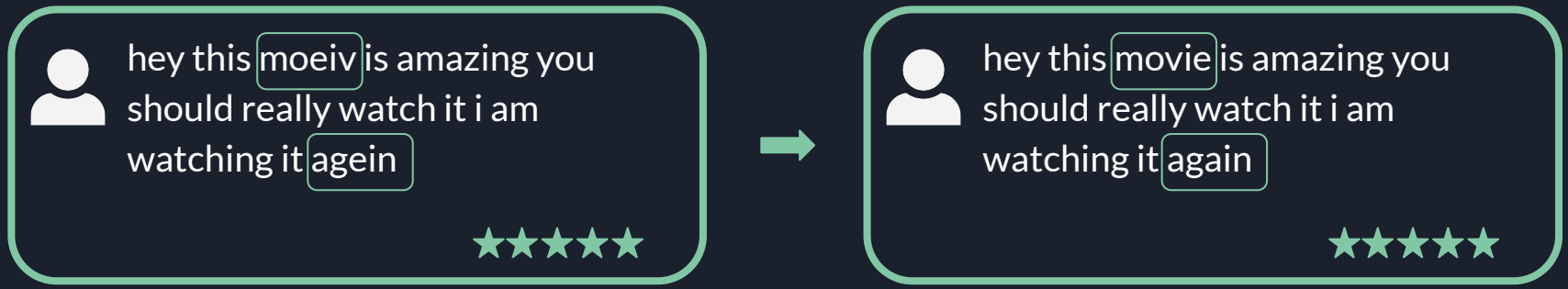
Preprocessing Steps 3/7

- Clean text (*remove urls, html tags, special characters…*)



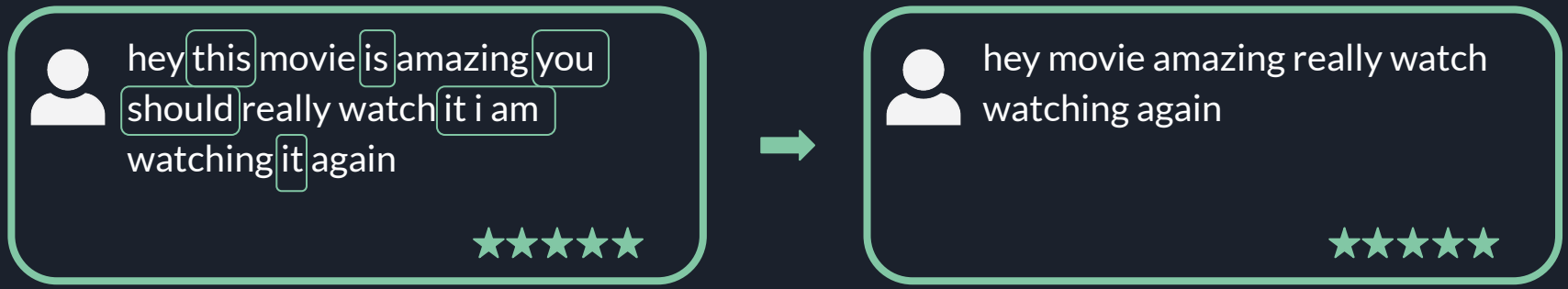
Preprocessing Steps 4/7

- Correct spelling mistakes



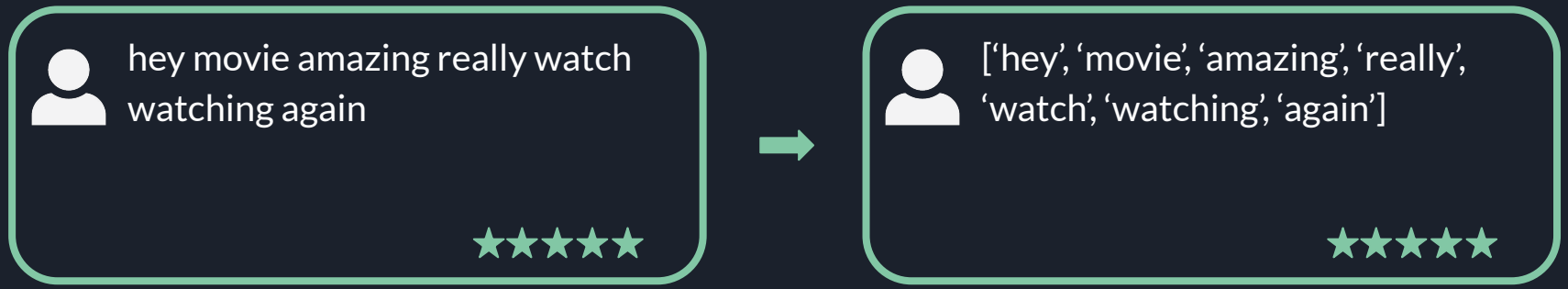
Preprocessing Steps 5/7

- Remove stop words (*the*, *a*, *is*, *what*,...)



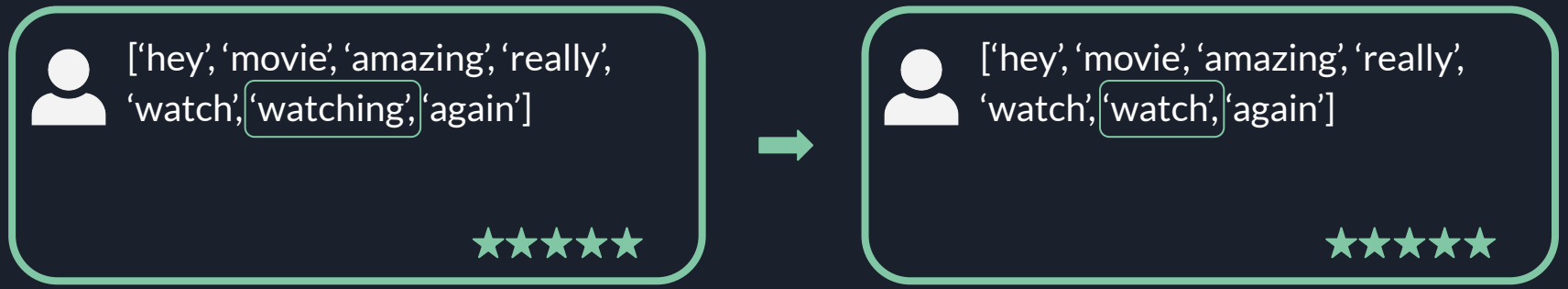
Preprocessing Steps 6/7

- Tokenization

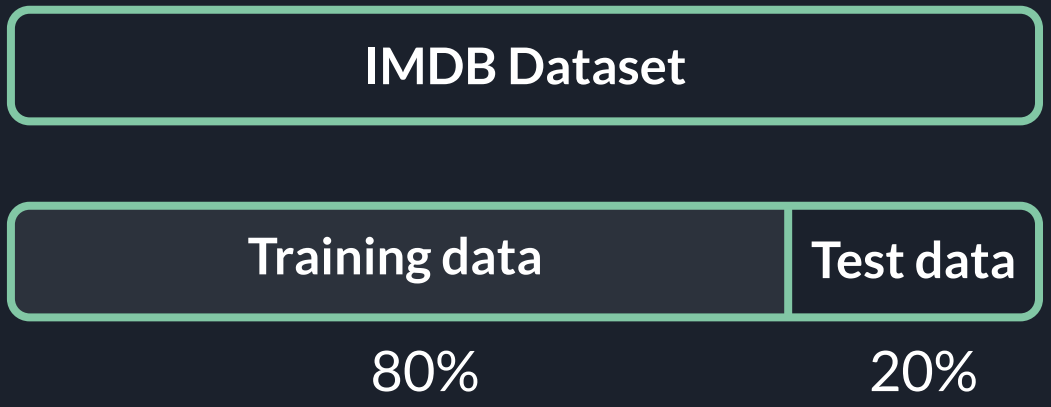


Preprocessing Steps 7/7

- Lemmatization (*meeting -> meet, was -> be, mice -> mouse,...*)



Train-test Split



TF-IDF Vectorization

$$TFIDF(t,d) = TF(t,d) \times IDF(t)$$

$$\text{Term Frequency} = \frac{\text{Word occurrences in a sentence}}{\text{No of words in a sentence}}$$

$$\text{Inverse Document Frequency} = \log\left(\frac{\text{Number of sentences}}{\text{Number of sentences containing word}}\right)$$

TF-IDF Vectorization

1. good movie
2. good book
3. movie book good

TF	1	2	3
G	1/2	1/2	1/3
M	1/2	0	1/3
B	0	1/2	1/3

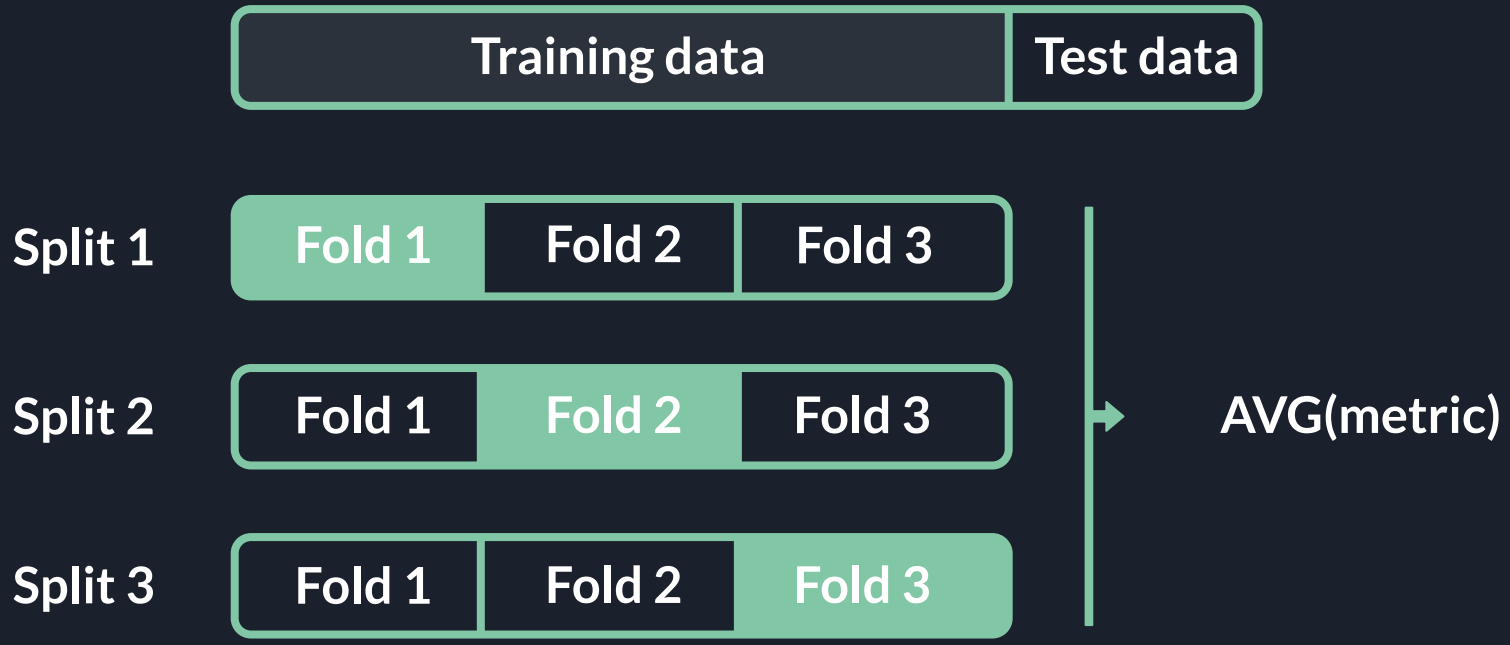
✖

	IDF
G	log(3/3)
M	log(3/2)
B	log(3/2)

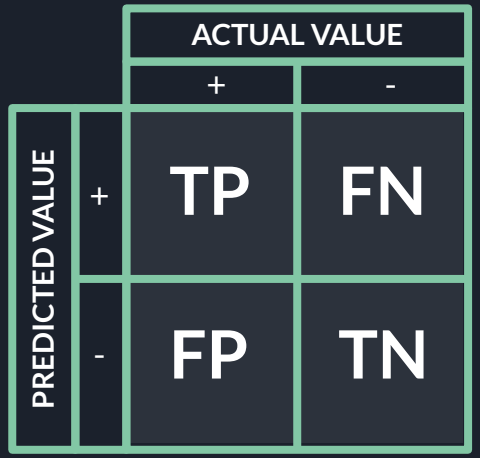
=

TF	G	M	B
1	0	½* log(3/2)	0
2	0	0	½* log(3/2)
3	0	1/3* log(3/2)	1/3* log(3/2)

K-split cross validation



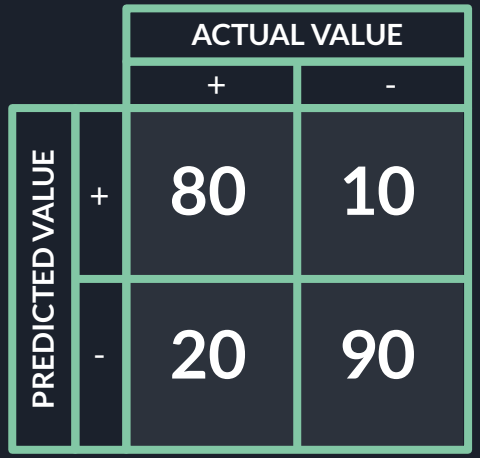
Performance Metrics



Confusion Matrix

Accuracy: $\frac{TP + TN}{TP + FN + FP + TN}$

Performance Metrics - Balanced



Confusion Matrix

$$\frac{TP + TN}{TP + FN + FP + TN}$$

$$\frac{80 + 90}{80 + 10 + 20 + 90} = 85\%$$

Performance Metrics - Imbalanced

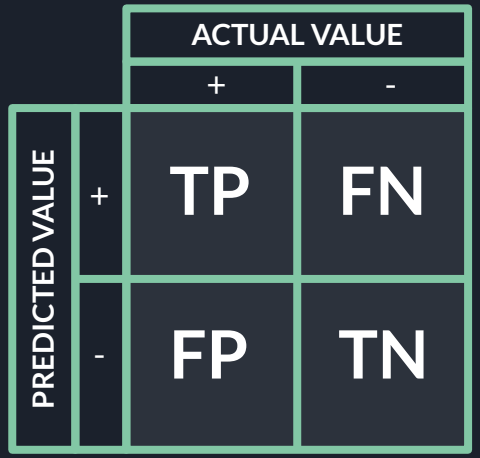
		ACTUAL VALUE +	ACTUAL VALUE -
PREDICTED VALUE	+	980	90
	-	20	10

Confusion Matrix

$$\frac{TP + TN}{TP + FN + FP + TN}$$

$$\frac{980 + 10}{980 + 20 + 90 + 10} = 90\%$$

Performance Metrics - Imbalanced



Confusion Matrix

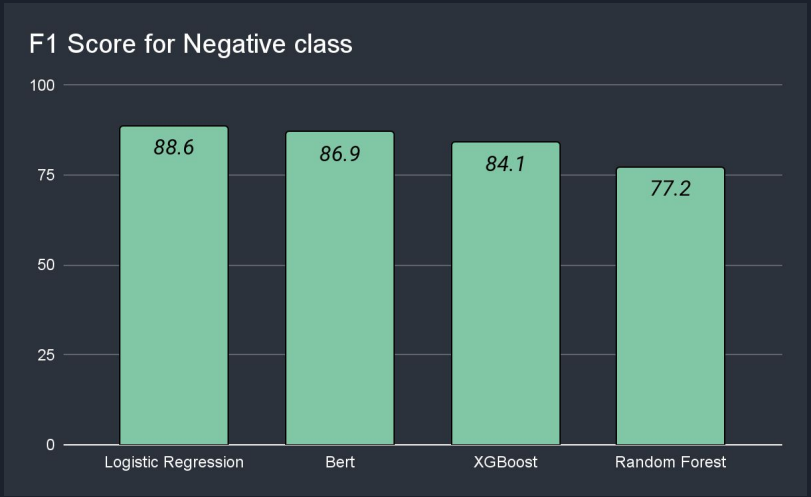
Precision: $\frac{TP}{TP + FP}$

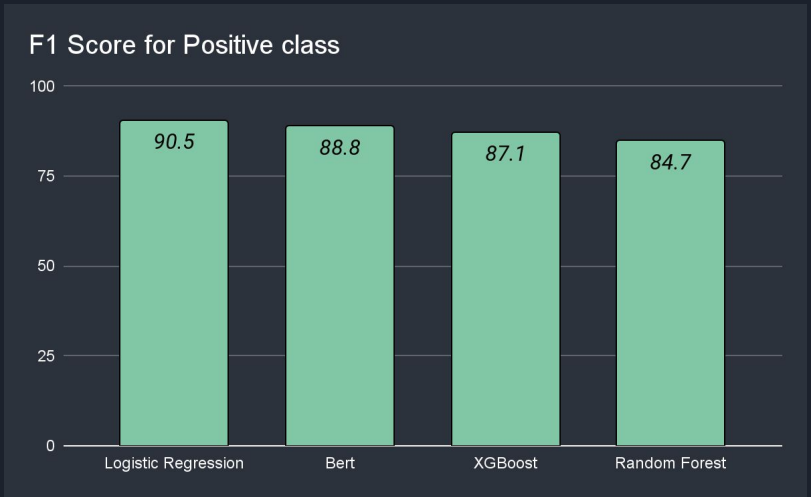
Recall: $\frac{TP}{TP + FN}$

F1 Score: $2 * \frac{Precision * Recall}{Precision + Recall}$

Results

- Best results for each model (*F1 Score*)





Results

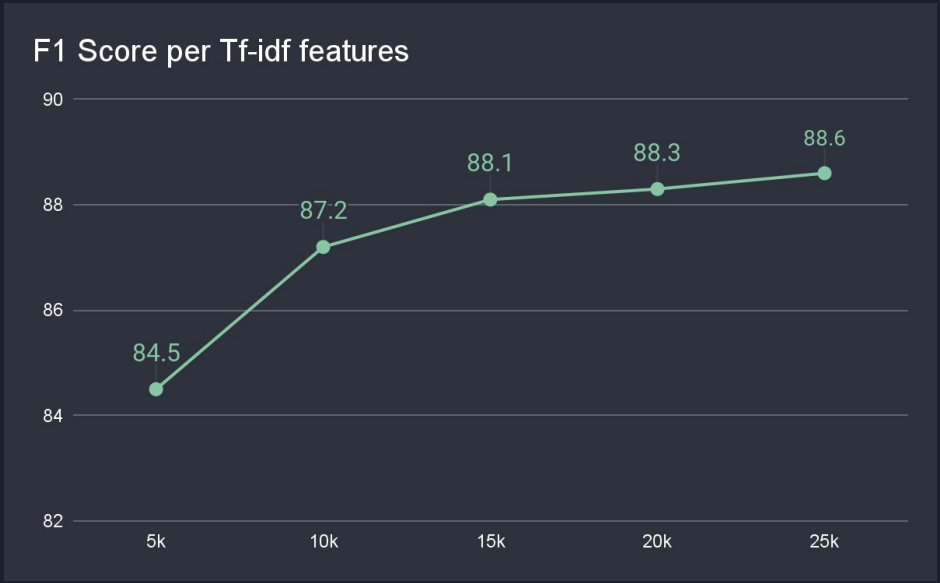
- Best performing dataset:
- Split Contraction, Lemmatization, Without Spelling, 25k features

Contractions expanded	150,492

URL’s	121
HTML tags	187,484
Other characters	1,822,452
Digits	150,344

Results

- Best TF-IDF features - 25000

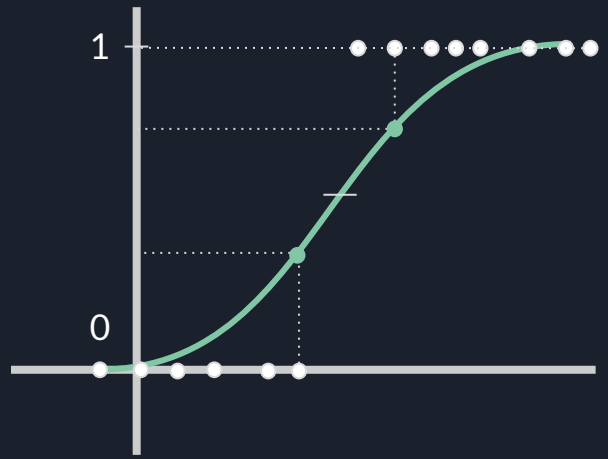


Machine learning models

- Logistic Regression
- Random Forest Tree
- XGBoost

Machine learning models

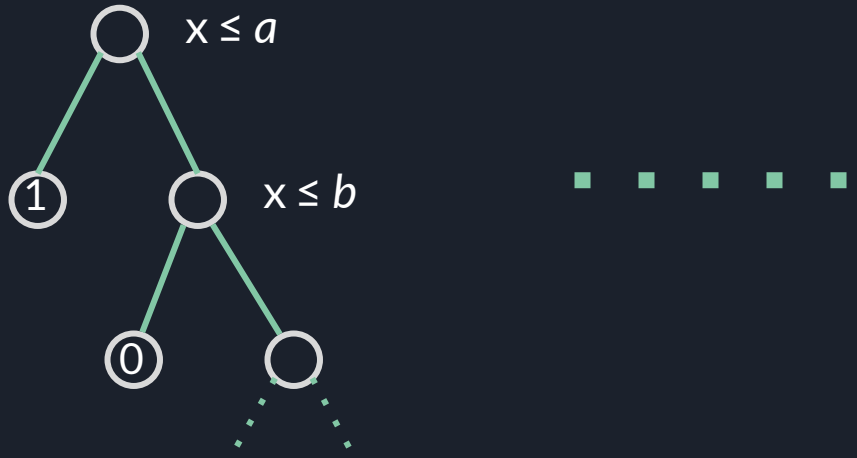
- Logistic Regression



$$f(z) = \frac{1}{1 + e^{z}}$$

Machine learning models

- Random Forest



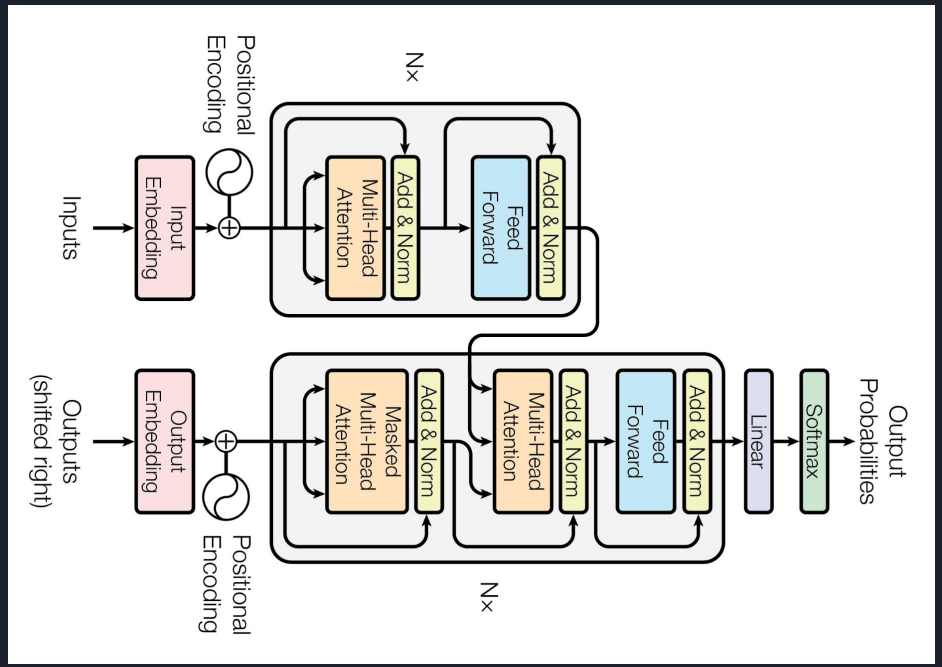
Deep Learning approach

Load pre-trained
Bert from Hugging Face

Tokenize data using
BertTokenizer

Fine tune model
on tokenized dataset

Deep Learning model - Transformer



Deep Learning model - BERT

- Bidirectional Encoder Representation from Transformers
- Pretraining - Masked language modeling

  - Next sentence prediction

Results

- Falsely classified reviews

Further improvements

- More data preprocessing (:) -> *‘good’*, *‘9/10’* -> *‘good’*, *balancing?*)
- Different ML Classifier
- Different Transformer

Thank you for your attention!