# TWITTER SENTIMENTAL ANALYSIS

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# AGENDA

PROBLEM STATEMENT

DATA DESCRIPTION

IMPLEMENTATION

ML MODELLING

CONCLUSION

# PROBLEM STATEMENT

- The focus of our machine learning project is to develop a sentiment analysis model for tweets
- Sentiment analysis plays a crucial role in understanding public opinion and can be applied in various domains, including business, politics, and social media monitoring
- Our goal is to create a model that accurately classifies tweets into positive and negative sentiments

## DATA DESCRIPTION

#### Context

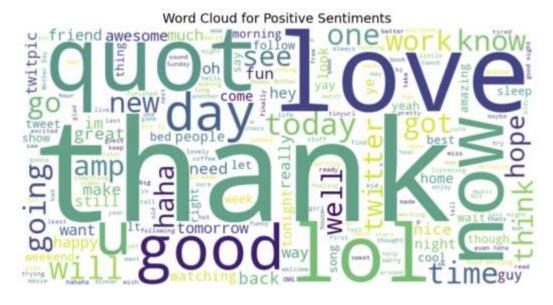
This is the sentiment140 dataset. It contains 1,600,000 tweets extracted using the Twitter API. The tweets have been annotated (0 = negative, 4 = positive) and can be used to detect sentiment.

#### Content

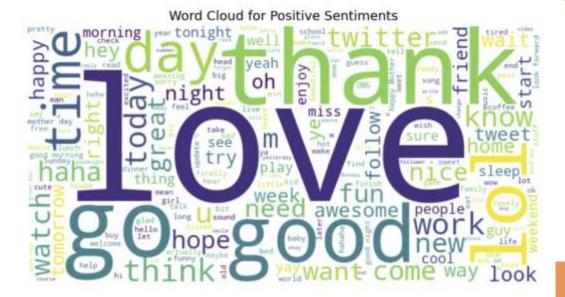
It contains the following 6 fields:

- target: the polarity of the tweet (0 = negative and 4 = positive)
- · ids: The id of the tweet (2087)
- date: the date of the tweet (Sat May 16 23:58:44 UTC 2009)
- flag: The query (lyx). If there is no query, then this value is NO\_QUERY.
- · user: the user that tweeted.
- · text: the text of the tweet.

#### **Before Preprocessing**



#### After Preprocessing



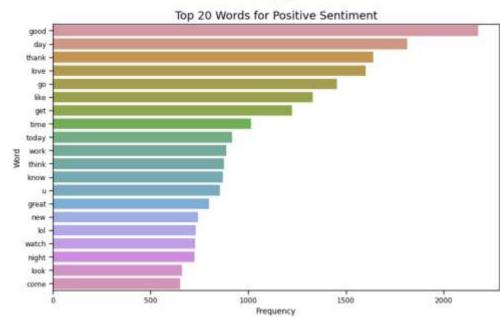
# IMPLEMENTATION - DATA PREPROCESSING

Used SpaCy library for preprocessing and perform these steps:

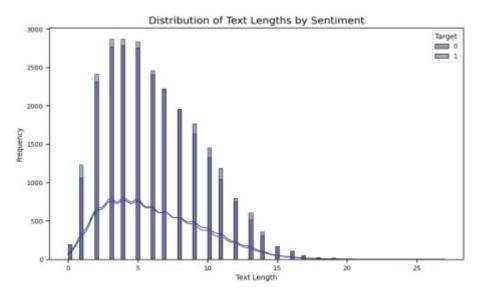
- Stop Words Removal
- URLs and @mentions removal
- Removal of HTML Character e.g. &quot

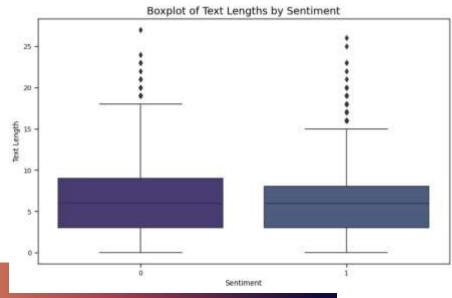
	Text	tokenized_text	Target
0	@Msfab1988 u so lucky @lamborghinibow answer	[u, lucky, answer, u]	0
1	@chrismusick didn't work still got em	[work, get, em]	0
2	Not doing to goodI hurt my knee last night	[good, hurt, knee, night, dance]	0
3	@dulani247 Yep, I do.	[Yep]	1
4	@capemaybooks i see kitteh fwendz at the #bund	[kitteh, fwendz, bunday, celeration]	1

#### Top 20 Words for Negative Sentiment work get day miss not ike want today good sad know need wish bad home 1000 1250 1500 1750 2000 Frequency



## IMPLEMENTATION-EDA



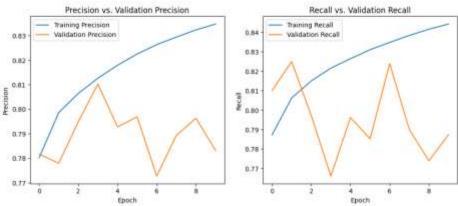


#### Loss vs. Validation Loss Accuracy vs. Validation Accuracy Training Accuracy - Training Loss Validation Loss Validation Accuracy 0.82 0.45 0.44 0.43 9 0.42 0.41 0.79 0.40 0.39 Precision vs. Validation Precision Recall vs. Validation Recall Training Precision 0.83 Validation Precision 0.82 0.81 0.81 Training Recall Validation Recall 0.79 0.78 0.78

## RNN

- Embedding size of 20
- RNN with 15 units
- Global Max Pooling
- Dense Layer with 32 units and RELU
- Dense Layer with 1 unit with Sigmoid for Binary Classification
- Adam Optimizer
- Binary Cross entropy Loss

#### Accuracy vs. Validation Accuracy Loss vs. Validation Loss 0.84 Training Accuracy 0.46 Validation Accuracy 0.83 0.44 0.82 E 081 0.40 0.80 0.38 0.79 Training Loss Validation Loss



## LSTM

- Embedding size of 20
- LSTM with 15 units
- Global Max Pooling
- Dense Layer with 32 units and RELU
- Dense Layer with 1 unit with Sigmoid for Binary Classification
- Adam Optimizer
- Binary Cross entropy Loss

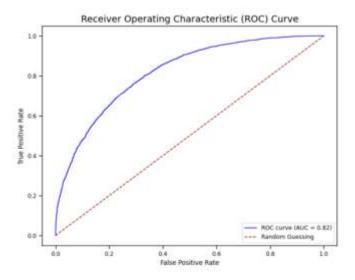


Fig. 5. ROC Curve

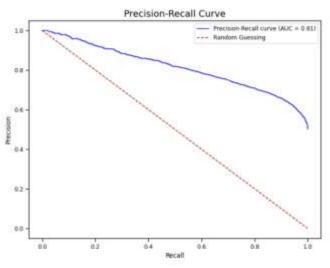


Fig. 6. Precision-Recall Curve

# NAÏVE BAYES CLASSIFIER

 After Hyperparameter tuning, got alpha =10 as the best parameter for naïve bayes classifier

# COMPARISON OF 3 MODELS

TABLE II
EVALUATION METRICS

Model	Accuracy	Precision	recall	F1-score
LSTM	0.79	0.78	0.80	0.79
RNN	0.79	0.78	0.79	0.79
Naive Bayes	0.74	0.77	0.69	0.73



## CONCLUSION

- The Neural Network models outperformed the Naïve Bayes Model
- Given the difficulty of sentiment analysis we were able to achieve only such good results
- The large vocab and infrequency of many words made this task even harder
- Given that the results are reasonably strong

# THANK YOU