

# Sentiment analysis of mobile reviews









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# **Problem Statement**



Sentiment analysis of mobile reviews. The final model classifies the reviews as positive/negative/neutral

## Motivation

- Lot of discussions about products on ecommerce platforms
- Business need to understand the product sentiments. Also aspects contributing to that
- Mobiles being focus of interest

#### **Dataset**

- ~1.2 Lakh Mobile reviews are scrapped from flipkart.com using scrapy python library
- Scrapped data contains mobile name, review text, rating, likes and dislikes
- ~1.5 Lakh Amazon reviews from <u>kaggle</u>



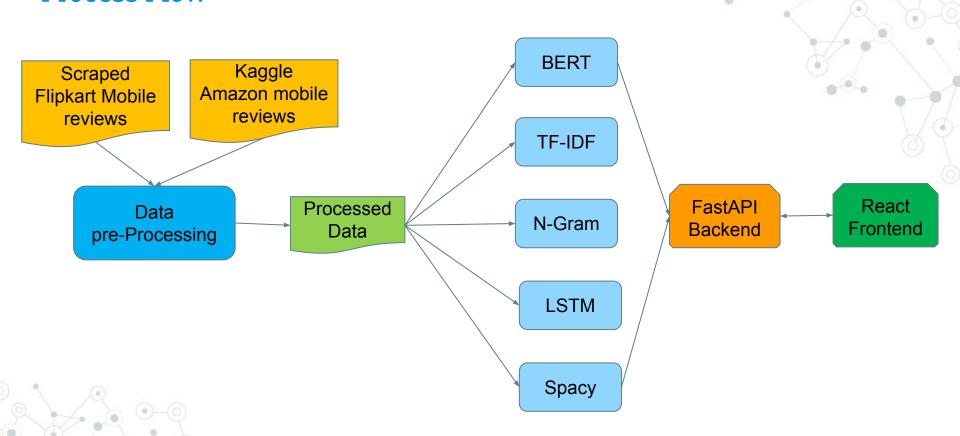


#### Process

We followed the below process while doing the sentiment analysis.

- Scrapping flipkart.com mobile reviews and merged with amazon mobile review datasets
- Data Cleaning, EDA & transformation of data: Punctuations, stop words, space removal, normalization of texts etc.
- Experiment with basic models: TF-IDF (LineraSVC), N-Grams (Multinomial NaiveBayes) & LSTM
- Experiment with state of the art Models: BERT
- Feature sentiment analysis through rule based dependency graphs using SpaCy
- Estimating the performance (Accuracy & F1) on unseen data

#### **Process Flow**



# Challenges faced

- Data collection: Duplication of reviews, processing required
- Understanding the semantic meaning of the review
- Fine tuning BERT model on the customized dataset
- Handling sarcasm





## **Results**

Model	Accuracy	Precision	Recall	F1	Hyperparamet ers	features
N-grams(1)	0.6	0.52	0.61	0.53	{'alpha': 1.0, 'fit_prior': True}	88280
N-grams(2)	0.6	0.51	0.69	0.51	{'alpha': 0.75, 'fit_prior': True}	1544246
N-grams(3)	0.6	0.51	0.60	0.49	{'alpha': 0.75, 'fit_prior': True}	4820742
TF-IDF(Logistic)	0.53	0.43	0.53	0.41	{'logisticC': 10}	127874
LSTM (Binary)	0.8*	0.96	0.8	0.25	dropout:0.5, activation: sigmoid	
BERT	0.96* 0.53 **				Epochs:3, bacth_size: 4	

**LSTM (Binary):** This was just trained on positive/negative reviews, hence have higher values but not preferred model

<sup>\*:</sup> At sentiment level (\_ve, -ve & neutral)

<sup>\*\*:</sup> At rating level (1, 2, 3, 4 & 5)

#### References

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# Ilhank You

Any Questions?