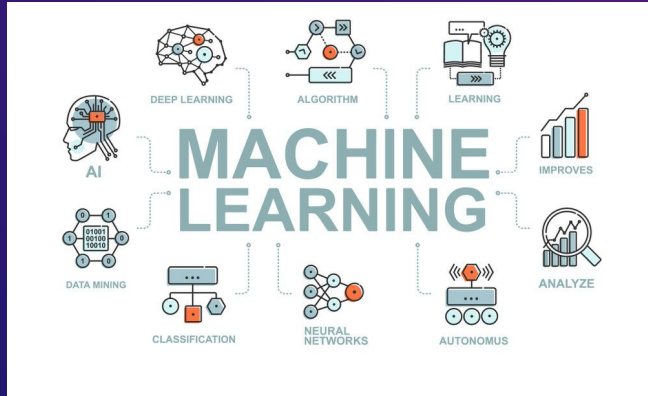

TWITTER SENTIMENT ANALYSIS PROJECT

Owen Andreasen & Justin Park



PROJECT DESCRIPTION



VS

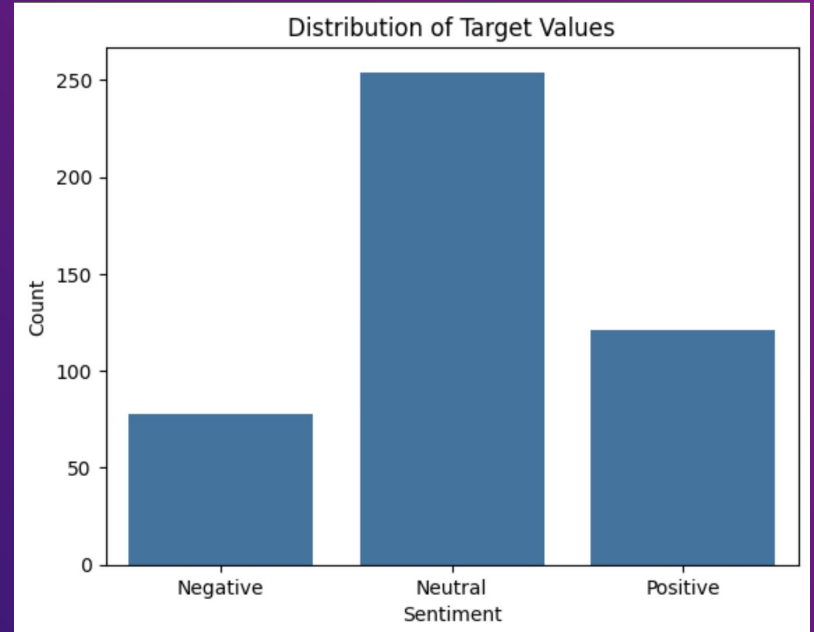


In this project, we aim to conduct a sentiment analysis on Twitter data. Our primary objective is to compare traditional statistical methods against modern AI/ML techniques to evaluate tweets. We plan to analyze the sentiment of tweets stored in the PostgreSQL Twitter database using different approaches and tools.

DATA SOURCE



```
Select distinct(status_id), text
from twitter.statuses s
where s.lang = 'en' and status_id not in (
    select status_id from twitter.statuses s2
    where text like '%https://%')
limit 1000
```

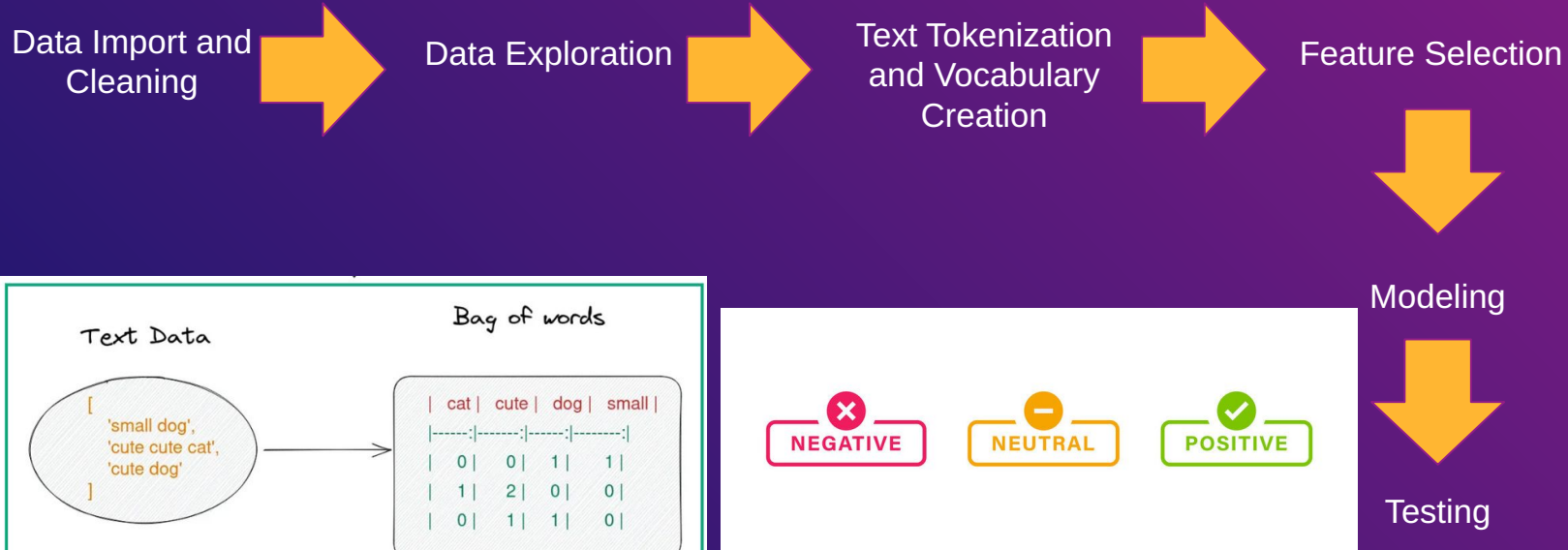


EVALUATION METRICS

- Accuracy: The proportion of correctly classified tweets
- Recall: The proportion of true positive tweets identified by the model
- Precision: The proportion of correctly classified positive tweets out of all predicted positive tweets
- F1-score: Combination of Recall and Precision



SAS



SAS RESULTS

Sentiment Metrics

Obs	sentiment	precision	recall	f_measure
1	Positive	0.56667	0.18889	0.28333
2	Negative	0.66667	0.13333	0.22222
3	Neutral	0.71948	0.95848	0.82196

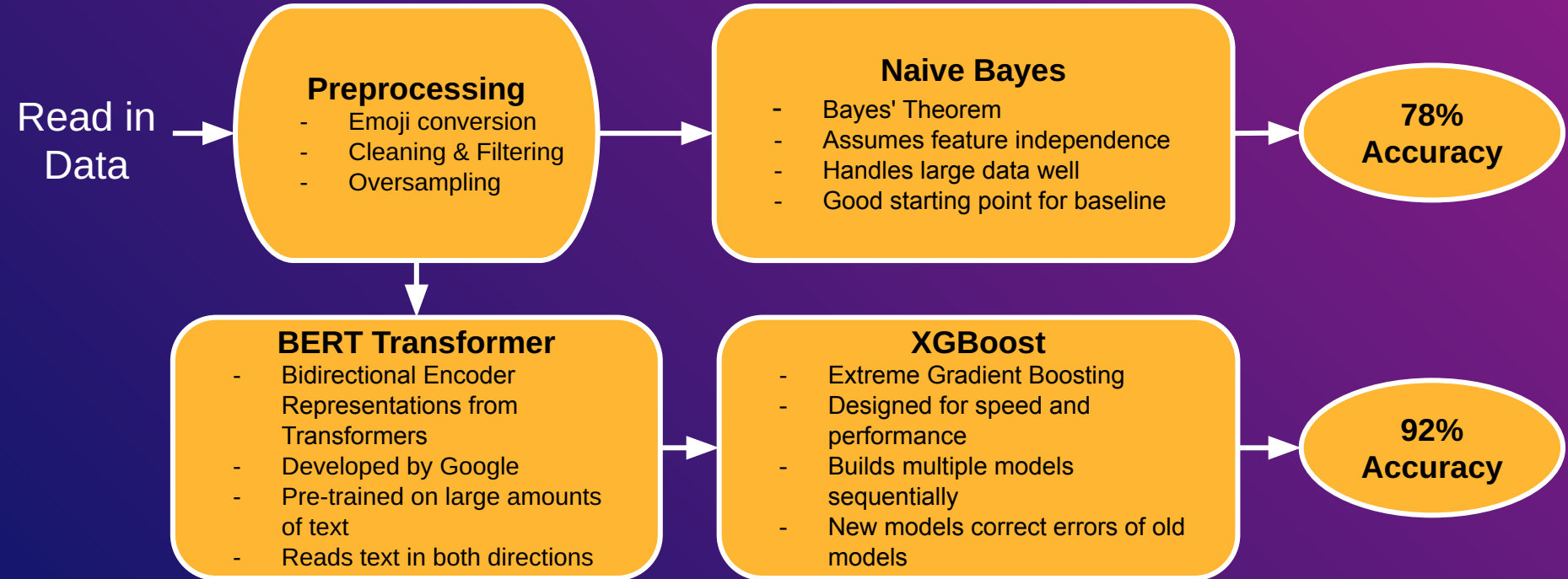
Obs	_FREQ_	accuracy	total_count
1	424	70.75%	300

SAS RESULT WITH STOP WORDS

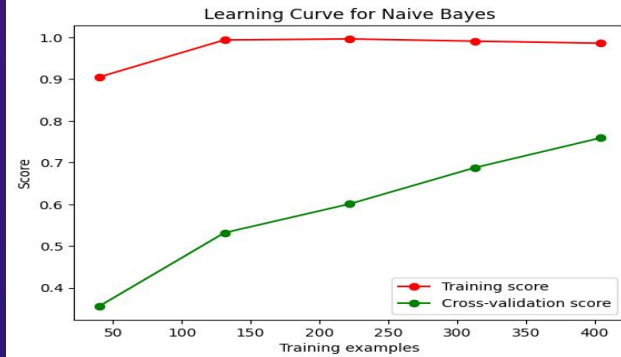
	sentiment	precision	recall	f_measure
1	Positive	1	0.4777777778	0.6466165414
2	Negative	0.7954545455	0.7777777778	0.7865168539
3	Neutral	0.8427299703	0.9826989619	0.9073482428

Obs	_FREQ_	accuracy	total_count
1	424	85.38%	362

MACHINE LEARNING MODELS

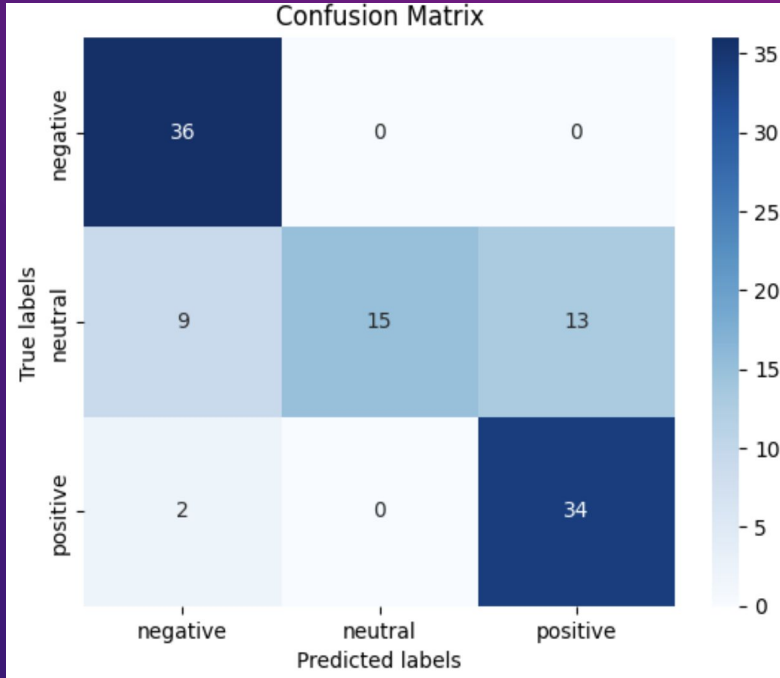


NAIVE BAYES RESULTS

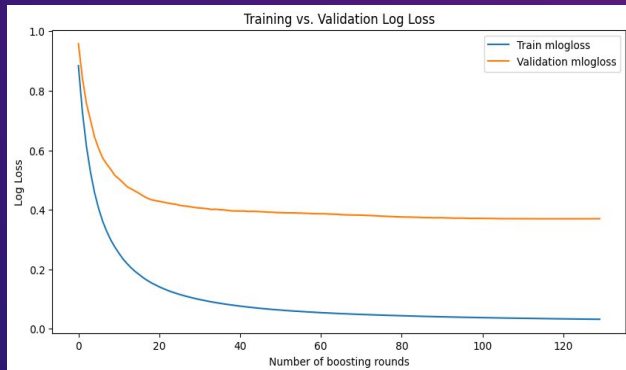


Classification Report for Naive Bayes:

	precision	recall	f1-score	support
negative	0.77	1.00	0.87	36
neutral	1.00	0.41	0.58	37
positive	0.72	0.94	0.82	36
accuracy			0.78	109
macro avg	0.83	0.78	0.75	109
weighted avg	0.83	0.78	0.75	109

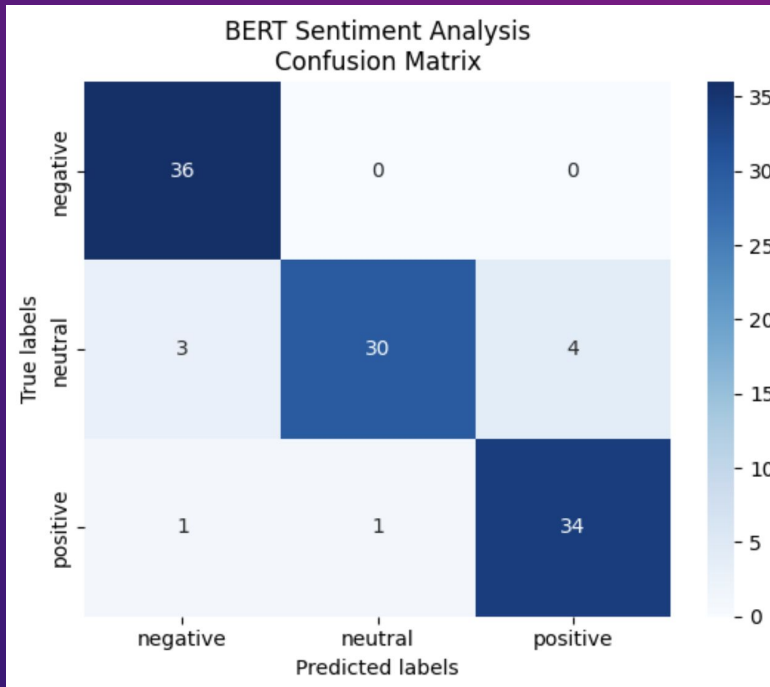


BERT+XGBOOST RESULTS



Classification Report for BERT:

	precision	recall	f1-score	support
Negative	0.90	1.00	0.95	36
Neutral	0.97	0.81	0.88	37
Positive	0.89	0.94	0.92	36
accuracy			0.92	109
macro avg	0.92	0.92	0.92	109
weighted avg	0.92	0.92	0.92	109



COMPARISON & DISCUSSION

“Muslim woman in Hijab makes valid points and audience members tell her to calm down Funny that Muslim woman who doesnt...”

NEGATIVE

“Please trash me on Wikipedia, I’m begging you”

NEGATIVE

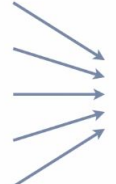
"Just spilled my coffee all over my white shirt.
Great start to the day! Can't wait to see what other
surprises are in store for me. "

NEGATIVE

IMPROVEMENTS

Stemming vs Lemmatization

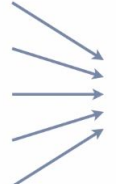
change
changing
changes
changed
changer



chang

Detailed description: A diagram illustrating stemming. On the left, five words are listed vertically: 'change', 'changing', 'changes', 'changed', and 'changer'. Five blue arrows point from each of these words to a single word on the right, 'chang', which is written in blue. This represents the process of reducing different inflected forms of a word to their common root.

change
changing
changes
changed
changer



change

Detailed description: A diagram illustrating lemmatization. On the left, the same five words are listed vertically: 'change', 'changing', 'changes', 'changed', and 'changer'. Five blue arrows point from each of these words to a single word on the right, 'change', which is written in green. This represents the process of reducing different inflected forms of a word to their base or dictionary form.

"We love NLP!"

Tokenization

"We" "love" "NLP" "!"



Detailed description: A diagram showing the tokenization process. At the top, the sentence "We love NLP!" is written. A pink arrow points down from the sentence to a pink rounded rectangle containing the word "Tokenization". From the bottom of this rectangle, four pink arrows point down to four separate tokens: "We", "love", "NLP", and "!". Each token is enclosed in pink double quotes.

THANKS!

QUESTIONS?
