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# Analyzing Community Sentiments in Online Tribes: A Natural Language Processing (NLP) Approach

Military and Mental Health  
Analysis

Speaker:  
Kyera Francis

# Table Of Content

Primary Goal:

To classify communities using NLP techniques and to identify and analyze sentiments within specific communities.

01

Introduction

02

Military Classification

03

Military Sentiment

04

Mental Health Classification

05

Mental Health Sentiment

06

Trend of Techonology

07

Future Application

08

Conclusions & Rec'mds

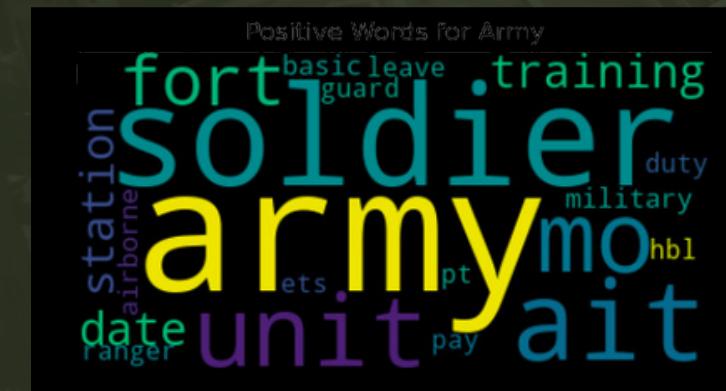
09

Q&A

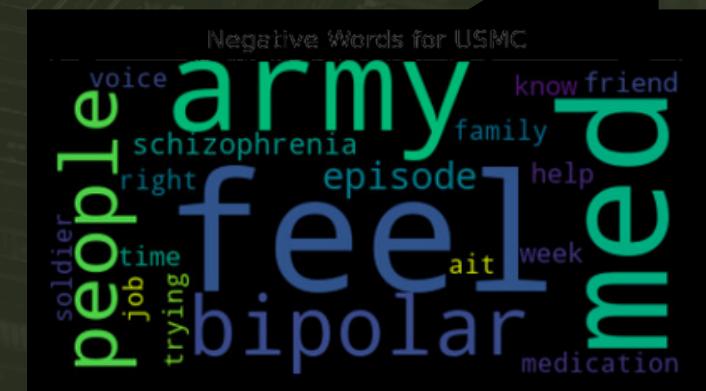
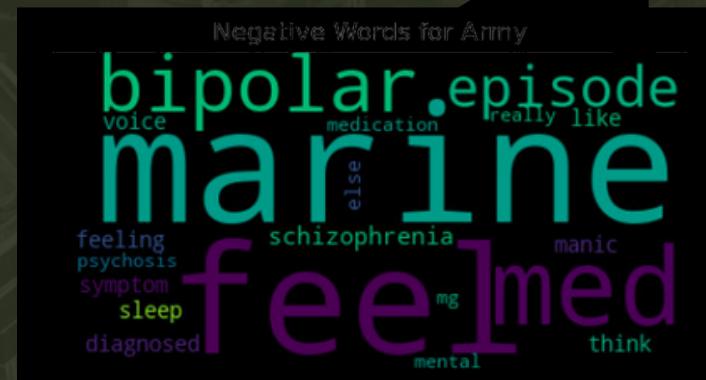
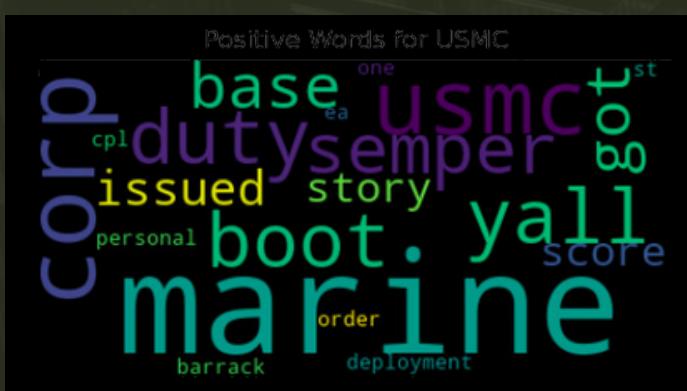


# POSITIVE NEGATIVE

ARMY



MARINE



# Introduction Baracks Banter: Decoding the Army-Marine Lexicon.

- SGT Francis, Kyera

Achievement:



# NLP Military Analysis

US Army vs US Marine Corps

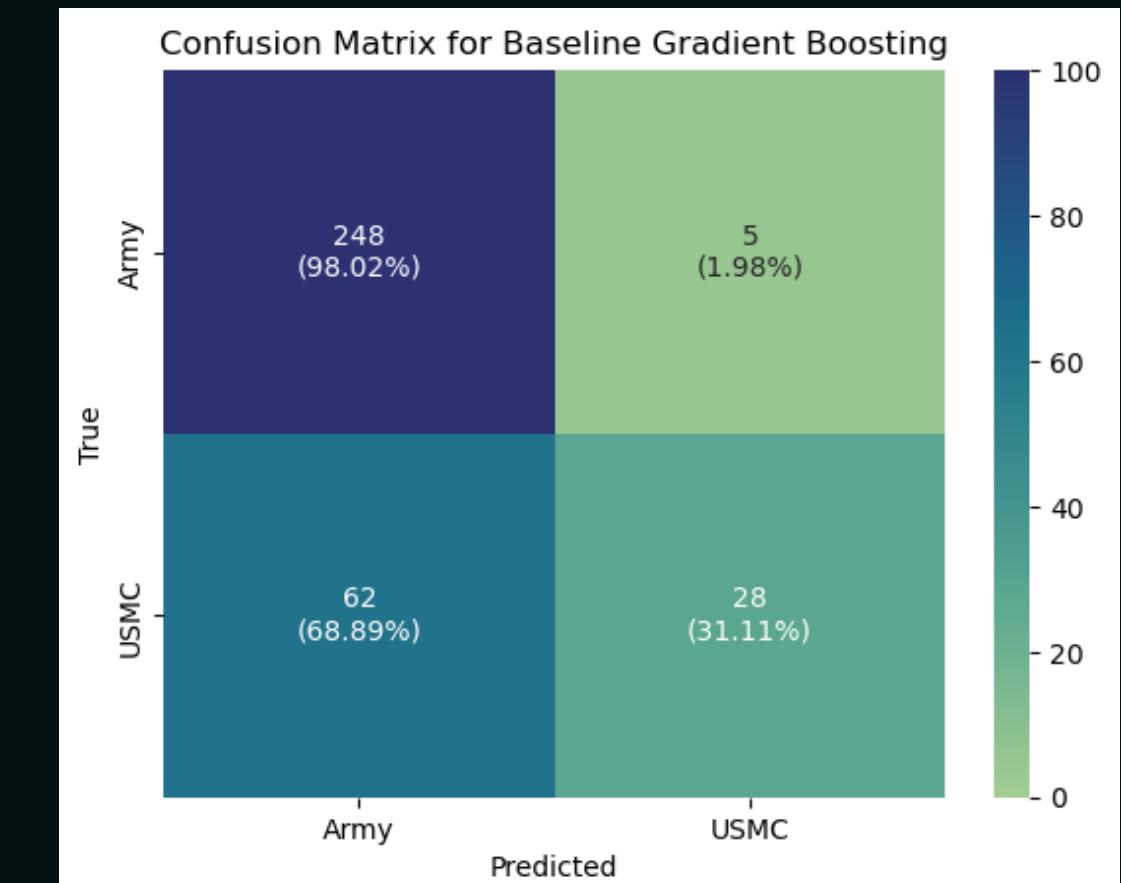
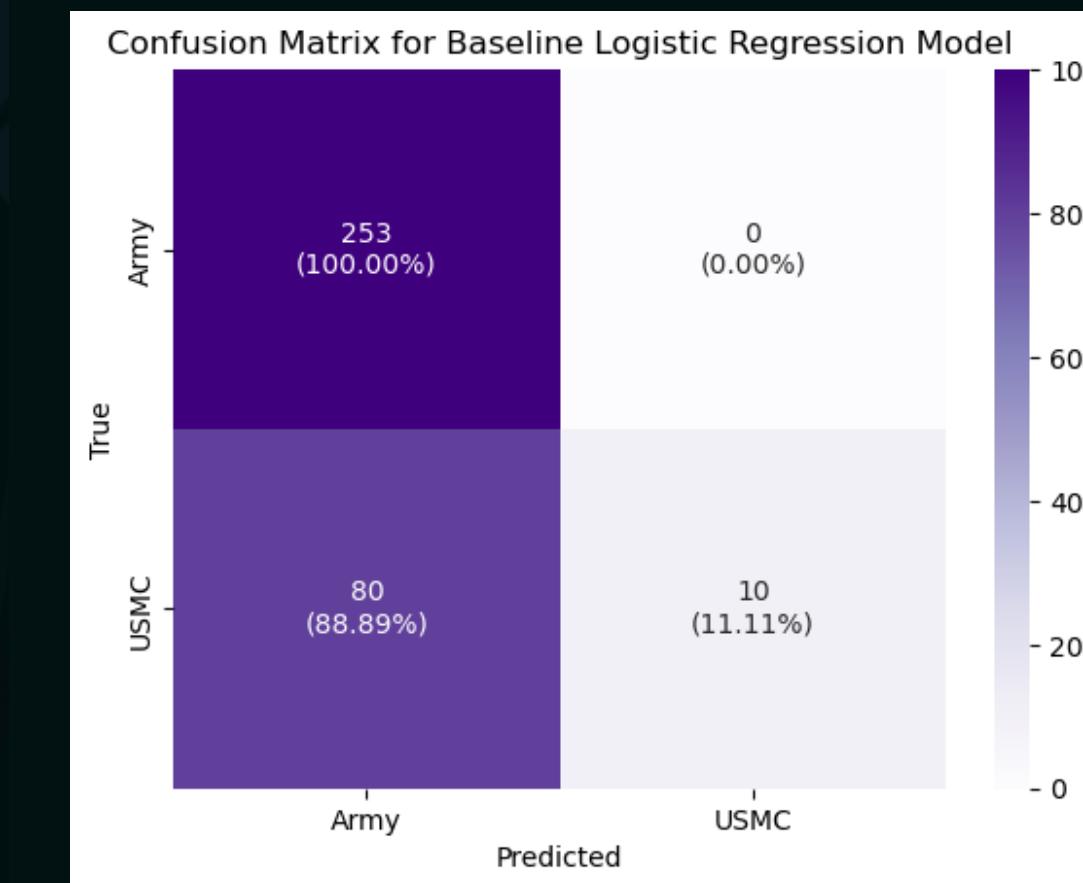
NLP Models: TF - IDF +

Logistical Regression and Gradient  
Boosting

Sentiment Model: TextBlob



## BASELINE



	precision	recall	f1-score	support
Army	0.76	1.00	0.86	253
USMC	1.00	0.11	0.20	90
accuracy			0.77	343
macro avg	0.88	0.56	0.53	343
weighted avg	0.82	0.77	0.69	343

	precision	recall	f1-score	support
Army	0.80	0.98	0.88	253
USMC	0.85	0.31	0.46	90
accuracy			0.80	343
macro avg	0.82	0.65	0.67	343
weighted avg	0.81	0.80	0.77	343

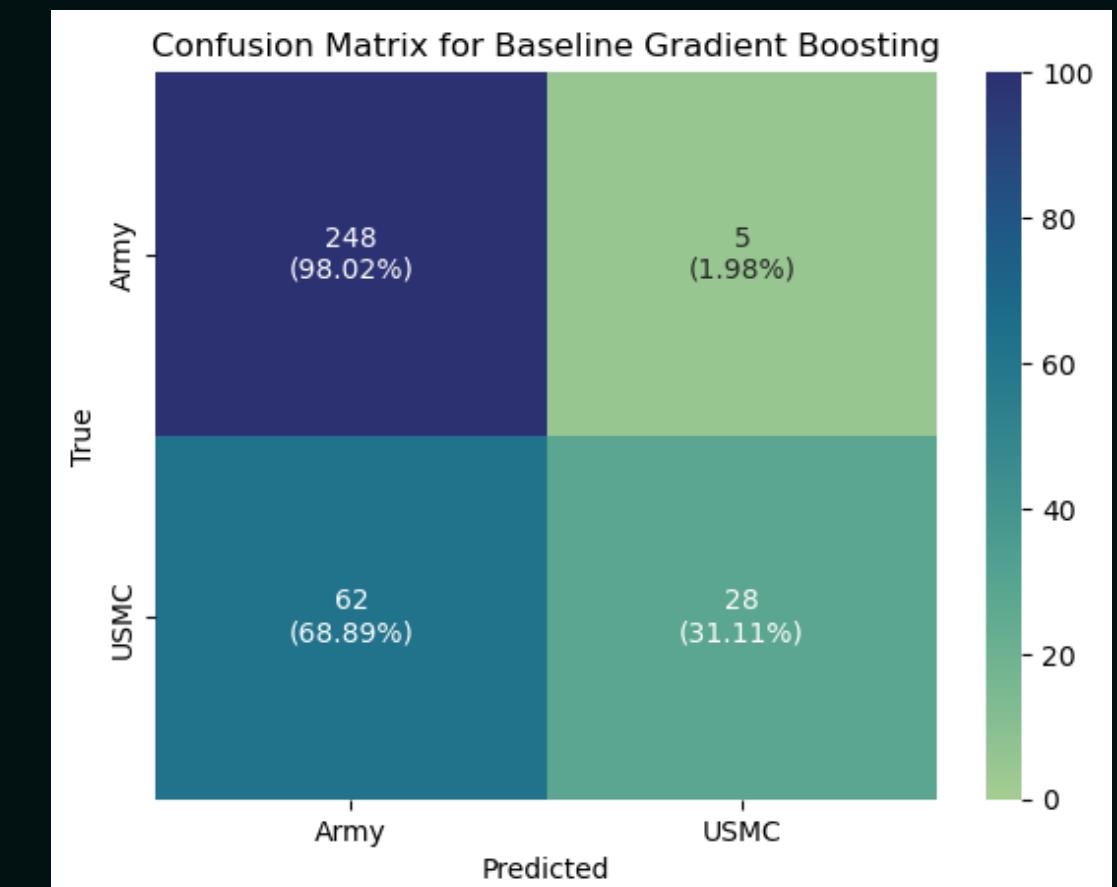
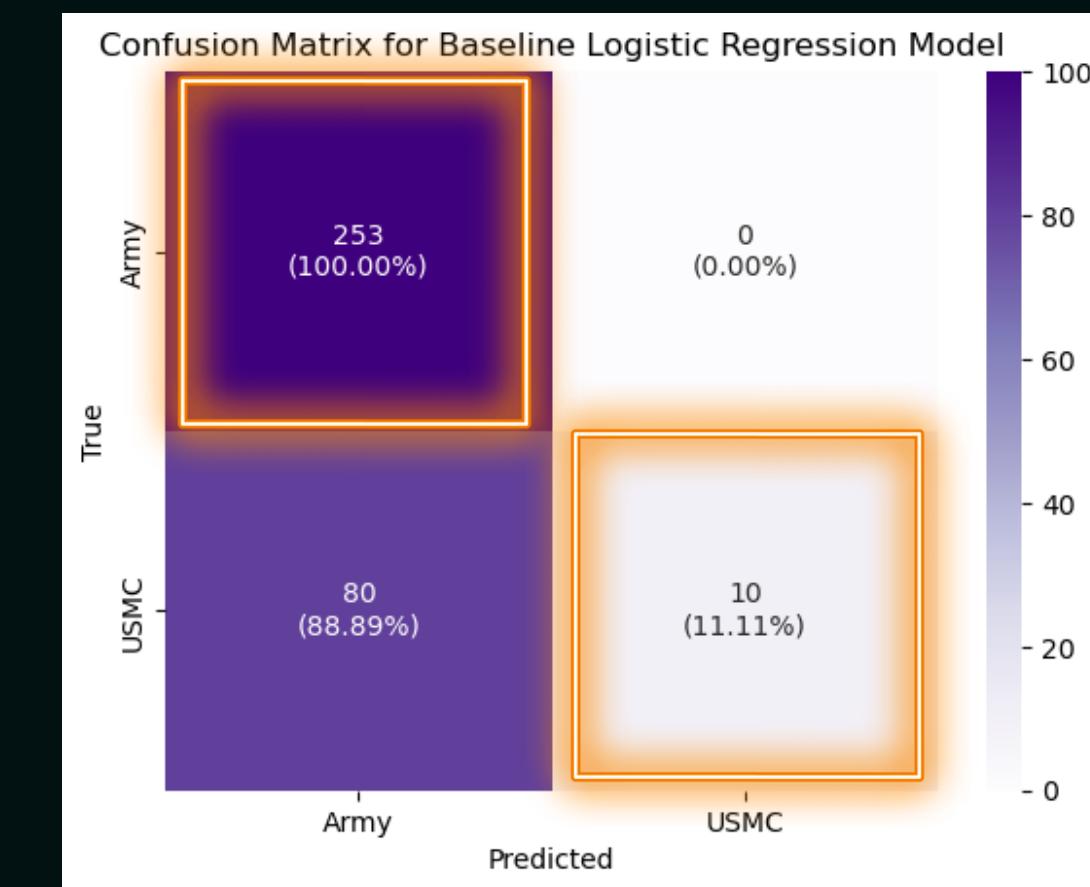
# NLP Military Analysis

US Army vs US Marine Corps

**NLP Models:** TF - IDF +  
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# NLP Military Analysis

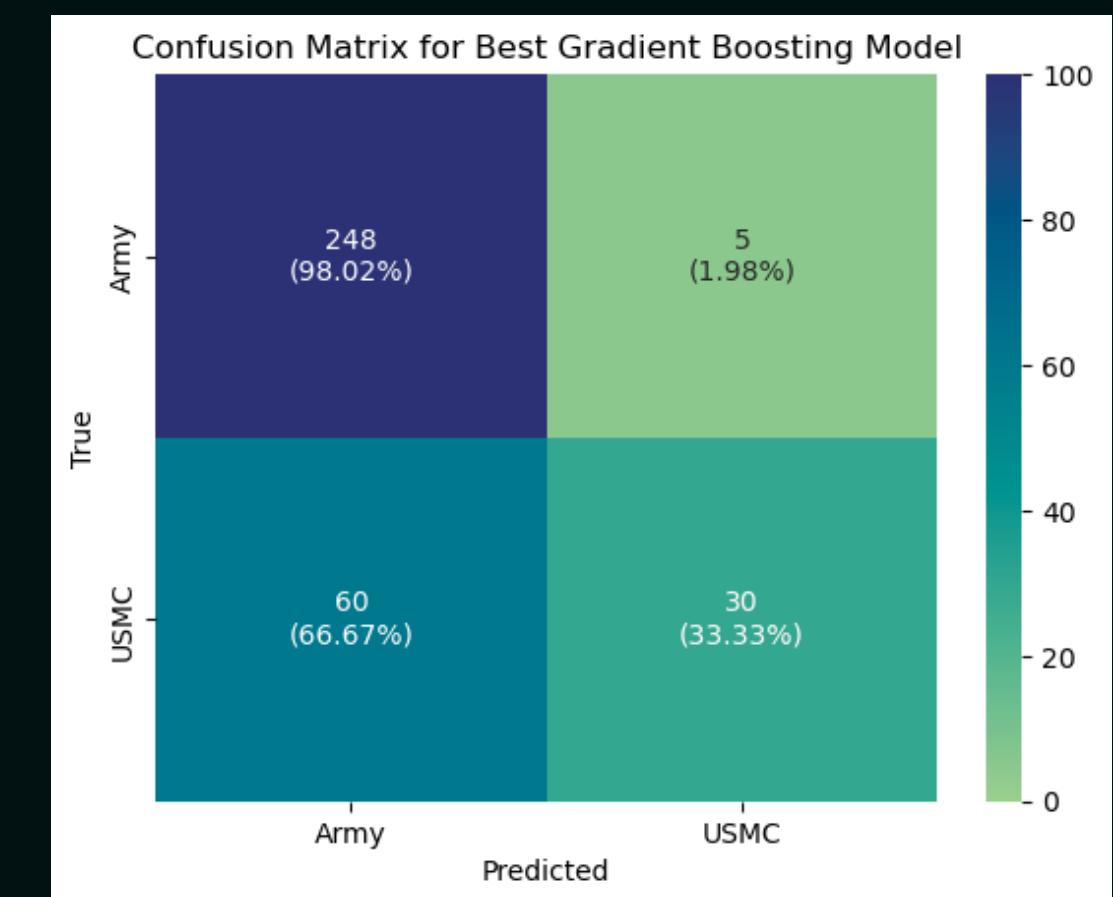
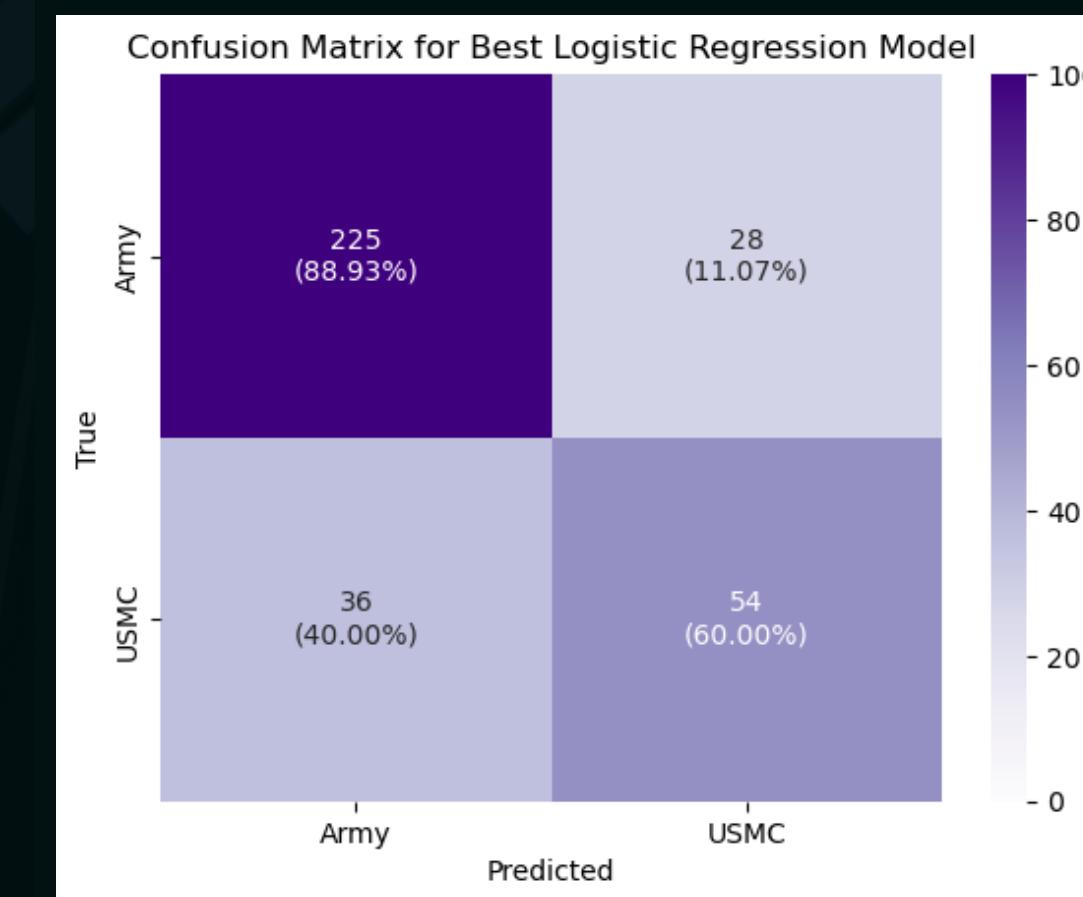
US Army vs US Marine Corps

NLP Models: TF - IDF +

Logistical Regression and Gradient  
Boosting

Sentiment Model: TextBlob

# BEST MODEL



	precision	recall	f1-score	support
Army	0.86	0.89	0.88	253
USMC	0.66	0.60	0.63	90
accuracy			0.81	343
macro avg	0.76	0.74	0.75	343
weighted avg	0.81	0.81	0.81	343

	precision	recall	f1-score	support
Army	0.81	0.98	0.88	253
USMC	0.86	0.33	0.48	90
accuracy			0.81	343
macro avg	0.83	0.66	0.68	343
weighted avg	0.82	0.81	0.78	343

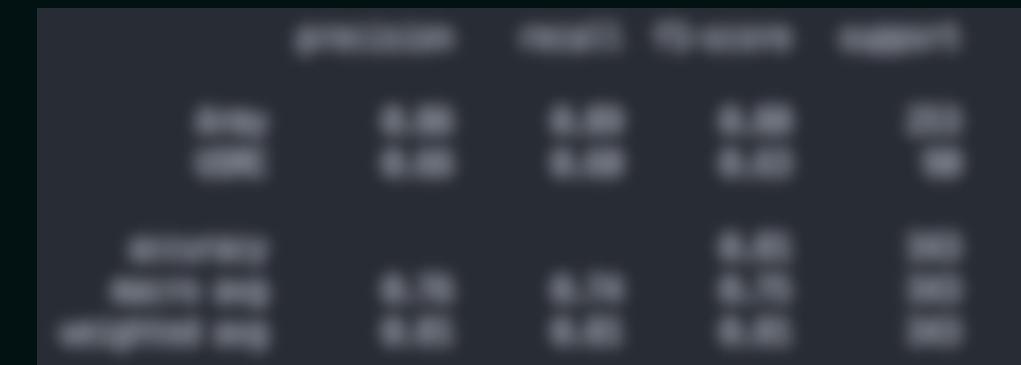
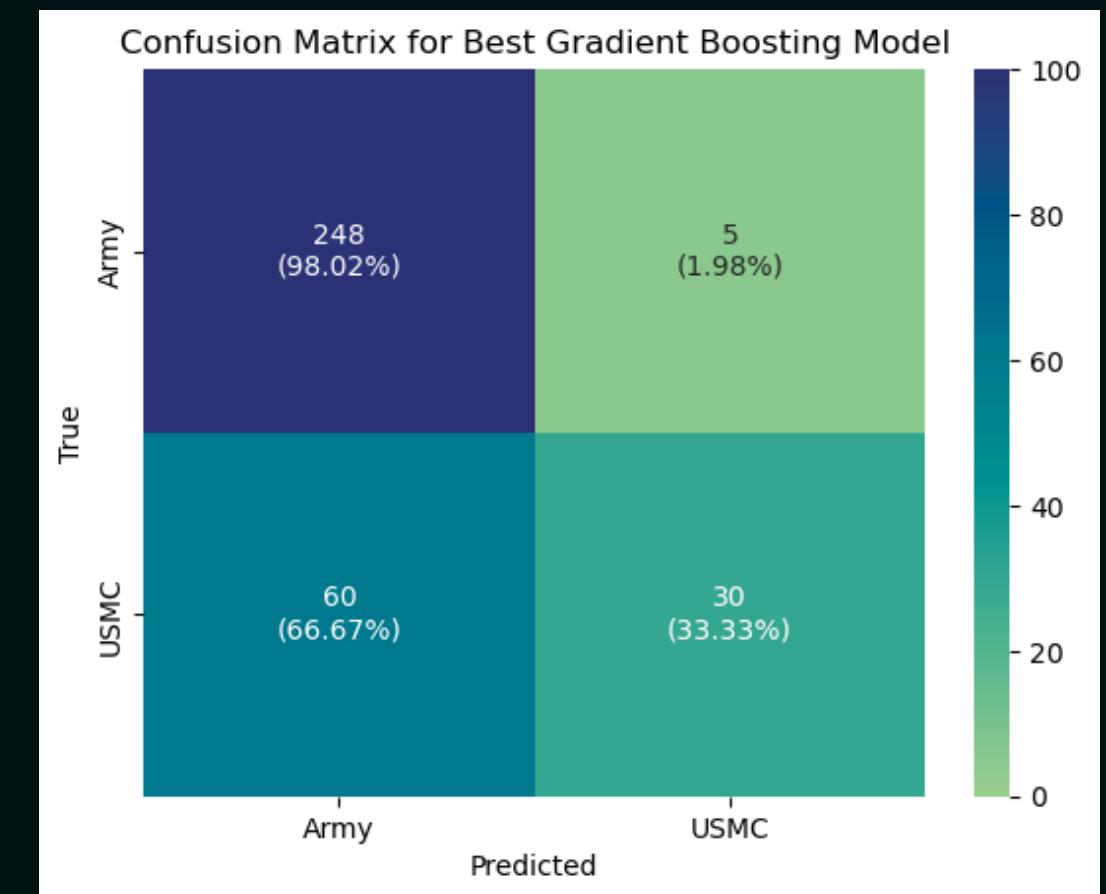
# NLP Military Analysis

US Army vs US Marine Corps

NLP Model: TF - IDF + Gradient  
Boosting

Sentiment Model: TextBlob

# BEST MODEL



	precision	recall	f1-score	support
Army	0.81	0.98	0.88	253
USMC	0.86	0.33	0.48	90
accuracy			0.81	343
macro avg	0.83	0.66	0.68	343
weighted avg	0.82	0.81	0.78	343

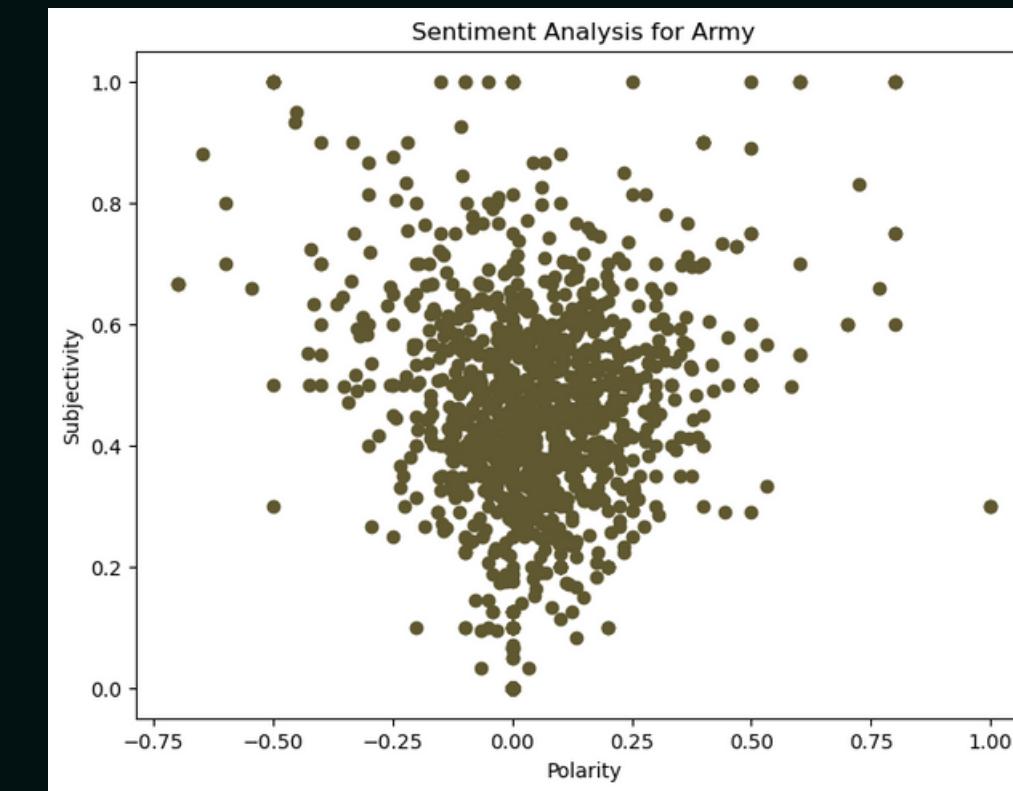
A detailed confusion matrix for the sentiment model. The columns represent predicted classes (Army, USMC) and the rows represent true classes (Army, USMC). The matrix shows high precision (0.81 for Army, 0.86 for USMC) and recall (0.98 for Army, 0.33 for USMC), leading to an overall accuracy of 0.81. The weighted average f1-score is 0.78.

# NLP Military Analysis

US Army vs US Marine Corps

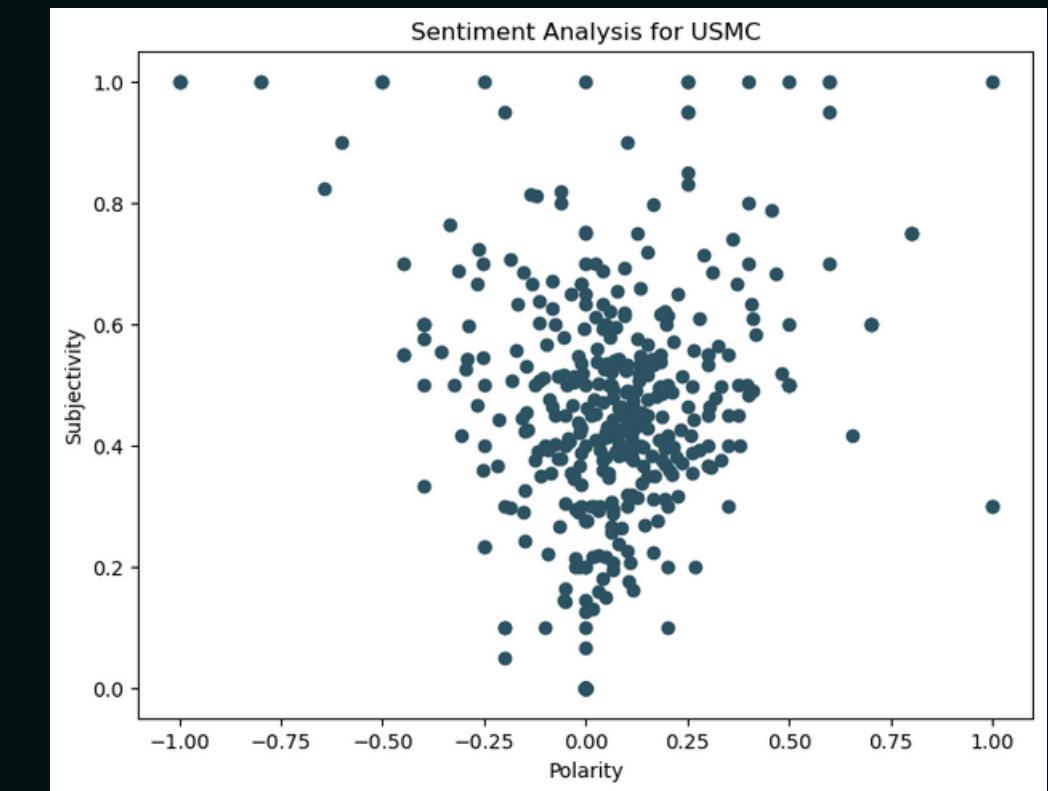
NLP Model: TF-IDF + Gradient Boosting

Sentiment Model: TextBlob



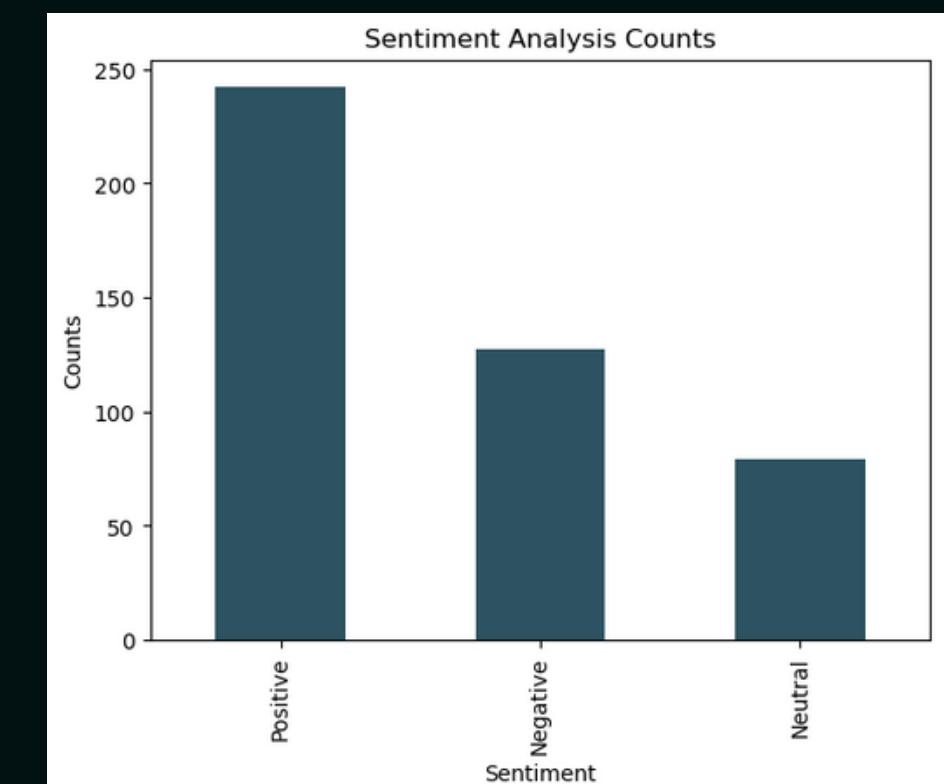
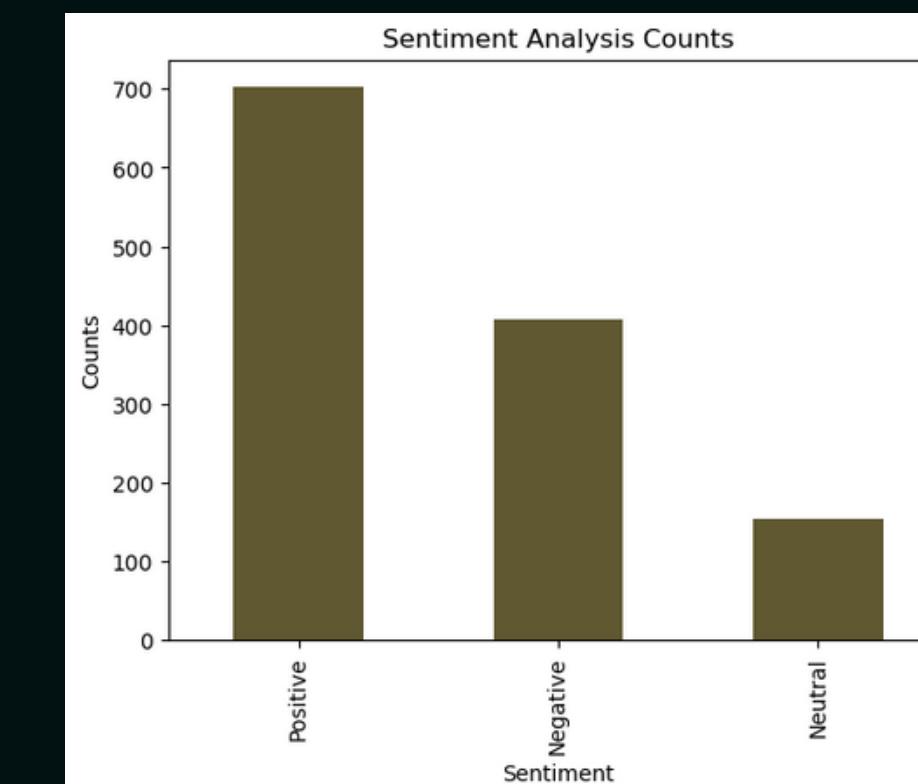
## Army

Positive Posts Percentage: 55.5%  
Negative Posts Percentage: 32.2%  
Neutral Posts Percentage: 12.3%



## Marine

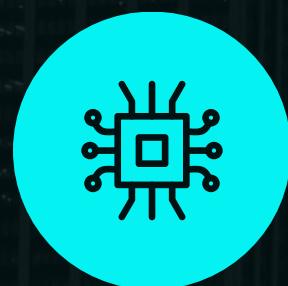
Positive Posts Percentage: 54.0%  
Negative Posts Percentage: 28.3%  
Neutral Posts Percentage: 17.6%



# Military vs. Mental Health

How efficient are our models?

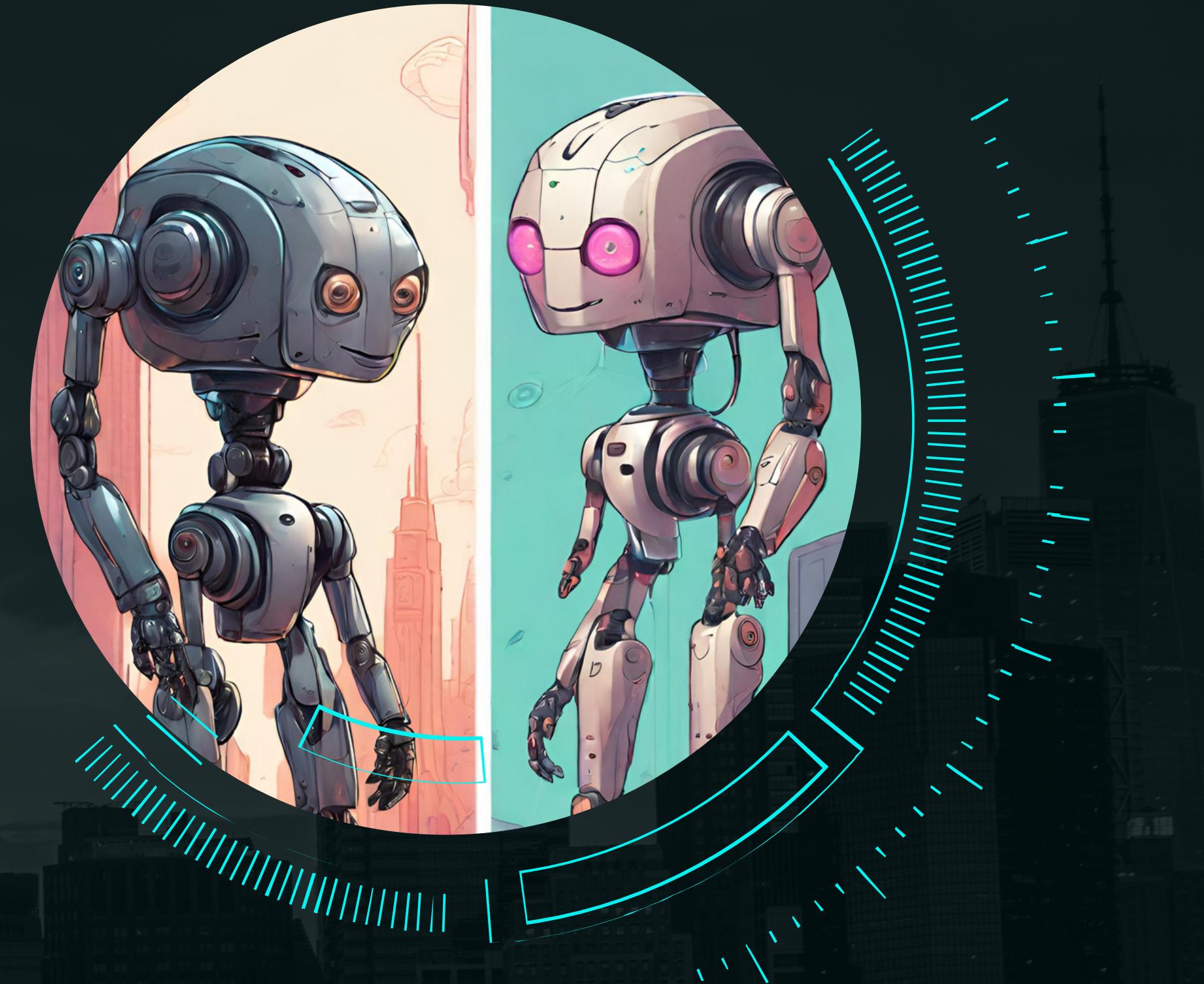
Can it perform effectively on another similiar subgroup  
of a community?



**TF-IDF +  
Gradient  
Boosting  
Classifier**



**TextBlob**



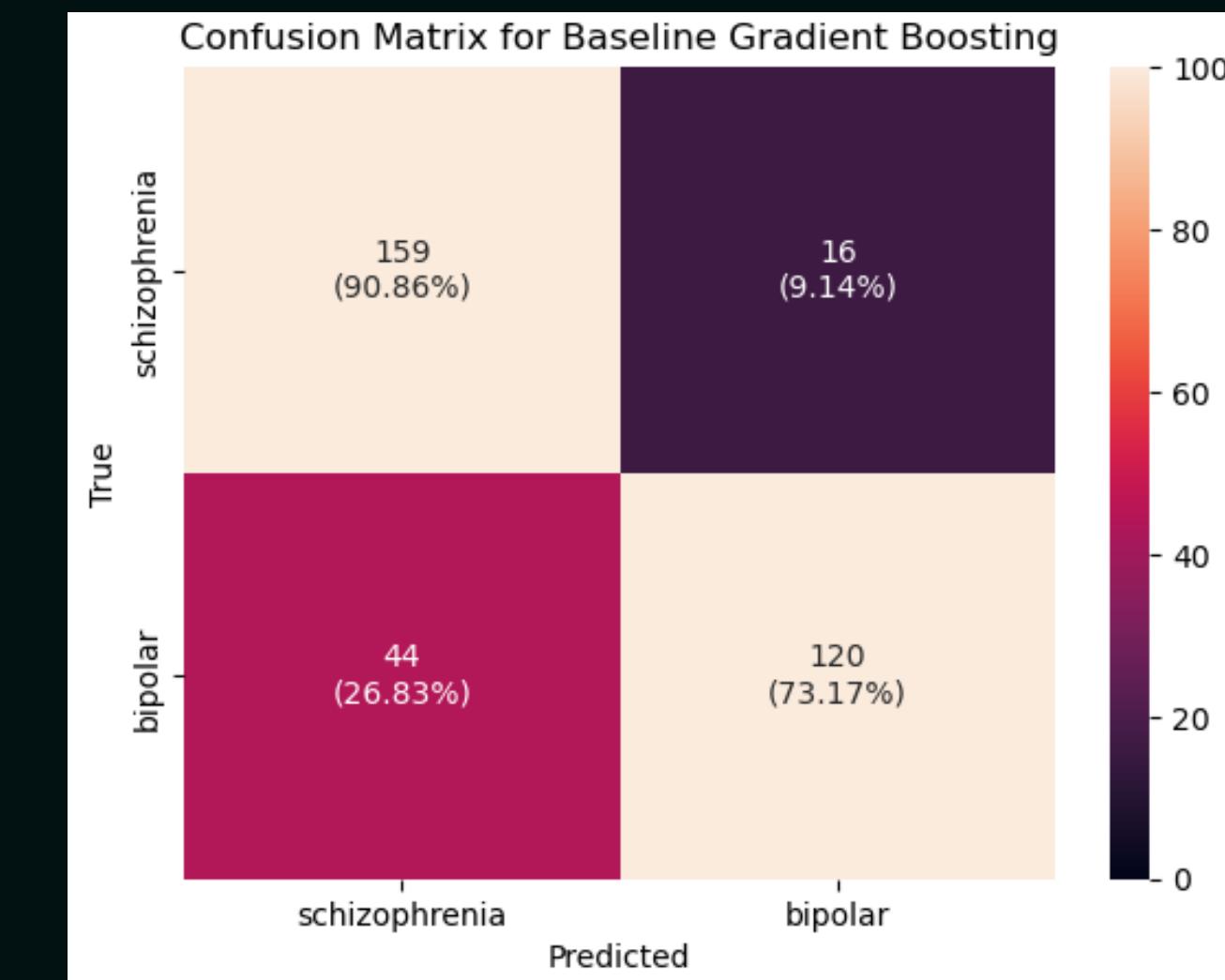
# NLP M. Health Analysis

Schizophrenic vs Bipolar

**NLP Model:** TF - IDF + Gradient  
Boosting

Sentiment Model: TextBlob

## BASELINE



Class	precision	recall	f1-score	support
bipolar	0.78	0.91	0.84	175.0
schizophrenia	0.88	0.73	0.80	164.0
accuracy			0.82	
macro avg	0.83	0.82	0.82	339.0
weighted avg	0.83	0.82	0.82	339.0

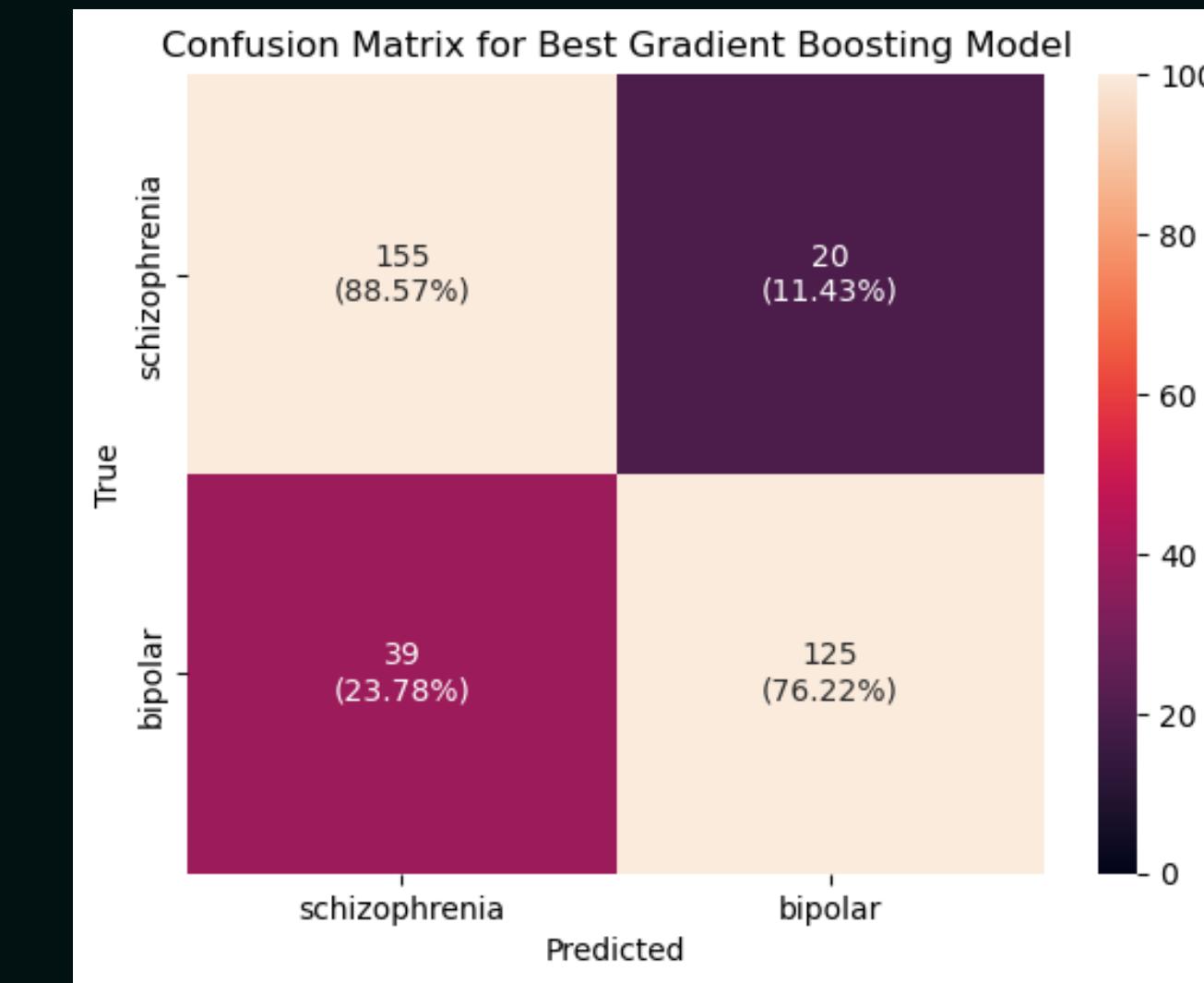
# NLP M. Health Analysis

Schizophrenic vs Bipolar

**NLP Model:** TF - IDF + Gradient  
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Sentiment Model: TextBlob

## BEST MODEL



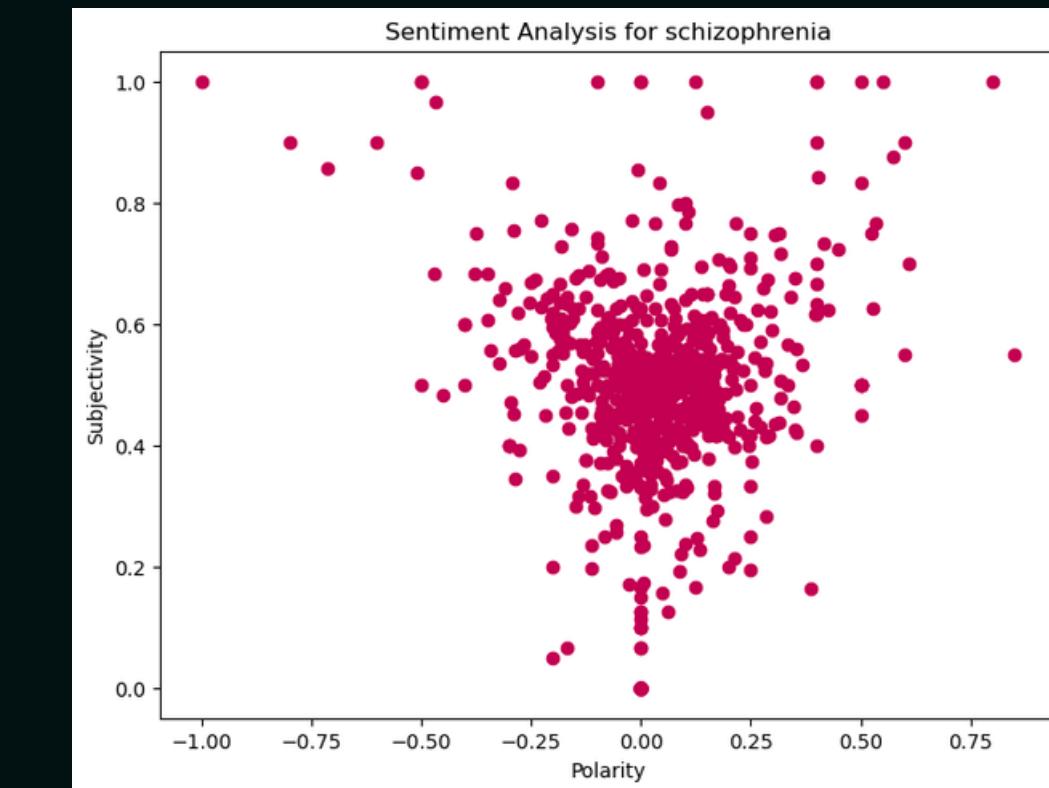
	precision	recall	f1-score	support
Class				
bipolar	0.8	0.89	0.84	175.0
schizophrenia	0.86	0.76	0.81	164.0
accuracy				0.83
macro avg	0.83	0.82	0.82	339.0
weighted avg	0.83	0.83	0.83	339.0

# NLP M. Health Analysis

Schizophrenic vs Bipolar

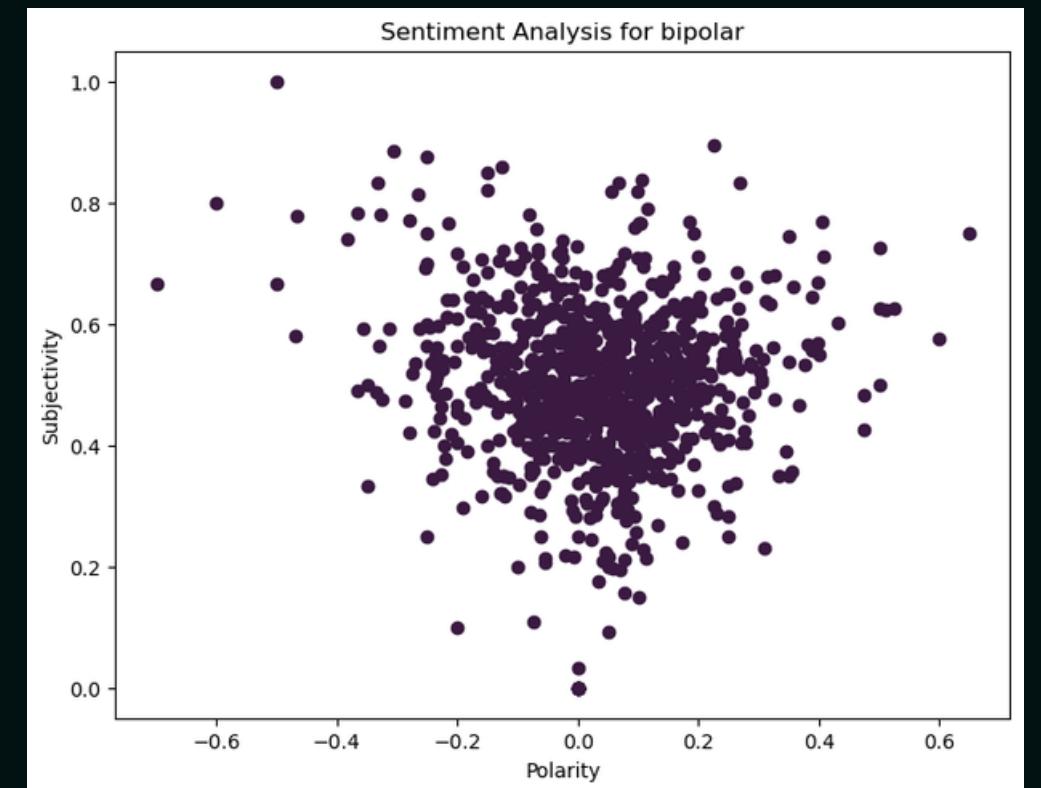
NLP Models: TF - IDF + Gradient Boosting

Sentiment Model: TextBlob



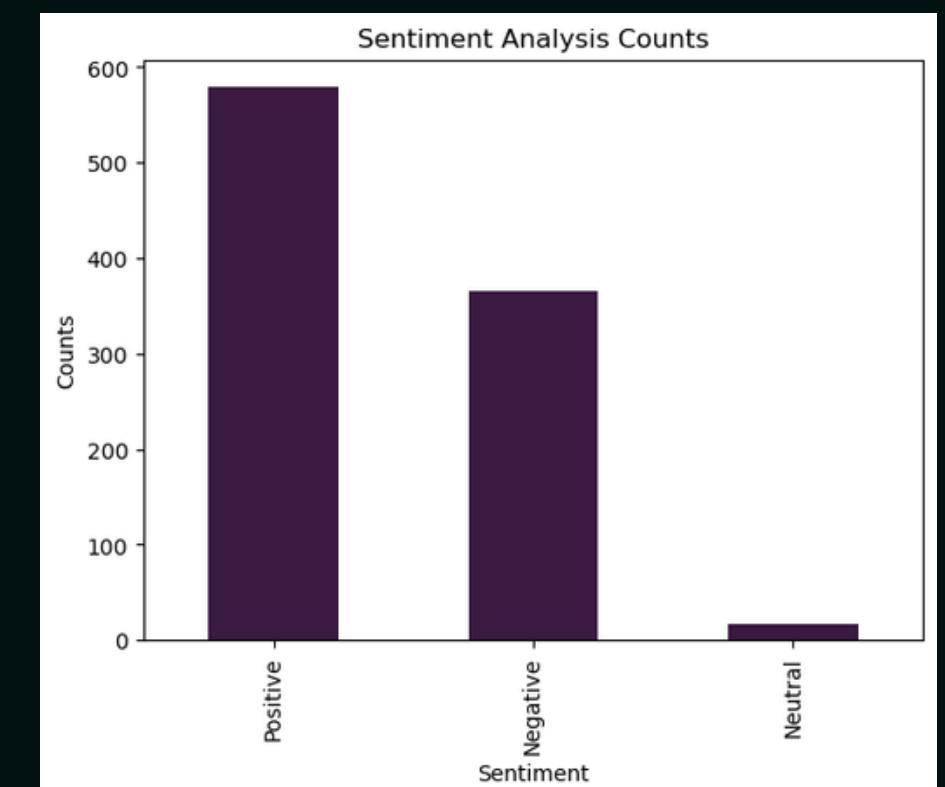
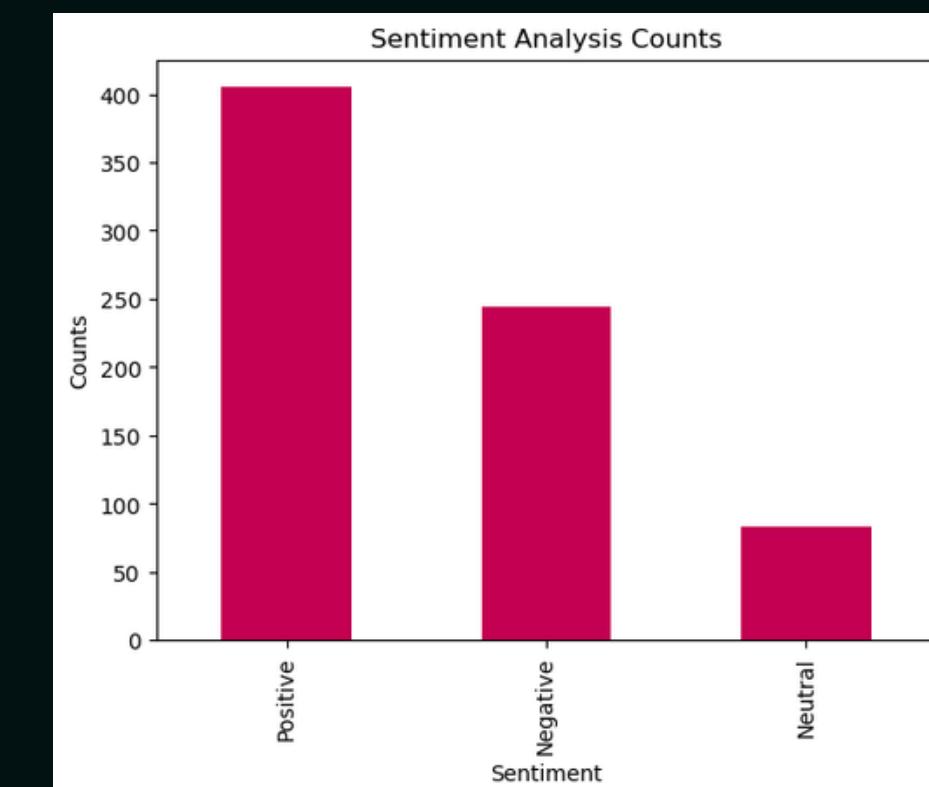
## Schizophrenia

Positive Posts Percentage: 55.3%  
Negative Posts Percentage: 33.3%  
Neutral Posts Percentage: 11.3%

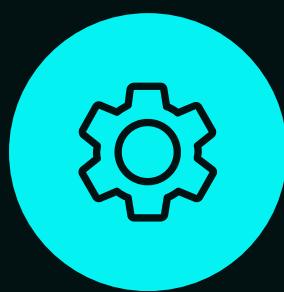


## Bipolar

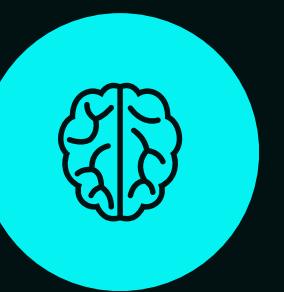
Positive Posts Percentage: 60.3%  
Negative Posts Percentage: 38.0%  
Neutral Posts Percentage: 1.7%



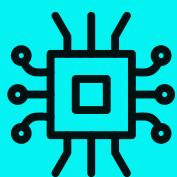
# The Function Of Technology



Progress  
80,83% +.01



Sentiments  
Positive



With each addition of 200 posts to the corpus, the model became 0.01 more accurate and precise.

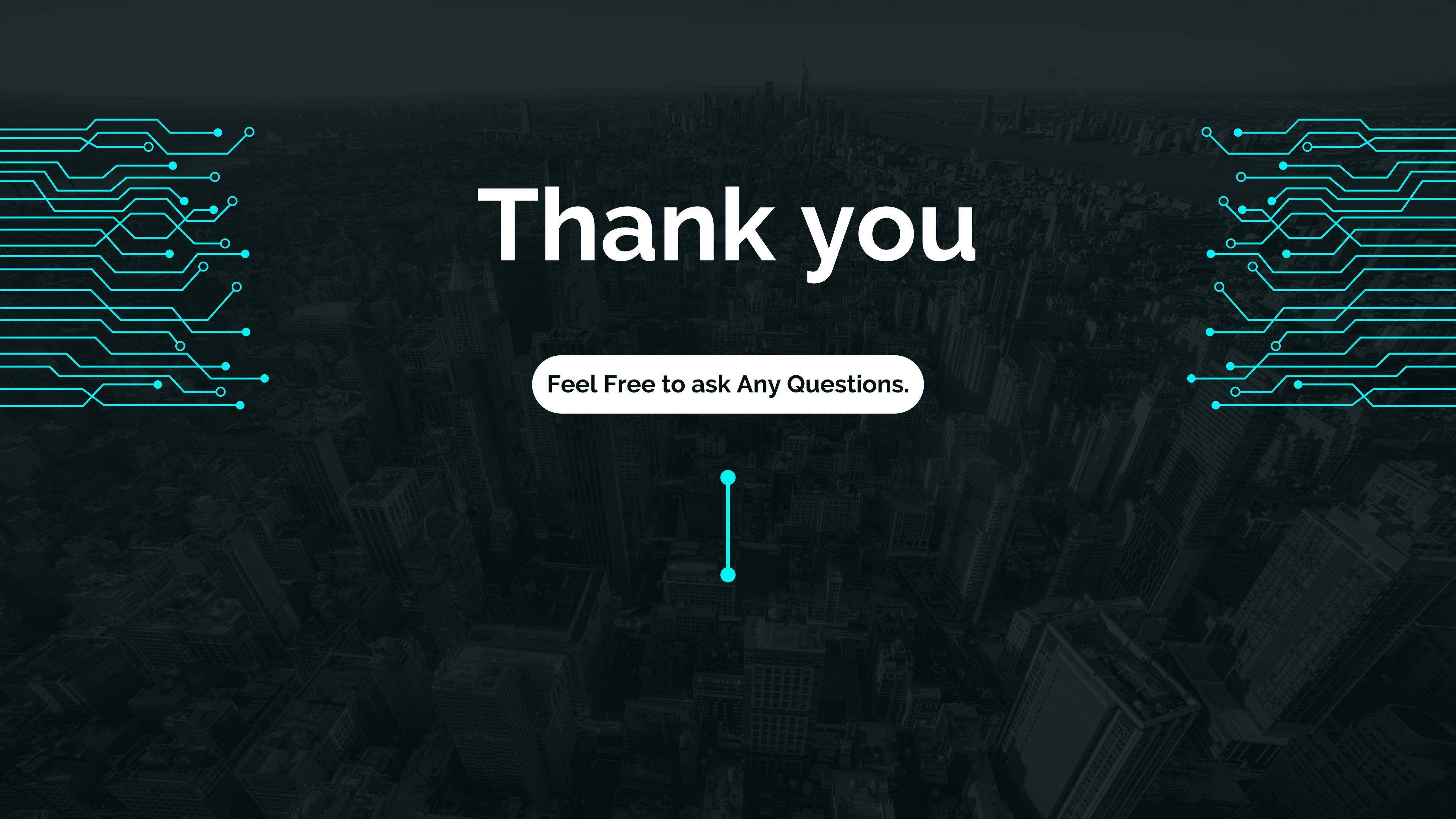


# Future Application

-Primary: Military Leadership, Mental Health Professionals

-Secondary: HR, Business Organization





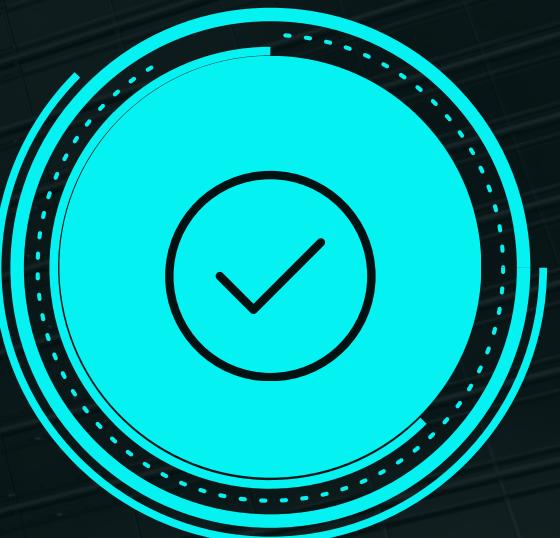
# Thank you

Feel Free to ask Any Questions.



# Challenges and Limitations

These are some challenges and limitations faced: Some are avoidable, and should be considered when reproducing this project; some are not and present a bottleneck for optimization



## Step 01

Data Collection  
Timeframe  
Holiday Season  
[1600-2800] - raw  
[400-1200] - clean

## Step 02

Record-keeping  
measures were not  
implemented from the  
beginning

## Step 03

Forum is anonymous, and  
no qualifying questions  
are asked to verify  
participant claim to group

## Step 04

Sentiment Analysis is not  
able to be cross-validated  
automatically, as it  
involved understand the  
semantics of language



# Conclusions & Recommendations



- Opt for models trained on comprehensive datasets rather than focusing solely on frequently used words.
- For sentiment analysis, consider model consistency in output before drawing conclusions.
- Recognize that aggregated sentiments might not reflect the entire community's sentiment.
- Conduct analyses outside holiday seasons to avoid seasonal influence, especially in military and mental health contexts.