SEPHORA

COSMETICS

Project 3: Web APIs & NLP

WHO ARE WE?

Data Science team at Sephora

WHO ARE YOU?

Social Media, Marketing and Management team at Sephora

AGENDA

1

INTRODUCTION

Background &
Problem Statement

2

EDA

Data Cleaning &
EDA

3

MODELING

Model Evaluation

4

CONCLUSION

Future
Enhancement

01

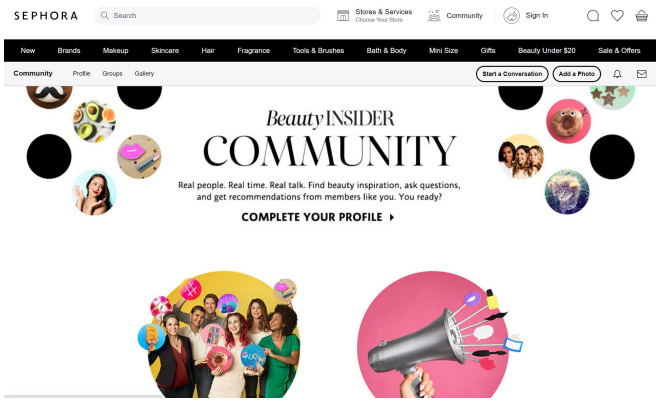
Introduction

BACKGROUND

- We have recently created our Sephora Beauty Insider Community Forum to help shoppers forge personal connections with like-minded beauty enthusiasts

- Our marketing team has identified the forum as a way to obtain data and insights directly from our customers and improve our understanding of customers' needs and wants.

- From these insights, we can better market and improve our product line according to customers' preferences and drive more sales.



PROBLEM STATEMENT

- Our Social Media department has informed us that users of our newly created Sephora Beauty Insider Community Forum have been posting in the wrong group.

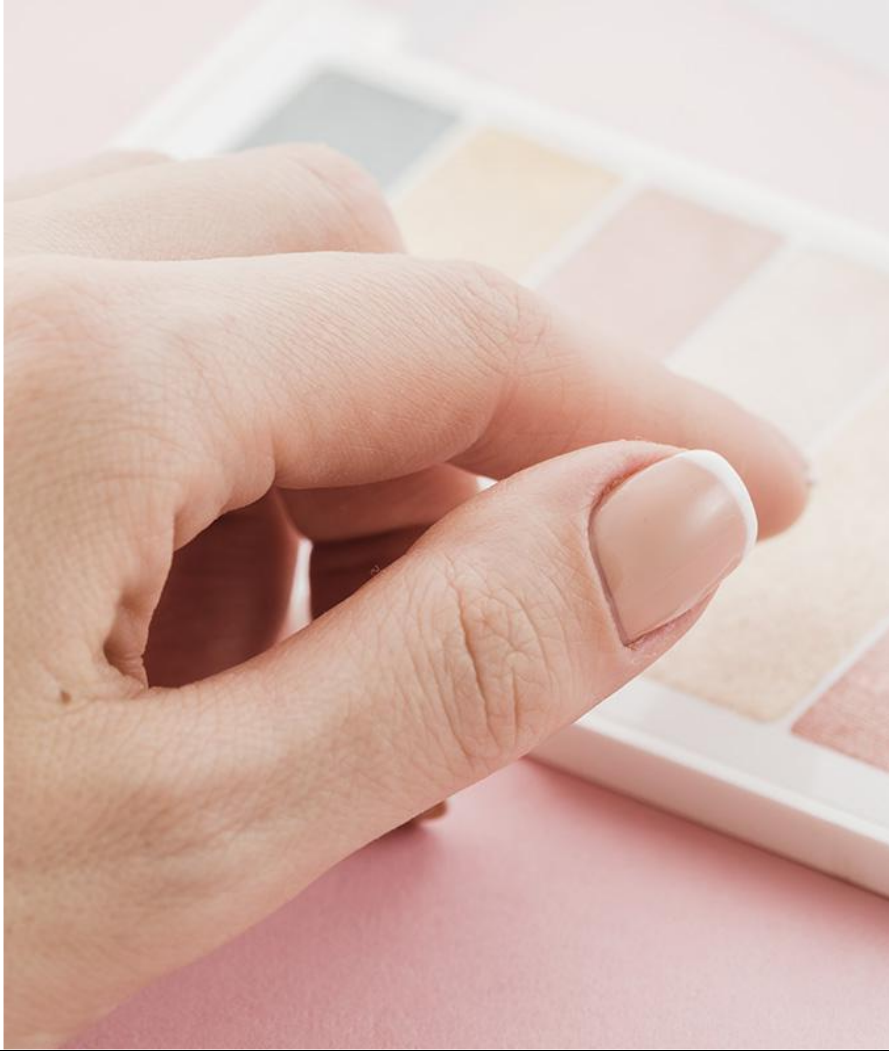
- The makeup and perfumes posts are posted in the General Discussion page and we need to find a way to classify their posts into **Makeup** and **Perfumes** categories for better analysis of their needs and interests.

OBJECTIVES

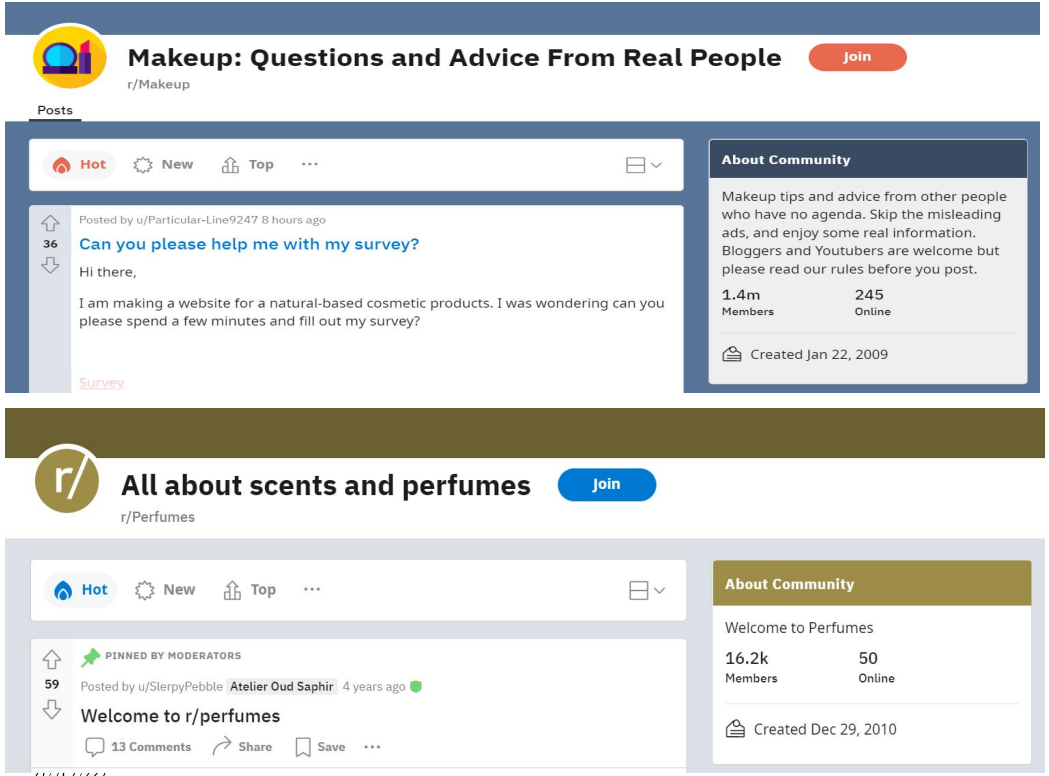
- Use Reddit posts from r/Makeup and r/Perfumes to create a text classifier model that can classify posts into the 2 categories with accuracy more than 50% (baseline accuracy).

  We can then use the model to classify the posts in our Sephora forum.

- Find out the trending words in each subreddit to guide our marketing department



SUBREDDITS



- **r/Makeup**
  1.4m members

  Community where people share makeup tips and advice

- **r/Perfumes**
  16.2k members

  Community where people discuss about scents and perfumes

DATA COLLECTION

- We used Pushshift's API to scrape posts from each of the two subreddits

  r/Makeup - 5000 most recent posts dating back to April 12, 2022
  r/Perfumes - 5000 most recent posts dating back to January 13, 2021

- We kept columns ‘Subreddit’, ‘Title’ and ‘Selftext’ which contain the category and text required for our EDA and modelling.

02

Data Cleaning

DATA CLEANING

- Combine the title and selftext columns
- Remove words such as “[removed]”, “[deleted]”, “NaN”
- Remove punctuations
- Tokenize the posts
- Remove stop words such as “I”, “we”, “and” etc
- Lemmatize the words
- Remove words with numbers, non-english words & additional stopwords

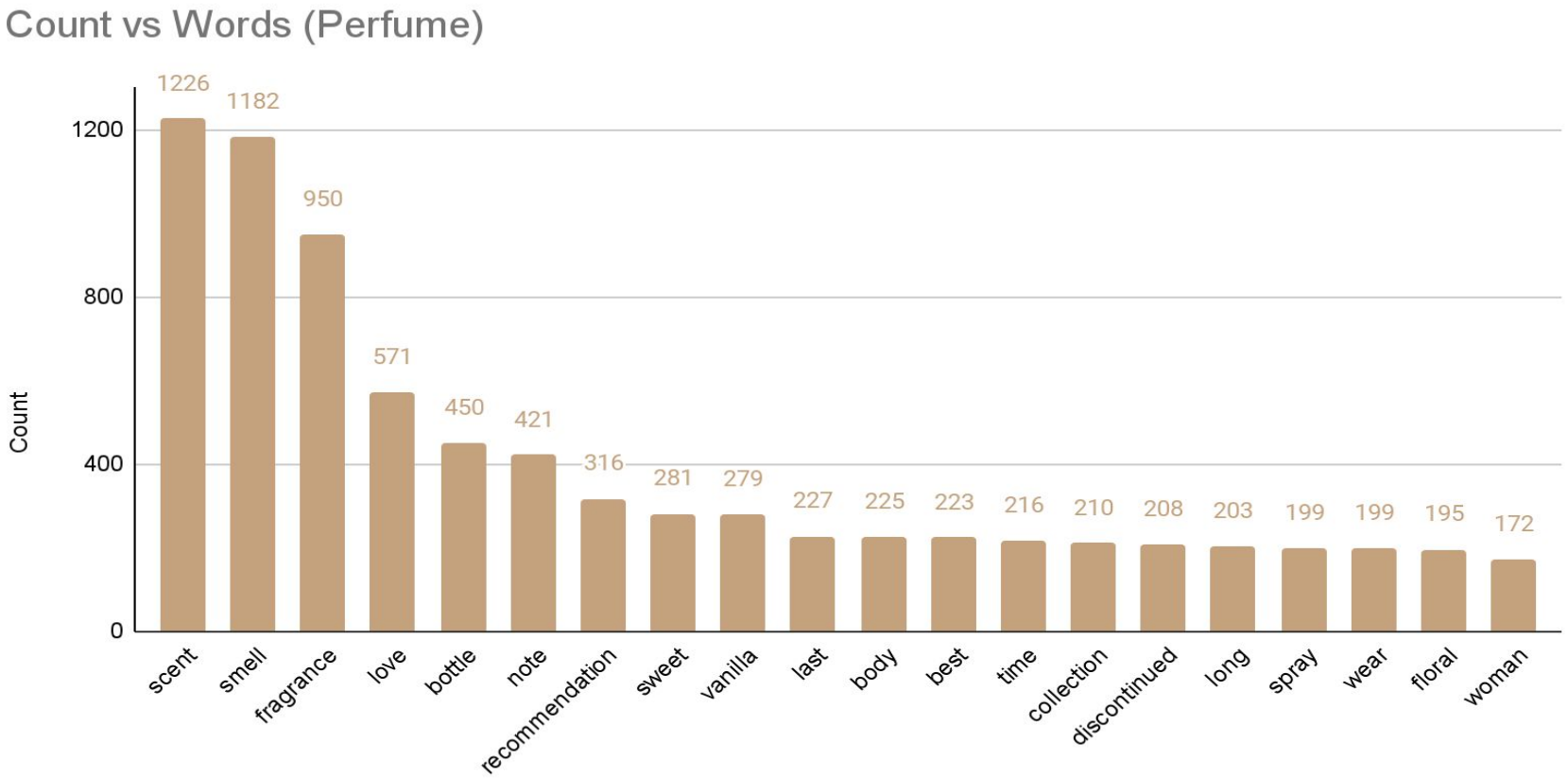
02
Exploratory Data Analytics (EDA)

MOST COMMON WORDS

Perfume Subreddit:

- Scent
- Smell
- Fragrance
- Love
- Bottle
- Note

MOST COMMON WORDS

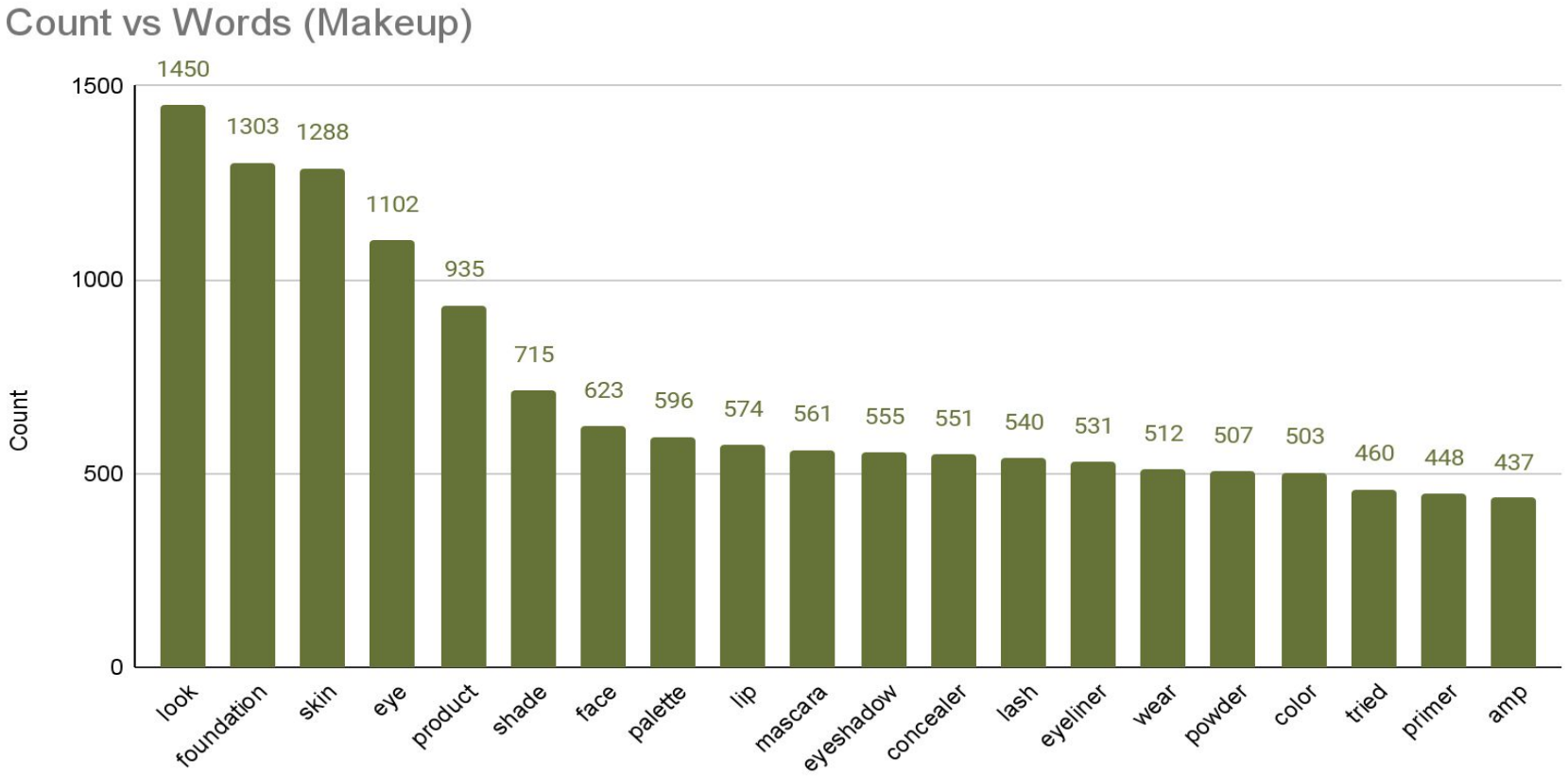


MOST COMMON WORDS

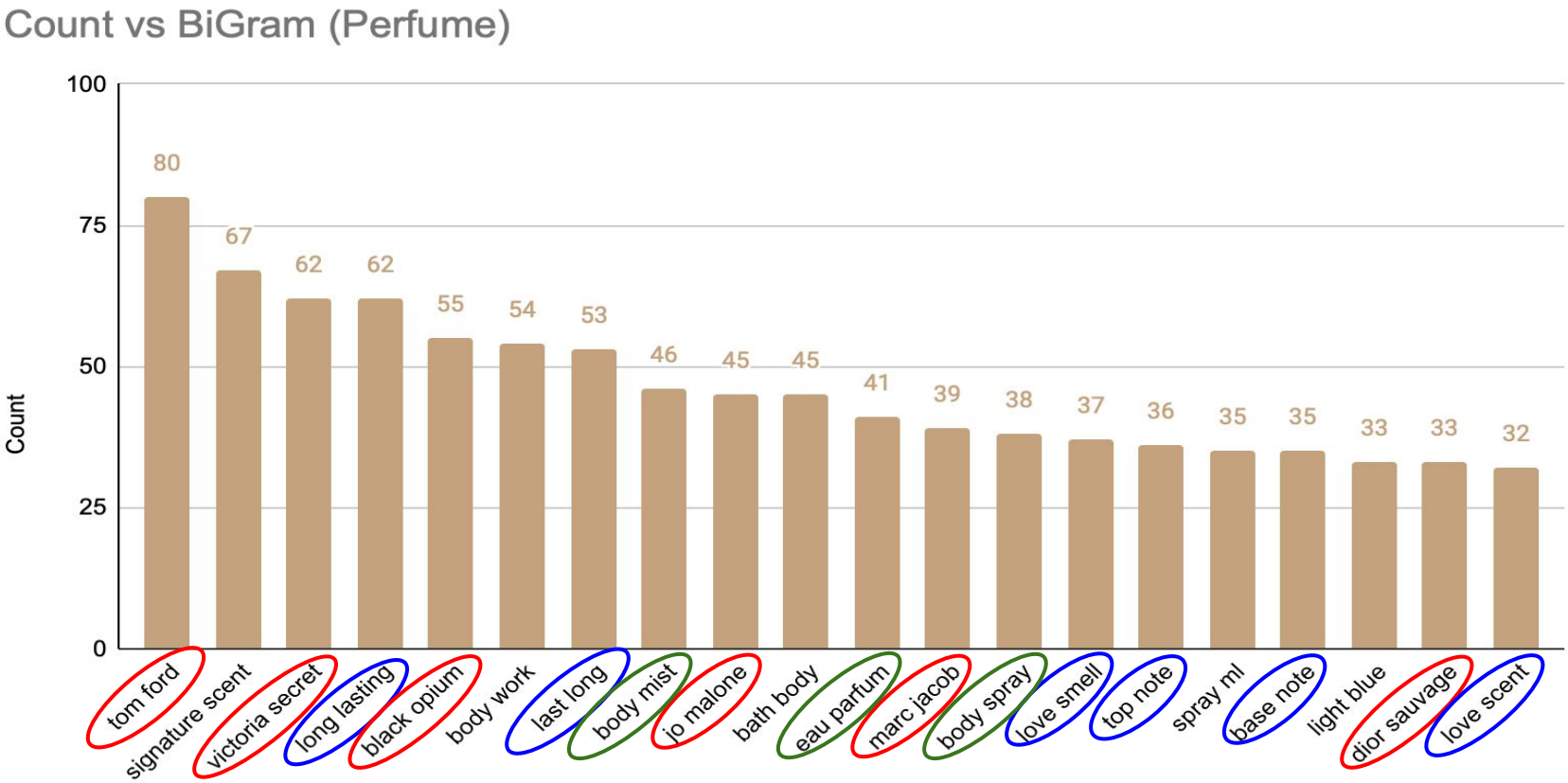
Makeup Subreddit:

- Look
- Foundation
- Skin
- Eye
- Product
- Shade

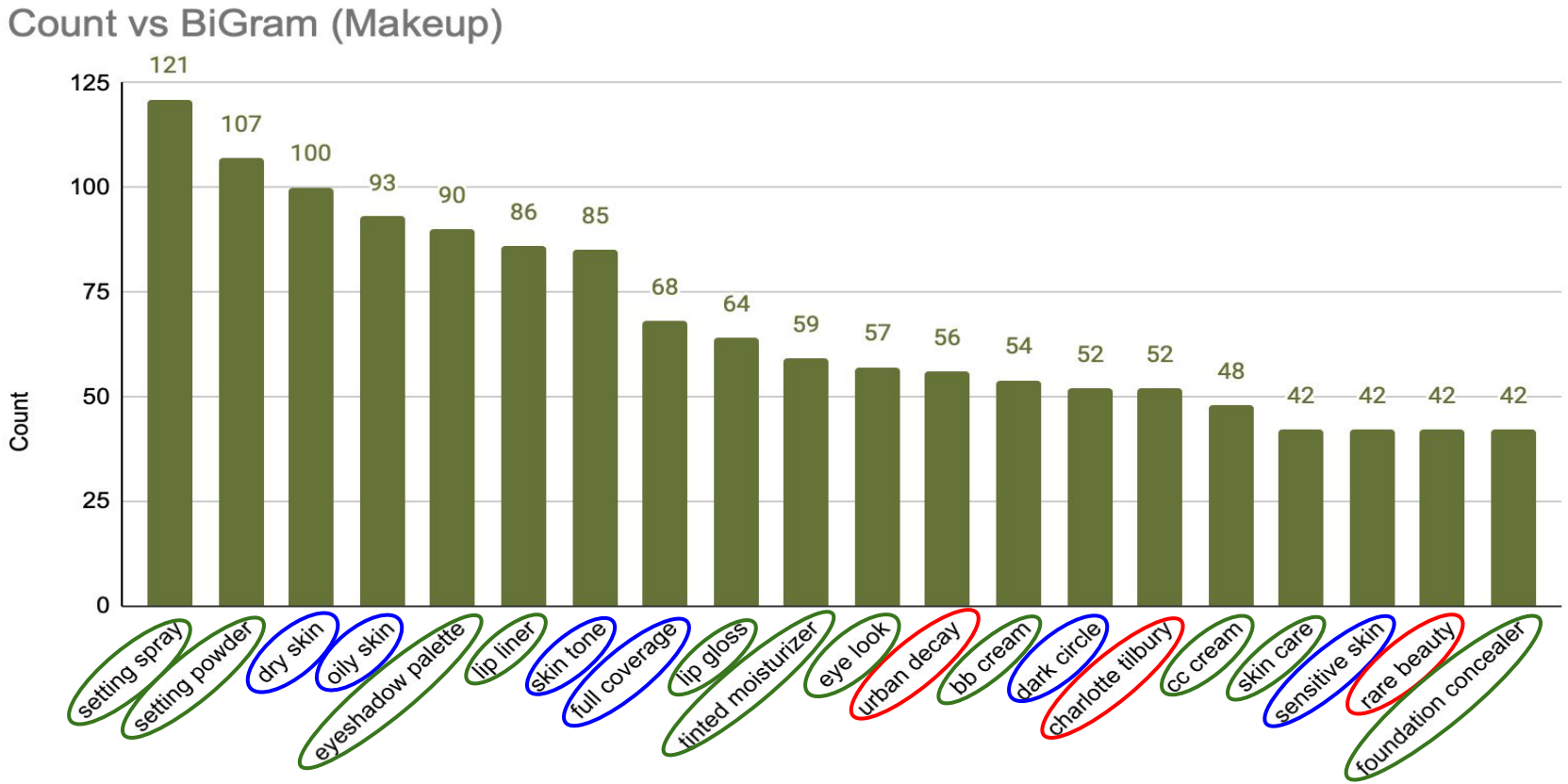
MOST COMMON WORDS



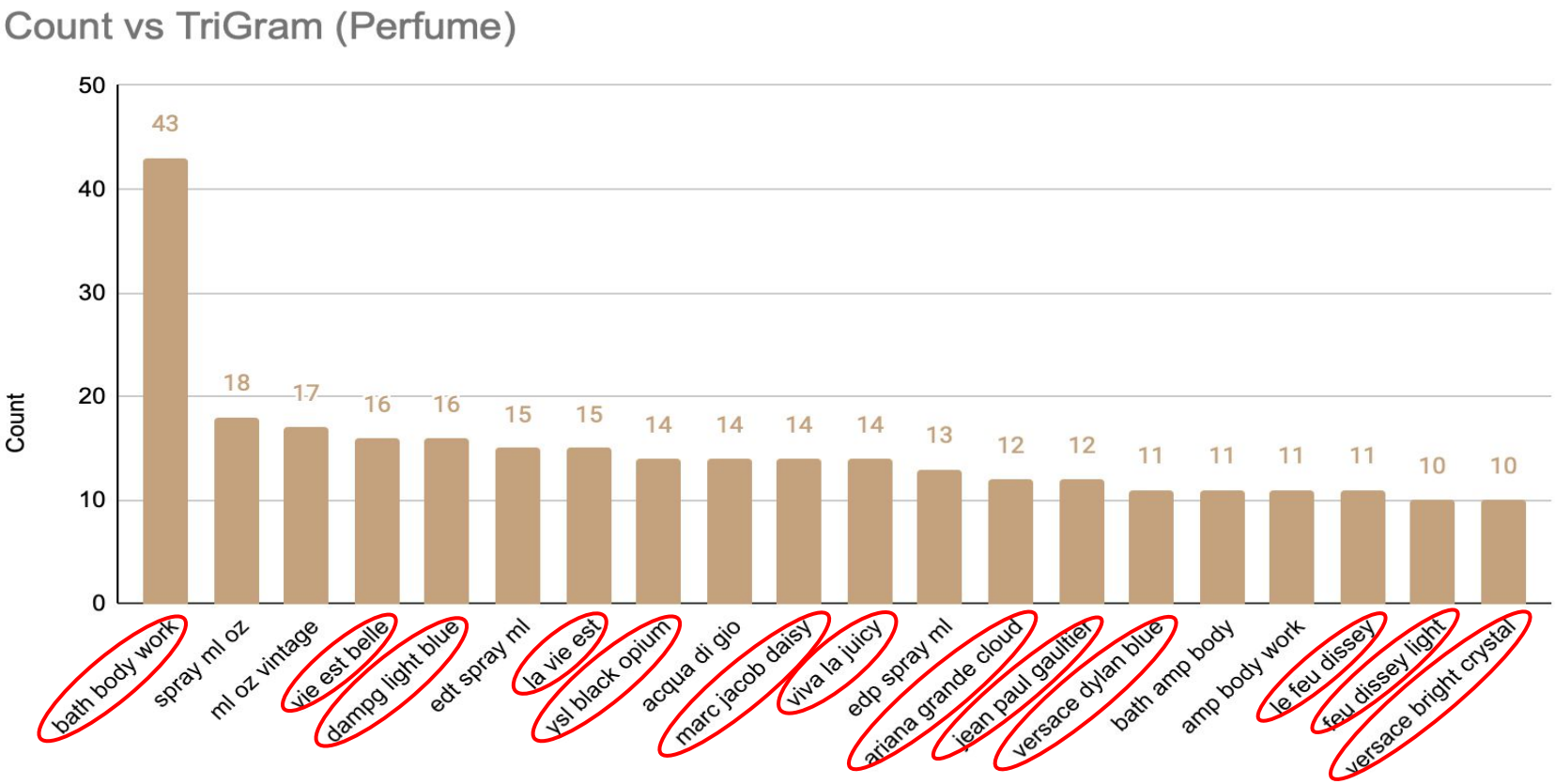
BIGRAM - PERFUME



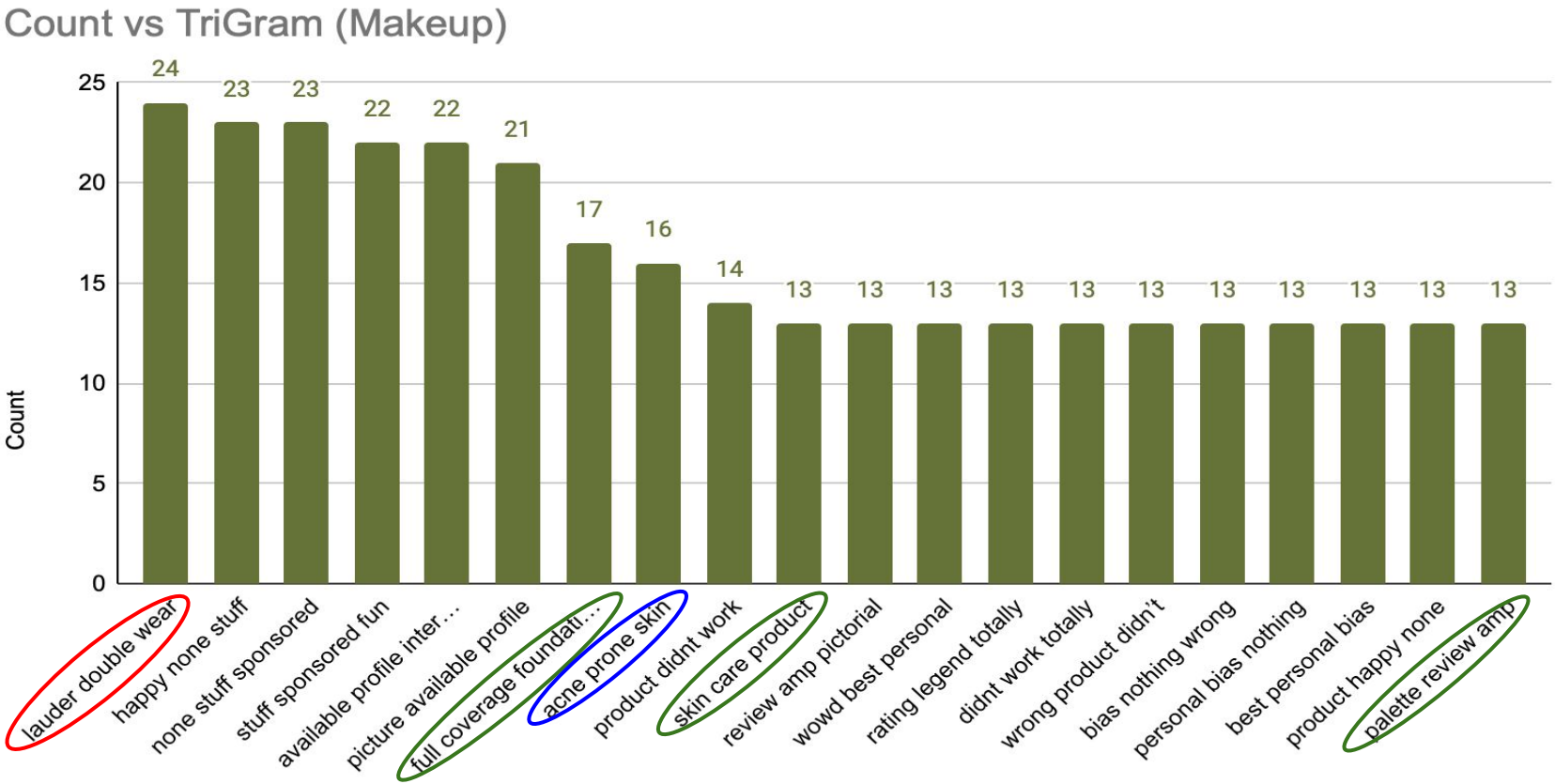
BIGRAM - MAKEUP



TRIGRAM - PERFUME



TRIGRAM - MAKEUP



RECOMMENDED BRANDS

PERFUMES:

- Tom Ford
- Victoria Secret
- Black Opium
- Jo Malone
- Marc Jacob
- Dior Sauvage
- Bath & Body Works
- D&G Light Blue
- La Vie Est Belle
- Viva La Juicy
- Marc Jacobs daisy
- Ariana Grande Cloud
- Jean Paul Gaultier
- Versace Dylan Blue
- La Feu Dissy Light
- Versace Bright Crystal

RECOMMENDED PRODUCTS

MAKEUP:

- Setting Spray
- Setting Powder
- Eyeshadow Palette
- Lip Liner
- Lip Gloss
- Tinted Moisturiser
- Eye Look Makeup
- BB Cream
- CC Cream
- Skin Care Products
- Foundation Concealer
- Full Covereage Foundation

RECOMMENDED FEATURES

PERFUME:

- Long Lasting
- Love Smell
- Top Note
- Base Note

MAKEUP:

- Dry Skin
- Oily Skin
- Skin Tone
- Dark Circle
- Sensitive Skin
- Acne Prone Skin

03a

Modelling

Model Selection

- Goal: Classify posts by their group
- Classification Models used:
  - Bernoulli Naïve Bayes
  - Multinomial Naïve Bayes
  - Gaussian Naïve Bayes
  - Logistic Regression
  - K-Nearest Neighbour

Vectorised Data Selection

1. Count
2. N-grams
    a. Bigrams
    b. Trigrams
3. TF-IDF
    a. Term Frequency-Inverse Document Frequency

Vectorised Data Selection

Vectorisation Type	Model Type	Train Results	Test Results
Count	Bernoulli NB	0.91082	0.90778
Count	Multinomial NB	0.96034	0.95417
Count	Gaussian NB	0.92742	0.92194
N-Gram	Bernoulli NB	0.87436	0.86889
N-Gram	Multinomial NB	0.84046	0.83472
N-Gram	Gaussian NB	0.85581	0.85139
TF-IDF	**Bernoulli NB**	**0.96027**	**0.95130**
TF-IDF	**Multinomial NB**	**0.97013**	**0.96361**
TF-IDF	**Gaussian NB**	**0.96325**	**0.94222**

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Model Optimisation

Model	Before	After
Bernoulli Naïve Bayes	binarize = 0.0	binarize = 0.2
Multinomial Naïve Bayes	fit_prior = True	fit_prior = False
Gaussian Naïve Bayes	n/a	n/a
Logistic Regression	solver = ‘liblinear’	n/a
K-Nearest Neighbour	n = 3	n = 2

Model Evaluation

Vectorisation Type	Model Type	Train Results	Test Results
TF-IDF	Bernoulli NB	0.96027	0.95130
TF-IDF	**Multinomial NB**	**0.97013**	**0.96361**
TF-IDF	Gaussian NB	0.96325	0.94222
TF-IDF	**Logistic Regression**	**0.98020**	**0.97000**
TF-IDF	K-Nearest Neighbour	0.95701	0.75278

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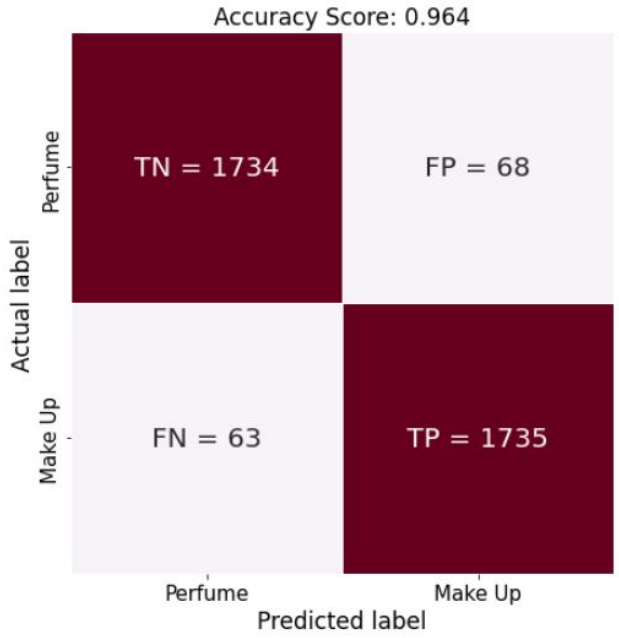
03b

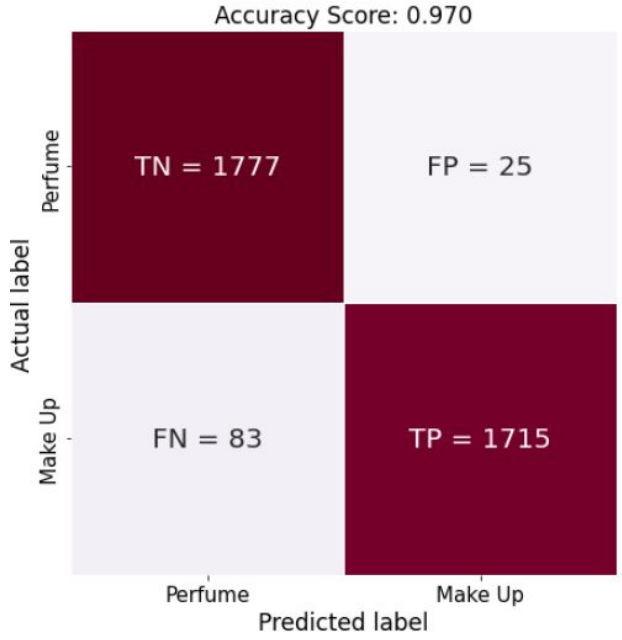
Model Comparisons

Confusion Matrix

Multinomial NB



Logistic Regression



Classification Report

Multinomial NB

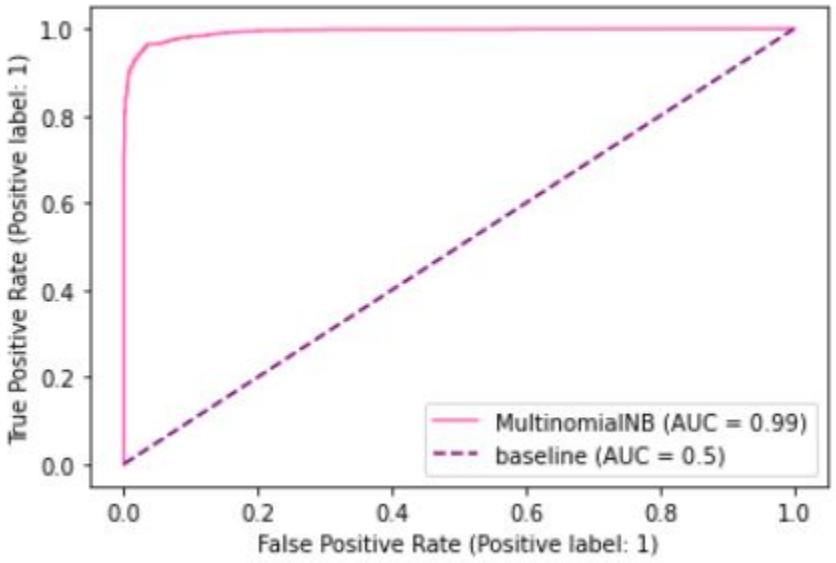
	precision	recall	f1-score	support
Perfume	0.9649	0.9623	0.9636	1802
Make Up	0.9623	0.9650	0.9636	1798
accuracy			0.9636	3600
macro avg	0.9636	0.9636	0.9636	3600
weighted avg	0.9636	0.9636	0.9636	3600

Logistic Regression

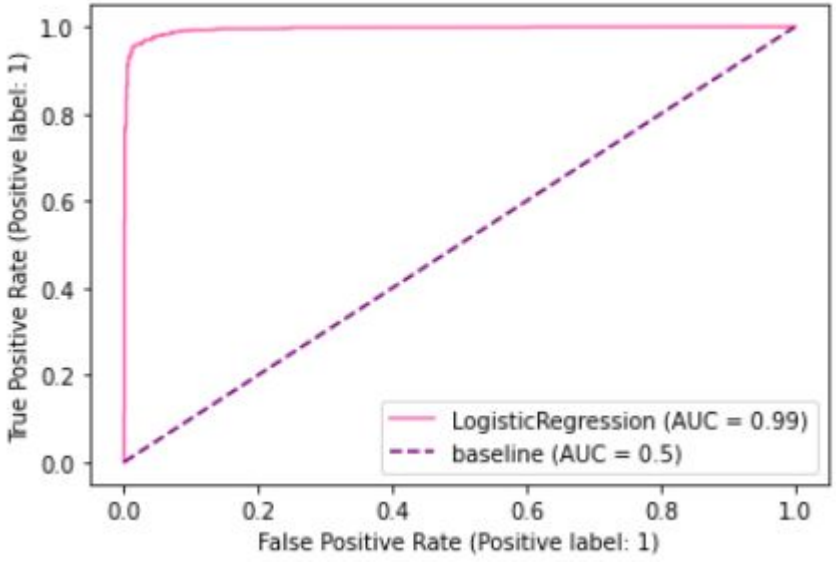
	precision	recall	f1-score	support
Perfume	0.9554	0.9861	0.9705	1802
Make Up	0.9856	0.9538	0.9695	1798
accuracy			0.9700	0.97
macro avg	0.9705	0.9700	0.9700	3600
weighted avg	0.9705	0.9700	0.9700	3600

ROC Curve

Multinomial NB



Logistic Regression



Logistic Regression

06

Conclusion

Future Enhancement

Conclusion

Logistic Regression

Improve Efficiency and Effectiveness of Marketing & Social Media Team

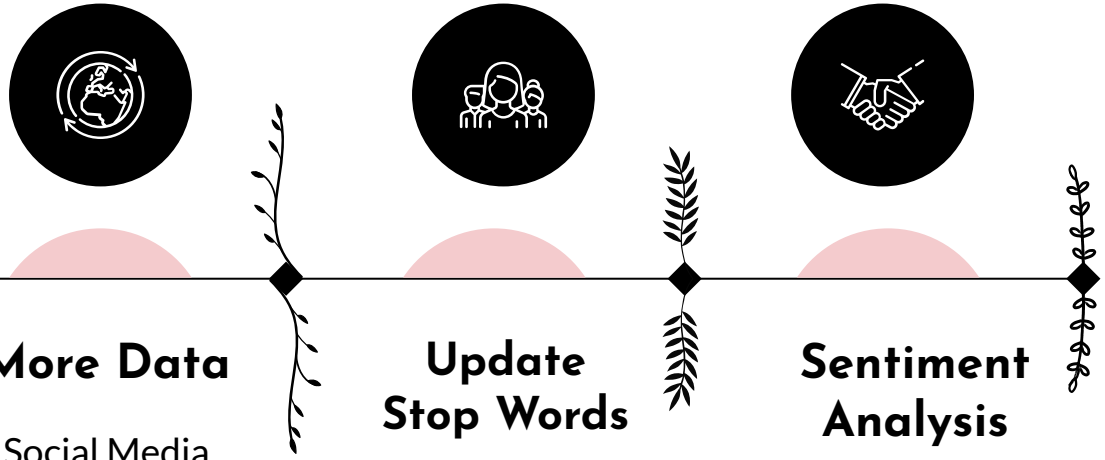
Trending Words

Develop Marketing Strategies as per trending words

Top Predictors

Identify the key words that can improve our product and services

Future Enhancements



More Data

Social Media Platform: Facebook, Twitter, Instagram

Update Stop Words

Input less meaningful words into stop words list

Sentiment Analysis

On Comments section on our forum

THANKS!