

The background of the slide is a light gray gradient, decorated with numerous realistic water droplets of various sizes. Some droplets are large and prominent, while others are small and subtle, scattered across the top and bottom edges of the frame.

# **GROUP NO - 19**

# **SENTIMENT ANALYSIS - AMAZON**

# **PRODUCT REVIEWS**

PARAM MADAN

# INTRODUCTION

- THE PRACTICE OF EVALUATING TEXT TO ASCERTAIN THE EMOTIONAL TONE OF THE AUTHOR'S MESSAGE IS KNOWN AS SENTIMENT ANALYSIS. SENTIMENT ANALYSIS IS THE PROCESS OF EXAMINING CUSTOMER REVIEWS OF PRODUCTS ON AMAZON TO ASCERTAIN WHETHER THEY ARE POSITIVE, NEGATIVE, OR NEUTRAL.
- IN THIS PROJECT, WE WILL EXAMINE AMAZON PRODUCT REVIEWS USING SENTIMENT ANALYSIS TECHNIQUES. MACHINE LEARNING TECHNIQUES WILL BE USED TO DETERMINE THE SENTIMENT THAT EACH REVIEW EXPRESSES. THE OBJECTIVE IS TO OFFER PERCEPTIONS OF CONSUMER PREFERENCES AND OPINIONS ABOUT A CERTAIN PRODUCT, WHICH CAN BE UTILIZED TO SUPPORT DATA-DRIVEN DECISIONS TO ENHANCE THE PRODUCT OR CREATE SUCCESSFUL MARKETING CAMPAIGNS.

# DATASET DESCRIPTION

- IT CONSISTS OF MORE THAN 500K REVIEWS.
- IT CONSISTS OF BOTH NUMERICAL AND TEXT DATA.
- THERE ARE 10 COLUMNS AND 568,454 ROWS.

REFERENCE LINK:

- [HTTP://WWW.KAGGLE.COM/DATASETS/ARHAMRUMI/AMAZON-PRODUCT-REVIEWS](http://www.kaggle.com/datasets/arhamrumi/amazon-product-reviews)

# METHODOLOGY

## STEP 1: IMPORTING ALL THE LIBRARIES

STEP 2: AFTER LOADING THE DATA, WE CHECKED FOR THE NULL VALUES AND THEN WE RAN A CODE TO REMOVE THE NULL VALUES FROM OUR DATASET, AND THEN WE RECHECK THE DATASET TO CHECK IF ANY NULL VALUE IS STILL PRESENT OR NO

```
import warnings
warnings.filterwarnings("ignore")
import time
import pandas as pd
import numpy as np
from nltk.corpus import stopwords
from textblob import TextBlob
from textblob import Word
from wordcloud import WordCloud
from wordcloud import STOPWORDS
import string
import nltk
from nltk.tokenize import word_tokenize
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import re
import os
import sys
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
vader=SentimentIntensityAnalyzer()
```

## #Checking Null values

```
APR_dataframe.isnull().sum()
```

```
] Id      0
   Product_ID  0
   User_ID  0
   ProfileName  16
   Help_num  0
   Help_denom  0
   Ratings  0
   Time  0
   Summary  27
   Comments  0
   dtype: int64
```

**STEP 3:** THEN WE MOVED TO THE STEP OF DATA CLEANING WHEREIN WE CREATED FUNCTIONS TO REMOVE THE PUNCTUATION MARKS AND SIGNS AND SYMBOLS WHICH ARE NOT REQUIRED.

**STEP 4:** AFTER REMOVING THE PUNCTUATION AND UNNECESSARY SYMBOLS FROM THE COMMENTS WE RAN A FUNCTION TO CHANGE REVIEWS INTO PLAIN TEXT FORMAT

**STEP 5:** LATER WE CONVERTED THE REVIEWS TO LOWERCASE FOR EASE AND THEN WE CONVERTED THE REVIEWS TO STRING FORMAT.

**STEP 6:** THEN WE SEPARATED EACH WORD IN THE REVIEWS AND ASSIGNED THEM TO INDIVIDUAL TOKENS

#### DATA CLEANING PROCESS

#Removing @ and punctuation from the column Summary and Comments

```
In [6]: > def cleancomments (text):  
        text = re.sub (r'@[A-Za-z0-9]+', '',text) #remove @  
        text = re.sub ('^[^\w\s]', '',text)  
        return text
```

```
In [7]: > mainframe['Comments']=mainframe['Comments'].apply(cleancomments)  
        mainframe['Summary']=mainframe['Summary'].apply(cleancomments)
```

```
In [8]: > stop= stopwords.words('english')  
        mainframe['Comments']=mainframe['Comments'].apply(lambda x: " ".join(x for x in x.split() if x not in stop))  
        stop= stopwords.words('english')  
        mainframe['Summary']=mainframe['Summary'].apply(lambda x: " ".join(x for x in x.split() if x not in stop))
```

#Converting the entire column of summary and comments to lower case

```
In [9]: > mainframe['Comments']=mainframe['Comments'].str.lower()  
        mainframe['Summary']=mainframe['Summary'].str.lower()
```

#Converting the entire column of summary and comments to String

```
In [10]: > mainframe['Comments']=mainframe['Comments'].astype(str)  
        mainframe['Summary']=mainframe['Summary'].astype(str)
```

#Creating tokens

```
> def CommentsTokenize(Comments):  
    tokenize = nltk.word_tokenize(Comments)  
    return [g for g in tokenize if g.isalpha()]
```

```
> mainframe['Comments_Tokens']=mainframe['Comments'].apply(CommentsTokenize)
```

**STEP 7:** WE THEN CREATED 2 FUNCTIONS NAMED “SUBJECTIVITY” AND “POLARITY” AND USING THE FEATURES OF TEXTBLOB WE GOT THE POLARITY SCORE WHICH RANGES BETWEEN -1 AND 1, WHERE -1 IS THE MOST NEGATIVE AND 1 IS THE MOST POSITIVE.

**STEP 8:** THE REVIEWERS HAVE GIVEN NUMBER RATINGS AS WELL TO THEIR REVIEWS SO NOW WE USE THOSE NUMBERS DIRECTLY USE THOSE NUMBERS AND CONSIDER THE REVIEWS AS POSITIVE, NEGATIVE OR NEUTRAL BASED ON THE NUMBERS WHERE IF THE RATING IS 2 OR LESS THAN 2 IT WILL BE CONSIDERED AS NEGATIVE, IF THE NUMBER IS 3 IT WILL BE CONSIDERED AS NEUTRAL AND IF THE RATING IS 3 OR MORE THAN 3 IT WILL BE CONSIDERED AS POSITIVE.

#Calculating polarity and subjectivity for each comment in the Comments column

```
def subjectivity(text):  
    return TextBlob(text).sentiment.subjectivity  
def polarity(text):  
    return TextBlob(text).sentiment.polarity  
text_blob['Subjectivity']=text_blob['Comments'].apply(subjectivity)  
text_blob['Polarity']=text_blob['Comments'].apply(polarity)
```

#Based on the polarity score, we are deriving the sentiment of comments into a positive, negative, or neutral value.

```
def polanalysis(score):  
    if score<0:  
        return 'Negative'  
    elif score==0:  
        return 'Neutral'  
    else:  
        return 'Positive'  
text_blob['Textblob_Analysis']=text_blob['Polarity'].apply(polanalysis)
```

#Based on Ratings provided from the user, We are deriving positive, negative, or neutral value.

```
def ratingsanalysis(Ratings):  
    if Ratings<3:  
        return 'Negative'  
    if Ratings==3:  
        return 'Neutral'  
    if Ratings>3:  
        return 'Positive'  
text_blob['Ratings_Analysis']=text_blob['Ratings'].apply(ratingsanalysis)
```

**STEP 9:** NOW WE USE THE VADER SENTIMENT ANALYSIS ON THE SAME REVIEWS, IT DIVIDES THE REVIEWS INTO 4 COLUMNS NEGATIVE, POSITIVE, NEUTRAL AND COMPOUND COLUMN, THE COMPOUND COLUMN GIVES A COMPOUNDED VALUE.

**STEP 10:** THEN WE EXTRACTED THE PERCENTAGES OF ALL 3 TECHNIQUES THAT IS VADER ANALYSIS, TEXTBLOB ANALYSIS AND ANALYSIS OF THE RATINGS OF THE REVIEW AND WE COMPARED THE PERCENTAGES OF ALL 3 ANALYSIS.

#Now we are using Vader Sentiment Analysis.

```
vader_data=mainframe

temp_data=[]
for row in vader_data['Comments']:
    ab= vader.polarity_scores(row)
    temp_data.append(ab)
vader_new=pd.DataFrame(temp_data)
```

#Based on the compound value, we are deriving sentiment of comments into a positive, negative, or neutral value.

```
def vaderanalysis(compound):
    if compound<0:
        return 'Negative'
    elif compound==0:
        return 'Neutral'
    else:
        return 'Positive'
vader_new['Vader_Analysis']= vader_new['compound'].apply(vaderanalysis)

vader_new=vader_new.drop(columns=['neg','neu','pos'])

new_combined_data= pd.concat([text_blob.reset_index(drop=True), vader_new], axis=1)
```

#We are calculating the percentage of positive, negative, and neutral values in Ratings analysis.

```
(new_combined_data['Ratings_Analysis'].value_counts()/new_combined_data['Ratings_Analysis'].count())*100
3]: Positive    78.071325
    Negative    14.427413
    Neutral      7.501262
    Name: Ratings_Analysis, dtype: float64
```

#We are calculating the percentage of positive, negative, and neutral values in Vader analysis.

```
(new_combined_data['Vader_Analysis'].value_counts()/new_combined_data['Vader_Analysis'].count())*100
4]: Positive    90.225910
    Negative     8.385833
    Neutral      1.388256
    Name: Vader_Analysis, dtype: float64
```

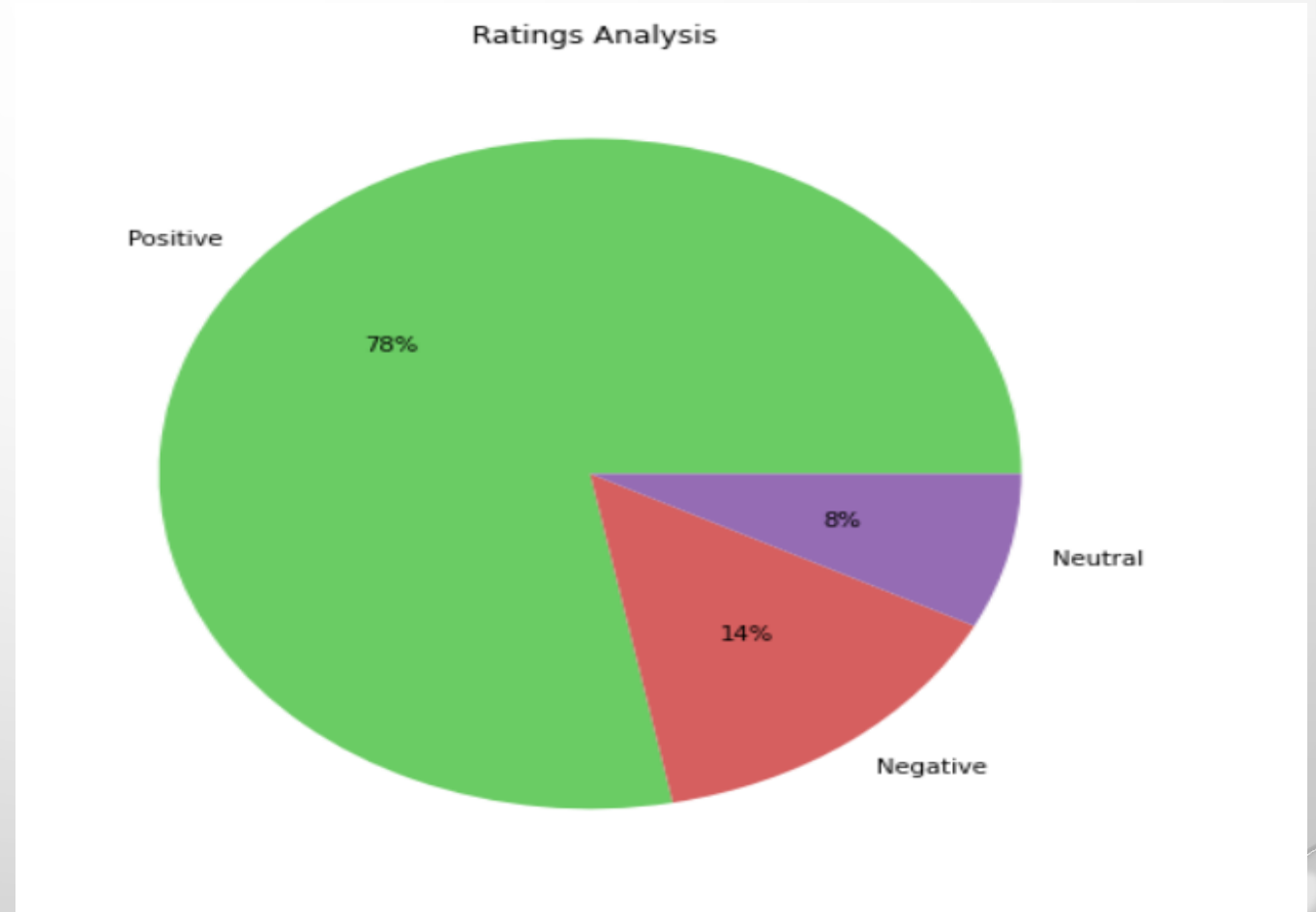
#We are calculating the percentage of positive, negative, and neutral values in textblob analysis.

```
(new_combined_data['Textblob_Analysis'].value_counts()/new_combined_data['Textblob_Analysis'].count())*100
22]: Positive    87.316924
    Negative    10.784978
    Neutral      1.898098
    Name: Textblob_Analysis, dtype: float64
```



## STEP 11: VISUALIZATION – PIE CHART

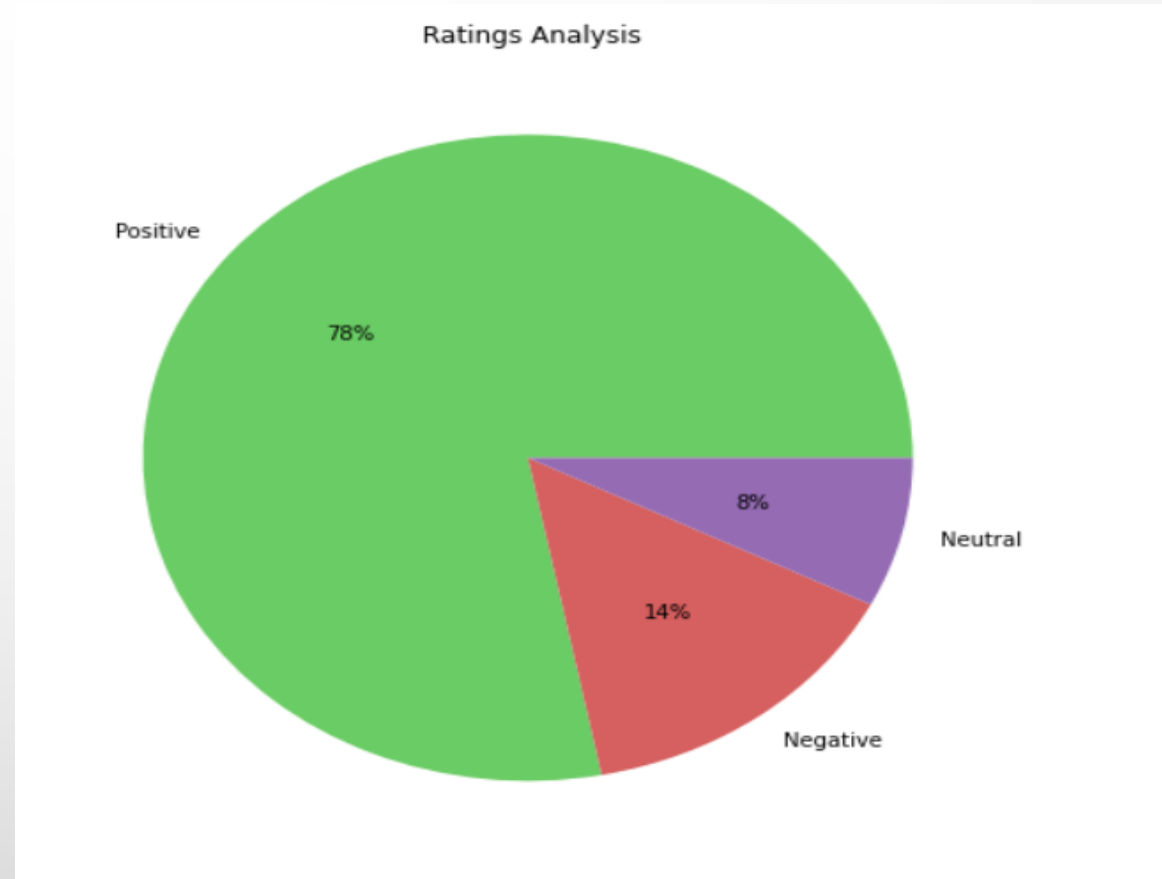
### PIE CHART FOR RATINGS ANALYSIS





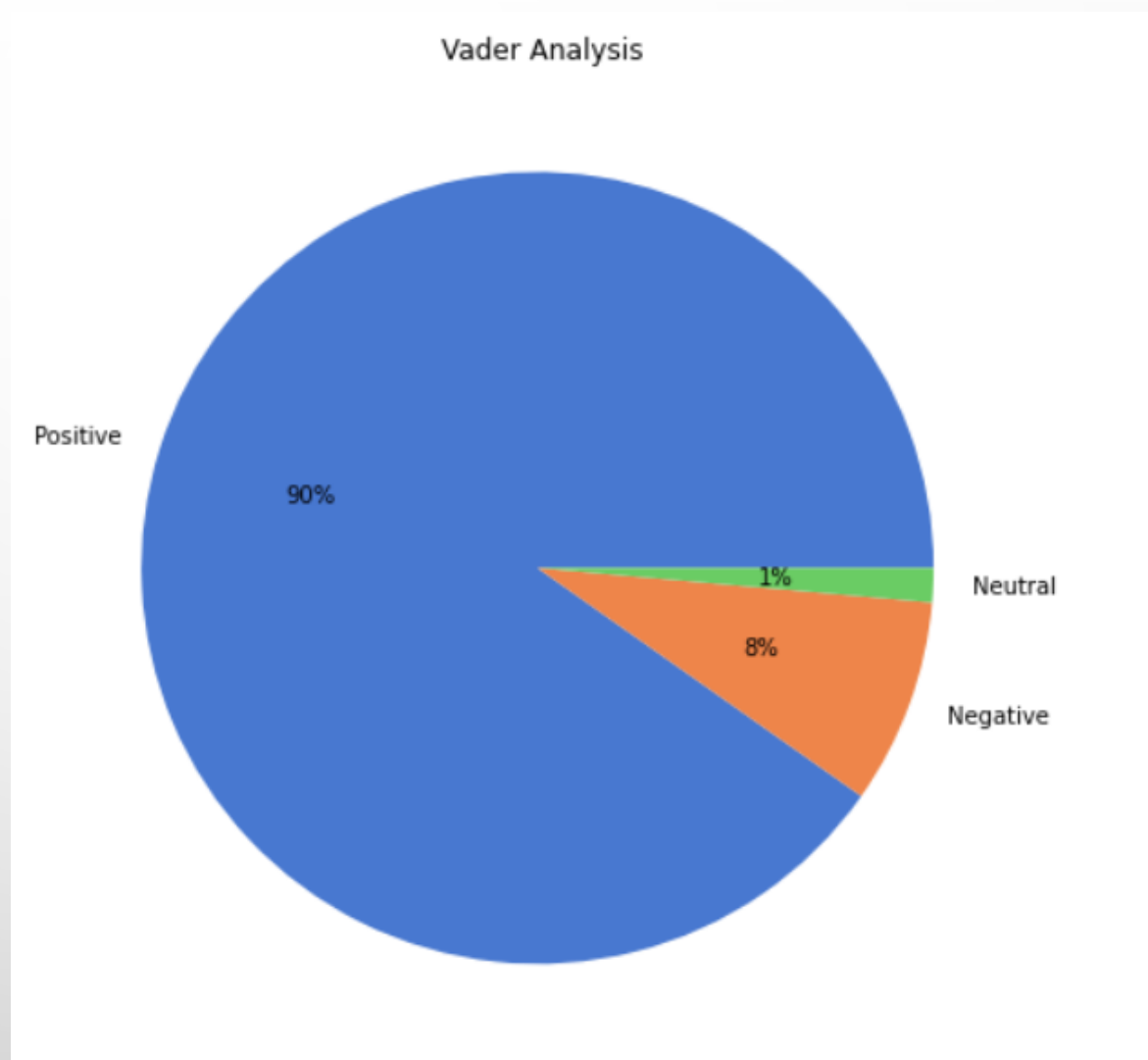
## STEP 12:

### PIE CHART FOR RATINGS ANALYSIS



## STEP 13:

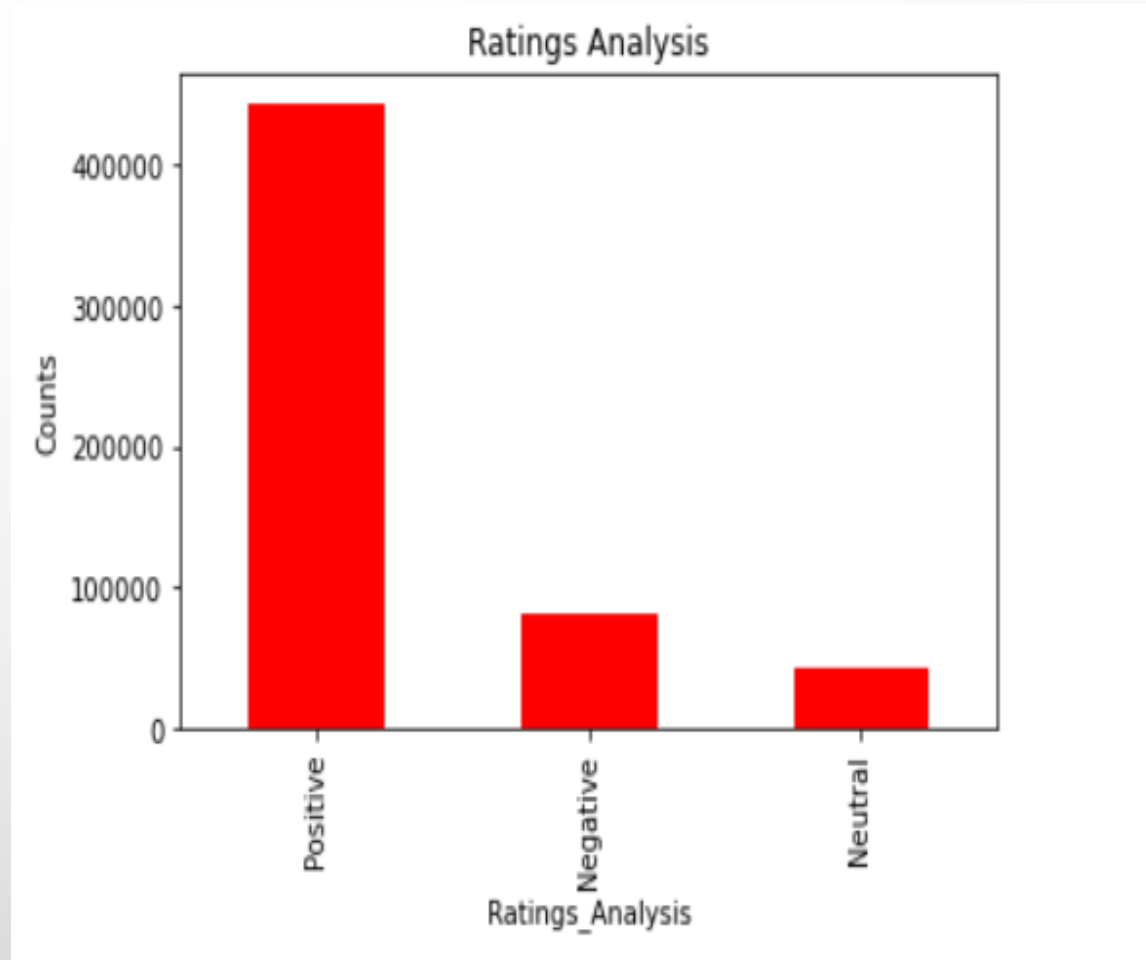
### PIE CHART FOR VADER ANALYSIS



## VISUALIZATION: BAR GRAPHS

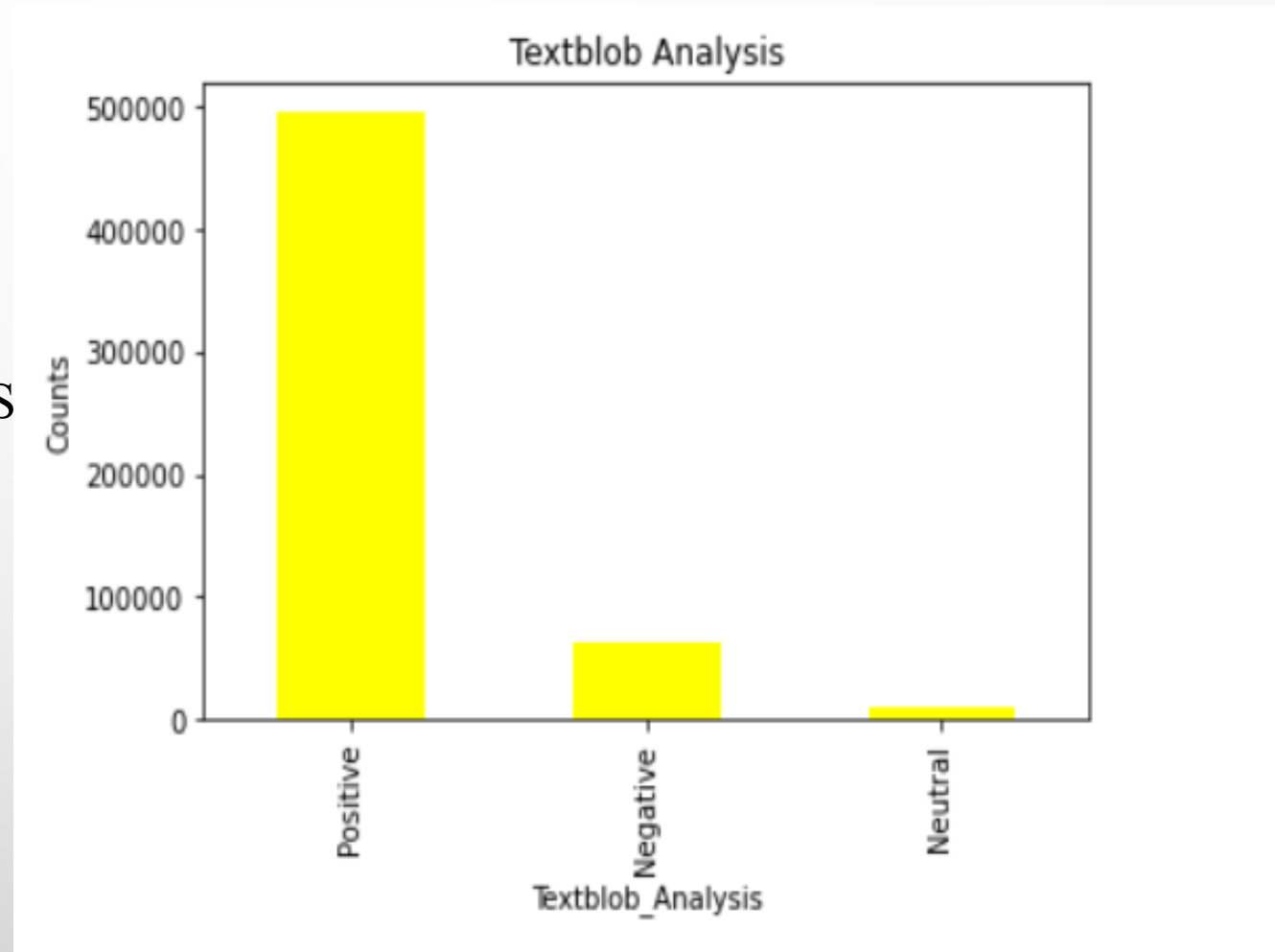
### STEP 14:

### BAR GRAPH FOR RATINGS ANALYSIS



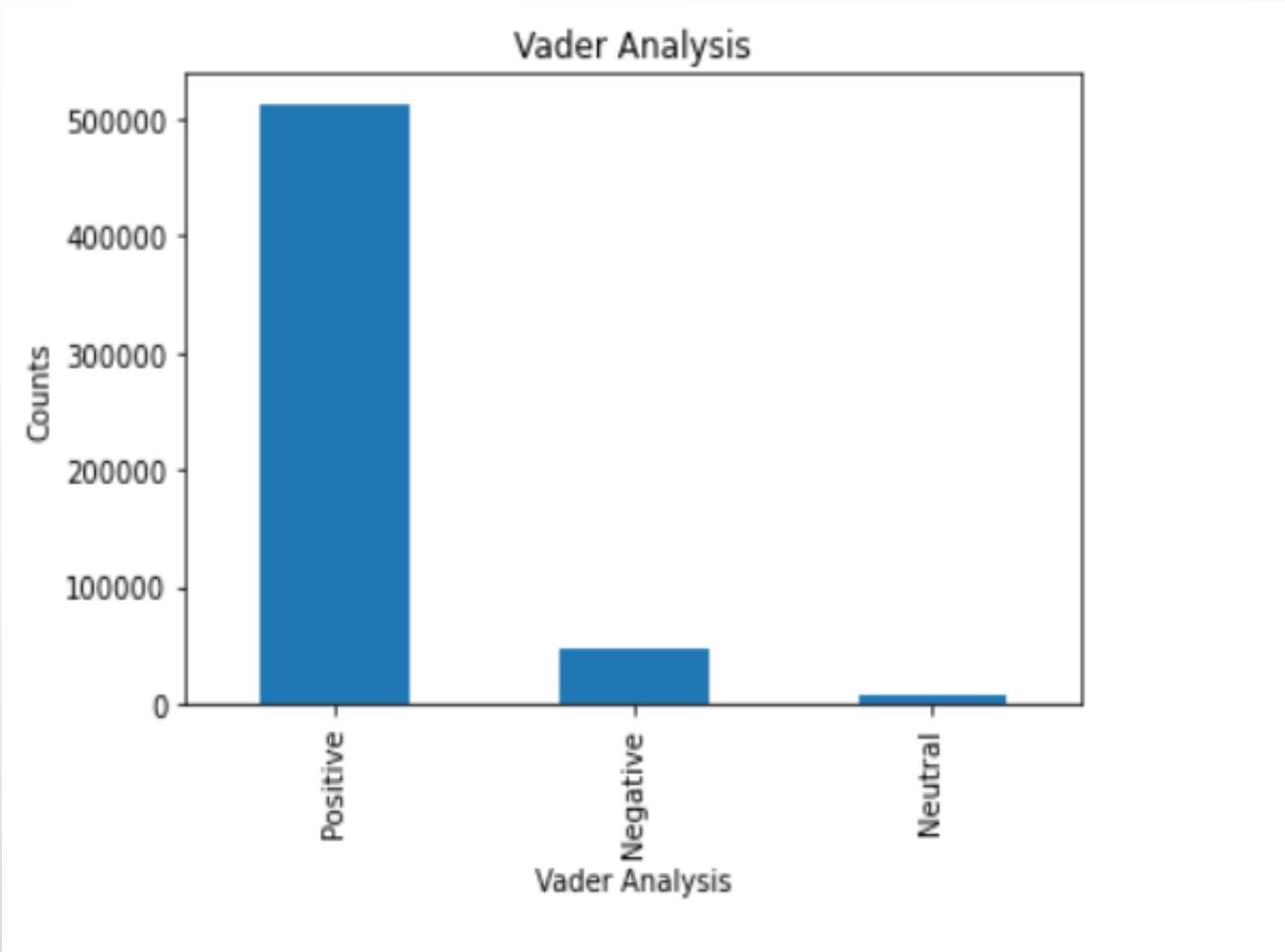
## STEP 15:

### BAR CHART FOR TEXTBLOB ANALYSIS



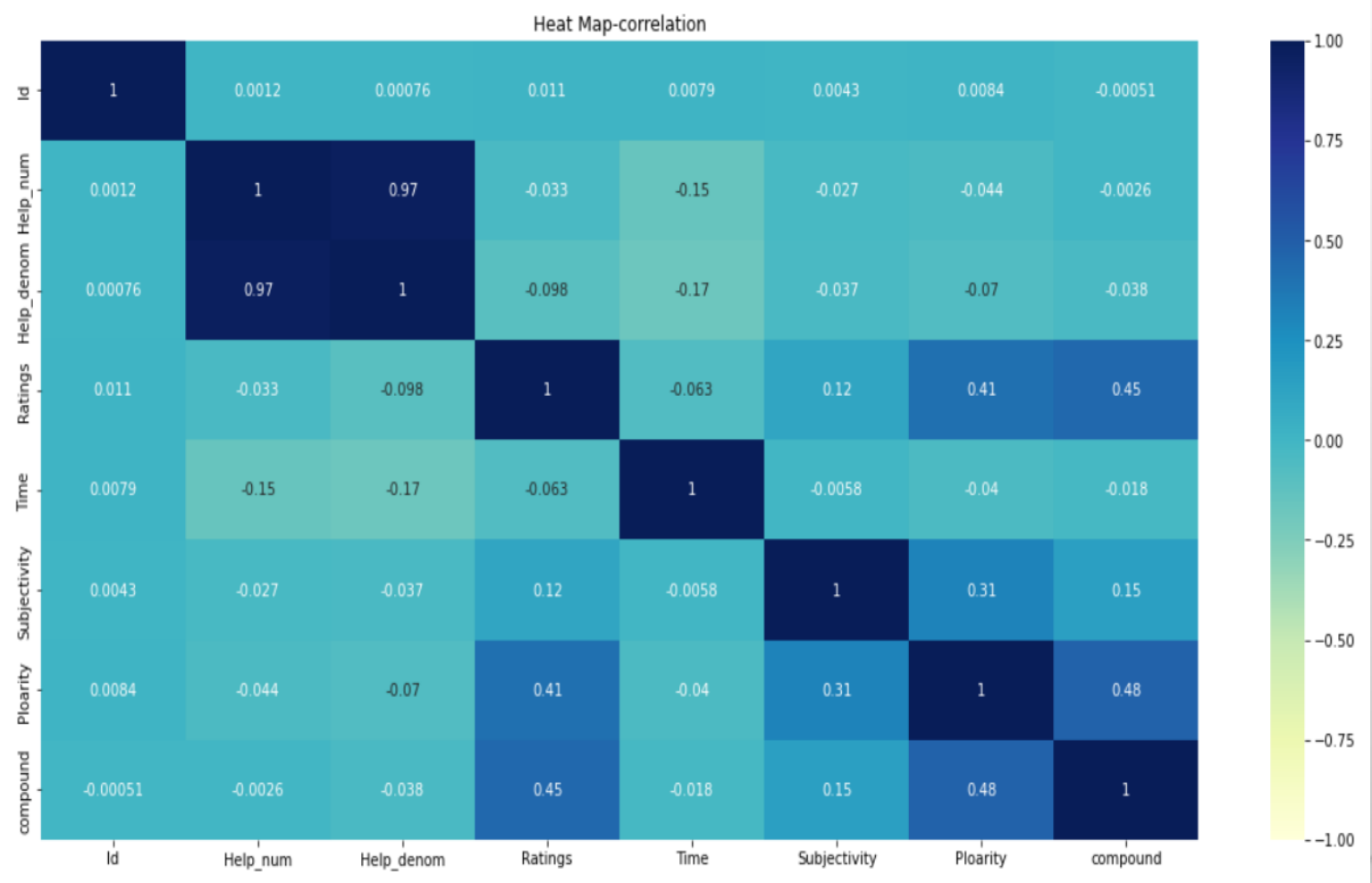
**STEP 16:**

**BAR CHART FOR VADER ANALYSIS**



STEP 17:

HEATMAP FOR THE CO-RELATION



## WORDCLOUD FOR GENERIC, POSITIVE AND NEGATIVE REVIEWS

## Positive Reviews



## Negative Reviews





**STEP 19:** FIRST, WE REMOVE ALL THE UNNECESSARY COLUMNS WHICH ARE NOT GOING TO BE USED IN THE M.L MODELS.

**STEP 20:** THEN WE DISCARD THE REVIEWS WHICH ARE NEUTRAL.

**STEP 21:** THEN WE ASSIGN VALUES 0 AND 1 TO THE NEGATIVE AND POSITIVE REVIEWS RESPECTIVELY.

```
model_data = model_data[model_data['Textblob_Analysis'] != 'Neutral']  
model_data = model_data[model_data['Vader_Analysis'] != 'Neutral']
```

```
Textblob_model = model_data
```

```
Textblob_model = Textblob_model.drop(columns=['Comments_Tokens', 'Ratings_Analysis', 'Vader_Analysis'])
```

```
def Sentiment(Textblob_Analysis):  
    if Textblob_Analysis == 'Negative':  
        return 0  
    else:  
        return 1
```

```
Textblob_model['Textblob_Analysis_Sentiment'] = Textblob_model['Textblob_Analysis'].apply(Sentiment)
```

**STEP 22:** WE NOW INSERT THE TEXT FROM THE REVIEWS IN X\_TRAIN AND WE INSERT THE SENTIMENT SCORE IN THE Y\_TRAIN NOW TO FIT THE DATA IN THE MACHINE LEARNING MODEL WE HAVE TRANSFORMED THE DATA BY USING TF-IDF, USING THIS, EACH WORD IN THE STRING HAS BEEN ASSIGNED A NUMERICAL VALUE SO THAT IT FITS PERFECTLY IN THE MACHINE LEARNING MODEL.

#We are using the TF-IDF ON Comments column and transforming it to numerical values.

```
from joblib import parallel_backend
with parallel_backend('threading', n_jobs=-1):
    tfidf_tb = TfidfVectorizer()
    X_train_tfidf_tb = tfidf_tb.fit_transform(X_train)

X_test_tfidf_tb = tfidf_tb.transform(X_test.astype('U'))
```

# MACHINE LEARNING ALGORITHM APPLICATION

## STEP 23: APPLYING XGBOOST ALGORITHM

### ML ALGORITHM XGBOOST

```
▶ from xgboost import XGBClassifier

▶ xgboost_model = XGBClassifier()
  xgboost_model.fit(X_train_tfidf_tb, y_train)
  xgboost_pred = xgboost_model.predict(X_test_tfidf_tb)
  print(xgboost_pred)

  [1 1 1 ... 1 1 1]

▶ xgboost_accuracy=accuracy_score(y_test,xgboost_pred)

▶ print("XGBoost Accuracy for Textblob Analysis is:",xgboost_accuracy*100)

  XGBoost Accuracy for Textblob Analysis is: 95.14915576479109
```

### ML ALGORITHMS FOR VADER ANALYSIS

```
▶ xgboost_model_v = XGBClassifier()

▶ xgboost_model_v.fit(X_train_tfidf_v, y_train)
  xgboost_pred_v = xgboost_model_v.predict(X_test_tfidf_v)

▶ xgboost_accuracy_v=accuracy_score(y_test,xgboost_pred_v)

▶ print("XGBoost Accuracy for Vader Analysis is:",xgboost_accuracy_v*100)

  XGBoost Accuracy for Vader Analysis is: 94.55343805169527
```

## STEP 24: APPLYING DECISION TREE ALGORITHM

Decision Tree

```
from sklearn.tree import DecisionTreeClassifier

Decisiontree_model= DecisionTreeClassifier(random_state=34, max_depth=80)

Decisiontree_model.fit(X_train_tfidf_tb,y_train)
56]: DecisionTreeClassifier(max_depth=80, random_state=34)

Decisiontree_pred = Decisiontree_model.predict(X_test_tfidf_tb)

Decisiontree_accuracy=accuracy_score(y_test,Decisiontree_pred)

print("Decision Tree Accuracy for Textblob Analysis is:",Decisiontree_accuracy*100)

Decision Tree Accuracy for Textblob Analysis is: 94.28907699968313
```

Decision Tree

```
Decisiontree_model_v= DecisionTreeClassifier(random_state=34, max_depth=80)

Decisiontree_model_v.fit(X_train_tfidf_v,y_train)
6]: DecisionTreeClassifier(max_depth=80, random_state=34)

Decisiontree_pred_v = Decisiontree_model_v.predict(X_test_tfidf_v)

decisiontree_accuracy_v=accuracy_score(Decisiontree_pred_v,y_test)

print("Decision Tree Accuracy for Vader Analysis is:",decisiontree_accuracy_v*100)

Decision Tree Accuracy for Vader Analysis is: 94.26101127155854
```

## STEP 25: APPLYING RANDOM FOREST ALGORITHM

### Random Forest

```
from sklearn.ensemble import RandomForestClassifier

Randomforest_model = RandomForestClassifier(n_estimators=90, max_depth=150)

Randomforest_model.fit(X_train_tfidf_tb,y_train)

1]: RandomForestClassifier(max_depth=150, n_estimators=90)

Randomtree_pred=Randomforest_model.predict(X_test_tfidf_tb)

Randomtree_accuracy=accuracy_score(y_test,randomtree_pred)

print("Random Tree Accuracy for Textblob Analysis is:",Randomtree_accuracy*100)

Random Tree Accuracy for Textblob Analysis is: 92.13254266443349
```

### Random Forest

```
Randomforest_model_v = RandomForestClassifier(n_estimators=90, max_depth=150)

Randomforest_model_v.fit(X_train_tfidf_v,y_train)

1]: RandomForestClassifier(max_depth=150, n_estimators=90)

Randomforest_pred_v = Randomforest_model_v.predict(X_test_tfidf_v)

Randomforest_accuracy_v=accuracy_score(Randomforest_pred_v,y_test)

print("Random Forest Accuracy for Vader Analysis is:",Randomforest_accuracy_v*100)

Random Forest Accuracy for Vader Analysis is: 93.52224887963423
```

# COMPARISONS / CONCLUSION:

XGBOOST - TEXTBLOB ANALYSIS - 95.14%

XGBOOST - VADER ANALYSIS - 94.53%

DECISION TREE - TEXTBLOB ANALYSIS -  
94.28%

DECISION TREE - VADER ANALYSIS - 94.26%

RANDOM FOREST - TEXTBLOB ANALYSIS -  
92.13%

RANDOM FOREST - VADER ANALYSIS - 93.52%

	ML Models	TB_Accuracy	Vader_Accuracy
0	XGBoost	95.149156	94.553438
1	Decision Tree	94.289077	94.261011
2	Random Forest	92.132543	93.522249

# REFERENCES

[HTTPS://MACHINELEARNINGMASTERY.COM/DEVELOP-FIRST-XGBOOST-MODEL-PYTHON-SCI-KIT-LEARN/](https://machinelearningmastery.com/develop-first-xgboost-model-python-sci-kit-learn/)

[HTTPS://YOUTU.BE/ANVRJNLKP0K](https://youtu.be/ANVRJNLKP0K)

[HTTPS://YOUTU.BE/TRNPSLOCBV0](https://youtu.be/TRNPSLOCBV0)

[HTTPS://YOUTU.BE/ALU\\_CCXNS-K](https://youtu.be/ALU_CCXNS-K)



The background is a light gray gradient. On the left side, there is a complex network diagram consisting of numerous small, multi-colored dots (red, orange, blue, purple, black) connected by thin, dark gray lines. Some dots are larger than others. To the left of the network is a faint, curved, light gray shape. Scattered across the top and bottom of the image are several realistic-looking water droplets of various sizes, rendered with soft shadows and highlights. The text 'THANK YOU' is positioned on the right side of the image.

THANK YOU