ML Lab Exam

Importing Libraries

```
!pip install pickle5
```

```
Collecting pickle5
  Downloading pickle5-0.0.11.tar.gz (132 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 132.1/132.1 kB 4.8 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
Building wheels for collected packages: pickle5
  Building wheel for pickle5 (setup.py) ... done
  Created wheel for pickle5: filename=pickle5-0.0.11-cp310-cp310-linux_x86_64.whl size=255318 sha256=6dd40e5c23207215aa5fc2ea31dc720a0ef
  Stored in directory: /root/.cache/pip/wheels/7d/14/ef/4aab19d27fa8e58772be5c71c16add0426acf9e1f64353235c
Successfully built pickle5
Installing collected packages: pickle5
Successfully installed pickle5-0.0.11
```

+ Code + Text

```
import re
import string
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import pickle5 as pickle
import scipy.sparse

#preprocessing and scoring
from sklearn.preprocessing import StandardScaler, MinMaxScaler, LabelEncoder
from nltk.corpus import stopwords
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, f1_score, accuracy_score, recall_score, precision_score
from nltk.stem import WordNetLemmatizer

#models and algos
from textblob import TextBlob
from nltk.sentiment.vader import SentimentIntensityAnalyzer

from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import BernoulliNB

from sklearn.decomposition import TruncatedSVD, LatentDirichletAllocation
```

```
#Pipeline function
from sklearn.base import BaseEstimator, TransformerMixin

#Feature Extraction
from sklearn.feature_extraction.text import TfidfVectorizer

#Hyperparameter tuning
from sklearn.model_selection import GridSearchCV

from sklearn.model_selection import StratifiedKFold
```

```
#nltk
import nltk
nltk.download('wordnet')
nltk.download('vader_lexicon')
nltk.download('stopwords')
from nltk.corpus import stopwords
print(stopwords.words('english'))
```

```
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data] Downloading package vader_lexicon to /root/nltk_data...
[nltk_data] Downloading package stopwords to /root/nltk_data...
['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've", "you'll", "you'd", 'your', 'yours', 'yourself',
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
from tqdm import tqdm
from sklearn.model_selection import ParameterGrid
```

```
from wordcloud import WordCloud
```

Creating Datasets

```
from google.colab import drive
drive.mount('/content/drive') #force_remount=True
```

```
Mounted at /content/drive
```

```
import zipfile

zip_path = '/content/drive/MyDrive/KaggleDatasets/twitterData.zip'
unzip_path = '/content/drive/MyDrive/KaggleDatasets/twitterData/'

# Unzip the file
with zipfile.ZipFile(zip_path, 'r') as zip_ref:
    zip_ref.extractall(unzip_path)
```

```
csv_file_path1 = '/content/drive/MyDrive/KaggleDatasets/twitterData/testdata.manual.2009.06.14.csv'
sentiment140 = pd.read_csv(csv_file_path1, encoding="Latin-1" ,names=["polarity","id", "date","query", "user", "tweet"])

csv_file_path2 = '/content/drive/MyDrive/KaggleDatasets/twitterData/training.1600000.processed.noemoticon.csv'
train = pd.read_csv(csv_file_path2, encoding="Latin-1" ,names=["polarity","id", "date","query", "user", "tweet"])
```

```
train.head()
```

	polarity	id	date	query	user	tweet
0	0	1467810369	Mon Apr 06 22:19:45 PDT 2009	NO_QUERY	_TheSpecialOne_	@switchfoot http://twitpic.com/2y1zl - Awww, t...
1	0	1467810672	Mon Apr 06 22:19:49 PDT 2009	NO_QUERY	scotthamilton	is upset that he can't update his Facebook by ...
2	0	1467810917	Mon Apr 06 22:19:53 PDT 2009	NO_QUERY	mattycus	@Kenichan I dived many times for the ball. Man...
3	0	1467811184	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	ElleCTF	my whole body feels itchy and like its on fire
4	0	1467811193	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	Karoli	@nationwideclass no, it's not behaving at all....

```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1600000 entries, 0 to 1599999
Data columns (total 6 columns):
 #   Column    Non-Null Count    Dtype
---  ------    --------------    -----
 0   polarity  1600000 non-null  int64
 1   id        1600000 non-null  int64
 2   date      1600000 non-null  object
 3   query     1600000 non-null  object
 4   user      1600000 non-null  object
 5   tweet     1600000 non-null  object
dtypes: int64(2), object(4)
memory usage: 73.2+ MB
```

```
sentiment140.head()
```

	polarity	id	date	query	user	tweet
0	4	3	Mon May 11 03:17:40 UTC 2009	kindle2	tpryan	@stellargirl I loooooooovvvvvveee my Kindle2. ...
1	4	4	Mon May 11 03:18:03 UTC 2009	kindle2	vcu451	Reading my kindle2... Love it... Lee childs i...
2	4	5	Mon May 11 03:18:54 UTC 2009	kindle2	chadfu	Ok, first assesment of the #kindle2 ...it fuck...
3	4	6	Mon May 11 03:19:04 UTC 2009	kindle2	SIX15	@kenburbary You'll love your Kindle2. I've had...
4	4	7	Mon May 11 03:21:41 UTC 2009	kindle2	yamarama	@mikefish Fair enough. But i have the Kindle2...

Next steps: Generate code with sentiment140 | View recommended plots | New interactive sheet

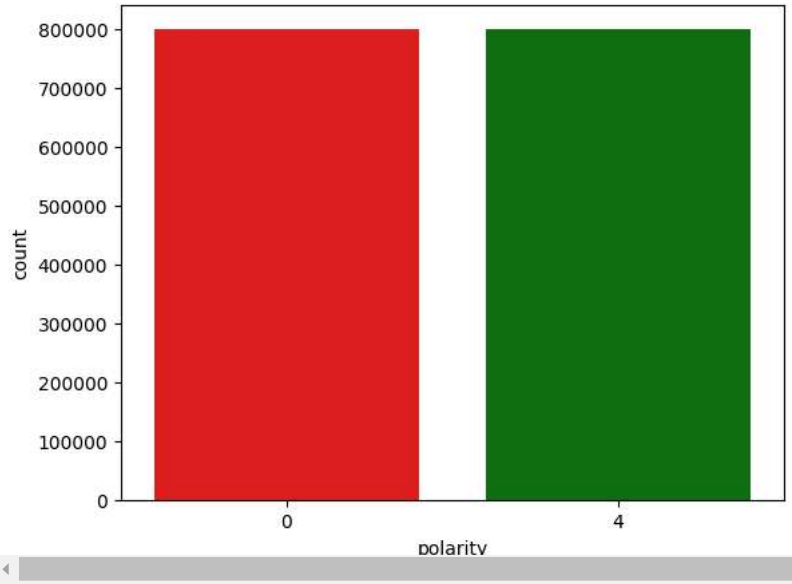
```
sentiment140.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 498 entries, 0 to 497
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   polarity  498 non-null    int64 
 1   id        498 non-null    int64 
 2   date      498 non-null    object
 3   query     498 non-null    object
 4   user      498 non-null    object
 5   tweet     498 non-null    object
dtypes: int64(2), object(4)
memory usage: 23.5+ KB
```

```
custom_palette = ["red", "green","blue"]
```

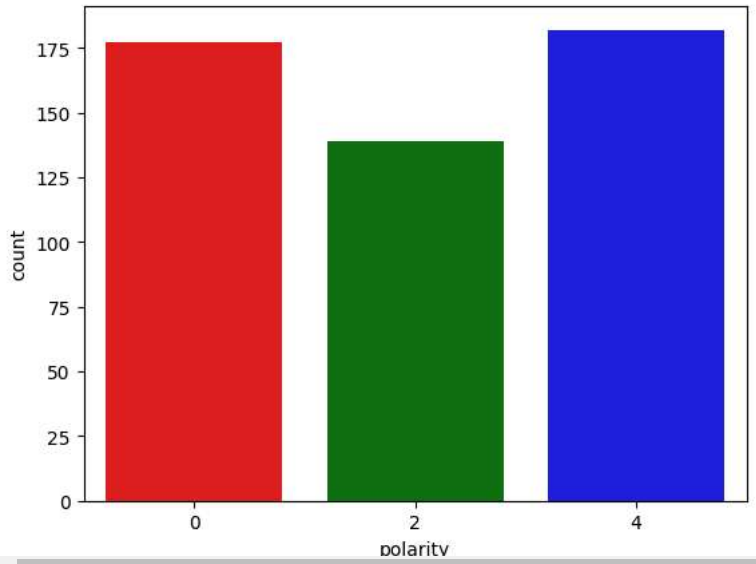
```
sns.countplot(data = train , x = "polarity", hue="polarity", palette=custom_palette, legend=False)
```

```
<ipython-input-15-94dae2869065>:1: UserWarning: The palette list has more values (3) than needed (2), which may not be intended.
  sns.countplot(data = train , x = "polarity", hue="polarity", palette=custom_palette, legend=False)
<Axes: xlabel='polarity', ylabel='count'>
```




```
sns.countplot(data = sentiment140 , x = "polarity", hue="polarity", palette=custom_palette, legend=False)
```

```
<Axes: xlabel='polarity', ylabel='count'>
```



```
#Replace values to have -1 negative, 0 neutral, 1 postive
train["polarity"]  = train["polarity"].replace(4,1)
train["polarity"]  = train["polarity"].replace(0,-1)

sentiment140["polarity"]  = sentiment140["polarity"].replace(4,1)
sentiment140["polarity"]  = sentiment140["polarity"].replace(0,-1)
sentiment140["polarity"]  = sentiment140["polarity"].replace(2,0)
```

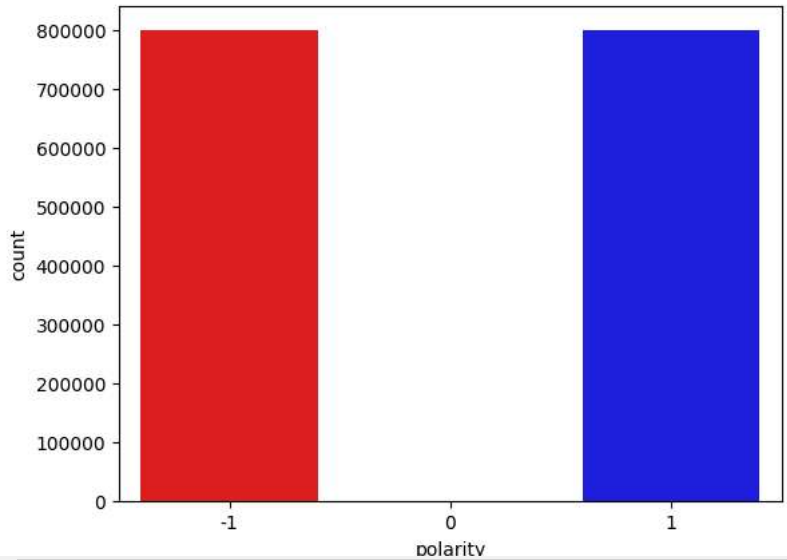
```
print("train: ", len(train))
print("sentiment140: ", len(sentiment140))
```

```
train:  1600000
sentiment140:  498
```

```
#Combining datasets
tweets_df = pd.concat([train,sentiment140],axis=0)
```

```
sns.countplot(data = tweets_df , x = "polarity", hue="polarity", palette=custom_palette, legend=False)
```

```
<Axes: xlabel='polarity', ylabel='count'>
```

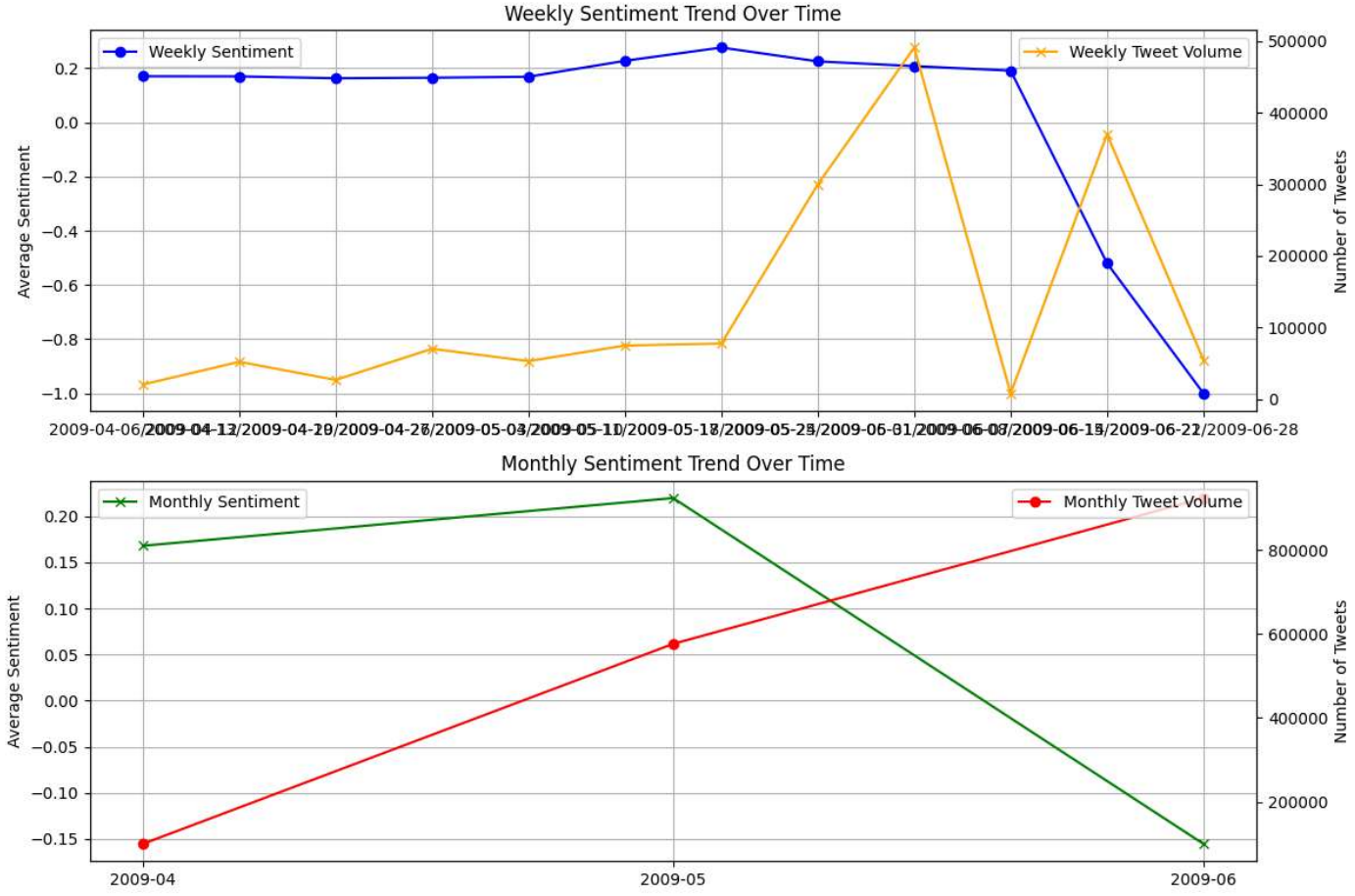


Visualize Trends in Sentiment Over Time

```
# Convert 'date' column to datetime format
tweets_df['date'] = pd.to_datetime(tweets_df['date'], errors='coerce')

# Group by week to get average sentiment per week and tweet volume
tweets_df['week'] = tweets_df['date'].dt.to_period('W')
weekly_sentiment = tweets_df.groupby('week')['polarity'].mean()
weekly_tweet_volume = tweets_df.groupby('week')['tweet'].size()

# Group by month to get average sentiment per month and tweet volume
tweets_df['month'] = tweets_df['date'].dt.to_period('M')
monthly_sentiment = tweets_df.groupby('month')['polarity'].mean()
monthly_tweet_volume = tweets_df.groupby('month')['tweet'].size()

# Plot the sentiment trends with tweet volume
plt.figure(figsize=(12, 8))

# Plot weekly sentiment trend
plt.subplot(2, 1, 1)
plt.plot(weekly_sentiment.index.astype(str), weekly_sentiment.values, color='blue', marker='o', label='Weekly Sentiment')
plt.ylabel('Average Sentiment')
plt.title('Weekly Sentiment Trend Over Time')
plt.grid(True)
plt.legend(loc='upper left')

# Plot weekly tweet volume
plt.twinx()  # This creates a second y-axis for tweet volume
```

```
plt.plot(weekly_tweet_volume.index.astype(str), weekly_tweet_volume.values, color='orange', marker='x', label='Weekly Tweet Volume')
plt.ylabel('Number of Tweets')
plt.legend(loc='upper right')

# Plot monthly sentiment trend
plt.subplot(2, 1, 2)
plt.plot(monthly_sentiment.index.astype(str), monthly_sentiment.values, color='green', marker='x', label='Monthly Sentiment')
plt.ylabel('Average Sentiment')
plt.title('Monthly Sentiment Trend Over Time')
plt.grid(True)
plt.legend(loc='upper left')

# Plot monthly tweet volume
plt.twinx()
plt.plot(monthly_tweet_volume.index.astype(str), monthly_tweet_volume.values, color='red', marker='o', label='Monthly Tweet Volume')
plt.ylabel('Number of Tweets')
plt.legend(loc='upper right')

# Rotate x-axis labels for better readability
plt.xticks(rotation=45)

# Adjust layout for better visualization
plt.tight_layout()

# Show the plot
plt.show()
```

```
<ipython-input-21-28e5f87119c9>:2: FutureWarning: Parsed string "Mon Apr 06 22:19:45 PDT 2009" included an un-recognized timezone "PDT".
  tweets_df['date'] = pd.to_datetime(tweets_df['date'], errors='coerce')
```



Top Influencers

```
# Group by user to calculate average sentiment and tweet volume
user_sentiment = tweets_df.groupby('user').agg(
    polarity_mean=('polarity', 'mean'),
    tweet_count=('tweet', 'size')
)

# Calculate a "sentiment score" that factors in both polarity and volume
user_sentiment['influence_score'] = user_sentiment['polarity_mean'] * user_sentiment['tweet_count']

# Sort by influence score to get the top influencers (both high sentiment and tweet volume)
top_influencers = user_sentiment.sort_values(by='influence_score', ascending=False).head(10)

# Display the top influencers
print("Top 10 Influencers (based on polarity and tweet volume):")
print(top_influencers[['polarity_mean', 'tweet_count', 'influence_score']])
```

```
Top 10 Influencers (based on polarity and tweet volume):
                polarity_mean  tweet_count  influence_score
user
what_bugs_u          1.000000          246            246.0
DarkPiano            0.957627          236            226.0
keza34               0.926941          219            203.0
shanajaca            0.915493          213            195.0
tsarnick             0.709677          248            176.0
TraceyHewins         0.829384          211            175.0
KevinEdwardsJr       1.000000          171            171.0
ramdomthoughts       0.759259          216            164.0
Scyranth             0.951807          166            158.0
VioletsCRUK          0.562724          279            157.0
```

Removing unwanted columns

```
tweets_df = tweets_df[["polarity", "tweet"]]
```

Understanding Length and Polarity

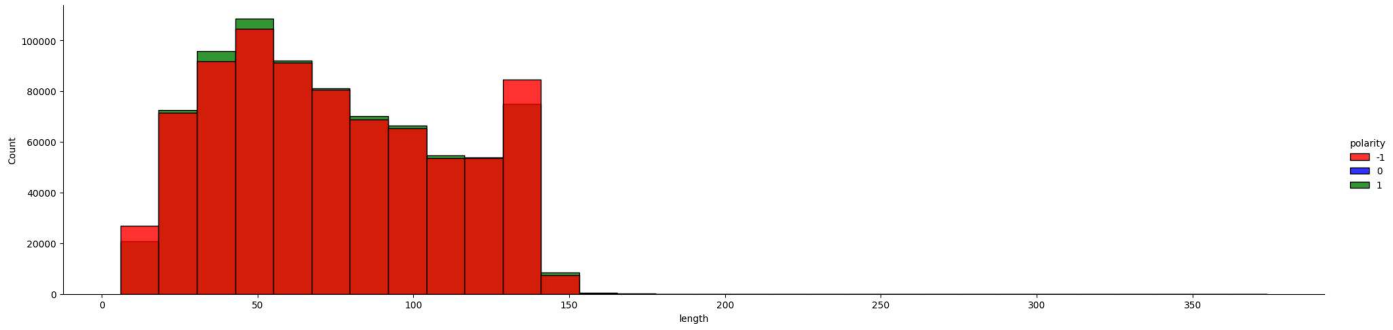
```
tweets_df["tweet"] = tweets_df["tweet"].astype(str)
tweets_df.reset_index(drop = True,inplace=True)
```

```
tweets_df["length"] = tweets_df["tweet"].apply(len)
tweets_df.groupby("polarity")["length"].describe()
```

polarity	count	mean	std	min	25%	50%	75%	max
-1	800177.0	74.304081	36.743642	6.0	44.0	70.0	104.0	359.0
0	139.0	72.517986	32.992391	11.0	48.0	69.0	95.0	144.0
1	800182.0	73.880350	36.135391	6.0	44.0	69.0	103.0	374.0

```
plt.figure(figsize=(15,5))

sns.displot(data = tweets_df, x= "length", hue= "polarity" ,palette={-1:"r",0:"b",1:"g"}, bins = 30,aspect= 4, alpha = 0.8)
```

```
<seaborn.axisgrid.FacetGrid at 0x7bd343ca2200>
<Figure size 1500x500 with 0 Axes>
```



Cleaning tweets

```
def clean_text(text):
    pat1 = r'@[^ ]+'                  # @ signs and value
    pat2 = r'https?://[A-Za-z0-9./]+'  # links
    pat3 = r'\'s'                     # floating s's
    pat4 = r'\#\w+'                    # hashtags and value
    pat5 = r'&amp '                 # & and
    pat6 = r'[^A-Za-z\s]'         #remove non-alphabet
    combined_pat = r'|'.join((pat1, pat2,pat3,pat4,pat5, pat6))
    text = re.sub(combined_pat,"",text).lower()
    return text.strip()
```

```
#clean
tweets_df["cleaned_tweet"] = tweets_df["tweet"].apply(clean_text)
```

```
#drop empty
tweets_df = tweets_df [ ~(tweets_df["cleaned_tweet"] =="")]
```

Lemmetization

```
lem = WordNetLemmatizer()

def tokenize_lem(sentence):
    outlist= []
    token = sentence.split()
    for tok in token:
        outlist.append(lem.lemmatize(tok))
    return " ".join(outlist)
```

```
%%time
tweets_df["cleaned_tweet"] = tweets_df["cleaned_tweet"].apply(tokenize_lem)
```

```
CPU times: user 1min 44s, sys: 780 ms, total: 1min 44s
Wall time: 1min 48s
```

```
tweets_df.head()
```

	polarity	tweet	length	cleaned_tweet
0	-1	@switchfoot http://twitpic.com/2y1zl - Awww, t...	115	awww that a bummer you shoulda got david carr ...
1	-1	is upset that he can't update his Facebook by ...	111	is upset that he cant update his facebook by t...
2	-1	@Kenichan I dived many times for the ball. Man...	89	i dived many time for the ball managed to save...
3	-1	my whole body feels itchy and like its on fire	47	my whole body feel itchy and like it on fire
4	-1	@nationwideclass no, it's not behaving at all....	111	no it not behaving at all im mad why am i here...

```
tweets_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1596552 entries, 0 to 1600497
Data columns (total 4 columns):
 #   Column         Non-Null Count    Dtype 
---  ------         --------------    ----- 
 0   polarity       1596552 non-null  int64 
 1   tweet          1596552 non-null  object
 2   length         1596552 non-null  int64 
 3   cleaned_tweet  1596552 non-null  object
dtypes: int64(2), object(2)
memory usage: 60.9+ MB
```

Split Data

```
X_train, X_test, y_train, y_test = train_test_split(tweets_df[["cleaned_tweet","length"]], tweets_df["polarity"], test_size=0.2, random_stat
```

TF-IDF

```
tfidf = TfidfVectorizer()
```

```
tfidf.fit(X_train["cleaned_tweet"])
```

```
TfidfVectorizer()
```

```
with open("tfidf_vectorizer.pickle", "wb") as f:
    pickle.dump(tfidf, f)
```

```
X_train_v = tfidf.transform(X_train["cleaned_tweet"])
X_test_v = tfidf.transform(X_test["cleaned_tweet"])
```

```
print(X_train_v.shape)
print(X_test_v.shape)
```

```
(1277241, 344343)
(319311, 344343)
```

```
#Add TFIDF to tweets vector and Scaling
scaler = MinMaxScaler()
scaler2 = MinMaxScaler()
```

```
scaler.fit([X_train["length"]])
scaler2.fit([X_test["length"]])
```

```
MinMaxScaler()
```

```
X_train_len = scaler.transform([X_train["length"]])
X_train_len = X_train_len.reshape( X_train_v.shape[0], 1)

X_train = scipy.sparse.hstack([X_train_v,X_train_len], format = "csr")
```

```
X_test_len = scaler2.transform([X_test["length"]])
X_test_len = X_test_len.reshape(X_test_v.shape[0], 1)

X_test = scipy.sparse.hstack([X_test_v,X_test_len], format = "csr")
```

Word Cloud

```
# Generate a Word Cloud for all the tweets
text = ' '.join(tweets_df['cleaned_tweet'].dropna())
wordcloud = WordCloud(width=800, height=400, background_color='white').generate(text)

# Plot the WordCloud
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show()
```

Topic Model (LDA)

```
lda = LatentDirichletAllocation(n_components=5, max_iter=5, batch_size=128, random_state=42, verbose=2)

# Fit the LDA model to the TF-IDF matrix (X_train_v)
lda.fit(X_train_v)

# Get the feature names (terms/words) from the TF-IDF vectorizer
terms = tfidf.get_feature_names_out()

# Display the top words for each topic
for topic_idx, topic in enumerate(lda.components_):
    print(f"Topic #{topic_idx}:")
    print(" ".join([terms[i] for i in topic.argsort()[:-11:-1]]))
```

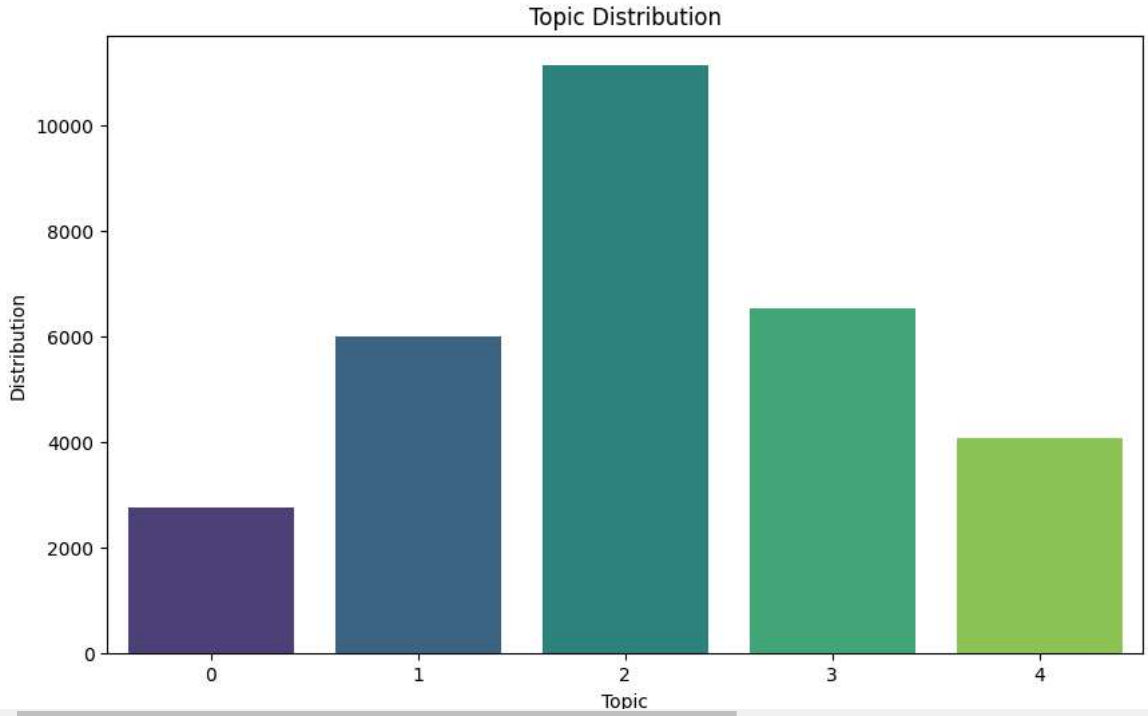
```
iteration: 1 of max_iter: 5
iteration: 2 of max_iter: 5
iteration: 3 of max_iter: 5
iteration: 4 of max_iter: 5
iteration: 5 of max_iter: 5
Topic #0:
to my the good you and is it for im
Topic #1:
the you to my it and is that im thank
Topic #2:
to the it my and is that in have you
Topic #3:
to it the you for my thanks is work me
Topic #4:
the to it you and in of my is for
```

Topic Model

```
from sklearn.decomposition import NMF

X = tweets_df['cleaned_tweet']  # Assuming cleaned tweets

# TF-IDF Vectorization
tfidf = TfidfVectorizer(stop_words='english', max_features=1000)
X_tfidf = tfidf.fit_transform(X)
```

```
# Fit NMF for topic modeling
n_topics = 5  # Set number of topics to identify
nmf = NMF(n_components=n_topics, random_state=42)
nmf.fit(X_tfidf)

# Get top words for each topic
feature_names = tfidf.get_feature_names_out()
n_top_words = 10  # Top 10 words per topic
topics = []

for topic_idx, topic in enumerate(nmf.components_):
    top_words_idx = topic.argsort()[-n_top_words:][::-1]
    top_words = [feature_names[i] for i in top_words_idx]
    topics.append(f"Topic {topic_idx + 1}: " + ", ".join(top_words))

# Print the topics
for topic in topics:
    print(topic)

# Optional: Plot the topic distribution
topic_values = nmf.transform(X_tfidf)
topic_distribution = topic_values.sum(axis=0)

plt.figure(figsize=(10, 6))
sns.barplot(x=range(n_topics), y=topic_distribution.flatten(), palette='viridis')
plt.title("Topic Distribution")
plt.xlabel("Topic")
plt.ylabel("Distribution")
plt.show()
```

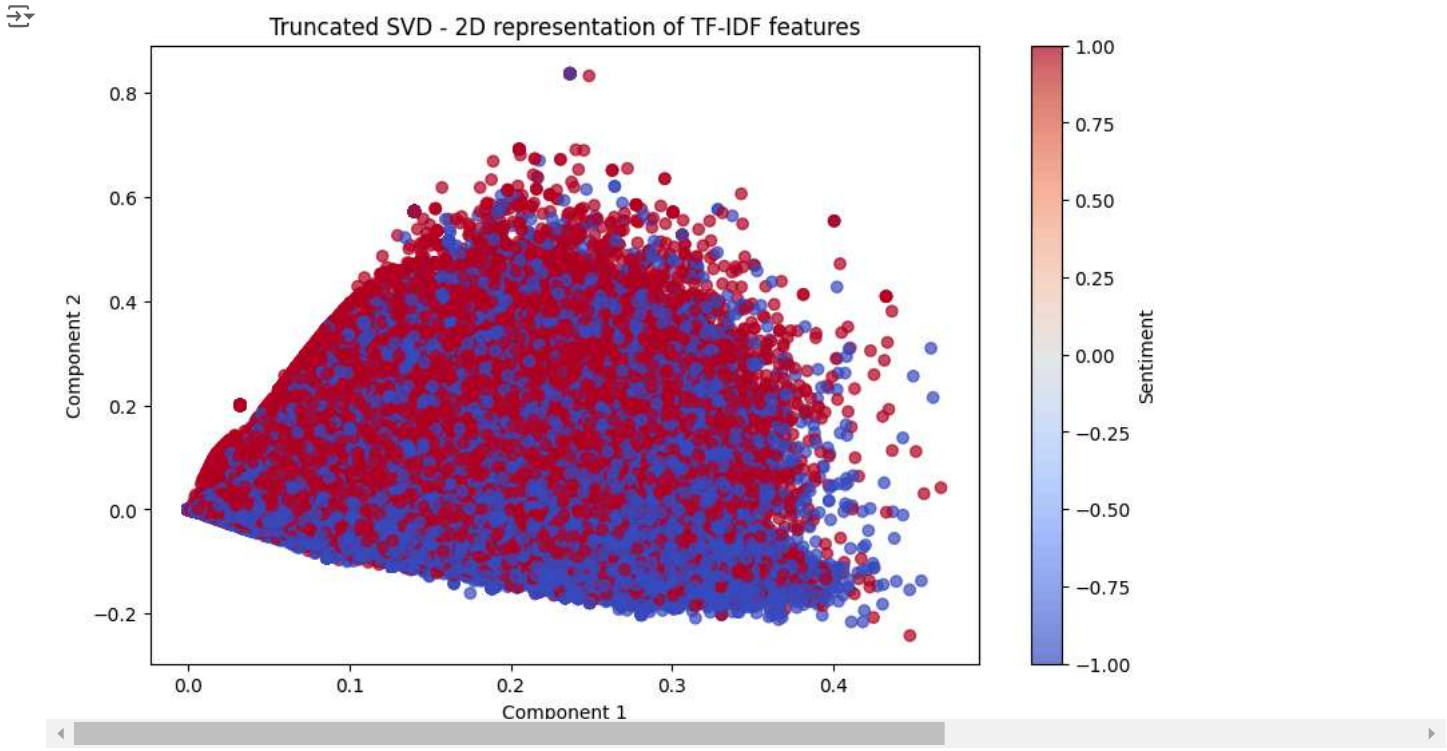
```
Topic 1: good, morning, night, luck, time, hope, feel, sound, thing, sleep
Topic 2: im, going, sorry, gonna, tired, sad, sure, miss, think, right
Topic 3: just, wa, like, dont, got, know, want, lol, time, really
Topic 4: day, work, today, going, tomorrow, happy, great, school, mother, hope
Topic 5: love, thanks, miss, song, new, haha, great, lol, guy, follow
<ipython-input-46-b58772c27762>:33: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legenc

  sns.barplot(x=range(n_topics), y=topic_distribution.flatten(), palette='viridis')
```



Clustering

```
svd = TruncatedSVD(n_components=2, random_state=42)
```

```
# Fit and transform the TF-IDF matrix to reduce dimensions
X_train_svd = svd.fit_transform(X_train_v)

# Optional: Plotting the 2D representation
plt.figure(figsize=(10, 6))
plt.scatter(X_train_svd[:, 0], X_train_svd[:, 1], c=y_train, cmap='coolwarm', alpha=0.7)
plt.title("Truncated SVD - 2D representation of TF-IDF features")
plt.xlabel("Component 1")
plt.ylabel("Component 2")
plt.colorbar(label='Sentiment')
plt.show()
```



GridSearchCV

```
kfold =StratifiedKFold(n_splits=5,shuffle=True,random_state=42)
```

```
model_score = pd.DataFrame(columns=["model_f1_train","params_used", "f1","precision","recall"])

def model_prediction(model, params):
    global X_train, y_train, X_test, y_test

    model = GridSearchCV(model, param_grid= params, cv= kfold, verbose = 2)
    print("\n\nMODEL: ", type(model.estimator).__name__)

    model.fit(X_train, y_train)

    y_pred = model.predict(X_test)

    print ("Model and params: ", model.best_estimator_, model.best_params_)
    print("\n")
    print("Train score: ", model.best_score_)
    print("test score: ",accuracy_score(y_test,y_pred))
    print("\n")
    print("Test Report:")
    print(classification_report(y_test,y_pred))
    return y_pred, model
```

```
def model_scoring(y_pred, model):
    global y_test
    global model_score

    df = pd.DataFrame(data = [[model.best_score_,
                           model.best_params_,
```

```
                        f1_score(y_test,y_pred,average="macro"),
                        precision_score(y_test,y_pred,average="macro"),
                        recall_score(y_test,y_pred,average="macro")
                       ]] ,
                 columns =model_score.columns,
                 index=[str(model.best_estimator_)])
    #model_score = model_score.append ( df )
    model_score = pd.concat([model_score, df])
```

```
#Set Parameters
gen_params = {"alpha":[1,3]}
logr_params = {
    "penalty": ["l2"],
    "C": [5],
    "max_iter": [10000]
}
```

```
#Instantiate
vader = SentimentIntensityAnalyzer()
#textblob does not required instantiation

##Using 2 models due to paucity of time
naivebern_i = BernoulliNB()
logr_i = LogisticRegression(solver="sag")
```

```
naivebern_pred, naivebern_m = model_prediction(naivebern_i, gen_params)
log_pred , logr_m = model_prediction(logr_i,logr_params)
```

```
[CV] END .....................................alpha=1; total time=   0.7s
[CV] END .....................................alpha=3; total time=   0.7s
[CV] END .....................................alpha=3; total time=   0.7s
[CV] END .....................................alpha=3; total time=   0.7s
[CV] END .....................................alpha=3; total time=   0.8s
[CV] END .....................................alpha=3; total time=   1.0s
Model and params:  BernoulliNB(alpha=3) {'alpha': 3}


Train score:  0.779100420323714
test score:  0.7786014261957778


Test Report:
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
              precision    recall  f1-score   support

          -1       0.78      0.78      0.78    158927
           0       0.00      0.00      0.00        29
           1       0.78      0.78      0.78    160355

    accuracy                           0.78    319311
   macro avg       0.52      0.52      0.52    319311
weighted avg       0.78      0.78      0.78    319311



MODEL:  LogisticRegression
Fitting 5 folds for each of 1 candidates, totalling 5 fits
[CV] END ....................C=5, max_iter=10000, penalty=l2; total time= 1.2min
[CV] END ....................C=5, max_iter=10000, penalty=l2; total time= 1.3min
[CV] END ....................C=5, max_iter=10000, penalty=l2; total time= 1.3min
[CV] END ....................C=5, max_iter=10000, penalty=l2; total time= 1.2min
[CV] END ....................C=5, max_iter=10000, penalty=l2; total time= 1.2min
Model and params:  LogisticRegression(C=5, max_iter=10000, solver='sag') {'C': 5, 'max_iter': 10000, 'penalty': 'l2'}


Train score:  0.7923696464433932
```

```
                1       0.79      0.80      0.79    106355

         accuracy                           0.79    319311
        macro avg       0.86      0.55      0.57    319311
     weighted avg       0.79      0.79      0.79    319311
```

```
model_scoring(naivebern_pred, naivebern_m)
model_scoring(log_pred, logr_m)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and be
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
<ipython-input-50-8c64bd3d644d>:14: FutureWarning: The behavior of DataFrame concatenation with empty or all-NA entries is deprecated. I
  model_score = pd.concat([model_score, df])
```

```
model_score
```

	model_f1_train	params_used	f1	precision	recall
BernoulliNB(alpha=3)	0.77910	{'alpha': 3}	0.519086	0.519067	0.519108
LogisticRegression(C=5, max_iter=10000, solver='sag')	0.79237	{'C': 5, 'max_iter': 10000, 'penalty': 'l2'}	0.571216	0.861556	0.551210

Next steps: Generate code with model_score | View recommended plots | New interactive sheet

Vader

```
def out_box_vader(x):
    x = vader.polarity_scores(x)["compound"]
    if x >0:
        x = 1
    elif x<0:
        x = -1
    else:
        x= 0
    return x
```

```
def out_box_score(y_true, prediction, name):
    global model_score
    df = pd.DataFrame(data = [[0,
                               0,
                               f1_score(y_true,prediction,average="macro"),
                               precision_score(y_true,prediction,average="macro"),
                               recall_score(y_true,prediction,average="macro")
                              ]] ,
                      columns=model_score.columns,
                      index=[name])
    model_score = pd.concat([model_score, df])
```

```
%%time
vader_pred = tweets_df["cleaned_tweet"].apply(out_box_vader)
out_box_score(tweets_df["polarity"],vader_pred, "Vader")
```

```
CPU times: user 5min 6s, sys: 844 ms, total: 5min 7s
Wall time: 5min 10s
```

```
model_score
```

	model_f1_train	params_used	f1	precision	recall
BernoulliNB(alpha=3)	0.77910	{'alpha': 3}	0.519086	0.519067	0.519108
LogisticRegression(C=5, max_iter=10000, solver='sag')	0.79237	{'C': 5, 'max_iter': 10000, 'penalty': 'l2'}	0.571216	0.861556	0.551210
Vader	0.00000	0	0.400271	0.483946	0.576141

Next steps: Generate code with model_score | View recommended plots | New interactive sheet

```
model_dict = {
    logr_m : "logr_m",
    naivebern_m:"naivebern_m"
            }
for m in model_dict.items():
    file = open(f'{m[1]}.pickle','wb')
    pickle.dump(m[0], file)
    file.close()
```

```
## save vocabulary
with open("vocabulary","wb") as f:
    pickle.dump(tfidf.vocabulary_,f)
    f.close()
```

Pipeline

```
from sklearn.pipeline import Pipeline

X = tweets_df["cleaned_tweet"]
y = tweets_df["polarity"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

```
pipe = Pipeline(steps = [
    ("tfidf", TfidfVectorizer()),
    ("logr" , GridSearchCV(logr_i, param_grid= logr_params, cv= kfold))
    ]
                )
```

```
pipe.fit(X,y)
```


```
print(classification_report(y_test, pipe.predict(X_test)))
```

```
              precision    recall  f1-score   support

          -1       0.85      0.85      0.85    238858
           0       1.00      0.22      0.36        45
           1       0.85      0.85      0.85    240063

    accuracy                           0.85    478966
   macro avg       0.90      0.64      0.69    478966
weighted avg       0.85      0.85      0.85    478966
```

```
#Save Pipeline
file = open('pipemodel_model.pickle','wb')
pickle.dump(pipe, file)
file.close()
```

Thus, Logistic Regression seems to have slightly better accuracy than Bernoulli Naive Bayes model for the given dataset.

----------END----------