TweetSentimentAnalysis / TweetSentimentAnalysis.ipynb

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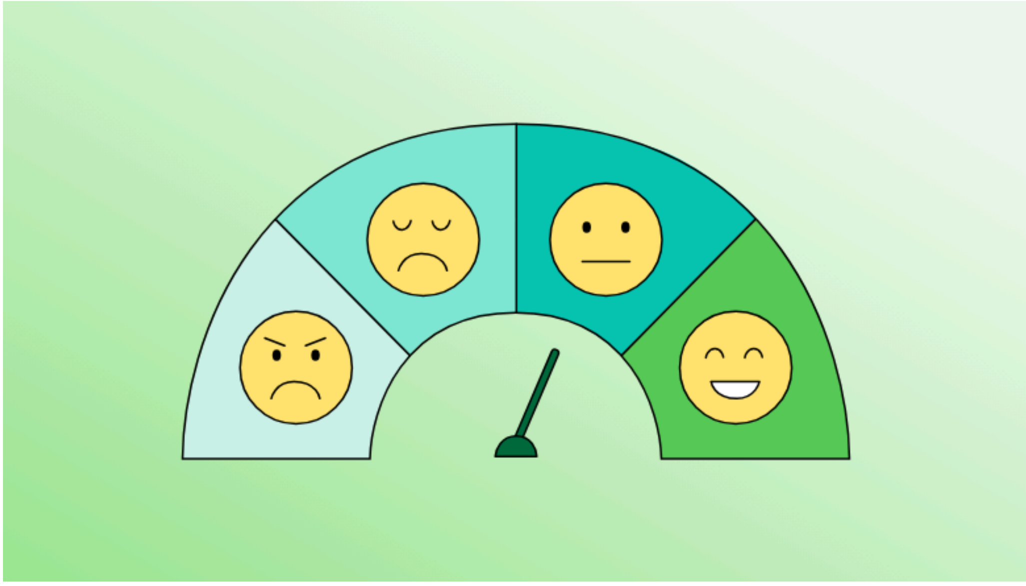
3399 lines (3399 loc) · 619 KB

Tweet Sentiment Analysis Project

by Brian Amani



Overview

Business Problem

Companies rely on social media to understand how customers feel about their brands and products. However, it's not always easy to tell whether a tweet expresses a clear opinion or which brand the sentiment is directed at, especially when multiple brands are mentioned.

This project will develop a sentiment analysis model that can:

- Classify tweets as positive, negative, or neutral.
- Correctly link emotions to the right brand or product.
- Track sentiment trends over time to spot issues or opportunities early.

With better sentiment tracking, businesses can fine-tune their marketing, improve customer engagement, and respond faster to brand perception shifts.

Data Overview

In this project, I will analyze a dataset from CrowdFlower (https://data.world/crowdflower/brands-and-product-emotions/) on the data.world website. The dataset contains over 9000 tweets with sentiments on apple and google products. These sentiments can be classified into positive, neutral and negative sentiments and a quick scan of the data shows they were collected during the SXSW (South by South West) concert seemingly in 2013.

Approach

My Thinking

I decided on an approach that would categorize the data into positive and non positive tweets, which would allow a binary approach further considering that positive sentiments would be the ones to most likely be used to drive sales up, and non positive sentiments be studied to establish where to improve products.

Accuracy:

I also endevoured to achieve as accurate a model as possible as it would allow me to avoid any false positive/negative results that would affect a users ability to utilize the output of the model.

Modelling

I used nltk's TweetTokenizer and RegexpTokenizer to tokenize the tweets. and further used vectorizer and tfidf vectorizer to vectorize them.

Techniques used:

- Naïve Bayes for baseline performance,
- Neural Networks to capture complex patterns in sentiment.

Which allowed me to test simple to complex approaches

Data Understanding

In [108…

```
# importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import nltk
from nltk.tokenize import RegexpTokenizer, TweetTokenizer
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
nltk.download('wordnet')
import re

from sklearn.model_selection import train_test_split, cross_validate
from numpy import array
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectoriz
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import ConfusionMatrixDisplay
from catboost import CatBoostClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_validate
from sklearn.pipeline import Pipeline
from tensorflow import keras
from keras import regularizers, layers
```

```
from keras import regularizers, layers
from tensorflow.keras.preprocessing.sequence import pad_sequences
from keras.models import Sequential
from keras.layers.core import Activation, Dropout, Dense
from keras.layers import Flatten
from tensorflow.keras.layers import Embedding
from keras.preprocessing.text import Tokenizer
```

```
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\Amani\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

In [108…

```
# Loading the dataset
df = pd.read_csv('data/judge-1377884607_tweet_product_company.csv', encodi
df.head()
```

Out[108…

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	iPhone	
1	@jessedee Know about @fludapp ? Awesome iPad/i...	iPad or iPhone App	
2	@swonderlin Can not wait for #iPad 2 also. The...	iPad	
3	@sxsw I hope this year's festival isn't as cra...	iPad or iPhone App	
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	

In [108…

```
print(df.describe)
```

```
<bound method NDFrame.describe of
tweet_text  \
0     .@wesley83 I have a 3G iPhone. After 3 hrs twe...
1     @jessedee Know about @fludapp ? Awesome iPad/i...
2     @swonderlin Can not wait for #iPad 2 also. The...
3     @sxsw I hope this year's festival isn't as cra...
4     @sxtxstate great stuff on Fri #SXSW: Marissa M...
...                                                 ...
9088                      Ipad everywhere. #SXSW {link}
```

```
9089  Wave, buzz... RT @mention We interrupt your re...
9090  Google's Zeiger, a physician never reported po...
9091  Some Verizon iPhone customers complained their...
9092  ŒÏ¡ŽÏàŠü_‹�Ê‹�Î‹�Ò‹�£‹�Á‹ââ‹�_‹�£‹��‹â_‹ÛâRT @...

     emotion_in_tweet_is_directed_at  \
0                               iPhone
1                   iPad or iPhone App
2                                 iPad
3                   iPad or iPhone App
4                               Google
...                                ...
9088                              iPad
9089                               NaN
9090                               NaN
9091                               NaN
9092                               NaN

     is_there_an_emotion_directed_at_a_brand_or_product
0                                      Negative emotion
1                                      Positive emotion
2                                      Positive emotion
3                                      Negative emotion
4                                      Positive emotion
...                                                 ...
9088                                   Positive emotion
9089                 No emotion toward brand or product
9090                 No emotion toward brand or product
9091                 No emotion toward brand or product
9092                 No emotion toward brand or product

[9093 rows x 3 columns]>
```

Data Cleaning

In [108…

```python
# Checking for duplicates
print('Duplicate rows')
print(df.duplicated().sum())
print(("-"*10))
print('Total null values')
print(df.isna().sum())
print(("-"*10))
print(df.info())
```

```
Duplicate rows
22
----------
Total null values
tweet_text                                               1
emotion_in_tweet_is_directed_at                       5802
is_there_an_emotion_directed_at_a_brand_or_product       0
dtype: int64
----------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9093 entries, 0 to 9092
Data columns (total 3 columns):
 #   Column                                              Non-Null Count  Dt
ype
---  ------                                              --------------  --
---
 0   tweet_text                                          9092 non-null   ob
ject
```

```
 1   emotion_in_tweet_is_directed_at                     3291 non-null   ob
ject
 2   is_there_an_emotion_directed_at_a_brand_or_product  9093 non-null   ob
ject
dtypes: object(3)
memory usage: 213.2+ KB
None
```

There are 22 duplicate rows and many null values. These need to be dropped.

In [109…

```
#dropping any NaN in the Tweet column
df['tweet_text'].dropna(inplace=True)
#dropping duplicates
df.drop_duplicates(inplace=True)
print(("-"*10))
print(df.info())
print(("-"*10))
print('Total duplicated rows')
print(df.duplicated().sum())
print(("-"*10))
print('Total null values')
print(df.isna().sum())
```

```
----------
<class 'pandas.core.frame.DataFrame'>
Index: 9071 entries, 0 to 9092
Data columns (total 3 columns):
 #   Column                                              Non-Null Count  Dt
ype
---  ------                                              --------------  --
---
 0   tweet_text                                          9070 non-null   ob
ject
 1   emotion_in_tweet_is_directed_at                     3282 non-null   ob
ject
 2   is_there_an_emotion_directed_at_a_brand_or_product  9071 non-null   ob
ject
dtypes: object(3)
memory usage: 283.5+ KB
None
----------
Total duplicated rows
0
----------
Total null values
tweet_text                                               1
emotion_in_tweet_is_directed_at                       5789
is_there_an_emotion_directed_at_a_brand_or_product       0
dtype: int64
```

In [109…

```
#Rename columns
df = df.rename(columns = {'tweet_text': 'Tweet',
                          'emotion_in_tweet_is_directed_at': 'Product',
                          'is_there_an_emotion_directed_at_a_brand_or_produ
df
```

Out[109…

	Tweet	Product	Sentiment
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	iPhone	Negative emotion

1	@jessedee Know about @fludapp ? Awesome iPad/i...	iPad or iPhone App	Positive emotion
2	@swonderlin Can not wait for #iPad 2 also. The...	iPad	Positive emotion
3	@sxsw I hope this year's festival isn't as cra...	iPad or iPhone App	Negative emotion
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emotion
...	...	...	...
9088	Ipad everywhere. #SXSW {link}	iPad	Positive emotion
9089	Wave, buzz... RT @mention We interrupt your re...	NaN	No emotion toward brand or product
9090	Google's Zeiger, a physician never reported po...	NaN	No emotion toward brand or product
9091	Some Verizon iPhone customers complained their...	NaN	No emotion toward brand or product
9092	ŒÏ¡ŽÏàŠü_‹ÛÊ‹ÛÎ‹ÛÒ‹Û£‹ÛÁ‹ââ‹Û_‹Û£‹ÛÛ‹â_‹ÛâRT @...	NaN	No emotion toward brand or product

9071 rows × 3 columns

In [109…

```python
def is_mostly_symbols(text, threshold=0.7):
    """Returns True if more than `threshold` fraction of characters are sp
    if not isinstance(text, str) or not text.strip():
        return True  # Remove empty or non-string values

    special_chars = sum(1 for char in text if not char.isalnum() and char
    return (special_chars / len(text)) > threshold  # Remove if too many s

# Keep only rows that are NOT mostly symbols
df = df[~df["Tweet"].apply(is_mostly_symbols)]

# Print first few rows to verify
df
```

Out[109…

	Tweet	Product	Sentiment
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	iPhone	Negative emotion
1	@jessedee Know about @fludapp ? Awesome iPad/i...	iPad or iPhone App	Positive emotion

	Tweet	Product	Sentiment
2	@swonderlin Can not wait for #iPad 2 also. The...	iPad	Positive emotion
3	@sxsw I hope this year's festival isn't as cra...	iPad or iPhone App	Negative emotion
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emotion
...	...	...	...
9088	Ipad everywhere. #SXSW {link}	iPad	Positive emotion
9089	Wave, buzz... RT @mention We interrupt your re...	NaN	No emotion toward brand or product
9090	Google's Zeiger, a physician never reported po...	NaN	No emotion toward brand or product
9091	Some Verizon iPhone customers complained their...	NaN	No emotion toward brand or product
9092	ŒÏ¡ŽÏàŠü_‹ÛÊ‹ÛÎ‹ÛÒ‹Û£‹ÛÁ‹ââ‹Û_‹Û£‹ÛÛ‹â_‹ÛâRT @...	NaN	No emotion toward brand or product

9070 rows × 3 columns

In [109…

```
df = df[df["Tweet"].apply(lambda x: x.encode('utf-8').decode('utf-8', 'igr
df
```

Out[109…

	Tweet	Product	Sentiment
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	iPhone	Negative emotion
1	@jessedee Know about @fludapp ? Awesome iPad/i...	iPad or iPhone App	Positive emotion
2	@swonderlin Can not wait for #iPad 2 also. The...	iPad	Positive emotion
3	@sxsw I hope this year's festival isn't as cra...	iPad or iPhone App	Negative emotion
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emotion
...	...	...	...
9088	Ipad everywhere. #SXSW {link}	iPad	Positive emotion
9089	Wave, buzz... RT @mention We interrupt your re...	NaN	No emotion toward brand

			or product
9090	Google's Zeiger, a physician never reported po...	NaN	No emotion toward brand or product
9091	Some Verizon iPhone customers complained their...	NaN	No emotion toward brand or product
9092	ŒÏ¡ŽÏàŠü_‹□Ê‹□Î‹□Ò‹□£‹□Á‹ââ‹□_‹□£‹□□‹â_‹ÛâRT @...	NaN	No emotion toward brand or product

9070 rows × 3 columns

In [109…

```
#drops Tweets with nonsensical characters
df.drop([1, 9092], inplace=True)
#Reset index
df.reset_index(inplace=True)
df.drop(columns="index", inplace = True)
df
```

Out[109…

	Tweet	Product	Sentiment
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	iPhone	Negative emotion
1	@swonderlin Can not wait for #iPad 2 also. The...	iPad	Positive emotion
2	@sxsw I hope this year's festival isn't as cra...	iPad or iPhone App	Negative emotion
3	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emotion
4	@teachntech00 New iPad Apps For #SpeechTherapy...	NaN	No emotion toward brand or product
...	...	...	...
9063	@mention Yup, but I don't have a third app yet...	NaN	No emotion toward brand or product
9064	Ipad everywhere. #SXSW {link}	iPad	Positive emotion
9065	Wave, buzz... RT @mention We interrupt your re...	NaN	No emotion toward brand or product
9066	Google's Zeiger, a physician never reported po...	NaN	No emotion toward brand or product
9067	Some Verizon iPhone customers complained their...	NaN	No emotion toward brand or product

9068 rows × 3 columns

There are still NaN values in "Product". I will fill those with "Unspecified" to make visualization easier

In [109…

```
#Filling NaN in "Product" with "Unspecified"
df['Product'].fillna("Unspecified", inplace = True)
df
```

```
C:\Users\Amani\AppData\Local\Temp\ipykernel_15644\1443895236.py:2: FutureWa
rning: A value is trying to be set on a copy of a DataFrame or Series throu
gh chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behav
es as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'd
f.method({col: value}, inplace=True)' or df[col] = df[col].method(value) in
stead, to perform the operation inplace on the original object.


  df['Product'].fillna("Unspecified", inplace = True)
```

Out[109…

	Tweet	Product	Sentiment
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	iPhone	Negative emotion
1	@swonderlin Can not wait for #iPad 2 also. The...	iPad	Positive emotion
2	@sxsw I hope this year's festival isn't as cra...	iPad or iPhone App	Negative emotion
3	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emotion
4	@teachntech00 New iPad Apps For #SpeechTherapy...	Unspecified	No emotion toward brand or product
...	...	...	...
9063	@mention Yup, but I don't have a third app yet...	Unspecified	No emotion toward brand or product
9064	Ipad everywhere. #SXSW {link}	iPad	Positive emotion
9065	Wave, buzz... RT @mention We interrupt your re...	Unspecified	No emotion toward brand or product
9066	Google's Zeiger, a physician never reported po...	Unspecified	No emotion toward brand or product
9067	Some Verizon iPhone customers complained their...	Unspecified	No emotion toward brand or product

9068 rows × 3 columns

In [109…

```
df["Product"].value_counts()
```

Out[109…

```
Product
Unspecified                        5787
iPad                                945
Apple                               659
iPad or iPhone App                  468
Google                              428
iPhone                              296
Other Google product or service     293
```

```
Android App                       80
Android                           77
Other Apple product or service    35
Name: count, dtype: int64
```

There are too many rows in which the product is not specified. I will attempt to scrape the data set and determine the product and then introduce a new classification called Brand.

In [109…

```
def find_brand(Product, Tweet):
    # Checking "Unspecified" column to identify brand
    brand = 'Unspecified'
    if ((Product.lower().__contains__('google')) or (Product.lower().__cor
        brand = 'Google'
    elif ((Product.lower().__contains__('apple')) or (Product.lower().__cc
        brand = 'Apple'

    if (brand == 'Unspecified'):
        lower_tweet = Tweet.lower()
        is_google = (lower_tweet.__contains__('google')) or (lower_tweet._
        is_apple = (lower_tweet.__contains__('apple')) or (lower_tweet.__c

        # Labelling the brands
        if (is_google and is_apple):
            brand = 'Both mentioned'
        elif (is_google):
            brand = 'Google'
        elif (is_apple):
            brand = 'Apple'

    return brand

df['Brand'] = df.apply(lambda x: find_brand(x['Product'], x['Tweet']), axi
df['Brand'].value_counts()
```

Out[109…

```
Brand
Apple             5360
Google            2756
Unspecified        739
Both mentioned     213
Name: count, dtype: int64
```

The data is now more presentable and can be used to train our model. Before we move to preprocessing for modelling, let us visualize the data and gather any insights we need

Data Visualization

In [109…

```
def countplot(df, col, hue=None, rotation=None):

    fig, ax = plt.subplots(figsize=(12,8))
    sns.countplot(data = df, x = col, hue = hue, order = df[col].value_cou
    ax.set_xticklabels(labels = ax.get_xticklabels(), rotation= rotation,
    ax.set_xlabel(xlabel = col, fontsize = 20)
    ax.tick_params(axis='y', which='major', labelsize=15)
    ax.set_ylabel(ylabel = "Number of Tweets", fontsize = 20)
    ax.set_title(f"Number of Tweets per {col}", fontsize = 30)
    plt.show()
```

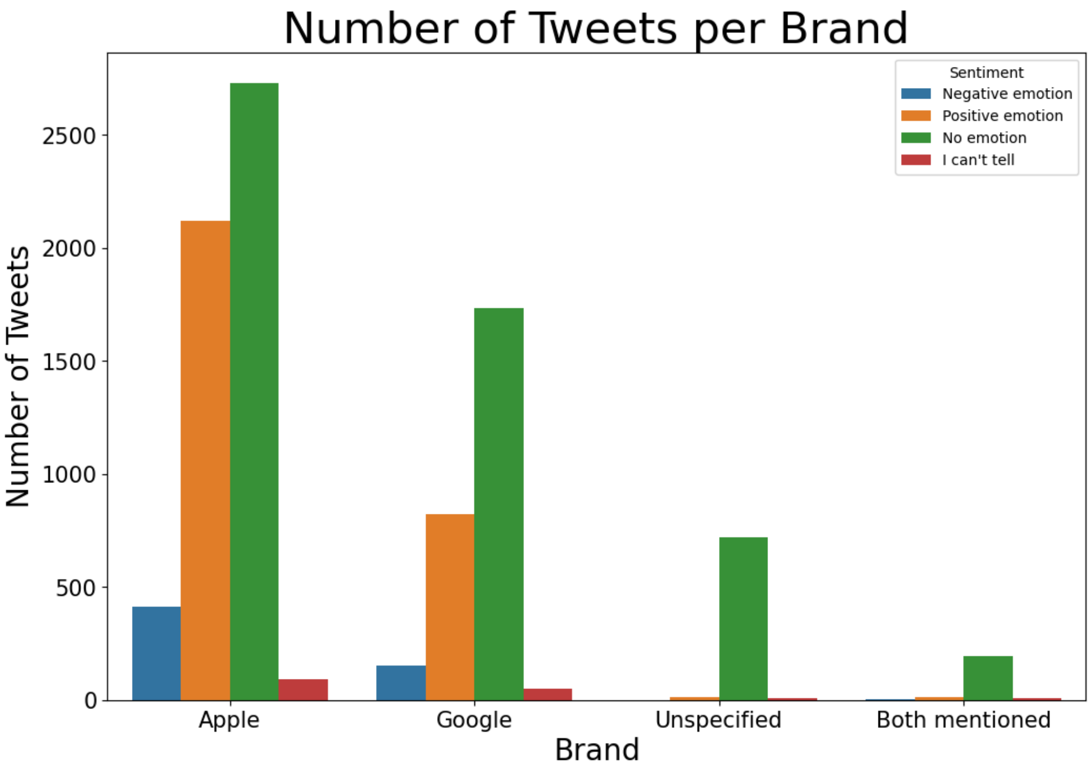
In [109…

```
# Rephrase "No emotion towards brand or product" to "No emotion"
df["Sentiment"] = df["Sentiment"].replace("No emotion toward brand or proc
```

In [110…

```
countplot(df, "Brand", hue = "Sentiment")
# Display this information quantitatively in a table
grouped = df.groupby(["Brand", "Sentiment"]).count()
print(grouped)
```

```
C:\Users\Amani\AppData\Local\Temp\ipykernel_15644\4197030935.py:5: UserWarn
ing: set_ticklabels() should only be used with a fixed number of ticks, i.
e. after set_ticks() or using a FixedLocator.
  ax.set_xticklabels(labels = ax.get_xticklabels(), rotation= rotation, fon
tsize = 15)
```



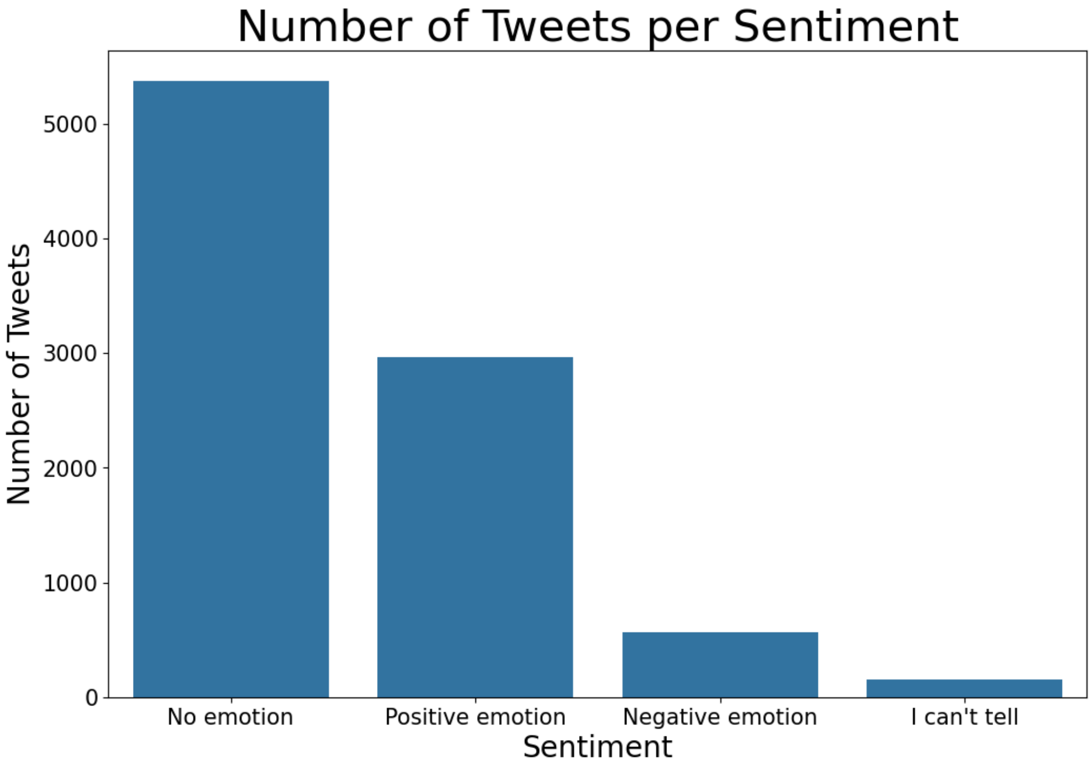

```
                                 Tweet  Product
Brand          Sentiment
Apple          I can't tell         93       93
               Negative emotion    415      415
               No emotion         2730     2730
               Positive emotion   2122     2122
Both mentioned I can't tell          7        7
               Negative emotion      3        3
               No emotion          192      192
               Positive emotion     11       11
Google         I can't tell         50       50
               Negative emotion    150      150
               No emotion         1733     1733
               Positive emotion    823      823
Unspecified    I can't tell          6        6
               Negative emotion      1        1
               No emotion          719      719
               Positive emotion     13       13
```

In [110…

```
countplot(df, "Sentiment")
```

```
countplot(df, 'Sentiment')
print(df['Sentiment'].value_counts())
```

```
C:\Users\Amani\AppData\Local\Temp\ipykernel_15644\4197030935.py:5: UserWarn
ing: set_ticklabels() should only be used with a fixed number of ticks, i.
e. after set_ticks() or using a FixedLocator.
  ax.set_xticklabels(labels = ax.get_xticklabels(), rotation= rotation, fon
tsize = 15)
```




```
Sentiment
No emotion          5374
Positive emotion    2969
Negative emotion     569
I can't tell         156
Name: count, dtype: int64
```

There are no major comments on the data. I moved to preprocessing for modelling.

- Training data will be the tweet
- Target data will be the sentiments

Based on the data as seen above, it is now important to have binary target data, in this case the sentiments. This will enable us to train our model effectively

Data Preprocessing

To make our target Binary we need two categories:

- Not positive: No emotion, negative emotion & I can't tell
- Positive: Positive emotion

In [110…

```
df['Sentiment'] = df['Sentiment'].map({'No emotion':0,
             'Positive emotion':1,
             'Negative emotion':0,
             "I can't tell": 0})
```

```
df
```

Out[110…

	Tweet	Product	Sentiment	Brand
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	iPhone	0	Apple
1	@swonderlin Can not wait for #iPad 2 also. The...	iPad	1	Apple
2	@sxsw I hope this year's festival isn't as cra...	iPad or iPhone App	0	Apple
3	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	1	Google
4	@teachntech00 New iPad Apps For #SpeechTherapy...	Unspecified	0	Apple
...	...	...	...	...
9063	@mention Yup, but I don't have a third app yet...	Unspecified	0	Google
9064	Ipad everywhere. #SXSW {link}	iPad	1	Apple
9065	Wave, buzz... RT @mention We interrupt your re...	Unspecified	0	Google
9066	Google's Zeiger, a physician never reported po...	Unspecified	0	Google
9067	Some Verizon iPhone customers complained their...	Unspecified	0	Apple

9068 rows × 4 columns

In [110…

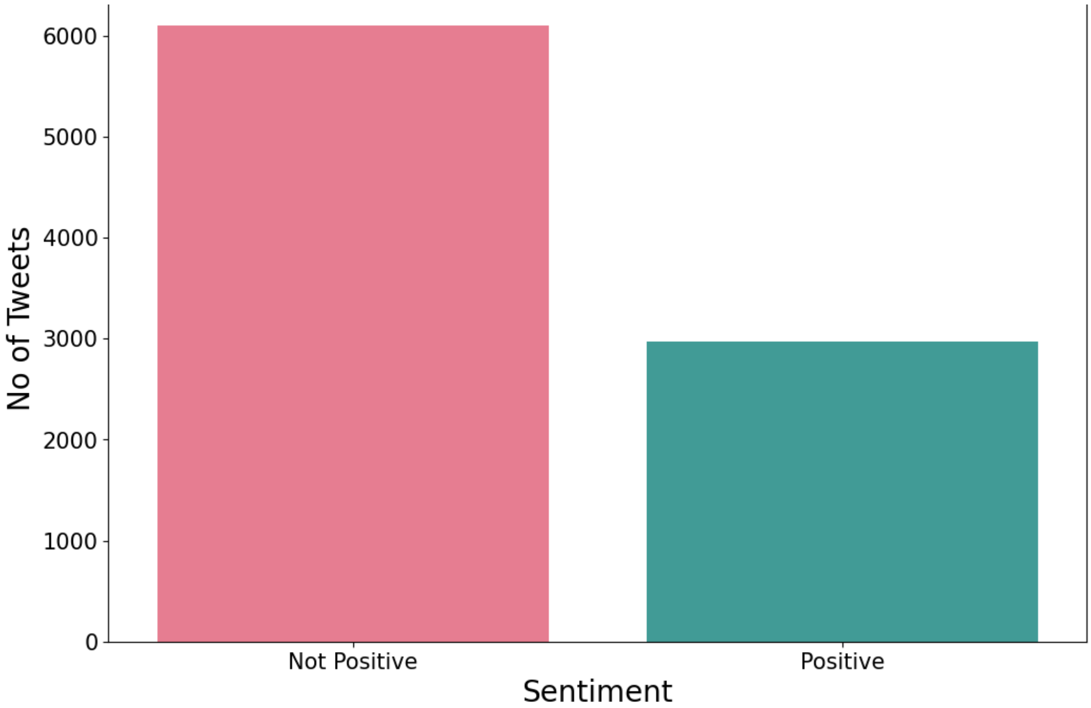
```
fig, ax = plt.subplots(figsize=(12,8))
sns.countplot(data = df, x = "Sentiment", order = df["Sentiment"].value_co
ax.set_xticklabels(labels = ["Not Positive", "Positive"], fontsize = 15)
ax.set_xlabel(xlabel = "Sentiment", fontsize = 20)
ax.tick_params(axis='y', which='major', labelsize=15)
ax.set_ylabel(ylabel = "No of Tweets", fontsize = 20)
ax.set_title(f"Tweets per Sentiment", fontsize = 30)
plt.show()
```

```
C:\Users\Amani\AppData\Local\Temp\ipykernel_15644\405641662.py:2: FutureWar
ning:

Passing `palette` without assigning `hue` is deprecated and will be removed
in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the
same effect.

  sns.countplot(data = df, x = "Sentiment", order = df["Sentiment"].value_c
ounts().index , palette="husl")
C:\Users\Amani\AppData\Local\Temp\ipykernel_15644\405641662.py:3: UserWarni
ng: set_ticklabels() should only be used with a fixed number of ticks, i.e.
after set_ticks() or using a FixedLocator.
  ax.set_xticklabels(labels = ["Not Positive", "Positive"], fontsize = 15)
```

Tweets per Sentiment



Before we can do a test-train split, let us clean our tweets. We will remove:

- stop words
- short words, punctuations and signs
- placeholders such as "link" and "video"
- websites
- special characters

In [110…

```
#Instantiate necessary tools
tokenizer = RegexpTokenizer(r"(?u)\w{3,}")
stopwords_list = stopwords.words("english")
stopwords_list.append("sxsw")
stopwords_list.append("link")
lemma = WordNetLemmatizer()
tweet_tknzr = TweetTokenizer(strip_handles=True)
```

In [110…

```
def cleaned_tweets(text):

    #Remove handles from tweets
    no_handle = tweet_tknzr.tokenize(text)
    tweet = " ".join(no_handle)
    #removing any punctuations, signs, placeholders, websites and special
    clean = re.sub("(https?:\/\/\S+) \
                   |(#[A-Za-z0-9_]+) \
                   |(\{([a-zA-Z].+)\}) \
                   |(&[a-z]+;) \
                   |(www\.[a-z]?\.?(com)+|[a-z]+\.(com))\
                   |({link})\
                   |(\[video\])\
                   |([^\x00-\x7F]+\ *(?:[^\x00-\x7F]| )*)"," ", tweet)
    #making lowercase
    lower = clean.lower()
    #Removing short words (less than 3 characters)
    token_list = tokenizer.tokenize(lower)
    # Removing stop words
    stopwords_removed=[token for token in token_list if token not in stopw
    #Lemmatizing remaining tokens
```

```
    lemma_list = [lemma.lemmatize(token) for token in stopwords_removed]

    cleaned_text = " ".join(lemma_list)
    return cleaned_text
```

Test-Train split

In [110…

```
# Tweets as input variables
X = df[['Tweet']]
# Sentiments as target
y = df['Sentiment']
#First train test split
X_tr, X_test, y_tr, y_test = train_test_split(X, y, test_size=0.10, random

#Second train test split
X_train, X_val, y_train, y_val = train_test_split(X_tr, y_tr, test_size=0.
X_train
```

Out[110…

	Tweet
4878	Really? So, no Google Me or Circles for now? R...
1605	Nice! RT @mention knitted staircase in attenda...
732	Posterous Joins The SXSW Pile On With Posterou...
4073	Hope people ask the tough questions. RT @menti...
2119	NYT, WSJ at #SXSW ask: Is there a future for b...
...	...
499	Is he the first person in the queue at the new...
7826	Qrafter is better than all paid or free QR Cod...
8834	@mention Was just chatting with someone about ...
2745	The iPhone version of Flipboard is being total...
2730	Front Gate Tickets Present The Morning After P...

6120 rows × 1 columns

In [110…

```
#Checking
cleaned_tweets(X_train['Tweet'].iloc[5622])
```

Out[110…

```
'actually giving away free taplynx iphone ipad app licence away bit pushsx
sw11 check'
```

In [110…

```
#Applying across our training data
X_train['Tweet'] = X_train['Tweet'].apply(lambda x: cleaned_tweets(x))
X_val['Tweet'] = X_val['Tweet'].apply(lambda x: cleaned_tweets(x))
print(X_train)
print("__________________")
print(X_val)
print("__________________")
print(y_train)
```

```
print("_________________")
print(y_val)
```

```
                                                  Tweet
4878  really google circle launching product plenty ...
1605  nice knitted staircase attendance party tomo 7...
732   posterous join pile posterous event iphone tec...
4073  hope people ask tough question reminder androi...
2119   nyt wsj ask future branded native news apps ipad
...                                                 ...
499       first person queue new apple store austin may
7826  qrafter better paid free code apps scan vcards...
8834  chatting someone proliferation ipad like ipad ...
2745  iphone version flipboard totally redesigned pl...
2730  front gate ticket present morning party http s...

[6120 rows x 1 columns]
_________________
                                                  Tweet
2437  google bing page rank panel ridiculously crowd...
8170  xcitng approaching soft launch plan android de...
8914  join lenewz free donut massage trade show boot...
8726  twitter buzz apple store temporary apple store...
7491  playing people people google party depeche mod...
...                                                 ...
5041   competing circle socialflow board resonant topic
4026   contextual discovery find answer question google
1581  finishing beta android iphone sunday couple gu...
6924  win ipad come meet aquent talent agent drop na...
1714                                          ipad rock

[2041 rows x 1 columns]
_________________
4878    0
1605    0
732     0
4073    0
2119    0
       ..
499     0
7826    1
8834    0
2745    0
2730    0
Name: Sentiment, Length: 6120, dtype: int64
_________________
2437    0
8170    0
8914    0
8726    0
7491    1
       ..
5041    0
4026    0
1581    0
6924    1
1714    1
Name: Sentiment, Length: 2041, dtype: int64
```

Data Modelling

Starting off with Naive Bayes

In [110…

```
#Creating a pipeline
pipe_naive = Pipeline(steps=[
    ('tfidf_vectorizer', TfidfVectorizer()),
    ('naive', MultinomialNB())
])
# Doing cross validation
crossval_naive = cross_validate(pipe_naive, X_train['Tweet'], y_train, ret
                        scoring=['accuracy', 'recall','roc_auc'])

print(crossval_naive)
print ("_______")

# Mean train accuracy
print("Mean train accuracy:", crossval_naive['train_accuracy'].mean())

# Mean test accuracy
print("Mean test accuracy:", crossval_naive['test_accuracy'].mean())
```

```
{'fit_time': array([0.13421106, 0.12179327, 0.11407495, 0.12049937, 0.12383
795]), 'score_time': array([0.07100677, 0.07505441, 0.06395674, 0.07056546,
0.06621814]), 'test_accuracy': array([0.70506536, 0.69771242, 0.71732026,
0.70669935, 0.70669935]), 'train_accuracy': array([0.79677288, 0.79575163,
0.79616013, 0.78982843, 0.79207516]), 'test_recall': array([0.13994911, 0.1
3231552, 0.18020305, 0.14213198, 0.14467005]), 'train_recall': array([0.384
7619 , 0.37650794, 0.38055909, 0.36658196, 0.3678526 ]), 'test_roc_auc': ar
ray([0.6978272 , 0.69006194, 0.70762797, 0.7128249 , 0.73314476]), 'train_r
oc_auc': array([0.89497847, 0.8977838 , 0.89386828, 0.89115113, 0.8911156
6])}
_______
Mean train accuracy: 0.7941176470588235
Mean test accuracy: 0.7066993464052288
```

The mean train accuracy is approx 79.41% while the mean train accuracy is approx 70.66%. This suggests overfitting since the model is performing better on the training than the testing

In [111…

```
# fitting training data to simple naive bayes
pipe_naive.fit(X_train["Tweet"], y_train)
```

Out[111…

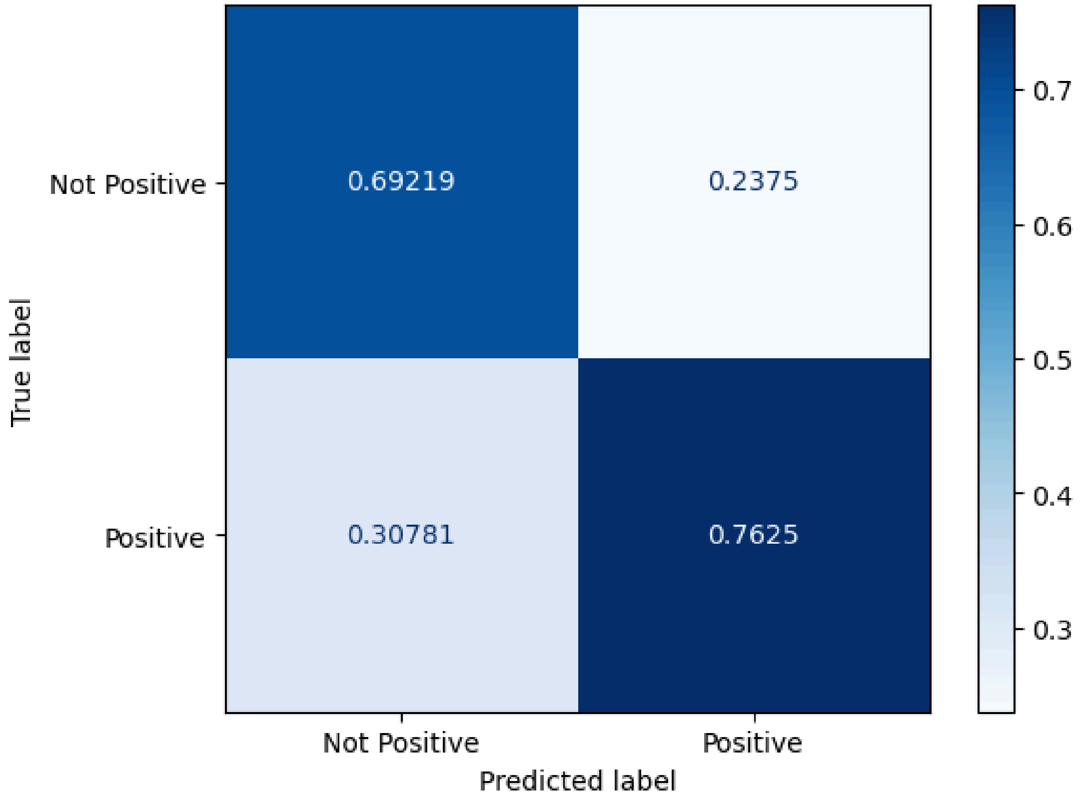
```
Pipeline(steps=[('tfidf_vectorizer', TfidfVectorizer()),
                ('naive', MultinomialNB())])
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [111…

```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
# plot confusion matrix
ConfusionMatrixDisplay.from_estimator(
    pipe_naive,
    X_val["Tweet"],
    y_val,
    display_labels=["Not Positive", "Positive"],
    cmap=plt.cm.Blues,
    values_format='.5g',
    normalize="pred"
)
```

```
)
plt.show()
```



Lets compare the accuracy of the model on the training and validation data set

In [111…

```
print('Training set accuracy:', pipe_naive.score(X_train['Tweet'], y_trair
print('Validation set accuracy:', pipe_naive.score(X_val['Tweet'], y_val))
```

```
Training set accuracy: 0.7928104575163398
Validation set accuracy: 0.6976972072513474
```

The training accuracy is higher than the validation accuracy suggesting overfitting.

Let us attempt hyperparameter tuning

In [111…

```
#Creating a pipeline with hyperparameter tuning
pipe_naive_tuned = Pipeline(steps=[
    ('tfidf_vectorizer_tuned', TfidfVectorizer(max_df=.99,min_df=0.005, ma
    ('naive_tuned', MultinomialNB(alpha=.1))
])
#Crossvalidation
crv_naive_tuned = cross_validate(pipe_naive_tuned, X_train['Tweet'], y_tra
                    scoring=['accuracy', 'recall','roc_auc'])

crv_naive_tuned
```

Out[111…

```
{'fit_time': array([0.19041491, 0.12466812, 0.13954592, 0.11134005, 0.1100
3804]),
 'score_time': array([0.0781343 , 0.07162333, 0.08534169, 0.05877233, 0.06
122136]),
 'test_accuracy': array([0.69607843, 0.69117647, 0.72058824, 0.7124183 ,
0.70506536]),
 'train_accuracy': array([0.72344771, 0.72589869, 0.72385621, 0.7183415 ,
```

```
0.72487745]),
 'test_recall': array([0.18829517, 0.18320611, 0.23604061, 0.1928934 , 0.1
9543147]),
 'train_recall': array([0.23809524, 0.24888889, 0.22808132, 0.23697586, 0.
23506989]),
 'test_roc_auc': array([0.66966744, 0.66884682, 0.69409822, 0.68786007, 0.
6763623 ]),
 'train_roc_auc': array([0.73708866, 0.74006863, 0.73549216, 0.73307345,
0.73968708])}
```

In [111…

```
# Mean train accuracy
print("Mean train accuracy:", crv_naive_tuned['train_accuracy'].mean())

# Mean test accuracy
print("Mean test accuracy:", crv_naive_tuned['test_accuracy'].mean())
```

```
Mean train accuracy: 0.7232843137254902
Mean test accuracy: 0.7050653594771242
```

The disparity in model accuracy is much smaller between train and test data. I shall attempt to fit on all training data

In [111…

```
#fitting tuned model on all training data
pipe_naive_tuned.fit(X_train["Tweet"], y_train)
```

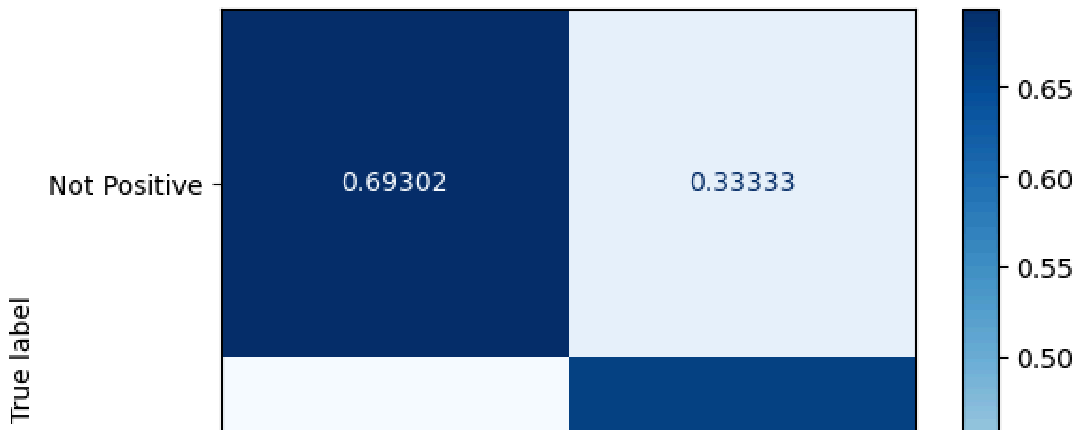
Out[111…

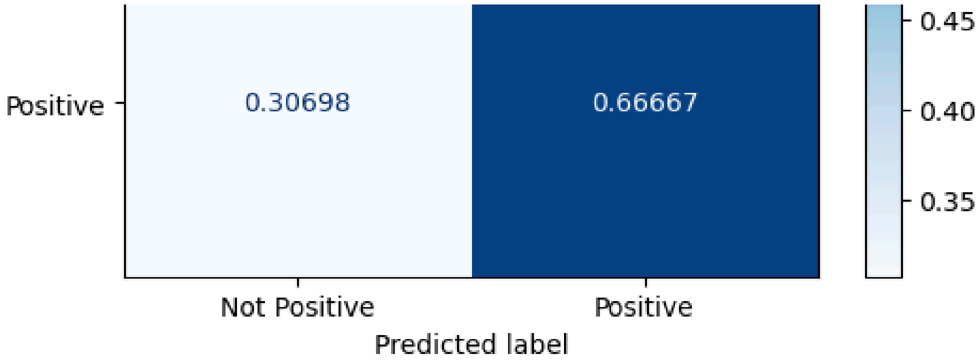
```
Pipeline(steps=[('tfidf_vectorizer_tuned',
                 TfidfVectorizer(max_df=0.99, max_features=900, min
_df=0.005)),
                ('naive_tuned', MultinomialNB(alpha=0.1))])
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [111…

```
# plot confusion matrix
ConfusionMatrixDisplay.from_estimator(
    pipe_naive_tuned,
    X_val["Tweet"],
    y_val,
    display_labels=["Not Positive", "Positive"],
    cmap=plt.cm.Blues,
    values_format='.5g',
    normalize="pred"
)
plt.show()
```





In [111…

```
print('Training set accuracy:', pipe_naive_tuned.score(X_train['Tweet'], y
print('Validation set accuracy:', pipe_naive_tuned.score(X_val['Tweet'], y
```

```
Training set accuracy: 0.7197712418300654
Validation set accuracy: 0.6903478686918177
```

The accuracy of the model is much better with training and validation data set accuracy having a very small margin of difference. Let us attempt using another method to see which is better. This time we will use neural network with regularization, and compare with naive bayes

Neural Network with Regularization

In [111…

```
# Setting the data as a series object so it runs on a neural network
X_train = X_train["Tweet"]
X_val = X_val["Tweet"]

print(type(X_train))
print(type(X_val))
```

```
<class 'pandas.core.series.Series'>
<class 'pandas.core.series.Series'>
```

In [111…

```
# Instatiating the Tokenizer
k_tokenizer = keras.preprocessing.text.Tokenizer()

#fitting tokenizer on training data
k_tokenizer.fit_on_texts(X_train)

#tokenizing text
X_train_token = k_tokenizer.texts_to_sequences(X_train)
X_val_token = k_tokenizer.texts_to_sequences(X_val)
```

In [112…

```
# Padding tweets to reach max length
max_length = max([len(tweet.split()) for tweet in X_train])

X_train_processed = keras.preprocessing.sequence.pad_sequences(
    X_train_token, maxlen=max_length, padding='post')
X_val_processed = keras.preprocessing.sequence.pad_sequences(
    X_val_token, maxlen=max_length, padding='post')
```

I created an embedding matrix from pre-trained GloVe embeddings for words in my vocabulary, using pretrained twitter words from "https://github.com/stanfordnlp/GloVe/blob/master/README.md#download-pre-trained-word-vectors"

In [112…

```
def create_embedding_matrix(glove_filepath, word_index, embedding_dim):
    vocab_size = len(word_index) + 1
    embedding_matrix = np.zeros((vocab_size, embedding_dim))

    with open(glove_filepath, encoding="utf8") as f:
        for line in f:
            word, *vector = line.split()
            if word in word_index:
                idx = word_index[word]
                embedding_matrix[idx] = np.array(
                    vector, dtype=np.float32)[:embedding_dim]

    return embedding_matrix
```

In [112…

```
#sets the embedding dimensions
embedding_dim = 100
embedding_matrix = create_embedding_matrix("C:\Moringa\Phase 4\Project\glo
                                           k_tokenizer.word_index,
                                           embedding_dim)
```

Now that I have an embedding matrix, I proceeded to define a neural network model to analyse the data set

In [112…

```
#Set vocabulary size
vocab_size = len(k_tokenizer.word_index) + 1
# Instantiate neural network
model = keras.models.Sequential()
# Embedding layer
model.add(layers.Embedding(vocab_size, embedding_dim,
                           weights=[embedding_matrix],
                           input_length=max_length,
                           trainable=True))
# Flattening layer
model.add(layers.Flatten())
# Dropout layer - Regularizing model by setting 50% of input to 0
model.add(Dropout(0.5))
# hidden layer
model.add(layers.Dense(350, activation='sigmoid',
                       kernel_regularizer=regularizers.l2(l2=1e-3),
                       bias_regularizer=regularizers.l2(1e-3),
                      activity_regularizer=regularizers.l2(1e-3)))
# Drop out half of hidden layer
model.add(Dropout(0.5))
# Add second dense layer
model.add(layers.Dense(350, activation='sigmoid',
                       kernel_regularizer=regularizers.l2(l2=1e-3),
                       bias_regularizer=regularizers.l2(1e-3),
                      activity_regularizer=regularizers.l2(1e-3)))
# Output layer
model.add(layers.Dense(1, activation='sigmoid'))
# Compiling model
model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

```
model.summary()
```

```
Model: "sequential_20"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_18 (Embedding)    (None, 18, 100)           709600

 flatten_18 (Flatten)        (None, 1800)              0

 dropout_36 (Dropout)        (None, 1800)              0

 dense_54 (Dense)            (None, 350)               630350

 dropout_37 (Dropout)        (None, 350)               0

 dense_55 (Dense)            (None, 350)               122850

 dense_56 (Dense)            (None, 1)                 351

=================================================================
Total params: 1,463,151
Trainable params: 1,463,151
Non-trainable params: 0
_________________________________________________________________
```

I can now fit the model to all training data. I will also include an early stopping callback so I dont overtrain the model.

In [112…

```
from keras.callbacks import EarlyStopping

# Instantiating early stopping callback
early_stopping = EarlyStopping(monitor='val_accuracy',
                               patience=3,  # Number of epochs to wait for
                               restore_best_weights=True,  # Restore model
                               verbose=1)

# Fitting the model
history = model.fit(X_train_processed, y_train,
                    batch_size=50,
                    epochs=5,
                    validation_data=(X_val_processed, y_val))
```

```
Epoch 1/5
123/123 [==============================] - 5s 26ms/step - loss: 1.1567 - ac
```