adammarianacci Updated Deliverables 81eff20 · 4 minutes ago History

1479 lines (1479 loc) · 111 KB

Twitter_Analysis / **notebook.ipynb**

Top

Preview Code Blame Raw

Introduction

Final Project Submission

- Student Name: Adam Marianacci
- Student Pace: Flex
- Scheduled project review date/time: 2/20/2024/1:00pm EST
- Instructor Name: Mark Barbour

Business Understanding

It is my job to help SXSW detect positive sentiment from tweets about their event so that they can continue to give people what they want and make improvements for future conferences.

Data Understanding

This dataset comes from 'CrowdFlower' via data.world. The initial dataframe contained roughly 9,000 tweets and information about the sentiment of the tweet as well as what brand or product the tweet was directed at. Some limitations of the dataset included missing values as well as a class imbalance in the sentiment of the tweets. Over 50% of the tweets showed no emotion, about 33% showed a positive emotion, and only around 6% showed a negative emotion. Due to this imbalance I combined some of the 'no emotion' tweets with the 'negative emotion' tweets to create a 'Not Positive' class to match the 'Positive' class. There was a lot of missing data from the emotion about the brands so I was unable to conduct analysis in this area. The dataset was also fairly small for predictive modeling. This dataset was suitable for the project because it allowed me to build a sentiment detection model from the text in the tweets against the target 'sentiment' of what tweets were considered positive and which were not.

Dataset: Brands and Product Emotions

Data Preperation

In [1]:

```
# Importing the necessary libraries

%load_ext autoreload
%autoreload 2

import os
import sys
module_path = os.path.abspath(os.path.join(os.pardir, os.pardir))
if module_path not in sys.path:
    sys.path.append(module_path)

import pandas as pd
import numpy as np
import nltk
from nltk.probability import FreqDist
from nltk.corpus import stopwords, wordnet
from nltk.tokenize import regexp_tokenize, word_tokenize, RegexpTokenizer
from nltk import pos_tag
from nltk.stem import WordNetLemmatizer
from nltk.corpus import stopwords
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.manifold import TSNE
from sklearn.metrics import accuracy_score, precision_score, confusion_matrix
from sklearn.model_selection import train_test_split
from collections import defaultdict
from collections import Counter
from sklearn.model_selection import GridSearchCV
import matplotlib.pyplot as plt
import seaborn as sns
import string
import re
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```python
# Loading the data, and looking at the shape of the df

corpus = pd.read_csv('data/twitter_sentiment.csv', encoding='latin1')
corpus.shape
```

Out[2]:
```
(9093, 3)
```

In [3]:
```python
# previewing the dataframe
corpus.head()
```

Out[3]:

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product
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

Checking for missing values - we have a significant amount missing in the 'emotion_in_tweet_is_directed_at' column.

In [4]:
```python
# Taking a look at the datatypes
corpus.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9093 entries, 0 to 9092
Data columns (total 3 columns):
 #   Column                                              Non-Null Count  Dtype 
---  ------                                              --------------  ----- 
 0   tweet_text                                          9092 non-null   object
 1   emotion_in_tweet_is_directed_at                     3291 non-null   object
 2   is_there_an_emotion_directed_at_a_brand_or_product  9093 non-null   object
dtypes: object(3)
```

```
memory usage: 213.2+ KB
```

Renaming columns for simplicity, inspecting values so we can map out how to set up our target variable classes.

In [5]:
```
# Dropping 'the emotion_in_tweet_is_directed_at' column, bc of missing values and not needed for our p
corpus.drop('emotion_in_tweet_is_directed_at', axis=1, inplace=True)
```

In [6]:
```
# renaming the 'is_there_an_emotion...' column to 'sentiment'
corpus.rename(columns={
    'is_there_an_emotion_directed_at_a_brand_or_product': 'sentiment'}, inplace=True)
```

In [7]:
```
# Inspecting the values in 'sentiment'. We have an imbalance in occurences.
corpus['sentiment'].value_counts()
```

Out[7]:
```
No emotion toward brand or product    5389
Positive emotion                      2978
Negative emotion                       570
I can't tell                           156
Name: sentiment, dtype: int64
```

In [8]:
```
# Dropping 'I can't tell' category because it is not useful and a relatively low amount.
corpus.drop(corpus[corpus['sentiment'] == "I can't tell"].index, inplace=True)
```

In [9]:
```
# Creating a mask to identify rows with "No emotion toward brand or product"
no_emotion_mask = corpus['sentiment'] == "No emotion toward brand or product"

# Locating the rows with the mask and redistribute 2,408 occurrences
no_emotion_indices = corpus[no_emotion_mask].sample(n=2408, random_state=42).index
corpus.loc[no_emotion_indices, 'sentiment'] = "Negative emotion"

# Verifying the changes
print(corpus['sentiment'].value_counts())
```

```
No emotion toward brand or product    2981
Negative emotion                      2978
Positive emotion                      2978
Name: sentiment, dtype: int64
```

In [10]:

In [10]:

```python
# Creating a mask to identify rows with "No emotion toward brand or product"
no_emotion_mask = corpus['sentiment'] == "No emotion toward brand or product"

# Drop the rows with this mask
corpus.drop(corpus[no_emotion_mask].index, inplace=True)

# Verify the changes
print(corpus['sentiment'].value_counts())
```

```
Negative emotion    2978
Positive emotion    2978
Name: sentiment, dtype: int64
```

In [11]:

```python
# Define the mapping of old values to new values
mapping = {'Positive emotion': 'Positive', 'Negative emotion': 'Not Positive'}

# Replace the categories in the 'sentiment' column
corpus['sentiment'] = corpus['sentiment'].replace(mapping)

# Verify the changes
print(corpus['sentiment'].value_counts())
```

```
Positive        2978
Not Positive    2978
Name: sentiment, dtype: int64
```

In [12]:

```python
# Assigning 'Positive' sentiment to 1 and 'Not Positive' to 0
corpus['sentiment'] = corpus['sentiment'].replace(
    {'Positive': 1, 'Not Positive': 0})
```

In cells 9-12 we have set this up to be a binary classification problem. We have combined values from "Negative emotion" with values from "No emotion toward brand or product". We did this because we had a class imbalance. We sampled 2,408 occurences from "No emotion toward brand or product" and combined them in the "Negative emotion" category to create a new category called "Not Positive". There were a lot more occurences of "Positive emotion" compared to "Negative emotion". By combining the categories we have now have a balance between 'Positive' and 'Not Positive' occurences. We have assigned sentiment values 'Positive' to 1 and 'Not Positive' to 0.

In [13]:

```python
# Inspecting the DF once again to make sure everything looks correct after all the changes we made.
corpus.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5956 entries, 0 to 9092
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   tweet_text  5956 non-null   object
 1   sentiment   5956 non-null   int64 
dtypes: int64(1), object(1)
memory usage: 139.6+ KB
```

In [14]:

```
# previewing the cleaned up df
corpus.head()
```

Out[14]:

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

Inspecting common words that could have low semantic value and could potentially be added to 'stopwords'

In [15]:

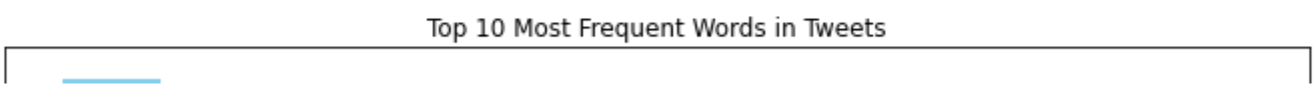
```
# Finding the top 10 most used words in the tweets
all_words = ' '.join(corpus['tweet_text']).split()

# Calculate the frequency distribution of words
word_freq = FreqDist(all_words)

# Get the top 10 most frequent words
top_20_words = word_freq.most_common(20)

# Print the top 10 most frequent words
for word, freq in top_20_words:
    print(f'{word}: {freq}')
```

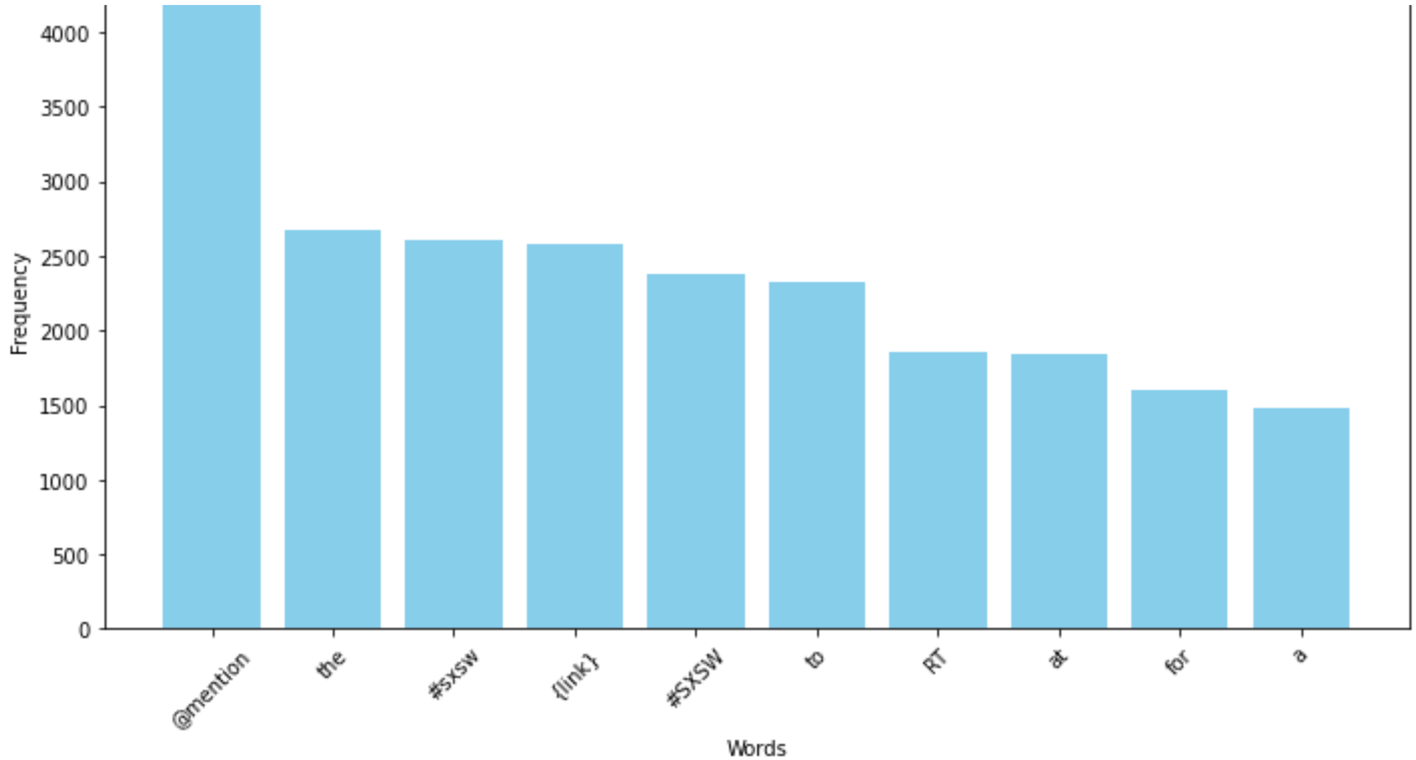
```
@mention: 4211
the: 2671
```

```
#sxsw: 2602
{link}: 2579
#SXSW: 2384
to: 2328
RT: 1851
at: 1848
for: 1594
a: 1484
iPad: 1206
in: 1181
of: 1151
is: 1141
and: 1022
Google: 994
Apple: 991
on: 817
I: 724
store: 618
```

In [16]:

```python
# Finding the top 10 most used words in the tweets
all_words = ' '.join(corpus['tweet_text']).split()

# Calculate the frequency distribution of words
word_freq = FreqDist(all_words)

# Get the top 10 most frequent words
top_10_words = word_freq.most_common(10)

# Extracting words and frequencies
words, frequencies = zip(*top_10_words)

# Creating a bar plot
plt.figure(figsize=(10, 6))
plt.bar(words, frequencies, color='skyblue')
plt.xlabel('Words')
plt.ylabel('Frequency')
plt.title('Top 10 Most Frequent Words in Tweets')
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
plt.tight_layout()
plt.show()
```





These should be removed because of low semantic value.

In [17]:

```
# Defining X and y
X = corpus.tweet_text
y = corpus.sentiment
```

Below is our holdout test set.

In [18]:

```
# Setting up train,test,split, 20% on testing
X_train, X_test, y_train, y_test = train_test_split(X,y, random_state=42, test_size=0.2)
```

Preprocess the training set. Using standard stop words, as well as additional words unique to the dataset, and words that were common in both the positive and not positive class. This is to remove words with low semantic value. To set up for modeling I also had to remove numbers and lower case all the words to prepare the data to eventually turn into numerical data. I also used lemmatization to reduce words like running and run to one word "run". This was to help trim down the amount of words in the corpus and reduce words that had the same meaning.

In [19]:
```
# bringing in stopwords

sw = stopwords.words('english')
# add additional words to the stopwords list
additional_stopwords = ['sxsw', 'apple', 'google', 'austin', 'ipad',
                         'iphone', 'mention', 'android', 'rt', 'link',
                        'app', 'quot', 'store', 'aaron', 'abc', 'aapl',
                        'ab', 'acc', 'adam', 'adele', 'abt', 'sxswi',
                        'new', 'launch', 'circle', 'line','go', 'new', 'get',
                        'pop', 'amp', 'via', 'open', 'come', 'tx', 'canada', 'fb',
                        'ch', 'free']
sw.extend(additional_stopwords)
```

In [20]:
```
# Translating nltk pos_tags to wordnet pos_tags using a function to ensure compatability between libr
# Preparing for lemmatization
def get_wordnet_pos(treebank_tag):
    '''
    Translate nltk POS to wordnet tags
    '''
    if treebank_tag.startswith('J'):
        return wordnet.ADJ
    elif treebank_tag.startswith('V'):
        return wordnet.VERB
    elif treebank_tag.startswith('N'):
        return wordnet.NOUN
    elif treebank_tag.startswith('R'):
        return wordnet.ADV
    else:
        return wordnet.NOUN
```

In [21]:
```
# creating a function; a for loop for iterating through the model
# removing punctuation, lower casing, removing numbers, lemmatizing the tweets
def tweet_preparer(tweet, stop_words=sw, ):
    regex_token = RegexpTokenizer(r"([a-zA-Z]+(?:’[a-z]+)?)")
    tweet = regex_token.tokenize(tweet)
    tweet = [word.lower() for word in tweet]
    tweet = [word for word in tweet if word not in sw]
    # print(tweet)
    tweet = pos_tag(tweet)
```

```
    tweet = pos_tag(tweet)
    tweet = [(word[0], get_wordnet_pos(word[1])) for word in tweet]
    lemmatizer = WordNetLemmatizer()
    tweet = [lemmatizer.lemmatize(word[0], word[1]) for word in tweet]
    return ' '.join(tweet)
```

Below is to inspect if my preprocessing worked. We can now compare the sample_tweet to the preprocessed tweet.

In [22]:
```
# Select a sample tweet from the corpus DataFrame
sample_tweet = corpus['tweet_text'].iloc[522]  #'tweet_text' is the column containing the tweets
print(sample_tweet)
# Apply tweet_preparer function to preprocess the sample tweet
preprocessed_tweet = tweet_preparer(sample_tweet)
print(preprocessed_tweet)
```

```
@mention  Its bigger than an iphone and smaller than a PC, so good for big events like #SXSW and meetin
g day? {link}
big small pc good big event like meeting day
```

In [23]:
```
# Creating the variable 'token_tweets' to preprocess all the tweets in the corpus using a list compre
token_tweets = [tweet_preparer(tweet, sw) for tweet in X_train]
```

In [24]:
```
# Secondary train-test split to build our baseline model to prevent data leakage
X_train2, X_val, y_train2, y_val = train_test_split(token_tweets, y_train, test_size=0.2, random_state
```

Here is where we start turning the data into numerical values.

In [25]:
```
# Instantiating a count vectorizer and fit/transforming on the data, converting the sparse matrix to a
cv = CountVectorizer()

X_train2_vec = cv.fit_transform(X_train2)
X_train2_vec = pd.DataFrame.sparse.from_spmatrix(X_train2_vec)
X_train2_vec.columns = sorted(cv.vocabulary_)
X_train2_vec.set_index(y_train2.index, inplace=True)
```

In [26]:
```
# We then transform the validation set. We do not refit the vectorizer

X_val_vec = cv.transform(X_val)
```

```
X_val_vec  = pd.DataFrame.sparse.from_spmatrix(X_val_vec)
X_val_vec.columns = sorted(cv.vocabulary_)
X_val_vec.set_index(y_val.index, inplace=True)
```

Bringing in the XGB classifier to gain information regarding the feature importances.

In [27]:

```
# importing the XGB classifier
from xgboost import XGBClassifier

# Training an XGBoost classifier
xgb = XGBClassifier()
xgb.fit(X_train2_vec, y_train2)

# Getting the feature importances
feature_importances = xgb.feature_importances_
```

As we can see the model seems to be pretty noisey with no words carrying any real significant importance.

In [28]:

```
# Getting indices of features sorted by importance
sorted_indices = np.argsort(feature_importances)[::-1]

# Get feature names (words)
feature_names = np.array(list(cv.vocabulary_.keys()))

# Get the top 50 words and their importances
top_50_words = feature_names[sorted_indices[:50]]
top_50_importances = feature_importances[sorted_indices[:50]]

# Display the top 50 words and their importances
for word, importance in zip(top_50_words, top_50_importances):
    print(f"Word: {word}, Importance: {importance}")
```

```
Word: observer, Importance: 0.016653718426823616
Word: security, Importance: 0.014861325733363628
Word: taker, Importance: 0.014209930785000324
Word: dandy, Importance: 0.013090299442410469
Word: magnet, Importance: 0.012500665150582790
Word: fee, Importance: 0.010696330107748508
Word: nyc, Importance: 0.010610351338982582
Word: ya, Importance: 0.00943165272474289
Word: fellow, Importance: 0.009033872745931149
```

```
Word: hatch, Importance: 0.008600357919931412
Word: tribune, Importance: 0.008430141024291515
Word: weve, Importance: 0.00792466290295124
Word: skinny, Importance: 0.007795257028192282
Word: possibly, Importance: 0.006902097724378109
Word: important, Importance: 0.006351662334054708
Word: stick, Importance: 0.006299799773842096
Word: socialnetwork, Importance: 0.006257825065404177
Word: international, Importance: 0.0061249383725225925
Word: lovely, Importance: 0.005995331332087517
Word: designingforkids, Importance: 0.005756525322794914
Word: oy, Importance: 0.0057503897696733475
Word: wu, Importance: 0.005731504410505295
Word: yea, Importance: 0.005605350714176893
Word: etc, Importance: 0.005566015839576721
Word: everywhere, Importance: 0.005547798238694668
Word: sleepy, Importance: 0.005422723945230246
Word: track, Importance: 0.005258433986455202
Word: myturnstone, Importance: 0.005173919722437859
Word: interested, Importance: 0.005041619762778282
Word: computer, Importance: 0.005040859337896109
Word: object, Importance: 0.004951857030391693
Word: samsung, Importance: 0.004904530942440033
Word: need, Importance: 0.004786336328834295
Word: mojo, Importance: 0.004748426377773285
Word: hill, Importance: 0.00469894427806139
Word: kidney, Importance: 0.0046403901651501656
Word: avoid, Importance: 0.004593315534293652
Word: squeal, Importance: 0.004504868760704994
Word: sony, Importance: 0.004464067053049803
Word: peek, Importance: 0.004449998494237661
Word: ago, Importance: 0.004409488290548325
Word: ability, Importance: 0.004379801917821169
Word: cute, Importance: 0.0043743751011788845
Word: founder, Importance: 0.004312662873417139
Word: topspin, Importance: 0.004288783296942711
Word: di, Importance: 0.004280270542949438
Word: friendly, Importance: 0.004280154127627611
Word: official, Importance: 0.004271283745765686
Word: sangre, Importance: 0.0042691919952631
Word: semantic, Importance: 0.0041810013353824615
```

I typed `zip function for python in lists` into google and found this solution

In [29]:

```python
# Function to count word frequencies for a given class
def count_word_frequencies(text_data, class_label):
    # Filter text data based on class label
    text_class = [text for text, label in zip(text_data, y_train2) if label == class_label]
    # Flatten the list of text data into a single list of words
    all_words = ' '.join(text_class).split()
    # Count word frequencies
    word_counts = Counter(all_words)
    return word_counts

# Count word frequencies for positive (class 1) and not positive (class 0) classes
positive_word_counts = count_word_frequencies(X_train2, 1)
not_positive_word_counts = count_word_frequencies(X_train2, 0)

# Get the top 20 words for each class
top_20_positive_words = positive_word_counts.most_common(20)
top_20_not_positive_words = not_positive_word_counts.most_common(20)

# Display the top 20 words for each class
print("Top 20 words in Positive (class 1) class:")
for word, count in top_20_positive_words:
    print(f"{word}: {count}")

print("\nTop 20 words in Not Positive (class 0) class:")
for word, count in top_20_not_positive_words:
    print(f"{word}: {count}")
```

```
Top 20 words in Positive (class 1) class:
party: 116
win: 104
one: 100
time: 95
great: 92
get: 84
like: 81
use: 81
cool: 79
circle: 77
day: 76
love: 75
see: 72
social: 71
today: 71
```

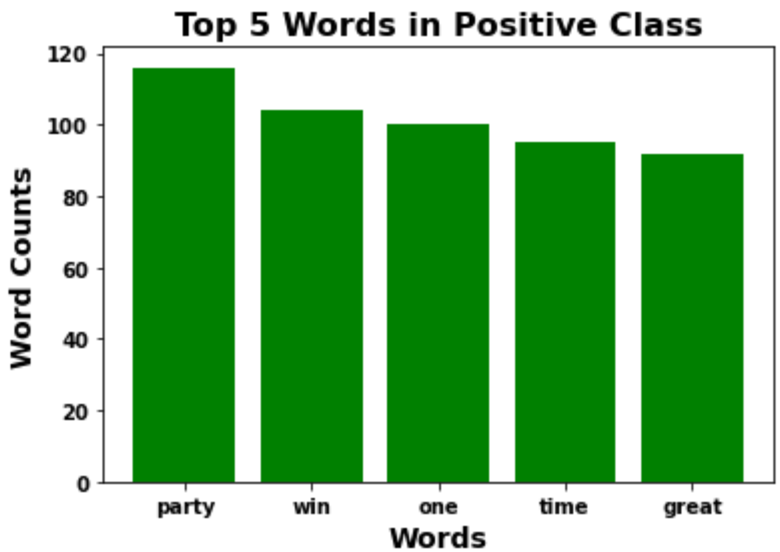
```
good: 70
check: 69
w: 69
map: 68
awesome: 66

Top 20 words in Not Positive (class 0) class:
social: 178
circle: 167
today: 134
network: 128
call: 109
party: 80
need: 78
major: 78
mobile: 66
make: 65
u: 65
see: 63
use: 63
like: 63
possibly: 63
say: 60
design: 57
go: 56
one: 53
temporary: 53
```

This was useful to see which words appeared in both classes. I removed many stop words that had a high count in both classes. I did leave some in, for example the word 'social' although was in both classes it showed up significantly more in the 'Not Positive' class so I decided to keep it in. These words could be used by the marketing team in advertising.

In [30]:

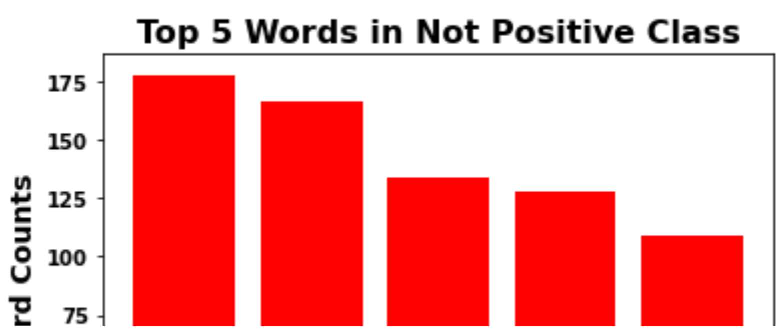
```
# Graphing the top 5 words and their counts for the Positive class
top_5_positive_words = top_20_positive_words[:5]
words_positive, counts_positive = zip(*top_5_positive_words)

# Create a bar chart for the positive class
plt.bar(words_positive, counts_positive, color='green')
plt.xlabel('Words', fontsize=14, fontweight='bold')  # Adjust fontsize and fontweight as needed
plt.ylabel('Word Counts', fontsize=14, fontweight='bold')  # Adjust fontsize and fontweight as needed
plt.title('Top 5 Words in Positive Class', fontsize=16, fontweight='bold')  # Adjust fontsize and fon
plt.xticks(fontsize=10, fontweight='bold')  # Adjust fontsize and fontweight as needed
plt.yticks(fontsize=10, fontweight='bold')  # Adjust fontsize and fontweight as needed
```

```
plt.show()
```



In [31]:

```
# Graphing the top 5 words and their counts for the Not Positive class
top_5_not_positive_words = top_20_not_positive_words[:5]
words_not_positive, counts_not_positive = zip(*top_5_not_positive_words)

# Creating a bar chart for the top 5 Not Positive class words
plt.bar(words_not_positive, counts_not_positive, color='red')
plt.xlabel('Words', fontsize=14, fontweight='bold')  # Adjust fontsize and fontweight as needed
plt.ylabel('Word Counts', fontsize=14, fontweight='bold')  # Adjust fontsize and fontweight as needed
plt.title('Top 5 Words in Not Positive Class', fontsize=16, fontweight='bold')  # Adjust fontsize and
plt.xticks(fontsize=10, fontweight='bold')  # Adjust fontsize and fontweight as needed
plt.yticks(fontsize=10, fontweight='bold')  # Adjust fontsize and fontweight as needed
plt.show()
```



Now that our text data is numerical and we have learned about some feature importances and top words that appear in both of our classes, we are now ready for modeling.

Modeling

In [32]:
```
# Fitting the Multinomial Naive Bayes Classifier on our training data
mnb = MultinomialNB(alpha=0.5)

mnb.fit(X_train2_vec, y_train2)
```

Out[32]: MultinomialNB(alpha=0.5)

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 [33]:
```
# Evaluating our training data
y_train_pred = mnb.predict(X_train2_vec)
accuracy_score(y_train2, y_train_pred)
```

Out[33]: 0.8672264497507216

In [34]:
```
# Generating model predictions and getting an accuracy score for our Testing Data
y_pred = mnb.predict(X_val_vec)
accuracy_score(y_val, y_pred)
```

Out[34]: 0.6484784889821616

In [35]:
```
# calculating a precision score
precision_score(y_val, y_pred)
```

```
precision_score(y_val, y_pred)
```

Out[35]: 0.6443202979515829

We got an 85% accuracy score on our training data and roughly a 65% accuracy score on our testing data. We had a similar score of 64% on precision. Our model did do significantly better on the training data most likely due to overfitting from noise in the training data (too many words with low feature importance).

In [36]:

```
# Define the hyperparameter grid
param_grid = {
    'alpha': [0.1, 0.5, 1.0],              # alpha parameter for MultinomialNB
}

# Initialize MultinomialNB classifier
mnb = MultinomialNB()

# Perform GridSearchCV with accuracy as the scoring metric with 5 folds
grid_search = GridSearchCV(mnb, param_grid, cv=5, scoring='accuracy')

# Training the GridSearchCV on the training data
grid_search.fit(X_train2_vec, y_train2)

# Geting the best accuracy score and hyperparameters
best_accuracy = grid_search.best_score_
best_params = grid_search.best_params_

print("Best Accuracy:", best_accuracy)
print("Best Parameters:", best_params)
```

```
Best Accuracy: 0.64917527510896
Best Parameters: {'alpha': 1.0}
```

The GridSearch helped reveal what the best alpha should be to improve accuracy.

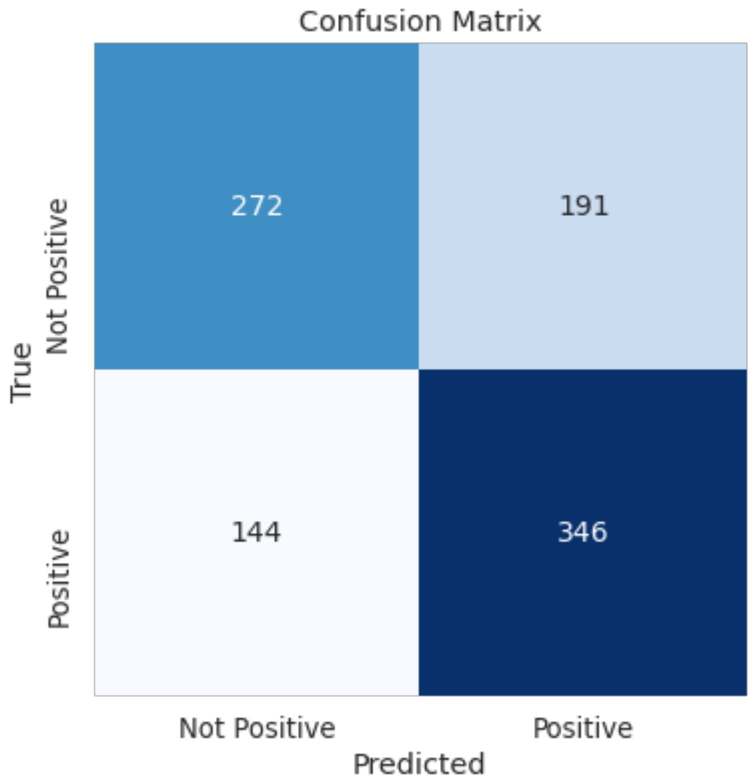
In [37]:

```
# Setting up a confusion matrix on our testing data
cm = confusion_matrix(y_val, y_pred)
```

In [38]:

```
# Set up a figure and axis
plt.figure(figsize=(8, 6))
sns.set(font_scale=1.2)  # Adjust font size for better readability
```

```python
# Create a heatmap of the confusion matrix
sns.heatmap(cm, annot=True, fmt='g', cmap='Blues', cbar=False,
            annot_kws={"size": 14}, square=True,
            xticklabels=['Not Positive', 'Positive'],
            yticklabels=['Not Positive', 'Positive'])

# Labeling and viewing the cm
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```



The confusion matrix showed roughly a 65% score on accuracy. True positive + true negatives divided by the total number of instances. (346 + 272) / 953 = 0.648

In [39]:
```python
# Fitting a tfidf on training data to make predictions with words that appear in 5%-95% of tweets
```

```
tfidf = TfidfVectorizer(min_df=0.05, max_df=0.95)
X_train2_vec = tfidf.fit_transform(X_train2)
X_val_vec = tfidf.transform(X_val)
mnb2 = MultinomialNB()
mnb2.fit(X_train2_vec, y_train2)
y_pred2 = mnb2.predict(X_val_vec)

accuracy_score(y_val, y_pred2)
```

Out[39]: 0.4858342077649528

The tfidf mnb model with min, max hyperparameters led to a worse accuracy score of almost 50%.

In [40]:

```
# Fitting a Random Forest Classifier on training data, and making predictions on validation data
rf = RandomForestClassifier(n_estimators=1000, max_features=5, max_depth=5)
rf.fit(X_train2_vec, y_train2)
y_pred3 = rf.predict(X_val_vec)
precision_score(y_val, y_pred3)
```

Out[40]: 0.5214368482039398

In [41]:

```
accuracy_score(y_val, y_pred3)
```

Out[41]: 0.5246589716684156

The random forest model with hyperparameters did not perform as well as the mnb model with alpha set to 0.5. This model had an accuracy score of 52%

Evaluation

Our best performing model was our Multinomial Bayes model that used a GridSearch with hyperparameters, the alpha was set to 0.5. This is an example of Laplace smoothing which avoids the problem of zero probabilities of unseen words in the training data. The model was trained on data using a count vectorizer of all the words in the corpus after preprocessing. The model scored an 85% on accuracy in the training data but only scored about 65% on the testing data which is not great in determining whether tweets had positive sentiment or not. It also had a precision score that was roughly the same. We looked at accuracy as the best metric because in terms of minimizing false/negatives and false/positives, one was not more looked at accuracy as the best metric because in terms of minimizing false/negatives and false/positives, one was not more important than the other. Therefore precision and recall didn't matter as much as accuracy. It was a better metric because we had a balance in our classes. Our confusion matrix confirmed this by showing we had 616 correct predictions out of 953 possible instances in our sample.

Conclusion

Our Multinomial Bayes model that was trained on vectorized data with the help of a Grid Search for hyperparameter tuning was our best performing model. This model had an 85% accuracy score on training data and a 65% accuracy on testing data. This is most likely due to overfitting from noise in the data. When we looked at feature importances and didn't see any words with significant importance which was most likely the contributing factor. The sample from our confusion matrix showed that the model correctly classified instances 616 times out of 953 instances. We discovered the top 5 frequently used words in the Positive class were 'party', 'win', 'one', 'time' and 'great'. The top 5 words for the Not Positive class were 'social', 'circle', 'today', 'network', and 'call'. We need to gather a lot more data, specifically with negative sentiment as this was lacking in the dataset forcing us to create a Not Positive class which was not ideal because there was a lot of data with no emotion mixed in with only a little bit of negative sentiment. We need to obtain 10x more data especially data with negative data to improve our model.

Recommendations

I would recommend a few of the top 5 words in the "positive" class be used by the SXSW marketing team. The words "party", "win", and "great" were among the top words used in positive sentiment tweets. I would recommend these words be used in advertising for the event to get people excited. I would also have the marketing team look deeper into a few of the top words that showed up in the "not positive" class such as "social", "circle", and "network". These 3 words could be and should be used in a more positive way when talking about a conference/event. I would recommend trying to use these words also in advertising, possibly together with the positive sentiment words to try to get them away from this no emotion or negative sentiment category that is composed of the "not positive" class.

Limitations

Some limitations of the data was that there was initially a pretty heavy class imbalance in sentiment. Over half of the data (in this case tweets) showed to have no emotion. With only 33% showing positive sentiment and only around 6% showing negative sentiment. This forced me to combine no emotion tweets and negative tweets to create a 'Not Positive' category. This contributed to our models not being very accurrate. There were also a lot of missing values (nearly 2/3) of the data was missing from the 'emotion_in_tweet_is_directed_at' column so I was not able to analyze sentiment regarding certain products. There was a lot of noise in the data, there were not many words with high significant importance. After cleaning the data we were only able to work with around 6,000 entries which is fairly low when it comes to building predictive models.

Next Steps

We need to gather more data on negative sentiment as well as positive sentiment. Negative sentiment is just as useful and in some cases more useful information to have to know what to avoid and how to make improvements. We need to gather 10x more data from other social media platforms as well, not just twitter. Gathering information on specific areas of the conference (whether it be in film, music, education or brands in tech) will help SXSW become an even better more well