Feature Extraction from Text

This notebook is divided into two sections:

- **First, we'll find out what what is necessary to build an NLP system that can turn a body of text into a numerical array of *features* by manually calcuating frequencies and building out TF-IDF.**
- **Next we'll show how to perform these steps using scikit-learn tools.**

Part One: Core Concepts on Feature Extraction

In this section we'll use basic Python to build a rudimentary NLP system. We'll build a *corpus of documents* (two small text files), create a *vocabulary* from all the words in both documents, and then demonstrate a *Bag of Words* technique to extract features from each document.

> **This first section is for illustration only!**
> **Don't worry about memorizing this code - later on we will let Scikit-Learn Preprocessing tools do this for us.**

Start with some documents:

For simplicity we won't use any punctuation in the text files One.txt and Two.txt. Let's quickly open them and read them. Keep in mind, you should avoid opening and reading entire files if they are very large, as Python could just display everything depending on how you open the file.

Reading entire text as a string

In [15]:

```
# It will return string
with open ('One.txt') as mytext:
    a = mytext.read()
```

In [16]:

```
# Here we can we that \n on end of line
a
```

Out[16]:

```
'This is a story about dogs\nour canine pets\nDogs are furry animals\n'
```

In [17]:

```
# for that we have to use
print(a)
```

```
This is a story about dogs
our canine pets
Dogs are furry animals
```

Reading Each Line as a List

In [27]:

```
# or we can try this and this will return list
with open ('One.txt') as mytext:
    b = mytext.readlines()
```

In [28]:

```
# Its showing in seprarte lines but still showing \n
b
```

Out[28]:

```
['This is a story about dogs\n',
 'our canine pets\n',
 'Dogs are furry animals\n']
```

In [29]:

```
print(b)
```

```
['This is a story about dogs\n', 'our canine pets\n', 'Dogs are furry animals\n']
```

In [30]:

```
type(a),type(b)
```

Out[30]:

```
(str, list)
```

In [32]:

```
# b is sting not list
b.lower().split()
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
Cell In[32], line 2
      1 # b is sting not list
----> 2 b.lower().split()

AttributeError: 'list' object has no attribute 'lower'
```

Reading in Words Separately

In [19]:

```
a.lower().split()
```

Out[19]:

```
['this',
 'is',
 'a',
 'story',
 'about',
 'dogs',
 'our',
 'canine',
 'pets',
 'dogs',
 'are',
 'furry',
 'animals']
```

Building a vocabulary (Creating a "Bag of Words")

Let's create dictionaries that correspond to unique mappings of the words in the documents. We can begin to think of this as mapping out all the possible words available for all (both) documents.

In [33]:

In [33]:

```
with open('one.txt') as f:
    words_one = f.read().lower().split()
```

In [34]:

```
words_one
```

Out[34]:

```
['this',
 'is',
 'a',
 'story',
 'about',
 'dogs',
 'our',
 'canine',
 'pets',
 'dogs',
 'are',
 'furry',
 'animals']
```

In [35]:

```
len(words_one)
```

Out[35]:

```
13
```

In [38]:

```
# If we want unique words from it we have to use set()
uni_words_one = set(words_one)
uni_words_one
```

Out[38]:

```
{'a',
 'about',
 'animals',
 'are',
 'canine',
 'dogs',
 'furry',
 'is',
 'our',
 'pets',
 'story',
 'this'}
```

Repeat for Two.txt

In [39]:

```
with open('Two.txt') as f:
    words_two = f.read().lower().split()
    uni_words_two = set(words_two)
```

In [40]:

```
uni_words_two
```

Out[40]:

```
{'a',
 'about',
 'catching',
 'fun',
 'is',
```

```
 'popular',
 'sport',
 'story',
 'surfing',
 'this',
 'water',
 'waves'}
```

Get all unique words across all documents

In [41]:

```
all_uni_words = set()
all_uni_words.update(uni_words_one)
all_uni_words.update(uni_words_two)
```

In [42]:

```
all_uni_words
```

Out[42]:

```
{'a',
 'about',
 'animals',
 'are',
 'canine',
 'catching',
 'dogs',
 'fun',
 'furry',
 'is',
 'our',
 'pets',
 'popular',
 'sport',
 'story',
 'surfing',
 'this',
 'water',
 'waves'}
```

In [43]:

```
full_vocab = dict()
i = 0
for word in all_uni_words:
    full_vocab[word] = i
    i = i+1
```

In [46]:

```
# Do not expect this to be in alphabetical order!
# The for loop goes through the set() in the most efficient way possible, not in alphabet
ical order!
full_vocab
```

Out[46]:

```
{'this': 0,
 'are': 1,
 'a': 2,
 'is': 3,
 'dogs': 4,
 'about': 5,
 'sport': 6,
 'surfing': 7,
 'catching': 8,
 'our': 9,
 'pets': 10,
 'water': 11,
 'animals': 12,
```

```
 'waves': 13,
 'story': 14,
 'popular': 15,
 'furry': 16,
 'canine': 17,
 'fun': 18}
```

Bag of Words to Frequency Counts

Now that we've encapsulated our "entire language" in a dictionary, let's perform *feature extraction* on each of our original documents:

Empty counts per doc

In [48]:

```
# Create an empty vector with space for each word in the vocabulary:
one_freq = [0]*len(full_vocab)
two_freq = [0]*len(full_vocab)
all_words = ['']*len(full_vocab)
```

In [49]:

```
one_freq
```

Out[49]:

```
[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
```

In [50]:

```
two_freq
```

Out[50]:

```
[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
```

In [51]:

```
all_words
```

Out[51]:

```
['', '', '', '', '', '', '', '', '', '', '', '', '', '', '', '', '', '', '']
```

Add in counts per word per doc:

In [56]:

```
# map the frequencies of each word in 1.txt to our vector:
with open('One.txt') as f:
    one_text = f.read().lower().split()

for word in one_text:
    word_ind = full_vocab[word]
    one_freq[word_ind] += 1
```

In [57]:

```
one_freq
```

Out[57]:

```
[1, 1, 1, 1, 2, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0]
```

In [58]:

```
# Do the same for the second document:
with open('Two.txt') as f:
```

```python
    two_text = f.read().lower().split()

for word in two_text:
    word_ind = full_vocab[word]
    two_freq[word_ind]+=1
```

In [59]:

```python
two_freq
```

Out[59]:

```
[1, 0, 1, 3, 0, 1, 1, 2, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1]
```

In [61]:

```python
for word in full_vocab:
    word_ind = full_vocab[word]
    all_words[word_ind] = word
```

In [62]:

```python
all_words
```

Out[62]:

```
['this',
 'are',
 'a',
 'is',
 'dogs',
 'about',
 'sport',
 'surfing',
 'catching',
 'our',
 'pets',
 'water',
 'animals',
 'waves',
 'story',
 'popular',
 'furry',
 'canine',
 'fun']
```

In [64]:

```python
import pandas as pd
```

In [66]:

```python
bow = pd.DataFrame(data=[one_freq,two_freq],columns=all_words)
```

In [67]:

```python
bow
```

Out[67]:

	this	are	a	is	dogs	about	sport	surfing	catching	our	pets	water	animals	waves	story	popular	furry	canine	fun
0	1	1	1	1	2	1	0	0	0	1	1	0	1	0	1	0	1	1	0
1	1	0	1	3	0	1	1	2	1	0	0	1	0	1	1	1	0	0	1

By comparing the vectors we see that some words are common to both, some appear only in `One.txt`, others only in `Two.txt`. Extending this logic to tens of thousands of documents, we would see the vocabulary dictionary grow to hundreds of thousands of words. Vectors would contain mostly zero values, making them sparse matrices.

sparse matrices.

Concepts to Consider:

Bag of Words and Tf-idf

In the above examples, each vector can be considered a *bag of words*. By itself these may not be helpful until we consider *term frequencies*, or how often individual words appear in documents. A simple way to calculate term frequencies is to divide the number of occurrences of a word by the total number of words in the document. In this way, the number of times a word appears in large documents can be compared to that of smaller documents.

However, it may be hard to differentiate documents based on term frequency if a word shows up in a majority of documents. To handle this we also consider *inverse document frequency*, which is the total number of documents divided by the number of documents that contain the word. In practice we convert this value to a logarithmic scale, as described here.

Together these terms become tf-idf.

Stop Words and Word Stems

Some words like "the" and "and" appear so frequently, and in so many documents, that we needn't bother counting them. Also, it may make sense to only record the root of a word, say `cat` in place of both `cat` and `cats`. This will shrink our vocab array and improve performance.

Tokenization and Tagging

When we created our vectors the first thing we did was split the incoming text on whitespace with `.split()`. This was a crude form of *tokenization* - that is, dividing a document into individual words. In this simple example we didn't worry about punctuation or different parts of speech. In the real world we rely on some fairly sophisticated *morphology* to parse text appropriately.

Once the text is divided, we can go back and *tag* our tokens with information about parts of speech, grammatical dependencies, etc. This adds more dimensions to our data and enables a deeper understanding of the context of specific documents. For this reason, vectors become ***high dimensional sparse matrices***.

Part Two: Feature Extraction with Scikit-Learn

Let's explore the more realistic process of using sklearn to complete the tasks mentioned above!

Scikit-Learn's Text Feature Extraction Options

In [70]:

```
text = ['This is a line',
           "This is another line",
       "Completely different line"]
```

CountVectorizer

In [72]:

```
from sklearn.feature_extraction.text import TfidfTransformer, TfidfVectorizer,CountVector
izer
```

In [73]:

```
cv = CountVectorizer()
```

```
cv = CountVectorizer()
```

In [74]:

```
cv.fit_transform(text)
```

Out[74]:

```
<3x6 sparse matrix of type '<class 'numpy.int64'>'
 with 10 stored elements in Compressed Sparse Row format>
```

In [75]:

```
sparse_mat = cv.fit_transform(text)
```

In [76]:

```
sparse_mat.todense()
```

Out[76]:

```
matrix([[0, 0, 0, 1, 1, 1],
        [1, 0, 0, 1, 1, 1],
        [0, 1, 1, 0, 1, 0]], dtype=int64)
```

In [77]:

```
cv.vocabulary_
```

Out[77]:

```
{'this': 5, 'is': 3, 'line': 4, 'another': 0, 'completely': 1, 'different': 2}
```

TfidfTransformer

TfidfVectorizer is used on sentences, while TfidfTransformer is used on an existing count matrix, such as one returned by CountVectorizer

In [78]:

```
tfidf_transformer = TfidfTransformer()
```

In [79]:

```
cv = CountVectorizer()
```

In [80]:

```
counts = cv.fit_transform(text)
```

In [81]:

```
counts
```

Out[81]:

```
<3x6 sparse matrix of type '<class 'numpy.int64'>'
 with 10 stored elements in Compressed Sparse Row format>
```

In [82]:

```
tfidf = tfidf_transformer.fit_transform(counts)
```

In [83]:

```
tfidf.todense()
```

Out[83]:

```
matrix([[0.        , 0.        , 0.        , 0.61980538, 0.48133417,
         0.61980538],
```

```
       [0.63174505, 0.        , 0.        , 0.4804584 , 0.37311881,
        0.4804584 ],
       [0.        , 0.65249088, 0.65249088, 0.        , 0.38537163,
        0.        ]])
```

In [84]:

```
from sklearn.pipeline import Pipeline
```

In [85]:

```
pipe = Pipeline([('cv',CountVectorizer()),('tfidf',TfidfTransformer())])
```

In [86]:

```
results = pipe.fit_transform(text)
```

In [87]:

```
results
```

Out[87]:

```
<3x6 sparse matrix of type '<class 'numpy.float64'>'
 with 10 stored elements in Compressed Sparse Row format>
```

In [88]:

```
results.todense()
```

Out[88]:

```
matrix([[0.        , 0.        , 0.        , 0.61980538, 0.48133417,
         0.61980538],
        [0.63174505, 0.        , 0.        , 0.4804584 , 0.37311881,
         0.4804584 ],
        [0.        , 0.65249088, 0.65249088, 0.        , 0.38537163,
         0.        ]])
```

TfIdfVectorizer

Does both above in a single step!

In [89]:

```
tfidf = TfidfVectorizer()
```

In [90]:

```
new = tfidf.fit_transform(text)
```

In [91]:

```
new.todense()
```

Out[91]:

```
matrix([[0.        , 0.        , 0.        , 0.61980538, 0.48133417,
         0.61980538],
        [0.63174505, 0.        , 0.        , 0.4804584 , 0.37311881,
         0.4804584 ],
        [0.        , 0.65249088, 0.65249088, 0.        , 0.38537163,
         0.        ]])
```

NLP and Supervised Learning

Classification of Text Data

The Data

Source: https://www.kaggle.com/crowdflower/twitter-airline-sentiment?select=Tweets.csv

This data originally came from Crowdflower's Data for Everyone library.

As the original source says,

A sentiment analysis job about the problems of each major U.S. airline. Twitter data was scraped from February of 2015 and contributors were asked to first classify positive, negative, and neutral tweets, followed by categorizing negative reasons (such as "late flight" or "rude service").

The Goal: Create a Machine Learning Algorithm that can predict if a tweet is positive, neutral, or negative. In the future we could use such an algorithm to automatically read and flag tweets for an airline for a customer service agent to reach out to contact.

In [92]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

In [93]:

```
df = pd.read_csv("D:\\Study\\Programming\\python\\Python course from udemy\\Udemy - 2022 Python for Machine Learning & Data Science Masterclass\\20 - Naive Bayes Classification and Natural Language Processing\\31640102-airline-tweets.csv")
```

In [94]:

```
df.head()
```

Out[94]:

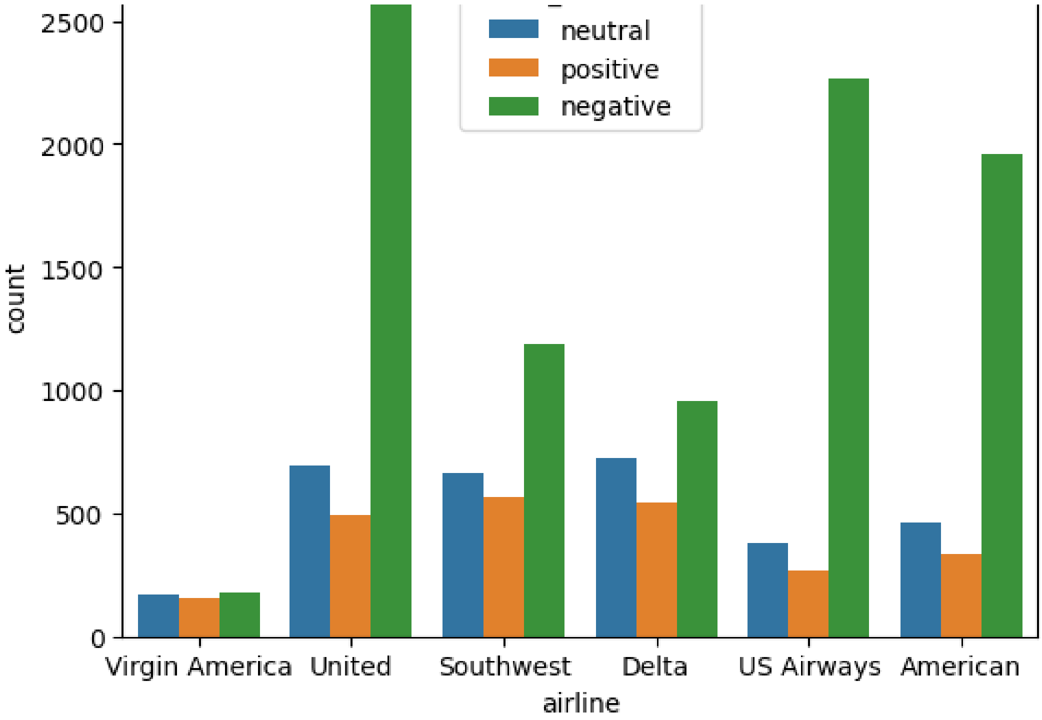
	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	negativereason_confidence	airline
0	570306133677760513	neutral	1.0000	NaN	NaN	Virgin America
1	570301130888122368	positive	0.3486	NaN	0.0000	Virgin America
2	570301083672813571	neutral	0.6837	NaN	NaN	Virgin America
3	570301031407624196	negative	1.0000	Bad Flight	0.7033	Virgin America
4	570300817074462722	negative	1.0000	Can't Tell	1.0000	Virgin America

In [95]:

```
sns.countplot(data=df,x='airline',hue='airline_sentiment')
```

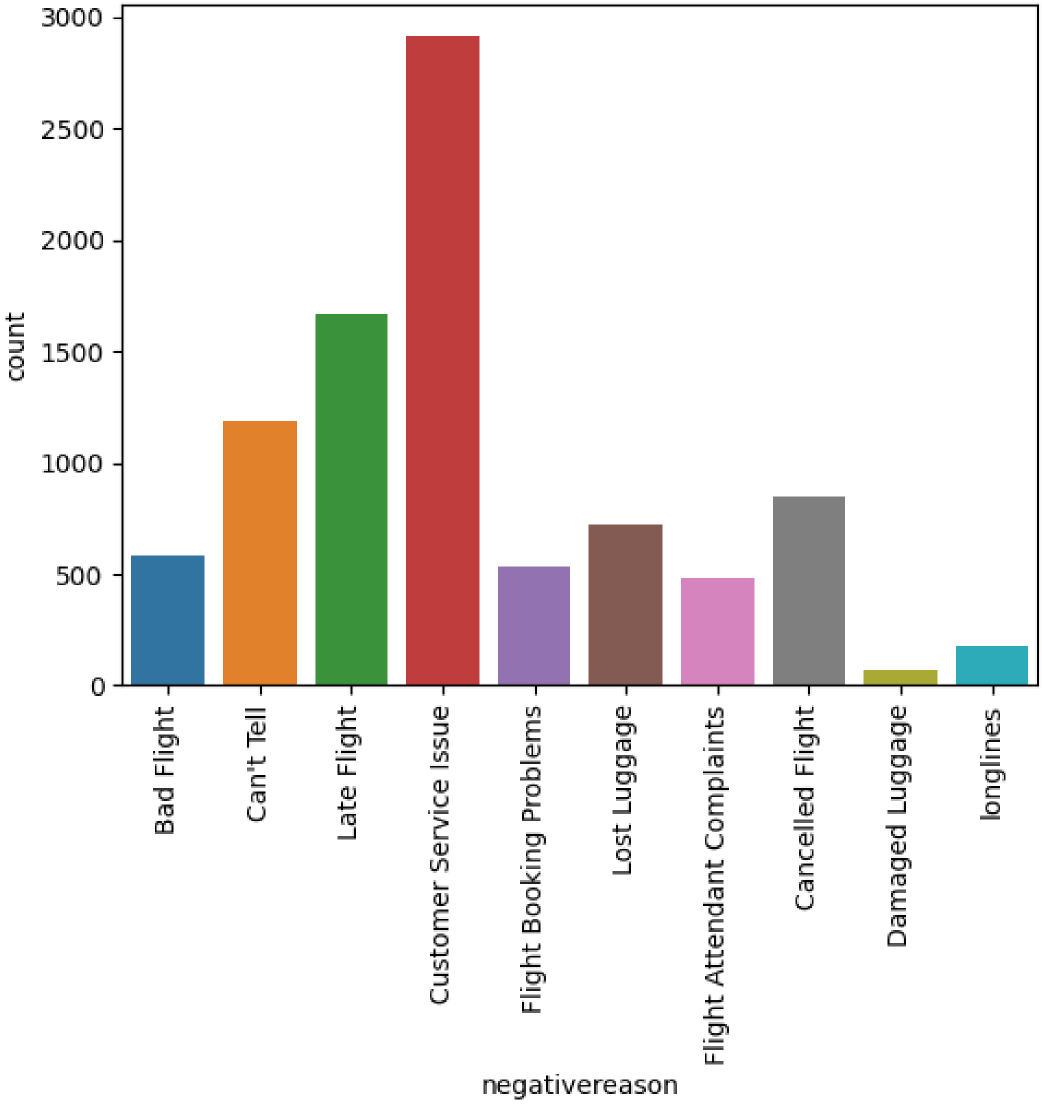
Out[95]:

```
<AxesSubplot: xlabel='airline', ylabel='count'>
```



In [96]:

```
sns.countplot(data=df,x='negativereason')
plt.xticks(rotation=90);
```

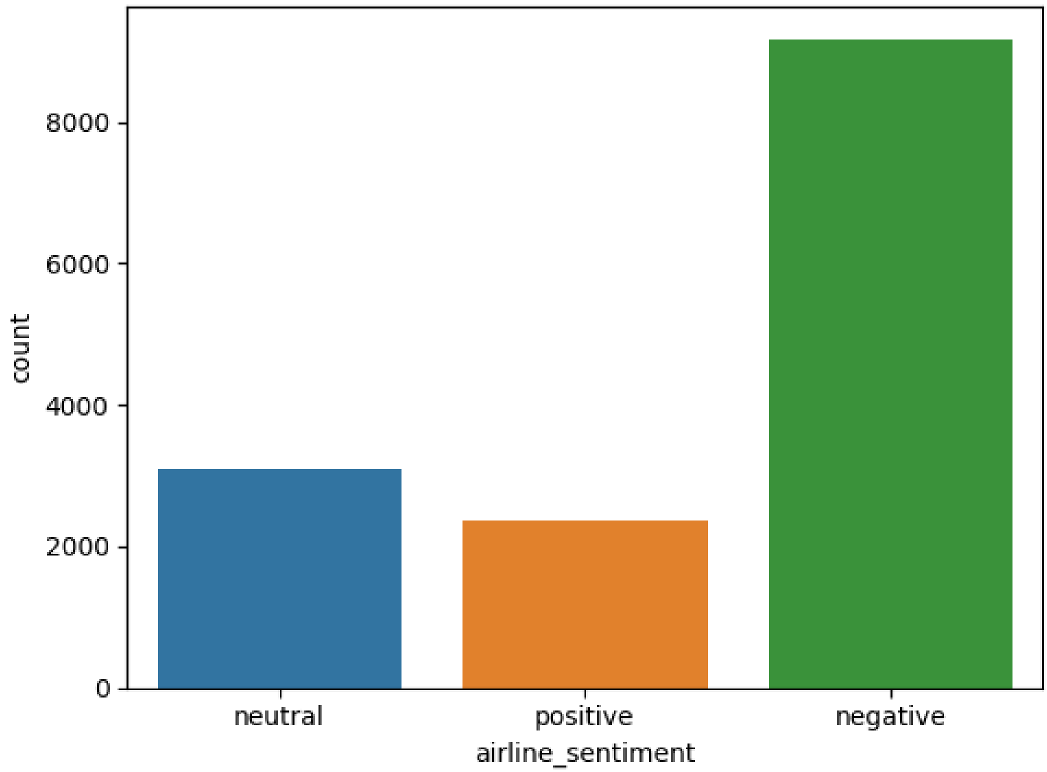


In [97]:

```
sns.countplot(data=df,x='airline_sentiment')
```

Out[97]:

```
<AxesSubplot: xlabel='airline_sentiment', ylabel='count'>
```



In [98]:

```python
df['airline_sentiment'].value_counts()
```

Out[98]:

```
negative    9178
neutral     3099
positive    2363
Name: airline_sentiment, dtype: int64
```

Features and Label

In [99]:

```python
data = df[['airline_sentiment','text']]
```

In [100]:

```python
data.head()
```

Out[100]:

	airline_sentiment	text
0	neutral	@VirginAmerica What @dhepburn said.
1	positive	@VirginAmerica plus you've added commercials t...
2	neutral	@VirginAmerica I didn't today... Must mean I n...
3	negative	@VirginAmerica it's really aggressive to blast...
4	negative	@VirginAmerica and it's a really big bad thing...

In [101]:

```python
X = df['text']
y = df['airline_sentiment']
```

Train Test Split

Train Test Split

In [106]:

```
from sklearn.model_selection import train_test_split
```

In [107]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=10
1)
```

Vectorization

In [108]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
```

In [109]:

```
tfidf = TfidfVectorizer(stop_words='english')
```

In [110]:

```
tfidf.fit(X_train)
```

Out[110]:

```
▾ TfidfVectorizer
TfidfVectorizer(stop_words='english')
```

In [112]:

```
X_train_tfidf = tfidf.transform(X_train)
X_test_tfidf = tfidf.transform(X_test)
```

In [113]:

```
X_train_tfidf
```

Out[113]:

```
<11712x12971 sparse matrix of type '<class 'numpy.float64'>'
 with 107073 stored elements in Compressed Sparse Row format>
```

DO NOT USE .todense() for such a large sparse matrix!!!

Model Comparisons - Naive Bayes,LogisticRegression, LinearSVC

In [114]:

```
from sklearn.naive_bayes import MultinomialNB
nb = MultinomialNB()
nb.fit(X_train_tfidf,y_train)
```

Out[114]:

```
▾ MultinomialNB
MultinomialNB()
```

In [115]:

```
from sklearn.linear_model import LogisticRegression
log = LogisticRegression(max_iter=1000)
log.fit(X_train_tfidf,y_train)
```

Out[115]:

```
▾ LogisticRegression
LogisticRegression(max_iter=1000)
```

In [117]:

```python
from sklearn.svm import LinearSVC,SVC
svc = LinearSVC()
svc.fit(X_train_tfidf,y_train)
```

Out[117]:

```
▾ LinearSVC
LinearSVC()
```

In [118]:

```python
rbf_svc = SVC()
rbf_svc.fit(X_train_tfidf,y_train)
```

Out[118]:

```
▾ SVC
SVC()
```

Performance Evaluation

In [121]:

```python
from sklearn.metrics import classification_report, confusion_matrix
```

In [122]:

```python
from mlxtend.plotting import plot_confusion_matrix
```

In [ ]:

```python

```

In [127]:

```python
def report(model):
    preds = model.predict(X_test_tfidf)
    print(classification_report(y_test,preds))
    mm= confusion_matrix(y_test,preds)
    plot_confusion_matrix(mm,colorbar=True)
```

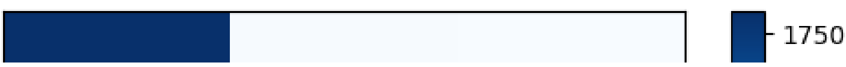
In [128]:

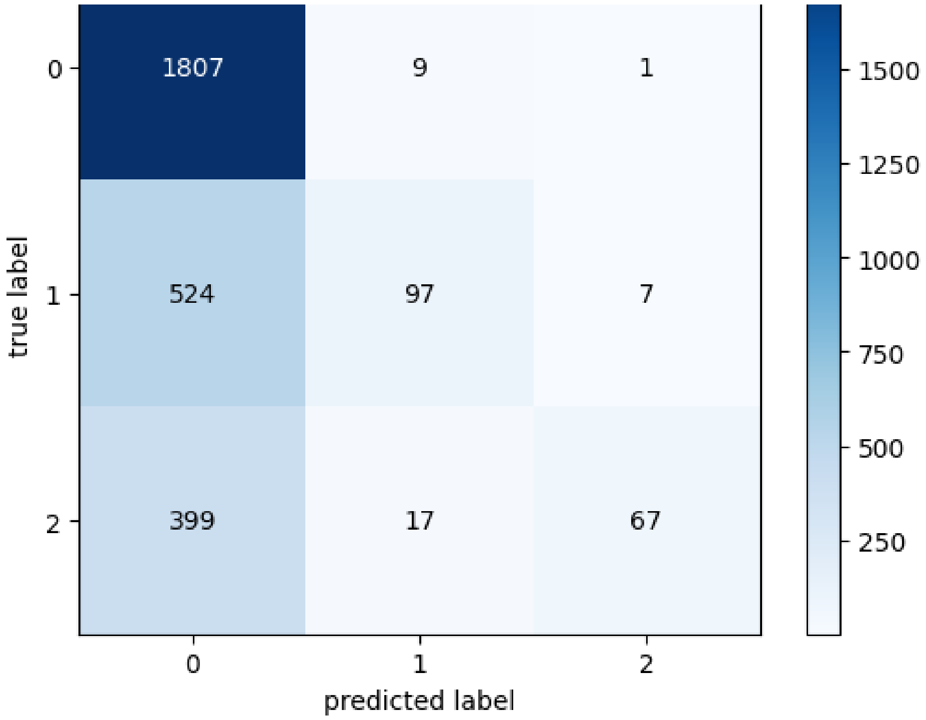
```python
print("NB MODEL")
report(nb)
```

```
NB MODEL
              precision    recall  f1-score   support

    negative       0.66      0.99      0.79      1817
     neutral       0.79      0.15      0.26       628
    positive       0.89      0.14      0.24       483

    accuracy                           0.67      2928
   macro avg       0.78      0.43      0.43      2928
weighted avg       0.73      0.67      0.59      2928
```





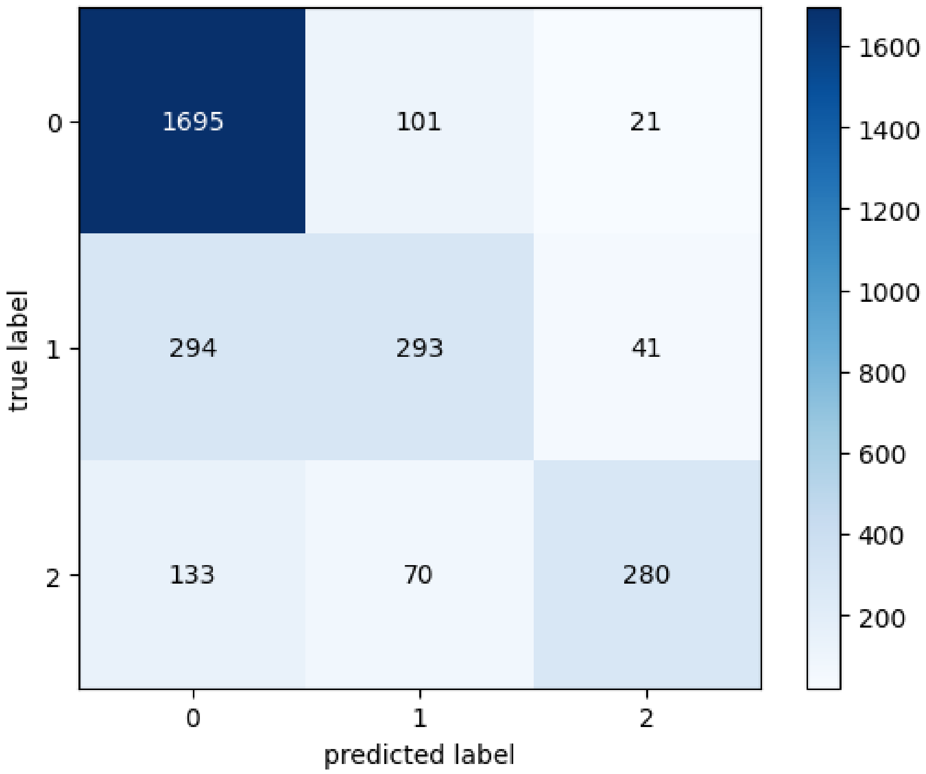
In [129]:

```
print("Logistic Regression")
report(log)
```

```
Logistic Regression
              precision    recall  f1-score   support

    negative       0.80      0.93      0.86      1817
     neutral       0.63      0.47      0.54       628
    positive       0.82      0.58      0.68       483

    accuracy                           0.77      2928
   macro avg       0.75      0.66      0.69      2928
weighted avg       0.77      0.77      0.76      2928
```



In [130]:

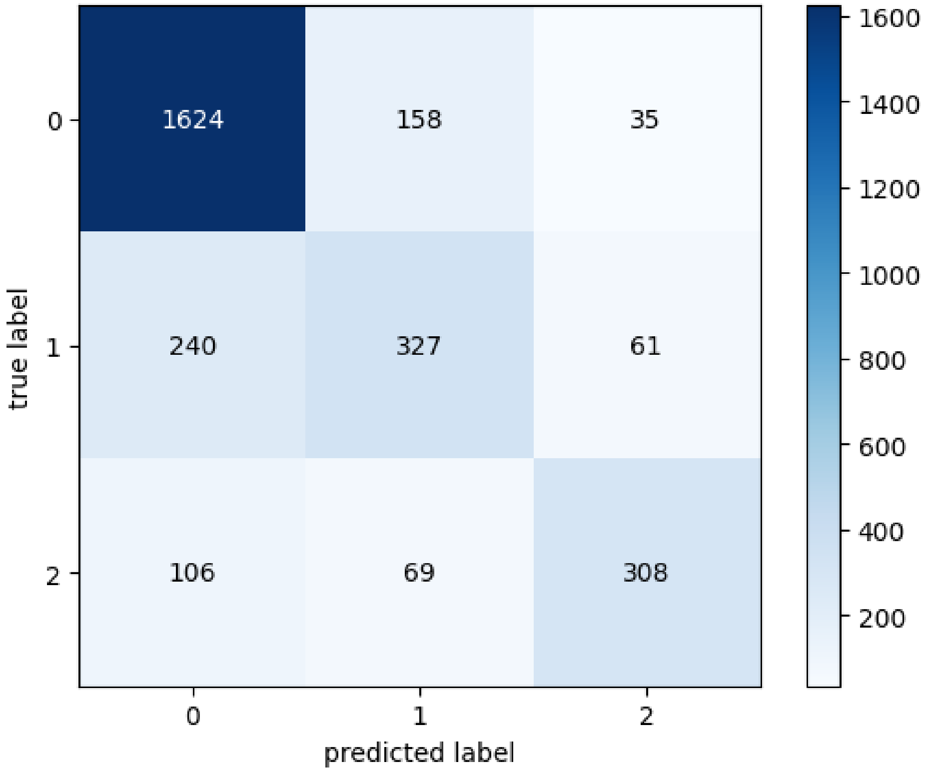
```
print('SVC')
```

```
report(svc)
```

```
SVC
              precision    recall  f1-score   support

    negative       0.82      0.89      0.86      1817
     neutral       0.59      0.52      0.55       628
    positive       0.76      0.64      0.69       483

    accuracy                           0.77      2928
   macro avg       0.73      0.68      0.70      2928
weighted avg       0.76      0.77      0.77      2928
```



Finalizing a PipeLine for Deployment on New Tweets

If we were satisfied with a model's performance, we should set up a pipeline that can take in a tweet directly.

In [131]:

```
from sklearn.pipeline import Pipeline
```

In [132]:

```
pipe = Pipeline([('tfidf',TfidfVectorizer()),('svc',LinearSVC())])
```

In [133]:

```
pipe.fit(df['text'],df['airline_sentiment'])
```

Out[133]:

```
▸ Pipeline
▸ TfidfVectorizer
▸ LinearSVC
```

In [134]:

```
new_tweet = ['good flight']
pipe.predict(new_tweet)
```

Out[134]:

```
array(['positive'], dtype=object)
```

In [135]:

```
new_tweet = ['bad flight']
pipe.predict(new_tweet)
```

Out[135]:

```
array(['negative'], dtype=object)
```

In [136]:

```
new_tweet = ['ok flight']
pipe.predict(new_tweet)
```

Out[136]:

```
array(['neutral'], dtype=object)
```