Project 4: NLP: Google and Apple Sentiment Analysis
Part 1: EDA and Data Viz

Introduction & Business Case
Welcome to the Phase 4 Project from Mark and Tim.
We are MT Head: A marketing and PR firm that works with tech companies like Apple and Google.
We help companies identify marketing and PR needs; product information requirements; alert them to possible customer service is
and provide ideas for product teams (changes to features or new features and products).

Let's do a little bit of time travel. The time is 2011. The place is Austin, Texas. The event is SXSW: the big music, movie, an
conference. We have been hired to gather information on how conference attendees (at SXSW Interactive) are feeling about our cl
products and services - specifically Apple and Google. One way we have chosen to do that is to examine tweets during the confe
We are specifically interested in those tweets that are positive in nature (as this can tell us where the companies mission and
products are resonating well with audiences) and tweets that are negative (so we can tell our clients where they need to change
messaging or products).
For context, 2011 is when the iPad 2 came out; this is just after the Japan earthquake/tsunami/nuclear disaster occurred; Maris
Mayer (Google and Yahoo fame) was one of the speakers; etc.

The Data
In this project we used the dataset provided for the project. It is a set of tweets from 2011 during the SXSW Conference. The s
includes 9093 tweets. Human raters first classified whether the tweet expressed a sentiment (3,548 were either pooitive or neg
with the remainder being "none" or "can't tell"). Then, if an emotion was expressed, the human raters indicated whether the twee
directed to either Apple or Google in general (1,091) or to a specific product from Apple (1,748) or Google (452).

We started with a set of 9,093 tweets > narrowed down to 3,182
Focus on positive and negative sentiment only (not neutrals)
Focus on just tweets with product or company mentioned (Apple, Google)

Advantages of tweets:
* timely
* event focused
* potentially lots of data (tweets) from many people
* limited length (so limits size of dataset)

Disadvantages of tweets:
* Limited length often means limited context and understandability
* Special characters and shorthand writing style can make it hard to tell meaning
* Tweets at a conference can span a lot of irrelevent topics - travel, entertainment, free stuff, food
* Unsure of legitimacy of poster and accuracy of information

In [1]:
```
# Load the relevant libraries and modules
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns

import nltk
from nltk.tokenize import word_tokenize, sent_tokenize
nltk.download('punkt')
from nltk.corpus import stopwords
import string
from nltk import FreqDist

from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import MultinomialNB

from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, explained_variance_score, confusion_matrix, accuracy_score, classification_report, log_lo
from math import sqrt

%matplotlib inline

# Set the basic plotting size; Increases the size of sns plots
sns.set(rc={'figure.figsize':(12,10)})
pd.set_option('display.max_columns', None)
```

```
[nltk_data] Downloading package punkt to /Users/markp/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

In [3]:
```
# Load the dataset (had to find correct coding to eliminate load error)
raw = pd.read_csv('tweet_product_company.csv', encoding = "ISO-8859-1")
raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9093 entries, 0 to 9092
Data columns (total 3 columns):
tweet_text                                            9092 non-null object
emotion_in_tweet_is_directed_at                       3291 non-null object
is_there_an_emotion_directed_at_a_brand_or_product    9093 non-null object
dtypes: object(3)
memory usage: 213.2+ KB
```

In [4]:
```
raw.shape
```
Out[4]: (9093, 3)

In [5]:
```
raw.head()
```
Out[5]:

	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

In [6]:
```
# Simplify column names
raw.rename(columns={'tweet_text': 'text', 'emotion_in_tweet_is_directed_at': 'brand', 'is_there_an_emotion_directed_at_a_brand_
```

In [7]:
```
raw.head()
```
Out[7]:

	text	brand	feelings
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

In [8]:
```
# Examine our class values - feelings
raw['feelings'].value_counts()
```
Out[8]:
```
No emotion toward brand or product    5389
Positive emotion                      2978
Negative emotion                       570
I can't tell                           156
Name: feelings, dtype: int64
```

In [9]:
```
raw['brand'].value_counts()
```
Out[9]:
```
iPad                               946
Apple                              661
iPad or iPhone App                 470
Google                             430
iPhone                             297
Other Google product or service    293
Android App                         81
Android                             78
Other Apple product or service      35
Name: brand, dtype: int64
```

In [10]:
```
# Check for null values - recall that brand was only assigned for positive and negative tweets.
print("Columns with null values")
display(raw.isnull().sum())
```
```
Columns with null values

text           1
brand       5802
feelings       0
dtype: int64
```

In [11]:
```
# Check for duplicated rows
duplicate = raw[raw.duplicated()]
duplicate.shape
```
Out[11]: (22, 3)

In [12]:
```
duplicate
```
Out[12]:

	text	brand	feelings
468	Before It Even Begins, Apple Wins #SXSW {link}	Apple	Positive emotion
776	Google to Launch Major New Social Network Call...	NaN	No emotion toward brand or product
2232	Marissa Mayer: Google Will Connect the Digital...	NaN	No emotion toward brand or product
2559	Counting down the days to #sxsw plus strong Ca...	Apple	Positive emotion
3950	Really enjoying the changes in Gowalla 3.0 for...	Android App	Positive emotion
3962	#SXSW is just starting, #CTIA is around the co...	Android	Positive emotion
4897	Oh. My. God. The #SXSW app for iPad is pure, u...	iPad or iPhone App	Positive emotion
5338	RT @mention ÷¼ GO BEYOND BORDERS! ÷_ {link} ...	NaN	No emotion toward brand or product
5341	RT @mention ÷¼ Happy Woman's Day! Make love, ...	NaN	No emotion toward brand or product
5881	RT @mention Google to Launch Major New Social ...	NaN	No emotion toward brand or product
5882	RT @mention Google to Launch Major New Social ...	NaN	No emotion toward brand or product
5883	RT @mention Google to Launch Major New Social ...	NaN	No emotion toward brand or product
5884	RT @mention Google to Launch Major New Social ...	NaN	No emotion toward brand or product
5885	RT @mention Google to Launch Major New Social ...	NaN	No emotion toward brand or product
6296	RT @mention Marissa Mayer: Google Will Connect...	Google	Positive emotion
6297	RT @mention Marissa Mayer: Google Will Connect...	NaN	No emotion toward brand or product
6298	RT @mention Marissa Mayer: Google Will Connect...	Google	Positive emotion
6299	RT @mention Marissa Mayer: Google Will Connect...	NaN	No emotion toward brand or product
6300	RT @mention Marissa Mayer: Google Will Connect...	NaN	No emotion toward brand or product
6546	RT @mention RT @mention Google to Launch Major...	NaN	No emotion toward brand or product
8483	I just noticed DST is coming this weekend. How...	iPhone	Negative emotion
8747	Need to buy an iPad2 while I'm in Austin at #s...	iPad	Positive emotion

Data cleanup and simplificiation

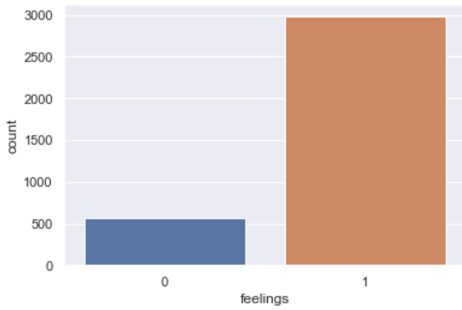
To keep things simple, we will narrow down the classes... just positive or negative sentiment, and I will collapse all specifi
products into just the 2 brands = Apple or Google.

In [13]:
```
raw2 = raw
```
In [14]:
```
# Brand consolidation step
company = {'iPad': 'Apple',
            'Apple': 'Apple',
            'iPad or iPhone App': 'Apple',
            'Google': 'Google',
            'iPhone': 'Apple',
            'Other Google product or service': 'Google',
            'Android App': 'Google',
            'Android': 'Google',
            'Other Apple product or service': 'Apple'}
raw2['brand'] = raw2['brand'].map(company)
```
In [15]:
```
raw2['brand'].value_counts()
```
Out[15]:
```
Apple     2409
Google     882
Name: brand, dtype: int64
```
In [16]:
```
raw3 = raw2
```
In [17]:
```
# Feelings class simplification (drop 2)
raw3.drop(raw3[raw3['feelings'] == "I can't tell"].index, inplace = True)
raw3.drop(raw3[raw3['feelings'] == "No emotion toward brand or product"].index, inplace = True)
raw3['feelings'].value_counts()
```
Out[17]:
```
Positive emotion    2978
Negative emotion     570
Name: feelings, dtype: int64
```
In [18]:
```
# Change 'feelings' to numeric labels
feels = {'Negative emotion': 0,'Positive emotion': 1,}
raw3['feelings'] = raw3['feelings'].map(feels)
```

In [19]:
```
# Doing some visualization of our classes: not very balanced.
print (raw3['feelings'].value_counts())
sns.countplot(x = 'feelings', data = raw3)
```

```
1    2978
0     570
Name: feelings, dtype: int64
```

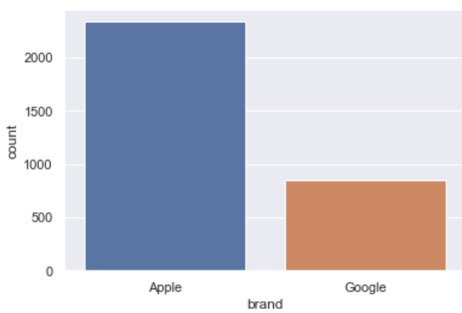
Out[19]: <AxesSubplot:xlabel='feelings', ylabel='count'>



In [20]:
```
print (raw3['brand'].value_counts())
sns.countplot(x = 'brand', data = raw3)
```

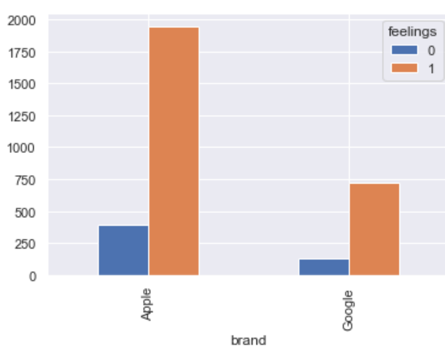
```
Apple     2337
Google     854
Name: brand, dtype: int64
```

Out[20]: <AxesSubplot:xlabel='brand', ylabel='count'>



In [21]:
```
pd.crosstab(raw3['brand'],raw3['feelings']).plot.bar()
```

Out[21]: <AxesSubplot:xlabel='brand'>



In [22]:
```
raw3.head()
```
Out[22]:

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

In [23]:
```
raw3.shape
```
Out[23]:
```
(3548, 3)
```

In [24]:
```
# Check for null values
print("Columns with null values")
display(raw3.isnull().sum())
```
```
Columns with null values

text          0
brand       357
feelings      0
dtype: int64
```

In [25]:
```
# Check for duplicated rows
duplicate = raw3[raw3.duplicated()]
duplicate.shape
```
Out[25]:
```
(9, 3)
```

In [26]:
```
raw4 = raw3
```

In [27]:
```
# drop the missing values in the brand column
raw4.dropna(subset=['brand'], inplace=True)
raw4.shape
```
Out[27]:
```
(3191, 3)
```

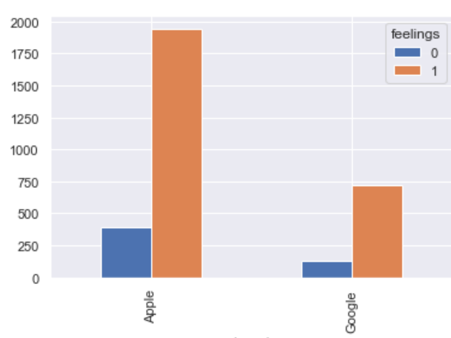
In [28]:
```
# Check for duplicated rows
duplicate = raw4[raw4.duplicated()]
duplicate.shape
```
Out[28]:
```
(9, 3)
```

In [29]:
```
raw5=raw4
```

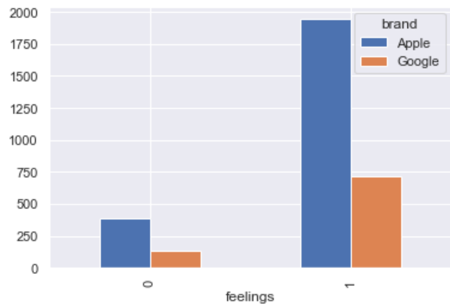
In [30]:
```
# Drop duplicate rows
raw5.drop_duplicates(keep='first',inplace=True)
raw5.shape
```
Out[30]:
```
(3182, 3)
```

In [31]:
```
print (raw5['feelings'].value_counts())
print (raw5['brand'].value_counts())
```
```
1    2664
0     518
Name: feelings, dtype: int64
Apple     2332
Google     850
Name: brand, dtype: int64
```

In [32]:
```
pd.crosstab(raw5['brand'],raw5['feelings']).plot.bar()
```
Out[32]:
```
<AxesSubplot:xlabel='brand'>
```



In [33]:
```
pd.crosstab(raw5['feelings'],raw5['brand']).plot.bar()
```
Out[33]: <AxesSubplot:xlabel='feelings'>



In [83]:
```
raw5.groupby('brand').count()
```
Out[83]:

	text	feelings	text_fixed	char_count	stopwords
brand					
Apple	2332	2332	2332	2332	2332
Google	850	850	850	850	850

In [84]:
```
raw5.groupby('feelings').count()
```
Out[84]:

	text	brand	text_fixed	char_count	stopwords
feelings					
0	518	518	518	518	518
1	2664	2664	2664	2664	2664

Observations after initial data cleaning and simplifying

By simplifying the classes and cleaning nulls and duplicates we have gone from 9093 to 3182 observations. As a result we have 2 classes of sentiments (0=negative; 1=positive) and 2 classes of brands (Apple and Google). There is a class imbance for each of these. The main one of concern is sentiment where positive sentiment makes up 84% of our tweets (16% is negative). Note sure ho will affect our models at this point. We may need to SMOTE.

In [ ]:

Criteria for Model Evaluation

We want to identify both positive and negative things people are saying about our clients and their services. However, we are r concerned with the negative things people are saying as these are areas for improvement, and in some cases may need immediate attention.

So we are concerned with model ACCURACY… for sure. But in addition to that, we are also concerned with RECALL (for the minority – negative tweets) … as we don't wan't to miss negative things that get predicted /coded as positive. Initially we have coded t negative class as 0 and the positive as 1. We may need to change that in the modeling phase – TBD.

In [34]:
```
raw5.head(2)
```
Out[34]:

	text	brand	feelings
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	Apple	0
1	@jessedee Know about @fludapp ? Awesome iPad/i...	Apple	1

In [98]:
```
raw5.text[1]
```
Out[98]:
```
"@jessedee Know about @fludapp ? Awesome iPad/iPhone app that you'll likely appreciate for its design. Also, they're giving fre
at #SXSW"
```

Text normalization and clean-up for NLP

Begin clean-up specifcaly for NLP. This includes creating a seperate column in the df for the cleaned text.

In [36]:
```
#Getting rid of upper cases. This avoids having multiple copies of the same words
raw5['text_fixed'] = raw5['text'].apply(lambda x: " ".join(x.lower() for x in x.split()))
raw5['text_fixed'].head()
```
Out[36]:
```
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...
Name: text_fixed, dtype: object
```

In [37]:
```
#Removing punctuation. To reduce the size of the data
raw5['text_fixed'] = raw5['text_fixed'].str.replace('[^\w\s]','')
raw5['text_fixed'].head()
```

Out[37]:
```
0    wesley83 i have a 3g iphone after 3 hrs tweeti...
1    jessedee know about fludapp  awesome ipadiphon...
2    swonderlin can not wait for ipad 2 also they s...
3    sxsw i hope this years festival isnt as crashy...
4    sxtxstate great stuff on fri sxsw marissa maye...
Name: text_fixed, dtype: object
```

In [38]:
```
# Take a look at standard stop word list
stop = stopwords.words('english')
print(stop)
```

```
['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've", "you'll", "you'd", 'your', 'yours', 'y
lf', 'yourselves', 'he', 'him', 'his', 'himself', 'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'the
'them', 'their', 'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll", 'these', 'those', 'am', 'is
re', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having', 'do', 'does', 'did', 'doing', 'a', 'an', 'the', 'and
ut', 'if', 'or', 'because', 'as', 'until', 'while', 'of', 'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'th
h', 'during', 'before', 'after', 'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'aga
'further', 'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'each', 'few', 'more', 'most',
er', 'some', 'such', 'no', 'nor', 'not', 'only', 'own', 'same', 'so', 'than', 'too', 'very', 's', 't', 'can', 'will', 'just',
"don't", 'should', "should've", 'now', 'd', 'll', 'm', 'o', 're', 've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'di
"didn't", 'doesn', "doesn't", 'hadn', "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn', "mightn't
ustn', "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn', "wasn't", 'weren', "weren't", 'won', "w
n't", 'wouldn', "wouldn't"]
```

In [39]:
```
len(stop)
```

Out[39]: 179

In [41]:
```
#how many characters in each tweet?
raw5['char_count'] = raw5['text_fixed'].str.len()
print(raw5[['text_fixed','char_count']].head())
print(raw5['char_count'].mean())
```

```
                                         text_fixed  char_count
0  wesley83 i have a 3g iphone after 3 hrs tweeti...         117
1  jessedee know about fludapp  awesome ipadiphon...         130
2  swonderlin can not wait for ipad 2 also they s...          74
3  sxsw i hope this years festival isnt as crashy...          76
4  sxtxstate great stuff on fri sxsw marissa maye...         117
98.95065996228787
```

In [42]:
```
#how many stop words are there per tweet?
raw5['stopwords'] = raw5['text_fixed'].apply(lambda x: len([x for x in x.split() if x in stop]))
raw5[['text_fixed','stopwords']].head(10)
```

Out[42]:

	text_fixed	stopwords
0	wesley83 i have a 3g iphone after 3 hrs tweeti...	10
1	jessedee know about fludapp awesome ipadiphon...	5
2	swonderlin can not wait for ipad 2 also they s...	8
3	sxsw i hope this years festival isnt as crashy...	5
4	sxtxstate great stuff on fri sxsw marissa maye...	1
7	sxsw is just starting ctia is around the corne...	15
8	beautifully smart and simple idea rt madebyman...	4
9	counting down the days to sxsw plus strong can...	5
10	excited to meet the samsungmobileus at sxsw so...	9
11	find amp start impromptu parties at sxsw with ...	5

In [43]:
```
print(raw5['stopwords'].mean())
```

```
5.674418604651163
```

In [45]:
```
raw5.head(5)
```

Out[45]:

	text	brand	feelings	text_fixed	char_count	stopwords
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	Apple	0	wesley83 i have a 3g iphone after 3 hrs tweeti...	117	10
1	@jessedee Know about @fludapp ? Awesome iPad/i...	Apple	1	jessedee know about fludapp awesome ipadiphon...	130	5
2	@swonderlin Can not wait for #iPad 2 also. The...	Apple	1	swonderlin can not wait for ipad 2 also they s...	74	8
3	@sxsw I hope this year's festival isn't as cra...	Apple	0	sxsw i hope this years festival isnt as crashy...	76	5
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	1	sxtxstate great stuff on fri sxsw marissa maye...	117	1

In [46]:
```
# Adding unique things to stopword list.
stop += ['link', 'quot', 'com', 'rt', 'mention', 'amp', 'sxsw', 'sxtx', '@mention']
stop_set = set(stop)
```

In [47]:
```python
#removing stopwords
raw5['text_fixed'] = raw5['text_fixed'].apply(lambda x: " ".join(x for x in x.split() if x not in stop_set))
raw5['text_fixed'].head()
```

Out[47]:
```
0    wesley83 3g iphone 3 hrs tweeting rise_austin ...
1    jessedee know fludapp awesome ipadiphone app y...
2                     swonderlin wait ipad 2 also sale
3     hope years festival isnt crashy years iphone app
4    sxtxstate great stuff fri marissa mayer google...
Name: text_fixed, dtype: object
```

In [48]:
```python
raw5.head()
```

Out[48]:

	text	brand	feelings	text_fixed	char_count	stopwords
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	Apple	0	wesley83 3g iphone 3 hrs tweeting rise_austin ...	117	10
1	@jessedee Know about @fludapp ? Awesome iPad/i...	Apple	1	jessedee know fludapp awesome ipadiphone app y...	130	5
2	@swonderlin Can not wait for #iPad 2 also. The...	Apple	1	swonderlin wait ipad 2 also sale	74	8
3	@sxsw I hope this year's festival isn't as cra...	Apple	0	hope years festival isnt crashy years iphone app	76	5
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	1	sxtxstate great stuff fri marissa mayer google...	117	1

In [101]:
```python
#most frequent words overall - hmmm lots of product names and general superlatives
freq = pd.Series(' '.join(raw5['text_fixed']).split()).value_counts()[:25]
freq
```

Out[101]:
```
ipad       1068
apple       863
google      666
iphone      603
store       532
2           492
app         408
new         357
austin      283
popup       210
ipad2       194
android     193
get         167
launch      157
like        134
great       131
via         131
line        131
time        130
social      126
one         122
cool        118
im          117
circles     112
party       112
dtype: int64
```

In [51]:
```python
raw6 = raw5
```

In [52]:
```python
raw6.head()
```

Out[52]:

	text	brand	feelings	text_fixed	char_count	stopwords
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	Apple	0	wesley83 3g iphone 3 hrs tweeting rise_austin ...	117	10
1	@jessedee Know about @fludapp ? Awesome iPad/i...	Apple	1	jessedee know fludapp awesome ipadiphone app y...	130	5
2	@swonderlin Can not wait for #iPad 2 also. The...	Apple	1	swonderlin wait ipad 2 also sale	74	8
3	@sxsw I hope this year's festival isn't as cra...	Apple	0	hope years festival isnt crashy years iphone app	76	5
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	1	sxtxstate great stuff fri marissa mayer google...	117	1

Update: Include more stop words

After some additional post modeling EDA decided to cut some of the really common words from our texts. Doing this on the raw6 dataset.

In [105]:
```python
# Adding MORE unique things to stopword list.
stop += ['link', 'quot', 'com', 'rt', 'mention', 'amp', 'sxsw', 'sxtx', '@mention', 'sxswi', 'store', 'link', 'http', '2', 'sxs
stop_set = set(stop)
```

In [131]:
```python
len(stop_set)
```

Out[131]:
```
210
```

In [106]:
```
#removing stopwords
raw6['text_fixed'] = raw6['text_fixed'].apply(lambda x: " ".join(x for x in x.split() if x not in stop_set))
raw6['text_fixed'].head()
```

Out[106]:
```
0    wesley83 3g 3 hrs tweeting rise_austin dead ne...
1    jessedee know fludapp awesome ipadiphone youll...
2                         swonderlin wait also sale
3                 hope years festival isnt crashy years
4    sxtxstate great stuff fri marissa mayer tim or...
Name: text_fixed, dtype: object
```

In [107]:
```
#most frequent words overall - after cutting out additional unique stopwords
freq = pd.Series(' '.join(raw6['text_fixed']).split()).value_counts()[:25]
freq
```

Out[107]:
```
popup        210
get          167
launch       157
like         134
great        131
via          131
line         131
time         130
social       126
cool         118
im           117
party        112
circles      112
day          105
free         103
maps         103
go           102
love          97
good          96
people        95
awesome       91
dont          89
temporary     88
opening       87
mobile        85
dtype: int64
```

In [ ]:

Diversion...Take a look at sentiment using TextBlob

We wanted to see how well an existing library / tool could detect sentiment in our set of tweets. Note that there are 2 scores from TextBlob: polarity (how negative or positive it is on scale of -1 to +1; and subjectivity which is on a 0 to 1 scale with being objective and 0 being subjective. UPDATED with raw6.

In [85]:
```
# Calculate the values and add them to our df.
raw5['polarity'] = raw5['text_fixed'].apply(lambda x: TextBlob(x).sentiment[0])
raw5['subjectivity'] = raw5['text_fixed'].apply(lambda x: TextBlob(x).sentiment[1])
raw5.head()
```

Out[85]:

	text	brand	feelings	text_fixed	char_count	stopwords	polarity	subjectivity
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	Apple	0	wesley83 3g iphone 3 hrs tweeting rise_austin ...	117	10	-0.200000	0.400000
1	@jessedee Know about @fludapp ? Awesome iPad/i...	Apple	1	jessedee know fludapp awesome ipadiphone app y...	130	5	0.466667	0.933333
2	@swonderlin Can not wait for #iPad 2 also. The...	Apple	1	swonderlin wait ipad 2 also sale	74	8	0.000000	0.000000
3	@sxsw I hope this year's festival isn't as cra...	Apple	0	hope years festival isnt crashy years iphone app	76	5	0.000000	0.000000
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	1	sxtxstate great stuff fri marissa mayer google...	117	1	0.800000	0.750000

In [88]:
```
# Create a table of summary stats for our whole df and can group by 'brand' or 'feelings.'
# display (raw5[raw5['brand'] == "Apple"] [['brand', 'polarity', 'subjectivity']].groupby ('brand').agg([np.mean, np.max, np.m:
# raw5[raw5['brand'] == "Google"] [['brand', 'polarity', 'subjectivity']].groupby ('brand').agg([np.mean, np.max, np.minimum, :
```

In [89]:
```
raw5.describe()
```

Out[89]:

	feelings	char_count	stopwords	polarity	subjectivity
count	3182.000000	3182.000000	3182.000000	3182.000000	3182.000000
mean	0.837209	98.950660	5.674419	0.180310	0.394471
std	0.369233	26.099363	3.045226	0.302532	0.321865
min	0.000000	23.000000	0.000000	-1.000000	0.000000
25%	1.000000	81.000000	3.000000	0.000000	0.000000
50%	1.000000	103.000000	5.000000	0.116553	0.425000
75%	1.000000	120.000000	8.000000	0.350000	0.642857
max	1.000000	153.000000	17.000000	1.000000	1.000000

In [90]:
```
raw5.groupby('brand').describe()
```

Out[90]:

				stopwords								polarity								subjectivity		
25%	50%	75%	max	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%	max	count	mean	std
79.0	102.0	119.0	153.0	2332.0	6.008148	3.070378	0.0	4.0	6.0	8.0	17.0	2332.0	0.175830	0.303132	-1.0	0.0	0.100000	0.350000	1.0	2332.0	0.393394	0.32
83.0	107.0	121.0	151.0	850.0	4.758824	2.777912	0.0	3.0	4.0	7.0	15.0	850.0	0.192602	0.300715	-1.0	0.0	0.136364	0.358929	1.0	850.0	0.397427	0.30

In [91]:
```
raw5.groupby('feelings').describe()
```

Out[91]:

	char_count								stopwords								polarity				
	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%
feelings																					
0	518.0	102.345560	26.315786	33.0	84.0	106.0	125.0	148.0	518.0	6.249035	3.198426	0.0	4.0	6.0	8.0	16.0	518.0	0.029767	0.334095	-1.0	-0.041
1	2664.0	98.290541	26.010621	23.0	80.0	102.0	119.0	153.0	2664.0	5.562688	3.002411	0.0	3.0	5.0	8.0	17.0	2664.0	0.209582	0.287043	-1.0	0.000

In [108]:
```
# RE-Run this with raw6... which has more stop words cut out.
# Calculate the values and add them to our df.
raw6['polarity'] = raw6['text_fixed'].apply(lambda x: TextBlob(x).sentiment[0])
raw6['subjectivity'] = raw6['text_fixed'].apply(lambda x: TextBlob(x).sentiment[1])
raw6.head()
```

Out[108]:

	text	brand	feelings	text_fixed	char_count	stopwords	polarity	subjectivity
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	Apple	0	wesley83 3g 3 hrs tweeting rise_austin dead ne...	117	10	-0.200000	0.400000
1	@jessedee Know about @fludapp ? Awesome iPad/i...	Apple	1	jessedee know fludapp awesome ipadiphone youll...	130	5	0.466667	0.933333
2	@swonderlin Can not wait for #iPad 2 also. The...	Apple	1	swonderlin wait also sale	74	8	0.000000	0.000000
3	@sxsw I hope this year's festival isn't as cra...	Apple	0	hope years festival isnt crashy years	76	5	0.000000	0.000000
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	1	sxtxstate great stuff fri marissa mayer tim or...	117	1	0.800000	0.750000

In [109]:
```
raw6.groupby('brand').describe()
```

Out[109]:

	feelings								char_count								stopwords				
	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%
brand																					
Apple	2332.0	0.834048	0.372117	0.0	1.0	1.0	1.0	1.0	2332.0	97.996569	26.169365	23.0	79.0	102.0	119.0	153.0	2332.0	6.008148	3.070378	0.0	4.0
Google	850.0	0.845882	0.361274	0.0	1.0	1.0	1.0	1.0	850.0	101.568235	25.740495	24.0	83.0	107.0	121.0	151.0	850.0	4.758824	2.777912	0.0	3.0

In [110]:
```
raw6.groupby('feelings').describe()
```

Out[110]:

	char_count								stopwords								polarity				
	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%
feelings																					
0	518.0	102.345560	26.315786	33.0	84.0	106.0	125.0	148.0	518.0	6.249035	3.198426	0.0	4.0	6.0	8.0	16.0	518.0	0.022475	0.340207	-1.0	-0.05
1	2664.0	98.290541	26.010621	23.0	80.0	102.0	119.0	153.0	2664.0	5.562688	3.002411	0.0	3.0	5.0	8.0	17.0	2664.0	0.209907	0.299760	-1.0	0.00

In [130]:
```
raw6.groupby(["feelings", "brand"]).describe()
```

Out[130]:

		char_count								stopwords								polarity			
		count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%	max	count	mean	std	mi
feelings	brand																				
0	Apple	387.0	101.085271	26.547942	33.0	82.0	105.0	124.0	148.0	387.0	6.439276	3.352875	0.0	4.0	6.0	9.0	16.0	387.0	0.025974	0.340228	-1
	Google	131.0	106.068702	25.351738	38.0	89.5	110.0	126.5	145.0	131.0	5.687023	2.622635	0.0	4.0	5.0	8.0	13.0	131.0	0.012140	0.341239	-1
1	Apple	1945.0	97.382005	26.056633	23.0	79.0	101.0	118.0	153.0	1945.0	5.922365	3.004564	0.0	4.0	6.0	8.0	17.0	1945.0	0.205774	0.301962	-1
	Google	719.0	100.748261	25.743416	24.0	82.0	106.0	120.0	151.0	719.0	4.589708	2.773724	0.0	3.0	4.0	6.0	15.0	719.0	0.221088	0.293634	-0

Observations on TextBlob Sentiment

```
Looking at the Polarity, it is interesting that the values are fairly neutral. The negative tweets only register as having a me
0.02, so just above zero. And the positive tweets only go up to an average of 0.21 ... so not that much above 0.
```

In [93]:
```
# save raw5 as csv file and upload to another notebook - this is non-tokenized df
raw5.to_csv(r'df5_tweets.csv')
```

Moving onward with pre-processing
This includes tokenizing and lematizing and doing some visualization of top words in our dataset.
UPDATE: adding the additional stopwords in raw6.

In [113]:
```
# Tokenizing the text to words (aka tokens)
text_str = ' '.join(raw6['text_fixed'].tolist())
```

In [114]:
```
tokens = nltk.word_tokenize(text_str) #tokenizing
print(len(tokens))
```

```
25486
```

In [115]:
```
raw7 = raw6
```

In [116]:
```
# Lemmatize the text - not work in simple form
from nltk.stem import WordNetLemmatizer
lemma = WordNetLemmatizer() #instantiate
```

In [118]:
```
# lemma.lemmatize(raw7['text_fixed'])
```

In [60]:
```
nltk.download('averaged_perceptron_tagger')
```

```
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /Users/markp/nltk_data...
[nltk_data]   Unzipping taggers/averaged_perceptron_tagger.zip.
```

Out[60]: True

In [119]:
```
# Looking at parts of speech (POS)
tokens_pos = nltk.pos_tag(tokens)
pos_df = pd.DataFrame(tokens_pos, columns = ('word','POS'))
pos_sum = pos_df.groupby('POS', as_index=False).count() # group by POS tags
pos_sum.sort_values(['word'], ascending=[False]) # in descending order of number of words per tag
```

Out[119]:

	POS	word
11	NN	9029
7	JJ	4944
13	NNS	2626
24	VBG	1476
26	VBP	1448
16	RB	1356
23	VBD	865
2	CD	705
22	VB	654
27	VBZ	588
6	IN	587
25	VBN	461
10	MD	171
9	JJS	102
12	NNP	80
3	DT	72
8	JJR	72
14	PRP	57
5	FW	50
17	RBR	36
19	RP	23
18	RBS	21
1	CC	17
20	TO	14
0	$	10
21	UH	9
29	WP	7
28	WDT	2
30	WRB	2
4	EX	1
15	PRP$	1

In [120]:

```
#POS: getting just the nouns
filtered_pos = [ ]
for one in tokens_pos:
    if one[1] == 'NN' or one[1] == 'NNS' or one[1] == 'NNP' or one[1] == 'NNPS':
        filtered_pos.append(one)
print (len(filtered_pos))
```

```
11735
```

In [124]:

```
#POS: the 100 most common nouns
fdist_pos = nltk.FreqDist(filtered_pos)
top_100_words = fdist_pos.most_common(50)
print(top_100_words)
```

```
[(('line', 'NN'), 131), (('time', 'NN'), 130), (('popup', 'NN'), 130), (('party', 'NN'), 112), (('circles', 'NNS'), 107), (('da
'NN'), 105), (('people', 'NNS'), 95), (('maps', 'NNS'), 89), (('launch', 'NN'), 87), (('network', 'NN'), 83), (('thanks', 'NNS
2), (('im', 'NN'), 67), (('users', 'NNS'), 64), (('dont', 'NN'), 64), (('design', 'NN'), 55), (('mayer', 'NN'), 55), (('techno
'NN'), 52), (('downtown', 'NN'), 50), (('ûïmention', 'NN'), 49), (('news', 'NN'), 47), (('get', 'NN'), 44), (('year', 'NN'), 4
(('shop', 'NN'), 44), (('video', 'NN'), 44), (('game', 'NN'), 42), (('team', 'NN'), 42), (('check', 'NN'), 42), (('panel', 'NN
2), (('way', 'NN'), 42), (('love', 'NN'), 40), (('wins', 'NNS'), 40), (('phone', 'NN'), 39), (('pop', 'NN'), 39), (('ones', 'NN
39), (('case', 'NN'), 38), (('thing', 'NN'), 38), (('everyone', 'NN'), 38), (('week', 'NN'), 37), (('session', 'NN'), 36), (('s
h', 'NN'), 35), (('years', 'NNS'), 33), (('music', 'NN'), 32), (('wait', 'NN'), 31), (('rumor', 'NN'), 31), (('marketing', 'NN
0), (('talk', 'NN'), 30), (('use', 'NN'), 30), (('tomorrow', 'NN'), 29), (('life', 'NN'), 29), (('fun', 'NN'), 27)]
```

In [125]:

```
top_words_df = pd.DataFrame(top_100_words, columns = ('pos','count'))
top_words_df['Word'] = top_words_df['pos'].apply(lambda x: x[0]) # split the tuple of POS
top_words_df = top_words_df.drop('pos', 1) # drop the previous column
top_words_df.head(25)
```

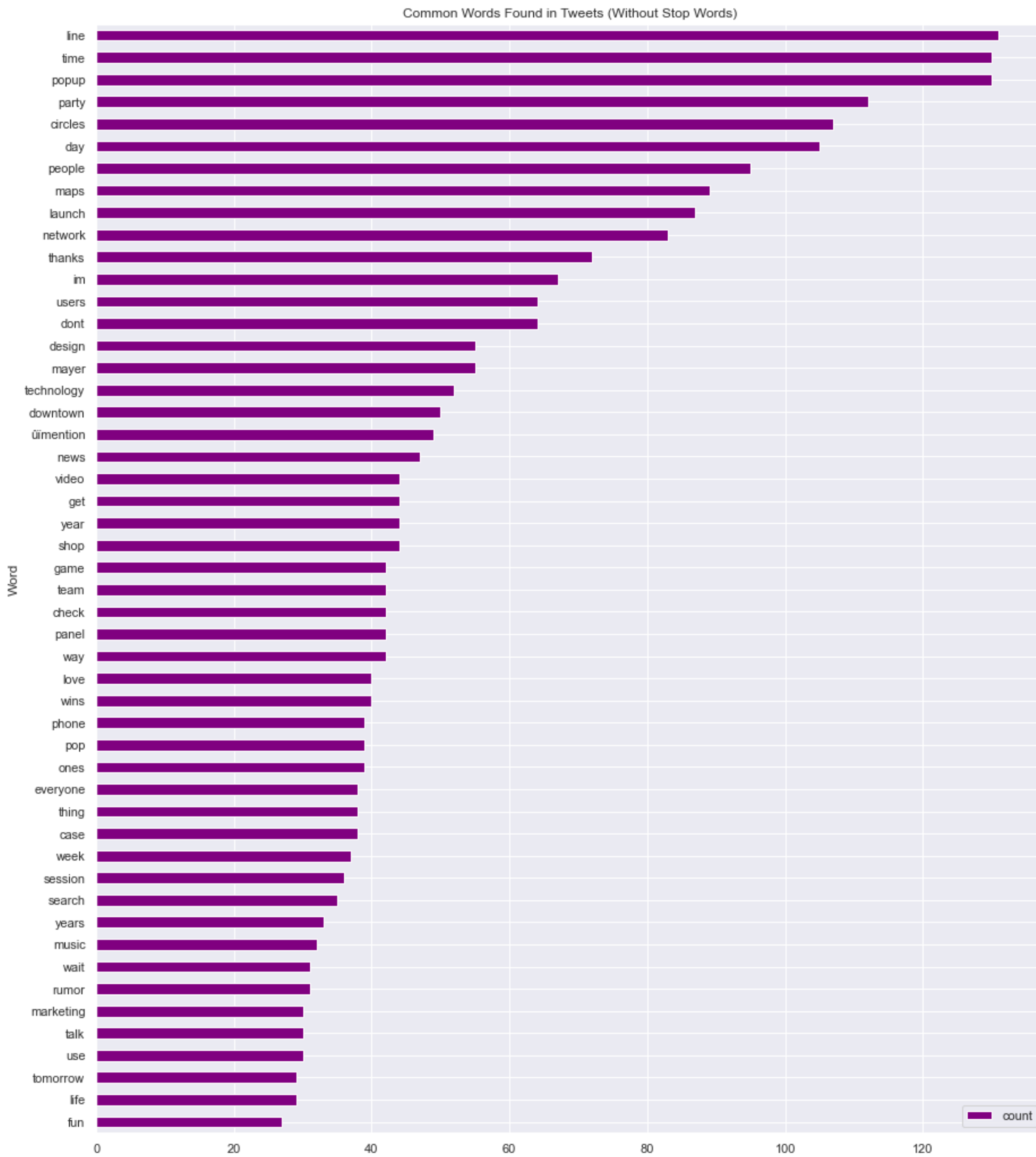
Out[125]:

	count	Word
0	131	line
1	130	time
2	130	popup
3	112	party
4	107	circles
5	105	day
6	95	people
7	89	maps
8	87	launch
9	83	network
10	72	thanks
11	67	im
12	64	users
13	64	dont
14	55	design
15	55	mayer
16	52	technology
17	50	downtown
18	49	ûïmention
19	47	news
20	44	get
21	44	year
22	44	shop
23	44	video
24	42	game

In [123]:

```
# top_words_df.head(50)
```

In [126]:
```
# The chart shows top 50 words - without stop words
fig, ax = plt.subplots(figsize=(15,18))
top_words_df.sort_values(by='count').plot.barh(x='Word', y='count', ax=ax, color="purple")
ax.set_title("Common Words Found in Tweets (Without Stop Words)")
plt.show()
```

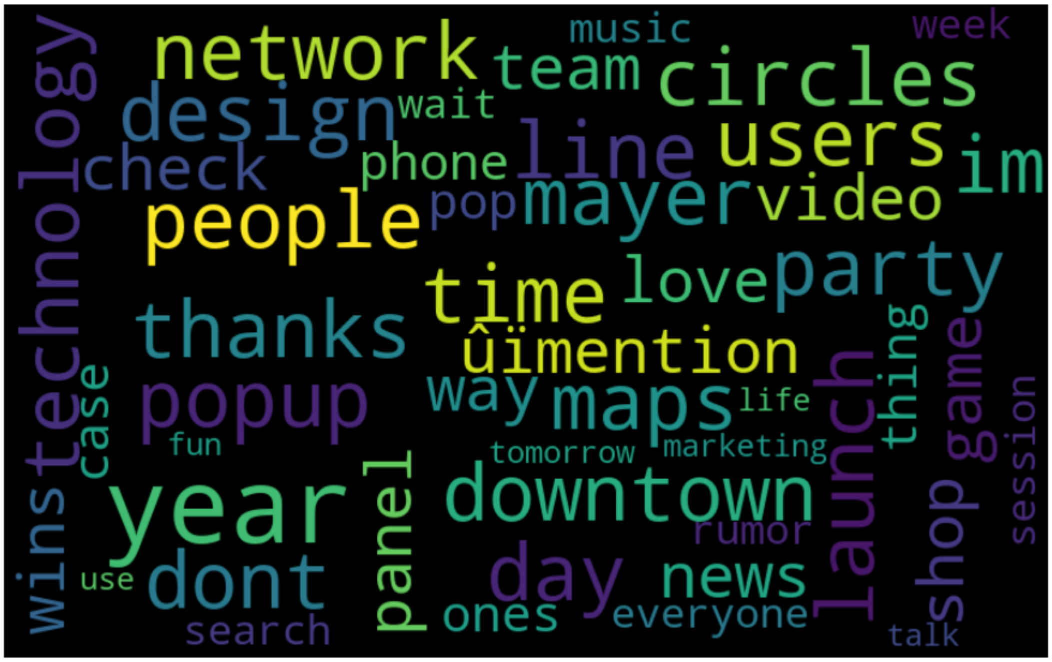


In [71]:
```
# Take a look at a word cloud
import textblob
import wordcloud
from textblob import TextBlob, Word
from wordcloud import WordCloud
```

In [127]:
```python
word_counts = ' '.join(top_words_df['Word'].tolist())
print(type(word_counts))
```

```
<class 'str'>
```

In [128]:
```python
# Plot is of top 50 words - same data as chart above.
plt.figure(figsize=(16,10))
wordcloud = WordCloud(width=800, height=500, max_font_size=80).generate(word_counts)
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
# plt.title('Top Words in Tweet Set')
plt.show()
```



Observations on initial word counts
Initially, when we did not remove unique stop words, we could see from the list, barchart and word cloud that there was a lot o
prodcut names and company names and a few things related to the conference process itself. Also we need to keep in mind this is
ALL texts so it is mostly the ones with positive sentiment. Also need to keep in mind that this is just the token counts... so
the result of TF-IDF or running a classificaltion model.

UPDATE: After removing the 32 unique stopwords some terms with a bit more meaning are showing up in the chart nd word cloud. Th
are things like specific apps or features that launched at SXSWi - circles, maps, news, and also references to the lines and go
downtown to the Apple popup store (to get the new iPad2). Later we will look at word clouds specific to the sentiment and the
company.

On to Classification Modeling...

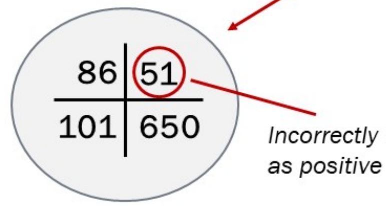
An iterative, layerd approach
We took an iterative approach in which we ran 3 different models (Logistic Regression, Random Forest, and Multinomial Naive Bay
layered on various pre-processing steps (vectorization and Lemmatization) and SMOTE (to help with the class imbalance). The det
steps are covered in another Notebook. The results of that modleing are included below. The model we selected as "best" was a
compromise between Accuracy and Recall. Recall is an important metric in this case as we want to be sure to accuratly classify
tweets with negative sentiment and not misclassify them as positive when they are in fact negative.

COUNT VECTORIZE	Accuracy	Precision	Recall	F1	TF-IDF	Accuracy	Precision	Recall	F1
Logistic Regression	0.84	0.51	0.42	0.46		0.87	0.63	0.54	0.58
Random Forest Vanilla	0.87	0.71	0.31	0.43		0.88	0.89	0.32	0.47
Multinomial Naive Bayes	0.86	0.65	0.28	0.4		0.85	1	0.08	0.15
SMOTE					AND SMOTED				
Logistic Regression	0.81	0.46	0.59	0.52		0.88	0.82	0.33	0.47
Random Forest Vanilla	0.77	0.39	*0.65*	0.49		0.88	0.86	0.23	0.37
Multinomial Naive Bayes	0.84	0.54	0.54	0.54		0.8	0.41	0.63	0.49

	LEMMATIZED CV	Accuracy	Precision	Recall	F1	LEMMATIZED TF-IDF	Accuracy	Precision	Recall
Logistic Regression		0.86	0.54	0.42	0.47		0.87	0.57	0.51
Random Forest Vanilla		**0.89**	0.81	0.32	0.46		**0.89**	0.77	0.35
Multinomial Naive Bayes		0.88	0.71	0.3	0.42		0.86	0.88	0.11
	AND SMOTED					AND SMOTED			
Logistic Regression		0.81	0.42	0.56	0.48		0.87	0.59	0.53
Random Forest Vanilla		0.79	0.38	0.55	0.45		**0.9**	0.84	0.4
Multinomial Naive Bayes		0.84	0.49	0.61	0.54		0.83	0.45	0.62

An iterative, layered approach...
total of 24 models run:

- Best Accuracy = **0.90**
- Best Recall = **0.65**



Best Model: a compromise of Accuracy & Recall

- Multinomial NB w/TFIDF vectorized + lemmatized + SMOTE = **0.83** accuracy
- With recall of **0.62** for class 0, there is still a 38% chance of predicting positive when tweet is negative

In [ ]: