Sentiment analysis on tweets dataset

> In my project I would like to experiment with the Twitter US Airline dataset which is available on the website *https://www.kaggle.com/crowdflower/twitter-airline-sentiment* and originally came from Crowdflower's Data for Everyone library. My goal is to do sentiment analysis, predict if tweets are positive, negative or neutral about flight.
>
> Firstly we need to load into Colab two files: our dataset *Tweets.csv* and *glove.6B.100d.txt*, which will be needed later.

1. Import libraries

At the beginning we have to import necessary Python libraries.

In [1]:
```
import numpy as np
import pandas as pd
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
import re
```

In [2]:
```
import nltk
nltk.download('wordnet')
```

```
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Unzipping corpora/wordnet.zip.
```

Out[2]: True

In [3]:
```
from wordcloud import WordCloud
```

In [4]:
```
from nltk.corpus import stopwords
nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

Out[4]: True

In [5]:
```
from sklearn.model_selection import train_test_split
```

In [6]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
```

In [7]:
```
import joblib
```

In [8]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RepeatedStratifiedKFold
```

In [9]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import MultinomialNB
```

In [10]:
```
from keras.preprocessing.text import Tokenizer
from tensorflow.keras.utils import to_categorical
from keras.preprocessing.sequence import pad_sequences
import tensorflow as tf
```

In [11]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Flatten
```

In [12]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score
from sklearn.metrics import classification_report
```

In [13]:
```
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
```

2. Loading dataset

In [14]:
```
dataset = pd.read_csv('Tweets.csv')
```

In [15]:
```
dataset.head(10)
```

Out[15]:

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	negativereason_c
0	570306133677760513	neutral	1.0000	NaN	
1	570301130888122368	positive	0.3486	NaN	
2	570301083672813571	neutral	0.6837	NaN	
3	570301031407624196	negative	1.0000	Bad Flight	
4	570300817074462722	negative	1.0000	Can't Tell	
5	570300767074181121	negative	1.0000	Can't Tell	
6	570300616901320704	positive	0.6745	NaN	

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	negativereason_c
7	570300248553349120	neutral	0.6340	NaN	
8	570299953286942721	positive	0.6559	NaN	
9	570295459631263746	positive	1.0000	NaN	

In [16]:
```
dataset.shape
```

Out[16]:
```
(14640, 15)
```

In [17]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14640 entries, 0 to 14639
Data columns (total 15 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   tweet_id                      14640 non-null  int64  
 1   airline_sentiment             14640 non-null  object 
 2   airline_sentiment_confidence  14640 non-null  float64
 3   negativereason                9178 non-null   object 
 4   negativereason_confidence     10522 non-null  float64
 5   airline                       14640 non-null  object 
 6   airline_sentiment_gold        40 non-null     object 
 7   name                          14640 non-null  object 
 8   negativereason_gold           32 non-null     object 
 9   retweet_count                 14640 non-null  int64  
 10  text                          14640 non-null  object 
 11  tweet_coord                   1019 non-null   object 
 12  tweet_created                 14640 non-null  object 
 13  tweet_location                9907 non-null   object 
 14  user_timezone                 9820 non-null   object 
dtypes: float64(2), int64(2), object(11)
memory usage: 1.7+ MB
```

The file contains 14640 rows and 15 columns. The included features are:

- **tweet id** - unique number of tweet,
- **sentiment** - positive, negative or neutral
- **sentiment confidence score**,
- **negative reason** - main reason for negative tweets,
- **negative reason confidence**,
- **airline** - name of airline company,
- **sentiment gold**,
- **name** - user name,
- **retweet count** - integer number how many times tweet was retweeted,

- **tweet text** - tweet message (string),
- **tweet coordinates** - cooridinates of localization,
- **time of tweet** - time posting tweet,
- **date of tweet** - date posting tweet,
- **tweet location**,
- **user time zone**.

3. Dataset analysis

We are going to do basic analysis to better understand the data.

In [18]:
```
100*dataset.isnull().sum()/len(dataset)
```

Out[18]:
```
tweet_id                         0.000000
airline_sentiment                0.000000
airline_sentiment_confidence     0.000000
negativereason                  37.308743
negativereason_confidence       28.128415
airline                          0.000000
airline_sentiment_gold          99.726776
name                             0.000000
negativereason_gold             99.781421
retweet_count                    0.000000
text                             0.000000
tweet_coord                     93.039617
tweet_created                    0.000000
tweet_location                  32.329235
user_timezone                   32.923497
dtype: float64
```

Airline_sentiment_gold, negativereason_gold and tweet_coord have more than 90% of missing values.

- negative reason

In [19]:
```
dataset.groupby(dataset['negativereason'].isnull())['airline_sentiment'].count()
```

Out[19]:
```
negativereason
False    9178
True     5462
Name: airline_sentiment, dtype: int64
```

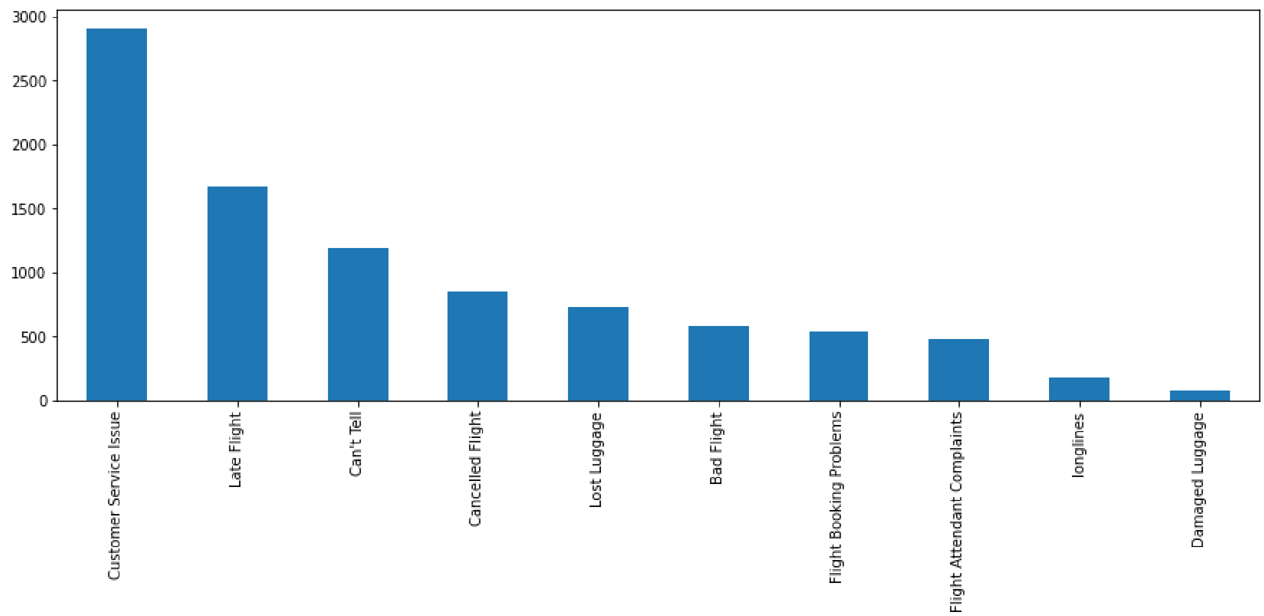
We have over 5400 missing values in *negative reason* feature.

In [20]:
```
dataset['negativereason'].value_counts()
```

Out[20]:
```
Customer Service Issue        2910
Late Flight                   1665
Can't Tell                    1190
Cancelled Flight               847
Lost Luggage                   724
Bad Flight                     580
Flight Booking Problems        529
Flight Attendant Complaints    481
longlines                      178
Damaged Luggage                 74
Name: negativereason, dtype: int64
```

In [21]:
```
dataset['negativereason'].value_counts().plot(kind='bar', figsize=(15,5))
```

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x7f002f36a0f0>



The most popular reasons are: Customer Service Issue, Late Flight.

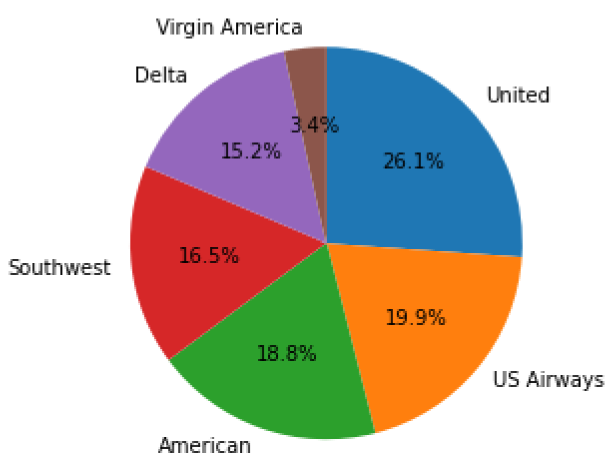
- airline

In [22]:
```
dataset['airline'].unique()
```

Out[22]:
```
array(['Virgin America', 'United', 'Southwest', 'Delta', 'US Airways',
       'American'], dtype=object)
```

In [23]:
```
def pieChart(df):
    sizes = df.value_counts()
    labels = df.value_counts().index.values
    fig1, ax1 = plt.subplots()
    ax1.pie(sizes, labels = labels, autopct='%1.1f%%', startangle=90, counterclock=Fals
    ax1.axis('equal')
```

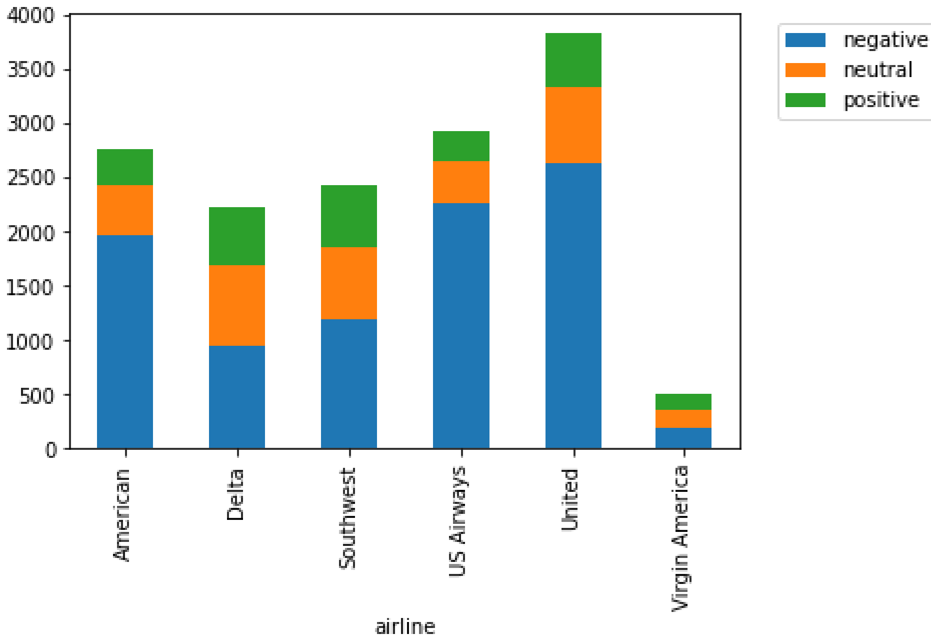
In [24]:
```
pieChart(dataset['airline'])
```



In dataset we have over one quarter tweets about United company, almost 20% tweets about US Airways and American. Then, around 15% tweets are about Southwest and Delta airlines and, last but not least, we have tweets about Virgin America.

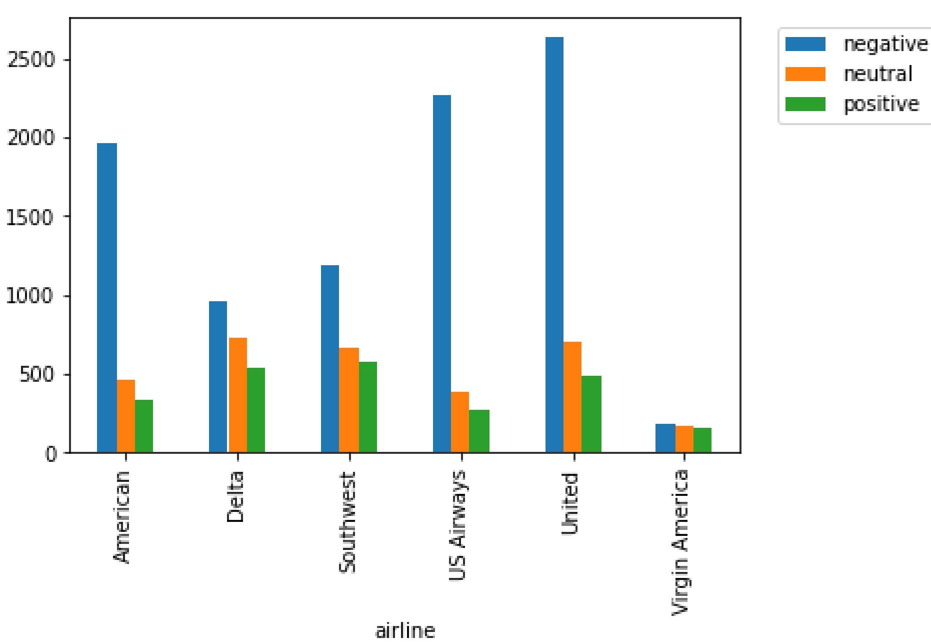
In [25]:
```
dataset_gb = dataset.groupby(['airline', 'airline_sentiment']).size().unstack(level=1)
dataset_gb.plot(kind = 'bar',stacked=True)
plt.legend(bbox_to_anchor=(1.04,1), loc="upper left")
```

Out[25]: <matplotlib.legend.Legend at 0x7f002edeec88>



In [26]:
```
dataset_gb.plot(kind = 'bar')
plt.legend(bbox_to_anchor=(1.04,1), loc="upper left")
```

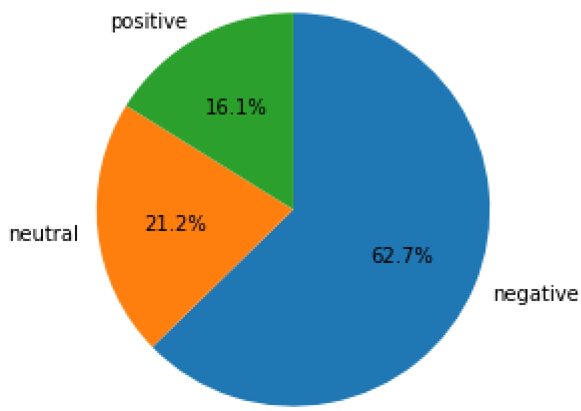
Out[26]: <matplotlib.legend.Legend at 0x7f002edab860>



It should be noted that for every airline company there is a lot of negative tweets. Delta, Southwest and Virgin America have fairly balanced tweets.

- airline sentiment

In [27]:
```
pieChart(dataset['airline_sentiment'])
```



On this chart we can see that a majority of negative comments (63%) were followed by neutral (21%) and positive (16%).

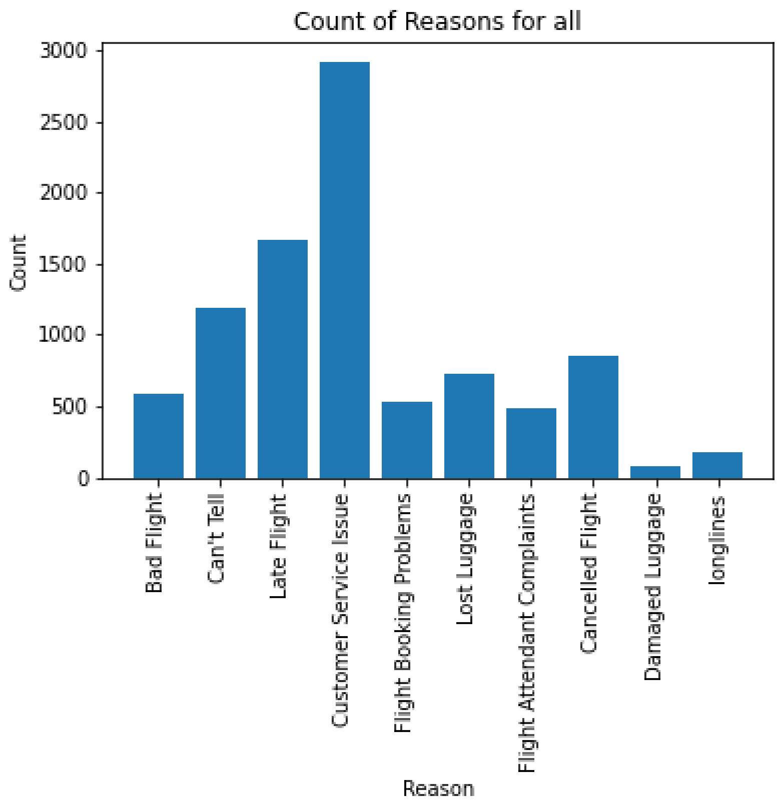
- airline vs reason

In [28]:
```
reason = dict(dataset['negativereason'].value_counts(sort=False))
```

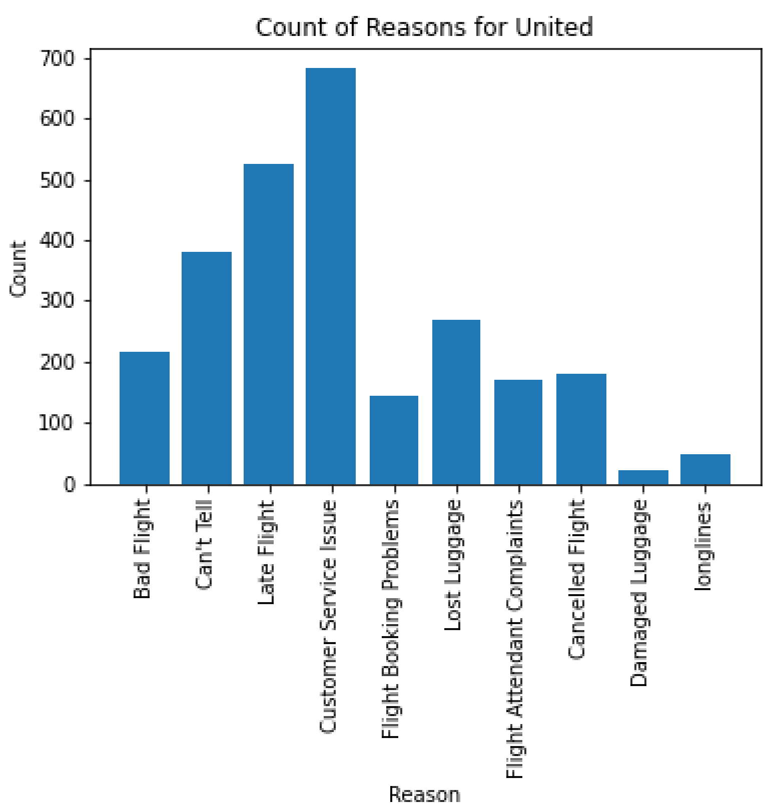
In [29]:
```
def count_reason(airline):
    if airline == 'all':
        df = dataset
    else:
        df = dataset[dataset['airline']==airline]
    airline_reason = dict(df['negativereason'].value_counts())
    unique_reason = list(dataset['negativereason'].unique())
    unique_reason = [x for x in unique_reason if str(x) != 'nan']
    reason_frame = pd.DataFrame({'reasons': unique_reason})
    reason_frame['count'] = reason_frame['reasons'].apply(lambda x : airline_reason[x])
    return reason_frame
```

In [30]:
```
def plot_reason(airline):
    df = count_reason(airline)
    count = df['count']
    Index = range(1,len(df)+1)
    plt.bar(Index,count)
    plt.xticks(Index,df['reasons'],rotation=90)
    plt.ylabel('Count')
    plt.xlabel('Reason')
    plt.title('Count of Reasons for '+airline)
```

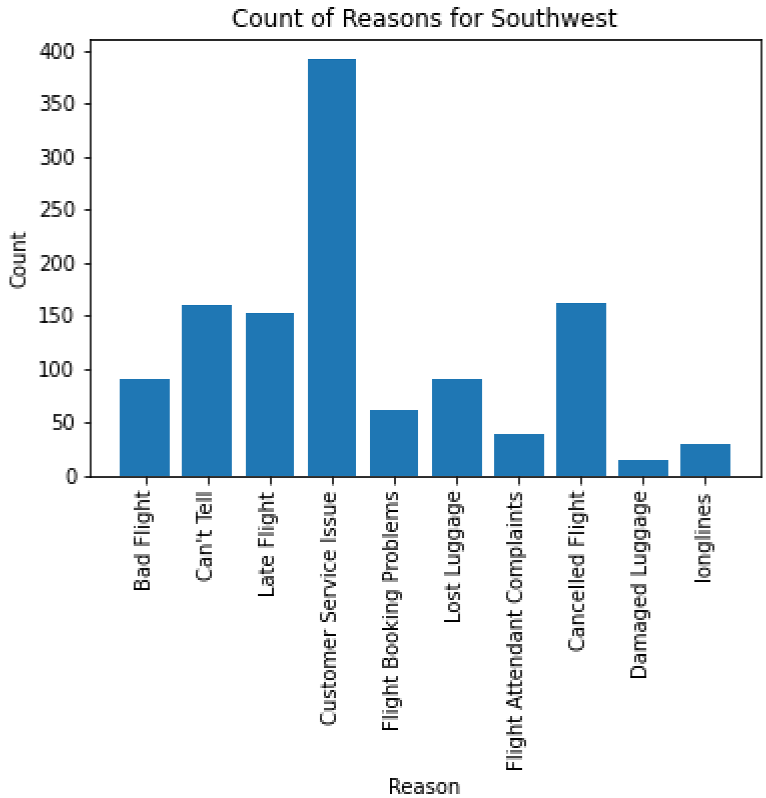
In [31]:
```
plot_reason('all')
```



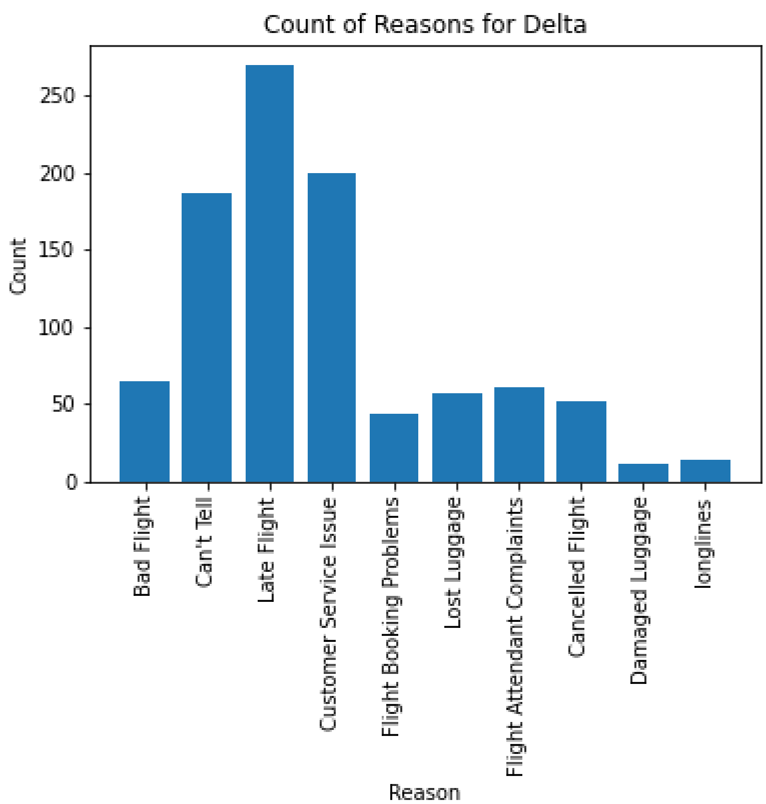
In [32]:
```
plot_reason('United')
```



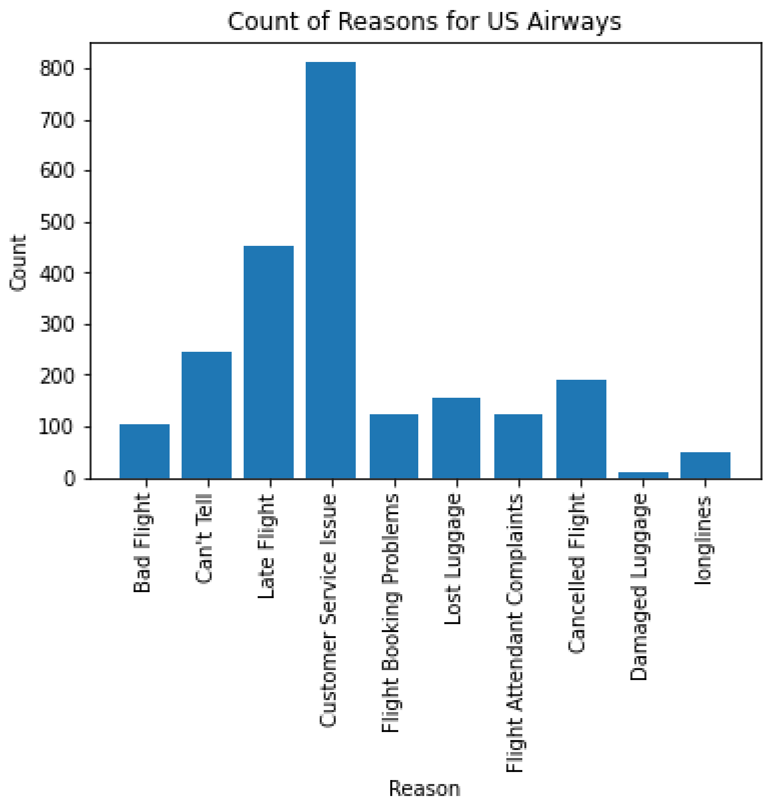
In [33]:
```
plot_reason('Southwest')
```



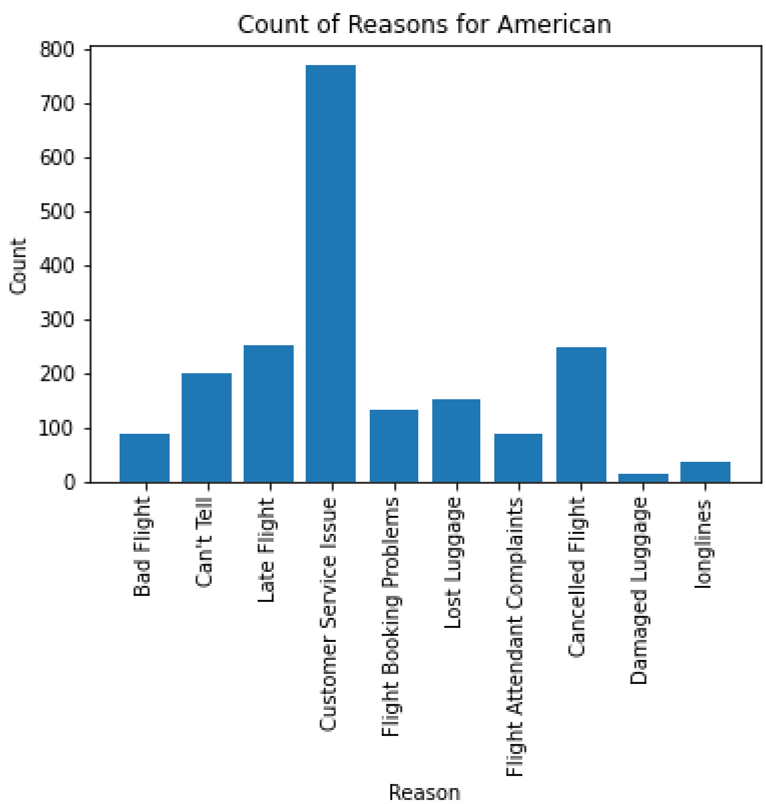
In [34]:
```
plot_reason('Delta')
```



In [35]:
```
plot_reason('US Airways')
```



In [36]:
```
plot_reason('American')
```



It should also be emphasized that the Customer Service Issue is the most popular reason for United, Southwest, US Airways and American companies.

4. Drop variables

In further work we need only 2 columns: text and sentiment.

In [37]:
```
dataset.drop(['tweet_id', 'name','retweet_count', 'tweet_created', 'tweet_location',
       'user_timezone', 'airline_sentiment_confidence', 'negativereason','negativereaso
       'airline_sentiment_gold', 'negativereason_gold', 'tweet_coord'], axis=1, inplace
```

In [38]:
```
dataset.to_csv('Tweets_cleaned.csv', index=False)
```

In [39]:
```
dataset.columns
```

Out[39]:
```
Index(['airline_sentiment', 'text'], dtype='object')
```

In [40]:
```
dataset.head()
```

Out[40]:

	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...

5. Processing data

Before we start training models, we need to transforming text into a analyzable form.

In [41]:
```
pd.set_option('display.max_colwidth', -1)
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:1: FutureWarning: Passing a
negative integer is deprecated in version 1.0 and will not be supported in future versio
n. Instead, use None to not limit the column width.
  """Entry point for launching an IPython kernel.
```

In [42]:
```
dataset['text']
```

Out[42]:
```
0        @VirginAmerica What @dhepburn said.
1        @VirginAmerica plus you've added commercials to the experience... tacky.
2        @VirginAmerica I didn't today... Must mean I need to take another trip!
3        @VirginAmerica it's really aggressive to blast obnoxious "entertainment" in you
r guests' faces &amp; they have little recourse
4        @VirginAmerica and it's a really big bad thing about it
                                        ...
14635    @AmericanAir thank you we got on a different flight to Chicago.
14636    @AmericanAir leaving over 20 minutes Late Flight. No warnings or communication
until we were 15 minutes Late Flight. That's called shitty customer svc
14637    @AmericanAir Please bring American Airlines to #BlackBerry10
14638    @AmericanAir you have my money, you change my flight, and don't answer your pho
nes! Any other suggestions so I can make my commitment??
14639    @AmericanAir we have 8 ppl so we need 2 know how many seats are on the next fli
ght. Plz put us on standby for 4 people on the next flight?
Name: text, Length: 14640, dtype: object
```

First, we are going to remove stopwords - there are frequent words such as "the", "is", etc. We will be using a list of English stopwords from nltk library. It might take about 20 seconds.

In [43]:
```
stopWords = stopwords.words('english')
stopWords.append('would')
stopWords.append("don't")
```

In [44]:
```
dataset['text'] = dataset['text'].apply(lambda x: ' '.join([word for word in x.split()
print('Stopwords removed')
```

```
Stopwords removed
```

Now we are going to processing using regular expression including convert all letters to lower case, remove numbers and punctuations.

In [45]:
```
def preprocesing_text(text):
    text = text.lower()
    text = re.sub('https?://[A-Za-z0-9./]+', ' ', text)   #remove url links
    text = re.sub("www.[A-Za-z0-9./]+", ' ', text)
    text = re.sub('@[^\s]+', ' ', text)      #remove user name
    text = re.sub('\d+', ' ', text)          #remove digits
    text = re.sub(r'[^\w\s]+', ' ', text)    #remove punctuations
    text = re.sub('_+', ' ', text)           #remove _ char
    text = re.sub('\n', ' ', text)
    text = re.sub(r'\b\w{1,2}\b', '', text) #remove words < 2
    text = re.sub(' +', ' ', text)           #convert two or more spaces into one space
    return text
```

In [46]:
```
dataset['text'] = dataset['text'].apply(preprocesing_text)
```

This is text after processing:

In [47]:
```
dataset['text']
```

Out[47]:
```
0         what said
1         plus added commercials experience tacky
2         today must mean need take another trip
3         really aggressive blast obnoxious entertainment guests faces amp little recour
se
4         really big bad thing
                 ...
14635     thank got different flight chicago
14636     leaving minutes late flight warnings communication minutes late flight that ca
lled shitty customer svc
14637     please bring american airlines blackberry
14638     money change flight answer phones any suggestions make commitment
14639     ppl need know many seats next flight plz put standby people next flight
Name: text, Length: 14640, dtype: object
```

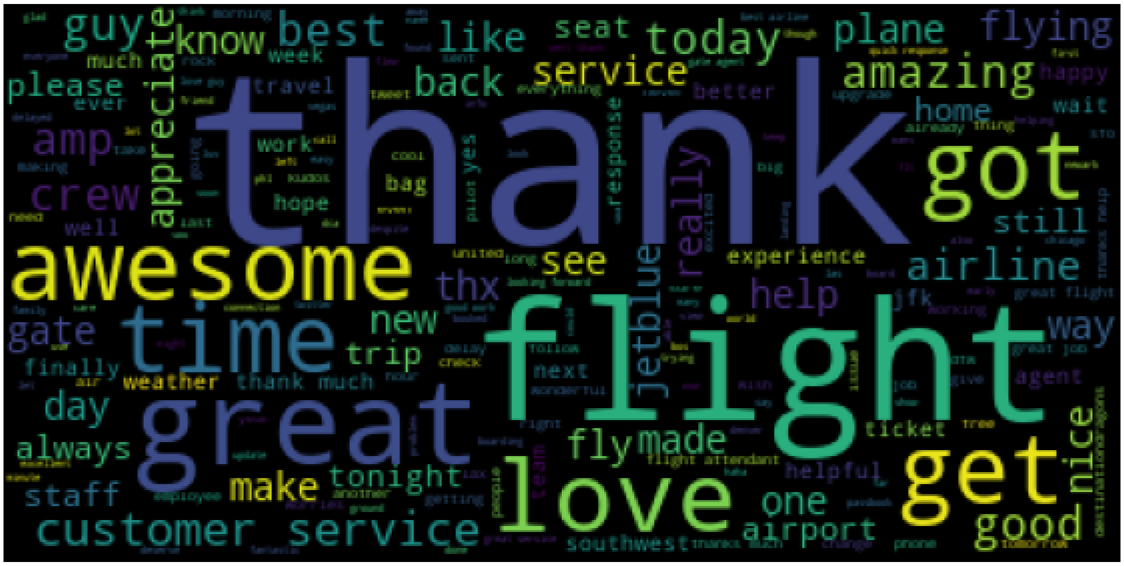
- word cloud

Let's generate WordClouds which represent the frequency of each word at this moment.

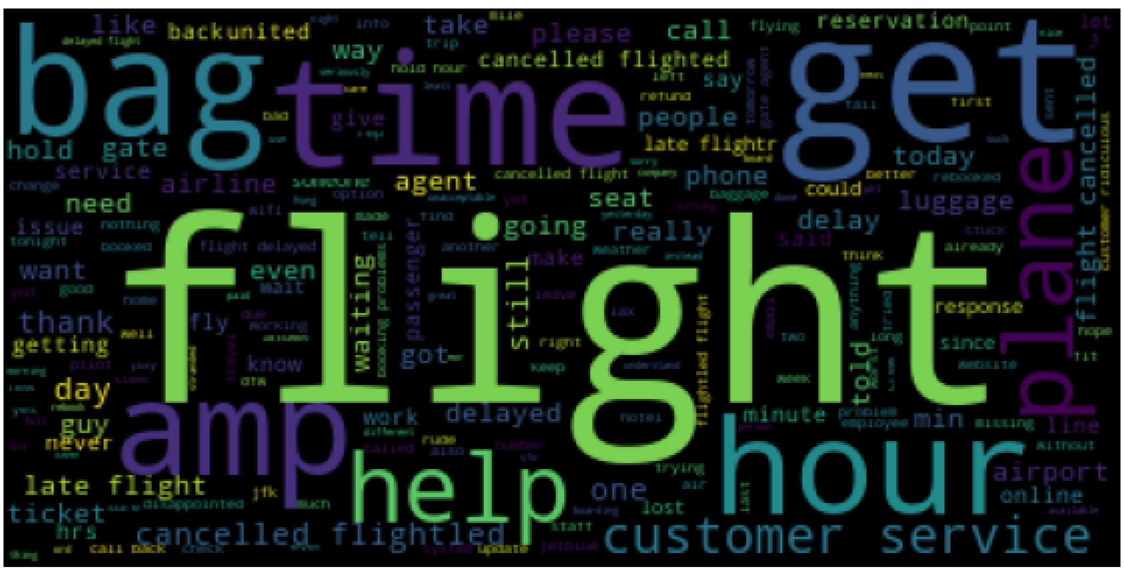
In [48]:
```
def wordCloud(sentiment):
    df = dataset[dataset['airline_sentiment'] == sentiment]
    textt = " ".join(review for review in df.text)
    wordcloud = WordCloud(stopwords = stopWords).generate(textt)
    plt.figure(figsize=(10,10))
    plt.imshow(wordcloud)
    plt.axis("off")
```

```
    plt.show()
    wordcloud.to_file("wordCloud_"+sentiment+".png")
```

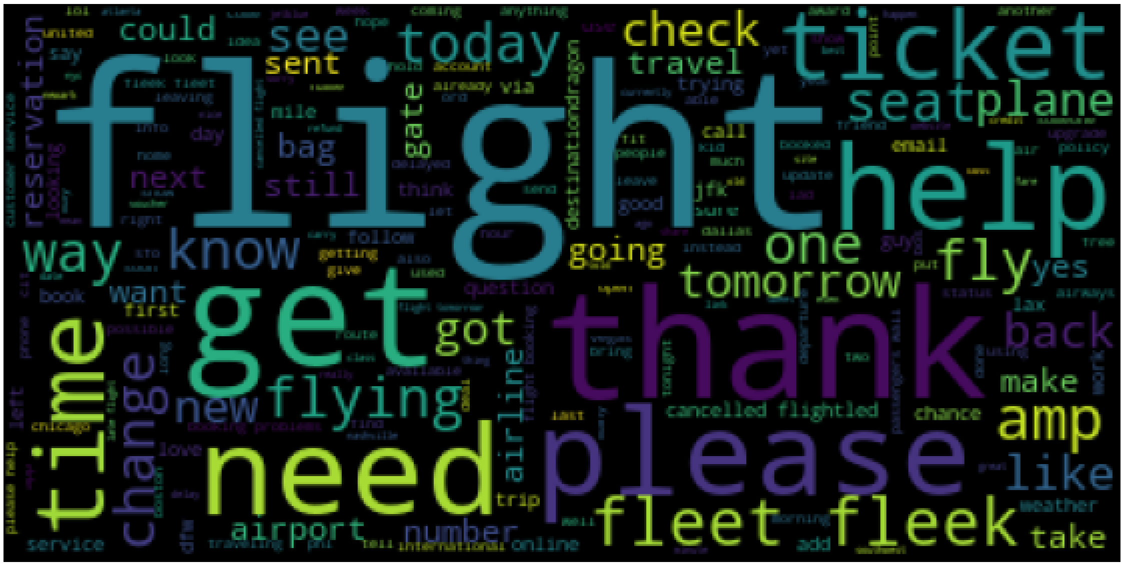
In [49]:
```
wordCloud('positive')
```



In [50]:
```
wordCloud('negative')
```



In [51]:
```
wordCloud('neutral')
```



We can observe that words such as 'thank', 'great' and 'awesome' are present more frequently in positive statements. In negative statements there is 'time', 'hour', 'help'.

In [52]:
```
dataset.to_csv('Tweets_processed.csv', index=False)
```

6. Split data

In [53]:
```
dataset.shape
```

Out[53]:
```
(14640, 2)
```

In [54]:
```
X = dataset.drop('airline_sentiment', inplace=False, axis=1)
y = dataset['airline_sentiment']
```

- encode labels

We have to replace the categorical value with a numeric value in labels.

In [55]:
```
sentiment_num = {'negative' : 0,  'neutral': 1, 'positive': 2}
```

In [56]:
```
y = y.map(sentiment_num)
```

In [57]:
```
y
```

Out[57]:
```
0        1
1        2
2        1
3        0
4        0
        ..
14635    2
14636    0
14637    1
14638    0
14639    1
Name: airline_sentiment, Length: 14640, dtype: int64
```

- split the data into train, validation, and test set

In [58]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.4, random_state
```

In [59]:
```
X_val, X_test, y_val, y_test = train_test_split(X_test, y_test, test_size=0.5, random_s
```

In [60]:
```
print('training features size: '+str(X_train.shape)+", validation features size: "+ str
print('training labels size: '+str(y_train.shape)+", validation labels size: "+str(y_va
```

```
training features size: (8784, 1), validation features size: (2928, 1), testing features
size: (2928, 1)
training labels size: (8784,), validation labels size: (2928,), testing labels size: (29
28,)
```

In [61]:
```
X_train.to_csv('X_train.csv', index=False)
X_val.to_csv('X_val.csv', index=False)
X_test.to_csv('X_test.csv', index=False)

y_train.to_csv('y_train.csv', index=False)
y_val.to_csv('y_val.csv', index=False)
y_test.to_csv('y_test.csv', index=False)
```

- Vectorizer

Next we are going to transform text to feature vectors that can be used as input to estimator using TfidfVectorizer. It converts a collection of raw documents to a matrix of TF-IDF features.

> Term frequency-inverse document frequency (tf-idf) can be used to downweight those frequently occurring words in the feature vectors. It is a product of the term frequency and the inverse document frequency:

$$\text{tf-idf}(t,d) = \text{tf (t,d)} \times \text{idf}(t,d)$$

> where the tf(t, d) — is the term frequency, the number of times a term t occurs in a document d and the inverse document frequency idf(t, d) can be calculated as:
>
> $$\text{idf}(t,d) = log\frac{1+n_d}{1+\text{df}(d,t)}$$
>
> where n_d is the total number of documents, and df(d, t) is the number of documents d that contain the term t. By default scikit-learn's TfidfTransformer applies the L2-normalization.

In [62]:
```
vectoriser = TfidfVectorizer(decode_error='replace', encoding='utf-8')
train_matrix = vectoriser.fit_transform(X_train['text'].apply(lambda x: np.str_(x)))
val_matrix = vectoriser.transform(X_val['text'].apply(lambda x: np.str_(x)))
test_matrix = vectoriser.transform(X_test['text'].apply(lambda x: np.str_(x)))
```

In [63]:
```
pd.DataFrame(train_matrix.toarray(), columns=vectoriser.get_feature_names())
```

Out[63]:

	aaadvantage	aadavantage	aadelay	aadv	aadvantage	aafail	aal	aaron	abandon	abandoned
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

	aaadvantage	aadavantage	aadelay	aadv	aadvantage	aafail	aal	aaron	abandon	abandoned
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...
8779	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8780	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8781	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8782	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8783	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

8784 rows × 8485 columns

In [65]:
```
# print(vectoriser.get_feature_names())
```

7. Models

At this time we apply various models to predict sentiments from tweet text data.

In [66]:
```
def print_results(results):
    print('BEST {} WITH PARAMS: {}\n'.format(round(results.best_score_, 6), results.bes

    means = results.cv_results_['mean_test_score']
    stds = results.cv_results_['std_test_score']
    for mean, std, params in zip(means, stds, results.cv_results_['params']):
        print('{} (+/-{}) for {}'.format(round(mean, 3), round(std * 2, 3), params))
```

In [67]:
```
accuracy_dict = {}
```

1. Logistic regression

We try to improve the model by tuning the hyperparameters like solvers and C-value which is inverse of regularization strength. It can takes about 5 minutes.

In [68]:
```
model_lr = LogisticRegression()
solvers = ['newton-cg', 'lbfgs','liblinear']
penalty = ['l2']
max_iter=[200]
c_values = [0.001, 0.01, 0.1, 1, 10, 100]

grid_lr = dict(solver=solvers, penalty=penalty, C=c_values, max_iter=max_iter)
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
```

In [69]:
```
grid_search_lr = GridSearchCV(estimator=model_lr, param_grid=grid_lr, n_jobs=-1, cv=cv,
grid_result_lr = grid_search_lr.fit(train_matrix, y_train)
print_results(grid_result_lr)
```

```
BEST 0.7733 WITH PARAMS: {'C': 10, 'max_iter': 200, 'penalty': 'l2', 'solver': 'liblinea
```

```
r'}

0.627 (+/-0.001) for {'C': 0.001, 'max_iter': 200, 'penalty': 'l2', 'solver': 'newton-c
g'}
0.627 (+/-0.001) for {'C': 0.001, 'max_iter': 200, 'penalty': 'l2', 'solver': 'lbfgs'}
0.627 (+/-0.001) for {'C': 0.001, 'max_iter': 200, 'penalty': 'l2', 'solver': 'liblinea
r'}
0.627 (+/-0.001) for {'C': 0.01, 'max_iter': 200, 'penalty': 'l2', 'solver': 'newton-c
g'}
0.627 (+/-0.001) for {'C': 0.01, 'max_iter': 200, 'penalty': 'l2', 'solver': 'lbfgs'}
0.627 (+/-0.001) for {'C': 0.01, 'max_iter': 200, 'penalty': 'l2', 'solver': 'liblinea
r'}
0.682 (+/-0.017) for {'C': 0.1, 'max_iter': 200, 'penalty': 'l2', 'solver': 'newton-cg'}
0.682 (+/-0.017) for {'C': 0.1, 'max_iter': 200, 'penalty': 'l2', 'solver': 'lbfgs'}
0.665 (+/-0.015) for {'C': 0.1, 'max_iter': 200, 'penalty': 'l2', 'solver': 'liblinear'}
0.769 (+/-0.022) for {'C': 1, 'max_iter': 200, 'penalty': 'l2', 'solver': 'newton-cg'}
0.768 (+/-0.022) for {'C': 1, 'max_iter': 200, 'penalty': 'l2', 'solver': 'lbfgs'}
0.756 (+/-0.019) for {'C': 1, 'max_iter': 200, 'penalty': 'l2', 'solver': 'liblinear'}
0.766 (+/-0.023) for {'C': 10, 'max_iter': 200, 'penalty': 'l2', 'solver': 'newton-cg'}
0.766 (+/-0.023) for {'C': 10, 'max_iter': 200, 'penalty': 'l2', 'solver': 'lbfgs'}
0.773 (+/-0.023) for {'C': 10, 'max_iter': 200, 'penalty': 'l2', 'solver': 'liblinear'}
0.736 (+/-0.025) for {'C': 100, 'max_iter': 200, 'penalty': 'l2', 'solver': 'newton-cg'}
0.736 (+/-0.026) for {'C': 100, 'max_iter': 200, 'penalty': 'l2', 'solver': 'lbfgs'}
0.744 (+/-0.024) for {'C': 100, 'max_iter': 200, 'penalty': 'l2', 'solver': 'liblinear'}
```

In [70]:
```
accuracy_dict.update({'logistic regression': format(round(grid_result_lr.best_score_, 6
```

In [71]:
```
joblib.dump(grid_result_lr.best_estimator_, 'LR_model.pkl')
```

Out[71]:
```
['LR_model.pkl']
```

In [72]:
```
model_lr = grid_result_lr.best_estimator_
```

1. Decision tree

In DecisionTreeClassifier we are going to tuning:

- max_depth - the maximum depth of the tree,
- max_features - number of features at each split.
- min_samples_leaf - the minimum number of samples required to be at a leaf node.

In [73]:
```
model_dt = DecisionTreeClassifier()
max_depth = [20, 75, None]
max_features =  [10, 20, 50, None]
min_samples_leaf = [8, 15, 20]

grid_dt = dict(max_depth=max_depth,  max_features=max_features, min_samples_leaf=min_sa
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
```

In [74]:
```
grid_search_dt = GridSearchCV(estimator=model_dt, param_grid=grid_dt, n_jobs=-1, cv=cv,
grid_result_dt = grid_search_dt.fit(train_matrix, y_train)
print_results(grid_result_dt)
```

```
BEST 0.700328 WITH PARAMS: {'max_depth': None, 'max_features': None, 'min_samples_leaf':
8}

0.627 (+/-0.003) for {'max_depth': 20, 'max_features': 10, 'min_samples_leaf': 8}
0.628 (+/-0.009) for {'max_depth': 20, 'max_features': 10, 'min_samples_leaf': 15}
0.627 (+/-0.002) for {'max_depth': 20, 'max_features': 10, 'min_samples_leaf': 20}
0.631 (+/-0.015) for {'max_depth': 20, 'max_features': 20, 'min_samples_leaf': 8}
```

```
0.628 (+/-0.007) for {'max_depth': 20, 'max_features': 20, 'min_samples_leaf': 15}
0.628 (+/-0.004) for {'max_depth': 20, 'max_features': 20, 'min_samples_leaf': 20}
0.638 (+/-0.024) for {'max_depth': 20, 'max_features': 50, 'min_samples_leaf': 8}
0.637 (+/-0.024) for {'max_depth': 20, 'max_features': 50, 'min_samples_leaf': 15}
0.635 (+/-0.022) for {'max_depth': 20, 'max_features': 50, 'min_samples_leaf': 20}
0.688 (+/-0.015) for {'max_depth': 20, 'max_features': None, 'min_samples_leaf': 8}
0.689 (+/-0.013) for {'max_depth': 20, 'max_features': None, 'min_samples_leaf': 15}
0.69 (+/-0.016) for {'max_depth': 20, 'max_features': None, 'min_samples_leaf': 20}
0.629 (+/-0.011) for {'max_depth': 75, 'max_features': 10, 'min_samples_leaf': 8}
0.627 (+/-0.002) for {'max_depth': 75, 'max_features': 10, 'min_samples_leaf': 15}
0.628 (+/-0.009) for {'max_depth': 75, 'max_features': 10, 'min_samples_leaf': 20}
0.634 (+/-0.029) for {'max_depth': 75, 'max_features': 20, 'min_samples_leaf': 8}
0.628 (+/-0.008) for {'max_depth': 75, 'max_features': 20, 'min_samples_leaf': 15}
0.627 (+/-0.004) for {'max_depth': 75, 'max_features': 20, 'min_samples_leaf': 20}
0.655 (+/-0.034) for {'max_depth': 75, 'max_features': 50, 'min_samples_leaf': 8}
0.642 (+/-0.023) for {'max_depth': 75, 'max_features': 50, 'min_samples_leaf': 15}
0.634 (+/-0.023) for {'max_depth': 75, 'max_features': 50, 'min_samples_leaf': 20}
0.695 (+/-0.022) for {'max_depth': 75, 'max_features': None, 'min_samples_leaf': 8}
0.699 (+/-0.022) for {'max_depth': 75, 'max_features': None, 'min_samples_leaf': 15}
0.697 (+/-0.027) for {'max_depth': 75, 'max_features': None, 'min_samples_leaf': 20}
0.629 (+/-0.013) for {'max_depth': None, 'max_features': 10, 'min_samples_leaf': 8}
0.627 (+/-0.003) for {'max_depth': None, 'max_features': 10, 'min_samples_leaf': 15}
0.627 (+/-0.004) for {'max_depth': None, 'max_features': 10, 'min_samples_leaf': 20}
0.632 (+/-0.013) for {'max_depth': None, 'max_features': 20, 'min_samples_leaf': 8}
0.631 (+/-0.017) for {'max_depth': None, 'max_features': 20, 'min_samples_leaf': 15}
0.627 (+/-0.003) for {'max_depth': None, 'max_features': 20, 'min_samples_leaf': 20}
0.656 (+/-0.036) for {'max_depth': None, 'max_features': 50, 'min_samples_leaf': 8}
0.645 (+/-0.034) for {'max_depth': None, 'max_features': 50, 'min_samples_leaf': 15}
0.641 (+/-0.029) for {'max_depth': None, 'max_features': 50, 'min_samples_leaf': 20}
0.7 (+/-0.027) for {'max_depth': None, 'max_features': None, 'min_samples_leaf': 8}
0.7 (+/-0.029) for {'max_depth': None, 'max_features': None, 'min_samples_leaf': 15}
0.699 (+/-0.032) for {'max_depth': None, 'max_features': None, 'min_samples_leaf': 20}
```

In [75]:
```
accuracy_dict.update({'decision tree': format(round(grid_result_dt.best_score_, 6))})
```

In [76]:
```
joblib.dump(grid_result_dt.best_estimator_, 'DT_model.pkl')
```

Out[76]:
```
['DT_model.pkl']
```

In [77]:
```
model_dt = grid_result_dt.best_estimator_
```

1. Random Forest

Hyperparametrs in RandomForestClassifier:

- n-estimators - the number of trees in the forest.
- max_depth - the maximum depth of the tree.

It can takes about 10-15 minutes.

In [78]:
```
model_rf = RandomForestClassifier()
n_estimators = [5,  100, 200]
max_depth = [16, 32, None]

grid_rf = dict(n_estimators=n_estimators, max_depth=max_depth)
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
```

In [79]:
```
grid_search_rf = GridSearchCV(estimator=model_rf, param_grid=grid_rf, n_jobs=-1, cv=cv,
grid_result_rf = grid_search_rf.fit(train_matrix, y_train)
print_results(grid_result_rf)
```

```
BEST 0.752999 WITH PARAMS: {'max_depth': None, 'n_estimators': 100}

0.639 (+/-0.014) for {'max_depth': 16, 'n_estimators': 5}
0.631 (+/-0.007) for {'max_depth': 16, 'n_estimators': 100}
0.63 (+/-0.004) for {'max_depth': 16, 'n_estimators': 200}
0.664 (+/-0.021) for {'max_depth': 32, 'n_estimators': 5}
0.663 (+/-0.016) for {'max_depth': 32, 'n_estimators': 100}
0.662 (+/-0.013) for {'max_depth': 32, 'n_estimators': 200}
0.717 (+/-0.028) for {'max_depth': None, 'n_estimators': 5}
0.753 (+/-0.023) for {'max_depth': None, 'n_estimators': 100}
0.753 (+/-0.022) for {'max_depth': None, 'n_estimators': 200}
```

In [80]:
```
accuracy_dict.update({'Random Forest': format(round(grid_result_rf.best_score_, 6))})
```

In [81]:
```
joblib.dump(grid_result_rf.best_estimator_, 'RF_model.pkl')
```

Out[81]:
```
['RF_model.pkl']
```

In [82]:
```
model_rf = grid_result_rf.best_estimator_
```

1. Support Vector Machine (SVM)

In Support Vector Machine we will examine the effect of changing kernel and C value to the model accuracy.

It can takes 10-15 minutes.

In [83]:
```
model_svc = SVC()
kernel = ['linear', 'poly']
C = [0.1, 1]

grid_svc = dict(kernel=kernel,C=C)
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
```

In [84]:
```
grid_search_svc = GridSearchCV(estimator=model_svc, param_grid=grid_svc, n_jobs=-1, cv=
grid_result_svc = grid_search_svc.fit(train_matrix, y_train)
print_results(grid_result_svc)
```

```
BEST 0.773225 WITH PARAMS: {'C': 1, 'kernel': 'linear'}

0.681 (+/-0.014) for {'C': 0.1, 'kernel': 'linear'}
0.64 (+/-0.007) for {'C': 0.1, 'kernel': 'poly'}
0.773 (+/-0.021) for {'C': 1, 'kernel': 'linear'}
0.676 (+/-0.015) for {'C': 1, 'kernel': 'poly'}
```

In [85]:
```
accuracy_dict.update({'SVM': format(round(grid_result_svc.best_score_, 6))})
```

In [86]:
```
joblib.dump(grid_result_svc.best_estimator_, 'SVM_model.pkl')
```

Out[86]:
```
['SVM_model.pkl']
```

In [87]:
```
model_svc = grid_result_svc.best_estimator_
```

1. Naive Bayes

In Multinomial Naive Bayes we will tuning the alpha value.

In [88]:
```
model_nb = MultinomialNB()
alpha = [ 0.001, 0.01, 0.1, 1, 1.5, 2.0]

grid_nb = dict(alpha = alpha)
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
```

In [89]:
```
grid_search_nb = GridSearchCV(estimator=model_nb, param_grid=grid_nb, n_jobs=-1, cv=cv,
grid_result_nb = grid_search_nb.fit(train_matrix, y_train)
print_results(grid_result_nb)
```

```
BEST 0.740969 WITH PARAMS: {'alpha': 0.1}

0.726 (+/-0.018) for {'alpha': 0.001}
0.733 (+/-0.017) for {'alpha': 0.01}
0.741 (+/-0.022) for {'alpha': 0.1}
0.684 (+/-0.012) for {'alpha': 1}
0.666 (+/-0.011) for {'alpha': 1.5}
0.657 (+/-0.009) for {'alpha': 2.0}
```

In [90]:
```
accuracy_dict.update({'Multionmial NB': format(round(grid_result_nb.best_score_, 6))})
```

In [91]:
```
joblib.dump(grid_result_nb.best_estimator_, 'NB_model.pkl')
```

Out[91]:
```
['NB_model.pkl']
```

In [92]:
```
model_nb = grid_result_nb.best_estimator_
```

1. Neural Network

To build neural network working with text data we need to transform our data differently.

We will be using Embedding Layer.

First of all, words are represented by dense vectors where a vector represents the projection of the word into a continuous vector space. Keras requires that the input data be integer encoded, so that each word is represented by a unique integer. This step can be performed using the Tokenizer API provided with Keras.

The Embedding layer is defined as the first hidden layer of a network. It must specify 3 arguments:

- input_dim : this is the size of the vocabulary in the text data.
- output_dim : the size of the vector space in which words will be embedded. For example, it could be 32 or 100.
- input_length : the length of input sequences

Should be noted that the layer is initialized with random weights and will learn an embedding for all of the words in the training dataset.

In [95]:
```
# create a copy of data to work with them
X_nn = X['text']
y_nn = y
```

In [96]:
```
t = Tokenizer()
t.fit_on_texts(X_nn)
```

In [97]:
```
# Find number of unique words in our tweets to estimate the vocabulary size
vocab_size = len(t.word_index) + 1
vocab_size
```

Out[97]:
```
10876
```

In [98]:
```
# integer encode everything
sequences = t.texts_to_sequences(X_nn)
```

In [99]:
```
# Find longest tweet in sequences to have all inputs the same length
def max_tweet():
    for i in range(1, len(sequences)):
        max_length = len(sequences[0])
        if len(sequences[i]) > max_length:
            max_length = len(sequences[i])
    return max_length
```

In [100…
```
tweet_num = max_tweet()
tweet_num
```

Out[100…
```
13
```

We will pad all input sequences to the same length with a Keras function, the pad_sequences().

In [101…
```
maxlen = tweet_num
padded_X = pad_sequences(sequences, padding='post', maxlen=maxlen)
```

In [102…
```
padded_X.shape
```

Out[102…
```
(14640, 13)
```

In [103…
```
# Convert labels
labels = to_categorical(np.asarray(y_nn))
```

In [104…
```
labels
```

Out[104…
```
array([[0., 1., 0.],
       [0., 0., 1.],
       [0., 1., 0.],
       ...,
       [0., 1., 0.],
       [1., 0., 0.],
       [0., 1., 0.]], dtype=float32)
```

In [105…
```
X_nn_train, X_nn_test, y_nn_train, y_nn_test = train_test_split(padded_X, labels, test_
```

In [106…
```
X_nn_val, X_nn_test, y_nn_val, y_nn_test = train_test_split(X_nn_test, y_nn_test, test_
```

In [107…
```
print('X_train size:', X_nn_train.shape)
print('y_train size:', y_nn_train.shape)
print('X_val size:', X_nn_val.shape)
print('y_val size:', y_nn_val.shape)
print('X_test size:', X_nn_test.shape)
print('y_test size:', y_nn_test.shape)
```

```
X_train size: (8784, 13)
y_train size: (8784, 3)
X_val size: (2928, 13)
```

```
y_val size: (2928, 3)
X_test size: (2928, 13)
y_test size: (2928, 3)
```

The Keras Embedding layer can also use a word embedding learned elsewhere.

For example, the researchers behind GloVe (Global Vectors for Word Representation) method provide a suite of pre-trained word embeddings on their website https://nlp.stanford.edu/projects/glove/

The smallest package of embeddings is “glove.6B.zip“. It was trained on a dataset of one billion tokens (words) with a vocabulary of 400 thousand words.

In [108…

```
embeddings_index = dict()
f = open('glove.6B.100d.txt')
for line in f:
    values = line.split()
    word = values[0]
    coefs = np.asarray(values[1:], dtype='float32')
    embeddings_index[word] = coefs
f.close()
print('Loaded %s word vectors.' % len(embeddings_index))
```

```
Loaded 400000 word vectors.
```

We will create an embedding matrix where each row number will correspond to the index of the word.

In [109…

```
# fill in matrix of embedding for each word in the training dataset.
embedding_matrix = np.zeros((vocab_size, 100))
for word, i in t.word_index.items():  # dictionary
    embedding_vector = embeddings_index.get(word) # gets embedded vector of word from G
    if embedding_vector is not None:
        # add to matrixb
        embedding_matrix[i] = embedding_vector # each row of matrix
```

Now then, we can define our model.

We are not training our own embeddings and using the GloVe embedding, we set trainable to *False* and in the weights attribute we pass our own embedding matrix.

The Flatten layer will squash output 13x1000 matrix to 1300-element vector.

In [110…

```
model_nn = Sequential()
model_nn.add(Embedding(input_dim=vocab_size, output_dim=100, weights=[embedding_matrix]
                           input_length = tweet_num, trainable=False))
model_nn.add(Flatten())
model_nn.add(Dense(10, activation='relu'))
model_nn.add(Dense(3, activation='softmax'))
model_nn.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['acc'])
model_nn.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 13, 100)           1087600
_________________________________________________________________
flatten (Flatten)            (None, 1300)              0
```

```
dense (Dense)                (None, 10)                13010
_________________________________________________________________
dense_1 (Dense)              (None, 3)                 33
=================================================================
Total params: 1,100,643
Trainable params: 13,043
Non-trainable params: 1,087,600
_________________________________________________________________
```

In [111…

```
history = model_nn.fit(X_nn_train, y_nn_train, epochs=100, batch_size=256, verbose = 1)
```

```
Epoch 1/100
35/35 [==============================] - 1s 3ms/step - loss: 0.8670 - acc: 0.6318
Epoch 2/100
35/35 [==============================] - 0s 3ms/step - loss: 0.7257 - acc: 0.6901
Epoch 3/100
35/35 [==============================] - 0s 3ms/step - loss: 0.6387 - acc: 0.7308
Epoch 4/100
35/35 [==============================] - 0s 2ms/step - loss: 0.5916 - acc: 0.7580
Epoch 5/100
35/35 [==============================] - 0s 3ms/step - loss: 0.5623 - acc: 0.7766
Epoch 6/100
35/35 [==============================] - 0s 3ms/step - loss: 0.5270 - acc: 0.7926
Epoch 7/100
35/35 [==============================] - 0s 2ms/step - loss: 0.5061 - acc: 0.8057
Epoch 8/100
35/35 [==============================] - 0s 2ms/step - loss: 0.4892 - acc: 0.8111
Epoch 9/100
35/35 [==============================] - 0s 3ms/step - loss: 0.4714 - acc: 0.8219
Epoch 10/100
35/35 [==============================] - 0s 2ms/step - loss: 0.4527 - acc: 0.8271
Epoch 11/100
35/35 [==============================] - 0s 2ms/step - loss: 0.4440 - acc: 0.8323
Epoch 12/100
35/35 [==============================] - 0s 3ms/step - loss: 0.4332 - acc: 0.8350
Epoch 13/100
35/35 [==============================] - 0s 3ms/step - loss: 0.4223 - acc: 0.8434
Epoch 14/100
35/35 [==============================] - 0s 3ms/step - loss: 0.4025 - acc: 0.8535
Epoch 15/100
35/35 [==============================] - 0s 3ms/step - loss: 0.3949 - acc: 0.8530
Epoch 16/100
35/35 [==============================] - 0s 3ms/step - loss: 0.3881 - acc: 0.8574
Epoch 17/100
35/35 [==============================] - 0s 3ms/step - loss: 0.3725 - acc: 0.8643
Epoch 18/100
35/35 [==============================] - 0s 3ms/step - loss: 0.3696 - acc: 0.8674
Epoch 19/100
35/35 [==============================] - 0s 3ms/step - loss: 0.3624 - acc: 0.8688
Epoch 20/100
35/35 [==============================] - 0s 3ms/step - loss: 0.3536 - acc: 0.8744
Epoch 21/100
35/35 [==============================] - 0s 3ms/step - loss: 0.3530 - acc: 0.8745
Epoch 22/100
35/35 [==============================] - 0s 3ms/step - loss: 0.3327 - acc: 0.8793
Epoch 23/100
35/35 [==============================] - 0s 3ms/step - loss: 0.3221 - acc: 0.8862
Epoch 24/100
35/35 [==============================] - 0s 3ms/step - loss: 0.3119 - acc: 0.8928
Epoch 25/100
35/35 [==============================] - 0s 3ms/step - loss: 0.3157 - acc: 0.8910
Epoch 26/100
35/35 [==============================] - 0s 3ms/step - loss: 0.3083 - acc: 0.8945
Epoch 27/100
```

```
35/35 [==============================] - 0s 3ms/step - loss: 0.3045 - acc: 0.8962
Epoch 28/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2886 - acc: 0.9041
Epoch 29/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2907 - acc: 0.9018
Epoch 30/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2717 - acc: 0.9075
Epoch 31/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2860 - acc: 0.9049
Epoch 32/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2692 - acc: 0.9103
Epoch 33/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2665 - acc: 0.9099
Epoch 34/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2703 - acc: 0.9042
Epoch 35/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2572 - acc: 0.9216
Epoch 36/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2473 - acc: 0.9203
Epoch 37/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2540 - acc: 0.9194
Epoch 38/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2330 - acc: 0.9291
Epoch 39/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2394 - acc: 0.9221
Epoch 40/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2398 - acc: 0.9222
Epoch 41/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2288 - acc: 0.9275
Epoch 42/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2230 - acc: 0.9326
Epoch 43/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2162 - acc: 0.9334
Epoch 44/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2153 - acc: 0.9365
Epoch 45/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2090 - acc: 0.9361
Epoch 46/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2119 - acc: 0.9378
Epoch 47/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1996 - acc: 0.9405
Epoch 48/100
35/35 [==============================] - 0s 3ms/step - loss: 0.2023 - acc: 0.9399
Epoch 49/100
35/35 [==============================] - 0s 2ms/step - loss: 0.1911 - acc: 0.9420
Epoch 50/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1924 - acc: 0.9420
Epoch 51/100
35/35 [==============================] - 0s 2ms/step - loss: 0.1863 - acc: 0.9444
Epoch 52/100
35/35 [==============================] - 0s 2ms/step - loss: 0.1901 - acc: 0.9419
Epoch 53/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1840 - acc: 0.9475
Epoch 54/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1737 - acc: 0.9492
Epoch 55/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1779 - acc: 0.9491
Epoch 56/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1797 - acc: 0.9460
Epoch 57/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1689 - acc: 0.9496
Epoch 58/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1654 - acc: 0.9529
Epoch 59/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1682 - acc: 0.9510
```

```
Epoch 60/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1585 - acc: 0.9560
Epoch 61/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1541 - acc: 0.9569
Epoch 62/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1615 - acc: 0.9551
Epoch 63/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1494 - acc: 0.9617
Epoch 64/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1518 - acc: 0.9581
Epoch 65/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1432 - acc: 0.9598
Epoch 66/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1396 - acc: 0.9616
Epoch 67/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1458 - acc: 0.9596
Epoch 68/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1387 - acc: 0.9606
Epoch 69/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1345 - acc: 0.9637
Epoch 70/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1334 - acc: 0.9652
Epoch 71/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1316 - acc: 0.9660
Epoch 72/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1244 - acc: 0.9664
Epoch 73/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1229 - acc: 0.9664
Epoch 74/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1265 - acc: 0.9669
Epoch 75/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1174 - acc: 0.9716
Epoch 76/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1160 - acc: 0.9712
Epoch 77/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1170 - acc: 0.9696
Epoch 78/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1119 - acc: 0.9707
Epoch 79/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1160 - acc: 0.9720
Epoch 80/100
35/35 [==============================] - 0s 2ms/step - loss: 0.1101 - acc: 0.9742
Epoch 81/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1076 - acc: 0.9723
Epoch 82/100
35/35 [==============================] - 0s 2ms/step - loss: 0.1098 - acc: 0.9724
Epoch 83/100
35/35 [==============================] - 0s 2ms/step - loss: 0.1051 - acc: 0.9746
Epoch 84/100
35/35 [==============================] - 0s 3ms/step - loss: 0.0991 - acc: 0.9766
Epoch 85/100
35/35 [==============================] - 0s 3ms/step - loss: 0.1036 - acc: 0.9746
Epoch 86/100
35/35 [==============================] - 0s 3ms/step - loss: 0.0975 - acc: 0.9777
Epoch 87/100
35/35 [==============================] - 0s 2ms/step - loss: 0.0985 - acc: 0.9764
Epoch 88/100
35/35 [==============================] - 0s 3ms/step - loss: 0.0985 - acc: 0.9754
Epoch 89/100
35/35 [==============================] - 0s 3ms/step - loss: 0.0912 - acc: 0.9804
Epoch 90/100
35/35 [==============================] - 0s 3ms/step - loss: 0.0962 - acc: 0.9778
Epoch 91/100
35/35 [==============================] - 0s 3ms/step - loss: 0.0919 - acc: 0.9798
Epoch 92/100
```

```
35/35 [==============================] - 0s 3ms/step - loss: 0.0972 - acc: 0.9762
Epoch 93/100
35/35 [==============================] - 0s 3ms/step - loss: 0.0908 - acc: 0.9794
Epoch 94/100
35/35 [==============================] - 0s 3ms/step - loss: 0.0849 - acc: 0.9802
Epoch 95/100
35/35 [==============================] - 0s 3ms/step - loss: 0.0855 - acc: 0.9819
Epoch 96/100
35/35 [==============================] - 0s 3ms/step - loss: 0.0844 - acc: 0.9815
Epoch 97/100
35/35 [==============================] - 0s 3ms/step - loss: 0.0843 - acc: 0.9806
Epoch 98/100
35/35 [==============================] - 0s 3ms/step - loss: 0.0845 - acc: 0.9807
Epoch 99/100
35/35 [==============================] - 0s 3ms/step - loss: 0.0774 - acc: 0.9849
Epoch 100/100
35/35 [==============================] - 0s 3ms/step - loss: 0.0731 - acc: 0.9861
```

In [112…

```
loss, accuracy = model_nn.evaluate(X_nn_train, y_nn_train, verbose=False)
print("Training Accuracy: {:.4f}".format(accuracy))
accuracy_dict.update({'neural network': format(round(accuracy, 6))})
```

```
Training Accuracy: 0.9855
```

8. Validation

At this time, we will evaluate models on the validation set and select the best one based on performance on the validation set.

In [113…

```
print("Accuracy for training data:")
accuracy_dict
```

```
Accuracy for training data:
```

Out[113…

```
{'Multionmial NB': '0.740969',
 'Random Forest': '0.752999',
 'SVM': '0.773225',
 'decision tree': '0.700328',
 'logistic regression': '0.7733',
 'neural network': '0.985542'}
```

- Evaluate our models on the validation set

In [117…

```
def evaluate(model, X_features, y_labels):
  pred = model.predict(X_features)
  accuracy = round(accuracy_score(y_labels, pred), 4)
  precision = round(precision_score(y_labels, pred, average='micro'), 4)
  recall = round(recall_score(y_labels, pred, average='micro'), 4)
  return ('accuracy: {} / precision: {} / recall: {}'.format(accuracy, precision, recal
```

In [118…

```
print("logistic regression: " + evaluate(model_lr, val_matrix, y_val))
print("decision tree: " + evaluate(model_dt, val_matrix, y_val))
print("random forest: " + evaluate(model_rf, val_matrix, y_val))
print("SVC: " + evaluate(model_svc, val_matrix, y_val))
print("naive bayess: " + evaluate(model_nb, val_matrix, y_val))
loss, accuracy = model_nn.evaluate(X_nn_val, y_nn_val, verbose=False)
print("neural network: Accuracy:  {:.4f}".format(accuracy))
```

```
logistic regression: accuracy: 0.7801 / precision: 0.7801 / recall: 0.7801
decision tree: accuracy: 0.7025 / precision: 0.7025 / recall: 0.7025
```

```
random forest: accuracy: 0.763 / precision: 0.763 / recall: 0.763
SVC: accuracy: 0.7777 / precision: 0.7777 / recall: 0.7777
naive bayess: accuracy: 0.7411 / precision: 0.7411 / recall: 0.7411
neural network: Accuracy:  0.6687
```

- Evaluate best model on test set

In [119…

```python
print("Accuracy for test data:")
print("logistic regression: " + evaluate(model_lr, test_matrix, y_test))
```

```
Accuracy for test data:
logistic regression: accuracy: 0.7684 / precision: 0.7684 / recall: 0.7684
```

In [120…

```python
# Classification Report
y_pred = model_lr.predict(test_matrix)
print(classification_report(y_test, y_pred, target_names = ['negative','neutral','posit
```

```
              precision    recall  f1-score   support

    negative       0.81      0.90      0.85      1822
     neutral       0.63      0.52      0.57       641
    positive       0.74      0.58      0.65       465

    accuracy                           0.77      2928
   macro avg       0.73      0.67      0.69      2928
weighted avg       0.76      0.77      0.76      2928
```

9. Unsupervised learning

Additionally an unsupervised learning model was built and as we can see below it uses k-means classification algorithm.

In [121…

```python
v = TfidfVectorizer(decode_error='replace', encoding='utf-8')
matrix = v.fit_transform(X['text'].apply(lambda x: np.str_(x)))
```

In [122…

```python
kmeans = KMeans(n_clusters=3)
```

In [123…

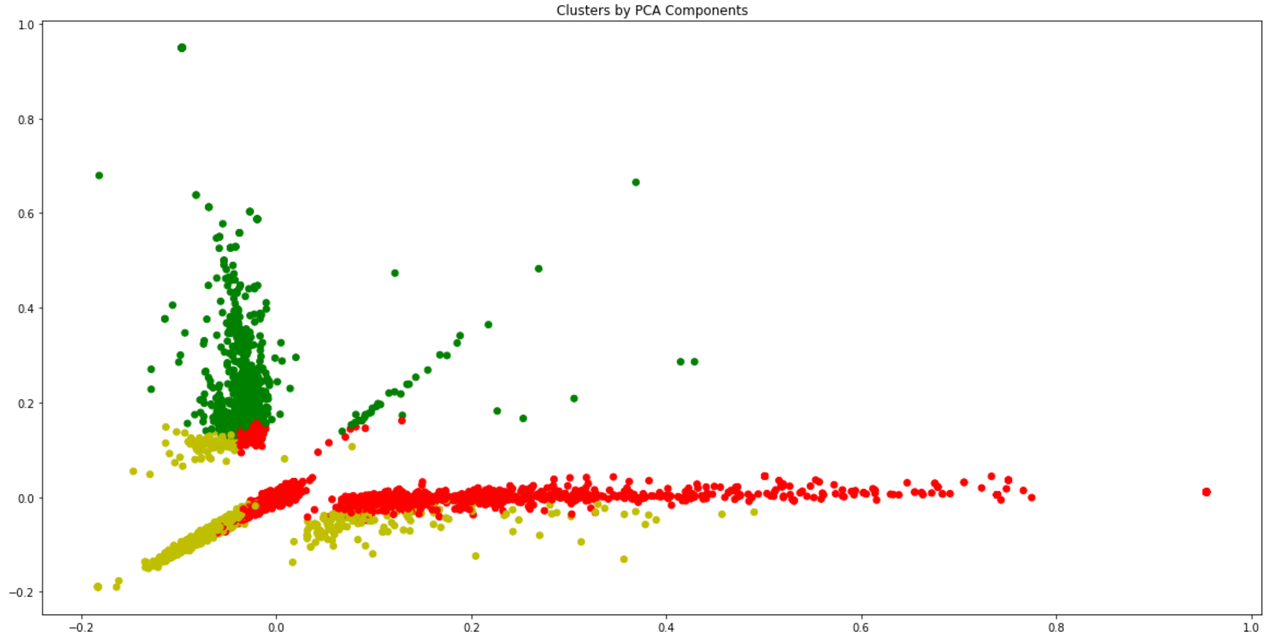
```python
kmean_indices = kmeans.fit_predict(matrix)
```

In [124…

```python
pca = PCA(n_components=2)
scatter_plot_points = pca.fit_transform(matrix.toarray())
```

In [125…

```python
colors = ["r", "g", "y" ]
x_axis = scatter_plot_points[:,0]
y_axis = scatter_plot_points[:,1]
fig, ax = plt.subplots(figsize=(20,10))
plt.title('Clusters by PCA Components')
ax.scatter(x_axis, y_axis, c=[colors[d] for d in kmean_indices])
plt.show()
```



In [126…

```
sorted_centroids = kmeans.cluster_centers_.argsort()[:, ::-1]

terms = v.get_feature_names()
for i in range(3):
    print("Cluster %d:" % i)
    for j in sorted_centroids[i, :5]:
        print(' %s' % terms[j])
    print()
```

```
Cluster 0:
 you
 thank
 get
 service
 customer

Cluster 1:
 thanks
 great
 much
 flight
 got

Cluster 2:
 flight
 cancelled
 flightled
 delayed
 get
```

As we can see cluster 0 can represent neutral sentiment, cluster 1 contains words with negative tone and cluster 2 can be responsible for positive statements.

In [ ]: