In [117]:
```
# Project : TWitter US Airline Sentiment - Problem Statement
```

https://olympus.mygreatlearning.com/courses/40613/assignments/123613?module_item_id=1143417 (https://olympus.mygreatlearning.com/courses/40613/assignments/123613?module_item_id=1143417)

Data Description

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")

Steps

- Import the necessary libraries
- Get the data
- Explore the data
- Do feature engineering (create relevant columns based on existing columns)
- Plot the wordcloud based on the relevant column
- Do pre-processing
- Noise removal (Special character, html tags, numbers, stopword removal)
- Lowercasing
- Stemming / lemmatization
- Text to number: Vectorization
- CountVectorizer
- TfidfVectorizer
- Build Machine Learning Model for Text Classification.
- Optimize the parameter
- Plot the worldcloud based on the most important features
- Check the performance of the model
- Summary

Load default libraries

In [118]:
```
pip install emoji --upgrade
```

```
Requirement already satisfied: emoji in /usr/local/lib/python3.7/dist
-packages (1.6.3)
```

In [119]:
```
!pip install contractions
```

```
Requirement already satisfied: contractions in /usr/local/lib/python
3.7/dist-packages (0.0.58)
Requirement already satisfied: textsearch>=0.0.21 in /usr/local/lib/p
ython3.7/dist-packages (from contractions) (0.0.21)
Requirement already satisfied: anyascii in /usr/local/lib/python3.7/d
ist-packages (from textsearch>=0.0.21->contractions) (0.3.0)
Requirement already satisfied: pyahocorasick in /usr/local/lib/python
3.7/dist-packages (from textsearch>=0.0.21->contractions) (1.4.2)
```

In [120]:
```
# Standard libraries as per MLS2 Session https://olympus.mygreatlearn
ing.com/courses/40613/files/4345649?module_item_id=2089508
import re, string, unicodedata
import contractions
from bs4 import BeautifulSoup

import os
import re
import nltk
nltk.download('stopwords')                                    # Download St
opwords.
nltk.download('punkt')
nltk.download('wordnet')
from nltk.stem import PorterStemmer
from nltk.corpus import stopwords                             # Import stop
words.
from nltk.tokenize import word_tokenize, sent_tokenize  # Import Toke
nizer.
from nltk.stem.wordnet import WordNetLemmatizer         # Import Lemm
atizer.

import gensim
import numpy as np
import pandas as pd
pd.set_option('display.max_colwidth', -1)
from time import time
import string
import emoji
from pprint import pprint
import collections

import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style="darkgrid")
sns.set(font_scale=1.3)

from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline, FeatureUnion

from mlxtend.plotting import plot_confusion_matrix
from sklearn.metrics import accuracy_score, confusion_matrix, f1_scor
e, classification_report
#from sklearn.externals import joblib
import joblib


### Models
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
```

```
#ensemble models
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.svm import LinearSVC
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:20: Futu
reWarning: Passing a negative integer is deprecated in version 1.0 an
d will not be supported in future version. Instead, use None to not l
imit the column width.
```

Getting a feel of the data

In [121]:
```
df = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/intro_natura
l_learning/project/Tweets.csv')
```

In [122]:
```
len(df)
```

Out[122]:
```
14640
```

In [123]:
```
df.head()
```

Out[123]:

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	negativ
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	

In [124]:
```
df.tail()
```

Out[124]:

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	ne
14635	569587686496825344	positive	0.3487	NaN	
14636	569587371693355008	negative	1.0000	Customer Service Issue	
14637	569587242672398336	neutral	1.0000	NaN	
14638	569587188687634433	negative	1.0000	Customer Service Issue	
14639	569587140490866689	neutral	0.6771	NaN	

In [125]:
```
# Check shape of DF and check for NULL values
print("Shape of DF ",df.shape)
print("Count of nulls in cols \n", df.isna().sum())
```

```
Shape of DF  (14640, 15)
Count of nulls in cols
 tweet_id                         0
airline_sentiment                0
airline_sentiment_confidence     0
negativereason                   5462
negativereason_confidence        4118
airline                          0
airline_sentiment_gold           14600
name                             0
negativereason_gold              14608
retweet_count                    0
text                             0
tweet_coord                      13621
tweet_created                    0
tweet_location                   4733
user_timezone                    4820
dtype: int64
```

In [126]:
```
print("% null/ na values in df")
print("======================")
((df.isnull() | df.isna()).sum() * 100 / df.index.size).round(1)
```

```
% null/ na values in df
======================
```

Out[126]:
```
tweet_id                        0.0
airline_sentiment               0.0
airline_sentiment_confidence    0.0
negativereason                  37.3
negativereason_confidence       28.1
airline                         0.0
airline_sentiment_gold          99.7
name                            0.0
negativereason_gold             99.8
retweet_count                   0.0
text                            0.0
tweet_coord                     93.0
tweet_created                   0.0
tweet_location                  32.3
user_timezone                   32.9
dtype: float64
```

Conclusions

- tweet_coord, airline_sentiment, negative_reasons have > 90% missind data. Need to delete them as they will skew analysis

In [127]:
```
# Delete cols with > 90% missing daaa
del df['tweet_coord']
del df['airline_sentiment_gold']
del df['negativereason_gold']
df.head()
```

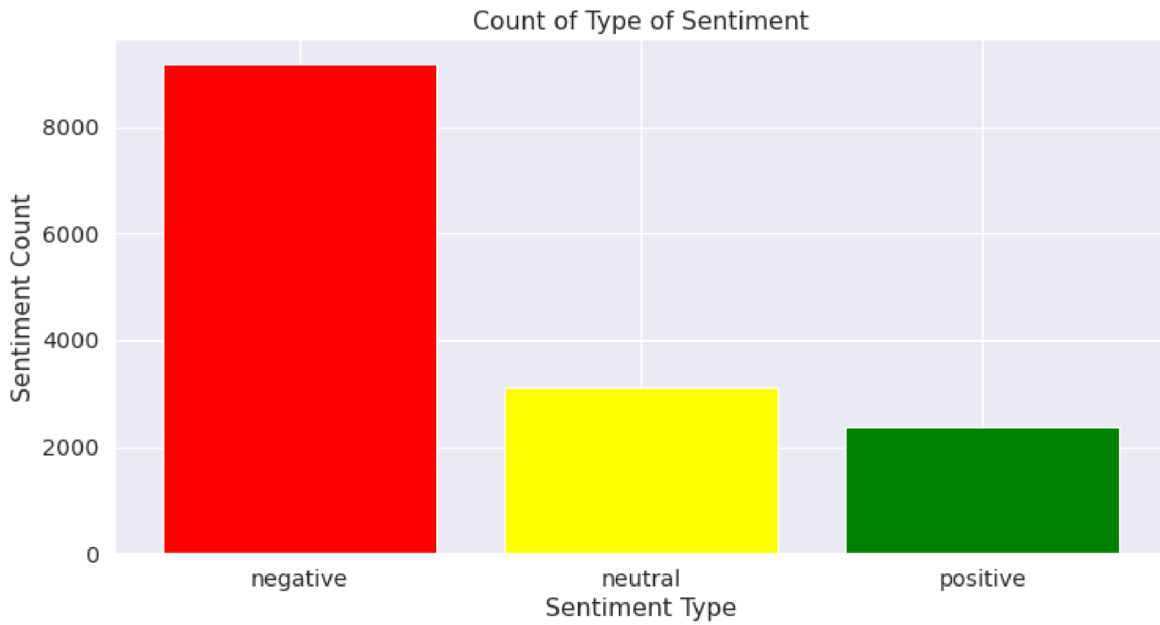
Out[127]:

	tweet_id	airline_sentiment	airline_sentiment_confidence	negativereason	negativ
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	

In [128]:
```
# EDA
```

In [129]:
```
# Bar chart of Sentimenent count
counter = df.airline_sentiment.value_counts()
index = [1,2,3]
plt.figure(1,figsize=(12,6))
plt.bar(index,counter,color=['red','yellow','green'])
plt.xticks(index,['negative','neutral','positive'],rotation=0)
plt.xlabel('Sentiment Type')
plt.ylabel('Sentiment Count')
plt.title('Count of Type of Sentiment')
```

Out[129]:
```
Text(0.5, 1.0, 'Count of Type of Sentiment')
```

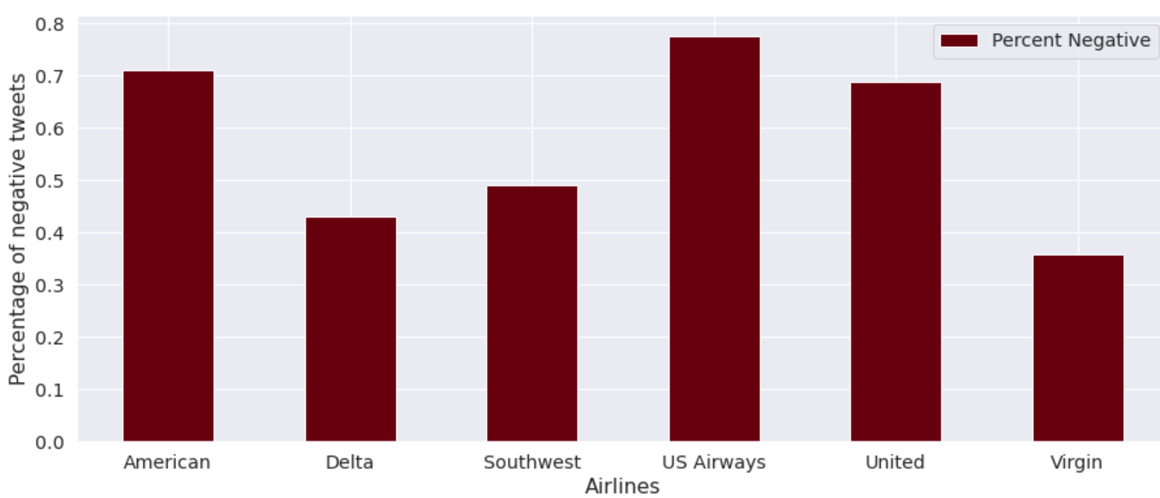


Observations

- A lot of customers have -ve flight experiences. Need to deep dive on this for the company

In [130]:
```
# Display perc plots to see the airlines sentiment feedback

neg_tweets = df.groupby(['airline','airline_sentiment']).count().iloc
[:,0]
total_tweets = df.groupby(['airline'])['airline_sentiment'].count()

my_dict = {'American':neg_tweets[0] / total_tweets[0],'Delta':neg_twe
ets[3] / total_tweets[1],'Southwest': neg_tweets[6] / total_tweets[2
],
'US Airways': neg_tweets[9] / total_tweets[3],'United': neg_tweets[12
] / total_tweets[4],'Virgin': neg_tweets[15] / total_tweets[5]}
perc = pd.DataFrame.from_dict(my_dict, orient = 'index')
perc.columns = ['Percent Negative']
print(perc)
ax = perc.plot(kind = 'bar', rot=0, colormap = 'Reds_r', figsize = (1
5,6))
ax.set_xlabel('Airlines')
ax.set_ylabel('Percentage of negative tweets')
plt.show()
```

```
            Percent Negative
American    0.710402
Delta       0.429793
Southwest   0.490083
US Airways  0.776862
United      0.688906
Virgin      0.359127
```

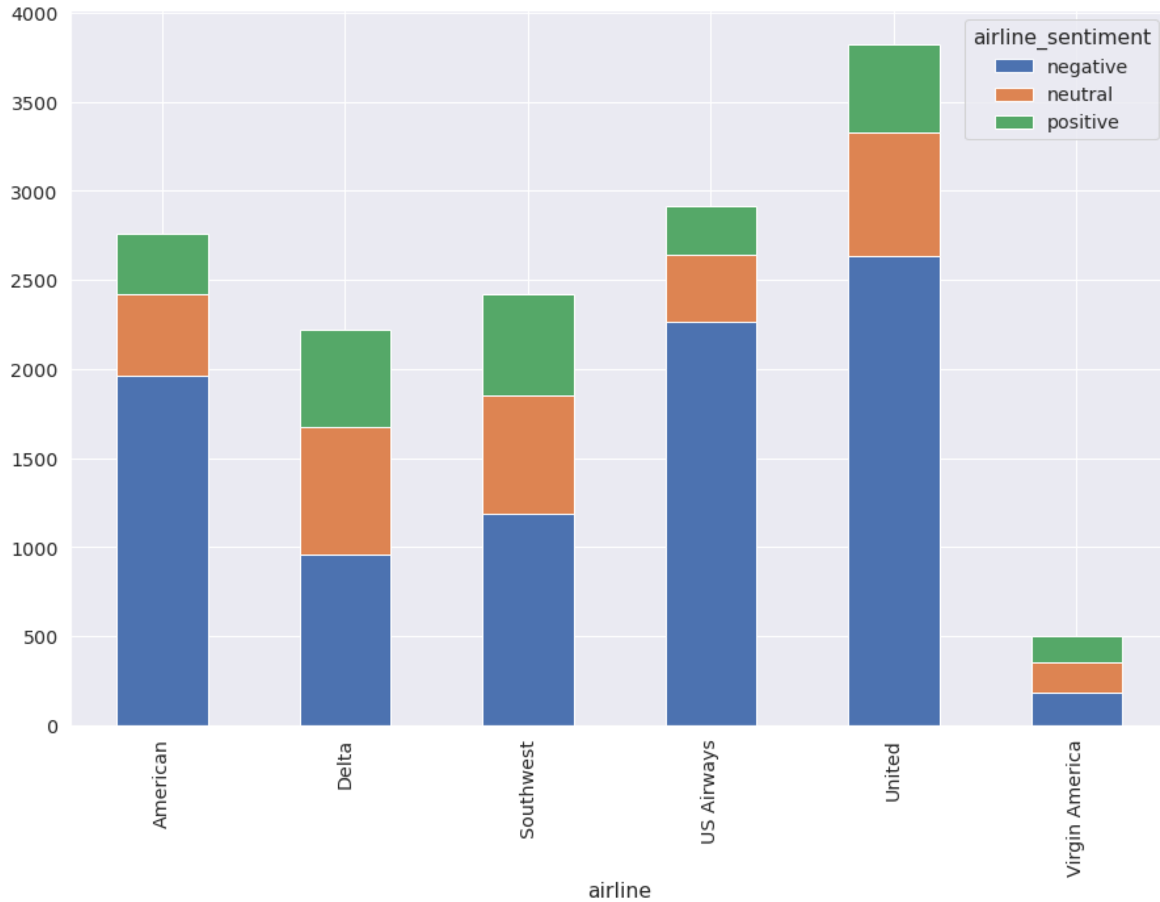


Observations

- US Airways, America, United are perceived to have bad feedback

In [131]:
```
# Check for each airline the break down of sentiments
f = df.groupby(['airline', 'airline_sentiment']).size()
f.unstack().plot(kind='bar', stacked=True, figsize=(15,10))
```

Out[131]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff4ee2d0bd0>



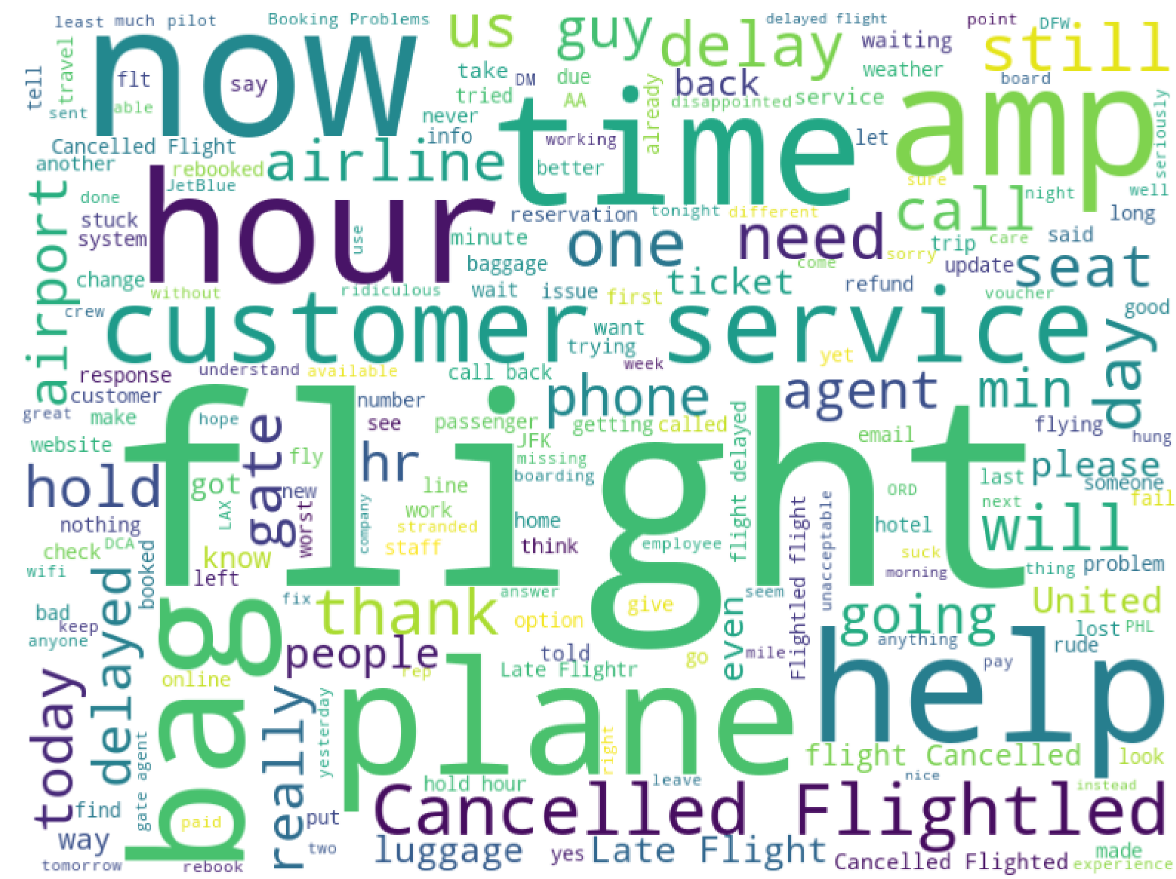
In [132]:
```
print(f)
```

```
airline         airline_sentiment
American        negative             1960
                neutral              463
                positive             336
Delta           negative             955
                neutral              723
                positive             544
Southwest       negative             1186
                neutral              664
                positive             570
US Airways      negative             2263
                neutral              381
                positive             269
United          negative             2633
                neutral              697
                positive             492
Virgin America  negative             181
                neutral              171
                positive             152
dtype: int64
```

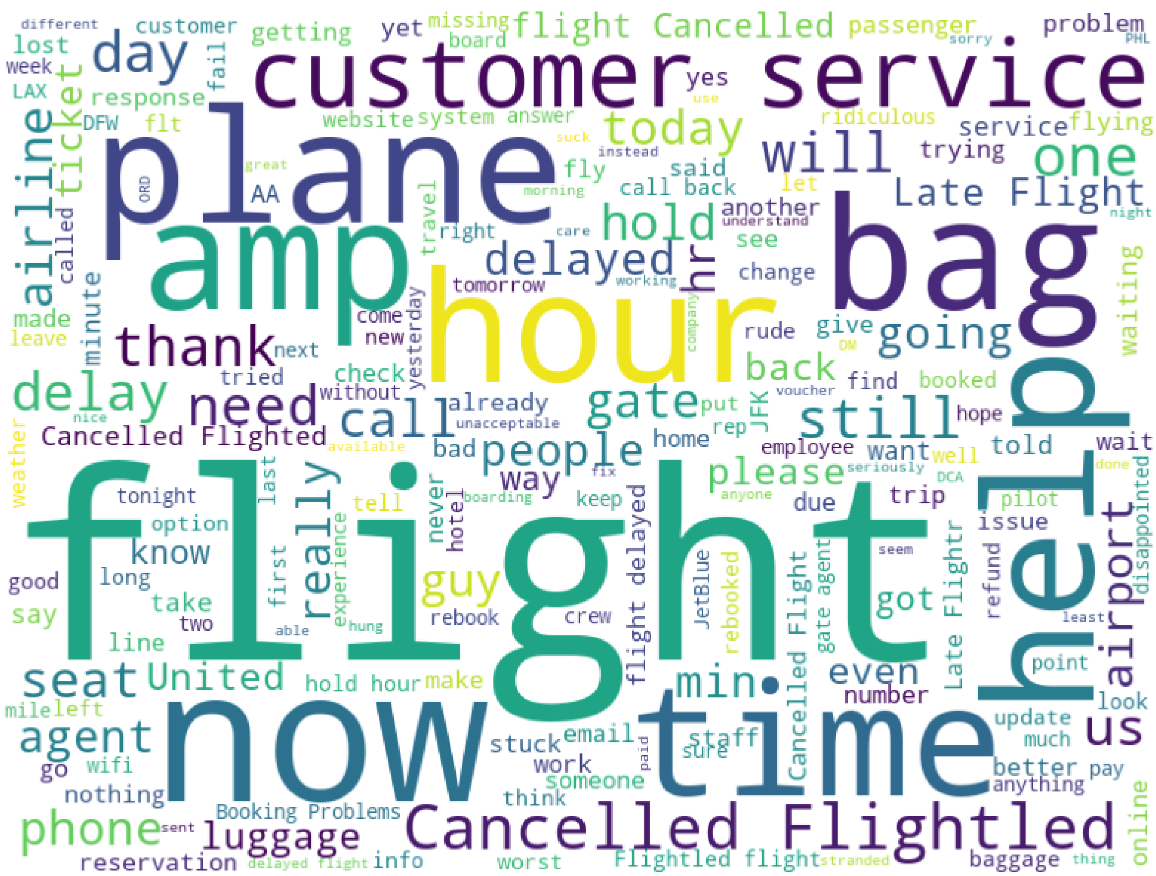
Most used words in +/- tweeks

In [133]:
```
from wordcloud import WordCloud,STOPWORDS
```

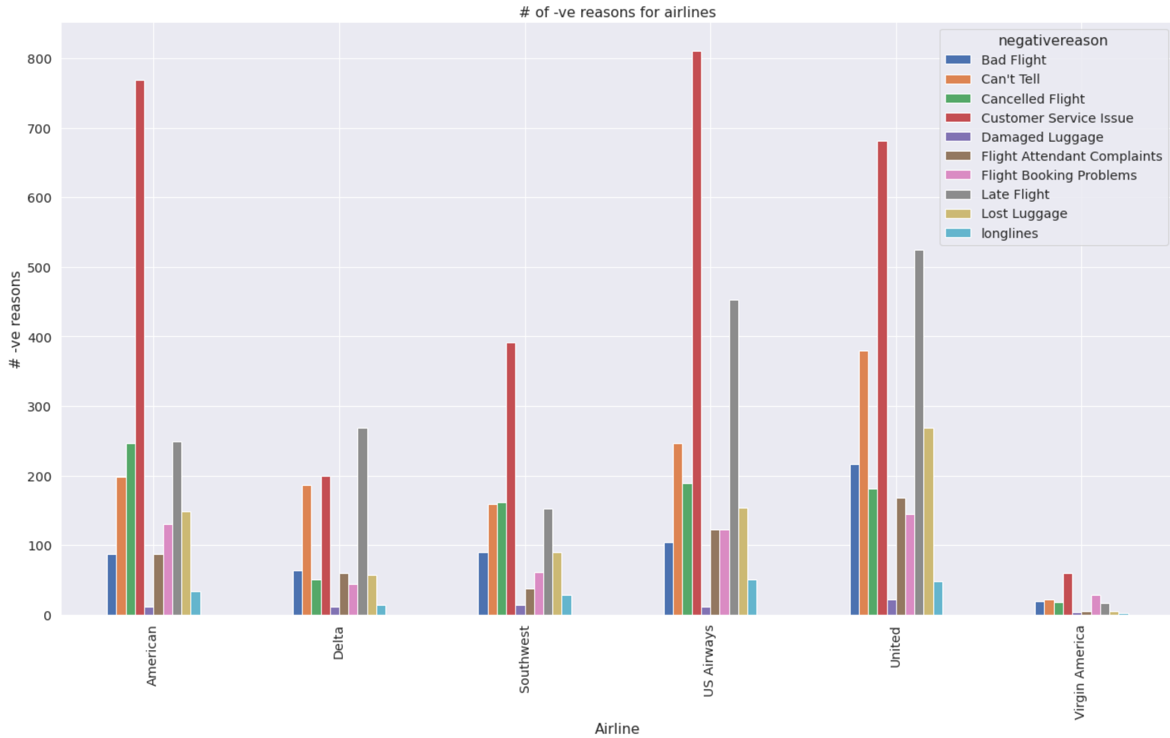
In [134]:
```
# WC for --ve tweets
df_copy=df[df['airline_sentiment']=='negative']
words = ' '.join(new_df['text'])
cleaned_word = " ".join([word for word in words.split()
                            if 'http' not in word
                                and not word.startswith('@')
                                and word != 'RT'
                            ])
wordcloud = WordCloud(stopwords=STOPWORDS,
                      background_color='white',
                      width=800,
                      height=600
                     ).generate(cleaned_word)
plt.figure(1,figsize=(14, 11))
plt.imshow(wordcloud)
plt.axis('off')
plt.show()
```



In [135]:
```python
# WC for +ve tweets
df_copy=df[df['airline_sentiment']=='positive']
words = ' '.join(new_df['text'])
cleaned_word = " ".join([word for word in words.split()
                            if 'http' not in word
                                and not word.startswith('@')
                                and word != 'RT'
                            ])
wordcloud = WordCloud(stopwords=STOPWORDS,
                      background_color='white',
                      width=800,
                      height=600
                     ).generate(cleaned_word)
plt.figure(1,figsize=(14, 11))
plt.imshow(wordcloud)
plt.axis('off')
plt.show()
```



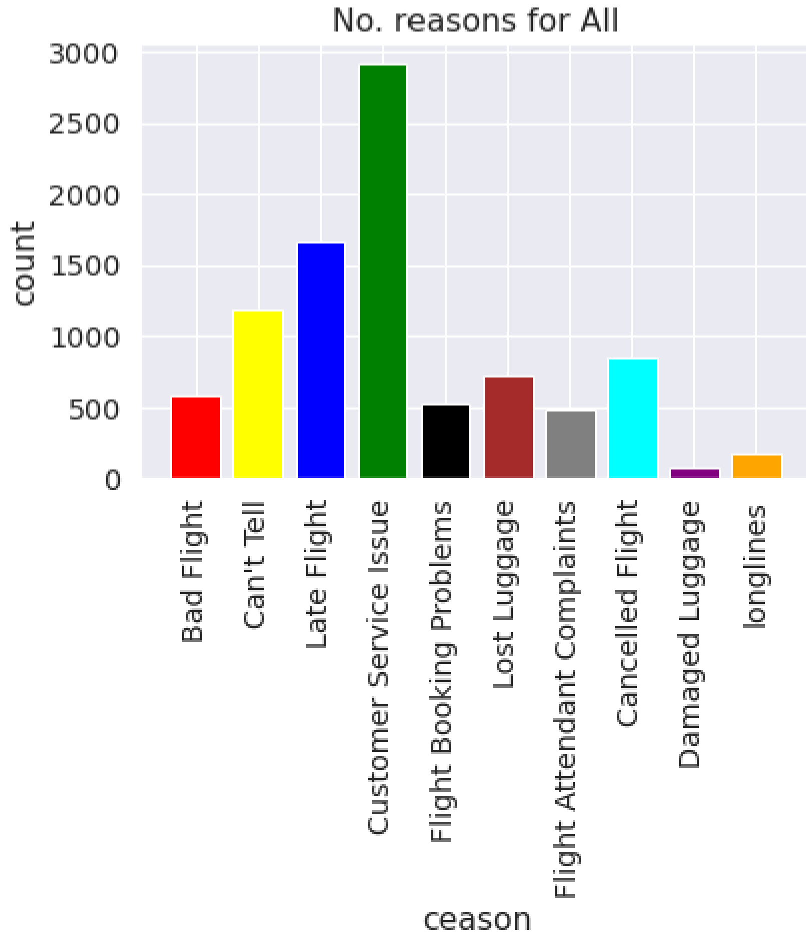
In [136]:
```
# Plot to deep dive on -ve reason tweets
negative_reasons = df.groupby('airline')['negativereason'].value_counts(ascending=True)
negative_reasons.groupby(['airline','negativereason']).sum().unstack().plot(kind='bar',figsize=(22,12))
plt.xlabel('Airline')
plt.ylabel('# -ve reasons')
plt.title("# of -ve reasons for airlines")
plt.show()
```

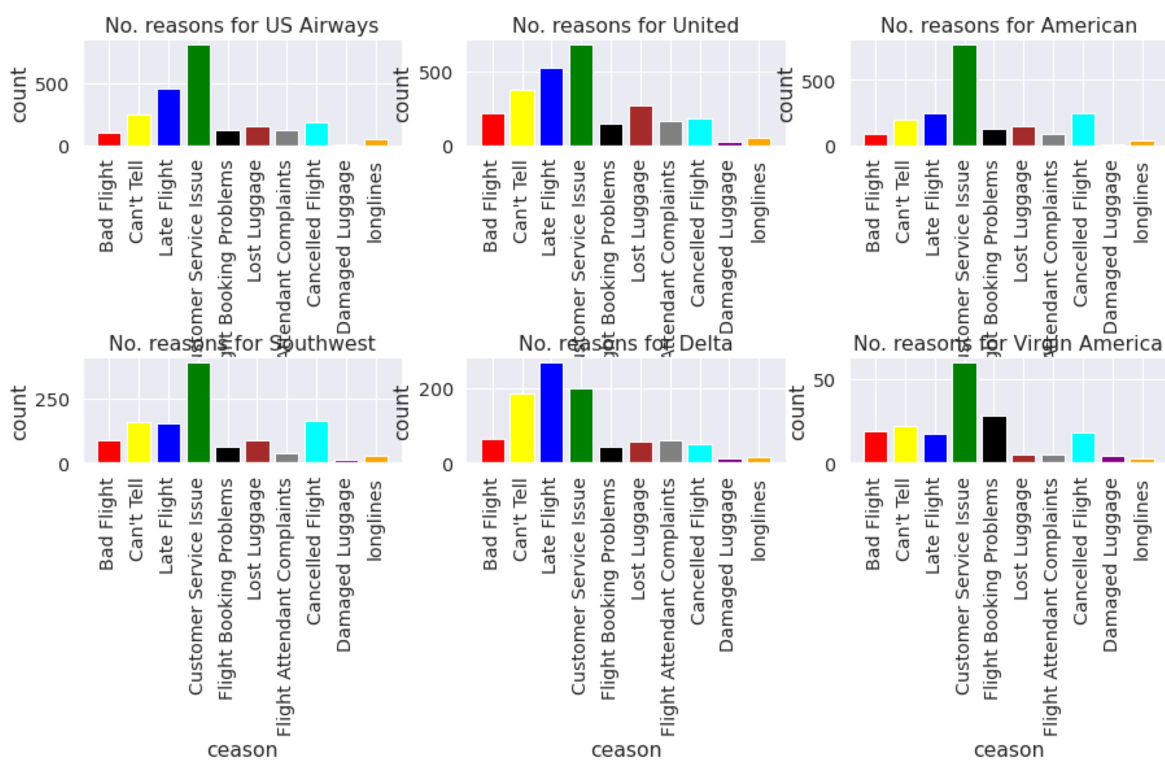


Observations

- Customer service is the biggest issue

In [137]:
```
#get the number of negative reasons
df['negativereason'].nunique()

neg_count=dict(df['negativereason'].value_counts(sort=False))
def neg_count(airline):
    if airline=='All':
        a=df
    else:
        a=df[df['airline']==airline]
    count=dict(a['negativereason'].value_counts())
    Unique_reason=list(df['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: cou
nt[x])
    return Reason_frame

def plot_reason(airline):

    a=neg_count(airline)
    count=a['count']
    Index = range(1,(len(a)+1))
    plt.bar(Index,count, color=['red','yellow','blue','green','black'
,'brown','gray','cyan','purple','orange'])
    plt.xticks(Index,a['Reasons'],rotation=90)
    plt.ylabel('count')
    plt.xlabel('ceason')
    plt.title('No. reasons for '+ airline)

plot_reason('All')
plt.figure(2,figsize=(15, 15))
for i in airlines:
    indices= airlines.index(i)
    plt.subplot(4,3,indices+1)
    plt.subplots_adjust(hspace=2)
    plot_reason(i)
```


No. reasons for All
3000
2500
2000
1500
1000
500
0
count
Bad Flight
Can't Tell
Late Flight
Customer Service Issue
Flight Booking Problems
Lost Luggage
Flight Attendant Complaints
Cancelled Flight
Damaged Luggage
longlines
ceason


No. reasons for US Airways
No. reasons for United
No. reasons for American
No. reasons for Southwest
No. reasons for Delta
No. reasons for Virgin America
count
Bad Flight
Can't Tell
Late Flight
Customer Service Issue
Flight Booking Problems
Lost Luggage
Flight Attendant Complaints
Cancelled Flight
Damaged Luggage
longlines
ceason

Observations

- Customer service biggest issue for the airliens with worse sentiment
- Delta is late flight

Pre-processing of text

In [138]:
```
df.head()
df = df.loc[:, ['text', 'airline_sentiment']]
```

In [139]:
```
#df = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/intro_natur
al_learning/project/Tweets.csv')
#df = df.reindex(np.random.permutation(df.index))
#df.drop('tweet_id',inplace=True,axis=1)
#df.reset_index(inplace=True)
df = df[['text', 'airline_sentiment']]
df.sample(10)
```

Out[139]:

	text	airline_sentiment
11903	@AmericanAir thanks	positive
11653	@USAirways been delayed three times now finally boarded. Been waiting 20 minutes. Now being told the plan has to be completely powered down.	negative
10709	@USAirways Already tried. How about Conf # via DM	negative
9055	@USAirways Hi! On my dividend miles account I accidentally listed my newly married name as opposed to my legal name. I am trying to book	neutral
6820	@JetBlue glad you like it. Feel free to steal it.	positive
312	@VirginAmerica brought it all the way across the country today I see http://t.co/TKaUyGcPmS	neutral
3037	@united yes. Houston Int'l, Bush.	neutral
8145	@JetBlue Airways Hits New 12-Month High at $17.58 (JBLU) - WKRB News http://t.co/XvBjCzlMDA	neutral
2912	@united I believe just customer service. At last post he was at Narita in Tokyo. They sent him to a motel to rest. Said standby maybe 2days	negative
7861	@JetBlue oh definitely. I kind of only fly JetBlue.	positive

In [140]:
```
## Check shape after drop
print("shape:",df.shape)
print("number of nulls in each column:", df.isna().sum())
df.head(5)
```

```
shape: (14640, 2)
number of nulls in each column: text                  0
airline_sentiment    0
dtype: int64
```

Out[140]:

	text	airline_sentiment
0	@VirginAmerica What @dhepburn said.	neutral
1	@VirginAmerica plus you've added commercials to the experience... tacky.	positive
2	@VirginAmerica I didn't today... Must mean I need to take another trip!	neutral
3	@VirginAmerica it's really aggressive to blast obnoxious "entertainment" in your guests' faces & they have little recourse	negative
4	@VirginAmerica and it's a really big bad thing about it	negative

In [141]:
```
print("% of na/nukk in df")
((df.isnull() | df.isna()).sum() * 100 / df.index.size).round(1)
```

```
% of na/nukk in df
```

Out[141]:
```
text                 0.0
airline_sentiment    0.0
dtype: float64
```

Conclusion

- Clean data no null

Text preprocessing - Remove stopwords, mentions

In [142]:
```
def strip_html(text):
    soup = BeautifulSoup(text, "html.parser")
    return soup.get_text()

df['text'] = df['text'].apply(lambda x: strip_html(x))
df.head()
```

Out[142]:

	text	airline_sentiment
0	@VirginAmerica What @dhepburn said.	neutral
1	@VirginAmerica plus you've added commercials to the experience... tacky.	positive
2	@VirginAmerica I didn't today... Must mean I need to take another trip!	neutral
3	@VirginAmerica it's really aggressive to blast obnoxious "entertainment" in your guests' faces & they have little recourse	negative
4	@VirginAmerica and it's a really big bad thing about it	negative

Text preprocessing - Replace contractions

In [143]:
```
def replace_contractions(text):
    """Replace contractions in string of text"""
    return contractions.fix(text)

df['text'] = df['text'].apply(lambda x: replace_contractions(x))
df.head()
```

Out[143]:

	text	airline_sentiment
0	@VirginAmerica What @dhepburn said.	neutral
1	@VirginAmerica plus you have added commercials to the experience... tacky.	positive
2	@VirginAmerica I did not today... Must mean I need to take another trip!	neutral
3	@VirginAmerica it is really aggressive to blast obnoxious "entertainment" in your guests' faces & they have little recourse	negative
4	@VirginAmerica and it is a really big bad thing about it	negative

Text processing - remove the numbers

In [144]:
```
def remove_numbers(text):
  text = re.sub(r'\d+', '', text)
  return text

df['text'] = df['text'].apply(lambda x: remove_numbers(x))
df.head()
```

Out[144]:

	text	airline_sentiment
0	@VirginAmerica What @dhepburn said.	neutral
1	@VirginAmerica plus you have added commercials to the experience... tacky.	positive
2	@VirginAmerica I did not today... Must mean I need to take another trip!	neutral
3	@VirginAmerica it is really aggressive to blast obnoxious "entertainment" in your guests' faces & they have little recourse	negative
4	@VirginAmerica and it is a really big bad thing about it	negative

Text processing - Tokenization

In [145]:
```
df['text'] = df.apply(lambda row: nltk.word_tokenize(row['text']), ax
is=1) # Tokenization of data
df.head()
```

Out[145]:

	text	airline_sentiment
0	[@, VirginAmerica, What, @, dhepburn, said, .]	neutral
1	[@, VirginAmerica, plus, you, have, added, commercials, to, the, experience, ..., tacky, .]	positive
2	[@, VirginAmerica, I, did, not, today, ..., Must, mean, I, need, to, take, another, trip, !]	neutral
3	[@, VirginAmerica, it, is, really, aggressive, to, blast, obnoxious, ``, entertainment, '', in, your, guests, ', faces, &, they, have, little, recourse]	negative
4	[@, VirginAmerica, and, it, is, a, really, big, bad, thing, about, it]	negative

Text Processing - list of stop words

In [146]:
```
stopwords = stopwords.words('english')

customlist = ['not', "couldn't", 'didn', "didn't", 'doesn', "doesn't"
, 'hadn', "hadn't", 'hasn',
        "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn',
"mightn't", 'mustn',
        "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn',
"shouldn't", 'wasn',
        "wasn't", 'weren', "weren't", 'won', "won't", 'wouldn', "woul
dn't"]

# Set custom stop-word's list as not, couldn't etc. words matter in S
entiment, so not removing them from original data.

stopwords = list(set(stopwords) - set(customlist))
```

In [147]:
```
# Helper functions
#  - remove special chars, lemmatize etc
lemmatizer = WordNetLemmatizer()

def remove_non_ascii(words):
    """Remove non-ASCII characters from list of tokenized words"""
    new_words = []
    for word in words:
        new_word = unicodedata.normalize('NFKD', word).encode('ascii'
, 'ignore').decode('utf-8', 'ignore')
        new_words.append(new_word)
    return new_words

def to_lowercase(words):
    """Convert all characters to lowercase from list of tokenized wor
ds"""
    new_words = []
    for word in words:
        new_word = word.lower()
        new_words.append(new_word)
    return new_words

def remove_punctuation(words):
    """Remove punctuation from list of tokenized words"""
    new_words = []
    for word in words:
        new_word = re.sub(r'[^\w\s]', '', word)
        if new_word != '':
            new_words.append(new_word)
    return new_words

def remove_stopwords(words):
    """Remove stop words from list of tokenized words"""
    new_words = []
    for word in words:
        if word not in stopwords:
            new_words.append(word)
    return new_words

def lemmatize_list(words):
    new_words = []
    for word in words:
      new_words.append(lemmatizer.lemmatize(word, pos='v'))
    return new_words

def normalize(words):
    words = remove_non_ascii(words)
    words = to_lowercase(words)
    words = remove_punctuation(words)
    words = remove_stopwords(words)
    words = lemmatize_list(words)
    return ' '.join(words)

df['text'] = df.apply(lambda row: normalize(row['text']), axis=1)
df.head()
```

Out[147]:

	text	airline_sentiment
0	virginamerica dhepburn say	neutral
1	virginamerica plus add commercials experience tacky	positive
2	virginamerica not today must mean need take another trip	neutral
3	virginamerica really aggressive blast obnoxious entertainment guests face little recourse	negative
4	virginamerica really big bad thing	negative

More data cleaning / preprocessing - remmoving more stops, mentions, convert all strings to lower case etc.

In [187]:
```
from nltk.corpus import stopwords
```

In [188]:
```
def remove_stopwords(input_text):
    stopwords_list = stopwords.words('english')
    #some words might give us something important for the sentiment a
nalysis like not, so we keep them
    wl = ["not", "no"]
    words = input_text.split()
    clean_words = [word for word in words if (word not in stopwords_l
ist or word in wl) and len(word) > 1]
    return " ".join(clean_words)

def remove_mentions(input_text):
    for i in range(len(input_text)):
        input_text[i] = re.sub(r'@\w+', '', input_text[i])
    return input_text

def lower_case(input_text):
    for i in range(len(input_text)):
        input_text[i] = input_text[i].lower()
    return input_text

def remove_http(input_text):
    for i in range(len(input_text)):
        input_text[i] = re.sub(r'http\S+', '',input_text[i])
    return input_text

def remove_punctuation(input_text):
    for i in range(len(input_text)):
        input_text[i] = re.sub(r'[^\w\s]','',input_text[i])
    return input_text
```

In [189]:
```
# Map sentiment to numbers - a bit messy code - got it from stakoverf
low
data_2 = df[['text', 'airline_sentiment']]
preprocessed_data = data_2.apply(remove_mentions).apply(remove_http).
apply(remove_punctuation).apply(lower_case)
clean_text = []
for tweet in preprocessed_data.text:
    clean = remove_stopwords(tweet)
    clean_text.append(clean)

X = clean_text
Y = preprocessed_data['airline_sentiment']
from sklearn.model_selection import train_test_split
Y = Y.map({'negative':0, 'positive':1, 'neutral':2}).astype(int)
X_train,X_test,y_train,y_test = train_test_split(X, Y, test_size=0.1,
random_state=42)
```

In [190]:
```
# Perform word representation - using TF-IDF
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer = TfidfVectorizer()
text_features_train = vectorizer.fit_transform(X_train)
text_features_test = vectorizer.transform(X_test)
```

In [ ]:
```
# Use word2sec from google - for fun... just to see
from gensim.models import Word2Vec
sentences = [line.split() for line in clean_text]
w2v = Word2Vec(sentences, size=50, min_count = 0, window = 5,workers=
4,iter=500)
```

In [ ]:
```
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt
X = w2v[w2v.wv.vocab]
tsne = TSNE(n_components=2)
X_tsne = tsne.fit_transform(X[0:100])
plt.rcParams["figure.figsize"] = (20,20)
plt.scatter(X_tsne[:, 0], X_tsne[:, 1])
labels = list(w2v.wv.vocab.keys())
for label, x, y in zip(labels, X_tsne[:, 0], X_tsne[:, 1]):
    plt.annotate(
        label,
        xy=(x, y), xytext=(-1, -1),
        textcoords='offset points', ha='right', va='bottom')

plt.show()
```

In [ ]:
```
# Replace every word by a token
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences


t = Tokenizer()
t.fit_on_texts(clean_text)
vocab_size = len(t.word_index) + 1
encoded_docs = t.texts_to_sequences(clean_text)
padded_docs = pad_sequences(encoded_docs, maxlen=20, padding='post')
embedding_dict = dict()
for i in w2v.wv.vocab:
    embedding_dict[i] = w2v[i]

embedding_matrix = np.zeros((vocab_size, 50))
for word, i in t.word_index.items():
    embedding_vector = embedding_dict.get(word)
    if embedding_vector is not None:
        embedding_matrix[i] = embedding_vector
```

ML Model Random Forest Classifier with CountVectorizer

In [148]:
```
## Random Forest with CountVectorizer
```

In [149]:
```
# Vectorization (Convert text data to numbers).
from sklearn.feature_extraction.text import CountVectorizer

vectorizer = CountVectorizer(max_features=1000)                # Keep
only 1000 features as number of features will increase the processing
time.
data_features = vectorizer.fit_transform(df['text'])

data_features = data_features.toarray()                        # Conv
ert the data features to array.
```

In [150]:
```
labels = df['airline_sentiment']
# labels = labels.astype('int')
```

In [161]:
```
# Split data into training and testing set.
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(data_features, la
bels, test_size=0.3, random_state=42)
```

In [160]:
```
# Using Random Forest to build model and calc. CV

from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score

forest = RandomForestClassifier(n_estimators=10, n_jobs=4)

forest = forest.fit(X_train, y_train)

print(forest)

print(np.mean(cross_val_score(forest, data_features, labels, cv=10)))
```

```
RandomForestClassifier(n_estimators=10, n_jobs=4)
0.7122267759562841
```

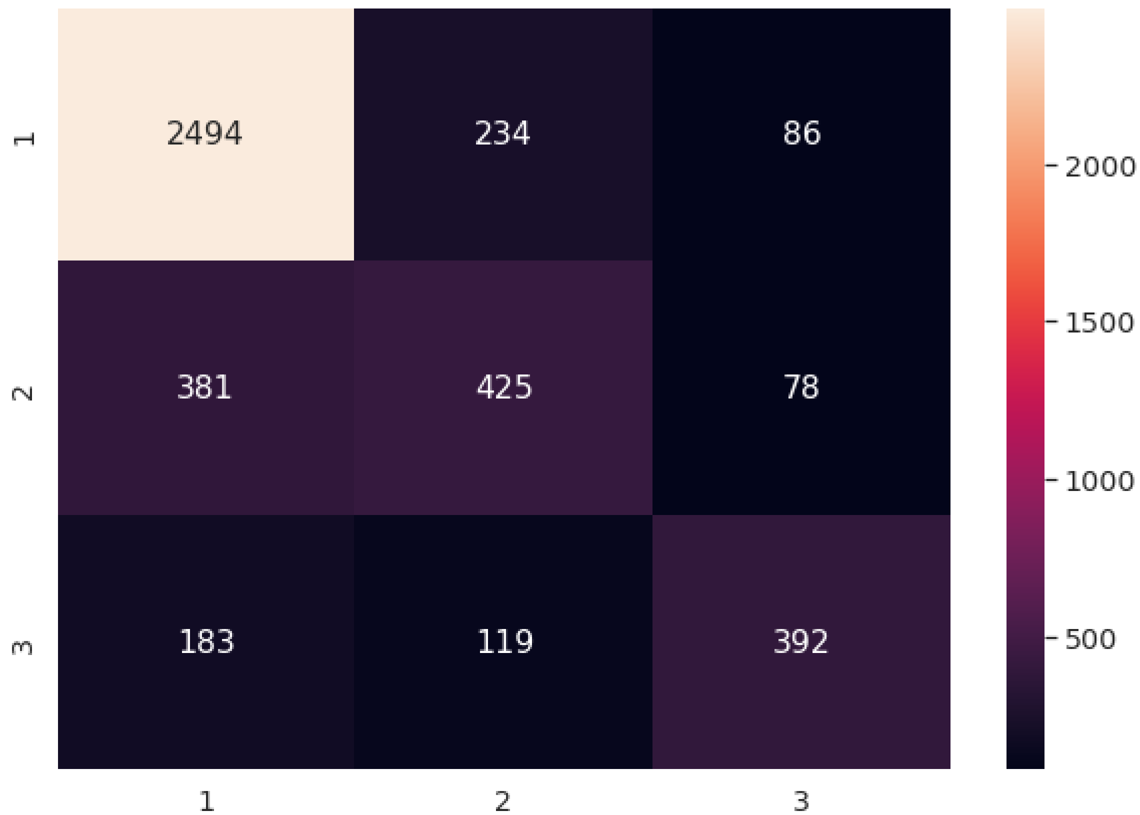
In [159]:
```
#Predict and print result
result = forest.predict(X_test)
print(result)
```

```
['positive' 'negative' 'negative' ... 'negative' 'negative' 'negativ
e']
```

In [157]:
```
# Plot conf. matrix
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix,accuracy_score

c = confusion_matrix(y_test, result)

print(c)
df_cm = pd.DataFrame(conf_mat, index = [i for i in "123"],
                     columns = [i for i in "123"])
plt.figure(figsize = (10,7))
sns.heatmap(df_cm, annot=True, fmt='g')
```

```
[[2494  234   86]
 [ 381  425   78]
 [ 183  119  392]]
```

Out[157]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff4ecd1e990>



Observations

- 71% accuracy. -ve predications are accurate
- (Key 1 = -ve, 2 = neutral, 3 = +ve)

ML Model - Random Forest with TfidfVectorizer

In [162]:
```
# Using TfidfVectoriz
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer = TfidfVectorizer(max_features=1000)
data_features = vectorizer.fit_transform(df['text'])
data_features = data_features.toarray()
data_features.shape
```

Out[162]:
```
(14640, 1000)
```

In [163]:
```
# Split data into training and testing set.

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(data_features, la
bels, test_size=0.3, random_state=42)
```

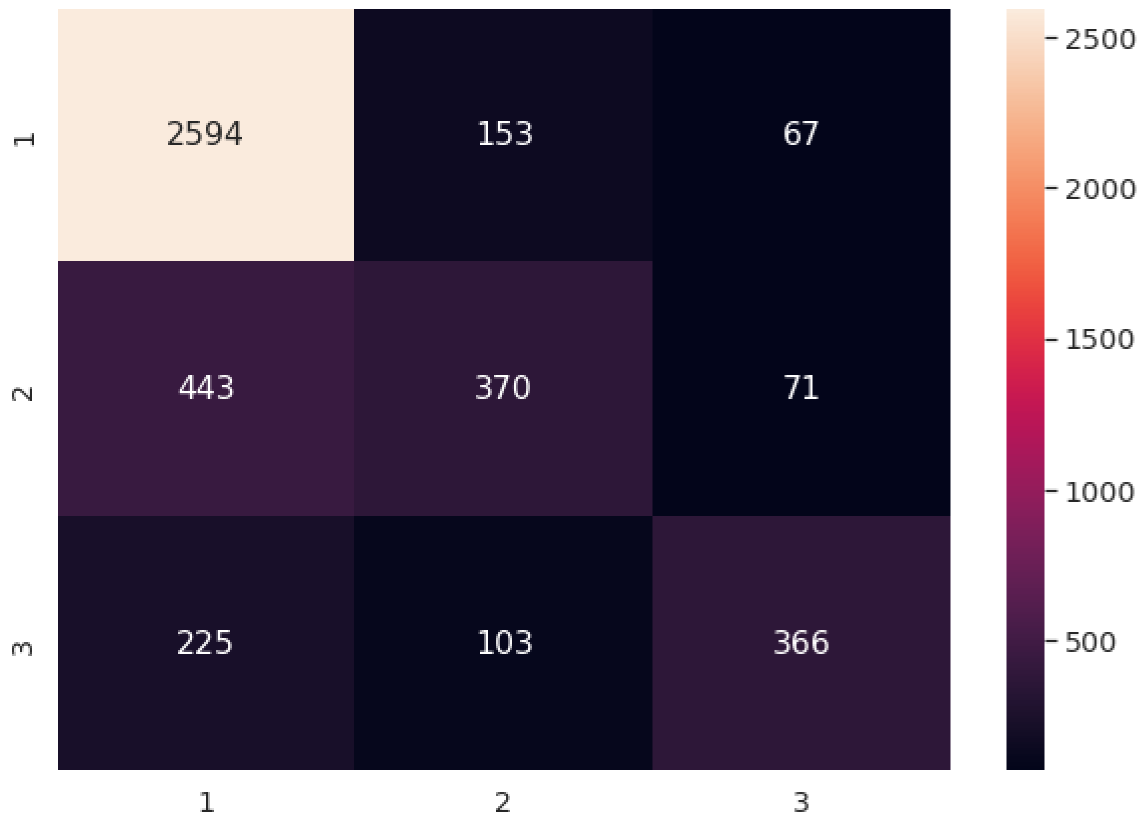
In [164]:
```
# Using Random Forest to build model and calculate CV score

from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score

import numpy as np
forest = RandomForestClassifier(n_estimators=10, n_jobs=4)
forest = forest.fit(X_train, y_train)
print(forest)
print(np.mean(cross_val_score(forest, data_features, labels, cv=10)))
```

```
RandomForestClassifier(n_estimators=10, n_jobs=4)
0.7120218579234973
```

In [165]:
```
result = forest.predict(X_test)
```

In [173]:
```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix

conf_mat = confusion_matrix(y_test, result)

df_cm = pd.DataFrame(conf_mat, index = [i for i in "123"],
                  columns = [i for i in "123"])
plt.figure(figsize = (10,7))
sns.heatmap(df_cm, annot=True, fmt='g')
```

Out[173]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff4f48cef10>



Observations

- (Key 1 = -ve, 2 = neutral, 3 = +ve)
- 71% accuracy, sames as previous model i.e RF with CountVectorizer

Other

In [176]:
```
from nltk.corpus import stopwords
```

In [177]:
```
def remove_stopwords(input_text):
    stopwords_list = stopwords.words('english')
    #some words might give us something important for the sentiment a
nalysis like not, so we keep them
    wl = ["not", "no"]
    words = input_text.split()
    clean_words = [word for word in words if (word not in stopwords_l
ist or word in wl) and len(word) > 1]
    return " ".join(clean_words)

def remove_mentions(input_text):
    for i in range(len(input_text)):
        input_text[i] = re.sub(r'@\w+', '', input_text[i])
    return input_text

def lower_case(input_text):
    for i in range(len(input_text)):
        input_text[i] = input_text[i].lower()
    return input_text

def remove_http(input_text):
    for i in range(len(input_text)):
        input_text[i] = re.sub(r'http\S+', '',input_text[i])
    return input_text

def remove_punctuation(input_text):
    for i in range(len(input_text)):
        input_text[i] = re.sub(r'[^\w\s]','',input_text[i])
    return input_text
```

In [178]:
```
data_2 = df[['text', 'airline_sentiment']]
preprocessed_data = data_2.apply(remove_mentions).apply(remove_http).
apply(remove_punctuation).apply(lower_case)
clean_text = []
for tweet in preprocessed_data.text:
    clean = remove_stopwords(tweet)
    clean_text.append(clean)

X = clean_text
Y = preprocessed_data['airline_sentiment']
from sklearn.model_selection import train_test_split
Y = Y.map({'negative':0, 'positive':1, 'neutral':2}).astype(int)
X_train,X_test,y_train,y_test = train_test_split(X, Y, test_size=0.1,
random_state=42)
```

In [181]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer = TfidfVectorizer()
text_features_train = vectorizer.fit_transform(X_train)
text_features_test = vectorizer.transform(X_test)
```

In [179]:
```
from gensim.models import Word2Vec
sentences = [line.split() for line in clean_text]
w2v = Word2Vec(sentences, size=50, min_count = 0, window = 5,workers=
4,iter=500)
```

In [180]:
```
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences


t = Tokenizer()
t.fit_on_texts(clean_text)
vocab_size = len(t.word_index) + 1
encoded_docs = t.texts_to_sequences(clean_text)
padded_docs = pad_sequences(encoded_docs, maxlen=20, padding='post')
embedding_dict = dict()
for i in w2v.wv.vocab:
    embedding_dict[i] = w2v[i]

embedding_matrix = np.zeros((vocab_size, 50))
for word, i in t.word_index.items():
    embedding_vector = embedding_dict.get(word)
    if embedding_vector is not None:
        embedding_matrix[i] = embedding_vector
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:12: Depr
ecationWarning: Call to deprecated `__getitem__` (Method will be remo
ved in 4.0.0, use self.wv.__getitem__() instead).
  if sys.path[0] == '':
```

Other Machine Learning Techniques with TfidfVectorizer

As I need > 75% accuracy, let me me try other ML techniques

In [174]:
```
def logistic_regression(training_features, labels_train, test_feature
s, labels_test):
    for c in [0.01, 0.05, 0.25, 0.5, 1, 5]:
    #changing the parameter C to get the optimal classification
        lr = LogisticRegression(C=c)
        lr.fit(training_features, labels_train)
        print ("Accuracy of logistic regression for C=%s: %s"
           % (c, accuracy_score(labels_test, lr.predict(test_features
))))
        results(labels_test, lr.predict(test_features))
```

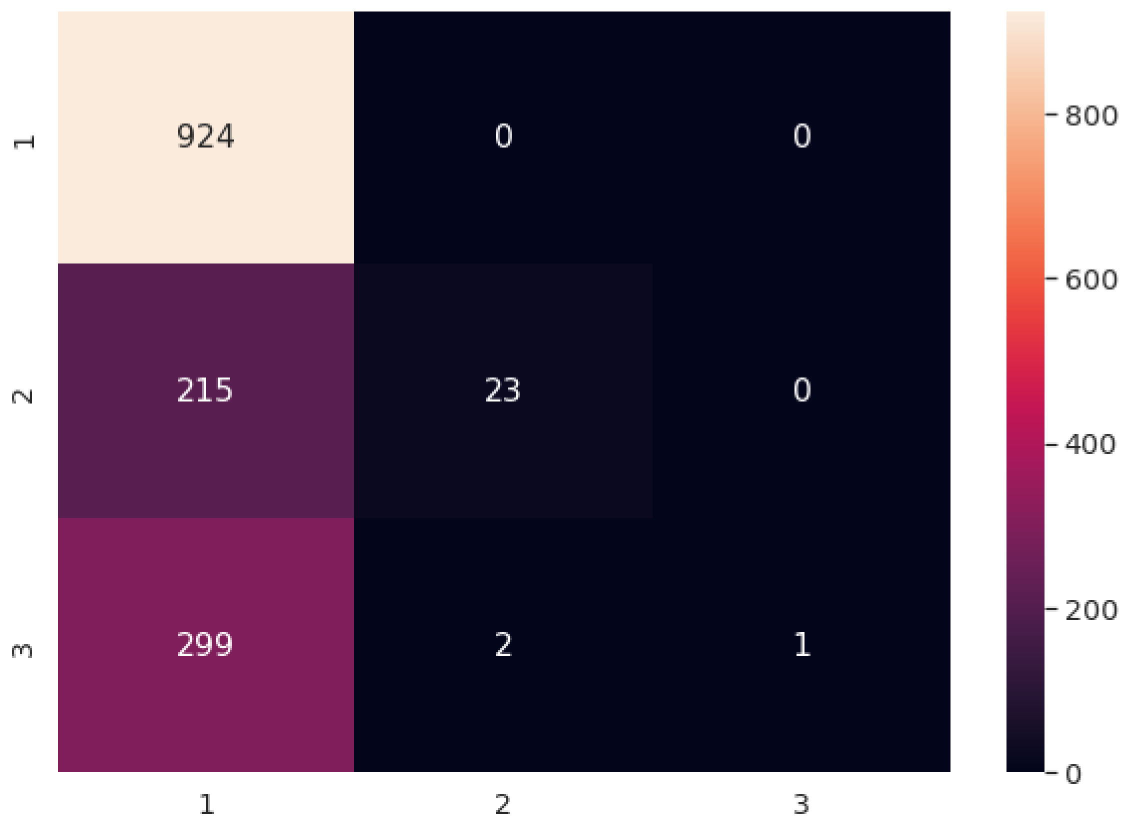
In [175]:
```
def results(labels, pred):
    conf_mat = confusion_matrix(labels,pred)
    df_cm = pd.DataFrame(conf_mat, index = [i for i in "123"],
                  columns = [i for i in "123"])
    plt.figure(figsize = (10,7))
    sns.heatmap(df_cm, annot=True, fmt='g')
    print(conf_mat)
    print(classification_report(labels,pred))
    print(accuracy_score(labels, pred))
```

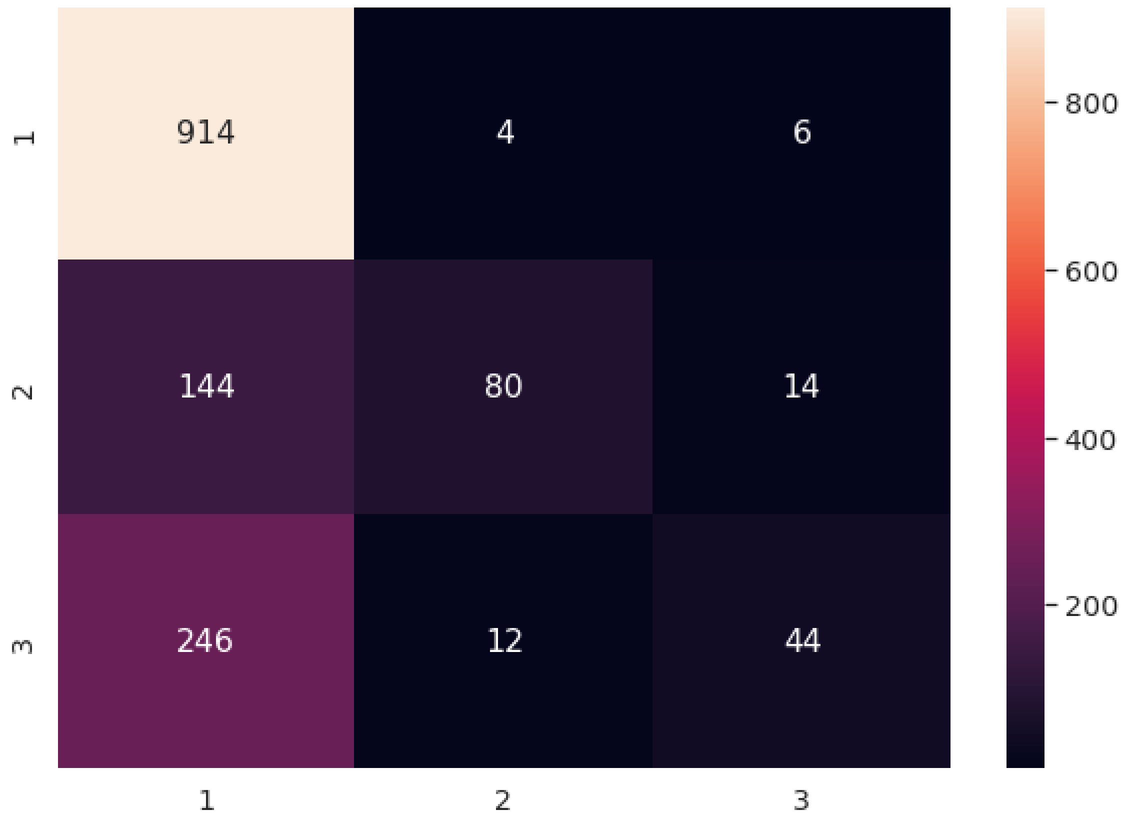
In [182]:
```
logistic_regression(text_features_train,y_train, text_features_test,y
_test)
```

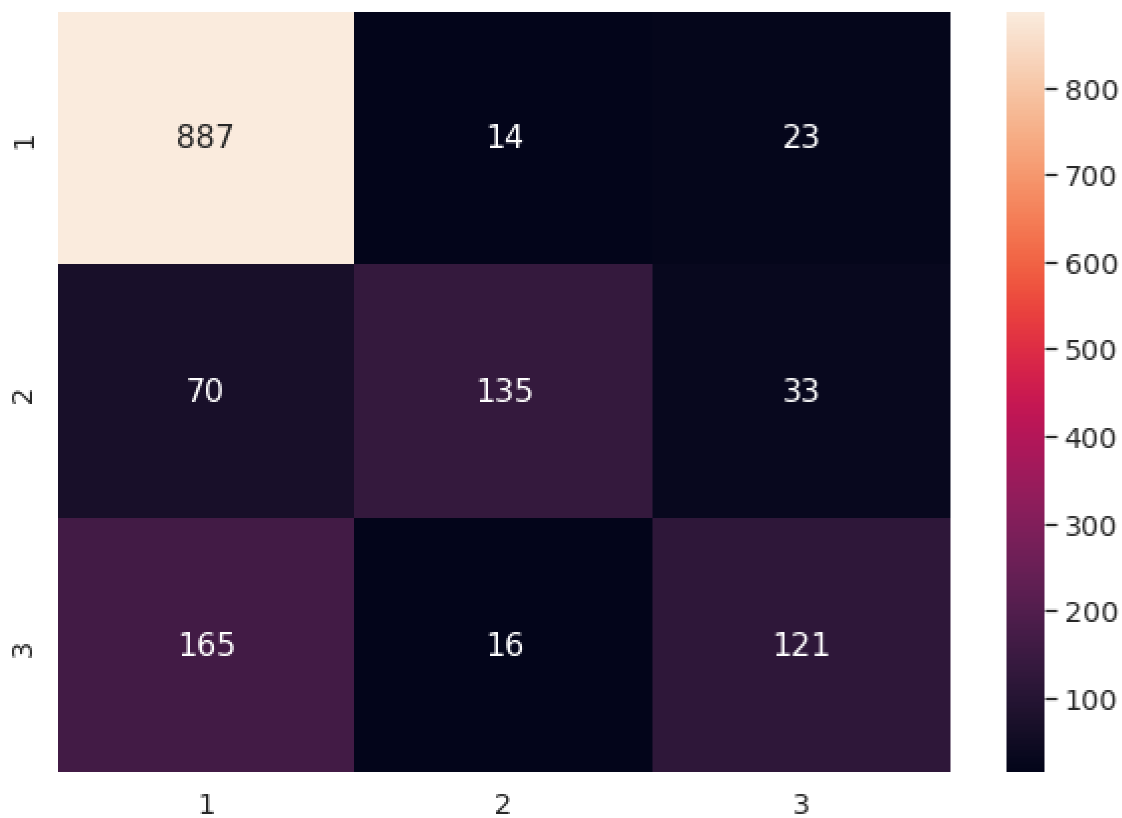
```
Accuracy of logistic regression for C=0.01: 0.6475409836065574
[[924   0   0]
 [215  23   0]
 [299   2   1]]
              precision    recall  f1-score   support

           0       0.64      1.00      0.78       924
           1       0.92      0.10      0.17       238
           2       1.00      0.00      0.01       302

    accuracy                           0.65      1464
   macro avg       0.85      0.37      0.32      1464
weighted avg       0.76      0.65      0.52      1464

0.6475409836065574
Accuracy of logistic regression for C=0.05: 0.7090163934426229
[[914   4   6]
 [144  80  14]
 [246  12  44]]
              precision    recall  f1-score   support

           0       0.70      0.99      0.82       924
           1       0.83      0.34      0.48       238
           2       0.69      0.15      0.24       302

    accuracy                           0.71      1464
   macro avg       0.74      0.49      0.51      1464
weighted avg       0.72      0.71      0.65      1464

0.7090163934426229
Accuracy of logistic regression for C=0.25: 0.7807377049180327
[[887  14  23]
 [ 70 135  33]
 [165  16 121]]
              precision    recall  f1-score   support

           0       0.79      0.96      0.87       924
           1       0.82      0.57      0.67       238
           2       0.68      0.40      0.51       302

    accuracy                           0.78      1464
   macro avg       0.76      0.64      0.68      1464
weighted avg       0.77      0.78      0.76      1464

0.7807377049180327
Accuracy of logistic regression for C=0.5: 0.7882513661202186
[[874  16  34]
 [ 61 145  32]
 [148  19 135]]
              precision    recall  f1-score   support

           0       0.81      0.95      0.87       924
           1       0.81      0.61      0.69       238
           2       0.67      0.45      0.54       302

    accuracy                           0.79      1464
   macro avg       0.76      0.67      0.70      1464
```

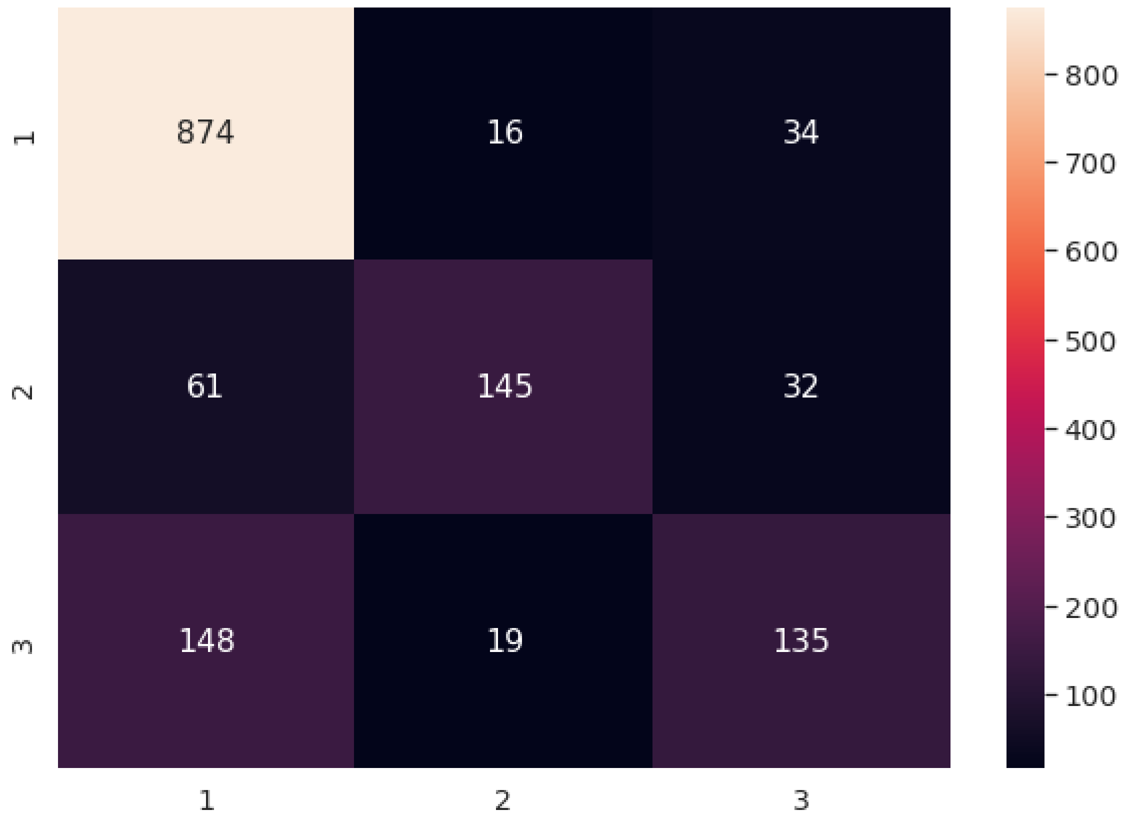
```
weighted avg       0.78      0.79      0.77      1464

0.7882513661202186

/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logisti
c.py:818: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as sho
wn in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver option
s:
    https://scikit-learn.org/stable/modules/linear_model.html#logisti
c-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,

Accuracy of logistic regression for C=1: 0.7971311475409836
[[859  20  45]
 [ 50 153  35]
 [121  26 155]]
              precision    recall  f1-score   support

           0       0.83      0.93      0.88       924
           1       0.77      0.64      0.70       238
           2       0.66      0.51      0.58       302

    accuracy                           0.80      1464
   macro avg       0.75      0.70      0.72      1464
weighted avg       0.79      0.80      0.79      1464

0.7971311475409836

/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logisti
c.py:818: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as sho
wn in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver option
s:
    https://scikit-learn.org/stable/modules/linear_model.html#logisti
c-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
```

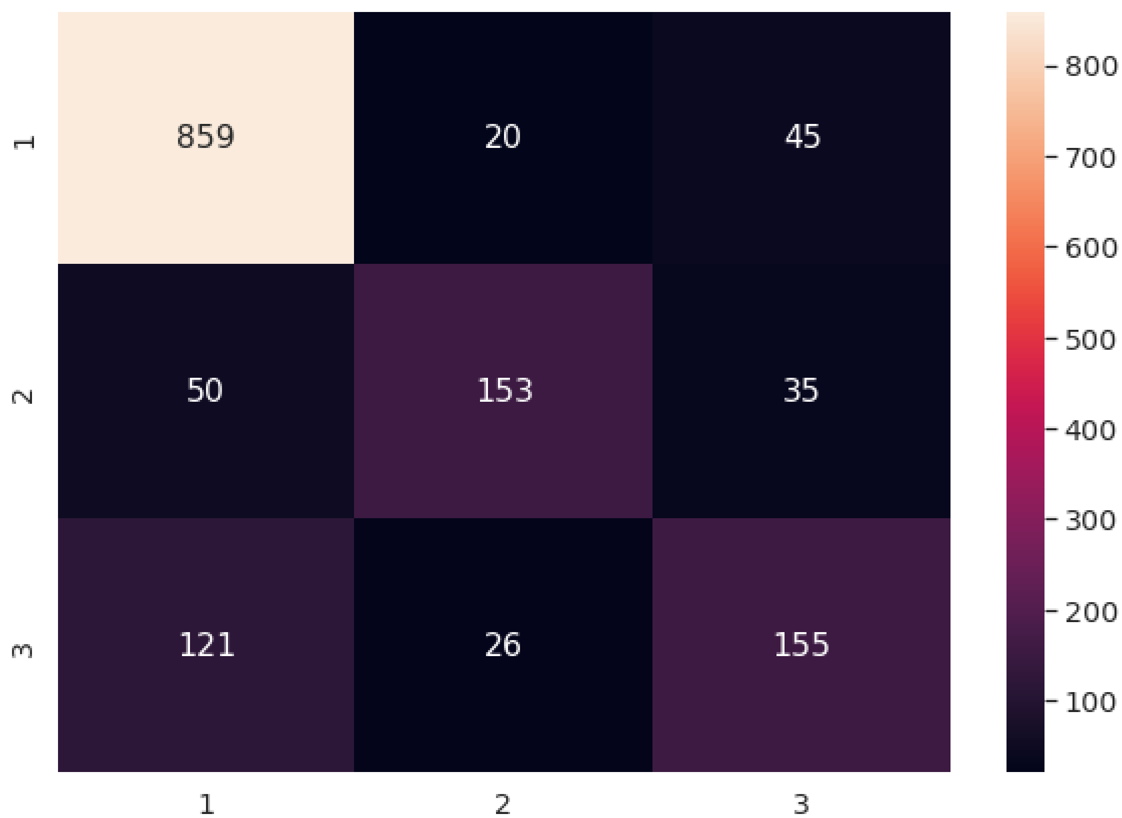
```
Accuracy of logistic regression for C=5: 0.7916666666666666
[[836  26  62]
 [ 38 167  33]
 [113  33 156]]
              precision    recall  f1-score   support

           0       0.85      0.90      0.87       924
           1       0.74      0.70      0.72       238
           2       0.62      0.52      0.56       302

    accuracy                           0.79      1464
   macro avg       0.74      0.71      0.72      1464
weighted avg       0.78      0.79      0.79      1464

0.7916666666666666
```

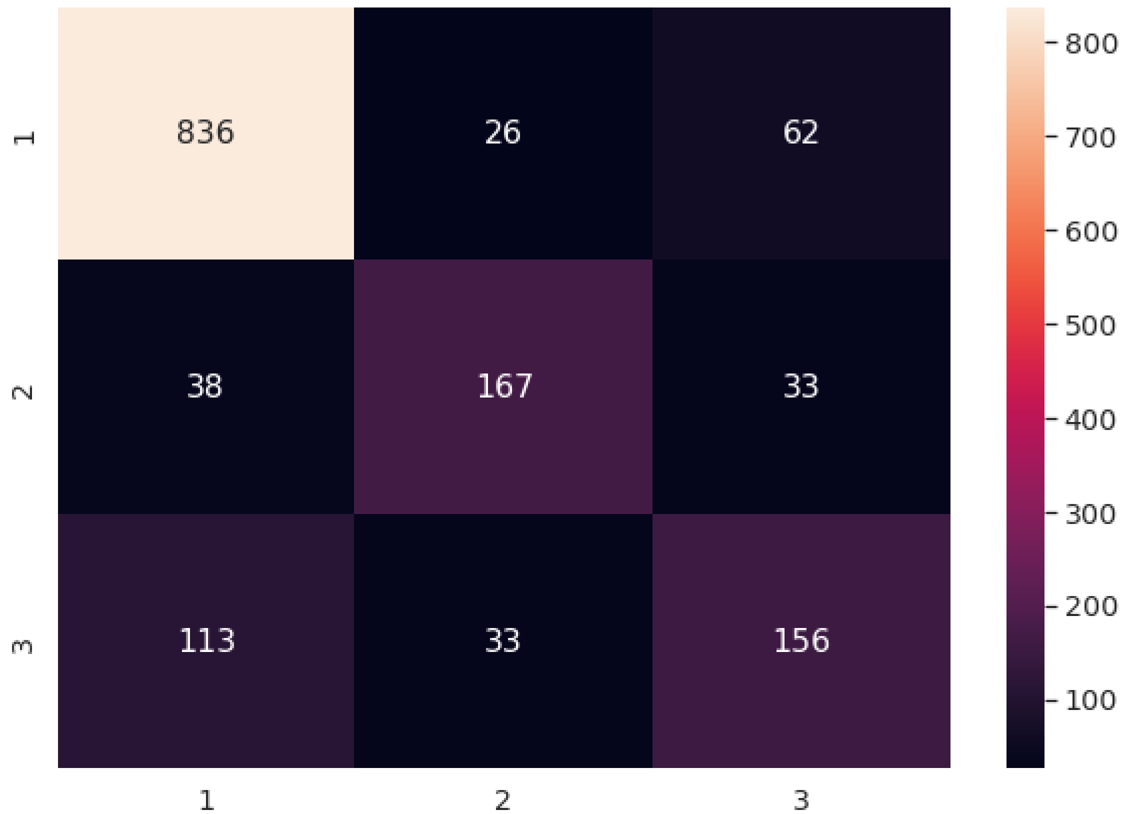



914
4
6
144
80
14
246
12
44
1
2
3
1
2
3
800
600
400
200


887
14
23
70
135
33
165
16
121
1
2
3
1
2
3
800
700
600
500
400
300
200
100


874
16
34
61
145
32
148
19
135
1
2
3
1
2
3
800
700
600
500
400
300
200
100


859
20
45
50
153
35
121
26
155
1
2
3
1
2
3
800
700
600
500
400
300
200
100



Observations

- with LR we get accuracy of 78% with C = 5 - this is really good and mathches what we are looking for

Summary and conclusions

- 3 ML models were used
- The training data is 13.1k while the testing data 1.4k.
- The ML techniques implemented were; Logistic regression, and Random Forest.

Tf-IDF was utilized as a word representation

Technique	Accuracy	Precision	Recall	F1Score
Random Forest with CountVectorizer	0.71%		--	--
Random Forest with TfidfVectorizer	0.71%	--	--	--
Logistic Regression	0.79	0.79	0.80	0.79

Confusion matrix insights

Random Forest with CountVectorizer

	negative	positive	neutral
negative	2495	243	76
positive	342	458	84
neutral	186	122	386

Random Forest with TfidfVectorizer

	negative	positive	neutral
negative	864	18	57
positive	436	392	56
neutral	224	122	348

Logistic regression

	negative	positive	neutral
negative	914	4	6
positive	144	80	14
neutral	246	12	44

- LR seems to be the best model here

Error analysis

- Accuracy of all techniques are better at classifying -ve reviews (probably due to the fact that training data has more -ve reviews - skewing the learning process algos)

```
In [ ]:
```