In [31]:
```
import json
import pandas as pd


#Import Required Module
#!pip install tensorflow
#!pip install keras
#!pip install wordcloud
#!pip install libomp
#!pip install --upgrade libomp
#!pip3 install xgboost
#!pip install --upgrade xgboost #ran this command on terminal on mac OS 'conda i
#!pip install gensim
#!pip install pronouncing
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import re,string
import nltk
from nltk import word_tokenize
from nltk.corpus import stopwords
from nltk.probability import FreqDist
stops = set(stopwords.words("english"))
punctuation = string.punctuation
from textblob import TextBlob
from sklearn.feature_extraction.text import CountVectorizer,TfidfVectorizer
from sklearn import model_selection, preprocessing, linear_model, naive_bayes, m
from sklearn.metrics import classification_report,roc_curve,confusion_matrix,auc
from sklearn.tree import DecisionTreeClassifier,ExtraTreeClassifier
from sklearn.ensemble import RandomForestClassifier,ExtraTreesClassifier,AdaBoos
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import label_binarize
from sklearn.naive_bayes import MultinomialNB
from sklearn.multiclass import OneVsRestClassifier
from sklearn.linear_model import LogisticRegression
from keras import layers, models, optimizers
from sklearn.decomposition import PCA,TruncatedSVD
import xgboost
import gensim
import warnings
warnings.filterwarnings('ignore')
import pronouncing
```

In [32]:
```
df_business = pd.read_json('yelp_training_set_business.json', lines=True)
print(df_business.head())

df_business.shape
```

```
              business_id                            full_address  \
0  rncjoVoEFUJGCUoC1JgnUA   8466 W Peoria Ave\nSte 6\nPeoria, AZ 85345
1  0FNFSzCFP_rGUoJx8W7tJg          2149 W Wood Dr\nPhoenix, AZ 85029
2  3f_lyB6vFK48ukH6ScvLHg        1134 N Central Ave\nPhoenix, AZ 85004
```

```
3  usAsSV36QmUej8--yvN-dg              845 W Southern Ave\nPhoenix, AZ 85041
4  PzOqRohWw7F7YEPBz6AubA  6520 W Happy Valley Rd\nSte 101\nGlendale Az, ...

   open                                         categories         city  \
0  True  [Accountants, Professional Services, Tax Servi...       Peoria
1  True                [Sporting Goods, Bikes, Shopping]      Phoenix
2  True                                               []      Phoenix
3  True                                  [Food, Grocery]      Phoenix
4  True               [Food, Bagels, Delis, Restaurants]  Glendale Az

   review_count                         name neighborhoods   longitude state  \
0             3      Peoria Income Tax Service            [] -112.241596    AZ
1             5                  Bike Doctor            [] -112.105933    AZ
2             4  Valley Permaculture Alliance            [] -112.073933    AZ
3             5                    Food City            [] -112.085377    AZ
4            14           Hot Bagels & Deli            [] -112.200264    AZ

   stars   latitude      type
0    5.0  33.581867  business
1    5.0  33.604054  business
2    5.0  33.460526  business
3    3.5  33.392210  business
4    3.5  33.712797  business
```

Out[32]: (11537, 13)

In [33]:

```python
import json
import pandas as pd

from ast import literal_eval


json_read = pd.read_json('yelp_training_set_review.json',  orient="records",line


df_review = pd.concat(json_read)
print(df_review.head())
df_review.shape

df = pd.DataFrame(df_review['votes'].values.tolist(), index=df_review.index)
print (df)
```

```
                                      votes                 user_id  \
0  {'funny': 0, 'useful': 5, 'cool': 2}  rLtl8ZkDX5vH5nAx9C3q5Q
1  {'funny': 0, 'useful': 0, 'cool': 0}  0a2KyEL0d3Yb1V6aivbIuQ
2  {'funny': 0, 'useful': 1, 'cool': 0}  0hT2KtfLiobPvh6cDC8JQg
3  {'funny': 0, 'useful': 2, 'cool': 1}  uZetl9T0NcROGOyFfughhg
4  {'funny': 0, 'useful': 0, 'cool': 0}  vYmM4KTsC8ZfQBg-j5MWkw

                review_id  stars        date  \
0  fWKvX83p0-ka4JS3dc6E5A      5 2011-01-26
1  IjZ33sJrzXqU-0X6U8NwyA      5 2011-07-27
2  IESLBzqUCLdSzSqm0eCSxQ      4 2012-06-14
3  G-WvGaISbqqaMHlNnByodA      5 2010-05-27
4  1uJFq2r5QfJG_6ExMRCaGw      5 2012-01-05

                                               text    type  \
0  My wife took me here on my birthday for breakf...  review
1  I have no idea why some people give bad review...  review
2  love the gyro plate. Rice is so good and I als...  review
3  Rosie, Dakota, and I LOVE Chaparral Dog Park!!...  review
4  General Manager Scott Petello is a good egg!!!...  review
```

```
                business_id
0  9yKzy9PApeiPPOUJEtnvkg
1  ZRJwVLyzEJq1VAihDhYiow
2  6oRAC4uyJCsJl1X0WZpVSA
3  _1QQZuf4zZOyFCvXc0o6Vg
4  6ozycU1RpktNG2-1BroVtw
        funny  useful  cool
0           0       5     2
1           0       0     0
2           0       1     0
3           0       2     1
4           0       0     0
...       ...     ...   ...
229902      0       0     0
229903      0       2     0
229904      0       0     0
229905      1       2     0
229906      1       0     1

[229907 rows x 3 columns]
```

In [34]:

```
df_user = pd.read_json('yelp_training_set_user.json', lines=True)
print(df_user.head())

df_user.shape
```

```
                                    votes                 user_id       name  \
0  {'funny': 0, 'useful': 7, 'cool': 0}  CR2y7yEm4X035ZMzrTtN9Q        Jim
1  {'funny': 0, 'useful': 1, 'cool': 0}  _9GXoHhdxc30ujPaQwh6Ew      Kelle
2  {'funny': 0, 'useful': 1, 'cool': 0}  8mM-nqxjg6pT04kwcjMbsw  Stephanie
3  {'funny': 0, 'useful': 2, 'cool': 0}  Ch6CdTR2IVaVANr-RglMOg          T
4  {'funny': 0, 'useful': 0, 'cool': 0}  NZrLmHRyiHmyT1JrfzkCOA       Beth

   average_stars  review_count  type
0            5.0             6  user
1            1.0             2  user
2            5.0             2  user
3            5.0             2  user
4            1.0             1  user
```

Out[34]: (43873, 6)

In [35]:

```
df_checkin = pd.read_json('yelp_training_set_checkin.json', lines=True)
print(df_checkin.head())
```

```
                                        checkin_info     type  \
0  {'11-3': 17, '8-5': 1, '15-0': 2, '15-3': 2, '...  checkin
1  {'0-5': 1, '2-6': 2, '2-5': 3, '3-6': 1, '3-5'...  checkin
2  {'13-4': 1, '7-4': 1, '15-3': 1, '18-5': 1, '2...  checkin
3  {'13-5': 1, '17-6': 1, '15-1': 1, '20-0': 1, '...  checkin
4  {'16-2': 1, '14-5': 1, '12-5': 2, '15-4': 1, '...  checkin

              business_id
0  KO9CpaSPOoqm0iCWm5scmg
1  oRqBAYtcBYZHXA7G8FlPaA
2  6cy2C9aBXUwkrh4bY1DApw
3  D0IB17N66FiyYDCzTlAI4A
4  HLQGo3EaYVvAv22bONGkIw
```

In [36]:

```
df_merge1=df_review.merge(df_business,how='left', on='business_id')
```

```
df_merge1.head()
```

Out[36]:

	votes	user_id	review_id	stars_x	date	text	type_
0	{'funny': 0, 'useful': 5, 'cool': 2}	rLtl8ZkDX5vH5nAx9C3q5Q	fWKvX83p0-ka4JS3dc6E5A	5	2011-01-26	My wife took me here on my birthday for breakf...	revie
1	{'funny': 0, 'useful': 0, 'cool': 0}	0a2KyEL0d3Yb1V6aivbIuQ	IjZ33sJrzXqU-0X6U8NwyA	5	2011-07-27	I have no idea why some people give bad review...	revie
2	{'funny': 0, 'useful': 1, 'cool': 0}	0hT2KtfLiobPvh6cDC8JQg	IESLBzqUCLdSzSqm0eCSxQ	4	2012-06-14	love the gyro plate. Rice is so good and I als...	revie
3	{'funny': 0, 'useful': 2, 'cool': 1}	uZetl9T0NcROGOyFfughhg	G-WvGaISbqqaMHlNnByodA	5	2010-05-27	Rosie, Dakota, and I LOVE Chaparral Dog Park!!...	revie
4	{'funny': 0, 'useful': 0, 'cool': 0}	vYmM4KTsC8ZfQBg-j5MWkw	1uJFq2r5QfJG_6ExMRCaGw	5	2012-01-05	General Manager Scott Petello is a good egg!!!...	revie

In [37]:

```
df_merge2=df_merge1.merge(df_checkin,how='left', on='business_id')
df_merge2.head()
```

Out[37]:

	votes	user_id	review_id	stars_x	date	text	type_
0	{'funny': 0, 'useful': 5, 'cool': 2}	rLtl8ZkDX5vH5nAx9C3q5Q	fWKvX83p0-ka4JS3dc6E5A	5	2011-01-26	My wife took me here on my birthday for breakf...	revie
1	{'funny': 0, 'useful': 0, 'cool': 0}	0a2KyEL0d3Yb1V6aivbIuQ	IjZ33sJrzXqU-0X6U8NwyA	5	2011-07-27	I have no idea why some people give bad review...	revie

	votes	user_id	review_id	stars_x	date	text	type_
2	{'funny': 0, 'useful': 1, 'cool': 0}	0hT2KtfLiobPvh6cDC8JQg	IESLBzqUCLdSzSqm0eCSxQ	4	2012-06-14	love the gyro plate. Rice is so good and I als...	revie
3	{'funny': 0, 'useful': 2, 'cool': 1}	uZetl9T0NcROGOyFfughhg	G-WvGaISbqqaMHlNnByodA	5	2010-05-27	Rosie, Dakota, and I LOVE Chaparral Dog Park!!...	revie
4	{'funny': 0, 'useful': 0, 'cool': 0}	vYmM4KTsC8ZfQBg-j5MWkw	1uJFq2r5QfJG_6ExMRCaGw	5	2012-01-05	General Manager Scott Petello is a good egg!!!...	revie

5 rows × 22 columns

In [38]:

```
df_merge4=df_merge2.merge(df_user,how='left', on='user_id')
df_merge4.head()
```

Out[38]:

	votes_x	user_id	review_id	stars_x	date	text	type_
0	{'funny': 0, 'useful': 5, 'cool': 2}	rLtl8ZkDX5vH5nAx9C3q5Q	fWKvX83p0-ka4JS3dc6E5A	5	2011-01-26	My wife took me here on my birthday for breakf...	revie
1	{'funny': 0, 'useful': 0, 'cool': 0}	0a2KyEL0d3Yb1V6aivbIuQ	IjZ33sJrzXqU-0X6U8NwyA	5	2011-07-27	I have no idea why some people give bad review...	revie
2	{'funny': 0, 'useful': 1, 'cool': 0}	0hT2KtfLiobPvh6cDC8JQg	IESLBzqUCLdSzSqm0eCSxQ	4	2012-06-14	love the gyro plate. Rice is so good and I als...	revie
3	{'funny': 0, 'useful': 2, 'cool': 1}	uZetl9T0NcROGOyFfughhg	G-WvGaISbqqaMHlNnByodA	5	2010-05-27	Rosie, Dakota, and I LOVE Chaparral Dog Park!!...	revie

	votes_x	user_id	review_id	stars_x	date	text	type_
4	{'funny': 0, 'useful': 0, 'cool': 0}	vYmM4KTsC8ZfQBg-j5MWkw	1uJFq2r5QfJG_6ExMRCaGw	5	2012-01-05	General Manager Scott Petello is a good egg!!!...	revie

5 rows × 27 columns

In [39]:

```
df_merge3=df_merge4.head(50000)
df_merge3.shape
```

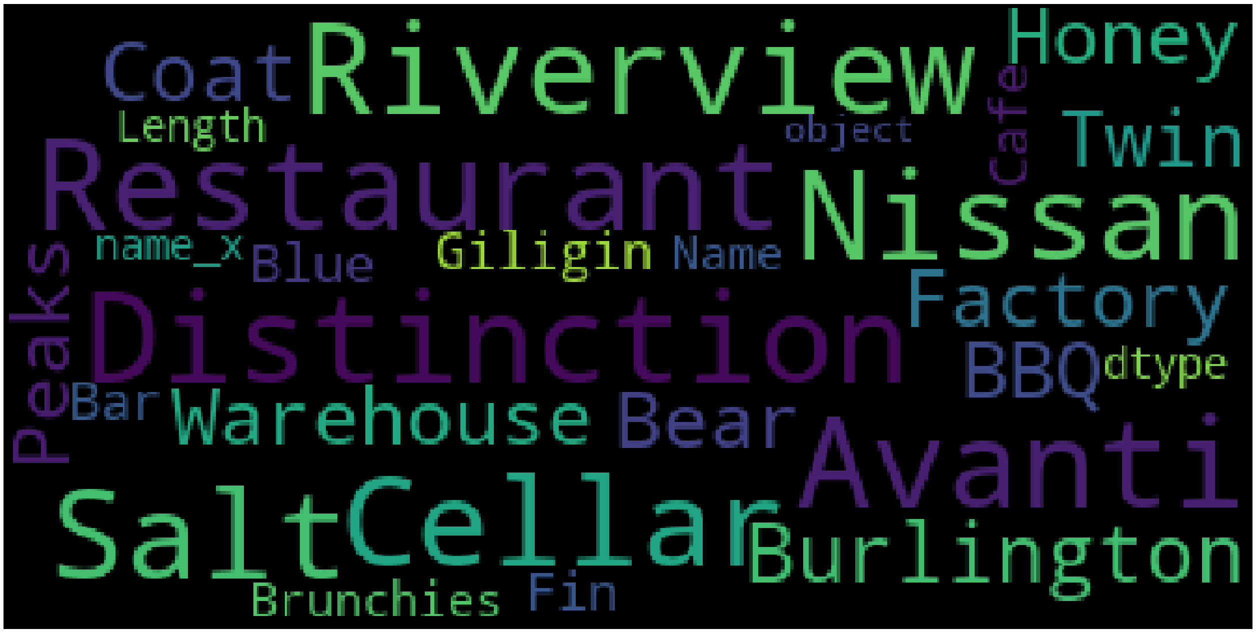
Out[39]: (50000, 27)

In [19]:

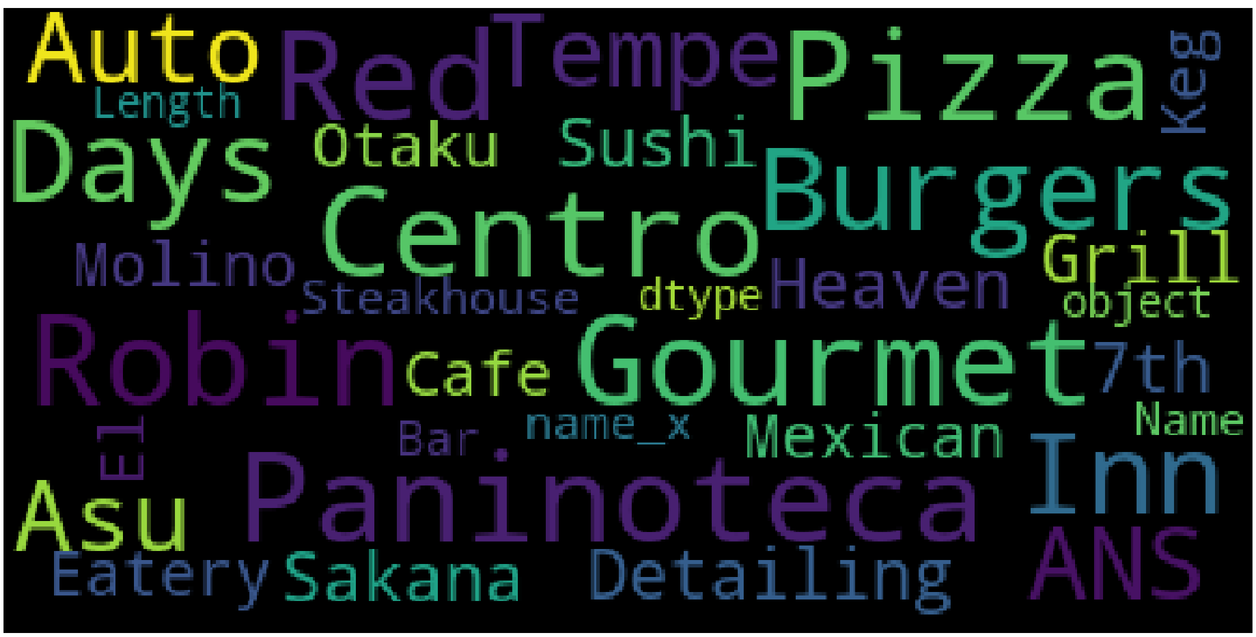
```
#Step6: Plot Word cloud for 1 star rating restaurants
print('\nWord cloud for 1 star rating restaurants\n')
from subprocess import check_output
from wordcloud import WordCloud, STOPWORDS

stopwords = set(STOPWORDS)
wordcloud = WordCloud(
                          background_color='black',
                          stopwords=stopwords,
                          max_words=200,
                          max_font_size=40,
                          random_state=42
                         ).generate(str(df_merge3[df_merge3['stars_x']==1]['name

fig = plt.figure(1,figsize=(12,18))
plt.imshow(wordcloud)
plt.axis('off')
plt.show()

#Step6: Plot Word cloud for 2 star rating restaurants
print('\nWord cloud for 2 star rating restaurants\n')
from subprocess import check_output
from wordcloud import WordCloud, STOPWORDS

stopwords = set(STOPWORDS)
wordcloud = WordCloud(
                          background_color='black',
                          stopwords=stopwords,
                          max_words=200,
                          max_font_size=40,
                          random_state=42
                         ).generate(str(df_merge3[df_merge3['stars_x']==2]['name

fig = plt.figure(1,figsize=(12,18))
plt.imshow(wordcloud)
plt.axis('off')
plt.show()

#Step6: Plot Word cloud for 3 star rating restaurants
```

```
print('\nWord cloud for 3 star rating restaurants\n')
from subprocess import check_output
from wordcloud import WordCloud, STOPWORDS

stopwords = set(STOPWORDS)
wordcloud = WordCloud(
                          background_color='black',
                          stopwords=stopwords,
                          max_words=200,
                          max_font_size=40,
                          random_state=42
                         ).generate(str(df_merge3[df_merge3['stars_x']==3]['name

fig = plt.figure(1,figsize=(12,18))
plt.imshow(wordcloud)
plt.axis('off')
plt.show()

#Step6: Plot Word cloud for 4 star rating restaurants
print('\nWord cloud for 4 star rating restaurants\n')
from subprocess import check_output
from wordcloud import WordCloud, STOPWORDS

stopwords = set(STOPWORDS)
wordcloud = WordCloud(
                          background_color='black',
                          stopwords=stopwords,
                          max_words=200,
                          max_font_size=40,
                          random_state=42
                         ).generate(str(df_merge3[df_merge3['stars_x']==4]['name

fig = plt.figure(1,figsize=(12,18))
plt.imshow(wordcloud)
plt.axis('off')
plt.show()

#Step6: Plot Word cloud for 5 star rating restaurants
print('\nWord cloud for 5 star rating restaurants\n')
from subprocess import check_output
from wordcloud import WordCloud, STOPWORDS

stopwords = set(STOPWORDS)
wordcloud = WordCloud(
                          background_color='black',
                          stopwords=stopwords,
                          max_words=200,
                          max_font_size=40,
                          random_state=42
                         ).generate(str(df_merge3[df_merge3['stars_x']==5]['name

fig = plt.figure(1,figsize=(12,18))
plt.imshow(wordcloud)
plt.axis('off')
plt.show()
```

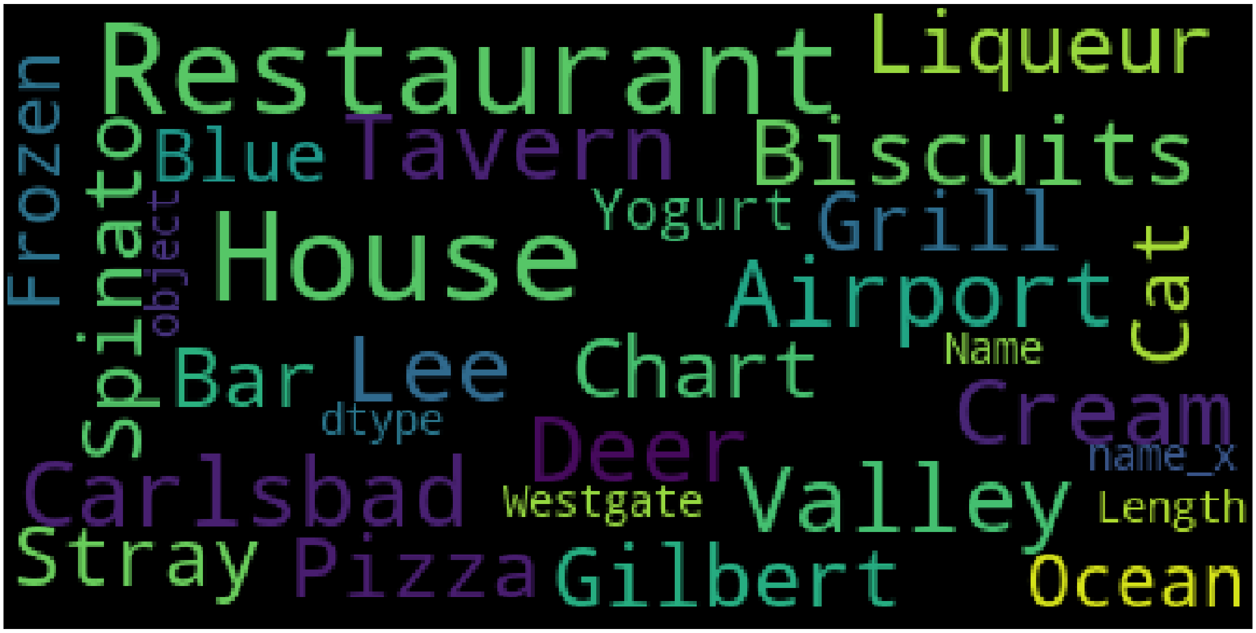
```
Word cloud for 1 star rating restaurants
```



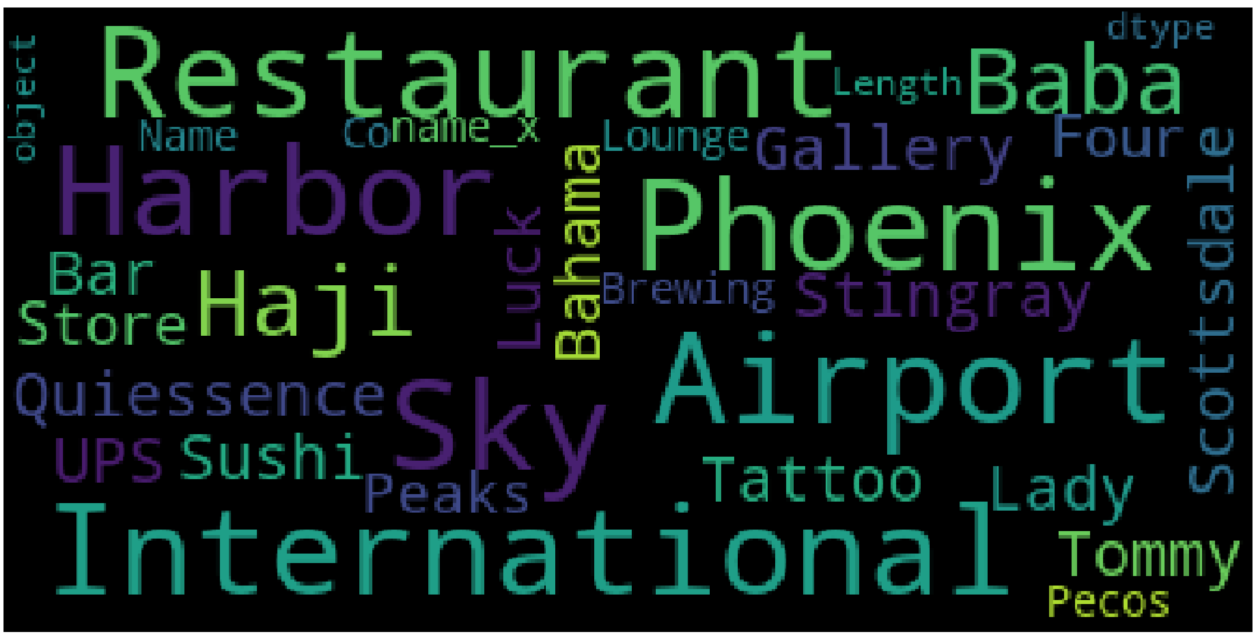
Word cloud for 2 star rating restaurants



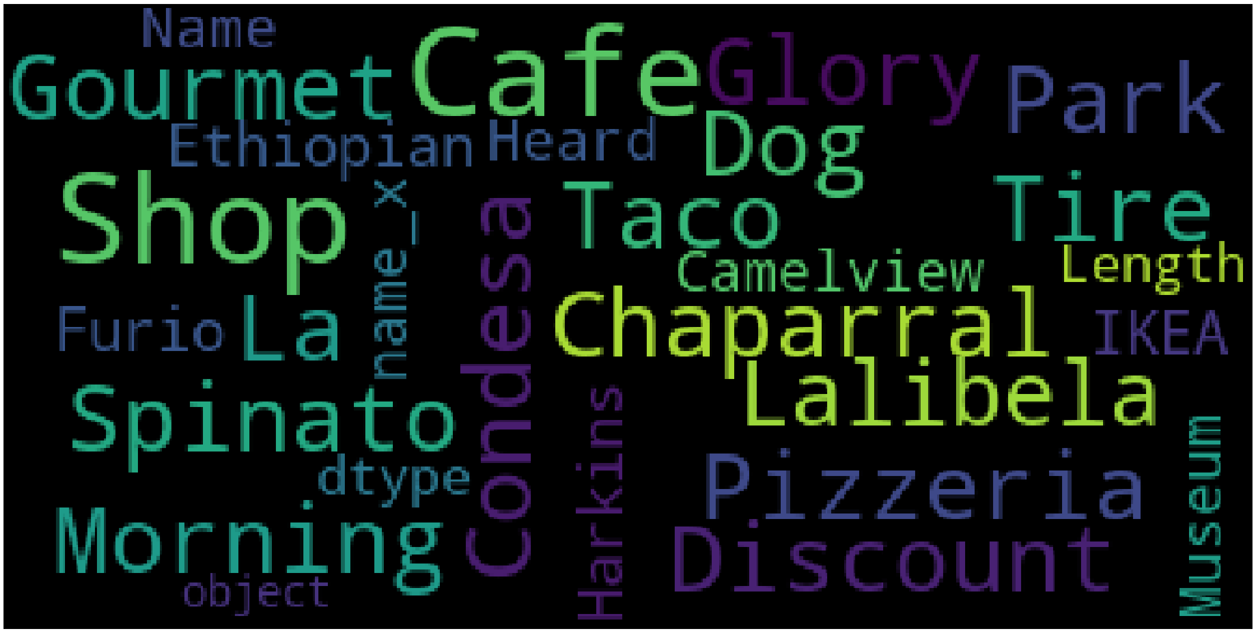
Word cloud for 3 star rating restaurants




```
Word cloud for 4 star rating restaurants
```



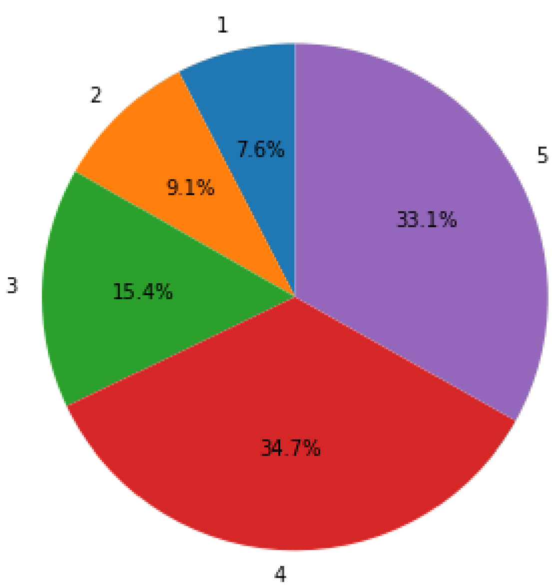

```
Word cloud for 5 star rating restaurants
```



In [20]:

```
################################### VISUALIZATION ################################

#Step4: Create a pie chart to show the percentage wise category distribution
print('\nPie Chart:\n')
labels = '1', '2', '3','4','5'
sizes = [17516, 20957, 35363,79878,76193]
fig1, ax1 = plt.subplots(figsize=(5,5))
ax1.pie(sizes, labels=labels, autopct='%1.1f%%',
        shadow=False, startangle=90)
ax1.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
plt.show()
```

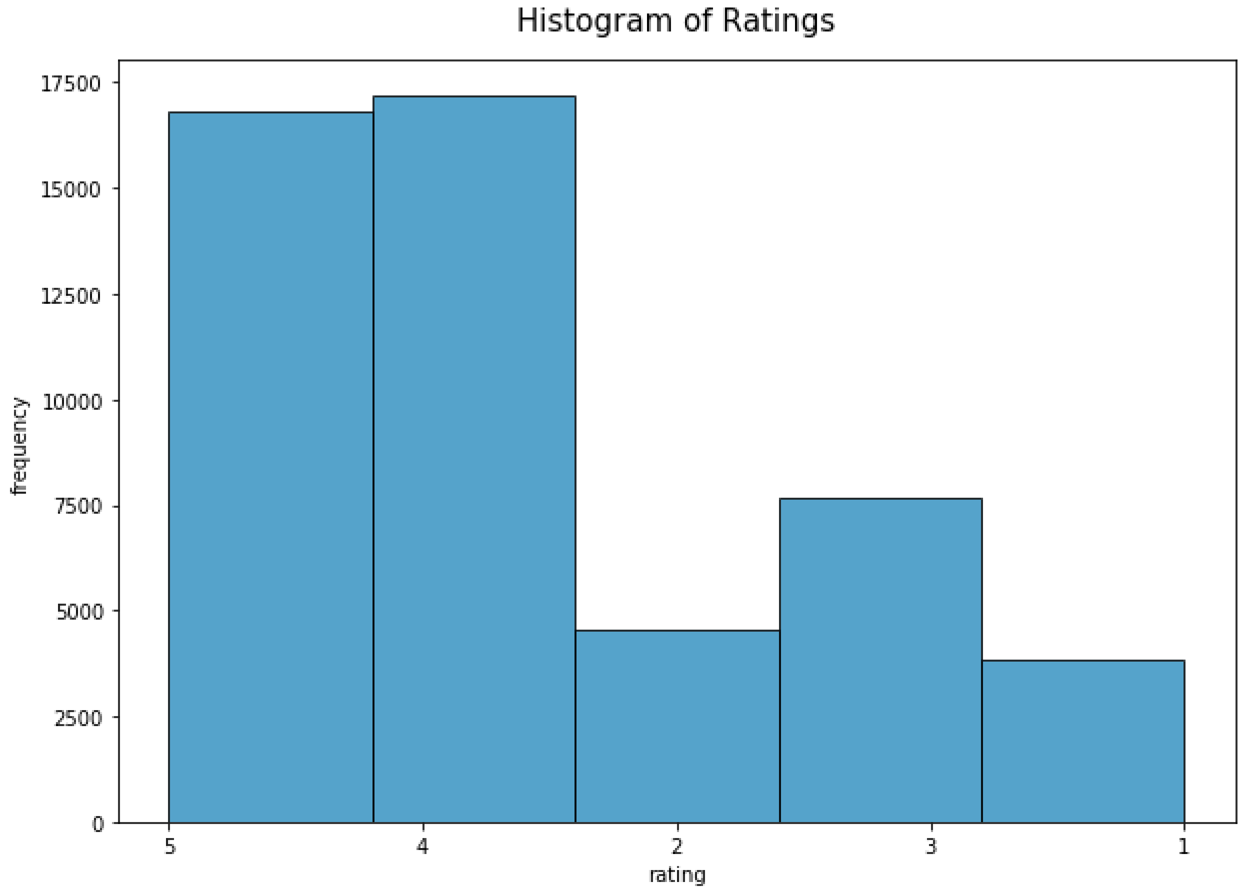
```
Pie Chart:
```

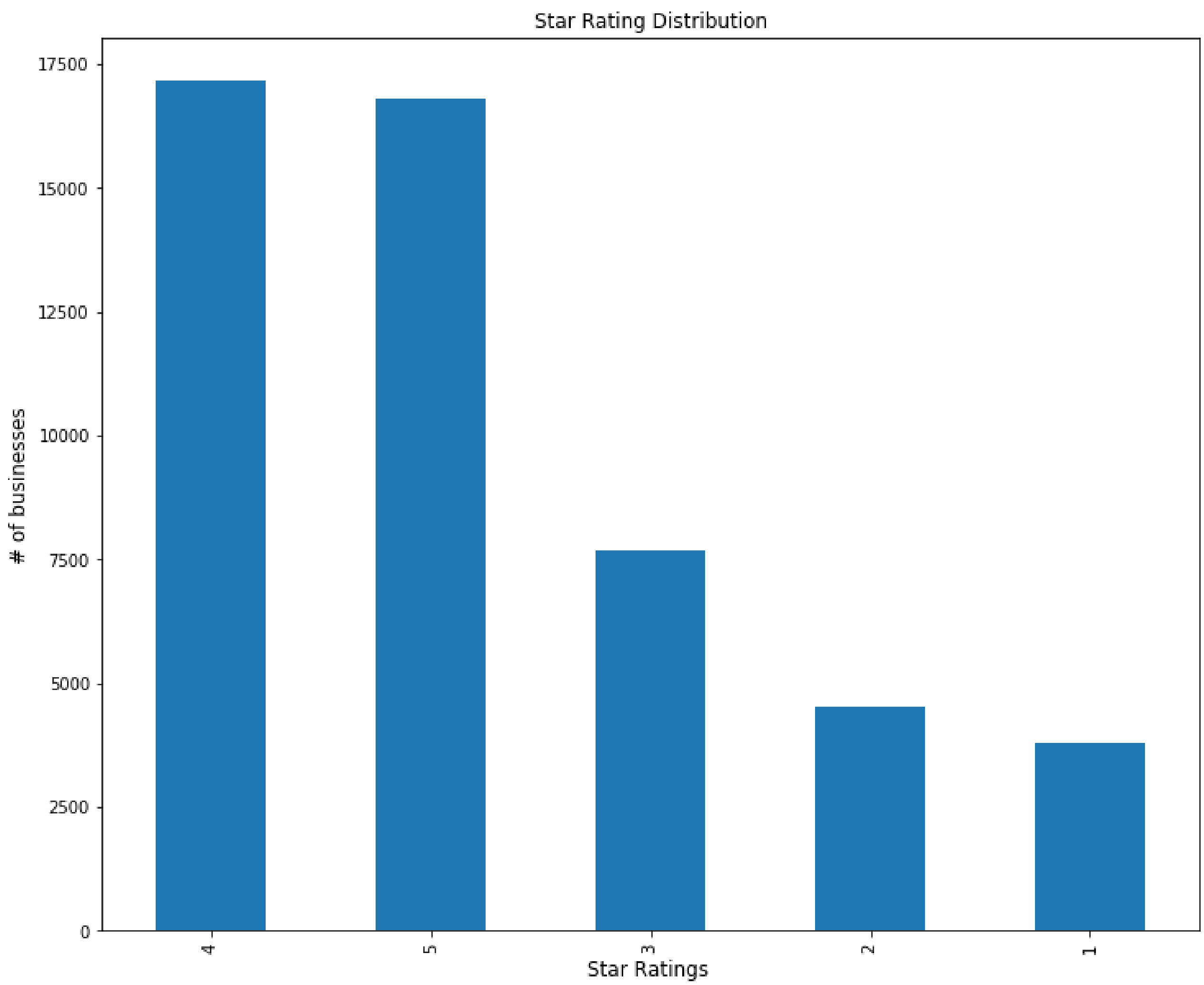


In [29]:

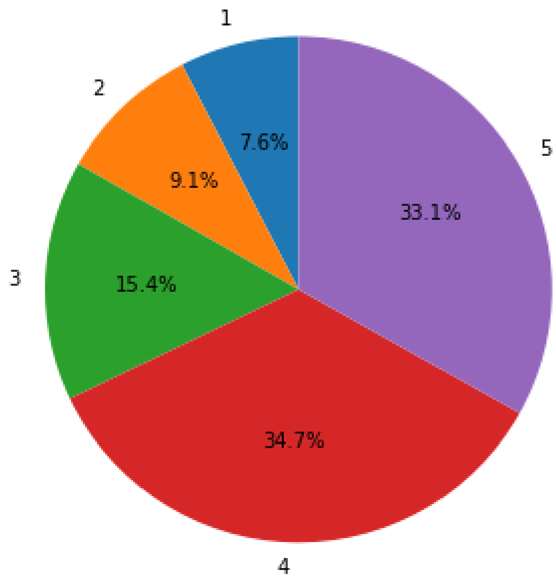
```
import matplotlib.pyplot as plt
num_bins = 5
```

```
fig, ax = plt.subplots(figsize = (10,7))

n, bins, patches = ax.hist(df_merge3['stars_x'], num_bins, facecolor='#2b8cbe',

ax.set_title('Histogram of Ratings', fontsize = 15, pad=15)
ax.set_xlabel('rating')
ax.set_ylabel('frequency')

plt.show()

import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np


x = df_merge3['stars_x']
y = df_merge3['stars_x'].value_counts(ascending=True)
fig, ax = plt.subplots(figsize=(12,10)  )
width = 0.75 # the width of the bars
df_merge3['stars_x'].value_counts().plot(kind='bar');
plt.title("Star Rating Distribution")
plt.ylabel('# of businesses', fontsize=12)
plt.xlabel('Star Ratings ', fontsize=12)
plt.show()

#Step4: Create a pie chart to show the percentage wise rating distribution
print('\nPie Chart:\n')
labels = '1', '2', '3','4','5'
sizes = [17516, 20957, 35363,79878,76193]
fig1, ax1 = plt.subplots(figsize=(5,5))
ax1.pie(sizes, labels=labels, autopct='%1.1f%%',
        shadow=False, startangle=90)
ax1.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
plt.show()
```


Histogram of Ratings
frequency
rating
0
2500
5000
7500
10000
12500
15000
17500
5
4
2
3
1


Star Rating Distribution
# of businesses
Star Ratings
0
2500
5000
7500
10000
12500
15000
17500
4
5
3
2
1

Pie Chart:



In [40]:

```
# bin the data into negative, neutral, and positive values
bins = [0, 2, 4, 6]

bin_names = ['negative', 'neutral', 'positive']

score_bin = pd.Series(df_merge3.stars_x, name = 'score')

score = pd.cut(score_bin, bins, labels=bin_names, right=False)

# number of counts per score

pd.value_counts(score)

df_merge3 = pd.concat([df_merge3, score], axis=1)

df_merge3.head(2)
```

Out[40]:

	votes_x	user_id	review_id	stars_x	date	text	type_x	
0	{'funny': 0, 'useful': 5, 'cool': 2}	rLtl8ZkDX5vH5nAx9C3q5Q	fWKvX83p0-ka4JS3dc6E5A	5	2011-01-26	My wife took me here on my birthday for breakf...	review	9yKzy9PAp
1	{'funny': 0, 'useful': 0, 'cool': 0}	0a2KyEL0d3Yb1V6aivbluQ	IjZ33sJrzXqU-0X6U8NwyA	5	2011-07-27	I have no idea why some people give bad review...	review	ZRJwVLyzE

2 rows × 28 columns

In [41]:
```
# number of counts per score


top_restaurants=df_merge3[(df_merge3['stars_x']==5 ) ]

# top 10 restaurants with most reviews
#top_restaurants_10= top_restaurants.head(10)
top_restaurants=top_restaurants.drop_duplicates(subset=['latitude','longitude','
top_restaurants_10 = top_restaurants.sort_values(['review_count_x'], ascending=[
print(top_restaurants_10.head())
#!pip install folium pandas
import folium
#!pip install --upgrade pandas


top_restaurants_10=top_restaurants_10[['latitude','longitude','name_x','review_c

#top_restaurants_10 = top_restaurants_10.sort_values(['review_count'], ascending



center = [33.581867      , -112.241596]
map_USA = folium.Map(location=center, zoom_start=8)
for index, top_restaurants_10 in top_restaurants_10.iterrows():
    location = [top_restaurants_10['latitude'], top_restaurants_10['longitude']]
    folium.Marker(location, popup = f'Latitude:{top_restaurants_10["latitude"]}\


map_USA
```

```
                                       votes_x                 user_id  \
2493  {'funny': 1, 'useful': 2, 'cool': 1}  -vRFUY8ixuNniCCNVvmkRQ
205   {'funny': 3, 'useful': 2, 'cool': 2}  qklF6QU-bi4Y4Bt4g6Sv8A
1321  {'funny': 0, 'useful': 0, 'cool': 0}  TL46g36OKxmgSDYRFJdPRg
1791  {'funny': 0, 'useful': 2, 'cool': 2}  8-2W5CmkDl9vrkxRpkiPRg
600   {'funny': 2, 'useful': 3, 'cool': 3}  5RxpP2Woo7CpOGUmKgDyAw

                   review_id  stars_x       date  \
2493  7VsG6-m3wNhuoMUeHQ8Vcw        5 2012-06-03
205   h2c-jLW9cLVIiiubGqTaog        5 2011-01-25
1321  XdAtb3hIzydAmzdFy0Ubyw        5 2010-08-05
1791  3eJ2M94guIOhVWexTM6iEw        5 2010-10-31
600   R3Dndbcc0jEAlXyr4JV1EA        5 2008-05-08

                                                   text  type_x  \
2493  It's called America's friendliest airport for ...  review
205   On one of my many visits to see mi amore, he t...  review
1321   Still solid, still delicious. I love this place!  review
1791  Matt's was absolutely fantastic. Got there at ...  review
600   After reading the great reviews and getting pl...  review

                 business_id                               full_address  open  \
2493  hW0Ne_HTHEAgGF1rAdmR-g  3400 E Sky Harbor Blvd\nPhoenix, AZ 85034  True
205   VVeogjZya58oiTxK7qUjAQ          623 E Adams St\nPhoenix, AZ 85004  True
1321  JokKtdXU7zXHcr20Lrk29A    1340 E 8th St\nSte 104\nTempe, AZ 85281  True
1791  ntN85eu27C04nwyPa8IHtw           801 N 1st St\nPhoenix, AZ 85004  True
600   EWMwV5V9BxNs_U6nNVMeqw      3815 N Central Ave\nPhoenix, AZ 85012  True

      ...   latitude    type_y  \
2493  ...  33.434750  business
```

```
205   ...  33.449233  business
1321  ...  33.419451  business
1791  ...  33.456696  business
600   ...  33.491645  business

                                              checkin_info   type_x  \
2493  {'2-5': 1, '22-6': 192, '22-5': 42, '22-4': 92...  checkin
205   {'10-0': 2, '17-0': 6, '18-4': 19, '13-5': 9, ...  checkin
1321  {'22-6': 11, '22-5': 36, '22-4': 41, '22-3': 2...  checkin
1791  {'7-0': 7, '11-3': 18, '3-0': 1, '5-6': 5, '11...  checkin
600   {'22-6': 5, '22-5': 10, '22-4': 12, '22-3': 2,...  checkin

                                          votes_y    name_y average_stars  \
2493       {'funny': 49, 'useful': 104, 'cool': 51}  Brittany          3.93
205          {'funny': 11, 'useful': 21, 'cool': 9}     Becca          3.89
1321  {'funny': 1050, 'useful': 1809, 'cool': 1331}  Jennifer          3.74
1791       {'funny': 49, 'useful': 124, 'cool': 51}     Chris          3.87
600     {'funny': 154, 'useful': 382, 'cool': 266}     Emily          4.19

      review_count_y  type_y     score
2493            58.0    user  positive
205             28.0    user  positive
1321           650.0    user  positive
1791            83.0    user  positive
600            169.0    user  positive

[5 rows x 28 columns]
```

Out[41]: Make this Notebook Trusted to load map: File -> Trust Notebook

In [45]:

```python
# number of counts per score

top_rated_restaurants = pd.Series(df_merge3['name_x'])
top_restaurants_counts = pd.value_counts(top_rated_restaurants)

# top 10 restaurants with most reviews
top_restaurants_counts.head(10)
```

Out[45]:

```
Pita Jungle                                  273
Oregano's Pizza Bistro                       199
```

```
Cornish Pasty Company                           192
Phoenix Sky Harbor International Airport        186
Lo-Lo's Chicken & Waffles                       182
Pizzeria Bianco                                 177
Four Peaks Brewing Co                           159
Matt's Big Breakfast                            158
Postino Arcadia                                 144
Cibo                                            144
Name: name_x, dtype: int64
```

In [46]:

```
import matplotlib.pyplot as plt


df_merge3['text_cleaned'] = df_merge3['text'].apply(lambda x: x.split())
df_merge3.head()





from collections import defaultdict
word_freq = defaultdict(int)
for sent in df_merge3['text_cleaned']:
    for i in sent:
        word_freq[i] += 1
len(word_freq)




sorted(word_freq, key=word_freq.get, reverse=True)[:10]


sentences = df_merge3['text_cleaned']
# Set values for various parameters
num_features = 100    # Word vector dimensionality
min_word_count = 40   # ignore all words with total frequency lower than this
num_workers = 4       # Number of threads to run in parallel
context = 10          # Context window size


# Initialize and train the model (this will take some time)
from gensim.models import word2vec


model = word2vec.Word2Vec(sentences,
                          workers=num_workers,
                          size=num_features,
                          min_count=min_word_count,
                          window=context)

print("Training finished!")

# save the model for later use. You can load it later using Word2Vec.load()
model_name = "Word_Embedding"
model.save(model_name)




# Get vocabulary count of the model
```

```
vocab_tmp = list(model.wv.vocab)
print('Vocab length:',len(vocab_tmp))
```

```
from sklearn.metrics.pairwise import cosine_similarity

model.similarity('dish', 'plate')
```

```
model.most_similar(positive=['tasty', 'pleased','health','enjoy'], negative=['ba
```

```
from gensim.models import Word2Vec
# Load the trained modelNumeric Representations of Words
model = Word2Vec.load("Word_Embedding")
```

```
vocab_tmp = list(model.wv.vocab)
print('Vocab length:',len(vocab_tmp))
```

```
# Get distributional representation of each word
X = model[vocab_tmp]
```

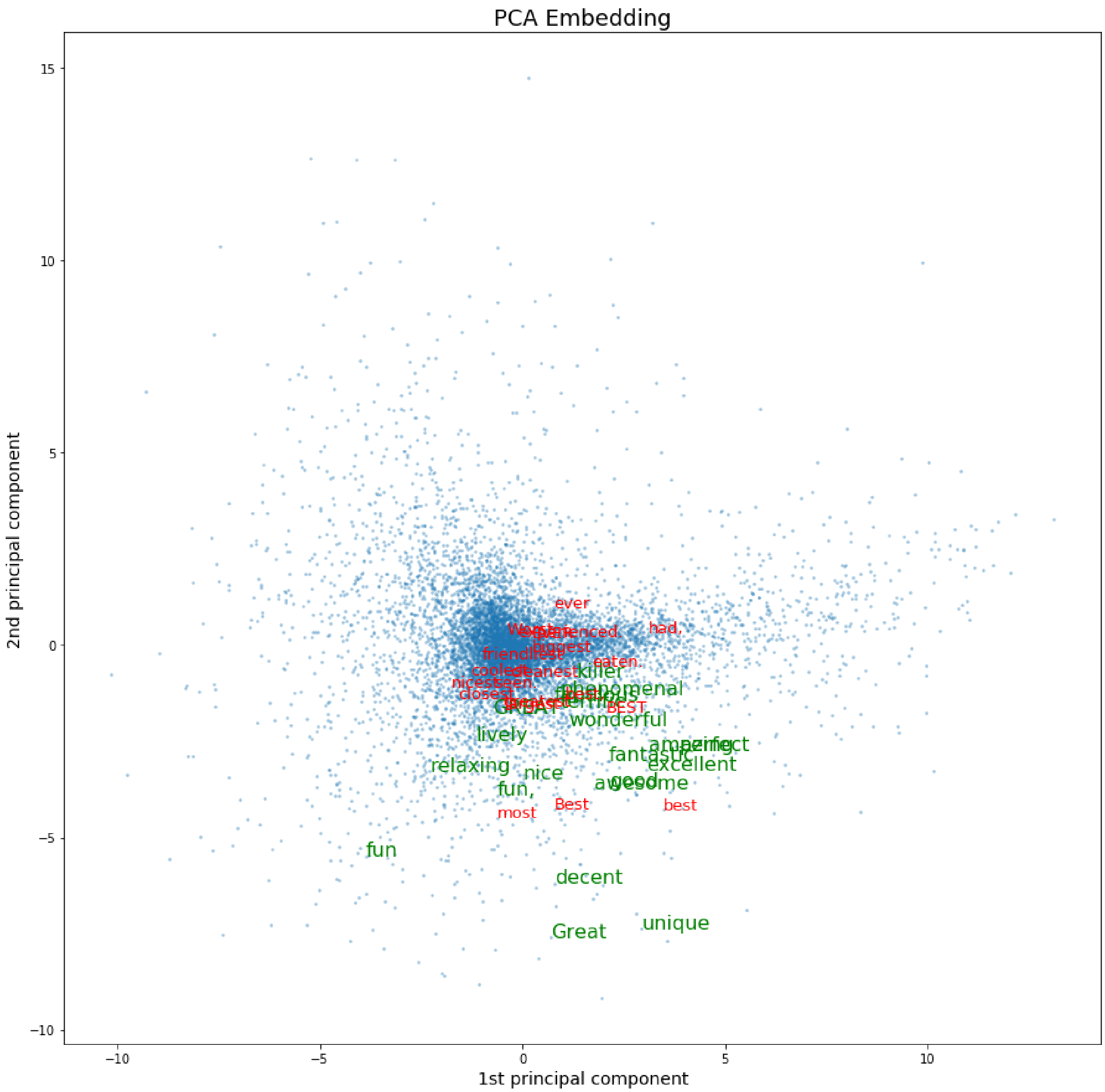
```
from sklearn import decomposition
# get two principle components of the feature space
pca = decomposition.PCA(n_components=2).fit_transform(X)
```

```
good_list = [x for x,y in model.most_similar('great',topn=20)]
bad_list = [x for x,y in model.most_similar('worst',topn=20)]
# good_list = [x for x,y in model.most_similar(positive=['good', 'great','health
```

```
# set figure settings
plt.figure(figsize=(15,15))

# save pca values and vocab in dataframe df
df = pd.concat([pd.DataFrame(pca),pd.Series(vocab_tmp)],axis=1)
df.columns = ['x', 'y', 'word']

plt.xlabel("1st principal component", fontsize=14)
plt.ylabel('2nd principal component', fontsize=14)

plt.scatter(x=df['x'], y=df['y'],s=3,alpha=0.3)

good_words = df[df['word'].isin(good_list)]['word']
for i, word in good_words.items():
    plt.annotate(word, (df['x'].iloc[i], df['y'].iloc[i]),fontsize=16,color='gre


bad_words = df[df['word'].isin(bad_list)]['word']
for i, word in bad_words.items():
    plt.annotate(word, (df['x'].iloc[i], df['y'].iloc[i]),fontsize=13,color='red
```

```python
plt.title("PCA Embedding", fontsize=18)


plt.show()
```

```
Training finished!
Vocab length: 9072
Vocab length: 9072
```



In [48]:

```python
########################################### FEATURE ENGINEERING ######################

# Step 9: NLP/Text based features such as char_count/word_count/punctuation_coun
# extract features from text
df_merge3['char_count'] = df_merge3['text'].apply(len)
df_merge3['word_count'] = df_merge3['text'].apply(lambda x: len(x.split()))
df_merge3['word_density'] = df_merge3['char_count'] / (df_merge3['word_count']+1
df_merge3['punctuation_count'] = df_merge3['text'].apply(lambda x: len("".join(_
df_merge3['title_word_count'] = df_merge3['text'].apply(lambda x: len([wrd for w
```

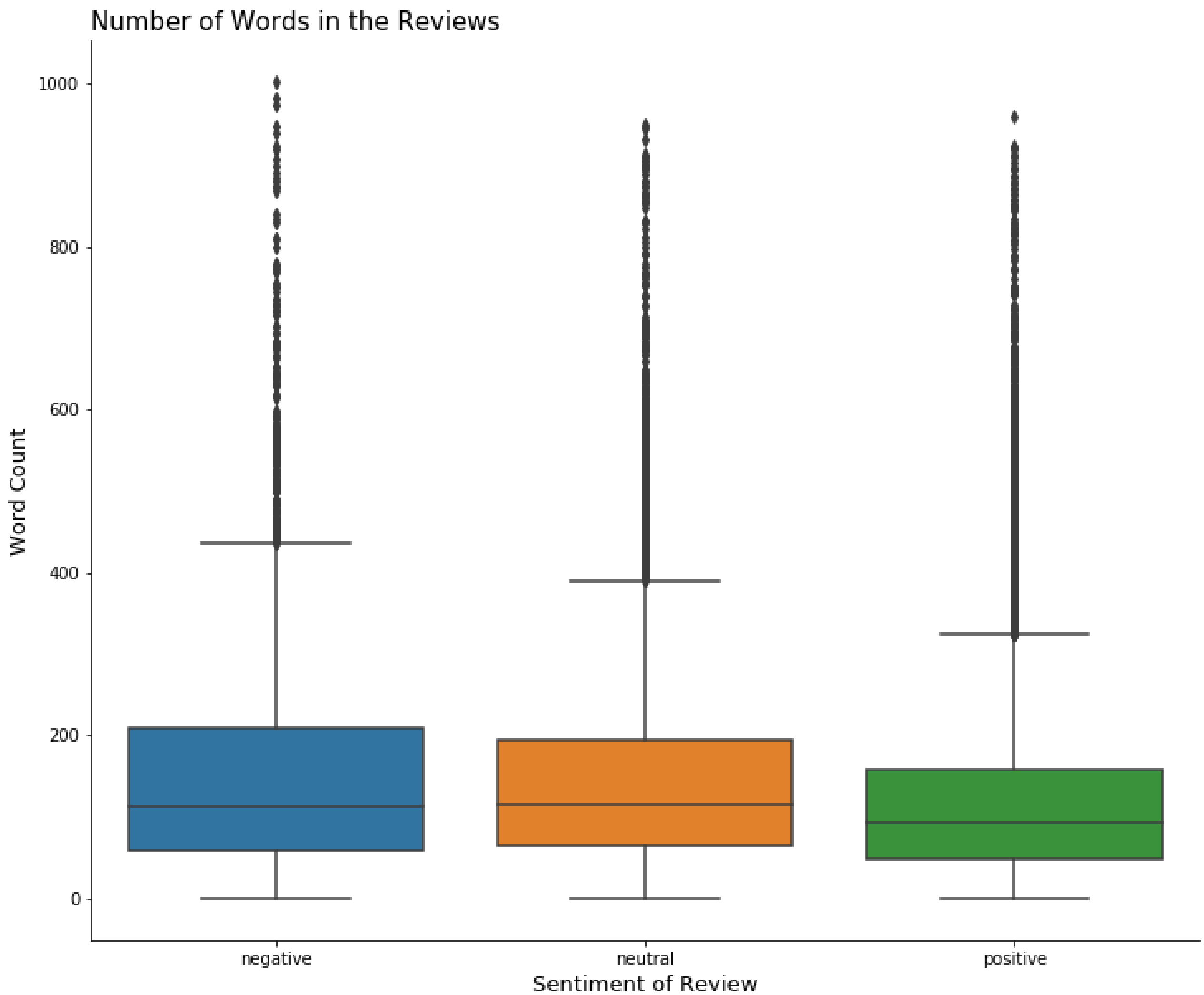
```
df_merge3['upper_case_word_count'] = df_merge3['text'].apply(lambda x: len([wrd
df_merge3['stopword_count'] = df_merge3['text'].apply(lambda x: len([wrd for wrd


df_merge3['line_count'] = df_merge3['text'].apply(lambda x: len([(line) for line
#print(df['line_count'])
print('\nPrint NLP/Text based features:\n')
print(df_merge3[['char_count', 'word_count', 'word_density', 'punctuation_count'
```

```
Print NLP/Text based features:

   char_count  word_count  word_density  punctuation_count  title_word_count  \
0         889         155      5.698718                 21                16
1        1345         257      5.213178                 36                25
2          76          16      4.470588                  3                 2
3         419          76      5.441558                 18                13
4         469          86      5.390805                 38                12
5        2094         366      5.705722                 64                33
6        1565         292      5.341297                 50                45
7         274          50      5.372549                  9                 9
8         349          62      5.539683                 13                 9
9         186          34      5.314286                  4                 4

   upper_case_word_count  stopword_count  line_count
0                      3              71           1
1                      6             134           1
2                      1               6           1
3                      2              33           1
4                      2              44           1
5                     10             171           1
6                     11             134           1
7                      3              25           1
8                      1              29           1
9                      0              16           1
```

In [49]:

```
counts_df = df_merge3[['score', 'text','word_count']]

# separate by positive and negative reviews
counts_pos = counts_df.loc[(counts_df['score']=='positive')]

counts_neg = counts_df.loc[(counts_df['score']=='negative')]

# create figure
fig, ax = plt.subplots(figsize = (12,10))

sns.boxplot(x=counts_df['score'], y=counts_df['word_count'])

# title
ax.set_title('Number of Words in the Reviews', fontsize = 15, loc = 'left')

# set x axis label
ax.set_xlabel('Sentiment of Review', fontsize = 13)

# set y axis label
ax.set_ylabel('Word Count', fontsize = 13)

# remove spines
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
ax.spines['left'].set_visible(True)
```

```
ax.spines['bottom'].set_visible(True)

plt.show()
```



In [51]:

```
#Step 12:  Clean text:  no punctuation/all lowercase/remove stop words




#Convert all cases to lower case
df_merge3 = df_merge3.astype(str).apply(lambda x: x.str.lower())
#print('\nFew sample records after converting strings to low case:\n')
#print(df.head())

#Remove the punctuations from the dataframe
def remove_punctuations(text):
    for punctuation in string.punctuation:
        text = text.replace(punctuation, '')
    return text

df_merge3['text'] = df_merge3['text'].apply(remove_punctuations)
#print('\nFew sample records after removing punctuations:\n')
#print(df.head())
```

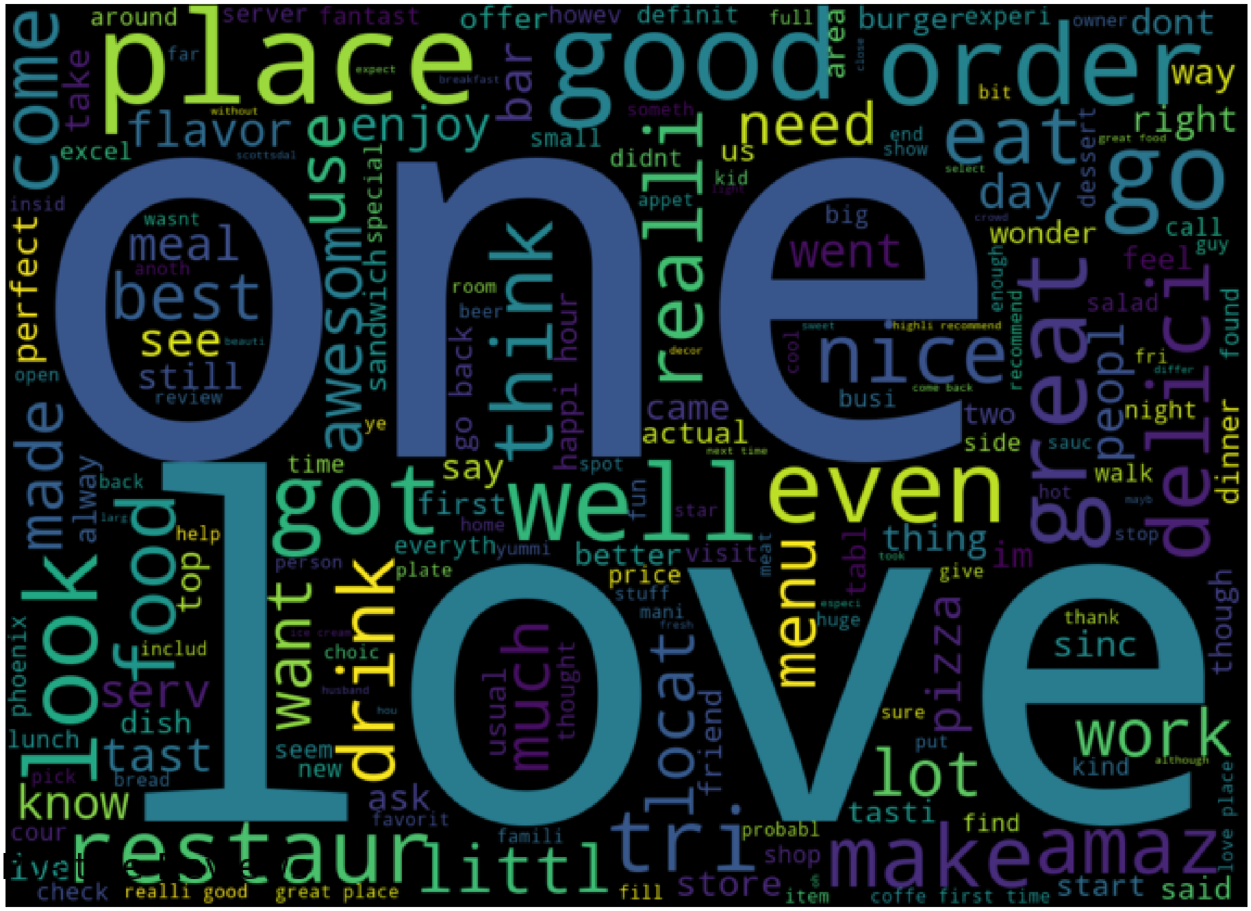
```
#Remove stop words from dataframe
df_merge3['text'] = df_merge3['text'].apply(lambda x: ' '.join([item for item in
#print('\nFew sample records after removing stop words:\n')
#print(df.head())

#Apply porter_stemmer on dataframe
from nltk.stem.porter import PorterStemmer
porter_stemmer = PorterStemmer()

df_merge3['txt_tokenized']=df_merge3['text'].apply(lambda x : filter(None,x.spli
df_merge3['txt_stemmed']=df_merge3['txt_tokenized'].apply(lambda x : [porter_ste
df_merge3['txt_stemmed_sentence']=df_merge3['txt_stemmed'].apply(lambda x : " ".
print('\nFew sample records after doing cleaning/preprocessing (convert to low c
print(df_merge3.head())
```

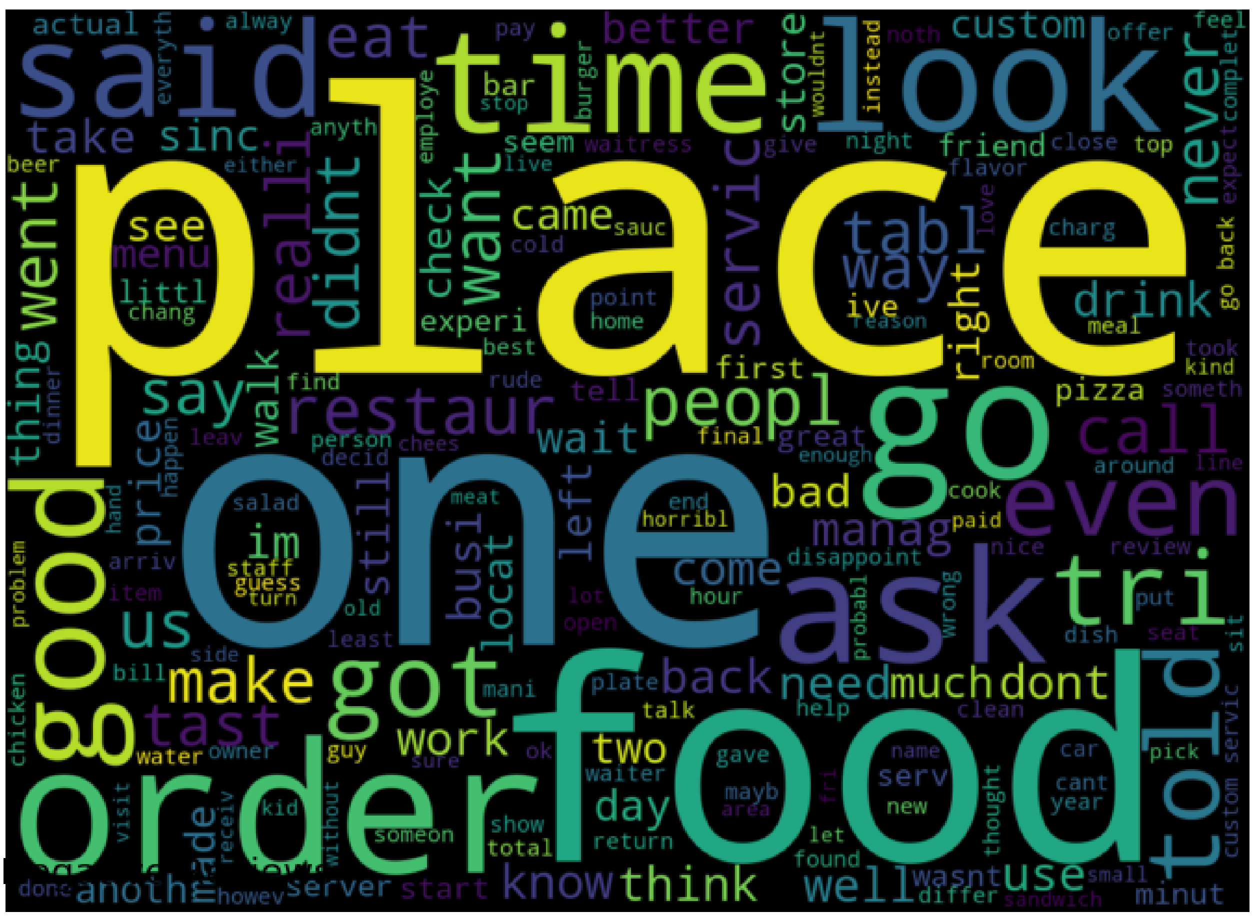
```
Few sample records after doing cleaning/preprocessing (convert to low case/remov
e punctuation/remove stopwords/apply porter stemmer:

                                 votes_x                 user_id  \
0  {'funny': 0, 'useful': 5, 'cool': 2}  rltl8zkdx5vh5nax9c3q5q
1  {'funny': 0, 'useful': 0, 'cool': 0}  0a2kyel0d3yb1v6aivbiuq
2  {'funny': 0, 'useful': 1, 'cool': 0}  0ht2ktfliobpvh6cdc8jqg
3  {'funny': 0, 'useful': 2, 'cool': 1}  uzetl9t0ncrogoyffughhg
4  {'funny': 0, 'useful': 0, 'cool': 0}  vymm4ktsc8zfqbg-j5mwkw

                review_id stars_x        date  \
0  fwkvx83p0-ka4js3dc6e5a       5  2011-01-26
1  ijz33sjrzxqu-0x6u8nwya       5  2011-07-27
2  ieslbzqucldszsqm0ecsxq       4  2012-06-14
3  g-wvgaisbqqamhlnnbyoda       5  2010-05-27
4  1ujfq2r5qfjg_6exmrcagw       5  2012-01-05

                                                text  type_x  \
0  wife took birthday breakfast excellent weather...  review
1  idea people give bad reviews place goes show p...  review
2  love gyro plate rice good also dig candy selec...  review
3  rosie dakota love chaparral dog park convenien...  review
4  general manager scott petello good egg go deta...  review

              business_id                             full_address  open  ...  \
0  9ykzy9papeippoujetnvkg         6106 s 32nd st\nphoenix, az 85042  true  ...
1  zrjwvlyzejq1vaihdhyiow  4848 e chandler blvd\nphoenix, az 85044  true  ...
2  6orac4uyjcsjl1x0wzpvsa      1513 e  apache blvd\ntempe, az 85281  true  ...
3  _1qqzuf4zzoyfcvxc0o6vg   5401 n hayden rd\nscottsdale, az 85250  true  ...
4  6ozycu1rpktng2-1brovtw        1357 s power road\nmesa, az 85206  true  ...

  word_count       word_density punctuation_count title_word_count  \
0        155  5.698717948717949                21               16
1        257  5.213178294573644                36               25
2         16  4.470588235294118                 3                2
3         76  5.441558441558442                18               13
4         86  5.390804597701149                38               12

  upper_case_word_count stopword_count line_count  \
0                     3             71          1
1                     6            134          1
2                     1              6          1
3                     2             33          1
4                     2             44          1

                        txt_tokenized  \
0  <filter object at 0x7fd8ff1bc410>
```

```
1  <filter object at 0x7fd8f1404fd0>
2  <filter object at 0x7fd8f14048d0>
3  <filter object at 0x7fd90275cf50>
4  <filter object at 0x7fd90047f990>

                                          txt_stemmed  \
0  [wife, took, birthday, breakfast, excel, weath...
1  [idea, peopl, give, bad, review, place, goe, s...
2  [love, gyro, plate, rice, good, also, dig, can...
3  [rosi, dakota, love, chaparr, dog, park, conve...
4  [gener, manag, scott, petello, good, egg, go, ...

                                 txt_stemmed_sentence
0  wife took birthday breakfast excel weather per...
1  idea peopl give bad review place goe show plea...
2    love gyro plate rice good also dig candi select
3  rosi dakota love chaparr dog park conveni surr...
4  gener manag scott petello good egg go detail l...

[5 rows x 40 columns]
```

In [53]:

```python
pos = df_merge3.loc[(df_merge3['score']=='positive')]
neg = df_merge3.loc[(df_merge3['score']=='negative')]

from wordcloud import WordCloud, ImageColorGenerator, STOPWORDS
stopwords = set(STOPWORDS)
pos_text = " ".join(review for review in pos.txt_stemmed_sentence)

# create figure
fig, ax = plt.subplots(figsize = (12,10))

wordcloud = WordCloud(width=1100, height=800, stopwords=stopwords).generate(pos_

plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")

ax.set_title('Positive Reviews', pad=15, fontsize = 20)
ax.title.set_position([.12, 0])


plt.show()


neg_text = " ".join(review for review in neg.txt_stemmed_sentence)

# create figure
fig, ax = plt.subplots(figsize = (12,10))

wordcloud = WordCloud(width=1100, height=800, stopwords=stopwords).generate(neg_

plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")

ax.set_title('Negative Reviews', pad=15, fontsize = 20)
ax.title.set_position([.13, 0])


plt.show()
```

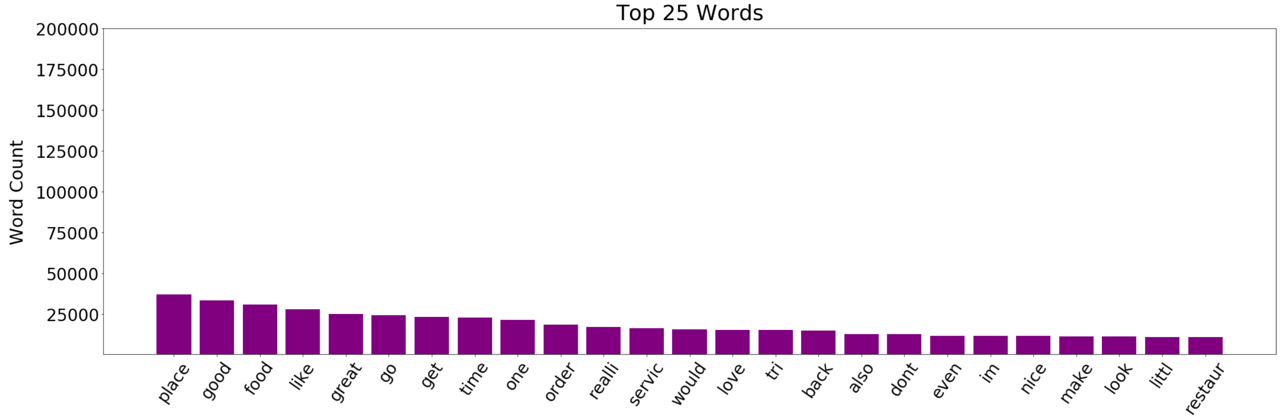




In [23]:
```python
big_string_proc = ' '.join(df_merge3.txt_stemmed_sentence)
```

```
all_words_proc = big_string_proc.split()
print(len(all_words_proc))


# create dictionary of word counts
fdist = FreqDist(all_words_proc)

# convert word counts to dataframe
fdist_df = pd.DataFrame(data=fdist.values(),index=fdist.keys(), columns=['word_c
fdist_df = fdist_df.sort_values('word_count',ascending=False)
top_25 = fdist_df.iloc[:25,:]
print(top_25)


# create labels and prettify the plot
plt.figure(figsize=(30,10))
plt.title('Top 25 Words', fontsize=36, pad=15)
plt.ylabel('Word Count', fontsize=30, labelpad=15)
plt.xticks(rotation=55, fontsize=28)
plt.yticks(fontsize=28)
plt.ylim(bottom=100, top=200000)

# plot top 25 words
plt.bar(top_25.index, top_25.word_count, color='purple')

# prepare to save and display
plt.tight_layout()
plt.show()
```

```
3349026
         word_count
place         36712
good          33369
food          30896
like          27648
great         25101
go            24018
get           23261
time          22616
one           21406
order         18553
realli        16821
servic        16142
would         15408
love          15145
tri           15031
back          14604
also          12522
dont          12408
even          11463
im            11438
nice          11425
make          11174
look          11051
littl         10887
restaur       10664
```



In [17]:

```
from sklearn.feature_selection import chi2
from sklearn.feature_extraction.text import TfidfVectorizer

# Check most important features in the dataset with chi2 score test

print('\nBelow are the most important features based on Chi2 score:\n')

Tfidf = TfidfVectorizer(min_df=5, ngram_range=(1, 2))
tfidf_features = Tfidf.fit_transform(df_merge3['txt_stemmed_sentence'])
tfidf_features.shape

N = 5
Number = 1
for rating in df_merge3['stars_x'].unique():
                features_chi2 = chi2(tfidf_features, df_merge3['stars_x'] == rat
                indices = np.argsort(features_chi2[0])
                feature_names = np.array(Tfidf.get_feature_names())[indices]
                unigrams = [x for x in feature_names if len(x.split(' ')) == 1]
                bigrams = [x for x in feature_names if len(x.split(' ')) == 2]
                print("{}. {} :".format(Number,rating))
                print("\t Unigrams :\n\t. {}".format('\n\t. '.join(unigrams[-N:]
                print("\t Bigrams :\n\t. {}".format('\n\t. '.join(bigrams[-N:]))
                Number += 1

print('\n')
```

```
Below are the most important features based on Chi2 score:

1. 5 :
         Unigrams :
        . highli
        . awesom
        . love
        . best
        . amaz
         Bigrams :
        . great food
        . pretti good
        . love love
        . highli recommend
        . love place
2. 4 :
         Unigrams :
        . ok
        . horribl
```

```
        . tasti
        . worst
        . good
         Bigrams :
        . happi hour
        . realli enjoy
        . good food
        . realli good
        . four star
3. 2 :
         Unigrams :
        . overpr
        . ok
        . meh
        . mediocr
        . bland
         Bigrams :
        . experienc better
        . want like
        . noth special
        . wont back
        . two star
4. 3 :
         Unigrams :
        . averag
        . pretti
        . aok
        . decent
        . ok
         Bigrams :
        . noth special
        . 35 star
        . food ok
        . pretti good
        . three star
5. 1 :
         Unigrams :
        . terribl
        . told
        . rude
        . horribl
        . worst
         Bigrams :
        . place suck
        . food poison
        . zero star
        . wast time
        . never go
```

In [24]:

```python
#df_merge3.drop('text',axis='columns', inplace=True)
print(list(df_merge3.columns))

df_merge3.drop('char_count',axis='columns', inplace=True)
df_merge3.drop('word_count',axis='columns', inplace=True)
df_merge3.drop('word_density',axis='columns', inplace=True)
df_merge3.drop('punctuation_count',axis='columns', inplace=True)
df_merge3.drop('title_word_count',axis='columns', inplace=True)
df_merge3.drop('upper_case_word_count',axis='columns', inplace=True)
df_merge3.drop('stopword_count',axis='columns', inplace=True)
df_merge3.drop('line_count',axis='columns', inplace=True)
```

```
df_merge3.drop('txt_tokenized',axis='columns', inplace=True)
df_merge3.drop('txt_stemmed',axis='columns', inplace=True)
```

```
['votes_x', 'user_id', 'review_id', 'stars_x', 'date', 'text', 'type_x', 'busine
ss_id', 'full_address', 'open', 'categories', 'city', 'review_count_x', 'name_
x', 'neighborhoods', 'longitude', 'state', 'stars_y', 'latitude', 'type_y', 'che
ckin_info', 'type_x', 'votes_y', 'name_y', 'average_stars', 'review_count_y', 't
ype_y', 'char_count', 'word_count', 'word_density', 'punctuation_count', 'title_
word_count', 'upper_case_word_count', 'stopword_count', 'line_count', 'txt_token
ized', 'txt_stemmed', 'txt_stemmed_sentence']
```

In [25]:

```
 ########################  MODEL BUILDING AND EVALUATIONS ######################

# split the dataset into training and validation datasets
train_x, valid_x, train_y, valid_y = model_selection.train_test_split(df_merge3[


# label encode the target variable
encoder = preprocessing.LabelEncoder()
train_y = encoder.fit_transform(train_y)
valid_y = encoder.fit_transform(valid_y)

################### Create features from text #########################

# create a count vectorizer object
count_vect = CountVectorizer(analyzer='word', token_pattern=r'\w{1,}')
count_vect.fit(df_merge3['txt_stemmed_sentence'])

# word level tf-idf
tfidf_vect = TfidfVectorizer(analyzer='word', token_pattern=r'\w{1,}', max_featu
tfidf_vect.fit(df_merge3['txt_stemmed_sentence'])
xtrain_tfidf =  tfidf_vect.transform(train_x)
xvalid_tfidf =  tfidf_vect.transform(valid_x)

# ngram level tf-idf
tfidf_vect_ngram = TfidfVectorizer(analyzer='word', token_pattern=r'\w{1,}', ngr
tfidf_vect_ngram.fit(df_merge3['txt_stemmed_sentence'])
xtrain_tfidf_ngram =  tfidf_vect_ngram.transform(train_x)
xvalid_tfidf_ngram =  tfidf_vect_ngram.transform(valid_x)

# characters level tf-idf
tfidf_vect_ngram_chars = TfidfVectorizer(analyzer='char', token_pattern=r'\w{1,}
tfidf_vect_ngram_chars.fit(df_merge3['txt_stemmed_sentence'])
xtrain_tfidf_ngram_chars =  tfidf_vect_ngram_chars.transform(train_x)
xvalid_tfidf_ngram_chars =  tfidf_vect_ngram_chars.transform(valid_x)

# transform the training and validation data using count vectorizer object
xtrain_count =  count_vect.transform(train_x)
xvalid_count =  count_vect.transform(valid_x)
```

In [23]:

```
######## Test with Truncated SVD technique to check the optimum number of compon
# Dimensionality reduction


for num_components in range(100):
                    svd = TruncatedSVD(n_components=num_components, random_state
```

```
                    X_svd = svd.fit_transform(xtrain_tfidf)
                    print(f"Total variance explained: {np.sum(svd.explained_vari

# Check explained variance ratio for 300 components/features
svd = TruncatedSVD(n_components=300, random_state=42)
X_svd = svd.fit_transform(xtrain_tfidf)
#print("\nTotal variance explained with 300 components: {np.sum(svd.explained_va
print(f"Total variance explained: {np.sum(svd.explained_variance_ratio_):.2f}",
```

```
Total variance explained: 0.00 number of components: 0
Total variance explained: 0.00 number of components: 1
Total variance explained: 0.01 number of components: 2
Total variance explained: 0.02 number of components: 3
Total variance explained: 0.02 number of components: 4
Total variance explained: 0.02 number of components: 5
Total variance explained: 0.03 number of components: 6
Total variance explained: 0.03 number of components: 7
Total variance explained: 0.04 number of components: 8
Total variance explained: 0.04 number of components: 9
Total variance explained: 0.04 number of components: 10
Total variance explained: 0.05 number of components: 11
Total variance explained: 0.05 number of components: 12
Total variance explained: 0.05 number of components: 13
Total variance explained: 0.05 number of components: 14
Total variance explained: 0.06 number of components: 15
Total variance explained: 0.06 number of components: 16
Total variance explained: 0.06 number of components: 17
Total variance explained: 0.06 number of components: 18
Total variance explained: 0.07 number of components: 19
Total variance explained: 0.07 number of components: 20
Total variance explained: 0.07 number of components: 21
Total variance explained: 0.07 number of components: 22
Total variance explained: 0.08 number of components: 23
Total variance explained: 0.08 number of components: 24
Total variance explained: 0.08 number of components: 25
Total variance explained: 0.08 number of components: 26
Total variance explained: 0.08 number of components: 27
Total variance explained: 0.09 number of components: 28
Total variance explained: 0.09 number of components: 29
Total variance explained: 0.09 number of components: 30
Total variance explained: 0.09 number of components: 31
Total variance explained: 0.09 number of components: 32
Total variance explained: 0.10 number of components: 33
Total variance explained: 0.10 number of components: 34
Total variance explained: 0.10 number of components: 35
Total variance explained: 0.10 number of components: 36
Total variance explained: 0.10 number of components: 37
Total variance explained: 0.10 number of components: 38
Total variance explained: 0.11 number of components: 39
Total variance explained: 0.11 number of components: 40
Total variance explained: 0.11 number of components: 41
Total variance explained: 0.11 number of components: 42
Total variance explained: 0.11 number of components: 43
Total variance explained: 0.11 number of components: 44
Total variance explained: 0.12 number of components: 45
Total variance explained: 0.12 number of components: 46
Total variance explained: 0.12 number of components: 47
Total variance explained: 0.12 number of components: 48
Total variance explained: 0.12 number of components: 49
Total variance explained: 0.12 number of components: 50
Total variance explained: 0.13 number of components: 51
Total variance explained: 0.13 number of components: 52
Total variance explained: 0.13 number of components: 53
Total variance explained: 0.13 number of components: 54
```

```
Total variance explained: 0.13 number of components: 55
Total variance explained: 0.13 number of components: 56
Total variance explained: 0.13 number of components: 57
Total variance explained: 0.14 number of components: 58
Total variance explained: 0.14 number of components: 59
Total variance explained: 0.14 number of components: 60
Total variance explained: 0.14 number of components: 61
Total variance explained: 0.14 number of components: 62
Total variance explained: 0.14 number of components: 63
Total variance explained: 0.14 number of components: 64
Total variance explained: 0.15 number of components: 65
Total variance explained: 0.15 number of components: 66
Total variance explained: 0.15 number of components: 67
Total variance explained: 0.15 number of components: 68
Total variance explained: 0.15 number of components: 69
Total variance explained: 0.15 number of components: 70
Total variance explained: 0.15 number of components: 71
Total variance explained: 0.16 number of components: 72
Total variance explained: 0.16 number of components: 73
Total variance explained: 0.16 number of components: 74
Total variance explained: 0.16 number of components: 75
Total variance explained: 0.16 number of components: 76
Total variance explained: 0.16 number of components: 77
Total variance explained: 0.16 number of components: 78
Total variance explained: 0.16 number of components: 79
Total variance explained: 0.17 number of components: 80
Total variance explained: 0.17 number of components: 81
Total variance explained: 0.17 number of components: 82
Total variance explained: 0.17 number of components: 83
Total variance explained: 0.17 number of components: 84
Total variance explained: 0.17 number of components: 85
Total variance explained: 0.17 number of components: 86
Total variance explained: 0.17 number of components: 87
Total variance explained: 0.18 number of components: 88
Total variance explained: 0.18 number of components: 89
Total variance explained: 0.18 number of components: 90
Total variance explained: 0.18 number of components: 91
Total variance explained: 0.18 number of components: 92
Total variance explained: 0.18 number of components: 93
Total variance explained: 0.18 number of components: 94
Total variance explained: 0.18 number of components: 95
Total variance explained: 0.18 number of components: 96
Total variance explained: 0.19 number of components: 97
Total variance explained: 0.19 number of components: 98
Total variance explained: 0.19 number of components: 99
Total variance explained: 0.36 number of components: 300
```

In [26]:

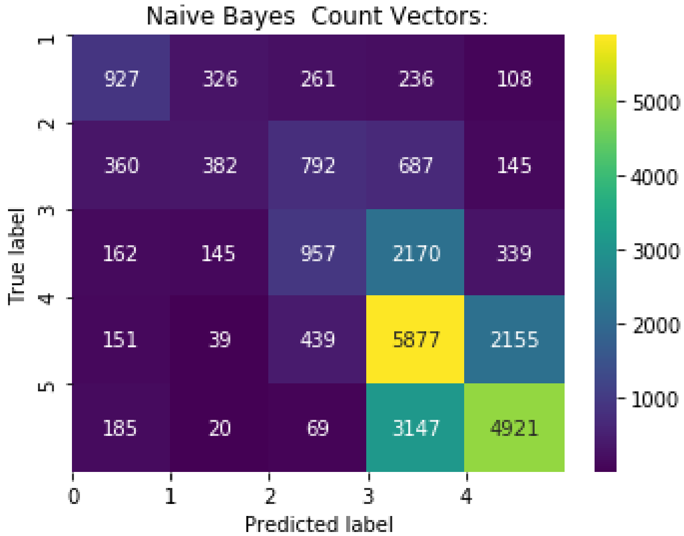
```python
############################### Train, Build and Evaluate the model ###########
#Write a function to train the model classifier that will calculate the accuracy
#The function will also plot the confusion matrix and will print the classificat

def train_model(model_name,classifier, feature_vector_train, label, feature_vect
    # fit the training dataset on the classifier
    classifier.fit(feature_vector_train, label)

    # predict the labels on validation dataset
    predictions = classifier.predict(feature_vector_valid)

    if is_neural_net:
        predictions = predictions.argmax(axis=-1)
    cf_matrix=confusion_matrix(valid_y, predictions)
    print('\nConfusion matrix for' ,model_name,'is:\n')
```

```
    print(confusion_matrix(valid_y, predictions))
    print('\nClassification report for',model_name,'is:\n')
    print(classification_report(valid_y, predictions,target_names=['1','2','3','
    index = ['0','1','2','3','4']
    columns = ['1','2','3','4','5']
    cm_df = pd.DataFrame(cf_matrix,columns,index)
    plt.figure(figsize=(5.5,4))
    sns.heatmap(cm_df, annot=True,cmap="viridis" ,fmt='g')
    plt.xticks([0,1,2,3,4])
    plt.yticks([0,1,2,3,4])
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.title(model_name)
    plt.show()

    return metrics.accuracy_score(predictions, valid_y)
```

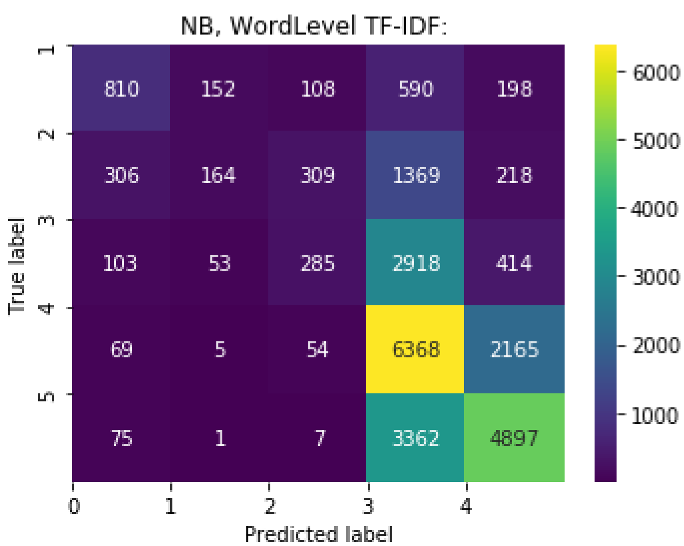
In [19]:

```
# Naive Bayes on Count Vectors
accuracy_nb_cv = train_model("Naive Bayes  Count Vectors:",naive_bayes.Multinomi
print( "Accuracy of Naive Bayes, Count Vectors Model is: ", "{:.2%}".format(accu

# Naive Bayes on Word Level TF IDF Vectors
accuracy_nb_tfidf = train_model("NB, WordLevel TF-IDF: ",naive_bayes.Multinomial
print( "Accuracy of Naive Bayes, WordLevel TF-IDF Model is: ", "{:.2%}".format(a

# Naive Bayes on Ngram Level TF IDF Vectors
accuracy_nb_ngtfidf = train_model("NB, N-Gram Vectors: ",naive_bayes.Multinomial
print( "Accuracy of Naive Bayes, N-Gram Vectors Model is: ", "{:.2%}".format(acc


# Naive Bayes on Character Level TF IDF Vectors
accuracy_nb_ctfidf = train_model("NB, CharLevel Vectors: ",naive_bayes.Multinomi
print( "Accuracy of Naive Bayes, CharLevel Vectors Model is: ", "{:.2%}".format(
```

```
Confusion matrix for Naive Bayes  Count Vectors: is:

[[ 927  326  261  236  108]
 [ 360  382  792  687  145]
 [ 162  145  957 2170  339]
 [ 151   39  439 5877 2155]
 [ 185   20   69 3147 4921]]

Classification report for Naive Bayes  Count Vectors: is:

              precision    recall  f1-score   support

           1       0.52      0.50      0.51      1858
           2       0.42      0.16      0.23      2366
           3       0.38      0.25      0.30      3773
           4       0.49      0.68      0.57      8661
           5       0.64      0.59      0.61      8342

    accuracy                           0.52     25000
   macro avg       0.49      0.44      0.45     25000
weighted avg       0.52      0.52      0.51     25000
```

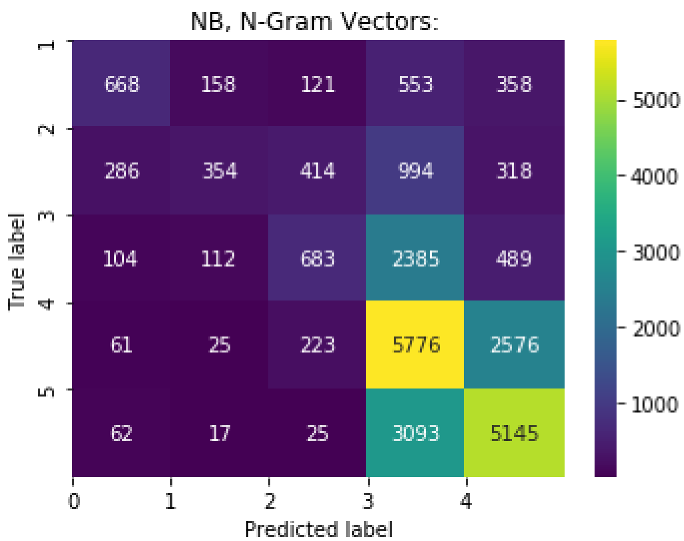



```
Accuracy of Naive Bayes, Count Vectors Model is:  52.26%

Confusion matrix for NB, WordLevel TF-IDF:  is:

[[ 810  152  108  590  198]
 [ 306  164  309 1369  218]
 [ 103   53  285 2918  414]
 [  69    5   54 6368 2165]
 [  75    1    7 3362 4897]]

Classification report for NB, WordLevel TF-IDF:  is:

              precision    recall  f1-score   support

           1       0.59      0.44      0.50      1858
           2       0.44      0.07      0.12      2366
           3       0.37      0.08      0.13      3773
           4       0.44      0.74      0.55      8661
           5       0.62      0.59      0.60      8342

    accuracy                           0.50     25000
   macro avg       0.49      0.38      0.38     25000
weighted avg       0.50      0.50      0.46     25000
```

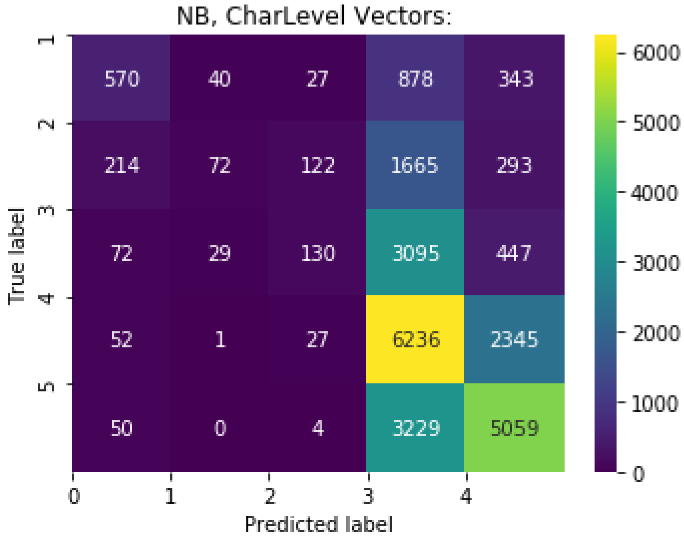



```
Accuracy of Naive Bayes, WordLevel TF-IDF Model is:  50.10%

Confusion matrix for NB, N-Gram Vectors:  is:
```

```
[[ 668  158  121  553  358]
 [ 286  354  414  994  318]
 [ 104  112  683 2385  489]
 [  61   25  223 5776 2576]
 [  62   17   25 3093 5145]]

Classification report for NB, N-Gram Vectors:  is:

              precision    recall  f1-score   support

           1       0.57      0.36      0.44      1858
           2       0.53      0.15      0.23      2366
           3       0.47      0.18      0.26      3773
           4       0.45      0.67      0.54      8661
           5       0.58      0.62      0.60      8342

    accuracy                           0.51     25000
   macro avg       0.52      0.39      0.41     25000
weighted avg       0.51      0.51      0.48     25000
```




```
Accuracy of Naive Bayes, N-Gram Vectors Model is:  50.50%

Confusion matrix for NB, CharLevel Vectors:  is:

[[ 570   40   27  878  343]
 [ 214   72  122 1665  293]
 [  72   29  130 3095  447]
 [  52    1   27 6236 2345]
 [  50    0    4 3229 5059]]

Classification report for NB, CharLevel Vectors:  is:

              precision    recall  f1-score   support

           1       0.59      0.31      0.40      1858
           2       0.51      0.03      0.06      2366
           3       0.42      0.03      0.06      3773
           4       0.41      0.72      0.52      8661
           5       0.60      0.61      0.60      8342

    accuracy                           0.48     25000
   macro avg       0.51      0.34      0.33     25000
weighted avg       0.50      0.48      0.43     25000
```

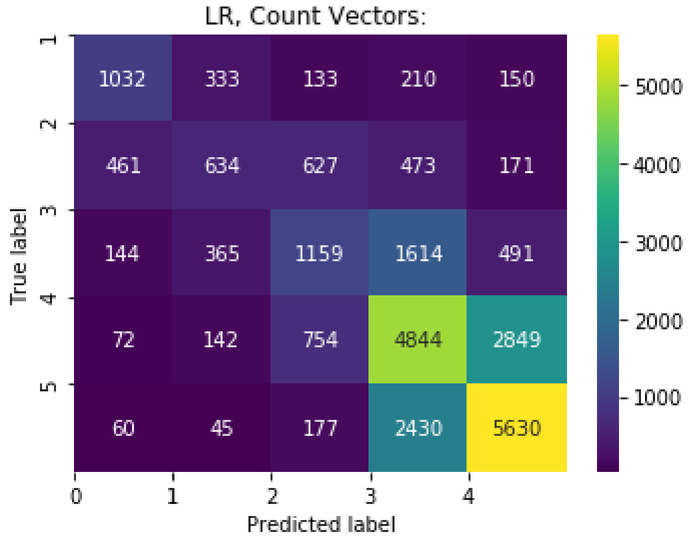



```
Accuracy of Naive Bayes, CharLevel Vectors Model is:  48.27%
```

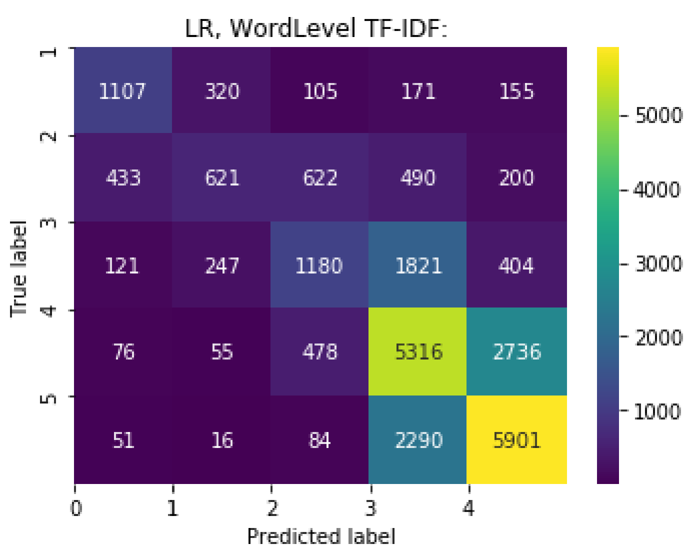
In [20]:

```
# Linear Classifier on Count Vectors
accuracy_lr_cv = train_model("LR, Count Vectors: ",linear_model.LogisticRegressi
print( "Accuracy of Liner Regression Count Vectors Model is: ", "{:.2%}".format(

# Linear Classifier on Word Level TF IDF Vectors
accuracy_lr_tfidf = train_model("LR, WordLevel TF-IDF: ",linear_model.LogisticRe
print( "Accuracy of Liner Regression TFIDF Model is: ", "{:.2%}".format(accuracy

# Linear Classifier on Ngram Level TF IDF Vectors
accuracy_lr_ngtfidf = train_model("LR, N-Gram Vectors: ",linear_model.LogisticRe
print( "Accuracy of Liner Regression N-Gram Level Model is: ", "{:.2%}".format(a

# Linear Classifier on Character Level TF IDF Vectors
accuracy_lr_ctfidf = train_model("LR, CharLevel TF-IDF: ",linear_model.LogisticR
print( "Accuracy of Liner Regression Char Level TFIDF Model is: ", "{:.2%}".form
```

```
Confusion matrix for LR, Count Vectors:  is:

[[1032  333  133  210  150]
 [ 461  634  627  473  171]
 [ 144  365 1159 1614  491]
 [  72  142  754 4844 2849]
 [  60   45  177 2430 5630]]

Classification report for LR, Count Vectors:  is:

              precision    recall  f1-score   support

           1       0.58      0.56      0.57      1858
           2       0.42      0.27      0.33      2366
           3       0.41      0.31      0.35      3773
           4       0.51      0.56      0.53      8661
           5       0.61      0.67      0.64      8342

    accuracy                           0.53     25000
   macro avg       0.50      0.47      0.48     25000
weighted avg       0.52      0.53      0.52     25000
```

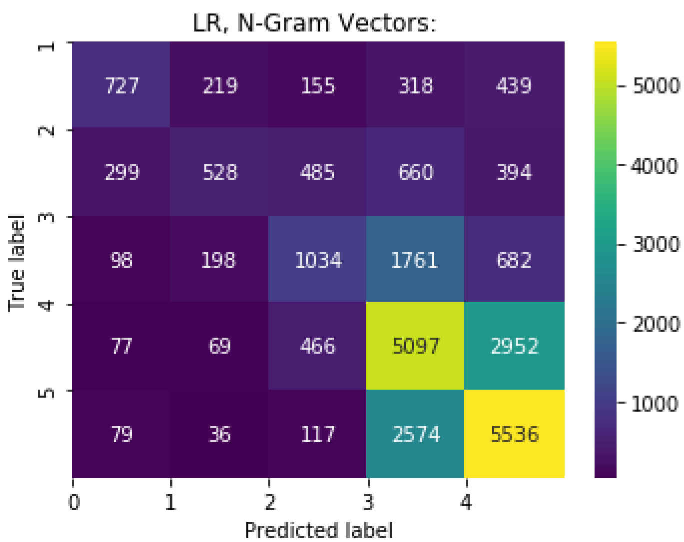



```
Accuracy of Liner Regression Count Vectors Model is:  53.20%

Confusion matrix for LR, WordLevel TF-IDF:  is:

[[1107  320  105  171  155]
 [ 433  621  622  490  200]
 [ 121  247 1180 1821  404]
 [  76   55  478 5316 2736]
 [  51   16   84 2290 5901]]

Classification report for LR, WordLevel TF-IDF:  is:

              precision    recall  f1-score   support

           1       0.62      0.60      0.61      1858
           2       0.49      0.26      0.34      2366
           3       0.48      0.31      0.38      3773
           4       0.53      0.61      0.57      8661
           5       0.63      0.71      0.67      8342

    accuracy                           0.56     25000
   macro avg       0.55      0.50      0.51     25000
weighted avg       0.56      0.56      0.55     25000
```

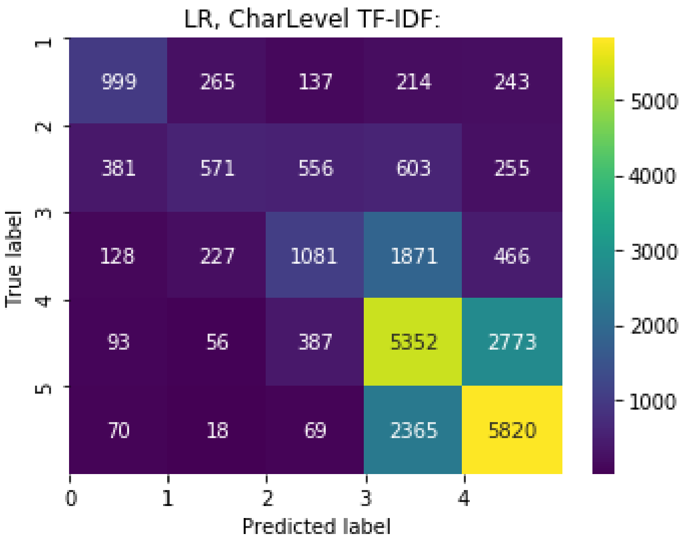



```
Accuracy of Liner Regression TFIDF Model is:  56.50%

Confusion matrix for LR, N-Gram Vectors:  is:
```

```
[[ 727  219  155  318  439]
 [ 299  528  485  660  394]
 [  98  198 1034 1761  682]
 [  77   69  466 5097 2952]
 [  79   36  117 2574 5536]]

Classification report for LR, N-Gram Vectors:  is:

              precision    recall  f1-score   support

           1       0.57      0.39      0.46      1858
           2       0.50      0.22      0.31      2366
           3       0.46      0.27      0.34      3773
           4       0.49      0.59      0.53      8661
           5       0.55      0.66      0.60      8342

    accuracy                           0.52     25000
   macro avg       0.51      0.43      0.45     25000
weighted avg       0.51      0.52      0.50     25000
```




```
Accuracy of Liner Regression N-Gram Level Model is:  51.69%

Confusion matrix for LR, CharLevel TF-IDF:  is:

[[ 999  265  137  214  243]
 [ 381  571  556  603  255]
 [ 128  227 1081 1871  466]
 [  93   56  387 5352 2773]
 [  70   18   69 2365 5820]]

Classification report for LR, CharLevel TF-IDF:  is:

              precision    recall  f1-score   support

           1       0.60      0.54      0.57      1858
           2       0.50      0.24      0.33      2366
           3       0.48      0.29      0.36      3773
           4       0.51      0.62      0.56      8661
           5       0.61      0.70      0.65      8342

    accuracy                           0.55     25000
   macro avg       0.54      0.48      0.49     25000
weighted avg       0.55      0.55      0.54     25000
```

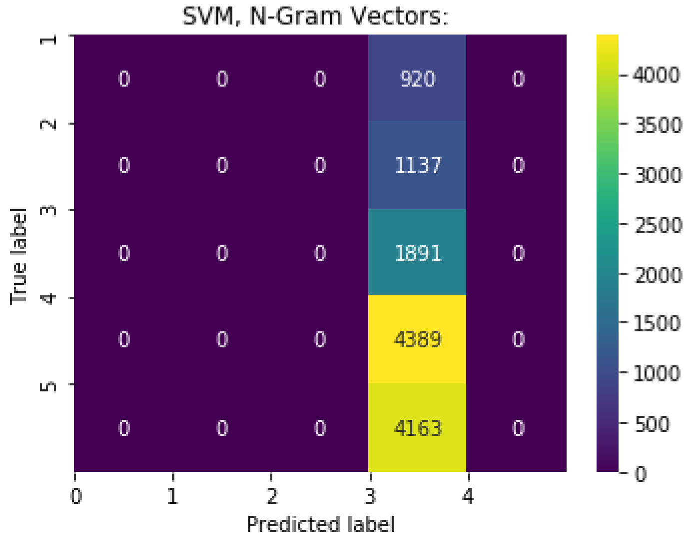



```
Accuracy of Liner Regression Char Level TFIDF Model is:  55.29%
```

In [18]:

```python
# SVM on Ngram Level TF IDF Vectors
accuracy_svm_ngtfidf = train_model("SVM, N-Gram Vectors: ",svm.SVC(), xtrain_tfi
print( "Accuracy of SVM, N-Gram Vectors Model is: ", "{:.2%}".format(accuracy_sv
```

```
Confusion matrix for SVM, N-Gram Vectors:  is:

[[    0     0     0   920     0]
 [    0     0     0  1137     0]
 [    0     0     0  1891     0]
 [    0     0     0  4389     0]
 [    0     0     0  4163     0]]

Classification report for SVM, N-Gram Vectors:  is:

              precision    recall  f1-score   support

           1       0.00      0.00      0.00       920
           2       0.00      0.00      0.00      1137
           3       0.00      0.00      0.00      1891
           4       0.35      1.00      0.52      4389
           5       0.00      0.00      0.00      4163

    accuracy                           0.35     12500
   macro avg       0.07      0.20      0.10     12500
weighted avg       0.12      0.35      0.18     12500
```

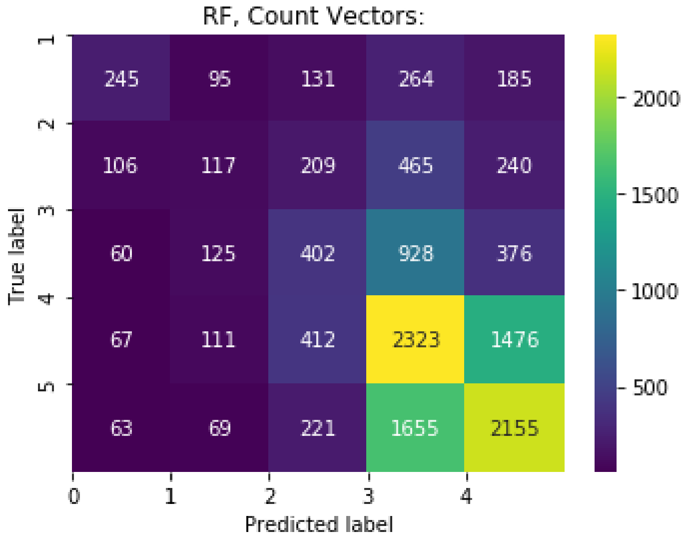



```
Accuracy of SVM, N-Gram Vectors Model is:  35.11%
```

In [19]:

```
# RF on Count Vectors
accuracy_rf_cv = train_model("RF, Count Vectors: ",ensemble.RandomForestClassifi
print( "Accuracy of Random Forest Count Vector Model is: ", "{:.2%}".format(accu
```

```
Confusion matrix for RF, Count Vectors:  is:

[[ 245   95  131  264  185]
 [ 106  117  209  465  240]
 [  60  125  402  928  376]
 [  67  111  412 2323 1476]
 [  63   69  221 1655 2155]]

Classification report for RF, Count Vectors:  is:

              precision    recall  f1-score   support

           1       0.45      0.27      0.34       920
           2       0.23      0.10      0.14      1137
           3       0.29      0.21      0.25      1891
           4       0.41      0.53      0.46      4389
           5       0.49      0.52      0.50      4163

    accuracy                           0.42     12500
   macro avg       0.37      0.33      0.34     12500
weighted avg       0.40      0.42      0.40     12500
```

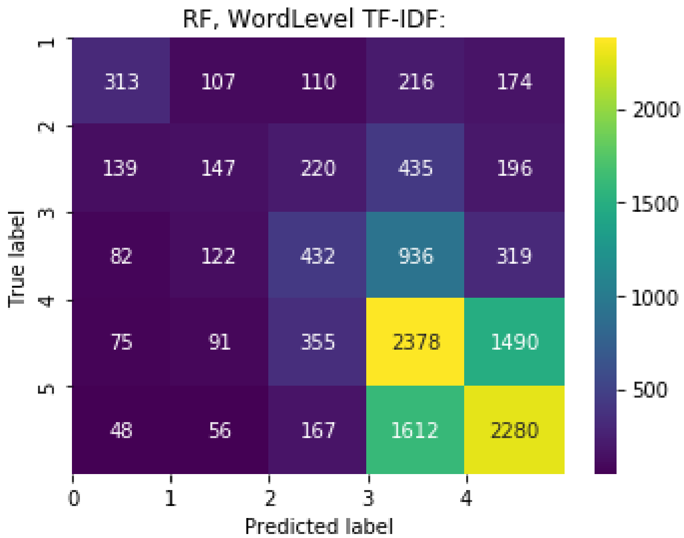



```
Accuracy of Random Forest Count Vector Model is:  41.94%
```

In [20]:

```python
# RF on Word Level TF IDF Vectors
accuracy_rf_tfidf = train_model("RF, WordLevel TF-IDF: ",ensemble.RandomForestCl
print( "Accuracy of Random Forest word level Model is: ", "{:.2%}".format(accura
```

```
Confusion matrix for RF, WordLevel TF-IDF:  is:

[[ 313  107  110  216  174]
 [ 139  147  220  435  196]
 [  82  122  432  936  319]
 [  75   91  355 2378 1490]
 [  48   56  167 1612 2280]]

Classification report for RF, WordLevel TF-IDF:  is:

              precision    recall  f1-score   support

           1       0.48      0.34      0.40       920
           2       0.28      0.13      0.18      1137
           3       0.34      0.23      0.27      1891
           4       0.43      0.54      0.48      4389
           5       0.51      0.55      0.53      4163

    accuracy                           0.44     12500
   macro avg       0.41      0.36      0.37     12500
weighted avg       0.43      0.44      0.43     12500
```

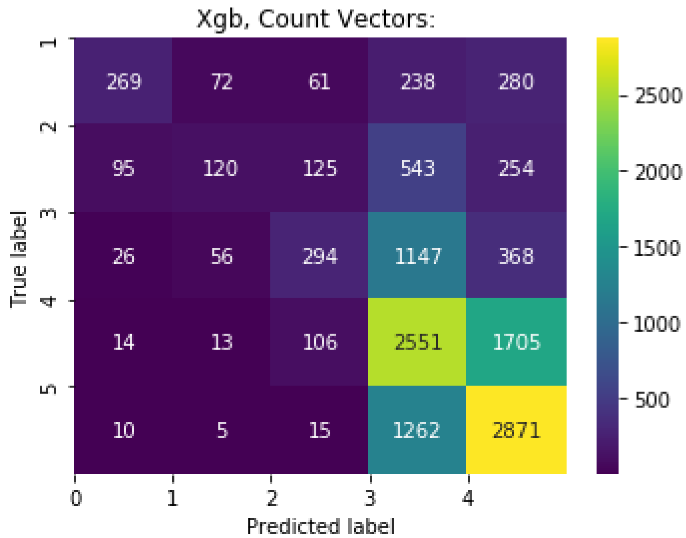



```
Accuracy of Random Forest word level Model is:  44.40%
```

In [21]:

```
# Exetreme Gradient Boosting on Count Vectors
accuracy_xgb_cv = train_model("Xgb, Count Vectors: ",xgboost.XGBClassifier(), xt
print( "Accuracy of Xgradient boost count vector Model is: ", "{:.2%}".format(ac
```

```
Confusion matrix for Xgb, Count Vectors:  is:

[[ 269   72   61  238  280]
 [   95  120  125  543  254]
 [   26   56  294 1147  368]
 [   14   13  106 2551 1705]
 [   10    5   15 1262 2871]]

Classification report for Xgb, Count Vectors:  is:

              precision    recall  f1-score   support

           1       0.65      0.29      0.40       920
           2       0.45      0.11      0.17      1137
           3       0.49      0.16      0.24      1891
           4       0.44      0.58      0.50      4389
           5       0.52      0.69      0.60      4163

    accuracy                           0.49     12500
   macro avg       0.51      0.36      0.38     12500
weighted avg       0.49      0.49      0.46     12500
```

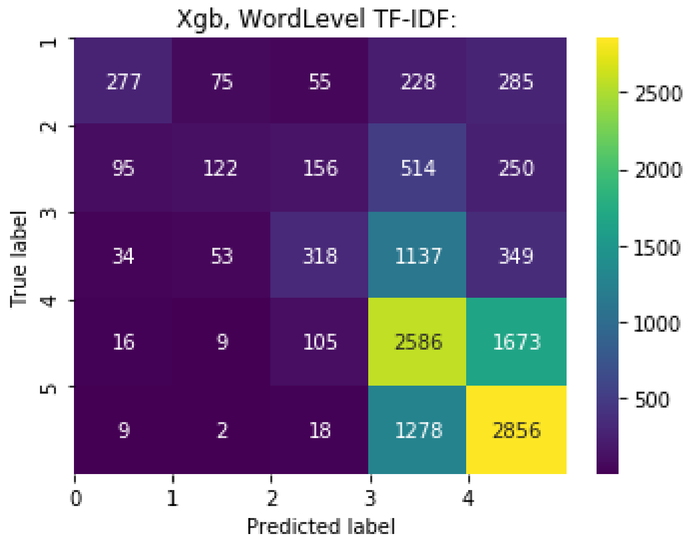



```
Accuracy of Xgradient boost count vector Model is:  48.84%
```

In [22]:

```
# Extereme Gradient Boosting on Word Level TF IDF Vectors
accuracy_xgb_tfidf = train_model("Xgb, WordLevel TF-IDF: ",xgboost.XGBClassifier
print( "Accuracy of Xgradient boost TFIDF vector Model is: ", "{:.2%}".format(ac
```

```
Confusion matrix for Xgb, WordLevel TF-IDF:  is:

[[ 277   75   55  228  285]
 [   95  122  156  514  250]
 [   34   53  318 1137  349]
 [   16    9  105 2586 1673]
 [    9    2   18 1278 2856]]

Classification report for Xgb, WordLevel TF-IDF:  is:

              precision    recall  f1-score   support

           1       0.64      0.30      0.41       920
           2       0.47      0.11      0.17      1137
           3       0.49      0.17      0.25      1891
           4       0.45      0.59      0.51      4389
           5       0.53      0.69      0.60      4163

    accuracy                           0.49     12500
   macro avg       0.52      0.37      0.39     12500
weighted avg       0.50      0.49      0.46     12500
```

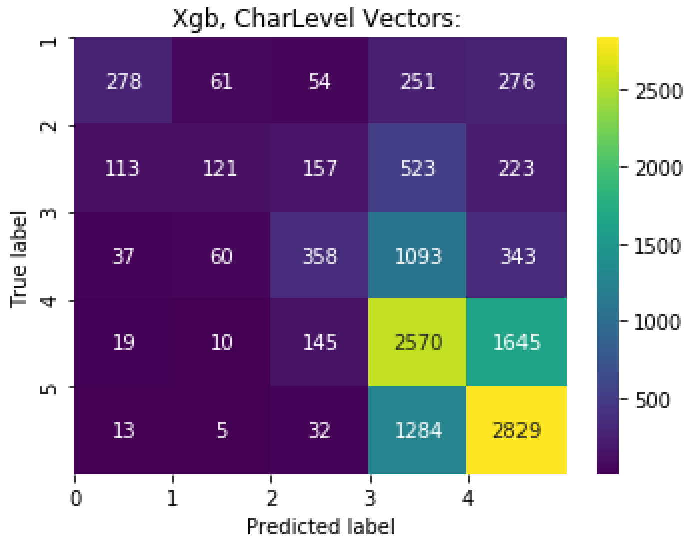



```
Accuracy of Xgradient boost TFIDF vector Model is:  49.27%
```

In [23]:

```
# Extereme Gradient Boosting on Character Level TF IDF Vectors
accuracy_xgb_cltfidf = train_model("Xgb, CharLevel Vectors: ",xgboost.XGBClassif
print( "Accuracy of Xgradient boost char level vector Model is:", "{:.2%}".forma
```

```
Confusion matrix for Xgb, CharLevel Vectors:  is:

[[ 278   61   54  251  276]
 [ 113  121  157  523  223]
 [  37   60  358 1093  343]
 [  19   10  145 2570 1645]
 [  13    5   32 1284 2829]]

Classification report for Xgb, CharLevel Vectors:  is:

              precision    recall  f1-score   support

           1       0.60      0.30      0.40       920
           2       0.47      0.11      0.17      1137
           3       0.48      0.19      0.27      1891
           4       0.45      0.59      0.51      4389
           5       0.53      0.68      0.60      4163

    accuracy                           0.49     12500
   macro avg       0.51      0.37      0.39     12500
weighted avg       0.49      0.49      0.46     12500
```



Accuracy of Xgradient boost char level vector Model is: 49.25%

In [37]:

```
train_x, valid_x, train_y, valid_y = model_selection.train_test_split(df_merge3[


# label encode the target variable
encoder = preprocessing.LabelEncoder()
train_y = encoder.fit_transform(train_y)
valid_y = encoder.fit_transform(valid_y)



# ngram level tf-idf
tfidf_vect_ngram = TfidfVectorizer(analyzer='word', token_pattern=r'\w{1,}', ngr
tfidf_vect_ngram.fit(df_merge3['txt_stemmed_sentence'])
xtrain_tfidf_ngram =  tfidf_vect_ngram.transform(train_x).toarray()
xvalid_tfidf_ngram =  tfidf_vect_ngram.transform(valid_x).toarray()


from keras.models import Sequential
from keras import layers

input_dim = xtrain_tfidf_ngram.shape[1]  # Number of features

model = Sequential()
model.add(layers.Dense(10, input_dim=input_dim, activation='relu'))
model.add(layers.Dense(5, activation='sigmoid'))
model.compile(loss='sparse_categorical_crossentropy',  optimizer='adam', metrics
model.summary()



history = model.fit(xtrain_tfidf_ngram, train_y, epochs=100, verbose=False, vali

loss, accuracy = model.evaluate(xtrain_tfidf_ngram, train_y, verbose=False)
print("Training Accuracy: {:.4f}".format(accuracy))
loss, accuracy = model.evaluate(xvalid_tfidf_ngram, valid_y, verbose=False)
print("Testing Accuracy:  {:.4f}".format(accuracy))
```

Model: "sequential_1"

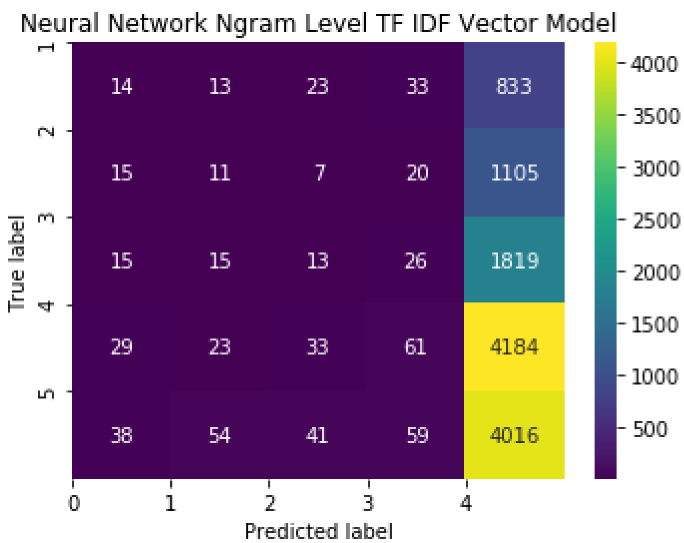
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_26 (Dense)             (None, 10)                50010     
_________________________________________________________________
dense_27 (Dense)             (None, 5)                 55        
=================================================================
Total params: 50,065
Trainable params: 50,065
Non-trainable params: 0
_________________________________________________________________
Training Accuracy: 0.8440
Testing Accuracy:  0.4385
```

In [35]:

```
# split the dataset into training and validation datasets
train_x, valid_x, train_y, valid_y = model_selection.train_test_split(df_merge3[


from sklearn.feature_extraction.text import CountVectorizer

vectorizer = CountVectorizer()
vectorizer.fit(df_merge3['txt_stemmed_sentence'])

X_train = vectorizer.transform(train_x)
X_test  = vectorizer.transform(valid_x)




# label encode the target variable
encoder = preprocessing.LabelEncoder()
train_y = encoder.fit_transform(train_y)
valid_y = encoder.fit_transform(valid_y)

print(X_train.shape)
print(X_test.shape)
print(train_y.shape)
print(valid_y.shape)




def create_model_architecture(input_size):
    # create input layer
    input_layer = layers.Input((input_size, ), sparse=True)

    # create hidden layer
    hidden_layer = layers.Dense(100, activation="relu")(input_layer)

    # create output layer
    output_layer = layers.Dense(5, activation="softmax")(hidden_layer)

    classifier = models.Model(inputs = input_layer, outputs = output_layer)
    classifier.compile(optimizer=optimizers.Adam(), loss='binary_crossentropy')
    return classifier

classifier = create_model_architecture(X_train.shape[1])
```

```
accuracy_neural_network = train_model("Neural Network Ngram Level TF IDF Vector
print( "Accuracy of Neural Network Ngram Level TF IDF Vector Model is:", "{:.2%}
```

```
(37500, 69182)
(12500, 69182)
(37500,)
(12500,)
1172/1172 [==============================] - 27s 23ms/step - loss: 4.0633

Confusion matrix for Neural Network Ngram Level TF IDF Vector Model is:

[[  14   13   23   33  833]
 [  15   11    7   20 1105]
 [  15   15   13   26 1819]
 [  29   23   33   61 4184]
 [  38   54   41   59 4016]]

Classification report for Neural Network Ngram Level TF IDF Vector Model is:

              precision    recall  f1-score   support

           1       0.13      0.02      0.03       916
           2       0.09      0.01      0.02      1158
           3       0.11      0.01      0.01      1888
           4       0.31      0.01      0.03      4330
           5       0.34      0.95      0.50      4208

    accuracy                           0.33     12500
   macro avg       0.19      0.20      0.12     12500
weighted avg       0.25      0.33      0.18     12500
```




```
Accuracy of Neural Network Ngram Level TF IDF Vector Model is: 32.92%
```

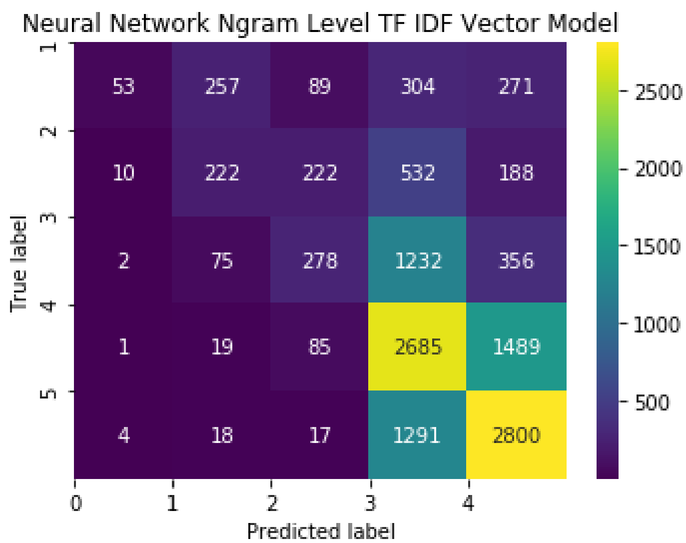
In [39]:

```
train_x, valid_x, train_y, valid_y = model_selection.train_test_split(df_merge3[


# label encode the target variable
encoder = preprocessing.LabelEncoder()
train_y = encoder.fit_transform(train_y)
valid_y = encoder.fit_transform(valid_y)



# ngram level tf-idf
```

```
tfidf_vect_ngram = TfidfVectorizer(analyzer='word', token_pattern=r'\w{1,}', ngr
tfidf_vect_ngram.fit(df_merge3['txt_stemmed_sentence'])
xtrain_tfidf_ngram =  tfidf_vect_ngram.transform(train_x).toarray()
xvalid_tfidf_ngram =  tfidf_vect_ngram.transform(valid_x).toarray()


from keras.models import Sequential
from keras import layers



print(X_train.shape)
print(X_test.shape)
print(train_y.shape)
print(valid_y.shape)



def create_model_architecture(input_size):
    # create input layer
    input_layer = layers.Input((input_size, ), sparse=True)

    # create hidden layer
    hidden_layer = layers.Dense(10, activation="relu")(input_layer)

    # create output layer
    output_layer = layers.Dense(5, activation="softmax")(hidden_layer)

    classifier = models.Model(inputs = input_layer, outputs = output_layer)
    classifier.compile(optimizer=optimizers.Adam(), loss='sparse_categorical_cro
    return classifier

classifier = create_model_architecture(xtrain_tfidf_ngram.shape[1])
accuracy_neural_network_ngram = train_model("Neural Network Ngram Level TF IDF V
print( "Accuracy of Neural Network Ngram Level TF IDF Vector Model is:", "{:.2%}
```

```
(37500, 69182)
(12500, 69182)
(37500,)
(12500,)
1172/1172 [==============================] - 1s 712us/step - loss: 1.3172

Confusion matrix for Neural Network Ngram Level TF IDF Vector Model is:

[[  53  257   89  304  271]
 [  10  222  222  532  188]
 [   2   75  278 1232  356]
 [   1   19   85 2685 1489]
 [   4   18   17 1291 2800]]

Classification report for Neural Network Ngram Level TF IDF Vector Model is:

              precision    recall  f1-score   support

           1       0.76      0.05      0.10       974
           2       0.38      0.19      0.25      1174
           3       0.40      0.14      0.21      1943
           4       0.44      0.63      0.52      4279
           5       0.55      0.68      0.61      4130
```

```
    accuracy                           0.48     12500
   macro avg       0.51      0.34      0.34     12500
weighted avg       0.49      0.48      0.44     12500
```




```
Accuracy of Neural Network Ngram Level TF IDF Vector Model is: 48.30%
```

In [44]:

```
#################### Word2vec word embedding using xgboost classifier ##########

test_size = 0.3
random_state = 1234

X_train, X_test, y_train, y_test = model_selection.train_test_split(df_merge3['t
import numpy as np
from sklearn.base import BaseEstimator, TransformerMixin
from gensim.models import Word2Vec


class GensimWord2VecVectorizer(BaseEstimator, TransformerMixin):
    """
    Word vectors are averaged across to create the document-level vectors/featur
    gensim's own gensim.sklearn_api.W2VTransformer doesn't support out of vocabu
    hence we roll out our own.
    All the parameters are gensim.models.Word2Vec's parameters.
    https://radimrehurek.com/gensim/models/word2vec.html#gensim.models.word2vec.
    """

    def __init__(self, size=100, alpha=0.025, window=5, min_count=5, max_vocab_s
                 sample=0.001, seed=1, workers=3, min_alpha=0.0001, sg=0, hs=0,
                 ns_exponent=0.75, cbow_mean=1, hashfxn=hash, iter=5, null_word=
                 trim_rule=None, sorted_vocab=1, batch_words=10000, compute_loss
                 callbacks=(), max_final_vocab=None):
        self.size = size
        self.alpha = alpha
        self.window = window
        self.min_count = min_count
        self.max_vocab_size = max_vocab_size
        self.sample = sample
        self.seed = seed
        self.workers = workers
        self.min_alpha = min_alpha
        self.sg = sg
```

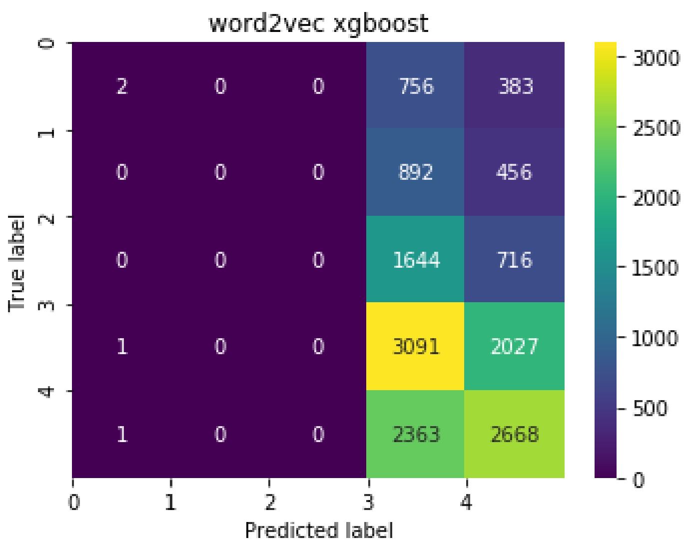
```
        self.hs = hs
        self.negative = negative
        self.ns_exponent = ns_exponent
        self.cbow_mean = cbow_mean
        self.hashfxn = hashfxn
        self.iter = iter
        self.null_word = null_word
        self.trim_rule = trim_rule
        self.sorted_vocab = sorted_vocab
        self.batch_words = batch_words
        self.compute_loss = compute_loss
        self.callbacks = callbacks
        self.max_final_vocab = max_final_vocab

    def fit(self, X, y=None):
        self.model_ = Word2Vec(
            sentences=X, corpus_file=None,
            size=self.size, alpha=self.alpha, window=self.window, min_count=self
            max_vocab_size=self.max_vocab_size, sample=self.sample, seed=self.se
            workers=self.workers, min_alpha=self.min_alpha, sg=self.sg, hs=self.
            negative=self.negative, ns_exponent=self.ns_exponent, cbow_mean=self
            hashfxn=self.hashfxn, iter=self.iter, null_word=self.null_word,
            trim_rule=self.trim_rule, sorted_vocab=self.sorted_vocab, batch_word
            compute_loss=self.compute_loss, callbacks=self.callbacks,
            max_final_vocab=self.max_final_vocab)
        return self

    def transform(self, X):
        X_embeddings = np.array([self._get_embedding(words) for words in X])
        return X_embeddings

    def _get_embedding(self, words):
        valid_words = [word for word in words if word in self.model_.wv.vocab]
        if valid_words:
            embedding = np.zeros((len(valid_words), self.size), dtype=np.float32
            for idx, word in enumerate(valid_words):
                embedding[idx] = self.model_.wv[word]

            return np.mean(embedding, axis=0)
        else:
            return np.zeros(self.size)
```

```
gensim_word2vec_tr = GensimWord2VecVectorizer(size=50, min_count=3, sg=1, alpha=
xgb = xgboost.XGBClassifier(learning_rate=0.01, n_estimators=100, n_jobs=-1)
w2v_xgb = Pipeline([('w2v', gensim_word2vec_tr),  ('xgb', xgb)])
#w2v_xgb

w2v_xgb.fit(X_train, y_train)
```

```
y_train_pred = w2v_xgb.predict(X_train)
print('\nConfusion Matrix for word2vec xgboost model:\n')
```

```
y_test_pred = w2v_xgb.predict(X_test)
print(confusion_matrix(y_test, y_test_pred))
accuracy_w2v_xgb=metrics.accuracy_score(y_test, y_test_pred)
print( "Accuracy of XGBoost word2vec model classifier is:", "{:.2%}".format(metr
cf_matrix=confusion_matrix(y_test, y_test_pred)
index = ['0','1','2','3','4']
columns = ['0','1','2','3','4']
cm_df = pd.DataFrame(cf_matrix,columns,index)
plt.figure(figsize=(5.5,4))
sns.heatmap(cm_df, annot=True,cmap="viridis" ,fmt='g')
plt.xticks([0,1,2,3,4])
plt.yticks([0,1,2,3,4])
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.title("word2vec xgboost")
plt.show()

print('\n Classification report for word2vec xgboost model:\n')
print(classification_report(y_test, y_test_pred,target_names=['1','2','3','4','5
```

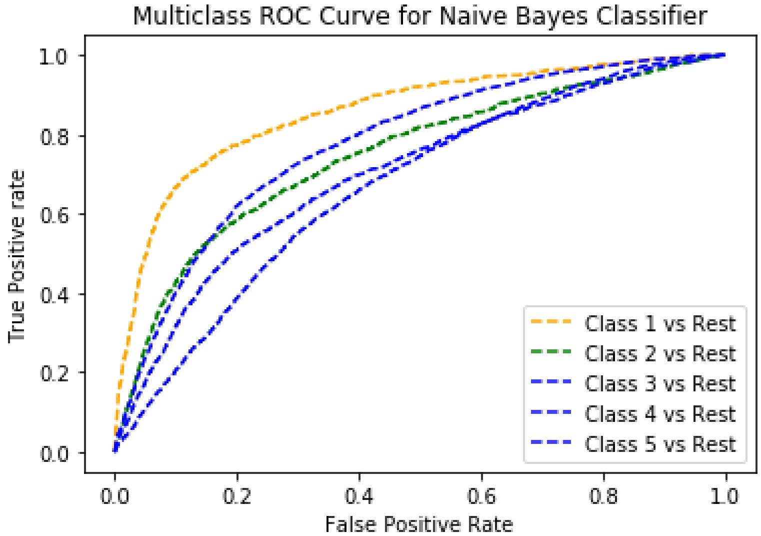
```
Confusion Matrix for word2vec xgboost model:

[[    2     0     0  756  383]
 [    0     0     0  892  456]
 [    0     0     0 1644  716]
 [    1     0     0 3091 2027]
 [    1     0     0 2363 2668]]
Accuracy of XGBoost word2vec model classifier is: 38.41%
```



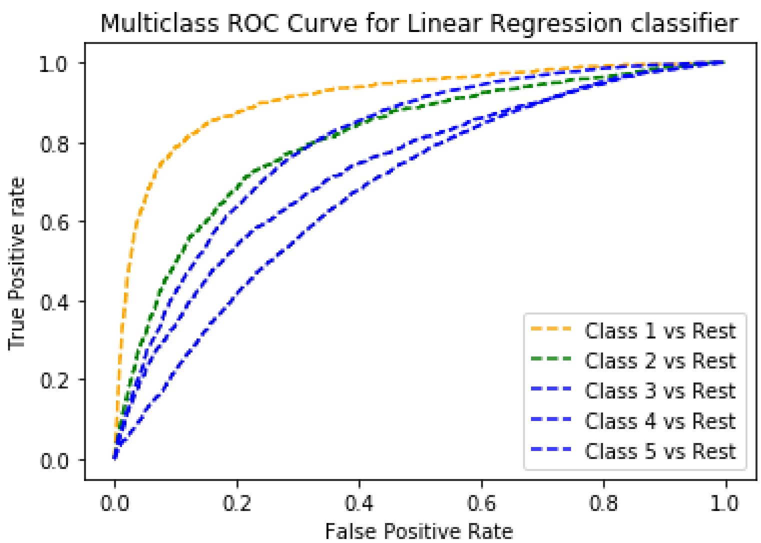

```
 Classification report for word2vec xgboost model:

              precision    recall  f1-score   support

           1       0.50      0.00      0.00      1141
           2       0.00      0.00      0.00      1348
           3       0.00      0.00      0.00      2360
           4       0.35      0.60      0.45      5119
           5       0.43      0.53      0.47      5032

    accuracy                           0.38     15000
   macro avg       0.26      0.23      0.18     15000
weighted avg       0.30      0.38      0.31     15000
```

In [27]:
```
# Function to Plot ROC curve for multi-class classification using different mode


def plot_roc(model_name,clf,xtrain_count,y_train,xvalid_count,y_test):
            #clf = MultinomialNB(alpha=.01)
    clf.fit(xtrain_count, y_train)
    pred = clf.predict(xvalid_count)
    pred_prob = clf.predict_proba(xvalid_count)
    print('\n',model_name,'\n')
            # roc curve for classes
    fpr = {}
    tpr = {}
    thresh ={}

    n_class = 5
    for i in range(n_class):
        fpr[i], tpr[i], thresh[i] = roc_curve(y_test, pred_prob[:,i], pos_label=
        print('AUC for Class {}: {}'.format(i+1, auc(fpr[i], tpr[i])))
              # plotting
    plt.plot(fpr[0], tpr[0], linestyle='--',color='orange', label='Class 1 vs Re
    plt.plot(fpr[1], tpr[1], linestyle='--',color='green', label='Class 2 vs Res
    plt.plot(fpr[2], tpr[2], linestyle='--',color='blue', label='Class 3 vs Rest
    plt.plot(fpr[3], tpr[3], linestyle='--',color='blue', label='Class 4 vs Rest
    plt.plot(fpr[4], tpr[4], linestyle='--',color='blue', label='Class 5 vs Rest
    plt.title(model_name)
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive rate')
    plt.legend(loc='best')
    plt.show()



#################  Plot ROC Curve for  4 different models #####################
plot_roc("Multiclass ROC Curve for Naive Bayes Classifier",MultinomialNB(alpha=.
plot_roc("Multiclass ROC Curve for Linear Regression classifier",OneVsRestClassi
#plot_roc("Multiclass ROC curve for SVM classifier",OneVsRestClassifier(svm.SVC(
plot_roc("Multiclass ROC curve for Random Foreset Classifier ",RandomForestClass
```

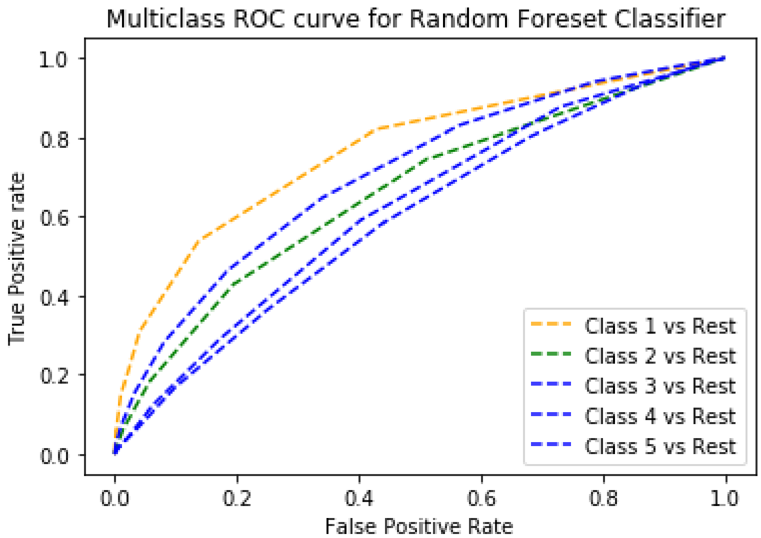
```
 Multiclass ROC Curve for Naive Bayes Classifier

AUC for Class 1: 0.857274061205751
AUC for Class 2: 0.7469341678064164
AUC for Class 3: 0.7025143189626548
AUC for Class 4: 0.6697238429213672
AUC for Class 5: 0.777215664481072
```




```
Multiclass ROC Curve for Linear Regression classifier

AUC for Class 1: 0.9115248794062333
AUC for Class 2: 0.808149981612878
AUC for Class 3: 0.7325261115582609
AUC for Class 4: 0.6844827056833233
AUC for Class 5: 0.8036822386692285
```




```
Multiclass ROC curve for Random Foreset Classifier

AUC for Class 1: 0.7665607144464763
AUC for Class 2: 0.659734461937398
AUC for Class 3: 0.6210340460235904
AUC for Class 4: 0.5956354856607776
AUC for Class 5: 0.7077988247761994
```


Multiclass ROC curve for Random Foreset Classifier
True Positive rate
False Positive Rate
Class 1 vs Rest
Class 2 vs Rest
Class 3 vs Rest
Class 4 vs Rest
Class 5 vs Rest
0.0
0.2
0.4
0.6
0.8
1.0