NLP Project - Food Reviews

The aim of this project is to create an NLP model with data based on Food Reviews.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud

from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from nltk.tokenize import word_tokenize

from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, GradientBoostingClassif
from sklearn.preprocessing import LabelEncoder

from xgboost import XGBClassifier

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, SimpleRNN, GRU, LSTM, Embedding
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing import sequence

from textblob import TextBlob

from string import punctuation

import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
df = pd.read_csv('food_review.csv')
df.shape
```

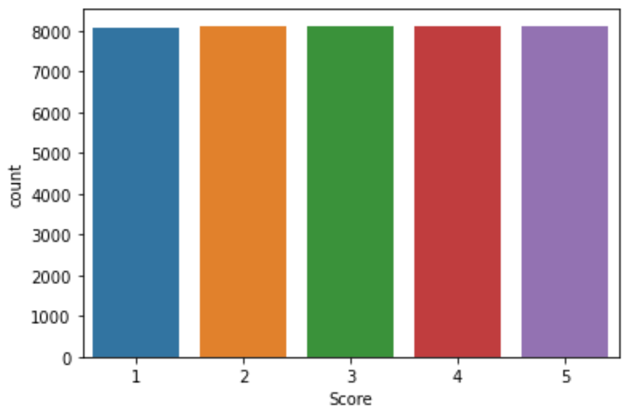
Out[2]: (40500, 3)

In [3]:
```
df.head()
```

Out[3]:

	Unnamed: 0	Text	Score
0	0	I bought these from a large chain pet store. a...	1
1	1	This soup is incredibly good! But honestly, I...	5
2	2	Our family loves these tasty and healthy sesam...	5
3	3	The local auto shop offers this free to it cus...	4
4	4	I brought 2 bottles. One I carry in my pocket...	5

In [4]:
```
plt.figure()
sns.countplot(df['Score'])
plt.show()
```



In [5]:
```
(df['Score'].value_counts()*100)/len(df)
```

Out[5]:
```
4    20.041975
5    20.014815
3    20.007407
2    19.987654
1    19.948148
Name: Score, dtype: float64
```

The data we have is evenly distributed.

In [6]:
```
df.drop('Unnamed: 0', axis=1, inplace=True)
```

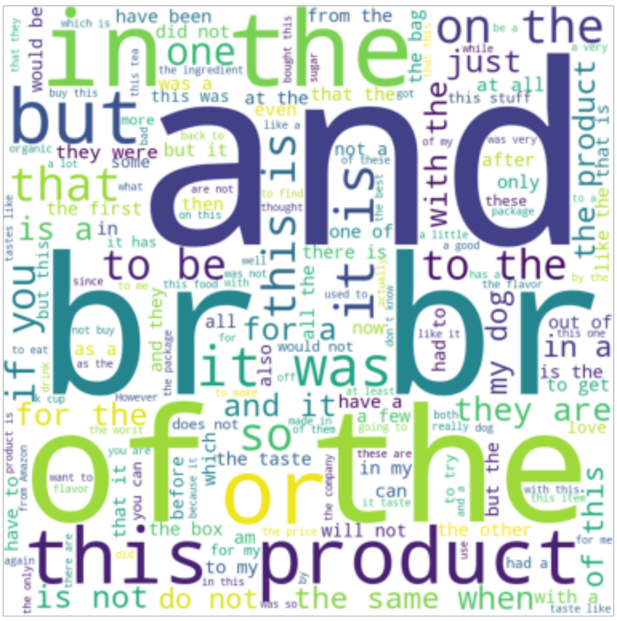
Function to generate the WordCloud

In [7]:
```
def word_cloud(n):
    wc = WordCloud(width=800, height=800, stopwords="english", min_font_size=10, background_colo

    wc.generate("".join(df[df["Score"]==n]["Text"]))

    plt.figure(figsize=(7,7))
    plt.imshow(wc)
    plt.axis("off")
    plt.show()
```

In [8]:
```
word_cloud(1)
```



Now that we can generate a wordcloud, we will clean the text uder df['Text'], and also remove the word 'br' from it.

Function to clean tokens from 'verified_reviews'

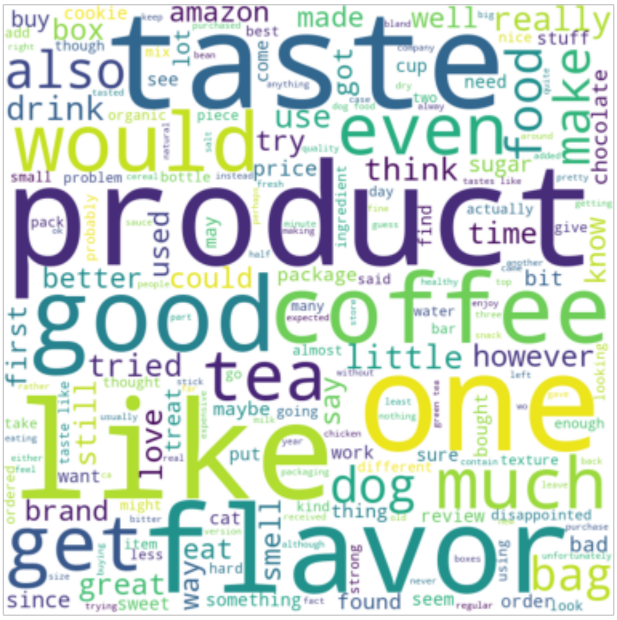
In [9]:
```
def clean_text(text):
    tokens = word_tokenize(WordNetLemmatizer().lemmatize(text.lower()))

    clean_tokens = [each for each in tokens if all([each not in bad_tokens, each.isalpha()])]
    return " ".join(clean_tokens)
```

In [10]:
```
bad_tokens = list(punctuation) + stopwords.words("english") + ['br']
df["Text"] = df["Text"].apply(clean_text)
```

In [11]:
```
word_cloud(1)
```

In [12]:
```
word_cloud(2)
```



In [13]:
```
word_cloud(3)
```

In [14]: `word_cloud(4)`

In [15]: `word_cloud(5)`


```
In [16]: df.head()
```

Out[16]:

	Text	Score
0	bought large chain pet store reading reviews c...	1
1	soup incredibly good honestly looking better d...	5
2	family loves tasty healthy sesame honey almond...	5
3	local auto shop offers free customers tried tw...	4
4	brought bottles one carry pocket home fell lov...	5

Function to clean the text

def clean_text(text): tokens = word_tokenize(WordNetLemmatizer().lemmatize(text.lower())) clean_tokens = [each for each in tokens if all([each not in bad_tokens, each.isalpha()])] return " ".join(clean_tokens)bad_tokens = list(punctuation) + stopwords.words('english')df["Text"] = df["Text"].apply(clean_text)

```
In [17]: le = LabelEncoder()

         df["Score"] = le.fit_transform(df["Score"])
```

```
In [18]: df.head()
```

Out[18]:

	Text	Score
0	bought large chain pet store reading reviews c...	0
1	soup incredibly good honestly looking better d...	4
2	family loves tasty healthy sesame honey almond...	4
3	local auto shop offers free customers tried tw...	3
4	brought bottles one carry pocket home fell lov...	4

```
In [19]: X = np.asarray(df['Text'])
         y = np.asarray(df['Score'])
```

```
In [20]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
```

Function to perform vectorization

```
In [21]: def vectorize(vect):
             X_train_cv = vect.fit_transform(X_train)
             X_test_cv = vect.transform(X_test)
             return X_train_cv, X_test_cv
```

Funtion to create an ML model

In [22]:
```
def ml_model(model, X_train_mod, X_test_mod):
    model.fit(X_train_mod, y_train)
    y_pred = model.predict(X_test_mod)
    print(classification_report(y_test, y_pred))
    return model
```

In [23]:
```
X_train_cv, X_test_cv = vectorize(CountVectorizer())
```

In [24]:
```
dtc_cv = ml_model(DecisionTreeClassifier(), X_train_cv, X_test_cv)
```

```
              precision    recall  f1-score   support

           0       0.52      0.51      0.51      1613
           1       0.39      0.41      0.40      1575
           2       0.40      0.38      0.39      1683
           3       0.38      0.38      0.38      1609
           4       0.48      0.49      0.49      1620

    accuracy                           0.43      8100
   macro avg       0.43      0.43      0.43      8100
weighted avg       0.43      0.43      0.43      8100
```

In [25]:
```
rfc_cv = ml_model(RandomForestClassifier(), X_train_cv, X_test_cv)
```

```
              precision    recall  f1-score   support

           0       0.58      0.71      0.64      1613
           1       0.53      0.42      0.47      1575
           2       0.52      0.43      0.47      1683
           3       0.50      0.44      0.47      1609
           4       0.57      0.72      0.63      1620

    accuracy                           0.54      8100
   macro avg       0.54      0.54      0.54      8100
weighted avg       0.54      0.54      0.54      8100
```

In [26]:
```
logreg_cv = ml_model(LogisticRegression(), X_train_cv, X_test_cv)
```

```
              precision    recall  f1-score   support

           0       0.62      0.61      0.61      1613
           1       0.47      0.45      0.46      1575
           2       0.47      0.44      0.45      1683
           3       0.46      0.48      0.47      1609
           4       0.61      0.65      0.63      1620

    accuracy                           0.53      8100
   macro avg       0.53      0.53      0.53      8100
weighted avg       0.53      0.53      0.53      8100
```

In [27]:
```
ada_cv = ml_model(AdaBoostClassifier(n_estimators=100), X_train_cv, X_test_cv)
```

```
              precision    recall  f1-score   support

           0       0.48      0.62      0.54      1613
           1       0.35      0.27      0.31      1575
           2       0.42      0.28      0.34      1683
           3       0.39      0.42      0.40      1609
           4       0.51      0.60      0.55      1620

    accuracy                           0.44      8100
   macro avg       0.43      0.44      0.43      8100
weighted avg       0.43      0.44      0.43      8100
```

In [28]:
```
grad_cv = ml_model(GradientBoostingClassifier(n_estimators=100), X_train_cv, X_test_cv)
```

```
              precision    recall  f1-score   support

           0       0.53      0.60      0.56      1613
           1       0.39      0.36      0.38      1575
           2       0.44      0.32      0.37      1683
           3       0.41      0.40      0.41      1609
           4       0.50      0.63      0.55      1620
```

```
    accuracy                           0.46      8100
   macro avg       0.45      0.46      0.45      8100
weighted avg       0.45      0.46      0.45      8100
```

In [29]:
```
xgb_cv = ml_model(XGBClassifier(n_estimators=200, reg_alpha=1), X_train_cv, X_test_cv)
```

```
[21:21:28] WARNING: ../src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluation met
ric used with the objective 'multi:softprob' was changed from 'merror' to 'mlogloss'. Explicitly
set eval_metric if you'd like to restore the old behavior.
              precision    recall  f1-score   support

           0       0.61      0.67      0.64      1613
           1       0.47      0.44      0.46      1575
           2       0.48      0.40      0.44      1683
           3       0.47      0.49      0.48      1609
           4       0.60      0.67      0.64      1620

    accuracy                           0.53      8100
   macro avg       0.53      0.53      0.53      8100
weighted avg       0.53      0.53      0.53      8100
```

In [30]:
```
X_train_tv, X_test_tv = vectorize(TfidfVectorizer())
```

In [31]:
```
dtc_tv = ml_model(DecisionTreeClassifier(), X_train_tv, X_test_tv)
```

```
              precision    recall  f1-score   support

           0       0.49      0.51      0.50      1613
           1       0.39      0.41      0.40      1575
           2       0.39      0.36      0.38      1683
           3       0.38      0.38      0.38      1609
           4       0.44      0.44      0.44      1620

    accuracy                           0.42      8100
   macro avg       0.42      0.42      0.42      8100
weighted avg       0.42      0.42      0.42      8100
```

In [32]:
```
tfc_tv = ml_model(RandomForestClassifier(), X_train_tv, X_test_tv)
```

```
              precision    recall  f1-score   support

           0       0.58      0.73      0.64      1613
           1       0.52      0.41      0.46      1575
           2       0.51      0.42      0.46      1683
           3       0.51      0.42      0.46      1609
           4       0.56      0.72      0.63      1620

    accuracy                           0.54      8100
   macro avg       0.53      0.54      0.53      8100
weighted avg       0.53      0.54      0.53      8100
```

In [33]:
```
logreg_tv = ml_model(LogisticRegression(), X_train_tv, X_test_tv)
```

```
              precision    recall  f1-score   support

           0       0.61      0.67      0.64      1613
           1       0.46      0.43      0.45      1575
           2       0.48      0.41      0.44      1683
           3       0.49      0.49      0.49      1609
           4       0.64      0.69      0.66      1620

    accuracy                           0.54      8100
   macro avg       0.53      0.54      0.54      8100
weighted avg       0.53      0.54      0.54      8100
```

In [34]:
```
ada_tv = ml_model(AdaBoostClassifier(n_estimators=100), X_train_tv, X_test_tv)
```

```
              precision    recall  f1-score   support

           0       0.48      0.61      0.54      1613
           1       0.35      0.26      0.29      1575
           2       0.39      0.28      0.32      1683
           3       0.38      0.41      0.40      1609
```

```
           4       0.50      0.61      0.55      1620

    accuracy                           0.43      8100
   macro avg       0.42      0.43      0.42      8100
weighted avg       0.42      0.43      0.42      8100
```

In [35]:
```python
grad_tv = ml_model(GradientBoostingClassifier(n_estimators=100), X_train_tv, X_test_tv)
```

```
              precision    recall  f1-score   support

           0       0.54      0.59      0.57      1613
           1       0.39      0.38      0.38      1575
           2       0.44      0.33      0.38      1683
           3       0.42      0.41      0.41      1609
           4       0.52      0.62      0.56      1620

    accuracy                           0.47      8100
   macro avg       0.46      0.47      0.46      8100
weighted avg       0.46      0.47      0.46      8100
```

In [36]:
```python
xgb_tv = ml_model(XGBClassifier(n_estimators=200, reg_alpha=1), X_train_tv, X_test_tv)
```

```
[21:26:33] WARNING: ../src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluation met
ric used with the objective 'multi:softprob' was changed from 'merror' to 'mlogloss'. Explicitly
set eval_metric if you'd like to restore the old behavior.
              precision    recall  f1-score   support

           0       0.59      0.64      0.62      1613
           1       0.45      0.44      0.45      1575
           2       0.47      0.40      0.44      1683
           3       0.48      0.49      0.48      1609
           4       0.60      0.65      0.62      1620

    accuracy                           0.52      8100
   macro avg       0.52      0.52      0.52      8100
weighted avg       0.52      0.52      0.52      8100
```

From the above models, the best predictions were achieved through RandomForest, Logistic, and XGB. This is for both Vectorizers.

Overall, we would select the RandomForest model.

Creating a new column that will have the count of the number of tokens for each document

In [37]:
```python
sent_len = []

for each in df["Text"]:
    sent_len.append(len(word_tokenize(each)))

df["sent_len"] = sent_len
```

In [38]:
```python
df.head()
```

Out[38]:

	Text	Score	sent_len
0	bought large chain pet store reading reviews c...	0	20
1	soup incredibly good honestly looking better d...	4	28
2	family loves tasty healthy sesame honey almond...	4	72
3	local auto shop offers free customers tried tw...	3	19
4	brought bottles one carry pocket home fell lov...	4	19

In [39]:
```python
max(sent_len)
```

Out[39]: 897

In [40]:
```python
np.quantile(sent_len, 0.95)
```

Out[40]: 110.0

In [41]:
```
np.quantile(sent_len, 0.98)
```

Out[41]:
```
153.0
```

The max number of tokens in a unit is 897. We will ignore 2% of the data. For this, we will set the max length for the model to 153.

In [42]:
```
max_len = 153
```

We will train the data. The unique words from the trained dat will be sequenced (given unique IDs).

In [43]:
```
le = LabelEncoder()

df["Score"] = le.fit_transform(df["Score"])
df.head()
```

Out[43]:

	Text	Score	sent_len
0	bought large chain pet store reading reviews c...	0	20
1	soup incredibly good honestly looking better d...	4	28
2	family loves tasty healthy sesame honey almond...	4	72
3	local auto shop offers free customers tried tw...	3	19
4	brought bottles one carry pocket home fell lov...	4	19

In [44]:
```
X = np.asarray(df["Text"])
y = np.asarray(df["Score"])

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1)
```

In [45]:
```
tok = Tokenizer()
tok.fit_on_texts(X_train)
```

In [46]:
```
# tok.index_word
```

In [47]:
```
len(tok.index_word)
```

Out[47]:
```
29811
```

In [48]:
```
vocab_len = len(tok.index_word)
```

Each unit in the document will be converted to a vector

In [49]:
```
seq_train = tok.texts_to_sequences(X_train)
# seq_train
```

We will now perform PADDING

In [50]:
```
sequence_matrix_train = sequence.pad_sequences(seq_train, maxlen=max_len)
sequence_matrix_train
```

Out[50]:
```
array([[   0,    0,    0, ...,  787,  405, 1366],
       [   0,    0,    0, ..., 1281,  384,  178],
       [   0,    0,    0, ..., 1351,   20,  259],
       ...,
       [   0,    0,    0, ...,   22, 1695, 1008],
       [   0,    0,    0, ...,   78,  826,  616],
       [   0,    0,    0, ...,  330,  463,  173]], dtype=int32)
```

Function to create the model

In [51]:
```python
def food_model(arch, nodes, ep, bs):
    model = Sequential()
    model.add(Embedding(vocab_len+1, 1000, input_length=max_len, mask_zero=True, input_shape=(se

    model.add(arch(nodes[0], activation="tanh"))

    for i in range(len(nodes)):
        model.add(Dense(nodes[i], activation="relu"))
        model.add(Dropout(0.2))

    model.add(Dense(5, activation="softmax"))

    model.summary()

    model.compile(optimizer="adam", loss="sparse_categorical_crossentropy")
    model.fit(sequence_matrix_train, y_train, epochs=ep, batch_size=bs)

    y_pred = model.predict(sequence.pad_sequences(tok.texts_to_sequences(X_test), maxlen=max_len
    y_pred = y_pred.argmax(axis=1)
    print(classification_report(y_test, y_pred))
```

In [52]:
```python
food_model(SimpleRNN, [32,16], 50, 50)
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 153, 1000)         29812000
_________________________________________________________________
simple_rnn (SimpleRNN)       (None, 32)                33056
_________________________________________________________________
dense (Dense)                (None, 32)                1056
_________________________________________________________________
dropout (Dropout)            (None, 32)                0
_________________________________________________________________
dense_1 (Dense)              (None, 16)                528
_________________________________________________________________
dropout_1 (Dropout)          (None, 16)                0
_________________________________________________________________
dense_2 (Dense)              (None, 5)                 85
=================================================================
Total params: 29,846,725
Trainable params: 29,846,725
Non-trainable params: 0
_________________________________________________________________
Epoch 1/50
567/567 [==============================] - 187s 329ms/step - loss: 1.5289
Epoch 2/50
567/567 [==============================] - 191s 336ms/step - loss: 1.1892
Epoch 3/50
567/567 [==============================] - 188s 332ms/step - loss: 0.8898
Epoch 4/50
567/567 [==============================] - 191s 337ms/step - loss: 0.6383
Epoch 5/50
567/567 [==============================] - 192s 339ms/step - loss: 0.4802
Epoch 6/50
567/567 [==============================] - 190s 335ms/step - loss: 0.3605
Epoch 7/50
567/567 [==============================] - 187s 330ms/step - loss: 0.2987
Epoch 8/50
567/567 [==============================] - 188s 331ms/step - loss: 0.2499
Epoch 9/50
567/567 [==============================] - 187s 330ms/step - loss: 0.2118
Epoch 10/50
567/567 [==============================] - 188s 331ms/step - loss: 0.1945
Epoch 11/50
567/567 [==============================] - 188s 332ms/step - loss: 0.1754
Epoch 12/50
567/567 [==============================] - 188s 332ms/step - loss: 0.1547
Epoch 13/50
567/567 [==============================] - 187s 331ms/step - loss: 0.1641
Epoch 14/50
567/567 [==============================] - 188s 331ms/step - loss: 0.1287
Epoch 15/50
567/567 [==============================] - 187s 330ms/step - loss: 0.1187
Epoch 16/50
567/567 [==============================] - 187s 330ms/step - loss: 0.1336
Epoch 17/50
```

```
567/567 [==============================] - 188s 331ms/step - loss: 0.1103
Epoch 18/50
567/567 [==============================] - 187s 331ms/step - loss: 0.0991
Epoch 19/50
567/567 [==============================] - 188s 331ms/step - loss: 0.1172
Epoch 20/50
567/567 [==============================] - 187s 330ms/step - loss: 0.1086
Epoch 21/50
567/567 [==============================] - 184s 325ms/step - loss: 0.1151
Epoch 22/50
567/567 [==============================] - 184s 325ms/step - loss: 0.0881
Epoch 23/50
567/567 [==============================] - 184s 325ms/step - loss: 0.1021
Epoch 24/50
567/567 [==============================] - 185s 325ms/step - loss: 0.1137
Epoch 25/50
567/567 [==============================] - 185s 326ms/step - loss: 0.0830
Epoch 26/50
567/567 [==============================] - 184s 324ms/step - loss: 0.1010
Epoch 27/50
567/567 [==============================] - 183s 324ms/step - loss: 0.0941
Epoch 28/50
567/567 [==============================] - 183s 324ms/step - loss: 0.1243
Epoch 29/50
567/567 [==============================] - 183s 323ms/step - loss: 0.1082
Epoch 30/50
567/567 [==============================] - 183s 323ms/step - loss: 0.0934
Epoch 31/50
567/567 [==============================] - 183s 323ms/step - loss: 0.0845
Epoch 32/50
567/567 [==============================] - 184s 324ms/step - loss: 0.0974
Epoch 33/50
567/567 [==============================] - 183s 323ms/step - loss: 0.1004
Epoch 34/50
567/567 [==============================] - 184s 324ms/step - loss: 0.1028
Epoch 35/50
567/567 [==============================] - 184s 324ms/step - loss: 0.0930
Epoch 36/50
567/567 [==============================] - 184s 324ms/step - loss: 0.0904
Epoch 37/50
567/567 [==============================] - 184s 324ms/step - loss: 0.0787
Epoch 38/50
567/567 [==============================] - 183s 323ms/step - loss: 0.0917
Epoch 39/50
567/567 [==============================] - 183s 323ms/step - loss: 0.0818
Epoch 40/50
567/567 [==============================] - 183s 323ms/step - loss: 0.1058
Epoch 41/50
567/567 [==============================] - 183s 323ms/step - loss: 0.0845
Epoch 42/50
567/567 [==============================] - 183s 323ms/step - loss: 0.0915
Epoch 43/50
567/567 [==============================] - 184s 324ms/step - loss: 0.0780
Epoch 44/50
567/567 [==============================] - 184s 324ms/step - loss: 0.1027
Epoch 45/50
567/567 [==============================] - 184s 324ms/step - loss: 0.0847
Epoch 46/50
567/567 [==============================] - 184s 325ms/step - loss: 0.0877
Epoch 47/50
567/567 [==============================] - 184s 325ms/step - loss: 0.0833
Epoch 48/50
567/567 [==============================] - 184s 325ms/step - loss: 0.0996
Epoch 49/50
567/567 [==============================] - 184s 324ms/step - loss: 0.0808
Epoch 50/50
567/567 [==============================] - 184s 324ms/step - loss: 0.0855
              precision    recall  f1-score   support

           0       0.49      0.53      0.51      2409
           1       0.41      0.40      0.41      2426
           2       0.40      0.36      0.38      2492
           3       0.38      0.41      0.40      2420
           4       0.51      0.49      0.50      2403

    accuracy                           0.44     12150
   macro avg       0.44      0.44      0.44     12150
weighted avg       0.44      0.44      0.44     12150
```

In [53]:
```
food_model(LSTM, [32,16], 50, 50)
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
embedding_1 (Embedding)      (None, 153, 1000)         29812000  
_________________________________________________________________
lstm (LSTM)                  (None, 32)                132224    
_________________________________________________________________
dense_3 (Dense)              (None, 32)                1056      
_________________________________________________________________
dropout_2 (Dropout)          (None, 32)                0         
_________________________________________________________________
dense_4 (Dense)              (None, 16)                528       
_________________________________________________________________
dropout_3 (Dropout)          (None, 16)                0         
_________________________________________________________________
dense_5 (Dense)              (None, 5)                 85        
=================================================================
Total params: 29,945,893
Trainable params: 29,945,893
Non-trainable params: 0
_________________________________________________________________
Epoch 1/50
567/567 [==============================] - 206s 359ms/step - loss: 1.4517
Epoch 2/50
567/567 [==============================] - 204s 359ms/step - loss: 1.0431
Epoch 3/50
567/567 [==============================] - 203s 358ms/step - loss: 0.8057
Epoch 4/50
567/567 [==============================] - 203s 358ms/step - loss: 0.6059
Epoch 5/50
567/567 [==============================] - 203s 359ms/step - loss: 0.4537
Epoch 6/50
567/567 [==============================] - 204s 359ms/step - loss: 0.3369
Epoch 7/50
567/567 [==============================] - 204s 359ms/step - loss: 0.2452
Epoch 8/50
567/567 [==============================] - 204s 360ms/step - loss: 0.1951
Epoch 9/50
567/567 [==============================] - 203s 359ms/step - loss: 0.1575
Epoch 10/50
567/567 [==============================] - 203s 359ms/step - loss: 0.1252
Epoch 11/50
567/567 [==============================] - 204s 359ms/step - loss: 0.1053
Epoch 12/50
567/567 [==============================] - 204s 360ms/step - loss: 0.0889
Epoch 13/50
567/567 [==============================] - 204s 359ms/step - loss: 0.0958
Epoch 14/50
567/567 [==============================] - 203s 359ms/step - loss: 0.0774
Epoch 15/50
567/567 [==============================] - 204s 359ms/step - loss: 0.0669
Epoch 16/50
567/567 [==============================] - 203s 359ms/step - loss: 0.0768
Epoch 17/50
567/567 [==============================] - 203s 358ms/step - loss: 0.0548
Epoch 18/50
567/567 [==============================] - 206s 363ms/step - loss: 0.0643
Epoch 19/50
567/567 [==============================] - 204s 360ms/step - loss: 0.0463
Epoch 20/50
567/567 [==============================] - 204s 360ms/step - loss: 0.0406
Epoch 21/50
567/567 [==============================] - 204s 360ms/step - loss: 0.0379
Epoch 22/50
567/567 [==============================] - 204s 360ms/step - loss: 0.0350
Epoch 23/50
567/567 [==============================] - 204s 360ms/step - loss: 0.0359
Epoch 24/50
567/567 [==============================] - 204s 361ms/step - loss: 0.0372
Epoch 25/50
567/567 [==============================] - 205s 361ms/step - loss: 0.0362
Epoch 26/50
567/567 [==============================] - 204s 360ms/step - loss: 0.0312
Epoch 27/50
567/567 [==============================] - 204s 360ms/step - loss: 0.0275
Epoch 28/50
```

```
567/567 [==============================] - 204s 361ms/step - loss: 0.0302
Epoch 29/50
567/567 [==============================] - 205s 361ms/step - loss: 0.0260
Epoch 30/50
567/567 [==============================] - 205s 362ms/step - loss: 0.0383
Epoch 31/50
567/567 [==============================] - 205s 362ms/step - loss: 0.0285
Epoch 32/50
567/567 [==============================] - 205s 362ms/step - loss: 0.0248
Epoch 33/50
567/567 [==============================] - 205s 362ms/step - loss: 0.0173
Epoch 34/50
567/567 [==============================] - 205s 361ms/step - loss: 0.0230
Epoch 35/50
567/567 [==============================] - 205s 362ms/step - loss: 0.0293
Epoch 36/50
567/567 [==============================] - 205s 362ms/step - loss: 0.0219
Epoch 37/50
567/567 [==============================] - 205s 362ms/step - loss: 0.0247
Epoch 38/50
567/567 [==============================] - 205s 362ms/step - loss: 0.0225
Epoch 39/50
567/567 [==============================] - 205s 362ms/step - loss: 0.0194
Epoch 40/50
567/567 [==============================] - 205s 362ms/step - loss: 0.0243
Epoch 41/50
567/567 [==============================] - 205s 361ms/step - loss: 0.0210
Epoch 42/50
567/567 [==============================] - 205s 362ms/step - loss: 0.0212
Epoch 43/50
567/567 [==============================] - 205s 362ms/step - loss: 0.0283
Epoch 44/50
567/567 [==============================] - 205s 361ms/step - loss: 0.0177
Epoch 45/50
567/567 [==============================] - 205s 361ms/step - loss: 0.0168
Epoch 46/50
567/567 [==============================] - 205s 361ms/step - loss: 0.0208
Epoch 47/50
567/567 [==============================] - 205s 361ms/step - loss: 0.0240
Epoch 48/50
567/567 [==============================] - 205s 361ms/step - loss: 0.0158
Epoch 49/50
567/567 [==============================] - 204s 361ms/step - loss: 0.0200
Epoch 50/50
567/567 [==============================] - 205s 361ms/step - loss: 0.0213
              precision    recall  f1-score   support

           0       0.54      0.61      0.58      2409
           1       0.46      0.46      0.46      2426
           2       0.43      0.46      0.44      2492
           3       0.46      0.43      0.44      2420
           4       0.64      0.57      0.60      2403

    accuracy                           0.50     12150
   macro avg       0.51      0.50      0.50     12150
weighted avg       0.51      0.50      0.50     12150
```

In [54]:
```
food_model(GRU, [32,16], 50, 50)
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_2 (Embedding)      (None, 153, 1000)         29812000
_________________________________________________________________
gru (GRU)                    (None, 32)                99264
_________________________________________________________________
dense_6 (Dense)              (None, 32)                1056
_________________________________________________________________
dropout_4 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_7 (Dense)              (None, 16)                528
_________________________________________________________________
dropout_5 (Dropout)          (None, 16)                0
_________________________________________________________________
dense_8 (Dense)              (None, 5)                 85
=================================================================
Total params: 29,912,933
Trainable params: 29,912,933
```

```
Non-trainable params: 0
_________________________________________________________________
Epoch 1/50
567/567 [==============================] - 199s 348ms/step - loss: 1.4966
Epoch 2/50
567/567 [==============================] - 197s 348ms/step - loss: 1.0745
Epoch 3/50
567/567 [==============================] - 198s 349ms/step - loss: 0.8012
Epoch 4/50
567/567 [==============================] - 198s 350ms/step - loss: 0.5800
Epoch 5/50
567/567 [==============================] - 198s 349ms/step - loss: 0.4047
Epoch 6/50
567/567 [==============================] - 198s 349ms/step - loss: 0.2961
Epoch 7/50
567/567 [==============================] - 198s 349ms/step - loss: 0.2212
Epoch 8/50
567/567 [==============================] - 198s 349ms/step - loss: 0.1812
Epoch 9/50
567/567 [==============================] - 198s 349ms/step - loss: 0.1456
Epoch 10/50
567/567 [==============================] - 198s 349ms/step - loss: 0.1176
Epoch 11/50
567/567 [==============================] - 198s 348ms/step - loss: 0.0979
Epoch 12/50
567/567 [==============================] - 198s 349ms/step - loss: 0.0782
Epoch 13/50
567/567 [==============================] - 198s 349ms/step - loss: 0.0871
Epoch 14/50
567/567 [==============================] - 198s 349ms/step - loss: 0.0643
Epoch 15/50
567/567 [==============================] - 198s 349ms/step - loss: 0.0502
Epoch 16/50
567/567 [==============================] - 198s 350ms/step - loss: 0.0566
Epoch 17/50
567/567 [==============================] - 199s 350ms/step - loss: 0.0526
Epoch 18/50
567/567 [==============================] - 199s 351ms/step - loss: 0.0420
Epoch 19/50
567/567 [==============================] - 199s 352ms/step - loss: 0.0446
Epoch 20/50
567/567 [==============================] - 200s 352ms/step - loss: 0.0351
Epoch 21/50
567/567 [==============================] - 200s 352ms/step - loss: 0.0399
Epoch 22/50
567/567 [==============================] - 200s 352ms/step - loss: 0.0218
Epoch 23/50
567/567 [==============================] - 200s 352ms/step - loss: 0.0316
Epoch 24/50
567/567 [==============================] - 200s 353ms/step - loss: 0.0426
Epoch 25/50
567/567 [==============================] - 200s 352ms/step - loss: 0.0321
Epoch 26/50
567/567 [==============================] - 199s 351ms/step - loss: 0.0210
Epoch 27/50
567/567 [==============================] - 200s 352ms/step - loss: 0.0235
Epoch 28/50
567/567 [==============================] - 200s 353ms/step - loss: 0.0267
Epoch 29/50
567/567 [==============================] - 200s 352ms/step - loss: 0.0214
Epoch 30/50
567/567 [==============================] - 200s 353ms/step - loss: 0.0195
Epoch 31/50
567/567 [==============================] - 200s 354ms/step - loss: 0.0174
Epoch 32/50
567/567 [==============================] - 200s 352ms/step - loss: 0.0231
Epoch 33/50
567/567 [==============================] - 200s 352ms/step - loss: 0.0251
Epoch 34/50
567/567 [==============================] - 199s 351ms/step - loss: 0.0209
Epoch 35/50
567/567 [==============================] - 199s 351ms/step - loss: 0.0228
Epoch 36/50
567/567 [==============================] - 199s 351ms/step - loss: 0.0163
Epoch 37/50
567/567 [==============================] - 199s 351ms/step - loss: 0.0206
Epoch 38/50
567/567 [==============================] - 199s 351ms/step - loss: 0.0127
Epoch 39/50
```

```
567/567 [==============================] - 199s 351ms/step - loss: 0.0146
Epoch 40/50
567/567 [==============================] - 199s 350ms/step - loss: 0.0232
Epoch 41/50
567/567 [==============================] - 199s 351ms/step - loss: 0.0229
Epoch 42/50
567/567 [==============================] - 199s 352ms/step - loss: 0.0135
Epoch 43/50
567/567 [==============================] - 199s 351ms/step - loss: 0.0192
Epoch 44/50
567/567 [==============================] - 199s 351ms/step - loss: 0.0158
Epoch 45/50
567/567 [==============================] - 200s 352ms/step - loss: 0.0153
Epoch 46/50
567/567 [==============================] - 199s 351ms/step - loss: 0.0150
Epoch 47/50
567/567 [==============================] - 199s 350ms/step - loss: 0.0194
Epoch 48/50
567/567 [==============================] - 199s 350ms/step - loss: 0.0195
Epoch 49/50
567/567 [==============================] - 198s 350ms/step - loss: 0.0197
Epoch 50/50
567/567 [==============================] - 198s 350ms/step - loss: 0.0221
              precision    recall  f1-score   support

           0       0.59      0.54      0.57      2409
           1       0.43      0.47      0.45      2426
           2       0.44      0.40      0.42      2492
           3       0.42      0.46      0.44      2420
           4       0.58      0.57      0.57      2403

    accuracy                           0.49     12150
   macro avg       0.49      0.49      0.49     12150
weighted avg       0.49      0.49      0.49     12150
```

Conclusion

The goal of this project was to create an NLP model based on Food Reviews. In order to achieve this, a few Machine Learning (ML) models were initially built, and then Neural Network (NN) models. Overall, better accuracy scores were achieved with the ML model.

Version 1.0

Here, focus on put on cleaning the text of the data (removing stopwords), and creating a NN model.

Version 2.0

We tried to see if we could better our score by create ML models, and it turns out that the accuracy score did improve by 0.04. Any small increase in score create a better model, thus improving overall business.

Version 3.0

Some data analysis was performed to see the top rated Anime, and those with the most numbe of members.
