```python
import os
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
import nltk
from nltk.corpus import RegexpTokenizer as regextoken
from nltk.corpus import stopwords
from nltk import FreqDist, bigrams, trigrams
from nltk import WordNetLemmatizer
import matplotlib
from matplotlib import pyplot as plt
import seaborn as sns
%matplotlib inline
from keras.preprocessing.text import Tokenizer
from sklearn.preprocessing import LabelEncoder
from keras.utils import to_categorical
from keras.preprocessing.sequence import pad_sequences
import gensim
from gensim.models.keyedvectors import KeyedVectors
from keras.models import Sequential
from keras.models import Model
from keras.layers import Dense, Flatten, Embedding, Conv1D, MaxPooling1D, Dropout, LSTM, GRU
from keras.regularizers import l1, l2
from sklearn.metrics import classification_report
import warnings
warnings.filterwarnings("ignore")

zomato = pd.read_csv("../input/zomato-bangalore-restaurants/zomato.csv", na_values = ["-", ""])
data = zomato.copy()
```

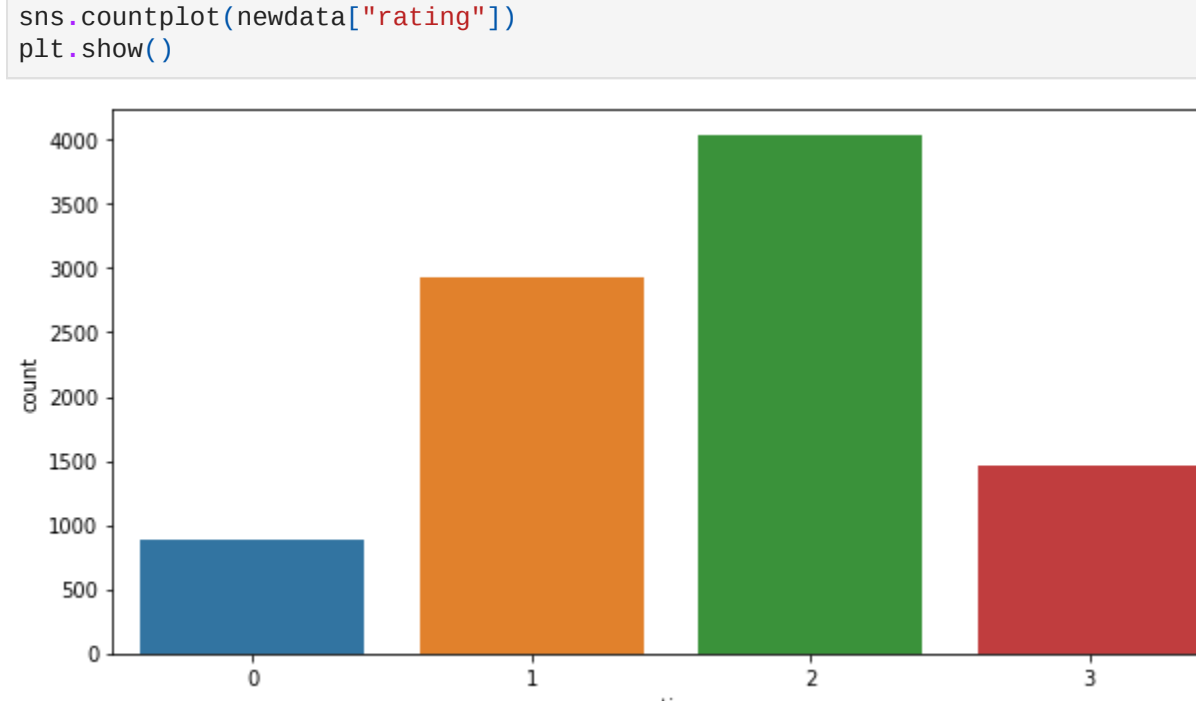
```
Using TensorFlow backend.
```

```python
grouped = data.groupby(["name", "address"]).agg({"listed_in(type)" : list})
newdata = pd.merge(grouped, data, on = (["name", "address"]))
newdata["listed_in(type)_x"] = newdata["listed_in(type)_x"].astype(str)
newdata.drop_duplicates(subset = ["name", "address", "listed_in(type)_x"], inplace = True)
newdata = newdata.reset_index(drop = True)
```

```python
newdata["rating"] = newdata["rate"].str[:3]
newdata = newdata[newdata.rating != "NEW"]

newdata = newdata.dropna(subset = ["rating"])

newdata["rating"] = pd.to_numeric(newdata["rating"])


newdata["rating"] = pd.cut(newdata["rating"], bins = [0, 3.0, 3.5, 4.0, 5.0], labels = ["0", "1", "2", "3"])
```

Our four rating bins (classes) will be 0 to 3 < 3 to 3.5 < 3.5 to 4 < 4 to 5. To make label encoding easier later, we'll label these classes 0, 1, 2, 3. We can think of these as Very Low, Low, Medium and High.

```python
plt.figure(figsize = (10, 5))
sns.countplot(newdata["rating"])
plt.show()
```




```python
newdata.describe(include = "all")
```

	name	address	listed_in(type)_x	url	online_order	book_table	rate	votes	phone	location	rest_type	dish_liked	cuisines	approx_cost(for two people)	reviews_list	menu_item
count	9316	9316	9316	9316	9316	9316	9316	9316.000000	9149	9316	9279	4577	9313	9284	9316	9316
unique	6512	8676	870	9316	2	2	59	NaN	8381	92	86	4249	2246	63	8964	1990
top	Cafe Coffee Day	Delivery Only	['Delivery', 'Dine-out']	https://www.zomato.com/bangalore/laddoos-elect...	Yes	No	3.7/5	NaN	080 43334321	Whitefield	Quick Bites	Biryani	North Indian	400	[]	[]
freq	49	21	872	1	5705	8393	706	NaN	55	617	3445	47	484	1370	332	7314
mean	NaN	NaN	NaN	NaN	NaN	NaN	NaN	242.149420	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
std	NaN	NaN	NaN	NaN	NaN	NaN	NaN	673.984948	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
min	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
25%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	16.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
50%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	53.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
75%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	191.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
max	NaN	NaN	NaN	NaN	NaN	NaN	NaN	16345.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

We will use the reviews_list, menu_item, dish_liked and cuisines columns for our analysis.

First, we will look at the customer reviews and pull out the most common words and phrases. Next, we will analyse cuisine listings and identify cuisines that are rare in Bangalore. Finally we will build a neural network with all four features to predict restaurant ratings.

```python
reviews_data = newdata[["reviews_list", "rating"]]

reviews_data["reviews_list"][0]
```

```
'[(\'Rated 5.0\', "RATED\\n  Had an egg chicken roll and a paneer roll... Really yummy... A must visit place... It would be good if you guys can keep the shop open on Sunday\'s as
well.. Good luck... :-)"), (\'Rated 5.0\', \'RATED\\n  Not just the Roll but the filling tastes great. I would highly recommend to others to try their rolls. Owners hospitality is
also good and very friendly.\'), (\'Rated 4.5\', \'RATED\\n  Very nice place complete value for money ? Highly recommend.Must visit for any foodie . I would recommend the egg chic
ken roll . #feeltheroll\'), (\'Rated 5.0\', \'RATED\\n  Had an amazing mouth-watering ?chicken roll?Worth every bite..A must try for every foodie?A variety of rolls and sandwiches
are available as well .. A budding rafflesia ?\')]'
```

```python
reviews_data["reviews_list"] = reviews_data["reviews_list"].apply(lambda x: x.lower())


tokenizer = regextoken("[a-zA-Z]+")
review_tokens = reviews_data["reviews_list"].apply(tokenizer.tokenize)
print(review_tokens[0])
```

```
['rated', 'rated', 'n', 'had', 'an', 'egg', 'chicken', 'roll', 'and', 'a', 'paneer', 'roll', 'really', 'yummy', 'a', 'must', 'visit', 'place', 'it', 'would', 'be', 'good', 'if',
'you', 'guys', 'can', 'keep', 'the', 'shop', 'open', 'on', 'sunday', 's', 'as', 'well', 'good', 'luck', 'rated', 'rated', 'n', 'not', 'just', 'the', 'roll', 'but', 'the', 'fillin
g', 'tastes', 'great', 'i', 'would', 'highly', 'recommend', 'to', 'others', 'to', 'try', 'their', 'rolls', 'owners', 'hospitality', 'is', 'also', 'good', 'and', 'very', 'friendl
y', 'rated', 'rated', 'n', 'very', 'nice', 'place', 'complete', 'value', 'for', 'money', 'highly', 'recommend', 'must', 'visit', 'for', 'any', 'foodie', 'i', 'would', 'recommend',
'the', 'egg', 'chicken', 'roll', 'feeltheroll', 'rated', 'rated', 'n', 'had', 'an', 'amazing', 'mouth', 'watering', 'chicken', 'roll', 'worth', 'every', 'bite', 'a', 'must', 'tr
y', 'for', 'every', 'foodie', 'a', 'variety', 'of', 'rolls', 'and', 'sandwiches', 'are', 'available', 'as', 'well', 'a', 'budding', 'rafflesia']
```

```python
# Importing and examining the English stopwords directory
stop = stopwords.words("english")
print(stop)
```

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

```python
# Adding custom words to stopwords
stop.extend(["rated", "n", "nan", "x"])

review_tokens = review_tokens.apply(lambda x: [token for token in x if token not in stop])

all_reviews = review_tokens.astype(str).str.cat()
cleaned_reviews = tokenizer.tokenize(all_reviews)


fd = FreqDist()
for word in cleaned_reviews:
    fd[word] += 1

fd.most_common(5)
```

```
[('good', 150929),
 ('food', 147551),
 ('place', 139169),
 ('chicken', 68678),
 ('ordered', 50928)]
```

```python
# Plotting the top 50 most frequent words
plt.figure(figsize = (10, 5))
fd.plot(50)
plt.show()
```

Observations

Of the 50 most frequent words across customer reviews, six reveal food preferences: **chicken, biryani, veg, pizza, rice, paneer**. The only negative word in the top 50 is "bad".

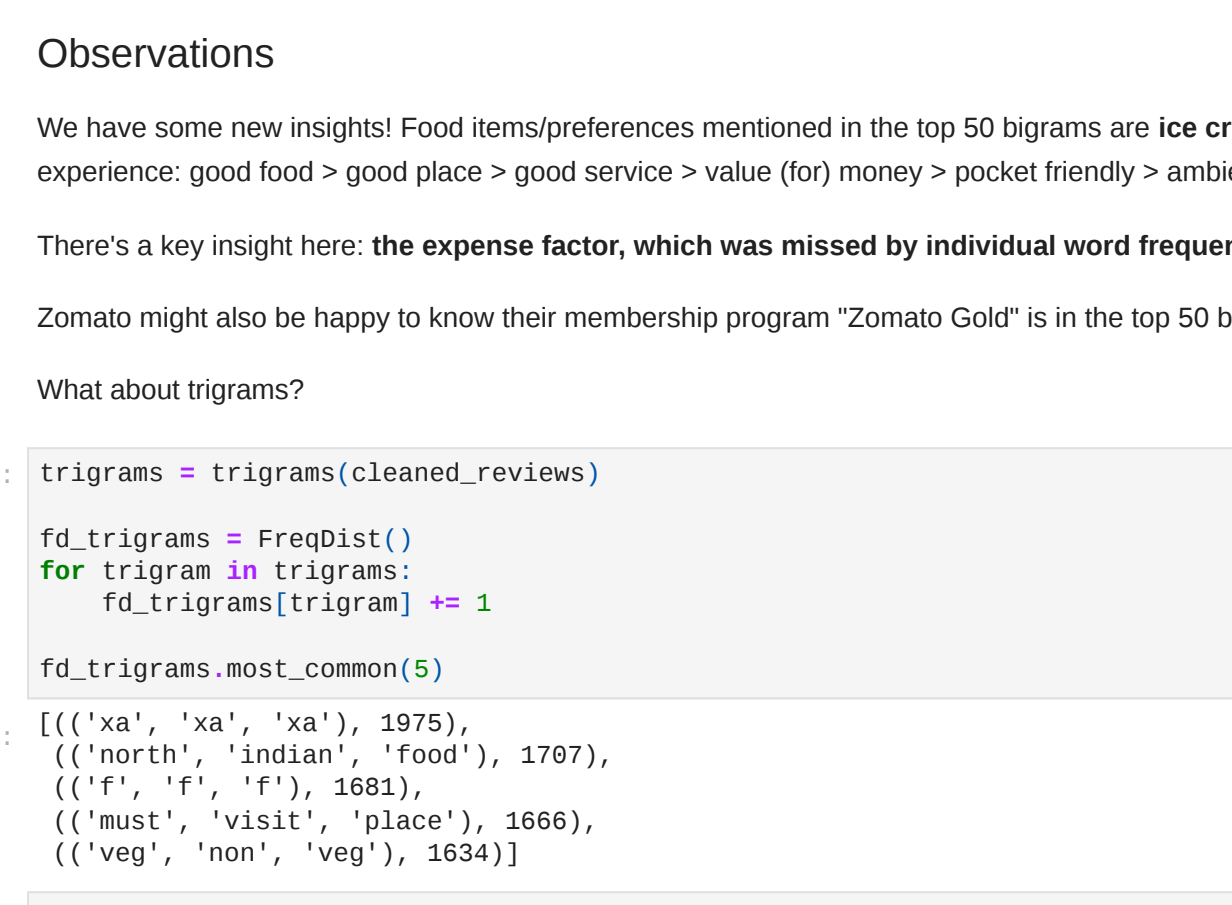
Factors contributing to restaurant experience are mentioned in the following (descending) order of frequency: place > taste > service > time > ambience > staff > quality > delivery > menu > quantity > friendly.

Now let us repeat the analysis on a bi-gram level. Bi-grams are pairs of words which can provide better context than individual words.

```python
bigrams = bigrams(cleaned_reviews)

fd_bigrams = FreqDist()
for bigram in bigrams:
    fd_bigrams[bigram] += 1
fd_bigrams.most_common(5)
```

```
[(('must', 'try'), 10719),
 (('really', 'good'), 9973),
 (('good', 'food'), 9939),
 (('food', 'good'), 9585),
 (('good', 'place'), 7871)]
```

```python
plt.figure(figsize = (10, 5))
fd_bigrams.plot(50)
plt.show()
```



Observations

We have some new insights! Food items/preferences mentioned in the top 50 bigrams are **ice cream, non veg, North Indian, chicken biryani, fried rice, chicken and South Indian**. Top six bigrams related to restaurant experience: good food > good place > good service > value (for) money > pocket friendly > ambience good.

There's a key insight here: **the expense factor, which was missed by individual word frequency counts, was picked up by the bigram frequency counts.**

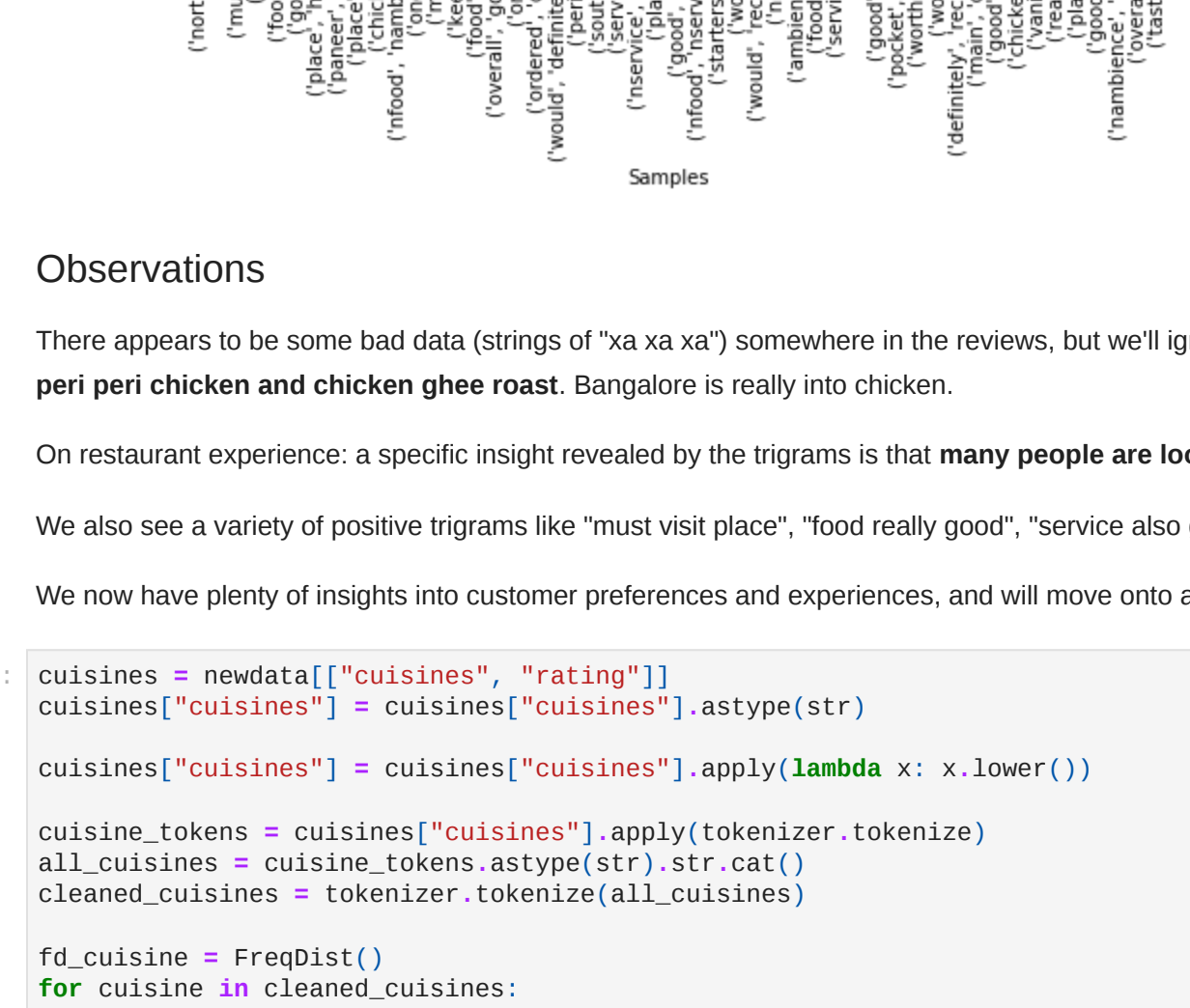
Zomato might also be happy to know their membership program "Zomato Gold" is in the top 50 bigrams, with 2593 mentions in the customer reviews.

What about trigrams?

```python
trigrams = trigrams(cleaned_reviews)

fd_trigrams = FreqDist()
for trigram in trigrams:
    fd_trigrams[trigram] += 1

fd_trigrams.most_common(5)
```

```
[(('xa', 'xa', 'xa'), 1975),
 (('north', 'indian', 'food'), 1707),
 (('f', 'f', 'f'), 1681),
 (('must', 'visit', 'place'), 1666),
 (('veg', 'non', 'veg'), 1634)]
```

```python
plt.figure(figsize = (10, 5))
fd_trigrams.plot(50)
plt.show()
```



Observations

There appears to be some bad data (strings of "xa xa xa") somewhere in the reviews, but we'll ignore that. The specific food preferences we can see here are **paneer butter masala, chicken fried rice, chicken biryani, peri peri chicken and chicken ghee roast**. Bangalore is really into chicken.

On restaurant experience: a specific insight revealed by the trigrams is that **many people are looking for places to hang out with their friends**.

We also see a variety of positive trigrams like "must visit place", "food really good", "service also good" and "worth every penny". However, there is only one negative trigram in the top 50 - "worst food ever".

We now have plenty of insights into customer preferences and experiences, and will move onto an analysis of Bangalore's cuisines.

```python
cuisines = newdata[["cuisines", "rating"]]
cuisines["cuisines"] = cuisines["cuisines"].astype(str)

cuisines["cuisines"] = cuisines["cuisines"].apply(lambda x: x.lower())

cuisine_tokens = cuisines["cuisines"].apply(tokenizer.tokenize)
all_cuisines = cuisine_tokens.astype(str).str.cat()
cleaned_cuisines = tokenizer.tokenize(all_cuisines)

fd_cuisine = FreqDist()
for cuisine in cleaned_cuisines:
    fd_cuisine[cuisine] += 1

print(fd_cuisine.most_common(50))
```

```
[('indian', 5506), ('north', 3860), ('chinese', 2836), ('food', 2512), ('south', 1633), ('fast', 1602), ('biryani', 1285), ('desserts', 985), ('beverages', 842), ('continental', 8
21), ('cafe', 674), ('street', 605), ('italian', 501), ('bakery', 495), ('pizza', 393), ('andhra', 379), ('ice', 374), ('cream', 374), ('burger', 369), ('seafood', 320), ('mughla
i', 305), ('rolls', 297), ('momos', 246), ('kerala', 244), ('mithai', 206), ('juices', 202), ('american', 200), ('arabian', 193), ('thai', 185), ('asian', 183), ('salad', 179),
('kebab', 174), ('sandwich', 167), ('finger', 159), ('healthy', 145), ('bbq', 126), ('mangalorean', 111), ('bengali', 106), ('european', 104), ('mexican', 98), ('mediterranean', 8
6), ('steak', 75), ('hyderabadi', 69), ('tea', 68), ('tibetan', 54), ('japanese', 43), ('chettinad', 38), ('chicken', 32), ('vietnamese', 31), ('rajasthani', 29)]
```

Observations

One must be careful when interpreting these lists. For example, "dogs" can't be a cuisine but the preceding word "hot" tells us that the cuisine is "hot dogs". Another tricky one is Cantonese, which comes under Chinese and so might not really be rare.

We've done our reviews and cuisines analysis and will now prepare all the text in the dataset for feeding into a neural network.

Text Preprocessing

```python
newdata[["reviews_list", "menu_item", "dish_liked", "cuisines"]] = newdata[["reviews_list", "menu_item", "dish_liked", "cuisines"]].astype("str")
newdata["text"] = newdata["reviews_list"] + " " + newdata["menu_item"] + " " + newdata["dish_liked"] + " " + newdata["cuisines"]
text_data = newdata[["text", "rating"]]

text_data["text"] = text_data["text"].apply(lambda x: x.lower())
tokens = text_data["text"].apply(tokenizer.tokenize)
tokens = tokens.apply(lambda x: [token for token in x if token not in stop])
```

```python
print(tokens[0])
```

```
['egg', 'chicken', 'roll', 'paneer', 'roll', 'really', 'yummy', 'must', 'visit', 'place', 'would', 'good', 'guys', 'keep', 'shop', 'open', 'sunday', 'well', 'good', 'luck', 'rol
l', 'filling', 'tastes', 'great', 'would', 'highly', 'recommend', 'others', 'try', 'rolls', 'owners', 'hospitality', 'also', 'good', 'friendly', 'nice', 'place', 'complete', 'valu
e', 'money', 'highly', 'recommend', 'must', 'visit', 'foodie', 'would', 'recommend', 'egg', 'chicken', 'roll', 'feeltheroll', 'amazing', 'mouth', 'watering', 'chicken', 'roll', 'w
orth', 'every', 'bite', 'must', 'try', 'every', 'foodie', 'variety', 'rolls', 'sandwiches', 'available', 'well', 'budding', 'rafflesia', 'fast', 'food']
```

```python
lmtzr = WordNetLemmatizer()
def lem(text):
    return [lmtzr.lemmatize(word) for word in text]

tokens_new = tokens.apply(lem)
```

```python
le = LabelEncoder()
target = le.fit_transform(text_data["rating"])
target = to_categorical(target)
```

```python
X_train, X_test, y_train, y_test = train_test_split(tokens_new, target, test_size = 0.3, random_state = 0, stratify = target)


t = Tokenizer()
t.fit_on_texts(X_train)

vocab_size = len(t.word_index) + 1
print(vocab_size)
```

```
46123
```

```python
train_sequences = t.texts_to_sequences(X_train)
test_sequences = t.texts_to_sequences(X_test)
train_padded = pad_sequences(train_sequences, maxlen=500)
test_padded = pad_sequences(test_sequences, maxlen=500)
```

Word embedding

We'll use Google's pre-trained Word2Vec word embeddings.

```python
word_vectors = KeyedVectors.load_word2vec_format('../input/googlenewsvectorsnegative300/GoogleNews-vectors-negative300.bin', binary=True)

embedding_dim = 300


embedding_matrix = np.zeros((vocab_size, embedding_dim))


for word, i in t.word_index.items():
    try:
        # get the Word2Vec vector representation for that word
        embedding_vector = word_vectors[word]

        embedding_matrix[i] = embedding_vector

    except KeyError:
        embedding_matrix[i]=np.random.normal(0,np.sqrt(0.25), embedding_dim)
```

```python
embedding_matrix.shape
```

```
(46123, 300)
```

```python
# Examining the words embeddings - vector representations of words
embedding_matrix
```

```
array([[ 0.        ,  0.        ,  0.        , ...,  0.        ,
         0.        ,  0.        ],
       [-0.18164062,  0.16503906, -0.16601562, ...,  0.15917969,
         0.12792969,  0.00222778],
       [ 0.04052734,  0.0625    , -0.01745605, ..., -0.15625   ,
         0.00193024, -0.06982422],
       ...,
       [-0.12304688, -0.23925781,  0.25976562, ...,  0.06201172,
         0.14746094,  0.12011719],
       [-0.09520624,  0.75744784, -0.0824335 , ...,  0.22752493,
         0.04909362, -0.49173217],
       [ 0.09049165, -1.06974566,  0.42920093, ...,  0.04468418,
         1.34594317, -0.38823108]])
```

Model Building

```python
# Building an LSTM neural network

warnings.filterwarnings("ignore")
max_length = 500

model = Sequential()
model.add(Embedding(vocab_size, embedding_dim, input_length=max_length, weights = [embedding_matrix], trainable = False))
model.add(LSTM(100, activation = "tanh"))
model.add(Dropout(0.5))
model.add(Dense(4, activation='softmax'))
model.compile(loss='categorical_crossentropy', optimizer = "adam", metrics=['accuracy'])
model.fit(train_padded, y_train, validation_data=(test_padded, y_test), epochs=15, batch_size=512)
```

```
Train on 6521 samples, validate on 2795 samples
Epoch 1/15
6521/6521 [==============================] - 8s 1ms/step - loss: 1.2629 - accuracy: 0.4240 - val_loss: 1.1785 - val_accuracy: 0.4923
Epoch 2/15
6521/6521 [==============================] - 8s 1ms/step - loss: 1.1399 - accuracy: 0.5039 - val_loss: 1.0858 - val_accuracy: 0.5070
Epoch 3/15
6521/6521 [==============================] - 7s 1ms/step - loss: 1.0600 - accuracy: 0.5209 - val_loss: 1.0296 - val_accuracy: 0.5474
Epoch 4/15
6521/6521 [==============================] - 7s 1ms/step - loss: 1.0345 - accuracy: 0.5398 - val_loss: 1.0110 - val_accuracy: 0.5488
Epoch 5/15
6521/6521 [==============================] - 7s 1ms/step - loss: 1.0055 - accuracy: 0.5528 - val_loss: 1.0019 - val_accuracy: 0.5606
Epoch 6/15
6521/6521 [==============================] - 7s 1ms/step - loss: 0.9915 - accuracy: 0.5619 - val_loss: 0.9867 - val_accuracy: 0.5674
Epoch 7/15
6521/6521 [==============================] - 7s 1ms/step - loss: 0.9719 - accuracy: 0.5694 - val_loss: 0.9792 - val_accuracy: 0.5657
Epoch 8/15
6521/6521 [==============================] - 7s 1ms/step - loss: 0.9581 - accuracy: 0.5769 - val_loss: 0.9814 - val_accuracy: 0.5678
Epoch 9/15
6521/6521 [==============================] - 7s 1ms/step - loss: 0.9400 - accuracy: 0.5948 - val_loss: 0.9870 - val_accuracy: 0.5725
Epoch 10/15
6521/6521 [==============================] - 7s 1ms/step - loss: 0.9239 - accuracy: 0.5953 - val_loss: 0.9673 - val_accuracy: 0.5742
Epoch 11/15
6521/6521 [==============================] - 7s 1ms/step - loss: 0.9091 - accuracy: 0.6143 - val_loss: 0.9535 - val_accuracy: 0.5796
Epoch 12/15
6521/6521 [==============================] - 7s 1ms/step - loss: 0.8928 - accuracy: 0.6155 - val_loss: 0.9458 - val_accuracy: 0.5807
Epoch 13/15
6521/6521 [==============================] - 7s 1ms/step - loss: 0.8766 - accuracy: 0.6209 - val_loss: 0.9659 - val_accuracy: 0.5760
Epoch 14/15
6521/6521 [==============================] - 7s 1ms/step - loss: 0.8597 - accuracy: 0.6277 - val_loss: 0.9629 - val_accuracy: 0.5657
Epoch 15/15
6521/6521 [==============================] - 7s 1ms/step - loss: 0.8483 - accuracy: 0.6338 - val_loss: 0.9569 - val_accuracy: 0.5728
```

```
&lt;keras.callbacks.callbacks.History at 0x7f36cc425c50&gt;
```

Evaluation

```python
# Predicting on the train data
pred_train = model.predict(train_padded)
pred_train = np.argmax(pred_train, axis=1)
y_train = np.argmax(y_train, axis=1)
print(classification_report(y_train, pred_train))
```

```
              precision    recall  f1-score   support

           0       0.56      0.05      0.09       619
           1       0.65      0.67      0.66      2050
           2       0.63      0.72      0.68      2826
           3       0.72      0.78      0.75      1026

    accuracy                           0.65      6521
   macro avg       0.64      0.56      0.54      6521
weighted avg       0.64      0.65      0.63      6521
```

```python
# Predicting on the test data
pred_test = model.predict(test_padded)
pred_test = np.argmax(pred_test, axis=1)
y_test = np.argmax(y_test, axis = 1)
print(classification_report(y_test, pred_test))
```

```
              precision    recall  f1-score   support

           0       0.47      0.03      0.06       265
           1       0.57      0.60      0.58       879
           2       0.56      0.63      0.59      1211
           3       0.62      0.69      0.65       440

    accuracy                           0.57      2795
   macro avg       0.56      0.49      0.47      2795
weighted avg       0.56      0.57      0.55      2795
```

Results summary

By applying text mining techniques to customer reviews and other data, **we discovered common food preferences which became more specific as we progressed (dish names)**. **We also noted which aspects of a restaurant people care about and in what order of priority. Then we identified the most and least common cuisines in the city along with their prevalence.**

The text mining activity was interesting from both a data science perspective and a business perspective, as it showed the usefulness of different NLTK tools and revealed actionable insights.

After processing the text, we fed it to an LSTM network with pre-trained Word2Vec word vectors to see if we could predict the four rating classes we created. Accuracy and average F1 scores were lower than what we got with XGBoost.