checkedcapstone1restaurants

January 31, 2023

1 Set Up

[1]:
```
# import modules and data
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

%matplotlib inline

countrycodes = pd.read_excel('Country-Code.xlsx')
restaurants = pd.read_excel('data.xlsx')

# merge datasets
df = pd.merge(countrycodes, restaurants, on='Country Code')
```

[2]:
```
df.head(2)
```

[2]:
```
   Country Code Country  Restaurant ID  \
0             1   India           2701
1             1   India         309548

                          Restaurant Name       City  \
0         Orient Express - Taj Palace Hotel  New Delhi
1  Tian - Asian Cuisine Studio - ITC Maurya  New Delhi

                                              Address  \
0  Taj Palace Hotel, Diplomatic Enclave, Chanakya…
1  ITC Maurya, Diplomatic Enclave, Chanakyapuri, …

                          Locality  \
0  The Taj Palace Hotel, Chanakyapuri
1             ITC Maurya, Chanakyapuri

                                   Locality Verbose  Longitude   Latitude  \
```

```
0  The Taj Palace Hotel, Chanakyapuri, New Delhi  77.170087  28.595008
1            ITC Maurya, Chanakyapuri, New Delhi  77.173455  28.597351

                                Cuisines  Average Cost for two  \
0                               European                  8000
1  Asian, Japanese, Korean, Thai, Chinese                  7000

            Currency Has Table booking Has Online delivery  Price range  \
0  Indian Rupees(Rs.)               Yes                  No            4
1  Indian Rupees(Rs.)                No                  No            4

   Aggregate rating Rating color Rating text  Votes
0               4.0        Green   Very Good    145
1               4.1        Green   Very Good    188
```

[3]:
```
# summary of dataframe
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9551 entries, 0 to 9550
Data columns (total 20 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Country Code          9551 non-null   int64
 1   Country               9551 non-null   object
 2   Restaurant ID         9551 non-null   int64
 3   Restaurant Name       9550 non-null   object
 4   City                  9551 non-null   object
 5   Address               9551 non-null   object
 6   Locality              9551 non-null   object
 7   Locality Verbose      9551 non-null   object
 8   Longitude             9551 non-null   float64
 9   Latitude              9551 non-null   float64
 10  Cuisines              9542 non-null   object
 11  Average Cost for two  9551 non-null   int64
 12  Currency              9551 non-null   object
 13  Has Table booking     9551 non-null   object
 14  Has Online delivery   9551 non-null   object
 15  Price range           9551 non-null   int64
 16  Aggregate rating      9551 non-null   float64
 17  Rating color          9551 non-null   object
 18  Rating text           9551 non-null   object
 19  Votes                 9551 non-null   int64
dtypes: float64(3), int64(5), object(12)
memory usage: 1.5+ MB
```

- the data has 20 columns and 9551 rows including headers
- cuisines appear to have an extra row

- datatypes appear correct

2 Data Wrangling

[4]:
```
# format columns to lower case
df.columns = df.columns.str.lower()

# remove spacing in columns
df.columns = df.columns.str.replace(' ', '')
```

[5]:
```
df.columns
```

[5]:
```
Index(['countrycode', 'country', 'restaurantid', 'restaurantname', 'city',
       'address', 'locality', 'localityverbose', 'longitude', 'latitude',
       'cuisines', 'averagecostfortwo', 'currency', 'hastablebooking',
       'hasonlinedelivery', 'pricerange', 'aggregaterating', 'ratingcolor',
       'ratingtext', 'votes'],
      dtype='object')
```

[6]:
```
# format to concise column names
df = df.rename(columns={'averagecostfortwo':'averagecost', 'hastablebooking':
 ↪'tablebooking', 'hasonlinedelivery':'onlinedelivery', 'aggregaterating':
 ↪'rating'})
```

[7]:
```
# convert datatype for feature engineering
df.countrycode = df.countrycode.apply(str)
```

[8]:
```
# check for duplicates
df.duplicated().any()
```

[8]:
```
False
```

[9]:
```
# % of missing values to assess most suitable treatment
round(df.isnull().sum().sort_values(ascending=False)/len(df)*100,2)
```

[9]:
```
cuisines          0.09
restaurantname    0.01
averagecost       0.00
ratingtext        0.00
ratingcolor       0.00
rating            0.00
pricerange        0.00
onlinedelivery    0.00
tablebooking      0.00
currency          0.00
countrycode       0.00
country           0.00
```

```
latitude           0.00
longitude          0.00
localityverbose    0.00
locality           0.00
address            0.00
city               0.00
restaurantid       0.00
votes              0.00
dtype: float64
```

[10]:
```
# Arbitrary Imputation of missing values
df.restaurantname.replace([np.nan], 'N/A - Missing Value', inplace=True)
```

[11]:
```
# fill cuisine missing values with mode
df.fillna(value={'cuisines':df['cuisines'].mode()[0]}, inplace=True)
```

[12]:
```
# final missing value check
df.isnull().sum()
```

[12]:
```
countrycode        0
country            0
restaurantid       0
restaurantname     0
city               0
address            0
locality           0
localityverbose    0
longitude          0
latitude           0
cuisines           0
averagecost        0
currency           0
tablebooking       0
onlinedelivery     0
pricerange         0
rating             0
ratingcolor        0
ratingtext         0
votes              0
dtype: int64
```

[13]:
```
# correct country names
df.city.replace({'BrasÌ_lia':'Brasil Lia', 'SÌ£o Paulo':'Sao Paulo',␣
↪'€¡stanbul':'Istanbul'}, inplace=True)
```

[14]:
```
# drop irrelevant columns
df.drop(['address', 'localityverbose'], axis=1, inplace=True)
```

```python
# reset df
df.reset_index(drop=True, inplace=True)
```

3 Exploratory Data Analysis

[15]:
```python
# statistics of df
df.describe(include='all')
```

[15]:

	countrycode	country	restaurantid	restaurantname	city
count	9551	9551	9.551000e+03	9551	9551
unique	15	15	NaN	7446	141
top	1	India	NaN	Cafe Coffee Day	New Delhi
freq	8652	8652	NaN	83	5473
mean	NaN	NaN	9.051128e+06	NaN	NaN
std	NaN	NaN	8.791521e+06	NaN	NaN
min	NaN	NaN	5.300000e+01	NaN	NaN
25%	NaN	NaN	3.019625e+05	NaN	NaN
50%	NaN	NaN	6.004089e+06	NaN	NaN
75%	NaN	NaN	1.835229e+07	NaN	NaN
max	NaN	NaN	1.850065e+07	NaN	NaN

	locality	longitude	latitude	cuisines
count	9551	9551.000000	9551.000000	9551
unique	1208	NaN	NaN	1825
top	Connaught Place	NaN	NaN	North Indian
freq	122	NaN	NaN	945
mean	NaN	64.126574	25.854381	NaN
std	NaN	41.467058	11.007935	NaN
min	NaN	-157.948486	-41.330428	NaN
25%	NaN	77.081343	28.478713	NaN
50%	NaN	77.191964	28.570469	NaN
75%	NaN	77.282006	28.642758	NaN
max	NaN	174.832089	55.976980	NaN

	averagecost	currency	tablebooking	onlinedelivery
count	9551.000000	9551	9551	9551
unique	NaN	12	2	2
top	NaN	Indian Rupees(Rs.)	No	No
freq	NaN	8652	8393	7100
mean	1199.210763	NaN	NaN	NaN
std	16121.183073	NaN	NaN	NaN
min	0.000000	NaN	NaN	NaN
25%	250.000000	NaN	NaN	NaN
50%	400.000000	NaN	NaN	NaN
75%	700.000000	NaN	NaN	NaN

```
max      800000.000000                  NaN           NaN             NaN

          pricerange       rating ratingcolor ratingtext           votes
count    9551.000000  9551.000000        9551       9551     9551.000000
unique           NaN          NaN           6          6             NaN
top              NaN          NaN      Orange    Average             NaN
freq             NaN          NaN        3737       3737             NaN
mean        1.804837     2.666370         NaN        NaN      156.909748
std         0.905609     1.516378         NaN        NaN      430.169145
min         1.000000     0.000000         NaN        NaN        0.000000
25%         1.000000     2.500000         NaN        NaN        5.000000
50%         2.000000     3.200000         NaN        NaN       31.000000
75%         2.000000     3.700000         NaN        NaN      131.000000
max         4.000000     4.900000         NaN        NaN    10934.000000
```

- There are 15 unique countries, with India being the most common country, appearing 8652 times
- There are 140 unique cities
- 'Cafe Coffee Day' is the most common 'restaurantname', implying there should be numerous branches
- New Delhi is the most common 'city' with 5473 restaurants
- North Indian is the most common 'cuisine'
- 'Orange' and 'Average' are the most common rating indicators
- The max 'average rating' is 4.9

[16]:
```python
# no. of unique restaurantid
df.restaurantid.nunique()
```

[16]: 9551

[17]:
```python
# no. of unique restaurantname
df.restaurantname.nunique()
```

[17]: 7446

Geographical Distribution

3.0.1 Total Resturants by Countries

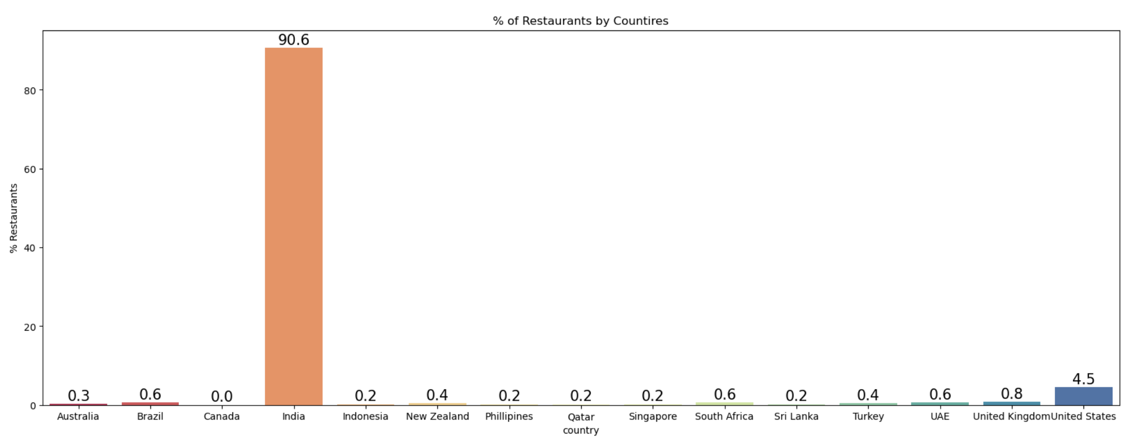
[18]:
```python
# restaurant count and % by country
geodf = df.groupby(['country'], as_index=False)['restaurantid'].count()
geodf.rename(columns={'restaurantid':'totalrestaurants'}, inplace=True)
geodf['percent'] = (geodf.totalrestaurants/geodf.totalrestaurants.sum()*100).
 ↪round(1)

geodf.sort_values(by='percent', ascending=False)
```

[18]:

	country	totalrestaurants	percent
3	India	8652	90.6
14	United States	434	4.5
13	United Kingdom	80	0.8
1	Brazil	60	0.6
9	South Africa	60	0.6
12	UAE	60	0.6
5	New Zealand	40	0.4
11	Turkey	34	0.4
0	Australia	24	0.3
4	Indonesia	21	0.2
6	Phillipines	22	0.2
7	Qatar	20	0.2
8	Singapore	20	0.2
10	Sri Lanka	20	0.2
2	Canada	4	0.0

[19]:

```
# Barplot of resturants vs countires

plt.figure(figsize = (20,7))
plot_annotate = sns.barplot(geodf, x='country', y='percent', palette='Spectral')

# annotate %
for bar in plot_annotate.patches:
    plot_annotate.annotate(format(bar.get_height(), '.1f'),
                  (bar.get_x() + bar.get_width()/2,
                  bar.get_height()), ha='center', va='center', size=15,
                  xytext=(0,8), textcoords='offset points')

plt.ylabel('% Restaurants')
plt.title('% of Restaurants by Countires')
plt.show()
```



3.0.2 Top 10 Cities with most Restaurants

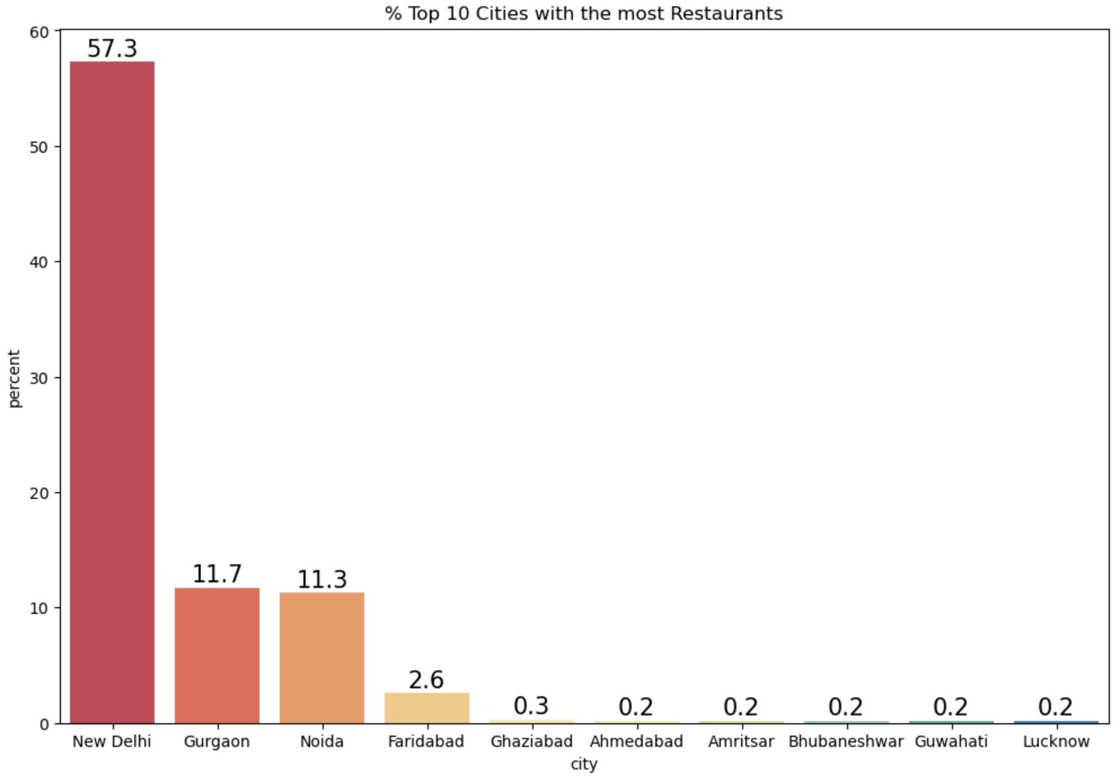
[20]:
```
city_df = df.groupby(['city'], as_index=False)['restaurantid'].count()
city_df.rename(columns={'restaurantid':'totalrestaurants'}, inplace=True)
city_df['percent'] = (city_df.totalrestaurants/sum(city_df.
 ↪totalrestaurants)*100).round(1)
```

[21]:
```
top_cities = city_df.nlargest(10, ['totalrestaurants'])
top_cities
```

[21]:

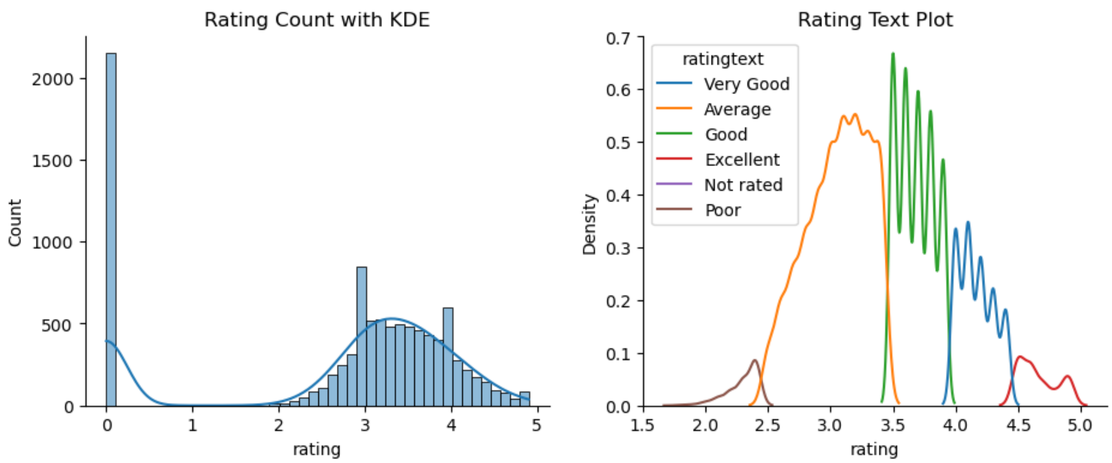
	city	totalrestaurants	percent
89	New Delhi	5473	57.3
50	Gurgaon	1118	11.7
90	Noida	1080	11.3
43	Faridabad	251	2.6
48	Ghaziabad	25	0.3
2	Ahmedabad	21	0.2
5	Amritsar	21	0.2
17	Bhubaneshwar	21	0.2
51	Guwahati	21	0.2
70	Lucknow	21	0.2

[22]:
```
plt.figure(figsize=(12,8))
graph = sns.barplot(top_cities, x='city', y='percent', palette='Spectral')

# annotate graph
for bar in graph.patches:
    graph.annotate(format(bar.get_height(), '.1f'),
                   (bar.get_x() + bar.get_width()/2,
                    bar.get_height()), ha='center',
                   va='center', size=15, xytext=(0,8), textcoords='offset␣
 ↪points'
                  )

plt.title('% Top 10 Cities with the most Restaurants')
plt.show()
```



3.0.3 Ratings Distribution

[23]:
```
fig, axes=plt.subplots(1,2,figsize=(11,4), sharey=False)
sns.histplot(df, x='rating', kde=True, palette='Spectral', ax=axes[0])
axes[0].set_title('Rating Count with KDE')
sns.kdeplot(df, x='rating', hue='ratingtext', ax=axes[1])
axes[1].set_title('Rating Text Plot')

sns.despine(right=True, top=True)
```



- Over 2000 ratings are 0, indicating no rating recorded
- Most valid ratings are between values 3 and 4
- 'Avearge' and 'Good' dominate 'textrating'
- 'Poor' and 'Excellent' appear almost equal in volume

3.0.4 Largest Franchises

[24]:
```
franchise = df.groupby(['country', 'restaurantname'],␣
    ↪as_index=False)['restaurantid'].count()
franchise.rename(columns={'restaurantid':'restcount'}, inplace=True)
```

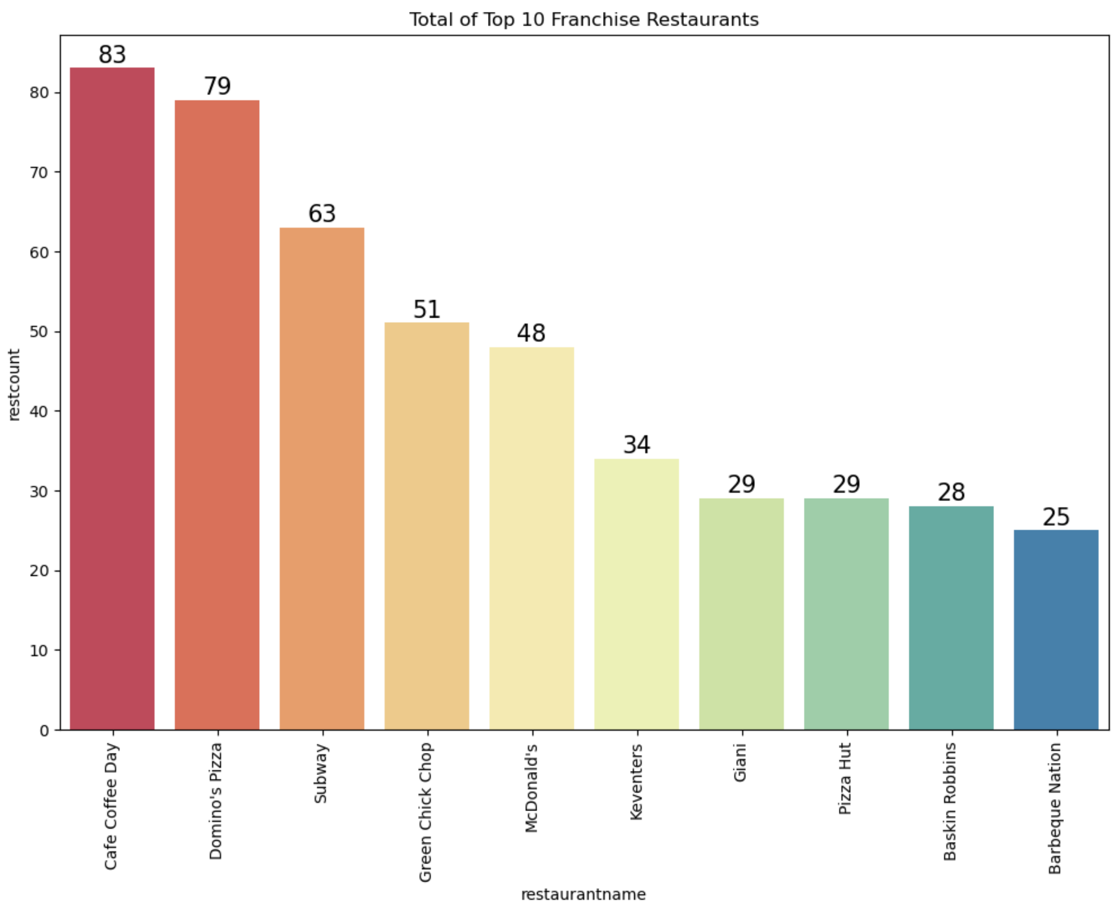
[25]:
```
# select top 10 largest franchises
top_franchise = franchise.nlargest(10, ['restcount'])
top_franchise
```

[25]:

	country	restaurantname	restcount
1061	India	Cafe Coffee Day	83
1975	India	Domino's Pizza	79
5523	India	Subway	63
2486	India	Green Chick Chop	51
3689	India	McDonald's	48
3169	India	Keventers	34
2408	India	Giani	29
4480	India	Pizza Hut	29
705	India	Baskin Robbins	28
690	India	Barbeque Nation	25

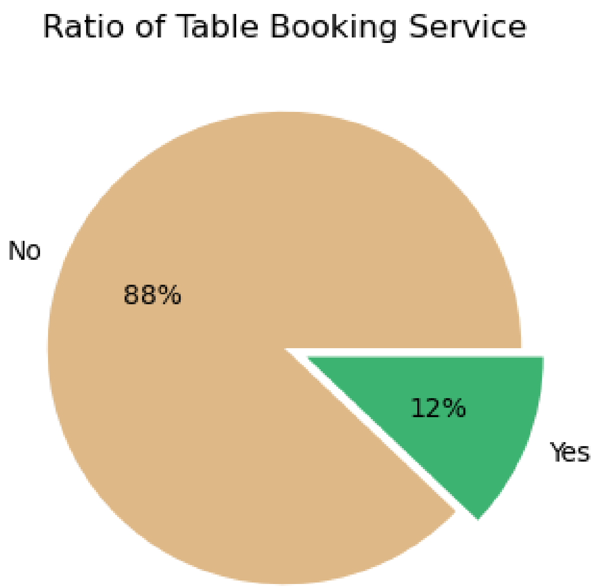
[26]:
```
# barplot
plt.figure(figsize=(12, 8))
```

```python
plots = sns.barplot(top_franchise, x='restaurantname', y='restcount',
    palette='Spectral')

# annotate bars
for bar in plots.patches:
    plots.annotate(format(bar.get_height(), '.0f'),
                   (bar.get_x() + bar.get_width() / 2,
                    bar.get_height()), ha='center', va='center',
                   size=15, xytext=(0, 8),
                   textcoords='offset points')

plt.xticks(rotation=90)
plt.title('Total of Top 10 Franchise Restaurants')
plt.show()
```



3.0.5 Ratio of Table Booking Service

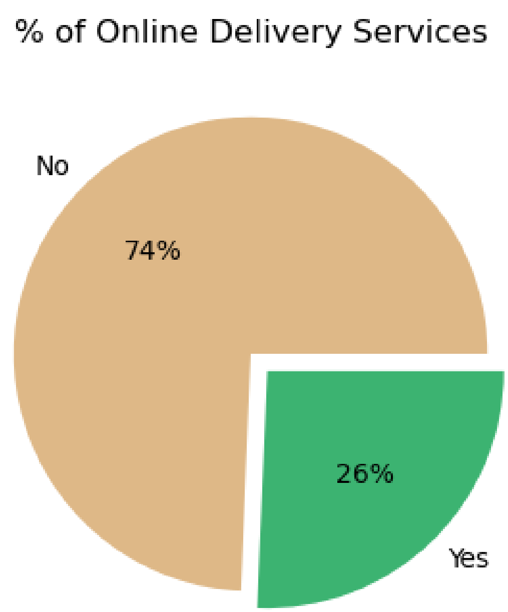
[27]:
```
plt.figure(figsize=(4,4))
plt.pie(x=df['tablebooking'].value_counts(), labels=df['tablebooking'].
 ↪value_counts().index,
       autopct='%.0f%%', explode=[0,0.1], colors=['burlywood',␣
 ↪'mediumseagreen'])
plt.title('Ratio of Table Booking Service')
plt.show()
```



- The ratio of table booking services is approximately 9:1
- Majority of resturants do not offer booking services

3.0.6 % of Online Delivery Service

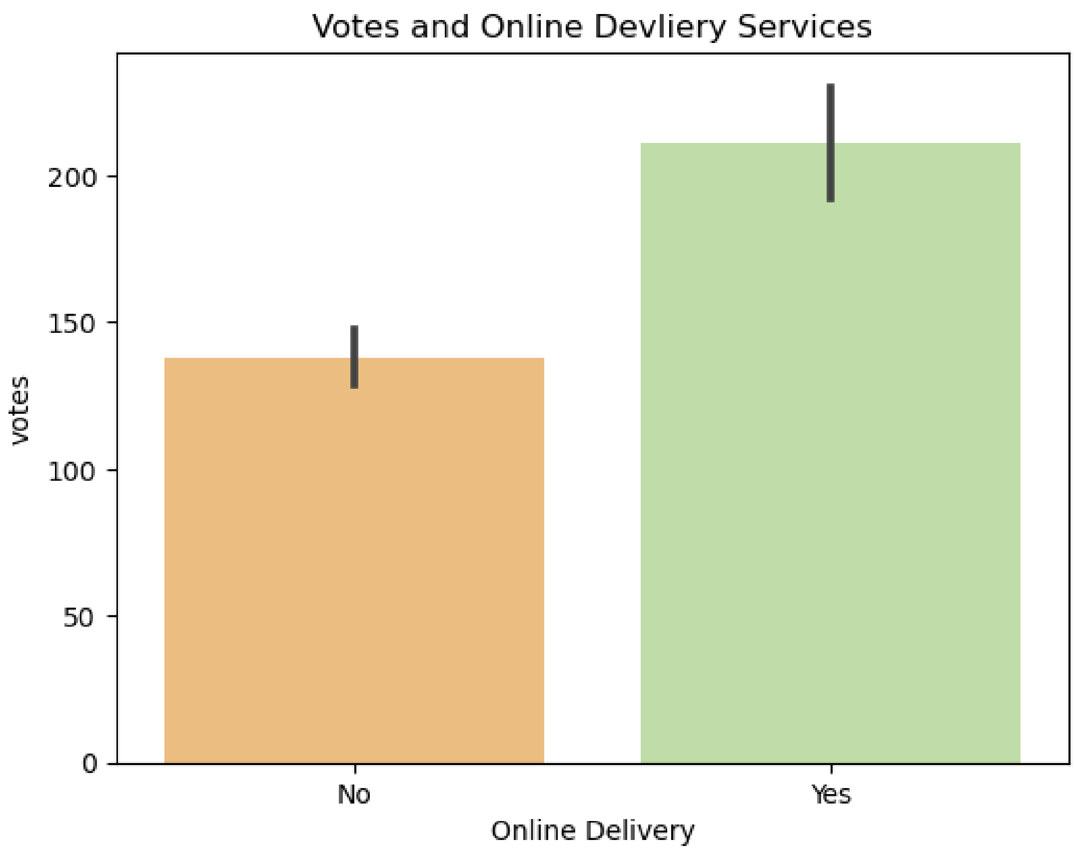
[28]:
```
plt.figure(figsize=(4,4))
plt.pie(x=df['onlinedelivery'].value_counts(), labels=df['onlinedelivery'].
 ↪value_counts().index ,
       autopct='%.0f%%', explode=[0,0.1], colors=['burlywood',␣
 ↪'mediumseagreen'])
plt.title('% of Online Delivery Services')
plt.show()
```



- Almost 75% of resturants don't offer online delivery services
- Most restaurants do not provide delivery services

3.0.7 Votes vs Online Delivery

[29]:
```
sns.barplot(df, x='onlinedelivery', y='votes', ci=95, palette='Spectral')
plt.title('Votes and Online Devliery Services')
plt.xlabel('Online Delivery')
plt.show()
```



- Higher volume of votes are seen for 'Yes' delivery services

3.1 Top Cuisines

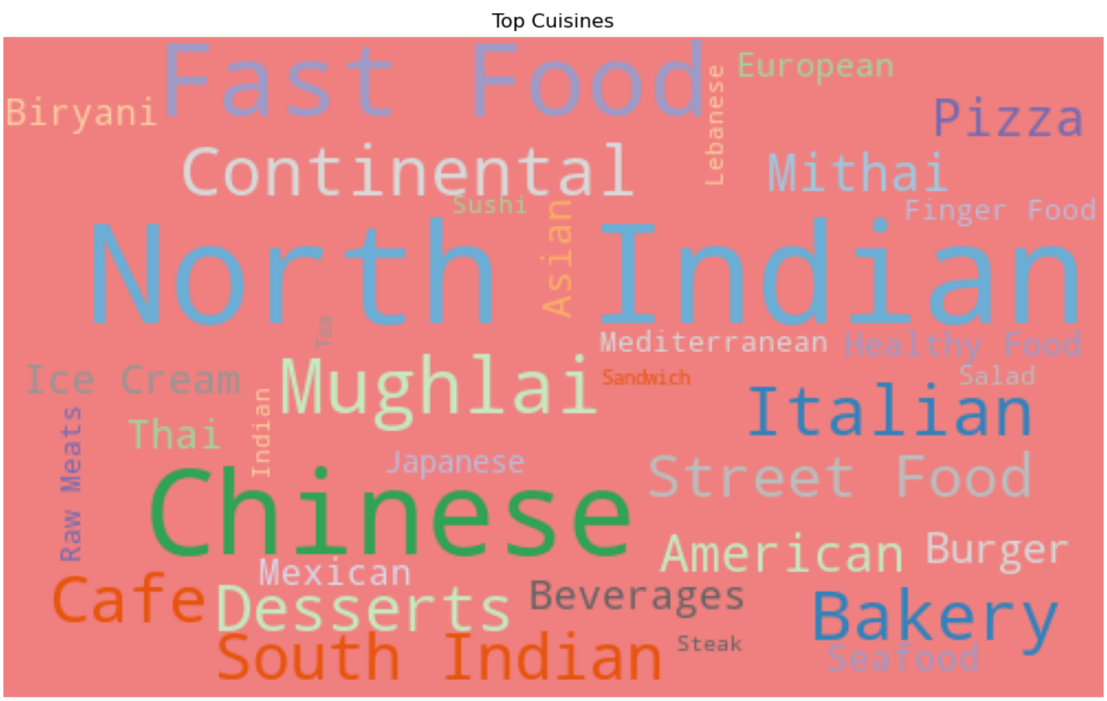
[30]:
```
# extract cuisines from string
l = []
for i in df.cuisines.str.split(', '):
    l.extend(i)
food = pd.Series([i.strip() for i in l])

# list of food value counts
food.value_counts()
```

[30]:
```
North Indian      3969
Chinese           2735
Fast Food         1986
Mughlai            995
Italian            764
                  …
Peranakan            1
```

```
BÌ_rek               1
DÌ_ner               1
Fish and Chips       1
Bubble Tea           1
Length: 145, dtype: int64
```

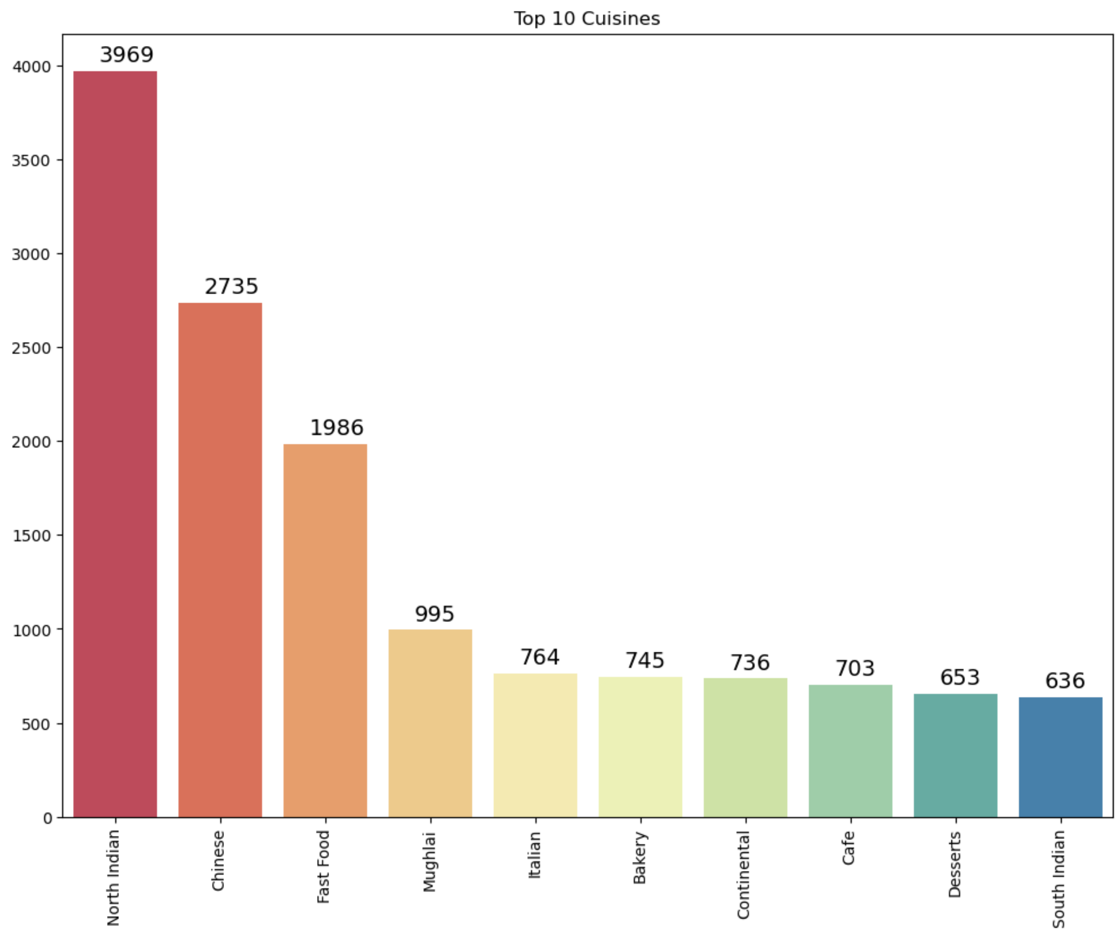
[31]:

```python
from wordcloud import WordCloud, STOPWORDS
stopwords = set(STOPWORDS)

wordcloud = (WordCloud(width=500, height=300, random_state=1, background_color='lightcoral',
                       colormap='tab20c', stopwords=stopwords).generate_from_frequencies(food.value_counts().head(35)))
fig = plt.figure(1,figsize=(12, 10))
plt.imshow(wordcloud)
plt.title('Top Cuisines')
plt.axis('off')
plt.show()
```



3.1.1 Top 10 Cuisines served in Restaurants

[32]:
```
plt.figure(figsize=(12,9))
sns.barplot(x = food.value_counts()[:10].index, y = food.value_counts()[:10],
    palette='Spectral' )

for i in range(10):
    plt.annotate(food.value_counts()[i], xy = (i-0.15,food.
    value_counts()[i]+50),
                 fontsize = 14)

plt.xticks(rotation=90)
plt.title('Top 10 Cuisines')
plt.show()
```



3.2 Total Cuisines served by Restaurant

[33]:
```
# create new column with cuisines count
df['cui_count'] = df.cuisines.apply(lambda x: len(x.split(', ')))
```

3.2.1 Maximum Cuisines

[34]:
```
# select top 5 largest counts
maxfood = df.nlargest(5, ['cui_count'])
maxfood[['restaurantname', 'city', 'rating', 'averagecost', 'currency',␣
↪'cui_count']]
```

[34]:
```
          restaurantname       city  rating  averagecost           currency  \
939                R' ADDA     Mumbai     4.0         1200  Indian Rupees(Rs.)
1200           Mumbai Vibe     Mumbai     3.8         1000  Indian Rupees(Rs.)
2716           Bikanervala    Gurgaon     3.4          600  Indian Rupees(Rs.)
3204   Indian Summer Cafe       Patna     3.4          600  Indian Rupees(Rs.)
3290           Bikanervala  New Delhi     3.5          550  Indian Rupees(Rs.)

      cui_count
939           8
1200          8
2716          8
3204          8
3290          8
```

- The maximum count of cuisines served in a resturant is 8

3.2.2 Minimum Cuisines

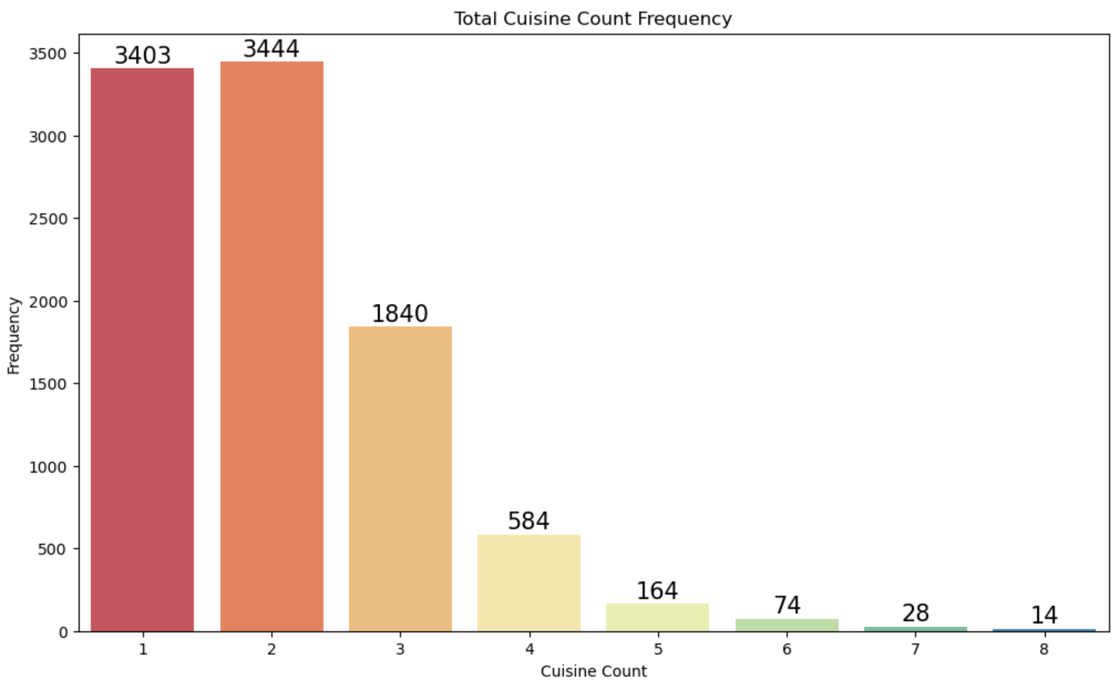
[35]:
```
# select top smallest counts
minfood = df.nsmallest(5, ['cui_count'])
minfood[['restaurantname', 'city', 'rating', 'averagecost', 'currency',␣
↪'cui_count']]
```

[35]:
```
                         restaurantname       city  rating  averagecost  \
0     Orient Express - Taj Palace Hotel  New Delhi     4.0         8000
2                  Bukhara - ITC Maurya  New Delhi     4.4         6500
8   House of Ming - The Taj Mahal Hotel  New Delhi     4.0         5500
10                Wildfire - Crowne Plaza    Gurgaon     3.7         5000
12                        Masala Library  New Delhi     4.9         5000

              currency  cui_count
0   Indian Rupees(Rs.)          1
2   Indian Rupees(Rs.)          1
8   Indian Rupees(Rs.)          1
10  Indian Rupees(Rs.)          1
12  Indian Rupees(Rs.)          1
```

- The minimum amount of cuisines served is 1

3.2.3 Frequency of Cuisine Counts

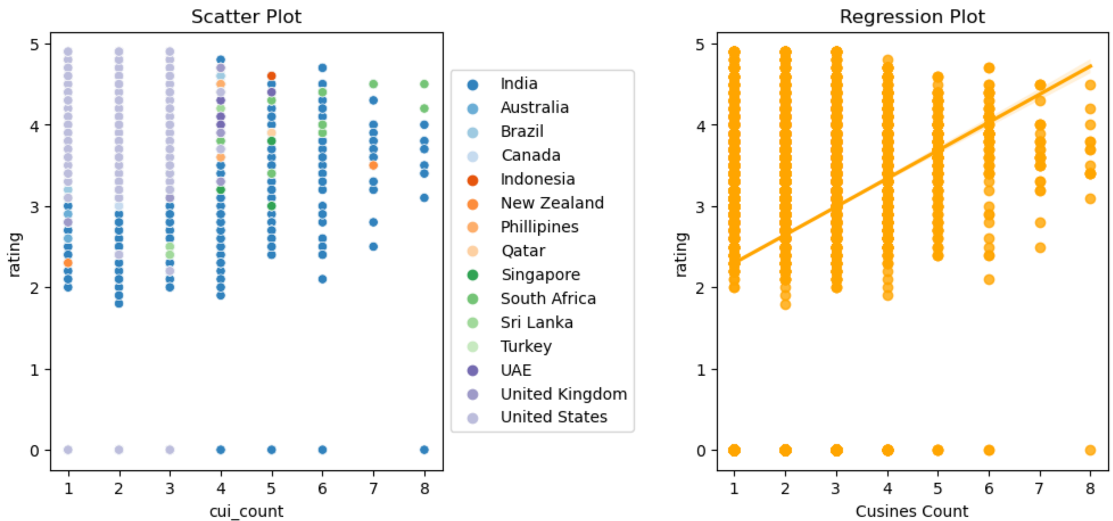
[36]:
```
plt.figure(figsize=(12,7))
plotting = sns.countplot(df, x='cui_count', palette='Spectral')
for bar in plotting.patches:
    plotting.annotate(format(bar.get_height(), '.0f'),
                      (bar.get_x() + bar.get_width() / 2,
                       bar.get_height()), ha='center', va='center',
                      size=15, xytext=(0, 8),
                      textcoords='offset points')

plt.title('Total Cuisine Count Frequency')
plt.xlabel('Cuisine Count')
plt.ylabel('Frequency')
plt.show()
```



3.3 Relationship of Ratings vs No. of Cuisines

[37]:
```
fig, axes = plt.subplots(1,2,figsize=(12,5))
plt.subplots_adjust(hspace = 0.5 , wspace = 0.7)
sns.scatterplot(df, x= 'cui_count', y= 'rating', hue='country',
                 ax = axes[0], palette = 'tab20c')
plt.xlabel('Cuisines Count')
```

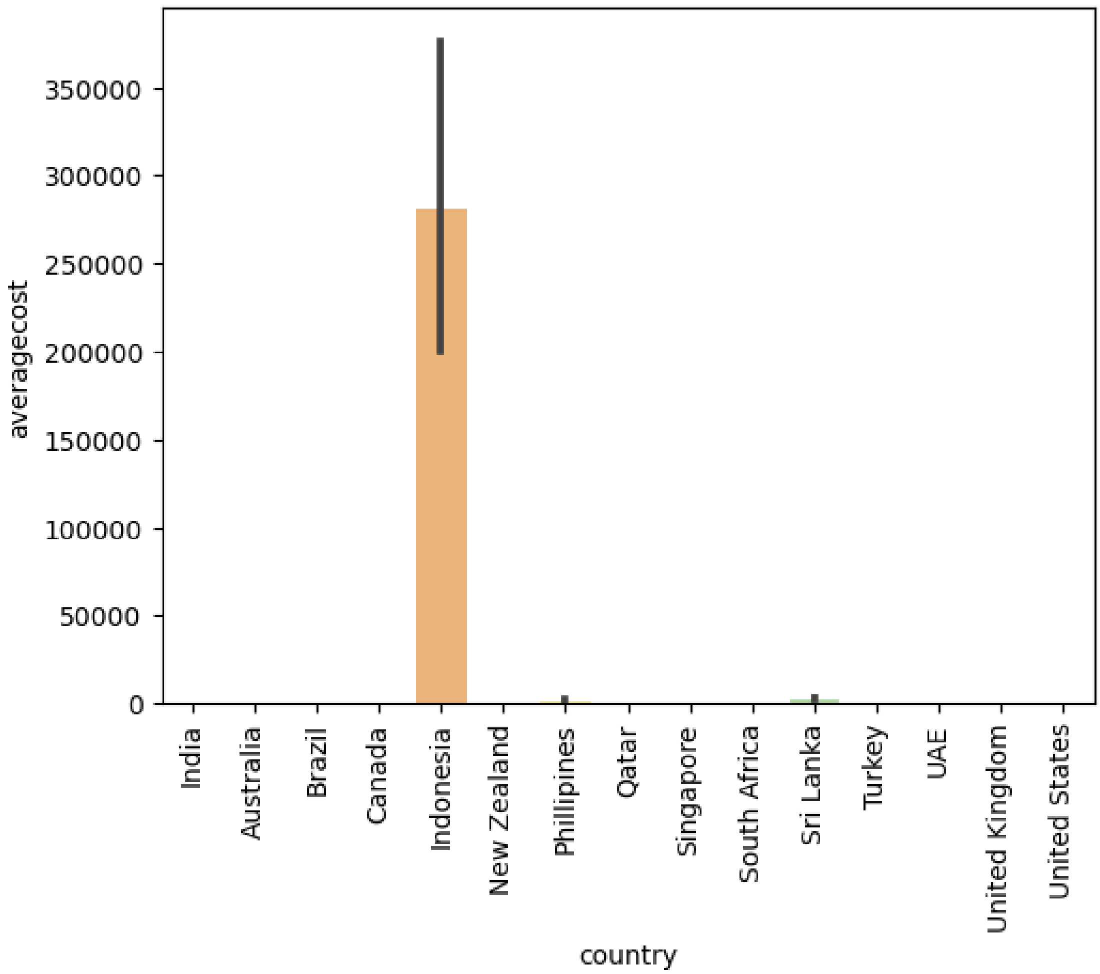
```
axes[0].legend(loc='center left', bbox_to_anchor=(1, 0.5))
axes[0].set_title('Scatter Plot')


sns.regplot(df, x= 'cui_count', y= 'rating', color='orange', ax = axes[1],␣
    ↪ci=80)
axes[1].set_title('Regression Plot')
plt.xlabel('Cusines Count')
plt.show()
```



- Restaurarnts serving less cuisines appear to receive higher averageratings than restaurants with more cuisines

3.4 Average Cost by Country

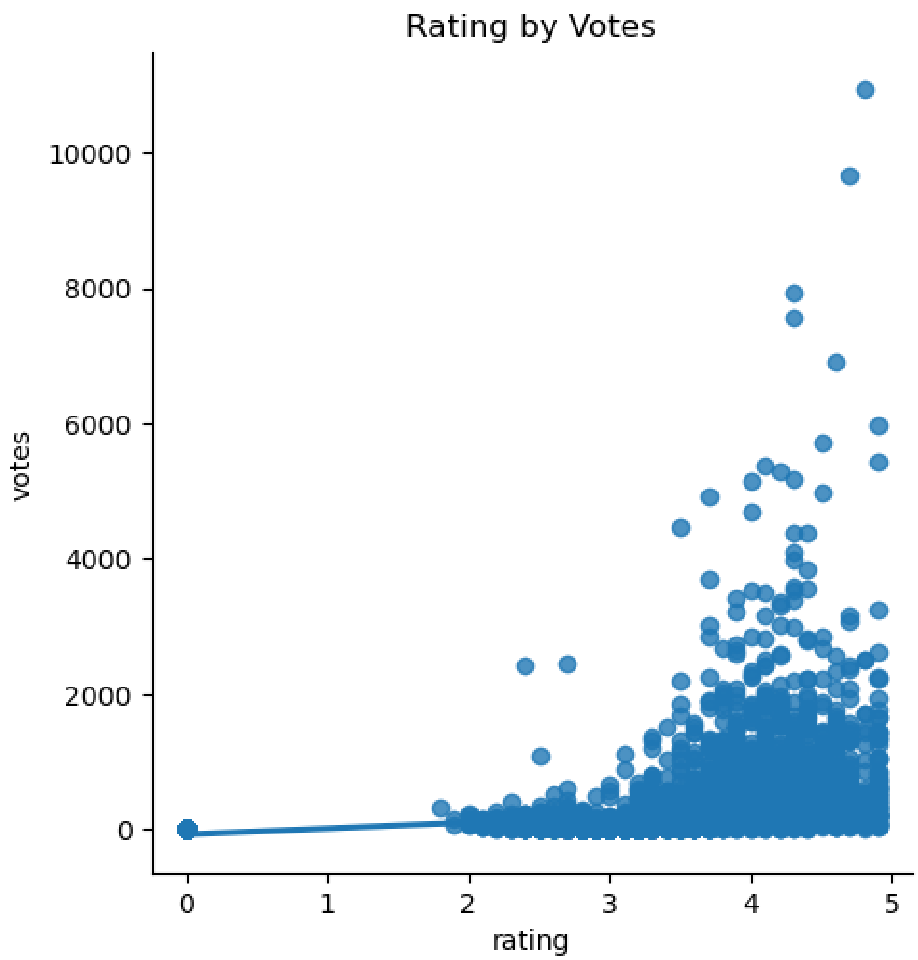
[38]:
```
sns.barplot(x='country',y='averagecost',palette="Spectral",data=df)
plt.xticks(rotation='90')
plt.show()
```



- it's difficult to compare the 'averagecost' amongst countries as each country's currency value and exchange rate is different
- Indonesia is appearing to have the highest 'averagecost' due to it's IDR currency which has many thousands but may not be equal in worth with other currencies

4 Relationships of Ratings

[39]:
```
sns.lmplot(df, x='rating', y='votes')
plt.title('Rating by Votes')
plt.show()
```



- Higher ratings are received with higher volume of votes

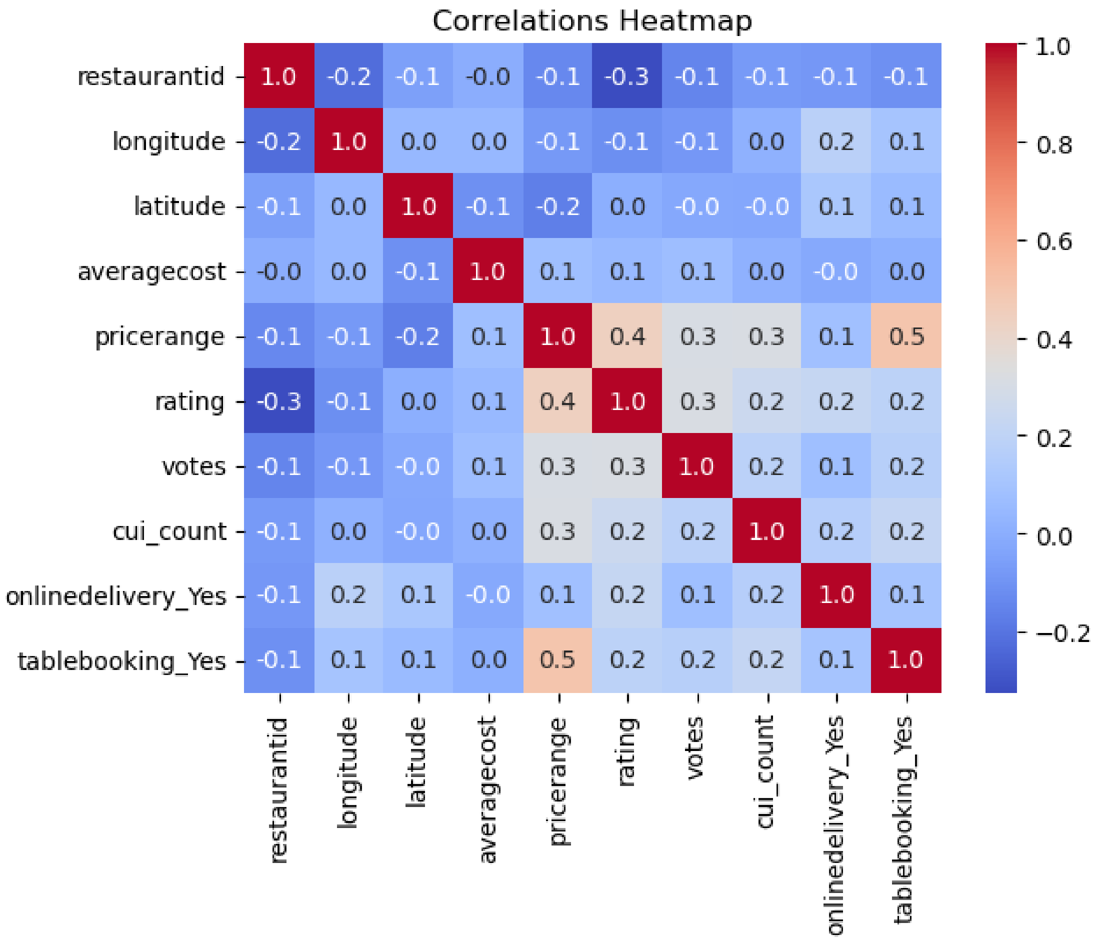
4.0.1 Correlations of Numerical Attributes

[40]:
```
# enumerate 'onlineodelivery' and 'tablebooking'
dummy_df = df.copy()
dummy_df = pd.get_dummies(dummy_df, columns=['onlinedelivery', 'tablebooking'],␣
↪drop_first=True)
dummy_df[['onlinedelivery_Yes', 'tablebooking_Yes']].head()
```

[40]:

	onlinedelivery_Yes	tablebooking_Yes
0	0	1
1	0	0
2	0	0
3	0	1
4	0	1

[41]:
```
sns.heatmap(dummy_df.corr(), annot=True, fmt='.1f', cmap='coolwarm')
plt.title('Correlations Heatmap')
plt.show()
```



- 'rating' and 'votes' have a correlation of 0.3, indicating the number of 'votes' affect the 'rating'
- 'pricerange' and 'rating' have a correlation of 0.4, suggesting a higher rating is recevied for more 'pricerange'
- 'pricerange' and 'tablebooking_yes' have a correlation of 0.5, implying resturants with more 'pricerange' has the 'tablebooking' service

4.0.2 Pairplot of Ratings vs other Attributes

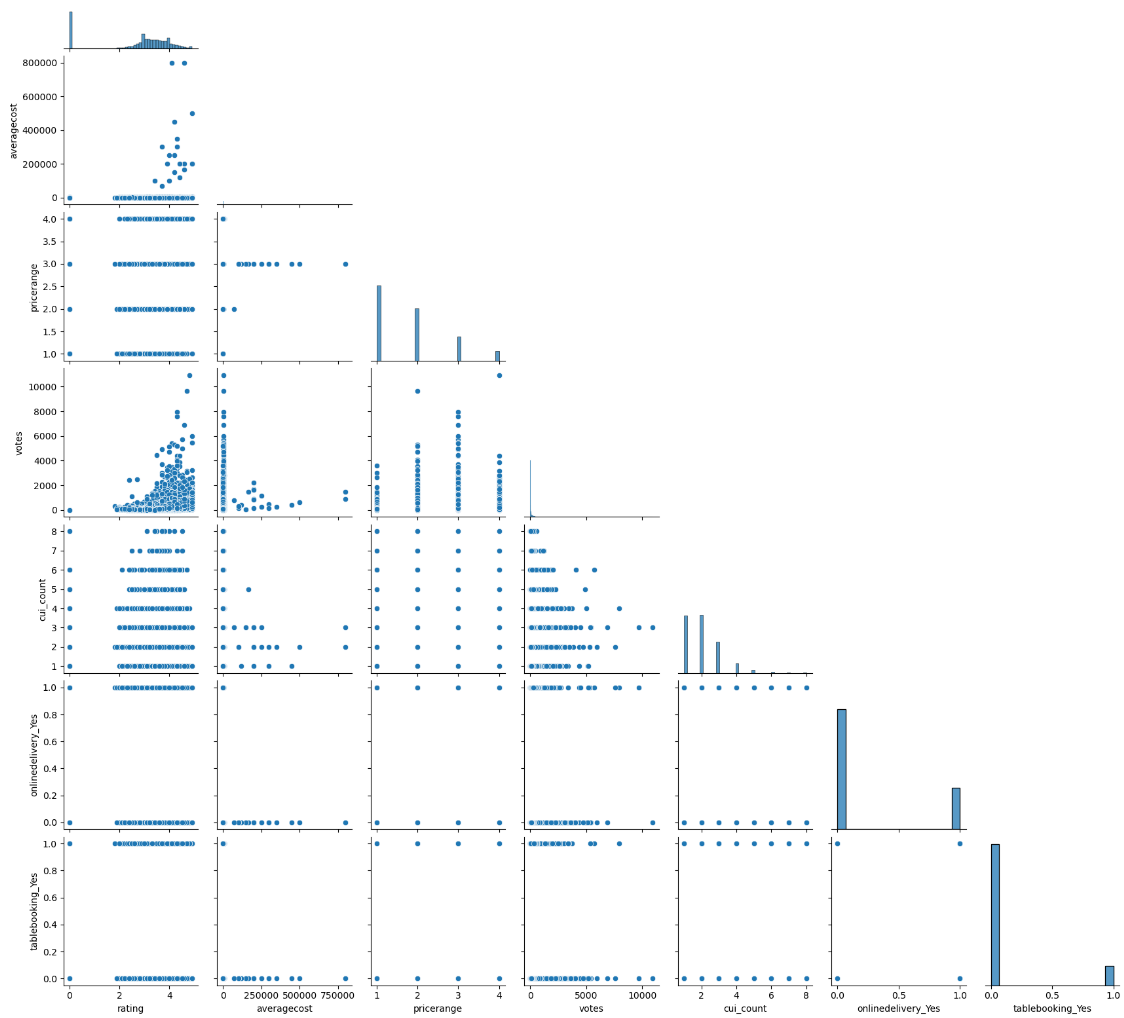
[42]:
```
to_pairplot = dummy_df[['rating', 'averagecost', 'pricerange', 'votes',␣
↪'cui_count', 'country', 'onlinedelivery_Yes', 'tablebooking_Yes']]
```

[43]:
```
plt.style.use('fast')
plt.figure(figsize=(12,6))
sns.pairplot(to_pairplot, palette='Spectral', corner=True)
```

```
plt.suptitle('Ratings vs Numerical Attributes', fontsize='30',
    fontweight='heavy')
plt.show()
```

<Figure size 1200x600 with 0 Axes>

Ratings vs Numerical Attributes



5 Conclusion

- From our EDA, the data presents that ‘rating’ is mostly correlated to ‘pricerange’, at 0.4. The higher the ‘pricerange’, the higher the ‘rating’ score.
- ‘rating’ and ‘votes’ are also correlated by 0.3 which suggests more ‘votes’ contributes to higher ‘rating’ scores.

- There appears to be more ‘rating’ scores for restuarants that have between 1-4 ‘cuisines’ than others
- The ‘rating’ is not clealrly affected by restaurants providing ‘onlinedelivery’ or ’tablebooking; services.

[44]:
```
df.to_excel('checkedcapstone1restaurants.xlsx')
```

5.0.1 Tableau Dashboard

Tableau Dashboard: https://public.tableau.com/views/RestaurantRatings_16749023337480/RestaurantDash?:lan
US&publish=yes&:display_count=n&:origin=viz_share_link