

DA Capston project 1-Identifying and recommending best restaurant

October 1, 2021

```
[1]: #importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statistics as stc
```

```
[2]: data = pd.read_excel('data.xlsx')
data.head()
```

```
[2]: Restaurant ID      Restaurant Name  Country Code  City \
0      7402935                Skye                94  Jakarta
1      7410290      Satoo - Hotel Shangri-La                94  Jakarta
2      7420899                Sushi Masa                94  Jakarta
3      7421967          3 Wise Monkeys                94  Jakarta
4      7422489  Avec Moi Restaurant and Bar                94  Jakarta
```

```
Address \
0  Menara BCA, Lantai 56, Jl. MH. Thamrin, Thamri...
1      Hotel Shangri-La, Jl. Jend. Sudirman
2      Jl. Tuna Raya No. 5, Penjaringan
3      Jl. Suryo No. 26, Senopati, Jakarta
4  Gedung PIC, Jl. Teluk Betung 43, Thamrin, Jakarta
```

```
Locality      Locality Verbose \
0  Grand Indonesia Mall, Thamrin  Grand Indonesia Mall, Thamrin, Jakarta
1      Hotel Shangri-La, Sudirman  Hotel Shangri-La, Sudirman, Jakarta
2      Penjaringan                Penjaringan, Jakarta
3      Senopati                  Senopati, Jakarta
4      Thamrin                  Thamrin, Jakarta
```

```
Longitude  Latitude      Cuisines  Average Cost for two \
0  106.821999 -6.196778      Italian, Continental      800000
1  106.818961 -6.203292  Asian, Indonesian, Western      800000
2  106.800144 -6.101298      Sushi, Japanese          500000
3  106.813400 -6.235241      Japanese                450000
```

4	106.821023	-6.196270	French, Western	350000
---	------------	-----------	-----------------	--------

	Currency	Has Table booking	Has Online delivery	Price range \
0	Indonesian Rupiah(IDR)	No	No	3
1	Indonesian Rupiah(IDR)	No	No	3
2	Indonesian Rupiah(IDR)	No	No	3
3	Indonesian Rupiah(IDR)	No	No	3
4	Indonesian Rupiah(IDR)	No	No	3

	Aggregate rating	Rating color	Rating text	Votes
0	4.1	Green	Very Good	1498
1	4.6	Dark Green	Excellent	873
2	4.9	Dark Green	Excellent	605
3	4.2	Green	Very Good	395
4	4.3	Green	Very Good	243

```
[3]: cc = pd.read_excel('Country-Code.xlsx')
```

```
[4]: merged = pd.merge(data,cc,on='Country Code',how='left')
merged.head()
```

```
[4]:
```

	Restaurant ID	Restaurant Name	Country Code	City \
0	7402935	Skye	94	Jakarta
1	7410290	Satoo - Hotel Shangri-La	94	Jakarta
2	7420899	Sushi Masa	94	Jakarta
3	7421967	3 Wise Monkeys	94	Jakarta
4	7422489	Avec Moi Restaurant and Bar	94	Jakarta

	Address \
0	Menara BCA, Lantai 56, Jl. MH. Thamrin, Thamri...
1	Hotel Shangri-La, Jl. Jend. Sudirman
2	Jl. Tuna Raya No. 5, Penjaringan
3	Jl. Suryo No. 26, Senopati, Jakarta
4	Gedung PIC, Jl. Teluk Betung 43, Thamrin, Jakarta

	Locality	Locality Verbose \
0	Grand Indonesia Mall, Thamrin	Grand Indonesia Mall, Thamrin, Jakarta
1	Hotel Shangri-La, Sudirman	Hotel Shangri-La, Sudirman, Jakarta
2	Penjaringan	Penjaringan, Jakarta
3	Senopati	Senopati, Jakarta
4	Thamrin	Thamrin, Jakarta

	Longitude	Latitude	Cuisines	Average Cost for two \
0	106.821999	-6.196778	Italian, Continental	800000
1	106.818961	-6.203292	Asian, Indonesian, Western	800000
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4	106.821023	-6.196270	French, Western	350000
---	------------	-----------	-----------------	--------

	Currency	Has Table booking	Has Online delivery	Price range \
0	Indonesian Rupiah(IDR)	No	No	3
1	Indonesian Rupiah(IDR)	No	No	3
2	Indonesian Rupiah(IDR)	No	No	3
3	Indonesian Rupiah(IDR)	No	No	3
4	Indonesian Rupiah(IDR)	No	No	3

	Aggregate rating	Rating color	Rating text	Votes	Country
0	4.1	Green	Very Good	1498	Indonesia
1	4.6	Dark Green	Excellent	873	Indonesia
2	4.9	Dark Green	Excellent	605	Indonesia
3	4.2	Green	Very Good	395	Indonesia
4	4.3	Green	Very Good	243	Indonesia

```
[5]: merged.info()
```

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

```
[6]: merged.isna().sum()
      #merged.isnull().sum() #total number of null entries per column
```

```
[6]: Restaurant ID      0
      Restaurant Name    1
      Country Code      0
      City              0
      Address           0
      Locality          0
      Locality Verbose  0
      Longitude         0
      Latitude          0
      Cuisines          9
      Average Cost for two 0
      Currency          0
      Has Table booking  0
      Has Online delivery 0
      Price range       0
      Aggregate rating   0
      Rating color      0
      Rating text       0
      Votes             0
      Country           0
      dtype: int64
```

```
[7]: #Since the restaurant name is missing, we dropped the record and reset the
      ↪ index.
      merged.dropna(axis=0,subset=['Restaurant Name'],inplace=True)
```

```
[8]: merged[merged['Cuisines'].isnull()]
```

```
[8]:      Restaurant ID      Restaurant Name  Country Code  \
9083      17374552      Corkscrew Cafe      216
9086      17501439      Dovetail      216
9094      17059060      Hillstone      216
9406      17284158      Jimmie's Hot Dogs      216
9494      17142698      Leonard's Bakery      216
9504      17616465      Tybee Island Social Club      216
9533      17284105      Cookie Shoppe      216
9535      17284211      Pearly's Famous Country Cookng      216
9539      17606621      HI Lite Bar & Lounge      216

      City      Address  \
9083      Gainesville      51 W Main St, Dahlonge, GA 30533
9086      Macon      543 Cherry St, Macon, GA 31201
9094      Orlando      215 South Orlando Avenue, Winter Park, FL 32789
9406      Albany      204 S Jackson St, Albany, GA 31701
```

9494	Rest of Hawaii	933 Kapahulu Ave, Honolulu, HI 96816
9504	Savannah	1311 Butler Ave, Tybee Island, GA 31328
9533	Albany	115 N Jackson St, Albany, GA 31701
9535	Albany	814 N Slappey Blvd, Albany, GA 31701
9539	Miller	109 N Broadway Ave, Miller, SD 57362

	Locality	Locality Verbose	Longitude	Latitude	Cuisines \
9083	Dahlonge	Dahlonge, Gainesville	-83.985800	34.531800	NaN
9086	Macon	Macon, Macon	-83.627979	32.836410	NaN
9094	Winter Park	Winter Park, Orlando	-81.365260	28.596682	NaN
9406	Albany	Albany, Albany	-84.153400	31.575100	NaN
9494	Kaimuki	Kaimuki, Rest of Hawaii	-157.813432	21.284586	NaN
9504	Tybee Island	Tybee Island, Savannah	-80.848297	31.995810	NaN
9533	Albany	Albany, Albany	-84.154000	31.577200	NaN
9535	Albany	Albany, Albany	-84.175900	31.588200	NaN
9539	Miller	Miller, Miller	-98.989100	44.515800	NaN

	Average Cost for two	Currency	Has Table booking	Has Online delivery \
9083	40	Dollar(\$)	No	No
9086	40	Dollar(\$)	No	No
9094	40	Dollar(\$)	No	No
9406	10	Dollar(\$)	No	No
9494	10	Dollar(\$)	No	No
9504	10	Dollar(\$)	No	No
9533	0	Dollar(\$)	No	No
9535	0	Dollar(\$)	No	No
9539	0	Dollar(\$)	No	No

	Price range	Aggregate rating	Rating color	Rating text	Votes \
9083	3	3.9	Yellow	Good	209
9086	3	3.8	Yellow	Good	102
9094	3	4.4	Green	Very Good	1158
9406	1	3.9	Yellow	Good	160
9494	1	4.7	Dark Green	Excellent	707
9504	1	3.9	Yellow	Good	309
9533	1	3.4	Orange	Average	34
9535	1	3.4	Orange	Average	36
9539	1	3.4	Orange	Average	11

	Country
9083	United States
9086	United States
9094	United States
9406	United States
9494	United States
9504	United States
9533	United States

```
9535 United States
9539 United States
```

```
[9]: #Since there were only 9 records without cuisines, we have replace the null
      ↪ values with Others.
merged['Cuisines'].fillna('Others',inplace=True)
```

```
[10]: #duplicate data finding
duplicateRowsDF = merged[merged.duplicated()]
print("Duplicate Rows except first occurrence based on all columns are :")
print(duplicateRowsDF)
```

Duplicate Rows except first occurrence based on all columns are :

Empty DataFrame

Columns: [Restaurant ID, Restaurant Name, Country Code, City, Address, Locality, Locality Verbose, Longitude, Latitude, Cuisines, Average Cost for two, Currency, Has Table booking, Has Online delivery, Price range, Aggregate rating, Rating color, Rating text, Votes, Country]

Index: []

1 EDA-1

Explore the geographical distribution of the restaurants

Finding out the cities with maximum / minimum number of restaurants

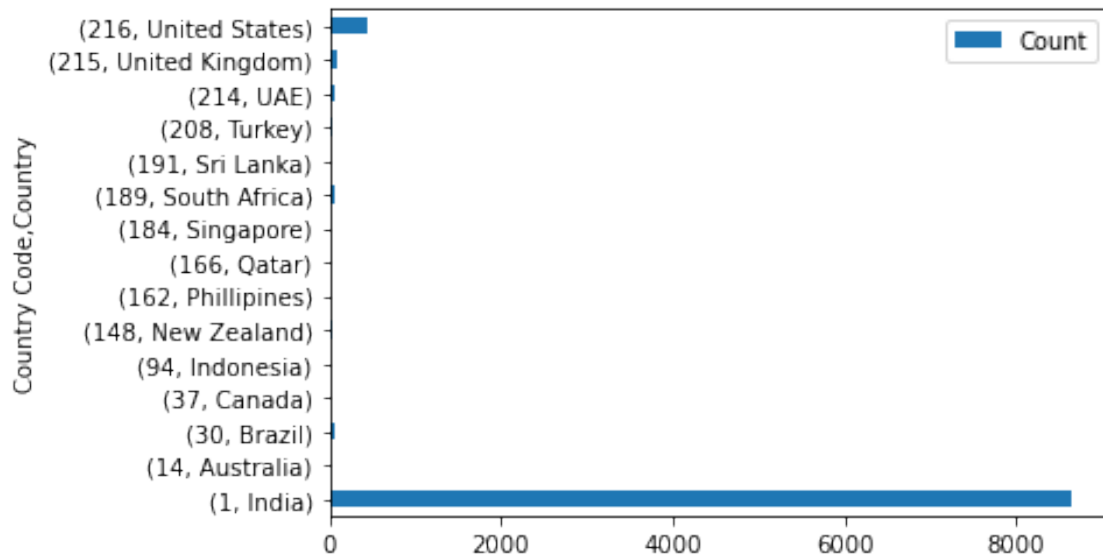
```
[11]: country_distri = merged.groupby(['Country Code','Country']).agg( Count =
      ↪ ('Restaurant ID','count'))
country_distri.sort_values(by='Count',ascending=False)
```

```
[11]:
```

	Country Code	Country	Count
1		India	8651
216		United States	434
215		United Kingdom	80
30		Brazil	60
189		South Africa	60
214		UAE	60
148		New Zealand	40
208		Turkey	34
14		Australia	24
162		Phillipines	22
94		Indonesia	21
166		Qatar	20
184		Singapore	20
191		Sri Lanka	20
37		Canada	4

```
[12]: country_distri.plot(kind='barh')
```

```
[12]: <AxesSubplot:ylabel='Country Code,Country'>
```



```
[13]: city_dist = merged.groupby(['Country','City']).agg(Count = ('Restaurant_ID', 'count'))
city_dist.describe()
```

```
[13]:
```

	Count
count	141.000000
mean	67.730496
std	476.723952
min	1.000000
25%	1.000000
50%	20.000000
75%	20.000000
max	5473.000000

```
[14]: city_dist.sort_values(by='Count',ascending=False)
# New Delhi has maximum number of restaurant
```

```
[14]:
```

Country	City	Count
India	New Delhi	5473
	Gurgaon	1118
	Noida	1080
	Faridabad	251
	Ghaziabad	25

```

...
Panchkula 1
Australia Balingup 1
Indonesia Bandung 1
Phillipines Quezon City 1
United States Winchester Bay 1

```

[141 rows x 1 columns]

```

[15]: # Minimum number of restaurant in following cities
min_cnt_rest = city_dist[city_dist['Count']==1]
min_cnt_rest.info()
min_cnt_rest

```

```

<class 'pandas.core.frame.DataFrame'>
MultiIndex: 46 entries, ('Australia', 'Armidale') to ('United States',
'Winchester Bay')
Data columns (total 1 columns):
#   Column  Non-Null Count  Dtype
---  -
0   Count    46 non-null       int64
dtypes: int64(1)
memory usage: 1.8+ KB

```

```

[15]:
Country      City      Count
Australia    Armidale    1
              Balingup    1
              Beechworth  1
              Dicky Beach  1
              East Ballina  1
              Flaxton      1
              Forrest      1
              Huskisson   1
              Inverloch   1
              Lakes Entrance 1
              Lorn        1
              Macedon     1
              Mayfield    1
              Middleton Beach 1
              Montville   1
              Palm Cove   1
              Paynesville 1
              Penola      1
              Phillip Island 1
              Tanunda     1
              Trentham East 1

```


	Victor Harbor	1
Canada	Chatham-Kent	1
	Consort	1
	Vineland Station	1
	Yorkton	1
India	Mohali	1
	Panchkula	1
Indonesia	Bandung	1
Phillipines	Quezon City	1
	Tagaytay City	1
South Africa	Randburg	1
United States	Clatskanie	1
	Cochrane	1
	Fernley	1
	Lakeview	1
	Lincoln	1
	Mc Millan	1
	Miller	1
	Monroe	1
	Ojo Caliente	1
	Potrero	1
	Princeton	1
	Vernonia	1
	Weirton	1
	Winchester Bay	1

```
[16]: # Find out the ratio between restaurants that allow table booking vs. those
      ↳ that do not allow table booking
merged1 = merged.copy()
merged1.columns
```

```
[16]: Index(['Restaurant ID', 'Restaurant Name', 'Country Code', 'City', 'Address',
          'Locality', 'Locality Verbose', 'Longitude', 'Latitude', 'Cuisines',
          'Average Cost for two', 'Currency', 'Has Table booking',
          'Has Online delivery', 'Price range', 'Aggregate rating',
          'Rating color', 'Rating text', 'Votes', 'Country'],
          dtype='object')
```

```
[17]: dummy = ['Has Table booking', 'Has Online delivery']
merged1 = pd.get_dummies(merged1, columns=dummy, drop_first=True)
merged1.head()
# 0 indicates 'NO'
# 1 indicates 'YES'
```

```
[17]: Restaurant ID      Restaurant Name  Country Code  City \
0      7402935                Skye                94  Jakarta
1      7410290      Satoo - Hotel Shangri-La                94  Jakarta
```

2	7420899	Sushi Masa	94	Jakarta
3	7421967	3 Wise Monkeys	94	Jakarta
4	7422489	Avec Moi Restaurant and Bar	94	Jakarta

	Address \
0	Menara BCA, Lantai 56, Jl. MH. Thamrin, Thamri...
1	Hotel Shangri-La, Jl. Jend. Sudirman
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	Locality	Locality Verbose \
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1	Hotel Shangri-La, Sudirman	Hotel Shangri-La, Sudirman, Jakarta
2	Penjaringan	Penjaringan, Jakarta
3	Senopati	Senopati, Jakarta
4	Thamrin	Thamrin, Jakarta

	Longitude	Latitude	Cuisines	Average Cost for two \
0	106.821999	-6.196778	Italian, Continental	800000
1	106.818961	-6.203292	Asian, Indonesian, Western	800000
2	106.800144	-6.101298	Sushi, Japanese	500000
3	106.813400	-6.235241	Japanese	450000
4	106.821023	-6.196270	French, Western	350000

	Currency	Price range	Aggregate rating	Rating color \
0	Indonesian Rupiah(IDR)	3	4.1	Green
1	Indonesian Rupiah(IDR)	3	4.6	Dark Green
2	Indonesian Rupiah(IDR)	3	4.9	Dark Green
3	Indonesian Rupiah(IDR)	3	4.2	Green
4	Indonesian Rupiah(IDR)	3	4.3	Green

	Rating text	Votes	Country	Has Table booking_Yes \
0	Very Good	1498	Indonesia	0
1	Excellent	873	Indonesia	0
2	Excellent	605	Indonesia	0
3	Very Good	395	Indonesia	0
4	Very Good	243	Indonesia	0

	Has Online delivery_Yes
0	0
1	0
2	0
3	0
4	0

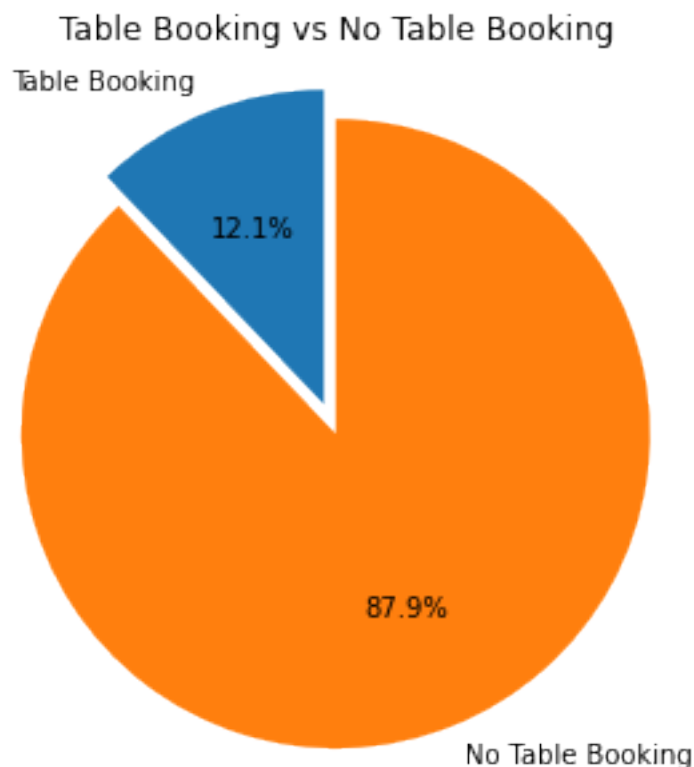
```
[19]: #Ratio between restaurants allowing table booking and those which dont
tbl_book_y = merged1[merged1['Has Table booking_Yes']==1]['Restaurant ID'].
        ↳count()
tbl_book_n = merged1[merged1['Has Table booking_Yes']==0]['Restaurant ID'].
        ↳count()
print('Ratio between restaurants that allow table booking vs. those that do not,
        ↳allow table booking: ',
        round((tbl_book_y/tbl_book_n),2))
```

Ratio between restaurants that allow table booking vs. those that do not allow table booking: 0.14

```
[20]: #Pie chart to show percentage of restaurants which allow table booking and
        ↳those which don't
labels = 'Table Booking', 'No Table Booking'
sizes = [tbl_book_y,tbl_book_n]
explode = (0.1, 0) # only "explode" the 2nd slice (i.e. 'Hogs')

fig1, ax1 = plt.subplots(figsize=(5,5))
ax1.pie(sizes, explode=explode, labels=labels, autopct='%1.1f%%', startangle=90)
ax1.set_title("Table Booking vs No Table Booking")
ax1.axis('equal') # Equal aspect ratio ensures that pie is drawn as a circle.

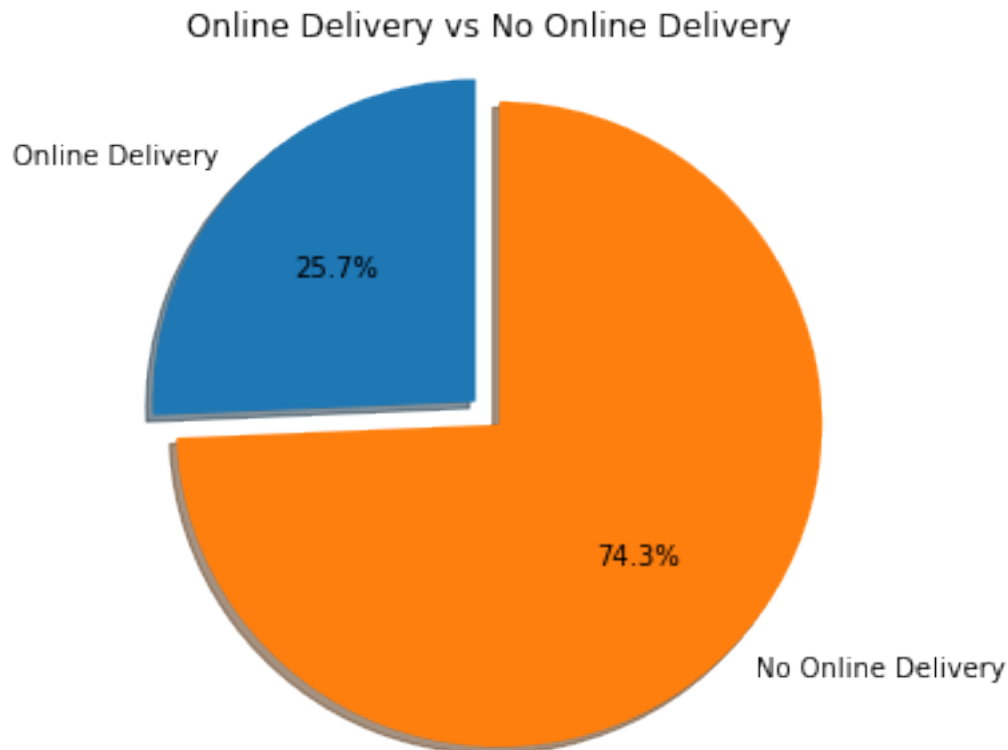
plt.show()
```



```
[22]: # Find out the percentage of restaurants providing online delivery
order_on = merged1[merged1['Has Online delivery_Yes'] == 1]['Restaurant ID'].
        ↪count()
order_off = merged1[merged1['Has Online delivery_Yes'] == 0]['Restaurant ID'].
        ↪count()
print('Percentage of restaurants providing online delivery : {} %'.
        ↪format((round(order_on/len(merged1),3)*100)))
```

Percentage of restaurants providing online delivery : 25.7 %

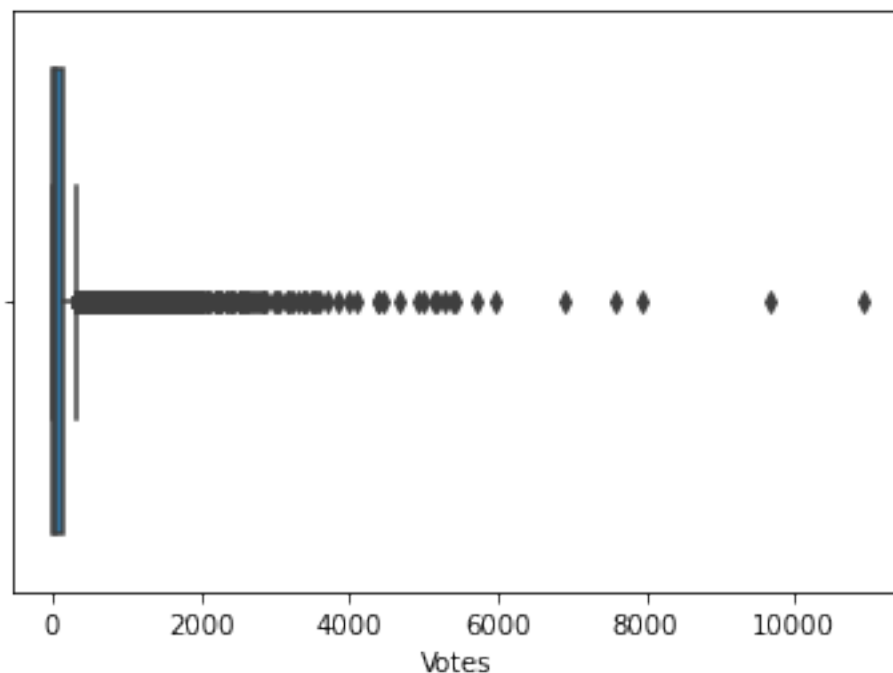
```
[22]: #pie chart to show percentages of restaurants allowing online delivery vs those
        ↪which do not have online delivery
labels = 'Online Delivery','No Online Delivery'
size = [order_on,order_off]
explode = (0.1,0)
fig1,ax1 = plt.subplots(figsize=(5,5))
ax1.pie(size,explode=explode,labels=labels,autopct='%1.
        ↪1f%%',shadow=True,startangle=90)
ax1.set_title("Online Delivery vs No Online Delivery")
ax1.axis('equal')
plt.show()
```



```
[23]: sns.boxplot(merged['Votes'])
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
```

```
[23]: <AxesSubplot:xlabel='Votes'>
```



```
[24]: # Calculate the difference in number of votes for the restaurants that deliver
      ↪ and the restaurants that do not deliver
      # first detect and remove (replace it with mean/closest possible value) outlier
      ↪ for VOTE
import sklearn
import pandas as pd

''' Detection '''
# IQR
Q1 = np.percentile(merged['Votes'], 25,
                    interpolation = 'midpoint')
```

```

Q3 = np.percentile(merged['Votes'], 75,
                    interpolation = 'midpoint')
IQR = Q3 - Q1

print("Old Shape: ", merged.shape)

# Upper bound
upper = np.where(merged['Votes'] >= (Q3+1.5*IQR))
#print("Upper bound:", upper)
#print(np.where(upper))
# Lower bound
lower = np.where(merged['Votes'] <= (Q1-1.5*IQR))

''' Removing the Outliers '''
merged.drop(upper[0], inplace = True)
merged.drop(lower[0], inplace = True)

print("New Shape: ", merged.shape)

```

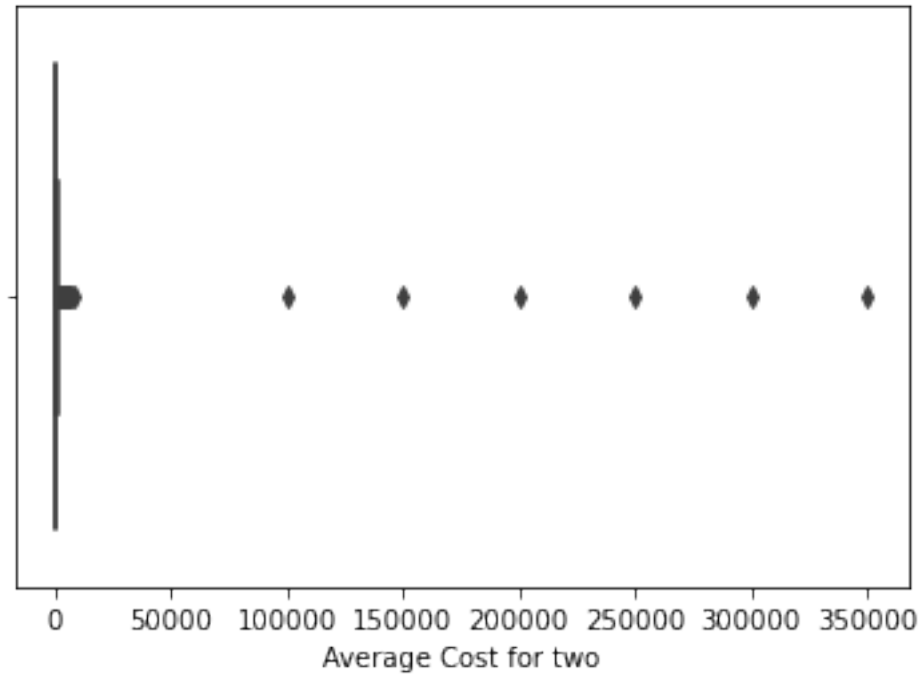
Old Shape: (9550, 20)

New Shape: (8423, 20)

```
[65]: sns.boxplot(merged['Average Cost for two'])
```

C:\Users\HP\anaconda3\lib\site-packages\seaborn_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
warnings.warn(

```
[65]: <AxesSubplot:xlabel='Average Cost for two'>
```



```
[27]: import sklearn
import pandas as pd

''' Detection '''
# IQR
Q1 = np.percentile(merged['Average_Cost_for_two'], 25,
                    interpolation = 'midpoint')

Q3 = np.percentile(merged['Average_Cost_for_two'], 75,
                    interpolation = 'midpoint')
IQR = Q3 - Q1

print("Old Shape: ", merged.shape)

# Upper bound
upper = np.where(merged['Average_Cost_for_two'] >= (Q3+1.5*IQR))
print("Upper bound:", upper)
print(np.where(upper))
# Lower bound
lower = np.where(merged['Average_Cost_for_two'] <= (Q1-1.5*IQR))

''' Removing the Outliers '''
merged.drop(upper[0], inplace = True)
merged.drop(lower[0], inplace = True)
```

```
print("New Shape: ", merged.shape)
```

Old Shape: (8423, 20)

Upper bound: (array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,

13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25,
26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38,
39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51,
52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64,
65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77,
78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90,
91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102, 103,
104, 105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116,
117, 118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129,
130, 131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142,
143, 144, 145, 146, 147, 148, 149, 150, 151, 152, 153, 154, 155,
156, 157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168,
169, 170, 171, 172, 173, 174, 175, 176, 177, 178, 179, 180, 181,
182, 183, 184, 185, 186, 187, 188, 189, 190, 191, 192, 193, 194,
195, 196, 197, 198, 199, 200, 201, 202, 203, 204, 205, 206, 207,
208, 209, 210, 211, 212, 213, 214, 215, 216, 217, 218, 219, 220,
221, 222, 223, 224, 225, 226, 227, 228, 229, 230, 231, 232, 233,
234, 235, 236, 237, 238, 239, 240, 241, 242, 243, 244, 245, 246,
247, 248, 249, 250, 251, 252, 253, 254, 255, 256, 257, 258, 259,
260, 261, 262, 263, 264, 265, 266, 267, 268, 269, 270, 271, 272,
273, 274, 275, 276, 277, 278, 279, 280, 281, 282, 283, 284, 285,
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664, 665, 666, 667, 668, 669, 670, 671, 672, 673, 674, 675, 676,
677], dtype=int64))

```

-----
KeyError                                Traceback (most recent call last)
<ipython-input-27-6da19423259a> in <module>
    21
    22 ''' Removing the Outliers '''
----> 23 merged.drop(upper[0], inplace = True)
    24 merged.drop(lower[0], inplace = True)
    25

~\anaconda3\lib\site-packages\pandas\core\frame.py in drop(self, labels, axis,
↳index, columns, level, inplace, errors)
    4306             weight 1.0      0.8
    4307         """
-> 4308         return super().drop(
    4309             labels=labels,
    4310             axis=axis,

~\anaconda3\lib\site-packages\pandas\core\generic.py in drop(self, labels, axis
↳index, columns, level, inplace, errors)
    4151         for axis, labels in axes.items():
    4152             if labels is not None:
-> 4153                 obj = obj._drop_axis(labels, axis, level=level,
↳errors=errors)
    4154
    4155         if inplace:

~\anaconda3\lib\site-packages\pandas\core\generic.py in _drop_axis(self, labels
↳axis, level, errors)
    4186             new_axis = axis.drop(labels, level=level, errors=errors)
    4187         else:
-> 4188             new_axis = axis.drop(labels, errors=errors)
    4189             result = self.reindex(**{axis_name: new_axis})
    4190

~\anaconda3\lib\site-packages\pandas\core\indexes\base.py in drop(self, labels,
↳errors)
    5589         if mask.any():
    5590             if errors != "ignore":
-> 5591                 raise KeyError(f"{labels[mask]} not found in axis")
    5592             indexer = indexer[~mask]
    5593         return self.delete(indexer)

```

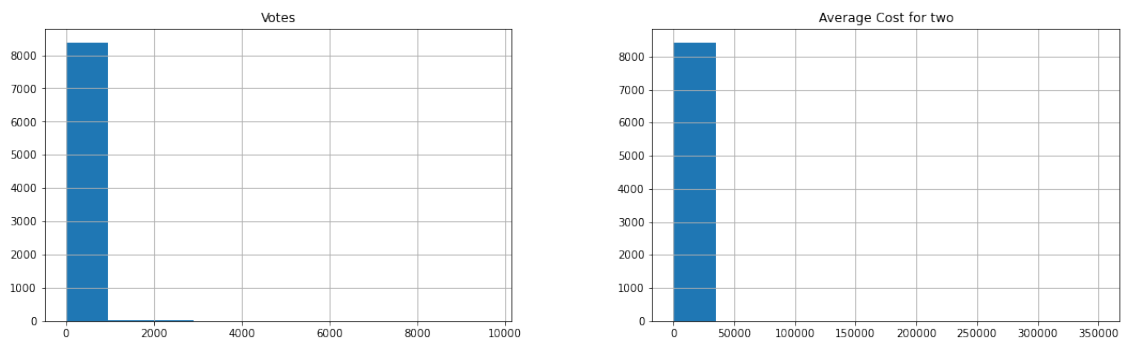
```

KeyError: '[ 0  1  2  3  5  7  9 11 12 13 14 15 17 19 20 23 24
→30\n 31 34 40 43 47 48 52 56 57 60 67 76 85 97 99 104 108 111\n
→112 120 131 135 145 153 154 160 161 165 166 176 177 178 189 197 198 205\n 209
→211 212 213 218 219 220 221 223 224 229 230 231 232 233 237 239 247\n 249 250
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→584 586 589 590 591 592 593 601\n 602 603 608 609 610 611 613 615 623 631 632
→633 634 635 639 643 644 647\n 648 649 651 657 658 663 664 665 666 667 672 674
→not found in axis'

```

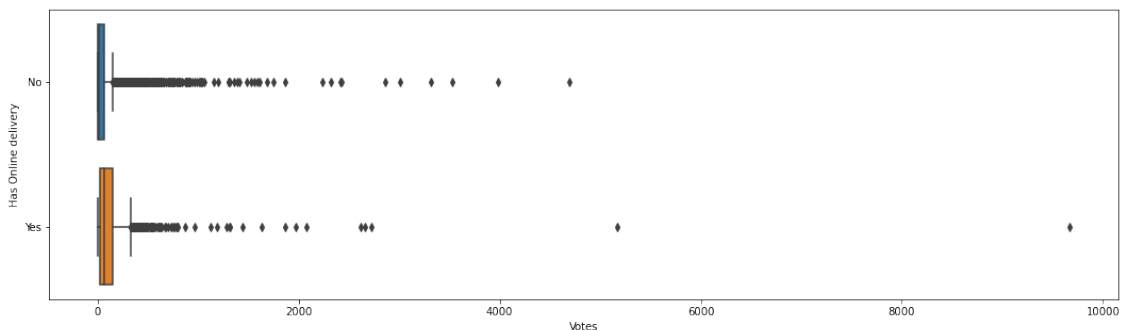
```
[27]: merged.hist(['Votes', 'Average Cost for two'], figsize=(18,5))
```

```
[27]: array([[<AxesSubplot:title={'center':'Votes'}>,
<AxesSubplot:title={'center':'Average Cost for two'}>]],
dtype=object)
```



```
[28]: dimen=(18,5)
fig, ax = plt.subplots(figsize=dimen)
sns.boxplot(x='Votes', y='Has Online delivery', data=merged, ax=ax)
```

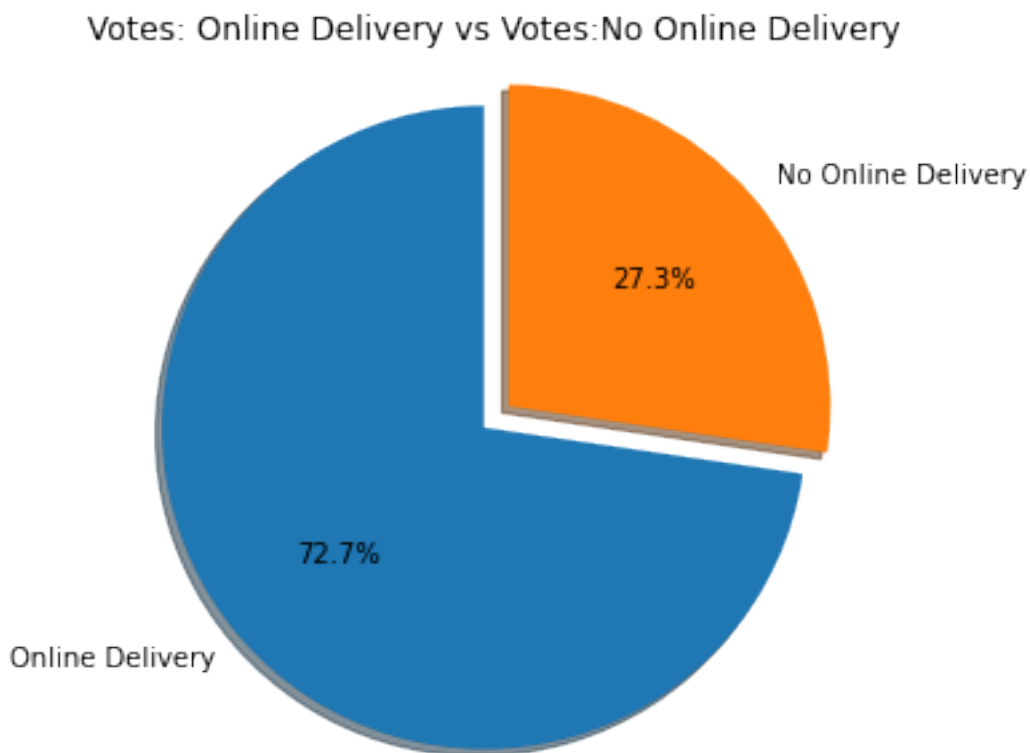
```
[28]: <AxesSubplot:xlabel='Votes', ylabel='Has Online delivery'>
```



```
[29]: rest_deliver = merged1[merged1['Has Table booking_Yes'] == 1]['Votes'].sum()
rest_ndeliver = merged1[merged1['Has Table booking_Yes'] == 0]['Votes'].sum()
print('Difference in number of votes for restaurants that deliver and dont_
    ↳deliver: ',abs((rest_deliver - rest_ndeliver)))
```

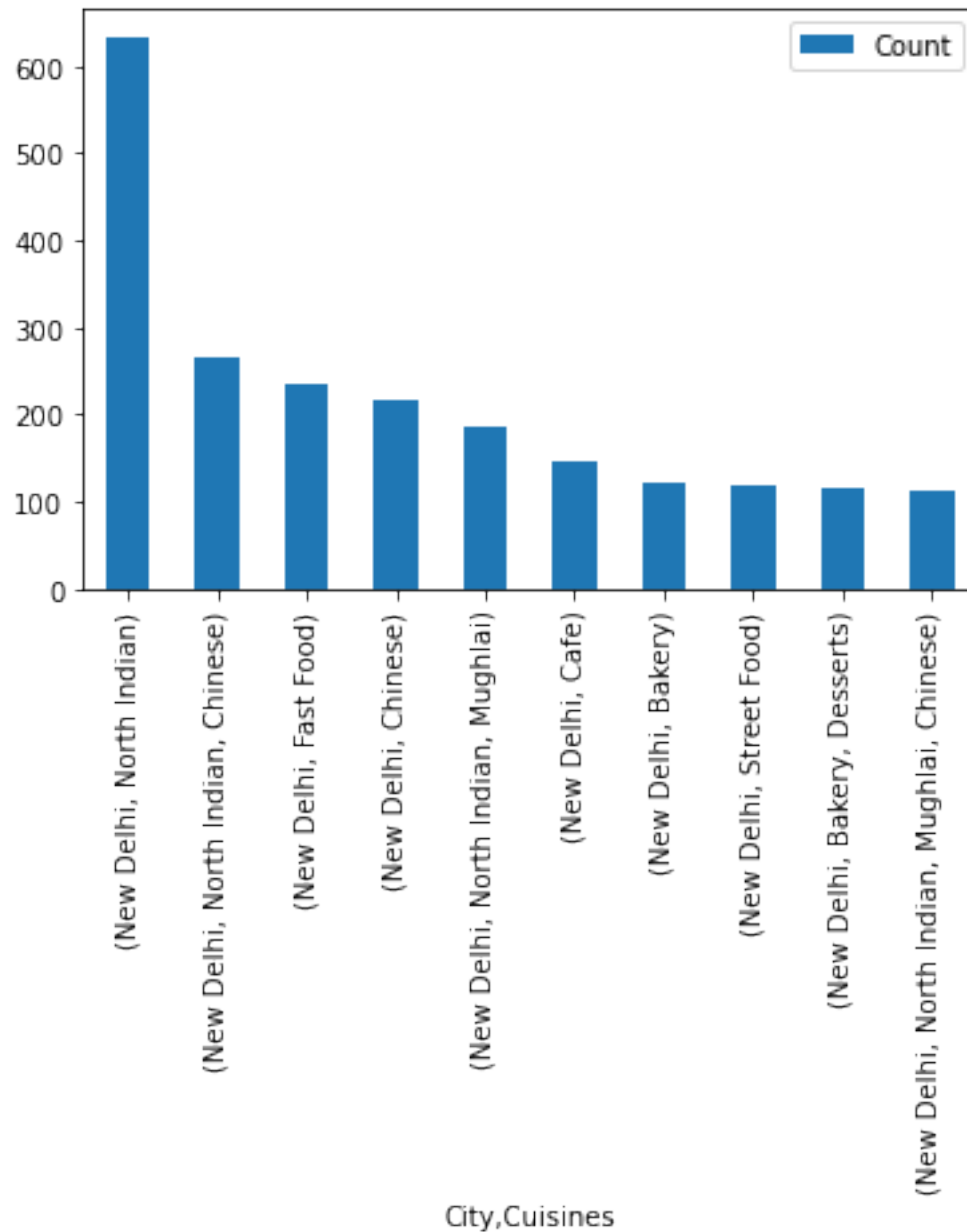
Difference in number of votes for restaurants that deliver and dont deliver:
680082

```
[30]: labels = 'Online Delivery','No Online Delivery'
size = [rest_ndeliver,rest_deliver]
explode = (0,0.1)
fig1,ax1 = plt.subplots(figsize=(5,5))
ax1.pie(size,explode=explode,labels=labels,autopct='%1.
    ↳1f%%',shadow=True,startangle=90)
ax1.set_title("Votes: Online Delivery vs Votes:No Online Delivery")
ax1.axis('equal')
plt.show()
#out of the total votes about 27.3% votes were given to restaurants that dont_
    ↳have online delivery option
#out of the total votes about 72.7% votes were given to restaurants that dont_
    ↳have online delivery option
#This clearly shows that restaurants that have online delivery are more likely_
    ↳to get a vote(feedback)
```



```
[31]: # What are the top 10 cuisines served across cities?
top_10_cuisines = merged.groupby(['City', 'Cuisines']).agg( Count =_
    ↳('Cuisines', 'count'))
df=top_10_cuisines.sort_values(by='Count',ascending=False)
#top_10_cuisines = merged['Cuisines'].value_counts()
#top_10_cuisines.head(10)
#top_10_cuisines.plot(kind='barh')
df.head(10).plot(kind='bar')
```

```
[31]: <AxesSubplot:xlabel='City,Cuisines'>
```



```
[33]: # What is the maximum and minimum number of cuisines that a restaurant serves?
cuis_count = merged.groupby(['Restaurant Name', 'Cuisines']).agg( Count = λ
    ↳ ('Cuisines', 'count'))
cuis_count.sort_values(by='Count', ascending=False)
```

```
[33]:
```

Restaurant Name	Cuisines	Count
Cafe Coffee Day	Cafe	82
Domino's Pizza	Pizza, Fast Food	72

Subway	American, Fast Food, Salad, Healthy Food	58
Green Chick Chop	Raw Meats, North Indian, Fast Food	46
McDonald's	Fast Food, Burger	42
...
Frozen Fantasy	Desserts, Beverages	1
Frozen Factory	Desserts, Ice Cream	1
	Desserts, Beverages	1
Frozen Adda	Ice Cream, Desserts	1
İstanbul Sofrası	Kebab, Izgara	1

[7044 rows x 1 columns]

```
[34]: # Also, which is the most served cuisine across the restaurant for each city?
cuis_count_ct = merged.groupby(['City', 'Cuisines']).agg(Count =
    ↳ ('Cuisines', 'count'))
cuis_count_ct.sort_values(by='Count', ascending=False)
```

```
[34]:
```

City	Cuisines	Count
New Delhi	North Indian	634
	North Indian, Chinese	267
	Fast Food	236
	Chinese	217
	North Indian, Mughlai	187
...
Inner City	Tapas	1
Indore	North Indian, Mughlai, Seafood	1
	North Indian, Continental, Mexican, Italian	1
	North Indian, Chinese, South Indian	1
İstanbul	World Cuisine, Patisserie, Cafe	1

[2358 rows x 1 columns]

```
[35]: merged.columns
```

```
[35]: Index(['Restaurant ID', 'Restaurant Name', 'Country Code', 'City', 'Address',
        'Locality', 'Locality Verbose', 'Longitude', 'Latitude', 'Cuisines',
        'Average Cost for two', 'Currency', 'Has Table booking',
        'Has Online delivery', 'Price range', 'Aggregate rating',
        'Rating color', 'Rating text', 'Votes', 'Country'],
        dtype='object')
```

```
[36]: cuisines = merged['Cuisines'].apply(lambda x: pd.Series(x.split(',')))
cuisines
```

```
[36]:
```

	0	1	2	3	4 \
4	French	Western	NaN	NaN	NaN

6	Indonesian		NaN	NaN	NaN	NaN
8	Western		Asian	Cafe	NaN	NaN
10	Korean		NaN	NaN	NaN	NaN
16	Cafe	Coffee and Tea		Western	NaN	NaN
...
9546	Chinese	North Indian		Fast Food	NaN	NaN
9547	Indian	Chinese		Continental	NaN	NaN
9548	Cafe	Continental		Desserts	Ice Cream	Italian
9549	Street Food		NaN	NaN	NaN	NaN
9550	Chinese	North Indian		NaN	NaN	NaN

	5	6	7
4	NaN	NaN	NaN
6	NaN	NaN	NaN
8	NaN	NaN	NaN
10	NaN	NaN	NaN
16	NaN	NaN	NaN
...
9546	NaN	NaN	NaN
9547	NaN	NaN	NaN
9548	Beverages	NaN	NaN
9549	NaN	NaN	NaN
9550	NaN	NaN	NaN

[8423 rows x 8 columns]

```
[37]: cuisines.columns =_
      → ['Cuisine_1', 'Cuisine_2', 'Cuisine_3', 'Cuisine_4', 'Cuisine_5', 'Cuisine_6', 'Cuisine_7', 'Cuisine_8']
      cuisines.tail()
```

[37]:	Cuisine_1	Cuisine_2	Cuisine_3	Cuisine_4	Cuisine_5	\
9546	Chinese	North Indian	Fast Food	NaN	NaN	
9547	Indian	Chinese	Continental	NaN	NaN	
9548	Cafe	Continental	Desserts	Ice Cream	Italian	
9549	Street Food		NaN	NaN	NaN	
9550	Chinese	North Indian	NaN	NaN	NaN	

	Cuisine_6	Cuisine_7	Cuisine_8
9546	NaN	NaN	NaN
9547	NaN	NaN	NaN
9548	Beverages	NaN	NaN
9549	NaN	NaN	NaN
9550	NaN	NaN	NaN

```
[38]: df_cuisines = pd.concat([merged, cuisines], axis=1)
      df_cuisines.head()
```

```

[38]:
Restaurant ID      Restaurant Name      Country Code      City \
4      7422489      Avec Moi Restaurant and Bar      94      Jakarta
6      18386856      Onokabe      94      Tangerang
8      18391256      MONKS      94      Jakarta
10     18425821      OJJU      94      Jakarta
16     18400530      Noah's Barn Coffeenery      94      Bandung

Address \
4      Gedung PIC, Jl. Teluk Betung 43, Thamrin, Jakarta
6      Alam Sutera Town Center, Jl. Alam Utama, Serpo...
8      Komplek Graha Boulevard Timur, Summarecon Kela...
10     Gandaria City, Lantai Upper Ground, Jl. Sultan...
16     Jl. Dayang Sumbi No. 2, Dago, Bandung

Locality \
4      Thamrin
6      Alam Sutera Town Center, Serpong Utara
8      Kelapa Gading
10     Gandaria City Mall, Gandaria
16     Dago

Locality Verbose      Longitude      Latitude \
4      Thamrin, Jakarta      106.821023      -6.196270
6      Alam Sutera Town Center, Serpong Utara, Tangerang      106.652688      -6.241792
8      Kelapa Gading, Jakarta      106.911335      -6.163948
10     Gandaria City Mall, Gandaria, Jakarta      106.783162      -6.244221
16     Dago, Bandung      107.612790      -6.887058

Cuisines ... Votes      Country      Cuisine_1 \
4      French, Western ...      243      Indonesia      French
6      Indonesian ...      155      Indonesia      Indonesian
8      Western, Asian, Cafe ...      259      Indonesia      Western
10     Korean ...      137      Indonesia      Korean
16     Cafe, Coffee and Tea, Western ...      22      Indonesia      Cafe

Cuisine_2      Cuisine_3      Cuisine_4      Cuisine_5      Cuisine_6      Cuisine_7 \
4      Western      NaN      NaN      NaN      NaN      NaN
6      NaN      NaN      NaN      NaN      NaN      NaN
8      Asian      Cafe      NaN      NaN      NaN      NaN
10     NaN      NaN      NaN      NaN      NaN      NaN
16     Coffee and Tea      Western      NaN      NaN      NaN      NaN

Cuisine_8
4      NaN
6      NaN
8      NaN
10     NaN

```

16 NaN

[5 rows x 28 columns]

```
[40]: cuisine_loc = pd.DataFrame(df_cuisines[['Country','City','Locality_
↳Verbose','Cuisine_1','Cuisine_2','Cuisine_3',
↳
↳'Cuisine_4','Cuisine_5','Cuisine_6','Cuisine_7','Cuisine_8']])
```

```
[41]: cuisine_loc_stack=pd.DataFrame(cuisine_loc.stack()) #stacking the columns
cuisine_loc.head()
```

```
[41]:
```

	Country	City	Locality Verbose \
4	Indonesia	Jakarta	Thamrin, Jakarta
6	Indonesia	Tangerang	Alam Sutera Town Center, Serpong Utara, Tangerang
8	Indonesia	Jakarta	Kelapa Gading, Jakarta
10	Indonesia	Jakarta	Gandaria City Mall, Gandaria, Jakarta
16	Indonesia	Bandung	Dago, Bandung

	Cuisine_1	Cuisine_2	Cuisine_3	Cuisine_4	Cuisine_5	Cuisine_6 \
4	French	Western	NaN	NaN	NaN	NaN
6	Indonesian	NaN	NaN	NaN	NaN	NaN
8	Western	Asian	Cafe	NaN	NaN	NaN
10	Korean	NaN	NaN	NaN	NaN	NaN
16	Cafe	Coffee and Tea	Western	NaN	NaN	NaN

	Cuisine_7	Cuisine_8
4	NaN	NaN
6	NaN	NaN
8	NaN	NaN
10	NaN	NaN
16	NaN	NaN

```
[42]: cuisine_loc_stack.head(10)
```

```
[42]:
```

	0
4 Country	Indonesia
City	Jakarta
Locality Verbose	Thamrin, Jakarta
Cuisine_1	French
Cuisine_2	Western
6 Country	Indonesia
City	Tangerang
Locality Verbose	Alam Sutera Town Center, Serpong Utara, Tangerang
Cuisine_1	Indonesian
8 Country	Indonesia

```
[43]: keys = [c for c in cuisine_loc if c.startswith('Cuisine')]
a=pd.melt(cuisine_loc, id_vars='Locality Verbose', value_vars=keys,
↳value_name='Cuisines')
#melting the stack into one row
a
```

```
[43]:
```

	Locality Verbose	variable \
0	Thamrin, Jakarta	Cuisine_1
1	Alam Sutera Town Center, Serpong Utara, Tangerang	Cuisine_1
2	Kelapa Gading, Jakarta	Cuisine_1
3	Gandaria City Mall, Gandaria, Jakarta	Cuisine_1
4	Dago, Bandung	Cuisine_1
...
67379	Jakhan, Dehradun	Cuisine_8
67380	Mall Road, Kanpur	Cuisine_8
67381	Parade, Kanpur	Cuisine_8
67382	Dashaswmedh Road, Varanasi	Cuisine_8
67383	Sigra, Varanasi	Cuisine_8

	Cuisines
0	French
1	Indonesian
2	Western
3	Korean
4	Cafe
...	...
67379	NaN
67380	NaN
67381	NaN
67382	NaN
67383	NaN

[67384 rows x 3 columns]

```
[44]: max_rate=pd.DataFrame(a.groupby(by=['Locality Verbose','variable','Cuisines']).
↳size().reset_index())
#find the highest restuarant in the city
max_rate
del max_rate['variable']
max_rate.columns=['Locality Verbose','Cuisines','Count']
max_rate
```

```
[44]:
```

	Locality Verbose	Cuisines	Count
0	ILD Trade Centre Mall, Sohna Road, Gurgaon	Cafe	1
1	ILD Trade Centre Mall, Sohna Road, Gurgaon	North Indian	1
2	ILD Trade Centre Mall, Sohna Road, Gurgaon	Beverages	1
3	ILD Trade Centre Mall, Sohna Road, Gurgaon	Mughlai	1

4	A Hotel, Gurdev Nagar, Ludhiana	North Indian	1
...
9001	İİmitkİ_y, Ankara	Kebab	1
9002	İİmitkİ_y, Ankara	Desserts	1
9003	İİmitkİ_y, Ankara	Turkish Pizza	1
9004	İàukurambar, Ankara	Patisserie	1
9005	İàukurambar, Ankara	Coffee and Tea	1

[9006 rows x 3 columns]

```
[45]: #find the highest restuarant in the city
loc=max_rate.sort_values('Count', ascending=False).groupby(by=['Locality_
↳Verbose'],as_index=False).first()
loc
```

	Locality Verbose	Cuisines	Count
0	ILD Trade Centre Mall, Sohna Road, Gurgaon	Cafe	1
1	A Hotel, Gurdev Nagar, Ludhiana	Fast Food	1
2	ARSS Mall, Paschim Vihar, New Delhi	Fast Food	1
3	Aaya Nagar, New Delhi	Cuisine Varies	1
4	Abu Dhabi Mall, Tourist Club Area (Al Zahiyah...	American	1
...
1042	Zoo Tiniali, Guwahati	Chinese	2
1043	ibis New Delhi, Aerocity, New Delhi	Ice Cream	1
1044	İÀguas Claras, Brasİ_lia	Grill	1
1045	İİmitkİ_y, Ankara	Turkish Pizza	1
1046	İàukurambar, Ankara	Patisserie	1

[1047 rows x 3 columns]

```
[47]: rating_res=loc.merge(merged1,left_on='Locality Verbose',right_on='Locality_
↳Verbose',how='inner')
#inner join to merge the two dataframe
rating_res
```

	Locality Verbose	Cuisines_x	Count	\
0	ILD Trade Centre Mall, Sohna Road, Gurgaon	Cafe	1	
1	ILD Trade Centre Mall, Sohna Road, Gurgaon	Cafe	1	
2	A Hotel, Gurdev Nagar, Ludhiana	Fast Food	1	
3	ARSS Mall, Paschim Vihar, New Delhi	Fast Food	1	
4	Aaya Nagar, New Delhi	Cuisine Varies	1	
...
9272	İÀguas Claras, Brasİ_lia	Grill	1	
9273	İÀguas Claras, Brasİ_lia	Grill	1	
9274	İÀguas Claras, Brasİ_lia	Grill	1	
9275	İİmitkİ_y, Ankara	Turkish Pizza	1	
9276	İàukurambar, Ankara	Patisserie	1	

	Restaurant ID	Restaurant Name	Country Code	City \
0	18237941	Pind Balluchi	1	Gurgaon
1	18396451	K Lab	1	Gurgaon
2	15239	Basant Restaurant	1	Ludhiana
3	310281	Haldiram's	1	New Delhi
4	18287358	Food Cloud	1	New Delhi
...
9272	6601515	Rovereto	30	Brasília
9273	6601602	Taco Pep	30	Brasília
9274	6601361	Buena Carne	30	Brasília
9275	6000921	Dönner	208	Ankara
9276	6003426	Liva	208	Ankara

	Address \
0	112/112-A, 1st Floor, ILD Trade Centre, Near S...
1	Shop GF-18, ILD Trade Centre, Sector 47, Near ...
2	Urban Estate, Main Market, Phase 1, Dugri, Lud...
3	1st Floor, ARSS Mall, Opposite Jwalaheri, Pasc...
4	Aaya Nagar, New Delhi
...	...
9272	Rua 13 Norte, Lote 4, Águas Claras, Brasília
9273	Vila Malls, Avenida das Castanheiras, Lote 106...
9274	Avenida Araucárias, 1325, Loja 19, Águas Cla...
9275	İmitkî Mahallesi, 2432. Cadde (8. Cadde), N...
9276	İaukurambar Mahallesi, Muhsin Yazıcıoğlu Ca...

	Locality	Longitude	...	\
0	ILD Trade Centre Mall, Sohna Road	77.039220	...	
1	ILD Trade Centre Mall, Sohna Road	77.039310	...	
2	A Hotel, Gurdev Nagar	75.842739	...	
3	ARSS Mall, Paschim Vihar	77.101544	...	
4	Aaya Nagar	0.000000	...	
...	
9272	Águas Claras	-48.019000	...	
9273	Águas Claras	-48.016667	...	
9274	Águas Claras	-48.019092	...	
9275	İmitkî	32.701775	...	
9276	İaukurambar	32.809146	...	

	Average Cost for two	Currency	Price range	Aggregate rating \
0	800 Indian Rupees(Rs.)		2	2.7
1	350 Indian Rupees(Rs.)		1	3.4
2	800 Indian Rupees(Rs.)		2	3.6
3	500 Indian Rupees(Rs.)		2	3.1
4	500 Indian Rupees(Rs.)		2	0.0
...

9272	100	Brazilian Real(R\$)	4	3.1
9273	100	Brazilian Real(R\$)	4	4.3
9274	60	Brazilian Real(R\$)	3	3.6
9275	70	Turkish Lira(TL)	3	4.2
9276	50	Turkish Lira(TL)	2	3.4

	Rating color	Rating text	Votes	Country	Has Table booking_Yes	\
0	Orange	Average	80	India		1
1	Orange	Average	16	India		0
2	Yellow	Good	93	India		0
3	Orange	Average	117	India		0
4	White	Not rated	2	India		0
...	
9272	Orange	Average	9	Brazil		0
9273	Green	Very Good	29	Brazil		0
9274	Yellow	Good	9	Brazil		0
9275	Green	Very Good	152	Turkey		0
9276	Orange	Average	115	Turkey		0

	Has Online delivery_Yes
0	1
1	0
2	0
3	0
4	0
...	...
9272	0
9273	0
9274	0
9275	0
9276	0

[9277 rows x 22 columns]

```
[48]: df=pd.DataFrame(rating_res[['Country','City','Locality_
↳Verbose','Cuisines_x','Count']])
#making a dataframe of rating restaurant
df
```

[48]:	Country	City	Locality Verbose	\
0	India	Gurgaon	ILD Trade Centre Mall, Sohna Road, Gurgaon	
1	India	Gurgaon	ILD Trade Centre Mall, Sohna Road, Gurgaon	
2	India	Ludhiana	A Hotel, Gurdev Nagar, Ludhiana	
3	India	New Delhi	ARSS Mall, Paschim Vihar, New Delhi	
4	India	New Delhi	Aaya Nagar, New Delhi	
...	
9272	Brazil	Brasília	Águas Claras, Brasília	

9273	Brazil	Brasília	Águas Claras, Brasília
9274	Brazil	Brasília	Águas Claras, Brasília
9275	Turkey	Ankara	İmitköy, Ankara
9276	Turkey	Ankara	Çukurambar, Ankara

	Cuisines_x	Count
0	Cafe	1
1	Cafe	1
2	Fast Food	1
3	Fast Food	1
4	Cuisine Varies	1
...
9272	Grill	1
9273	Grill	1
9274	Grill	1
9275	Turkish Pizza	1
9276	Patisserie	1

[9277 rows x 5 columns]

```
[49]: country=rating_res.sort_values('Count', ascending=False).
      ↳groupby(by=['Country'],as_index=False).first()
      #grouping the data by country code
      country
```

[49]:	Country	Locality Verbose \
0	Australia	Tanunda, Tanunda
1	Brazil	Leme, Rio de Janeiro
2	Canada	Yorkton, Yorkton
3	India	Mahipalpur, New Delhi
4	Indonesia	Thamrin, Jakarta
5	New Zealand	Te Aro, Wellington City
6	Phillipines	UP Town Center, Diliman, Quezon City, Quezon City
7	Qatar	The Westin Doha Hotel & Spa, Fereej Bin Mahmoud...
8	Singapore	Telok Ayer Street, Outram, Singapore
9	South Africa	CBD, Cape Town
10	Sri Lanka	Cinnamon Gardens, Colombo 07, Colombo
11	Turkey	Gazi Osman Paşı, Ankara
12	UAE	Abu Shagara, Sharjah
13	United Kingdom	Old Town, Edinburgh
14	United States	Dubuque, Dubuque

	Cuisines_x	Count	Restaurant ID \
0	Australian	1	16608059
1	Brazilian	2	7302637
2	Asian	1	16668008
3	North Indian	45	305189

4	Western	1	7422489
5	Cafe	5	7101483
6	Mexican	1	6318433
7	Thai	1	18261203
8	Finger Food	1	18483446
9	Cafe	2	6400421
10	Cafe	2	5800891
11	World Cuisine	2	6000409
12	Indian	2	5602751
13	Cafe	2	7600097
14	American	9	17342771

	Restaurant Name	Country Code	City \
0	1918 Bistro & Grill	14	Tanunda
1	Leme Light	30	Rio de Janeiro
2	Arigato Sushi	37	Yorkton
3	Yadav Sweets	1	New Delhi
4	Avec Moi Restaurant and Bar	94	Jakarta
5	Burger Liquor	148	Wellington City
6	Silantro Fil-Mex	162	Quezon City
7	Sabai Thai - The Westin Doha Hotel & Spa	166	Doha
8	Bitters & Love	184	Singapore
9	Truth Coffee	189	Cape Town
10	The Paddington	191	Colombo
11	Cafemiz	208	Ankara
12	Vadakkan Pepper	214	Sharjah
13	Love Crumbs	215	Edinburgh
14	Fiesta Cancun	216	Dubuque

	Address \
0	94 Murray St, Tanunda, SA
1	Rua Gustavo Sampaio, 798, Leme, Rio de Janeiro
2	14 Second Ave North, Yorkton, SK S3N 1G1
3	Old Rangpuri, Near Sabzi Mandi, Mahipalpur, Ne...
4	Gedung PIC, Jl. Teluk Betung 43, Thamrin, Jakarta
5	129 Willis Street, Te Aro, Wellington City
6	Second Floor, UP Town Center, Katipunan Avenue...
7	Ground Floor, The Westin Doha Hotel & Spa, Fer...
8	118 Telok Ayer Street 068587
9	36 Buitenkant Street, CBD, Cape Town
10	36, Barnes Place, Cinnamon Gardens, Colombo 07
11	GaziosmanpaÅa Mahallesi, Arjantin Caddesi, No...
12	Near New City Center Supermarket, Abu Shagara,...
13	155 West Port, Old Town, Edinburgh EH3 9DP
14	2515 NW Arterial, Dubuque, IA 52002

Locality ... \

0	Tanunda	...
1	Leme	...
2	Yorkton	...
3	Mahipalpur	...
4	Thamrin	...
5	Te Aro	...
6	UP Town Center, Diliman, Quezon City	...
7	The Westin Doha Hotel & Spa, Fereej Bin Mahmoud	...
8	Telok Ayer Street, Outram	...
9	CBD	...
10	Cinnamon Gardens, Colombo 07	...
11	Gazi Osman PaÅŰa	...
12	Abu Shagara	...
13	Old Town	...
14	Dubuque	...

	Cuisines_y	Average Cost for two	\
0	Modern Australian, Australian	30	
1	Brazilian	40	
2	Asian	25	
3	Mithai, Street Food	150	
4	French, Western	350000	
5	American	55	
6	Filipino, Mexican	800	
7	Thai	445	
8	Finger Food	40	
9	Cafe	150	
10	Cafe, Italian	2000	
11	World Cuisine, Mexican, Italian	150	
12	South Indian	70	
13	Bakery, Cafe	15	
14	Mexican	10	

	Currency	Price range	Aggregate rating	Rating color	\
0	Dollar(\$)	3	4.4	Green	
1	Brazilian Real(R\$)	2	4.2	Green	
2	Dollar(\$)	2	3.3	Orange	
3	Indian Rupees(Rs.)	1	0.0	White	
4	Indonesian Rupiah(IDR)	3	4.3	Green	
5	NewZealand(\$)	3	4.1	Green	
6	Botswana Pula(P)	3	4.8	Dark Green	
7	Qatari Rial(QR)	4	4.3	Green	
8	Dollar(\$)	3	3.9	Yellow	
9	Rand(R)	2	4.4	Green	
10	Sri Lankan Rupee(LKR)	3	3.6	Yellow	
11	Turkish Lira(TL)	4	4.4	Green	
12	Emirati Diram(AED)	3	3.8	Yellow	

13	Pounds(£)	2	4.1	Green
14	Dollar(\$)	1	3.6	Yellow

	Rating text	Votes	Has Table booking_Yes	Has Online delivery_Yes
0	Very Good	339	0	0
1	Very Good	7	0	0
2	Average	26	0	0
3	Not rated	1	0	0
4	Very Good	243	0	0
5	Very Good	116	0	0
6	Excellent	294	0	0
7	Very Good	73	0	0
8	Good	35	0	0
9	Very Good	514	0	0
10	Good	83	0	0
11	Very Good	115	0	0
12	Good	210	0	1
13	Very Good	57	0	0
14	Good	156	0	0

[15 rows x 22 columns]

```
[52]: con=pd.DataFrame(country[['Country','City','Locality','Cuisines_x','Count']])
con.columns=['Country','City','Locality','Cuisines','Number of restaurants in_
↳the country']
#renaming the columns
con
```

```
[52]:
```

	Country	City \
0	Australia	Tanunda
1	Brazil	Rio de Janeiro
2	Canada	Yorkton
3	India	New Delhi
4	Indonesia	Jakarta
5	New Zealand	Wellington City
6	Phillipines	Quezon City
7	Qatar	Doha
8	Singapore	Singapore
9	South Africa	Cape Town
10	Sri Lanka	Colombo
11	Turkey	Ankara
12	UAE	Sharjah
13	United Kingdom	Edinburgh
14	United States	Dubuque

	Locality	Cuisines \
0	Tanunda	Australian

1		Leme	Brazilian
2		Yorkton	Asian
3		Mahipalpur	North Indian
4		Thamrin	Western
5		Te Aro	Cafe
6	UP Town Center, Diliman, Quezon City		Mexican
7	The Westin Doha Hotel & Spa, Fereej Bin Mahmoud		Thai
8	Telok Ayer Street, Outram		Finger Food
9		CBD	Cafe
10	Cinnamon Gardens, Colombo 07		Cafe
11		Gazi Osman PaÅŸa	World Cuisine
12		Abu Shagara	Indian
13		Old Town	Cafe
14		Dubuque	American

	Number of restaurants in the country
0	1
1	2
2	1
3	45
4	1
5	5
6	1
7	1
8	1
9	2
10	2
11	2
12	2
13	2
14	9

```
[53]: con1=con.sort_values('Number of restaurants in the country', ascending=False)
      #sorting the restaurants on the basis of the number of restaurants in the
      ↪country
      con1[:10]
```

	Country	City	Locality \
3	India	New Delhi	Mahipalpur
14	United States	Dubuque	Dubuque
5	New Zealand	Wellington City	Te Aro
1	Brazil	Rio de Janeiro	Leme
9	South Africa	Cape Town	CBD
10	Sri Lanka	Colombo	Cinnamon Gardens, Colombo 07
11	Turkey	Ankara	Gazi Osman PaÅŸa
12	UAE	Sharjah	Abu Shagara
13	United Kingdom	Edinburgh	Old Town

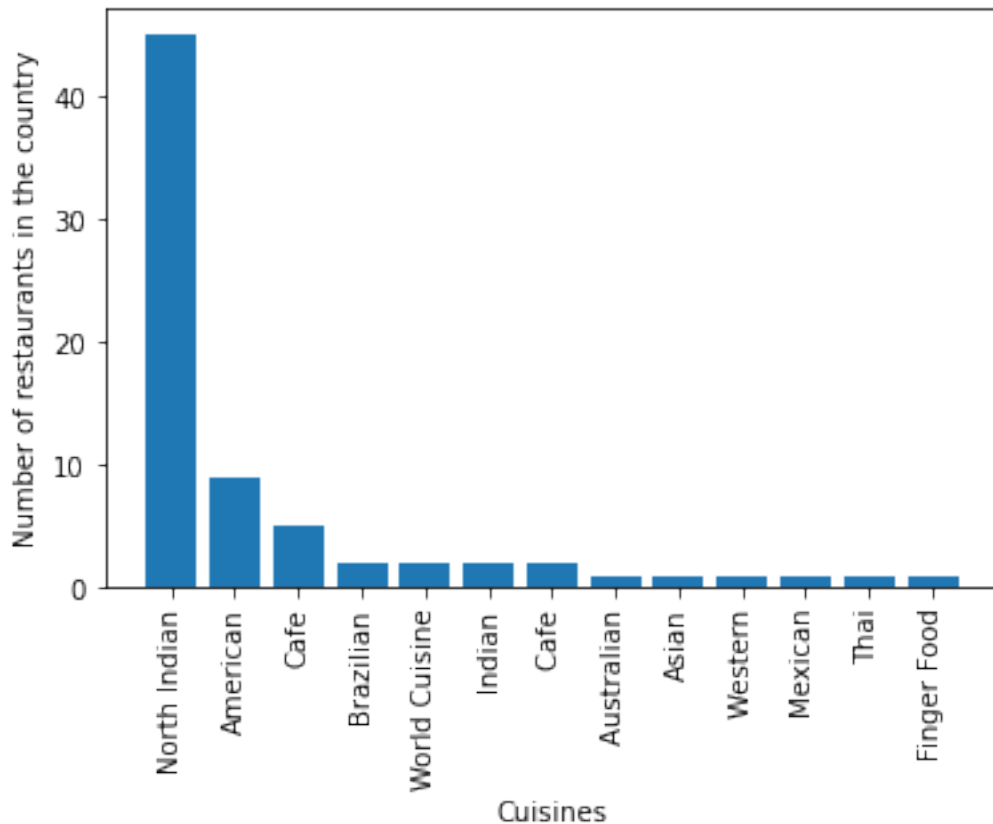
0	Australia	Tanunda	Tanunda
	Cuisines	Number of restaurants in the country	
3	North Indian	45	
14	American	9	
5	Cafe	5	
1	Brazilian	2	
9	Cafe	2	
10	Cafe	2	
11	World Cuisine	2	
12	Indian	2	
13	Cafe	2	
0	Australian	1	

```
[54]: import matplotlib.pyplot as plt
plt.bar(con1['Cuisines'],con1['Number of restaurants in the country'])

plt.xlabel("Cuisines")
plt.ylabel("Number of restaurants in the country")
plt.xticks(rotation=90)

#con1.plot(kind='bar')
```

```
[54]: ([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12],
[Text(0, 0, ''),
Text(0, 0, ''),
Text(0, 0, ''),
Text(0, 0, ''),
Text(0, 0, ''),
Text(0, 0, ''),
Text(0, 0, ''),
Text(0, 0, ''),
Text(0, 0, ''),
Text(0, 0, ''),
Text(0, 0, ''),
Text(0, 0, ''),
Text(0, 0, ''),
Text(0, 0, ''),
Text(0, 0, '')]])
```



```
[56]: rest_cuisine = pd.DataFrame(df_cuisines[['Restaurant_␣
↳Name', 'City', 'Cuisine_1', 'Cuisine_2', 'Cuisine_3', 'Cuisine_4',
␣
↳'Cuisine_5', 'Cuisine_6', 'Cuisine_7', 'Cuisine_8']])
rest_cuisine_stack=pd.DataFrame(rest_cuisine.stack()) #stacking the columns
rest_cuisine.head()
```

```
[56]:
```

	Restaurant Name	City	Cuisine_1	Cuisine_2 \
4	Avec Moi Restaurant and Bar	Jakarta	French	Western
6	Onokabe	Tangerang	Indonesian	NaN
8	MONKS	Jakarta	Western	Asian
10	OJJU	Jakarta	Korean	NaN
16	Noah's Barn Coffeenery	Bandung	Cafe	Coffee and Tea

	Cuisine_3	Cuisine_4	Cuisine_5	Cuisine_6	Cuisine_7	Cuisine_8
4	NaN	NaN	NaN	NaN	NaN	NaN
6	NaN	NaN	NaN	NaN	NaN	NaN
8	Cafe	NaN	NaN	NaN	NaN	NaN
10	NaN	NaN	NaN	NaN	NaN	NaN
16	Western	NaN	NaN	NaN	NaN	NaN

```
[57]: keys1 = [c for c in rest_cuisine if c.startswith('Cuisine')]
b=pd.melt(rest_cuisine, id_vars='Restaurant Name', value_vars=keys1,
↳value_name='Cuisines')
#melting the stack into one row
max_rate1=pd.DataFrame(b.groupby(by=['Restaurant Name','variable','Cuisines']).
↳size().reset_index())
#find the highest restuarant in the city
max_rate1
del max_rate1['variable']
max_rate1.columns=['Restaurant Name','Cuisines','Count']
max_rate1.head(10)
```

```
[57]:
```

	Restaurant Name	Cuisines	Count
0	12212	Fast Food	1
1	Let's Burrp	Chinese	1
2	Let's Burrp	North Indian	1
3	#45	Cafe	1
4	#Dilliwaala6	North Indian	1
5	#InstaFreeze	Ice Cream	1
6	#Urban Cafÿ©	North Indian	1
7	#Urban Cafÿ©	Chinese	1
8	#Urban Cafÿ©	Italian	1
9	#hashtag	Cafe	1

```
[58]: max_rate1.sort_values('Count',ascending=False)
#Cafe Coffee Day has the max number of cuisines and The least number of
↳cuisines in a resaurant is 1.
```

```
[58]:
```

	Restaurant Name	Cuisines	Count
2139	Cafe Coffee Day	Cafe	82
4031	Domino's Pizza	Pizza	73
4032	Domino's Pizza	Fast Food	72
11200	Subway	Healthy Food	59
11199	Subway	Salad	59
...
4775	Frontier - The Ashok	North Indian	1
4776	Frontier - The Ashok	Mughlai	1
4777	Frontier Restaurant	North Indian	1
4778	Frontier Restaurant	Chinese	1
13694	İàukura€Ûa Sofras€±	Izgara	1

[13695 rows x 3 columns]

```
[59]: rating = merged1[['Restaurant ID','Restaurant Name','Country','City','Aggregate
↳rating','Average Cost for two','Votes','Price range','Has Table
↳booking_Yes','Has Online delivery_Yes']]
```

```
[61]: rating = rating.merge(max_rate1,left_on='Restaurant Name',right_on='Restaurant_
↳Name',how='left')
rating
```

```
[61]:
```

	Restaurant ID	Restaurant Name	Country	City \
0	7402935	Skye	Indonesia	Jakarta
1	7410290	Satoo - Hotel Shangri-La	Indonesia	Jakarta
2	7420899	Sushi Masa	Indonesia	Jakarta
3	7421967	3 Wise Monkeys	Indonesia	Jakarta
4	7422489	Avec Moi Restaurant and Bar	Indonesia	Jakarta
...
21975	18312106	UrbanCrave	India	Kanpur
21976	18312106	UrbanCrave	India	Kanpur
21977	3900245	Deena Chat Bhandar	India	Varanasi
21978	18246202	VNS Live Studio	India	Varanasi
21979	18246202	VNS Live Studio	India	Varanasi

	Aggregate rating	Average Cost for two	Votes	Price range \
0	4.1	800000	1498	3
1	4.6	800000	873	3
2	4.9	500000	605	3
3	4.2	450000	395	3
4	4.3	350000	243	3
...
21975	3.9	0	127	1
21976	3.9	0	127	1
21977	3.8	0	78	1
21978	3.5	0	109	1
21979	3.5	0	109	1

	Has Table booking_Yes	Has Online delivery_Yes	Cuisines	Count
0	0	0	NaN	NaN
1	0	0	NaN	NaN
2	0	0	NaN	NaN
3	0	0	NaN	NaN
4	0	0	French	1.0
...
21975	0	0	Italian	1.0
21976	0	0	Beverages	1.0
21977	0	0	Street Food	1.0
21978	0	0	Chinese	1.0
21979	0	0	North Indian	1.0

[21980 rows x 12 columns]

```
[62]: merged1.corr()
```


[62]:

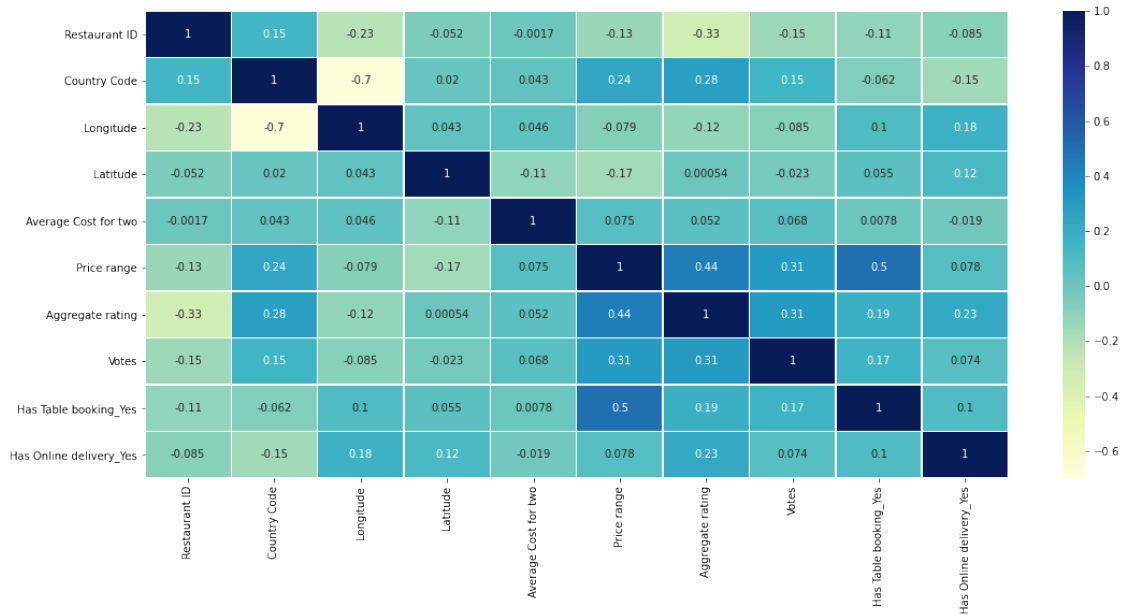
	Restaurant ID	Country Code	Longitude	Latitude	\
Restaurant ID	1.000000	0.148447	-0.226073	-0.052111	
Country Code	0.148447	1.000000	-0.698298	0.019784	
Longitude	-0.226073	-0.698298	1.000000	0.043213	
Latitude	-0.052111	0.019784	0.043213	1.000000	
Average Cost for two	-0.001696	0.043224	0.045892	-0.111089	
Price range	-0.134419	0.243393	-0.078974	-0.166668	
Aggregate rating	-0.326144	0.282234	-0.116843	0.000541	
Votes	-0.146895	0.154593	-0.085141	-0.022927	
Has Table booking_Yes	-0.110118	-0.061695	0.100497	0.054648	
Has Online delivery_Yes	-0.085157	-0.154627	0.178773	0.118709	

	Average Cost for two	Price range	Aggregate rating	\
Restaurant ID	-0.001696	-0.134419	-0.326144	
Country Code	0.043224	0.243393	0.282234	
Longitude	0.045892	-0.078974	-0.116843	
Latitude	-0.111089	-0.166668	0.000541	
Average Cost for two	1.000000	0.075093	0.051797	
Price range	0.075093	1.000000	0.437874	
Aggregate rating	0.051797	0.437874	1.000000	
Votes	0.067794	0.309308	0.313598	
Has Table booking_Yes	0.007757	0.502025	0.190045	
Has Online delivery_Yes	-0.018976	0.078007	0.225772	

	Votes	Has Table booking_Yes	\
Restaurant ID	-0.146895	-0.110118	
Country Code	0.154593	-0.061695	
Longitude	-0.085141	0.100497	
Latitude	-0.022927	0.054648	
Average Cost for two	0.067794	0.007757	
Price range	0.309308	0.502025	
Aggregate rating	0.313598	0.190045	
Votes	1.000000	0.169497	
Has Table booking_Yes	0.169497	1.000000	
Has Online delivery_Yes	0.074399	0.101204	

	Has Online delivery_Yes
Restaurant ID	-0.085157
Country Code	-0.154627
Longitude	0.178773
Latitude	0.118709
Average Cost for two	-0.018976
Price range	0.078007
Aggregate rating	0.225772
Votes	0.074399
Has Table booking_Yes	0.101204
Has Online delivery_Yes	1.000000

```
[63]: fig, ax = plt.subplots(figsize=(18,8))
      dataplot = sns.heatmap(merged1.corr(), cmap="YlGnBu", annot=True,linewidth=0.
      ↪5,ax=ax)
      #heat = merged1.pivot("Average_Cost_for_two", "Aggregate_rating")
      #ax = sns.heatmap(heat, annot=True, fmt="d")
```



We see that there is no single variable that affects the rating strongly, however table booking,online delivery,avg price for two and price range, number of votes do play a part in affecting the rating of a restaurant.