```
[1]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

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

1 1. Data Preliminary analysis:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9551 entries, 0 to 9550

- Perform preliminary data inspection and report the findings as the structure of the data, missing values, duplicates etc.
- Based on the findings from the previous questions identify duplicates and remove them.

```
[3]: data.info()
```

```
Data columns (total 19 columns):
Restaurant ID
                        9551 non-null int64
Restaurant Name
                        9550 non-null object
Country Code
                        9551 non-null int64
                        9551 non-null object
City
Address
                        9551 non-null object
                        9551 non-null object
Locality
Locality Verbose
                        9551 non-null object
                        9551 non-null float64
Longitude
Latitude
                        9551 non-null float64
                        9542 non-null object
Cuisines
Average Cost for two
                        9551 non-null int64
Currency
                        9551 non-null object
                        9551 non-null object
Has Table booking
Has Online delivery
                        9551 non-null object
Price range
                        9551 non-null int64
Aggregate rating
                        9551 non-null float64
Rating color
                        9551 non-null object
                        9551 non-null object
Rating text
Votes
                        9551 non-null int64
```

```
dtypes: float64(3), int64(5), object(11)
```

memory usage: 1.4+ MB

2 Clean variable names

```
[48]: data.columns = data.columns.str.replace(' ','_')
```

2.1 values given as 0 are missing

```
[49]: (data == 0).sum()
[49]: Restaurant_ID
                                  0
      Restaurant_Name
                                  0
      Country_Code
                                  0
      City
                                  0
      Address
                                  0
      Locality
                                  0
      Locality_Verbose
                                  0
      Longitude
                                498
      Latitude
                                498
      Cuisines
                                  0
      Average_Cost_for_two
                                 18
      Currency
                                  0
      Has_Table_booking
                                  0
      Has_Online_delivery
                                  0
      Price_range
                                  0
      Aggregate_rating
                               2148
      Rating_color
                                  0
      Rating_text
                                  0
      Votes
                               1094
      dtype: int64
```

3 Missing values for Latitude and Longitude

```
[51]: missing_city = data[(data.Longitude ==0)|(data.Latitude == 0)].City.unique() len(missing_city)
```

[51]: 28

4 fill in Missing using the city names

5 duplicates

```
[9]: print('Any Duplicated Rows ? :' , data.duplicated().any())
    print('No. of Duplicated Rows :', data.duplicated().sum())

Any Duplicated Rows ? : False
    No. of Duplicated Rows : 0

[10]: data.duplicated('Restaurant_ID').any()

[10]: False
[11]: print('No. of unique Restaurant_IDs :', data.Restaurant_ID.nunique())
    print('No. of unique Restaurant_Names :', data.Restaurant_Name.nunique())

No. of unique Restaurant_IDs : 9551
    No. of unique Restaurant_Names : 7445
```

• Above data provides information that the restaurant ids are unique however there is an overlap in Restaurant names

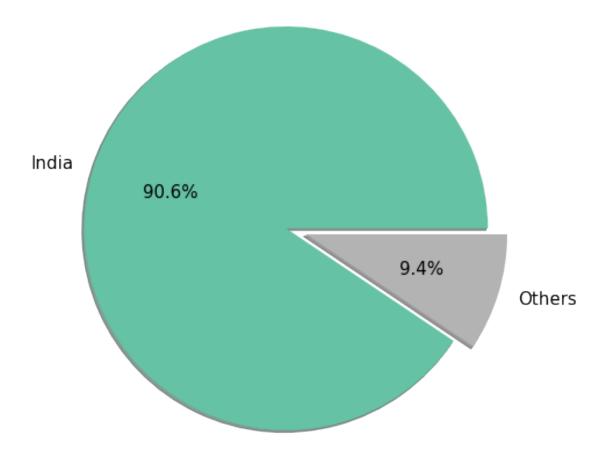
5.1 Geographical distribution

```
[12]: country_code = pd.read_excel('Country-Code.xlsx')
    country_code.columns = country_code.columns.str.replace(' ','_')

[13]: data = pd.merge(data,country_code, on = 'Country_Code')
```

5.2 Explore the geographical distribution of the restaurants, finding out the cities with maximum / minimum number of restaurants.

```
8000 - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% - 90.6% -
```



Quick Inferences - * Zomato's largest market is in India itself, nobody even comes close. * Analysing data from India should give us a pretty accurate representation of the entire data. * One important thing that might vary across different regions is the types of Cusinies. So it should be interesting to see how many cusinies are served throughout the world.

```
[16]: data = data[data.Country == 'India']
```

6 Explore how ratings are distributed overall.

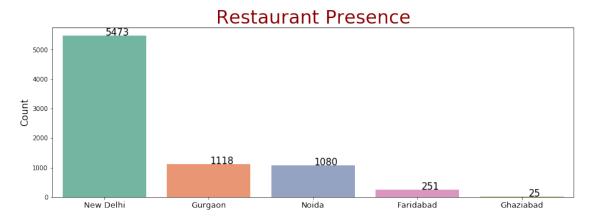


```
[19]: data["Rating_color"].value_counts()
      Color_represents = data.groupby(['Rating_color'],as_index =__
       →False)['Aggregate_rating'].mean()
[20]: Color_represents.columns = ['Rating_color','Average_rating']
[21]: Color_represents = Color_represents.
       →sort_values(by='Average_rating',ascending=False)
[22]: Color represents = Color represents[0:5]
      Color_represents['Ratings'] = ['Excellent','Very Good','Good','Okay','Poor']
[23]: Color_represents
[23]:
        Rating_color
                      Average_rating
                                        Ratings
          Dark Green
                            4.646552 Excellent
      0
      1
               Green
                            4.153324 Very Good
                            3.677423
      5
              Yellow
                                           Good
      2
                            3.048722
              Orange
                                           Okay
      3
                 Red
                            2.296111
                                           Poor
```

7 Restaurant franchise is a thriving venture. So, it becomes very important to explore the franchise with most national presence.

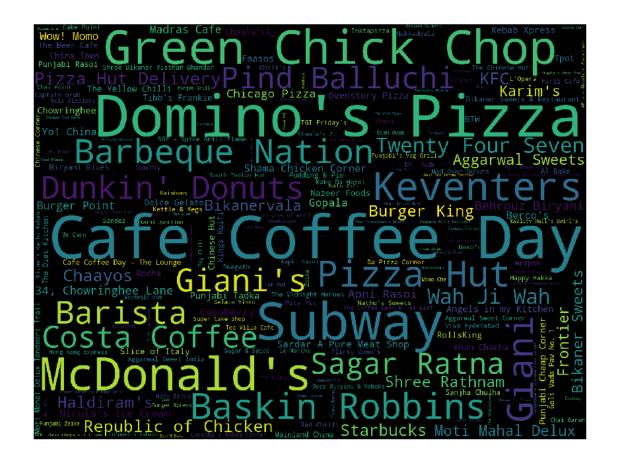
```
[25]: plt.figure(figsize = (15,5))
  vc = data.City.value_counts()[:5]
  g = sns.barplot(x = vc.index, y = vc.values, palette = 'Set2')
  g.set_xticklabels(g.get_xticklabels(),fontsize = 13)
  for i in range(5):
     value = vc[i]
```

```
g.text(y = value - 2,x = i +0.125 , s = value, color='black', ha="center", of ontsize = 15)
g.set_ylabel('Count', fontsize = 15)
g.set_title('Restaurant Presence', fontsize = 30, color = 'darkred')
plt.show()
```

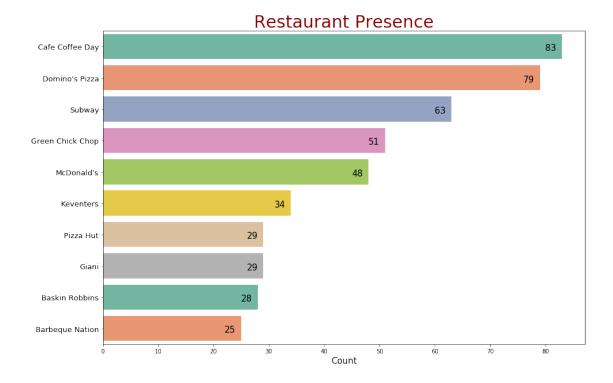


Here we can see that New Delhi has most no. of restaurants ,gurgaon,noida and Faridabad are behind it but by very huge margin,and other cities like Ahmedabad ,Amritsar,Bhubaneshwar have least no. of restaurants.It is a noticable point that there is not even a single city outside india to be in top 10 in no. of restaurants.

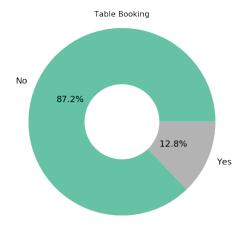
```
[]:
```

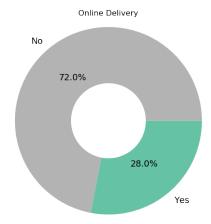


```
plt.figure(figsize = (15,10))
  vc = data.Restaurant_Name.value_counts()[:10]
  g = sns.barplot(y = vc.index, x = vc.values, palette = 'Set2')
  g.set_yticklabels(g.get_yticklabels(),fontsize = 13)
  for i in range(10):
     value = vc[i]
     g.text(x = value - 2,y = i +0.125 , s = value, color='black', ha="center", \( \)
  \  \times fontsize = 15)
  g.set_xlabel('Count', fontsize = 15)
  g.set_title('c', fontsize = 30, color = 'darkred')
  plt.show()
```



- 7.1 What is the ratio between restaurants that allow table booking vs that do not allow table booking?
- 7.2 What is the percentage of restaurants providing online delivery?



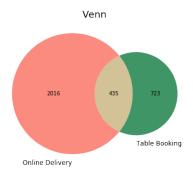


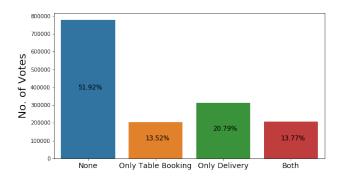
```
[29]: pd.crosstab(data.Has_Online_delivery,data.Has_Table_booking)
```

```
[29]: Has_Table_booking No Yes
Has_Online_delivery
No 5545 684
Yes 1996 427
```

[30]: import matplotlib.pyplot as plt from matplotlib_venn import venn2

```
[54]: fig, ax = plt.subplots(1,2,figsize = (20,5))
      s1 = set(data[data.Has_Online_delivery == 'Yes'].Restaurant_ID)
      s2 = set(data[data.Has_Table_booking== 'Yes'].Restaurant_ID)
      out = venn2([s1,s2],['Online Delivery','Table Booking'], ['salmon','seagreen'],
      \rightarrowalpha = .91, ax = ax[0])
      ax[0].set_title('Venn',fontsize =18)
      #plt.show()
      dc= data.pivot_table(index = ['Has_Online_delivery', 'Has_Table_booking'],_
      →values = 'Votes', aggfunc = 'sum')
      dc.index = ['None','Only Table Booking','Only Delivery','Both']
      dc['Perc'] = (dc.Votes / dc.Votes.sum() *100).round(2)
      sns.barplot(x = dc.index, y = dc.Votes, ax = ax[1])
      plt.xticks( rotation = 0, fontsize = 14)
      plt.xlabel('')
      for i in range(len(dc)):
          plt.annotate(str(dc.Perc.iloc[i]) + '%',xy = (i-0.15, int(dc.Votes.iloc[i]/
      \hookrightarrow2)), fontsize = 12)
      plt.ylabel('No. of Votes',fontsize = 20)
      plt.show()
```





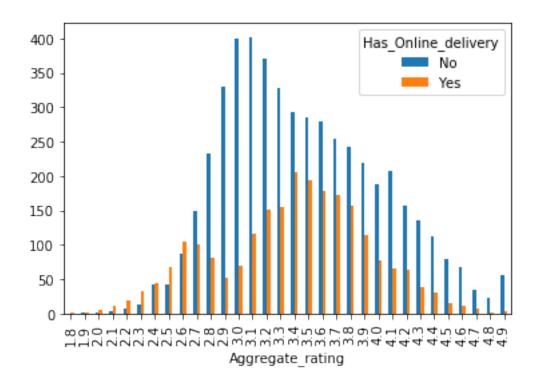
```
[55]: dc
```

```
[55]: Votes Perc
None 778156 51.92
Only Table Booking 202575 13.52
Only Delivery 311592 20.79
Both 206322 13.77
```

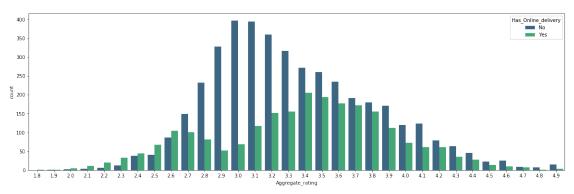
7.3 Is there a difference in no. of votes for the restaurants that deliver and the restaurant that don't?

```
[56]: d = data[data.Aggregate_rating != 0]
pd.crosstab(d.Aggregate_rating, d.Has_Online_delivery).plot.bar()
```

[56]: <matplotlib.axes._subplots.AxesSubplot at 0x1a21679dd0>







7.4 Restaurants across city

```
[33]: top10 = data.City.value_counts()[:10] top10[:2]

[33]: New Delhi 5473
```

[33]: New Delhi 5473
Gurgaon 1118
Name: City, dtype: int64

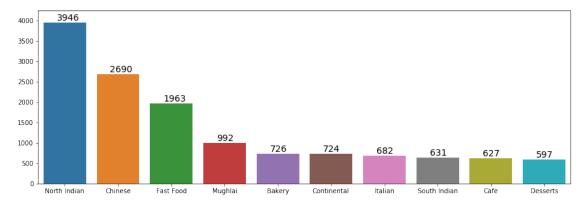
8 What are the top 10 cuisines served across cities?

```
North Eastern Franch Lebanese

North Eastern Franch Lebanese
```

```
[35]: plt.figure(figsize = (15,5)) sns.barplot(x = s.value_counts()[:10].index, y = s.value_counts()[:10])
```

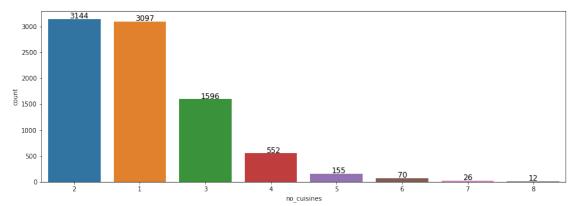
```
for i in range(10):
    plt.annotate(s.value_counts()[i], xy = (i-0.15,s.value_counts()[i]+50),
    ofontsize = 14)
plt.ylim(0, round(s.value_counts()[0]+300))
plt.show()
```



9 What is the maximum and minimum no. of cuisines that a restaurant serves? Also, what is the relationship between No. of cuisines served and Ratings

```
[36]: data['no_cuisines'] = data.Cuisines.str.split(',').apply(len)

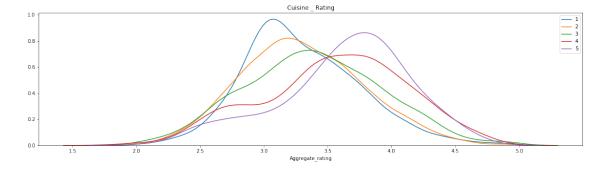
[37]: plt.figure(figsize = (15,5))
    vc = data.no_cuisines.value_counts()
    sns.countplot('no_cuisines', data=data, order = vc.index)
    for i in range(len(vc)):
        plt.annotate(vc.iloc[i], xy = (i-0.07,vc.iloc[i]+10), fontsize = 12)
    plt.show()
```



10 No of Cuisines vs Rating

```
[38]: data.columns
[38]: 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', 'Rating_cat',
             'no_cuisines'],
            dtype='object')
[39]: plt.figure(figsize = (20,5))
      fusion_rate = data.loc[data.Aggregate_rating >0,['no_cuisines', 'Rating_cat',_
      → 'Aggregate_rating']].copy()
      fusion_rate.loc[fusion_rate['no_cuisines'] > 5, 'no_cuisines'] = 5
      fusion_rate = fusion_rate.loc[fusion_rate.Aggregate_rating != -1, :]
      pal = sns.color_palette('Oranges', 11)
      for i in range(1,6):
              num_ix = fusion_rate['no_cuisines'] == i
              sns.distplot(fusion_rate.loc[num_ix, 'Aggregate_rating'], label =__
       ⇒str(i), hist = False)
              plt.legend()
              plt.title('Rating Distribution for fusion_number')
      plt.title('Cuisine _ Rating')
```

[39]: Text(0.5, 1.0, 'Cuisine _ Rating')



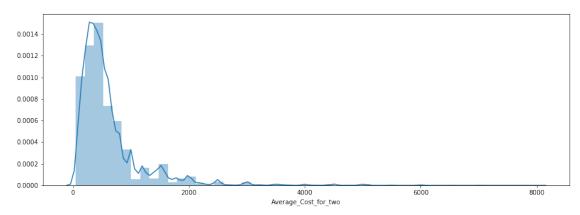
10.1 "More Number of Cusine, Higer Rate Restaruant."

Cuisine is a complex variables. It contains two types, Country and Kind of Food. I maybe have to divide them into two variables, country_cu/kind_cu. Most of restaraunt provided under 4 cusine, but More Number of Cusine, Higer Rate Restaruant

- the maximum no of cuisines served by a single restaurant is 8
- most of the restaurant are serving at least 2 or 1 cuisine

11 Discuss the cost vs the other variables

```
[40]: plt.figure(figsize = (15,5))
sns.distplot(data[data.Average_Cost_for_two != 0].Average_Cost_for_two)
plt.show()
```



12 Explain the factors in the data that may have an effect on ratings e.g. No. of cuisines, cost, delivery option etc.

```
[41]: data['Average_Cost_for_two_cat'] = pd.cut(data[data.Average_Cost_for_two != 0].

→Average_Cost_for_two,

bins = [0, 200, 500, 1000, 3000, 5000,10000, 800000000],

labels = ['<=200', '<=500', '<=1000', '<=3000', '<=5000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=10000', '<=1000', '<=10000', '<=1000', '<=10000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000', '<=1000',
```

```
[42]: f = plt.figure(figsize = (20,10))

ax = plt.subplot2grid((2,5), (0,0),colspan = 2)
sns.countplot(data['Average_Cost_for_two_cat'], ax = ax, palette = sns.

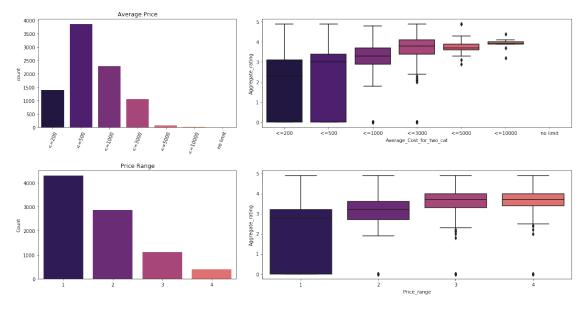
color_palette('magma', 7))
ax.set_title('Average Price')
```

```
ax.set_xlabel('')
ax.tick_params('x', rotation = 70)
ax = plt.subplot2grid((2,5), (0,2), colspan = 3)
sns.boxplot(x = 'Average_Cost_for_two_cat', y = 'Aggregate_rating', data =_

→data, ax = ax, palette = sns.color_palette('magma', 7))

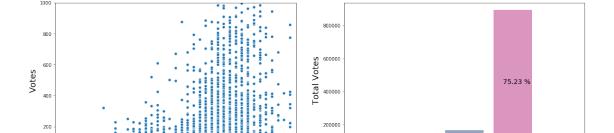
count = data['Price_range'].value_counts().reset_index()
count.columns = ['Price_range', 'Count']
ax = plt.subplot2grid((2,5), (1,0),colspan = 2)
sns.barplot(x = 'Price_range', y = 'Count', data = count, ax=ax, palette = sns.
ax.set_title('Price Range')
ax.set_xlabel('')
ax = plt.subplot2grid((2,5), (1,2), colspan = 3)
sns.boxplot(x='Price_range', y ='Aggregate_rating', data = data, ax = ax, u
→palette = sns.color_palette('magma', 5))
plt.subplots_adjust(wspace = 0.3, hspace = 0.4,)
plt.suptitle('Price Count & Rating Distribution', size = 30)
plt.show()
```

Price Count & Rating Distribution



12.1 Aggregate Rating vs Votes

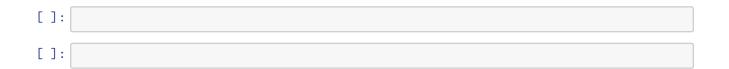
```
[43]: f,ax = plt.subplots(1,2,figsize=(20,6))
      sns.scatterplot(data=data,x='Aggregate_rating',y='Votes', ax = ax[0], palette =__
      agg = data.pivot_table(index = 'Rating_cat', values = 'Votes', aggfunc = 'sum').
      →reset_index()
      agg['Perc_votes'] = (agg.Votes/agg.Votes.sum()*100).round(2)
      sns.barplot(x = 'Rating_cat', y = 'Votes', data = agg, ax = ax[1], palette=___
      for i in range(len(agg)):
          ax[1].annotate(str(agg.Perc_votes[i])+' %', xy = (i-0.2,int(agg.Votes[i]/
      →2)), fontsize = 14, fontweight = 'medium')
      ax[0].set_ylim(0,1000)
      ax[0].set_xlim(1,5)
      ax[0].set_ylabel('Votes',fontsize = 18 )
      ax[0].set_xlabel('Aggregate Rating',fontsize = 18 )
      ax[0].set_xticklabels(ax[0].get_xticks(),fontsize = 12)
      ax[1].set_ylabel('Total Votes',fontsize = 18 )
      ax[1].set_xlabel('Rating Category',fontsize = 18 )
      ax[1].set_xticklabels(agg.Rating_cat,fontsize = 12)
      plt.suptitle('Aggregate Rating Vs Votes', size = 30)
      plt.show()
```



14.09 9

Rating Category

Aggregate Rating Vs Votes



2.5 3.0 3.5 Aggregate Rating