Zomato Reviews: Analyzing the Relationship between Price, Cuisine, and Rating Factors

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Background & Introduction

Founded in 2008, Zomato is a restaurant search service based in India. Much like Yelp, the company seeks to provide users with restaurant information like cuisine and general price and to allow them to leave reviews. Zomato operates in 24 countries and thus has global footprint.

We were interested in seeing the relationship specifically between a restaurant's price and cuisine and its rating. Certain cuisines tend to be considered "high-end" and therefore command a higher price point for a meal. Moreover, because price tends to signal quality, especially in the restaurant industry, the food and service should be relatively better.

Through analysis of Zomato data, we hope to test two hypotheses as follows: restaurants with cuisines that connotate fine dining (specifically French and Japanese) will have a higher price point and thus rating, and restaurants with a higher price will have higher ratings left by reviewers.

Data

The data we will use comes from Kaggle (https://www.kaggle.com/shrutimehta/zomato-restaurants-data) (https://www.kaggle.com/shrutimehta/zomato-restaurants-data)). The two data sets that will be utilized from this source are the main zomato.csv file and the country-code.xlsx file.

The author of these data sets mentions that the main file is "Analyzing the best restaurants of the major cities".

Data Set at a Glance

Here, we begin to run our code.

In [1]:
```
import pandas as pd #analyze data
import matplotlib.pyplot as plt #visualize data
import numpy as np #facilitate mathematical operations

path = 'https://github.com/kenneth-yu19/Data_Bootcamp_Final_Project/blob/master/z
exc_data = pd.read_excel(path) #read the excel data from source

zom = pd.DataFrame(exc_data) #convert excel data into pandas dataframe
zom
```

Out[1]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Local Verbo
0	6317637	Le Petit Souffle	162	Makati City	Third Floor, Century City Mall, Kalayaan Avenu...	Century City Mall, Poblacion, Makati City	Century C Mall, Poblaci Makati C Ma
1	6304287	Izakaya Kikufuji	162	Makati City	Little Tokyo, 2277 Chino Roces Avenue, Legaspi...	Little Tokyo, Legaspi Village, Makati City	Little Tok Legaspi Villa Makati C M
2	6300002	Heat - Edsa Shangri-La	162	Mandaluyong City	Edsa Shangri-La, 1 Garden Way, Ortigas, Mandal...	Edsa Shangri-La, Ortigas, Mandaluyong City	Edsa Shan La, Ortig Mandaluyo City, M
				Mandaluyong	Third Floor, Mega Fashion	SM Megamall, Ortigas	SM Megam Ortig

In [2]:
```
zom.shape
```

Out[2]: (9551, 21)

Here, we see that our DataFrame has 21 columns and 9551 rows. This means that the original data set analyzes 9,551 restaurants based on 21 different qualities. Looking through the columns, we see that not all of them are necessary for our data analysis to test our various hypotheses, so we would like to remove a few to clean up our DataFrame.

Cleaning Data

In [3]:
```
zom = zom.drop(columns=['Address','Locality','Locality Verbose','Longitude','Lati
#removing unnecessary columns from df

zom
```

...

We have now removed unnecessary columns from our DataFrame. Details like specific geographical aspects will not help in our hypothesis testing.

Now, looking closer at the contents of our DataFrame, we see that a few of the "Aggregate rating" entries actually contain "0.0", which essentially equates to a null value; this will not help us in our data analysis, so we will remove the restaurants with this value. Though first, we will try to see why these restaurants receive the "0.0" rating. We assume that the number of votes may not be sufficient, so we will sort the DataFrame by the last column in ascending order.

In [4]:
```
zom.sort_values(by=['Votes'], ascending=True)
```

Out[4]:

	Restaurant ID	Restaurant Name	Country Code	City	Cuisines	Average Cost for two	Currency	Price range
5799	18460302	Khalsa Eating Point	1	New Delhi	North Indian	300	Indian Rupees(Rs.)	1
7411	18431145	Radha Swami Chaat Bhandar	1	New Delhi	Street Food	100	Indian Rupees(Rs.)	1
7414	18430905	Ram Ram Ji Kachori Bhandar	1	New Delhi	Street Food	50	Indian Rupees(Rs.)	1
7415	18430907	Rana's Food Corner	1	New Delhi	North Indian	200	Indian Rupees(Rs.)	1
7416	18451597	Sanjay Chicken Shop	1	New Delhi	Raw Meats, Fast Food	350	Indian Rupees(Rs.)	1

From sorting the data, we draw three conclusions: a restaurant gets a null rating if the "Rating text" is "Not rated", the "Rating color" is "White", and if the number of "Votes" is less than "4". We now have to decide which of the columns to use as the parameter for removing the null-value rows. We choose the "Rating color" "White" designation, as it will be simplest to remove rows based on this value.

However, before we do this, we must now replace all spaces DataFrame's column headers with underscores. We will rename some columns completely to shorten the header.

In [5]:
```
zom = zom.rename(index=str, columns={"Restaurant ID": "ID","Restaurant Name": "Na
#renaming columns

zom = zom[zom.Color != 'White'] #utilizing boolean indexing to remove rows with "
zom
```

Out[5]:

	ID	Name	Country_Code	City	Cuisines	Cost	Currency	Price
0	6317637	Le Petit Souffle	162	Makati City	French, Japanese, Desserts	1100	Botswana Pula(P)	3
1	6304287	Izakaya Kikufuji	162	Makati City	Japanese	1200	Botswana Pula(P)	3
2	6300002	Heat - Edsa Shangri-La	162	Mandaluyong City	Seafood, Asian, Filipino, Indian	4000	Botswana Pula(P)	4
3	6318506	Ooma	162	Mandaluyong City	Japanese, Sushi	1500	Botswana Pula(P)	4
4	6314302	Sambo Kojin	162	Mandaluyong City	Japanese, Korean	1500	Botswana Pula(P)	4
5	18189371	Din Tai Fung	162	Mandaluyong City	Chinese	1000	Botswana Pula(P)	3

We have now removed the null vales for ratings.

We would now like to clean the data a little bit more. In terms of geography, we have "City" and "Country_Code". Our analysis doesn't need to be so granular to look at a restaurant's city, but we also can't directly tell the restaurant's country location by the "Country_Code" alone. Luckily, the Kaggle user from whom we got the data included an Excel workbook that shows what country pertains to each "Country_Code". We must thus import this new workbook as a dataframe and perform a sort of VLOOKUP -> replace into our original 'zom' DataFrame. The replacing part seems a little complicated, so we opted to use a merge/join operation then manually delete the "Country_Code" column.

In [6]:
```
path2 = 'https://github.com/kenneth-yu19/Data_Bootcamp_Final_Project/blob/master/
exc_data2 = pd.read_excel(path2)
concode = pd.DataFrame(exc_data2) #convert excel data into pandas dataframe
concode = concode.rename(index=str, columns={"Country Code": "Country_Code"}) #re
concode
```

Out[6]:

	Country_Code	Country
0	1	India
1	14	Australia
2	30	Brazil
3	37	Canada
4	94	Indonesia
5	148	New Zealand
6	162	Phillipines
7	166	Qatar
8	184	Singapore
9	189	South Africa
10	191	Sri Lanka
11	208	Turkey
12	214	UAE
13	215	United Kingdom
14	216	United States

In [7]:
```
zom = zom.merge(concode, on='Country_Code', how='left') #left merge using "Countr
zom = zom.drop(columns=['Country_Code','City']) #dropping unnecessary columns
zom = zom[['ID','Name','Country','Cuisines','Cost','Currency','Price','Rating','C
zom
```

Out[7]:

	ID	Name	Country	Cuisines	Cost	Currency	Price	Rating	Color	
0	6317637	Le Petit Souffle	Phillipines	French, Japanese, Desserts	1100	Botswana Pula(P)	3	4.8	Dark Green	E:
1	6304287	Izakaya Kikufuji	Phillipines	Japanese	1200	Botswana Pula(P)	3	4.5	Dark Green	E:
2	6300002	Heat - Edsa Shangri-La	Phillipines	Seafood, Asian, Filipino, Indian	4000	Botswana Pula(P)	4	4.4	Green	
3	6318506	Ooma	Phillipines	Japanese, Sushi	1500	Botswana Pula(P)	4	4.9	Dark Green	E:
4	6314302	Sambo Kojin	Phillipines	Japanese, Korean	1500	Botswana Pula(P)	4	4.8	Dark Green	E:
5	18189371	Din Tai Fung	Phillipines	Chinese	1000	Botswana Pula(P)	3	4.4	Green	

Above we remove the "Country_Code" and "City" columns and move over the "Country" column so that it's the third column.

Now, there is another column we need to address in our data cleaning: "Currency". We want to normalize the currency, or at least get a relative measure of priciness of a restaurant, as price is a factor in some of our hypotheses, and we think it would be useful to know the extent of priciness for restaurants. Luckily, we have a price rating in the "Price" column and a few restaurants in the U.S. We will eventually remove the "Currency" column, but we would first like to see what exactly are the prices for each of the price ratings (1 to 5). Thus, we create a new DataFrame 'uszom' to anaylze.

In [8]:
```
uszom = zom.loc[zom['Country'] == 'United States'] #finding restaurants with "Cou
print(uszom.shape)
```

```
(431, 11)
```

We have 431 U.S. restaurants, which provides a pretty good sample for analyzing prices. However, some of the values in the "Cost" column are "0", which isn't helpful, so we will remove those rows.

In [9]:
```
uszom = uszom[uszom.Cost != 0] #utilizing boolean indexing to remove rows with "0
uszom
```

Out[9]:

	ID	Name	Country	Cuisines	Cost	Currency	Price	Rating	Color	T
77	17284404	Austin's BBQ and Oyster Bar	United States	BBQ, Burger, Seafood	25	Dollar($)	2	3.3	Orange	Aver
78	17284203	BJ's Country Buffet	United States	American, BBQ	10	Dollar($)	1	3.3	Orange	Aver
81	17284397	Elements Coffee Co - Northwest	United States	Coffee and Tea, Sandwich	10	Dollar($)	1	3.4	Orange	Aver
83	17284094	Chick-fil-A	United States	Fast Food	10	Dollar($)	1	3.5	Yellow	G
84	17284409	Guang Zhou Chinese Restaurant	United States	Asian, Chinese, Vegetarian	10	Dollar($)	1	3.9	Yellow	G
				Pizza, Bar						

We still have 422 restaurants, which is good. To find the price range of each price rating, we will create a new DataFrame with the price rating, minimum cost for a meal for two, and the maximum cost as the columns. This will utilize the "Cost" and "Price" columns of our 'uszom' DataFrame.

In [10]:
```
print(uszom.loc[uszom['Price'] == 1, 'Cost'].min(),uszom.loc[uszom['Price'] == 1,
print(uszom.loc[uszom['Price'] == 2, 'Cost'].min(),uszom.loc[uszom['Price'] == 2,
print(uszom.loc[uszom['Price'] == 3, 'Cost'].min(),uszom.loc[uszom['Price'] == 3,
print(uszom.loc[uszom['Price'] == 4, 'Cost'].min(),uszom.loc[uszom['Price'] == 4,
print(uszom.loc[uszom['Price'] == 5, 'Cost'].min(),uszom.loc[uszom['Price'] == 5,
```

```
10 10
25 25
30 45
50 100
nan nan
```

Interestingly, the price range is 1 to 4, not 1 to 5 like the overall restaurant ranking. We see here that a restaurant is ranked 1 if the average price is USD10, 2 if USD25, 3 if between USD30 and USD45, and 4 if between USD50 and USD100. This calculation just serves as a contextual reference for price; these numbers won't necessarily be used in our graphing, but we wanted to have them to put more color to our analysis. We can now remove the "Cost" and "Currency" columns of our 'zom' DataFrame.

In [11]:
```
zom = zom.drop(columns=['Cost','Currency']) #dropping unnecessary columns
zom
```

...

Now, we have one final step in data cleaning! We want to look at individual cuisines in our hypotheses, and we see that the "Cuisines" column has up to 4 cuisines/types of food listed. First, we will do a text-to-columns operation to separate the cuisines, then we will look at the unique cuisines, then we will choose the cuisines we want to analyze, then we will attribute those respective cuisines as the main cuisine.

In [12]:
```
cuisine = zom["Cuisines"].str.split(", ", n = 3, expand = True) #create 'cuisine'
zom["Cuisine1"]= cuisine[0] #append first column to original 'zom' df
zom["Cuisine2"]= cuisine[1] #append second column to original 'zom' df
zom["Cuisine3"]= cuisine[2] #append third column to original 'zom' df
zom["Cuisine4"]= cuisine[2] #append fourth column to original 'zom' df

cuis = pd.unique(zom[['Cuisine1','Cuisine2','Cuisine3','Cuisine4']].values.ravel(
cuis = cuis.astype(str) #convert from object to string
cuis.sort() #sort array alphabetically
print(cuis)
print(len(cuis)) #finding the number of unique cuisines that show up
```

```
['Afghani' 'African' 'American' 'Andhra' 'Arabian' 'Argentine' 'Asian'
 'Asian Fusion' 'Assamese' 'Australian' 'Awadhi' 'BBQ' 'Bakery' 'Bar Food'
 'Belgian' 'Bengali' 'Beverages' 'Bihari' 'Biryani' 'Brazilian'
 'Breakfast' 'British' 'Burger' 'Burmese' 'Bí_rek' 'Cafe' 'Cajun'
 'Canadian' 'Cantonese' 'Caribbean' 'Charcoal Grill' 'Chettinad' 'Chinese'
 'Coffee and Tea' 'Contemporary' 'Continental' 'Cuban' 'Curry' 'Deli'
 'Desserts' 'Dim Sum' 'Diner' 'Drinks Only' 'Durban' 'Dí_ner' 'European'
 'Fast Food' 'Filipino' 'Finger Food' 'Fish and Chips' 'French' 'Fusion'
 'German' 'Goan' 'Gourmet Fast Food' 'Greek' 'Grill' 'Gujarati' 'Hawaiian'
 'Healthy Food' 'Hyderabadi' 'Ice Cream' 'Indian' 'Indonesian'
 'International' 'Iranian' 'Irish' 'Italian' 'Izgara' 'Japanese' 'Juices'
 'Kashmiri' 'Kebab' 'Kerala' 'Kiwi' 'Korean' 'Latin American' 'Lebanese'
 'Lucknowi' 'Maharashtrian' 'Malaysian' 'Malwani' 'Mangalorean'
 'Mediterranean' 'Mexican' 'Middle Eastern' 'Mithai' 'Modern Australian'
 'Modern Indian' 'Moroccan' 'Mughlai' 'Naga' 'Nepalese' 'New American'
 'None' 'North Eastern' 'North Indian' 'Oriya' 'Pakistani' 'Parsi'
 'Patisserie' 'Peranakan' 'Persian' 'Peruvian' 'Pizza' 'Portuguese'
 'Pub Food' 'Rajasthani' 'Ramen' 'Raw Meats' 'Restaurant Cafe' 'Salad'
 'Sandwich' 'Scottish' 'Seafood' 'Singaporean' 'Soul Food' 'South African'
 'South American' 'South Indian' 'Southern' 'Southwestern' 'Spanish'
 'Sri Lankan' 'Steak' 'Street Food' 'Sunda' 'Sushi' 'Taiwanese' 'Tapas'
 'Tea' 'Teriyaki' 'Tex-Mex' 'Thai' 'Tibetan' 'Turkish' 'Turkish Pizza'
 'Vegetarian' 'Vietnamese' 'Western' 'World Cuisine' 'nan']
142
```

Here, we have a decision to make. We have all unique cuisines/types of food that show up in the DataFrame, but we need to choose which one will represent the restaurant. It's clear that the cuisines aren't listed in alphabetical order if the restaurant has multiple, so we assume that the cuisines are listed by saliency. Thus, we will use the cuisine in the "Cuisine1" column as the representative cuisine.

In [13]:
```
zom = zom.drop(columns=['Cuisines','Cuisine2','Cuisine3','Cuisine4']) #dropping u
zom = zom.rename(index=str, columns={"Cuisine1": "Cuisine"}) #renaming column
zom = zom[['ID','Name','Country','Cuisine','Price','Rating','Color','Text','Votes
zom
```

...

In [14]:
```
zom.dtypes #checking the column types to ensure they're able to be graphed
```

Out[14]:
```
ID            int64
Name         object
Country      object
Cuisine      object
Price         int64
Rating      float64
Color        object
Text         object
Votes         int64
dtype: object
```

And with that, we've cleaned all our data! Above, we checked to see that the "Price", "Rating", and "Votes" columns were either integers or floats so that we can plot them and perform calculations on them. We're now ready to analyze our DataFrame to look at some basic statistics and test our hypotheses through data analysis. We still have 7,403 restaurants, which is quite a sizeable data set to use for our analysis.

Pivot Table Analysis

Here, we want to profile our data, so we use pivot tables to garner a few insights. We can utilize pivot tables to test our hypotheses.

In [15]:
```
countryvotes = pd.pivot_table(zom, values='Votes', index='Country', aggfunc=np.su
countryvotes.sort_values(['Votes'], ascending=[True], inplace=True) #sort country
countryvotes
```

Out[15]:

Country	Votes
Canada	412
Singapore	638
Brazil	1170
Australia	2674
Sri Lanka	2929
Qatar	3276
Phillipines	8963
New Zealand	9721
Turkey	14670
Indonesia	16214
United Kingdom	16436
South Africa	18910
UAE	29611
United States	185842
India	1185310
All	1496776

This pivot table shows the total number of reviews by country. Of course, India has the most votes at 1,185,310 reviews left, as Zomato is based in that country. Zomato operates in 24 countries, but we only have 15 countries represented in the data. Therefore, we must keep in mind that this data set of 1,496,776 votes isn't completely representative of the Zomato population.

In [16]:
```
cuisdata_p = pd.pivot_table(zom, index='Cuisine', values=['Price','Rating','Votes
cuisdata_p.sort_values(['Price', 'Rating', 'Votes'], ascending=[True, False, Fals
cuisdata_p.tail(10) #display first 10 rows
```

Out[16]:

Cuisine	Price	Rating	Votes
French	3.785714	4.178571	176.0
Argentine	4.000000	4.500000	602.0
African	4.000000	4.450000	319.0
Irish	4.000000	4.300000	782.0
Gourmet Fast Food	4.000000	4.300000	68.0
Kiwi	4.000000	4.200000	271.0
Asian Fusion	4.000000	3.850000	73.5
Peruvian	4.000000	3.600000	5.0
South American	4.000000	3.500000	72.5
Drinks Only	4.000000	3.500000	45.0

We see here that French cuisine is the 10th most expensive cuisine in the data set. This confirms the first part of our first hypothesis that French cuisine, which is usually related to fine dining, does usually command a high price. Another thing to note is that a few of the top cuisines have an average less than 50 votes, and with 1.5 million votes, such a figure is quite insignificant and could present misleading skew.

In [17]:
```
cuisdata_r = pd.pivot_table(zom, index='Cuisine', values=['Rating','Price','Votes
cuisdata_r.sort_values(['Rating', 'Price', 'Votes'], ascending=[True, False, Fals
cuisdata_r.tail(10) #display first 10 rows
```

Out[17]:

Cuisine	Price	Rating	Votes
Hawaiian	3.400000	4.480000	1149.800000
Argentine	4.000000	4.500000	602.000000
World Cuisine	3.333333	4.500000	414.666667
Ramen	3.000000	4.600000	418.000000
Persian	3.000000	4.600000	177.000000
Filipino	3.000000	4.616667	454.500000
Taiwanese	2.500000	4.650000	192.000000
Scottish	3.000000	4.700000	163.000000
Cajun	2.000000	4.700000	1412.000000
Sunda	3.000000	4.900000	1838.000000

Here we see the top 10 cuisines based on average rating. The second part of our first hypothesis and our second hypothesis do not hold: cuisine is not necessarily a signal for a high rating. In fact, Sunda cuisine, a particular type of Indonesian food, has both the highest average rating and number of votes, while maintaining an average price level of 3. Only Argentine food has the highest price level of 4 as well as a high rating. However, the rest of the cuisines have an average price level under 3.50 while maintaining a top 10 average rating.

In [18]:
```
cuisdata_c = pd.pivot_table(zom, index=['Cuisine','Price'],values=['Rating','Vote
cuisdata_c
```

Out[18]:

		Rating	Votes
Cuisine	**Price**		
Afghani	**2**	2.900000	39.000000
African	**4**	4.450000	319.000000
American	**1**	3.847826	214.956522
	2	3.428873	276.485915
	3	3.947761	590.507463
	4	3.910526	570.210526
Andhra	**1**	3.400000	139.000000
	2	3.550000	139.000000
Arabian	**1**	3.500000	95.000000
	2	3.000000	44.500000
	3	3.950000	226.000000
Argentine	**4**	4.500000	602.000000
Asian	**1**	3.930769	373.538462
	2	3.805263	179.473684
	3	3.984615	483.346154
	4	4.007143	385.857143
Asian Fusion	**4**	3.850000	73.500000
Assamese	**1**	2.800000	45.000000
	2	3.500000	218.000000
Australian	**2**	4.100000	87.000000
Awadhi	**2**	3.800000	86.000000
BBQ	**1**	4.116667	167.166667
	2	4.060000	445.600000
	3	4.500000	674.000000
	4	4.300000	39.000000
Bakery	**1**	3.285993	77.817590
	2	3.513514	152.342342
	3	3.469231	78.769231
	4	4.400000	13.000000
Bar Food	**1**	4.400000	546.000000
...	**...**	...	...
Sushi	**2**	3.675000	44.000000

Cuisine	Price	Rating	Votes
	3	4.157143	203.428571
	4	3.700000	10.500000
Taiwanese	2	4.900000	161.000000
	3	4.400000	223.000000
Tapas	2	3.900000	502.000000
	4	4.900000	194.000000
Tea	1	3.040000	125.600000
	2	3.400000	18.000000
	3	3.500000	37.000000
	4	4.100000	68.000000
Tex-Mex	3	4.000000	911.000000
Thai	1	4.050000	207.500000
	2	3.760000	152.800000
	3	4.011111	205.555556
	4	4.137500	183.625000
Tibetan	1	2.971429	69.428571
	2	3.375000	232.750000
	3	3.700000	807.000000
Turkish	2	3.450000	133.750000
	3	4.100000	788.000000
	4	4.300000	43.000000
Turkish Pizza	2	4.300000	103.000000
Vietnamese	1	4.100000	270.000000
	2	4.300000	96.000000
	3	4.000000	83.000000
Western	3	4.200000	259.000000
	4	3.200000	32.000000
World Cuisine	3	4.550000	564.500000
	4	4.400000	115.000000

289 rows × 2 columns

Here, we further explore the relationship between price level and rating. We break down each cuisine by the restaurants in each price level and find the average rating and number of votes that correspond to them. From eying the pivot table and looking at a few cuisines that have restaurants in all 4 price levels, it's clear that our second hypothesis definitely does not hold. American restaurants at price level 1 had a rating (3.85) almost the same as those with price level 4 (3.91).

The same goes for Asian and Thai cuisine. The average rating at price level 1 is very close to that at price level 4. If our hypothesis had held, we would have seen the rating increase as price level increases. but that is not the case in the data set. Fine dining and higher prices do not equate to a better dining experience for Zomato users.

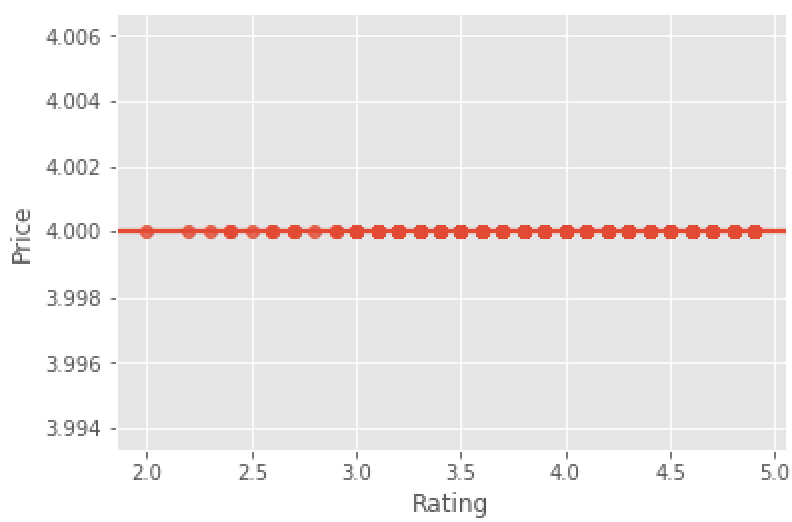
Data Visualization

Though we have just tested our hypotheses using pivot tables, we'd like to visualize our data to analyze our hypotheses in a different lens. First we'll look at the relationship between price and rating.

In [21]:
```
#setup for data visualization

import sys
import matplotlib.pyplot as plt #plotting visualizations
from math import pi
import datetime
from scipy.stats.stats import linregress
import seaborn as sns #statistical graphs

plt.style.use("ggplot") #data vizualization

%matplotlib inline

import warnings
warnings.filterwarnings('ignore') #ignore warnings that may pop up in plotting
```

In [22]:
```
high_price = zom.loc[zom['Price']==zom['Price'].max(),:]
sns.regplot(x = high_price['Rating'], y=high_price['Price'])
```

Out[22]:
```
<matplotlib.axes._subplots.AxesSubplot at 0xab61c4b240>
```



Here, we find all restaurants with a price level of 4 and plot their ratings on the x-axis. Under our second assumption, we should see a very heavy right skew in the dots, but the graph clearly shows that these restaurants have ratings that are widely distributed; thus, our second hypothesis does not hold.

Now, let's compare the other price levels to their respective ratings.

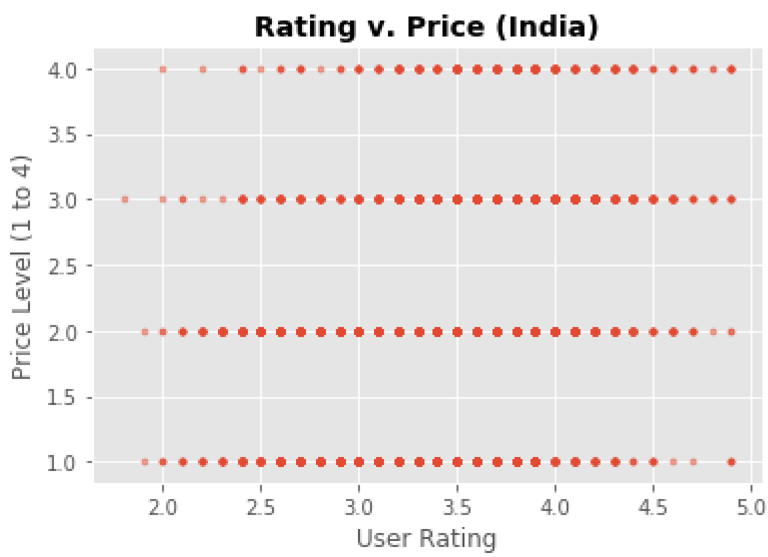
In [23]:
```
fig, ax = plt.subplots()
ax.scatter(zom["Rating"], zom["Price"])

ax.set_title('Rating v. Price ', loc='center', fontsize=14, fontweight = "bold")


ax.set_xlabel("User Rating")
ax.set_ylabel("Price Level (1 to 4)")
```

Out[23]: `Text(0,0.5,'Price Level (1 to 4)')`

Again, we see that price level really has no correlation with overall ratings. All price levels exhibit no skew to a low or high rating.

In [25]:
```
in_rst = zom.loc[zom['Country'] == 'India',:]

fig, ax = plt.subplots()
ax.scatter(in_rst["Rating"], in_rst["Price"], alpha= 0.50,
           s=10)

ax.set_title('Rating v. Price (India)', loc='center', fontsize=14, fontweight = "


ax.set_xlabel("User Rating")
ax.set_ylabel("Price Level (1 to 4)")
```

Out[25]: Text(0,0.5,'Price Level (1 to 4)')

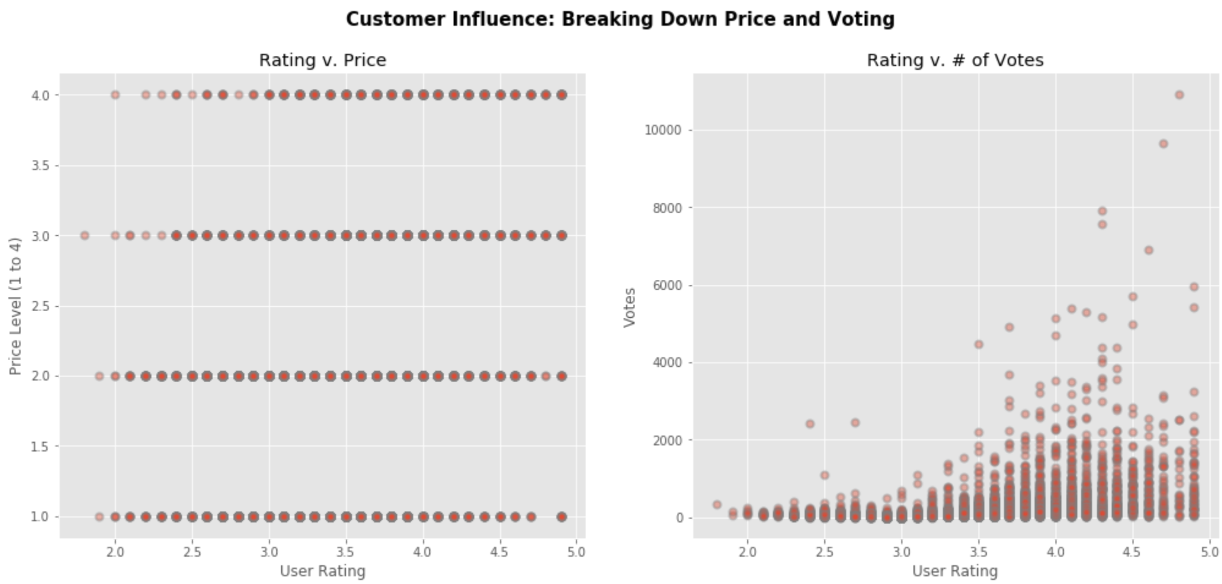


Now, we look at only India's restaurants (as it has the greatest share of the sample size) to see if the same result occurs: it does. We can garner no clear correlation between the price level of the restaurant and its user rating.

In fact, all ratings at each price level seem to concentrate between 3 and 4. This is actually an interesting phenomenon in platforms that allow consumers to leave reviews (eBay, Yelp, etc.). All factors (price, cuisine, etc.) notwithstanding, the probability a user will leave a certain rating is the same; that rating varies from platform to platform, but the pattern remains the same.

We can plot a histogram comparing user ratings on restaurants and the number of votes that begot the rating.

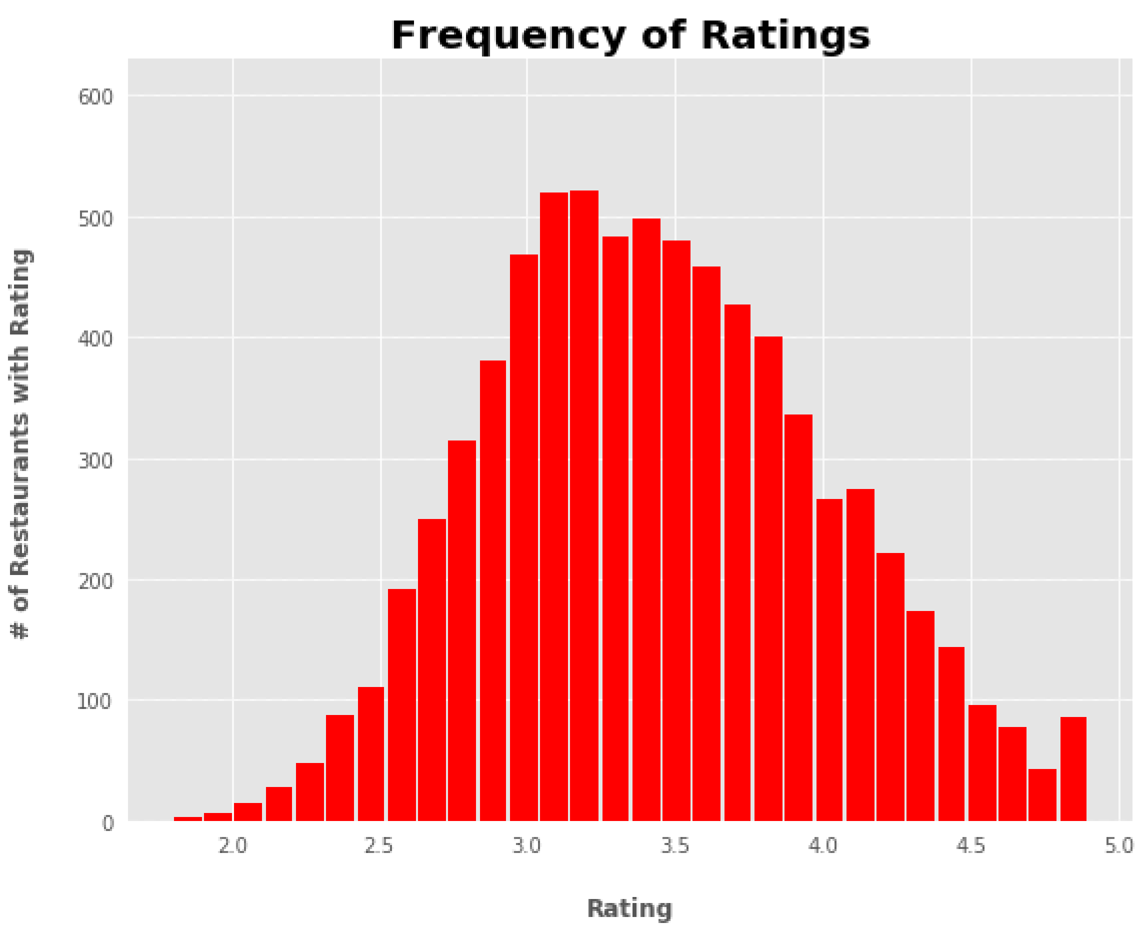
In [26]:
```
fig, (ax1, ax2) = plt.subplots(1, 2, sharex ="col", figsize = (17, 7))
plt.xlabel("the X axis")
plt.ylabel("the Y axis")
plt.suptitle("Customer Influence: Breaking Down Price and Voting", fontsize = 15,

ar = np.float64(zom["Rating"])
pr = np.float64(zom["Price"])
v = np.float64(zom["Votes"])

ax1.scatter(ar, pr, cmap="Blues", alpha=0.4, edgecolors="grey", linewidth=2) #add

ax1.set_title("Rating v. Price")
ax1.set_xlabel('User Rating')
ax1.set_ylabel('Price Level (1 to 4)')

ax2.scatter(ar, v, cmap="Blues", alpha=0.4, edgecolors="grey", linewidth=2)
ax2.set_title("Rating v. # of Votes")
ax2.set_xlabel('User Rating')
ax2.set_ylabel('Votes')

plt.show()
```



Here we actually see that restaurants that received more than 2,000 votes tend to achieve overall ratings between 4 and 5, not 3 and 4. Below the 2,000 vote mark, it's a little hard to tell, but it's clear that restaurants with ratings less than 3.5 do not get a large number of votes. From the right graph, we can conclude that a restaurant with more than 2,000 votes is more likely to have a higher rating.

Now, we will make a histogram showing the frequency with which an individual restaurant achives a certain rating.

In [27]:
```
ax = zom.hist(column='Rating', bins=30, grid=True, figsize=(9,7), color='r', zord

ax = ax[0]
for x in ax:

    #despine
    x.spines['right'].set_visible(False)
    x.spines['top'].set_visible(False)
    x.spines['left'].set_visible(False)

    #switch off ticks
    x.tick_params(axis="both", which="both", bottom="off", top="off", labelbottom

    #draw horizontal axis lines
    vals = x.get_yticks()
    for tick in vals:
        x.axhline(y=tick, linestyle='dashed', alpha=0.4, color='#eeeeee', zorder=

    #set main title
    x.set_title("Frequency of Ratings", weight='bold', size=20)

    #set x-axis label
    x.set_xlabel("Rating", labelpad=20, weight='bold', size=12)

    #set y-axis label
    x.set_ylabel("# of Restaurants with Rating", labelpad=20, weight='bold', size
```



In [28]:
```
zom[['Price','Rating']].corr()
```

Out[28]:

	Price	Rating
Price	1.000000	0.403169
Rating	0.403169	1.000000

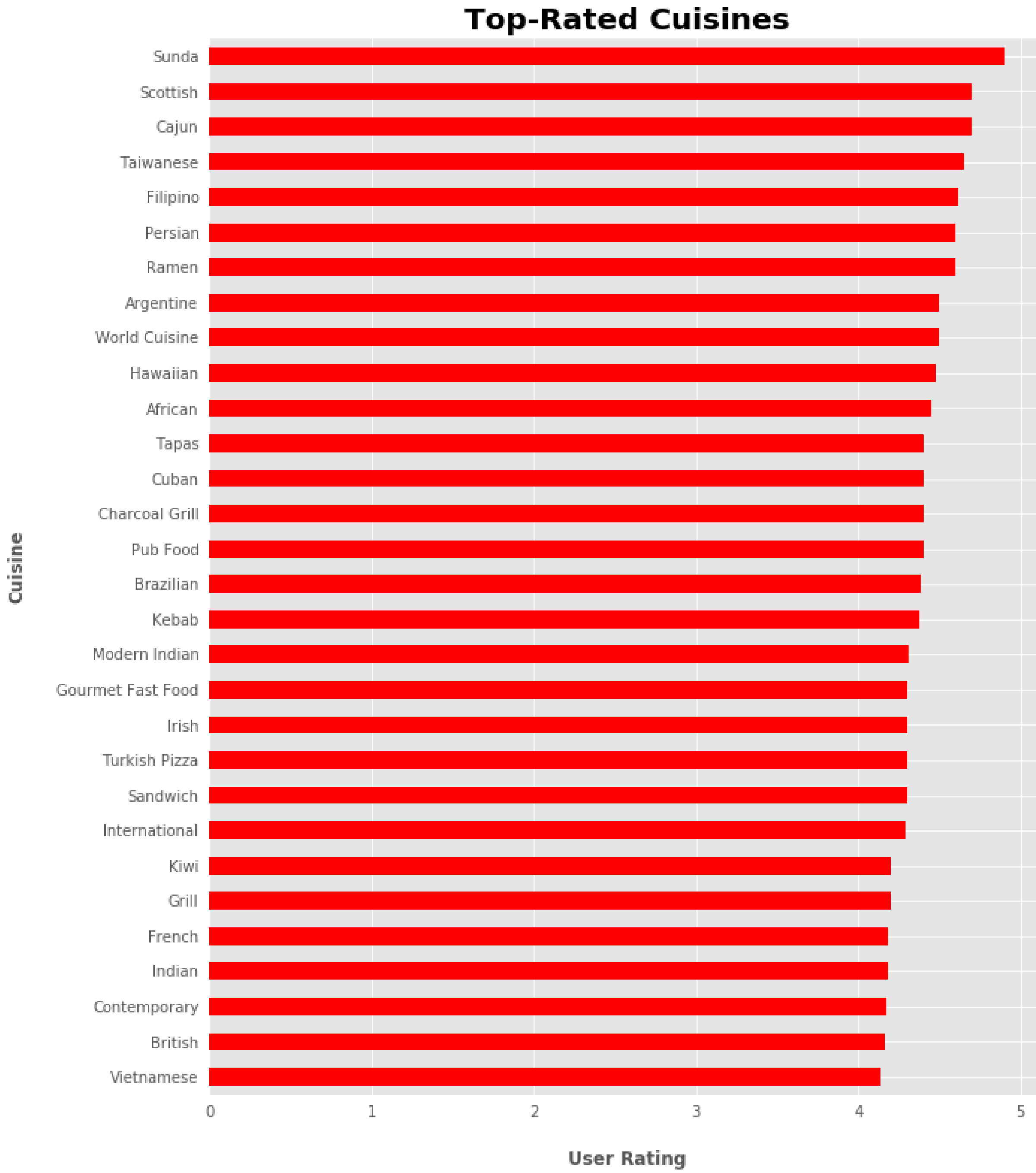
This is more in line with our previous observation that all ratings seemed to concentrate between a rating of 3 and 4 (more accurately, between 2.9 and 3.8). Very few restaurants received a rating below 2.50; there is definitely a skew towards the higher ratings.

Above we also explicitly calculate the correlation between price and rating, and the conclusions from our graphs match the result. There is no convincing correlation, but restaurants with a higher price probably won't have a relatively low rating.

Now we want to visualize cuisine and ratings.

In [29]:
```
x1 = zom.groupby('Cuisine')['Rating'].mean().sort_values().tail(30)

ax = x1.plot(kind='barh', figsize=(10, 13), color='r', zorder=2, width=0.5)

#despine
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
ax.spines['left'].set_visible(False)
ax.spines['bottom'].set_visible(False)

#switch off ticks
ax.tick_params(axis="both", which="both", bottom="off", top="off", labelbottom="o

#set main title
ax.set_title("Top-Rated Cuisines", weight='bold', size=20)

#set x-axis label
ax.set_xlabel("User Rating", labelpad=20, weight='bold', size=12)

#set y-axis label
ax.set_ylabel("Cuisine", labelpad=20, weight='bold', size=12)
```

Out[29]:
```
Text(0,0.5,'Cuisine')
```



This graph shows the same information as the cuisdata_r pivot table. We expanded it to show the top 30 cuisines so that we could find French cuisine, which ranks at 26th. This is quite low, as there over 100 cuisines. Again, we cannot find convincing data that the connotation of French cuisine to fine dining and good dining experiences holds true.

Conclusion & Next Steps

Through this project, we have conclude that cuisines that are usually considered high-dining experiences like French and Japanese are not necessarily the most expensive and are definitely not the highest-rated. Moreover, from the data set, the cuisines with highest average rating were not the most expensive. This data sample from Zomato effectively disproves our two original hypotheses that we inferred based on prior knowledge and experiences.

We do note a few limitations in the data:

- Zomato is based in India, and this data set is highly concentrated on restaurants in the country
- India's restaurant ecosystem should not be taken as representative of the global restaurant industry
- Haute cuisines like French and Japanese may not be fully developed in the Indian market (or there may not be a big enough market for them yet)
- This data set by no mean represents the population of Zomato votes; it's merely a sample
- We did cull quite a bit of the data when cleaning it, so the sample became further constrained
- The cuisines we chose as the representative cuisine for the restaurant may not have been truly representative

To further explore this topic, we propose these next steps:

- Compare data sets from other restaurant search platforms like TripAdvisor and Yelp
- Find a representative sample for the global restaurant industry
- Further research the implicit biases and platform dynamics that occur when leaving review/ratings

Ultimately, this project is quite constrained, and the analysis performed was elementary. Further insight can be gained by expanding the data set and using more complex data analysis tools to further test relationships between restaurant qualities and ratings.

GitHub Link

https://github.com/kenneth-yu19/Data_Bootcamp_Final_Project (https://github.com/kenneth-yu19/Data_Bootcamp_Final_Project)