Sejal Sanas

Build a machine learning model to predict the aggregate rating of a restaurant based on other features.

In [1]:
```
# Importing the Libraries
import pandas as pd
import numpy as np
```

In [2]:
```
import warnings
warnings.filterwarnings("ignore")
```

Pre-Processing Steps

In [3]:
```
# Creating the Dataframe
df=pd.read_csv(r'C:/Users/Shejal Sanas/Downloads/Dataset.csv')
```

In [4]:
```
df
```

Out[4]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude
0	6317637	Le Petit Souffle	162	Makati City	Third Floor, Century City Mall, Kalayaan Avenu...	Century City Mall, Poblacion, Makati City	Century City Mall, Poblacion, Makati City, Mak...	121.027535	14.565443
1	6304287	Izakaya Kikufuji	162	Makati City	Little Tokyo, 2277 Chino Roces Avenue, Legaspi...	Little Tokyo, Legaspi Village, Makati City	Little Tokyo, Legaspi Village, Makati City, Ma...	121.014101	14.553708
2	6300002	Heat - Edsa Shangri-La	162	Mandaluyong City	Edsa Shangri-La, 1 Garden Way, Ortigas, Mandal...	Edsa Shangri-La, Ortigas, Mandaluyong City	Edsa Shangri-La, Ortigas, Mandaluyong City, Ma...	121.056831	14.581404
3	6318506	Ooma	162	Mandaluyong City	Third Floor, Mega Fashion Hall, SM Megamall, O...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.056475	14.585318
4	6314302	Sambo Kojin	162	Mandaluyong City	Third Floor, Mega Atrium, SM Megamall, Ortigas...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.057508	14.584450
...	...	...	...	...	...	...	...	...	...
9546	5915730	Naml\ Gurme	208	��stanbul	Kemanke�� Karamustafa Pa���a Mahallesi, R\ht\m ...	Karak�_y	Karak�_y, ��stanbul	28.977392	41.022793
9547	5908749	Ceviz A��ac\	208	��stanbul	Ko��uyolu Mahallesi, Muhittin ��st�_nda�� Cadd...	Ko��uyolu	Ko��uyolu, ��stanbul	29.041297	41.009847
9548	5915807	Huqqa	208	��stanbul	Kuru�_e��me Mahallesi, Muallim Naci Caddesi, N...	Kuru�_e��me	Kuru�_e��me, ��stanbul	29.034640	41.055817
9549	5916112	A���k Kahve	208	��stanbul	Kuru�_e��me Mahallesi, Muallim Naci Caddesi, N...	Kuru�_e��me	Kuru�_e��me, ��stanbul	29.036019	41.057979
9550	5927402	Walter's Coffee Roastery	208	��stanbul	Cafea��a Mahallesi, Bademalt\ Sokak, No 21/B, ...	Moda	Moda, ��stanbul	29.026016	40.984776

9551 rows × 21 columns

In [5]:
```
df = df.drop('Restaurant ID', axis=1)
df = df.drop('Restaurant Name', axis=1)
df = df.drop('Country Code', axis=1)
df = df.drop('City', axis=1)
df = df.drop('Address', axis=1)
df = df.drop('Locality', axis=1)
df = df.drop('Locality Verbose', axis=1)
df = df.drop('Longitude', axis=1)
df = df.drop('Latitude', axis=1)
df = df.drop('Cuisines', axis=1)
df = df.drop('Currency', axis=1)
```

In [6]:
```
df
```

Out[6]:

	Average Cost for two	Has Table booking	Has Online delivery	Is delivering now	Switch to order menu	Price range	Aggregate rating	Rating color	Rating text	Votes
0	1100	Yes	No	No	No	3	4.8	Dark Green	Excellent	314
1	1200	Yes	No	No	No	3	4.5	Dark Green	Excellent	591
2	4000	Yes	No	No	No	4	4.4	Green	Very Good	270
3	1500	No	No	No	No	4	4.9	Dark Green	Excellent	365
4	1500	Yes	No	No	No	4	4.8	Dark Green	Excellent	229
...	...	...	...	...	...	...	...	...	...	...
9546	80	No	No	No	No	3	4.1	Green	Very Good	788
9547	105	No	No	No	No	3	4.2	Green	Very Good	1034
9548	170	No	No	No	No	4	3.7	Yellow	Good	661
9549	120	No	No	No	No	4	4.0	Green	Very Good	901
9550	55	No	No	No	No	2	4.0	Green	Very Good	591

9551 rows × 10 columns

In [7]:
```
df.shape
```

Out[7]:
```
(9551, 10)
```

In [8]:
```
df.info
```

Out[8]:
```
<bound method DataFrame.info of       Average Cost for two Has Table booking Has Online delivery  \
0                     1100              Yes                  No
1                     1200              Yes                  No
2                     4000              Yes                  No
3                     1500               No                  No
4                     1500              Yes                  No
...                    ...              ...                 ...
9546                    80               No                  No
9547                   105               No                  No
9548                   170               No                  No
9549                   120               No                  No
9550                    55               No                  No

     Is delivering now Switch to order menu  Price range  Aggregate rating  \
0                   No                    No            3               4.8
1                   No                    No            3               4.5
2                   No                    No            4               4.4
3                   No                    No            4               4.9
4                   No                    No            4               4.8
...                ...                   ...          ...               ...
9546                No                    No            3               4.1
9547                No                    No            3               4.2
9548                No                    No            4               3.7
9549                No                    No            4               4.0
9550                No                    No            2               4.0

     Rating color Rating text  Votes
0      Dark Green   Excellent    314
1      Dark Green   Excellent    591
2           Green   Very Good    270
3      Dark Green   Excellent    365
4      Dark Green   Excellent    229
...           ...         ...    ...
9546        Green   Very Good    788
9547        Green   Very Good   1034
9548       Yellow        Good    661
9549        Green   Very Good    901
9550        Green   Very Good    591

[9551 rows x 10 columns]>
```

In [9]:
```
df.describe()
```

Out[9]:

	Average Cost for two	Price range	Aggregate rating	Votes
count	9551.000000	9551.000000	9551.000000	9551.000000
mean	1199.210763	1.804837	2.666370	156.909748
std	16121.183073	0.905609	1.516378	430.169145
min	0.000000	1.000000	0.000000	0.000000
25%	250.000000	1.000000	2.500000	5.000000
50%	400.000000	2.000000	3.200000	31.000000
75%	700.000000	2.000000	3.700000	131.000000
max	800000.000000	4.000000	4.900000	10934.000000

In [10]:
```
df.isnull().sum()
```

Out[10]:
```
Average Cost for two    0
Has Table booking       0
Has Online delivery     0
Is delivering now       0
Switch to order menu    0
Price range             0
Aggregate rating        0
Rating color            0
Rating text             0
Votes                   0
dtype: int64
```

In [11]:
```
# Checking for duplicated values
df.duplicated().sum()
```

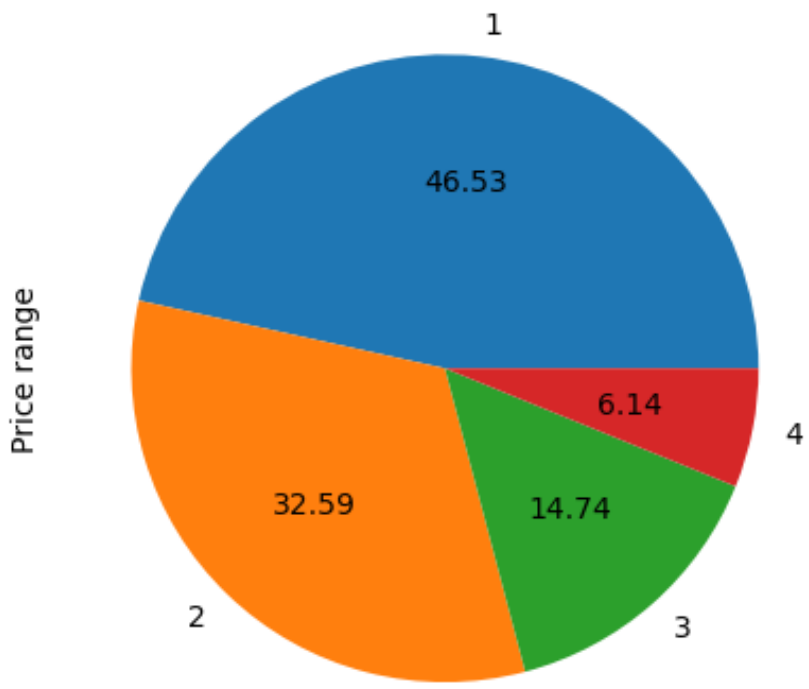
Out[11]:
```
2871
```

In [12]:
```
df.dropna(inplace=True)
```

In [13]:
```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

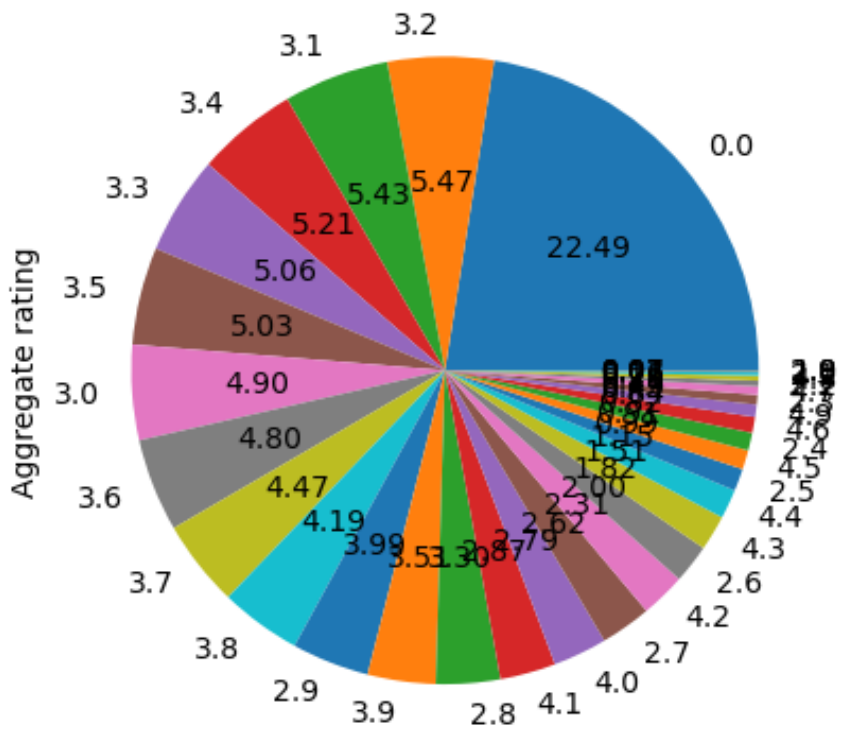
In [14]:
```
df['Price range'].value_counts().plot(kind='pie', autopct = '%.2f')
```

Out[14]: <Axes: ylabel='Price range'>



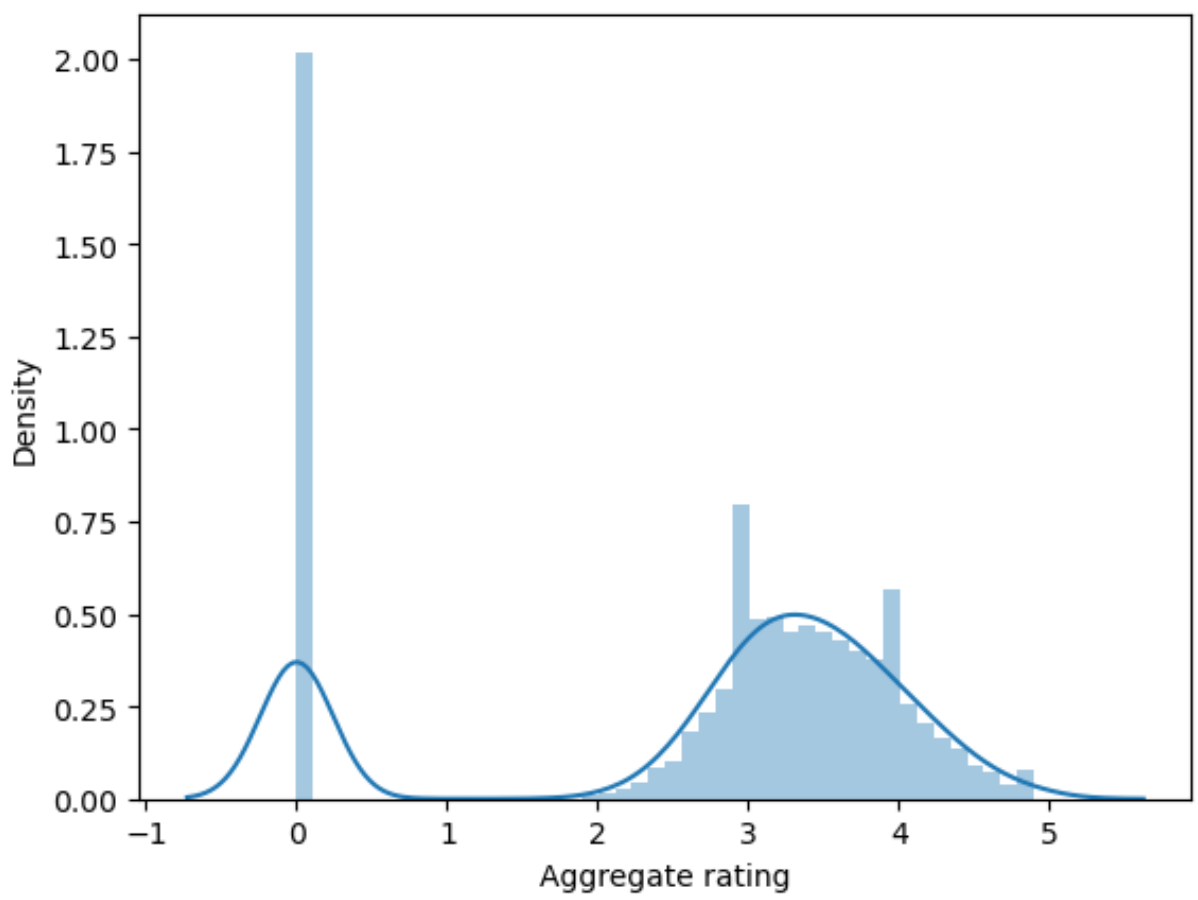
In [15]:
```
df['Aggregate rating'].value_counts().plot(kind='pie', autopct = '%.2f')
```

Out[15]: <Axes: ylabel='Aggregate rating'>



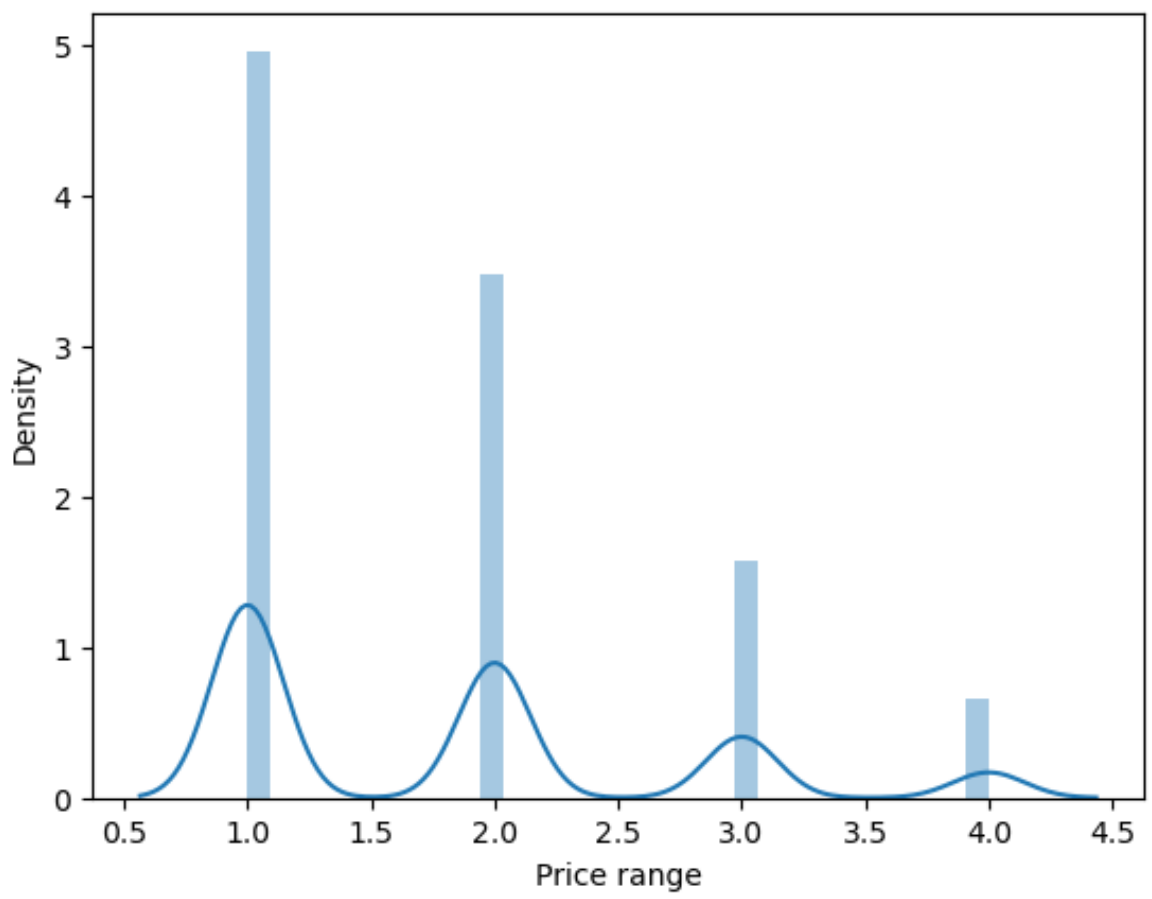
In [16]:
```
sns.distplot(df['Aggregate rating'])
```

Out[16]: <Axes: xlabel='Aggregate rating', ylabel='Density'>



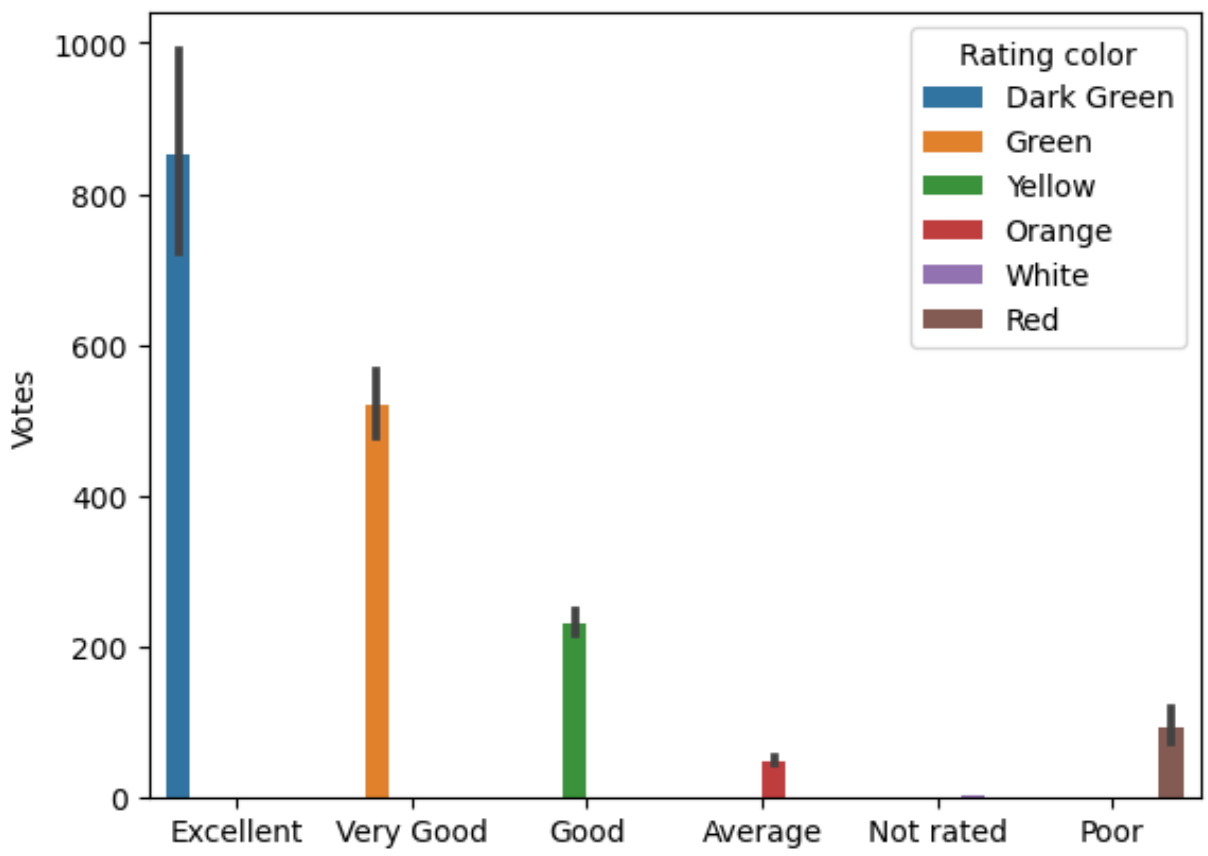
In [17]:
```
sns.distplot(df['Price range'])
```

Out[17]: <Axes: xlabel='Price range', ylabel='Density'>



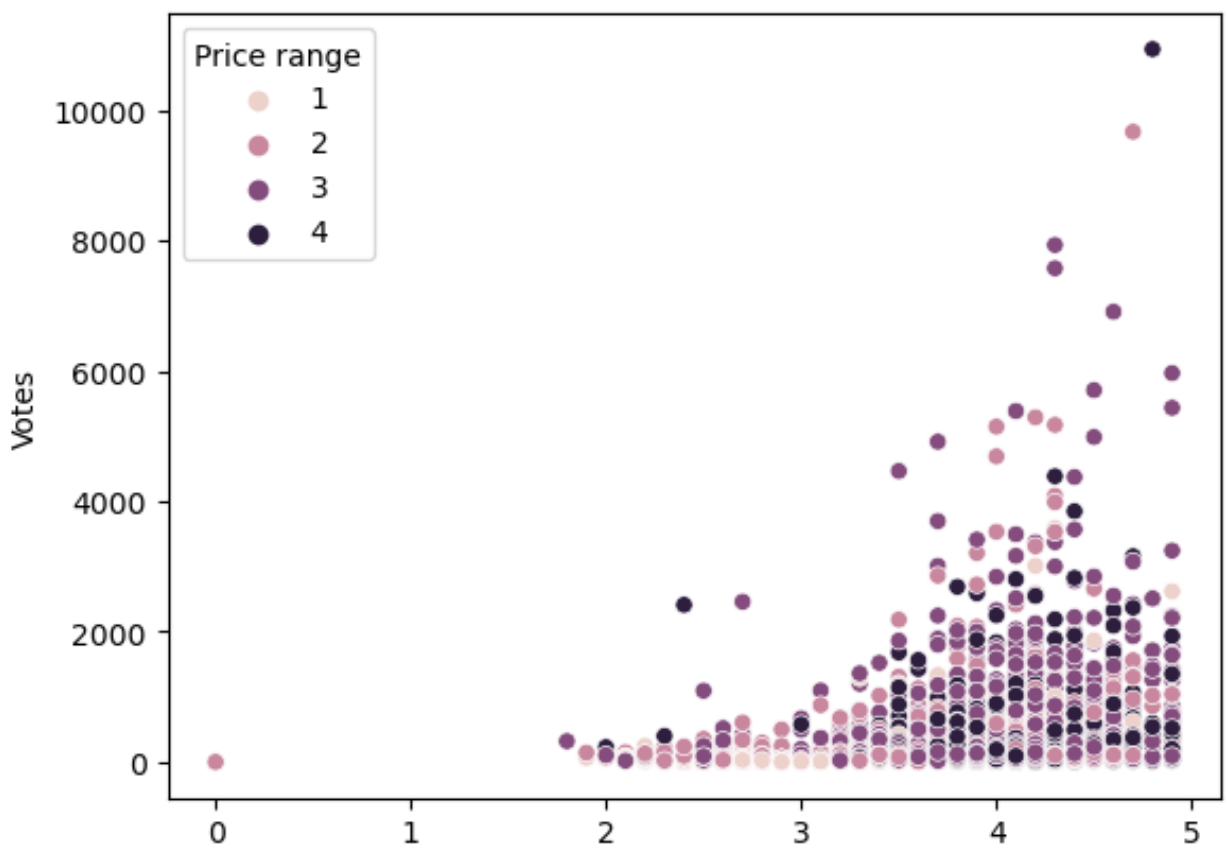
In [18]:
```
sns.barplot(x=df["Rating text"],y=df["Votes"],hue =df["Rating color"])
```

Out[18]: <Axes: xlabel='Rating text', ylabel='Votes'>



In [19]:
```
sns.scatterplot(x=df["Aggregate rating"],y=df["Votes"],hue=df["Price range"])
```

Out[19]: <Axes: xlabel='Aggregate rating', ylabel='Votes'>



In [20]:
```
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
df['Has Table booking'] = label_encoder.fit_transform(df['Has Table booking'])
df['Has Online delivery'] = label_encoder.fit_transform(df['Has Online delivery'])
df['Is delivering now'] = label_encoder.fit_transform(df['Is delivering now'])
df['Switch to order menu'] = label_encoder.fit_transform(df['Switch to order menu'])
df['Rating color'] = label_encoder.fit_transform(df['Rating color'])
df['Rating text'] = label_encoder.fit_transform(df['Rating text'])
```

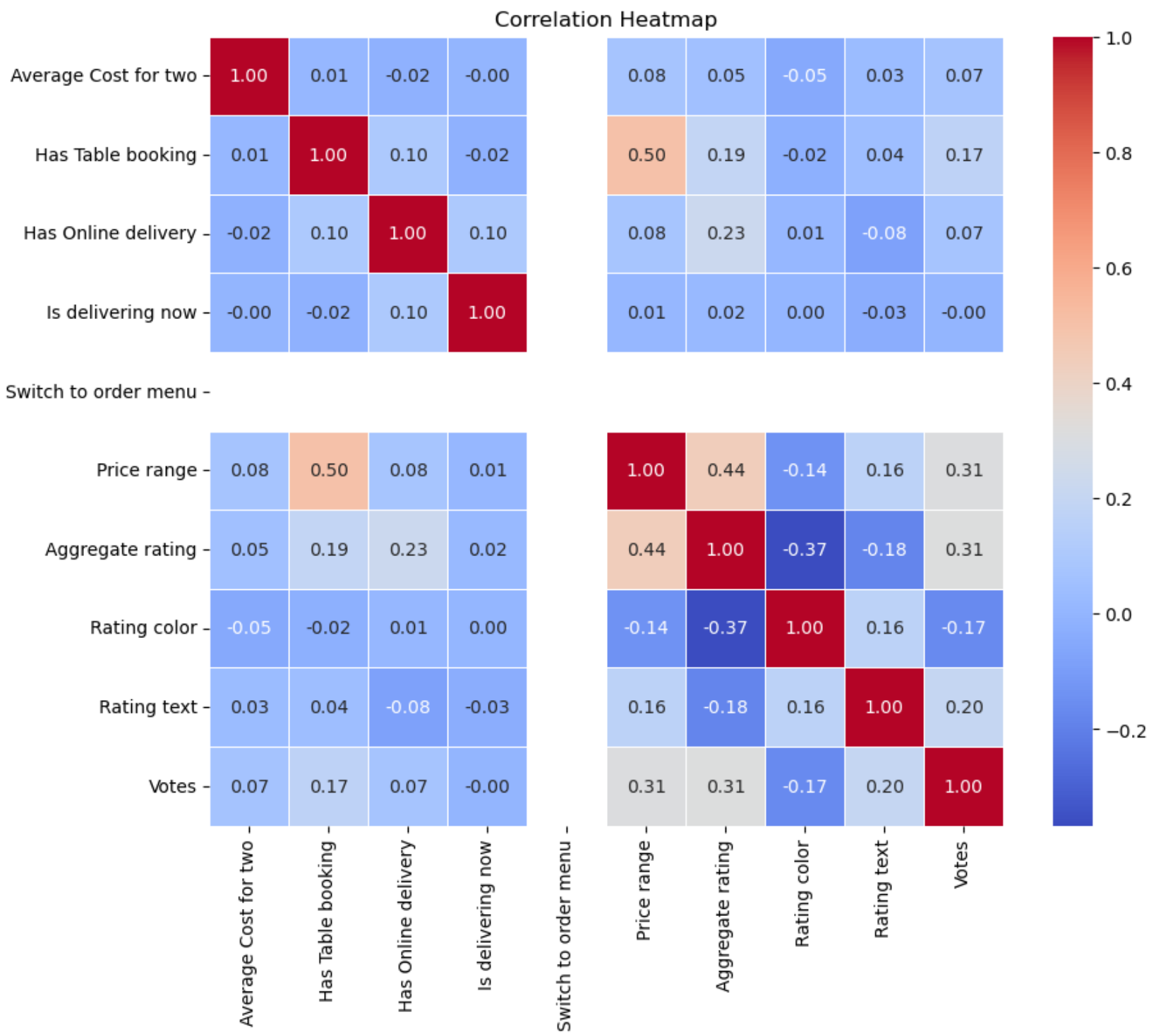
In [21]:
```
df
```

Out[21]:

	Average Cost for two	Has Table booking	Has Online delivery	Is delivering now	Switch to order menu	Price range	Aggregate rating	Rating color	Rating text	Votes
0	1100	1	0	0	0	3	4.8	0	1	314
1	1200	1	0	0	0	3	4.5	0	1	591
2	4000	1	0	0	0	4	4.4	1	5	270
3	1500	0	0	0	0	4	4.9	0	1	365
4	1500	1	0	0	0	4	4.8	0	1	229
...	...	...	...	...	...	...	...	...	...	...
9546	80	0	0	0	0	3	4.1	1	5	788
9547	105	0	0	0	0	3	4.2	1	5	1034
9548	170	0	0	0	0	4	3.7	5	2	661
9549	120	0	0	0	0	4	4.0	1	5	901
9550	55	0	0	0	0	2	4.0	1	5	591

9551 rows × 10 columns

In [22]:
```
correlation_matrix = df.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()
```



In [23]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import r2_score
```

In [24]:
```
x = df.drop('Aggregate rating', axis=1)
y = df['Aggregate rating']
```

In [25]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=.1,random_state=353)
x_train.head()
y_train.head()
```

Out[25]:
```
8696    0.0
1164    4.0
4824    3.2
7574    3.2
2961    2.3
Name: Aggregate rating, dtype: float64
```

Running the Linear Regression Model

In [26]:
```
reg=LinearRegression()
reg.fit(x_train,y_train)
y_pred=reg.predict(x_test)
from sklearn.metrics import r2_score
r2_score(y_test,y_pred)
```

Out[26]:
```
0.44846419965192574
```

In [27]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
reg = LinearRegression()
reg.fit(x_train, y_train)
y_pred = reg.predict(x_test)
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error (MSE): {mse:.2f}")
r2 = r2_score(y_test, y_pred)
print(f"R-squared (R2) Error: {r2:.2f}")
```

```
Mean Squared Error (MSE): 1.36
R-squared (R2) Error: 0.45
```

Building the Decision Tree Regressor

In [28]:
```
from sklearn.tree import DecisionTreeRegressor
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=.1,random_state=105)
DTree=DecisionTreeRegressor(min_samples_leaf=.0001)
DTree.fit(x_train,y_train)
y_predict=DTree.predict(x_test)
from sklearn.metrics import r2_score
r2_score(y_test,y_predict)
```

Out[28]:
```
0.9772850223351995
```

In [29]:
```
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score

DTree = DecisionTreeRegressor(min_samples_leaf=0.0001)

DTree.fit(x_train, y_train)

y_predict = DTree.predict(x_test)

# Calculate Mean Squared Error (MSE)
mse = mean_squared_error(y_test, y_predict)
print(f"Mean Squared Error (RMSE): {mse:.2f}")

# Calculate R-squared (R2) Error
r2 = r2_score(y_test, y_predict)
print(f"R-squared (R2) Error: {r2:.2f}")
```

```
Mean Squared Error (RMSE): 0.05
R-squared (R2) Error: 0.98
```

Conclusion: MSE of 0.05 indicates that model's predictions are very accurate & low errors. R2 value of 0.98 suggests that model is highly effective at explaining & predicting the target variable. Decision Tree Regressor model is performing exceptionally well on your test data.