Assignment 2 - Linear Regression

In [ ]:
```
# This code appears in every demonstration Notebook.
# By default, when you run each cell, only the last output of the codes will show.
# This code makes all outputs of a cell show.
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

The dataset is based on Gyódi and Nawaro (2021)'s research on Airbnb prices in European cities. We take a sub dataset of Airbnb listings in Barcelona, Spain during weekdays and intend to build a model to predict listing price using the features.

The variables are as follows.
price --- Listing price
bedrooms --- number of bedrooms
person_capacity --- maximum number of guests
room_private --- dummy for private rooms
room_shared --- dummy for shared rooms
cleanliness --- guest reviews: scale to 10
guest_satisfaction --- guest reviews:scale to 100
superhost --- dummy for hosts with the superhost status
multi --- dummy for listings offered by hosts with 2–4 listings
biz --- dummy for listings offered by hosts with more than 4 listings
dist --- distance to the city centre in kilometres
metro_dist --- distance to the closest metro station in kilometres
attr_index --- attraction index: scale to 100, measuring the accessibility to attractions
rest_index --- restaurant index: scale to 100, measuring the accessibility to restaurants
lng --- Longitude of the listing location
lat --- Latitude of the listing location

Ref:
Gyódi, K. and L. Nawaro (2021). Determinants of Airbnb prices in European cities: A spatial econometrics approach. Tourism Management, Vol. 86.

1. Import the necessary packages.

In [3]:
```
import pandas as pd
import statsmodels.api as sm
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

It will import the necessary package required to perform linear regression in python, and statsmodels module provides classes and functions to estimate different statistical models.

1. Read in the dataset, 'Barcelona.csv'. Display the data.

In [4]:
```
barcelona = pd.read_csv('Barcelona.csv')
barcelona.head(10)
```

Out[4]:

	price	bedrooms	room_shared	room_private	person_capacity	superhost	multi	biz	cleanliness	guest_satisfaction	dist	metr
0	474.317499	1	False	False	4	False	0	1	10	91	1.111996	0.6
1	169.897829	1	False	True	2	True	1	0	10	88	1.751839	0.1
2	161.984779	1	False	True	4	False	0	1	9	88	1.670493	0.0
3	367.956804	1	False	False	3	False	0	1	10	91	1.475847	0.0
4	196.895292	1	False	True	3	False	1	0	9	91	1.855452	0.2
5	330.951661	2	False	False	3	False	0	1	9	100	2.565611	0.7
6	141.271208	1	False	True	3	False	0	1	9	86	1.648304	0.0
7	173.388880	1	False	True	2	False	0	0	9	96	1.474228	0.5
8	225.754649	1	False	True	4	False	1	0	9	84	0.962655	0.3
9	150.580678	1	False	True	2	False	1	0	9	91	1.819600	0.2

The above code chunks will read the dataset 'Barcelona.csv' and will print the result as barcelona. barcelona.head() will fetch the 1st few rows the dataset,in this case it will fetch the first 10 rows.

1. How many observations? Display the variable names.

In [5]:
```
# Define the observations i.e., how many rows and colums are there in the 'Barcelona.csv' dataset.
barcelona.shape
```

Out[5]:
```
(1555, 16)
```

In [6]:
```
barcelona.columns
```

Out[6]:
```
Index(['price', 'bedrooms', 'room_shared', 'room_private', 'person_capacity',
       'superhost', 'multi', 'biz', 'cleanliness', 'guest_satisfaction',
       'dist', 'metro_dist', 'attr_index', 'rest_index', 'lng', 'lat'],
      dtype='object')
```

The code chunks provided above will print all the variable names.

4.1 Explore the variable 'price'. First, Let's find out the statistics using describe(). Then we use a graph to explore the distribution. What do you find?

In [7]:
```
type('price') # class of the variable 'price'.
```

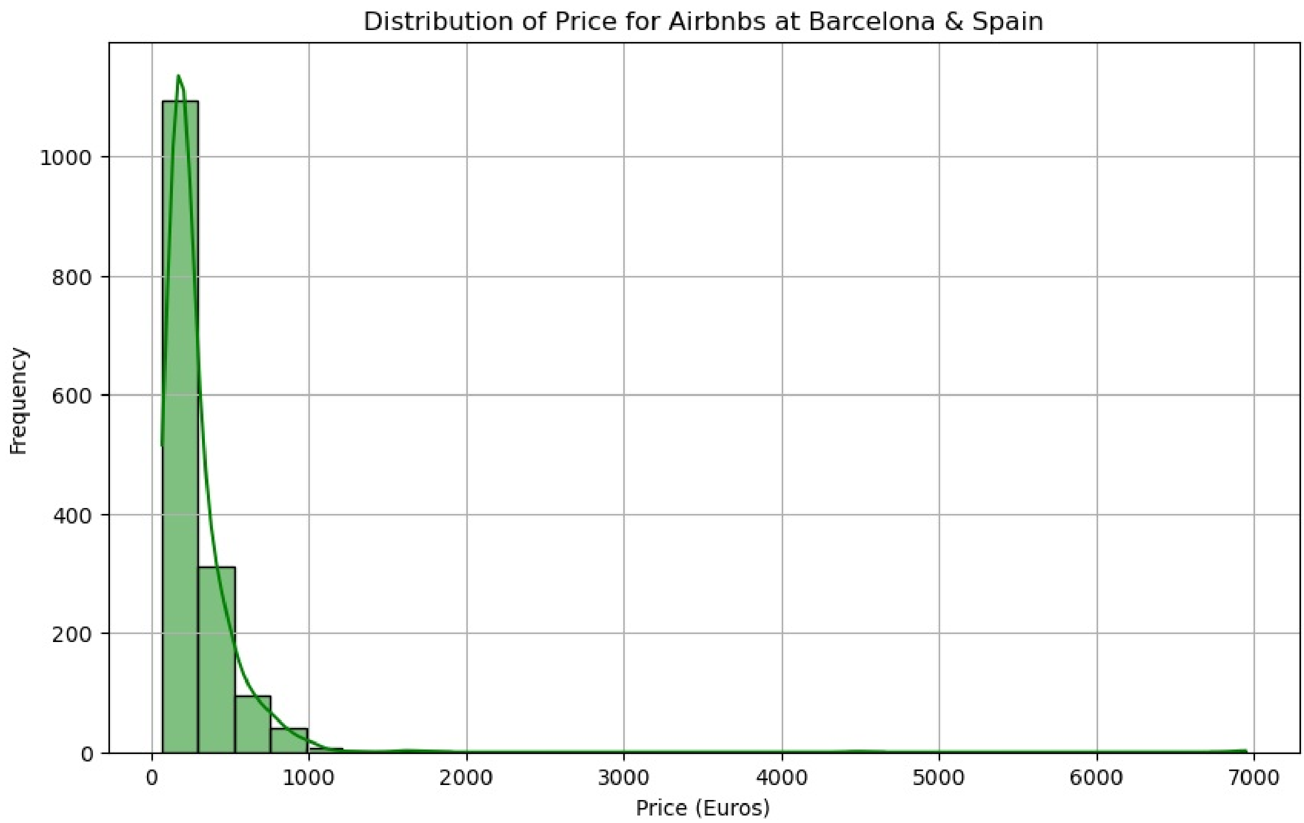
Out[7]:
```
str
```

In [8]:
```
price_stats = barcelona['price'].describe()
price_stats
```

Out[8]:
```
count    1555.000000
mean      288.391667
std       321.180435
min        69.588289
25%       161.984779
50%       208.532129
75%       335.373659
max      6943.700980
Name: price, dtype: float64
```

Here, we are exploring the statistical aspect of the variable 'Price'.This calculate the statistics (mean, standard deviation, minimum, 25th percentile, median, 75th percentile, and maximum) for the 'Price' variable using the describe() method.

In [9]:
```
plt.figure(figsize=(10, 6))
custom_colors = ['lightgreen', 'mediumgreen', 'darkgreen', 'green']
sns.histplot(barcelona['price'], bins=30, kde=True, color ='green')
plt.title('Distribution of Price for Airbnbs at Barcelona & Spain')
plt.xlabel('Price (Euros)')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
#Bins: 30
#Interpretation: The data range is divided into 30 intervals.
#Visual Effect: The resulting histogram will have 30 bars.
```



This histogram provides the distribution of the price for the Airbnbs'in Barcelona and Spain,the spread of the histogram indicates the variability in prices across the 'Barcelona.csv dataset'. The graph is skewed to the right (positive skew), suggests that prices are concentrated towards the lower end. This graph is plotted without the removal of outliers.

4.2 We decide to remove the price outliers (defined as three standard deviation away from the mean) and repeat the graph. What do you find?

In [10]:
```
np.var(barcelona['price']) # variance of the variable 'price'.
```
Out[10]:
```
103090.53317038735
```

In [11]:
```
mean_price = barcelona['price'].mean()
mean_price
# 'mean()' will calculate the average of the price variable.
```
Out[11]:
```
288.39166706715116
```

In [13]:
```
std_dev_price = barcelona['price'].std()
std_dev_price
# 'std()', This code will calculate the standard deviation of the price variable.
```
Out[13]:
```
321.1804352615852
```

In [14]:
```
low_up = barcelona['price'].mean() + 3 * barcelona['price'].std()
low_up
```
Out[14]:
```
1251.932972851907
```

The above code chunks will define the upper_bound for identifying outliers.'low_up' contains the upper limit of a 3-sigma confidence interval for the 'price' variable in the 'barcelona' dataset. Any data point above this upper limit may be considered an outlier.

In [15]:
```
normal_price = barcelona[barcelona['price']<1251.932972851907]
normal_price
```
Out[15]:

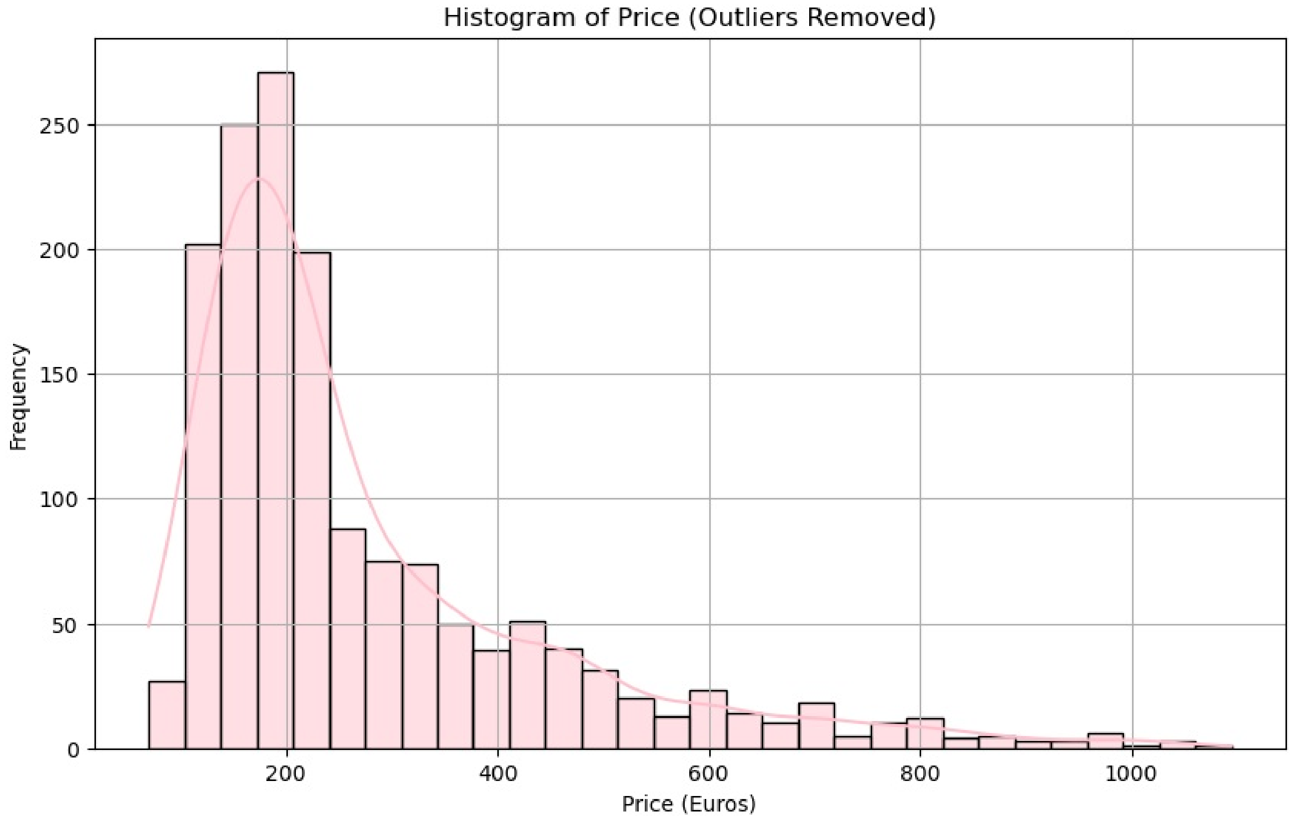
	price	bedrooms	room_shared	room_private	person_capacity	superhost	multi	biz	cleanliness	guest_satisfaction	dist	m
0	474.317499	1	False	False	4	False	0	1	10	91	1.111996	
1	169.897829	1	False	True	2	True	1	0	10	88	1.751839	
2	161.984779	1	False	True	4	False	0	1	9	88	1.670493	
3	367.956804	1	False	False	3	False	0	1	10	91	1.475847	
4	196.895292	1	False	True	3	False	1	0	9	91	1.855452	
...	...	...	...	...	...	...	...	...	...	...	...	
1549	300.928620	1	False	True	2	False	0	0	10	100	2.394839	
1550	769.660437	3	False	False	6	False	0	1	8	84	2.503374	
1551	318.151139	1	False	True	2	True	1	0	9	98	2.619616	
1552	248.562851	1	False	True	2	True	1	0	10	98	2.700091	
1554	543.905788	1	False	False	4	False	1	0	9	94	2.403086	

1548 rows × 16 columns

In [16]:
```
normal_price.shape
```
Out[16]:
```
(1548, 16)
```

The above code shows that 'price' of the Airbnbs' fall within the range of lower bound and upper bound specified by removing the outliers.

In [17]:
```
plt.figure(figsize=(10, 6))
sns.histplot(normal_price['price'], bins=30, kde=True, color ='pink')
plt.title('Histogram of Price (Outliers Removed)')
plt.xlabel('Price (Euros)')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```



This histogram provides the distribution of the prices for Airbnbs'listings in Barcelona and Spain after the outliers has been removed.

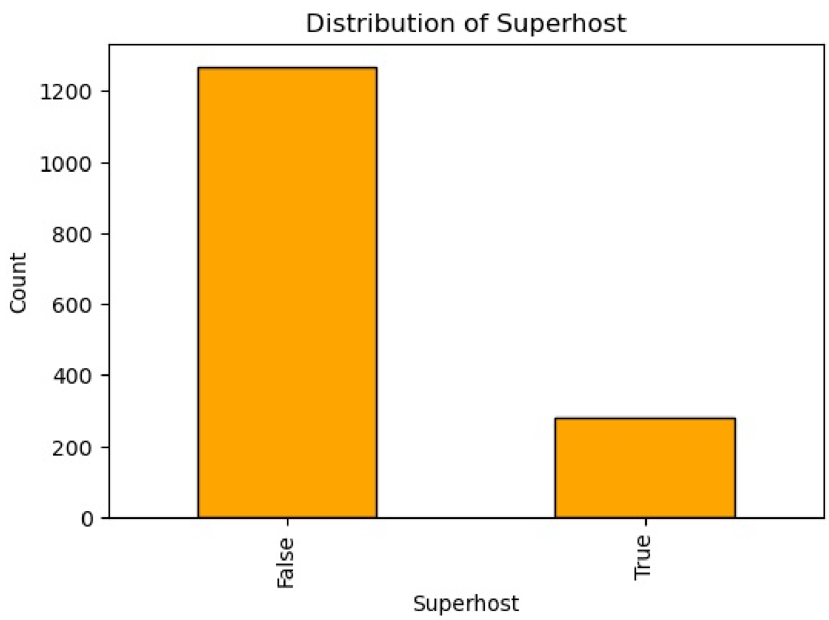
1. How many superhosts are there? Create a graph to display as well.

In [19]:
```
superhost_count = normal_price['superhost'].value_counts()
superhost_count
```

Out[19]:
```
superhost
False    1269
True      279
Name: count, dtype: int64
```

The above code provides the number of counts for superhosts in the dataset. That is the count is 1555 in total and the datatype is boolean - 'True' = 279, 'False' = 1269.

In [20]:
```
plt.figure(figsize=(6, 4))
superhost_count.plot(kind = 'bar', color ='orange', edgecolor = 'black')
plt.title('Distribution of Superhost')
plt.xlabel('Superhost')
plt.ylabel('Count')
plt.show()
```



While the value_counts summary gives the exact counts of each superhost, This plot help us understand the distribution of superhost for the Airbnbs in 'Barcelona.csv' dataset.The bar plot provides a visual representation of the count of each superhost. From the graph, the bar plot displays the count of listings categorized as superhosts versus non-superhosts.

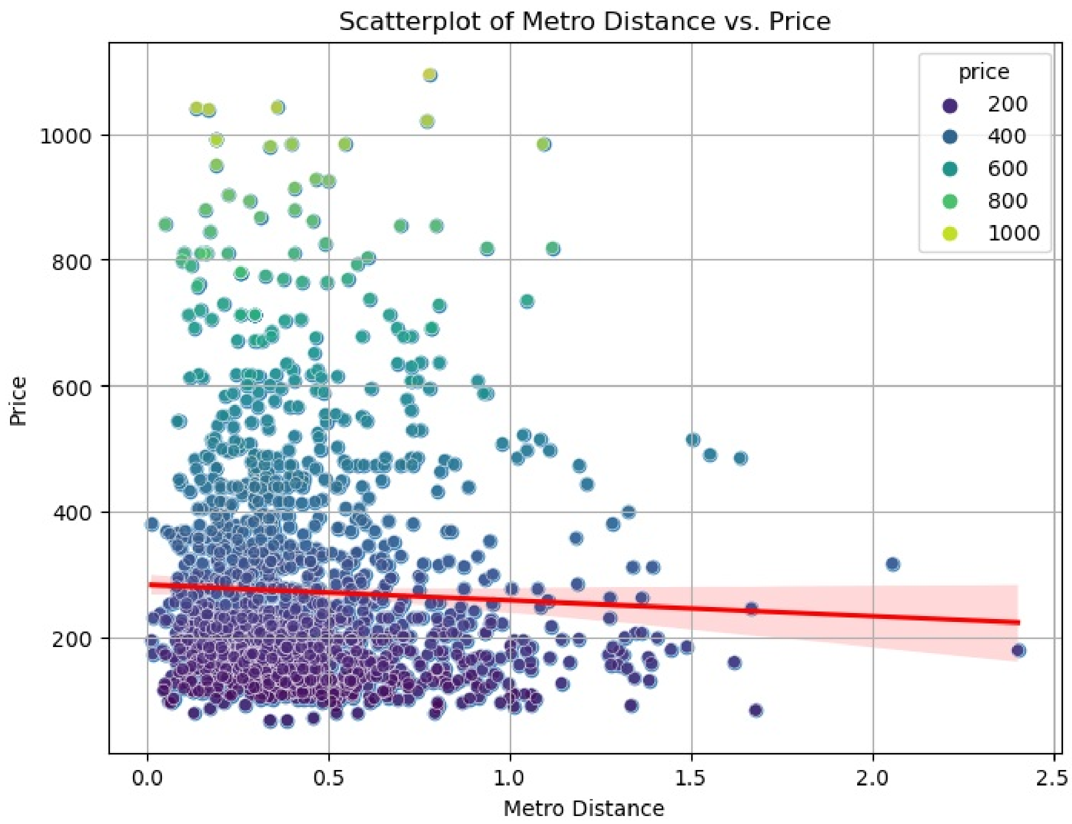
1. Is there possible correlation between the distance to the closest metro station and price?

In [21]:
```
correlation_coeff = normal_price['metro_dist'].corr(normal_price['price'])
correlation_coeff
# Calculates the correlation coefficient between the variable 'metro_dist' and 'price'.
```

Out[21]:
```
-0.03942016657108458
```

The correlation coefficient calculated is -0.03942016657108458, The negative sign of the correlation coefficient indicates a negative correlation. This means that as one variable increases, the other variable tends to decrease slightly. However, the strength of this relationship is almost negligible.The correlation coefficient is very close to 0, indicating an extremely weak correlation. This suggests that distance to the closest metro station (metro_dist) is not a significant factor influencing the price (price) in this dataset.

In [22]:
```
plt.figure(figsize=(8, 6))
sns.regplot(x = 'metro_dist',y ='price', data = normal_price, line_kws={'color':'red'})
sns.scatterplot(x='metro_dist', y='price', hue='price', data=normal_price, palette='viridis', alpha=0.7)
plt.title('Scatterplot of Metro Distance vs. Price')
plt.xlabel('Metro Distance')
plt.ylabel('Price')
plt.grid(True)
plt.show()
```



The code suggests visualizing the relationship between the distance to the closest metro station and the price of listings in Barcelona. The scatterplot with the regression line helps to assess the direction and strength of this relationship between the closest metro station and the price. We can see that the listing price of the Airbnbs' is falling as the distance of the metro station is increasing.

1. Run a linear regression model with the dataset. 'price' is the target variable and all other features (except longitude and latitude) as predictor variables. Follow the steps we have practiced in class. Display the results.
   Hint: You need to turn True/False Boolean variables (room_private, room_shared, and superhost) into 1/0 before applying statsmodels models. You can use .astype(int). Remember to save the changes by assigning the changed outcome back to the variable, such as *car['price'] = car['price']/1000*.

In [30]:
```
# Turning True/False Boolean variables (room_private, room_shared, and superhost) into 1/0:
normal_price.loc[:, 'room_private'] = normal_price['room_private'].astype(int)
normal_price.loc[:, 'room_shared']= normal_price['room_shared'].astype(int)
normal_price.loc[:, 'superhost']= normal_price['superhost'].astype(int)

# Defining the predictors (dropping the columns: price, longitute and latitude) and target variable
x = normal_price.drop(columns=['price', 'lng', 'lat'])
y = normal_price['price']

# Add a constant term to the predictor variables
x_with_intercept = sm.add_constant(x)
```

```python
# Fit the linear regression model
model = sm.OLS(y,x_with_intercept)

# Display the results
results = model.fit()
results.summary()
```

Out[30]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.693
Model:	OLS	**Adj. R-squared:**	0.691
Method:	Least Squares	**F-statistic:**	266.7
Date:	Mon, 19 Feb 2024	**Prob (F-statistic):**	0.00
Time:	20:02:10	**Log-Likelihood:**	-9274.5
No. Observations:	1548	**AIC:**	1.858e+04
Df Residuals:	1534	**BIC:**	1.865e+04
Df Model:	13		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	96.4191	35.751	2.697	0.007	26.294	166.545
bedrooms	38.0055	6.858	5.542	0.000	24.553	51.458
room_shared	-270.6826	35.552	-7.614	0.000	-340.418	-200.947
room_private	-169.8302	9.195	-18.470	0.000	-187.866	-151.794
person_capacity	47.5661	3.574	13.310	0.000	40.556	54.576
superhost	15.5403	6.797	2.286	0.022	2.207	28.873
multi	-3.8143	6.241	-0.611	0.541	-16.056	8.428
biz	19.1618	7.005	2.736	0.006	5.422	32.901
cleanliness	-2.7610	3.567	-0.774	0.439	-9.757	4.235
guest_satisfaction	1.5329	0.425	3.609	0.000	0.700	2.366
dist	-10.6433	3.450	-3.085	0.002	-17.411	-3.876
metro_dist	23.3560	10.040	2.326	0.020	3.662	43.051
attr_index	0.6253	0.387	1.614	0.107	-0.135	1.385
rest_index	0.6377	0.479	1.332	0.183	-0.301	1.577

Omnibus:	561.132	**Durbin-Watson:**	1.657
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3437.329
Skew:	1.562	**Prob(JB):**	0.00
Kurtosis:	9.598	**Cond. No.**	1.41e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.41e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

1. Which variables are important to predict the prices? Which are not?

bedrooms, room_shared, room_private, person_capacity, superhost, biz, guest_satisfaction, dist, metro_dist,all have p-value less than 0.05 indicating that they play a significant role in determining the prices of the Airbnbs' in Barcelona. On the other hand, multi, cleanliness, attr_index, rest_index are considered non-significant variables to predict the variable 'price' for the Airbnbs' in Barcelona & Spain because their p-value is greater than 0.05, and any p-value greater than the significance level we fail to reject the null hypothesis that the variables do not impact on the prediction of price.

1. Interpret the impact of metro_dist on the price.

The coefficient of 'metro_dist' in the regression results is 23.3560. This indicates that for each unit increase in the distance to the closest metro station (measured in meters), the price of the property is expected to increase by approximately 23.3560 units, holding all other variables constant. Since the coefficient of 'metro_dist' is positive, it suggests that there is a positive relationship between the distance to the closest metro station and the price of the property. In other words, properties located farther away from the metro station tend to have higher prices, according to the model.

1. Interpret the impact of being a superhost.

The statistically significant coefficient (15.5403) for superhost indicates that being a superhost is associated with higher prices for Airbnb listings in Barcelona. Records with superhost status are estimated to have prices approximately 15.5403 higher compared to records without superhost status, assuming all other variables constant. P value is less than 0.05, assures that this relationship is statistically reliable.