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Student Name(s)

Please enter the names of the students in your group here.

Final Project Intro

This notebook contains three sections for you to complete your final project:

1. Data Inspection and Exploratory Data Analysis
2. Explanatory Model
3. Predictive Models

In each section, we provide detailed instructions for what we expect you to complete, as well as the corresponding point allocation. We have included a single code cell for you to begin working. Please add code cells and markdown cells as needed and as appropriate!

Keep in mind that your final should look like a report: code cells should be used for generating output and commentary should be in markdown cells. Steps that should be answered by using code are numbered and given in black. Questions that should be answered using a markdown cell are in purple and bulleted.

We will deduct points if you answer the questions given in purple in a code cell.

Problem Description and Data Dictionary

You are an analyst working for a real estate company seeking to diversify its portfolio by offering short-term AirBnB rentals in New York City. The company has managed to collect data on AirBnB listings in the area, which includes both the price per night and unit features. Having never offered AirBnB rentals in this area before, the company would like to use this data to do the following:

1. Understand which factors influence AirBnB pricing and how.
2. Develop a model to predict the appropriate list price for a unit based on its features.

The data dictionary is as follows, where *price* is the outcome variable:

Variable	Description
ID	Unique identifier for listing
name	Listing name

Variable	Description
host_id	Unique identifier for a specific host
neighbourhood_group	The borough the listing is located
neighbourhood	Neighborhood listing is located
latitude	Exact Location
longitude	Exact Location
room_type	Type of space for rent
minimum_nights	Minimum length of rental
number_of_reviews	Total reviews for a listing
last_review	Date of most recent review
reviews_per_month	How many reviews a listing receives each month
calculated_host_listings_count	Amount of listings per host
availability_365	How many available nights there are for booking
price	Price per night

Section 0: Import packages and the dataset (10 points)

Import packages as needed and read the dataset. (The dataset link is on the project page.)

```
!pip install dmba
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/publ
Requirement already satisfied: dmba in /usr/local/lib/python3.10/dist-packages (0.2.3)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (fr
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (from d
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from dm
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from dm
Requirement already satisfied: graphviz in /usr/local/lib/python3.10/dist-packages (from
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-package
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packa
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packa
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-pa
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-pa
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from
```

```
import numpy as np
import pandas as pd
```

```
from sklearn.model_selection import train_test_split
import statsmodels.formula.api as smf

# decision tree algorithm
from sklearn.tree import DecisionTreeClassifier

# tree visualization and model evaluation
from dmba import classificationSummary, regressionSummary, plotDecisionTree, textDecisionTre


# model evaluation and roc curve
from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_auc_score, roc_curve
import matplotlib.pylab as plt
```

```
import seaborn as sns
import matplotlib.pylab as plt
```

```
%matplotlib inline
```

```
df = pd.read_csv("https://raw.githubusercontent.com/irenebao2020/badm211/main/airbnb.csv")
```

```
# Create as many additional cells as needed
```

Section 1: Dataset Inspection, Exploratory Data Analysis, and Preprocessing (40 points)

Complete the following steps and answer the following questions. For each step, please make sure to have one (or more) code cells and then create a markdown cell immediately following it in which to answer the question.

In this section, point allocations for each step will be based on both your code and response to the question.

Data Inspection and Preprocessing (20 points)

1. (*1 pt)* Print the first five rows.

- Name three categorical and three numerical variables.

2. (*2 pts)* Print the descriptive statistics.

- Describe 2-3 insights from this output.

3. (*1 pt)* Print datatypes of the columns.
4. (*4 pts)* Use `groupby()` to show summary statistics for two numerical variables across different values of (at least) one categorical variable. (This simply asks for one `groupby` statement.)

- What insights do you gain from this output?

5. (*2 pts)* For two categorical variables of your choice, show the *proportion* of categories (AKA values) that each takes.

- What can be said about the data based on these outputs?

6. (*2 pts)* Check for missing values and handle them appropriately.

- Are there any missing values in the data? If yes, which variable had the most missing values?

7. (*2 pts)* Check for duplicate rows and handle them appropriately.

- Are there any duplicate rows? If yes, how many?

8. (*2 pts)* Show 5 rows of the data. By looking at the output you just generated, are there any variables that do *not* contain useful or relevant information about records? If so, be sure to remove them from the data. You may choose to remove multiple variables.
9. (*4 pts)* Identify what the outcome variable is. Depending on the variable type, provide summary statistics or the distribution of the outcome variable. If your outcome variable is a categorical variable, convert the text values to 0/1.

- Is this a regression or classification problem? Why?

Data Visualization (15 points)

For this section, you can choose which variables you want to visualize. When completing this section, we encourage you to think about the relationships you are trying to explore and what you will ultimately be predicting.

10. (*5 pts)* Draw a scatterplot.

- Comment on your scatterplot.

11. (*5 pts)* Draw a histogram.

- Comment on your histogram.

12. (*5 pts)* Draw a bar chart. Use mean as the summary statistic.

- Comment on the bar chart.

Data Preprocessing (5 points)

13. (*5 pts)* Dummy code your categorical variables.

- How many variables are in the resulting dataframe?

```
df.head()
```

	listing_id	name	host_id	host_name	neighbourhood_
0	2539	Clean_&_quiet_apt_home_by_the_park	2787.0	John	Br
1	2539	Clean_&_quiet_apt_home_by_the_park	2787.0	John	Br
2	2595	Skylit_Midtown_Castle	2845.0	Jennifer	Man
3	3647	THE_VILLAGE_OF_HARLEM....NEW_YORK_!	4632.0	Elisabeth	Man
4	3831	Cozy_Entire_Floor_of_Brownstone	4869.0	LisaRoxanne	Br

Categorical: neighbourhood_group, neighbourhood, room_type Numerical: latitude, longitude, number_of_reviews

```
df.describe()
```

	listing_id	host_id	latitude	longitude	minimum_nights	number_of_
count	4.886300e+04	4.886200e+04	48863.000000	48861.000000	48863.000000	48860
mean	1.901845e+07	6.763310e+07	40.728950	-73.952158	6.630354	23
std	1.098382e+07	7.861868e+07	0.054532	0.046158	13.959867	44
min	2.539000e+03	2.438000e+03	40.499790	-74.244420	1.000000	0
25%	9.472744e+06	7.822737e+06	40.690090	-73.983070	1.000000	1
50%	1.968202e+07	3.080252e+07	40.723080	-73.955680	3.000000	5
75%	2.915256e+07	1.074344e+08	40.763130	-73.936230	5.000000	24

On average, the minimum required nights spent is 6.63 and the maximum allowed is 23.29. There are 48,860 total reviews. The median price is $106 (assumed currency).

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48863 entries, 0 to 48862
Data columns (total 16 columns):
 #   Column                          Non-Null Count  Dtype
```

```
---  ------                          --------------  -----
 0   listing_id                      48863 non-null  int64
 1   name                            48848 non-null  object
 2   host_id                         48862 non-null  float64
 3   host_name                       48840 non-null  object
 4   neighbourhood_group             48862 non-null  object
 5   neighbourhood                   48863 non-null  object
 6   latitude                        48863 non-null  float64
 7   longitude                       48861 non-null  float64
 8   room_type                       48862 non-null  object
 9   minimum_nights                  48863 non-null  int64
 10  number_of_reviews               48860 non-null  float64
 11  last_review                     38826 non-null  object
 12  reviews_per_month               38829 non-null  float64
 13  calculated_host_listings_count  48863 non-null  int64
 14  availability_365                48863 non-null  int64
 15  price                           48863 non-null  int64
dtypes: float64(5), int64(5), object(6)
memory usage: 6.0+ MB
```

```
df.groupby("neighbourhood_group")["price", "reviews_per_month"].mean()
```

```
<ipython-input-70-9e046fc10072>:1: FutureWarning: Indexing with multiple keys (implicit]
  df.groupby("neighbourhood_group")["price", "reviews_per_month"].mean()
```

neighbourhood_group	price	reviews_per_month
Bronx	87.453297	1.836948
Brooklyn	124.318799	1.283765
Manhattan	196.875167	1.272835
Queens	98.760862	1.941500
[illegible]	[illegible]	[illegible]

From this output, we can tell that staying in the Bronx is the cheapest and Manhattan is the most expensive. People who stay in Queens tend to write the most reviews per month.

```
df["neighbourhood_group"].value_counts(normalize = True)
```

```
Manhattan        0.442982
Brooklyn         0.411178
Queens           0.115877
Bronx            0.022349
Staten_Island    0.007613
Name: neighbourhood_group, dtype: float64
```

```
df["room_type"].value_counts(normalize = True)
```

```
Entire_home/apt    0.519524
Private_room       0.456756
Shared_room        0.023720
Name: room_type, dtype: float64
```

This shows us that nearly 85% of AirBnBs are in Manhattan and Brooklyn. Also, 52% of AirBnBs are entire home/apartment rentals.

```
df = df.drop(columns = ['last_review','reviews_per_month'])
```

```
df.isnull().sum()
```

```
listing_id                         0
name                              15
host_id                            1
host_name                         23
neighbourhood_group                1
neighbourhood                      0
latitude                           0
longitude                          2
room_type                          1
minimum_nights                     0
number_of_reviews                  3
calculated_host_listings_count     0
availability_365                   0
price                              0
dtype: int64
```

```
df.dropna(inplace = True)
```

```
df.isnull().sum()
```

```
listing_id                        0
name                              0
host_id                           0
host_name                         0
neighbourhood_group               0
neighbourhood                     0
latitude                          0
longitude                         0
room_type                         0
minimum_nights                    0
number_of_reviews                 0
calculated_host_listings_count    0
availability_365                  0
price                             0
dtype: int64
```

Before handling the missing values, the variable "host_name" had the most missing values. We dropped columns last_review and reviews_per_month so those variables we not included in the count of missing values.

```
df.duplicated().sum()
```

```
11
```

```
df.drop_duplicates(inplace = True)
```

```
df.duplicated().sum()
```

```
0
```

Before dropping the duplicated values, there were 11.

```
df.head()
```

	listing_id	name	host_id	host_name	neighbour
0	2539	Clean_&_quiet_apt_home_by_the_park	2787.0	John	
2	2595	Skylit_Midtown_Castle	2845.0	Jennifer	
3	3647	THE_VILLAGE_OF_HARLEM....NEW_YORK_!	4632.0	Elisabeth	
4	3831	Cozy_Entire_Floor_of_Brownstone	4869.0	LisaRoxanne	
5	5022	Entire_Apt:_Spacious_Studio/Loft_by_central_park	7192.0	Laura	

The following variables do not contain useful or relevant information: listing_id and host_id.

```
df = df.drop(columns = ['host_id', 'listing_id'])
```

```
df.head()
```

	name	host_name	neighbourhood_group	neighbour
0	Clean_&_quiet_apt_home_by_the_park	John	Brooklyn	Kensi
2	Skylit_Midtown_Castle	Jennifer	Manhattan	Mic
3	THE_VILLAGE_OF_HARLEM....NEW_YORK_!	Elisabeth	Manhattan	H
4	Cozy_Entire_Floor_of_Brownstone	LisaRoxanne	Brooklyn	Clinto
5	Entire_Apt:_Spacious_Studio/Loft_by_central_park	Laura	Manhattan	East_H

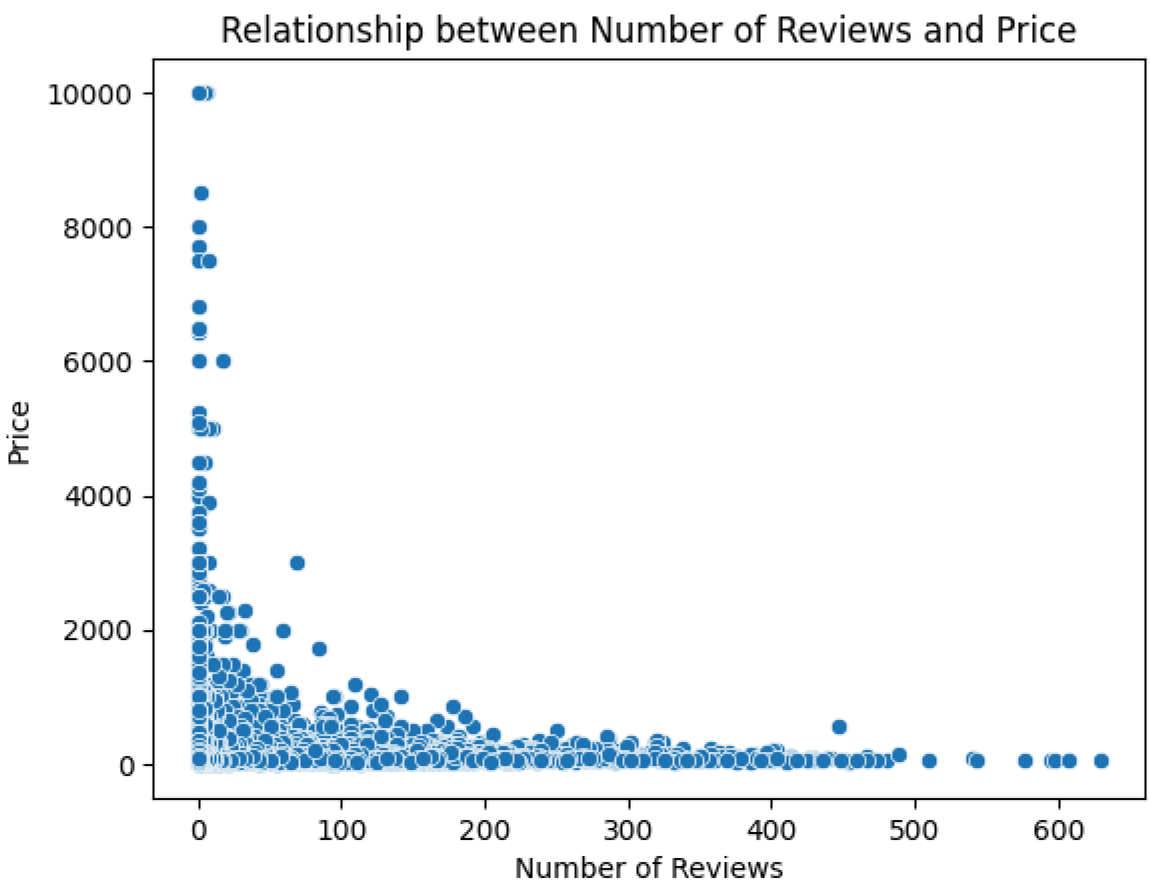
The outcome variable is *price*.

```
df["price"].describe()
```

```
count    48807.000000
mean       152.628803
std        239.952136
min          0.000000
25%         69.000000
50%        106.000000
75%        175.000000
max      10000.000000
Name: price, dtype: float64
```

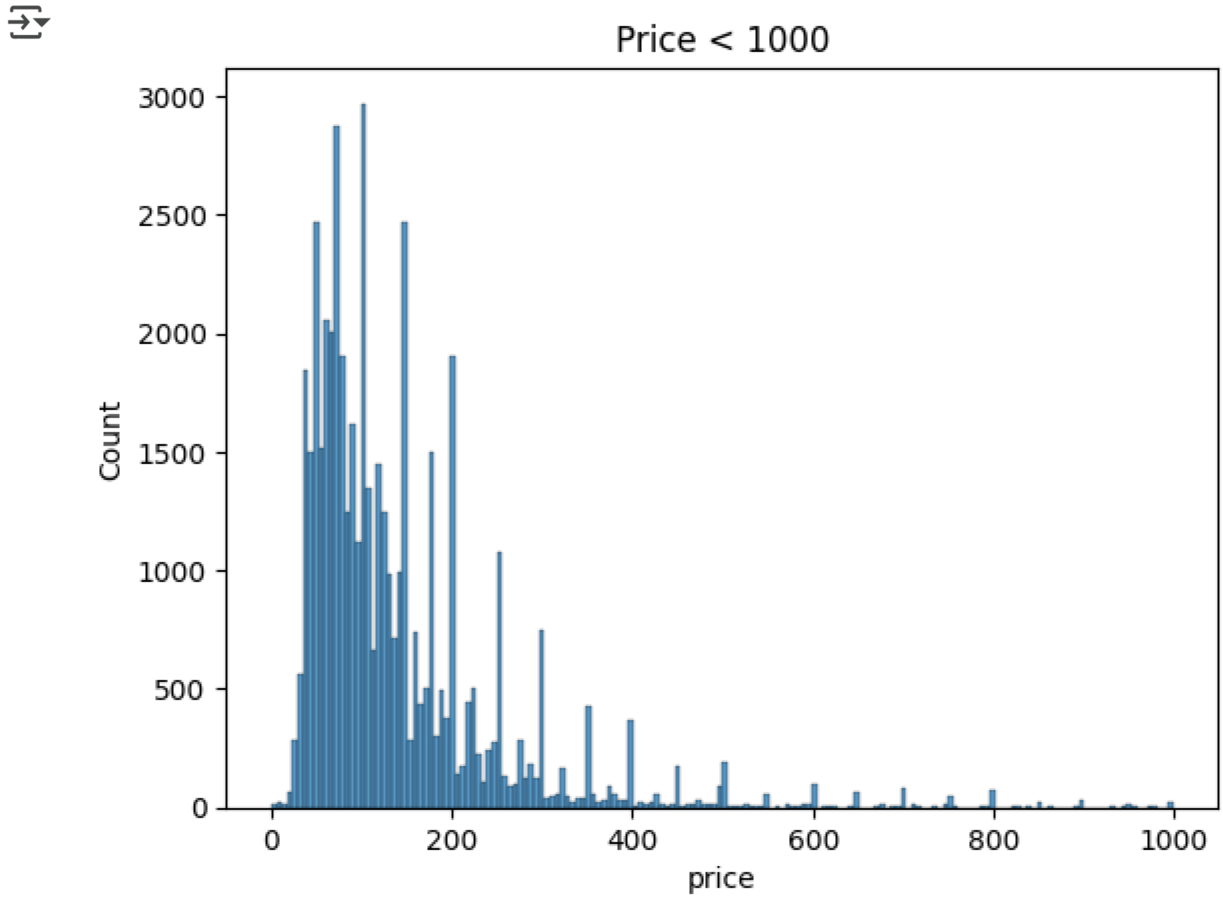
This is a regression problem because the outcome variable price is a continuous numerical outcome.

```
sns.scatterplot(x=df["number_of_reviews"], y=df["price"])

plt.xlabel("Number of Reviews")
plt.ylabel("Price")
plt.title("Relationship between Number of Reviews and Price")

plt.show()
```

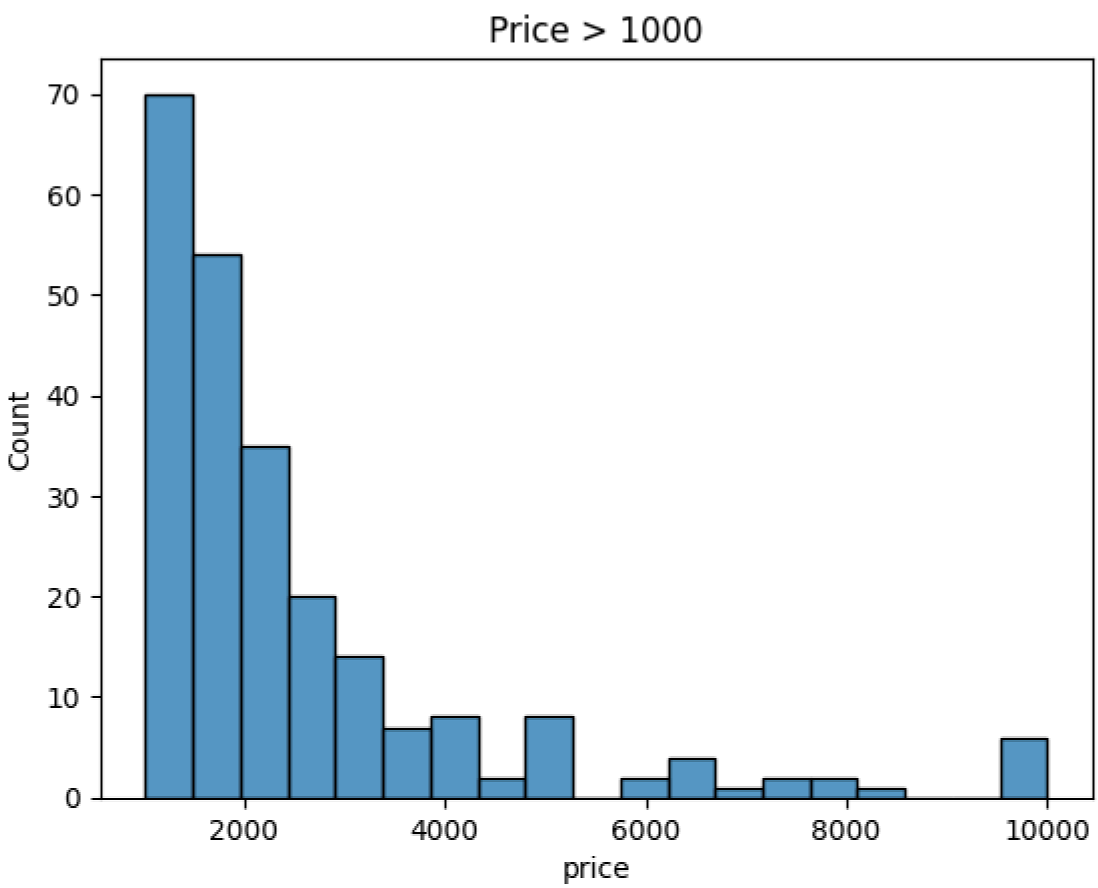


This scatterplot shows that the more expensive AirBnBs tend to have less reviews. One inference we could make is that this is because less people have rented out the more expensive AirBnBs.

```
sns.histplot(data =df[df["price"]<1000], x = "price")

plt.title('Price < 1000')
plt.show()
# df[df[var]<x]
```

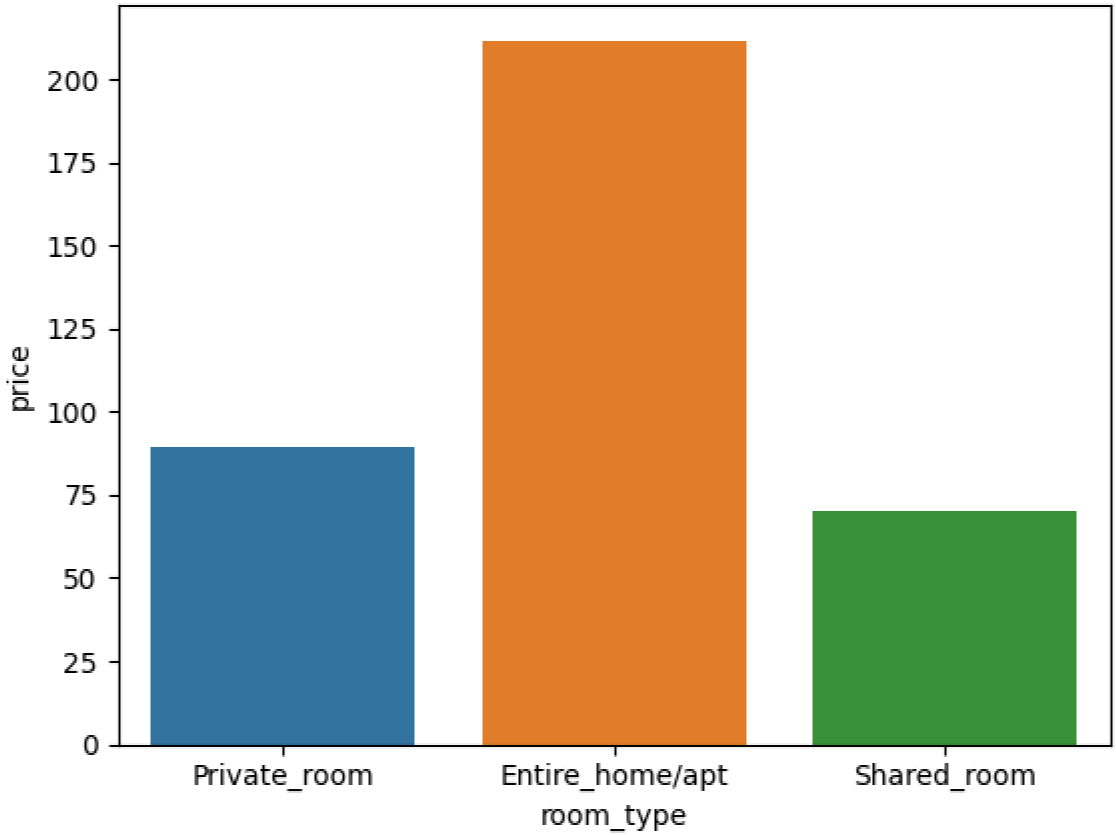



```
sns.histplot(data =df[df["price"]>1000], x = "price")

plt.title('Price > 1000')
plt.show()
```



This histogram demonstrates that the large majority of AirBnBs cost anywhere from zero to $4000/night.

```
sns.barplot(x=df["room_type"],y=df["price"], errorbar = None, estimator = "mean")
plt.show()
```



The most expensive AirBnBs tend to be ones that offer an entire home/apartment, then private rooms, and finally, at the least expensive price, are shared room AirBnBs.

```
df.columns
```

```
Index(['name', 'host_name', 'neighbourhood_group', 'neighbourhood', 'latitude',
       'longitude', 'room_type', 'minimum_nights', 'number_of_reviews',
       'calculated_host_listings_count', 'availability_365', 'price'],
      dtype='object')
```

```
df = df.drop(columns = ["name", "host_name", "neighbourhood"])
```

```
df = pd.get_dummies(df, drop_first = True)
df.columns
```

```
Index(['latitude', 'longitude', 'minimum_nights', 'number_of_reviews',
       'calculated_host_listings_count', 'availability_365', 'price',
       'neighbourhood_group_Brooklyn', 'neighbourhood_group_Manhattan',
       'neighbourhood_group_Queens', 'neighbourhood_group_Staten_Island',
       'room_type_Private_room', 'room_type_Shared_room'],
      dtype='object')
```

There are 13 variables in the resulting dataframe ater dummy coding. 12 Predictive and 1 outcome variable

Section 2: Explanatory Modeling (30 points)

1. *(15 pts)* Fit an explanatory model using the whole dataset (after dropping irrelevant predictors), and print its output.

- *(5 pts)* Are any of the variables insignificant? Which ones?
- *(10 pts)* Interpret the coefficients of the independent variables that *are* significant. Do this for at least three variables, doing this at least dummy variable and one numerical variable.

```
# Your code here
mod_spec = "price ~ latitude+longitude+minimum_nights+number_of_reviews+calculated_host_list



exp_model = smf.ols(mod_spec, data = df).fit()


print(exp_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.099
Model:                            OLS   Adj. R-squared:                  0.098
Method:                 Least Squares   F-statistic:                     445.2
Date:                Thu, 04 May 2023   Prob (F-statistic):               0.00
Time:                        17:06:29   Log-Likelihood:            -3.3420e+05
No. Observations:               48807   AIC:                         6.684e+05
Df Residuals:                   48794   BIC:                         6.685e+05
Df Model:                          12
Covariance Type:            nonrobust
==================================================================================================
                                     coef    std err          t      P>|t|      [0.02
--------------------------------------------------------------------------------------------------
Intercept                      -2.908e+04   3204.693     -9.075      0.000   -3.54e+0
latitude                        -203.6894     31.352     -6.497      0.000    -265.14
longitude                       -508.0578     35.992    -14.116      0.000    -578.60
minimum_nights                    -0.1649      0.077     -2.133      0.033      -0.31
number_of_reviews                 -0.3085      0.024    -12.917      0.000      -0.35
calculated_host_listings_count    -0.1664      0.033     -4.991      0.000      -0.23
availability_365                   0.1965      0.008     23.163      0.000       0.18
neighbourhood_group_Brooklyn     -32.6127      8.772     -3.718      0.000     -49.80
neighbourhood_group_Manhattan     29.0587      7.956      3.652      0.000      13.46
neighbourhood_group_Queens        -4.5474      8.446     -0.538      0.590     -21.16
neighbourhood_group_Staten_Island -152.9516   16.702     -9.158      0.000    -185.68
room_type_Private_room          -106.4334      2.163    -49.205      0.000    -110.67
```

```
room_type_Shared_room              -142.7203      6.883    -20.736      0.000    -156.21
==============================================================================
Omnibus:                   110407.034   Durbin-Watson:                   1.847
Prob(Omnibus):                  0.000   Jarque-Bera (JB):       1007231602.379
Skew:                          21.551   Prob(JB):                         0.00
Kurtosis:                     705.446   Cond. No.                     5.74e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
[2] The condition number is large, 5.74e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

There is only one variable that is insignificant and it is neighbourhood_group[T.Queens] with a p value of 0.590

A majority of the variables are significant in this explanatory model. One dummy variable that is significant is neighbourhood_group[T.Manhattan] . This dummy has a p value of 0.000 making it significant. When a AirBnB is in the Brooklyn neighbourhood group, there is a 29.06 dollar increase in price relative to the Bronx. Another significant variable is minimum_nights. This is a numerical variable and has a p value of 0.033. With a increase of 1 night, there a 0.16 dollar decrease in price. The final significant variable is number_of_reviews with a p value of 0.000. When there is an additional number of reviews, there is a 0.31 dollar decrease in price

Section 3: Predictive Modeling (40 (Regression) or 45 (Classification) points)

Data Preprocessing (10 points)

1. *(3 pts)* Split the data into `X` and `y`.
2. *(4 pts)* Create training and test sets, with 80% of the data in the training set and 20% in the test set, and save them as *train_X*, *test_X*, *train_y*, and *test_y*.

- *(3 pts)* Why do we partition data when doing predictive modeling?

Fitting and Predicting the Models (30 points for Regression, 35 points for Classification)

Next, you will create three predictive models:

- `Model1` : either logistic regression (for classification) or MLR (for regression)
- `Model2` : decision tree (with or without grid search)
- `Model3` : random forest (with or without grid search)

Repeat steps 3 through 6 for each model.

3. *(2 pts x 3)* Fit the predictive model.
4. *(3 pts x 2)* Print the model coefficients (for `Model1`) or visualize the tree (for `Model2`). No output for `Model3`.
5. *(3 pts x 3)* Make predictions on the training and test sets.
6. *(2 pts x 3)* For regression problems, print the predictive accuracy measures (e.g., ME, MAE, etc.). For classification problems, display the confusion matrix.
7. *(5 pts)* For classification problems, plot the ROC curves for all three models.

- *(3 pts)* Which model performs the best? What are you basing this off of?

```
# Your code here
# Create as many additional cells as needed
y = df["price"]
X =df.drop(columns='price')
train_X, test_X, train_y, test_y = train_test_split(X, y, test_size = .2, random_state= 7)
```

We partition data when doing predictive modeling to avoid overfitting

```
from sklearn.linear_model import LinearRegression
Model1 = LinearRegression()
Model1.fit(train_X, train_y)
pd.DataFrame(data=Model1.coef_, index=train_X.columns)
```

	0
latitude	-212.433363
longitude	-537.010812
minimum_nights	-0.140345
number_of_reviews	-0.310402
calculated_host_listings_count	-0.182085
availability_365	0.201353
neighbourhood_group_Brooklyn	-37.539853
neighbourhood_group_Manhattan	26.424362
neighbourhood_group_Queens	-4.488852
neighbourhood_group_Staten_Island	-156.987358
room_type_Private_room	-105.948419
room_type_Shared_room	-142.140826

```
train_pred_y_Model1 = Model1.predict(train_X) # predictions on the training data
regressionSummary(train_y, train_pred_y_Model1)
```

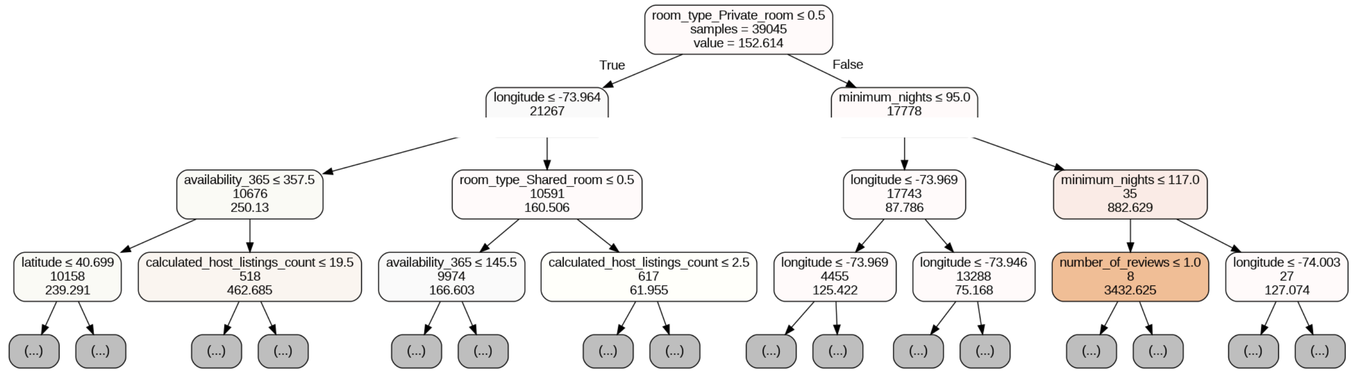
```
Regression statistics

               Mean Error (ME) : -0.0000
Root Mean Squared Error (RMSE) : 225.2013
     Mean Absolute Error (MAE) : 73.8248
```

```
test_pred_y_Model1 = Model1.predict(test_X) # predictions on the testing data
regressionSummary(test_y, test_pred_y_Model1)
```

```
Regression statistics

                      Mean Error (ME) : 0.4754
       Root Mean Squared Error (RMSE) : 237.9531
            Mean Absolute Error (MAE) : 74.4609
          Mean Percentage Error (MPE) : -31.7062
Mean Absolute Percentage Error (MAPE) : 55.3764
```

```
from sklearn.tree import DecisionTreeRegressor

Model2=DecisionTreeRegressor(max_depth=5, min_samples_split=5, min_impurity_decrease=0.003,
```

```
Model2=Model2.fit(train_X, train_y)
plotDecisionTree(Model2,feature_names=train_X.columns, max_depth=3)
```




```
train_pred_y_Model2=Model2.predict(train_X) #predictions on training set
regressionSummary(train_y, train_pred_y_Model2)
```

```
Regression statistics

               Mean Error (ME) : -0.0000
Root Mean Squared Error (RMSE) : 212.3400
     Mean Absolute Error (MAE) : 69.4477
```

```
test_pred_y_Model2=Model2.predict(test_X) #predictions on test set
regressionSummary(test_y, test_pred_y_Model2)
```

```
Regression statistics

                      Mean Error (ME) : 2.2109
       Root Mean Squared Error (RMSE) : 237.2130
            Mean Absolute Error (MAE) : 70.3267
          Mean Percentage Error (MPE) : -31.3959
Mean Absolute Percentage Error (MAPE) : 49.2353
```

GRID SEARCH

```
param_grid = {
    'max_depth': [10,20,30],
    'min_impurity_decrease': [0, 0.0001, 0.001, 0.01],
    'min_samples_split': [10,15,20,40,50],
    'random_state': [1]}
```

```
from sklearn.model_selection import train_test_split, GridSearchCV
```

```
regTree = GridSearchCV(DecisionTreeRegressor(), param_grid)

regTree.fit(train_X, train_y)
```

```
▸ GridSearchCV
▸ estimator: DecisionTreeRegressor
  ▸ DecisionTreeRegressor
```

```
regTree.best_estimator_
```

```
▾ DecisionTreeRegressor
DecisionTreeRegressor(max_depth=10, min_impurity_decrease=0,
                      min_samples_split=50, random_state=1)
```

```
regTree_train_predictions = regTree.predict(train_X)

regTree_test_predictions = regTree.predict(test_X)
```

```
regressionSummary(train_y, regTree_train_predictions)

regressionSummary(test_y, regTree_test_predictions)
```

```
Regression statistics

               Mean Error (ME) : 0.0000
Root Mean Squared Error (RMSE) : 202.7409
     Mean Absolute Error (MAE) : 64.6186

Regression statistics

                      Mean Error (ME) : 2.5251
       Root Mean Squared Error (RMSE) : 238.4051
            Mean Absolute Error (MAE) : 68.1125
          Mean Percentage Error (MPE) : -26.6518
Mean Absolute Percentage Error (MAPE) : 45.3599
```

RANDOM FOREST

```
from sklearn.ensemble import RandomForestRegressor


Model3=RandomForestRegressor(n_estimators=500,  min_impurity_decrease = 0.001, random_state=
Model3=Model3.fit(train_X,train_y)



train_pred_y_Model3=Model3.predict(train_X)
regressionSummary(train_y, train_pred_y_Model3)
```

```
Regression statistics

                  Mean Error (ME) : -1.7815
   Root Mean Squared Error (RMSE) : 81.7150
        Mean Absolute Error (MAE) : 24.5783
```

```
test_pred_y_Model3=Model3.predict(test_X)
regressionSummary(test_y,test_pred_y_Model3)
```

```
Regression statistics

                      Mean Error (ME) : -2.6983
       Root Mean Squared Error (RMSE) : 234.3981
            Mean Absolute Error (MAE) : 65.7387
          Mean Percentage Error (MPE) : -26.9388
Mean Absolute Percentage Error (MAPE) : 43.7546
```

The model that works the best is Model3 or the random forest. We are basing this off of mean absolute error of the test set between the 3 models. Model3 has the lowest MAE making it the model that performs the best.

GRID SEARCH

```
param_grid2 = {
    'min_impurity_decrease': [0, 0.0001, 0.001, 0.01],
    'min_samples_split': [10,15,20,40,50],
    'max_depth':[10,20,30],
    "random_state": [1]}


RF_reg = GridSearchCV(RandomForestRegressor(), param_grid2)
RF_reg.fit(train_X, train_y)
```

```
GridSearchCV
estimator: RandomForestRegressor
RandomForestRegressor
```

```
RF_reg.best_estimator_
```

```
RandomForestRegressor
RandomForestRegressor(max_depth=20, min_impurity_decrease=0.01,
                      min_samples_split=40, random_state=1)
```

```
RF_train_predictions = RF_reg.predict(train_X)

RF_test_predictions = RF_reg.predict(test_X)


regressionSummary(train_y, RF_train_predictions)

regressionSummary(test_y, RF_test_predictions)
```

```
Regression statistics

               Mean Error (ME) : -0.6696
Root Mean Squared Error (RMSE) : 185.6161
     Mean Absolute Error (MAE) : 54.8709

Regression statistics

                      Mean Error (ME) : -0.5951
       Root Mean Squared Error (RMSE) : 232.8412
            Mean Absolute Error (MAE) : 65.3811
          Mean Percentage Error (MPE) : -27.3063
Mean Absolute Percentage Error (MAPE) : 43.9569
```

Section 4: Computing the value of your work (Regression) (20 points)

In this section, you will compare the performance of two models:

- a naive model (in which the predicted variable is simply the *average of the outcome variable* in the data used to fit the model); and
- one of your models from above.

1. *(6 pts)* Create a dataframe that contains three columns:
    - the actual outcome variable for the test set;
    - the predicted outcome variable for the test set for your chosen model; and
    - the predicted outcome variable for the test set using the naive model.

Hint: We did something similar in the Class 21 notebook. Alternately, a little Googling should help.

Problem Setup

For your dataset, the host will incur a cost from renting out each AirBnB. Assume that this is equal to 70% of the *actual* listing price.

If the predicted price exceeds the actual listing price by more than 10%, the unit will not be rented,