In [ ]:
```
from sklearn.model_selection import StratifiedShuffleSplit
# let's first start by creating our train and test sets
split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_index, test_index in split.split(housing, housing["income_cat"]):
    train_set = housing.loc[train_index]
    test_set = housing.loc[test_index]
```

In [ ]:
```
housing_training = train_set.drop("median_house_value", axis=1) # drop labels for training set features
                                                                # the input to the model should not contain the true label
housing_labels = train_set["median_house_value"].copy()
```

In [ ]:
```
housing_testing = test_set.drop("median_house_value", axis=1) # drop labels for training set features
                                                              # the input to the model should not contain the true label
housing__test_labels = test_set["median_house_value"].copy()
```

Select a model and train

Once we have prepared the dataset it's time to choose a model.

As our task is to predict the median_house_value (a floating value), regression is well suited for this.

In [ ]:
```
from sklearn.linear_model import LinearRegression

lin_reg = LinearRegression()
lin_reg.fit(housing_training, housing_labels)
```

Out[ ]:
```
LinearRegression()
```

In [ ]:
```
# let's try our model on a few testing instances
data = housing_testing.iloc[:5]
labels = housing__test_labels.iloc[:5]

print("Predictions:", lin_reg.predict(data))
print("Actual labels:", list(labels))
```

```
Predictions: [412720.84851599 308250.79784537 236395.96466479 191878.53496752
 252722.41196865]
Actual labels: [500001.0, 162500.0, 204600.0, 159700.0, 184000.0]
```

We can evaluate our model using certain metrics, a fitting metric for regresison is the mean-squared-loss

$$L(\hat{Y}, Y) = \sum_{i}^{N} (\hat{y}_i - y_i)^2$$

where $\hat{y}$ is the predicted value, and y is the ground truth label.

In [ ]:
```
from sklearn.metrics import mean_squared_error

preds = lin_reg.predict(housing_testing)
mse = mean_squared_error(housing__test_labels, preds)
rmse = np.sqrt(mse)
rmse
```

Out[ ]:
```
68330.90371034428
```

Is this a good result? What do you think an acceptable error rate is for this sort of problem?

TODO: Applying the end-end ML steps to a different dataset.

Ok now it's time to get to work! We will apply what we've learnt to another dataset (airbnb dataset). For this project we will attempt to **predict the airbnb rental price based on other features in our given dataset.**

Visualizing Data

Load the data + statistics

Let's do the following set of tasks to get us warmed up:

- load the dataset
- display the first few rows of the data
- drop the following columns: name, host_id, host_name, last_review, neighbourhood
- display a summary of the statistics of the loaded data

In [2]:
```
import pandas as pd
# load the dataset
airbnb = pd.read_csv('AB_NYC_2019.csv')
# display the first few rows of the data
airbnb.head()
```

Out[2]:

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimu
0	2539	Clean & quiet apt home by the park	2787	John	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	
1	2595	Skylit Midtown Castle	2845	Jennifer	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	
2	3647	THE VILLAGE OF HARLEM....NEW YORK !	4632	Elisabeth	Manhattan	Harlem	40.80902	-73.94190	Private room	150	
3	3831	Cozy Entire Floor of Brownstone	4869	LisaRoxanne	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	Laura	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	

In [3]:
```
# drop the following columns: name, host_id, host_name, last_review, neighbourhood
airbnb_data = airbnb.drop(["name","host_id","host_name","last_review","neighbourhood"],axis=1)
# display a summary of the statistics of the loaded data
airbnb_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 11 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              48895 non-null  int64
 1   neighbourhood_group             48895 non-null  object
 2   latitude                        48895 non-null  float64
 3   longitude                       48895 non-null  float64
 4   room_type                       48895 non-null  object
 5   price                           48895 non-null  int64
 6   minimum_nights                  48895 non-null  int64
 7   number_of_reviews               48895 non-null  int64
 8   reviews_per_month               38843 non-null  float64
 9   calculated_host_listings_count  48895 non-null  int64
 10  availability_365                48895 non-null  int64
dtypes: float64(3), int64(6), object(2)
memory usage: 4.1+ MB
```

Some Basic Visualizations

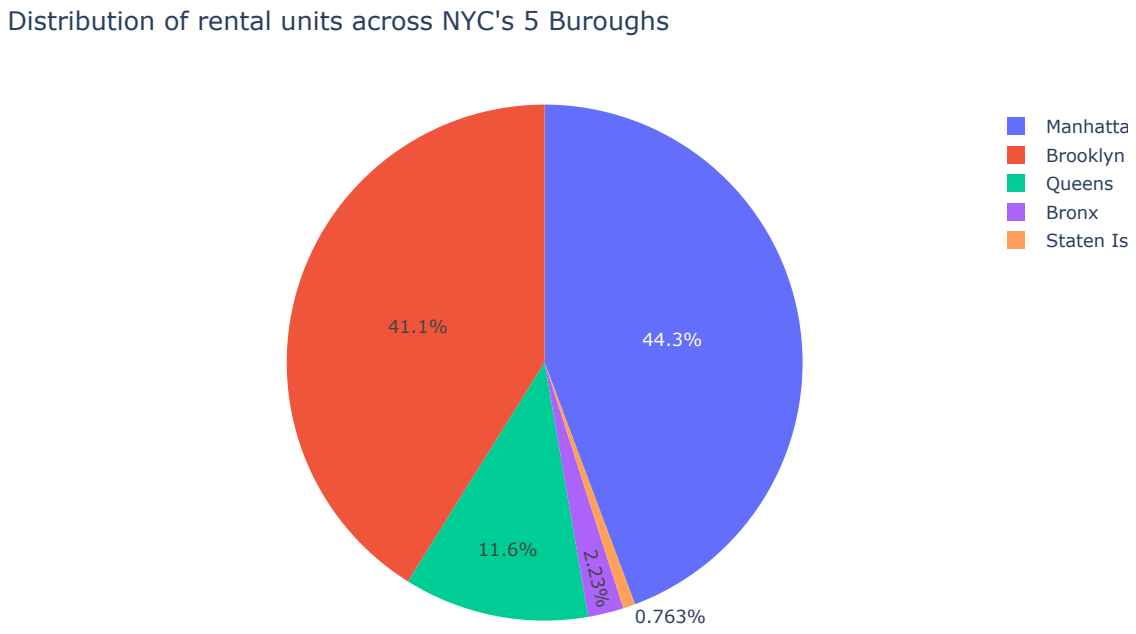
Let's try another popular python graphics library: Plotly.

You can find documentation and all the examples you'll need here: Plotly Documentation

Let's start out by getting a better feel for the distribution of rentals in the market.

Generate a pie chart showing the distribution of rental units across NYC's 5 Buroughs (`neighbourhood_groups` in the dataset)####

In [4]:
```
import plotly.express as px
# set pie chart
fig = px.pie(airbnb_data, names='neighbourhood_group', title='Distribution of rental units across NYC\'s 5 Buroug
fig.show()
```



Plot the total number_of_reviews per neighbourhood_group

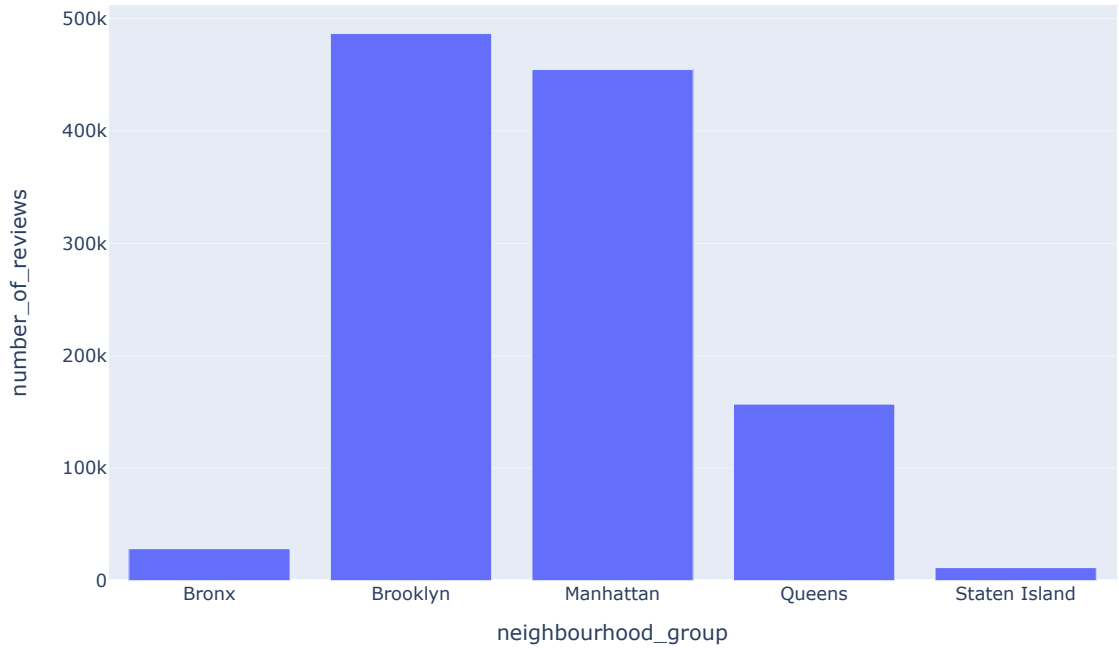
We now want to see the total number of reviews left for each neighborhood group in the form of a Bar Chart (where the X-axis is the neighbourhood group and the Y-axis is a count of review.

This is a two step process:

1. You'll have to sum up the reviews per neighbourhood group **(hint! try using the groupby function)**
2. Then use Plotly to generate the graph

In [7]:
```
# count total reviews in groups
total_reviews = airbnb_data.groupby("neighbourhood_group").agg("sum")
# set bar chart
fig = px.bar(total_reviews, x=total_reviews.index, y='number_of_reviews')
fig.show()
```

```
C:\Users\zhang\AppData\Local\Temp\ipykernel_42072\297917217.py:2: FutureWarning:

The default value of numeric_only in DataFrameGroupBy.sum is deprecated. In a future version, numeric_only will
default to False. Either specify numeric_only or select only columns which should be valid for the function.
```

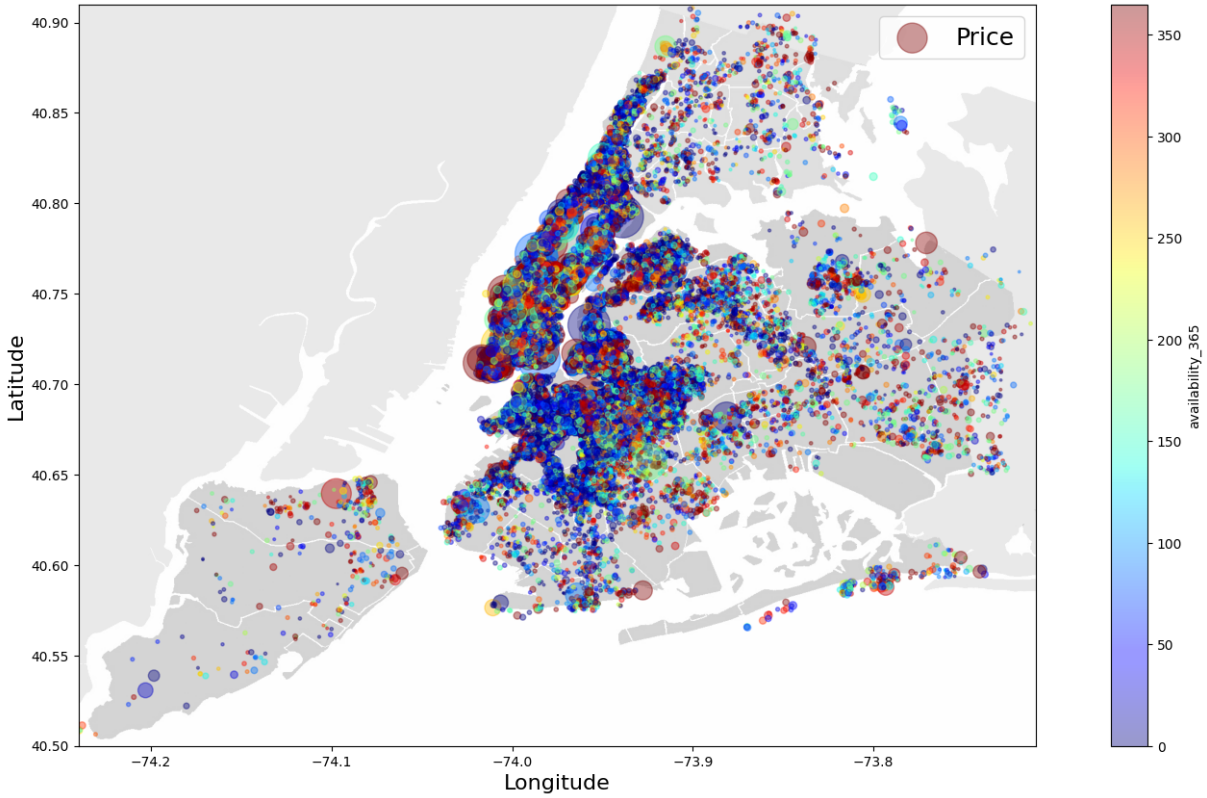


In [ ]:

Plot a map of airbnbs throughout New York (if it gets too crowded take a subset of the data, and try to make it look nice if you can :)).

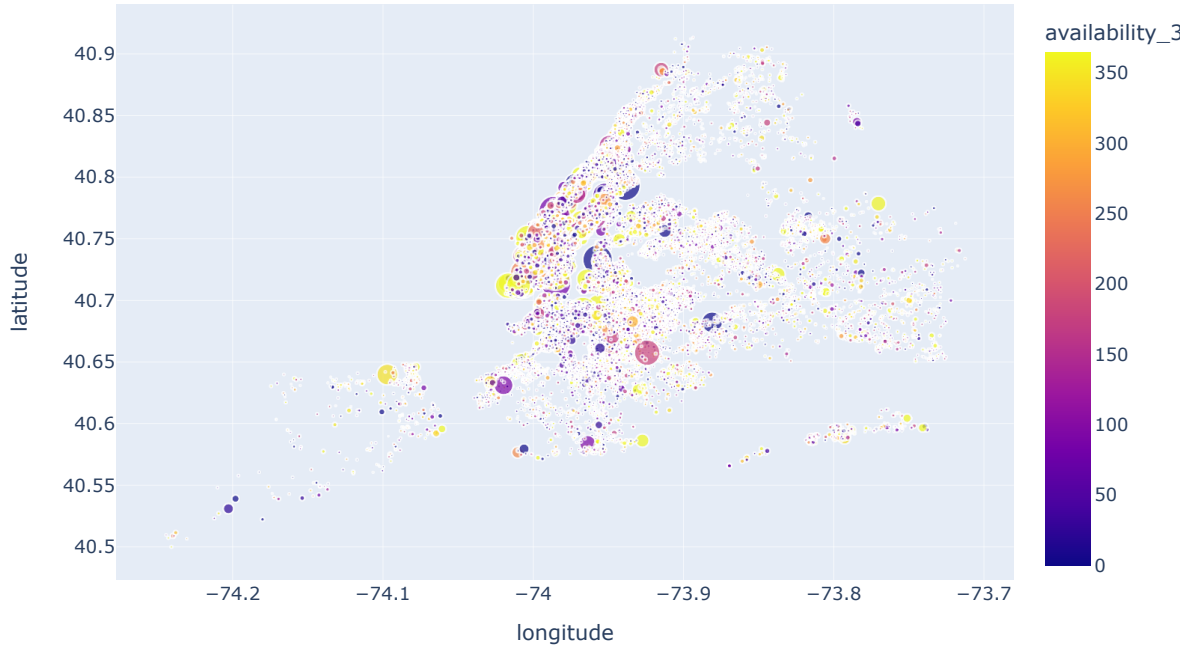
For reference you can use the Matplotlib code above to replicate this graph here.

In [8]:
```
import matplotlib.image as mpimg

# Load image
nyc_img=mpimg.imread('nyc.png')

ax = airbnb_data.plot(kind="scatter", x="longitude", y="latitude", figsize=(20,10),
                      s = airbnb_data["price"]/10, label="Price",
                      c = "availability_365", cmap=plt.get_cmap("jet"), colorbar=True, alpha=0.4)
plt.imshow(nyc_img, extent=[-74.24, -73.71, 40.50, 40.91],alpha=0.3, cmap=plt.get_cmap("jet"))
plt.ylabel("Latitude", fontsize=16)
plt.xlabel("Longitude", fontsize=16)
plt.legend(fontsize=18)
plt.show()
```



Now try to recreate this plot using Plotly's Scatterplot functionality. Note that the increased interactivity of the plot allows for some very cool functionality

In [9]:
```
import plotly.express as px
fig = px.scatter(airbnb_data, x="longitude", y="latitude", color="availability_365",
                 size="price", hover_data=['neighbourhood_group'])
fig.show()
```



Use Plotly to plot the average price of room types in Brooklyn who have at least 10 Reviews.

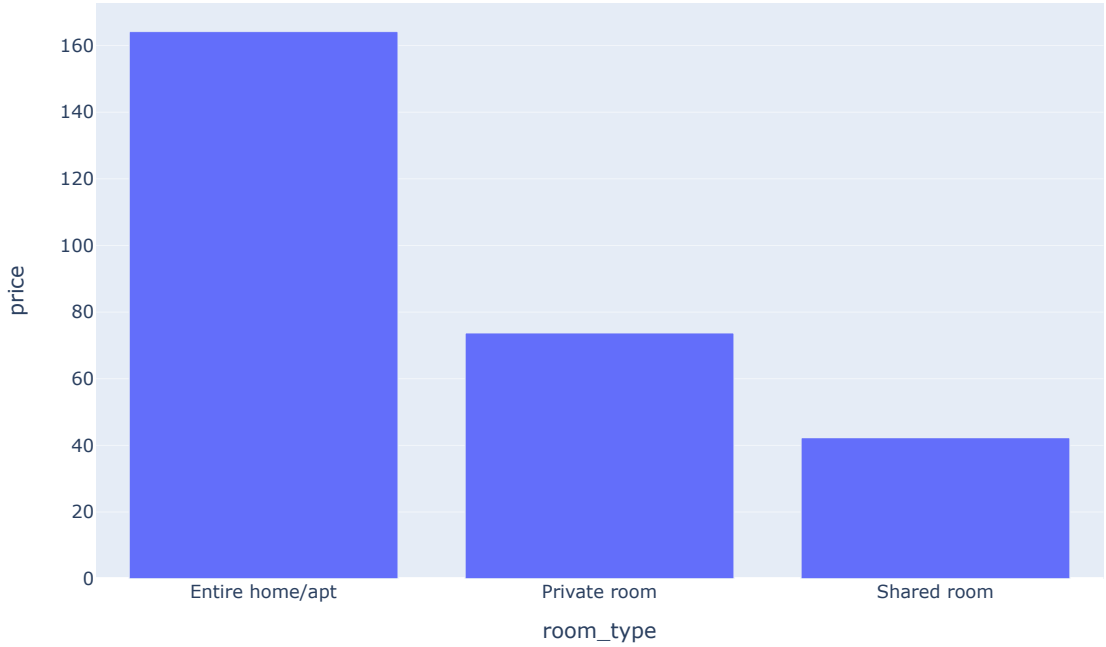
Like with the previous example you'll have to do a little bit of data engineering before you actually generate the plot.

Generally I'd recommend the following series of steps:

1. Filter the data by neighborhood group and number of reviews to arrive at the subset of data relevant to this graph.
2. Groupby the room type
3. Take the mean of the price for each roomtype group
4. FINALLY (seriously!?!?) plot the result

In [10]:
```
# Filter the data by neighborhood group and number of reviews to arrive at the subset of data relevant to this gr
airbnb_avg = airbnb.where((airbnb["neighbourhood_group"] == "Brooklyn") & (airbnb["number_of_reviews"] >= 10)).gr
fig = px.bar(airbnb_avg, x=airbnb_avg.index, y='price')
fig.show()
```

```
C:\Users\zhang\AppData\Local\Temp\ipykernel_42072\3981640182.py:2: FutureWarning:

The default value of numeric_only in DataFrameGroupBy.mean is deprecated. In a future version, numeric_only will
default to False. Either specify numeric_only or select only columns which should be valid for the function.
```



Prepare the Data

Feature Engineering

Let's create a new binned feature, `price_cat` that will divide our dataset into quintiles (1-5) in terms of price level (you can choose the levels to assign)

Do a value count to check the distribution of values

In [11]:
```
airbnb_data["income_cat"] = pd.cut(airbnb["price"], bins=[0., 50., 100., 150., 200., np.inf], labels=[1, 2, 3, 4,
airbnb_data["income_cat"].value_counts()
```

Out[11]:
```
2    17367
3    10029
5     8384
4     6554
1     6550
Name: income_cat, dtype: int64
```

Now engineer at least one new feature.

In [12]:
```
# new feature
# minimum cost for each visitor
airbnb_data["minimum_cost"] = airbnb_data["minimum_nights"] * airbnb_data["price"]
airbnb_data["minimum_cost"].head()
```

Out[12]:
```
0    149
1    225
2    450
3     89
4    800
Name: minimum_cost, dtype: int64
```

Data Imputation

Determine if there are any null-values and if there are impute them.

In [13]:
```
# check which values is null
airbnb_data[airbnb_data.isnull().any(axis=1)].head()
# fill 0 for reviews per month
airbnb_data["reviews_per_month"].fillna(0, inplace=True)
```

Numeric Conversions

Finally, review what features in your dataset are non-numeric and convert them.

In [14]:
```
from sklearn.preprocessing import LabelEncoder

# creating instance of labelencoder
labelencoder = LabelEncoder()
# Assigning numerical values and storing in another column
airbnb_data['income_cat'] = labelencoder.fit_transform(airbnb_data['income_cat'])
airbnb_data['neighbourhood_group'] = labelencoder.fit_transform(airbnb_data['neighbourhood_group'])
airbnb_data['room_type'] = labelencoder.fit_transform(airbnb_data['room_type'])
airbnb_data.head()
```

Out[14]:

	id	neighbourhood_group	latitude	longitude	room_type	price	minimum_nights	number_of_reviews	reviews_per_month	calc
0	2539	1	40.64749	-73.97237	1	149	1	9	0.21	
1	2595	2	40.75362	-73.98377	0	225	1	45	0.38	
2	3647	2	40.80902	-73.94190	1	150	3	0	0.00	
3	3831	1	40.68514	-73.95976	0	89	1	270	4.64	
4	5022	2	40.79851	-73.94399	0	80	10	9	0.10	

Prepare data for Machine Learning

Set aside 20% of the data as test test (80% train, 20% test).

Using our `StratifiedShuffleSplit` function example from above, let's split our data into a 80/20 Training/Testing split using `neighbourhood_group` to partition the dataset

In [15]:
```
from sklearn.model_selection import StratifiedShuffleSplit
# let's first start by creating our train and test sets
split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_index, test_index in split.split(airbnb_data, airbnb_data["neighbourhood_group"]):
    train_set = airbnb_data.loc[train_index]
    test_set = airbnb_data.loc[test_index]
```

Finally, remove your labels `price` from your testing and training cohorts, and create separate label features.

In [16]:
```
# drop labels for training set features
# the input to the model should not contain the true label
airbnb_training = train_set.drop("price", axis=1)
airbnb_labels = train_set["price"].copy()
airbnb_testing = test_set.drop("price", axis=1)
airbnb_test_labels = test_set["price"].copy()
```

Fit a model of your choice

The task is to predict the price, you could refer to the housing example on how to train and evaluate your model using **MSE**. Provide both **test and train set MSE values**.

In [17]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

lin_reg = LinearRegression()
lin_reg.fit(airbnb_training, airbnb_labels)

# let's try our model on a few testing instances
data = airbnb_testing.iloc[:5]
labels = airbnb_test_labels.iloc[:5]

print("Predictions:", lin_reg.predict(data))
print("Actual labels:", list(labels))
```

```
Predictions: [164.9075733  -23.19648225 227.88475143  58.8144876  154.35592636]
Actual labels: [120, 35, 200, 75, 150]
```

In [18]:
```
# MSE of testing set
preds_test = lin_reg.predict(airbnb_testing)
mse_test = mean_squared_error(airbnb_test_labels, preds_test)
mse_test
```

Out[18]:
```
38331.46265848855
```

In [19]:
```
# MSE of training set
preds_training = lin_reg.predict(airbnb_training)
mse_training = mean_squared_error(airbnb_labels, preds_training)
mse_training
```

Out[19]:
```
33827.50638958112
```