CSM148_Project_1_W24_TODO

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0.1 24W-COM SCI-M148 Project 1

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0.1.1 Submission Guidelines (Due: Jan 27 before the class)

1. Please fill in your name and UID above.
2. Please submit a **PDF printout** of your Jupyter Notebook to **Gradescope**. If you have any trouble accessing Gradescope, please let a TA know ASAP.
3. When submitting to Gradescope, you will be taken to a page that asks you to assign questions and pages. As the PDF can get long, please make sure to assign pages to corresponding questions to ensure the readers know where to look.

0.2 Introduction

Welcome to **CS148 - Introduction to Data Science!** As we're planning to move through topics aggressively in this course, to start out, we'll look to do an end-to-end walkthrough of a datascience project, and then ask you to replicate the code yourself for a new dataset.

Please note: We don't expect you to fully grasp everything happening here in either code or theory. This content will be reviewed throughout the quarter. Rather we hope that by giving you the full perspective on a data science project it will better help to contextualize the pieces as they're covered in class

In that spirit, we will first work through an example project from end to end to give you a feel for the steps involved.

Here are the main steps:

1. Get the data
2. Visualize the data for insights
3. Preprocess the data for your machine learning algorithm
4. Select a machine learning model and train it
5. Evaluate its performance

0.3 Working with Real Data

It is best to experiment with real-data as opposed to aritifical datasets.

There are many different open datasets depending on the type of problems you might be interested in!

Here are a few data repositories you could check out: - UCI Datasets - Kaggle Datasets - AWS Datasets

Below we will run through an California Housing example collected from the 1990's.

0.4 Setup

We'll start by importing a series of libraries we'll be using throughout the project.

[ ]:
```
!pip install kaleido
```

```
Requirement already satisfied: kaleido in /usr/local/lib/python3.11/dist-
packages (0.2.1)
```

[ ]:
```
# restart process

os.kill(os.getpid(), 9)
```

[ ]:
```
import sys
assert sys.version_info >= (3, 5) # python>=3.5
import sklearn
#assert sklearn.__version__ >= "0.20" # sklearn >= 0.20

import numpy as np #numerical package in python
%matplotlib inline
import matplotlib.pyplot as plt #plotting package

# to make this notebook's output identical at every run
np.random.seed(42)

#matplotlib magic for inline figures
%matplotlib inline
import matplotlib # plotting library
import matplotlib.pyplot as plt

# for plotly figures
import kaleido # might need to !pip install kaleido, then restart process by os.
↪kill(os.getpid(), 9)
from IPython.display import Image
```

0.5 Intro to Data Exploration Using Pandas

In this section we will load the dataset, and visualize different features using different types of plots.

Packages we will use: - **Pandas:** is a fast, flexibile and expressive data structure widely used for tabular and multidimensional datasets. - **Matplotlib**: is a 2d python plotting library which you can use to create quality figures (you can plot almost anything if you're willing to code it out!) - other plotting libraries:seaborn, ggplot2

Note: If you're working in CoLab for this project, the CSV file first has to be loaded into the environment. This can be done manually using the sidebar menu option, or using the following code here.

If you're running this notebook locally on your device, simply proceed to the next step.

[ ]:
```
# from google.colab import files
# files.upload()
```

We'll now begin working with Pandas. Pandas is the principle library for data management in python. It's primary mechanism of data storage is the dataframe, a two dimensional table, where each column represents a datatype, and each row a specific data element in the set.

To work with dataframes, we have to first read in the csv file and convert it to a dataframe using the code below.

[ ]:
```
# We'll now import the holy grail of python datascience: Pandas!
import pandas as pd
housing = pd.read_csv('housing.csv')
```

[ ]:
```
housing.head() # show the first few elements of the dataframe
               # typically this is the first thing you do
               # to see how the dataframe looks like
```

[ ]:
```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -122.23     37.88                41.0        880.0           129.0
1    -122.22     37.86                21.0       7099.0          1106.0
2    -122.24     37.85                52.0       1467.0           190.0
3    -122.25     37.85                52.0       1274.0           235.0
4    -122.25     37.85                52.0       1627.0           280.0

   population  households  median_income  median_house_value ocean_proximity
0       322.0       126.0         8.3252            452600.0        NEAR BAY
1      2401.0      1138.0         8.3014            358500.0        NEAR BAY
2       496.0       177.0         7.2574            352100.0        NEAR BAY
3       558.0       219.0         5.6431            341300.0        NEAR BAY
4       565.0       259.0         3.8462            342200.0        NEAR BAY
```

A dataset may have different types of features - real valued - Discrete (integers) - categorical (strings) - Boolean

The two categorical features are essentialy the same as you can always map a categorical string/character to an integer.

In the dataset example, all our features are real valued floats, except ocean proximity which is categorical.

[ ]:
```
# to see a concise summary of data types, null values, and counts
# use the info() method on the dataframe
housing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   longitude           20640 non-null  float64
 1   latitude            20640 non-null  float64
 2   housing_median_age  20640 non-null  float64
 3   total_rooms         20640 non-null  float64
 4   total_bedrooms      20433 non-null  float64
 5   population          20640 non-null  float64
 6   households          20640 non-null  float64
 7   median_income       20640 non-null  float64
 8   median_house_value  20640 non-null  float64
 9   ocean_proximity     20640 non-null  object
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

[ ]:
```
# you can access individual columns similarly
# to accessing elements in a python dict
housing["ocean_proximity"].head() # added head() to avoid printing many columns.
  ↪.
```

[ ]:
```
0    NEAR BAY
1    NEAR BAY
2    NEAR BAY
3    NEAR BAY
4    NEAR BAY
Name: ocean_proximity, dtype: object
```

[ ]:
```
# to access a particular row we can use iloc
housing.iloc[1]
```

[ ]:
```
longitude              -122.22
latitude                 37.86
housing_median_age        21.0
total_rooms             7099.0
total_bedrooms          1106.0
population              2401.0
households              1138.0
median_income           8.3014
median_house_value    358500.0
ocean_proximity       NEAR BAY
```

```
Name: 1, dtype: object
```

[ ]:
```
# one other function that might be useful is
# value_counts(), which counts the number of occurences
# for categorical features
housing["ocean_proximity"].value_counts()
```

[ ]:
```
ocean_proximity
<1H OCEAN     9136
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: count, dtype: int64
```

[ ]:
```
# The describe function compiles your typical statistics for each
# column
housing.describe()
```

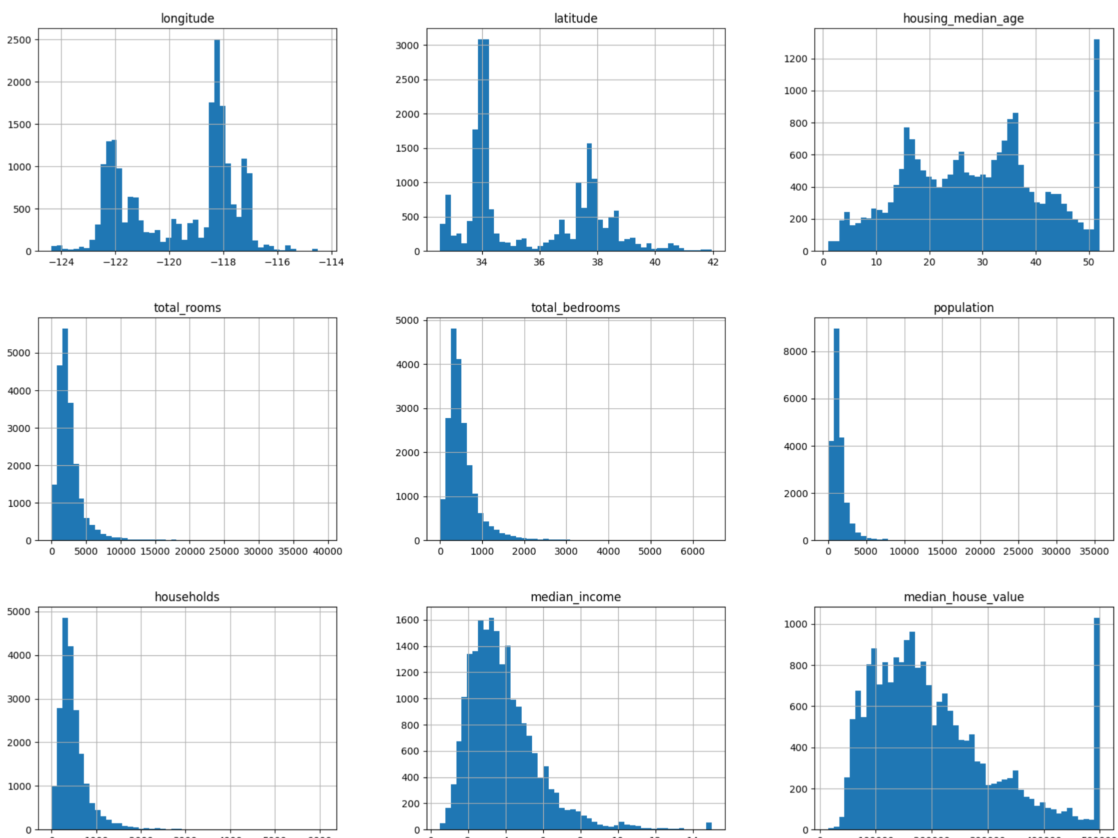
[ ]:
```
          longitude      latitude  housing_median_age   total_rooms  \
count  20640.000000  20640.000000        20640.000000  20640.000000
mean    -119.569704     35.631861           28.639486   2635.763081
std        2.003532      2.135952           12.585558   2181.615252
min     -124.350000     32.540000            1.000000      2.000000
25%     -121.800000     33.930000           18.000000   1447.750000
50%     -118.490000     34.260000           29.000000   2127.000000
75%     -118.010000     37.710000           37.000000   3148.000000
max     -114.310000     41.950000           52.000000  39320.000000

       total_bedrooms    population    households  median_income  \
count    20433.000000  20640.000000  20640.000000   20640.000000
mean       537.870553   1425.476744    499.539680       3.870671
std        421.385070   1132.462122    382.329753       1.899822
min          1.000000      3.000000      1.000000       0.499900
25%        296.000000    787.000000    280.000000       2.563400
50%        435.000000   1166.000000    409.000000       3.534800
75%        647.000000   1725.000000    605.000000       4.743250
max       6445.000000  35682.000000   6082.000000      15.000100

       median_house_value
count        20640.000000
mean        206855.816909
std         115395.615874
min          14999.000000
25%         119600.000000
50%         179700.000000
75%         264725.000000
```

```
max          500001.000000
```

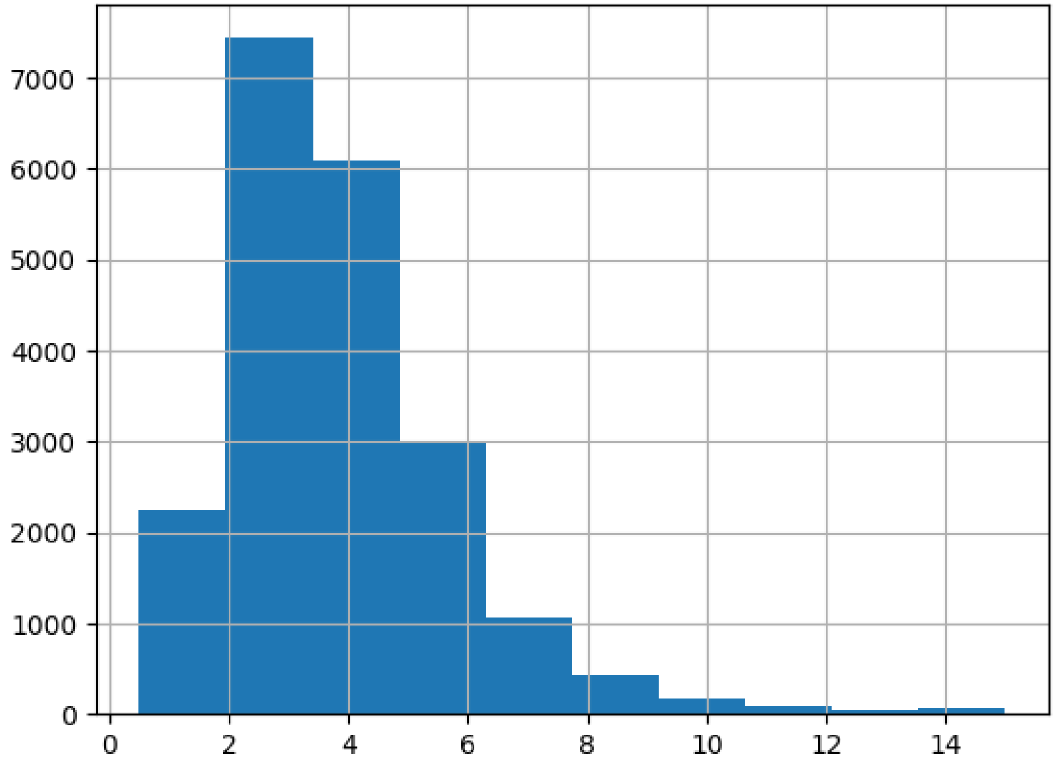
If you want to learn about different ways of accessing elements or other functions it's useful to check out the getting started section here

0.6 Let's start visualizing the dataset

[ ]:
```python
# We can draw a histogram for each of the dataframes features
# using the hist function
housing.hist(bins=50, figsize=(20,15))
# save_fig("attribute_histogram_plots")
plt.show() # pandas internally uses matplotlib, and to display all the figures
           # the show() function must be called
```



[ ]:
```python
# if you want to have a histogram on an individual feature:
housing["median_income"].hist()
plt.show()
```



We can convert a floating point feature to a categorical feature by binning or by defining a set of intervals.

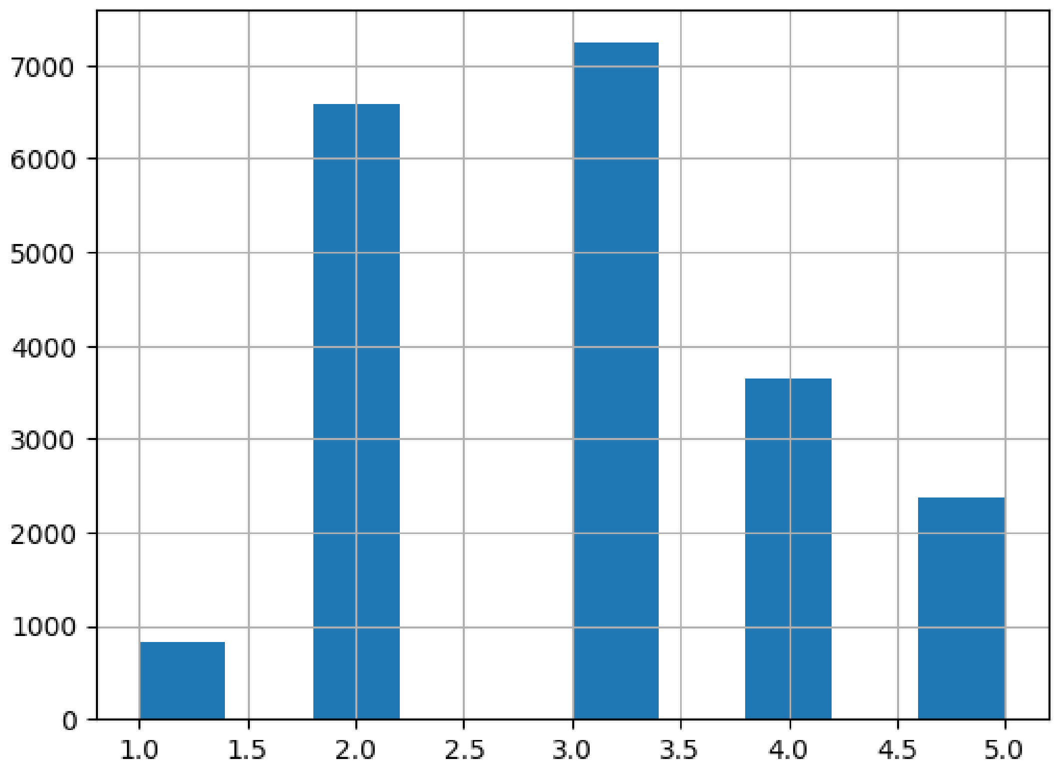
For example, to bin the households based on median_income we can use the pd.cut function

[ ]:
```
# assign each bin a categorical value [1, 2, 3, 4, 5] in this case.
housing["income_cat"] = pd.cut(housing["median_income"],
                               bins=[0., 1.5, 3.0, 4.5, 6., np.inf],
                               labels=[1, 2, 3, 4, 5])

housing["income_cat"].value_counts()
```

[ ]:
```
income_cat
3    7236
2    6581
4    3639
5    2362
1     822
Name: count, dtype: int64
```

[ ]:
```
housing["income_cat"].hist()
```

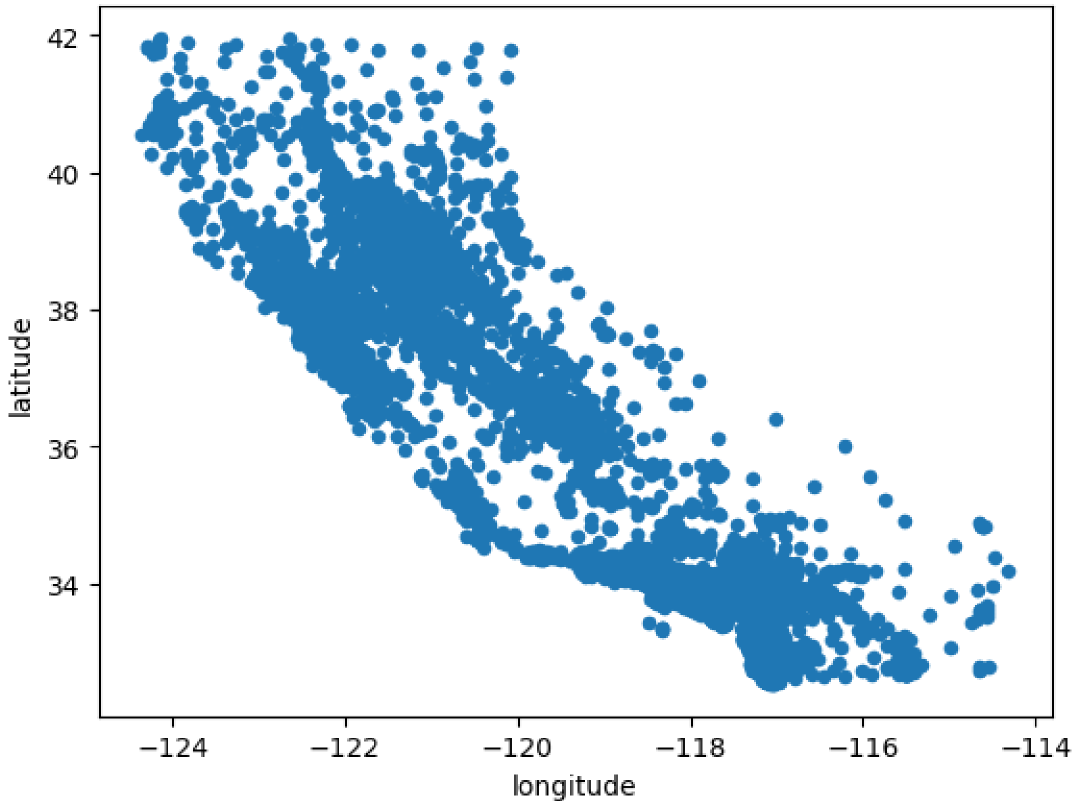
[ ]:
```
<Axes: >
```



Next let's visualize the household incomes based on latitude & longitude coordinates

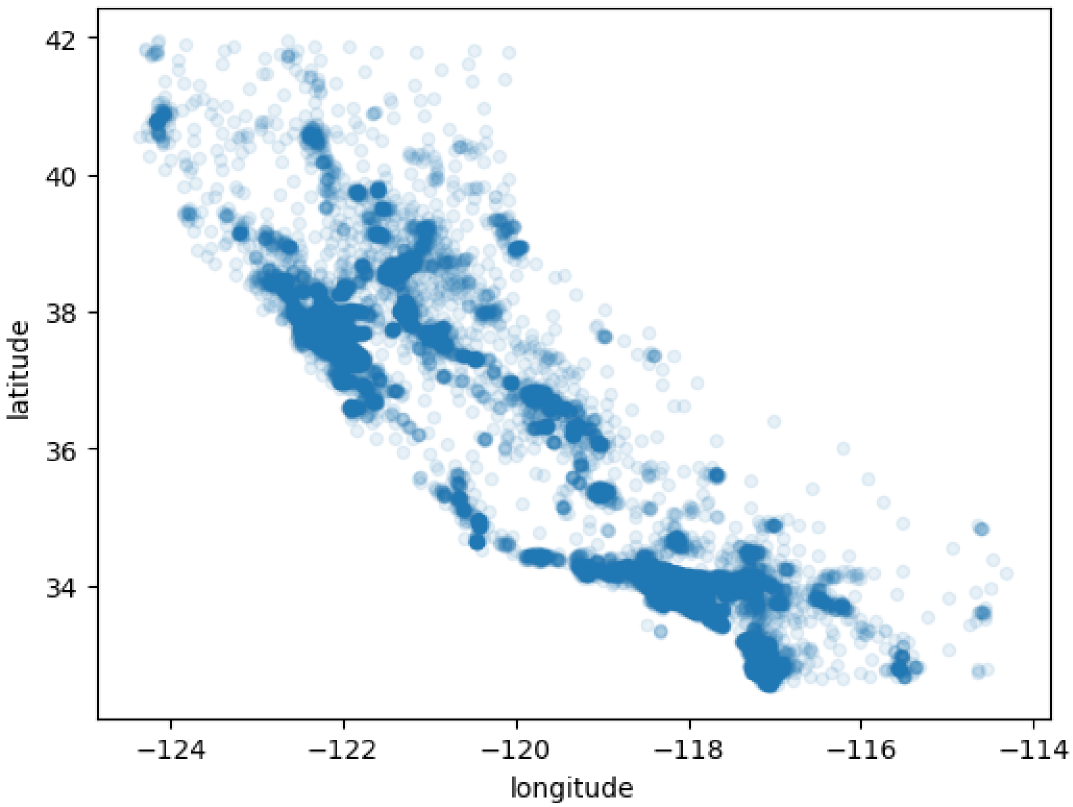
[ ]:
```
## here's a not so interestting way plotting it
housing.plot(kind="scatter", x="longitude", y="latitude")
```

[ ]: <Axes: xlabel='longitude', ylabel='latitude'>



[ ]:
```
# we can make it look a bit nicer by using the alpha parameter,
# it simply plots less dense areas lighter.
housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.1)
```

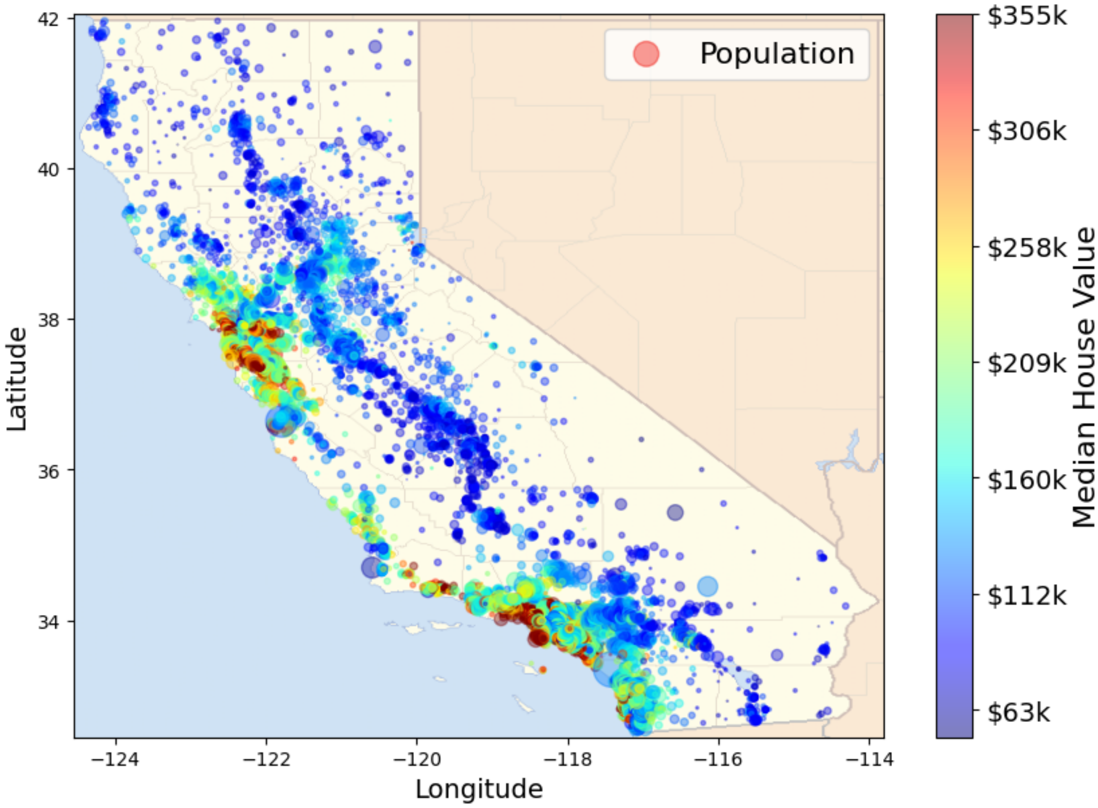
[ ]:
```
<Axes: xlabel='longitude', ylabel='latitude'>
```



[ ]:
```
# A more interesting plot is to color code (heatmap) the dots
# based on income. The code below achieves this

# Please note: In order for this to work, ensure that you've loaded an image
# of california (california.png) into this directory prior to running this

import matplotlib.image as mpimg
california_img=mpimg.imread('california.png')
ax = housing.plot(kind="scatter", x="longitude", y="latitude", figsize=(10,7),
                       s=housing['population']/100, label="Population",
                       c="median_house_value", cmap=plt.get_cmap("jet"),
                       colorbar=False, alpha=0.4,
                      )
# overlay the califronia map on the plotted scatter plot
# note: plt.imshow still refers to the most recent figure
# that hasn't been plotted yet.
plt.imshow(california_img, extent=[-124.55, -113.80, 32.45, 42.05], alpha=0.5,
           cmap=plt.get_cmap("jet"))
plt.ylabel("Latitude", fontsize=14)
plt.xlabel("Longitude", fontsize=14)
```

```
# setting up heatmap colors based on median_house_value feature
prices = housing["median_house_value"]
tick_values = np.linspace(prices.min(), prices.max(), 11)
cb = plt.colorbar()
cb.ax.set_yticklabels(["$%dk"%(round(v/1000)) for v in tick_values],␣
 ↪fontsize=14)
cb.set_label('Median House Value', fontsize=16)

plt.legend(fontsize=16)
plt.show()
```

```
<ipython-input-17-f4f6d29f5992>:26: UserWarning: set_ticklabels() should only be
used with a fixed number of ticks, i.e. after set_ticks() or using a
FixedLocator.
  cb.ax.set_yticklabels(["$%dk"%(round(v/1000)) for v in tick_values],
fontsize=14)
```



Not suprisingly, the most expensive houses are concentrated around the San Francisco/Los Angeles areas.

Up until now we have only visualized feature histograms and basic statistics.

When developing machine learning models the predictiveness of a feature for a particular target of intrest is what's important.

It may be that only a few features are useful for the target at hand, or features may need to be augmented by applying certain transfomrations.

None the less we can explore this using correlation matrices.

[ ]:
```
# Select only numeric columns
numeric_housing = housing.select_dtypes(include=[float, int])

# Compute the correlation matrix
corr_matrix = numeric_housing.corr()
```

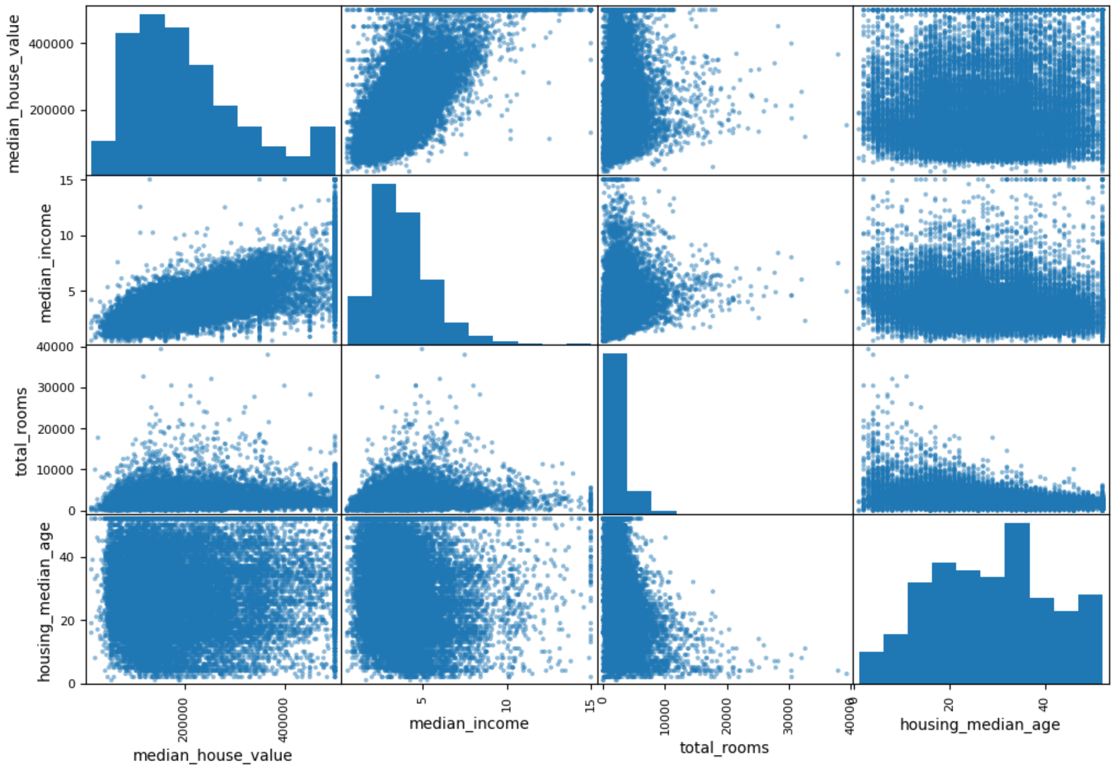
[ ]:
```
# for example if the target is "median_house_value", most correlated features␣
↪can be sorted
# which happens to be "median_income". This also intuitively makes sense.
corr_matrix["median_house_value"].sort_values(ascending=False)
```

[ ]:
```
median_house_value    1.000000
median_income         0.688075
total_rooms           0.134153
housing_median_age    0.105623
households            0.065843
total_bedrooms        0.049686
population           -0.024650
longitude            -0.045967
latitude             -0.144160
Name: median_house_value, dtype: float64
```

[ ]:
```
# the correlation matrix for different attributes/features can also be plotted
# some features may show a positive correlation/negative correlation or
# it may turn out to be completely random!
from pandas.plotting import scatter_matrix
attributes = ["median_house_value", "median_income", "total_rooms",
              "housing_median_age"]
scatter_matrix(housing[attributes], figsize=(12, 8))
```

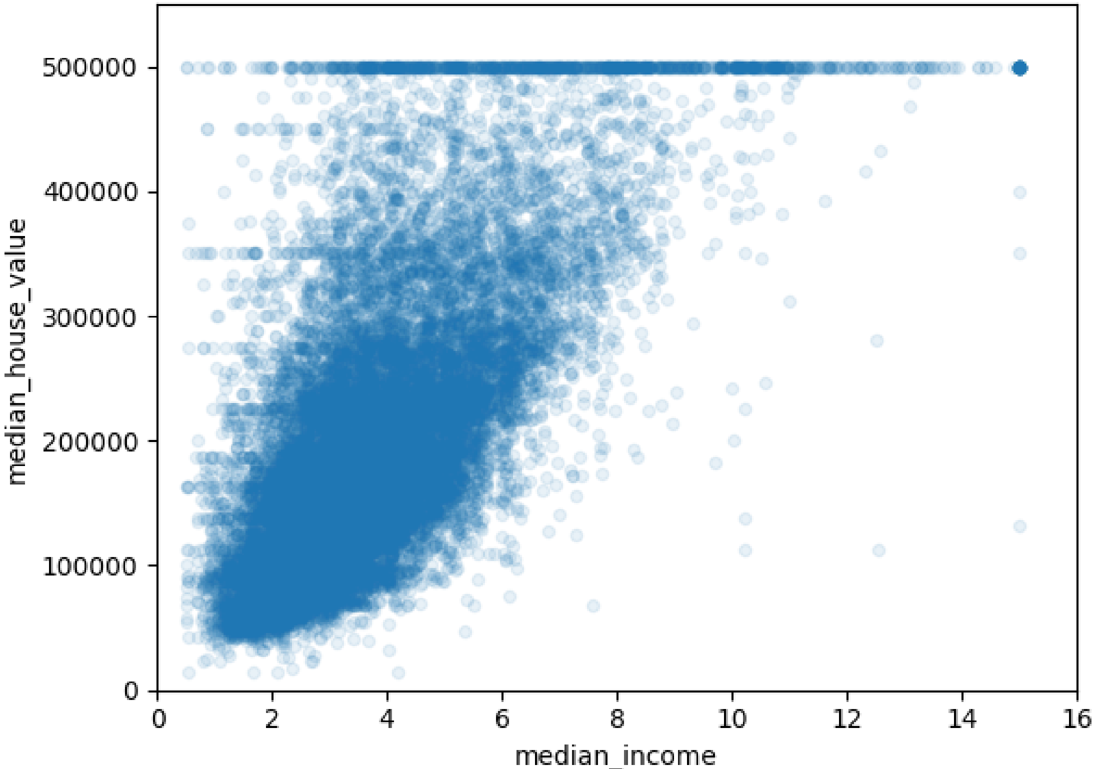
[ ]:
```
array([[<Axes: xlabel='median_house_value', ylabel='median_house_value'>,
        <Axes: xlabel='median_income', ylabel='median_house_value'>,
        <Axes: xlabel='total_rooms', ylabel='median_house_value'>,
        <Axes: xlabel='housing_median_age', ylabel='median_house_value'>],
       [<Axes: xlabel='median_house_value', ylabel='median_income'>,
        <Axes: xlabel='median_income', ylabel='median_income'>,
        <Axes: xlabel='total_rooms', ylabel='median_income'>,
        <Axes: xlabel='housing_median_age', ylabel='median_income'>],
       [<Axes: xlabel='median_house_value', ylabel='total_rooms'>,
        <Axes: xlabel='median_income', ylabel='total_rooms'>,
        <Axes: xlabel='total_rooms', ylabel='total_rooms'>,
```

```
 <Axes: xlabel='housing_median_age', ylabel='total_rooms'>],
[<Axes: xlabel='median_house_value', ylabel='housing_median_age'>,
 <Axes: xlabel='median_income', ylabel='housing_median_age'>,
 <Axes: xlabel='total_rooms', ylabel='housing_median_age'>,
 <Axes: xlabel='housing_median_age', ylabel='housing_median_age'>]],
dtype=object)
```



[ ]:
```python
# median income vs median house vlue plot plot 2 in the first row of top figure
housing.plot(kind="scatter", x="median_income", y="median_house_value",
             alpha=0.1)
plt.axis([0, 16, 0, 550000])
```

[ ]: (0.0, 16.0, 0.0, 550000.0)



0.7 Preparing Dastaset for ML

0.7.1 Dealing With Incomplete Data

[ ]:
```
# have you noticed when looking at the dataframe summary certain rows
# contained null values? we can't just leave them as nulls and expect our
# model to handle them for us...
sample_incomplete_rows = housing[housing.isnull().any(axis=1)].head()
sample_incomplete_rows
```

[ ]:
```
     longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
290    -122.16     37.77                47.0       1256.0             NaN
341    -122.17     37.75                38.0        992.0             NaN
538    -122.28     37.78                29.0       5154.0             NaN
563    -122.24     37.75                45.0        891.0             NaN
696    -122.10     37.69                41.0        746.0             NaN

     population  households  median_income  median_house_value  \
290       570.0       218.0         4.3750            161900.0
341       732.0       259.0         1.6196             85100.0
538      3741.0      1273.0         2.5762            173400.0
563       384.0       146.0         4.9489            247100.0
```

```
696       387.0       161.0          3.9063             178400.0

    ocean_proximity income_cat
290        NEAR BAY          3
341        NEAR BAY          2
538        NEAR BAY          2
563        NEAR BAY          4
696        NEAR BAY          3
```

[ ]:
```python
sample_incomplete_rows.dropna(subset=["total_bedrooms"])    # option 1: simply drop rows that have null values
```

[ ]:
```
Empty DataFrame
Columns: [longitude, latitude, housing_median_age, total_rooms, total_bedrooms,
population, households, median_income, median_house_value, ocean_proximity,
income_cat]
Index: []
```

[ ]:
```python
sample_incomplete_rows.drop("total_bedrooms", axis=1)       # option 2: drop the complete feature
```

[ ]:
```
     longitude  latitude  housing_median_age  total_rooms  population  \
290    -122.16     37.77                47.0       1256.0       570.0
341    -122.17     37.75                38.0        992.0       732.0
538    -122.28     37.78                29.0       5154.0      3741.0
563    -122.24     37.75                45.0        891.0       384.0
696    -122.10     37.69                41.0        746.0       387.0

     households  median_income  median_house_value ocean_proximity income_cat
290       218.0         4.3750            161900.0        NEAR BAY          3
341       259.0         1.6196             85100.0        NEAR BAY          2
538      1273.0         2.5762            173400.0        NEAR BAY          2
563       146.0         4.9489            247100.0        NEAR BAY          4
696       161.0         3.9063            178400.0        NEAR BAY          3
```

[ ]:
```python
median = housing["total_bedrooms"].median()
sample_incomplete_rows["total_bedrooms"].fillna(median, inplace=True) # option 3: replace na values with median values
sample_incomplete_rows
```

```
<ipython-input-25-855601105a83>:2: FutureWarning: A value is trying to be set on
a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.
```

```
For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  sample_incomplete_rows["total_bedrooms"].fillna(median, inplace=True) # option
3: replace na values with median values
```

[ ]:

```
     longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
290    -122.16     37.77                47.0       1256.0           435.0
341    -122.17     37.75                38.0        992.0           435.0
538    -122.28     37.78                29.0       5154.0           435.0
563    -122.24     37.75                45.0        891.0           435.0
696    -122.10     37.69                41.0        746.0           435.0

     population  households  median_income  median_house_value  \
290       570.0       218.0         4.3750            161900.0
341       732.0       259.0         1.6196             85100.0
538      3741.0      1273.0         2.5762            173400.0
563       384.0       146.0         4.9489            247100.0
696       387.0       161.0         3.9063            178400.0

    ocean_proximity income_cat
290        NEAR BAY          3
341        NEAR BAY          2
538        NEAR BAY          2
563        NEAR BAY          4
696        NEAR BAY          3
```

Now that we've played around with this, lets finalize this approach by replacing the nulls in our final dataset

[ ]:

```python
housing["total_bedrooms"].fillna(median, inplace=True)
```

```
<ipython-input-26-3087f14a5ecd>:1: FutureWarning: A value is trying to be set on
a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  housing["total_bedrooms"].fillna(median, inplace=True)
```

Could you think of another plausible imputation for this dataset?

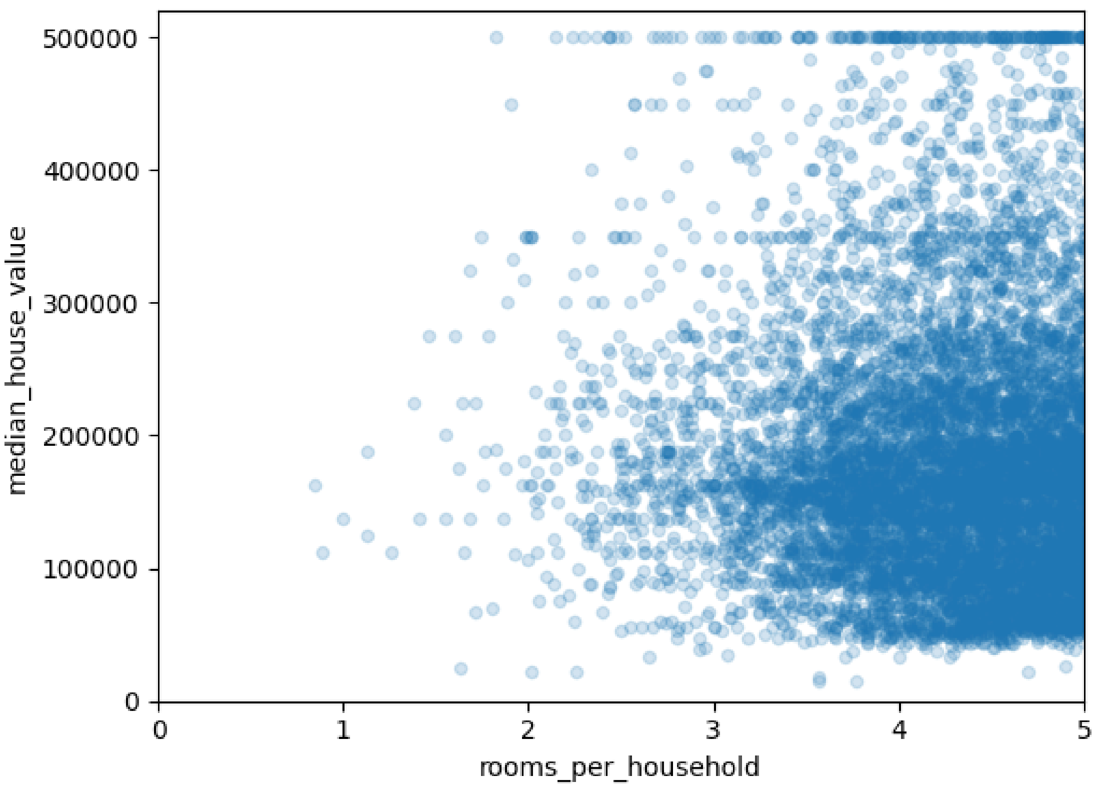
0.7.2 Augmenting Features

New features can be created by combining different columns from our data set.

- rooms_per_household = total_rooms / households
- bedrooms_per_room = total_bedrooms / total_rooms
- etc.

[ ]:
```
housing["rooms_per_household"] = housing["total_rooms"]/(housing["households"]␣
↪+ 1e-6)
housing["bedrooms_per_room"] = housing["total_bedrooms"]/
↪(housing["total_rooms"] + 1e-6)
housing["population_per_household"]=housing["population"]/
↪(housing["households"] + 1e-6)
```

[ ]:
```
housing.plot(kind="scatter", x="rooms_per_household", y="median_house_value",
             alpha=0.2)
plt.axis([0, 5, 0, 520000])
plt.show()
```



0.7.3 Dealing with Non-Numeric Data

So we're almost ready to feed our dataset into a machine learning model, but we're not quite there yet!

Generally speaking all models can only work with numeric data, which means that if you have Categorical data you want included in your model, you'll need to do a numeric conversion. We'll explore this more later, but for now we'll take one approach to converting our `ocean_proximity` field into a numeric one.

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

# creating instance of labelencoder
labelencoder = LabelEncoder()
# Assigning numerical values and storing in another column
housing['ocean_proximity'] = labelencoder.
  ↪fit_transform(housing['ocean_proximity'])
housing.head()
```

[ ]:
```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -122.23     37.88                41.0        880.0           129.0
1    -122.22     37.86                21.0       7099.0          1106.0
2    -122.24     37.85                52.0       1467.0           190.0
3    -122.25     37.85                52.0       1274.0           235.0
4    -122.25     37.85                52.0       1627.0           280.0

   population  households  median_income  median_house_value  ocean_proximity  \
0       322.0       126.0         8.3252            452600.0                3
1      2401.0      1138.0         8.3014            358500.0                3
2       496.0       177.0         7.2574            352100.0                3
3       558.0       219.0         5.6431            341300.0                3
4       565.0       259.0         3.8462            342200.0                3

  income_cat  rooms_per_household  bedrooms_per_room  population_per_household
0          5             6.984127           0.146591                  2.555556
1          5             6.238137           0.155797                  2.109842
2          5             8.288136           0.129516                  2.802260
3          4             5.817352           0.184458                  2.547945
4          3             6.281853           0.172096                  2.181467
```

0.7.4 Divide up the Dataset for Machine Learning

After having cleaned your dataset you're ready to train your machine learning model.

To do so you'll aim to divide your data into: - train set - test set

In some cases you might also have a validation set as well for tuning hyperparameters (don't worry if you're not familiar with this term yet..)

In supervised learning setting your train set and test set should contain (**feature**, **target**) tuples. -

feature: is the input to your model - **target**: is the ground truth label - when target is categorical the task is a classification task - when target is floating point the task is a regression task

We will make use of **scikit-learn** python package for preprocessing.

Scikit learn is pretty well documented and if you get confused at any point simply look up the function/object!

[ ]:
```
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]
```

[ ]:
```
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()
```

[ ]:
```
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()
```

0.7.5 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.

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

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

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

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

print("Predictions:", np.round(lin_reg.predict(data), 1))
print("Actual labels:", list(labels))
```

```
Predictions: [418197.2 305620.5 232253.  188754.6 251166.4]
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

$$L(\hat{Y}, Y) = \frac{1}{N}\sum_{i}^{N}(\hat{y_i} - y_i)^2$$

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

[ ]:
```
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
```

[ ]:
```
67694.08184344426
```

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

1 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.**

2 Visualizing Data

2.0.1 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

[ ]:
```
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()

# drop the following columns
airbnb_drop = airbnb.drop(['name', 'host_id', 'host_name', 'last_review',␣
 ↪'neighbourhood'], axis=1)
```

```
[ ]: # display a summary of the statistcs
airbnb_drop.describe()
```

```
[ ]:                  id      latitude     longitude         price  minimum_nights  \
count  4.889500e+04  48895.000000  48895.000000  48895.000000    48895.000000
mean   1.901714e+07     40.728949    -73.952170    152.720687        7.029962
std    1.098311e+07      0.054530      0.046157    240.154170       20.510550
min    2.539000e+03     40.499790    -74.244420      0.000000        1.000000
25%    9.471945e+06     40.690100    -73.983070     69.000000        1.000000
50%    1.967728e+07     40.723070    -73.955680    106.000000        3.000000
75%    2.915218e+07     40.763115    -73.936275    175.000000        5.000000
max    3.648724e+07     40.913060    -73.712990  10000.000000     1250.000000

       number_of_reviews  reviews_per_month  calculated_host_listings_count  \
count       48895.000000       38843.000000                    48895.000000
mean           23.274466           1.373221                        7.143982
std            44.550582           1.680442                       32.952519
min             0.000000           0.010000                        1.000000
25%             1.000000           0.190000                        1.000000
50%             5.000000           0.720000                        1.000000
75%            24.000000           2.020000                        2.000000
max           629.000000          58.500000                      327.000000

       availability_365
count      48895.000000
mean         112.781327
std          131.622289
min            0.000000
25%            0.000000
50%           45.000000
75%          227.000000
max          365.000000
```

```
[ ]: airbnb_drop.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
```

2.0.2 Some Basic Visualizations

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

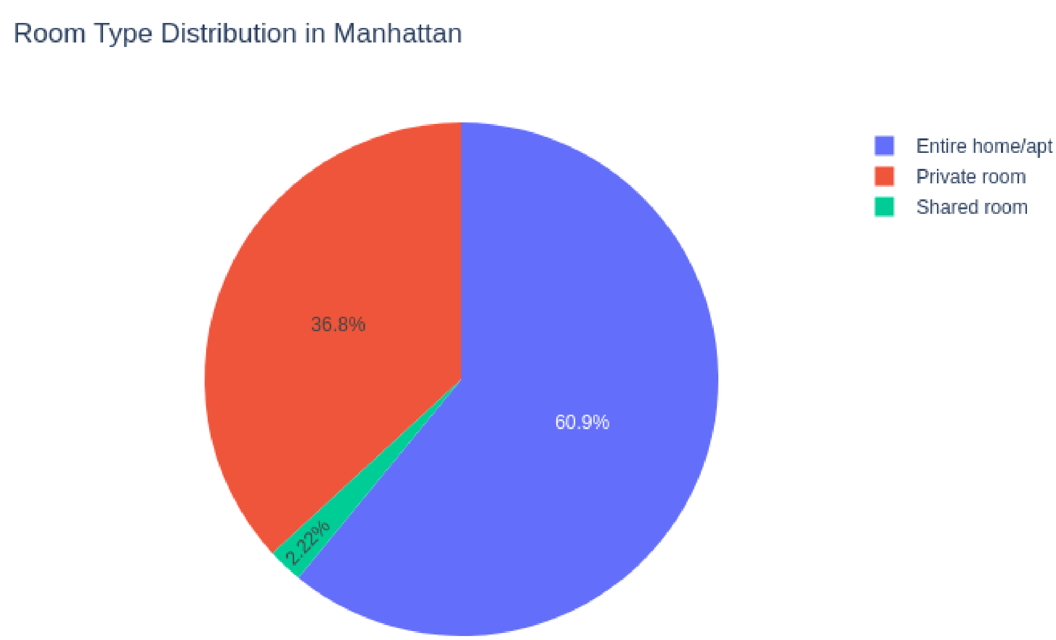
You can find documentation and all the examples you'll need here: Plotly Documentation

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 room type (`room_type` in the dataset) across NYC's 'Manhattan' Buroughs (fitlered by `neighbourhood_group` in the dataset)

[ ]:
```
import plotly.express as px

manhattan_data = airbnb_drop[airbnb_drop['neighbourhood_group'] == 'Manhattan']

fig = px.pie(manhattan_data, names='room_type', title='Room Type Distribution␣
↪in Manhattan')
fig.show()
```

[ ]:



Plot the total number_of_reviews per room_type We now want to see the total number of reviews left for each room type group in the form of a Bar Chart (where the X-axis is the room type 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 room type group **(hint! try using the groupby function)** 2. Then use Plotly to generate the graph

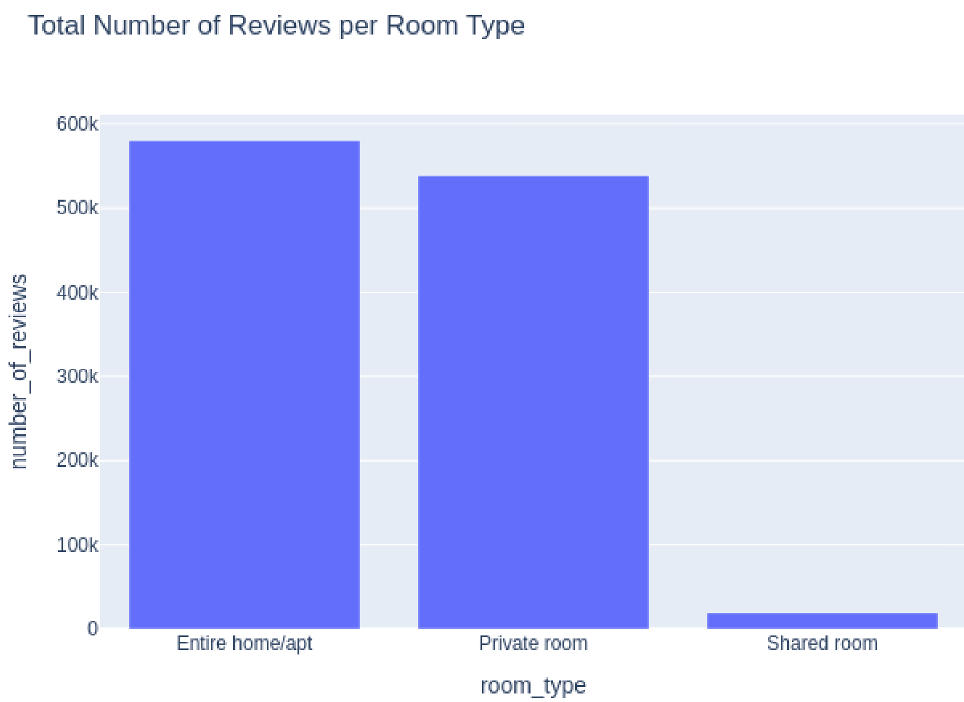
[13]:
```
room = airbnb_drop.groupby('room_type')['number_of_reviews'].sum().reset_index()
room.head()
```

[13]:

	room_type	number_of_reviews
0	Entire home/apt	580403
1	Private room	538346
2	Shared room	19256

```
[14]: fig = px.bar(room, x='room_type', y='number_of_reviews', title='Total Number of Reviews per Room Type')
fig.show()
```

[14]:

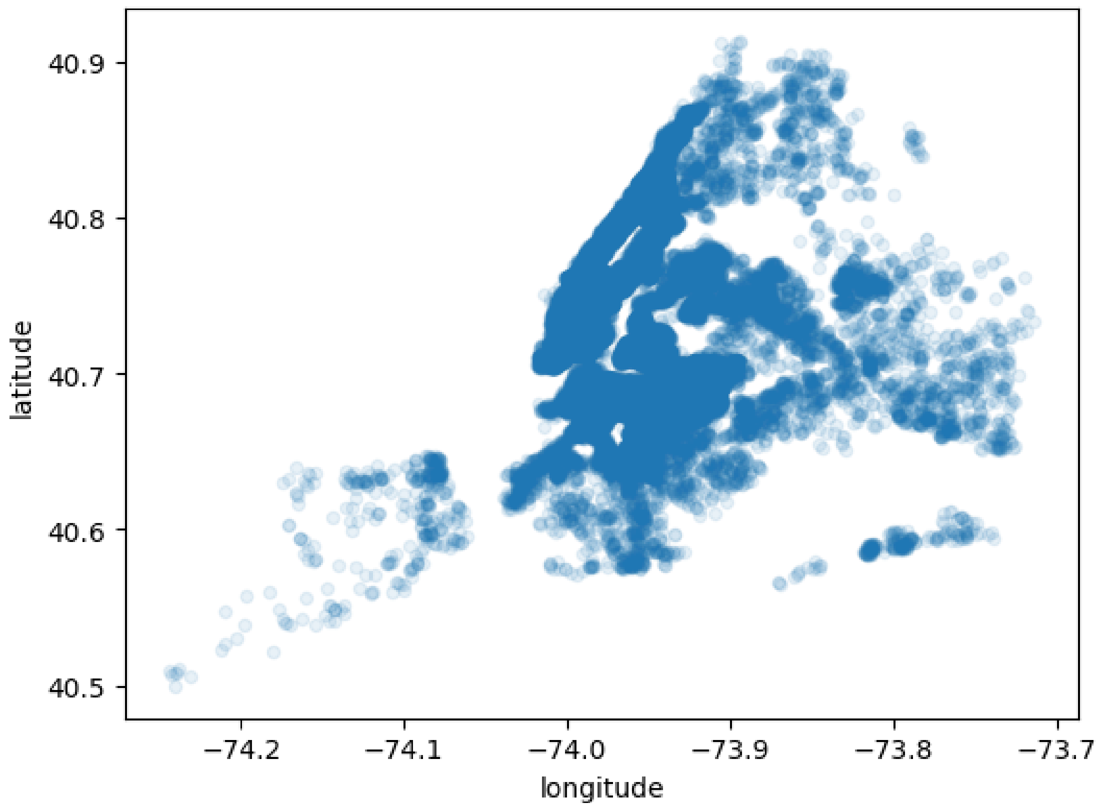


2.0.3 Plot a map of airbnbs throughout New York (if it gets too crowded take a subset of the data, and try to make it look nice if you can :)).

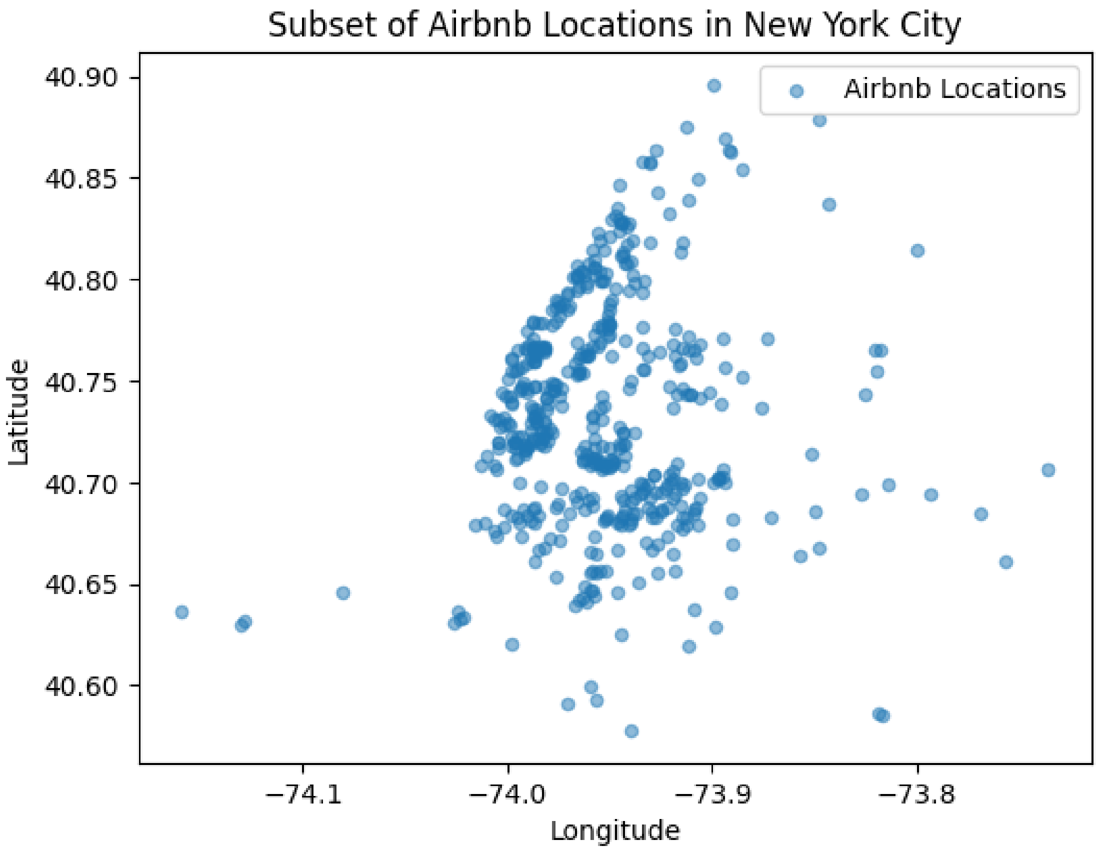
For reference you can use the Matplotlib code above to replicate this graph here.

```
[15]: airbnb.plot(kind="scatter", x="longitude", y="latitude", alpha=0.1)
```

```
[15]: <Axes: xlabel='longitude', ylabel='latitude'>
```



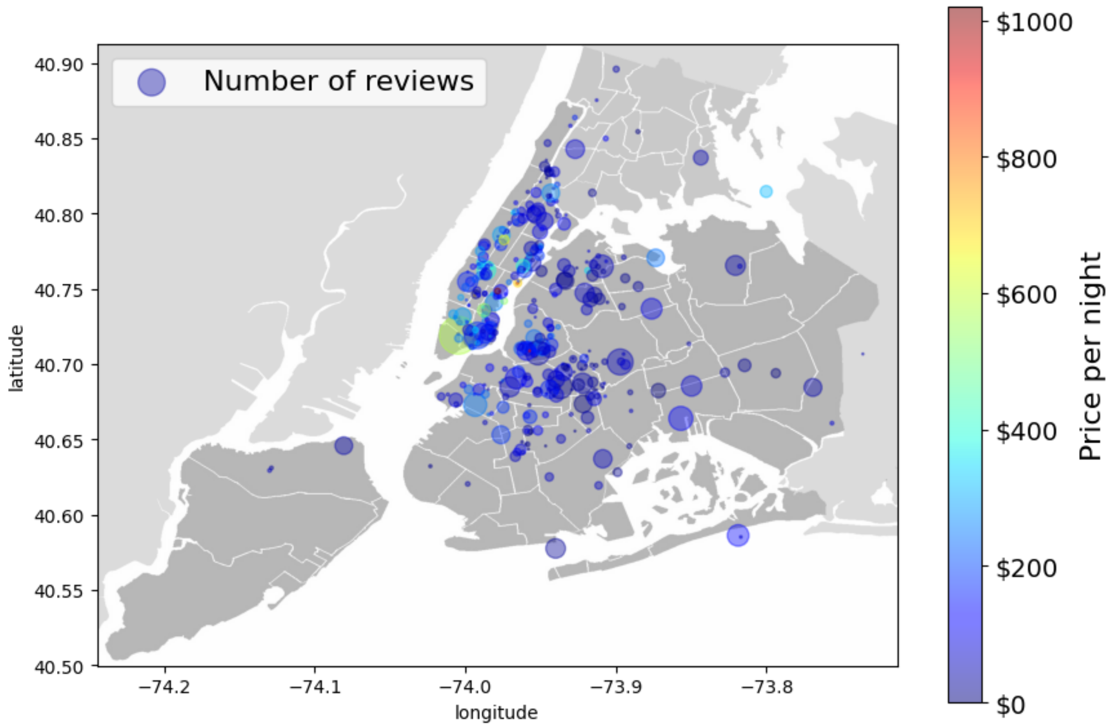
[36]:
```
miniairbnb = airbnb.sample(frac=.01)  # 1% sample

miniairbnb.plot(kind="scatter", x="longitude", y="latitude", alpha=0.5,
                label="Airbnb Locations")

plt.title("Subset of Airbnb Locations in New York City")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.legend()
plt.show()
```



[37]:
```
# A more interesting plot is to color code (heatmap) the dots
# based on income. The code below achieves this

# load an image of New York
import matplotlib.image as mpimg
nyc_img=mpimg.imread('nyc.png', -1)

# overlay the NYC map on the plotted scatter plot
# note: plt.imshow still refers to the most recent figure
# that hasn't been plotted yet.

ax = miniairbnb.plot(kind="scatter", x="longitude", y="latitude",␣
↪figsize=(10,7),
                     s=miniairbnb['number_of_reviews'], label="Number of␣
↪reviews", # size markers proportional to number of reviews (Piazza @22)
                     c="price", cmap=plt.get_cmap("jet"), colorbar=False,␣
↪alpha=0.4
                     )
```

```python
# get longitude and latitude limits from the dataset
min_longitude = airbnb["longitude"].min()
max_longitude = airbnb["longitude"].max()
min_latitude = airbnb["latitude"].min()
max_latitude = airbnb["latitude"].max()

# Overlay the NYC map
plt.imshow(nyc_img, extent=[min_longitude, max_longitude, min_latitude,␣
↪max_latitude],
           alpha=0.5, cmap=plt.get_cmap("jet"))

# setting up heatmap colors based on price feature
prices = miniairbnb["price"]
tick_values = np.linspace(0, prices.max(), 6) # narrow price range (Piazza @22)
cb = plt.colorbar()
cb.ax.set_yticklabels(["$%d" % v for v in tick_values], fontsize=14)
cb.set_label('Price per night', fontsize=16)


plt.legend(fontsize=16)
plt.show()
```

```
<ipython-input-37-1a8faf63cfbc>:31: UserWarning:

set_ticklabels() should only be used with a fixed number of ticks, i.e. after
set_ticks() or using a FixedLocator.
```

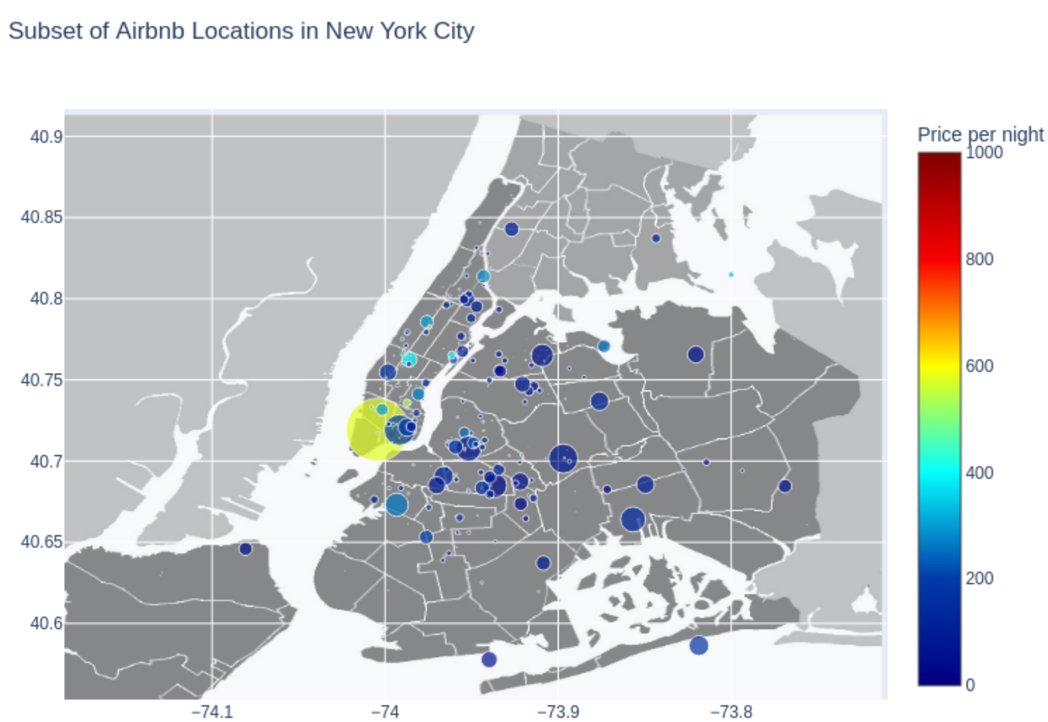


Now try to recreate this plot using Plotly's Scatterplot functionality. Note that the increased interactivity of the plot allows for some very cool functionality

[38]:
```
import plotly.graph_objects as go
fig = go.Figure(data=go.Scatter(
    x=miniairbnb['longitude'],
    y=miniairbnb['latitude'],
    mode='markers',
    name='Number of reviews',
    marker=dict(
        size=miniairbnb['number_of_reviews']/10,
        color=miniairbnb['price'],
        colorscale='Jet',
        colorbar=dict(title='Price per night'),
        cmin = 0,
        cmax = prices.max(),
    ),
    text=miniairbnb['price']
))

import base64
#set a local image as a background
image_filename = 'nyc.png'
plotly_logo = base64.b64encode(open(image_filename, 'rb').read())
```

```
fig.update_layout(
    title='Subset of Airbnb Locations in New York City',
    width=800,
    height=600,
    images=[dict(
        source='data:image/png;base64,{}'.format(plotly_logo.decode()),
        xref="x",
        yref="y",
        x=airbnb['longitude'].min(),
        y=airbnb['latitude'].max(),
        sizex=airbnb['longitude'].max() - airbnb['longitude'].min(),
        sizey=airbnb['latitude'].max() - airbnb['latitude'].min(),
        sizing="stretch",
        opacity=0.8,  # Adjust opacity as needed
        layer="below"
    )]
)

fig.show()
```

[38]:



2.0.4 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

[39]:
```
subgroup = airbnb_drop[(airbnb_drop['neighbourhood_group'] == 'Brooklyn') &␣
↪(airbnb_drop['number_of_reviews'] >= 10)].groupby('room_type')['price'].
↪mean().reset_index()
```

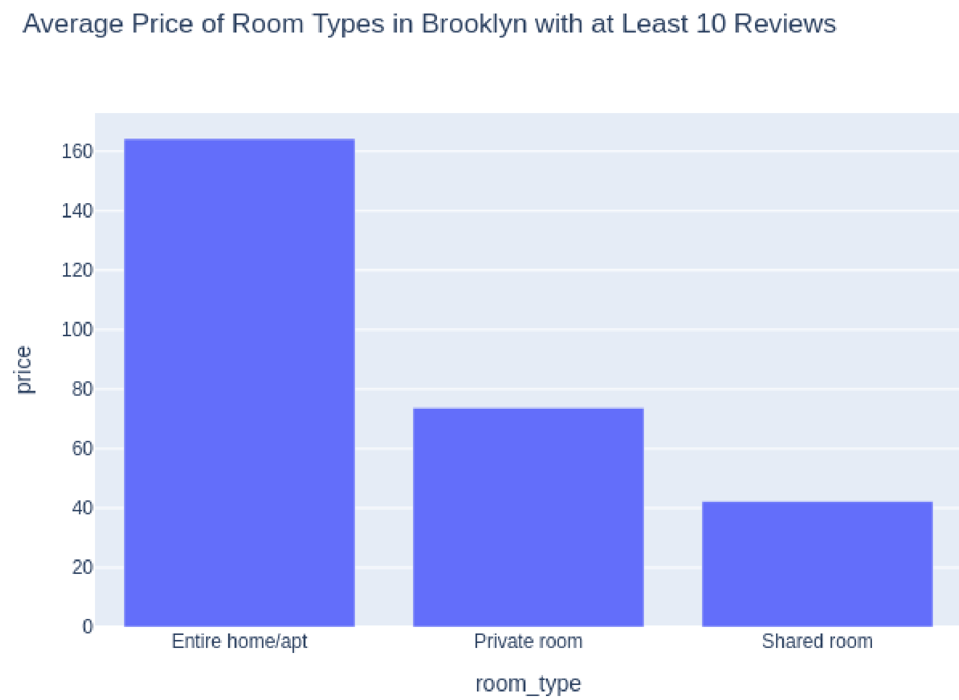
[40]:
```
subgroup
```

[40]:

	room_type	price
0	Entire home/apt	164.191258
1	Private room	73.743515
2	Shared room	42.291667

[41]:
```
fig = px.bar(subgroup, x='room_type', y='price', title='Average Price of Room␣
↪Types in Brooklyn with at Least 10 Reviews')
fig.show()
```

[41]:



3 Prepare the Data

[ ]:
```
airbnb_drop.head()
```

[ ]:
```
     id neighbourhood_group  latitude  longitude        room_type  price  \
0  2539            Brooklyn  40.64749  -73.97237     Private room    149
1  2595           Manhattan  40.75362  -73.98377  Entire home/apt    225
2  3647           Manhattan  40.80902  -73.94190     Private room    150
3  3831            Brooklyn  40.68514  -73.95976  Entire home/apt     89
4  5022           Manhattan  40.79851  -73.94399  Entire home/apt     80

   minimum_nights  number_of_reviews  reviews_per_month  \
0               1                  9               0.21
1               1                 45               0.38
2               3                  0                NaN
3               1                270               4.64
4              10                  9               0.10
```

```
   calculated_host_listings_count  availability_365
0                               6               365
1                               2               355
2                               1               365
3                               1               194
4                               1                 0
```

3.0.1 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

[ ]:
```
# assign each bin a categorical value [1, 2, 3, 4, 5] in this case.
airbnb_drop["price_cat"] = pd.qcut(airbnb_drop["price"], q=5, labels=[1, 2, 3,␣
↪4, 5])

airbnb_drop["price_cat"].value_counts()
```

[ ]:
```
price_cat
4    10809
1    10063
2     9835
3     9804
5     8384
Name: count, dtype: int64
```

3.0.2 Data Imputation

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

[ ]:
```
airbnb_drop.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 12 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
 11  price_cat                       48895 non-null  category
dtypes: category(1), float64(3), int64(6), object(2)
memory usage: 4.2+ MB
```

[ ]:
```
airbnb_drop['reviews_per_month'] = airbnb_drop['reviews_per_month'].
↪fillna(airbnb_drop['reviews_per_month'].median())
airbnb_drop.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 12 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               48895 non-null  float64
 9   calculated_host_listings_count  48895 non-null  int64
 10  availability_365                48895 non-null  int64
 11  price_cat                       48895 non-null  category
dtypes: category(1), float64(3), int64(6), object(2)
memory usage: 4.2+ MB
```

3.0.3 Numeric Conversions

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

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

# Non-numeric features
non_numeric_features = airbnb_drop.select_dtypes(include=['object',␣
↪'category']).columns

# Create a LabelEncoder instance
labelencoder = LabelEncoder()

# Iterate through non-numeric features and apply Label Encoding
for feature in non_numeric_features:
    airbnb_drop[feature] = labelencoder.fit_transform(airbnb_drop[feature])

# Display the updated DataFrame
```

```
airbnb_drop.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 12 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              48895 non-null  int64
 1   neighbourhood_group             48895 non-null  int64
 2   latitude                        48895 non-null  float64
 3   longitude                       48895 non-null  float64
 4   room_type                       48895 non-null  int64
 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               48895 non-null  float64
 9   calculated_host_listings_count  48895 non-null  int64
 10  availability_365                48895 non-null  int64
 11  price_cat                       48895 non-null  int64
dtypes: float64(3), int64(9)
memory usage: 4.5 MB
```

4 Prepare Data for Machine Learning

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

[ ]:
```
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_drop,
 ↪airbnb_drop["price_cat"]):
    train_set = airbnb_drop.loc[train_index]
    test_set = airbnb_drop.loc[test_index]
```

[ ]:
```
test_set.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 9779 entries, 34229 to 20813
Data columns (total 12 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              9779 non-null   int64
 1   neighbourhood_group             9779 non-null   int64
 2   latitude                        9779 non-null   float64
```

```
 3   longitude                       9779 non-null   float64
 4   room_type                       9779 non-null   int64
 5   price                           9779 non-null   int64
 6   minimum_nights                  9779 non-null   int64
 7   number_of_reviews               9779 non-null   int64
 8   reviews_per_month               9779 non-null   float64
 9   calculated_host_listings_count  9779 non-null   int64
 10  availability_365                9779 non-null   int64
 11  price_cat                       9779 non-null   int64
dtypes: float64(3), int64(9)
memory usage: 993.2 KB
```

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

[ ]:
```
training = train_set.drop(['price', 'price_cat'], axis=1)  # Drop both
training_labels = train_set[['price', 'price_cat']].copy()  # Create labels for both

testing = test_set.drop(['price', 'price_cat'], axis=1)  # Drop both
testing_labels = test_set[['price', 'price_cat']].copy()  # Create labels for both
```

[ ]:
```
training.head()
```

[ ]:
```
             id  neighbourhood_group  latitude  longitude  room_type  \
40334  31283904                    2  40.72846  -73.98457          0
12438   9578325                    1  40.67924  -73.98718          0
35502  28181243                    1  40.66891  -73.93495          0
6553    4750578                    1  40.68589  -73.95759          0
19465  15529937                    1  40.60983  -73.95887          1

       minimum_nights  number_of_reviews  reviews_per_month  \
40334               1                 10               1.67
12438               1                120               2.73
35502               3                  2               0.24
6553                1                  0               0.72
19465               2                 26               0.98

       calculated_host_listings_count  availability_365
40334                               1               332
12438                               2               275
35502                               1               362
6553                                1                 0
19465                               3               101
```

5 Fit a linear regression model

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**.

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

# Create and train the model
model = LinearRegression()
model.fit(training, training_labels['price'])  # Use training data and 'price'␣
 ↪labels

# Make predictions on training and testing sets
train_predictions = model.predict(training)
test_predictions = model.predict(testing)

# Calculate MSE for training and testing sets
train_mse = mean_squared_error(training_labels['price'], train_predictions)
test_mse = mean_squared_error(testing_labels['price'], test_predictions)

# Print the results
print(f"Training MSE: {train_mse}")
print(f"Testing MSE: {test_mse}")
```

```
Training MSE: 56062.46938087336
Testing MSE: 38352.06181543438
```

[ ]:
```
# Print predictions and actual labels for a few instances from training set
sample_data_train = training.iloc[:5]  # Select first 5 instances from training␣
 ↪set
sample_labels_train = training_labels['price'].iloc[:5]  # Select corresponding␣
 ↪labels

print("Training Set:")
print("Predictions:", np.round(model.predict(sample_data_train), 1))
print("Actual labels:", list(sample_labels_train))

# Print predictions and actual labels for a few instances from testing set
sample_data_test = testing.iloc[:5]  # Select first 5 instances from testing set
sample_labels_test = testing_labels['price'].iloc[:5]  # Select corresponding␣
 ↪labels

print("\nTesting Set:")
print("Predictions:", np.round(model.predict(sample_data_test), 1))
print("Actual labels:", list(sample_labels_test))
```

```
Training Set:
```

```
Predictions: [281.7 212.4 237.2 173.3  76.8]
Actual labels: [399, 129, 200, 110, 39]

Testing Set:
Predictions: [203.4 142.8 208.1 177.5 196.8]
Actual labels: [132, 68, 205, 167, 105]
```