Project 1

● Graded

Student

ARNAV KRISHNAKUMAR MARDA

Total Points

95 / 100 pts

Question 1

Visualizing the Data — **35** / 35 pts

1.1 **Load the data + statistics** — **10** / 10 pts

- ✔ **– 0 pts** Correct
- **– 5 pts** Did not call describe method or info for summary output
- **– 2.5 pts** No code for removing columns is provided.
- **– 2.5 pts** No code provided for the head method

1.2 **Some basic visualizations** — **10** / 10 pts

- ✔ **– 0 pts** Correct
- **– 5 pts** Wrong plot
- **– 10 pts** Missing plot
- **– 1 pt** Missing .sum()

1.3 **Plot a map with matplotlib** — **5** / 5 pts

- ✔ **– 0 pts** Correct. [As long as the type and layout of the plots are correct, it's acceptable. For instance, with the map plots, as long as they have scatter points overlaid on a map and the positioning is well aligned, they will be credited.]
- **– 5 pts** Missing plot
- **– 3 pts** Unrecognizable plot, but correct functions are used.

1.4 **Plot a map with Plotly** — **5** / 5 pts

- ✔ **– 0 pts** Correct
- **– 5 pts** Missing plot
- **– 3 pts** Unrecognizable plot, but correct functions are used.

1.5 **Plot the average price of room types** — **5** / 5 pts

- ✔ **– 0 pts** Correct
- **– 5 pts** Missing plot
- **– 3 pts** Unrecognizable plot, but correct functions are used.
- **– 1 pt** Minor mistake (e.g. missing one filtering condition)

Question 2

Prepare the Data **45** / 50 pts

2.1 **Feature engineering** **10** / 10 pts

✔ **– 0 pts** Correct

– 10 pts No binning of Data

2.2 **Data Inputation** **5** / 10 pts

– 0 pts Correct

– 10 pts No inputation.

✔ **– 5 pts** Filled null values with 0. fillna() should be applied to individual columns with mean, median, or mode as the default value.

– 5 pts Dropped features instead of filling null values.

– 5 pts Didn't check all features. [The `fillna` function should be used, and the output of `info` should display 48895 non-null entries for each feature. If the student didn't use `info`, check if they have processed at least two features `reviews_per_month` and `price_cat`.]

2.3 **Numeric Conversions** **10** / 10 pts

✔ **– 0 pts** Correct

– 10 pts Not answered or wrong answer. [At least two features should be processed: `neighbourhood_group` and `room_type`.]

2.4 **Prepare data for machine learning** **20** / 20 pts

✔ **– 0 pts** Correct

– 20 pts Stratified Sampling is not performed on "price_cat"

– 10 pts Incorrect train/test split

– 10 pts No stratified sampling

Question 3

Fit a Linear Regression Model **15** / 15 pts

✔ **– 0 pts** Correct. [The value does not have to match exactly that in the provided answer.]

– 15 pts No answer

– 5 pts Didn't drop both "price_cat" and “price”

– 5 pts Didn't fit a model

– 5 pts Didn't report MSE.

No questions assigned to the following page.

CSM148_Project_1_W24_TODO

January 25, 2024

0.1 24W-COM SCI-M148 Project 1

Name: Arnav Marda

UID: 405772661

0.1.1 Submission Guidelines (Due: Jan 29 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.

No questions assigned to the following page.

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.

[1]:
```
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
```

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.

No questions assigned to the following page.

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

[4]:
```
# We'll now import the holy grail of python datascience: Pandas!
import pandas as pd
housing = pd.read_csv('housing.csv')
```

[5]:
```
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
```

[5]:

	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.

[6]:
```
# 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
```

No questions assigned to the following page.

```
 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
```

[7]:
```
# you can access individual columns similarly
# to accessing elements in a python dict
housing["ocean_proximity"].head() # added head() to avoid printing many columns.
 ↪.
```

[7]:
```
0    NEAR BAY
1    NEAR BAY
2    NEAR BAY
3    NEAR BAY
4    NEAR BAY
Name: ocean_proximity, dtype: object
```

[8]:
```
# to access a particular row we can use iloc
housing.iloc[1]
```

[8]:
```
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
```

[9]:
```
# one other function that might be useful is
# value_counts(), which counts the number of occurences
# for categorical features
housing["ocean_proximity"].value_counts()
```

[9]:
```
ocean_proximity
<1H OCEAN     9136
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: count, dtype: int64
```

[10]:
```
# The describe function compiles your typical statistics for each
# column
```

No questions assigned to the following page.

```
housing.describe()
```

[10]:

```
          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
```

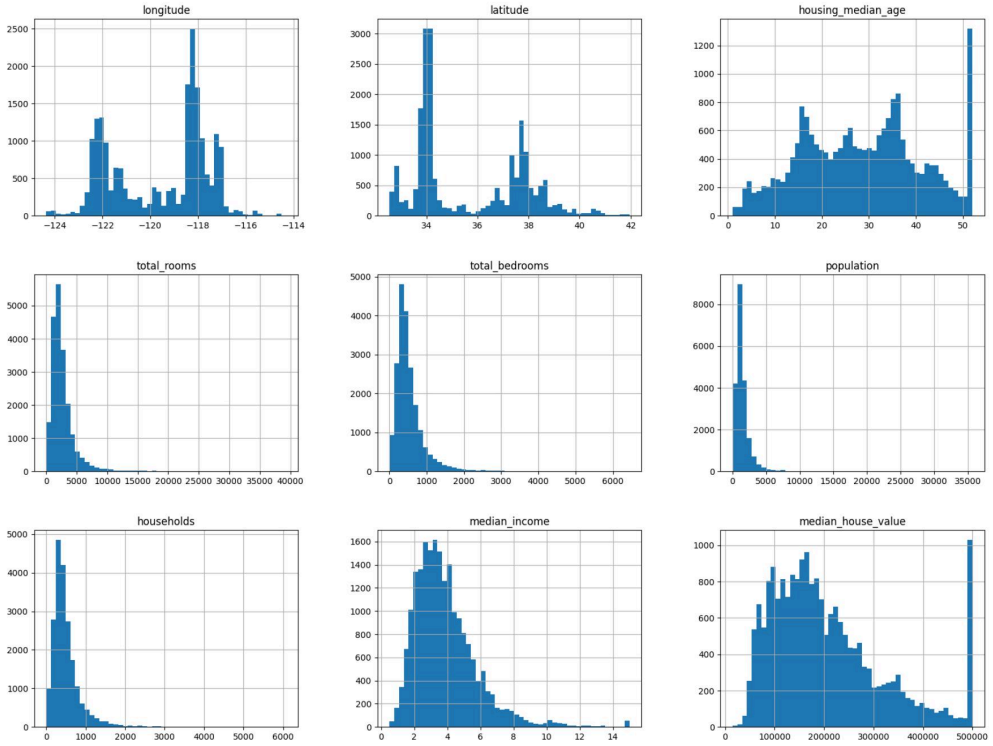
If you want to learn about different ways of accessing elements or other functions it's useful to check out the getting started section here

0.6 Let's start visualizing the dataset

[11]:

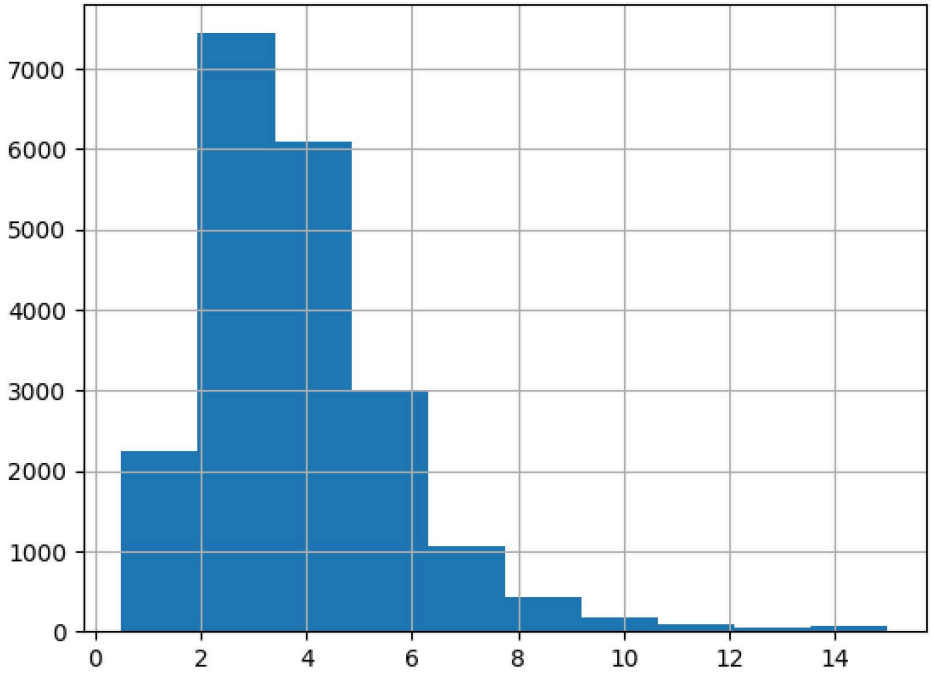
```
# We can draw a histogram for each of the dataframes features
# using the hist function
housing.hist(bins=50, figsize=(20,15))
# save_fig("attribute_histogram_plots")
plt.show() # pandas internally uses matplotlib, and to display all the figures
           # the show() function must be called
```

No questions assigned to the following page.



[12]:
```
# if you want to have a histogram on an individual feature:
housing["median_income"].hist()
plt.show()
```

No questions assigned to the following page.



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

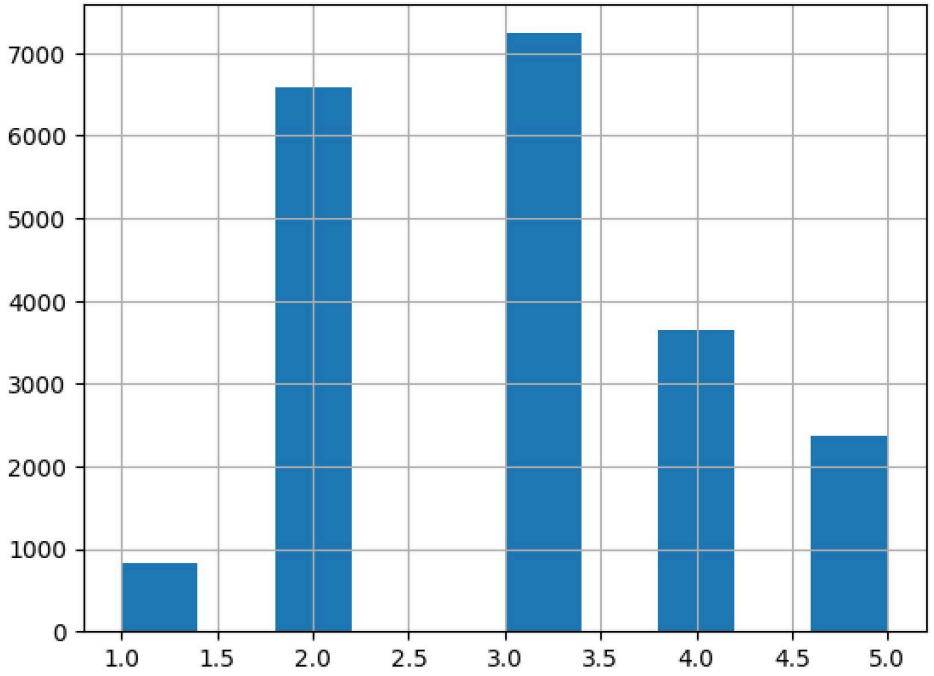
[13]:
```
# assign each bin a categorical value [1, 2, 3, 4, 5] in this case.
housing["income_cat"] = pd.cut(housing["median_income"],
                               bins=[0., 1.5, 3.0, 4.5, 6., np.inf],
                               labels=[1, 2, 3, 4, 5])

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

[13]:
```
income_cat
3    7236
2    6581
4    3639
5    2362
1     822
Name: count, dtype: int64
```

[14]:
```
housing["income_cat"].hist()
```

[14]:
```
<Axes: >
```

No questions assigned to the following page.

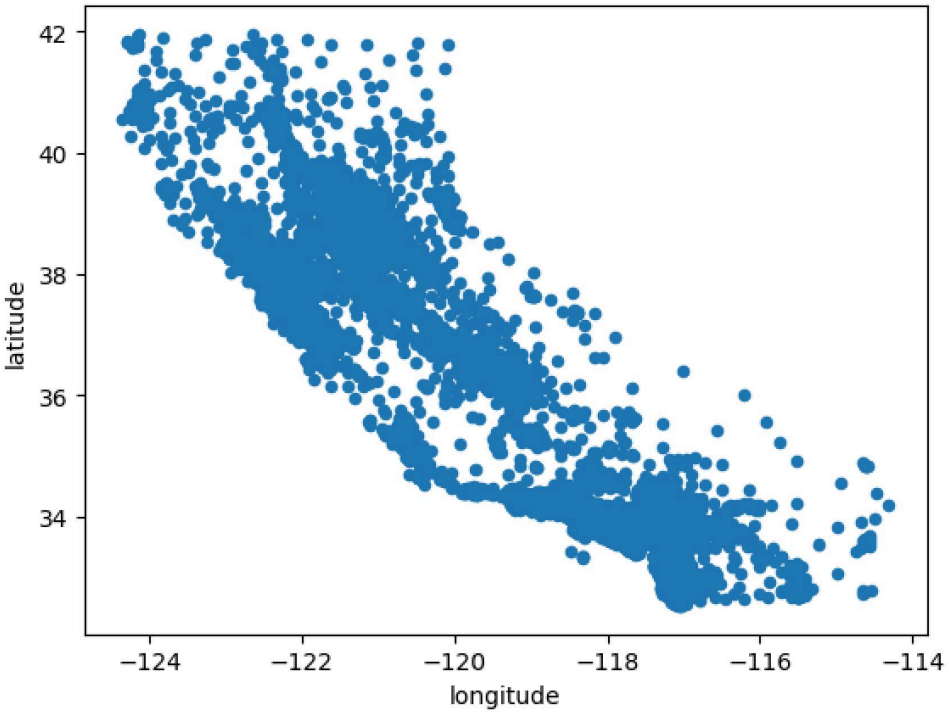


Next let's visualize the household incomes based on latitude & longitude coordinates

[15]:
```
## here's a not so interestting way plotting it
housing.plot(kind="scatter", x="longitude", y="latitude")
```

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

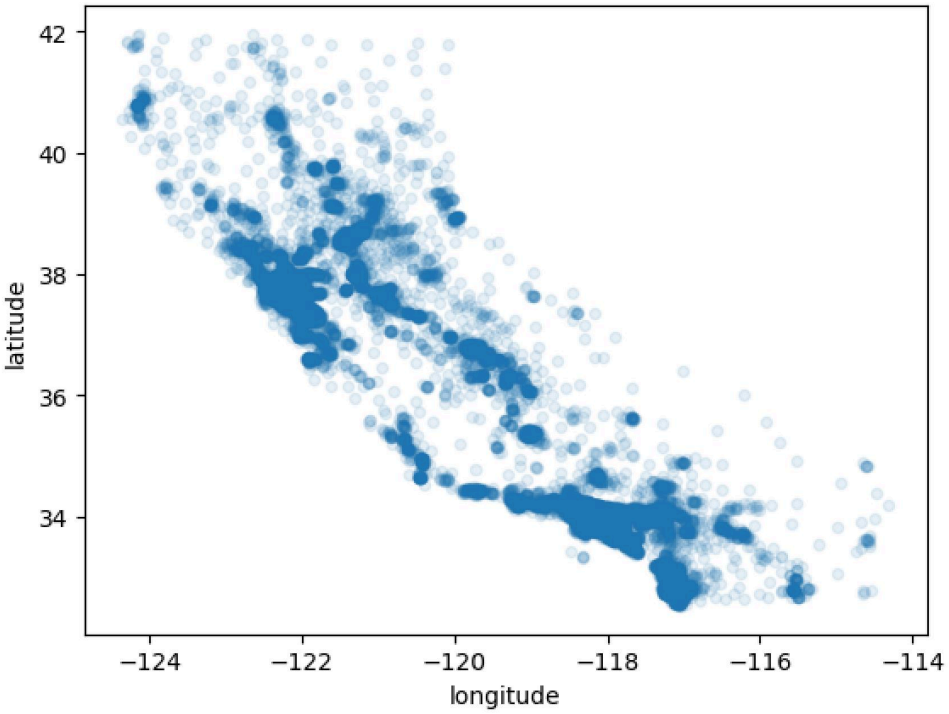
No questions assigned to the following page.



[16]:
```
# 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)
```

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

No questions assigned to the following page.

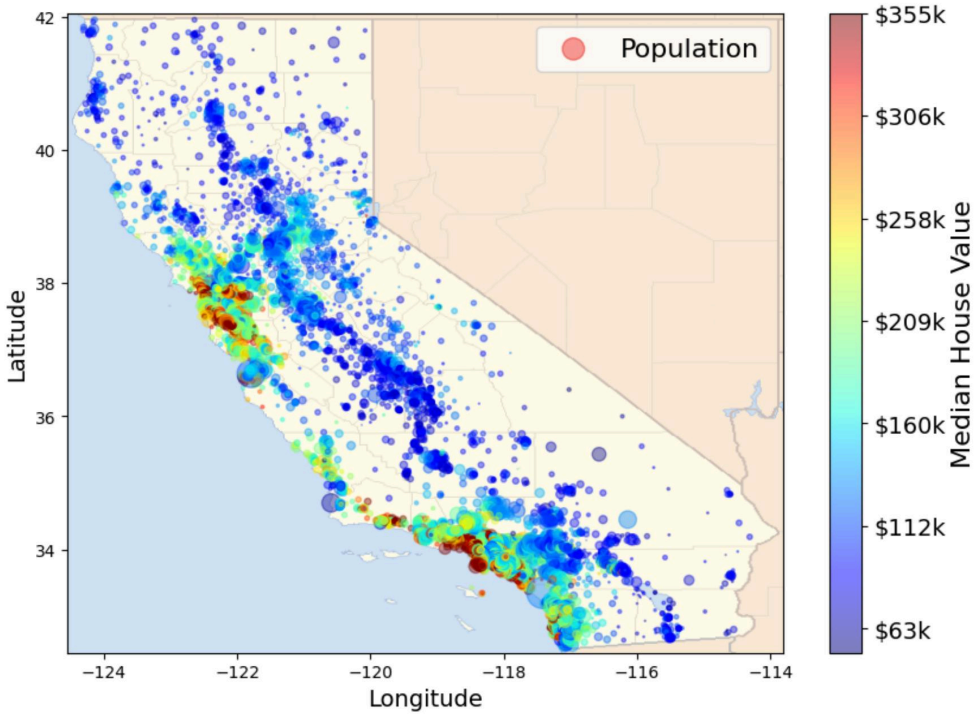


[17]:
```
# A more interesting plot is to color code (heatmap) the dots
# based on income. The code below achieves this

# 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)
```

No questions assigned to the following page.

```
# 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()
```

```
/var/folders/gm/vrdtz7g16f33wxq7p4dhwbhc0000gn/T/ipykernel_47625/2129115766.py:2
6: UserWarning: FixedFormatter should only be used together with 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.

No questions assigned to the following page.

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.

[18]:
```
corr_matrix = housing.corr(numeric_only=True)
```

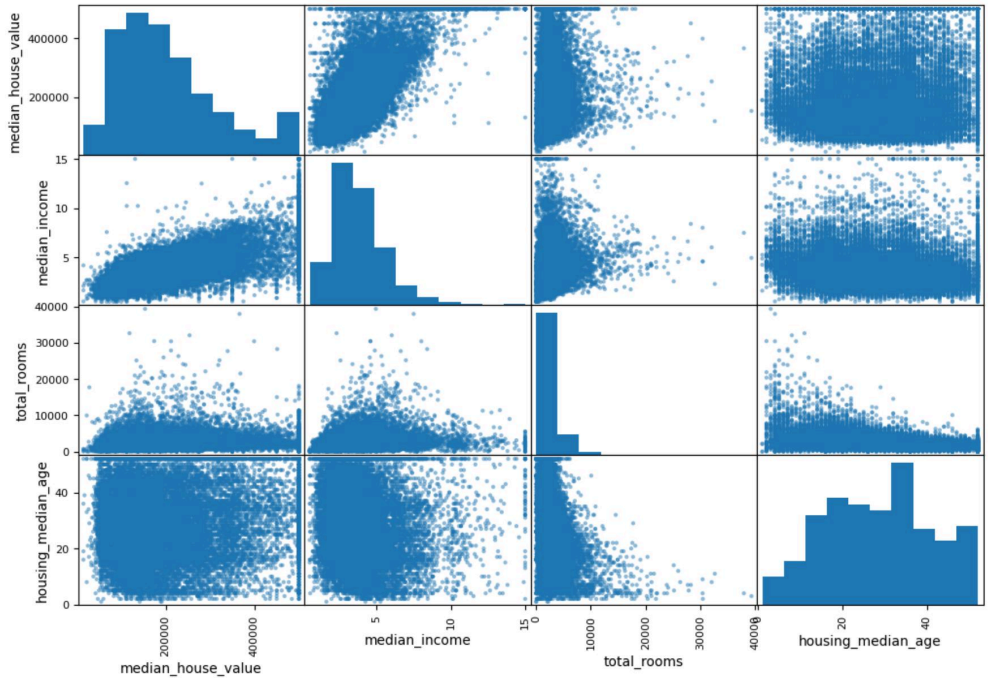
[19]:
```
# for example if the target is "median_house_value", most correlated features␣
↪can be sorted
# which happens to be "median_income". This also intuitively makes sense.
corr_matrix["median_house_value"].sort_values(ascending=False)
```

[19]:
```
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
```

[20]:
```
# 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))
```

[20]:
```
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)
```

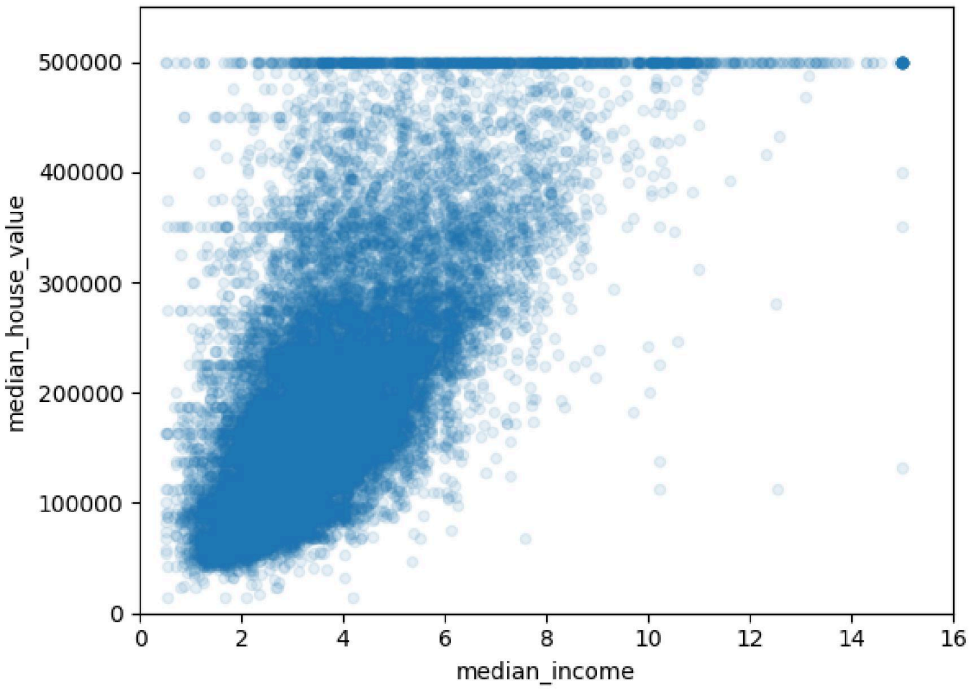
No questions assigned to the following page.



[21]:
```
# 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])
```

[21]: (0.0, 16.0, 0.0, 550000.0)

No questions assigned to the following page.



[22]:
```
# obtain new correlations
corr_matrix = housing.corr(numeric_only=True)
corr_matrix["median_house_value"].sort_values(ascending=False)
```

[22]:
```
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
```

No questions assigned to the following page.

0.7 Preparing Dastaset for ML

0.7.1 Dealing With Incomplete Data

[23]:
```
# 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
```

[23]:
```
     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
```

[24]:
```
sample_incomplete_rows.dropna(subset=["total_bedrooms"])    # option 1: simply␣
↪drop rows that have null values
```

[24]:
```
Empty DataFrame
Columns: [longitude, latitude, housing_median_age, total_rooms, total_bedrooms,
population, households, median_income, median_house_value, ocean_proximity,
income_cat]
Index: []
```

[25]:
```
sample_incomplete_rows.drop("total_bedrooms", axis=1)       # option 2: drop␣
↪the complete feature
```

[25]:
```
     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
```

No questions assigned to the following page.

```
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
```

[26]:
```
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
```

[26]:
```
     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

[27]:
```
housing["total_bedrooms"].fillna(median, inplace=True)
```

Could you think of another plausible imputation for this dataset?

0.7.2 Augmenting Features

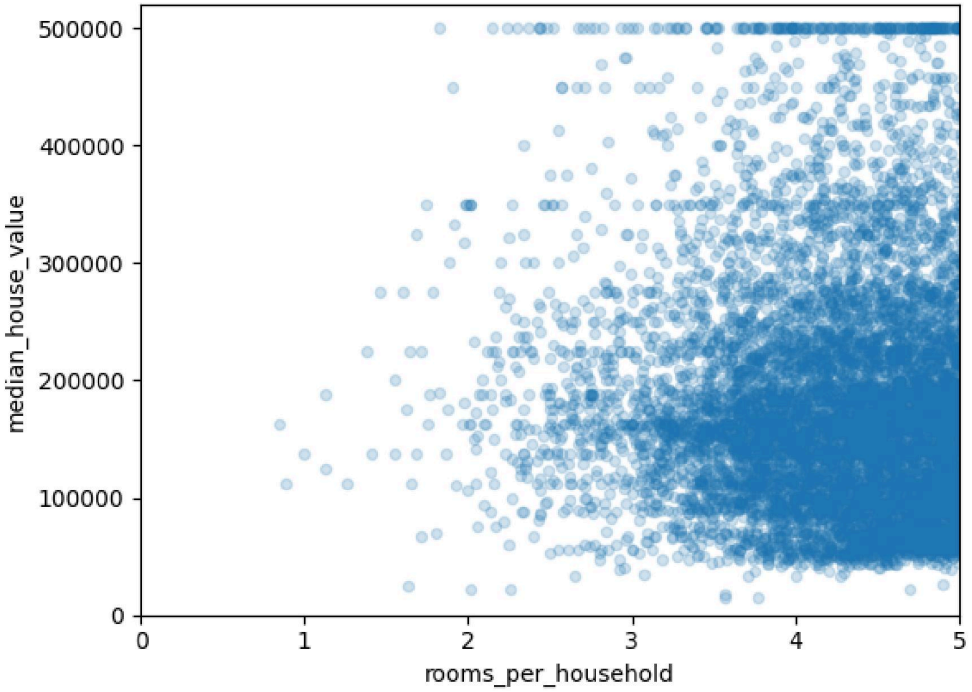
New features can be created by combining different columns from our data set.

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

No questions assigned to the following page.

[28]:
```
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)
```

[29]:
```
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.

No questions assigned to the following page.

[30]:
```
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()
```

[30]:

	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!

[31]:
```
from sklearn.model_selection import StratifiedShuffleSplit
# let's first start by creating our train and test sets
```

No questions assigned to the following page.

```
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]
```

[32]:
```
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()
```

[33]:
```
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.

[34]:
```
from sklearn.linear_model import LinearRegression

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

[34]:
```
LinearRegression()
```

[35]:
```
# 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: [418197.21048506 305620.51781478 232253.02900543 188754.57142335
 251166.41766858]
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.

Question assigned to the following page: 1.1

[36]:
```
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
```

[36]:
```
67694.0818434439
```

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

[37]:
```
import pandas as pd
airbnb =  pd.read_csv('AB_NYC_2019.csv') # we load the pandas dataframe

airbnb.head() # show the first few elements of the dataframe
```

[37]:

	id	name	host_id	\
0	2539	Clean & quiet apt home by the park	2787	
1	2595	Skylit Midtown Castle	2845	
2	3647	THE VILLAGE OF HARLEM…NEW YORK !	4632	
3	3831	Cozy Entire Floor of Brownstone	4869	
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	

	host_name	neighbourhood_group	neighbourhood	latitude	longitude	\
0	John	Brooklyn	Kensington	40.64749	-73.97237	
1	Jennifer	Manhattan	Midtown	40.75362	-73.98377	
2	Elisabeth	Manhattan	Harlem	40.80902	-73.94190	
3	LisaRoxanne	Brooklyn	Clinton Hill	40.68514	-73.95976	
4	Laura	Manhattan	East Harlem	40.79851	-73.94399	

	room_type	price	minimum_nights	number_of_reviews	last_review	\
0	Private room	149	1	9	2018-10-19	
1	Entire home/apt	225	1	45	2019-05-21	
2	Private room	150	3	0	NaN	

Question assigned to the following page: 1.1

```
3  Entire home/apt     89               1                270  2019-07-05
4  Entire home/apt     80              10                  9  2018-11-19

   reviews_per_month  calculated_host_listings_count  availability_365
0               0.21                               6               365
1               0.38                               2               355
2                NaN                               1               365
3               4.64                               1               194
4               0.10                               1                 0
```

[38]:
```
airbnb_drop = airbnb.drop(columns=["name", "host_id", "host_name",␣
↪"last_review", "neighbourhood"])# WRITE YOUR CODE HERE #
```

[39]:
```
airbnb_drop.describe()
```

[39]:
```
                 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
```

[40]:
```
airbnb_drop.info()
```

Questions assigned to the following page: 1.1 and 1.2

```
<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.

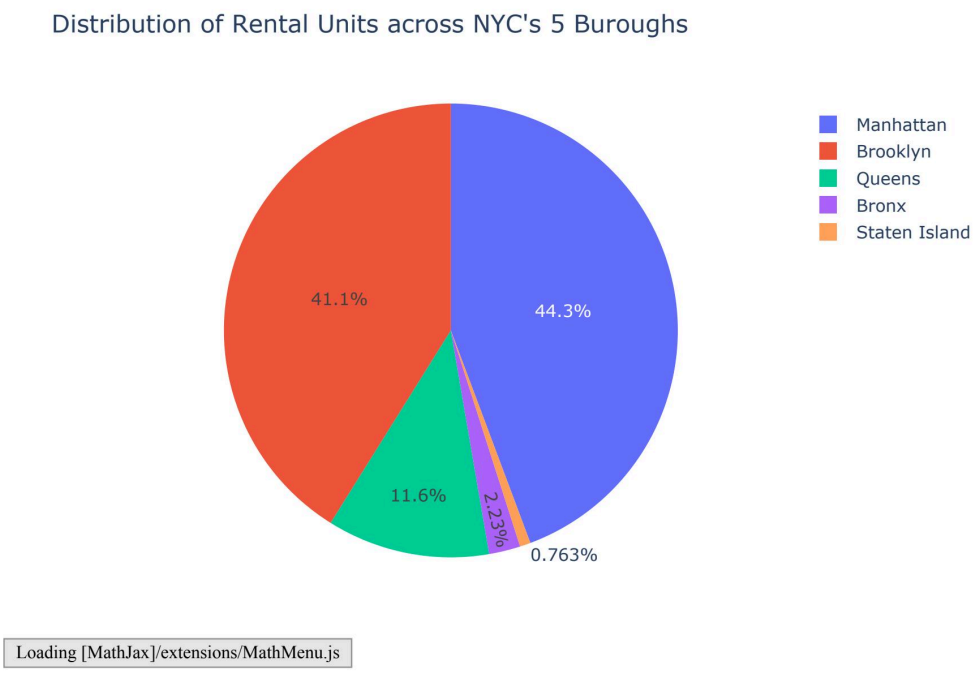
You can find documentation and all the examples you'll need here: Plotly Documentation

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 rental units across NYC's 5 Buroughs (neighbourhood_groups in the dataset)####

[41]:
```
import plotly.express as px

# Need for proper exporting into pdf
import plotly.io as pio
pio.renderers.default = "notebook+pdf"
#######################################

vc = airbnb_drop['neighbourhood_group'].value_counts()
counts = vc.values
labels = vc.index.values
fig = px.pie(values=counts, names=labels, title="Distribution of Rental Units␣
 ↪across NYC's 5 Buroughs")
fig.show()
```

Question assigned to the following page: 1.2



Loading [MathJax]/extensions/MathMenu.js

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

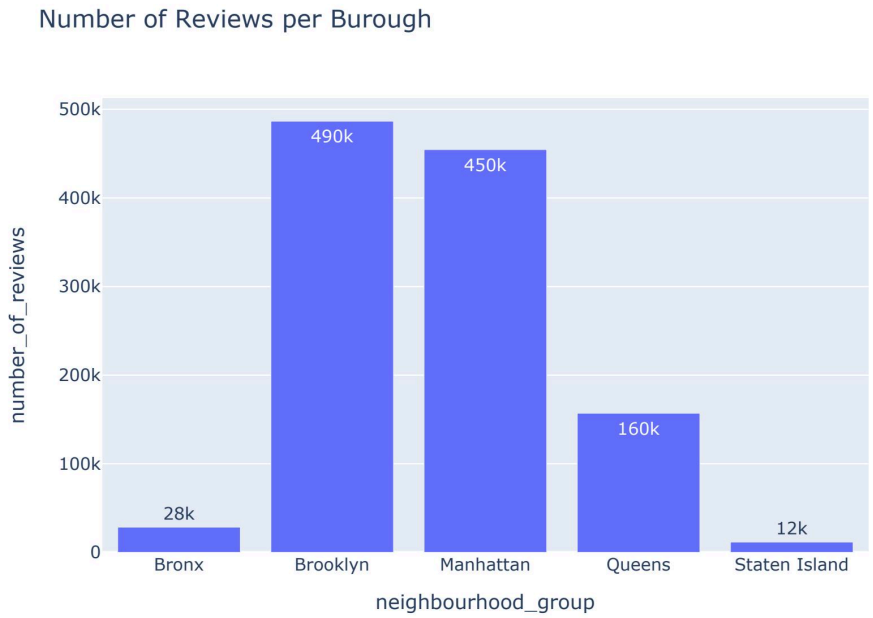
[42]:
```
neighborhood = airbnb_drop.
↪groupby(by=['neighbourhood_group'])["number_of_reviews"].sum().reset_index()
neighborhood.head()
```

[42]:

	neighbourhood_group	number_of_reviews
0	Bronx	28371
1	Brooklyn	486574
2	Manhattan	454569
3	Queens	156950
4	Staten Island	11541

[43]:
```
fig = px.bar(neighborhood, x='neighbourhood_group', y='number_of_reviews',␣
↪title="Number of Reviews per Burough", text_auto='.2s')
fig.show()
```

Questions assigned to the following page: 1.2 and 1.3



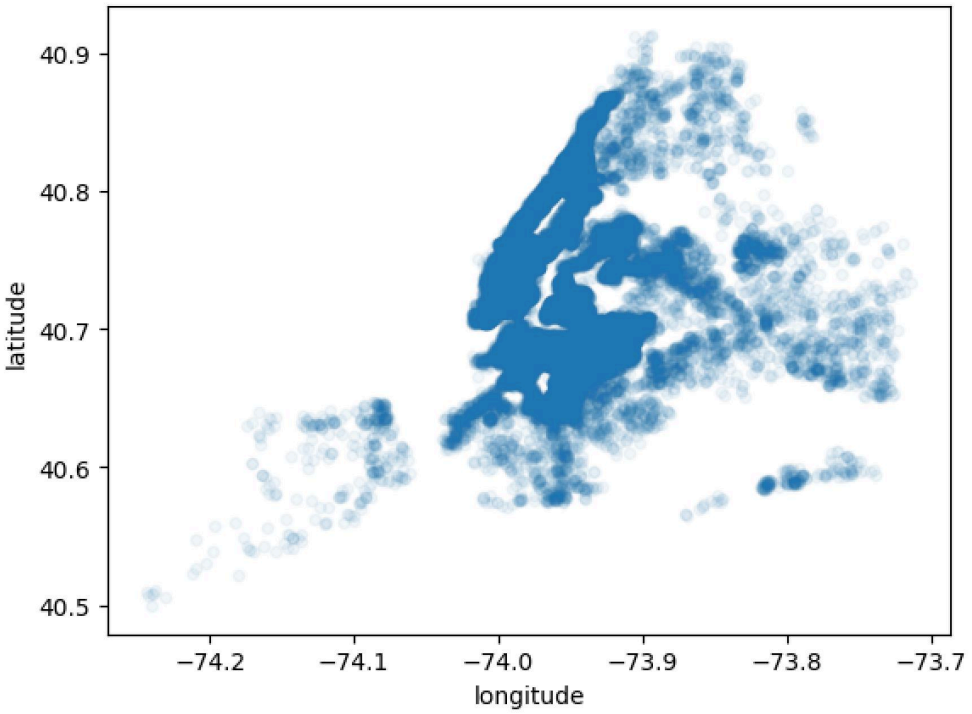
2.0.3 Plot a map of airbnbs throughout New York (if it gets too crowded take a subset of the data, and try to make it look nice if you can :)).

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

[44]:
```
airbnb.plot(kind="scatter", x="longitude", y="latitude", alpha=0.05)
```

[44]:
```
<Axes: xlabel='longitude', ylabel='latitude'>
```

Question assigned to the following page: 1.3



[45]:
```
miniairbnb = airbnb.sample(n=500, weights=1/(airbnb["price"]+1e-6))# WRITE YOUR␣
↪CODE HERE
miniairbnb.describe()
# ny_clean.plot(kind='scatter', x='longitude', y='latitude', alpha=0.4,␣
↪c=ny_clean['price'], s=8, cmap=plt.get_cmap('jet'), figsize=(12,8));
```

[45]:

	id	host_id	latitude	longitude	price	\
count	5.000000e+02	5.000000e+02	500.000000	500.000000	500.000000	
mean	1.877840e+07	6.777222e+07	40.720624	-73.946261	89.538000	
std	1.046170e+07	7.669822e+07	0.062416	0.052239	70.861663	
min	6.357300e+04	2.881000e+03	40.511330	-74.238030	0.000000	
25%	9.620491e+06	1.064687e+07	40.682765	-73.971885	48.750000	
50%	1.966489e+07	3.385766e+07	40.706920	-73.950240	70.000000	
75%	2.802231e+07	1.012206e+08	40.760433	-73.925155	105.000000	
max	3.648223e+07	2.718857e+08	40.889990	-73.729010	650.000000	

	minimum_nights	number_of_reviews	reviews_per_month	\
count	500.000000	500.000000	406.000000	
mean	5.726000	23.936000	1.412315	
std	12.724888	40.124355	1.774351	
min	1.000000	0.000000	0.010000	

Questions assigned to the following page: 1.2 and 1.3

```
25%          1.000000          1.000000          0.222500
50%          2.000000          6.000000          0.680000
75%          4.000000         28.250000          2.087500
max        180.000000        255.000000         14.000000

       calculated_host_listings_count  availability_365
count                      500.000000        500.00000
mean                         3.960000        107.80000
std                         19.459387        131.29506
min                          1.000000          0.00000
25%                          1.000000          0.00000
50%                          1.000000         36.50000
75%                          2.000000        217.75000
max                        327.000000        365.00000
```

[46]:
```
# 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 califronia map on the plotted scatter plot
# note: plt.imshow still refers to the most recent figure
# that hasn't been plotted yet.

# WRITE YOUR CODE HERE #

ax = miniairbnb.plot(
    kind="scatter",
    x="longitude",
    y="latitude",
    figsize=(10, 7),
    s=miniairbnb["price"]/5,
    c=miniairbnb["price"],
    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(
    nyc_img,
    extent=[-74.23, -73.72, 40.51, 40.9],
    alpha=0.5,
```

Question assigned to the following page: 1.3

```
    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 = miniairbnb["price"]
tick_values = np.linspace(prices.min(), prices.max(), 5)
cb = plt.colorbar()
cb.ax.set_yticklabels(["$%d" % (round(v)) for v in tick_values], fontsize=14)
cb.set_label("Price", fontsize=16)

plt.title("Airbnb Prices in NYC", fontsize=16)
plt.legend(fontsize=16)
plt.show()
```

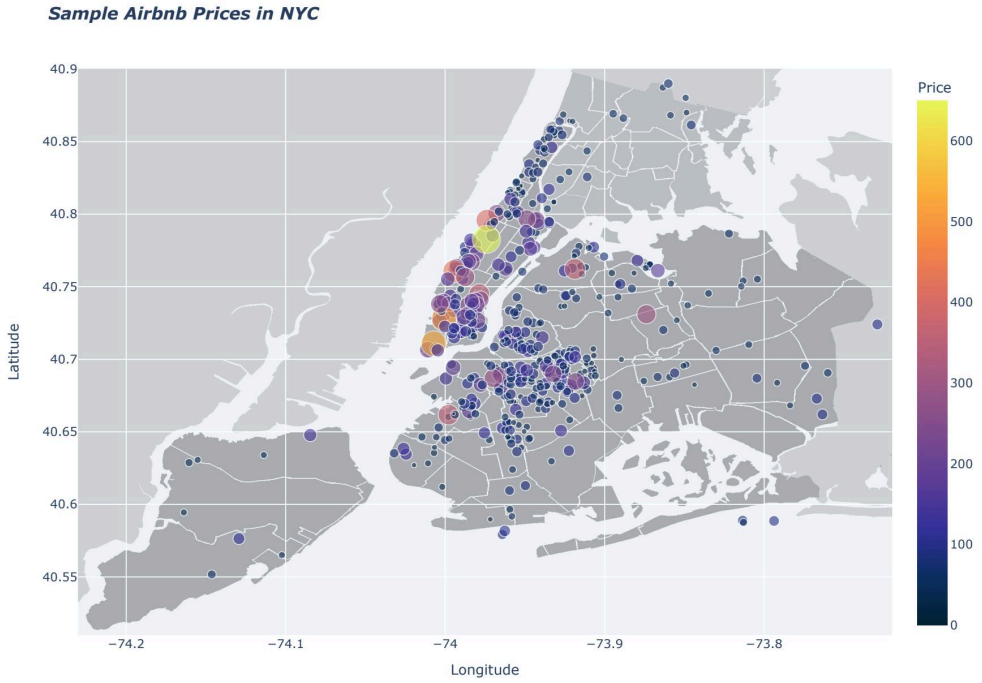
```
/var/folders/gm/vrdtz7g16f33wxq7p4dhwbhc0000gn/T/ipykernel_47625/3059222260.py:4
2: UserWarning:

FixedFormatter should only be used together with FixedLocator

No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```

Question assigned to the following page: 1.4

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

[47]:
```
fig = px.scatter(miniairbnb,
                 x="longitude",
                 y="latitude",
                 height=750,
                 width=1000,
                 color="price",
                 size="price",
                 color_continuous_scale="thermal",
                 opacity=0.6,
                 labels={
                    "longitude": "Longitude",
                    "latitude": "Latitude",
                    "price": "Price",
                 },
                 title="<em>Sample Airbnb Prices in NYC<em>"
                )# WRITE YOUR CODE HERE #
# fig = px.imshow(nyc_img, binary_string=True, height=750, width=1000)
import base64
from PIL import Image
import plotly.graph_objects as go
#set a local image as a background
image_filename = 'nyc.png'
plotly_logo = base64.b64encode(open(image_filename, 'rb').read())

# WRITE YOUR CODE HERE #
fig.update_xaxes(range=[-74.23, -73.72])
fig.update_yaxes(range=[40.51, 40.9])
fig.add_layout_image(
    source=Image.open("nyc.png"),
    x=-74.23,
    y=40.51,
    xref="x",
    yref="y",
    sizex=0.51,
    sizey=0.39,
    yanchor="bottom",
    xanchor="left",
    sizing="stretch",
    layer="below",
    opacity=0.5
)
fig.show()
```

Question assigned to the following page: 1.4



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

[48]:
```
# WRITE YOUR CODE HERE #
subgroup = airbnb[(airbnb["neighbourhood_group"] == "Brooklyn") &␣
↪(airbnb["number_of_reviews"] >= 10)]
```

[49]:
```
subgroup
```

[49]:

	id	name	host_id	\
3	3831	Cozy Entire Floor of Brownstone	4869	
6	5121	BlissArtsSpace!	7356	
12	5803	Lovely Room 1, Garden, Best Area, Legal rental	9744	

Question assigned to the following page: 1.4

```
15         6848                    Only 2 stops to Manhattan studio      15991
16         7097                  Perfect for Your Parents + Garden       17571
…           …                                                   …         …
45471  34777979  The Red Brick Abode, in the heart of Williamsburg   15010925
45551  34819702                 Private Pristine Studio in Brooklyn   10700780
45581  34839277                     Cozy & Comfortable Private Room   40085320
45690  34907354       You can find everything in the neighborhood.  246351353
46067  35059840     Coote Luxe Suite - Modern and Comfortable  APT  263969450

           host_name neighbourhood_group              neighbourhood  latitude  \
3        LisaRoxanne            Brooklyn               Clinton Hill  40.68514
6             Garon            Brooklyn         Bedford-Stuyvesant  40.68688
12           Laurie            Brooklyn                South Slope  40.66829
15    Allen & Irina            Brooklyn               Williamsburg  40.70837
16             Jane            Brooklyn                Fort Greene  40.69169
…               …                 …                         …       …
45471         Carlos            Brooklyn               Williamsburg  40.71317
45551           Rose            Brooklyn            Windsor Terrace  40.64932
45581           Alaa            Brooklyn  Prospect-Lefferts Gardens  40.66261
45690          Erica            Brooklyn  Prospect-Lefferts Gardens  40.66197
46067         Damiso            Brooklyn                   Canarsie  40.64127

       longitude        room_type  price  minimum_nights  number_of_reviews  \
3      -73.95976  Entire home/apt     89               1                270
6      -73.95596     Private room     60              45                 49
12     -73.98779     Private room     89               4                167
15     -73.95352  Entire home/apt    140               2                148
16     -73.97185  Entire home/apt    215               2                198
…          …              …    …             …                 …
45471  -73.96066  Entire home/apt    160               1                 13
45551  -73.98018  Entire home/apt     90               1                 11
45581  -73.94399     Private room     55               2                 11
45690  -73.95952     Private room     42               2                 12
46067  -73.89119  Entire home/apt    100               2                 11

      last_review  reviews_per_month  calculated_host_listings_count  \
3      2019-07-05               4.64                               1
6      2017-10-05               0.40                               1
12     2019-06-24               1.34                               3
15     2019-06-29               1.20                               1
16     2019-06-28               1.72                               1
…          …                   …                                  …
45471  2019-07-01               7.96                               1
45551  2019-06-23               7.17                               1
45581  2019-07-07               9.17                               2
45690  2019-07-08               9.47                               1
46067  2019-07-05               7.50                               1
```

Question assigned to the following page: 1.4

```
        availability_365
3                    194
6                      0
12                   314
15                    46
16                   321
…                      …
45471                120
45551                  3
45581                 44
45690                 53
46067                167

[8222 rows x 16 columns]
```

[50]:
```
# WRITE YOUR CODE HERE #
groups = subgroup.groupby(by=["room_type"])["price"].mean()
labels = groups.index.values
values = groups.values.round(2)
fig = px.bar(x=labels, y=values, title="Average Price per Room Type in Brooklyn␣
 ↪(Listings must have at least 10 reviews)", text=values, labels={"x": "Room␣
 ↪Type", "y": "Average Price"})
fig.show()
```

Question assigned to the following page: 2.1

3 Prepare the Data

[51]:
```
airbnb_drop.head()
```

[51]:
```
     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

[52]:
```
# 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=False) + 1

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

[52]:
```
price_cat
4    10809
1    10063
2     9835
3     9804
5     8384
Name: count, dtype: int64
```

Question assigned to the following page: 2.2

3.0.2 Data Imputation

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

[53]:
```
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  int64
dtypes: float64(3), int64(7), object(2)
memory usage: 4.5+ MB
```

[54]:
```
# WRITE YOUR CODE HERE #
airbnb_drop = airbnb_drop.fillna(0)
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  int64
dtypes: float64(3), int64(7), object(2)
memory usage: 4.5+ MB
```

Questions assigned to the following page: 2.3 and 2.4

3.0.3 Numeric Conversions

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

[55]:
```
# WRITE YOUR CODE HERE #
airbnb_drop["neighbourhood_group"] = labelencoder.
 ↪fit_transform(airbnb_drop["neighbourhood_group"])
airbnb_drop["room_type"] = labelencoder.fit_transform(airbnb_drop["room_type"])
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

[56]:
```
from sklearn.model_selection import StratifiedShuffleSplit

# let's first start by creating our train and test sets

# WRITE YOUR CODE HERE #
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]
```

[57]:
```
test_set.info()
```

Question assigned to the following page: 2.4

```
<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.

[58]:
```
# WRITE YOUR CODE HERE #
training = train_set.drop(["price", "price_cat"], axis=1)
training_labels = train_set["price"].copy()

testing = test_set.drop(["price", "price_cat"], axis=1)
testing_labels = test_set["price"].copy()
```

[59]:
```
training.head()
```

[59]:

	id	neighbourhood_group	latitude	longitude	room_type	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability_365
40334	31283904	2	40.72846	-73.98457	0	1	10	1.67	1	332
12438	9578325	1	40.67924	-73.98718	0	1	120	2.73		
35502	28181243	1	40.66891	-73.93495	0	3	2	0.24		
6553	4750578	1	40.68589	-73.95759	0	1	0	0.00		
19465	15529937	1	40.60983	-73.95887	1	2	26	0.98		

Questions assigned to the following page: 3 and 2.4

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**.

[60]:
```
# WRITE YOUR CODE HERE #
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

model = LinearRegression()
model.fit(training, training_labels)

preds = model.predict(testing)
mse = mean_squared_error(testing_labels, preds)
rmse = np.sqrt(mse)
print("Test Mean Squared Error: ", mse)
print("Test Root Mean Squared Error: ", rmse)

preds = model.predict(training)
mse = mean_squared_error(training_labels, preds)
rmse = np.sqrt(mse)
print("Training Mean Squared Error: ", mse)
print("Training Root Mean Squared Error: ", rmse)
```

```
Test Mean Squared Error:  38333.39269471032
Test Root Mean Squared Error:  195.789153669733
Training Mean Squared Error:  56032.574858050575
Training Root Mean Squared Error:  236.71200826753716
```