24W-COM SCI-M148 Project 1

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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.

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

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.

Setup

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

```
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
```

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.

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	populati
0	-122.23	37.88	41.0	880.0	129.0	32
1	-122.22	37.86	21.0	7099.0	1106.0	240
2	-122.24	37.85	52.0	1467.0	190.0	49
3	-122.25	37.85	52.0	1274.0	235.0	55
4	-122.25	37.85	52.0	1627.0	280.0	56

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
```

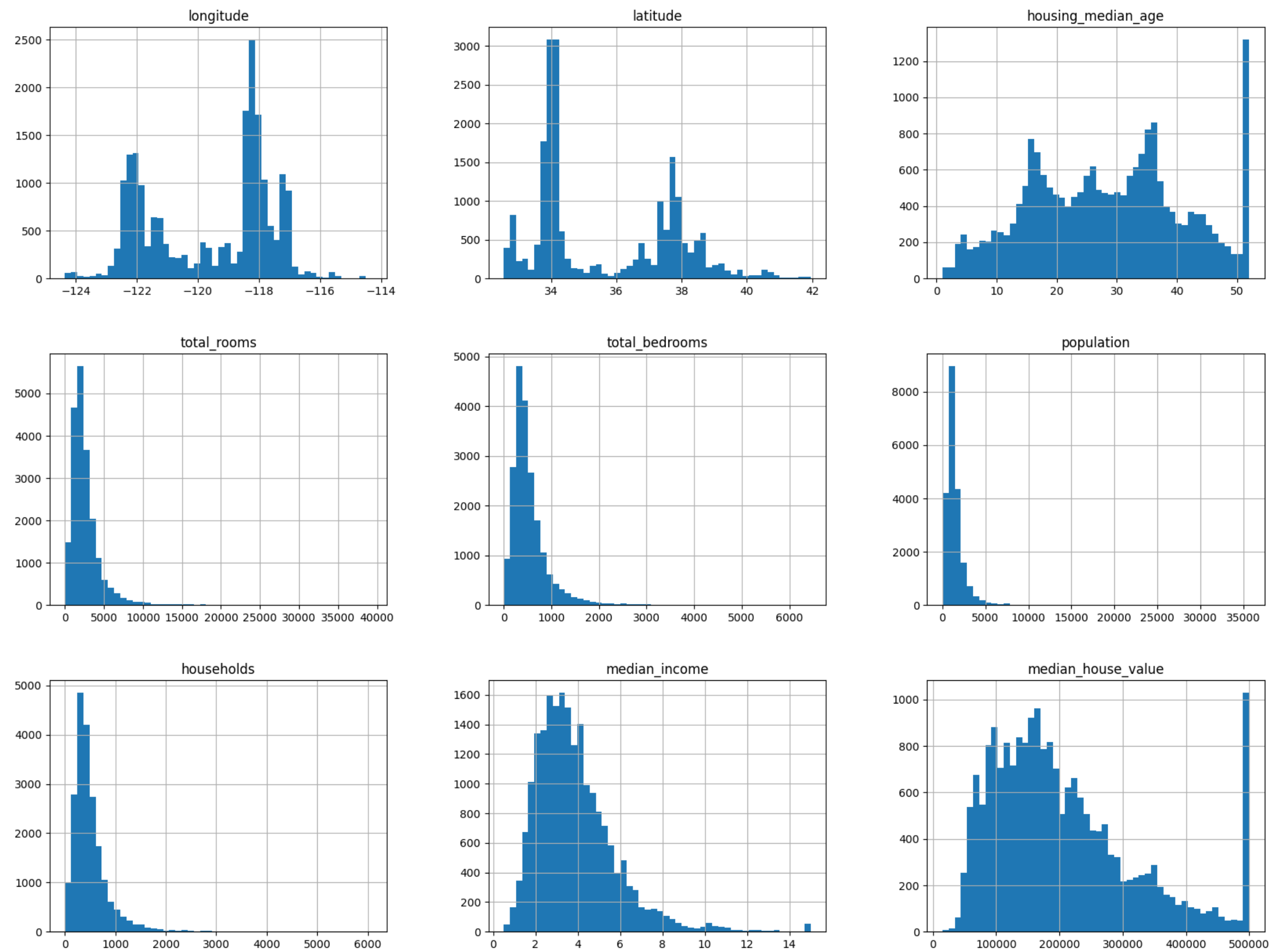
```
# The describe function compiles your typical statistics for each
# column
housing.describe()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553
std	2.003532	2.135952	12.585558	2181.615252	421.385070
min	-124.350000	32.540000	1.000000	2.000000	1.000000
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000

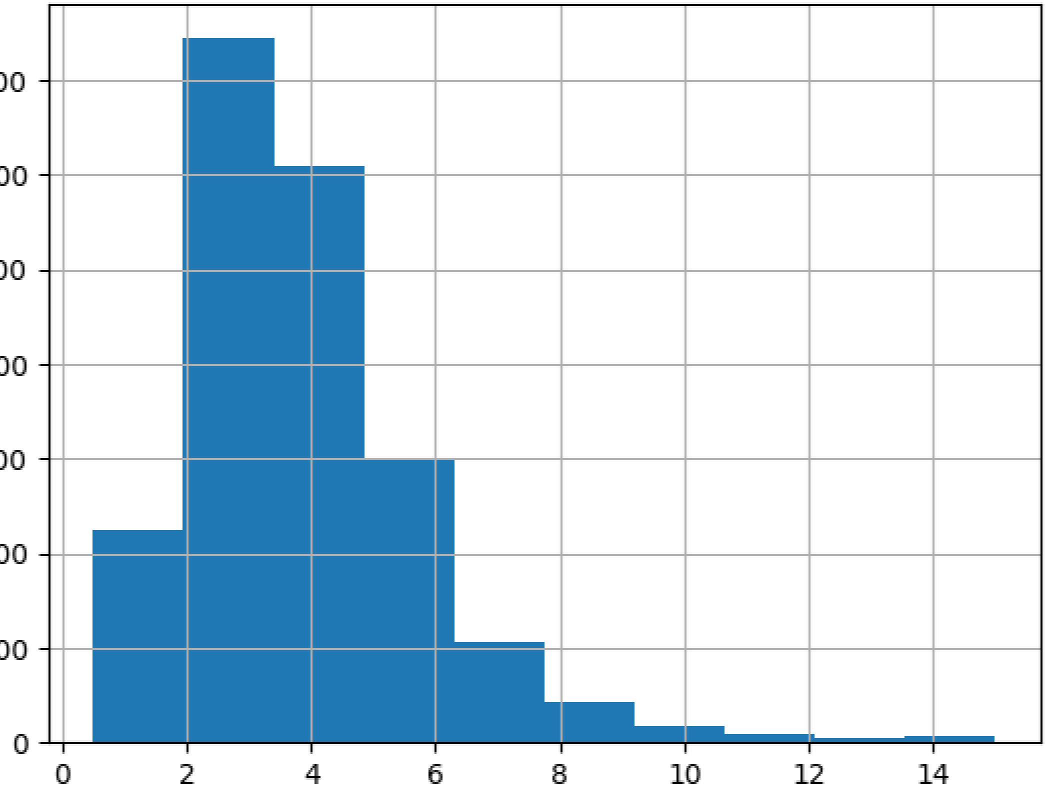
If you want to learn about different ways of accessing elements or other functions it's useful to check out the getting started section here

Let's start visualizing the dataset

```
# 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
```




```
# 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.

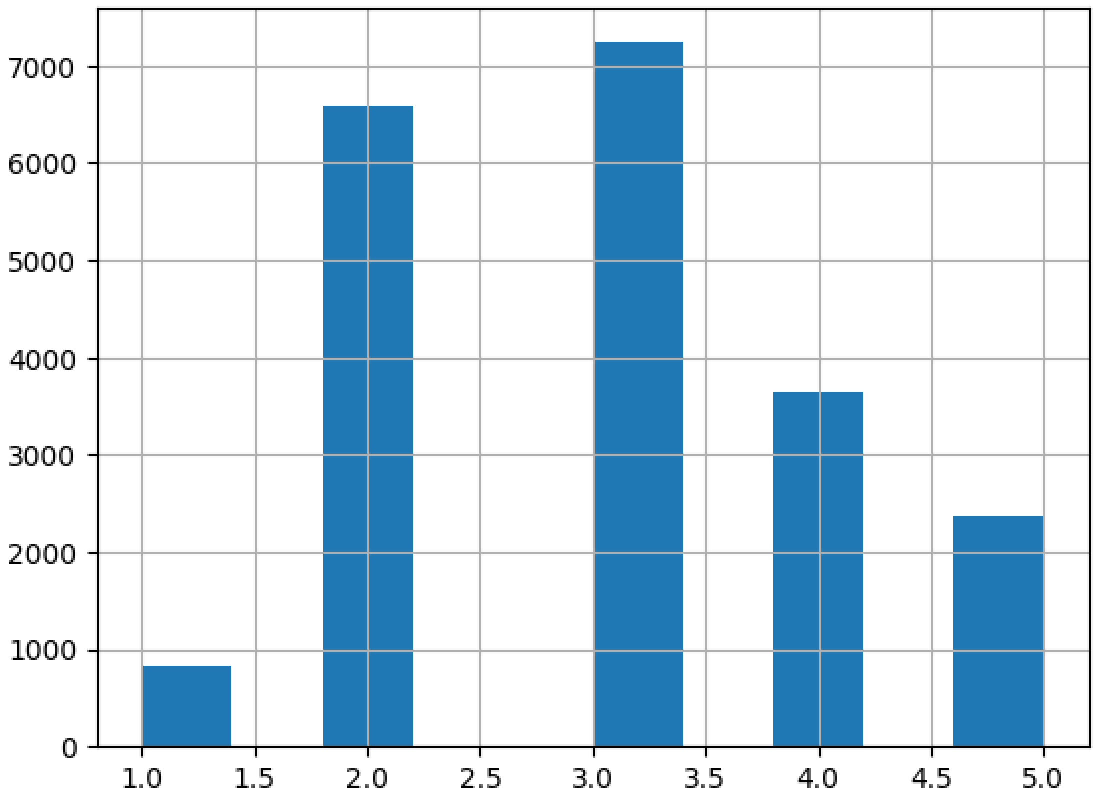
For example, to bin the households based on median_income we can use the pd.cut function

```
# 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()
```

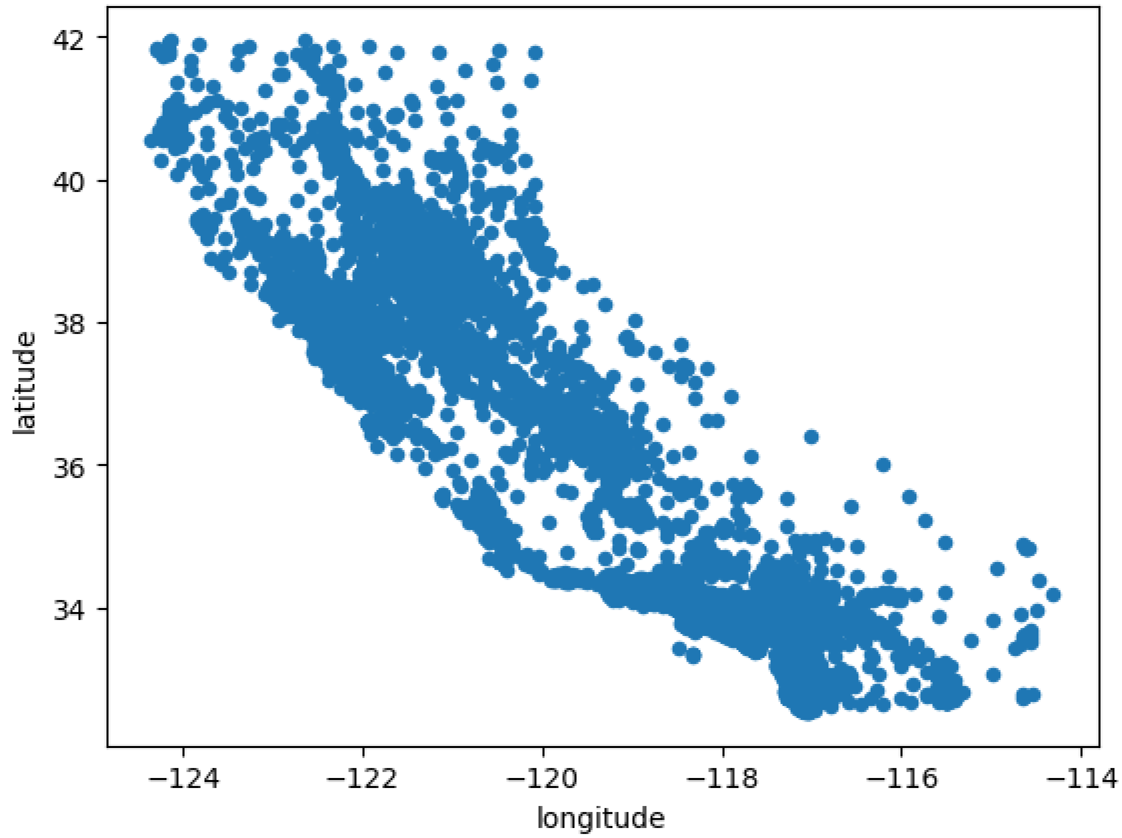
```
<Axes: >
```



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

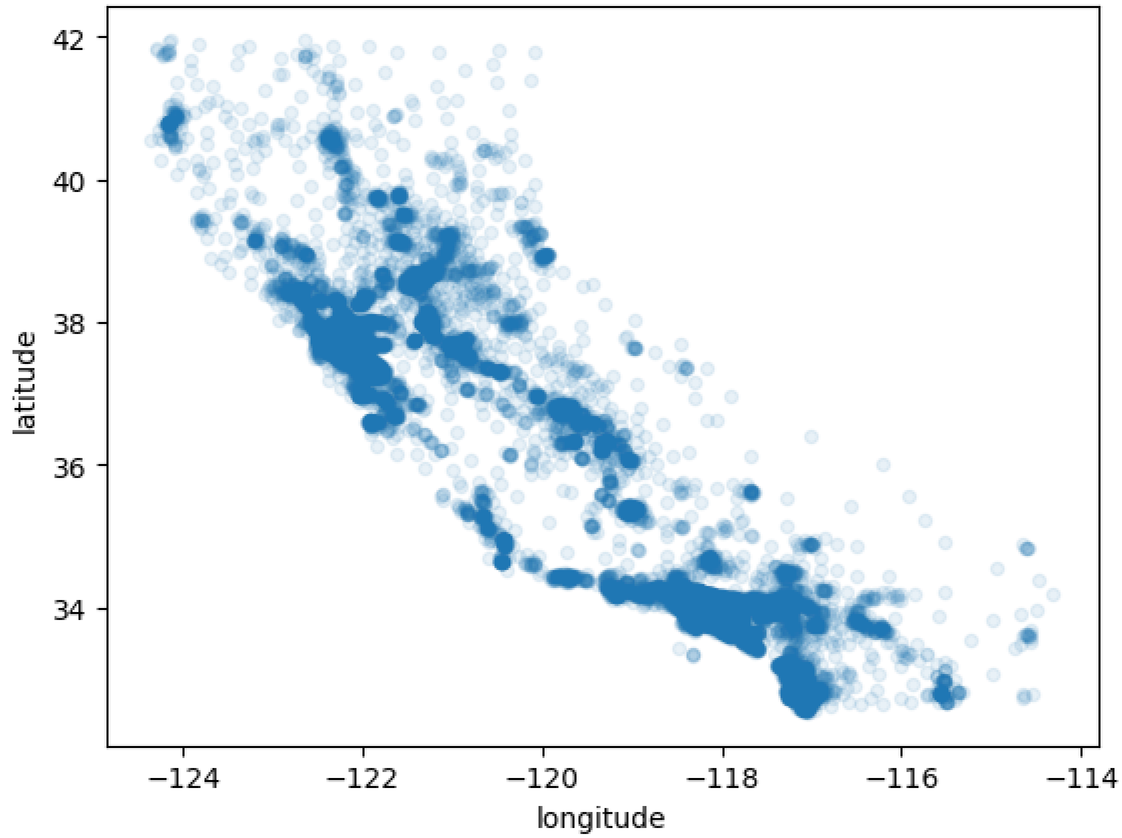
```
## here's a not so interestting way plotting it
housing.plot(kind="scatter", x="longitude", y="latitude")
```

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



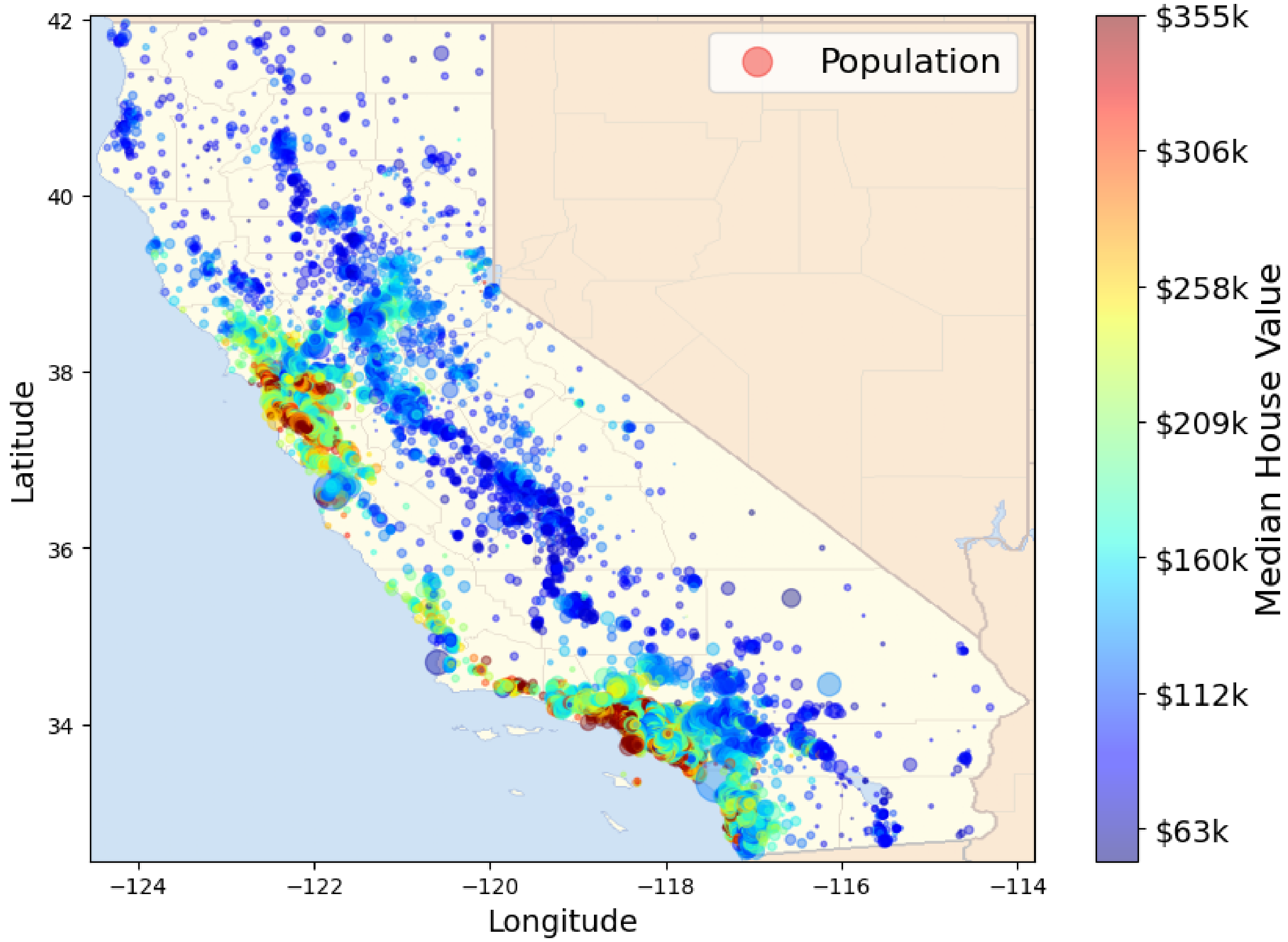

```
# we can make it look a bit nicer by using the alpha parameter,
# it simply plots less dense areas lighter.
housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.1)
```

```
<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()
```

```
/var/folders/jl/_k9n1dsd7rg1x3mrfs7130y40000gn/T/ipykernel_3132/2129115766.py:26
set_ticklabels() should only be used with a fixed number of ticks, i.e. after se
```



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 interest 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.

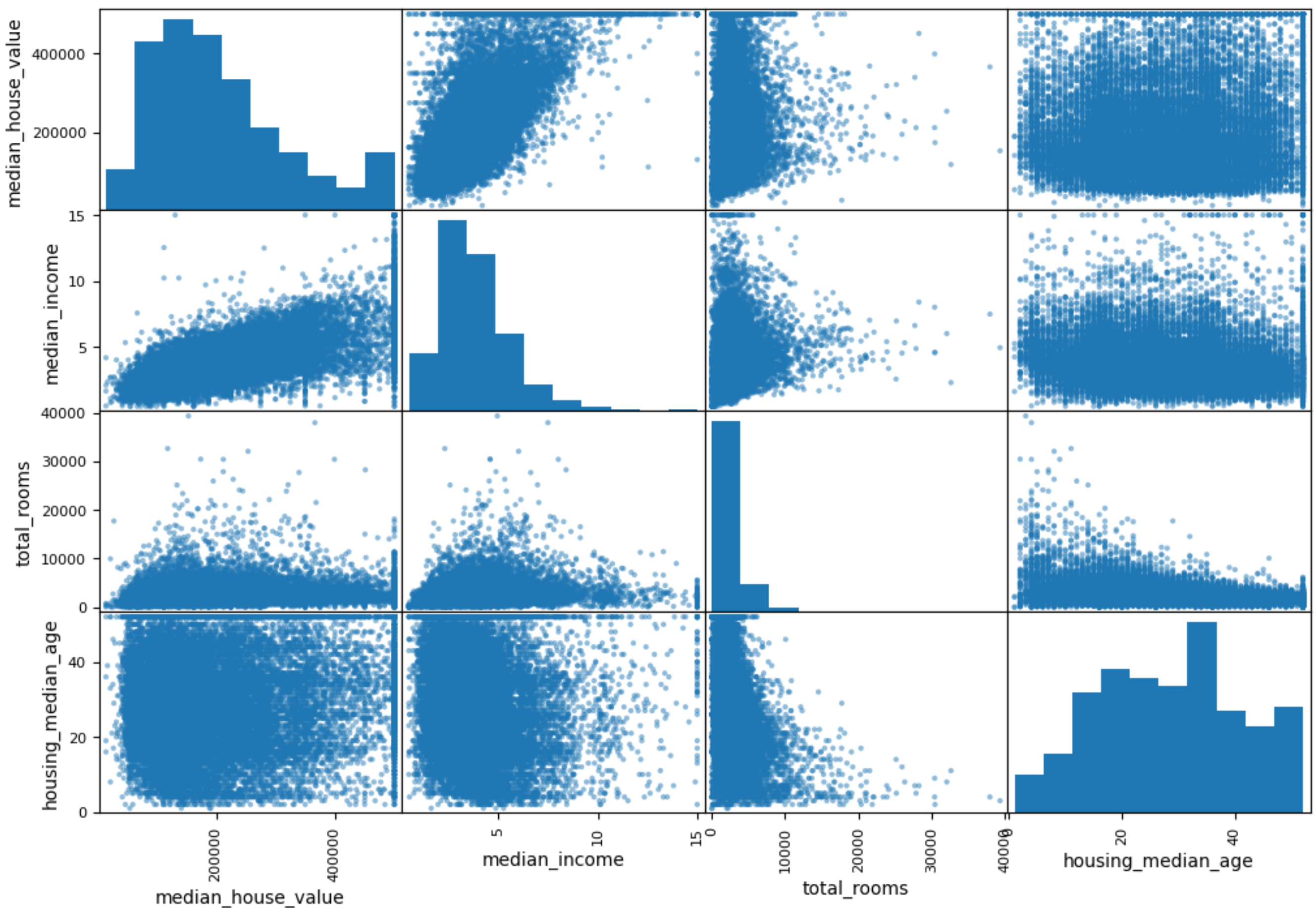
```
corr_matrix = housing.corr(numeric_only=True)
```

```
# for example if the target is "median_house_value", most correlated features can be
# 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
```

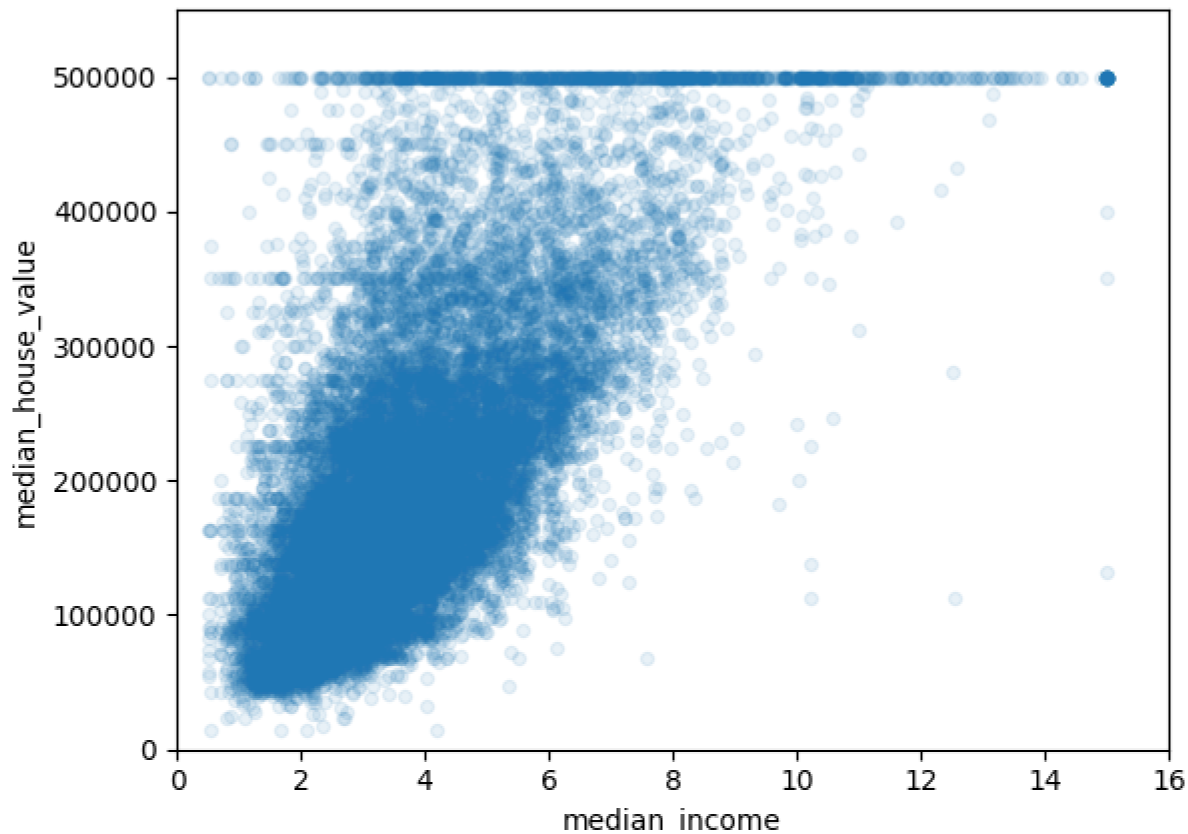
```
# the correlation matrix for different attributes/features can also be plotted
# some features may show a positive correlation/negative correlation or
# it may turn out to be completely random!
from pandas.plotting import scatter_matrix
attributes = ["median_house_value", "median_income", "total_rooms",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



```
# 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)
```




```
# obtain new correlations
corr_matrix = housing.corr(numeric_only=True )
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
```

Preparing Dastaset for ML

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	popula
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	3
563	-122.24	37.75	45.0	891.0	NaN	
696	-122.10	37.69	41.0	746.0	NaN	

```
sample_incomplete_rows = housing[housing.isnull().any(axis=1)].head()
sample_incomplete_rows
sample_incomplete_rows.dropna(subset=["total_bedrooms"])    # option 1: simply drop
```

longitude	latitude	housing_median_age	total_rooms	total_bedrooms	populatio

```
sample_incomplete_rows.drop("total_bedrooms", axis=1)       # option 2: drop the co
```

	longitude	latitude	housing_median_age	total_rooms	population	households
290	-122.16	37.77	47.0	1256.0	570.0	218.0
341	-122.17	37.75	38.0	992.0	732.0	259.0
538	-122.28	37.78	29.0	5154.0	3741.0	1273.0
563	-122.24	37.75	45.0	891.0	384.0	146.0
696	-122.10	37.69	41.0	746.0	387.0	161.0

```
median = housing["total_bedrooms"].median()
sample_incomplete_rows["total_bedrooms"].fillna(median, inplace=True) # option 3: r
sample_incomplete_rows
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	popula
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	3'
563	-122.24	37.75	45.0	891.0	435.0	:
696	-122.10	37.69	41.0	746.0	435.0	:

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

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

Could you think of another plausible imputation for this dataset?

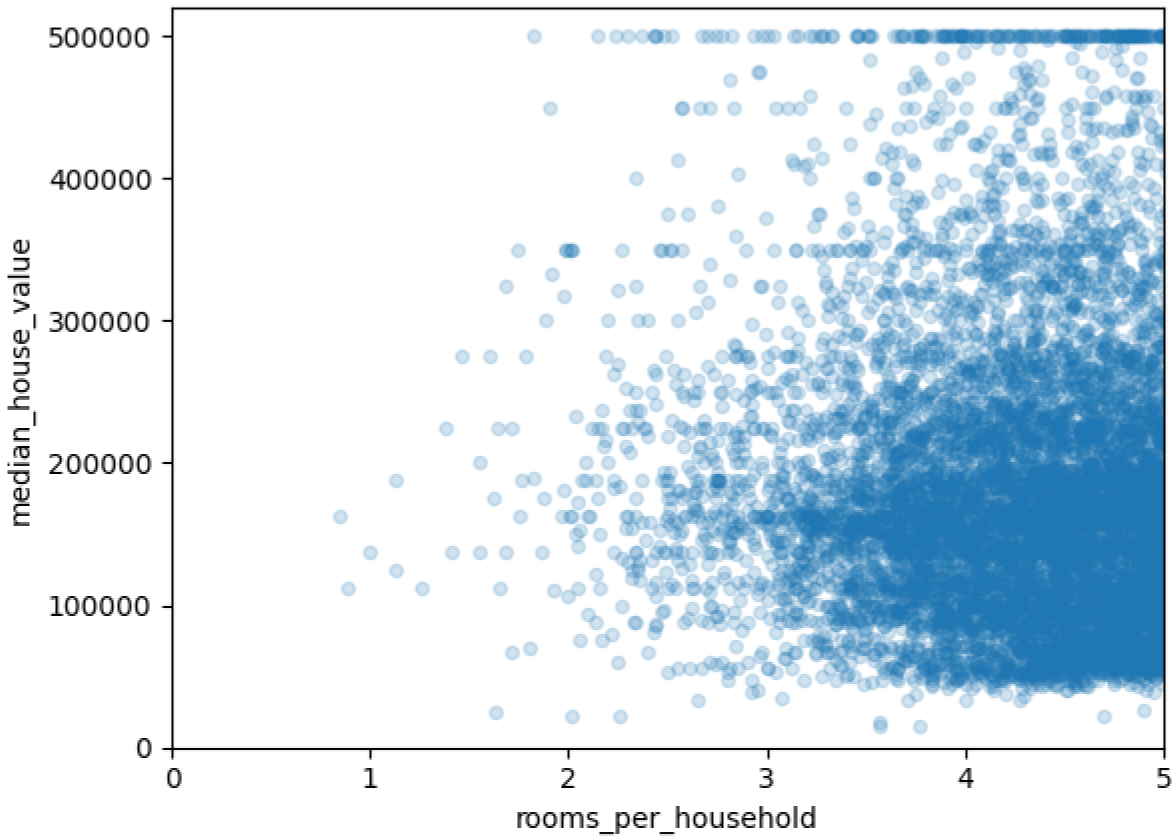
Augmenting Features

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
housing["rooms_per_household"] = housing["total_rooms"]/(housing["households"] + 1e-
housing["bedrooms_per_room"] = housing["total_bedrooms"]/(housing["total_rooms"] + 1
housing["population_per_household"]=housing["population"]/(housing["households"] + 1
```

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



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	populati
0	-122.23	37.88	41.0	880.0	129.0	32
1	-122.22	37.86	21.0	7099.0	1106.0	240
2	-122.24	37.85	52.0	1467.0	190.0	49
3	-122.25	37.85	52.0	1274.0	235.0	55
4	-122.25	37.85	52.0	1627.0	280.0	56

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 t
                                                    # the input to the model sho
housing_labels = train_set["median_house_value"].copy()
```

```
housing_testing = test_set.drop("median_house_value", axis=1) # drop labels for tra
                                                              # the input to the model shou
housing__test_labels = test_set["median_house_value"].copy()
```

Select a model and train

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

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

```
from sklearn.linear_model import LinearRegression

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

```
▾ LinearRegression
LinearRegression()
```

```
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.

```
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
```

```
67694.0818434439
```

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

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

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

Visualizing Data

Load the data + statistics

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

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

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

```
airbnb_drop = airbnb.head() # WRITE YOUR CODE HERE #
airbnb_drop
```

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	l
0	2539	Clean & quiet apt home by the park	2787	John	Brooklyn	Kensington	
1	2595	Skylit Midtown Castle	2845	Jennifer	Manhattan	Midtown	
2	3647	THE VILLAGE OF HARLEM....NEW YORK !	4632	Elisabeth	Manhattan	Harlem	
3	3831	Cozy Entire Floor of Brownstone	4869	LisaRoxanne	Brooklyn	Clinton Hill	
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	Laura	Manhattan	East Harlem	

```
airbnb_drop.describe()
```

	id	host_id	latitude	longitude	price	minimum_nights	numb
count	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000	
mean	3526.800000	4465.000000	40.738756	-73.960358	138.600000	3.200000	
std	1023.060213	1807.464937	0.070592	0.018037	58.303516	3.898718	
min	2539.000000	2787.000000	40.647490	-73.983770	80.000000	1.000000	
25%	2595.000000	2845.000000	40.685140	-73.972370	89.000000	1.000000	
50%	3647.000000	4632.000000	40.753620	-73.959760	149.000000	1.000000	
75%	3831.000000	4869.000000	40.798510	-73.943990	150.000000	3.000000	
max	5022.000000	7192.000000	40.809020	-73.941900	225.000000	10.000000	

```
airbnb_drop.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5 entries, 0 to 4
Data columns (total 16 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              5 non-null      int64
 1   name                            5 non-null      object
```

```
 2   host_id                         5 non-null      int64
 3   host_name                       5 non-null      object
 4   neighbourhood_group             5 non-null      object
 5   neighbourhood                   5 non-null      object
 6   latitude                        5 non-null      float64
 7   longitude                       5 non-null      float64
 8   room_type                       5 non-null      object
 9   price                           5 non-null      int64
 10  minimum_nights                  5 non-null      int64
 11  number_of_reviews               5 non-null      int64
 12  last_review                     4 non-null      object
 13  reviews_per_month               4 non-null      float64
 14  calculated_host_listings_count  5 non-null      int64
 15  availability_365                5 non-null      int64
dtypes: float64(3), int64(7), object(6)
memory usage: 772.0+ bytes
```

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)

```
import os
import pandas as pd
import nbformat
os.system("pip install plotly --upgrade")
print(nbformat.__version__)
import plotly.express as px
neighborhood = pd.DataFrame(airbnb)
neighborhood.head()
fig = px.pie(neighborhood, names='neighbourhood_group', title='Distribution of Renta
fig.show()
```

```
Requirement already satisfied: plotly in /opt/homebrew/lib/python3.11/site-packa
Requirement already satisfied: tenacity>=6.2.0 in /opt/homebrew/lib/python3.11/s
Requirement already satisfied: packaging in /Users/krishpatel/Library/Python/3.1
5.9.2
```

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

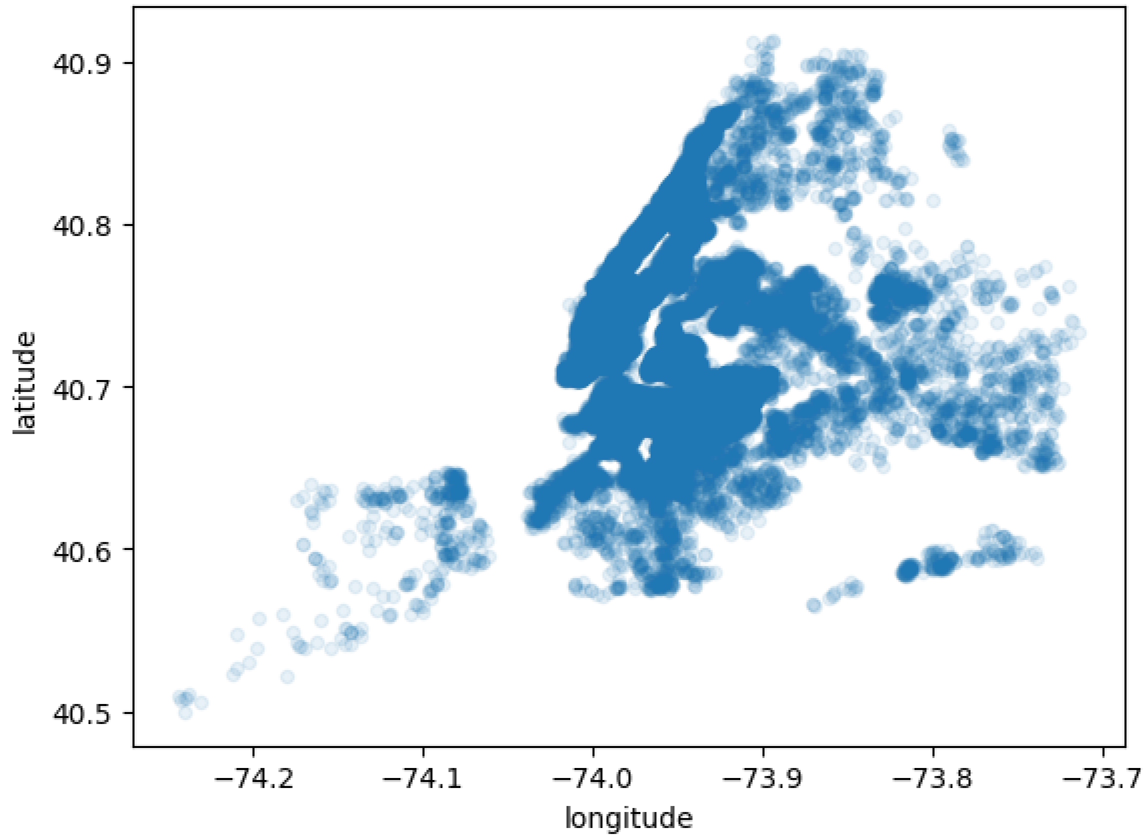
```
grouped_data = neighborhood.groupby('neighbourhood_group')['number_of_reviews'].sum

fig = px.bar(grouped_data, x='neighbourhood_group', y='number_of_reviews', labels={
             title='Total Number of Reviews per Neighbourhood Group')
fig.update_xaxes(title='Neighbourhood Group')
fig.update_yaxes(title='Total Number of Reviews')


fig.show()
```

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 :)).

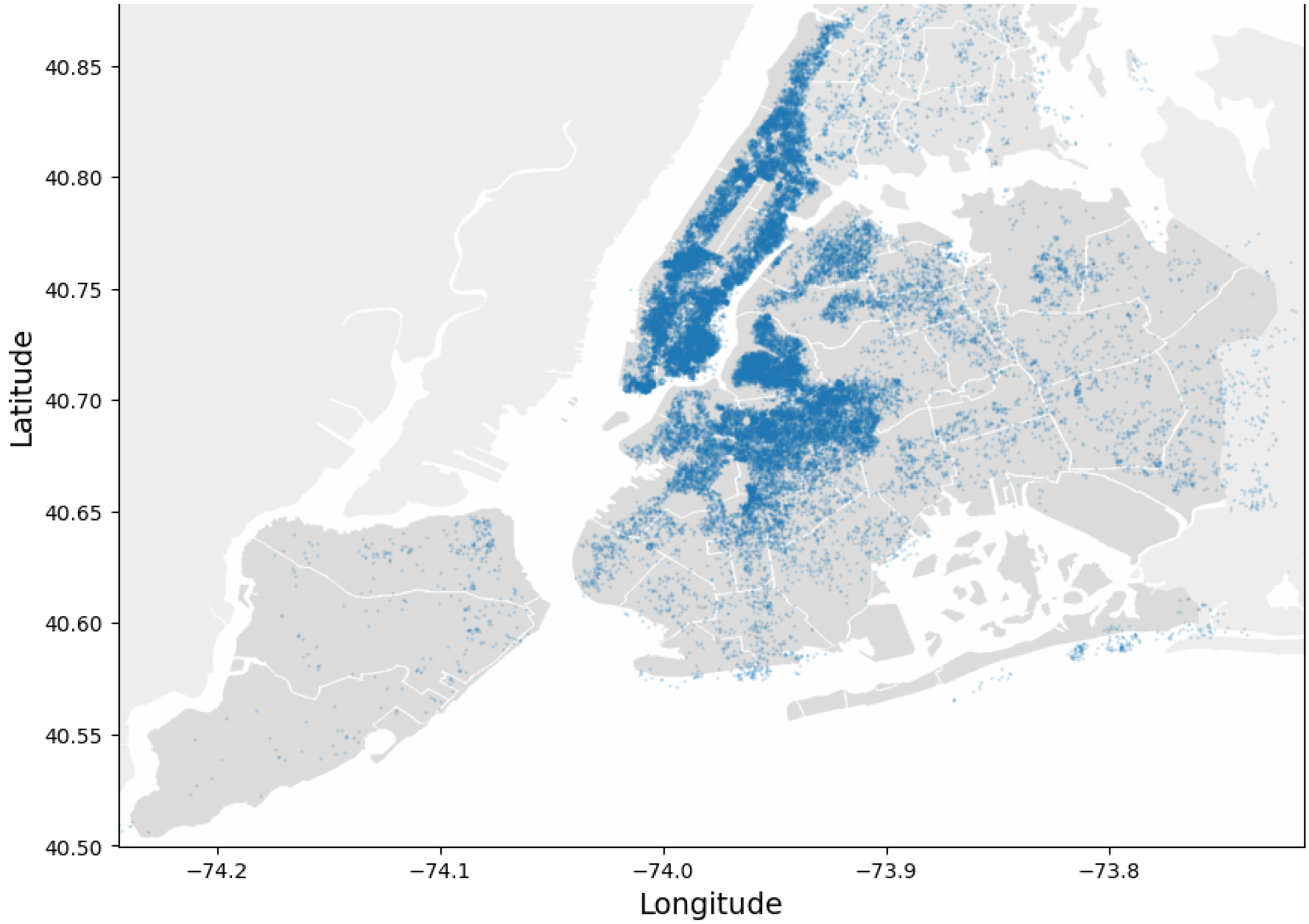
For reference you can use the Matplotlib code above to replicate this graph here.

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

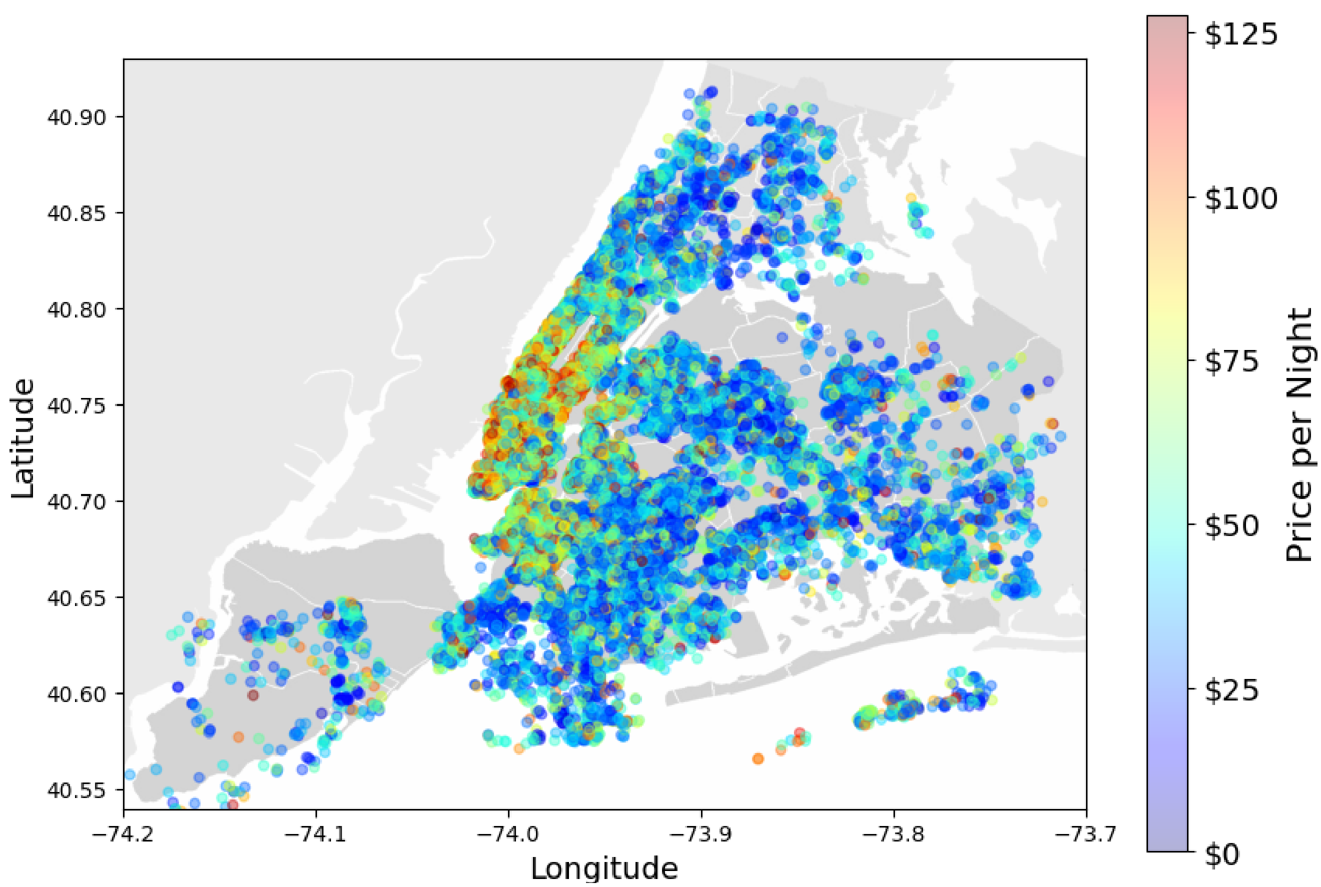
```
<Axes: xlabel='longitude', ylabel='latitude'>
```



```
miniairbnb = airbnb.sample(frac=1.0)


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.

ax2 = airbnb.plot(kind="scatter", x="longitude", y="latitude", alpha=0.25, figsize=
plt.imshow(nyc_img, extent=[-74.244420, -73.712990, 40.499790, 40.913060], alpha=0.
plt.xlabel("Longitude", fontsize=14)
plt.ylabel("Latitude", fontsize=14)
plt.title("Airbnbs throughout New York City")
plt.show()
# WRITE YOUR CODE HERE #


#for the heatmap:
miniairbnb[miniairbnb["price"] >= 250] = 250
ax = miniairbnb.plot(kind="scatter", x="longitude", y="latitude", figsize=(10,7),
                        cmap=plt.get_cmap("jet"), c="price", colorbar=False, alpha=

plt.imshow(nyc_img, extent=[-74.2, -73.7, 40.54, 40.93], alpha=0.3, cmap=plt.get_cm
plt.ylabel("Latitude", fontsize=14)
plt.xlabel("Longitude", fontsize=14)

prices = miniairbnb["price"]
tick_values = np.linspace(prices.min(), prices.max(), 11)
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.show()
```




```
/var/folders/jl/_k9n1dsd7rg1x3mrfs7130y40000gn/T/ipykernel_3132/2757423461.py:32

set_ticklabels() should only be used with a fixed number of ticks, i.e. after se
```



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

```
miniairbnb = airbnb.sample(frac=1.0)

# Limiting price values to 250 as per your commented line
# miniairbnb[miniairbnb["price"] >= 250] = 250

latitudes = miniairbnb['latitude'].to_numpy()
longitudes = miniairbnb['longitude'].to_numpy()
print(latitudes)

fig = px.scatter(miniairbnb, x="longitude", y="latitude")
extent = [-74.2, -73.7, 40.54, 40.93]
nyc_img = Image.open("./nyc.png")
fig.add_layout_image(
    dict(
        source=nyc_img,
        xref="x",
        yref="y",
        x=extent[0],
        y=extent[3],
        sizex=extent[1]-extent[0],
        sizey=extent[3]-extent[2],
        sizing="stretch",
        opacity=0.3,
        layer="below"
    )
)
fig.update_xaxes(range=[extent[0], extent[1]])
fig.update_yaxes(range=[extent[2], extent[3]])

fig.show()
```

```
[40.75318 40.6455  40.68257 ... 40.72912 40.82831 40.83878]
```

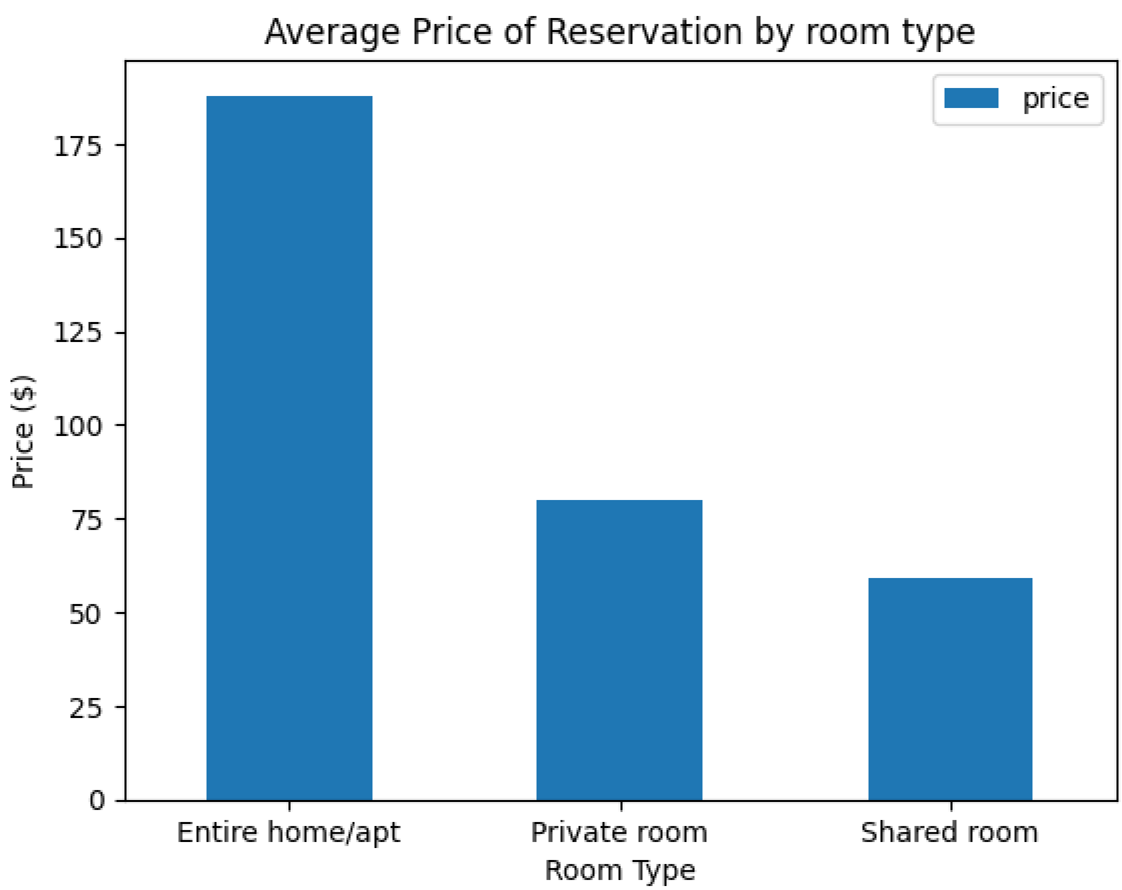
Use Plotly to plot the average price of room types in Brooklyn who have at least 10 Reviews.

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

```
airbnb["price"] = pd.to_numeric(airbnb["price"], errors='coerce')
airbnb["price"].fillna(0, inplace=True)

avg_reviews_prices = airbnb[airbnb["number_of_reviews"] > 10].groupby("room_type")['
avg_reviews_prices = avg_reviews_prices.reset_index()

fig = avg_reviews_prices.plot.bar(x="room_type", y="price", rot=0)
plt.xlabel("Room Type")
plt.ylabel("Price ($)")
plt.title("Average Price of Reservation by room type")
plt.show()
```



Prepare the Data

```
airbnb.head()
```

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	l
0	2539	Clean & quiet apt home by the park	2787	John	Brooklyn	Kensington	
1	2595	Skylit Midtown Castle	2845	Jennifer	Manhattan	Midtown	
2	3647	THE VILLAGE OF HARLEM....NEW YORK !	4632	Elisabeth	Manhattan	Harlem	
3	3831	Cozy Entire Floor of Brownstone	4869	LisaRoxanne	Brooklyn	Clinton Hill	
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	Laura	Manhattan	East Harlem	

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

```
airbnb["price_cat"] = pd.cut(airbnb["price"],
                              bins=[0, 60, 120, 180, 240., np.inf],
                              labels=[1, 2, 3, 4, 5])
airbnb["price_cat"].value_counts()
```

```
price_cat
2    17490
1    10052
3     9902
5     6523
4     4917
Name: count, dtype: int64
```

Data Imputation

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