CS148_Project_1_To_Do

January 16, 2023

0.1 Introduction

Welcome to **CS148 - Data Science Fundamentals!** 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

0.2 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.

0.3 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
import warnings
warnings.filterwarnings('ignore')
import plotly.io as pio
#pio.kaleido.scope.default_format = "svg"
#pio.renderers.default="notebook" DID NOT WORK
```

0.4 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.

[2]:
```
#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.

[3]:
```
# We'll now import the holy grail of python datascience: Pandas!
import pandas as pd
import os
HOUSING_PATH = os.path.join("datasets","housing","housing.csv")
housing = pd.read_csv(HOUSING_PATH)
```

[4]:
```
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
```

[4]:
```
   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.

[5]:
```
# 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
```

[6]:
```
# you can access individual columns similarly
# to accessing elements in a python dict
```

```
housing["ocean_proximity"].head() # added head() to avoid printing many columns.
  ↪.
```

[6]:
```
0    NEAR BAY
1    NEAR BAY
2    NEAR BAY
3    NEAR BAY
4    NEAR BAY
Name: ocean_proximity, dtype: object
```

[7]:
```
# to access a particular row we can use iloc
housing.iloc[1]
```

[7]:
```
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
```

[8]:
```
# one other function that might be useful is
# value_counts(), which counts the number of occurences
# for categorical features
housing["ocean_proximity"].value_counts()
```

[8]:
```
<1H OCEAN     9136
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: ocean_proximity, dtype: int64
```

[9]:
```
# The describe function compiles your typical statistics for each
# column
housing.describe()
```

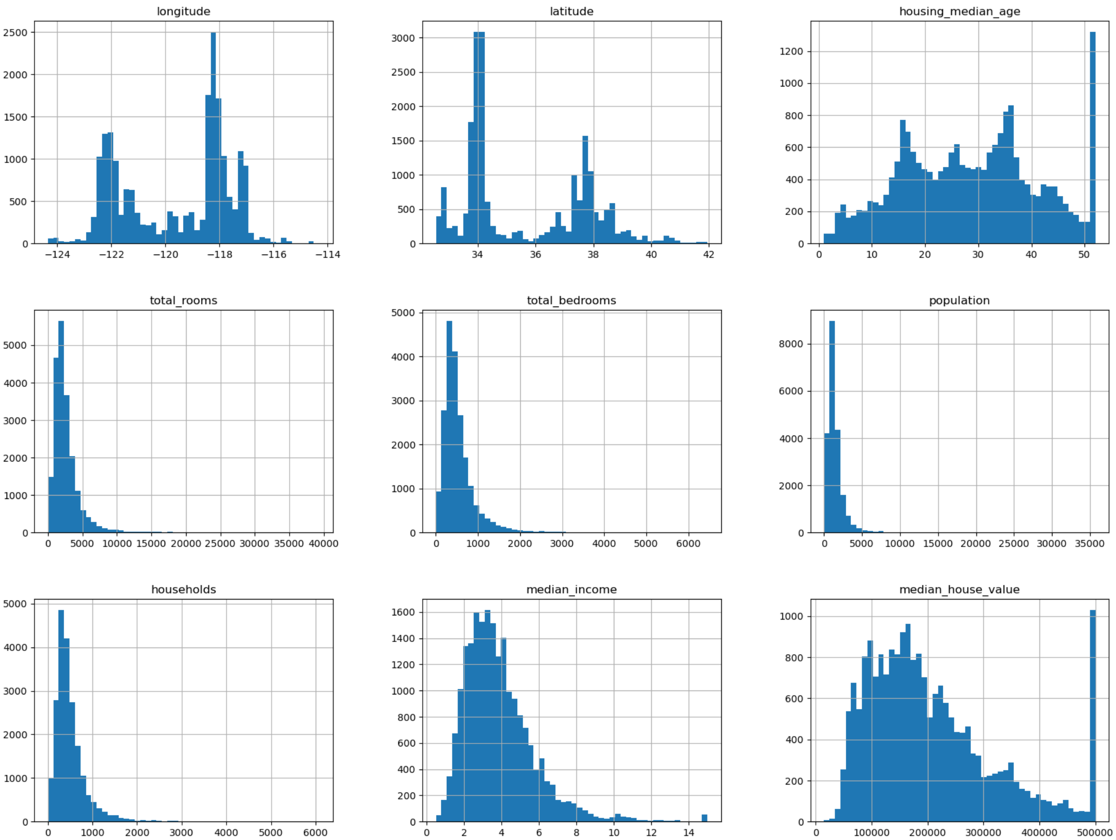
[9]:
```
          longitude      latitude  housing_median_age   total_rooms  \
count  20640.000000  20640.000000        20640.000000  20640.000000
mean    -119.569704     35.631861           28.639486   2635.763081
std        2.003532      2.135952           12.585558   2181.615252
min     -124.350000     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
```

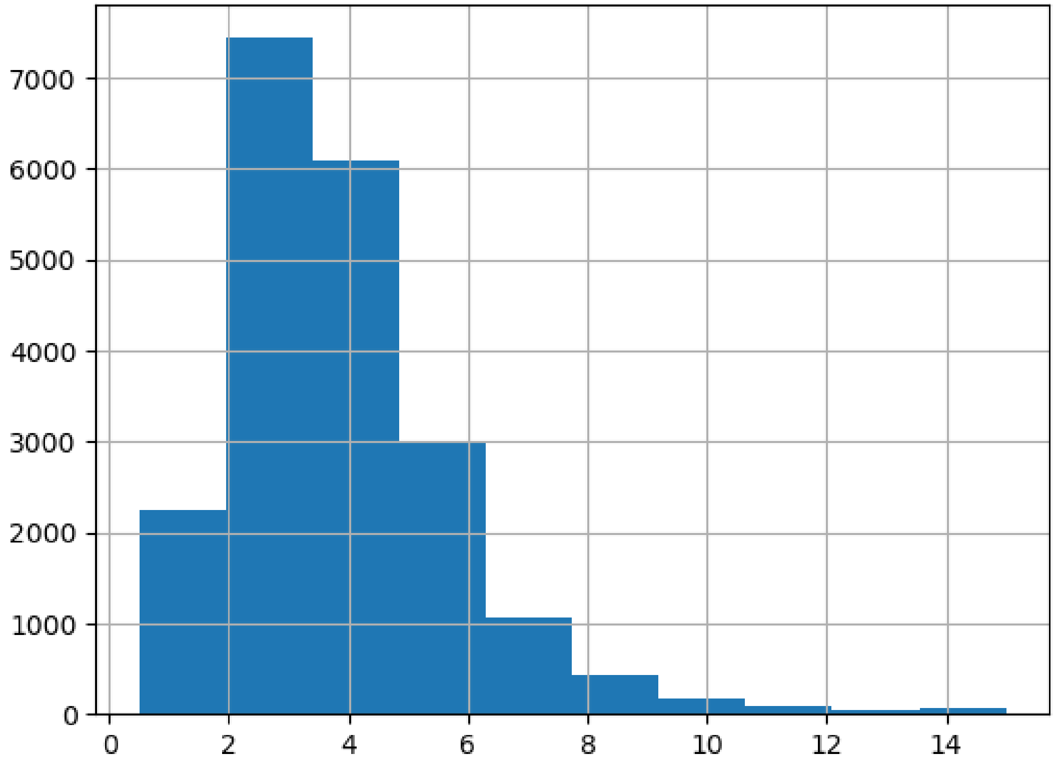
If you want to learn about different ways of accessing elements or other functions it's useful to check out the getting started section here

0.5 Let's start visualizing the dataset

[10]:
```
# 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
```



[11]:
```
# if you want to have a histogram on an individual feature:
housing["median_income"].hist()
plt.show()
```



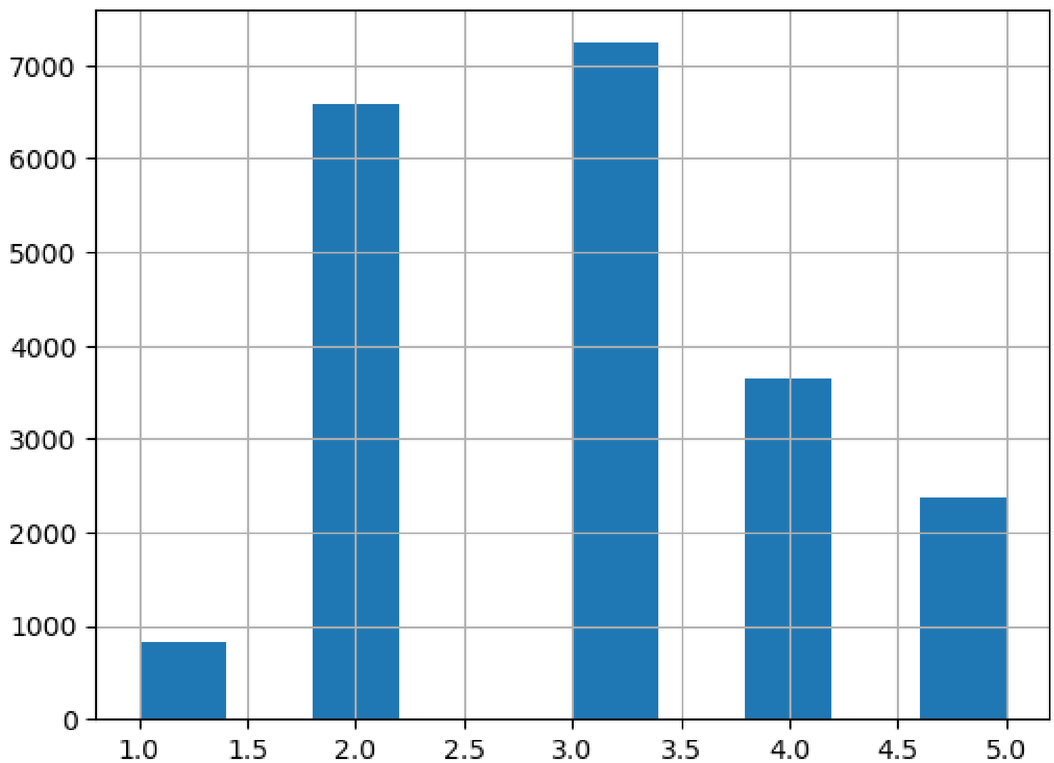
We can convert a floating point feature to a categorical feature by binning or by defining a set of intervals.

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

[12]:
```
# 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()
```

[12]:
```
3    7236
2    6581
4    3639
5    2362
1     822
Name: income_cat, dtype: int64
```

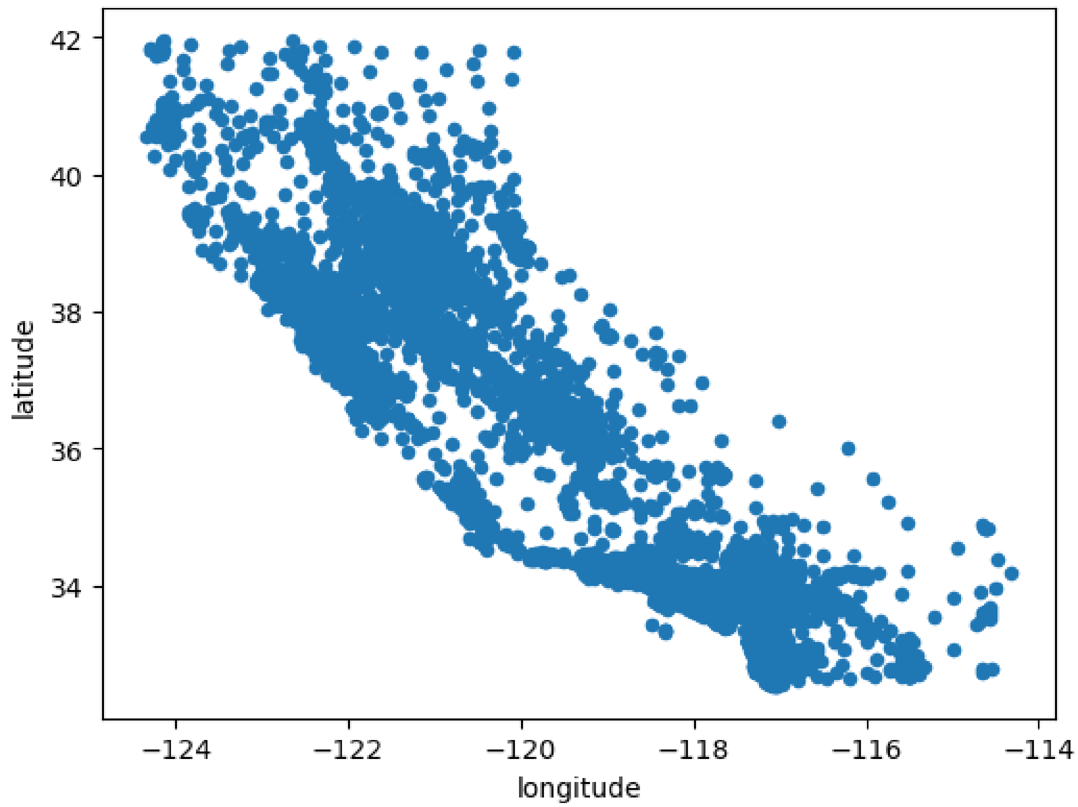
[13]:
```
housing["income_cat"].hist()
plt.show()
```



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

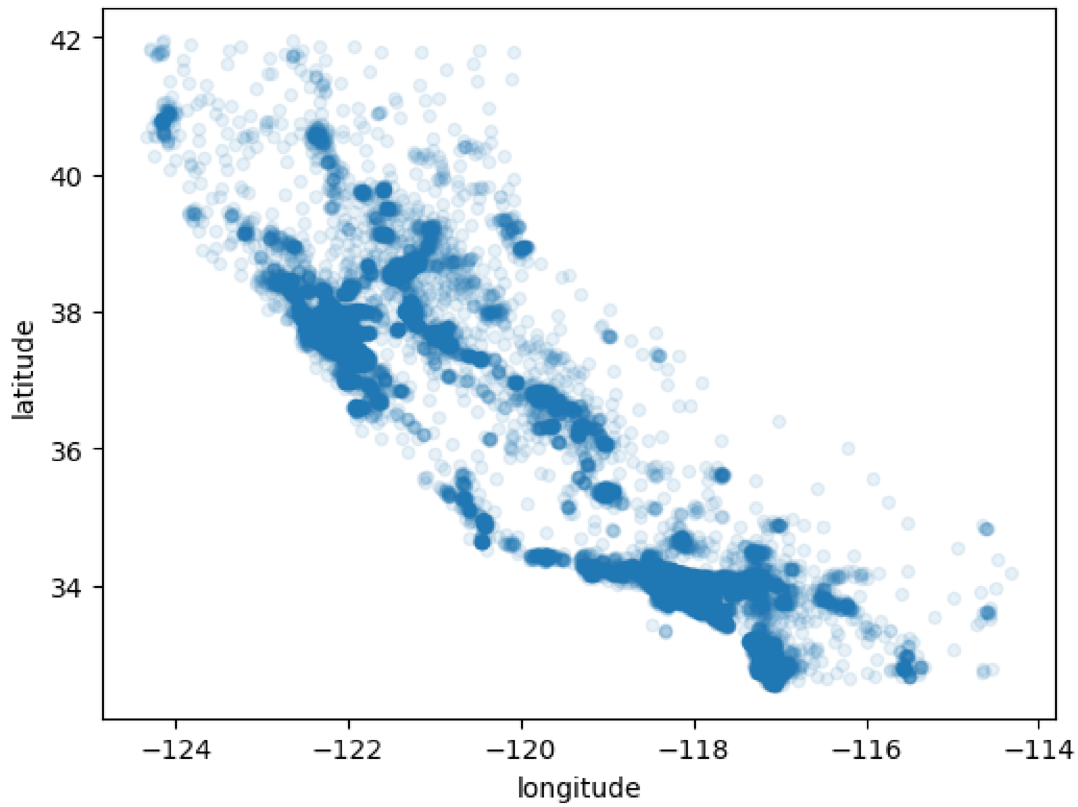
[14]:
```
## here's a not so interestting way plotting it
housing.plot(kind="scatter", x="longitude", y="latitude")
```

[14]:
```
<AxesSubplot:xlabel='longitude', ylabel='latitude'>
```



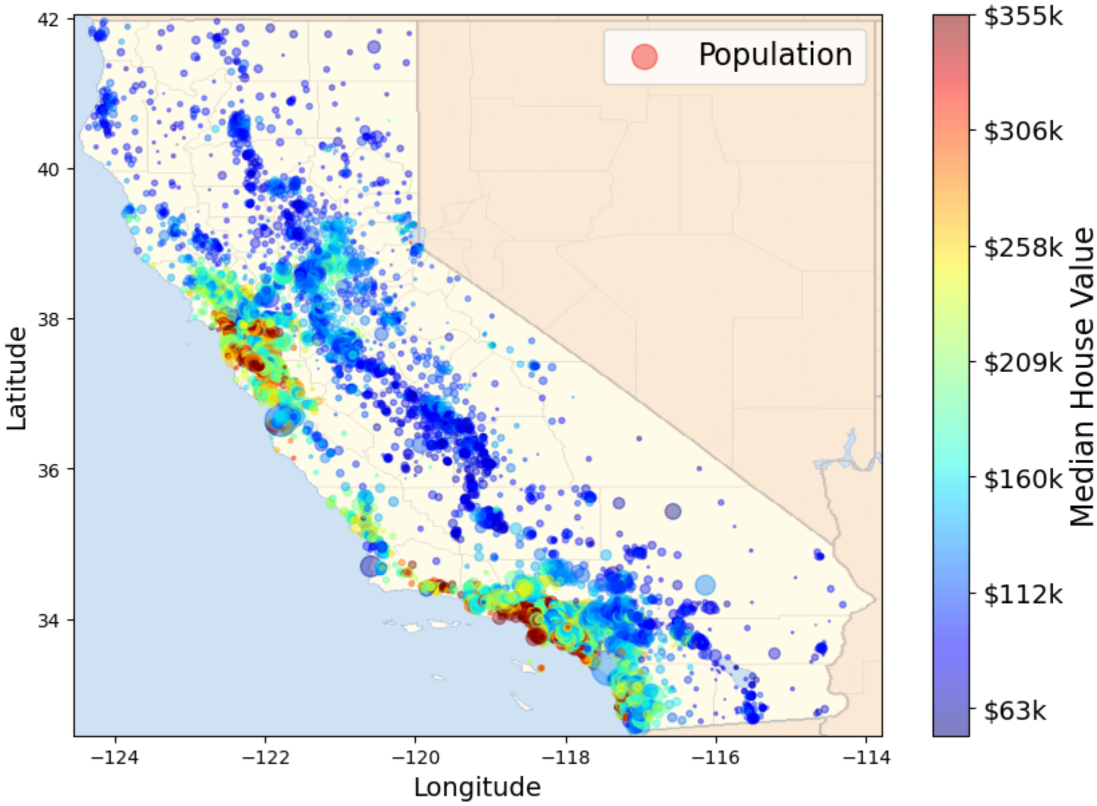

```
[15]: # we can make it look a bit nicer by using the alpha parameter,
      # it simply plots less dense areas lighter.
      housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.1)
```

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



[16]:
```
# 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
CALI_IMAGE_PATH = os.path.join("images","california.png")
california_img=mpimg.imread(CALI_IMAGE_PATH)
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()
```



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.

[17]:
```
corr_matrix = housing.corr()
```

[18]:
```
corr_matrix["median_house_value"]
```

[18]:
```
longitude            -0.045967
latitude             -0.144160
housing_median_age    0.105623
total_rooms           0.134153
total_bedrooms        0.049686
population           -0.024650
households            0.065843
median_income         0.688075
median_house_value    1.000000
Name: median_house_value, dtype: float64
```

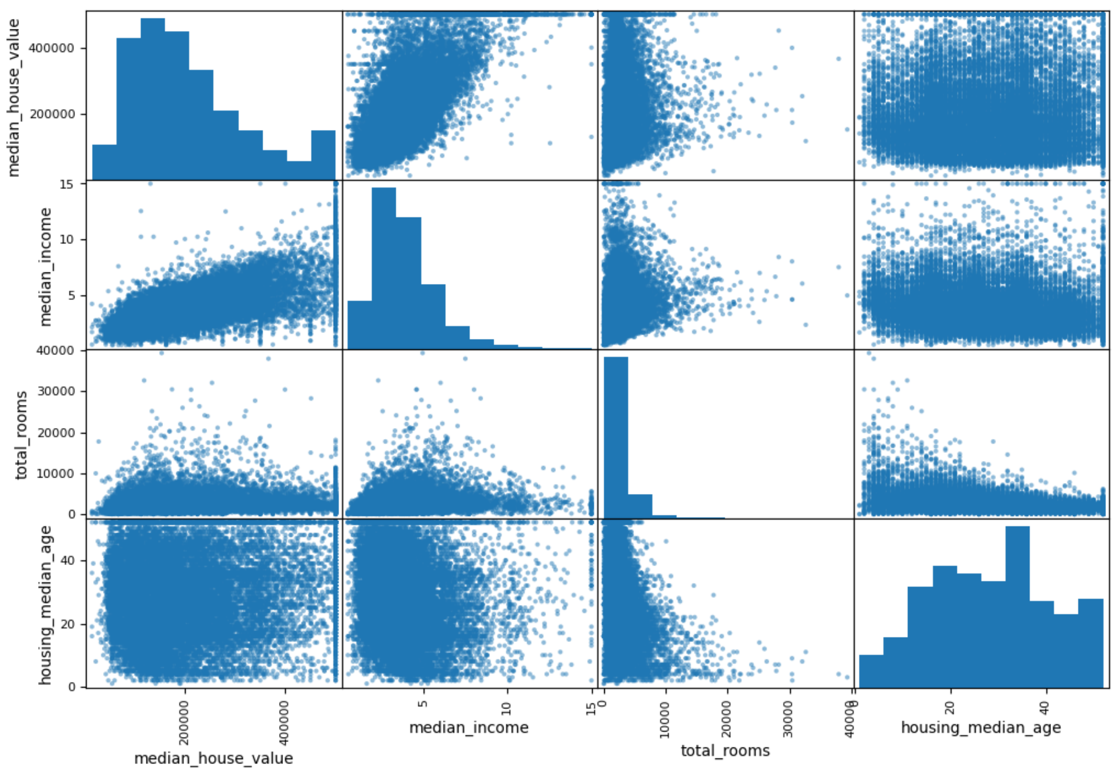
[19]:
```
# for example if the target is "median_house_value", most correlated features␣
 ↪can be sorted
# which happens to be "median_income". This also intuitively makes sense.
corr_matrix["median_house_value"].sort_values(ascending=False)
```

[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))
```

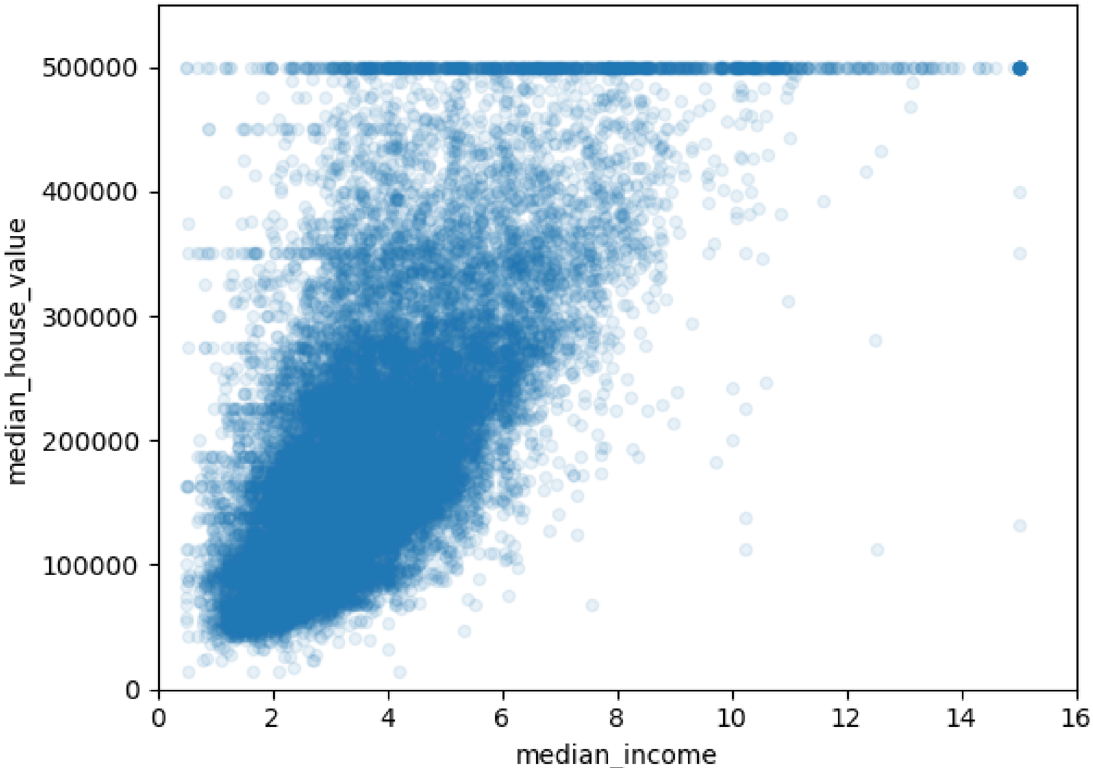
[20]:
```
array([[<AxesSubplot:xlabel='median_house_value', ylabel='median_house_value'>,
        <AxesSubplot:xlabel='median_income', ylabel='median_house_value'>,
        <AxesSubplot:xlabel='total_rooms', ylabel='median_house_value'>,
        <AxesSubplot:xlabel='housing_median_age', ylabel='median_house_value'>],
       [<AxesSubplot:xlabel='median_house_value', ylabel='median_income'>,
        <AxesSubplot:xlabel='median_income', ylabel='median_income'>,
        <AxesSubplot:xlabel='total_rooms', ylabel='median_income'>,
```

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



[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])
```

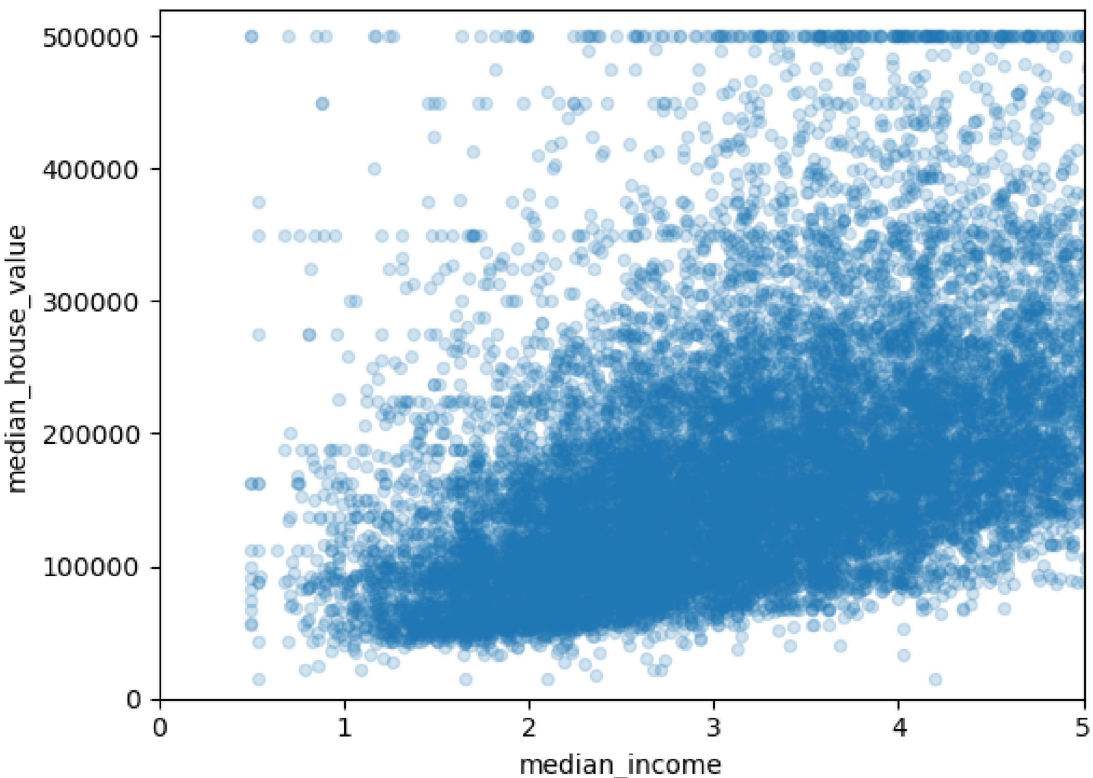
[21]: `(0.0, 16.0, 0.0, 550000.0)`



[22]:
```
# obtain new correlations
corr_matrix = housing.corr()
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
```

[23]:
```
housing.plot(kind="scatter", x="median_income", y="median_house_value",
             alpha=0.2)
plt.axis([0, 5, 0, 520000])
plt.show()
```



0.6 Preparing Dataset for ML

0.6.1 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.

[24]:
```
housing["rooms_per_household"] = housing["total_rooms"]/housing["households"]
housing["bedrooms_per_room"] = housing["total_bedrooms"]/housing["total_rooms"]
housing["population_per_household"]=housing["population"]/housing["households"]
```

0.6.2 Dealing With Incomplete Data

[25]:
```
# 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
```

[25]:
```
     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  rooms_per_household  bedrooms_per_room  \
290        NEAR BAY          3             5.761468                NaN
341        NEAR BAY          2             3.830116                NaN
538        NEAR BAY          2             4.048704                NaN
563        NEAR BAY          4             6.102740                NaN
696        NEAR BAY          3             4.633540                NaN

     population_per_household
290                  2.614679
341                  2.826255
538                  2.938727
563                  2.630137
696                  2.403727
```

[26]:
```
sample_incomplete_rows.dropna(subset=["total_bedrooms"])    # option 1: simply␣
↪drop rows that have null values
```

[26]:
```
Empty DataFrame
Columns: [longitude, latitude, housing_median_age, total_rooms, total_bedrooms,
population, households, median_income, median_house_value, ocean_proximity,
income_cat, rooms_per_household, bedrooms_per_room, population_per_household]
Index: []
```

[27]:
```
sample_incomplete_rows.drop("total_bedrooms", axis=1)       # option 2: drop␣
↪the complete feature
```

[27]:
```
     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

     rooms_per_household  bedrooms_per_room  population_per_household
290             5.761468                NaN                  2.614679
341             3.830116                NaN                  2.826255
538             4.048704                NaN                  2.938727
563             6.102740                NaN                  2.630137
696             4.633540                NaN                  2.403727
```

[28]:
```
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
```

[28]:
```
     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  rooms_per_household  bedrooms_per_room  \
290        NEAR BAY          3             5.761468                NaN
341        NEAR BAY          2             3.830116                NaN
538        NEAR BAY          2             4.048704                NaN
563        NEAR BAY          4             6.102740                NaN
696        NEAR BAY          3             4.633540                NaN

     population_per_household
290                  2.614679
341                  2.826255
538                  2.938727
563                  2.630137
696                  2.403727
```

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

[29]:
```
housing["total_bedrooms"].fillna(median, inplace=True)
```

Could you think of another plausible imputation for this dataset?

[30]:
```
median = housing["bedrooms_per_room"].median()
housing["bedrooms_per_room"].fillna(median, inplace=True)
```

0.6.3 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.

[31]:
```
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()
```

[31]:
```
   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
```

0.6.4 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!

[32]:
```
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]
```

[33]:
```
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()
```

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

0.6.5 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.

[35]:
```
from sklearn.linear_model import LinearRegression

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

[35]:
```
LinearRegression()
```

[36]:
```python
# 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: [423969.88487578 298939.35075414 227783.64452614 185030.00931653
 244874.28030822]
Actual labels: [500001.0, 162500.0, 204600.0, 159700.0, 184000.0]
```

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

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

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

[37]:
```python
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
```

[37]:
```
67538.56731651393
```

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

[38]:
```python
import pandas as pd
import os
import sys
assert sys.version_info >= (3, 5) # python>=3.5
```

```python
import sklearn
assert sklearn.__version__ >= "0.20" # sklearn >= 0.20

import numpy as np #numerical package in python

# 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
import plotly.express as px
```

[39]:
```python
# NOTE TO GRADER, I WAS NOT ABLE TO PROPERLY EXPORT PLOTLY GRAPHS TO PDF, SO I␣
↪HAVE ADDED THEIR PNGS AT THE END OF THE DOCUMENT.
# NOTE TO GRADER, I WAS NOT ABLE TO PROPERLY EXPORT PLOTLY GRAPHS TO PDF, SO I␣
↪HAVE ADDED THEIR PNGS AT THE END OF THE DOCUMENT.
# NOTE TO GRADER, I WAS NOT ABLE TO PROPERLY EXPORT PLOTLY GRAPHS TO PDF, SO I␣
↪HAVE ADDED THEIR PNGS AT THE END OF THE DOCUMENT.
# NOTE TO GRADER, I WAS NOT ABLE TO PROPERLY EXPORT PLOTLY GRAPHS TO PDF, SO I␣
↪HAVE ADDED THEIR PNGS AT THE END OF THE DOCUMENT.
# NOTE TO GRADER, I WAS NOT ABLE TO PROPERLY EXPORT PLOTLY GRAPHS TO PDF, SO I␣
↪HAVE ADDED THEIR PNGS AT THE END OF THE DOCUMENT.
# NOTE TO GRADER, I WAS NOT ABLE TO PROPERLY EXPORT PLOTLY GRAPHS TO PDF, SO I␣
↪HAVE ADDED THEIR PNGS AT THE END OF THE DOCUMENT.
```

[40]:
```python
#1 Load the dataset
AIRBNB_PATH = os.path.join("datasets","airbnb","AB_NYC_2019.csv")
airbnb = pd.read_csv(AIRBNB_PATH)
```

[41]:
```python
#2 Display the first few rows of the data
airbnb.head()
```

[41]:
```
     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
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
```

[42]:
```python
#3 Drop the following columns:name, host_id, host_name, last_review,␣
↪neighbourhood
airbnb_modified = airbnb.drop(["name", "host_id", "host_name", "last_review"],␣
↪axis=1)
```

[43]:
```python
#4 Display a summary of the statistics of the loaded data
airbnb_modified.describe()
```

[43]:
```
                 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
```

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)####

[44]:
```
airbnb_modified["neighbourhood_group"].value_counts()
```

[44]:
```
Manhattan        21661
Brooklyn         20104
Queens            5666
Bronx             1091
Staten Island      373
Name: neighbourhood_group, dtype: int64
```

[45]:
```
#Pie chart showing the distribution of rental units acroos NYC's 5 Buroughs
fig = px.pie(airbnb_modified, names='neighbourhood_group', title='The␣
 ↪distribution of rental units across NYC\'s 5 Buroughs')
fig.show()
```

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

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

[46]:
```
#1 Sum up reviews
bar_data = airbnb_modified.groupby("neighbourhood_group")["number_of_reviews"].
 ↪count()
```

[47]:
```
#2 Plot the bar graph
fig = px.bar(bar_data, y = "number_of_reviews", title = " Number of reviews per␣
 ↪neighbourhood_group")
fig.show()
```

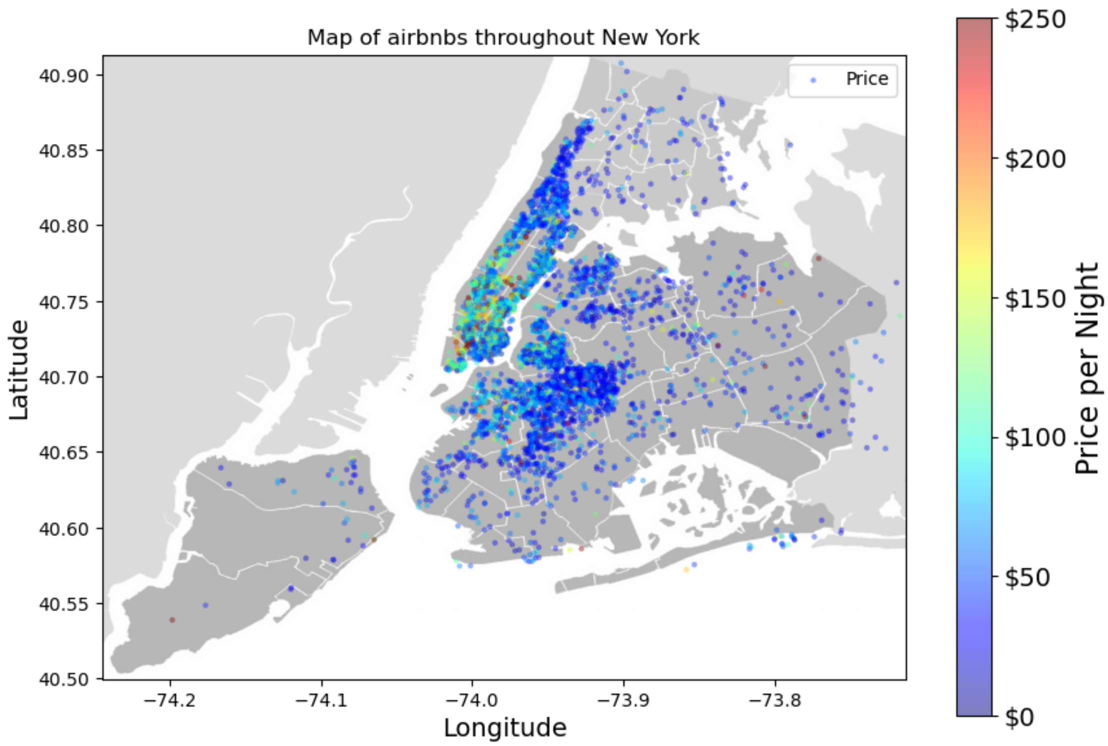
2.0.3 Plot a map of airbnbs throughout New York (if it gets too crowded take a subset of the data, and try to make it look nice if you can :)).

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

[48]:
```
sampled_airbnb = airbnb_modified.sample(frac = 0.1) # shuffling data and taking␣
 ↪subset of the data
```

[49]:
```
# Cutting of the price at value 500 for better map plot.
sampled_airbnb["price"][sampled_airbnb["price"] >= 500] = 500
```

[50]:
```
import matplotlib.image as mpimg
NYC_IMAGE_PATH = os.path.join("images","nyc.png")
nyc_img=mpimg.imread(NYC_IMAGE_PATH)

ax = sampled_airbnb.plot(kind="scatter", x="longitude", y="latitude",
                          figsize=(10,7), label="Price", s = 5,
                          cmap=plt.get_cmap("jet"),colorbar=False, c = "price"
                          ,alpha=0.3)
# 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.
summary_airbnb = airbnb_modified.describe()
lon_min = summary_airbnb["longitude"]["min"]
lon_max = summary_airbnb["longitude"]["max"]
lat_min = summary_airbnb["latitude"]["min"]
lat_max = summary_airbnb["latitude"]["max"]
plt.imshow(nyc_img,extent=[lon_min, lon_max, lat_min, lat_max], alpha = 0.5,
           cmap=plt.get_cmap("jet"))
plt.ylabel("Latitude", fontsize=14)
plt.xlabel("Longitude", fontsize=14)
plt.title("Map of airbnbs throughout New York")

prices = sampled_airbnb["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()
```



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

[51]:
```
from PIL import Image
fig = px.scatter(sampled_airbnb, x="longitude", y="latitude",color = "price",␣
 ↪title = "Map of Airbnbs throughout New York")
import base64
#set a local image as a background
plotly_logo = base64.b64encode(open(NYC_IMAGE_PATH, 'rb').read())

fig.update_layout(
                images= [dict(
                    source='data:image/png;base64,{}'.format(plotly_logo.
 ↪decode()),
                    xref="paper", yref="paper",
                    x=0, y=1,
                    sizex=1, sizey=1,
                    xanchor="left",
                    yanchor="top",
                    sizing="stretch",
                    layer="below")])

summary_airbnb = airbnb_modified.describe()
```

```
lon_min = summary_airbnb["longitude"]["min"]
lon_max = summary_airbnb["longitude"]["max"]
lat_min = summary_airbnb["latitude"]["min"]
lat_max = summary_airbnb["latitude"]["max"]
fig.update_xaxes(range=[lon_min, lon_max])
fig.update_yaxes(range=[lat_min, lat_max])

fig.show()
```

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

[52]:
```
# Filter the data by neighborhood group and number of reviews to arrive at the␣
↪subset of data relevant to this graph.
brooklyn_airbnb = airbnb_modified.loc[airbnb_modified["neighbourhood_group"] ==␣
↪"Brooklyn"]
at_least_10_brooklyn_airbnb = brooklyn_airbnb.
↪loc[brooklyn_airbnb["number_of_reviews"] >= 10]
```

[53]:
```
#Groupby the room type
grouped_data = at_least_10_brooklyn_airbnb[["room_type", "price"]].
↪groupby("room_type")
```

[54]:
```
#take the mean
averaged_grouped_data = grouped_data.mean()
```

[55]:
```
#plot the result
fig = px.bar(averaged_grouped_data, title = "Average price of rooms in Brooklyn␣
↪who have at least 10 Reviews")
fig.show()
```

3 Prepare the Data

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

[56]:
```
# assign each bin a categorical value [1, 2, 3, 4, 5] in this case.
airbnb_modified["price_cat"] = pd.cut(airbnb_modified["price"],
                                      bins=[-1, 50, 100, 250, 1000, 20000],
                                      labels=[1, 2, 3, 4, 5])

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

[56]:
```
3    19759
2    17367
1     6561
4     4969
5      239
Name: price_cat, dtype: int64
```

Now engineer at least one new feature.

[57]:
```
# Computing maximum number of stays from availability and minimum nights can be␣
↪useful.
airbnb_modified["maximum_stays"] = airbnb_modified["availability_365"] /␣
↪airbnb_modified["minimum_nights"]
```

[58]:
```
airbnb_modified.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 14 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              48895 non-null  int64
 1   neighbourhood_group             48895 non-null  object
 2   neighbourhood                   48895 non-null  object
 3   latitude                        48895 non-null  float64
 4   longitude                       48895 non-null  float64
 5   room_type                       48895 non-null  object
 6   price                           48895 non-null  int64
 7   minimum_nights                  48895 non-null  int64
 8   number_of_reviews               48895 non-null  int64
 9   reviews_per_month               38843 non-null  float64
 10  calculated_host_listings_count  48895 non-null  int64
 11  availability_365                48895 non-null  int64
 12  price_cat                       48895 non-null  category
 13  maximum_stays                   48895 non-null  float64
dtypes: category(1), float64(4), int64(6), object(3)
memory usage: 4.9+ MB
```

3.0.2 Data Imputation

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

```
[59]: #reviews_per_month feature has null values only when number_of_reviews are 0,␣
      ↪so it is wise to fill reviews_per_month with 0.
      airbnb_modified[airbnb_modified.isnull().any(axis=1)].head()
```

```
[59]:        id neighbourhood_group       neighbourhood  latitude  longitude  \
      2    3647           Manhattan              Harlem  40.80902  -73.94190
      19   7750           Manhattan         East Harlem  40.79685  -73.94872
      26   8700           Manhattan              Inwood  40.86754  -73.92639
      36  11452            Brooklyn  Bedford-Stuyvesant  40.68876  -73.94312
      38  11943            Brooklyn            Flatbush  40.63702  -73.96327

               room_type  price  minimum_nights  number_of_reviews  \
      2     Private room    150               3                  0
      19 Entire home/apt    190               7                  0
      26    Private room     80               4                  0
      36    Private room     35              60                  0
      38    Private room    150               1                  0

          reviews_per_month  calculated_host_listings_count  availability_365  \
      2                 NaN                               1               365
      19                NaN                               2               249
      26                NaN                               1                 0
      36                NaN                               1               365
      38                NaN                               1               365

         price_cat  maximum_stays
      2          3     121.666667
      19         3      35.571429
      26         2       0.000000
      36         1       6.083333
      38         3     365.000000
```

```
[60]: airbnb_modified["reviews_per_month"].fillna(0,inplace = True)
```

```
[61]: airbnb_modified[airbnb_modified.isnull().any(axis=1)].head() #there is no null␣
      ↪value left.
```

```
[61]: Empty DataFrame
      Columns: [id, neighbourhood_group, neighbourhood, latitude, longitude,
      room_type, price, minimum_nights, number_of_reviews, reviews_per_month,
      calculated_host_listings_count, availability_365, price_cat, maximum_stays]
      Index: []
```

3.0.3 Numeric Conversions

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

[62]:
```
airbnb_modified.info()
# Non-numeric features
# 1) neighbourhood_group
# 2) neighbourhood
# 3) room_type
# 4) price_cat # new feature created by binning prices
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 14 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              48895 non-null  int64
 1   neighbourhood_group             48895 non-null  object
 2   neighbourhood                   48895 non-null  object
 3   latitude                        48895 non-null  float64
 4   longitude                       48895 non-null  float64
 5   room_type                       48895 non-null  object
 6   price                           48895 non-null  int64
 7   minimum_nights                  48895 non-null  int64
 8   number_of_reviews               48895 non-null  int64
 9   reviews_per_month               48895 non-null  float64
 10  calculated_host_listings_count  48895 non-null  int64
 11  availability_365                48895 non-null  int64
 12  price_cat                       48895 non-null  category
 13  maximum_stays                   48895 non-null  float64
dtypes: category(1), float64(4), int64(6), object(3)
memory usage: 4.9+ MB
```

[63]:
```
from sklearn.preprocessing import LabelEncoder

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

[63]:
```
     id  neighbourhood_group  neighbourhood  latitude  longitude  room_type  \
0  2539                    1            108  40.64749  -73.97237          1
1  2595                    2            127  40.75362  -73.98377          0
```

```
2  3647                        2              94  40.80902  -73.94190          1
3  3831                        1              41  40.68514  -73.95976          0
4  5022                        2              61  40.79851  -73.94399          0

   price  minimum_nights  number_of_reviews  reviews_per_month  \
0    149               1                  9               0.21
1    225               1                 45               0.38
2    150               3                  0               0.00
3     89               1                270               4.64
4     80              10                  9               0.10

   calculated_host_listings_count  availability_365  price_cat  maximum_stays
0                               6               365          2     365.000000
1                               2               355          2     355.000000
2                               1               365          2     121.666667
3                               1               194          1     194.000000
4                               1                 0          1       0.000000
```

4 Prepare data for Machine Learning

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

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

[64]:
```python
from sklearn.model_selection import StratifiedShuffleSplit

split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_index, test_index in split.split(airbnb_modified,␣
 ↪airbnb_modified["neighbourhood_group"]):
    train_set = airbnb_modified.loc[train_index]
    test_set = airbnb_modified.loc[test_index]
```

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

[65]:
```python
airbnb_training_data = train_set.drop("price", axis=1) # drop labels for␣
 ↪training set features
airbnb_training_label = train_set["price"].copy()
```

[66]:
```python
airbnb_test_data = test_set.drop("price", axis=1) # drop labels for test set␣
 ↪features
airbnb_test_label = test_set["price"].copy()
```

5 Fit a model of your choice

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

[67]:

```python
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

lin_reg = LinearRegression()
lin_reg.fit(airbnb_training_data, airbnb_training_label)

train_prediction = lin_reg.predict(airbnb_training_data)
train_mse = mean_squared_error(airbnb_training_label, train_prediction)
print("Train MSE:", train_mse)

test_prediction = lin_reg.predict(airbnb_test_data)
test_mse = mean_squared_error(airbnb_test_label, test_prediction)
print("Test MSE:", test_mse)
```

```
Train MSE: 42298.50070176791
Test MSE: 43045.73995015371
```