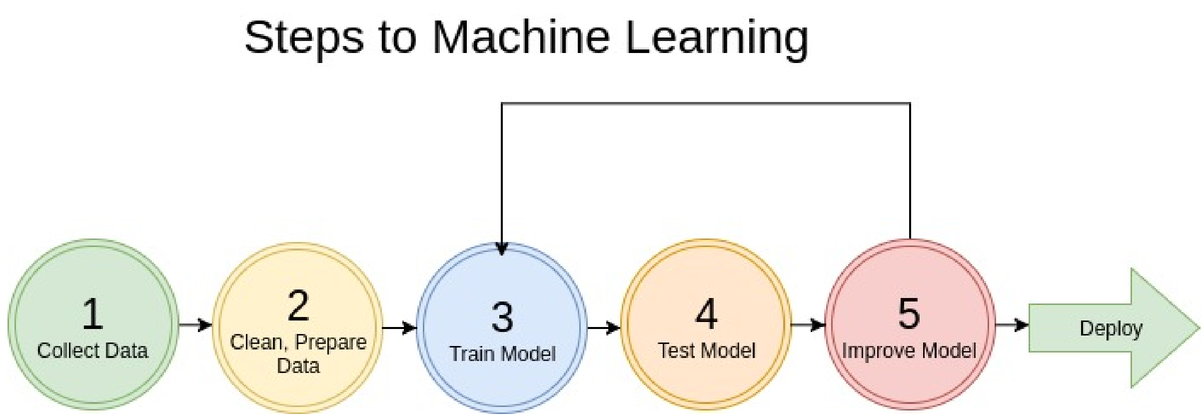
Introduction

Welcome to **CS188 - Data Science Fundamentals!** We plan on having you go through some grueling training so you can start crunching data out there... in today's day and age "data is the new oil" or perhaps "snake oil" nonetheless, there's a lot of it, each with different purity (so pure that perhaps you could feed off it for a life time) or dirty which then at that point you can either decide to dump it or try to weed out something useful (that's where they need you...)

In this project you will work through an example project end to end.

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 model and train
5. Does it meet the requirements? Fine tune the model



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 (http://archive.ics.uci.edu/ml/)
- Kaggle Datasets (kaggle.com)
- AWS Datasets (https://registry.opendata.aws)

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

Setup

In [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
import os
%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

# Where to save the figures
ROOT_DIR = "."
IMAGES_PATH = os.path.join(ROOT_DIR, "images")
os.makedirs(IMAGES_PATH, exist_ok=True)

def save_fig(fig_name, tight_layout=True, fig_extension="png", resolution=300):
    '''
        plt.savefig wrapper. refer to
        https://matplotlib.org/3.1.1/api/_as_gen/matplotlib.pyplot.savefig.html
    '''
    path = os.path.join(IMAGES_PATH, fig_name + "." + fig_extension)
    print("Saving figure", fig_name)
    if tight_layout:
        plt.tight_layout()
    plt.savefig(path, format=fig_extension, dpi=resolution)
```

In [2]:
```
import os
import tarfile
import urllib
DATASET_PATH = os.path.join("datasets", "housing")
```

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 (https://pandas.pydata.org)](https://pandas.pydata.org):** is a fast, flexibile and expressive data structure widely used for tabular and multidimensional datasets.
- **[Matplotlib (https://matplotlib.org)](https://matplotlib.org)**: 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 (https://seaborn.pydata.org)](https://seaborn.pydata.org), [ggplot2 (https://ggplot2.tidyverse.org)](https://ggplot2.tidyverse.org)

In [3]:
```
import pandas as pd

def load_housing_data(housing_path):
    csv_path = os.path.join(housing_path, "housing.csv")
    return pd.read_csv(csv_path)
```

In [4]:
```
housing = load_housing_data(DATASET_PATH) # we load the pandas dataframe
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
```

Out[4]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	medi
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	

A dataset may have different types of features

- real valued
- Discrete (integers)
- categorical (strings)

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.

In [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):
longitude             20640 non-null float64
latitude              20640 non-null float64
housing_median_age    20640 non-null float64
total_rooms           20640 non-null float64
total_bedrooms        20433 non-null float64
population            20640 non-null float64
households            20640 non-null float64
median_income         20640 non-null float64
median_house_value    20640 non-null float64
ocean_proximity       20640 non-null object
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

In [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..
```

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

In [7]:

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

Out[7]:

```
longitude                -122.22
latitude                   37.86
housing_median_age            21
total_rooms                 7099
total_bedrooms              1106
population                  2401
households                  1138
median_income             8.3014
median_house_value        358500
ocean_proximity         NEAR BAY
Name: 1, dtype: object
```

In [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()
```

Out[8]:

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

In [9]:

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

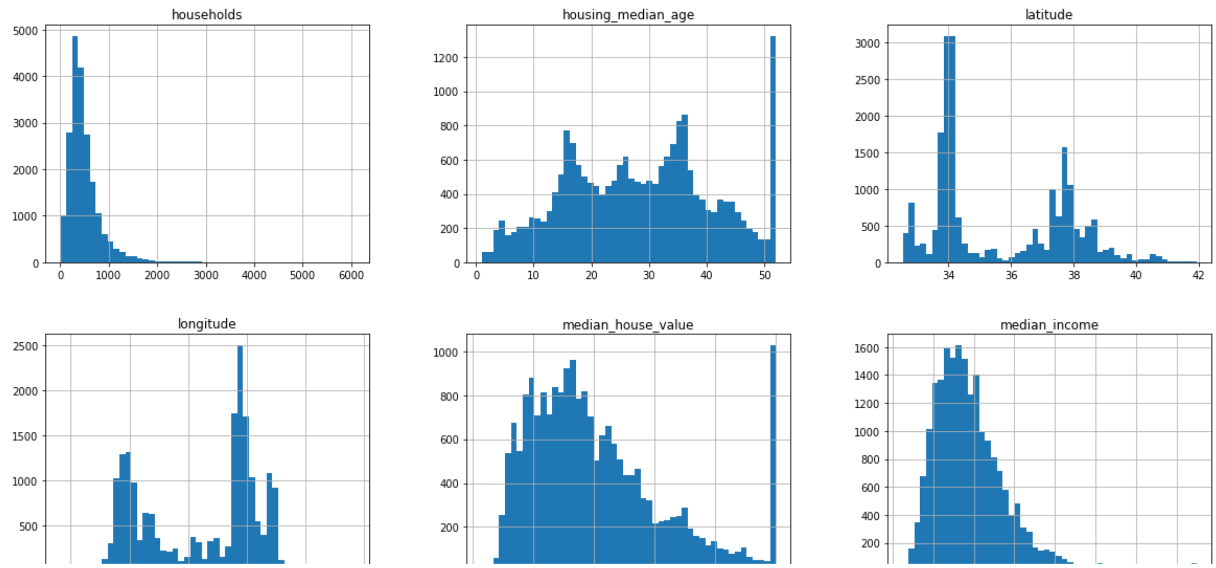
Out[9]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	me
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000000	20640.000000	2
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744	499.539680	
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462122	382.329753	
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000	1.000000	
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000000	280.000000	
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000000	409.000000	
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000000	605.000000	
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000000	6082.000000	

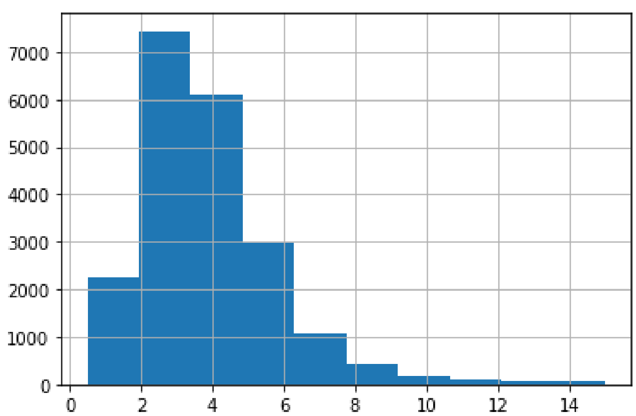
If you want to learn about different ways of accessing elements or other functions it's useful to check out the getting started section [here (https://pandas.pydata.org/pandas-docs/stable/getting_started/index.html)](https://pandas.pydata.org/pandas-docs/stable/getting_started/index.html)

Let's start visualizing the dataset

In [10]:
```python
# We can draw a histogram for each of the dataframes features
# using the hist function
housing.hist(bins=50, figsize=(20,15))
# save_fig("attribute_histogram_plots")
plt.show() # pandas internally uses matplotlib, and to display all the figures
           # the show() function must be called
```



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



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

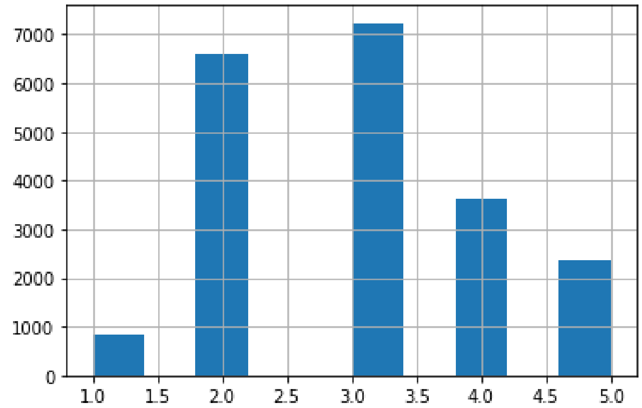
For example, to bin the households based on median_income we can use the pd.cut function

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

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

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

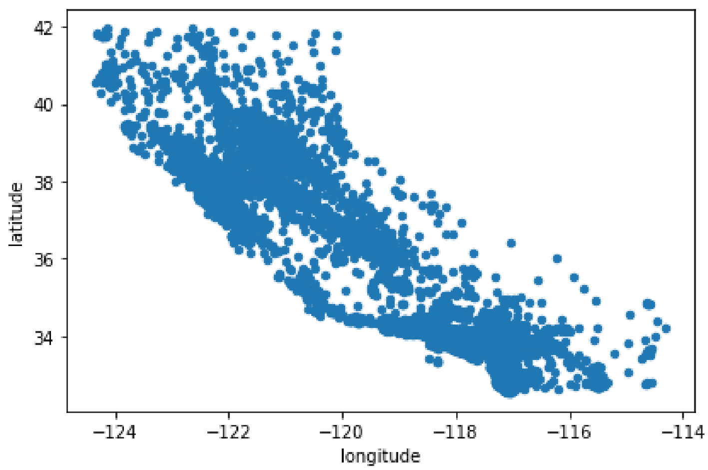
Out[13]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2b7b4db4c08>
```



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

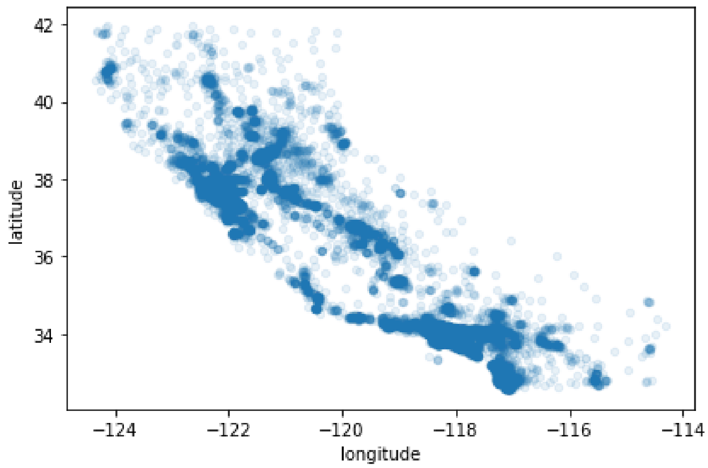
In [14]:
```
## here's a not so interestting way plotting it
housing.plot(kind="scatter", x="longitude", y="latitude")
save_fig("bad_visualization_plot")
```

```
Saving figure bad_visualization_plot
```



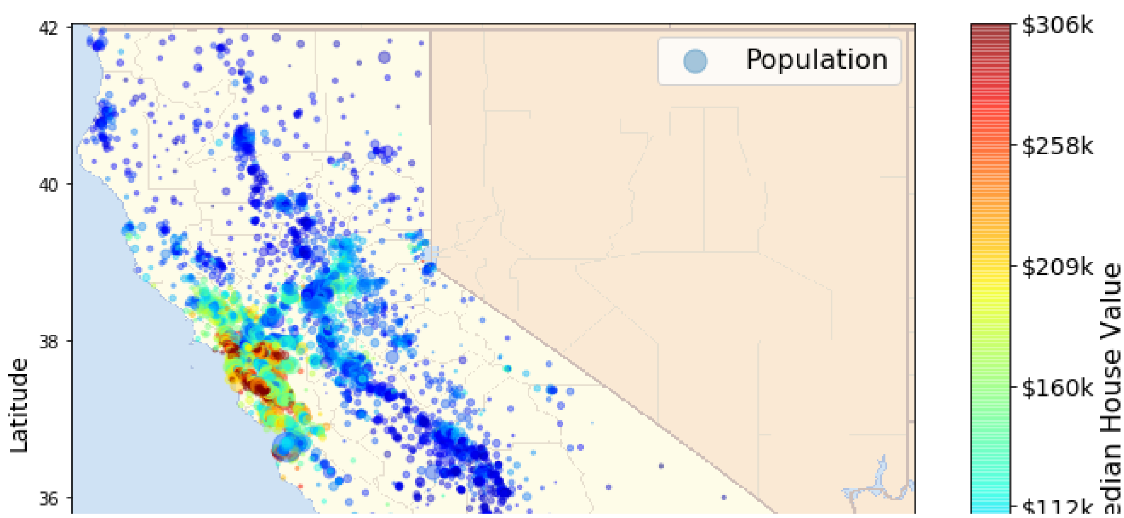
In [15]:
```
# we can make it look a bit nicer by using the alpha parameter,
# it simply plots less dense areas lighter.
housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.1)
save_fig("better_visualization_plot")
```

```
Saving figure better_visualization_plot
```



In [16]:
```
# A more interesting plot is to color code (heatmap) the dots
# based on income. The code below achieves this

# Load an image of california
images_path = os.path.join('./', "images")
os.makedirs(images_path, exist_ok=True)
filename = "california.png"

import matplotlib.image as mpimg
california_img=mpimg.imread(os.path.join(images_path, filename))
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)
save_fig("california_housing_prices_plot")
plt.show()
```

```
Saving figure california_housing_prices_plot
```



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.

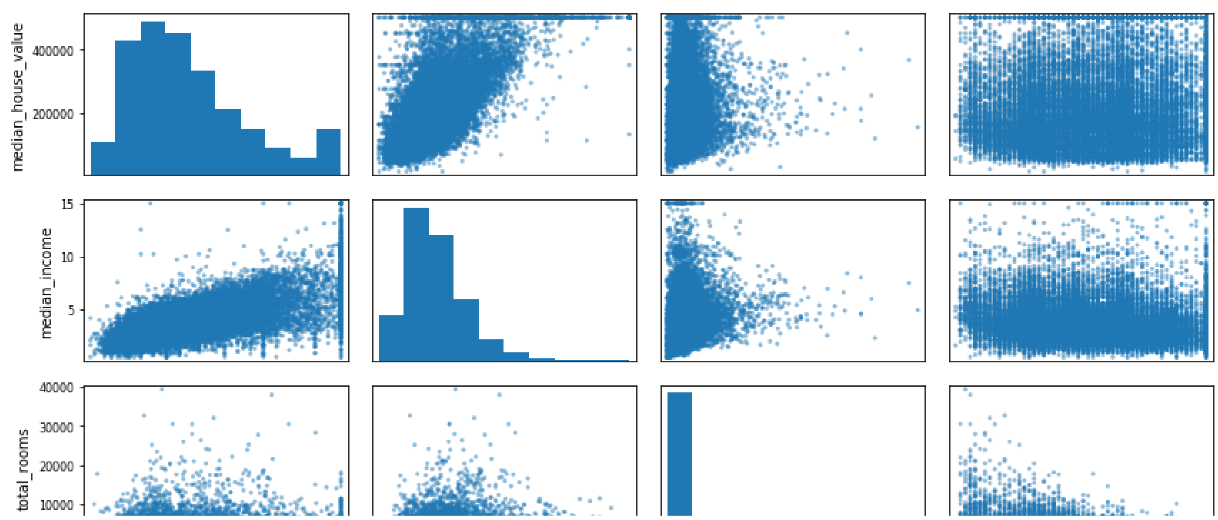
In [17]:
```
corr_matrix = housing.corr()
```

In [18]:
```
# 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)
```

Out[18]:
```
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
```

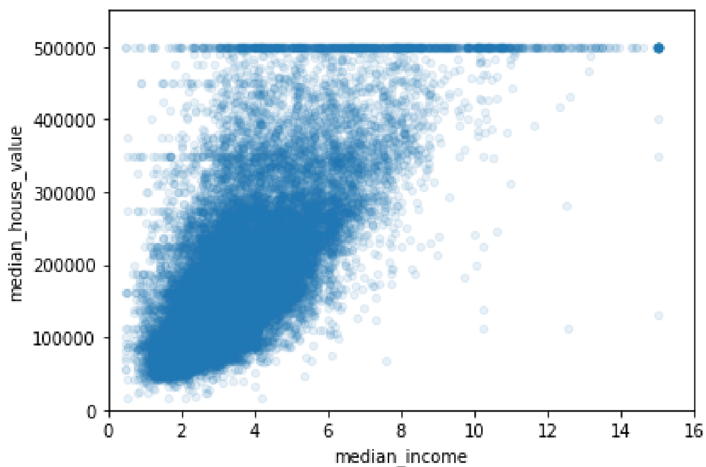
In [19]:
```
# the correlation matrix for different attributes/features can also be plotted
# some features may show a positive correlation/negative correlation or
# it may turn out to be completely random!
from pandas.plotting import scatter_matrix
attributes = ["median_house_value", "median_income", "total_rooms",
              "housing_median_age"]
scatter_matrix(housing[attributes], figsize=(12, 8))
save_fig("scatter_matrix_plot")
```

```
Saving figure scatter_matrix_plot
```



In [20]:
```
# 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])
save_fig("income_vs_house_value_scatterplot")
```

```
Saving figure income_vs_house_value_scatterplot
```



Augmenting Features

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

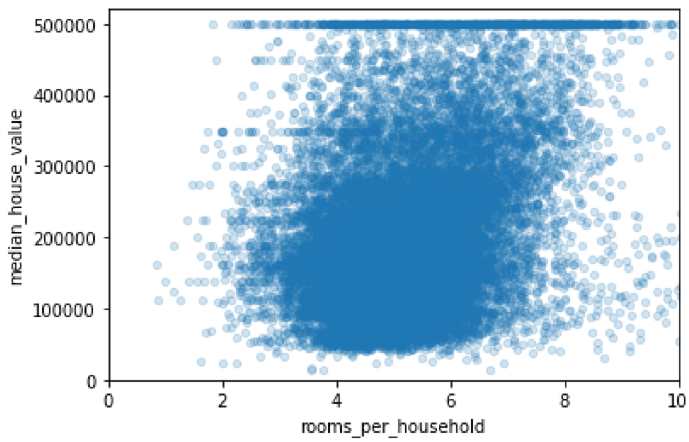
- rooms_per_household = total_rooms / households
- bedrooms_per_room = total_bedrooms / total_rooms
- etc.

In [21]:
```
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"]
```

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

Out[22]:
```
median_house_value          1.000000
median_income               0.688075
rooms_per_household         0.151948
total_rooms                 0.134153
housing_median_age          0.105623
households                  0.065843
total_bedrooms              0.049686
population_per_household   -0.023737
population                 -0.024650
longitude                  -0.045967
latitude                   -0.144160
bedrooms_per_room          -0.255880
Name: median_house_value, dtype: float64
```

In [23]:
```
housing.plot(kind="scatter", x="rooms_per_household", y="median_house_value",
             alpha=0.2)
plt.axis([0, 10, 0, 520000])
plt.show()
```



In [24]:
```
housing.describe()
```

Out[24]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	me
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000000	20640.000000	2
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744	499.539680	
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462122	382.329753	
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000	1.000000	
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000000	280.000000	
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000000	409.000000	
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000000	605.000000	
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000000	6082.000000	

Preparing Dastaset for ML

Once we've visualized the data, and have a certain understanding of how the data looks like. It's time to clean!

Most of your time will be spent on this step, although the datasets used in this project are relatively nice and clean... it could get real dirty.

After having cleaned your dataset you're aiming for:

- 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 (https://scikit-learn.org/stable/)](https://scikit-learn.org/stable/) python package for preprocessing.

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

In [25]:
```
from sklearn.model_selection import StratifiedShuffleSplit
# let's first start by creating our train and test sets
split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_index, test_index in split.split(housing, housing["income_cat"]):
    train_set = housing.loc[train_index]
    test_set = housing.loc[test_index]
```

In [26]:
```
housing = train_set.drop("median_house_value", axis=1) # drop labels for training set features
                                                       # the input to the model should not contai
housing_labels = train_set["median_house_value"].copy()
```

Dealing With Incomplete Data

In [27]:
```
# 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
```

Out[27]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income
4629	-118.30	34.07	18.0	3759.0	NaN	3296.0	1462.0	2.2708
6068	-117.86	34.01	16.0	4632.0	NaN	3038.0	727.0	5.1762
17923	-121.97	37.35	30.0	1955.0	NaN	999.0	386.0	4.6328
13656	-117.30	34.05	6.0	2155.0	NaN	1039.0	391.0	1.6675
19252	-122.79	38.48	7.0	6837.0	NaN	3468.0	1405.0	3.1662

In [28]:
```
sample_incomplete_rows.dropna(subset=["total_bedrooms"])    # option 1: simply drop rows that hav
```

Out[28]:

longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean

In [29]:
```
sample_incomplete_rows.drop("total_bedrooms", axis=1)       # option 2: drop the complete feature
```

Out[29]:

	longitude	latitude	housing_median_age	total_rooms	population	households	median_income	ocean_proximity
4629	-118.30	34.07	18.0	3759.0	3296.0	1462.0	2.2708	<1H OCEAN
6068	-117.86	34.01	16.0	4632.0	3038.0	727.0	5.1762	<1H OCEAN
17923	-121.97	37.35	30.0	1955.0	999.0	386.0	4.6328	<1H OCEAN
13656	-117.30	34.05	6.0	2155.0	1039.0	391.0	1.6675	INLAND
19252	-122.79	38.48	7.0	6837.0	3468.0	1405.0	3.1662	<1H OCEAN

In [30]:
```
median = housing["total_bedrooms"].median()
sample_incomplete_rows["total_bedrooms"].fillna(median, inplace=True) # option 3: replace na valu
sample_incomplete_rows
```

Out[30]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income
4629	-118.30	34.07	18.0	3759.0	433.0	3296.0	1462.0	2.2708
6068	-117.86	34.01	16.0	4632.0	433.0	3038.0	727.0	5.1762
17923	-121.97	37.35	30.0	1955.0	433.0	999.0	386.0	4.6328
13656	-117.30	34.05	6.0	2155.0	433.0	1039.0	391.0	1.6675
19252	-122.79	38.48	7.0	6837.0	433.0	3468.0	1405.0	3.1662

Could you think of another plausible imputation for this dataset? (Not graded)

Prepare Data

In [31]:
```python
# This cell implements the complete pipeline for preparing the data
# using sklearns TransformerMixins
# Earlier we mentioned different types of features: categorical, and floats.
# In the case of floats we might want to convert them to categories.
# On the other hand categories in which are not already represented as integers must be mapped to
# feeding to the model.

# Additionally, categorical values could either be represented as one-hot vectors or simple as no
# Here we encode them using one hot vectors.

from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer

from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder

from sklearn.base import BaseEstimator, TransformerMixin


imputer = SimpleImputer(strategy="median") # use median imputation for missing values
housing_num = housing.drop("ocean_proximity", axis=1) # remove the categorical feature
# column index
rooms_ix, bedrooms_ix, population_ix, households_ix = 3, 4, 5, 6

#
class AugmentFeatures(BaseEstimator, TransformerMixin):
    '''
    implements the previous features we had defined
    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"]
    '''
    def __init__(self, add_bedrooms_per_room = True):
        self.add_bedrooms_per_room = add_bedrooms_per_room
    def fit(self, X, y=None):
        return self  # nothing else to do
    def transform(self, X):
        rooms_per_household = X[:, rooms_ix] / X[:, households_ix]
        population_per_household = X[:, population_ix] / X[:, households_ix]
        if self.add_bedrooms_per_room:
            bedrooms_per_room = X[:, bedrooms_ix] / X[:, rooms_ix]
            return np.c_[X, rooms_per_household, population_per_household,
                         bedrooms_per_room]
        else:
            return np.c_[X, rooms_per_household, population_per_household]

attr_adder = AugmentFeatures(add_bedrooms_per_room=False)
housing_extra_attribs = attr_adder.transform(housing.values)

num_pipeline = Pipeline([
        ('imputer', SimpleImputer(strategy="median")),
        ('attribs_adder', AugmentFeatures()),
        ('std_scaler', StandardScaler()),
    ])

housing_num_tr = num_pipeline.fit_transform(housing_num)
numerical_features = list(housing_num)
categorical_features = ["ocean_proximity"]

full_pipeline = ColumnTransformer([
        ("num", num_pipeline, numerical_features),
        ("cat", OneHotEncoder(), categorical_features),
    ])

housing_prepared = full_pipeline.fit_transform(housing)
```

Select a model and train

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

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

In [32]:
```
from sklearn.linear_model import LinearRegression

lin_reg = LinearRegression()
lin_reg.fit(housing_prepared, housing_labels)

# let's try the full preprocessing pipeline on a few training instances
data = test_set.iloc[:5]
labels = housing_labels.iloc[:5]
data_prepared = full_pipeline.transform(data)

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

```
Predictions: [425717.48517515 267643.98033218 227366.19892733 199614.48287493
 161425.25185885]
Actual labels: [286600.0, 340600.0, 196900.0, 46300.0, 254500.0]
```

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

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

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

In [33]:
```
from sklearn.metrics import mean_squared_error

preds = lin_reg.predict(housing_prepared)
mse = mean_squared_error(housing_labels, preds)
rmse = np.sqrt(mse)
rmse
```

Out[33]:
```
67784.32202861732
```

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

We will apply what we've learnt to another dataset (airbnb dataset). We will predict airbnb price based on other features.

[25 pts] Visualizing Data

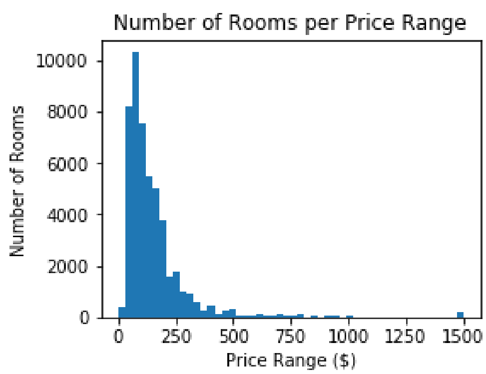
[5 pts] Load the data + statistics

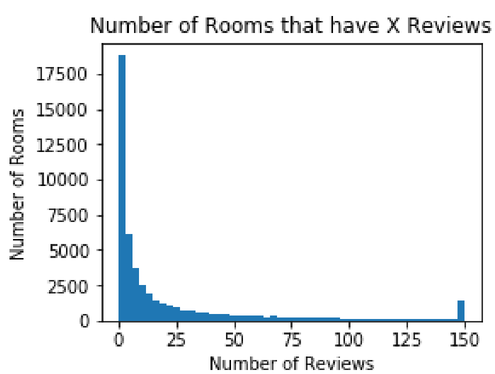
- load the dataset
- display the first few rows of the data
- drop the following columns: name, host_id, host_name, last_review
- display a summary of the statistics of the loaded data
- plot histograms for 3 features of your choice

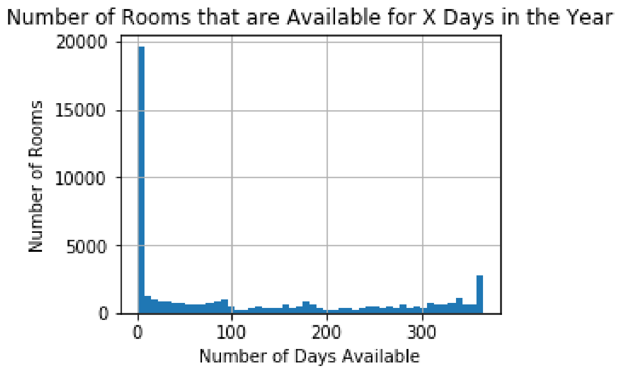
In [8]:
```
import os
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

#load the dataset
DATASET_PATH = os.path.join("datasets", "airbnb")

def load_airbnb_data(airbnb_path):
    csv_path = os.path.join(airbnb_path, "AB_NYC_2019.csv")
    return pd.read_csv(csv_path)

airbnb = load_airbnb_data(DATASET_PATH)

#display the first few rows of the data
print(airbnb.head())

#drop the listed columns
airbnb_data = airbnb.drop(["name", "host_id", "host_name", "last_review"], axis=1)

#display a summary of the statistics of the loaded data
print(airbnb_data.describe())

#plot histograms for price, number_of_reviews and availability_365
#values greater than 1500 are aggregated into the last bin
np.clip(airbnb_data["price"], 0, 1500).hist(bins=50, figsize=(4,3), grid=False)
plt.title("Number of Rooms per Price Range")
plt.xlabel("Price Range ($)")
plt.ylabel("Number of Rooms")
plt.show()

#values greater than 150 are aggregated into the last bin
np.clip(airbnb_data["number_of_reviews"], 0, 150).hist(bins=50, figsize=(4,3), grid=False)
plt.title("Number of Rooms that have X Reviews")
plt.xlabel("Number of Reviews")
plt.ylabel("Number of Rooms")
plt.show()


airbnb_data["availability_365"].hist(bins=50, figsize=(4,3))
plt.title("Number of Rooms that are Available for X Days in the Year")
plt.xlabel("Number of Days Available")
plt.ylabel("Number of Rooms")
plt.show()
```

```
     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
                 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
```



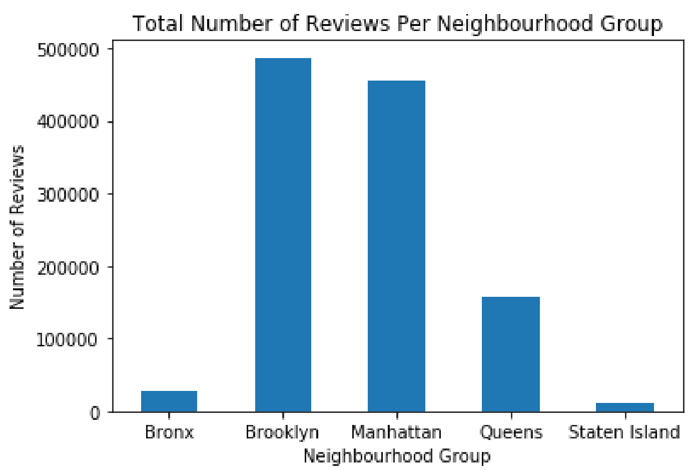




[5 pts] Plot total number_of_reviews per neighbourhood_group

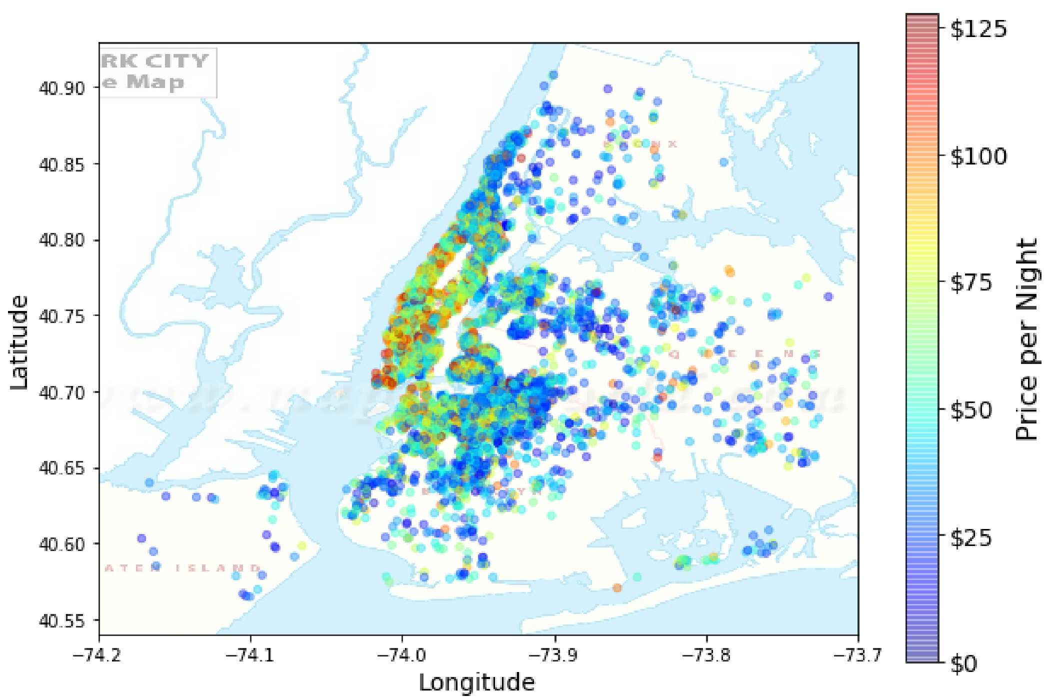
In [4]:
```
sum_neighbourhood_grps = airbnb_data.groupby("neighbourhood_group").sum()
sum_neighbourhood_grps = sum_neighbourhood_grps.reset_index()
sum_neighbourhood_grps.plot.bar(x="neighbourhood_group",
                                y="number_of_reviews",
                                rot=0,
                                legend=False)
plt.xlabel("Neighbourhood Group")
plt.ylabel("Number of Reviews")
plt.title("Total Number of Reviews Per Neighbourhood Group")
```

Out[4]:
```
Text(0.5, 1.0, 'Total Number of Reviews Per Neighbourhood Group')
```



[5 pts] Plot 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 :)).

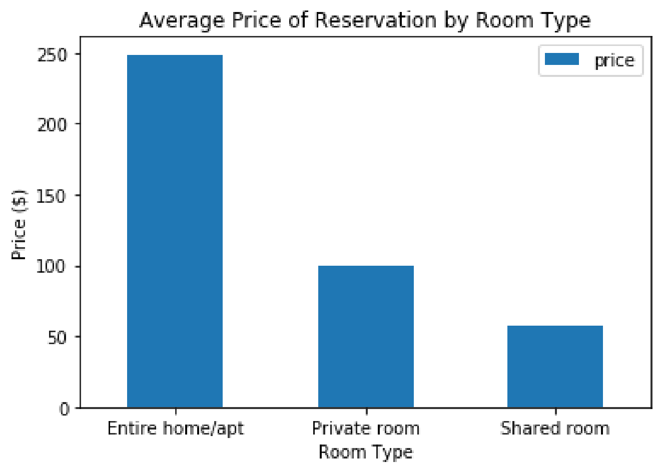
In [5]:
```
images_path = os.path.join("./", "images")
os.makedirs(images_path, exist_ok=True)
filename = "new_york_city_1.jpg"

import matplotlib.image as mpimg
nyc_img = mpimg.imread(os.path.join(images_path, filename))

sample_airbnb_data = airbnb_data.sample(frac=0.15)

#any price greater than $250 is set to $250, so it is aggregated into
#the same price category and shows up as the same color
sample_airbnb_data[sample_airbnb_data["price"] >= 250] = 250
ax = sample_airbnb_data.plot(kind="scatter", x="longitude",
                             y="latitude", figsize=(10,7),
                             cmap=plt.get_cmap("jet"), c="price",
                             colorbar=False, alpha=0.4)

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

prices = sample_airbnb_data["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()
```



[5 pts] Plot average price of room types who have availability greater than 180 days.

In [32]:
```
avg_room_type_prices = airbnb_data.where(airbnb_data["availability_365"] >
                                         180).groupby("room_type").mean()
avg_room_type_prices = avg_room_type_prices.reset_index()
avg_room_type_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")
```

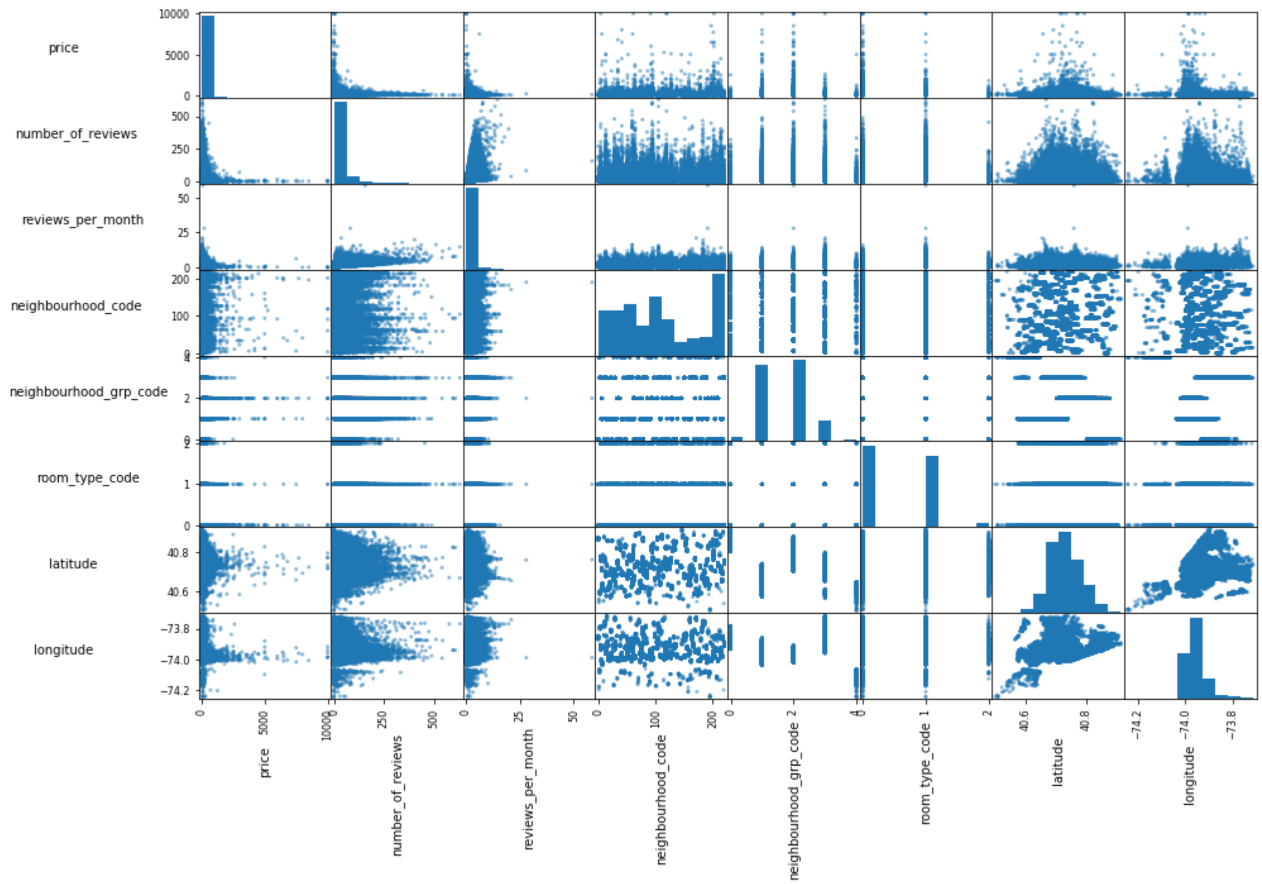
Out[32]:
```
Text(0.5, 1.0, 'Average Price of Reservation by Room Type')
```



[5 pts] Plot correlation matrix

- which features have positive correlation?
- which features have negative correlation?

In [7]:
```
from pandas.plotting import scatter_matrix
from matplotlib.artist import setp

#wanted to see correlation between price and neighbourhood, as well as price and
#room type, so enumerated values
airbnb_data.neighbourhood = pd.Categorical(airbnb_data.neighbourhood)
airbnb_data["neighbourhood_code"] = airbnb_data.neighbourhood.cat.codes

airbnb_data.neighbourhood_group = pd.Categorical(airbnb_data.neighbourhood_group)
airbnb_data["neighbourhood_grp_code"] = airbnb_data.neighbourhood_group.cat.codes

airbnb_data.room_type = pd.Categorical(airbnb_data.room_type)
airbnb_data["room_type_code"] = airbnb_data.room_type.cat.codes

attributes = ["price", "number_of_reviews",
              "reviews_per_month", "neighbourhood_code",
              "neighbourhood_grp_code", "room_type_code",
              "latitude", "longitude"]
matrix = scatter_matrix(airbnb_data[attributes], figsize=(15, 10))
for x in range(len(attributes)):
    for y in range(len(attributes)):
        ax = matrix[x, y]
        ax.xaxis.label.set_rotation(90)
        ax.yaxis.label.set_rotation(0)
        ax.yaxis.labelpad = 75

# Now drop the created columns
airbnb_data.drop("neighbourhood_code", axis=1, inplace=True)
airbnb_data.drop("neighbourhood_grp_code", axis=1, inplace=True)
airbnb_data.drop("room_type_code", axis=1, inplace=True)
```



[25 pts] Prepare the Data

[5 pts] Set aside 20% of the data as test test (80% train, 20% test).

In [26]:
```
from sklearn.model_selection import StratifiedShuffleSplit

split = StratifiedShuffleSplit(n_splits=1, test_size=0.2)
# made a "price_cat" column so we can stratify by this variable
airbnb_data["price_cat"] = pd.cut(airbnb_data["price"],
                                  bins=[-1., 50., 100., 150., 200., 250., 300., 350., np.inf],
                                  labels=[1,2,3,4,5,6,7,8])

for train_index, test_index in split.split(airbnb_data, airbnb_data["price_cat"]):
    train_set = airbnb_data.loc[train_index]
    test_set = airbnb_data.loc[test_index]

# Drop the "price_cat" column because we have used it for StratifiedShuffleSplit
training_data = train_set.drop("price_cat", axis=1)

# Save the labels of the test and training set
airbnb_labels = train_set["price"].copy()
test_labels = test_set["price"].copy()
```

[5 pts] Augment the dataframe with two other features which you think would be useful

In [33]:
```
training_data["lifespan_months"] = airbnb_data["number_of_reviews"] / airbnb_data[
    "reviews_per_month"]
test_set["lifespan_months"] = airbnb_data["number_of_reviews"] / airbnb_data["reviews_per_month"]
training_data["max_stays"] = airbnb_data["availability_365"] / airbnb_data["minimum_nights"]
test_set["max_stays"] = airbnb_data["availability_365"] / airbnb_data["minimum_nights"]

training_data
```

Out[33]:

	neighbourhood_group	neighbourhood	latitude	longitude	room_type	minimum_nights	number_of_reviews
11601	Manhattan	Financial District	40.70776	-74.01514	Entire home/apt	30	2
48297	Queens	Long Island City	40.74717	-73.94254	Entire home/apt	1	0
29257	Brooklyn	Bushwick	40.68868	-73.90655	Private room	3	55
35094	Manhattan	Midtown	40.75497	-73.96289	Entire home/apt	29	0
13442	Brooklyn	Bedford-Stuyvesant	40.68273	-73.94786	Private room	1	18
...	...	...	...	...	...	...	...
30596	Manhattan	Midtown	40.74653	-73.98717	Entire home/apt	1	4

[5 pts] Impute any missing feature with a method of your choice, and briefly discuss why you chose this imputation method

In [28]:
```
training_data["reviews_per_month"].fillna(0, inplace=True)
test_set["reviews_per_month"].fillna(0, inplace=True)

median_lifespan = training_data["lifespan_months"].median()
training_data["lifespan_months"].fillna(median_lifespan, inplace=True)
test_set["lifespan_months"].fillna(median_lifespan, inplace=True)

# check if there exists any row with Null values
#training_data[training_data.isnull().any(axis=1)]
```

In [ ]:
```
# We fill in "reviews_per_month" column with the value 0, because it
# seems that they correspond to the rows where "number_of_reviews"
# value was also 0. Therefore, it makes sense that the row also has 0
# reviews per month.
#
# Next, the "lifespan_months" column is also a null value as it
# calculated using the "reviews_per_month" and "number_of_reviews"
# columns. We replace these values with the median value, because it
# is the most accurate representation of the age/lifespan of the row.
```

[10 pts] Code complete data pipeline using sklearn mixins

In [29]:
```
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer

from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder

from sklearn.base import BaseEstimator, TransformerMixin

imputer = SimpleImputer(strategy="median")

# Dropping "id" and "price" columns
current_columns = training_data.columns.tolist()

if "price" in current_columns:
    training_data.drop("price", axis=1, inplace=True)

if "id" in current_columns:
    training_data.drop("id", axis=1, inplace=True)

# Remove categorical columns
airbnb_num = training_data.copy()
current_columns = airbnb_num.columns.tolist()
categorical_features = []
ng = "neighbourhood_group"
nh = "neighbourhood"
rt = "room_type"
ident = "id"

if ng in current_columns:
    airbnb_num.drop("neighbourhood_group", axis=1, inplace=True)
    categorical_features.append(ng)

if nh in current_columns:
    airbnb_num.drop("neighbourhood", axis=1, inplace=True)
    categorical_features.append(nh)

if rt in current_columns:
    airbnb_num.drop("room_type", axis=1, inplace=True)
    categorical_features.append(rt)

# Get column indices
num_reviews_i, reviews_per_month_i, availability_365_i, min_nights_i = 3, 4, 6, 2

# Augment Features
class AugmentFeatures(BaseEstimator, TransformerMixin):
    def __init__ (self, add_lifespan_months=True, add_min_price=True):
        self.add_lifespan_months = add_lifespan_months
        self.add_min_price = add_min_price
    def fit(self, X, y=None):
        return self
    def transform(self, X):
        ret_val = X
        if self.add_lifespan_months:
            with np.errstate(divide='ignore', invalid='ignore'):
                lifespan_months = np.true_divide(X[:, num_reviews_i], X[:, reviews_per_month_i])
                lifespan_months[lifespan_months == np.inf] = 0
                lifespan_months = np.nan_to_num(lifespan_months)
            ret_val = np.c_[X, lifespan_months]

        if self.add_min_price:
            min_price = X[:, availability_365_i] / X[:, min_nights_i]
            ret_val = np.c_[X, min_price]

        return ret_val

attr_adder = AugmentFeatures()
```

```
airbnb_extra_attribs = attr_adder.transform(airbnb_num.values)

num_pipeline = Pipeline([
    ("imputer", SimpleImputer(strategy="median")),
    ("attribs_adder", AugmentFeatures()),
    ("std_scaler", StandardScaler())
])

airbnb_num_tr = num_pipeline.fit_transform(airbnb_extra_attribs)
numerical_features = list(airbnb_num)

full_pipeline = ColumnTransformer([
    ("num", num_pipeline, numerical_features),
    ("cat", OneHotEncoder(handle_unknown="ignore"), categorical_features)
])

airbnb_prepared = full_pipeline.fit_transform(training_data)
```

[15 pts] Fit a model of your choice

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

In [30]:
```
from sklearn.linear_model import LinearRegression

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

# Try pipeline on a few instances
data = test_set.iloc[:5]
labels = airbnb_labels.iloc[:5]
data_prepared = full_pipeline.transform(data)

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

# Use pipeline on full test data set
from sklearn.metrics import mean_squared_error

predictions_train = lin_reg.predict(airbnb_prepared)
mse = mean_squared_error(airbnb_labels, predictions_train)
rmse = np.sqrt(mse)
print("train mse: {}, train rmse: {}".format(mse, rmse))

current_columns = test_set.columns.tolist()

if "price" in current_columns:
    test_set.drop("price", axis=1, inplace=True)

if "price_cat" in current_columns:
    test_set.drop("price_cat", axis=1, inplace=True)

if "id" in current_columns:
    test_set.drop("id", axis=1, inplace=True)

airbnb_prepared_2 = full_pipeline.transform(test_set)
predictions_test = lin_reg.predict(airbnb_prepared_2)
mse = mean_squared_error(test_labels, predictions_test)
rmse = np.sqrt(mse)
print("test mse: {}, test rmse: {}".format(mse, rmse))
```

```
Predictions: [129.66915388  81.77575092 177.37539874 111.7425667  188.2421434 ]
Actual labels: [169, 200, 55, 204, 55]
train mse: 50337.9727114227, train rmse: 224.3612549247813
test mse: 52716.32476768819, test rmse: 229.6003588143716
```