Introduction

Welcome to **CS188 - Data Science Fundamentals!** This course is designed to equip you with the tools and experiences necessary to start you off on a life-long exploration of datascience. We do not assume a prerequisite knowledge or experience in order to take the course.

For this first project we will introduce you to the end-to-end process of doing a datascience project. Our goals for this project are to:

1. Familiarize you with the development environment for doing datascience
2. Get you comfortable with the python coding required to do datascience
3. Provide you with an sample end-to-end project to help you visualize the steps needed to complete a project on your own
4. Ask you to recreate a similar project on a separate dataset

In this project you will work through an example project end to end. Many of the concepts you will encounter will be unclear to you. That is OK! The course is designed to teach you these concepts in further detail. For now our focus is simply on having you replicate the code successfully and seeing a project through from start to finish.

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

steps

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)

Submission Instructions

When you have completed this assignment please save the notebook as a PDF file and submit the assignment via Gradescope

Example Datascience Exercise

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

Setup

In [175]:

```
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

        Args:
            fig_name (str): name of the figrue
            tight_layout (bool): adjust subplot to fit in the figure area
            fig_extension (str): file format to save the figure in
            resolution (int): figure resolution
    '''
    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 [176]:

```
import os
import tarfile
import urllib
DATASET_PATH = os.path.join("datasets", "housing")
```

Step 1. Getting the data

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

In [177]:

```
import pandas as pd

def load_housing_data(housing_path):
    '''
        loads housing.csv dataset stored

        Args:
            housing_path (str): path to folder containing housing datased

        Returns:
            pd.DataFrame
    '''
    csv_path = os.path.join(housing_path, "housing.csv")
    return pd.read_csv(csv_path)
```

In [178]:

```
pd.DataFrame
```

Out[178]:

```
pandas.core.frame.DataFrame
```

In [179]:

```
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[179]:

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

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 [180]:

```
# 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
```

In [181]:

```
# 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[181]:

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

In [182]:

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

Out[182]:

```
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 [183]:

```
# 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[183]:

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

In [184]:

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

Out[184]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	popula
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000

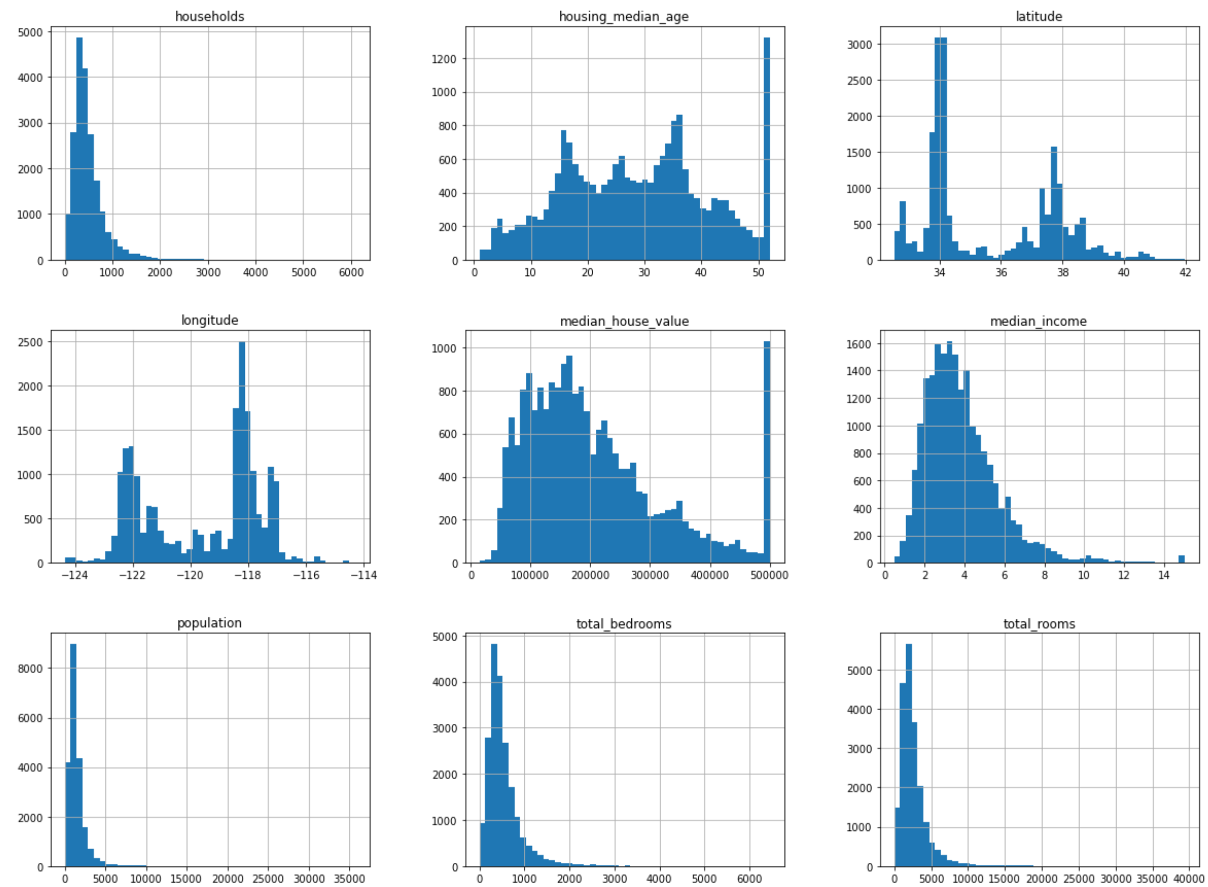
If you want to learn about different ways of accessing elements or other functions it's useful to check out the getting started section [here (https://pandas.pydata.org/pandas-docs/stable/getting_started/index.html)](https://pandas.pydata.org/pandas-docs/stable/getting_started/index.html)

Step 2. Visualizing the data

Let's start visualizing the dataset

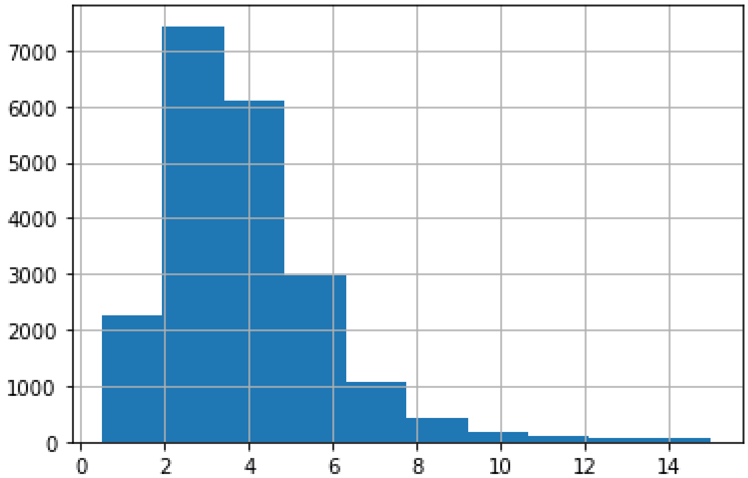
In [185]:

```
# 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 [186]:

```
# 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 [187]:

```
# 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[187]:

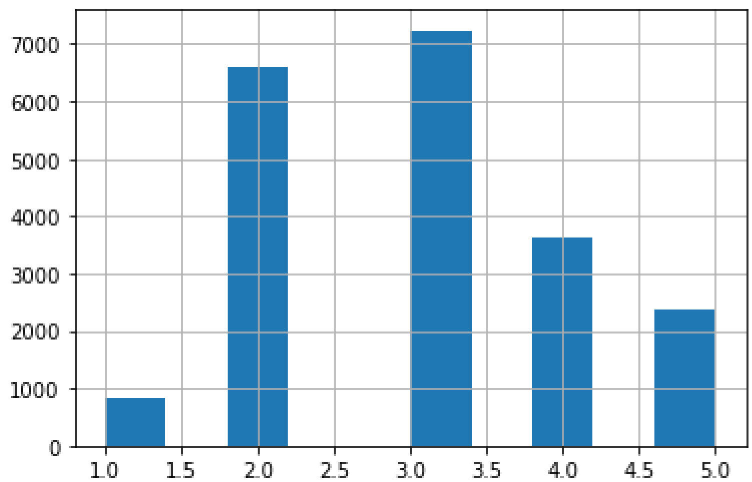
```
3    7236
2    6581
4    3639
5    2362
1     822
Name: income_cat, dtype: int64
```

In [188]:

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

Out[188]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc2302d7af0>
```

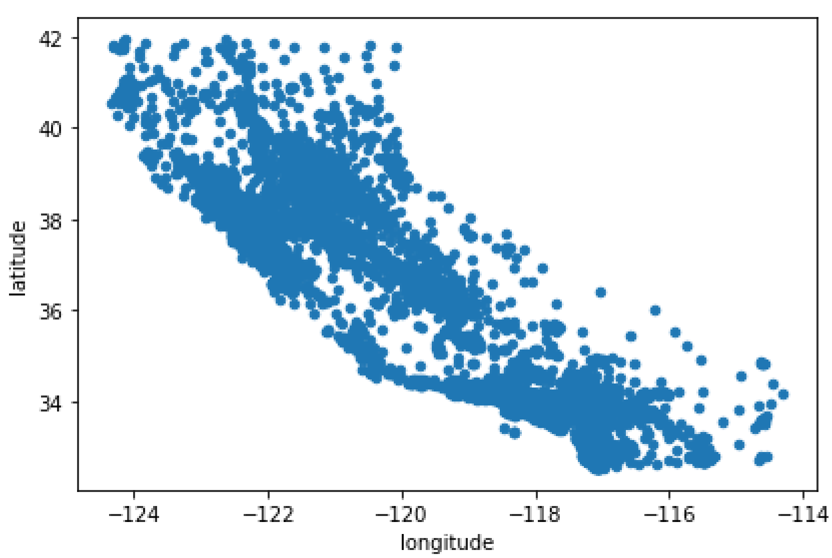


Next let's visualize the household incomes based on latitude & longitude coordinates

In [189]:

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

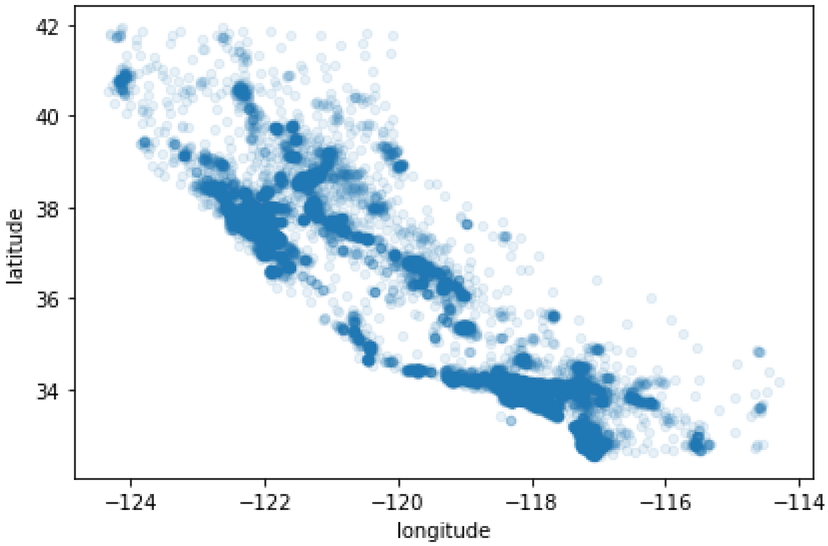
```
Saving figure bad_visualization_plot
```



In [190]:

```
# 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")
```

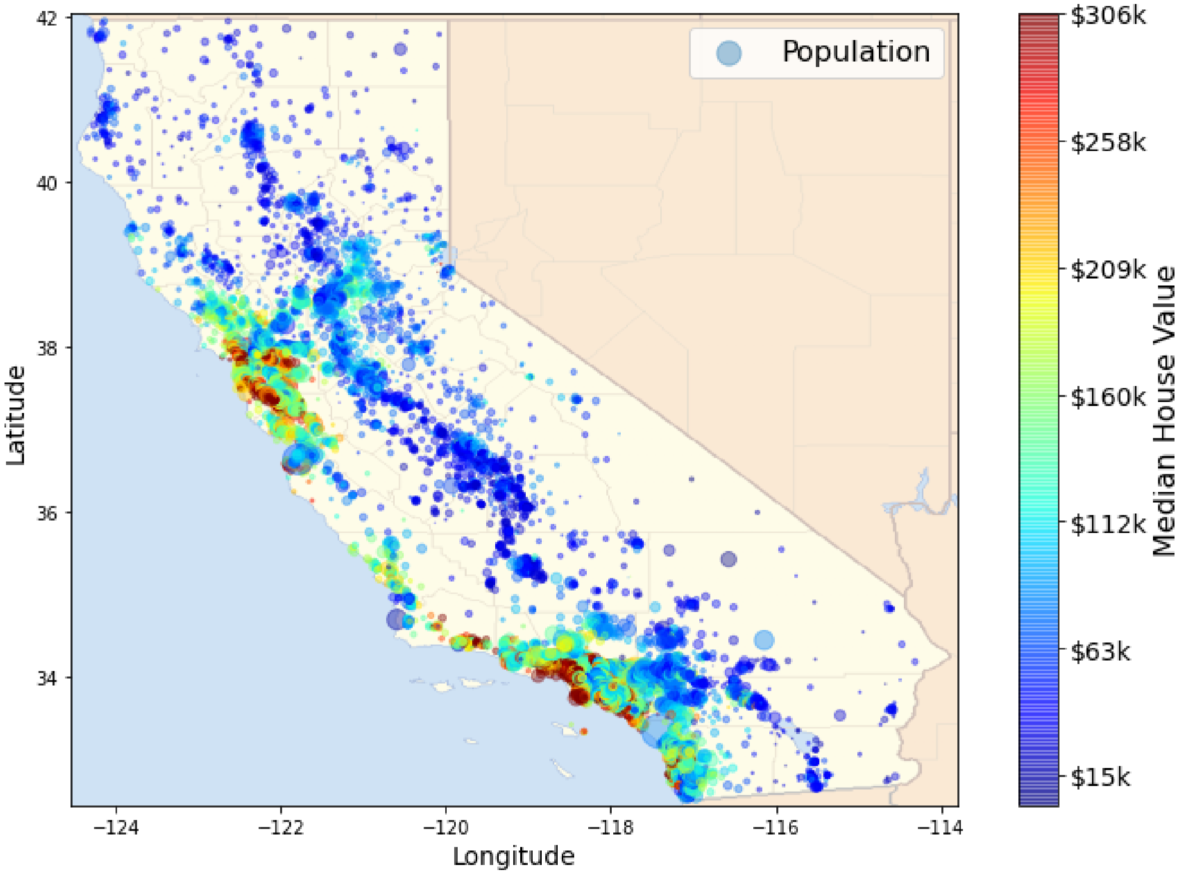
Saving figure better_visualization_plot



In [191]:

```
# 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, we can see that 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 transformations.

None the less we can explore this using correlation matrices. If you need to brush up on correlation take a look [here (https://www.kdnuggets.com/2017/02/datascience-introduction-correlation.html)](https://www.kdnuggets.com/2017/02/datascience-introduction-correlation.html).

In [192]:

```
corr_matrix = housing.corr() # compute the correlation matrix
```

In [193]:

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

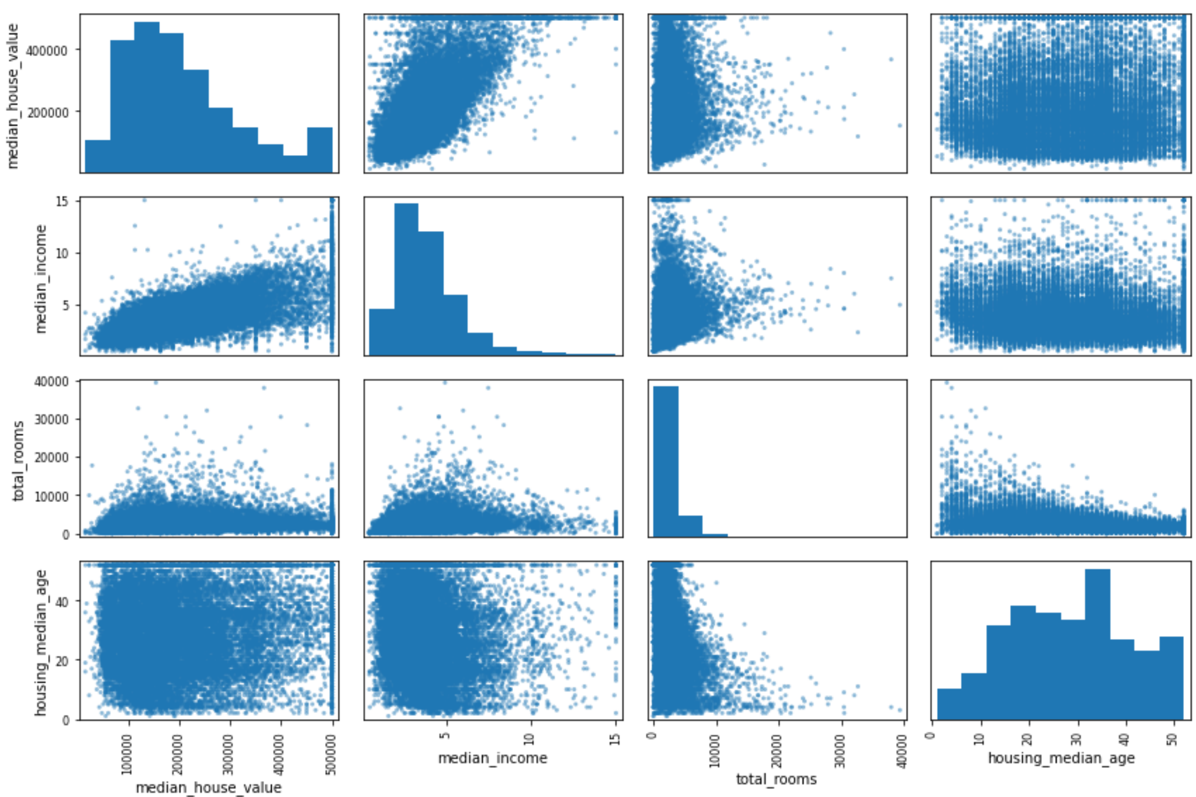
Out[193]:

```
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 [194]:

```
# 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")
```

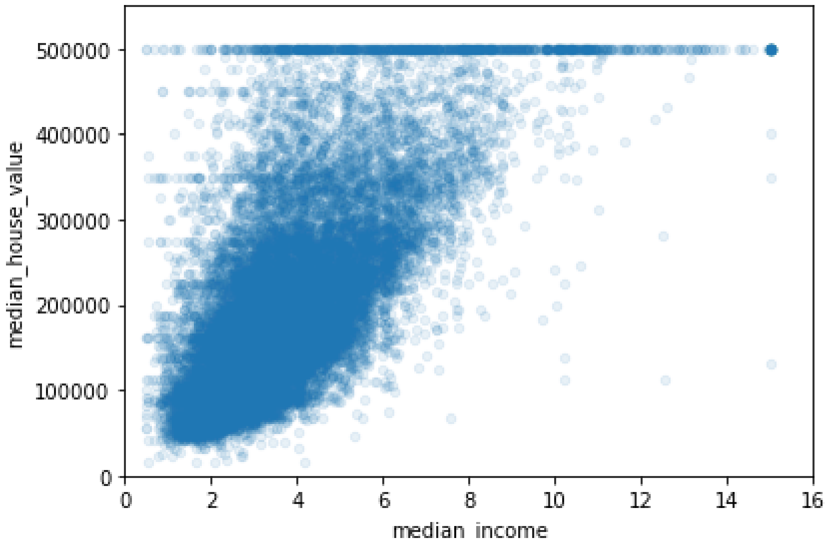
Saving figure scatter_matrix_plot



In [195]:

```
# 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 [196]:

```
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 [197]:

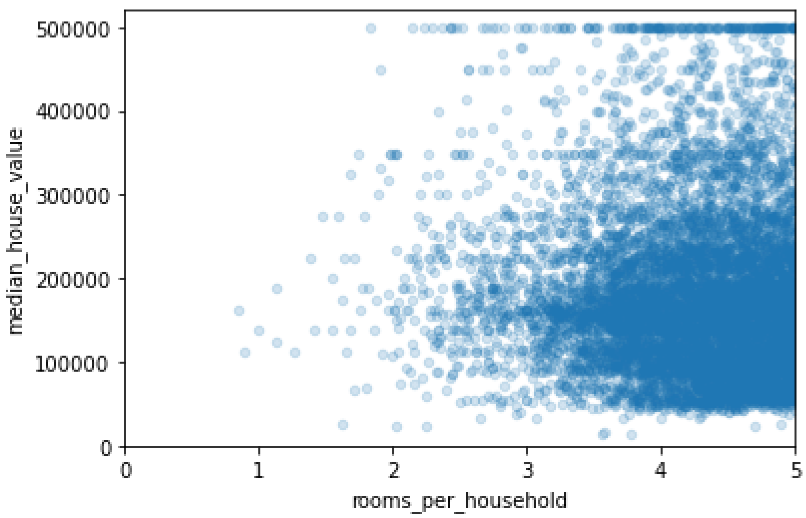
```
# obtain new correlations
corr_matrix = housing.corr()
corr_matrix["median_house_value"].sort_values(ascending=False)
```

Out[197]:

```
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
```

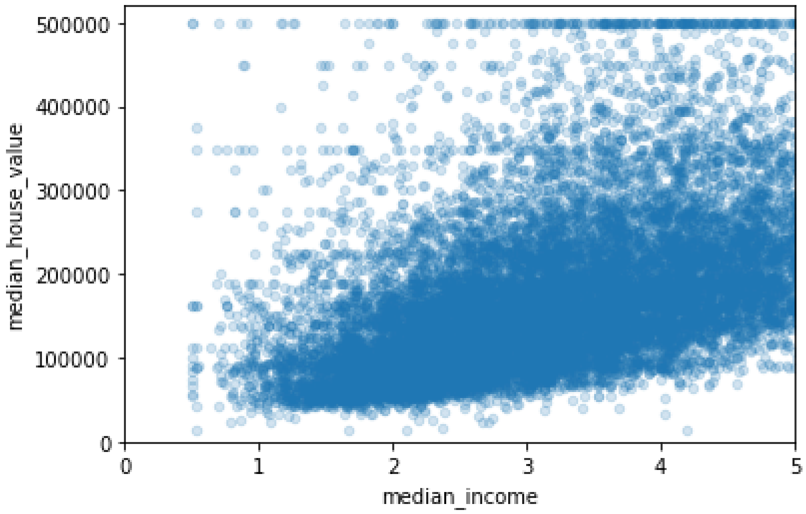
In [198]:

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



In [199]:

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



In [200]:

```
housing.describe()
```

Out[200]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	popula
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000

Step 3. Preprocess the data for your machine learning algorithm

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... in the real world 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!

Dealing With Incomplete Data

In [201]:

```
# 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 so we'll have to devise a method for dealing with the
m...
sample_incomplete_rows = housing[housing.isnull().any(axis=1)].head()
sample_incomplete_rows
```

Out[201]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	household
290	-122.16	37.77	47.0	1256.0	NaN	570.0	218.
341	-122.17	37.75	38.0	992.0	NaN	732.0	259.
538	-122.28	37.78	29.0	5154.0	NaN	3741.0	1273.
563	-122.24	37.75	45.0	891.0	NaN	384.0	146.
696	-122.10	37.69	41.0	746.0	NaN	387.0	161.

In [202]:

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

Out[202]:

longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households

In [203]:

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

Out[203]:

	longitude	latitude	housing_median_age	total_rooms	population	households	median_incom
290	-122.16	37.77	47.0	1256.0	570.0	218.0	4.375
341	-122.17	37.75	38.0	992.0	732.0	259.0	1.619
538	-122.28	37.78	29.0	5154.0	3741.0	1273.0	2.576
563	-122.24	37.75	45.0	891.0	384.0	146.0	4.948
696	-122.10	37.69	41.0	746.0	387.0	161.0	3.906

In [204]:

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

Out[204]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	household
290	-122.16	37.77	47.0	1256.0	435.0	570.0	218.
341	-122.17	37.75	38.0	992.0	435.0	732.0	259.
538	-122.28	37.78	29.0	5154.0	435.0	3741.0	1273.
563	-122.24	37.75	45.0	891.0	435.0	384.0	146.
696	-122.10	37.69	41.0	746.0	435.0	387.0	161.

Could you think of another plausible imputation for this dataset? (Not graded) - Yes, we can replace with mode or mean value.

Prepare Data

Recall we are trying to predict the median house value, our features will contain longitude, latitude, housing_median_age... and our target will be median_house_value

In [205]:

```
housing_features = housing.drop("median_house_value", axis=1) # drop labels for tra
ining set features
                                                            # the input to the model sho
uld not contain the true label
housing_labels = housing["median_house_value"].copy()
```

In [206]:

```
housing_features.head()
```

Out[206]:

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

In [207]:

```
# 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 mus
t be mapped to integers before
# feeding to the model.

# Additionally, categorical values could either be represented as one-hot vectors o
r simple as normalized/unnormalized integers.
# Here we encode them using one hot vectors.

# DO NOT WORRY IF YOU DO NOT UNDERSTAND ALL THE STEPS OF THIS PIPELINE. CONCEPTS LI
KE NORMALIZATION,
# ONE-HOT ENCODING ETC. WILL ALL BE COVERED IN DISCUSSION

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 valu
es
housing_num = housing_features.drop("ocean_proximity", axis=1) # remove the categor
ical feature
# column index
rooms_idx, bedrooms_idx, population_idx, households_idx = 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_idx] / X[:, households_idx]
        population_per_household = X[:, population_idx] / X[:, households_idx]
        if self.add_bedrooms_per_room:
            bedrooms_per_room = X[:, bedrooms_idx] / X[:, rooms_idx]
            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) # generate new feature
s

# this will be are numirical pipeline
# 1. impute, 2. augment the feature set 3. normalize using StandardScaler()
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_features)
```

Splitting our dataset

First we need to carve out our dataset into a training and testing cohort. To do this we'll use train_test_split, a very elementary tool that arbitrarily splits the data into training and testing cohorts.

In [208]:

```
from sklearn.model_selection import train_test_split
data_target = housing['median_house_value']
train, test, target, target_test = train_test_split(housing_prepared, data_target,
test_size=0.3, random_state=0)
```

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 [209]:

```
from sklearn.linear_model import LinearRegression

lin_reg = LinearRegression()
lin_reg.fit(train, target)

# let's try the full preprocessing pipeline on a few training instances
data = test
labels = target_test

print("Predictions:", lin_reg.predict(data)[:5])
print("Actual labels:", list(labels)[:5])
```

```
Predictions: [207828.06448011 281099.80175494 176021.36890539  93643.46
744928
 304674.47047758]
Actual labels: [136900.0, 241300.0, 200700.0, 72500.0, 460000.0]
```

In [210]:

```
from sklearn.metrics import mean_squared_error

preds = lin_reg.predict(test)
mse = mean_squared_error(target_test, preds)
rmse = np.sqrt(mse)
rmse
```

Out[210]:

```
67879.86844243006
```

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.

[35 pts] Visualizing Data

[5 pts] Load the data + statistics

- load the dataset
- display the first few rows of the data

In [211]:

```
def load_data(file):
    data_path = os.path.join("datasets", "airbnb", file)
    return pd.read_csv(data_path)

data = load_data("AB_NYC_2019.csv")
print(data.head())
# print(data.isna().sum())
```

```
     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_revie
w  \
0     Private room    149               1                  9  2018-10-1
9
1  Entire home/apt    225               1                 45  2019-05-2
1
2     Private room    150               3                  0         Na
N
3  Entire home/apt     89               1                270  2019-07-0
5
4  Entire home/apt     80              10                  9  2018-11-1
9

   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
```

- pull up info on the data type for each of the data fields. Will any of these be problemmatic feeding into your model (you may need to do a little research on this)? Discuss:

In [212]:

```
print(data.dtypes)
```

```
id                                  int64
name                               object
host_id                             int64
host_name                          object
neighbourhood_group                object
neighbourhood                      object
latitude                          float64
longitude                         float64
room_type                          object
price                               int64
minimum_nights                      int64
number_of_reviews                   int64
last_review                        object
reviews_per_month                 float64
calculated_host_listings_count      int64
availability_365                    int64
dtype: object
```

Text data such as "name", "host_name", "neighborhood_group", "neighborhood", "room_type", "last_review" can be a challenge for a linear regression model. For features like "last_review", we can transform the date string to a numerical value, and for "room_type" we can encode values as 0,1,2,3 for example.

- drop the following columns: name, host_id, host_name, and last_review
- display a summary of the statistics of the loaded data

In [213]:

```
data = data.drop(columns = ['name', 'host_id', 'host_name', 'last_review'])
data.head()
```

Out[213]:

	id	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_
0	2539	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	
1	2595	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	
2	3647	Manhattan	Harlem	40.80902	-73.94190	Private room	150	
3	3831	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	
4	5022	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	

In [214]:

```
data.describe()
```

Out[214]:

	id	latitude	longitude	price	minimum_nights	number_of_revie
count	4.889500e+04	48895.000000	48895.000000	48895.000000	48895.000000	48895.000
mean	1.901714e+07	40.728949	-73.952170	152.720687	7.029962	23.274
std	1.098311e+07	0.054530	0.046157	240.154170	20.510550	44.550
min	2.539000e+03	40.499790	-74.244420	0.000000	1.000000	0.000
25%	9.471945e+06	40.690100	-73.983070	69.000000	1.000000	1.000
50%	1.967728e+07	40.723070	-73.955680	106.000000	3.000000	5.000
75%	2.915218e+07	40.763115	-73.936275	175.000000	5.000000	24.000
max	3.648724e+07	40.913060	-73.712990	10000.000000	1250.000000	629.000

[5 pts] Boxplot 3 features of your choice

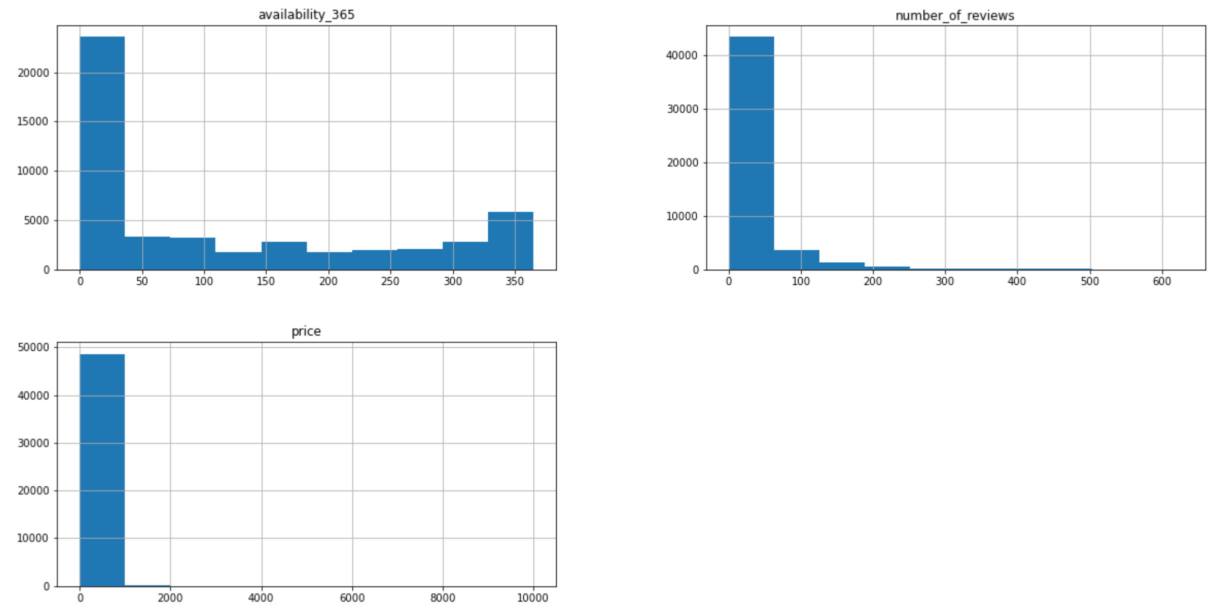
- plot boxplots for 3 features of your choice

In [215]:

```
data.hist(column= ['number_of_reviews', 'price', 'availability_365'], figsize=(20,1
0), bins = 10)
```

Out[215]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fc240d8b6a0
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fc2425da640
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fc23fe5da00
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fc240d789d0
>]],
      dtype=object)
```



- describe what you expected to see with these features and what you actually observed

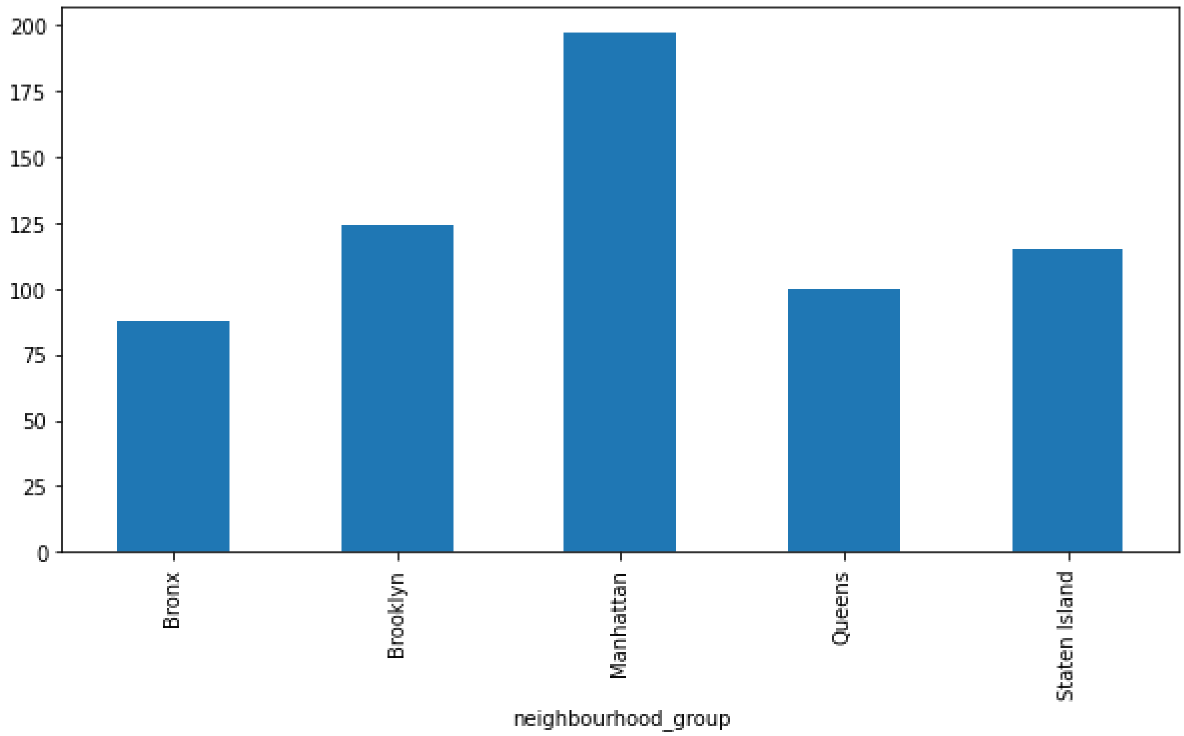
High variability in price with long tail values. The majority of values are between 0 and 1000, though. Review numbers much more compact also with a long tail. Availability is more variant, with peaks on both the left and right.

[10 pts] Plot average price of a listing per neighbourhood_group

In [216]:

```
price_by_neighbourhood_group = data.groupby('neighbourhood_group').mean()
print(price_by_neighbourhood_group['price'])
price_by_neighbourhood_group['price'].plot.bar(y = 'price', figsize = (10,5))
plt.show()
```

```
neighbourhood_group
Bronx              87.496792
Brooklyn          124.383207
Manhattan         196.875814
Queens             99.517649
Staten Island     114.812332
Name: price, dtype: float64
```



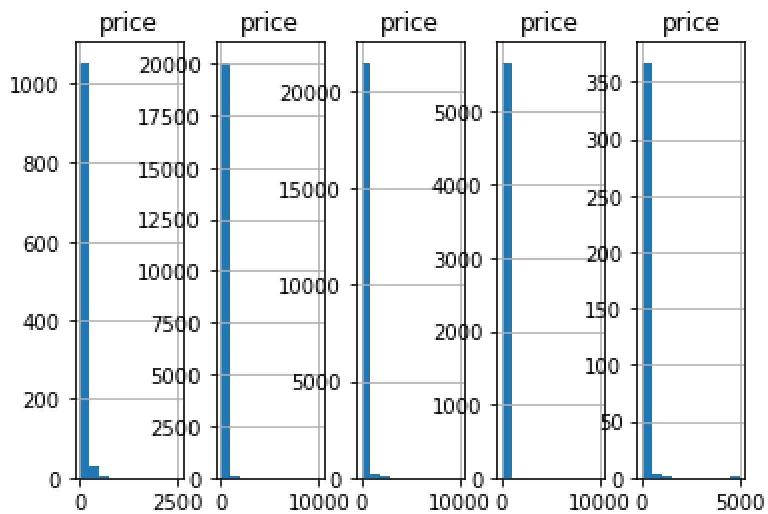
- describe what you expected to see with these features and what you actually observed

We were asked to plot price by neighborhood, but since neighborhood is a categorical feature, the x-axis doesn't mean much. We can still see that Manhattan is the most expensive, followed by Brooklyn, Staten Island, Queens, and the Bronx.

- So we can see different neighborhoods have dramatically different pricepoints, but how does the price breakdown by range. To see let's do a histogram of price by neighborhood to get a better sense of the distribution.

In [217]:

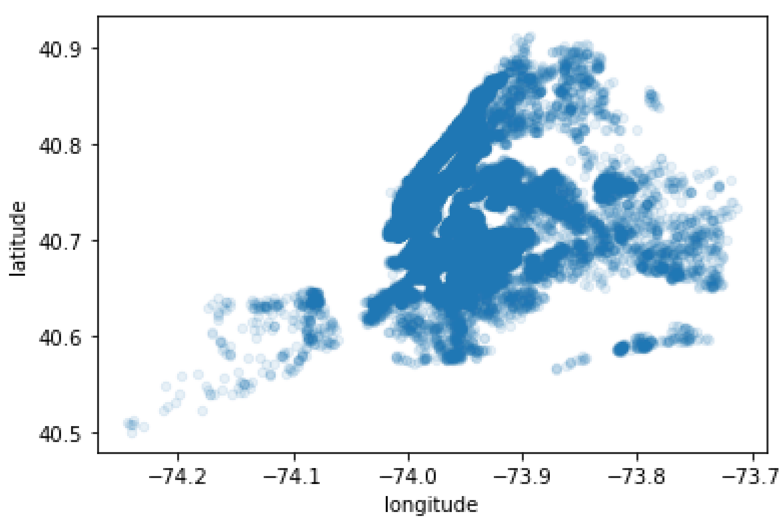
```
fig, axes = plt.subplots(1, 5)

neighborhoods = ['Bronx', 'Brooklyn', 'Manhattan','Queens','Staten Island' ]

for i, neighborhood in enumerate(neighborhoods):
    this_neighborhood = data.loc[data['neighbourhood_group'] == neighborhood]
    this_neighborhood.hist(column= ['price'], figsize=(20,20), bins = 10, ax=axes[i
])

plt.show()
```



[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 [218]:

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



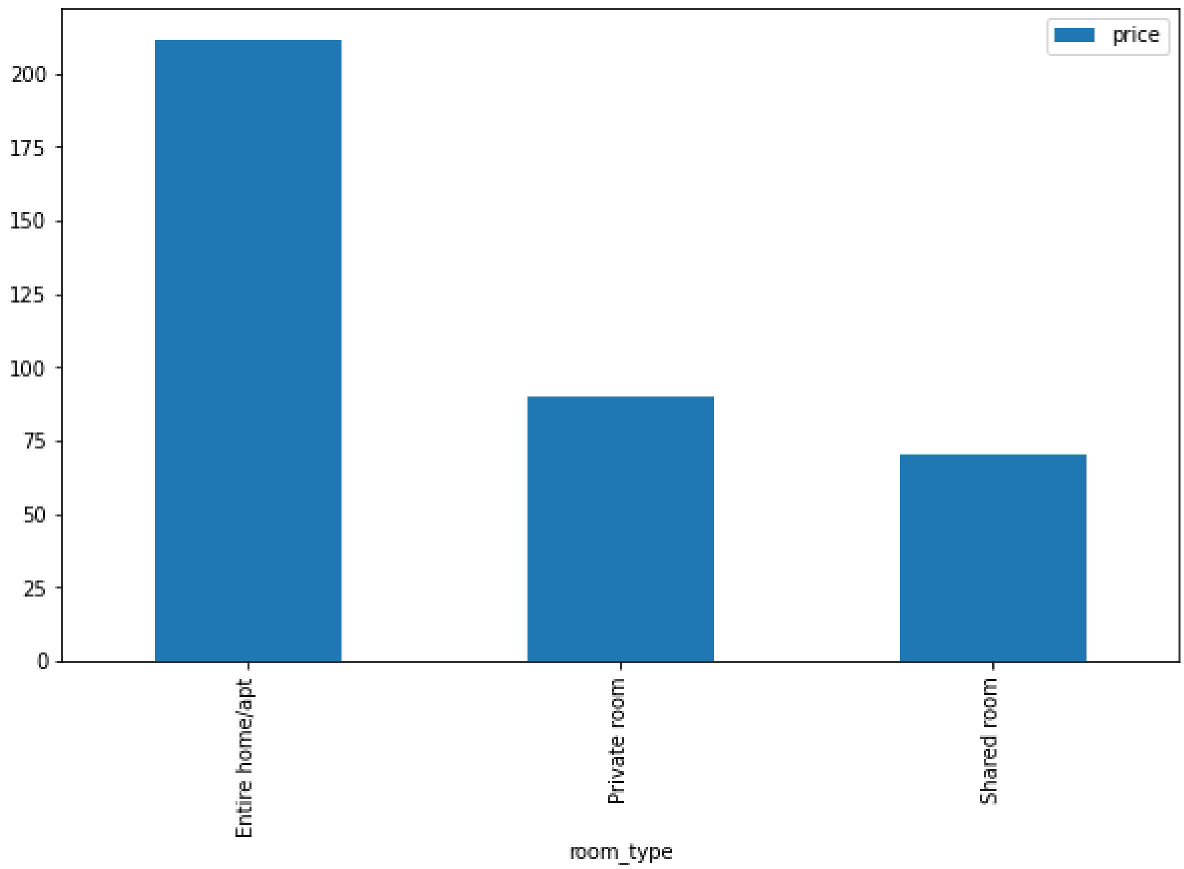
[5 pts] Plot average price of room types who have availability greater than 180 days and neighbourhood_group is Manhattan

In [219]:

```
grouped_room_type = data.loc[data['availability_365'] > 180]
grouped_room_type = grouped_room_type.loc[grouped_room_type['neighbourhood_group']
== "Manhattan"]
grouped_room_type = data.groupby('room_type').mean()
grouped_room_type.plot.bar(y = 'price', figsize = (10,6))
```

Out[219]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc241ae7250>
```



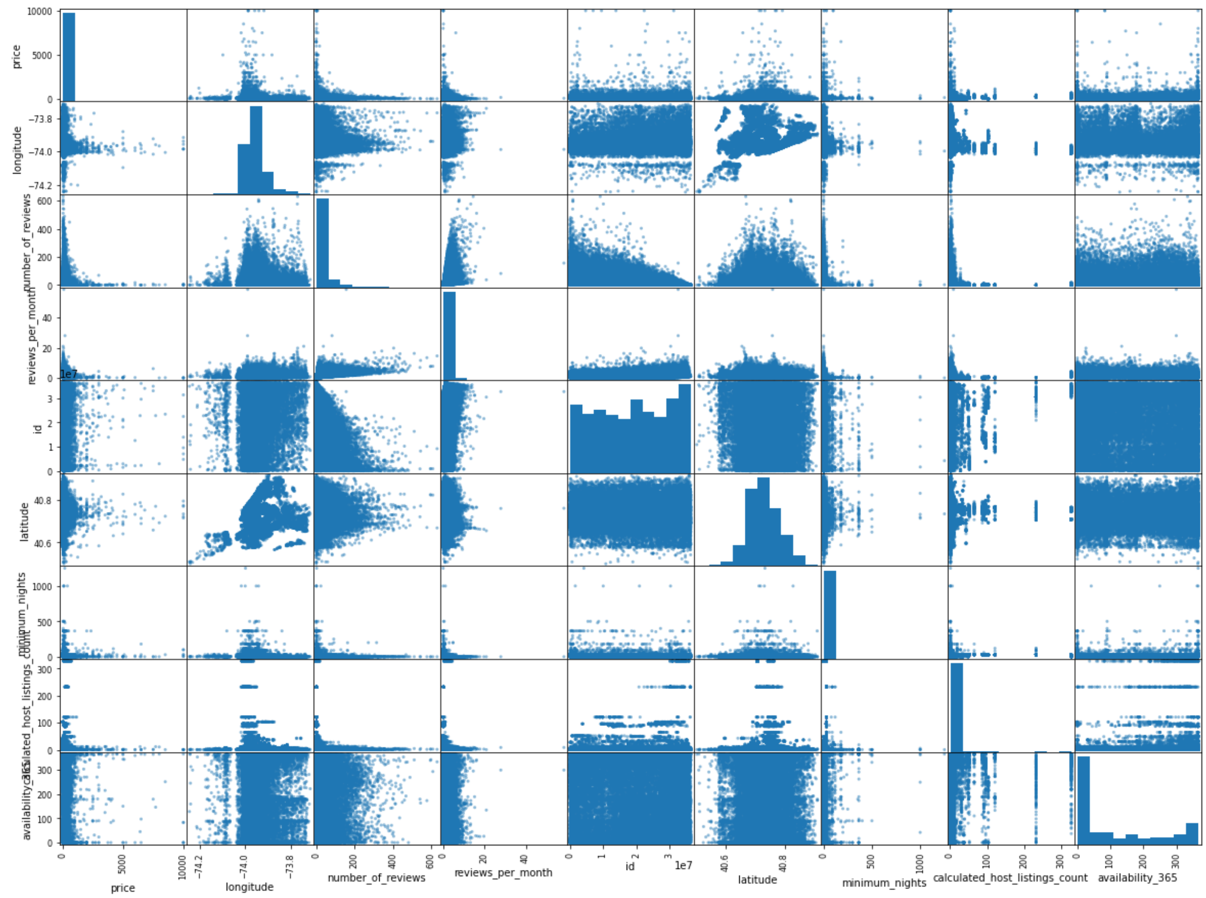
[5 pts] Plot correlation matrix

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

In [220]:

```
correlation_matrix = data.corr()
correlation_matrix = correlation_matrix['price'].sort_values()
print(correlation_matrix)
attributes = ["price", "longitude", "number_of_reviews", "reviews_per_month",
              "id", 'latitude', 'minimum_nights', 'calculated_host_listings_count',
'availability_365']
scatter_matrix(data[attributes], figsize=(20, 15))
plt.show()
```

```
longitude                        -0.150019
number_of_reviews                -0.047954
reviews_per_month                -0.030608
id                                0.010619
latitude                          0.033939
minimum_nights                    0.042799
calculated_host_listings_count    0.057472
availability_365                  0.081829
price                             1.000000
Name: price, dtype: float64
```



Positive: id, latitude, minimum_nights, calculated_host_listings_count, availability_365

Negative: longitude, number_of_reviews, reviews_per_month

Note price has corr of 1 with itself.

[30 pts] Prepare the Data

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

In [221]:

```
augmented=data.copy()
augmented['max_yearly_bookings'] = augmented['availability_365']/augmented['minimum_nights']
augmented['total_reviews_per_month'] = augmented['reviews_per_month']*augmented['calculated_host_listings_count']
augmented.head()
```

Out[221]:

	id	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_
0	2539	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	
1	2595	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	
2	3647	Manhattan	Harlem	40.80902	-73.94190	Private room	150	
3	3831	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	
4	5022	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	

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

In [222]:

```
augmented["max_yearly_bookings"].fillna(median, inplace=True) # this is likely due
 to minimum_nights being set to 0 or N/A so we give the median value
augmented["total_reviews_per_month"].fillna(0, inplace=True) # this is likely due t
o no reviews per month or no other listings so we give 0

augmented.fillna(0, inplace=True)

augmented.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               48895 non-null  float64
 10  calculated_host_listings_count  48895 non-null  int64  
 11  availability_365                48895 non-null  int64  
 12  max_yearly_bookings             48895 non-null  float64
 13  total_reviews_per_month         48895 non-null  float64
dtypes: float64(5), int64(6), object(3)
memory usage: 5.2+ MB
```

[15 pts] Code complete data pipeline using sklearn mixins

In [223]:

```
airbnb_features = data.drop("price", axis=1) # drop labels for training set feature
s
                                                    # the input to the model sho
uld not contain the true label
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

data_num = airbnb_features.drop(columns = ['neighbourhood_group', 'neighbourhood',
'room_type']) # drop categorical fields

number_of_reviews_idx = data_num.columns.get_loc("number_of_reviews")
reviews_per_month_idx = data_num.columns.get_loc("reviews_per_month")
calculated_host_listings_count_idx =  data_num.columns.get_loc("calculated_host_lis
tings_count")
minimum_nights_idx =  data_num.columns.get_loc("minimum_nights")

class AugmentFeatures(BaseEstimator, TransformerMixin):

    def __init__(self, add_features=True):
        self.add_features = add_features
    def fit(self, X, y=None):
        return self
    def transform(self, X):
        num_reviews = X[:, number_of_reviews_idx]
        calculated_host_listings_count = X[:, number_of_reviews_idx]
        reviews_per_month = X[:, reviews_per_month_idx]
        reviews_per_month[reviews_per_month == 0] = 1 #this avoids a divide by zero
error without changing final result

        total_reviews_per_month = reviews_per_month * calculated_host_listings_coun
t
        months_being_reviewed = num_reviews / reviews_per_month
        return np.c_[X, total_reviews_per_month, months_being_reviewed]

num_pipeline = Pipeline([
        ('imputer', SimpleImputer(strategy='constant', fill_value = 0)),
        ('attribs_adder', AugmentFeatures()),
        ('std_scaler', StandardScaler()),
    ])

numerical_features = list(data_num)
categorical_features = ['neighbourhood_group', 'neighbourhood', 'room_type']

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

data_prepared = full_pipeline.fit_transform(airbnb_features)
```

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

In [224]:

```
data_target = data['price']
train, test, target, target_test = train_test_split(data_prepared, data_target, tes
t_size=0.2, random_state=0)
```

[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 [225]:

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

lin_reg = LinearRegression()
lin_reg.fit(train, target)

preds = lin_reg.predict(train)
mse = mean_squared_error(target, preds)
print('train mse: ', mse)
rmse = np.sqrt(mse)
print('train rmse: ', rmse)

preds = lin_reg.predict(test)
mse = mean_squared_error(target_test, preds)
print('test mse: ', mse)
rmse = np.sqrt(mse)
print('test rmse: ', rmse)
```

```
train mse:  51541.93011933607
train rmse:  227.0284786526485
test mse:  47876.333637486125
test rmse:  218.80661241718937
```

In [ ]:

In [ ]: