Introduction

Welcome to **CSM148 - Data Science!** 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

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
- Kaggle Datasets
- AWS Datasets

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:** 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

In [3]:

```
import pandas as pd

def load_housing_data(housing_path):
```

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

In [4]:

```python
housing = load_housing_data(DATASET_PATH) # we load the pandas dataframe
housing.head(5) # show the first five rows 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	median_house_value	ocean_proximity
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0	NEAR BAY
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0	NEAR BAY
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	NEAR BAY
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	NEAR BAY
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0	NEAR BAY

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]:

```python
# 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 [6]:

```python
# 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]:

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

Out[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
```

In [8]:

```python
# 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]:

```python
# 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	median_income	median_house_value

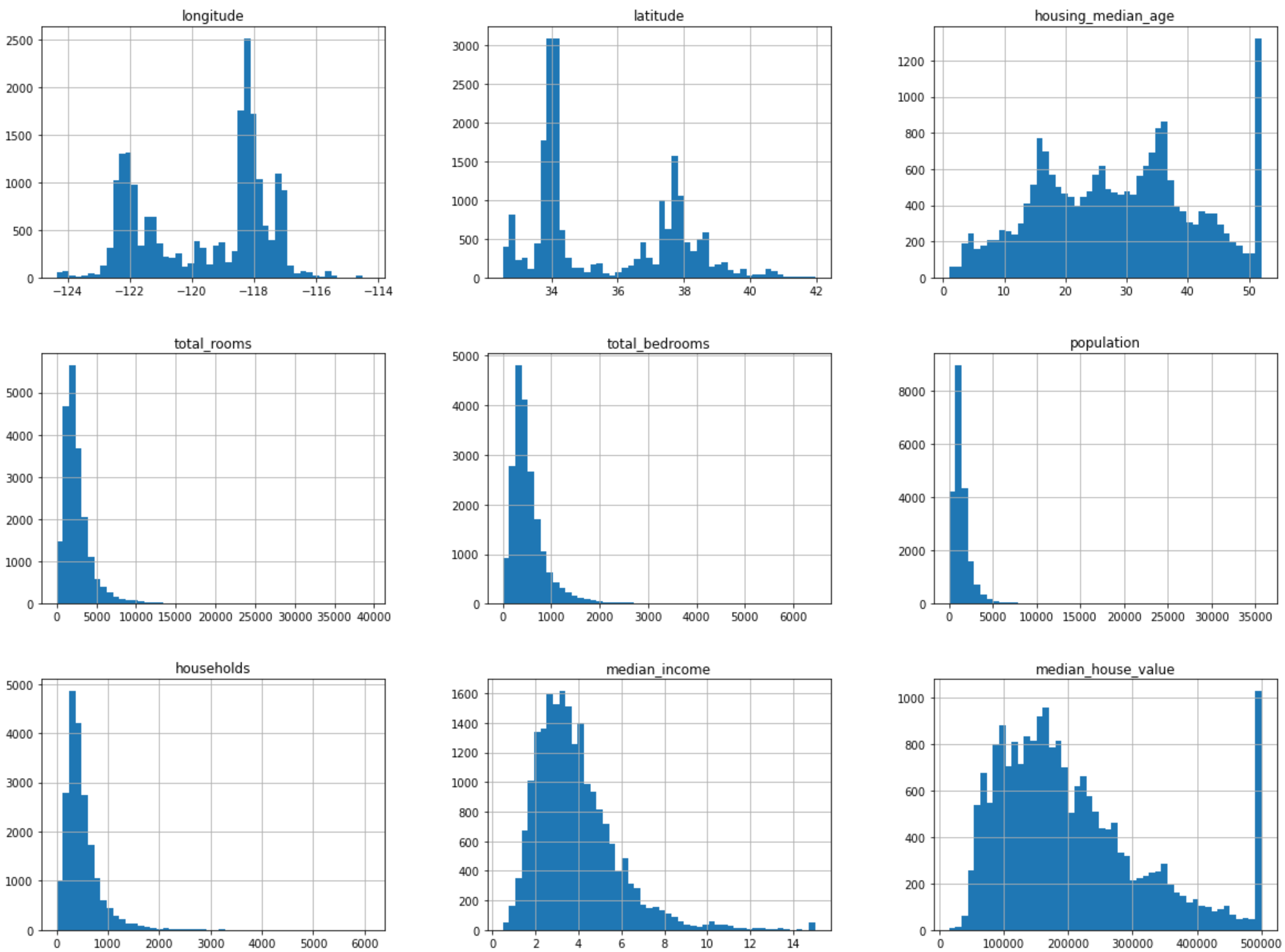
	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744	499.539680	3.870671	206855.816909
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462122	382.329753	1.899822	115395.615874
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000	1.000000	0.499900	14999.000000
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000000	280.000000	2.563400	119600.000000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000000	409.000000	3.534800	179700.000000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000000	605.000000	4.743250	264725.000000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000000	6082.000000	15.000100	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

Let's start visualizing the dataset

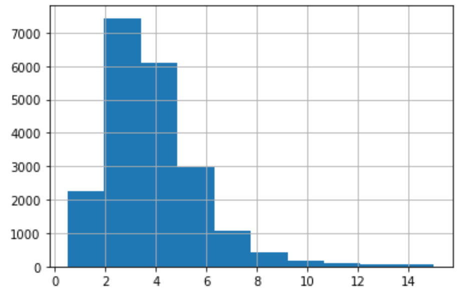
In [10]:

```
# 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
```



In [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.

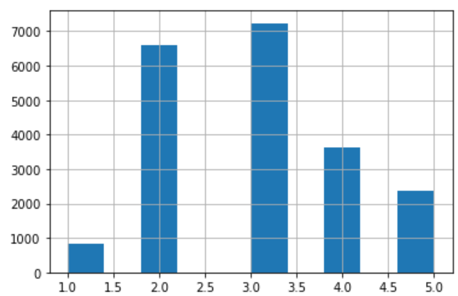
For example, to bin the households based on median_income we can use the pd.cut function

In [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()
```

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

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

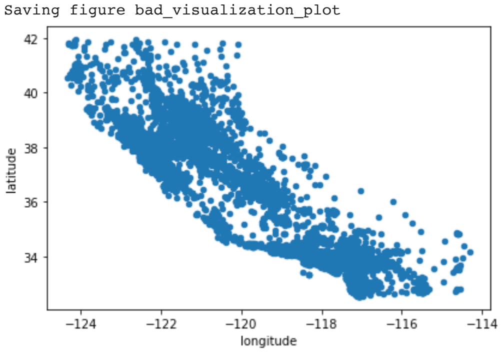
Out[13]:
```
<AxesSubplot:>
```



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

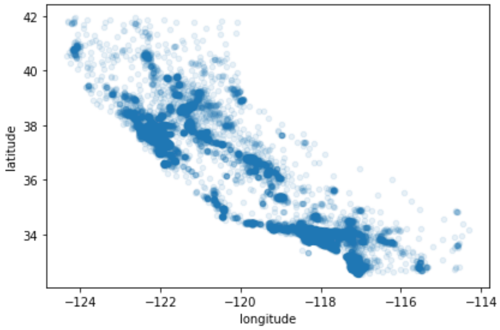
In [14]:
```
## here's a not so interestting way plotting it
housing.plot(kind="scatter", x="longitude", y="latitude")
save_fig("bad_visualization_plot")
```

```
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")
```

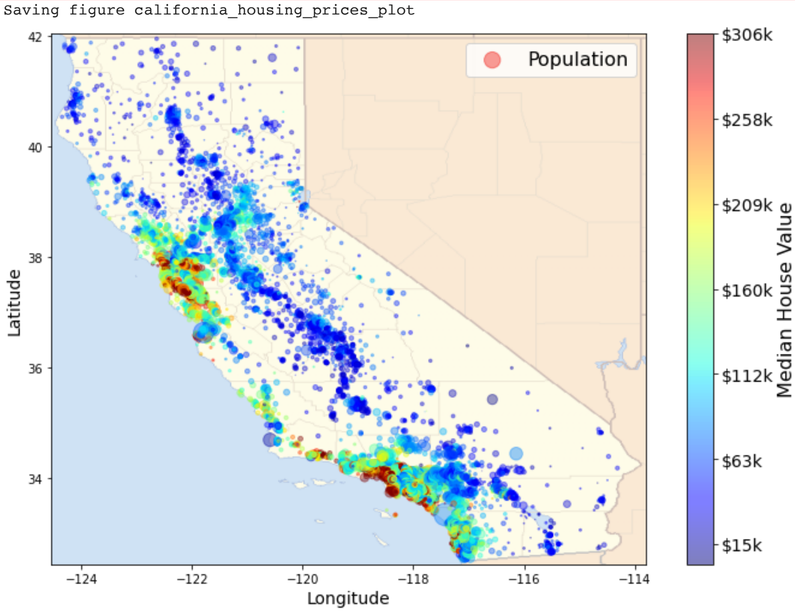
```
Saving figure better_visualization_plot
```



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()
```

```
/var/folders/ry/zrhyljyj7m310x6q60g91fqr0000gn/T/ipykernel_3245/399246598.py:28: UserWarning: FixedFormatter should only be used together with F
ixedLocator
  cb.ax.set_yticklabels(["$%dk"%(round(v/1000)) for v in tick_values], fontsize=14)
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)
```

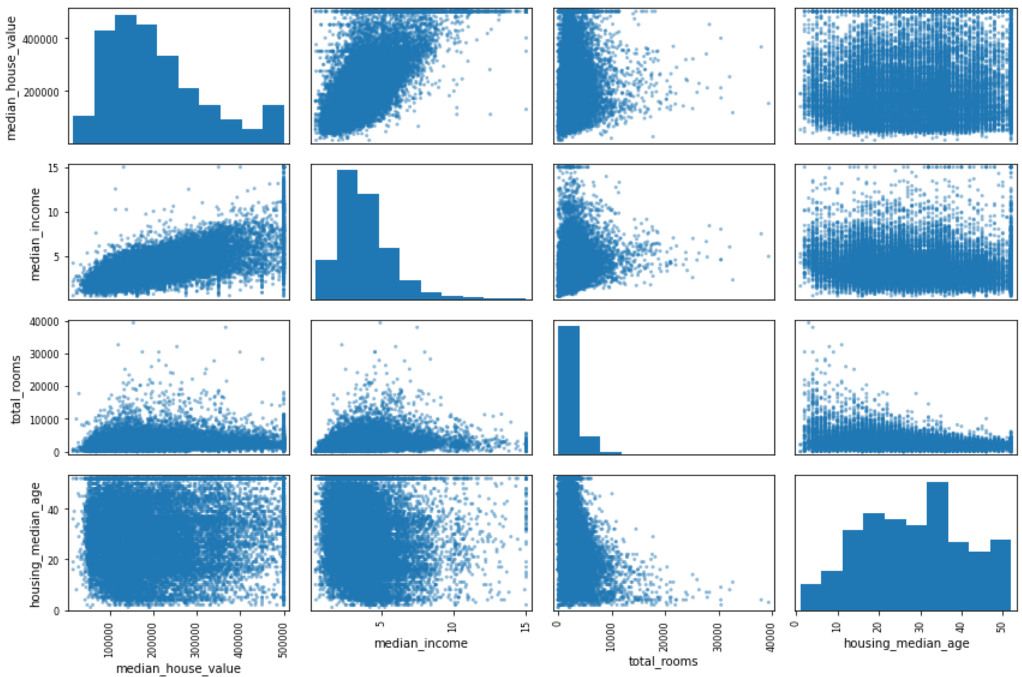
Out[18]:

```
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")
```

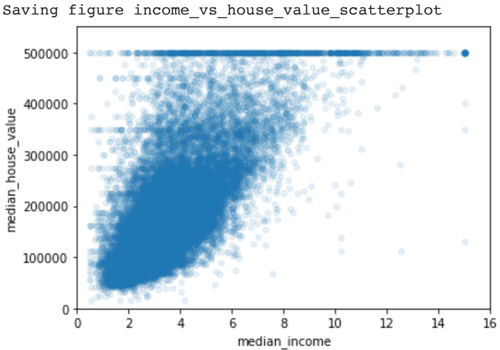
```
Saving figure scatter_matrix_plot
```



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]:

```python
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]:

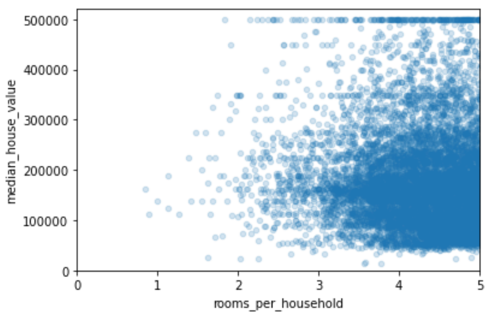
```python
# obtain new correlations
corr_matrix = housing.corr()
corr_matrix["median_house_value"].sort_values(ascending=False)
```

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]:

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



In [24]:

```python
housing.describe()
```

Out[24]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	rooms_per_ho
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744	499.539680	3.870671	206855.816909	5.
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462122	382.329753	1.899822	115395.615874	2
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000	1.000000	0.499900	14999.000000	0
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000000	280.000000	2.563400	119600.000000	4
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000000	409.000000	3.534800	179700.000000	5
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000000	605.000000	4.743250	264725.000000	6
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000000	6082.000000	15.000100	500001.000000	141

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** 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]:

```python
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 contain the true label
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	ocean_proximity	income_cat	rooms_per_household
4629	-118.30	34.07	18.0	3759.0	NaN	3296.0	1462.0	2.2708	<1H OCEAN	2	2.571135
6068	-117.86	34.01	16.0	4632.0	NaN	3038.0	727.0	5.1762	<1H OCEAN	4	6.371389
17923	-121.97	37.35	30.0	1955.0	NaN	999.0	386.0	4.6328	<1H OCEAN	4	5.064767
13656	-117.30	34.05	6.0	2155.0	NaN	1039.0	391.0	1.6675	INLAND	2	5.511509
19252	-122.79	38.48	7.0	6837.0	NaN	3468.0	1405.0	3.1662	<1H OCEAN	3	4.866192

In [28]:

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

Out[28]:

longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximity	income_cat	rooms_per_household	bedro

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	income_cat	rooms_per_household	bedrooms_per_ro
4629	-118.30	34.07	18.0	3759.0	3296.0	1462.0	2.2708	<1H OCEAN	2	2.571135	N
6068	-117.86	34.01	16.0	4632.0	3038.0	727.0	5.1762	<1H OCEAN	4	6.371389	N
17923	-121.97	37.35	30.0	1955.0	999.0	386.0	4.6328	<1H OCEAN	4	5.064767	N
13656	-117.30	34.05	6.0	2155.0	1039.0	391.0	1.6675	INLAND	2	5.511509	N
19252	-122.79	38.48	7.0	6837.0	3468.0	1405.0	3.1662	<1H OCEAN	3	4.866192	N

In [30]:

```
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
```

Out[30]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximity	income_cat	rooms_per_household
4629	-118.30	34.07	18.0	3759.0	433.0	3296.0	1462.0	2.2708	<1H OCEAN	2	2.571135
6068	-117.86	34.01	16.0	4632.0	433.0	3038.0	727.0	5.1762	<1H OCEAN	4	6.371389
17923	-121.97	37.35	30.0	1955.0	433.0	999.0	386.0	4.6328	<1H OCEAN	4	5.064767
13656	-117.30	34.05	6.0	2155.0	433.0	1039.0	391.0	1.6675	INLAND	2	5.511509
19252	-122.79	38.48	7.0	6837.0	433.0	3468.0	1405.0	3.1662	<1H OCEAN	3	4.866192

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

Prepare Data

In [31]:

```
# 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 integers before
# feeding to the model.

# Additionally, categorical values could either be represented as one-hot vectors or simple as normalized/unnormalized integers.
# 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)

test_set.drop("median_house_value", axis=1, inplace=True)
```

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] # wrong
data = housing.iloc[:5] # NEW https://piazza.com/class/ktuxvlqye5v3tz?cid=29
labels = housing_labels.iloc[:5]
data_prepared = full_pipeline.transform(data)

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

```
Predictions: [200860.48973484 325527.93559759 201882.47991703  54956.04539331
 188116.26928254]
Actual labels: [286600.0, 340600.0, 196900.0, 46300.0, 254500.0]
```

We can evaluate our model using certain metrics, one possible metric for regression is the mean absolute error

$$\mathrm{MAE} = \frac{\sum_i^n |\hat{y}_i - y_i|}{n}$$

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

In [33]:

```
from sklearn.metrics import mean_absolute_error

preds = lin_reg.predict(housing_prepared)
rmse = mean_absolute_error(housing_labels, preds)
rmse
```

Out[33]:

```
49145.9385616408
```

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

In [34]:

```
# load the dataset
```

```
airbnb = pd.read_csv('datasets/airbnb/AB_NYC_2019.csv')
```

In [35]:

```
# display the first 10 rows of the data
airbnb.head(10)
```

Out[35]:

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_reviews	last_revie
0	2539	Clean & quiet apt home by the park	2787	John	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	1	9	2018-10-
1	2595	Skylit Midtown Castle	2845	Jennifer	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	1	45	2019-05-
2	3647	THE VILLAGE OF HARLEM....NEW YORK !	4632	Elisabeth	Manhattan	Harlem	40.80902	-73.94190	Private room	150	3	0	N
3	3831	Cozy Entire Floor of Brownstone	4869	LisaRoxanne	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	1	270	2019-07-
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	Laura	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	10	9	2018-11-
5	5099	Large Cozy 1 BR Apartment In Midtown East	7322	Chris	Manhattan	Murray Hill	40.74767	-73.97500	Entire home/apt	200	3	74	2019-06-
6	5121	BlissArtsSpace!	7356	Garon	Brooklyn	Bedford-Stuyvesant	40.68688	-73.95596	Private room	60	45	49	2017-10-
7	5178	Large Furnished Room Near B'way	8967	Shunichi	Manhattan	Hell's Kitchen	40.76489	-73.98493	Private room	79	2	430	2019-06-
8	5203	Cozy Clean Guest Room - Family Apt	7490	MaryEllen	Manhattan	Upper West Side	40.80178	-73.96723	Private room	79	2	118	2017-07-
9	5238	Cute & Cozy Lower East Side 1 bdrm	7549	Ben	Manhattan	Chinatown	40.71344	-73.99037	Entire home/apt	150	1	160	2019-06-

In [36]:

```
# drop the following columns: name, host_name, last_review
airbnb.drop(columns=["name", "host_name", "last_review"], axis=1, inplace=True)
# display a summary of the statistics of the loaded data
airbnb.info()
airbnb.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 13 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   id                              48895 non-null  int64  
 1   host_id                         48895 non-null  int64  
 2   neighbourhood_group             48895 non-null  object 
 3   neighbourhood                   48895 non-null  object 
 4   latitude                        48895 non-null  float64
 5   longitude                       48895 non-null  float64
 6   room_type                       48895 non-null  object 
 7   price                           48895 non-null  int64  
 8   minimum_nights                  48895 non-null  int64  
 9   number_of_reviews               48895 non-null  int64  
 10  reviews_per_month               38843 non-null  float64
 11  calculated_host_listings_count  48895 non-null  int64  
 12  availability_365                48895 non-null  int64  
dtypes: float64(3), int64(7), object(3)
memory usage: 4.8+ MB
```

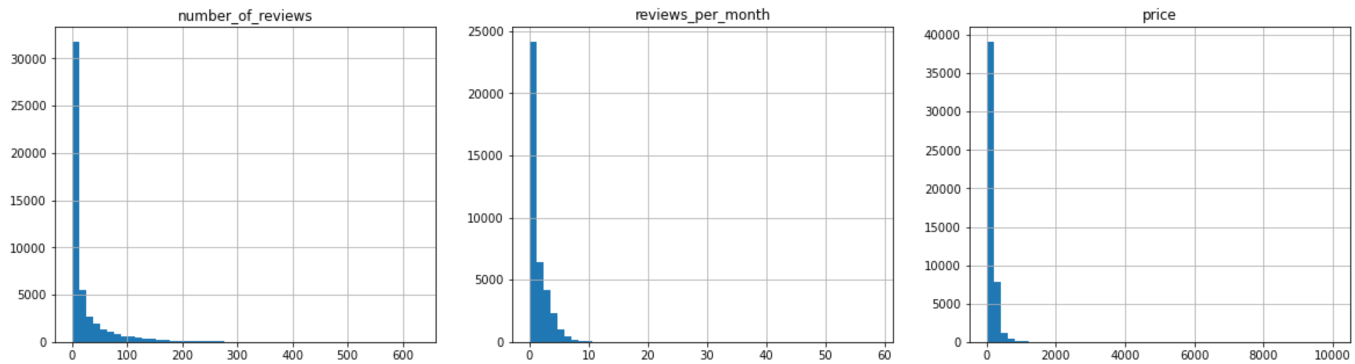
Out[36]:

	id	host_id	latitude	longitude	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	a
count	4.889500e+04	4.889500e+04	48895.000000	48895.000000	48895.000000	48895.000000	48895.000000	38843.000000	48895.000000	
mean	1.901714e+07	6.762001e+07	40.728949	-73.952170	152.720687	7.029962	23.274466	1.373221	7.143982	
std	1.098311e+07	7.861097e+07	0.054530	0.046157	240.154170	20.510550	44.550582	1.680442	32.952519	
min	2.539000e+03	2.438000e+03	40.499790	-74.244420	0.000000	1.000000	0.000000	0.010000	1.000000	
25%	9.471945e+06	7.822033e+06	40.690100	-73.983070	69.000000	1.000000	1.000000	0.190000	1.000000	
50%	1.967728e+07	3.079382e+07	40.723070	-73.955680	106.000000	3.000000	5.000000	0.720000	1.000000	
75%	2.915218e+07	1.074344e+08	40.763115	-73.936275	175.000000	5.000000	24.000000	2.020000	2.000000	
max	3.648724e+07	2.743213e+08	40.913060	-73.712990	10000.000000	1250.000000	629.000000	58.500000	327.000000	

In [37]:

```
# plot histograms for 3 features of your choice
fig, (ax1,ax2,ax3) = plt.subplots(nrows=1, ncols=3,figsize=(20,5))
val1, val2, val3 = 'number_of_reviews', 'reviews_per_month', 'price'

ax1.title.set_text(val1)
airbnb[val1].hist(
    ax=ax1,
    bins=50)

ax2.title.set_text(val2)
airbnb[val2].hist(
    ax=ax2,
```

```
    bins=50)

ax3.title.set_text(val3)
airbnb[val3].hist(
    ax=ax3,
    bins=50)

plt.show()
```

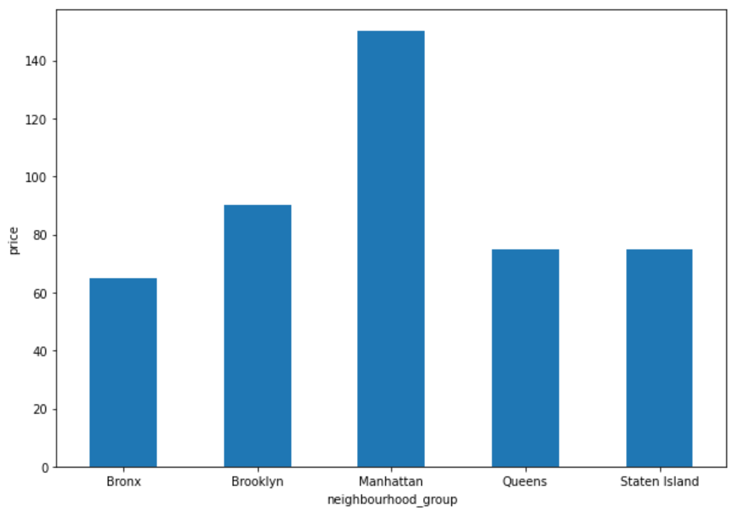


[5 pts] Plot median price per neighbourhood_group

In [38]:

```
airbnb.groupby(['neighbourhood_group']).median()['price'].plot.bar(ylabel='price', rot=0, figsize=(10,7))
```

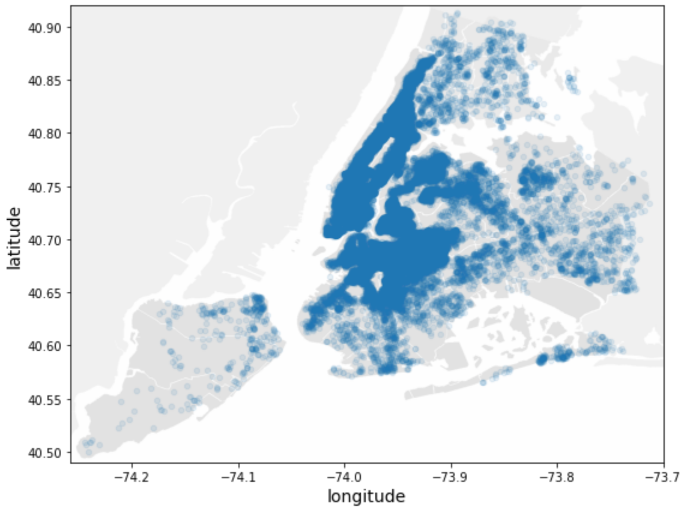
Out[38]: <AxesSubplot:xlabel='neighbourhood_group', ylabel='price'>



[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 [39]:

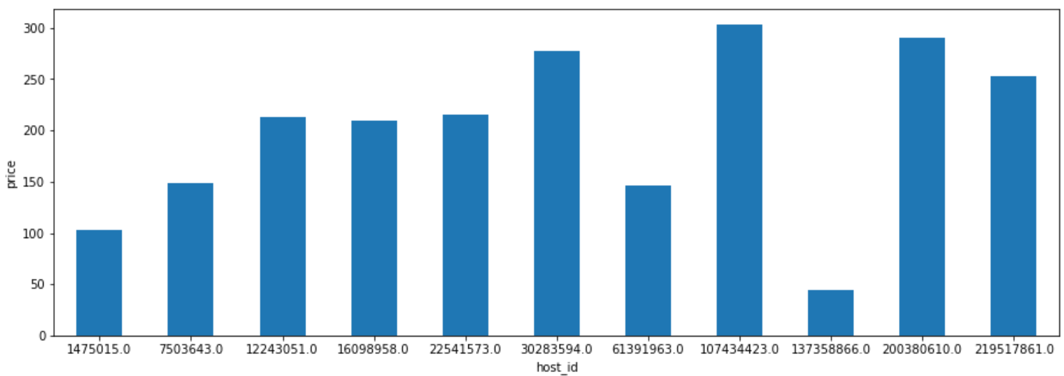
```
x = "longitude"
y = "latitude"
ax = airbnb.plot(
    kind="scatter",
    x=x,
    y=y,
    figsize=(10,7),
    alpha=0.1)
plt.imshow(
    mpimg.imread('images/newyork.png'),
    extent = [-74.258, -73.7, 40.49,40.92],
    alpha=0.2)
plt.xlabel(x, fontsize=14)
plt.ylabel(y, fontsize=14)
plt.show()
```



[5 pts] Plot average price of hosts (host_id) who have more than 50 listings.

In [40]:
```python
airbnb.where(airbnb['calculated_host_listings_count'] > 50) \
    .groupby('host_id') \
    .mean('price')['price'] \
    .plot.bar(ylabel='price', figsize=(15,5), rot=0)
```

Out[40]:
```
<AxesSubplot:xlabel='host_id', ylabel='price'>
```



[5 pts] Plot correlation matrix

- which features have positive correlation?
  - `reviews_per_month` and `number_of_reviews` have a strong positive correlation.
  - `availability_365` and `minimum_nights` have a slight positive correlation
  - `calculated_host_listings_count` and `minimum_nights` have a slight positive correlation
- which features have negative correlation?
  - `longitude` and `price` have a very slight negative correlation.
  - `reviews_per_month` and `minimum_nights` have a slight negative correlation
  - `longitude` and `calculated_host_listings_count` have a small negative correlation

Overall the correlation plot gives us very little information about the interconnectedness of the attributes.

In [41]:
```python
corr_matrix = airbnb.corr()
```

In [42]:
```python
attributes = [
    'price',
    'longitude',
    'latitude',
    'minimum_nights',
    'number_of_reviews',
    'reviews_per_month',
    'calculated_host_listings_count',
    'availability_365']
for attribute in attributes:
    print(f'{attribute}\n{corr_matrix[attribute].sort_values(ascending=False)}\n')
```

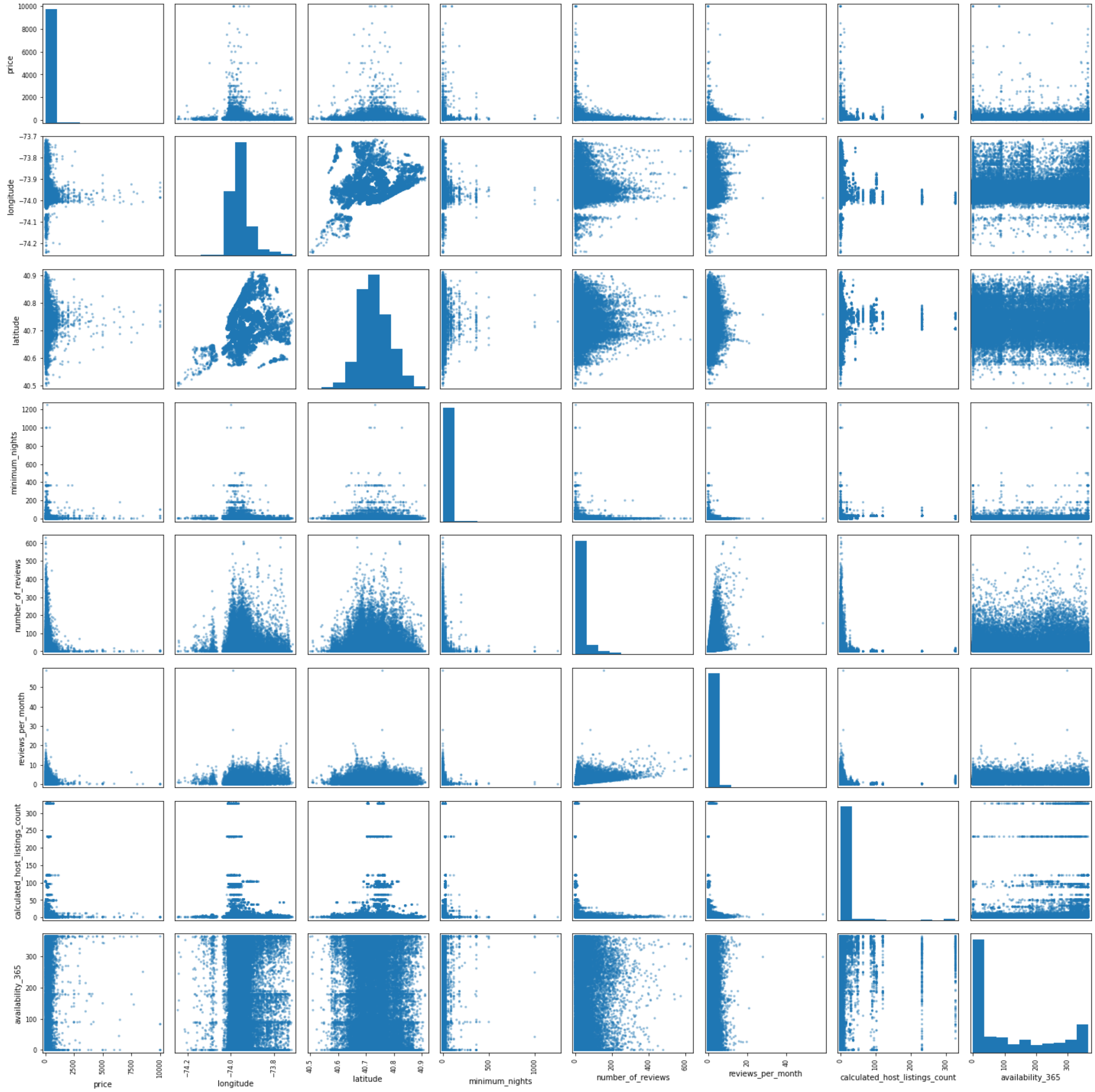
```
price
price                             1.000000
availability_365                  0.081829
calculated_host_listings_count    0.057472
minimum_nights                    0.042799
latitude                          0.033939
host_id                           0.015309
id                                0.010619
reviews_per_month                -0.030608
number_of_reviews                -0.047954
```

```
longitude                        -0.150019
Name: price, dtype: float64

longitude
longitude                         1.000000
reviews_per_month                 0.145948
host_id                           0.127055
id                                0.090908
latitude                          0.084788
availability_365                  0.082731
number_of_reviews                 0.059094
minimum_nights                   -0.062747
calculated_host_listings_count   -0.114713
price                            -0.150019
Name: longitude, dtype: float64

latitude
latitude                          1.000000
longitude                         0.084788
price                             0.033939
minimum_nights                    0.024869
host_id                           0.020224
calculated_host_listings_count    0.019517
id                               -0.003125
reviews_per_month                -0.010142
availability_365                 -0.010983
number_of_reviews                -0.015389
Name: latitude, dtype: float64

minimum_nights
minimum_nights                    1.000000
availability_365                  0.144303
calculated_host_listings_count    0.127960
price                             0.042799
latitude                          0.024869
id                               -0.013224
host_id                          -0.017364
longitude                        -0.062747
number_of_reviews                -0.080116
reviews_per_month                -0.121702
Name: minimum_nights, dtype: float64

number_of_reviews
number_of_reviews                 1.000000
reviews_per_month                 0.549868
availability_365                  0.172028
longitude                         0.059094
latitude                         -0.015389
price                            -0.047954
calculated_host_listings_count   -0.072376
minimum_nights                   -0.080116
host_id                          -0.140106
id                               -0.319760
Name: number_of_reviews, dtype: float64

reviews_per_month
reviews_per_month                 1.000000
number_of_reviews                 0.549868
host_id                           0.296417
id                                0.291828
availability_365                  0.185791
longitude                         0.145948
calculated_host_listings_count   -0.009421
latitude                         -0.010142
price                            -0.030608
minimum_nights                   -0.121702
Name: reviews_per_month, dtype: float64

calculated_host_listings_count
calculated_host_listings_count    1.000000
availability_365                  0.225701
host_id                           0.154950
id                                0.133272
minimum_nights                    0.127960
price                             0.057472
latitude                          0.019517
reviews_per_month                -0.009421
number_of_reviews                -0.072376
longitude                        -0.114713
Name: calculated_host_listings_count, dtype: float64

availability_365
availability_365                  1.000000
calculated_host_listings_count    0.225701
host_id                           0.203492
reviews_per_month                 0.185791
number_of_reviews                 0.172028
minimum_nights                    0.144303
id                                0.085468
longitude                         0.082731
price                             0.081829
latitude                         -0.010983
Name: availability_365, dtype: float64
```

In [43]:

```python
scatter_matrix(airbnb[attributes], figsize=(20,20))
save_fig('correlation')
plt.show()
```

```
Saving figure correlation
```



[25 pts] Prepare the Data

[5 pts] Set aside 25% of the data as test set (75% train, 25% test).

In [44]:
```
airbnb.describe()
```

Out[44]:

	id	host_id	latitude	longitude	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	a
count	4.889500e+04	4.889500e+04	48895.000000	48895.000000	48895.000000	48895.000000	48895.000000	38843.000000	48895.000000	
mean	1.901714e+07	6.762001e+07	40.728949	-73.952170	152.720687	7.029962	23.274466	1.373221	7.143982	
std	1.098311e+07	7.861097e+07	0.054530	0.046157	240.154170	20.510550	44.550582	1.680442	32.952519	
min	2.539000e+03	2.438000e+03	40.499790	-74.244420	0.000000	1.000000	0.000000	0.010000	1.000000	
25%	9.471945e+06	7.822033e+06	40.690100	-73.983070	69.000000	1.000000	1.000000	0.190000	1.000000	
50%	1.967728e+07	3.079382e+07	40.723070	-73.955680	106.000000	3.000000	5.000000	0.720000	1.000000	
75%	2.915218e+07	1.074344e+08	40.763115	-73.936275	175.000000	5.000000	24.000000	2.020000	2.000000	
max	3.648724e+07	2.743213e+08	40.913060	-73.712990	10000.000000	1250.000000	629.000000	58.500000	327.000000	

In [45]:
```
price = 'price'
categorical_price = 'categorical_price'
```

```python
bins = [-1,100.0, 200.0, 300.0, 400.0, 500.0, 600.0, 700.0, 800.0, 900.0, 1000.0, 2500.0, 5000.0, 10000.0, np.inf]
for i in range(1,len(bins)):
    assert(bins[i]-bins[i-1]>0)
airbnb[categorical_price] = pd.cut(airbnb[price],bins = bins,labels = [i for i in range(1, len(bins))])

sss = StratifiedShuffleSplit(n_splits=1, test_size=0.25, random_state=42)
for train_index, test_index in sss.split(airbnb, airbnb[categorical_price]):
    abnb_train_set = airbnb.loc[train_index]
    abnb_test_set = airbnb.loc[test_index]


# labels are actual price
abnb_test_labels = abnb_test_set[price].copy()
abnb_train_labels = abnb_train_set[price].copy()

# train set should not contain actual price
abnb_train_set.drop(price, axis=1, inplace=True)

# test set should not include price
abnb_test_set.drop(price, axis=1, inplace=True)
```

In [46]:

```python
abnb_train_set.describe()
```

Out[46]:

	id	host_id	latitude	longitude	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability_365
count	3.667100e+04	3.667100e+04	36671.000000	36671.000000	36671.000000	36671.000000	29220.000000	36671.000000	36671.000000
mean	1.895560e+07	6.741661e+07	40.729026	-73.952103	7.022715	23.416242	1.368056	7.156309	112.870770
std	1.097103e+07	7.855348e+07	0.054523	0.046339	20.777483	44.880430	1.687344	33.079026	131.655161
min	3.647000e+03	2.438000e+03	40.499790	-74.244420	1.000000	0.000000	0.010000	1.000000	0.000000
25%	9.422985e+06	7.737249e+06	40.690160	-73.983030	1.000000	1.000000	0.190000	1.000000	0.000000
50%	1.960362e+07	3.037019e+07	40.723200	-73.955650	2.000000	5.000000	0.710000	1.000000	46.000000
75%	2.905732e+07	1.074344e+08	40.763155	-73.936150	5.000000	24.000000	2.020000	2.000000	227.000000
max	3.648724e+07	2.743115e+08	40.913060	-73.716900	1250.000000	629.000000	58.500000	327.000000	365.000000

In [47]:

```python
abnb_test_set.describe()
```

Out[47]:

	id	host_id	latitude	longitude	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability_365
count	1.222400e+04	1.222400e+04	12224.000000	12224.000000	12224.000000	12224.000000	9623.000000	12224.000000	12224.000000
mean	1.920178e+07	6.823019e+07	40.728718	-73.952369	7.051702	22.849149	1.388907	7.107003	112.513007
std	1.101764e+07	7.878324e+07	0.054552	0.045606	19.688882	43.545117	1.659298	32.571374	131.528644
min	2.539000e+03	2.787000e+03	40.522110	-74.198260	1.000000	0.000000	0.010000	1.000000	0.000000
25%	9.606994e+06	8.055524e+06	40.689880	-73.983190	1.000000	1.000000	0.200000	1.000000	0.000000
50%	1.988499e+07	3.216326e+07	40.722540	-73.955875	3.000000	5.000000	0.740000	1.000000	43.000000
75%	2.946058e+07	1.074344e+08	40.763042	-73.936690	5.000000	23.000000	2.020000	2.000000	225.000000
max	3.648561e+07	2.743213e+08	40.911670	-73.712990	999.000000	576.000000	17.820000	327.000000	365.000000

In [48]:

```python
abnb_test_labels, abnb_train_labels
```

Out[48]:

```
(8048      75
 16686    175
 32367    160
 35840     80
 9220     155
          ...
 34916    170
 45515    499
 46000    650
 48801    155
 44136     70
 Name: price, Length: 12224, dtype: int64,
 5822      80
 24749    150
 6081     200
 9623      40
 4713      44
          ...
 4613      55
 24840     65
 22868     40
 48563    343
 32423     69
 Name: price, Length: 36671, dtype: int64)
```

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

In [49]:

```python
# months since they have been posting
num_months_posting = 'num_months_posting'
number_of_reviews = 'number_of_reviews'
reviews_per_month = 'reviews_per_month'
abnb_train_set[num_months_posting] = abnb_train_set[number_of_reviews] / abnb_train_set[reviews_per_month]
abnb_test_set[num_months_posting] = abnb_test_set[number_of_reviews] / abnb_test_set[reviews_per_month]
abnb_train_set[num_months_posting].fillna(0,inplace=True)
abnb_test_set[num_months_posting].fillna(0,inplace=True)

# how much of the year does a single booking take up
```

```
one_stay_percent_of_year = 'one_stay_percent_of_year'
availability_365 = 'availability_365'
minimum_nights = 'minimum_nights'
abnb_train_set[one_stay_percent_of_year] = abnb_train_set[minimum_nights] / abnb_train_set[availability_365]
abnb_test_set[one_stay_percent_of_year] = abnb_test_set[minimum_nights] / abnb_test_set[availability_365]
```

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

In [50]:
```
# ANSWER
# nan reviews per month => assume median number of reviews
# If there is a NaN for the number of reviews per month I will set it to the medain of the whole dataset
reviews_per_month = 'reviews_per_month'
median_reviews_per_month = airbnb[reviews_per_month].median()
abnb_train_set[reviews_per_month].fillna(median_reviews_per_month,inplace=True)
abnb_test_set[reviews_per_month].fillna(median_reviews_per_month,inplace=True)
```

In [51]:
```
airbnb.values
```

Out[51]:
```
array([[2539, 2787, 'Brooklyn', ..., 6, 365, 2],
       [2595, 2845, 'Manhattan', ..., 2, 355, 3],
       [3647, 4632, 'Manhattan', ..., 1, 365, 2],
       ...,
       [36485431, 23492952, 'Manhattan', ..., 1, 27, 2],
       [36485609, 30985759, 'Manhattan', ..., 6, 2, 1],
       [36487245, 68119814, 'Manhattan', ..., 1, 23, 1]], dtype=object)
```

In [52]:
```
airbnb.head()
```

Out[52]:

	id	host_id	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_li
0	2539	2787	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	1	9	0.21	
1	2595	2845	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	1	45	0.38	
2	3647	4632	Manhattan	Harlem	40.80902	-73.94190	Private room	150	3	0	NaN	
3	3831	4869	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	1	270	4.64	
4	5022	7192	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	10	9	0.10	

In [53]:
```
airbnb.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   host_id                         48895 non-null  int64
 2   neighbourhood_group             48895 non-null  object
 3   neighbourhood                   48895 non-null  object
 4   latitude                        48895 non-null  float64
 5   longitude                       48895 non-null  float64
 6   room_type                       48895 non-null  object
 7   price                           48895 non-null  int64
 8   minimum_nights                  48895 non-null  int64
 9   number_of_reviews               48895 non-null  int64
 10  reviews_per_month               38843 non-null  float64
 11  calculated_host_listings_count  48895 non-null  int64
 12  availability_365                48895 non-null  int64
 13  categorical_price               48895 non-null  category
dtypes: category(1), float64(3), int64(7), object(3)
memory usage: 4.9+ MB
```

[10 pts] Code complete data pipeline using sklearn mixins

In [54]:
```
from sklearn.model_selection import train_test_split
airbnb = pd.read_csv('datasets/airbnb/AB_NYC_2019.csv')
airbnb_true_vals = airbnb['price'].copy()
airbnb.drop(columns=["name", "host_name", "last_review","id", "host_id", "price"], axis=1, inplace=True)
cat_feat = ['neighbourhood_group', 'neighbourhood', 'room_type']
numeric_columns = airbnb.drop(columns=cat_feat,axis=1)
numeric_features = list(numeric_columns)
print(f'{numeric_features=}')

print(airbnb.info())
```

```
numeric_features=['latitude', 'longitude', 'minimum_nights', 'number_of_reviews', 'reviews_per_month', 'calculated_host_listings_count', 'availa
bility_365']
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 10 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   neighbourhood_group             48895 non-null  object
 1   neighbourhood                   48895 non-null  object
 2   latitude                        48895 non-null  float64
 3   longitude                       48895 non-null  float64
 4   room_type                       48895 non-null  object
 5   minimum_nights                  48895 non-null  int64
 6   number_of_reviews               48895 non-null  int64
```

```
 7   reviews_per_month               38843 non-null  float64
 8   calculated_host_listings_count  48895 non-null  int64
 9   availability_365                48895 non-null  int64
dtypes: float64(3), int64(4), object(3)
memory usage: 3.7+ MB
None
```

In [55]:

```
# imputer = SimpleImputer(strategy="median") # use median imputation for missing values
minimum_nights_ix = 2
number_of_reviews_ix = 3
reviews_per_month_ix = 4
availability_365_ix = 6

class AbnbAugmentFeatures(BaseEstimator, TransformerMixin):
    def fit(self, X, y=None):
        return self  # nothing else to do
    def transform(self, X):
        v1 = X[:, number_of_reviews_ix]
        v2 = X[:, reviews_per_month_ix]
        num_months_posting = np.divide(v1,v2,out=np.zeros_like(v1),where= v2 != 0)
        v3 = X[:, minimum_nights_ix]
        v4 = X[:, availability_365_ix]
        one_stay_percent_of_year = np.divide(v3,v4,out=np.zeros_like(v3),where= v4 != 0)
        return np.c_[X, num_months_posting, one_stay_percent_of_year]

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

full_pipeline = ColumnTransformer([
        ("num", num_pipeline, numeric_features),
        ("cat", OneHotEncoder(), cat_feat),
    ])

airbnb_prepared = full_pipeline.fit_transform(airbnb)
train_set, test_set, train_label, test_label = train_test_split(airbnb_prepared,
                                                                airbnb_true_vals,
                                                                test_size=0.25,
                                                                random_state=42)
```

[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 Mean Absolute Error (MAE). Provide both test and train set MAE values.

In [56]:

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

lin_reg = LinearRegression()
lin_reg.fit(train_set, train_label)

train_pred = lin_reg.predict(train_set)
test_pred = lin_reg.predict(test_set)

train_mae = mean_absolute_error(train_label, train_pred)
test_mae = mean_absolute_error(test_label, test_pred)

print(f'{train_mae=}')
print(f'{test_mae=}')
```

```
train_mae=72.86928149499015
test_mae=68.79961790008474
```