In [ ]:
```
%%HTML
<style>
    body {
        --vscode-font-family: "Noto Serif"
    }
</style>
```

Understanding the Data

In [ ]:
```python
import os
import tarfile
from six.moves import urllib
import pandas as pd

DOWNLOAD_ROOT = "https://raw.githubusercontent.com/ageron/handson-ml2/master/"
HOUSING_PATH = os.path.join("datasets", "housing")
HOUSING_URL = DOWNLOAD_ROOT + "datasets/housing/housing.tgz"


def fetch_housing_data(housing_url=HOUSING_URL, housing_path=HOUSING_PATH):
    if not os.path.isdir(housing_path):
        os.makedirs(housing_path)
    tgz_path = os.path.join(housing_path, "housing.tgz")
    urllib.request.urlretrieve(housing_url, tgz_path)
    housing_tgz = tarfile.open(tgz_path)
    housing_tgz.extractall(path=housing_path)
    housing_tgz.close()
```

upon calling the function `fetch_housing_data()`, it

1. creates datasets/housing directory
2. downloads housing.tgz
3. extracts housing.csv in the directory

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

In [ ]:
```python
fetch_housing_data() # get the csv

housing = load_housing_data() # load it
housing.head()
```

Out[ ]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342

In [ ]:
```python
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 [ ]:
```python
# examine the ocean_proximity column

housing["ocean_proximity"].value_counts()
```

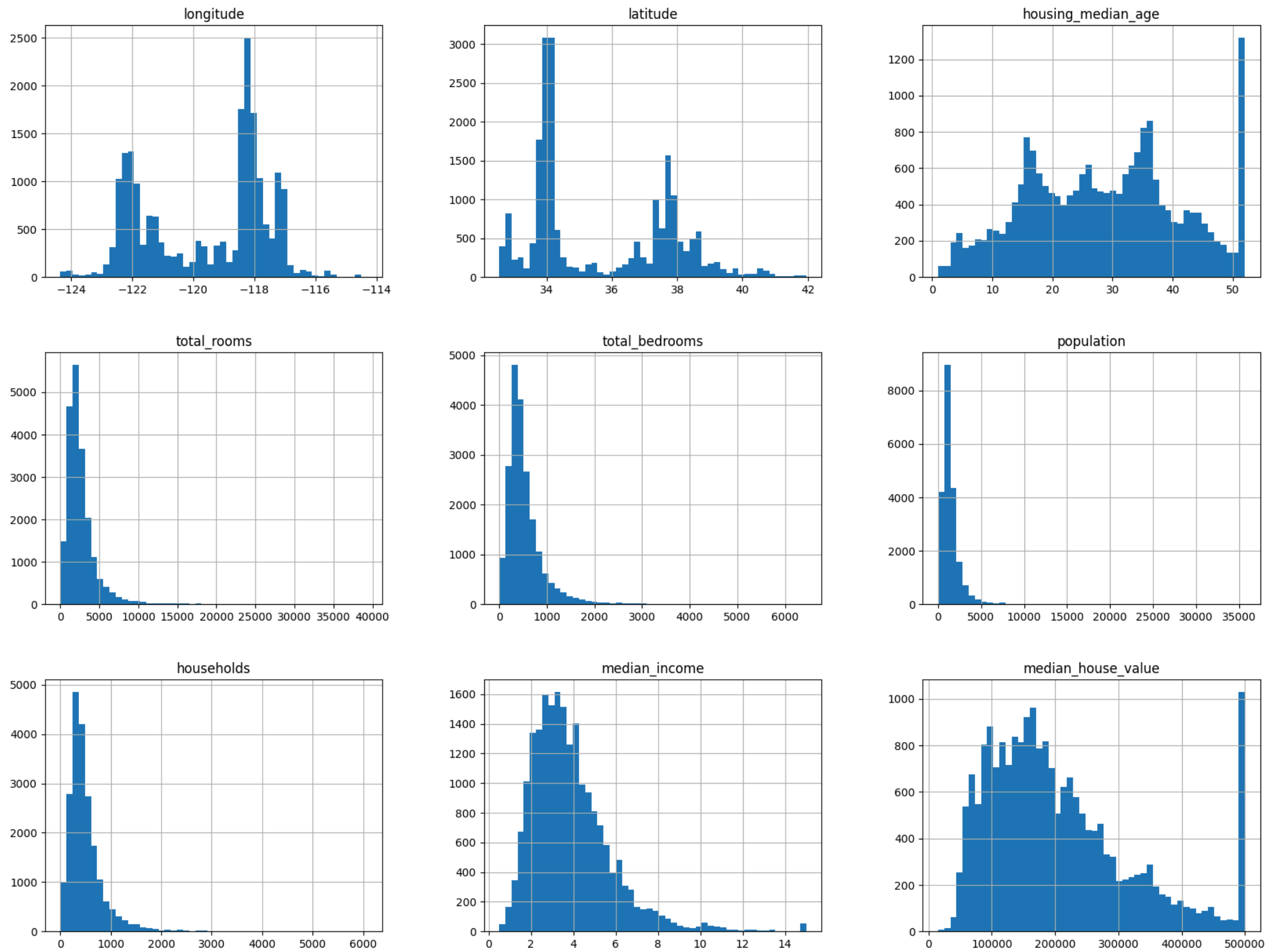
Out[ ]:
```
ocean_proximity
<1H OCEAN     9136
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: count, dtype: int64
```

In [ ]:
```python
housing.describe() # describes the summary of numerical attributes
```

Out[ ]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_incom
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000000	20640.000000	20640.00000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744	499.539680	3.87067
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462122	382.329753	1.89982
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000	1.000000	0.49990
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000000	280.000000	2.56340
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000000	409.000000	3.53480
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000000	605.000000	4.74325
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000000	6082.000000	15.00010

In [ ]:
```python
housing.hist(bins=50, figsize=(20,15))
__import__("matplotlib").pyplot.show()
```



Vertical Axis $\longrightarrow$ Number of entries/instances of the value

Horizontal Axis $\longrightarrow$ range of values

In [ ]:
```
housing["median_income"]
```

Out[ ]:
```
0        8.3252
1        8.3014
2        7.2574
3        5.6431
4        3.8462
          ...
20635    1.5603
20636    2.5568
20637    1.7000
20638    1.8672
20639    2.3886
Name: median_income, Length: 20640, dtype: float64
```

You find out that the median_income is represented in ten thousands of US dollars.

eg: 8 means $80,000

Making a Test Set and Training Set

In [ ]:
```
# creating a test set (generally 20% of the dataset or even less if dataset is too large)

import numpy as np

def split_train_test(data, test_ratio):
    shuffled_indices = np.random.permutation(len(data))
    test_set_size = int(len(data) * test_ratio)
    test_indices, train_indices = shuffled_indices[:test_set_size], shuffled_indices[test_set_size:]
    return data.iloc[test_indices], data.iloc[train_indices]

test_set, train_set = split_train_test(housing, 0.2)
test_set.head()
```

Out[ ]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_ho
20035	-119.01	36.07	44.0	2450.0	575.0	1330.0	508.0	1.6103	
2487	-120.35	36.16	18.0	1519.0	296.0	846.0	272.0	2.7792	
8278	-118.16	33.78	29.0	3684.0	1301.0	3891.0	1143.0	1.6955	
1328	-121.87	38.02	31.0	3644.0	746.0	2229.0	678.0	3.1389	
17476	-119.92	34.44	17.0	2143.0	324.0	1073.0	330.0	6.0321	

Break-proofing the split approach

The next time the code is run again, it will choose different set of indices, over time, the model will get to see the whole dataset which is to be avoided.

Solutions:

1. Save test set on first run and load it in subsequent runs
2. Set a random number generator's seed before calling permutation() so it generates same shuffled indices

But both the solutions will break when fetching an updated dataset.

In [ ]:
```
# Best solution

from zlib import crc32

def test_set_check(identifier, test_ratio):
    return crc32(np.int64(identifier)) & 0xffffffff < test_ratio * 2 ** 32

def split_train_test_by_id(data, test_ratio, id_column_name):
    ids = data[id_column_name]
    in_test_set = ids.apply(lambda id_: test_set_check(id_, test_ratio))
    return data.loc[~in_test_set], data.loc[in_test_set]
```

Working of the test_set_check

1. the identifier is converted into a 64-bit integer.
2. The crc32 function returns the hash of the 64-bit identifier and it is masked with the highest value of 32 bit integer which is 0xffffffff to truncate it into a 32-bit integer.
3. the test_ratio is multiplied with 2^{32} to maintain the scale.
4. The hash is checked with the test_ratio

In [ ]:
```
# Add a custom ID column to the dataset since it does not have it

housing
```

Out[ ]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_ho
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	
...	...	...	...	...	...	...	...	...	
20635	-121.09	39.48	25.0	1665.0	374.0	845.0	330.0	1.5603	
20636	-121.21	39.49	18.0	697.0	150.0	356.0	114.0	2.5568	
20637	-121.22	39.43	17.0	2254.0	485.0	1007.0	433.0	1.7000	
20638	-121.32	39.43	18.0	1860.0	409.0	741.0	349.0	1.8672	
20639	-121.24	39.37	16.0	2785.0	616.0	1387.0	530.0	2.3886	

20640 rows × 10 columns

In [ ]:
```
housing_with_id = housing.reset_index() # adds an index column
housing_with_id
```

Out[ ]:

	index	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	me
0	0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	
1	1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	
2	2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	
3	3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	
4	4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	
...	...	...	...	...	...	...	...	...	...	
20635	20635	-121.09	39.48	25.0	1665.0	374.0	845.0	330.0	1.5603	
20636	20636	-121.21	39.49	18.0	697.0	150.0	356.0	114.0	2.5568	
20637	20637	-121.22	39.43	17.0	2254.0	485.0	1007.0	433.0	1.7000	
20638	20638	-121.32	39.43	18.0	1860.0	409.0	741.0	349.0	1.8672	
20639	20639	-121.24	39.37	16.0	2785.0	616.0	1387.0	530.0	2.3886	

20640 rows × 11 columns

In [ ]:
```
train_set, test_set = split_train_test_by_id(housing_with_id, 0.2, "index")

test_set
```

Out[ ]:

	index	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	me
2	2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	
5	5	-122.25	37.85	52.0	919.0	213.0	413.0	193.0	4.0368	
12	12	-122.26	37.85	52.0	2491.0	474.0	1098.0	468.0	3.0750	
16	16	-122.27	37.85	52.0	1966.0	347.0	793.0	331.0	2.7750	
23	23	-122.27	37.84	52.0	1688.0	337.0	853.0	325.0	2.1806	
...	...	...	...	...	...	...	...	...	...	
20615	20615	-121.54	39.08	23.0	1076.0	216.0	724.0	197.0	2.3598	
20617	20617	-121.53	39.06	20.0	561.0	109.0	308.0	114.0	3.3021	
20622	20622	-121.44	39.00	20.0	755.0	147.0	457.0	157.0	2.4167	
20626	20626	-121.43	39.18	36.0	1124.0	184.0	504.0	171.0	2.1667	
20629	20629	-121.39	39.12	28.0	10035.0	1856.0	6912.0	1818.0	2.0943	

4128 rows × 11 columns

Same thing can be done with Scikit-Learns train_test_split method:

In [ ]:
```python
from sklearn.model_selection import train_test_split

train_test, test_set = train_test_split(housing, test_size=0.2, random_state=42) # the integer 42 is just a convent
test_set # run it as many times as you want and the result will be the same (unless you change the random_state)
```

Out[ ]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_ho
20046	-119.01	36.06	25.0	1505.0	NaN	1392.0	359.0	1.6812	
3024	-119.46	35.14	30.0	2943.0	NaN	1565.0	584.0	2.5313	
15663	-122.44	37.80	52.0	3830.0	NaN	1310.0	963.0	3.4801	
20484	-118.72	34.28	17.0	3051.0	NaN	1705.0	495.0	5.7376	
9814	-121.93	36.62	34.0	2351.0	NaN	1063.0	428.0	3.7250	
...	...	...	...	...	...	...	...	...	
15362	-117.22	33.36	16.0	3165.0	482.0	1351.0	452.0	4.6050	
16623	-120.83	35.36	28.0	4323.0	886.0	1650.0	705.0	2.7266	
18086	-122.05	37.31	25.0	4111.0	538.0	1585.0	568.0	9.2298	
2144	-119.76	36.77	36.0	2507.0	466.0	1227.0	474.0	2.7850	
3665	-118.37	34.22	17.0	1787.0	463.0	1671.0	448.0	3.5521	

4128 rows × 10 columns

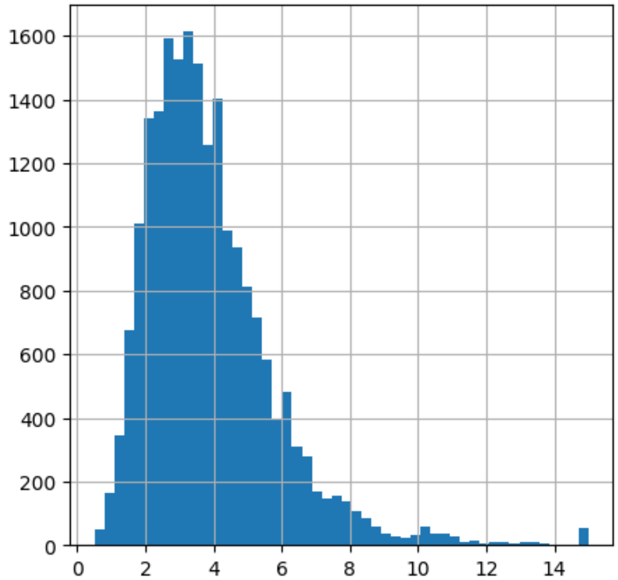
Avoiding Sampling Bias

It is important for a model to consider each and every category of an attribute to avoid sampling bias. for example, a survey on population of a country consisting of 55% males and 45% females need to take into consideration of 55 males and 45 females in a 100 people. If the percentages does not represent the whole population of the country, then the survey may be considered as biased.

Suppose the experts told you that the median income is a very important attribute to predict median housing prices. You should ensure that the test set is representative of the various categories of incomes in the whole dataset.

In [ ]:
```python
plt = __import__("matplotlib").pyplot # using matplotlib's pyplot
```

In [ ]:
```python
housing["median_income"].hist(figsize=(5, 5), bins=50)

plt.show()
```



In [ ]:
```
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[["median_income", "income_cat"]]
```

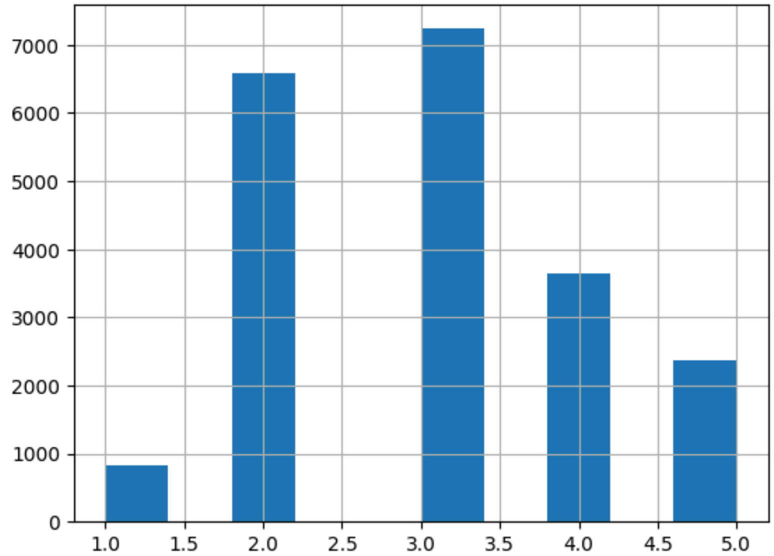
Out[ ]:

	median_income	income_cat
0	8.3252	5
1	8.3014	5
2	7.2574	5
3	5.6431	4
4	3.8462	3
...	...	...
20635	1.5603	2
20636	2.5568	2
20637	1.7000	2
20638	1.8672	2
20639	2.3886	2

20640 rows × 2 columns

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

Out[ ]: <Axes: >



Stratified Sampling

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

split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_indexes, test_indexes in split.split(housing, housing["income_cat"]):
    strat_train_set = housing.loc[train_indexes]
    strat_test_set = housing.loc[test_indexes]

strat_train_set
```

Out[ ]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_ho
12655	-121.46	38.52	29.0	3873.0	797.0	2237.0	706.0	2.1736	
15502	-117.23	33.09	7.0	5320.0	855.0	2015.0	768.0	6.3373	
2908	-119.04	35.37	44.0	1618.0	310.0	667.0	300.0	2.8750	
14053	-117.13	32.75	24.0	1877.0	519.0	898.0	483.0	2.2264	
20496	-118.70	34.28	27.0	3536.0	646.0	1837.0	580.0	4.4964	
...	...	...	...	...	...	...	...	...	
15174	-117.07	33.03	14.0	6665.0	1231.0	2026.0	1001.0	5.0900	
12661	-121.42	38.51	15.0	7901.0	1422.0	4769.0	1418.0	2.8139	
19263	-122.72	38.44	48.0	707.0	166.0	458.0	172.0	3.1797	
19140	-122.70	38.31	14.0	3155.0	580.0	1208.0	501.0	4.1964	
19773	-122.14	39.97	27.0	1079.0	222.0	625.0	197.0	3.1319	

16512 rows × 11 columns

In [ ]:
```
# percentage of categories in train set
highest = max([j for _,j in strat_train_set["income_cat"].value_counts().items()])
for i,j in strat_train_set["income_cat"].value_counts().items():
    print(str(i) + ":", str((j/highest)*100) + "%")
```

```
3: 100.0%
2: 90.9483503195716%
4: 50.28502332008983%
5: 32.64812575574365%
1: 11.349110381758507%
```

In [ ]:
```
# percentage of categories in test set
highest = max([j for _,j in strat_test_set["income_cat"].value_counts().items()])
for i,j in strat_test_set["income_cat"].value_counts().items():
    print(str(i) + ":", str((j/highest)*100) + "%")
```

```
3: 100.0%
2: 90.94678645473392%
4: 50.310988251554946%
5: 32.61921216309606%
1: 11.402902557014514%
```

Since both the train set and test set have the same number of categories shuffled randomly, the likelyhood of a Sampling Bias is significantly reduced.

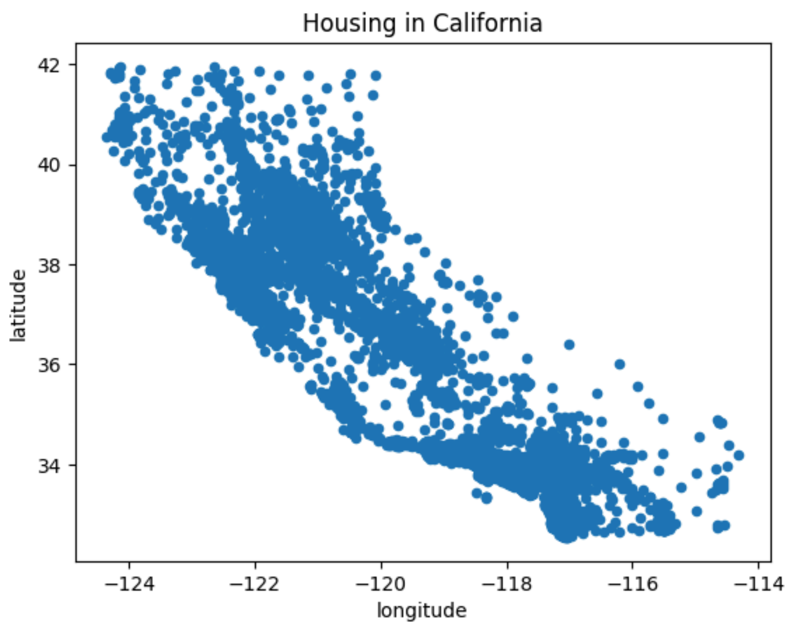
You should remove the income_cat attribute so the data is back to its original state.

In [ ]:
```
# Removing income_cat column
for set_ in (strat_train_set, strat_test_set):
    set_.drop("income_cat", axis=1, inplace=True)
```

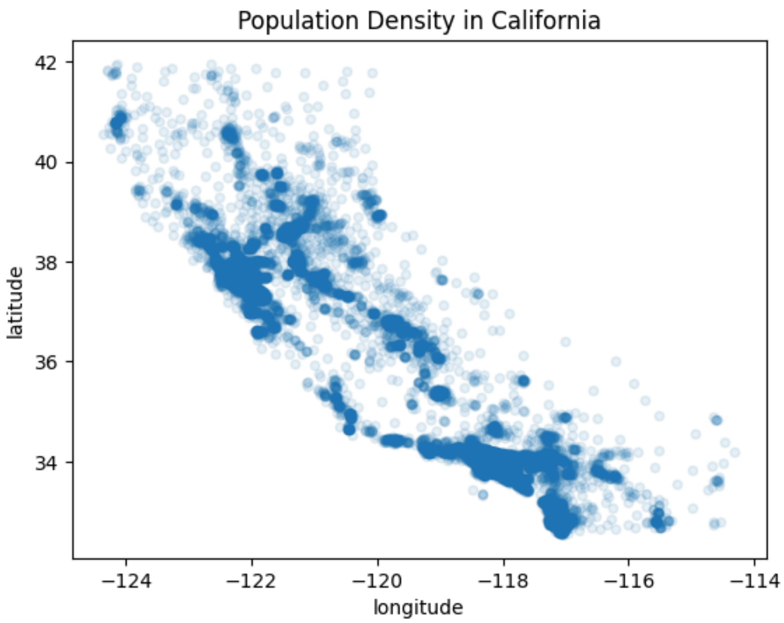
Visualize the Data

The goal is to go a little more in-depth into understanding of the data. First, make sure the test-set is left aside and only the training set is explored.
Note: If the training set is very large, you may want to sample an exploration set, to make manipulations easy and fast. In this case, the training set is fairly small so you can directly work on the full set.

In [ ]:
```
# Plotting latitudes and longitudes to see the location of all districts

housing.plot(kind="scatter", x="longitude", y="latitude")
plt.title("Housing in California")
plt.show()
```



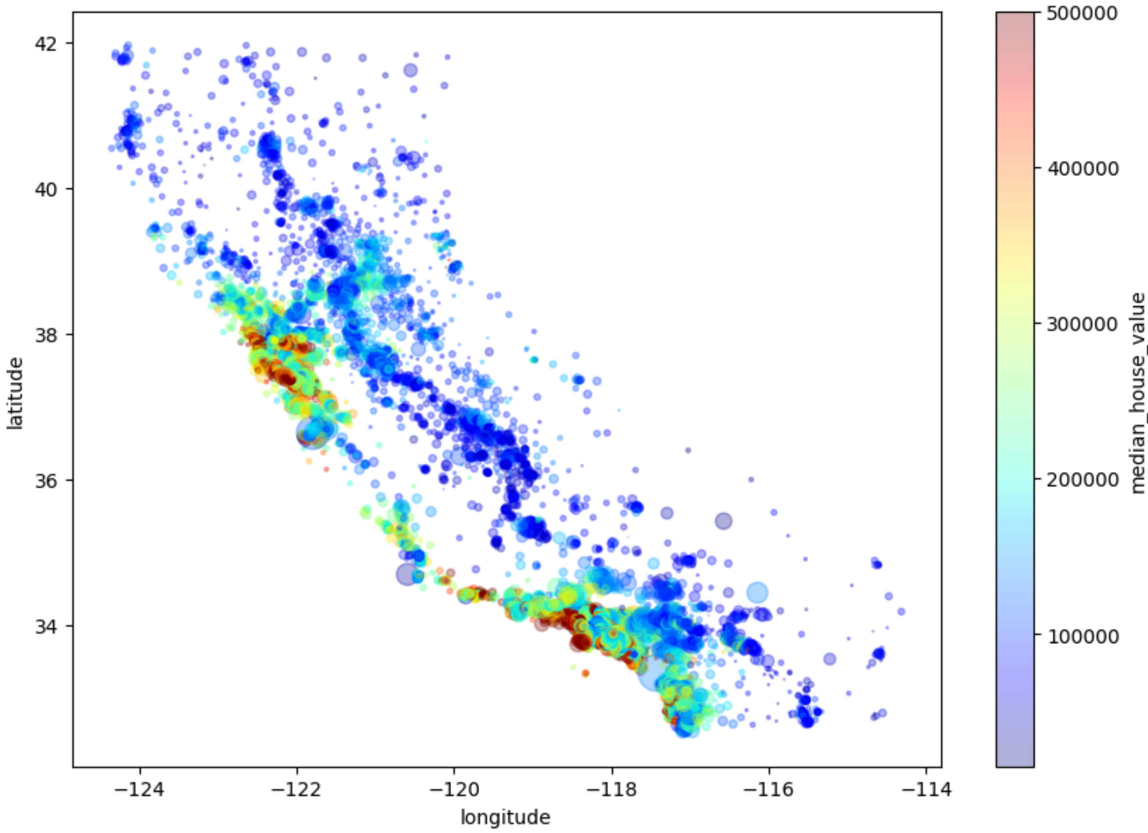
In [ ]:
```
housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.1)
plt.title("Population Density in California")
plt.show()
```



highly densed areas can now be seen clearly.

Now let's visualize the population of each district in the state. The radius of the circles represents the district's population and the color represents the price (blue meaning more affordable and red being more expensive).

In [ ]:
```
housing.plot(
    kind="scatter",
    alpha=0.3,
    x="longitude",
    y="latitude",
    s=housing["population"]/100,
    c="median_house_value",
    cmap=plt.get_cmap("jet"),
    colorbar=True,
    figsize=(10,7)
)
plt.show()
```



Takeaways from the graph:

1. The housing prices are related to the location(eg, close to the ocean)
2. The housing prices are related to population density

Looking for Correlations

We can compute the standard correlation coefficient between every pair of attributes using the corr() method.

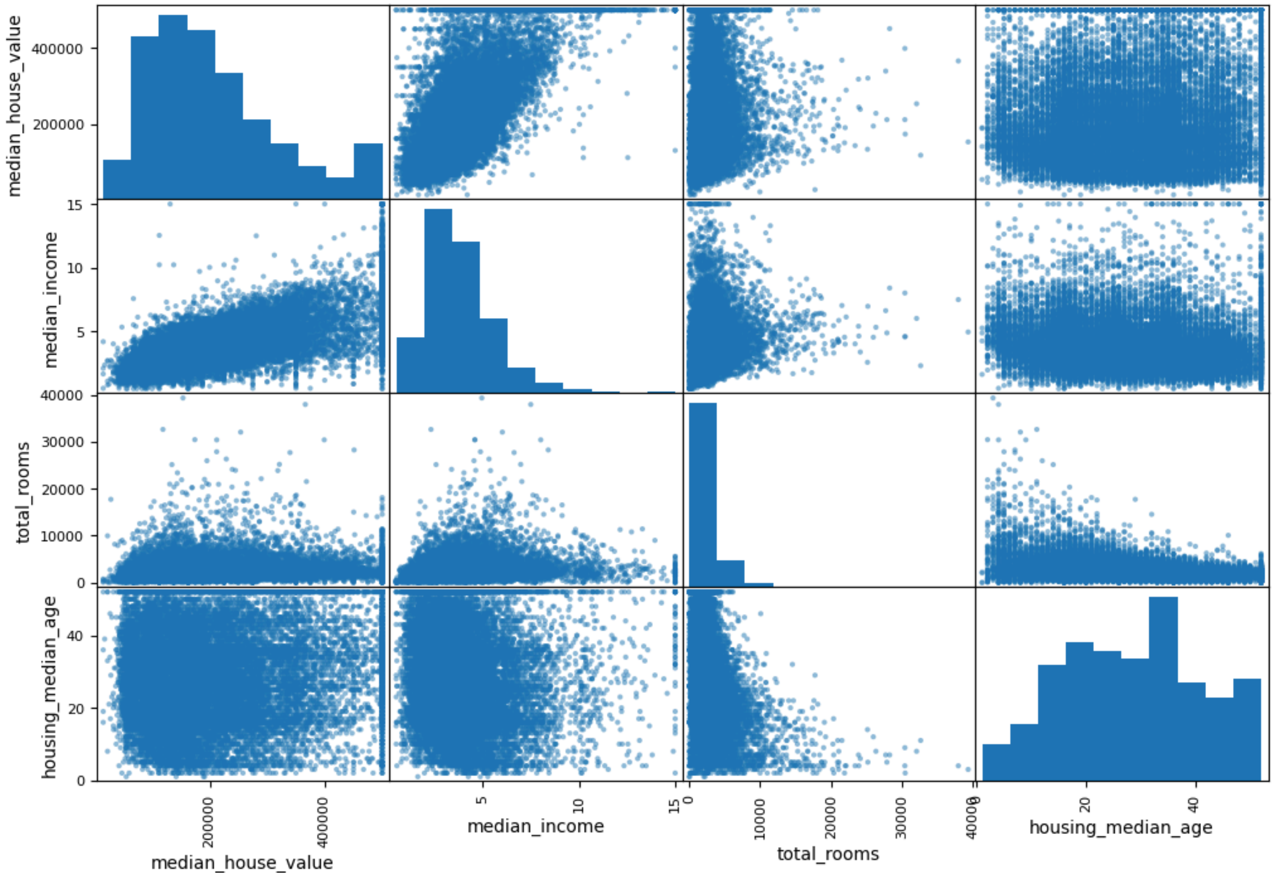
In [ ]:
```python
# housing_numeric_only = housing.select_dtypes(include=[np.number])
# corr_matrix = housing_numeric_only.corr()
# corr_matrix["median_house_value"].sort_values(ascending=False)

# (or)

corr_matrix = housing.corr(numeric_only=True)
corr_matrix["median_house_value"].sort_values(ascending=False)
```

Out[ ]:
```
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
```

These correlations co-efficients are with respect the the `median_house_value`. For example, the `median_house_value` tends to go up when the `median_income` goes up, because the correlation coefficient between the two is 0.688, which is pretty close to 1 and has a strong positive correlation.
Also, the `median_house_value` tends to go a little up the more you travel to the south because of the negative correlation between `median_house_value` and `latitude`.

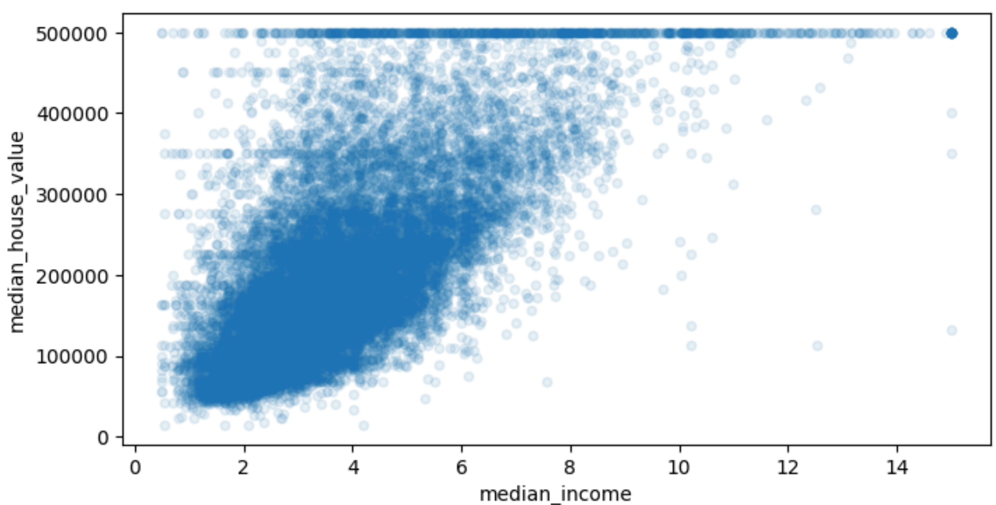
Another way is to use `pandas.plotting.scatter_matrix` function, which plots every numerical attribute against every other numerical attribute. This results in 11^2 = 121 correlations and 121 plots which won't fit in the graph. So we will only focus on a few promising attributes that seem most correlated with the `median_house_value`.

In [ ]:
```python
from pandas.plotting import scatter_matrix

attributes = ["median_house_value", "median_income", "total_rooms", "housing_median_age"]

_ = scatter_matrix(housing[attributes], figsize=(12, 8))
plt.show()
```



Since the most useful attribute is the `median_income` attribute, we will focus on that.

In [ ]:
```python
housing.plot(kind="scatter", x="median_income", y="median_house_value", alpha=0.1, figsize=(8,4))
plt.show()
```



Attribute Combinations

So far, we have identified

1. Few data quirks to be cleaned up before feeding it to an ML algorithm

2. correlations between attributes
3. tail-heavy distribution in some attributes

The total number of rooms in a district is not very useful without the number of households in the district. What we really want is the number of rooms per household, not number of rooms per district. The population per household is also an interesting attribute combination to look at.

In [ ]:
```
housing[["households", "total_rooms", "total_bedrooms"]]
```

Out[ ]:

	households	total_rooms	total_bedrooms
0	126.0	880.0	129.0
1	1138.0	7099.0	1106.0
2	177.0	1467.0	190.0
3	219.0	1274.0	235.0
4	259.0	1627.0	280.0
...	...	...	...
20635	330.0	1665.0	374.0
20636	114.0	697.0	150.0
20637	433.0	2254.0	485.0
20638	349.0	1860.0	409.0
20639	530.0	2785.0	616.0

20640 rows × 3 columns

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

If we look at the correlation matrix again...

In [ ]:
```
corr_matrix = housing.corr(numeric_only=True)
corr_matrix["median_house_value"].sort_values(ascending=False)
```

Out[ ]:
```
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
```

The correlation between `median_house_value` with the attributes like `rooms_per_household` and `bedrooms_per_room` seems to be more informative than the correlation with `total_rooms` or `total_bedrooms`. Apparently the houses with a lower bedroom to room ratio tend to be more expensive. And the house price tends to go up when there are more rooms per household. Obviously the larger the house, more the price.

Preparing the Data for Machine Learning Algorithms

It is time to **prepare the data** for your Machine Learning Algorithms. Instead of just doing this manually, writing functions to do the tasks is much more preferred for the following reasons:

1. Reproduce transformations easily on the dataset
2. Gradually build up library of transformation functions that can be reused in future projects
3. The functions can be used in live system to transform the new data before feeding it to your algorithms
4. This will make it possible for you to easily try various transformations and see which combination of transformations work the best.

Let's begin with a clean training set by copying the `strat_train_set` and let's separate the predictors and labels since we don't necessarily want to apply the same transformations to the predictors and the target values.

In [ ]:
```
housing = strat_train_set.drop("median_house_value", axis=1)
housing_labels = strat_train_set["median_house_value"].copy()
```

In [ ]:
```
housing_labels
```

Out[ ]:
```
12655     72100.0
15502    279600.0
2908      82700.0
14053    112500.0
20496    238300.0
           ...
15174    268500.0
12661     90400.0
19263    140400.0
19140    258100.0
19773     62700.0
Name: median_house_value, Length: 16512, dtype: float64
```

Data Cleaning

Most ML Algorithms cannot work with **missing features**. Let's create few functions to take care of them.
We noticed that the `total_bedrooms` attribute has some missing values.

In [ ]:
```
housing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 16512 entries, 12655 to 19773
Data columns (total 9 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   longitude           16512 non-null  float64
 1   latitude            16512 non-null  float64
 2   housing_median_age  16512 non-null  float64
 3   total_rooms         16512 non-null  float64
 4   total_bedrooms      16354 non-null  float64
 5   population          16512 non-null  float64
 6   households          16512 non-null  float64
 7   median_income       16512 non-null  float64
 8   ocean_proximity     16512 non-null  object
dtypes: float64(8), object(1)
memory usage: 1.3+ MB
```

In [ ]:
```
housing["total_bedrooms"].isna().sum() # number of missing values
```

Out[ ]:
```
158
```

Option 1: get rid of corresponding districts
Option 2: get rid of the whole attribute
Option 3: Set the values to some value (eg, zero, mean, median etc)

In [ ]:
```
# housing.dropna(subset=["total_bedrooms"]) -> Option 1
# housing.drop("total_bedrooms", axis=1) -> Option 2
# housing["total_bedrooms"].fillna(housing["total_bedrooms"].median(skipna=True), inplace=True) -> Option 3
```

Scikit-learn provides a handy class to take care of Missing values: `SimpleImputer`.
First create a `SimpleImputer` instance, sppecifying that you want to replace each attribute's missing values with the median of that attribute.

In [ ]:
```
from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy="median")

housing_numeric = housing.drop("ocean_proximity", axis=1) # since median can only be computed on numerical attribut

imputer.fit(housing_numeric)
```

Out[ ]:
```
▾ SimpleImputer
SimpleImputer(strategy='median')
```

The imputer has simply computed the median of each attribute and stored the results in its `statistics_` instance variable. Only the `total_bedrooms` attribute had some missing values, but we can't be sure that there won't be any missing values in new data after the system goes live.

In [ ]:
```
imputer.statistics_
```

Out[ ]:
```
array([-118.51    ,   34.26    ,   29.      , 2119.      ,  433.      ,
       1164.      ,  408.      ,    3.54155])
```

Now the "trained" imputer can be used to transform the training set by replacing the missing values by the learned medians.

In [ ]:
```
X = imputer.transform(housing_numeric) # result is a numpy array containing transformed features.
X
```

Out[ ]:
```
array([[-1.2146e+02,  3.8520e+01,  2.9000e+01, ...,  2.2370e+03,
         7.0600e+02,  2.1736e+00],
       [-1.1723e+02,  3.3090e+01,  7.0000e+00, ...,  2.0150e+03,
         7.6800e+02,  6.3373e+00],
       [-1.1904e+02,  3.5370e+01,  4.4000e+01, ...,  6.6700e+02,
         3.0000e+02,  2.8750e+00],
       ...,
       [-1.2272e+02,  3.8440e+01,  4.8000e+01, ...,  4.5800e+02,
         1.7200e+02,  3.1797e+00],
       [-1.2270e+02,  3.8310e+01,  1.4000e+01, ...,  1.2080e+03,
         5.0100e+02,  4.1964e+00],
       [-1.2214e+02,  3.9970e+01,  2.7000e+01, ...,  6.2500e+02,
         1.9700e+02,  3.1319e+00]])
```

In [ ]:
```
housing_tr = pd.DataFrame(X, columns=housing_numeric.columns)
housing_tr
```

Out[ ]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income
0	-121.46	38.52	29.0	3873.0	797.0	2237.0	706.0	2.1736
1	-117.23	33.09	7.0	5320.0	855.0	2015.0	768.0	6.3373
2	-119.04	35.37	44.0	1618.0	310.0	667.0	300.0	2.8750
3	-117.13	32.75	24.0	1877.0	519.0	898.0	483.0	2.2264
4	-118.70	34.28	27.0	3536.0	646.0	1837.0	580.0	4.4964
...	...	...	...	...	...	...	...	...
16507	-117.07	33.03	14.0	6665.0	1231.0	2026.0	1001.0	5.0900
16508	-121.42	38.51	15.0	7901.0	1422.0	4769.0	1418.0	2.8139
16509	-122.72	38.44	48.0	707.0	166.0	458.0	172.0	3.1797
16510	-122.70	38.31	14.0	3155.0	580.0	1208.0	501.0	4.1964
16511	-122.14	39.97	27.0	1079.0	222.0	625.0	197.0	3.1319

16512 rows × 8 columns

Handling Text and Categorical Attributes

In [ ]:
```
housing_cat = housing[["ocean_proximity"]]
housing_cat.head(10)
```

Out[ ]:

	ocean_proximity
12655	INLAND
15502	NEAR OCEAN
2908	INLAND
14053	NEAR OCEAN
20496	<1H OCEAN
1481	NEAR BAY
18125	<1H OCEAN
5830	<1H OCEAN
17989	<1H OCEAN
4861	<1H OCEAN

In [ ]:
```
housing_cat.value_counts()
```

Out[ ]:
```
ocean_proximity
<1H OCEAN         7277
INLAND            5262
NEAR OCEAN        2124
NEAR BAY          1847
ISLAND               2
Name: count, dtype: int64
```

Most ML algorithms prefer to work with numbers anywa, so converting these categories from text to numbers will prove to be very useful. We will use Scikit-Learn's `OrdinalEncoder` class.

In [ ]:
```
from sklearn.preprocessing import OrdinalEncoder

ordinal_encoder = OrdinalEncoder()
```

In [ ]:
```
housing_cat_encoded = ordinal_encoder.fit_transform(housing_cat)
housing_cat_encoded[:10]
```

Out[ ]:
```
array([[1.],
       [4.],
       [1.],
       [4.],
       [0.],
       [3.],
       [0.],
       [0.],
       [0.],
       [0.]])
```

You can get a list of categories using the categories_ instance variable.

In [ ]:
```
ordinal_encoder.categories_
```

Out[ ]:
```
[array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],
       dtype=object)]
```

One issue with ML Algorithms is that it will assume two nearby values are more similar than distant values. For cases like "good", "average", "bad", "worst" it's fine, but it is certainly not the case for `ocean_proximity` column. Eg, value categories 0 and 4 are more similar than values 0 and 1.
To fix the issue, we go with the **one-hot encoding** approach.

The idea is to create one binary attribute per category: one attribute will be equal to 1 when the category equals "<1H OCEAN" (0 otherwise) and so on. The new attributes are sometimes called *dummy attributes*. Scikit Learn provides a `OneHotEncoder` class to convert categorical values into one-hot vectors. watch this video to learn more about it.

In [ ]:
```
from sklearn.preprocessing import OneHotEncoder

category_encoder = OneHotEncoder()
housing_cat_1hot = category_encoder.fit_transform(housing_cat)
housing_cat_1hot
```

Out[ ]:
```
<16512x5 sparse matrix of type '<class 'numpy.float64'>'
        with 16512 stored elements in Compressed Sparse Row format>
```

The output is a Sparse Matrix, instead of a NumPy array. This is very useful when you have categorical attributes with thousands of categories. After one-hot encoding, we get a matrix with thousands of columns, and the matrix is full of zeroes except for a single 1 per row.
Storing tons of memory mostly to store zeroes would be very wasteful, so instead the sparse matrix only stores the location of the non-zero elements. It can be used mostly like a 2-D array, but if you wish to convert it to a dense array, you can use the `toarray()` method to do so.

In [ ]:
```
housing_cat_1hot.toarray()
```

Out[ ]:
```
array([[0., 1., 0., 0., 0.],
       [0., 0., 0., 0., 1.],
       [0., 1., 0., 0., 0.],
       ...,
       [1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0.]])
```

In [ ]:
```
category_encoder.categories_
```

Out[ ]:
```
[array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],
       dtype=object)]
```

Note:
If a categorical attribute has a large number of possible categories (eg, country code, profession, etc) then one-hot encoding might be very expensive on hardware and may slow down the performance. You may want to replace the categorical input with useful numerical features related to categorries (eg, replace ocean_proximity with distance to the ocean, replace country code with it's population or gdp per capita). Alternatively, you could replace each category with a learnable low dimensional vector called *embedding* (available in Chapter 13).

Custom Transformers

Sometimes you will need to write your own customized Transformers for tasks such as custom cleanup operations or combining specific attribtues. Since Scikit Learn relies on Duck Typing (instead of inheritance), all you need to do is implement 3 methods:

1. `fit()`
2. `transform()`
3. `fit_transform()`

For example, here is a custom small transformer that adds combined attributes we discussed earlier:

In [ ]:
```
housing_numeric.columns
```

Out[ ]:
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income'],
      dtype='object')
```

the indexing for `total_rooms`, `total_bedrooms`, `population` and `households` is 3, 4, 5 and 6 respectively.

In [ ]:
```
housing.values
```

Out[ ]:
```
array([[-121.46, 38.52, 29.0, ..., 706.0, 2.1736, 'INLAND'],
       [-117.23, 33.09, 7.0, ..., 768.0, 6.3373, 'NEAR OCEAN'],
       [-119.04, 35.37, 44.0, ..., 300.0, 2.875, 'INLAND'],
       ...,
       [-122.72, 38.44, 48.0, ..., 172.0, 3.1797, '<1H OCEAN'],
       [-122.7, 38.31, 14.0, ..., 501.0, 4.1964, '<1H OCEAN'],
       [-122.14, 39.97, 27.0, ..., 197.0, 3.1319, 'INLAND']], dtype=object)
```

In [ ]:
```
from sklearn.base import BaseEstimator, TransformerMixin

rooms_ix, bedrooms_ix, population_ix, households_ix = 3, 4, 5, 6

class CombinedAttributesAdder(BaseEstimator, TransformerMixin):
    def __init__(self, add_bedrooms_per_room=True): # add_bedrooms_per_room -> hyperparameter
        self.add_bedrooms_per_room = add_bedrooms_per_room

    def fit(self, X, y=None):
        return self

    def transform(self, X, y=None):
        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, bedrooms_per_room, population_per_household]
        else:
            return np.c_[X,  rooms_per_household, population_per_household]

    def getColumns(self):
        if self.add_bedrooms_per_room:
            return np.append([i for i in housing.columns], ["rooms_per_household", "bedrooms_per_room", "population
        return np.append([i for i in housing.columns], ["rooms_per_household", "population_per_household"])


attr_adder = CombinedAttributesAdder(add_bedrooms_per_room=False)
housing_extra_attribs = attr_adder.transform(housing.values)
```

In [ ]:
```
housing_extra_attribs
```

Out[ ]:
```
array([[-121.46, 38.52, 29.0, ..., 'INLAND', 5.485835694050992,
        3.168555240793201],
       [-117.23, 33.09, 7.0, ..., 'NEAR OCEAN', 6.927083333333333,
        2.6236979166666665],
       [-119.04, 35.37, 44.0, ..., 'INLAND', 5.3933333333333335,
        2.223333333333333],
       ...,
       [-122.72, 38.44, 48.0, ..., '<1H OCEAN', 4.1104651162790695,
        2.6627906976744184],
       [-122.7, 38.31, 14.0, ..., '<1H OCEAN', 6.297405189620759,
        2.411177644710579],
       [-122.14, 39.97, 27.0, ..., 'INLAND', 5.477157360406092,
        3.1725888324873095]], dtype=object)
```

In [ ]:
```
pd.DataFrame(data=housing_extra_attribs, columns=attr_adder.getColumns()).head()
```

Out[ ]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximit
0	-121.46	38.52	29.0	3873.0	797.0	2237.0	706.0	2.1736	INLANI
1	-117.23	33.09	7.0	5320.0	855.0	2015.0	768.0	6.3373	NEAR OCEAI
2	-119.04	35.37	44.0	1618.0	310.0	667.0	300.0	2.875	INLANI
3	-117.13	32.75	24.0	1877.0	519.0	898.0	483.0	2.2264	NEAR OCEAI
4	-118.7	34.28	27.0	3536.0	646.0	1837.0	580.0	4.4964	<1H OCEAI

In this example, the transformer has one **Hyperparameter**, `add_bedrooms_per_room`, set to `True` by default. This hyperparameter will allow you to easily find out whether adding this unique attribute helps the ML algorithms or not. You can add a hyperparameter to gate any data preparation step that you are not 100% sure about.

Feature Scaling

Feature Scaling is one of the most important transformations to apply to your data. ML Algorithms usually do not perform well when the input numerical attributes have very different scales.
For example, the **total number of rooms** ranges from 6 to $39,320$, while the **median incomes** only range from 0 to 15. Note that that scaling the target values is generally not required.

In [ ]:
```
housing["total_rooms"].min(), housing["total_rooms"].max()
```

Out[ ]:
```
(6.0, 39320.0)
```

In [ ]:
```
housing["median_income"].min(), housing["median_income"].max()
```

Out[ ]:
```
(0.4999, 15.0001)
```

Two ways to get all attributes to have same scale:

1. Min-Max Scaling / Normalization
2. Standardization

Min-Max Scaling

Values are shifted and rescaled so that they end up ranging from 0 to 1. We do this by subtracting by the min value and dividing by the max minus the min.

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

There is a scikit-learn transformer called `MinMaxScaler` that let's you do this. It has a `feature_range` hyperparameter that lets you change the range if you don't want 0-1 for some reason.

Standardization

It subtracts value by the mean value and then divides by the standard deviation. Unlike min-max scaling, standardization does not have bound values to a specific range, which may be a problem for some algorithms (eg, neural networks often expect input value ranging from 0 to 1). However, standardization is much less affected by outliers.

$$x_{std} = \frac{x - \mu_X}{\sigma_X}, \forall x \in X$$

Note:
As with all transformations, it is important to fit the scalers to the training data only, not to the full dataset (including test set). Only then can you use them to transform the training set and the test set (and new data).

Problem with Min-Max Scaling and Standardization

Unlike min-max scaling, standardization does not bound values to a specific range, which may be a problem for some algorithms (for eg, neural networks expect an input value ranging from 0 to 1). However, standardization is much less affected by **outliers**. for example,

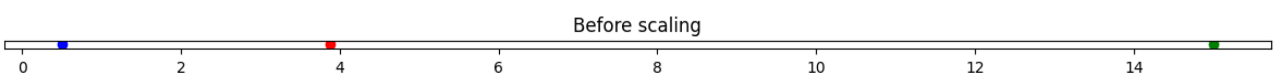
In [ ]:
```
housing["median_income"].mean()
```

Out[ ]:
```
3.875884278100775
```

In [ ]:
```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
scaler.fit(housing[["median_income"]])

scaler.data_min_, housing["median_income"].mean(), scaler.data_max_
```

Out[ ]:
```
(array([0.4999]), 3.875884278100775, array([15.0001]))
```

In [ ]:
```
plt.figure(figsize=(15, 0.1))
number_line = np.arange(scaler.data_min_[0], scaler.data_max_[0], (scaler.data_max_[0] - scaler.data_min_[0]) / 10)
plt.plot(number_line, np.zeros_like(number_line), markersize=8, linestyle='')
plt.plot(scaler.data_min_, 0, marker='o', color='blue')
plt.plot(housing["median_income"].mean(), 0, marker='o', color='red')
plt.plot(scaler.data_max_, 0, marker='o', color='green')
plt.yticks([])
plt.title("Before scaling")
plt.show()
```



* = min
* = mean
* = max

In [ ]:
```
scaled_median_income = scaler.transform(housing[["median_income"]]).copy()
```

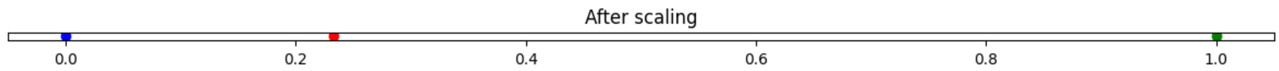
In [ ]:
```
scaled_median_income
```

Out[ ]:
```
array([[0.11542599],
       [0.40257376],
       [0.16379774],
       ...,
       [0.18481124],
       [0.25492752],
       [0.18151474]])
```

In [ ]:
```
scaled_median_income.min(), scaled_median_income.mean(), scaled_median_income.max()
```

```
Out[ ]: (0.0, 0.23282329058225237, 1.0)
```

```
In [ ]: plt.figure(figsize=(15, 0.1))
number_line = np.arange(scaled_median_income.min(), scaled_median_income.max(), (scaled_median_income.max() - scale
plt.plot(number_line, np.zeros_like(number_line), markersize=8, linestyle='')
plt.plot(scaled_median_income.min(), 0, marker='o', color='blue')
plt.plot(scaled_median_income.mean(), 0, marker='o', color='red')
plt.plot(scaled_median_income.max(), 0, marker='o', color='green')
plt.yticks([])
plt.title("After scaling")
plt.show()
```



* = min

* = mean

* = max

In case there was an outlier, say 100 in the `median_income`,

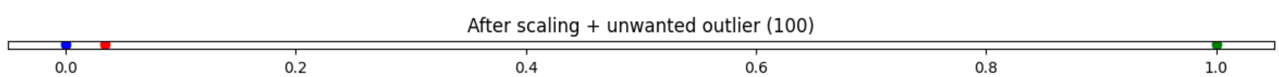
```
In [ ]: median_income_with_outlier = np.append(housing["median_income"].array, 100.0)
median_income_with_outlier = np.c_[median_income_with_outlier]
median_income_with_outlier
```

```
Out[ ]: array([[  2.1736],
       [  6.3373],
       [  2.875 ],
       ...,
       [  4.1964],
       [  3.1319],
       [100.    ]])
```

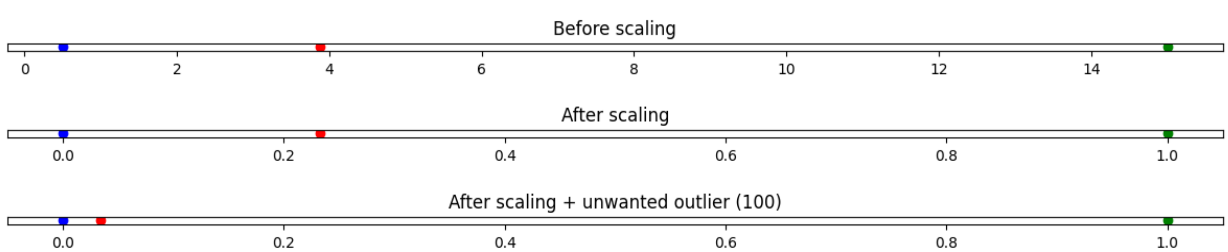
```
In [ ]: scaler = MinMaxScaler()
scaler.fit(median_income_with_outlier)
scaled_median_income = scaler.transform(median_income_with_outlier).copy()

# scaled_median_income.len
scaled_median_income.min(), scaled_median_income.mean(), scaled_median_income.max()
```

```
Out[ ]: (0.0, 0.03398795976837012, 0.9999999999999999)
```

```
In [ ]: plt.figure(figsize=(15, 0.1))
number_line = np.arange(scaled_median_income.min(), scaled_median_income.max(), (scaled_median_income.max() - scale
plt.plot(number_line, np.zeros_like(number_line), markersize=8, linestyle='')
plt.plot(scaled_median_income.min(), 0, marker='o', color='blue')
plt.plot(scaled_median_income.mean(), 0, marker='o', color='red')
plt.plot(scaled_median_income.max(), 0, marker='o', color='green')
plt.yticks([])
plt.title("After scaling + unwanted outlier (100)")
plt.show()
```



From the above 3 plots,



* = min

* = mean

* = max

The min-max scaling crushes all the other values from 0-15 down to 0-0.15. Outliers must be dealt with when transforming them through min-max scaling.