In [1]:

```
# Python ≥3.5 is required
import sys
assert sys.version_info >= (3, 5)

# Scikit-Learn ≥0.20 is required
import sklearn
assert sklearn.__version__ >= "0.20"

# Common imports
import numpy as np
import os

# To plot pretty figures
%matplotlib inline
import matplotlib as mpl
import matplotlib.pyplot as plt
mpl.rc('axes', labelsize=14)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)

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

def save_fig(fig_id, tight_layout=True, fig_extension="png", resolution=300):
    path = os.path.join(IMAGES_PATH, fig_id + "." + fig_extension)
    print("Saving figure", fig_id)
    if tight_layout:
        plt.tight_layout()
    plt.savefig(path, format=fig_extension, dpi=resolution)

# Ignore useless warnings (see SciPy issue #5998)
import warnings
warnings.filterwarnings(action="ignore", message="^internal gelsd")
```

In [2]:
```python
import os
import tarfile
import urllib

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()
```

In [3]:
```python
fetch_housing_data()
```

In [4]:
```python
import pandas as pd

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

In [5]:
```python
housing = load_housing_data()
housing.head()
```

Out[5]:

	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

In [6]:
```
housing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
longitude             20640 non-null float64
latitude              20640 non-null float64
housing_median_age    20640 non-null float64
total_rooms           20640 non-null float64
total_bedrooms        20433 non-null float64
population            20640 non-null float64
households            20640 non-null float64
median_income         20640 non-null float64
median_house_value    20640 non-null float64
ocean_proximity       20640 non-null object
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

In [7]:
```
housing["ocean_proximity"].value_counts()
```

Out[7]:
```
<1H OCEAN     9136
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: ocean_proximity, dtype: int64
```

In [8]:
```
housing.describe()
```

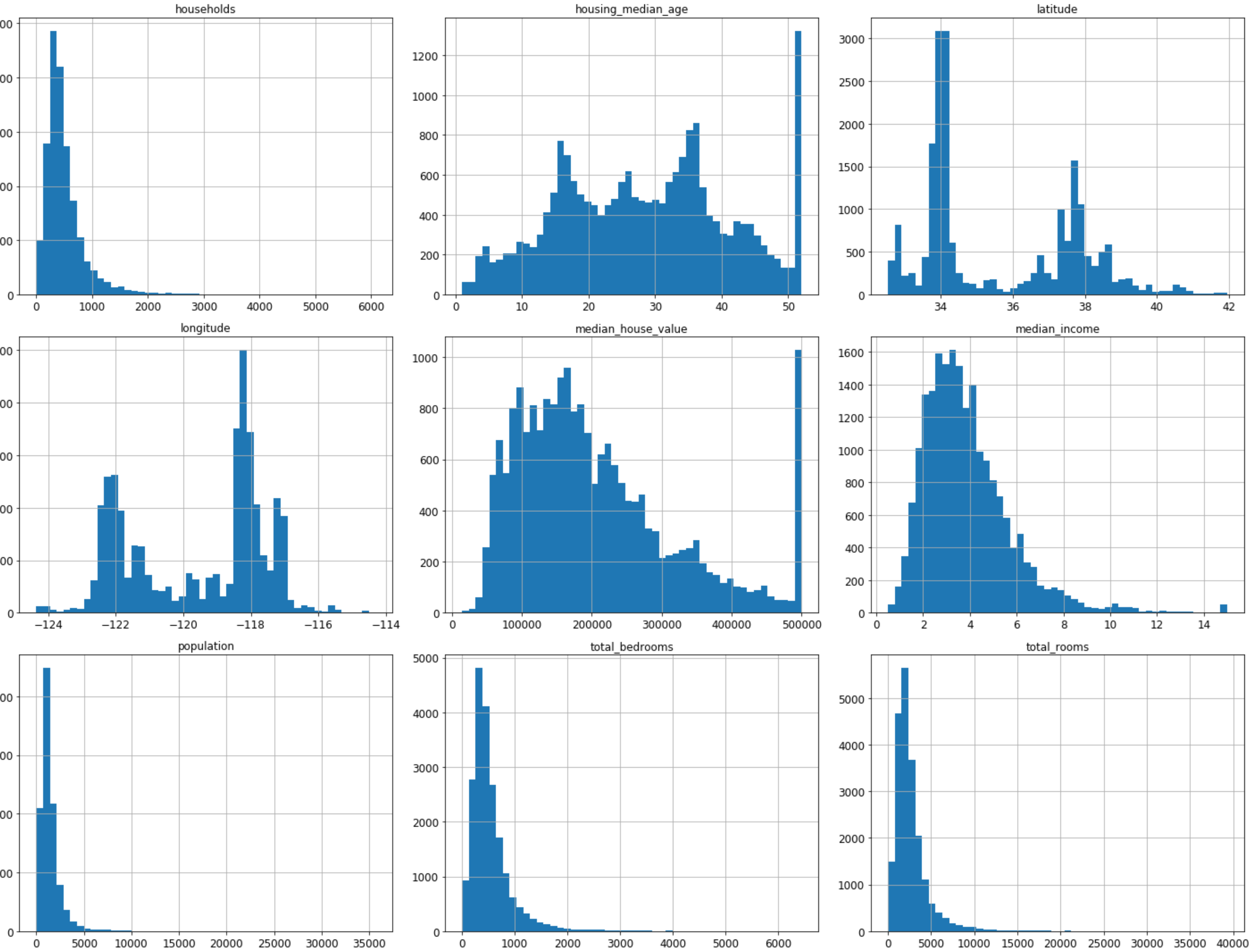
Out[8]:

	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

In [9]:

```
%matplotlib inline
import matplotlib.pyplot as plt
housing.hist(bins=50, figsize=(20,15))
save_fig("attribute_histogram_plots")
plt.show()
```

```
Saving figure attribute_histogram_plots
```


households
0 1000 2000 3000 4000 5000 6000
0 1000 2000 3000 4000 5000
housing_median_age
0 10 20 30 40 50
0 200 400 600 800 1000 1200
latitude
34 36 38 40 42
0 500 1000 1500 2000 2500 3000
longitude
−124 −122 −120 −118 −116 −114
0 500 1000 1500 2000 2500
median_house_value
0 100000 200000 300000 400000 500000
0 200 400 600 800 1000
median_income
0 2 4 6 8 10 12 14
0 200 400 600 800 1000 1200 1400 1600
population
0 5000 10000 15000 20000 25000 30000 35000
0 2000 4000 6000 8000
total_bedrooms
0 1000 2000 3000 4000 5000 6000
0 1000 2000 3000 4000 5000
total_rooms
0 5000 10000 15000 20000 25000 30000 35000 40000
0 1000 2000 3000 4000 5000

In [10]:
```python
# to make this notebook's output identical at every run
np.random.seed(42)
```

In [11]:
```python
import numpy as np

# For illustration only. Sklearn has train_test_split()
def split_train_test(data, test_ratio):
    shuffled_indices = np.random.permutation(len(data))
    test_set_size = int(len(data) * test_ratio)
    test_indices = shuffled_indices[:test_set_size]
    train_indices = shuffled_indices[test_set_size:]
    return data.iloc[train_indices], data.iloc[test_indices]
```

In [12]:
```python
train_set, test_set = split_train_test(housing, 0.2)
len(train_set)
```

Out[12]:
```
16512
```

In [13]:
```python
len(test_set)
```

Out[13]:
```
4128
```

In [14]:
```python
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):
    ids = data[id_column]
    in_test_set = ids.apply(lambda id_: test_set_check(id_, test_ratio))
    return data.loc[~in_test_set], data.loc[in_test_set]
```

In [15]:
```python
import hashlib

def test_set_check(identifier, test_ratio, hash=hashlib.md5):
    return hash(np.int64(identifier)).digest()[-1] < 256 * test_ratio
```

In [16]:
```python
def test_set_check(identifier, test_ratio, hash=hashlib.md5):
    return bytearray(hash(np.int64(identifier)).digest())[-1] < 256 * test_ratio
```

In [17]:
```python
housing_with_id = housing.reset_index()   # adds an `index` column
train_set, test_set = split_train_test_by_id(housing_with_id, 0.2, "index")
```

In [18]:
```python
housing_with_id["id"] = housing["longitude"] * 1000 + housing["latitude"]
train_set, test_set = split_train_test_by_id(housing_with_id, 0.2, "id")
```

In [19]:
```
test_set.head()
```
Out[19]:

	index	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_proximity	id
8	8	-122.26	37.84	42.0	2555.0	665.0	1206.0	595.0	2.0804	226700.0	NEAR BAY	-122222.16
10	10	-122.26	37.85	52.0	2202.0	434.0	910.0	402.0	3.2031	281500.0	NEAR BAY	-122222.15
11	11	-122.26	37.85	52.0	3503.0	752.0	1504.0	734.0	3.2705	241800.0	NEAR BAY	-122222.15
12	12	-122.26	37.85	52.0	2491.0	474.0	1098.0	468.0	3.0750	213500.0	NEAR BAY	-122222.15
13	13	-122.26	37.84	52.0	696.0	191.0	345.0	174.0	2.6736	191300.0	NEAR BAY	-122222.16

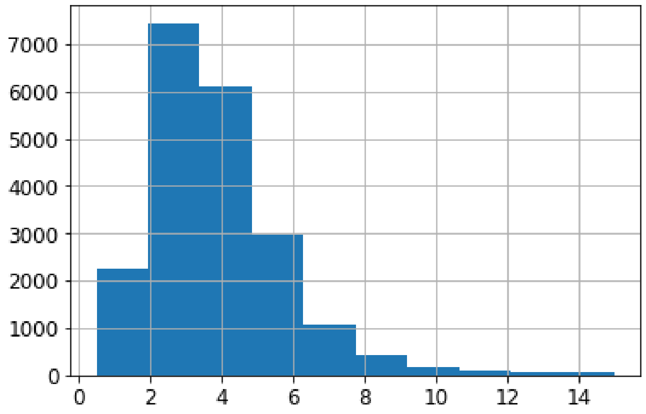
In [20]:
```
from sklearn.model_selection import train_test_split

train_set, test_set = train_test_split(housing, test_size=0.2, random_state=42)
```

In [21]:
```
test_set.head()
```
Out[21]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_proximity
20046	-119.01	36.06	25.0	1505.0	NaN	1392.0	359.0	1.6812	47700.0	INLAND
3024	-119.46	35.14	30.0	2943.0	NaN	1565.0	584.0	2.5313	45800.0	INLAND
15663	-122.44	37.80	52.0	3830.0	NaN	1310.0	963.0	3.4801	500001.0	NEAR BAY
20484	-118.72	34.28	17.0	3051.0	NaN	1705.0	495.0	5.7376	218600.0	<1H OCEAN
9814	-121.93	36.62	34.0	2351.0	NaN	1063.0	428.0	3.7250	278000.0	NEAR OCEAN

In [22]:
```
housing["median_income"].hist()
```

Out[22]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x105702400>
```



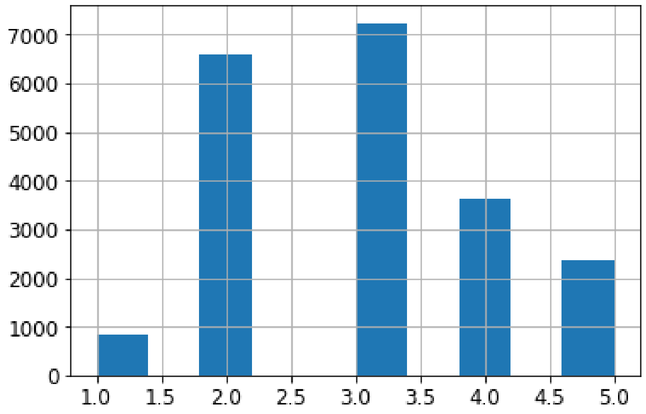
In [23]:
```
housing["income_cat"] = pd.cut(housing["median_income"],
                               bins=[0., 1.5, 3.0, 4.5, 6., np.inf],
                               labels=[1, 2, 3, 4, 5])
```

In [24]:
```
housing["income_cat"].value_counts()
```

Out[24]:
```
3    7236
2    6581
4    3639
5    2362
1     822
Name: income_cat, dtype: int64
```

In [25]:
```
housing["income_cat"].hist()
```

Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0x1057024e0>



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

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

In [27]:
```
strat_test_set["income_cat"].value_counts() / len(strat_test_set)
```

Out[27]:
```
3    0.350533
2    0.318798
4    0.176357
5    0.114583
1    0.039729
Name: income_cat, dtype: float64
```

In [28]:
```
housing["income_cat"].value_counts() / len(housing)
```

Out[28]:
```
3    0.350581
2    0.318847
4    0.176308
5    0.114438
1    0.039826
Name: income_cat, dtype: float64
```

In [29]:
```
def income_cat_proportions(data):
    return data["income_cat"].value_counts() / len(data)

train_set, test_set = train_test_split(housing, test_size=0.2, random_state=42)

compare_props = pd.DataFrame({
    "Overall": income_cat_proportions(housing),
    "Stratified": income_cat_proportions(strat_test_set),
    "Random": income_cat_proportions(test_set),
}).sort_index()
compare_props["Rand. %error"] = 100 * compare_props["Random"] / compare_props["Overall"] - 100
compare_props["Strat. %error"] = 100 * compare_props["Stratified"] / compare_props["Overall"] - 100
```

In [30]:
```
compare_props
```

Out[30]:

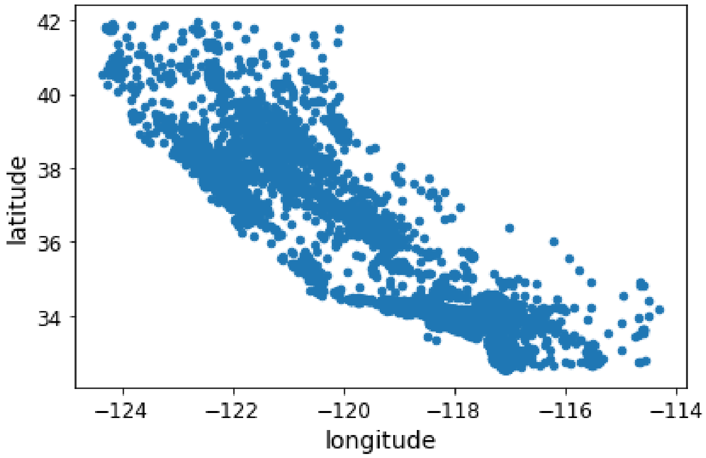
	Overall	Stratified	Random	Rand. %error	Strat. %error
1	0.039826	0.039729	0.040213	0.973236	-0.243309
2	0.318847	0.318798	0.324370	1.732260	-0.015195
3	0.350581	0.350533	0.358527	2.266446	-0.013820
4	0.176308	0.176357	0.167393	-5.056334	0.027480
5	0.114438	0.114583	0.109496	-4.318374	0.127011

In [31]:
```
for set_ in (strat_train_set, strat_test_set):
    set_.drop("income_cat", axis=1, inplace=True)
```

In [32]:
```
housing = strat_train_set.copy()
```

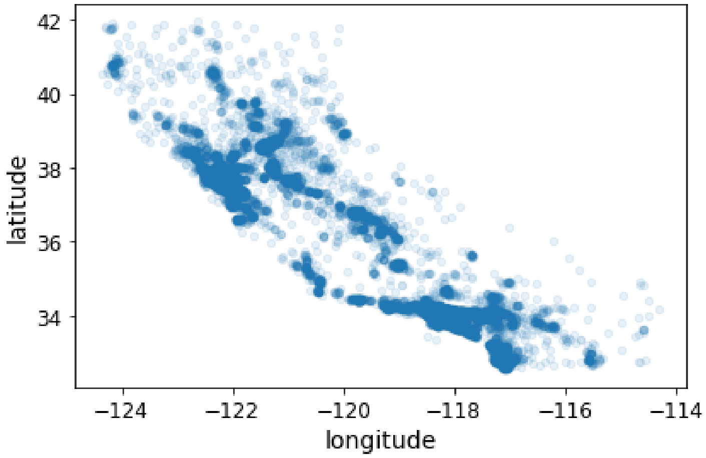
In [33]:
```
housing.plot(kind="scatter", x="longitude", y="latitude")
save_fig("bad_visualization_plot")
```

```
Saving figure bad_visualization_plot
```



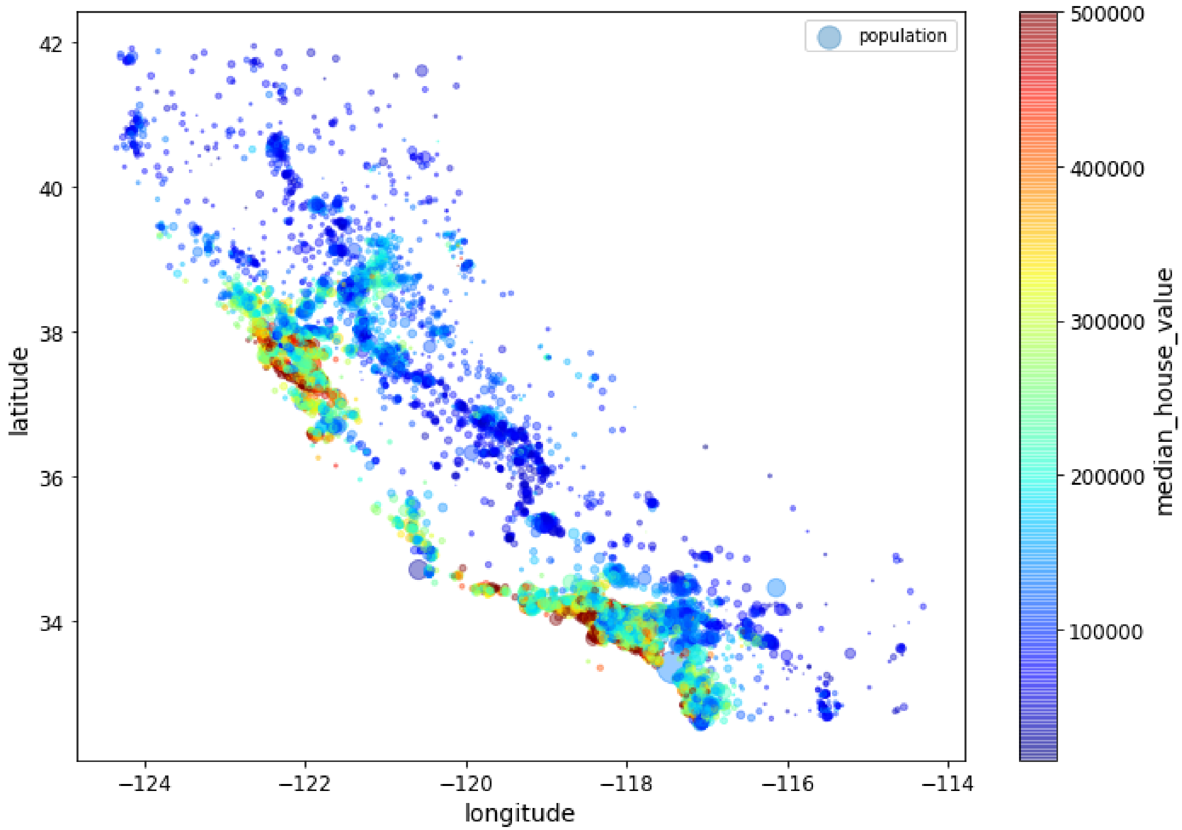
In [34]:
```
housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.1)
save_fig("better_visualization_plot")
```

```
Saving figure better_visualization_plot
```



In [35]:
```
housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.4,
    s=housing["population"]/100, label="population", figsize=(10,7),
    c="median_house_value", cmap=plt.get_cmap("jet"), colorbar=True,
    sharex=False)
plt.legend()
save_fig("housing_prices_scatterplot")
```

```
Saving figure housing_prices_scatterplot
```



In [36]:
```
# Download the California image
images_path = os.path.join(PROJECT_ROOT_DIR, "images", "end_to_end_project")
os.makedirs(images_path, exist_ok=True)
DOWNLOAD_ROOT = "https://raw.githubusercontent.com/ageron/handson-ml2/master/"
filename = "california.png"
print("Downloading", filename)
url = DOWNLOAD_ROOT + "images/end_to_end_project/" + filename
urllib.request.urlretrieve(url, os.path.join(images_path, filename))
```

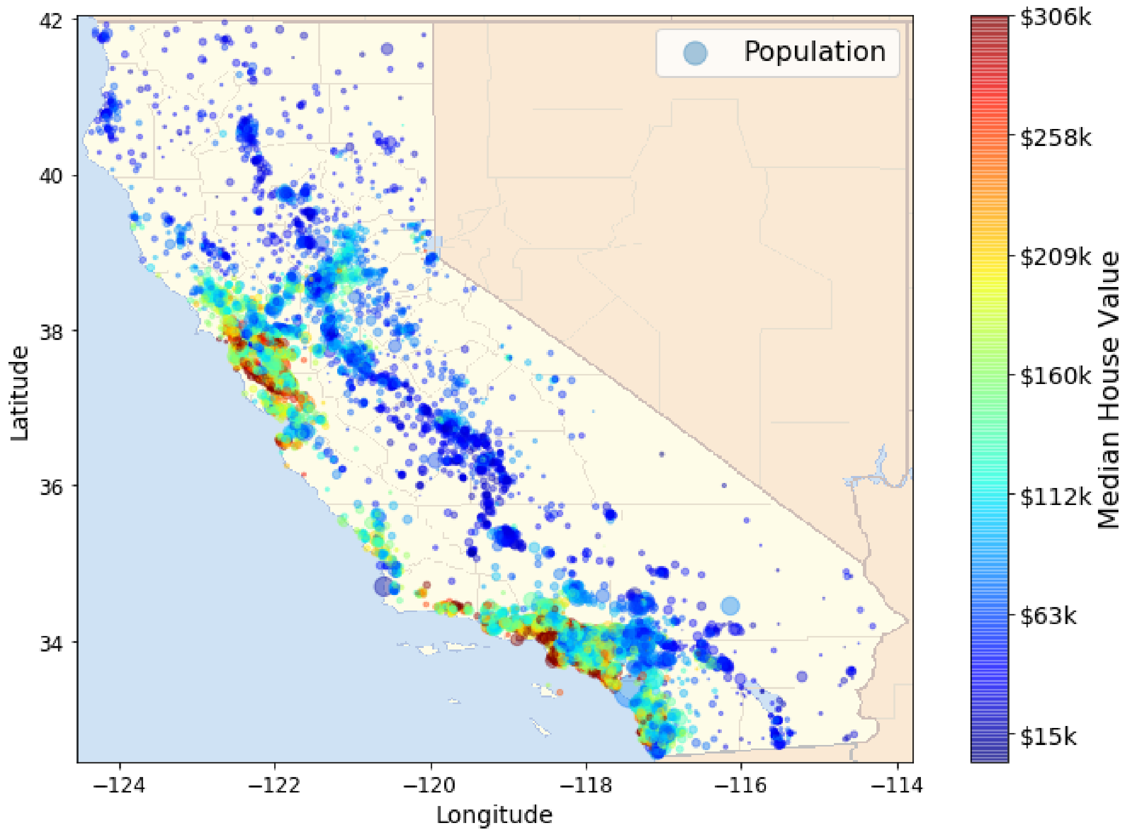
```
Downloading california.png
```

Out[36]:
```
('./images/end_to_end_project/california.png',
 <http.client.HTTPMessage at 0x1047fa2e8>)
```

In [37]:

```
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,
                      )
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)

prices = housing["median_house_value"]
tick_values = np.linspace(prices.min(), prices.max(), 11)
cbar = plt.colorbar()
cbar.ax.set_yticklabels(["$%dk"%(round(v/1000)) for v in tick_values], fontsize=14)
cbar.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
```



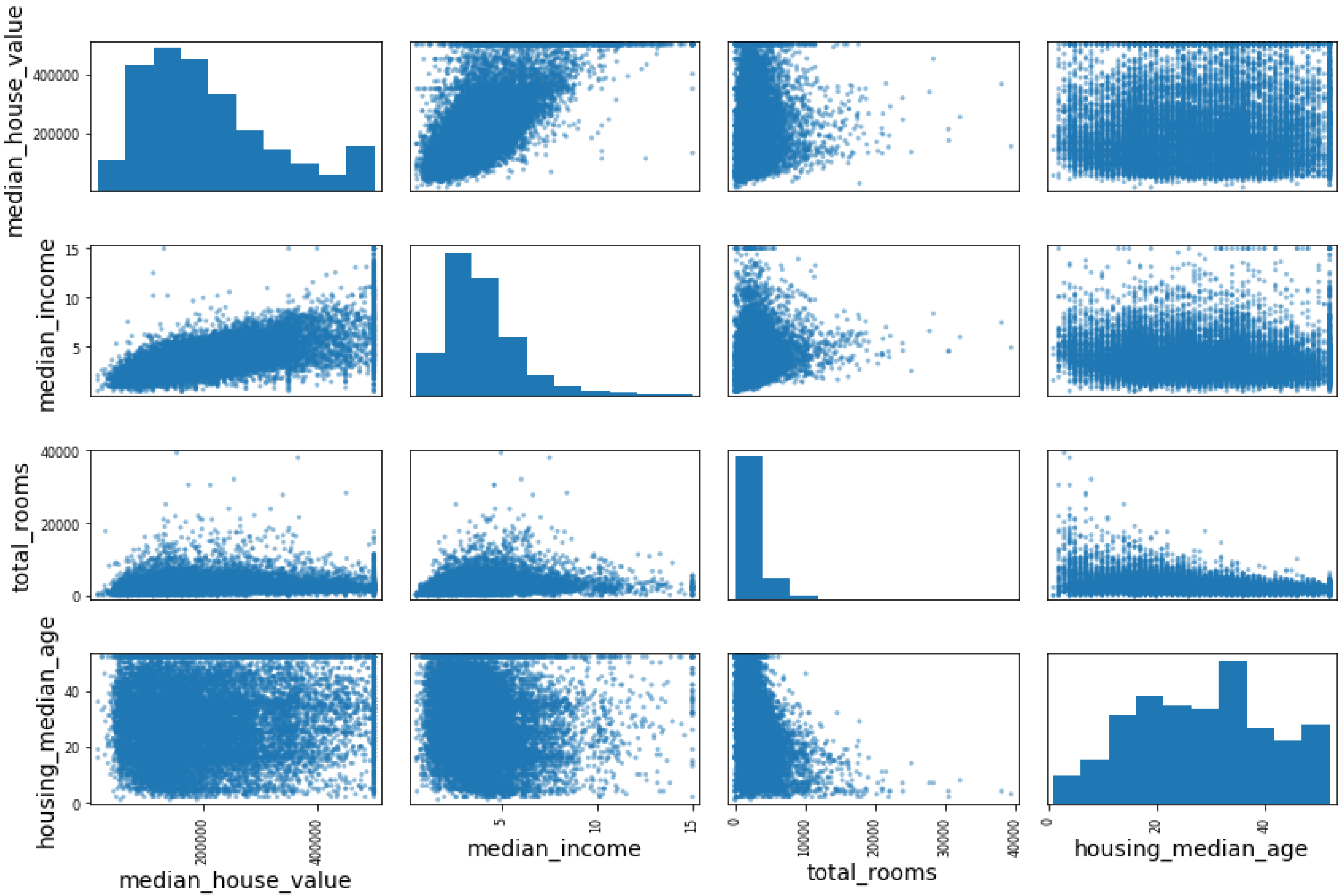
In [38]:
```python
corr_matrix = housing.corr()
```

In [39]:
```python
corr_matrix["median_house_value"].sort_values(ascending=False)
```

Out[39]:
```
median_house_value     1.000000
median_income          0.687160
total_rooms            0.135097
housing_median_age     0.114110
households             0.064506
total_bedrooms         0.047689
population            -0.026920
longitude             -0.047432
latitude              -0.142724
Name: median_house_value, dtype: float64
```

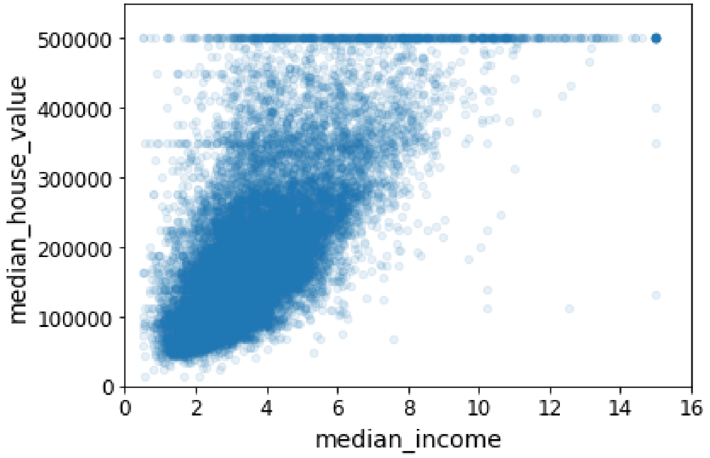
In [40]:
```
from pandas.plotting import scatter_matrix

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 [41]:
```python
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
```

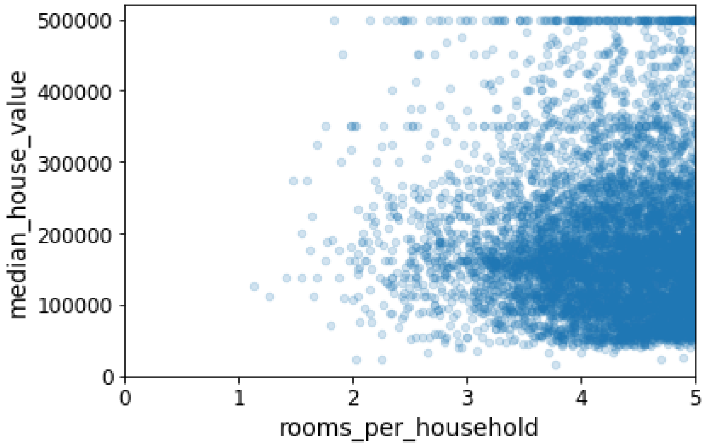


In [42]:
```python
housing["rooms_per_household"] = housing["total_rooms"]/housing["households"]
housing["bedrooms_per_room"] = housing["total_bedrooms"]/housing["total_rooms"]
housing["population_per_household"]=housing["population"]/housing["households"]
```

In [43]:
```python
corr_matrix = housing.corr()
corr_matrix["median_house_value"].sort_values(ascending=False)
```

Out[43]:
```
median_house_value          1.000000
median_income               0.687160
rooms_per_household         0.146285
total_rooms                 0.135097
housing_median_age          0.114110
households                  0.064506
total_bedrooms              0.047689
population_per_household   -0.021985
population                 -0.026920
longitude                  -0.047432
latitude                   -0.142724
bedrooms_per_room          -0.259984
Name: median_house_value, dtype: float64
```

In [44]:
```
housing.plot(kind="scatter", x="rooms_per_household", y="median_house_value",
             alpha=0.2)
plt.axis([0, 5, 0, 520000])
plt.show()
```



In [45]:
```
housing.describe()
```

Out[45]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	rooms_per_household
count	16512.000000	16512.000000	16512.000000	16512.000000	16354.000000	16512.000000	16512.000000	16512.000000	16512.000000	16512.000000
mean	-119.575834	35.639577	28.653101	2622.728319	534.973890	1419.790819	497.060380	3.875589	206990.920724	5.440341
std	2.001860	2.138058	12.574726	2138.458419	412.699041	1115.686241	375.720845	1.904950	115703.014830	2.611712
min	-124.350000	32.540000	1.000000	6.000000	2.000000	3.000000	2.000000	0.499900	14999.000000	1.130435
25%	-121.800000	33.940000	18.000000	1443.000000	295.000000	784.000000	279.000000	2.566775	119800.000000	4.442040
50%	-118.510000	34.260000	29.000000	2119.500000	433.000000	1164.000000	408.000000	3.540900	179500.000000	5.232284
75%	-118.010000	37.720000	37.000000	3141.000000	644.000000	1719.250000	602.000000	4.744475	263900.000000	6.056361
max	-114.310000	41.950000	52.000000	39320.000000	6210.000000	35682.000000	5358.000000	15.000100	500001.000000	141.909091

In [46]:
```
#Prepaing data for ML algorithm
housing = strat_train_set.drop("median_house_value", axis=1) # drop labels for training set
housing_labels = strat_train_set["median_house_value"].copy()
```

In [47]:
```python
sample_incomplete_rows = housing[housing.isnull().any(axis=1)].head()
sample_incomplete_rows
```

Out[47]:

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

In [48]:
```python
sample_incomplete_rows.dropna(subset=["total_bedrooms"])    # option 1, ignoring rows with NA's
```

Out[48]:

longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximity

In [49]:
```python
sample_incomplete_rows.drop("total_bedrooms", axis=1)       # option 2, dropping the whole column
```

Out[49]:

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

In [50]:
```python
median = housing["total_bedrooms"].median()
sample_incomplete_rows["total_bedrooms"].fillna(median, inplace=True) # option 3, replacing NA's with mean value
```

In [51]:
```
sample_incomplete_rows
```

Out[51]:

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

In [52]:
```
from sklearn.impute import SimpleImputer   # Scikit's method to deal with NA's
imputer = SimpleImputer(strategy="median")
```

In [53]:
```
housing_num = housing.drop("ocean_proximity", axis=1)#Dropping the text column as above method works only on numeric data
# alternatively: housing_num = housing.select_dtypes(include=[np.number])
```

In [54]:
```
imputer.fit(housing_num)
```

Out[54]:
```
SimpleImputer(copy=True, fill_value=None, missing_values=nan,
       strategy='median', verbose=0)
```

In [55]:
```
imputer.statistics_
```

Out[55]:
```
array([-118.51   ,   34.26   ,   29.    , 2119.5   ,  433.    , 1164.    ,
        408.    ,    3.5409])
```

In [56]:
```
housing_num.median().values #chcking above method manually
```

Out[56]:
```
array([-118.51   ,   34.26   ,   29.    , 2119.5   ,  433.    , 1164.    ,
        408.    ,    3.5409])
```

In [57]:
```
X = imputer.transform(housing_num)
```

In [58]:
```
housing_tr = pd.DataFrame(X, columns=housing_num.columns,
                          index=housing.index)
```

In [59]:
```
housing_tr.loc[sample_incomplete_rows.index.values]
```

Out[59]:

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

In [60]:
```
imputer.strategy
```

Out[60]: 'median'

In [61]:
```
housing_tr = pd.DataFrame(X, columns=housing_num.columns,
                          index=housing_num.index)
```

In [62]:
```
housing_tr.head()
```

Out[62]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income
17606	-121.89	37.29	38.0	1568.0	351.0	710.0	339.0	2.7042
18632	-121.93	37.05	14.0	679.0	108.0	306.0	113.0	6.4214
14650	-117.20	32.77	31.0	1952.0	471.0	936.0	462.0	2.8621
3230	-119.61	36.31	25.0	1847.0	371.0	1460.0	353.0	1.8839
3555	-118.59	34.23	17.0	6592.0	1525.0	4459.0	1463.0	3.0347

In [63]:
```python
housing_cat = housing[["ocean_proximity"]]
housing_cat.head(10)
```

Out[63]:

	ocean_proximity
17606	<1H OCEAN
18632	<1H OCEAN
14650	NEAR OCEAN
3230	INLAND
3555	<1H OCEAN
19480	INLAND
8879	<1H OCEAN
13685	INLAND
4937	<1H OCEAN
4861	<1H OCEAN

In [64]:
```python
from sklearn.preprocessing import OrdinalEncoder

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

Out[64]:
```
array([[0.],
       [0.],
       [4.],
       [1.],
       [0.],
       [1.],
       [0.],
       [1.],
       [0.],
       [0.]])
```

In [65]:
```python
ordinal_encoder.categories_
```

Out[65]:
```
[array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],
       dtype=object)]
```

In [66]:
```python
from sklearn.preprocessing import OneHotEncoder

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

Out[66]:
```
<16512x5 sparse matrix of type '<class 'numpy.float64'>'
        with 16512 stored elements in Compressed Sparse Row format>
```

In [67]:
```python
housing_cat_1hot.toarray()
```

Out[67]:
```
array([[1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [0., 0., 0., 0., 1.],
       ...,
       [0., 1., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [0., 0., 0., 1., 0.]])
```

In [68]:
```python
cat_encoder = OneHotEncoder(sparse=False)
housing_cat_1hot = cat_encoder.fit_transform(housing_cat)
housing_cat_1hot
```

Out[68]:
```
array([[1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [0., 0., 0., 0., 1.],
       ...,
       [0., 1., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [0., 0., 0., 1., 0.]])
```

In [69]:
```python
cat_encoder.categories_
```

Out[69]:
```
[array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],
       dtype=object)]
```

In [70]:
```python
from sklearn.base import BaseEstimator, TransformerMixin

# column index
rooms_ix, bedrooms_ix, population_ix, households_ix = 3, 4, 5, 6

class CombinedAttributesAdder(BaseEstimator, TransformerMixin):
    def __init__(self, add_bedrooms_per_room = True): # no *args or **kargs
        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 = CombinedAttributesAdder(add_bedrooms_per_room=False)
housing_extra_attribs = attr_adder.transform(housing.values)
```

In [71]:
```python
housing_extra_attribs = pd.DataFrame(
    housing_extra_attribs,
    columns=list(housing.columns)+["rooms_per_household", "population_per_household"],
    index=housing.index)
housing_extra_attribs.head()
```

Out[71]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximity	rooms_per_household	population_per_ho
17606	-121.89	37.29	38	1568	351	710	339	2.7042	<1H OCEAN	4.62537	
18632	-121.93	37.05	14	679	108	306	113	6.4214	<1H OCEAN	6.00885	
14650	-117.2	32.77	31	1952	471	936	462	2.8621	NEAR OCEAN	4.22511	
3230	-119.61	36.31	25	1847	371	1460	353	1.8839	INLAND	5.23229	
3555	-118.59	34.23	17	6592	1525	4459	1463	3.0347	<1H OCEAN	4.50581	

In [72]:
```python
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler

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

housing_num_tr = num_pipeline.fit_transform(housing_num)
```

In [73]:
```python
housing_num_tr
```

Out[73]:
```
array([[-1.15604281,  0.77194962,  0.74333089, ..., -0.31205452,
        -0.08649871,  0.15531753],
       [-1.17602483,  0.6596948 , -1.1653172 , ...,  0.21768338,
        -0.03353391, -0.83628902],
       [ 1.18684903, -1.34218285,  0.18664186, ..., -0.46531516,
        -0.09240499,  0.4222004 ],
       ...,
       [ 1.58648943, -0.72478134, -1.56295222, ...,  0.3469342 ,
        -0.03055414, -0.52177644],
       [ 0.78221312, -0.85106801,  0.18664186, ...,  0.02499488,
         0.06150916, -0.30340741],
       [-1.43579109,  0.99645926,  1.85670895, ..., -0.22852947,
        -0.09586294,  0.10180567]])
```

In [74]:
```python
from sklearn.compose import ColumnTransformer

num_attribs = list(housing_num)
cat_attribs = ["ocean_proximity"]

full_pipeline = ColumnTransformer([
        ("num", num_pipeline, num_attribs),
        ("cat", OneHotEncoder(), cat_attribs),
    ])

housing_prepared = full_pipeline.fit_transform(housing)
```

In [75]:
```
housing_prepared
```

Out[75]:
```
array([[-1.15604281,  0.77194962,  0.74333089, ...,  0.        ,
         0.        ,  0.        ],
       [-1.17602483,  0.6596948 , -1.1653172 , ...,  0.        ,
         0.        ,  0.        ],
       [ 1.18684903, -1.34218285,  0.18664186, ...,  0.        ,
         0.        ,  1.        ],
       ...,
       [ 1.58648943, -0.72478134, -1.56295222, ...,  0.        ,
         0.        ,  0.        ],
       [ 0.78221312, -0.85106801,  0.18664186, ...,  0.        ,
         0.        ,  0.        ],
       [-1.43579109,  0.99645926,  1.85670895, ...,  0.        ,
         1.        ,  0.        ]])
```

In [76]:
```
housing_prepared.shape
```

Out[76]:
```
(16512, 16)
```

In [77]:
```
from sklearn.linear_model import LinearRegression

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

Out[77]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

In [78]:
```
# let's try the full preprocessing pipeline on a few training instances
some_data = housing.iloc[:5]
some_labels = housing_labels.iloc[:5]
some_data_prepared = full_pipeline.transform(some_data)

print("Predictions:", lin_reg.predict(some_data_prepared))
```

```
Predictions: [210644.60459286 317768.80697211 210956.43331178  59218.98886849
 189747.55849879]
```

In [79]:
```
print("Labels:", list(some_labels))
```

```
Labels: [286600.0, 340600.0, 196900.0, 46300.0, 254500.0]
```

In [80]:
```python
some_data_prepared
```

Out[80]:
```
array([[-1.15604281,  0.77194962,  0.74333089, -0.49323393, -0.44543821,
        -0.63621141, -0.42069842, -0.61493744, -0.31205452, -0.08649871,
         0.15531753,  1.        ,  0.        ,  0.        ,  0.        ,
         0.        ],
       [-1.17602483,  0.6596948 , -1.1653172 , -0.90896655, -1.0369278 ,
        -0.99833135, -1.02222705,  1.33645936,  0.21768338, -0.03353391,
        -0.83628902,  1.        ,  0.        ,  0.        ,  0.        ,
         0.        ],
       [ 1.18684903, -1.34218285,  0.18664186, -0.31365989, -0.15334458,
        -0.43363936, -0.0933178 , -0.5320456 , -0.46531516, -0.09240499,
         0.4222004 ,  0.        ,  0.        ,  0.        ,  0.        ,
         1.        ],
       [-0.01706767,  0.31357576, -0.29052016, -0.36276217, -0.39675594,
         0.03604096, -0.38343559, -1.04556555, -0.07966124,  0.08973561,
        -0.19645314,  0.        ,  1.        ,  0.        ,  0.        ,
         0.        ],
       [ 0.49247384, -0.65929936, -0.92673619,  1.85619316,  2.41221109,
         2.72415407,  2.57097492, -0.44143679, -0.35783383, -0.00419445,
         0.2699277 ,  1.        ,  0.        ,  0.        ,  0.        ,
         0.        ]])
```

In [81]:
```python
from sklearn.metrics import mean_squared_error

housing_predictions = lin_reg.predict(housing_prepared)
lin_mse = mean_squared_error(housing_labels, housing_predictions)
lin_rmse = np.sqrt(lin_mse)
lin_rmse
```

Out[81]:
```
68628.19819848923
```

In [82]:
```python
from sklearn.metrics import mean_absolute_error

lin_mae = mean_absolute_error(housing_labels, housing_predictions)
lin_mae
```

Out[82]:
```
49439.89599001897
```

In [83]:
```python
housing_predictions
```

Out[83]:
```
array([210644.60459286, 317768.80697211, 210956.43331178, ...,
        95464.57062437, 214353.22541713, 276426.4692067 ])
```

In [84]:
```python
from sklearn.tree import DecisionTreeRegressor

tree_reg = DecisionTreeRegressor(random_state=42)
tree_reg.fit(housing_prepared, housing_labels)
```

Out[84]:
```
DecisionTreeRegressor(criterion='mse', max_depth=None, max_features=None,
           max_leaf_nodes=None, min_impurity_decrease=0.0,
           min_impurity_split=None, min_samples_leaf=1,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           presort=False, random_state=42, splitter='best')
```

In [85]:
```python
housing_predictions = tree_reg.predict(housing_prepared)
tree_mse = mean_squared_error(housing_labels, housing_predictions)
tree_rmse = np.sqrt(tree_mse)
tree_rmse
```

Out[85]:
```
0.0
```

In [86]:
```python
from sklearn.model_selection import cross_val_score

scores = cross_val_score(tree_reg, housing_prepared, housing_labels,
                         scoring="neg_mean_squared_error", cv=10)
tree_rmse_scores = np.sqrt(-scores)
```

In [87]:
```python
def display_scores(scores):
    print("Scores:", scores)
    print("Mean:", scores.mean())
    print("Standard deviation:", scores.std())

display_scores(tree_rmse_scores)
```

```
Scores: [70194.33680785 66855.16363941 72432.58244769 70758.73896782
 71115.88230639 75585.14172901 70262.86139133 70273.6325285
 75366.87952553 71231.65726027]
Mean: 71407.68766037929
Standard deviation: 2439.4345041191004
```

In [88]:
```
lin_scores = cross_val_score(lin_reg, housing_prepared, housing_labels,
                             scoring="neg_mean_squared_error", cv=10)
lin_rmse_scores = np.sqrt(-lin_scores)
display_scores(lin_rmse_scores)
```

```
Scores: [66782.73843989 66960.118071   70347.95244419 74739.57052552
 68031.13388938 71193.84183426 64969.63056405 68281.61137997
 71552.91566558 67665.10082067]
Mean: 69052.46136345083
Standard deviation: 2731.674001798349
```

In [89]:
```
from sklearn.ensemble import RandomForestRegressor

forest_reg = RandomForestRegressor(n_estimators=100, random_state=42)
forest_reg.fit(housing_prepared, housing_labels)
```

Out[89]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=None,
           oob_score=False, random_state=42, verbose=0, warm_start=False)
```

In [90]:
```
housing_predictions = forest_reg.predict(housing_prepared)
forest_mse = mean_squared_error(housing_labels, housing_predictions)
forest_rmse = np.sqrt(forest_mse)
forest_rmse
```

Out[90]:
```
18603.515021376355
```

In [94]:
```
from sklearn.model_selection import cross_val_score

forest_scores = cross_val_score(forest_reg, housing_prepared, housing_labels,
                                scoring="neg_mean_squared_error", cv=10)
forest_rmse_scores = np.sqrt(-forest_scores)
display_scores(forest_rmse_scores)
```

```
Scores: [49519.80364233 47461.9115823  50029.02762854 52325.28068953
 49308.39426421 53446.37892622 48634.8036574  47585.73832311
 53490.10699751 50021.5852922 ]
Mean: 50182.303100336096
Standard deviation: 2097.0810550985693
```

In [95]:
```python
scores = cross_val_score(lin_reg, housing_prepared, housing_labels, scoring="neg_mean_squared_error", cv=10)

pd.Series(np.sqrt(-scores)).describe()
```

Out[95]:
```
count       10.000000
mean     69052.461363
std       2879.437224
min      64969.630564
25%      67136.363758
50%      68156.372635
75%      70982.369487
max      74739.570526
dtype: float64
```

In [96]:
```python
from sklearn.svm import SVR

svm_reg = SVR(kernel="linear")
svm_reg.fit(housing_prepared, housing_labels)
housing_predictions = svm_reg.predict(housing_prepared)
svm_mse = mean_squared_error(housing_labels, housing_predictions)
svm_rmse = np.sqrt(svm_mse)
svm_rmse
```

Out[96]:
```
111094.6308539982
```

In [97]:
```python
from sklearn.model_selection import GridSearchCV

param_grid = [
    # try 12 (3×4) combinations of hyperparameters
    {'n_estimators': [3, 10, 30], 'max_features': [2, 4, 6, 8]},
    # then try 6 (2×3) combinations with bootstrap set as False
    {'bootstrap': [False], 'n_estimators': [3, 10], 'max_features': [2, 3, 4]},
  ]

forest_reg = RandomForestRegressor(random_state=42)
# train across 5 folds, that's a total of (12+6)*5=90 rounds of training
grid_search = GridSearchCV(forest_reg, param_grid, cv=5,
                           scoring='neg_mean_squared_error',
                           return_train_score=True)
grid_search.fit(housing_prepared, housing_labels)
```

Out[97]:
```
GridSearchCV(cv=5, error_score='raise-deprecating',
       estimator=RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators='warn', n_jobs=None,
           oob_score=False, random_state=42, verbose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid=[{'n_estimators': [3, 10, 30], 'max_features': [2, 4, 6, 8]}, {'bootstrap': [False], 'n_estimators': [3, 10],
'max_features': [2, 3, 4]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring='neg_mean_squared_error', verbose=0)
```

In [98]:
```python
grid_search.best_params_
```

Out[98]:
```
{'max_features': 8, 'n_estimators': 30}
```

In [99]:
```python
grid_search.best_estimator_
```

Out[99]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features=8, max_leaf_nodes=None, min_impurity_decrease=0.0,
           min_impurity_split=None, min_samples_leaf=1,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           n_estimators=30, n_jobs=None, oob_score=False, random_state=42,
           verbose=0, warm_start=False)
```

In [100]:
```python
cvres = grid_search.cv_results_
for mean_score, params in zip(cvres["mean_test_score"], cvres["params"]):
    print(np.sqrt(-mean_score), params)
```

```
63669.05791727153 {'max_features': 2, 'n_estimators': 3}
55627.16171305252 {'max_features': 2, 'n_estimators': 10}
53384.57867637289 {'max_features': 2, 'n_estimators': 30}
60965.99185930139 {'max_features': 4, 'n_estimators': 3}
52740.98248528835 {'max_features': 4, 'n_estimators': 10}
50377.344409590376 {'max_features': 4, 'n_estimators': 30}
58663.84733372485 {'max_features': 6, 'n_estimators': 3}
52006.15355973719 {'max_features': 6, 'n_estimators': 10}
50146.465964159885 {'max_features': 6, 'n_estimators': 30}
57869.25504027614 {'max_features': 8, 'n_estimators': 3}
51711.09443660957 {'max_features': 8, 'n_estimators': 10}
49682.25345942335 {'max_features': 8, 'n_estimators': 30}
62895.088889905004 {'bootstrap': False, 'max_features': 2, 'n_estimators': 3}
54658.14484390074 {'bootstrap': False, 'max_features': 2, 'n_estimators': 10}
59470.399594730654 {'bootstrap': False, 'max_features': 3, 'n_estimators': 3}
52725.01091081235 {'bootstrap': False, 'max_features': 3, 'n_estimators': 10}
57490.612956065226 {'bootstrap': False, 'max_features': 4, 'n_estimators': 3}
51009.51445842374 {'bootstrap': False, 'max_features': 4, 'n_estimators': 10}
```

In [101]:
```
pd.DataFrame(grid_search.cv_results_)
```

Out[101]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_features	param_n_estimators	param_bootstrap	params	split0_test_score	split1_test_score
0	0.067311	0.013484	0.003808	0.000232	2	3	NaN	{'max_features': 2, 'n_estimators': 3}	-3.837622e+09	-4.147108e+09
1	0.206839	0.007902	0.011261	0.001797	2	10	NaN	{'max_features': 2, 'n_estimators': 10}	-3.047771e+09	-3.254861e+09
2	0.614305	0.010618	0.034848	0.009672	2	30	NaN	{'max_features': 2, 'n_estimators': 30}	-2.689185e+09	-3.021086e+09
3	0.099256	0.001032	0.003355	0.000233	4	3	NaN	{'max_features': 4, 'n_estimators': 3}	-3.730181e+09	-3.786886e+09
4	0.323640	0.002283	0.008854	0.000534	4	10	NaN	{'max_features': 4, 'n_estimators': 10}	-2.666283e+09	-2.784511e+09
5	0.981263	0.007037	0.030582	0.002164	4	30	NaN	{'max_features': 4, 'n_estimators': 30}	-2.387153e+09	-2.588448e+09
6	0.136442	0.004478	0.003718	0.000302	6	3	NaN	{'max_features': 6, 'n_estimators': 3}	-3.119657e+09	-3.586319e+09
7	0.466119	0.011197	0.011113	0.001169	6	10	NaN	{'max_features': 6, 'n_estimators': 10}	-2.549663e+09	-2.782039e+09
8	1.376538	0.030661	0.029462	0.004335	6	30	NaN	{'max_features': 6, 'n_estimators': 30}	-2.370010e+09	-2.583638e+09
9	0.171699	0.001843	0.003471	0.000349	8	3	NaN	{'max_features': 8, 'n_estimators': 3}	-3.353504e+09	-3.348552e+09
10	0.586707	0.008500	0.011020	0.001052	8	10	NaN	{'max_features': 8, 'n_estimators': 10}	-2.571970e+09	-2.718994e+09

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_features	param_n_estimators	param_bootstrap	params	split0_test_score	split1_test_score
11	1.757874	0.018076	0.029640	0.003076	8	30	NaN	{'max_features': 8, 'n_estimators': 30}	-2.357390e+09	-2.546640e+09
12	0.098745	0.004214	0.004431	0.000682	2	3	False	{'bootstrap': False, 'max_features': 2, 'n_est...	-3.785816e+09	-4.166012e+09
13	0.317325	0.003440	0.011101	0.000829	2	10	False	{'bootstrap': False, 'max_features': 2, 'n_est...	-2.810721e+09	-3.107789e+09
14	0.125696	0.001922	0.004290	0.000671	3	3	False	{'bootstrap': False, 'max_features': 3, 'n_est...	-3.618324e+09	-3.441527e+09
15	0.422643	0.004466	0.012567	0.000663	3	10	False	{'bootstrap': False, 'max_features': 3, 'n_est...	-2.757999e+09	-2.851737e+09
16	0.159518	0.006842	0.004415	0.000307	4	3	False	{'bootstrap': False, 'max_features': 4, 'n_est...	-3.134040e+09	-3.559375e+09
17	0.534765	0.011351	0.012249	0.001461	4	10	False	{'bootstrap': False, 'max_features': 4, 'n_est...	-2.525578e+09	-2.710011e+09

18 rows × 23 columns

In [102]:
```python
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint

param_distribs = {
        'n_estimators': randint(low=1, high=200),
        'max_features': randint(low=1, high=8),
    }

forest_reg = RandomForestRegressor(random_state=42)
rnd_search = RandomizedSearchCV(forest_reg, param_distributions=param_distribs,
                                n_iter=10, cv=5, scoring='neg_mean_squared_error', random_state=42)
rnd_search.fit(housing_prepared, housing_labels)
```

Out[102]:
```
RandomizedSearchCV(cv=5, error_score='raise-deprecating',
          estimator=RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators='warn', n_jobs=None,
           oob_score=False, random_state=42, verbose=0, warm_start=False),
          fit_params=None, iid='warn', n_iter=10, n_jobs=None,
          param_distributions={'n_estimators': <scipy.stats._distn_infrastructure.rv_frozen object at 0x105557b38>, 'max_feature
s': <scipy.stats._distn_infrastructure.rv_frozen object at 0x105557da0>},
          pre_dispatch='2*n_jobs', random_state=42, refit=True,
          return_train_score='warn', scoring='neg_mean_squared_error',
          verbose=0)
```

In [103]:
```python
cvres = rnd_search.cv_results_
for mean_score, params in zip(cvres["mean_test_score"], cvres["params"]):
    print(np.sqrt(-mean_score), params)
```

```
49150.657232934034 {'max_features': 7, 'n_estimators': 180}
51389.85295710133 {'max_features': 5, 'n_estimators': 15}
50796.12045980556 {'max_features': 3, 'n_estimators': 72}
50835.09932039744 {'max_features': 5, 'n_estimators': 21}
49280.90117886215 {'max_features': 7, 'n_estimators': 122}
50774.86679035961 {'max_features': 3, 'n_estimators': 75}
50682.75001237282 {'max_features': 3, 'n_estimators': 88}
49608.94061293652 {'max_features': 5, 'n_estimators': 100}
50473.57642831875 {'max_features': 3, 'n_estimators': 150}
64429.763804893395 {'max_features': 5, 'n_estimators': 2}
```

In [104]:
```python
feature_importances = grid_search.best_estimator_.feature_importances_
feature_importances
```

Out[104]:
```
array([7.33442355e-02, 6.29090705e-02, 4.11437985e-02, 1.46726854e-02,
       1.41064835e-02, 1.48742809e-02, 1.42575993e-02, 3.66158981e-01,
       5.64191792e-02, 1.08792957e-01, 5.33510773e-02, 1.03114883e-02,
       1.64780994e-01, 6.02803867e-05, 1.96041560e-03, 2.85647464e-03])
```

In [105]:
```python
extra_attribs = ["rooms_per_hhold", "pop_per_hhold", "bedrooms_per_room"]
#cat_encoder = cat_pipeline.named_steps["cat_encoder"] # old solution
cat_encoder = full_pipeline.named_transformers_["cat"]
cat_one_hot_attribs = list(cat_encoder.categories_[0])
attributes = num_attribs + extra_attribs + cat_one_hot_attribs
sorted(zip(feature_importances, attributes), reverse=True)
```

Out[105]:
```
[(0.3661589806181342, 'median_income'),
 (0.1647809935615905, 'INLAND'),
 (0.10879295677551573, 'pop_per_hhold'),
 (0.07334423551601242, 'longitude'),
 (0.0629090704826203, 'latitude'),
 (0.05641917918195401, 'rooms_per_hhold'),
 (0.05335107734767581, 'bedrooms_per_room'),
 (0.041143798478729635, 'housing_median_age'),
 (0.014874280890402767, 'population'),
 (0.014672685420543237, 'total_rooms'),
 (0.014257599323407807, 'households'),
 (0.014106483453584102, 'total_bedrooms'),
 (0.010311488326303787, '<1H OCEAN'),
 (0.002856474637320158, 'NEAR OCEAN'),
 (0.00196041559947807, 'NEAR BAY'),
 (6.028038672736599e-05, 'ISLAND')]
```

In [106]:
```python
final_model = grid_search.best_estimator_

X_test = strat_test_set.drop("median_house_value", axis=1)
y_test = strat_test_set["median_house_value"].copy()

X_test_prepared = full_pipeline.transform(X_test)
final_predictions = final_model.predict(X_test_prepared)

final_mse = mean_squared_error(y_test, final_predictions)
final_rmse = np.sqrt(final_mse)
```

In [107]:
```python
final_rmse
```

Out[107]:
```
47730.22690385927
```

In [108]:
```
from scipy import stats

confidence = 0.95
squared_errors = (final_predictions - y_test) ** 2
np.sqrt(stats.t.interval(confidence, len(squared_errors) - 1,
                         loc=squared_errors.mean(),
                         scale=stats.sem(squared_errors)))
```

Out[108]:
```
array([45685.10470776, 49691.25001878])
```

In [109]:
```
m = len(squared_errors) # Computing t score manually
mean = squared_errors.mean()
tscore = stats.t.ppf((1 + confidence) / 2, df=m - 1)
tmargin = tscore * squared_errors.std(ddof=1) / np.sqrt(m)
np.sqrt(mean - tmargin), np.sqrt(mean + tmargin)
```

Out[109]:
```
(45685.10470776, 49691.25001877858)
```

In [110]:
```
# Alternatively we can use z score
zscore = stats.norm.ppf((1 + confidence) / 2)
zmargin = zscore * squared_errors.std(ddof=1) / np.sqrt(m)
np.sqrt(mean - zmargin), np.sqrt(mean + zmargin)
```

Out[110]:
```
(45685.717918136455, 49690.68623889413)
```