02_end_to_end_machine_learning_project

December 23, 2020

Chapter 2 – End-to-end Machine Learning project

Welcome to Machine Learning Housing Corp.! Your task is to predict median house values in Californian districts, given a number of features from these districts.

This notebook contains all the sample code and solutions to the exercices in chapter 2.

Note: You may find little differences between the code outputs in the book and in these Jupyter notebooks: these slight differences are mostly due to the random nature of many training algorithms: although I have tried to make these notebooks' outputs as constant as possible, it is impossible to guarantee that they will produce the exact same output on every platform. Also, some data structures (such as dictionaries) do not preserve the item order. Finally, I fixed a few minor bugs (I added notes next to the concerned cells) which lead to slightly different results, without changing the ideas presented in the book.

1 Setup

First, let's make sure this notebook works well in both python 2 and 3, import a few common modules, ensure MatplotLib plots figures inline and prepare a function to save the figures:

[1]:
```
# To support both python 2 and python 3
from __future__ import division, print_function, unicode_literals

# Common imports
import numpy as np
import os

# to make this notebook's output stable across runs
np.random.seed(42)

# 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
```

```python
PROJECT_ROOT_DIR = "."
CHAPTER_ID = "end_to_end_project"
IMAGES_PATH = os.path.join(PROJECT_ROOT_DIR, "images", CHAPTER_ID)

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")
```

2 Get the data

[2]:
```python
import os
import tarfile
from six.moves import urllib

DOWNLOAD_ROOT = "https://raw.githubusercontent.com/ageron/handson-ml/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):
    os.makedirs(housing_path, exist_ok=True)
    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()
```

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

[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)
```

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

[5]:
```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -122.23     37.88                41.0        880.0           129.0
```

```
1    -122.22     37.86                    21.0       7099.0          1106.0
2    -122.24     37.85                    52.0       1467.0           190.0
3    -122.25     37.85                    52.0       1274.0           235.0
4    -122.25     37.85                    52.0       1627.0           280.0

   population  households  median_income  median_house_value ocean_proximity
0       322.0       126.0         8.3252            452600.0        NEAR BAY
1      2401.0      1138.0         8.3014            358500.0        NEAR BAY
2       496.0       177.0         7.2574            352100.0        NEAR BAY
3       558.0       219.0         5.6431            341300.0        NEAR BAY
4       565.0       259.0         3.8462            342200.0        NEAR BAY
```

[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
```

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

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

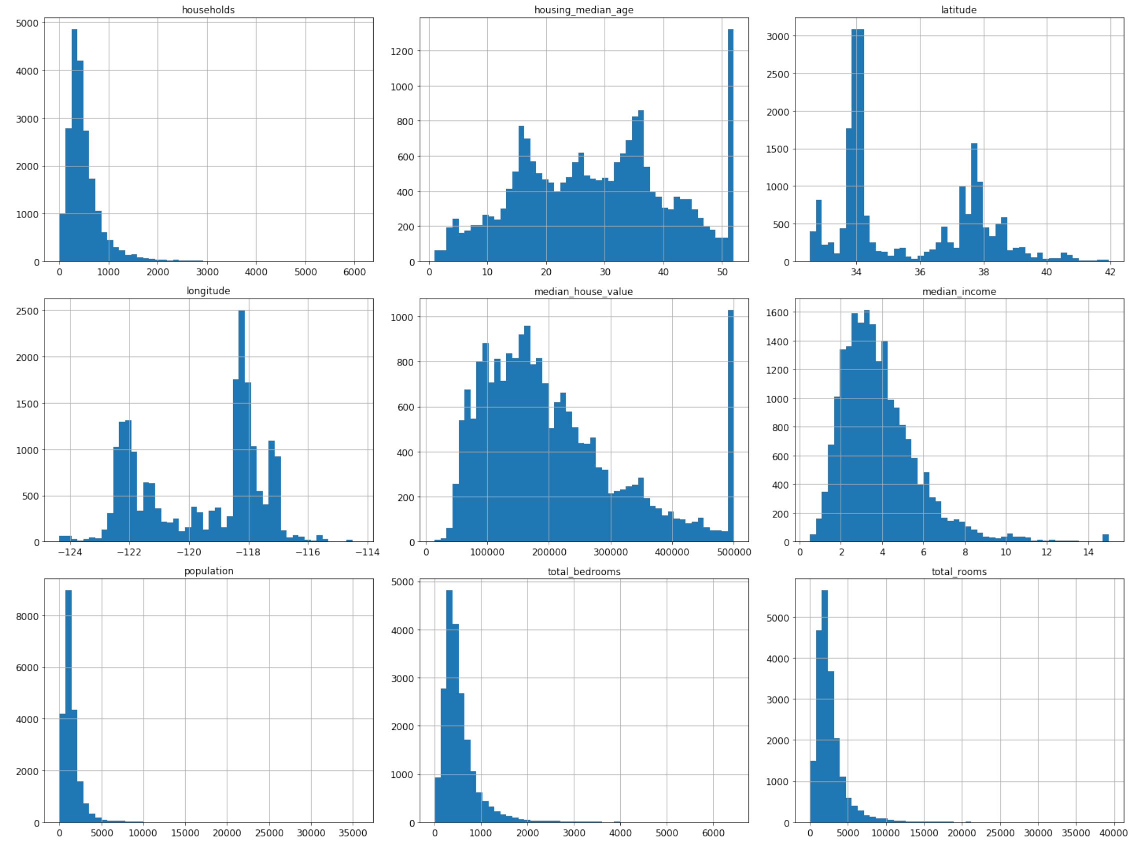
[8]:
```
housing.describe()
```

[8]:
```
          longitude      latitude  housing_median_age   total_rooms  \
count  20640.000000  20640.000000        20640.000000  20640.000000
mean    -119.569704     35.631861           28.639486   2635.763081
std        2.003532      2.135952           12.585558   2181.615252
min     -124.350000     32.540000            1.000000      2.000000
25%     -121.800000     33.930000           18.000000   1447.750000
```

```
50%     -118.490000     34.260000           29.000000    2127.000000
75%     -118.010000     37.710000           37.000000    3148.000000
max     -114.310000     41.950000           52.000000   39320.000000

       total_bedrooms    population    households  median_income   \
count     20433.000000  20640.000000  20640.000000   20640.000000
mean        537.870553   1425.476744    499.539680       3.870671
std         421.385070   1132.462122    382.329753       1.899822
min           1.000000      3.000000      1.000000       0.499900
25%         296.000000    787.000000    280.000000       2.563400
50%         435.000000   1166.000000    409.000000       3.534800
75%         647.000000   1725.000000    605.000000       4.743250
max        6445.000000  35682.000000   6082.000000      15.000100

       median_house_value
count        20640.000000
mean        206855.816909
std         115395.615874
min          14999.000000
25%         119600.000000
50%         179700.000000
75%         264725.000000
max         500001.000000
```

[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
```



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

[11]:
```
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]
```

[12]:
```
train_set, test_set = split_train_test(housing, 0.2)
print(len(train_set), "train +", len(test_set), "test")
```

```
16512 train + 4128 test
```

[13]:
```
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]
```

The implementation of `test_set_check()` above works fine in both Python 2 and Python 3. In earlier releases, the following implementation was proposed, which supported any hash function, but was much slower and did not support Python 2:

[14]:
```
import hashlib

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

If you want an implementation that supports any hash function and is compatible with both Python 2 and Python 3, here is one:

[15]:
```
def test_set_check(identifier, test_ratio, hash=hashlib.md5):
    return bytearray(hash(np.int64(identifier)).digest())[-1] < 256 * test_ratio
```

[16]:
```
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")
```

[17]:
```
housing_with_id["id"] = housing["longitude"] * 1000 + housing["latitude"]
train_set, test_set = split_train_test_by_id(housing_with_id, 0.2, "id")
```

[18]:
```
test_set.head()
```

[18]:
```
    index  longitude  latitude  housing_median_age  total_rooms  \
8       8    -122.26     37.84                42.0       2555.0
10     10    -122.26     37.85                52.0       2202.0
11     11    -122.26     37.85                52.0       3503.0
12     12    -122.26     37.85                52.0       2491.0
13     13    -122.26     37.84                52.0        696.0

    total_bedrooms  population  households  median_income  median_house_value  \
8            665.0      1206.0       595.0         2.0804            226700.0
10           434.0       910.0       402.0         3.2031            281500.0
11           752.0      1504.0       734.0         3.2705            241800.0
12           474.0      1098.0       468.0         3.0750            213500.0
13           191.0       345.0       174.0         2.6736            191300.0

   ocean_proximity         id
8         NEAR BAY -122222.16
10        NEAR BAY -122222.15
```

```
11         NEAR BAY -122222.15
12         NEAR BAY -122222.15
13         NEAR BAY -122222.16
```

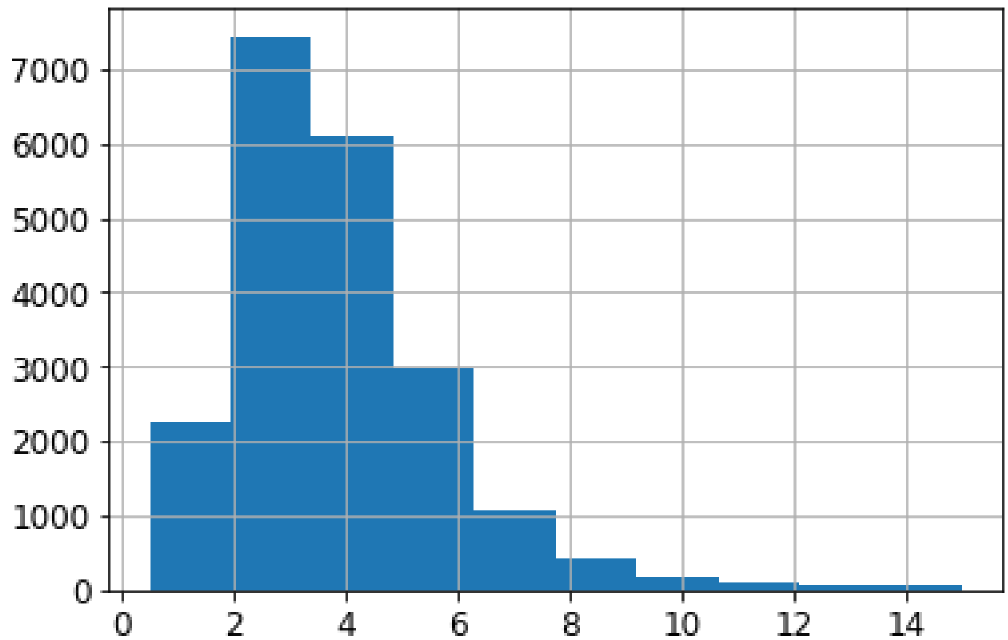
[19]:
```
from sklearn.model_selection import train_test_split

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

[20]:
```
test_set.head()
```

[20]:
```
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
20046    -119.01     36.06                25.0       1505.0             NaN
3024     -119.46     35.14                30.0       2943.0             NaN
15663    -122.44     37.80                52.0       3830.0             NaN
20484    -118.72     34.28                17.0       3051.0             NaN
9814     -121.93     36.62                34.0       2351.0             NaN

       population  households  median_income  median_house_value  \
20046      1392.0       359.0         1.6812             47700.0
3024       1565.0       584.0         2.5313             45800.0
15663      1310.0       963.0         3.4801            500001.0
20484      1705.0       495.0         5.7376            218600.0
9814       1063.0       428.0         3.7250            278000.0

      ocean_proximity
20046          INLAND
3024           INLAND
15663        NEAR BAY
20484       <1H OCEAN
9814       NEAR OCEAN
```

[21]:
```
housing["median_income"].hist()
```

[21]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x114f7c828>
```



Warning: in the book, I did not use `pd.cut()`, instead I used the code below. The `pd.cut()` solution gives the same result (except the labels are integers instead of floats), but it is simpler to understand:

```
# Divide by 1.5 to limit the number of income categories
housing["income_cat"] = np.ceil(housing["median_income"] / 1.5)
# Label those above 5 as 5
housing["income_cat"].where(housing["income_cat"] < 5, 5.0, inplace=True)
```

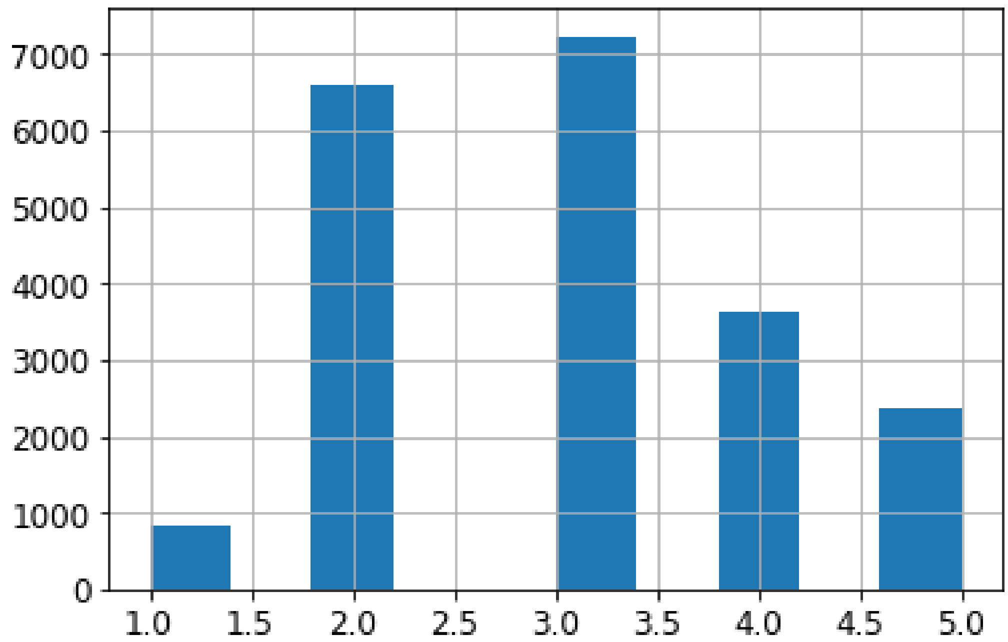
[22]:
```
housing["income_cat"] = pd.cut(housing["median_income"],
                               bins=[0., 1.5, 3.0, 4.5, 6., np.inf],
                               labels=[1, 2, 3, 4, 5])
```

[23]:
```
housing["income_cat"].value_counts()
```

[23]:
```
3    7236
2    6581
4    3639
5    2362
1     822
Name: income_cat, dtype: int64
```

[24]:
```
housing["income_cat"].hist()
```

[24]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x12b945588>
```



[25]:
```
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]
```

[26]:
```
strat_test_set["income_cat"].value_counts() / len(strat_test_set)
```

[26]:
```
3    0.350533
2    0.318798
4    0.176357
5    0.114583
1    0.039729
Name: income_cat, dtype: float64
```

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

[27]:
```
3    0.350581
2    0.318847
4    0.176308
5    0.114438
1    0.039826
Name: income_cat, dtype: float64
```

[28]:
```python
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
```

[29]:
```python
compare_props
```

[29]:

	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

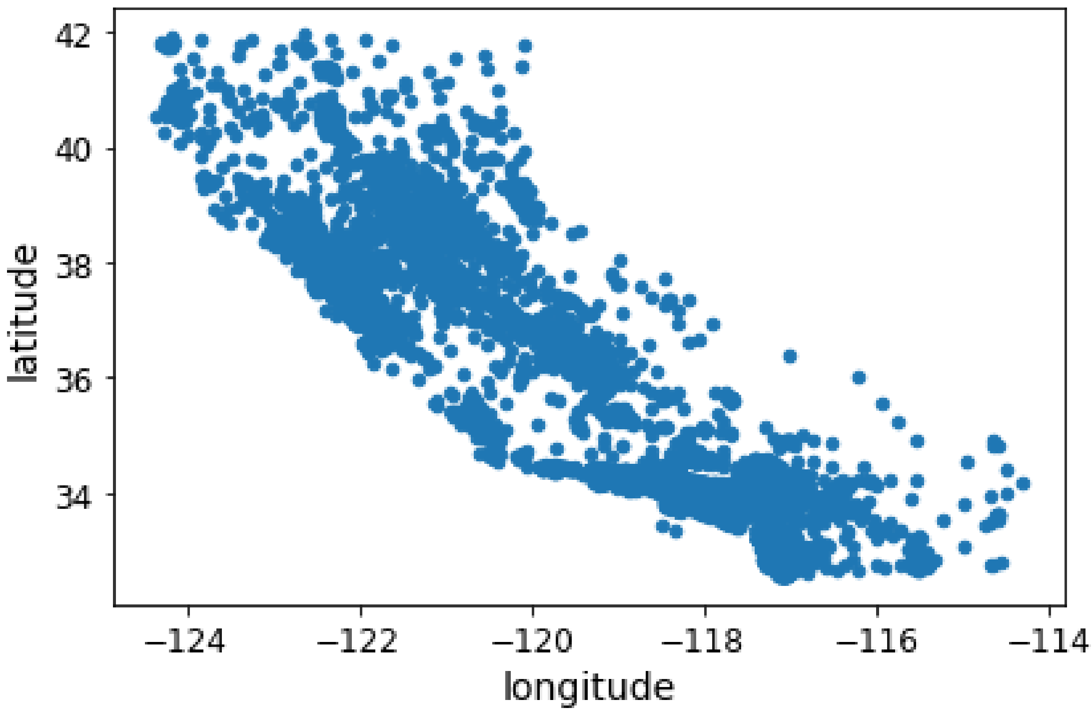
[30]:
```python
for set_ in (strat_train_set, strat_test_set):
    set_.drop("income_cat", axis=1, inplace=True)
```

3 Discover and visualize the data to gain insights

[31]:
```python
housing = strat_train_set.copy()
```

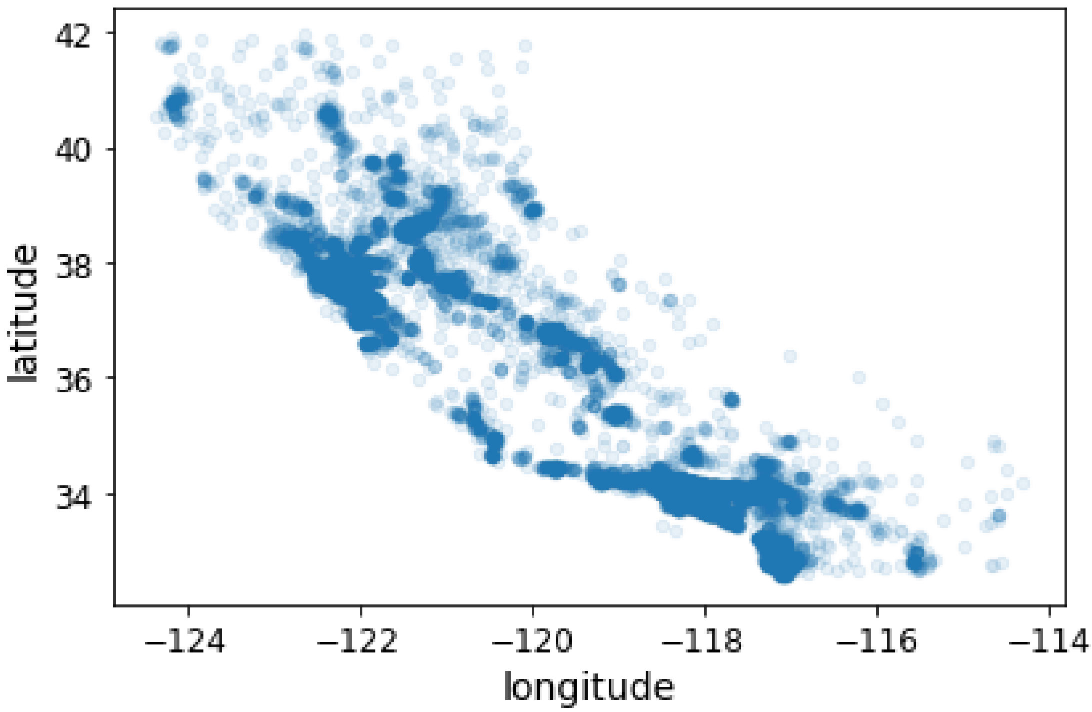
[32]:
```python
housing.plot(kind="scatter", x="longitude", y="latitude")
save_fig("bad_visualization_plot")
```

```
Saving figure bad_visualization_plot
```



[33]:
```
housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.1)
save_fig("better_visualization_plot")
```

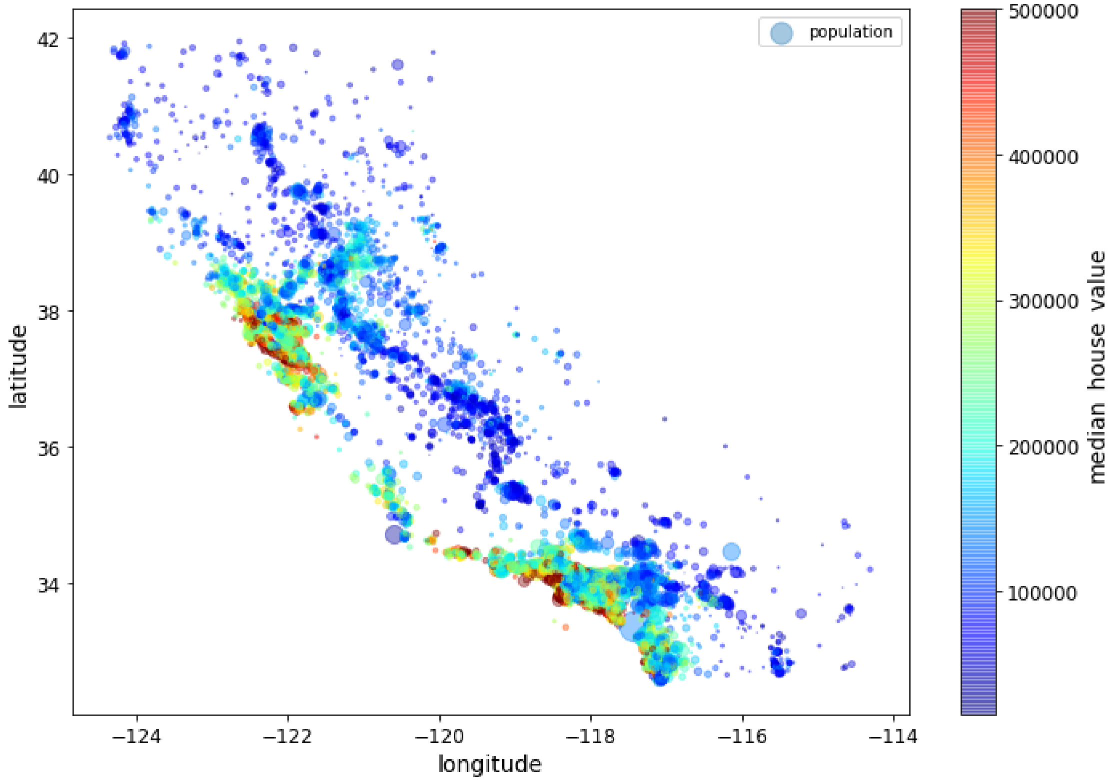
```
Saving figure better_visualization_plot
```



The argument `sharex=False` fixes a display bug (the x-axis values and legend were not displayed). This is a temporary fix (see: https://github.com/pandas-dev/pandas/issues/10611). Thanks to Wilmer Arellano for pointing it out.

[34]:
```
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")
```

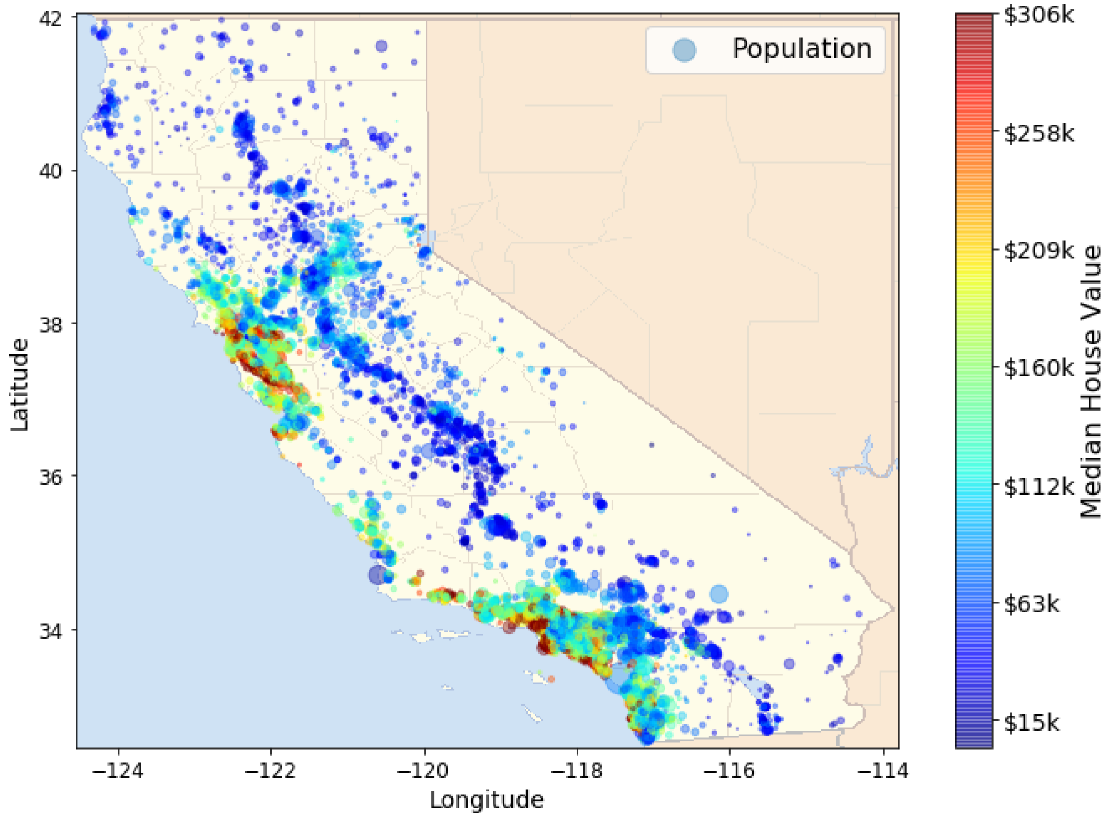
```
Saving figure housing_prices_scatterplot
```



[35]:
```
import matplotlib.image as mpimg
california_img=mpimg.imread(PROJECT_ROOT_DIR + '/images/end_to_end_project/
↪california.png')
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
```



[36]:
```
corr_matrix = housing.corr()
```

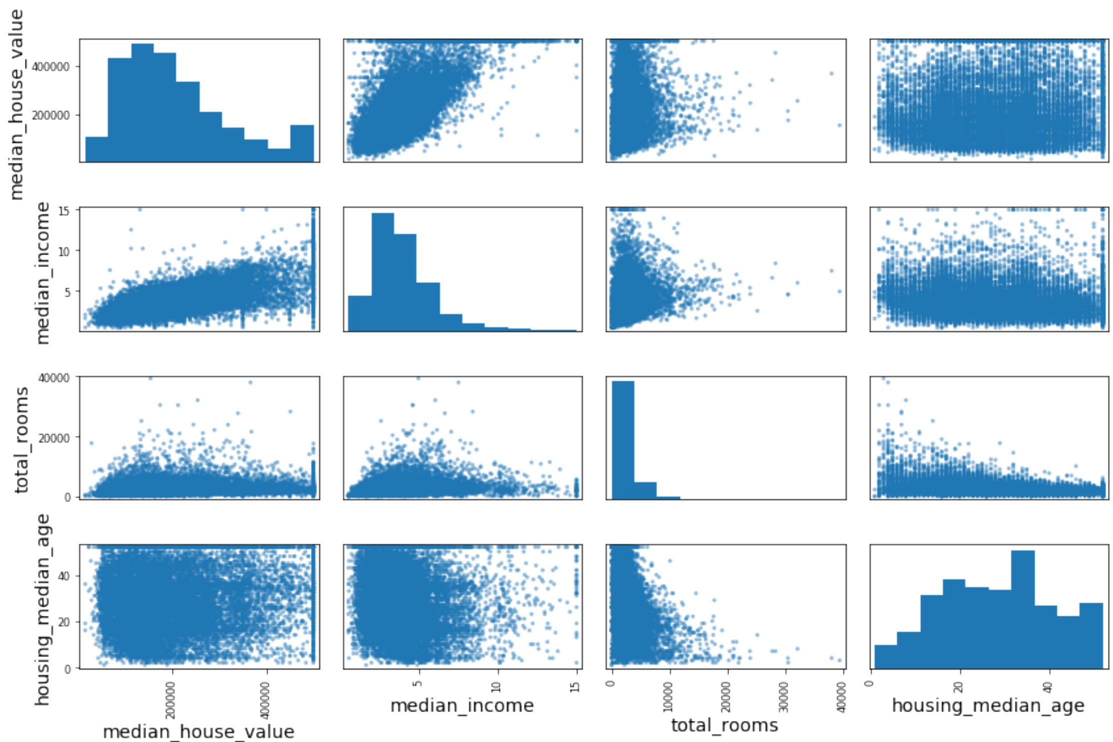
[37]:
```
corr_matrix["median_house_value"].sort_values(ascending=False)
```

[37]:
```
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
```

[38]:
```
# from pandas.tools.plotting import scatter_matrix # For older versions of␣
↪Pandas
```

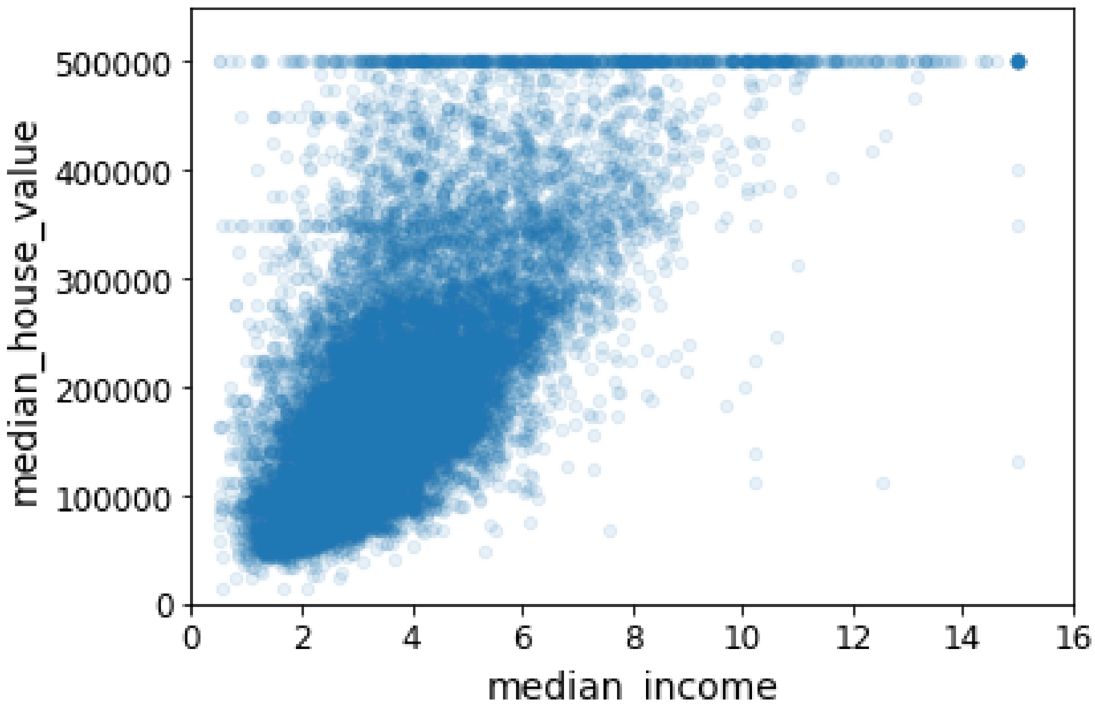
```python
from pandas.plotting import scatter_matrix

attributes = ["median_house_value", "median_income", "total_rooms",
              "housing_median_age"]
scatter_matrix(housing[attributes], figsize=(12, 8))
save_fig("scatter_matrix_plot")
```

Saving figure scatter_matrix_plot



[39]:
```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



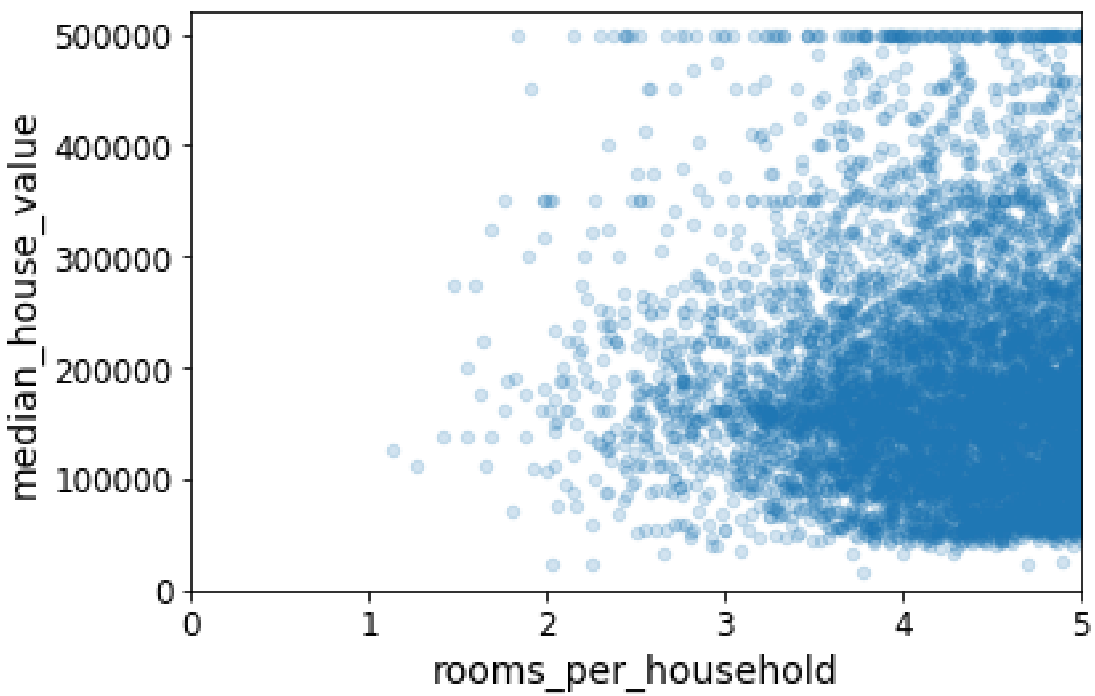
[40]:
```
housing["rooms_per_household"] = housing["total_rooms"]/housing["households"]
housing["bedrooms_per_room"] = housing["total_bedrooms"]/housing["total_rooms"]
housing["population_per_household"]=housing["population"]/housing["households"]
```

Note: there was a bug in the previous cell, in the definition of the `rooms_per_household` attribute. This explains why the correlation value below differs slightly from the value in the book (unless you are reading the latest version).

[41]:
```
corr_matrix = housing.corr()
corr_matrix["median_house_value"].sort_values(ascending=False)
```

[41]:
```
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
```

[42]:
```
housing.plot(kind="scatter", x="rooms_per_household", y="median_house_value",
             alpha=0.2)
plt.axis([0, 5, 0, 520000])
plt.show()
```



[43]:
```
housing.describe()
```

[43]:

	longitude	latitude	housing_median_age	total_rooms	\
count	16512.000000	16512.000000	16512.000000	16512.000000	
mean	-119.575834	35.639577	28.653101	2622.728319	
std	2.001860	2.138058	12.574726	2138.458419	
min	-124.350000	32.540000	1.000000	6.000000	
25%	-121.800000	33.940000	18.000000	1443.000000	
50%	-118.510000	34.260000	29.000000	2119.500000	
75%	-118.010000	37.720000	37.000000	3141.000000	
max	-114.310000	41.950000	52.000000	39320.000000	

	total_bedrooms	population	households	median_income	\
count	16354.000000	16512.000000	16512.000000	16512.000000	
mean	534.973890	1419.790819	497.060380	3.875589	
std	412.699041	1115.686241	375.720845	1.904950	
min	2.000000	3.000000	2.000000	0.499900	
25%	295.000000	784.000000	279.000000	2.566775	
50%	433.000000	1164.000000	408.000000	3.540900	

```
75%       644.000000   1719.250000    602.000000       4.744475
max      6210.000000  35682.000000   5358.000000      15.000100

       median_house_value  rooms_per_household  bedrooms_per_room  \
count        16512.000000         16512.000000       16354.000000
mean        206990.920724             5.440341           0.212878
std         115703.014830             2.611712           0.057379
min          14999.000000             1.130435           0.100000
25%         119800.000000             4.442040           0.175304
50%         179500.000000             5.232284           0.203031
75%         263900.000000             6.056361           0.239831
max         500001.000000           141.909091           1.000000

       population_per_household
count              16512.000000
mean                   3.096437
std                   11.584826
min                    0.692308
25%                    2.431287
50%                    2.817653
75%                    3.281420
max                 1243.333333
```

4 Prepare the data for Machine Learning algorithms

[44]:
```
housing = strat_train_set.drop("median_house_value", axis=1) # drop labels for training set
housing_labels = strat_train_set["median_house_value"].copy()
```

[45]:
```
sample_incomplete_rows = housing[housing.isnull().any(axis=1)].head()
sample_incomplete_rows
```

[45]:
```
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
4629     -118.30     34.07                18.0       3759.0             NaN
6068     -117.86     34.01                16.0       4632.0             NaN
17923    -121.97     37.35                30.0       1955.0             NaN
13656    -117.30     34.05                 6.0       2155.0             NaN
19252    -122.79     38.48                 7.0       6837.0             NaN

       population  households  median_income ocean_proximity
4629       3296.0      1462.0         2.2708       <1H OCEAN
6068       3038.0       727.0         5.1762       <1H OCEAN
17923       999.0       386.0         4.6328       <1H OCEAN
13656      1039.0       391.0         1.6675          INLAND
19252      3468.0      1405.0         3.1662       <1H OCEAN
```

[46]:
```
sample_incomplete_rows.dropna(subset=["total_bedrooms"])    # option 1
```

[46]:
```
Empty DataFrame
Columns: [longitude, latitude, housing_median_age, total_rooms, total_bedrooms,
population, households, median_income, ocean_proximity]
Index: []
```

[47]:
```
sample_incomplete_rows.drop("total_bedrooms", axis=1)       # option 2
```

[47]:
```
       longitude  latitude  housing_median_age  total_rooms  population  \
4629     -118.30     34.07                18.0       3759.0      3296.0
6068     -117.86     34.01                16.0       4632.0      3038.0
17923    -121.97     37.35                30.0       1955.0       999.0
13656    -117.30     34.05                 6.0       2155.0      1039.0
19252    -122.79     38.48                 7.0       6837.0      3468.0

       households  median_income ocean_proximity
4629       1462.0         2.2708       <1H OCEAN
6068        727.0         5.1762       <1H OCEAN
17923       386.0         4.6328       <1H OCEAN
13656       391.0         1.6675          INLAND
19252      1405.0         3.1662       <1H OCEAN
```

[48]:
```
median = housing["total_bedrooms"].median()
sample_incomplete_rows["total_bedrooms"].fillna(median, inplace=True) # option 3
sample_incomplete_rows
```

[48]:
```
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
4629     -118.30     34.07                18.0       3759.0           433.0
6068     -117.86     34.01                16.0       4632.0           433.0
17923    -121.97     37.35                30.0       1955.0           433.0
13656    -117.30     34.05                 6.0       2155.0           433.0
19252    -122.79     38.48                 7.0       6837.0           433.0

       population  households  median_income ocean_proximity
4629       3296.0      1462.0         2.2708       <1H OCEAN
6068       3038.0       727.0         5.1762       <1H OCEAN
17923       999.0       386.0         4.6328       <1H OCEAN
13656      1039.0       391.0         1.6675          INLAND
19252      3468.0      1405.0         3.1662       <1H OCEAN
```

Warning: Since Scikit-Learn 0.20, the `sklearn.preprocessing.Imputer` class was replaced by the `sklearn.impute.SimpleImputer` class.

[49]:
```
try:
    from sklearn.impute import SimpleImputer # Scikit-Learn 0.20+
except ImportError:
```

```
    from sklearn.preprocessing import Imputer as SimpleImputer

imputer = SimpleImputer(strategy="median")
```

Remove the text attribute because median can only be calculated on numerical attributes:

[50]:
```
housing_num = housing.drop('ocean_proximity', axis=1)
# alternatively: housing_num = housing.select_dtypes(include=[np.number])
```

[51]:
```
imputer.fit(housing_num)
```

[51]:
```
SimpleImputer(copy=True, fill_value=None, missing_values=nan,
       strategy='median', verbose=0)
```

[52]:
```
imputer.statistics_
```

[52]:
```
array([-118.51    ,   34.26    ,   29.     , 2119.5    ,  433.     , 1164.     ,
        408.     ,    3.5409])
```

Check that this is the same as manually computing the median of each attribute:

[53]:
```
housing_num.median().values
```

[53]:
```
array([-118.51    ,   34.26    ,   29.     , 2119.5    ,  433.     , 1164.     ,
        408.     ,    3.5409])
```

Transform the training set:

[54]:
```
X = imputer.transform(housing_num)
```

[55]:
```
housing_tr = pd.DataFrame(X, columns=housing_num.columns,
                          index=housing.index)
```

[56]:
```
housing_tr.loc[sample_incomplete_rows.index.values]
```

[56]:
```
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
4629     -118.30     34.07                18.0       3759.0           433.0
6068     -117.86     34.01                16.0       4632.0           433.0
17923    -121.97     37.35                30.0       1955.0           433.0
13656    -117.30     34.05                 6.0       2155.0           433.0
19252    -122.79     38.48                 7.0       6837.0           433.0

       population  households  median_income
4629       3296.0      1462.0         2.2708
6068       3038.0       727.0         5.1762
17923       999.0       386.0         4.6328
13656      1039.0       391.0         1.6675
19252      3468.0      1405.0         3.1662
```

[57]:
```
imputer.strategy
```

[57]:
```
'median'
```

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

[58]:
```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -121.89     37.29                38.0       1568.0           351.0
1    -121.93     37.05                14.0        679.0           108.0
2    -117.20     32.77                31.0       1952.0           471.0
3    -119.61     36.31                25.0       1847.0           371.0
4    -118.59     34.23                17.0       6592.0          1525.0

   population  households  median_income
0       710.0       339.0         2.7042
1       306.0       113.0         6.4214
2       936.0       462.0         2.8621
3      1460.0       353.0         1.8839
4      4459.0      1463.0         3.0347
```

Now let's preprocess the categorical input feature, `ocean_proximity`:

[59]:
```
housing_cat = housing[['ocean_proximity']]
housing_cat.head(10)
```

[59]:
```
      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
```

Warning: earlier versions of the book used the `LabelEncoder` class or Pandas' `Series.factorize()` method to encode string categorical attributes as integers. However, the `OrdinalEncoder` class that was introduced in Scikit-Learn 0.20 (see PR #10521) is preferable since it is designed for input features (`X` instead of labels `y`) and it plays well with pipelines (introduced later in this notebook). If you are using an older version of Scikit-Learn (<0.20), then you can import it from `future_encoders.py` instead.

[60]:
```
try:
    from sklearn.preprocessing import OrdinalEncoder
except ImportError:
    from future_encoders import OrdinalEncoder # Scikit-Learn < 0.20
```

[61]:
```
ordinal_encoder = OrdinalEncoder()
housing_cat_encoded = ordinal_encoder.fit_transform(housing_cat)
housing_cat_encoded[:10]
```

[61]:
```
array([[0.],
       [0.],
       [4.],
       [1.],
       [0.],
       [1.],
       [0.],
       [1.],
       [0.],
       [0.]])
```

[62]:
```
ordinal_encoder.categories_
```

[62]:
```
[array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],
       dtype=object)]
```

Warning: earlier versions of the book used the `LabelBinarizer` or `CategoricalEncoder` classes to convert each categorical value to a one-hot vector. It is now preferable to use the `OneHotEncoder` class. Since Scikit-Learn 0.20 it can handle string categorical inputs (see PR #10521), not just integer categorical inputs. If you are using an older version of Scikit-Learn, you can import the new version from `future_encoders.py`:

[63]:
```
try:
    from sklearn.preprocessing import OrdinalEncoder # just to raise an␣
↪ImportError if Scikit-Learn < 0.20
    from sklearn.preprocessing import OneHotEncoder
except ImportError:
    from future_encoders import OneHotEncoder # Scikit-Learn < 0.20

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

[63]:
```
<16512x5 sparse matrix of type '<class 'numpy.float64'>'
        with 16512 stored elements in Compressed Sparse Row format>
```

By default, the `OneHotEncoder` class returns a sparse array, but we can convert it to a dense array if needed by calling the `toarray()` method:

[64]:
```
housing_cat_1hot.toarray()
```

[64]:
```
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.]])
```

Alternatively, you can set `sparse=False` when creating the `OneHotEncoder`:

[65]:
```
cat_encoder = OneHotEncoder(sparse=False)
housing_cat_1hot = cat_encoder.fit_transform(housing_cat)
housing_cat_1hot
```

[65]:
```
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.]])
```

[66]:
```
cat_encoder.categories_
```

[66]:
```
[array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],
       dtype=object)]
```

Let's create a custom transformer to add extra attributes:

[67]:
```
housing.columns
```

[67]:
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'ocean_proximity'],
      dtype='object')
```

[68]:
```
from sklearn.base import BaseEstimator, TransformerMixin

# get the right column indices: safer than hard-coding indices 3, 4, 5, 6
rooms_ix, bedrooms_ix, population_ix, household_ix = [
    list(housing.columns).index(col)
    for col in ("total_rooms", "total_bedrooms", "population", "households")]

class CombinedAttributesAdder(BaseEstimator, TransformerMixin):
    def __init__(self, add_bedrooms_per_room = True): # no *args or **kwargs
        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, y=None):
        rooms_per_household = X[:, rooms_ix] / X[:, household_ix]
        population_per_household = X[:, population_ix] / X[:, household_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)
```

Alternatively, you can use Scikit-Learn's `FunctionTransformer` class that lets you easily create a transformer based on a transformation function (thanks to Hanmin Qin for suggesting this code). Note that we need to set `validate=False` because the data contains non-float values (`validate` will default to `False` in Scikit-Learn 0.22).

[69]:
```
from sklearn.preprocessing import FunctionTransformer

def add_extra_features(X, add_bedrooms_per_room=True):
    rooms_per_household = X[:, rooms_ix] / X[:, household_ix]
    population_per_household = X[:, population_ix] / X[:, household_ix]
    if 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 = FunctionTransformer(add_extra_features, validate=False,
                                 kw_args={"add_bedrooms_per_room": False})
housing_extra_attribs = attr_adder.fit_transform(housing.values)
```

[70]:
```
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()
```

[70]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	\
0	-121.89	37.29	38	1568	351	710	
1	-121.93	37.05	14	679	108	306	
2	-117.2	32.77	31	1952	471	936	

```
3   -119.61    36.31                   25        1847            371        1460
4   -118.59    34.23                   17        6592           1525        4459

  households median_income ocean_proximity rooms_per_household  \
0        339        2.7042       <1H OCEAN             4.62537
1        113        6.4214       <1H OCEAN             6.00885
2        462        2.8621      NEAR OCEAN             4.22511
3        353        1.8839          INLAND             5.23229
4       1463        3.0347       <1H OCEAN             4.50581

  population_per_household
0                   2.0944
1                  2.70796
2                  2.02597
3                  4.13598
4                  3.04785
```

Now let's build a pipeline for preprocessing the numerical attributes (note that we could use `CombinedAttributesAdder()` instead of `FunctionTransformer(...)` if we preferred):

[71]:
```python
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler

num_pipeline = Pipeline([
        ('imputer', SimpleImputer(strategy="median")),
        ('attribs_adder', FunctionTransformer(add_extra_features,␣
 ↪validate=False)),
        ('std_scaler', StandardScaler()),
    ])

housing_num_tr = num_pipeline.fit_transform(housing_num)
```

[72]:
```python
housing_num_tr
```

[72]:
```
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]])
```

Warning: earlier versions of the book applied different transformations to different columns using a solution based on a `DataFrameSelector` transformer and a `FeatureUnion` (see below). It is now preferable to use the `ColumnTransformer` class that was introduced in Scikit-Learn 0.20. If you are using an older version of Scikit-Learn, you can import it from `future_encoders.py`:

[73]:
```
try:
    from sklearn.compose import ColumnTransformer
except ImportError:
    from future_encoders import ColumnTransformer # Scikit-Learn < 0.20
```

[74]:
```
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)
```

[75]:
```
housing_prepared
```

[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.        ]])
```

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

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

For reference, here is the old solution based on a `DataFrameSelector` transformer (to just select a subset of the Pandas `DataFrame` columns), and a `FeatureUnion`:

[77]:
```
from sklearn.base import BaseEstimator, TransformerMixin

# Create a class to select numerical or categorical columns
class OldDataFrameSelector(BaseEstimator, TransformerMixin):
    def __init__(self, attribute_names):
```

```
        self.attribute_names = attribute_names
    def fit(self, X, y=None):
        return self
    def transform(self, X):
        return X[self.attribute_names].values
```

Now let's join all these components into a big pipeline that will preprocess both the numerical and the categorical features (again, we could use `CombinedAttributesAdder()` instead of `FunctionTransformer(...)` if we preferred):

[78]:
```
num_attribs = list(housing_num)
cat_attribs = ["ocean_proximity"]

old_num_pipeline = Pipeline([
        ('selector', OldDataFrameSelector(num_attribs)),
        ('imputer', SimpleImputer(strategy="median")),
        ('attribs_adder', FunctionTransformer(add_extra_features,␣
 ↪validate=False)),
        ('std_scaler', StandardScaler()),
    ])

old_cat_pipeline = Pipeline([
        ('selector', OldDataFrameSelector(cat_attribs)),
        ('cat_encoder', OneHotEncoder(sparse=False)),
    ])
```

[79]:
```
from sklearn.pipeline import FeatureUnion

old_full_pipeline = FeatureUnion(transformer_list=[
        ("num_pipeline", old_num_pipeline),
        ("cat_pipeline", old_cat_pipeline),
    ])
```

[80]:
```
old_housing_prepared = old_full_pipeline.fit_transform(housing)
old_housing_prepared
```

[80]:
```
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.        ]])
```

The result is the same as with the ColumnTransformer:

[81]:
```
np.allclose(housing_prepared, old_housing_prepared)
```

[81]:
```
True
```

5 Select and train a model

[82]:
```
from sklearn.linear_model import LinearRegression

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

[82]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

[83]:
```
# 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]
```

Compare against the actual values:

[84]:
```
print("Labels:", list(some_labels))
```

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

[85]:
```
some_data_prepared
```

[85]:
```
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.        ]])
```

[86]:
```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
```

[86]:
```
68628.19819848922
```

[87]:
```python
from sklearn.metrics import mean_absolute_error

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

[87]:
```
49439.89599001897
```

[88]:
```python
from sklearn.tree import DecisionTreeRegressor

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

[88]:
```
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')
```

[89]:
```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
```

[89]:
```
0.0
```

6 Fine-tune your model

[90]:
```
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)
```

[91]:
```
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
```

[92]:
```
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: 2731.674001798348
```

Note: we specify `n_estimators=10` to avoid a warning about the fact that the default value is going to change to 100 in Scikit-Learn 0.22.

[93]:
```
from sklearn.ensemble import RandomForestRegressor

forest_reg = RandomForestRegressor(n_estimators=10, random_state=42)
forest_reg.fit(housing_prepared, housing_labels)
```

[93]:
```
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=10, n_jobs=None,
           oob_score=False, random_state=42, verbose=0, warm_start=False)
```

[94]:
```python
housing_predictions = forest_reg.predict(housing_prepared)
forest_mse = mean_squared_error(housing_labels, housing_predictions)
forest_rmse = np.sqrt(forest_mse)
forest_rmse
```

[94]: 21933.31414779769

[95]:
```python
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: [51646.44545909 48940.60114882 53050.86323649 54408.98730149
 50922.14870785 56482.50703987 51864.52025526 49760.85037653
 55434.21627933 53326.10093303]
Mean: 52583.72407377466
Standard deviation: 2298.353351147122
```

[96]:
```python
scores = cross_val_score(lin_reg, housing_prepared, housing_labels,␣
 ↪scoring="neg_mean_squared_error", cv=10)
pd.Series(np.sqrt(-scores)).describe()
```

[96]:
```
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
```

[97]:
```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
```

[97]: 111094.6308539982

[98]:
```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)
```

[98]:
```
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)
```

The best hyperparameter combination found:

[99]:
```
grid_search.best_params_
```

[99]:
```
{'max_features': 8, 'n_estimators': 30}
```

[100]:
```
grid_search.best_estimator_
```

[100]:
```
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)
```

Let's look at the score of each hyperparameter combination tested during the grid search:

[101]:
```
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}
```

[102]:

```python
pd.DataFrame(grid_search.cv_results_)
```

[102]:

```
    mean_fit_time  std_fit_time  mean_score_time  std_score_time  \
0        0.060251      0.001252         0.004077        0.000397
1        0.195211      0.001845         0.010179        0.000394
2        0.589625      0.003846         0.030403        0.003266
3        0.098321      0.001313         0.003398        0.000078
4        0.322361      0.002503         0.010031        0.000395
5        0.964709      0.003208         0.026985        0.000617
6        0.132895      0.003371         0.003408        0.000064
7        0.443695      0.005027         0.010141        0.000682
8        1.343336      0.004695         0.027562        0.001805
9        0.169927      0.001055         0.003458        0.000110
10       0.570730      0.004385         0.010258        0.000573
11       1.724103      0.005320         0.027100        0.000618
12       0.093079      0.001465         0.004737        0.000253
13       0.309217      0.002585         0.011903        0.000335
14       0.124233      0.002787         0.004212        0.000185
15       0.408420      0.003067         0.012991        0.000480
16       0.154712      0.002472         0.004148        0.000244
17       0.512536      0.001934         0.012041        0.000309

   param_max_features param_n_estimators param_bootstrap  \
0                   2                  3             NaN
1                   2                 10             NaN
2                   2                 30             NaN
3                   4                  3             NaN
4                   4                 10             NaN
```

```
5                   4                30            NaN
6                   6                 3            NaN
7                   6                10            NaN
8                   6                30            NaN
9                   8                 3            NaN
10                  8                10            NaN
11                  8                30            NaN
12                  2                 3          False
13                  2                10          False
14                  3                 3          False
15                  3                10          False
16                  4                 3          False
17                  4                10          False

                                               params  split0_test_score  \
0             {'max_features': 2, 'n_estimators': 3}      -3.837622e+09
1            {'max_features': 2, 'n_estimators': 10}      -3.047771e+09
2            {'max_features': 2, 'n_estimators': 30}      -2.689185e+09
3             {'max_features': 4, 'n_estimators': 3}      -3.730181e+09
4            {'max_features': 4, 'n_estimators': 10}      -2.666283e+09
5            {'max_features': 4, 'n_estimators': 30}      -2.387153e+09
6             {'max_features': 6, 'n_estimators': 3}      -3.119657e+09
7            {'max_features': 6, 'n_estimators': 10}      -2.549663e+09
8            {'max_features': 6, 'n_estimators': 30}      -2.370010e+09
9             {'max_features': 8, 'n_estimators': 3}      -3.353504e+09
10           {'max_features': 8, 'n_estimators': 10}      -2.571970e+09
11           {'max_features': 8, 'n_estimators': 30}      -2.357390e+09
12  {'bootstrap': False, 'max_features': 2, 'n_est…      -3.785816e+09
13  {'bootstrap': False, 'max_features': 2, 'n_est…      -2.810721e+09
14  {'bootstrap': False, 'max_features': 3, 'n_est…      -3.618324e+09
15  {'bootstrap': False, 'max_features': 3, 'n_est…      -2.757999e+09
16  {'bootstrap': False, 'max_features': 4, 'n_est…      -3.134040e+09
17  {'bootstrap': False, 'max_features': 4, 'n_est…      -2.525578e+09

    split1_test_score       …        mean_test_score  std_test_score  \
0       -4.147108e+09       …          -4.053749e+09    1.519609e+08
1       -3.254861e+09       …          -3.094381e+09    1.327046e+08
2       -3.021086e+09       …          -2.849913e+09    1.626879e+08
3       -3.786886e+09       …          -3.716852e+09    1.631421e+08
4       -2.784511e+09       …          -2.781611e+09    1.268562e+08
5       -2.588448e+09       …          -2.537877e+09    1.214603e+08
6       -3.586319e+09       …          -3.441447e+09    1.893141e+08
7       -2.782039e+09       …          -2.704640e+09    1.471542e+08
8       -2.583638e+09       …          -2.514668e+09    1.285063e+08
9       -3.348552e+09       …          -3.348851e+09    1.241864e+08
10      -2.718994e+09       …          -2.674037e+09    1.392720e+08
11      -2.546640e+09       …          -2.468326e+09    1.091647e+08
```

12	-4.166012e+09	…	-3.955792e+09	1.900966e+08
13	-3.107789e+09	…	-2.987513e+09	1.539231e+08
14	-3.441527e+09	…	-3.536728e+09	7.795196e+07
15	-2.851737e+09	…	-2.779927e+09	6.286611e+07
16	-3.559375e+09	…	-3.305171e+09	1.879203e+08
17	-2.710011e+09	…	-2.601971e+09	1.088031e+08

	rank_test_score	split0_train_score	split1_train_score	\
0	18	-1.064113e+09	-1.105142e+09	
1	11	-5.927175e+08	-5.870952e+08	
2	9	-4.381089e+08	-4.391272e+08	
3	16	-9.865163e+08	-1.012565e+09	
4	8	-5.097115e+08	-5.162820e+08	
5	3	-3.838835e+08	-3.880268e+08	
6	14	-9.245343e+08	-8.886939e+08	
7	6	-4.980344e+08	-5.045869e+08	
8	2	-3.838538e+08	-3.804711e+08	
9	13	-9.228123e+08	-8.553031e+08	
10	5	-4.932416e+08	-4.815238e+08	
11	1	-3.841658e+08	-3.744500e+08	
12	17	-0.000000e+00	-0.000000e+00	
13	10	-6.056477e-02	-0.000000e+00	
14	15	-0.000000e+00	-0.000000e+00	
15	7	-2.089484e+01	-0.000000e+00	
16	12	-0.000000e+00	-0.000000e+00	
17	4	-0.000000e+00	-1.514119e-02	

	split2_train_score	split3_train_score	split4_train_score	\
0	-1.116550e+09	-1.112342e+09	-1.129650e+09	
1	-5.776964e+08	-5.716332e+08	-5.802501e+08	
2	-4.371702e+08	-4.376955e+08	-4.452654e+08	
3	-9.169425e+08	-1.037400e+09	-9.707739e+08	
4	-4.962893e+08	-5.436192e+08	-5.160297e+08	
5	-3.790867e+08	-4.040957e+08	-3.845520e+08	
6	-9.353135e+08	-9.009801e+08	-8.624664e+08	
7	-4.994664e+08	-4.990325e+08	-5.055542e+08	
8	-3.805218e+08	-3.856095e+08	-3.901917e+08	
9	-8.603321e+08	-8.881964e+08	-9.151287e+08	
10	-4.730979e+08	-5.155367e+08	-4.985555e+08	
11	-3.773239e+08	-3.882250e+08	-3.810005e+08	
12	-0.000000e+00	-0.000000e+00	-0.000000e+00	
13	-0.000000e+00	-0.000000e+00	-2.967449e+00	
14	-0.000000e+00	-0.000000e+00	-6.072840e+01	
15	-0.000000e+00	-0.000000e+00	-5.465556e+00	
16	-0.000000e+00	-0.000000e+00	-0.000000e+00	
17	-0.000000e+00	-0.000000e+00	-0.000000e+00	

```
    mean_train_score  std_train_score
0       -1.105559e+09     2.220402e+07
1       -5.818785e+08     7.345821e+06
2       -4.394734e+08     2.966320e+06
3       -9.848396e+08     4.084607e+07
4       -5.163863e+08     1.542862e+07
5       -3.879289e+08     8.571233e+06
6       -9.023976e+08     2.591445e+07
7       -5.013349e+08     3.100456e+06
8       -3.841296e+08     3.617057e+06
9       -8.883545e+08     2.750227e+07
10      -4.923911e+08     1.459294e+07
11      -3.810330e+08     4.871017e+06
12       0.000000e+00     0.000000e+00
13      -6.056027e-01     1.181156e+00
14      -1.214568e+01     2.429136e+01
15      -5.272080e+00     8.093117e+00
16       0.000000e+00     0.000000e+00
17      -3.028238e-03     6.056477e-03

[18 rows x 23 columns]
```

[103]:

```
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)
```

[103]:

```
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 0x1210939e8>,
```

```
'max_features': <scipy.stats._distn_infrastructure.rv_frozen object at
0x121093710>},
          pre_dispatch='2*n_jobs', random_state=42, refit=True,
          return_train_score='warn', scoring='neg_mean_squared_error',
          verbose=0)
```

[104]:
```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}
```

[105]:
```python
feature_importances = grid_search.best_estimator_.feature_importances_
feature_importances
```

[105]:
```
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])
```

[106]:
```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)
```

[106]:
```
[(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')]
```

[107]:
```
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)
```

[108]:
```
final_rmse
```

[108]:
```
47730.22690385927
```

We can compute a 95% confidence interval for the test RMSE:

[109]:
```
from scipy import stats
```

[110]:
```
confidence = 0.95
squared_errors = (final_predictions - y_test) ** 2
mean = squared_errors.mean()
m = len(squared_errors)

np.sqrt(stats.t.interval(confidence, m - 1,
                         loc=np.mean(squared_errors),
                         scale=stats.sem(squared_errors)))
```

[110]:
```
array([45685.10470776, 49691.25001878])
```

We could compute the interval manually like this:

[111]:
```
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)
```

[111]:
```
(45685.10470776014, 49691.25001877871)
```

Alternatively, we could use a z-scores rather than t-scores:

[112]:
```
zscore = stats.norm.ppf((1 + confidence) / 2)
zmargin = zscore * squared_errors.std(ddof=1) / np.sqrt(m)
```

```python
np.sqrt(mean - zmargin), np.sqrt(mean + zmargin)
```

[112]: (45685.717918136594, 49690.68623889426)

7 Extra material

7.1 A full pipeline with both preparation and prediction

[113]:
```python
full_pipeline_with_predictor = Pipeline([
        ("preparation", full_pipeline),
        ("linear", LinearRegression())
    ])

full_pipeline_with_predictor.fit(housing, housing_labels)
full_pipeline_with_predictor.predict(some_data)
```

[113]: array([210644.60459286, 317768.80697211, 210956.43331178, 59218.98886849,
        189747.55849879])

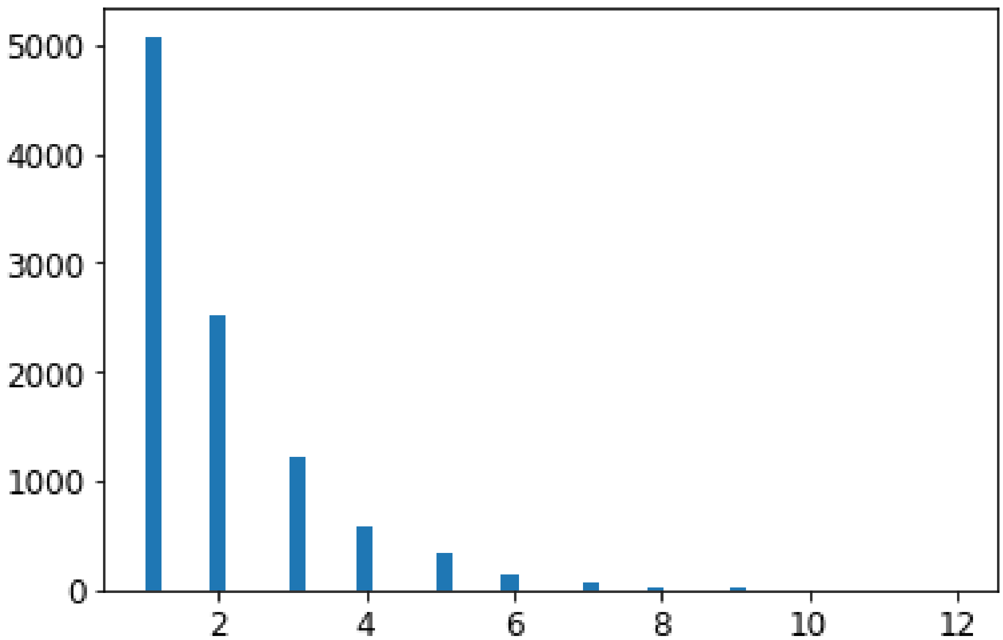
7.2 Model persistence using joblib

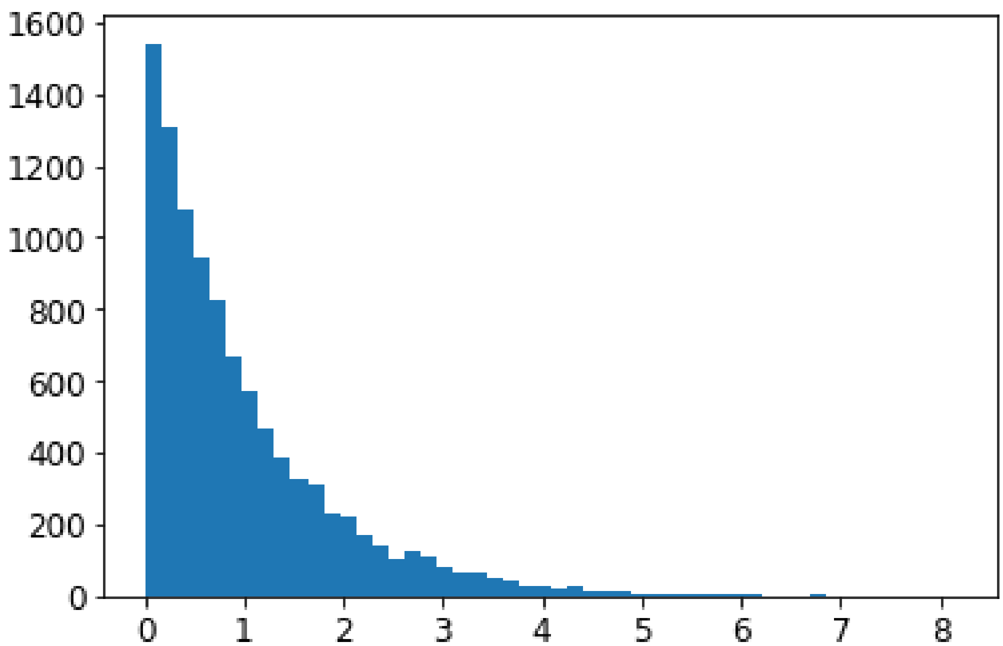
[114]:
```python
my_model = full_pipeline_with_predictor
```

[115]:
```python
from sklearn.externals import joblib
joblib.dump(my_model, "my_model.pkl") # DIFF
#...
my_model_loaded = joblib.load("my_model.pkl") # DIFF
```

7.3 Example SciPy distributions for RandomizedSearchCV

[116]:
```python
from scipy.stats import geom, expon
geom_distrib=geom(0.5).rvs(10000, random_state=42)
expon_distrib=expon(scale=1).rvs(10000, random_state=42)
plt.hist(geom_distrib, bins=50)
plt.show()
plt.hist(expon_distrib, bins=50)
plt.show()
```


5000
4000
3000
2000
1000
0
2
4
6
8
10
12


1600
1400
1200
1000
800
600
400
200
0
0
1
2
3
4
5
6
7
8

8 Exercise solutions

8.1 1.

Question: Try a Support Vector Machine regressor (`sklearn.svm.SVR`), with various hyperparameters such as `kernel="linear"` (with various values for the `C` hyperparameter) or `kernel="rbf"` (with various values for the `C` and `gamma` hyperparameters). Don't worry about what these hyperparameters mean for now. How does the best `SVR` predictor perform?

[117]:
```
from sklearn.model_selection import GridSearchCV

param_grid = [
        {'kernel': ['linear'], 'C': [10., 30., 100., 300., 1000., 3000., 10000.
 ↪, 30000.0]},
        {'kernel': ['rbf'], 'C': [1.0, 3.0, 10., 30., 100., 300., 1000.0],
         'gamma': [0.01, 0.03, 0.1, 0.3, 1.0, 3.0]},
    ]

svm_reg = SVR()
grid_search = GridSearchCV(svm_reg, param_grid, cv=5,␣
 ↪scoring='neg_mean_squared_error', verbose=2, n_jobs=4)
grid_search.fit(housing_prepared, housing_labels)
```

```
Fitting 5 folds for each of 50 candidates, totalling 250 fits
```

```
[Parallel(n_jobs=4)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  33 tasks      | elapsed:  1.5min
[Parallel(n_jobs=4)]: Done 154 tasks      | elapsed:  9.4min
[Parallel(n_jobs=4)]: Done 250 out of 250 | elapsed: 15.4min finished
```

[117]:
```
GridSearchCV(cv=5, error_score='raise-deprecating',
       estimator=SVR(C=1.0, cache_size=200, coef0=0.0, degree=3, epsilon=0.1,
  gamma='auto_deprecated', kernel='rbf', max_iter=-1, shrinking=True,
  tol=0.001, verbose=False),
       fit_params=None, iid='warn', n_jobs=4,
       param_grid=[{'kernel': ['linear'], 'C': [10.0, 30.0, 100.0, 300.0,
1000.0, 3000.0, 10000.0, 30000.0]}, {'kernel': ['rbf'], 'C': [1.0, 3.0, 10.0,
30.0, 100.0, 300.0, 1000.0], 'gamma': [0.01, 0.03, 0.1, 0.3, 1.0, 3.0]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='neg_mean_squared_error', verbose=2)
```

The best model achieves the following score (evaluated using 5-fold cross validation):

[118]:
```
negative_mse = grid_search.best_score_
rmse = np.sqrt(-negative_mse)
rmse
```

[118]:
```
70363.90313964167
```

That's much worse than the RandomForestRegressor. Let's check the best hyperparameters found:

[119]:
```
grid_search.best_params_
```

[119]:
```
{'C': 30000.0, 'kernel': 'linear'}
```

The linear kernel seems better than the RBF kernel. Notice that the value of C is the maximum tested value. When this happens you definitely want to launch the grid search again with higher values for C (removing the smallest values), because it is likely that higher values of C will be better.

8.2 2.

Question: Try replacing GridSearchCV with RandomizedSearchCV.

[120]:
```
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import expon, reciprocal

# see https://docs.scipy.org/doc/scipy/reference/stats.html
# for `expon()` and `reciprocal()` documentation and more probability␣
 ↪distribution functions.

# Note: gamma is ignored when kernel is "linear"
param_distribs = {
        'kernel': ['linear', 'rbf'],
        'C': reciprocal(20, 200000),
        'gamma': expon(scale=1.0),
    }

svm_reg = SVR()
rnd_search = RandomizedSearchCV(svm_reg, param_distributions=param_distribs,
                                n_iter=50, cv=5,␣
 ↪scoring='neg_mean_squared_error',
                                verbose=2, n_jobs=4, random_state=42)
rnd_search.fit(housing_prepared, housing_labels)
```

```
Fitting 5 folds for each of 50 candidates, totalling 250 fits
```

```
[Parallel(n_jobs=4)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  33 tasks      | elapsed:  1.9min
[Parallel(n_jobs=4)]: Done 154 tasks      | elapsed: 12.1min
[Parallel(n_jobs=4)]: Done 250 out of 250 | elapsed: 19.6min finished
```

[120]:
```
RandomizedSearchCV(cv=5, error_score='raise-deprecating',
          estimator=SVR(C=1.0, cache_size=200, coef0=0.0, degree=3, epsilon=0.1,
  gamma='auto_deprecated', kernel='rbf', max_iter=-1, shrinking=True,
  tol=0.001, verbose=False),
          fit_params=None, iid='warn', n_iter=50, n_jobs=4,
          param_distributions={'kernel': ['linear', 'rbf'], 'C':
<scipy.stats._distn_infrastructure.rv_frozen object at 0x13a243278>, 'gamma':
```

```
<scipy.stats._distn_infrastructure.rv_frozen object at 0x13a243e48>},
          pre_dispatch='2*n_jobs', random_state=42, refit=True,
          return_train_score='warn', scoring='neg_mean_squared_error',
          verbose=2)
```

The best model achieves the following score (evaluated using 5-fold cross validation):

[121]:
```
negative_mse = rnd_search.best_score_
rmse = np.sqrt(-negative_mse)
rmse
```

[121]:
```
54767.99053704408
```

Now this is much closer to the performance of the `RandomForestRegressor` (but not quite there yet). Let's check the best hyperparameters found:

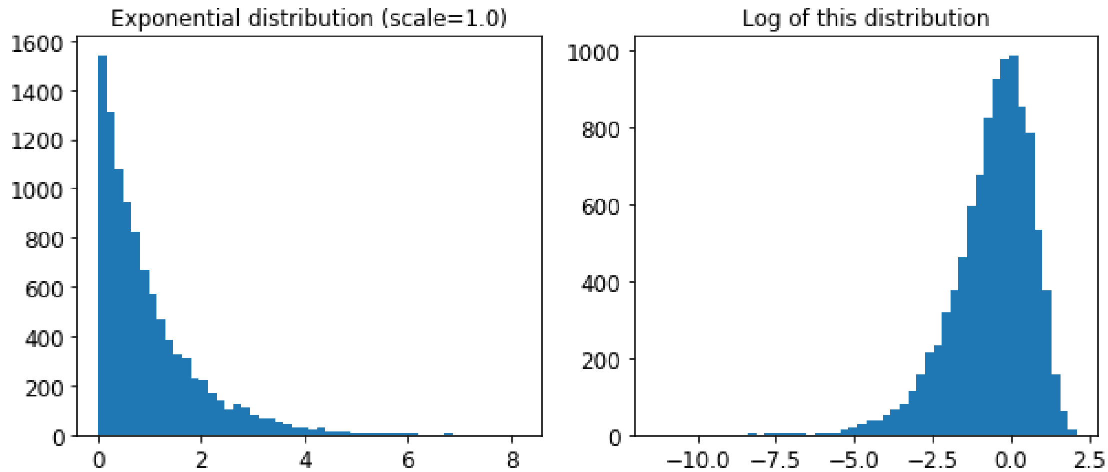
[122]:
```
rnd_search.best_params_
```

[122]:
```
{'C': 157055.10989448498, 'gamma': 0.26497040005002437, 'kernel': 'rbf'}
```

This time the search found a good set of hyperparameters for the RBF kernel. Randomized search tends to find better hyperparameters than grid search in the same amount of time.

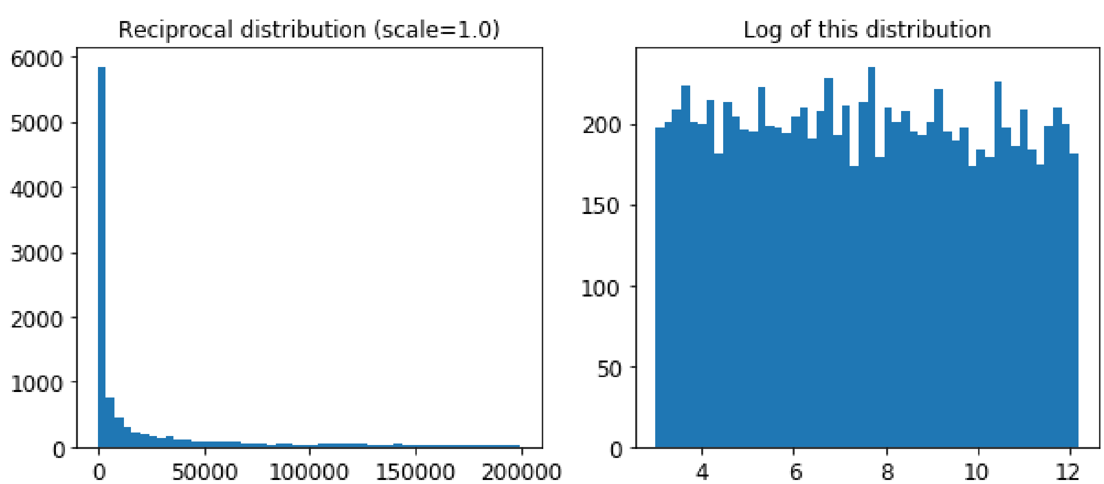
Let's look at the exponential distribution we used, with `scale=1.0`. Note that some samples are much larger or smaller than 1.0, but when you look at the log of the distribution, you can see that most values are actually concentrated roughly in the range of exp(-2) to exp(+2), which is about 0.1 to 7.4.

[123]:
```
expon_distrib = expon(scale=1.)
samples = expon_distrib.rvs(10000, random_state=42)
plt.figure(figsize=(10, 4))
plt.subplot(121)
plt.title("Exponential distribution (scale=1.0)")
plt.hist(samples, bins=50)
plt.subplot(122)
plt.title("Log of this distribution")
plt.hist(np.log(samples), bins=50)
plt.show()
```



The distribution we used for `C` looks quite different: the scale of the samples is picked from a uniform distribution within a given range, which is why the right graph, which represents the log of the samples, looks roughly constant. This distribution is useful when you don't have a clue of what the target scale is:

[124]:
```
reciprocal_distrib = reciprocal(20, 200000)
samples = reciprocal_distrib.rvs(10000, random_state=42)
plt.figure(figsize=(10, 4))
plt.subplot(121)
plt.title("Reciprocal distribution (scale=1.0)")
plt.hist(samples, bins=50)
plt.subplot(122)
plt.title("Log of this distribution")
plt.hist(np.log(samples), bins=50)
plt.show()
```



The reciprocal distribution is useful when you have no idea what the scale of the hyperparameter should be (indeed, as you can see on the figure on the right, all scales are equally likely, within the given range), whereas the exponential distribution is best when you know (more or less) what the scale of the hyperparameter should be.

8.3 3.

Question: Try adding a transformer in the preparation pipeline to select only the most important attributes.

[125]:
```
from sklearn.base import BaseEstimator, TransformerMixin

def indices_of_top_k(arr, k):
    return np.sort(np.argpartition(np.array(arr), -k)[-k:])

class TopFeatureSelector(BaseEstimator, TransformerMixin):
    def __init__(self, feature_importances, k):
        self.feature_importances = feature_importances
        self.k = k
    def fit(self, X, y=None):
        self.feature_indices_ = indices_of_top_k(self.feature_importances, self.
↪k)
        return self
    def transform(self, X):
        return X[:, self.feature_indices_]
```

Note: this feature selector assumes that you have already computed the feature importances somehow (for example using a `RandomForestRegressor`). You may be tempted to compute them directly in the `TopFeatureSelector`'s `fit()` method, however this would likely slow down grid/randomized search since the feature importances would have to be computed for every hyperparameter combination (unless you implement some sort of cache).

Let's define the number of top features we want to keep:

[126]:
```
k = 5
```

Now let's look for the indices of the top k features:

[127]:
```
top_k_feature_indices = indices_of_top_k(feature_importances, k)
top_k_feature_indices
```

[127]:
```
array([ 0,  1,  7,  9, 12])
```

[128]:
```
np.array(attributes)[top_k_feature_indices]
```

[128]:
```
array(['longitude', 'latitude', 'median_income', 'pop_per_hhold',
       'INLAND'], dtype='<U18')
```

Let's double check that these are indeed the top k features:

[129]:
```
sorted(zip(feature_importances, attributes), reverse=True)[:k]
```

[129]:
```
[(0.36615898061813422, 'median_income'),
 (0.1647809935615905, 'INLAND'),
 (0.10879295677551573, 'pop_per_hhold'),
 (0.07334423551601242, 'longitude'),
 (0.0629090704826203, 'latitude')]
```

Looking good... Now let's create a new pipeline that runs the previously defined preparation pipeline, and adds top k feature selection:

[130]:
```
preparation_and_feature_selection_pipeline = Pipeline([
    ('preparation', full_pipeline),
    ('feature_selection', TopFeatureSelector(feature_importances, k))
])
```

[131]:
```
housing_prepared_top_k_features = preparation_and_feature_selection_pipeline.
 ↪fit_transform(housing)
```

Let's look at the features of the first 3 instances:

[132]:
```
housing_prepared_top_k_features[0:3]
```

[132]:
```
array([[-1.15604281,  0.77194962, -0.61493744, -0.08649871,  0.        ],
       [-1.17602483,  0.6596948 ,  1.33645936, -0.03353391,  0.        ],
       [ 1.18684903, -1.34218285, -0.5320456 , -0.09240499,  0.        ]])
```

Now let's double check that these are indeed the top k features:

[133]:
```
housing_prepared[0:3, top_k_feature_indices]
```

[133]:
```
array([[-1.15604281,  0.77194962, -0.61493744, -0.08649871,  0.        ],
       [-1.17602483,  0.6596948 ,  1.33645936, -0.03353391,  0.        ],
       [ 1.18684903, -1.34218285, -0.5320456 , -0.09240499,  0.        ]])
```

Works great! :)

8.4 4.

Question: Try creating a single pipeline that does the full data preparation plus the final prediction.

[134]:
```
prepare_select_and_predict_pipeline = Pipeline([
    ('preparation', full_pipeline),
    ('feature_selection', TopFeatureSelector(feature_importances, k)),
    ('svm_reg', SVR(**rnd_search.best_params_))
])
```

[135]:
```
prepare_select_and_predict_pipeline.fit(housing, housing_labels)
```

[135]:
```
Pipeline(memory=None,
     steps=[('preparation', ColumnTransformer(n_jobs=1, remainder='drop',
sparse_threshold=0.3,
         transformer_weights=None,
         transformers=[('num', Pipeline(memory=None,
     steps=[('imputer', SimpleImputer(copy=True, fill_value=None,
missing_values=nan,
       strategy='median', verbose=0… gamma=0.26497040005002437, kernel='rbf',
max_iter=-1, shrinking=True,
  tol=0.001, verbose=False))])
```

Let's try the full pipeline on a few instances:

[136]:
```
some_data = housing.iloc[:4]
some_labels = housing_labels.iloc[:4]

print("Predictions:\t", prepare_select_and_predict_pipeline.predict(some_data))
print("Labels:\t\t", list(some_labels))
```

```
Predictions:      [203214.28978849 371846.88152572 173295.65441612  47328.3970888
]
Labels:           [286600.0, 340600.0, 196900.0, 46300.0]
```

Well, the full pipeline seems to work fine. Of course, the predictions are not fantastic: they would be better if we used the best `RandomForestRegressor` that we found earlier, rather than the best `SVR`.

8.5 5.

Question: Automatically explore some preparation options using `GridSearchCV`.

[137]:
```
param_grid = [{
    'preparation__num__imputer__strategy': ['mean', 'median', 'most_frequent'],
    'feature_selection__k': list(range(1, len(feature_importances) + 1))
}]

grid_search_prep = GridSearchCV(prepare_select_and_predict_pipeline,␣
 ↪param_grid, cv=5,
                                scoring='neg_mean_squared_error', verbose=2,␣
 ↪n_jobs=4)
grid_search_prep.fit(housing, housing_labels)
```

```
Fitting 5 folds for each of 48 candidates, totalling 240 fits
```

```
[Parallel(n_jobs=4)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  33 tasks      | elapsed:  1.5min
```

```
[Parallel(n_jobs=4)]: Done 154 tasks      | elapsed:  9.7min
[Parallel(n_jobs=4)]: Done 240 out of 240 | elapsed: 19.8min finished
```

[137]:
```
GridSearchCV(cv=5, error_score='raise-deprecating',
       estimator=Pipeline(memory=None,
     steps=[('preparation', ColumnTransformer(n_jobs=1, remainder='drop',
sparse_threshold=0.3,
         transformer_weights=None,
         transformers=[('num', Pipeline(memory=None,
     steps=[('imputer', SimpleImputer(copy=True, fill_value=None,
missing_values=nan,
       strategy='median', verbose=0… gamma=0.26497040005002437, kernel='rbf',
max_iter=-1, shrinking=True,
  tol=0.001, verbose=False))]),
       fit_params=None, iid='warn', n_jobs=4,
       param_grid=[{'preparation__num__imputer__strategy': ['mean', 'median',
'most_frequent'], 'feature_selection__k': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11,
12, 13, 14, 15, 16]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='neg_mean_squared_error', verbose=2)
```

[138]:
```
grid_search_prep.best_params_
```

[138]:
```
{'feature_selection__k': 15,
 'preparation__num__imputer__strategy': 'most_frequent'}
```

The best imputer strategy is `most_frequent` and apparently almost all features are useful (15 out of 16). The last one (`ISLAND`) seems to just add some noise.

Congratulations! You already know quite a lot about Machine Learning. :)