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.

Run in Google Colab

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:

```
# 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
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)
```

Get the data

```
import os
import tarfile
import urllib.request

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()
```

```
fetch_housing_data()
```

```
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)
```

```
housing = load_housing_data()
housing.head()
```

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

```
housing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   longitude           20640 non-null  float64
 1   latitude            20640 non-null  float64
 2   housing_median_age  20640 non-null  float64
 3   total_rooms         20640 non-null  float64
 4   total_bedrooms      20433 non-null  float64
 5   population          20640 non-null  float64
 6   households          20640 non-null  float64
 7   median_income       20640 non-null  float64
 8   median_house_value  20640 non-null  float64
 9   ocean_proximity     20640 non-null  object 
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

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

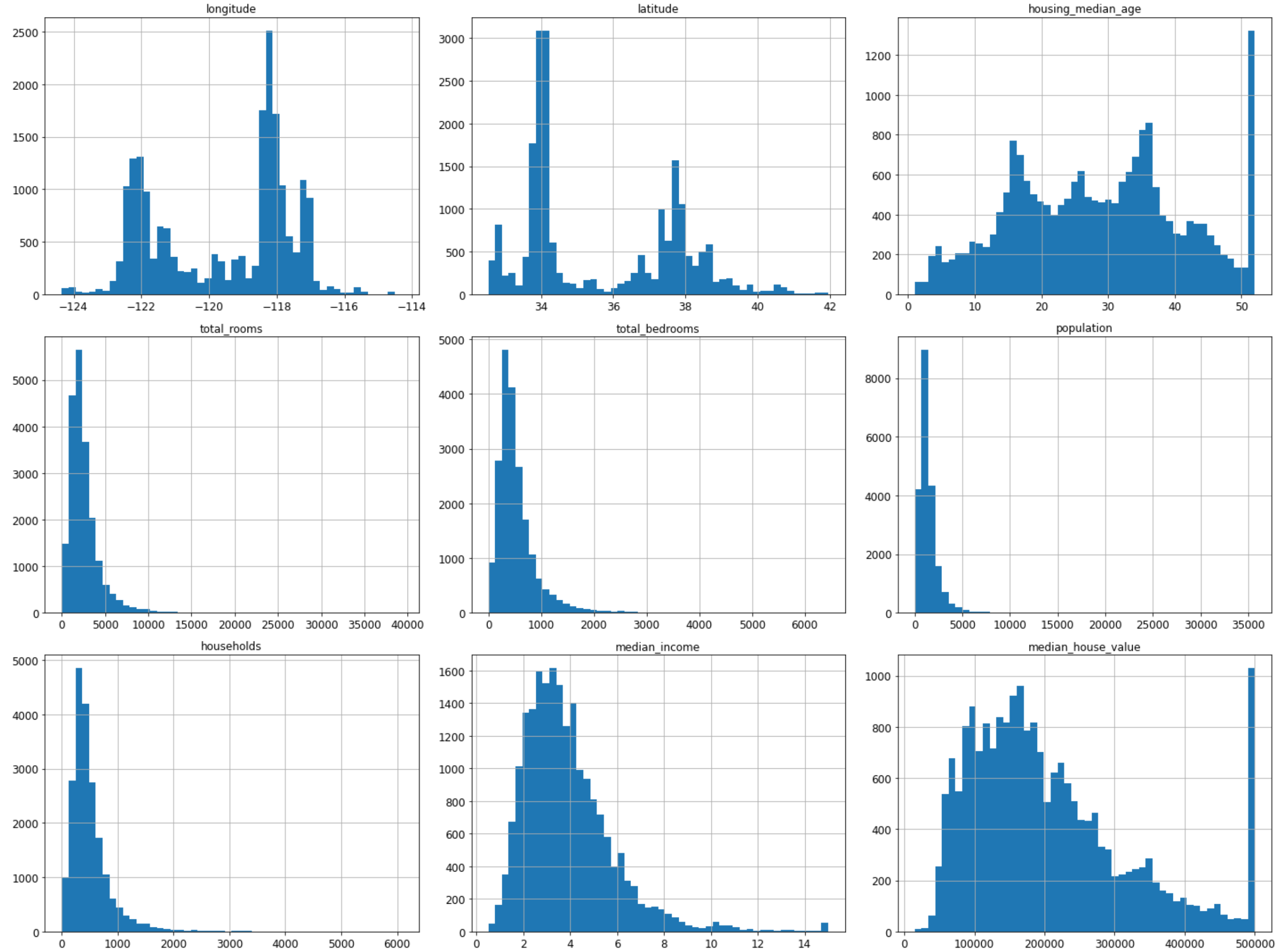
```
<1H OCEAN     9136
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: ocean_proximity, dtype: int64
```

```
housing.describe()
```

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

```
%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
```




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

```
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]
```

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

```
16512 train + 4128 test
```

```
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:

```
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:

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

```
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")
```

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

```
test_set.head()
```

	index	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	med
8	8	-122.26	37.84	42.0	2555.0	665.0	1206.0	595.0	2.0804	
10	10	-122.26	37.85	52.0	2202.0	434.0	910.0	402.0	3.2031	
11	11	-122.26	37.85	52.0	3503.0	752.0	1504.0	734.0	3.2705	
12	12	-122.26	37.85	52.0	2491.0	474.0	1098.0	468.0	3.0750	
13	13	-122.26	37.84	52.0	696.0	191.0	345.0	174.0	2.6736	

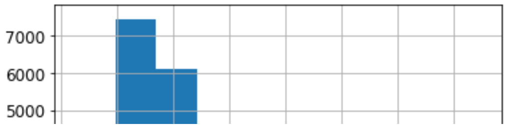
```
from sklearn.model_selection import train_test_split

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

```
test_set.head()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_
20046	-119.01	36.06	25.0	1505.0	NaN	1392.0	359.0	1.6812	
3024	-119.46	35.14	30.0	2943.0	NaN	1565.0	584.0	2.5313	
15663	-122.44	37.80	52.0	3830.0	NaN	1310.0	963.0	3.4801	
20484	-118.72	34.28	17.0	3051.0	NaN	1705.0	495.0	5.7376	
9814	-121.93	36.62	34.0	2351.0	NaN	1063.0	428.0	3.7250	

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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f86c8c962b0>
```



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)
```

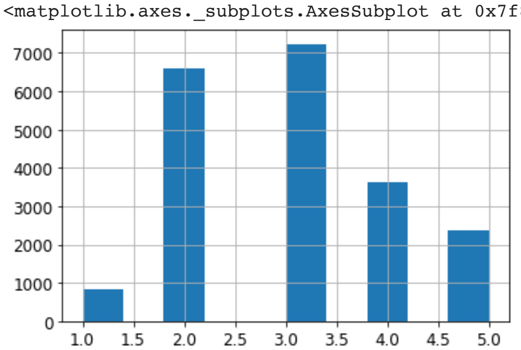
```
housing["income_cat"] = pd.cut(housing["median_income"],
                               bins=[0., 1.5, 3.0, 4.5, 6., np.inf],
                               labels=[1, 2, 3, 4, 5])
```

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

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

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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f86bcfa15e0>
```




```
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]
```

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

```
3    0.350533
2    0.318798
4    0.176357
5    0.114341
1    0.039971
Name: income_cat, dtype: float64
```

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

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

```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
```

```python
compare_props
```

	Overall	Stratified	Random	Rand. %error	Strat. %error
1	0.039826	0.039971	0.040213	0.973236	0.364964
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	0.114341	0.109496	-4.318374	-0.084674

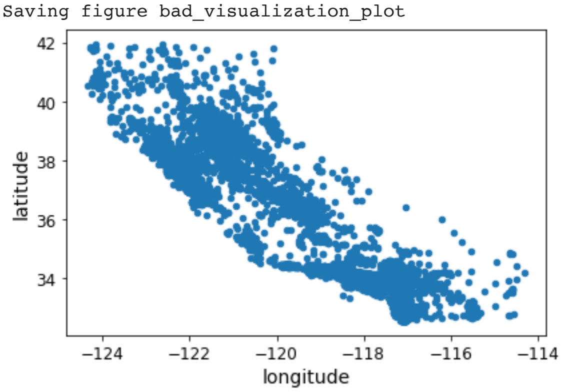
```python
for set_ in (strat_train_set, strat_test_set):
    set_.drop("income_cat", axis=1, inplace=True)
```

Discover and visualize the data to gain insights

```python
housing = strat_train_set.copy()
```

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

```
Saving figure bad_visualization_plot
```

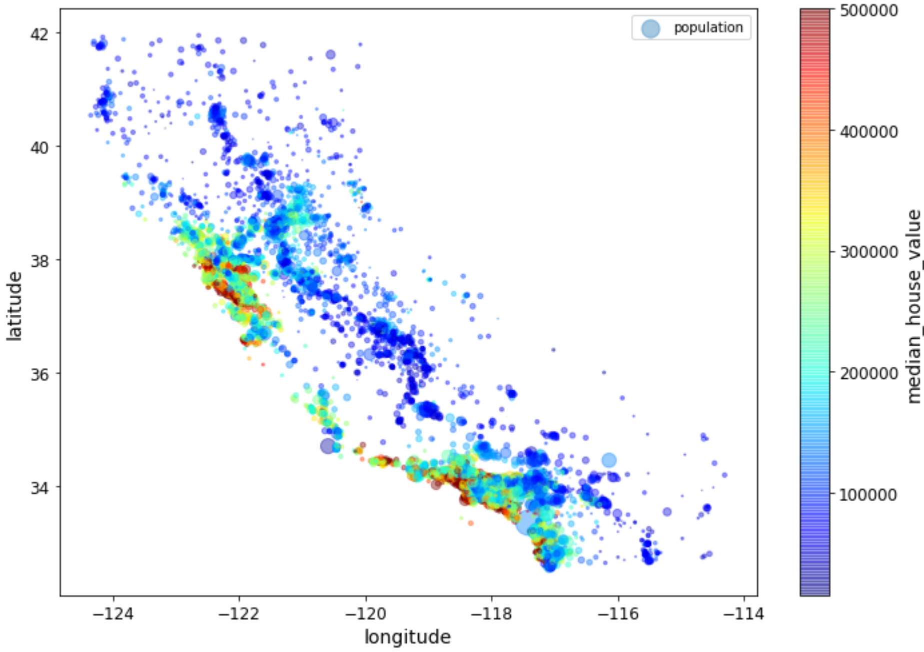



```python
housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.1)
save_fig("better_visualization_plot")
```

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.

```
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
```

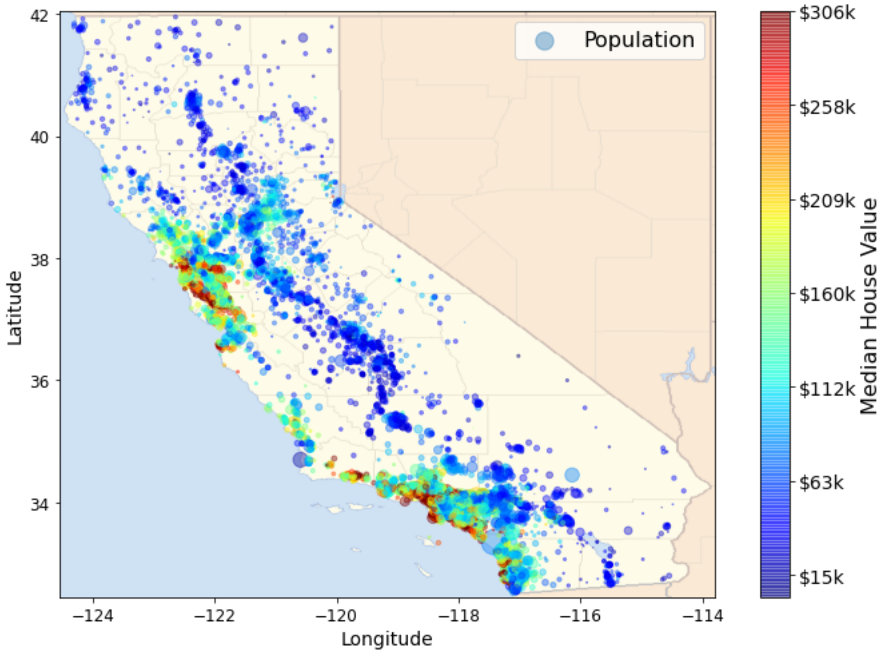



```
# Download the California image
images_path = os.path.join(PROJECT_ROOT_DIR, "images", "end_to_end_project")
os.makedirs(images_path, exist_ok=True)
DOWNLOAD_ROOT = "https://raw.githubusercontent.com/ageron/handson-ml/master/"
filename = "california.png"
print("Downloading", filename)
url = DOWNLOAD_ROOT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

```
Downloading california.png
('./images/end_to_end_project/california.png',
 <http.client.HTTPMessage at 0x7f86bce35670>)
```

```
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
```




```
corr_matrix = housing.corr()
```

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

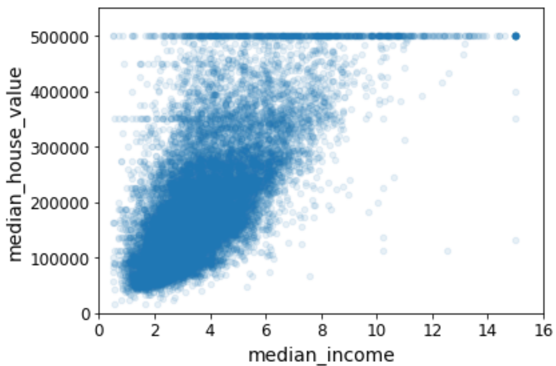
```
median_house_value    1.000000
median_income         0.687151
total_rooms           0.135140
housing_median_age    0.114146
households            0.064590
total_bedrooms        0.047781
population           -0.026882
longitude            -0.047466
latitude             -0.142673
Name: median_house_value, dtype: float64
```

```
# from pandas.tools.plotting import scatter_matrix # For older versions of Pandas
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
```

```
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
```



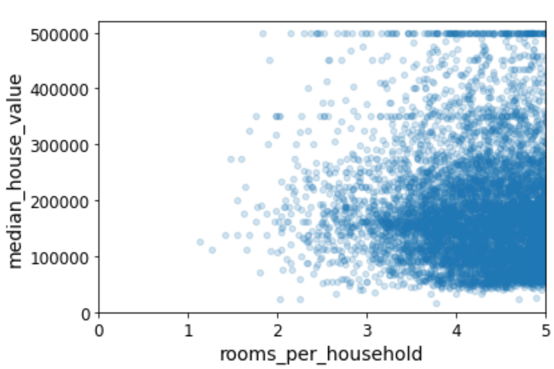
```
housing["rooms_per_household"] = housing["total_rooms"]/housing["households"]
housing["bedrooms_per_room"] = housing["total_bedrooms"]/housing["total_rooms"]
housing["population_per_household"]=housing["population"]/housing["households"]
```

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).

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

```
median_house_value          1.000000
median_income               0.687151
rooms_per_household         0.146255
total_rooms                 0.135140
housing_median_age          0.114146
households                  0.064590
total_bedrooms              0.047781
population_per_household   -0.021991
population                 -0.026882
longitude                  -0.047466
latitude                   -0.142673
bedrooms_per_room          -0.259952
Name: median_house_value, dtype: float64
```

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




```
housing.describe()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	m
count	16512.000000	16512.000000	16512.000000	16512.000000	16354.000000	16512.000000	16512.000000	16512.000000	
mean	-119.575635	35.639314	28.653404	2622.539789	534.914639	1419.687379	497.011810	3.875884	
std	2.001828	2.137963	12.574819	2138.417080	412.665649	1115.663036	375.696156	1.904931	
min	-124.350000	32.540000	1.000000	6.000000	2.000000	3.000000	2.000000	0.499900	
25%	-121.800000	33.940000	18.000000	1443.000000	295.000000	784.000000	279.000000	2.566950	
50%	-118.510000	34.260000	29.000000	2119.000000	433.000000	1164.000000	408.000000	3.541550	
75%	-118.010000	37.720000	37.000000	3141.000000	644.000000	1719.000000	602.000000	4.745325	
max	-114.310000	41.950000	52.000000	39320.000000	6210.000000	35682.000000	5358.000000	15.000100	

Prepare the data for Machine Learning algorithms

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

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

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_p
1606	-122.08	37.88	26.0	2947.0	NaN	825.0	626.0	2.9330	
10915	-117.87	33.73	45.0	2264.0	NaN	1970.0	499.0	3.4193	<
19150	-122.70	38.35	14.0	2313.0	NaN	954.0	397.0	3.7813	<
4186	-118.23	34.13	48.0	1308.0	NaN	835.0	294.0	4.2891	<
16885	-122.40	37.58	26.0	3281.0	NaN	1145.0	480.0	6.3580	NE/

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

longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proxi

```
sample_incomplete_rows.drop("total_bedrooms", axis=1)       # option 2
```

	longitude	latitude	housing_median_age	total_rooms	population	households	median_income	ocean_proximity
1606	-122.08	37.88	26.0	2947.0	825.0	626.0	2.9330	NEAR BAY
10915	-117.87	33.73	45.0	2264.0	1970.0	499.0	3.4193	<1H OCEAN
19150	-122.70	38.35	14.0	2313.0	954.0	397.0	3.7813	<1H OCEAN
4186	-118.23	34.13	48.0	1308.0	835.0	294.0	4.2891	<1H OCEAN
16885	-122.40	37.58	26.0	3281.0	1145.0	480.0	6.3580	NEAR OCEAN

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

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_p
1606	-122.08	37.88	26.0	2947.0	433.0	825.0	626.0	2.9330	
10915	-117.87	33.73	45.0	2264.0	433.0	1970.0	499.0	3.4193	<
19150	-122.70	38.35	14.0	2313.0	433.0	954.0	397.0	3.7813	<
4186	-118.23	34.13	48.0	1308.0	433.0	835.0	294.0	4.2891	<
16885	-122.40	37.58	26.0	3281.0	433.0	1145.0	480.0	6.3580	NE/

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

```
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:

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

```
imputer.fit(housing_num)
```

```
SimpleImputer(strategy='median')
```

```
imputer.statistics_
```

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

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

```
housing_num.median().values
```

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

Transform the training set:

```
X = imputer.transform(housing_num)
```

```
housing_tr = pd.DataFrame(X, columns=housing_num.columns,
                          index=housing.index)
```

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

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income
1606	-122.08	37.88	26.0	2947.0	433.0	825.0	626.0	2.9330
10915	-117.87	33.73	45.0	2264.0	433.0	1970.0	499.0	3.4193
19150	-122.70	38.35	14.0	2313.0	433.0	954.0	397.0	3.7813
4186	-118.23	34.13	48.0	1308.0	433.0	835.0	294.0	4.2891
16885	-122.40	37.58	26.0	3281.0	433.0	1145.0	480.0	6.3580

```
imputer.strategy
```

```
'median'
```

```
housing_tr = pd.DataFrame(X, columns=housing_num.columns,
                          index=housing_num.index)
housing_tr.head()
```

longitude latitude housing_median_age total_rooms total_bedrooms population households median_income

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

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

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

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.

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

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

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

```
ordinal_encoder.categories_
```

```
[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`:

```
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
```

```
<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:

```
housing_cat_1hot.toarray()
```

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

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

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

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

```
cat_encoder.categories_
```

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

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

```
housing.columns
```

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

```
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).

```
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)
```

```
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()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_p
12655	-121.46	38.52	29.0	3873.0	797.0	2237.0	706.0	2.1736	
15502	-117.23	33.09	7.0	5320.0	855.0	2015.0	768.0	6.3373	NE/
2908	-119.04	35.37	44.0	1618.0	310.0	667.0	300.0	2.875	
14053	-117.13	32.75	24.0	1877.0	519.0	898.0	483.0	2.2264	NE/
20496	-118.7	34.28	27.0	3536.0	646.0	1837.0	580.0	4.4964	<

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

```
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)
```

```
housing_num_tr
```

```
array([[-0.94135046,  1.34743822,  0.02756357, ...,  0.01739526,
         0.00622264, -0.12112176],
       [ 1.17178212, -1.19243966, -1.72201763, ...,  0.56925554,
        -0.04081077, -0.81086696],
       [ 0.26758118, -0.1259716 ,  1.22045984, ..., -0.01802432,
        -0.07537122, -0.33827252],
       ...,
       [-1.5707942 ,  1.31001828,  1.53856552, ..., -0.5092404 ,
        -0.03743619,  0.32286937],
       [-1.56080303,  1.2492109 , -1.1653327 , ...,  0.32814891,
        -0.05915604, -0.45702273],
       [-1.28105026,  2.02567448, -0.13148926, ...,  0.01407228,
         0.00657083, -0.12169672]])
```

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`:

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

```
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)
```

```
housing_prepared
```

```
array([[-0.94135046,  1.34743822,  0.02756357, ...,  0.        ,
         0.        ,  0.        ],
       [ 1.17178212, -1.19243966, -1.72201763, ...,  0.        ,
         0.        ,  1.        ],
       [ 0.26758118, -0.1259716 ,  1.22045984, ...,  0.        ,
         0.        ,  0.        ],
       ...,
       [-1.5707942 ,  1.31001828,  1.53856552, ...,  0.        ,
         0.        ,  0.        ],
       [-1.56080303,  1.2492109 , -1.1653327 , ...,  0.        ,
         0.        ,  0.        ],
       [-1.28105026,  2.02567448, -0.13148926, ...,  0.        ,
         0.        ,  0.        ]])
```

```
housing_prepared.shape
```

```
(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`:

```
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):

```
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)),
    ])
```

```
from sklearn.pipeline import FeatureUnion

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

```
        ("cat_pipeline", old_cat_pipeline),
```

```
old_housing_prepared = old_full_pipeline.fit_transform(housing)
old_housing_prepared
```

```
array([[-0.94135046,  1.34743822,  0.02756357, ...,  0.        ,
         0.        ,  0.        ],
       [ 1.17178212, -1.19243966, -1.72201763, ...,  0.        ,
         0.        ,  1.        ],
       [ 0.26758118, -0.1259716 ,  1.22045984, ...,  0.        ,
         0.        ,  0.        ],
       ...,
       [-1.5707942 ,  1.31001828,  1.53856552, ...,  0.        ,
         0.        ,  0.        ],
       [-1.56080303,  1.2492109 , -1.1653327 , ...,  0.        ,
         0.        ,  0.        ],
       [-1.28105026,  2.02567448, -0.13148926, ...,  0.        ,
         0.        ,  0.        ]])
```

The result is the same as with the `ColumnTransformer`:

```
np.allclose(housing_prepared, old_housing_prepared)
```

```
True
```

Select and train a model

```
from sklearn.linear_model import LinearRegression

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

```
LinearRegression()
```

```
# 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: [ 85657.90192014 305492.60737488 152056.46122456 186095.70946094
 244550.67966089]
```

Compare against the actual values:

```
print("Labels:", list(some_labels))
```

```
Labels: [72100.0, 279600.0, 82700.0, 112500.0, 238300.0]
```

```
some_data_prepared
```

```
array([[-0.94135046,  1.34743822,  0.02756357,  0.58477745,  0.64037127,
         0.73260236,  0.55628602, -0.8936472 ,  0.01739526,  0.00622264,
        -0.12112176,  0.        ,  1.        ,  0.        ,  0.        ,
         0.        ],
       [ 1.17178212, -1.19243966, -1.72201763,  1.26146668,  0.78156132,
         0.53361152,  0.72131799,  1.292168  ,  0.56925554, -0.04081077,
        -0.81086696,  0.        ,  0.        ,  0.        ,  0.        ,
         1.        ],
       [ 0.26758118, -0.1259716 ,  1.22045984, -0.46977281, -0.54513828,
        -0.67467519, -0.52440722, -0.52543365, -0.01802432, -0.07537122,
        -0.33827252,  0.        ,  1.        ,  0.        ,  0.        ,
         0.        ],
       [ 1.22173797, -1.35147437, -0.37006852, -0.34865152, -0.03636724,
        -0.46761716, -0.03729672, -0.86592882, -0.59513997, -0.10680295,
         0.96120521,  0.        ,  0.        ,  0.        ,  0.        ,
         1.        ],
       [ 0.43743108, -0.63581817, -0.13148926,  0.42717947,  0.27279028,
         0.37406031,  0.22089846,  0.32575178,  0.2512412 ,  0.00610923,
        -0.47451338,  1.        ,  0.        ,  0.        ,  0.        ,
         0.        ]])
```

```
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
```

```
68627.87390018745
```

```
from sklearn.metrics import mean_absolute_error

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

```
49438.66860915802
```

```
from sklearn.tree import DecisionTreeRegressor

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

```
DecisionTreeRegressor(random_state=42)
```

```
housing_predictions = tree_reg.predict(housing_prepared)
tree_mse = mean_squared_error(housing_labels, housing_predictions)
tree_rmse = np.sqrt(tree_mse)
tree_rmse
```

```
0.0
```

Fine-tune your model

```
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)
```

```
def display_scores(scores):
    print("Scores:", scores)
    print("Mean:", scores.mean())
    print("Standard deviation:", scores.std())

display_scores(tree_rmse_scores)
```

```
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: [71762.76364394 64114.99166359 67771.17124356 68635.19072082
 66846.14089488 72528.03725385 73997.08050233 68802.33629334
 66443.28836884 70139.79923956]
Mean: 69104.07998247063
Standard deviation: 2880.3282098180634
```

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.

```
from sklearn.ensemble import RandomForestRegressor

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

```
RandomForestRegressor(n_estimators=10, random_state=42)
```

```
housing_predictions = forest_reg.predict(housing_prepared)
forest_mse = mean_squared_error(housing_labels, housing_predictions)
forest_rmse = np.sqrt(forest_mse)
forest_rmse
```

```
22413.454658589766
```

```
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: [53519.05518628 50467.33817051 48924.16513902 53771.72056856
 50810.90996358 54876.09682033 56012.79985518 52256.88927227
 51527.73185039 55762.56008531]
Mean: 52792.92669114079
Standard deviation: 2262.8151900582
```

```
scores = cross_val_score(lin_reg, housing_prepared, housing_labels, scoring="neg_mean_squared_error", cv=10)
pd.Series(np.sqrt(-scores)).describe()
```

```
count       10.000000
mean     69104.079982
std       3036.132517
min      64114.991664
25%      67077.398482
50%      68718.763507
75%      71357.022543
max      73997.080502
dtype: float64
```

```
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
```

```
111095.06635291968
```

```
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)
```

```
GridSearchCV(cv=5, estimator=RandomForestRegressor(random_state=42),
             param_grid=[{'max_features': [2, 4, 6, 8],
                          'n_estimators': [3, 10, 30]},
                         {'bootstrap': [False], 'max_features': [2, 3, 4],
                          'n_estimators': [3, 10]}],
             return_train_score=True, scoring='neg_mean_squared_error')
```

The best hyperparameter combination found:

```
grid_search.best_params_
```

```
{'max_features': 8, 'n_estimators': 30}
```

```
grid_search.best_estimator_
```

```
RandomForestRegressor(max_features=8, n_estimators=30, random_state=42)
```

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

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

```
63895.161577951665 {'max_features': 2, 'n_estimators': 3}
54916.32386349543 {'max_features': 2, 'n_estimators': 10}
52885.86715332332 {'max_features': 2, 'n_estimators': 30}
60075.3680329983 {'max_features': 4, 'n_estimators': 3}
52495.01284985185 {'max_features': 4, 'n_estimators': 10}
50187.24324926565 {'max_features': 4, 'n_estimators': 30}
58064.73529982314 {'max_features': 6, 'n_estimators': 3}
51519.32062366315 {'max_features': 6, 'n_estimators': 10}
49969.80441627874 {'max_features': 6, 'n_estimators': 30}
58895.824998155826 {'max_features': 8, 'n_estimators': 3}
52459.79624724529 {'max_features': 8, 'n_estimators': 10}
49898.98913455217 {'max_features': 8, 'n_estimators': 30}
62381.765106921855 {'bootstrap': False, 'max_features': 2, 'n_estimators': 3}
54476.57050944266 {'bootstrap': False, 'max_features': 2, 'n_estimators': 10}
59974.60028085155 {'bootstrap': False, 'max_features': 3, 'n_estimators': 3}
52754.5632813202 {'bootstrap': False, 'max_features': 3, 'n_estimators': 10}
57831.136061214274 {'bootstrap': False, 'max_features': 4, 'n_estimators': 3}
51278.37877140253 {'bootstrap': False, 'max_features': 4, 'n_estimators': 10}
```

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

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_features	param_n_estimators	param_bootstrap
0	0.070521	0.001859	0.005390	0.000674	2	3	NaN
1	0.231319	0.012147	0.013777	0.000302	2	10	NaN
2	0.676404	0.012335	0.039669	0.003132	2	30	NaN
3	0.112226	0.001885	0.004928	0.000053	4	3	NaN
4	0.369924	0.008944	0.015067	0.002453	4	10	NaN
5	1.255543	0.214540	0.038651	0.001850	4	30	NaN
6	0.147990	0.001848	0.005060	0.000122	6	3	NaN
7	0.500964	0.003588	0.013439	0.000229	6	10	NaN

```
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)
```

```
RandomizedSearchCV(cv=5, estimator=RandomForestRegressor(random_state=42),
                   param_distributions={'max_features': <scipy.stats._distn_infrastructure.rv_frozen object at
0x7f86bca20fd0>,
                                        'n_estimators': <scipy.stats._distn_infrastructure.rv_frozen object at
0x7f86bce50130>},
                   random_state=42, scoring='neg_mean_squared_error')
```

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

```
49117.55344336652 {'max_features': 7, 'n_estimators': 180}
51450.63202856348 {'max_features': 5, 'n_estimators': 15}
50692.53588182537 {'max_features': 3, 'n_estimators': 72}
50783.614493515 {'max_features': 5, 'n_estimators': 21}
49162.89877456354 {'max_features': 7, 'n_estimators': 122}
50655.798471042704 {'max_features': 3, 'n_estimators': 75}
50513.856319990606 {'max_features': 3, 'n_estimators': 88}
49521.17201976928 {'max_features': 5, 'n_estimators': 100}
50302.90440763418 {'max_features': 3, 'n_estimators': 150}
65167.02018649492 {'max_features': 5, 'n_estimators': 2}
```

```
feature_importances = grid_search.best_estimator_.feature_importances_
feature_importances
```

```
array([6.96542523e-02, 6.04213840e-02, 4.21882202e-02, 1.52450557e-02,
       1.55545295e-02, 1.58491147e-02, 1.49346552e-02, 3.79009225e-01,
       5.47789150e-02, 1.07031322e-01, 4.82031213e-02, 6.79266007e-03,
       1.65706303e-01, 7.83480660e-05, 1.52473276e-03, 3.02816106e-03])
```

```
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)
```

```
[(0.3790092248170967, 'median_income'),
 (0.16570630316895876, 'INLAND'),
 (0.10703132208204354, 'pop_per_hhold'),
 (0.06965425227942929, 'longitude'),
 (0.0604213840080722, 'latitude'),
 (0.054778915018283726, 'rooms_per_hhold'),
 (0.048203121338269206, 'bedrooms_per_room'),
 (0.04218822024391753, 'housing_median_age'),
 (0.015849114744428634, 'population'),
 (0.015554529490469328, 'total_bedrooms'),
 (0.01524505568840977, 'total_rooms'),
 (0.014934655161887776, 'households'),
 (0.006792660074259966, '<1H OCEAN'),
 (0.0030281610628962747, 'NEAR OCEAN'),
 (0.0015247327555504937, 'NEAR BAY'),
 (7.834806602687504e-05, 'ISLAND')]
```

```
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)
```

```
final_rmse
```

```
47873.26095812988
```

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

```
from scipy import stats
```

```
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)))
```

```
array([45893.36082829, 49774.46796717])
```

We could compute the interval manually like this:

```
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)
```

```
(45893.360828285535, 49774.46796717361)
```

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

```
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)
```

```
(45893.9540110131, 49773.921030650374)
```

Extra material

A full pipeline with both preparation and prediction

```
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)
```

```
array([ 85657.90192014, 305492.60737488, 152056.46122456, 186095.70946094,
        244550.67966089])
```

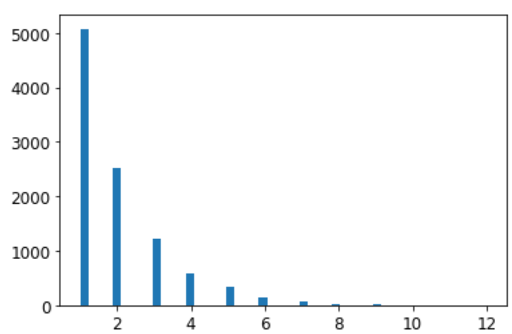
Model persistence using joblib

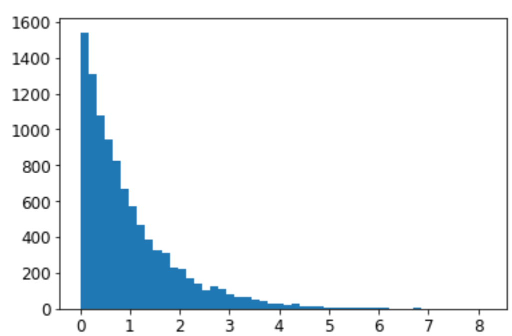
```
my_model = full_pipeline_with_predictor
```

```
#from sklearn.externals import joblib # deprecated, use import joblib instead
import joblib

joblib.dump(my_model, "my_model.pkl") # DIFF
#...
my_model_loaded = joblib.load("my_model.pkl") # DIFF
```

Example SciPy distributions for `RandomizedSearchCV`

```
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()
```





Exercise solutions

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?

```
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
GridSearchCV(cv=5, estimator=SVR(), n_jobs=4,
             param_grid=[{'C': [10.0, 30.0, 100.0, 300.0, 1000.0, 3000.0,
                                10000.0, 30000.0],
                          'kernel': ['linear']},
                         {'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],
                          'kernel': ['rbf']}],
             scoring='neg_mean_squared_error', verbose=2)
```

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

```
negative_mse = grid_search.best_score_
rmse = np.sqrt(-negative_mse)
rmse
```

```
70286.61835383571
```

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

```
grid_search.best_params_
```

```
{'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.

2.

Question: Try replacing `GridSearchCV` with `RandomizedSearchCV`.

```
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
RandomizedSearchCV(cv=5, estimator=SVR(), n_iter=50, n_jobs=4,
                   param_distributions={'C': <scipy.stats._distn_infrastructure.rv_frozen object at 0x7f86b5b45970>,
                                        'gamma': <scipy.stats._distn_infrastructure.rv_frozen object at 0x7f86b5b45be0>,
                                        'kernel': ['linear', 'rbf']},
                   random_state=42, scoring='neg_mean_squared_error',
                   verbose=2)
```

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

```
negative_mse = rnd_search.best_score_
rmse = np.sqrt(-negative_mse)
rmse
```

```
54751.69009488048
```

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

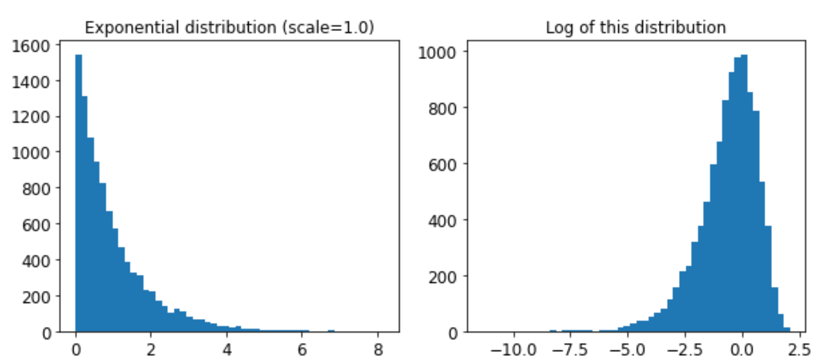
```
rnd_search.best_params_
```

```
{'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.

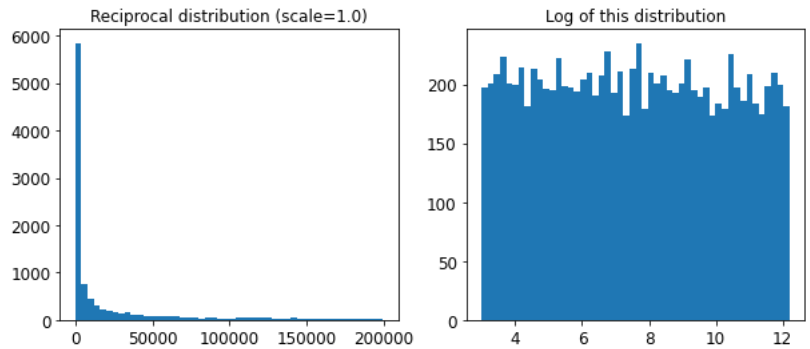
Let's look at the exponential distribution we used, with `scale=1.0`. Note that some samples are much larger or smaller than 1.0, but when you look at the log of the distribution, you can see that most values are actually concentrated roughly in the range of exp(-2) to exp(+2), which is about 0.1 to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

```
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:

```
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.

3.

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

```
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:

```
k = 5
```

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

```
top_k_feature_indices = indices_of_top_k(feature_importances, k)
top_k_feature_indices
```

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

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

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

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

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

```
[(0.3790092248170967, 'median_income'),
 (0.16570630316895876, 'INLAND'),
 (0.10703132208204354, 'pop_per_hhold'),
 (0.06965425227942929, 'longitude'),
 (0.0604213840080722, 'latitude')]
```

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

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

```
housing_prepared_top_k_features = preparation_and_feature_selection_pipeline.fit_transform(housing)
```

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

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

```
array([[-0.94135046,  1.34743822, -0.8936472 ,  0.00622264,  1.        ],
       [ 1.17178212, -1.19243966,  1.292168  , -0.04081077,  0.        ],
       [ 0.26758118, -0.1259716 , -0.52543365, -0.07537122,  1.        ]])
```

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

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

```
array([[-0.94135046,  1.34743822, -0.8936472 ,  0.00622264,  1.        ],
       [ 1.17178212, -1.19243966,  1.292168  , -0.04081077,  0.        ],
       [ 0.26758118, -0.1259716 , -0.52543365, -0.07537122,  1.        ]])
```

Works great! :)

4.

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

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

```
prepare_select_and_predict_pipeline.fit(housing, housing_labels)
```

```
Pipeline(steps=[('preparation',
                 ColumnTransformer(transformers=[('num',
                                                  Pipeline(steps=[('imputer',
                                                                   SimpleImputer(strategy='median')),
                                                                  ('attribs_adder',
                                                                   FunctionTransformer(func=<function add_extra_features at
0x7f86bc86aca0>)),
                                                                  ('std_scaler',
                                                                   StandardScaler())]),
                                                  ['longitude', 'latitude',
                                                   'housing_median_age',
                                                   'total_rooms',
                                                   'total_bedrooms',
```

```
                                                   'population', 'househ...
                 TopFeatureSelector(feature_importances=array([6.96542523e-02, 6.04213840e-02, 4.21882202e-02, 1.52450557e-
02,
       1.55545295e-02, 1.58491147e-02, 1.49346552e-02, 3.79009225e-01,
       5.47789150e-02, 1.07031322e-01, 4.82031213e-02, 6.79266007e-03,
       1.65706303e-01, 7.83480660e-05, 1.52473276e-03, 3.02816106e-03]),
                                    k=5)),
                ('svm_reg',
                 SVR(C=157055.10989448498, gamma=0.26497040005002437))])
```

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

```
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:     [ 83384.49158095 299407.90439234  92272.03345144 150173.16199041]
Labels:          [72100.0, 279600.0, 82700.0, 112500.0]
```

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`.

5.

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

```
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
/usr/local/lib/python3.8/dist-packages/sklearn/model_selection/_validation.py:372: FitFailedWarning:
9 fits failed out of a total of 240.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
9 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.8/dist-packages/sklearn/model_selection/_validation.py", line 680, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.8/dist-packages/sklearn/pipeline.py", line 390, in fit
    Xt = self._fit(X, y, **fit_params_steps)
  File "/usr/local/lib/python3.8/dist-packages/sklearn/pipeline.py", line 348, in _fit
    X, fitted_transformer = fit_transform_one_cached(
  File "/usr/local/lib/python3.8/dist-packages/joblib/memory.py", line 349, in __call__
    return self.func(*args, **kwargs)
  File "/usr/local/lib/python3.8/dist-packages/sklearn/pipeline.py", line 893, in _fit_transform_one
    res = transformer.fit_transform(X, y, **fit_params)
  File "/usr/local/lib/python3.8/dist-packages/sklearn/base.py", line 855, in fit_transform
    return self.fit(X, y, **fit_params).transform(X)
  File "<ipython-input-126-6a801ecaa128>", line 14, in transform
IndexError: index 15 is out of bounds for axis 1 with size 15

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/usr/local/lib/python3.8/dist-packages/sklearn/model_selection/_search.py:969: UserWarning: One or more of the test scores a
 nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan
 nan nan nan nan nan nan nan nan nan nan nan nan]
  warnings.warn(
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('preparation',
                                        ColumnTransformer(transformers=[('num',
                                                                         Pipeline(steps=[('imputer',
                                                                                          SimpleImputer(strategy='median')),
                                                                                         ('attribs_adder',
                                                                                          FunctionTransformer(func=<function
add_extra_features at 0x7f86bc86aca0>)),
```

```
                                                                                               ('std_scaler',
                                                                                                StandardScaler())]),
                                                                                ['longitude',
                                                                                 'latitude',
                                                                                 'housing_median_age',
                                                                                 'total_rooms',
                                                                                 'total_be...
        5.47789150e-02, 1.07031322e-01, 4.82031213e-02, 6.79266007e-03,
        1.65706303e-01, 7.83480660e-05, 1.52473276e-03, 3.02816106e-03]),
                                                                    k=5)),
                                             ('svm_reg',
                                              SVR(C=157055.10989448498,
                                                  gamma=0.26497040005002437))]),
              n_jobs=4,
              param_grid=[{'feature_selection__k': [1, 2, 3, 4, 5, 6, 7, 8, 9,
                                                    10, 11, 12, 13, 14, 15, 16],
                           'preparation__num__imputer__strategy': ['mean',
                                                                   'median',
                                                                   'most_frequent']}],
              scoring='neg_mean_squared_error', verbose=2)
```

```
grid_search_prep.best_params_
```

```
{'feature_selection__k': 1, 'preparation__num__imputer__strategy': 'mean'}
```

The best imputer strategy is `mean`

✓ 0s completed at 3:39 PM