Tools -ML sample project

Data Analysis

2023-06-20

Table of contents

Setup

First, let's import a few common modules, ensure MatplotLib plots figures inline and prepare a function to save the figures. We also check that Python 3.5 or later is installed (although Python 2.x may work, it is deprecated so we strongly recommend you use Python 3 instead), as well as Scikit-Learn ≥0.20.

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

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

# Common imports
import numpy as np
import os

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

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

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

```
    if tight_layout:
        plt.tight_layout()
    plt.savefig(path, format=fig_extension, dpi=resolution)
```

Get the Data

Download the Data

```
import os
import tarfile
import urllib.request

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

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

```
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)
```

Take a Quick Look at the Data Structure

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

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

```python
housing.info()
```

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

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

```
<1H OCEAN     9136
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
```

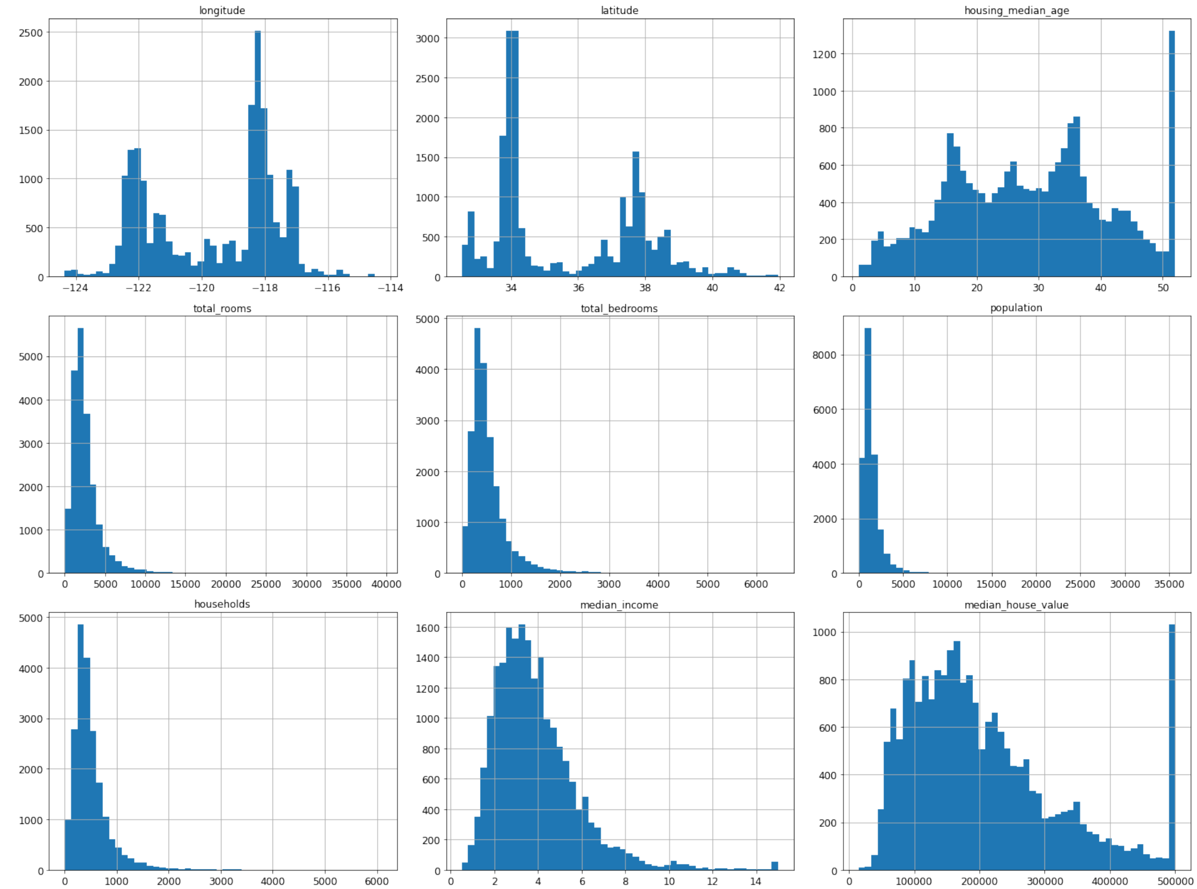
```
ISLAND           5
Name: ocean_proximity, dtype: int64
```

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

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.00000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462122
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.00000

```python
%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
```



Create a Test Set

```
# 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]
```

```python
train_set, test_set = split_train_test(housing, 0.2)
len(train_set)
```

```
16512
```

```python
len(test_set)
```

```
4128
```

```python
from zlib import crc32

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

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

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:

```python
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:

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

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

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

```python
test_set.head()
```

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

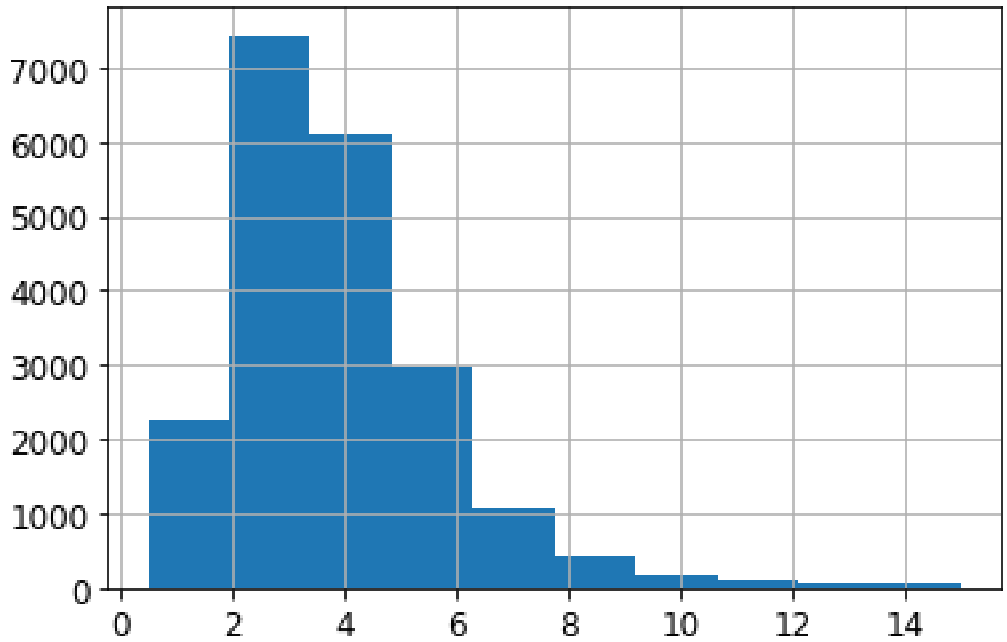
```python
from sklearn.model_selection import train_test_split

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

```python
test_set.head()
```

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

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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7faaf0489250>
```



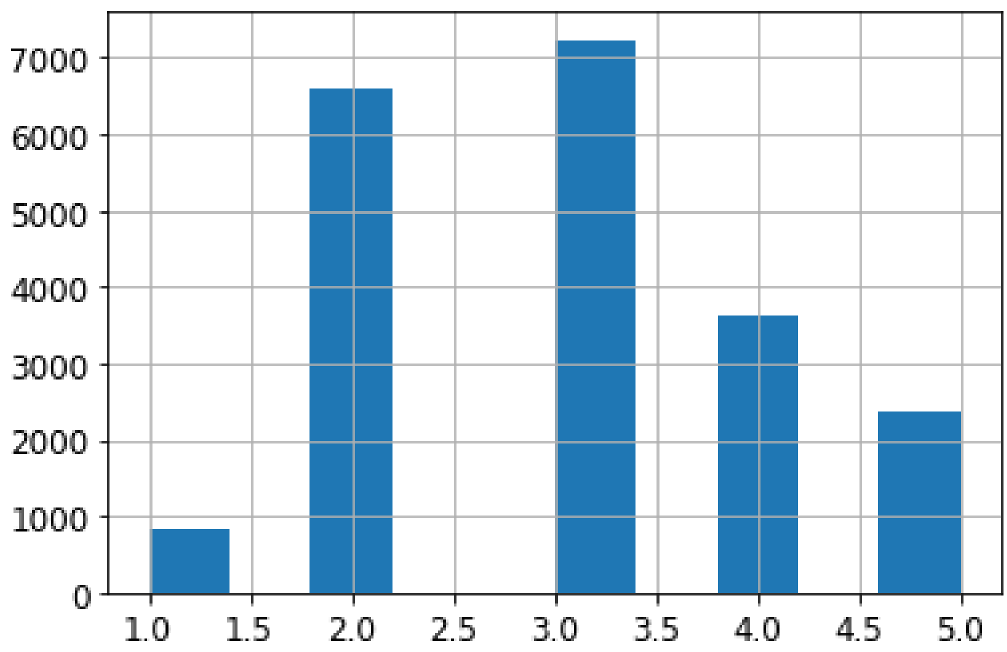

```
housing["income_cat"] = pd.cut(housing["median_income"],
                               bins=[0., 1.5, 3.0, 4.5, 6., np.inf],
                               labels=[1, 2, 3, 4, 5])
```

```
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 0x7faaee3e31d0>
```




```
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    0.114583
1    0.039729
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
```

```
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"] -
compare_props["Strat. %error"] = 100 * compare_props["Stratified"] / compare_props["Overal
```

```
compare_props
```

	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

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

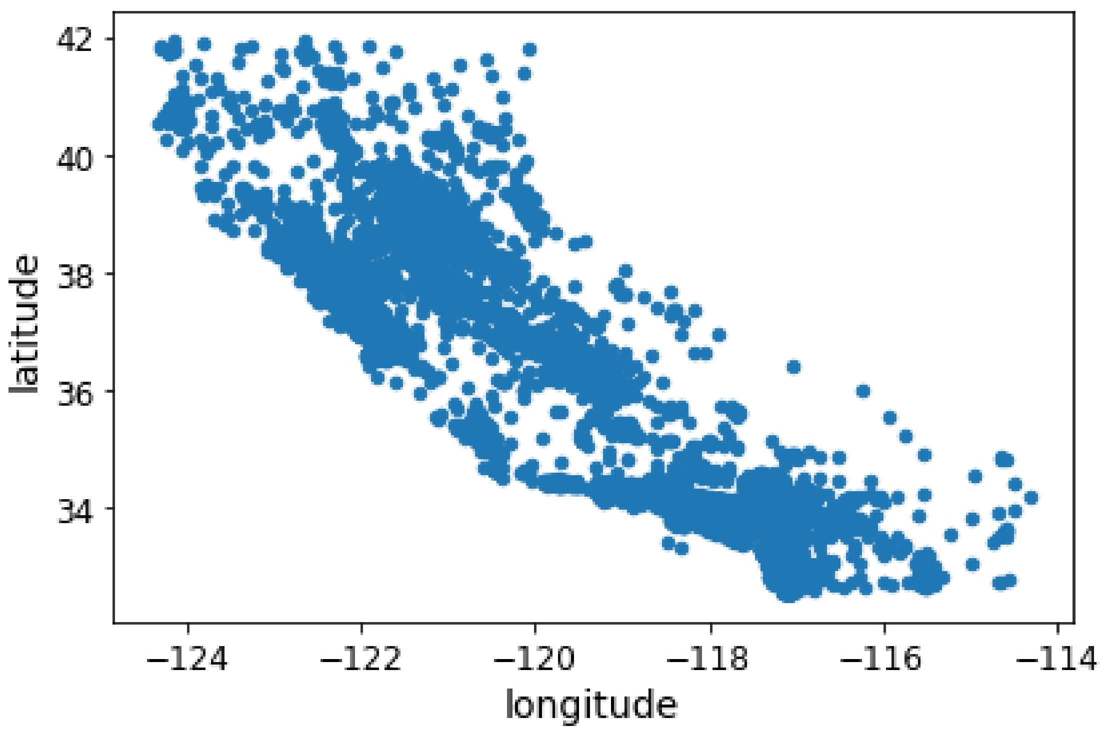
Discover and Visualize the Data to Gain Insights

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

Visualizing Geographical Data

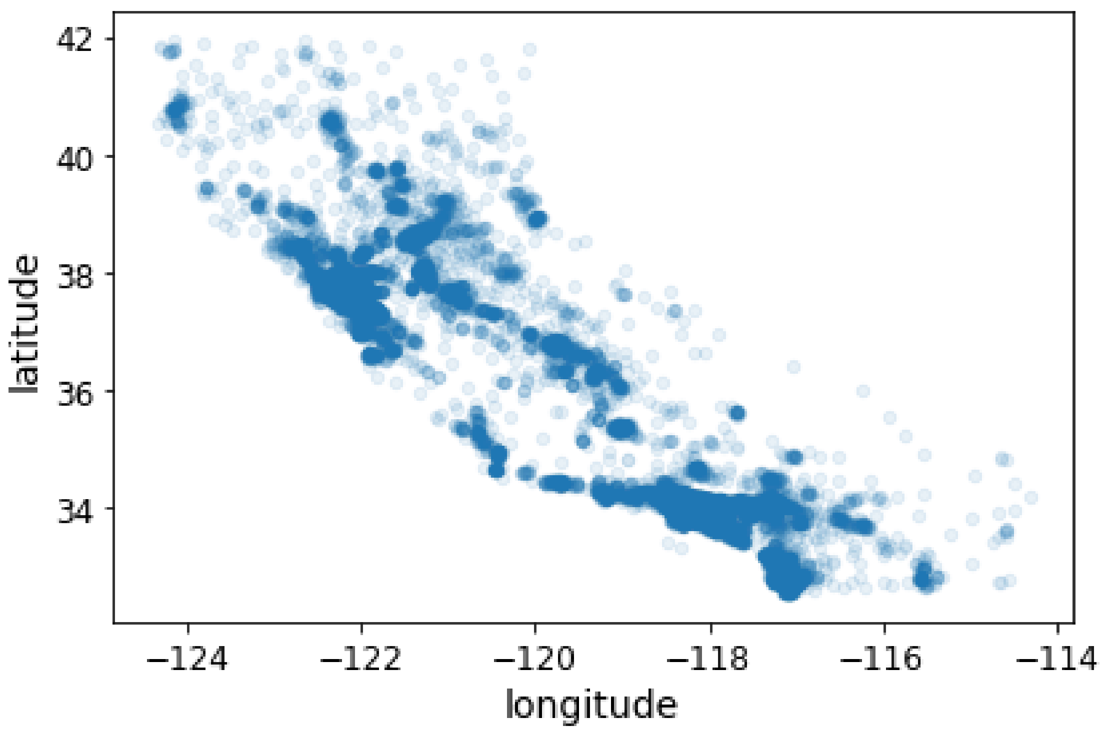
```
housing.plot(kind="scatter", x="longitude", y="latitude")
save_fig("bad_visualization_plot")
```

```
Saving figure bad_visualization_plot
```




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

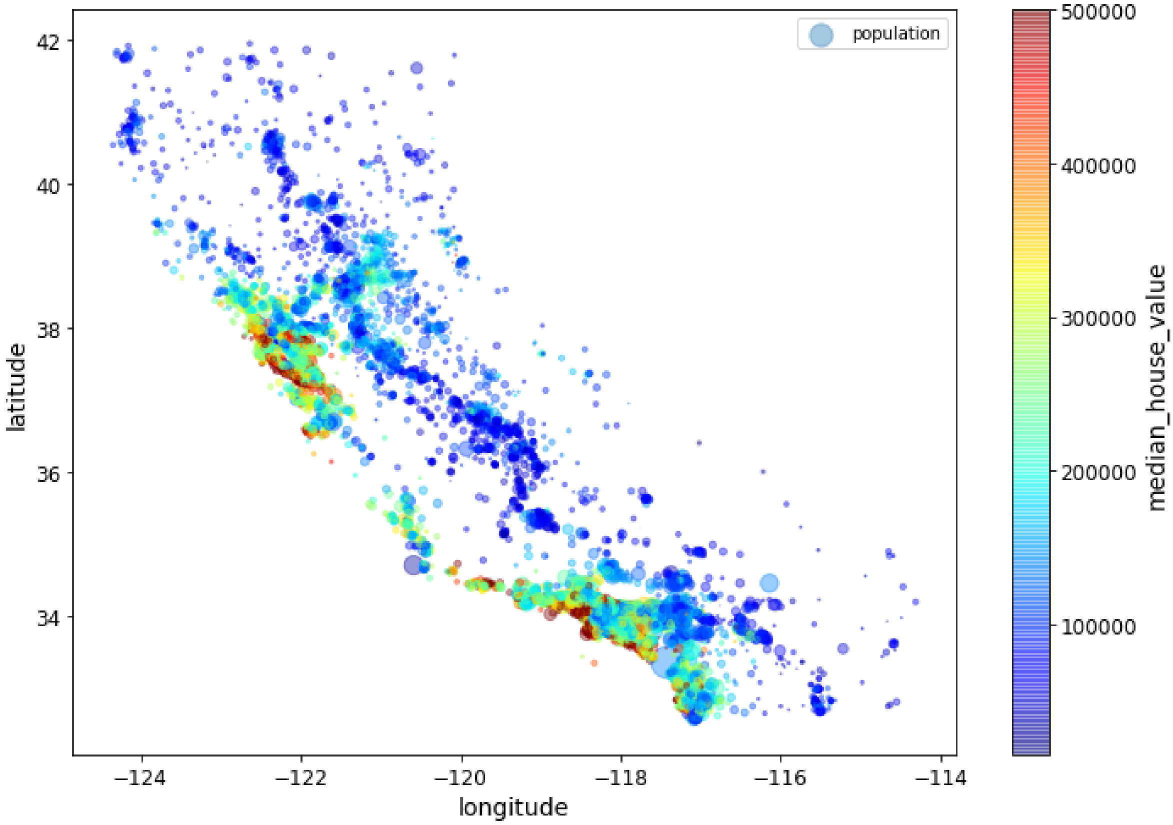
```
Saving figure better_visualization_plot
```



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.

```
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
```



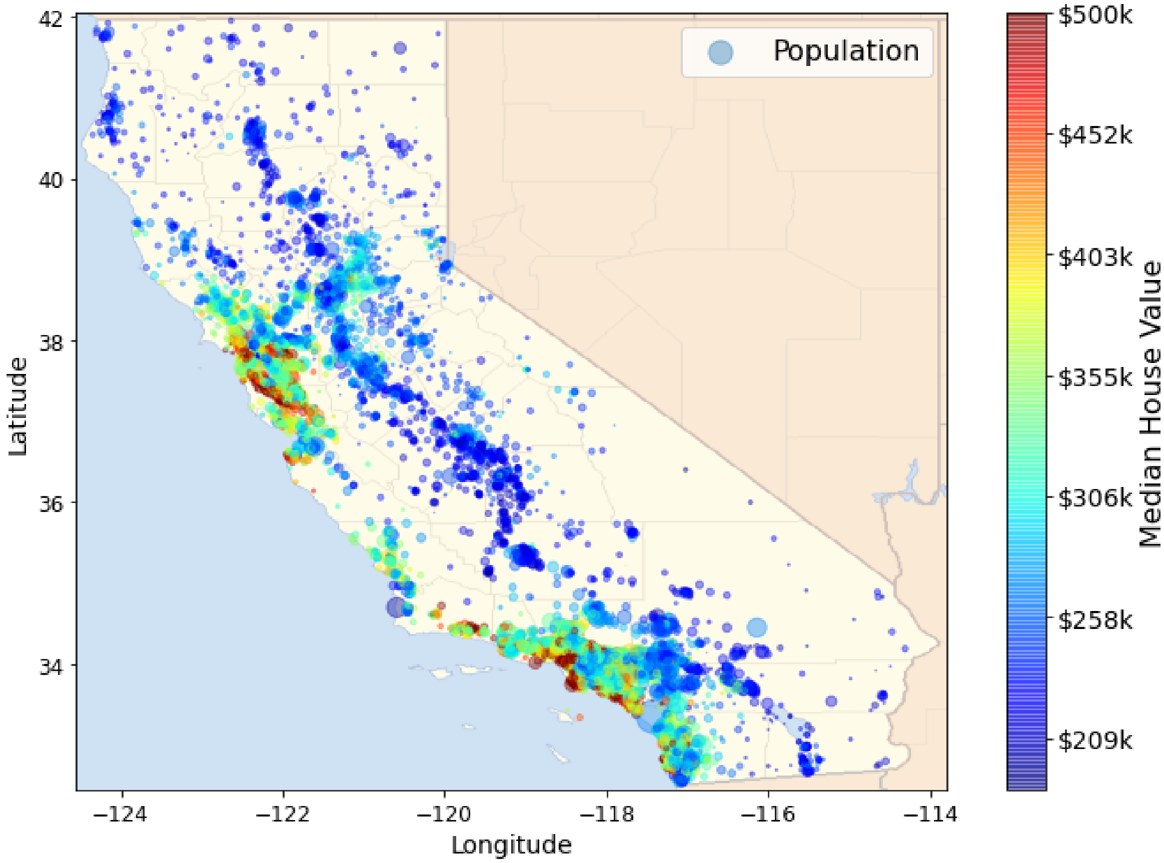

```
# Download the California image
images_path = os.path.join(PROJECT_ROOT_DIR, "images", "end_to_end_project")
os.makedirs(images_path, exist_ok=True)
DOWNLOAD_ROOT = "https://raw.githubusercontent.com/ageron/handson-ml2/master/"
filename = "california.png"
print("Downloading", filename)
url = DOWNLOAD_ROOT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

```
Downloading california.png
```

```
('./images/end_to_end_project/california.png',
 <http.client.HTTPMessage at 0x7fd1784e5050>)
```

```python
import matplotlib.image as mpimg
california_img=mpimg.imread(os.path.join(images_path, filename))
ax = housing.plot(kind="scatter", x="longitude", y="latitude", figsize=(10,7),
                  s=housing['population']/100, label="Population",
                  c="median_house_value", cmap=plt.get_cmap("jet"),
                  colorbar=False, alpha=0.4)
plt.imshow(california_img, extent=[-124.55, -113.80, 32.45, 42.05], alpha=0.5,
           cmap=plt.get_cmap("jet"))
plt.ylabel("Latitude", fontsize=14)
plt.xlabel("Longitude", fontsize=14)

prices = housing["median_house_value"]
tick_values = np.linspace(prices.min(), prices.max(), 11)
cbar = plt.colorbar(ticks=tick_values/prices.max())
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
```



Looking for Correlations

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

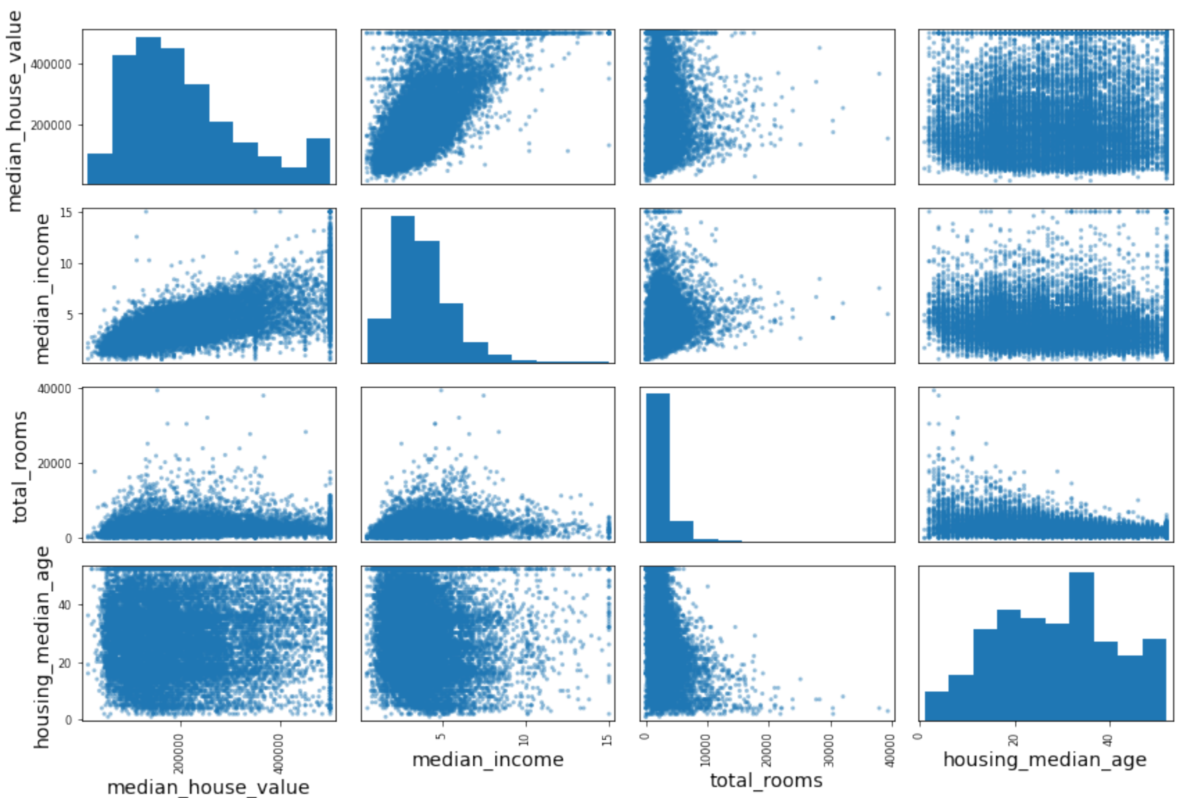
```
corr_matrix["median_house_value"].sort_values(ascending=False)
```

```
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
```

```python
# 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")
```

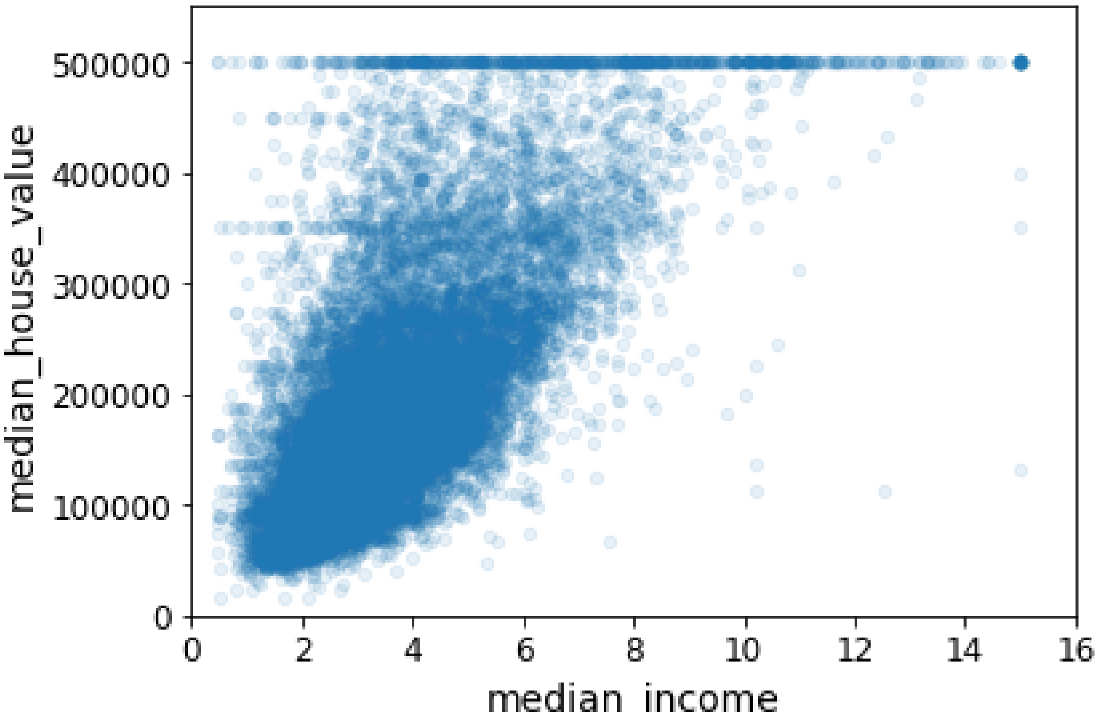
```
Saving figure scatter_matrix_plot
```




```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
```



Experimenting with Attribute Combinations

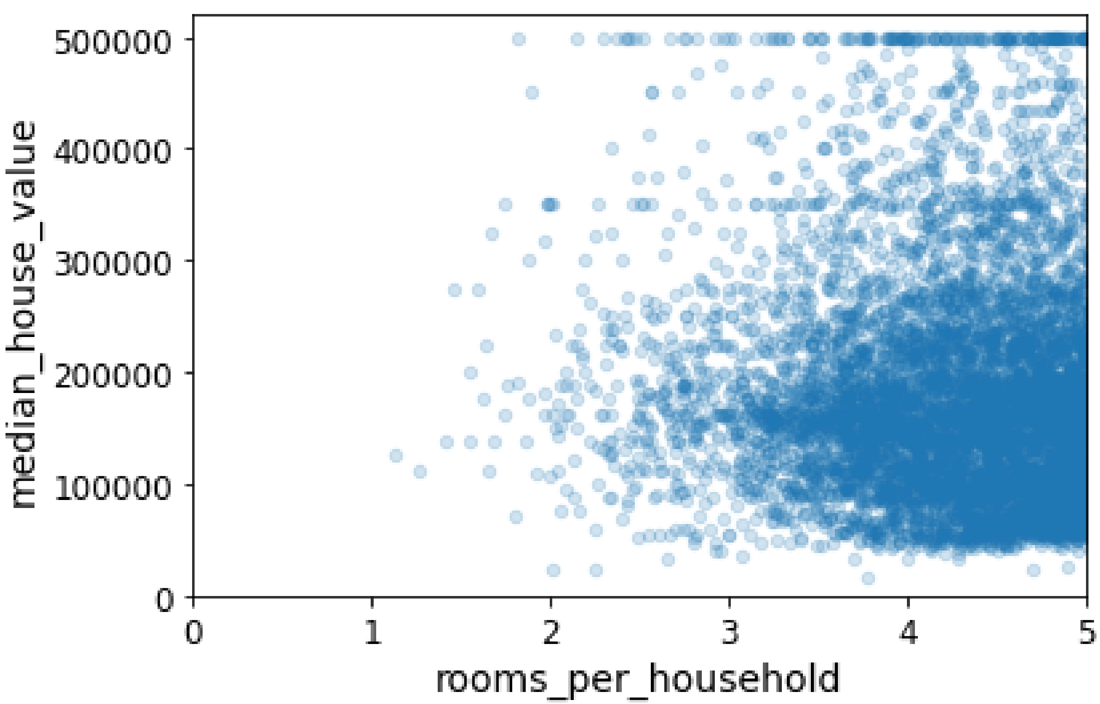
```
housing["rooms_per_household"] = housing["total_rooms"]/housing["households"]
housing["bedrooms_per_room"] = housing["total_bedrooms"]/housing["total_rooms"]
housing["population_per_household"]=housing["population"]/housing["households"]
```

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

```
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
```

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




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

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population
count	16512.000000	16512.000000	16512.000000	16512.000000	16354.000000	16512.000000
mean	-119.575834	35.639577	28.653101	2622.728319	534.973890	1419.790819
std	2.001860	2.138058	12.574726	2138.458419	412.699041	1115.686241
min	-124.350000	32.540000	1.000000	6.000000	2.000000	3.000000
25%	-121.800000	33.940000	18.000000	1443.000000	295.000000	784.000000
50%	-118.510000	34.260000	29.000000	2119.500000	433.000000	1164.000000
75%	-118.010000	37.720000	37.000000	3141.000000	644.000000	1719.250000
max	-114.310000	41.950000	52.000000	39320.000000	6210.000000	35682.000000

Prepare the Data for Machine Learning Algorithms

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

Data Cleaning

In the book 3 options are listed:

```
housing.dropna(subset=["total_bedrooms"])    # option 1
housing.drop("total_bedrooms", axis=1)       # option 2
median = housing["total_bedrooms"].median()  # option 3
housing["total_bedrooms"].fillna(median, inplace=True)
```

To demonstrate each of them, let's create a copy of the housing dataset, but keeping only the rows that contain at least one null. Then it will be easier to visualize exactly what each option does:

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

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

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

longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	m

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

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

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

```python
sample_incomplete_rows
```

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

```python
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy="median")
```

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

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

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

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

```
imputer.statistics_
```

```
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:

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

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

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	household
4629	-118.30	34.07	18.0	3759.0	433.0	3296.0	1462.0
6068	-117.86	34.01	16.0	4632.0	433.0	3038.0	727.0
17923	-121.97	37.35	30.0	1955.0	433.0	999.0	386.0
13656	-117.30	34.05	6.0	2155.0	433.0	1039.0	391.0
19252	-122.79	38.48	7.0	6837.0	433.0	3468.0	1405.0

```
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	household
17606	-121.89	37.29	38.0	1568.0	351.0	710.0	339.0
18632	-121.93	37.05	14.0	679.0	108.0	306.0	113.0
14650	-117.20	32.77	31.0	1952.0	471.0	936.0	462.0
3230	-119.61	36.31	25.0	1847.0	371.0	1460.0	353.0
3555	-118.59	34.23	17.0	6592.0	1525.0	4459.0	1463.0

Handling Text and Categorical Attributes

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

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

	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

```
from sklearn.preprocessing import OrdinalEncoder

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

```
array([[0.],
       [0.],
       [4.],
```

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

```python
ordinal_encoder.categories_
```

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

```python
from sklearn.preprocessing import OneHotEncoder

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:

```python
housing_cat_1hot.toarray()
```

```
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`:

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

```
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.]])
```

```
cat_encoder.categories_
```

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

Custom Transformers

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

```
from sklearn.base import BaseEstimator, TransformerMixin

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

class CombinedAttributesAdder(BaseEstimator, TransformerMixin):
    def __init__(self, add_bedrooms_per_room=True): # no *args or **kargs
        self.add_bedrooms_per_room = add_bedrooms_per_room
    def fit(self, X, y=None):
        return self  # nothing else to do
    def transform(self, X):
        rooms_per_household = X[:, rooms_ix] / X[:, households_ix]
        population_per_household = X[:, population_ix] / X[:, households_ix]
        if self.add_bedrooms_per_room:
            bedrooms_per_room = X[:, bedrooms_ix] / X[:, rooms_ix]
            return np.c_[X, rooms_per_household, population_per_household,
                         bedrooms_per_room]
        else:
```

```
            return np.c_[X, rooms_per_household, population_per_household]

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

Note that I hard coded the indices (3, 4, 5, 6) for concision and clarity in the book, but it would be much cleaner to get them dynamically, like this:

```
col_names = "total_rooms", "total_bedrooms", "population", "households"
rooms_ix, bedrooms_ix, population_ix, households_ix = [
    housing.columns.get_loc(c) for c in col_names] # get the column indices
```

Also, `housing_extra_attribs` is a NumPy array, we've lost the column names (unfortunately, that's a problem with Scikit-Learn). To recover a `DataFrame`, you could run this:

```
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	household
17606	-121.89	37.29	38.0	1568.0	351.0	710.0	339.0
18632	-121.93	37.05	14.0	679.0	108.0	306.0	113.0
14650	-117.2	32.77	31.0	1952.0	471.0	936.0	462.0
3230	-119.61	36.31	25.0	1847.0	371.0	1460.0	353.0
3555	-118.59	34.23	17.0	6592.0	1525.0	4459.0	1463.0

Transformation Pipelines

Now let's build a pipeline for preprocessing the numerical attributes:

```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler

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

```python
    ])

housing_num_tr = num_pipeline.fit_transform(housing_num)
```

```python
housing_num_tr
```

```
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]])
```

```python
from sklearn.compose import ColumnTransformer

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

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

housing_prepared = full_pipeline.fit_transform(housing)
```

```python
housing_prepared
```

```
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.        ]])
```

```
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:

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

old_num_pipeline = Pipeline([
        ('selector', OldDataFrameSelector(num_attribs)),
        ('imputer', SimpleImputer(strategy="median")),
        ('attribs_adder', CombinedAttributesAdder()),
        ('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([[-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`:

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

```
True
```

Select and Train a Model

Training and Evaluating on the Training Set

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

Compare against the actual values:

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

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

```
some_data_prepared
```

```
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.        ]])
```

```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
```

```
68628.19819848923
```

Note: since Scikit-Learn 0.22, you can get the RMSE directly by calling the `mean_squared_error()` function with `squared=False`.

```python
from sklearn.metrics import mean_absolute_error

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

```
49439.89599001897
```

```python
from sklearn.tree import DecisionTreeRegressor

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

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

```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
```

```
0.0
```

Better Evaluation Using Cross-Validation

```python
from sklearn.model_selection import cross_val_score

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

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

display_scores(tree_rmse_scores)
```

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

```python
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: 2731.674001798342
```

Note: we specify `n_estimators=100` to be future-proof since the default value is going to change to 100 in Scikit-Learn 0.22 (for simplicity, this is not shown in the book).

```python
from sklearn.ensemble import RandomForestRegressor

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

```
RandomForestRegressor(random_state=42)
```

```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
```

```
18603.515021376355
```

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

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

```
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
```

```
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
```

```
111094.6308539982
```

Fine-Tune Your Model

Grid Search

```
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)
```

```
63669.11631261028 {'max_features': 2, 'n_estimators': 3}
55627.099719926795 {'max_features': 2, 'n_estimators': 10}
53384.57275149205 {'max_features': 2, 'n_estimators': 30}
60965.950449450494 {'max_features': 4, 'n_estimators': 3}
52741.04704299915 {'max_features': 4, 'n_estimators': 10}
50377.40461678399 {'max_features': 4, 'n_estimators': 30}
58663.93866579625 {'max_features': 6, 'n_estimators': 3}
52006.19873526564 {'max_features': 6, 'n_estimators': 10}
50146.51167415009 {'max_features': 6, 'n_estimators': 30}
57869.25276169646 {'max_features': 8, 'n_estimators': 3}
51711.127883959234 {'max_features': 8, 'n_estimators': 10}
49682.273345071546 {'max_features': 8, 'n_estimators': 30}
62895.06951262424 {'bootstrap': False, 'max_features': 2, 'n_estimators': 3}
54658.176157539405 {'bootstrap': False, 'max_features': 2, 'n_estimators': 10}
59470.40652318466 {'bootstrap': False, 'max_features': 3, 'n_estimators': 3}
52724.9822587892 {'bootstrap': False, 'max_features': 3, 'n_estimators': 10}
57490.5691951261 {'bootstrap': False, 'max_features': 4, 'n_estimators': 3}
51009.495668875716 {'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
0	0.050905	0.004097	0.002766	0.000256	2	3
1	0.143706	0.002170	0.007205	0.000304	2	10
2	0.410306	0.004403	0.019903	0.000964	2	30
3	0.069762	0.000987	0.002409	0.000080	4	3
4	0.227188	0.001444	0.006829	0.000090	4	10
5	0.711381	0.038618	0.020686	0.001864	4	30

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_features	param_n
6	0.094580	0.003861	0.002426	0.000118	6	3
7	0.311034	0.005247	0.006980	0.000283	6	10
8	0.979656	0.048790	0.021028	0.001812	6	30
9	0.118484	0.001009	0.002239	0.000068	8	3
10	0.401726	0.005465	0.007028	0.000345	8	10
11	1.236572	0.036875	0.019325	0.000252	8	30
12	0.064666	0.001042	0.002780	0.000240	2	3
13	0.213941	0.000996	0.007956	0.000267	2	10
14	0.090480	0.003167	0.002681	0.000082	3	3
15	0.286396	0.004578	0.008019	0.000384	3	10
16	0.109239	0.002999	0.003399	0.001579	4	3
17	0.370459	0.017424	0.007863	0.000056	4	10

Randomized Search

```
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_
rnd_search.fit(housing_prepared, housing_labels)
```

```
RandomizedSearchCV(cv=5, estimator=RandomForestRegressor(random_state=42),
                   param_distributions={'max_features': <scipy.stats._distn_infrastructure.rv
                                        'n_estimators': <scipy.stats._distn_infrastructure.rv
                   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)
```

```
49150.70756927707 {'max_features': 7, 'n_estimators': 180}
51389.889203389284 {'max_features': 5, 'n_estimators': 15}
50796.155224308866 {'max_features': 3, 'n_estimators': 72}
50835.13360315349 {'max_features': 5, 'n_estimators': 21}
49280.9449827171 {'max_features': 7, 'n_estimators': 122}
50774.90662363929 {'max_features': 3, 'n_estimators': 75}
50682.78888164288 {'max_features': 3, 'n_estimators': 88}
49608.99608105296 {'max_features': 5, 'n_estimators': 100}
50473.61930350219 {'max_features': 3, 'n_estimators': 150}
64429.84143294435 {'max_features': 5, 'n_estimators': 2}
```

Analyze the Best Models and Their Errors

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

```
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])
```

```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)
```

```
[(0.36615898061813423, 'median_income'),
 (0.16478099356159054, 'INLAND'),
 (0.10879295677551575, 'pop_per_hhold'),
 (0.07334423551601243, 'longitude'),
 (0.06290907048262032, 'latitude'),
 (0.056419179181954014, 'rooms_per_hhold'),
 (0.053351077347675815, 'bedrooms_per_room'),
 (0.04114379847872964, 'housing_median_age'),
 (0.014874280890402769, 'population'),
 (0.014672685420543239, 'total_rooms'),
 (0.014257599323407808, 'households'),
```

```
(0.014106483453584104, 'total_bedrooms'),
(0.010311488326303788, '<1H OCEAN'),
(0.0028564746373201584, 'NEAR OCEAN'),
(0.0019604155994780706, 'NEAR BAY'),
(6.0280386727366e-05, 'ISLAND')]
```

Evaluate Your System on the Test Set

```python
final_model = grid_search.best_estimator_

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

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

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

```python
final_rmse
```

```
47730.22690385927
```

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

```python
from scipy import stats

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

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

We could compute the interval manually like this:

```python
m = len(squared_errors)
mean = squared_errors.mean()
tscore = stats.t.ppf((1 + confidence) / 2, df=m - 1)
tmargin = tscore * squared_errors.std(ddof=1) / np.sqrt(m)
np.sqrt(mean - tmargin), np.sqrt(mean + tmargin)
```

```
(45685.10470776014, 49691.25001877871)
```

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

```python
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)
```

```
(45685.717918136594, 49690.68623889426)
```

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([210644.60459286, 317768.80697211, 210956.43331178,  59218.98886849,
       189747.55849879])
```

Model persistence using joblib

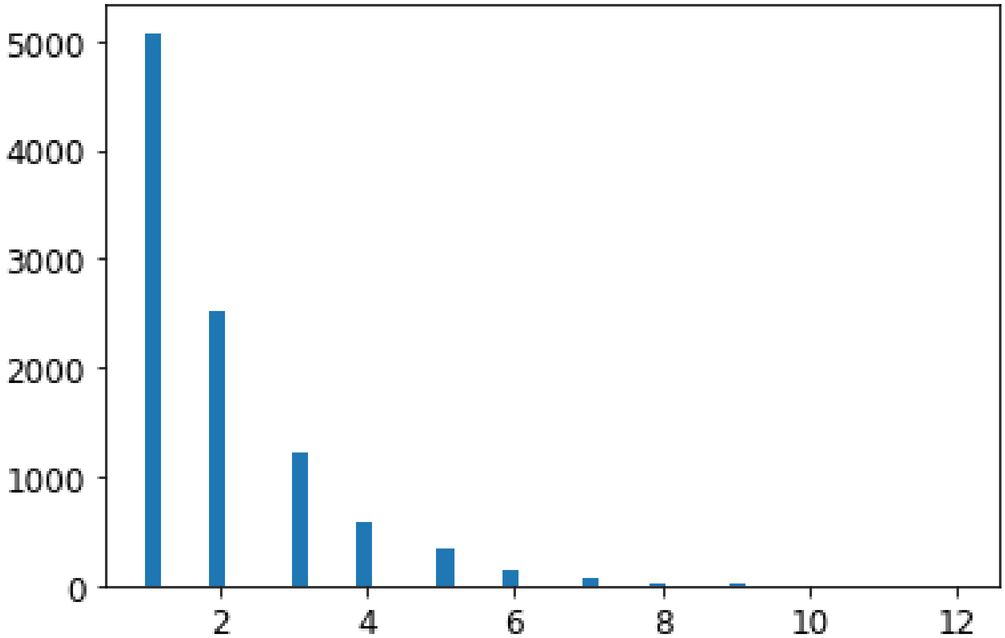
```
my_model = full_pipeline_with_predictor
```

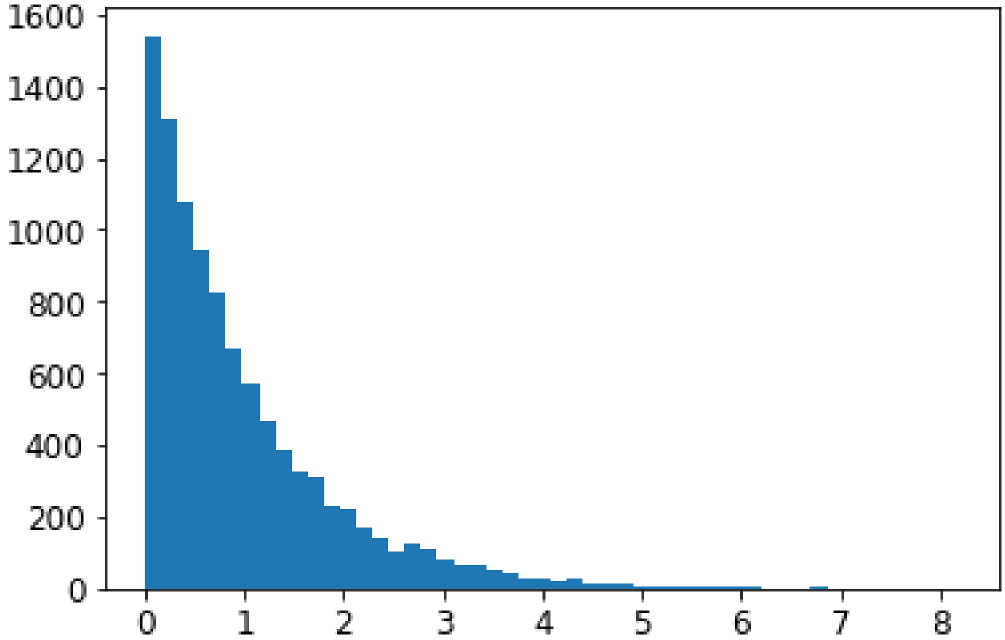
```
import joblib
joblib.dump(my_model, "my_model.pkl") # DIFF
#...
my_model_loaded = joblib.load("my_model.pkl") # DIFF
```

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()
```




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

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?

Warning: the following cell may take close to 30 minutes to run, or more depending on your hardware.

```
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', ve
grid_search.fit(housing_prepared, housing_labels)
```

```
Fitting 5 folds for each of 50 candidates, totalling 250 fits
[CV] C=10.0, kernel=linear .........................................
[CV] .......................... C=10.0, kernel=linear, total=   3.9s
[CV] C=10.0, kernel=linear .........................................
[CV] .......................... C=10.0, kernel=linear, total=   3.9s
[CV] C=10.0, kernel=linear .........................................
[CV] .......................... C=10.0, kernel=linear, total=   4.6s
[CV] C=10.0, kernel=linear .........................................
[CV] .......................... C=10.0, kernel=linear, total=   4.2s
[CV] C=10.0, kernel=linear .........................................
[CV] .......................... C=10.0, kernel=linear, total=   4.5s
[CV] C=30.0, kernel=linear .........................................
```

```
[CV] ............................ C=30.0, kernel=linear, total=   4.1s
[CV] C=30.0, kernel=linear ............................................
[CV] ............................ C=30.0, kernel=linear, total=   4.2s
[CV] C=30.0, kernel=linear ............................................
[CV] ............................ C=30.0, kernel=linear, total=   4.3s
[CV] C=30.0, kernel=linear ............................................
[CV] ............................ C=30.0, kernel=linear, total=   4.0s
[CV] C=30.0, kernel=linear ............................................
[CV] ............................ C=30.0, kernel=linear, total=   3.9s
[CV] C=100.0, kernel=linear ...........................................
[CV] ........................... C=100.0, kernel=linear, total=   3.9s
[CV] C=100.0, kernel=linear ...........................................
[CV] ........................... C=100.0, kernel=linear, total=   4.0s
[CV] C=100.0, kernel=linear ...........................................
[CV] ........................... C=100.0, kernel=linear, total=   4.0s
[CV] C=100.0, kernel=linear ...........................................
[CV] ........................... C=100.0, kernel=linear, total=   4.0s
[CV] C=100.0, kernel=linear ...........................................
[CV] ........................... C=100.0, kernel=linear, total=   3.9s
[CV] C=300.0, kernel=linear ...........................................
[CV] ........................... C=300.0, kernel=linear, total=   4.1s
<<434 more lines>>
[CV] C=1000.0, gamma=0.1, kernel=rbf ..................................
[CV] .................. C=1000.0, gamma=0.1, kernel=rbf, total=   6.7s
[CV] C=1000.0, gamma=0.1, kernel=rbf ..................................
[CV] .................. C=1000.0, gamma=0.1, kernel=rbf, total=   6.8s
[CV] C=1000.0, gamma=0.3, kernel=rbf ..................................
[CV] .................. C=1000.0, gamma=0.3, kernel=rbf, total=   6.7s
[CV] C=1000.0, gamma=0.3, kernel=rbf ..................................
[CV] .................. C=1000.0, gamma=0.3, kernel=rbf, total=   6.7s
[CV] C=1000.0, gamma=0.3, kernel=rbf ..................................
[CV] .................. C=1000.0, gamma=0.3, kernel=rbf, total=   6.7s
[CV] C=1000.0, gamma=0.3, kernel=rbf ..................................
[CV] .................. C=1000.0, gamma=0.3, kernel=rbf, total=   6.7s
[CV] C=1000.0, gamma=0.3, kernel=rbf ..................................
[CV] .................. C=1000.0, gamma=0.3, kernel=rbf, total=   6.7s
[CV] C=1000.0, gamma=1.0, kernel=rbf ..................................
[CV] .................. C=1000.0, gamma=1.0, kernel=rbf, total=   6.7s
[CV] C=1000.0, gamma=1.0, kernel=rbf ..................................
[CV] .................. C=1000.0, gamma=1.0, kernel=rbf, total=   6.8s
[CV] C=1000.0, gamma=1.0, kernel=rbf ..................................
[CV] .................. C=1000.0, gamma=1.0, kernel=rbf, total=   6.7s
[CV] C=1000.0, gamma=1.0, kernel=rbf ..................................
```

```
[CV] .................. C=1000.0, gamma=1.0, kernel=rbf, total=   6.7s
[CV] C=1000.0, gamma=1.0, kernel=rbf ................................
[CV] .................. C=1000.0, gamma=1.0, kernel=rbf, total=   6.7s
[CV] C=1000.0, gamma=3.0, kernel=rbf ................................
[CV] .................. C=1000.0, gamma=3.0, kernel=rbf, total=   7.4s
[CV] C=1000.0, gamma=3.0, kernel=rbf ................................
[CV] .................. C=1000.0, gamma=3.0, kernel=rbf, total=   7.4s
[CV] C=1000.0, gamma=3.0, kernel=rbf ................................
[CV] .................. C=1000.0, gamma=3.0, kernel=rbf, total=   7.4s
[CV] C=1000.0, gamma=3.0, kernel=rbf ................................
[CV] .................. C=1000.0, gamma=3.0, kernel=rbf, total=   7.4s
[CV] C=1000.0, gamma=3.0, kernel=rbf ................................
[CV] .................. C=1000.0, gamma=3.0, kernel=rbf, total=   7.3s
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    3.9s remaining:    0.0s
[Parallel(n_jobs=1)]: Done 250 out of 250 | elapsed: 26.4min finished
```

```
GridSearchCV(cv=5, estimator=SVR(),
             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
```

```
70363.84006944533
```

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`.

Warning: the following cell may take close to 45 minutes to run, or more depending on your hardware.

```
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 functio

# 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, random_state=42)
rnd_search.fit(housing_prepared, housing_labels)
```

```
Fitting 5 folds for each of 50 candidates, totalling 250 fits
[CV] C=629.782329591372, gamma=3.010121430917521, kernel=linear ......
[CV]  C=629.782329591372, gamma=3.010121430917521, kernel=linear, total=   4.2s
[CV] C=629.782329591372, gamma=3.010121430917521, kernel=linear ......
[CV]  C=629.782329591372, gamma=3.010121430917521, kernel=linear, total=   4.0s
[CV] C=629.782329591372, gamma=3.010121430917521, kernel=linear ......
[CV]  C=629.782329591372, gamma=3.010121430917521, kernel=linear, total=   4.5s
[CV] C=629.782329591372, gamma=3.010121430917521, kernel=linear ......
```

```
[CV]  C=629.782329591372, gamma=3.010121430917521, kernel=linear, total=   4.5s
[CV] C=629.782329591372, gamma=3.010121430917521, kernel=linear ......
[CV]  C=629.782329591372, gamma=3.010121430917521, kernel=linear, total=   4.3s
[CV] C=26290.206464300216, gamma=0.9084469696321253, kernel=rbf ......
[CV]  C=26290.206464300216, gamma=0.9084469696321253, kernel=rbf, total=   8.6s
[CV] C=26290.206464300216, gamma=0.9084469696321253, kernel=rbf ......
[CV]  C=26290.206464300216, gamma=0.9084469696321253, kernel=rbf, total=   9.1s
[CV] C=26290.206464300216, gamma=0.9084469696321253, kernel=rbf ......
[CV]  C=26290.206464300216, gamma=0.9084469696321253, kernel=rbf, total=   8.8s
[CV] C=26290.206464300216, gamma=0.9084469696321253, kernel=rbf ......
[CV]  C=26290.206464300216, gamma=0.9084469696321253, kernel=rbf, total=   8.9s
[CV] C=26290.206464300216, gamma=0.9084469696321253, kernel=rbf ......
[CV]  C=26290.206464300216, gamma=0.9084469696321253, kernel=rbf, total=   9.0s
[CV] C=84.14107900575871, gamma=0.059838768608680676, kernel=rbf .....
[CV]  C=84.14107900575871, gamma=0.059838768608680676, kernel=rbf, total=   7.0s
[CV] C=84.14107900575871, gamma=0.059838768608680676, kernel=rbf .....
[CV]  C=84.14107900575871, gamma=0.059838768608680676, kernel=rbf, total=   7.0s
[CV] C=84.14107900575871, gamma=0.059838768608680676, kernel=rbf .....
[CV]  C=84.14107900575871, gamma=0.059838768608680676, kernel=rbf, total=   6.9s
[CV] C=84.14107900575871, gamma=0.059838768608680676, kernel=rbf .....
[CV]  C=84.14107900575871, gamma=0.059838768608680676, kernel=rbf, total=   7.0s
[CV] C=84.14107900575871, gamma=0.059838768608680676, kernel=rbf .....
[CV]  C=84.14107900575871, gamma=0.059838768608680676, kernel=rbf, total=   7.0s
[CV] C=432.37884813148855, gamma=0.15416196746656105, kernel=linear ..
[CV]  C=432.37884813148855, gamma=0.15416196746656105, kernel=linear, total=   4.6s
<<434 more lines>>
[CV] C=61217.04421344494, gamma=1.6279689407405564, kernel=rbf .......
[CV]  C=61217.04421344494, gamma=1.6279689407405564, kernel=rbf, total=  25.2s
[CV] C=61217.04421344494, gamma=1.6279689407405564, kernel=rbf .......
[CV]  C=61217.04421344494, gamma=1.6279689407405564, kernel=rbf, total=  23.2s
[CV] C=926.9787684096649, gamma=2.147979593060577, kernel=rbf ........
[CV]  C=926.9787684096649, gamma=2.147979593060577, kernel=rbf, total=   5.7s
[CV] C=926.9787684096649, gamma=2.147979593060577, kernel=rbf ........
[CV]  C=926.9787684096649, gamma=2.147979593060577, kernel=rbf, total=   5.7s
[CV] C=926.9787684096649, gamma=2.147979593060577, kernel=rbf ........
[CV]  C=926.9787684096649, gamma=2.147979593060577, kernel=rbf, total=   5.7s
[CV] C=926.9787684096649, gamma=2.147979593060577, kernel=rbf ........
[CV]  C=926.9787684096649, gamma=2.147979593060577, kernel=rbf, total=   5.8s
[CV] C=926.9787684096649, gamma=2.147979593060577, kernel=rbf ........
[CV]  C=926.9787684096649, gamma=2.147979593060577, kernel=rbf, total=   5.6s
[CV] C=33946.157064934, gamma=2.2642426492862313, kernel=linear ......
[CV]  C=33946.157064934, gamma=2.2642426492862313, kernel=linear, total=  10.0s
[CV] C=33946.157064934, gamma=2.2642426492862313, kernel=linear ......
```

```
[CV]  C=33946.157064934, gamma=2.2642426492862313, kernel=linear, total=   9.7s
[CV] C=33946.157064934, gamma=2.2642426492862313, kernel=linear ......
[CV]  C=33946.157064934, gamma=2.2642426492862313, kernel=linear, total=   8.9s
[CV] C=33946.157064934, gamma=2.2642426492862313, kernel=linear ......
[CV]  C=33946.157064934, gamma=2.2642426492862313, kernel=linear, total=  10.4s
[CV] C=33946.157064934, gamma=2.2642426492862313, kernel=linear ......
[CV]  C=33946.157064934, gamma=2.2642426492862313, kernel=linear, total=   9.3s
[CV] C=84789.82947739525, gamma=0.3176359085304841, kernel=linear ....
[CV]  C=84789.82947739525, gamma=0.3176359085304841, kernel=linear, total=  25.8s
[CV] C=84789.82947739525, gamma=0.3176359085304841, kernel=linear ....
[CV]  C=84789.82947739525, gamma=0.3176359085304841, kernel=linear, total=  18.5s
[CV] C=84789.82947739525, gamma=0.3176359085304841, kernel=linear ....
[CV]  C=84789.82947739525, gamma=0.3176359085304841, kernel=linear, total=  28.3s
[CV] C=84789.82947739525, gamma=0.3176359085304841, kernel=linear ....
[CV]  C=84789.82947739525, gamma=0.3176359085304841, kernel=linear, total=  20.8s
[CV] C=84789.82947739525, gamma=0.3176359085304841, kernel=linear ....
[CV]  C=84789.82947739525, gamma=0.3176359085304841, kernel=linear, total=  15.6s

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    4.2s remaining:    0.0s
[Parallel(n_jobs=1)]: Done 250 out of 250 | elapsed: 44.0min finished
```

```
RandomizedSearchCV(cv=5, estimator=SVR(), n_iter=50,
                   param_distributions={'C': <scipy.stats._distn_infrastructure.rv_frozen obj
                                        'gamma': <scipy.stats._distn_infrastructure.rv_frozen
                                        '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
```

```
54767.960710084146
```

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

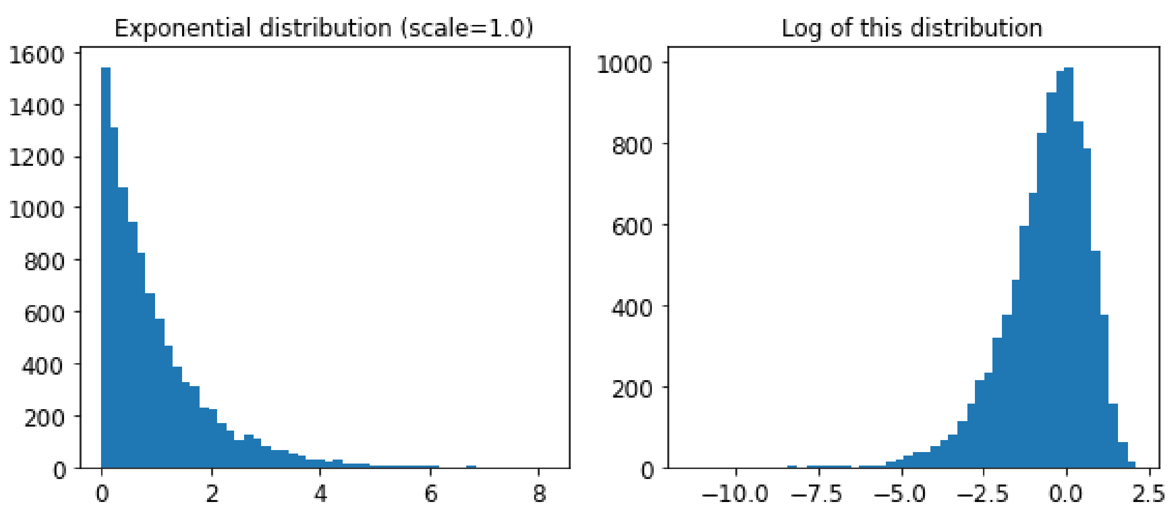
```
rnd_search.best_params_
```

```
{'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.

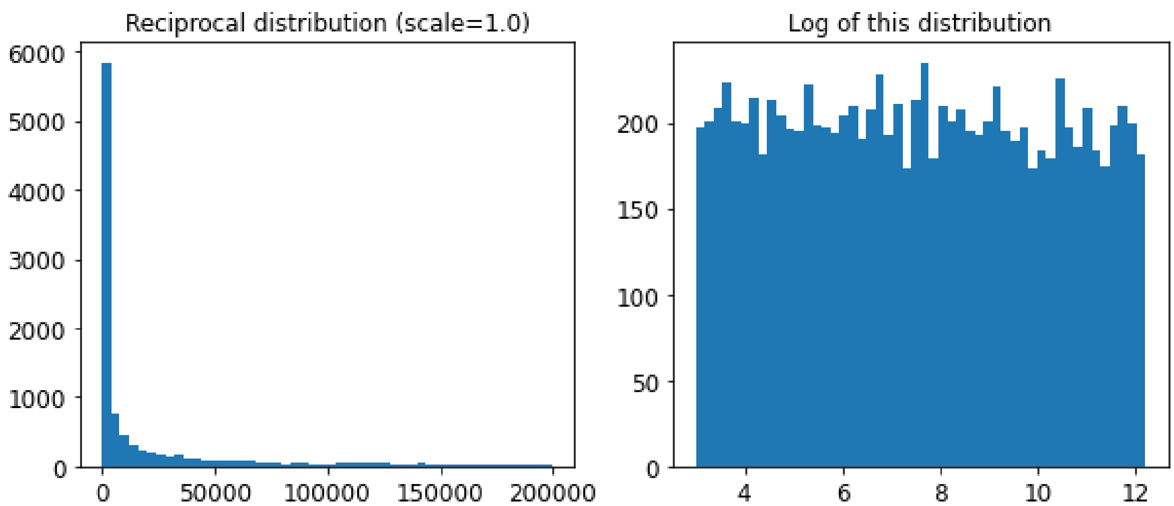
Let's look at the exponential distribution we used, with `scale=1.0`. Note that some samples are much larger or smaller than 1.0, but when you look at the log of the distribution, you can see that most values are actually concentrated roughly in the range of exp(-2) to exp(+2), which is about 0.1 to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

```python
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:

```python
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.

```python
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]
```

```
[(0.36615898061813423, 'median_income'),
 (0.16478099356159054, 'INLAND'),
```

 (0.10879295677551575, 'pop_per_hhold'),
 (0.07334423551601243, 'longitude'),
 (0.06290907048262032, '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
```

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

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

```
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:

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

```
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! :)

4.

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

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

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

```
Pipeline(steps=[('preparation',
                 ColumnTransformer(transformers=[('num',
                                                  Pipeline(steps=[('imputer',
                                                                   SimpleImputer(strategy='me
                                                                  ('attribs_adder',
                                                                   CombinedAttributesAdder()
                                                                  ('std_scaler',
                                                                   StandardScaler())]),
                                                   ['longitude', 'latitude',
                                                    'housing_median_age',
                                                    'total_rooms',
                                                    'total_bedrooms',
                                                    'population', 'households',
                                                    'median_income']),
                                                  ('cat', OneHotEncoder(...
                 TopFeatureSelector(feature_importances=array([7.33442355e-02, 6.29090705e-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]),
                                    k=5)),
                ('svm_reg',
                 SVR(C=157055.10989448498, gamma=0.26497040005002437))])
```

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

```python
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`.

5.

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

Warning: the following cell may take close to 45 minutes to run, or more depending on your hardware.

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

```
Fitting 5 folds for each of 48 candidates, totalling 240 fits
[CV] feature_selection__k=1, preparation__num__imputer__strategy=mean
[CV]  feature_selection__k=1, preparation__num__imputer__strategy=mean, total=   4.2s
[CV] feature_selection__k=1, preparation__num__imputer__strategy=mean
[CV]  feature_selection__k=1, preparation__num__imputer__strategy=mean, total=   5.2s
[CV] feature_selection__k=1, preparation__num__imputer__strategy=mean
[CV]  feature_selection__k=1, preparation__num__imputer__strategy=mean, total=   4.7s
[CV] feature_selection__k=1, preparation__num__imputer__strategy=mean
[CV]  feature_selection__k=1, preparation__num__imputer__strategy=mean, total=   4.7s
[CV] feature_selection__k=1, preparation__num__imputer__strategy=mean
[CV]  feature_selection__k=1, preparation__num__imputer__strategy=mean, total=   4.8s
[CV] feature_selection__k=1, preparation__num__imputer__strategy=median
[CV]  feature_selection__k=1, preparation__num__imputer__strategy=median, total=   5.1s
[CV] feature_selection__k=1, preparation__num__imputer__strategy=median
[CV]  feature_selection__k=1, preparation__num__imputer__strategy=median, total=   4.9s
[CV] feature_selection__k=1, preparation__num__imputer__strategy=median
[CV]  feature_selection__k=1, preparation__num__imputer__strategy=median, total=   4.7s
[CV] feature_selection__k=1, preparation__num__imputer__strategy=median
[CV]  feature_selection__k=1, preparation__num__imputer__strategy=median, total=   4.3s
[CV] feature_selection__k=1, preparation__num__imputer__strategy=median
[CV]  feature_selection__k=1, preparation__num__imputer__strategy=median, total=   4.2s
```

```
[CV] feature_selection__k=1, preparation__num__imputer__strategy=most_frequent
[CV]  feature_selection__k=1, preparation__num__imputer__strategy=most_frequent, total=   4.
[CV] feature_selection__k=1, preparation__num__imputer__strategy=most_frequent
[CV]  feature_selection__k=1, preparation__num__imputer__strategy=most_frequent, total=   4.
[CV] feature_selection__k=1, preparation__num__imputer__strategy=most_frequent
[CV]  feature_selection__k=1, preparation__num__imputer__strategy=most_frequent, total=   4.
[CV] feature_selection__k=1, preparation__num__imputer__strategy=most_frequent
[CV]  feature_selection__k=1, preparation__num__imputer__strategy=most_frequent, total=   4.
[CV] feature_selection__k=1, preparation__num__imputer__strategy=most_frequent
[CV]  feature_selection__k=1, preparation__num__imputer__strategy=most_frequent, total=   4.
[CV] feature_selection__k=2, preparation__num__imputer__strategy=mean
[CV]  feature_selection__k=2, preparation__num__imputer__strategy=mean, total=   4.8s
<<414 more lines>>
[CV] feature_selection__k=15, preparation__num__imputer__strategy=most_frequent
[CV]  feature_selection__k=15, preparation__num__imputer__strategy=most_frequent, total=  15
[CV] feature_selection__k=15, preparation__num__imputer__strategy=most_frequent
[CV]  feature_selection__k=15, preparation__num__imputer__strategy=most_frequent, total=  19
[CV] feature_selection__k=16, preparation__num__imputer__strategy=mean
[CV]  feature_selection__k=16, preparation__num__imputer__strategy=mean, total=  17.9s
[CV] feature_selection__k=16, preparation__num__imputer__strategy=mean
[CV]  feature_selection__k=16, preparation__num__imputer__strategy=mean, total=  19.2s
[CV] feature_selection__k=16, preparation__num__imputer__strategy=mean
[CV]  feature_selection__k=16, preparation__num__imputer__strategy=mean, total=  18.2s
[CV] feature_selection__k=16, preparation__num__imputer__strategy=mean
[CV]  feature_selection__k=16, preparation__num__imputer__strategy=mean, total=  19.1s
[CV] feature_selection__k=16, preparation__num__imputer__strategy=mean
[CV]  feature_selection__k=16, preparation__num__imputer__strategy=mean, total=  16.4s
[CV] feature_selection__k=16, preparation__num__imputer__strategy=median
[CV]  feature_selection__k=16, preparation__num__imputer__strategy=median, total=  17.9s
[CV] feature_selection__k=16, preparation__num__imputer__strategy=median
[CV]  feature_selection__k=16, preparation__num__imputer__strategy=median, total=  19.2s
[CV] feature_selection__k=16, preparation__num__imputer__strategy=median
[CV]  feature_selection__k=16, preparation__num__imputer__strategy=median, total=  20.5s
[CV] feature_selection__k=16, preparation__num__imputer__strategy=median
[CV]  feature_selection__k=16, preparation__num__imputer__strategy=median, total=  17.1s
[CV] feature_selection__k=16, preparation__num__imputer__strategy=median
[CV]  feature_selection__k=16, preparation__num__imputer__strategy=median, total=  20.3s
[CV] feature_selection__k=16, preparation__num__imputer__strategy=most_frequent
[CV]  feature_selection__k=16, preparation__num__imputer__strategy=most_frequent, total=  16
[CV] feature_selection__k=16, preparation__num__imputer__strategy=most_frequent
[CV]  feature_selection__k=16, preparation__num__imputer__strategy=most_frequent, total=  19
[CV] feature_selection__k=16, preparation__num__imputer__strategy=most_frequent
[CV]  feature_selection__k=16, preparation__num__imputer__strategy=most_frequent, total=  17
```

```
[CV] feature_selection__k=16, preparation__num__imputer__strategy=most_frequent
[CV]  feature_selection__k=16, preparation__num__imputer__strategy=most_frequent, total=  17
[CV] feature_selection__k=16, preparation__num__imputer__strategy=most_frequent
[CV]  feature_selection__k=16, preparation__num__imputer__strategy=most_frequent, total=  19

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    4.2s remaining:    0.0s
[Parallel(n_jobs=1)]: Done 240 out of 240 | elapsed: 42.3min finished
```

```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('preparation',
                                        ColumnTransformer(transformers=[('num',
                                                                         Pipeline(steps=[('in
                                                                                          Sim
                                                                                         ('at
                                                                                          Com
                                                                                         ('st
                                                                                          Sta
                                                                         ['longitude',
                                                                          'latitude',
                                                                          'housing_median_age
                                                                          'total_rooms',
                                                                          'total_bedrooms',
                                                                          'population',
                                                                          'households',
                                                                          'median_inc...
       5.64191792e-02, 1.08792957e-01, 5.33510773e-02, 1.03114883e-02,
       1.64780994e-01, 6.02803867e-05, 1.96041560e-03, 2.85647464e-03]),
                                                               k=5)),
                                       ('svm_reg',
                                        SVR(C=157055.10989448498,
                                            gamma=0.26497040005002437))]),
             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': 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. :)