```
In [1]: # To support both python 2 and python 3 : California Housing Prices dataset \ a multivariate regression
        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(456)
In [2]: # 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)
In [3]: # 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)
        def save fig(fig id, tight layout=True, fig extension="png", resolution=300):
            path = os.path.join(IMAGES_PATH, fig_id + "." + fig_extension)
            print("Saving figure", fig_id)
            if tight layout:
                plt.tight_layout()
            plt.savefig(path, format=fig extension, dpi=resolution)
        # Ignore useless warnings (see SciPy issue #5998)
        import warnings
        warnings.filterwarnings(action="ignore", message="^internal gelsd")
```

```
In [4]: # Automating the process of fetching the data is also useful if you need to install the dataset on multiple machines.
        import os
        import tarfile
                          # download a single compressed file, housing.tgz
        from six.moves import urllib
        DOWNLOAD_ROOT = "https://raw.githubusercontent.com/ageron/handson-ml/master/"
        HOUSING PATH = os.path.join("datasets", "housing")
        HOUSING URL = DOWNLOAD ROOT + "datasets/housing/housing.tgz" # download a single compressed file, housing.tgz
        # creates a datasets/housing directory in your workspace
        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()
```

```
In [5]: fetch_housing_data()
```

```
In [7]: # Save into housing = Load_housing_data
housing = load_housing_data()
housing.head()
```

Out[7]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_proximity
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0	NEAR BAY
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0	NEAR BAY
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	NEAR BAY
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	NEAR BAY
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0	NEAR BAY

```
In [8]: # The info() method is useful to get a quick description of the data
        housing.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 20640 entries, 0 to 20639
        Data columns (total 10 columns):
                              20640 non-null float64
        longitude
        latitude
                              20640 non-null float64
        housing median age
                              20640 non-null float64
        total_rooms
                              20640 non-null float64
        total_bedrooms
                              20433 non-null float64
        population
                              20640 non-null float64
        households
                              20640 non-null float64
        median income
                              20640 non-null float64
        median house value
                              20640 non-null float64
        ocean_proximity
                              20640 non-null object
        dtypes: float64(9), object(1)
        memory usage: 1.6+ MB
In [9]: # meaning that 207 districts are missing this feature
        housing["ocean_proximity"].value_counts()
Out[9]: <1H OCEAN
                      9136
        INLAND
                      6551
        NEAR OCEAN
                      2658
        NEAR BAY
                      2290
        ISLAND
                         5
        Name: ocean_proximity, dtype: int64
```

In [10]: housing["population"].value_counts()

Out[10]:	891.0 761.0 1227.0 850.0 1052.0 825.0 999.0 782.0 1005.0 781.0 1098.0 753.0 872.0 1056.0 1158.0 899.0 837.0 804.0 1011.0 926.0 1155.0 1203.0 1047.0 986.0 861.0	25 24 24 24 23 22 22 21 21 21 21 20 20 20 20 20 20 20 20 20 20 20 20 20
	735.0 1301.0 1054.0 928.0 866.0	20 20 20 19 19
	8738.0 8907.0 3663.0 4100.0 3297.0 5116.0 5595.0 5731.0 116.0 4089.0 7009.0 3886.0 3549.0 4531.0 3926.0 3303.0 3794.0 3147.0 3589.0 4625.0 3284.0	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

7305.0	1
1033.0	1
5110.0	1
11973.0	1
2994.0	1
1333.0	1
3891.0	1
5087.0	1
3591.0	1

Name: population, Length: 3888, dtype: int64

In [15]: housing.describe()

Out[15]:

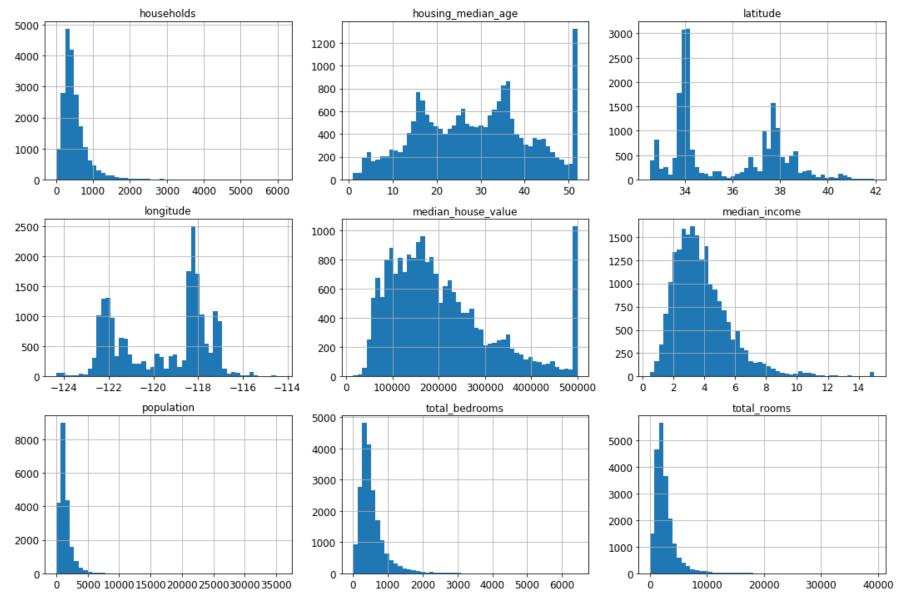
	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744	499.539680	3.870671	206855.816909
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462122	382.329753	1.899822	115395.615874
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000	1.000000	0.499900	14999.000000
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000000	280.000000	2.563400	119600.000000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000000	409.000000	3.534800	179700.000000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000000	605.000000	4.743250	264725.000000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000000	6082.000000	15.000100	500001.000000

Saving figure Attribute of histogram_plots

```
FileNotFoundError
                                          Traceback (most recent call last)
<ipython-input-17-eb356ebb4b0d> in <module>
      2 import matplotlib.pyplot as plt
      3 housing.hist(bins=50, figsize=(15,10))
----> 4 save fig("Attribute of histogram_plots")
      5 plt.show()
<ipython-input-3-f6435d47e026> in save fig(fig id, tight_layout, fig_extension, resolution)
           if tight layout:
    10
                plt.tight layout()
            plt.savefig(path, format=fig_extension, dpi=resolution)
---> 11
    12
    13 # Ignore useless warnings (see SciPy issue #5998)
~\Anaconda3\lib\site-packages\matplotlib\pyplot.py in savefig(*args, **kwargs)
    714 def savefig(*args, **kwargs):
   715
            fig = gcf()
--> 716
            res = fig.savefig(*args, **kwargs)
            fig.canvas.draw idle() # need this if 'transparent=True' to reset colors
    717
   718
            return res
~\Anaconda3\lib\site-packages\matplotlib\figure.py in savefig(self, fname, transparent, **kwargs)
   2178
                    self.patch.set visible(frameon)
   2179
-> 2180
                self.canvas.print figure(fname, **kwargs)
   2181
   2182
                if frameon:
~\Anaconda3\lib\site-packages\matplotlib\backend bases.py in print figure(self, filename, dpi, facecolor, edgecolor, orientatio
n, format, bbox_inches, **kwargs)
   2080
                            orientation=orientation.
   2081
                            bbox_inches_restore=_bbox_inches_restore,
-> 2082
                            **kwargs)
   2083
                    finally:
   2084
                        if bbox_inches and restore_bbox:
~\Anaconda3\lib\site-packages\matplotlib\backends\backend_agg.py in print png(self, filename_or_obj, metadata, pil kwargs, *arg
s, **kwargs)
                    renderer = self.get renderer()
    528
                    with cbook. setattr cm(renderer, dpi=self.figure.dpi), \
    529
                            cbook.open file cm(filename or obj, "wb") as fh:
--> 530
                        png.write_png(renderer._renderer, fh,
    531
    532
                                       self.figure.dpi, metadata=metadata)
~\Anaconda3\lib\contextlib.py in enter (self)
                del self.args, self.kwds, self.func
   110
    111
                try:
--> 112
                    return next(self.gen)
   113
                except StopIteration:
   114
                    raise RuntimeError("generator didn't yield") from None
```

```
~\Anaconda3\lib\site-packages\matplotlib\cbook\__init__.py in open_file_cm(path_or_file, mode, encoding)
    445 def open_file_cm(path_or_file, mode="r", encoding=None):
            r""Pass through file objects and context-manage `.PathLike`\s."""
    446
            fh, opened = to_filehandle(path_or_file, mode, True, encoding)
--> 447
            if opened:
    448
               with fh:
    449
~\Anaconda3\lib\site-packages\matplotlib\cbook\__init__.py in to_filehandle(fname, flag, return_opened, encoding)
                    fh = bz2.BZ2File(fname, flag)
    431
                else:
                    fh = open(fname, flag, encoding=encoding)
--> 432
                opened = True
    433
            elif hasattr(fname, 'seek'):
    434
```

FileNotFoundError: [Errno 2] No such file or directory: '.\\images\\end_to_end_project\\Attribute of histogram_plots.png'



In [18]: # to make this notebook's output identical at every run
np.random.seed(456)

```
In [19]: # the housing dataset does not have an identifier column. The simplest solution is to use the row index as the ID:
         import numpy as np
         # For illustration only. Sklearn has train test split()
         def split_train_test(data, test_ratio):
             shuffled indices = np.random.permutation(len(data))
             test set size = int(len(data) * test ratio)
             test indices = shuffled indices[:test set size]
             train_indices = shuffled_indices[test_set_size:]
             return data.iloc[train indices], data.iloc[test indices]
In [20]: train set, test set = split train test(housing, 0.2)
         print(len(train_set), "train +", len(test_set), "test")
         16512 train + 4128 test
In [21]: from zlib import crc32
         def test set check(identifier, test ratio):
             return crc32(np.int64(identifier)) & 0xffffffff < test ratio * 2**32</pre>
         def split train test by id(data, test ratio, id column):
             ids = data[id column]
             in_test_set = ids.apply(lambda id_: test_set_check(id_, test_ratio))
             return data.loc[~in test set], data.loc[in test set]
In [22]: import hashlib
         def test_set_check(identifier, test_ratio, hash=hashlib.md5):
             return hash(np.int64(identifier)).digest()[-1] < 256 * test ratio</pre>
         def test set check(identifier, test ratio, hash=hashlib.md5):
In [24]:
             return bytearray(hash(np.int64(identifier)).digest())[-1] < 256 * test_ratio</pre>
In [25]:
         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"]
In [26]:
         train set, test set = split train test by id(housing with id, 0.2, "id")
```

In [27]: test_set.head()

Out[27]:

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

In [30]: from sklearn.model_selection import train_test_split

train_set, test_set = train_test_split(housing, test_size=0.2, random_state=456)

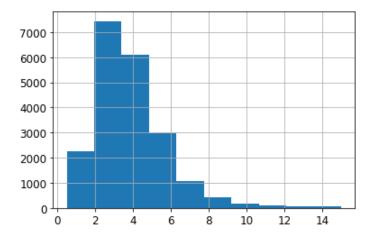
In [31]: test_set.head()

Out[31]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_proximity
12165	-117.06	33.78	17.0	2813.0	565.0	1345.0	488.0	2.5847	145300.0	INLAND
11628	-118.07	33.80	22.0	1391.0	338.0	810.0	295.0	3.8792	218200.0	<1H OCEAN
8230	-118.20	33.77	24.0	2404.0	819.0	1566.0	753.0	1.5076	145800.0	NEAR OCEAN
6756	-118.11	34.11	50.0	2131.0	294.0	753.0	284.0	6.7099	352200.0	<1H OCEAN
17074	-122.21	37.48	20.0	505.0	216.0	326.0	216.0	2.9286	237500.0	NEAR BAY

In [32]: housing["median_income"].hist()

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x7b08ed4198>



```
In [33]: housing["income cat"] = pd.cut(housing["median income"],
                                         bins=[0., 1.5, 3.0, 4.5, 6., np.inf],
                                         labels=[1, 2, 3, 4, 5])
In [34]: housing["income cat"].value counts()
Out[34]: 3
              7236
         2
              6581
              3639
         5
              2362
               822
         Name: income_cat, dtype: int64
In [35]: housing["income_cat"].hist()
Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x7b09513208>
          7000
           6000
           5000
          4000
          3000
          2000
          1000
                    1.5
                          2.0
                               2.5 3.0
                                         3.5
                                              4.0
In [36]: from sklearn.model_selection import StratifiedShuffleSplit
         split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
         for train index, test index in split.split(housing, housing["income cat"]):
             strat train_set = housing.loc[train_index]
             strat_test_set = housing.loc[test_index]
In [37]: | strat_test_set["income_cat"].value_counts() / len(strat_test_set)
Out[37]: 3
              0.350533
              0.318798
         4
              0.176357
         5
              0.114583
```

0.039729

Name: income cat, dtype: float64

```
In [38]: housing["income cat"].value counts() / len(housing)
Out[38]: 3
               0.350581
               0.318847
         4
              0.176308
               0.114438
               0.039826
         Name: income_cat, dtype: float64
In [39]:
         def income_cat_proportions(data):
              return data["income_cat"].value_counts() / len(data)
          train set, test set = train test split(housing, test size=0.2, random state=42)
          compare props = pd.DataFrame({
              "Overall": income_cat_proportions(housing),
              "Stratified": income_cat_proportions(strat_test_set),
              "Random": income cat proportions(test set),
          }).sort index()
          compare_props["Rand. %error"] = 100 * compare_props["Random"] / compare_props["Overall"] - 100
          compare props["Strat. %error"] = 100 * compare props["Stratified"] / compare props["Overall"] - 100
In [40]:
          compare_props
Out[40]:
              Overall Stratified Random Rand. %error Strat. %error
          1 0.039826 0.039729 0.040213
                                          0.973236
                                                     -0.243309
          2 0.318847 0.318798 0.324370
                                          1.732260
                                                     -0.015195
          3 0.350581 0.350533 0.358527
                                          2.266446
                                                     -0.013820
          4 0.176308 0.176357 0.167393
                                          -5.056334
                                                      0.027480
          5 0.114438 0.114583 0.109496
                                          -4.318374
                                                      0.127011
In [41]:
          for set_ in (strat_train_set, strat_test_set):
              set .drop("income cat", axis=1, inplace=True)
In [42]: #Discover and visualize the data to gain insights
          housing = strat train set.copy()
```

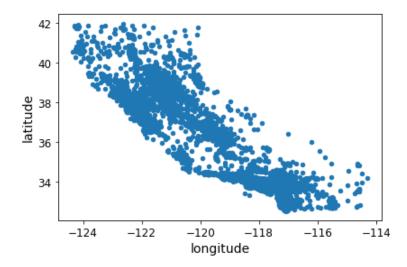
```
In [43]: # it is a good idea to create a scatterplot of all districts to visualize the data
housing.plot(kind="scatter", x="longitude", y="latitude")
save_fig("bad_visualization_plot")
```

Saving figure bad_visualization_plot

```
FileNotFoundError
                                          Traceback (most recent call last)
<ipython-input-43-04b7bb0c99fe> in <module>
     1 housing.plot(kind="scatter", x="longitude", y="latitude")
----> 2 save fig("bad visualization plot")
<ipython-input-3-f6435d47e026> in save_fig(fig_id, tight_layout, fig_extension, resolution)
           if tight layout:
    10
                plt.tight layout()
            plt.savefig(path, format=fig extension, dpi=resolution)
---> 11
    12
    13 # Ignore useless warnings (see SciPy issue #5998)
~\Anaconda3\lib\site-packages\matplotlib\pyplot.py in savefig(*args, **kwargs)
    714 def savefig(*args, **kwargs):
   715
           fig = gcf()
--> 716
           res = fig.savefig(*args, **kwargs)
    717
           fig.canvas.draw idle() # need this if 'transparent=True' to reset colors
   718
           return res
~\Anaconda3\lib\site-packages\matplotlib\figure.py in savefig(self, fname, transparent, **kwargs)
   2178
                    self.patch.set visible(frameon)
   2179
-> 2180
                self.canvas.print figure(fname, **kwargs)
   2181
  2182
                if frameon:
~\Anaconda3\lib\site-packages\matplotlib\backend_bases.py in print figure(self, filename, dpi, facecolor, edgecolor, orientatio
n, format, bbox_inches, **kwargs)
   2080
                            orientation=orientation,
   2081
                            bbox inches restore = bbox inches restore,
-> 2082
                            **kwargs)
   2083
                    finally:
   2084
                        if bbox inches and restore bbox:
~\Anaconda3\lib\site-packages\matplotlib\backends\backend_agg.py in print_png(self, filename_or_obj, metadata, pil_kwargs, *arg
s, **kwargs)
   528
                    renderer = self.get renderer()
                    with cbook. setattr cm(renderer, dpi=self.figure.dpi), \
   529
--> 530
                            cbook.open file cm(filename or obj, "wb") as fh:
                        png.write png(renderer. renderer, fh,
    531
    532
                                       self.figure.dpi, metadata=metadata)
~\Anaconda3\lib\contextlib.py in enter (self)
                del self.args, self.kwds, self.func
   110
   111
                try:
--> 112
                    return next(self.gen)
   113
                except StopIteration:
   114
                    raise RuntimeError("generator didn't yield") from None
~\Anaconda3\lib\site-packages\matplotlib\cbook\__init__.py in open_file_cm(path_or_file, mode, encoding)
    445 def open_file_cm(path_or_file, mode="r", encoding=None):
```

```
r"""Pass through file objects and context-manage `.PathLike`\s."""
    446
            fh, opened = to_filehandle(path_or_file, mode, True, encoding)
--> 447
            if opened:
    448
               with fh:
    449
~\Anaconda3\lib\site-packages\matplotlib\cbook\__init__.py in to_filehandle(fname, flag, return_opened, encoding)
                    fh = bz2.BZ2File(fname, flag)
    431
                else:
--> 432
                    fh = open(fname, flag, encoding=encoding)
                opened = True
    433
            elif hasattr(fname, 'seek'):
   434
```

FileNotFoundError: [Errno 2] No such file or directory: '.\\images\\end_to_end_project\\bad_visualization_plot.png'



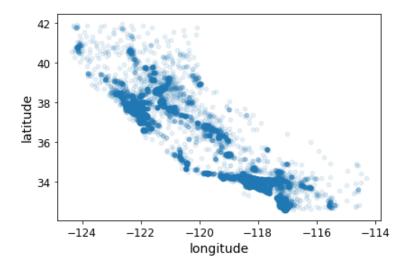
```
In [44]: # 0.1 makes it much easier to visualize the places where there is a high density of data points
housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.1)
save_fig("better_visualization_plot")
```

Saving figure better_visualization_plot

```
FileNotFoundError
                                          Traceback (most recent call last)
<ipython-input-44-8737c00d5aba> in <module>
     1 housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.1)
----> 2 save fig("better visualization plot")
<ipython-input-3-f6435d47e026> in save_fig(fig_id, tight_layout, fig_extension, resolution)
           if tight layout:
    10
                plt.tight layout()
            plt.savefig(path, format=fig extension, dpi=resolution)
---> 11
    12
    13 # Ignore useless warnings (see SciPy issue #5998)
~\Anaconda3\lib\site-packages\matplotlib\pyplot.py in savefig(*args, **kwargs)
    714 def savefig(*args, **kwargs):
   715
           fig = gcf()
--> 716
           res = fig.savefig(*args, **kwargs)
    717
           fig.canvas.draw idle() # need this if 'transparent=True' to reset colors
   718
           return res
~\Anaconda3\lib\site-packages\matplotlib\figure.py in savefig(self, fname, transparent, **kwargs)
   2178
                    self.patch.set visible(frameon)
   2179
-> 2180
                self.canvas.print figure(fname, **kwargs)
   2181
  2182
                if frameon:
~\Anaconda3\lib\site-packages\matplotlib\backend_bases.py in print figure(self, filename, dpi, facecolor, edgecolor, orientatio
n, format, bbox_inches, **kwargs)
   2080
                            orientation=orientation,
   2081
                            bbox inches restore = bbox inches restore,
-> 2082
                            **kwargs)
   2083
                    finally:
   2084
                        if bbox inches and restore bbox:
~\Anaconda3\lib\site-packages\matplotlib\backends\backend_agg.py in print_png(self, filename_or_obj, metadata, pil_kwargs, *arg
s, **kwargs)
   528
                    renderer = self.get renderer()
                    with cbook. setattr cm(renderer, dpi=self.figure.dpi), \
   529
--> 530
                            cbook.open file cm(filename or obj, "wb") as fh:
                        png.write png(renderer. renderer, fh,
    531
    532
                                       self.figure.dpi, metadata=metadata)
~\Anaconda3\lib\contextlib.py in enter (self)
                del self.args, self.kwds, self.func
   110
   111
                try:
--> 112
                    return next(self.gen)
   113
                except StopIteration:
   114
                    raise RuntimeError("generator didn't yield") from None
~\Anaconda3\lib\site-packages\matplotlib\cbook\__init__.py in open_file_cm(path_or_file, mode, encoding)
    445 def open_file_cm(path_or_file, mode="r", encoding=None):
```

```
r"""Pass through file objects and context-manage `.PathLike`\s."""
    446
            fh, opened = to_filehandle(path_or_file, mode, True, encoding)
--> 447
            if opened:
    448
               with fh:
    449
~\Anaconda3\lib\site-packages\matplotlib\cbook\__init__.py in to_filehandle(fname, flag, return_opened, encoding)
                    fh = bz2.BZ2File(fname, flag)
    431
                else:
--> 432
                    fh = open(fname, flag, encoding=encoding)
                opened = True
    433
            elif hasattr(fname, 'seek'):
   434
```

FileNotFoundError: [Errno 2] No such file or directory: '.\\images\\end_to_end_project\\better_visualization_plot.png'

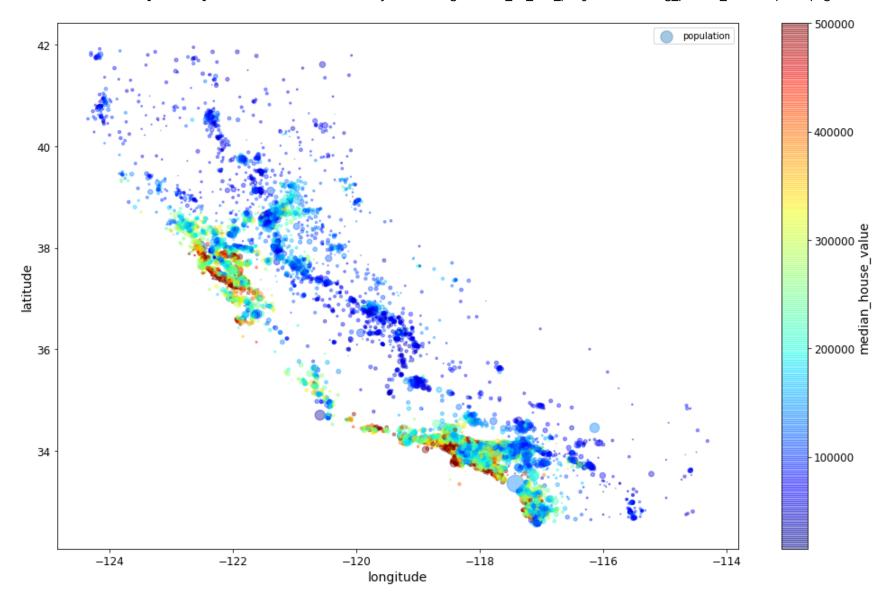


Saving figure housing_prices_scatterplot

```
FileNotFoundError
                                          Traceback (most recent call last)
<ipython-input-46-32cdb2663f27> in <module>
            sharex=False)
      5 plt.legend()
----> 6 save fig("housing_prices_scatterplot")
<ipython-input-3-f6435d47e026> in save_fig(fig_id, tight_layout, fig_extension, resolution)
      9
            if tight layout:
    10
                plt.tight layout()
            plt.savefig(path, format=fig extension, dpi=resolution)
---> 11
    12
    13 # Ignore useless warnings (see SciPy issue #5998)
~\Anaconda3\lib\site-packages\matplotlib\pyplot.py in savefig(*args, **kwargs)
    714 def savefig(*args, **kwargs):
   715
            fig = gcf()
--> 716
            res = fig.savefig(*args, **kwargs)
    717
            fig.canvas.draw idle() # need this if 'transparent=True' to reset colors
   718
            return res
~\Anaconda3\lib\site-packages\matplotlib\figure.py in savefig(self, fname, transparent, **kwargs)
   2178
                    self.patch.set_visible(frameon)
   2179
-> 2180
                self.canvas.print figure(fname, **kwargs)
   2181
                if frameon:
   2182
~\Anaconda3\lib\site-packages\matplotlib\backend_bases.py in print figure(self, filename, dpi, facecolor, edgecolor, orientatio
n, format, bbox inches, **kwargs)
   2080
                            orientation=orientation,
   2081
                            bbox_inches_restore=_bbox_inches_restore,
-> 2082
                            **kwargs)
   2083
                    finally:
   2084
                        if bbox_inches and restore_bbox:
~\Anaconda3\lib\site-packages\matplotlib\backends\backend_agg.py in print_png(self, filename_or_obj, metadata, pil_kwargs, *arg
s, **kwargs)
                    renderer = self.get renderer()
    528
                    with cbook. setattr cm(renderer, dpi=self.figure.dpi), \
    529
--> 530
                            cbook.open file cm(filename or obj, "wb") as fh:
    531
                        _png.write_png(renderer._renderer, fh,
    532
                                       self.figure.dpi, metadata=metadata)
~\Anaconda3\lib\contextlib.py in enter (self)
                del self.args, self.kwds, self.func
    110
   111
                try:
--> 112
                    return next(self.gen)
   113
                except StopIteration:
   114
                    raise RuntimeError("generator didn't yield") from None
~\Anaconda3\lib\site-packages\matplotlib\cbook\__init__.py in open_file_cm(path_or_file, mode, encoding)
```

```
445 def open_file_cm(path_or_file, mode="r", encoding=None):
            r"""Pass through file objects and context-manage `.PathLike`\s."""
    446
            fh, opened = to filehandle(path or file, mode, True, encoding)
--> 447
            if opened:
    448
    449
                with fh:
~\Anaconda3\lib\site-packages\matplotlib\cbook\__init__.py in to_filehandle(fname, flag, return_opened, encoding)
                    fh = bz2.BZ2File(fname, flag)
    430
    431
                else:
                    fh = open(fname, flag, encoding=encoding)
--> 432
                opened = True
    433
            elif hasattr(fname, 'seek'):
    434
```

FileNotFoundError: [Errno 2] No such file or directory: '.\\images\\end_to_end_project\\housing_prices_scatterplot.png'



```
In [48]: 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()
         FileNotFoundError
                                                   Traceback (most recent call last)
         <ipython-input-48-b4b47ed4e188> in <module>
               1 import matplotlib.image as mpimg
         ---> 2 california img=mpimg.imread(PROJECT ROOT DIR + '/images/end to end project/california.png')
               3 ax = housing.plot(kind="scatter", x="longitude", y="latitude", figsize=(10,7),
               4
                                        s=housing['population']/100, label="Population",
               5
                                         c="median house value", cmap=plt.get cmap("jet"),
         ~\Anaconda3\lib\site-packages\matplotlib\image.py in imread(fname, format)
            1424
                             return handler(fd)
            1425
                         else:
         -> 1426
                             with open(fname, 'rb') as fd:
            1427
                                 return handler(fd)
            1428
                     else:
         FileNotFoundError: [Errno 2] No such file or directory: './images/end to end project/california.png'
In [49]: | corr matrix = housing.corr()
```

```
In [50]: corr_matrix["median_house_value"].sort_values(ascending=False)
Out[50]: 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
```

Saving figure scatter_matrix_plot

```
FileNotFoundError
                                          Traceback (most recent call last)
<ipython-input-51-695aaa819555> in <module>
                      "housing_median_age"]
     6 scatter matrix(housing[attributes], figsize=(12, 8))
----> 7 save fig("scatter_matrix_plot")
<ipython-input-3-f6435d47e026> in save_fig(fig_id, tight_layout, fig_extension, resolution)
     9
            if tight layout:
                plt.tight layout()
    10
            plt.savefig(path, format=fig extension, dpi=resolution)
---> 11
    12
    13 # Ignore useless warnings (see SciPy issue #5998)
~\Anaconda3\lib\site-packages\matplotlib\pyplot.py in savefig(*args, **kwargs)
    714 def savefig(*args, **kwargs):
   715
           fig = gcf()
--> 716
            res = fig.savefig(*args, **kwargs)
    717
            fig.canvas.draw idle() # need this if 'transparent=True' to reset colors
   718
            return res
~\Anaconda3\lib\site-packages\matplotlib\figure.py in savefig(self, fname, transparent, **kwargs)
   2178
                    self.patch.set_visible(frameon)
   2179
-> 2180
                self.canvas.print figure(fname, **kwargs)
   2181
                if frameon:
   2182
~\Anaconda3\lib\site-packages\matplotlib\backend_bases.py in print figure(self, filename, dpi, facecolor, edgecolor, orientatio
n, format, bbox inches, **kwargs)
   2080
                            orientation=orientation,
   2081
                            bbox_inches_restore=_bbox_inches_restore,
-> 2082
                            **kwargs)
   2083
                    finally:
   2084
                        if bbox_inches and restore_bbox:
~\Anaconda3\lib\site-packages\matplotlib\backends\backend_agg.py in print_png(self, filename_or_obj, metadata, pil_kwargs, *arg
s, **kwargs)
                    renderer = self.get renderer()
    528
                    with cbook. setattr cm(renderer, dpi=self.figure.dpi), \
    529
--> 530
                            cbook.open file cm(filename or obj, "wb") as fh:
    531
                        _png.write_png(renderer._renderer, fh,
    532
                                       self.figure.dpi, metadata=metadata)
~\Anaconda3\lib\contextlib.py in enter (self)
                del self.args, self.kwds, self.func
    110
   111
                try:
--> 112
                    return next(self.gen)
   113
                except StopIteration:
   114
                    raise RuntimeError("generator didn't yield") from None
~\Anaconda3\lib\site-packages\matplotlib\cbook\__init__.py in open_file_cm(path_or_file, mode, encoding)
```

```
445 def open_file_cm(path_or_file, mode="r", encoding=None):
             r"""Pass through file objects and context-manage `.PathLike`\s."""
    446
             fh, opened = to filehandle(path or file, mode, True, encoding)
--> 447
             if opened:
    448
    449
                 with fh:
~\Anaconda3\lib\site-packages\matplotlib\cbook\__init__.py in to_filehandle(fname, flag, return_opened, encoding)
                     fh = bz2.BZ2File(fname, flag)
    430
    431
                 else:
                     fh = open(fname, flag, encoding=encoding)
--> 432
                 opened = True
    433
             elif hasattr(fname, 'seek'):
    434
FileNotFoundError: [Errno 2] No such file or directory: '.\\images\\end_to_end_project\\scatter_matrix_plot.png'
 median_house_value
   200000
    median_income
    40000
  total_rooms
    20000
   housing_median_age
                                                                                                  ង
housing_median_age
                                                              15
                                           median_income
```

median_house_value

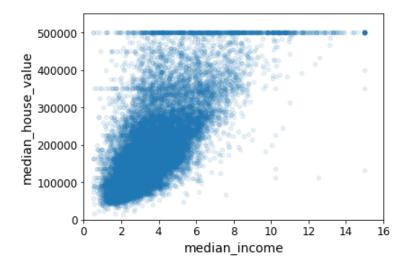
total_rooms

Saving figure income_vs_house_value_scatterplot

```
FileNotFoundError
                                          Traceback (most recent call last)
<ipython-input-54-50ae954e87f8> in <module>
                     alpha=0.1)
     3 plt.axis([0, 16, 0, 550000])
---> 4 save_fig("income_vs_house_value_scatterplot")
<ipython-input-3-f6435d47e026> in save_fig(fig_id, tight_layout, fig_extension, resolution)
     9
            if tight layout:
                plt.tight layout()
    10
            plt.savefig(path, format=fig extension, dpi=resolution)
---> 11
    12
    13 # Ignore useless warnings (see SciPy issue #5998)
~\Anaconda3\lib\site-packages\matplotlib\pyplot.py in savefig(*args, **kwargs)
    714 def savefig(*args, **kwargs):
   715
           fig = gcf()
--> 716
            res = fig.savefig(*args, **kwargs)
    717
            fig.canvas.draw idle() # need this if 'transparent=True' to reset colors
   718
            return res
~\Anaconda3\lib\site-packages\matplotlib\figure.py in savefig(self, fname, transparent, **kwargs)
   2178
                    self.patch.set_visible(frameon)
   2179
-> 2180
                self.canvas.print figure(fname, **kwargs)
   2181
                if frameon:
   2182
~\Anaconda3\lib\site-packages\matplotlib\backend_bases.py in print figure(self, filename, dpi, facecolor, edgecolor, orientatio
n, format, bbox inches, **kwargs)
   2080
                            orientation=orientation,
   2081
                            bbox_inches_restore=_bbox_inches_restore,
-> 2082
                            **kwargs)
   2083
                    finally:
   2084
                        if bbox_inches and restore_bbox:
~\Anaconda3\lib\site-packages\matplotlib\backends\backend_agg.py in print_png(self, filename_or_obj, metadata, pil_kwargs, *arg
s, **kwargs)
                    renderer = self.get renderer()
    528
    529
                    with cbook. setattr cm(renderer, dpi=self.figure.dpi), \
--> 530
                            cbook.open file cm(filename or obj, "wb") as fh:
    531
                        _png.write_png(renderer._renderer, fh,
    532
                                       self.figure.dpi, metadata=metadata)
~\Anaconda3\lib\contextlib.py in enter (self)
                del self.args, self.kwds, self.func
    110
   111
                try:
--> 112
                    return next(self.gen)
   113
                except StopIteration:
   114
                    raise RuntimeError("generator didn't yield") from None
~\Anaconda3\lib\site-packages\matplotlib\cbook\__init__.py in open_file_cm(path_or_file, mode, encoding)
```

```
445 def open_file_cm(path_or_file, mode="r", encoding=None):
            r"""Pass through file objects and context-manage `.PathLike`\s."""
    446
            fh, opened = to filehandle(path or file, mode, True, encoding)
--> 447
            if opened:
    448
    449
                with fh:
~\Anaconda3\lib\site-packages\matplotlib\cbook\__init__.py in to_filehandle(fname, flag, return_opened, encoding)
                    fh = bz2.BZ2File(fname, flag)
    430
    431
                else:
--> 432
                    fh = open(fname, flag, encoding=encoding)
                opened = True
    433
            elif hasattr(fname, 'seek'):
    434
```

FileNotFoundError: [Errno 2] No such file or directory: '.\\images\\end_to_end_project\\income_vs_house_value_scatterplot.png'



```
In [55]: housing["rooms_per_household"] = housing["total_rooms"]/housing["households"]
housing["bedrooms_per_room"] = housing["total_bedrooms"]/housing["total_rooms"]
housing["population_per_household"]=housing["population"]/housing["households"]
```

```
In [56]:
          corr matrix = housing.corr()
          corr_matrix["median_house_value"].sort_values(ascending=False)
Out[56]: median_house_value
                                       1.000000
          median_income
                                        0.687160
          rooms_per_household
                                       0.146285
          total_rooms
                                        0.135097
          housing_median_age
                                        0.114110
         households
                                        0.064506
          total_bedrooms
                                        0.047689
          population_per_household
                                       -0.021985
          population
                                       -0.026920
          longitude
                                       -0.047432
          latitude
                                       -0.142724
          bedrooms_per_room
                                      -0.259984
         Name: median_house_value, dtype: float64
In [63]:
          housing.plot(kind="scatter", x="rooms_per_household", y="median_house_value",
                        alpha=0.3)
          plt.axis([0, 5, 0, 520000])
          plt.show()
             500000
           median_house_value
300000
100000
100000
```

0 -

rooms_per_household

```
In [64]:
           housing.describe()
Out[64]:
                      longitude
                                     latitude housing median age
                                                                    total rooms total bedrooms
                                                                                                  population
                                                                                                               households median income median house value roor
           count 16512.000000
                                16512.000000
                                                     16512.000000
                                                                  16512.000000
                                                                                  16354.000000
                                                                                                16512.000000
                                                                                                              16512.000000
                                                                                                                             16512.000000
                                                                                                                                                  16512.000000
            mean
                    -119.575834
                                   35.639577
                                                        28.653101
                                                                   2622.728319
                                                                                    534.973890
                                                                                                 1419.790819
                                                                                                               497.060380
                                                                                                                                 3.875589
                                                                                                                                                 206990.920724
                      2.001860
                                    2.138058
              std
                                                        12.574726
                                                                   2138.458419
                                                                                    412.699041
                                                                                                 1115.686241
                                                                                                               375.720845
                                                                                                                                 1.904950
                                                                                                                                                 115703.014830
             min
                    -124.350000
                                   32.540000
                                                         1.000000
                                                                       6.000000
                                                                                      2.000000
                                                                                                    3.000000
                                                                                                                  2.000000
                                                                                                                                 0.499900
                                                                                                                                                  14999.000000
             25%
                    -121.800000
                                   33.940000
                                                        18.000000
                                                                   1443.000000
                                                                                    295.000000
                                                                                                  784.000000
                                                                                                               279.000000
                                                                                                                                 2.566775
                                                                                                                                                 119800.000000
             50%
                    -118.510000
                                   34.260000
                                                        29.000000
                                                                   2119.500000
                                                                                    433.000000
                                                                                                 1164.000000
                                                                                                               408.000000
                                                                                                                                 3.540900
                                                                                                                                                 179500.000000
             75%
                                   37.720000
                    -118.010000
                                                        37.000000
                                                                   3141.000000
                                                                                    644.000000
                                                                                                 1719.250000
                                                                                                               602.000000
                                                                                                                                 4.744475
                                                                                                                                                 263900.000000
                                                        52.000000 39320.000000
             max
                    -114.310000
                                   41.950000
                                                                                   6210.000000 35682.000000
                                                                                                              5358.000000
                                                                                                                                15.000100
                                                                                                                                                 500001.000000
          4
           housing = strat train set.drop("median house value", axis=1)
In [65]:
           # drop labels for training set
           housing labels = strat train set["median house value"].copy()
In [66]:
           sample incomplete rows = housing[housing.isnull().any(axis=1)].head()
           sample incomplete rows
Out[66]:
                   longitude latitude housing_median_age total_rooms total_bedrooms population households median_income ocean_proximity
             4629
                     -118.30
                               34.07
                                                    18.0
                                                               3759.0
                                                                                NaN
                                                                                          3296.0
                                                                                                      1462.0
                                                                                                                      2.2708
                                                                                                                                  <1H OCEAN
                     -117.86
             6068
                               34.01
                                                    16.0
                                                               4632.0
                                                                                NaN
                                                                                          3038.0
                                                                                                       727.0
                                                                                                                      5.1762
                                                                                                                                  <1H OCEAN
           17923
                     -121.97
                               37.35
                                                    30.0
                                                               1955.0
                                                                                NaN
                                                                                           999.0
                                                                                                       386.0
                                                                                                                      4.6328
                                                                                                                                  <1H OCEAN
           13656
                     -117.30
                               34.05
                                                     6.0
                                                               2155.0
                                                                                NaN
                                                                                          1039.0
                                                                                                       391.0
                                                                                                                      1.6675
                                                                                                                                     INLAND
                     -122.79
           19252
                               38.48
                                                     7.0
                                                               6837.0
                                                                                NaN
                                                                                          3468.0
                                                                                                      1405.0
                                                                                                                      3.1662
                                                                                                                                  <1H OCEAN
In [67]:
           sample incomplete rows.dropna(subset=["total bedrooms"])
                                                                                 # option 1
```

longitude latitude housing median age total rooms total bedrooms population households median income ocean proximity

Out[67]:

```
In [69]:
          sample incomplete rows.drop("total bedrooms", axis=1)
                                                                             # option 2
Out[69]:
                  longitude latitude housing median age total rooms population households median income ocean proximity
                    -118.30
            4629
                             34.07
                                                  18.0
                                                           3759.0
                                                                      3296.0
                                                                                  1462.0
                                                                                                 2.2708
                                                                                                            <1H OCEAN
            6068
                   -117.86
                                                           4632.0
                                                                      3038.0
                             34.01
                                                  16.0
                                                                                   727.0
                                                                                                 5.1762
                                                                                                            <1H OCEAN
           17923
                   -121.97
                             37.35
                                                  30.0
                                                           1955.0
                                                                       999.0
                                                                                   386.0
                                                                                                 4.6328
                                                                                                            <1H OCEAN
                                                                      1039.0
           13656
                    -117.30
                             34.05
                                                   6.0
                                                           2155.0
                                                                                   391.0
                                                                                                 1.6675
                                                                                                               INLAND
           19252
                   -122.79
                                                                      3468.0
                                                                                  1405.0
                             38.48
                                                   7.0
                                                           6837.0
                                                                                                 3.1662
                                                                                                            <1H OCEAN
In [70]:
          median = housing["total bedrooms"].median()
          sample incomplete rows["total bedrooms"].fillna(median, inplace=True) # option 3
          sample incomplete rows
Out[70]:
                  longitude latitude housing_median_age total_rooms total_bedrooms population households median_income ocean_proximity
                    -118.30
            4629
                             34.07
                                                  18.0
                                                            3759.0
                                                                            433.0
                                                                                     3296.0
                                                                                                 1462.0
                                                                                                                2.2708
                                                                                                                           <1H OCEAN
            6068
                   -117.86
                             34.01
                                                  16.0
                                                           4632.0
                                                                            433.0
                                                                                     3038.0
                                                                                                  727.0
                                                                                                                5.1762
                                                                                                                           <1H OCEAN
           17923
                   -121.97
                             37.35
                                                  30.0
                                                            1955.0
                                                                            433.0
                                                                                      999.0
                                                                                                  386.0
                                                                                                                4.6328
                                                                                                                           <1H OCEAN
           13656
                    -117.30
                             34.05
                                                   6.0
                                                           2155.0
                                                                           433.0
                                                                                     1039.0
                                                                                                  391.0
                                                                                                                1.6675
                                                                                                                              INLAND
           19252
                   -122.79
                             38.48
                                                   7.0
                                                           6837.0
                                                                            433.0
                                                                                     3468.0
                                                                                                 1405.0
                                                                                                                3.1662
                                                                                                                           <1H OCEAN
In [71]: try:
               from sklearn.impute import SimpleImputer # Scikit-Learn 0.20+
          except ImportError:
               from sklearn.preprocessing import Imputer as SimpleImputer
          imputer = SimpleImputer(strategy="median")
          housing num = housing.drop('ocean proximity', axis=1)
In [72]:
          # alternatively: housing num = housing.select dtypes(include=[np.number])
In [73]:
          imputer.fit(housing num)
Out[73]: SimpleImputer(add indicator=False, copy=True, fill value=None,
                          missing values=nan, strategy='median', verbose=0)
In [74]: imputer.statistics
Out[74]: array([-118.51
                                34.26 ,
                                             29.
                                                     , 2119.5
                                                                    433.
                                                                             , 1164.
                   408.
                                 3.54091)
```

```
In [75]:
           housing_num.median().values
Out[75]: array([-118.51 ,
                                              29.
                                                      , 2119.5
                                                                               , 1164.
                                 34.26 ,
                                                                 , 433.
                    408.
                                   3.5409])
In [76]: X = imputer.transform(housing num)
           housing tr = pd.DataFrame(X, columns=housing num.columns,
In [77]:
                                         index=housing.index)
In [78]: housing tr.loc[sample incomplete rows.index.values]
Out[78]:
                   longitude latitude housing_median_age total_rooms total_bedrooms population households median_income
                    -118.30
             4629
                              34.07
                                                   18.0
                                                             3759.0
                                                                              433.0
                                                                                        3296.0
                                                                                                    1462.0
                                                                                                                   2.2708
             6068
                    -117.86
                                                   16.0
                                                             4632.0
                                                                              433.0
                                                                                        3038.0
                                                                                                     727.0
                                                                                                                   5.1762
                              34.01
           17923
                    -121.97
                                                   30.0
                                                                              433.0
                                                                                                     386.0
                                                                                                                   4.6328
                              37.35
                                                             1955.0
                                                                                         999.0
           13656
                                                    6.0
                                                                              433.0
                                                                                        1039.0
                                                                                                     391.0
                    -117.30
                              34.05
                                                             2155.0
                                                                                                                   1.6675
           19252
                    -122.79
                                                             6837.0
                                                                              433.0
                                                                                                    1405.0
                              38.48
                                                    7.0
                                                                                        3468.0
                                                                                                                   3.1662
In [79]:
           imputer.strategy
Out[79]: 'median'
           housing_tr = pd.DataFrame(X, columns=housing_num.columns,
In [80]:
                                         index=housing num.index)
           housing_tr.head()
Out[80]:
                   longitude latitude housing_median_age total_rooms total_bedrooms population households median_income
           17606
                    -121.89
                              37.29
                                                   38.0
                                                              1568.0
                                                                              351.0
                                                                                         710.0
                                                                                                     339.0
                                                                                                                   2.7042
           18632
                    -121.93
                              37.05
                                                   14.0
                                                                              108.0
                                                                                         306.0
                                                                                                     113.0
                                                                                                                   6.4214
                                                              679.0
           14650
                    -117.20
                              32.77
                                                   31.0
                                                              1952.0
                                                                              471.0
                                                                                         936.0
                                                                                                     462.0
                                                                                                                   2.8621
             3230
                    -119.61
                                                   25.0
                                                                              371.0
                                                                                        1460.0
                                                                                                     353.0
                                                                                                                   1.8839
                              36.31
                                                             1847.0
```

1525.0

4459.0

1463.0

3.0347

3555

-118.59

34.23

17.0

6592.0

```
In [81]: # Now Let's preprocess the categorical input feature, ocean proximity:
          housing cat = housing[['ocean proximity']]
          housing_cat.head(10)
Out[81]:
                 ocean_proximity
          17606
                    <1H OCEAN
          18632
                    <1H OCEAN
          14650
                   NEAR OCEAN
           3230
                        INLAND
           3555
                    <1H OCEAN
          19480
                        INLAND
           8879
                    <1H OCEAN
          13685
                       INLAND
           4937
                    <1H OCEAN
           4861
                    <1H OCEAN
In [82]:
          try:
              from sklearn.preprocessing import OrdinalEncoder
          except ImportError:
              from future_encoders import OrdinalEncoder # Scikit-Learn < 0.20</pre>
          ordinal encoder = OrdinalEncoder()
In [83]:
          housing_cat_encoded = ordinal_encoder.fit_transform(housing cat)
          housing cat encoded[:10]
Out[83]: array([[0.],
                 [0.],
                 [4.],
                 [1.],
                 [0.],
                 [1.],
                 [0.],
                 [1.],
                 [0.],
                 [0.]])
In [84]: ordinal_encoder.categories_
Out[84]: [array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],</pre>
                 dtype=object)]
```

```
In [85]: 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</pre>
          cat encoder = OneHotEncoder()
          housing cat 1hot = cat encoder.fit transform(housing cat)
          housing_cat_1hot
Out[85]: <16512x5 sparse matrix of type '<class 'numpy.float64'>'
                 with 16512 stored elements in Compressed Sparse Row format>
In [86]: housing cat 1hot.toarray()
Out[86]: array([[1., 0., 0., 0., 0.],
                [1., 0., 0., 0., 0.],
                [0., 0., 0., 0., 1.],
                 . . . ,
                [0., 1., 0., 0., 0.]
                [1., 0., 0., 0., 0.],
                [0., 0., 0., 1., 0.]
In [87]: | # 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
Out[87]: array([[1., 0., 0., 0., 0.],
                [1., 0., 0., 0., 0.],
                [0., 0., 0., 0., 1.],
                . . . ,
                [0., 1., 0., 0., 0.]
                [1., 0., 0., 0., 0.]
                [0., 0., 0., 1., 0.]
In [88]: cat_encoder.categories_
Out[88]: [array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],</pre>
                dtype=object)]
In [89]: housing.columns
Out[89]: Index(['longitude', 'latitude', 'housing median age', 'total rooms',
                 'total bedrooms', 'population', 'households', 'median income',
                 'ocean proximity'],
               dtype='object')
```

```
In [90]: 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)
```

```
In [92]:
         housing extra attribs = pd.DataFrame(
              housing_extra_attribs,
              columns=list(housing.columns)+["rooms per household", "population per household"],
              index=housing.index)
          housing extra attribs.head()
Out[92]:
                 longitude latitude housing median age total rooms total bedrooms population households median income ocean proximity rooms per household
          17606
                  -121.89
                           37.29
                                                38
                                                          1568
                                                                         351
                                                                                   710
                                                                                              339
                                                                                                          2.7042
                                                                                                                    <1H OCEAN
                                                                                                                                           4.62537
          18632
                  -121.93
                           37.05
                                                14
                                                          679
                                                                         108
                                                                                   306
                                                                                              113
                                                                                                          6.4214
                                                                                                                                           6.00885
                                                                                                                    <1H OCEAN
          14650
                   -117.2
                           32.77
                                                31
                                                          1952
                                                                         471
                                                                                   936
                                                                                              462
                                                                                                          2.8621
                                                                                                                   NEAR OCEAN
                                                                                                                                           4.22511
                  -119.61
           3230
                           36.31
                                                25
                                                          1847
                                                                        371
                                                                                  1460
                                                                                              353
                                                                                                          1.8839
                                                                                                                       INLAND
                                                                                                                                           5.23229
           3555
                  -118.59
                           34.23
                                                17
                                                         6592
                                                                        1525
                                                                                  4459
                                                                                             1463
                                                                                                          3.0347
                                                                                                                    <1H OCEAN
                                                                                                                                           4.50581
In [93]:
         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)
In [94]: housing num tr
Out[94]: array([[-1.15604281, 0.77194962, 0.74333089, ..., -0.31205452,
                  -0.08649871, 0.15531753],
                 [-1.17602483, 0.6596948, -1.1653172, ..., 0.21768338,
                  -0.03353391, -0.83628902],
                 [ 1.18684903, -1.34218285, 0.18664186, ..., -0.46531516,
                  -0.09240499, 0.4222004 ],
                 [ 1.58648943, -0.72478134, -1.56295222, ..., 0.3469342 ,
                  -0.03055414, -0.52177644],
                 [0.78221312, -0.85106801, 0.18664186, ..., 0.02499488]
                   0.06150916, -0.30340741],
                 [-1.43579109, 0.99645926, 1.85670895, ..., -0.22852947,
                  -0.09586294, 0.10180567]])
In [95]: try:
              from sklearn.compose import ColumnTransformer
          except ImportError:
              from future encoders import ColumnTransformer # Scikit-Learn < 0.20</pre>
```

```
In [96]: | num attribs = list(housing num)
         cat attribs = ["ocean proximity"]
         full pipeline = ColumnTransformer([
                ("num", num_pipeline, num_attribs),
                ("cat", OneHotEncoder(), cat attribs),
            1)
         housing prepared = full pipeline.fit transform(housing)
In [97]:
         housing prepared
Out[97]: 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.
                                      ],
               [ 0.78221312, -0.85106801, 0.18664186, ..., 0.
                       , 0.
               [-1.43579109, 0.99645926, 1.85670895, ..., 0.
                           , 0.
                                       11)
In [98]: housing prepared.shape
Out[98]: (16512, 16)
In [99]: 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
```

```
In [100]:
          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)),
              ])
In [101]: from sklearn.pipeline import FeatureUnion
          old full pipeline = FeatureUnion(transformer list=[
                  ("num pipeline", old num pipeline),
                  ("cat pipeline", old cat pipeline),
             ])
In [102]: old housing prepared = old full pipeline.fit transform(housing)
          old housing prepared
Out[102]: array([[-1.15604281, 0.77194962, 0.74333089, ..., 0.
                   0.
                           , 0.
                 [-1.17602483, 0.6596948, -1.1653172, ..., 0.
                         , 0.
                 [ 1.18684903, -1.34218285, 0.18664186, ..., 0.
                   0.
                            , 1.
                                         1,
                 [ 1.58648943, -0.72478134, -1.56295222, ..., 0.
                            , 0.
                   0.
                 [ 0.78221312, -0.85106801, 0.18664186, ..., 0.
                 [-1.43579109, 0.99645926, 1.85670895, ..., 0.
                            , 0.
                                         ]])
                   1.
In [103]: np.allclose(housing prepared, old housing prepared)
Out[103]: True
```

```
In [104]: # Select and train a model
          # working Linear Regression model
          from sklearn.linear_model import LinearRegression
          lin reg = LinearRegression()
          lin_reg.fit(housing_prepared, housing labels)
Out[104]: LinearRegression(copy X=True, fit intercept=True, n jobs=None, normalize=False)
In [105]: # let's try the full preprocessing pipeline on a few training instances
          # It works, although the predictions are not exactly accurate (e.g., the second prediction is off by more than 50%!).
          some data = housing.iloc[:5]
          some labels = housing labels.iloc[:5]
          some data prepared = full pipeline.transform(some data)
          print("Predictions:", lin reg.predict(some data prepared))
          Predictions: [210644.60459286 317768.80697211 210956.43331178 59218.98886849
          189747.55849879]
In [106]: print("Labels:", list(some labels))
          Labels: [286600.0, 340600.0, 196900.0, 46300.0, 254500.0]
In [107]: | some data prepared
Out[107]: 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.
                           1,
                [-1.17602483, 0.6596948 , -1.1653172 , -0.90896655, -1.0369278 ,
                 -0.99833135, -1.02222705, 1.33645936, 0.21768338, -0.03353391,
                                    , 0.
                 -0.83628902, 1.
                                                 , 0.
                                                              , 0.
                  0.
                            1,
                [ 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,
                                      , 1.
                 -0.19645314, 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.
                           11)
                  0.
```

```
In [108]: # typical prediction error of $68,628 is not very satisfying. This is an example of a model underfitting the training data.
          from sklearn.metrics import mean squared error
          housing predictions = lin reg.predict(housing prepared)
          lin_mse = mean_squared_error(housing_labels, housing_predictions)
          lin_rmse = np.sqrt(lin_mse)
          lin rmse
Out[108]: 68628.19819848923
In [109]: from sklearn.metrics import mean absolute error
          lin_mae = mean_absolute_error(housing_labels, housing_predictions)
          lin mae
Out[109]: 49439.89599001897
In [111]: # select a more powerful model, to feed the training algorithm with better features, or to reduce the constraints on the model.
          # Let's train a DecisionTreeRegressor. This is a powerful model, capable of finding complex nonlinear relationships in the data
          from sklearn.tree import DecisionTreeRegressor
          tree_reg = DecisionTreeRegressor(random_state=456)
          tree_reg.fit(housing_prepared, housing labels)
Out[111]: DecisionTreeRegressor(criterion='mse', max depth=None, max features=None,
                                max_leaf_nodes=None, min_impurity_decrease=0.0,
                                min_impurity_split=None, min_samples_leaf=1,
                                min samples split=2, min weight fraction leaf=0.0,
                                presort=False, random state=456, splitter='best')
In [112]: # Could this model really be absolutely perfect
          #$ the model has badly overfit the data
          housing_predictions = tree_reg.predict(housing_prepared)
          tree_mse = mean_squared_error(housing_labels, housing_predictions)
          tree rmse = np.sqrt(tree mse)
          tree rmse
Out[112]: 0.0
In [113]: | ### Fine-tune your model ####
          # The following code performs K-fold cross-validation: it randomly splits the training set into 10 distinct subsets called
          # folds, then it trains and evaluates the Decision Tree model 10 times, picking a different fold for evaluation every time and
          # training on the other 9 folds. The result is an array containing the 10 evaluation scores:
          from sklearn.model_selection import cross val score
          scores = cross val score(tree reg, housing prepared, housing labels,
                                   scoring="neg mean squared error", cv=10)
          tree rmse scores = np.sqrt(-scores)
```

```
In [114]: def display scores(scores):
              print("Scores:", scores)
              print("Mean:", scores.mean())
              print("Standard deviation:", scores.std())
          display_scores(tree_rmse_scores)
          ## Now the Decision Tree doesn't look as good as it did earlier. In fact,
          ## it seems to perform worse than the Linear Regression model!
          Scores: [69685.73500968 66395.31605095 72034.76264608 68598.59209804
           71700.64818069 73674.45171191 70677.84500106 70836.72321577
           75232.90321974 70927.34637046]
          Mean: 70976.43235043726
          Standard deviation: 2354.9763744322877
In [115]: 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: 2731.6740017983493
In [117]: | ## we specify n estimators=10 to avoid a warning about the fact that the default value is going to change to 100 in Scikit-Lear
          # try one last model now: the RandomForestRegressor.
          from sklearn.ensemble import RandomForestRegressor
          forest reg = RandomForestRegressor(n estimators=10, random state=456)
          forest reg.fit(housing prepared, housing labels)
Out[117]: RandomForestRegressor(bootstrap=True, criterion='mse', max depth=None,
                                max features='auto', max leaf nodes=None,
                                min impurity decrease=0.0, min impurity split=None,
                                min samples leaf=1, min samples split=2,
                                min weight fraction leaf=0.0, n estimators=10,
                                n_jobs=None, oob_score=False, random state=456, verbose=0,
                                warm start=False)
```

```
In [118]: housing predictions = forest reg.predict(housing prepared)
          forest mse = mean squared error(housing labels, housing predictions)
          forest rmse = np.sqrt(forest mse)
          forest rmse
          ## Random Forests Look very promising
Out[118]: 22803.989217850758
In [119]: | 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: [52172.27833732 49843.26720706 51931.98899916 55314.52433594
           51941.40376951 55218.3402264 52484.1762354 50145.52727709
           55579.43135802 52896.94021734]
          Mean: 52752.78779632276
          Standard deviation: 1940.5270472422412
In [120]: | scores = cross_val_score(lin_reg, housing_prepared, housing_labels, scoring="neg_mean_squared_error", cv=10)
          pd.Series(np.sqrt(-scores)).describe()
Out[120]: count
                      10.000000
                   69052.461363
          mean
                    2879,437224
          std
                   64969.630564
          min
          25%
                   67136.363758
          50%
                   68156.372635
          75%
                   70982.369487
          max
                   74739.570526
          dtype: float64
In [121]: from sklearn.svm import SVR
          svm reg = SVR(kernel="linear")
          svm reg.fit(housing prepared, housing labels)
          housing_predictions = svm_reg.predict(housing_prepared)
          svm mse = mean squared error(housing labels, housing predictions)
          svm_rmse = np.sqrt(svm_mse)
          svm_rmse
```

Out[121]: 111094.6308539982

```
In [123]: ## evaluate all the possible combinations of hyperparameter values
          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=456)
          # train across 5 folds, that's a total of (12+6)*5=90 rounds of training
          grid search = GridSearchCV(forest reg, param grid, cv=5,
                                     scoring='neg mean squared error', return train score=True)
          grid search.fit(housing prepared, housing labels)
Out[123]: GridSearchCV(cv=5, error score='raise-deprecating',
                       estimator=RandomForestRegressor(bootstrap=True, criterion='mse',
                                                       max depth=None,
                                                       max features='auto',
                                                       max leaf nodes=None,
                                                       min impurity decrease=0.0,
                                                       min_impurity_split=None,
                                                       min samples leaf=1,
                                                       min samples split=2,
                                                       min weight fraction leaf=0.0,
                                                       n estimators='warn', n jobs=None,
                                                       oob score=False, random state=456,
                                                       verbose=0, warm start=False),
                       iid='warn', n jobs=None,
                       param grid=[{'max features': [2, 4, 6, 8],
                                    'n estimators': [3, 10, 30]},
                                   {'bootstrap': [False], 'max_features': [2, 3, 4],
                                    'n estimators': [3, 10]}],
                       pre dispatch='2*n jobs', refit=True, return train score=True,
                       scoring='neg mean squared error', verbose=0)
In [124]: ## The best hyperparameter combination found:
          grid search.best params
Out[124]: {'max features': 8, 'n estimators': 30}
```

```
In [125]: grid search.best estimator
Out[125]: RandomForestRegressor(bootstrap=True, criterion='mse', max depth=None,
                                max features=8, max leaf nodes=None,
                                min impurity decrease=0.0, min impurity split=None,
                                min samples leaf=1, min samples split=2,
                                min weight fraction leaf=0.0, n estimators=30,
                                n jobs=None, oob score=False, random state=456, verbose=0,
                                warm start=False)
In [126]: ## 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)
          64468.241451500224 {'max features': 2, 'n estimators': 3}
          56020.18893461684 {'max_features': 2, 'n_estimators': 10}
          53315.8660113502 {'max features': 2, 'n estimators': 30}
          59943.83252456937 {'max features': 4, 'n estimators': 3}
          53171.32152057854 {'max features': 4, 'n estimators': 10}
          50645.705692833915 {'max features': 4, 'n estimators': 30}
          59142.38014614101 {'max_features': 6, 'n_estimators': 3}
          52676.33094596141 {'max features': 6, 'n estimators': 10}
          50317.055877563944 {'max_features': 6, 'n_estimators': 30}
          58386.66081229148 {'max_features': 8, 'n_estimators': 3}
          52178.13689933393 {'max features': 8, 'n estimators': 10}
          50190.581922030906 {'max features': 8, 'n estimators': 30}
          62801.3232888978 {'bootstrap': False, 'max features': 2, 'n estimators': 3}
          54724.442718324346 {'bootstrap': False, 'max features': 2, 'n estimators': 10}
          60750.13269511117 {'bootstrap': False, 'max features': 3, 'n estimators': 3}
          53126.6236793922 {'bootstrap': False, 'max features': 3, 'n estimators': 10}
          58636.38654396156 {'bootstrap': False, 'max features': 4, 'n estimators': 3}
          52012.67396220179 {'bootstrap': False, 'max features': 4, 'n estimators': 10}
```

In [127]: 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	params	split0_test_score
0	0.122098	0.003035	0.005807	0.000402	2	3	NaN	{'max_features': 2, 'n_estimators': 3}	-3.885432e+09
1	0.431626	0.027912	0.016717	0.000877	2	10	NaN	{'max_features': 2, 'n_estimators': 10}	-2.927840e+09
2	1.199080	0.012779	0.047028	0.001670	2	30	NaN	{'max_features': 2, 'n_estimators': 30}	-2.696168e+09
3	0.185539	0.002339	0.006004	0.000633	4	3	NaN	{'max_features': 4, 'n_estimators': 3}	-3.593934e+09
4	0.651067	0.028065	0.017216	0.001476	4	10	NaN	{'max_features': 4, 'n_estimators': 10}	-2.659265e+09
5	2.035062	0.099283	0.047837	0.003660	4	30	NaN	{'max_features': 4, 'n_estimators': 30}	-2.378088e+09
6	0.266990	0.015927	0.006605	0.000490	6	3	NaN	{'max_features': 6, 'n_estimators': 3}	-3.389611e+09
7	0.937065	0.077307	0.016815	0.000749	6	10	NaN	{'max_features': 6, 'n_estimators': 10}	-2.572952e+09
8	2.732968	0.070698	0.050836	0.009689	6	30	NaN	{'max_features': 6, 'n_estimators': 30}	-2.343883e+09
9	0.336639	0.016826	0.006004	0.000633	8	3	NaN	{'max_features': 8, 'n_estimators': 3}	-3.254609e+09
10	1.178857	0.065689	0.018010	0.002192	8	10	NaN	{'max_features': 8, 'n_estimators': 10}	-2.522807e+09
11	3.361637	0.094524	0.046236	0.000753	8	30	NaN	{'max_features': 8, 'n_estimators': 30}	-2.346582e+09

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_features	param_n_estimators	param_bootstrap	params	split0_test_score
12	0.191335	0.002137	0.006606	0.000490	2	3	False	{'bootstrap': False, 'max_features': 2, 'n_est	-3.790663e+09
13	0.638260	0.007079	0.018216	0.000399	2	10	False	{'bootstrap': False, 'max_features': 2, 'n_est	-2.862670e+09
14	0.247182	0.002687	0.006809	0.000402	3	3	False	{'bootstrap': False, 'max_features': 3, 'n_est	-3.382557e+09
15	0.942389	0.101655	0.020215	0.002928	3	10	False	{'bootstrap': False, 'max_features': 3, 'n_est	-2.590158e+09
16	0.302418	0.003192	0.006405	0.000490	4	3	False	{'bootstrap': False, 'max_features': 4, 'n_est	-3.229346e+09
17	1.056156	0.061352	0.018813	0.001166	4	10	False	{'bootstrap': False, 'max_features': 4, 'n_est	-2.537274e+09

18 rows × 23 columns

4

```
In [130]: | 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=456)
          rnd_search = RandomizedSearchCV(forest_reg, param_distributions=param_distribs,
                                           n iter=10, cv=5, scoring='neg mean squared error', random state=42)
          rnd_search.fit(housing_prepared, housing_labels)
Out[130]: RandomizedSearchCV(cv=5, error score='raise-deprecating',
                             estimator=RandomForestRegressor(bootstrap=True,
                                                              criterion='mse',
                                                              max depth=None,
                                                              max_features='auto',
                                                              max leaf nodes=None,
                                                              min impurity decrease=0.0,
                                                              min impurity split=None,
                                                              min samples leaf=1,
                                                              min samples split=2,
                                                              min_weight_fraction_leaf=0.0,
                                                              n estimators='warn',
                                                              n jobs=None, oob score=False,
                                                              random sta...
                                                              warm_start=False),
                             iid='warn', n iter=10, n jobs=None,
                             param_distributions={'max_features': <scipy.stats._distn_infrastructure.rv_frozen object at 0x0000007B15B615C
          0>,
                                                   'n estimators': <scipy.stats. distn infrastructure.rv frozen object at 0x0000007B15B6132
          0>},
                             pre dispatch='2*n jobs', random state=42, refit=True,
                             return train score=False, scoring='neg mean squared error',
                             verbose=0)
In [131]: cvres = rnd search.cv results
          for mean_score, params in zip(cvres["mean_test_score"], cvres["params"]):
              print(np.sqrt(-mean_score), params)
          49138.34350627016 {'max_features': 7, 'n_estimators': 180}
          51016.640434110166 {'max features': 5, 'n estimators': 15}
          50745.93937668918 {'max_features': 3, 'n_estimators': 72}
          50499.23542597587 {'max_features': 5, 'n_estimators': 21}
          49199.76606594992 {'max_features': 7, 'n_estimators': 122}
          50704.7725743003 {'max features': 3, 'n estimators': 75}
          50578.41323880302 {'max_features': 3, 'n_estimators': 88}
          49278.36148584473 {'max_features': 5, 'n_estimators': 100}
          50309.221904590486 {'max features': 3, 'n estimators': 150}
          63405.37600274506 {'max features': 5, 'n estimators': 2}
```

```
In [132]: feature importances = grid search.best estimator .feature importances
          feature importances
Out[132]: array([7.27757602e-02, 6.43307108e-02, 4.15876610e-02, 1.54680286e-02,
                 1.47917922e-02, 1.54825018e-02, 1.36596396e-02, 3.77683075e-01,
                 4.14196745e-02, 1.12041045e-01, 6.31432957e-02, 7.94461562e-03,
                 1.54802112e-01, 9.28233619e-05, 2.07122723e-03, 2.70603698e-03])
In [133]: extra_attribs = ["rooms_per_hhold", "pop_per_hhold", "bedrooms_per_room"]
          #cat encoder = cat pipeline.named steps["cat encoder"] # old solution
          cat encoder = full_pipeline.named_transformers_["cat"]
          cat one hot attribs = list(cat encoder.categories [0])
          attributes = num attribs + extra attribs + cat one hot attribs
          sorted(zip(feature importances, attributes), reverse=True)
Out[133]: [(0.3776830751371189, 'median_income'),
           (0.1548021123341523, 'INLAND'),
           (0.11204104488089804, 'pop per hhold'),
           (0.07277576023549523, 'longitude'),
           (0.0643307107957676, 'latitude'),
           (0.06314329569219225, 'bedrooms per room'),
           (0.04158766102908416, 'housing_median_age'),
           (0.041419674485049914, 'rooms_per_hhold'),
           (0.015482501822875196, 'population'),
           (0.015468028588720607, 'total rooms'),
           (0.014791792176536374, 'total bedrooms'),
           (0.013659639634435587, 'households'),
           (0.007944615618082284, '<1H OCEAN'),
           (0.0027060369796617053, 'NEAR OCEAN'),
           (0.002071227227994808, 'NEAR BAY'),
           (9.282336193511499e-05, 'ISLAND')]
In [134]: final model = grid search.best estimator
          X test = strat test set.drop("median house value", axis=1)
          y test = strat test set["median house value"].copy()
          X test prepared = full pipeline.transform(X test)
          final predictions = final model.predict(X test prepared)
          final_mse = mean_squared_error(y_test, final_predictions)
          final rmse = np.sqrt(final mse)
In [135]: final rmse
Out[135]: 47585.462194452804
In [136]:
          ### We can compute a 95% confidence interval for the test RMSE:
          from scipy import stats
```

```
In [137]: | 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)))
Out[137]: array([45576.45099334, 49513.02393685])
In [138]: tscore = stats.t.ppf((1 + confidence) / 2, df=m - 1)
          tmargin = tscore * squared errors.std(ddof=1) / np.sqrt(m)
          np.sqrt(mean - tmargin), np.sqrt(mean + tmargin)
Out[138]: (45576.450993336584, 49513.02393685269)
In [139]: ## 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)
Out[139]: (45577.053174264045, 49512.46962604134)
In [140]:
          ### A full pipeline with both preparation and prediction
          full pipeline with predictor = Pipeline([
                  ("preparation", full_pipeline),
                  ("linear", LinearRegression())
              1)
          full pipeline with predictor.fit(housing, housing labels)
          full pipeline with predictor.predict(some data)
Out[140]: array([210644.60459286, 317768.80697211, 210956.43331178, 59218.98886849,
                 189747.55849879])
In [141]:
          ## Model persistence using joblib
          my model = full pipeline with predictor
```

```
In [142]: from sklearn.externals import joblib
    joblib.dump(my_model, "my_model.pkl") # DIFF
#...
    my_model_loaded = joblib.load("my_model.pkl") # DIFF
```

C:\Users\nilesh\Anaconda3\lib\site-packages\sklearn\externals\joblib__init__.py:15: DeprecationWarning: sklearn.externals.joblib is deprecated in 0.21 and will be removed in 0.23. Please import this functionality directly from joblib, which can be install ed with: pip install joblib. If this warning is raised when loading pickled models, you may need to re-serialize those models with scikit-learn 0.21+.

warnings.warn(msg, category=DeprecationWarning)

In []: ### Example SciPy distributions for RandomizedSearchCV

