Chapter 2 – End-to-end Machine Learning project

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

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

Run in Google Colab (https://colab.research.google.com/github/ageron/handson-ml2/blob/master/02_end_to_end_machine_learning_project.ipynb)

Setup

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

In [1]:
```
# Python ≥3.5 is required
import sys
assert sys.version_info >= (3, 5)

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

# Common imports
import numpy as np
import os

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

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

def save_fig(fig_id, tight_layout=True, fig_extension="png", resolution=30
0):
    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")
```

Get the data

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

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

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

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

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

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

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

Out[5]:

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

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

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

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

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

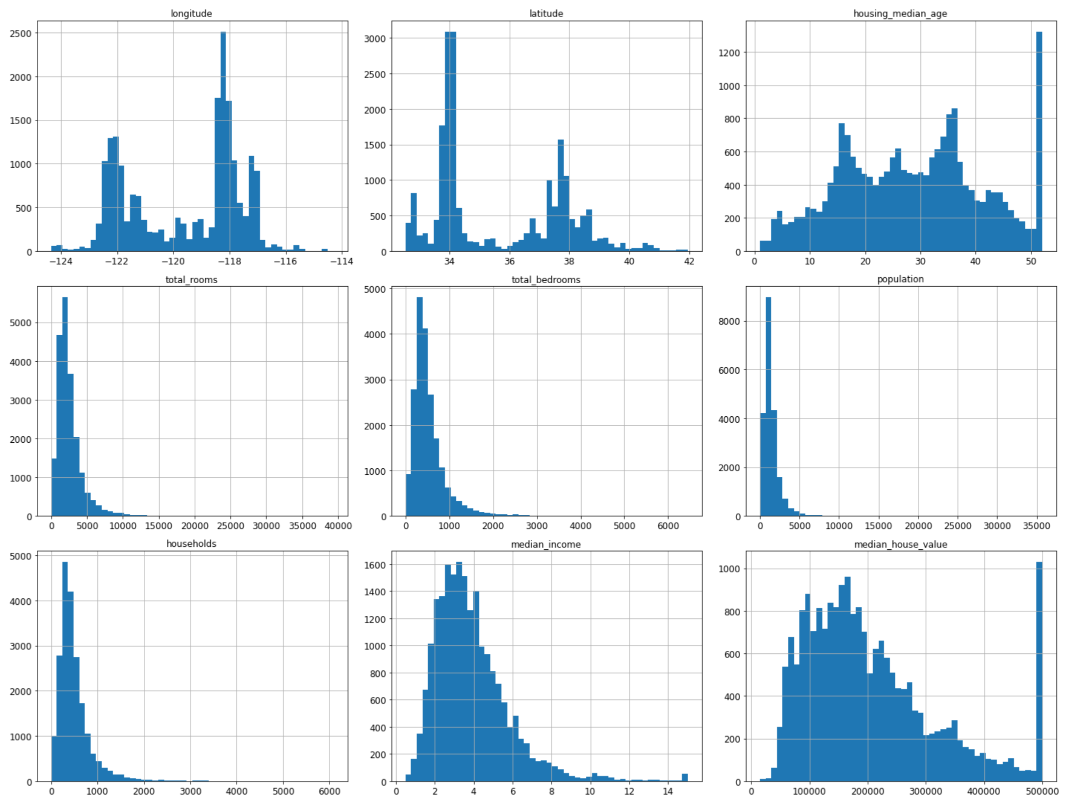
In [8]:
```
housing.describe()
```

Out[8]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462122
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000000

In [9]:
```
%matplotlib inline
import matplotlib.pyplot as plt
housing.hist(bins=50, figsize=(20,15))
save_fig("attribute_histogram_plots")
plt.show()
```

```
Saving figure attribute_histogram_plots
```



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

In [11]:
```
from sklearn.model_selection import train_test_split

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

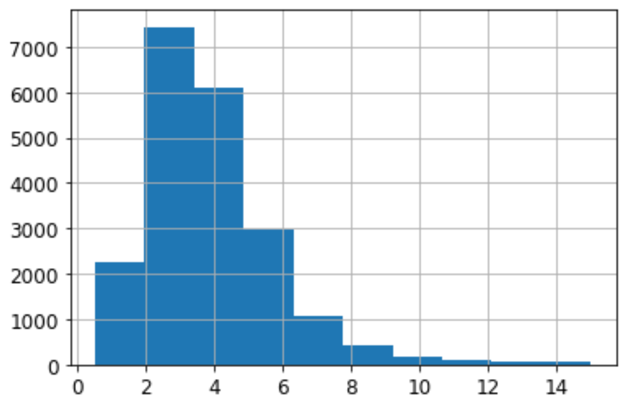
In [12]:
```
test_set.head()
```

Out[12]:

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

In [12]:
```
housing["median_income"].hist()
```

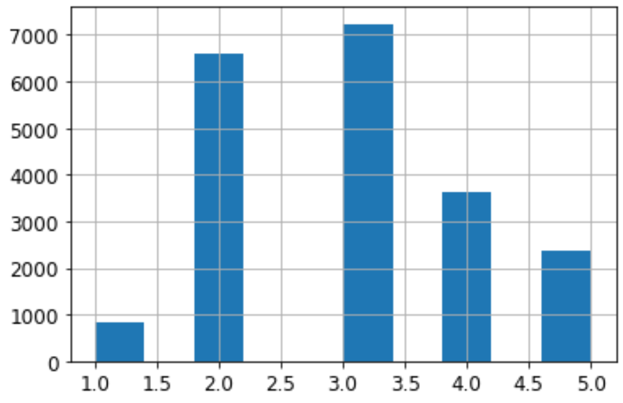
Out[12]:
```
<AxesSubplot:>
```



In [14]:
```
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 [15]:
```
housing["income_cat"].value_counts()
```

Out[15]:
```
3    7236
2    6581
4    3639
5    2362
1     822
Name: income_cat, dtype: int64
```

In [16]:
```
housing["income_cat"].hist()
```
Out[16]:
```
<AxesSubplot:>
```


In [17]:
```
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 [18]:
```
strat_test_set["income_cat"].value_counts() / len(strat_test_set)
```
Out[18]:
```
3    0.350533
2    0.318798
4    0.176357
5    0.114583
1    0.039729
Name: income_cat, dtype: float64
```

In [19]:
```
housing["income_cat"].value_counts() / len(housing)
```
Out[19]:
```
3    0.350581
2    0.318847
4    0.176308
5    0.114438
1    0.039826
Name: income_cat, dtype: float64
```

In [20]:
```
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_prop
s["Overall"] - 100
compare_props["Strat. %error"] = 100 * compare_props["Stratified"] / compare
_props["Overall"] - 100
```

In [21]:
```
compare_props
```

Out[21]:

	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

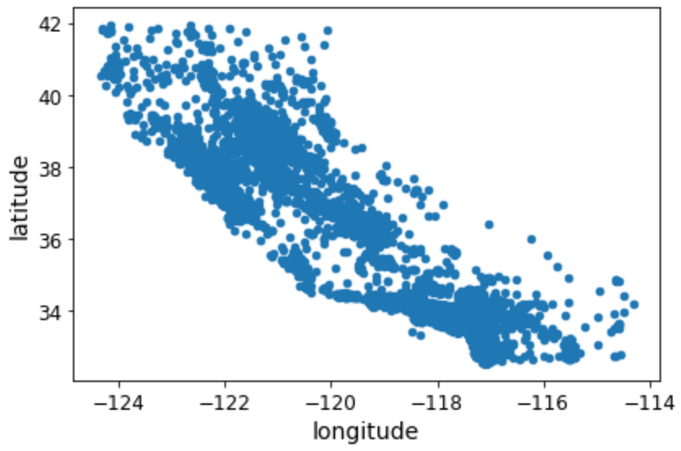
In [22]:
```
for set_ in (strat_train_set, strat_test_set):
    set_.drop("income_cat", axis=1, inplace=True)
```

Discover and visualize the data to gain insights

In [23]:
```
housing = strat_train_set.copy()
```

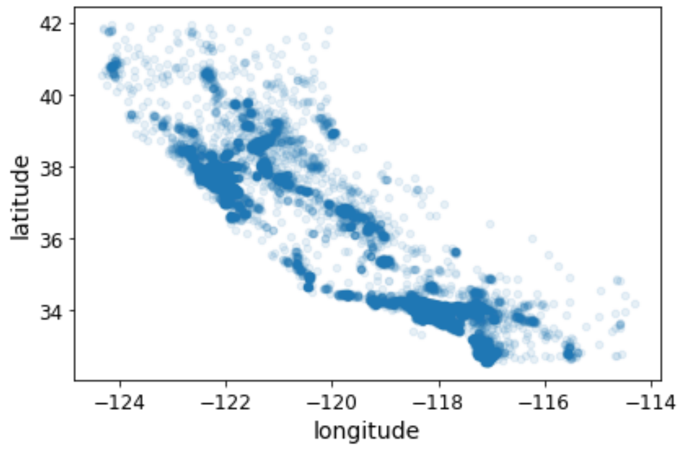
In [24]:
```
housing.plot(kind="scatter", x="longitude", y="latitude")
save_fig("bad_visualization_plot")
```

```
Saving figure bad_visualization_plot
```



In [25]:
```
housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.1)
save_fig("better_visualization_plot")
```

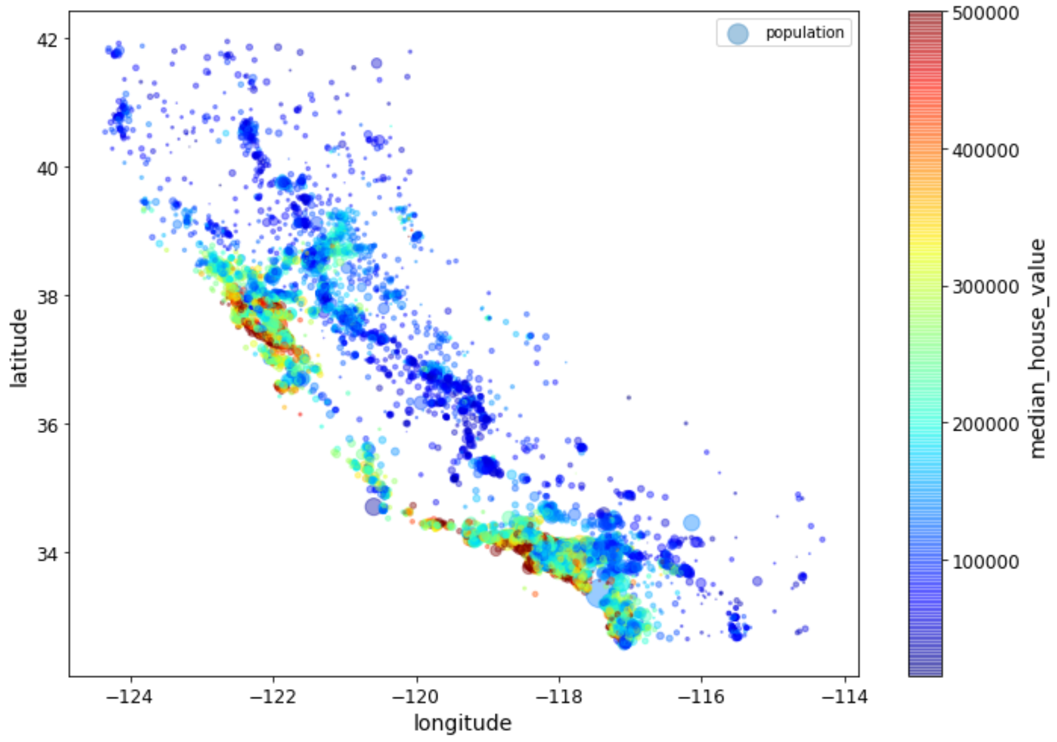
```
Saving figure better_visualization_plot
```



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

In [26]:
```
housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.4,
    s=housing["population"]/100, label="population", figsize=(10,7),
    c="median_house_value", cmap=plt.get_cmap("jet"), colorbar=True,
    sharex=False)
plt.legend()
save_fig("housing_prices_scatterplot")
```

```
Saving figure housing_prices_scatterplot
```



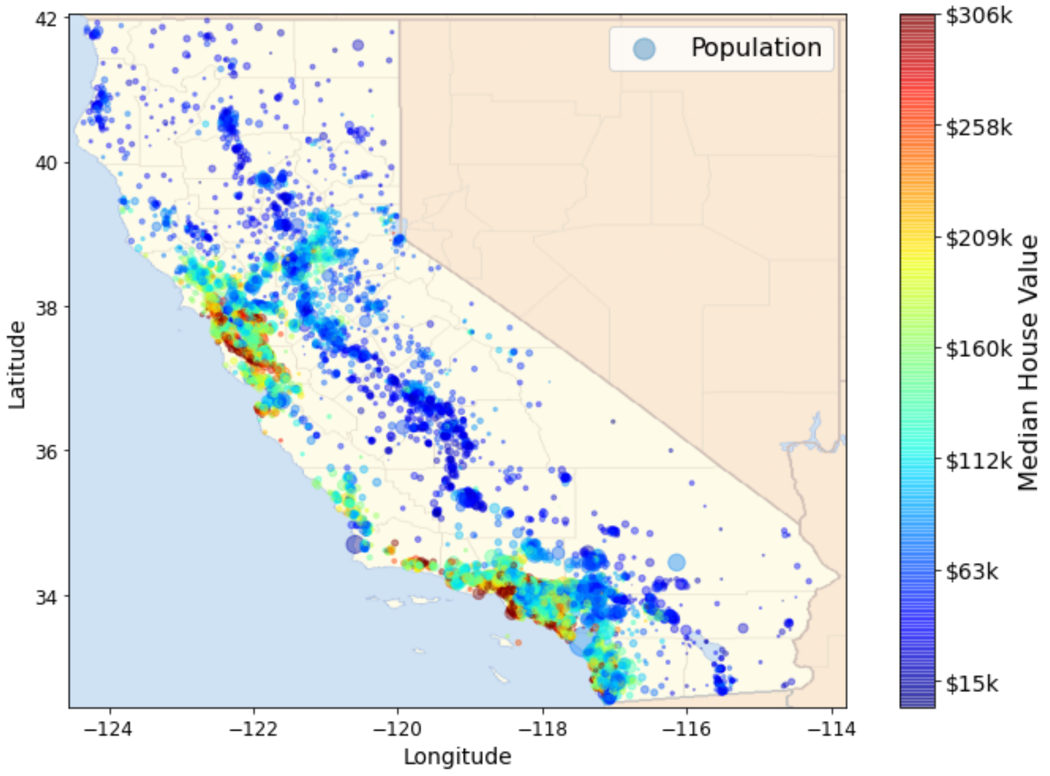
In [27]:
```
# Download the California image
images_path = os.path.join(PROJECT_ROOT_DIR, "images", "end_to_end_project")
os.makedirs(images_path, exist_ok=True)
DOWNLOAD_ROOT = "https://raw.githubusercontent.com/ageron/handson-ml2/master
/"
filename = "california.png"
print("Downloading", filename)
url = DOWNLOAD_ROOT + "images/end_to_end_project/" + filename
urllib.request.urlretrieve(url, os.path.join(images_path, filename))
```

```
Downloading california.png
```

Out[27]:
```
('.\\images\\end_to_end_project\\california.png',
 <http.client.HTTPMessage at 0x2703853d508>)
```

In [28]:
```
import matplotlib.image as mpimg
california_img=mpimg.imread(os.path.join(images_path, filename))
ax = housing.plot(kind="scatter", x="longitude", y="latitude", figsize=(10,
7),
                       s=housing['population']/100, label="Population",
                       c="median_house_value", cmap=plt.get_cmap("jet"),
                       colorbar=False, alpha=0.4,
                      )
plt.imshow(california_img, extent=[-124.55, -113.80, 32.45, 42.05], alpha=0.
5,
           cmap=plt.get_cmap("jet"))
plt.ylabel("Latitude", fontsize=14)
plt.xlabel("Longitude", fontsize=14)

prices = housing["median_house_value"]
tick_values = np.linspace(prices.min(), prices.max(), 11)
cbar = plt.colorbar()
cbar.ax.set_yticklabels(["$%dk"%(round(v/1000)) for v in tick_values], fonts
ize=14)
cbar.set_label('Median House Value', fontsize=16)

plt.legend(fontsize=16)
save_fig("california_housing_prices_plot")
plt.show()
```

```
C:\Users\Tamy\Anaconda3\envs\tf\lib\site-packages\ipykernel_launcher.py:16: U
serWarning: FixedFormatter should only be used together with FixedLocator
  app.launch_new_instance()

Saving figure california_housing_prices_plot
```



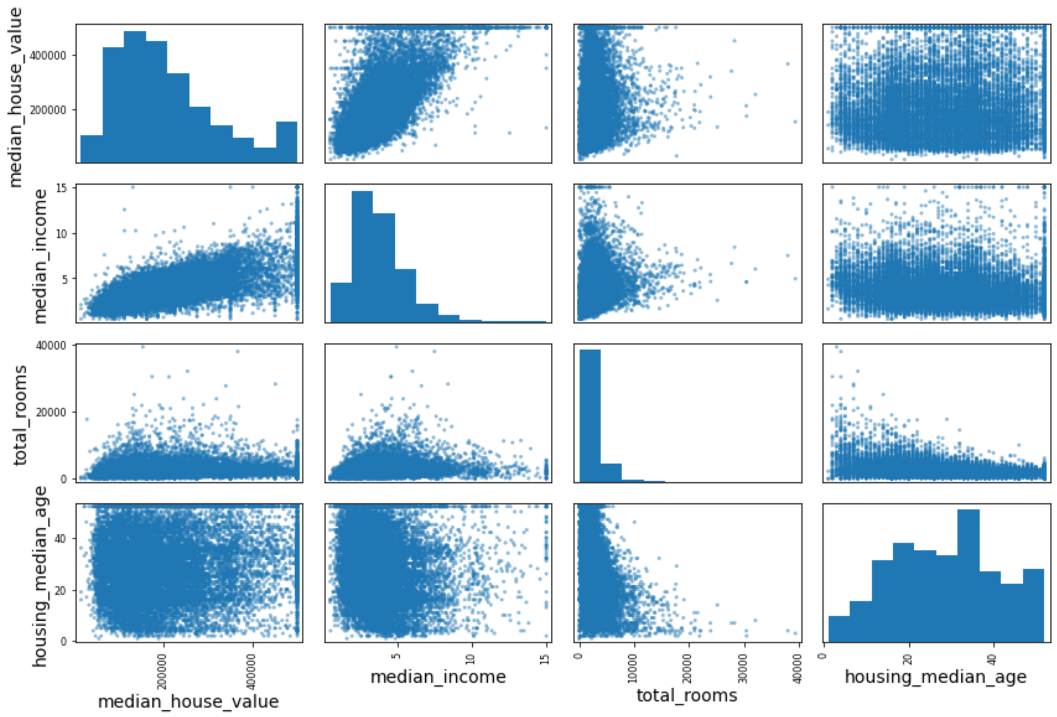
In [29]:
```
corr_matrix = housing.corr()
```

In [30]:
```
corr_matrix["median_house_value"].sort_values(ascending=False)
```

Out[30]:
```
median_house_value    1.000000
median_income         0.687160
total_rooms           0.135097
housing_median_age    0.114110
households            0.064506
total_bedrooms        0.047689
population           -0.026920
longitude            -0.047432
latitude             -0.142724
Name: median_house_value, dtype: float64
```

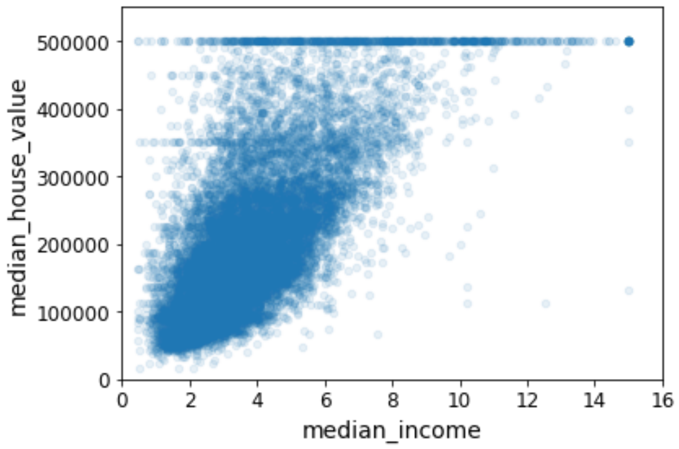
In [31]:
```
# from pandas.tools.plotting import scatter_matrix # For older versions of P
andas
from pandas.plotting import scatter_matrix

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

```
Saving figure scatter_matrix_plot
```



In [32]:
```
housing.plot(kind="scatter", x="median_income", y="median_house_value",
             alpha=0.1)
plt.axis([0, 16, 0, 550000])
save_fig("income_vs_house_value_scatterplot")
```

```
Saving figure income_vs_house_value_scatterplot
```

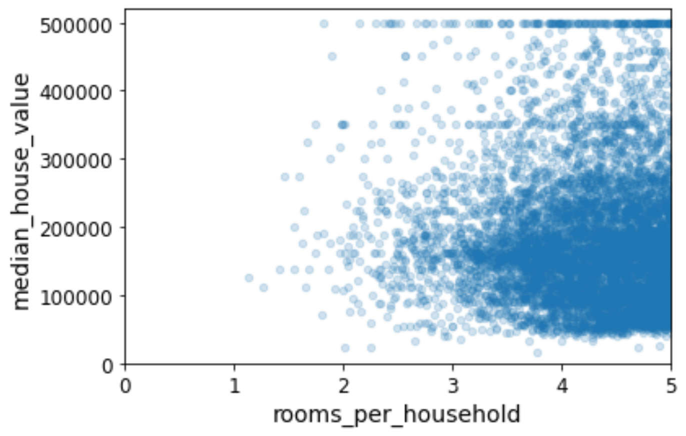


In [33]:
```
housing["rooms_per_household"] = housing["total_rooms"]/housing["households"]
housing["bedrooms_per_room"] = housing["total_bedrooms"]/housing["total_rooms"]
housing["population_per_household"]=housing["population"]/housing["households"]
```

In [34]:
```
corr_matrix = housing.corr()
corr_matrix["median_house_value"].sort_values(ascending=False)
```

Out[34]:
```
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 [35]:
```
housing.plot(kind="scatter", x="rooms_per_household", y="median_house_valu
e",
             alpha=0.2)
plt.axis([0, 5, 0, 520000])
plt.show()
```



In [36]:
```
housing.describe()
```

Out[36]:

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

Prepare the data for Machine Learning algorithms

In [37]:
```
housing = strat_train_set.drop("median_house_value", axis=1) # drop labels f
or training set
housing_labels = strat_train_set["median_house_value"].copy()
```

In [38]:
```
sample_incomplete_rows = housing[housing.isnull().any(axis=1)].head()
sample_incomplete_rows
```

Out[38]:

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

In [39]:
```
sample_incomplete_rows.dropna(subset=["total_bedrooms"])    # option 1
```

Out[39]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_

In [40]:
```
sample_incomplete_rows.drop("total_bedrooms", axis=1)       # option 2
```

Out[40]:

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

In [41]:
```
median = housing["total_bedrooms"].median()
sample_incomplete_rows["total_bedrooms"].fillna(median, inplace=True) # opti
on 3
```

In [42]:
```
sample_incomplete_rows
```

Out[42]:

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

In [43]:
```
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy="median")
```

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

In [44]:
```
housing_num = housing.drop("ocean_proximity", axis=1)
# alternatively: housing_num = housing.select_dtypes(include=[np.number])
```

In [45]:
```
imputer.fit(housing_num)
```

Out[45]:
```
SimpleImputer(strategy='median')
```

In [46]:
```
imputer.statistics_
```

Out[46]:
```
array([-118.51  ,   34.26  ,   29.    , 2119.5   ,  433.    , 1164.    ,
        408.    ,    3.5409])
```

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

In [47]:
```
housing_num.median().values
```

Out[47]:
```
array([-118.51  ,   34.26  ,   29.    , 2119.5   ,  433.    , 1164.    ,
        408.    ,    3.5409])
```

Transform the training set:

In [48]:
```
X = imputer.transform(housing_num)
```

In [49]:
```
housing_tr = pd.DataFrame(X, columns=housing_num.columns,
                          index=housing.index)
```

In [50]:
```
housing_tr.loc[sample_incomplete_rows.index.values]
```

Out[50]:

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

In [51]:
```
imputer.strategy
```

Out[51]:
```
'median'
```

In [52]:
```
housing_tr = pd.DataFrame(X, columns=housing_num.columns,
                          index=housing_num.index)
```

In [53]:
```
housing_tr.head()
```

Out[53]:

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

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

In [54]:
```python
housing_cat = housing[["ocean_proximity"]]
housing_cat.head(10)
```

Out[54]:

	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 [55]:
```python
from sklearn.preprocessing import OrdinalEncoder

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

Out[55]:
```
array([[0.],
       [0.],
       [4.],
       [1.],
       [0.],
       [1.],
       [0.],
       [1.],
       [0.],
       [0.]])
```

In [56]:
```python
ordinal_encoder.categories_
```

Out[56]:
```
[array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],
       dtype=object)]
```

In [57]:
```python
from sklearn.preprocessing import OneHotEncoder

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

Out[57]:
```
<16512x5 sparse matrix of type '<class 'numpy.float64'>'
	with 16512 stored elements in Compressed Sparse Row format>
```

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

```
In [58]: housing_cat_1hot.toarray()

Out[58]: array([[1., 0., 0., 0., 0.],
                [1., 0., 0., 0., 0.],
                [0., 0., 0., 0., 1.],
                ...,
                [0., 1., 0., 0., 0.],
                [1., 0., 0., 0., 0.],
                [0., 0., 0., 1., 0.]])
```

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

```
In [59]: cat_encoder = OneHotEncoder(sparse=False)
         housing_cat_1hot = cat_encoder.fit_transform(housing_cat)
         housing_cat_1hot

Out[59]: 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 [60]: cat_encoder.categories_

Out[60]: [array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],
                dtype=object)]
```

```
In [ ]:
```