Machine Learning - End to End Project

- **Setup**

❖ Make sure this notebook works well in both python 2 and 3, import a few common modules, ensure MatplotLib plots figures inline and prepare a function to save the figures

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

# Common imports
import numpy as np
import os

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

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

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

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

Machine Learning - End to End Project

- **Get the data**

❖ Download a single compressed file, housing.tgz and decompress the file to the hard disk in the directory /workspace/datasets/housing

- Option 1: Manually
  - Download housing.tgz from Internet
  - tar xzf housing.tgz
- Option 2: Programmably

```
import os
import tarfile
from six.moves import urllib

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

###############################################################################################
# 1. all fetch_housing_data() to create a
#    datasets/housing directory in your workspace
# 2. downloads the housing.tgz file,
#       https://raw.githubusercontent.com/ageron/handson-ml/master/datasets/housing/housing.tgz
#    and extracts the
#    housing.csv from it in this directory.
###############################################################################################
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()
```

tep 2: Load the data to the RAM using Pandas

```
import pandas as pd

#############################################################
# This function returns a Pandas DataFrame object containing
# all the data.
#############################################################
def load_housing_data(housing_path=HOUSING_PATH):
    csv_path = os.path.join(housing_path, "housing.csv")
    return pd.read_csv(csv_path)
```

Machine Learning - End to End Project

- **Get the data**

❖ Download a single compressed file, housing.tgz and decompress the file to the hard disk in the directory /workspace/datasets/housing

❖ Display data

```
[2] import os
    import tarfile
    import urllib.request

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

    def fetch_housing_data(housing_url=HOUSING_URL, housing_path=HOUSING_PATH):
        os.makedirs(housing_path, exist_ok=True)
        tgz_path = os.path.join(housing_path, "housing.tgz")
        urllib.request.urlretrieve(housing_url, tgz_path)
        housing_tgz = tarfile.open(tgz_path)
        housing_tgz.extractall(path=housing_path)
        housing_tgz.close()
```

```
[3] fetch_housing_data()
```

```
[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)
```

Machine Learning - End to End Project

- **Get the data**

❖ Download a single compressed file, housing.tgz and decompress the file to the hard disk in the directory /workspace/datasets/housing

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

	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

```
[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
```

Machine Learning - End to End Project

- **Get the data**

❖ Download a single compressed file, housing.tgz and decompress the file to the hard disk in the directory /workspace/datasets/housing

❖ Display data

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

	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

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

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

Machine Learning - End to End Project

- **Get the data**

- Download a single compressed file, housing.tgz and decompress the file to the hard disk in the directory /workspace/datasets/housing
- Display data

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

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value
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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

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

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

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

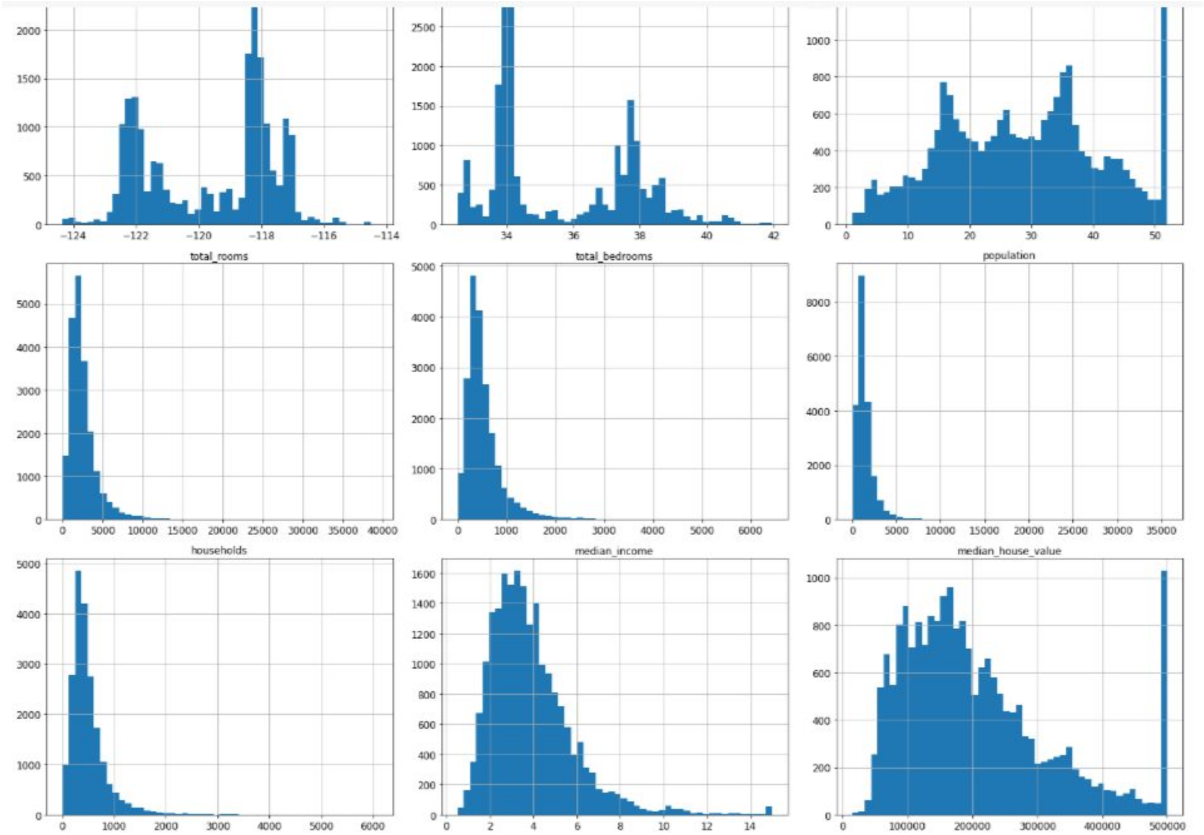
Machine Learning - End to End Project

- **Get the data**

❖ Download a single compressed file, housing.tgz and decompress the file to the hard disk in the directory /workspace/datasets/housing

❖ Show attribute histogram plots

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



Machine Learning - End to End Project

- Get the data

❖ Download a single compressed file, housing.tgz and decompress the file to the hard disk in the directory /workspace/datasets/housing

❖ Implement Test Check

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

```
[11] import numpy as np

     # For illustration only. Sklearn has train_test_split()
     def split_train_test(data, test_ratio):
         shuffled_indices = np.random.permutation(len(data))
         test_set_size = int(len(data) * test_ratio)
         test_indices = shuffled_indices[:test_set_size]
         train_indices = shuffled_indices[test_set_size:]
         return data.iloc[train_indices], data.iloc[test_indices]
```

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

     16512 train + 4128 test
```

```
[13] from zlib import crc32

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

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

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

Machine Learning - End to End Project

- Get the data

❖ Download a single compressed file, housing.tgz and decompress the file to the hard disk in the directory /workspace/datasets/housing

❖ Check if the test_set_check() in the previous clide works fine in both Python 2 and Python 3

```
[14] import hashlib

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

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

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

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

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

Machine Learning - End to End Project

```
test_set.head()
```

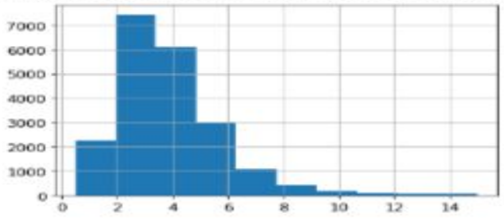
	index	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_proximity	id
8	8	-122.26	37.84	42.0	2555.0	665.0	1206.0	595.0	2.0804	226700.0	NEAR BAY	-122222.16
10	10	-122.26	37.85	52.0	2202.0	434.0	910.0	402.0	3.2031	281500.0	NEAR BAY	-122222.15
11	11	-122.26	37.85	52.0	3503.0	752.0	1504.0	734.0	3.2705	241800.0	NEAR BAY	-122222.15
12	12	-122.26	37.85	52.0	2491.0	474.0	1098.0	468.0	3.0750	213500.0	NEAR BAY	-122222.15
13	13	-122.26	37.84	52.0	696.0	191.0	345.0	174.0	2.6736	191300.0	NEAR BAY	-122222.16

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

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

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

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_proximity
20046	-119.01	36.06	25.0	1505.0	NaN	1392.0	359.0	1.6812	47700.0	INLAND
3024	-119.46	35.14	30.0	2943.0	NaN	1565.0	584.0	2.5313	45800.0	INLAND
15663	-122.44	37.80	52.0	3830.0	NaN	1310.0	963.0	3.4801	500001.0	NEAR BAY
20484	-118.72	34.28	17.0	3051.0	NaN	1705.0	495.0	5.7376	218600.0	<1H OCEAN
9814	-121.93	36.62	34.0	2351.0	NaN	1063.0	428.0	3.7250	278000.0	NEAR OCEAN

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

<matplotlib.axes._subplots.AxesSubplot at 0x7fcee5b522e0>
```



Machine Learning - End to End Project

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

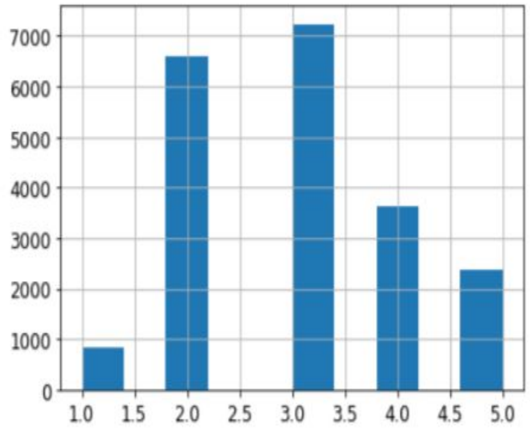
```
[22] housing["income_cat"] = pd.cut(housing["median_income"],
                                    bins=[0., 1.5, 3.0, 4.5, 6., np.inf],
                                    labels=[1, 2, 3, 4, 5])
```

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

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

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

<matplotlib.axes._subplots.AxesSubplot at 0x7fcee5aaaf40>




```
[25] from sklearn.model_selection import StratifiedShuffleSplit

     split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
     for train_index, test_index in split.split(housing, housing["income_cat"]):
         strat_train_set = housing.loc[train_index]
         strat_test_set = housing.loc[test_index]
```

Machine Learning - End to End Project

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

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

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

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

[28]
```
def income_cat_proportions(data):
    return data["income_cat"].value_counts() / len(data)

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

compare_props = pd.DataFrame({
    "Overall": income_cat_proportions(housing),
    "Stratified": income_cat_proportions(strat_test_set),
    "Random": income_cat_proportions(test_set),
}).sort_index()
compare_props["Rand. %error"] = 100 * compare_props["Random"] / compare_props["Overall"] - 100
compare_props["Strat. %error"] = 100 * compare_props["Stratified"] / compare_props["Overall"] - 100
```

[29]
```
compare_props
```

	Overall	Stratified	Random	Rand. %error	Strat. %error
1	0.039826	0.039971	0.040213	0.973236	0.364964
2	0.318847	0.318798	0.324370	1.732260	-0.015195
3	0.350581	0.350533	0.358527	2.266446	-0.013820
4	0.176308	0.176357	0.167393	-5.056334	0.027480
5	0.114438	0.114341	0.109496	-4.318374	-0.084674

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

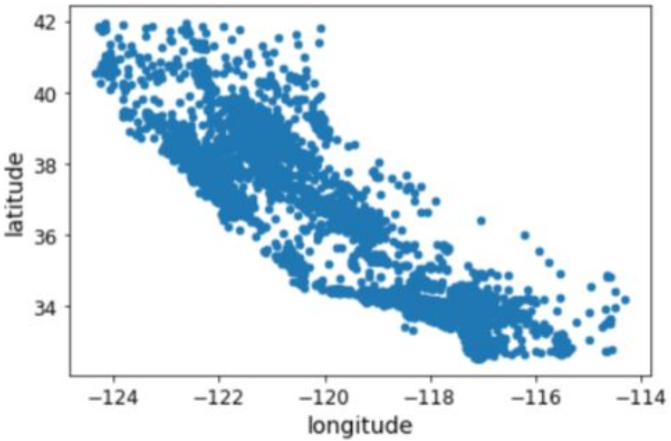
Machine Learning - End to End Project

❖ Discover and visualize the data to gain insights

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

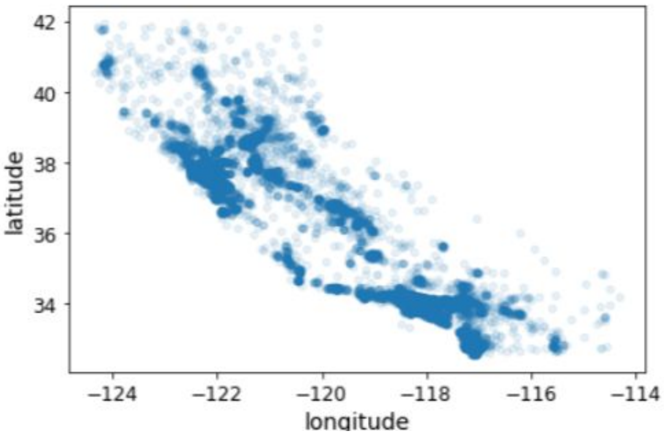
```
housing.plot(kind="scatter", x="longitude", y="latitude")
save_fig("bad_visualization_plot")
```

Saving figure bad_visualization_plot




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

Saving figure better_visualization_plot

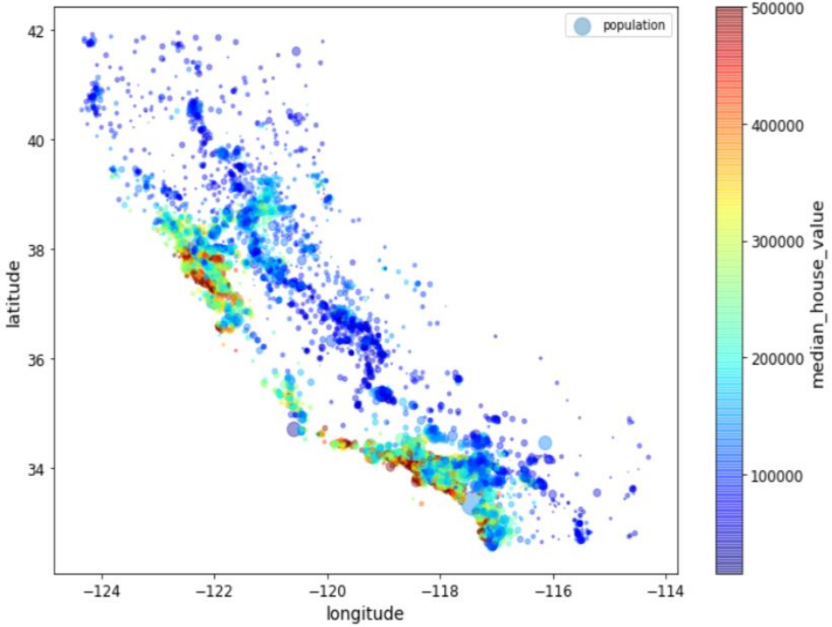



```
[34] housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.4,
         s=housing["population"]/100, label="population", figsize=(10,7),
         c="median_house_value", cmap=plt.get_cmap("jet"), colorbar=True,
         sharex=False)
     plt.legend()
     save_fig("housing_prices_scatterplot")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

Machine Learning - End to End Project

- Discover and visualize the data to gain insights

Saving figure housing_prices_scatterplot




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

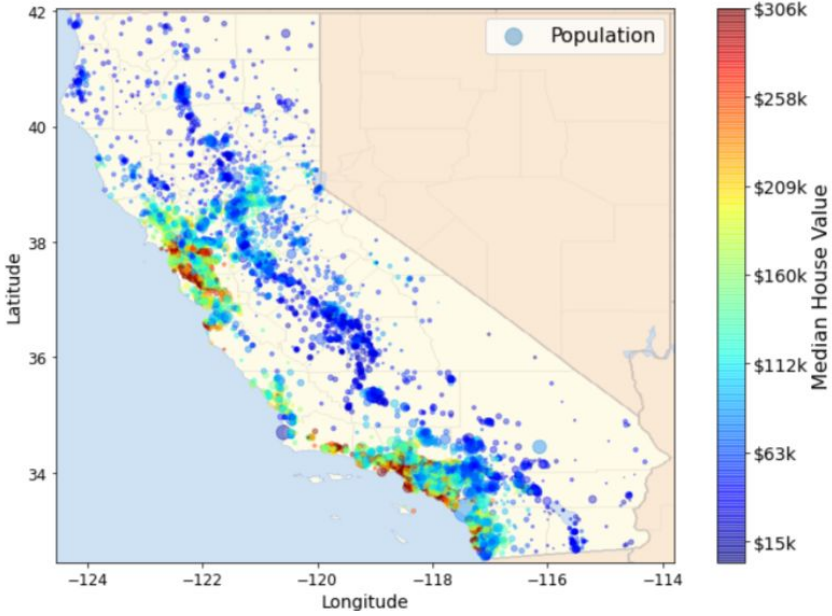
```
Downloading california.png
('./images/end_to_end_project/california.png',
 <http.client.HTTPMessage at 0x7fcee598dbe0>)
```

```
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()
```

Machine Learning - End to End Project

❖ Discover and visualize the data to gain insights

Saving figure california_housing_prices_plot




```
[37] corr_matrix = housing.corr()
```

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

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

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

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

Machine Learning - End to End Project

❖ Discover and visualize the data to gain insights

```
[37] corr_matrix = housing.corr()
```

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

```
median_house_value    1.000000
median_income         0.687151
total_rooms           0.135140
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total_bedrooms        0.047781
population           -0.026882
longitude            -0.047466
latitude             -0.142673
Name: median_house_value, dtype: float64
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# from pandas.tools.plotting import scatter_matrix # For older versions of Pandas
from pandas.plotting import scatter_matrix

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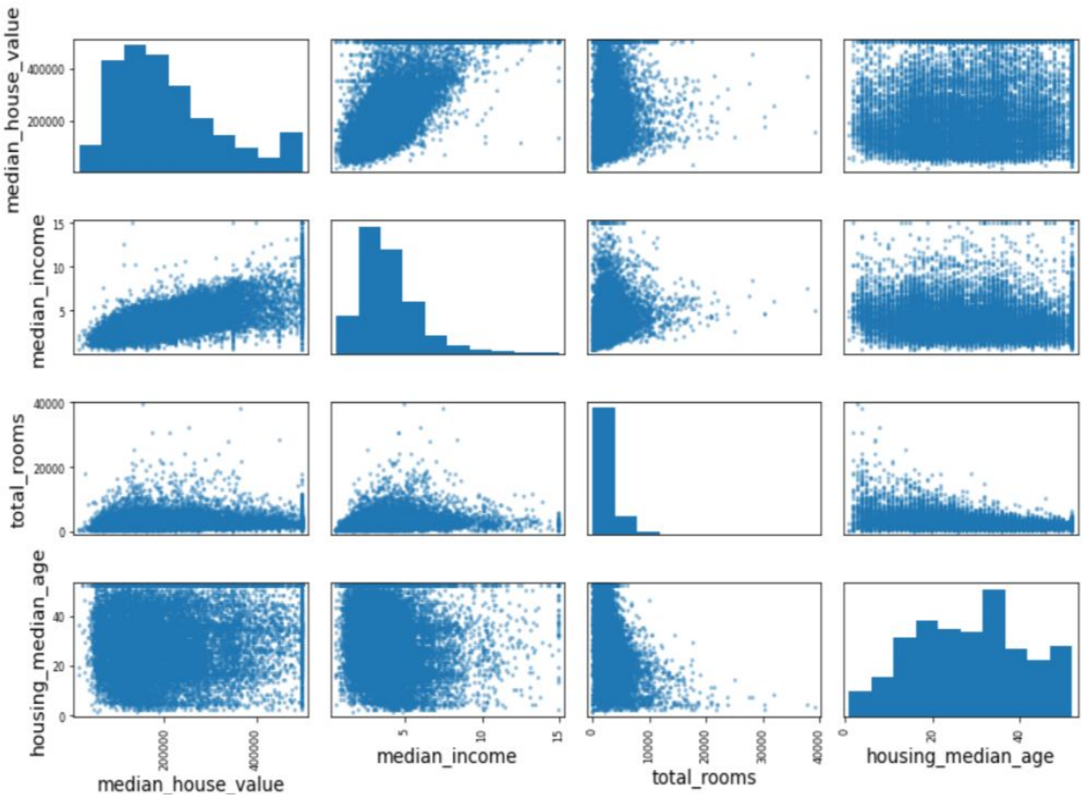

```
Saving figure scatter_matrix_plot
```

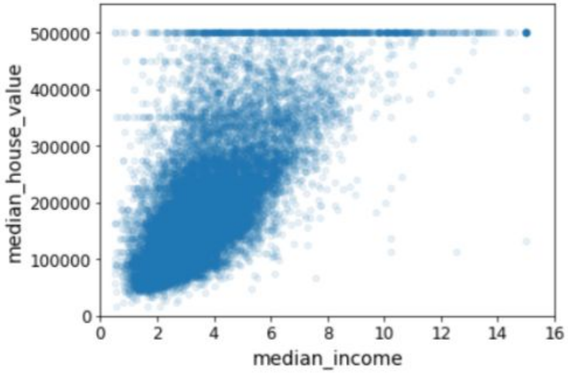


Machine Learning - End to End Project

❖ Discover and visualize the data to gain insights

[40]
```
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
```



[41]
```
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"]
```


[41]
```
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"]
```

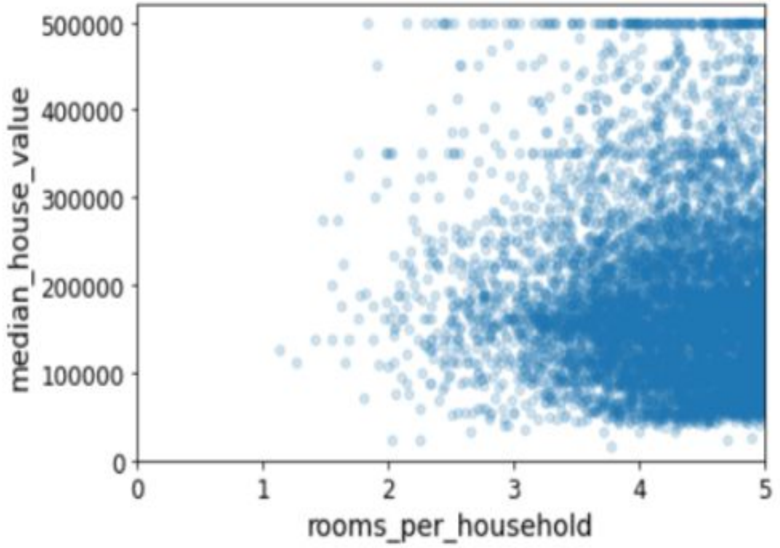

[42]
```
corr_matrix = housing.corr()
corr_matrix["median_house_value"].sort_values(ascending=False)
```

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

Machine Learning - End to End Project

❖ Discover and visualize the data to gain insights

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



Machine Learning - End to End Project

❖ Discover and visualize the data to gain insights

```
[44] housing.describe()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	rooms_per_household	bedrooms_per_room	population_per_household
count	16512.000000	16512.000000	16512.000000	16512.000000	16354.000000	16512.000000	16512.000000	16512.000000	16512.000000	16512.000000	16354.000000	16512.000000
mean	-119.575635	35.639314	28.653404	2622.539789	534.914639	1419.687379	497.011810	3.875884	207005.322372	5.440406	0.212873	3.096469
std	2.001828	2.137963	12.574819	2138.417080	412.665649	1115.663036	375.696156	1.904931	115701.297250	2.611696	0.057378	11.584825
min	-124.350000	32.540000	1.000000	6.000000	2.000000	3.000000	2.000000	0.499900	14999.000000	1.130435	0.100000	0.692308
25%	-121.800000	33.940000	18.000000	1443.000000	295.000000	784.000000	279.000000	2.566950	119800.000000	4.442168	0.175304	2.431352
50%	-118.510000	34.260000	29.000000	2119.000000	433.000000	1164.000000	408.000000	3.541550	179500.000000	5.232342	0.203027	2.817661
75%	-118.010000	37.720000	37.000000	3141.000000	644.000000	1719.000000	602.000000	4.745325	263900.000000	6.056361	0.239816	3.281420
max	-114.310000	41.950000	52.000000	39320.000000	6210.000000	35682.000000	5358.000000	15.000100	500001.000000	141.909091	1.000000	1243.333333

Machine Learning - End to End Project

- Prepare the data for Machine Learning algorithms

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

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

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

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

longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximity

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

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

Machine Learning - End to End Project

- Prepare the data for Machine Learning algorithms

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

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximity
1606	-122.08	37.88	26.0	2947.0	433.0	825.0	626.0	2.9330	NEAR BAY
10915	-117.87	33.73	45.0	2264.0	433.0	1970.0	499.0	3.4193	<1H OCEAN
19150	-122.70	38.35	14.0	2313.0	433.0	954.0	397.0	3.7813	<1H OCEAN
4186	-118.23	34.13	48.0	1308.0	433.0	835.0	294.0	4.2891	<1H OCEAN
16885	-122.40	37.58	26.0	3281.0	433.0	1145.0	480.0	6.3580	NEAR OCEAN

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

```
[50] try:
         from sklearn.impute import SimpleImputer # Scikit-Learn 0.20+
     except ImportError:
         from sklearn.preprocessing import Imputer as SimpleImputer

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

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

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

```
[52] imputer.fit(housing_num)
```

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

Machine Learning - End to End Project

- Prepare the data for Machine Learning algorithms

```
[53] imputer.statistics_
```

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

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

```
[54] housing_num.median().values
```

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

Transform the training set:

```
[55] X = imputer.transform(housing_num)
```

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

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

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

Machine Learning - End to End Project

- Prepare the data for Machine Learning algorithms

[58]
```
imputer.strategy
```

```
'median'
```

[59]
```
housing_tr = pd.DataFrame(X, columns=housing_num.columns,
                          index=housing_num.index)
housing_tr.head()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income
12655	-121.46	38.52	29.0	3873.0	797.0	2237.0	706.0	2.1736
15502	-117.23	33.09	7.0	5320.0	855.0	2015.0	768.0	6.3373
2908	-119.04	35.37	44.0	1618.0	310.0	667.0	300.0	2.8750
14053	-117.13	32.75	24.0	1877.0	519.0	898.0	483.0	2.2264
20496	-118.70	34.28	27.0	3536.0	646.0	1837.0	580.0	4.4964

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

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

Machine Learning - End to End Project

- Prepare the data for Machine Learning algorithms

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

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

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

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

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

```
[63] ordinal_encoder.categories_

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

Machine Learning - End to End Project

- Prepare the data for Machine Learning algorithms

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

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

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

```
[65] housing_cat_1hot.toarray()
```

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

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

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

Machine Learning - End to End Project

❖ Prepare the data for Machine Learning algorithms

```
[67] cat_encoder.categories_

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

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

```
[68] housing.columns

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

```
[69] 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)
```

Machine Learning - End to End Project

- Prepare the data for Machine Learning algorithms

```
[70] from sklearn.preprocessing import FunctionTransformer

     def add_extra_features(X, add_bedrooms_per_room=True):
         rooms_per_household = X[:, rooms_ix] / X[:, household_ix]
         population_per_household = X[:, population_ix] / X[:, household_ix]
         if add_bedrooms_per_room:
             bedrooms_per_room = X[:, bedrooms_ix] / X[:, rooms_ix]
             return np.c_[X, rooms_per_household, population_per_household,
                          bedrooms_per_room]
         else:
             return np.c_[X, rooms_per_household, population_per_household]

     attr_adder = FunctionTransformer(add_extra_features, validate=False,
                                      kw_args={"add_bedrooms_per_room": False})
     housing_extra_attribs = attr_adder.fit_transform(housing.values)
```

```
[71] 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()
```

Machine Learning - End to End Project

❖ Prepare the data for Machine Learning algorithms

```
[71] housing_extra_attribs = pd.DataFrame(
         housing_extra_attribs,
         columns=list(housing.columns)+["rooms_per_household", "population_per_household"],
         index=housing.index)
     housing_extra_attribs.head()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximity	rooms_per_household	population_per_household
12655	-121.46	38.52	29.0	3873.0	797.0	2237.0	706.0	2.1736	INLAND	5.485836	3.168555
15502	-117.23	33.09	7.0	5320.0	855.0	2015.0	768.0	6.3373	NEAR OCEAN	6.927083	2.623698
2908	-119.04	35.37	44.0	1618.0	310.0	667.0	300.0	2.875	INLAND	5.393333	2.223333
14053	-117.13	32.75	24.0	1877.0	519.0	898.0	483.0	2.2264	NEAR OCEAN	3.886128	1.859213
20496	-118.7	34.28	27.0	3536.0	646.0	1837.0	580.0	4.4964	<1H OCEAN	6.096552	3.167241

```
[72] 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)
```

Machine Learning - End to End Project

- Prepare the data for Machine Learning algorithms

```
[76] housing_prepared

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

```
[77] housing_prepared.shape

(16512, 16)
```

```
[78] 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
```

Machine Learning - End to End Project

❖ Prepare the data for Machine Learning algorithms

```
[79] 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)),
         ])
```

```
[80] from sklearn.pipeline import FeatureUnion

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

```
[81] old_housing_prepared = old_full_pipeline.fit_transform(housing)
     old_housing_prepared
```

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

Machine Learning - End to End Project

- ❖ Prepare the data for Machine Learning algorithms

```
[81] old_housing_prepared = old_full_pipeline.fit_transform(housing)
     old_housing_prepared
```

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

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

```
[82] np.allclose(housing_prepared, old_housing_prepared)
```

```
True
```

Machine Learning - End to End Project

- Select and train a model

```
[83] from sklearn.linear_model import LinearRegression

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

```
LinearRegression()
```

```
[84] # let's try the full preprocessing pipeline on a few training instances
     some_data = housing.iloc[:5]
     some_labels = housing_labels.iloc[:5]
     some_data_prepared = full_pipeline.transform(some_data)

     print("Predictions:", lin_reg.predict(some_data_prepared))
```

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

Machine Learning - End to End Project

- **Select and train a model**

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

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

```
[86] some_data_prepared

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

```
[87] from sklearn.metrics import mean_squared_error

     housing_predictions = lin_reg.predict(housing_prepared)
     lin_mse = mean_squared_error(housing_labels, housing_predictions)
     lin_rmse = np.sqrt(lin_mse)
     lin_rmse

68627.87390018745
```

Machine Learning - End to End Project

- **Select and train a model**

```
[87] from sklearn.metrics import mean_squared_error

     housing_predictions = lin_reg.predict(housing_prepared)
     lin_mse = mean_squared_error(housing_labels, housing_predictions)
     lin_rmse = np.sqrt(lin_mse)
     lin_rmse

     68627.87390018745
```

```
[88] from sklearn.metrics import mean_absolute_error

     lin_mae = mean_absolute_error(housing_labels, housing_predictions)
     lin_mae

     49438.66860915802
```

```
[89] from sklearn.tree import DecisionTreeRegressor

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

     DecisionTreeRegressor(random_state=42)
```

Machine Learning - End to End Project

- **Select and train a model**

```
[89] from sklearn.tree import DecisionTreeRegressor

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

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

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

```
0.0
```

Machine Learning - End to End Project

- **Fine-tune your model**

```
[91] 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)
```

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

     display_scores(tree_rmse_scores)
```

```
Scores: [72831.45749112 69973.18438322 69528.56551415 72517.78229792
 69145.50006909 79094.74123727 68960.045444   73344.50225684
 69826.02473916 71077.09753998]
Mean: 71629.89009727491
Standard deviation: 2914.035468468928
```

```
[93] lin_scores = cross_val_score(lin_reg, housing_prepared, housing_labels,
                                  scoring="neg_mean_squared_error", cv=10)
     lin_rmse_scores = np.sqrt(-lin_scores)
     display_scores(lin_rmse_scores)
```

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

Machine Learning - End to End Project

- **Fine-tune your model**

[94]
```python
from sklearn.ensemble import RandomForestRegressor

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

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

[95]
```python
housing_predictions = forest_reg.predict(housing_prepared)
forest_mse = mean_squared_error(housing_labels, housing_predictions)
forest_rmse = np.sqrt(forest_mse)
forest_rmse
```

```
22413.454658589766
```

[96]
```python
from sklearn.model_selection import cross_val_score

forest_scores = cross_val_score(forest_reg, housing_prepared, housing_labels,
                                scoring="neg_mean_squared_error", cv=10)
forest_rmse_scores = np.sqrt(-forest_scores)
display_scores(forest_rmse_scores)
```

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

Machine Learning - End to End Project

- **Fine-tune your model**

[97]
```
scores = cross_val_score(lin_reg, housing_prepared, housing_labels, scoring="neg_mean_squared_error", cv=10)
pd.Series(np.sqrt(-scores)).describe()
```

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

[98]
```
from sklearn.svm import SVR

svm_reg = SVR(kernel="linear")
svm_reg.fit(housing_prepared, housing_labels)
housing_predictions = svm_reg.predict(housing_prepared)
svm_mse = mean_squared_error(housing_labels, housing_predictions)
svm_rmse = np.sqrt(svm_mse)
svm_rmse
```

```
111095.06635291968
```

Machine Learning - End to End Project

- **Fine-tune your model**

[99]
```python
from sklearn.model_selection import GridSearchCV

param_grid = [
    # try 12 (3×4) combinations of hyperparameters
    {'n_estimators': [3, 10, 30], 'max_features': [2, 4, 6, 8]},
    # then try 6 (2×3) combinations with bootstrap set as False
    {'bootstrap': [False], 'n_estimators': [3, 10], 'max_features': [2, 3, 4]},
  ]

forest_reg = RandomForestRegressor(random_state=42)
# train across 5 folds, that's a total of (12+6)*5=90 rounds of training
grid_search = GridSearchCV(forest_reg, param_grid, cv=5,
                           scoring='neg_mean_squared_error', return_train_score=True)
grid_search.fit(housing_prepared, housing_labels)
```

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

Machine Learning - End to End Project

- **Fine-tune your model**

```
[100] grid_search.best_params_
```

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

```
[101] grid_search.best_estimator_
```

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

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

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

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

Machine Learning - End to End Project

- **Fine-tune your model**

[103]
```
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
0	0.070690	0.002954	0.005014	0.000416	2	3	NaN	{'max_features': 2, 'n_estimators': 3}
1	0.228352	0.005127	0.013284	0.000306	2	10	NaN	{'max_features': 2, 'n_estimators': 10}
2	0.678972	0.003835	0.037574	0.000445	2	30	NaN	{'max_features': 2, 'n_estimators': 30}
3	0.123015	0.006240	0.005090	0.000254	4	3	NaN	{'max_features': 4, 'n_estimators': 3}
4	0.521846	0.071917	0.015017	0.000973	4	10	NaN	{'max_features': 4, 'n_estimators': 10}
5	1.173602	0.080077	0.036734	0.000463	4	30	NaN	{'max_features': 4, 'n_estimators': 30}
6	0.154594	0.005501	0.004940	0.000140	6	3	NaN	{'max_features': 6, 'n_estimators': 3}
7	0.515183	0.004015	0.013928	0.001642	6	10	NaN	{'max_features': 6, 'n_estimators': 10}
8	2.184718	0.521543	0.038772	0.004474	6	30	NaN	{'max_features': 6, 'n_estimators': 30}
9	0.211697	0.022682	0.005253	0.000543	8	3	NaN	{'max_features': 8, 'n_estimators': 3}
10	0.823374	0.142736	0.014312	0.001462	8	10	NaN	{'max_features': 8, 'n_estimators': 10}
11	2.172679	0.282331	0.038129	0.002469	8	30	NaN	{'max_features': 8, 'n_estimators': 30}
12	0.108231	0.003607	0.005651	0.000064	2	3	False	{'bootstrap': False, 'max_features': 2, 'n_est...
13	0.355103	0.005781	0.015427	0.000100	2	10	False	{'bootstrap': False, 'max_features': 2, 'n_est...
14	0.143458	0.001361	0.005613	0.000049	3	3	False	{'bootstrap': False, 'max_features': 3, 'n_est...
15	0.473989	0.005306	0.015575	0.000148	3	10	False	{'bootstrap': False, 'max_features': 3, 'n_est...
16	0.185815	0.004963	0.005749	0.000327	4	3	False	{'bootstrap': False, 'max_features': 4, 'n_est...
17	0.723392	0.144256	0.017068	0.001026	4	10	False	{'bootstrap': False, 'max_features': 4, 'n_est...

Machine Learning - End to End Project

❖ Fine-tune your model

param_bootstrap	params	split0_test_score	split1_test_score	...	mean_test_score	std_test_score	rank_test_score	split0_train_score	split1_train_score	split2_train_score	split3_train_score	split4_train_score	mean_train_score	std_train_score
NaN	{'max_features': 2, 'n_estimators': 3}	-4.119912e+09	-3.723465e+09	...	-4.082592e+09	1.867375e+08	18	-1.155630e+09	-1.089726e+09	-1.153843e+09	-1.118149e+09	-1.093446e+09	-1.122159e+09	2.834288e+07
NaN	{'max_features': 2, 'n_estimators': 10}	-2.973521e+09	-2.810319e+09	...	-3.015803e+09	1.139808e+08	11	-5.982947e+08	-5.904781e+08	-6.123850e+08	-5.727681e+08	-5.905210e+08	-5.928894e+08	1.284978e+07
NaN	{'max_features': 2, 'n_estimators': 30}	-2.801229e+09	-2.671474e+09	...	-2.796915e+09	7.980892e+07	9	-4.412567e+08	-4.326398e+08	-4.553722e+08	-4.320746e+08	-4.311606e+08	-4.385008e+08	9.184397e+06
NaN	{'max_features': 4, 'n_estimators': 3}	-3.528743e+09	-3.490303e+09	...	-3.609050e+09	1.375683e+08	16	-9.782368e+08	-9.806455e+08	-1.003780e+09	-1.016515e+09	-1.011270e+09	-9.980896e+08	1.577372e+07
NaN	{'max_features': 4, 'n_estimators': 10}	-2.742620e+09	-2.609311e+09	...	-2.755726e+09	1.182604e+08	7	-5.063215e+08	-5.257983e+08	-5.081984e+08	-5.174405e+08	-5.282066e+08	-5.171931e+08	8.882622e+06
NaN	{'max_features': 4, 'n_estimators': 30}	-2.522176e+09	-2.440241e+09	...	-2.518759e+09	8.488084e+07	3	-3.776568e+08	-3.902106e+08	-3.885042e+08	-3.830866e+08	-3.894779e+08	-3.857872e+08	4.774229e+06
NaN	{'max_features': 6, 'n_estimators': 3}	-3.362127e+09	-3.311863e+09	...	-3.371513e+09	1.378086e+08	13	-8.909397e+08	-9.583733e+08	-9.000201e+08	-8.964731e+08	-9.151927e+08	-9.121998e+08	2.444837e+07
NaN	{'max_features': 6, 'n_estimators': 10}	-2.622099e+09	-2.669655e+09	...	-2.654240e+09	6.967978e+07	5	-4.939906e+08	-5.145996e+08	-5.023512e+08	-4.959467e+08	-5.147087e+08	-5.043194e+08	8.880106e+06
NaN	{'max_features': 6, 'n_estimators': 30}	-2.446142e+09	-2.446594e+09	...	-2.496981e+09	7.357046e+07	2	-3.760968e+08	-3.876636e+08	-3.875307e+08	-3.760938e+08	-3.861056e+08	-3.826981e+08	5.418747e+06
NaN	{'max_features': 8, 'n_estimators': 3}	-3.590333e+09	-3.232664e+09	...	-3.468718e+09	1.293758e+08	14	-9.505012e+08	-9.166119e+08	-9.033910e+08	-9.070642e+08	-9.459386e+08	-9.247014e+08	1.973471e+07
NaN	{'max_features': 8, 'n_estimators': 10}	-2.721311e+09	-2.675886e+09	...	-2.752030e+09	6.258030e+07	6	-4.998373e+08	-4.997970e+08	-5.099880e+08	-5.047868e+08	-5.348043e+08	-5.098427e+08	1.303601e+07
NaN	{'max_features': 8, 'n_estimators': 30}	-2.492636e+09	-2.444818e+09	...	-2.489909e+09	7.086483e+07	1	-3.801679e+08	-3.832972e+08	-3.823818e+08	-3.778452e+08	-3.817589e+08	-3.810902e+08	1.916605e+06
False	{'bootstrap': False, 'max_features': 2, 'n_est...	-4.020842e+09	-3.951861e+09	...	-3.891485e+09	8.648595e+07	17	-0.000000e+00	-4.306828e+01	-1.051392e+04	-0.000000e+00	-0.000000e+00	-2.111398e+03	4.201294e+03
False	{'bootstrap': False, 'max_features': 2, 'n_est...	-2.901352e+09	-3.036875e+09	...	-2.967697e+09	4.582448e+07	10	-0.000000e+00	-3.876145e+00	-9.462528e+02	-0.000000e+00	-0.000000e+00	-1.900258e+02	3.781165e+02
False	{'bootstrap': False, 'max_features': 3, 'n_est...	-3.687132e+09	-3.446245e+09	...	-3.596953e+09	8.011960e+07	15	-0.000000e+00	-0.000000e+00	-0.000000e+00	-0.000000e+00	-0.000000e+00	0.000000e+00	0.000000e+00
False	{'bootstrap': False, 'max_features': 3, 'n_est...	-2.837028e+09	-2.619558e+09	...	-2.783044e+09	8.862580e+07	8	-0.000000e+00	-0.000000e+00	-0.000000e+00	-0.000000e+00	-0.000000e+00	0.000000e+00	0.000000e+00
False	{'bootstrap': False, 'max_features': 4, 'n_est...	-3.549428e+09	-3.318176e+09	...	-3.344440e+09	1.099355e+08	12	-0.000000e+00	-0.000000e+00	-0.000000e+00	-0.000000e+00	-0.000000e+00	0.000000e+00	0.000000e+00
False	{'bootstrap': False, 'max_features': 4, 'n_est...	-2.692499e+09	-2.542704e+09	...	-2.629472e+09	8.510266e+07	4	-0.000000e+00	-0.000000e+00	-0.000000e+00	-0.000000e+00	-0.000000e+00	0.000000e+00	0.000000e+00

Machine Learning - End to End Project

- **Fine-tune your model**

```
[104] from sklearn.model_selection import RandomizedSearchCV
      from scipy.stats import randint

      param_distribs = {
              'n_estimators': randint(low=1, high=200),
              'max_features': randint(low=1, high=8),
          }

      forest_reg = RandomForestRegressor(random_state=42)
      rnd_search = RandomizedSearchCV(forest_reg, param_distributions=param_distribs,
                                      n_iter=10, cv=5, scoring='neg_mean_squared_error', random_state=42)
      rnd_search.fit(housing_prepared, housing_labels)
```

```
RandomizedSearchCV(cv=5, estimator=RandomForestRegressor(random_state=42),
                   param_distributions={'max_features': <scipy.stats._distn_infrastructure.rv_frozen object at 0x7ff91fe73220>,
                                        'n_estimators': <scipy.stats._distn_infrastructure.rv_frozen object at 0x7ff91fd44ca0>},
                   random_state=42, scoring='neg_mean_squared_error')
```

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

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

Machine Learning - End to End Project

- **Fine-tune your model**

```
[106] feature_importances = grid_search.best_estimator_.feature_importances_
      feature_importances
```

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

```
[107] extra_attribs = ["rooms_per_hhold", "pop_per_hhold", "bedrooms_per_room"]
      #cat_encoder = cat_pipeline.named_steps["cat_encoder"] # old solution
      cat_encoder = full_pipeline.named_transformers_["cat"]
      cat_one_hot_attribs = list(cat_encoder.categories_[0])
      attributes = num_attribs + extra_attribs + cat_one_hot_attribs
      sorted(zip(feature_importances, attributes), reverse=True)
```

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

Machine Learning - End to End Project

- **Fine-tune your model**

```
[108] 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)
```

```
[109] final_rmse

      47873.26095812988
```

Machine Learning - End to End Project

❖ **Summary**

Google slides link:

https://docs.google.com/presentation/d/1KofnCzH8WTaH1ofAvZjOGxZDWZW_ewyxH5gEXypc-eI/edit?usp=sharing

GitHub link:
https://github.com/momer22/Machine-Learning---End-to-End-Project

This project aimed to predict the median house values in California districts based on several features. We started by setting up a notebook and ensuring that it worked well in both Python 2 and 3. We imported common modules and made sure that Matplotlib plotted figures inline, and we prepared a function to save the figures.

Next, we imported a CSV file containing the housing data into Google Colab. We cleaned and preprocessed the data, and set up visualizations to draw insights from the data. We then prepared the data for machine learning algorithms, including feature scaling and splitting into training and testing sets.

We followed by selecting and training various machine learning models and fine-tuned them by optimizing the hyperparameters. After careful evaluation and comparison of the models, we obtained the best combination of hyperparameters and achieved a final RMSE of 47873.26 with 95% test RMSE accuracy.
Overall, this project successfully predicted median house values in California districts and demonstrated the importance of data preparation, feature selection, and hyperparameter optimization in machine learning.