Housing

August 1, 2021

[11]:
```python
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"

import os
import tarfile
import urllib

DOWNLOAD_ROOT = "https://raw.githubusercontent.com/ageron/handson-ml/master/"

HOUSING_URL = DOWNLOAD_ROOT + "datasets/housing/housing.tgz"
HOUSING_PATH = os.path.join("datasets", "housing")

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()
#     print(os.listdir(housing_path))

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)

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

[11]:
```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -122.23     37.88                41.0        880.0           129.0
1    -122.22     37.86                21.0       7099.0          1106.0
2    -122.24     37.85                52.0       1467.0           190.0
```

```
3    -122.25     37.85                52.0       1274.0           235.0
4    -122.25     37.85                52.0       1627.0           280.0

   population  households  median_income  median_house_value ocean_proximity
0       322.0       126.0         8.3252            452600.0        NEAR BAY
1      2401.0      1138.0         8.3014            358500.0        NEAR BAY
2       496.0       177.0         7.2574            352100.0        NEAR BAY
3       558.0       219.0         5.6431            341300.0        NEAR BAY
4       565.0       259.0         3.8462            342200.0        NEAR BAY
```

```
<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
```

[12]:

```
housing.ocean_proximity.value_counts()
housing.describe()
```

[12]:

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

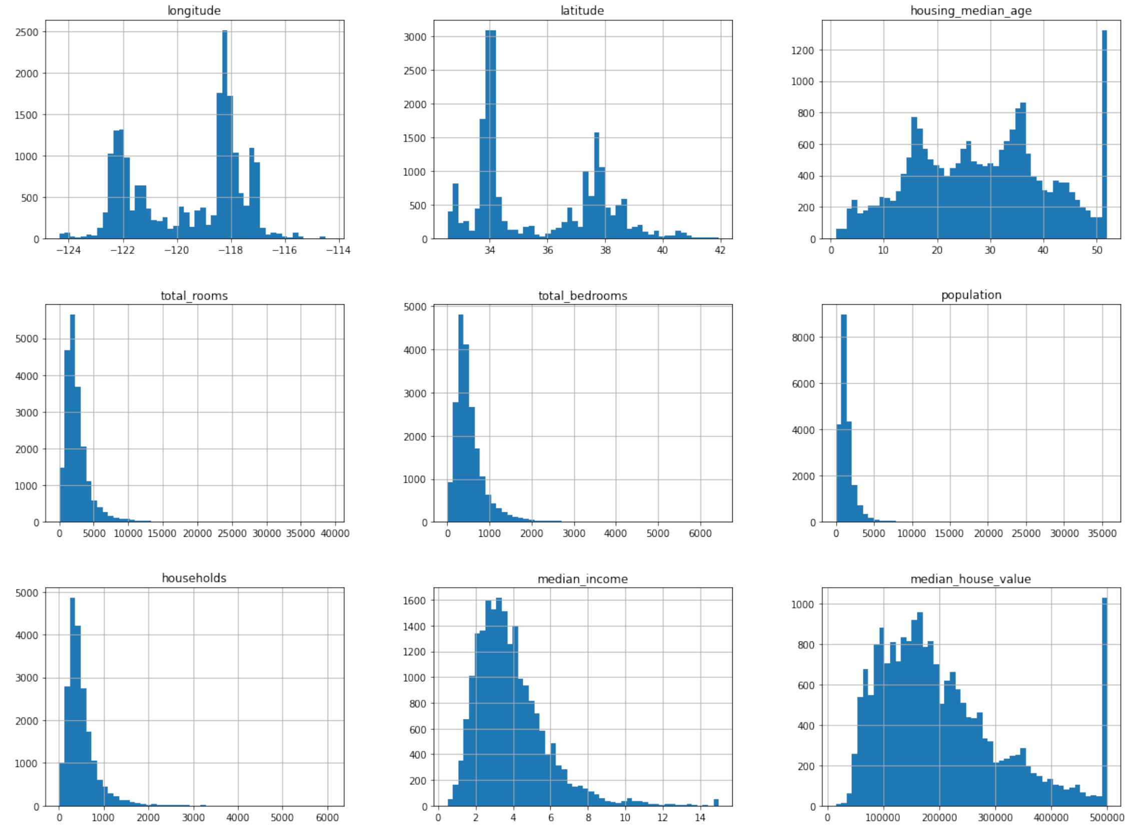
[12]:

```
          longitude      latitude  housing_median_age   total_rooms  \
count  20640.000000  20640.000000        20640.000000  20640.000000
mean    -119.569704     35.631861           28.639486   2635.763081
std        2.003532      2.135952           12.585558   2181.615252
min     -124.350000     32.540000            1.000000      2.000000
25%     -121.800000     33.930000           18.000000   1447.750000
50%     -118.490000     34.260000           29.000000   2127.000000
75%     -118.010000     37.710000           37.000000   3148.000000
max     -114.310000     41.950000           52.000000  39320.000000
```

```
       total_bedrooms    population    households  median_income  \
count    20433.000000  20640.000000  20640.000000   20640.000000
mean       537.870553   1425.476744    499.539680       3.870671
std        421.385070   1132.462122    382.329753       1.899822
min          1.000000      3.000000      1.000000       0.499900
25%        296.000000    787.000000    280.000000       2.563400
50%        435.000000   1166.000000    409.000000       3.534800
75%        647.000000   1725.000000    605.000000       4.743250
max       6445.000000  35682.000000   6082.000000      15.000100

       median_house_value
count        20640.000000
mean        206855.816909
std         115395.615874
min          14999.000000
25%         119600.000000
50%         179700.000000
75%         264725.000000
max         500001.000000
```

[13]:
```
%matplotlib inline
import matplotlib.pyplot as plt
housing.hist(bins=50, figsize=(20,15))
plt.show()
```

[13]:
```
array([[<AxesSubplot:title={'center':'longitude'}>,
        <AxesSubplot:title={'center':'latitude'}>,
        <AxesSubplot:title={'center':'housing_median_age'}>],
       [<AxesSubplot:title={'center':'total_rooms'}>,
        <AxesSubplot:title={'center':'total_bedrooms'}>,
        <AxesSubplot:title={'center':'population'}>],
       [<AxesSubplot:title={'center':'households'}>,
        <AxesSubplot:title={'center':'median_income'}>,
        <AxesSubplot:title={'center':'median_house_value'}>]],
      dtype=object)
```



[14]:

```
# Create the test set
import numpy as np

# Splitting strategy 1: Shuffle. (Con: cannot handle new data.)
def split_train_set(data, test_ratio=0.2):
    shuffled_indicies = np.random.permutation(len(data))
    test_set_size = int(len(data) * test_ratio)
    test_indices = shuffled_indicies[:test_set_size]
    train_indices = shuffled_indicies[test_set_size:]
    return data.iloc[train_indices], data.iloc[test_indices]
train_set, test_set = split_train_set(housing, 0.2)
print("{} training datapoints, {} test datapoints".format(len(train_set),␣
 ↪len(test_set)))

import hashlib

# Splitting strategy 2: Split by identifiers (Indexed Identifier Hash vs.␣
 ↪Unique Feature Combination)
def test_set_check(identifier, test_ratio, hash_func):
    # Digest the identifier hash and test the last byte.
    return hash_func(np.int64(identifier)).digest()[-1] < 256 * test_ratio
```

```
def split_train_test_by_id(data, test_ratio, id_column, hash_func=hashlib.md5):
    ids = data[id_column]
    in_test_set_flags = ids.apply(lambda id: test_set_check(id, test_ratio,␣
 ↪hash_func))
    return data.loc[~in_test_set_flags], data.loc[in_test_set_flags]

housing_with_id = housing.reset_index() # Creates a new index column.
train_set, test_set = split_train_test_by_id(housing_with_id, test_ratio=0.2,␣
 ↪id_column="index")
print("{} training datapoints, {} test datapoints".format(len(train_set),␣
 ↪len(test_set)))

# Con: prone to sampling bias when multiple datapoints end up with the same␣
 ↪identifier)
housing_with_id["id"] = housing.longitude * 1000 + housing.latitude
train_set, test_set = split_train_test_by_id(housing_with_id, test_ratio=0.2,␣
 ↪id_column="id" )
print("{} training datapoints, {} test datapoints".format(len(train_set),␣
 ↪len(test_set)))

# from sklearn.model_selection import train_test_split
# train_set, test_set = train_test_split(housing, test_size=0.2,␣
 ↪random_state=42)
```

```
16512 training datapoints, 4128 test datapoints
16362 training datapoints, 4278 test datapoints
16267 training datapoints, 4373 test datapoints
```

[15]:

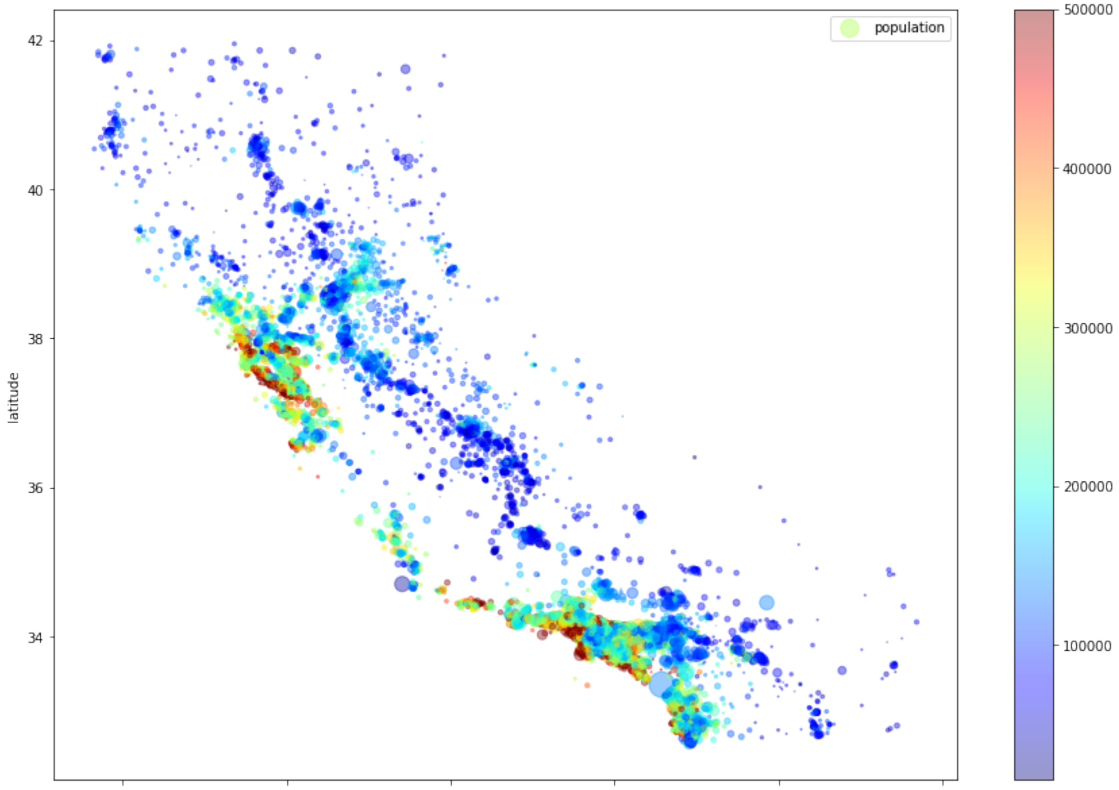
```
# Stratified Sampling
housing["income_cat"] = np.ceil(housing.median_income / 1.5)
housing["income_cat"].where(housing["income_cat"] < 5, 5.0, inplace=True)
# housing.hist(column="income_cat", bins=50, figsize=(20,15))

from sklearn.model_selection import StratifiedShuffleSplit

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

# Remove incoming category column.
strat_train_set.drop("income_cat", axis=1, inplace=True)
strat_test_set.drop("income_cat", axis=1, inplace=True)
```

[15]:
```
3.0    0.350533
2.0    0.318798
4.0    0.176357
5.0    0.114583
1.0    0.039729
Name: income_cat, dtype: float64
```

[16]:
```
# Visualize and play with a sample or a copy of the training set to gain more␣
 ↪insights.
housing = strat_train_set.copy()
housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.4,
             s=housing.population/100, label="population", figsize=(15,10.5),
             c=housing.median_house_value, cmap=plt.get_cmap("jet"),␣
 ↪colorbar=True
             ) # Use more transparent dots to indicate density.
plt.legend()
```

[16]:
```
<AxesSubplot:xlabel='longitude', ylabel='latitude'>
```

[16]:
```
<matplotlib.legend.Legend at 0x11d1400a0>
```



[17]:

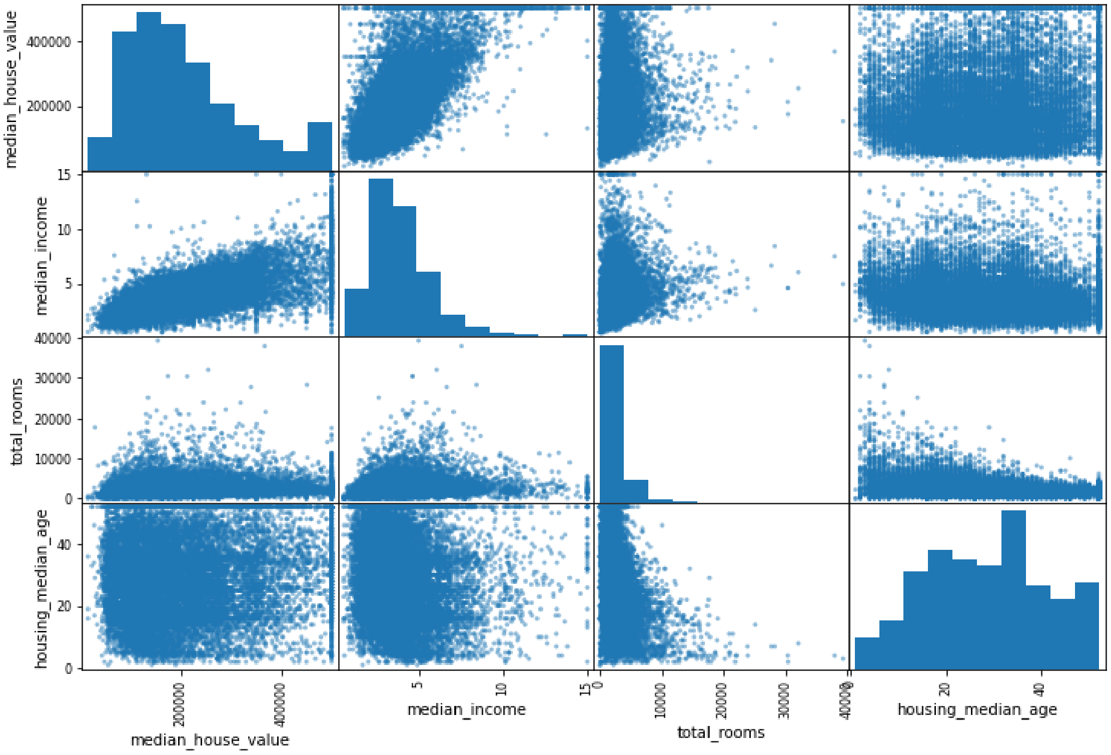
```python
# Look for correlations.
corr_matrix = housing.corr()
corr_matrix.median_house_value.sort_values(ascending=False)

from pandas.plotting import scatter_matrix
attributes = ["median_house_value", "median_income", "total_rooms",␣
 ↪"housing_median_age"]
scatter_matrix(housing[attributes], figsize=(12,8))
```

[17]:

```
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
```

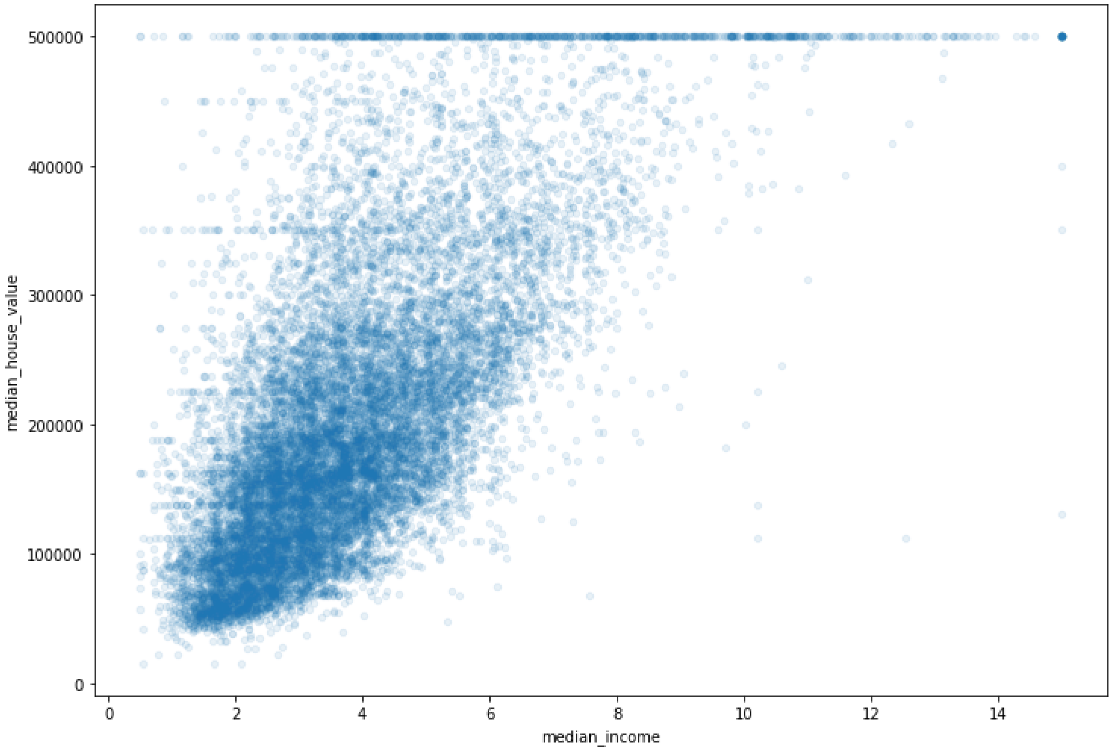
[17]:

```
array([[<AxesSubplot:xlabel='median_house_value', ylabel='median_house_value'>,
        <AxesSubplot:xlabel='median_income', ylabel='median_house_value'>,
        <AxesSubplot:xlabel='total_rooms', ylabel='median_house_value'>,
        <AxesSubplot:xlabel='housing_median_age', ylabel='median_house_value'>],
       [<AxesSubplot:xlabel='median_house_value', ylabel='median_income'>,
        <AxesSubplot:xlabel='median_income', ylabel='median_income'>,
        <AxesSubplot:xlabel='total_rooms', ylabel='median_income'>,
        <AxesSubplot:xlabel='housing_median_age', ylabel='median_income'>],
       [<AxesSubplot:xlabel='median_house_value', ylabel='total_rooms'>,
        <AxesSubplot:xlabel='median_income', ylabel='total_rooms'>,
        <AxesSubplot:xlabel='total_rooms', ylabel='total_rooms'>,
        <AxesSubplot:xlabel='housing_median_age', ylabel='total_rooms'>],
       [<AxesSubplot:xlabel='median_house_value', ylabel='housing_median_age'>,
        <AxesSubplot:xlabel='median_income', ylabel='housing_median_age'>,
        <AxesSubplot:xlabel='total_rooms', ylabel='housing_median_age'>,
        <AxesSubplot:xlabel='housing_median_age',
ylabel='housing_median_age'>]],
      dtype=object)
```



```
[18]: # Focus on the correlation between median_house_value vs. median_income.
      housing.plot(kind="scatter", x="median_income", y="median_house_value", alpha=0.
       ↪1, figsize=(12, 8.4))
```

```
[18]: <AxesSubplot:xlabel='median_income', ylabel='median_house_value'>
```



```
[19]: #␣
       ↪longitude        latitude        housing_median_age        total_rooms        total_bedroom
      #␣
       ↪population        households        median_income        median_house_value        ocean_pr
      housing["rooms_per_household"] = housing["total_rooms"] / housing["households"]
      housing["bedrooms_per_room"] = housing["total_bedrooms"] /␣
       ↪housing["total_rooms"]
      housing["population_per_household"] = housing["population"] /␣
       ↪housing["households"]
      corr_matrix = housing.corr()
      corr_matrix.median_house_value.sort_values(ascending=False)
```

```
[19]: 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
```

[20]:

```
# Prepare the data for meachine learning algorithms
housing = strat_train_set.
```

```
  File "<ipython-input-20-79d478df1636>", line 2
    housing = strat_train_set.
                              ^
SyntaxError: invalid syntax
```

[ ]:

```

```