Introduction

February 27, 2023

1 House Price Prediction

[1]:
```python
import pandas as pd
```

[2]:
```python
def load_housing_data(csv_path = './housing.csv'):
#     csv_path = './housing.csv'
    return pd.read_csv(csv_path)
```

[3]:
```python
housing = load_housing_data()
```

[4]:
```python
housing.head()
```

[4]:
```
   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
```

1.1 See info

[5]:
```python
housing.info()
```

Ocean_proximity is oject (i.e. string, since it came from csv).

1.2 Let's see each category and their counts in ocean_proximity

[6]:
```python
housing['ocean_proximity'].value_counts()
```

[6]:
```
<1H OCEAN     9136
INLAND        6551
```

```
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: ocean_proximity, dtype: int64
```

1.3 Now to see description of numeric fields

[7]:
```python
housing.describe()
```

[7]:
```
          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
```

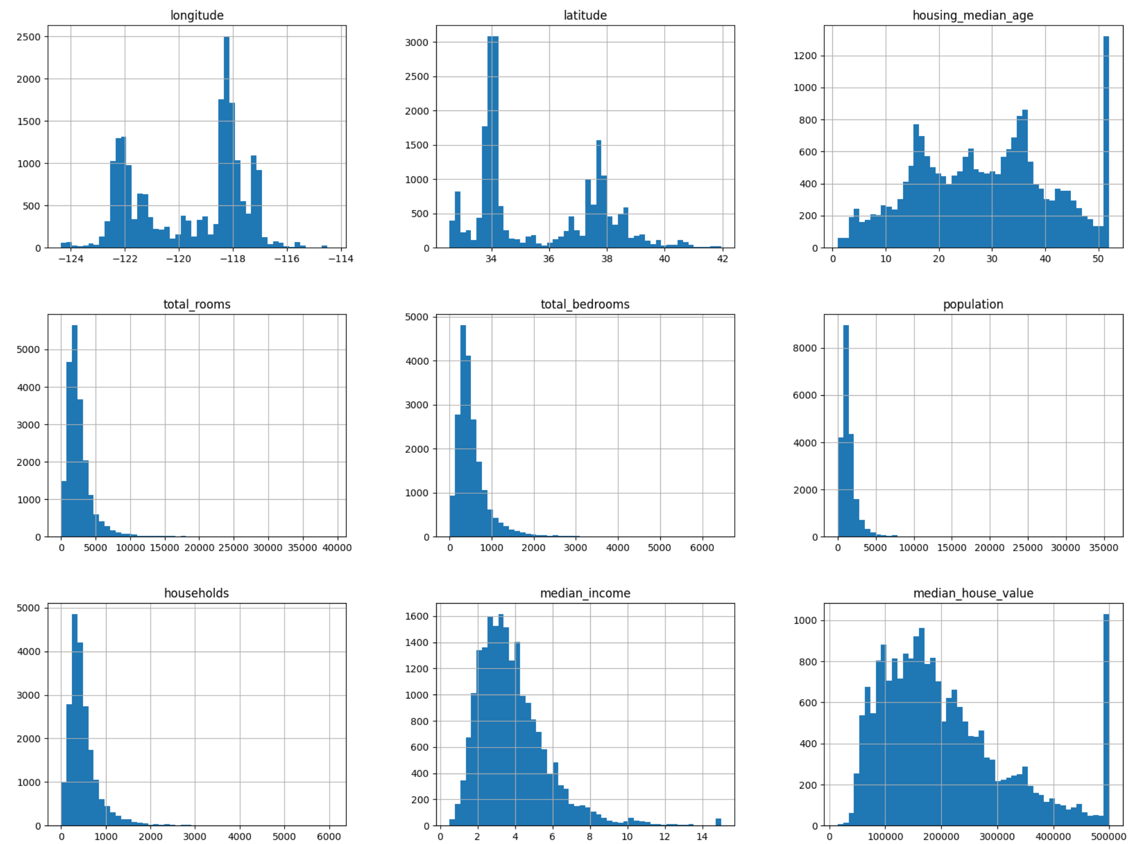
25% (1st quartile), 50% (median), 75% (3rd quartile) For eg. housing_median_age, at 25% is 18.000. It means 25% of the data pts have housing_median_age less than or eq to 18.000

1.4 Plotting

[8]:
```python
import matplotlib.pyplot as plt
```

```
[9]: # matplotlib requires user specified graphical backened.
     #use jupyter's own backend
     %matplotlib inline

     housing.hist(bins=50, figsize=(20, 15))
     plt.show()
```



X axis respresents the values of the attribute. Y axis represents the count (nos.) of that attribute at that given pt (on X axis)

1.5 Train Test Split

```
[10]: import numpy as np
```

```
[11]: def split_train_test(data, test_ratio):
          shuffled_indices = np.random.permutation(len(data)) #return random perm of
       ↪nos from 0 - 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), len(test_set))
```

```
16512 4128
```

But this will give different output in diff run (and subsequently our ML model will see the whole data set) To prevent this np.random.seed(42) #or any other number before using np.random.permutation

1.5.1 Another Way

[13]:
```
from sklearn.model_selection import train_test_split
```

[14]:
```
train_set, test_set = train_test_split(housing, test_size=0.2, random_state=42)
```

or split based on an unique identifier (so that it won't break if dataset is updated)

1.5.2 Stratified Split

The above processes may introduce sampling bais (if dataset is not large enough compared to the no. of attributes) The stats of the whole data set should be preserved in the split data sets For eg, if whole data set has 48.7% males and 51.3% females The train and test data sets should also contain the same percentage of male and female. This is called **stratified sampling**. The population is split into homogenous subgroups called **strata** and the right no. of instances are sampled from each stratum to guarrentee that the test set is representative of the overall population.

in our case **median__incomne** is important and the test set should be represenative of the income distribution. But it is continous. So we make it into **categorical attribute** using **pd.cut** From histogram we see that median income is centered aroung 1.5 - 6 There should be sufficient no. of instances in each stratum And the no. of strata should not be too much. Here we make **5** strata.

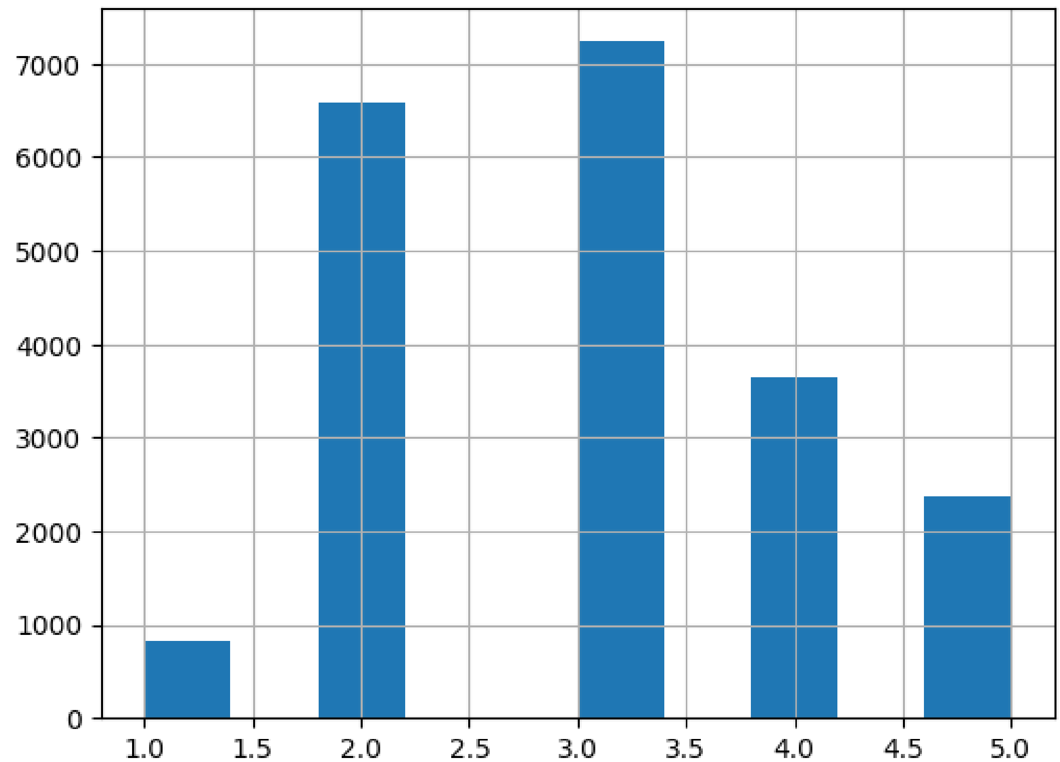
[15]:
```
housing['income_cat'] = pd.cut(housing['median_income'],
                               bins=[0., 1.5, 3.0, 4.5, 6., np.inf], #majority␣
 ↪is less than 6
                               labels=[1, 2, 3, 4, 5])
```

[16]:
```
housing['income_cat']
```

[16]:
```
0        5
1        5
2        5
3        4
4        3
        ..
20635    2
20636    2
20637    2
20638    2
```

```
20639    2
Name: income_cat, Length: 20640, dtype: category
Categories (5, int64): [1 < 2 < 3 < 4 < 5]
```

[17]:
```
housing['income_cat'].hist()
plt.show()
```



[18]:
```
from sklearn.model_selection import StratifiedShuffleSplit
```

[19]:
```
split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
```

[20]:
```
split
```

[20]:
```
StratifiedShuffleSplit(n_splits=1, random_state=42, test_size=0.2,
            train_size=None)
```

[21]:
```
split.split(housing, housing['income_cat'])
```

[21]:
```
<generator object BaseShuffleSplit.split at 0x7fe36b664ac0>
```

[22]:
```
for train_index, test_index in split.split(housing, housing['income_cat']):
#     print(test_index) #prints a list
```

```
#     print('xD')  # after list prints. in the func n_splits = 1 == no of loops␣
↪that occur here
    strat_train_set = housing.loc[train_index]
    strat_test_set = housing.loc[test_index]
```

Now check if the stats are preserved

[23]:
```
strat_test_set['income_cat'].value_counts() / len(strat_test_set)
```

[23]:
```
3    0.350533
2    0.318798
4    0.176357
5    0.114341
1    0.039971
Name: income_cat, dtype: float64
```

[24]:
```
housing['income_cat'].value_counts() / len(housing)
```

[24]:
```
3    0.350581
2    0.318847
4    0.176308
5    0.114438
1    0.039826
Name: income_cat, dtype: float64
```

They are similar ^

1.5.3 Now drop the categorical column that we added

[25]:
```
for set_ in (strat_train_set, strat_test_set):
    set_.drop('income_cat', axis=1, inplace=True)
```

[26]:
```
#i = (strat_train_set, strat_test_set).__iter__()
```

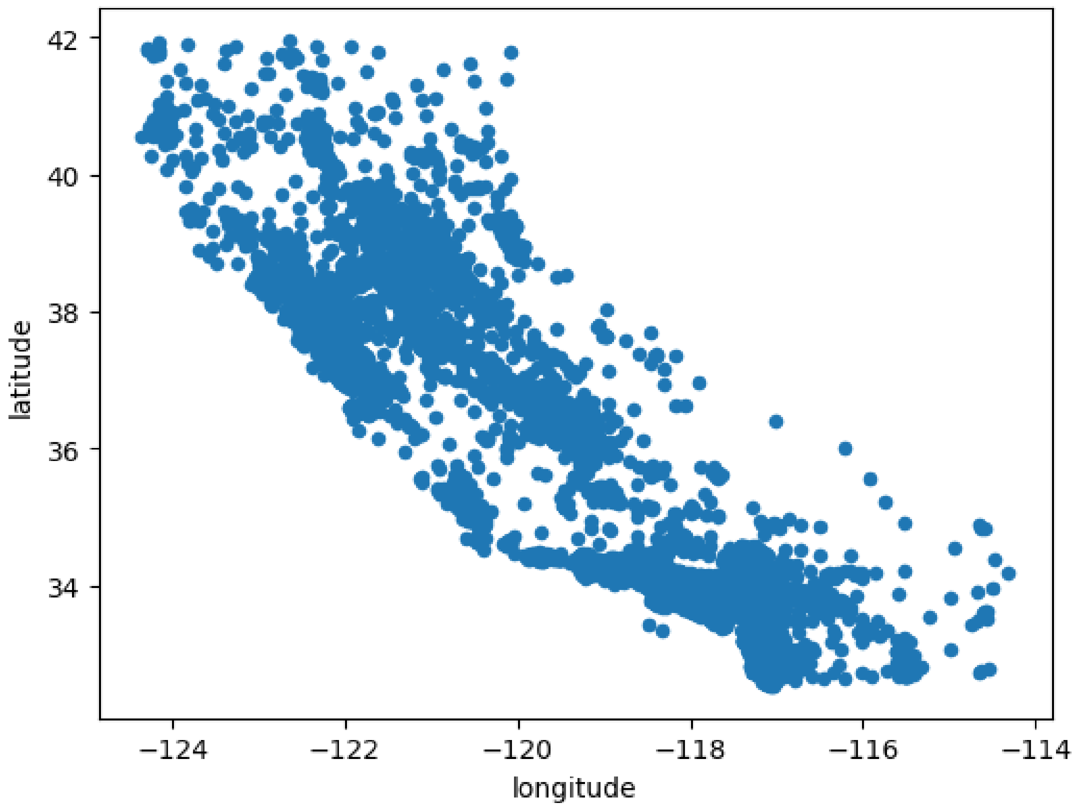
[27]:
```
#i.__next__()
```

Note for self getting iterator on a dataFrame (like strat_train_set) would allow us to access the col names (like latitute) and not the rows and data in them But (strat_train_set, strat_test_set) is a **tuple**. An iterator on this object will give us the whole dataFrames one by one (first ***strat_train_set***, the ***strat_test_set***)

1.6 Plotting Geographical Data

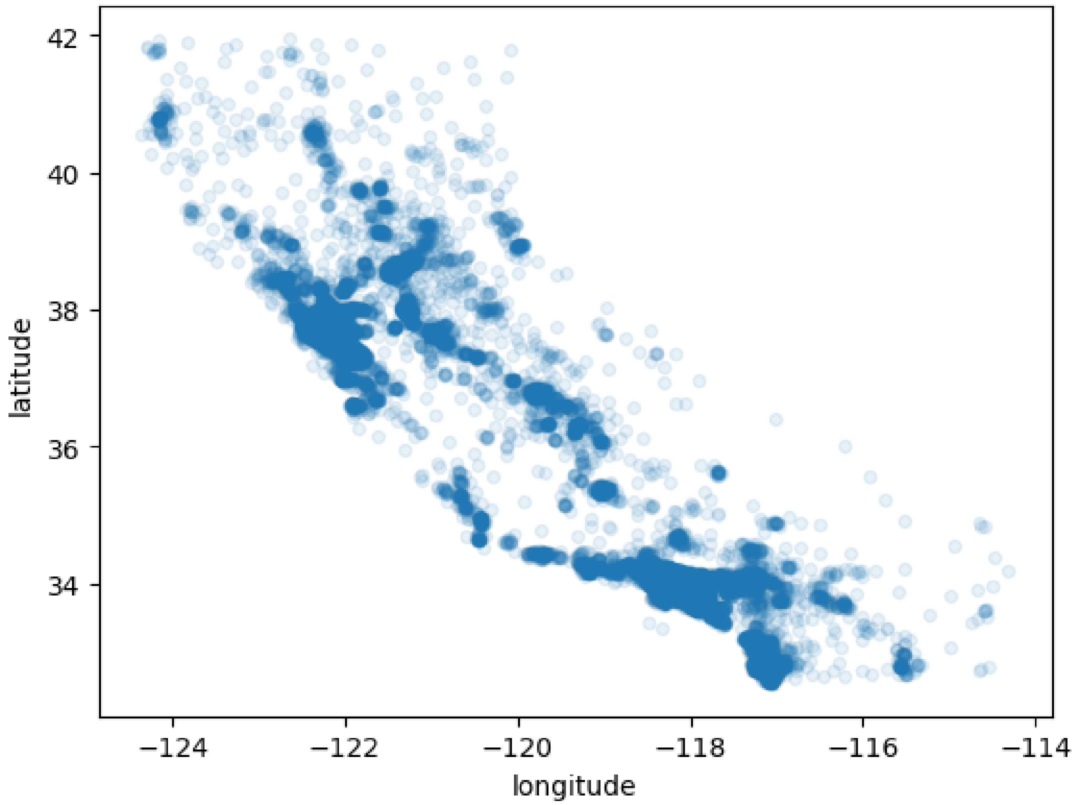
[28]:
```
housing1 = strat_train_set.copy() #for safety. xD
```

[29]:
```
housing1.plot(kind='scatter', x='longitude', y='latitude')
plt.show()
```




```
[30]: housing1.plot(kind='scatter', x='longitude', y='latitude', alpha=0.1)
      #makes easy to visualise places with high density of data pts
```

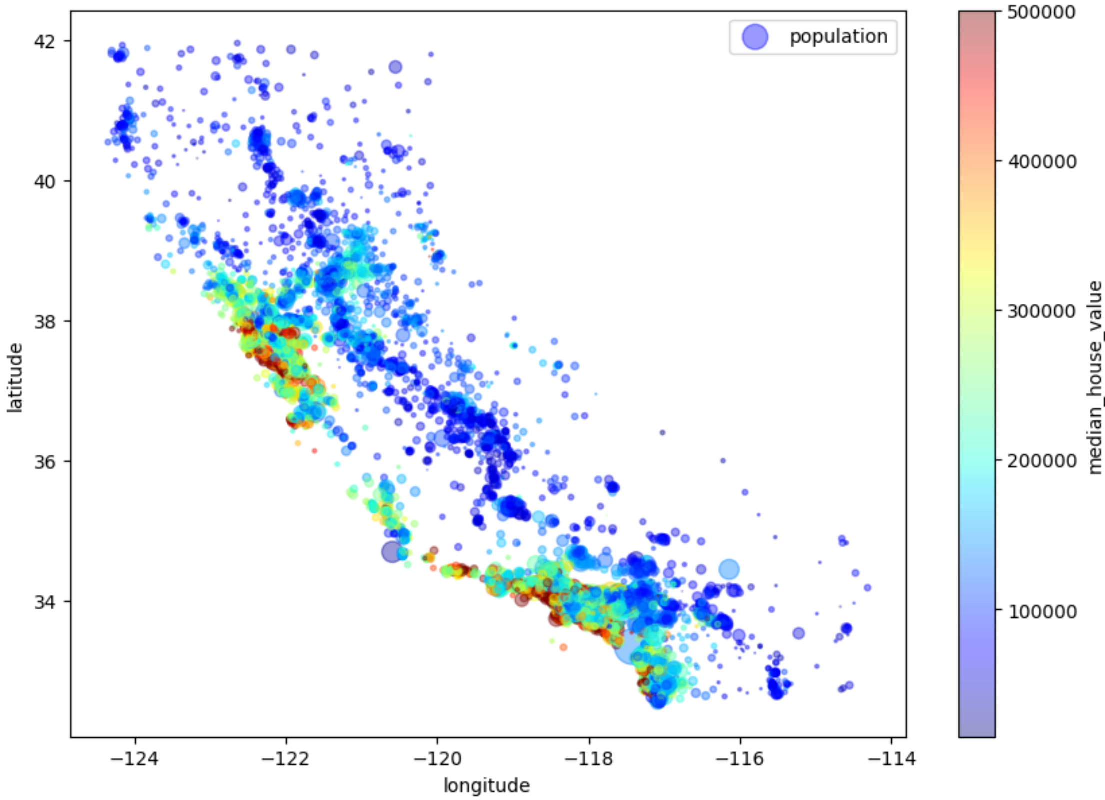
```
[30]: <AxesSubplot: xlabel='longitude', ylabel='latitude'>
```



[31]:
```
# radius of each circle -> population (option s)
# color of circle -> price (option c)
# we use predefined color map (cmap) called 'jet'

housing1.plot(kind='scatter', x='longitude', y='latitude', alpha=0.4,
             s=housing1['population']/100, label='population',
             figsize=(10, 7), c='median_house_value',
             cmap=plt.get_cmap('jet'), colorbar=True
             )
plt.legend()
```

[31]: <matplotlib.legend.Legend at 0x7fe36b5e1610>



1.7 Looking For Correlations

[32]:
```
# standard correlation coeff (Pearson's r)
# between every pair of attributes
corr_matrix = housing1.corr(numeric_only=True)

# with respect to 'median_house_value'
corr_matrix['median_house_value'].sort_values(ascending=False)
```

[32]:
```
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
```

[33]:
```
# corr_matrix #(n X n matrix (dataframe))
```

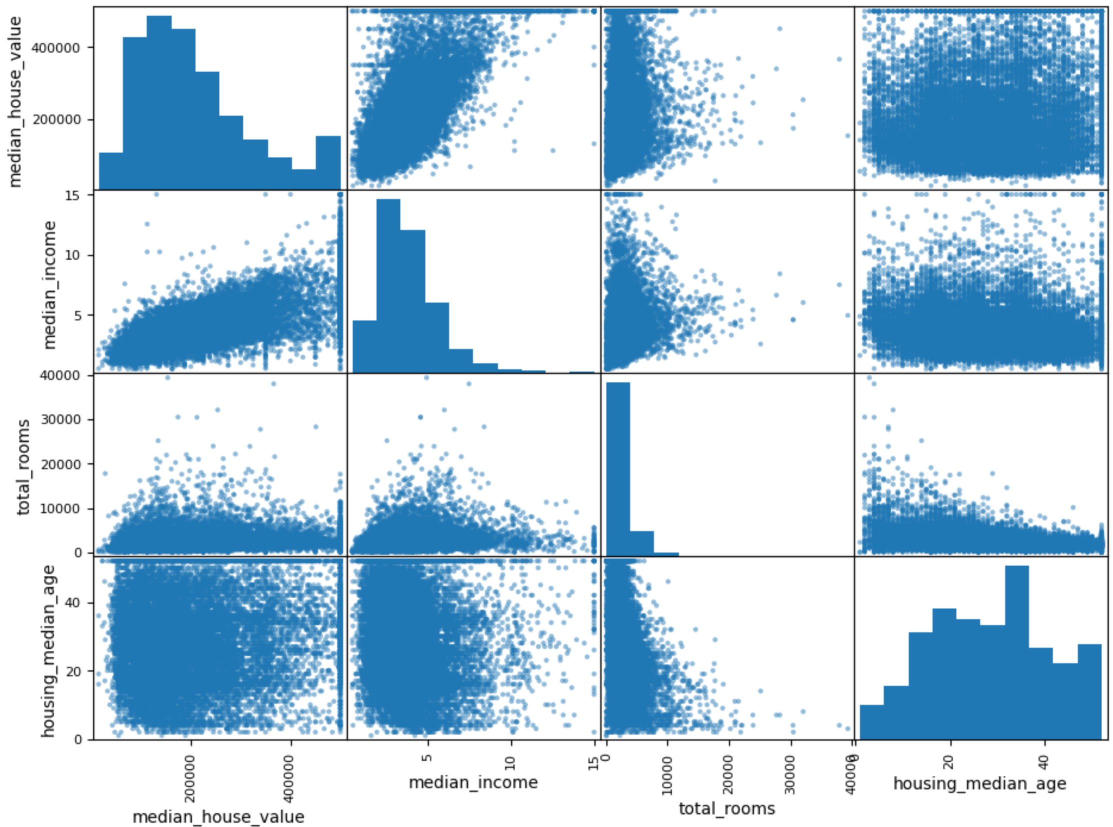
price decrease towards north. if income is more, house price is more … etc …

[34]:
```python
from pandas.plotting import scatter_matrix
```

[35]:
```python
# scatter_matrix can plot for all pair of values.
# we select a few

attributes = ['median_house_value', 'median_income',
              'total_rooms', 'housing_median_age']
scatter_matrix(housing1[attributes], figsize=(11, 8))
# the principal diag would have all straight line plots (useless)
# so scatter_matrix() plots histogram instead
# plt.show()
```

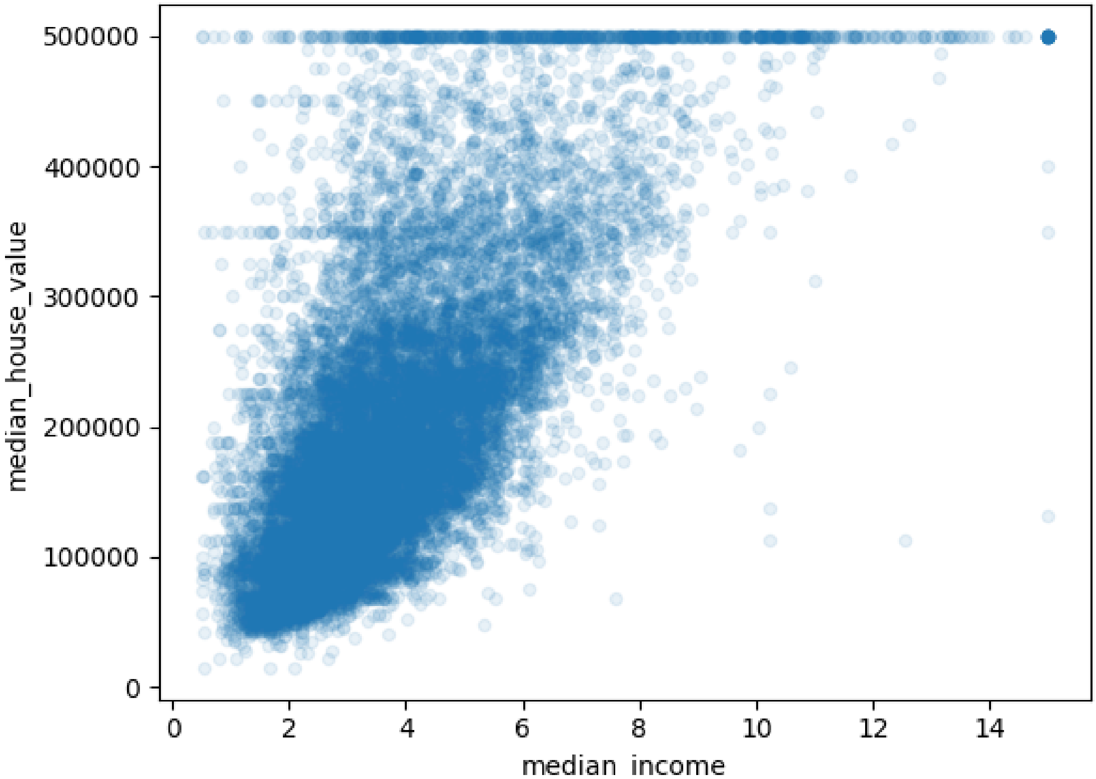
[35]:
```
array([[<AxesSubplot: xlabel='median_house_value', ylabel='median_house_value'>,
        <AxesSubplot: xlabel='median_income', ylabel='median_house_value'>,
        <AxesSubplot: xlabel='total_rooms', ylabel='median_house_value'>,
        <AxesSubplot: xlabel='housing_median_age',
ylabel='median_house_value'>],
       [<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)
```



[36]:
```
# The most promising one looks median_house_val vs median_income

housing1.plot(kind='scatter', x='median_income',
              y='median_house_value', alpha=0.1)
```

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



Horizontal line around 5K denotes the price cap other horizontal lines around $ 4.5 K and $ 3.5 K We may want to remove these corresponding districts to prevent the algorithm from reproducing these data quirks

1.8 Adding New Attributes

[37]:
```
# rooms per household is better measure than tot rooms in district
# bedrooms per room is better measure than tot bedrooms in district
# etc
housing1['rooms_per_household'] = housing1['total_rooms'] /␣
 ↪housing1['households']
housing1['bedrooms_per_room'] = housing1['total_bedrooms'] /␣
 ↪housing1['total_rooms']
housing1['population_per_household'] = housing1['population'] /␣
 ↪housing1['households']
```

[38]:
```
corr_matrix = housing1.corr(numeric_only=True)
corr_matrix['median_house_value'].sort_values(ascending=False)
```

[38]:
```
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
```

We see our new attributes have better correlation with median__house__value than the previous ones

1.9 Prepare Data

[39]:
```
# going back to the original data set
# coz the book says so
housing2 = strat_train_set.drop('median_house_value', axis=1)
housing2_labels = strat_train_set['median_house_value'].copy()
```

[40]:
```
#### tot_bedroom had null values

## 3 ways
# 1 (delete rows where null value exists)
# housing2.dropna(subset=['total_bedrooms'])

# 2 (remove the entire total_bedrooms column)
# housing2.drop('total_bedrooms', axis=1)

# 3 (replace null values with median)
## use this same median to fill in null vals of test dataset
# median = housing2['total_bedrooms'].median()
# housing2['total_bedrooms'].fillna(median, inplace=True)***
```

[41]:
```
## Or, use sklearn
```

[42]:
```
from sklearn.impute import SimpleImputer
```

[43]:
```
imputer = SimpleImputer(strategy='median')
```

[44]:
```
# median can only be calculated on numeric attributes
# so create a copy of the dataset without non numeric attr

housing2_num = housing2.drop('ocean_proximity', axis=1)
```

[45]:
```
# only total_bedrooms attr had missing data
# but we apply imputer to entire data coz we don't
# know what will hapeen when the dataset gets updated
imputer.fit(housing2_num)
```

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

[46]:
```
# imputer calculates the median of each val
# and stores in statistics_ instance variable

imputer.statistics_
```

[46]:
```
array([-118.51    ,   34.26    ,   29.     , 2119.     ,  433.     ,
       1164.     ,  408.     ,    3.54155])
```

[47]:
```
housing2_num.median().values
```

[47]:
```
array([-118.51    ,   34.26    ,   29.     , 2119.     ,  433.     ,
       1164.     ,  408.     ,    3.54155])
```

[48]:
```
X = imputer.transform(housing2_num)
```

[49]:
```
X  # numpy arr
```

[49]:
```
array([[-1.2146e+02,  3.8520e+01,  2.9000e+01, …,  2.2370e+03,
         7.0600e+02,  2.1736e+00],
       [-1.1723e+02,  3.3090e+01,  7.0000e+00, …,  2.0150e+03,
         7.6800e+02,  6.3373e+00],
       [-1.1904e+02,  3.5370e+01,  4.4000e+01, …,  6.6700e+02,
         3.0000e+02,  2.8750e+00],
       …,
       [-1.2272e+02,  3.8440e+01,  4.8000e+01, …,  4.5800e+02,
         1.7200e+02,  3.1797e+00],
       [-1.2270e+02,  3.8310e+01,  1.4000e+01, …,  1.2080e+03,
         5.0100e+02,  4.1964e+00],
       [-1.2214e+02,  3.9970e+01,  2.7000e+01, …,  6.2500e+02,
         1.9700e+02,  3.1319e+00]])
```

[50]:
```
# can convert back to pd.DataFrame
housing2_tr = pd.DataFrame(X, columns=housing2_num.columns,
                          index=housing2_num.index)
```

[51]:
```
housing2_tr
```

[51]:
```
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
12655    -121.46     38.52                29.0       3873.0           797.0
15502    -117.23     33.09                 7.0       5320.0           855.0
2908     -119.04     35.37                44.0       1618.0           310.0
```

```
14053    -117.13     32.75                 24.0        1877.0            519.0
20496    -118.70     34.28                 27.0        3536.0            646.0
…          …       …                 …          …             …
15174    -117.07     33.03                 14.0        6665.0           1231.0
12661    -121.42     38.51                 15.0        7901.0           1422.0
19263    -122.72     38.44                 48.0         707.0            166.0
19140    -122.70     38.31                 14.0        3155.0            580.0
19773    -122.14     39.97                 27.0        1079.0            222.0

       population  households  median_income
12655      2237.0       706.0         2.1736
15502      2015.0       768.0         6.3373
2908        667.0       300.0         2.8750
14053       898.0       483.0         2.2264
20496      1837.0       580.0         4.4964
…             …          …            …
15174      2026.0      1001.0         5.0900
12661      4769.0      1418.0         2.8139
19263       458.0       172.0         3.1797
19140      1208.0       501.0         4.1964
19773       625.0       197.0         3.1319

[16512 rows x 8 columns]
```

1.10 Handling Categorical Attributes

[52]:
```python
housing2_cat = housing2[['ocean_proximity']]
# [] returns Series
# [[]] returns DataFrame
```

[53]:
```python
# type(housing2_cat)
```

[54]:
```python
housing2_cat.head(10)
```

[54]:
```
      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
```

1.10.1 Ordinal Encoding

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

[56]:
```
ordinal_encoder = OrdinalEncoder()
housing2_cat_encoded = ordinal_encoder.fit_transform(housing2_cat)
housing2_cat_encoded[:10]
```

[56]:
```
array([[1.],
       [4.],
       [1.],
       [4.],
       [0.],
       [3.],
       [0.],
       [0.],
       [0.],
       [0.]])
```

[57]:
```
ordinal_encoder.categories_
```

[57]:
```
[array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],
       dtype=object)]
```

Drawbacks does not give proper sense of closeness. 1H OCEAN is encoded as 0 INLAND as 1 … NEAR OCEAN as 4

But ***'NEAR OCEAN'*** is closer to ***'1H OCEAN'*** than ***'INLAND'*** is

1.10.2 One Hot Encoding

[58]:
```
from sklearn.preprocessing import OneHotEncoder
```

[59]:
```
cat_encoder = OneHotEncoder()
housing2_cat_1hot = cat_encoder.fit_transform(housing2_cat)
housing2_cat_1hot
```

[59]:
```
<16512x5 sparse matrix of type '<class 'numpy.float64'>'
        with 16512 stored elements in Compressed Sparse Row format>
```

[60]:
```
# convert to numpy array
housing2_cat_1hot.toarray()
```

[60]:
```
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.]])
```

[61]:
```
cat_encoder.categories_
```

[61]:
```
[array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],
       dtype=object)]
```

1.11 Custom Transformers

To work seamlessly with other scikitklearn functions

Create a class and implement 3 methods ***fit()*** (returning self) ***transform()*** and ***fit_transform()*** We get the last one for free if we inherit from the **TransformerMixin** class.

If we also inherit from **Base Estimator** (and avoid *args and **kwargs in our constructor), we also get 2 extra methods -> ***get_params()*** and ***set_params()*** (useful for automatic hyperparameter tuning)

[62]:
```
from sklearn.base import BaseEstimator, TransformerMixin
```

[63]:
```
rooms_ix, bedrooms_ix, population_ix, households_ix = 3, 4, 5, 6

class CombinedAttributesAdder(BaseEstimator, TransformerMixin):
    def __init__(self, add_bedrooms_per_room=True):  # no *args or **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[:, households_ix]
        population_per_household = X[:, population_ix] / X[:, households_ix]

        if self.add_bedrooms_per_room:
            bedrooms_per_room = X[:, bedrooms_ix] / X[:, rooms_ix]
            return np.c_[X, rooms_per_household, population_per_household,
                        bedrooms_per_room]
        else:
            return np.c_[X, rooms_per_household, population_per_household]
```

[64]:
```
attr_adder = CombinedAttributesAdder(add_bedrooms_per_room=False)
```

[65]:
```
attr_adder
```

[65]:
```
CombinedAttributesAdder(add_bedrooms_per_room=False)
```

[66]:
```
housing2_extra_attrib = attr_adder.transform(housing2.values)
```

[67]:
```
# housing2.values # returns np array
```

[68]:
```
housing2_extra_attrib
```

[68]:
```
array([[-121.46, 38.52, 29.0, …, 'INLAND', 5.485835694050992,
        3.168555240793201],
       [-117.23, 33.09, 7.0, …, 'NEAR OCEAN', 6.927083333333333,
        2.6236979166666665],
       [-119.04, 35.37, 44.0, …, 'INLAND', 5.3933333333333335,
        2.223333333333333],
       …,
       [-122.72, 38.44, 48.0, …, '<1H OCEAN', 4.1104651162790695,
        2.6627906976744184],
       [-122.7, 38.31, 14.0, …, '<1H OCEAN', 6.297405189620759,
        2.411177644710579],
       [-122.14, 39.97, 27.0, …, 'INLAND', 5.477157360406092,
        3.1725888324873095]], dtype=object)
```

[69]:
```
# cols = list(housing2.columns) + ['rooms_per_household',␣
 ↪'population_per_household']
# pd.DataFrame(housing2_extra_attrib, columns=cols, index=housing2.index)
```

1.12 Feature Scaling

[70]:
```
# MinMaxScaler or StandardScaler
```

[71]:
```
from sklearn.preprocessing import StandardScaler
```

[72]:
```
s = StandardScaler()
x = s.fit_transform(housing2_num)
x
```

[72]:
```
array([[-0.94135046,  1.34743822,  0.02756357, …,  0.73260236,
         0.55628602, -0.8936472 ],
       [ 1.17178212, -1.19243966, -1.72201763, …,  0.53361152,
         0.72131799,  1.292168  ],
       [ 0.26758118, -0.1259716 ,  1.22045984, …, -0.67467519,
        -0.52440722, -0.52543365],
       …,
       [-1.5707942 ,  1.31001828,  1.53856552, …, -0.86201341,
        -0.86511838, -0.36547546],
       [-1.56080303,  1.2492109 , -1.1653327 , …, -0.18974707,
         0.01061579,  0.16826095],
       [-1.28105026,  2.02567448, -0.13148926, …, -0.71232211,
        -0.79857323, -0.390569  ]])
```

1.13 Transformation Pipeline

[73]:
```
from sklearn.pipeline import Pipeline
```

[74]:
```
num_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='median')),
    ('attrins_adder', CombinedAttributesAdder()),
    ('std_scaler', StandardScaler())
])
```

Constructor takes an array of tuples All except maybe last estimator should be transformers The pipeline calls ***fit_transform()*** on every estimator except last one The pipeline exposes same methods as the last estimator Estimator names can be anything (as long as they are **unique** and not not conatin **double underscore ___**)

[75]:
```
housing2_num_tr = num_pipeline.fit_transform(housing2_num)
```

[76]:
```
housing2_num_tr
```

[76]:
```
array([[-0.94135046,  1.34743822,  0.02756357, …,  0.01739526,
         0.00622264, -0.12112176],
       [ 1.17178212, -1.19243966, -1.72201763, …,  0.56925554,
        -0.04081077, -0.81086696],
       [ 0.26758118, -0.1259716 ,  1.22045984, …, -0.01802432,
        -0.07537122, -0.33827252],
       …,
       [-1.5707942 ,  1.31001828,  1.53856552, …, -0.5092404 ,
        -0.03743619,  0.32286937],
       [-1.56080303,  1.2492109 , -1.1653327 , …,  0.32814891,
        -0.05915604, -0.45702273],
       [-1.28105026,  2.02567448, -0.13148926, …,  0.01407228,
         0.00657083, -0.12169672]])
```

1.13.1 To Handle Categorical and Numerical Attributes Together …

[77]:
```
from sklearn.compose import ColumnTransformer
```

[78]:
```
num_attribs = list(housing2_num)
cat_attribs = ['ocean_proximity']

cat_enc = OneHotEncoder()
full_pipeline = ColumnTransformer([
    ('num', num_pipeline, num_attribs),
    ('cat', OneHotEncoder(), cat_attribs) # or use cat_enc here
])
```

[79]:
```
housing2_prepared = full_pipeline.fit_transform(housing2)
```

[80]:
```
housing2_prepared
```

[80]:
```
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.        ]])
```

Instead of specifying a transformer Specify the string **'drop'** if we want the columns to be dropped or **'pass through'** if we want the columns to be left untouched By default, Remaing columns (which are not mentioned) are **dropped** We can set the remainder hyperparameter to any transformer (or to **'passthrough'**) if we want the cols to be handled differently.

1.14 Train

1.14.1 Linear Regression

[81]:
```
from sklearn.linear_model import LinearRegression
```

[82]:
```
lin_reg = LinearRegression()
lin_reg.fit(housing2_prepared, housing2_labels)
```

[82]:
```
LinearRegression()
```

[83]:
```
some_data = housing2.iloc[:5]
some_labels = housing2_labels.iloc[:5]

some_data_prepared = full_pipeline.transform(some_data)

print('Predictions: ', lin_reg.predict(some_data_prepared))
print('Labels: ', list(some_labels))
```

```
Predictions:  [ 85657.90192014 305492.60737488 152056.46122456 186095.70946094
 244550.67966089]
Labels:  [72100.0, 279600.0, 82700.0, 112500.0, 238300.0]
```

[84]:
```
from sklearn.metrics import mean_squared_error
```

In-sample Error

[85]:
```
housing2_predictions = lin_reg.predict(housing2_prepared)
lin_mse = mean_squared_error(housing2_labels, housing2_predictions)
lin_rmse = np.sqrt(lin_mse)
lin_rmse
```

[85]:
```
68627.87390018745
```

1.14.2 Decision Tree Regression

[86]:
```
from sklearn.tree import DecisionTreeRegressor
```

[87]:
```
tree_reg = DecisionTreeRegressor()
tree_reg.fit(housing2_prepared, housing2_labels)
```

[87]:
```
DecisionTreeRegressor()
```

In-sample Error

[88]:
```
housing2_predictions = tree_reg.predict(housing2_prepared)
tree_mse = mean_squared_error(housing2_labels, housing2_predictions)
tree_rmse = np.sqrt(tree_mse)
tree_rmse
```

[88]:
```
0.0
```

Over Fitting (Maybe) ^

1.15 Cross-Validation

[89]:
```
# We keep a small part of train set for validation.
# Repeat this k times with diff validation sets
```

[90]:
```
from sklearn.model_selection import cross_val_score
```

[91]:
```
# scores = cross_val_score(tree_reg, housing2_prepared,
#                          housing2_labels, scoring='neg_mean_squared_error',
#                          cv=10)
# also works
scores = cross_val_score(DecisionTreeRegressor(), housing2_prepared,
                        housing2_labels, scoring='neg_mean_squared_error',
                        cv=10) # 10 fold cross validation
```

[92]:
```
tree_rmse_scores = np.sqrt(-scores)
```

sklearn's validation feature expects a **utility function** (greater is better) rather than a **cost function** (lesser is better). So the scoring func is opposite of MSE (ie **negative MSE**). So we do np.sqrt(-scores)

[93]:
```python
def display_scores(score):
    print('Scores: ', score)
    print('Mean: ', score.mean())
    print('Standard Deviation: ', score.std())
```

[94]:
```python
display_scores(tree_rmse_scores)
```

```
Scores:  [72928.81689994 69905.46845225 67736.83442307 70173.4706294
 69094.00003168 76435.1156725  70025.98117165 72938.98490266
 68232.93055879 71890.812505  ]
Mean:  70936.24152469456
Standard Deviation:  2500.8197953609197
```

Non 0 error

1.15.1 Linear Regression with Cross-Validation

[95]:
```python
scores_lin = cross_val_score(LinearRegression(), housing2_prepared,
                             housing2_labels, scoring='neg_mean_squared_error',
                             cv=10)
```

[96]:
```python
lin_rmse_scores = np.sqrt(-scores_lin)
```

[97]:
```python
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:  2880.3282098180694
```

Decision Tree is performing worse than Linear Regression due to overfitting

1.16 Random Forest

[98]:
```python
from sklearn.ensemble import RandomForestRegressor
```

[99]:
```python
forest_reg = RandomForestRegressor()

forest_reg.fit(housing2_prepared, housing2_labels)
```

[99]:
```
RandomForestRegressor()
```

In-sample Error

[100]:
```python
housing2_predictions = forest_reg.predict(housing2_prepared)
forest_mse = mean_squared_error(housing2_labels, housing2_predictions)
forest_rmse = np.sqrt(forest_mse)
forest_rmse
```

[100]: 18772.030706185174

1.16.1 Cross-Validation

[101]:
```python
scores_forest = cross_val_score(RandomForestRegressor(), housing2_prepared,
                               housing2_labels,␣
 ↪scoring='neg_mean_squared_error',
                               cv=10)
```

[102]:
```python
forest_rmse = np.sqrt(-scores_forest)
```

[103]:
```python
display_scores(forest_rmse)
```

```
Scores:  [51399.05445742 48679.97473273 46679.4832476  52247.98814612
 47061.62775983 51940.3727087  52461.65904767 49909.77173122
 48246.26035636 53782.36236503]
Mean:  50240.855455267825
Standard Deviation:  2346.227624545286
```

Random Forest performs better

1.17 Fine Tuning

We can fine tune our model by chosing different values of the hyperparameters. We can use **GridSearchCV** or **RandomizedSearchCV** **GridSearchCV** will do cross validation to evaluate all the possible combination of hyper parameter values (from the list provided)

1.17.1 GridSearchCV

[104]:
```python
from sklearn.model_selection import GridSearchCV
```

[105]:
```python
param_grid = [
    {
        'n_estimators': [3, 10, 30],
        'max_features': [2, 4, 6, 8]
    },
    {
        'bootstrap': [False],
        'n_estimators': [3, 10],
        'max_features': [2, 3, 4]
    }
]

forest_reg = RandomForestRegressor()

grid_search = GridSearchCV(forest_reg, param_grid, cv=5,
                          scoring='neg_mean_squared_error',
                          return_train_score=True)
```

[106]:
```
grid_search.fit(housing2_prepared, housing2_labels)
```

[106]:
```
GridSearchCV(cv=5, estimator=RandomForestRegressor(),
             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')
```

param_grid is a **list of dictionaries** it tells sklearn to evaluate all 3 X 4 = 12 combinations of ***n_estimators*** and ***max_features*** hyper parameters in the first dict. and 2 X 3 = 6 combinations of hyper parameter values in the second dict. ie 12 + 6 = 18 cv = 5, means **cross validation 5 times**. therefore, no. of training rounds = 18 X 5 = **90**

[107]:
```
# best combination of hyper parameter
grid_search.best_params_
```

[107]:
```
{'max_features': 6, 'n_estimators': 30}
```

[108]:
```
# get the best estimator directly
grid_search.best_estimator_
```

[108]:
```
RandomForestRegressor(max_features=6, n_estimators=30)
```

[109]:
```
# evaluation scores
cvres = grid_search.cv_results_
grid_search.cv_results_.keys()
```

[109]:
```
dict_keys(['mean_fit_time', 'std_fit_time', 'mean_score_time', 'std_score_time',
'param_max_features', 'param_n_estimators', 'param_bootstrap', 'params',
'split0_test_score', 'split1_test_score', 'split2_test_score',
'split3_test_score', 'split4_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'])
```

[110]:
```
for mean_score, params in zip(cvres['mean_test_score'], cvres['params']):
    print(np.sqrt(-mean_score), params)
```

```
63273.66955927675 {'max_features': 2, 'n_estimators': 3}
55382.39852513334 {'max_features': 2, 'n_estimators': 10}
52848.43922048276 {'max_features': 2, 'n_estimators': 30}
60903.94446026712 {'max_features': 4, 'n_estimators': 3}
52693.345954306096 {'max_features': 4, 'n_estimators': 10}
50399.88249291672 {'max_features': 4, 'n_estimators': 30}
58851.27383038806 {'max_features': 6, 'n_estimators': 3}
52369.62190715339 {'max_features': 6, 'n_estimators': 10}
50160.78254392673 {'max_features': 6, 'n_estimators': 30}
58698.44345830117 {'max_features': 8, 'n_estimators': 3}
```

```
52239.472586957716 {'max_features': 8, 'n_estimators': 10}
50351.54063006674 {'max_features': 8, 'n_estimators': 30}
63032.11788739821 {'bootstrap': False, 'max_features': 2, 'n_estimators': 3}
54813.910235321644 {'bootstrap': False, 'max_features': 2, 'n_estimators': 10}
59261.17053785971 {'bootstrap': False, 'max_features': 3, 'n_estimators': 3}
52092.7192902424 {'bootstrap': False, 'max_features': 3, 'n_estimators': 10}
58109.441433584485 {'bootstrap': False, 'max_features': 4, 'n_estimators': 3}
51220.0336271174 {'bootstrap': False, 'max_features': 4, 'n_estimators': 10}
```

[111]:
```
# cvres # dict. key: value. (all values are array of 18 elem)
```

The best estimator was *{'max_features': 8, 'n_estimators': 30}* Which is the **highest** val in the hyperparams we provided

So we may try GridSearchCV again with higher values of the hyperparameters to see if there is any more improvement

GridSearchCV suitable for exploring relatively **few combinations of hyper paramter values***. **When hyperparameter search space is large, it is preferable to use Ramdomized-SearchCV.**

1.17.2 RandomizedSearchCV

It evaluates a given no. of random combinations by selecting a random value of each hyperparameter in each iteration.

1.18 Analyse Best Model

1.18.1 Find The Important Features

[112]:
```
feature_importances = grid_search.best_estimator_.feature_importances_
feature_importances
```

[112]:
```
array([8.31860398e-02, 7.33497114e-02, 4.00858397e-02, 1.74642489e-02,
       1.58839939e-02, 1.73393969e-02, 1.59457200e-02, 3.17160945e-01,
       6.89764708e-02, 1.10943588e-01, 7.26974513e-02, 1.16363546e-02,
       1.47800254e-01, 8.20908563e-05, 3.40332484e-03, 4.04456956e-03])
```

[113]:
```
extra_attribs = ['rooms_per_hhold', 'pop_per_hhold', 'bdrooms_per_room']
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)
```

[113]:
```
[(0.31716094546400553, 'median_income'),
 (0.14780025368066282, 'INLAND'),
 (0.11094358836326317, 'pop_per_hhold'),
 (0.08318603978176052, 'longitude'),
 (0.07334971142971058, 'latitude'),
```

```
 (0.07269745134678646, 'bdrooms_per_room'),
 (0.06897647075976776, 'rooms_per_hhold'),
 (0.04008583973789735, 'housing_median_age'),
 (0.0174642488636006, 'total_rooms'),
 (0.017339396868415624, 'population'),
 (0.01594571999311998, 'households'),
 (0.01588399390739492, 'total_bedrooms'),
 (0.011636354551262157, '<1H OCEAN'),
 (0.004044569557189336, 'NEAR OCEAN'),
 (0.0034033248388917916, 'NEAR BAY'),
 (8.20908562713625e-05, 'ISLAND')]
```

[114]:
```python
full_pipeline.named_transformers_  # just to see what's inside
```

[114]:
```
{'num': Pipeline(steps=[('imputer', SimpleImputer(strategy='median')),
                 ('attrins_adder', CombinedAttributesAdder()),
                 ('std_scaler', StandardScaler())]),
 'cat': OneHotEncoder()}
```

Inference - From feature importance We see ***median_income*** is most influencial. Only one ***ocean_proximity*** category is really useful. (We may remove the non important attributes)

1.19 Test Model

[ ]:
```python
final_model = grid_search.best_estimator_
```

[ ]:
```python
X_test = strat_test_set.drop('median_house_value', axis=1)
Y_test = strat_test_set['median_house_value'].copy()
```

[ ]:
```python
X_test_prepared = full_pipeline.transform(X_test)
# do NOT fit TEST data. ONLY transform
# the transformer sould be fitted with TRAINING data
```

[ ]:
```python
final_predictions = final_model.predict(X_test_prepared)
```

[ ]:
```python
final_mse = mean_squared_error(Y_test, final_predictions)
final_rmse = np.sqrt(final_mse)
final_rmse
```

Calc 95% confidence interval for generalization error using scipy.stats.t.interval()

[ ]:
```python
from scipy import stats
```

[ ]:
```python
confidence=0.95

squared_errors = (final_predictions - Y_test) ** 2
```

```python
np.sqrt(stats.t.interval(
    confidence, len(squared_errors)-1,
    loc=squared_errors.mean(),
    scale=stats.sem(squared_errors)
))
```

[ ]:

```python

```