Calfornia Housing price

Downloading the data

When we get the data, we get a file in the tgz form
So we nee d extract tgz file

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

HOUSING_PATH = "datasets\\housing"

```

```
DOWNLOAD_ROOT = "https://raw.githubusercontent.com/ageron/handson-ml/master/"
HOUSING_URL = DOWNLOAD_ROOT + HOUSING_PATH + "\\housing.tgz"
def fetch_housing_data(housing_url=HOUSING_URL, housing_path=HOUSING_PATH):
    if not os.path.isdir(housing_path):
        os.makedirs(housing_path)
        tgz_path = os.path.join(housing_path, "housing.tgz")
        urllib.request.urlretrieve(housing_url, tgz_path)
        # extract tgz file
        housing_tgz = tarfile.open(tgz_path)
        housing_tgz.extractall(path=housing_path)
        housing_tgz.close()

fetch_housing_data()
```

Loading csv file

> use pandas to load csv file

```
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)
```

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

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

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

```
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
```

- All the attributes are numerical except `ocean_proximity`.
  And it is probably a catogries attribute. And we can use `value_counts` to find out

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

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

- And we can also look at the numerical attributes

```
housing.describe()
```

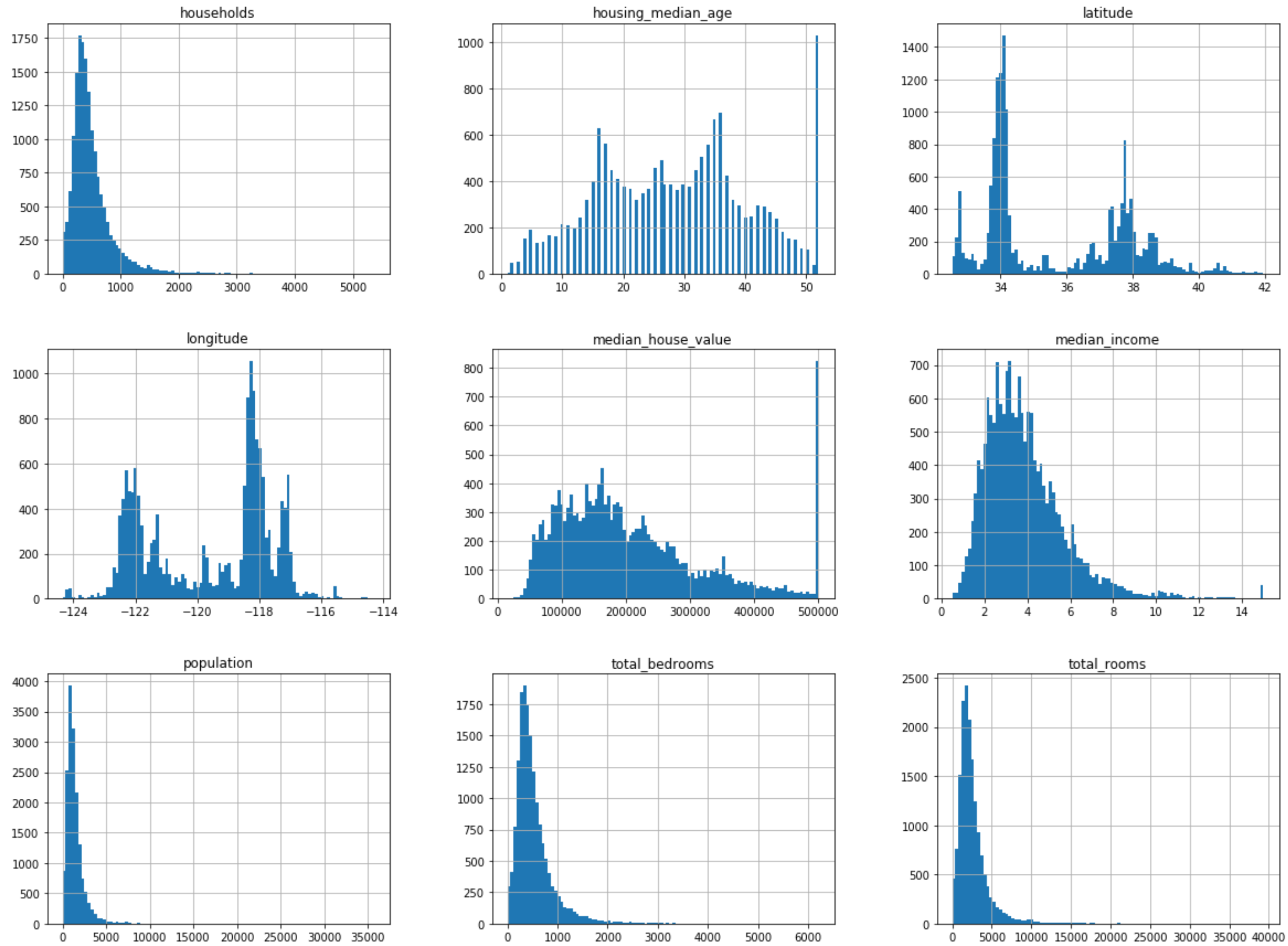
```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

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

we can also plot the histogram for each numerical attribute

```
%matplotlib inline
# only in jupyter notebook
import matplotlib.pyplot as plt
housing.hist(bins = 100, figsize=(20,15)) # figure size #bin : the number of the catogories
plt.show()
```



Create a Test Set

Create a test set: pick some examples randomly, approximately 20% of the dataset

```
import numpy as np

def split_train_test(data, test_ratio):
    random_indices = np.random.permutation(len(data))
    test_set_size = int( len(data) * test_ratio)
    test_indices = random_indices[:test_set_size]
    train_indices = random_indices[test_set_size:]
    return data.iloc[train_indices], data.iloc[test_indices]
```

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

```
16512 train + 4128 test 0.2
```

> We got some problem using the method above
> that is when every time we apply the funciton, it generates different data

So we can generate random indices in the first time.

But if the dataset is updated?

One common way is using each instance's identifier to descide whether or not it should go in the test set

```
import hashlib

def test_set_check(identifier, test_ratio, hash):
    return hash(np.int64(identifier)).digest()[-1] < 256 * test_ratio # the last byte of the md5 < 256 * ratio


def split_train_test_id(data, test_ratio, id_column, hash=hashlib.md5):
    ids = data[id_column]
    in_test_set = ids.apply(lambda id_: test_set_check(id_, test_ratio, hash)) # apply each id[i] to the funciton
    # lambda : anomynous function
    return data.loc[~in_test_set], data.loc[in_test_set]
```

Since the dataset do not have identifier column, we can set row index as ID:

```
housing_with_id = housing.reset_index() # add index column
housing_with_id["index"].head()
```

```
0    0
1    1
2    2
3    3
4    4
Name: index, dtype: int64
```

However, using index as indentier, we have to make sure that new data could only be added at the end of the dataset and no row ever get deleted.

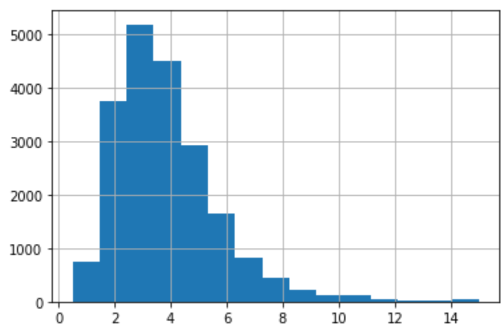
Since the latitude and longitude for a city won't change for a short period, we can set them as identifier

```
housing_with_id["id"] = housing["longitude"] * 1000 +  housing["latitude"]
housing_with_id["id"].head()
train_set, test_set = split_train_test_id(housing_with_id, 0.2, "id")
```

```
from sklearn.model_selection import train_test_split
train_set, test_set = train_test_split(housing, test_size=0.2, random_state=42) # done by skilt-learn
```

```
housing["median_income"].hist(bins = 15)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f15e6437f0>
```



To sample test set and training set according to the meadian income, we first generated categories through meadian_income from each city

```
housing["income_cat"] = np.ceil(housing["median_income"] / 1.5)
housing["income_cat"].where(housing["income_cat"] < 5, 5.0, inplace=True)
# make catogries which is greater than 5 merge into 5
```

Now using stratified sampling based on the income categries

```
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]

# To see the proportion of each categories
housing["income_cat"].value_counts() /len(housing)
```

```
3.0    0.350581
2.0    0.318847
4.0    0.176308
5.0    0.114438
1.0    0.039826
Name: income_cat, dtype: float64
```

Then remove column income_categories

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

Exporing the data and visualize the data

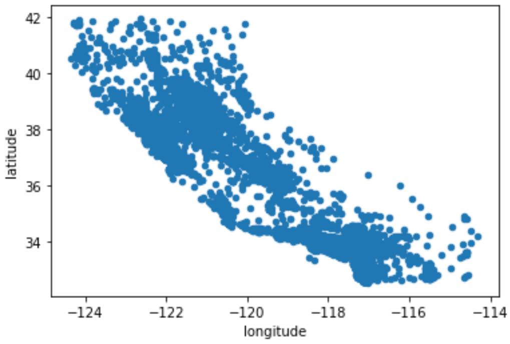
For not harming the training set, let's copy the data

```
housing = strat_train_set.copy()
```

Visualizing geographical data

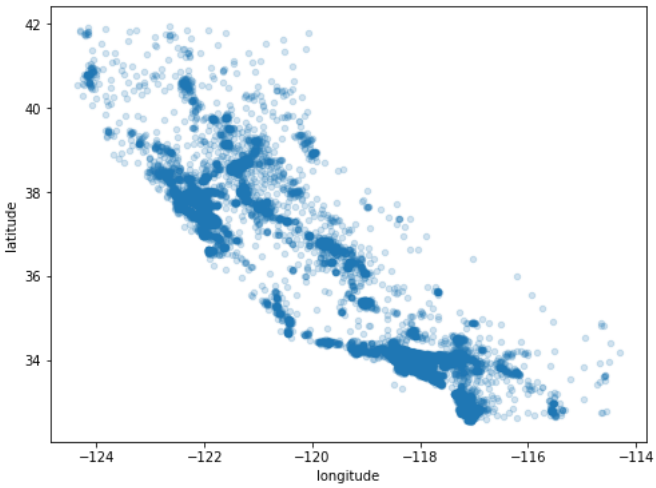
```
housing.plot(kind = "scatter", x = "longitude", y = "latitude") # scatter means discrete point
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1785b2ebbe0>
```




```
housing.plot(kind = "scatter", x = "longitude", y = "latitude", alpha=0.2,
             figsize = (8,6)) # alpha shows the density
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x17856ba2be0>
```

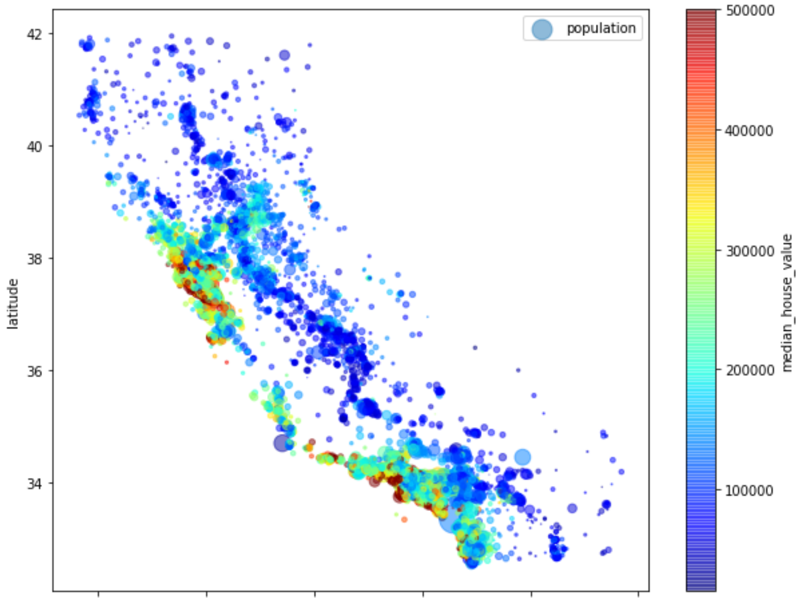


Now we are goint to plot a figure that can show the density by the radius of each circle, price by the color

> using predifeined color map `jet` which ranges from blue to red

```
housing.plot(kind = "scatter", x = "longitude", y= "latitude", alpha = 0.5,
             s = housing["population"]/80, label = "population",
             c = "median_house_value", cmap = plt.get_cmap("jet"), colorbar = True,
             figsize = (10,8))
plt.legend()
```

```
<matplotlib.legend.Legend at 0x1785baaaf28>
```



Looking for Correlations

```
corr_matrix = housing.corr()
```

Looking at each attribute correlates with the median house value:

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

```
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
```

Another way to check correlation is check every numerical attribute agianst every other attribute.

There are 11 numerical attributes, we would get 121 plots which would not fit on a page. So we would use the data that most correlated with the median housing price

```
housing.columns.tolist()
```

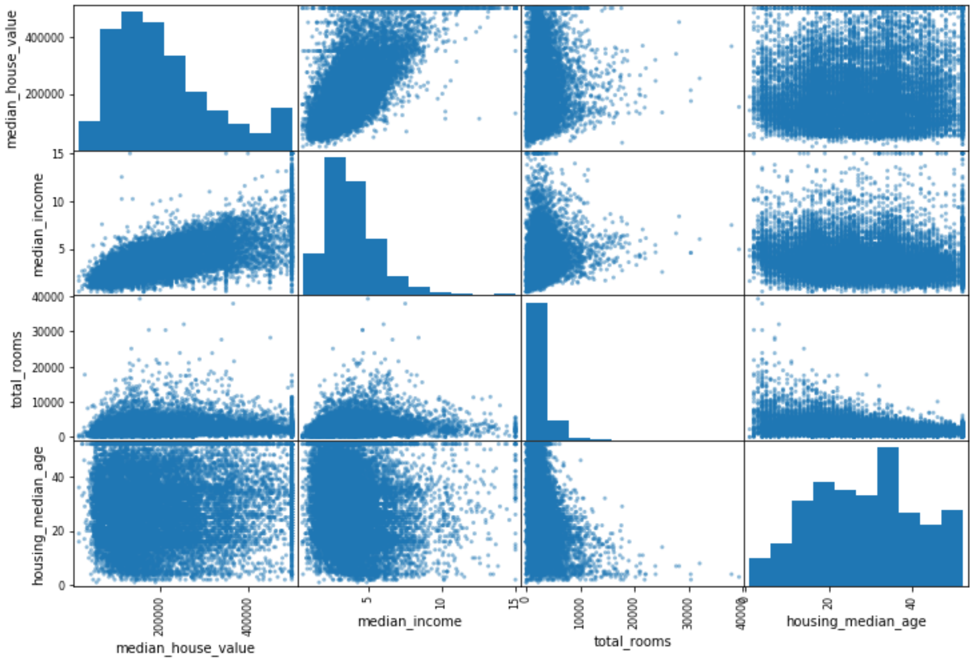
```
['longitude',
 'latitude',
 'housing_median_age',
 'total_rooms',
 'total_bedrooms',
 'population',
 'households',
 'median_income',
 'median_house_value',
 'ocean_proximity']
```

```
from pandas.plotting import scatter_matrix

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

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000001F15E3496D8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001F15E453EF0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001F15E42D390>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001F15E422908>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001F15E66CEB8>,
```

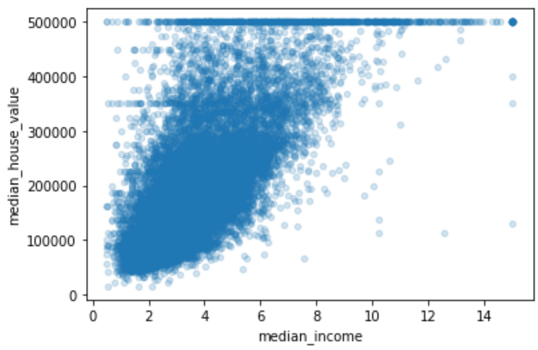
```
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001F15E5C54A8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001F15E999A58>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001F15ECC0080>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001F15ECC00B8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001F15E96ABA8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001F15E555198>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001F15EC64630>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001F15EC6CBA8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001F15E12C198>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001F15E11B748>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001F15E1C7CF8>]],
      dtype=object)
```



The most correlated attribute is median income, let's look closely

```
housing.plot(kind = "scatter", x = "median_income", y = "median_house_value", alpha = 0.2)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f15e1e1fd0>
```



Attribute Combinations

the total number of rooms in a district is not very useful if we don't know how many households there are.

What we really want is the number of rooms per household.

Similaryly, the totao numer of bedrooms by itself is not useful.

```
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"]
```

Let's look the correlation of the new matrix

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

```
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
```

Prepare the Data for Machine Learning

First we copy the data, and let the data become labels and non-labels

```
housing = strat_train_set.drop("median_house_value", axis = 1)
housing_labels = strat_train_set["median_house_value"].copy()
housing.head()
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_prox
17606	-121.89	37.29	38.0	1568.0	351.0	710.0	339.0	2.7042	<1H OCEAN
18632	-121.93	37.05	14.0	679.0	108.0	306.0	113.0	6.4214	<1H OCEAN
14650	-117.20	32.77	31.0	1952.0	471.0	936.0	462.0	2.8621	NEAR OCEA
3230	-119.61	36.31	25.0	1847.0	371.0	1460.0	353.0	1.8839	INLAND
3555	-118.59	34.23	17.0	6592.0	1525.0	4459.0	1463.0	3.0347	<1H OCEAN

There are some missing values in total_bedrooms, so they are three options:

- Get rid of the corresponding cistricts
- Get rid of the whole attribute
- Set the values to some value (zero, the mean, the median, etc.)

```
housing.dropna(subset=["total_bedrooms"]) # option 1
housing.drop("total_bedrooms", axis = 1)  # option 2
median = housing["total_bedrooms"].median()
housing["total_bedrooms"].fillna(median)  # option 3
```

```
17606     351.0
18632     108.0
14650     471.0
3230      371.0
3555     1525.0
          ...
6563      236.0
12053     294.0
13908     872.0
11159     380.0
15775     682.0
Name: total_bedrooms, Length: 16512, dtype: float64
```

If option 3 is chosen, we need save `median` sklearn apply a function Imputer instance

```
from sklearn.preprocessing import Imputer

imputer = Imputer(strategy = "median")

housing_num = housing.drop("ocean_proximity", axis = 1) # drop the non numerical attributes
```

```
C:\Users\Archibald Chain\AppData\Roaming\Python\Python37\site-packages\sklearn\utils\deprecation.py:66: DeprecationWarning: Class Imputer is deprecated; Imputer was deprecated in version 0.20 and will be removed in 0.22. Import impute.SimpleImputer from sklearn instead.
  warnings.warn(msg, category=DeprecationWarning)
```

```
# fit the imputer instance to the training data using the fit() method:
imputer.fit(housing_num)
imputer.statistics_

```

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

```
X = imputer.transform(housing_num)
housing_tr = pd.DataFrame(X, columns = housing_num.columns)
```

Handling Text and Categorical Atrributes

Since the categories attributes are all in the 'string' type, we should turn every type into a catogories.

```
from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
housing_cat = housing["ocean_proximity"]
housing_cat_encoded = encoder.fit_transform(housing_cat)
housing_cat_encoded
```

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

```
encoder.classes_
```

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

However, the suitable solution should be giving 0 and 1 for each categories

```
from sklearn.preprocessing import OneHotEncoder
encoder = OneHotEncoder()
housing_cat_1hot = encoder.fit_transform(housing_cat_encoded.reshape(-1,1))
housing_cat_1hot
```

```
C:\Users\Archibald Chain\AppData\Roaming\Python\Python37\site-packages\sklearn\preprocessing\_encoders.py:415: FutureWarning: The handling of integer data will change in version 0.22. Currently, the categories are determined based on the range [0, max(values)], while in the future they will be determined based on the unique values.
If you want the future behaviour and silence this warning, you can specify "categories='auto'".
In case you used a LabelEncoder before this OneHotEncoder to convert the categories to integers, then you can now use the OneHotEncoder directly.
  warnings.warn(msg, FutureWarning)
```

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

The output a Scipy sparse matrix, instead of Numpy array. This is useful when with thousands of categorical attributes with thousands of categories

```
housing_cat_1hot.toarray()
```

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

- We can apply both transformations (from text categories to integer categories, then from integer categories to one-hot vectors) in one shot using the LabelBinarizer class:

```
from sklearn.preprocessing import LabelBinarizer
encoder = LabelBinarizer( sparse_output=True) # parameter true, it generate spares categories.
housing_cat_1hot = encoder.fit_transform(housing_cat)
housing_cat_1hot
```

```
<16512x5 sparse matrix of type '<class 'numpy.int32'>'
    with 16512 stored elements in Compressed Sparse Row format>
```

Custom Transformer

We can construct our own custom transformer

- with TransformerMixin, we get fit_transformer()
- with BaseEstimator, we get set_parameter() and get_parameter()

```
from sklearn.base import BaseEstimator, TransformerMixin

rooms_ix, bedrooms_ix, population_ix, household_ix = 3, 4, 5, 6
class CombinedAttributesAdder(BaseEstimator, TransformerMixin):
    def __init__(self, add_bedrooms_per_room = True):
        self.add_bedrooms_per_room = add_bedrooms_per_room
    def fit(self, X, y = None):
        return self
    def transform(self, X, y = None): # we get a numpy matrix rather than a pandas DataFrame
        rooms_per_household = X[:, 3]/ X[:, household_ix]
        population_per_household = X[:, population_ix] / X[:, bedrooms_ix]
        if self.add_bedrooms_per_room:
            bedrooms_per_room = X[:, rooms_ix]/ X[:,bedrooms_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=True)
housing_extra_attribs = attr_adder.transform(housing.values)
housing_extra_attribs
```

```
array([[-121.89, 37.29, 38.0, ..., 4.625368731563422, 2.022792022792023,
        4.467236467236467],
       [-121.93, 37.05, 14.0, ..., 6.008849557522124, 2.8333333333333335,
        6.287037037037037],
       [-117.2, 32.77, 31.0, ..., 4.225108225108225, 1.9872611464968153,
        4.144373673036093],
       ...,
       [-116.4, 34.09, 9.0, ..., 6.34640522875817, 2.4059633027522938,
        5.567660550458716],
       [-118.01, 33.82, 31.0, ..., 5.50561797752809, 3.568421052631579,
        5.157894736842105],
       [-122.45, 37.77, 52.0, ..., 4.843505477308295, 1.8607038123167154,
        4.538123167155425]], dtype=object)
```

```
class DataFrameSelector(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
```

Featuring Scaling

Two method to do it min-max scaling and standardization:

- Min-max scaling (many people call this normalization) is quite simple: values are shifted and rescaled so that they end up ranging from 0 to 1.
- Standardization is quite different: first it subtracts the mean value (so standardized values always have a zero mean), and then it divides by the variance so that the result-ing distribution has unit variance.

Transfomation Pipline

```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
num_pipeline = Pipeline([
    ('imputer', Imputer(strategy="median")),
    ('attribs_adder', CombinedAttributesAdder()),
    ('std_scaler', StandardScaler()),
        ])
housing_num_tr = num_pipeline.fit_transform(housing_num)
```

```
C:\Users\Archibald Chain\AppData\Roaming\Python\Python37\site-packages\sklearn\utils\deprecation.py:66: DeprecationWarning: Class Imputer is deprecated; Imputer was deprecated in version 0.20 and will be removed in 0.22. Import impute.SimpleImputer from sklearn instead.
  warnings.warn(msg, category=DeprecationWarning)
```

When call FeautreUnion's it runs each transformer's `transform()` method in parallel, waits for their output, and then concatenates them and returns the result

> In the latest version of sklearn, there are some problems when using pipeline on LabelBinarizer
>
> LabelBinarizer fit_transform() only have two parameters, while pipeline thought it has three
>
> Solution given by stack over flow is add a custom LabelBinarizer

```
from sklearn.base import TransformerMixin #gives fit_transform method for free
class MyLabelBinarizer(TransformerMixin):
    def __init__(self):
        self.encoder = LabelBinarizer()
    def fit(self, x, y=0):
        return self
    def transform(self, x, y=0):
        return self.encoder.fit_transform(x)
```

> Howver, using the LabelBinarizer above is still a problem.
>
> We can using the following way to solve it

```
from sklearn.base import TransformerMixin #gives fit_transform method for free
class MyLabelBinarizer2(TransformerMixin):
    def __init__(self, sparser_output = False):
        self.encoder1 = LabelEncoder()
        self.encoder2 = OneHotEncoder()#categories='auto')
        self.sparser_output = False
    def fit(self, x, y=0):
        return self
    def transform(self, x, y=0):
        encoded = self.encoder1.fit_transform(housing_cat)
        if self.sparser_output:
            return self.encoder2.fit_transform(encoded.reshape(-1,1))
        else:
            return self.encoder2.fit_transform(encoded.reshape(-1,1)).toarray()
```

```
from sklearn.pipeline import FeatureUnion

num_attribs = list(housing_num)  # return string index of each column as a list
cat_attribs = ["ocean_proximity"]

num_pipeline = Pipeline([
    ('selector', DataFrameSelector(num_attribs)),
    ('imputer', Imputer(strategy="median")),            #defined previous
    ('attribs_adder', CombinedAttributesAdder()),       # defined previous
    ('std_scaler', StandardScaler())
```

```
])
cat_pipeline = Pipeline([
    ('selector', DataFrameSelector(num_attribs)),
    ('label_binarizer', MyLabelBinarizer2())
])
full_pipeline = FeatureUnion(transformer_list=[
    ("num_pipeline", num_pipeline),
    ("cat_pipline", cat_pipeline)
])
```

```
C:\Users\Archibald Chain\AppData\Roaming\Python\Python37\site-packages\sklearn\utils\deprecation.py:66: DeprecationWarning: Class Imputer is deprecated; Imputer was deprecated in version 0.20 and will be removed in 0.22. Import impute.SimpleImputer from sklearn instead.
  warnings.warn(msg, category=DeprecationWarning)
```

```
# To apply the pipeline
housing_prepared = full_pipeline.fit_transform(housing)

```

```
C:\Users\Archibald Chain\AppData\Roaming\Python\Python37\site-packages\sklearn\preprocessing\_encoders.py:415: FutureWarning: The handling of integer data will change in version 0.22. Currently, the categories are determined based on the range [0, max(values)], while in the future they will be determined based on the unique values.
If you want the future behaviour and silence this warning, you can specify "categories='auto'".
In case you used a LabelEncoder before this OneHotEncoder to convert the categories to integers, then you can now use the OneHotEncoder directly.
  warnings.warn(msg, FutureWarning)
```

```
housing_prepared
```

```
array([[-1.15604281,  0.77194962,  0.74333089, ...,  0.        ,
         0.        ,  0.        ],
       [-1.17602483,  0.6596948 , -1.1653172 , ...,  0.        ,
         0.        ,  0.        ],
       [ 1.18684903, -1.34218285,  0.18664186, ...,  0.        ,
         0.        ,  1.        ],
       ...,
       [ 1.58648943, -0.72478134, -1.56295222, ...,  0.        ,
         0.        ,  0.        ],
       [ 0.78221312, -0.85106801,  0.18664186, ...,  0.        ,
         0.        ,  0.        ],
       [-1.43579109,  0.99645926,  1.85670895, ...,  0.        ,
         1.        ,  0.        ]])
```

Training and Evaluating on the Training Set

Linear Regression Model

```
from sklearn.linear_model import LinearRegression

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

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

Let's try it out on few instances

```
some_data = housing.iloc[:]
some_data = np.array(list(some_data))
some_labels = housing_labels.iloc[:5]
some_data_prepared = full_pipeline.transform(some_data)
print("Predictions:\t", lin_reg.predict(some_data_prepared))
print("Labels:\t\t", list(some_labels))
```

```
C:\Users\Archibald Chain\AppData\Roaming\Python\Python37\site-packages\ipykernel_launcher.py:7: FutureWarning: Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be interpreted as an array index, `arr[np.array(seq)]`, which will result either in an error or a different result.
  import sys
```

```
---------------------------------------------------------------------------

IndexError                                Traceback (most recent call last)

<ipython-input-219-343b2027d11d> in <module>
      2 some_data = np.array(list(some_data))
      3 some_labels = housing_labels.iloc[:5]
----> 4 some_data_prepared = full_pipeline.transform(some_data)
      5 print("Predictions:\t", lin_reg.predict(some_data_prepared))
      6 print("Labels:\t\t", list(some_labels))
```

```
~\AppData\Roaming\Python\Python37\site-packages\sklearn\pipeline.py in transform(self, X)
    958         Xs = Parallel(n_jobs=self.n_jobs)(
    959             delayed(_transform_one)(trans, X, None, weight)
--> 960             for name, trans, weight in self._iter())
    961         if not Xs:
    962             # All transformers are None
```

```
~\AppData\Roaming\Python\Python37\site-packages\joblib\parallel.py in __call__(self, iterable)
    919             # remaining jobs.
    920             self._iterating = False
--> 921             if self.dispatch_one_batch(iterator):
    922                 self._iterating = self._original_iterator is not None
    923
```

```
~\AppData\Roaming\Python\Python37\site-packages\joblib\parallel.py in dispatch_one_batch(self, iterator)
    757                 return False
    758             else:
--> 759                 self._dispatch(tasks)
    760                 return True
    761
```

```
~\AppData\Roaming\Python\Python37\site-packages\joblib\parallel.py in _dispatch(self, batch)
    714         with self._lock:
    715             job_idx = len(self._jobs)
--> 716             job = self._backend.apply_async(batch, callback=cb)
    717             # A job can complete so quickly than its callback is
    718             # called before we get here, causing self._jobs to
```

```
~\AppData\Roaming\Python\Python37\site-packages\joblib\_parallel_backends.py in apply_async(self, func, callback)
    180     def apply_async(self, func, callback=None):
    181         """Schedule a func to be run"""
--> 182         result = ImmediateResult(func)
    183         if callback:
    184             callback(result)
```

```
~\AppData\Roaming\Python\Python37\site-packages\joblib\_parallel_backends.py in __init__(self, batch)
    547         # Don't delay the application, to avoid keeping the input
    548         # arguments in memory
--> 549         self.results = batch()
    550
    551     def get(self):
```

```
~\AppData\Roaming\Python\Python37\site-packages\joblib\parallel.py in __call__(self)
    223         with parallel_backend(self._backend, n_jobs=self._n_jobs):
    224             return [func(*args, **kwargs)
--> 225                     for func, args, kwargs in self.items]
    226
    227     def __len__(self):
```

```
~\AppData\Roaming\Python\Python37\site-packages\joblib\parallel.py in <listcomp>(.0)
    223         with parallel_backend(self._backend, n_jobs=self._n_jobs):
    224             return [func(*args, **kwargs)
--> 225                     for func, args, kwargs in self.items]
    226
    227     def __len__(self):
```

```
~\AppData\Roaming\Python\Python37\site-packages\sklearn\pipeline.py in _transform_one(transformer, X, y, weight, **fit_params)
    693
    694 def _transform_one(transformer, X, y, weight, **fit_params):
--> 695     res = transformer.transform(X)
    696     # if we have a weight for this transformer, multiply output
    697     if weight is None:
```

```
~\AppData\Roaming\Python\Python37\site-packages\sklearn\pipeline.py in _transform(self, X)
    538         Xt = X
    539         for _, _, transform in self._iter():
--> 540             Xt = transform.transform(Xt)
    541         return Xt
    542
```

```
<ipython-input-66-2a3b4f0f19d9> in transform(self, X)
      5         return self
      6     def transform(self, X):
----> 7         return X[self.attribute_names].values
```

```
IndexError: only integers, slices (`:`), ellipsis (`...`), numpy.newaxis (`None`) and integer or boolean arrays are valid indices
```

```
from sklearn.metrics import mean_squared_error
housing_predictions = lin_reg.predict(housing_prepared)
lin_rmse = mean_squared_error(housing_labels, housing_predictions)
lin_rmse
```

```
4723628725.279794
```

Decession Tree Regression

```
from sklearn.tree import DecisionTreeRegressor

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

```
DecisionTreeRegressor(criterion='mse', max_depth=None, max_features=None,
                      max_leaf_nodes=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      presort=False, random_state=None, splitter='best')
```

```
housing_predictions = tree_reg.predict(housing_prepared)
tree_mse = mean_squared_error(housing_labels, housing_predictions)
tree_mse = np.sqrt(tree_mse)
tree_mse
```

```
0.0
```

Using Cross-Validation

We don't want to touch the test set until we are ready launch a model that we are very confident.

So we can use `train_test_split` to split the training set into a smaller training set and a validation set, then train the model against the smaller training set and evaluate them against the validation set.

K-fold cross-validation: it randomly splits the training set into 10 distinct
subsets called folds, then train the Decision Tree Model 10 times. picking a different fold for evaluation every time and training on the other 9 folds.
The result is an array containing 10 evaluation error:

```
from sklearn.model_selection import cross_val_score
tree_scores = cross_val_score(tree_reg, housing_prepared, housing_labels, scoring = "neg_mean_squared_error", cv = 10)
tree_rmse_scores = np.sqrt(-tree_scores)
```

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

display_scores(tree_rmse_scores)
```

```
Scores: [69050.64876384 65660.63657415 75056.13197538 74405.72582172
 75109.89210238 71037.39765743 69461.54545119 69014.78516735
 74549.56823219 71807.09541249]
Mean: 71515.34271581142
Standard deviation: 3068.4773994700613
```

```
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: [67017.10226888 67116.66376981 68070.49102354 74774.53394933
 68465.44788446 71478.52891582 65132.61122812 68494.45813594
 71953.12890783 67969.53501985]
Mean: 69047.25011035803
Standard deviation: 2703.5105098669956
```

It seems the Linear Regression Model performs better than Decision Tree Model. That's true, The decession Tree model is overfitting so badly.

Random Forest Model

```
from sklearn.ensemble import RandomForestRegressor
forest_reg = RandomForestRegressor()
forest_reg.fit(housing_prepared, housing_labels)
forest_rmse = mean_squared_error(housing_labels, forest_reg.predict(housing_prepared))
forest_rmse = np.sqrt(forest_rmse)
forest_rmse
```

```
C:\Users\Archibald Chain\AppData\Roaming\Python\Python37\site-packages\sklearn\ensemble\forest.py:245: FutureWarning: The default value of n_estimators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

```
22826.619828397306
```

```
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)
```

```
array([52886.91087803, 50029.92959489, 52265.17651867, 55219.16916582,
       53784.50474138, 56045.76721275, 51640.28748997, 51755.10523981,
       55944.04380411, 53207.74971784])
```

```
display_scores(forest_rmse_scores)
```

```
Scores: [52886.91087803 50029.92959489 52265.17651867 55219.16916582
 53784.50474138 56045.76721275 51640.28748997 51755.10523981
 55944.04380411 53207.74971784]
Mean: 53277.864436327225
Standard deviation: 1884.8867018860176
```

Now we need to save the model

```
from sklearn.externals import joblib

joblib.dump(forest_reg, "my_model.pkl")
```

```
['my_model.pkl']
```

```
forest_reg = joblib.load("my_model.pkl")
```

Fine-Tune Model

Grid Search

```python
from sklearn.model_selection import GridSearchCV

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')

grid_search.fit(housing_prepared, housing_labels)
```

```
GridSearchCV(cv=5, error_score='raise-deprecating',
             estimator=RandomForestRegressor(bootstrap=True, criterion='mse',
                                             max_depth=None,
                                             max_features='auto',
                                             max_leaf_nodes=None,
                                             min_impurity_decrease=0.0,
                                             min_impurity_split=None,
                                             min_samples_leaf=1,
                                             min_samples_split=2,
                                             min_weight_fraction_leaf=0.0,
                                             n_estimators='warn', n_jobs=None,
                                             oob_score=False, random_state=None,
                                             verbose=0, warm_start=False),
             iid='warn', n_jobs=None,
             param_grid=[{'max_features': [2, 4, 6, 8],
                          'n_estimators': [3, 10, 30]},
                         {'bootstrap': [False], 'max_features': [2, 3, 4],
                          'n_estimators': [3, 10]}],
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='neg_mean_squared_error', verbose=0)
```

```python
final_model = grid_search.best_estimator_
```

Evaluate system on Test Set

```python
X_test
```

```css
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_prox
5241	-118.39	34.12	29.0	6447.0	1012.0	2184.0	960.0	8.2816	<1H OCEAN
10970	-117.86	33.77	39.0	4159.0	655.0	1669.0	651.0	4.6111	<1H OCEAN
20351	-119.05	34.21	27.0	4357.0	926.0	2110.0	876.0	3.0119	<1H OCEAN
6568	-118.15	34.20	52.0	1786.0	306.0	1018.0	322.0	4.1518	INLAND
13285	-117.68	34.07	32.0	1775.0	314.0	1067.0	302.0	4.0375	INLAND
...	...	...	...	...	...	...	...	...	...
20519	-121.53	38.58	33.0	4988.0	1169.0	2414.0	1075.0	1.9728	INLAND
17430	-120.44	34.65	30.0	2265.0	512.0	1402.0	471.0	1.9750	NEAR OCEA
4019	-118.49	34.18	31.0	3073.0	674.0	1486.0	684.0	4.8984	<1H OCEAN
12107	-117.32	33.99	27.0	5464.0	850.0	2400.0	836.0	4.7110	INLAND
2398	-118.91	36.79	19.0	1616.0	324.0	187.0	80.0	3.7857	INLAND

4128 rows × 9 columns

```python
X_test = strat_test_set.drop("median_house_value", axis = 1)
X_test_cat = X_test["ocean_proximity"]
X_test_num = X_test.drop("ocean_proximity", axis = 1)

X_test_num_array = num_pipeline.fit_transform(X_test_num)

myLabelBinarizer = MyLabelBinarizer()
X_test_cat_array = myLabelBinarizer.fit_transform(X_test_cat)
y_test = strat_test_set["median_house_value"].copy()


X_test_prepared = np.hstack((X_test_num_array, X_test_cat_array))

```

```
(4128, 11)
```

```python
final_predictions = final_model.predict(X_test_prepared)
final_mse = mean_squared_error(y_test, final_predictions)
final_rmse = np.sqrt(final_mse)
```

```python
final_rmse
```

```
64692.9060362774
```