House Price Prediction

December 29, 2023

[75]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[76]:
```
df = pd.read_csv('/content/drive/MyDrive/Datasets/housing.csv')
```

[77]:
```
df.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
```

[78]:
```
df.dropna(inplace=True)
```

[79]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20433 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   longitude           20433 non-null  float64
 1   latitude            20433 non-null  float64
```

```
 2   housing_median_age  20433 non-null  float64
 3   total_rooms         20433 non-null  float64
 4   total_bedrooms      20433 non-null  float64
 5   population          20433 non-null  float64
 6   households          20433 non-null  float64
 7   median_income       20433 non-null  float64
 8   median_house_value  20433 non-null  float64
 9   ocean_proximity     20433 non-null  object
dtypes: float64(9), object(1)
memory usage: 1.7+ MB
```

[80]:
```
from sklearn.model_selection import train_test_split

x = df.drop(['median_house_value'], axis=1)
y = df['median_house_value']
```

[81]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2)
```

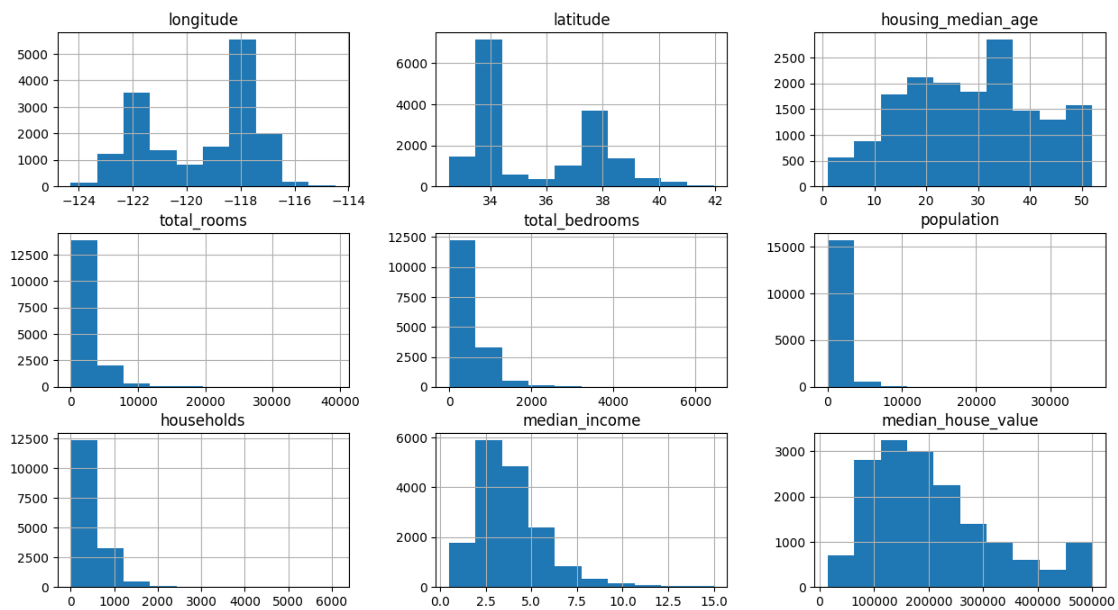
[82]:
```
train_data = x_train.join(y_train)
```

[83]:
```
train_data
```

[83]:
```
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
9377     -122.49     37.92                26.0       2170.0           347.0
19590    -120.85     37.57                27.0        819.0           157.0
14244    -117.10     32.70                28.0        633.0           137.0
2812     -119.03     35.41                41.0       1808.0           435.0
656      -122.14     37.71                18.0       3905.0          1007.0
…            …        …                    …           …              …
16185    -121.30     37.95                 9.0        674.0           242.0
5947     -117.86     34.14                33.0       2344.0           363.0
403      -122.26     37.90                52.0       1927.0           279.0
4681     -118.34     34.08                52.0       2756.0           542.0
19125    -122.64     38.25                31.0       2554.0           515.0

       population  households  median_income ocean_proximity  \
9377        849.0       318.0         6.2953        NEAR BAY
19590       451.0       150.0         3.4934          INLAND
14244       525.0       170.0         3.6042      NEAR OCEAN
2812       1005.0       373.0         1.7857          INLAND
656        2197.0      1044.0         3.6932        NEAR BAY
…             …          …             …             …
16185       575.0       193.0         2.2024          INLAND
5947       1098.0       359.0         6.2089          INLAND
403         705.0       288.0         7.8864        NEAR BAY
4681        971.0       510.0         5.5871       <1H OCEAN
19125      1507.0       533.0         3.8000       <1H OCEAN
```

```
       median_house_value
9377             386200.0
19590            193800.0
14244             95600.0
2812              54300.0
656              166800.0
…                       …
16185             45000.0
5947             283400.0
403              357300.0
4681             500001.0
19125            162600.0

[16346 rows x 10 columns]
```

[84]:
```python
train_data.hist(figsize=(15,8))
plt.show()
```



[85]:
```python
train_data.corr()
```

```
<ipython-input-85-8d2cc80a8830>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  train_data.corr()
```

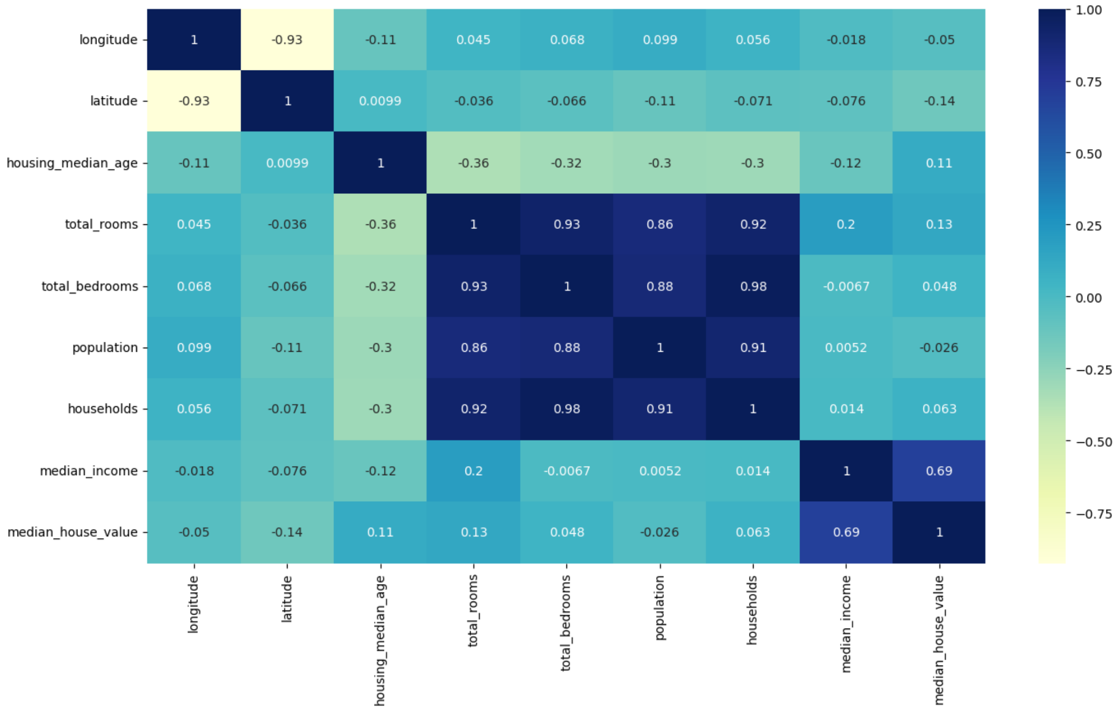
[85]:

```
                    longitude  latitude  housing_median_age  total_rooms  \
longitude            1.000000 -0.925421           -0.105819     0.044695
latitude            -0.925421  1.000000            0.009850    -0.036113
housing_median_age  -0.105819  0.009850            1.000000    -0.360089
total_rooms          0.044695 -0.036113           -0.360089     1.000000
total_bedrooms       0.067614 -0.065503           -0.320204     0.931190
population           0.099370 -0.107356           -0.296598     0.858012
households           0.056183 -0.070956           -0.304010     0.920539
median_income       -0.018377 -0.075814           -0.118598     0.196369
median_house_value  -0.049919 -0.138808            0.106341     0.131387

                    total_bedrooms  population  households  median_income  \
longitude                 0.067614    0.099370    0.056183      -0.018377
latitude                 -0.065503   -0.107356   -0.070956      -0.075814
housing_median_age       -0.320204   -0.296598   -0.304010      -0.118598
total_rooms               0.931190    0.858012    0.920539       0.196369
total_bedrooms            1.000000    0.877945    0.980765      -0.006667
population                0.877945    1.000000    0.906147       0.005187
households                0.980765    0.906147    1.000000       0.013973
median_income            -0.006667    0.005187    0.013973       1.000000
median_house_value        0.047656   -0.026165    0.062594       0.687044

                    median_house_value
longitude                    -0.049919
latitude                     -0.138808
housing_median_age            0.106341
total_rooms                   0.131387
total_bedrooms                0.047656
population                   -0.026165
households                    0.062594
median_income                 0.687044
median_house_value            1.000000
```

[86]:

```
plt.figure(figsize=(15,8))
sns.heatmap(train_data.corr(),annot=True,cmap="YlGnBu")
plt.show()
```

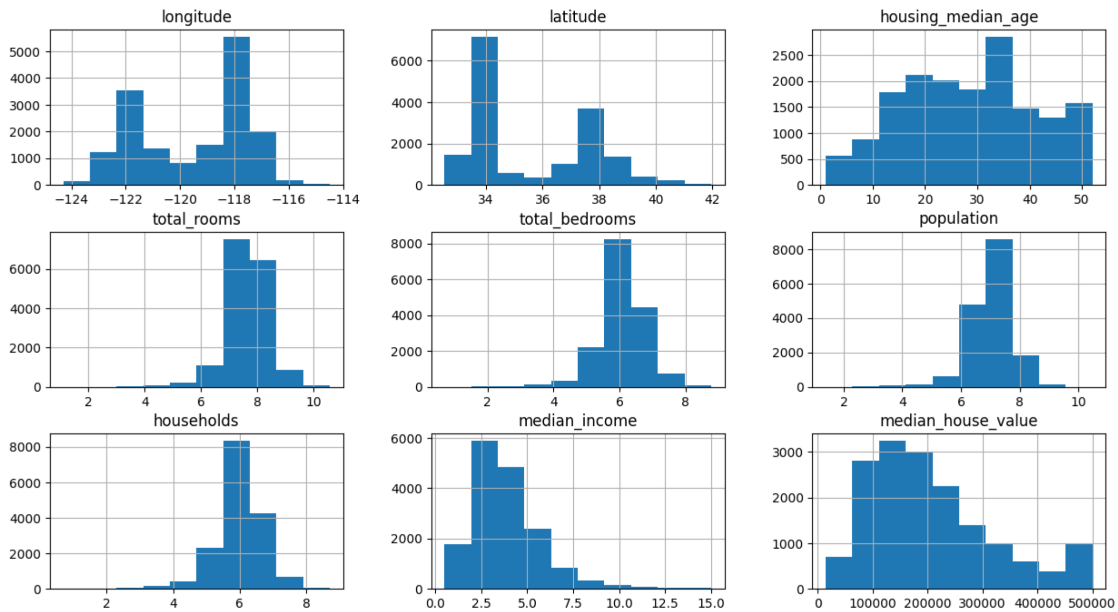
```
<ipython-input-86-94cd29a15e09>:2: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  sns.heatmap(train_data.corr(),annot=True,cmap="YlGnBu")
```



0.0.1 Turning the right screwed data graphs into gaussian bell curve we use log to make this and use +1 to get +ve value

[87]:
```
train_data['total_rooms'] = np. log(train_data['total_rooms'] + 1)
train_data['total_bedrooms'] = np.log(train_data['total_bedrooms'] + 1)
train_data['population'] = np.log(train_data['population'] + 1)
train_data['households'] = np.log(train_data['households'] + 1)
```

[88]:
```
train_data.hist(figsize=(15,8))
plt.show()
```



[89]:
```
train_data.ocean_proximity.value_counts()
```

[89]:
```
<1H OCEAN     7267
INLAND        5191
NEAR OCEAN    2084
NEAR BAY      1801
ISLAND           3
Name: ocean_proximity, dtype: int64
```

0.0.2 Replacing the categorical values of Ocean proximity column into numerical values

[90]:
```
train_data = train_data.join(pd.get_dummies(train_data['ocean_proximity'])).
↪drop(['ocean_proximity'], axis=1)
```

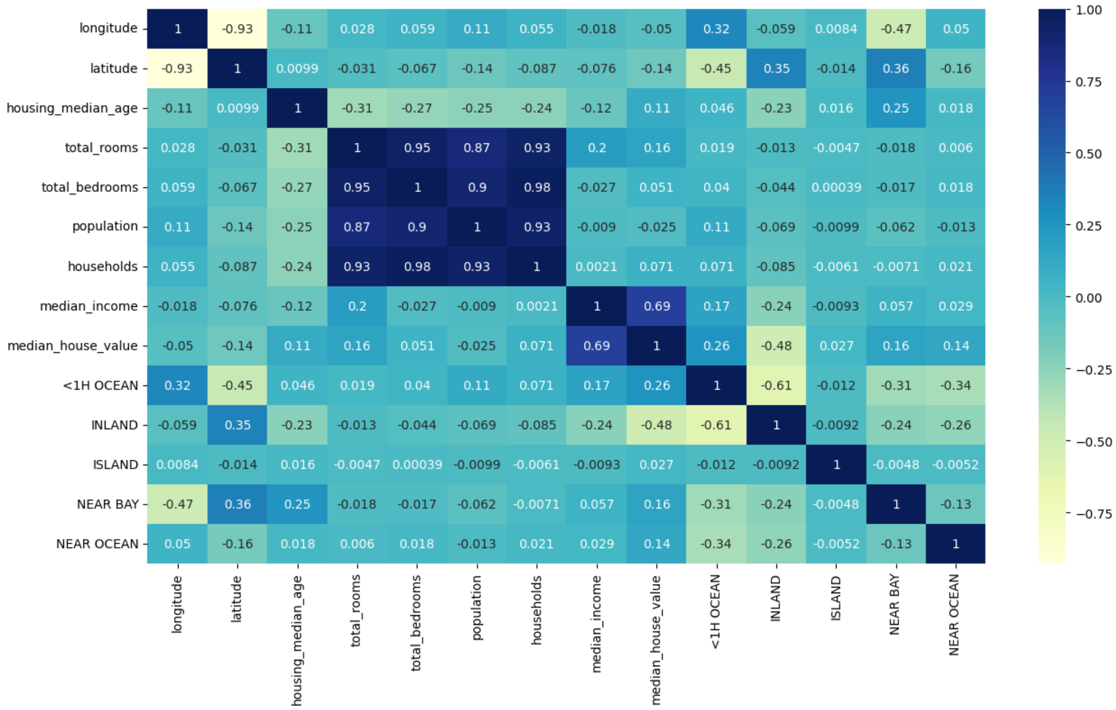
[91]:
```
train_data
```

[91]:

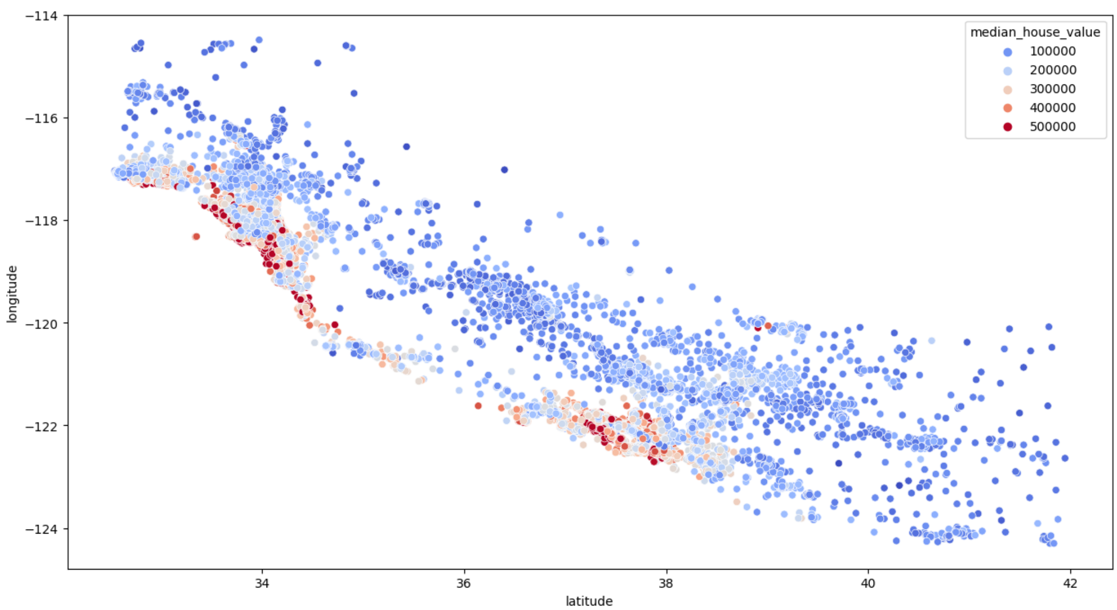
	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	\
9377	-122.49	37.92	26.0	7.682943	5.852202	
19590	-120.85	37.57	27.0	6.709304	5.062595	
14244	-117.10	32.70	28.0	6.452049	4.927254	
2812	-119.03	35.41	41.0	7.500529	6.077642	
656	-122.14	37.71	18.0	8.270269	6.915723	
…	…	…	…	…	…	
16185	-121.30	37.95	9.0	6.514713	5.493061	
5947	-117.86	34.14	33.0	7.760041	5.897154	
403	-122.26	37.90	52.0	7.564238	5.634790	

```
4681     -118.34    34.08                 52.0     7.921898         6.297109
19125    -122.64    38.25                 31.0     7.845808         6.246107

       population  households  median_income  median_house_value  <1H OCEAN  \
9377     6.745236    5.765191         6.2953            386200.0          0
19590    6.113682    5.017280         3.4934            193800.0          0
14244    6.265301    5.141664         3.6042             95600.0          0
2812     6.913737    5.924256         1.7857             54300.0          0
656      7.695303    6.951772         3.6932            166800.0          0
…             …           …            …                   …          …
16185    6.356108    5.267858         2.2024             45000.0          0
5947     7.002156    5.886104         6.2089            283400.0          0
403      6.559615    5.666427         7.8864            357300.0          0
4681     6.879356    6.236370         5.5871            500001.0          1
19125    7.318540    6.280396         3.8000            162600.0          1

       INLAND  ISLAND  NEAR BAY  NEAR OCEAN
9377        0       0         1           0
19590       1       0         0           0
14244       0       0         0           1
2812        1       0         0           0
656         0       0         1           0
…         …      …       …         …
16185       1       0         0           0
5947        1       0         0           0
403         0       0         1           0
4681        0       0         0           0
19125       0       0         0           0

[16346 rows x 14 columns]
```

[92]:
```
plt.figure(figsize=(15,8))
sns.heatmap(train_data.corr(),annot=True,cmap="YlGnBu")
plt.show()
```



[93]:
```
plt.figure(figsize=(15, 8))
sns.scatterplot(x="latitude", y="longitude", data=train_data,␣
↪hue="median_house_value", palette="coolwarm")
plt.show()
```

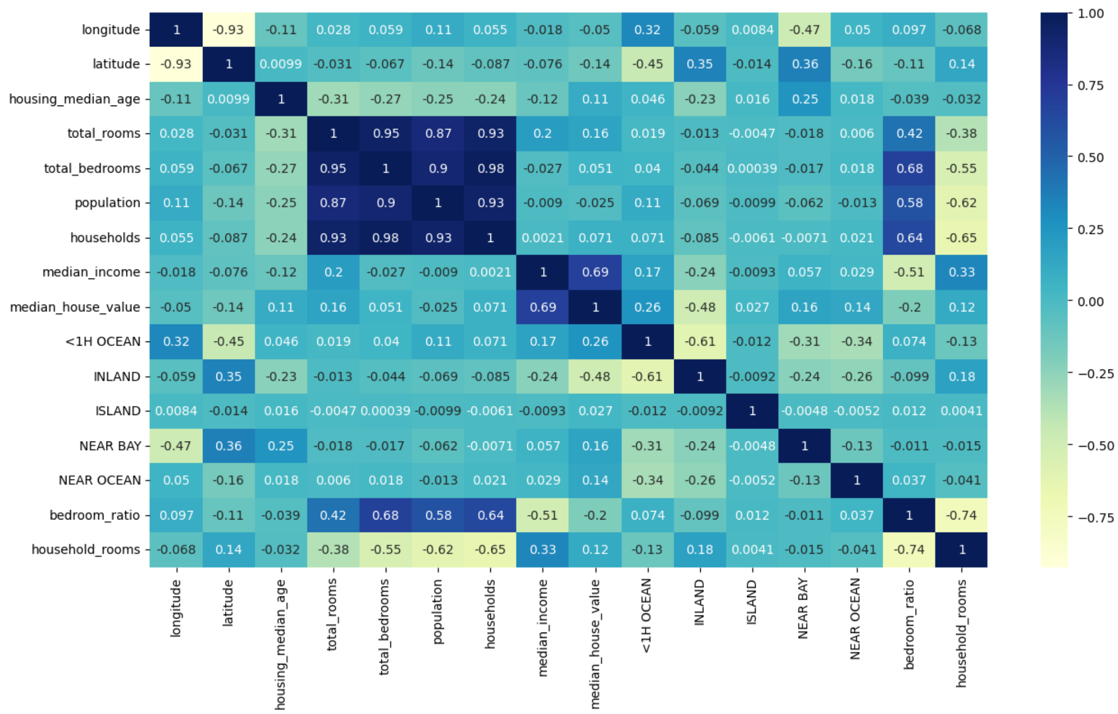


Houses which are near the Shore has a high house price when compared to the Inland houses.

1 Feature Engineering

[94]:
```
train_data['bedroom_ratio'] = train_data['total_bedrooms] /␣
↪train_data['total_rooms']
train_data['household_rooms'] = train_data['total_rooms'] /␣
↪train_data['households']
```

[95]:
```
plt.figure(figsize=(15,8))
sns.heatmap(train_data.corr(),annot=True,cmap="YlGnBu")
plt.show()
```



[96]:
```
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

x_train, y_train = train_data.drop(['median_house_value'], axis=1),␣
↪train_data['median_house_value']
x_train_s = scaler.fit_transform(x_train)

reg = LinearRegression()
```

```
reg.fit(x_train_s, y_train)
```

[96]: LinearRegression()

1.0.1 LinearRegression()

[97]:
```
test_data = x_test.join(y_test)

test_data['total_rooms'] = np.log(test_data['total_rooms'] + 1)
test_data['total_bedrooms'] = np.log(test_data['total_bedrooms'] + 1)
test_data['population'] = np.log(test_data['population'] + 1)
test_data['households'] = np.log(test_data['households'] + 1)

test_data = test_data.join(pd.get_dummies(test_data['ocean_proximity'])).
 ↪drop(['ocean_proximity'], axis=1)

test_data['bedroom_ratio'] = test_data['total_bedrooms'] /␣
 ↪test_data['total_rooms']
test_data['household_rooms'] = test_data['total_rooms'] /␣
 ↪test_data['households']
```

[98]:
```
x_test, y_test = test_data.drop(['median_house_value'], axis=1),␣
 ↪test_data['median_house_value']
```

[99]:
```
x_test_s = scaler.transform(x_test)
```

[100]:
```
reg.score(x_test_s, y_test)
```

[100]: 0.6853251973247589

1.0.2 Random Forest()

[101]:
```
from sklearn.ensemble import RandomForestRegressor
forest = RandomForestRegressor()
forest.fit(x_train_s, y_train)
```

[101]: RandomForestRegressor()

[102]:
```
forest.score(x_test_s, y_test)
```

[102]: 0.8295300182260509

[103]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestRegressor
```

```python
forest = RandomForestRegressor()

param_grid = {
    "n_estimators": [100, 200, 300],
    "min_samples_split": [2, 4],
    "max_depth": [None, 4, 8]
}

grid_search = GridSearchCV(forest, param_grid, cv=5,
                           scoring="neg_mean_squared_error",
                           return_train_score=True)

grid_search.fit(x_train_s, y_train)
```

[103]:
```
GridSearchCV(cv=5, estimator=RandomForestRegressor(),
             param_grid={'max_depth': [None, 4, 8], 'min_samples_split': [2, 4],
                         'n_estimators': [100, 200, 300]},
             return_train_score=True, scoring='neg_mean_squared_error')
```

[104]:
```python
grid_search.best_estimator_
```

[104]:
```
RandomForestRegressor(min_samples_split=4, n_estimators=300)
```

[105]:
```python
grid_search.best_estimator_.score(x_test_s,y_test)
```

[105]:
```
0.8298321486261955
```