# The question is: predict the median house value

Linear Regression For Price Prediction

In [3]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# set_option to format our numeric values
pd.set_option('display.precision',2) # precison mean the numbers after the dicem

# reset all options, *** ignore the warning that may appear ***
#pd.reset_option('all')

housing_data=pd.read_csv('housing.csv')

housing_data.sample(5)
```

Out[3]:

| | longitude | latitude | housing_median_age | total_rooms | total_bedrooms | population | househol |
|---|---|---|---|---|---|---|---|
| **1018** | -121.79 | 37.67 | 26.0 | 2163.0 | 339.0 | 947.0 | 34 |
| **5460** | -118.47 | 34.00 | 37.0 | 2586.0 | 765.0 | 1801.0 | 73 |
| **26** | -122.28 | 37.85 | 49.0 | 1130.0 | 244.0 | 607.0 | 23 |
| **14127** | -117.09 | 32.75 | 24.0 | 1245.0 | 376.0 | 1230.0 | 36 |
| **12246** | -116.96 | 33.74 | 19.0 | 3649.0 | 755.0 | 1717.0 | 69 |

# Data preparation

In [4]:
```
housing_data.shape
```

Out[4]: (20640, 10)

In [5]:
```
housing_data.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
```

In [6]:
```
# drop of fix null values, here wil just drop all rows with nulls
housing_data=housing_data.dropna()
housing_data.shape
```

Out[6]: (20433, 10)

In [7]:
```
# check to see if this field is a categorical field
housing_data['ocean_proximity'].unique()
```

Out[7]:
```
array(['NEAR BAY', '<1H OCEAN', 'INLAND', 'NEAR OCEAN', 'ISLAND'],
      dtype=object)
```

In [8]:
```
# convert the categorical columns to numeric data, this will add 4 new columns ar
housing_data=pd.get_dummies(housing_data,columns=['ocean_proximity'])
housing_data.shape
```

Out[8]: (20433, 14)

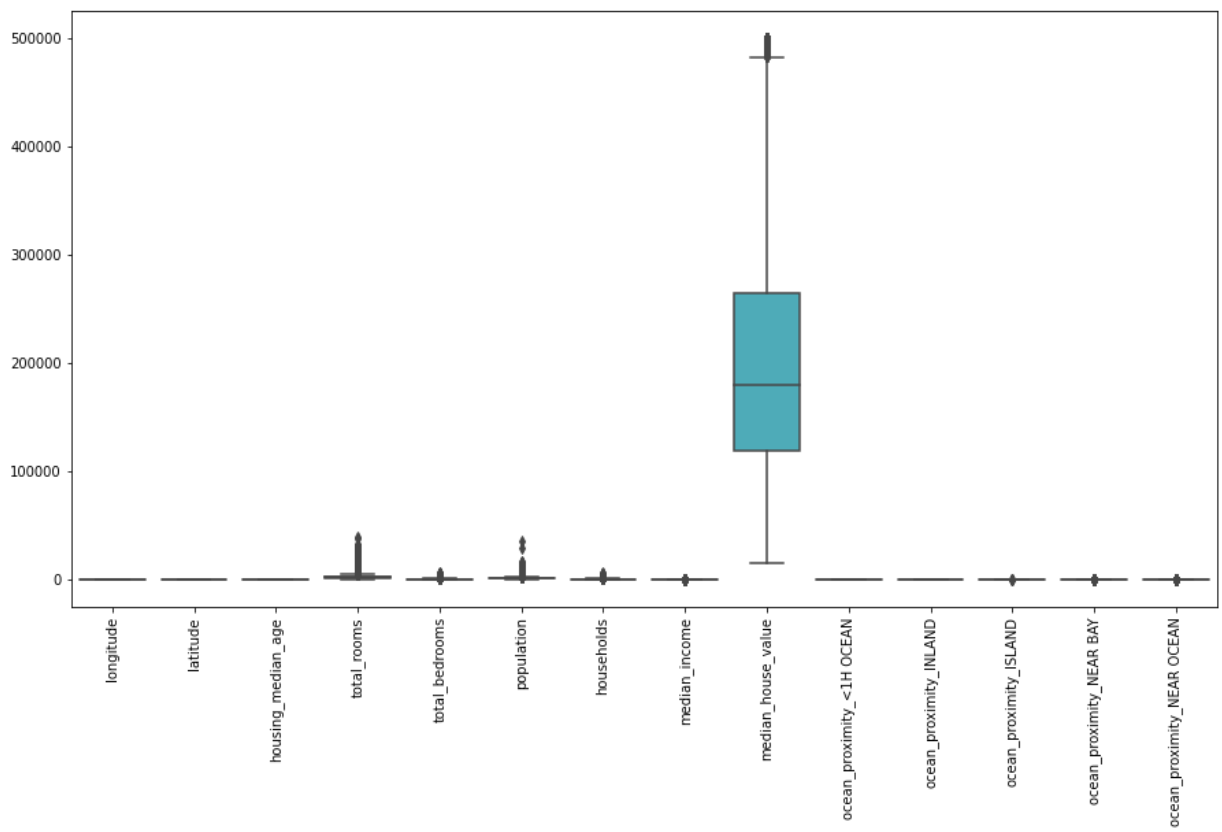
In [9]:
```
housing_data.head()
```

Out[9]:

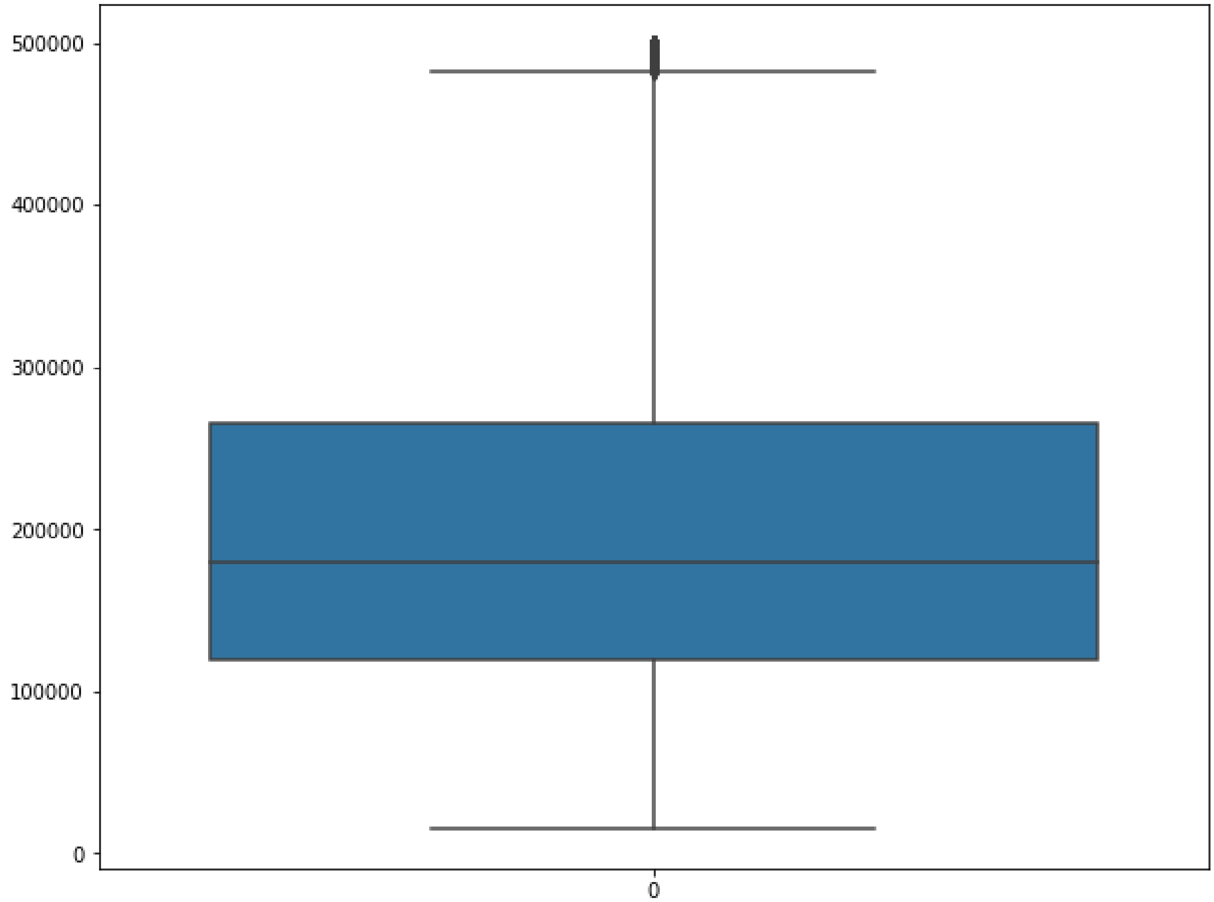
| | longitude | latitude | housing_median_age | total_rooms | total_bedrooms | population | households |
|---|---|---|---|---|---|---|---|
| **0** | -122.23 | 37.88 | 41.0 | 880.0 | 129.0 | 322.0 | 126.0 |
| **1** | -122.22 | 37.86 | 21.0 | 7099.0 | 1106.0 | 2401.0 | 1138.0 |
| **2** | -122.24 | 37.85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

In [10]:
```python
#we need to find out if there is any outliers i our data
# will draw boxplot for all columns
fig,ax=plt.subplots(figsize=(15,8))
bp=sns.boxplot(data=housing_data)
bp.set_xticklabels(bp.get_xticklabels(),rotation=90) # label rotation
```

Out[10]:
```
[Text(0, 0, 'longitude'),
 Text(1, 0, 'latitude'),
 Text(2, 0, 'housing_median_age'),
 Text(3, 0, 'total_rooms'),
 Text(4, 0, 'total_bedrooms'),
 Text(5, 0, 'population'),
 Text(6, 0, 'households'),
 Text(7, 0, 'median_income'),
 Text(8, 0, 'median_house_value'),
 Text(9, 0, 'ocean_proximity_<1H OCEAN'),
 Text(10, 0, 'ocean_proximity_INLAND'),
 Text(11, 0, 'ocean_proximity_ISLAND'),
 Text(12, 0, 'ocean_proximity_NEAR BAY'),
 Text(13, 0, 'ocean_proximity_NEAR OCEAN')]
```



In [11]:
```
# will draw boxplot for all columns
fig,ax=plt.subplots(figsize=(10,8))
bp=sns.boxplot(data=housing_data['median_house_value'])
```



In [12]:
```
# now we need to find out the max of 'median_house_value' to remove the outliers
housing_data.describe()
```

Out[12]:

| | longitude | latitude | housing_median_age | total_rooms | total_bedrooms | population | househo |
|---|---|---|---|---|---|---|---|
| count | 20433.00 | 20433.00 | 20433.00 | 20433.00 | 20433.00 | 20433.00 | 2043 |
| mean | -119.57 | 35.63 | 28.63 | 2636.50 | 537.87 | 1424.95 | 49 |
| std | 2.00 | 2.14 | 12.59 | 2185.27 | 421.39 | 1133.21 | 38 |
| min | -124.35 | 32.54 | 1.00 | 2.00 | 1.00 | 3.00 | |
| 25% | -121.80 | 33.93 | 18.00 | 1450.00 | 296.00 | 787.00 | 28 |
| 50% | -118.49 | 34.26 | 29.00 | 2127.00 | 435.00 | 1166.00 | 40 |
| 75% | -118.01 | 37.72 | 37.00 | 3143.00 | 647.00 | 1722.00 | 60 |
| max | -114.31 | 41.95 | 52.00 | 39320.00 | 6445.00 | 35682.00 | 608 |

In [13]:
```
# filter the data using loc and get the count
housing_data.loc[housing_data['median_house_value']==500001].count()
# 958 rows of data could skewness يحرف our training model result, so it is better
```

Out[13]:
```
longitude                     958
latitude                      958
housing_median_age            958
total_rooms                   958
total_bedrooms                958
population                    958
households                    958
median_income                 958
median_house_value            958
ocean_proximity_<1H OCEAN     958
ocean_proximity_INLAND        958
ocean_proximity_ISLAND        958
ocean_proximity_NEAR BAY      958
ocean_proximity_NEAR OCEAN    958
dtype: int64
```

In [14]:
```
# housing_data.drop(rows or columns indexies)
housing_data=housing_data.drop(housing_data.loc[housing_data['median_house_value'
housing_data.shape
```

Out[14]:
```
(19475, 14)
```

In [15]:
```
# now we need to get two sets of data
# x for train (features) and y for prediction (target)
# since we need to predict the median_house_value, so we need to drop it from our
X=housing_data.drop('median_house_value',axis=1) # axis=0 => rows and axis=1 => c
Y=housing_data['median_house_value']
```

In [16]:
```
X.columns
```

Out[16]:
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'ocean_proximity_<1H OCEAN', 'ocean_proximity_INLAND',
       'ocean_proximity_ISLAND', 'ocean_proximity_NEAR BAY',
       'ocean_proximity_NEAR OCEAN'],
      dtype='object')
```

# Train our model -spliting data

In [17]:
```
# we use the train data to train our model, and later will use the test data to m
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(X,Y,test_size=0.2)
```

In [18]:
```
x_train.shape,x_test.shape
```

Out[18]:
```
((15580, 13), (3895, 13))
```

In [19]:
```
y_train.shape,y_test.shape
```

Out[19]:
```
((15580,), (3895,))
```

Normalization scales all numersic features to be between 0 and 1.

Note: Having features in the same scale can vastly improve the performance of your ML model.

fit=Fit the linear model on the training data i.e. train the linear model using our features and target values.

In [20]:
```
from sklearn.linear_model import LinearRegression
linear_model=LinearRegression(normalize=True).fit(x_train,y_train)
```

# evaluation for training score

In [21]:
```
#print the evaluation score (R-square ) ,
# this shown how well our linear model capture the underlying variation in our tr
print("Training_score :",linear_model.score(x_train,y_train))
#0.6144045851306654 it is not fantastic but not bad
```

```
Training_score : 0.6129260115752351
```

In [22]:
```
predictors=x_train.columns
predictors
```

Out[22]:
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'ocean_proximity_<1H OCEAN', 'ocean_proximity_INLAND',
       'ocean_proximity_ISLAND', 'ocean_proximity_NEAR BAY',
       'ocean_proximity_NEAR OCEAN'],
      dtype='object')
```

In [23]:
```
# the coef is the facter that effect our prediction
# nagative values will lower the price
# we can indecate that the most expensive houses these located in on island
coef=pd.Series(linear_model.coef_,predictors).sort_values()
print(coef)
```

```
longitude                    -2.39e+04
latitude                     -2.19e+04
population                   -3.00e+01
total_rooms                  -7.93e+00
households                    4.66e+01
total_bedrooms                9.15e+01
housing_median_age            9.08e+02
median_income                 3.85e+04
ocean_proximity_INLAND        1.17e+17
ocean_proximity_NEAR BAY      1.17e+17
ocean_proximity_<1H OCEAN     1.17e+17
ocean_proximity_NEAR OCEAN    1.17e+17
ocean_proximity_ISLAND        1.17e+17
dtype: float64
```

In [24]:
```
# let us predict using the x_test
y_pred=linear_model.predict(x_test)
```

In [25]:
```
# to take a look on our model prediction using our eyes
#we want to compare between our actual data and predicted data
df_pred_actual=pd.DataFrame({'predicted':y_pred,'actual':y_test})
df_pred_actual.head(10)
```

Out[25]:

| | predicted | actual |
|---|---|---|
| **15821** | 223088.0 | 262500.0 |
| **16022** | 360640.0 | 394100.0 |
| **19983** | 59216.0 | 54400.0 |
| **6951** | 180496.0 | 163300.0 |
| **16825** | 229440.0 | 254100.0 |
| **12428** | 45552.0 | 100000.0 |
| **13523** | 129504.0 | 122200.0 |
| **12778** | 75488.0 | 58500.0 |
| **7276** | 123776.0 | 100300.0 |
| **14341** | 224352.0 | 466700.0 |

# evaluation for test score

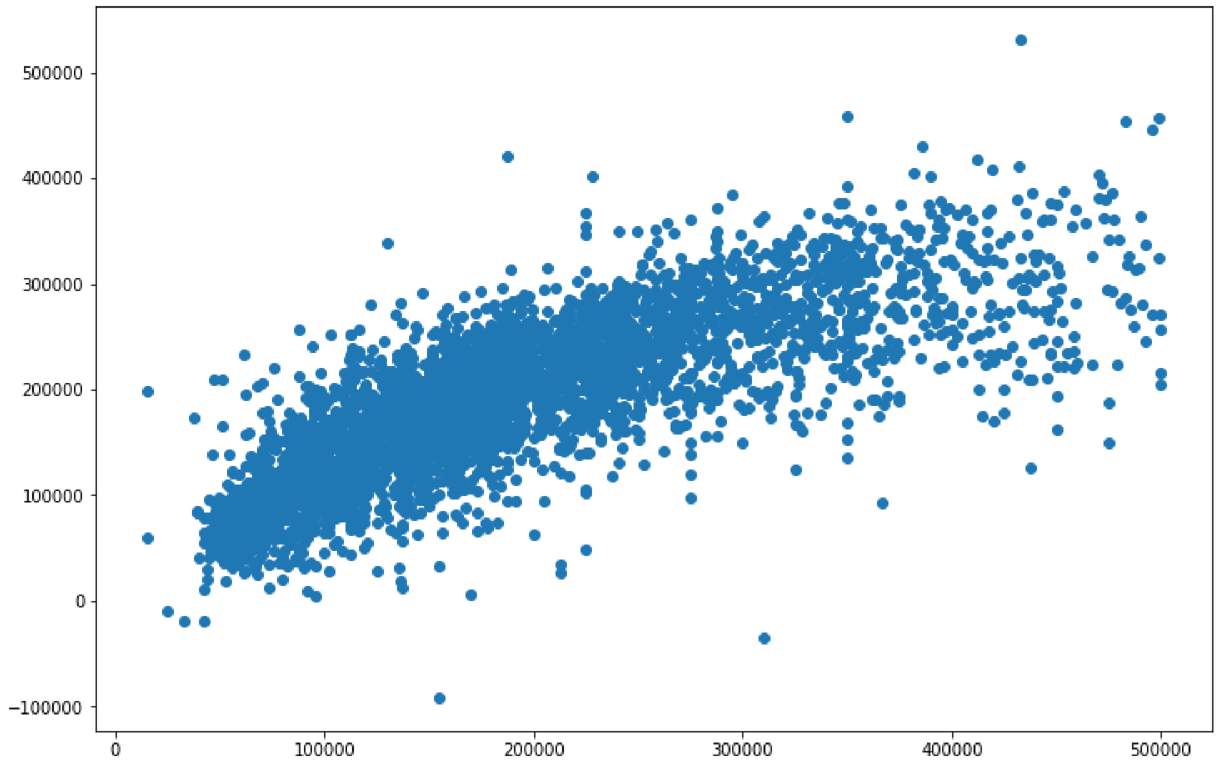
#### ***the best way to calculate the evaluate a model is to calculate an R-squared score (r2_score) on your test data***

In [26]:
```
from sklearn.metrics import r2_score
print('Testing_score :',r2_score(y_test,y_pred))
# we can see here that our test score almost same as our Training_score : 0.61644
```

```
Testing_score : 0.6128240315911189
```

In [ ]:
```
```

In [27]:
```
fig,ax=plt.subplots(figsize=(12,8))
plt.scatter(y_test,y_pred)
plt.show()
```



In [28]:
```
# we want to take a sample of 100 rows and plot
df_pred_actual_sample=df_pred_actual.sample(100)
df_pred_actual_sample=df_pred_actual_sample.reset_index()
df_pred_actual_sample.head()
```

Out[28]:

| | index | predicted | actual |
|---|---|---|---|
| **0** | 15363 | 275696.0 | 331300.0 |
| **1** | 17535 | 247712.0 | 199000.0 |
| **2** | 3204 | 148896.0 | 90600.0 |
| **3** | 1845 | 339008.0 | 333700.0 |
| **4** | 19931 | 185840.0 | 113000.0 |

In [29]:
```
# we plot our sample data (100 rows), comparing between actual and predicted datc
plt.figure(figsize=(20,10))
plt.plot(df_pred_actual_sample['predicted'],label='Predicted')
plt.plot(df_pred_actual_sample['actual'],label='Actual')

plt.ylabel('median_house_value')

plt.legend()
plt.show()
#notice: Predicted is blue and Actual is orange
```