Logistic Regression For Price Classification

predict the classification of house above or below the medain house value

In [1]:
```
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 dice

# 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[1]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	househol
13783	-117.06	34.03	27.0	1945.0	446.0	859.0	41
1706	-122.32	37.95	37.0	1887.0	353.0	895.0	35
8385	-118.36	33.98	45.0	1559.0	305.0	891.0	34
7753	-118.11	33.91	19.0	3056.0	759.0	1561.0	74
16120	-122.46	37.78	52.0	2594.0	622.0	1421.0	59

Data preparation

In [2]:
```
housing_data.shape
```

Out[2]:
```
(20640, 10)
```

In [3]:
```
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 [4]:
```
# drop of fix null values, here wil just drop all rows with nulls
housing_data=housing_data.dropna()
housing_data.shape
```

Out[4]:
```
(20433, 10)
```

In [5]:
```
# check to see if this field is a categorical field
housing_data['ocean_proximity'].unique()
```

Out[5]:
```
array(['NEAR BAY', '<1H OCEAN', 'INLAND', 'NEAR OCEAN', 'ISLAND'],
      dtype=object)
```

In [6]:
```
# convert the categorical columns to numeric data, this will add 4 new columns ar
housing_data=pd.get_dummies(housing_data,columns=['ocean_proximity']) # this step
housing_data.shape
```

Out[6]:
```
(20433, 14)
```

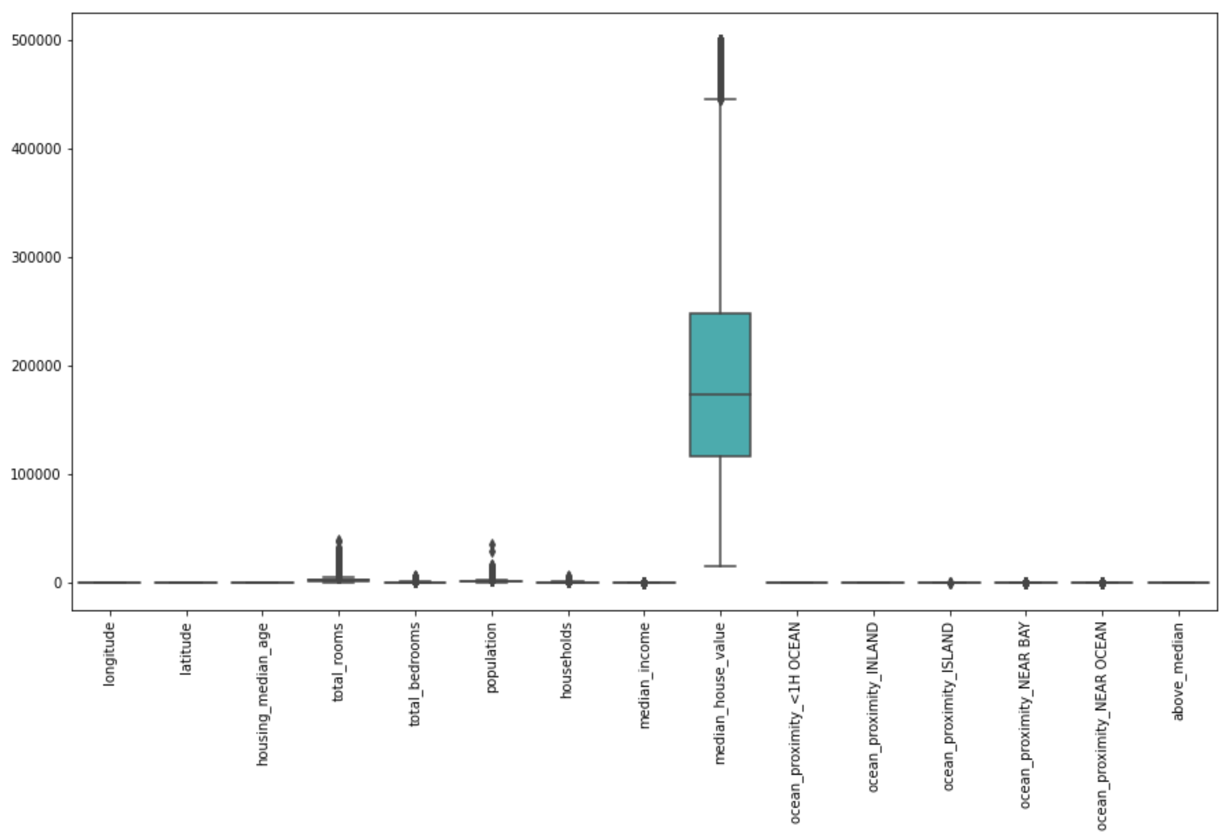
In [7]:
```
housing_data.head()
```

Out[7]:

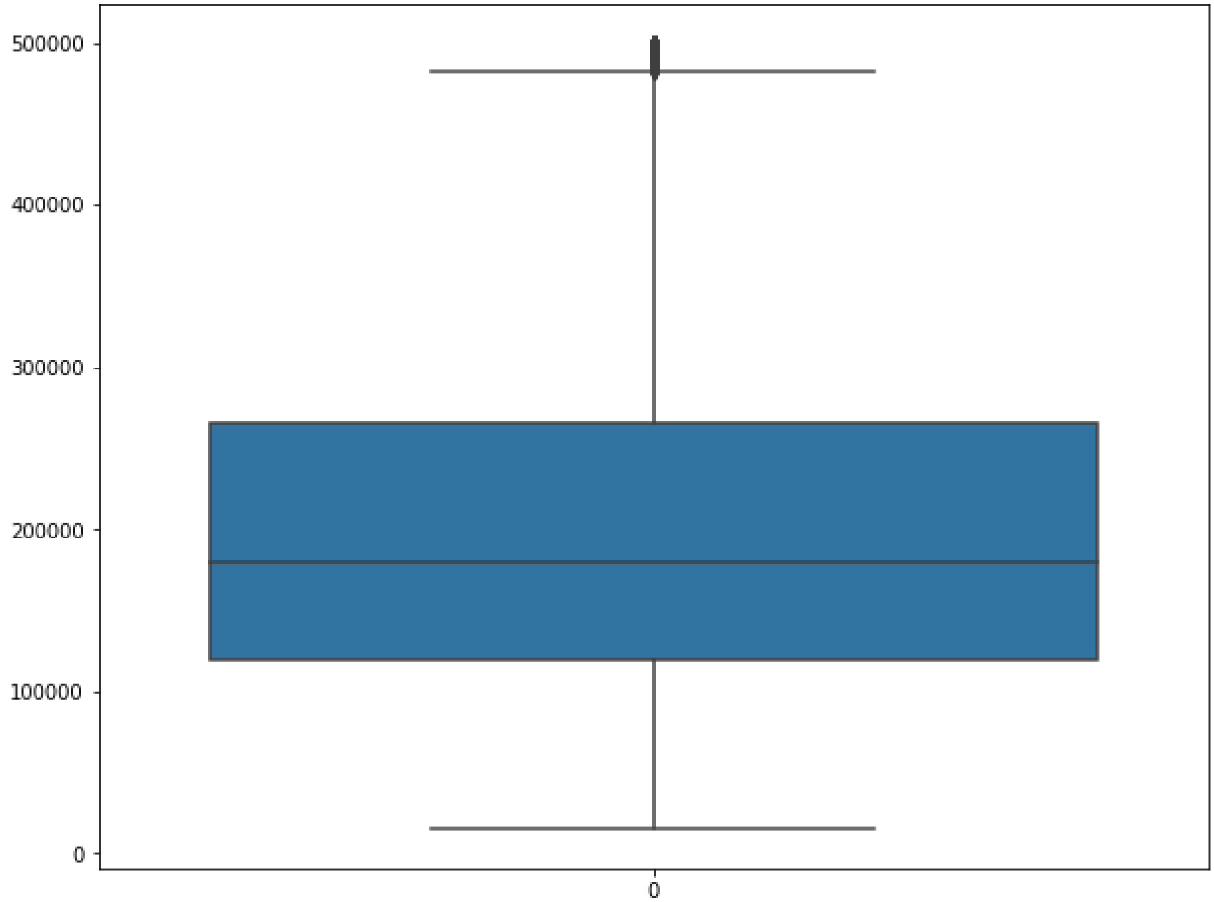
	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0
4	-122.25	37.85	52.0	1627.0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

In [31]:
```
#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[31]:
```
[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'),
 Text(14, 0, 'above_median')]
```



In [9]:
```
# will draw boxplot for all columns
fig,ax=plt.subplots(figsize=(10,8))
bp=sns.boxplot(data=housing_data['median_house_value'])
```



In [10]:
```
# now we need to find out the max of 'median_house_value' to remove the outliers
housing_data.describe()
```

Out[10]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	populati
count	20433.000000	20433.000000	20433.000000	20433.000000	20433.000000	20433.0000
mean	-119.570689	35.633221	28.633094	2636.504233	537.870553	1424.9469
std	2.003578	2.136348	12.591805	2185.269567	421.385070	1133.2084
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.0000
25%	-121.800000	33.930000	18.000000	1450.000000	296.000000	787.0000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.0000
75%	-118.010000	37.720000	37.000000	3143.000000	647.000000	1722.0000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.0000

In [11]:
```
# 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[11]:
```
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 [12]:
```
# housing_data.drop(rows or columns indexies)
housing_data=housing_data.drop(housing_data.loc[housing_data['median_house_value'
housing_data.shape
```

Out[12]:
```
(19475, 14)
```

Train our model - spliting data

In [13]:
```
# we need to convert our data to be classification (LogisticRegression)
# will get the median and compare to see if price below or above the median
median=housing_data['median_house_value'].median()
median
```

Out[13]: 173800.0

In [14]:
```
# will add new column call above_median
housing_data['above_median']=(housing_data['median_house_value']-median)>0
housing_data.sample(5)
# we see blow if the price is below median (179700.0) will be False otherwaise wi
```

Out[14]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	househol
7426	-118.20	33.95	35.0	1924.0	520.0	2101.0	54
4930	-118.25	33.99	42.0	2261.0	574.0	2496.0	52
7913	-118.08	33.88	27.0	923.0	186.0	1014.0	20
10226	-117.88	33.87	35.0	1919.0	349.0	1302.0	34
11975	-117.43	33.99	18.0	3307.0	547.0	1738.0	45

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','above_median'],axis=1) # axis=0 => row
Y=housing_data['above_median'] # our output will be True or False (classificatior
```

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')
```

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,))

Apply LogisticRegression

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 LogisticRegression
# the liblinear solver is a good choice for samll dataset and binary classificati
logistic_model=LogisticRegression(solver='liblinear').fit(x_train,y_train)
```

evaluation training score

print the evaluation score, this shown how well our linear model capture the underlying variation in our training data

In [21]:
```
print("Training_score :",logistic_model.score(x_train,y_train))
#0.6144045851306654 it is not fantastic but not bad
```

```
Training_score : 0.8188703465982028
```

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 [24]:
```
# let us predict using the x_test
y_pred=logistic_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
5093	False	False
499	False	False
4565	False	False
5546	True	True
12194	True	False
5165	False	False
11168	True	True
8298	True	True
18013	True	True
12425	False	False

evaluate the accuracy for our test data - using accuracy_score

In [26]:
```
from sklearn.metrics import accuracy_score
print('Testing_score :',accuracy_score(y_test,y_pred))
# we can see the score about 82%, that mean 82% of our model predication is corre
```

```
Testing_score : 0.824390243902439
```

In [30]:
```
# here we can't plot our prediction because it is just True/False values
```