# California Housing Price Prediction Machine Learning Project

May 31, 2023

[1]:
```
#Import Necessary Libraries:
import pandas as pd
import numpy as np

from sklearn.preprocessing import LabelEncoder,StandardScaler
from sklearn.linear_model import LinearRegression,Ridge,Lasso,ElasticNet
from sklearn.tree import DecisionTreeRegressor
import statsmodels.formula.api as smf

from sklearn.metrics import mean_squared_error,r2_score
from math import sqrt

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')

from matplotlib.axes._axes import _log as matplotlib_axes_logger
matplotlib_axes_logger.setLevel('ERROR')
```

[2]:
```
df_house=pd.read_excel("1553768847_housing.xlsx")
df_house.head()
```

[2]:
```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -122.23     37.88                  41          880           129.0
1    -122.22     37.86                  21         7099          1106.0
2    -122.24     37.85                  52         1467           190.0
3    -122.25     37.85                  52         1274           235.0
4    -122.25     37.85                  52         1627           280.0

   population  households  median_income ocean_proximity  median_house_value
0         322         126         8.3252        NEAR BAY              452600
1        2401        1138         8.3014        NEAR BAY              358500
2         496         177         7.2574        NEAR BAY              352100
3         558         219         5.6431        NEAR BAY              341300
```

```
4          565          259          3.8462          NEAR BAY          342200
```

[3]:
```
import math
print(math.log(452600))
```

```
13.022764012181574
```

[4]:
```
df_house.columns
```

[4]:
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'ocean_proximity', 'median_house_value'],
      dtype='object')
```

[5]:
```
df_house.isnull().sum()
```

[5]:
```
longitude               0
latitude                0
housing_median_age      0
total_rooms             0
total_bedrooms        207
population              0
households              0
median_income           0
ocean_proximity         0
median_house_value      0
dtype: int64
```

[6]:
```
df_house.total_bedrooms=df_house.total_bedrooms.fillna(df_house.total_bedrooms.
  ↪mean())
df_house.isnull().sum()
```

[6]:
```
longitude             0
latitude              0
housing_median_age    0
total_rooms           0
total_bedrooms        0
population            0
households            0
median_income         0
ocean_proximity       0
median_house_value    0
dtype: int64
```

[7]:
```
le = LabelEncoder()
df_house["ocean_proximity"]=le.fit_transform(df_house["ocean_proximity"])
```

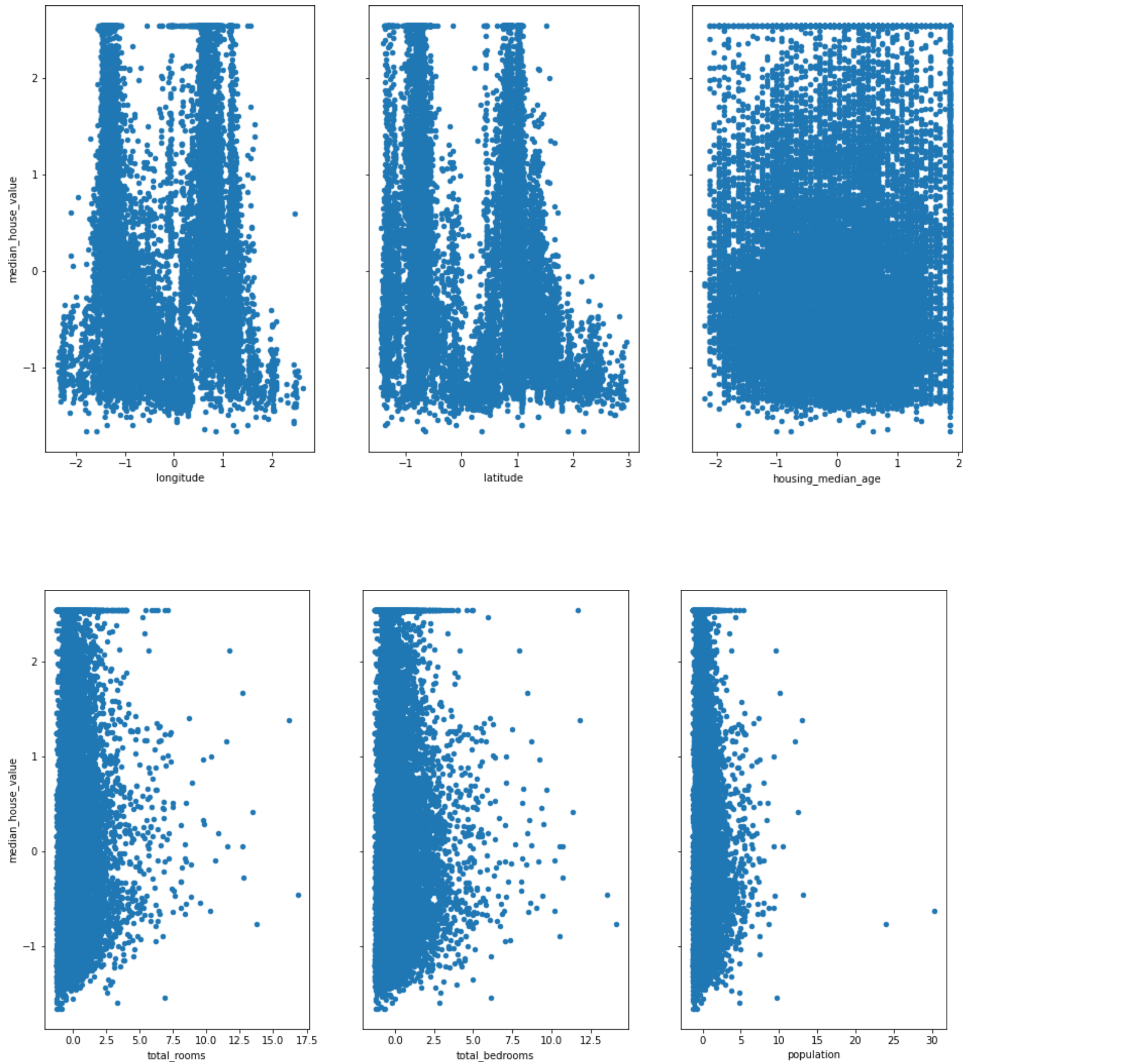
[8]:
```python
# Get column names first
names = df_house.columns
# Create the Scaler object
scaler = StandardScaler()
# Fit your data on the scaler object
scaled_df = scaler.fit_transform(df_house)
scaled_df = pd.DataFrame(scaled_df, columns=names)
scaled_df.head()
```

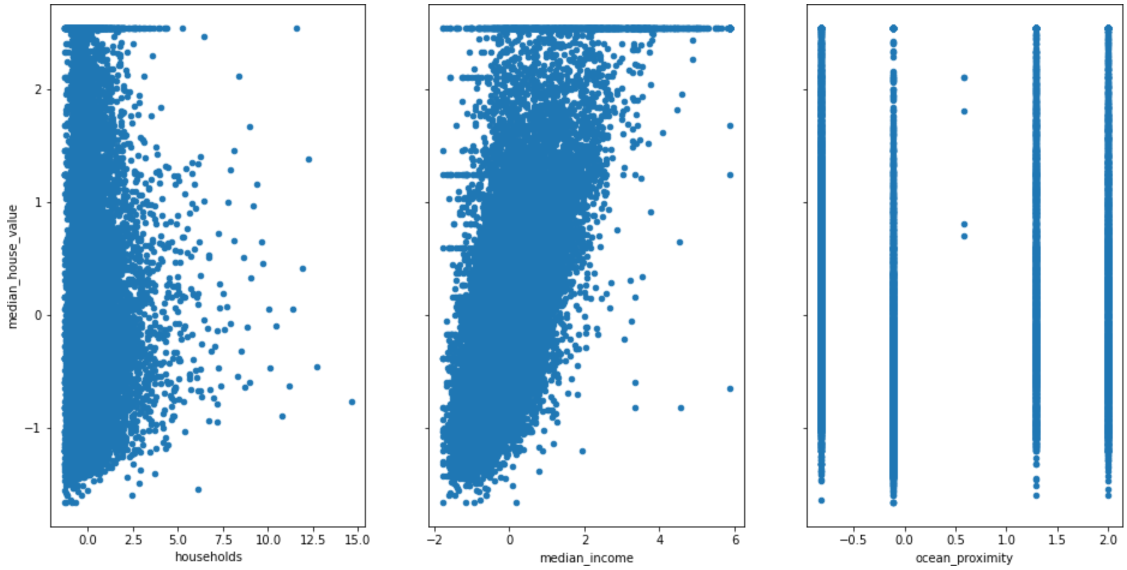
[8]:
```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0  -1.327835  1.052548            0.982143    -0.804819       -0.975228
1  -1.322844  1.043185           -0.607019     2.045890        1.355088
2  -1.332827  1.038503            1.856182    -0.535746       -0.829732
3  -1.337818  1.038503            1.856182    -0.624215       -0.722399
4  -1.337818  1.038503            1.856182    -0.462404       -0.615066

   population  households  median_income  ocean_proximity  median_house_value
0   -0.974429   -0.977033       2.344766         1.291089  2.129631
1    0.861439    1.669961       2.332238         1.291089            1.314156
2   -0.820777   -0.843637       1.782699         1.291089            1.258693
3   -0.766028   -0.733781       0.932968         1.291089            1.165100
4   -0.759847   -0.629157      -0.012881         1.291089            1.172900
```

[9]:
```python
#plot graphs
fig,axs=plt.subplots(1,3,sharey=True)
scaled_df.
↪plot(kind="scatter",x="longitude",y="median_house_value",ax=axs[0],figsize=(16,8))
scaled_df.
↪plot(kind="scatter",x="latitude",y="median_house_value",ax=axs[1],figsize=(16,8))
scaled_df.
↪plot(kind="scatter",x="housing_median_age",y="median_house_value",ax=axs[2],figsize=(16,8))

#plot graphs
fig,axs=plt.subplots(1,3,sharey=True)
scaled_df.
↪plot(kind="scatter",x="total_rooms",y="median_house_value",ax=axs[0],figsize=(16,8))
scaled_df.
↪plot(kind="scatter",x="total_bedrooms",y="median_house_value",ax=axs[1],figsize=(16,8))
scaled_df.
↪plot(kind="scatter",x="population",y="median_house_value",ax=axs[2],figsize=(16,8))

#plot graphs
fig,axs=plt.subplots(1,3,sharey=True)
scaled_df.
↪plot(kind="scatter",x="households",y="median_house_value",ax=axs[0],figsize=(16,8))
```

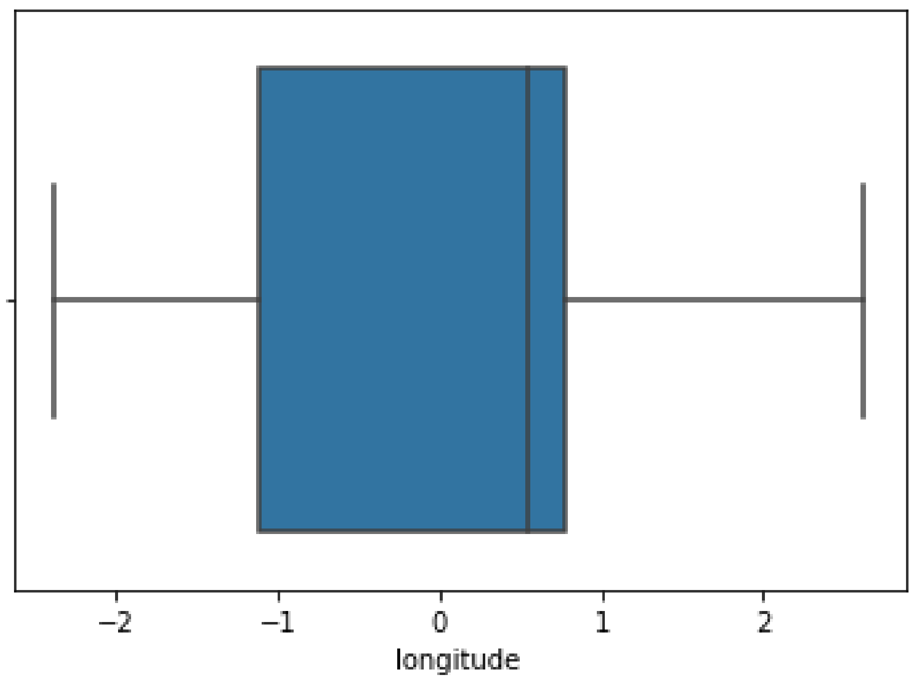
```
scaled_df.
↪plot(kind="scatter",x="median_income",y="median_house_value",ax=axs[1],figsize=(16,8))
scaled_df.
↪plot(kind="scatter",x="ocean_proximity",y="median_house_value",ax=axs[2],figsize=(16,8))
```

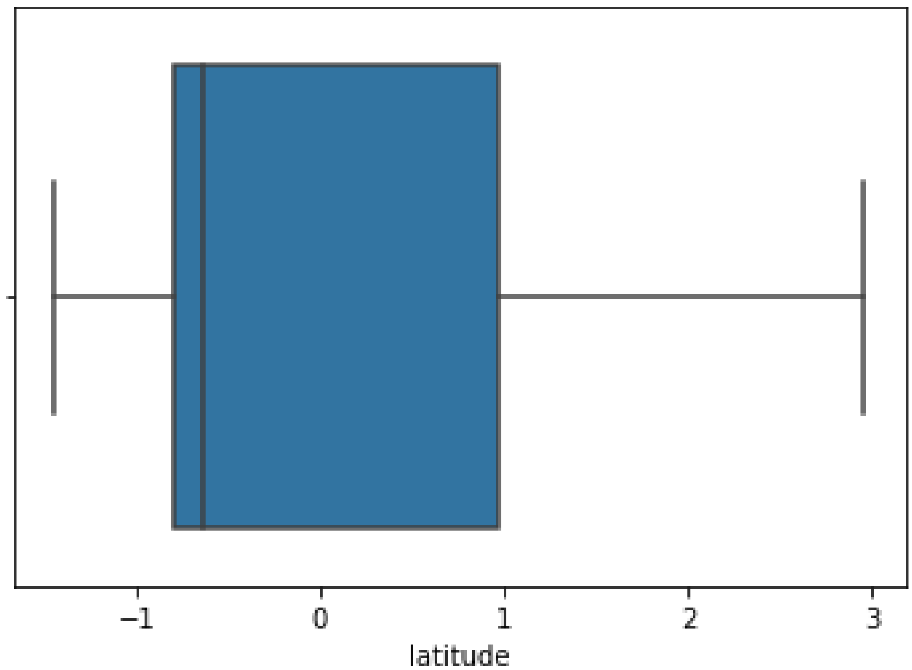
[9]: <AxesSubplot:xlabel='ocean_proximity', ylabel='median_house_value'>

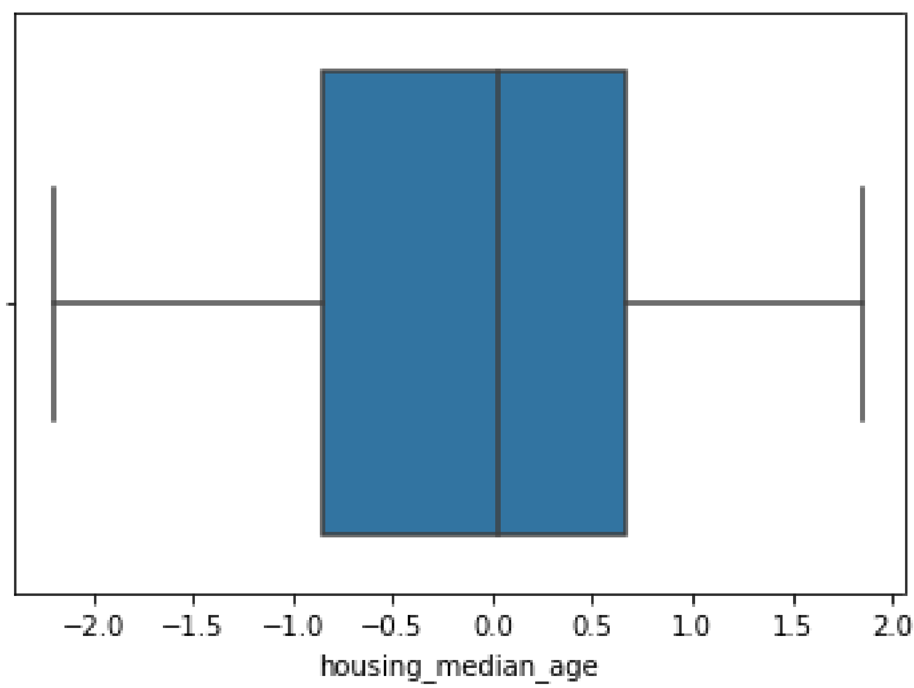


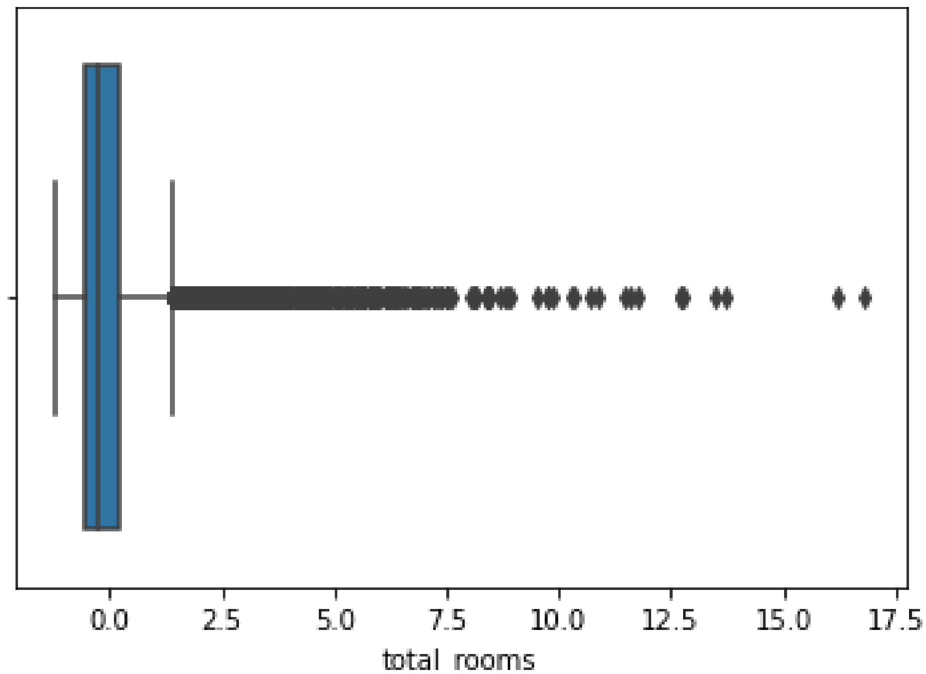


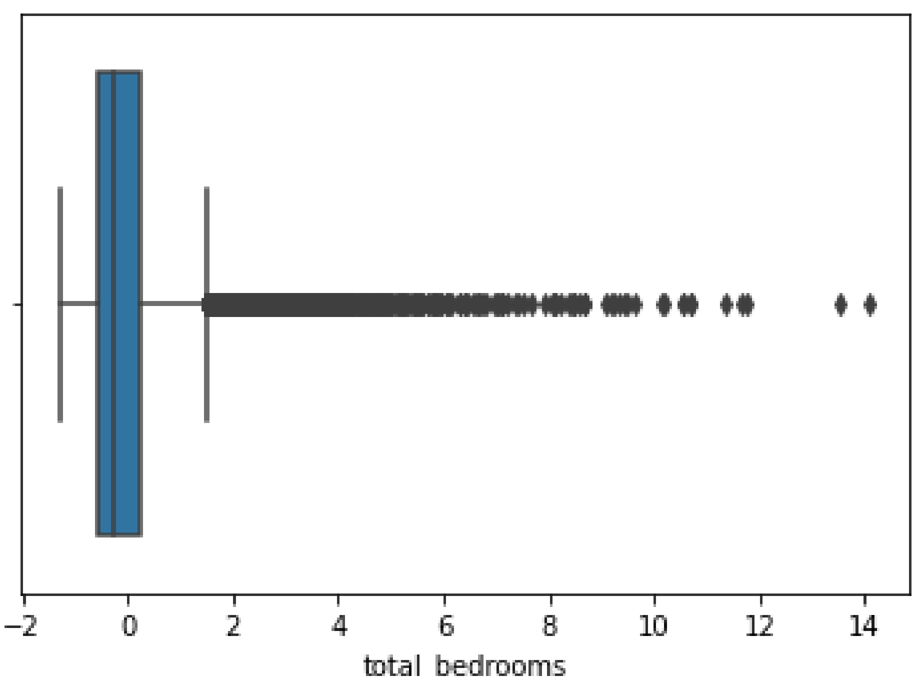

[10]:
```
for column in scaled_df:
    plt.figure()
    sns.boxplot(x=scaled_df[column])
```

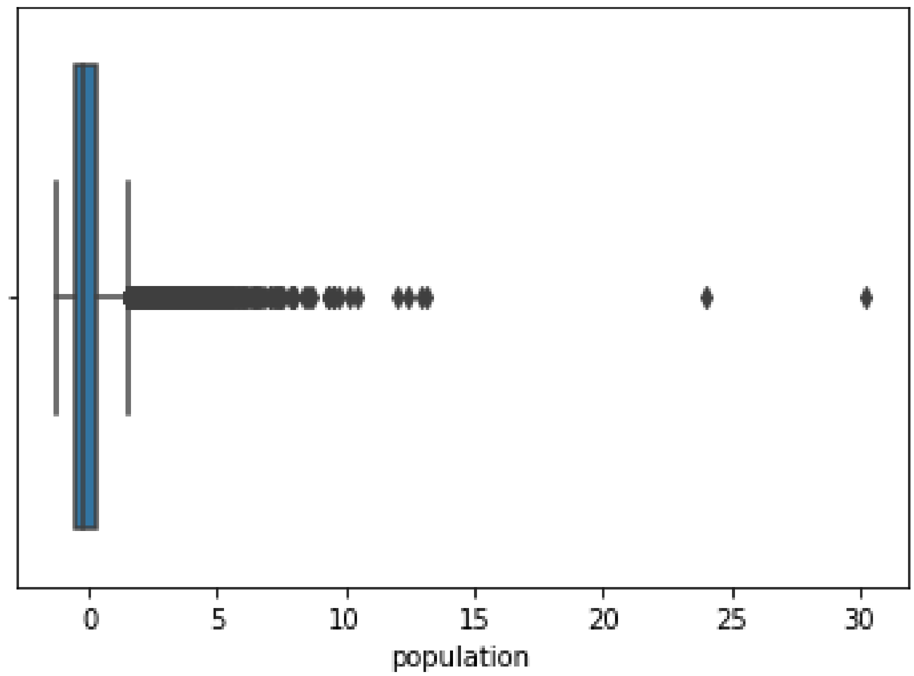


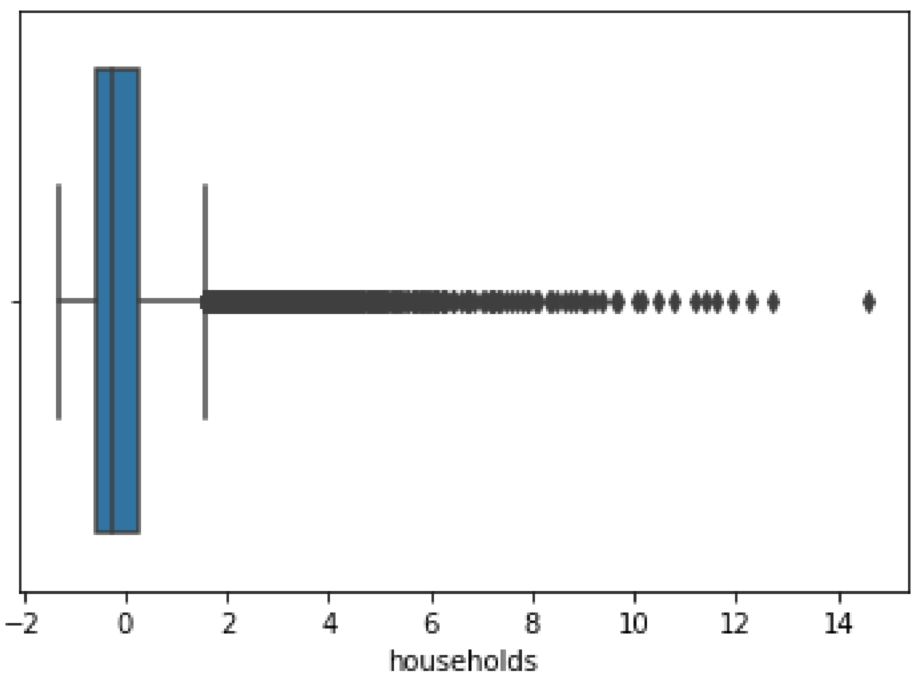

−1
0
1
2
3
latitude

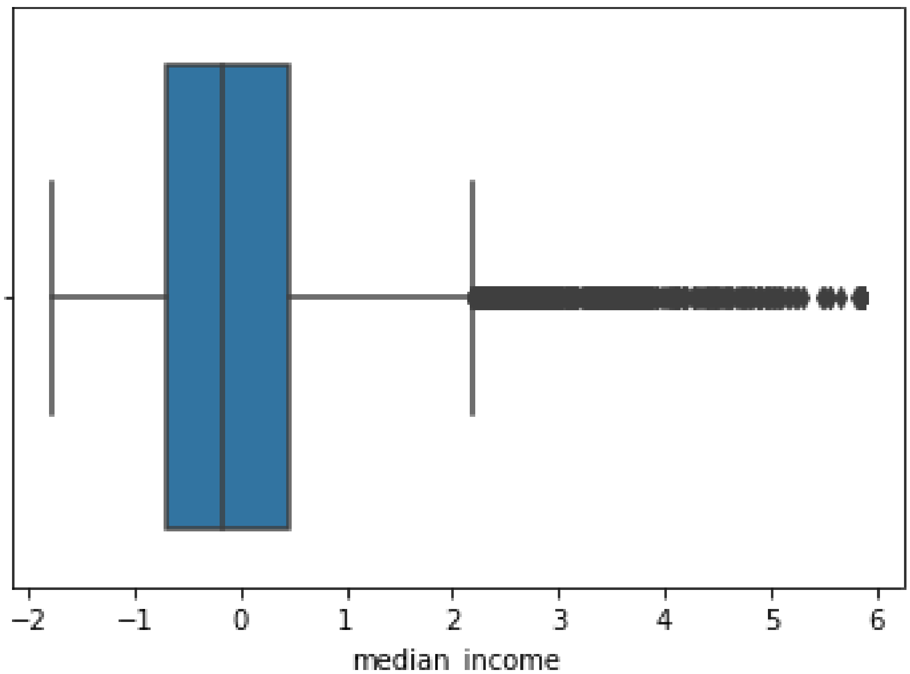

−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
housing_median_age


0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
total_rooms

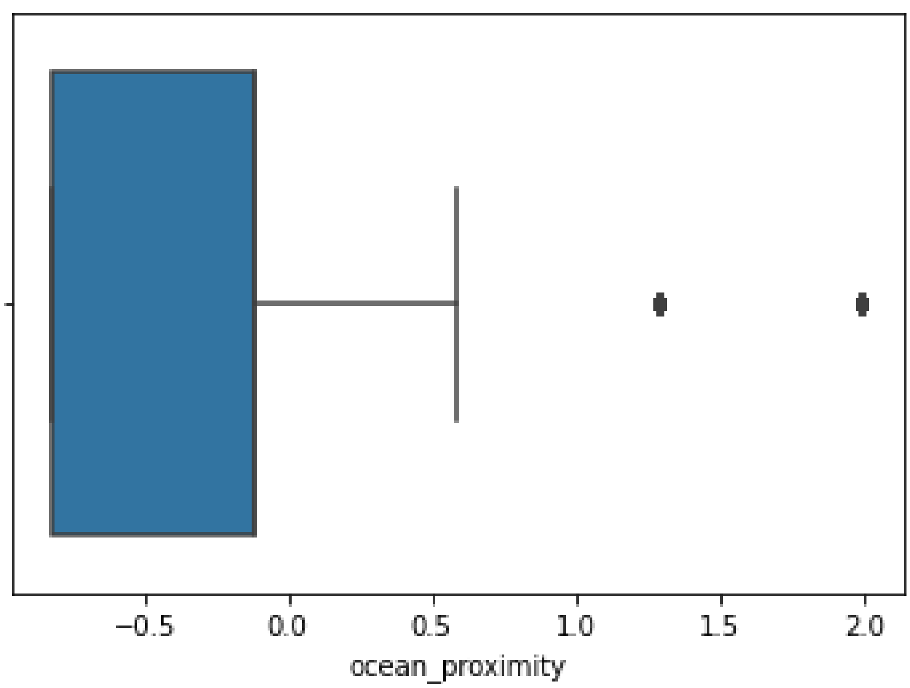

−2
0
2
4
6
8
10
12
14
total_bedrooms


0
5
10
15
20
25
30
population

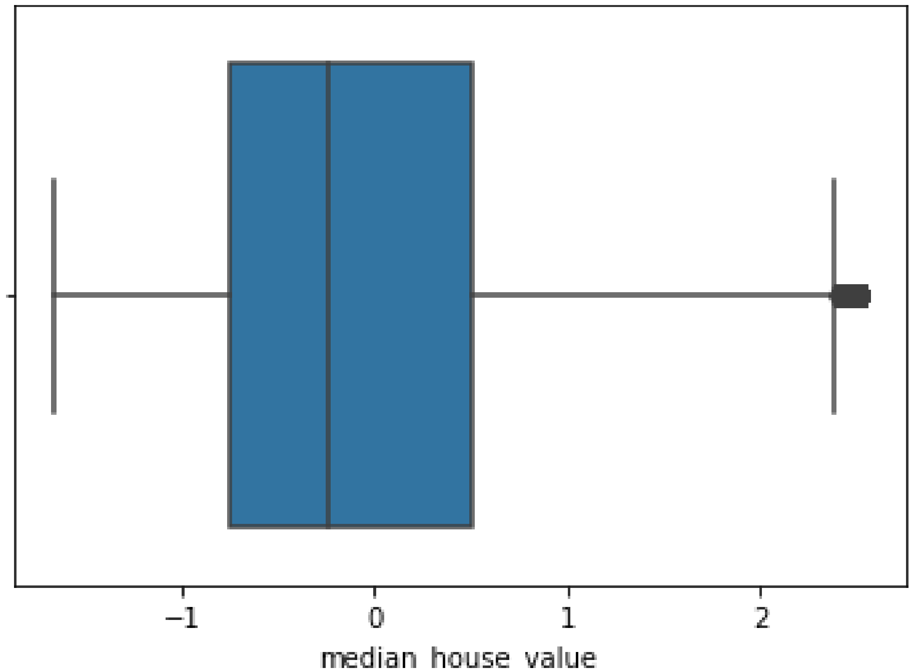

−2
0
2
4
6
8
10
12
14
households



−2
−1
0
1
2
3
4
5
6
median_income

−0.5
0.0
0.5
1.0
1.5
2.0
ocean_proximity




[11]:
```
X_Features=['longitude', 'latitude', 'housing_median_age', 'total_rooms',
        'total_bedrooms', 'population', 'households', 'median_income',
        'ocean_proximity']
X=scaled_df[X_Features]
Y=scaled_df['median_house_value']

print(type(X))
print(type(Y))
```

```
<class 'pandas.core.frame.DataFrame'>
<class 'pandas.core.series.Series'>
```

[12]:
```
print(df_house.shape)
print(X.shape)
print(Y.shape)
```

```
(20640, 10)
(20640, 9)
(20640,)
```

[13]:
```
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,random_state=1)

print (x_train.shape, y_train.shape)
print (x_test.shape, y_test.shape)
```

```
(16512, 9) (16512,)
(4128, 9) (4128,)
```

[14]:
```
linreg=LinearRegression()
linreg.fit(x_train,y_train)
```

[14]:
```
LinearRegression()
```

[15]:
```
y_predict = linreg.predict(x_test)
```

[16]:
```
print(sqrt(mean_squared_error(y_test,y_predict)))
print((r2_score(y_test,y_predict)))
```

```
0.6056598120301221
0.6276223517950295
```

[17]:
```
dtreg=DecisionTreeRegressor()
dtreg.fit(x_train,y_train)
```

[17]:
```
DecisionTreeRegressor()
```

[18]:
```
y_predict = dtreg.predict(x_test)
print(sqrt(mean_squared_error(y_test,y_predict)))
print((r2_score(y_test,y_predict)))
```

```
0.5925633790037315
0.6435523907257298
```

[21]:
```
lassoreg=Lasso(alpha=0.001,normalize=True)
lassoreg.fit(x_train,y_train)
print(sqrt(mean_squared_error(y_test,lassoreg.predict(x_test))))
print("R2 Value/Coefficient of determination:{}".format(lassoreg.
 ↪score(x_test,y_test)))
```

```
0.719314096707071
R2 Value/Coefficient of determination:0.4747534206169961
```

[22]:
```
ridgereg=Ridge(alpha=0.001,normalize=True)
ridgereg.fit(x_train,y_train)
print(sqrt(mean_squared_error(y_test,ridgereg.predict(x_test))))
print("R2 Value/Coefficient of determination:{}".format(ridgereg.
 ↪score(x_test,y_test)))
```

```
0.6056048844852343
R2 Value/Coefficient of determination:0.6276898909055972
```

[23]:
```
from sklearn.linear_model import ElasticNet
elasticreg=ElasticNet(alpha=0.001,normalize=True)
```

```
elasticreg.fit(x_train,y_train)
print(sqrt(mean_squared_error(y_test,elasticreg.predict(x_test))))
print('R2 Value/Coefficient of determination:{}'.format(elasticreg.
↪score(x_test,y_test)))
```

```
0.944358169398106
R2 Value/Coefficient of determination:0.09468529806704551
```

[24]:
```
lm=smf.ols(formula='median_house_value ~␣
↪longitude+latitude+housing_median_age+total_rooms+total_bedrooms+population+households+medi
↪fit()
```

[25]:
```
lm.summary()
```

[25]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:     median_house_value   R-squared:                       0.636
Model:                            OLS   Adj. R-squared:                  0.635
Method:                 Least Squares   F-statistic:                     3999.
Date:                Mon, 26 Sep 2022   Prob (F-statistic):               0.00
Time:                        15:17:42   Log-Likelihood:                -18868.
No. Observations:               20640   AIC:                         3.776e+04
Df Residuals:                   20630   BIC:                         3.783e+04
Df Model:                           9
Covariance Type:            nonrobust
==============================================================================
======
                         coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
------
Intercept          -3.469e-17      0.004  -8.26e-15      1.000      -0.008
0.008
longitude             -0.7393      0.013    -57.263      0.000      -0.765
-0.714
latitude              -0.7858      0.013    -61.664      0.000      -0.811
-0.761
housing_median_age     0.1248      0.005     26.447      0.000       0.116
0.134
total_rooms           -0.1265      0.015     -8.609      0.000      -0.155
-0.098
total_bedrooms         0.2995      0.022     13.630      0.000       0.256
0.343
population            -0.3907      0.011    -36.927      0.000      -0.411
-0.370
```

```
households          0.2589      0.022     11.515      0.000       0.215
0.303
median_income       0.6549      0.005    119.287      0.000       0.644
0.666
ocean_proximity     0.0009      0.005      0.190      0.850      -0.008
0.010
==============================================================================
Omnibus:                     5037.491   Durbin-Watson:                   0.965
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            18953.000
Skew:                           1.184   Prob(JB):                         0.00
Kurtosis:                       7.054   Cond. No.                         14.2
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

[26]:
```
x_train_Income=x_train[['median_income']]
x_test_Income=x_test[['median_income']]
print(x_train_Income.shape)
print(y_train.shape)
```

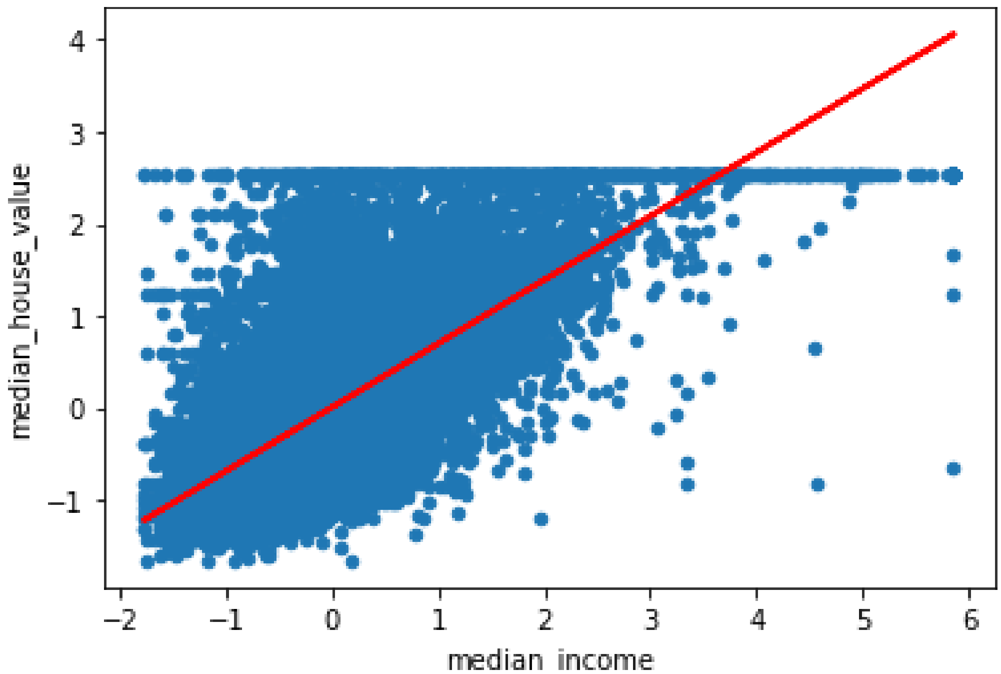
```
(16512, 1)
(16512,)
```

[27]:
```
linreg=LinearRegression()
linreg.fit(x_train_Income,y_train)
y_predict = linreg.predict(x_test_Income)
#print intercept and coefficient of the linear equation
print(linreg.intercept_, linreg.coef_)
print(sqrt(mean_squared_error(y_test,y_predict)))
print((r2_score(y_test,y_predict)))
```

```
0.005623019866893164 [0.69238221]
0.7212595914243148
0.47190835934467734
```

[28]:
```
#plot least square line
scaled_df.plot(kind='scatter',x='median_income',y='median_house_value')
plt.plot(x_test_Income,y_predict,c='red',linewidth=2)
```

[28]: [<matplotlib.lines.Line2D at 0x7f7e75ad1890>]




[29]:
```
lm=smf.ols(formula='median_house_value ~ median_income',data=scaled_df).fit()
lm.summary()
```

[29]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:     median_house_value   R-squared:                       0.473
Model:                            OLS   Adj. R-squared:                  0.473
Method:                 Least Squares   F-statistic:                 1.856e+04
Date:                Mon, 26 Sep 2022   Prob (F-statistic):               0.00
Time:                        15:18:49   Log-Likelihood:                -22668.
No. Observations:               20640   AIC:                         4.534e+04
Df Residuals:                   20638   BIC:                         4.536e+04
Df Model:                           1
Covariance Type:            nonrobust
=================================================================================
=
                    coef    std err          t      P>|t|      [0.025
0.975]
---------------------------------------------------------------------------------
-
Intercept      1.735e-16      0.005   3.43e-14      1.000      -0.010
0.010
```

```
median_income      0.6881      0.005    136.223      0.000      0.678
0.698
==============================================================================
Omnibus:                     4245.795   Durbin-Watson:                   0.655
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             9273.446
Skew:                           1.191   Prob(JB):                         0.00
Kurtosis:                       5.260   Cond. No.                         1.00
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

```
[ ]:
```