import pandas as pd import seaborn as sns import sklearn.datasets from sklearn.model\_selection import train\_test\_split from xgboost import XGBRegressor from sklearn import metrics import matplotlib.pyplot as plt In [2]: #loading the dataset from sklearn house\_price\_dataset = sklearn.datasets.fetch\_california\_housing() print(house\_price\_dataset) {'data': array([[ 6.98412698, ..., 41. 2.5555556, 8.3252 , -122.23 37.88 , 21. 8.3014 6.23813708, ..., 2.10984183, , -122.22 37.86 7.2574 , 52. 2.80225989, 8.28813559, ..., , -122.24 37.85 • • • • [ 1.7 5.20554273, ..., , 17. 2.3256351, 39.43 , -121.22 , 18. 5.32951289, ..., 1.8672 2.12320917, , -121.32 39.43 , 16. 2.3886 5.25471698, ..., 2.61698113, 39.37 ]]), 'target': array([4.526, 3.585, 3.521, ..., 0.923, 0.847, 0.894]), 'frame': None, 'target\_names': ['MedHouseVal'], 'feature\_names': , -121.24 ['MedInc', 'HouseAge', 'AveRooms', 'AveBedrms', 'Population', 'AveOccup', 'Latitude', 'Longitude'], 'DESCR': '.. \_california\_housing\_dataset:\n\nCalifornia Housing dataset\n-median house age in block group\n :Attribute Information:\n MedInc HouseAge median income in block group\n - AveRooms average average number of bedrooms per household\n Population block group population\n number of rooms per household\n - AveOccup AveBedrms ge number of household members\n - Latitude block group latitude\n - Longitude block group longitude\n\n :Missing Attribute Values: None\n\nThis dat aset was obtained from the StatLib repository.\nhttps://www.dcc.fc.up.pt/~ltorgo/Regression/cal\_housing.html\n\nThe target variable is the median house value for California d istricts,\nexpressed in hundreds of thousands of dollars (\$100,000).\n\nThis dataset was derived from the 1990 U.S. census, using one row per census\nblock group. A block gro up is the smallest geographical unit for which the U.S.\nCensus Bureau publishes sample data (a block group typically has a population\nof 600 to 3,000 people).\n\nAn househo Id is a group of people residing within a home. Since the average\nnumber of rooms and bedrooms in this dataset are provided per household, these\ncolumns may take surpinsing ly large values for block groups with few households\nand many empty houses, such as vacation resorts.\n\nIt can be downloaded/loaded using the\n:func:`sklearn.datasets.fetch \_california\_housing` function.\n\n.. topic:: References\n\n - Pace, R. Kelley and Ronald Barry, Sparse Spatial Autoregressions,\n Statistics and Probability Letters, 33 (1997) 291-297\n'} #converting it to dataframe house price dataframe=pd.DataFrame(house price dataset.data,columns=house price dataset.feature names) In [17]: house\_price\_dataframe.head() Out[17]: MedInc HouseAge AveRooms AveBedrms Population AveOccup Latitude Longitude 8.3252 6.984127 1.023810 2.555556 -122.23 37.88 41.0 322.0 6.238137 8.3014 0.971880 2401.0 2.109842 -122.22 37.86 21.0 7.2574 8.288136 2.802260 -122.24 1.073446 496.0 52.0 37.85 5.817352 558.0 2.547945 5.6431 52.0 1.073059 37.85 -122.25 3.8462 52.0 6.281853 2.181467 -122.25 1.081081 565.0 37.85 #adding the target (price column to DF) house\_price\_dataframe['Price']=house\_price\_dataset.target house\_price\_dataframe.head() In [19]: Out[19]: MedInc HouseAge AveRooms AveBedrms Population AveOccup Latitude Longitude Price 6.984127 2.555556 41.0 1.023810 322.0 8.3252 37.88 -122.23 4.526 8.3014 6.238137 2.109842 -122.22 3.585 0.971880 2401.0 21.0 37.86 -122.24 3.521 7.2574 8.288136 1.073446 2.802260 52.0 496.0 37.85 -122.25 3.413 5.817352 558.0 2.547945 5.6431 1.073059 52.0 37.85 3.8462 6.281853 1.081081 2.181467 -122.25 3.422 52.0 565.0 37.85 #No of row and columns house\_price\_dataframe.shape (20640, 9)Out[21]: #checking missing value In [22]: house\_price\_dataframe.isnull().sum() MedInc Out[22]: HouseAge AveRooms AveBedrms Population Ave0ccup Latitude Longitude Price dtype: int64 #checking Statistics of DF In [24]: house\_price\_dataframe.describe() Out[24]: MedInc **AveBedrms Price** HouseAge **AveRooms Population AveOccup** Latitude Longitude **count** 20640.000000 20640.000000 20640.000000 20640.000000 20640.000000 20640.000000 20640.000000 20640.000000 20640.000000 3.870671 28.639486 5.429000 1.096675 1425.476744 3.070655 35.631861 -119.569704 2.068558 mean 2.474173 1132.462122 2.135952 1.153956 1.899822 12.585558 0.473911 10.386050 2.003532 std 3.000000 32.540000 -124.350000 0.333333 0.499900 1.000000 0.846154 0.692308 0.149990 min -121.800000 2.563400 18.000000 4.440716 1.006079 787.000000 2.429741 33.930000 25% 1.196000 **50%** 3.534800 29.000000 1.048780 1166.000000 2.818116 34.260000 -118.490000 5.229129 1.797000 **75**% 4.743250 37.000000 6.052381 1.099526 1725.000000 3.282261 37.710000 -118.010000 2.647250 15.000100 52.000000 34.066667 35682.000000 41.950000 5.000010 141.909091 1243.333333 -114.310000 max #finding correlation btw various feature in data house\_price\_dataframe.corr() Out[28]: MedInc HouseAge AveRooms AveBedrms Population AveOccup Latitude Longitude **Price MedInc** 1.000000 -0.119034 0.326895 -0.062040 0.004834 0.018766 -0.079809 -0.015176 0.688075 -0.153277 **HouseAge** -0.119034 1.000000 -0.077747 -0.296244 0.013191 -0.108197 **AveRooms** 0.326895 -0.153277 1.000000 0.847621 -0.072213 -0.004852 0.106389 -0.027540 0.151948 -0.077747 **AveBedrms** -0.062040 0.847621 1.000000 -0.066197 -0.006181 0.069721 0.013344 -0.046701 -0.296244 -0.072213 -0.066197 -0.108785 0.099773 **Population** 0.004834 1.000000 0.069863 -0.024650 **AveOccup** 0.018766 0.013191 -0.004852 -0.006181 0.069863 1.000000 0.002366 0.002476 -0.023737 **Latitude** -0.079809 0.011173 0.106389 0.069721 -0.108785 0.002366 1.000000 -0.924664 -0.144160 **Longitude** -0.015176 -0.108197 -0.027540 0.002476 -0.924664 0.013344 1.000000 -0.045967 0.099773 **Price** 0.688075 0.105623 0.151948 -0.046701 -0.023737 -0.144160 -0.024650 -0.045967 1.000000 sns.heatmap(house\_price\_dataframe.corr(),cmap="viridis",cbar=True,square=True,annot=True) <Axes: > Out[38]: - 1.00 -0.12 0.33 -0.0620.00480.019 -0.08-0.015 0.69 MedInc -- 0.75 HouseAge --0.12 -0.15-0.078 -0.3 0.013 0.011 -0.11 0.11 - 0.50 AveRooms - 0.33 -0.15 1 0.85 -0.0720.00490.11 -0.028 0.15 AveBedrms -0.062-0.078 0.85 -0.06@.00620.07 0.013-0.047 - 0.25 Population -0.0048 -0.3 -0.072-0.066 0.07 -0.11 0.1 -0.025 - 0.00 0.00240.00250.024 AveOccup -0.019 0.0130.0049.00620.07 -0.25Latitude -- 0.08 0.011 0.11 0.07 -0.110.0024 -0.92 -0.14 - -0.50 Longitude -0.015-0.11-0.0280.013 0.1 0.0025-0.92 -0.046 - -0.75 Price - 0.69 0.11 0.15 -0.047-0.025-0.024-0.14-0.046 AveBedrms AveOccup Longitude Population MedInc #SPlit the dataset in data & label/target(price) X=house\_price\_dataframe.drop(['Price'],axis=1) Y=house\_price\_dataframe['Price'] In [40]: print(X) print(Y) MedInc HouseAge AveRooms AveBedrms Population AveOccup Latitude Longitude 8.3252 41.0 6.984127 1.023810 322.0 2.555556 -122.23 37.88 21.0 6.238137 0.971880 2401.0 2.109842 8.3014 37.86 -122.22 52.0 8.288136 496.0 2.802260 7.2574 -122.24 1.073446 37.85 52.0 5.817352 1.073059 558.0 2.547945 -122.25 5.6431 37.85 52.0 6.281853 565.0 2.181467 -122.25 3.8462 1.081081 37.85 . . . . . . • • • 5.045455 1.133333 845.0 2.560606 -121.09 20635 1.5603 25.0 39.48 20636 2.5568 18.0 6.114035 1.315789 356.0 3.122807 -121.21 39.49 20637 1.7000 17.0 5.205543 1007.0 2.325635 -121.22 1.120092 39.43 18.0 5.329513 20638 1.8672 1.171920 741.0 2.123209 -121.32 39.43 20639 2.3886 16.0 5.254717 -121.24 1.162264 1387.0 2.616981 39.37 [20640 rows x 8 columns] 4.526 3.585 3.521 3.413 3.422 • • • 20635 0.781 0.771 20636 20637 0.923 20638 0.847 0.894 20639 Name: Price, Length: 20640, dtype: float64 In [41]: #SPLIT Into Training And Test Data X\_train,X\_test,Y\_train,Y\_test=train\_test\_split(X,Y,test\_size=0.2,random\_state=2) In [44]: print(X.shape,X\_test.shape,X\_train.shape) (20640, 8) (4128, 8) (16512, 8) In [45]: #MODEL TRAINING\_XGBOOST REGRESSOR( Decision tree model) model=XGBRegressor() model.fit(X\_train,Y\_train) In [46]: Out[46]: ▼ XGBRegressor XGBRegressor(base\_score=None, booster=None, callbacks=None, colsample\_bylevel=None, colsample\_bynode=None, colsample\_bytree=None, early\_stopping\_rounds=None, enable\_categorical=False, eval\_metric=None, feature\_types=None, gamma=None, gpu\_id=None, grow\_policy=None, importance\_type=None, interaction\_constraints=None, learning\_rate=None, max\_bin=None, max\_cat\_threshold=None, max\_cat\_to\_onehot=None, max\_delta\_step=None, max\_depth=None, max\_leaves=None, min\_child\_weight=None, missing=nan, monotone\_constraints=None, n\_estimators=100, n\_jobs=None, num\_parallel\_tree=None, predictor=None, random state=None, ...) In [47]: #EVALUATION & PREDICTION training\_data\_pred=model.predict(X\_train) In [48]: print(training\_data\_pred) [0.6893792 2.986824 0.48874274 ... 1.8632544 1.7800125 0.7565893 ] In [50]: #R square & mean absolute erro metric for regression score\_1=metrics.r2\_score(Y\_train,training\_data\_pred) #Mena absolute error score\_2=metrics.mean\_absolute\_error(Y\_train,training\_data\_pred) print('R square error:',score\_1) print('Mean absolute error:',score\_2) R square error: 0.9451221492760822 Mean absolute error: 0.1919170860794262 In [ ]: #less size data thatswhy used XGBR In [51]: #Prediction on Test Data test\_data\_pred=model.predict(X\_test) In [52]: print(test\_data\_pred) [2.787383 1.9628428 0.782536 ... 1.5060123 0.8763797 1.9317917] In [53]: #R square & mean absolute erro metric for regression score\_3=metrics.r2\_score(Y\_test,test\_data\_pred) #Mena absolute error score\_4=metrics.mean\_absolute\_error(Y\_test,test\_data\_pred) print('R square error:',score\_3) print('Mean absolute error:',score\_4) R square error: 0.8412904408180302 Mean absolute error: 0.30753655785801337 In [56]: #Visualising the actual and predicted prices plt.scatter(Y\_train,training\_data\_pred) plt.xlabel("actual Price") plt.ylabel("pREDICTED Price") Text(0, 0.5, 'pREDICTED Price') 5 pREDICTED Price 2 actual Price

#value predicted are close to acutal prices hence our model works fine.

import numpy as np

In [55]: