```
Start coding or generate with AI.
```

Importing the Dependencies

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn.datasets
from sklearn.model_selection import train_test_split
from xgboost import XGBRegressor
from sklearn import metrics
```

importing boston house dataset

```
house_price_dataset=sklearn.datasets.fetch_california_housing()
```

```
print(house_price_dataset)
```

```
{'data': array([[   8.3252    ,   41.        ,    6.98412698, ...,    2.55555556,
          37.88      , -122.23      ],
       [   8.3014    ,   21.        ,    6.23813708, ...,    2.10984183,
          37.86      , -122.22      ],
       [   7.2574    ,   52.        ,    8.28813559, ...,    2.80225989,
          37.85      , -122.24      ],
       ...,
       [   1.7       ,   17.        ,    5.20554273, ...,    2.3256351 ,
          39.43      , -121.22      ],
       [   1.8672    ,   18.        ,    5.32951289, ...,    2.12320917,
          39.43      , -121.32      ],
       [   2.3886    ,   16.        ,    5.25471698, ...,    2.61698113,
          39.37      , -121.24      ]]), 'target': array([4.526, 3.585, 3.521, ..., 0.923, 0.847, 0.894]), 'frame': None, 'target_na
```

```
# loading the dataset to pandas dataframe
house_price_dataframe=pd.DataFrame(house_price_dataset.data,columns=house_price_dataset.feature_names)
```

```
#print first 5 rows of data
house_price_dataframe.head()
```

| | MedInc | HouseAge | AveRooms | AveBedrms | Population | AveOccup | Latitude | Longitude |
|---|---|---|---|---|---|---|---|---|
| **0** | 8.3252 | 41.0 | 6.984127 | 1.023810 | 322.0 | 2.555556 | 37.88 | -122.23 |
| **1** | 8.3014 | 21.0 | 6.238137 | 0.971880 | 2401.0 | 2.109842 | 37.86 | -122.22 |
| **2** | 7.2574 | 52.0 | 8.288136 | 1.073446 | 496.0 | 2.802260 | 37.85 | -122.24 |
| **3** | 5.6431 | 52.0 | 5.817352 | 1.073059 | 558.0 | 2.547945 | 37.85 | -122.25 |
| **4** | 3.8462 | 52.0 | 6.281853 | 1.081081 | 565.0 | 2.181467 | 37.85 | -122.25 |

```
#add the target price column in dataframe
house_price_dataframe['price']=house_price_dataset.target
```

```
house_price_dataframe.head()
```

| | MedInc | HouseAge | AveRooms | AveBedrms | Population | AveOccup | Latitude | Longitude | price |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 8.3252 | 41.0 | 6.984127 | 1.023810 | 322.0 | 2.555556 | 37.88 | -122.23 | 4.526 |
| **1** | 8.3014 | 21.0 | 6.238137 | 0.971880 | 2401.0 | 2.109842 | 37.86 | -122.22 | 3.585 |
| **2** | 7.2574 | 52.0 | 8.288136 | 1.073446 | 496.0 | 2.802260 | 37.85 | -122.24 | 3.521 |
| **3** | 5.6431 | 52.0 | 5.817352 | 1.073059 | 558.0 | 2.547945 | 37.85 | -122.25 | 3.413 |
| **4** | 3.8462 | 52.0 | 6.281853 | 1.081081 | 565.0 | 2.181467 | 37.85 | -122.25 | 3.422 |

```
#checking number of rows and columns in data frame
house_price_dataframe.shape
```

```
(20640, 9)
```

```
#check for missing values
house_price_dataframe.isnull().sum()
```

| | 0 |
|---|---|
| MedInc | 0 |
| HouseAge | 0 |
| AveRooms | 0 |
| AveBedrms | 0 |
| Population | 0 |
| AveOccup | 0 |
| Latitude | 0 |
| Longitude | 0 |
| price | 0 |

```
#statistical measures of dataset
house_price_dataframe.describe()
```

| | MedInc | HouseAge | AveRooms | AveBedrms | Population | AveOccup | Latitude | Longitude | price |
|---|---|---|---|---|---|---|---|---|---|
| count | 20640.000000 | 20640.000000 | 20640.000000 | 20640.000000 | 20640.000000 | 20640.000000 | 20640.000000 | 20640.000000 | 20640.000000 |
| mean | 3.870671 | 28.639486 | 5.429000 | 1.096675 | 1425.476744 | 3.070655 | 35.631861 | -119.569704 | 2.068558 |
| std | 1.899822 | 12.585558 | 2.474173 | 0.473911 | 1132.462122 | 10.386050 | 2.135952 | 2.003532 | 1.153956 |
| min | 0.499900 | 1.000000 | 0.846154 | 0.333333 | 3.000000 | 0.692308 | 32.540000 | -124.350000 | 0.149990 |
| 25% | 2.563400 | 18.000000 | 4.440716 | 1.006079 | 787.000000 | 2.429741 | 33.930000 | -121.800000 | 1.196000 |
| 50% | 3.534800 | 29.000000 | 5.229129 | 1.048780 | 1166.000000 | 2.818116 | 34.260000 | -118.490000 | 1.797000 |
| 75% | 4.743250 | 37.000000 | 6.052381 | 1.099526 | 1725.000000 | 3.282261 | 37.710000 | -118.010000 | 2.647250 |
| max | 15.000100 | 52.000000 | 141.909091 | 34.066667 | 35682.000000 | 1243.333333 | 41.950000 | -114.310000 | 5.000010 |

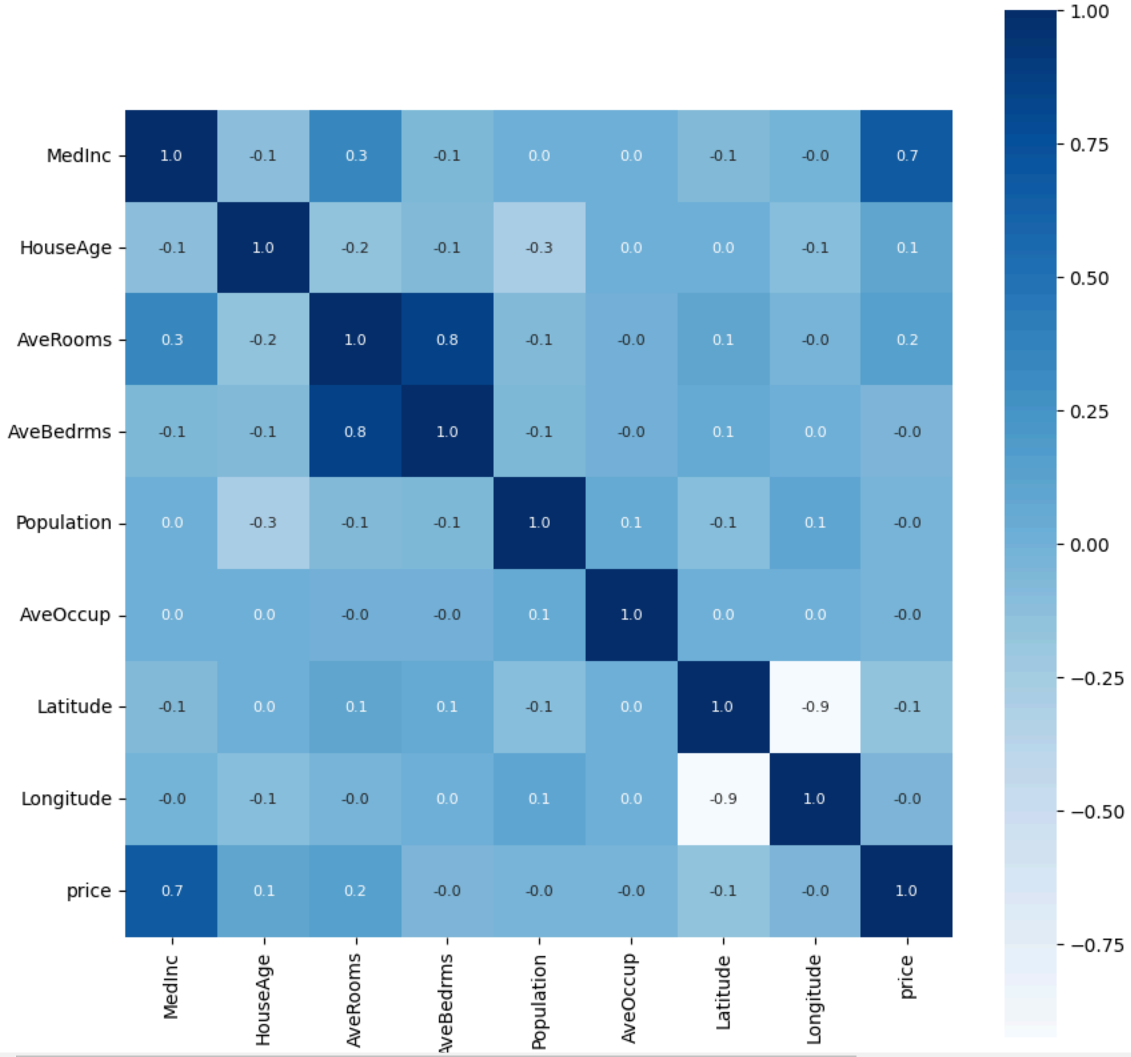
understanding correlation bw various fetaures in dataset

1. Positive correlation
2. negative correlation

```
correlation=house_price_dataframe.corr()
```

```
# constructing heatmap to understand correlation cbar=colourbar + =pos correaltion and - means negative correlation
#fmt how many float vaues you want to see like 0.1,0.01 etc
#annot annotations house age etc
#cmap=color of map
#-ve corr means one increse and other decrease
# +ve means one increases other also increases
plt.figure(figsize=(10,10))
sns.heatmap(correlation,cbar=True,square=True,fmt='.1f',annot=True,annot_kws={'size':8},cmap='Blues')
```

```
<Axes: >
```




Splitting the data and target

```
X=house_price_dataframe.drop(['price'],axis=1)
Y=house_price_dataframe['price']
```

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

```
       MedInc  HouseAge  AveRooms  AveBedrms  Population  AveOccup  Latitude  \
0      8.3252      41.0  6.984127   1.023810       322.0  2.555556     37.88
1      8.3014      21.0  6.238137   0.971880      2401.0  2.109842     37.86
2      7.2574      52.0  8.288136   1.073446       496.0  2.802260     37.85
3      5.6431      52.0  5.817352   1.073059       558.0  2.547945     37.85
4      3.8462      52.0  6.281853   1.081081       565.0  2.181467     37.85
...       ...       ...       ...        ...         ...       ...       ...
20635  1.5603      25.0  5.045455   1.133333       845.0  2.560606     39.48
20636  2.5568      18.0  6.114035   1.315789       356.0  3.122807     39.49
20637  1.7000      17.0  5.205543   1.120092      1007.0  2.325635     39.43
20638  1.8672      18.0  5.329513   1.171920       741.0  2.123209     39.43
20639  2.3886      16.0  5.254717   1.162264      1387.0  2.616981     39.37

       Longitude
0        -122.23
1        -122.22
2        -122.24
3        -122.25
4        -122.25
...          ...
20635    -121.09
20636    -121.21
20637    -121.22
20638    -121.32
20639    -121.24

[20640 rows x 8 columns]
0        4.526
1        3.585
2        3.521
```

```
3        3.413
4        3.422
         ...
20635    0.781
20636    0.771
20637    0.923
20638    0.847
20639    0.894
Name: price, Length: 20640, dtype: float64
```

Splitting the data into training data and test data

```
#testsize=0.2 means 20% is testing and other trainng
#random state 2 means splitting data in same way
X_train, X_test, Y_train, Y_test=train_test_split(X, Y,test_size=0.2,random_state=2)
```

```
print(X.shape, X_train.shape, X_test.shape)
```

```
(20640, 8) (16512, 8) (4128, 8)
```

model training

XGBoost regressor-decision tree model

```
#loading the model
model=XGBRegressor()
```

```
#training the model with X_train
model.fit(X_train, Y_train)
```

```
XGBRegressor
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=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,
             multi_strategy=None, n_estimators=None, n_jobs=None,
             num_parallel_tree=None, random_state=None, ...)
```

Evaluation

Prediction on trainng data

```
# accuracy for prediction on traing data
training_data_prediction=model.predict(X_train)
```

```
print(training_data_prediction)
```

```
[0.5523039 3.0850039 0.5835302 ... 1.9204227 1.952873  0.6768683]
```

```
# R sqaured error means variance
score_1=metrics.r2_score(Y_train,training_data_prediction)
#mean absolute error
score_2=metrics.mean_absolute_error(Y_train,training_data_prediction)

print("R squared error:" ,score_1)#should be close to 0 for accuracy
print('Mean absolute error MAE:',score_2)
```

```
R squared error: 0.943650140819218
Mean absolute error MAE: 0.1933648700612105
```

Visualise the actual prices and predicted prices

```
plt.scatter(Y_train,training_data_prediction)
plt.xlabel("actual prices")
plt.ylabel("predicted prices")
plt.title("actual price vs predicted price")
plt.show()
```


prediction on test data

```
test_data_prediction=model.predict(X_test)
```

```
print(test_data_prediction)
```

```
[2.8649795  1.790346   0.92074925 ... 1.5385513  0.92647874 2.043316  ]
```

```
# R sqaured error means variance
score_1=metrics.r2_score(Y_test,test_data_prediction)
#mean absolute error
score_2=metrics.mean_absolute_error(Y_test,test_data_prediction)

print("R squared error:" ,score_1)#should be close to 0 for accuracy
print('Mean absolute error MAE:',score_2)
```

```
R squared error: 0.8338000331788725
Mean absolute error MAE: 0.3108631800268186
```