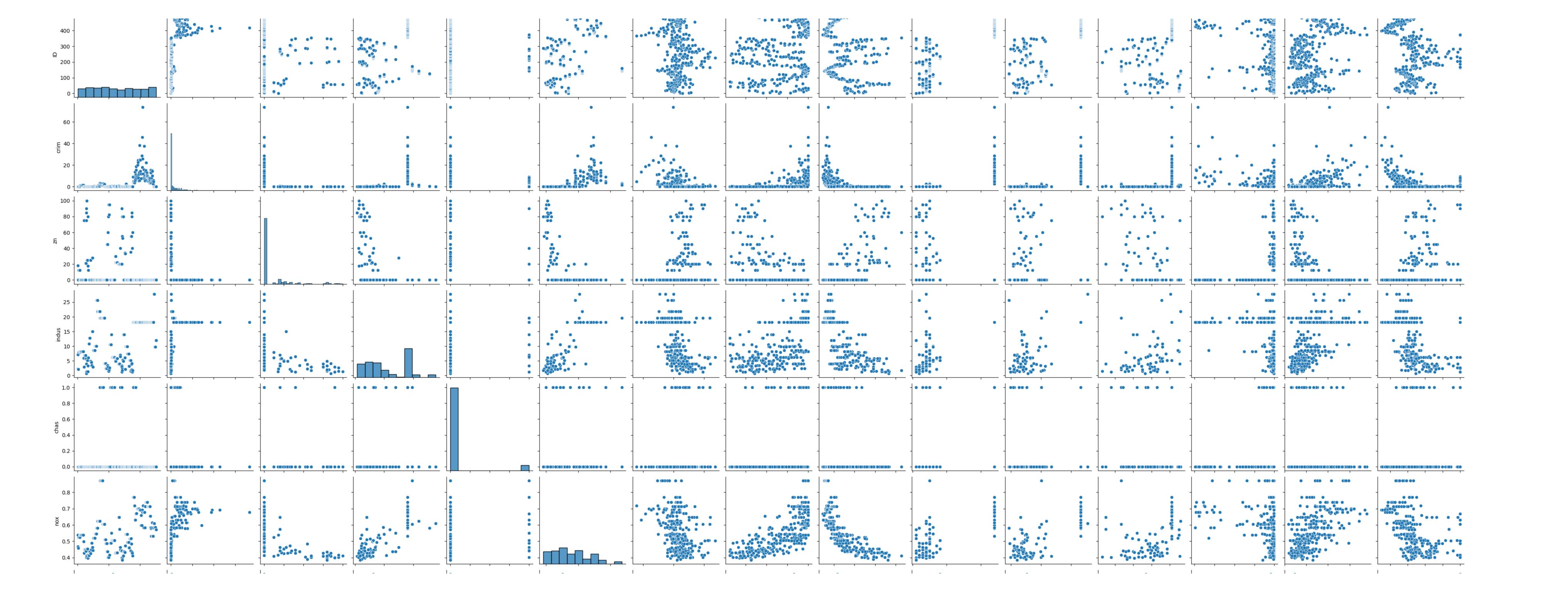
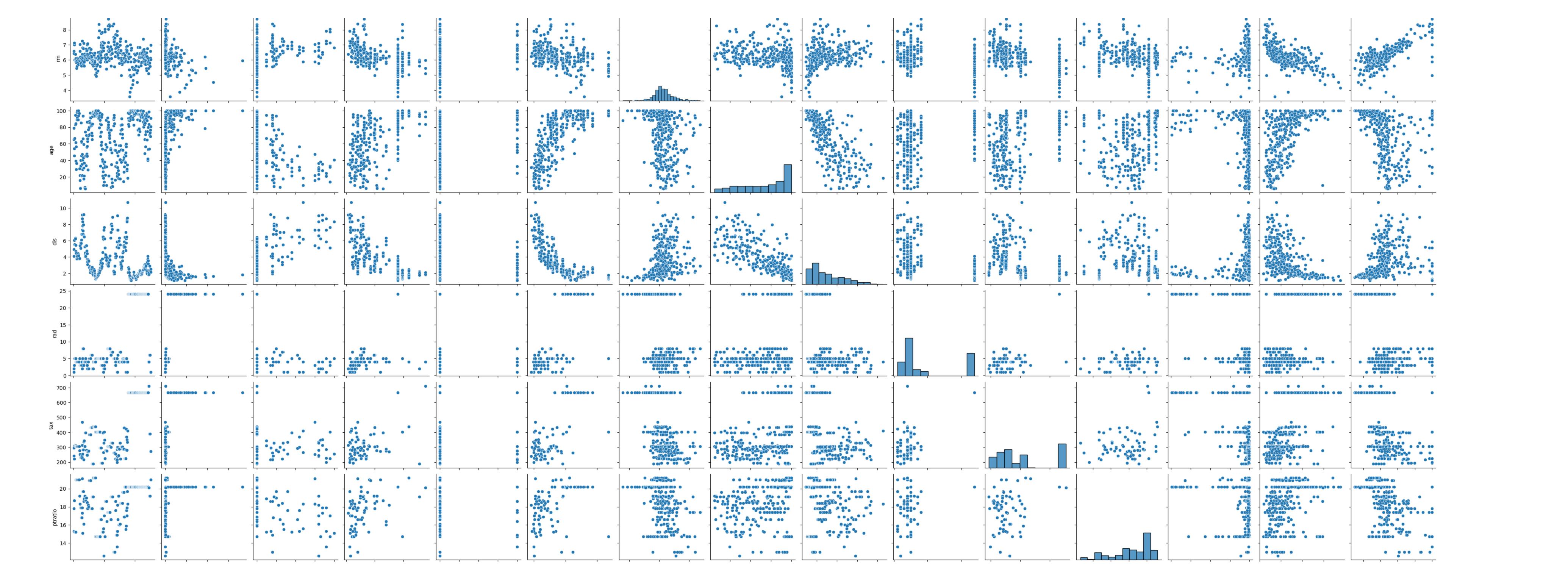
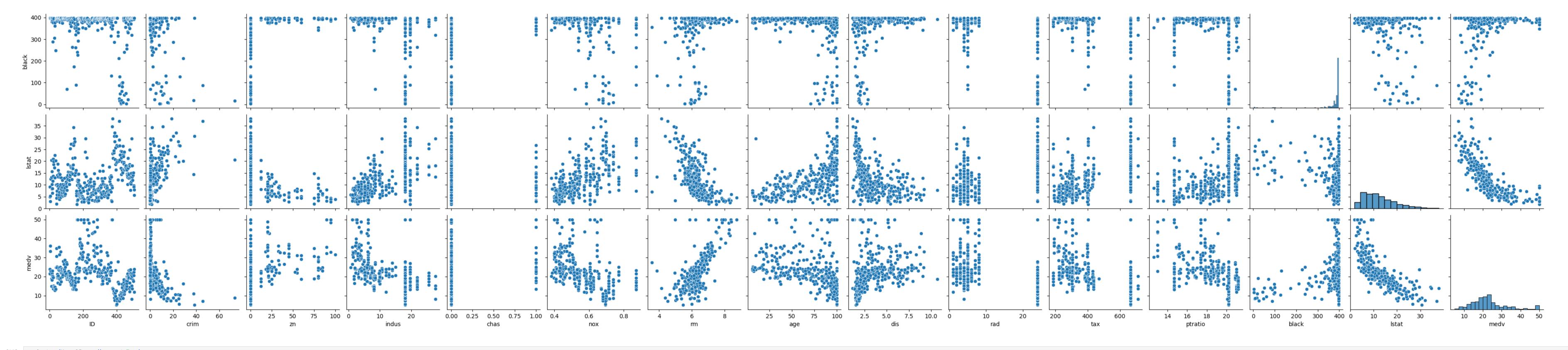
In [13]: # importing required lib # to work on data sets import pandas as pd import numpy as np # for scientific and math calculation import seaborn as sns # to visualize data using matplot import matplotlib.pyplot as plt # make visuals of data such as graph, bar graph, scatter plot etc... %matplotlib inline In [14]: # reading the data for training the model HouseDF = pd.read_csv("boston-housing/train.csv") In [15]: # top 5 element/row of the training data HouseDF.head() Out[15]: ID crim zn indus chas nox rm age dis rad tax ptratio black Istat medv **0** 1 0.00632 18.0 2.31 0 0.538 6.575 65.2 4.0900 1 296 15.3 396.90 4.98 24.0 **1** 2 0.02731 0.0 7.07 0 0.469 6.421 78.9 4.9671 2 242 17.8 396.90 9.14 21.6 **2** 4 0.03237 0.0 2.18 0 0.458 6.998 45.8 6.0622 3 222 18.7 394.63 2.94 33.4 **3** 5 0.06905 0.0 2.18 0 0.458 7.147 54.2 6.0622 3 222 18.7 396.90 5.33 36.2 **4** 7 0.08829 12.5 7.87 0 0.524 6.012 66.6 5.5605 5 311 15.2 395.60 12.43 22.9 In [16]: # information about the colums of the data set # we did not found any null values so we can proceed withoud removing null values <class 'pandas.core.frame.DataFrame'> RangeIndex: 333 entries, 0 to 332 Data columns (total 15 columns): # Column Non-Null Count Dtype --- ----- ------0 ID 333 non-null int64 1 crim 333 non-null float64 2 zn 333 non-null float64 3 indus 333 non-null float64 4 chas 333 non-null int64 5 nox 333 non-null float64 6 rm 333 non-null float64 7 age 333 non-null float64 8 dis 333 non-null float64 9 rad 333 non-null int64 10 tax 333 non-null int64 11 ptratio 333 non-null float64 12 black 333 non-null float64 13 lstat 333 non-null float64 14 medv 333 non-null float64 dtypes: float64(11), int64(4) memory usage: 39.2 KB In [7]: # describe data set and values like mean, deviation, min, max etc... HouseDF.describe() ID crim zn indus chas nox rm age dis rad tax ptratio black Istat medv count 333.000000 333.000000 333.000000 333.000000 333.000000 333.000000 333.000000 333.000000 333.000000 333.000000 333.000000 333.000000 333.000000 333.000000 mean 250.951952 3.360341 10.689189 11.293483 0.060060 0.557144 6.265619 68.226426 3.709934 9.633634 409.279279 18.448048 359.466096 12.515435 22.768769 std 147.859438 7.352272 22.674762 6.998123 0.237956 0.114955 0.703952 28.133344 1.981123 8.742174 170.841988 2.151821 86.584567 7.067781 9.173468 min 1.000000 0.006320 0.000000 0.740000 0.000000 0.385000 3.561000 6.000000 1.129600 1.000000 188.000000 12.600000 3.500000 1.730000 5.000000 **25**% 123.000000 0.078960 0.000000 5.130000 0.000000 0.453000 5.884000 45.400000 2.122400 4.000000 279.000000 17.400000 376.730000 7.180000 17.400000 **50**% 244.000000 0.261690 0.000000 9.900000 0.000000 0.538000 6.202000 76.700000 3.092300 5.000000 330.000000 19.000000 392.050000 10.970000 21.600000 **75**% 377.000000 3.678220 12.500000 18.100000 0.000000 0.631000 6.595000 93.800000 5.116700 24.000000 666.000000 20.200000 396.240000 16.420000 25.000000 max 506.000000 73.534100 100.000000 27.740000 1.000000 0.871000 8.725000 100.000000 10.710300 24.000000 711.000000 21.200000 396.900000 37.970000 50.000000 In [19]: HouseDF.columns Out[19]: Index(['ID', 'crim', 'zn', 'indus', 'chas', 'nox', 'rm', 'age', 'dis', 'rad', 'tax', 'ptratio', 'black', 'lstat', 'medv'], dtype='object') In [21]: sns.pairplot(HouseDF) Out[21]: <seaborn.axisgrid.PairGrid at 0x228fe421a00>







In [22]: sns.heatmap(HouseDF.corr(), annot=True)

ID - 1 0.460.160.470.006.440.1 D.260.360.710.650.310.270.280.22 crim -0.46 1 0.2 D.420.040.460.3 D.38-0.40.670.620.310.480.530.41 zn -0.160.21 1 0.50.0240.50.330.540.64-0.30.330.380.170.390.34 indus -0.420.420.52 1 0.03 0.750.440.64-0.70.570.710.390.340.610.47 chas -0.008.040.02403 1 0.080.1 D.068.08.200707020.16.06-20.050.2 nox -0.440.46-0.50.750.750.08 1 0.340.740.770.610.670.190.370.6-0.41 mm -0.130.3 D.330.440.110.34 1 0.250.270.270.360.370.160.620.69 age -0.260.380.540.60.060.740.25 1 0.760.450.510.260.2 D.590.36 dis -0.360.4 0.64-0.70.08 0.77 D.270.76 1 0.480.530.230.280.5 D.25 rad -0.710.67-0.30.507.007076-0.270.450.46 1 0.90.470.4 D.480.35 tax -0.690.620.310.740.020.670.360.510.550.9 1 0.470.4 D.540.45 ptratio -0.310.310.380.390.130.190.370.260.230.470.47 1 0.160.370.48 black -0.270.480.170.380.390.130.190.370.260.230.470.47 1 0.160.370.48 black -0.270.480.170.380.390.130.160.270.280.440.440.16 1 0.360.34 lstat -0.280.530.350.640.050.640.050.600.590.550.550.550.370.360.370.36 1 0.74

y = HouseDF['medv']

```
In [24]: # importing moduls to split the data to train and test
          from sklearn.model_selection import train_test_split
In [25]: # splitting data into training and testing data
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.40, random_state=101)
In [27]: #importing linear regression model to train our model
         from sklearn.linear_model import LinearRegression
In [28]: lm = LinearRegression()
In [30]: # fitting the model
lm.fit(X_train, y_train)
Out[30]: ▼ LinearRegression ①
         LinearRegression()
In [31]: coeff_DF = pd.DataFrame(lm.coef_, X.columns, columns=['Coefficient'])
            crim -0.097415
             zn 0.056597
            indus 0.094682
           chas 4.634273
             nox -13.323376
             rm 3.230758
            age -0.013663
             dis -1.509314
             rad 0.397022
            tax -0.017004
          ptratio -0.804268
           black 0.011120
            Istat -0.566284
 In [36]: # predicting the data
          predictions = lm.predict(X_test)
 In [37]: plt.scatter(y_test, predictions)
 Out[37]: <matplotlib.collections.PathCollection at 0x22893891ee0>
```

In [46]: sns.displot((y_test-predictions), bins=20)

Out[46]: <seaborn.axisgrid.FacetGrid at 0x228970d4dd0>

