In [5]: #PRACTICAL NO.8

#Aim: Hyperparameter tuning for lasso regression can be done in python without

import pandas as pd

df=pd.read_csv("BostonHousing.csv")

df

Out[5]:

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	b	Istat	med
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.98	24.
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14	21.
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03	34.
3	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	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	5.33	36.
501	0.06263	0.0	11.93	0	0.573	6.593	69.1	2.4786	1	273	21.0	391.99	9.67	22.
502	0.04527	0.0	11.93	0	0.573	6.120	76.7	2.2875	1	273	21.0	396.90	9.08	20.
503	0.06076	0.0	11.93	0	0.573	6.976	91.0	2.1675	1	273	21.0	396.90	5.64	23.
504	0.10959	0.0	11.93	0	0.573	6.794	89.3	2.3889	1	273	21.0	393.45	6.48	22.
505	0.04741	0.0	11.93	0	0.573	6.030	80.8	2.5050	1	273	21.0	396.90	7.88	11.

506 rows × 14 columns

In [6]: df.head(3)

Out[6]:

		crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	b	Istat	medv	
_	0	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	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	0 02720	0.0	7.07	0	0.460	7 185	61 1	4 0671	2	2/12	17 Q	302 83	4 N3	3/17	

1 of 4

```
In [7]: x=df.iloc[:,:-1]
          Х
 Out[7]:
                   crim
                          zn indus chas
                                                               dis rad
                                                                        tax ptratio
                                                                                         b Istat
                                            nox
                                                   rm
                                                       age
             0 0.00632 18.0
                               2.31
                                        0 0.538 6.575
                                                       65.2 4.0900
                                                                        296
                                                                               15.3 396.90
                                                                                            4.98
             1 0.02731
                          0.0
                               7.07
                                        0 0.469 6.421
                                                      78.9 4.9671
                                                                     2
                                                                        242
                                                                               17.8 396.90
                                                                                            9.14
               0.02729
                          0.0
                               7.07
                                        0 0.469 7.185 61.1
                                                            4.9671
                                                                     2
                                                                        242
                                                                               17.8 392.83
                                                                                           4.03
                0.03237
                          0.0
                               2.18
                                        0 0.458 6.998
                                                      45.8
                                                            6.0622
                                                                        222
                                                                               18.7 394.63
                                                                                            2.94
                0.06905
                          0.0
                                          0.458 \quad 7.147 \quad 54.2
                                                                        222
                                                                                            5.33
                               2.18
                                                            6.0622
                                                                     3
                                                                               18.7
                                                                                    396.90
                          ...
                0.06263
            501
                         0.0
                              11.93
                                        0 0.573 6.593 69.1 2.4786
                                                                        273
                                                                               21.0 391.99
                                                                                            9.67
            502 0.04527
                          0.0
                              11.93
                                        0 0.573 6.120 76.7
                                                            2.2875
                                                                        273
                                                                               21.0 396.90
                                                                                            9.08
            503 0.06076
                          0.0
                              11.93
                                        0 0.573 6.976 91.0
                                                            2.1675
                                                                        273
                                                                               21.0 396.90
                                                                                            5.64
           504 0.10959
                         0.0
                              11.93
                                        0 0.573 6.794 89.3 2.3889
                                                                        273
                                                                               21.0 393.45 6.48
            505 0.04741
                             11.93
                                        0 0.573 6.030 80.8 2.5050
                                                                        273
                                                                               21.0 396.90
                                                                                           7.88
                         0.0
          506 rows × 13 columns
 In [8]: y=df.iloc[:,-1]
 Out[8]:
          0
                   24.0
           1
                   21.6
           2
                   34.7
           3
                   33.4
          4
                   36.2
                   . . .
           501
                   22.4
           502
                   20.6
           503
                   23.9
           504
                   22.0
          505
                   11.9
          Name: medv, Length: 506, dtype: float64
 In [9]:
          from sklearn.linear_model import Lasso
          model=Lasso()
          from sklearn.model_selection import train_test_split
          xtrain,xtest,ytrain,ytest=train_test_split(x,y,random_state=1,test_size=0.25)
In [11]:
          model.fit(xtrain,ytrain)
Out[11]: Lasso()
```

2 of 4 19-03-2024, 09:13

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In [12]: from sklearn.model_selection import RepeatedKFold
         cv=RepeatedKFold(n_splits=10,n_repeats=3,random_state=1)
In [13]: | from sklearn.metrics import r2_score
         ypred=model.predict(xtest)
         r2_score(ytest,ypred)
Out[13]: 0.6621980770523261
In [14]: from sklearn.preprocessing import StandardScaler
         sc=StandardScaler()
         x_sc=sc.fit_transform(x)
         xtrain,xtest,ytrain,ytest=train_test_split(x_sc,y,random_state=1,test_size=0.2
         model1=Lasso()
         parms={'alpha':[0.00001,0.0001,0.001,0.01]}
         from sklearn.model_selection import GridSearchCV
         search=GridSearchCV(model1,parms,cv=cv)
         result=search.fit(x_sc,y)
         result.best_params_
Out[14]: {'alpha': 0.01}
In [15]: model2=Lasso(alpha=0.01)
         model2.fit(xtrain,ytrain)
Out[15]: Lasso(alpha=0.01)
In [16]: ypred=model2.predict(xtest)
         r2_score(ytest,ypred)
Out[16]: 0.7787372388293925
In [17]: | from sklearn.linear_model import Ridge
         model2=Ridge()
In [18]: from sklearn.model_selection import train_test_split
         xtrain,xtest,ytrain,ytest=train_test_split(x,y,random_state=1,test_size=0.25)
In [19]: model2.fit(xtrain,ytrain)
Out[19]: Ridge()
In [20]: from sklearn.model_selection import RepeatedKFold
         cv=RepeatedKFold(n_splits=10,n_repeats=3,random_state=1)
In [21]: from sklearn.metrics import r2_score
         ypred=model.predict(xtest)
         r2_score(ytest,ypred)
Out[21]: 0.6621980770523261
```

3 of 4 19-03-2024, 09:13

```
In [22]: from sklearn.preprocessing import StandardScaler
         sc=StandardScaler()
         x_sc=sc.fit_transform(x)
         xtrain,xtest,ytrain,ytest=train_test_split(x_sc,y,random_state=1,test_size=0.2
         model2=Ridge()
         parms={'alpha':[0.00001,0.0001,0.001,0.01]}
         from sklearn.model_selection import GridSearchCV
         search=GridSearchCV(model1,parms,cv=cv)
         result=search.fit(x_sc,y)
         result.best_params_
Out[22]: {'alpha': 0.01}
In [23]: model2=Lasso(alpha=0.01)
         model2.fit(xtrain,ytrain)
Out[23]: Lasso(alpha=0.01)
In [24]: ypred=model2.predict(xtest)
         r2_score(ytest,ypred) #RIDGE REGRESSION
Out[24]: 0.7787372388293925
In [ ]:
```

4 of 4