# Ex-07-Feature-Selection

## AIM

To Perform the various feature selection techniques on a dataset and save the data to a file.

# Explanation

Feature selection is to find the best set of features that allows one to build useful models. Selecting the best features helps the model to perform well.

# ALGORITHM

## STEP 1

Read the given Data

## STEP 2

Clean the Data Set using Data Cleaning Process

## STEP 3

Apply Feature selection techniques to all the features of the data set

## STEP 4

Save the data to the file

# CODE

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```
from sklearn.datasets import load_boston
boston_data=load_boston()
import pandas as pd
boston = pd.DataFrame(boston_data.data, columns=boston_data.feature_names)
boston['MEDV'] = boston_data.target
dummies = pd.get_dummies(boston.RAD)
boston = boston.drop(columns='RAD').merge(dummies,left_index=True,right_index=True)
X = boston.drop(columns='MEDV')
y = boston.MEDV
```

```
boston.head(10)

from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import KFold
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import cross_val_predict
from sklearn.linear_model import LinearRegression
from math import sqrt

cv = KFold(n_splits=10, random_state=None, shuffle=False)
classifier_pipeline = make_pipeline(StandardScaler(),
KNeighborsRegressor(n_neighbors=10))
y_pred = cross_val_predict(classifier_pipeline, X, y, cv=cv)
print("RMSE: " + str(round(sqrt(mean_squared_error(y,y_pred)),2)))
print("R_squared: " + str(round(r2_score(y,y_pred),2)))

boston.var()

X = X.drop(columns = ['NOX','CHAS'])
y_pred = cross_val_predict(classifier_pipeline, X, y, cv=cv)
print("RMSE: " + str(round(sqrt(mean_squared_error(y,y_pred)),2)))
print("R_squared: " + str(round(r2_score(y,y_pred),2)))

# Filter Features by Correlation
import seaborn as sn
import matplotlib.pyplot as plt
fig_dims = (12, 8)
fig, ax = plt.subplots(figsize=fig_dims)
sn.heatmap(boston.corr(), ax=ax)
plt.show()
abs(boston.corr()["MEDV"])
abs(boston.corr()["MEDV"][abs(boston.corr()["MEDV"])>0.5].drop('MEDV')).index.tolist()
vals = [0.1,0.2,0.3,0.4,0.5,0.6,0.7]
for val in vals:
    features = abs(boston.corr()["MEDV"][abs(boston.corr()
["MEDV"])>val].drop('MEDV')).index.tolist()

    X = boston.drop(columns='MEDV')
    X=X[features]

    print(features)

    y_pred = cross_val_predict(classifier_pipeline, X, y, cv=cv)
    print("RMSE: " + str(round(sqrt(mean_squared_error(y,y_pred)),2)))
    print("R_squared: " + str(round(r2_score(y,y_pred),2)))

# Feature Selection Using a Wrapper

boston = pd.DataFrame(boston_data.data, columns=boston_data.feature_names)
boston['MEDV'] = boston_data.target
boston['RAD'] = boston['RAD'].astype('category')
```

```
dummies = pd.get_dummies(boston.RAD)
boston = boston.drop(columns='RAD').merge(dummies,left_index=True,right_index=True)
X = boston.drop(columns='MEDV')
y = boston.MEDV

from mlxtend.feature_selection import SequentialFeatureSelector as SFS

sfs1 = SFS(classifier_pipeline,
           k_features=1,
           forward=False,
           scoring='neg_mean_squared_error',
           cv=cv)

X = boston.drop(columns='MEDV')
sfs1.fit(X,y)
sfs1.subsets_

X = boston.drop(columns='MEDV')[['CRIM','RM','PTRATIO','LSTAT']]
y = boston['MEDV']
y_pred = cross_val_predict(classifier_pipeline, X, y, cv=cv)
print("RMSE: " + str(round(sqrt(mean_squared_error(y,y_pred)),3)))
print("R_squared: " + str(round(r2_score(y,y_pred),3)))

boston[['CRIM','RM','PTRATIO','LSTAT','MEDV']].corr()

boston['RM*LSTAT']=boston['RM']*boston['LSTAT']

X = boston.drop(columns='MEDV')[['CRIM','RM','PTRATIO','LSTAT']]
y = boston['MEDV']
y_pred = cross_val_predict(classifier_pipeline, X, y, cv=cv)
print("RMSE: " + str(round(sqrt(mean_squared_error(y,y_pred)),3)))
print("R_squared: " + str(round(r2_score(y,y_pred),3)))

sn.pairplot(boston[['CRIM','RM','PTRATIO','LSTAT','MEDV']])

boston = boston.drop(boston[boston['MEDV']==boston['MEDV'].max()].index.tolist())

X = boston.drop(columns='MEDV')[['CRIM','RM','PTRATIO','LSTAT','RM*LSTAT']]
y = boston['MEDV']
y_pred = cross_val_predict(classifier_pipeline, X, y, cv=cv)
print("RMSE: " + str(round(sqrt(mean_squared_error(y,y_pred)),3)))
print("R_squared: " + str(round(r2_score(y,y_pred),3)))

boston['LSTAT_2']=boston['LSTAT']**2

X = boston.drop(columns='MEDV')[['CRIM','RM','PTRATIO','LSTAT']]
y_pred = cross_val_predict(classifier_pipeline, X, y, cv=cv)
print("RMSE: " + str(round(sqrt(mean_squared_error(y,y_pred)),3)))
print("R_squared: " + str(round(r2_score(y,y_pred),3)))
```

OUPUT

| | CRIM | ZN | INDUS | CHAS | NOX | RM | AGE | DIS | TAX | PTRATIO | ... | MEDV | 1.0 | 2.0 | 3.0 | 4.0 | 5.0 | 6.0 | 7.0 | 8.0 | 24.0 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.00632 | 18.0 | 2.31 | 0.0 | 0.538 | 6.575 | 65.2 | 4.0900 | 296.0 | 15.3 | ... | 24.0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **1** | 0.02731 | 0.0 | 7.07 | 0.0 | 0.469 | 6.421 | 78.9 | 4.9671 | 242.0 | 17.8 | ... | 21.6 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **2** | 0.02729 | 0.0 | 7.07 | 0.0 | 0.469 | 7.185 | 61.1 | 4.9671 | 242.0 | 17.8 | ... | 34.7 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **3** | 0.03237 | 0.0 | 2.18 | 0.0 | 0.458 | 6.998 | 45.8 | 6.0622 | 222.0 | 18.7 | ... | 33.4 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| **4** | 0.06905 | 0.0 | 2.18 | 0.0 | 0.458 | 7.147 | 54.2 | 6.0622 | 222.0 | 18.7 | ... | 36.2 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| **5** | 0.02985 | 0.0 | 2.18 | 0.0 | 0.458 | 6.430 | 58.7 | 6.0622 | 222.0 | 18.7 | ... | 28.7 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| **6** | 0.08829 | 12.5 | 7.87 | 0.0 | 0.524 | 6.012 | 66.6 | 5.5605 | 311.0 | 15.2 | ... | 22.9 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| **7** | 0.14455 | 12.5 | 7.87 | 0.0 | 0.524 | 6.172 | 96.1 | 5.9505 | 311.0 | 15.2 | ... | 27.1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| **8** | 0.21124 | 12.5 | 7.87 | 0.0 | 0.524 | 5.631 | 100.0 | 6.0821 | 311.0 | 15.2 | ... | 16.5 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| **9** | 0.17004 | 12.5 | 7.87 | 0.0 | 0.524 | 6.004 | 85.9 | 6.5921 | 311.0 | 15.2 | ... | 18.9 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |

10 rows × 22 columns

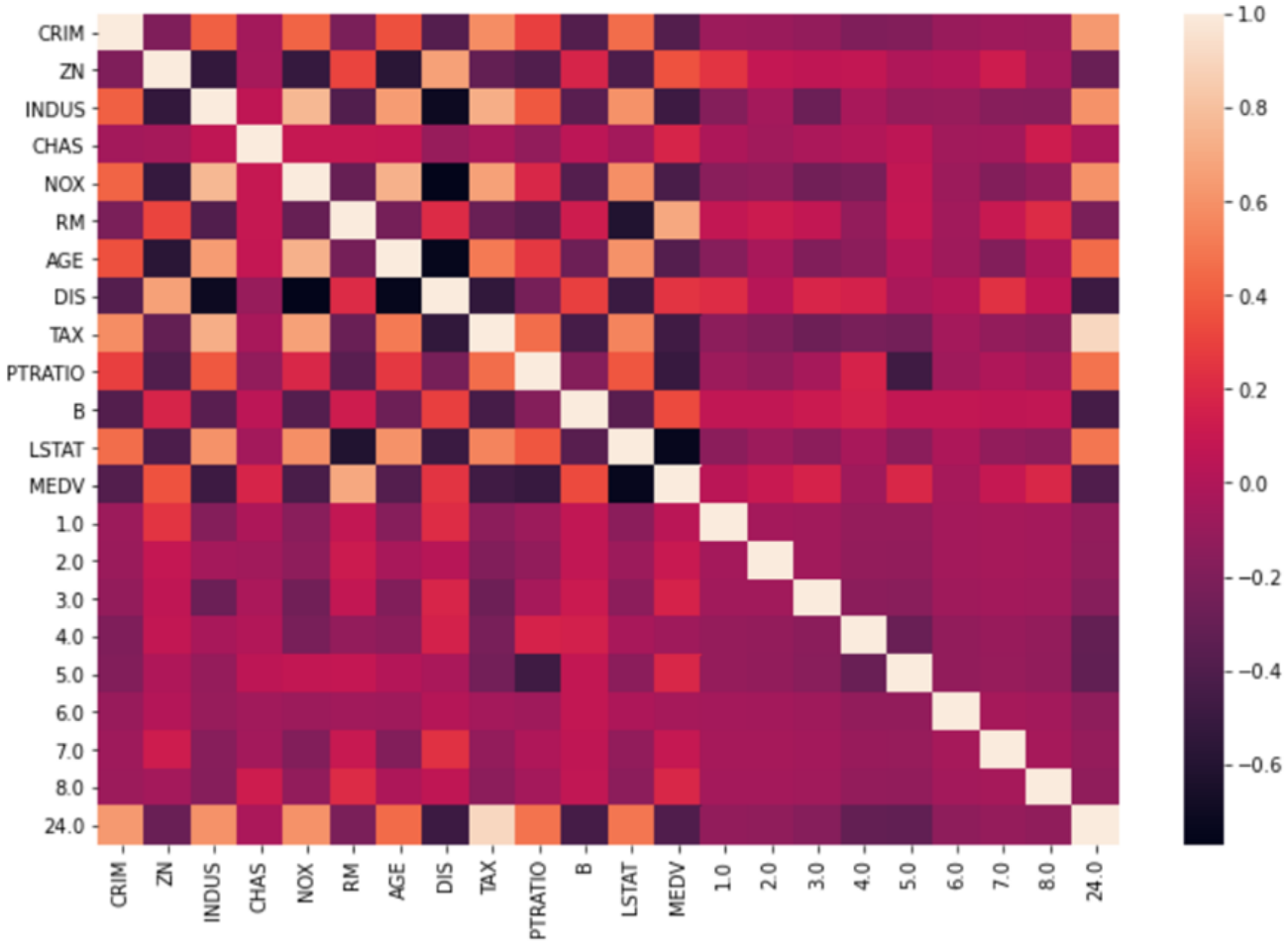
```
RMSE: 6.51
R_squared: 0.5
```

Out[44]:

| | |
|---|---|
| CRIM | 73.986578 |
| ZN | 543.936814 |
| INDUS | 47.064442 |
| CHAS | 0.064513 |
| NOX | 0.013428 |
| RM | 0.493671 |
| AGE | 792.358399 |
| DIS | 4.434015 |
| TAX | 28404.759488 |
| PTRATIO | 4.686989 |
| B | 8334.752263 |
| LSTAT | 50.994760 |
| MEDV | 84.586724 |
| 1.0 | 0.038039 |
| 2.0 | 0.045271 |
| 3.0 | 0.069597 |
| 4.0 | 0.170469 |
| 5.0 | 0.175968 |
| 6.0 | 0.048840 |
| 7.0 | 0.032532 |
| 8.0 | 0.045271 |
| 24.0 | 0.193198 |

dtype: float64

```
RMSE: 6.28
R_squared: 0.53
```


CRIM
ZN
INDUS
CHAS
NOX
RM
AGE
DIS
TAX
PTRATIO
B
LSTAT
MEDV
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
24.0
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6

```
CRIM        0.388305
ZN          0.360445
INDUS       0.483725
CHAS        0.175260
NOX         0.427321
RM          0.695360
AGE         0.376955
DIS         0.249929
TAX         0.468536
PTRATIO     0.507787
B           0.333461
LSTAT       0.737663
MEDV        1.000000
1.0         0.040453
2.0         0.104444
3.0         0.167352
4.0         0.065711
5.0         0.187356
6.0         0.039411
7.0         0.092802
8.0         0.190053
24.0        0.396297
Name: MEDV, dtype: float64

['RM', 'PTRATIO', 'LSTAT']
```

```
['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'TAX', 'PTRATIO', 'B', 'LSTAT', 2.0, 3.0, 5.0, 8.0, 24.0]
RMSE: 6.47
R_squared: 0.5
['CRIM', 'ZN', 'INDUS', 'NOX', 'RM', 'AGE', 'DIS', 'TAX', 'PTRATIO', 'B', 'LSTAT', 24.0]
RMSE: 5.27
R_squared: 0.67
['CRIM', 'ZN', 'INDUS', 'NOX', 'RM', 'AGE', 'TAX', 'PTRATIO', 'B', 'LSTAT', 24.0]
RMSE: 5.42
R_squared: 0.65
['INDUS', 'NOX', 'RM', 'TAX', 'PTRATIO', 'LSTAT']
RMSE: 4.89
R_squared: 0.72
['RM', 'PTRATIO', 'LSTAT']
RMSE: 4.73
R_squared: 0.74
['RM', 'LSTAT']
RMSE: 4.8
R_squared: 0.73
['LSTAT']
RMSE: 5.7
R_squared: 0.61
```

```
Out[54]: {21: {'feature_idx': (0,
                               1,
                               2,
                               3,
                               4,
                               5,
                               6,
                               7,
                               8,
                               9,
                               10,
                               11,
                               12,
                               13,
                               14,
                               15,
                               16,
                               17,
                               18,
```

```
'cv_scores': array([ -20.02093922,  -20.02723725,  -17.22919608,  -57.94924706,
        -30.63476667,  -50.08086275,  -15.757356  , -110.244478  ,
        -21.41984   ,  -16.222326  ]),
'avg_score': -35.95862490196079,
'feature_names': ('CRIM',
 'ZN',
 'INDUS',
 'NOX',
 'RM',
 'AGE',
 'DIS',
 'TAX',
 'PTRATIO',
 'B',
 'LSTAT',
 1.0,
 2.0,
 3.0,
 4.0,
```

RMSE: 4.458

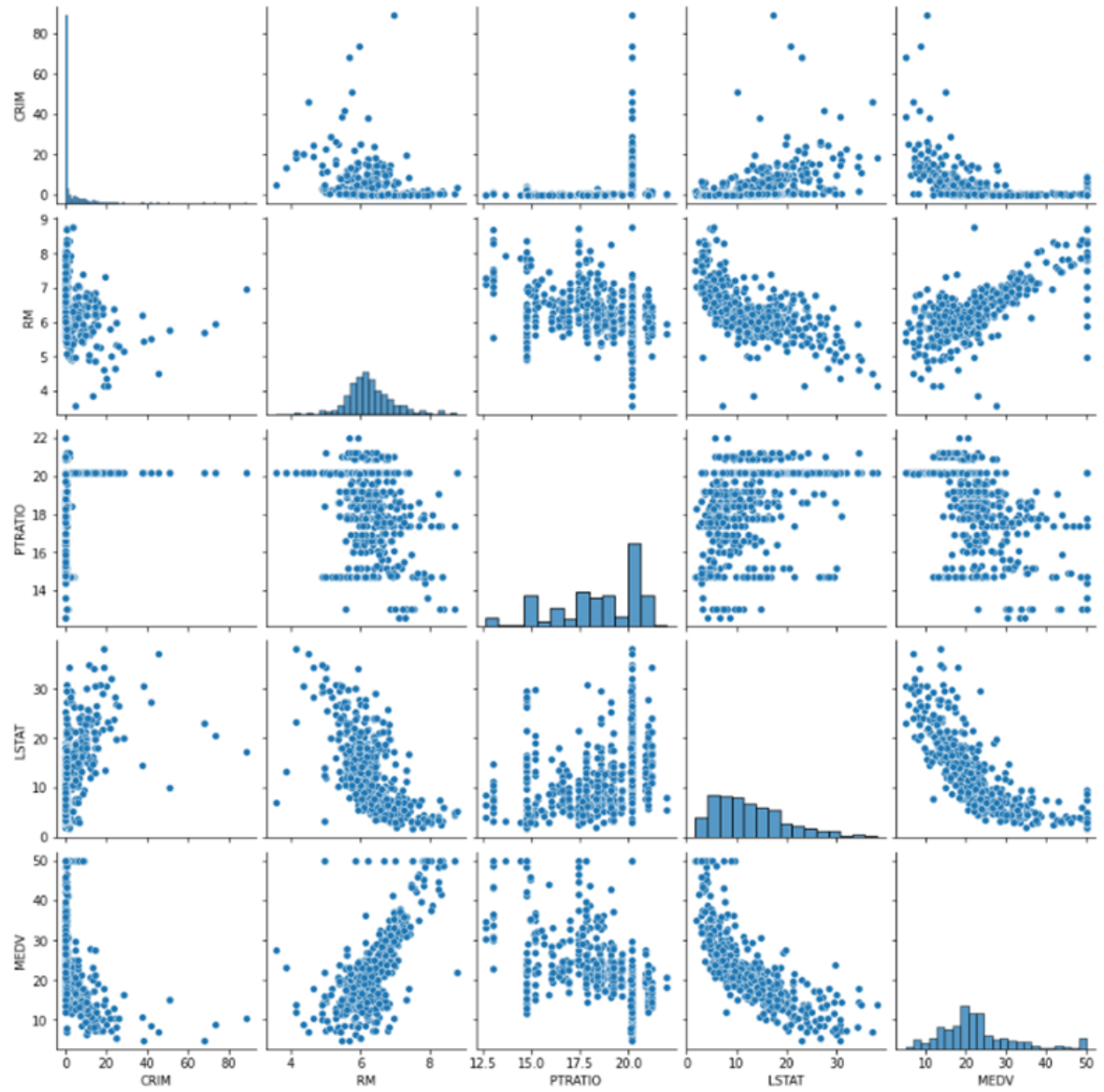
R_squared: 0.765

:

| | CRIM | RM | PTRATIO | LSTAT | MEDV |
|---|---|---|---|---|---|
| **CRIM** | 1.000000 | -0.219247 | 0.289946 | 0.455621 | -0.388305 |
| **RM** | -0.219247 | 1.000000 | -0.355501 | -0.613808 | 0.695360 |
| **PTRATIO** | 0.289946 | -0.355501 | 1.000000 | 0.374044 | -0.507787 |
| **LSTAT** | 0.455621 | -0.613808 | 0.374044 | 1.000000 | -0.737663 |
| **MEDV** | -0.388305 | 0.695360 | -0.507787 | -0.737663 | 1.000000 |

```
RMSE: 4.458
R_squared: 0.765
```

Out[59]: <seaborn.axisgrid.PairGrid at 0x2c2ad24b220>




RMSE: 3.509
R_squared: 0.801

RMSE: 3.548
R_squared: 0.796

## RESULT

The various feature selection techniques has been performed on a dataset and saved the data to a file.