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:

```
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=0, shuffle=True)
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)))

import seaborn as sn
import matplotlib.pyplot as plt

fig_dims = (10, 6)
fig, ax = plt.subplots(figsize=fig_dims)
sn.heatmap(boston.corr(), ax=ax,cmap="Blues")
plt.show()

abs(boston.corr()["MEDV"])

abs(boston.corr()["MEDV"][abs(boston.corr()["MEDV"])>0.5].drop('MEDV')).index.toli
st()

vals = [0.1,0.2,0.3,0.4,0.5]
for val in vals:
    features =
abs(boston.corr()["MEDV"][abs(boston.corr()["MEDV"])>val].drop('MEDV')).index.toli
st()

    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)))

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()

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']])
```

OUPUT:

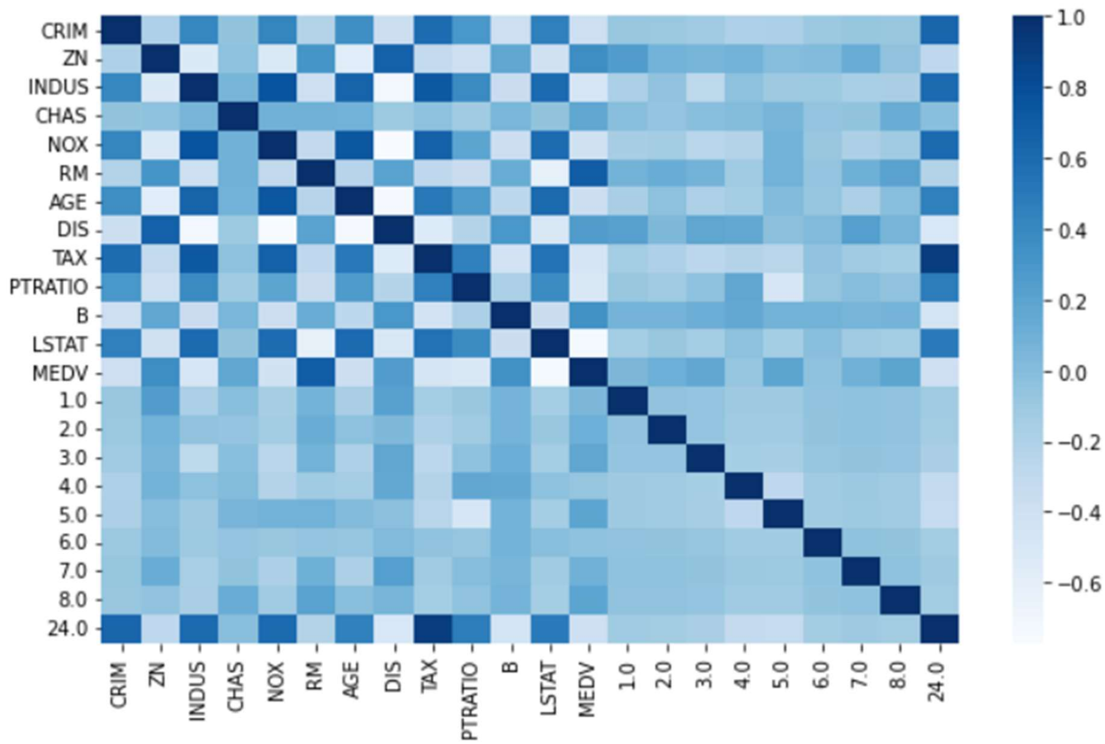
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	TAX	PTRATIO	...	MEDV	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	24.0
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	296.0	15.3	...	24.0	1	0	0	0	0	0	0	0	0
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	242.0	17.8	...	21.6	0	1	0	0	0	0	0	0	0
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	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

```
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: 5.39
R_squared: 0.66
```

```
RMSE: 5.07
R_squared: 0.7
```



```
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
```

```
['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'TAX', 'PTRATIO', 'B', 'LSTAT', 2.0, 3.0, 5.0, 8.0, 24.0]
RMSE: 5.14
R_squared: 0.69
['CRIM', 'ZN', 'INDUS', 'NOX', 'RM', 'AGE', 'DIS', 'TAX', 'PTRATIO', 'B', 'LSTAT', 24.0]
RMSE: 4.42
R_squared: 0.77
['CRIM', 'ZN', 'INDUS', 'NOX', 'RM', 'AGE', 'TAX', 'PTRATIO', 'B', 'LSTAT', 24.0]
RMSE: 4.33
R_squared: 0.78
['INDUS', 'NOX', 'RM', 'TAX', 'PTRATIO', 'LSTAT']
RMSE: 4.28
R_squared: 0.78
['RM', 'PTRATIO', 'LSTAT']
RMSE: 4.3
R_squared: 0.78
```

```
RMSE: 4.102
R_squared: 0.801
```

	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: 4.102
R_squared: 0.801
```

```
RMSE: 4.102
R_squared: 0.801

<seaborn.axisgrid.PairGrid at 0x23d5939aa60>
```