EXNO:4-DS

AIM:

To read the given data and perform Feature Scaling and Feature Selection process and save the data to a file.

ALGORITHM:

STEP 1:Read the given Data. STEP 2:Clean the Data Set using Data Cleaning Process. STEP 3:Apply Feature Scaling for the feature in the data set. STEP 4:Apply Feature Selection for the feature in the data set. STEP 5:Save the data to the file.

FEATURE SCALING:

1. Standard Scaler: It is also called Z-score normalization. It calculates the z-score of each value and replaces the value with the calculated Z-score. The features are then rescaled with $\bar{x}$ =0 and σ=1
2. MinMaxScaler: It is also referred to as Normalization. The features are scaled between 0 and 1. Here, the mean value remains same as in Standardization, that is,0.
3. Maximum absolute scaling: Maximum absolute scaling scales the data to its maximum value; that is,it divides every observation by the maximum value of the variable.The result of the preceding transformation is a distribution in which the values vary approximately within the range of -1 to 1.
4. RobustScaler: RobustScaler transforms the feature vector by subtracting the median and then dividing by the interquartile range (75% value — 25% value).

FEATURE SELECTION:

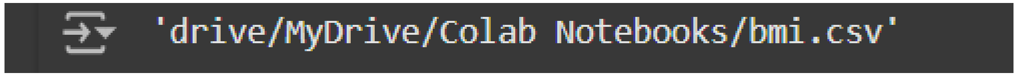
Feature selection is to find the best set of features that allows one to build useful models. Selecting the best features helps the model to perform well. The feature selection techniques used are: 1.Filter Method 2.Wrapper Method 3.Embedded Method

CODING AND OUTPUT:

from google.colab import drive

drive.mount('/content/drive')

ls drive/MyDrive/'Colab Notebooks'/bmi.csv



ls drive/MyDrive/'Colab Notebooks'/'income(1) (1).csv'

```
'drive/MyDrive/Colab Notebooks/income(1) (1).csv'
```

import pandas as pd

import numpy as np

from scipy import stats

df=pd.read_csv("drive/MyDrive/Colab Notebooks/bmi.csv")

df

	Gender	Height	Weight	Index
0	Male	174	96	4
1	Male	189	87	2
2	Female	185	110	4
3	Female	195	104	3
4	Male	149	61	3
...	...	...	...	...
495	Female	150	153	5
496	Female	184	121	4
497	Female	141	136	5
498	Male	150	95	5
499	Male	173	131	5

500 rows × 4 columns

df.head()

	Gender	Height	Weight	Index
0	Male	174	96	4
1	Male	189	87	2
2	Female	185	110	4
3	Female	195	104	3
4	Male	149	61	3

df.dropna()

	Gender	Height	Weight	Index
0	Male	174	96	4
1	Male	189	87	2
2	Female	185	110	4
3	Female	195	104	3
4	Male	149	61	3
...	...	...	...	...
495	Female	150	153	5
496	Female	184	121	4
497	Female	141	136	5
498	Male	150	95	5
499	Male	173	131	5

500 rows × 4 columns

max_vals = np.max(np.abs(df[['Height','Weight']]))

max_vals

max_vals

df1=pd.read_csv("drive/MyDrive/Colab Notebooks/bmi.csv") df1

	Gender	Height	Weight	Index
0	Male	174	96	4
1	Male	189	87	2
2	Female	185	110	4
3	Female	195	104	3
4	Male	149	61	3
...	...	...	...	...
495	Female	150	153	5
496	Female	184	121	4
497	Female	141	136	5
498	Male	150	95	5
499	Male	173	131	5

500 rows × 4 columns

from sklearn.preprocessing import StandardScaler

sc=StandardScaler()

df1[['Height','Weight']] = sc.fit_transform(df1[['Height','Weight']]) df.head(10)

	Gender	Height	Weight	Index
0	Male	174	96	4
1	Male	189	87	2
2	Female	185	110	4
3	Female	195	104	3
4	Male	149	61	3
5	Male	189	104	3
6	Male	147	92	5
7	Male	154	111	5
8	Male	174	90	3
9	Female	169	103	4

from sklearn.preprocessing import MinMaxScaler

Scaler=MinMaxScaler()

df[['Height','Weight']]=Scaler.fit_transform(df[['Height','Weight']])

df.head(0)

Gender	Height	Weight	Index

df2=pd.read_csv("drive/MyDrive/Colab Notebooks/bmi.csv")

df2

	Gender	Height	Weight	Index
0	Male	174	96	4
1	Male	189	87	2
2	Female	185	110	4
3	Female	195	104	3
4	Male	149	61	3
...	...	...	...	...
495	Female	150	153	5
496	Female	184	121	4
497	Female	141	136	5
498	Male	150	95	5
499	Male	173	131	5

500 rows × 4 columns

from sklearn.preprocessing import Normalizer

Scaler=Normalizer()

df2[['Height','Weight']]=Scaler.fit_transform(df2[['Height','Weight']])

df2

	Gender	Height	Weight	Index
0	Male	0.875578	0.483077	4
1	Male	0.908381	0.418144	2
2	Female	0.859536	0.511075	4
3	Female	0.882353	0.470588	3
4	Male	0.925448	0.378875	3
...	...	...	...	...
495	Female	0.700071	0.714073	5
496	Female	0.835527	0.549450	4
497	Female	0.719753	0.694230	5
498	Male	0.844819	0.535052	5
499	Male	0.797227	0.603680	5

500 rows × 4 columns

df3=pd.read_csv("drive/MyDrive/Colab Notebooks/bmi.csv")

df3

	Gender	Height	Weight	Index
0	Male	174	96	4
1	Male	189	87	2
2	Female	185	110	4
3	Female	195	104	3
4	Male	149	61	3
...	...	...	...	...
495	Female	150	153	5
496	Female	184	121	4
497	Female	141	136	5
498	Male	150	95	5
499	Male	173	131	5

500 rows × 4 columns

from sklearn.preprocessing import MaxAbsScaler

Scaler=MaxAbsScaler()

df3[['Height','Weight']]=Scaler.fit_transform(df3[['Height','Weight']])

df3

	Gender	Height	Weight	Index
0	Male	0.874372	0.60000	4
1	Male	0.949749	0.54375	2
2	Female	0.929648	0.68750	4
3	Female	0.979899	0.65000	3
4	Male	0.748744	0.38125	3
...	...	...	...	...
495	Female	0.753769	0.95625	5
496	Female	0.924623	0.75625	4
497	Female	0.708543	0.85000	5
498	Male	0.753769	0.59375	5
499	Male	0.869347	0.81875	5

500 rows × 4 columns

df4=pd.read_csv("drive/MyDrive/Colab Notebooks/bmi.csv")

from sklearn.preprocessing import RobustScaler

Scaler=RobustScaler()

df4[['Height','Weight']]=Scaler.fit_transform(df4[['Height','Weight']])

df4.head()

	Gender	Height	Weight	Index
0	Male	0.125000	-0.178571	4
1	Male	0.660714	-0.339286	2
2	Female	0.517857	0.071429	4
3	Female	0.875000	-0.035714	3
4	Male	-0.767857	-0.803571	3

import matplotlib

import matplotlib.pyplot as plt

import seaborn as sns

import statsmodels.api as sm

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LinearRegression

from sklearn.feature_selection import RFE

from sklearn.linear_model import RidgeCV,LassoCV,Ridge,Lasso from sklearn.feature_selection import SelectKBest

from sklearn.feature_selection import mutual_info_classif

from sklearn.feature_selection import mutual_info_regression

from sklearn.feature_selection import chi2

df=pd.read_csv('drive/MyDrive/Colab Notebooks/income(1) (1).csv')

df.columns

```
Index(['age', 'JobType', 'EdType', 'maritalstatus', 'occupation',
       'relationship', 'race', 'gender', 'capitalgain', 'capitalloss',
       'hoursperweek', 'nativecountry', 'SalStat'],
      dtype='object')
```

df1.columns

```
Index(['Gender', 'Height', 'Weight', 'Index'], dtype='object')
```

import pandas as pd

from sklearn.feature_selection import SelectKBest

from sklearn.feature_selection import chi2

data=pd.read_csv('drive/MyDrive/Colab Notebooks/bmi.csv')

data=data.dropna()

df.columns

df

	age	JobType	EdType	maritalstatus	occupation	relationship	race	gender	capitalgain	capitalloss	hoursperweek	nativecountry	SalStat
0	45	Private	HS-grad	Divorced	Adm-clerical	Not-in-family	White	Female	0	0	28	United-States	less than or equal to 50,000
1	24	Federal-gov	HS-grad	Never-married	Armed-Forces	Own-child	White	Male	0	0	40	United-States	less than or equal to 50,000
2	44	Private	Some-college	Married-civ-spouse	Prof-specialty	Husband	White	Male	0	0	40	United-States	greater than 50,000
3	27	Private	9th	Never-married	Craft-repair	Other-relative	White	Male	0	0	40	Mexico	less than or equal to 50,000
4	20	Private	Some-college	Never-married	Sales	Not-in-family	White	Male	0	0	35	United-States	less than or equal to 50,000
...	...	...	...	...	...	...	...	...	...	...	...	...	...
31973	34	Local-gov	HS-grad	Never-married	Farming-fishing	Not-in-family	Black	Male	594	0	60	United-States	less than or equal to 50,000
31974	34	Local-gov	Some-college	Never-married	Protective-serv	Not-in-family	White	Female	0	0	40	United-States	less than or equal to 50,000
31975	23	Private	Some-college	Married-civ-spouse	Adm-clerical	Husband	White	Male	0	0	40	United-States	less than or equal to 50,000
31976	42	Local-gov	Some-college	Married-civ-spouse	Adm-clerical	Wife	White	Female	0	0	40	United-States	less than or equal to 50,000
31977	29	Private	Bachelors	Never-married	Prof-specialty	Not-in-family	White	Male	0	0	40	United-States	less than or equal to 50,000

31978 rows × 13 columns

import pandas as pd

import numpy as np

from scipy.stats import chi2_contingency

import seaborn as sns

tips=sns.load_dataset('tips')

tips.head()

	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4

RESULT:

```
THUS THE ABOVE CODE IS EXECUETED SUCCESSFULLY
```