FACULTY OF ENGINEERING AND TECHNOLOGY

JAIN DEEMED-TO-BE UNIVERSITY

Department of Computer Science & Engineering
(Artificial Intelligence and Machine Learning)

LAB RECORD

21CS5AM09L – Advanced Machine Learning LAB

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Global Campus

Jakkasandra Post, Kanakapura Taluk,
Ramanagara District - Pin Code: 562 112

SCHOOL OF ENGINEERING AND TECHNOLOGY

Department of Computer Science & Engineering (Artificial Intelligence and Machine Learning)

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21CS5AM08L – DATA WAREHOUSING AND MINING LAB

2023-2024

Register No: 21BTRCL059

It is hereby certified that this is the bona fide record of work done by Mr./Ms. M.SHRAVANI PRIYA during the academic year 2023-2024 and submitted for the University Practical Examination held on 27-11-20203.

Over All Marks

Staff-in-charge **Head of the Department**

Internal Examiner **External Examiner**

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Experiment: 1 **Date:**

Aim: To implement logistic regression with 2 different datasets and evaluate the classification accuracy.

Procedure:

Data Loading and Inspection:

- Import the dataset using Pandas and inspect the first few rows, data types, and missing values.

Data Preprocessing:

- Extract features (X) and labels (Y) from the dataset. Handle missing values if any.
- Encode categorical labels using Label Encoder.

Data Splitting:

- Split the dataset into training and testing sets for model evaluation.

Logistic Regression Model Training and Evaluation:

- Create a logistic regression model and train it on the training set.
- Evaluate the model on the test set and assess classification accuracy.

Source Code:

```
import pandas as pd
import numpy as np
from pandas_profiling import ProfileReport
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import mode
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import LabelEncoder
import warnings
warnings.filterwarnings("ignore")
data3=pd.read_csv(“iris.csv")
data3.head()
data3.info()
```

```
from sklearn.preprocessing import LabelEncoder
X= data3.iloc[:,1:5]
Y = data3.iloc[:,-1]

label_encoder = LabelEncoder()
label = label_encoder.fit_transform(Y)
Y= label_encoder.transform(Y)
from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size=0.2,random_state=2)
from sklearn.linear_model import LogisticRegression
reg = LogisticRegression()
reg.fit(X_train,Y_train)
y_pred=reg.predict(X_test)
from sklearn.metrics import accuracy_score,confusion_matrix,precision_score,recall_score,f1_score
accuracy = accuracy_score(Y_test,y_pred)
accuracy
```

Output:

```
In [18]:   1 y_pred
Out[18]: array([0, 0, 2, 0, 0, 2, 0, 2, 2, 0, 0, 0, 0, 0, 1, 1, 0, 1, 2, 1, 2, 1,
                2, 1, 1, 0, 0, 2, 0, 2])

In [16]:   1 from sklearn.metrics import accuracy_score,confusion_matrix,precision_score,recall_score,f1_score
           2 accuracy = accuracy_score(Y_test,y_pred)

In [17]:   1 accuracy
Out[17]: 0.9666666666666667
```

Result:

Logistic Regression was implemented and the results were noted.

Experiment: 2 **Date:**

Aim: To implement support vector machine with various datasets and evaluate the classification accuracy.

Procedure:

Data Loading and Inspection:

- Import required libraries and read the Iris dataset.
- Display the first few rows of the dataset.

Data Preprocessing:

- Separate features (X) and labels (Y) from the dataset.
- Split the data into training and testing sets.

Support Vector Classification:

- Create a linear SVM classifier, fit it on the training set, and make predictions on the test set.
- Evaluate the classification performance using metrics such as accuracy, confusion matrix, and classification report.

Support Vector Regression:

- Load the Real Estate dataset and prepare features (x) and target variable (y).
- Split the data into training and testing sets.

Support Vector Regression Evaluation:

- Create an SVR model, fit it on the training set, and predict on the test set.
- Evaluate the regression performance using metrics such as R-squared, Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

Source Code:

```
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
df = pd.read_csv(“iris.csv")
df.head()
Y = df['Species']
X = df.drop(['Id','Species'], axis=1)
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3)

from sklearn.svm import SVC
svc = SVC(kernel='linear',C=1E10)
svc.fit(X_train, Y_train)
y_pred = svc.predict(X_test)
svc.score(X_test, Y_test)
svc.support_vectors_
from sklearn.metrics import classification_report
print(classification_report(Y_test, y_pred))
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
cm=confusion_matrix(Y_test,y_pred)
ac=accuracy_score(Y_test, y_pred)
print(cm)
print(ac)

# Support Vector Regression
# svm for regression.
import pandas as pd
from sklearn.svm import SVR
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
df = pd.read_csv("Real estate.csv")
y = df.pop("Y house price of unit area")
df.head()
x = df.drop(['No'], axis = 1)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2)
svr = SVR()
svr.fit(x_train, y_train)
y_pred = svr.predict(x_test)
```

```
from sklearn.metrics import r2_score
result = r2_score(y_test, y_pred)
print(result)

#If True returns MSE value, if False returns RMSE value.
from sklearn.metrics import mean_squared_error
result=  mean_squared_error(y_test,y_pred,squared=False)
result1=   mean_squared_error(y_test,y_pred,squared=True)
print(result)
print(result1)
```

Output:

```
In [7]:
from sklearn.metrics import classification_report
print(classification_report(Y_test, y_pred))
```

```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        18
Iris-versicolor       0.79      0.94      0.86        16
 Iris-virginica       0.88      0.64      0.74        11

       accuracy                           0.89        45
      macro avg       0.89      0.86      0.86        45
   weighted avg       0.89      0.89      0.88        45
```

```
In [8]:
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix

cm=confusion_matrix(Y_test,y_pred)
ac=accuracy_score(Y_test, y_pred)
print(cm)
print(ac)
```

```
[[18  0  0]
 [ 0 15  1]
 [ 0  4  7]]
0.8888888888888888
```

Result:

Support Vector Machine and Support Vector Regression was implemented and the results were noted.

Experiment: 3 **Date:**

Aim: To implement K- Nearest Neighbor algorithm with 2 different datasets and evaluate the classification accuracy.

Procedure:

Data Loading and Inspection:

- Import required libraries and read the first dataset (tested.csv).[Titanic Dataset]
- Display the first few rows of the dataset

Data Preprocessing:

- Separate features (x) and labels (y) from the dataset.
- Drop irrelevant columns and encode categorical variables.

Data Splitting:

- Split the dataset into training and testing sets.
- K-Nearest Neighbours (KNN) Model Training and Evaluation:

Create a KNN classifier, fit it on the training set, and predict on the test set.

- Evaluate the classification performance using metrics such as accuracy and confusion matrix.

Prediction on New Data:

- Make predictions on new data points using the trained KNN model.

Source Code:

```
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
df=pd.read_csv(r"tested.csv")
df.head()
from sklearn.preprocessing import LabelEncoder
y = df['Survived']
x = df.drop(['Survived'],axis=1)data3=pd.read_csv("iris.csv")
x.head()
```

```
x=x.drop(['Name'],axis=1)
x=x.drop(['Ticket'],axis=1)
x=x.drop(['SibSp'],axis=1)
x=x.drop(['Parch'],axis=1)
x=x.drop(['Cabin'],axis=1)
x=x.drop([‘Embarked'],axis=1)

from sklearn.preprocessing import LabelEncoder
# Create a LabelEncoder instance
label_encoder = LabelEncoder()
# Encode the 'Sex' column
x['Sex'] = label_encoder.fit_transform(x['Sex'])
x.head()
x.fillna("0")
x.isna().sum()
mean_age = x['Age'].mean()
x['Age'].fillna(mean_age, inplace=True)
mean_age = x['Fare'].mean()
x['Fare'].fillna(mean_age, inplace=True)
import numpy as np
x.replace([np.inf, -np.inf], 1e10, inplace=True)
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size= 0.2 )
from sklearn.neighbors import KNeighborsClassifier
knn1 = KNeighborsClassifier(n_neighbors=4)
knn1.fit(x_train,y_train)
y_pred = knn1.predict(x_test)
y_pred
from sklearn.metrics import accuracy_score
accuracy_score(y_pred,y_test)
```

```
from sklearn.metrics import confusion_matrix
cm=confusion_matrix(y_pred,y_test)
print(cm)
result=knn1.predict([[3,1,34.5,7.8292]])
result
knn1.predict_proba([[3,1,34,7.05]])
```

Output:

```
In [46]:  y_pred = knn1.predict(x_test)
          y_pred

Out[46]: array([0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
                0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0], dtype=int64)

In [47]:  from sklearn.metrics import accuracy_score
          accuracy_score(y_pred,y_test)

Out[47]: 0.7142857142857143

In [48]:  from sklearn.metrics import confusion_matrix
          cm=confusion_matrix(y_pred,y_test)
          print(cm)

         [[49 21]
          [ 3 11]]

In [49]:  result=knn1.predict([[3,1,34.5,7.8292]])
          result

Out[49]: array([0], dtype=int64)

In [51]:  knn1.predict_proba([[3,1,34,7.05]])

Out[51]: array([[1., 0.]])

In [ ]:
```

Result:

K Nearest Neighbor was implemented and the results were noted.

Experiment: 4 **Date:**

Aim: To implement and demonstrate the working of the decision tree based ID3 algorithm. Use an appropriate data set for building the decision tree and apply this knowledge to classify a new sample.

Procedure:

Data Loading and Inspection:

- Import required libraries and read the Iris dataset.
- Display the first few rows of the dataset and check for information.

Data Preprocessing:

- Separate features (x) and labels (y) from the dataset.
- Drop irrelevant columns ('Id').

Decision Tree Model Training:

- Create a Decision Tree classifier with entropy as the criterion.
- Fit the model on the features and labels.

Decision Tree Visualization:

- Visualize the trained Decision Tree.

Prediction with Decision Tree:

- Make a prediction using the trained Decision Tree model for a new data point.

Source Code:

```
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import numpy as np
data1 = pd.read_csv("iris.csv")
data1.head()
y = data1['Species']
x = data1.drop('Species', axis=1)
x=x.drop('Id',axis=1)
```

data1.info()

x.head()

x.shape

x.head()

x.shape

from sklearn.tree import DecisionTreeClassifier

dt = DecisionTreeClassifier(criterion='entropy')

dt.fit(x,y)

from sklearn import tree

dtree = tree.plot_tree(dt, filled=True)

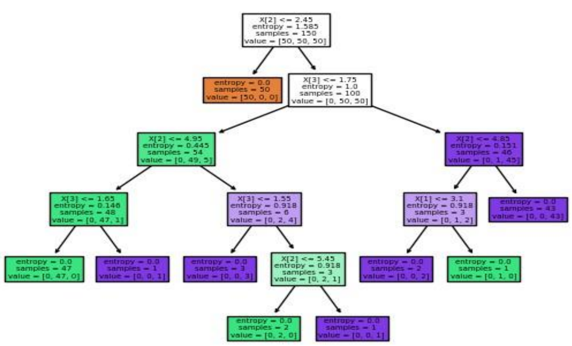
#outlook,temperature,humidity,windy

dt.predict([[1,2,1,0]])

Output:

```
In [16]:
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier(criterion='entropy')

dt.fit(x,y)

Out[16]: DecisionTreeClassifier(criterion='entropy')
```

```
In [17]:
from sklearn import tree
dtree = tree.plot_tree(dt, filled=True)
```




```
In [18]:
#outlook,temperature,humidity,windy
dt.predict([[1,2,1,0]])

Out[18]: array(['Iris-setosa'], dtype=object)
```

Result:

Decision Tree based ID3 algorithm was implemented and the results were noted.

Experiment: 5 **Date:**

Aim: To implement the Naïve Bayes classifier for a sample training data set stored as a .CSV file. Compute the accuracy of the classifier, considering few test data sets.

Procedure:

Data Loading and Inspection:

- Read the zoo dataset.
- Encode categorical variable ('animal_name') using LabelEncoder.

Data Preprocessing:

- Split the dataset into inputs and target.
- Split the data into training and testing sets.

Naive Bayes Model Training:

- Create and train a Gaussian Naive Bayes classifier using the training set.

Prediction and Confusion Matrix:

- Make predictions on the test set.
- Calculate and print the confusion matrix.

Source Code:

```
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
import sklearn.metrics as metrics
# Load the dataset
df = pd.read_csv(r" zoo.csv”)
```

```
# Encode the 'animal_name' column
le = LabelEncoder()
df['animal_name'] = le.fit_transform(df['animal_name'])
# Split the data into inputs and target
inputs = df.drop('class_type', axis='columns')
target = df[‘class_type']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(inputs, target, test_size=0.2, random_state=42)
# Create and train the Gaussian Naive Bayes classifier on the training set
classifier = GaussianNB()
classifier.fit(X_train, y_train)
# Make predictions on the test set
y_pred = classifier.predict(X_test)
# Calculate and print the confusion matrix
confusion_matrix = metrics.confusion_matrix(y_test, y_pred)
print(confusion_matrix)
```

Output:

```
# Calculate and print the confusion matrix
confusion_matrix = metrics.confusion_matrix(y_test, y_pred)
print(confusion_matrix)

[[12  0  0  0  0  0]
 [ 0  2  0  0  0  0]
 [ 0  0  0  1  0  0]
 [ 0  0  0  2  0  0]
 [ 0  0  0  0  3  0]
 [ 0  0  0  0  0  1]]

In [20]:  y_pred = classifier.predict(X_test)
          y_pred

Out[20]: array([1, 1, 1, 1, 1, 6, 1, 1, 1, 1, 4, 6, 6, 2, 7, 1, 1, 2, 4, 1, 4],
               dtype=int64)
```

Result:

Naïve Bayes Classifier algorithm was implemented and the results were noted.

Experiment: 6 **Date:**

Aim: To implement hierarchical clustering with two different datasets.

Procedure:

Data Loading and Inspection:

- Read the iris dataset.

Data Preprocessing:

- Extract relevant features (SepalLengthCm, PetalWidthCm, PetalLengthCm).
- Encode the 'Species' column using LabelEncoder.

Hierarchical Clustering Dendrogram:

- Perform hierarchical clustering on the selected features.
- Visualize the dendrogram

Agglomerative Clustering:

- Perform agglomerative clustering with a specified number of clusters (e.g., 3).
- Visualize the dendrogram for the clustering result.

Source Code:

```
import warnings
warnings.filterwarnings('ignore')
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.preprocessing import LabelEncoder
df=pd.read_csv(r" iris.csv")
df
import numpy as np
import matplotlib.pyplot as plt
from scipy.cluster.hierarchy import dendrogram, linkage
X = df[['SepalLengthCm', 'PetalWidthCm', 'PetalLengthCm']]
label_encoder = LabelEncoder()
```

```
df['encoded_category'] = label_encoder.fit_transform(df['Species'])
y = df['encoded_category']
linkage_matrix = linkage(X, method='ward')
plt.figure(figsize=(12, 6))
dendrogram(linkage_matrix)
plt.title('Hierarchical Clustering Dendrogram')
plt.xlabel('Data Points')
plt.ylabel('Distance')
plt.show()
from sklearn.cluster import AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram, linkage
n_clusters = 3 # You can choose the number of clusters based on the d
agg_clustering = AgglomerativeClustering(n_clusters=n_clusters)
agg_clustering.fit(X)
linkage_data = linkage(X, method='ward', metric='euclidean')
linkage_data
dendrogram(linkage_data)
plt.show()
```

Output:

Result:

Hierarchical clustering was implemented and results were noted.

Experiment: 7 **Date:**

Aim: To implement K- Mean clustering algorithm.

Procedure:

Data Generation:

- Create a synthetic dataset using **make_blobs** from **sklearn. datasets**. Data Preprocessing:

K – Means Clustering:

- Import the KMeans module from **sklearn.cluster**.
- Create a KMeans model with a specified number of clusters (e.g., 4).
- Fit the model and predict cluster labels for the dataset.

Visualization:

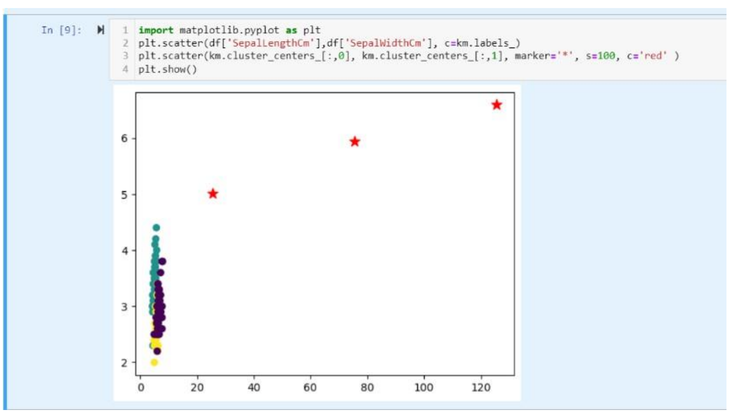
- Create Plot the data points with colors representing the predicted clusters.
- Mark the cluster centers with red asterisks.

Source Code:

```
from sklearn.cluster import KMeans
import sklearn.cluster as KMeans
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
# label encoding
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
df=pd.read_csv(r" iris.csv")
le.fit(df['Species'])
df['Species']=le.transform(df['Species'])
df.head()
from sklearn.cluster import KMeans
km=KMeans(n_clusters=3)
km.fit(df)
km.fit_predict(df)
import matplotlib.pyplot as plt
```

```
plt.scatter(df['SepalLengthCm'],df['SepalWidthCm'], c=km.labels_)
plt.scatter(km.cluster_centers_[:,0], km.cluster_centers_[:,1], marker='*', s=100, c='red' )
plt.show()
```

Output:



Result:

K-Means Clustering was implemented and results were noted.

Experiment: 8 **Date:**

Aim: Using feature forward selection approaches, reduce the dimensionality of the KDD.

Procedure:

Data Loading:

- Import the dataset and read. [Diabetes Dataset]

Data Preprocessing:

- Extract features (X) and labels (Y) from the dataset. Handle missing values if any.
- Split the dataset into training and testing sets for model evaluation.
- Implement Forward Feature Elimination using SequentialFeatureSelector from mlxtend.
- View the selected features and their corresponding scores.

Source Code:

```
import warnings
warnings.filterwarnings('ignore')
import mlxtend
import pandas as pd
import numpy as np
df=pd.read_csv(r" diabetes.csv")
df.head()
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from mlxtend.feature_selection import SequentialFeatureSelector
df1=df['Outcome']
df=df.drop('Outcome',axis=1)
x_train, x_test, y_train, y_test = train_test_split(df, df1, test_size=0.2, random_state=42)
lr = LogisticRegression(max_iter=1000)
sfs = SequentialFeatureSelector(lr, k_features=(1, 8), forward=True, verbose=2, cv=5)
sfs = sfs.fit(x_train, y_train)
```

import pandas as pd

pd.DataFrame.from_dict(sfs.get_metric_dict()).T #.T is for transform

sfs.k_feature_names_

sfs.k_score_

Output:

In [13]:
```
import pandas as pd
pd.DataFrame.from_dict(sfs.get_metric_dict()).T #.T is for transform
```

Out[13]:

	feature_idx	cv_scores	avg_score	feature_names	ci_bound	std_dev	std_err
1	(1,)	[0.7073170731707317, 0.7642276422764228, 0.772...	0.745942	(Glucose,)	0.030379	0.023636	0.011818
2	(1, 5)	[0.7479674796747967, 0.7804878048780488, 0.756...	0.758976	(Glucose, BMI)	0.018987	0.014772	0.007386
3	(0, 1, 5)	[0.7560975609756098, 0.8048780487804879, 0.788...	0.775263	(Pregnancies, Glucose, BMI)	0.030485	0.023718	0.011859
4	(0, 1, 5, 6)	[0.7479674796747967, 0.8048780487804879, 0.780...	0.770399	(Pregnancies, Glucose, BMI, DiabetesPedigreeFu...	0.038965	0.030316	0.015158
5	(0, 1, 2, 5, 6)	[0.7560975609756098, 0.8048780487804879, 0.780...	0.775277	(Pregnancies, Glucose, BloodPressure, BMI, Dia...	0.031057	0.024164	0.012082
6	(0, 1, 2, 3, 5, 6)	[0.7560975609756098, 0.7967479674796748, 0.772...	0.768759	(Pregnancies, Glucose, BloodPressure, SkinThic...	0.029634	0.023057	0.011528
7	(0, 1, 2, 3, 5, 6, 7)	[0.7560975609756098, 0.8048780487804879, 0.739...	0.767146	(Pregnancies, Glucose, BloodPressure, SkinThic...	0.035516	0.027632	0.013816
8	(0, 1, 2, 3, 4, 5, 6, 7)	[0.7642276422764228, 0.8048780487804879, 0.739...	0.765507	(Pregnancies, Glucose, BloodPressure, SkinThic...	0.03548	0.027605	0.013802

In [14]:
```
sfs.k_feature_names_
```

Out[14]: ('Pregnancies', 'Glucose', 'BloodPressure', 'BMI', 'DiabetesPedigreeFunction')

In [15]:
```
sfs.k_score_
```

Out[15]: 0.7752765560442489

Result:

Forward Feature Elimination with logistic regression was implemented and results were noted.

Experiment: 9 **Date:**

Aim: Using feature backward elimination approaches, reduce the dimensionality.

Procedure:

Data Loading and Inspection:

- Import the dataset using Pandas and inspect the first few rows, data types, and missing values.

Data Preprocessing:

- Extract features (X) and labels (Y) from the dataset. Handle missing values if any.
- Encode categorical labels using Label Encoder.

Data Splitting:

- Split the dataset into training and testing sets for model evaluation.

Linear Regression Model Training and Evaluation:

- Create a linear regression model and train it on the training set.
- Implement Backward Feature Elimination using SequentialFeatureSelector from mlxtend.

Source Code:

```
import warnings
warnings.filterwarnings('ignore')
import mlxtend
import pandas as pd
import numpy as np
df=pd.read_csv(r" diabetes.csv")
df.head()
df1=df.pop('Outcome')
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(df, df1, test_size = 0.2)
#from sklearn.ensemble import RandomForestClassifier
#rfc=RandomForestClassifier()
from sklearn.linear_model import LinearRegression
lr=LinearRegression()
#cv =  cross validation
```

from mlxtend.feature_selection import SequentialFeatureSelector

sfs1=SequentialFeatureSelector(lr, k_features=(1,8), forward=False, verbose=4, cv=5)

sfs1.fit(x_train, y_train)

pd.DataFrame.from_dict(sfs1.get_metric_dict()).T #.T is for transform

sfs1.k_feature_names_

sfs1.k_score_

Output:

```
Out[5]: SequentialFeatureSelector(estimator=LinearRegression(), forward=False,
                                  k_features=(1, 8), scoring='r2', verbose=4)

In [6]: pd.DataFrame.from_dict(sfs1.get_metric_dict()).T #.T is for transform

Out[6]:
```

	feature_idx	cv_scores	avg_score	feature_names	ci_bound	std_dev	std_err
8	(0, 1, 2, 3, 4, 5, 6, 7)	[0.20901624463622348, 0.3087911216482687, 0.24...	0.278643	(Pregnancies, Glucose, BloodPressure, SkinThic...	0.054754	0.042601	0.0213
7	(0, 1, 2, 4, 5, 6, 7)	[0.21737536816585878, 0.30895531888097927, 0.2...	0.283598	(Pregnancies, Glucose, BloodPressure, Insulin,...	0.053882	0.041922	0.020961
6	(0, 1, 2, 5, 6, 7)	[0.2228971652203401, 0.3114343154764604, 0.244...	0.283168	(Pregnancies, Glucose, BloodPressure, BMI, Dia...	0.052663	0.040973	0.020487
5	(0, 1, 2, 5, 7)	[0.22732537423811172, 0.3087821643969013, 0.23...	0.280087	(Pregnancies, Glucose, BloodPressure, BMI, Age)	0.053772	0.041836	0.020918
4	(0, 1, 2, 5)	[0.23521673996445824, 0.29051266934722964, 0.2...	0.27591	(Pregnancies, Glucose, BloodPressure, BMI)	0.051855	0.040345	0.020172
3	(0, 1, 5)	[0.23352772274668687, 0.2737858461720529, 0.22...	0.273143	(Pregnancies, Glucose, BMI)	0.050812	0.039534	0.019767
2	(1, 5)	[0.2115335520235463, 0.249405064513207, 0.1990...	0.244159	(Glucose, BMI)	0.04799	0.037338	0.018669
1	(1,)	[0.19061102637016603, 0.24191516232035293, 0.1...	0.215243	(Glucose,)	0.059148	0.046019	0.023009

```
In [7]: sfs1.k_feature_names_
Out[7]: ('Pregnancies',
         'Glucose',
         'BloodPressure',
         'Insulin',
         'BMI',
         'DiabetesPedigreeFunction',
         'Age')

In [8]: sfs1.k_score_
Out[8]: 0.28359816505388025
```

Result:

Forward Feature Elimination with logistic regression was implemented and results were noted.

Experiment: 10 **Date:**

Aim: To implement DBSCAN algorithm with two different datasets.

Procedure:

Importing the Required Libraries:

- Import necessary libraries for clustering

Loading the Data:

- Read the dataset and preprocess it by dropping irrelevant columns. [House Dataset]

Preprocessing the Data:

- Scale and normalize the data.

Reducing Dimensionality:

- Apply PCA to reduce data to 2 dimensions for visualization.

Building the Clustering Model:

- Apply DBSCAN clustering.

Visualizing the Clustering:

- Plot the clustering results.

Tuning Model Parameters:

- Adjust DBSCAN parameters.

Visualizing Parameter Tuning:

- Plot the clustering results with tuned parameters.

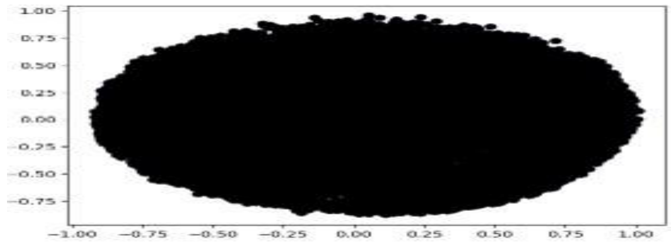
Source Code:

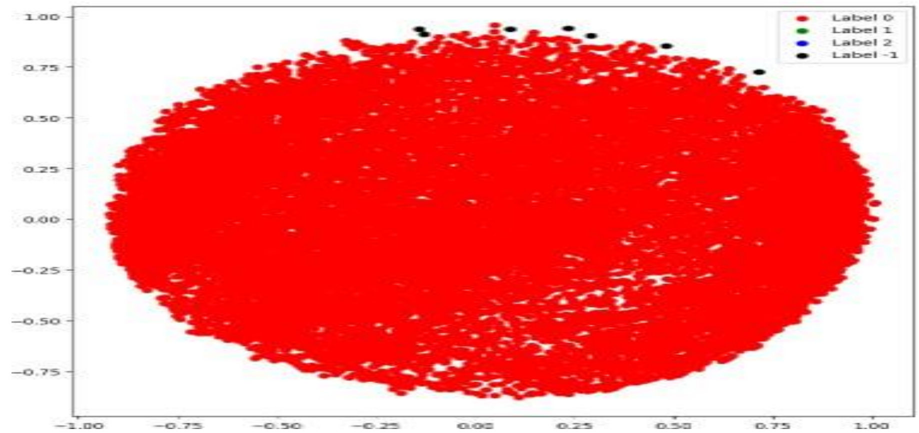
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import DBSCAN
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import normalize
from sklearn.decomposition import PCA
X = pd.read_csv(r kc_house_data.csv")
X.drop(['id','date'],axis=1,inplace=True)
```

```
X.head()
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_normalized = normalize(X_scaled)
X_normalized = pd.DataFrame(X_normalized)
pca = PCA(n_components = 2)
X_principal = pca.fit_transform(X_normalized)
X_principal = pd.DataFrame(X_principal)
X_principal.columns = ['P1', 'P2']
print(X_principal.head())
db_default = DBSCAN(eps = 0.0375, min_samples = 3).fit(X_principal)
labels = db_default.labels_
colours = {}
colours[0] = 'r'
colours[1] = 'g'
colours[2] = 'b'
colours[-1] = 'k'
cvec = [colours[label] for label in labels]

# For the construction of the legend of the plot
r = plt.scatter(X_principal['P1'], X_principal['P2'], color ='r');
g = plt.scatter(X_principal['P1'], X_principal['P2'], color ='g');
b = plt.scatter(X_principal['P1'], X_principal['P2'], color ='b');
k = plt.scatter(X_principal['P1'], X_principal['P2'], color ='k');

# Plotting P1 on the X-Axis and P2 on the Y-Axis
# according to the colour vector defined
plt.figure(figsize =(9, 9))
plt.scatter(X_principal['P1'], X_principal['P2'], c = cvec)

# Building the legend
plt.legend((r, g, b, k), ('Label 0', 'Label 1', 'Label 2', 'Label -1'))

plt.show()
```

```
db = DBSCAN(eps = 0.0375, min_samples = 50).fit(X_principal)
labels1 = db.labels_

colours1 = {}
colours1[0] = 'r'
colours1[1] = 'g'
colours1[2] = 'b'
colours1[3] = 'c'
colours1[4] = 'y'
colours1[5] = 'm'
colours1[-1] = 'k'

cvec = [colours1[label] for label in labels]
colors = ['r', 'g', 'b', 'c', 'y', 'm', 'k' ]

r = plt.scatter(X_principal['P1'], X_principal['P2'], marker ='o', color = colors[0])
g = plt.scatter(X_principal['P1'], X_principal['P2'], marker ='o', color = colors[1])
b = plt.scatter(X_principal['P1'], X_principal['P2'], marker ='o', color = colors[2])
c = plt.scatter(X_principal['P1'], X_principal['P2'], marker ='o', color = colors[3])
y = plt.scatter(X_principal['P1'], X_principal['P2'], marker ='o', color = colors[4])
m = plt.scatter(X_principal['P1'], X_principal['P2'], marker ='o', color = colors[5])
k = plt.scatter(X_principal['P1'], X_principal['P2'], marker ='o', color = colors[6])
plt.figure(figsize =(9, 9))

plt.scatter(X_principal['P1'], X_principal['P2'], c = cvec)
plt.legend((r, g, b, c, y, m, k),('Label 0', 'Label 1', 'Label 2', 'Label 3', 'Label 4','Label 5', 'Label
-1'),scatterpoints = 1,loc ='upper left',ncol = 3,fontsize = 8)
plt.show()
```

Output:





Result:

DBSCAN Algorithm was implemented and results were noted.