CSE-3024 Web Mining

Lab Assignment - 4

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19BCE2555

Decision Tree

Aim

Using a Decision Tree Classifier, divide the given network intrusion dataset into normal and abnormal categories. Along with the classification, the following items must be printed:

- Confusion Matrix
- Accuracy of model on Test data
- Decision Tree visualization.

Dataset Used: The network intrusion dataset from Kaggle.

Link to which is:
https://www.kaggle.com/datasets/sampadab17/network-intrusion-detection?select=Train_data.csv

Procedure:

- First, we import the necessary numpy, pandas, matplotlib, and tree libraries.

- The dataset is then imported into our workspace. The set of independent and dependent attributes is also defined.

- Next, we used a 7.5:2.5 ratio to divide the dataset into training and test sets.

- Then, using DecisionTreeClassifier from sklearn.tree, we train our decision tree model.

- Next, we look for the test set results that our model anticipated.

- Then, using the expected and test set findings, we print our confusion matrix.

- Similarly, we print the model's accuracy based on the test set and anticipated result.

- Finally, we visualise our model using the sklearn tree.

Code:

```
#19BCE2555
#Importing libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn import tree


#Importing dataset
dataset = pd.read_csv("Train_data.csv")
X = dataset.iloc[:, 4:41].values
y = dataset.iloc[:, -1].values


#Splitting the dataset
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,
random_state=0)


#Fitting our model
from sklearn.tree import DecisionTreeClassifier
classifier = DecisionTreeClassifier(criterion = 'entropy' ,random_state = 0)
classifier.fit (X_train, y_train)


#Predicting the Test set Results
```

```
y_pred = classifier.predict(X_test)


#Printing the confusion matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)


#Printing the accuracy of our model
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_test, y_pred)
print(accuracy)


#Defining the labels of our dataset
classes = ["Anamoly", "Normal"]


#Printing the visualized decision tree
fig = plt.figure(figsize=(25,20))
_ = tree.plot_tree(classifier,
            feature_names=dataset.columns,
            class_names=classes,
            filled=True)


#Printing the feature wise break points of our decision tree
test_representation = tree.export_text(classifier)
print(test_representation)
```

Code Snippets and Outputs:

```
In [1]: #19BCE2555
        #Importing libraries
        import numpy as np
        import matplotlib.pyplot as plt
        import pandas as pd
        from sklearn import tree
```

We're importing our libraries right now. Nupmy is imported as np, pandas is imported as pd, matplotlib's pyplot extension is imported as plt, and finally tree is imported from sklearn.

```
In [2]: #Importing dataset
        dataset = pd.read_csv("Train_data.csv")
        X = dataset.iloc[:, 4:41].values
        y = dataset.iloc[:, -1].values
```

We're using pandas to import our Network Intrusion Dataset into our workspace. Then a set of dependent and independent qualities is defined. The set of independent qualities is labelled X, while the set of dependent attributes is labelled y.

```
In [3]: #Splitting the dataset
        from sklearn.model_selection import train_test_split
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=0)
```

We're going to divide our dataset into two parts: a training set and a test set. We're going to maintain 25% of the dataset in the test set and 75% in the training set.

```
In [4]: #Fitting our model
        from sklearn.tree import DecisionTreeClassifier
        classifier = DecisionTreeClassifier(criterion = 'entropy' ,random_state = 0)
        classifier.fit (X_train, y_train)

Out[4]: DecisionTreeClassifier(criterion='entropy', random_state=0)
```

We're taking data from the training set to train our model. For our decision tree classifier, we employed "entropy" as the deciding factor.

```
In [5]: #Predicting the Test set Results
        y_pred = classifier.predict(X_test)
```

We're collecting our anticipated test set results from the classifier and saving them in the y pred variable.

```
In [6]: #Printing the confusion matrix
        from sklearn.metrics import confusion_matrix
        cm = confusion_matrix(y_test, y_pred)
        print(cm)

        [[2898   13]
         [  16 3371]]
```

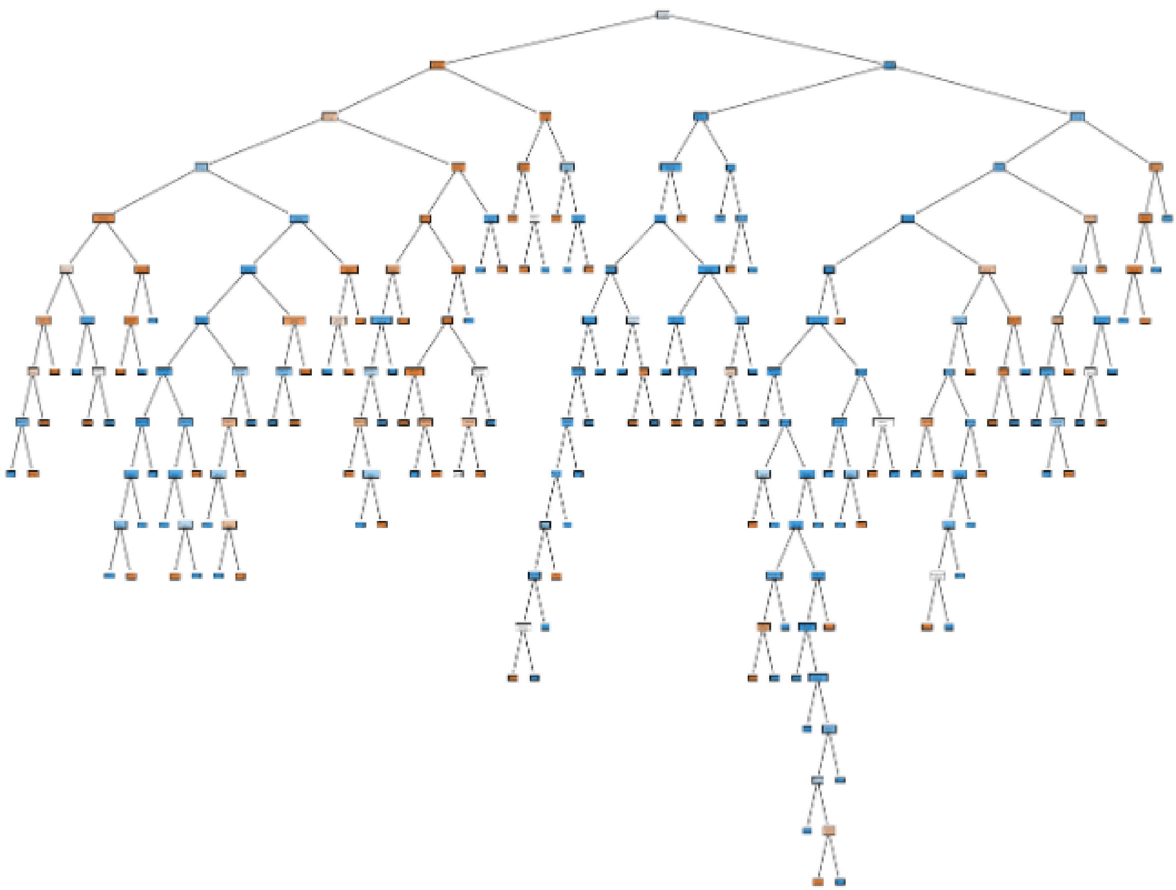
```
In [7]: #Printing the accuracy of our model
        from sklearn.metrics import accuracy_score
        accuracy = accuracy_score(y_test, y_pred)
        print(accuracy)

        0.9953953636074945
```

The confusion matrix and accuracy of our decision tree classifier are printed here. Our model's accuracy with the test dataset is 99.53953636 percent.

```
In [8]: #Defining the labels of our dataset
        classes = ["Anamoly", "Normal"]
```

We're using sklearn's tree library to visualise our decision tree.

In [9]:
```
#Printing the visualized decision tree
fig = plt.figure(figsize=(25,20))
_ = tree.plot_tree(classifier,
                   feature_names=dataset.columns,
                   class_names=classes,
                   filled=True)
```



```
In [10]: #Printing the feature wise break points of our decision tree
         test_representation = tree.export_text(classifier)
         print(test_representation)
```

```
|--- feature_0 <= 28.50
|   |--- feature_18 <= 8.50
|   |   |--- feature_31 <= 0.50
|   |   |   |--- feature_28 <= 2.50
|   |   |   |   |--- feature_35 <= 0.01
|   |   |   |   |   |--- feature_1 <= 7.50
|   |   |   |   |   |   |--- feature_27 <= 156.00
|   |   |   |   |   |   |   |--- feature_0 <= 0.50
|   |   |   |   |   |   |   |   |--- feature_29 <= 0.51
|   |   |   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |   |   |   |--- feature_29 >  0.51
|   |   |   |   |   |   |   |   |   |--- class: anomaly
|   |   |   |   |   |   |   |--- feature_0 >  0.50
|   |   |   |   |   |   |   |   |--- class: anomaly
|   |   |   |   |   |   |--- feature_27 >  156.00
|   |   |   |   |   |   |   |--- class: anomaly
|   |   |   |   |   |--- feature_1 >  7.50
|   |   |   |   |   |   |--- feature_25 <= 0.75
|   |   |   |   |   |   |   |--- class: normal
```

The categorization criterion of our decision tree is presented here. We can see that feature 0 is our classifier's root node, followed by multiple middle nodes.

Results and Output

Confusion Matrix:

```
[[2898   13]
 [  16 3371]]
```

This is our confusion matrix.

True Negatives: 3488

True Positives: 4032

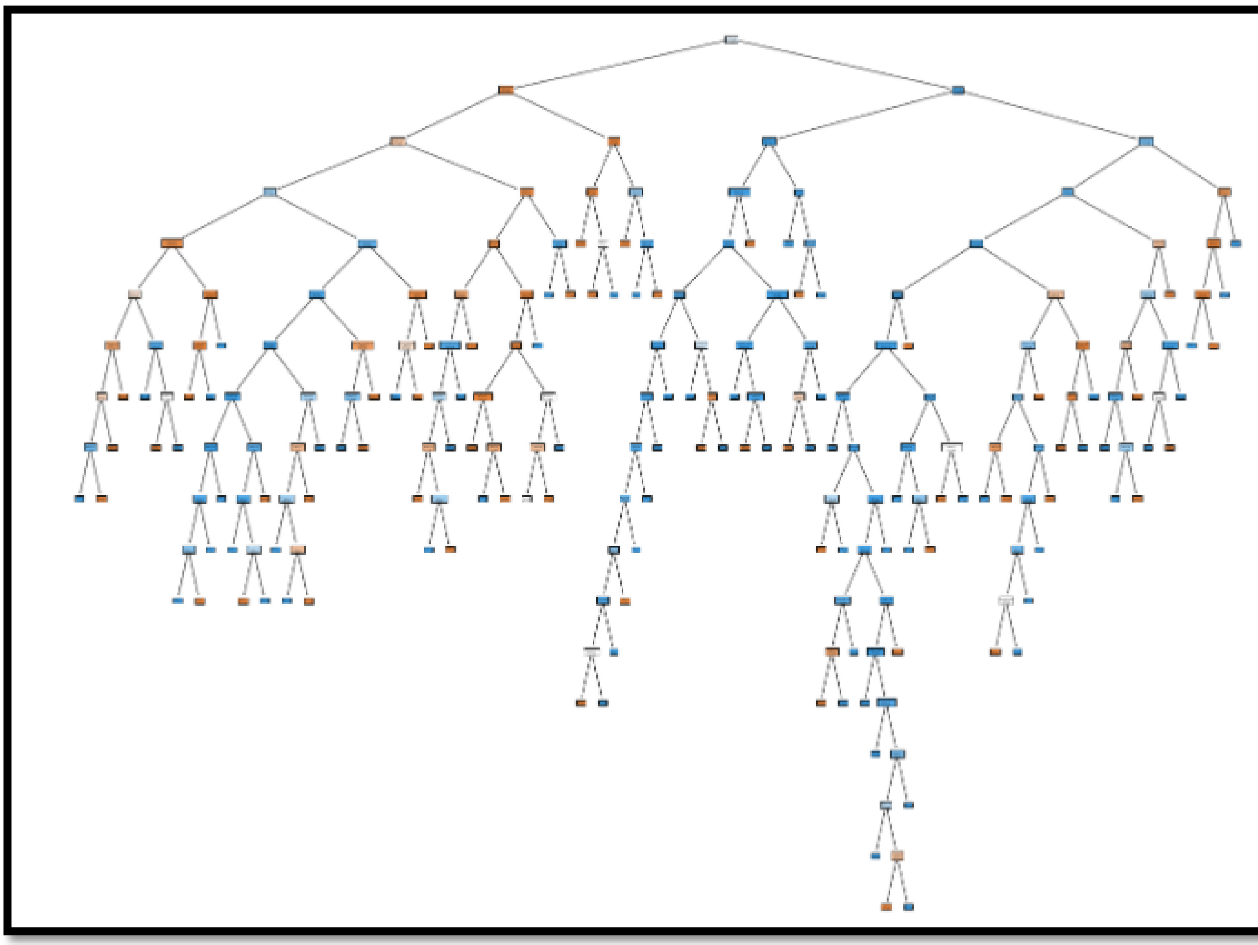
False Positives: 17

False Negatives: 21

Accuracy:

The accuracy of our model stands at 99.49%

Decision Tree Visualization:



Classification Points:

```
|   |   |   |   |   |   |--- feature_27 >  156.00
|   |   |   |   |   |   |   |--- class: anomaly
|   |   |   |   |   |--- feature_1 >  7.50
|   |   |   |   |   |   |--- feature_25 <= 0.75
|   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |   |--- feature_25 >  0.75
|   |   |   |   |   |   |   |--- feature_1 <= 122.50
|   |   |   |   |   |   |   |   |--- class: anomaly
|   |   |   |   |   |   |   |--- feature_1 >  122.50
|   |   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |--- feature_35 >  0.01
|   |   |   |   |   |--- feature_1 <= 201.00
|   |   |   |   |   |   |--- feature_29 <= 0.59
|   |   |   |   |   |   |   |--- class: anomaly
|   |   |   |   |   |   |--- feature_29 >  0.59
|   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |--- feature_1 >  201.00
|   |   |   |   |   |   |--- class: normal
|   |   |   |--- feature_28 >  2.50
|   |   |   |   |--- feature_33 <= 0.87
```

```
|   |   |   |   |--- feature_33 <= 0.87
|   |   |   |   |   |--- feature_30 <= 0.57
|   |   |   |   |   |   |--- feature_18 <= 3.50
|   |   |   |   |   |   |   |--- feature_30 <= 0.13
|   |   |   |   |   |   |   |   |--- feature_29 <= 0.03
|   |   |   |   |   |   |   |   |   |--- feature_1 <= 18.00
|   |   |   |   |   |   |   |   |   |   |--- feature_28 <= 6.00
|   |   |   |   |   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |   |   |   |   |   |--- feature_28 >  6.00
|   |   |   |   |   |   |   |   |   |   |   |--- class: anomaly
|   |   |   |   |   |   |   |   |   |--- feature_1 >  18.00
|   |   |   |   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |   |   |   |--- feature_29 >  0.03
|   |   |   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |   |   |--- feature_30 >  0.13
|   |   |   |   |   |   |   |   |--- feature_28 <= 135.00
|   |   |   |   |   |   |   |   |   |--- feature_27 <= 119.00
|   |   |   |   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |   |   |   |   |--- feature_27 >  119.00
|   |   |   |   |   |   |   |   |   |   |--- feature_30 <= 0.36
```

```
|   |   |   |   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |   |   |   |   |--- feature_27 >  119.00
|   |   |   |   |   |   |   |   |   |   |--- feature_30 <= 0.36
|   |   |   |   |   |   |   |   |   |   |   |--- class: anomaly
|   |   |   |   |   |   |   |   |   |   |--- feature_30 >  0.36
|   |   |   |   |   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |   |   |   |--- feature_28 >  135.00
|   |   |   |   |   |   |   |   |   |--- class: anomaly
|   |   |   |   |   |   |--- feature_18 >  3.50
|   |   |   |   |   |   |   |--- feature_32 <= 0.01
|   |   |   |   |   |   |   |   |--- feature_31 <= 0.01
|   |   |   |   |   |   |   |   |   |--- feature_30 <= 0.05
|   |   |   |   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |   |   |   |   |--- feature_30 >  0.05
|   |   |   |   |   |   |   |   |   |   |--- feature_27 <= 109.50
|   |   |   |   |   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |   |   |   |   |   |--- feature_27 >  109.50
|   |   |   |   |   |   |   |   |   |   |   |--- class: anomaly
|   |   |   |   |   |   |   |   |--- feature_31 >  0.01
|   |   |   |   |   |   |   |   |   |--- class: anomaly
```

```
|   |   |   |   |   |   |   |--- feature_32 >  0.01
|   |   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |--- feature_30 >  0.57
|   |   |   |   |   |   |--- feature_35 <= 0.25
|   |   |   |   |   |   |   |--- feature_32 <= 0.50
|   |   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |   |   |--- feature_32 >  0.50
|   |   |   |   |   |   |   |   |--- class: anomaly
|   |   |   |   |   |   |--- feature_35 >  0.25
|   |   |   |   |   |   |   |--- class: anomaly
|   |   |   |   |--- feature_33 >  0.87
|   |   |   |   |   |--- feature_34 <= 0.11
|   |   |   |   |   |   |--- feature_30 <= 0.06
|   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |   |--- feature_30 >  0.06
|   |   |   |   |   |   |   |--- class: anomaly
|   |   |   |   |   |--- feature_34 >  0.11
|   |   |   |   |   |   |--- class: anomaly
|   |   |--- feature_31 >  0.50
|   |   |   |--- feature_7 <= 0.50
```

```
|   |   |--- feature_31 >  0.50
|   |   |   |--- feature_7 <= 0.50
|   |   |   |   |--- feature_0 <= 0.50
|   |   |   |   |   |--- feature_27 <= 4.00
|   |   |   |   |   |   |--- feature_36 <= 0.10
|   |   |   |   |   |   |   |--- feature_28 <= 179.50
|   |   |   |   |   |   |   |   |--- feature_20 <= 0.25
|   |   |   |   |   |   |   |   |   |--- class: anomaly
|   |   |   |   |   |   |   |   |--- feature_20 >  0.25
|   |   |   |   |   |   |   |   |   |--- feature_32 <= 0.36
|   |   |   |   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |   |   |   |   |--- feature_32 >  0.36
|   |   |   |   |   |   |   |   |   |   |--- class: anomaly
|   |   |   |   |   |   |   |--- feature_28 >  179.50
|   |   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |   |--- feature_36 >  0.10
|   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |--- feature_27 >  4.00
|   |   |   |   |   |   |--- class: anomaly
|   |   |   |   |--- feature_0 >  0.50
```

```
|   |   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |   |   |--- feature_0 >  1133.50
|   |   |   |   |   |   |   |   |--- class: anomaly
|   |   |   |   |   |   |--- feature_30 >  0.00
|   |   |   |   |   |   |   |--- class: normal
|   |   |   |   |--- feature_0 >  6052.00
|   |   |   |   |   |--- class: anomaly
|   |   |--- feature_18 >  42.50
|   |   |   |--- feature_1 <= 2.00
|   |   |   |   |--- feature_7 <= 0.50
|   |   |   |   |   |--- feature_31 <= 0.00
|   |   |   |   |   |   |--- class: normal
|   |   |   |   |   |--- feature_31 >  0.00
|   |   |   |   |   |   |--- class: anomaly
|   |   |   |   |--- feature_7 >  0.50
|   |   |   |   |   |--- class: normal
|   |   |   |--- feature_1 >  2.00
|   |   |   |   |--- class: normal
```

K-Means

Problem statement:

Illustrate the k-means clustering to cluster the data points for at least five epoch properly.

How to Implementing K-Means Clustering?

- **Using the elbow method to determine the optimal number of clusters for kmeans clustering**
- **Visualising the clusters**
- **Plotting the centroids of the clusters**

Dataset used:

- **Shopping-data**
- https://archive.ics.uci.edu/ml/machine-learning-databases/

Procedure:

- Import necessary libraries - sklearn, numpy, pandas, etc.

-Using pandas, we first import the dataset into our workspace.

- Select the number of clusters for the dataset (K)

- Select K number of centroids

- By calculating the Euclidean distance or Manhattan distance assign the points to the nearest centroid, thus creating K groups

- Now find the original centroid in each group

- Again reassign the whole data point based on this new centroid, then repeat step 4 until the position of the centroid doesn’t change.

- Using the elbow method to determine the optimal number of clusters for kmeans clustering

- Visualising the clusters and Plotting the centroids of the clusters

Code:

```
#Importing Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

#Importing the Datasets
dataset = pd.read_csv('shopping-data.csv')
X = dataset.iloc[:, 3:].values


#Elbow method to find the optimal number of clusters
from sklearn.cluster import KMeans
wcss = []
for i in range(1, 11):
   kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300,
n_init=10)
   kmeans.fit(X)
   wcss.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss)
plt.title('The Elbow Method')
```

```
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
plt.show()


#Applying Kmeans to the dataset
kmeans = KMeans(n_clusters=5, init='k-means++', max_iter=300,
n_init=10);
y_kmeans = kmeans.fit_predict(X)


#Printing out the cluster each input belongs to
y_kmeans


# Visualising the clusters
plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s = 100, c =
'red', label = 'Standard Customers')
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s = 100, c =
'blue', label = 'Careless Customers')
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s = 100, c =
'cyan', label = 'Target Customers')
plt.scatter(X[y_kmeans == 3, 0], X[y_kmeans == 3, 1], s = 100, c =
'magenta', label = 'Sensible Customers')
plt.scatter(X[y_kmeans == 4, 0], X[y_kmeans == 4, 1], s = 100, c =
'green', label = 'Careful Customers')
plt.scatter(kmeans.cluster_centers_[:, 0],
kmeans.cluster_centers_[:, 1], s = 300, c = 'yellow', label =
'Centroids')
plt.title ('Clusters of Clients')
plt.xlabel ('Annual Income (k$)')
plt.ylabel ('Spending Score (1-100)')
plt.legend()
plt.show()
```

Code Snippets and Outputs:

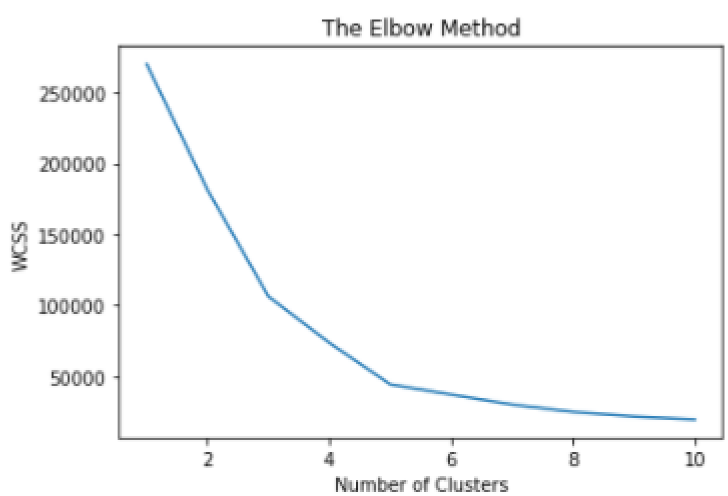
In [1]:
```
#importing libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import sklearn
```

Import necessary libraries - sklearn, numpy, pandas, etc.

In [2]:
```
dataset = pd.read_csv('shopping-data.csv')
X = dataset.iloc[:, 3:].values
```

Using pandas, we first import the dataset into our workspace and are assigning the income attribute along with shopping score as independent variables.

In [4]:
```
#Elbow method to find the optimal number of clusters
from sklearn.cluster import KMeans
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)

plt.plot(range(1, 11), wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
plt.show()
```



Here we are plotting a graph that marks Within Cluster Sum of Squares (WCSS) with the increase in number of clusters. We can see an elbow formation when the number of clusters is 5 and hence, we assume that optimal number of clusters in our dataset is 5

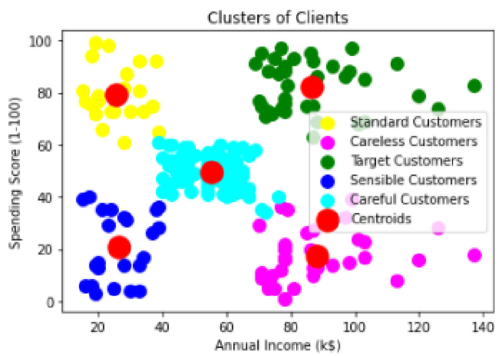
```
In [5]: #Applying Kmeans to the dataset
        kmeans = KMeans(n_clusters=5, init='k-means++', max_iter=300, n_init=10);
        y_kmeans = kmeans.fit_predict(X)
```

Here we are training our k-means model with 5 clusters. We are also generating the y_kmeans array that stores the cluster index of each input attribute from 0 to 4

```
In [9]: y_kmeans

Out[9]: array([3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0,
               3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 4,
               3, 0, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
               4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
               4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
               4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 2, 1, 2, 4, 2, 1, 2, 1, 2,
               4, 2, 1, 2, 1, 2, 1, 2, 1, 2, 4, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2,
               1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2,
               1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2,
               1, 2])
```

Here we are printing our y_kmeans array and we can see that each input cell is assigned a value between 0 and 4, both inclusive. This corresponds to the cluster index of each input.

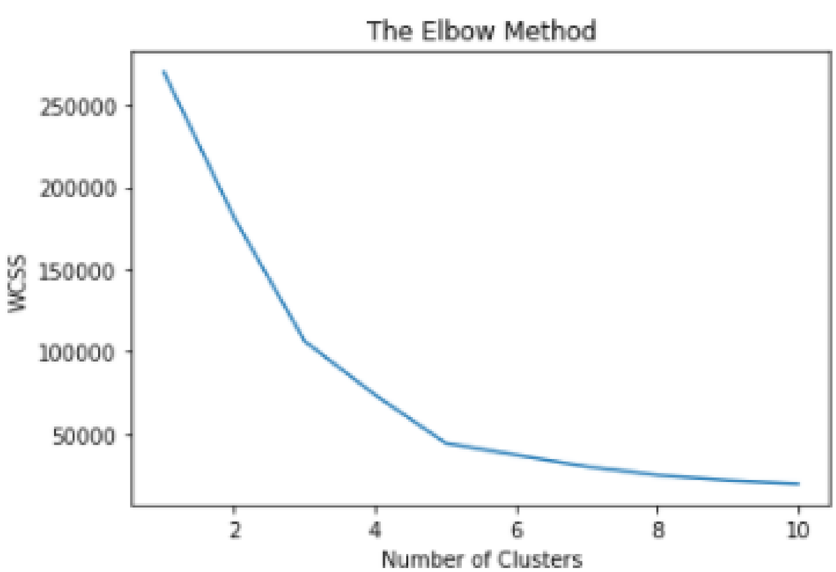
```python
# Visualising the clusters
plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s = 100, c = 'yellow', label = 'Standard Customers')
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s = 100, c = 'magenta', label = 'Careless Customers')
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s = 100, c = 'green', label = 'Target Customers')
plt.scatter(X[y_kmeans == 3, 0], X[y_kmeans == 3, 1], s = 100, c = 'blue', label = 'Sensible Customers')
plt.scatter(X[y_kmeans == 4, 0], X[y_kmeans == 4, 1], s = 100, c = 'cyan', label = 'Careful Customers')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 300, c = 'red', label = 'Centroids')
plt.title ('Clusters of Clients')
plt.xlabel ('Annual Income (k$)')
plt.ylabel ('Spending Score (1-100)')
plt.legend()
plt.show()
```



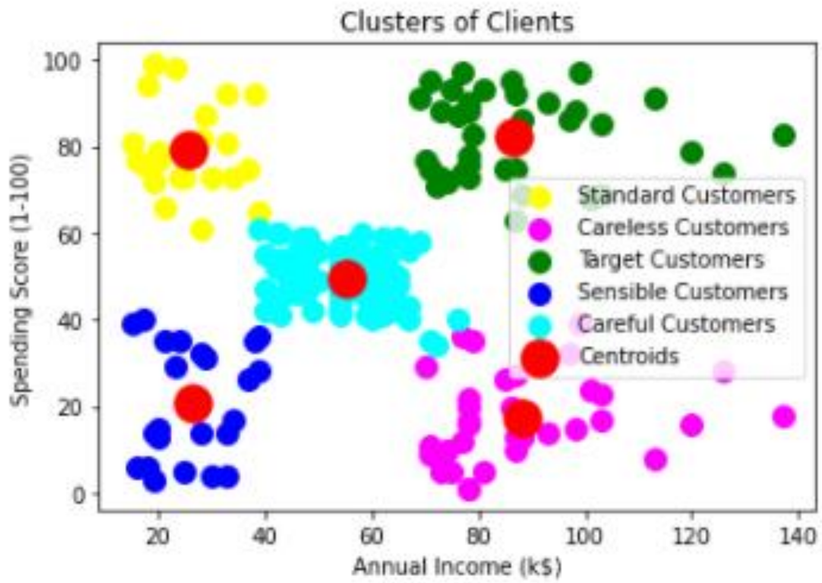
Here we have visualized our results. We have labelled different clusters as blue, green, pink, yellow and cyan. Each cluster correspond to different category of target audience. We have also marked centroids of each cluster which are red in colour.

Results and Output

Elbow Method Graph



Clustering Graph:



Here different clusters are marked as blue, yellow, magenta, cyan and green. The red dot over each cluster represents its centroid.

We can categorise these clusters as: -

- **Yellow Cluster corresponds to careless customers as they have low income but high spending.**
- **Blue Cluster as Sensible customers, becoz they have low income and low spending.**
- **Cyan Clusters are standard cluster that suggest they have median income and median spending.**
- **The pink coloured cluster correspond to Target Customers, as they have high income but low spending, the shopping company can give them offers and attractions as they are capable of spending more but they aren't doing it currently.**
- **Finally, the Green coloured clusters are Careful customers. They have high income and thus high spending as well.**

Random Forest

Question:

The following are the basic steps involved in performing the random forest algorithm:

1. Pick N random records from the dataset.

2. Build a decision tree based on these N records.

3. Choose the number of trees you want in your algorithm and repeat steps 1 and 2.

4. In case of a regression problem, for a new record, each tree in the forest predicts a value for Y (output). The final value can be calculated by taking the average of all the values predicted by all the trees in forest. Or, in case of a classification problem, each tree in the forest predicts the category to which the new record belongs. Finally, the new record is assigned to the category that wins the majority vote.

Dataset Used:

petrol_consumption.csv, bill_authentication.csv.

Procedure:

-Using pandas, we first import the dataset into our workspace.

-Next we define the set of dependent and independent attributes.

- We then import the random forest regressor from sklean rn.ensemble and train our model using the independent and dependent attributes.

- Next, we have printed the results of independent set as predicted by our regressor.

- Lastly, To check for the performance of our dataset, we have printed all the evaluation metrics

Since it has less Number of Rows we haven't split the dataset

Petrol_consumption dataset

Code

```
#Importing Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

#Importing the Dataset
dataset = pd.read_csv("petrol_consumption.csv")

#First few rows of our dataset
dataset.head(10)

#Checcking for null values
print(dataset.info())

X = dataset.iloc[:, 0:4].values
y = dataset.iloc[:, -1].values

#Training our Random Forest Regression Model
from sklearn.ensemble import RandomForestRegressor
regressor = RandomForestRegressor(n_estimators=200, random_state=0)
regressor.fit(X, y)

#Predictions by Regressor
y_pred = regressor.predict(X)

#Printing Mean Absolute Error
from sklearn.metrics import mean_absolute_error
mean_absolute_error(y, y_pred)

#Printing Mean Absolute Error
from sklearn.metrics import mean_squared_error
mean_squared_error(y, y_pred)

#Printing Root Mean Squared Error
np.sqrt(mean_squared_error(y, y_pred))

#Printing Root Mean Sqaured Log Error
```

np.log(np.sqrt(mean_squared_error(y, y_pred)))

#Printing R-square value
from sklearn.metrics import r2_score
r2_score(y, y_pred)

Code Snippets and Explanation:

```
In [1]: #Importing Libraries
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
```

Here we are importing the required Libraries

```
In [2]: #Importing the Dataset
        dataset = pd.read_csv("petrol_consumption.csv")
```

Using Pandas we are importing the data

```
In [3]: #First few rows of our dataset
        dataset.head(10)
```

Out[3]:

	Petrol_tax	Average_income	Paved_Highways	Population_Driver_licence(%)	Petrol_Consumption
0	9.0	3571	1976	0.525	541
1	9.0	4092	1250	0.572	524
2	9.0	3865	1586	0.580	561
3	7.5	4870	2351	0.529	414
4	8.0	4399	431	0.544	410
5	10.0	5342	1333	0.571	457
6	8.0	5319	11868	0.451	344
7	8.0	5126	2138	0.553	467
8	8.0	4447	8577	0.529	464
9	7.0	4512	8507	0.552	498

Printing the first few rows.

In [4]:
```
#Checcking for null values
print(dataset.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48 entries, 0 to 47
Data columns (total 5 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   Petrol_tax                      48 non-null     float64
 1   Average_income                  48 non-null     int64
 2   Paved_Highways                  48 non-null     int64
 3   Population_Driver_licence(%)    48 non-null     float64
 4   Petrol_Consumption              48 non-null     int64
dtypes: float64(2), int64(3)
memory usage: 2.0 KB
None
```

Here we are checking for the null values.

In [5]:
```
#Set of independent and dependent attributes
X = dataset.iloc[:, 0:4].values
y = dataset.iloc[:, -1].values
```

In [6]:
```
#Training our Random Forest Regression Model
from sklearn.ensemble import RandomForestRegressor
regressor = RandomForestRegressor(n_estimators=200, random_state=0)
regressor.fit(X, y)
```

Out[6]:
```
RandomForestRegressor(n_estimators=200, random_state=0)
```

We have Defined set of Dependent and Independent attributes.The n_estimators here indicate the number of decision trees that we are using to train our random forest regressor. Hence we are using 200 decision trees for prediction. For final value we have used the average value of each decision tree to find the final consumption of petrol of a particular region.

In [7]:
```
#Predictions by Regressor
y_pred = regressor.predict(X)
```

In [8]:
```
#Printing Mean Absolute Error
from sklearn.metrics import mean_absolute_error
mean_absolute_error(y, y_pred)
```

Out[8]: 16.542083333333327

Printing the Mean Absolute Error

In [9]:
```
#Printing Mean Absolute Error
from sklearn.metrics import mean_squared_error
mean_squared_error(y, y_pred)
```

Out[9]: 676.4954427083334

Printing the Mean Squared Error

In [10]:
```
#Printing Root Mean Squared Error
np.sqrt(mean_squared_error(y, y_pred))
```

Out[10]: 26.00952599930136

Printing the Root Mean Squared Error

In [11]:
```
#Printing Root Mean Sqaured Log Error
np.log(np.sqrt(mean_squared_error(y, y_pred)))
```

Out[11]: 3.258462855507552

Printing the Root Mean Sqaured Log Error

In [12]:
```
#Printing R-square value
from sklearn.metrics import r2_score
r2_score(y, y_pred)
```

Out[12]: 0.9448102799874128

Printing the R-square value

Results and Conclusions:

Mean Absolute Error from cell8 is 16.542083333333327
Mean absolute error from cell 9 is 676.4954427083334
Root Mean Squared Error from cell10 is 26.00952599930136
Root Mean Squared Log Error from cell11 is 3.25846285550 7552
R-square value from cell12 is 0.9448102799874128

Bill_authentication dataset

Code

```
#Importing Libraries
import pandas as pd

#importing the bill_authentication dataset
dataset = pd.read_csv('bill_authentication.csv')

#Displaying the first few rows of the dataset
dataset.head()

X = dataset.iloc[:, 0:4].values
y = dataset.iloc[:, 4].values

#Training our Random Forest Regression Model
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()

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=0)

from sklearn.ensemble import RandomForestClassifier
classifier= RandomForestClassifier(n_estimators=20, random_state=0)
```

classifier.fit(X_train, y_train)

y_pred = classifier.predict(X_test)

from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
print(confusion_matrix(y_test,y_pred))

#printing classification_report
print(classification_report(y_test,y_pred))

#printing Accuracy
print(accuracy_score(y_test, y_pred))

Code Snippets and Explaination

In [1]:
```
#Importing Libraries
import pandas as pd
```

In [2]:
```
#importing the bill_authentication dataset
dataset = pd.read_csv('bill_authentication.csv')
```

Here we are importing the required Libraries. Using Pandas we are importing the data

In [3]:
```
#Displaying the first few rows of the dataset
dataset.head()
```

Out[3]:

	Variance	Skewness	Curtosis	Entropy	Class
0	3.62160	8.6661	-2.8073	-0.44699	0
1	4.54590	8.1674	-2.4586	-1.46210	0
2	3.86600	-2.6383	1.9242	0.10645	0
3	3.45660	9.5228	-4.0112	-3.59440	0
4	0.32924	-4.4552	4.5718	-0.98880	1

Printing the first few rows.

```
In [7]:
X = dataset.iloc[:, 0:4].values
y = dataset.iloc[:, 4].values
```

Defining the Dependent and Independent variables

```
In [9]: #Training our Random Forest Regression Model
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
```

Here we are training our Random forest Regression model

```
In [12]: 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=0)

In [13]: from sklearn.ensemble import RandomForestClassifier
classifier= RandomForestClassifier(n_estimators=20, random_state=0)
classifier.fit(X_train, y_train)

Out[13]: RandomForestClassifier(n_estimators=20, random_state=0)

In [14]: y_pred = classifier.predict(X_test)

In [15]: from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
print(confusion_matrix(y_test,y_pred))

[[147   6]
 [  7 115]]
```

Here we are printing the Confusion Matrix

```
In [16]: #printing classification_report
print(classification_report(y_test,y_pred))

              precision    recall  f1-score   support

           0       0.95      0.96      0.96       153
           1       0.95      0.94      0.95       122

    accuracy                           0.95       275
   macro avg       0.95      0.95      0.95       275
weighted avg       0.95      0.95      0.95       275
```

Here we are printing the Classification Report

```
In [17]: #printing Accuracy
         print(accuracy_score(y_test, y_pred))

0.9527272727272728
```

The Accuracy of the model is 0.9527272727272728

Results and Conclusion

Confusion Matrix

```
[[147   6]
 [  7 115]]
```

Classification Report

```
              precision    recall  f1-score   support

           0       0.95      0.96      0.96       153
           1       0.95      0.94      0.95       122

    accuracy                           0.95       275
   macro avg       0.95      0.95      0.95       275
weighted avg       0.95      0.95      0.95       275
```

Accuracy of the dataset is: 0.9527272727272728