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```
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier,plot_tree
from sklearn.metrics import classification_report
import warnings
warnings.filterwarnings('ignore')
```

```
In [18]: dataset = pd.read_csv('churn.csv')[0:201]
    dataset
```

Out[18]:		CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Estim
	0	619	France	Female	42	2	0.00	1	1	1	
	1	608	Spain	Female	41	1	83807.86	1	0	1	
	2	502	France	Female	42	8	159660.80	3	1	0	
	3	699	France	Female	39	1	0.00	2	0	0	
	4	850	Spain	Female	43	2	125510.82	1	1	1	
	•••										
	196	616	Spain	Female	32	6	0.00	2	1	1	
	197	721	Germany	Male	37	3	107720.64	1	1	1	
	198	501	France	Male	57	10	0.00	2	1	1	
	199	521	France	Male	35	6	96423.84	1	1	0	
	200	850	Spain	Male	30	2	141040.01	1	1	1	

201 rows × 11 columns

```
In [19]: # EDA

print('Columns : ',list(dataset.columns))
print()
print('Number of missing values : ',dataset.isnull().sum().sum())
print()
dataset.describe()
```

Columns: ['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProduc ts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary', 'Exited']

Number of missing values: 0

```
Out[19]:
                  CreditScore
                                                             Balance NumOfProducts HasCrCard IsActiveMember EstimatedS
                                     Age
                                               Tenure
                                           201.000000
                                                                                                                        201.00
                   201.000000
                               201.000000
                                                          201.000000
                                                                           201.000000
                                                                                       201.000000
                                                                                                        201.000000
           count
                   640.467662
                                37.965174
                                             5.174129
                                                        74504.686269
                                                                             1.542289
                                                                                         0.676617
                                                                                                          0.482587
                                                                                                                      99189.93
           mean
                   108.463313
                                 9.763902
                                                                             0.591145
                                                                                         0.468935
                                                                                                          0.500944
                                                                                                                      57641.0!
                                             2.987395
                                                        62726.490142
             std
                   376.000000
                                19.000000
                                             0.000000
                                                            0.000000
                                                                             1.000000
                                                                                         0.000000
                                                                                                          0.000000
                                                                                                                        600.36
             min
                                                                                                                      47125.1°
            25%
                   553.000000
                                32.000000
                                             2.000000
                                                            0.000000
                                                                             1.000000
                                                                                         0.000000
                                                                                                          0.000000
            50%
                                36.000000
                                                                             2.000000
                                                                                                                      99449.86
                   646.000000
                                             5.000000
                                                        96645.540000
                                                                                         1.000000
                                                                                                          0.000000
            75%
                   722.000000
                                43.000000
                                             8.000000
                                                       125851.930000
                                                                             2.000000
                                                                                         1.000000
                                                                                                          1.000000
                                                                                                                     147132.46
                   850.000000
                                75.000000
                                            10.000000 213146.200000
                                                                             4.000000
                                                                                         1.000000
                                                                                                          1.000000
                                                                                                                     199725.39
            max
In [20]:
            # Data Analysis
            print (dataset['Geography'].unique())
            print(dataset['Gender'].unique())
           ['France' 'Spain' 'Germany']
           ['Female' 'Male']
```

In [21]:	# Data Preprocessing
	<pre>le = LabelEncoder() dataset['Gender'] = le.fit_transform(dataset['Gender'])</pre>
	<pre>dataset = pd.get_dummies(dataset,columns = ['Geography']) dataset</pre>

Out[21]:		CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	E
	0	619	0	42	2	0.00	1	1	1	101348.88	
	1	608	0	41	1	83807.86	1	0	1	112542.58	
	2	502	0	42	8	159660.80	3	1	0	113931.57	
	3	699	0	39	1	0.00	2	0	0	93826.63	
	4	850	0	43	2	125510.82	1	1	1	79084.10	
	•••										
	196	616	0	32	6	0.00	2	1	1	43001.46	
	197	721	1	37	3	107720.64	1	1	1	158591.12	
	198	501	1	57	10	0.00	2	1	1	47847.19	
	199	521	1	35	6	96423.84	1	1	0	10488.44	
	200	850	1	30	2	141040.01	1	1	1	5978.20	

201 rows × 13 columns

:		Geography_France	Geography_Germany	Geography_Spain	EstimatedSalary	Exited
	0	1	0	0	101348.88	1
	1	0	0	1	112542.58	0
	2	1	0	0	113931.57	1
	3	1	0	0	93826.63	0
	4	0	0	1	79084.10	0
	•••					
	196	0	0	1	43001.46	0
	197	0	1	0	158591.12	0
	198	1	0	0	47847.19	0
	199	1	0	0	10488.44	0
	200	0	0	1	5978.20	0

201 rows × 5 columns

Out[23]:

```
In [6]:
                Feature Importance
             plt.figure(figsize=(10, 4))
             correl matrix = dataset.corr().round(2)
             sns.heatmap(data=correl matrix, annot=True)
             plt.show()
                                                                                                                                      - 1.0
                      CreditScore -
                                      1
                                           0.01 -0.03 0.04
                                                                0.08
                                                                       -0.12
                                                                              0.07
                                                                                      0.1
                                                                                            0.13 -0.05
                                                                                                          -0.07
                                                                                                                 0.08
                                                  -0.05
                                                         0.09
                                                                0.08
                                                                       -0.05
                                                                                     -0.03
                                                                                                                        -0.07
                                                                                                                                      - 0.8
                              Age
                                           -0.05
                                                         -0.04
                                                                -0.03
                                                                       -0.07
                                                                               0.1
                                                                                     0.06
                                                                                                          0.05
                                                                                                                        0.03
                                                                                            -0.07
                                                                -0.02
                                                                       0.08
                                                                                     -0.07
                                                                                                                 0.07
                                                                                                                                      - 0.6
                           Tenure -
                                           0.09
                                                  -0.04
                                                           1
                                                                              0.08
                                                                                                    -0.1
                                                                                                          -0.04
                                                                                                                        -0.02
                          Balance
                                                                       -0.27 -0.03
                                                                                     -0.05
                                                                                            -0.01
                                                                                                   0.06
                                                                                                                        -0.13
                                                                                                                                      - 0.4
                  NumOfProducts
                                           -0.05
                                                         0.08
                                                                         1
                                                                              0.04
                                                                                     -0.08
                                                                                            0.02
                                                                                                   -0.05
                                                                                                          0.02
                                                                                                                        -0.06
                                           -0.16
                                                                                     -0.01
                       HasCrCard -
                                                                -0.03
                                                                       0.04
                                                                               1
                                                                                            0.01
                                                                                                   0.17
                                                                                                          -0.01
                                                                                                                        -0.02
                                                                                                                                      - 0.2
                 IsActiveMember
                                           -0.03
                                                  0.06
                                                         -0.07
                                                                -0.05
                                                                       -0.08
                                                                              -0.01
                                                                                      1
                                                                                            -0.04 -0.24
                                                                                                          -0.09
                                                                                                                        0.11
                 EstimatedSalary
                                           -0.09
                                                  -0.07
                                                         0.18
                                                                -0.01
                                                                       0.02
                                                                              0.01
                                                                                     -0.04
                                                                                                   -0.05
                                                                                                          -0.07
                                                                                                                        -0.03
                                                                                                                                      0.0
                                                                                             1
                                                                                     -0.24
                                                                0.06
                                                                       -0.05
                                                                                                                                       -0.2
               Geography_France
                                    -0.07
                                           0.02
                                                  0.05
                                                         -0.04
                                                               -0.33
                                                                       0.02
                                                                              -0.01
                                                                                     -0.09
                                                                                            -0.07
                                                                                                  -0.12
                                                                                                                 -0.56
                                                                                                                        -0.55
                                                                                                          -0.56
            Geography_Germany -
                                                  -0.08
                                                                       0.04
                                                                                                                        -0.39
                                     0.08
                                           0.05
                                                                              0.03
                                                                                            0.11
                                                                                                                  1
                                                         -0.02
                                                               -0.13
                                                                              -0.02
                                                                                            -0.03
                                                                                                   0.07
                                                                                                          -0.55
                                           -0.07
                                                  0.03
                                                                       -0.06
                                                                                     0.11
                Geography_Spain ·
                                                          Enure
                                                                 Balance .
                                                                        NumOfProducts
                                                                               HasCrCard
                                                                                             EstimatedSalary
                                                                                      sActiveMember
```

Hence we can see that most important features for predicting class label 'Exited' are : Age, isActiveMember, HasCrCard, Gender, Geography_France

1			
	1	1	0
0	1	0	0
1	0	1	0
1	0	0	0
0	1	1	0
			•••
0	1	1	0
0	1	1	1
1	1	1	1
1	0	1	1
0	1	1	1
9	0 2 1 1 3 0 0 7 0 7 1 5 1	0 1 2 1 0 3 1 0 3 1 0 3 1 0 3 0 1	0 1 0 1 0 1 2 1 0 0 3 0 1 1 4 0 1 1 7 0 1 1 7 1 1 1 5 1 0 1

201 rows × 5 columns

Out[7]:

```
In [8]:
               1
Out[8]:
        1
               0
        2
               1
        3
               0
        196
              0
        197
        198
               0
        199
        200
        Name: Exited, Length: 201, dtype: int64
In [9]:
        # Train test split
        X train1, X test1, y train1, y test1 = train test split(X,y,test size=0.1,
                                                                  random state=13)
        X_train2, X_test2, y_train2, y_test2 = train_test_split(X,y,test_size=0.2,
                                                                  random state=13)
        X_train3, X_test3, y_train3, y_test3 = train_test_split(X,y,test_size=0.3,
                                                                  random state=13)
        X train1
```

Out[9]:		Age	Geography_France	IsActiveMember	HasCrCard	Gender
	143	52	0	0	1	1
	68	35	0	1	0	0
	7	29	0	0	1	0
	125	42	1	0	1	1
	175	35	0	1	1	0
	•••					

	Age	Geography_France	IsActiveMember	HasCrCard	Gender
98	22	0	0	0	1
16	58	0	0	1	1
74	36	1	1	0	1
176	30	1	1	1	0
82	36	1	0	0	0

180 rows × 5 columns

```
In [10]:
          y train1
         143
                1
Out[10]:
         68
         7
         125
         175
         98
                0
         16
         74
         176
         82
         Name: Exited, Length: 180, dtype: int64
```

Decision Tree Classifier (90-10 Split)

```
In [11]:
          # Decision Tree Classifier for 90-10 Split
         dtree = DecisionTreeClassifier(random state=13)
         dtree.fit(X train1, y train1)
         y pred train1 = dtree.predict(X train1)
         y pred test1 = dtree.predict(X test1)
         print('90-10 Model performance on Training Set : \n')
         print(classification report(y train1,y pred train1))
         print()
         print()
         print('90-10 Model performance on Test Set : \n')
         print(classification report(y test1, y pred test1))
         print()
         print()
         X \text{ ip} = list(map(int,
                input ("Enter Age, isActiveMember, HasCrCard, Gender, Geography France: ")
                          .split()))[:5]
         print('Predicted class : ',dtree.predict([X_ip])[0])
         print()
         print()
         print('Result : ')
         pd.DataFrame({'Actual':y test1,'Predicted':y pred test1})
```

90-10 Model performance on Training Set:

```
precision recall f1-score support

0 0.96 0.99 0.98 147
1 0.96 0.82 0.89 33

accuracy 0.96 180
```

macro	avg	0.96	0.91	0.93	180
weighted	avg	0.96	0.96	0.96	180

90-10 Model performance on Test Set :

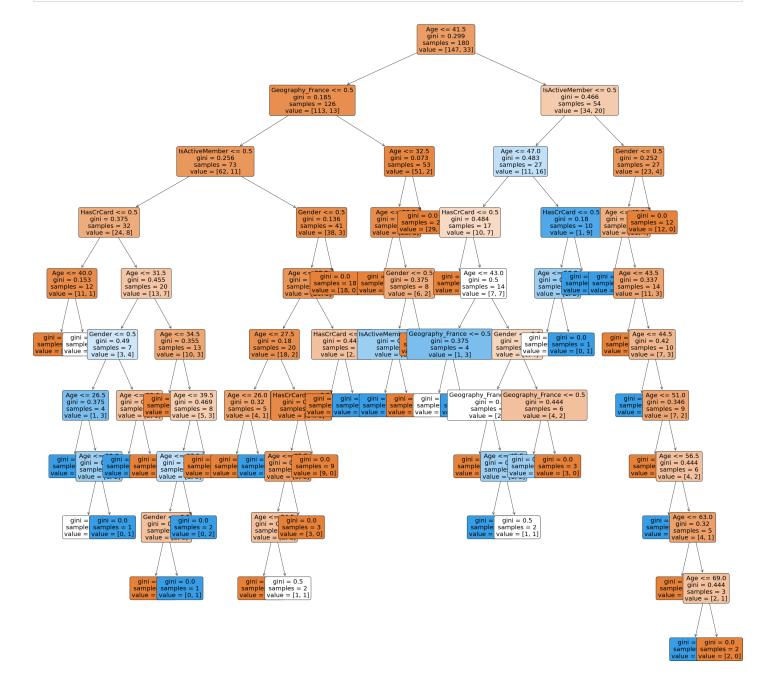
support	f1-score	recall	precision	
13	0.67	0.69	0.64	0
8	0.40	0.38	0.43	1
21	0.57			accuracy
21	0.53	0.53	0.54	macro avg
21	0.57	0.57	0.56	weighted avg

Enter Age, isActiveMember, HasCrCard, Gender, Geography_France : 40 0 1 1 0 Predicted class: 1

Result :

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	IT.		- 1	- 1	- 1	

Res	ult :	
Out[11]:	Actual	Predicted
101	0	0
87	0	0
23	0	0
140	0	1
114	1	0
190	1	0
65	0	0
111	0	1
33	0	1
196	0	0
194	0	0
30	1	1
70	1	1
169	0	0
164	1	0
132	0	0
103	0	1
179	1	1
105	1	0
184	1	0
191	0	0



Training set gave 96% accuracy and test set gave 57% accuracy hence model is overfitted

Decision Tree Classifier (80-20 Split)

80-20 Model performance on Training Set :

	precision	recall	f1-score	support
0	0.97 0.96	0.99	0.98	133 27
accuracy			0.97	160
macro avg weighted avg	0.96 0.97	0.92	0.94	160 160

80-20 Model performance on Test Set :

	precision	recall	f1-score	support
0 1	0.74	0.85	0.79 0.50	27 14
accuracy			0.71	41
macro avg	0.67	0.64	0.65	41
weighted avg	0.69	0.71	0.69	41

Enter Age, is ActiveMember, HasCrCard, Gender, Geography_France : 40 0 1 1 0 Predicted class : 0

Result :

Out[13]:		Actual	Predicted
	101	0	0

23	0	0
140	0	1

87 0 0

114	1	0

190	1	0

65	U	U

11	11	0	1

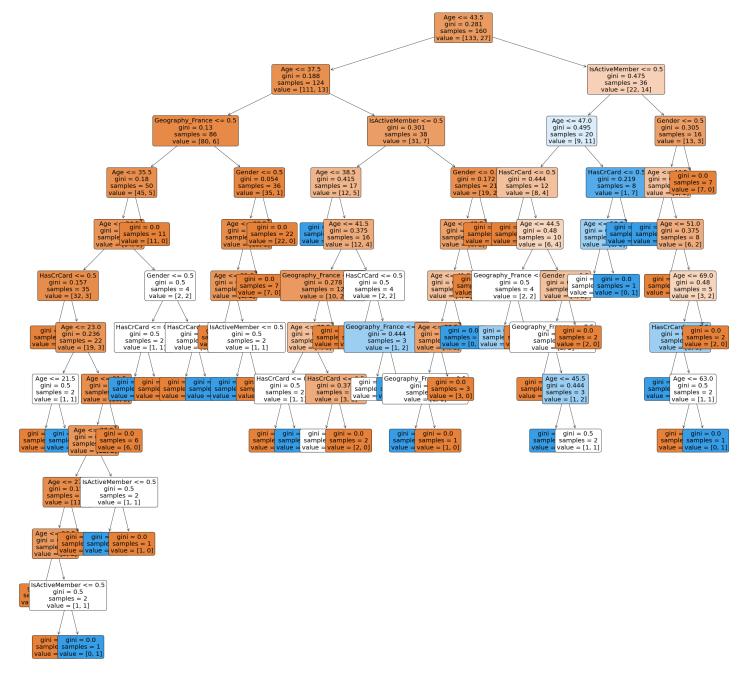
33	0	1

196	0	0

194	0	0

30 1 1

	Actual	Predicted
70	1	1
169	0	0
164	1	0
132	0	0
103	0	0
179	1	1
105	1	0
184	1	0
191	0	0
143	1	1
68	0	1
7	1	0
125	1	1
175	0	0
124	0	0
144	1	0
127	1	1
166	1	0
79	0	0
97	0	0
102	0	0
106	0	0
10	0	0
92	0	0
13	0	0
42	0	0
15	0	0
131	0	0
95	0	0



Training set gave 97% accuracy and test set gave 71% accuracy hence model is slightly overfitted

Decision Tree Classifier (70-30 Split)

```
In [15]: # Decision Tree Classifier for 70-30 Split

    dtree = DecisionTreeClassifier(random_state=13)
    dtree.fit(X_train3,y_train3)
    y_pred_train3 = dtree.predict(X_train3)
    y_pred_test3 = dtree.predict(X_test3)

    print('70-30 Model performance on Training Set : \n')
    print(classification_report(y_train3,y_pred_train3))
    print()
    print()
    print('70-30 Model performance on Test Set : \n')
    print(classification_report(y_test3,y_pred_test3))
    print()
    print()
    x_ip = list(map(int, input("Enter Age, isActiveMember, HasCrCard, Gender, Geography_France : ")
```

```
.split()))[:5]
print('Predicted class : ',dtree.predict([X_ip])[0])
print()
print()
print('Result : ')
pd.DataFrame({'Actual':y_test3,'Predicted':y_pred_test3})
```

70-30 Model performance on Training Set :

	precision	recall	f1-score	support
0	0.97 0.96	0.99	0.98 0.92	114 26
accuracy macro avg weighted avg	0.97 0.97	0.94 0.97	0.97 0.95 0.97	140 140 140

70-30 Model performance on Test Set :

	precision	recall	f1-score	support
0	0.83	0.83	0.83	46
1	0.47	0.47	0.47	15
accuracy			0.74	61
macro avg	0.65	0.65	0.65	61
weighted avg	0.74	0.74	0.74	61

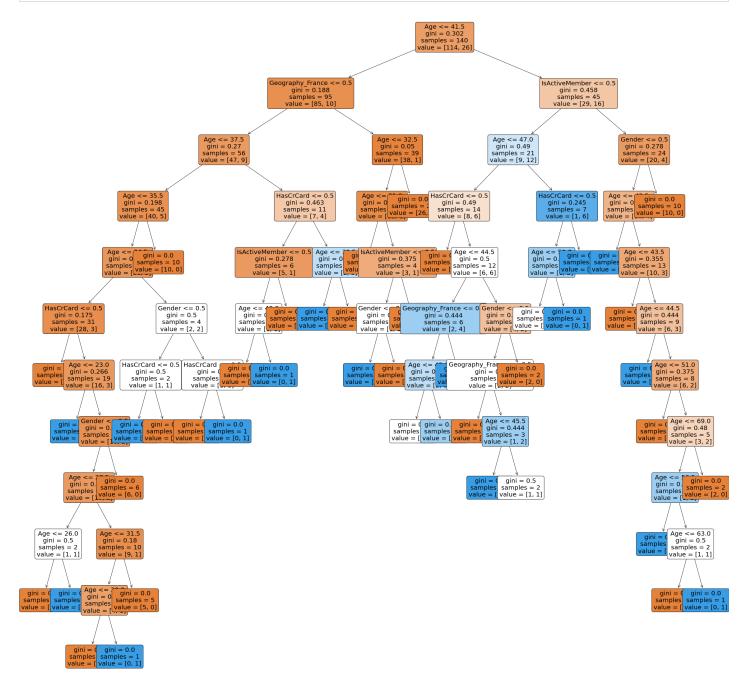
Enter Age, is ActiveMember, HasCrCard, Gender, Geography_France : 40 0 1 1 0 Predicted class : 0

Result :

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()	IT.		-	\neg	- 1	

	Actual	Predicted
101	0	0
87	0	0
23	0	0
140	0	1
114	1	0
•••		
32	0	1
19	0	0
17	0	0
173	0	0
193	0	0

61 rows × 2 columns



Training set gave 97% accuracy and test set gave 74% accuracy hence model is slightly overfitted

Conclusion: Best model obtained using 70% data for training and 30% data for testing with accuracy of 97% on training set and 74% on test set. Also, it has been observed that as we decrease the training set size, the test set accuracy increases and hence overfitting reduces.