In [54]:
```
from warnings import filterwarnings
filterwarnings('ignore')
```

In [55]:
```
#importing all neccesary packages
#setting the style and colour of the plot to be created
import pandas as pd
import numpy as np
from sklearn import preprocessing
from sklearn import metrics
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
plt.rc("font", size=14)
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import RFE, f_regression
from sklearn.linear_model import (LinearRegression)
from sklearn.preprocessing import MinMaxScaler
from sklearn.ensemble import RandomForestRegressor
import seaborn as sns
sns.set(style="white")
sns.set(style="whitegrid", color_codes=True)
```

Data Cleaning and Exploratory Analysis

In [56]:
```
#accessing all datasets and storing them
dataset1= "Att18.xlsx"
dataset2="Att19.xlsx"
dataset3="Drop18.xlsx"
dataset4="Drop19.xlsx"
#reading the datasets using pandas and storing in different dataframes
df1= pd.read_excel(dataset1)
df2= pd.read_excel(dataset2)
df3= pd.read_excel(dataset3)
df4= pd.read_excel(dataset4)
#joining all dataframes into one
dataframe=[df1,df2,df3,df4]
df=pd.concat(dataframe, ignore_index=True, sort =False)
```

In [57]:
```
df.head()
```

Out[57]:

	S.No.	Expert Group	Section Code	Reference No.	Course Code	Course Description	Course Type	Program Type	Start Date	End Date	...	Superior Designation	Superior level	Training Coordinator	P D
0	1	RM	JBD	PJEE181701	PJEE18	Electrical Safety and SDL Trailing Cable handling	Request	Safety	26-04-2017	26-04-2017	...	NaN	NaN	Vishal Goyal	S
1	2	RM	JBD	PJEE181701	PJEE18	Electrical Safety and SDL Trailing Cable handling	Request	Safety	26-04-2017	26-04-2017	...	NaN	NaN	Basant Kumar Singh	S
2	3	RM	JBD	PJEE181701	PJEE18	Electrical Safety and SDL Trailing Cable handling	Request	Safety	26-04-2017	26-04-2017	...	NaN	NaN	Saheb Ram Mahto	S
3	4	RM	JBD	PJEE181701	PJEE18	Electrical Safety and SDL Trailing Cable handling	Request	Safety	26-04-2017	26-04-2017	...	NaN	NaN	Mrinal Kanti Khan	S
4	5	RM	SUK	SKL0011702	SKL001	O.E.M. Training to Dumper Operator of Vendors	Request	Other Program	05-04-2017	06-04-2017	...	NaN	NaN	MD KALIM	

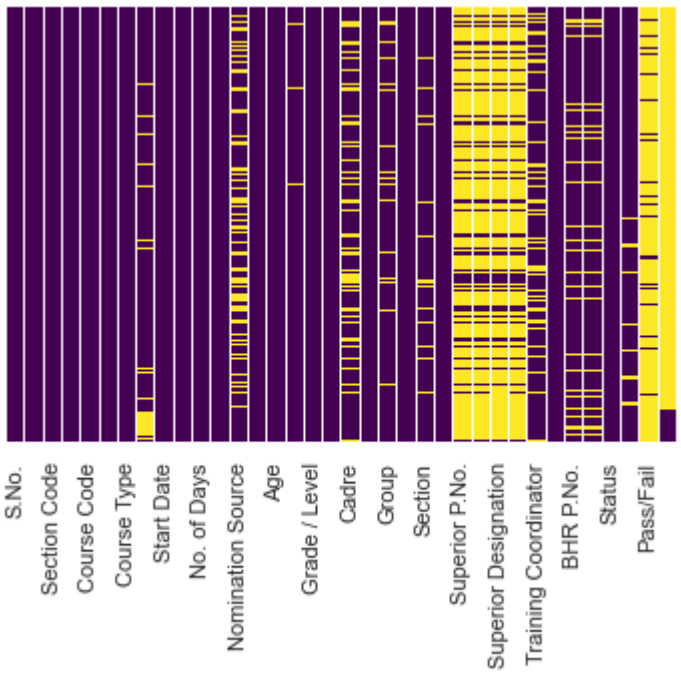
5 rows × 36 columns

In [58]:
```
df.isnull().sum()
```

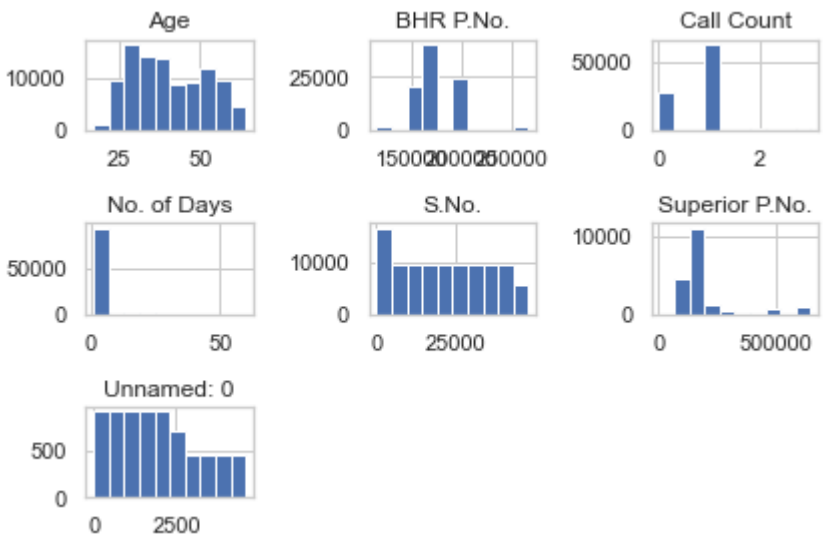
Out[58]:
```
S.No.                   0
Expert Group            0
Section Code            0
Reference No.           0
Course Code             0
Course Description      0
Course Type             0
Program Type         9294
Start Date              0
End Date                0
No. of Days             0
Agency                  0
Nomination Source   23107
Gender                  0
Age                     1
Designation          1166
Grade / Level         151
Category                0
Cadre               19425
Executive Head         25
Group                4133
Department             41
Section              5830
Employee Location       0
Superior P.No.      78964
Superior Name       78964
Superior Designation    78991
Superior level      78964
Training Coordinator    18362
Program Director           11
BHR P.No.            9773
BHR Name             9773
Status                  0
Call Count           3911
Pass/Fail           87178
Unnamed: 0          90871
dtype: int64
```

In [59]:
```
#showing the attributes that have missing data
sns.heatmap(df.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

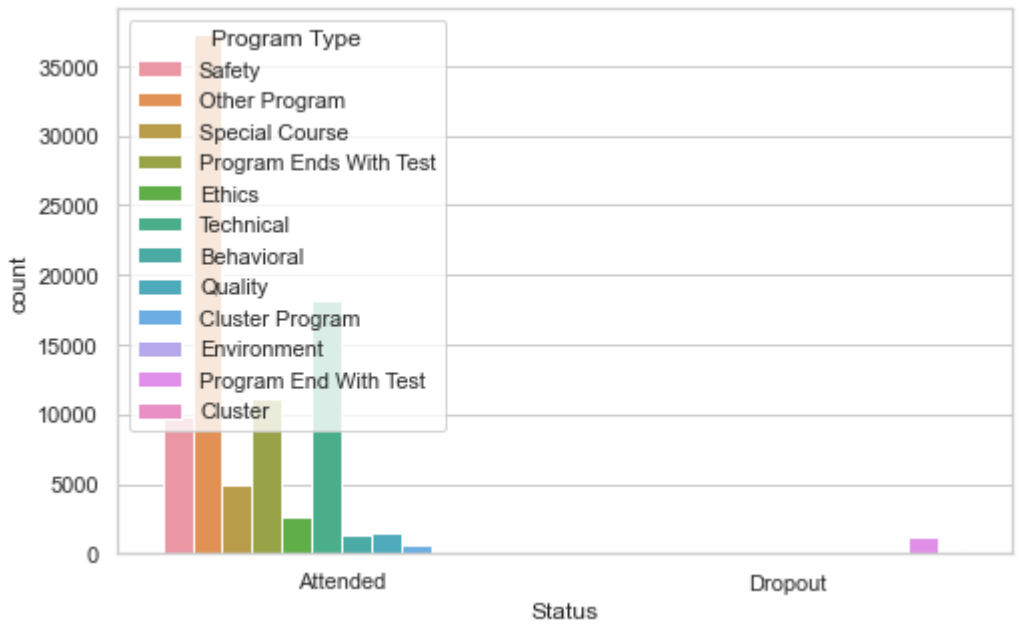
Out[59]: <matplotlib.axes._subplots.AxesSubplot at 0x1fafac09cd0>



In [60]:
```
#these plots are to see the varaition in data
df.hist()
plt.tight_layout()
plt.show()
```

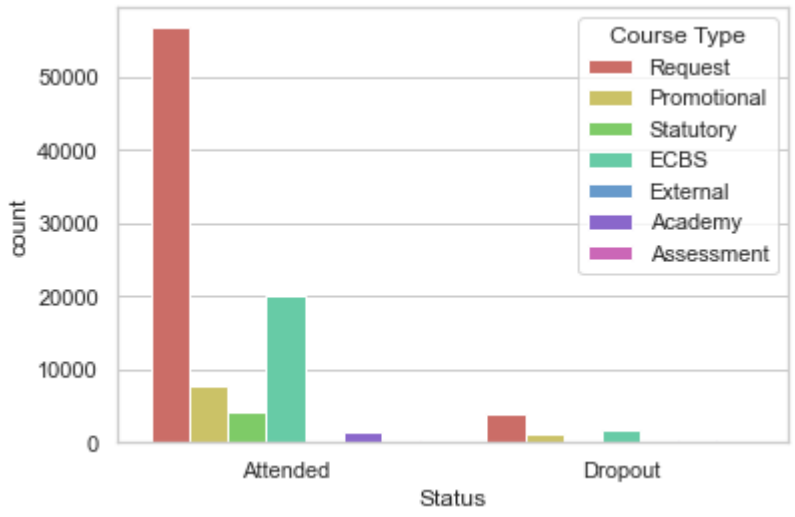


In [61]:
```
#count-plot of people who attended based on course type
plt.figure(figsize=(8,5)) # this creates a figure 8 inch wide, 4 inch high
sns.countplot(x='Status', hue='Program Type', data=df)
plt.show()
```



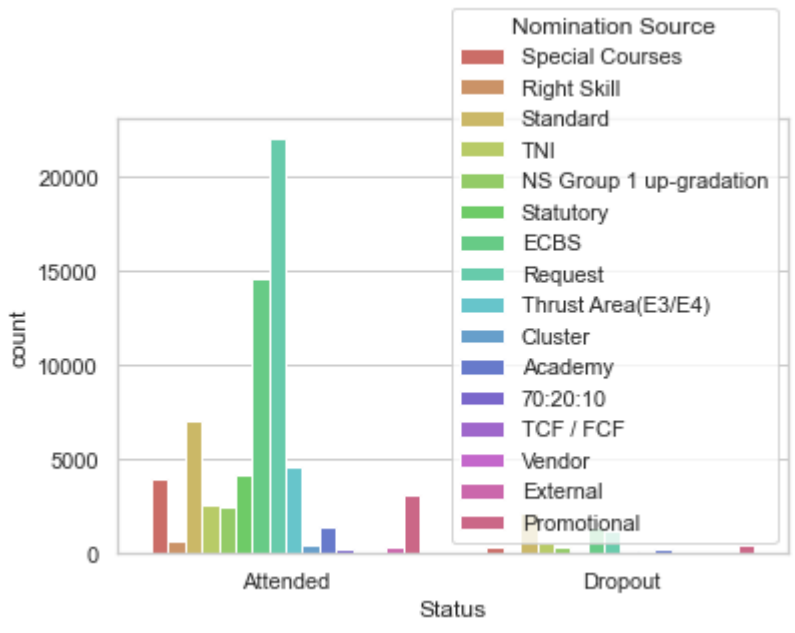
In [62]:
```
#count-plot of people who attended based on course type
sns.countplot(x='Status', hue='Course Type', data=df, palette='hls')
```

Out[62]: <matplotlib.axes._subplots.AxesSubplot at 0x1fafb816ee0>



In [63]:
```
sns.countplot(x='Status', hue='Nomination Source', data=df, palette='hls')
```

Out[63]: <matplotlib.axes._subplots.AxesSubplot at 0x1faf9c02040>



In [64]:
```
df['Status'].value_counts()
```

Out[64]:
```
Attended    90871
Dropout      7140
Name: Status, dtype: int64
```

The following attributes were chosen in accordance wth my analysis above such as 'Superior Name', 'Pass/Fail' and others after talking to my supervisor such as name.

In [65]:
```
to_drop= ['S.No.','Start Date','End Date','Superior Designation','Superior level', 'Training Coordinator','Cadre','Superior P.No.', 'Superior Name', 'BHR P.No.', 'BHR Name', 'Pass/Fail', 'Unnamed: 0', 'Call Count']
df.drop(to_drop, inplace=True, axis=1)
```

In [66]:
```
df.head()
```

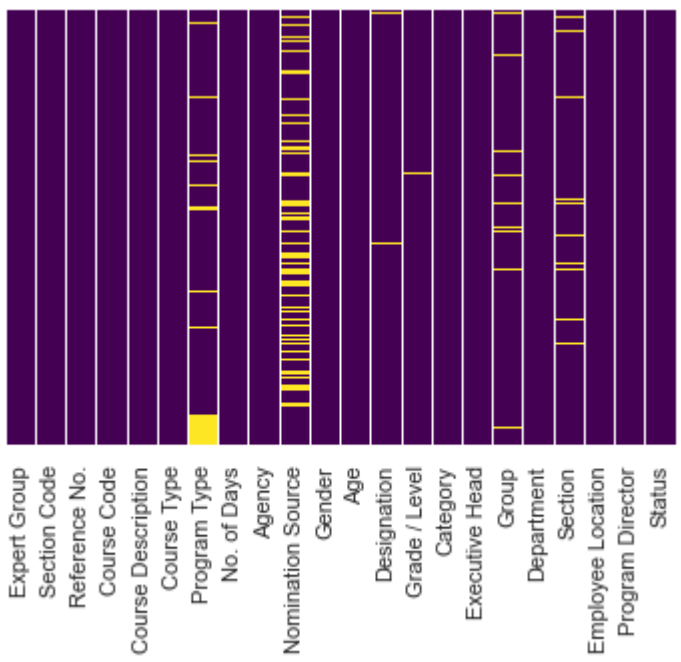
Out[66]:

	Expert Group	Section Code	Reference No.	Course Code	Course Description	Course Type	Program Type	No. of Days	Agency	Nomination Source	...	Designation	Grade / Level	Categor
0	RM	JBD	PJEE181701	PJEE18	Electrical Safety and SDL Trailing Cable handling	Request	Safety	1	PTI	Special Courses	...	SDL CREW	PB 01	WR
1	RM	JBD	PJEE181701	PJEE18	Electrical Safety and SDL Trailing Cable handling	Request	Safety	1	PTI	Special Courses	...	SDL CREW	MC 01	SU
2	RM	JBD	PJEE181701	PJEE18	Electrical Safety and SDL Trailing Cable handling	Request	Safety	1	PTI	Special Courses	...	BANKSMAN	DC 04	WR
3	RM	JBD	PJEE181701	PJEE18	Electrical Safety and SDL Trailing Cable handling	Request	Safety	1	PTI	Special Courses	...	SDL CREW	PM 01	WR
4	RM	SUK	SKL0011702	SKL001	O.E.M. Training to Dumper Operator of Vendors	Request	Other Program	2	VTC	Right Skill	...	SENIOR MACK OPERATOR	VRO08	WR

5 rows × 22 columns

In [67]:
```
#showing the attributes that have missing data
sns.heatmap(df.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

Out[67]: <matplotlib.axes._subplots.AxesSubplot at 0x1fafad355e0>



In [68]:
```
#df.drop(['Course Type', 'Program Type', 'Agency', 'Gender', 'Category'], inplace=True, axis=1)
```

In [69]:
```
df.dtypes
```

Out[69]:
```
Expert Group          object
Section Code          object
Reference No.         object
Course Code           object
Course Description    object
Course Type           object
Program Type          object
No. of Days            int64
Agency                object
Nomination Source     object
Gender                object
Age                  float64
Designation           object
Grade / Level         object
Category              object
Executive Head        object
Group                 object
Department            object
Section               object
Employee Location     object
Program Director      object
Status                object
dtype: object
```

In [70]:
```
df.isnull().sum()
```

Out[70]:
```
Expert Group              0
Section Code              0
Reference No.             0
Course Code               0
Course Description        0
Course Type               0
Program Type           9294
No. of Days               0
Agency                    0
Nomination Source     23107
Gender                    0
Age                       1
Designation            1166
Grade / Level           151
Category                  0
Executive Head           25
Group                  4133
Department               41
Section                5830
Employee Location         0
Program Director         11
Status                    0
dtype: int64
```

I used Label encoders to make model implementation easy.

In [71]:
```
#Encode target labels with value between 0 and n_classes-1.
le = LabelEncoder()
#use of label encoder
```

In [72]:
```
df['Program Type'] = le.fit_transform(df['Program Type'].astype(str))
df['Designation'] = le.fit_transform(df['Designation'].astype(str))
df['Grade / Level'] = le.fit_transform(df['Grade / Level'].astype(str))
df['Executive Head'] = le.fit_transform(df['Executive Head'].astype(str))
df['Group'] = le.fit_transform(df['Group'].astype(str))
df['Department'] = le.fit_transform(df['Department'].astype(str))
df['Section'] = le.fit_transform(df['Section'].astype(str))
df['Program Director'] = le.fit_transform(df['Program Director'].astype(str))
df['Nomination Source'] = le.fit_transform(df['Nomination Source'].astype(str))
```

Using Label Encoder to convert the categorical data to Numeric Data

In [73]:
```
# apply "le.fit_transform"
df_encoded = df.apply(le.fit_transform)
print(df_encoded)
```

```
       Expert Group  Section Code  Reference No.  Course Code  \
0                10            10           2712          568
1                10            10           2712          568
2                10            10           2712          568
3                10            10           2712          568
4                10            26           3826          862
...             ...           ...            ...          ...
98006             8             5           1549          218
98007             0             4           4665         1023
98008             0             2           3599          802
98009             4            13           4773         1085
98010             4            13           4759         1083

       Course Description  Course Type  Program Type  No. of Days  Agency  \
0                     311            5             9            0       9
1                     311            5             9            0       9
2                     311            5             9            0       9
3                     311            5             9            0       9
4                     706            5             5            1      12
...                   ...          ...           ...          ...     ...
98006                 271            0            12            4      11
98007                 958            0            12            1      11
98008                 942            0            12            2      11
98009                 776            2             6            0      11
98010                  91            2            12            0      11

       Nomination Source  ...  Designation  Grade / Level  Category  \
0                      9  ...         3292            183         2
1                      9  ...         3292            102         1
2                      9  ...          517             29         2
3                      9  ...         3292            193         2
4                      8  ...         3371            268         2
...                  ...  ...          ...            ...       ...
98006                  1  ...         4276             89         0
98007                  1  ...         4231             89         0
98008                  1  ...         2405             91         0
98009                  3  ...         1786            231         2
98010                  3  ...         1786            231         2

       Executive Head  Group  Department  Section  Employee Location  \
0                  18     37         142      935                 32
1                  18     37           1      931                 32
2                  18     78          48      934                 32
3                  18     37         640      935                 32
4                  18     27         660      743                 62
...               ...    ...         ...      ...                ...
98006              20     48         300      514                 30
98007              20     22         652      598                 30
98008              20     22         368      493                 30
98009              17     23          77      194                 29
98010              17     23         650      506                 29

       Program Director  Status
0                    66       0
1                    66       0
2                    66       0
3                    66       0
4                   108       0
...                 ...     ...
98006               163       1
98007               238       1
98008               199       1
98009               122       1
98010               226       1

[98011 rows x 22 columns]
```

In [74]:
```
df = df_encoded.reindex(np.random.permutation(df_encoded.index))
df.head
```

Out[74]:
```
<bound method NDFrame.head of        Expert Group  Section Code  Reference No.  Course Code  \
95296              1            24           4581         1000
81879              9            23           1086          193
58057              4            14           1952          321
78520              2             9            514          131
33738             10            10           3054          652
...              ...           ...            ...          ...
50196              2             9            495          119
84546              2             9            509          126
1859               8             5           3746          828
2286               1            24            194           78
4817               2             9            459          119

       Course Description  Course Type  Program Type  No. of Days  Agency  \
95296                 992            2            12            0      11
81879                 295            5             5            0       3
58057                 273            5             5            0      11
78520                 234            5             9            0      11
33738                 400            6             7            4       9
...                   ...          ...           ...          ...     ...
50196                 227            5             5            0      11
84546                 232            2            11            0      11
1859                  948            5            11            1      11
2286                  925            5            10            0      11
4817                  227            5             5            0      11

       Nomination Source  ...  Designation  Grade / Level  Category  \
95296                  3  ...         3072            165         2
81879                 16  ...         3037            226         2
58057                  7  ...         1789            230         2
78520                  7  ...          996            244         1
33738                 11  ...         3292            193         2
...                  ...  ...          ...            ...       ...
50196                 16  ...         3154             91         0
84546                  7  ...         1823            167         2
1859                  14  ...         3315              8         2
2286                  10  ...         3315              8         2
4817                   7  ...         3865             89         0

       Executive Head  Group  Department  Section  Employee Location  \
95296              21     45         316     1190                 30
81879              17      0         395      778                 29
58057              17     13         645     1296                 29
78520              21     46         692      427                 30
33738              18     37         640      935                 32
...               ...    ...         ...      ...                ...
50196               1     75         633     1277                  7
84546              20     22         299     1201                 30
1859               20     48         369      114                 30
2286               21     45          73     1206                 30
4817               18     87         372      742                 67

       Program Director  Status
95296               234       1
81879                70       0
58057               240       0
78520                52       0
33738               193       0
...                 ...     ...
50196                54       0
84546                52       0
1859                163       0
2286                158       0
4817                 52       0

[98011 rows x 22 columns]>
```

Logistic Regression Model

In [75]:
```
x = df.drop('Status', axis=1)
y = df['Status']
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.33, random_state=1)
#test and train sets created to be tested
logmodel = LogisticRegression()
logmodel.fit(x_train, y_train)
#training my model using train sets
```

Out[75]:
```
LogisticRegression()
```

In [76]:
```
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix,accuracy_score
```

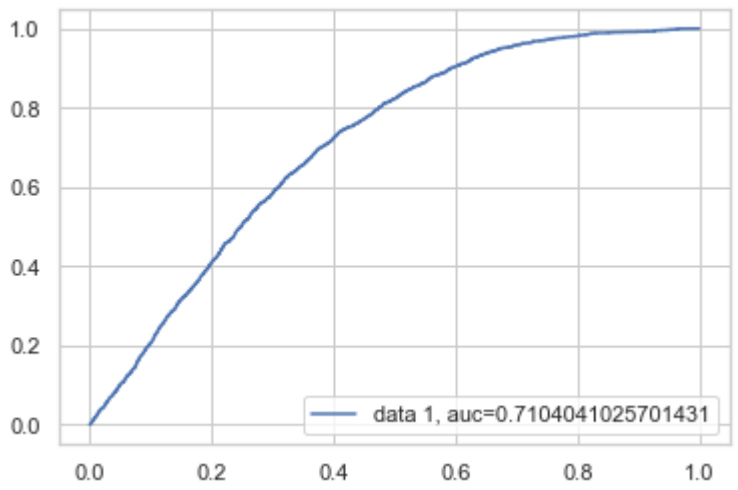
The classification report displays the Precision, Recall , F1 and Support scores for the model.

In [77]:
```
#Precision score means the the level up-to which the prediction made by the model is precise.
#Recall is the amount up-to which the model can predict the outcome.
#F1 and Support scores are the amount of data tested for the predictions.
predictions = logmodel.predict(x_test)
print(classification_report(y_test, predictions))
print(confusion_matrix(y_test, predictions))
print(accuracy_score(y_test, predictions))
print("Accuracy:",metrics.accuracy_score(y_test, predictions))
print("Precision:",metrics.precision_score(y_test, predictions))
print("Recall:",metrics.recall_score(y_test, predictions))
```

```
              precision    recall  f1-score   support

           0       0.93      1.00      0.96     29964
           1       0.12      0.00      0.00      2380

    accuracy                           0.93     32344
   macro avg       0.52      0.50      0.48     32344
weighted avg       0.87      0.93      0.89     32344

[[29941    23]
 [ 2377     3]]
0.9257976749938165
Accuracy: 0.9257976749938165
Precision: 0.11538461538461539
Recall: 0.0012605042016806723
```

The Area Under the Curve (AUC) is the measure of the ability of a classifier to distinguish between classes and is used as a summary of the ROC curve. The higher the AUC, the better the performance of the model at distinguishing between the positive and negative classes. This model is okay.

In [78]:
```
y_pred_proba = logmodel.predict_proba(x_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_proba)
auc = metrics.roc_auc_score(y_test, y_pred_proba)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



Decision Tree Model

In [79]:
```
from sklearn import tree
model= tree.DecisionTreeClassifier()
```

In [81]:
```
#Defining Features and lables
features= list(df.columns)
features.remove('Status')
```

In [82]:
```
X = df.drop('Status', axis=1)
Y = df['Status']
X_train, X_test, y_train, y_test = train_test_split( X, Y, test_size = 0.2, random_state = 100)
```

In [83]:
```
model.fit(X_train, y_train)
```

Out[83]:
```
DecisionTreeClassifier()
```

In [84]:
```
model.score(X_test, y_test)
```

Out[84]:
```
0.9958679793909095
```

In [85]:
```
predictions_2 = model.predict(X_test)
print(classification_report(y_test, predictions_2))
print(confusion_matrix(y_test, predictions_2))
print(accuracy_score(y_test, predictions_2))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     18190
           1       0.97      0.97      0.97      1413

    accuracy                           1.00     19603
   macro avg       0.99      0.98      0.98     19603
weighted avg       1.00      1.00      1.00     19603

[[18152    38]
 [   43  1370]]
0.9958679793909095
```

In [86]:
```
print("Accuracy:",metrics.accuracy_score(y_test, predictions_2))
print("Precision:",metrics.precision_score(y_test, predictions_2))
print("Recall:",metrics.recall_score(y_test, predictions_2))
```

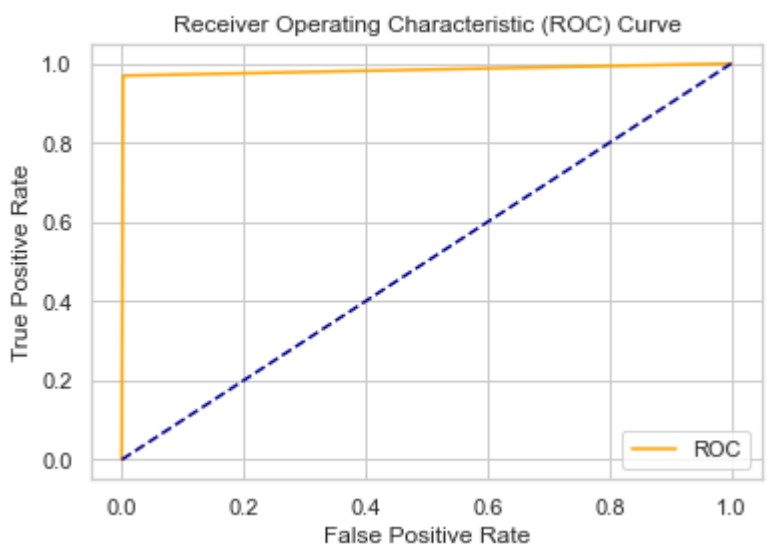
```
Accuracy: 0.9958679793909095
Precision: 0.9730113636363636
Recall: 0.9695682944090588
```

The data above tell us how accurate the model is. The plot below is a ROC curve that plots true positive rate (TPR) against the false positive rate (FPR). The closer the curve is to a 45* angle i.e cut the graph in half, the less accurate it is.

In [87]:
```
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
```

In [88]:
```
def plot_roc_curve(fpr, tpr):
    plt.plot(fpr, tpr, color='orange', label='ROC')
    plt.plot([0, 1], [0, 1], color='darkblue', linestyle='--')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC) Curve')
    plt.legend()
    plt.show()
```

In [89]:
```
fpr, tpr, thresholds = roc_curve(y_test, predictions_2)
plot_roc_curve(fpr, tpr)
```



This model is better.

In [ ]: