```
In [2]:
 1
   import numpy as np
   import matplotlib.pyplot as plt
 3 import pandas as pd
In [3]:
   dataset = pd.read csv('/Users/myyntiimac/Desktop/Social Network Ads.csv')
   X = dataset.iloc[:, [2, 3]].values
 3 y = dataset.iloc[:, -1].values
In [4]:
   from sklearn.preprocessing import StandardScaler
   sc = StandardScaler()
 3 X = sc.fit_transform(X)
In [5]:
   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
In [37]:
   from sklearn.tree import DecisionTreeClassifier
In [38]:
   classifier=DecisionTreeClassifier()
In [39]:
 1 classifier.fit(X_train, y_train)
Out[39]:
▼ DecisionTreeClassifier
DecisionTreeClassifier()
In [40]:
 1 y_pred = classifier.predict(X_test)
In [41]:
   from sklearn.metrics import confusion_matrix
   cm = confusion_matrix(y_test, y_pred)
 3 print(cm)
[[62 6]
[ 4 28]]
In [45]:
 1 from sklearn.metrics import accuracy_score
   # Calculate the accuracy score
   accuracy = accuracy_score(y_test, y_pred)
 3
 4
   accuracy
Out[45]:
0.9
```

```
In [42]:
```

```
bias =classifier.score(X_train, y_train)
bias
```

## Out[42]:

1.0

### In [43]:

```
variance = classifier.score(X_test, y_test)
variance
```

### Out[43]:

0.9

## In [46]:

```
1 #ROC AND AUC
2 from sklearn.metrics import roc_curve, roc_auc_score
```

# In [47]:

```
# Compute the False Positive Rate (FPR), True Positive Rate (TPR), and thresholds
fpr, tpr, thresholds = roc_curve(y_test, y_pred)
```

## In [48]:

```
1 auc = roc_auc_score(y_test, y_pred)
2 auc
```

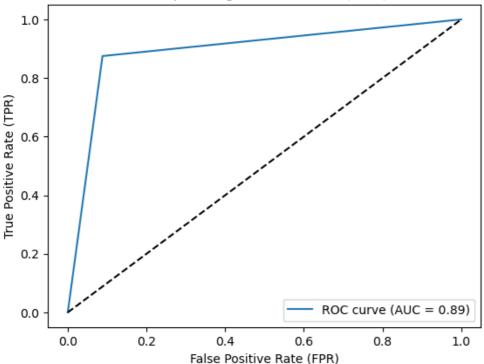
### Out[48]:

0.8933823529411764

#### In [49]:

```
# Plotting the ROC curve
plt.plot(fpr, tpr, label='ROC curve (AUC = {:.2f})'.format(auc))
plt.plot([0, 1], [0, 1], 'k--') # Random guess line
plt.xlabel('False Positive Rate (FPR)')
plt.ylabel('True Positive Rate (TPR)')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

# Receiver Operating Characteristic (ROC) Curve



Insight:In the case of AUC = 0.89, the model demonstrates reasonable discriminative ability, but there is still room for improvement. It correctly ranks 89% of the positive samples higher than the negative samples, on average, across different classification thresholds. However, it might misclassify some instances, leading to false positives or false negatives.

## In [50]:

```
from sklearn.model_selection import cross_val_score
accuracies = cross_val_score(estimator = classifier, X = X_train, y = y_train, cv = 10)
print("Accuracy: {:.2f} %".format(accuracies.mean()*100))
print("Standard Deviation: {:.2f} %".format(accuracies.std()*100))
```

Accuracy: 86.00 % Standard Deviation: 5.33 %

#### In [51]:

1 from sklearn.model selection import GridSearchCV

# In [35]:

```
param_grid = {
    'penalty': ['12'], # Regularization penalty term
    'C': [0.1, 1.0, 10.0], # Inverse of regularization strength
    'solver': ['liblinear', 'lbfgs', 'saga'], # Solver algorithm
    'max_iter': [100, 200, 300], # Maximum number of iterations
    'fit_intercept': [True, False], # Include intercept term
    'class_weight': [None, 'balanced'] # Class weights
}
```

### In [55]:

```
# Create the GridSearchCV object
grid_search = GridSearchCV(estimator=classifier, param_grid=param_grid, cv=10)
grid_search = GridSearchCV(classifier, param_grid, cv=10)
grid_search = grid_search.fit(X_train, y_train)
best_accuracy = grid_search.best_score_
best_parameters = grid_search.best_params_
print("Best Accuracy: {:.2f} %".format(best_accuracy*100))
print("Best Parameters:", best_parameters)
```

```
Best Accuracy: 89.33 %
Best Parameters: {'criterion': 'entropy', 'max_depth': 5, 'max_features': None, 'mi
n_samples_leaf': 4, 'min_samples_split': 5}
```

## In [ ]:

1