## In [1]:

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

# **Data Preparation**

## In [2]:

```
df = pd.read_csv("E:/UCI_Credit_Card.csv", index_col = "ID")
```

## In [3]:

df.head()

## Out[3]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	
ID											
1	20000.0	2	2	1	24	2	2	-1	-1	-2	
2	120000.0	2	2	2	26	-1	2	0	0	0	
3	90000.0	2	2	2	34	0	0	0	0	0	
4	50000.0	2	2	1	37	0	0	0	0	0	
5	50000.0	1	2	1	57	-1	0	-1	0	0	
5 rows × 24 columns											

## In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30000 entries, 1 to 30000
Data columns (total 24 columns):
```

#	Column	Non-Null Count	Dtype
0	LIMIT_BAL	30000 non-null	float64
1	SEX	30000 non-null	int64
2	EDUCATION	30000 non-null	int64
3	MARRIAGE	30000 non-null	int64
4	AGE	30000 non-null	int64
5	PAY_0	30000 non-null	int64
6	PAY_2	30000 non-null	int64
7	PAY_3	30000 non-null	int64
8	PAY_4	30000 non-null	int64
9	PAY_5	30000 non-null	int64
10	PAY_6	30000 non-null	int64
11	BILL_AMT1	30000 non-null	float64
12	BILL_AMT2	30000 non-null	float64
13	BILL_AMT3	30000 non-null	float64
14	BILL_AMT4	30000 non-null	float64
15	BILL_AMT5	30000 non-null	float64
16	BILL_AMT6	30000 non-null	float64
17	PAY_AMT1	30000 non-null	float64
18	PAY_AMT2	30000 non-null	float64
19	PAY_AMT3	30000 non-null	float64
20	PAY_AMT4	30000 non-null	float64
21	PAY_AMT5	30000 non-null	float64
22	PAY_AMT6	30000 non-null	float64
23	<pre>default.payment.next.month</pre>	30000 non-null	int64
44	£1+C4/12\ :-+C4/11\		

dtypes: float64(13), int64(11)

memory usage: 5.7 MB

#### In [5]:

```
df[['LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0', 'PAY_2', 'PAY_3', 'PAY_4',
```

## Out[5]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0
count	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000
mean	167484.322667	1.603733	1.853133	1.551867	35.485500	-0.016700
std	129747.661567	0.489129	0.790349	0.521970	9.217904	1.123802
min	10000.000000	1.000000	0.000000	0.000000	21.000000	-2.000000
25%	50000.000000	1.000000	1.000000	1.000000	28.000000	-1.000000
50%	140000.000000	2.000000	2.000000	2.000000	34.000000	0.000000
75%	240000.000000	2.000000	2.000000	2.000000	41.000000	0.000000
max	1000000.000000	2.000000	6.000000	3.000000	79.000000	8.000000
4						•

#### In [6]:

```
# Data preprocessing
df = df.rename(columns={'PAY_0': 'PAY_1'}) # Renaming the column
# The 0 in Marriage can be considered as same as 3 category (others)
df.loc[df.MARRIAGE == 0, 'MARRIAGE'] = 3
# The 0, 5 and 6 category in Education column can be considered as 4 category (others)
fil = (df.EDUCATION == 5) \mid (df.EDUCATION == 6) \mid (df.EDUCATION == 0)
df.loc[fil, 'EDUCATION'] = 4
# According to our documentation, the PAY_n variables indicate the number of
# months of delay and indicates "pay duly"with -1. Then what is -2?
# And what is 0? It seems to me the label has to be adjusted to 0 for pay duly.
fil = (df.PAY_1 == -2) | (df.PAY_1 == -1) | (df.PAY_1 == 0)
df.loc[fil, 'PAY_1'] = 0
fil = (df.PAY_2 == -2) | (df.PAY_2 == -1) | (df.PAY_2 == 0)
df.loc[fil, 'PAY_2'] = 0
fil = (df.PAY_3 == -2) | (df.PAY_3 == -1) | (df.PAY_3 == 0)
df.loc[fil, 'PAY_3'] = 0
fil = (df.PAY_4 == -2) | (df.PAY_4 == -1) | (df.PAY_4 == 0)
df.loc[fil, 'PAY_4'] = 0
fil = (df.PAY_5 == -2) | (df.PAY_5 == -1) | (df.PAY_5 == 0)
df.loc[fil, 'PAY 5'] = 0
fil = (df.PAY_6 == -2) | (df.PAY_6 == -1) | (df.PAY_6 == 0)
df.loc[fil, 'PAY_6'] = 0
```

## In [7]:

df.head()

### Out[7]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_1	PAY_2	PAY_3	PAY_4	PAY_5	
ID											
1	20000.0	2	2	1	24	2	2	0	0	0	
2	120000.0	2	2	2	26	0	2	0	0	0	
3	90000.0	2	2	2	34	0	0	0	0	0	
4	50000.0	2	2	1	37	0	0	0	0	0	
5	50000.0	1	2	1	57	0	0	0	0	0	
5 ro	5 rows × 24 columns										

```
In [8]:
```

```
df = pd.get_dummies(df, columns = ['SEX', 'EDUCATION', 'MARRIAGE'], drop_first = True)
```

```
In [9]:
```

```
df.head()
```

#### Out[9]:

```
LIMIT_BAL AGE PAY_1 PAY_2 PAY_3 PAY_4 PAY_5 PAY_6 BILL_AMT1 BILL_AMT2
ID
 1
       20000.0
                           2
                                   2
                                                  0
                                                          0
                                                                 0
                                                                         3913.0
                                                                                     3102.
                  24
                                          0
 2
      120000.0
                                   2
                                                                 2
                  26
                           0
                                          0
                                                  0
                                                          0
                                                                         2682.0
                                                                                     1725.
       90000.0
 3
                                   0
                                                                        29239.0
                  34
                           0
                                          0
                                                  0
                                                          0
                                                                 0
                                                                                    14027.
 4
       50000.0
                                   0
                                                                 0
                                                                        46990.0
                                                                                    48233.
                  37
                           0
                                          0
                                                  0
                                                          0
       50000.0
                                                                                     5670.
 5
                  57
                           n
                                   n
                                          0
                                                  0
                                                          0
                                                                 0
                                                                         8617.0
5 rows × 27 columns
```

## In [10]:

```
df = df[["LIMIT_BAL", "AGE", "SEX_2", "EDUCATION_2", "EDUCATION_3", "EDUCATION_4", "MARRIAG
```

## In [11]:

```
df.head()
```

#### Out[11]:

#### LIMIT\_BAL AGE SEX\_2 EDUCATION\_2 EDUCATION\_3 EDUCATION\_4 MARRIAGE\_2 MAF

ID							
1	20000.0	24	1	1	0	0	0
2	120000.0	26	1	1	0	0	1
3	90000.0	34	1	1	0	0	1
4	50000.0	37	1	1	0	0	0
5	50000.0	57	0	1	0	0	0

5 rows × 27 columns

```
→
```

#### In [12]:

```
# Dividing the dataset
X = df.iloc[:, 1:-1].values # Independent variables
y = df.iloc[:, -1].values # Dependent variable
```

#### In [13]:

```
# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state =
```

```
In [14]:
```

```
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

#### In [15]:

## Logistic regression

### In [16]:

```
# Training the Logistic Regression model on the Training set
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

#### Out[16]:

### In [17]:

```
# Predicting the Test set results
y_pred = logreg.predict(X_test)
y_pred_prob = logreg.predict_proba(X_test)[:, 1]
```

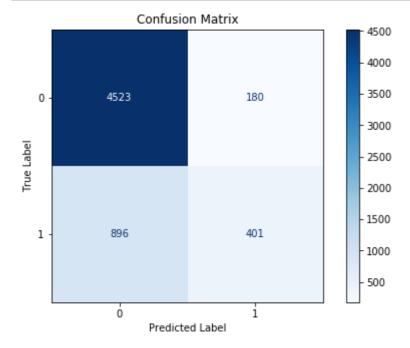
#### In [18]:

```
# Making the Confusion Matrix
from sklearn.metrics import accuracy_score, precision_score, recall_score, confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy = accuracy_score(y_test, y_pred)
print(accuracy)
metric.loc['accuracy', 'Logistic Regression'] = accuracy_score(y_pred = y_pred, y_true = y_metric.loc['precision', 'Logistic Regression'] = precision_score(y_pred = y_pred, y_true = metric.loc['recall', 'Logistic Regression'] = recall_score(y_pred = y_pred, y_true = y_test
```

```
[[4523 180]
[ 896 401]]
0.82066666666666667
```

#### In [19]:

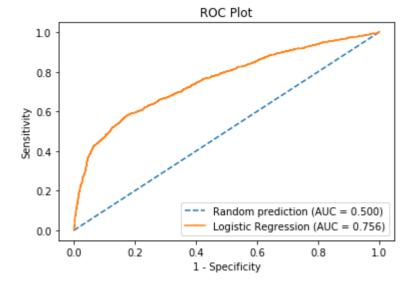
```
matrix = plot_confusion_matrix(logreg, X_test, y_test, values_format = 'd', cmap = plt.cm.B
matrix.ax_.set_title('Confusion Matrix', color = 'black')
plt.xlabel('Predicted Label', color = 'black')
plt.ylabel('True Label', color = 'black')
plt.gcf().axes[0].tick_params(color = 'black')
plt.gcf().axes[1].tick_params(color = 'black')
plt.gcf().set_size_inches(8, 5)
plt.show()
```



#### In [20]:

```
r_probs = [0 for _ in range(len(y_test))]
LR_probs = logreg.predict_proba(X_test)
LR_probs = LR_probs[:, 1]
from sklearn.metrics import roc_curve, roc_auc_score
r_auc = roc_auc_score(y_test, r_probs)
LR_auc = roc_auc_score(y_test, LR_probs)
print('Random (chance) Prediction: AUC = %.3f' % (r_auc))
print('Logistic Regression: AUC = %.3f' % (LR_auc))
r_fpr, r_tpr, _ = roc_curve(y_test, r_probs)
LR_fpr, LR_tpr, _ = roc_curve(y_test, LR_probs)
plt.plot(r_fpr, r_tpr, linestyle='--', label='Random prediction (AUC = %0.3f)' % r_auc)
plt.plot(LR_fpr, LR_tpr, marker=',', label='Logistic Regression (AUC = %0.3f)' % LR_auc)
# Title
plt.title('ROC Plot')
# Axis labels
plt.xlabel('1 - Specificity')
plt.ylabel('Sensitivity')
# Show Legend
plt.legend() #
# Show plot
plt.show()
```

Random (chance) Prediction: AUC = 0.500
Logistic Regression: AUC = 0.756



## **KNN Classifier**

#### In [21]:

```
# train your model using all data and the best known parameters
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors = 24)
knn.fit(X_train, y_train)
```

#### Out[21]:

#### In [22]:

```
# Predicting the Test set results
y_pred = knn.predict(X_test)
y_pred_prob = logreg.predict_proba(X_test)[:, 1]
```

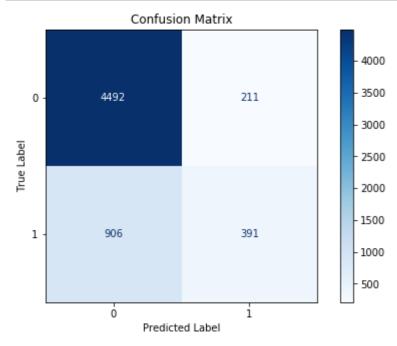
## In [23]:

```
# Making the Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy = accuracy_score(y_test, y_pred)
print(accuracy)
metric.loc['accuracy', 'KNN'] = accuracy_score(y_pred = y_pred, y_true = y_test)
metric.loc['precision', 'KNN'] = precision_score(y_pred = y_pred, y_true = y_test)
metric.loc['recall', 'KNN'] = recall_score(y_pred = y_pred, y_true = y_test)
```

```
[[4492 211]
[ 906 391]]
0.81383333333333333
```

#### In [24]:

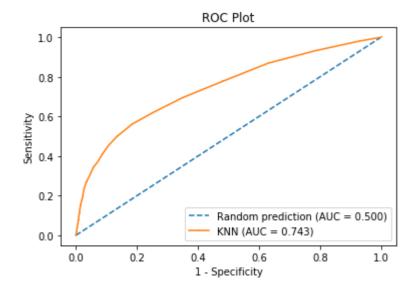
```
matrix = plot_confusion_matrix(knn, X_test, y_test, values_format = 'd', cmap = plt.cm.Blue
matrix.ax_.set_title('Confusion Matrix', color = 'black')
plt.xlabel('Predicted Label', color = 'black')
plt.ylabel('True Label', color = 'black')
plt.gcf().axes[0].tick_params(color = 'black')
plt.gcf().axes[1].tick_params(color = 'black')
plt.gcf().set_size_inches(8, 5)
plt.show()
```



#### In [25]:

```
r_probs = [0 for _ in range(len(y_test))]
KNN_probs = knn.predict_proba(X_test)
KNN_probs = KNN_probs[:, 1]
from sklearn.metrics import roc_curve, roc_auc_score
r_auc = roc_auc_score(y_test, r_probs)
KNN_auc = roc_auc_score(y_test, KNN_probs)
print('Random (chance) Prediction: AUC = %.3f' % (r_auc))
print('KNN: AUC = %.3f' % (KNN_auc))
r_fpr, r_tpr, _ = roc_curve(y_test, r_probs)
KNN_fpr, KNN_tpr, _ = roc_curve(y_test, KNN_probs)
plt.plot(r_fpr, r_tpr, linestyle='--', label='Random prediction (AUC = %0.3f)' % r_auc)
plt.plot(KNN_fpr, KNN_tpr, marker=',', label='KNN (AUC = %0.3f)' % KNN_auc)
# Title
plt.title('ROC Plot')
# Axis labels
plt.xlabel('1 - Specificity')
plt.ylabel('Sensitivity')
# Show Legend
plt.legend() #
# Show plot
plt.show()
```

Random (chance) Prediction: AUC = 0.500 KNN: AUC = 0.743



## **Decision Tree Classifier**

#### In [26]:

```
# Training the Decision Tree model on the Training set
from sklearn.tree import DecisionTreeClassifier
DTC = DecisionTreeClassifier(min_samples_split = 30, min_samples_leaf = 10)
DTC.fit(X_train, y_train)
```

#### Out[26]:

```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini', max_depth=None, max_features=None, max_leaf_nodes=None,

e,

min_impurity_decrease=0.0, min_impurity_split=None,
 min_samples_leaf=10, min_samples_split=30,
 min_weight_fraction_leaf=0.0, presort='deprecated',
 random_state=None, splitter='best')
```

### In [27]:

```
# Predicting the Test set results
y_pred = DTC.predict(X_test)
```

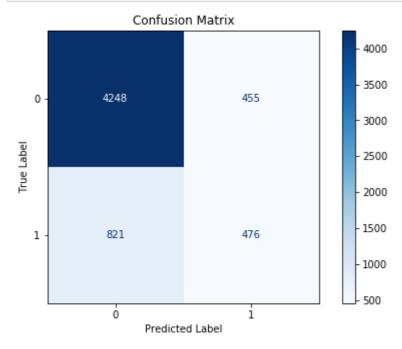
#### In [28]:

```
# Making the Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy = accuracy_score(y_test, y_pred)
print(accuracy)
metric.loc['accuracy', 'Decision Tree'] = accuracy_score(y_pred = y_pred, y_true = y_test)
metric.loc['precision', 'Decision Tree'] = precision_score(y_pred = y_pred, y_true = y_test)
metric.loc['recall', 'Decision Tree'] = recall_score(y_pred = y_pred, y_true = y_test)
```

```
[[4248 455]
[ 821 476]]
0.78733333333333333
```

#### In [29]:

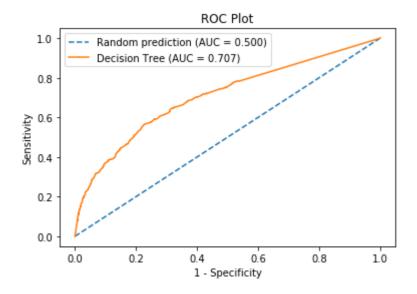
```
matrix = plot_confusion_matrix(DTC, X_test, y_test, values_format = 'd', cmap = plt.cm.Blue
matrix.ax_.set_title('Confusion Matrix', color = 'black')
plt.xlabel('Predicted Label', color = 'black')
plt.ylabel('True Label', color = 'black')
plt.gcf().axes[0].tick_params(color = 'black')
plt.gcf().axes[1].tick_params(color = 'black')
plt.gcf().set_size_inches(8, 5)
plt.show()
```



#### In [30]:

```
r_probs = [0 for _ in range(len(y_test))]
DT_probs = DTC.predict_proba(X_test)
DT_probs = DT_probs[:, 1]
from sklearn.metrics import roc_curve, roc_auc_score
r_auc = roc_auc_score(y_test, r_probs)
DT_auc = roc_auc_score(y_test, DT_probs)
print('Random (chance) Prediction: AUC = %.3f' % (r_auc))
print('Decision Tree: AUC = %.3f' % (DT_auc))
r_fpr, r_tpr, _ = roc_curve(y_test, r_probs)
DT_fpr, DT_tpr, _ = roc_curve(y_test, DT_probs)
plt.plot(r_fpr, r_tpr, linestyle='--', label='Random prediction (AUC = %0.3f)' % r_auc)
plt.plot(DT_fpr, DT_tpr, marker=',', label='Decision Tree (AUC = %0.3f)' % DT_auc)
# Title
plt.title('ROC Plot')
# Axis labels
plt.xlabel('1 - Specificity')
plt.ylabel('Sensitivity')
# Show Legend
plt.legend() #
# Show plot
plt.show()
```

Random (chance) Prediction: AUC = 0.500 Decision Tree: AUC = 0.707



## **Random Forest classifier**

#### In [31]:

```
# Training the Random Forest model on the Training set
from sklearn.ensemble import RandomForestClassifier
RFC = RandomForestClassifier(n_estimators = 100, min_samples_split = 30, min_samples_leaf =
RFC.fit(X_train, y_train)
```

### Out[31]:

```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None, criterion='gini', max_depth=None, max_features='aut o',

max_leaf_nodes=None, max_samples=None, min_impurity_decrease=0.0, min_impurity_split=None, min_samples_leaf=10, min_samples_split=30, min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=None, oob_score=False, random_state=None, verbose=0, warm_start=False)
```

#### In [32]:

```
# Predicting the Test set results
y_pred = RFC.predict(X_test)
```

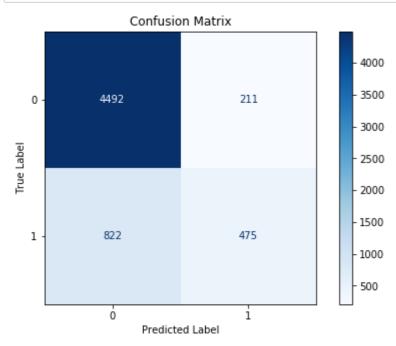
#### In [33]:

```
# Making the Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy = accuracy_score(y_test, y_pred)
print(accuracy)
metric.loc['accuracy', 'Random Forest'] = accuracy_score(y_pred = y_pred, y_true = y_test)
metric.loc['precision', 'Random Forest'] = precision_score(y_pred = y_pred, y_true = y_test)
metric.loc['recall', 'Random Forest'] = recall_score(y_pred = y_pred, y_true = y_test)
```

```
[[4492 211]
[ 822 475]]
0.82783333333333333
```

#### In [34]:

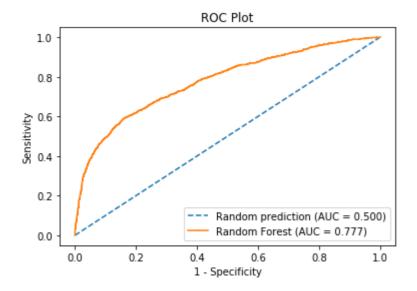
```
matrix = plot_confusion_matrix(RFC, X_test, y_test, values_format = 'd', cmap = plt.cm.Blue
matrix.ax_.set_title('Confusion Matrix', color = 'black')
plt.xlabel('Predicted Label', color = 'black')
plt.ylabel('True Label', color = 'black')
plt.gcf().axes[0].tick_params(color = 'black')
plt.gcf().axes[1].tick_params(color = 'black')
plt.gcf().set_size_inches(8, 5)
plt.show()
```



#### In [35]:

```
r_probs = [0 for _ in range(len(y_test))]
RF_probs = RFC.predict_proba(X_test)
RF_probs = RF_probs[:, 1]
from sklearn.metrics import roc_curve, roc_auc_score
r_auc = roc_auc_score(y_test, r_probs)
RF_auc = roc_auc_score(y_test, RF_probs)
print('Random (chance) Prediction: AUC = %.3f' % (r_auc))
print('Random Forest: AUC = %.3f' % (RF_auc))
r_fpr, r_tpr, _ = roc_curve(y_test, r_probs)
RF_fpr, RF_tpr, _ = roc_curve(y_test, RF_probs)
plt.plot(r_fpr, r_tpr, linestyle='--', label='Random prediction (AUC = %0.3f)' % r_auc)
plt.plot(RF_fpr, RF_tpr, marker=',', label='Random Forest (AUC = %0.3f)' % RF_auc)
# Title
plt.title('ROC Plot')
# Axis labels
plt.xlabel('1 - Specificity')
plt.ylabel('Sensitivity')
# Show Legend
plt.legend() #
# Show plot
plt.show()
```

Random (chance) Prediction: AUC = 0.500 Random Forest: AUC = 0.777



# **Naive Bayes Classifier**

#### In [36]:

```
# Training the Naive Bayes model on the Training set
from sklearn.naive_bayes import GaussianNB
NBC = GaussianNB()
NBC.fit(X_train, y_train)
```

### Out[36]:

GaussianNB(priors=None, var\_smoothing=1e-09)

#### In [37]:

```
# Predicting the Test set results
y_pred = NBC.predict(X_test)
```

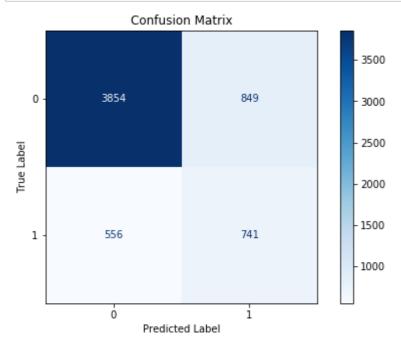
### In [38]:

```
# Making the Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy = accuracy_score(y_test, y_pred)
print(accuracy)
metric.loc['accuracy', 'Naive Bayes'] = accuracy_score(y_pred = y_pred, y_true = y_test)
metric.loc['precision', 'Naive Bayes'] = precision_score(y_pred = y_pred, y_true = y_test)
metric.loc['recall', 'Naive Bayes'] = recall_score(y_pred = y_pred, y_true = y_test)
```

```
[[3854 849]
[556 741]]
0.76583333333333334
```

#### In [39]:

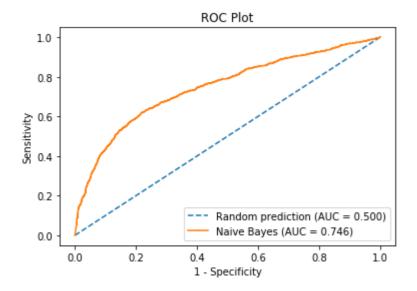
```
matrix = plot_confusion_matrix(NBC, X_test, y_test, values_format = 'd', cmap = plt.cm.Blue
matrix.ax_.set_title('Confusion Matrix', color = 'black')
plt.xlabel('Predicted Label', color = 'black')
plt.ylabel('True Label', color = 'black')
plt.gcf().axes[0].tick_params(color = 'black')
plt.gcf().axes[1].tick_params(color = 'black')
plt.gcf().set_size_inches(8, 5)
plt.show()
```



#### In [40]:

```
r_probs = [0 for _ in range(len(y_test))]
NB_probs = NBC.predict_proba(X_test)
NB_probs = NB_probs[:, 1]
from sklearn.metrics import roc_curve, roc_auc_score
r_auc = roc_auc_score(y_test, r_probs)
NB_auc = roc_auc_score(y_test, NB_probs)
print('Random (chance) Prediction: AUC = %.3f' % (r_auc))
print('Naive Bayes: AUC = %.3f' % (NB_auc))
r_fpr, r_tpr, _ = roc_curve(y_test, r_probs)
NB_fpr, NB_tpr, _ = roc_curve(y_test, NB_probs)
plt.plot(r_fpr, r_tpr, linestyle='--', label='Random prediction (AUC = %0.3f)' % r_auc)
plt.plot(NB_fpr, NB_tpr, marker=',', label='Naive Bayes (AUC = %0.3f)' % NB_auc)
# Title
plt.title('ROC Plot')
# Axis labels
plt.xlabel('1 - Specificity')
plt.ylabel('Sensitivity')
# Show Legend
plt.legend() #
# Show plot
plt.show()
```

Random (chance) Prediction: AUC = 0.500 Naive Bayes: AUC = 0.746



## **Neural Network Classifier**

#### In [41]:

```
# Training the Naive Bayes model on the Training set
from sklearn.neural_network import MLPClassifier
NNC = MLPClassifier(solver='sgd', alpha=1e-5)
NNC.fit(X_train, y_train)
```

### Out[41]:

```
MLPClassifier(activation='relu', alpha=1e-05, batch_size='auto', beta_1=0.9, beta_2=0.999, early_stopping=False, epsilon=1e-08, hidden_layer_sizes=(100,), learning_rate='constant', learning_rate_init=0.001, max_fun=15000, max_iter=200, momentum=0.9, n_iter_no_change=10, nesterovs_momentum=True, power_t=0.5, random_state=None, shuffle=True, solver='sgd', tol=0.0001, validation_fraction=0.1, verbose=False, warm_start=False)
```

#### In [42]:

```
# Predicting the Test set results
y_pred = NNC.predict(X_test)
```

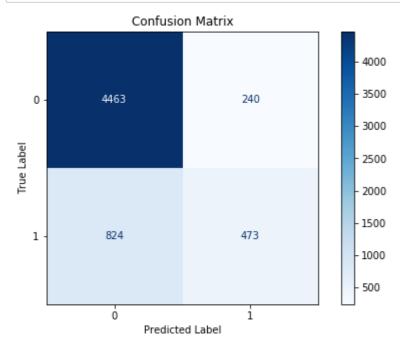
#### In [43]:

```
# Making the Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy = accuracy_score(y_test, y_pred)
print(accuracy)
metric.loc['accuracy', 'Neural Network'] = accuracy_score(y_pred = y_pred, y_true = y_test)
metric.loc['precision', 'Neural Network'] = precision_score(y_pred = y_pred, y_true = y_test)
metric.loc['recall', 'Neural Network'] = recall_score(y_pred = y_pred, y_true = y_test)
```

```
[[4463 240]
[824 473]]
0.82266666666666667
```

#### In [44]:

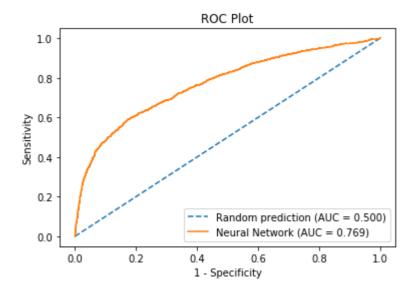
```
matrix = plot_confusion_matrix(NNC, X_test, y_test, values_format = 'd', cmap = plt.cm.Blue
matrix.ax_.set_title('Confusion Matrix', color = 'black')
plt.xlabel('Predicted Label', color = 'black')
plt.ylabel('True Label', color = 'black')
plt.gcf().axes[0].tick_params(color = 'black')
plt.gcf().axes[1].tick_params(color = 'black')
plt.gcf().set_size_inches(8, 5)
plt.show()
```



#### In [45]:

```
r_probs = [0 for _ in range(len(y_test))]
NN_probs = NNC.predict_proba(X_test)
NN_probs = NN_probs[:, 1]
from sklearn.metrics import roc_curve, roc_auc_score
r_auc = roc_auc_score(y_test, r_probs)
NN_auc = roc_auc_score(y_test, NN_probs)
print('Random (chance) Prediction: AUC = %.3f' % (r_auc))
print('Neural Network: AUC = %.3f' % (NN_auc))
r_fpr, r_tpr, _ = roc_curve(y_test, r_probs)
NN_fpr, NN_tpr, _ = roc_curve(y_test, NN_probs)
plt.plot(r_fpr, r_tpr, linestyle='--', label='Random prediction (AUC = %0.3f)' % r_auc)
plt.plot(NN_fpr, NN_tpr, marker=',', label='Neural Network (AUC = %0.3f)' % NN_auc)
# Title
plt.title('ROC Plot')
# Axis labels
plt.xlabel('1 - Specificity')
plt.ylabel('Sensitivity')
# Show Legend
plt.legend() #
# Show plot
plt.show()
```

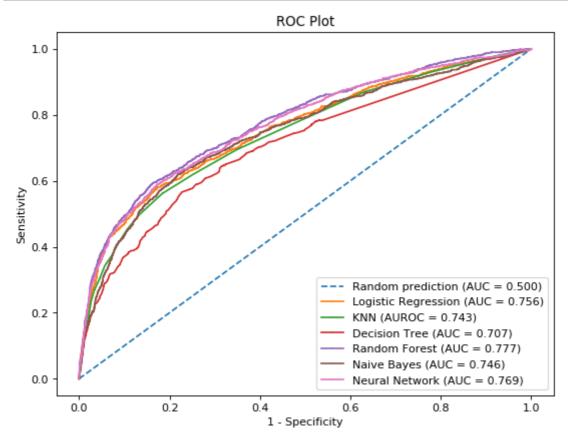
Random (chance) Prediction: AUC = 0.500 Neural Network: AUC = 0.769



# **Models comparison**

#### In [48]:

```
from matplotlib.pyplot import figure
figure(num=None, figsize=(8, 6), dpi=80, facecolor='w', edgecolor='k')
plt.plot(r_fpr, r_tpr, linestyle='--', label='Random prediction (AUC = %0.3f)' % r_auc)
plt.plot(LR_fpr, LR_tpr, marker=',', label='Logistic Regression (AUC = %0.3f)' % LR_auc) plt.plot(KNN_fpr, KNN_tpr, marker=',', label='KNN (AUROC = %0.3f)' % KNN_auc)
plt.plot(DT_fpr, DT_tpr, marker=',', label='Decision Tree (AUC = %0.3f)' % DT_auc)
plt.plot(RF_fpr, RF_tpr, marker=',', label='Random Forest (AUC = %0.3f)' % RF_auc) plt.plot(NB_fpr, NB_tpr, marker=',', label='Naive Bayes (AUC = %0.3f)' % NB_auc)
plt.plot(NN fpr, NN tpr, marker=',', label='Neural Network (AUC = %0.3f)' % NN auc)
# Title
plt.title('ROC Plot')
# Axis labels
plt.xlabel('1 - Specificity')
plt.ylabel('Sensitivity')
# Show Legend
plt.legend() #
# Show plot
plt.show()
```



## In [47]:

100\*metric

## Out[47]:

	Logistic Regression	KNN	Decision Tree	Random Forest	Naive Bayes	Neural Network
accuracy	82.0667	81.3833	78.7333	82.7833	76.5833	82.2667
precision	69.0189	64.9502	51.1278	69.242	46.6038	66.3394
recall	30.9175	30.1465	36.7001	36.623	57.1318	36.4688