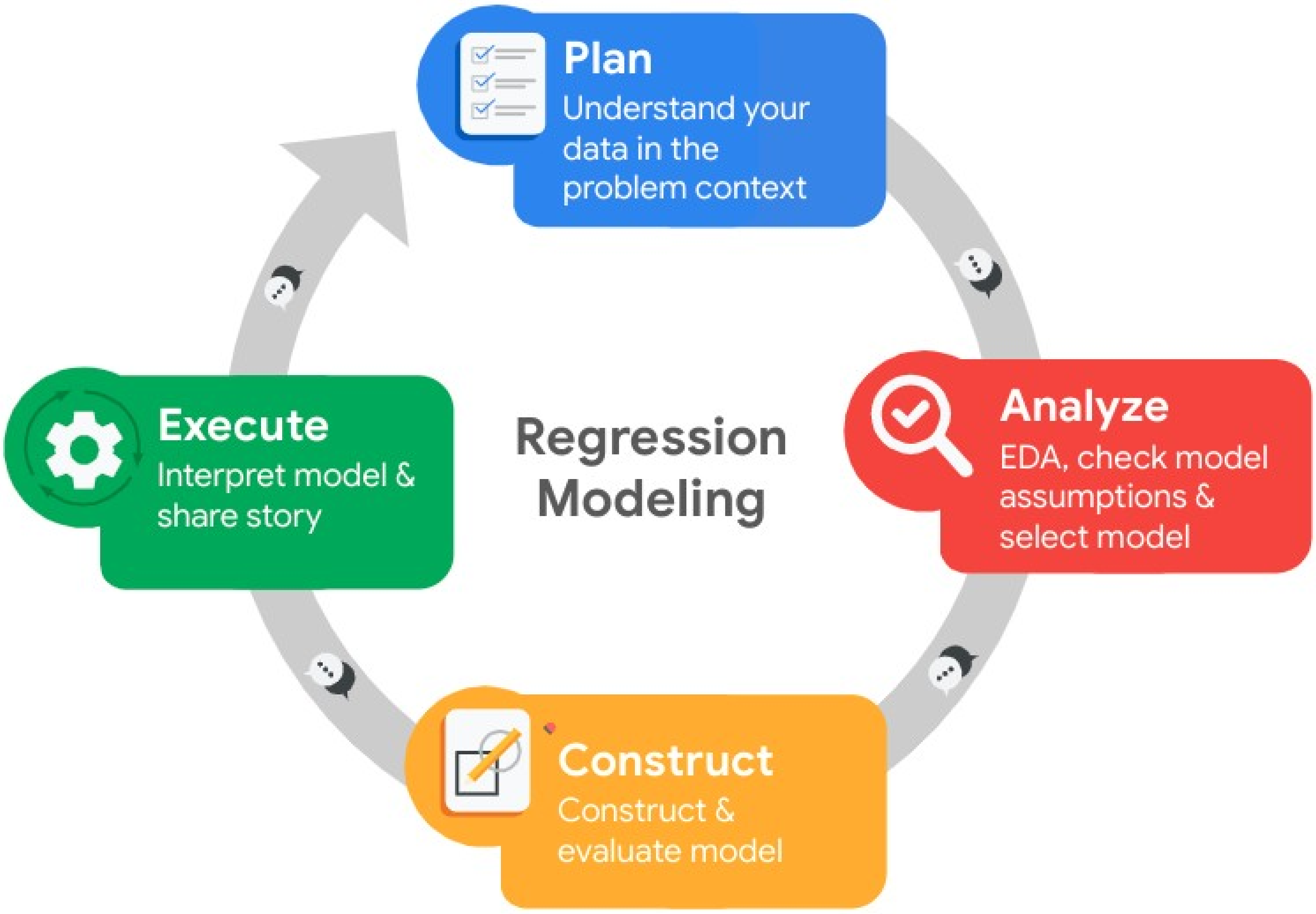
PACE Stages: The Project Framework



Pace: Plan Stage

Case Study Introduction:

The modeling objective is to build and test a classification model that uses banking data to predict whether a customer will churn.

If a customer churns, it means they left the bank and took their business elsewhere. If we can predict customers who are likely to churn, we can take measures to retain them before they do.

These measures could be promotions, discounts, or other incentives to boost customer satisfaction and, therefore, retention.

Our data dictionary shows that there is a column called Exited. This is a Boolean value that indicates whether or not a customer left the bank (0 = did not leave, 1 = did leave)

This will be our target variable. In other words, for each customer, our model should predict whether he should have a 0 or a 1 in the Exited column.

Upon that, We conclude the key considerations in the following points:

Modeling objective: To predict whether a customer will churn—a binary classification task.

Target variable: `Exited` column—0 or 1.

Class balance: The data is imbalanced 80/20 (not churned/churned).

Primary evaluation metric: F1 score.

Modeling workflow and model selection: The champion model will be the model with the best validation F1 score.

Step 1. Imports

```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

from imblearn.over_sampling import SMOTE
from collections import Counter

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import recall_score, precision_score, f1_score, accuracy_score, roc_auc_score,\
                            ConfusionMatrixDisplay, confusion_matrix, RocCurveDisplay
```

```python
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier, plot_importance

import warnings
warnings.filterwarnings('ignore')

# This module lets us save our models once we fit them.
import pickle

# This lets us see all of the columns, preventing Juptyer from redacting them.
pd.set_option('display.max_columns', None)
```

Step 2. Data Exploration (Initial EDA and data cleaning)

Gather basic information about the data

```python
original_df = pd.read_csv(r"D:\Google Advanced Data Analytics\Nuts & Bolts of Machine Learning\
Churn_Modelling.csv")
original_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   RowNumber        10000 non-null  int64
 1   CustomerId       10000 non-null  int64
 2   Surname          10000 non-null  object
 3   CreditScore      10000 non-null  int64
 4   Geography        10000 non-null  object
 5   Gender           10000 non-null  object
 6   Age              10000 non-null  int64
 7   Tenure           10000 non-null  int64
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64
 10  HasCrCard        10000 non-null  int64
 11  IsActiveMember   10000 non-null  int64
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

Gather descriptive statistics about the data

```python
original_df.describe(include= "all")
```

```
          RowNumber    CustomerId Surname   CreditScore Geography Gender  \
count   10000.00000  1.000000e+04   10000  10000.000000     10000  10000
unique          NaN           NaN    2932           NaN         3      2
top             NaN           NaN   Smith           NaN    France   Male
freq            NaN           NaN      32           NaN      5014   5457
mean     5000.50000  1.569094e+07     NaN    650.528800       NaN    NaN
std      2886.89568  7.193619e+04     NaN     96.653299       NaN    NaN
min         1.00000  1.556570e+07     NaN    350.000000       NaN    NaN
25%      2500.75000  1.562853e+07     NaN    584.000000       NaN    NaN
50%      5000.50000  1.569074e+07     NaN    652.000000       NaN    NaN
75%      7500.25000  1.575323e+07     NaN    718.000000       NaN    NaN
max     10000.00000  1.581569e+07     NaN    850.000000       NaN    NaN

                Age        Tenure        Balance  NumOfProducts    HasCrCard  \
count  10000.000000  10000.000000   10000.000000   10000.000000  10000.00000
unique          NaN           NaN            NaN            NaN          NaN
top             NaN           NaN            NaN            NaN          NaN
freq            NaN           NaN            NaN            NaN          NaN
mean      38.921800      5.012800   76485.889288       1.530200      0.70550
std       10.487806      2.892174   62397.405202       0.581654      0.45584
min       18.000000      0.000000       0.000000       1.000000      0.00000
25%       32.000000      3.000000       0.000000       1.000000      0.00000
50%       37.000000      5.000000   97198.540000       1.000000      1.00000
75%       44.000000      7.000000  127644.240000       2.000000      1.00000
max       92.000000     10.000000  250898.090000       4.000000      1.00000

        IsActiveMember  EstimatedSalary        Exited
count     10000.000000     10000.000000  10000.000000
unique             NaN              NaN           NaN
top                NaN              NaN           NaN
freq               NaN              NaN           NaN
mean          0.515100    100090.239881      0.203700
std           0.499797     57510.492818      0.402769
min           0.000000        11.580000      0.000000
25%           0.000000     51002.110000      0.000000
50%           1.000000    100193.915000      0.000000
75%           1.000000    149388.247500      0.000000
max           1.000000    199992.480000      1.000000
```

Check missing values

```
original_df.isna().sum()
```

```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

Check duplicates

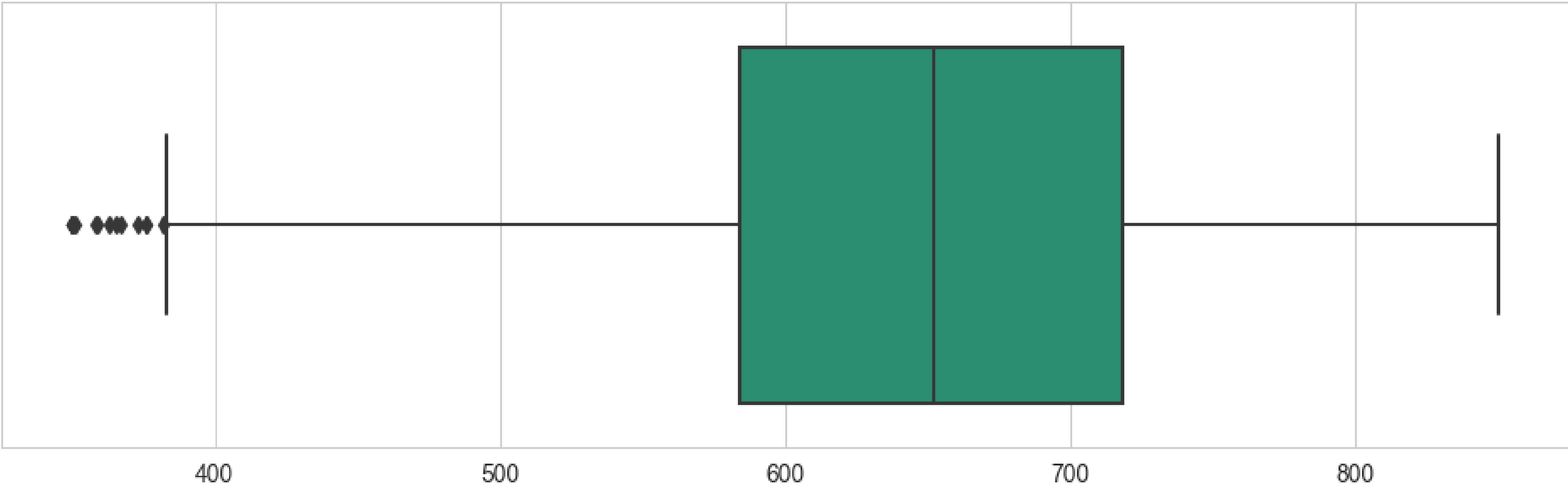
```
original_df.duplicated().sum()
```

```
0
```

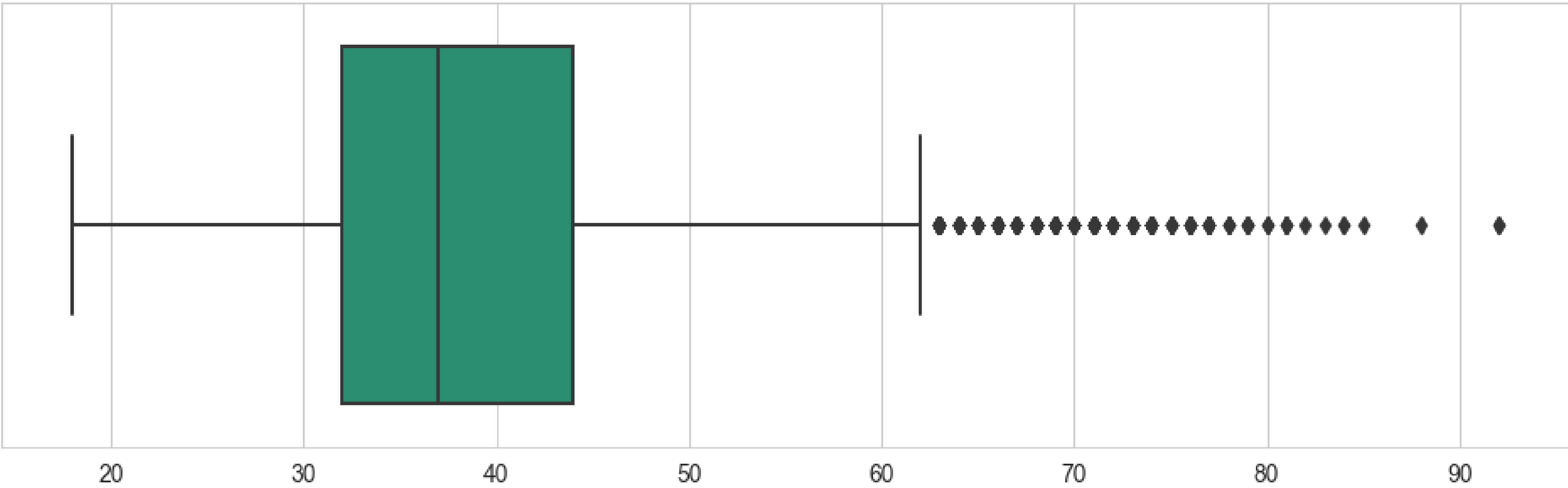
Check outliers

```
sns.set_style("whitegrid")
sns.set_palette("Dark2")

fig, ax = plt.subplots(6, 1, figsize= (12, 24))

sns.boxplot(x= original_df["CreditScore"], showfliers= True, ax= ax[0])
ax[0].set_title("Distribution of Credit Scores", fontsize= 12, fontweight= "bold")
ax[0].set_xlabel("")

sns.boxplot(x= original_df["Age"], showfliers= True, ax= ax[1])
ax[1].set_title("Distribution of Ages", fontsize= 12, fontweight= "bold")
ax[1].set_xlabel("")

sns.boxplot(x= original_df["Tenure"], showfliers= True, ax= ax[2])
ax[2].set_title("Distribution of Customers' Tenure", fontsize= 12, fontweight= "bold")
ax[2].set_xlabel("")

sns.boxplot(x= original_df["Balance"], showfliers= True, ax= ax[3])
ax[3].set_title("Distribution of Customers' Balance", fontsize= 12, fontweight= "bold")
ax[3].set_xlabel("")

sns.boxplot(x= original_df["NumOfProducts"], showfliers= True, ax= ax[4])
ax[4].set_title("Distribution of Products' Number", fontsize= 12, fontweight= "bold")
ax[4].set_xlabel("")

sns.boxplot(x= original_df["EstimatedSalary"], showfliers= True, ax= ax[5])
ax[5].set_title("Distribution of Customers' Estimated Salaries", fontsize= 12, fontweight= "bold")
ax[5].set_xlabel("")

plt.show()
```

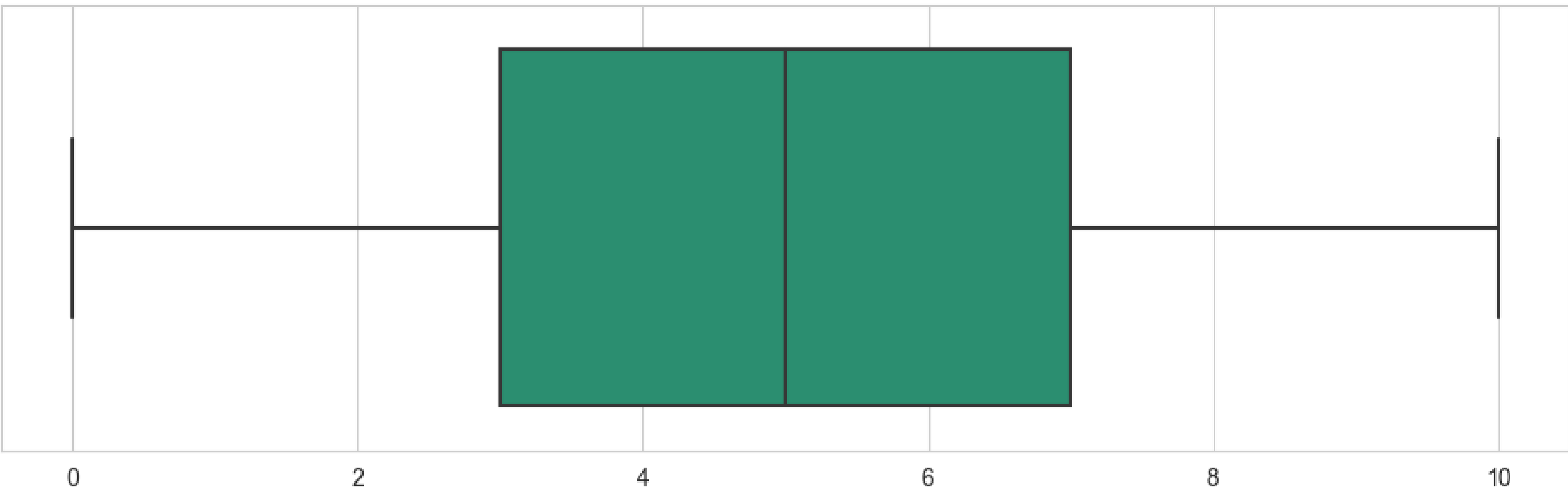
Distribution of Credit Scores



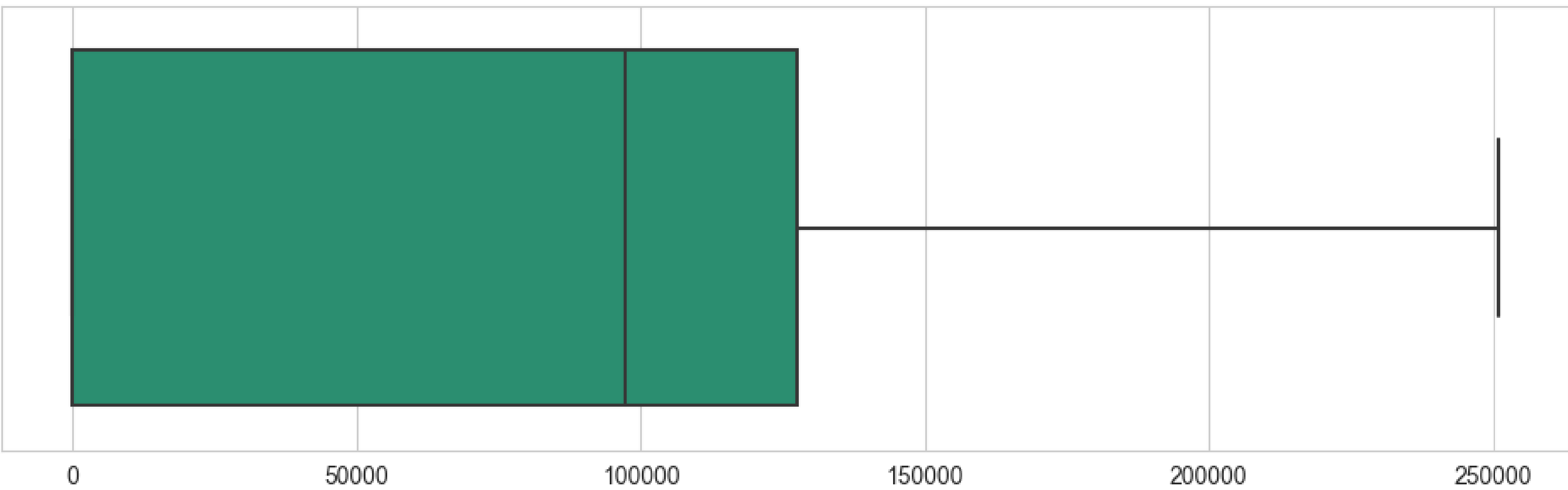
Distribution of Ages



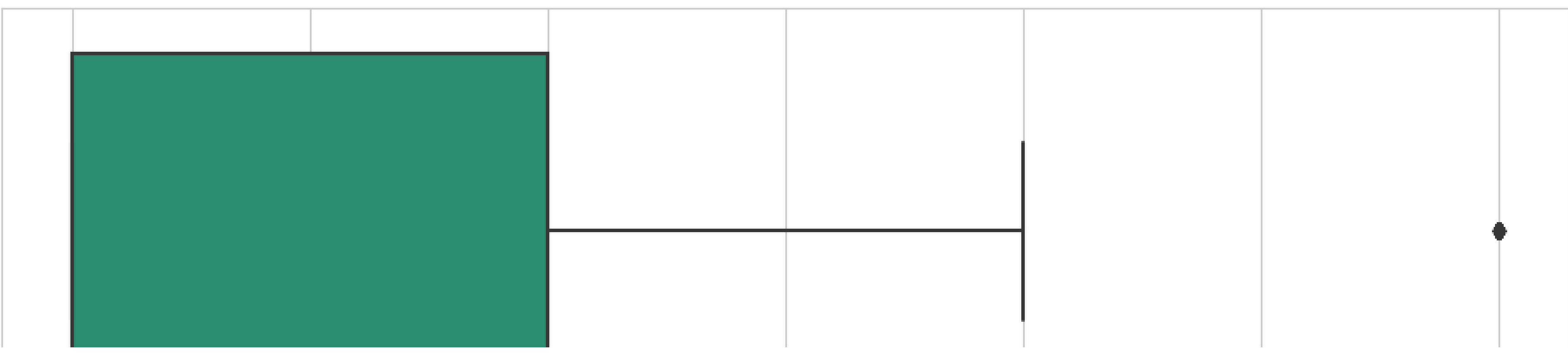
Distribution of Customers' Tenure



Distribution of Customers' Balance



Distribution of Products' Number



```python
def num_outliers(column_name:str):
    percentile_25 = original_df[column_name].quantile(0.25)
    percentile_75 = original_df[column_name].quantile(0.75)
    iqr = percentile_75 - percentile_25
    upper_limit = percentile_75 + 1.5 * iqr
    lower_limit = percentile_25 - 1.5 * iqr
    num_outliers = len(original_df[(original_df[column_name] > upper_limit) | (original_df[column_name] <
lower_limit)])

    print("Upper Limit =", upper_limit)
    print("Lower Limit =", lower_limit)
    print("Number of outliers =", num_outliers)
```

```python
num_outliers("CreditScore")
```

```
Upper Limit = 919.0
Lower Limit = 383.0
Number of outliers = 15
```

```python
num_outliers("Age")
```

```
Upper Limit = 62.0
Lower Limit = 14.0
Number of outliers = 359
```

```python
num_outliers("NumOfProducts")
```

```
Upper Limit = 3.5
Lower Limit = -0.5
Number of outliers = 60
```

pAce: Analyze Stage

Step 2. Data Exploration (Continue EDA)

```python
original_df.groupby(["Exited"])[["CreditScore", "Age", "Tenure", "Balance", "NumOfProducts", "HasCrCard",
"IsActiveMember", "EstimatedSalary"]].median(numeric_only= True)
```

```
        CreditScore   Age  Tenure    Balance  NumOfProducts  HasCrCard  \
Exited
0             653.0  36.0     5.0   92072.68            2.0        1.0
1             646.0  45.0     5.0  109349.29            1.0        1.0

        IsActiveMember  EstimatedSalary
Exited
0                  1.0         99645.04
1                  0.0        102460.84
```

From the above grouping, we notice the following:

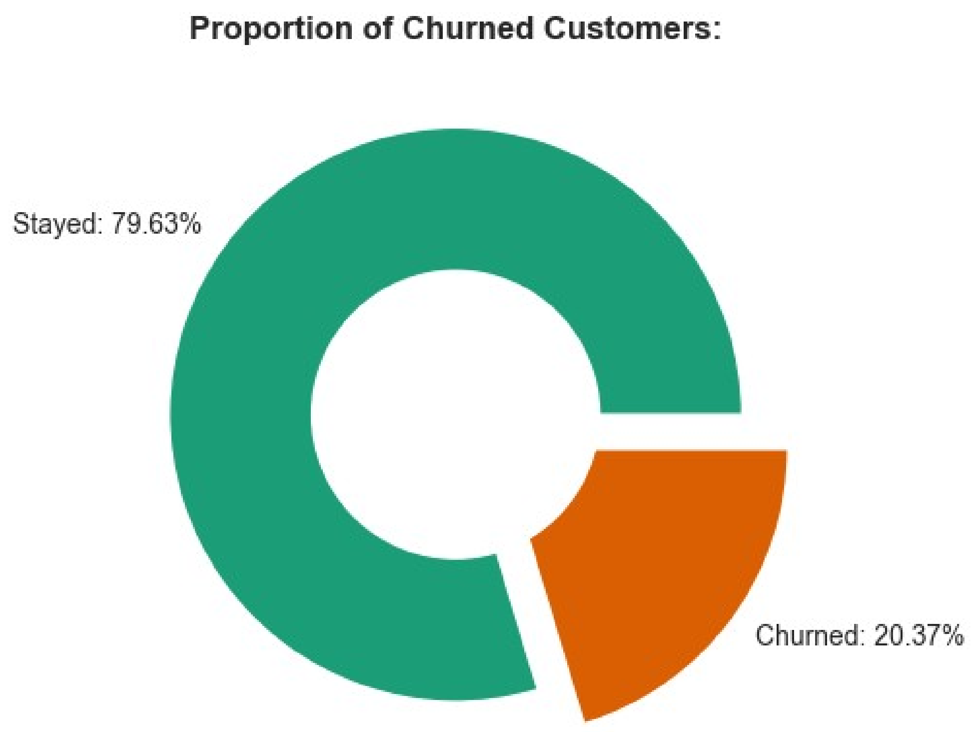
1. on median the churned customer has less credit score with 7 points than the retained customer, given that the credit score ranges between 350 to 850 points.
2. on median the churned customer ages 9 years older than the retained customer.
3. on median the churned customer has almost 18000 dollars on their balance greater than the retained customer.

Data Visualizations 1: Proportions

```python
original_df["Exited"].value_counts(normalize= True) * 100
```

```
0    79.63
1    20.37
Name: Exited, dtype: float64
```

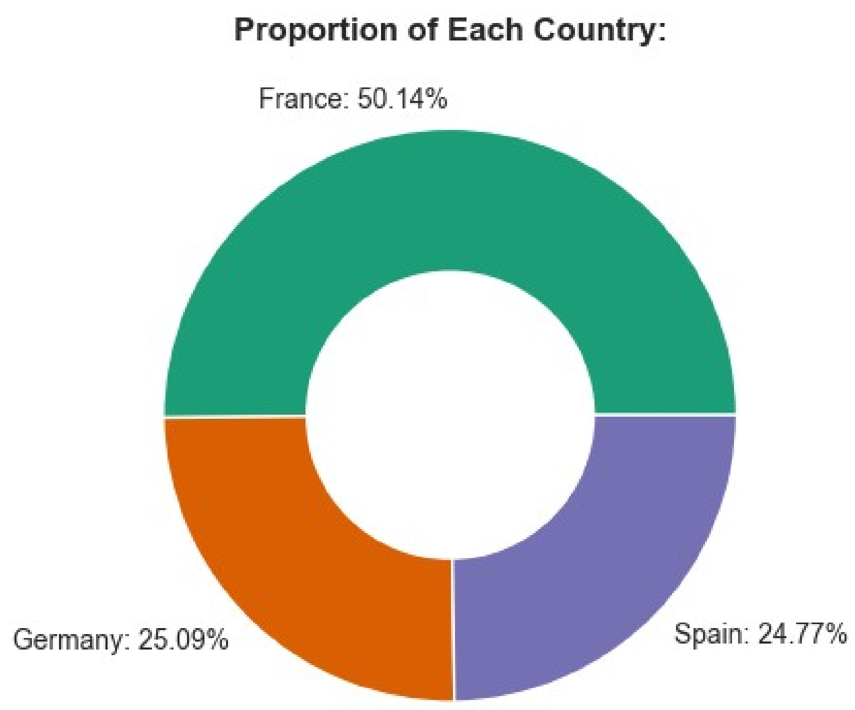
```python
plt.pie(original_df["Exited"].value_counts(), labels= ["Stayed: 79.63%", "Churned: 20.37%"], explode= [0, 0.2])
my_circle = plt.Circle( (0,0), 0.5, color= 'white')
p= plt.gcf()
p.gca().add_artist(my_circle)

plt.title("Proportion of Churned Customers:", fontweight= "bold")
plt.show()
```




```
original_df["Geography"].value_counts(normalize= True) * 100
```

```
France     50.14
Germany    25.09
Spain      24.77
Name: Geography, dtype: float64
```

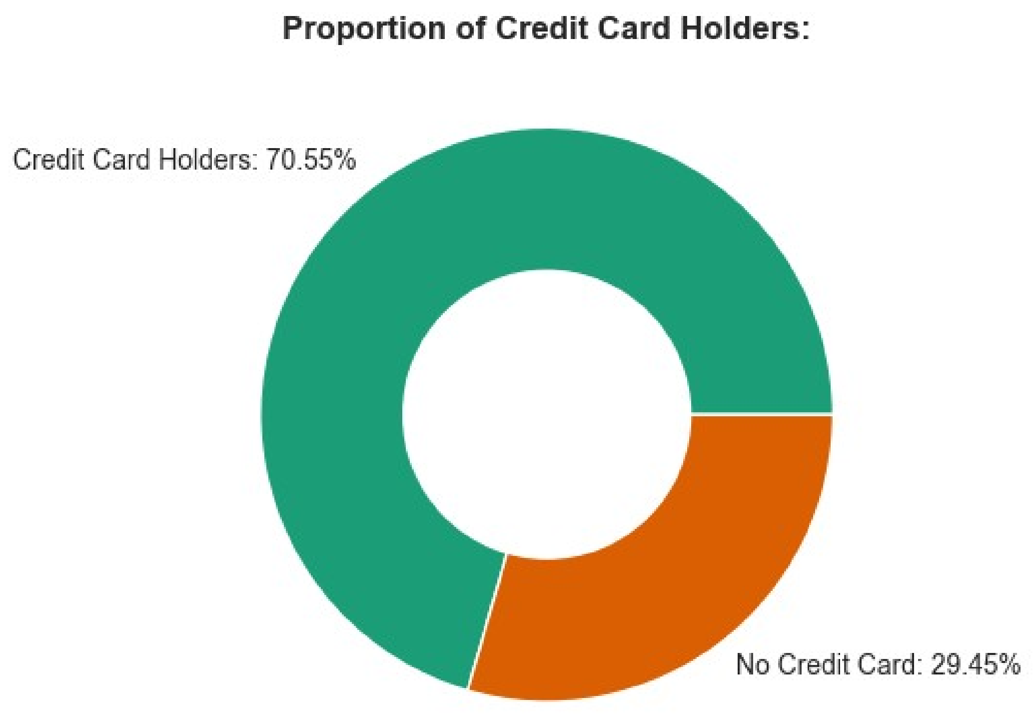
```
plt.pie(original_df["Geography"].value_counts(), labels= ["France: 50.14%", "Germany: 25.09%", "Spain: 24.77%"])
my_circle = plt.Circle( (0,0), 0.5, color= 'white')
p= plt.gcf()
p.gca().add_artist(my_circle)

plt.title("Proportion of Each Country:", fontweight= "bold")
plt.show()
```




```
original_df["HasCrCard"].value_counts(normalize= True) * 100
```

```
1    70.55
0    29.45
Name: HasCrCard, dtype: float64
```

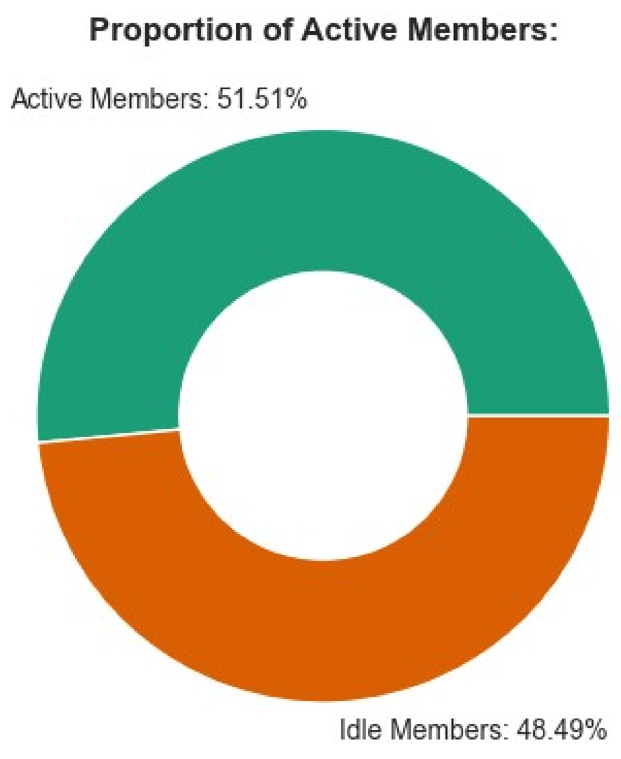
```
plt.pie(original_df["HasCrCard"].value_counts(), labels= ["Credit Card Holders: 70.55%", "No Credit Card: 29.45%"])
my_circle = plt.Circle( (0,0), 0.5, color= 'white')
p= plt.gcf()
p.gca().add_artist(my_circle)

plt.title("Proportion of Credit Card Holders:", fontweight= "bold")
plt.show()
```




```
original_df["IsActiveMember"].value_counts(normalize= True) * 100
```

```
1    51.51
0    48.49
Name: IsActiveMember, dtype: float64
```

```
plt.pie(original_df["IsActiveMember"].value_counts(), labels= ["Active Members: 51.51%", "Idle Members: 48.49%"])
my_circle = plt.Circle( (0,0), 0.5, color= 'white')
p= plt.gcf()
p.gca().add_artist(my_circle)

plt.title("Proportion of Active Members:", fontweight= "bold")
plt.show()
```

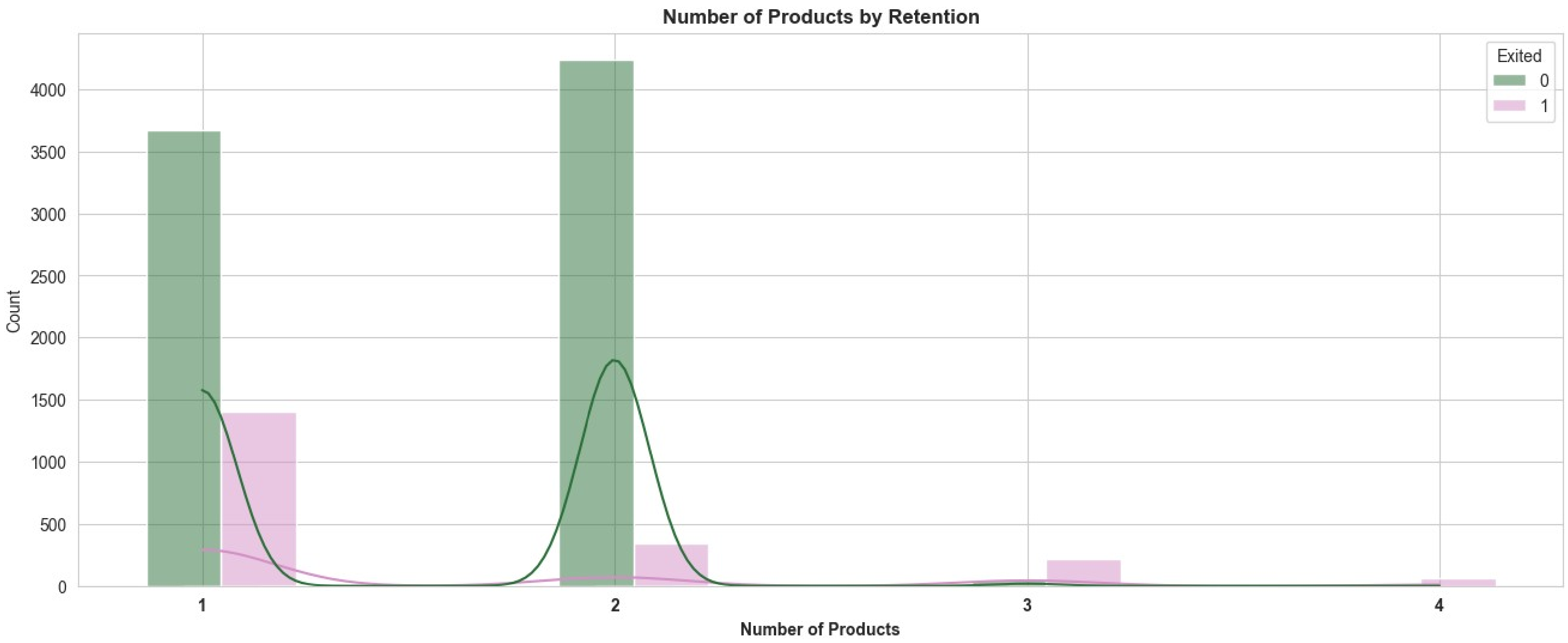


Data Visualizations 2: Relationships

```
original_df["NumOfProducts"].value_counts(normalize= True) * 100
```

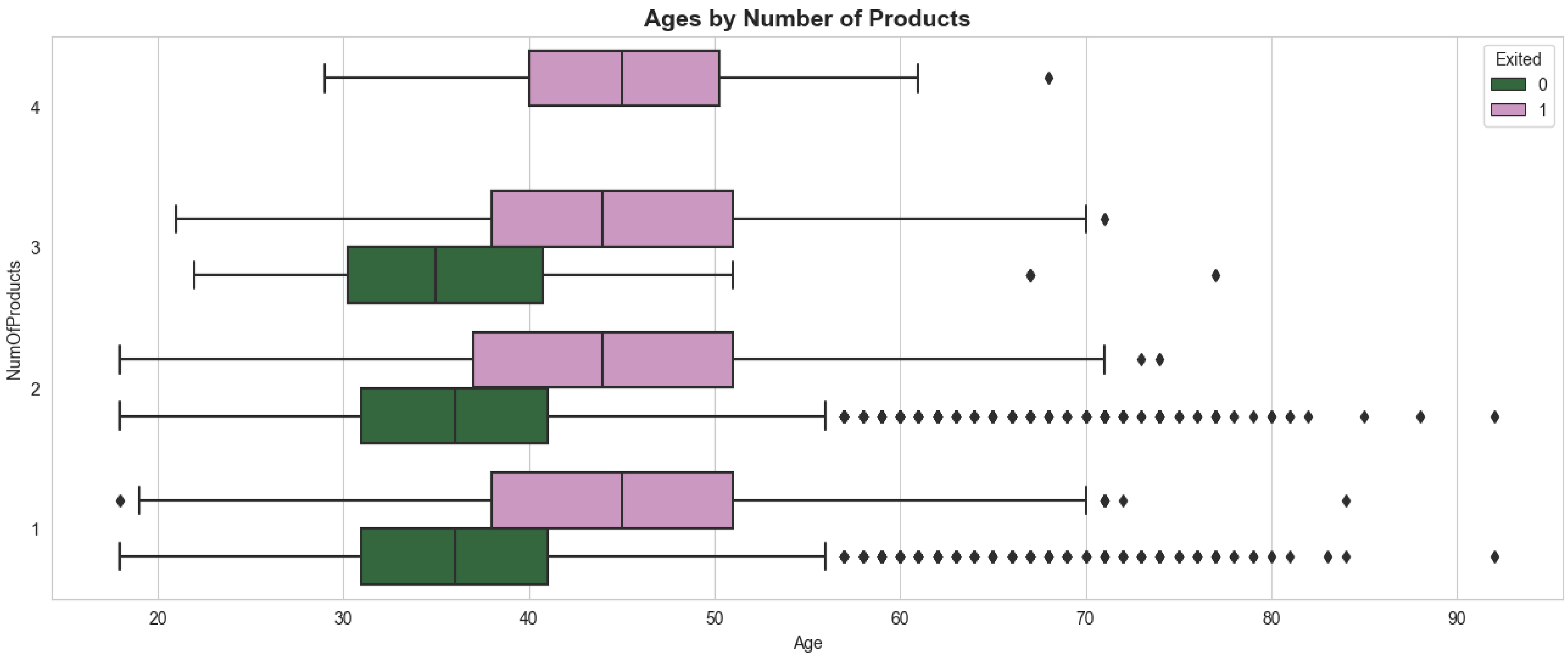
```
1    50.84
2    45.90
3     2.66
4     0.60
Name: NumOfProducts, dtype: float64
```

```
plt.figure(figsize= (16, 6))
sns.histplot(data= original_df, x= "NumOfProducts", shrink= 4, hue= "Exited", multiple= "dodge", palette= "cubehelix", kde= True)
plt.title("Number of Products by Retention", fontsize= 12, fontweight= "bold")

plt.xlabel("Number of Products", fontsize= 10, fontweight= "bold")
plt.xticks([1, 2, 3, 4], fontweight= "bold")
plt.show()
```



It's obvious from the above histogram that proportion of customers who have more than 2 products is less than 5% of all customers, and that percentage of churned customers who have 2 products is less than those who have only one product, let's explore than further regarding the customers' age and balance.

```
plt.figure(figsize= (16, 6))
box = sns.boxplot(data= original_df, x= 'Age', y= 'NumOfProducts', hue= 'Exited', orient="h", palette=
"cubehelix")
box.invert_yaxis()

plt.title("Ages by Number of Products", fontsize= 14, fontweight= "bold")
plt.show()
```



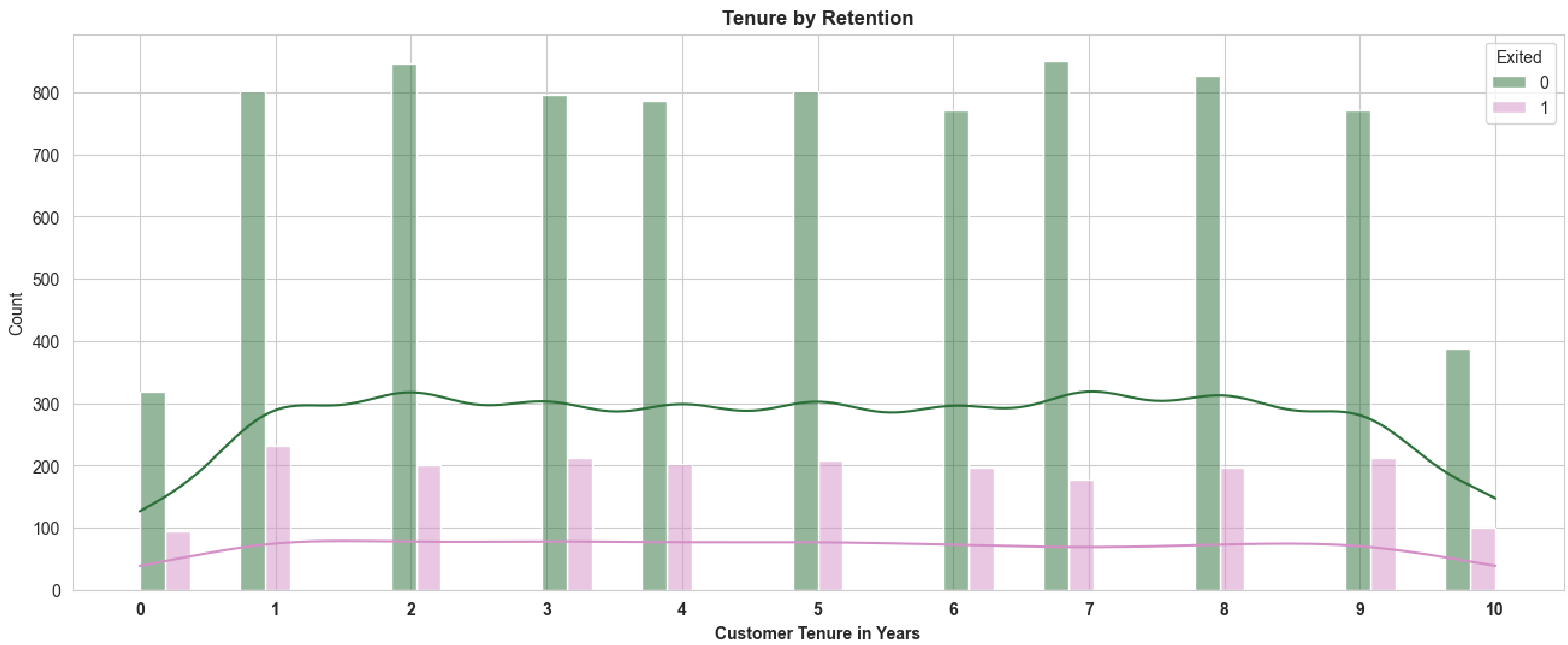
From the above boxplots, we conclude that the median age of retained customers is 36 years, while that of churned customers is 45 years.

```
plt.figure(figsize= (16, 6))
box = sns.boxplot(data= original_df, x= 'Balance', y= 'NumOfProducts', hue= 'Exited', orient="h", palette=
"cubehelix")
box.invert_yaxis()

plt.title("Customers' Balance by Number of Products", fontsize= 14, fontweight= "bold")
plt.show()
```


```
original_df["Tenure"].value_counts(normalize= True) * 100
```

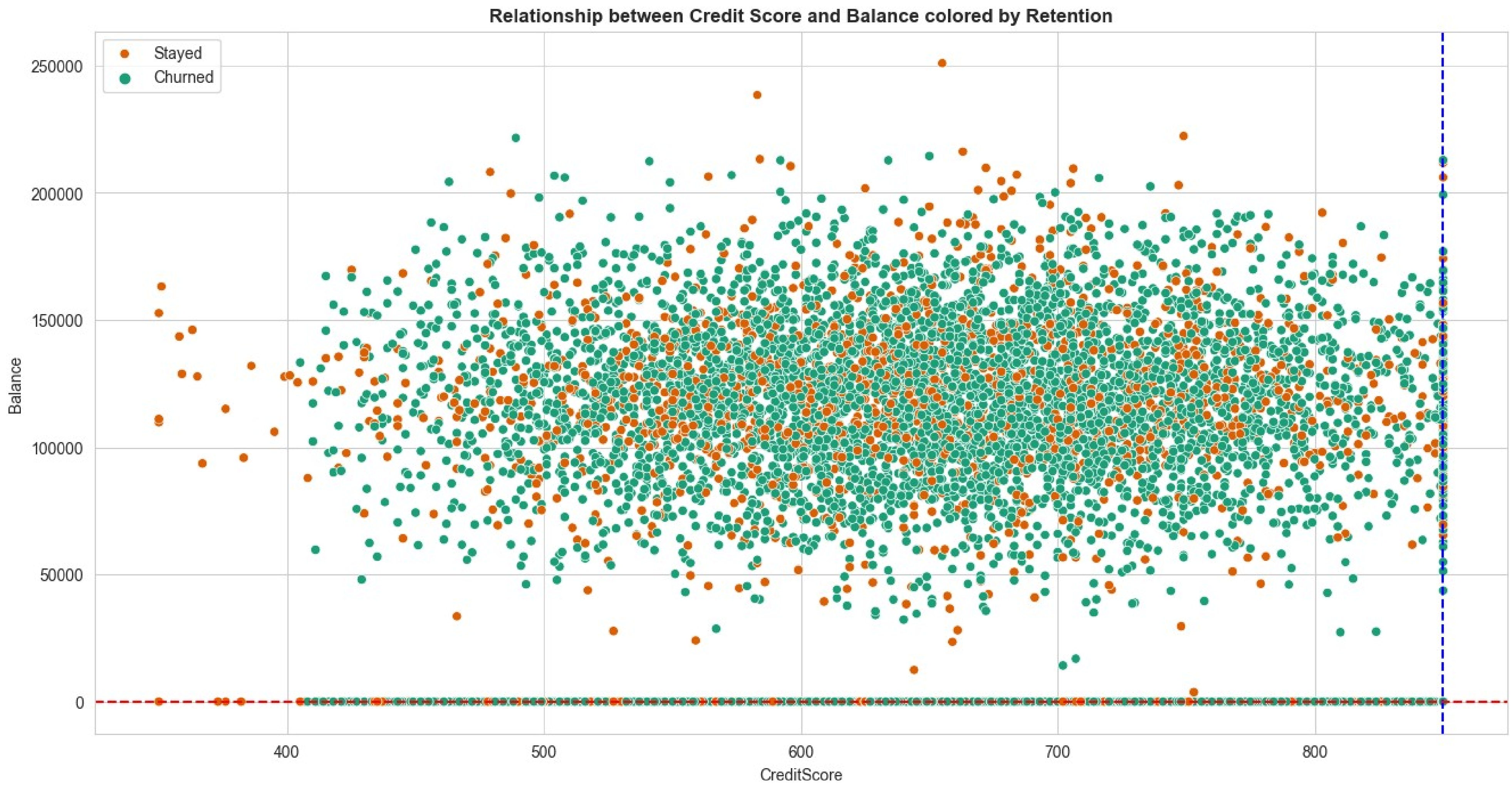
```
2     10.48
1     10.35
7     10.28
8     10.25
5     10.12
3     10.09
4      9.89
9      9.84
6      9.67
10     4.90
0      4.13
Name: Tenure, dtype: float64
```

```
plt.figure(figsize= (16, 6))
sns.histplot(data= original_df, x= "Tenure", hue= "Exited", multiple= "dodge", palette= "cubehelix", kde= True)
plt.title("Tenure by Retention", fontsize= 12, fontweight= "bold")

plt.xlabel("Customer Tenure in Years", fontsize= 10, fontweight= "bold")
plt.xticks(range(0, 11), fontweight= "bold")
plt.show()
```



The homogeneous distribution of customers' tenure is obvious, however the proportion of churned customers are roughly stable across all tenures.

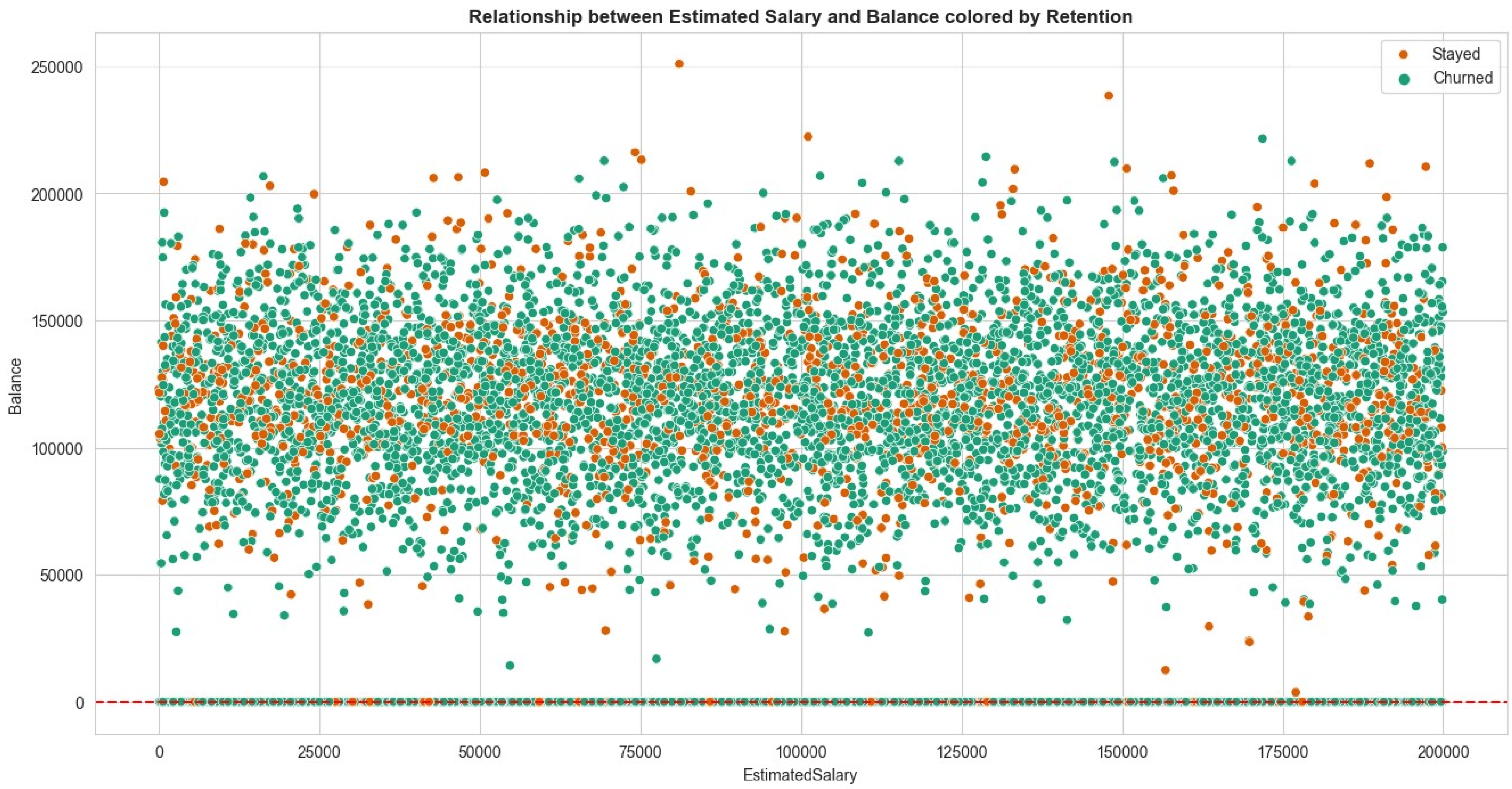
```
plt.figure(figsize= (16, 8))
sns.scatterplot(data= original_df, x= "CreditScore", y= "Balance", hue= "Exited")
plt.title("Relationship between Credit Score and Balance colored by Retention", fontsize= 12, fontweight=
"bold")

plt.axvline(x= 850, color= "blue", ls= "dashed")
plt.axhline(y= 0, color= "red", ls= "dashed")
plt.legend(["Stayed", "Churned"])
plt.show()
```



From the above scatter plot, we can draw 3 conclusions, which are:

1. Churned customers are distributed across all credit scores and account balance.
2. There are considerable proportion of customers who have a balance of Zero.
3. There are many customers have the full credit score of 850 points.

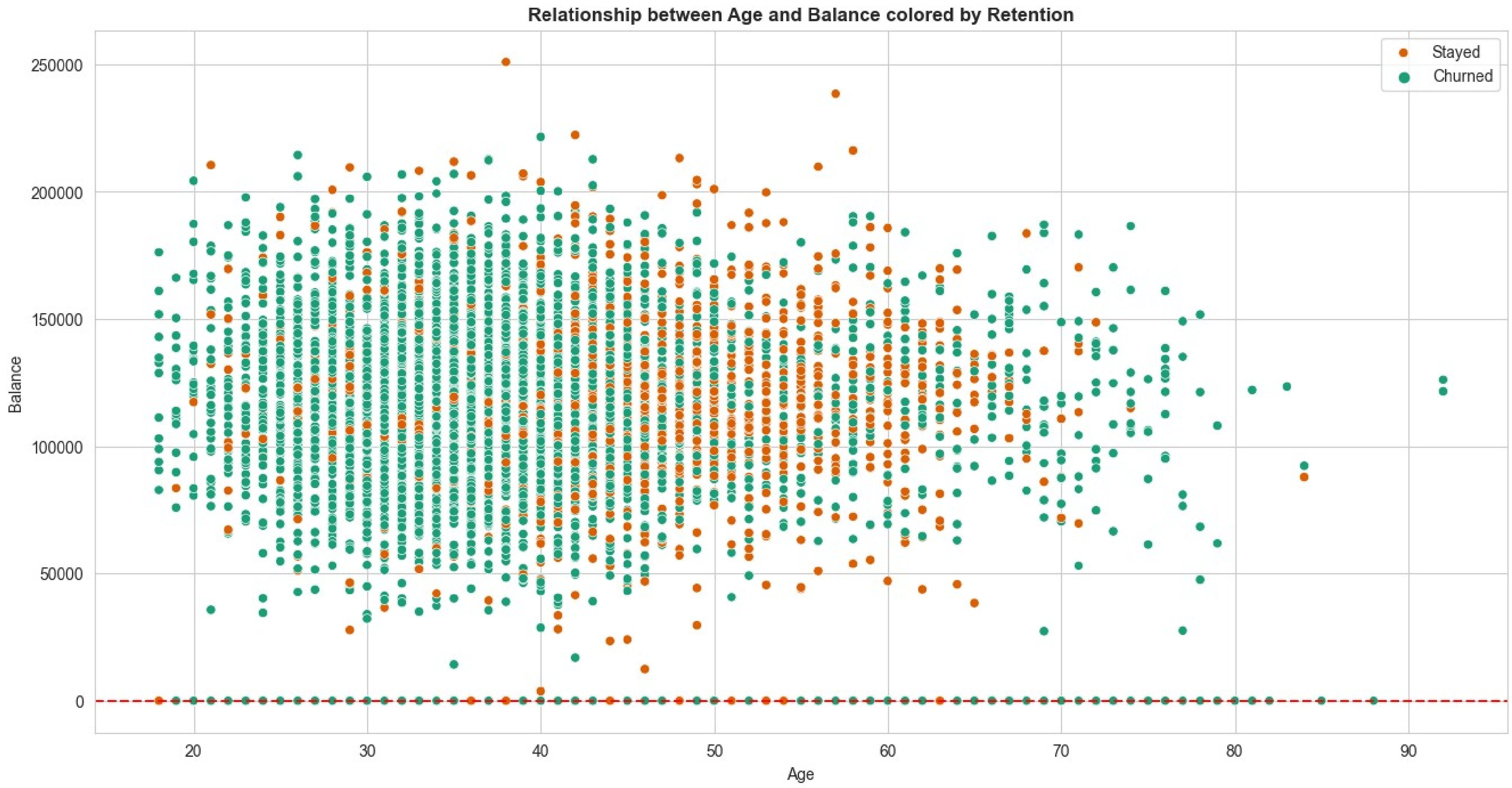
```
plt.figure(figsize= (16, 8))
sns.scatterplot(data= original_df, x= "EstimatedSalary", y= "Balance", hue= "Exited")
plt.title("Relationship between Estimated Salary and Balance colored by Retention", fontsize= 12, fontweight=
"bold")

plt.axhline(y= 0, color= "red", ls= "dashed")
plt.legend(["Stayed", "Churned"])
plt.show()
```



The estimated salary variable is distributed very homogeneously across customers, which may be a data collection error or due to data synthesis.

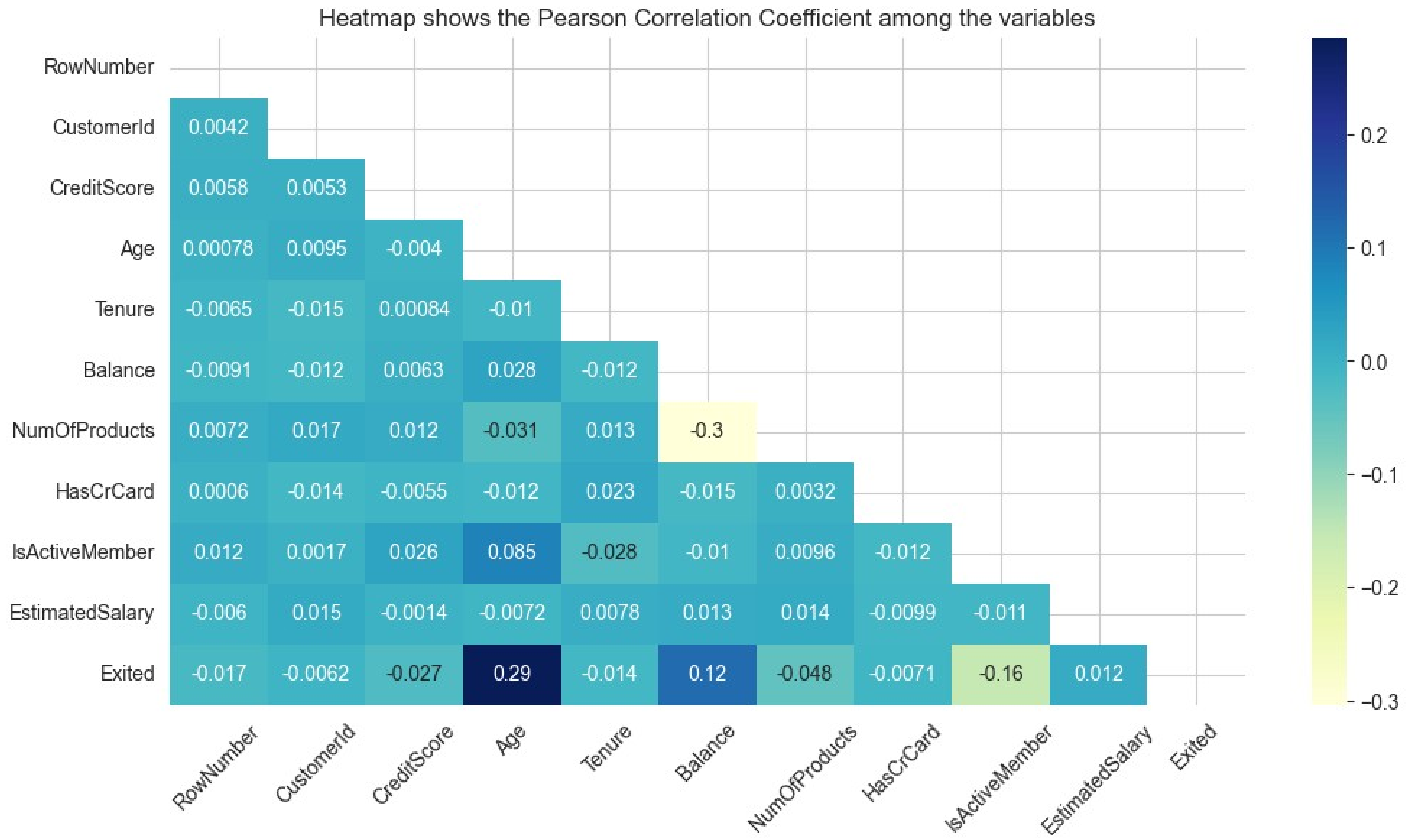
```
plt.figure(figsize= (16, 8))
sns.scatterplot(data= original_df, x= "Age", y= "Balance", hue= "Exited")
plt.title("Relationship between Age and Balance colored by Retention", fontsize= 12, fontweight= "bold")

plt.axhline(y= 0, color= "red", ls= "dashed")
```

```
plt.legend(["Stayed", "Churned"])
plt.show()
```



We can easily observe from the above scatter plot how proportion of churned customers increases with aging.

```
plt.figure(figsize= (12, 6))

mask_heatmap = np.triu(np.ones_like(original_df.corr(numeric_only= True)))
fig = sns.heatmap(data= original_df.corr(numeric_only= True), annot= True, cmap= "YlGnBu", mask= mask_heatmap)
fig.set_title("Heatmap shows the Pearson Correlation Coefficient among the variables")

plt.xticks(rotation= 45)
plt.show()
```



The heatmap shows a positive correlation between the target variable `Exited` and each of the `Age`and the `Balance` variables, while there is a negative correlation between the target variable and whether the customer is active or not. These assumptions is important before the modelling to understand relationships between the features.

```python
#The cost of every churned customer:
avg_churned_bal = round(original_df[original_df["Exited"] == 1]["Balance"].mean(), 2)
avg_churned_bal
```

```
91108.54
```

Feature Engineering:

Feature Extraction:

```python
original_df["Loyalty"] = round(original_df["Tenure"] / original_df["Age"] * 100, 2)
original_df["Loyalty"].describe()
```

```
count    10000.000000
mean        13.793457
std          8.950456
min          0.000000
25%          6.450000
50%         12.900000
75%         20.000000
max         55.560000
Name: Loyalty, dtype: float64
```

Feature Selection:

```python
churn_df = original_df.drop(["RowNumber", "CustomerId", "Surname", "Gender"], axis= 1)
churn_df.head(5)
```

```
   CreditScore Geography  Age  Tenure    Balance  NumOfProducts  HasCrCard  \
0          619    France   42       2       0.00              1          1
1          608     Spain   41       1   83807.86              1          0
2          502    France   42       8  159660.80              3          1
3          699    France   39       1       0.00              2          0
4          850     Spain   43       2  125510.82              1          1

   IsActiveMember  EstimatedSalary  Exited  Loyalty
0               1        101348.88       1     4.76
1               1        112542.58       0     2.44
2               0        113931.57       1    19.05
3               0         93826.63       0     2.56
4               1         79084.10       0     4.65
```

Feature Transformation:

```python
churn_df["Geography"].value_counts(normalize= True) * 100
```

```
France     50.14
Germany    25.09
Spain      24.77
Name: Geography, dtype: float64
```

```python
churn_df = pd.get_dummies(churn_df)
churn_df.head(5)
```

```
   CreditScore  Age  Tenure    Balance  NumOfProducts  HasCrCard  \
0          619   42       2       0.00              1          1
1          608   41       1   83807.86              1          0
2          502   42       8  159660.80              3          1
3          699   39       1       0.00              2          0
4          850   43       2  125510.82              1          1

   IsActiveMember  EstimatedSalary  Exited  Loyalty  Geography_France  \
0               1        101348.88       1     4.76                 1
1               1        112542.58       0     2.44                 0
2               0        113931.57       1    19.05                 1
3               0         93826.63       0     2.56                 1
4               1         79084.10       0     4.65                 0

   Geography_Germany  Geography_Spain
0                  0                0
1                  0                1
2                  0                0
3                  0                0
4                  0                1
```

paCe: Construct Stage

Modelling:

Splitting the data:

```python
y = churn_df["Exited"]

X = churn_df.copy()
X = churn_df.drop("Exited", axis= 1)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size= 0.25, stratify= y, random_state= 42)
```

Scaling the data:

Scaling the data based on their mean and standard deviation, since the naive bayes and logistic regression models requires this scaling to perform properly.

```
#Import the scaler function
from sklearn.preprocessing import StandardScaler

# Instantiate the scaler
scaler = StandardScaler()

# Fit the scaler to the training data
scaler.fit(X_train)

# Scale the training data
X_train = scaler.transform(X_train)

# Scale the test data
X_test = scaler.transform(X_test)
```

Oversampling the minority class:

Oversampling the class of churned customers from 20% to 60%, since the class imbalance problem often skews the model's predictions to the majority class.

```
# Initial class distribution in the training set
print("Original class distribution in training set:", Counter(y_train))

# Apply SMOTE to oversample the minority class in the training set
smote = SMOTE(sampling_strategy= 0.6, random_state= 42)
X_resampled, y_resampled = smote.fit_resample(X_train, y_train)

# New class distribution after resampling
print("Resampled class distribution in training set:", Counter(y_resampled))
```

```
Original class distribution in training set: Counter({0: 5972, 1: 1528})
Resampled class distribution in training set: Counter({0: 5972, 1: 3583})
```

1-Logistic Regression Model Construction:

```
%%time

lr_scaled = LogisticRegression(max_iter= 500, random_state= 17)
lr_scaled.fit(X_resampled, y_resampled)
```

```
CPU times: total: 0 ns
Wall time: 509 ms
```

```
LogisticRegression(max_iter=500, random_state=17)
```

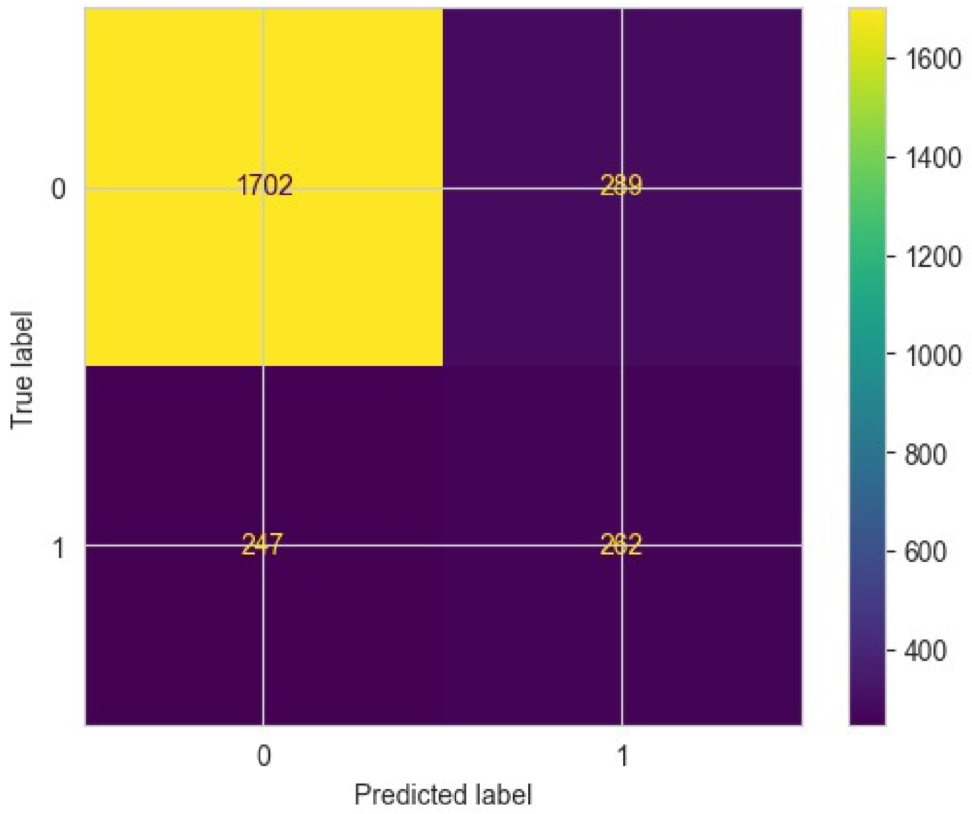
```
# Get the predictions on test data
y_pred_lr_scaled = lr_scaled.predict(X_test)
```

```
print('F1 Score:', '%.3f' % f1_score(y_test, y_pred_lr_scaled))
print('Precision:', '%.3f' % precision_score(y_test, y_pred_lr_scaled))
print('Recall:', '%.3f' % recall_score(y_test, y_pred_lr_scaled))
print('Accuracy:', '%.3f' % accuracy_score(y_test, y_pred_lr_scaled))
```

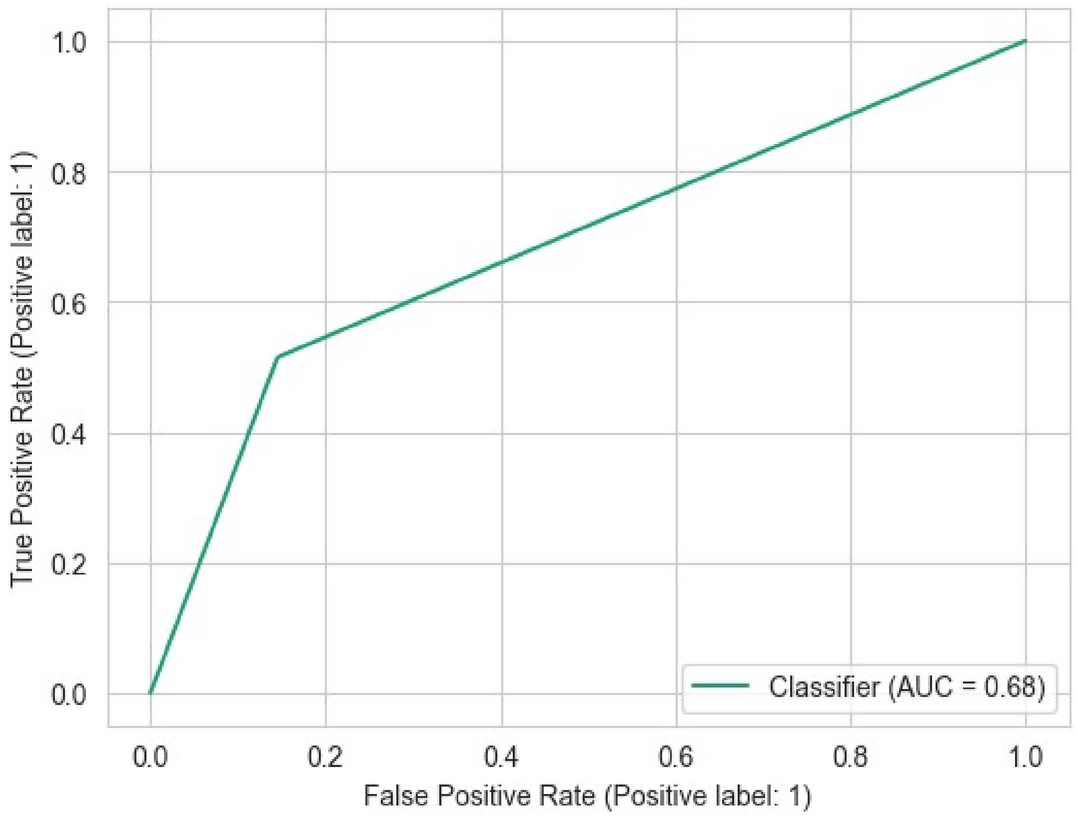
```
F1 Score: 0.494
Precision: 0.475
Recall: 0.515
Accuracy: 0.786
```

```
def conf_matrix_plot(model, x_data, y_data):
    model_pred = model.predict(x_data)
    cm = confusion_matrix(y_data, model_pred, labels= model.classes_)
    disp = ConfusionMatrixDisplay(confusion_matrix= cm, display_labels= model.classes_)
    disp.plot(values_format= "")
    plt.show()
```

```
conf_matrix_plot(lr_scaled, X_test, y_test)
```



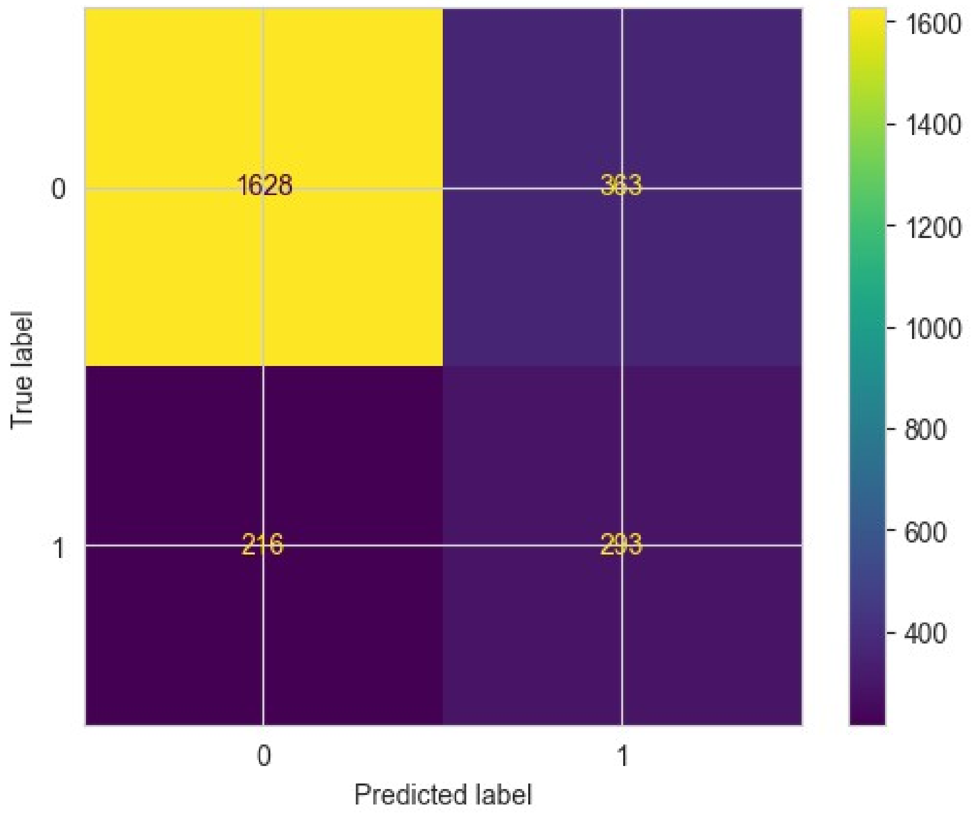

```
RocCurveDisplay.from_predictions(y_test, y_pred_lr_scaled)
plt.show()

print("roc_auc_score:", round(roc_auc_score(y_test, y_pred_lr_scaled), 3))
```



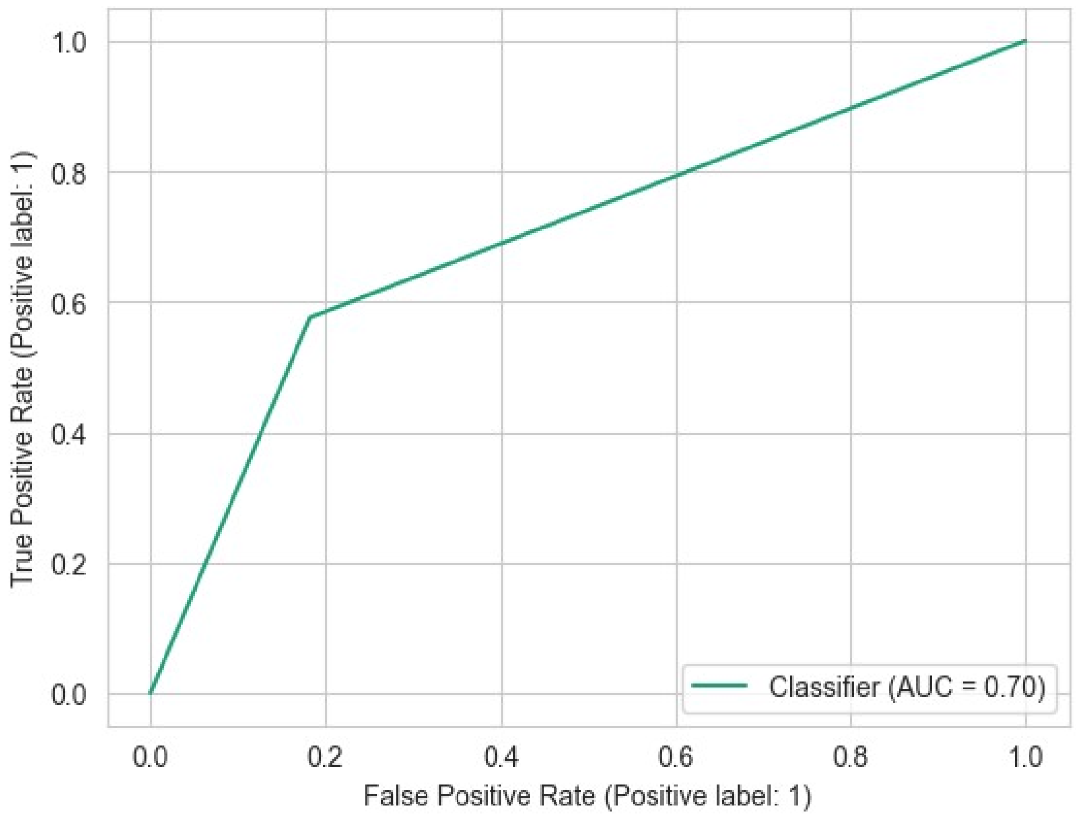

```
roc_auc_score: 0.685
```

2-Gaussian Naive Bayes Model Construction

```
%%time

gnb_scaled = GaussianNB()
gnb_scaled.fit(X_resampled, y_resampled)

CPU times: total: 0 ns
Wall time: 4.45 ms

GaussianNB()

# Get the predictions on test data
y_pred_gnb_scaled = gnb_scaled.predict(X_test)

print('F1 Score:', '%.3f' % f1_score(y_test, y_pred_gnb_scaled))
print('Precision:', '%.3f' % precision_score(y_test, y_pred_gnb_scaled))
print('Recall:', '%.3f' % recall_score(y_test, y_pred_gnb_scaled))
print('Accuracy:', '%.3f' % accuracy_score(y_test, y_pred_gnb_scaled))

F1 Score: 0.503
Precision: 0.447
Recall: 0.576
Accuracy: 0.768

conf_matrix_plot(gnb_scaled, X_test, y_test)
```




```
RocCurveDisplay.from_predictions(y_test, y_pred_gnb_scaled)
plt.show()

print("roc_auc_score:", round(roc_auc_score(y_test, y_pred_gnb_scaled), 3))
```




```
roc_auc_score: 0.697
```

3-Decision Tree Model Construction

Splitting the data & Oversampling the minority class:

```
y = churn_df["Exited"]

X = churn_df.copy()
X = churn_df.drop("Exited", axis= 1)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size= 0.25, stratify= y, random_state= 42)

# Initial class distribution in the training set
print("Original class distribution in training set:", Counter(y_train))

# Apply SMOTE to oversample the minority class in the training set
smote = SMOTE(sampling_strategy= 0.6, random_state= 42)
X_resampled, y_resampled = smote.fit_resample(X_train, y_train)

# New class distribution after resampling
print("Resampled class distribution in training set:", Counter(y_resampled))

Original class distribution in training set: Counter({0: 5972, 1: 1528})
Resampled class distribution in training set: Counter({0: 5972, 1: 3583})

dt = DecisionTreeClassifier(random_state= 42)

tree_para = {"max_depth": [3, 4, 5, 6, 7, 8, 9, 10], "min_samples_leaf": [2, 3, 4, 5, 6, 7, 8]}
```

```
scoring = ['accuracy', 'precision', 'recall', 'f1']
```

```
dt_cv = GridSearchCV(estimator= dt, param_grid= tree_para, scoring= scoring, cv= 5, refit= 'f1', n_jobs= -1,
verbose= 1)
```

```
%%time
```

```
dt_cv.fit(X_resampled, y_resampled)
```

```
Fitting 5 folds for each of 56 candidates, totalling 280 fits
CPU times: total: 500 ms
Wall time: 5.47 s
```

```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(random_state=42), n_jobs=-1,
             param_grid={'max_depth': [3, 4, 5, 6, 7, 8, 9, 10],
                         'min_samples_leaf': [2, 3, 4, 5, 6, 7, 8]},
             refit='f1', scoring=['accuracy', 'precision', 'recall', 'f1'],
             verbose=1)
```

```
print("Best Parameters for the Decision Tree Model:\n", dt_cv.best_params_)
```

```
print("\nBest Avgerage Cross-validation F1-score:", "%.3f" % dt_cv.best_score_)
```

```
Best Parameters for the Decision Tree Model:
 {'max_depth': 9, 'min_samples_leaf': 7}

Best Avgerage Cross-validation F1-score: 0.758
```

```
def make_results(model_name, model_object):
    cv_results = pd.DataFrame(model_object.cv_results_)
    best_estimator_results = cv_results.iloc[cv_results["mean_test_f1"].idxmax(), :]
    precision = best_estimator_results.mean_test_precision
    recall = best_estimator_results.mean_test_recall
    f1 = best_estimator_results.mean_test_f1
    accuracy = best_estimator_results.mean_test_accuracy

    table = pd.DataFrame({"Model": [model_name], "F1": [f1], "Precision": [precision], "Recall": [recall],
"Accuracy": [accuracy]})
    return table
```

```
dt_cv_results = make_results("Decision_Tree", dt_cv)
```

```
dt_cv_results
```

	Model	F1	Precision	Recall	Accuracy
0	Decision_Tree	0.757611	0.799311	0.725431	0.830141

Constructing the optimal Decision Tree Classifier based on the best cross-validation results:

```
decision_tree = DecisionTreeClassifier(max_depth= 9, min_samples_leaf= 7, random_state= 42)
decision_tree.fit(X_resampled, y_resampled)
```

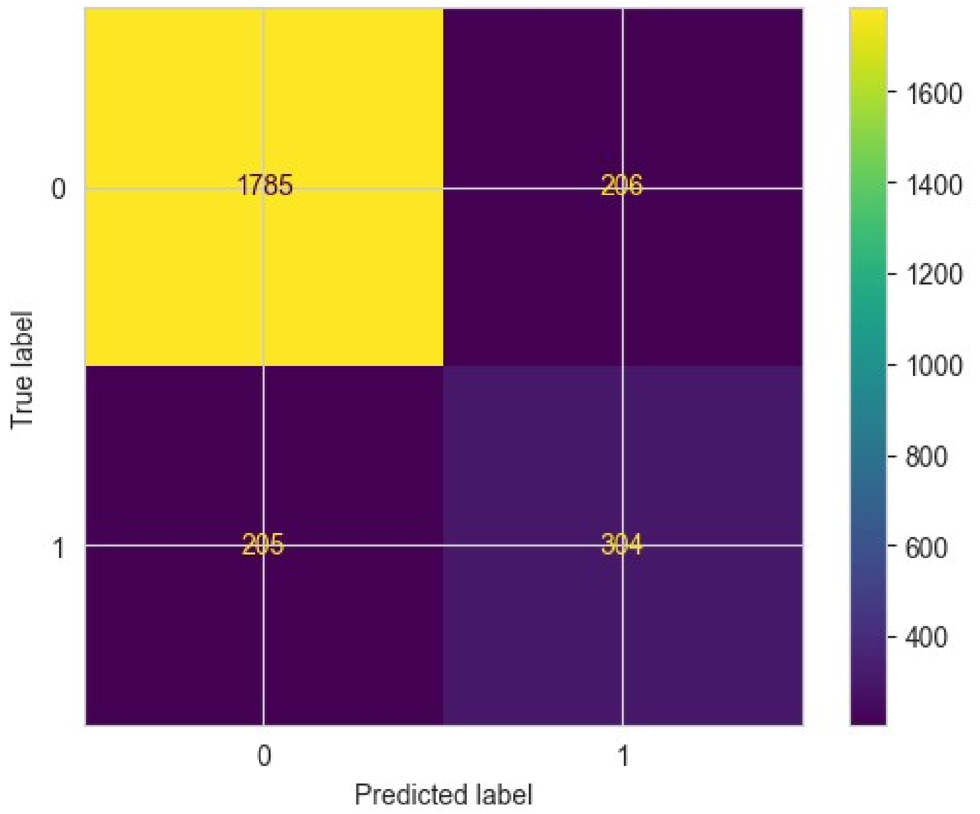
```
DecisionTreeClassifier(max_depth=9, min_samples_leaf=7, random_state=42)
```

```
y_pred_dt = decision_tree.predict(X_test)
```

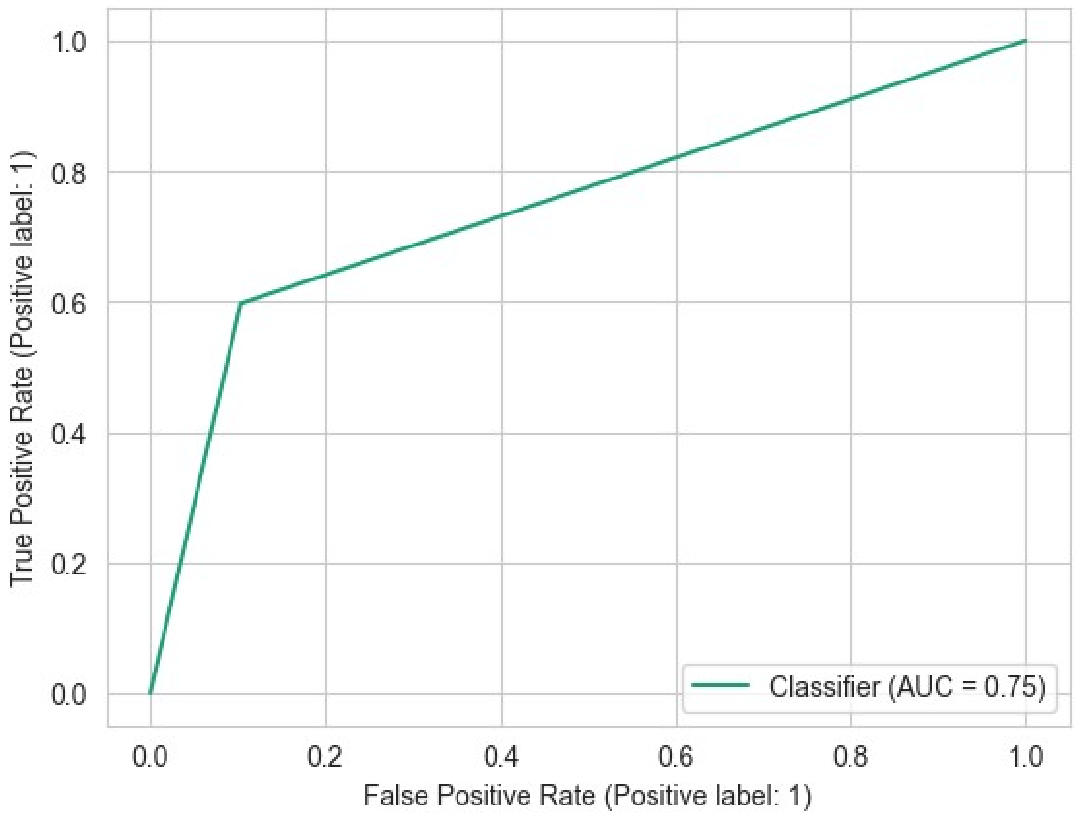
```
print('F1 Score:', '%.3f' % f1_score(y_test, y_pred_dt))
print('Precision:', '%.3f' % precision_score(y_test, y_pred_dt))
print('Recall:', '%.3f' % recall_score(y_test, y_pred_dt))
print('Accuracy:', '%.3f' % accuracy_score(y_test, y_pred_dt))
```

```
F1 Score: 0.597
Precision: 0.596
Recall: 0.597
Accuracy: 0.836
```

```
conf_matrix_plot(decision_tree, X_test, y_test)
```




```
RocCurveDisplay.from_predictions(y_test, y_pred_dt)
plt.show()

print("roc_auc_score:", round(roc_auc_score(y_test, y_pred_dt), 3))
```




```
roc_auc_score: 0.747
```

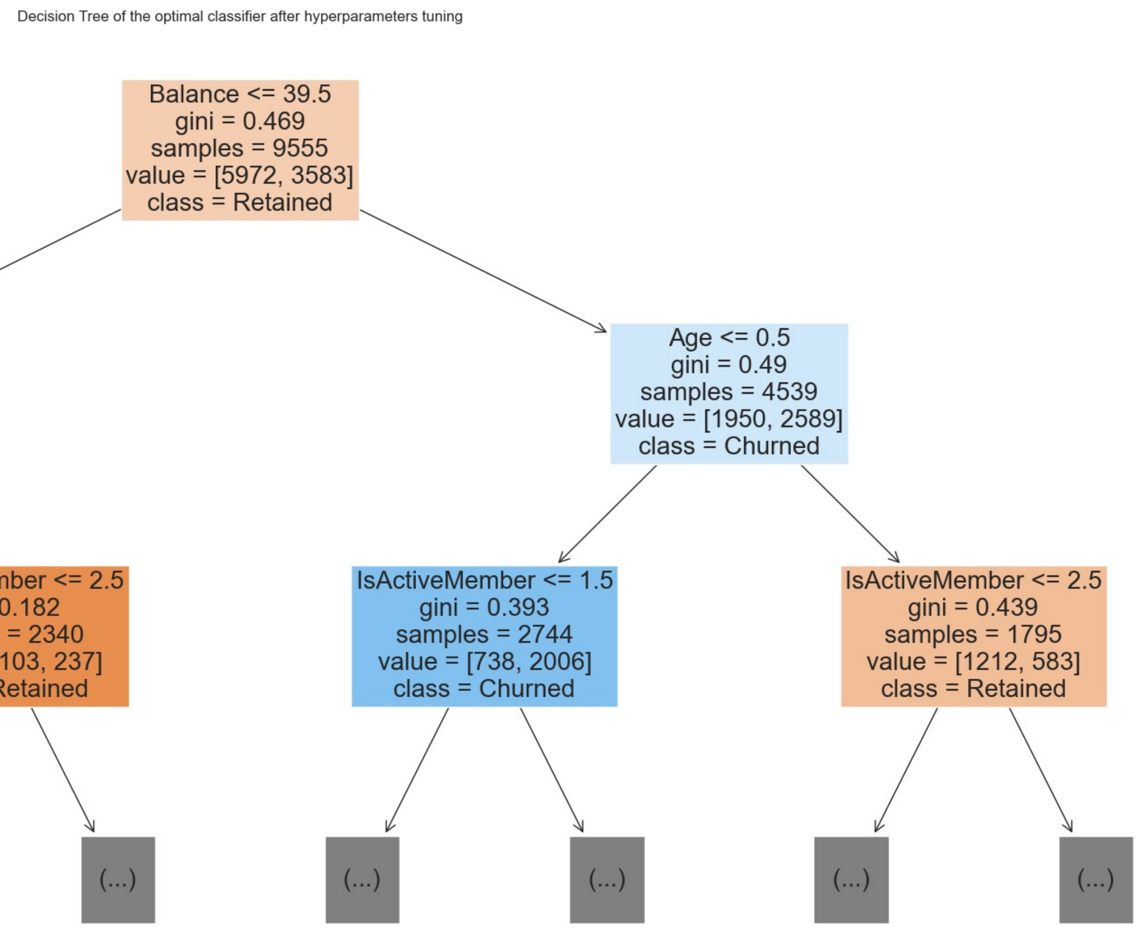
```
comparing_models = pd.DataFrame()

comparing_models = comparing_models.append({"Model": "Decision_Tree", "F1": 0.597, "Precision": 0.596,
"Recall": 0.597, "Accuracy": 0.836}, ignore_index= True)

comparing_models = comparing_models.append({"Model": "Naive_Bayes", "F1": 0.503, "Precision": 0.447, "Recall":
0.576, "Accuracy": 0.768}, ignore_index= True)

comparing_models = comparing_models.append({"Model": "Logistic_Regression", "F1": 0.494, "Precision": 0.475,
"Recall": 0.515, "Accuracy": 0.786}, ignore_index= True)

comparing_models
```

	Model	F1	Precision	Recall	Accuracy
0	Decision_Tree	0.597	0.596	0.597	0.836
1	Naive_Bayes	0.503	0.447	0.576	0.768
2	Logistic_Regression	0.494	0.475	0.515	0.786

We notice that the F1 Score -which is our benchmark- is higher in the decision tree model (0.525) than the naive bayes model (0.425) and the logistic regression model (0.439), however the False Positives are still higher than the False Negatives despite of the oversampling technique we've conducted earlier.

```
plt.figure(figsize= (28, 14))
plot_tree(decision_tree, max_depth= 2, fontsize= 20,
          feature_names= ['CreditScore', 'Balance', 'NumOfProducts', 'HasCrCard', 'IsActiveMember',
'EstimatedSalary', 'Age', 'Tenure', 'Loyalty', 'Geography_Germany', 'Geography_Spain', 'Geography_France'],
class_names= ["Retained", "Churned"], filled= True)
```

```python
plt.title("Decision Tree of the optimal classifier after hyperparameters tuning")
plt.show()
```

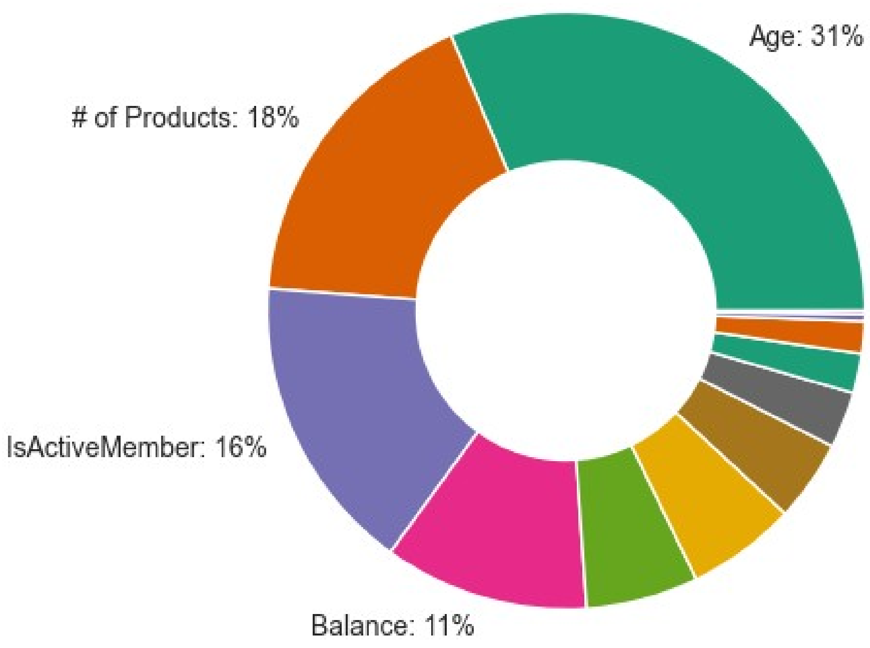



```python
importances = decision_tree.feature_importances_ * 100

forest_importances = pd.DataFrame(importances, index= X.columns, columns= ["affect"]).sort_values(by= "affect", ascending= False)
forest_importances
```

```
                      affect
Age                31.298165
NumOfProducts      17.522073
IsActiveMember     16.185259
Balance            11.096547
Geography_France    6.086130
Geography_Spain     5.919848
Geography_Germany   4.395243
EstimatedSalary     3.054795
Loyalty             2.131416
CreditScore         1.745237
Tenure              0.389989
HasCrCard           0.175299
```

```python
plt.figure( figsize= (10, 5))
plt.pie(x= forest_importances["affect"], labels= ["Age: 31%", "# of Products: 18%", "IsActiveMember: 16%", "Balance: 11%", "", "", "", "", "", "", "", ""])
plt.title("Key Factors affecting Customer Churn by 77%:")

my_circle = plt.Circle( (0,0), 0.5, color= 'white')
p= plt.gcf()
p.gca().add_artist(my_circle)
plt.show()
```

Key Factors affecting Customer Churn by 77%:



Recommendations for Stakeholders Based on the results of the Decision Tree algorithm, the most effective features on the customer churn rate are:

1- Age of the customer.

2- Number of Products in which the customer is being involved in.

3- Whether the customer is considered as active or not.

4- Balance Amount in the customer's account.

The algorithm determined the above features as the most effective ones by approximately 76%, while the other 5 features are not considered effective.

4-Random Forest Model Construction

Cross-validated hyperparameter tuning

```
rf = RandomForestClassifier(random_state= 42)

cv_params = {'max_depth': [6, 7, 8, 9, 10],
             'min_samples_leaf': [1, 2, 3],
             'min_samples_split': [2, 3, 4],
             'max_features': [2, 3, 4],
             'n_estimators': [75, 100, 125]}

scoring = ['accuracy', 'precision', 'recall', 'f1']

rf_cv = GridSearchCV(estimator= rf, param_grid= cv_params, scoring=scoring, cv=5, refit='f1', n_jobs= -1,
verbose= 1)

#%%time

#rf_cv.fit(X_resampled, y_resampled)

path = "D:/Google Advanced Data Analytics/Nuts & Bolts of Machine Learning/Fitted_Models/"

# Pickle the model
#with open(path+'rf_cv_model.pickle', 'wb') as to_write:
#    pickle.dump(rf_cv, to_write)

# Read in pickled model
with open(path + 'rf_cv_model.pickle', 'rb') as to_read:
    rf_cv = pickle.load(to_read)

print("Best Parameters for the Random Forest Model:\n", rf_cv.best_params_)

print("\nBest Avgerage Cross-validation F1-score:", "%.3f" % rf_cv.best_score_)

Best Parameters for the Random Forest Model:
 {'max_depth': 10, 'max_features': 4, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 125}

Best Avgerage Cross-validation F1-score: 0.788

rf_cv_results = make_results('Random Forest CV', rf_cv)
rf_cv_results

              Model        F1  Precision    Recall  Accuracy
0  Random Forest CV  0.788366   0.852622  0.743864  0.857143
```

Constructing the optimal Random Forest Classifier based on the best cross-validation results:

```
random_forest = RandomForestClassifier(max_depth= 10, max_features= 4, min_samples_leaf= 1, min_samples_split=
2, n_estimators= 125, random_state= 42)
random_forest.fit(X_resampled, y_resampled)
```

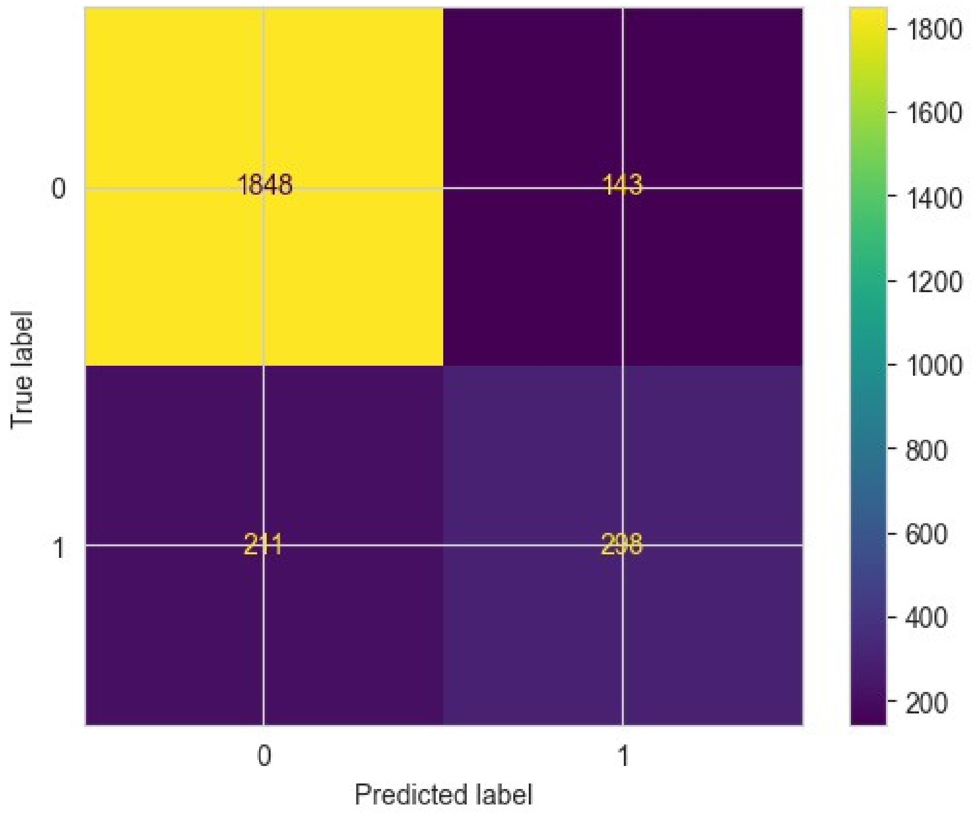
```
RandomForestClassifier(max_depth=10, max_features=4, n_estimators=125,
                       random_state=42)
```

```
y_pred_rf = random_forest.predict(X_test)
```

```
print('F1 Score:', '%.3f' % f1_score(y_test, y_pred_rf))
print('Precision:', '%.3f' % precision_score(y_test, y_pred_rf))
print('Recall:', '%.3f' % recall_score(y_test, y_pred_rf))
print('Accuracy:', '%.3f' % accuracy_score(y_test, y_pred_rf))
```

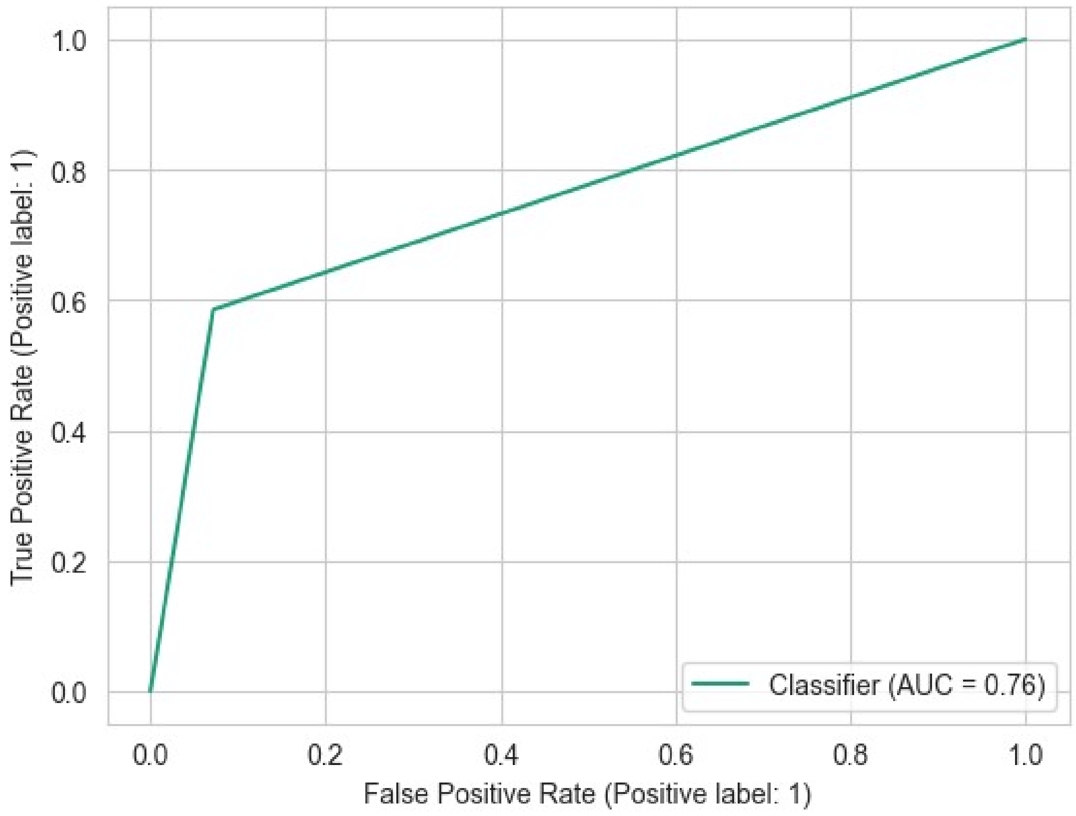
```
F1 Score: 0.627
Precision: 0.676
Recall: 0.585
Accuracy: 0.858
```

```
conf_matrix_plot(random_forest, X_test, y_test)
```




```
RocCurveDisplay.from_predictions(y_test, y_pred_rf)
plt.show()
```

```
print("roc_auc_score:", round(roc_auc_score(y_test, y_pred_rf), 3))
```




```
roc_auc_score: 0.757
```

```
comparing_models = comparing_models.append({"Model": "Random_Forest", "F1": 0.627, "Precision": 0.676,
"Recall": 0.585, "Accuracy": 0.858}, ignore_index= True)
```

```
comparing_models = comparing_models.sort_values(by= "F1", ascending= False).reset_index(drop= True)
```

```
comparing_models
```

	Model	F1	Precision	Recall	Accuracy
0	Random_Forest	0.627	0.676	0.585	0.858
1	Decision_Tree	0.597	0.596	0.597	0.836
2	Naive_Bayes	0.503	0.447	0.576	0.768
3	Logistic_Regression	0.494	0.475	0.515	0.786

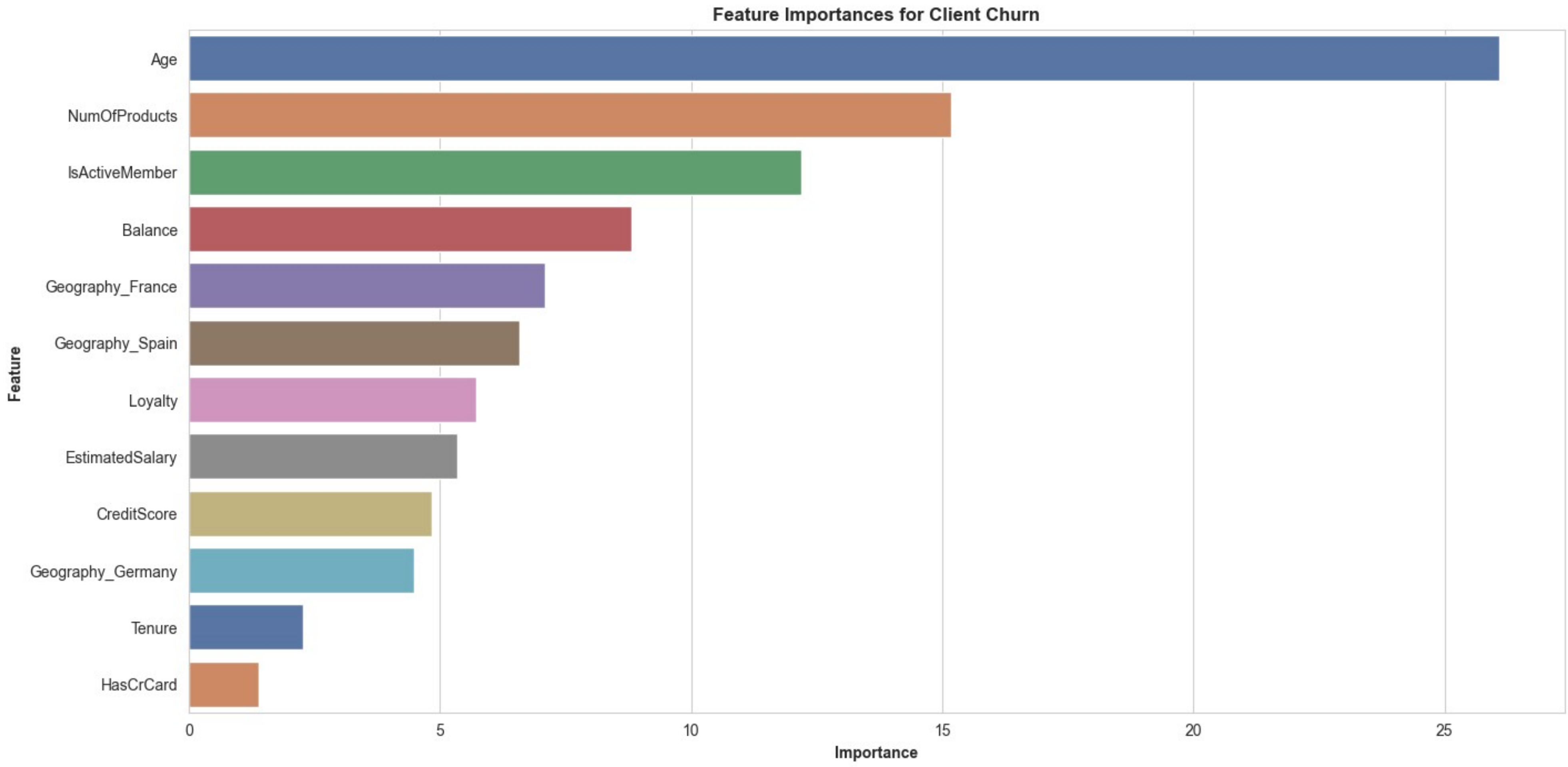
```
feature_importances = random_forest.feature_importances_
feature_importances
```

```
array([0.04835111, 0.26089744, 0.02279709, 0.08810593, 0.15171378,
       0.01385651, 0.12187607, 0.05356716, 0.0571959 , 0.07097223,
       0.04484391, 0.06582285])
```

```
forest_importances = pd.DataFrame(list(X.columns), columns= ["feature"])
forest_importances["importance"] = feature_importances * 100
forest_importances = forest_importances[forest_importances["importance"] > 0].sort_values(by="importance",
ascending= False)
forest_importances
```

	feature	importance
1	Age	26.089744
4	NumOfProducts	15.171378
6	IsActiveMember	12.187607
3	Balance	8.810593
9	Geography_France	7.097223
11	Geography_Spain	6.582285
8	Loyalty	5.719590
7	EstimatedSalary	5.356716
0	CreditScore	4.835111
10	Geography_Germany	4.484391
2	Tenure	2.279709
5	HasCrCard	1.385651

```
plt.figure(figsize= (16, 8))
sns.barplot(data= forest_importances, x= "importance", y= "feature", palette= "deep", orient= "h")
plt.title("Feature Importances for Client Churn", fontweight= "bold")
plt.ylabel("Feature", fontweight= "bold")
plt.xlabel("Importance", fontweight= "bold")
plt.show()
```



The plot above shows that in this random forest model, age, number of products, member activity and client's balance have the highest importance, in that order. These variables are most helpful in predicting the outcome variable,Exitedt, and they are the same as the onerefered toed by the decision tree model.

5-XGBoost Model Construction

Cross-validated hyperparameter tuning

```
xgb = XGBClassifier(objective= "binary:logistic", random_state=0)

cv_params = {'max_depth': [2, 3, 4, 5, 6], 'min_child_weight': [1, 2, 3, 4, 5], 'learning_rate': [0.05, 0.1,
0.2],
             'n_estimators': [75, 100, 125], 'colsample_bytree': [0.8, 1], 'subsample': [0.8, 1]}

scoring = ['accuracy', 'precision', 'recall', 'f1']

xgb_cv = GridSearchCV(estimator= xgb, param_grid= cv_params, scoring=scoring, cv=5, refit='f1', n_jobs= -1,
verbose= 1)
```

```
#%%time

#xgb_cv.fit(X_resampled, y_resampled)
```

```
# Pickle the model
#with open(path+'xgb_cv_model.pickle', 'wb') as to_write:
#    pickle.dump(xgb_cv, to_write)

# Read in pickled model
with open(path + 'xgb_cv_model.pickle', 'rb') as to_read:
    xgb_cv = pickle.load(to_read)

print("Best Parameters for the Random Forest Model:\n", xgb_cv.best_params_)

print("\nBest Avgerage Cross-validation F1-score:", "%.3f" % xgb_cv.best_score_)
```

```
Best Parameters for the Random Forest Model:
 {'colsample_bytree': 0.8, 'learning_rate': 0.2, 'max_depth': 6, 'min_child_weight': 3, 'n_estimators': 100,
'subsample': 0.8}

Best Avgerage Cross-validation F1-score: 0.795
```

```
xgb_cv_results = make_results('XGBoost CV', xgb_cv)
xgb_cv_results
```

	Model	F1	Precision	Recall	Accuracy
0	XGBoost CV	0.79467	0.846097	0.763966	0.860492

Constructing the optimal XGBoost Classifier based on the best cross-validation results:

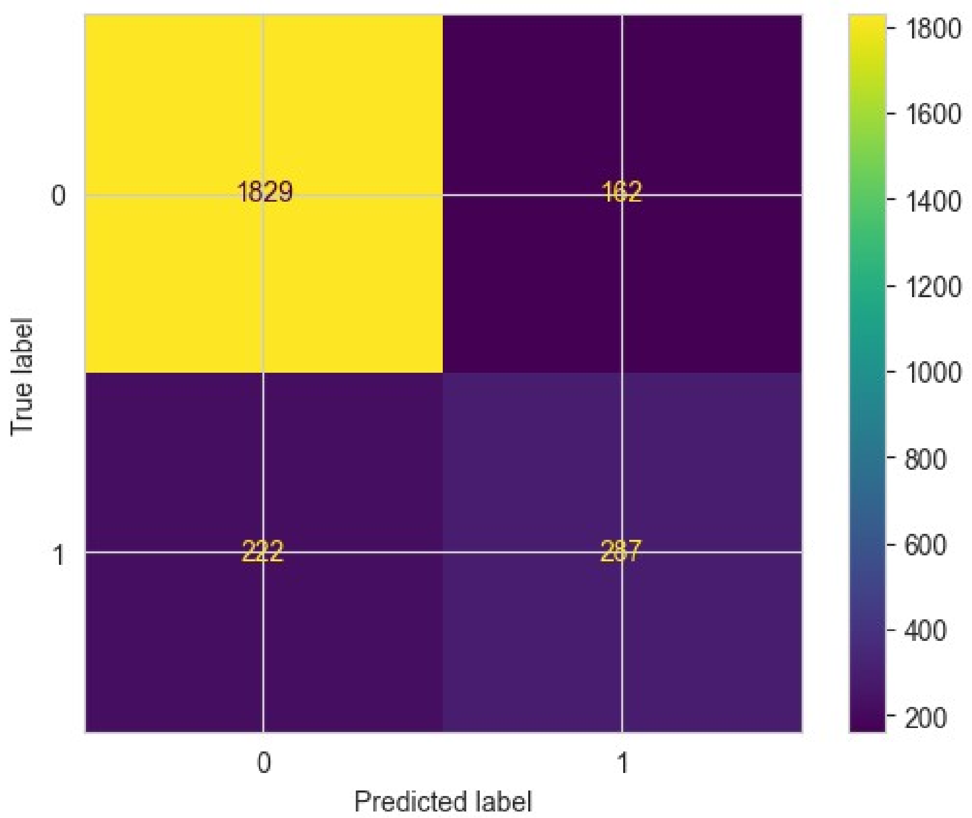
```
xgboost = XGBClassifier(objective = "binary:logistic", max_depth= 6, min_child_weight= 3, learning_rate= 0.2,\
                        n_estimators= 100, colsample_bytree= 0.8, subsample= 0.8, random_state= 42)
xgboost.fit(X_resampled, y_resampled)
```

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=0.8, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.2, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=6, max_leaves=None,
              min_child_weight=3, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=100, n_jobs=None,
              num_parallel_tree=None, random_state=42, ...)
```

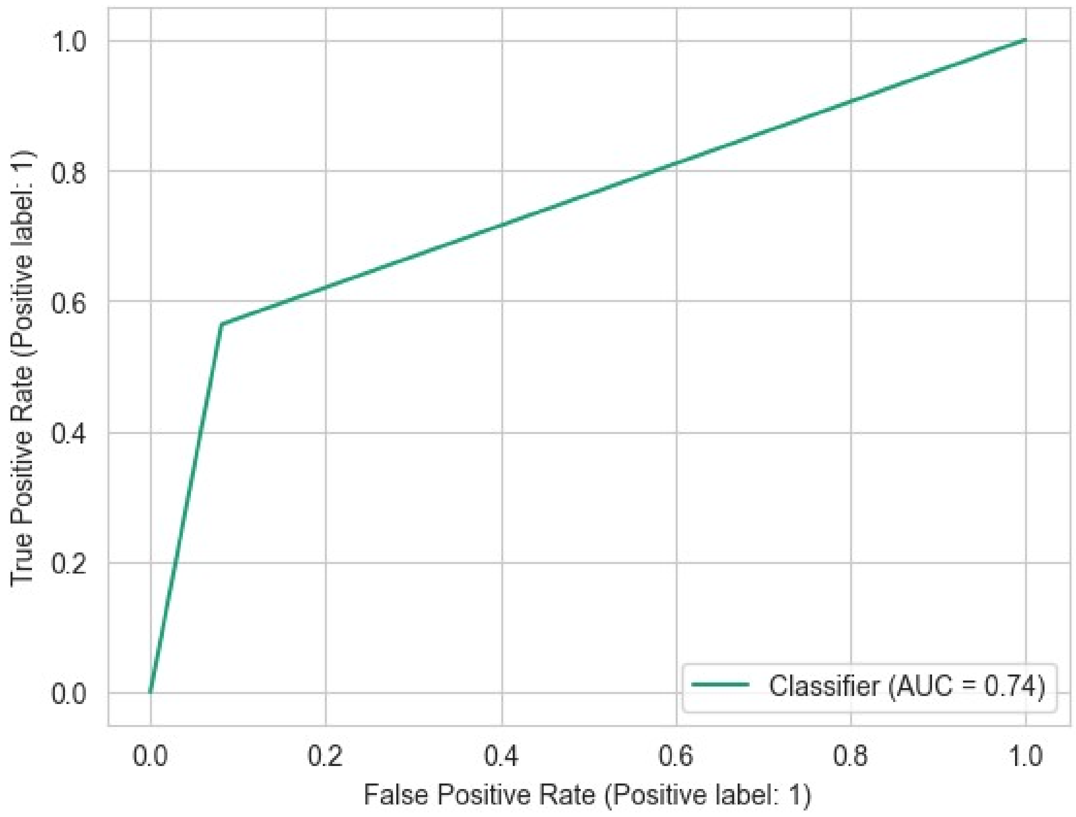
```
y_pred_xgb = xgboost.predict(X_test)

print('F1 Score:', '%.3f' % f1_score(y_test, y_pred_xgb))
print('Precision:', '%.3f' % precision_score(y_test, y_pred_xgb))
print('Recall:', '%.3f' % recall_score(y_test, y_pred_xgb))
print('Accuracy:', '%.3f' % accuracy_score(y_test, y_pred_xgb))
```

```
F1 Score: 0.599
Precision: 0.639
Recall: 0.564
Accuracy: 0.846
```

```
conf_matrix_plot(xgboost, X_test, y_test)
```




```
RocCurveDisplay.from_predictions(y_test, y_pred_xgb)
plt.show()

print("roc_auc_score:", round(roc_auc_score(y_test, y_pred_xgb), 3))
```




```
roc_auc_score: 0.741
```

```
comparing_models = comparing_models.append({"Model": "XGBoost", "F1": 0.599, "Precision": 0.639, "Recall": 0.564, "Accuracy": 0.846}, ignore_index= True)
```

```
comparing_models = comparing_models.sort_values(by= "F1", ascending= False).reset_index(drop= True)
```

```
comparing_models
```

```
                 Model     F1  Precision  Recall  Accuracy
0        Random_Forest  0.627      0.676   0.585     0.858
1              XGBoost  0.599      0.639   0.564     0.846
2        Decision_Tree  0.597      0.596   0.597     0.836
3          Naive_Bayes  0.503      0.447   0.576     0.768
4  Logistic_Regression  0.494      0.475   0.515     0.786
```

pacE: Execute Stage

Comparing the 5 models across the different evaluation metrics based on the testing data:

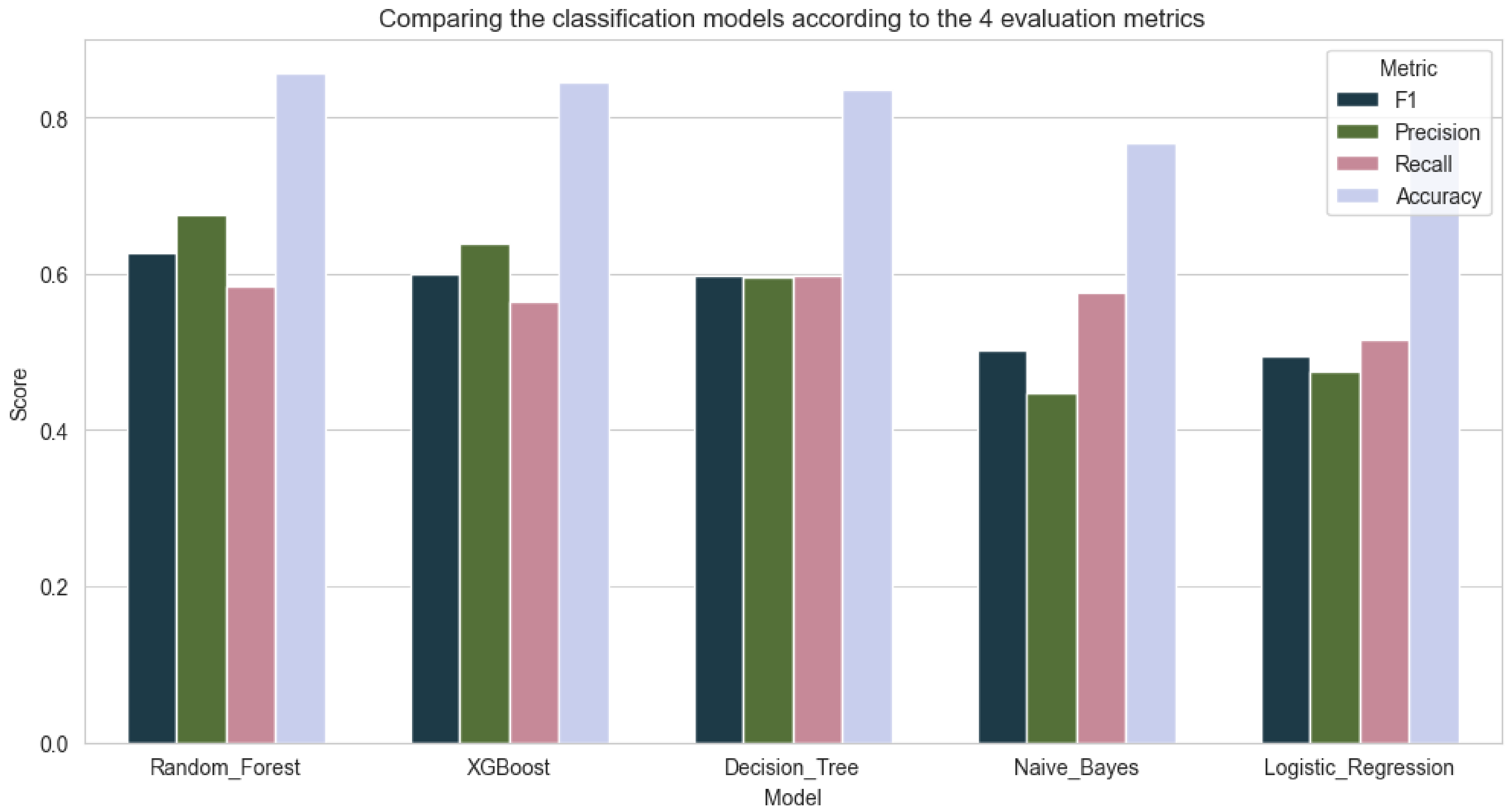
```
data = {"Model": ["Random_Forest", "Random_Forest", "Random_Forest", "Random_Forest", "XGBoost", "XGBoost", "XGBoost", "XGBoost", "Decision_Tree", "Decision_Tree", "Decision_Tree", "Decision_Tree", "Naive_Bayes", "Naive_Bayes", "Naive_Bayes", "Naive_Bayes", "Logistic_Regression", "Logistic_Regression", "Logistic_Regression", "Logistic_Regression"],\
       "Metric": ["F1", "Precision", "Recall", "Accuracy", "F1", "Precision", "Recall", "Accuracy", "F1", "Precision", "Recall", "Accuracy", "F1", "Precision", "Recall", "Accuracy", "F1", "Precision", "Recall", "Accuracy"],\
       "Score": [0.627, 0.676, 0.585, 0.858, 0.599, 0.639, 0.564, 0.846, 0.597, 0.596, 0.597, 0.836, 0.503, 0.447, 0.576, 0.768, 0.494, 0.475, 0.515, 0.786]}
```

```
comparing_models_ = pd.DataFrame(data)
comparing_models_
```

```
                  Model     Metric  Score
0         Random_Forest         F1  0.627
1         Random_Forest  Precision  0.676
2         Random_Forest     Recall  0.585
3         Random_Forest   Accuracy  0.858
4               XGBoost         F1  0.599
5               XGBoost  Precision  0.639
6               XGBoost     Recall  0.564
7               XGBoost   Accuracy  0.846
8         Decision_Tree         F1  0.597
9         Decision_Tree  Precision  0.596
10        Decision_Tree     Recall  0.597
11        Decision_Tree   Accuracy  0.836
12          Naive_Bayes         F1  0.503
13          Naive_Bayes  Precision  0.447
14          Naive_Bayes     Recall  0.576
15          Naive_Bayes   Accuracy  0.768
16  Logistic_Regression         F1  0.494
17  Logistic_Regression  Precision  0.475
18  Logistic_Regression     Recall  0.515
19  Logistic_Regression   Accuracy  0.786
```

```
plt.figure( figsize= (12, 6))
fig = sns.barplot(data= comparing_models_, y= "Score", x= "Model", hue= "Metric", palette= "cubehelix", width= 0.7, dodge= True)
```

```
fig.set_title("Comparing the classification models according to the 4 evaluation metrics")
plt.show()
```



We could observe that the Random Forest Model performs the best based on the `F1 Score`. However, all the models are underrated according to the supposed bank accuracy metrics, so that we can't deploy anyone of them.

Key Takeaways: We need more predictive features to improve the evaluation metrics of our models, since the models perform well on the cross-validation metrics, but they are poorly performing on the testing data.