```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import missingno as msno

import plotly.offline as py
py.init_notebook_mode(connected=True)


import warnings
warnings.filterwarnings('ignore')


from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler,LabelEncoder
```

## Dataset Describe

```
import pandas as pd

# Load the dataset to understand its structure and content
file_path = 'churn.csv'
data = pd.read_csv(file_path)

# Displaying the first few rows of the dataset
data.head()
```

| | customer_id | credit_score | country | gender | age | tenure | balance | products_number |
|---|---|---|---|---|---|---|---|---|
| **0** | 15634602 | 619 | France | Female | 42 | 2 | 0.00 | 1 |
| **1** | 15647311 | 608 | Spain | Female | 41 | 1 | 83807.86 | 1 |
| **2** | 15619304 | 502 | France | Female | 42 | 8 | 159660.80 | 3 |
| **3** | 15701354 | 699 | France | Female | 39 | 1 | 0.00 | 2 |
| **4** | 15737888 | 850 | Spain | Female | 43 | 2 | 125510.82 | 1 |

```
data.describe().transpose()
```

| | count | mean | std | min | 25% | |
|---|---|---|---|---|---|---|
| **customer_id** | 10000.0 | 1.569094e+07 | 71936.186123 | 15565701.00 | 15628528.25 | 1.569074e- |
| **credit_score** | 10000.0 | 6.505288e+02 | 96.653299 | 350.00 | 584.00 | 6.520000e- |
| **age** | 10000.0 | 3.892180e+01 | 10.487806 | 18.00 | 32.00 | 3.700000e- |
| **tenure** | 10000.0 | 5.012800e+00 | 2.892174 | 0.00 | 3.00 | 5.000000e- |
| **balance** | 10000.0 | 7.648589e+04 | 62397.405202 | 0.00 | 0.00 | 9.719854e- |
| **products_number** | 10000.0 | 1.530200e+00 | 0.581654 | 1.00 | 1.00 | 1.000000e- |
| **credit_card** | 10000.0 | 7.055000e-01 | 0.455840 | 0.00 | 0.00 | 1.000000e- |
| **active_member** | 10000.0 | 5.151000e-01 | 0.499797 | 0.00 | 0.00 | 1.000000e- |
| **estimated_salary** | 10000.0 | 1.000902e+05 | 57510.492818 | 11.58 | 51002.11 | 1.001939e- |
| **churn** | 10000.0 | 2.037000e-01 | 0.402769 | 0.00 | 0.00 | 0.000000e- |

## handling missing values

```
# Descriptive statistical analysis
descriptive_stats = data.describe()

# Checking for missing values
missing_values = data.isnull().sum()

descriptive_stats, missing_values
```

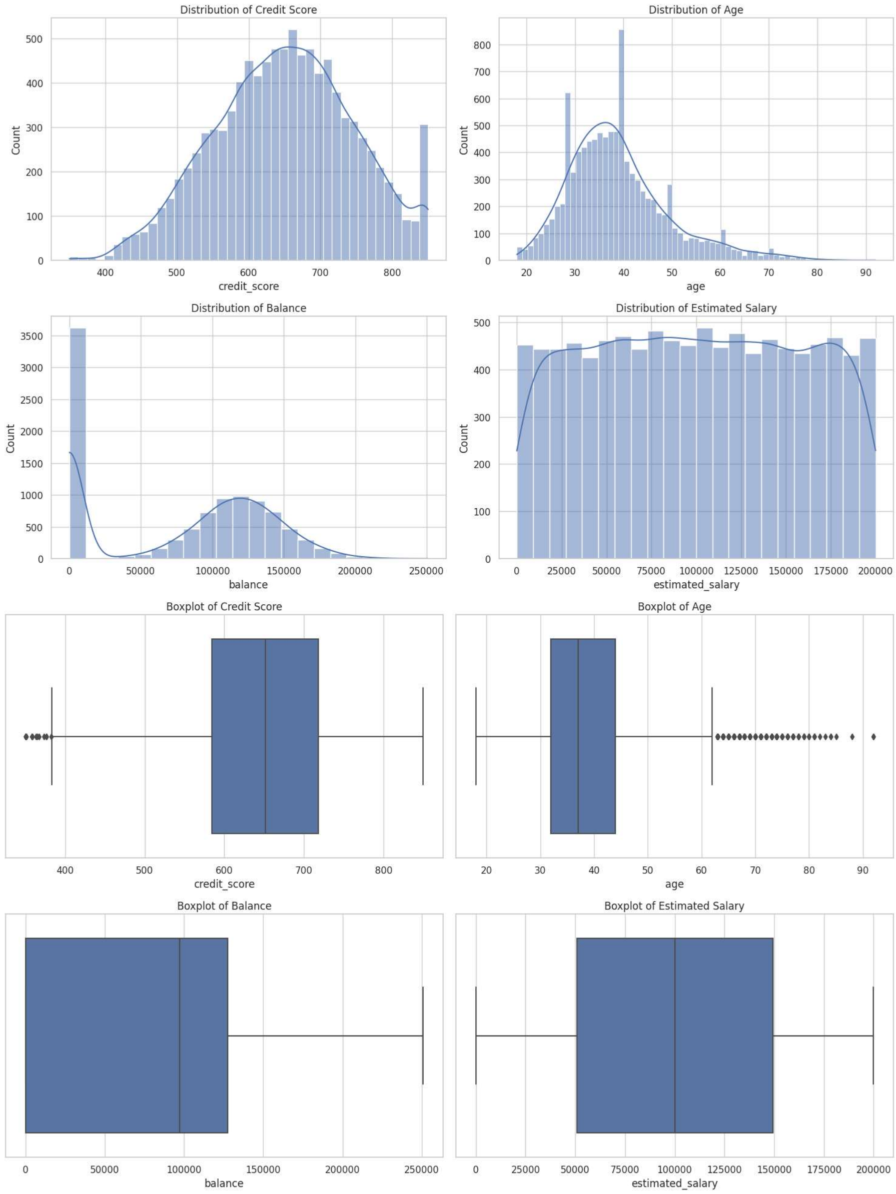
```
(        customer_id  credit_score           age        tenure        balance  \
 count  1.000000e+04  10000.000000  10000.000000  10000.000000   10000.000000
 mean   1.569094e+07    650.528800     38.921800      5.012800   76485.889288
 std    7.193619e+04     96.653299     10.487806      2.892174   62397.405202
 min    1.556570e+07    350.000000     18.000000      0.000000       0.000000
 25%    1.562853e+07    584.000000     32.000000      3.000000       0.000000
 50%    1.569074e+07    652.000000     37.000000      5.000000   97198.540000
 75%    1.575323e+07    718.000000     44.000000      7.000000  127644.240000
 max    1.581569e+07    850.000000     92.000000     10.000000  250898.090000

        products_number  credit_card  active_member  estimated_salary  \
 count     10000.000000  10000.00000   10000.000000      10000.000000
 mean          1.530200      0.70550       0.515100     100090.239881
 std           0.581654      0.45584       0.499797      57510.492818
 min           1.000000      0.00000       0.000000         11.580000
 25%           1.000000      0.00000       0.000000      51002.110000
 50%           1.000000      1.00000       1.000000     100193.915000
 75%           2.000000      1.00000       1.000000     149388.247500
 max           4.000000      1.00000       1.000000     199992.480000

               churn
 count  10000.000000
 mean       0.203700
 std        0.402769
 min        0.000000
 25%        0.000000
 50%        0.000000
 75%        0.000000
 max        1.000000  ,
 customer_id         0
 credit_score        0
 country             0
 gender              0
 age                 0
 tenure              0
 balance             0
 products_number     0
 credit_card         0
 active_member       0
 estimated_salary    0
 churn               0
 dtype: int64)
```

## EDA

```
data.describe().T.sort_values(ascending = 0,by = "mean").style.background_gradient(cmap = "BuGn")\
.bar(subset = ["std"], color ="red").bar(subset = ["mean"], color ="blue")
```

| | count | mean | std | min | |
|---|---|---|---|---|---|
| **customer_id** | 10000.000000 | 15690940.569400 | 71936.186123 | 15565701.000000 | 15628528.2 |
| **estimated_salary** | 10000.000000 | 100090.239881 | 57510.492818 | 11.580000 | 51002.1 |
| **balance** | 10000.000000 | 76485.889288 | 62397.405202 | 0.000000 | 0.0 |
| **credit_score** | 10000.000000 | 650.528800 | 96.653299 | 350.000000 | 584.0 |
| **age** | 10000.000000 | 38.921800 | 10.487806 | 18.000000 | 32.0 |
| **tenure** | 10000.000000 | 5.012800 | 2.892174 | 0.000000 | 3.0 |
| **products_number** | 10000.000000 | 1.530200 | 0.581654 | 1.000000 | 1.0 |
| **credit_card** | 10000.000000 | 0.705500 | 0.455840 | 0.000000 | 0.0 |
| **active_member** | 10000.000000 | 0.515100 | 0.499797 | 0.000000 | 0.0 |
| **churn** | 10000.000000 | 0.203700 | 0.402769 | 0.000000 | 0.0 |

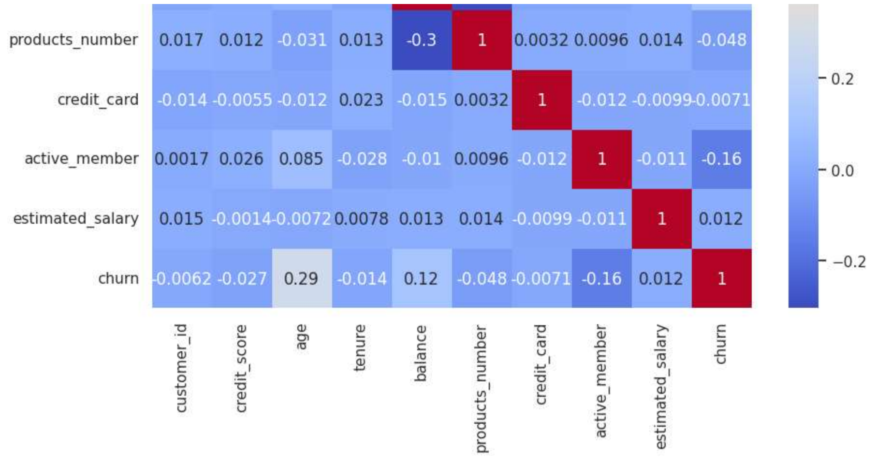
```
import matplotlib.pyplot as plt
import seaborn as sns

# Setting the aesthetic style of the plots
sns.set(style="whitegrid")

# Creating a figure with multiple subplots
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(15, 10))

# Plotting distributions of key variables
sns.histplot(data['credit_score'], kde=True, ax=axes[0, 0])
axes[0, 0].set_title('Distribution of Credit Score')

sns.histplot(data['age'], kde=True, ax=axes[0, 1])
axes[0, 1].set_title('Distribution of Age')

sns.histplot(data['balance'], kde=True, ax=axes[1, 0])
axes[1, 0].set_title('Distribution of Balance')

sns.histplot(data['estimated_salary'], kde=True, ax=axes[1, 1])
axes[1, 1].set_title('Distribution of Estimated Salary')

plt.tight_layout()
plt.show()

# Creating boxplots to identify outliers
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(15, 10))

sns.boxplot(x='credit_score', data=data, ax=axes[0, 0])
axes[0, 0].set_title('Boxplot of Credit Score')

sns.boxplot(x='age', data=data, ax=axes[0, 1])
axes[0, 1].set_title('Boxplot of Age')

sns.boxplot(x='balance', data=data, ax=axes[1, 0])
axes[1, 0].set_title('Boxplot of Balance')

sns.boxplot(x='estimated_salary', data=data, ax=axes[1, 1])
axes[1, 1].set_title('Boxplot of Estimated Salary')

plt.tight_layout()
plt.show()
```

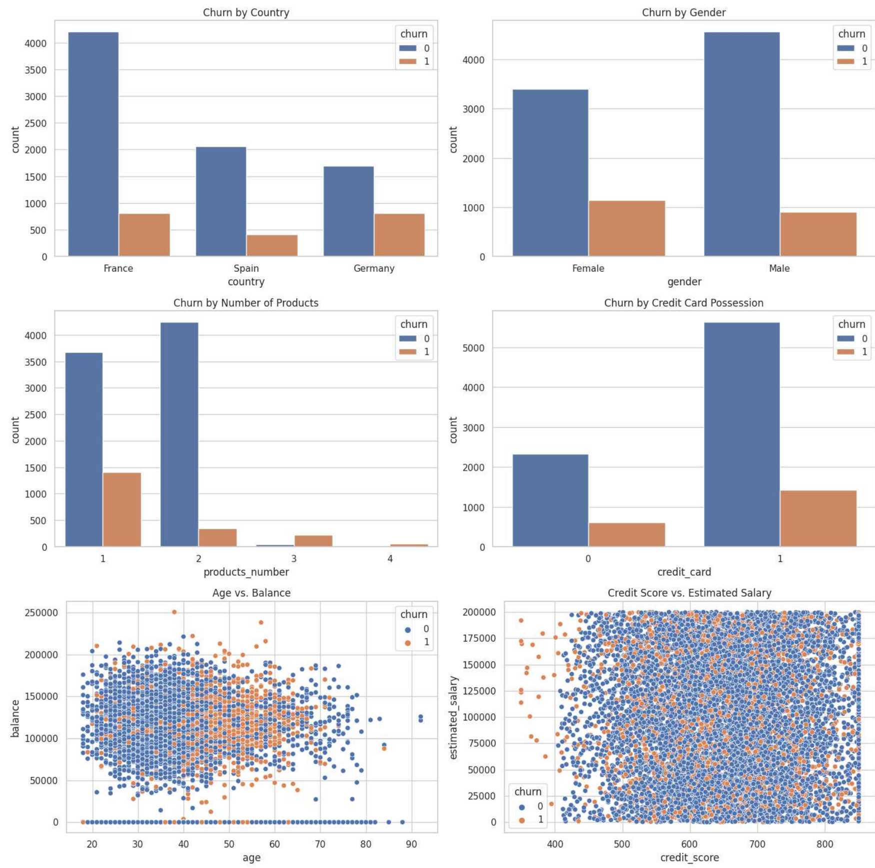



```
fig = px.histogram(data, x="age", y="balance", color="churn", marginal="box",hover_data=data.columns)
fig.show()
```

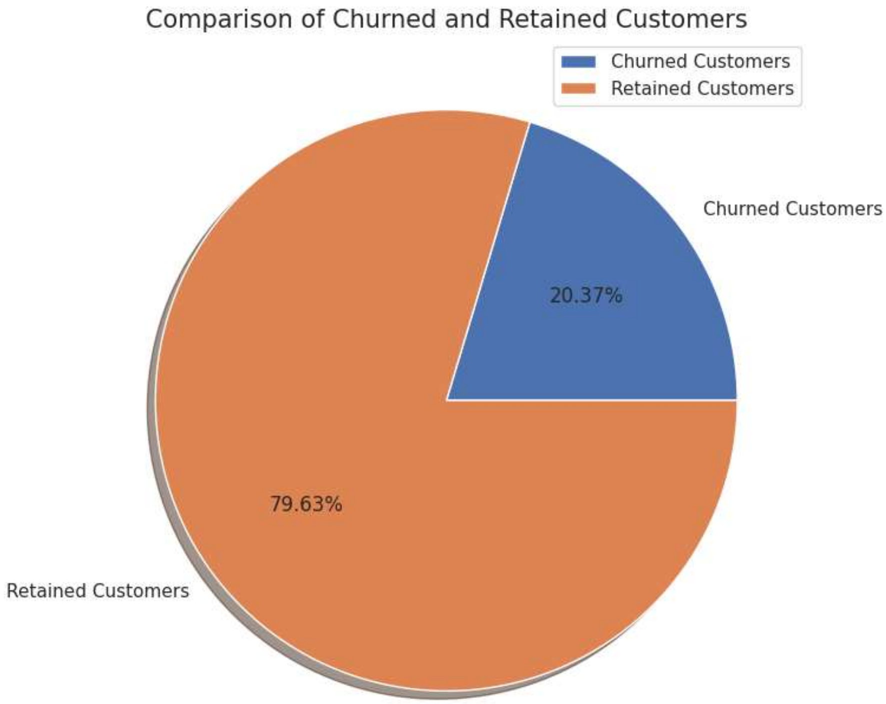
```
def plot_correlation_heatmap(data):
    numeric_data = data.select_dtypes(include=[np.number])
    plt.figure(figsize=(10, 8))
    sns.heatmap(numeric_data.corr(), annot=True, cmap='coolwarm')
    plt.title('Correlation Heatmap')
    plt.show()



def plot_categorical_churn(data):
    fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(15, 10))

    sns.countplot(x='country', hue='churn', data=data, ax=axes[0, 0])
    axes[0, 0].set_title('Churn by Country')

    sns.countplot(x='gender', hue='churn', data=data, ax=axes[0, 1])
    axes[0, 1].set_title('Churn by Gender')

    sns.countplot(x='products_number', hue='churn', data=data, ax=axes[1, 0])
    axes[1, 0].set_title('Churn by Number of Products')

    sns.countplot(x='credit_card', hue='churn', data=data, ax=axes[1, 1])
    axes[1, 1].set_title('Churn by Credit Card Possession')

    plt.tight_layout()
    plt.show()



def plot_numerical_scatter(data):
    fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15, 5))

    sns.scatterplot(x='age', y='balance', hue='churn', data=data, ax=axes[0])
    axes[0].set_title('Age vs. Balance')

    sns.scatterplot(x='credit_score', y='estimated_salary', hue='churn', data=data, ax=axes[1])
    axes[1].set_title('Credit Score vs. Estimated Salary')

    plt.tight_layout()
    plt.show()
```

```
def plot_churn_distribution(data):
    churn_counts = [data[data['churn'] == 1].shape[0], data[data['churn'] == 0].shape[0]]
    churn_labels = ['Churned Customers', 'Retained Customers']
    fig, ax = plt.subplots(figsize=(10, 8))
    ax.pie(churn_counts, labels=churn_labels, shadow=True, autopct='%1.2f%%')
    plt.legend()
    plt.title("Comparison of Churned and Retained Customers", size=15)
    plt.show()



def display_grouped_statistics(data):
    numeric_columns = data.select_dtypes(include=[np.number]).columns
    feature_columns = numeric_columns.drop('churn') if 'churn' in numeric_columns else numeric_columns
    grouped_mean = data.groupby('churn')[feature_columns].mean().style.background_gradient(cmap="cool")
    grouped_median = data.groupby('churn')[feature_columns].median().style.background_gradient(cmap="cool")
    return grouped_mean, grouped_median



plot_correlation_heatmap(data)
plot_categorical_churn(data)
plot_numerical_scatter(data)
```




```
plot_churn_distribution(data)
mean_display, median_display = display_grouped_statistics(data)
mean_display
```




| churn | customer_id | credit_score | age | tenure | balance | products_number |
|---|---|---|---|---|---|---|
| 0 | 15691167.881703 | 651.853196 | 37.408389 | 5.033279 | 72745.296779 | 1.544267 |
| 1 | 15690051.964654 | 645.351497 | 44.837997 | 4.932744 | 91108.539337 | 1.475209 |

median_display

| churn | customer_id | credit_score | age | tenure | balance | products_number |
|---|---|---|---|---|---|---|
| 0 | 15691543.000000 | 653.000000 | 36.000000 | 5.000000 | 92072.680000 | 2.000000 |
| 1 | 15688963.000000 | 646.000000 | 45.000000 | 5.000000 | 109349.290000 | 1.000000 |

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer

# Defining the features and target variable
features = data.drop(['churn', 'customer_id'], axis=1)  # Dropping 'customer_id' as it's not useful for prediction
target = data['churn']

# Identifying categorical and numeric columns
categorical_cols = features.select_dtypes(include=['object', 'category']).columns
numeric_cols = features.select_dtypes(include=['int64', 'float64']).columns

# Creating transformers for numeric and categorical columns
numeric_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),  # Imputing missing values if any
    ('scaler', StandardScaler())])  # Scaling numeric features

categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='constant', fill_value='missing')),  # Imputing missing values if any
    ('onehot', OneHotEncoder(handle_unknown='ignore'))])  # One-hot encoding for categorical variables

# Combining transformers into a ColumnTransformer
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_cols),
        ('cat', categorical_transformer, categorical_cols)])

# Splitting the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=0.2, random_state=42)

# Applying the transformations to the training data
X_train = preprocessor.fit_transform(X_train)
X_test = preprocessor.transform(X_test)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((8000, 13), (2000, 13), (8000,), (2000,))
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

# Initializing the Logistic Regression model
logistic_model = LogisticRegression(random_state=42)

# Training the model
logistic_model.fit(X_train, y_train)

# Predicting on the test set
y_pred = logistic_model.predict(X_test)

# Calculating accuracy and other metrics
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)

print(accuracy)
```

```
0.811
```

```
conf_matrix
```

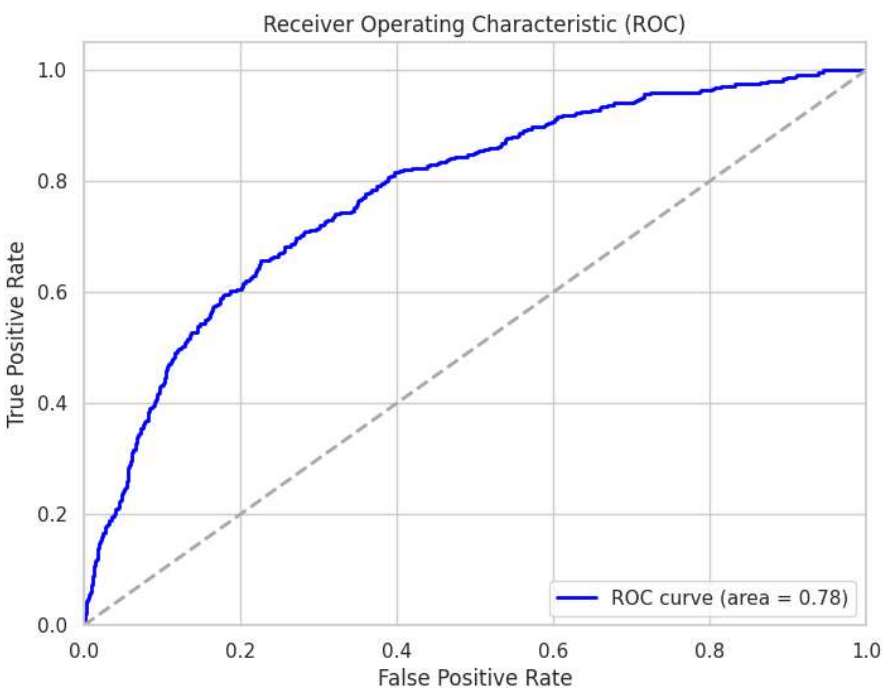
```
array([[1543,   64],
       [ 314,   79]])
```

```
print(class_report)
```

```
              precision    recall  f1-score   support

           0       0.83      0.96      0.89      1607
           1       0.55      0.20      0.29       393

    accuracy                           0.81      2000
```

```
   macro avg       0.69      0.58      0.59      2000
weighted avg       0.78      0.81      0.77      2000
```

```
from sklearn.metrics import roc_curve, auc

# Calculating the probabilities of the predictions
y_prob = logistic_model.predict_proba(X_test)[:, 1]

# Generating ROC curve values: fpr, tpr, thresholds
fpr, tpr, thresholds = roc_curve(y_test, y_prob)

# Calculating AUC
roc_auc = auc(fpr, tpr)

# Plotting ROC Curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='darkgray', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc="lower right")
plt.show()

roc_auc
```




```
0.7788792987423027
```

## Quantitative Analysis

```
import statsmodels.api as sm

# Reconstructing the logistic model using statsmodels for detailed statistics
# Adding a constant to the features for the intercept
X_train_sm = sm.add_constant(X_train)

# Building the logistic model using statsmodels
logit_model = sm.Logit(y_train, X_train_sm)
result = logit_model.fit()

# Displaying the summary of the logistic regression model
model_summary = result.summary2()
model_summary
```

```
Optimization terminated successfully.
         Current function value: 0.431349
         Iterations 7
```

| | | | |
|---|---|---|---|
| Model: | Logit | Method: | MLE |
| Dependent Variable: | churn | Pseudo R-squared: | 0.151 |
| Date: | 2023-11-18 19:57 | AIC: | 6925.5774 |
| No. Observations: | 8000 | BIC: | 7009.4237 |
| Df Model: | 11 | Log-Likelihood: | -3450.8 |
| Df Residuals: | 7988 | LL-Null: | -4063.5 |
| Converged: | 1.0000 | LLR p-value: | 5.5571e-256 |
| No. Iterations: | 7.0000 | Scale: | 1.0000 |

| | **Coef.** | **Std.Err.** | **z** | **P>\|z\|** | **[0.025** | **0.975]** |
|---|---|---|---|---|---|---|
| **const** | -0.8403 | 2089977.5504 | -0.0000 | 1.0000 | -4096281.5677 | 4096279.8870 |
| **x1** | -0.0678 | 0.0302 | -2.2454 | 0.0247 | -0.1269 | -0.0086 |
| **x2** | 0.7551 | 0.0300 | 25.1575 | 0.0000 | 0.6963 | 0.8139 |
| **x3** | -0.0427 | 0.0301 | -1.4198 | 0.1557 | -0.1018 | 0.0163 |
| **x4** | 0.1609 | 0.0357 | 4.5059 | 0.0000 | 0.0909 | 0.2308 |
| **x5** | -0.0606 | 0.0305 | -1.9914 | 0.0464 | -0.1203 | -0.0010 |
| **x6** | -0.0103 | 0.0301 | -0.3410 | 0.7331 | -0.0694 | 0.0488 |
| **x7** | -0.5341 | 0.0321 | -16.6386 | 0.0000 | -0.5970 | -0.4712 |
| **x8** | 0.0158 | 0.0304 | 0.5188 | 0.6039 | -0.0438 | 0.0753 |
| **x9** | -0.5703 | nan | nan | nan | nan | nan |
| **x10** | 0.2089 | nan | nan | nan | nan | nan |
| **x11** | -0.4790 | nan | nan | nan | nan | nan |
| **x12** | -0.1540 | nan | nan | nan | nan | nan |
| **x13** | -0.6863 | nan | nan | nan | nan | nan |

```
# Calculating Odds Ratios and their 97.5% Confidence Intervals
odds_ratios = pd.DataFrame()
odds_ratios['Coefficient'] = result.params
odds_ratios['Odds Ratio'] = np.exp(result.params)
odds_ratios['P-value'] = result.pvalues
odds_ratios['[0.025 CI]'] = np.exp(result.conf_int().iloc[:, 0])
odds_ratios['[0.975 CI]'] = np.exp(result.conf_int().iloc[:, 1])

odds_ratios
```