Bank Data Chrun

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset
df = pd.read_csv(r'C:\Users\jerme\Downloads\Data Science␣
↪project\churn_prediction.csv')

# Display the first few rows
print(df.head())

# Summary statistics
print(df.describe())

# Check for missing values
print(df.isnull().sum())

# Visualize the distribution of the 'age' feature
sns.histplot(df['age'], kde=True)
plt.title('Age Distribution')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()

# Visualize the distribution of the 'current_balance' feature
sns.histplot(df['current_balance'], kde=True)
plt.title('Current Balance Distribution')
plt.xlabel('Current Balance')
plt.ylabel('Frequency')
plt.show()
```

```
   customer_id  vintage  age gender  dependents     occupation    city  \
0            1     3135   66   Male         0.0  self_employed   187.0
1            2      310   35   Male         0.0  self_employed     NaN
2            4     2356   31   Male         0.0       salaried   146.0
3            5      478   90    NaN         NaN  self_employed  1020.0
4            6     2531   42   Male         2.0  self_employed  1494.0
```

```
   customer_nw_category  branch_code  days_since_last_transaction  ...  \
0                     2          755                        224.0  ...
1                     2         3214                         60.0  ...
2                     2           41                          NaN  ...
3                     2          582                        147.0  ...
4                     3          388                         58.0  ...

   previous_month_end_balance  average_monthly_balance_prevQ  \
0                     1458.71                        1458.71
1                     8704.66                        7799.26
2                     5815.29                        4910.17
3                     2291.91                        2084.54
4                     1401.72                        1643.31

   average_monthly_balance_prevQ2  current_month_credit  \
0                         1449.07                  0.20
1                        12419.41                  0.56
2                         2815.94                  0.61
3                         1006.54                  0.47
4                         1871.12                  0.33

   previous_month_credit  current_month_debit  previous_month_debit  \
0                   0.20                 0.20                  0.20
1                   0.56              5486.27                100.56
2                   0.61              6046.73                259.23
3                   0.47                 0.47               2143.33
4                 714.61               588.62               1538.06

   current_month_balance  previous_month_balance  churn
0                1458.71                 1458.71      0
1                6496.78                 8787.61      0
2                5006.28                 5070.14      0
3                2291.91                 1669.79      1
4                1157.15                 1677.16      1

[5 rows x 21 columns]
        customer_id       vintage           age    dependents          city  \
count  28382.000000  28382.000000  28382.000000  25919.000000  27579.000000
mean   15143.508667   2364.336446     48.208336      0.347236    796.109576
std     8746.454456   1610.124506     17.807163      0.997661    432.872102
min        1.000000    180.000000      1.000000      0.000000      0.000000
25%     7557.250000   1121.000000     36.000000      0.000000    409.000000
50%    15150.500000   2018.000000     46.000000      0.000000    834.000000
75%    22706.750000   3176.000000     60.000000      0.000000   1096.000000
max    30301.000000  12899.000000     90.000000     52.000000   1649.000000

       customer_nw_category   branch_code  days_since_last_transaction  \
count          28382.000000  28382.000000                 25159.000000
```

mean	2.225530	925.975019	69.997814
std	0.660443	937.799129	86.341098
min	1.000000	1.000000	0.000000
25%	2.000000	176.000000	11.000000
50%	2.000000	572.000000	30.000000
75%	3.000000	1440.000000	95.000000
max	3.000000	4782.000000	365.000000

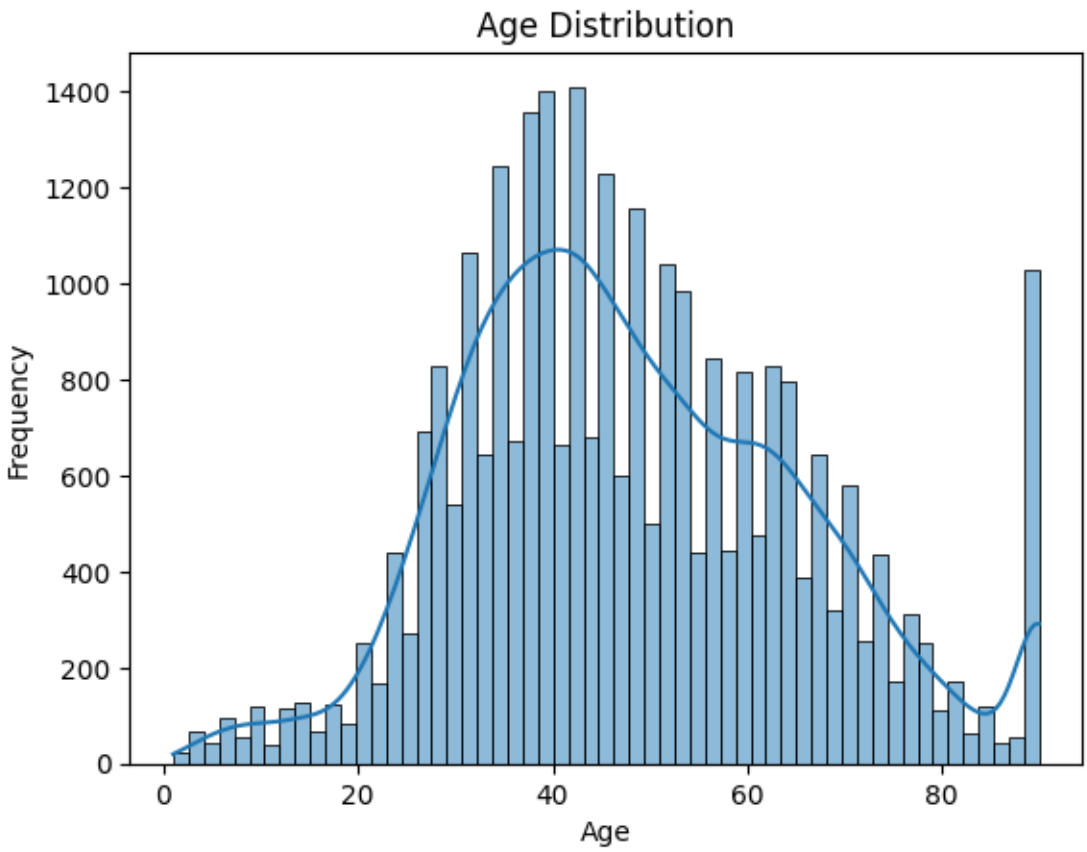
	current_balance	previous_month_end_balance
count	2.838200e+04	2.838200e+04
mean	7.380552e+03	7.495771e+03
std	4.259871e+04	4.252935e+04
min	-5.503960e+03	-3.149570e+03
25%	1.784470e+03	1.906000e+03
50%	3.281255e+03	3.379915e+03
75%	6.635820e+03	6.656535e+03
max	5.905904e+06	5.740439e+06

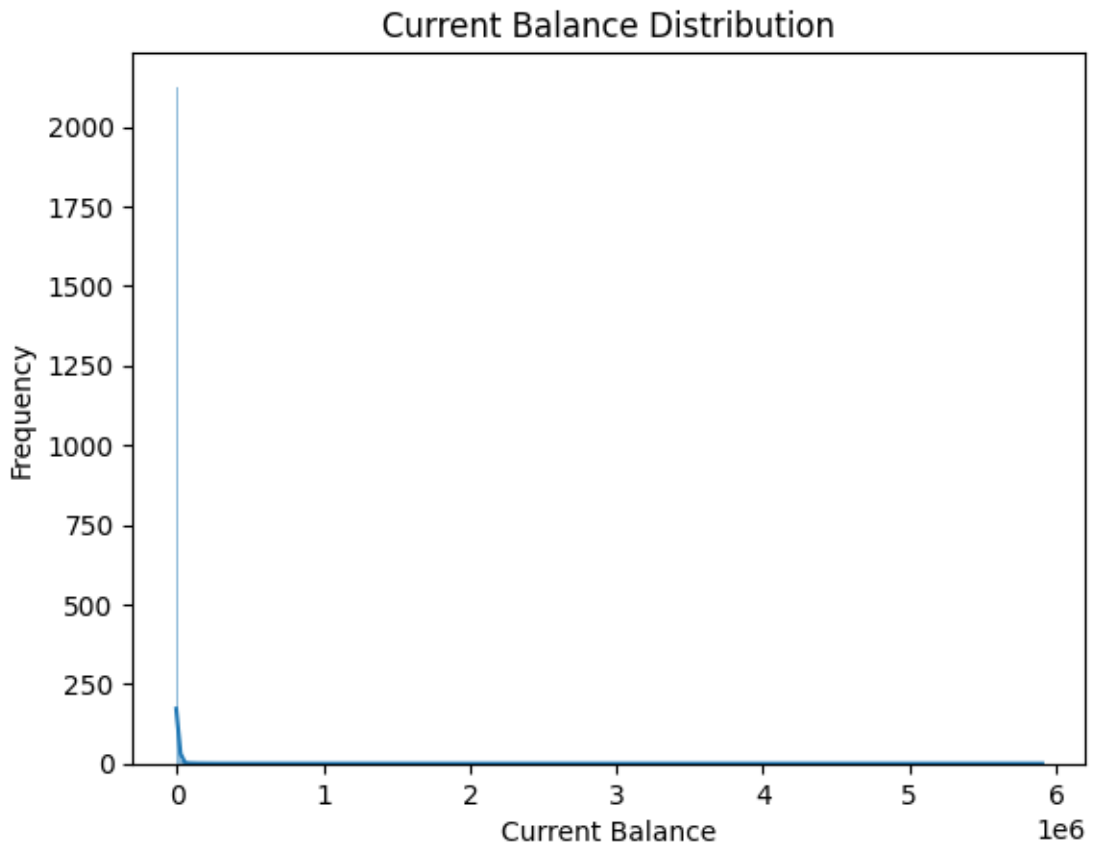
	average_monthly_balance_prevQ	average_monthly_balance_prevQ2
count	2.838200e+04	2.838200e+04
mean	7.496780e+03	7.124209e+03
std	4.172622e+04	4.457581e+04
min	1.428690e+03	-1.650610e+04
25%	2.180945e+03	1.832507e+03
50%	3.542865e+03	3.359600e+03
75%	6.666887e+03	6.517960e+03
max	5.700290e+06	5.010170e+06

	current_month_credit	previous_month_credit	current_month_debit
count	2.838200e+04	2.838200e+04	2.838200e+04
mean	3.433252e+03	3.261694e+03	3.658745e+03
std	7.707145e+04	2.968889e+04	5.198542e+04
min	1.000000e-02	1.000000e-02	1.000000e-02
25%	3.100000e-01	3.300000e-01	4.100000e-01
50%	6.100000e-01	6.300000e-01	9.193000e+01
75%	7.072725e+02	7.492350e+02	1.360435e+03
max	1.226985e+07	2.361808e+06	7.637857e+06

	previous_month_debit	current_month_balance	previous_month_balance
count	2.838200e+04	2.838200e+04	2.838200e+04
mean	3.339761e+03	7.451133e+03	7.495177e+03
std	2.430111e+04	4.203394e+04	4.243198e+04
min	1.000000e-02	-3.374180e+03	-5.171920e+03
25%	4.100000e-01	1.996765e+03	2.074407e+03
50%	1.099600e+02	3.447995e+03	3.465235e+03
75%	1.357553e+03	6.667958e+03	6.654693e+03
max	1.414168e+06	5.778185e+06	5.720144e+06

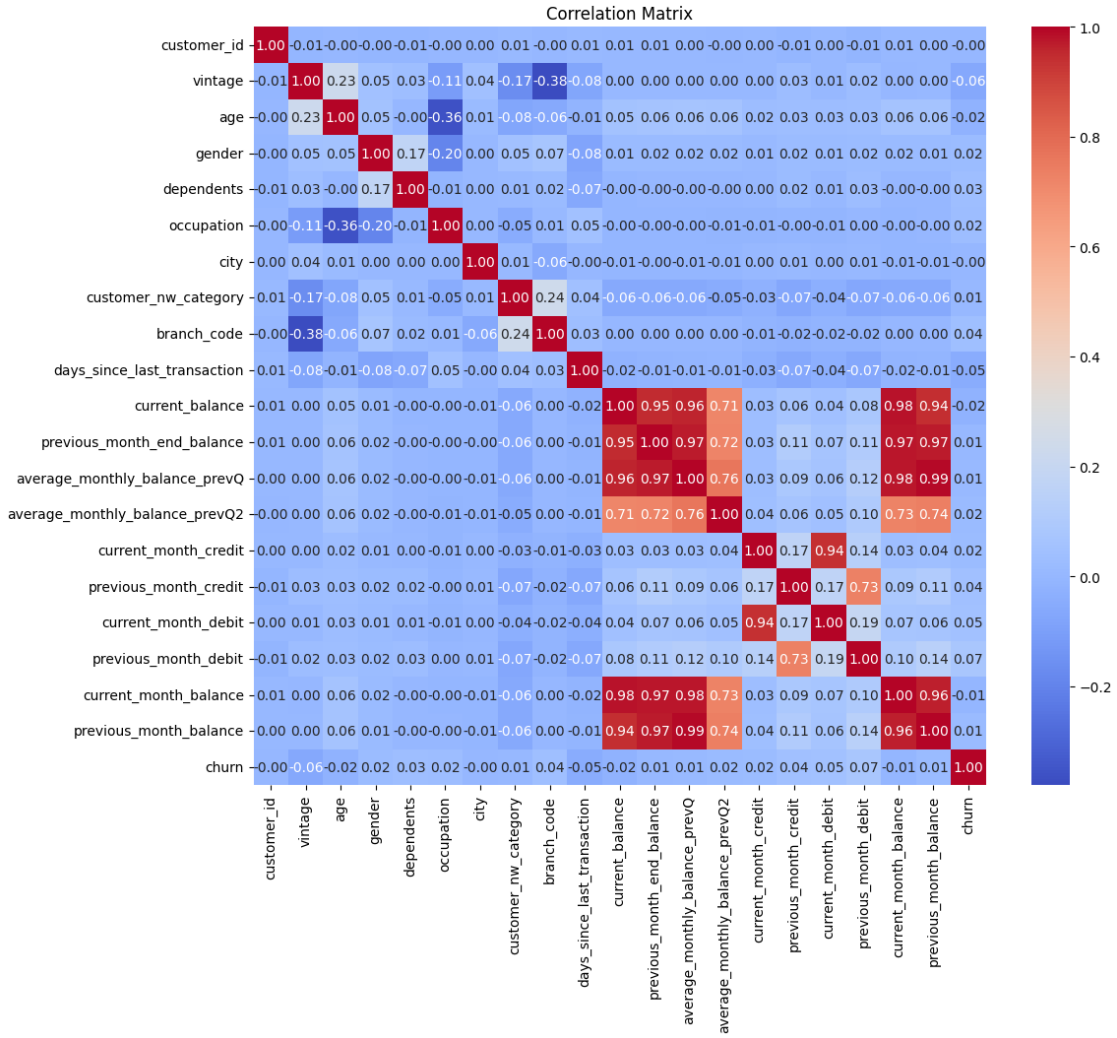
```
                churn
count  28382.000000
mean       0.185329
std        0.388571
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        1.000000
customer_id                          0
vintage                              0
age                                  0
gender                             525
dependents                        2463
occupation                          80
city                               803
customer_nw_category                 0
branch_code                          0
days_since_last_transaction       3223
current_balance                      0
previous_month_end_balance           0
average_monthly_balance_prevQ        0
average_monthly_balance_prevQ2       0
current_month_credit                 0
previous_month_credit                0
current_month_debit                  0
previous_month_debit                 0
current_month_balance                0
previous_month_balance               0
churn                                0
dtype: int64
```


Age Distribution
Frequency
Age
0
200
400
600
800
1000
1200
1400
0
20
40
60
80



[2]:
```
from sklearn.preprocessing import StandardScaler, LabelEncoder

# Fill missing values
df.fillna(method='ffill', inplace=True)

# Encode categorical variables
le = LabelEncoder()
df['gender'] = le.fit_transform(df['gender'].astype(str))
df['occupation'] = le.fit_transform(df['occupation'].astype(str))

# Normalize numerical features
scaler = StandardScaler()
numerical_features = ['vintage', 'age', 'dependents', 'customer_nw_category',␣
 ↪'days_since_last_transaction', 'current_balance',␣
 ↪'previous_month_end_balance', 'average_monthly_balance_prevQ',␣
 ↪'average_monthly_balance_prevQ2', 'current_month_credit',␣
 ↪'previous_month_credit', 'current_month_debit', 'previous_month_debit',␣
 ↪'current_month_balance', 'previous_month_balance']
df[numerical_features] = scaler.fit_transform(df[numerical_features])
```

```
# Visualize the correlation matrix
plt.figure(figsize=(12, 10))
sns.heatmap(df.corr(), annot=True, fmt='.2f', cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



[3]:
```
from sklearn.model_selection import train_test_split

X = df.drop(['churn', 'customer_id'], axis=1)
y = df['churn']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[11]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report

# Initialize and train the classifier
model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)

# Predictions
y_pred = model.predict(X_test)

# Evaluate the model
print(f'Accuracy: {accuracy_score(y_test, y_pred)}')
print(classification_report(y_test, y_pred))
```

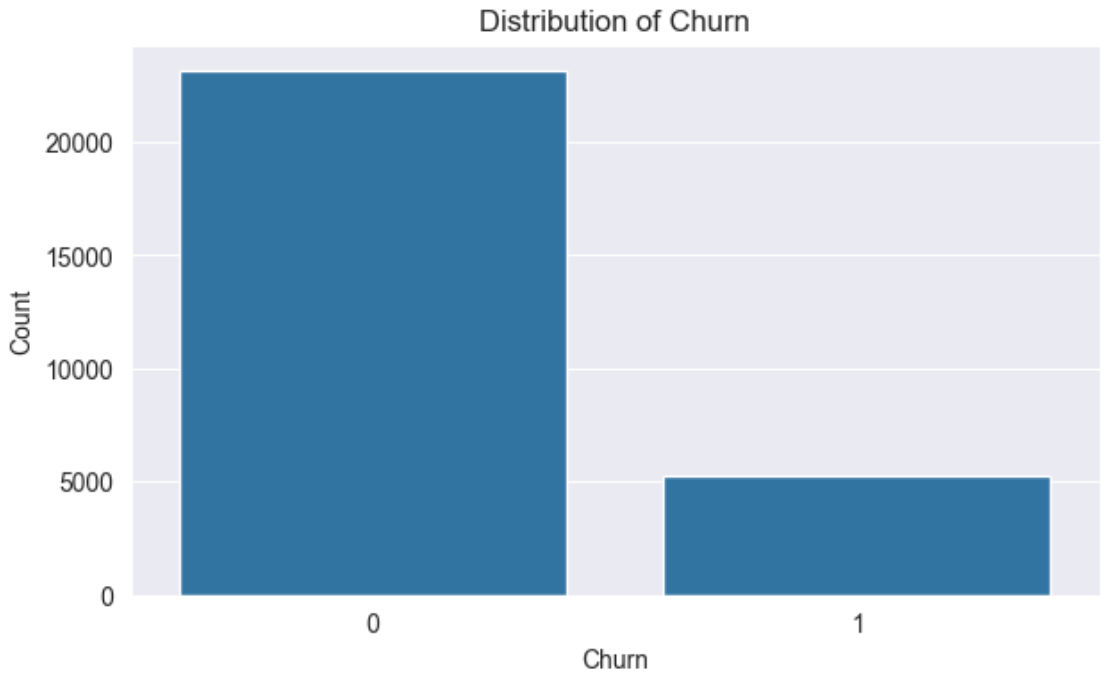
```
Accuracy: 0.8682402677470495
              precision    recall  f1-score   support

           0       0.88      0.97      0.92      4639
           1       0.74      0.43      0.55      1038

    accuracy                           0.87      5677
   macro avg       0.81      0.70      0.73      5677
weighted avg       0.86      0.87      0.85      5677
```

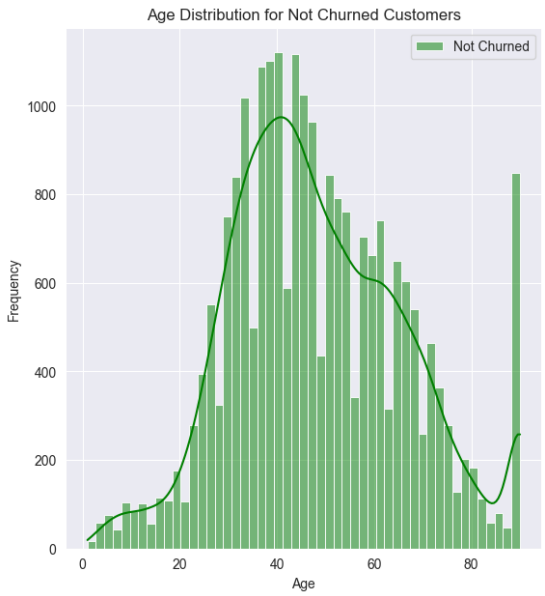
[12]:
```
from sklearn.model_selection import GridSearchCV

# Define the parameter grid
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [5, 10, 15],
    'min_samples_split': [2, 5, 10]
}

# Initialize the grid search model
grid_search = GridSearchCV(estimator=RandomForestClassifier(random_state=42),␣
 ↪param_grid=param_grid, cv=3, n_jobs=-1, verbose=2)

# Fit the grid search to the data
grid_search.fit(X_train, y_train)

# Print the best parameters and best score
print(f"Best Parameters: {grid_search.best_params_}")
print(f"Best Score: {grid_search.best_score_}")
```

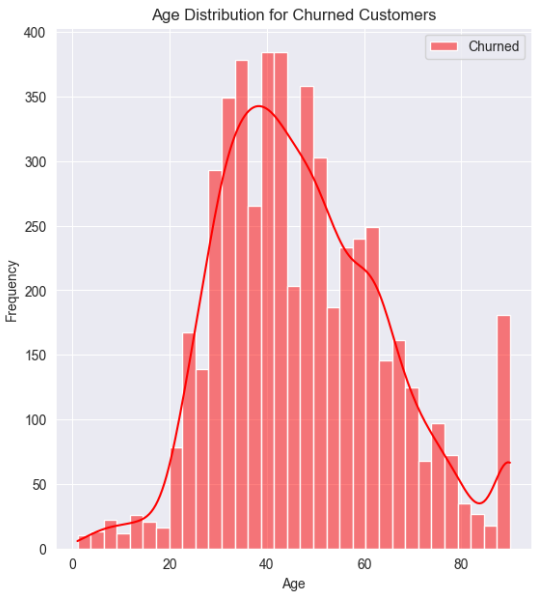
```
Fitting 3 folds for each of 27 candidates, totalling 81 fits
Best Parameters: {'max_depth': 15, 'min_samples_split': 10, 'n_estimators': 100}
Best Score: 0.8643471022663843
```

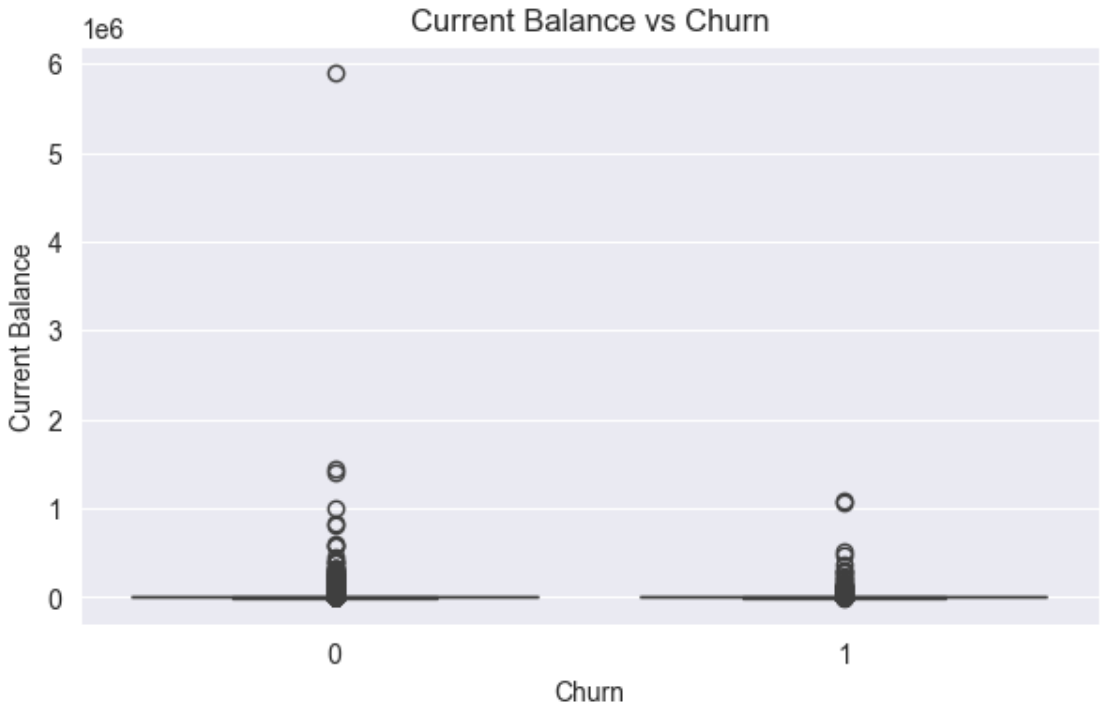
[9]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
# Load the dataset
df = pd.read_csv(r'C:\Users\jerme\Downloads\Data Science␣
↪project\churn_prediction.csv')
# Visualize the distribution of churn
plt.figure(figsize=(7, 4))
sns.countplot(x='churn', data=df)
plt.title('Distribution of Churn')
plt.xlabel('Churn')
plt.ylabel('Count')
plt.show()
# Visualize the distribution of age for churned and retained customers
plt.figure(figsize=(14, 7))
plt.subplot(1, 2, 1)
sns.histplot(df[df['churn'] == 0]['age'], kde=True, color='green', label='Not␣
↪Churned')
plt.title('Age Distribution for Not Churned Customers')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.legend()

plt.subplot(1, 2, 2)
sns.histplot(df[df['churn'] == 1]['age'], kde=True, color='red', label='Churned')
plt.title('Age Distribution for Churned Customers')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.legend()
plt.show()

# Visualize the relationship between balance and churn
plt.figure(figsize=(7, 4))
sns.boxplot(x='churn', y='current_balance', data=df)
plt.title('Current Balance vs Churn')
plt.xlabel('Churn')
plt.ylabel('Current Balance')
plt.show()

# Feature importance from the model
feature_importances = pd.Series(model.feature_importances_, index=X.columns)
plt.figure(figsize=(12, 6))
feature_importances.nlargest(10).sort_values().plot(kind='barh')
plt.title('Top 10 Feature Importances')
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.show()
```

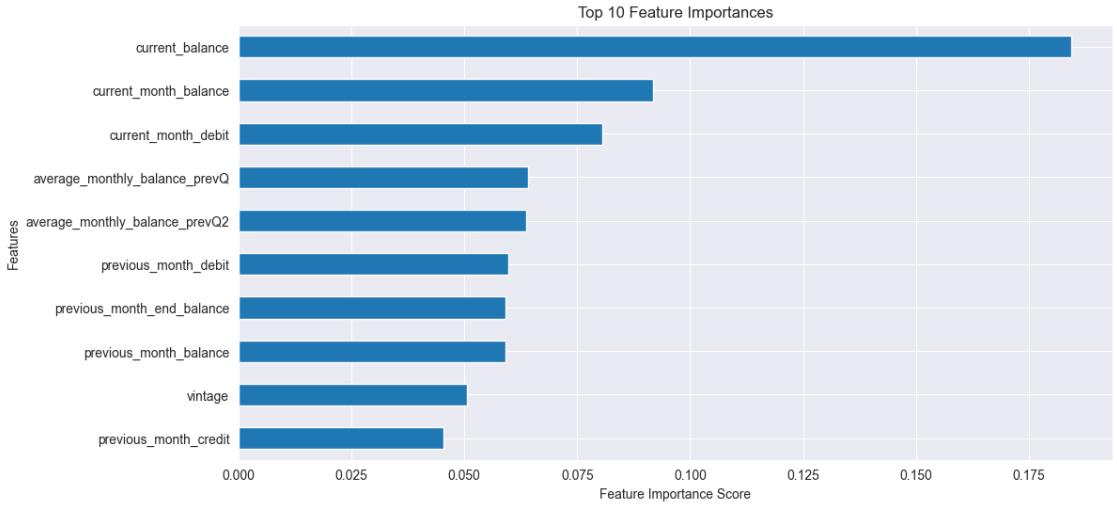
```
# ROC Curve
from sklearn.metrics import roc_curve, auc

# Calculate the fpr and tpr for all thresholds of the classification
probs = model.predict_proba(X_test)
preds = probs[:, 1]
fpr, tpr, threshold = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(7, 7))
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.title('Receiver Operating Characteristic')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc = 'lower right')
plt.show()
```

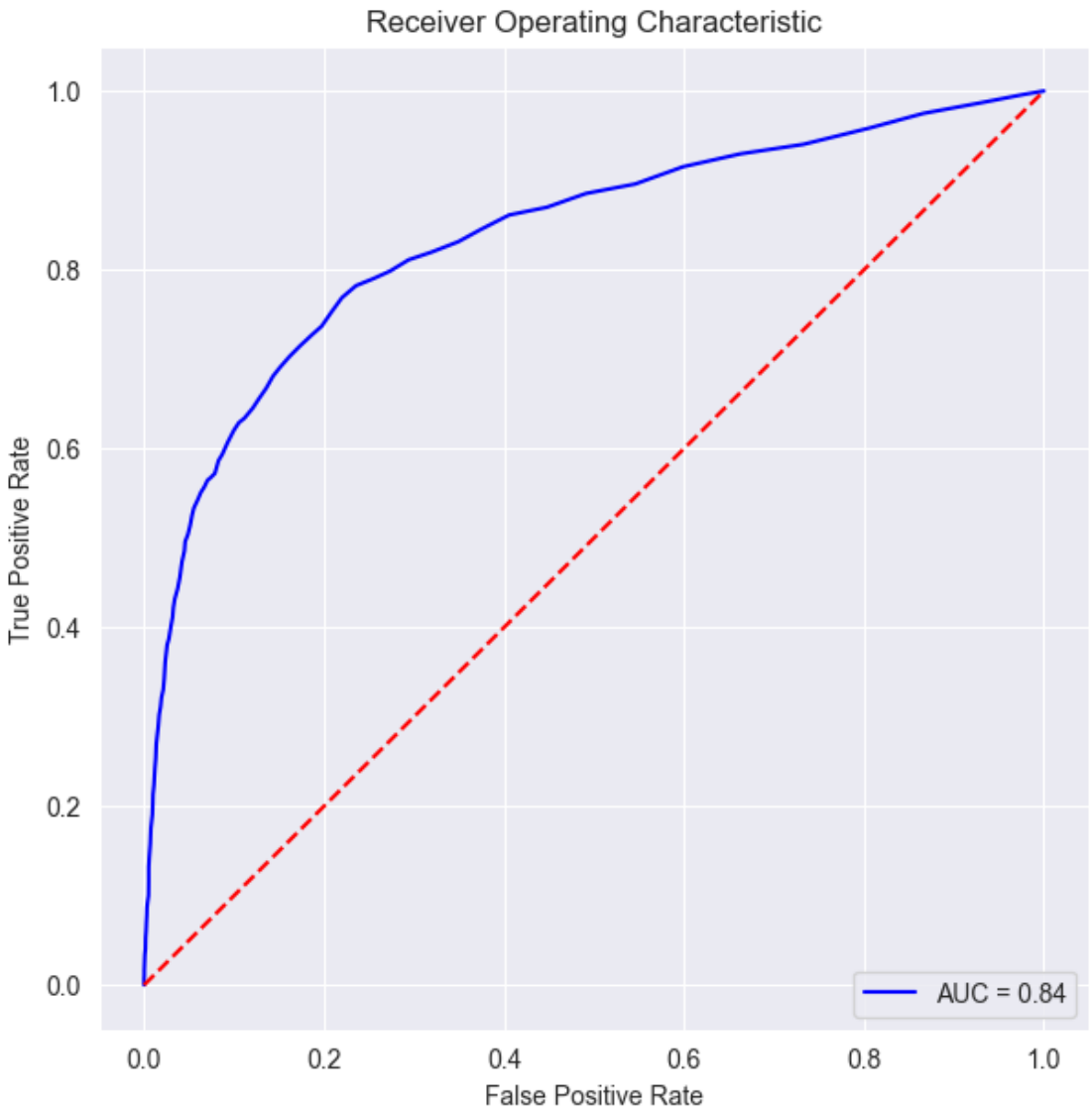



Age Distribution for Not Churned Customers
Not Churned
Frequency
Age
0
200
400
600
800
1000
0
20
40
60
80

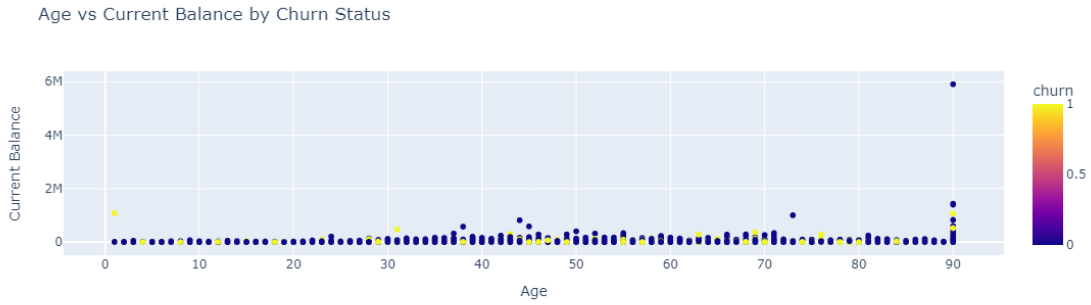

Age Distribution for Churned Customers
Churned
Frequency
Age
0
50
100
150
200
250
300
350
400
0
20
40
60
80


Current Balance vs Churn
1e6
Current Balance
Churn
0
1
2
3
4
5
6
0
1

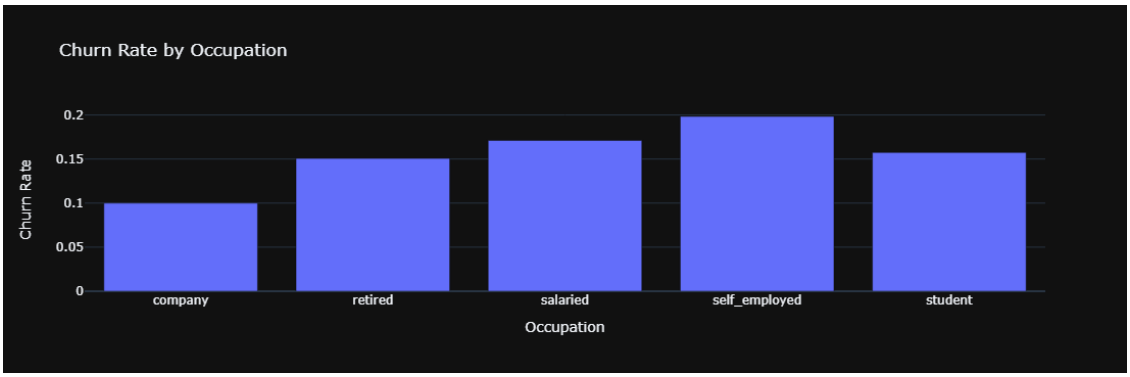

Top 10 Feature Importances
current_balance
current_month_balance
current_month_debit
average_monthly_balance_prevQ
average_monthly_balance_prevQ2
previous_month_debit
previous_month_end_balance
previous_month_balance
vintage
previous_month_credit
Features
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
Feature Importance Score



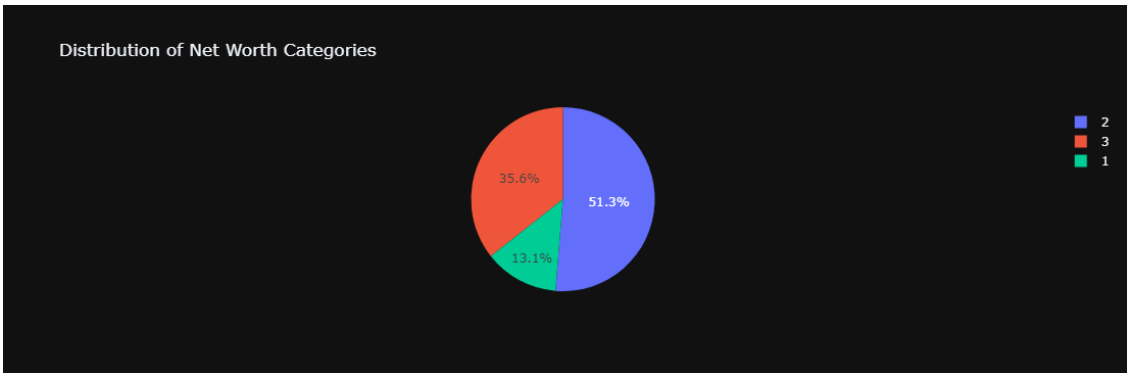
[10]:
```
import plotly.express as px

# Assuming 'df' is your DataFrame with the 'age', 'current_balance', and 'churn' columns
fig = px.scatter(df, x='age', y='current_balance',
                 color='churn',  # Differentiate points by churn
                 title='Age vs Current Balance by Churn Status',
                 labels={'current_balance': 'Current Balance', 'age': 'Age'},
                 hover_data=['customer_id'])  # Show customer_id on hover

fig.update_layout(transition_duration=500)
fig.show()
```



[13]:
```
fig = px.bar(df.groupby('occupation')['churn'].mean().reset_index(),
             x='occupation', y='churn',
             title='Churn Rate by Occupation',
             labels={'churn': 'Churn Rate', 'occupation': 'Occupation'})
fig.show()
```



[14]:
```
fig = px.pie(df, names='customer_nw_category', title='Distribution of Net Worth␣
↪Categories',
             labels={'customer_nw_category': 'Customer Net Worth Category'})
fig.show()
```



[15]:
```
import joblib

# Save the model to disk
joblib.dump(grid_search.best_estimator_, 'final_model.joblib')
```

[15]:
```
['final_model.joblib']
```

[ ]:
```

```