```
from google.colab import files
uploaded=files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

Saving dataset.csv to dataset.csv

Installing all Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, classification_report, ConfusionMatrixDisplay
from imblearn.over_sampling import RandomOverSampler
from xgboost import XGBClassifier
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

2. Load and Preprocess Data

```
# Read CSV
df = pd.read_csv('dataset.csv')
```

```
df
```

	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	Num Of Products	Has Credit Card	Is Active Member	Estimated Salary	Churn
0	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	15606229	Obijiaku	771	France	Male	39	5	0.00	2	1	0	96270.64	0
9996	15569892	Johnstone	516	France	Male	35	10	57369.61	1	1	1	101699.77	0
9997	15584532	Liu	709	France	Female	36	7	0.00	1	0	1	42085.58	1
9998	15682355	Sabbatini	772	Germany	Male	42	3	75075.31	2	1	0	92888.52	1
9999	15628319	Walker	792	France	Female	28	4	130142.79	1	1	0	38190.78	0

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   CustomerId        10000 non-null  int64
 1   Surname           10000 non-null  object
 2   CreditScore       10000 non-null  int64
 3   Geography         10000 non-null  object
 4   Gender            10000 non-null  object
 5   Age               10000 non-null  int64
 6   Tenure            10000 non-null  int64
 7   Balance           10000 non-null  float64
 8   Num Of Products   10000 non-null  int64
 9   Has Credit Card   10000 non-null  int64
 10  Is Active Member  10000 non-null  int64
 11  Estimated Salary  10000 non-null  float64
 12  Churn             10000 non-null  int64
dtypes: float64(2), int64(8), object(3)
memory usage: 1015.8+ KB
```

```
df.isnull().sum()
```

	0
CustomerId	0
Surname	0
CreditScore	0
Geography	0
Gender	0
Age	0
Tenure	0
Balance	0
Num Of Products	0
Has Credit Card	0
Is Active Member	0
Estimated Salary	0
Churn	0

dtype: int64

```
df.columns
```

```
Index(['CreditScore', 'Age', 'Tenure', 'Balance', 'Num Of Products',
       'Has Credit Card', 'Is Active Member', 'Estimated Salary', 'Churn',
       'Geography_Germany', 'Geography_Spain', 'Gender_Male'],
      dtype='object')
```

3. Data Analysis

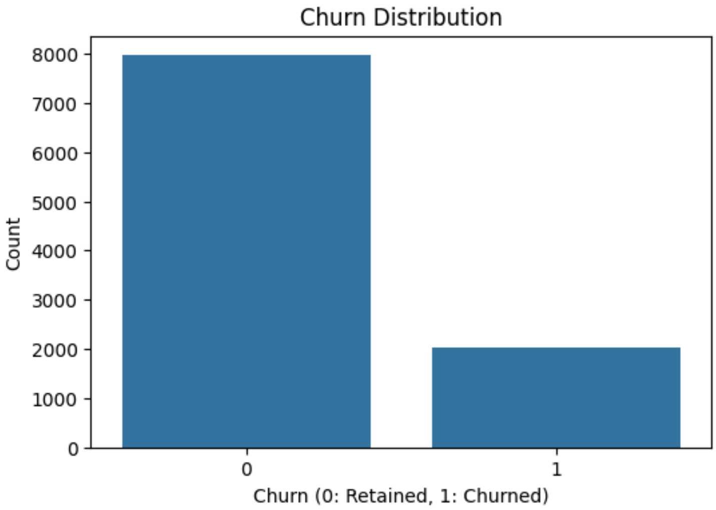
```
# Churn distribution
print('Churn Distribution (%):')
print(df['Churn'].value_counts(normalize=True) * 100)

# Summary statistics by Churn
numerical_cols = ['CreditScore', 'Age', 'Tenure', 'Balance', 'Num Of Products', 'Estimated Salary']
print('\nSummary Statistics by Churn:')
print(df.groupby('Churn')[numerical_cols].agg(['mean', 'std', 'min', 'max']))

# Correlation with Churn
print('\nCorrelations with Churn:')
print(df.corr()['Churn'].sort_values(ascending=False))
```

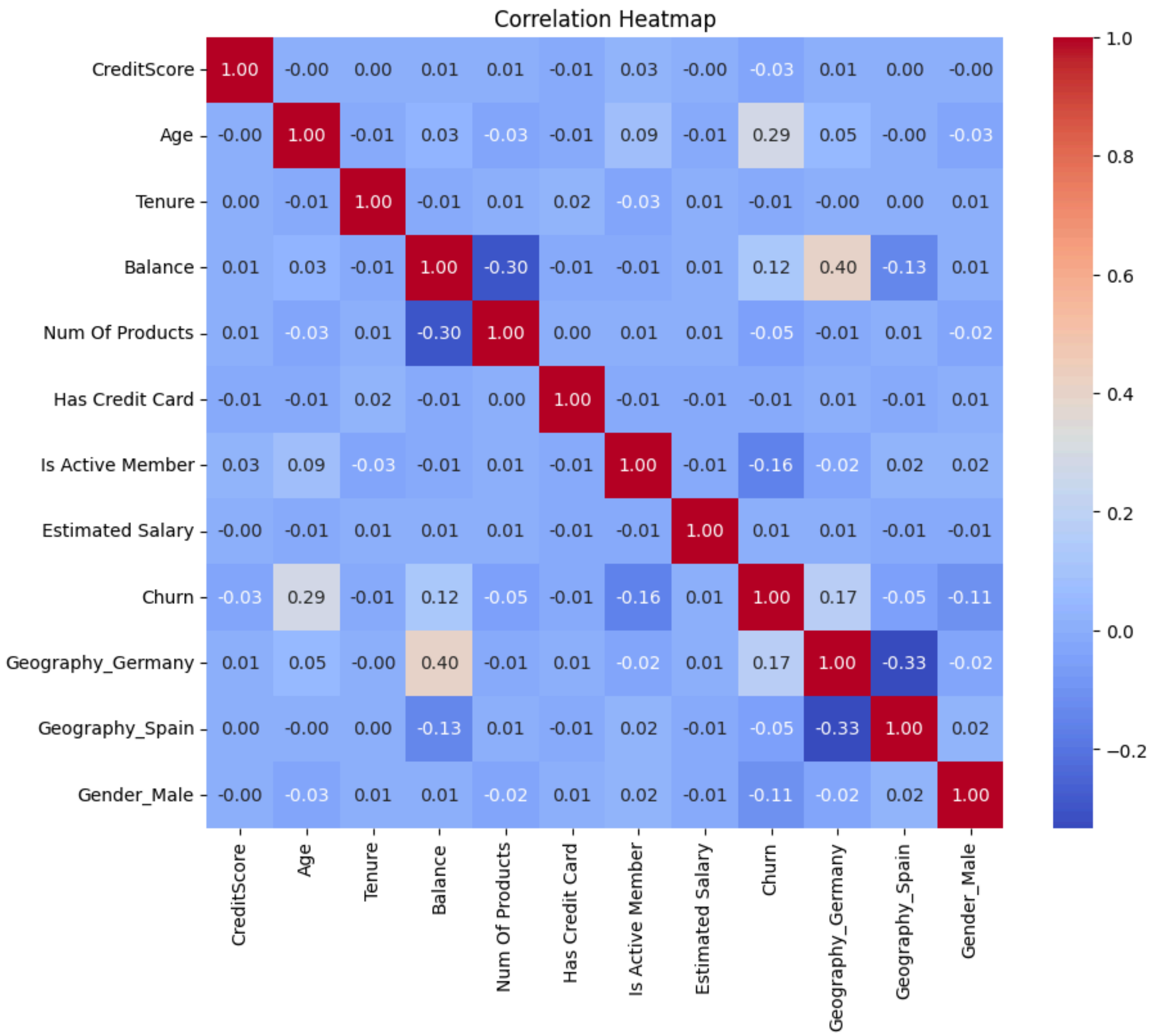
```
Churn Distribution (%):
Churn
0    79.63
1    20.37
Name: proportion, dtype: float64

Summary Statistics by Churn:
      CreditScore                                          Age                    \
             mean       std       min       max      mean      std       min   
Churn                                                                          
0        0.013703  0.989709 -2.540431  2.063884 -0.144309  0.96549 -1.994969   
1       -0.053568  1.038004 -3.109504  2.063884  0.564131  0.93080 -1.994969   

                  Tenure            ...   Balance           Num Of Products  \
            max      mean       std  ...       min       max            mean   
Churn                                ...                                       
0      5.061197  0.007081  0.996068  ... -1.225848  2.324683        1.544267   
1      4.298368 -0.027682  1.015241  ... -1.225848  2.795323        1.475209   

                     Estimated Salary                                
            std min max            mean           std    min        max  
Churn                                                                    
0      0.509536   1   3     99738.391772  57405.586966  90.07  199992.48  
1      0.801521   1   4    101465.677531  57912.418071  11.58  199808.10  

[2 rows x 24 columns]

Correlations with Churn:
Churn                1.000000
Age                  0.285323
Geography_Germany    0.173488
Balance              0.118533
Estimated Salary     0.012097
Has Credit Card     -0.007138
Tenure              -0.014001
CreditScore         -0.027094
Num Of Products     -0.047820
```

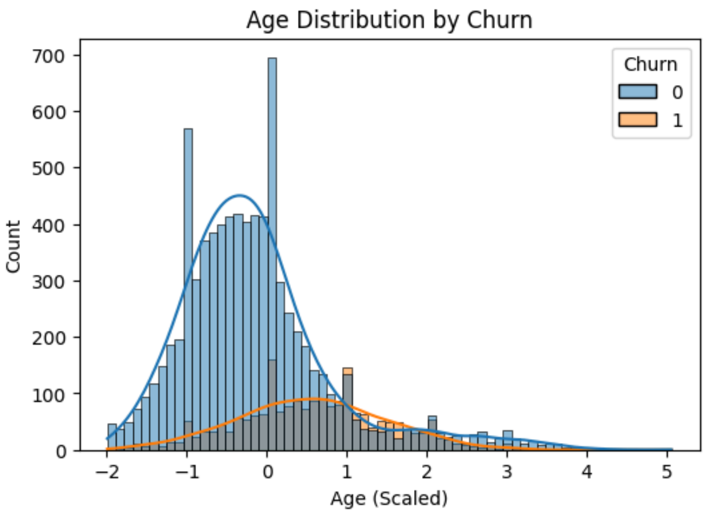
```
Geography_Spain     -0.052667
Gender_Male         -0.106512
Is Active Member    -0.156128
Name: Churn, dtype: float64
```

4. Visualizations

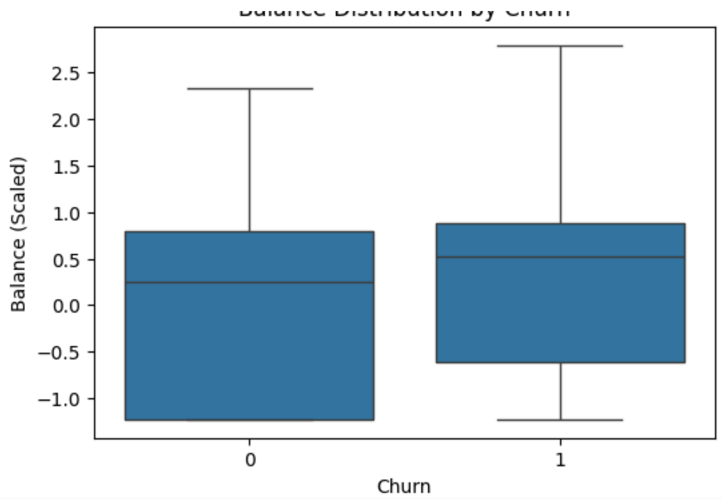
```
# Churn distribution
plt.figure(figsize=(6, 4))
sns.countplot(x='Churn', data=df)
plt.title('Churn Distribution')
plt.xlabel('Churn (0: Retained, 1: Churned)')
plt.ylabel('Count')
plt.savefig('churn_distribution.png')
plt.show()

# Correlation heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap')
plt.savefig('correlation_heatmap.png')
plt.show()

# Age distribution by Churn
plt.figure(figsize=(6, 4))
sns.histplot(data=df, x='Age', hue='Churn', kde=True)
plt.title('Age Distribution by Churn')
plt.xlabel('Age (Scaled)')
plt.savefig('age_distribution.png')
plt.show()

# Balance boxplot by Churn
plt.figure(figsize=(6, 4))
sns.boxplot(x='Churn', y='Balance', data=df)
plt.title('Balance Distribution by Churn')
plt.xlabel('Churn')
plt.ylabel('Balance (Scaled)')
plt.savefig('balance_boxplot.png')
plt.show()
```







Balance Distribution by Churn



5. Class Imbalance

```
ros = RandomOverSampler(random_state=42)
X_ros, y_ros = ros.fit_resample(X, y)
X_train, X_test, y_train, y_test = train_test_split(X_ros, y_ros, test_size=0.2, random_state=42)
print('Original Class Distribution:', y.value_counts())
print('Oversampled Class Distribution:', pd.Series(y_ros).value_counts())
print('Train Shape:', X_train.shape, 'Test Shape:', X_test.shape)
```

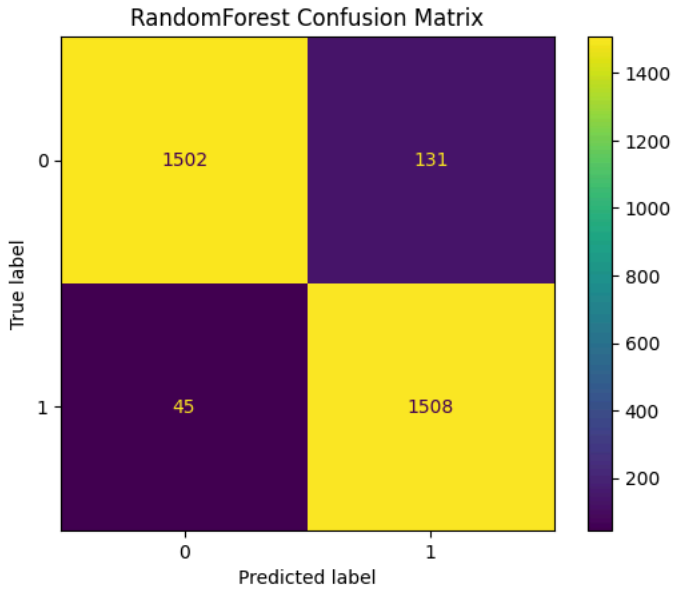
```
Original Class Distribution: Churn
0    7963
1    2037
Name: count, dtype: int64
Oversampled Class Distribution: Churn
1    7963
0    7963
Name: count, dtype: int64
Train Shape: (12740, 11) Test Shape: (3186, 11)
```

6. Model Training

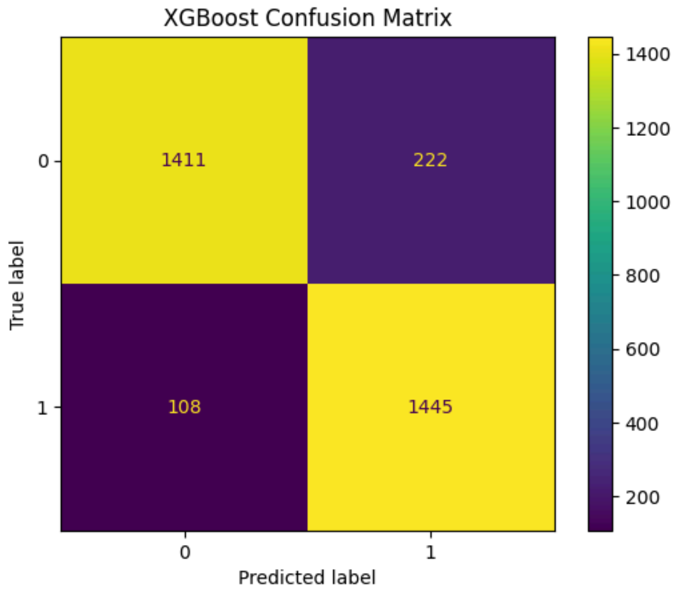
```
# RandomForest with RandomizedSearchCV
rf = RandomForestClassifier(random_state=42)
param_dist = {
    'n_estimators': [100, 200, 300],
    'max_depth': [10, 20, 30, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['sqrt', 'log2']
}
random_search = RandomizedSearchCV(rf, param_distributions=param_dist, n_iter=10, cv=3, random_state=42, n_jobs=-1)
random_search.fit(X_train, y_train)
print('Best RandomForest Parameters:', random_search.best_params_)

# Evaluate RandomForest
y_pred_rf = random_search.predict(X_test)
print('RandomForest Confusion Matrix:')
print(confusion_matrix(y_test, y_pred_rf))
print('RandomForest Classification Report:')
print(classification_report(y_test, y_pred_rf))

# Plot confusion matrix
plt.figure(figsize=(6, 4))
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_rf)
plt.title('RandomForest Confusion Matrix')
plt.savefig('rf_confusion_matrix.png')
plt.show()

# XGBoost baseline
xgb = XGBClassifier(random_state=42, eval_metric='logloss')
xgb.fit(X_train, y_train)

# Evaluate XGBoost
y_pred_xgb = xgb.predict(X_test)
print('XGBoost Confusion Matrix:')
print(confusion_matrix(y_test, y_pred_xgb))
print('XGBoost Classification Report:')
print(classification_report(y_test, y_pred_xgb))

# Plot confusion matrix
```

```
plt.figure(figsize=(6, 4))
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_xgb)
plt.title('XGBoost Confusion Matrix')
plt.savefig('xgb_confusion_matrix.png')
plt.show()
```

```
Best RandomForest Parameters: {'n_estimators': 200, 'min_samples_split': 5, 'min_samples_leaf': 1, 'max_features': 'log2', 'max_depth': 30}
RandomForest Confusion Matrix:
[[1502  131]
 [  45 1508]]
RandomForest Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.92      0.94      1633
           1       0.92      0.97      0.94      1553

    accuracy                           0.94      3186
   macro avg       0.95      0.95      0.94      3186
weighted avg       0.95      0.94      0.94      3186

<Figure size 600x400 with 0 Axes>
```




```
XGBoost Confusion Matrix:
[[1411  222]
 [ 108 1445]]
XGBoost Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.86      0.90      1633
           1       0.87      0.93      0.90      1553

    accuracy                           0.90      3186
   macro avg       0.90      0.90      0.90      3186
weighted avg       0.90      0.90      0.90      3186

<Figure size 600x400 with 0 Axes>
```



7. Feature Importance

```python
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

# Feature importance
feature_importance = pd.DataFrame({
    'Feature': X.columns,
    'Importance': random_search.best_estimator_.feature_importances_
}).sort_values('Importance', ascending=False)
print('Feature Importance (RandomForest):')
print(feature_importance)

# Plot feature importance
plt.figure(figsize=(8, 6))
sns.barplot(x='Importance', y='Feature', data=feature_importance)
plt.title('RandomForest Feature Importance')
plt.tight_layout()
plt.savefig('feature_importance.png', dpi=300, bbox_inches='tight')
plt.show()
plt.close()
```

```
Feature Importance (RandomForest):
              Feature  Importance
1                 Age    0.259071
3             Balance    0.143464
4     Num Of Products    0.137925
7    Estimated Salary    0.133283
0         CreditScore    0.130522
2              Tenure    0.075847
6    Is Active Member    0.037143
8   Geography_Germany    0.032559
10        Gender_Male    0.020173
5     Has Credit Card    0.017025
9     Geography_Spain    0.012988
```