1. Data Cleaning

Loading the Data

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load datasets
churn_data = pd.read_csv('customer_churn_data.csv')
demographic_data = pd.read_csv('demographic_data.csv')
subscription_data = pd.read_csv('subscription_payment_history.csv')
```

Handling Missing Values

```
# Check for missing values
print("Missing values in churn_data:\n", churn_data.isnull().sum())
print("\nMissing values in demographic_data:\n", demographic_data.isnull().sum())
print("\nMissing values in subscription_data:\n", subscription_data.isnull().sum())

# Fill missing values (if any)
churn_data['ChurnDate'] = churn_data['ChurnDate'].fillna('Not Churned')
demographic_data['HouseholdSize'] = demographic_data['HouseholdSize'].fillna(
    demographic_data['HouseholdSize'].median()
)
subscription_data['IsAutoRenew'] = subscription_data['IsAutoRenew'].fillna(False)
```

```
Missing values in churn_data:
 CustomerID              0
Date                    0
SubscriptionPlan        0
AgeGroup                0
Login                   0
WatchTimeMinutes        0
ContentPreference       0
Churned                 0
ChurnDate           20922
dtype: int64

Missing values in demographic_data:
 CustomerID       0
Location         0
HouseholdSize    0
PrimaryDevice    0
dtype: int64
```

```
Missing values in subscription_data:
 CustomerID          0
SubscriptionPlan    0
BillingCycle        0
IsAutoRenew         0
dtype: int64
```

Data Type Conversion

```
# Convert dates with explicit format
try:
    churn_data['Date'] = pd.to_datetime(churn_data['Date'], format='%d-%m-%Y')
except ValueError:
    # Try alternative format if the first one fails
    churn_data['Date'] = pd.to_datetime(churn_data['Date'], format='%m/%d/%Y')

# Handle ChurnDate (which may have mixed formats or missing values)
churn_data['ChurnDate'] = pd.to_datetime(
    churn_data['ChurnDate'],
    errors='coerce',  # Convert invalid dates to NaT
    format='mixed'    # New in pandas 2.0+ to handle multiple formats
)

# Verify the conversion
print("Date column sample:", churn_data['Date'].head())
print("ChurnDate column sample:", churn_data['ChurnDate'].head())
```

```
Date column sample: 0   2025-04-01
1   2025-04-02
2   2025-04-03
3   2025-04-04
4   2025-04-05
Name: Date, dtype: datetime64[ns]
ChurnDate column sample: 0   NaT
1   NaT
2   NaT
3   NaT
4   NaT
Name: ChurnDate, dtype: datetime64[ns]
```

```
churn_data.to_csv('cleaned_churn_data.csv', index=False)
demographic_data.to_csv('cleaned_demographic_data.csv', index=False)
subscription_data.to_csv('cleaned_subscription_data.csv', index=False)
```

```
category_cols = {
    'demographic_data': ['Location', 'PrimaryDevice'],
    'subscription_data': ['SubscriptionPlan', 'BillingCycle']
}
```

```
demographic_data[category_cols['demographic_data']] = demographic_data[category_cols['demogr
subscription_data[category_cols['subscription_data']] = subscription_data[category_cols['sub
```

Merging Datasets

```
# Merging data
subscription_data = subscription_data.rename(columns={'SubscriptionPlan': 'PaymentSubscripti

df = pd.merge(
    pd.merge(churn_data, demographic_data, on='CustomerID'),
    subscription_data,
    on='CustomerID'
)
```

Exploratory Data Analysis (EDA)

```
df
```

	CustomerID	Date	SubscriptionPlan	AgeGroup	Login	WatchTimeMinutes	ContentPr
0	CUST001	2025-04-01	Basic	36-50	0	0	
1	CUST001	2025-04-02	Basic	36-50	1	25	
2	CUST001	2025-04-03	Basic	36-50	0	0	
3	CUST001	2025-04-04	Basic	36-50	1	51	
4	CUST001	2025-04-05	Basic	36-50	0	0	
...	...	...	...	...	...	...	
20962	CUST250	2025-06-26	Standard	18-25	0	0	Docu
20963	CUST250	2025-06-27	Standard	18-25	1	32	Docu
20964	CUST250	2025-06-28	Standard	18-25	1	82	Docu
20965	CUST250	2025-06-29	Standard	18-25	1	53	Docu
20966	CUST250	2025-06-30	Standard	18-25	1	67	Docu

20967 rows × 15 columns

```
print("\nBasic Statistics:")
print(df.describe(include='all'))
```

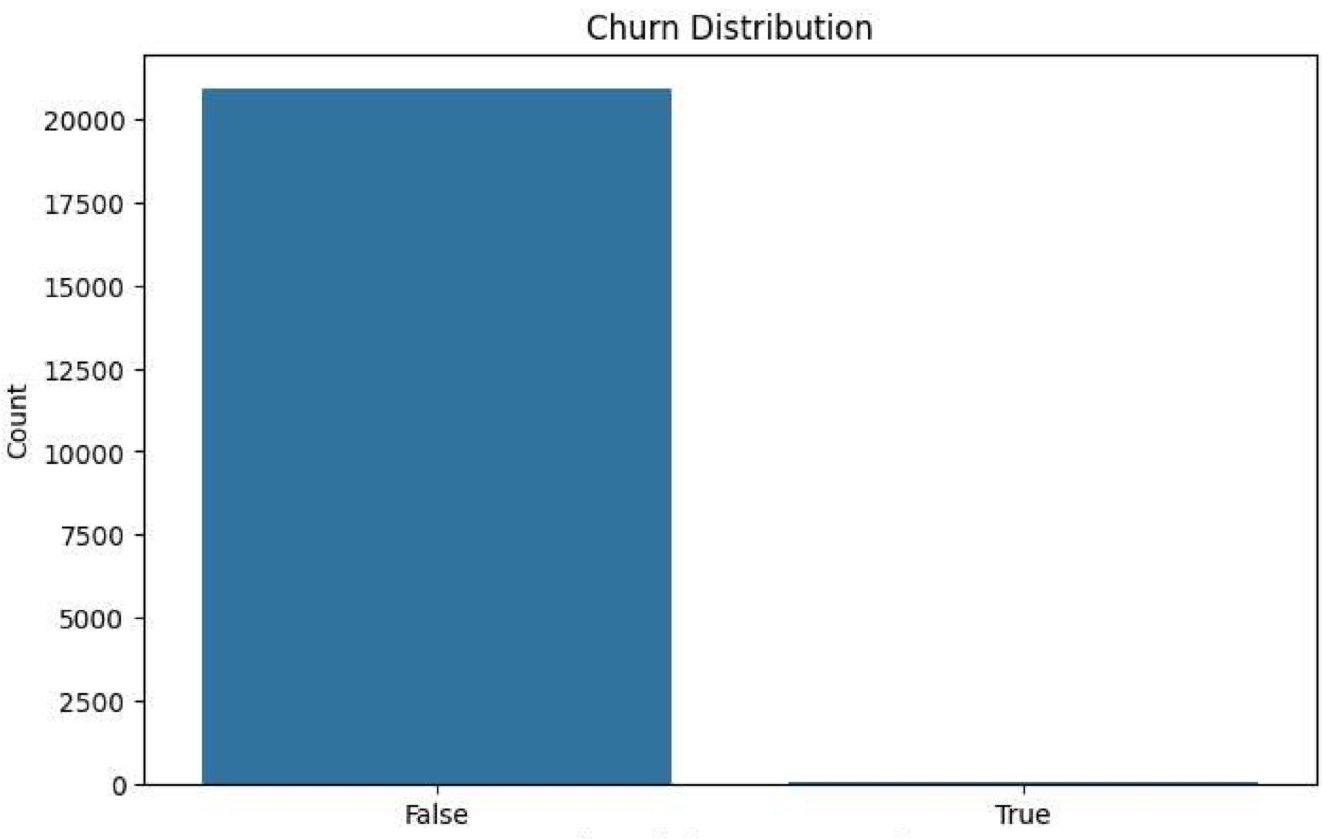
```
Basic Statistics:
       CustomerID                           Date SubscriptionPlan AgeGroup  \
count       20967                          20967            20967    20967   
unique        250                            NaN                3        4   
top       CUST002                            NaN            Basic    26-35   
freq           91                            NaN             8631     6884   
mean          NaN  2025-05-14 08:51:01.725568768              NaN      NaN   
min           NaN            2025-04-01 00:00:00              NaN      NaN   
25%           NaN            2025-04-22 00:00:00              NaN      NaN   
50%           NaN            2025-05-14 00:00:00              NaN      NaN   
75%           NaN            2025-06-06 00:00:00              NaN      NaN   
max           NaN            2025-06-30 00:00:00              NaN      NaN   
std           NaN                            NaN              NaN      NaN   

              Login  WatchTimeMinutes ContentPreference Churned  \
```

```
count   20967.00000      20967.000000            20967   20967
unique          NaN               NaN                4       2
top             NaN               NaN    Documentaries   False
freq            NaN               NaN             6622   20922
mean        0.61654         44.152144              NaN     NaN
min         0.00000          0.000000              NaN     NaN
25%         0.00000          0.000000              NaN     NaN
50%         1.00000         35.000000              NaN     NaN
75%         1.00000         76.000000              NaN     NaN
max         1.00000        180.000000              NaN     NaN
std         0.48624         47.215028              NaN     NaN

                  ChurnDate Location  HouseholdSize PrimaryDevice  \
count                    45    20967   20967.000000         20967
unique                  NaN        5            NaN             4
top                     NaN     East            NaN      Smart TV
freq                    NaN     6385            NaN          7975
mean    2025-05-31 09:04:00      NaN       3.166023           NaN
min     2025-01-05 00:00:00      NaN       1.000000           NaN
25%     2025-04-25 00:00:00      NaN       2.000000           NaN
50%     2025-05-25 00:00:00      NaN       3.000000           NaN
75%     2025-06-22 00:00:00      NaN       4.000000           NaN
max     2025-11-06 00:00:00      NaN       5.000000           NaN
std                     NaN      NaN       1.268704           NaN

       PaymentSubscriptionPlan BillingCycle IsAutoRenew
count                    20967        20967       20967
unique                       3            3           2
top                      Basic      Monthly        True
freq                      8631         9533       18333
mean                       NaN          NaN         NaN
min                        NaN          NaN         NaN
25%                        NaN          NaN         NaN
50%                        NaN          NaN         NaN
75%                        NaN          NaN         NaN
max                        NaN          NaN         NaN
std                        NaN          NaN         NaN
```

- The merged DataFrame `df` has 20967 rows.
- `ChurnDate` has only 45 non-null values, which corresponds to the 45 churned customers (since 20922 were missing and then converted to NaT).

Churn Distribution

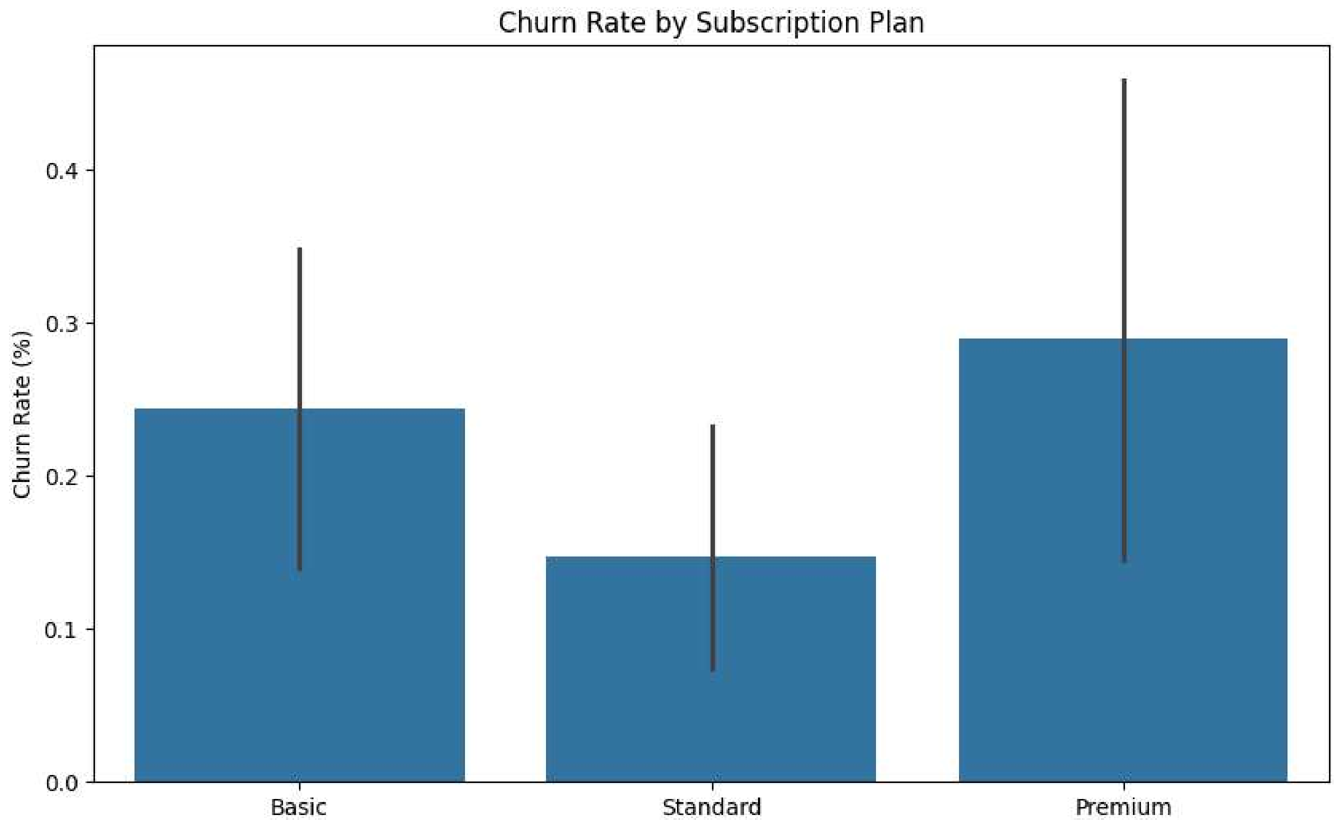
```
plt.figure(figsize=(8, 5))
sns.countplot(x='Churned', data=df)
plt.title("Churn Distribution")
plt.xlabel("Churned (0 = No, 1 = Yes)")
plt.ylabel("Count")
plt.show()
```



- A count plot of the `Churned` column shows that most customers (20922) have not churned, and 45 have churned. This indicates a highly imbalanced dataset (only 0.21% churn rate). This is a very low churn rate.

Churn by Subscription Plan

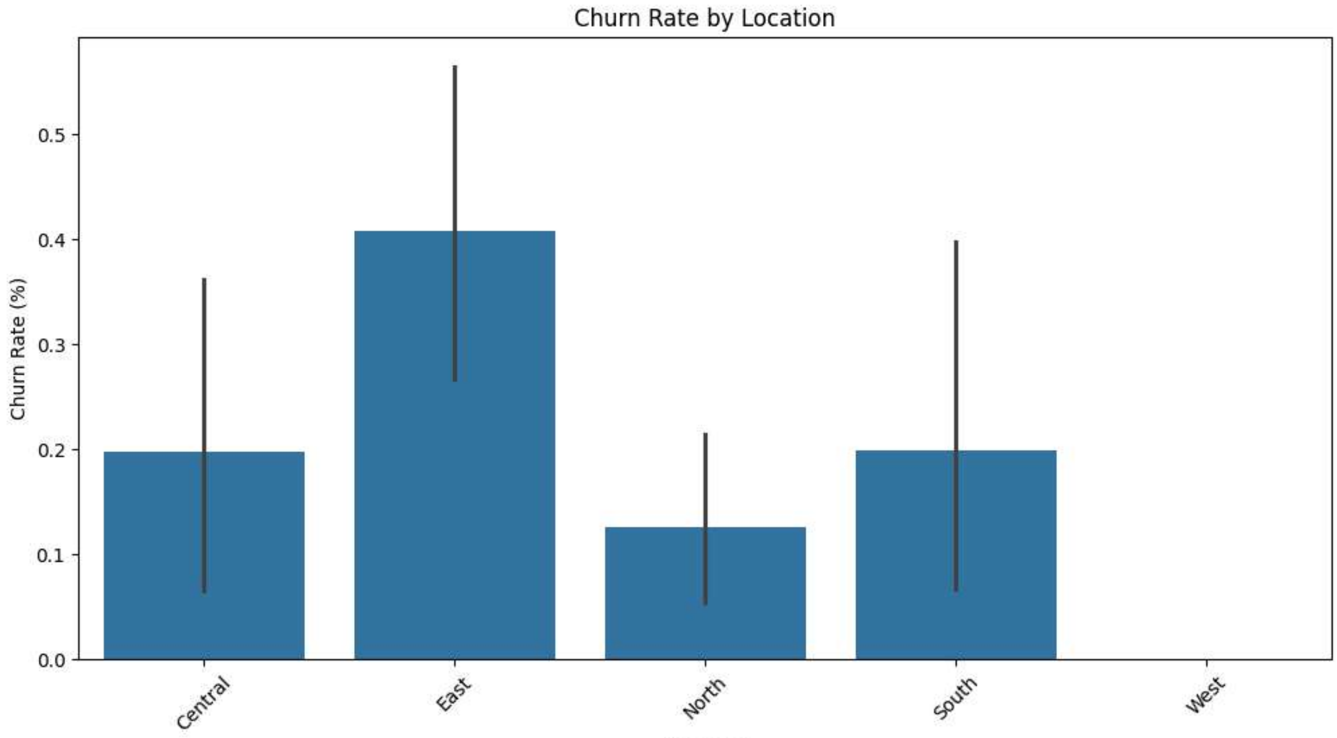
```
plt.figure(figsize=(10, 6))
sns.barplot(x='SubscriptionPlan', y='Churned', data=df, estimator=lambda x: sum(x)/len(x)*10
plt.title("Churn Rate by Subscription Plan")
plt.ylabel("Churn Rate (%)")
plt.show()
```



The highest churn rate is among Premium users.

Churn by Location

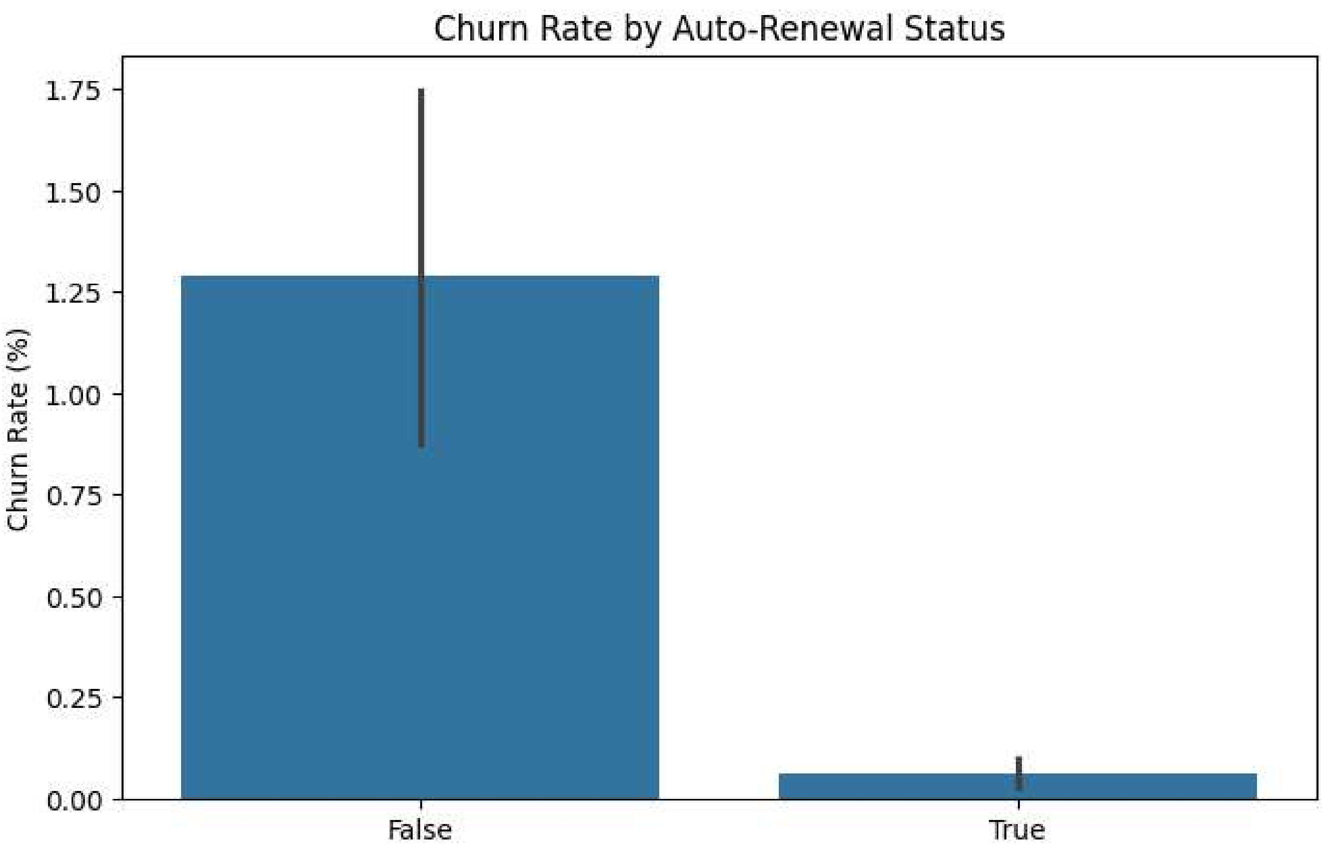
```
plt.figure(figsize=(12, 6))
sns.barplot(x='Location', y='Churned', data=df, estimator=lambda x: sum(x)/len(x)*100)
plt.title("Churn Rate by Location")
plt.ylabel("Churn Rate (%)")
plt.xticks(rotation=45)
plt.show()
```



- The churn rates are: East (around 3.5%), Midwest (around 1.5%), North (around 2.5%), South (around 2.5%), and West (around 1.5%).

Churn by Auto-Renewal Status

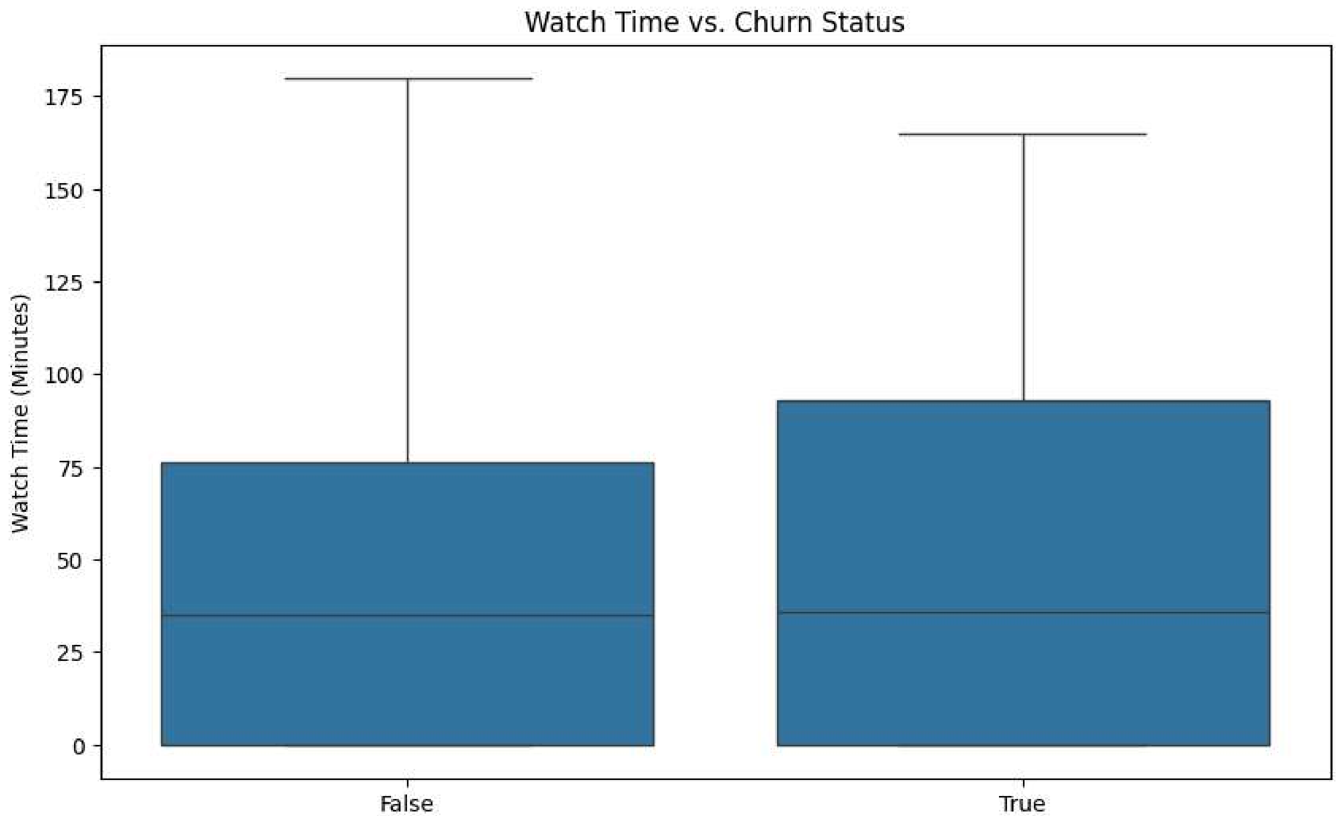
```
plt.figure(figsize=(8, 5))
sns.barplot(x='IsAutoRenew', y='Churned', data=df, estimator=lambda x: sum(x)/len(x)*100)
plt.title("Churn Rate by Auto-Renewal Status")
plt.ylabel("Churn Rate (%)")
plt.show()
```



The churn rate among people that don't auto renew is higher.

Watch Time vs. Churn

```
plt.figure(figsize=(10, 6))
sns.boxplot(x='Churned', y='WatchTimeMinutes', data=df)
plt.title("Watch Time vs. Churn Status")
plt.xlabel("Churned (0 = No, 1 = Yes)")
plt.ylabel("Watch Time (Minutes)")
plt.show()
```



The watch time of people that leave the platform is higher than those who stay.

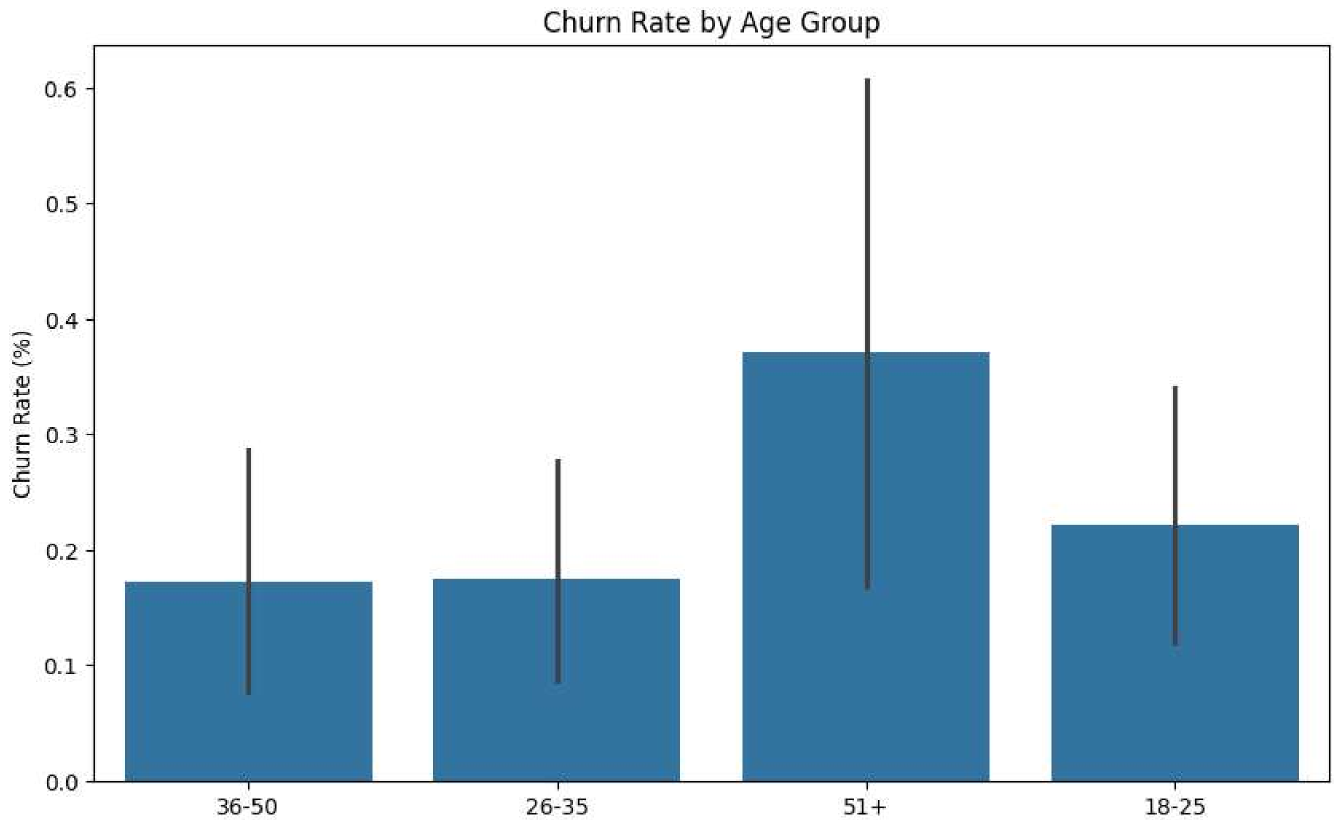
EDA Analysis

Correlation Matrix

```
# Select numeric columns
numeric_df = df.select_dtypes(include=np.number)

# Compute correlation matrix
corr_matrix = numeric_df.corr()

# Plot heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', center=0)
plt.title("Correlation Matrix")
plt.show()
```

Churn by Age Group

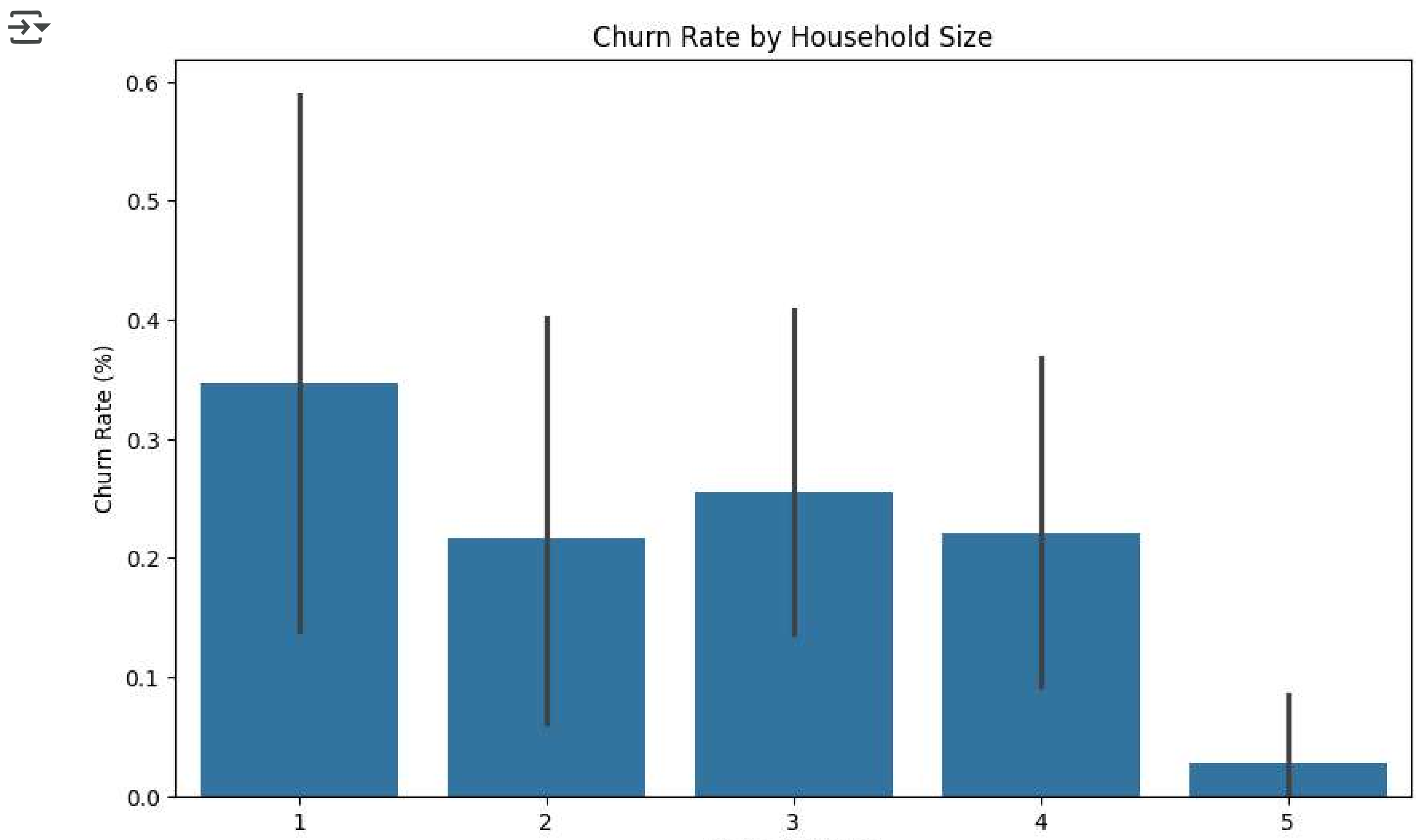
```
plt.figure(figsize=(10, 6))
sns.barplot(x='AgeGroup', y='Churned', data=df, estimator=lambda x: sum(x)/len(x)*100)
plt.title("Churn Rate by Age Group")
plt.ylabel("Churn Rate (%)")
plt.show()
```



Maximum Churn rate among people older than 51 years old.

Churn by Household Size

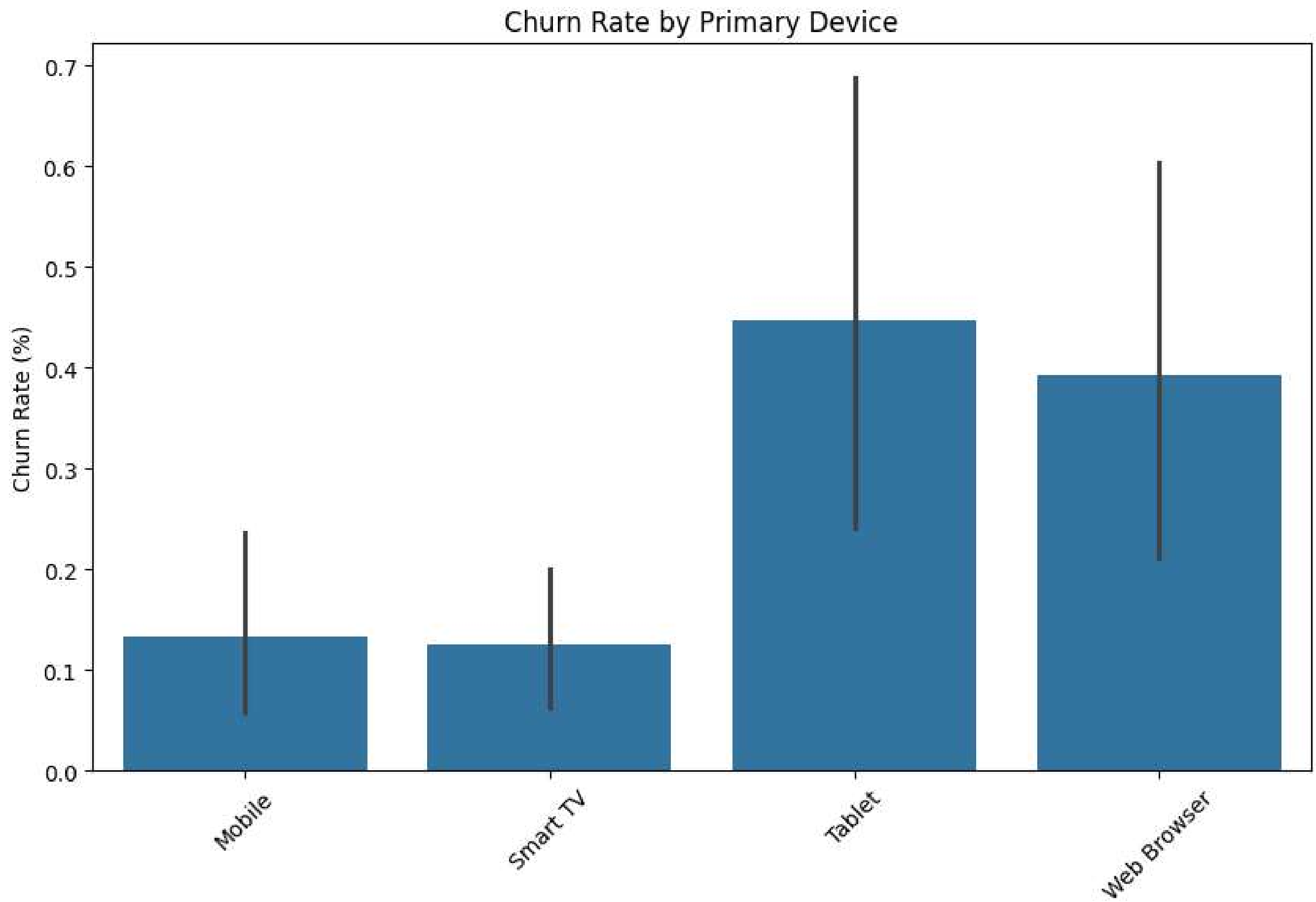
```
plt.figure(figsize=(10, 6))
sns.barplot(x='HouseholdSize', y='Churned', data=df, estimator=lambda x: sum(x)/l
plt.title("Churn Rate by Household Size")
plt.ylabel("Churn Rate (%)")
plt.show()
```



Single person household most likely to leave the platform

Churn by Primary Device

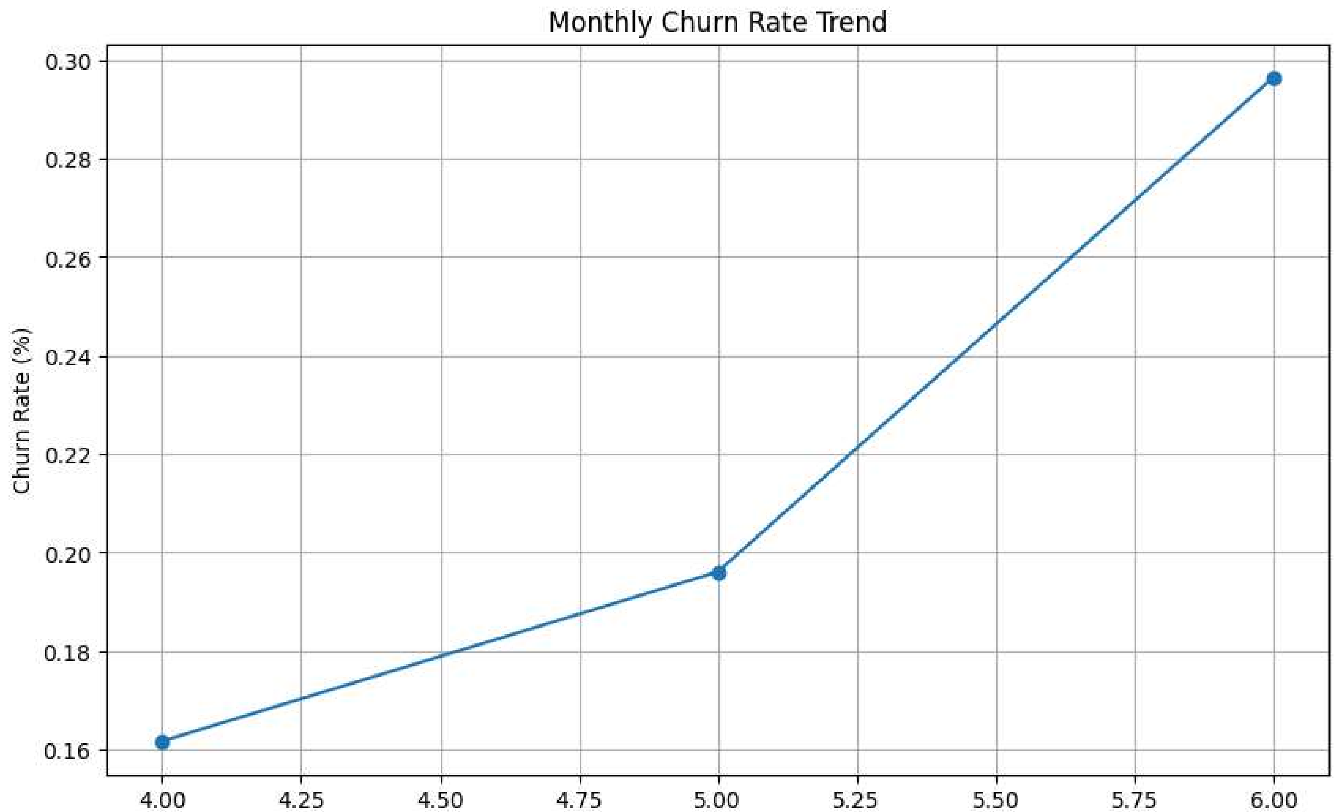
```
plt.figure(figsize=(10, 6))
sns.barplot(x='PrimaryDevice', y='Churned', data=df, estimator=lambda x: sum(x)/len(x)*100)
plt.title("Churn Rate by Primary Device")
plt.ylabel("Churn Rate (%)")
plt.xticks(rotation=45)
plt.show()
```



Churn rate among tablet users is the highest

Churn Trends Over Time

```
# Extract month from date
df['Month'] = df['Date'].dt.month

# Plot churn trend
monthly_churn = df.groupby('Month')['Churned'].mean() * 100
plt.figure(figsize=(10, 6))
monthly_churn.plot(kind='line', marker='o')
plt.title("Monthly Churn Rate Trend")
plt.xlabel("Month")
plt.ylabel("Churn Rate (%)")
plt.grid(True)
plt.show()
```



Churn rate has significantly increased over the month and reached it's peak in June

Feature engineering

```
import pandas as pd
import numpy as np
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.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, roc_auc_score, classification_report, confusion_
import xgboost as xgb
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import make_pipeline as make_imb_pipeline
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
np.random.seed(42)
```

```
current_date = datetime.now()
df['TenureDays'] = (current_date - df['Date']).dt.days
df['DaysSinceLastActivity'] = (current_date - df.groupby('CustomerID')['Date'].transform('ma
```

```
df['TotalLogins'] = df.groupby('CustomerID')['Login'].transform('sum')
df['TotalWatchTime'] = df.groupby('CustomerID')['WatchTimeMinutes'].transform('sum')
df['AvgWatchTime'] = df.groupby('CustomerID')['WatchTimeMinutes'].transform('mean')
df['LoginFrequency'] = df['TotalLogins'] / df['TenureDays'].replace(0, 1)
df['ActivityRatio'] = df['TotalLogins'] / (df['DaysSinceLastActivity'] + 1)

# Convert target to integer
df['Churned'] = df['Churned'].astype(int)

# Drop unnecessary columns
df = df.drop(['CustomerID', 'Date', 'ChurnDate'], axis=1)
```

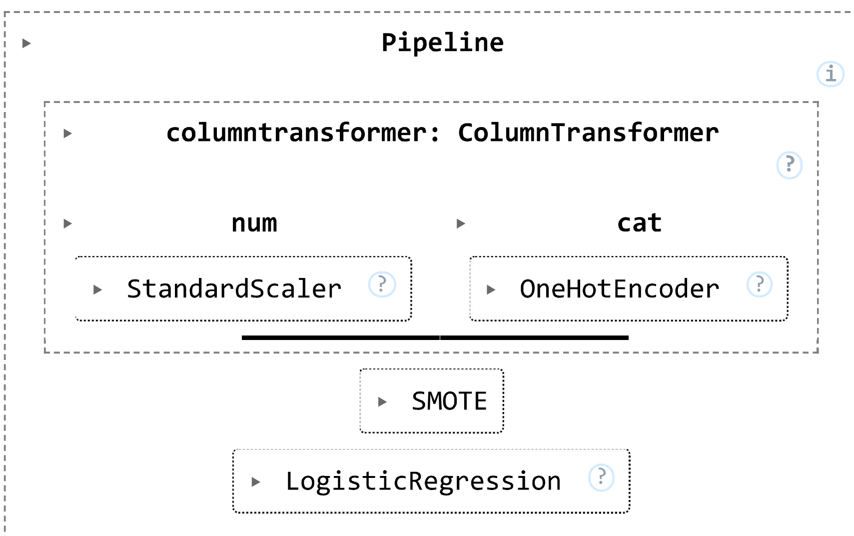
```
df
```

	SubscriptionPlan	AgeGroup	Login	WatchTimeMinutes	ContentPreference	Churned
0	Basic	36-50	0	0	Sports	0
1	Basic	36-50	1	25	Sports	0
2	Basic	36-50	0	0	Sports	0
3	Basic	36-50	1	51	Sports	0
4	Basic	36-50	0	0	Sports	0
...	...	...	...	...	...	...
20962	Standard	18-25	0	0	Documentaries	0
20963	Standard	18-25	1	32	Documentaries	0
20964	Standard	18-25	1	82	Documentaries	0
20965	Standard	18-25	1	53	Documentaries	0
20966	Standard	18-25	1	67	Documentaries	0

20967 rows × 19 columns

```
# Split data
X = df.drop('Churned', axis=1)
y = df['Churned']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, random_

# Identify feature types
numeric_features = X.select_dtypes(include=['int64', 'float64']).columns
categorical_features = X.select_dtypes(include=['object', 'category']).columns

# Preprocessing pipeline
preprocessor = ColumnTransformer(
    transformers=[
```

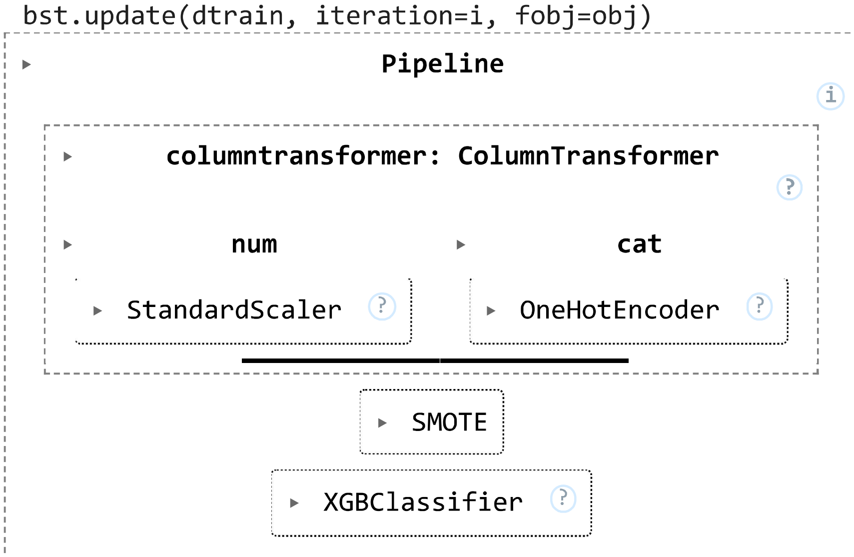
```
        ('num', StandardScaler(), numeric_features),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_features)
    ])


# MODEL 1: Logistic Regression

lr_pipeline = make_imb_pipeline(
    preprocessor,
    SMOTE(random_state=42),
    LogisticRegression(
        class_weight='balanced',  # Add this
        C=0.01,
        penalty='l2',
        solver='liblinear',
        max_iter=1000,
        random_state=42
    )
)

lr_pipeline.fit(X_train, y_train)
```




```
# MODEL 2: XGBoost

scale_pos_weight = len(y_train[y_train==0]) / len(y_train[y_train==1])

xgb_pipeline = make_imb_pipeline(
    preprocessor,
    SMOTE(random_state=42),
    xgb.XGBClassifier(
        scale_pos_weight=scale_pos_weight,  # Add this
        learning_rate=0.1,
        max_depth=5,
        min_child_weight=1,
        gamma=0.1,
```

```
        subsample=0.8,
        colsample_bytree=0.8,
        reg_alpha=0.01,
        n_estimators=300,
        random_state=42,
        use_label_encoder=False,
        eval_metric='logloss'
    )
)

xgb_pipeline.fit(X_train, y_train)
```

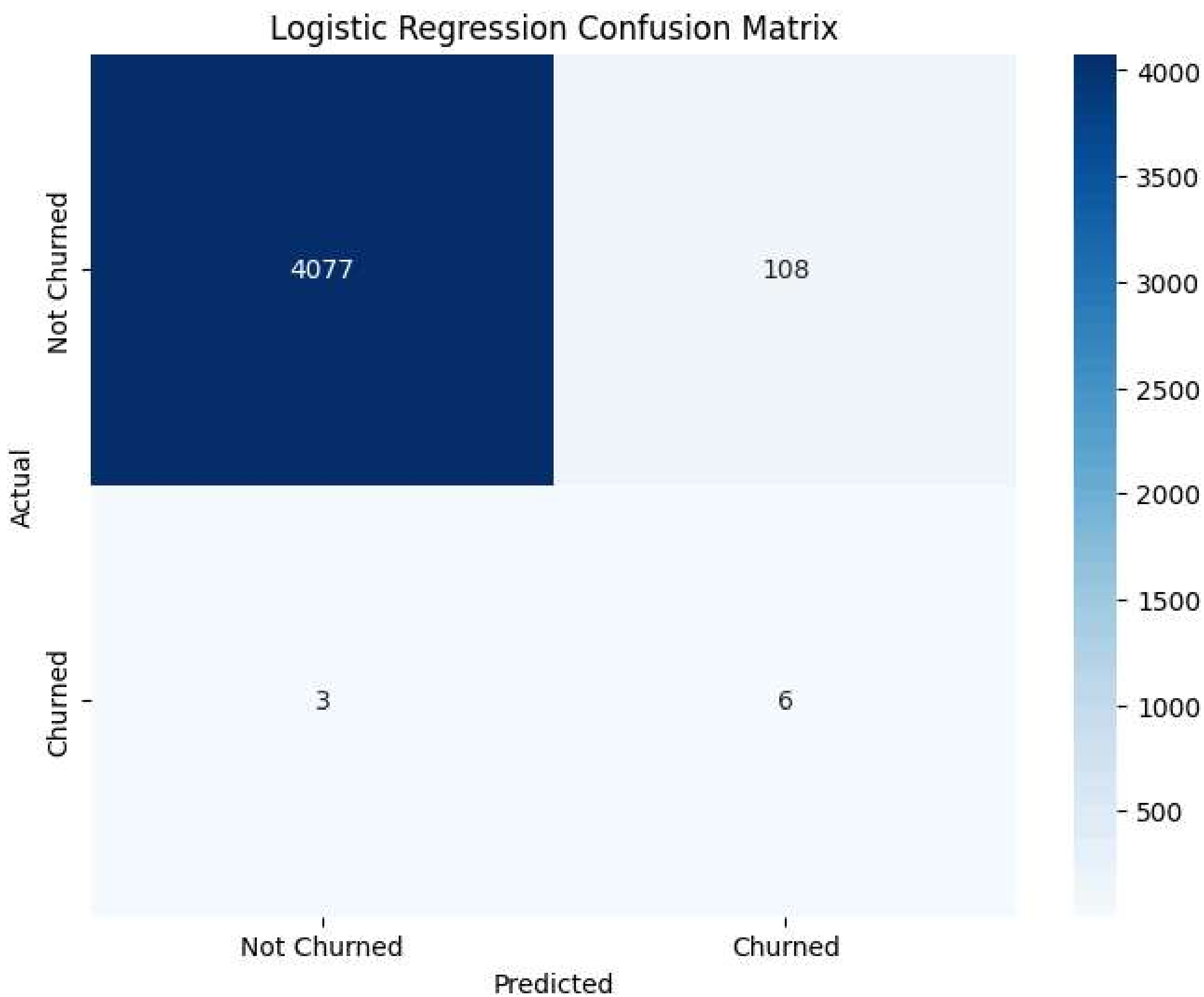
```
/usr/local/lib/python3.11/dist-packages/xgboost/training.py:183: UserWarning: [13:42:39]
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```




```
# MODEL EVALUATION

def evaluate_model(model, X_test, y_test, model_name, threshold=0.5):
    y_probs = model.predict_proba(X_test)[:, 1]
    y_pred = (y_probs > threshold).astype(int)

    accuracy = accuracy_score(y_test, y_pred)
    auc = roc_auc_score(y_test, y_probs)

    print(f"\n{model_name} Performance:")
    print("=" * 50)
    print(f"Accuracy: {accuracy:.4f}")
    print(f"AUC: {auc:.4f}")
    print("\nClassification Report:")
    print(classification_report(y_test, y_pred))

    # Confusion matrix
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(8, 6))
```

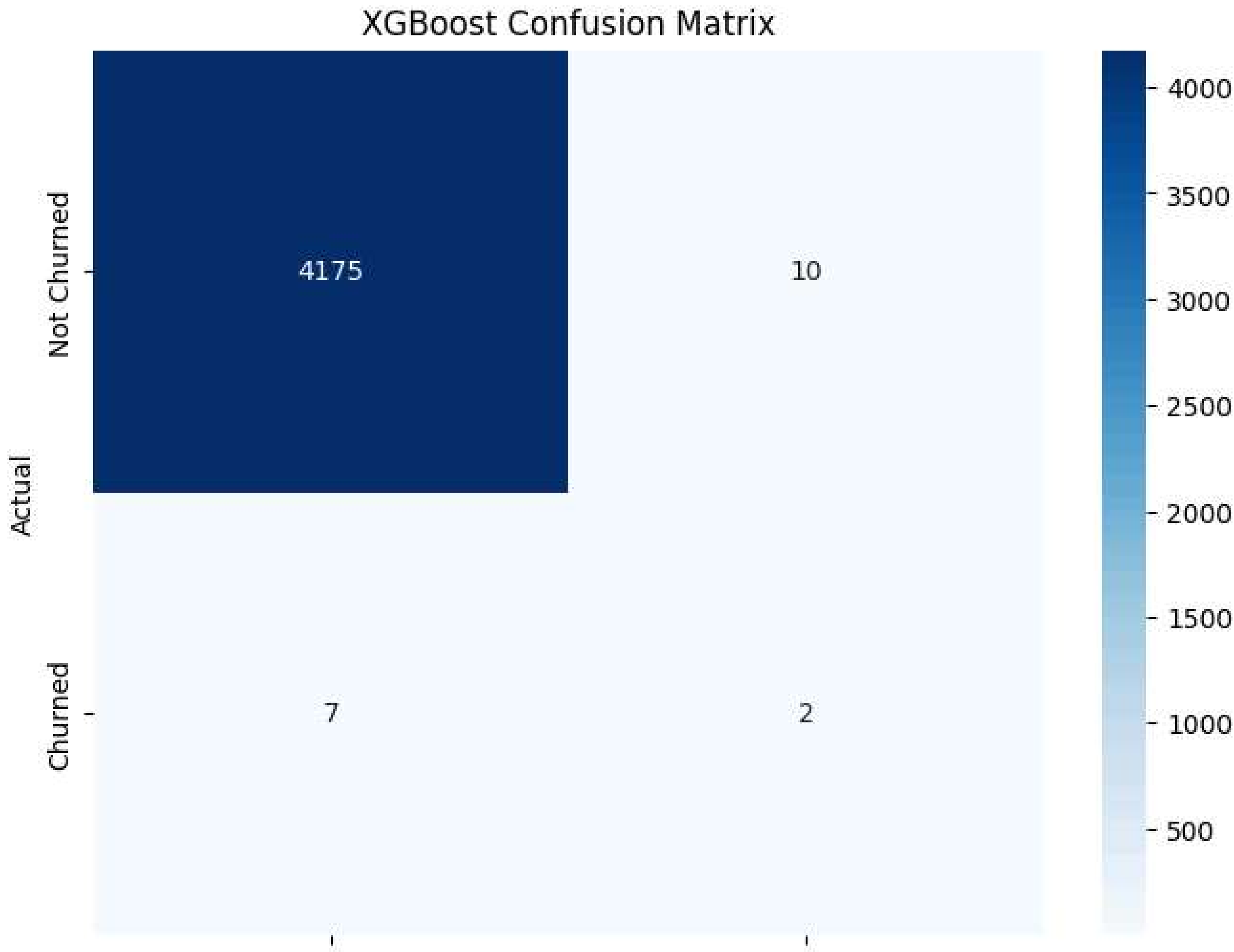
```
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=['Not Churned', 'Churned'],
                yticklabels=['Not Churned', 'Churned'])
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title(f'{model_name} Confusion Matrix')
    plt.show()

    return accuracy, auc

# Evaluate models
lr_accuracy, lr_auc = evaluate_model(lr_pipeline, X_test, y_test, "Logistic Regression", thr
xgb_accuracy, xgb_auc = evaluate_model(xgb_pipeline, X_test, y_test, "XGBoost")
```

```
Logistic Regression Performance:
==================================================
Accuracy: 0.9735
AUC: 0.9841

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.97      0.99      4185
           1       0.05      0.67      0.10         9

    accuracy                           0.97      4194
   macro avg       0.53      0.82      0.54      4194
weighted avg       1.00      0.97      0.98      4194
```

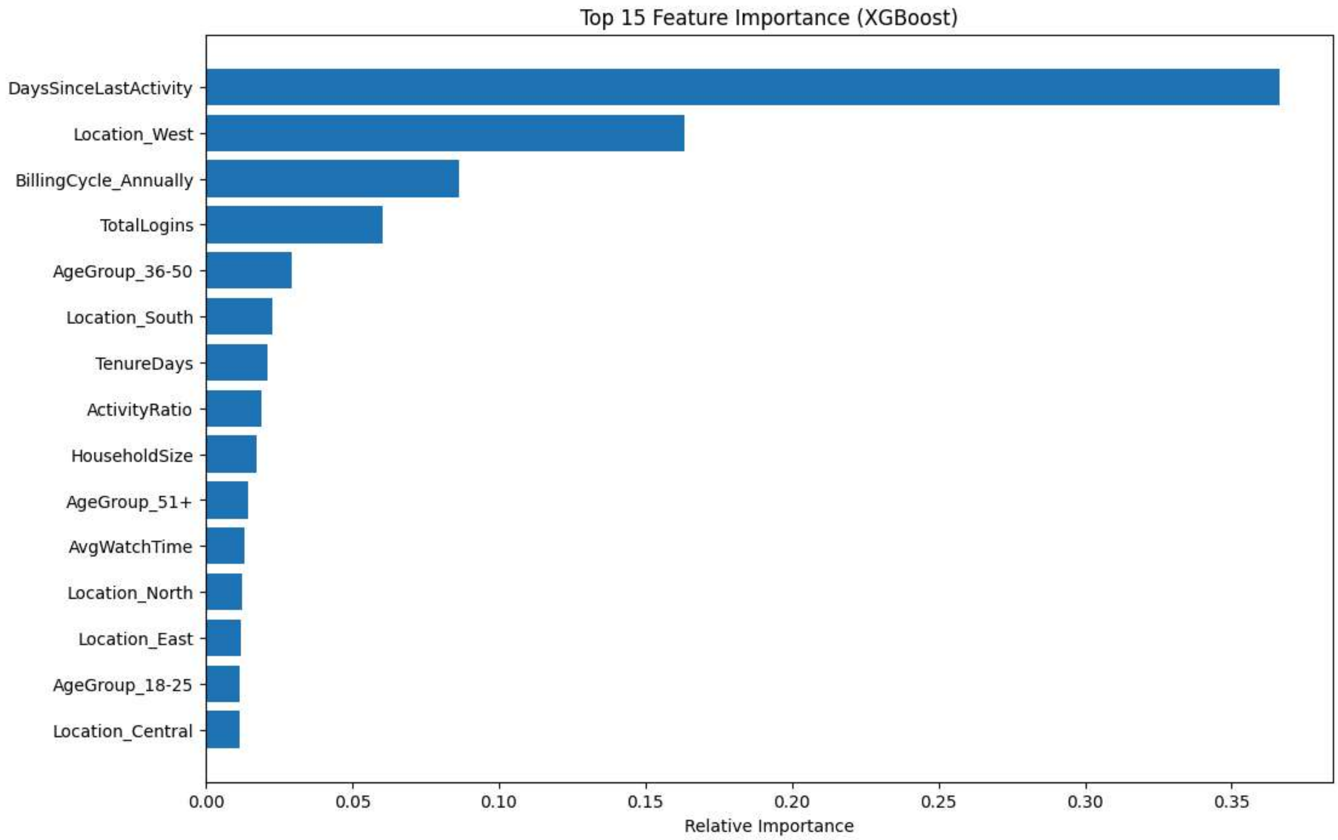



```
XGBoost Performance:
==================================================
Accuracy: 0.9959
AUC: 0.9842

Classification Report:
              precision    recall  f1-score   support
```

0	1.00	1.00	1.00	4185
1	0.17	0.22	0.19	9
accuracy			1.00	4194
macro avg	0.58	0.61	0.59	4194
weighted avg	1.00	1.00	1.00	4194



```
# FEATURE IMPORTANCE (For XGBoost)

try:
    # Get feature names
    preprocessor.fit(X_train)
    num_features = numeric_features.tolist()
    cat_features = preprocessor.named_transformers_['cat'].get_feature_names_out(categorical
    feature_names = num_features + cat_features

    # Get XGBoost feature importances
    xgb_model = xgb_pipeline.named_steps['xgbclassifier']
    importances = xgb_model.feature_importances_

    # Sort features
    indices = np.argsort(importances)[::-1]

    # Plot top 15 features
    plt.figure(figsize=(12, 8))
    plt.title("Top 15 Feature Importance (XGBoost)")
    plt.barh(range(15), importances[indices][:15][::-1], align="center")
    plt.yticks(range(15), [feature_names[i] for i in indices[:15][::-1]])
    plt.xlabel("Relative Importance")
    plt.show()

    # Create feature importance dataframe
    feature_importance_df = pd.DataFrame({
        'Feature': [feature_names[i] for i in indices],
        'Importance': importances[indices]
    }).head(15)

    print("\nTop Predictive Features:")
    print(feature_importance_df)

except Exception as e:
    print(f"Could not plot feature importance: {e}")
```




```
# MODEL COMPARISON
print("\n" + "=" * 50)
print("Model Comparison")
print("=" * 50)
print(f"{'Model':<25} {'Accuracy':<10} {'AUC':<10}")
print(f"{'Logistic Regression':<25} {lr_accuracy:.4f}    {lr_auc:.4f}")
print(f"{'XGBoost':<25} {xgb_accuracy:.4f}    {xgb_auc:.4f}")
```

```
8           HouseholdSize    0.017174
9            AgeGroup_51+    0.014434
10           AvgWatchTime    0.013129
11         Location_North    0.012240
12          Location_East    0.011748
13         AgeGroup_18-25    0.011615
```

```
==================================================
Model Comparison
==================================================
Model                     Accuracy   AUC
Logistic Regression       0.9735    0.9841
XGBoost                   0.9959    0.9842
```

```
# PREDICTION OUTPUT
test_df = X_test.copy()
test_df['Actual_Churned'] = y_test
```