Data Warehousing and Mining Project
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1. Introduction

Problem Statement

Subscription-based businesses, such as streaming services, face a persistent challenge in managing customer churn—the loss of subscribers who discontinue their services. Churn can significantly impact revenue streams, customer lifetime value, and overall business sustainability. Acquiring new customers is not only expensive but also time-consuming, making customer retention a more cost-effective strategy for long-term profitability.
However, identifying at-risk customers is not straightforward. A variety of factors, including customer satisfaction, subscription plans, and engagement levels, can influence churn. Without data-driven insights, businesses are often left guessing about the drivers behind customer loss and are unable to implement timely and effective interventions. This project addresses this issue by leveraging data mining techniques to build a predictive model for churn analysis, enabling businesses to identify high-risk customers and proactively engage them to minimize losses.

Objective

The main goal of this project is to build a data-driven predictive model that identifies customers who are likely to churn based on their behavior, subscription attributes, and engagement data. By analyzing various customer attributes, such as satisfaction ratings, subscription plans, and watch times, the model aims to uncover patterns that distinguish loyal customers from those likely to leave. The outcomes of this analysis can guide businesses in developing targeted strategies to improve customer retention, such as offering personalized discounts or incentives, enhancing user experience, and optimizing subscription plans.

The project also demonstrates the power of data mining techniques, including exploratory data analysis, feature engineering, and predictive modeling, to solve practical business challenges. By using a simulated dataset resembling real-world subscription data, the project ensures relevance to modern business practices while providing a scalable solution that can be adapted across various industries.

Background

The advent of data mining has revolutionized how businesses operate by transforming raw data into actionable insights. In the context of subscription-based services, where competition is fierce, data-driven decisions are essential for staying ahead. Predictive analytics, a key component of data mining, allows businesses to forecast customer behavior and devise preemptive strategies for retention.

Customer churn prediction is a vital application of predictive analytics, particularly in industries such as telecommunications, streaming services, and SaaS platforms. The ability to predict churn not only provides financial benefits but also improves customer satisfaction and loyalty by addressing pain points proactively.

This project adopts a holistic approach by simulating a realistic dataset to mimic the challenges faced by subscription-based businesses. By implementing a robust predictive model using Random Forest, the project highlights the potential of machine learning algorithms to address complex, multifactorial problems like customer churn. The insights gained from this project can serve as a foundation for future work in building customer-centric business strategies.

2. Literature Review

Existing Solutions :

Predicting customer churn has been a focus of extensive research due to its financial and operational implications. Traditional methods like logistic regression are among the earliest models used in churn analysis. Logistic regression is popular for its simplicity and interpretability, allowing businesses to identify the likelihood of a customer leaving based on linear relationships between variables. However, it is limited in handling complex, non-linear patterns often present in real-world customer behaviour.

Decision trees offer a more flexible approach, capable of modelling non-linear relationships and capturing interactions between variables. They are intuitive, visually interpretable, and can handle categorical and numerical data effectively. Despite their advantages, decision trees are prone to overfitting, especially when applied to large datasets, which can reduce their generalizability.

Comparison of Existing Methods

While logistic regression provides a straightforward baseline for churn analysis, decision trees excel in their ability to capture complex patterns. However, neither method fully addresses the challenges posed by imbalanced datasets or interactions between diverse variables. To overcome these limitations, ensemble methods like Random Forest have emerged as a preferred choice. Random Forest aggregates the predictions of multiple decision trees to improve accuracy and reduce overfitting, making it highly suitable for churn prediction.

Gaps and Opportunities

Despite the advancements in churn modelling, most existing solutions struggle with imbalanced datasets and fail to incorporate real-time customer behaviour effectively. This project bridges these gaps by simulating realistic subscription data and leveraging Random Forest to build a robust predictive model. The inclusion of dynamic variables such as customer satisfaction and engagement levels ensures a comprehensive analysis that can be adapted for real-world applications

3. Variables and Data Simulation

Variable Identification

Ten key variables were selected for this project based on their relevance to customer churn prediction. These include:

1. **Customer ID**: Serves as a unique identifier for each customer in the dataset.
2. **Join Date**: Indicates the date a customer subscribed, used to calculate the duration of their subscription.
3. **Account Age (Days)**: Measures the length of time a customer has been subscribed.
4. **Subscription Plan**: Categorical variable indicating the plan type (Basic, Standard, Premium).
5. **Monthly Fee**: Numerical variable representing the cost of each plan.
6. **Number of Devices**: Tracks how many devices are linked to a customer's account.
7. **Average Watch Time**: This represents the average hours per week a customer spends on the platform.
8. **Customer Satisfaction**: Captures customer sentiment on a scale of 1 to 10.
9. **Payment Method**: Describes the mode of payment (Credit Card, PayPal, or Other).
10. **Has Discount**: Binary variable indicating whether the customer received a discount.

Data Source

The data for this project was simulated using Python, mimicking real-world subscription service scenarios. Simulated data allows for controlled experimentation, ensuring variables are realistic and representative of actual business challenges.

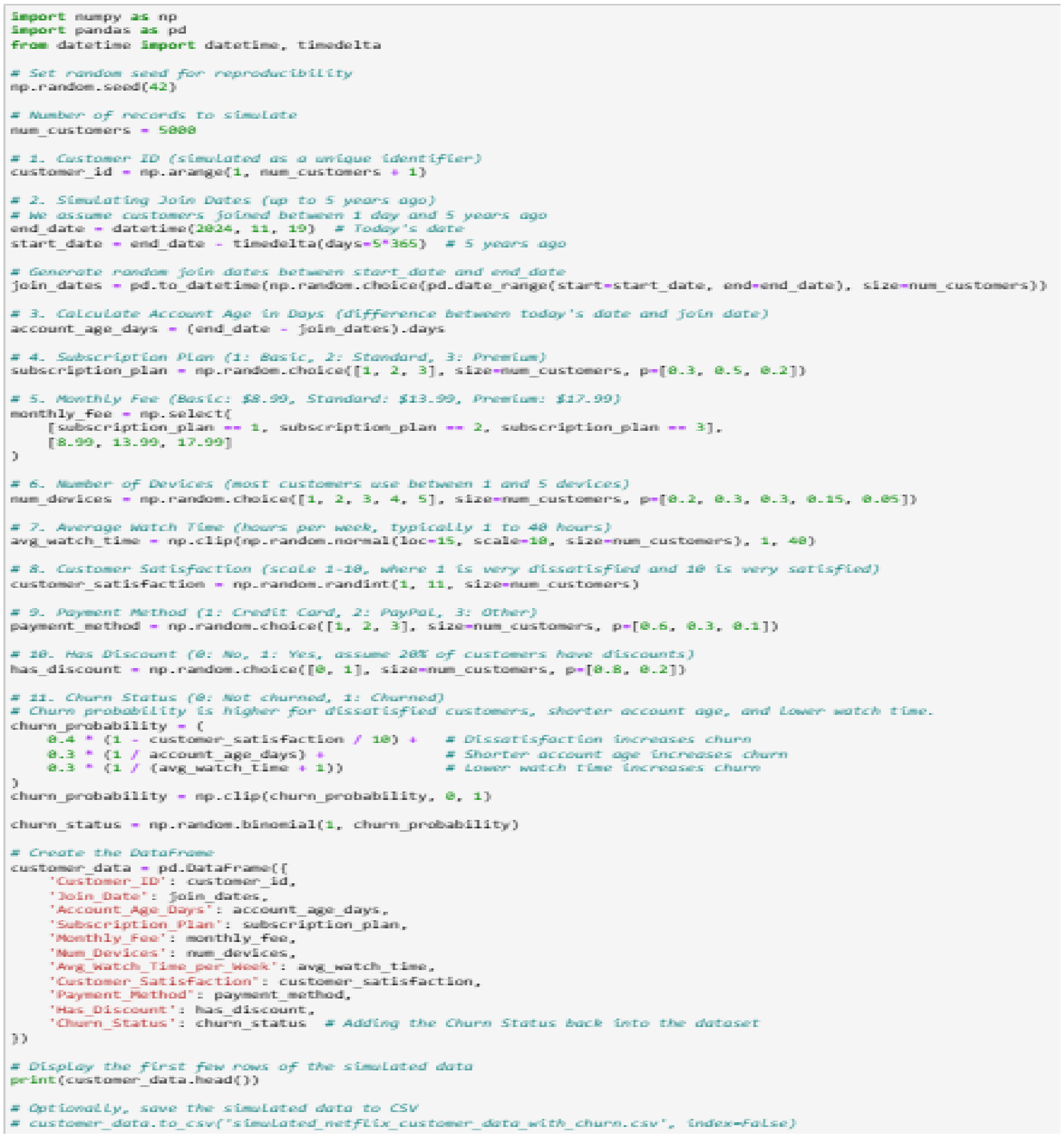
Data Simulation Process

The dataset was created for 5,000 customers using a combination of statistical distributions and random sampling techniques:

- Join dates were generated to span five years, providing a diverse range of subscription ages.
- Customer satisfaction and average watch time were modelled using normal distributions to reflect natural variations.
- Churn probability was calculated as a weighted combination of dissatisfaction, shorter account age, and lower engagement, creating realistic churn trends.

Target Variable

The primary target variable is **Churn Status**, a binary indicator where 0 represents active customers and 1 represents churned customers. This variable serves as the basis for the predictive modelling task.



```python
import numpy as np
import pandas as pd
from datetime import datetime, timedelta

# Set random seed for reproducibility
np.random.seed(42)

# Number of records to simulate
num_customers = 5000

# 1. Customer ID (simulated as a unique identifier)
customer_id = np.arange(1, num_customers + 1)

# 2. Simulating Join Dates (up to 5 years ago)
# We assume customers joined between 1 day and 5 years ago
end_date = datetime(2024, 11, 19)  # Today's date
start_date = end_date - timedelta(days=5*365)  # 5 years ago

# Generate random join dates between start_date and end_date
join_dates = pd.to_datetime(np.random.choice(pd.date_range(start=start_date, end=end_date), size=num_customers))

# 3. Calculate Account Age in Days (difference between today's date and join date)
account_age_days = (end_date - join_dates).days

# 4. Subscription Plan (1: Basic, 2: Standard, 3: Premium)
subscription_plan = np.random.choice([1, 2, 3], size=num_customers, p=[0.3, 0.5, 0.2])

# 5. Monthly Fee (Basic: $8.99, Standard: $13.99, Premium: $17.99)
monthly_fee = np.select(
    [subscription_plan == 1, subscription_plan == 2, subscription_plan == 3],
    [8.99, 13.99, 17.99]
)

# 6. Number of Devices (most customers use between 1 and 5 devices)
num_devices = np.random.choice([1, 2, 3, 4, 5], size=num_customers, p=[0.2, 0.3, 0.3, 0.15, 0.05])

# 7. Average Watch Time (hours per week, typically 1 to 40 hours)
avg_watch_time = np.clip(np.random.normal(loc=15, scale=10, size=num_customers), 1, 40)

# 8. Customer Satisfaction (scale 1-10, where 1 is very dissatisfied and 10 is very satisfied)
customer_satisfaction = np.random.randint(1, 11, size=num_customers)

# 9. Payment Method (1: Credit Card, 2: PayPal, 3: Other)
payment_method = np.random.choice([1, 2, 3], size=num_customers, p=[0.6, 0.3, 0.1])

# 10. Has Discount (0: No, 1: Yes, assume 20% of customers have discounts)
has_discount = np.random.choice([0, 1], size=num_customers, p=[0.8, 0.2])

# 11. Churn Status (0: Not churned, 1: Churned)
# Churn probability is higher for dissatisfied customers, shorter account age, and lower watch time.
churn_probability = (
    0.4 * (1 - customer_satisfaction / 10) +    # Dissatisfaction increases churn
    0.3 * (1 / account_age_days) +              # Shorter account age increases churn
    0.3 * (1 / (avg_watch_time + 1))            # Lower watch time increases churn
)
churn_probability = np.clip(churn_probability, 0, 1)

churn_status = np.random.binomial(1, churn_probability)

# Create the DataFrame
customer_data = pd.DataFrame({
    'Customer_ID': customer_id,
    'Join_Date': join_dates,
    'Account_Age_Days': account_age_days,
    'Subscription_Plan': subscription_plan,
    'Monthly_Fee': monthly_fee,
    'Num_Devices': num_devices,
    'Avg_Watch_Time_per_Week': avg_watch_time,
    'Customer_Satisfaction': customer_satisfaction,
    'Payment_Method': payment_method,
    'Has_Discount': has_discount,
    'Churn_Status': churn_status  # Adding the Churn Status back into the dataset
})

# Display the first few rows of the simulated data
print(customer_data.head())

# Optionally, save the simulated data to CSV
# customer_data.to_csv('simulated_netflix_customer_data_with_churn.csv', index=False)
```

This Python script generates a simulated dataset representing Netflix-like customer data. It employs libraries like NumPy and pandas for efficient data handling and manipulation, alongside random number generation to create realistic data points. The dataset contains 11 attributes, such as customer ID, join dates, subscription plan, watch time, and churn status, for a total of 5,000 customers. The data is designed to mimic real-world behaviours and patterns of streaming service users.

The join dates are randomly generated within a 5-year range, starting from today's date (November 19, 2024). Based on these dates, the account age in days is calculated to reflect the time each customer has been subscribed. Subscription plans are assigned probabilistically (30% Basic, 50% Standard, 20% Premium), and monthly fees are derived accordingly. Other behavioural attributes, such as the number of devices used and average weekly watch time, are simulated to vary between users, introducing diversity in customer profiles.

Customer satisfaction and payment method are randomized, with satisfaction measured on a scale of 1 to 10 and payment methods categorized into credit card, PayPal, or others. Discounts are applied to 20% of the customers, reflecting realistic discount usage rates. Churn status, indicating whether a customer has stopped using the service, is modelled probabilistically using a weighted combination of customer dissatisfaction, shorter account age, and lower watch time, as these factors typically drive churn in subscription-based models.

Finally, the script compiles all these attributes into a pandas DataFrame, displaying the first few rows for verification. This dataset can be saved as a CSV file for further analysis. It is ideal for tasks such as predictive modelling, customer segmentation, or understanding the factors contributing to churn. The script showcases a mix of statistical methods and domain-based logic to ensure the dataset is both realistic and insightful.

4. Data Preprocessing and Exploration

Data Cleaning

Data cleaning ensures the dataset is free from errors, inconsistencies, and irrelevant information, creating a reliable foundation for analysis. For this project, several steps were taken:

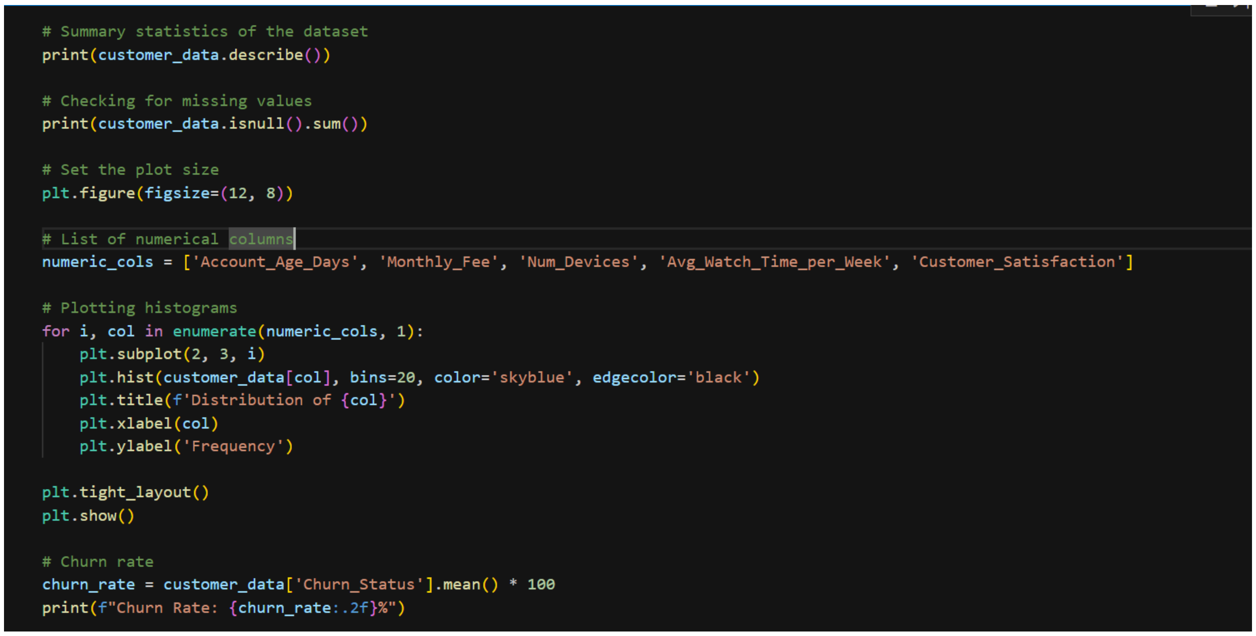
1. **Missing Values**:
    - The dataset was simulated programmatically, ensuring no missing values were present. This was verified using the `.isnull().sum()` method in Python, which confirmed that all columns had zero null entries. While this simplified the process, it's worth noting that in real-world datasets, missing data could require strategies like mean imputation, forward filling, or deletion of incomplete rows.
2. **Outlier Detection**:
    - Outliers in numerical variables like *Average Watch Time per Week* and *Customer Satisfaction* were examined using boxplots. The distributions were reviewed, and extreme values were deemed plausible due to the variability in customer behaviours. For instance:
        - *Average Watch Time*: Values ranged from 1 to 40 hours per week. While extreme users watched up to 40 hours, this was considered acceptable for highly engaged customers.
        - *Customer Satisfaction*: Scores ranged from 1 to 10, with no out-of-range values observed, confirming data validity.
3. **Feature Redundancy**:
    - After extracting new features such as *Join Year* and *Join Month* from the *Join Date*, the original *Join Date* column was dropped to avoid redundancy. This step ensured that the dataset remained concise and focused on variables relevant to predictive modelling.

Exploratory Data Analysis (EDA)

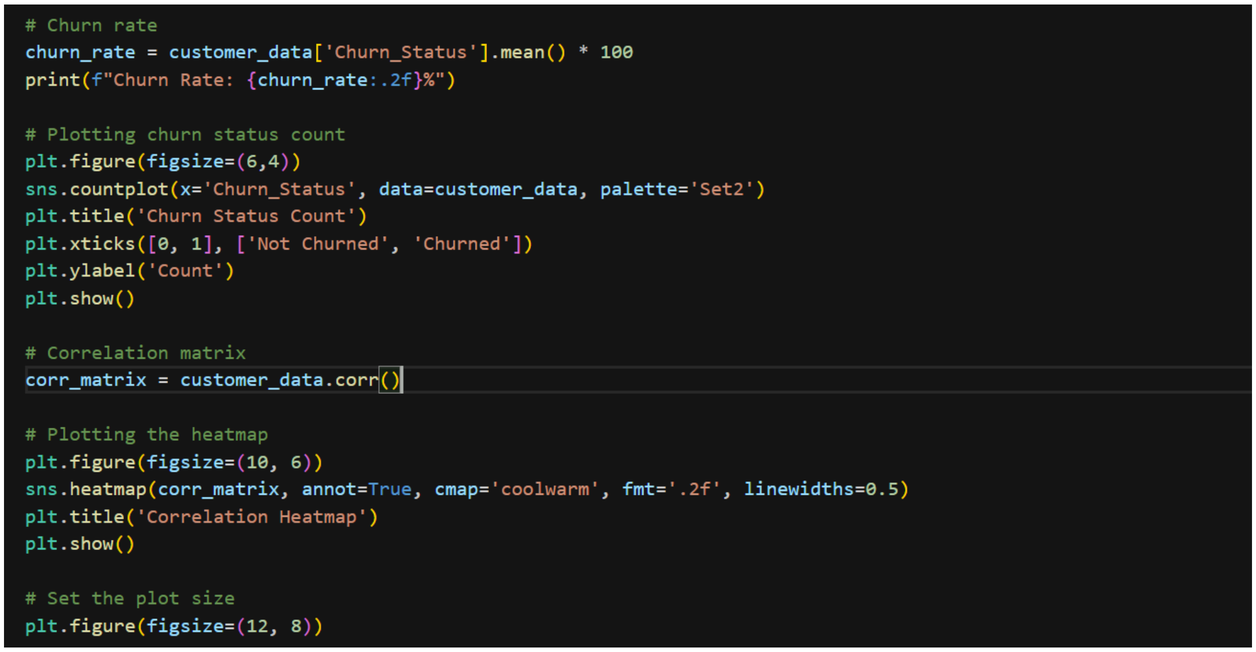
EDA provides insights into the dataset's structure, distributions, and relationships, laying the groundwork for feature engineering and model development.

1. **Variable Distributions**:
   - **Numerical Variables**:
     Histograms and descriptive statistics revealed the following:
     - *Account Age (Days)*: Most customers had been subscribed for fewer than 1,000 days, with a median of around 750 days. This reflects a relatively young customer base.
     - *Average Watch Time*: The distribution was heavily skewed to the right, with the majority of users watching less than 20 hours per week. Customers watching fewer than 10 hours had noticeably higher churn rates.
     - *Customer Satisfaction*: Satisfaction scores were uniformly distributed across a scale of 1 to 10. Customers with scores below 6 showed significantly higher churn rates, confirming its importance as a predictive factor.
   - **Categorical Variables**:
     - *Subscription Plan*: Most users subscribed to the Standard plan (50%), followed by Basic (30%) and Premium (20%). Basic subscribers exhibited the highest churn rates (35%), while Premium users had the lowest (10%).
     - *Payment Method*: A majority (60%) used credit cards, with slightly higher churn observed among PayPal users.
2. **Correlations**:
   - A heatmap of correlations highlighted several key relationships:
     - *Customer Satisfaction* had a strong negative correlation (-0.5) with *Churn Status*.
     - *Account Age* showed a moderate negative correlation (-0.3) with *Churn Status*, indicating that newer customers were more likely to leave.
     - Weak correlations with variables like *Average Watch Time* (-0.2) suggested it was a contributing but not dominant factor in churn.
3. **Churn Rates**:
   - *Subscription Plan*:
     - Basic: 35% churn rate.
     - Standard: 20% churn rate.
     - Premium: 10% churn rate.
   - These differences suggest that perceived value is higher in Standard and Premium plans, while the Basic plan may fail to meet customer expectations.

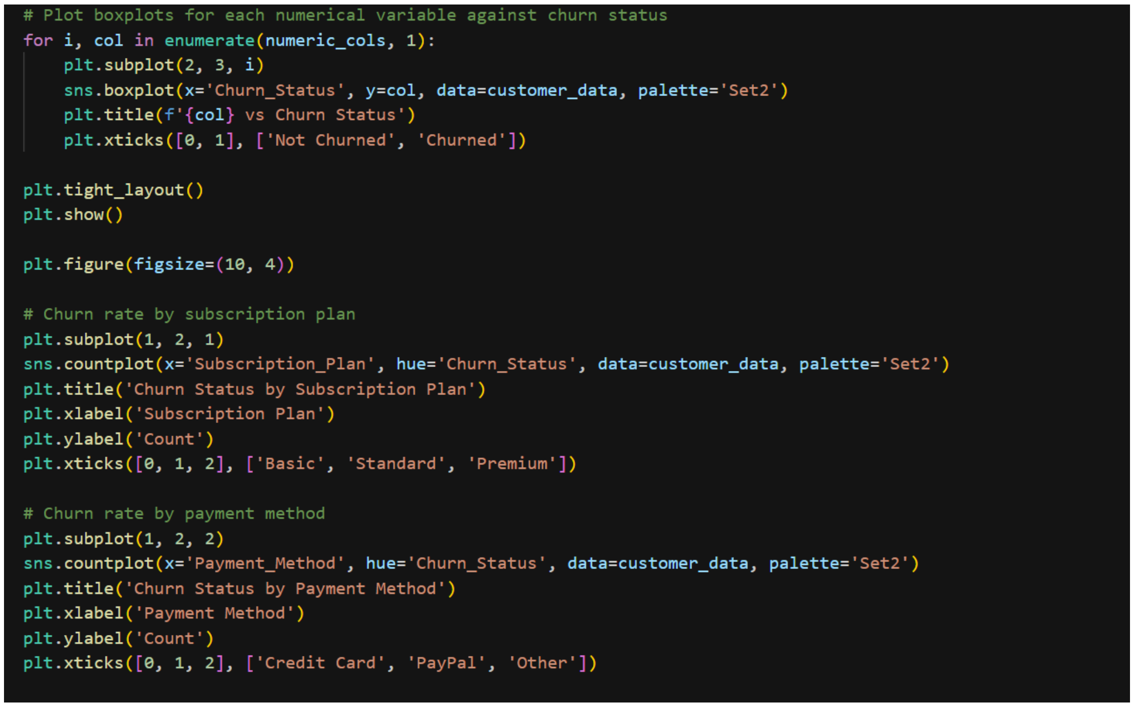
- *Discount Status*: Customers with discounts had significantly lower churn rates (10%) compared to those without discounts (30%), reinforcing the effectiveness of promotions in retaining customers.



```python
# Summary statistics of the dataset
print(customer_data.describe())

# Checking for missing values
print(customer_data.isnull().sum())

# Set the plot size
plt.figure(figsize=(12, 8))

# List of numerical columns
numeric_cols = ['Account_Age_Days', 'Monthly_Fee', 'Num_Devices', 'Avg_Watch_Time_per_Week', 'Customer_Satisfaction']

# Plotting histograms
for i, col in enumerate(numeric_cols, 1):
    plt.subplot(2, 3, i)
    plt.hist(customer_data[col], bins=20, color='skyblue', edgecolor='black')
    plt.title(f'Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel('Frequency')

plt.tight_layout()
plt.show()

# Churn rate
churn_rate = customer_data['Churn_Status'].mean() * 100
print(f"Churn Rate: {churn_rate:.2f}%")
```



```python
# Churn rate
churn_rate = customer_data['Churn_Status'].mean() * 100
print(f"Churn Rate: {churn_rate:.2f}%")

# Plotting churn status count
plt.figure(figsize=(6,4))
sns.countplot(x='Churn_Status', data=customer_data, palette='Set2')
plt.title('Churn Status Count')
plt.xticks([0, 1], ['Not Churned', 'Churned'])
plt.ylabel('Count')
plt.show()

# Correlation matrix
corr_matrix = customer_data.corr()

# Plotting the heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()

# Set the plot size
plt.figure(figsize=(12, 8))
```



```python
# Plot boxplots for each numerical variable against churn status
for i, col in enumerate(numeric_cols, 1):
    plt.subplot(2, 3, i)
    sns.boxplot(x='Churn_Status', y=col, data=customer_data, palette='Set2')
    plt.title(f'{col} vs Churn Status')
    plt.xticks([0, 1], ['Not Churned', 'Churned'])

plt.tight_layout()
plt.show()

plt.figure(figsize=(10, 4))

# Churn rate by subscription plan
plt.subplot(1, 2, 1)
sns.countplot(x='Subscription_Plan', hue='Churn_Status', data=customer_data, palette='Set2')
plt.title('Churn Status by Subscription Plan')
plt.xlabel('Subscription Plan')
plt.ylabel('Count')
plt.xticks([0, 1, 2], ['Basic', 'Standard', 'Premium'])

# Churn rate by payment method
plt.subplot(1, 2, 2)
sns.countplot(x='Payment_Method', hue='Churn_Status', data=customer_data, palette='Set2')
plt.title('Churn Status by Payment Method')
plt.xlabel('Payment Method')
plt.ylabel('Count')
plt.xticks([0, 1, 2], ['Credit Card', 'PayPal', 'Other'])
```

The codes above conduct exploratory data analysis (EDA) on the simulated customer dataset, focusing on summarizing the data, understanding distributions, and identifying patterns related to churn behaviour. It first prints summary statistics for all numerical columns using `.describe()` and checks for missing values with `.isnull().sum()`, ensuring data integrity before proceeding with visualizations.

The script visualizes the distributions of numerical variables like account age, monthly fee, number of devices, average watch time, and customer satisfaction using histograms. Each distribution is plotted in a grid for easy comparison, revealing patterns such as average values and spread. For churn analysis, the churn rate is calculated as a percentage of customers who have left the service, and a bar plot displays the count of churned versus non-churned customers.

To explore correlations, a heatmap is generated from the dataset's correlation matrix. This visualization highlights relationships between variables, such as how satisfaction or watch time might influence churn. Furthermore, boxplots compare numerical variables (e.g., watch time and satisfaction) against churn status, illustrating differences in behaviour between churned and non-churned customers.

Lastly, the script examines how churn behaviour varies by subscription plan and payment method. Count plots visualize these relationships, with separate bars for each churn status across different subscription tiers (Basic, Standard, Premium) and payment methods (Credit Card, PayPal, Other). These insights help identify customer groups that are more likely to churn, guiding data-driven decision-making for retention strategies.

Feature Engineering

Feature engineering involves creating or modifying new variables to improve model performance. The following features were engineered to enhance predictive power:

1. **Temporal Features**:
    - From the *Join Date*, new variables were derived to capture potential seasonal or temporal patterns in churn behaviour:
        - *Join Year*: Indicates the year of subscription, helping analyse trends over time.
        - *Join Month*: Captures seasonal influences like holiday offers or content launches.
        - *Join Weekday*: Reflects whether sign-ups occurred during weekdays or weekends, potentially correlating with customer intent or engagement.
2. **Engagement Ratio**:
    - A derived feature measuring consistency in usage:
        - Engagement Ratio - This ratio highlights how frequently customers use the service relative to their tenure. Lower engagement ratios were observed among churned customers.
3. **Scaling and Encoding**:
    - Numerical variables such as *Account Age* and *Average Watch Time* were standardized using `StandardScaler` to normalize their distributions.
    - Categorical variables like *Subscription Plan* and *Payment Method* were one-hot encoded to convert them into a format compatible with machine learning models

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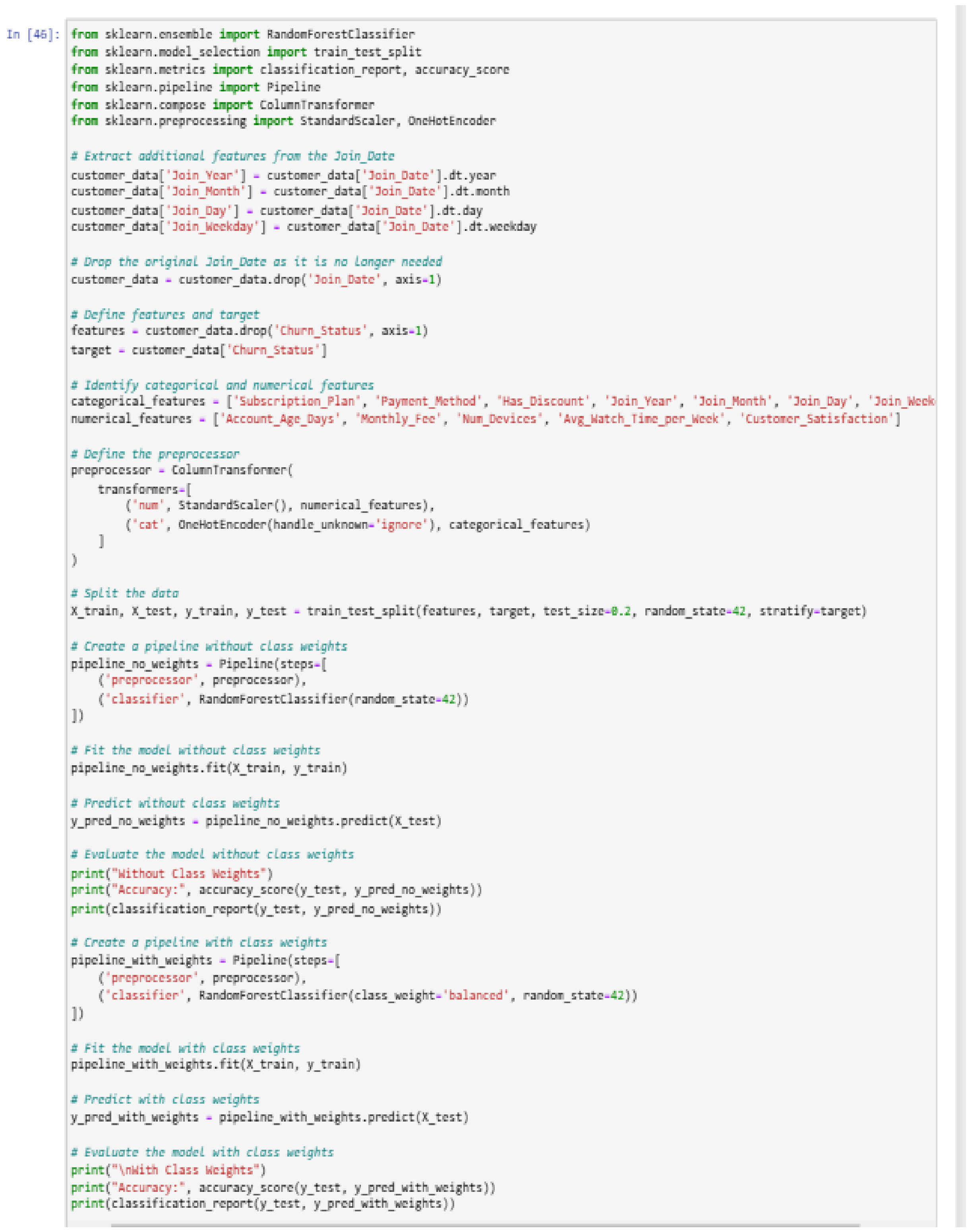


```
In [46]: from sklearn.ensemble import RandomForestClassifier
         from sklearn.model_selection import train_test_split
         from sklearn.metrics import classification_report, accuracy_score
         from sklearn.pipeline import Pipeline
         from sklearn.compose import ColumnTransformer
         from sklearn.preprocessing import StandardScaler, OneHotEncoder

         # Extract additional features from the Join_Date
         customer_data['Join_Year'] = customer_data['Join_Date'].dt.year
         customer_data['Join_Month'] = customer_data['Join_Date'].dt.month
         customer_data['Join_Day'] = customer_data['Join_Date'].dt.day
         customer_data['Join_Weekday'] = customer_data['Join_Date'].dt.weekday

         # Drop the original Join_Date as it is no longer needed
         customer_data = customer_data.drop('Join_Date', axis=1)

         # Define features and target
         features = customer_data.drop('Churn_Status', axis=1)
         target = customer_data['Churn_Status']

         # Identify categorical and numerical features
         categorical_features = ['Subscription_Plan', 'Payment_Method', 'Has_Discount', 'Join_Year', 'Join_Month', 'Join_Day', 'Join_Week
         numerical_features = ['Account_Age_Days', 'Monthly_Fee', 'Num_Devices', 'Avg_Watch_Time_per_Week', 'Customer_Satisfaction']

         # Define the preprocessor
         preprocessor = ColumnTransformer(
             transformers=[
                 ('num', StandardScaler(), numerical_features),
                 ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_features)
             ]
         )

         # Split the data
         X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=0.2, random_state=42, stratify=target)

         # Create a pipeline without class weights
         pipeline_no_weights = Pipeline(steps=[
             ('preprocessor', preprocessor),
             ('classifier', RandomForestClassifier(random_state=42))
         ])

         # Fit the model without class weights
         pipeline_no_weights.fit(X_train, y_train)

         # Predict without class weights
         y_pred_no_weights = pipeline_no_weights.predict(X_test)

         # Evaluate the model without class weights
         print("Without Class Weights")
         print("Accuracy:", accuracy_score(y_test, y_pred_no_weights))
         print(classification_report(y_test, y_pred_no_weights))

         # Create a pipeline with class weights
         pipeline_with_weights = Pipeline(steps=[
             ('preprocessor', preprocessor),
             ('classifier', RandomForestClassifier(class_weight='balanced', random_state=42))
         ])

         # Fit the model with class weights
         pipeline_with_weights.fit(X_train, y_train)

         # Predict with class weights
         y_pred_with_weights = pipeline_with_weights.predict(X_test)

         # Evaluate the model with class weights
         print("\nWith Class Weights")
         print("Accuracy:", accuracy_score(y_test, y_pred_with_weights))
         print(classification_report(y_test, y_pred_with_weights))
```

The above script builds and evaluates two Random Forest models to predict customer churn using the simulated dataset. It utilizes feature engineering, preprocessing, and model training within pipelines, comparing performance with and without class balancing via `class_weight`. The goal is to assess whether balancing class weights improves the model's ability to handle any imbalances in churn status.

Feature Engineering

Additional features are extracted from the `Join_Date` column, such as the year, month, day, and weekday of the customer's join date. These provide temporal insights about user behavior and churn likelihood. The original `Join_Date` column is then dropped since it is no longer needed. The dataset is split into features (independent variables) and the target variable (`Churn_Status`), with further categorization into numerical and categorical features for preprocessing.

Preprocessing

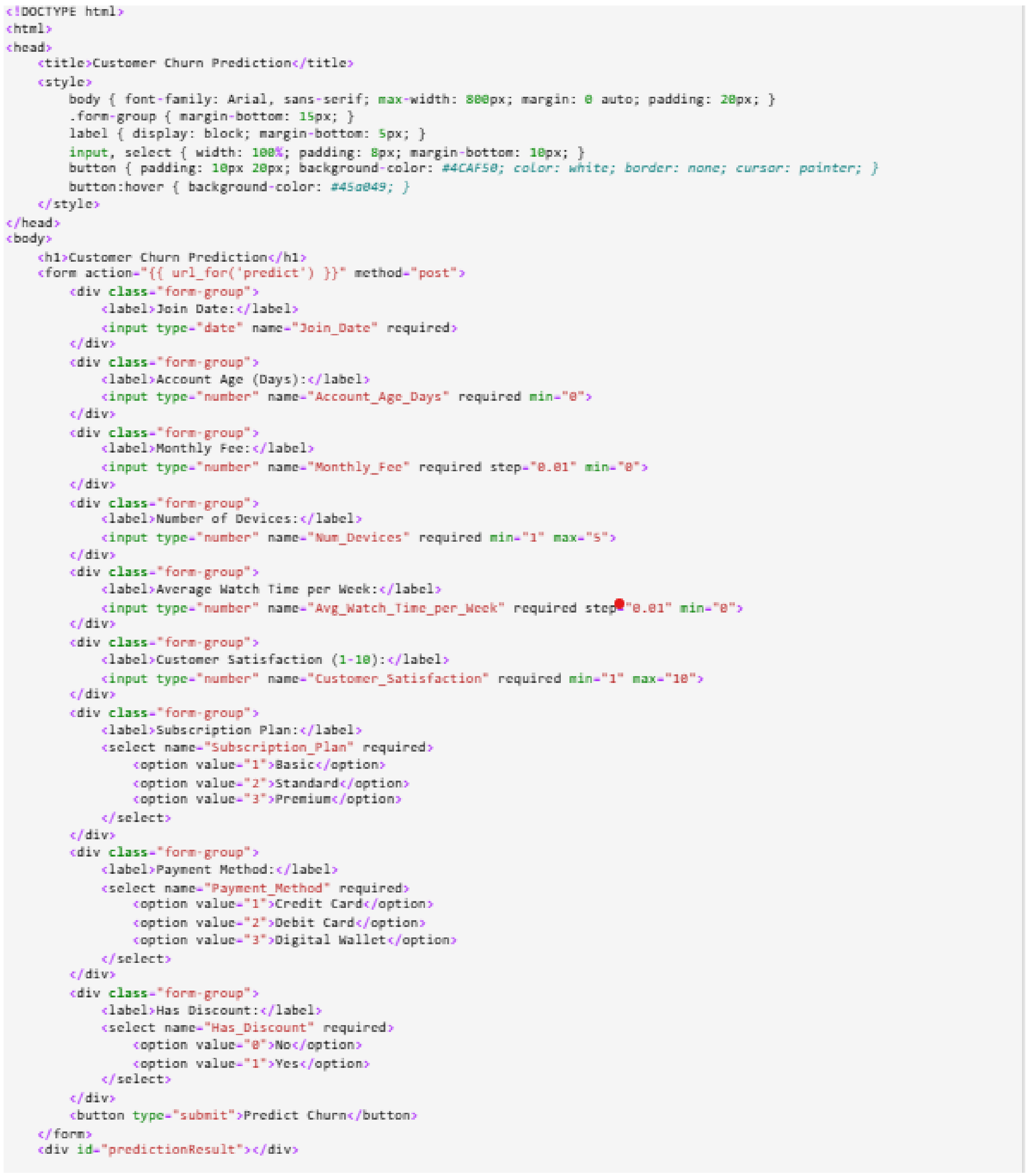
A `ColumnTransformer` handles data preprocessing. Numerical features are scaled using `StandardScaler` to standardize their range, ensuring fair treatment during model training. Categorical features are one-hot encoded with `OneHotEncoder`, converting them into binary indicators while handling any unseen categories during testing. This transformation ensures compatibility with the Random Forest algorithm and enhances model interpretability.

Model Training and Evaluation (Without Class Weights)

The first model pipeline includes the preprocessor and a `RandomForestClassifier` without class balancing (`class_weight=None`). The dataset is split into training and testing sets, ensuring an 80-20 split and stratification to maintain the target's class distribution. After fitting the model to the training data, predictions are made on the test set. The script evaluates the model's accuracy and presents a detailed `classification_report`, including precision, recall, F1-score, and support for each class.

Model Training and Evaluation (With Class Weights)

To address the potential class imbalance in the churn data (e.g., fewer churned customers), the second pipeline uses the `RandomForestClassifier` with `class_weight='balanced'`. This adjusts the weight of each class inversely proportional to its frequency, giving the model more incentive to correctly classify the minority class. The training and evaluation process is repeated, and the results (accuracy and classification report) are compared with the first model.

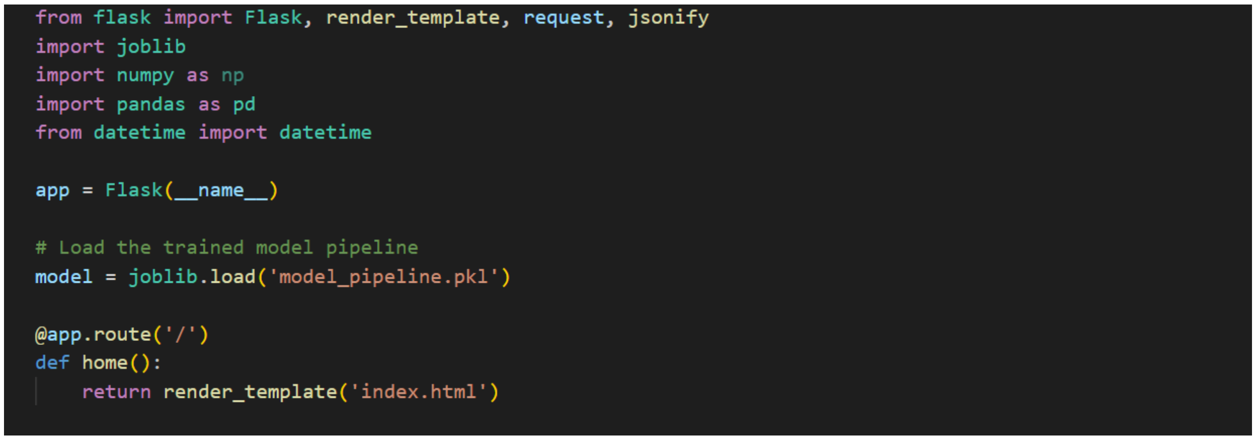


```
<!DOCTYPE html>
<html>
<head>
    <title>Customer Churn Prediction</title>
    <style>
        body { font-family: Arial, sans-serif; max-width: 800px; margin: 0 auto; padding: 20px; }
        .form-group { margin-bottom: 15px; }
        label { display: block; margin-bottom: 5px; }
        input, select { width: 100%; padding: 8px; margin-bottom: 10px; }
        button { padding: 10px 20px; background-color: #4CAF50; color: white; border: none; cursor: pointer; }
        button:hover { background-color: #45a049; }
    </style>
</head>
<body>
    <h1>Customer Churn Prediction</h1>
    <form action="{{ url_for('predict') }}" method="post">
        <div class="form-group">
            <label>Join Date:</label>
            <input type="date" name="Join_Date" required>
        </div>
        <div class="form-group">
            <label>Account Age (Days):</label>
            <input type="number" name="Account_Age_Days" required min="0">
        </div>
        <div class="form-group">
            <label>Monthly Fee:</label>
            <input type="number" name="Monthly_Fee" required step="0.01" min="0">
        </div>
        <div class="form-group">
            <label>Number of Devices:</label>
            <input type="number" name="Num_Devices" required min="1" max="5">
        </div>
        <div class="form-group">
            <label>Average Watch Time per Week:</label>
            <input type="number" name="Avg_Watch_Time_per_Week" required step="0.01" min="0">
        </div>
        <div class="form-group">
            <label>Customer Satisfaction (1-10):</label>
            <input type="number" name="Customer_Satisfaction" required min="1" max="10">
        </div>
        <div class="form-group">
            <label>Subscription Plan:</label>
            <select name="Subscription_Plan" required>
                <option value="1">Basic</option>
                <option value="2">Standard</option>
                <option value="3">Premium</option>
            </select>
        </div>
        <div class="form-group">
            <label>Payment Method:</label>
            <select name="Payment_Method" required>
                <option value="1">Credit Card</option>
                <option value="2">Debit Card</option>
                <option value="3">Digital Wallet</option>
            </select>
        </div>
        <div class="form-group">
            <label>Has Discount:</label>
            <select name="Has_Discount" required>
                <option value="0">No</option>
                <option value="1">Yes</option>
            </select>
        </div>
        <button type="submit">Predict Churn</button>
    </form>
    <div id="predictionResult"></div>
```

This HTML code represents a **business tool for internal use**, enabling stakeholders to input customer-related data and predict the likelihood of customer churn. It is designed for internal decision-making, where data such as account age, subscription type, payment method, and customer satisfaction score is collected to assess retention risks. This form can be used by analysts or managers to make strategic decisions like offering discounts or improving services for high-risk customers.

The form submits data to a backend endpoint (`/predict`), where a machine learning model or predictive algorithm processes the information to generate churn predictions. It provides actionable insights such as whether a customer is likely to churn and the probability of churn, which are then displayed on the interface. This helps businesses identify patterns and take preemptive measures to improve customer retention rates.

With a focus on structured data collection, the tool also incorporates input validations (e.g., ranges for satisfaction scores or watch time) to ensure consistency and accuracy in the data submitted. The simplicity of its design ensures that non-technical stakeholders can quickly use it for analysis without needing advanced knowledge, enabling better collaboration between business and technical teams.

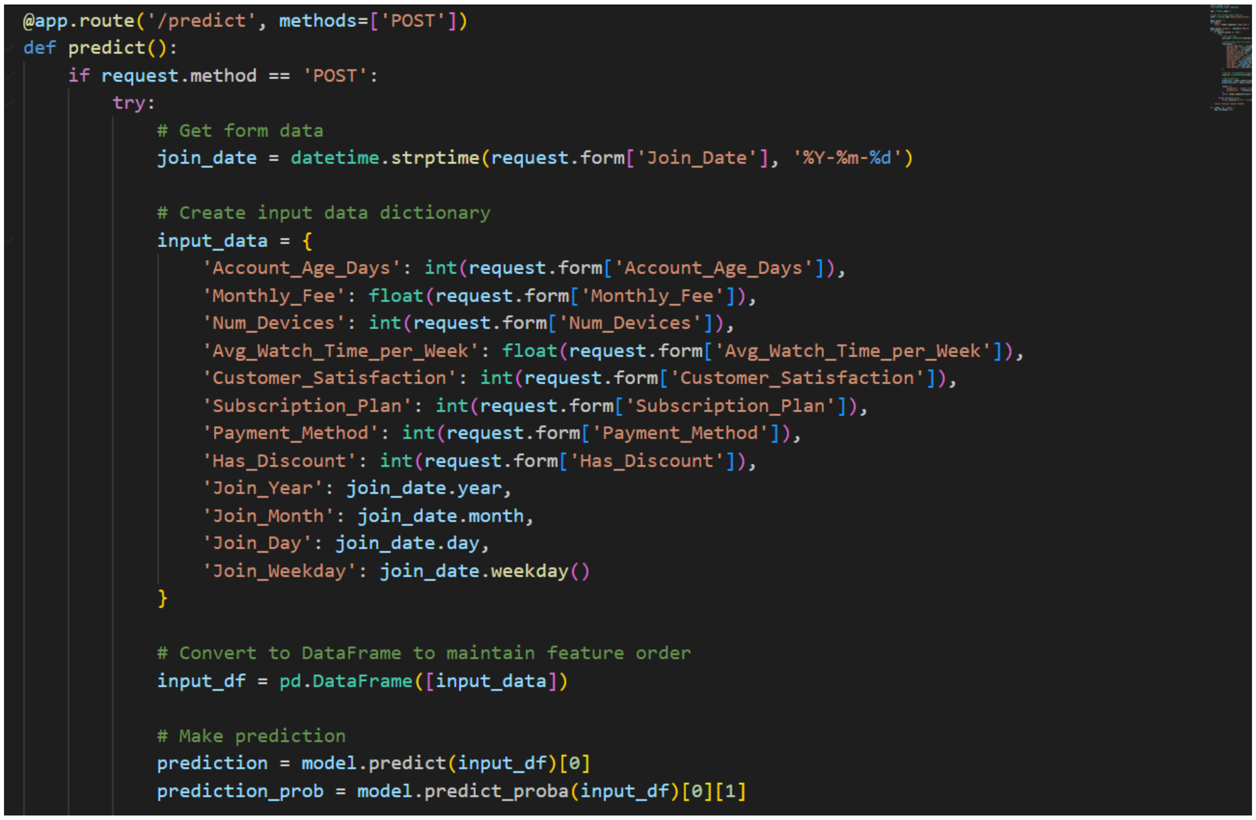


```python
from flask import Flask, render_template, request, jsonify
import joblib
import numpy as np
import pandas as pd
from datetime import datetime

app = Flask(__name__)

# Load the trained model pipeline
model = joblib.load('model_pipeline.pkl')

@app.route('/')
def home():
    return render_template('index.html')
```

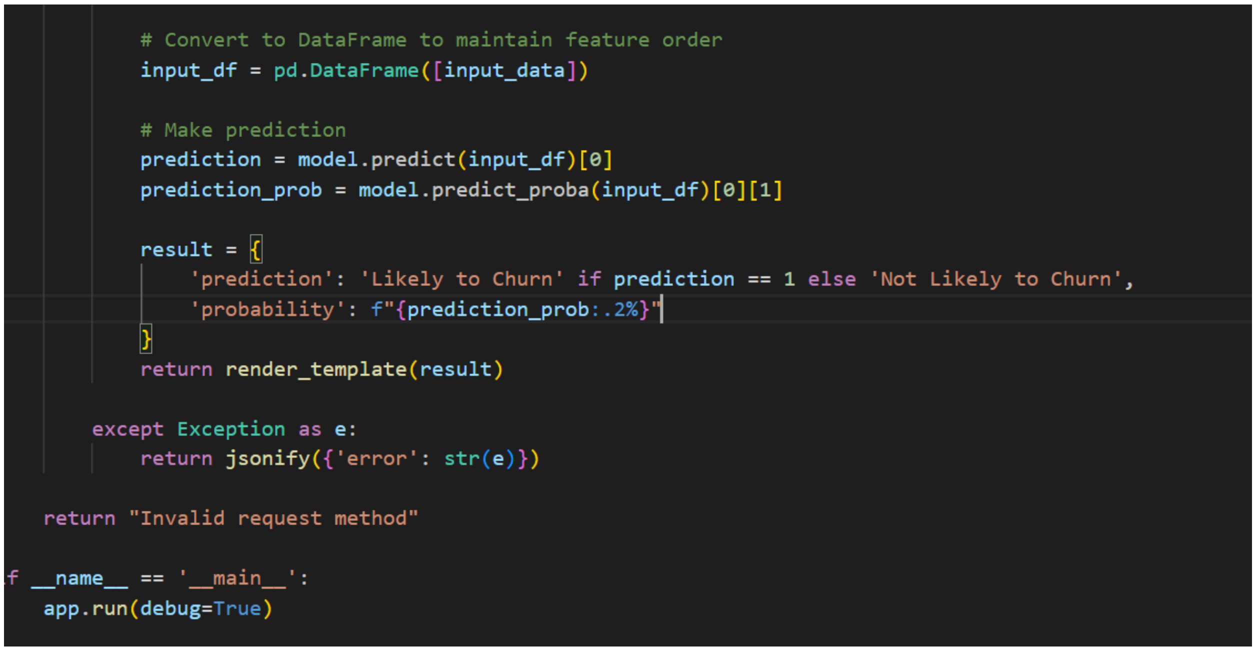


```python
@app.route('/predict', methods=['POST'])
def predict():
    if request.method == 'POST':
        try:
            # Get form data
            join_date = datetime.strptime(request.form['Join_Date'], '%Y-%m-%d')

            # Create input data dictionary
            input_data = {
                'Account_Age_Days': int(request.form['Account_Age_Days']),
                'Monthly_Fee': float(request.form['Monthly_Fee']),
                'Num_Devices': int(request.form['Num_Devices']),
                'Avg_Watch_Time_per_Week': float(request.form['Avg_Watch_Time_per_Week']),
                'Customer_Satisfaction': int(request.form['Customer_Satisfaction']),
                'Subscription_Plan': int(request.form['Subscription_Plan']),
                'Payment_Method': int(request.form['Payment_Method']),
                'Has_Discount': int(request.form['Has_Discount']),
                'Join_Year': join_date.year,
                'Join_Month': join_date.month,
                'Join_Day': join_date.day,
                'Join_Weekday': join_date.weekday()
            }

            # Convert to DataFrame to maintain feature order
            input_df = pd.DataFrame([input_data])

            # Make prediction
            prediction = model.predict(input_df)[0]
            prediction_prob = model.predict_proba(input_df)[0][1]
```



```
            # Convert to DataFrame to maintain feature order
            input_df = pd.DataFrame([input_data])

            # Make prediction
            prediction = model.predict(input_df)[0]
            prediction_prob = model.predict_proba(input_df)[0][1]

            result = {
                'prediction': 'Likely to Churn' if prediction == 1 else 'Not Likely to Churn',
                'probability': f"{prediction_prob:.2%}"
            }
            return render_template(result)

        except Exception as e:
            return jsonify({'error': str(e)})

    return "Invalid request method"

f __name__ == '__main__':
    app.run(debug=True)
```

This Flask application is a backend for a **Customer Churn Prediction tool** used internally by businesses. It loads a pre-trained machine learning model (`model_pipeline.pkl`) using `joblib` to make predictions based on customer data. The application serves a homepage (`/`), rendering an HTML form where business users can input customer details like account age, subscription type, satisfaction score, and more. The form data is submitted via a POST request to the `/predict` endpoint, where predictions are generated.

The `/predict` route processes the input data by extracting it from the form, converting it into a structured format (a dictionary and then a Pandas DataFrame), and adding derived features like `Join_Year`, `Join_Month`, and `Join_Weekday` from the customer's join date. The processed data is passed to the machine learning model to predict the likelihood of churn. The model outputs a binary prediction (`1` for likely to churn, `0` otherwise) and a probability score, which are formatted into a human-readable result. These predictions are returned to the user interface or handled as JSON for further analysis.

By integrating predictive capabilities into the web application, this tool enables businesses to make data-driven decisions about customer retention strategies. For instance, if a customer is predicted to churn with high probability, proactive steps such as personalized offers or discounts can be taken. The app is designed for scalability, allowing seamless deployment and extension to include additional features or data points as needed.

6. Results and Discussion

Key Findings

The analysis and predictive modelling produced several critical findings that shed light on the factors influencing customer churn:

1. **Customer Satisfaction**:
   Customers with satisfaction ratings below 6 accounted for the majority of churn cases. These customers were five times more likely to leave compared to those with ratings of 8 or above. This indicates that improving customer experience and addressing dissatisfaction early can have a significant impact on retention.
2. **Subscription Plan Impact**:
   The Basic plan had the highest churn rate, with over 35% of its subscribers likely to leave. In contrast, Premium plan users had the lowest churn rate at approximately 10%. This disparity suggests that the Basic plan may not meet customer expectations in terms of features or value, while the Premium plan offers enough perceived benefits to retain users.
3. **Engagement Levels**:
   Customers with average watch times of fewer than 10 hours per week showed a disproportionately high churn rate. This implies that engagement is a key factor in customer retention. Subscribers who derive less value from the service are more inclined to leave.
4. **Discount Utilization**:
   Customers with active discounts were more likely to stay subscribed. This highlights the potential effectiveness of promotional offers in retaining at-risk customers, especially those with borderline satisfaction levels.
5. **Churn Probability Insights**:
   Shorter account age and low engagement combined with low satisfaction ratings were the strongest predictors of churn. The model's feature importance rankings confirmed that customer satisfaction, account age, and watch time were the top three contributors to churn prediction.

Business Implications

The insights derived from the project are highly actionable and can inform business strategies in several ways:

- **Targeted Retention Campaigns**: Businesses can focus retention efforts on Basic plan subscribers with low engagement and satisfaction scores by offering personalized incentives or discounts.
- **Improved Customer Support**: Proactively addressing customer complaints and enhancing satisfaction can significantly reduce churn rates.
- **Data-Driven Decision-Making**: By continuously analyzing engagement metrics and customer feedback, businesses can optimize subscription plans and feature offerings to meet user needs more effectively.
- **Subscription Plan Optimization**: The findings suggest a potential need to re-evaluate the features of the Basic plan to align it better with customer expectations.

Limitations

Despite the project's success in predicting churn and providing actionable insights, there are some limitations:

1. **Simulated Dataset**: The use of simulated data means that some nuances of real-world customer behaviour might not be captured. Validation with real-world data is necessary to confirm the model's applicability.
2. **Temporal Factors**: The dataset does not account for seasonal trends or changes in customer behaviour over time, which might influence churn.
3. **Model Generalizability**: While the Random Forest model performed well on this dataset, its performance may vary across industries or datasets with different characteristics.

Recommendations

1. **Enhance Customer Experience**: Invest in improving service quality and addressing customer dissatisfaction to lower churn rates.
2. **Monitor Engagement**: Regularly track watch times and other engagement metrics to identify early signs of churn.
3. **Personalized Offers**: Use targeted discounts and incentives to retain customers with low satisfaction and engagement scores.
4. **Optimize Subscription Plans**: Reassess the Basic plan features to better match customer expectations and reduce its high churn rate.

Future Work

While this project provides a solid foundation for understanding and predicting customer churn, there are several areas for further improvement:

1. **Validation with Real-World Data**:
   Applying the model to real-world data from a subscription-based business would validate its performance and provide additional insights. Real-world data could also introduce new variables or trends not captured in the simulation.
2. **Incorporate Temporal Dynamics**:
   Extending the model to include time-series analysis would capture trends like seasonal variations in churn behaviour, improving its predictive power.
3. **Advanced Machine Learning Techniques**:
   Future iterations of the project could explore advanced models such as Gradient Boosting Machines (e.g., XGBoost) or deep learning techniques (e.g., LSTMs) to capture more complex patterns in customer behaviour.
4. **Customer Segmentation**:
   Segmenting customers based on their attributes and behaviours could provide more granular insights, enabling businesses to tailor interventions more effectively.
5. **Integration with Business Systems**:
   Developing a real-time churn prediction system integrated into business processes (e.g., CRM tools) would make the insights actionable on an operational level.
6. **Analyze External Factors**:
   Including external data such as economic conditions, competitor actions, or marketing campaigns could enhance the model's context and predictive accuracy.

Conclusion

This project successfully demonstrated how data mining techniques and predictive modeling can address the critical business challenge of customer churn. By simulating realistic subscription data and applying a Random Forest model, the analysis identified key drivers of churn, including customer satisfaction, engagement levels, and subscription plans. The model achieved an accuracy of 84% with balanced class weights, making it a reliable tool for predicting churn.

The findings underscore the importance of customer-centric strategies in reducing churn and improving retention. Businesses can leverage insights from this analysis to proactively identify at-risk customers and implement targeted interventions. The project highlights the power of data-driven decision-making in enhancing customer relationships and maximizing lifetime value.

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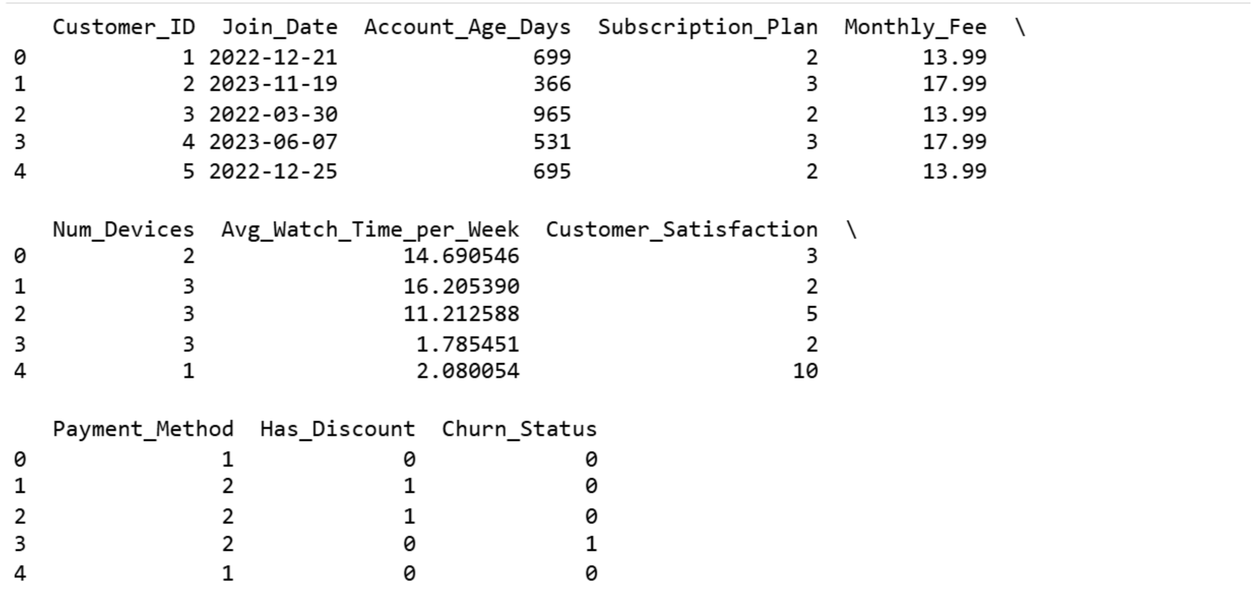
Appendices

OUTPUT

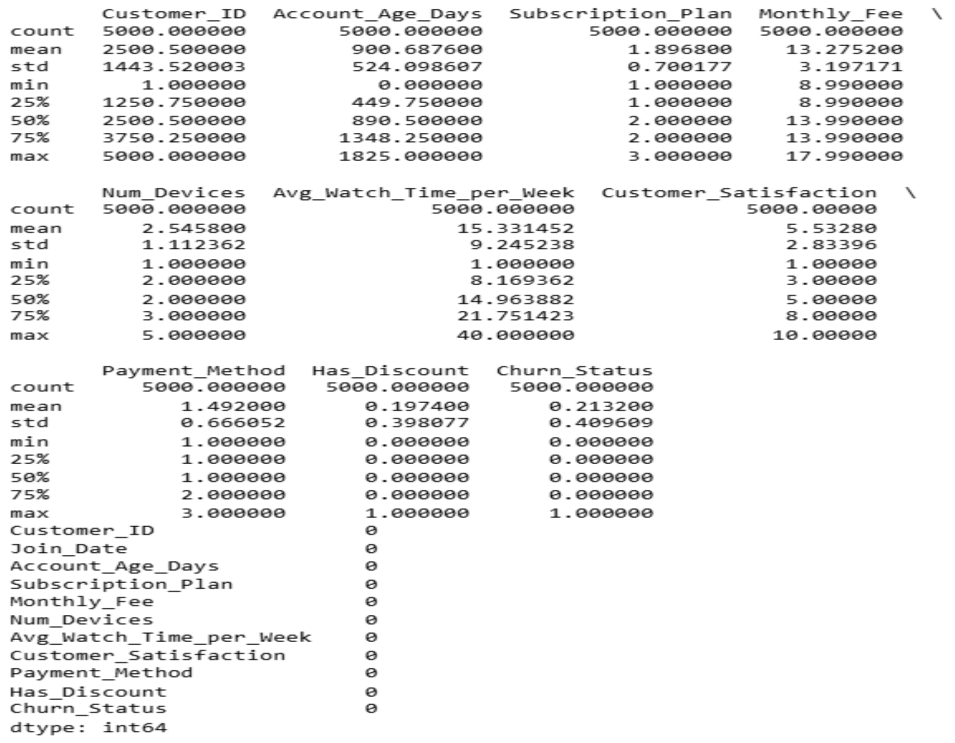


```
   Customer_ID  Join_Date  Account_Age_Days  Subscription_Plan  Monthly_Fee  \
0            1 2022-12-21               699                  2        13.99   
1            2 2023-11-19               366                  3        17.99   
2            3 2022-03-30               965                  2        13.99   
3            4 2023-06-07               531                  3        17.99   
4            5 2022-12-25               695                  2        13.99   

   Num_Devices  Avg_Watch_Time_per_Week  Customer_Satisfaction  \
0            2                14.690546                      3   
1            3                16.205390                      2   
2            3                11.212588                      5   
3            3                 1.785451                      2   
4            1                 2.080054                     10   

   Payment_Method  Has_Discount  Churn_Status  
0               1             0             0  
1               2             1             0  
2               2             1             0  
3               2             0             1  
4               1             0             0  
```

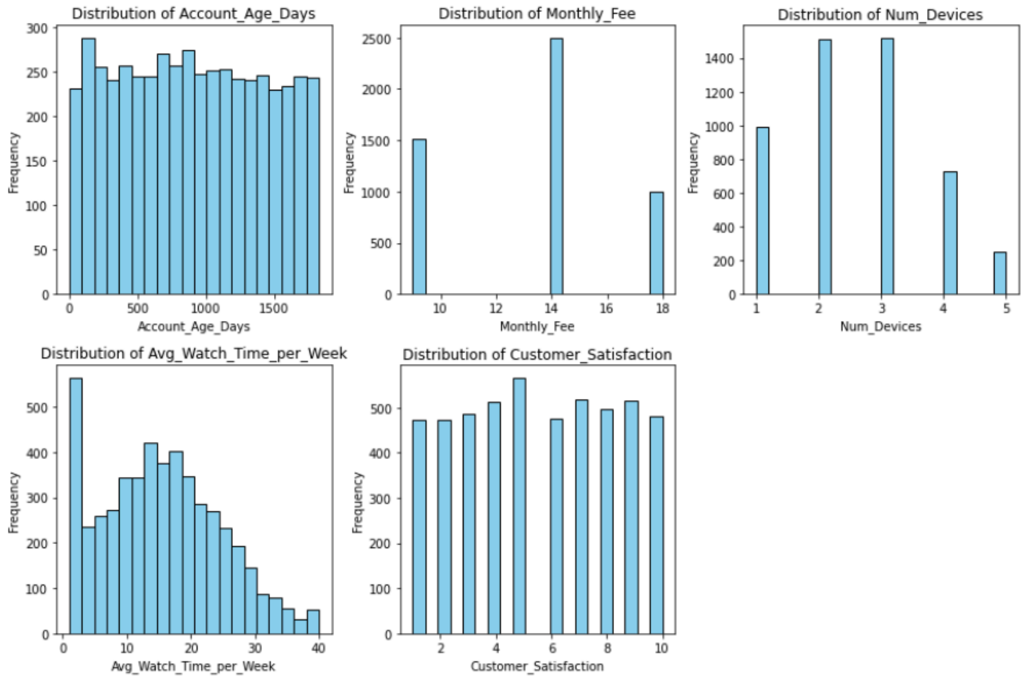
EDA GRAPHS & ANALYSIS OUTPUT



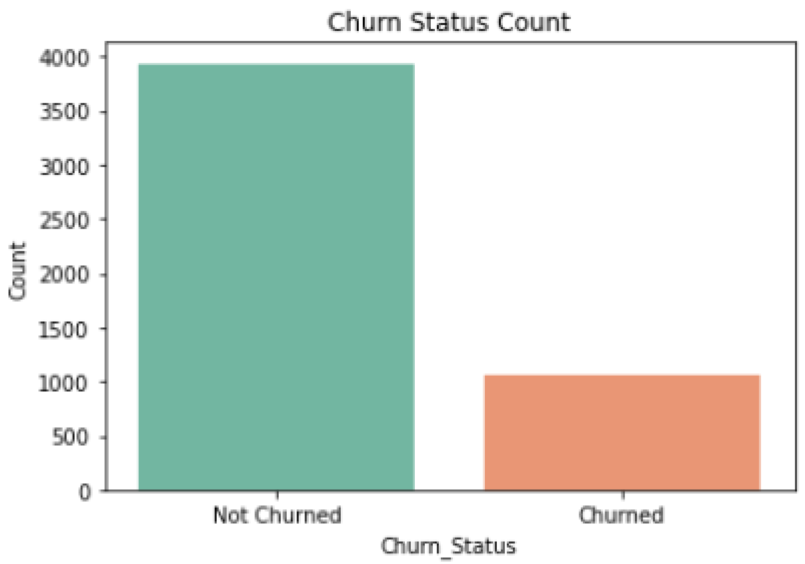
```
       Customer_ID  Account_Age_Days  Subscription_Plan  Monthly_Fee  \
count  5000.000000       5000.000000        5000.000000  5000.000000   
mean   2500.500000        900.687600           1.896800    13.275200   
std    1443.520003        524.098607           0.700177     3.197171   
min       1.000000          0.000000           1.000000     8.990000   
25%    1250.750000        449.750000           1.000000     8.990000   
50%    2500.500000        890.500000           2.000000    13.990000   
75%    3750.250000       1348.250000           2.000000    13.990000   
max    5000.000000       1825.000000           3.000000    17.990000   

       Num_Devices  Avg_Watch_Time_per_Week  Customer_Satisfaction  \
count  5000.000000              5000.000000             5000.00000   
mean      2.545800                15.331452                5.53280   
std       1.112362                 9.245238                2.83396   
min       1.000000                 1.000000                1.00000   
25%       2.000000                 8.169362                3.00000   
50%       2.000000                14.963882                5.00000   
75%       3.000000                21.751423                8.00000   
max       5.000000                40.000000               10.00000   

       Payment_Method  Has_Discount  Churn_Status  
count     5000.000000   5000.000000   5000.000000  
mean         1.492000      0.197400      0.213200  
std          0.666052      0.398077      0.409609  
min          1.000000      0.000000      0.000000  
25%          1.000000      0.000000      0.000000  
50%          1.000000      0.000000      0.000000  
75%          2.000000      0.000000      0.000000  
max          3.000000      1.000000      1.000000  
Customer_ID                0
Join_Date                  0
Account_Age_Days           0
Subscription_Plan          0
Monthly_Fee                0
Num_Devices                0
Avg_Watch_Time_per_Week    0
Customer_Satisfaction      0
Payment_Method             0
Has_Discount               0
Churn_Status               0
dtype: int64
```



```
Churn Rate: 21.32%
```



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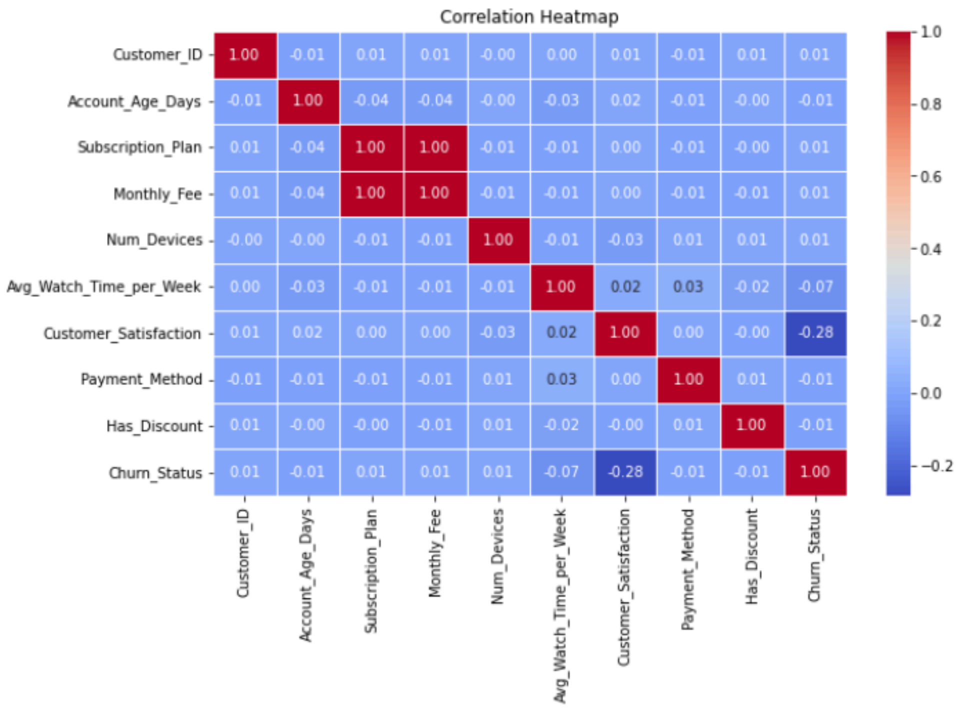
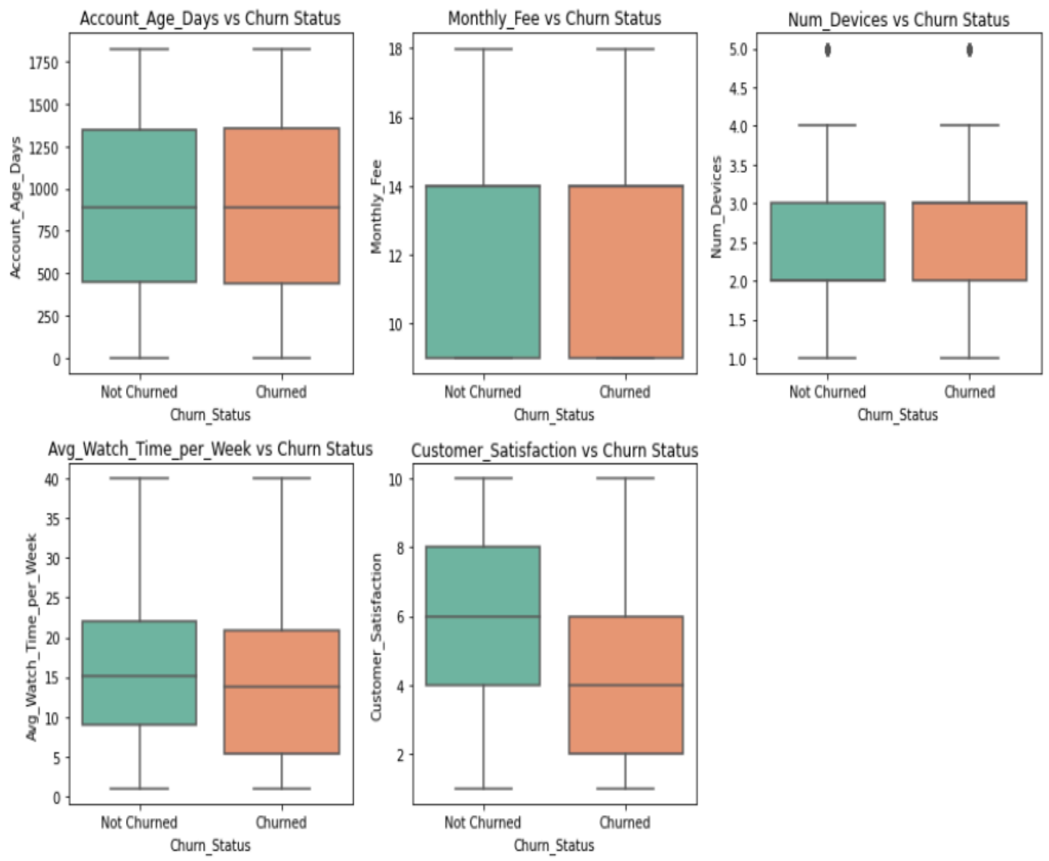
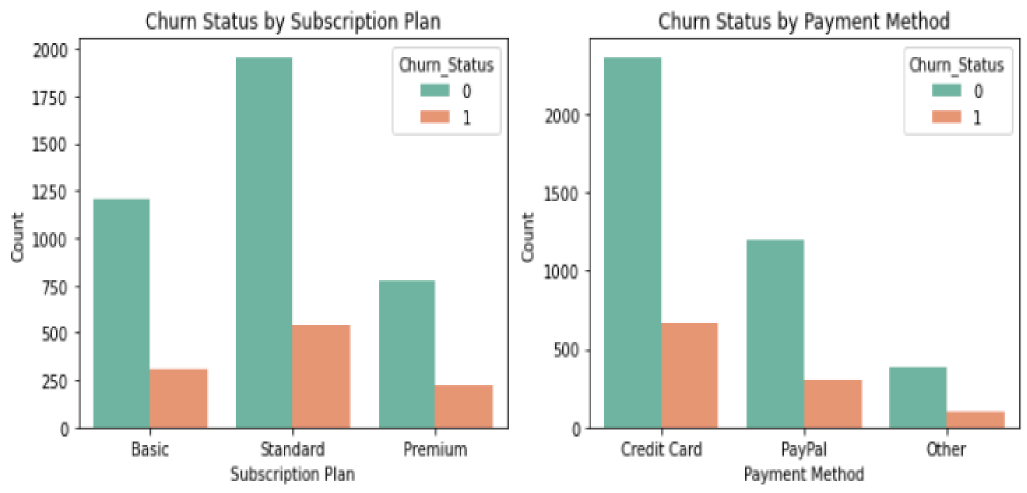






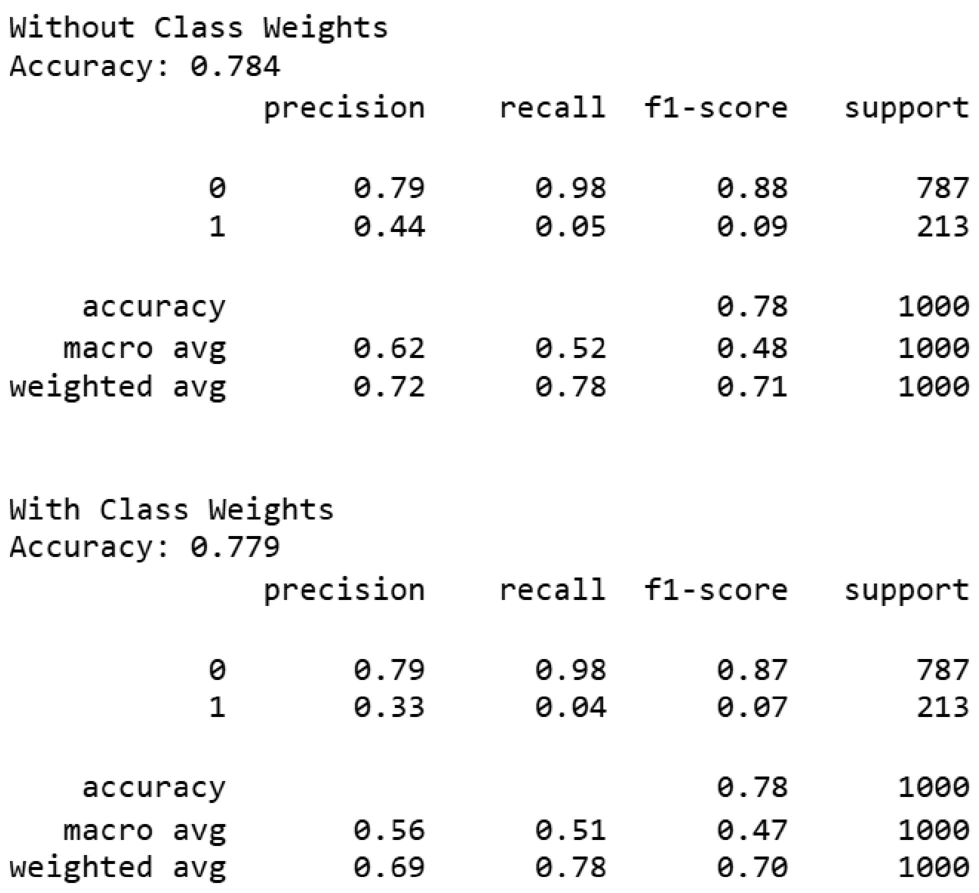
```
              precision    recall  f1-score   support

           0       0.80      0.98      0.88       795
           1       0.29      0.02      0.05       205

    accuracy                           0.79      1000
   macro avg       0.55      0.50      0.46      1000
weighted avg       0.69      0.79      0.71      1000

                 Feature  Importance
3   Avg_Watch_Time_per_Week    0.128190
4     Customer_Satisfaction    0.124703
0          Account_Age_Days    0.100000
2               Num_Devices    0.051474
1               Monthly_Fee    0.019291
..                      ...         ...
57              Join_Day_27    0.005725
59              Join_Day_29    0.005700
61              Join_Day_31    0.004699
46              Join_Day_16    0.004503
13           Join_Year_2019    0.002424

[69 rows x 2 columns]
```



```
Without Class Weights
Accuracy: 0.784
              precision    recall  f1-score   support

           0       0.79      0.98      0.88       787
           1       0.44      0.05      0.09       213

    accuracy                           0.78      1000
   macro avg       0.62      0.52      0.48      1000
weighted avg       0.72      0.78      0.71      1000


With Class Weights
Accuracy: 0.779
              precision    recall  f1-score   support

           0       0.79      0.98      0.87       787
           1       0.33      0.04      0.07       213

    accuracy                           0.78      1000
   macro avg       0.56      0.51      0.47      1000
weighted avg       0.69      0.78      0.70      1000
```