Introduction

Customer churn, or the percentage of customers who discontinue a service within a given time frame, is a critical business metric for subscription-based services such as Netflix. This study aims to identify the key drivers of customer churn and uncover patterns that can help in reducing churn rates. Through a comprehensive exploration of the Netflix customer churn dataset, various statistical techniques and exploratory data analysis (EDA) methods were employed to gain insights into customer behaviour.

Objectives

The primary objectives of this study are as follows:

- To analyse customer churn behaviour using statistical methods.
- To identify significant variables contributing to churn.
- To develop a basic predictive model to estimate the likelihood of churn.
- To suggest actionable strategies for retention based on findings.

Data Understanding

Dataset Description

The dataset used for this analysis consists of customer data from Netflix, including variables such as:

- customer_id: Unique identifier for each customer.
- gender: Gender of the customer.
- age: Age in years.
- monthly_fee: Subscription fee paid by the customer.
- watch_time: Average monthly watch time (in hours).
- plan_type: Type of subscription plan.
- signup_date: Date of registration.
- last_active_date: Most recent date of activity.
- churned: Binary variable indicating whether the customer has churned (1 = Yes, 0 = No).

The data spans over multiple months and includes both numerical and categorical attributes relevant for churn analysis.

Data Preprocessing

Prior to analysis, the dataset was cleaned and processed using the following steps:

- Categorical variables were encoded using label encoding or one-hot encoding where required.
- Outliers were detected using boxplots and treated accordingly.
- Derived variables such as customer tenure were created to enhance feature relevance.

Exploratory Data Analysis (EDA)

The EDA phase focused on understanding the distribution of data and relationships between variables. Key observations include:

- Churn Rate: Approximately 50.3% of customers were identified as churned.
- Gender Distribution: Balanced representation across genders.
- Plan Type vs Churn: Basic plans had a higher churn rate compared to premium plans.
- Watch Time and Churn: Customers with lower average watch times were more likely to churn.
- Monthly Fee: Churned customers generally subscribed to lower-priced plans.
- Correlation analysis showed significant relationships between watch_time, monthly_fee, and churn.

Various visualization techniques such as histograms, boxplots, and bar graphs were used to support these findings.

Statistical Testing

The following statistical tests were applied to validate assumptions:

- Independent t-test: Applied to determine if average monthly_fee and watch_time differ significantly between churned and non-churned customers.
- **Chi-square test**: Used to test the independence between categorical variables such as plan_type and churned.
- ANOVA: Applied to compare monthly_fee across multiple churn categories or plan types.
- **Correlation Analysis:** To check how numeric variables (e.g., monthly_fee, watch_hours) relate to each other.

• **Logistic Regression**: A binary classification model was built to identify variables that significantly predict churn. Key predictors included monthly_fee, plan_type, and watch_time.

Findings and Interpretation

- Customers on lower-tier plans and with less engagement (low watch time) are more prone to churn.
- Plan type and usage patterns can be used to segment at-risk customers.
- Pricing strategies and personalized engagement can play a key role in retention.

Conclusion

This study provided valuable insights into the factors contributing to Netflix customer churn. By leveraging statistical analysis and machine learning, patterns and trends were uncovered that can support data-driven decision-making. Future work can incorporate time-series analysis and real-time churn prediction for ongoing business optimization.