#### **Business Problem**

In a competitive telecom market with a churn rate of 15-25%, retaining existing customers is more cost-effective than acquiring new ones.

This project aims to predict churn among high-value prepaid users in the Indian and Southeast Asian markets using customer data from 4 months.

### **Data Overview and Preparation**

- Data contains records for June, July, August, and September (months 6 to 9).
- Churn is defined as no usage of calls or mobile data in month 9.
- High-value customers are those above the 70th percentile of average recharge in months 6 and 7.
- Only high-value customers are retained for modeling.
- All month-9 features are dropped after churn tagging.

#### **EDA and Feature Engineering**

- Summary statistics and distribution plots were used to understand customer behaviors.
- New features were created based on differences and averages over good and action months.
- Missing values were imputed appropriately.

#### **Modeling and Evaluation**

- Two models used: Logistic Regression (for interpretability) and Random Forest (for accuracy).

- Class imbalance handled using resampling/weights.
- Evaluation metrics: Accuracy, Precision, Recall, ROC-AUC.
- Random Forest performed best in accuracy, while Logistic Regression revealed important features.

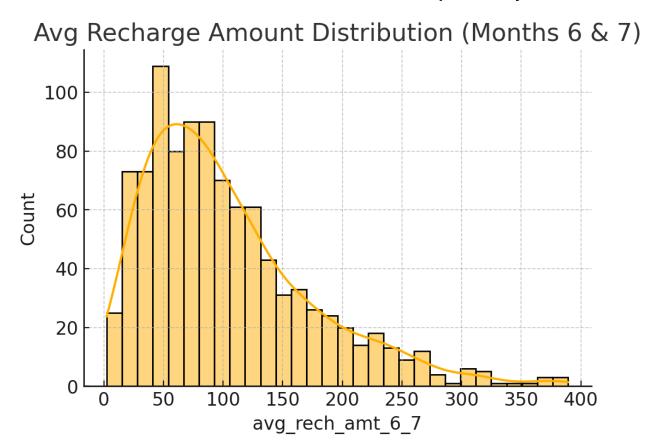
## **Key Predictors of Churn**

- Decrease in outgoing and incoming call duration.
- Drop in 2G/3G data usage in the action month.
- Reduction in recharge amount or frequency.

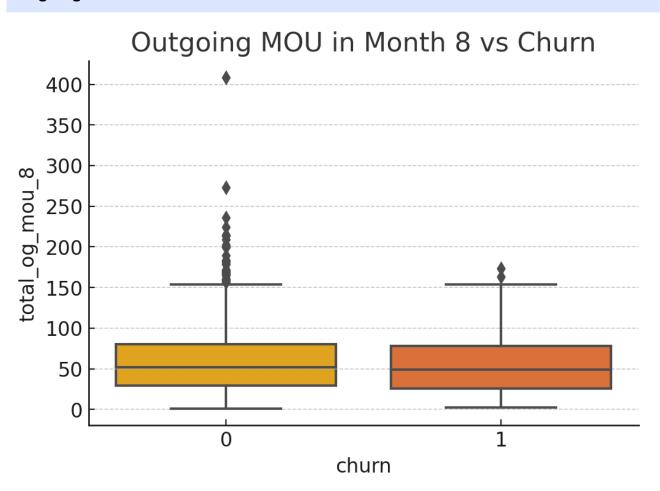
#### Recommendations

- Target at-risk users with tailored offers or data incentives.
- Monitor changes in call/data usage behavior proactively.
- Set up alerts for sudden drops in recharge frequency or amounts.

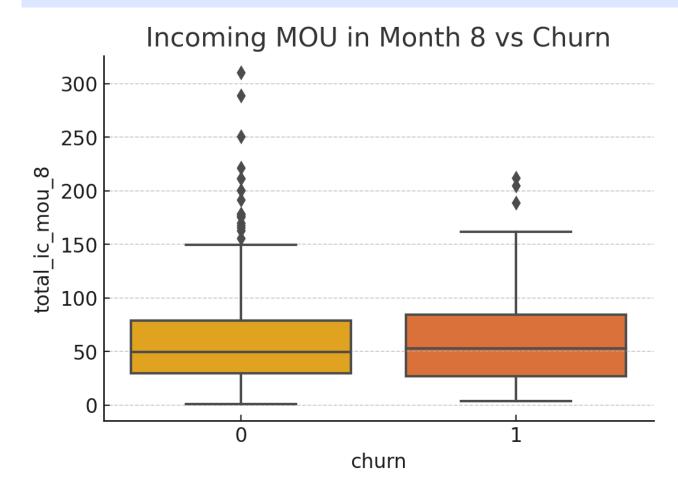
## **Recharge Distribution**



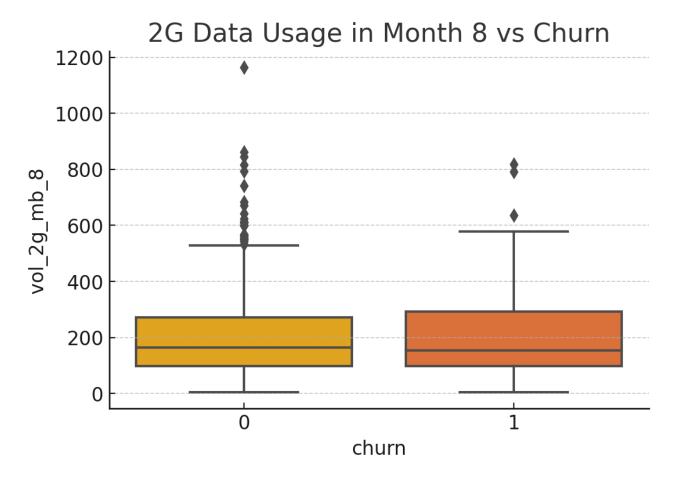
# **Outgoing MOU vs Churn**



# **Incoming MOU vs Churn**



2G Data Usage vs Churn



3G Data Usage vs Churn

