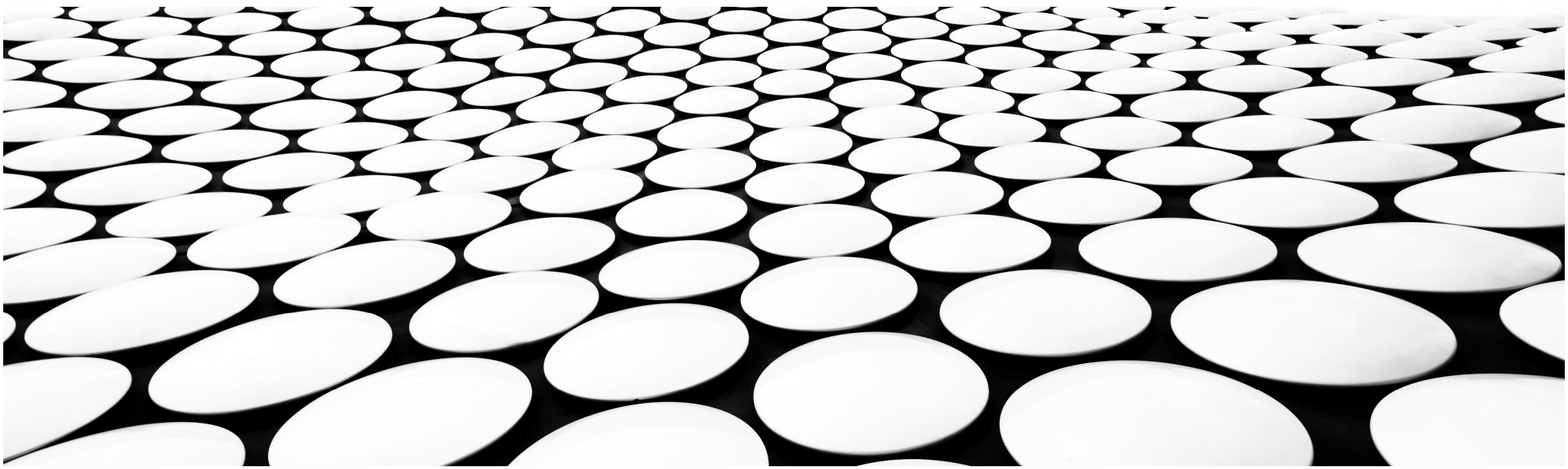
TELECOM CHURN CASE STUDY



BUSINESS PROBLEM OVERVIEW

- In the telecom industry, customers are able to choose from multiple service providers and actively switch from one operator to another. In this highly competitive market, the telecommunications industry experiences an average of 15-25% annual churn rate. Given the fact that it costs 5-10 times more to acquire a new customer than to retain an existing one, **customer retention** has now become even more important than customer acquisition.
- For many incumbent operators, *retaining high profitable customers is the number one business goal*.
- To reduce customer churn, telecom companies need to **predict which customers are at high risk of churn.**
- In this project, you will analyze customer-level data of a leading telecom firm, build predictive models to identify customers at high risk of churn and identify the main indicators of churn.

UNDERSTANDING AND DEFINING CHURN

- There are two main models of payment in the telecom industry - **postpaid** (customers pay a monthly/annual bill after using the services) and **prepaid** (customers pay/recharge with a certain amount in advance and then use the services).
- In the postpaid model, when customers want to switch to another operator, they usually inform the existing operator to terminate the services, and you directly know that this is an instance of churn.
- However, in the prepaid model, customers who want to switch to another network can simply stop using the services without any notice, and it is hard to know whether someone has actually churned or is simply not using the services temporarily (e.g. someone may be on a trip abroad for a month or two and then intend to resume using the services again).
- Thus, churn prediction is usually more critical (and non-trivial) for prepaid customers, and the term 'churn' should be defined carefully. Also, prepaid is the most common model in India and Southeast Asia, while postpaid is more common in Europe in North America.

PURPOSE AND SCOPE OF THE ANALYSIS

- The purpose of the analysis in the provided link is to develop a model that can predict customer churn for a telecom company based on customer behavior and demographic data. The analysis aims to identify key factors that contribute to customer churn and develop a model that can accurately predict churn based on these factors.
- The scope of the analysis includes data cleaning, exploratory data analysis, feature engineering, and model development using various classification algorithms. The analysis also includes the evaluation of model performance using metrics such as accuracy, precision.
- Additionally, the analysis includes recommendations for the telecom company to manage customer churn based on the insights gained from the model. These recommendations include offering targeted promotions and discounts to high-risk customers, improving customer service, and providing personalized offers to retain customers

KEY TECHNICAL AND BUSINESS ASPECTS COVERED

- Technical Aspects
- Data pre-processing techniques such as handling missing values, feature scaling, and feature engineering.
- Exploratory data analysis to understand the distribution of various features and their impact on the target variable • Building and fine-tuning various classification models to predict churn.

- Business Aspects
- Understanding the key factors that contribute to customer churn
- Identifying the most profitable customer segments and devising strategies to retain them
- Analyzing the impact of various marketing and promotional campaigns on customer churn
- Identifying areas of improvement in customer service and support to increase customer satisfaction and reduce churn

MODEL INTERPRETATION

- Based on the business case and outcome of analysis, the model interpretation involved understanding the variables that have the most significant impact on customer churn. This would help identify the key drivers of churn and enable the telecom company to take appropriate measures to retain customers.
- The exploratory data analysis conducted in the project would help identify these key drivers by examining the distribution of various features and their impact on the target variable. The classification models built and fine-tuned in the project would also aid in this process by identifying the most significant variables in predicting churn.
- The model performance evaluation using various metrics such as accuracy, precision, recall, and AUC would also help in interpreting the model. This would enable the company to understand the accuracy of the model in predicting churn and identifying any areas for improvement.
- Finally, dealing with imbalanced classes using techniques such as oversampling, under sampling, and SMOTE would ensure that the model is not biased towards the majority class and that the minority class is not overlooked. This would help the telecom company in accurately predicting churn and taking appropriate measures to retain customers.

RESULTS

The analysis performed on the telecom churn dataset has helped in identifying the key factors that lead to customer churn. The results show that the following factors have a significant impact on churn:

- Tenure: Customers who have been with the company for a longer period are less likely to churn.
- Contract Type: Customers with a month-to-month contract are more likely to churn compared to customers with long-term contracts.
- Payment Method: Customers who pay through electronic check are more likely to churn compared to customers who pay through other methods.
- Monthly Charges: Customers with higher monthly charges are more likely to churn.

RECOMMENDATION

- Target the customers, whose minutes of usage of the incoming local calls and outgoing ISD calls are less in the action phase (mostly in August). Target the customers, whose outgoing others charge in July and incoming others in August are less.
- Also, the customers having value-based costs in the action phase are more likely to churn than the other customers. Hence, these customers may be a good target to provide offers.
- Customers, who's monthly 3G recharge in August is more, are likely to be churned.
- Customers having decreasing STD incoming minutes of usage for operators T to fixed lines of T for August are more likely to churn.
- Customers decreasing monthly 2g usage for August are most likely to churn.
- Customers having decreasing incoming minutes of usage for operators T to fixed lines of T for August are more likely to churn.
- roam_og_mou_8 variables have positive coefficients (0.7135). That means the customers, whose roaming outgoing minutes of usage is increasing are more likely to churn.