## Introduction

The data consists of customer churn, churn means customers leaving the product or the service. The dataset consists of various factors affecting the customer churn. It is a crucial concern in the telecom industry. This report provides the overview the insights into factors influencing the customer retention and attritions in a telecommunication industry.

The dataset was originally made available by IBM as part of their Sample Data Sets collection for analytics and machine learning. It has since become a popular resource for studying customer behaviour and developing predictive models in the telecom sector.

## Dataset Exploration

The Telco Customer Churn dataset comprises various characteristics of customers as well as their service usage, where the information as to whether they have churned or not is thereby captured. The list of variables it includes, are as follows:

* Customer demographics (gender, age range, partner status, dependents)
* Account information (contract type, billing method, monthly charges)
* Services subscribed (telecommunication, internet, TVs, online security, online backup, online streaming movies, device protection)
* Customer tenure and churn status

There are vast data through the thousands of customers enumerated which gives a broad and detailed view of the data on customer churn.

## Initial Observations

I have observed the following from Telco Customer Churn dataset.

It might have some correlation to the churn rate. The month-to-month contracts have more churn, where the long-term ones have fewer churning.

These are the subscribers (multi-service) who use both internet and phone services who are not disloyal and so they contribute the most to the retention of the company and thus have a smaller turnover rate than the single-service holders.

The customers with different tenure lengths have an effect on churn, the customers with long standing tenure are less likely to churn.

## Questions

1. How are tenure and monthly charges dependent on each other?
2. How does the contract type affect the likelihood of customer churn?
3. Do customers with more services (e.g., internet, phone, streaming TV) have lower churn rates?

## Importance of above questions

1. Understanding the relationship between tenure and monthly charges can help telecom companies develop more effective pricing strategies. It can reveal whether long-term customers are paying more or less, informing decisions on loyalty discounts or premium services for established customers.
2. Analysing the impact of contract types on churn is crucial for designing retention strategies. It can guide companies in structuring their contract offerings to minimize churn and maximize customer lifetime value.
3. Knowing how the number of services affects churn rates is vital for cross-selling and bundling strategies. It can inform decisions on product offerings and help in developing targeted marketing campaigns to increase customer engagement and reduce churn.

# Sample statements of outcome

1. Initial analysis suggests a potential relationship between customer tenure and monthly charges. Further statistical analysis is needed to determine the exact nature and strength of this relationship.
2. Preliminary data examination indicates that contract type may be associated with churn rates. Customers with month-to-month contracts appear to have higher churn rates compared to those with longer-term contracts, but detailed statistical testing is required to confirm this trend and quantify the difference.
3. Initial observations suggest that customers with multiple services might have lower churn rates compared to those with fewer services . However, rigorous statistical analysis is necessary to verify this pattern and determine its significance.

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Further studies

**introductionPurpose REFERENCES**

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