May 19, 2025

CUSTOMER CHURN PREDICTION

MCI Data Analyst Intern test assignment

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CHURN PREDICTION PROBLEM

Customer churn prediction is the task of identifying customers who are likely to stop using a company's services. It is crucial for businesses to take early action and improve customer retention strategies.
This problem is highly relevant in many industries, such as:

- Telecommunications
- Banking and Finance
- E-commerce
- Subscription services
- Insurance

By predicting churn, companies can proactively offer promotions, support, or engagement efforts to retain valuable customers.

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IMPACT OF CHURN RATE ON STAKEHOLDERS

- Customer:
  - A rising churn rate could highlight service issues or pricing misalignment, prompting the need for better retention strategies.
- MCI:
  - Churn reflects their experience and the availability of better alternatives in the market.
- Investors and decision-makers:
  - Churn rate trends offer valuable signals about business health and future revenue stability.

DATASET OVERVIEW

The dataset consists of customer data from a telecom company, aiming to predict churn behavior. It includes the following types of information:

- Geographic and account information:
    - State, Area code, Account length
- Service plans:
    - International plan, Voice mail plan, Number vmail messages
- Usage statistics:
    - Daily, evening, night, and international call minutes, number of calls, and corresponding charges:
        - e.g. Total day minutes, Total eve calls, Total intl charge, etc.
- Customer behavior:
    - Customer service calls (number of support interactions)
- Target label:
    - Churn (whether the customer has churned: True/False)

This dataset enables both behavioral and usage-based analysis to identify patterns associated with customer churn.

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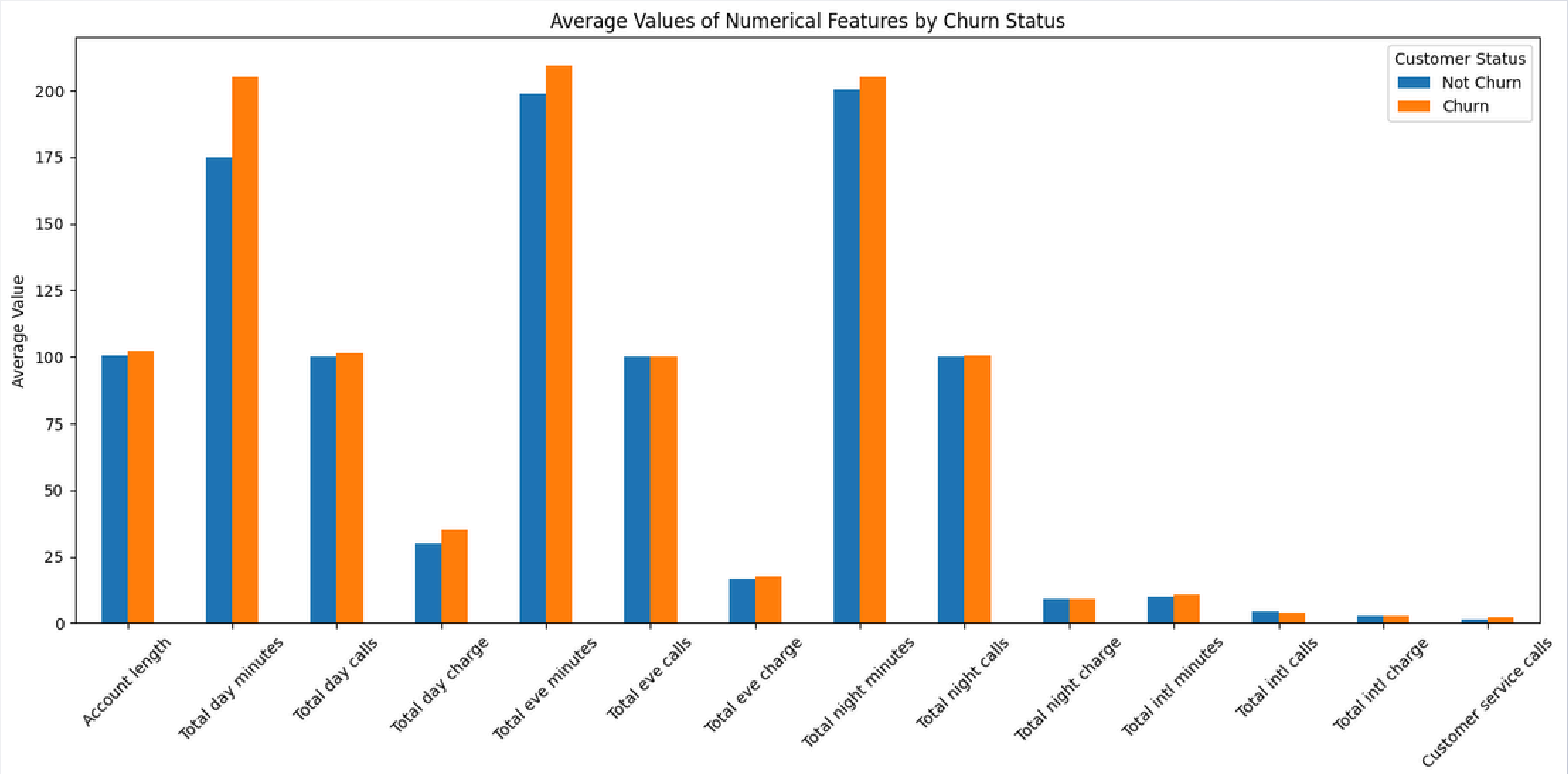
CHURN VS. NON-CHURN: CUSTOMER TRAITS

- **Churn**

They tend to have higher values for:

- Account length
- Total day minutes
- Total day charge
- Total evening minutes
- Total night minutes
- Most of them do not use the Voice Mail Plan.
- They make many customer service calls.



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CHURN VS. NON-CHURN: CUSTOMER TRAITS

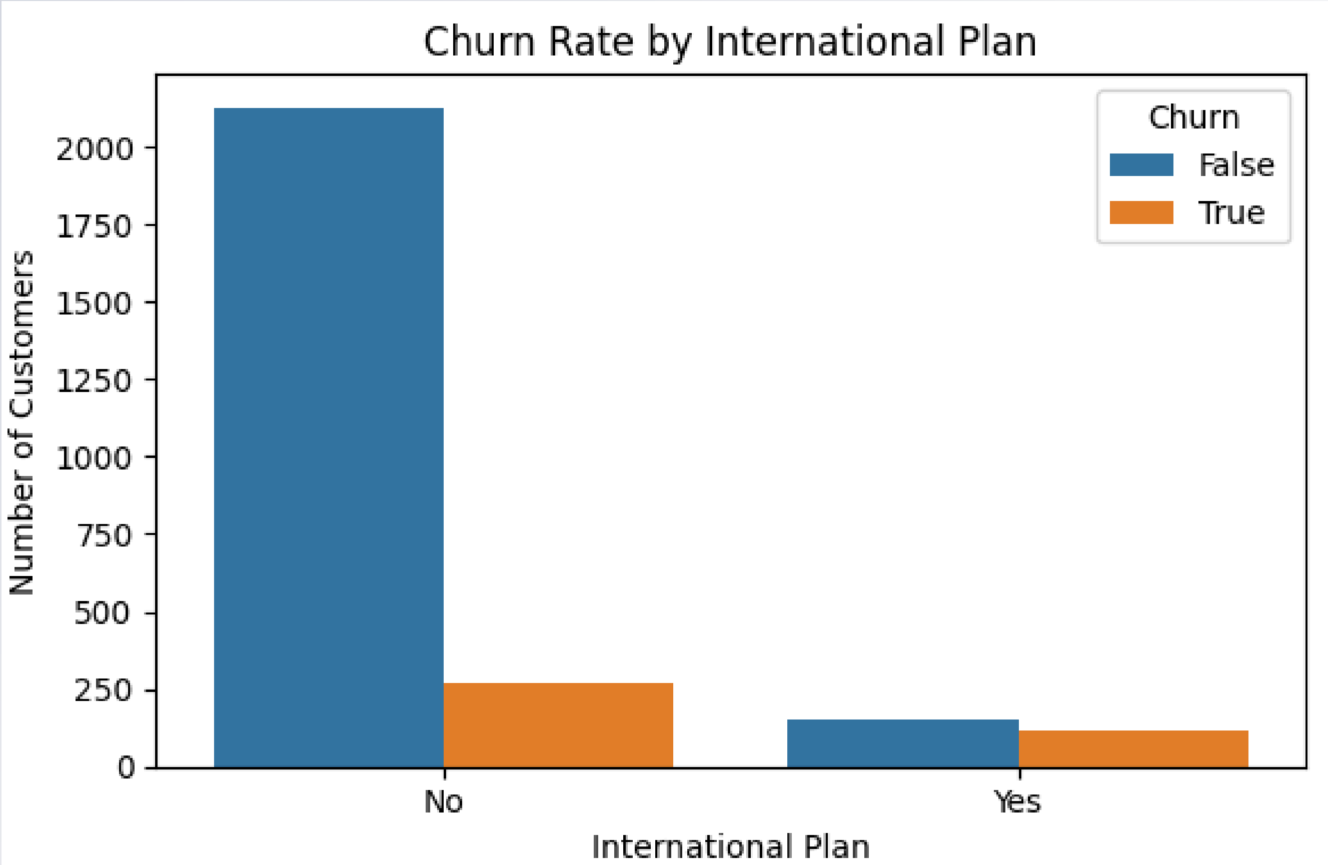
- **Churn**

Interpretation:

- These customers are heavy users, especially during the day, which results in high charges. If the perceived value doesn't match what they're paying, it may lead to dissatisfaction.
- Frequent customer service calls suggest problems or dissatisfaction. If those issues are not resolved effectively, customers are more likely to leave.

CHURN VS. NON-CHURN: CUSTOMER TRAITS

- **Non-churn**



- Most of them use don’t international plan.

CHURN VS. NON-CHURN: CUSTOMER TRAITS

- **Non-churn**

Interpretation:

- These customers likely incur lower overall charges, especially by avoiding international calls, which are typically more expensive.
- Their simpler service usage patterns may lead to fewer complications and fewer negative experiences, contributing to greater satisfaction and loyalty.

MODELING APPROACH AND RESULTS

- **Modeling Approach**

For binary classification churn prediction, several machine learning models can be implemented: Logistic Regression, Tree-based model likes Decision Trees, Random Forest, Gradient Boosting Machines, Support Vector Machine. In this project, I implemented Logistic Regression, Random Forest, LightGBM.

- **Features input**

Beside original provided features, there are synthetic features created in feature engineering

- Average call durations: avg_day_call_duration, avg_eve_call_duration, avg_night_call_duration, avg_intl_call_duration
- Proportion of call activity : day_ratio, eve_ratio, night_ratio, intl_ratio.
- Summarize overall call activity: total_minutes, total_calls, intl_calls_ratio.

MODELING APPROACH AND RESULTS

- **Logistic Regression results and features important.**

Model results:

- In 95 churn customer, model can correctly predict for 74 customer, with recall 77.9%. while in 572 no churn customer, 75.17% of them truly predicted.

Feature importance: The plot displays the top 5 most important features ,ranked by how much they contribute to improving the model's predictions of customer churn.

- Day_ratio: A higher proportion of daytime calls is associated with lower churn
- Night_ratio: In contrast, A higher proportion of night time calls is associated with higher churn
- Total day minutes: Higher usage during the day may lead to higher rate to churn.
- Total day charge: Higher charges (correlated with more minutes) are associated with higher churn risk.
- Intl_calls_ratio: A higher share of international calls slightly reduces churn.

MODELING APPROACH AND RESULTS

- **Random Forest results and features important.**

Model results:

- Model can precisely predict 78.95% churn customer and 99.3% no churn customer.

Feature importance:

- Total charge: Overall charges seem to be the most critical factor—high billing may increase churn risk.
- Customer service calls: Frequent contact with customer service can indicate issues or dissatisfaction, likely leading to churn.
- Total day minutes: High day-time usage may reflect higher bills or certain user behavior linked to churn.
- Total_minutes: Total call time (across all periods) reflects overall engagement; could correlate with cost or service usage habits.
- Total day charge: Like total day minutes, but directly related to cost—higher charges may drive churn.

MODELING APPROACH AND RESULTS

- **LightGBM results and features important.**

Model results:

- In 95 churn customer, model can predict true for 13 customer, with recall 0.86. while in 572 no churn customer, 98% of them truly predicted.

Feature importance:

- State_freq: Frequency or encoding of the customer's state.
- Avg_intl_call_duration: Average length of international calls. Longer calls may suggest business or high-value users with different churn behavior.
- Total_minutes: usage level in minute, reflect engagement with the service.
- Total charge: Total cost incurred by the customer. High charges might lead to dissatisfaction and churn
- Intl_calls_ratio: The proportion of international calls relative to total calls. A strong indicator—perhaps churners use more/less international calls.
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RETENTION STRATEGIES BASED ON QUALITATIVE & QUANTITATIVE ANALYSIS

- **Quantitative Actions**

  These are actions based on numerical data and measurable outcomes.
  - Build churn prediction models using customer activity, complaint records, or billing history.
  - Segment users into groups (like heavy users or occasional users) to offer more suitable retention tactics.
  - Try A/B testing to compare different offers and see which one encourages customers to stay.
  - Use RFM analysis to spot those who recently reduced their activity and may churn.
  - Estimate customer lifetime value to focus on keeping the most valuable users.
- **Qualitative Actions**

  These are actions based on non-numerical insights such as opinions, experiences, or observations.
  - Ask customers why they leave through exit surveys and try to find common patterns.
  - Check social media or call center feedback for early signs of dissatisfaction.
  - Reach out personally to loyal or high-value users who may churn soon.
  - Look at competitors to understand what they’re offering that attracts your customers.
  - Create loyalty programs to reward long-term users and keep them engaged.

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THANK YOU !

There may still be some shortcomings in this work, and I sincerely welcome any feedback for improvement.

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