Customer Churn Analysis

Interpretable Machine Learning for Human-Centered Retention Strategy

Prepared by: Junior Data Scientist

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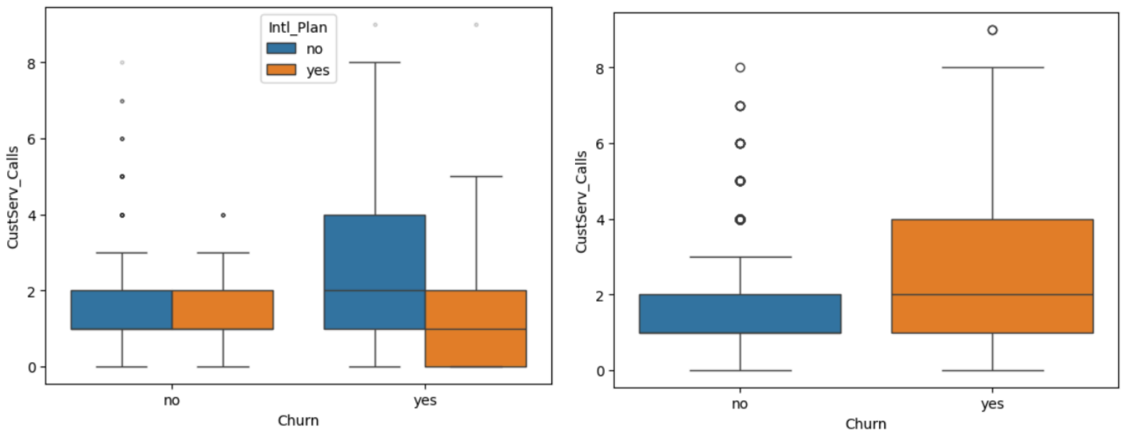
Problem Statement

The goal was to identify which behaviors signal a high likelihood of churn and to build a predictive model that businesses can use to intervene before customers leave. The project prioritizes recall to ensure we capture as many potential churners as possible a choice rooted in real-world cost considerations, where missing a churner is more damaging than falsely flagging a loyal customer.

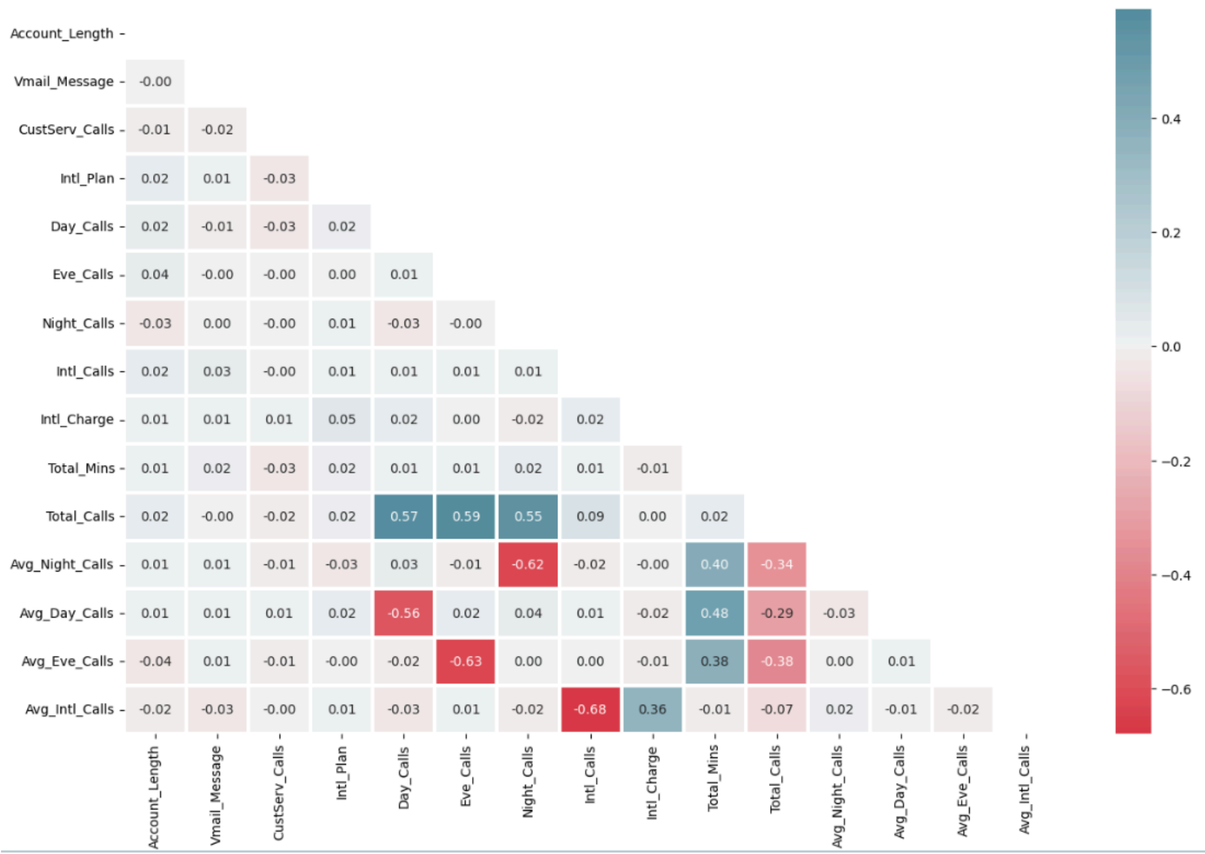
Exploratory Data Analysis

Initial analysis revealed strong behavioral indicators:- Customers who churn often have higher customer service call frequency.- However, those with international plans show different patterns; they may churn less despite frequent service calls. These findings indicate that churn isn't driven by single variables but interactions between behaviors, which motivated the use of ensemble models and feature interaction plots later on.



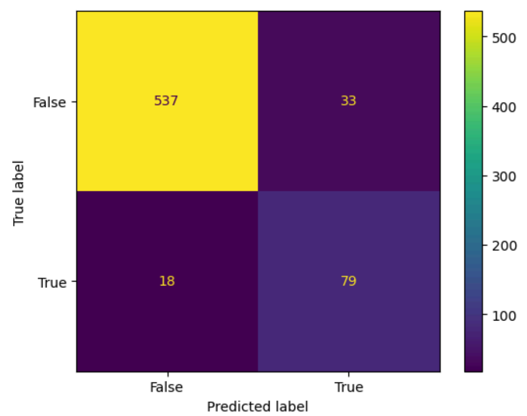
Feature Engineering and Data Preparation

Key preprocessing steps included:- Removing multicollinear features (e.g., Total_Mins, Total_Charge) to avoid leakage.- Dropping conditionally dependent features like Vmail_Message, which is functionally tied to whether a user has a voicemail plan.- Special care was taken to avoid data leakage, such as scaling after splitting the dataset.



Model Building and Performance

Both logistic regression and random forest were used to compare interpretability and predictive power. The Customer Churn Analysis Project final Random Forest model showed:- ROC AUC: 0.91- Recall: 0.81- F1 Score: 0.76. The classification threshold was tuned to 0.39 instead of the default 0.5 to better align with the business goal, making the model more sensitive to actual churners with forest importance variables by the model.

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              precision    recall  f1-score   support

   Not Churn       0.97      0.94      0.95       570
       Churn       0.71      0.81      0.76        97

    accuracy                           0.92       667
   macro avg       0.84      0.88      0.86       667
weighted avg       0.93      0.92      0.93       667
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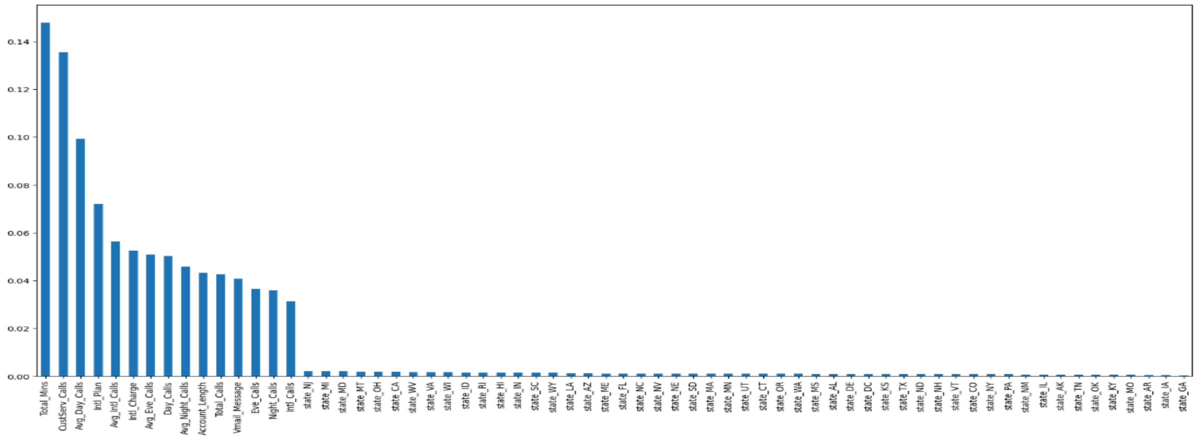
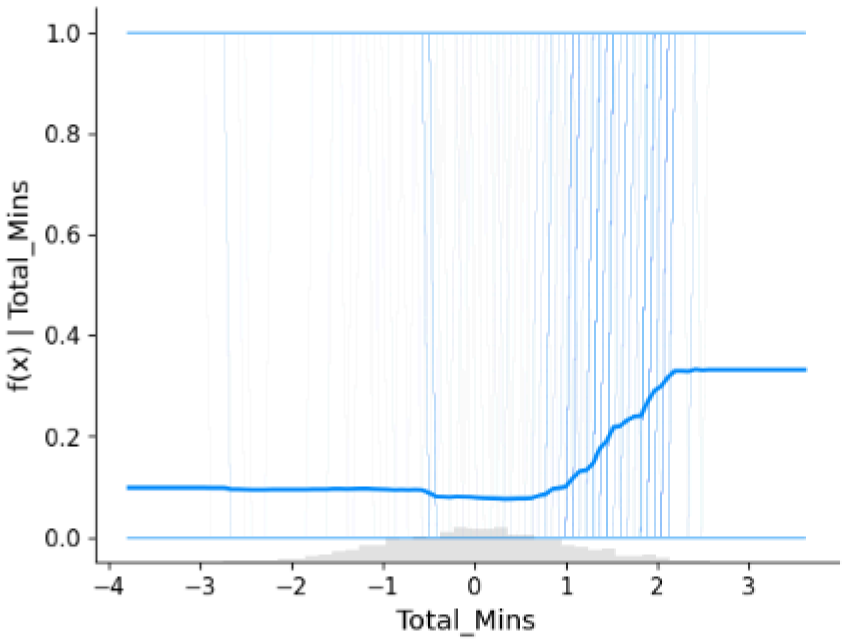


Model Interpretability (XAI)

Using Partial Dependence Plots, I visualized how individual features affected churn probability. For instance, churn likelihood jumped sharply when Total_Mins reached a certain range, then plateaued. This allowed business teams to understand why the model made certain predictions.



1.0
0.8
0.6
0.4
0.2
0.0
f(x) | Total_Mins
−4
−3
−2
−1
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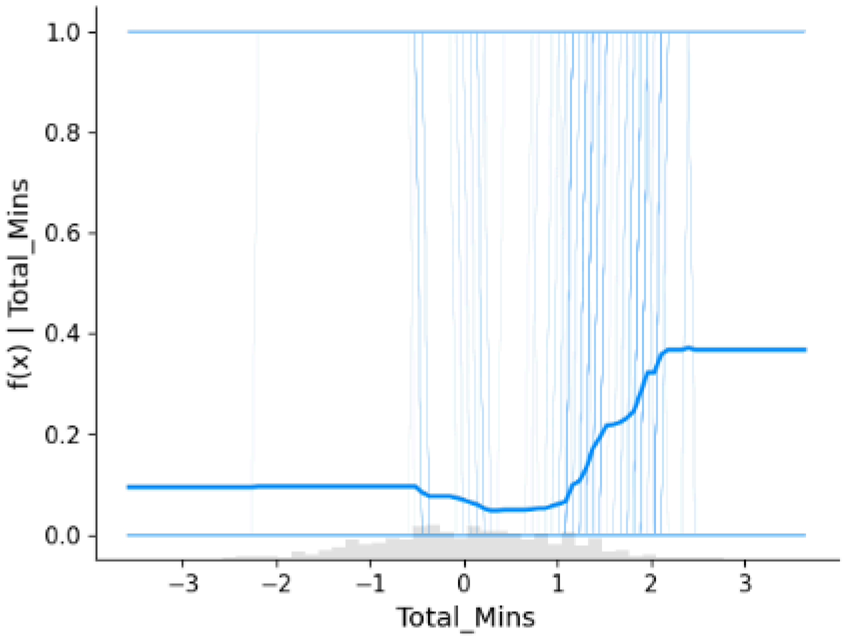
1
2
3
Total_Mins



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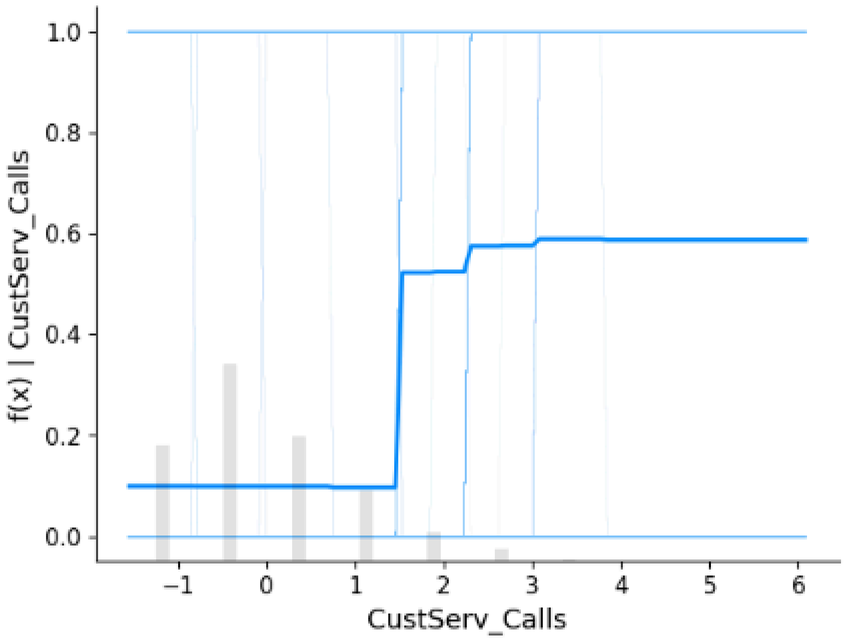

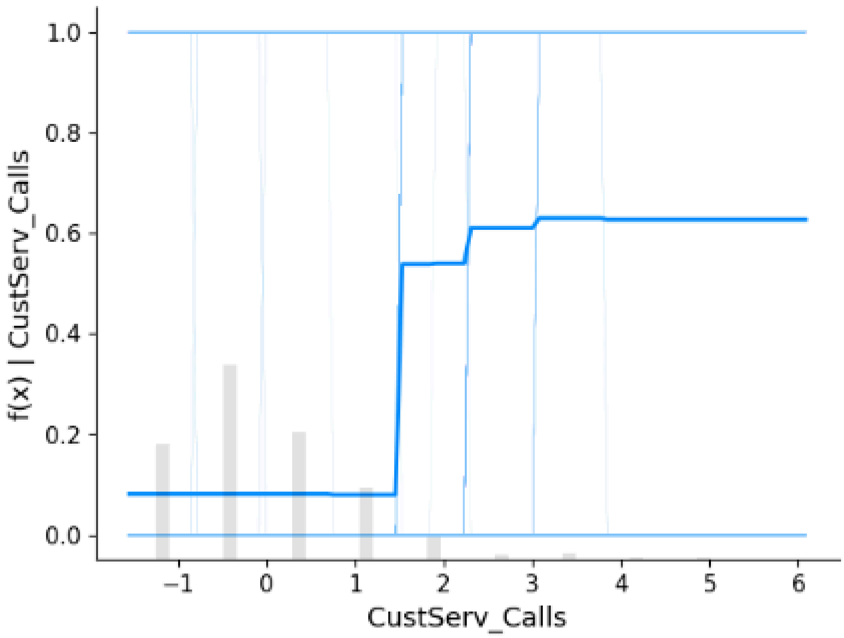

Final Insights

This project proved that behavioral signals like calls, plan types, and usage patterns can effectively predict churn. More importantly, it showed that with thoughtful modeling and communication, we can bridge data science and marketing decision-making. The model supports proactive retention, customer segmentation, and campaign prioritization all with human behavior at the core