Reducing Customer Churn: A Data-Driven Retention StrategyReducing Customer Churn: A Data-Driven Retention Strategy

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Overview

Goal: To build a predictive model that identifies customers at high risk of leaving (churning).

Value Proposition: By predicting churn before it happens, the company can proactively intervene with targeted retention offers, saving revenue and reducing customer acquisition costs.

Key Finding: Our models can successfully distinguish between loyal and at-risk clients 81% of the time.

Business and Data Understanding

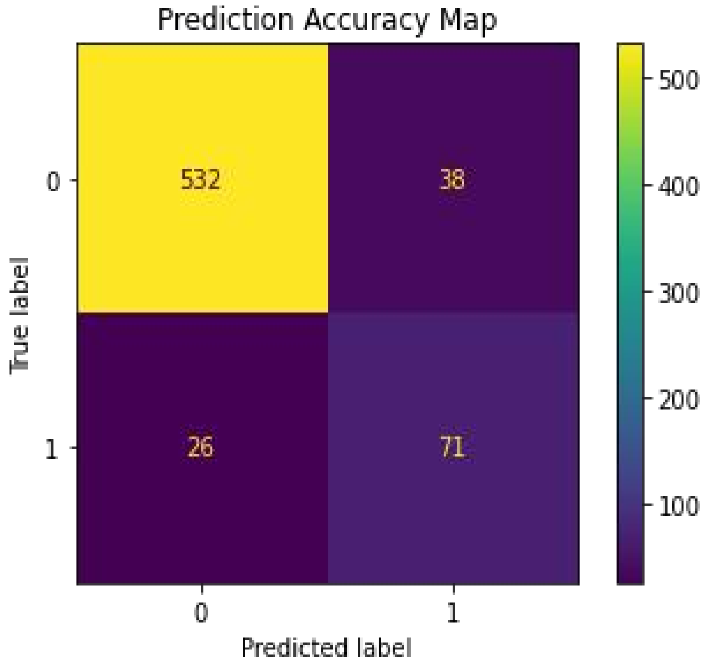
- **The Problem**: Customer churn directly impacts the bottom line. Understanding *why* and *who* is leaving is critical for growth.
- **The Data**: Analyzed 3,333 customer records containing 21 features, including:
- **Usage Patterns**: Day, evening, and international call minutes/charges.
- **Account Details**: Account length, area codes, and specific service plans (International/Voice Mail).
- **Customer Feedback**: Number of customer service calls made.
- **Data Insight**: Only ~14.5% of customers in the dataset churned, requiring specialized techniques (like SMOTE) to ensure the model could recognize this minority group accurately.

Modeling Strategy

•**Approach**: We tested two primary industry-standard methods to ensure reliability:

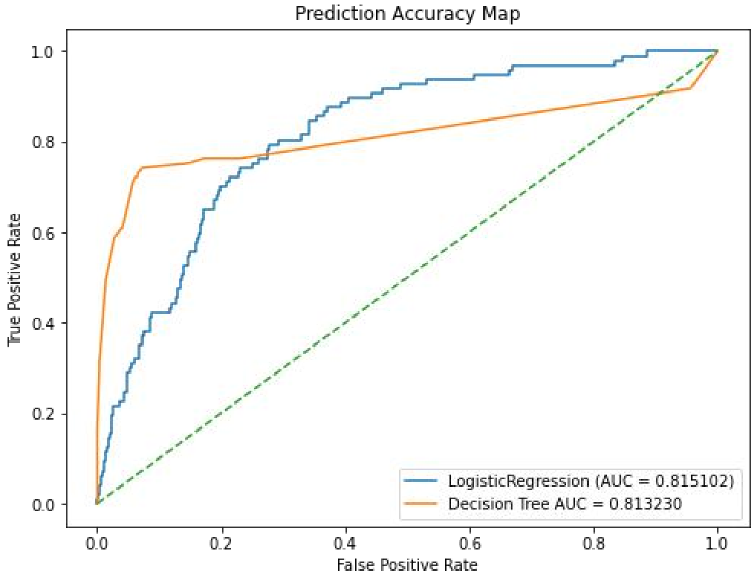
1. **Logistic Regression**: A statistical model used to determine the probability of an event (churn).
2. **Decision Tree**: A logic-based model that maps out customer characteristics to reach a prediction.

•**Ensuring Fairness**: We utilized a "Pipeline" approach to standardize data and handle the imbalance in churned vs. non-churned customers, ensuring the results aren't biased toward the majority.



Performance Evaluation

- **Success Metric (AUC)**: Both models achieved an **AUC of 0.81**.
- **What this means for you**:
- The models have "good discrimination ability".
- In plain terms: If you pick one churned customer and one loyal customer at random, the model will correctly identify the at-risk customer 81% of the time.
- **Consistency**: The identical performance across different model types confirms the stability of our predictions.



Key Drivers of Churn (Recommendations)

- Based on the data analysis, stakeholders should focus on:
- **Customer Service Interventions**: High correlation exists between customer service calls and churn. Customers calling frequently are likely frustrated and need immediate attention.
- **High Usage Costs**: Total day minutes and charges are significant indicators of churn. Consider offering "Unlimited" or "High-Volume" loyalty tiers for these power users.
- **Plan Optimization**: International plans and their associated charges should be reviewed to ensure they remain competitive.

Next Steps

1

Pilot Program: Deploy the Decision Tree model on a small subset of current customers to test real-world predictive accuracy.

2

Proactive Retention: Equip the customer service team with "Save Desk" offers specifically for customers flagged by the model.

3

Feedback Loop: Regularly update the model with new customer data to account for changing market trends and competitor offers.

Conclusion & Thank You

Summary: We have developed a tool that provides an 81% accuracy rate in identifying at-risk clients, directly supporting a data-backed customer retention strategy.

Call to Action: Let's integrate these insights into the CRM to start reducing churn this quarter.

Questions?