SimuTel Churn Prediction

Data-Driven Insights for Customer Retention

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INTRODUCTION

Business Problem

- □ **Challenge:** SimuTel is experiencing customer churn but lacks tools to identify at-risk customers in advance.
- ☐ **Impact:** Losing customers increases acquisition costs and reduces profitability
- **Goal:** Build a predictive model to flag customers likely to churn and guide retention actions.





Project Objectives

- Clean and prepare telecom customer data
- Understand churn drivers using historical features
- Understand churn drivers using customer data

- Build and evaluate classification models
- ☐ Generate churn risk scores
- ☐ Recommend actions to reduce churn





DATA EXPLORATION

Dataset Overview

Data Source

- ☐ Kaggle Telecom Churn Dataset
- □ 3,333 customer records
- ☐ Target Variable: Churn (Yes/No)

Features

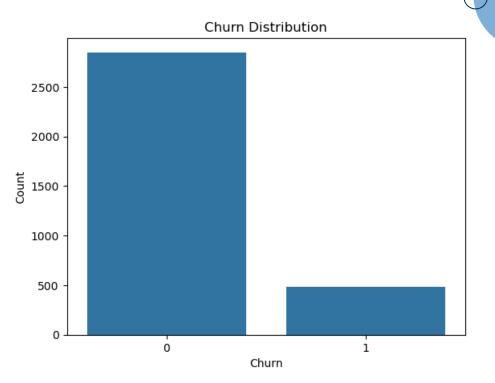
- ☐ Plan types (international, voicemail)
- ☐ Call & charge metrics
- ☐ Customer service calls
- ☐ State & area code

Data Cleaning

- □ Dropped irrelevant fields (e.g., phone number)
- □ Converted 'yes/no' fields to binary (1/0)
- One-hot encoded state and area code
- Scaled features for linear models (e.g., Logistic Regression)

Exploratory Analysis

- Majority of customers have not churned, showing a class imbalance.
- Only 14.5% of customers churned
- Strong churn predictors based on correlation heatmap:
 - Having an international plan
 - High total day charge
 - Frequent customer service calls



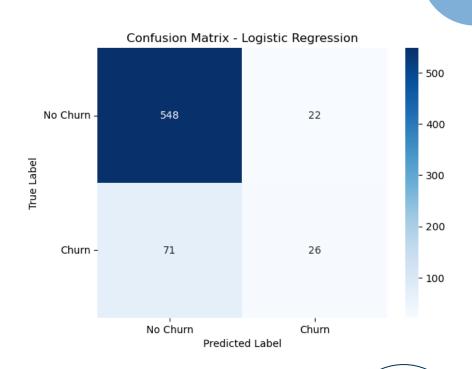
CLASSIFICATION MODELS

Model Approach

- **Baseline Model:** Logistic Regression for interpretability
- **Advanced Model:** Random Forest for performance and feature analysis
- Evaluation Metrics:
 - Precision
 - Recall
 - F1-score
 - Confusion Matrix
 - ROC AUC Score

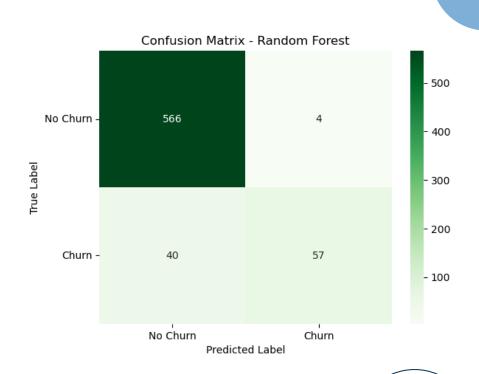
Logistic Regression

- □ **Precision:** 56% of predicted churners were actually churners.
- **Recall:** 0.31 Missed ~69% of actual churners.
- **F1-score:** 0.40 Balance between catching and correctly identifying churners.
- **ROC AUC:** 0.85 Strong ranking ability but misses many churners.



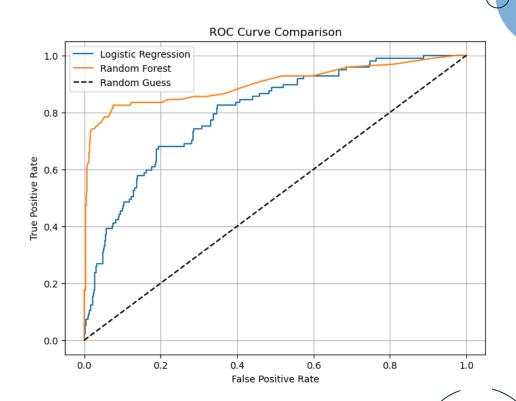
Random Forest

- ☐ **Precision:** 0.61 More accurate churn predictions.
- **Recall:** 0.51 Captures over half of all actual churners.
- **F1-score:** 0.56 Higher overall effectiveness in detecting churn.
- **ROC AUC:** 0.94 Excellent separation between churners and non-churners.

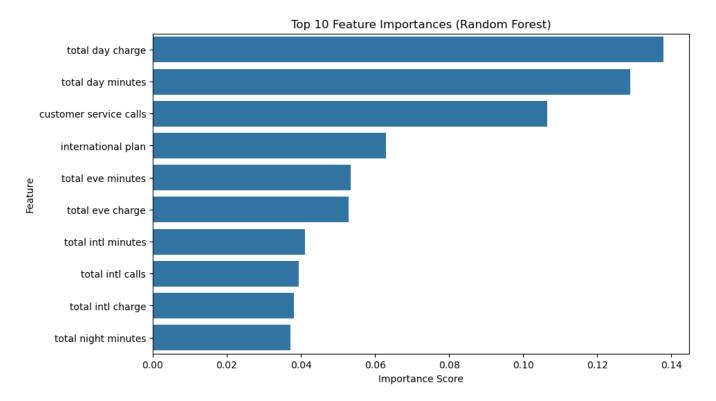


Model Performance

- Logistic Regression offers simplicity and interpretability.
- Random Forest is significantly better at identifying churners and minimizing business risk.



Feature Importance



CONCLUSION

Business Recommendations

- □ Proactively engage customers with:
 - International plans
 - High daytime usage
 - Frequent support calls

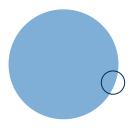
- Use model scores to:
 - Prioritize outreach
 - Personalize retention offers
- ☐ Choose model based on:
 - ☐ Performance: Random Forest
 - ☐ Transparency: Logistic Regression





Next Steps

- Test model on live or recent customer data
- ✓ Automate weekly churn risk scoring
- ✓ Integrate into CRM marketing platforms
- ✓ Track success of retention interventions



Thanks!

Do you have any questions?

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