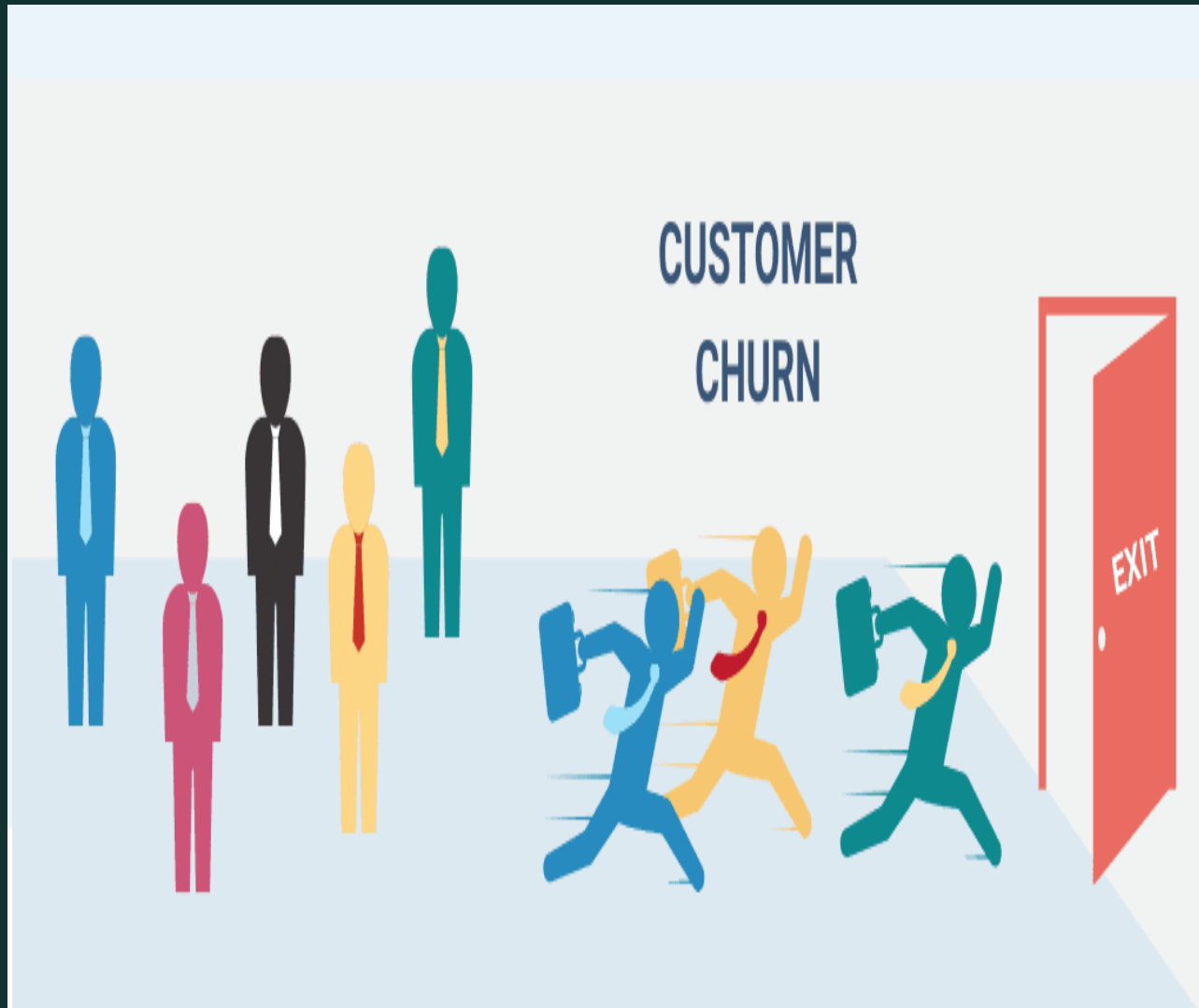




# SyriaTel Customer Churn Prediction

Identifying at-risk customers before  
they leave

# Overview



## Business Challenge

Customer churn poses a major threat to SyriaTel, leading to revenue loss and increased marketing expenses

## Our Approach

Build a predictive model that identifies customers at high risk of churning, allowing SyriaTel to act before they leave

## Business Value

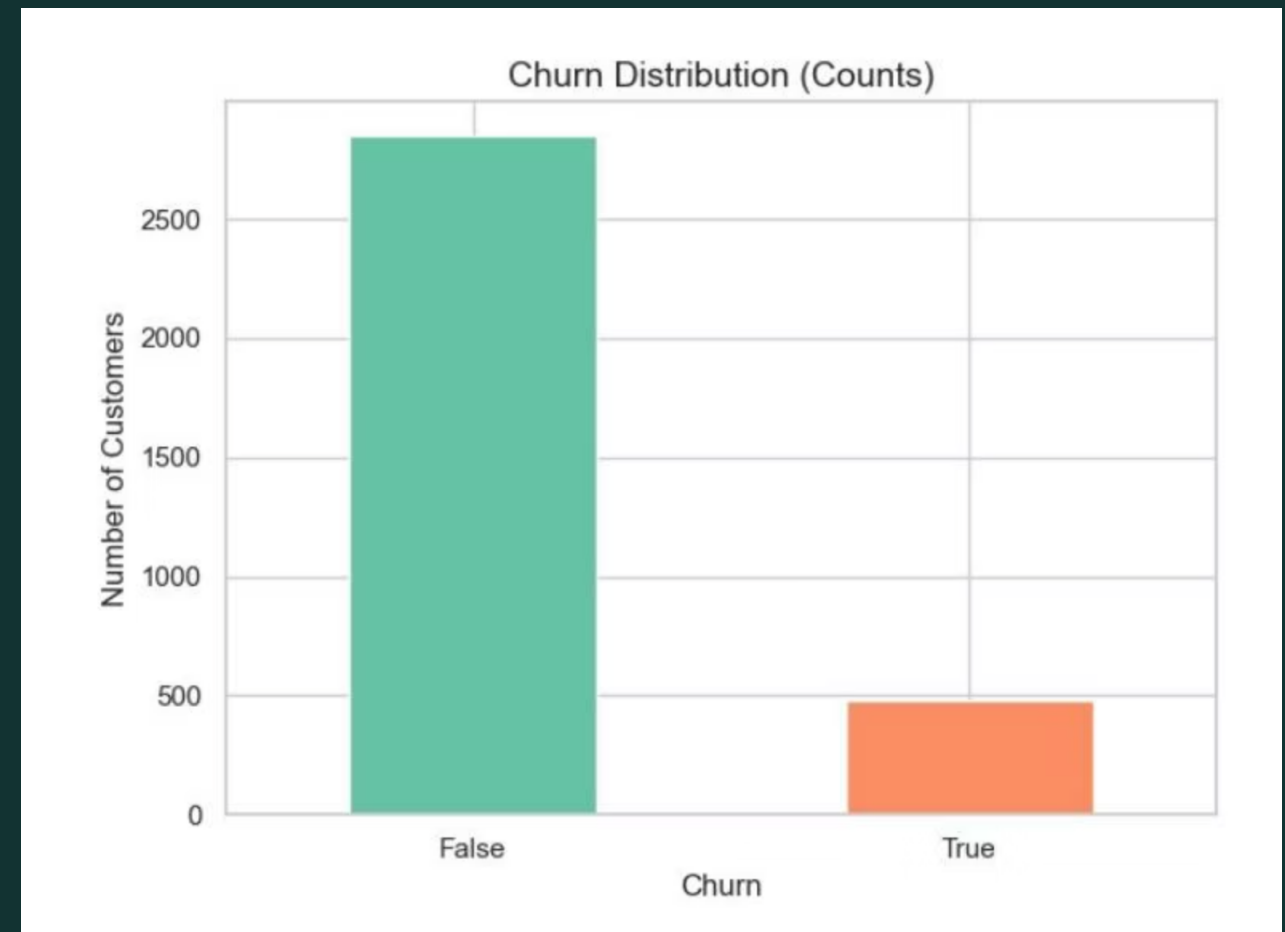
Retaining existing customers is significantly more cost-effective than acquiring new ones

# Business and Data Understanding

We analyzed SyriaTel's customer data to understand churn patterns:

- 3,333 customer records analyzed
- 21 features including call patterns, billing, and service interactions
- 14.5% overall churn rate (483 customers)

Our goal: Identify which factors most strongly predict when a customer will leave SyriaTel.



# Key Churn Indicators



## Customer Service Calls

Customers who contacted customer service multiple times were significantly more likely to churn



## Total Charges

Higher bills strongly correlated with increased churn risk



## International Plan

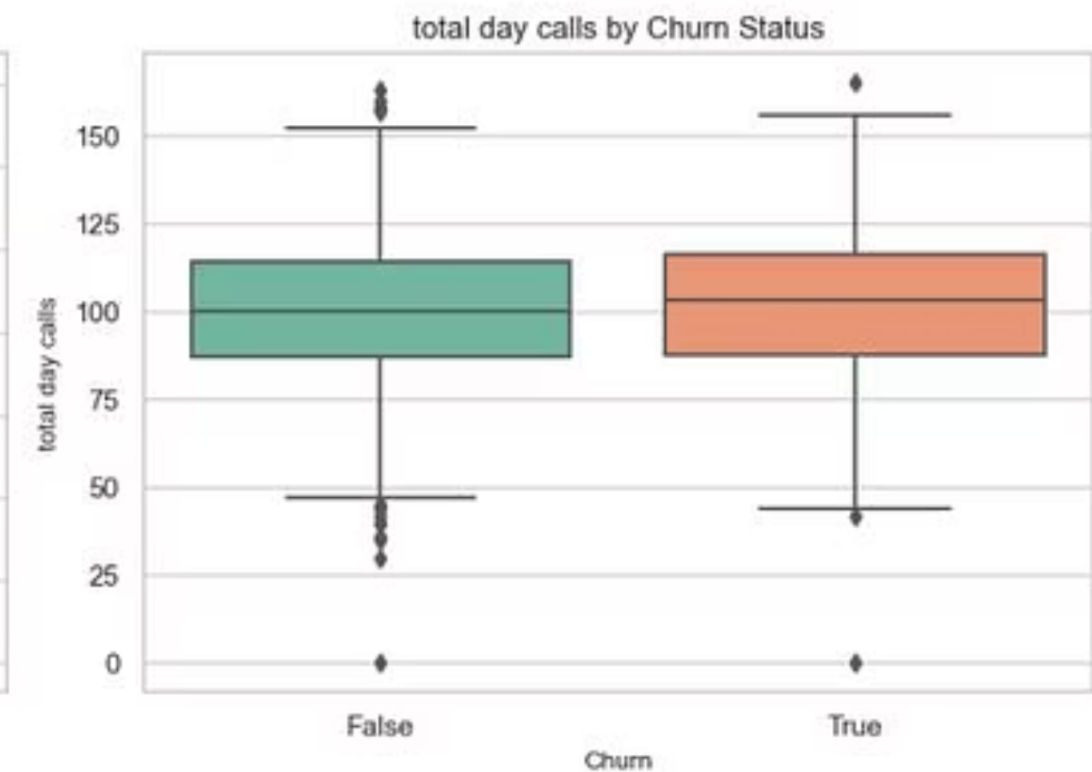
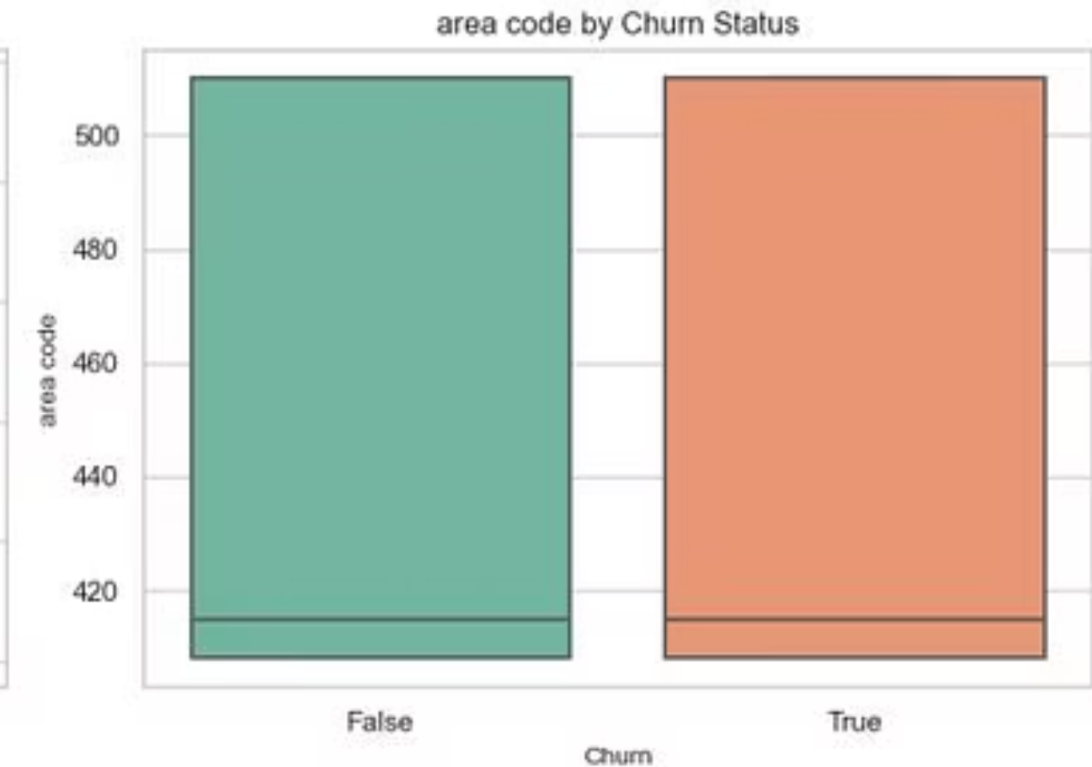
Customers with international plans showed disproportionately higher churn rates

These patterns suggest customers are leaving due to billing concerns and unresolved service issues.

# Customer Usage Patterns

Customers who churn tend to have:

- Higher daytime minutes and charges
- More customer service calls
- Fewer voicemail messages



# Modeling Approach

## Our Process

1. Prepared data by creating meaningful derived variables
2. Selected the 15 most predictive features
3. Tested four different prediction algorithms
4. Optimized the best-performing model

We focused on creating a model that would minimize false positives - never flagging a customer as "at risk" unless they were truly likely to churn.

1

### Logistic Regression

Simple, interpretable baseline model

2

### Decision Tree

Captures non-linear relationships

3

### Random Forest

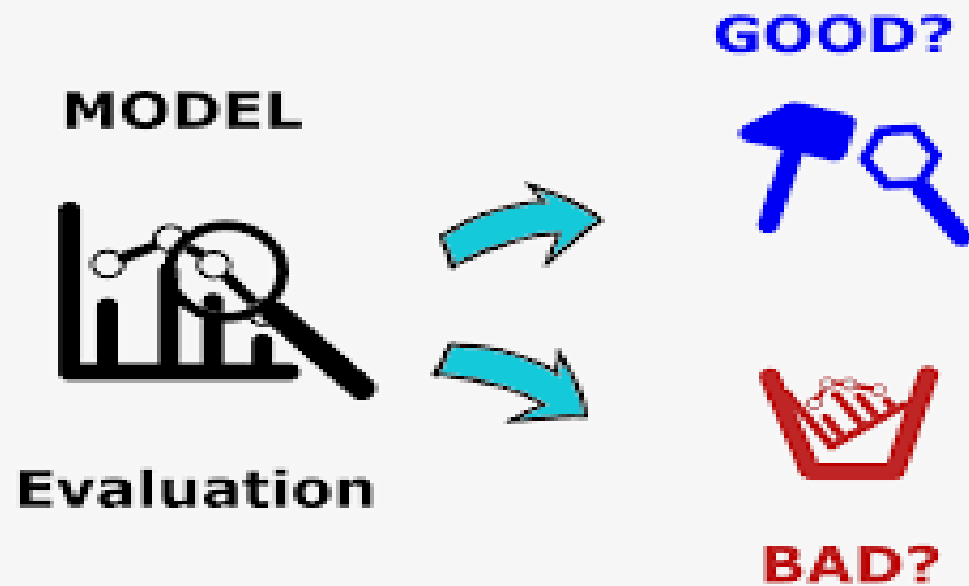
Ensemble of multiple decision trees

4

### Gradient Boosting

Advanced sequential ensemble method

# Model Evaluation

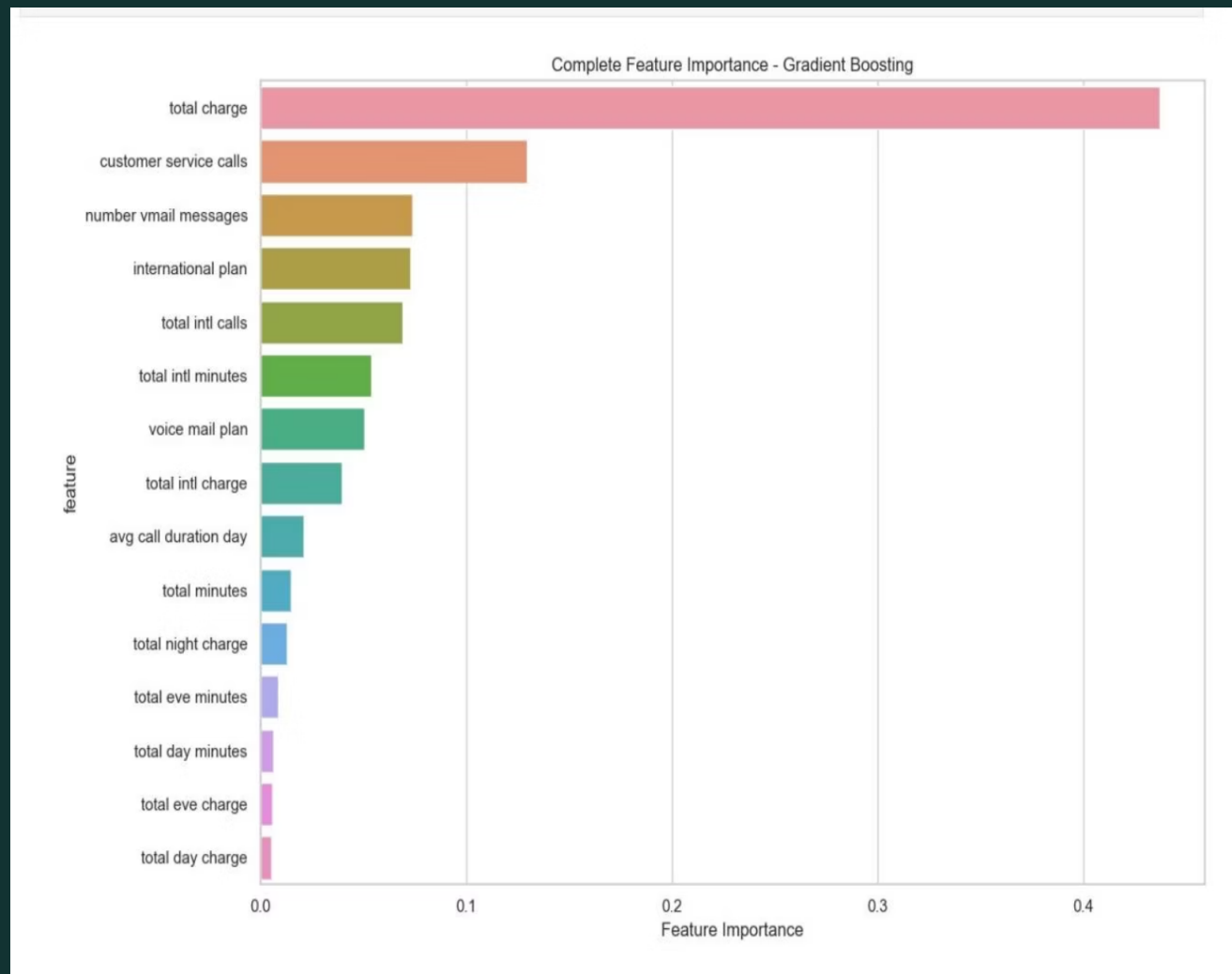


Gradient boosting emerged as our best model with:

- 97.3% overall accuracy
- 100% precision – every customer flagged as “high risk” actually churned
- 81.4% recall – identified over 4 out of 5 customers who would churn



# What Drives Customer Churn?



## Top 3 Churn Predictors:

1 Total Charges (45%)

Customers with higher bills are most likely to leave

2 Customer Service Calls (12%)

Multiple support interactions signal dissatisfaction

3 Voicemail Usage (8%)

Unusual voicemail patterns correlate with churn risk



# Recommendations

## Monitor High-Bill Customers

Establish automated alerts for customers with bills exceeding specific thresholds. Create tiered discount programs offering 10-20% reductions for high-value customers showing early warning signs.

## Transform Customer Service

Train representatives to flag customers with multiple recent contacts and immediately escalate them to specialized retention teams. Every service call should be viewed as both a problem-solving opportunity and a churn prevention intervention.

## Deploy Real-Time Risk Monitoring

Create a daily dashboard identifying the highest-risk customers requiring immediate attention. With 100% precision, retention teams can act with complete confidence.

# Implementation Plan

## Phase 1: Immediate Wins (30 Days)

Target the high-risk customers identified by the model with personalized retention campaigns focusing on billing adjustments and service issue resolution.

1

2

3

## Phase 3: Competitive Advantage (180 Days)

Develop predictive customer lifetime value models using churn predictions to optimize acquisition spending and retention investment.

## Phase 2: Systematic Prevention (90 Days)

Implement automated monitoring systems for the top three churn drivers to catch customers transitioning from low-risk to medium-risk status.

Thank you! Questions?