

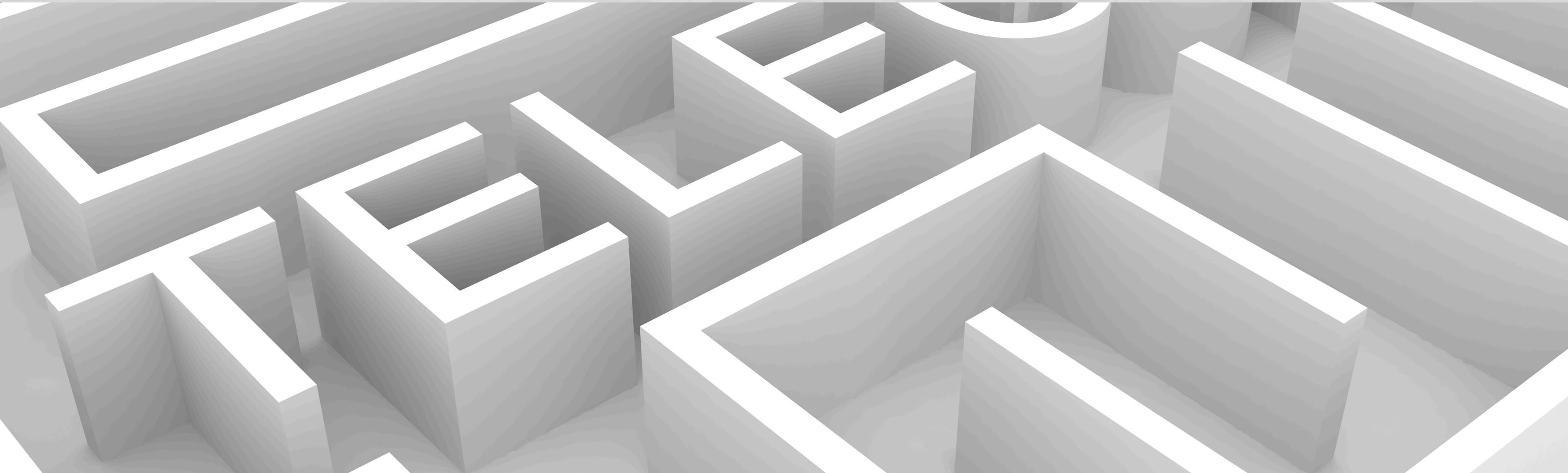
SyriaTel: Reducing Customer Churn Through Predictive Analysis

A Data-Driven Future



Project overview

Using historical data and
machine learning to predict
and mitigate customer churn



Business context and Understanding

Churn : refers to customer attrition where individuals stop using a service or product

Importance

- Causes loss of revenue, market share, and brand reputation

Strategic goal

- Proactively identify high-risk customers and mitigate attrition



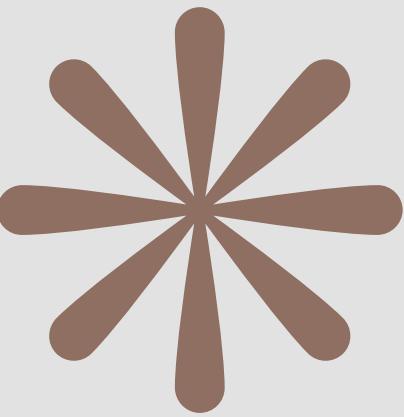
Project Objectives

Main Objective :

- Predict which customers are likely to churn.

Specific objectives:

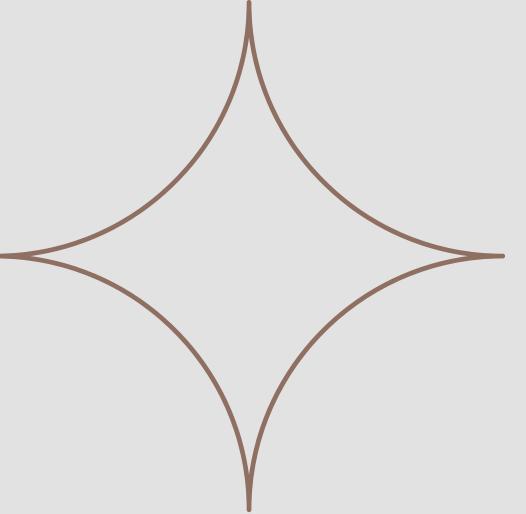
- Understand key drivers behind customer churn.
- Inform targeted retention strategies



Data understanding

Data description

- Scope: Customer usage patterns, subscriptions, and customer service interaction
- Account-Level: Account length.
- Subscription Plans: International plan and voice mail plan.
- Day usage: total day minutes, day calls, total day charge
- Evening usage: total evening minutes, evening calls, evening charge
- Night usage: total night minutes, night calls, night charge
- International usage: total international minutes, calls, charge
- Support Interactions: Number of customer service calls.
- Target Variable: Churn (1 = yes, 0 = no)



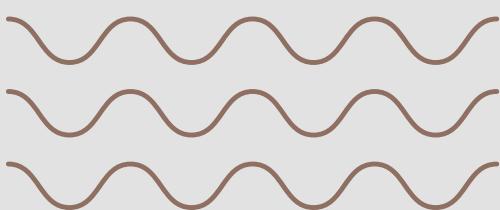
Data pre-processing

- Dropped irrelevant column (phone number)
- one hot encoded categorical features and label encoded the target
- Standardized the numerical features
- Split the data into training (80%) and testing (20%)
- Addressed class imbalance by using SMOTE(Synthetic Minority oversampling Technique)

Modelling approach

Evaluated 4 models

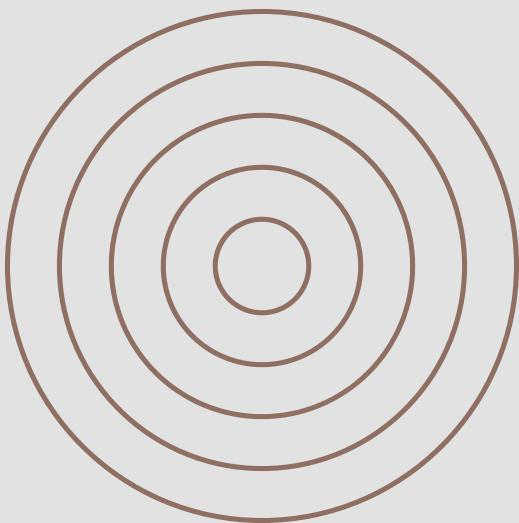
1. Logistic regression
2. Decision tree
3. LGBoost
4. Random Forest



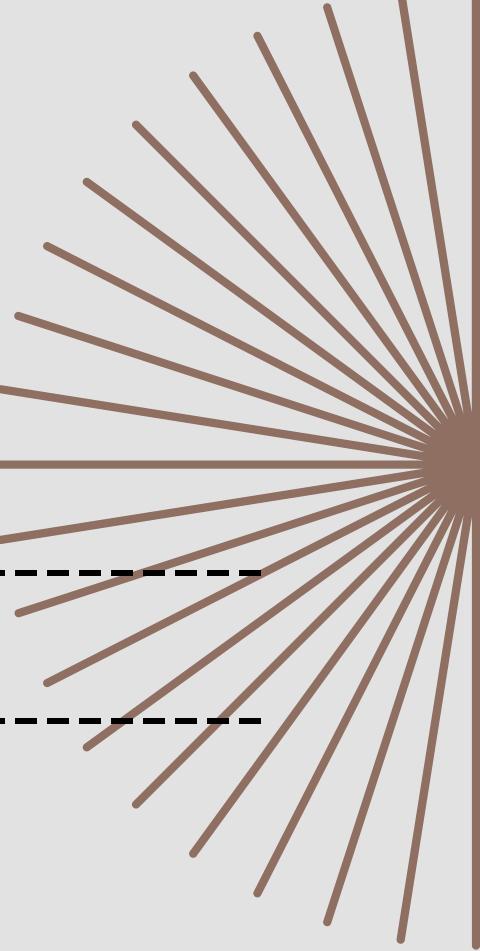
Model Performance evaluation

Evaluation Metrics used

- Accuracy for overall correctness of prediction
- Confusion metric for a detailed breakdown of predictions
- Precision, Recall, and F1 score on churn detection
- ROC-AUC for model discrimination ability
- Feature importance



Results and insights



Logistic Regression Model Evaluation

Accuracy: 0.7886056971514243

Confusion Matrix:

```
[[450 116]
 [ 25  76]]
```

Classification Report:

	precision	recall	f1-score	support
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0	0.95	0.80	0.86	566
1	0.40	0.75	0.52	101

accuracy			0.79	667
macro avg	0.67	0.77	0.69	667
weighted avg	0.86	0.79	0.81	667

ROC AUC Score: 0.8307560438022599

Decision Tree Results

Accuracy: 0.9385307346326837

Confusion Matrix:

```
[[558  8]
 [ 33  68]]
```

Classification Report:

	precision	recall	f1-score	support
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0	0.94	0.99	0.96	566
1	0.89	0.67	0.77	101

accuracy			0.94	667
macro avg	0.92	0.83	0.87	667
weighted avg	0.94	0.94	0.93	667

ROC AUC Score: 0.8295665255571495

Results and insights



XGBoost Results

Accuracy: 0.9580209895052474

Confusion Matrix:

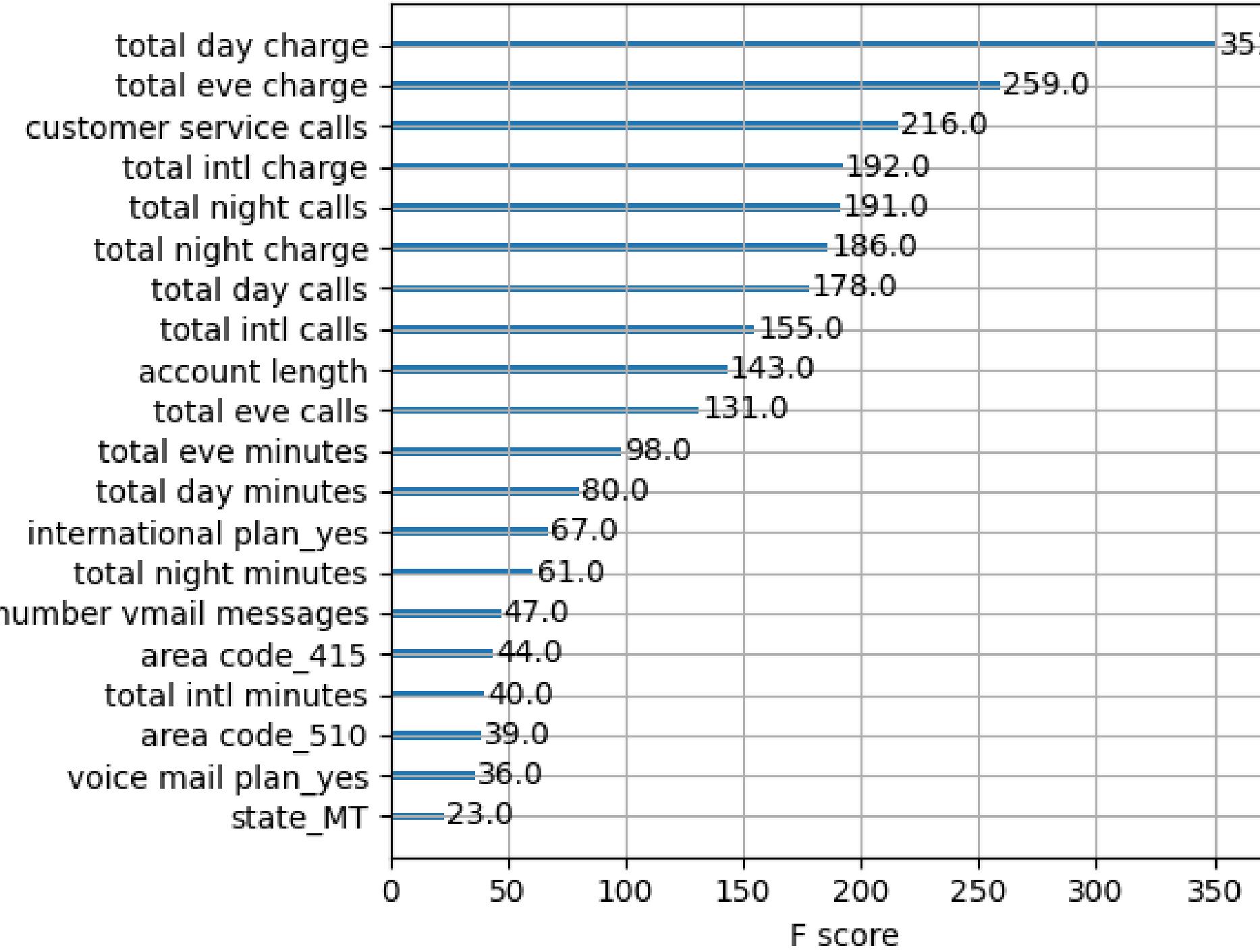
```
[ [558  8]
 [ 20  81]]
```

Classification Report:

	precision	recall	f1-score	support
0	0.97	0.99	0.98	566
1	0.91	0.80	0.85	101
accuracy			0.96	667
macro avg	0.94	0.89	0.91	667
weighted avg	0.96	0.96	0.96	667

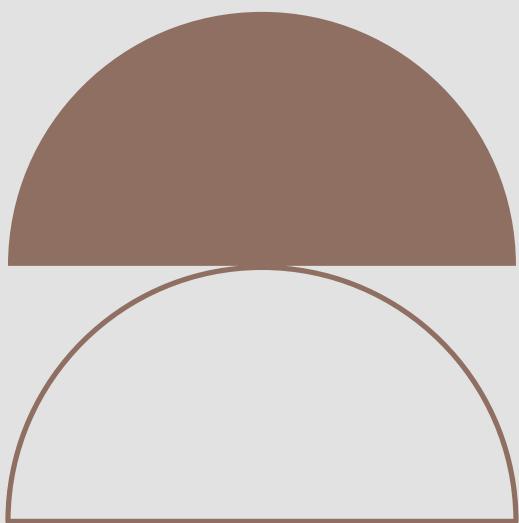
ROC AUC Score: 0.8939229612007138

XGBoost Feature Importance - Weight



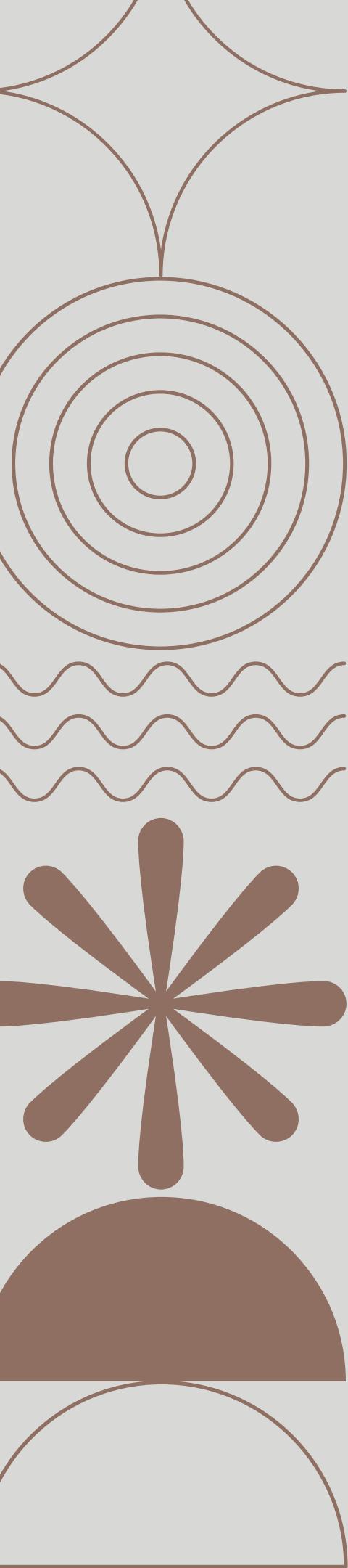
Recommendations

- The XGBoost model had the overall best performance
- High feature importance in
 1. Customer service calls: Need to focus on the quality of customer service
 2. Usage metrics evening, day charges: need to consider incentives



Next steps

- Hyperparameter tuning for the Decision Tree, Random Forest, and XGBoost
- Further analysis of customer feedback to assist in developing targeted churn mitigation interventions



Thank you!

