

Predicting Customer Churn in Telecom

A Machine Learning Approach

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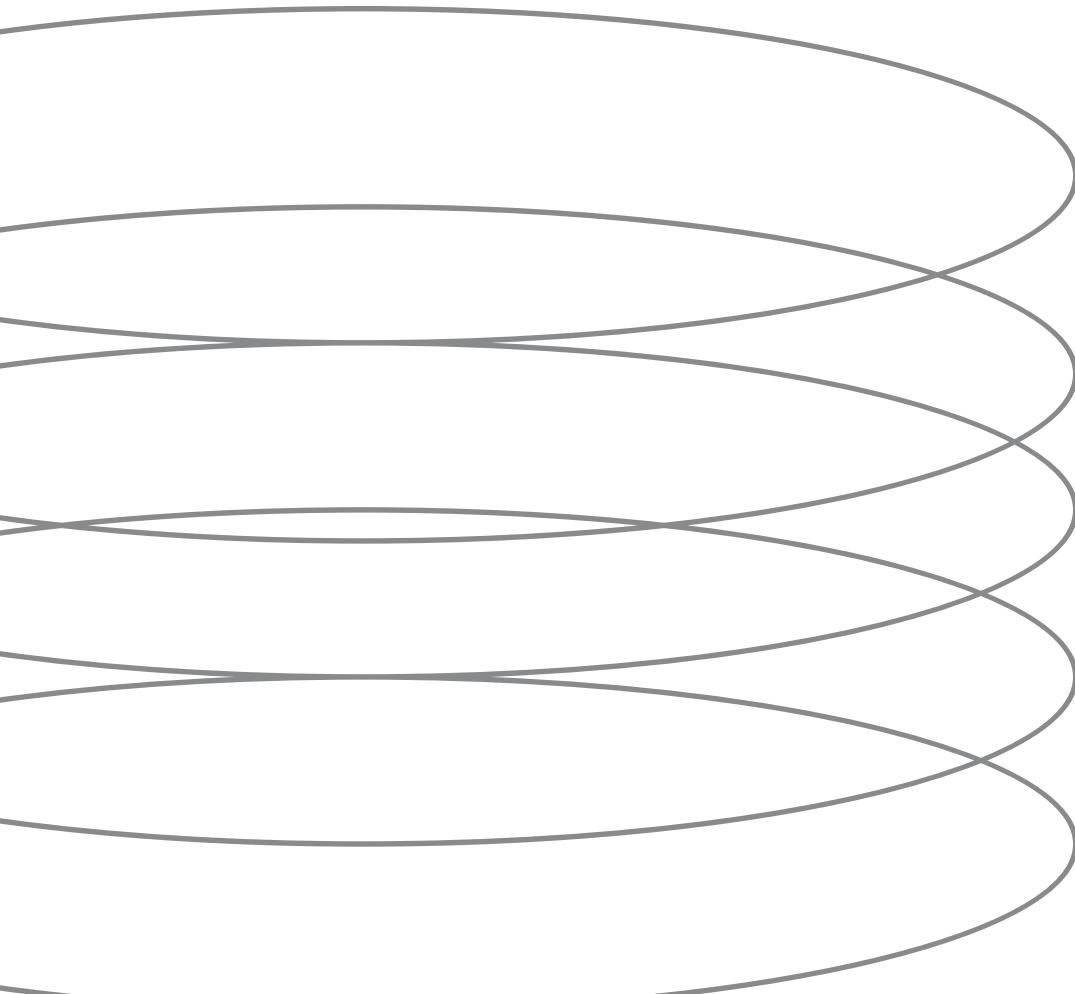


Overview

CRISP-DM Approach

1. Business Understanding
2. Data Understanding
3. Data Preparation
4. Modeling
5. Evaluation
6. Deployment
7. Conclusion and Recommendations





1. Business Understanding

- Background
- Gap Analysis
- Problem Statement
- Goals
- Analytic Approach
- Metric Evaluation
- Success Criteria

Business Understanding

Background

Customer Churn Definition

Customer churn in telecom refers to the rate at which customers stop using services, significantly impacting revenue and profitability.

Causes of Churn

Factors contributing to customer churn include dissatisfaction with service quality, pricing, customer support, and competitive offers.

Importance of Retention

Retaining existing customers is more cost-effective than acquiring new ones, making churn management crucial for financial health and growth.

Business Understanding

Gap Analysis

Lack of Predictive Model

The company currently lacks a predictive model to identify at-risk customers, hindering effective retention strategies.

Data Quality and Engagement Issues

There are significant gaps in data quality and stakeholder engagement that impact informed decision-making.

Need for Continuous Improvement

Establishing a process for continuous improvement is essential to adapt to changing customer behaviors and integrate predictive insights into operations.

Business Understanding

Problem Statement

Which customers are likely to churn?

Identifying At-Risk Customers: The primary question is to determine which customers are likely to churn.

What factors influence customer churn the most?

Influential Factors: Understanding the key factors that influence customer churn is crucial for developing effective strategies.

How can the company reduce churn and improve customer retention?

Strategies for Retention: Finding ways to reduce churn and improve customer retention is a central concern for the company.



Business Understanding

Goals

Develop Predictive Model

Create a model to classify customers as likely to churn or not, using historical data and machine learning techniques.

Identify Key Features

Analyze which factors most significantly impact customer churn to inform retention strategies.

Actionable Insights

Provide insights that enable the company to implement targeted strategies to reduce churn, such as personalized plans and improved customer support.



Business Understanding

Approaches

Rule Based

Widely used by companies.

Machine Learning Based

To overcome rule-based limitations: uncovering hidden patterns in customer behavior.



Business Understanding

Metric Evaluation

Customer Acquisition Cost (CAC)

CAC measures the total cost of acquiring a new customer, essential for evaluating marketing efficiency and profitability.

Customer Retention Cost (CRC)

CRC reflects the costs associated with retaining customers, including salaries and loyalty programs.

Recall as Evaluation Metric

Recall is critical for assessing the effectiveness of churn prediction models, focusing on capturing at-risk customers for targeted retention efforts.



Business Understanding

Success Criteria

High Recall Performance

Achieve a recall rate of 80% or higher for effective churn prediction.

Reliable Prediction Model

Develop a dependable model that accurately predicts customer churn.

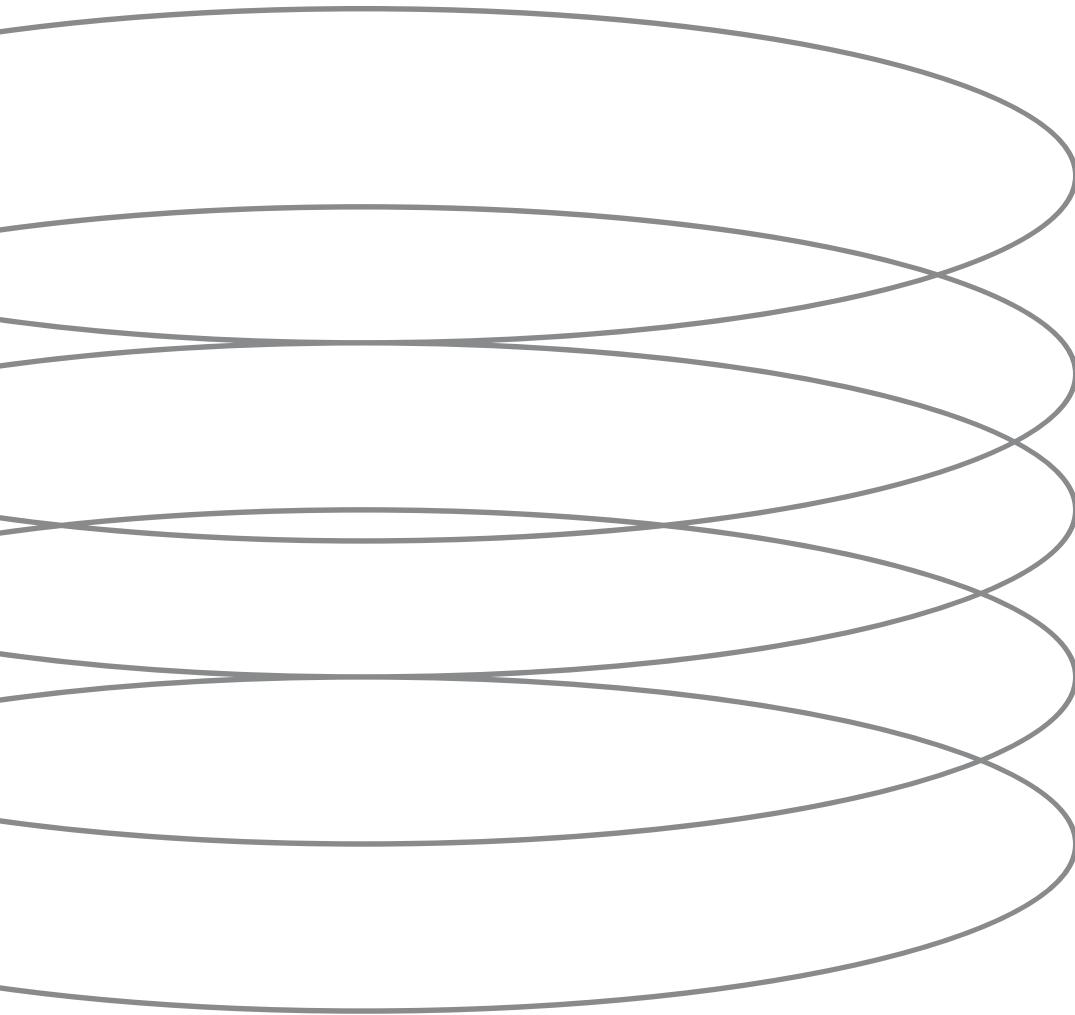
Reduce Customer Acquisition Cost and Retention Cost.

Achieve a total annual cost reduction rate of 20% or higher.

Interpretable Insights

Provide insights that are interpretable and actionable for informed business decisions, ultimately reducing acquisition and retention costs.





2. Data Understanding

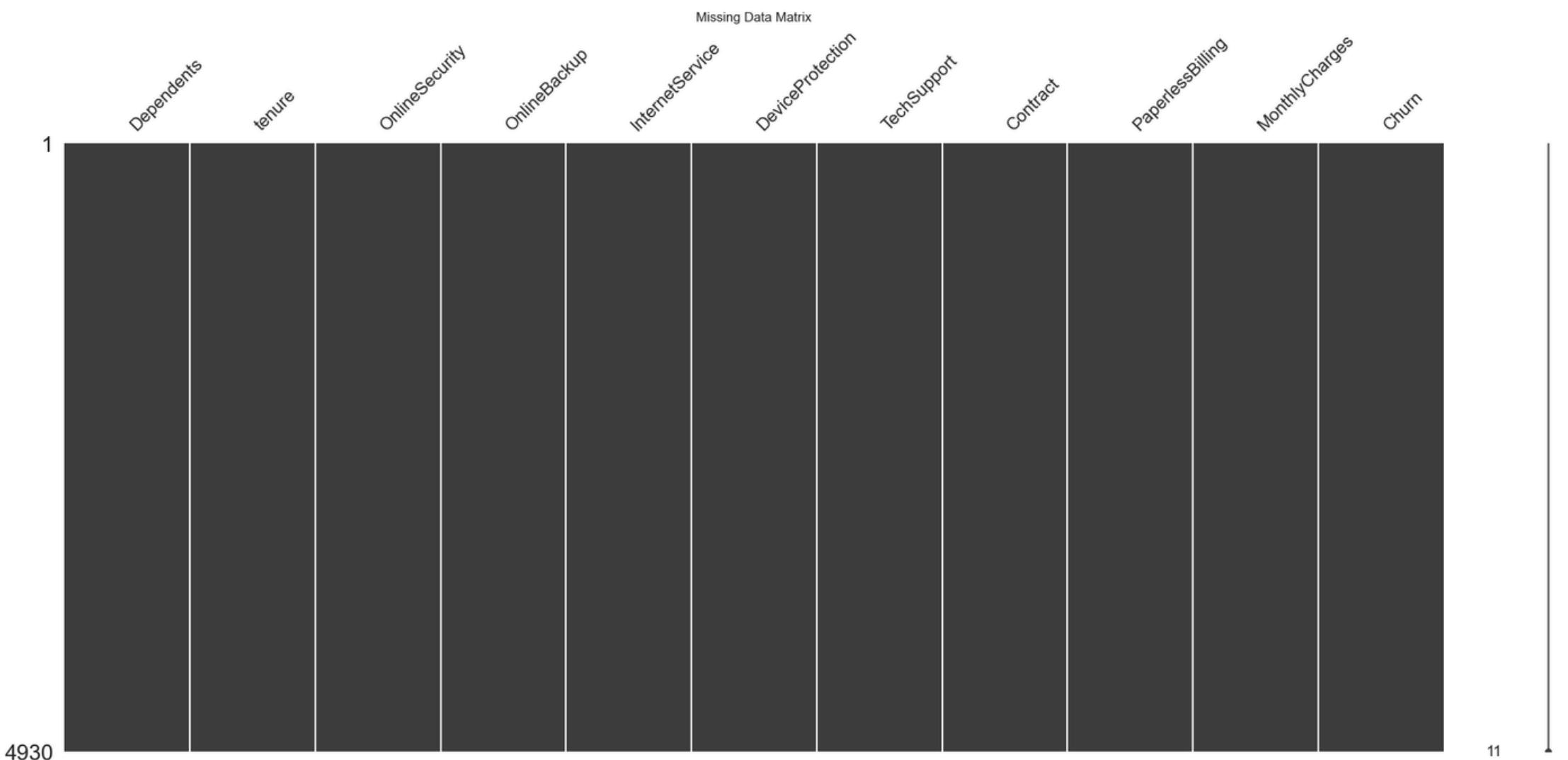
- Dataset Information
- Missing Values Checking
- Duplicated Values Checking
- Exploratory Data Analysis (EDA)

Data Understanding

Dataset Information

| Column Name | Importance | Impact to Business |
|------------------|------------|--|
| Dependents | Moderate | Understanding customer demographics can aid in targeted marketing strategies. |
| Tenure | High | Longer tenure often indicates customer loyalty, impacting retention strategies. |
| OnlineSecurity | High | Customers with online security are likely to feel safer, reducing churn. |
| OnlineBackup | Moderate | Offering online backup can enhance customer satisfaction and retention. |
| InternetService | High | Understanding service subscriptions helps in optimizing service offerings. |
| DeviceProtection | Moderate | Device protection can be a key selling point for tech-savvy customers. |
| TechSupport | High | Good tech support can significantly reduce churn and improve customer satisfaction. |
| Contract | High | Contract types influence customer retention and revenue predictability. |
| PaperlessBilling | Moderate | Encouraging paperless billing can reduce costs and appeal to environmentally conscious customers. |
| MonthlyCharges | High | Understanding pricing impacts customer acquisition and retention strategies. |
| Churn | Critical | Churn rate is a key performance indicator for business health and customer satisfaction. This column will be used as target. |

Data Understanding



Missing Values Checking

- No missing values.
- No need to use imputer in pre-processing.

Data Understanding

Duplicated Values Checking

Number of duplicated rows: 77

Action: Retain Duplicates

Validity of Duplicates

Duplicated rows may represent legitimate repeated observations or transactions, crucial for accurate analysis, particularly in datasets involving transactional data or repeated measurements.

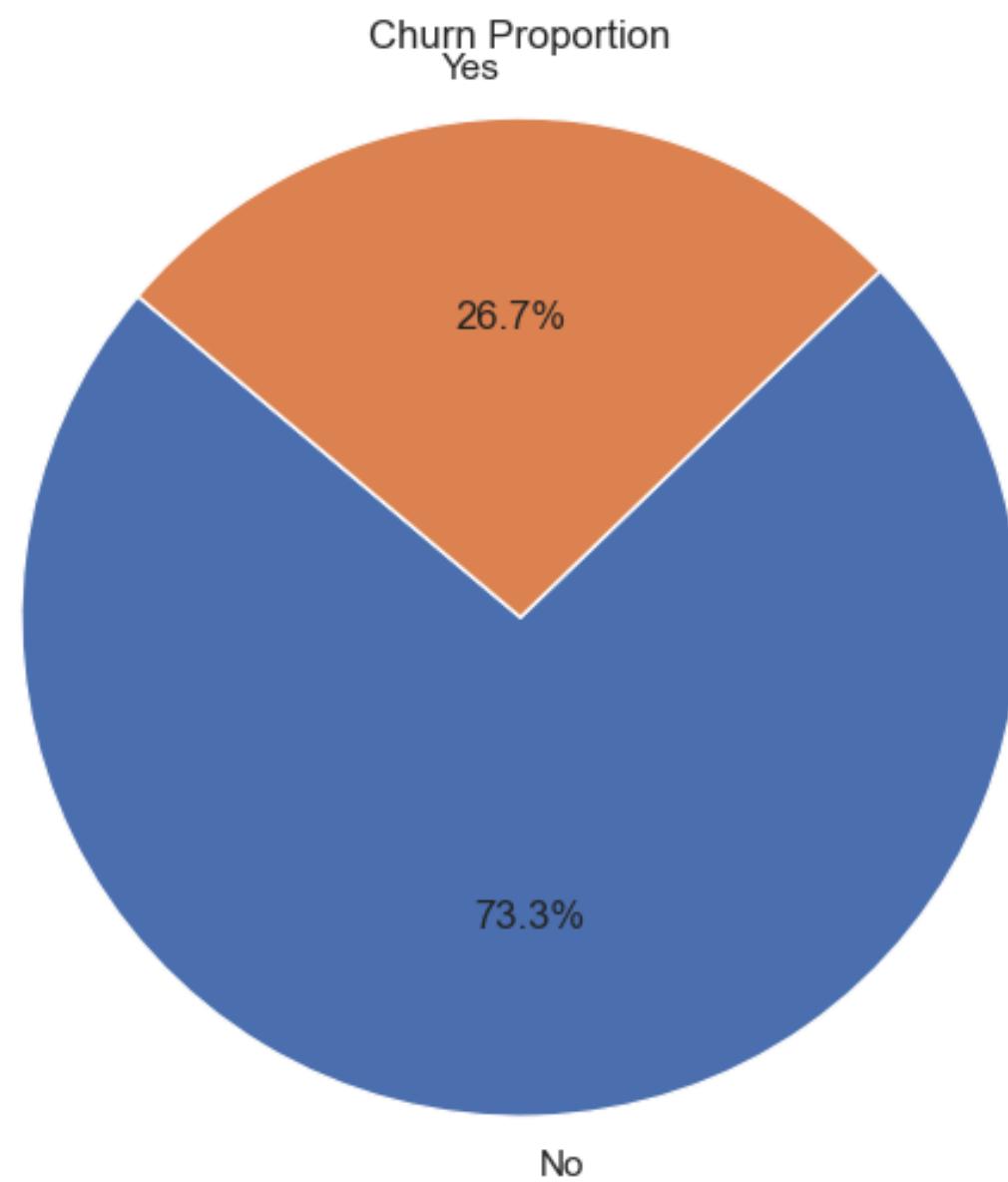
Impact on Data Integrity

Removing duplicates without understanding their context can distort data distributions and compromise data integrity, potentially leading to misleading results and affecting the validity of analyses.

Analytical Significance

Duplicates can provide meaningful information in certain analytical methods and visualizations, highlighting the importance of assessing their origin and significance before deciding to remove them.

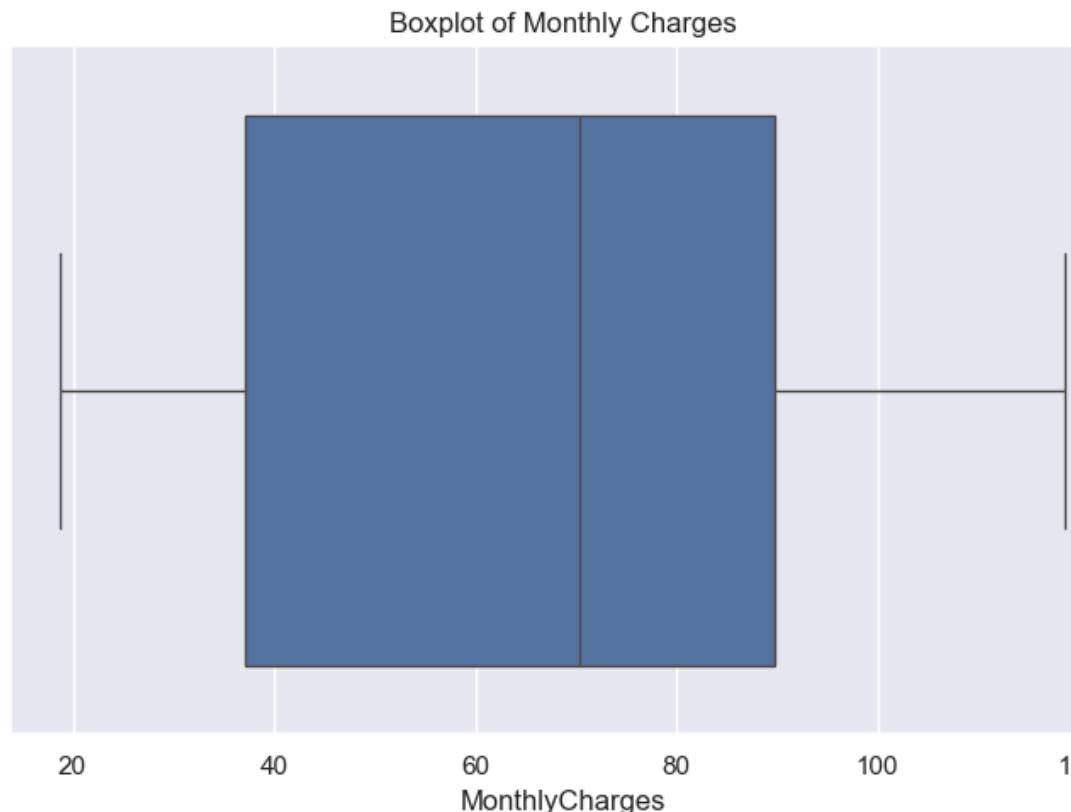
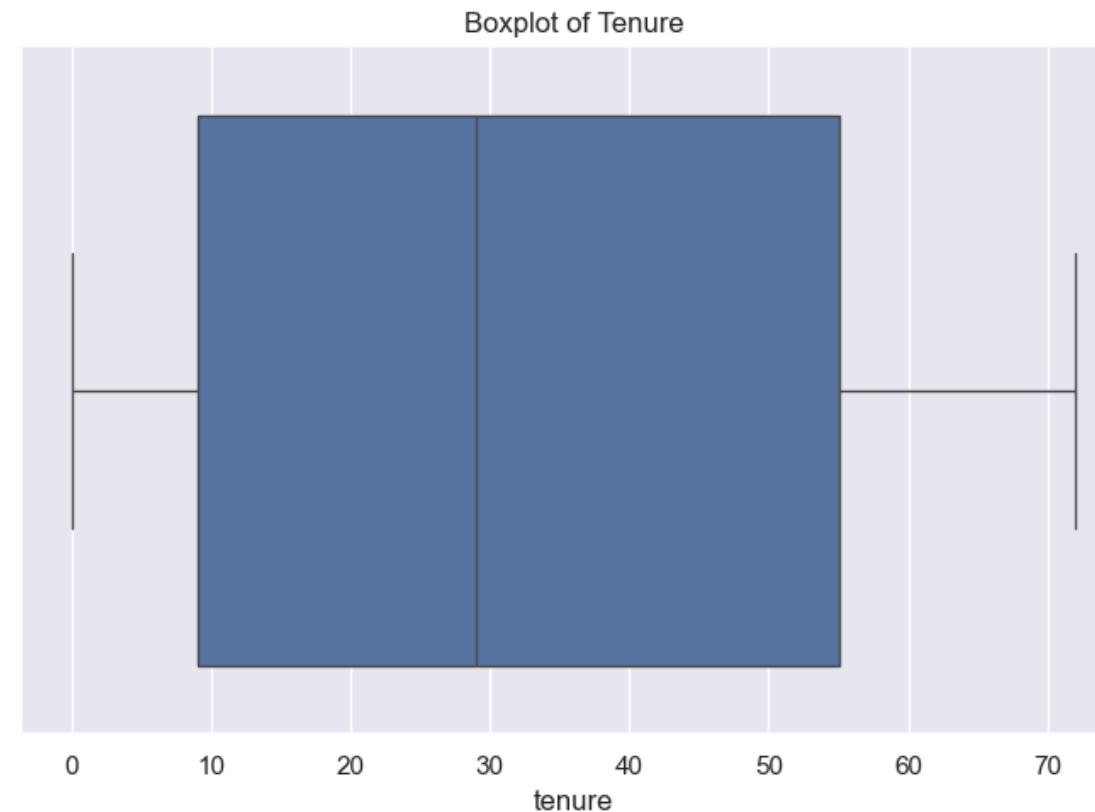
Data Understanding



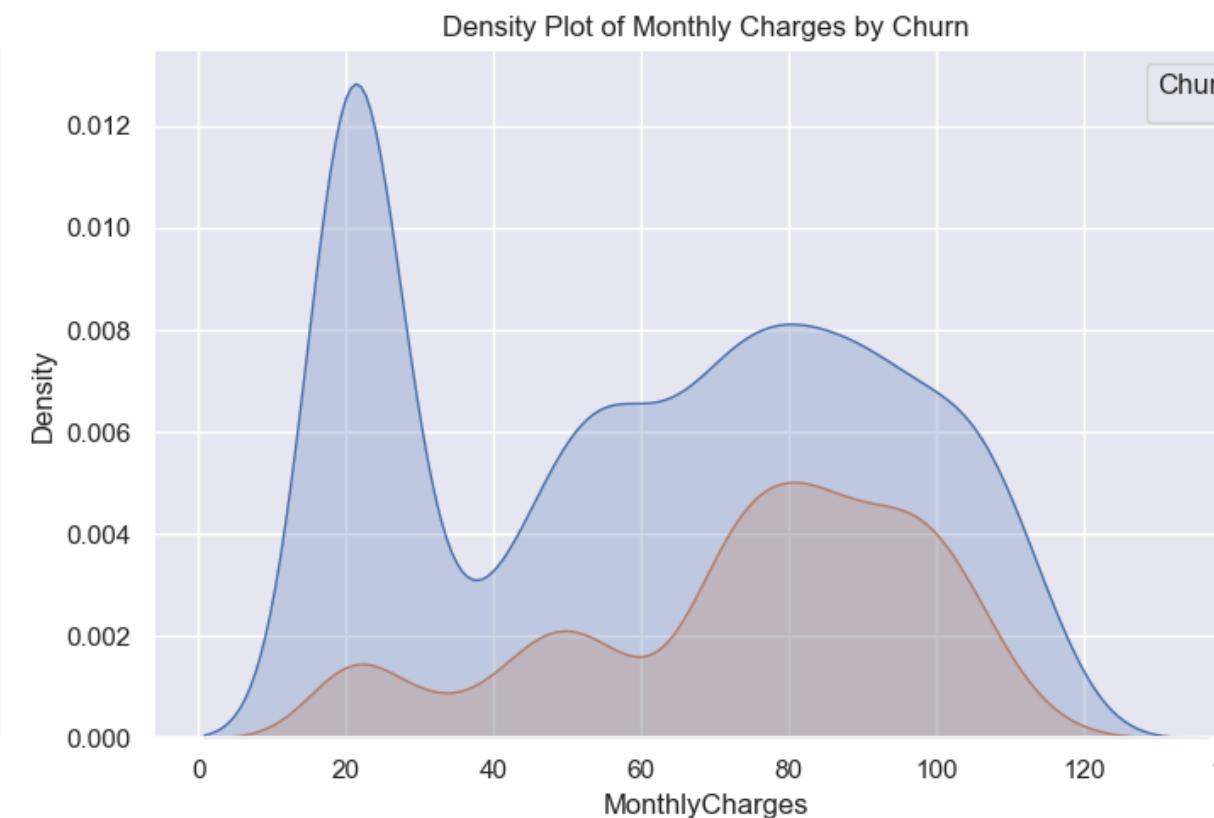
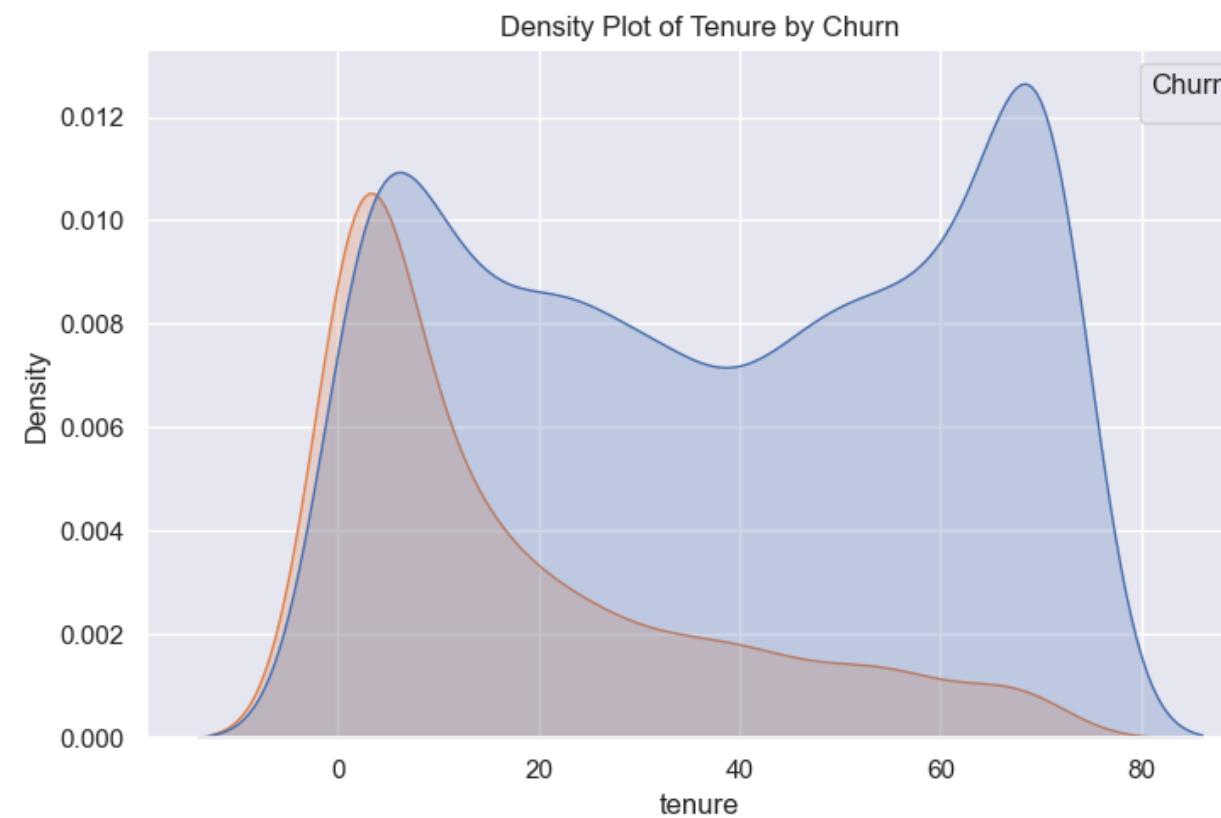
EDA - Churn Proportion

- Churn: 26.7 %
- Not Churn: 73.3%
- Imbalanced Dataset
- Need to oversampling dataset

Data Understanding - EDA - Numerical Features Analysis



- No negative values
- Not normally distributed
- Action: Benchmark MinMax and Robust Scaler in Preprocessor



| | count | mean | std | min | 25% | 50% | 75% | max |
|----------------|-------|------------|------------|------|-------|-------|-------|--------|
| tenure | 4930 | 32.401.217 | 24.501.193 | 0 | 9 | 29 | 55 | 72 |
| MonthlyCharges | 4930 | 64.883.032 | 29.923.960 | 18.8 | 37.05 | 70.35 | 89.85 | 118.65 |

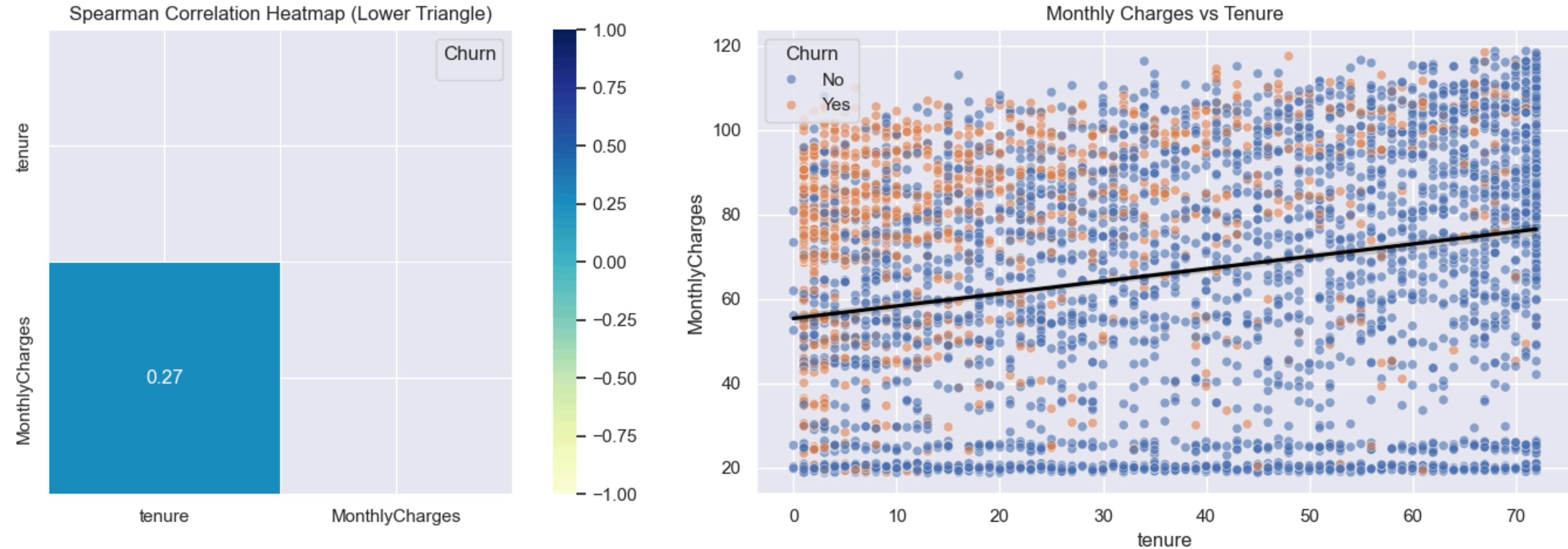
Data Understanding

| | Unique Value Counts | Most Frequent Values |
|------------------|---------------------|----------------------|
| Dependents | 2 | No |
| OnlineSecurity | 3 | No |
| OnlineBackup | 3 | No |
| InternetService | 3 | Fiber optic |
| DeviceProtection | 3 | No |
| TechSupport | 3 | No |
| Contract | 3 | Month-to-month |
| PaperlessBilling | 2 | Yes |
| Churn | 2 | No |

EDA - Categorical Feature Analysis

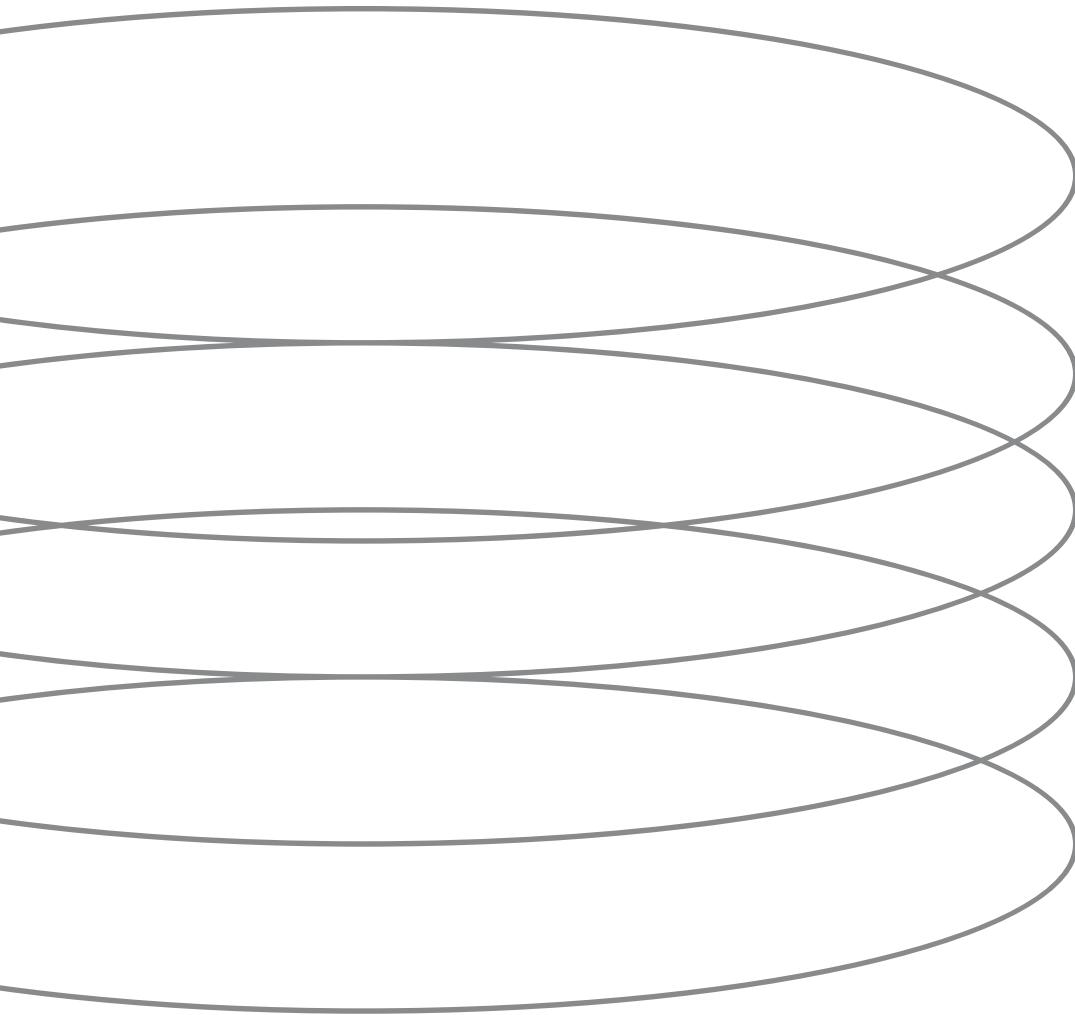
- All categorical columns are nominal, **except Contract columns (ordinal)**.
- Actions: To use ordinal encoder for Contract columns and one hot encoder for the rest while pre-processing.

Data Understanding



Correlation Analysis

- Low monotonic relationship
- Directly proportional



3. Data Preparation

- Feature Engineering
- Binning
- Target Labeling
- Define X and y
- Train-Test Split
- Data Transformation Setup

Data Preparation

Feature Engineering

Total Charges = tenure x Monthly Charges

Binning

Equal frequencies based on quarter quantile on tenure, monthly charges, and total charges.

Target Labeling

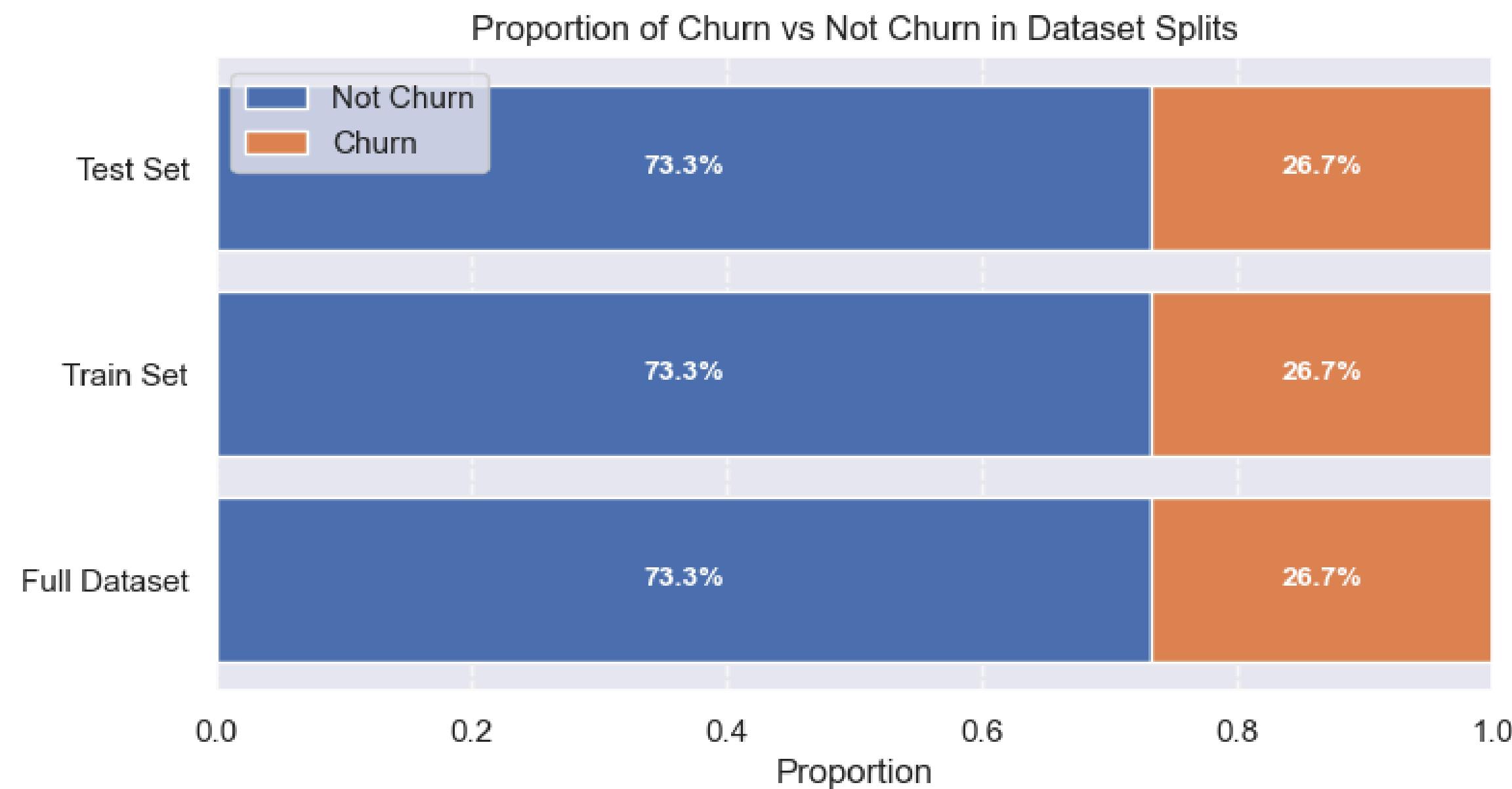
Churn → 1, Not Churn → 0

Define Features and Target

Features (X): All columns except Churn

Target (y): Churn

Data Preparation



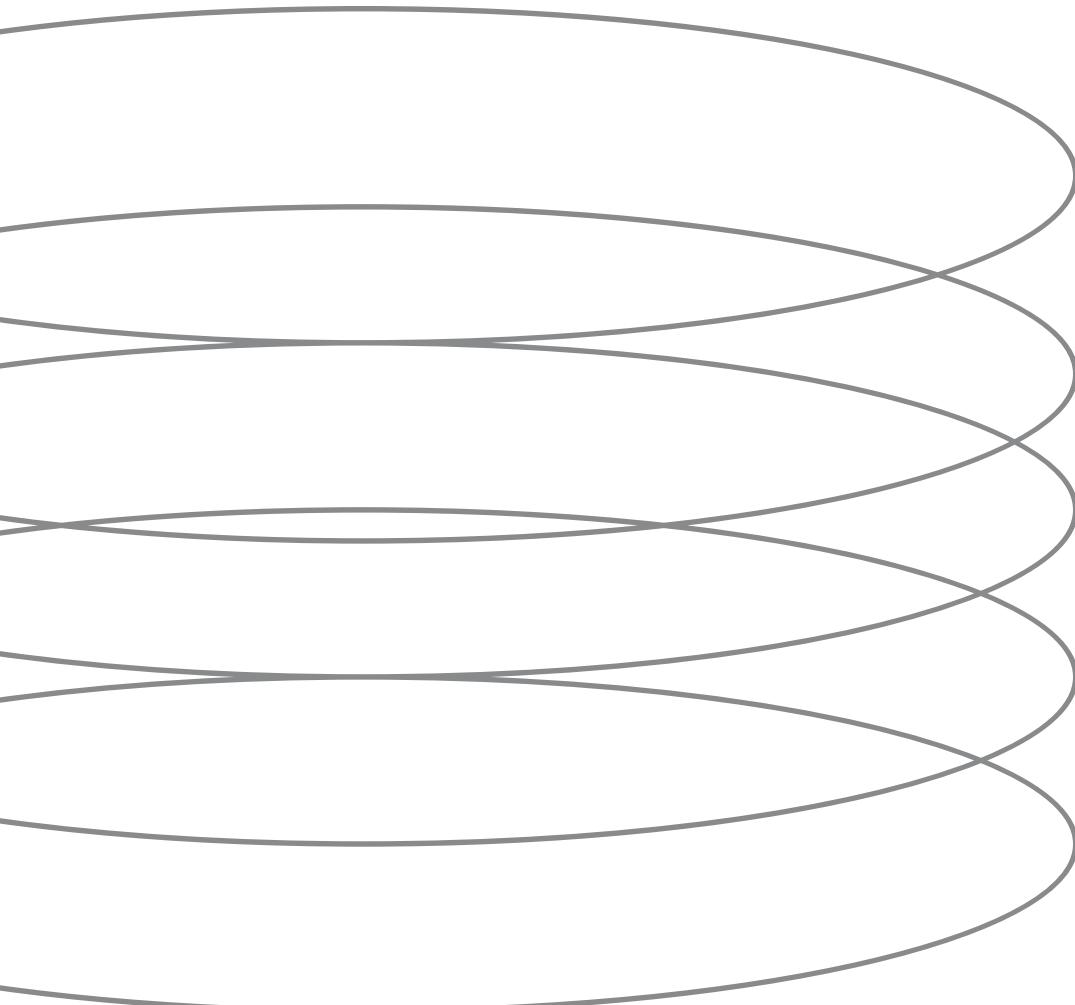
Train-Test Split

- Train Size: 80 %
- Test Size: 20 %
- Stratify on target

Data Preparation

Data Transformation Setup

| Step 1 | Step 2 | Step 3 | Step 4 | Step 5 |
|---|---|--|---|--|
| <u>Identify Columns</u> Extract categorical columns (excluding Churn and Contract), numeric columns, and binary columns (with exactly 2 unique values) to categorize the data appropriately for preprocessing. | <u>Define Ordinal Categories</u> Specify the ordinal categories for the Contract column to ensure that the model understands the inherent order in these categories during training. | <u>Binary Mapping Function</u> Create a function to map binary values ('No' to 0 and 'Yes' to 1) to convert categorical binary features into a numerical format suitable for machine learning algorithms. | <u>Numeric Transformer Pipeline</u> Define a pipeline for scaling numeric features using a specified scaler (e.g., RobustScaler or MinMaxScaler) to standardize the range of numeric data and improve model performance. | <u>Preprocessor Creation</u> Create a preprocessor that combines transformations for numeric, binary, ordinal, and categorical features, allowing for a streamlined and efficient data preparation process. |

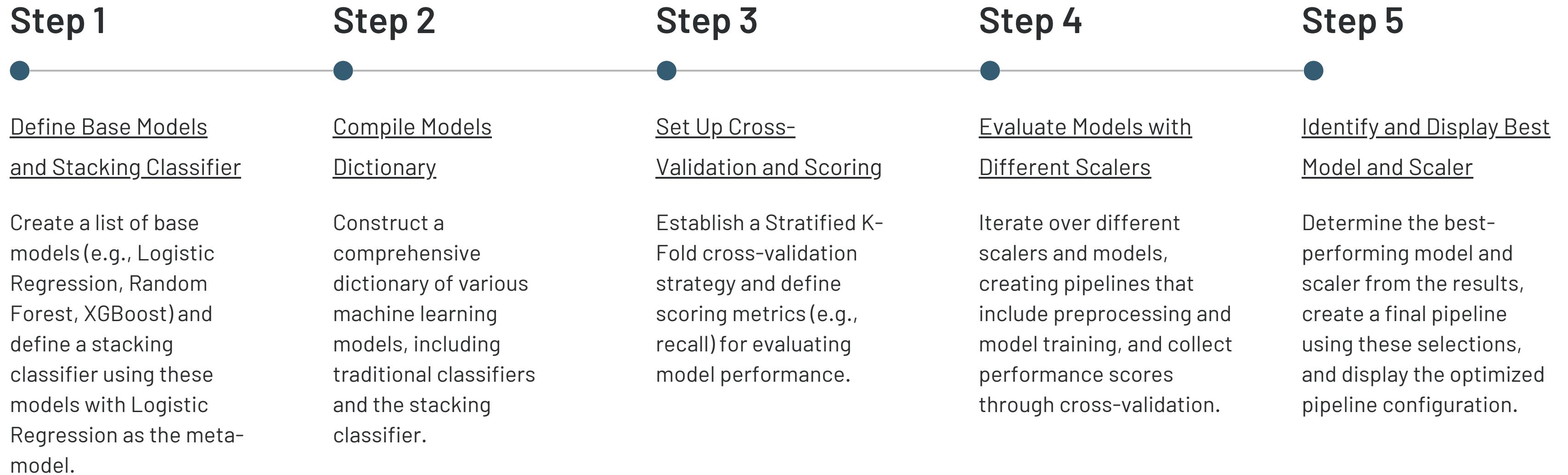


4. Modeling

- Model Initialization and Benchmarking
- Hyperparameter Tuning
- Learning Curve
- Threshold Tuning

Modeling

Model Benchmark Initialization



Modeling

Best Model Benchmark Initialization

- Metric: Recall
- Model: AdaBoost
- Scaler: Robust
- Mean Score: 0.54
- Std Dev: 0.04

Modeling

AdaBoost Algorithm

AdaBoost, short for Adaptive Boosting, is an ensemble learning algorithm designed to enhance the performance of weak classifiers by combining them into a stronger model. It works by sequentially training a series of classifiers, each focusing on the misclassified samples from the previous ones, thereby improving the model's ability to handle difficult cases. The final prediction is made by aggregating the weighted outputs of all the classifiers, making AdaBoost effective for various classification tasks while also providing insights into feature importance.

Step 1



Initialize Weights

Assign equal weights to all training samples to ensure each sample contributes equally to the learning process.

Step 2



Train Base Classifier

Train a simple base classifier (e.g., a shallow decision tree) on the weighted training data and evaluate its performance to identify misclassified samples.

Step 3



Update Weights

Adjust the weights of the training samples by increasing the weights of misclassified samples and decreasing the weights of correctly classified ones, emphasizing difficult cases for the next classifier.

Step 4



Combine Classifiers

Train multiple base classifiers iteratively, combining their predictions by weighting them according to their accuracy to create a strong ensemble model.

Step 5



Make Predictions and Evaluate

Use the combined model to make predictions on new data, and assess its performance using various metrics, while also providing insights into feature importance.

AdaBoost

Parameters

estimator

To specify the type of base classifier used in the AdaBoost ensemble. The default classifier estimator in AdaBoost is a decision tree classifier with a maximum depth of 1

n_estimators

Controls the number of weak classifiers to be combined in the ensemble. More classifiers potentially improving performance but also increasing the risk of overfitting.

learning_rate

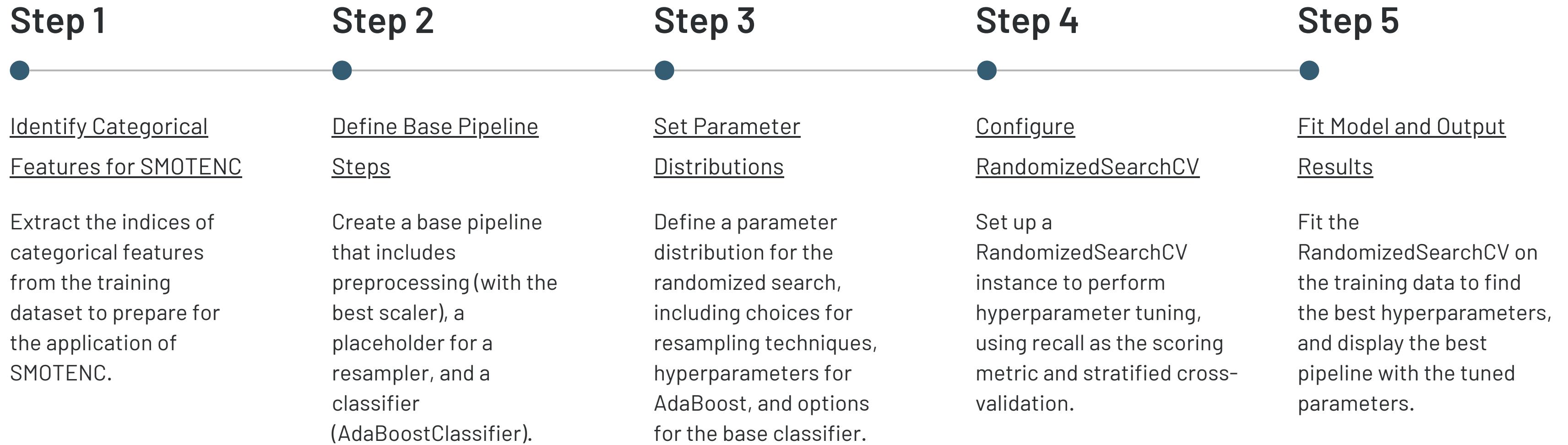
Adjusts the contribution of each weak classifier to the final model. A larger learning rate can speed up learning but may lead to overfitting.

algorithm

specifies the algorithm used for combining the weak classifiers

Modeling

Searching The Best Model

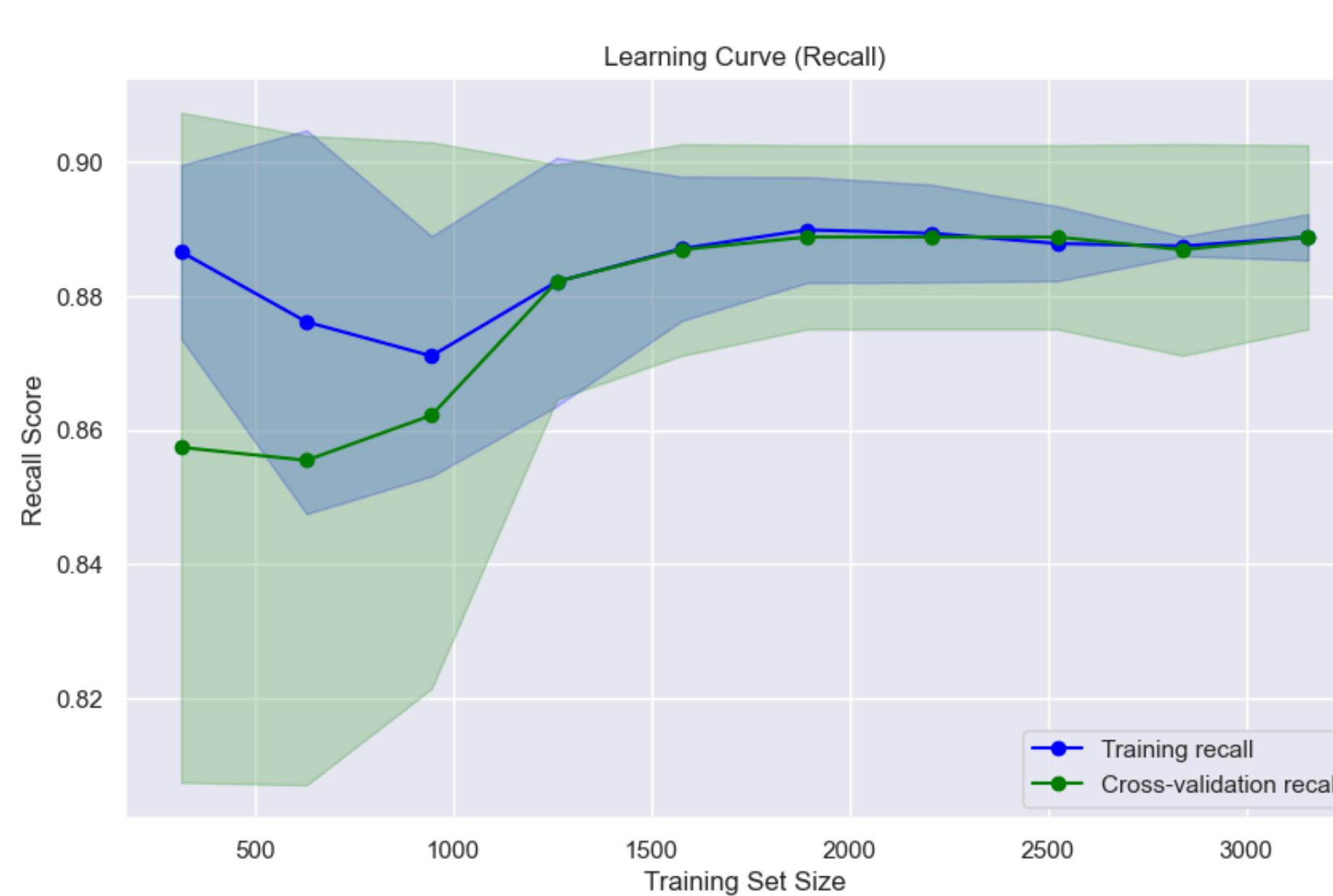


Modeling

Best AdaBoost Model After Hyperparameter Tuning

- Fitting 5 folds for each of 50 candidates, totalling 250 fits
- Best Hyperparameters:
 - 'resampler': RandomOverSampler(random_state=42),
 - 'classifier__n_estimators': 250,
 - 'classifier__learning_rate': 0.01,
 - 'classifier__estimator': DecisionTreeClassifier(max_depth=1),
 - 'classifier__algorithm': 'SAMME'
- Recall Score: 0.92 → Increases around 70% From Base Model

Modeling



Recall Learning Curve

- Training Recall Stability:

The training recall scores remained consistently high (around 0.88 to 0.89) across varying training sizes, with low variability indicated by a narrow standard deviation.

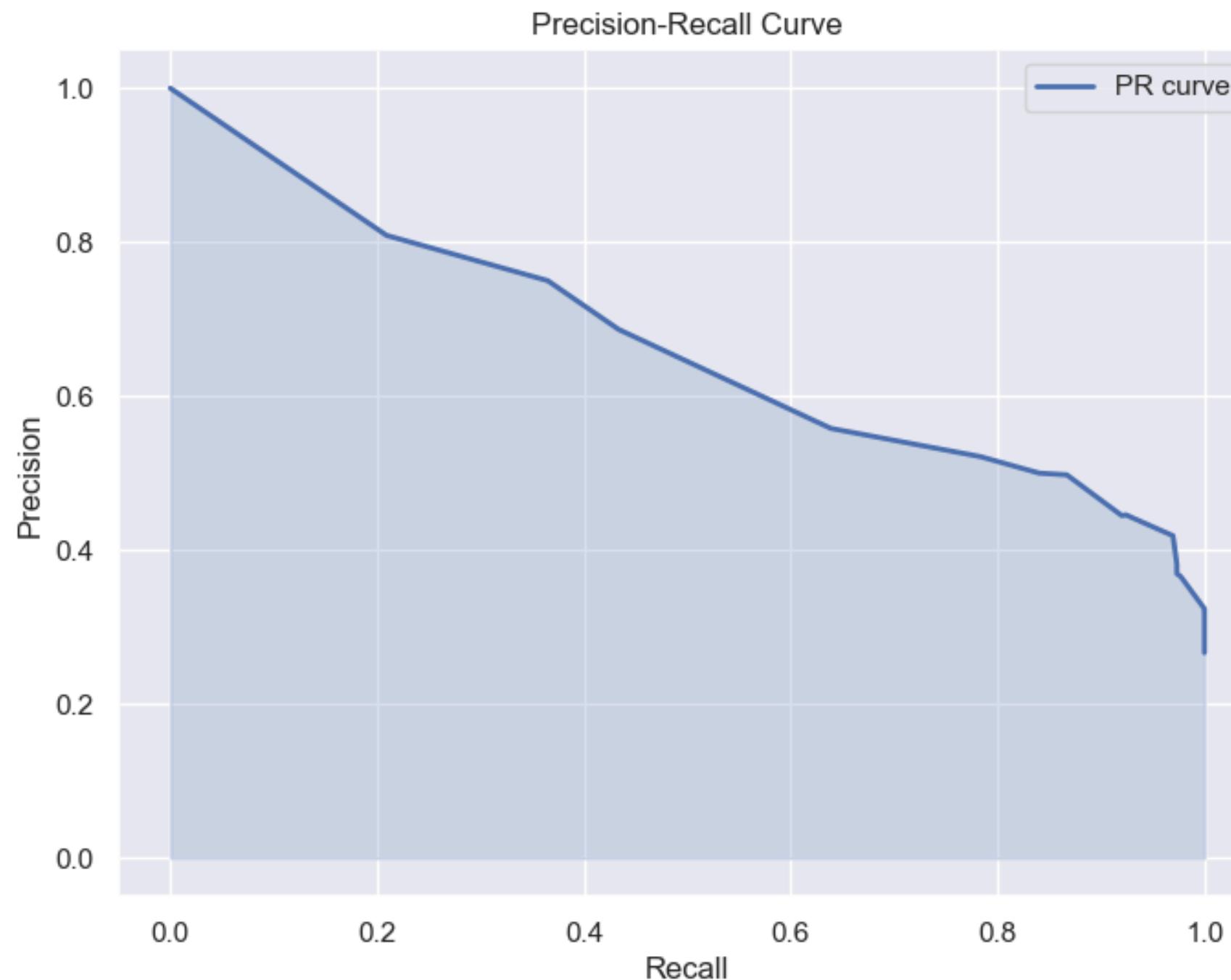
- Cross-Validation Improvement:

Initially lower cross-validation recall scores improved and converged towards the training recall as training size increased, showing reduced variability with more data, indicating a well-fitted model.

- Model Performance and Capacity:

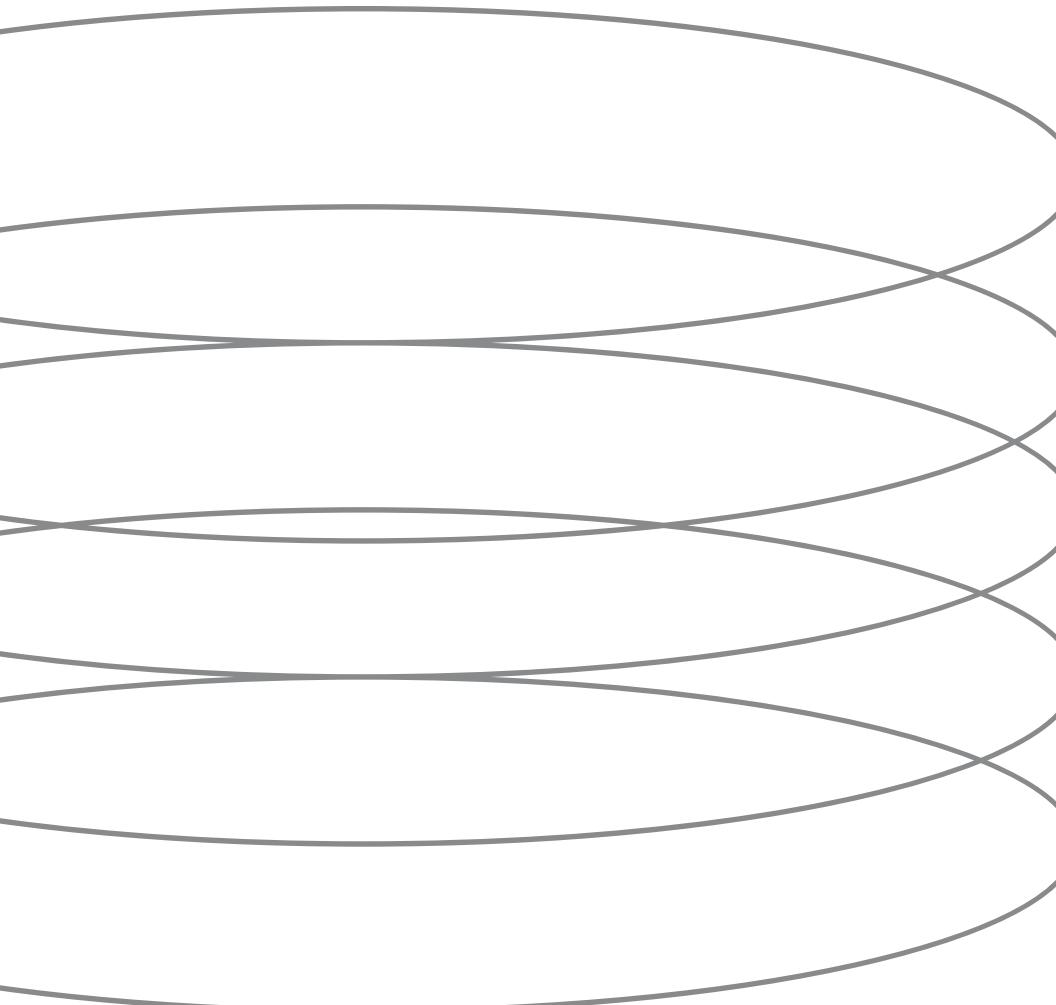
The model demonstrated good performance by minimizing false negatives, and recall scores stabilized at larger training sizes, suggesting that the model's capacity was reached with the current features and algorithm, with no significant improvements from additional data.

Modeling



Threshold Tuning

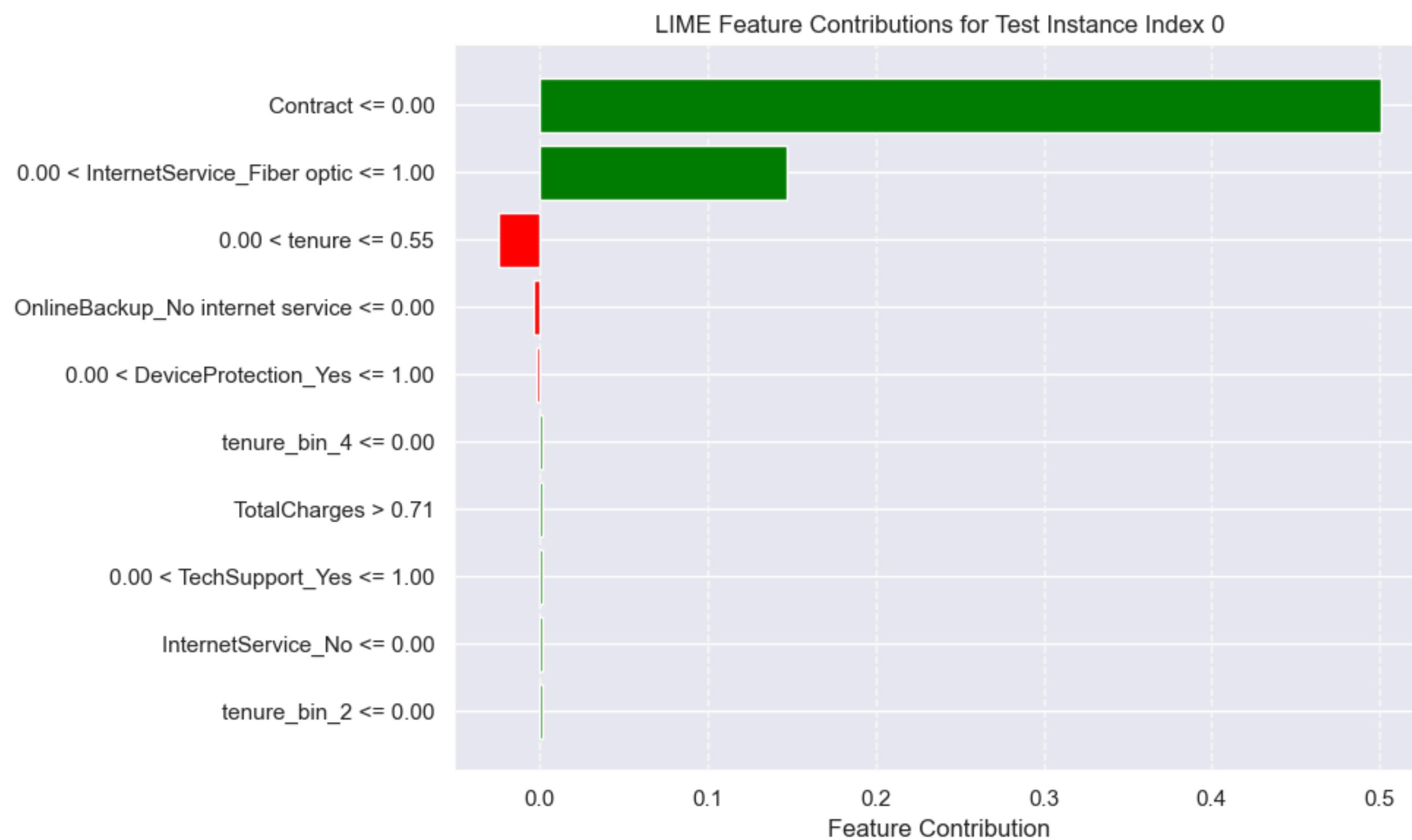
- Best threshold by Recall score: 0.1192
- Recall score at this threshold: 1.0000
- Decision: "No Go"; Too good to be true



5. Evaluation

- Feature Importance Using LIME Analysis
- Rule Based vs Machine Learning Based

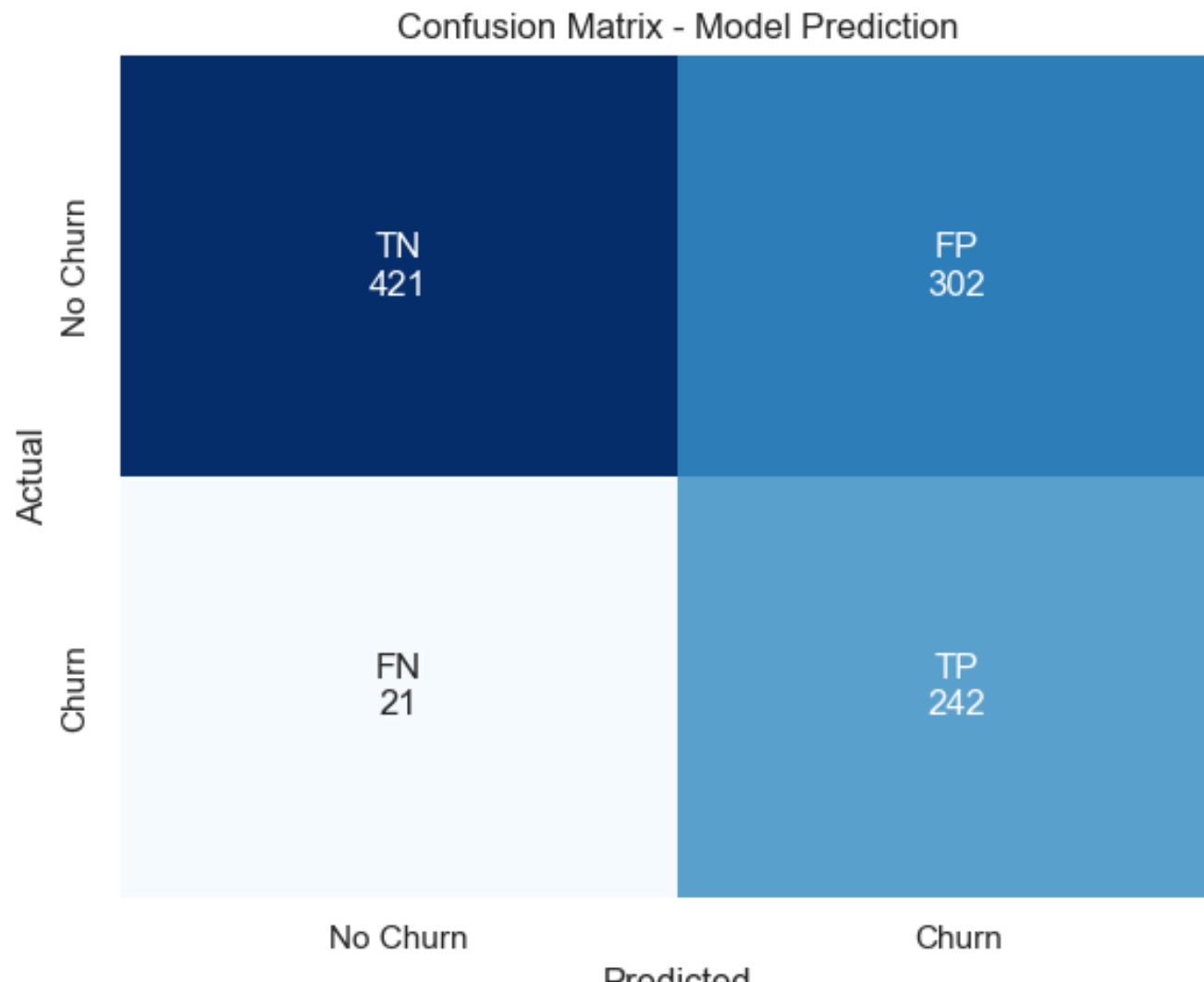
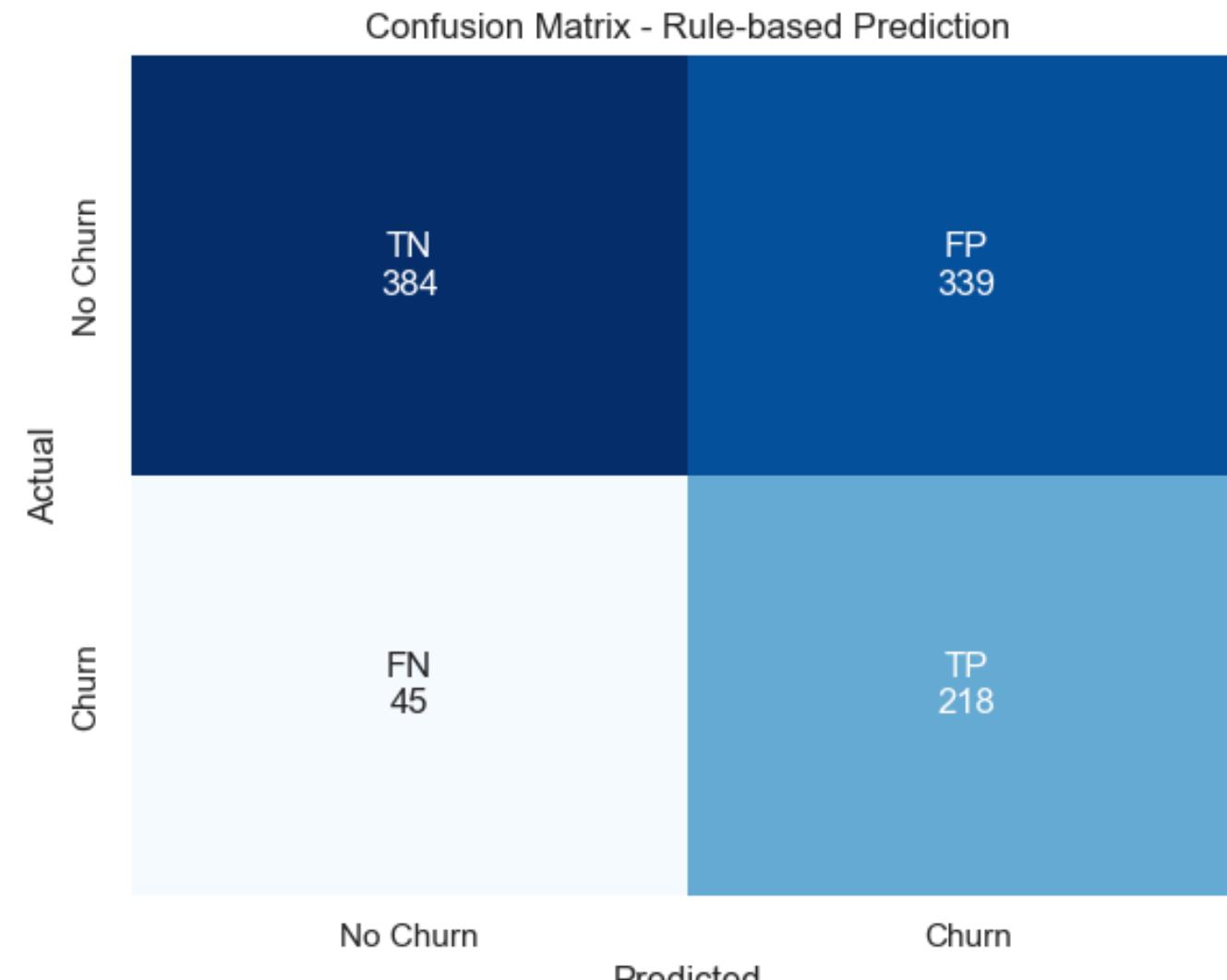
Evaluation



Feature Importances - LIME

- Key Positive Contributors:
 - Contract: Most significant positive impact, crucial for favorable predictions.
 - InternetService_Fiber optic: Also positively influences the prediction.
- Key Negative Contributor:
 - Tenure ($0.00 < \text{tenure} \leq 0.55$): Has a negative contribution, suggesting that this range decreases the likelihood of the predicted outcome.

Evaluation



Recall Score Rule: 0.8289
 Recall Score ML: 0.9202
 Differences: 9.13%

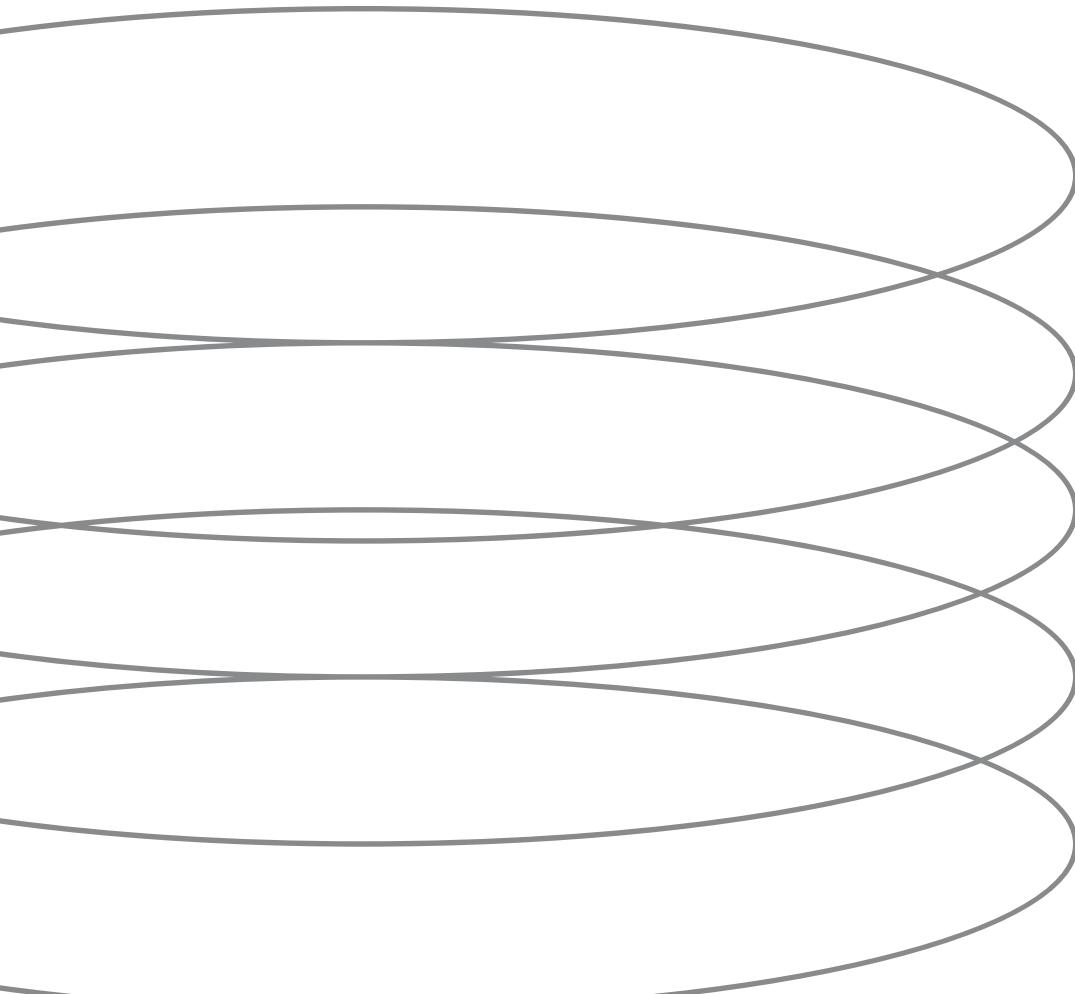
Rule-Based Scenario:
 Loss from FN: \$9,000
 Cost from FP: \$16,950
 Total Monthly Loss: \$25,950
 Total Annual Loss: \$311,400

Machine Learning Scenario:
 Loss from FN: \$4,200
 Cost from FP: \$15,100
 Total Monthly Loss: \$19,300
 Total Annual Loss: \$231,600

Rule Based vs Machine Learning Based

- With Machine Learning Model, recall score increases 9.13 % compared to the rule based.
- The company also can saves 25.63% based on Machine Learning Model instead of rule based.

Differences: \$79,800
 Percentages savings: 25.63%



6. Deployment

- Joblib Deployment
- Model Limitations

Deployment

Joblib Deployment File

models\best_tuned_pipeline.joblib

Limitations 1 - Data Dependence and Bias

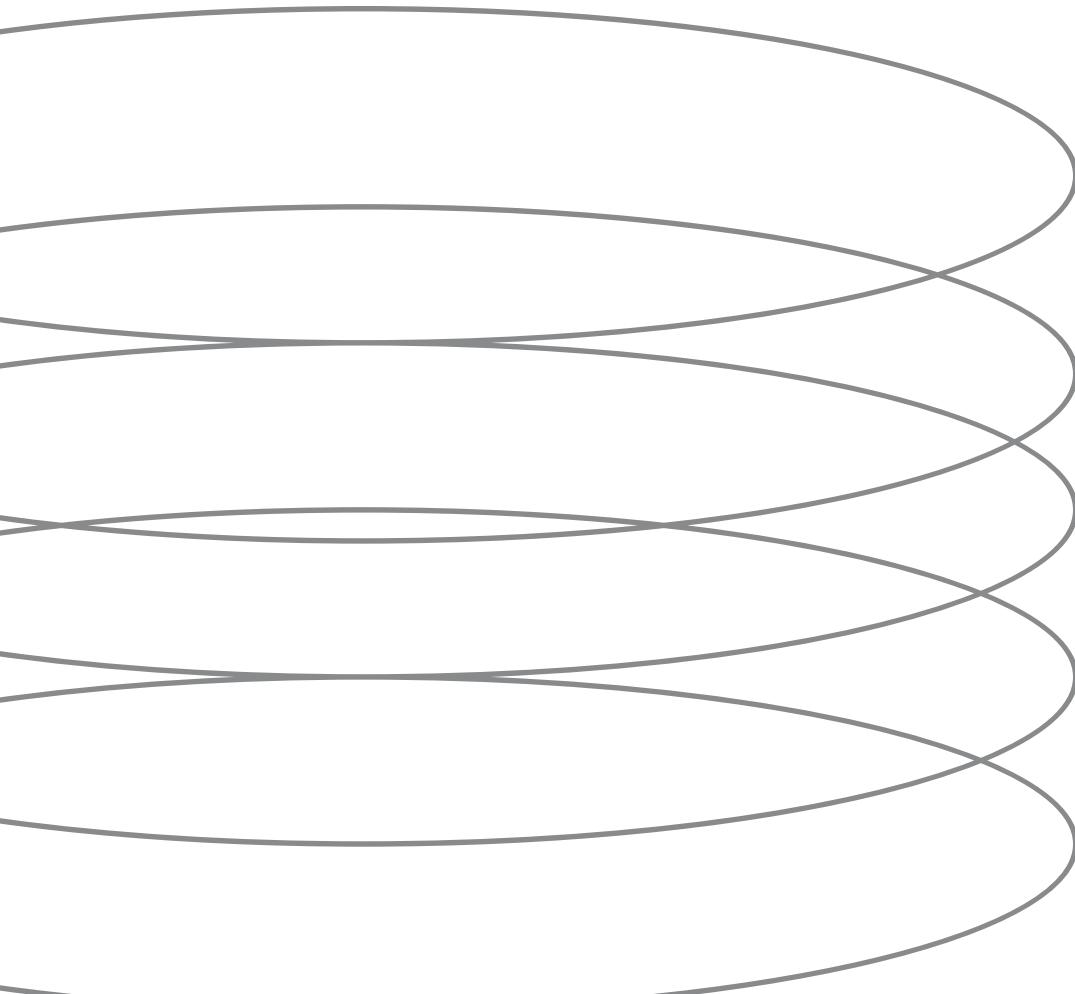
The model's accuracy is heavily reliant on the quality and representativeness of the training data, which may contain biases that affect predictions and limit its generalizability.

Limitations 2 - Pattern Recognition and Adaptability

The model's ability to identify complex patterns or rare events is constrained by the selected features. Additionally, it may not adapt well to changes in customer behavior or external factors unless regularly updated.

Limitations 3 - Overfitting and Interpretability

There is a risk of overfitting or underfitting if the model is not properly tuned. Furthermore, the model may have limited interpretability, and the evaluation metrics used might not capture all aspects of its performance effectively.



7. Conclusion and Recommendations

- Conclusion
- Business Recommendations
- Model Recommendations

Conclusion and Recommendations

Conclusions

- **Contract has the strongest positive contribution to churn prediction** – customers with certain contract types are more likely to churn.
- **InternetService_Fiber optic also positively contribute** to churn risk.
- **Tenure has a negative contribution** – shorter tenure customers are more likely to churn.
- **The Machine Learning Scenario significantly increases recall score around 9%** and reduces False Negatives and False Positives losses, **saving nearly \$80,000 annually**, a quarter of the total losses under the Rule-Based system.

Conclusion and Recommendations

Business Recommendations

- **Contract Optimization:** Promote contract types that enhance customer retention and satisfaction, offering incentives to encourage selection.
- **Internet Service Offerings:** Invest in expanding fiber optic infrastructure and promote its benefits to attract more customers.
- **Customer Retention Strategies:** Develop targeted strategies for customers with short tenures, including personalized outreach and loyalty programs.
- **Feature Awareness Campaigns:** Educate customers on the advantages of additional features like online backups and device protection.
- **Customer Feedback Loop:** Implement feedback mechanisms to refine service offerings and address customer pain points.
- **Analyze Customer Segments:** Conduct analysis to understand diverse customer needs, enabling tailored marketing and services.
- **Retention Metrics Monitoring:** Regularly track key metrics related to contracts and service usage to identify trends and adjust strategies.

Conclusion and Recommendations

Model Recommendations

- **Balance Precision and Recall:**

Instead of focusing solely on maximizing recall, the company can tune the model to achieve a better balance between precision and recall. This can be done by adjusting the classification threshold or using evaluation metrics like the F1-score that consider both precision and recall.

- **Regular Model Retraining:**

Customer behavior and market conditions change over time. Regularly retraining the model with new data ensures that it adapts to recent trends and maintains accuracy.

**“It is the greatest truth of our age:
Information is not knowledge.”**

— Caleb Carr

Thank You :D

