

# Analyzing Feature Importance in Customer Churn Using Shapley Values

*Trần Thiên Anh, Tô Vĩnh An, Nguyễn Minh Chính*

*26/12/2024*

## Abstract

This report investigates the factors contributing to customer churn by analyzing feature importance using Shapley values. Logistic Regression was employed to train a predictive model, and SHAP (Shapley Additive Explanations) was utilized to interpret feature contributions. The study uses the Telco Customer Churn dataset, highlighting preprocessing, modeling, and visualization techniques. A production-ready demo was also developed using Streamlit, allowing users to explore churn predictions interactively.

## 1 Introduction

Understanding the factors that drive customer churn is crucial for businesses aiming to improve retention strategies and service effectiveness. In this study, we use SHAP (SHapley Additive exPlanations) to evaluate the impact of various factors on churn decisions. Logistic Regression, known for its simplicity and effectiveness in binary classification tasks, was chosen as the predictive model. SHAP enhances the interpretability of the model by leveraging its coefficients to quantify the importance of input features. By combining SHAP with Logistic Regression, we aim to provide a detailed analysis of the factors influencing customer churn, offering actionable insights for businesses.

**Key objectives include:**

- Preprocessing and exploring the Telco Customer Churn dataset.
- Training a Logistic Regression model for churn prediction.
- Interpreting feature importance using SHAP.
- Developing a web application for interactive churn analysis.

## 2 Problem Setup

### 2.1 Dataset Overview

The **Telco Customer Churn dataset**, sourced from Kaggle [1], includes customer demographics, service details, and churn labels. The target variable, **Churn**, indicates whether a customer discontinued the service. The details of the dataset can be seen in table 1

<b>CustomerID</b>	A unique identifier for each customer	<b>OnlineBackup</b>	Indicates if the customer has online backup service
<b>Gender</b>	The gender of the customer.	<b>DeviceProtection</b>	Indicates if the customer has device protection service
<b>SeniorCitizen</b>	Indicates if the customer is a senior citizen	<b>TechSupport</b>	Indicates if the customer has a tech support service
<b>Partner</b>	Indicates if the customer has a partner	<b>StreamingTV</b>	Indicates if the customer has streamingTV service.
<b>Dependents</b>	Indicates if the customer has dependents	<b>StreamingMovies</b>	Indicates if the customer has a streamingmovie service
<b>Tenure</b>	The number of months the customer has stayed with the company.	<b>Contract</b>	The type of contract the customer has
<b>PhoneService</b>	Indicates if the customer has phone service	<b>PaperlessBilling</b>	Indicates if the customer has paperlessbilling
<b>MultipleLines</b>	Indicates if the customer has multiplelines	<b>PaymentMethod</b>	The payment method used by the customer
<b>InternetService</b>	The type of internet service the customerhas	<b>MonthlyCharges</b>	The amount charged to the customer monthly.
<b>OnlineSecurity</b>	Indicates if the customer has online security service	<b>TotalCharges</b>	The total amountcharged to the customer.

Table 1: Features of dataset

## 2.2 Challenges and Solutions

Identifying the factors contributing to customer churn often relies on traditional methods such as analyzing coefficients in Logistic Regression. However, these approaches are often limited by their difficulty in explaining the contribution of each factor or their reliance on linear assumptions. To overcome these challenges, SHAP offers a modern and transparent approach, enabling precise measurement of each factor’s impact and helping companies develop more effective marketing strategies.

## 3 Methods

### 3.1 Preprocessing

Key steps included:

- **Fixing Data Types:** Converted **TotalCharges** to numeric.
- **Handling Missing Values:** Dropped rows with null values.
- **Feature selection:** Dropping feature with low correlation value with churn in figure 1.
- **Data Quality Issues:** Null values and non-numeric columns were cleaned and standardized.
- **Encoding:** Applied one-hot encoding to multi-category features and label encoding for binary features.
- **Standardization:** Scaled continuous features for consistency.
- **Splitting Data:** Divided into 70% training and 30% testing sets.

### 3.2 Logistic Regression

Logistic Regression models the probability of churn using a logistic function:

$$P(y = 1|X) = \frac{1}{1 + e^{-\beta_0 - \beta_1 X_1 - \dots - \beta_n X_n}}. \quad (1)$$

Its interpretability and effectiveness in binary classification made it ideal for this task.

The churn prediction model directly impacts Shapley values, with higher accuracy leading to more precise and reliable Shapley values. This helps businesses understand the factors influencing customer decisions and develop effective churn reduction strategies. Logistic regression is a popular model due to its simplicity and ease of implementation in binary classification tasks.

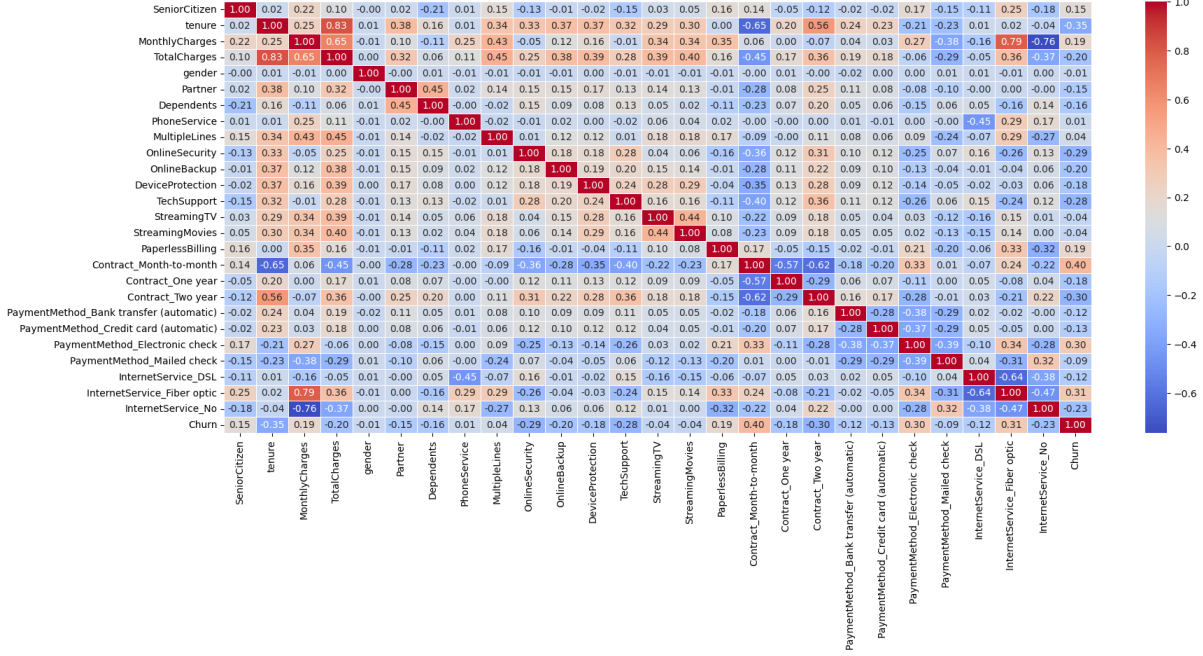


Figure 1: Correlation between features

### 3.3 SHAP (Shapley Additive Explanations)

SHAP values provide local and global interpretability by quantifying each feature's contribution to the model's predictions. Visualizations such as SHAP summary plots were used to identify key churn drivers.

The SHAP value for a feature  $i$  is given by:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)]$$

SHAP values indicate each feature's contribution to the model's prediction relative to the base value (average model output). A positive SHAP value means the feature increases the likelihood of churn, while a negative value decreases it. The magnitude of the SHAP value represents the strength of the feature's impact – larger absolute values indicate stronger influence on the prediction. For example, a SHAP value of 0.2 means the feature increases the probability of churn by pushing the prediction 0.2 units higher than the base value.

## 4 Experiments and Results

### 4.1 Stratified k-fold Cross-Validation

We use Stratified k-fold Cross-Validation to ensure that each fold in the training and testing process has a similar class distribution. This method helps evaluate the model accurately and fairly,

minimizing the impact of folds that may not be representative of the entire dataset.

How Stratified k-Fold Cross-Validation Works:

- **Splitting the Data:** The dataset is divided into (k) folds (subsets), ensures that each fold has approximately the same percentage of samples of each target class as the entire dataset.
- **Training and Testing:** The model is trained on (k-1) folds and tested on the remaining fold. This process is repeated (k) times, with each fold being used as the test set exactly once.
- **Averaging the Results:** The performance metrics (e.g., accuracy, precision, recall) are averaged over the (k) iterations

## 4.2 Model Performance

The Logistic Regression model achieved:

Metric	Value
Test Accuracy	0.8128
Cross-Validation Accuracy (Average)	0.8040

Table 2: Performance metrics for Logistic Regression.

The accuracies are quite close (0.8128 vs. 0.8040), indicating that the model's performance is consistent. This suggests that the model is not overfitting to the training data and generalizes well to unseen data.

The slight drop in accuracy from 0.8128 to 0.8040 suggests that the model might perform slightly worse on new, unseen data compared to the training data. However, the difference is small, indicating good generalization ability.

## 4.3 Feature Importance

SHAP analysis revealed the following top features:

Feature	Shapley Value
Tenure	0.17884
Contract_Month-to-month	0.05472
Contract_Two year	0.0416
...	...
MonthlyCharges	-0.0126
TotalCharges	-0.1180

Table 3: Features sorted based on the SHAP values

Table 3 indicates that the 'Tenure' (0.17884) is the most influential factor in predicting churn. Customers with shorter tenures are more likely to churn. Additionally, contract type plays a significant role, with 'Month-to-month' contracts having a higher churn risk compared to 'Two-year' contracts. The analysis also shows that 'TotalCharges' (-0.1180) and 'MonthlyCharges' (-0.0126) negatively impact churn, with higher charges being associated with lower churn likelihood.

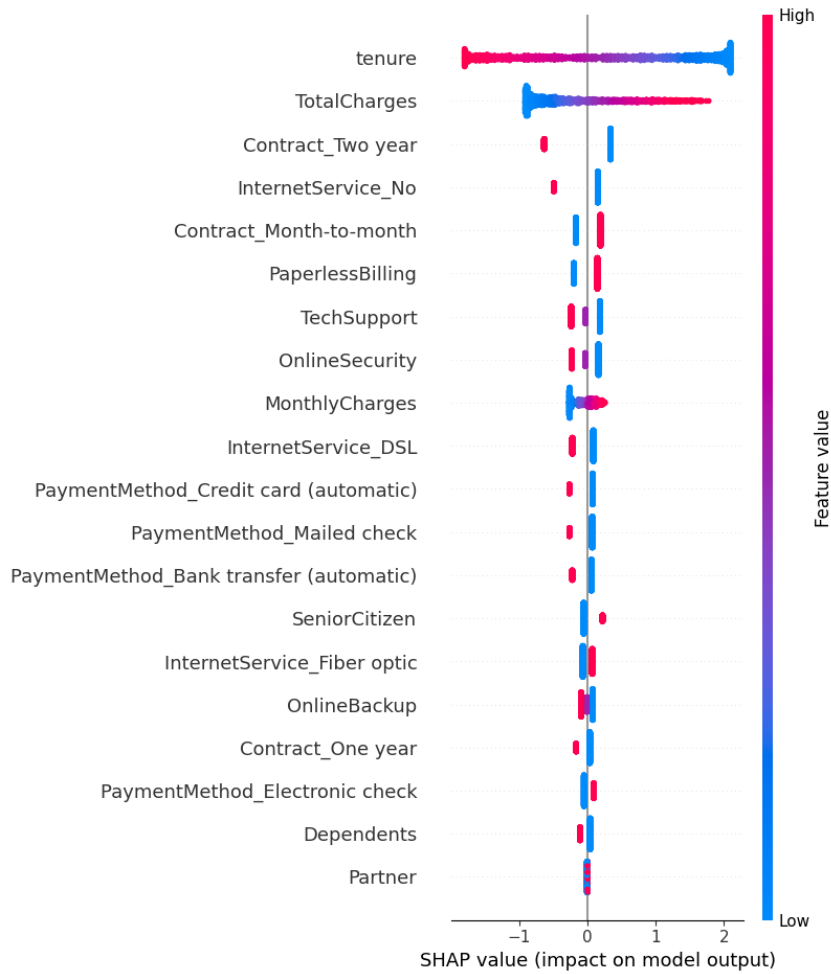


Figure 2: Summary Shapley value

Based on the results from Figure 3, we can observe that the factors most strongly influencing customer churn include: tenure (duration of service usage), TotalCharges, and contract type. Notably, customers with shorter tenure (low tenure - blue color) and those with month-to-month contracts show a higher tendency to churn. In contrast, factors such as Partner, Dependents, and PaymentMethod have minimal impact. This suggests that focusing on customer retention strategies during the initial service period and encouraging long-term service package subscriptions could be effective approaches.

## 5 Production: Streamlit Demo

To demonstrate the results interactively, a web application was developed using **Streamlit**. The application allows users to:

- Upload customer data for churn prediction.
- View SHAP visualizations for feature importance.
- Experiment with hypothetical customer scenarios.

The Streamlit interface provides a user-friendly platform for exploring churn insights and testing retention strategies.

## 6 Conclusion and Tasks Assigned

### 6.1 Conclusion

This report highlights the potential of SHAP for analyzing customer churn, with **Tenure** and **TotalCharges** identified as critical factors. The Logistic Regression model achieved reliable accuracy, and the interactive Streamlit demo offers practical utility for users.

### 6.2 Tasks Assigned

- **Tô Vĩnh An:** Responsible for SHAP analysis and visualizations, developing the Streamlit application, and integrating the results.
- **Trần Thiên Anh:** In charge of data collection and writing the technical report.
- **Nguyễn Minh Chính:** Responsible for data preprocessing and building the Logistic Regression model.

## Acknowledgments

We thank the contributors of the Telco Customer Churn dataset on Kaggle for their valuable data.

## References

- [1] Telco Customer Churn Dataset: <https://www.kaggle.com/datasets/blastchar/telco-customer-churn>
- [2] SHAP Documentation: <https://shap.readthedocs.io/>