

Customer Churn Analysis

1. Overview

This project focuses on understanding customer churn—why customers leave a business—and developing a data-driven solution to predict and reduce it. Using customer data, we aim to uncover key factors that contribute to churn and build a model that can help the business proactively retain customers.

Customer churn is a critical metric for subscription-based and service industries. High churn rates translate to lost revenue, increased marketing costs, and reduced lifetime value. Our goal is to empower the business with actionable insights and a predictive model to address churn effectively.

2. Business and Data Understanding

Business Understanding

The primary business question is: "Which customers are at risk of leaving the service, and what can we do to retain them?"

Retaining customers is often more cost-effective than acquiring new ones. Therefore, understanding churn behavior is not just analytical—it's strategic.

Data Understanding

We used the **Telco Customer Churn** dataset, which contains over 7,000 entries of customer demographics, services used, billing information, and churn status. The dataset includes:

- Customer Demographics: gender, senior citizen status, partner/dependents
- Service Details: phone service, internet service, streaming options
- Account Details: contract type, tenure, paperless billing, payment method
- Financial Metrics: monthly and total charges
- Target Variable: whether the customer churned or not

This dataset is ideal for our goal because it mirrors typical customer behavior in a service-oriented business and provides the variables needed to identify churn predictors.

3. Modeling

We applied a **classification modeling approach** to predict whether a customer is likely to churn. The target variable was binary (Churn: Yes/No). The general steps included:

- Data preprocessing: Cleaning and encoding categorical features, handling missing values
- Feature engineering: Selecting and transforming relevant features
- Model selection: Multiple models were considered, including logistic regression and tree-based algorithms
- **Training and testing**: The dataset was split into training and testing subsets for unbiased performance evaluation

We selected the model that provided the best trade-off between accuracy and interpretability.

4. Evaluation

The final model was evaluated using several performance metrics including:

- Accuracy: How often the model correctly predicted churn
- Precision & Recall: Important to balance false positives and false negatives
- Confusion Matrix: Provided a clear view of misclassifications
- ROC Curve and AUC: Assessed model performance across thresholds

The model achieved an accuracy close to **80%**, which is a strong result for a churn prediction problem. More importantly, it provides **actionable churn scores** for each customer, enabling proactive retention strategies.

5. Conclusion

The analysis revealed clear patterns in customer behavior. For example, customers with month-to-month contracts, shorter tenures, and higher monthly charges were significantly more likely to churn. These insights, combined with the predictive model, equip the business to:

- Identify high-risk customers early
- Design personalized retention strategies
- Monitor churn trends over time

This project serves as a bridge between technical insights and business strategy, aligning data science outcomes with operational goals.



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