



Telco Customer Churn Analysis

Insights, Strategies, and Predictive Modeling

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Agenda



- **Introduction and Business Problem:** Overview of customer churn and its impact on telecom companies.
- **Dataset and Methodology:** Summary of the dataset, preprocessing steps, and modeling approach.
- **Exploratory Insights:** Key trends and visualizations discovered during the analysis.
- **Retention Strategies:** Actionable recommendations to reduce churn and improve retention.
- **Conclusion and Future Directions:** Summary of findings, ethical considerations, and next steps.

Introduction and Business Problem



- **Customer churn** is a critical issue for telecom companies, leading to revenue losses and higher customer acquisition costs.
- Retaining existing customers is more cost-effective than acquiring new ones, making churn reduction a strategic priority.
- This presentation explores the factors driving churn and provides actionable insights to improve customer retention.

Dataset Overview

| WA_Fn-UseC_-Telco-Customer-Churn.csv (977.5 kB) | | | | | | | | | |
|---|--|--|---|--|---|---|--|---|--|
| Detail Compact Column 10 of 21 columns | | | | | | | | | |
| <p>About this file</p> <p>Telcom Customer Churn</p> <p>Each row represents a customer, each column contains customer's attributes described on the column Metadata.</p> <p>The raw data contains 7043 rows (customers) and 21 columns (features).</p> <p>The "Churn" column is our target.</p> | | | | | | | | | |
| customerID | gender | SeniorCitizen | Partner | Dependents | tenure | PhoneService | MultipleLines | InternetService | |
| Customer ID | Whether the customer is a male or a female | Whether the customer is a senior citizen or not (1, 0) | Whether the customer has a partner or not (Yes, No) | Whether the customer has dependents or not (Yes, No) | Number of months the customer has stayed with the company | Whether the customer has a phone service or not (Yes, No) | Whether the customer has multiple lines or not (Yes, No, No phone service) | Customer's internet service provider (DSL, Fiber optic, No) | |
| 7043 unique values | Male 50% Female 50% | 50% 50% | true 0 0% false 0 0% | true 0 0% false 0 0% | 0 72 | true 0 0% false 0 0% | No 48% Yes 42% Other (DSL) 10% | Fiber optic DSL Other (DSL) | |
| 7598-WHEG | Female | 0 | Yes | No | 1 | No | No phone service | DSL | |
| 5575-WNOE | Male | 0 | No | No | 34 | Yes | No | DSL | |
| 3668-OPBK | Male | 0 | No | No | 2 | Yes | No | DSL | |
| 7795-CPCK | Male | 0 | No | No | 45 | No | No phone service | DSL | |
| 9237-HULTU | Female | 0 | No | No | 2 | Yes | No | Fiber optic | |
| 9385-CSSIC | Female | 0 | No | No | 8 | Yes | Yes | Fiber optic | |
| 1452-KDOVK | Male | 0 | No | Yes | 22 | Yes | Yes | Fiber optic | |
| 6713-ONMC | Female | 0 | No | No | 18 | No | No phone service | DSL | |
| 7892-PPOKP | Female | 0 | Yes | No | 29 | Yes | Yes | Fiber optic | |
| 6388-TABGU | Male | 0 | No | Yes | 62 | Yes | No | DSL | |
| 9763-GRSD | Male | 0 | Yes | Yes | 13 | Yes | No | DSL | |
| 7469-LRBCI | Male | 0 | No | No | 16 | Yes | No | No | |
| 8891-TTVAX | Male | 0 | Yes | No | 58 | Yes | Yes | Fiber optic | |
| 8288-KJEX | Male | 0 | No | No | 49 | Yes | Yes | Fiber optic | |
| 5129-JLPIB | Male | 0 | No | No | 25 | Yes | No | Fiber optic | |
| 9655-SNHY7 | Female | 0 | Yes | Yes | 44 | Yes | Yes | Fiber optic | |

- **Source: Kaggle - Telco Customer Churn Dataset**
- **7,043 records with 21 features, including:**
 - ❖ Customer demographics (e.g., senior citizen, gender).
 - ❖ Service details (e.g., internet service type, contract type).
 - ❖ Billing information (e.g., monthly and total charges).
- **Target: Churn (Yes/No)**

Methodology

WA_Fn-UseC_-Telco-Customer-Churn.csv (977.5 kB)

Detail

Compact

Column

10 of 21 columns

About this file

Add Suggestion

Telcom Customer Churn

Each row represents a customer, each column contains customer's attributes described on the column Metadata.

The raw data contains 7043 rows (customers) and 21 columns (features).

The "Churn" column is our target.

| customerID | gender | SeniorCitizen | Partner | Dependents | tenure | PhoneService | MultipleLines | InternetService |
|-----------------------|--|--|---|--|---|---|--|---|
| Customer ID | Whether the customer is a male or a female | Whether the customer is a senior citizen or not (1, 0) | Whether the customer has a partner or not (Yes, No) | Whether the customer has dependents or not (Yes, No) | Number of months the customer has stayed with the company | Whether the customer has a phone service or not (Yes, No) | Whether the customer has multiple lines or not (Yes, No, No phone service) | Customer's internet service provider (DSL, Fiber optic, No) |
| 7043 unique values | Male 50% Female 50% | | true 0 0% false 0 0% | true 0 0% false 0 0% | | true 0 0% false 0 0% | No 48% Yes 42% Other (662) 10% | Fiber optic DSL Other (1526) |
| 7598-VHVEG | Female | 0 | Yes | No | 1 | No | No phone service | DSL |
| 5575-ONVOE | Male | 0 | No | No | 34 | Yes | No | DSL |
| 3668-QP9KH | Male | 0 | No | No | 2 | Yes | No | DSL |
| 7795-CFOCW | Male | 0 | No | No | 45 | No | No phone service | DSL |
| 9237-HQLTU | Female | 0 | No | No | 2 | Yes | No | Fiber optic |
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| 7469-LHBCI | Male | 0 | No | No | 16 | Yes | No | No |
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Data Explorer

Version 1 (977.5 kB)

WA_Fn-UseC_-Telco-Customer-Churn.csv

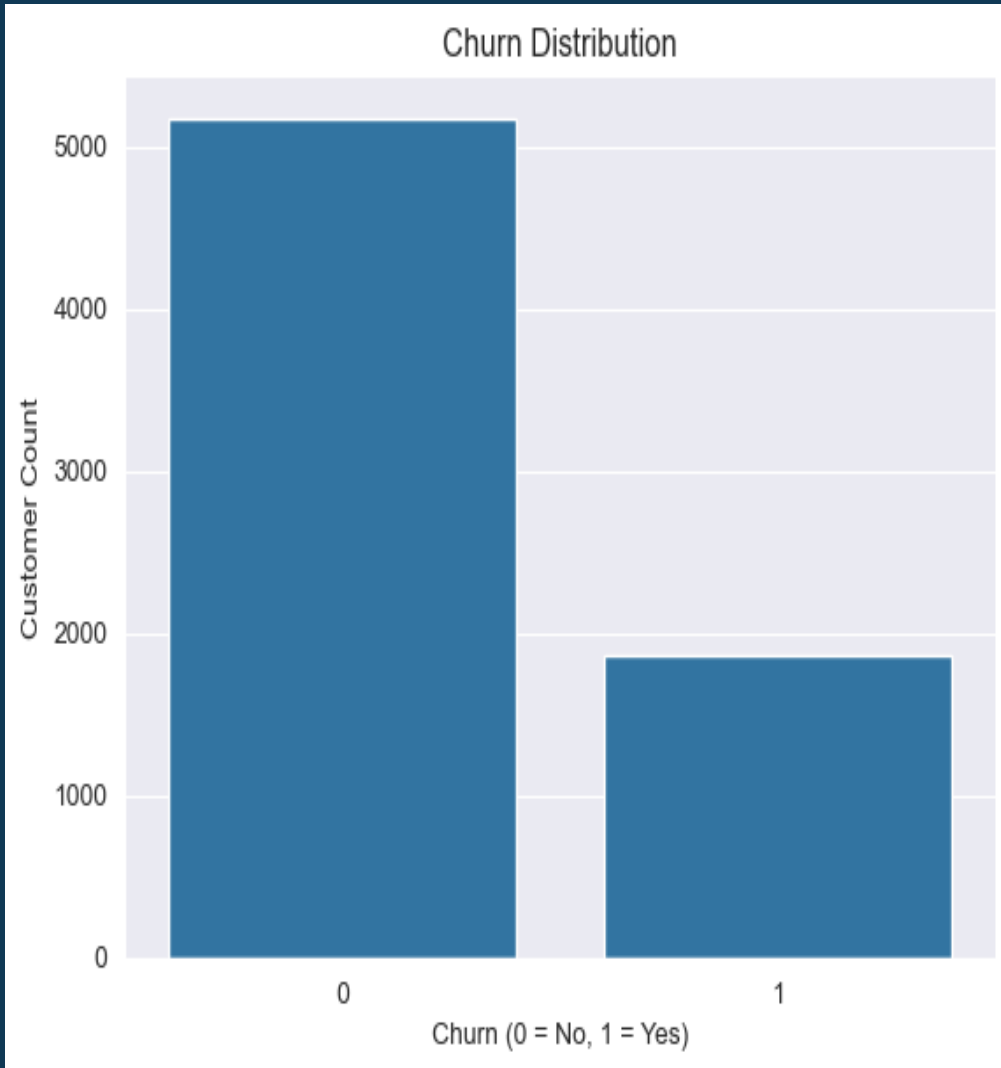
Summary

1 file

21 columns

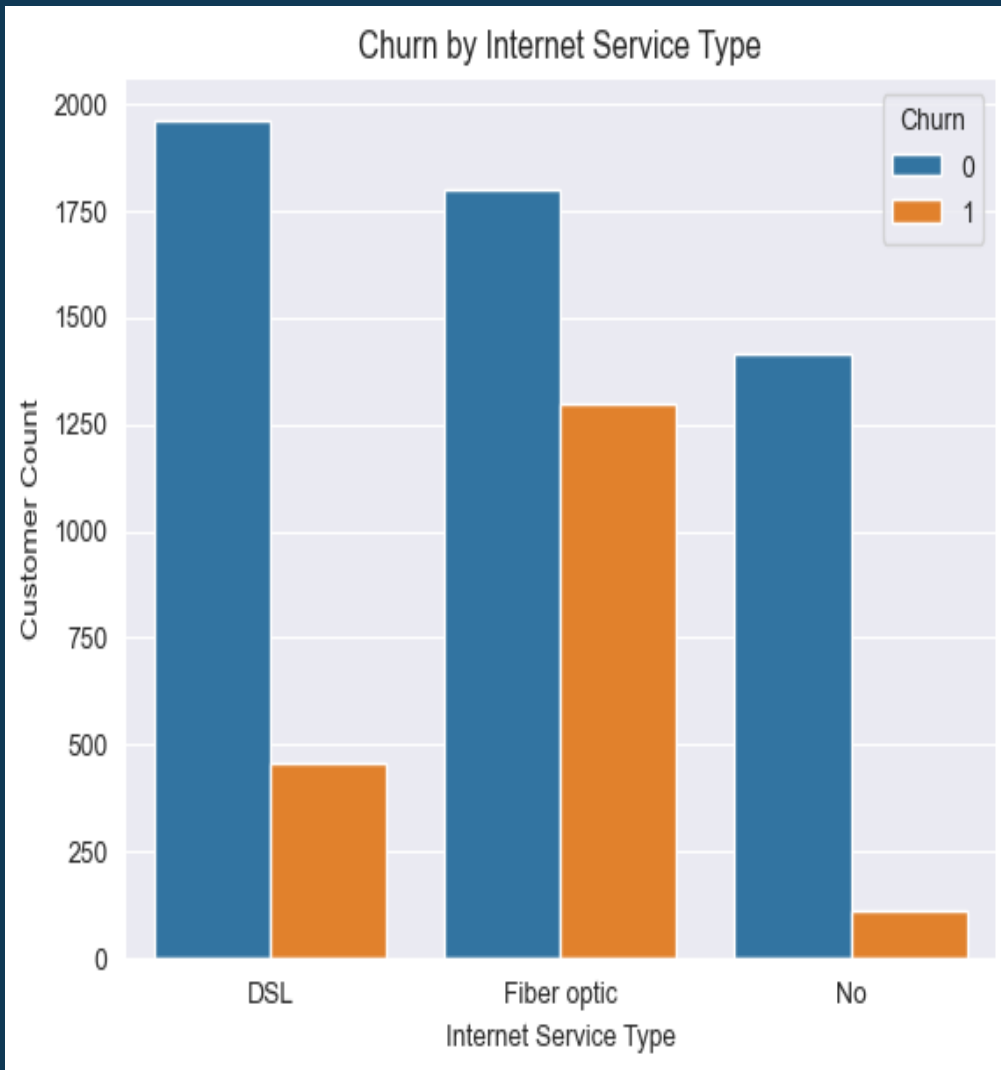
- Missing values in TotalCharges handled by median imputation.
- Categorical variables (e.g., Contract, PaymentMethod) one-hot encoded.
- Numerical features (e.g., MonthlyCharges, TotalCharges) scaled.
- Dataset split: 80% training, 20% testing.
- SMOTE applied to address class imbalance.

Data Analysis – Churn Distribution



- Approximately 26% of customers in the dataset have churned.
- Highlights a significant imbalance between churned and non-churned customers.
- The churned customer segment, though smaller, has a disproportionately high impact on revenue loss and customer acquisition costs.
- Understanding churn distribution helps prioritize strategies aimed at retaining at-risk customers.

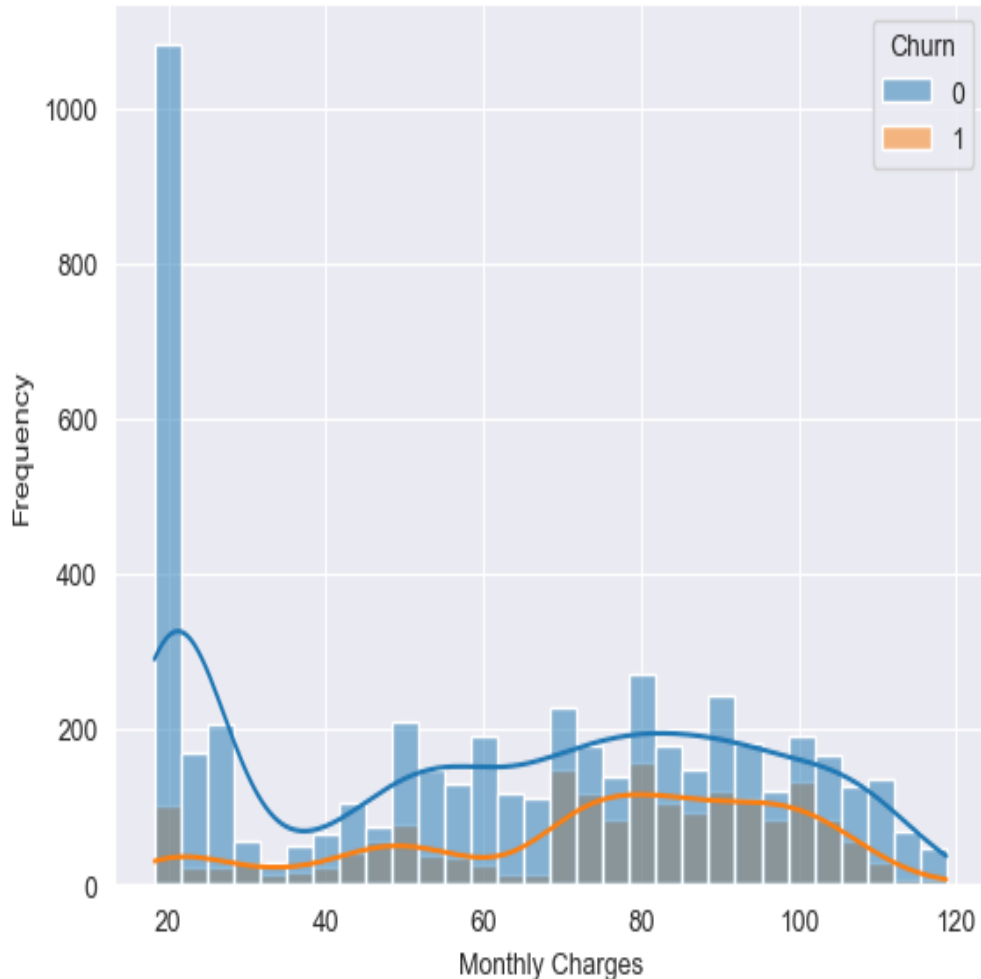
Data Analysis – Internet Service Type



- Fiber-optic internet users exhibit significantly higher churn rates compared to DSL or no internet services.
- DSL users show lower churn rates, indicating relatively higher satisfaction or fewer competitive alternatives in this segment.
- Customers with no internet service have the lowest churn rates, possibly due to fewer service dependencies or simpler billing structures.

Data Analysis – Monthly Charges

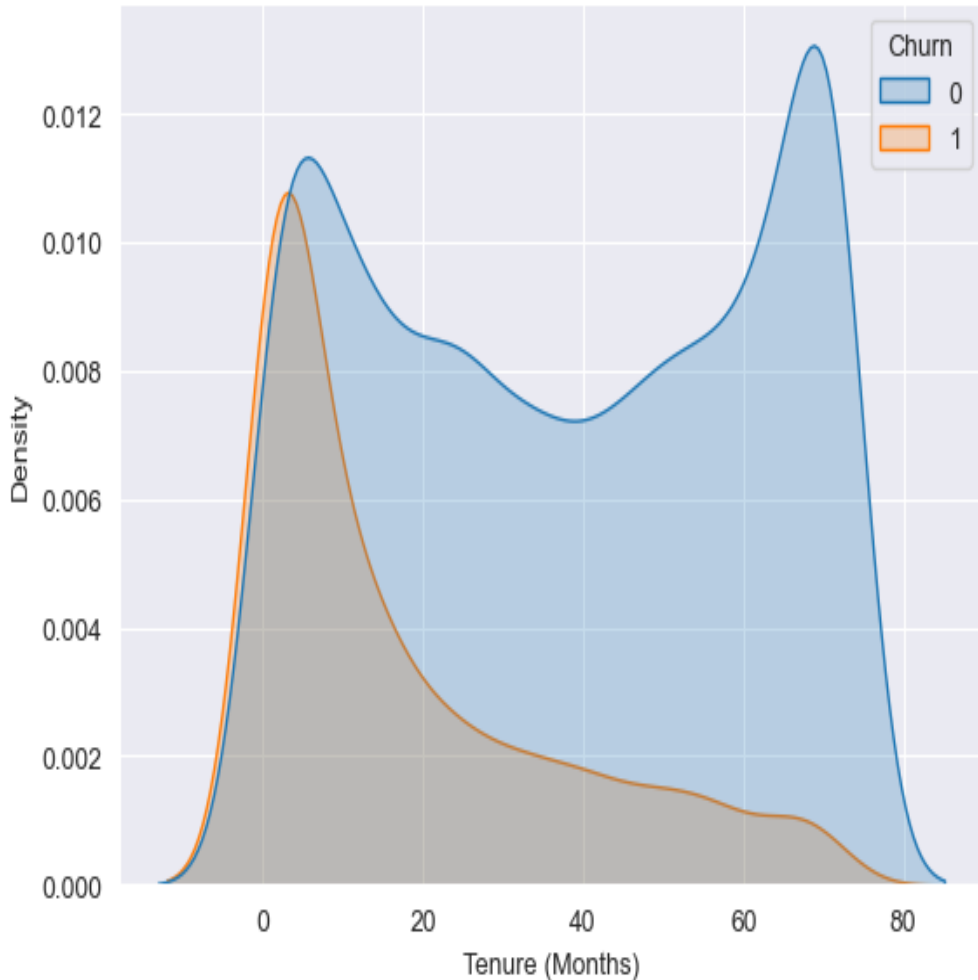
Monthly Charges Distribution by Churn



- Higher monthly charges are strongly correlated with increased churn rates.
- Customers on premium plans may feel dissatisfied with the value for money offered.
- Price-sensitive customers are more likely to leave when faced with rising costs or competitive alternatives.
- Low-cost plans appear to provide more stability, retaining customers over a longer period.
- Customers with low charges may perceive better affordability and alignment with their needs.

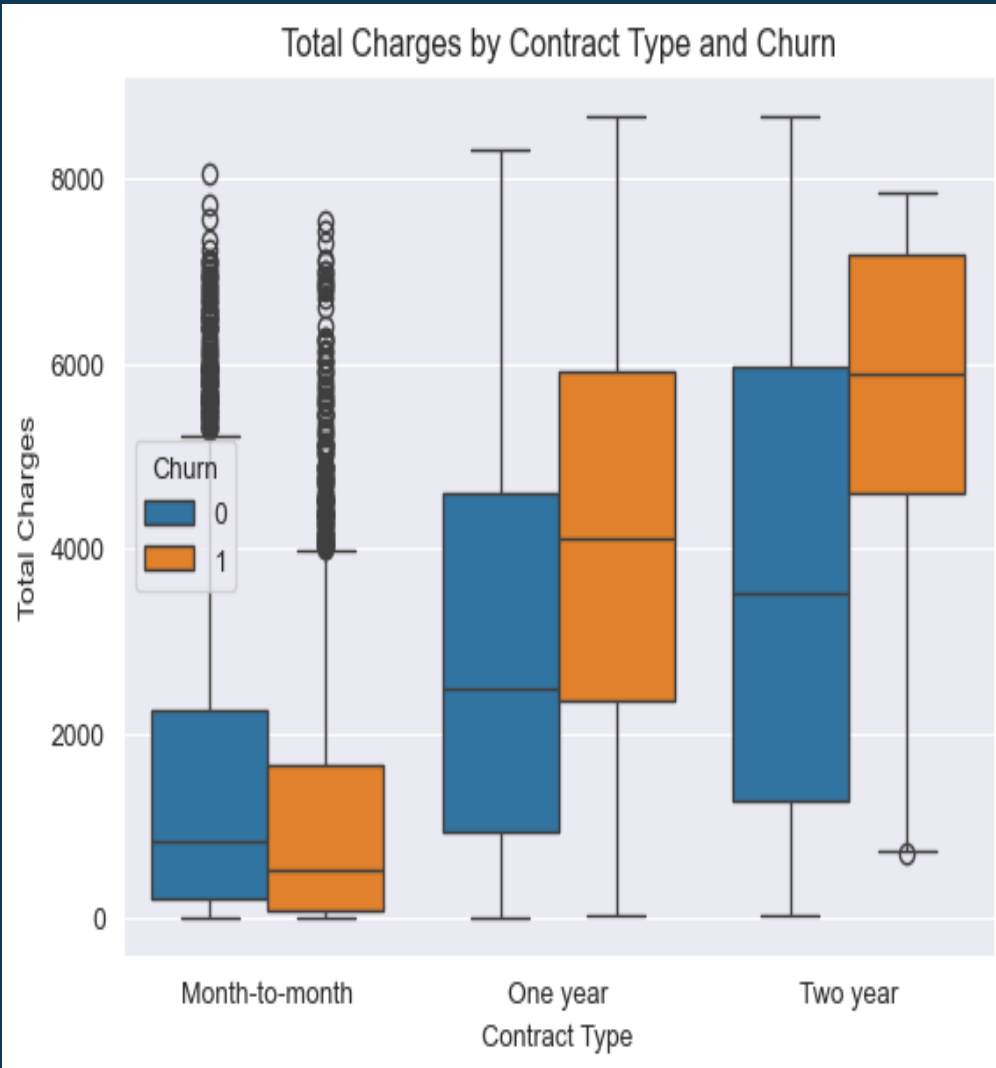
Data Analysis – Tenure Insights

Tenure Distribution by Churn



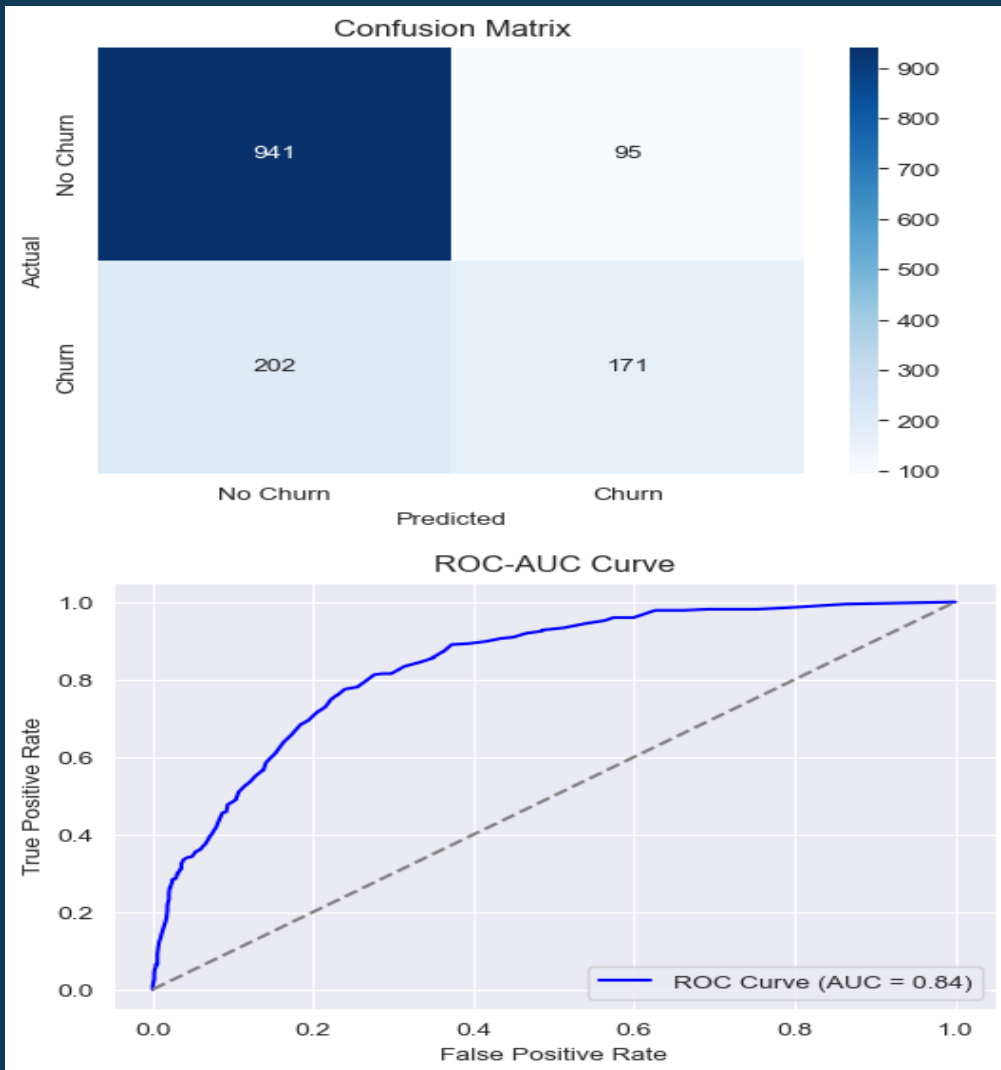
- Short-tenure customers (those with fewer months of service) have a significantly higher likelihood of churning.
- New customers may feel uncertain about the value or quality of the service during the initial months.
- Early churn suggests possible gaps in onboarding, support, or initial expectations not being met.
- Long-tenure customers are more likely to stay, indicating loyalty builds over time with positive experiences.

Data Analysis – Total Charges Insights



- Long-term contracts (1-year, 2-year) are associated with higher total charges but significantly lower churn rates, indicating customer loyalty.
- Month-to-month contracts have higher churn rates due to their flexibility, making it easier for customers to leave.
- Promoting long-term contracts with incentives or discounts could help reduce churn while maintaining revenue stability.

Predictive Modeling



Model Accuracy: 0.79

F1-Score: 0.54

Classification Report:

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.82 | 0.91 | 0.86 | 1036 |
| 1 | 0.64 | 0.46 | 0.54 | 373 |
| accuracy | | | 0.79 | 1409 |
| macro avg | 0.73 | 0.68 | 0.70 | 1409 |
| weighted avg | 0.78 | 0.79 | 0.78 | 1409 |

- The Random Forest model achieved an accuracy of 79%, an F1-score of 0.54, and an ROC-AUC of 0.84, showing moderate performance in churn prediction.
- Precision (0.82 for non-churn, 0.64 for churn) and recall (0.91 for non-churn, 0.46 for churn) highlight the model's strength in predicting non-churn but limitations for churned customers.
- Enhancing the model through techniques like addressing class imbalance can improve its effectiveness in driving retention strategies and reducing churn.

Retention Strategies



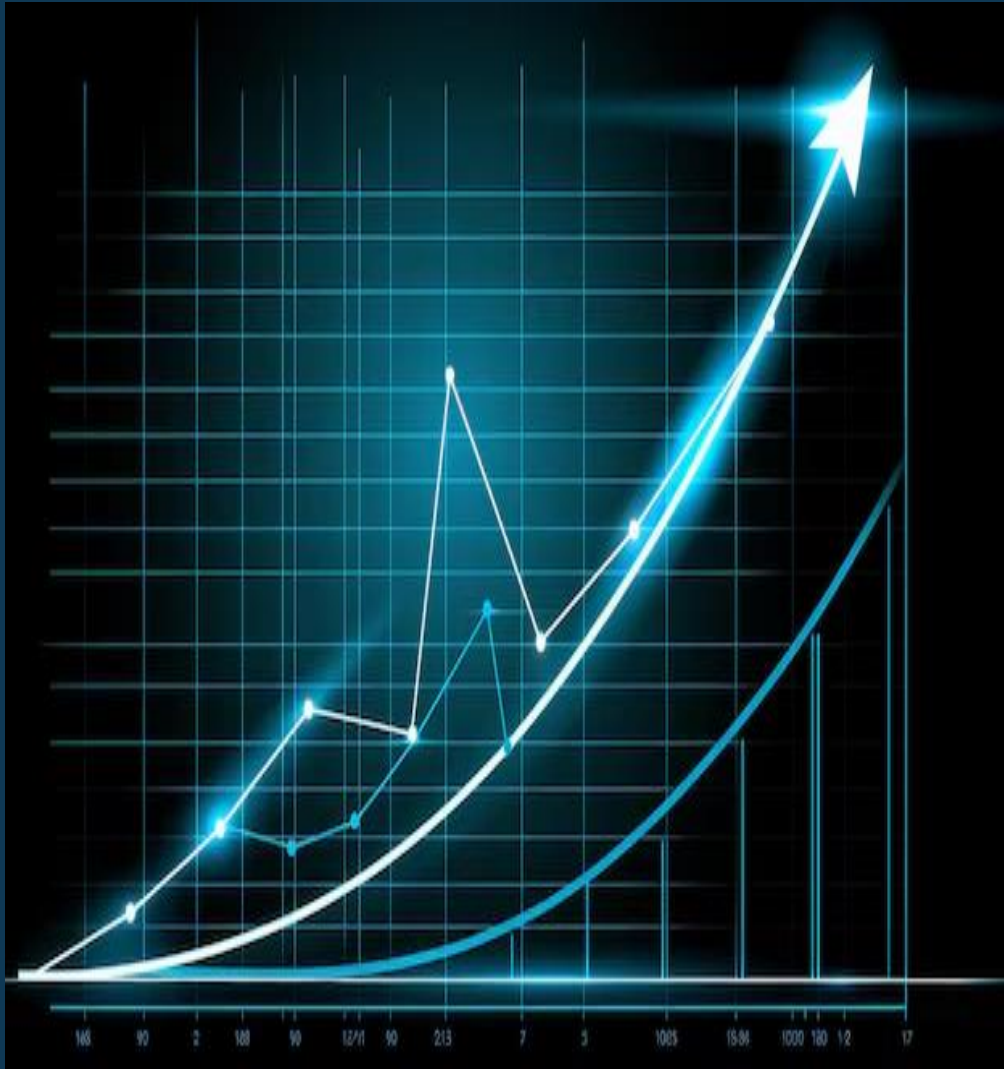
- Provide attractive discounts and incentives to encourage customers to opt for long-term contracts, fostering loyalty.
- Enhance service quality and tailored support for senior citizens, a demographic that may require additional attention.
- Introduce flexible pricing plans to address cost-related concerns and retain price-sensitive customers.
- Implement proactive monitoring systems to identify customer issues early and resolve complaints swiftly to improve satisfaction.

Challenges and Ethical Considerations



- Manage class imbalance effectively by applying techniques like SMOTE to improve model accuracy for underrepresented churn cases.
- Ensure fairness in predictions by mitigating potential biases in the data and algorithms.
- Safeguard customer privacy through robust data security measures and compliance with regulations.
- Promote transparency in model outcomes to build trust and support ethical decision-making.

Conclusion



- Tenure, contract type, and monthly charges are the most influential predictors of customer churn.
- Implementing targeted strategies based on these predictors can effectively reduce churn rates and enhance retention.
- The model's strong performance offers actionable insights to drive data-informed decision-making.
- Leveraging these insights enables businesses to focus on high-impact areas for improving customer satisfaction and loyalty.

Future Directions



- Implement real-time churn prediction systems to proactively identify at-risk customers and take timely action.
- Integrate predictive analytics with CRM platforms to enable personalized customer engagement and targeted retention efforts.
- Enhance the dataset by incorporating additional behavioral attributes to improve model accuracy and insight depth.
- Use advanced analytics to continuously refine retention strategies and address emerging customer needs.



Thank You