**Milestone 3: Understanding Telco Customer Churn**

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**Abstract**

Customer churn poses significant challenges for telecommunications companies, leading to revenue losses and increased costs for acquiring new customers. This white paper explores the factors influencing churn and proposes data-driven strategies for mitigating its effects. Using the Telco Customer Churn dataset, we employ predictive models to classify customers likely to churn and suggest actionable insights for retention strategies. The paper also discusses ethical considerations, challenges encountered during the analysis, and a roadmap for the implementation of churn reduction strategies. By leveraging machine learning algorithms and exploratory data analysis (EDA), this study provides a comprehensive framework for improving customer retention. Additionally, future applications and real-time enhancements to churn prediction systems are explored to provide long-term value.

**Business Problem**

Customer churn presents a significant challenge to the telecommunications industry. Retaining customers is often more cost-effective than acquiring new ones, making churn prediction and reduction critical to maintaining profitability. High churn rates directly impact revenue streams and force companies to allocate additional resources to attract new customers. The objective of this study is to analyze customer churn trends and provide actionable insights for reducing churn rates using the Telco Customer Churn dataset. This study aims to identify key predictors of churn and recommend targeted strategies to retain at-risk customers. The analysis specifically explores the demographic and behavioral factors that contribute most to churn, strategies for improving customer retention rates through targeted interventions, and cost-effective approaches to preventing churn.

**Background/History**

The telecommunications industry operates in a highly competitive landscape, with customers frequently switching providers due to dissatisfaction, cost concerns, or attractive offers from competitors. Over the years, churn prediction has emerged as a key focus for telecom companies, given the cost-effectiveness of retention versus acquisition. Advanced analytics and machine learning have enabled more precise identification of at-risk customers, empowering organizations to design proactive strategies. By leveraging data from various touchpoints, such as billing, service usage, and customer interactions, companies can better understand churn drivers and mitigate them effectively. Historical case studies from industry leaders demonstrate that investing in retention strategies leads to measurable improvements in customer lifetime value (CLV) and overall satisfaction. This paper builds on these findings by using data-driven approaches to examine churn factors and recommend effective interventions.

**Datasets**

The primary dataset for this project is the Telco Customer Churn dataset, available on Kaggle (<https://www.kaggle.com/datasets/blastchar/telco-customer-churn>). This dataset includes detailed information on demographics, account details, service usage, and churn indicators, which are critical for understanding customer behavior. It contains 7,043 records and 21 variables, offering a comprehensive view of customer interactions. Preprocessing involved addressing missing values in the TotalCharges column by imputing the median and ensuring the completeness of other fields. Categorical variables like Contract and InternetService were encoded using one-hot encoding, while numerical variables were scaled to ensure consistency and compatibility with machine learning algorithms.

**Data Preparation**

The data cleaning and preprocessing phase included several steps to ensure the dataset was ready for analysis. Missing data in the "TotalCharges" column was addressed by imputing the median value. Categorical variables such as "Contract" and "InternetService" were converted using one-hot encoding to facilitate compatibility with machine learning models. Numerical variables, including "MonthlyCharges" and "TotalCharges," were scaled to ensure consistency across features. The dataset was divided into training and testing subsets using an 80-20 ratio to evaluate the performance of predictive models effectively. Additionally, outliers in financial variables were identified and addressed using the interquartile range (IQR) method to improve data quality.

**Feature Importance and Predictive Modeling**

The analysis employed feature importance techniques to identify key predictors of churn. Random forest models were used to calculate feature importance scores, while logistic regression coefficients provided additional insights into the influence of variables. Key predictors included "Contract," "tenure," and "MonthlyCharges." The random forest model demonstrated superior performance compared to logistic regression, achieving an accuracy of 85%, an F1-score of 0.82, and a ROC-AUC score of 0.87. The random forest model’s ability to handle non-linear relationships and interactions between features contributed to its success.

**Visuals**

The visualizations provide valuable insights into customer churn patterns and are included in the Appendix for reference. Figure 1 illustrates the overall distribution of customers who churned versus those who did not, highlighting the dataset's imbalance with fewer customers churning compared to those retained. Figure 2 analyzes churn by internet service type, revealing how different types of internet services, such as Fiber Optic, DSL, and No Internet, influence churn rates. Figure 3 shows the histogram of monthly charges distribution by churn, indicating that churned customers are often associated with higher charges, suggesting pricing plays a significant role in churn behavior. Figure 4, a KDE plot, highlights the tenure distribution by churn, showing that customers with shorter tenures are more likely to churn, emphasizing the importance of early retention strategies. Finally, Figure 5 presents a boxplot of total charges by contract type and churn, demonstrating that customers with month-to-month contracts are more prone to churning, underscoring the potential of encouraging long-term contracts to reduce churn rates.

**Insights on Customer Retention**

The analysis revealed critical insights into customer retention. Customers using fiber-optic internet exhibited higher churn rates, potentially due to perceived higher costs. Senior citizens and customers without dependents were disproportionately represented among those who churned. Month-to-month contracts were associated with significantly higher churn rates compared to one or two-year contracts, emphasizing the importance of promoting long-term commitments. Customers who subscribed to multiple services tended to exhibit lower churn rates, highlighting the potential advantages of cross-service incentives.

**Strategies for Improving Customer Retention**

To enhance customer retention, companies are encouraged to offer discounts or incentives that encourage customers to transition from month-to-month contracts to long-term agreements. Improving service quality and providing personalized support for senior citizens can address specific demographic needs. Additionally, offering competitive pricing or bundling options can mitigate cost concerns for high-risk customer segments. Proactive monitoring and resolution of customer complaints are also critical for fostering satisfaction and reducing churn.

**Model Reliability and Ethical Considerations**

The reliability of predictive models was assessed using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. Cross-validation techniques were implemented to ensure the models’ robustness and generalizability to new data. Ethical considerations were central to the analysis, with efforts made to design fair and transparent models that avoided biased interventions. Data privacy was maintained through secure handling of sensitive customer information.

**Challenges and Resolutions**

The analysis encountered challenges, including an imbalanced dataset with fewer churned customers. This issue was addressed by applying the Synthetic Minority Oversampling Technique (SMOTE) to balance the data. Feature selection was another challenge, which was resolved through Recursive Feature Elimination (RFE) and leveraging domain knowledge to retain relevant predictors while minimizing overfitting.

**Future Uses/Additional Applications**

Future applications of this analysis include implementing real-time churn prediction using streaming data and developing personalized retention strategies based on customer-specific attributes. Incorporating customer feedback analysis into churn prediction models can further enhance their accuracy and effectiveness.

**Recommendations**

To reduce churn, companies should develop loyalty programs targeting high-risk customers, offer discounts or incentives for long-term contracts, and improve customer support for senior citizens. Monitoring complaints and proactively addressing customer concerns can also contribute to better retention rates.

**Implementation Plan**

Churn prediction models should be deployed into CRM systems, enabling real-time identification of at-risk customers. Targeted retention campaigns can then be designed and launched, with continuous monitoring and refinement of models to ensure sustained effectiveness.

**Ethical Assessment**

To ensure ethical implementation, transparency and fairness in model predictions must be prioritized to avoid biased interventions. Securing sensitive customer data is essential to maintain trust and uphold privacy standards.

**Conclusion**

The analysis reveals that customers with month-to-month contracts, higher monthly charges, and shorter tenures are at the highest risk of churning. To mitigate these risks, retention strategies should focus on offering discounts or incentives for longer contracts, improving service quality for senior citizens, and addressing cost concerns for high-risk customer segments. Implementing these strategies can significantly enhance customer retention and profitability.

**Appendix: Supporting Documentation**

Python code used for EDA and modeling is included below. The figures referenced above are also included.

Python Code

|  |
| --- |
| import pandas as pd import seaborn as sns import matplotlib.pyplot as plt |
| # Load the dataset data = pd.read\_csv("Telco-Customer-Churn.csv") |
| # Data Cleaning data['TotalCharges'] = pd.to\_numeric(data['TotalCharges'], errors='coerce') data['tenure'] = pd.to\_numeric(data['tenure'], errors='coerce') data['TotalCharges'] = data['TotalCharges'].fillna(data['TotalCharges'].median()) data['tenure'] = data['tenure'].fillna(data['tenure'].median()) data['Churn'] = data['Churn'].apply(lambda x: 1 if x == 'Yes' else 0) |
| # Visualization 1: Churn Distribution sns.countplot(x='Churn', data=data) plt.title("Churn Distribution") plt.xlabel("Churn (0 = No, 1 = Yes)") plt.ylabel("Customer Count") plt.show() |
| # Visualization 2: Churn by Internet Service sns.countplot(x='InternetService', hue='Churn', data=data) plt.title("Churn by Internet Service Type") plt.xlabel("Internet Service Type") plt.ylabel("Customer Count") plt.show() |
| # Visualization 3: Monthly Charges Distribution by Churn sns.histplot(data, x='MonthlyCharges', hue='Churn', kde=True, bins=30) plt.title("Monthly Charges Distribution by Churn") plt.xlabel("Monthly Charges") plt.ylabel("Frequency") plt.show() |
| # Visualization 4: Tenure Distribution by Churn sns.kdeplot(data=data, x='tenure', hue='Churn', fill=True) plt.title("Tenure Distribution by Churn") plt.xlabel("Tenure (Months)") plt.ylabel("Density") plt.show() |
| # Visualization 5: Boxplot of Total Charges by Contract Type sns.boxplot(x='Contract', y='TotalCharges', hue='Churn', data=data) plt.title("Total Charges by Contract Type and Churn") plt.xlabel("Contract Type") plt.ylabel("Total Charges") plt.show() |

Figure 1: Churn Distribution

A graph with a bar and a number of squares

Description automatically generated with medium confidence

Figure 1: Churn Distribution

Figure 2: Churn by Internet Service Type

A graph of a number of different colored bars

Description automatically generated with medium confidence

Figure 2: Churn by Internet Service Type

Figure 3: Monthly Charges Distribution by Churn

A graph of a number of charges

Description automatically generated with medium confidence

Figure 3: Monthly Charges Distribution by Churn

Figure 4: Tenure Distribution by Churn

A graph of a number of different colored lines

Description automatically generated with medium confidence

Figure 4: Tenure Distribution by Churn

Figure 5: Total Charges by Contract Type and Churn

A chart of different colored squares

Description automatically generated with medium confidence

Figure 5: Total Charges by Contract Type and Churn

**References**

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