Customer Churn Analytics Report
Detailed Data Analysis and Marketing Insights

Your Name

June 28, 2025

Contents

1 Introduction

This report details an end-to-end churn prediction analysis for a telecommunications company, combining exploratory data analysis (EDA), preprocessing, and modeling. A particular emphasis is placed on interpretability of the tuned Logistic Regression model, as its performance and coefficients provide actionable marketing insights.

2 Dataset Overview

The raw dataset contains **7,043 records** and 21 features. After removing rows with missing `TotalCharges`, we retained 7,032 records for analysis. The dataset represents customer profiles from a telecommunications company, including demographics, account details, services subscribed, billing, and churn labels.

2.1 Feature Summary

Table 1: Dataset Features and Descriptions

Feature	**Type**	**Description**
customerID	ID	Unique customer identifier (dropped before modeling)
gender	Categorical	Customer gender (Male/Female)
SeniorCitizen	Binary (0/1)	Indicates if the customer is a senior (1=yes)
Partner	Categorical	Whether the customer has a partner (Yes/No)
Dependents	Categorical	Whether the customer has dependents (Yes/No)
tenure	Numerical	Number of months the customer has stayed
PhoneService	Categorical	Whether the customer has phone service (Yes/No)
MultipleLines	Categorical	Multiple phone lines (Yes, No, No phone service)
InternetService	Categorical	Type of internet service (DSL, Fiber optic, No)
OnlineSecurity	Categorical	Online security add-on (Yes, No, No internet service)
OnlineBackup	Categorical	Online backup add-on (Yes, No, No internet service)
DeviceProtection	Categorical	Device protection add-on (Yes, No, No internet service)
TechSupport	Categorical	Technical support add-on (Yes, No, No internet service)
StreamingTV	Categorical	Streaming TV add-on (Yes, No, No internet service)
StreamingMovies	Categorical	Streaming movies add-on (Yes, No, No internet service)
Contract	Categorical	Contract type (Month-to-month, One year, Two year)
PaperlessBilling	Categorical	Whether paperless billing is enabled (Yes/No)
PaymentMethod	Categorical	Payment method (Electronic check, Mailed check, Bank transfer automatic, Credit card automatic)
MonthlyCharges	Numerical	Current monthly billing amount (USD)
TotalCharges	Numerical	Total amount charged during tenure (USD)
Churn	Binary (Yes/No)	Target: whether the customer left the company

2.2 Key Statistics

- **Churn Rate**: Approximately 26.5% of customers have churned.
- **Contract Types**: 55% month-to-month, 22% one-year, 23% two-year.
- **Internet Services**: 44% DSL, 34% Fiber optic, 22% no internet service.
- **Senior Citizens**: About 16% of customers are senior citizens (SeniorCitizen=1).
- **TotalCharges** ranges from $18.80 to over $8,600.

2.3 Data Cleaning

Essential data cleaning tasks were performed to ensure data quality and consistency:

1. **Missing Values**: Detected and removed 11 rows with missing or blank `TotalCharges` values, reducing the dataset from 7,043 to 7,032 records.
2. **Data Type Conversion**: Converted `TotalCharges` from object to numeric format.
3. **Duplicate Check**: Verified no duplicate rows existed in the dataset (0 duplicates found).
4. **Outlier Detection**: Boxplots of numerical features (`tenure`, `MonthlyCharges`, `TotalCharges`) showed no extreme outliers requiring removal, but revealed different scales across variables, highlighting the need for scaling prior to modeling (see Figure 1).
5. **Cardinality Check**: Examined all categorical columns to confirm expected unique value counts and identify potential data entry issues; none were found.

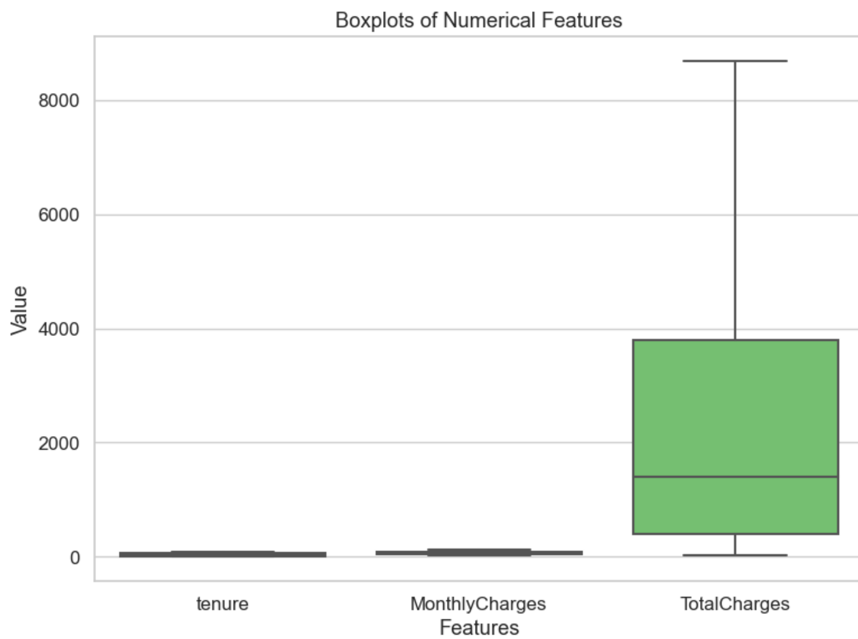

Figure 1: Boxplots of `tenure`, `MonthlyCharges`, and `TotalCharges`. No extreme outliers observed; differences in feature scale justified scaling prior to modeling.

2.4 Feature Engineering and Preprocessing

To prepare the cleaned data for modeling, the following feature engineering and preprocessing steps were completed:

1. **Feature Dropping**: Removed `customerID` as it carried no predictive value.
2. **Target Encoding**: Encoded the target variable `Churn` as binary (0=No, 1=Yes).
3. **Encoding Categorical Features**:
   - Applied Label Encoding to binary categorical features (`gender`, `Partner`, `Dependents`, `PhoneService`, `PaperlessBilling`).
   - Applied One-Hot Encoding to multi-class categorical features (`MultipleLines`, `InternetService`, `OnlineSecurity`, `OnlineBackup`, `DeviceProtection`, `TechSupport`, `StreamingTV`, `StreamingMovies`, `Contract`, `PaymentMethod`), using drop-first to avoid multicollinearity.
4. **Scaling**: Standardized numerical features (`tenure`, `MonthlyCharges`, `TotalCharges`) with `StandardScaler` to ensure comparable scales across predictors.
5. **Train-Test Split**: Split the dataset into training (80%) and test (20%) sets with stratification on churn, resulting in 5,625 training records and 1,407 test records. The final processed feature set consisted of 30 columns.

3 Exploratory Data Analysis (EDA)

3.1 Churn Distribution

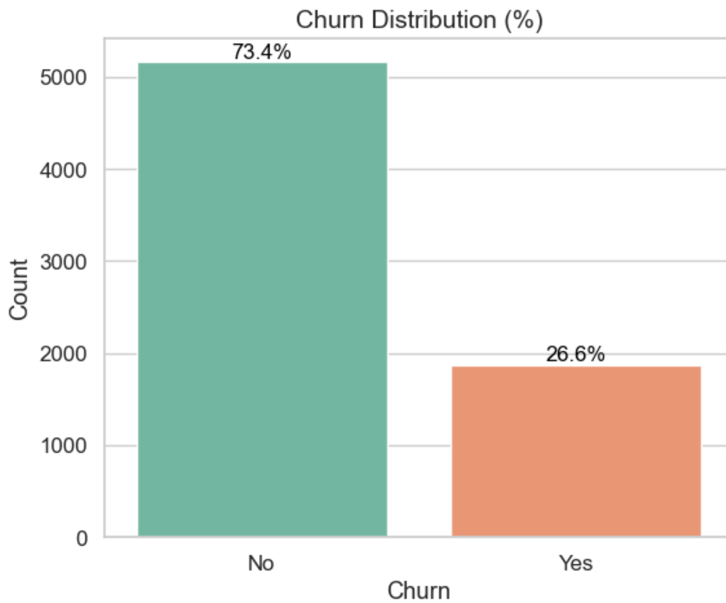

Figure 2: Churn distribution with percentage annotations, showing class imbalance in the dataset.

3.2 Monthly Charges and Churn

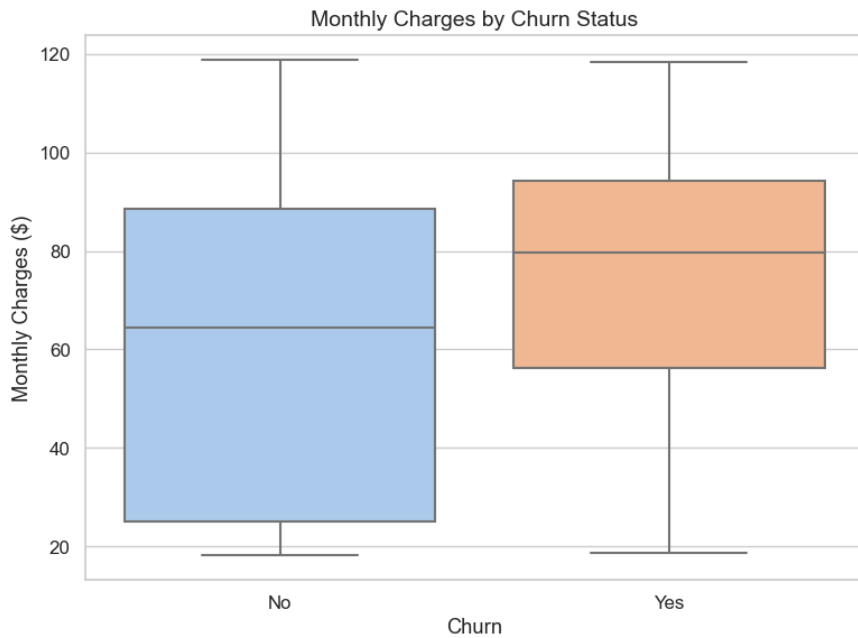

Figure 3: Boxplot of monthly charges by churn status. Customers who churn tend to have higher monthly charges.

3.3 Contract Type and Churn

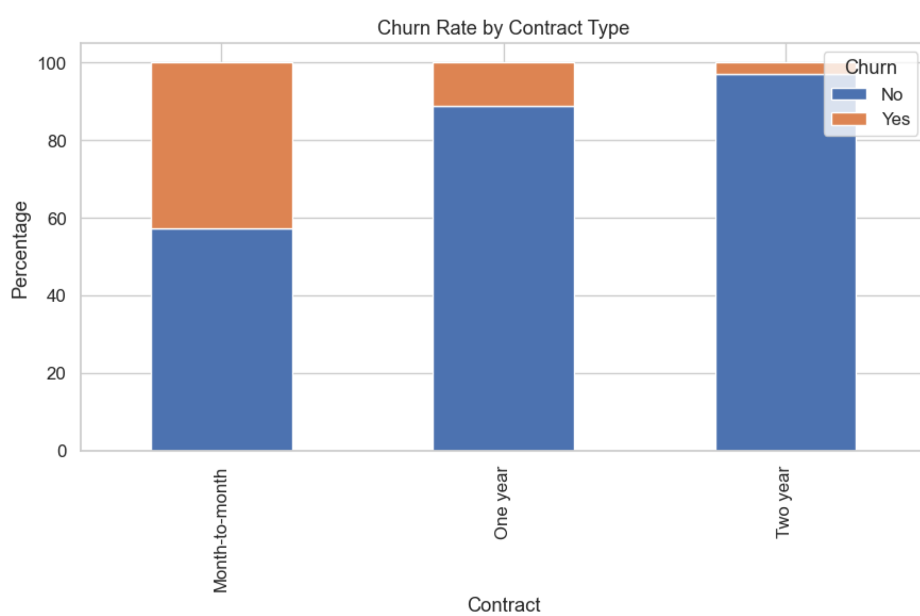

Figure 4: Stacked bar chart showing churn percentage by contract type. Month-to-month contracts have a significantly higher churn rate compared to longer-term contracts.

3.4 Correlation Heatmap

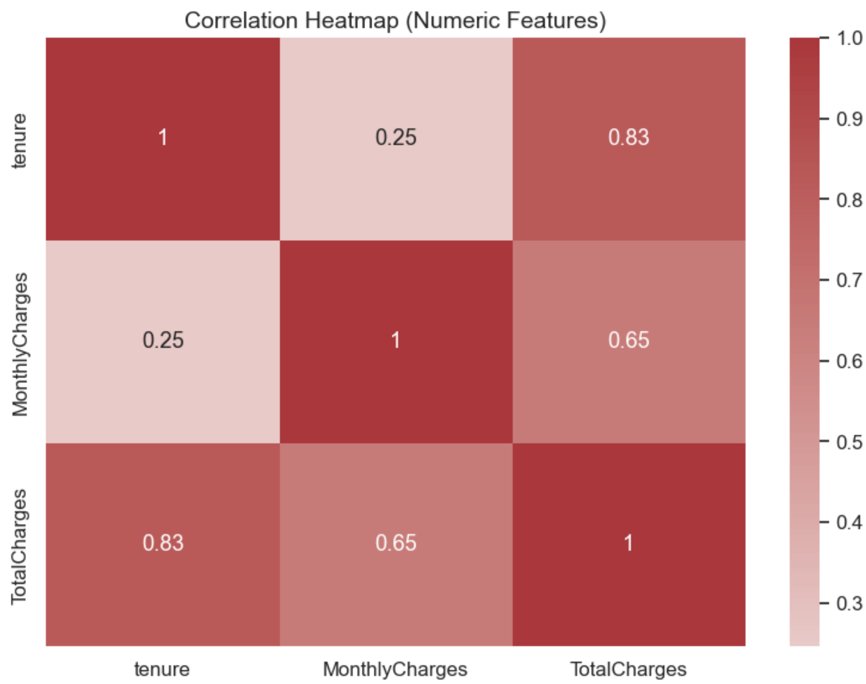

Figure 5: Correlation heatmap of numeric features including churn. Tenure and total charges are highly correlated. Monthly charges show a moderate relationship with churn.

4 Modeling and Evaluation

Three classifiers were trained:

- Logistic Regression
- Decision Tree
- Random Forest

Their test performance is summarized in Table 2, highlighting Logistic Regression as the best-balanced model.

Table 2: Model Performance on Test Data

Model	**Accuracy**	**F1 Score**	**ROC AUC**
Logistic Regression	0.805	0.609	0.836
Decision Tree	0.711	0.454	0.629
Random Forest	0.787	0.558	0.814

5 Tuned Logistic Regression

GridSearchCV selected the best hyperparameters: `C=10`, `penalty=l2`, `solver=liblinear`. Cross-validation confirmed model stability with mean ROC AUC of 0.8443 (standard deviation 0.0100).

5.1 ROC Curve

Figure 6 shows the ROC curve, demonstrating strong model discrimination.

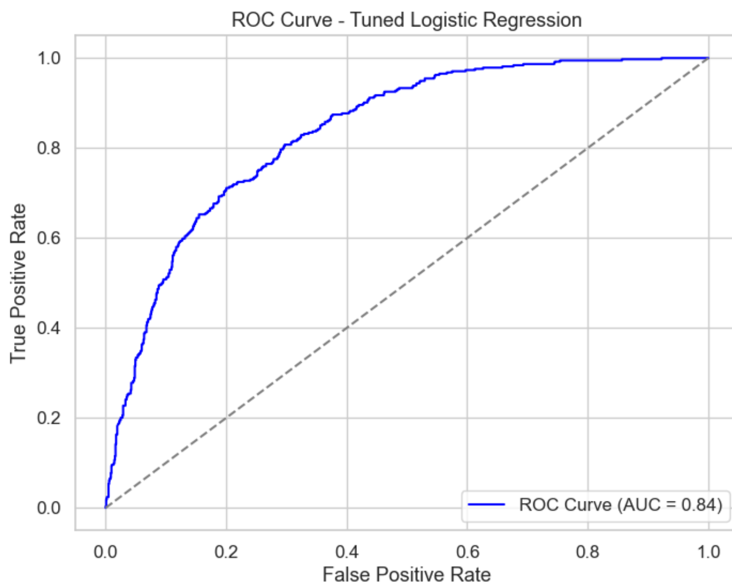

Figure 6: ROC Curve for Tuned Logistic Regression

6 Feature Importance: Coefficients and Odds Ratios

Figures 7 and 8 display the magnitude and direction of each feature's effect on churn probability. Features with coefficients > 0 increase churn likelihood (odds ratio > 1), while coefficients < 0 reduce churn risk (odds ratio < 1).

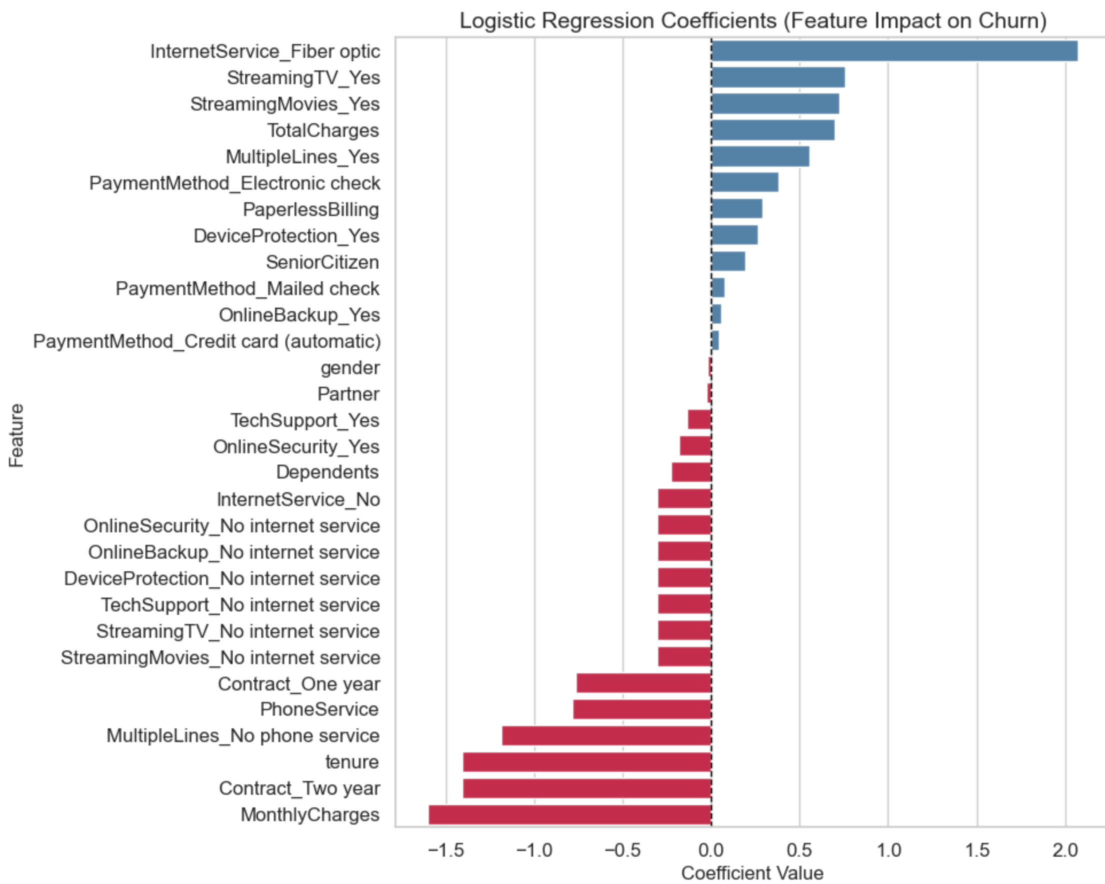

Figure 7: Logistic Regression Coefficients by Feature

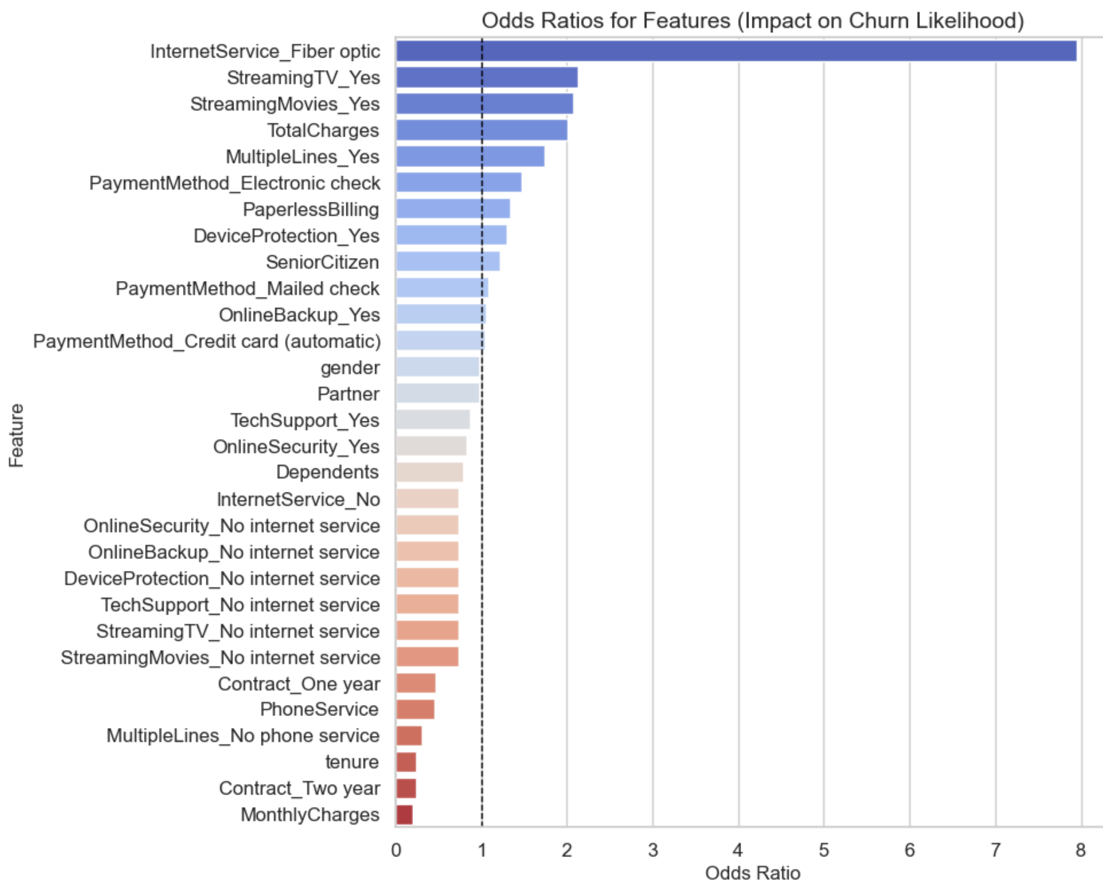

Figure 8: Odds Ratios of Features (Impact on Churn Likelihood)

Table 3: Top Features with Coefficients and Odds Ratios

Feature	**Coefficient**	**Odds Ratio**
InternetService_Fiber optic	2.07	7.95
StreamingTV_Yes	0.75	2.13
StreamingMovies_Yes	0.73	2.07
TotalCharges	0.70	2.01
MultipleLines_Yes	0.56	1.74
MonthlyCharges	-1.60	0.20
Contract_Two year	-1.41	0.24
tenure	-1.40	0.25
MultipleLines_No phone service	-1.19	0.31
Contract_One year	-0.76	0.47

7 Interpretation

- **Positive influencers on churn**: Customers with `Fiber optic` internet or who have enabled `StreamingTV/Movies` are significantly more likely to churn (odds ratios > 2).
- **Negative influencers on churn**: Longer tenure, multi-year contracts, and lower monthly charges reduce churn risk considerably (odds ratios well below 1).
- Odds ratios near 1 (e.g., gender, partner status) have minimal influence on churn.

8 Marketing Recommendations

Based on the feature importances:

1. **Retention focus on fiber optic customers**, as they show the highest churn odds; exclusive loyalty offers or service bundling may improve retention.
2. **Encourage longer contracts**, especially two-year plans, since customers with these plans have over 75% lower odds of churning.
3. **Early intervention for high-monthly-charge customers**: proactive engagement within their first months can lower churn risk.
4. **Upsell tech support and security services**: while features like TechSupport_Yes reduce churn, many customers lack these services — converting them could aid retention.

9 Conclusion

The tuned Logistic Regression model provides a robust, interpretable approach to predict churn. Leveraging actionable insights from coefficients and odds ratios enables targeted marketing strategies that can materially reduce churn and improve customer lifetime value.

Contact

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A Appendix: Full Notebook Code

ML for marketing

June 28, 2025

1 1 Project Overview & Objectives

- Project Goal: Analyze customer data from a telecommunications company to uncover patterns related to customer churn.
- Business Objective: Identify drivers of churn to inform marketing strategies that reduce customer attrition.
- Dataset: telco.csv with customer demographics, services subscribed, and churn labels.

2 2 Setup & Libraries

[37]:
```
# Basic
import pandas as pd
import numpy as np

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Preprocessing & Modeling
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪roc_auc_score, roc_curve, accuracy_score, precision_score, recall_score,␣
 ↪f1_score, auc
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
# Hyperparameter Tuning
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV

# Config
pd.set_option('display.max_columns', None)
sns.set(style='whitegrid', palette='muted', font_scale=1.1)
```

3 3 Data Loading

[2]:
```python
# Load dataset
telco_raw = pd.read_csv(r"C:
↪\Users\USER\Documents\my_DS_projects\SUPERVISED\CLASSIFICATION\ML for␣
↪Marketing\telco.csv")

# Quick check
telco_raw.head()
```

[2]:
```
   customerID  gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  7590-VHVEG  Female              0     Yes         No       1           No
1  5575-GNVDE    Male              0      No         No      34          Yes
2  3668-QPYBK    Male              0      No         No       2          Yes
3  7795-CFOCW    Male              0      No         No      45           No
4  9237-HQITU  Female              0      No         No       2          Yes

      MultipleLines InternetService OnlineSecurity OnlineBackup  \
0  No phone service             DSL             No          Yes
1                No             DSL            Yes           No
2                No             DSL            Yes          Yes
3  No phone service             DSL            Yes           No
4                No     Fiber optic             No           No

  DeviceProtection TechSupport StreamingTV StreamingMovies        Contract  \
0               No          No          No              No  Month-to-month
1              Yes          No          No              No        One year
2               No          No          No              No  Month-to-month
3              Yes         Yes          No              No        One year
4               No          No          No              No  Month-to-month

  PaperlessBilling              PaymentMethod  MonthlyCharges TotalCharges  \
0              Yes           Electronic check           29.85        29.85
1               No               Mailed check           56.95       1889.5
2              Yes               Mailed check           53.85       108.15
3               No  Bank transfer (automatic)           42.30      1840.75
4              Yes           Electronic check           70.70       151.65

  Churn
0    No
1    No
2   Yes
3    No
4   Yes
```

4 4 Data Understanding

[3]:
```
# Dataset shape
print(f"Shape: {telco_raw.shape}")

# Column types & non-null info
telco_raw.info()

# Descriptive stats (numerical features)
telco_raw.describe()

# Descriptive stats (categorical features)
telco_raw.describe(include='object')
```

```
Shape: (7043, 21)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   gender            7043 non-null   object
 2   SeniorCitizen     7043 non-null   int64
 3   Partner           7043 non-null   object
 4   Dependents        7043 non-null   object
 5   tenure            7043 non-null   int64
 6   PhoneService      7043 non-null   object
 7   MultipleLines     7043 non-null   object
 8   InternetService   7043 non-null   object
 9   OnlineSecurity    7043 non-null   object
 10  OnlineBackup      7043 non-null   object
 11  DeviceProtection  7043 non-null   object
 12  TechSupport       7043 non-null   object
 13  StreamingTV       7043 non-null   object
 14  StreamingMovies   7043 non-null   object
 15  Contract          7043 non-null   object
 16  PaperlessBilling  7043 non-null   object
 17  PaymentMethod     7043 non-null   object
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object
 20  Churn             7043 non-null   object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

[3]:
```
        customerID gender Partner Dependents PhoneService MultipleLines  \
count         7043   7043    7043       7043         7043          7043
unique        7043      2       2          2            2             3
top     7590-VHVEG   Male      No         No          Yes            No
```

```
freq              1   3555    3641       4933         6361           3390

       InternetService OnlineSecurity OnlineBackup DeviceProtection  \
count             7043           7043         7043             7043
unique               3              3            3                3
top        Fiber optic             No           No               No
freq              3096           3498         3088             3095

       TechSupport StreamingTV StreamingMovies        Contract  \
count         7043        7043            7043            7043
unique           3           3               3               3
top             No          No              No  Month-to-month
freq          3473        2810            2785            3875

       PaperlessBilling     PaymentMethod TotalCharges Churn
count              7043              7043         7043  7043
unique                2                 4         6531     2
top                 Yes  Electronic check                 No
freq               4171              2365           11  5174
```

Based on the output above the following was observed - The dataset has 7,043 rows and 21 columns, with many categorical features and some numerical ones. - `TotalCharges` is stored as an object, indicating potential data quality issues. - No missing values in most columns, but we need to confirm after converting `TotalCharges`. **Action Plan**:
- Convert `TotalCharges` to numeric and handle any missing values. - Encode categorical columns for modeling. - Drop unnecessary columns like `customerID`.

5 5 Data Cleaning

Key Tasks: - Check for missing values - Convert TotalCharges from object to numeric - Identify and handle inconsistent values - Checkign duplicates values - Checking outliers - Checking Cardinality

[4]:
```
# Missing values
telco_raw.isnull().sum()

# Convert 'TotalCharges' to numeric (coerce errors → NaN)
telco_raw['TotalCharges'] = pd.to_numeric(telco_raw['TotalCharges'],␣
 ↪errors='coerce')

# Recheck missing
telco_raw.isnull().sum()

# Remove rows with missing TotalCharges (or fill)
telco_raw.dropna(subset=['TotalCharges'], inplace=True)

# Confirm cleaning
```

```
telco_raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7032 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7032 non-null   object
 1   gender            7032 non-null   object
 2   SeniorCitizen     7032 non-null   int64
 3   Partner           7032 non-null   object
 4   Dependents        7032 non-null   object
 5   tenure            7032 non-null   int64
 6   PhoneService      7032 non-null   object
 7   MultipleLines     7032 non-null   object
 8   InternetService   7032 non-null   object
 9   OnlineSecurity    7032 non-null   object
 10  OnlineBackup      7032 non-null   object
 11  DeviceProtection  7032 non-null   object
 12  TechSupport       7032 non-null   object
 13  StreamingTV       7032 non-null   object
 14  StreamingMovies   7032 non-null   object
 15  Contract          7032 non-null   object
 16  PaperlessBilling  7032 non-null   object
 17  PaymentMethod     7032 non-null   object
 18  MonthlyCharges    7032 non-null   float64
 19  TotalCharges      7032 non-null   float64
 20  Churn             7032 non-null   object
dtypes: float64(2), int64(2), object(17)
memory usage: 1.2+ MB
```

We noticed that after cleaning the number of rows reduced from 7043 to 7032, that means about 11 rows were dropped as a result of the `TotalCharges` column. Now after cleaning we have a total of 4 numeric features and 17 objects features

5.1 Checking duplicates values

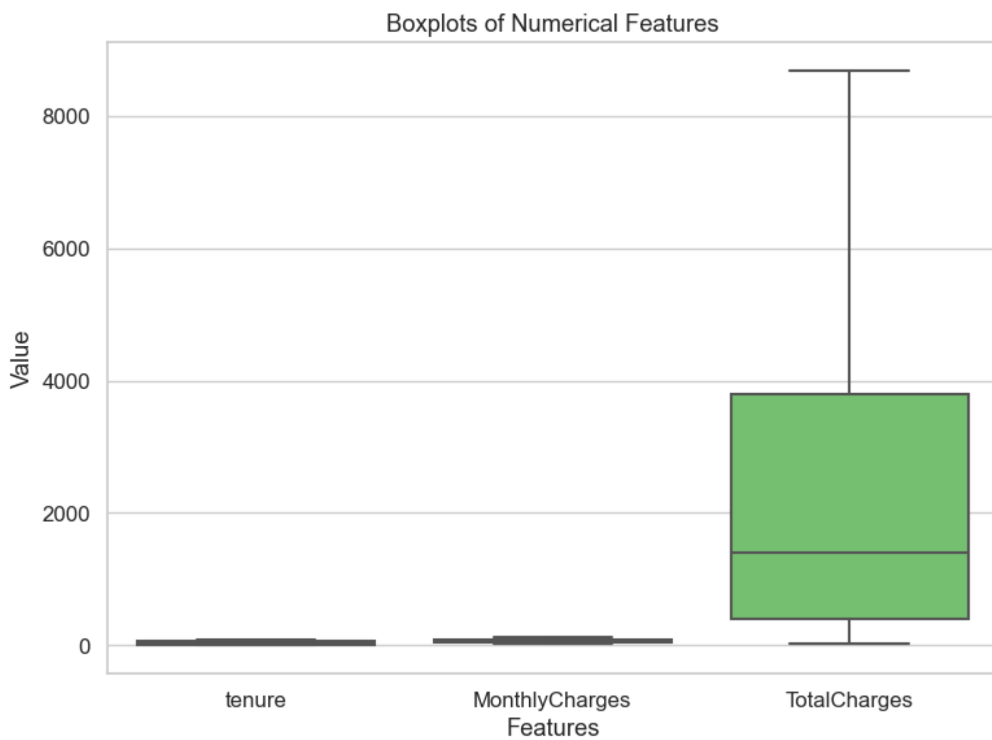
[5]:
```
# Check for duplicate rows based on all columns
duplicate_rows = telco_raw.duplicated().sum()
print(f"Total duplicate rows: {duplicate_rows}")
```

```
Total duplicate rows: 0
```

Even though each customer should have a unique customerID, it's wise to confirm

5.2 Checking for outliers

[6]:
```
# Numerical columns you want to compare
num_cols = ['tenure', 'MonthlyCharges', 'TotalCharges']

# Melt the dataframe to long format
telco_melted = telco_raw[num_cols].melt(var_name='Feature', value_name='Value')

# Create a single boxplot
plt.figure(figsize=(8, 6))
sns.boxplot(data=telco_melted, x='Feature', y='Value')
plt.title('Boxplots of Numerical Features')
plt.xlabel('Features')
plt.ylabel('Value')
plt.tight_layout()
plt.show()
```



We see that there isn't an issue of outlier but we need to adjust the scales before we go ahead with modeling.

5.3 Checking high cardinality

[7]:
```
# Select object columns
cat_cols = telco_raw.select_dtypes(include='object').columns

# Check unique values
for col in cat_cols:
    print(f"{col}: {telco_raw[col].nunique()} unique values")
```

```
customerID: 7032 unique values
gender: 2 unique values
Partner: 2 unique values
Dependents: 2 unique values
PhoneService: 2 unique values
MultipleLines: 3 unique values
InternetService: 3 unique values
OnlineSecurity: 3 unique values
OnlineBackup: 3 unique values
DeviceProtection: 3 unique values
TechSupport: 3 unique values
StreamingTV: 3 unique values
StreamingMovies: 3 unique values
Contract: 3 unique values
PaperlessBilling: 2 unique values
PaymentMethod: 4 unique values
Churn: 2 unique values
```

We do not have problematic high-cardinality categorical features, except `customerID` which we will need to drop now.

[8]:
```
telco_raw.drop('customerID', axis=1, inplace=True)
telco_raw.info()
```

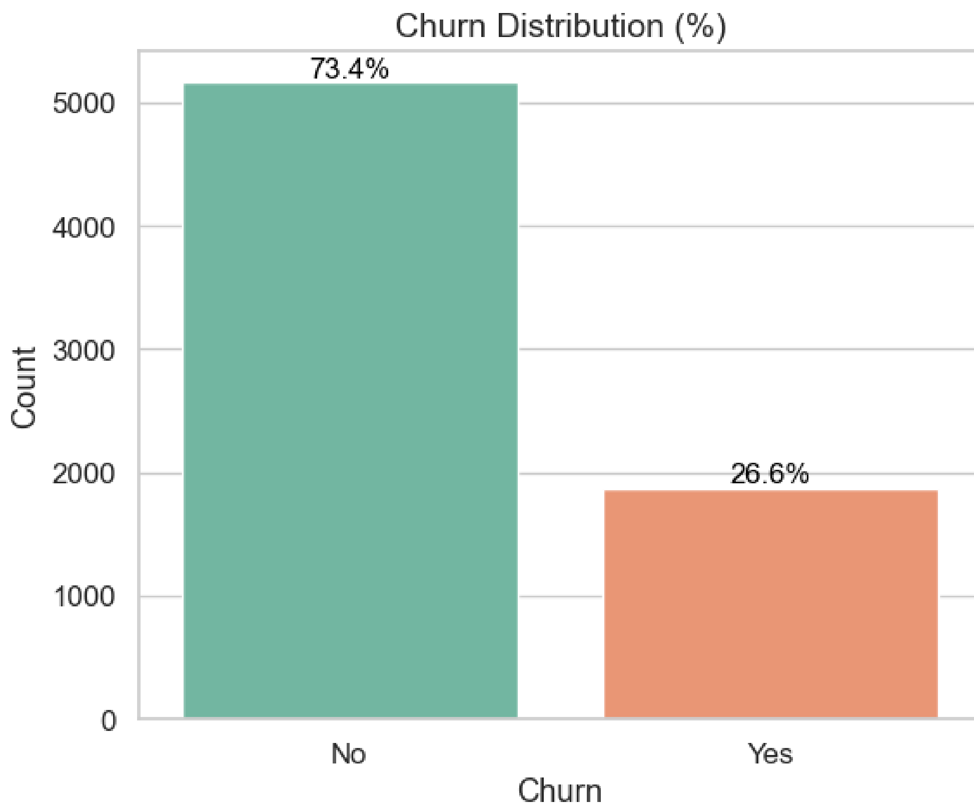
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7032 entries, 0 to 7042
Data columns (total 20 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   gender            7032 non-null   object
 1   SeniorCitizen     7032 non-null   int64
 2   Partner           7032 non-null   object
 3   Dependents        7032 non-null   object
 4   tenure            7032 non-null   int64
 5   PhoneService      7032 non-null   object
 6   MultipleLines     7032 non-null   object
 7   InternetService   7032 non-null   object
 8   OnlineSecurity    7032 non-null   object
 9   OnlineBackup      7032 non-null   object
 10  DeviceProtection  7032 non-null   object
```

```
 11  TechSupport       7032 non-null   object
 12  StreamingTV       7032 non-null   object
 13  StreamingMovies   7032 non-null   object
 14  Contract          7032 non-null   object
 15  PaperlessBilling  7032 non-null   object
 16  PaymentMethod     7032 non-null   object
 17  MonthlyCharges    7032 non-null   float64
 18  TotalCharges      7032 non-null   float64
 19  Churn             7032 non-null   object
dtypes: float64(2), int64(2), object(16)
memory usage: 1.1+ MB
```

6 6 Exploratory Data Analysis (EDA)

6.1 6.1 Target Variable (Churn)

[ ]:
```python
# Distribution of Churn
plt.figure(figsize=(6,5))
ax = sns.countplot(data=telco_raw, x='Churn', palette='Set2')
for p in ax.patches:
    height = p.get_height()
    ax.annotate(f'{100*height/len(telco_raw):.1f}%', (p.get_x()+p.get_width()/2.
 ↪, height),
                ha='center', va='bottom', fontsize=12, color='black')
plt.title('Churn Distribution (%)', fontsize=14)
plt.xlabel('Churn')
plt.ylabel('Count')
plt.tight_layout()
plt.show()
```



We noticed from the visuals above that there are more customers that did not churn.

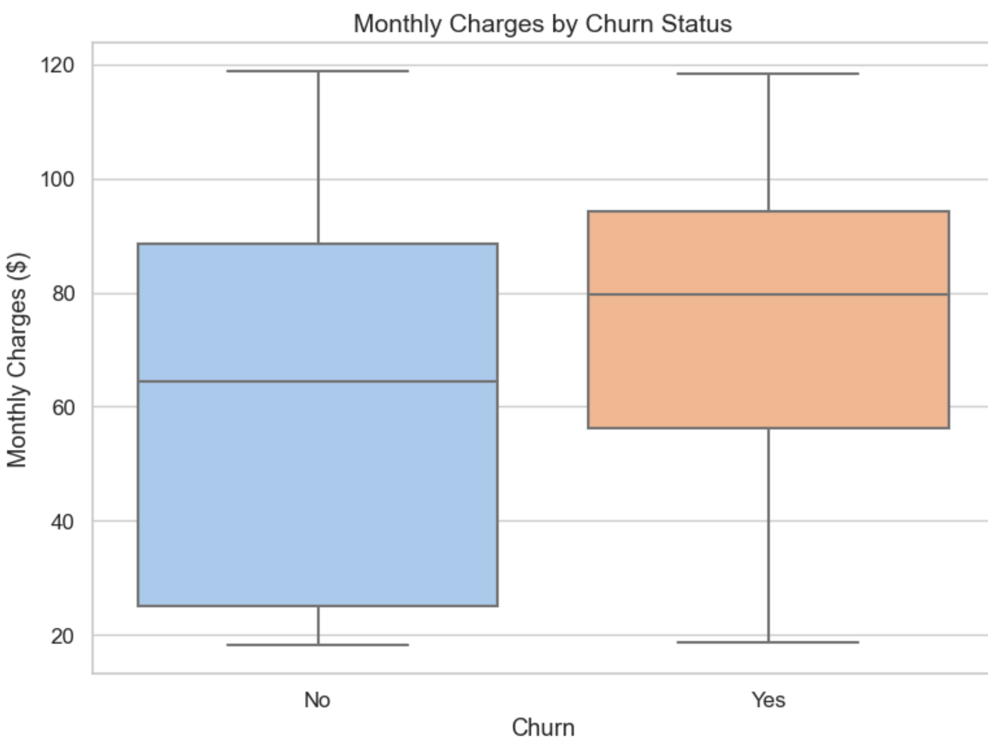
```
[ ]: telco_raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7032 entries, 0 to 7042
Data columns (total 20 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   gender            7032 non-null   object
 1   SeniorCitizen     7032 non-null   int64
 2   Partner           7032 non-null   object
 3   Dependents        7032 non-null   object
 4   tenure            7032 non-null   int64
 5   PhoneService      7032 non-null   object
 6   MultipleLines     7032 non-null   object
 7   InternetService   7032 non-null   object
 8   OnlineSecurity    7032 non-null   object
 9   OnlineBackup      7032 non-null   object
```

```
 10  DeviceProtection  7032 non-null   object
 11  TechSupport       7032 non-null   object
 12  StreamingTV       7032 non-null   object
 13  StreamingMovies   7032 non-null   object
 14  Contract          7032 non-null   object
 15  PaperlessBilling  7032 non-null   object
 16  PaymentMethod     7032 non-null   object
 17  MonthlyCharges    7032 non-null   float64
 18  TotalCharges      7032 non-null   float64
 19  Churn             7032 non-null   object
dtypes: float64(2), int64(2), object(16)
memory usage: 1.1+ MB
```

6.2 6.2 Monthly Charges vs. Churn (Boxplot)

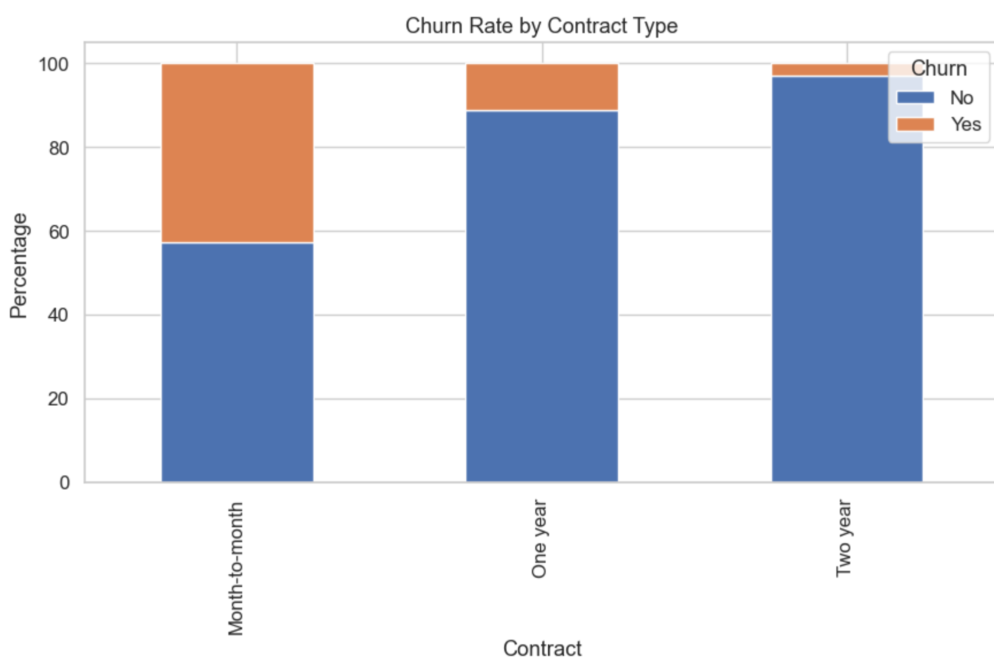
[ ]:
```
plt.figure(figsize=(8,6))
sns.boxplot(data=telco_raw, x='Churn', y='MonthlyCharges', palette='pastel')
plt.title('Monthly Charges by Churn Status', fontsize=14)
plt.xlabel('Churn')
plt.ylabel('Monthly Charges ($)')
plt.tight_layout()
plt.show()
```



10

6.3 6.3 Contract Type vs. Churn (Stacked Bar)

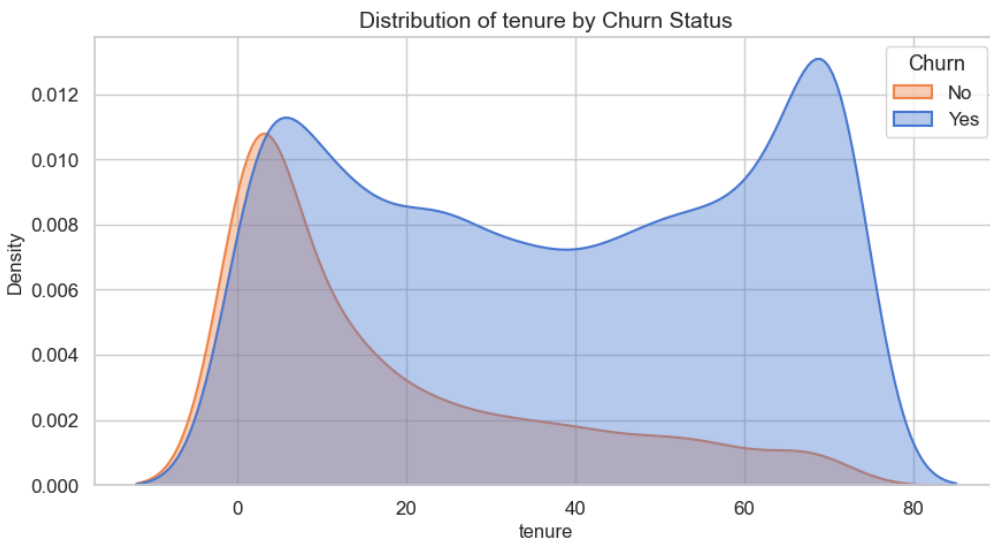
[ ]:
```
contract_churn = telco_raw.groupby(['Contract', 'Churn']).size().unstack().
 ↪fillna(0)
contract_churn_pct = contract_churn.div(contract_churn.sum(axis=1), axis=0) *␣
 ↪100

contract_churn_pct.plot(kind='bar', stacked=True, figsize=(9,6),
                        color=['#4C72B0', '#DD8452'])
plt.title('Churn Rate by Contract Type')
plt.ylabel('Percentage')
plt.legend(title='Churn', loc='upper right')
plt.tight_layout()
plt.show()
```

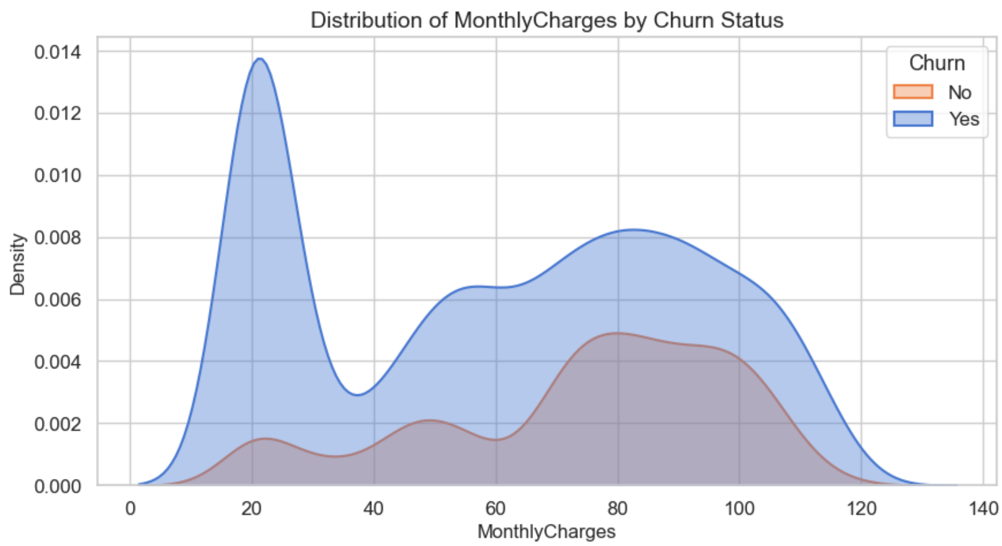


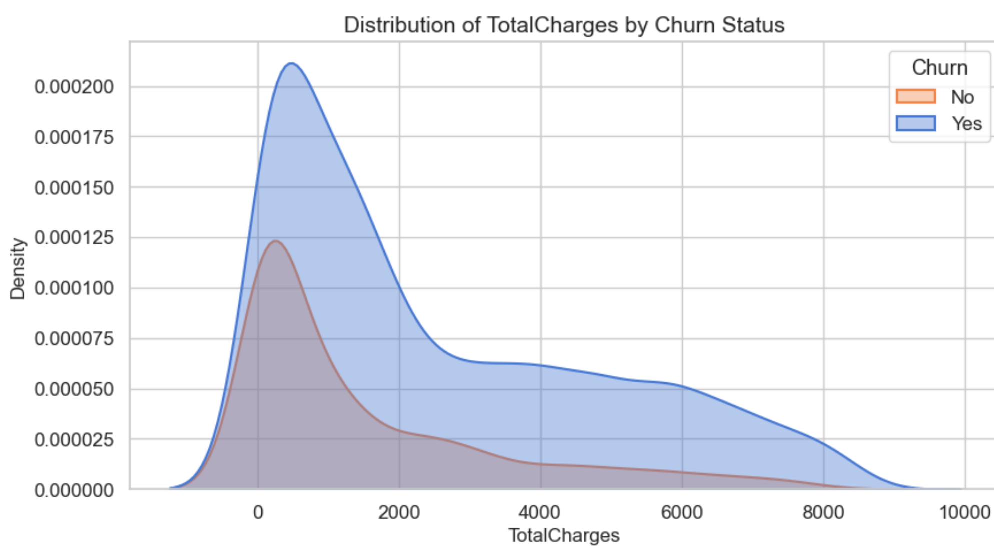
6.4 6.4 Numerical Features vs Churn

[ ]:
```
num_features = ['tenure', 'MonthlyCharges', 'TotalCharges']

for col in num_features:
    plt.figure(figsize=(9, 5))
```

```python
    ax = sns.kdeplot(
        data=telco_raw, x=col, hue='Churn', fill=True, alpha=0.4, linewidth=1.5
    )
    ax.set_title(f"Distribution of {col} by Churn Status", fontsize=14)
    ax.set_xlabel(col, fontsize=12)
    ax.set_ylabel("Density", fontsize=12)
    plt.legend(title='Churn', labels=['No', 'Yes'])
    plt.tight_layout()
    plt.savefig(f"{col}_distribution.png", dpi=300)  # Save for LaTeX inclusion
    plt.show()
```



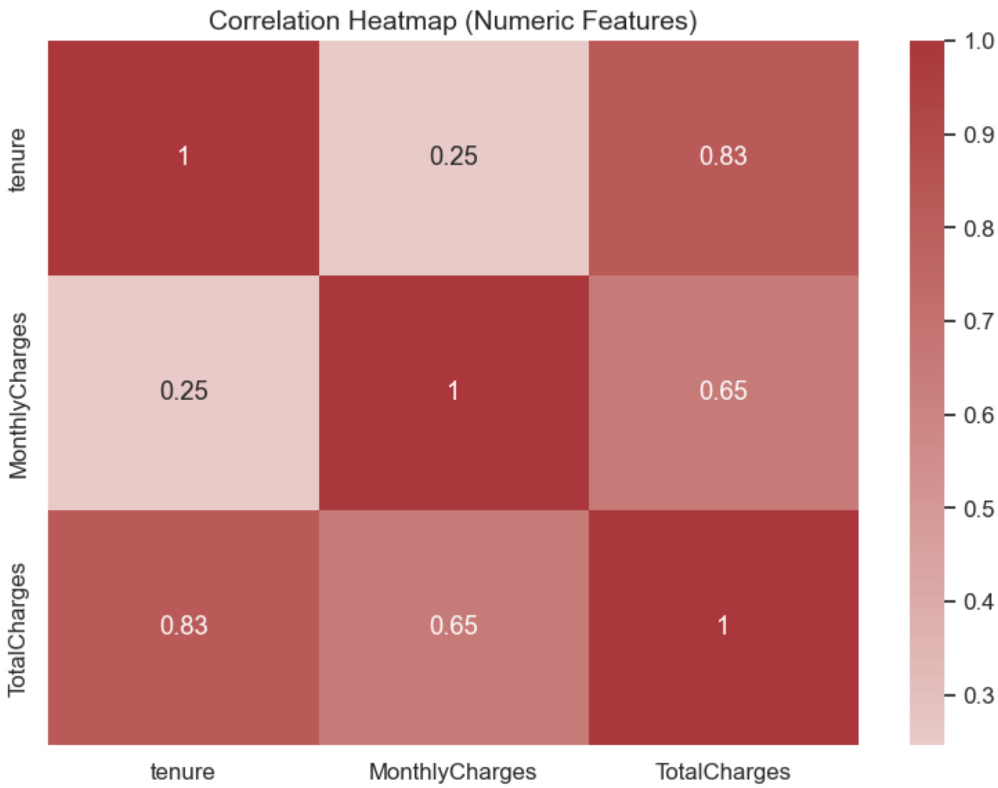




6.5 6.5 Correlation Heatmap of Numeric Features

[ ]:
```
num_cols = ['tenure', 'MonthlyCharges', 'TotalCharges', 'Churn']
plt.figure(figsize=(8,6))
sns.heatmap(telco_raw[num_cols].corr(numeric_only=True), annot=True,␣
↪cmap='vlag', center=0)
plt.title('Correlation Heatmap (Numeric Features)', fontsize=14)
```

```
plt.tight_layout()
plt.show();
```



7 7 Feature Engineering & Preprocessing

Steps: - Encode categorical variables - Scale numerical variables - Create training & test sets

[23]:
```
# Encode target variable
telco_raw['Churn'] = telco_raw['Churn'].map({'No':0, 'Yes':1})

# Encode binary categorical features
binary_cols = ['gender', 'Partner', 'Dependents', 'PhoneService',␣
 ↪'PaperlessBilling']

le = LabelEncoder()
for col in binary_cols:
    telco_raw[col] = le.fit_transform(telco_raw[col])

# One-hot encode multi-class categorical features
```

14

```
multi_cols = ['MultipleLines', 'InternetService', 'OnlineSecurity',␣
↪'OnlineBackup',
              'DeviceProtection', 'TechSupport', 'StreamingTV',␣
↪'StreamingMovies',
              'Contract', 'PaymentMethod']

telco_raw = pd.get_dummies(telco_raw, columns=multi_cols, drop_first=True)
```

[26]:
```
# Split features and target
X = telco_raw.drop('Churn', axis=1)
y = telco_raw['Churn']

# Train-test split (stratified to preserve churn ratio)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42
)

# Scale numerical features
scaler = StandardScaler()
num_cols = ['tenure', 'MonthlyCharges', 'TotalCharges']

X_train[num_cols] = scaler.fit_transform(X_train[num_cols])
X_test[num_cols] = scaler.transform(X_test[num_cols])

# Check shapes to confirm
print("Train features shape:", X_train.shape)
print("Test features shape:", X_test.shape)
```

```
Train features shape: (5625, 30)
Test features shape: (1407, 30)
```

8 Modeling

[30]:
```
# Function for Evaluation
def evaluate_model(model, X_test, y_test, model_name="Model"):
    y_pred = model.predict(X_test)
    y_prob = model.predict_proba(X_test)[:,1] if hasattr(model,␣
↪"predict_proba") else None

    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred)
    rec = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    roc_auc = roc_auc_score(y_test, y_prob) if y_prob is not None else␣
↪roc_auc_score(y_test, y_pred)
```

```
    print(f"\n  {model_name} Performance:")
    print(f"Accuracy: {acc:.4f}")
    print(f"Precision: {prec:.4f}")
    print(f"Recall: {rec:.4f}")
    print(f"F1 Score: {f1:.4f}")
    print(f"ROC AUC: {roc_auc:.4f}")
```

[38]:
```
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
evaluate_model(rf_model, X_train, y_train, model_name="Random Forest (Train)")
evaluate_model(rf_model, X_test, y_test, model_name="Random Forest (Test)")
```

```
  Random Forest (Train) Performance:
Accuracy: 0.9988
Precision: 0.9987
Recall: 0.9967
F1 Score: 0.9977
ROC AUC: 1.0000

  Random Forest (Test) Performance:
Accuracy: 0.7868
Precision: 0.6217
Recall: 0.5053
F1 Score: 0.5575
ROC AUC: 0.8142
```

[40]:
```
dt_model = DecisionTreeClassifier(random_state=42)
dt_model.fit(X_train, y_train)
evaluate_model(dt_model, X_train, y_train, model_name="Decision Tree(Train)")
evaluate_model(dt_model, X_test, y_test, model_name="Decision Tree (Test)")
```

```
  Decision Tree(Train) Performance:
Accuracy: 0.9988
Precision: 0.9993
Recall: 0.9960
F1 Score: 0.9977
ROC AUC: 1.0000

  Decision Tree (Test) Performance:
Accuracy: 0.7114
Precision: 0.4568
Recall: 0.4519
F1 Score: 0.4543
ROC AUC: 0.6286
```

[41]:
```
lr_model = LogisticRegression(max_iter=1000, random_state=42)
lr_model.fit(X_train, y_train)
evaluate_model(lr_model, X_train, y_train, model_name="Logistic␣
 ↪Regression(Train)")
evaluate_model(lr_model, X_test, y_test, model_name="Logistic Regression(Test)")
```

```
 Logistic Regression(Train) Performance:
Accuracy: 0.8048
Precision: 0.6592
Recall: 0.5498
F1 Score: 0.5996
ROC AUC: 0.8506

 Logistic Regression(Test) Performance:
Accuracy: 0.8045
Precision: 0.6505
Recall: 0.5722
F1 Score: 0.6088
ROC AUC: 0.8361
```

8.0.1 Comparing the results

[44]:
```
results = []

# === RANDOM FOREST ===
# Train metrics
y_train_pred_rf = rf_model.predict(X_train)
y_train_prob_rf = rf_model.predict_proba(X_train)[:,1]
results.append({
    'Model': 'Random Forest',
    'Set': 'Train',
    'Accuracy': accuracy_score(y_train, y_train_pred_rf),
    'Precision': precision_score(y_train, y_train_pred_rf),
    'Recall': recall_score(y_train, y_train_pred_rf),
    'F1 Score': f1_score(y_train, y_train_pred_rf),
    'ROC AUC': roc_auc_score(y_train, y_train_prob_rf)
})

# Test metrics
y_test_pred_rf = rf_model.predict(X_test)
y_test_prob_rf = rf_model.predict_proba(X_test)[:,1]
results.append({
    'Model': 'Random Forest',
    'Set': 'Test',
    'Accuracy': accuracy_score(y_test, y_test_pred_rf),
    'Precision': precision_score(y_test, y_test_pred_rf),
```

```python
    'Recall': recall_score(y_test, y_test_pred_rf),
    'F1 Score': f1_score(y_test, y_test_pred_rf),
    'ROC AUC': roc_auc_score(y_test, y_test_prob_rf)
})


# === DECISION TREE ===
# Train metrics
y_train_pred_dt = dt_model.predict(X_train)
y_train_prob_dt = dt_model.predict_proba(X_train)[:,1]
results.append({
    'Model': 'Decision Tree',
    'Set': 'Train',
    'Accuracy': accuracy_score(y_train, y_train_pred_dt),
    'Precision': precision_score(y_train, y_train_pred_dt),
    'Recall': recall_score(y_train, y_train_pred_dt),
    'F1 Score': f1_score(y_train, y_train_pred_dt),
    'ROC AUC': roc_auc_score(y_train, y_train_prob_dt)
})

# Test metrics
y_test_pred_dt = dt_model.predict(X_test)
y_test_prob_dt = dt_model.predict_proba(X_test)[:,1]
results.append({
    'Model': 'Decision Tree',
    'Set': 'Test',
    'Accuracy': accuracy_score(y_test, y_test_pred_dt),
    'Precision': precision_score(y_test, y_test_pred_dt),
    'Recall': recall_score(y_test, y_test_pred_dt),
    'F1 Score': f1_score(y_test, y_test_pred_dt),
    'ROC AUC': roc_auc_score(y_test, y_test_prob_dt)
})


# === LOGISTIC REGRESSION ===
# Train metrics
y_train_pred_lr = lr_model.predict(X_train)
y_train_prob_lr = lr_model.predict_proba(X_train)[:,1]
results.append({
    'Model': 'Logistic Regression',
    'Set': 'Train',
    'Accuracy': accuracy_score(y_train, y_train_pred_lr),
    'Precision': precision_score(y_train, y_train_pred_lr),
    'Recall': recall_score(y_train, y_train_pred_lr),
    'F1 Score': f1_score(y_train, y_train_pred_lr),
    'ROC AUC': roc_auc_score(y_train, y_train_prob_lr)
})
```

```python
# Test metrics
y_test_pred_lr = lr_model.predict(X_test)
y_test_prob_lr = lr_model.predict_proba(X_test)[:,1]
results.append({
    'Model': 'Logistic Regression',
    'Set': 'Test',
    'Accuracy': accuracy_score(y_test, y_test_pred_lr),
    'Precision': precision_score(y_test, y_test_pred_lr),
    'Recall': recall_score(y_test, y_test_pred_lr),
    'F1 Score': f1_score(y_test, y_test_pred_lr),
    'ROC AUC': roc_auc_score(y_test, y_test_prob_lr)
})


# === Create DataFrame ===
results_df = pd.DataFrame(results).set_index(['Model', 'Set'])
display(results_df)
```

Model	Set	Accuracy	Precision	Recall	F1 Score	ROC AUC
Random Forest	Train	0.998756	0.998660	0.996656	0.997657	0.999958
	Test	0.786780	0.621711	0.505348	0.557522	0.814197
Decision Tree	Train	0.998756	0.999329	0.995987	0.997655	0.999995
	Test	0.711443	0.456757	0.451872	0.454301	0.628600
Logistic Regression	Train	0.804800	0.659182	0.549833	0.599562	0.850569
	Test	0.804549	0.650456	0.572193	0.608819	0.836071

[45]:
```python
param_grid = {
    'C': [0.01, 0.1, 1, 10],
    'penalty': ['l1', 'l2'],
    'solver': ['liblinear']
}

grid = GridSearchCV(LogisticRegression(max_iter=1000, random_state=42),␣
 ↪param_grid, cv=5, scoring='roc_auc')
grid.fit(X_train, y_train)

print("Best parameters:", grid.best_params_)
evaluate_model(grid.best_estimator_, X_test, y_test, model_name="Tuned Logistic␣
 ↪Regression")
```

```
Best parameters: {'C': 10, 'penalty': 'l2', 'solver': 'liblinear'}

 Tuned Logistic Regression Performance:
Accuracy: 0.8010
Precision: 0.6407
Recall: 0.5722
```

```
F1 Score: 0.6045
ROC AUC: 0.8354
```

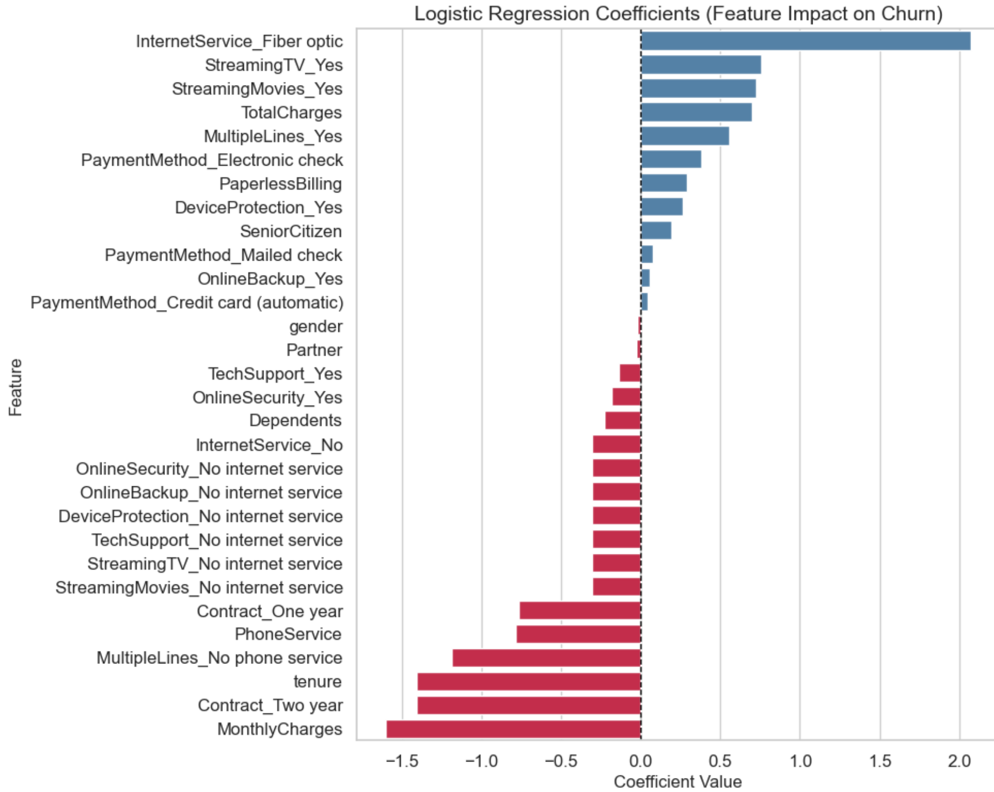
[46]:
```
cv_scores = cross_val_score(grid.best_estimator_, X, y, cv=5, scoring='roc_auc')
print("Cross-validated ROC AUC scores:", cv_scores)
print("Mean ROC AUC: {:.4f}".format(cv_scores.mean()))
print("Standard Deviation: {:.4f}".format(cv_scores.std()))
```

```
Cross-validated ROC AUC scores: [0.85706447 0.85592299 0.83443288 0.83612113
0.83796843]
Mean ROC AUC: 0.8443
Standard Deviation: 0.0100
```

9 Result interpretation

[54]:
```
# Create DataFrame as before
coefficients = pd.DataFrame({
    'Feature': X.columns,
    'Coefficient': grid.best_estimator_.coef_[0]
})

# Add absolute value for sorting convenience
coefficients['AbsCoefficient'] = coefficients['Coefficient'].abs()

# Sort: first by sign (positive first), then by absolute magnitude descending
coefficients_sorted = coefficients.sort_values(
    by=['Coefficient', 'AbsCoefficient'],
    ascending=[False, False]  # positive first, largest magnitude first
).drop(columns='AbsCoefficient').reset_index(drop=True)

display(coefficients_sorted)

plt.figure(figsize=(10, 8))
sns.barplot(
    x='Coefficient',
    y='Feature',
    data=coefficients_sorted,
    palette=['crimson' if c < 0 else 'steelblue' for c in␣
 ↪coefficients_sorted['Coefficient']]
)
plt.axvline(0, color='black', linestyle='--', linewidth=1)
plt.title("Logistic Regression Coefficients (Feature Impact on Churn)",␣
 ↪fontsize=14)
plt.xlabel("Coefficient Value", fontsize=12)
plt.ylabel("Feature", fontsize=12)
plt.tight_layout()
plt.show()
```

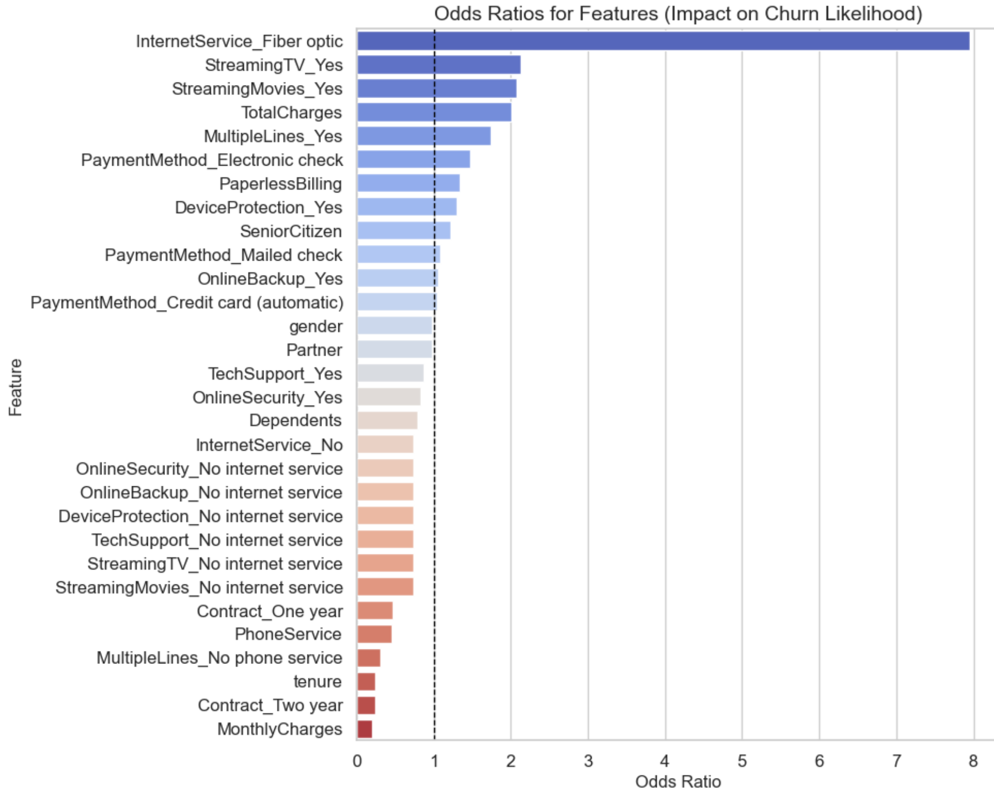
	Feature	Coefficient
0	InternetService_Fiber optic	2.073051
1	StreamingTV_Yes	0.754252
2	StreamingMovies_Yes	0.727223
3	TotalCharges	0.698652
4	MultipleLines_Yes	0.555584
5	PaymentMethod_Electronic check	0.383086
6	PaperlessBilling	0.289443
7	DeviceProtection_Yes	0.265422
8	SeniorCitizen	0.193575
9	PaymentMethod_Mailed check	0.076093
10	OnlineBackup_Yes	0.057393
11	PaymentMethod_Credit card (automatic)	0.042106
12	gender	-0.022692
13	Partner	-0.026531
14	TechSupport_Yes	-0.138415
15	OnlineSecurity_Yes	-0.182745
16	Dependents	-0.229527
17	InternetService_No	-0.303386
18	OnlineSecurity_No internet service	-0.303386
19	OnlineBackup_No internet service	-0.303386
20	DeviceProtection_No internet service	-0.303386
21	TechSupport_No internet service	-0.303386
22	StreamingTV_No internet service	-0.303386
23	StreamingMovies_No internet service	-0.303386
24	Contract_One year	-0.761825
25	PhoneService	-0.782985
26	MultipleLines_No phone service	-1.186315
27	tenure	-1.403817
28	Contract_Two year	-1.409528
29	MonthlyCharges	-1.598564



[ ]:
```
# Create a DataFrame with features, coefficients, and odds ratios
odds_df = coefficients_sorted[['Feature', 'Coefficient']].copy()
odds_df['Odds Ratio'] = np.exp(odds_df['Coefficient'])

# Reset index for a neat presentation
odds_df.reset_index(drop=True, inplace=True)

display(odds_df)

# Calculate Odds Ratios on your sorted DataFrame
coefficients_sorted['Odds Ratio'] = np.exp(coefficients_sorted['Coefficient'])

plt.figure(figsize=(10, 8))
sns.barplot(
    x='Odds Ratio',
    y='Feature',
    data=coefficients_sorted,
    palette='coolwarm'
)
```

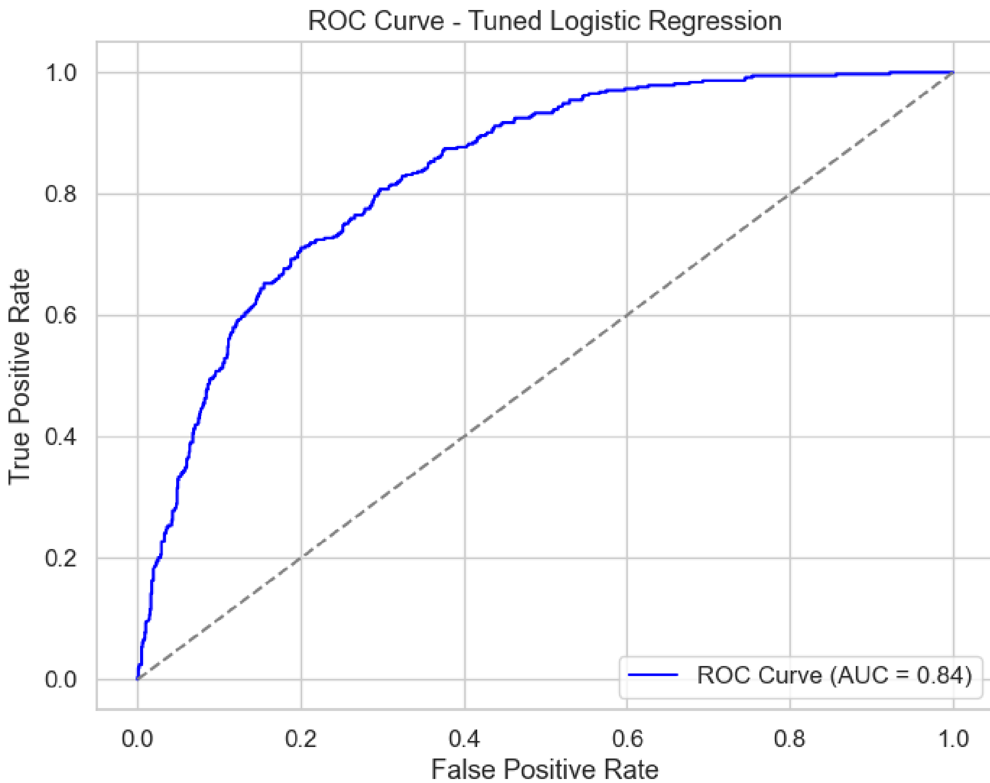
```python
plt.axvline(1, color='black', linestyle='--', linewidth=1)
plt.title("Odds Ratios for Features (Impact on Churn Likelihood)", fontsize=14)
plt.xlabel("Odds Ratio", fontsize=12)
plt.ylabel("Feature", fontsize=12)
plt.tight_layout()
plt.show();
```

	Feature	Coefficient	Odds Ratio
0	InternetService_Fiber optic	2.073051	7.949035
1	StreamingTV_Yes	0.754252	2.126021
2	StreamingMovies_Yes	0.727223	2.069327
3	TotalCharges	0.698652	2.011041
4	MultipleLines_Yes	0.555584	1.742959
5	PaymentMethod_Electronic check	0.383086	1.466805
6	PaperlessBilling	0.289443	1.335683
7	DeviceProtection_Yes	0.265422	1.303981
8	SeniorCitizen	0.193575	1.213580
9	PaymentMethod_Mailed check	0.076093	1.079062
10	OnlineBackup_Yes	0.057393	1.059072
11	PaymentMethod_Credit card (automatic)	0.042106	1.043006
12	gender	-0.022692	0.977563
13	Partner	-0.026531	0.973818
14	TechSupport_Yes	-0.138415	0.870737
15	OnlineSecurity_Yes	-0.182745	0.832980
16	Dependents	-0.229527	0.794909
17	InternetService_No	-0.303386	0.738314
18	OnlineSecurity_No internet service	-0.303386	0.738314
19	OnlineBackup_No internet service	-0.303386	0.738314
20	DeviceProtection_No internet service	-0.303386	0.738314
21	TechSupport_No internet service	-0.303386	0.738314
22	StreamingTV_No internet service	-0.303386	0.738314
23	StreamingMovies_No internet service	-0.303386	0.738314
24	Contract_One year	-0.761825	0.466814
25	PhoneService	-0.782985	0.457040
26	MultipleLines_No phone service	-1.186315	0.305344
27	tenure	-1.403817	0.245658
28	Contract_Two year	-1.409528	0.244259
29	MonthlyCharges	-1.598564	0.202187



[ ]:

```
y_test_prob = grid.best_estimator_.predict_proba(X_test)[:,1]
fpr, tpr, _ = roc_curve(y_test, y_test_prob)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, label=f"ROC Curve (AUC = {roc_auc:.2f})", color='blue')
plt.plot([0, 1], [0, 1], linestyle='--', color='gray')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - Tuned Logistic Regression')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```


ROC Curve - Tuned Logistic Regression
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC Curve (AUC = 0.84)