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
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression

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

3 3 Data Loading

[2]:
```
# 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
```

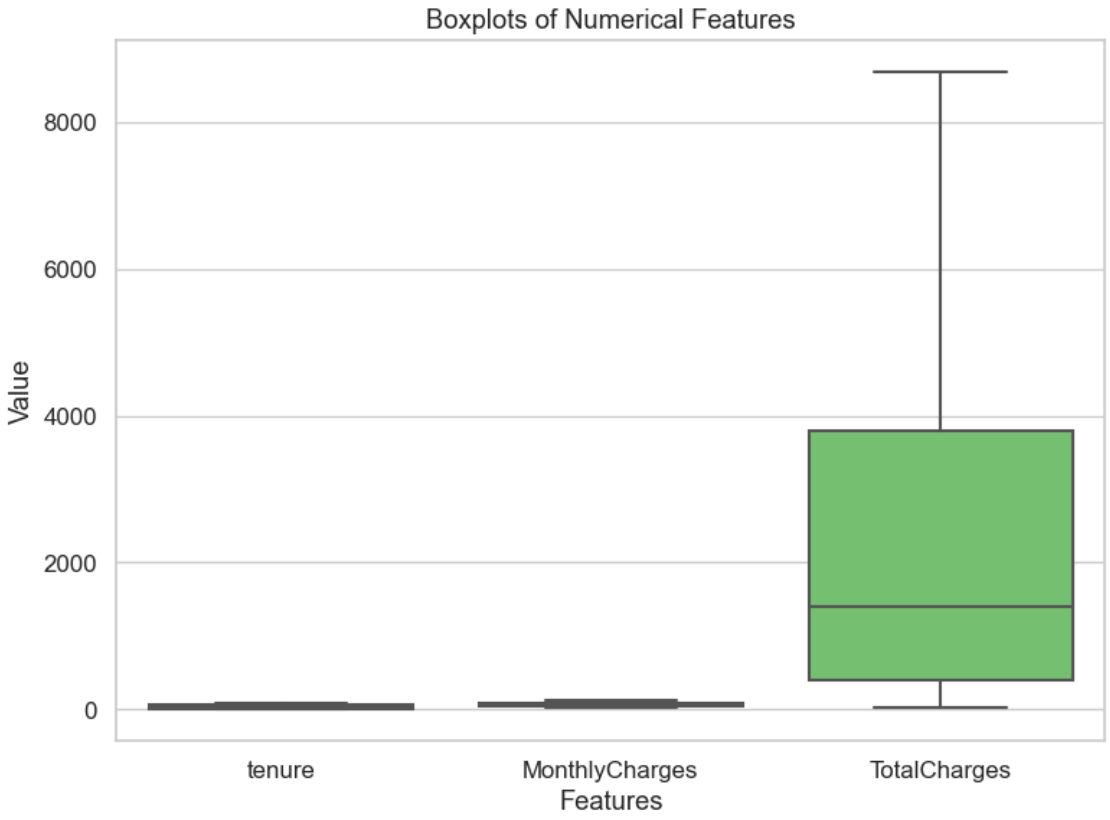
Even though each customer should have a unique customerID, it's wise to confirm

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
```

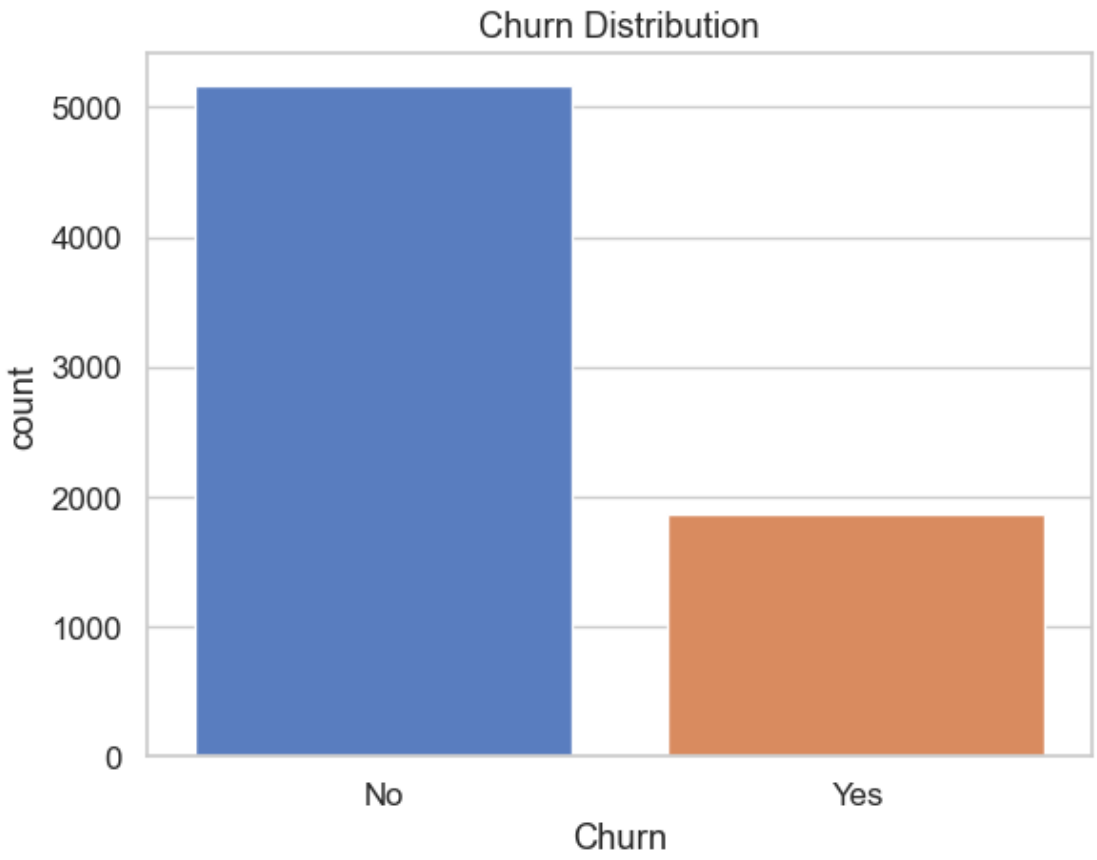
```
 11  TechSupport       7032 non-null   object
 12  StreamingTV       7032 non-null   object
 13  StreamingMovies   7032 non-null   object
 14  Contract          7032 non-null   object
 15  PaperlessBilling  7032 non-null   object
 16  PaymentMethod     7032 non-null   object
 17  MonthlyCharges    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)

[9]:
```
# Distribution of Churn
sns.countplot(data=telco_raw, x='Churn')
plt.title('Churn Distribution')
plt.show()

# Churn ratio
churn_rate = telco_raw['Churn'].value_counts(normalize=True)
print(f"Churn Rate:\n{churn_rate}")
```

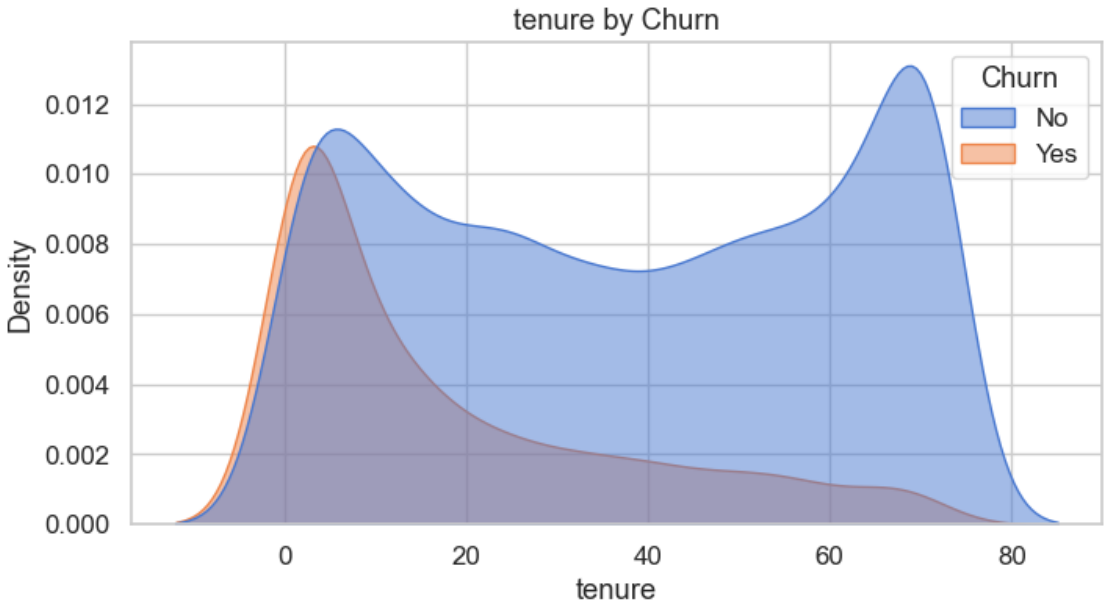


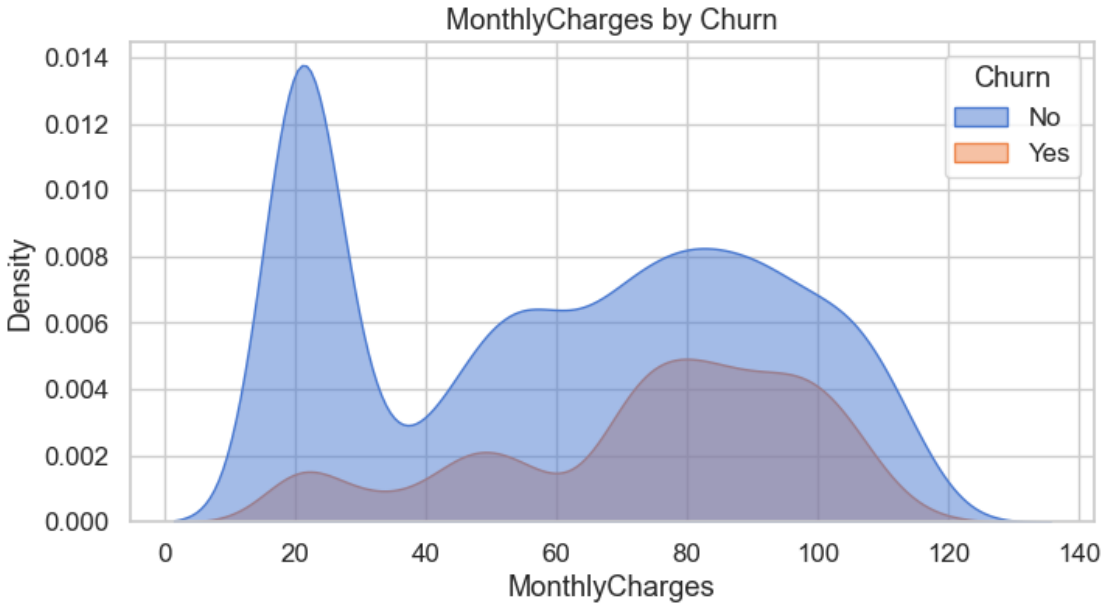

```
Churn Rate:
No     0.734215
Yes    0.265785
Name: Churn, dtype: float64
```

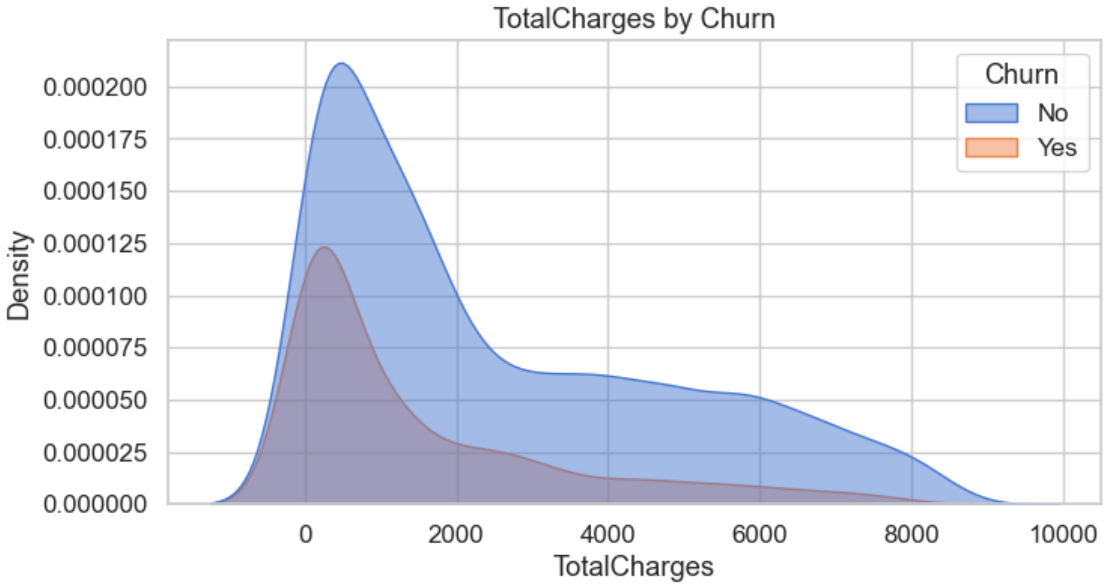
We noticed from the visuals above that there are more customers that did not churn.

6.2 6.2 Numerical Features vs Churn

[10]:
```
num_features = ['tenure', 'MonthlyCharges', 'TotalCharges']
for col in num_features:
    plt.figure(figsize=(8,4))
    sns.kdeplot(data=telco_raw, x=col, hue='Churn', fill=True, alpha=0.5)
    plt.title(f'{col} by Churn')
    plt.show()
```


tenure by Churn
Churn
No
Yes
Density
0.012
0.010
0.008
0.006
0.004
0.002
0.000
0
20
40
60
80
tenure


MonthlyCharges by Churn
Churn
No
Yes
Density
0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
0
20
40
60
80
100
120
140
MonthlyCharges

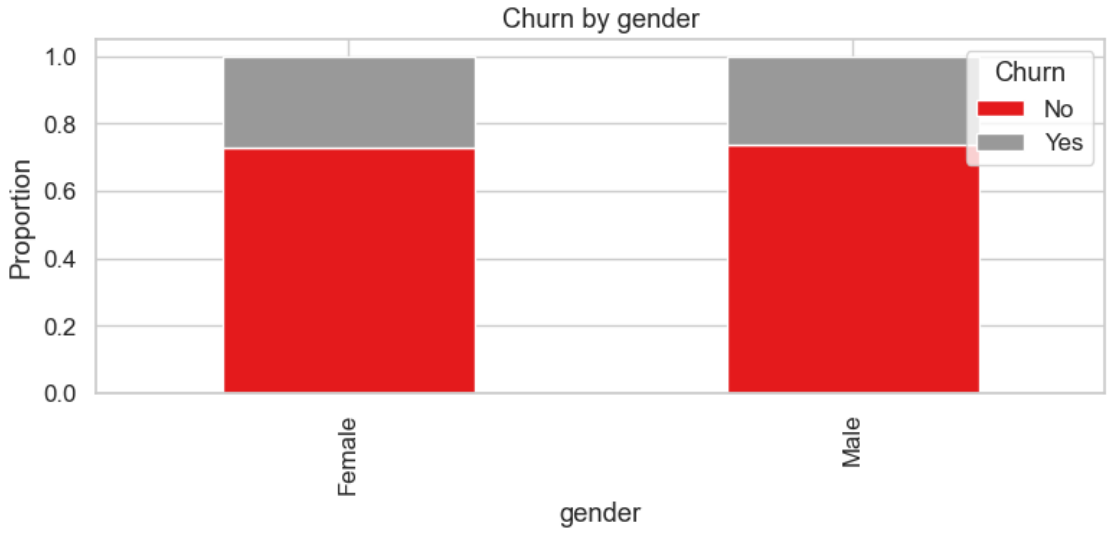


6.3 6.3 Categorical Features vs Churn

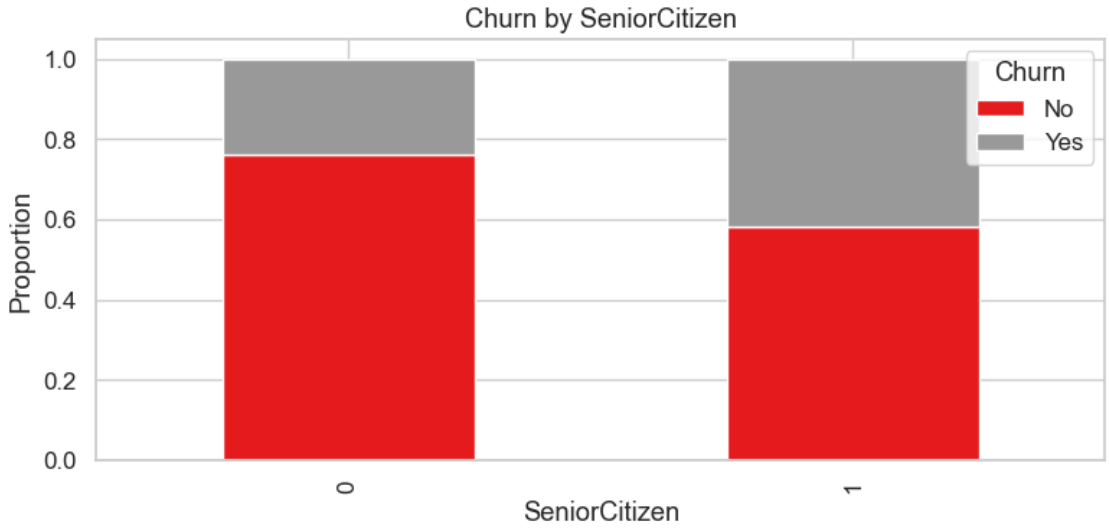
[11]:
```
cat_features = ['gender', 'SeniorCitizen', 'Partner', 'Dependents',␣
 ↪'PhoneService',
                'MultipleLines', 'InternetService', 'OnlineSecurity',␣
 ↪'OnlineBackup',
                'DeviceProtection', 'TechSupport', 'StreamingTV',␣
 ↪'StreamingMovies',
                'Contract', 'PaperlessBilling', 'PaymentMethod']

for col in cat_features:
    plt.figure(figsize=(8,4))
    churn_pct = telco_raw.groupby(col)['Churn'].value_counts(normalize=True).
 ↪unstack()
    churn_pct.plot(kind='bar', stacked=True, colormap='Set1', figsize=(8,4))
    plt.title(f'Churn by {col}')
    plt.ylabel('Proportion')
    plt.legend(title='Churn', loc='upper right')
    plt.tight_layout()
    plt.show();
```

```
<Figure size 800x400 with 0 Axes>
```




```
<Figure size 800x400 with 0 Axes>
```




```
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```

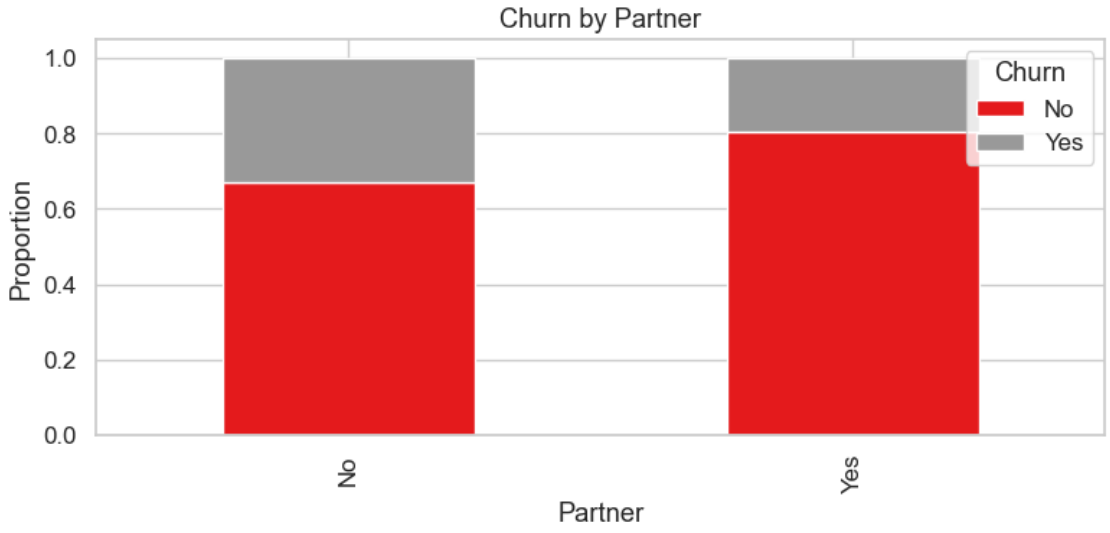

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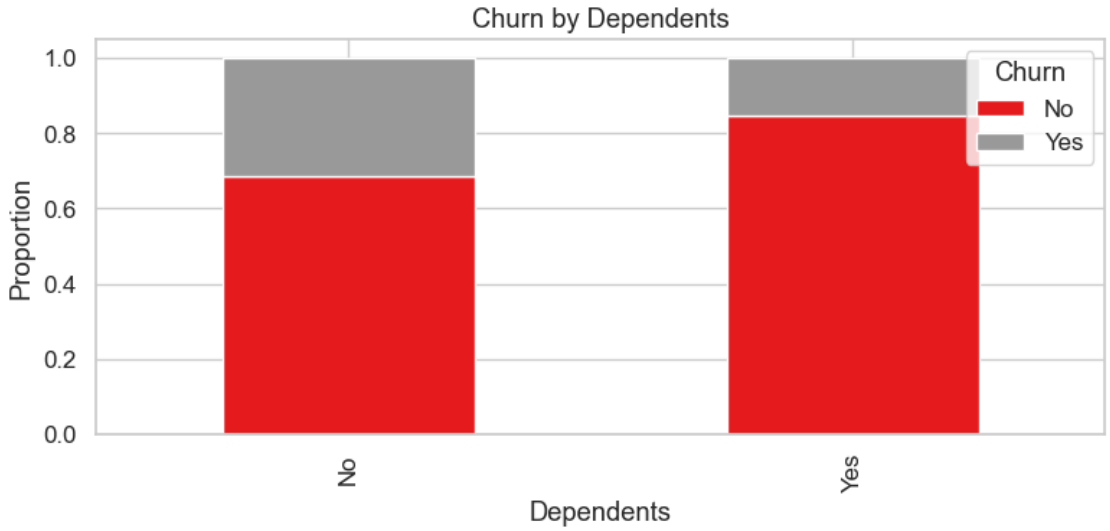

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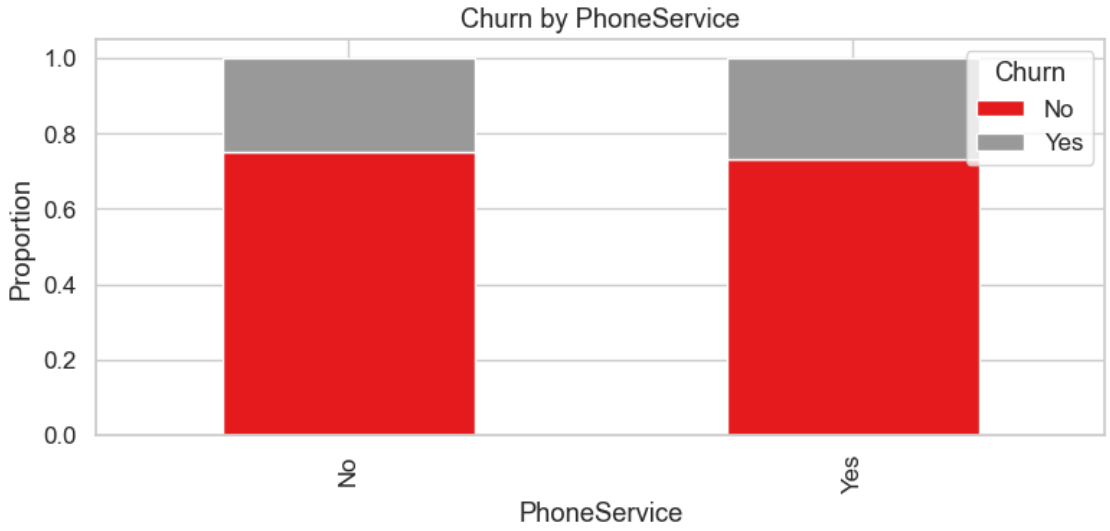
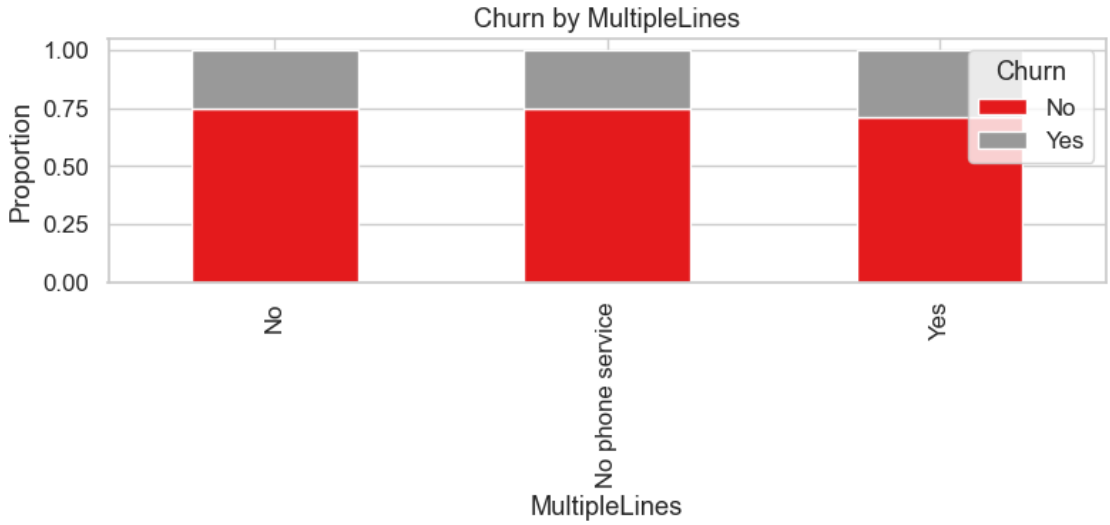



```
<Figure size 800x400 with 0 Axes>
```




```
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```
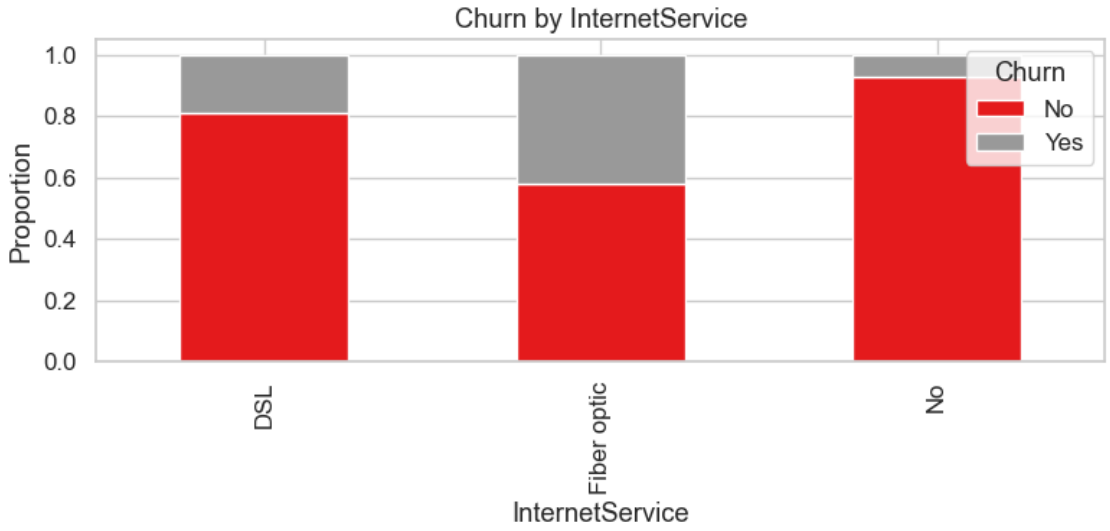
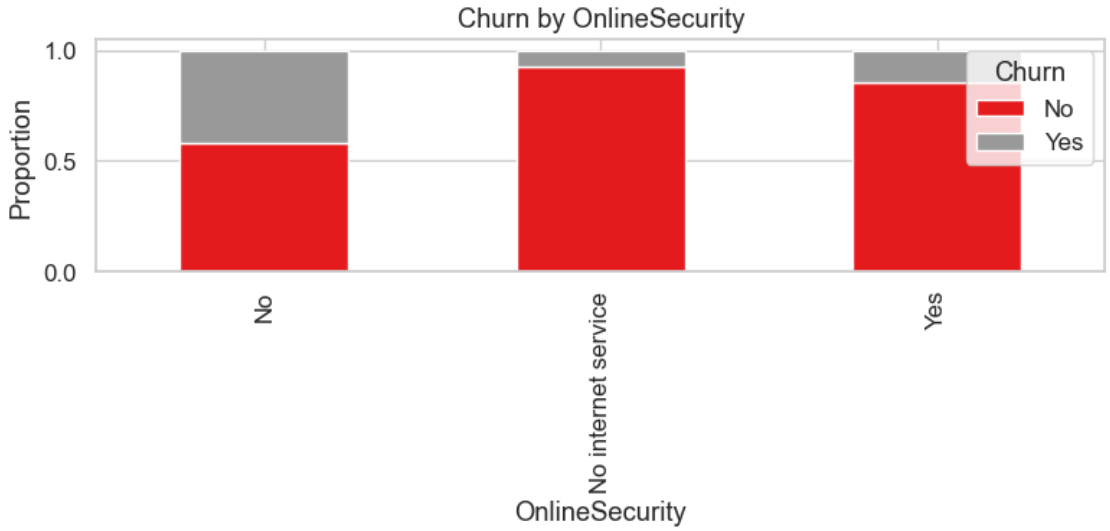
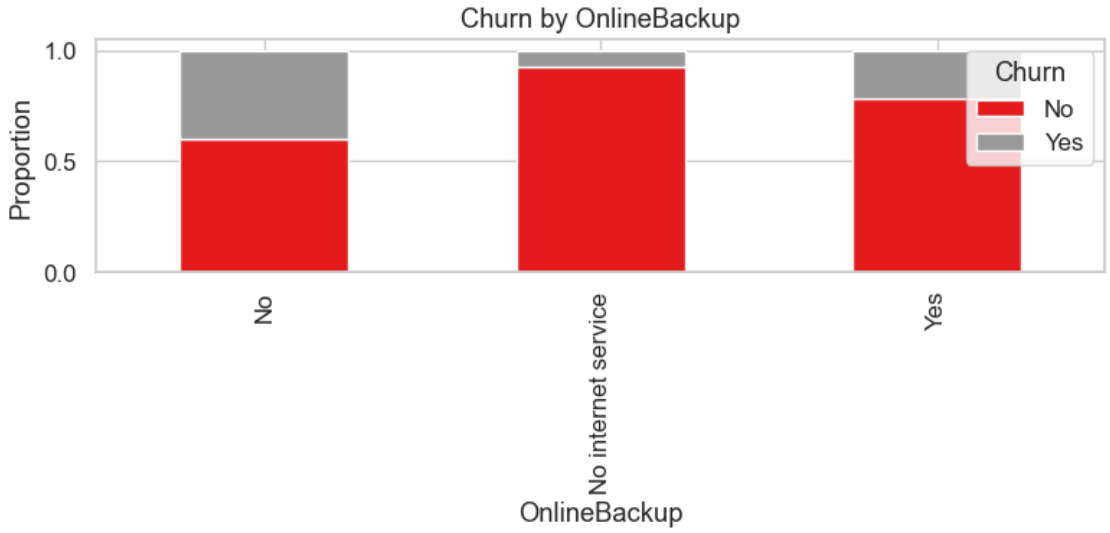



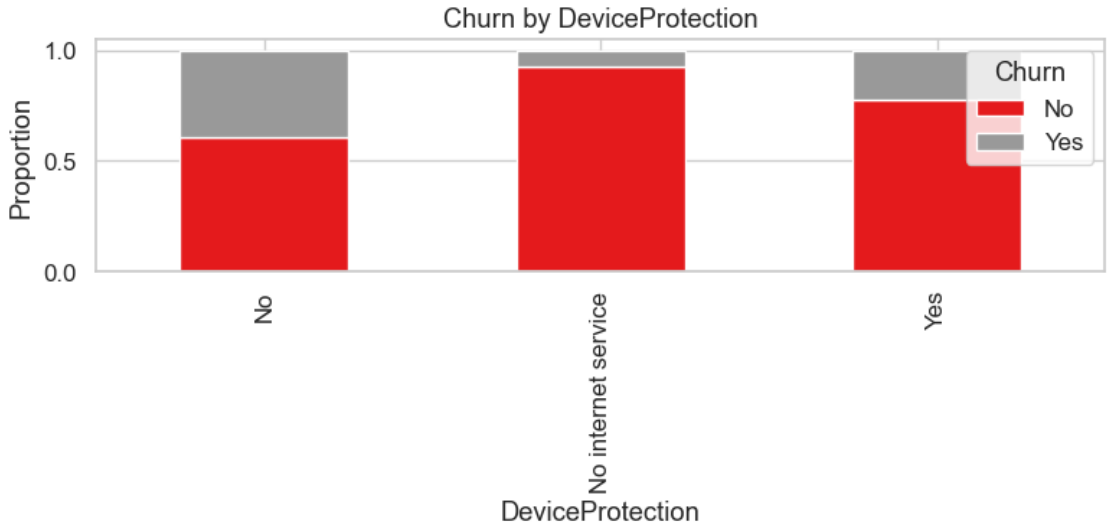

```
<Figure size 800x400 with 0 Axes>
```



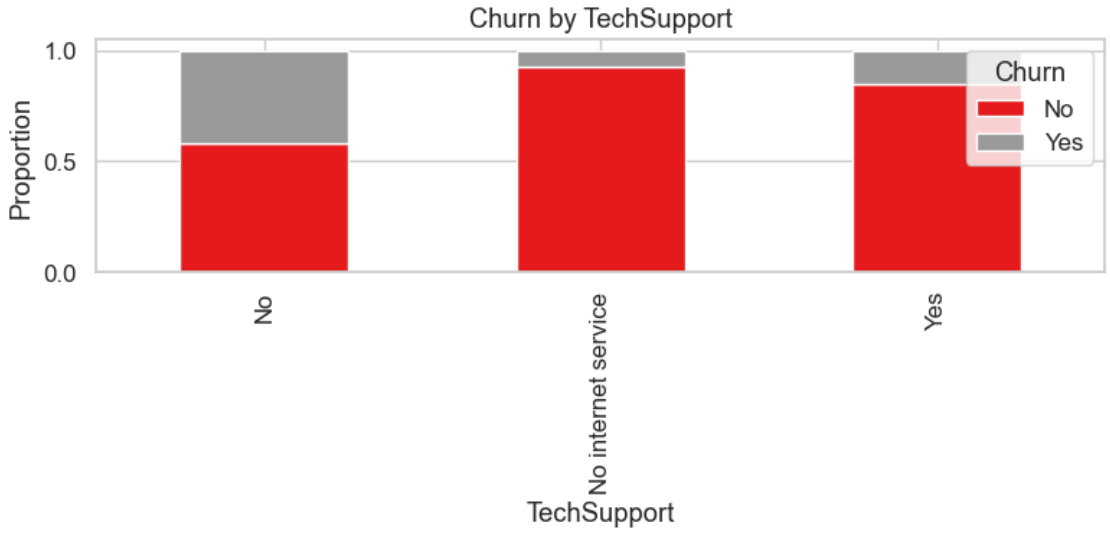

```
<Figure size 800x400 with 0 Axes>
```



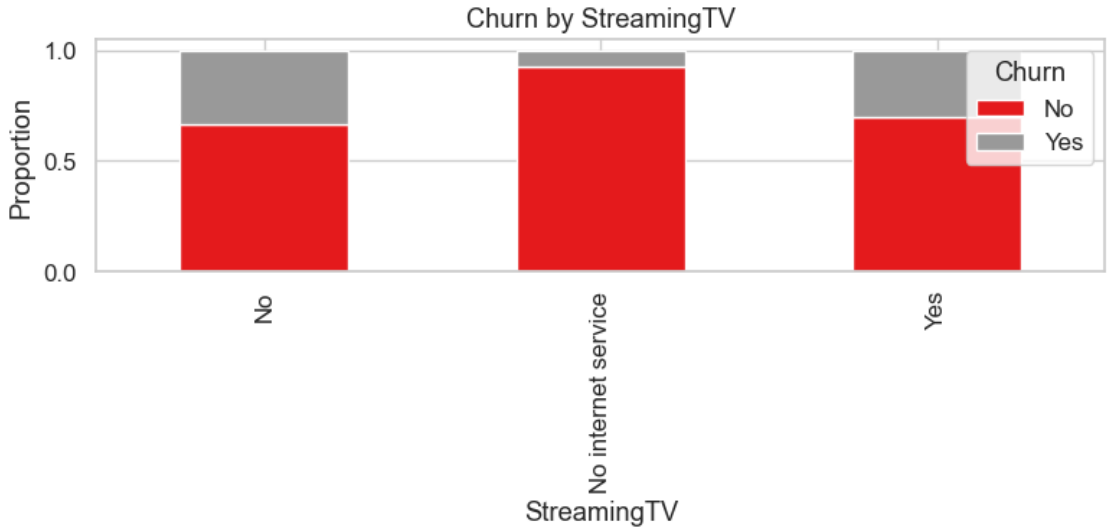

```
<Figure size 800x400 with 0 Axes>
```



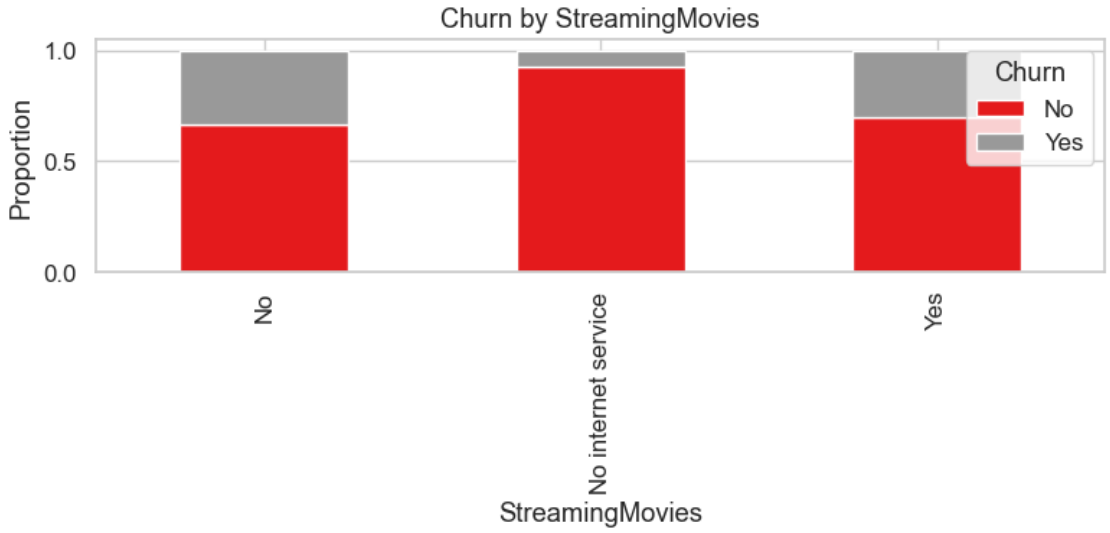

```
<Figure size 800x400 with 0 Axes>
```



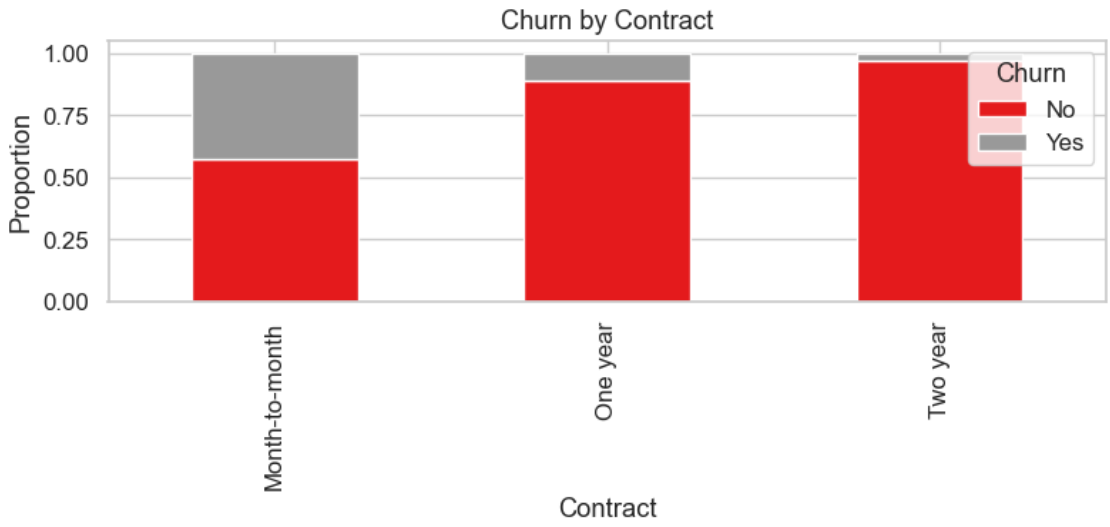

```
<Figure size 800x400 with 0 Axes>
```



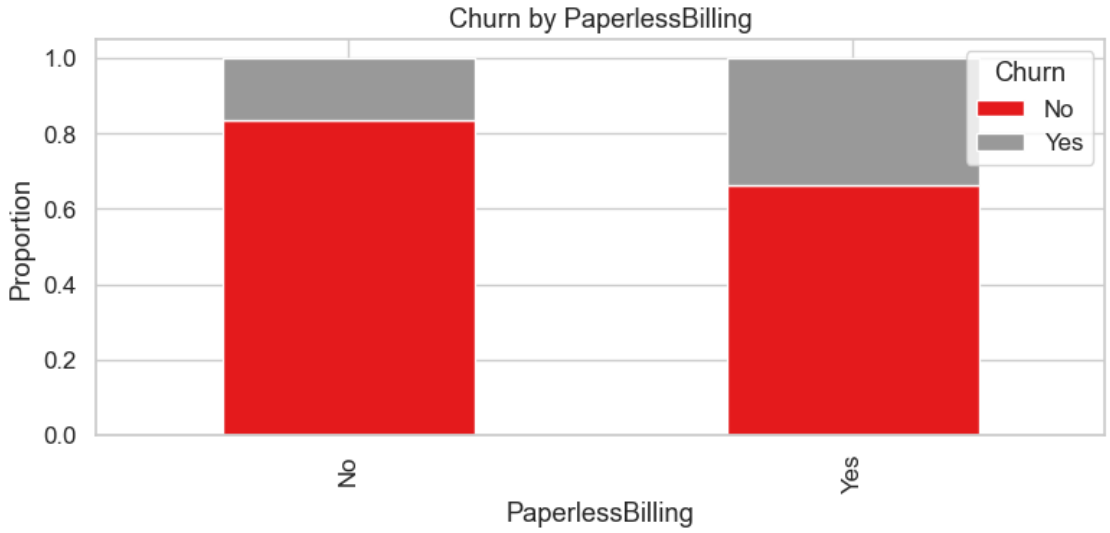

```
<Figure size 800x400 with 0 Axes>
```



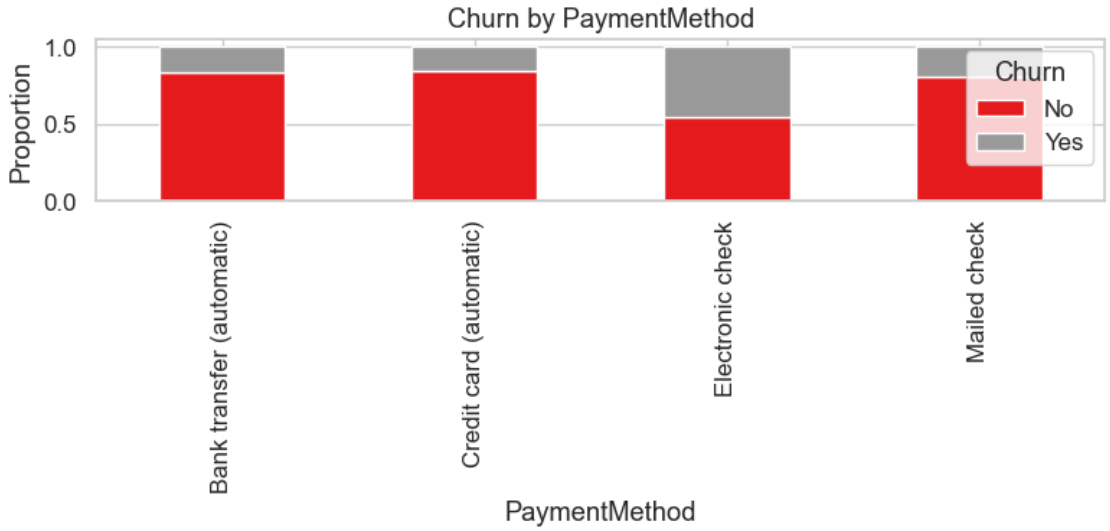

```
<Figure size 800x400 with 0 Axes>
```




```
<Figure size 800x400 with 0 Axes>
```




```
<Figure size 800x400 with 0 Axes>
```



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
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(model, X_train, y_train, model_name="Random Forest (Train)")
evaluate_model(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(model, X_train, y_train, model_name="Decision Tree(Train)")
evaluate_model(model, X_test, y_test, model_name="Decision Tree (Test)")
```

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

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

[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),
    '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)
})

# 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)
```

		Accuracy	Precision	Recall	F1 Score	ROC AUC
Model	Set					
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]:
```
from sklearn.model_selection import GridSearchCV
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]:
```
from sklearn.model_selection import cross_val_score

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()))
```

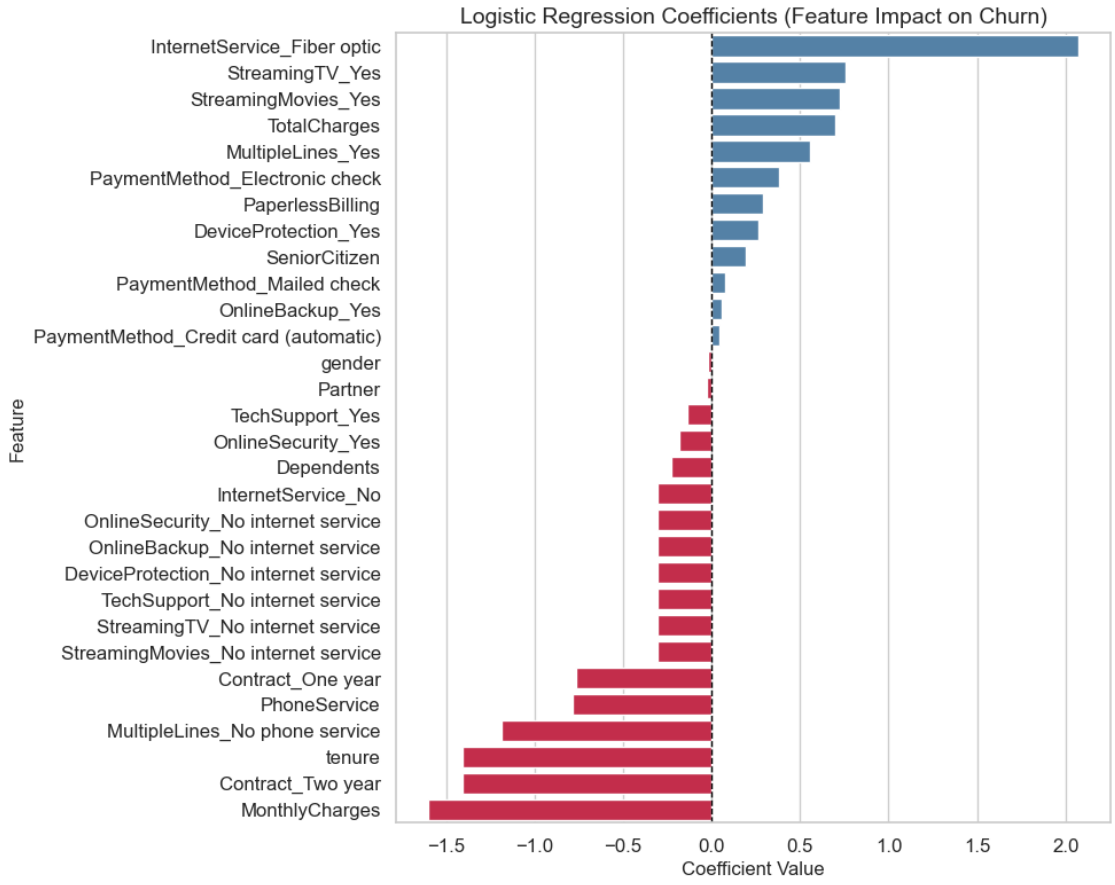
```
Cross-validated ROC AUC scores: [0.85706447 0.85592299 0.83443288 0.83612113
0.83796843]
Mean ROC AUC: 0.8443
Standard Deviation: 0.0100
```

[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)
```

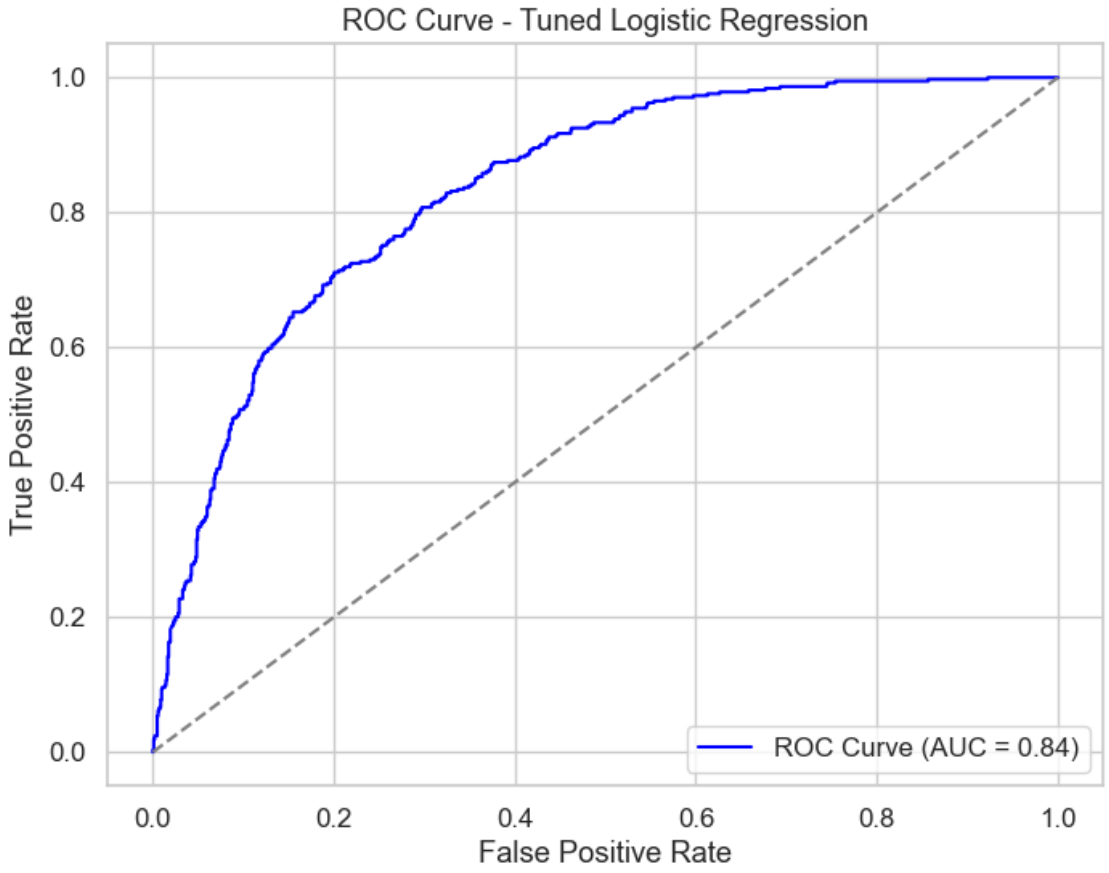
	Feature	Coefficient
0	InternetService_Fiber optic	2.073051
1	StreamingTV_Yes	0.754252
2	StreamingMovies_Yes	0.727223
3	TotalCharges	0.698652
4	MultipleLines_Yes	0.555584
5	PaymentMethod_Electronic check	0.383086
6	PaperlessBilling	0.289443

```
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
```

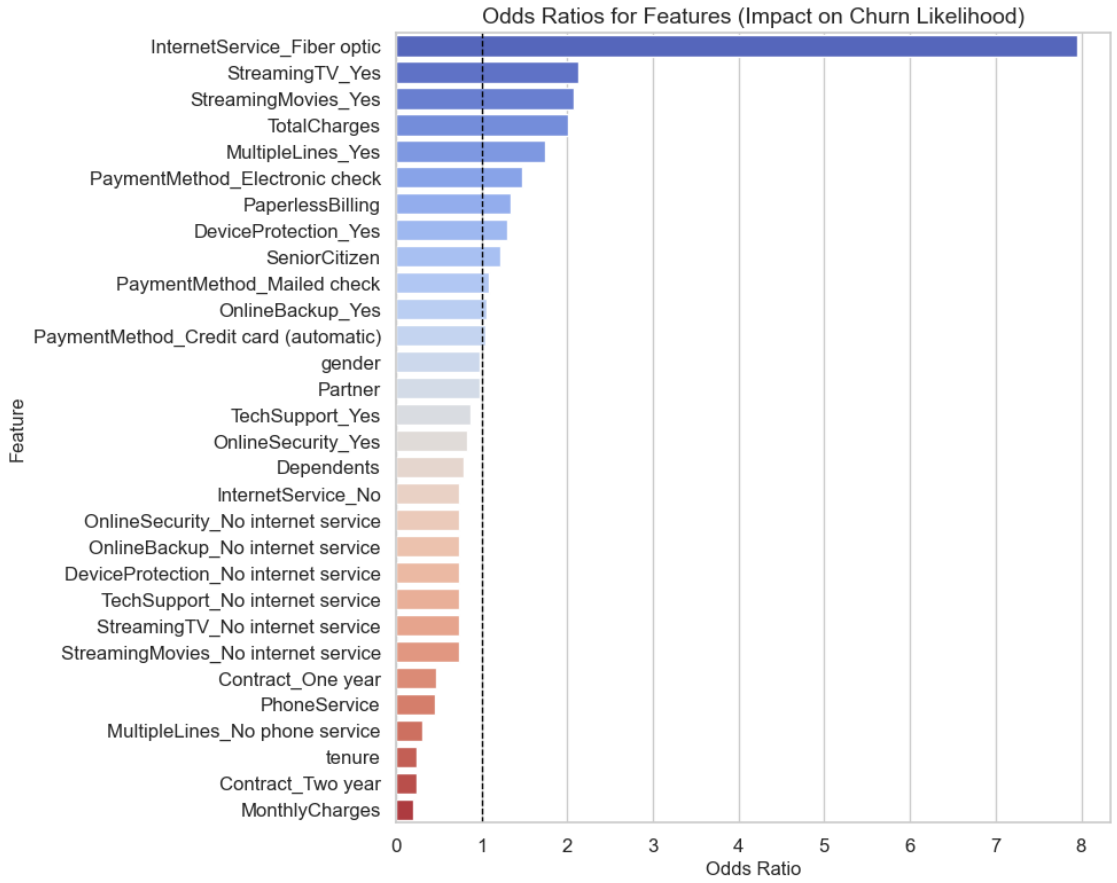
[ ]:
```
plt.figure(figsize=(10, 8))
sns.barplot(
    x='Coefficient',
    y='Feature',
    data=coefficients_sorted,
    palette=['crimson' if c < 0 else 'steelblue' for c in␣
 ↪coefficients_sorted['Coefficient']]
)
plt.axvline(0, color='black', linestyle='--', linewidth=1)
plt.title("Logistic Regression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



[ ]:
```
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()
```



[58]:
```
# 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'
)
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();
```



9 Unsupervised Learning

[ ]:
```
from sklearn.cluster import KMeans
import pandas as pd

# Initialize KMeans with 3 clusters
kmeans = KMeans(n_clusters=3, random_state=42)

# Fit model
kmeans.fit(telco_raw[numerical])

# Assign cluster values
data.assign(Cluster = kmeans.labels_)

# Explore Results
data.groupby('cluster').mean()
```

10 Churn prediction and drivers

10.1 Regularization

[ ]:
```
# Initialize logistic regression instance
logreg = LogisticRegression(penalty='l1', C=0.025, solver='liblinear')

# Fit the model on training data
logreg.fit(train_X, train_Y)

# Predict churn values on test data
pred_test_Y = logreg.predict(test_X)

# Print the accuracy score on test data
print('Test accuracy:', round(accuracy_score(test_Y, pred_test_Y), 4))

C = [1, .5, .25, .1, .05, .025, .01, .005, .0025]
l1_metrics = np.zeros((len(C), 5))
l1_metrics[:, 0] = C

for index in range(0, len(C)):
    logreg = LogisticRegression(penalty = 'l1', C = C[index], solver =␣
 ↪'liblinear', random_state = 42)
    logreg.fit(train_X, train_Y)
    pred_train_Y = logreg.predict(test_X)
    l1_metrics[index, 1] = np.count_nonzero(logreg.coef_)
    l1_metrics[index, 2] = accuracy_score(test_Y, pred_test_Y)
    l1_metrics[index, 3] = precision_score(test_Y, pred_test_Y)
    l1_metrics[index, 4] = recall_score(test_Y, pred_test_Y)
```

[ ]:
```
from sklearn import tree
import graphviz

exported = tree.export_graphviz(decision_tree= mytree, out_file=None,␣
 ↪feature_names=cols, precision = 1, class_names = ['churn', 'not churn'],␣
 ↪filled = True )
graph = graghviz.Source(exported)
display(graph)

# Extracting logistic regression coefficients
logreg_coef = pd.DataFrame(logreg.coef_.T, index=train_X.columns,␣
 ↪columns=['Coefficient'])

coefficients = pd.concat([pd.DataFrame(train_X.columns), pd.DataFrame(logreg.
 ↪coef_.T)], axis=1)
coefficients.columns = ['Feature', 'Coefficient']
coefficients['Exp_Coefficient'] = np.exp(coefficients['Coefficient'])
```

```
coefficients = coefficients[coefficients['Coefficient']!= 0]
print(coefficients.sort_values(by = ['Coefficient'], ascending=False))
```

11 Customer Lifetime Values(CLV)

[ ]:
```
cohort_sizes = cohort_counts.iloc[:,0]
retention = cohort_counts.divide(cohort_sizes, axis = 0)
churn = 1 - retention
sns.heatmap(retention, annot=True, fvmin = 0, vmax = 0.5, mt='.0%',␣
 ↪cmap='YlGn', linewidths=0.5, linecolor='black')
```