Milestone 4 - Westyn Hilliard and Matthew Garlock

November 7, 2024

1 DSC 630 Assignment

Predictive Analytics

DSC630

WESTYN HILLIARD AND MATTHEW GARLOCK

[2]:
```
cd /Users/westynhilliard/Desktop/S C H O O L/Masters/DSC630 - Predicitve␣
 ↪Analytics/Group Project
```

```
/Users/westynhilliard/Desktop/S C H O O L/Masters/DSC630 - Predicitve
Analytics/GROUP Project
```

[3]:
```
# Imports -
import pandas as pd
import warnings
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.metrics import classification_report, roc_auc_score,␣
 ↪confusion_matrix
```

2 Data Loading

[4]:
```
# Load the dataset
file_path = 'Telco-Customer-Churn.csv'
data = pd.read_csv(file_path)

# Display the first few rows of the dataset to understand its structure
data.head()
```

[4]:
```
   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  … DeviceProtection  \
0  No phone service             DSL             No  …               No
1                No             DSL            Yes  …              Yes
2                No             DSL            Yes  …               No
3  No phone service             DSL            Yes  …              Yes
4                No     Fiber optic             No  …               No

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

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

[5 rows x 21 columns]
```

The dataset consists of customer information from a telecommunications company, containing 21 columns with various features. Here's a breakdown of some key columns:

2.0.1 Customer Demographics:

customerID: Unique identifier for each customer.

gender: Indicates the gender of the customer (e.g., Male, Female).

SeniorCitizen: Binary indicator if the customer is a senior citizen (0 = No, 1 = Yes).

Partner and Dependents: Indicate if the customer has a partner or dependents (Yes/No).

2.0.2 Account Information:

tenure: Number of months the customer has been with the company.

Contract: Type of contract the customer has (e.g., Month-to-month, One year).

PaperlessBilling: Indicates if the customer uses paperless billing (Yes/No).

PaymentMethod: Method of payment used by the customer (e.g., Electronic check, Mailed check).

2.0.3 Services and Usage:

PhoneService: Indicates if the customer has phone service (Yes/No).

MultipleLines: Indicates if the customer has multiple phone lines.

InternetService: Type of internet service (e.g., DSL, Fiber optic, No).

OnlineSecurity, DeviceProtection, TechSupport, StreamingTV, StreamingMovies: Indicate if the customer subscribes to these additional services (Yes/No).

2.0.4 Billing Information:

MonthlyCharges: The monthly charge for the customer.

TotalCharges: Total charges incurred by the customer.

2.0.5 Target Variable:

Churn: Indicates if the customer has churned (Yes/No).

This dataset is well-suited for analyzing factors that contribute to customer churn, allowing for predictive modeling and customer retention strategies.

[5]:

```
# Checking for missing values in the dataset
missing_values = data.isnull().sum()

# Summary statistics of the dataset
summary_stats = data.describe(include='all')

missing_values, summary_stats
```

[5]:

```
(customerID          0
 gender              0
 SeniorCitizen       0
 Partner             0
 Dependents          0
 tenure              0
 PhoneService        0
 MultipleLines       0
 InternetService     0
 OnlineSecurity      0
 OnlineBackup        0
 DeviceProtection    0
 TechSupport         0
 StreamingTV         0
 StreamingMovies     0
 Contract            0
 PaperlessBilling    0
 PaymentMethod       0
 MonthlyCharges      0
```

```
TotalCharges        0
Churn               0
dtype: int64,
        customerID gender  SeniorCitizen Partner Dependents       tenure  \
count         7043   7043    7043.000000    7043       7043  7043.000000
unique        7043      2            NaN       2          2          NaN
top     7590-VHVEG   Male            NaN      No         No          NaN
freq             1   3555            NaN    3641       4933          NaN
mean           NaN    NaN       0.162147     NaN        NaN    32.371149
std            NaN    NaN       0.368612     NaN        NaN    24.559481
min            NaN    NaN       0.000000     NaN        NaN     0.000000
25%            NaN    NaN       0.000000     NaN        NaN     9.000000
50%            NaN    NaN       0.000000     NaN        NaN    29.000000
75%            NaN    NaN       0.000000     NaN        NaN    55.000000
max            NaN    NaN       1.000000     NaN        NaN    72.000000

       PhoneService MultipleLines InternetService OnlineSecurity  …  \
count          7043          7043            7043           7043  …
unique            2             3               3              3  …
top             Yes            No     Fiber optic             No  …
freq           6361          3390            3096           3498  …
mean            NaN           NaN             NaN            NaN  …
std             NaN           NaN             NaN            NaN  …
min             NaN           NaN             NaN            NaN  …
25%             NaN           NaN             NaN            NaN  …
50%             NaN           NaN             NaN            NaN  …
75%             NaN           NaN             NaN            NaN  …
max             NaN           NaN             NaN            NaN  …

       DeviceProtection TechSupport StreamingTV StreamingMovies  \
count              7043        7043        7043            7043
unique                3           3           3               3
top                  No          No          No              No
freq               3095        3473        2810            2785
mean                NaN         NaN         NaN             NaN
std                 NaN         NaN         NaN             NaN
min                 NaN         NaN         NaN             NaN
25%                 NaN         NaN         NaN             NaN
50%                 NaN         NaN         NaN             NaN
75%                 NaN         NaN         NaN             NaN
max                 NaN         NaN         NaN             NaN

              Contract PaperlessBilling     PaymentMethod MonthlyCharges  \
count             7043             7043              7043    7043.000000
unique               3                2                 4            NaN
top     Month-to-month              Yes  Electronic check            NaN
freq              3875             4171              2365            NaN
```

```
mean               NaN            NaN               NaN      64.761692
std                NaN            NaN               NaN      30.090047
min                NaN            NaN               NaN      18.250000
25%                NaN            NaN               NaN      35.500000
50%                NaN            NaN               NaN      70.350000
75%                NaN            NaN               NaN      89.850000
max                NaN            NaN               NaN     118.750000

        TotalCharges Churn
count           7043  7043
unique          6531     2
top                     No
freq              11  5174
mean             NaN   NaN
std              NaN   NaN
min              NaN   NaN
25%              NaN   NaN
50%              NaN   NaN
75%              NaN   NaN
max              NaN   NaN

[11 rows x 21 columns])
```

2.0.6 Missing Values:

There are no missing values in any column of the dataset.

2.0.7 Categorical Columns:

Many columns are categorical, such as gender, Partner, Dependents, PhoneService, InternetService, and Churn.

2.0.8 Key points for some categorical columns:

Gender: 2 unique values (Male, Female)

Partner and Dependents: Majority have 'No' values.

InternetService: 3 unique types (DSL, Fiber optic, No)

Contract: Most customers are on a month-to-month contract.

Churn: Indicates a class imbalance with more "No" (5,174) than "Yes".

2.0.9 Numerical Columns:

tenure:

- Range: 0 to 72 months
- Average tenure: ~32.4 months

MonthlyCharges:

- Range: 18.25 dollars to 118.75 dollars
- Average monthly charge: ~$64.76

TotalCharges:

- Converted to numeric, initially had some non-numeric values.
- 11 entries have NaN values.

Key Observations:

- Class Imbalance: There is a significant imbalance in the Churn column, with a majority of customers not churning.
- Customer Contracts: Most customers are on month-to-month contracts.
- Billing: Most customers use electronic checks as their payment method.

3 Data Cleaning

[6]:

```
# Attempting to convert 'TotalCharges' to numeric, coercing errors to NaN
data['TotalCharges'] = pd.to_numeric(data['TotalCharges'], errors='coerce')

# Checking if there are any NaN values introduced in 'TotalCharges'
total_charges_missing = data['TotalCharges'].isna().sum()
print(f"Number of missing values in 'TotalCharges': {total_charges_missing}")
```

```
Number of missing values in 'TotalCharges': 11
```

- The TotalCharges column was converted to a numeric type.
- There are 11 entries in TotalCharges that were non-numeric and have been converted to NaN. This requires further handling to either impute these values or remove the affected rows.

[7]:

```
# Dropping rows with missing values in 'TotalCharges'
data_cleaned = data.dropna(subset=['TotalCharges'])

# Checking the shape of the dataset after dropping rows
data_cleaned.shape
```

[7]:

```
(7032, 21)
```

- Dropped the 11 rows with missing values in the TotalCharges column.

Result: The dataset now has fewer rows, removing entries with non-numeric TotalCharges values to ensure the integrity of the numerical analysis.

4 Data Processing

[8]:

```python
# Encode categorical variables
data_encoded = data_cleaned.copy()
label_encoders = {}

# Encoding all categorical columns
categorical_columns = data_encoded.select_dtypes(include=['object']).columns
for col in categorical_columns:
    if col != 'customerID':
        label_encoders[col] = LabelEncoder()
        data_encoded[col] = label_encoders[col].fit_transform(data_encoded[col])

# Splitting the data into features and target
X = data_encoded.drop(columns=['Churn', 'customerID'])
y = data_encoded['Churn']

# Split the dataset into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
```

Encoding:

Categorical variables are encoded using LabelEncoder to convert them into a numerical format.

Splitting:

The dataset is split into training and test sets (80% training, 20% testing).

5 Model Training and Evaluation

[9]:

```python
# Initialize models
logistic_model = LogisticRegression(max_iter=1000)
random_forest_model = RandomForestClassifier(n_estimators=100, random_state=42)
gbm_model = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1,␣
 ↪random_state=42)

# Train Logistic Regression
logistic_model.fit(X_train, y_train)
logistic_pred = logistic_model.predict(X_test)
logistic_prob = logistic_model.predict_proba(X_test)[:, 1]

# Train Random Forest
random_forest_model.fit(X_train, y_train)
rf_pred = random_forest_model.predict(X_test)
rf_prob = random_forest_model.predict_proba(X_test)[:, 1]

# Train Gradient Boosting Machine
```

```
gbm_model.fit(X_train, y_train)
gbm_pred = gbm_model.predict(X_test)
gbm_prob = gbm_model.predict_proba(X_test)[:, 1]

# Evaluation Function
def evaluate_model(y_true, y_pred, y_prob, model_name):
    print(f"Model: {model_name}")
    print(classification_report(y_true, y_pred))
    print(f"AUC-ROC: {roc_auc_score(y_true, y_prob)}")
    print("Confusion Matrix:")
    print(confusion_matrix(y_true, y_pred))
    print("\n")

# Evaluate Logistic Regression
evaluate_model(y_test, logistic_pred, logistic_prob, "Logistic Regression")

# Evaluate Random Forest
evaluate_model(y_test, rf_pred, rf_prob, "Random Forest")

# Evaluate Gradient Boosting Machine
evaluate_model(y_test, gbm_pred, gbm_prob, "Gradient Boosting Machine")
```

```
Model: Logistic Regression
              precision    recall  f1-score   support

           0       0.84      0.88      0.86      1033
           1       0.62      0.52      0.57       374

    accuracy                           0.79      1407
   macro avg       0.73      0.70      0.71      1407
weighted avg       0.78      0.79      0.78      1407

AUC-ROC: 0.8295939866750184
Confusion Matrix:
[[912 121]
 [178 196]]



Model: Random Forest
              precision    recall  f1-score   support

           0       0.83      0.90      0.86      1033
           1       0.63      0.48      0.54       374

    accuracy                           0.79      1407
   macro avg       0.73      0.69      0.70      1407
weighted avg       0.77      0.79      0.78      1407
```

```
AUC-ROC: 0.8123993767180375
Confusion Matrix:
[[928 105]
 [195 179]]


Model: Gradient Boosting Machine
              precision    recall  f1-score   support

           0       0.83      0.91      0.87      1033
           1       0.65      0.49      0.56       374

    accuracy                           0.80      1407
   macro avg       0.74      0.70      0.71      1407
weighted avg       0.78      0.80      0.79      1407

AUC-ROC: 0.835711623380321
Confusion Matrix:
[[935  98]
 [190 184]]
```

Model Training:

Trained Logistic Regression, Random Forest, and GBM models on the training data.

Model Evaluation:

Evaluated each model using:

- Classification Report: Provides precision, recall, and F1-score for each class.
- AUC-ROC: Measures the model's ability to distinguish between churn and non-churn customers.
- Confusion Matrix: Shows the true positives, true negatives, false positives, and false negatives.

5.0.1 1. Logistic Regression:

Precision:

- For class 0 (No Churn): 84% of predicted non-churn customers were correct.
- For class 1 (Churn): 62% of predicted churn customers were correct.

Recall:

- For class 0: 88% of actual non-churn customers were correctly identified.
- For class 1: 52% of actual churn customers were correctly identified.

F1-Score: A balance between precision and recall:

- For class 0: 0.86

- For class 1: 0.57

AUC-ROC:

0.83, indicating good discrimination between churn and non-churn customers.

Confusion Matrix:

Shows that it correctly classified a majority of non-churn customers but struggled with some false negatives (178 actual churns predicted as non-churn).

5.0.2 2. Random Forest:

Precision:

- For class 0: 83%
- For class 1: 63%

Recall:

- For class 0: 90% (better than Logistic Regression)
- For class 1: 48% (lower than Logistic Regression)
- F1-Score: Similar to Logistic Regression with a slightly lower recall for the churn class.

AUC-ROC:

0.81, slightly lower than Logistic Regression, indicating slightly less effective discrimination between classes.

Confusion Matrix:

Correctly identified a majority of non-churn customers but had some false negatives (195).

5.0.3 3. Gradient Boosting Machine (GBM):

Precision:

- For class 0: 83%
- For class 1: 65% (higher than both Logistic Regression and Random Forest)

Recall:

- For class 0: 91% (highest among all models)
- For class 1: 49% (similar to Random Forest, slightly better)

F1-Score:

- For class 0: 0.87 (highest among the models)
- For class 1: 0.56

AUC-ROC:

0.84, the highest among the three models, indicating the best discrimination capability.

Confusion Matrix:

Better performance overall with the highest correctly predicted churners (184).

5.0.4 Summary of Model Performance:

Logistic Regression:

Performed well with a high AUC-ROC of 0.83, indicating good overall discrimination. However, it struggled with recall for the churn class, indicating it missed a significant number of actual churners.

Random Forest:

Offered a similar performance to Logistic Regression with a slight drop in AUC-ROC to 0.81. It had a better recall for non-churners but a lower recall for churners, resulting in more false negatives.

Gradient Boosting Machine (GBM):

Outperformed the other models with the highest AUC-ROC of 0.84. It had the best balance between precision and recall, especially for the churn class, making it the most effective model for this problem.

5.0.5 Conclusion:

Best Model:

The Gradient Boosting Machine (GBM) has the highest AUC-ROC and a better balance in performance metrics, making it the best model among the three for predicting customer churn.

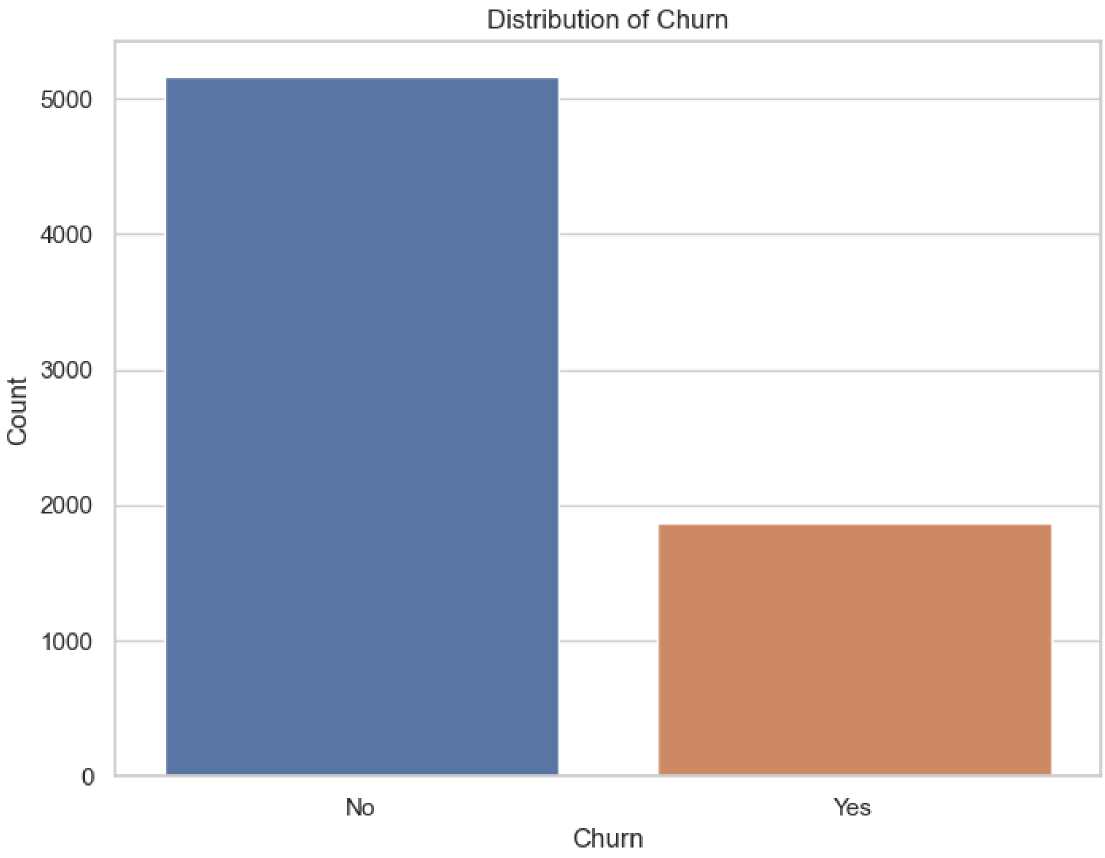
Recommendations: GBM should be used for predicting churn as it captures complex relationships in the data better than the others. Further feature analysis can be done to understand what influences churn the most, using feature importance from the Random Forest and GBM models.

6 Visualizations

[10]:

```
# Set up the style for the plots
sns.set(style='whitegrid')

# Churn Distribution
plt.figure(figsize=(8, 6))
sns.countplot(data=data_cleaned, x='Churn')
plt.title('Distribution of Churn')
plt.xlabel('Churn')
plt.ylabel('Count')
plt.show()
```



Interpretation of Churn Distribution:

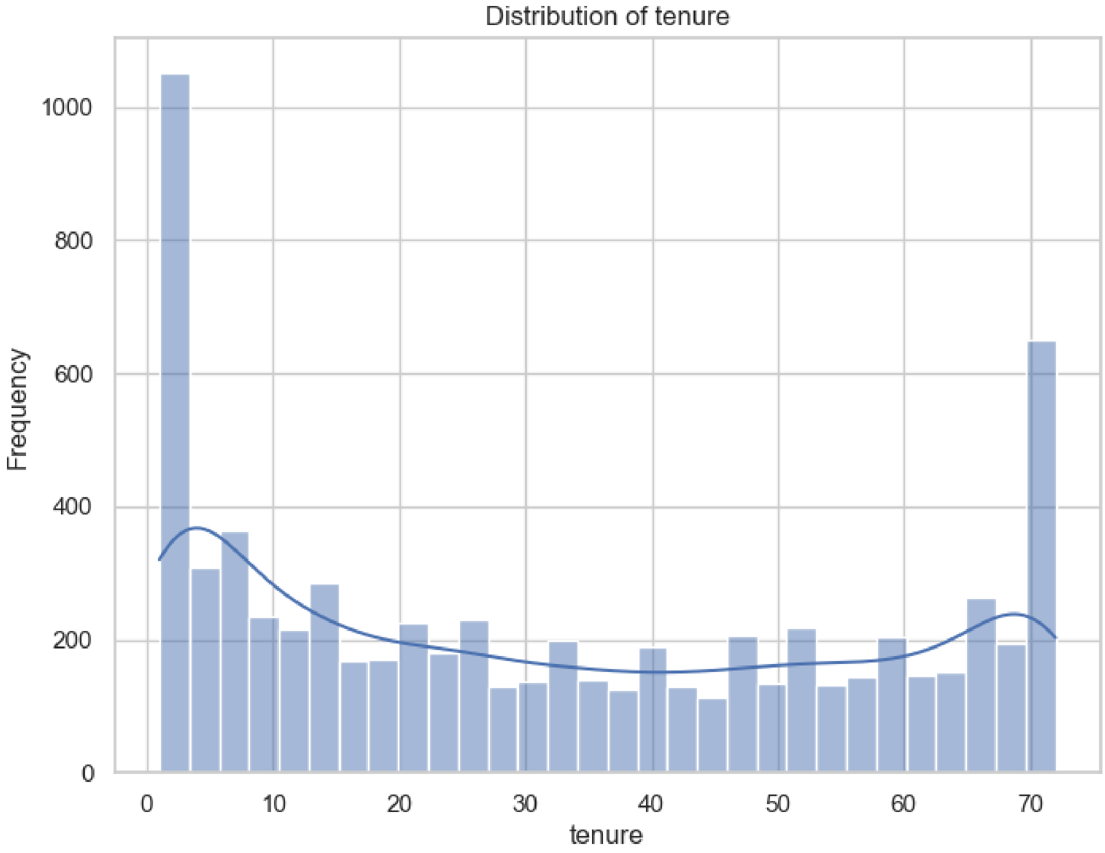
- **Class Imbalance:** The plot shows a significant imbalance between customers who did not churn (majority) and those who did churn (minority). This imbalance is important to consider when building predictive models, as it can affect the model's ability to accurately predict the minority class (churn).
- **Implications for Modeling:** Since most customers did not churn, models trained on this data might be biased towards predicting the majority class (no churn). Special techniques, such as resampling or adjusting class weights, might be needed to ensure the model adequately captures patterns leading to churn.

[11]:

```
# Suppress specific warnings
warnings.filterwarnings("ignore", category=FutureWarning)

# Plotting the distribution of tenure again without showing the warning
plt.figure(figsize=(8, 6))
sns.histplot(data_cleaned['tenure'], kde=True, bins=30)
plt.title('Distribution of tenure')
plt.xlabel('tenure')
plt.ylabel('Frequency')
plt.show()

# Resetting the warning filter back to default
warnings.filterwarnings("default", category=FutureWarning)
```



Interpretation of Tenure Distribution:

- **Short Tenure:** There is a high frequency of customers with a very short tenure (close to 0 months), indicating that many customers leave shortly after joining.
- **Long Tenure:** There's also a spike at the maximum tenure, suggesting a group of loyal customers who have been with the company for an extended period (around 70 months).
- **Overall Spread:** The distribution has a somewhat bimodal shape with a higher concentration of customers at both very short and very long tenures, with fewer customers in the middle range.

Insights for Churn:

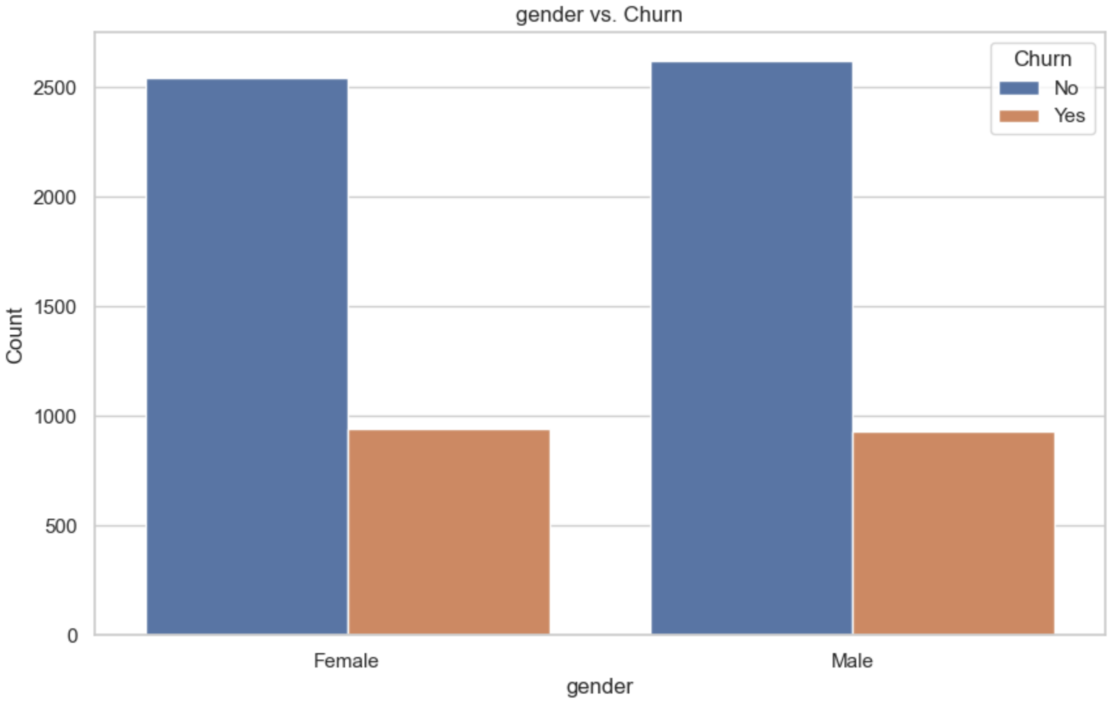
- Customers with shorter tenure might be more likely to churn, potentially due to dissatisfaction early in their relationship with the company.
- Understanding why customers with short tenure churn can help the company implement

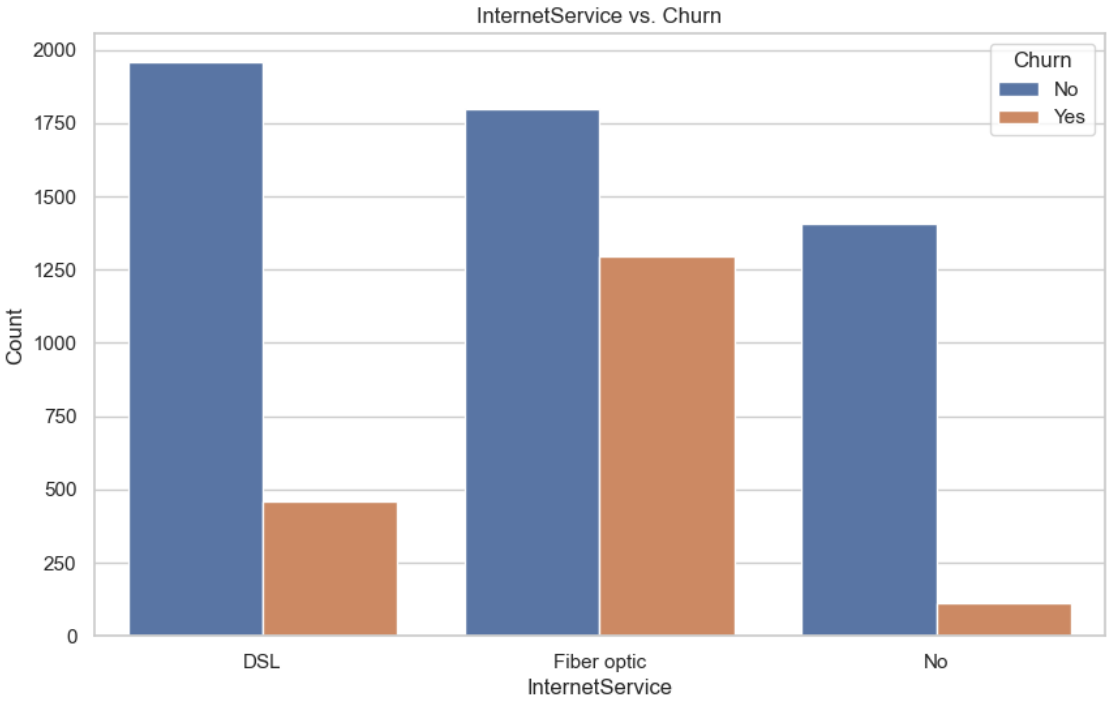
strategies to improve customer retention early on.

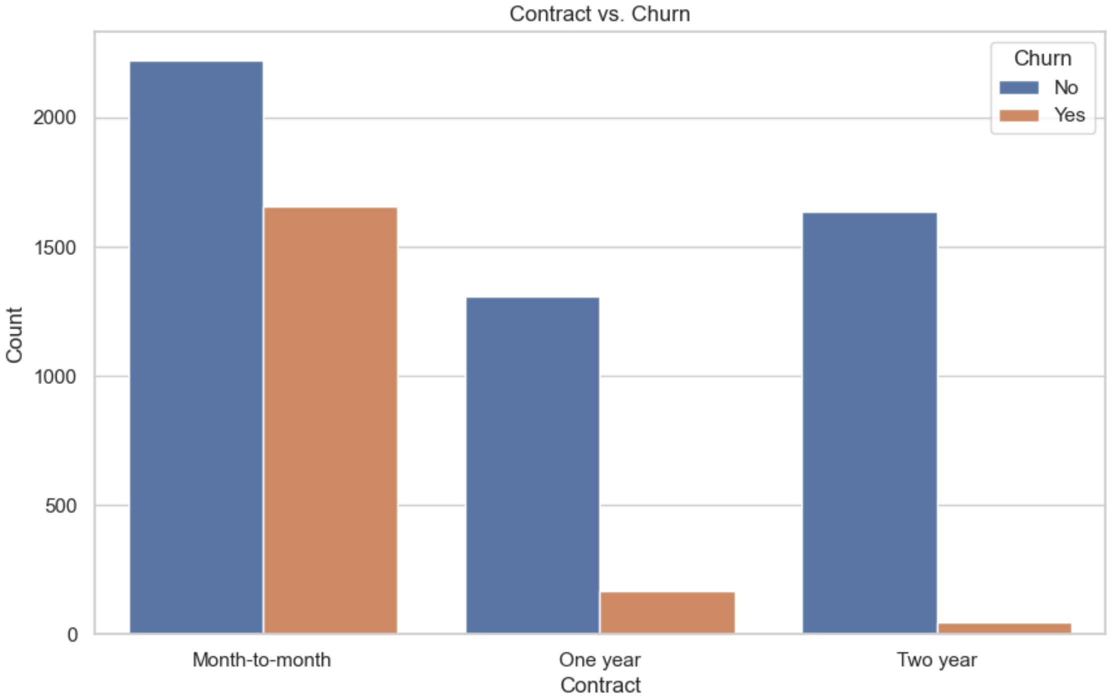
[12]:

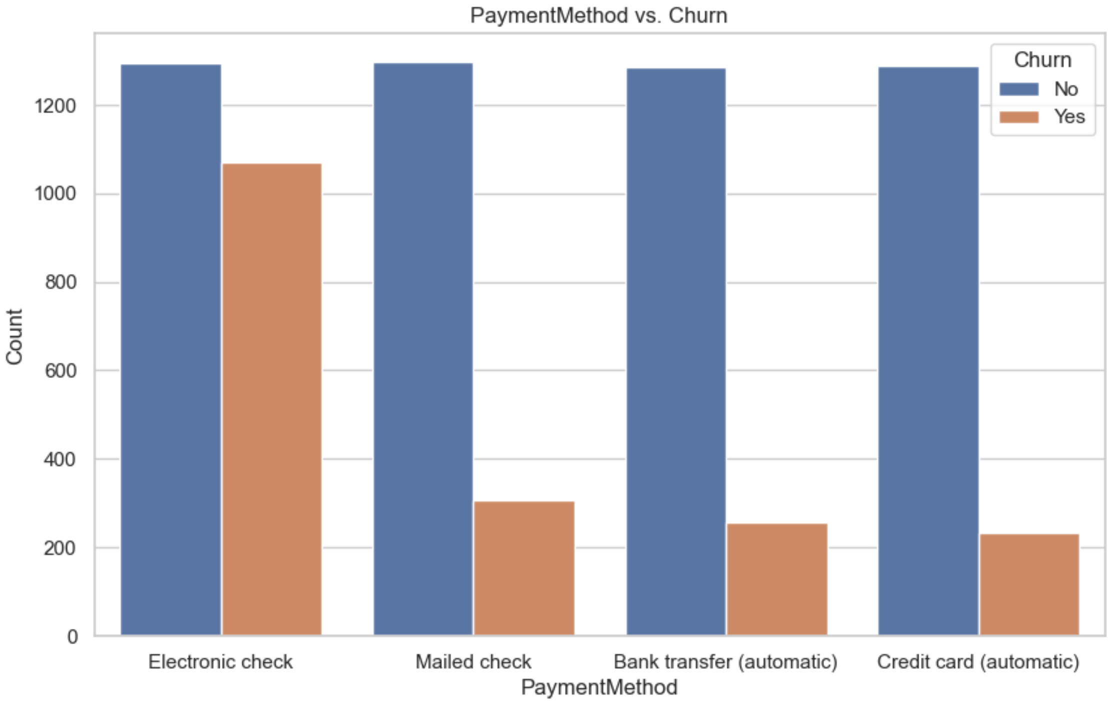
```
# Categorical features to visualize with Churn
categorical_features = ['gender', 'InternetService', 'Contract',␣
 ↪'PaymentMethod']

for feature in categorical_features:
    plt.figure(figsize=(10, 6))
    sns.countplot(data=data_cleaned, x=feature, hue='Churn')
    plt.title(f'{feature} vs. Churn')
    plt.xlabel(feature)
    plt.ylabel('Count')
    plt.legend(title='Churn')
    plt.show()
```




InternetService vs. Churn
Count
2000
1750
1500
1250
1000
750
500
250
0
DSL
Fiber optic
No
InternetService
Churn
No
Yes


Contract vs. Churn
Count
2000
1500
1000
500
0
Month-to-month
One year
Two year
Contract
Churn
No
Yes



6.0.1 Interpretation of Gender vs. Churn:

- **Observation:** Similar churn rates for both males and females.

Insight: Gender does not appear to be a significant predictor of churn, suggesting that other factors are more influential.

6.0.2 Interpretation of InternetService vs. Churn:

- **Fiber Optic:** Higher churn rate compared to DSL and those with no internet service.
- **DSL and No Internet Service:** Lower churn rates, with most customers staying.

Insight: Internet service type impacts churn, with Fiber optic users more likely to churn. This suggests a need to investigate and improve Fiber optic customer satisfaction.

6.0.3 Interpretation of Contract vs. Churn:

- **Month-to-Month Contracts:** Higher churn rate, as nearly equal numbers of customers churn and stay.
- **One-Year and Two-Year Contracts:** Lower churn rates, with most customers staying.

Insight: Customers on longer-term contracts are less likely to churn, suggesting a strategy to encourage longer commitments could help reduce churn.

6.0.4 Interpretation of Payment Method Vs. Churn

- **Electronic Check:** Higher churn rate compared to other payment methods.
- **Mailed Check, Bank Transfer, Credit Card:** Lower churn rates, with most customers staying.

Insight: Customers using electronic checks are more likely to churn, indicating potential dissatisfaction with this payment method or its associated convenience/fees. This suggests focusing on understanding and improving the experience for these customers.

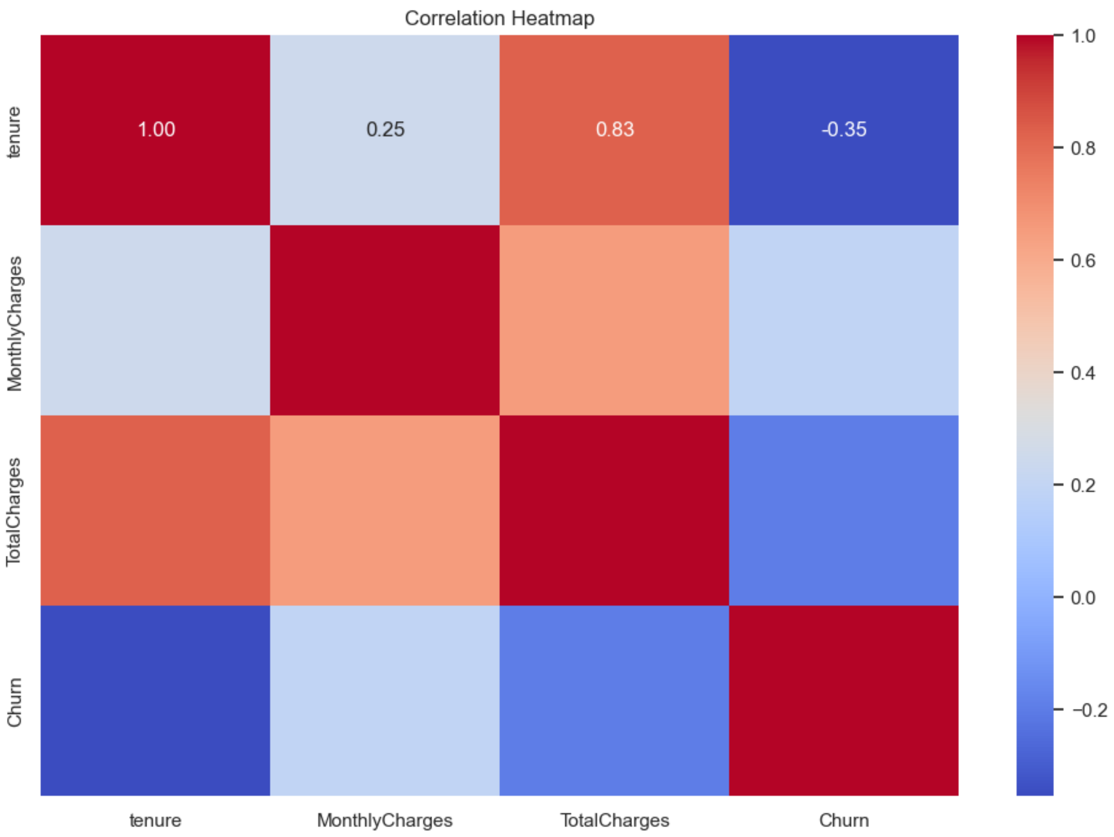
[13]:

```
# Convert 'Churn' column to numeric: 1 for 'Yes', 0 for 'No'
data_cleaned['Churn'] = data_cleaned['Churn'].apply(lambda x: 1 if x == 'Yes'␣
  ↪else 0)

# Correlation heatmap for numerical features
plt.figure(figsize=(12, 8))
correlation = data_cleaned[['tenure', 'MonthlyCharges', 'TotalCharges',␣
  ↪'Churn']].corr()
sns.heatmap(correlation, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap')
plt.show()
```

```
/var/folders/67/hl77bzs97pggp3g9r_hnl9kw0000gn/T/ipykernel_1668/1760577846.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data_cleaned['Churn'] = data_cleaned['Churn'].apply(lambda x: 1 if x == 'Yes'
else 0)
```



6.0.5 Interpretation of Correlation Heatmap

- **Tenure and Churn:** Moderate negative correlation (-0.35) — longer tenure means lower churn.
- **TotalCharges and Tenure:** Strong positive correlation (0.83) — higher total charges usually mean longer tenure.

Insight:

- **Retention Focus:** Shorter-tenure customers are more prone to churn, indicating a need for early engagement.

```
[ ]:
```