Customer Churn

May 27, 2025

0.1 # Customer Churn Prediction

0.1.1 Summary:

This project analyzes customer churn data to identify the key factors influencing whether a customer leaves a telecom service. Using skills in data wrangling, exploratory data analysis (EDA), and statistical correlation, the project uncovers that features like contract type, tenure, and payment method are highly associated with customer retention. Visualization, feature interpretation, and data storytelling are applied to translate patterns into actionable insights for improving customer retention strategies.

0.2 Overview & Background:

A business will measure **customer churn** as the loss of existing customers continuing doing business or using their service with the company, compared to the total number of customers in a given period of time. Analyzing customer churn is important for a business to understand why a customer will stop using their service or want to stop doing business with them. Improving their customer retention is good for building brand loyalty and increasing overall customer satisfaction and profitability. While there are formulas that are easy to calculate what the customer churn is, it is difficult to accurately predict.

This dataset that I will be using comes from a telecommunication company and it provides the home phone and internet services to 7043 customers in California.

The data set includes information about: * **Customers who left within the last month** – the column is called `Churn` * **Services that each customer has signed up for** – phone, multiple lines, internet, online security, online backup, device protection, tech support, and streaming TV and movies * **Customer account information** – how long they've been a customer, contract, payment method, paperless billing, monthly charges, and total charges * **Demographic info about customers** – gender, age range, and if they have partners and dependents

In this project I will analyze the different factors that affect customer churn by creating regression models to identify correlation as well as creating a survival analysis model. I also create a prediction model using classification machine learning to accuractely predict the likeliness of a customer to churn.

Objectives: * What is the current churn percentage for this company? * What factors directly affect customer churn, and how does it differ? * Does demographics or type of telecommunication service affect whether or not a customer will churn? * Which services are the most profitable? * How long before a customer will change companies or churn?

The data comes from Kaggle and can be accessed here.

0.3 Understanding the Data

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

[50]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from lifelines.plotting import plot_lifetimes
from lifelines import KaplanMeierFitter
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import cross_val_score, train_test_split
from sklearn.ensemble import RandomForestClassifier
import statsmodels.api as sm
from sklearn import metrics
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.metrics import accuracy_score, classification_report, log_loss
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_curve, auc
from sklearn.pipeline import Pipeline
from sklearn.ensemble import GradientBoostingClassifier
import xgboost as xgb
from xgboost import XGBClassifier
```

[2]:
```python
df = pd.read_csv('WA_Fn-UseC_-Telco-Customer-Churn.csv')
df
```

[2]:
```
      customerID  gender  SeniorCitizen Partner Dependents  tenure  \
0     7590-VHVEG  Female              0     Yes         No       1
1     5575-GNVDE    Male              0      No         No      34
2     3668-QPYBK    Male              0      No         No       2
3     7795-CFOCW    Male              0      No         No      45
4     9237-HQITU  Female              0      No         No       2
…            …       …             …       …          …      …
7038  6840-RESVB    Male              0     Yes        Yes      24
7039  2234-XADUH  Female              0     Yes        Yes      72
7040  4801-JZAZL  Female              0     Yes        Yes      11
7041  8361-LTMKD    Male              1     Yes         No       4
7042  3186-AJIEK    Male              0      No         No      66

     PhoneService     MultipleLines InternetService OnlineSecurity  …  \
0              No  No phone service             DSL             No  …
1             Yes                No             DSL            Yes  …
```

```
2             Yes                No            DSL            Yes  …
3              No  No phone service            DSL            Yes  …
4             Yes                No    Fiber optic             No  …
…           …                …             …            …  …
7038          Yes               Yes            DSL            Yes  …
7039          Yes               Yes    Fiber optic             No  …
7040           No  No phone service            DSL            Yes  …
7041          Yes               Yes    Fiber optic             No  …
7042          Yes                No    Fiber optic            Yes  …

     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
…                …         …         …             …             …
7038              Yes         Yes         Yes             Yes        One year
7039              Yes          No         Yes             Yes        One year
7040               No          No          No              No  Month-to-month
7041               No          No          No              No  Month-to-month
7042              Yes         Yes         Yes             Yes        Two year

     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
…                 …                         …             …            …
7038              Yes               Mailed check          84.80        1990.5
7039              Yes    Credit card (automatic)         103.20        7362.9
7040              Yes           Electronic check          29.60        346.45
7041              Yes               Mailed check          74.40         306.6
7042              Yes  Bank transfer (automatic)         105.65        6844.5

     Churn
0       No
1       No
2      Yes
3       No
4      Yes
…     …
7038    No
7039    No
7040    No
7041   Yes
```

```
7042    No

[7043 rows x 21 columns]
```

[3]:
```
df.info()
```

```
<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
```

[4]:
```
df.columns
```

[4]:
```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

We will focus on the column `Churn` and all of the different columns/attributes that will correlate and affect customer churn. There is data on 7043 customers and 21 columns/attributes on each customer.

0.4 Data Cleaning

The first step is to check every column in the dataset for missing values. However, I noticed that the `TotalCharges` column is listed as an "object" instead of a "float64". We will change only the `TotalCharges` column into a number value and then track the number of missing values.

[5]:
```
# Turn total charges into a number value and check for missing values
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors = 'coerce')
df.isnull().sum()
```

[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        11
Churn                0
dtype: int64
```

I decided to replace the missing data as the media of the column to account for any outliers within the data.

[6]:
```
# Replace NaN with the column mean
df['TotalCharges'] = df['TotalCharges'].fillna(df['TotalCharges'].median())
df.isnull().sum()
```

[6]:
```
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
```

[7]:
```python
df = df.drop('customerID', axis = 1)
df
```

[7]:
```
      gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0     Female              0     Yes         No       1           No
1       Male              0      No         No      34          Yes
2       Male              0      No         No       2          Yes
3       Male              0      No         No      45           No
4     Female              0      No         No       2          Yes
…        …             …      …        …       …          …
7038    Male              0     Yes        Yes      24          Yes
7039  Female              0     Yes        Yes      72          Yes
7040  Female              0     Yes        Yes      11           No
7041    Male              1     Yes         No       4          Yes
7042    Male              0      No         No      66          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
…                 …               …              …           …
7038               Yes             DSL            Yes           No
7039               Yes     Fiber optic             No          Yes
7040  No phone service             DSL            Yes           No
7041               Yes     Fiber optic             No           No
7042                No     Fiber optic            Yes           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
…                …          …          …             …             …
7038                Yes          Yes          Yes               Yes         One year
7039                Yes           No          Yes               Yes         One year
7040                 No           No           No                No   Month-to-month
7041                 No           No           No                No   Month-to-month
7042                Yes          Yes          Yes               Yes         Two year

     PaperlessBilling              PaymentMethod  MonthlyCharges  \
0                 Yes           Electronic check           29.85
1                  No               Mailed check           56.95
2                 Yes               Mailed check           53.85
3                  No  Bank transfer (automatic)           42.30
4                 Yes           Electronic check           70.70
…                …                          …              …
7038              Yes               Mailed check           84.80
7039              Yes    Credit card (automatic)          103.20
7040              Yes           Electronic check           29.60
7041              Yes               Mailed check           74.40
7042              Yes  Bank transfer (automatic)          105.65

      TotalCharges Churn
0            29.85    No
1          1889.50    No
2           108.15   Yes
3          1840.75    No
4           151.65   Yes
…              …   …
7038       1990.50    No
7039       7362.90    No
7040        346.45    No
7041        306.60   Yes
7042       6844.50    No

[7043 rows x 20 columns]
```

[8]:
```
df.isnull().sum()
```

[8]:
```
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
```

[9]:
```
df.describe()
```

[9]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges
count	7043.000000	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692	2281.916928
std	0.368612	24.559481	30.090047	2265.270398
min	0.000000	0.000000	18.250000	18.800000
25%	0.000000	9.000000	35.500000	402.225000
50%	0.000000	29.000000	70.350000	1397.475000
75%	0.000000	55.000000	89.850000	3786.600000
max	1.000000	72.000000	118.750000	8684.800000

The data now seems to be accounted for when it comes to missing data and so now we can move onto the visualizations.

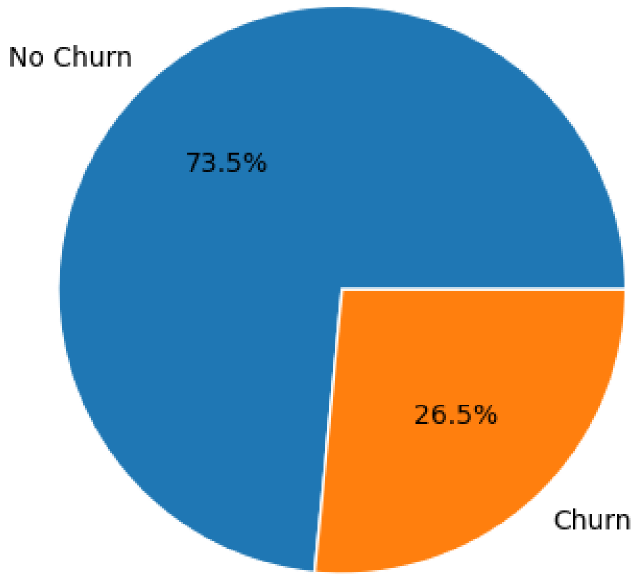
0.5 Data Visualizations

In this section I am going to create frequency tables that will compare the attribute of the customer to the churn. This is to look closely at the exact numbers between what is most common for customers to churn.

[10]:
```
# Frequency of Churn/No Churn
churn_stats = df['Churn'].value_counts(normalize=True) * 100
churn_stats
```

[10]:
```
Churn
No     73.463013
Yes    26.536987
Name: proportion, dtype: float64
```

[11]:
```
# Data visualization to churn/no churn

labels = 'No Churn', 'Churn'
sizes = [73.463013, 26.536987]

fig, ax = plt.subplots()
ax.pie(sizes, labels=labels,
      wedgeprops=dict(edgecolor='white'), autopct='%1.1f%%')
plt.show()
```



There is overall a lot of “No Churn” from the customers, however there was about a quarter of the customers who did churn. We will look closer at why these customers might have churned and the factors that correlate with churning.

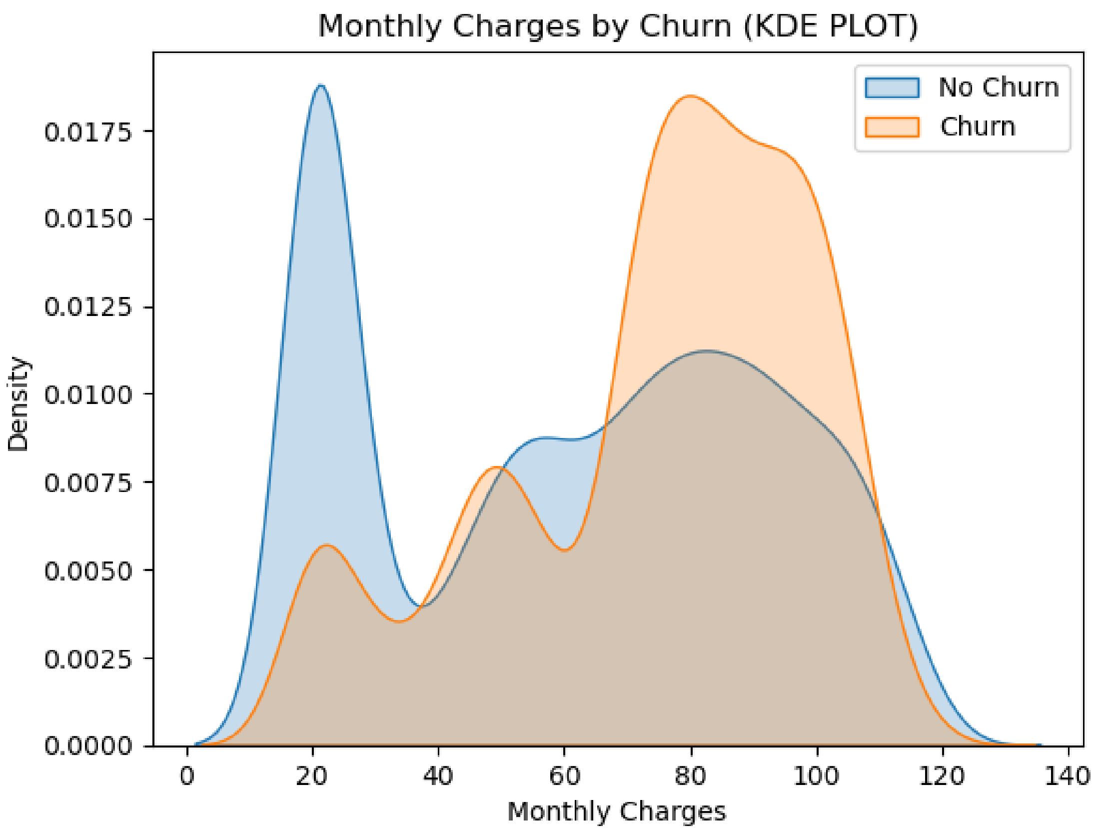
[12]:
```
# Calculate the average of monthly charges for no churn
no_churn = df[df['Churn'] == 'No']
average_monthly_no_churn = no_churn['MonthlyCharges'].mean()
print(f"Average Monthly Charges for No Churn: {average_monthly_no_churn}")

# Calculate the median of monthly charges for no churn
median_monthly_no_churn = no_churn['MonthlyCharges'].median()
print(f"Median Monthly Charges for No Churn: {median_monthly_no_churn}")

# Calculate the average of monthly charges for churn
```

```
yes_churn = df[df['Churn'] == 'Yes']
average_monthly_yes_churn = yes_churn['MonthlyCharges'].mean()
print(f"Average Monthly Charges for Churn: {average_monthly_yes_churn}")

# Calculate the average of monthly charges for churn
median_monthly_yes_churn = yes_churn['MonthlyCharges'].median()
print(f"Median Monthly Charges for Churn: {median_monthly_yes_churn}")
```

```
Average Monthly Charges for No Churn: 61.26512369540008
Median Monthly Charges for No Churn: 64.42500000000001
Average Monthly Charges for Churn: 74.44133226324237
Median Monthly Charges for Churn: 79.65
```

The customers who churned generally have **higher monthly bills**. This could indicate that higher pricing is linked to dissatisfaction, especially if they feel it doesn't match the value they get. Median being higher than average (especially for churners) hints at some lower outliers — but many churners are paying high monthly fees.

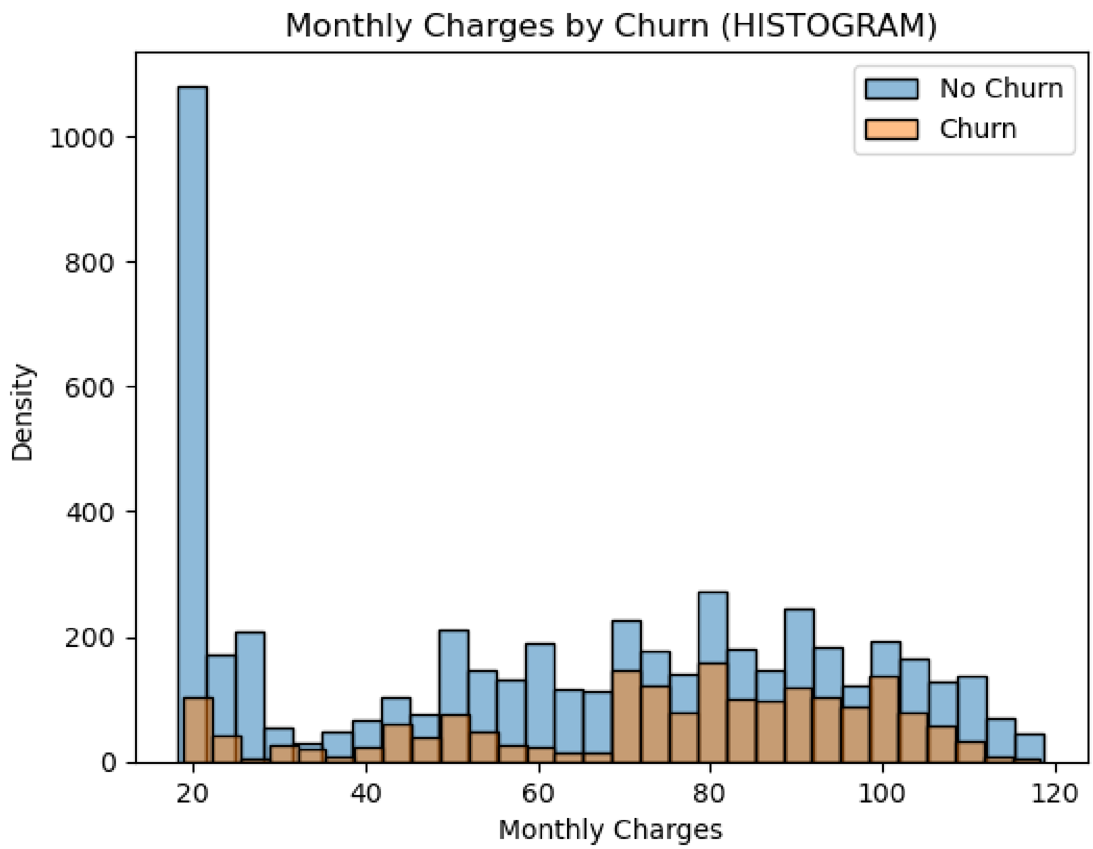
[13]:
```
# Data visualization of churn/no churn based on monthly charges

# Filter and plot the data for 'Churn' == 0 and 'Churn' == 1
sns.kdeplot(df.MonthlyCharges[df["Churn"] == 'No'], fill = True, label="No␣
↪Churn")
sns.kdeplot(df.MonthlyCharges[df["Churn"] == 'Yes'], fill = True, label="Churn")

# Add labels and title
plt.title('Monthly Charges by Churn (KDE PLOT)')
plt.xlabel('Monthly Charges')
plt.ylabel('Density')
plt.legend()

# Display the legend and the plot
plt.show()
```



Customers who churned had higher monthly charges on average. You can see the orange curve peaking around 70–100 USD. Customers who did not churn have two notable clusters: one peak at low monthly charges (around 20 USD) and another smaller one around 70–90 USD. This smooth curve helps you see general distribution trends and compare how spread out or concentrated the values are.

[14]:
```python
# Data visualization of churn/no churn based on monthly charges (histogram)

# Filter and plot the data for 'Churn' == 0 and 'Churn' == 1
sns.histplot(df.MonthlyCharges[df["Churn"] == 'No'], bins = 30, alpha = 0.5,␣
 ↪label="No Churn")
sns.histplot(df.MonthlyCharges[df["Churn"] == 'Yes'], bins = 30, alpha = 0.5,␣
 ↪label="Churn")

# Add labels and title
plt.title('Monthly Charges by Churn (HISTOGRAM)')
plt.xlabel('Monthly Charges')
plt.ylabel('Density')
plt.legend()

# Display the legend and the plot
```

```
plt.show()
```



A huge spike around 20 USD: A lot of customers are paying the minimum monthly charge, and most of them don't churn (blue bars dominate). Customers who churn tend to be more evenly distributed across higher charge brackets. This plot is more literal and helps in understanding raw counts or frequency.

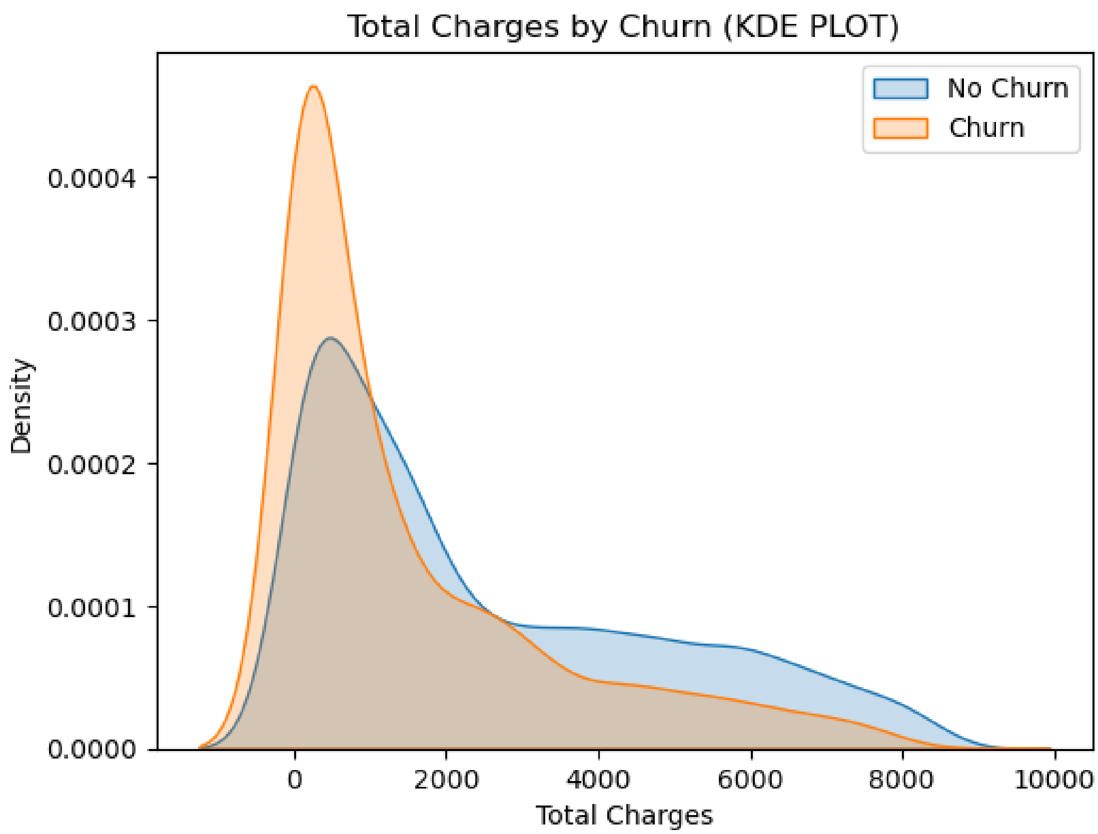
[15]:
```
# Calculate the average of total charges for no churn
average_total_no_churn = no_churn['TotalCharges'].mean()
print(f"Average Total Charges for No Churn : {average_total_no_churn}")

# Calculate the average of total charges for churn
average_total_yes_churn = yes_churn['TotalCharges'].mean()
print(f"Average Total Charges for Churn: {average_total_yes_churn}")

# Calculate the median of total charges for no churn
median_total_no_churn = no_churn['TotalCharges'].median()
print(f"Median Total Charges for No Churn: {median_total_no_churn}")

# Calculate the median of total charges for churn
```

```python
median_total_yes_churn = yes_churn['TotalCharges'].median()
print(f"Median Total Charges for Churn: {median_total_yes_churn}")
```

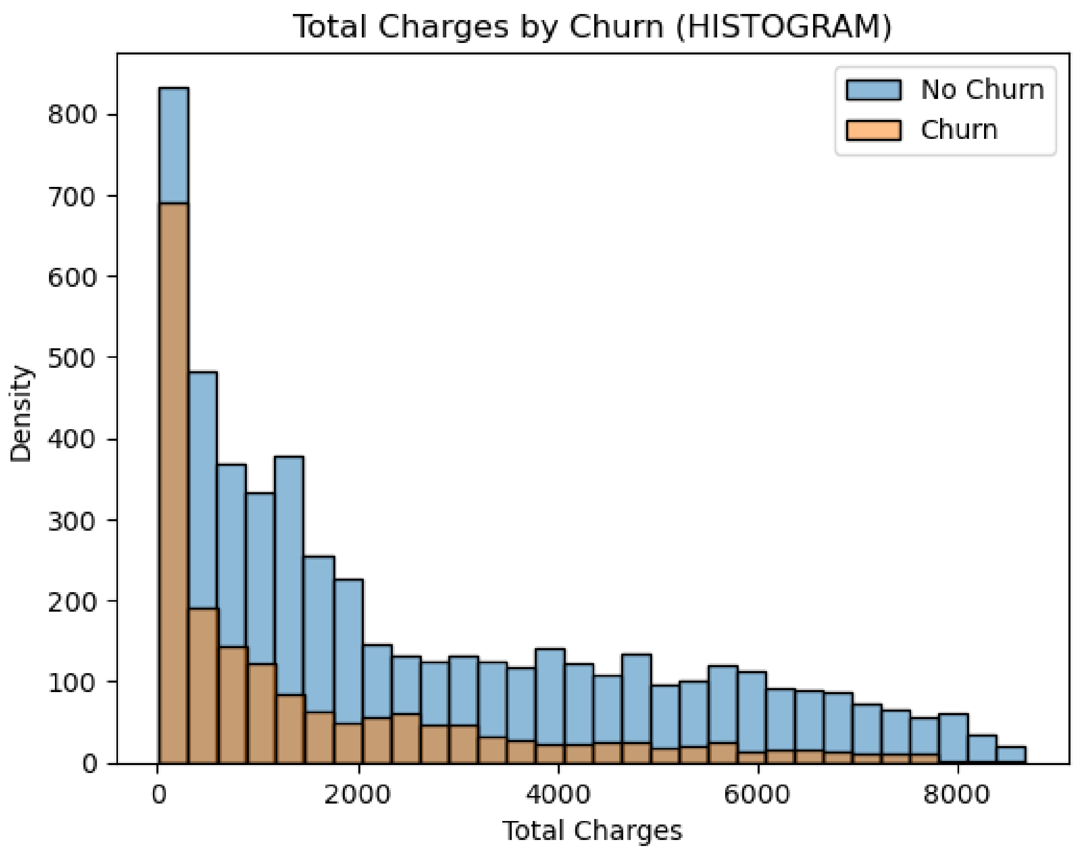
```
Average Total Charges for No Churn : 2552.882494201778
Average Total Charges for Churn: 1531.7960941680042
Median Total Charges for No Churn: 1679.525
Median Total Charges for Churn: 703.55
```

Non-churners have spent much more over time, which makes sense since they've stayed longer. The huge gap between median for churners (703 USD) and non-churners (1,679 USD) shows churners often leave before investing much. This is very similar to the monthly charges but takes tenure into account.

[16]:
```python
# Data visualization of churn/no churn based on total charges (kde plot)

# Filter and plot the data for 'Churn' == 0 and 'Churn' == 1
sns.kdeplot(df.TotalCharges[df["Churn"] == 'No'], fill = True, label="No Churn")
sns.kdeplot(df.TotalCharges[df["Churn"] == 'Yes'], fill = True, label="Churn")

# Add labels and title
plt.title('Total Charges by Churn (KDE PLOT)')
plt.xlabel('Total Charges')
plt.ylabel('Density')
plt.legend()

# Display the legend and the plot
plt.show()
```



[17]:
```
# Data visualization of churn/no churn based on total charges

# Filter and plot the data for 'Churn' == 0 and 'Churn' == 1
sns.histplot(df.TotalCharges[df["Churn"] == 'No'], bins = 30, alpha = 0.5,␣
 ↪label="No Churn")
sns.histplot(df.TotalCharges[df["Churn"] == 'Yes'], bins = 30, alpha = 0.5,␣
 ↪label="Churn")

# Add labels and title
plt.title('Total Charges by Churn (HISTOGRAM)')
plt.xlabel('Total Charges')
plt.ylabel('Density')
plt.legend()

# Display the legend and the plot
plt.show()
```



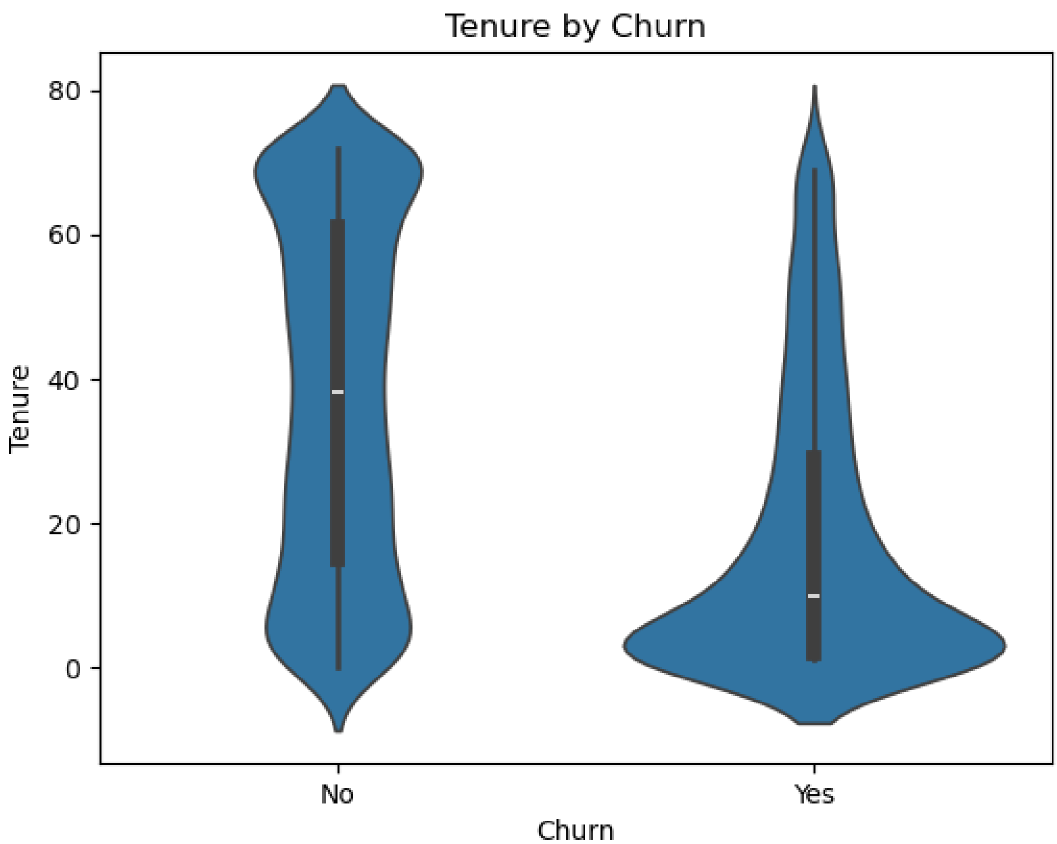
Churned customers (orange) are clustered at low total charges, typically under 2000 USD, with a sharp peak very early. Non-churned customers (blue) are more widely distributed, with a long tail reaching 8000–9000 USD, suggesting they've been with the company longer.

[18]:
```
# Calculate the average tenure for no churn
average_tenure_no_churn = no_churn['tenure'].mean()
print(f"Average Tenure for No Churn : {average_tenure_no_churn}")

# Calculate the median tenure for no churn
median_tenure_no_churn = no_churn['tenure'].median()
print(f"Median Tenure for No Churn: {median_tenure_no_churn}")

# Calculate the average tenure for churn
average_tenure_yes_churn = yes_churn['tenure'].mean()
print(f"Average Tenure for Churn: {average_tenure_yes_churn}")

# Calculate the median tenure for churn
median_tenure_yes_churn = yes_churn['tenure'].median()
print(f"Median Tenure for Churn: {median_tenure_yes_churn}")
```

```
Average Tenure for No Churn : 37.56996521066873
```

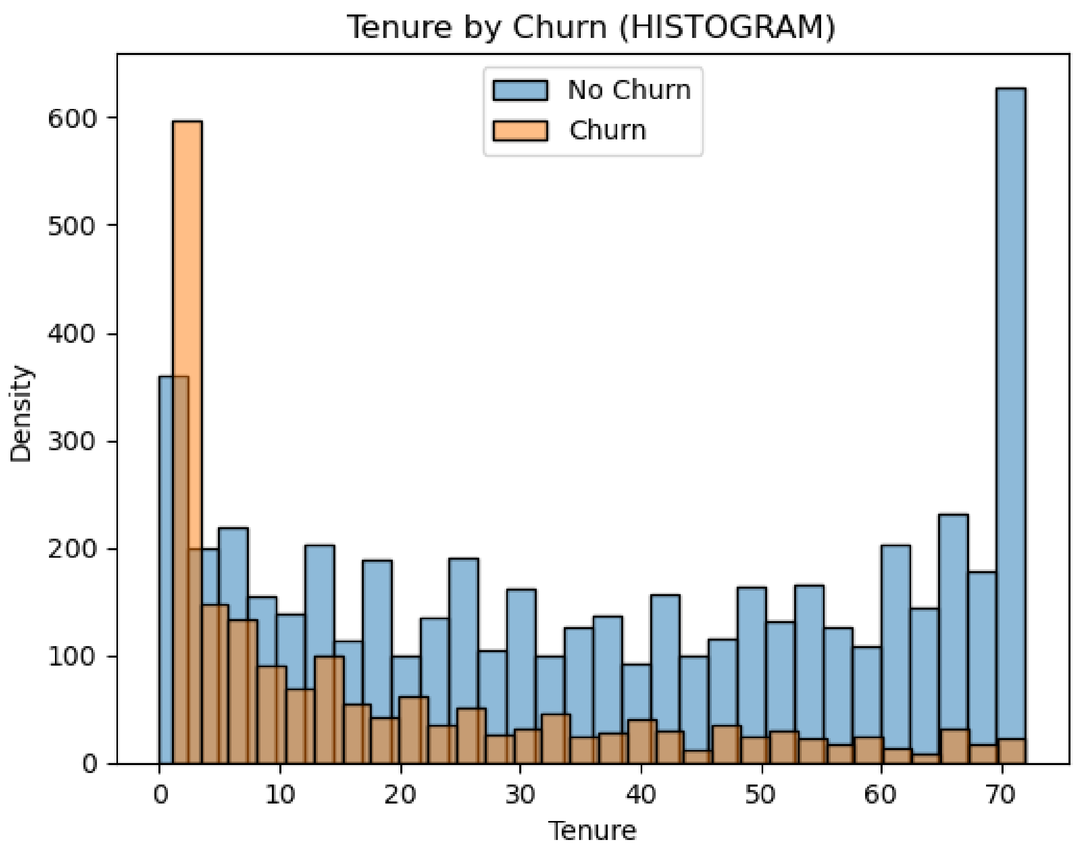
```
Median Tenure for No Churn: 38.0
Average Tenure for Churn: 17.979133226324237
Median Tenure for Churn: 10.0
```

[19]:
```
# Data visualization for tenure by churn
sns.violinplot(data = df, x = 'Churn', y = 'tenure')

# Add labels and title
plt.title('Tenure by Churn')
plt.xlabel('Churn')
plt.ylabel('Tenure')

# Display the legend and the plot
plt.show()
```



[20]:
```
# Filter and plot the data for 'Churn' == 0 and 'Churn' == 1
sns.histplot(df.tenure[df["Churn"] == 'No'], bins = 30, alpha = 0.5, label="No␣
 ↪Churn")
sns.histplot(df.tenure[df["Churn"] == 'Yes'], bins = 30, alpha = 0.5,␣
 ↪label="Churn")
```

```
# Add labels and title
plt.title('Tenure by Churn (HISTOGRAM)')
plt.xlabel('Tenure')
plt.ylabel('Density')
plt.legend()

# Display the legend and the plot
plt.show()
```



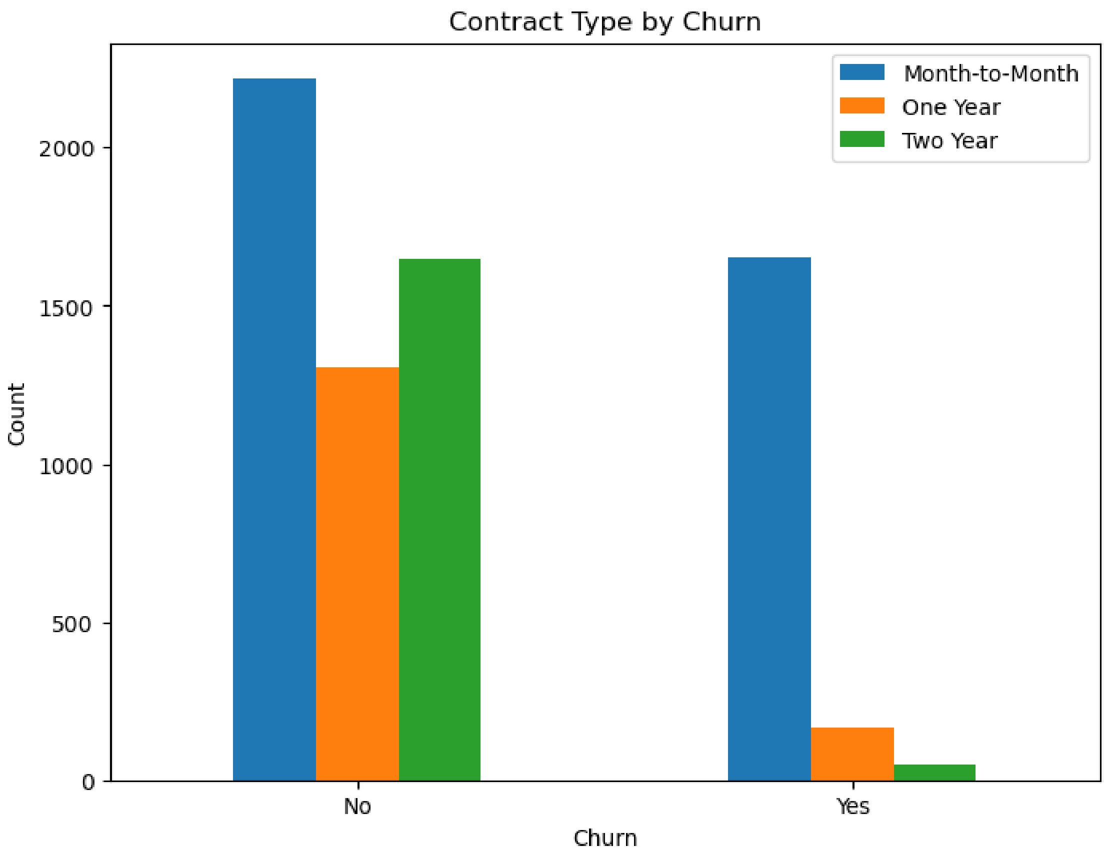
The histogram and violin plot are similar in the fact that the distribution for the non-churned customers is even shows a normal distribution while the churned customers shows a larger concentration around 0-10 months while showing a right skew. This shows that those who churn have used the service for a short amount of time.

The customers who churn overall have lower monthly and total charges and will churn after a shorter amount of time. This is a sign of the company possibly not being able to keep customer retention in the beginning of the service. There is a lot of customer loyalty since the tenure for non-churned customers is almost double those who do churn and monthly charges are also overall higher.

[21]:

```
# Data visualization for Contract Type by Churn

#Frequency Table for contract type
contracttype_churn_counts = df.groupby(['Churn', 'Contract']).size().
 ↪unstack(fill_value=0)
print(contracttype_churn_counts)
print("\n")

# Normalized frequency table for the contract type
contract_table_percent = contracttype_churn_counts.
 ↪div(contracttype_churn_counts.sum(axis=1), axis=0) * 100
print(contract_table_percent)

# Create bar chart

# Plot the bar chart
contracttype_churn_counts.plot(kind='bar', figsize=(8, 6))
plt.title('Contract Type by Churn')
plt.xlabel('Churn')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.legend(['Month-to-Month', 'One Year', 'Two Year'], loc='upper right')

# Show the chart
plt.show()
```

```
Contract  Month-to-month  One year  Two year
Churn
No                  2220      1307      1647
Yes                 1655       166        48


Contract  Month-to-month   One year   Two year
Churn
No             42.906842  25.260920  31.832238
Yes            88.550027   8.881755   2.568218
```



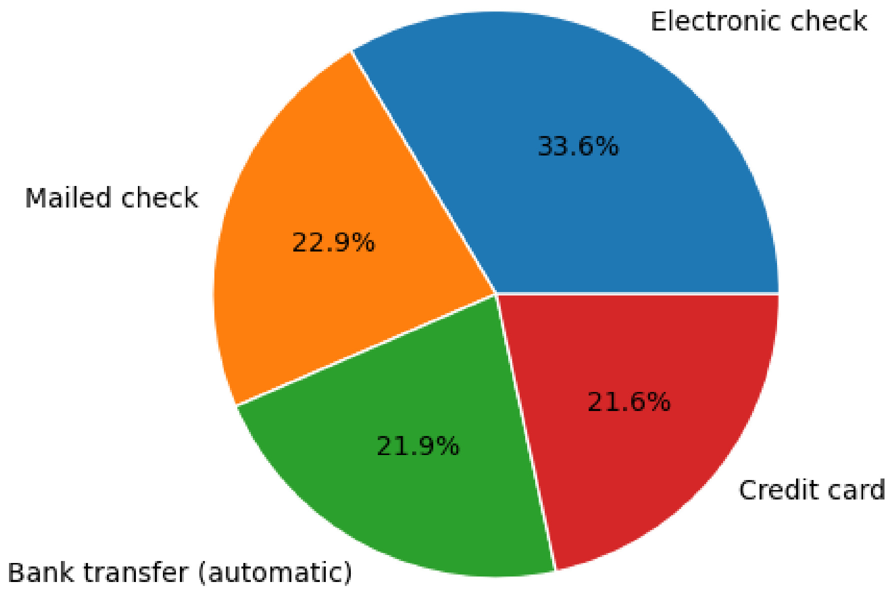
About 88% of the churned-customers had a contract type that was month-to-month compared to the rest of the 12% that had One or Two year contracts. This might be because customers prefer to have more flexibility when it comes to their subscriptions so that they would be able to leave more easily. This explains why there are higher monthly charges for churned customers since those who might have chosen the one or two year contract could've gotten a discount. This also explain the lower total charges and shorter tenure.

[22]:
```
# Frequency for each type of payment method
payment_stats = df['PaymentMethod'].value_counts(normalize=True) * 100
payment_stats
```

[22]:
```
PaymentMethod
Electronic check             33.579441
Mailed check                 22.887974
Bank transfer (automatic)    21.922476
Credit card (automatic)      21.610109
Name: proportion, dtype: float64
```

[23]:
```
# Data visualization to show disitrbution of all four payment methods
```

```
labels = 'Electronic check', 'Mailed check', 'Bank transfer (automatic)',␣
  ↪'Credit card'
sizes = [33.579441, 22.887974, 21.922476, 21.610109]

fig, ax = plt.subplots()
ax.pie(sizes, labels=labels,
      wedgeprops=dict(edgecolor='white'), autopct='%1.1f%%')
plt.show()
```



[24]:
```
payment_dist = df.groupby('Churn')['PaymentMethod'].value_counts().unstack()
print(payment_dist)
print('\n')

# Percentage for Payment Method in Customer Churn overall
payment_churn_percentage = df.groupby('Churn')['PaymentMethod'].
  ↪value_counts(normalize=True).mul(100).unstack()
print(payment_churn_percentage)
```

```
PaymentMethod  Bank transfer (automatic)  Credit card (automatic)  \
Churn
No                                  1286                     1290
Yes                                  258                      232
```

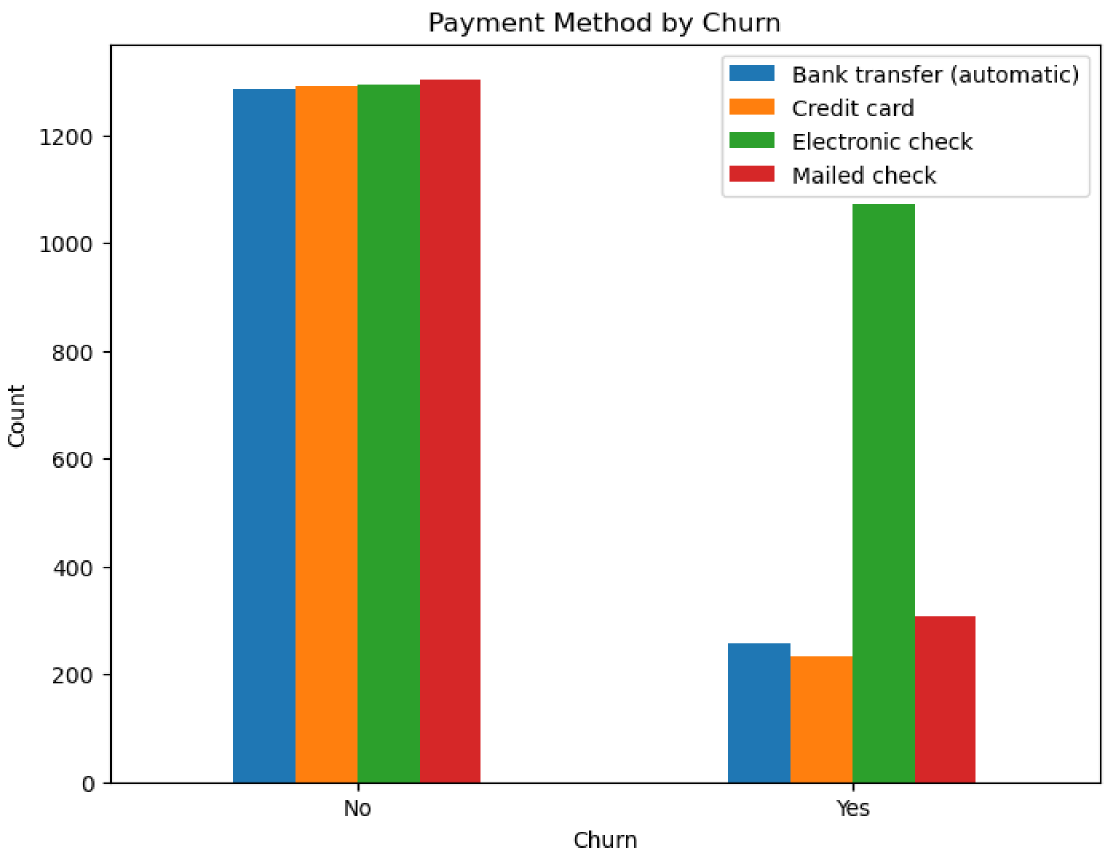
```
PaymentMethod  Electronic check  Mailed check
Churn
No                         1294          1304
Yes                        1071           308


PaymentMethod  Bank transfer (automatic)  Credit card (automatic)  \
Churn
No                          24.855044                24.932354
Yes                         13.804173                12.413055

PaymentMethod  Electronic check  Mailed check
Churn
No                    25.009664     25.202938
Yes                   57.303371     16.479401
```

[25]:

```python
# Data visualization for payment method by Churn

#Frequency Table for contract type
payment_churn_counts = df.groupby(['Churn', 'PaymentMethod']).size().
 ↪unstack(fill_value=0)
print(payment_churn_counts)
print("\n")

# Normalized frequency table for the contract type
payment_table_percent = payment_churn_counts.div(payment_churn_counts.
 ↪sum(axis=1), axis=0) * 100
print(payment_table_percent)

# Create bar chart

# Plot the bar chart
payment_churn_counts.plot(kind='bar', figsize=(8, 6))
plt.title('Payment Method by Churn')
plt.xlabel('Churn')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.legend(['Bank transfer (automatic)', 'Credit card', 'Electronic check',␣
 ↪'Mailed check'], loc='upper right')

# Show the chart
plt.show()
```

```
PaymentMethod  Bank transfer (automatic)  Credit card (automatic)  \
Churn
No                               1286                     1290
```

```
Yes                                    258                        232

PaymentMethod  Electronic check  Mailed check
Churn
No                         1294          1304
Yes                        1071           308


PaymentMethod  Bank transfer (automatic)  Credit card (automatic)  \
Churn
No                             24.855044                24.932354
Yes                            13.804173                12.413055

PaymentMethod  Electronic check  Mailed check
Churn
No                    25.009664     25.202938
Yes                   57.303371     16.479401
```



More than half of the churned-customers (57%) had been paying with electronic check and the other types of payment methods were pretty evenly distributed. While the payment method is pretty evenly distributed among those who don't churn, the payment method may strongly influence those to leave. The electronic checks are likely for younger customers who are not always reliable and more budget-conscious, hence why there might be more cancellations. Mailed checks are associated with older customers Additionally, since it is a manual type of payment method compared to the automatic type that is bank transfers and credit cards, this will explain why those who do use electronic checks will want to cancel.

[26]:
```
df = df.rename(columns={
    'PhoneService': 'Phone Service',
    'MultipleLines': 'Multiple Lines',
    'InternetService': 'Internet Service',
    'OnlineSecurity': 'Online Security',
    'OnlineBackup': 'Online Backup',
    'DeviceProtection': 'Device Protection',
    'TechSupport': 'Tech Support',
    'StreamingTV': 'Streaming TV',
    'StreamingMovies': 'Streaming Movies',
})

service = ['Phone Service', 'Multiple Lines', 'Internet Service', 'Online␣
 ↪Security',
            'Online Backup', 'Device Protection', 'Tech Support', 'Streaming␣
 ↪TV', 'Streaming Movies']
def generate_service_frequency_by_churn(df, service):
    for col in service:
        print(f"\nFrequency Table for '{col}' (Grouped by Churn):")
        print(df.groupby('Churn')[col].value_counts())  # Raw counts
        print("\nPercentage Distribution by Churn:")
        print(df.groupby('Churn')[col].value_counts(normalize=True).mul(100).
 ↪round(2))  # Percentage
        print("-" * 60)

# Call function on the service columns
generate_service_frequency_by_churn(df, service)
```

```
Frequency Table for 'Phone Service' (Grouped by Churn):
Churn  Phone Service
No     Yes              4662
       No                512
Yes    Yes              1699
       No                170
Name: count, dtype: int64

Percentage Distribution by Churn:
Churn  Phone Service
No     Yes              90.1
       No                9.9
Yes    Yes              90.9
```

```
       No                9.1
Name: proportion, dtype: float64
------------------------------------------------------------

Frequency Table for 'Multiple Lines' (Grouped by Churn):
Churn  Multiple Lines
No     No                  2541
       Yes                 2121
       No phone service     512
Yes    Yes                  850
       No                   849
       No phone service     170
Name: count, dtype: int64

Percentage Distribution by Churn:
Churn  Multiple Lines
No     No                  49.11
       Yes                 40.99
       No phone service     9.90
Yes    Yes                 45.48
       No                  45.43
       No phone service     9.10
Name: proportion, dtype: float64
------------------------------------------------------------

Frequency Table for 'Internet Service' (Grouped by Churn):
Churn  Internet Service
No     DSL                 1962
       Fiber optic         1799
       No                  1413
Yes    Fiber optic         1297
       DSL                  459
       No                   113
Name: count, dtype: int64

Percentage Distribution by Churn:
Churn  Internet Service
No     DSL                 37.92
       Fiber optic         34.77
       No                  27.31
Yes    Fiber optic         69.40
       DSL                 24.56
       No                   6.05
Name: proportion, dtype: float64
------------------------------------------------------------

Frequency Table for 'Online Security' (Grouped by Churn):
Churn  Online Security
```

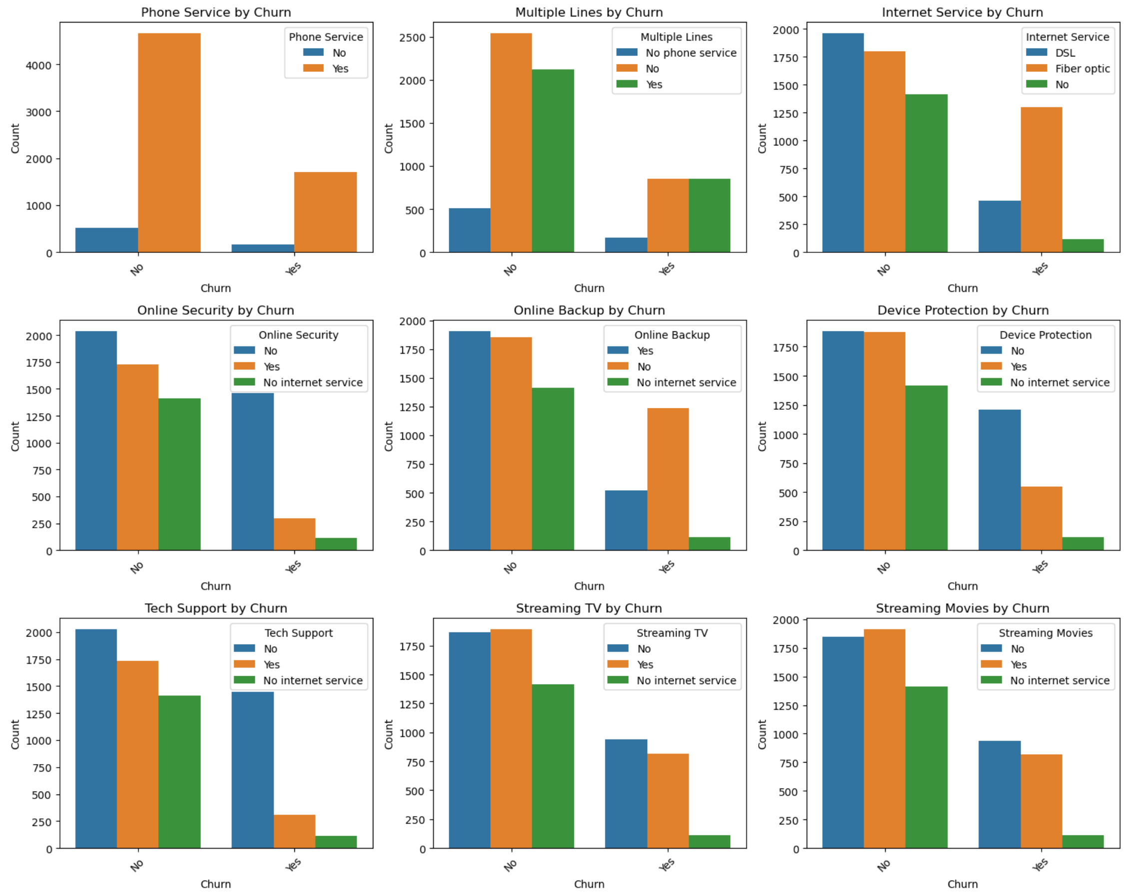
```
No     No                     2037
       Yes                    1724
       No internet service    1413
Yes    No                     1461
       Yes                     295
       No internet service     113
Name: count, dtype: int64

Percentage Distribution by Churn:
Churn  Online Security
No     No                     39.37
       Yes                    33.32
       No internet service    27.31
Yes    No                     78.17
       Yes                    15.78
       No internet service     6.05
Name: proportion, dtype: float64
------------------------------------------------------------

Frequency Table for 'Online Backup' (Grouped by Churn):
Churn  Online Backup
No     Yes                    1906
       No                     1855
       No internet service    1413
Yes    No                     1233
       Yes                     523
       No internet service     113
Name: count, dtype: int64

Percentage Distribution by Churn:
Churn  Online Backup
No     Yes                    36.84
       No                     35.85
       No internet service    27.31
Yes    No                     65.97
       Yes                    27.98
       No internet service     6.05
Name: proportion, dtype: float64
------------------------------------------------------------

Frequency Table for 'Device Protection' (Grouped by Churn):
Churn  Device Protection
No     No                     1884
       Yes                    1877
       No internet service    1413
Yes    No                     1211
       Yes                     545
       No internet service     113
```

```
Name: count, dtype: int64

Percentage Distribution by Churn:
Churn  Device Protection
No     No                     36.41
       Yes                    36.28
       No internet service    27.31
Yes    No                     64.79
       Yes                    29.16
       No internet service     6.05
Name: proportion, dtype: float64
------------------------------------------------------------

Frequency Table for 'Tech Support' (Grouped by Churn):
Churn  Tech Support
No     No                     2027
       Yes                    1734
       No internet service    1413
Yes    No                     1446
       Yes                     310
       No internet service     113
Name: count, dtype: int64

Percentage Distribution by Churn:
Churn  Tech Support
No     No                     39.18
       Yes                    33.51
       No internet service    27.31
Yes    No                     77.37
       Yes                    16.59
       No internet service     6.05
Name: proportion, dtype: float64
------------------------------------------------------------

Frequency Table for 'Streaming TV' (Grouped by Churn):
Churn  Streaming TV
No     Yes                    1893
       No                     1868
       No internet service    1413
Yes    No                      942
       Yes                     814
       No internet service     113
Name: count, dtype: int64

Percentage Distribution by Churn:
Churn  Streaming TV
No     Yes                    36.59
       No                     36.10
```

```
        No internet service    27.31
Yes     No                     50.40
        Yes                    43.55
        No internet service     6.05
Name: proportion, dtype: float64
------------------------------------------------------------

Frequency Table for 'Streaming Movies' (Grouped by Churn):
Churn   Streaming Movies
No      Yes                    1914
        No                     1847
        No internet service    1413
Yes     No                      938
        Yes                     818
        No internet service     113
Name: count, dtype: int64

Percentage Distribution by Churn:
Churn   Streaming Movies
No      Yes                    36.99
        No                     35.70
        No internet service    27.31
Yes     No                     50.19
        Yes                    43.77
        No internet service     6.05
Name: proportion, dtype: float64
------------------------------------------------------------
```

[27]:

```python
# Data visualization for different telecommunication services by Churn

# Set up the figure and axes
fig, axes = plt.subplots(nrows=3, ncols=3, figsize=(15, 12))  # 3x3 grid
axes = axes.flatten()  # Flatten to loop easily

# Generate bar charts for each service column
for i, col in enumerate(service):
    sns.countplot(data=df, x='Churn', hue=col, ax=axes[i])
    axes[i].set_title(f"{col} by Churn")
    axes[i].set_xlabel("Churn")
    axes[i].set_ylabel("Count")
    axes[i].tick_params(axis='x', rotation=45)  # Rotate x-axis labels for readability

# Adjust layout to avoid overlap
plt.tight_layout()
plt.show()
```



Phone Service by Churn: * Most customers who churn have phone service. * Very few customers without phone service churn. * Customers without phone service might already have minimal plans and less to be dissatisfied with. * Customers who have phone service might expect more value and are more likely to leave if unsatisfied.

Multiple Lines by Churn: * More churn occurs among those with multiple lines. * Fewer customers with no phone service churn. * Customers with multiple lines may be managing costs or service across several users—if service isn't up to expectations, they're quicker to switch. * Could indicate dissatisfaction with bundled services.

Internet Service by Churn: * Fiber optic users have higher churn compared to DSL. * Those without internet service rarely churn. * Fiber users may be more tech-savvy or expect top-tier service—if performance doesn't match, they churn. * DSL users might be more passive or in areas with fewer options. * No internet service group likely has simpler needs and fewer reasons to churn.

Online Security by Churn: * Customers without online security churn more than those with it. * Those with no internet service churn the least. * Online security might indicate higher engagement and investment in services—leading to greater retention. * Lack of this service could signal lower satisfaction or less trust in provider.

Device Protection by Churn: * Those without device protection churn more. * Protection services increase perceived value, and customers are less likely to churn when they've invested in extras. *

It may also indicate that they are more digitally engaged and have more devices, leading to higher reliance on provider.

Tech Support by Churn: * More churn among customers without tech support. * Tech support adds convenience and problem-solving, reducing frustration. * Those without support may feel neglected when issues arise, increasing churn.

Streaming TV by Churn: * Churn is higher among those not using streaming TV. * Streaming services add entertainment value—more features keep customers engaged. * Those not using this feature might feel they're paying for services they don't use.

Streaming Movies by Churn: * Very similar to Streaming TV—higher churn for those not using it. * The more services a customer uses (like streaming), the more value they perceive and the less likely they are to leave. * Customers who don't use streaming may not see enough benefit to stay.

[28]:
```python
# Create frequency table for each demographic

# Rename columns
df = df.rename(columns = {
    'gender' : 'Gender',
    'SeniorCitizen' : 'Senior Citizen'
})

# Rename values in the 'Senior Citizen' column
df['Senior Citizen'] = df['Senior Citizen'].replace({0: 'No', 1: 'Yes'})

# Data visualization for demographics
demographics = ['Gender', 'Senior Citizen', 'Partner', 'Dependents']

# Frequency table function
def generate_demographic_frequency_by_churn(df, demographics):
    for col in demographics:
        print(f"\nFrequency Table for '{col}' (Grouped by Churn):")
        print(df.groupby('Churn')[col].value_counts())  # Raw counts
        print("\nPercentage Distribution by Churn:")
        print(df.groupby('Churn')[col].value_counts(normalize=True).mul(100).
 ↪round(2))  # Percentage
        print("-" * 60)

# Call function on the demographics columns
generate_service_frequency_by_churn(df, demographics)
```

```
Frequency Table for 'Gender' (Grouped by Churn):
Churn  Gender
No     Male      2625
       Female    2549
Yes    Female     939
       Male       930
```

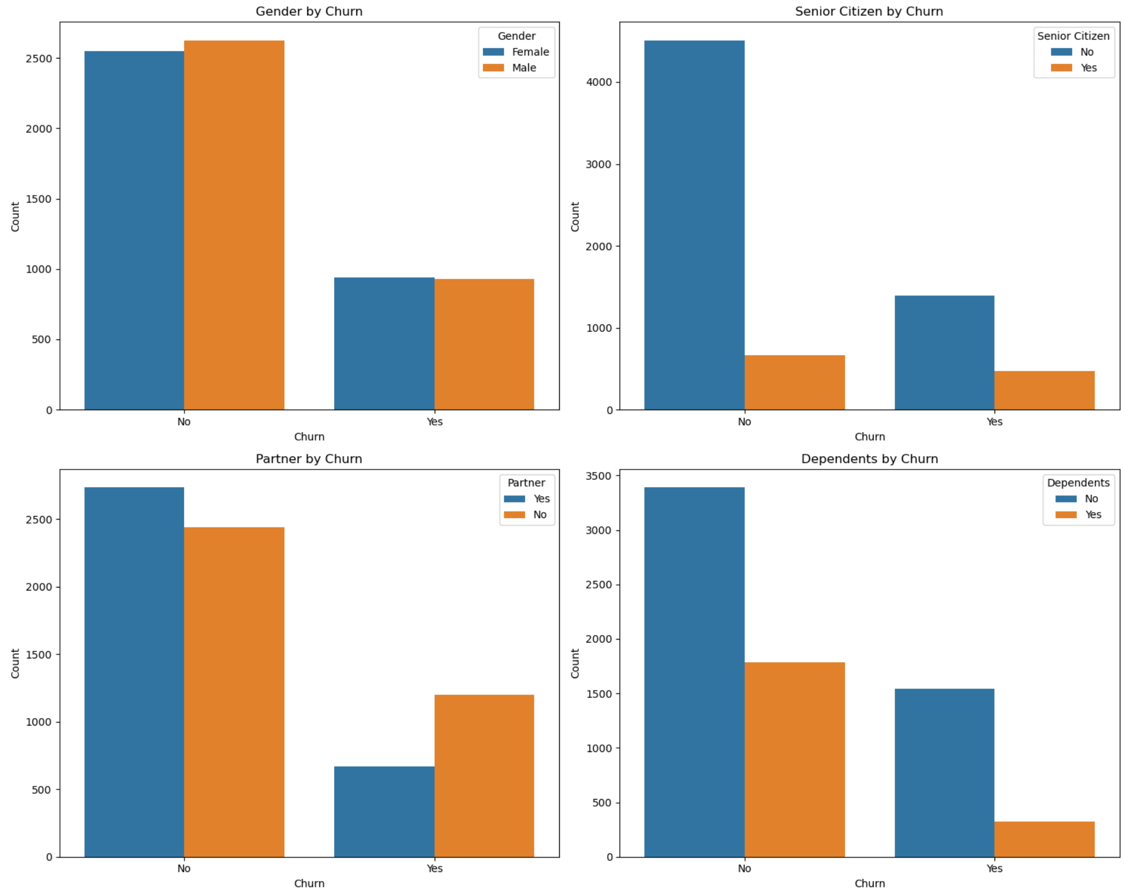
```
Name: count, dtype: int64

Percentage Distribution by Churn:
Churn  Gender
No     Male      50.73
       Female    49.27
Yes    Female    50.24
       Male      49.76
Name: proportion, dtype: float64
------------------------------------------------------------

Frequency Table for 'Senior Citizen' (Grouped by Churn):
Churn  Senior Citizen
No     No                4508
       Yes                666
Yes    No                1393
       Yes                476
Name: count, dtype: int64

Percentage Distribution by Churn:
Churn  Senior Citizen
No     No                87.13
       Yes               12.87
Yes    No                74.53
       Yes               25.47
Name: proportion, dtype: float64
------------------------------------------------------------

Frequency Table for 'Partner' (Grouped by Churn):
Churn  Partner
No     Yes        2733
       No         2441
Yes    No         1200
       Yes         669
Name: count, dtype: int64

Percentage Distribution by Churn:
Churn  Partner
No     Yes        52.82
       No         47.18
Yes    No         64.21
       Yes        35.79
Name: proportion, dtype: float64
------------------------------------------------------------

Frequency Table for 'Dependents' (Grouped by Churn):
Churn  Dependents
No     No            3390
```

```
        Yes            1784
Yes     No             1543
        Yes             326
Name: count, dtype: int64

Percentage Distribution by Churn:
Churn   Dependents
No      No             65.52
        Yes            34.48
Yes     No             82.56
        Yes            17.44
Name: proportion, dtype: float64
------------------------------------------------------------
```

[29]:
```
# Set up the figure (for a 2x2 grid layout)
fig, axes = plt.subplots(2, 2, figsize=(10, 8))  # 2x2 grid for 4 demographic␣
↪features
axes = axes.flatten()

# Loop through demographic columns to create pie charts
for i, col in enumerate(demographics):
    ax = axes[i]

    # Get the value counts for the demographic column
    demographic_counts = df[col].value_counts()

    # Create pie chart for the demographic distribution
    ax.pie(
        demographic_counts, labels=demographic_counts.index, autopct='%1.1f%%',␣
↪startangle=90,
        colors=['skyblue', 'salmon'], wedgeprops={'edgecolor': 'white'}
    )
    ax.set_title(f'{col} Distribution')

# Adjust layout and display the pie charts
plt.tight_layout()
plt.show()
```

[30]:
```python
# Set up the figure and axes
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(15, 12))  # 2x2 grid
axes = axes.flatten()  # Flatten to loop easily

# Generate bar charts for each service column
for i, col in enumerate(demographics):
    sns.countplot(data=df, x='Churn', hue=col, ax=axes[i])
    axes[i].set_title(f"{col} by Churn")
    axes[i].set_xlabel("Churn")
    axes[i].set_ylabel("Count")
    axes[i].tick_params(axis='x', rotation=0)  # Rotate x-axis labels for␣
 ↪readability

# Adjust layout to avoid overlap
plt.tight_layout()
```

```
plt.show()
```



Gender: * The distributions are practically the same, which means that gender probably does not affect whether someone churns or not.

Partner vs. No Partner: * Overall distributions for non-churned customers look the same, which might show that having a partner is not significant to whether a customer will churn. * Lower commitment/stability: People without a partner may be more mobile or less tied down, making them more likely to switch providers. * Financial independence: Solo individuals may be more cost-sensitive and quicker to cut services they don't find essential.

Senior Citizens: * The nearly equal churn rate suggests that age alone isn't a strong predictor of churn. * Some senior citizens may stay for familiarity, while others may churn due to changes in needs (e.g., downsizing, switching to simpler plans).

Dependents v. No Dependents: * Customers without dependents has a significantly higher proportion of churning than those with a dependent. * Stability and routine: Families are often more reluctant to change providers due to the inconvenience. * Higher service bundling: Families may use more services (like internet, streaming, tech support), making them less likely to leave. * Shared responsibility: Parents or caretakers may rely more heavily on stable service for work, education, or entertainment at home.

0.6 Survival Analysis Model

Survival Function

Using the cdf, we can calculate the survival function, or the probability that the event has not occurred by the time t. This means that, S(t) gives us the proportion of population with the time to event value more than t. The survival function looks like:

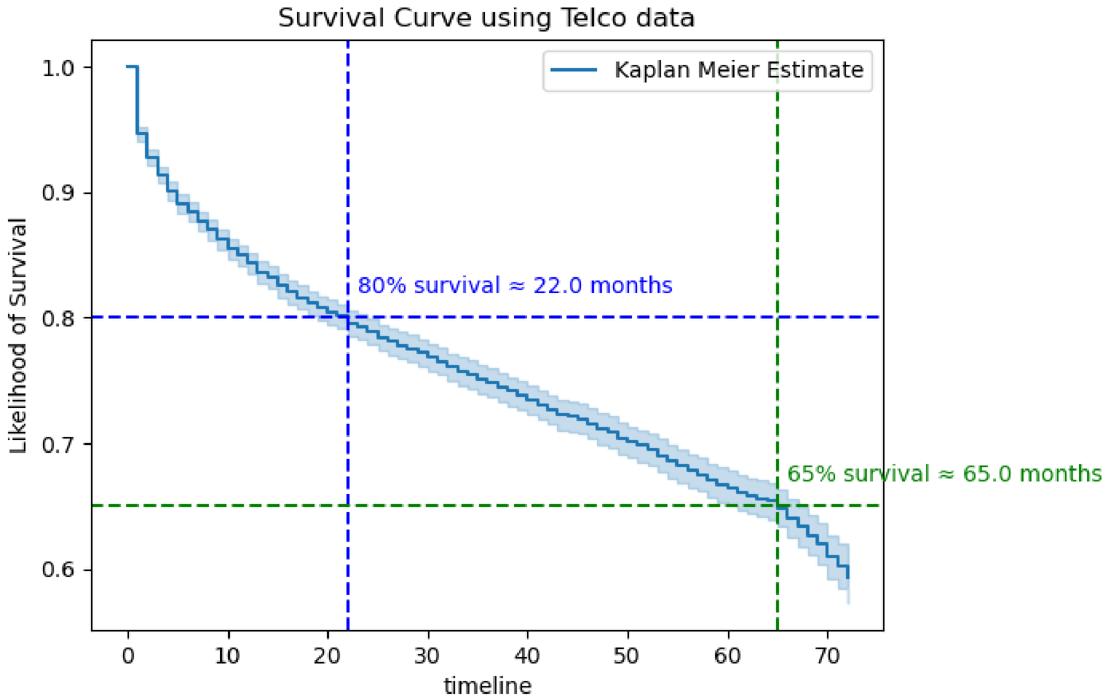
$$S(t) = 1 - F(t) = P(T \geq t)$$

We can also express this as an integral:

$$\int_t^\infty f(x)dx$$

[31]:
```
df['Churn'] = df['Churn'].map({'Yes': 1, 'No': 0})
durations = df['tenure']
event_observed = df['Churn']

km = KaplanMeierFitter()

km.fit(durations, event_observed, label='Kaplan Meier Estimate')

km.plot()
# Helper function to find the time when survival function drops below a given␣
↪probability
def time_at_survival_threshold(kmf, threshold):
    sf = kmf.survival_function_
    return sf[sf[kmf._label] <= threshold].index.min()

# Thresholds
thresholds = [0.8, 0.65]
colors = ['blue', 'green']

for thresh, color in zip(thresholds, colors):
    time = time_at_survival_threshold(km, thresh)
    if pd.notna(time):
        # Horizontal and vertical lines
        plt.axhline(thresh, color=color, linestyle='dashed')
        plt.axvline(time, color=color, linestyle='dashed')

        # Annotate the point
        plt.text(time + 1, thresh + 0.02,
                 f"{int(thresh*100)}% survival   {time} months",
                 color=color, fontsize=10)
```

```
plt.title('Survival Curve using Telco data')
plt.ylabel('Likelihood of Survival');
```



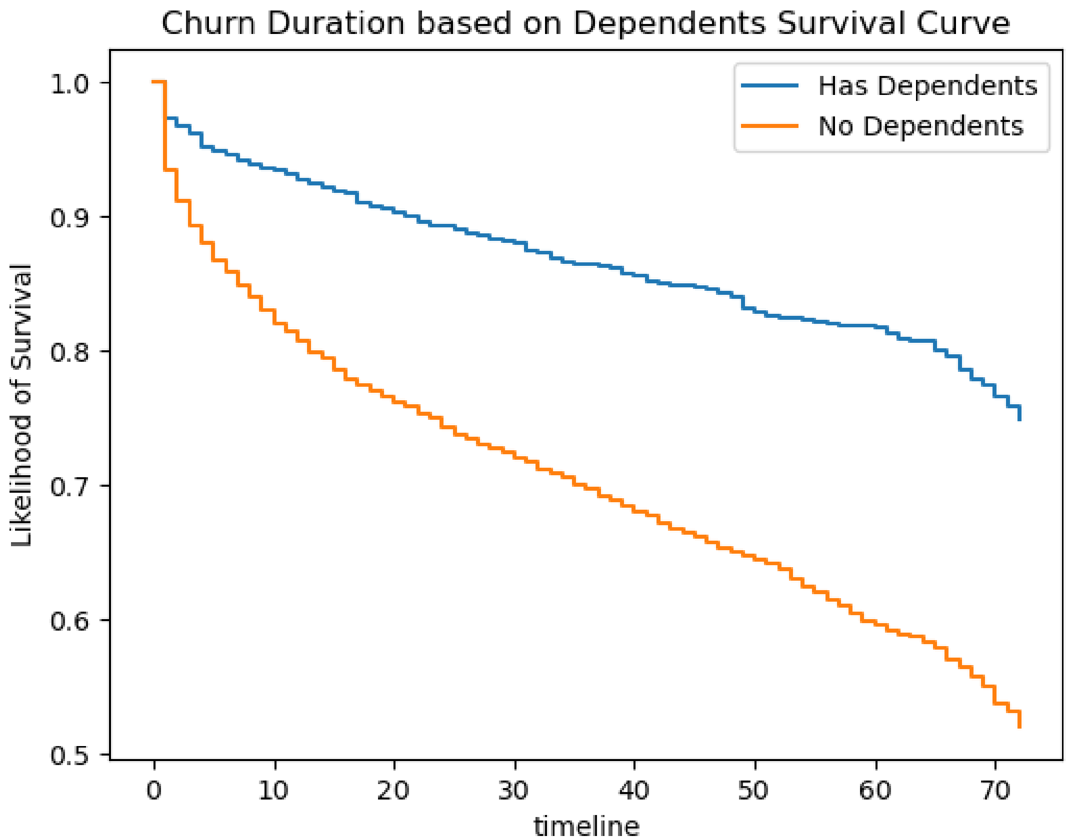
Analysis of this graph:

There is *80% probability of survival* beyond about 22 months and *65% probability of survival* beyond about 65 months.

This graph represents the likeliness of survival (not churning), how long a customer will stay before changing companies or churning.

[32]:
```
# Group 1: Has Dependents
kmf_ch1 = KaplanMeierFitter()
T1 = df.loc[df['Dependents'] == 'Yes', 'tenure']
E1 = df.loc[df['Dependents'] == 'Yes', 'Churn']
kmf_ch1.fit(T1, E1, label='Has Dependents')
ax = kmf_ch1.plot(ci_show=False)

# Group 2: Doesn't have Dependents
kmf_ch2 = KaplanMeierFitter()
T2 = df.loc[df['Dependents'] == 'No', 'tenure']
E2 = df.loc[df['Dependents'] == 'No', 'Churn']
kmf_ch2.fit(T2, E2, label='No Dependents')
ax = kmf_ch2.plot(ci_show=False)
```

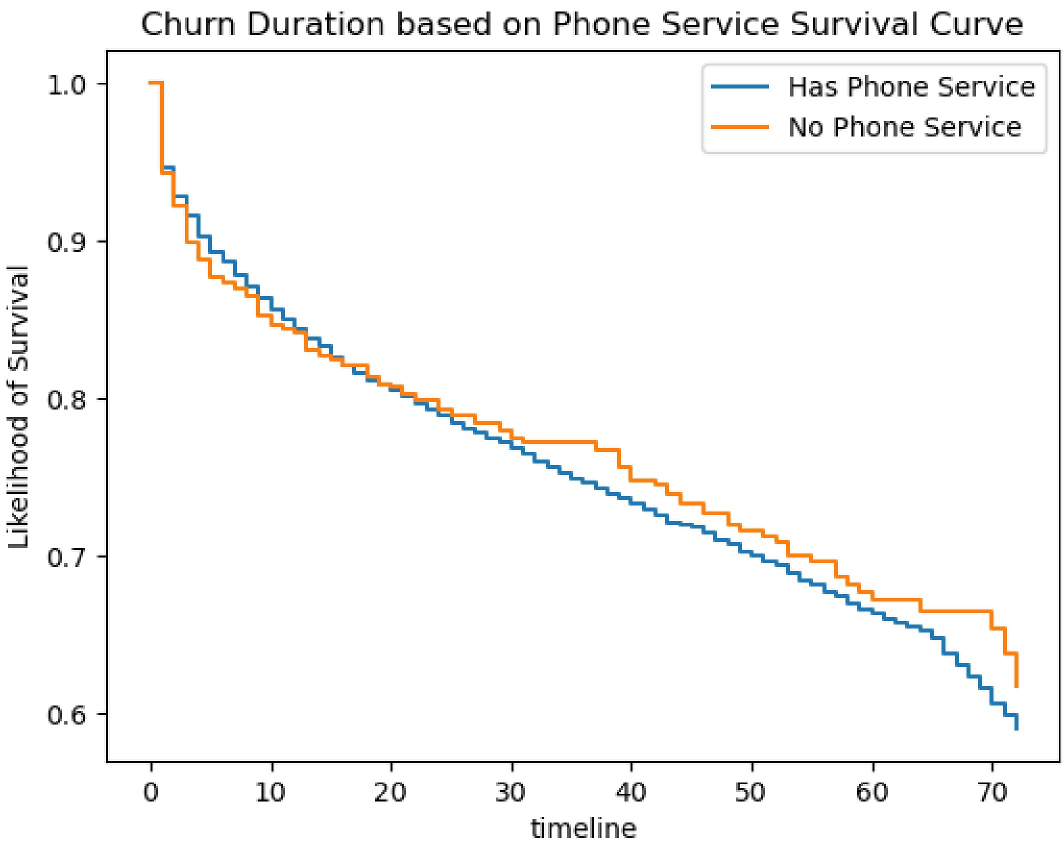
```
plt.title("Churn Duration based on Dependents Survival Curve")
plt.ylabel('Likelihood of Survival');
```



Customers with dependents consistently have a higher survival rate (are more likely to stay over time). Customers without dependents churn at a faster rate, as shown by the steeper drop in the orange line. Dependents may increase financial and logistical reliance on services, making customers less likely to switch or cancel. People with dependents might value stability and convenience more, leading them to stick with their current provider. Those without dependents may feel freer to shop around or cancel, especially if they're younger or more budget-conscious. They might also be more sensitive to price increases or less invested in bundled features (like family plans or protection services).

[33]:
```
# Group 1: Has Phone Service
kmf_ch1 = KaplanMeierFitter()
T1 = df.loc[df['Phone Service'] == 'Yes', 'tenure']
E1 = df.loc[df['Phone Service'] == 'Yes', 'Churn']
kmf_ch1.fit(T1, E1, label='Has Phone Service')
ax = kmf_ch1.plot(ci_show=False)

# Group 2: Doesn't have Phone Service
```

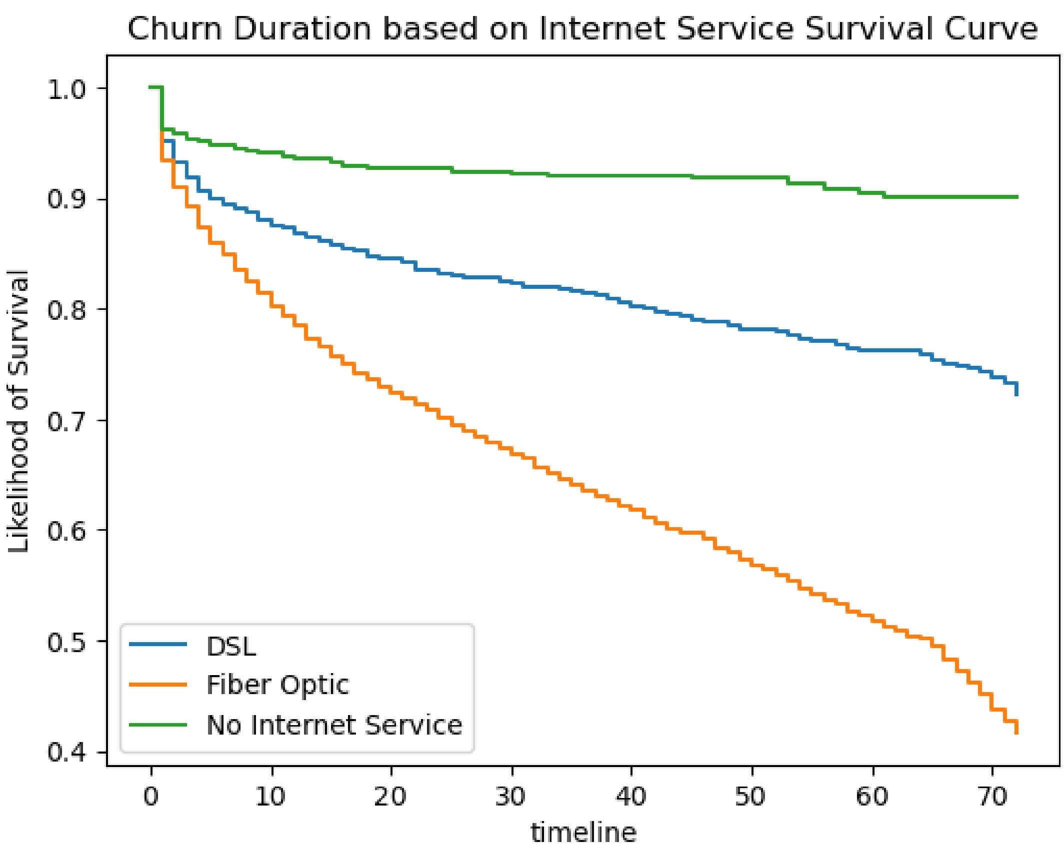
```
kmf_ch2 = KaplanMeierFitter()
T2 = df.loc[df['Phone Service'] == 'No', 'tenure']
E2 = df.loc[df['Phone Service'] == 'No', 'Churn']
kmf_ch2.fit(T2, E2, label='No Phone Service')
ax = kmf_ch2.plot(ci_show=False)

plt.title("Churn Duration based on Phone Service Survival Curve")
plt.ylabel('Likelihood of Survival');
```



Having a phone service or not does not necessarily affect whether someone churns or not. Phone service might not be the primary reason customers choose or stay with the provider. Things like internet service or bundled packages may carry more weight in their decision-making. If the majority of customers opt into phone service by default, the variable doesn't have enough variation to show a strong effect on churn. Those who opted out of phone service may not need it, so they're not missing anything, and this doesn't push them to churn either.

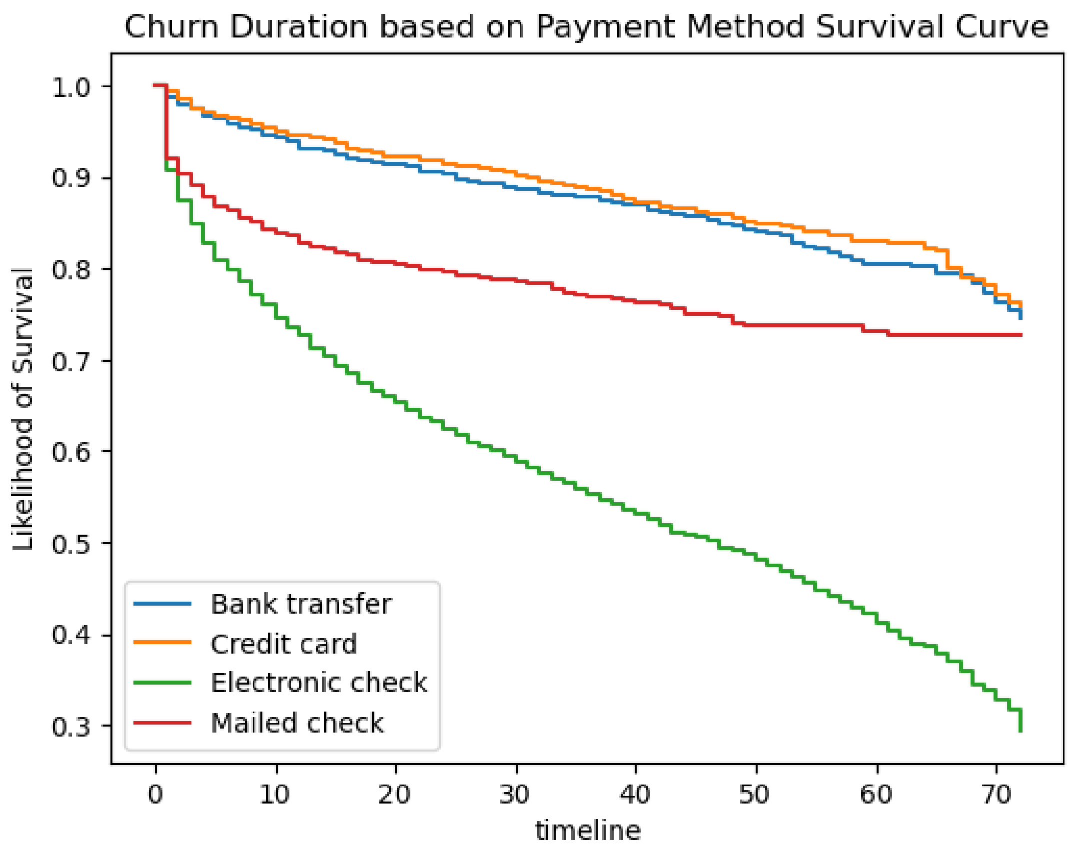
[34]:
```
# Group 1: DSL Internet Service
kmf_ch1 = KaplanMeierFitter()
T1 = df.loc[df['Internet Service'] == 'DSL', 'tenure']
E1 = df.loc[df['Internet Service'] == 'DSL', 'Churn']
```

```
kmf_ch1.fit(T1, E1, label='DSL')
ax = kmf_ch1.plot(ci_show=False)

# Group 2: Fiber Optic Internet Service
kmf_ch2 = KaplanMeierFitter()
T2 = df.loc[df['Internet Service'] == 'Fiber optic', 'tenure']
E2 = df.loc[df['Internet Service'] == 'Fiber optic', 'Churn']
kmf_ch2.fit(T2, E2, label='Fiber Optic')
ax = kmf_ch2.plot(ci_show=False)

# Group 3: No Internet Service
kmf_ch3= KaplanMeierFitter()
T3 = df.loc[df['Internet Service'] == 'No', 'tenure']
E3 = df.loc[df['Internet Service'] == 'No', 'Churn']
kmf_ch3.fit(T3, E3, label='No Internet Service')
ax = kmf_ch3.plot(ci_show=False)

plt.title("Churn Duration based on Internet Service Survival Curve")
plt.ylabel('Likelihood of Survival');
```



The high customer churn for the fiber optic internet is likely due to customers having high expectations and then left dissatisfied with the outcome. Fiber Optic is marketed as premium, high-speed internet. If the service doesn't meet expectations, users may be quick to leave. It's usually more expensive. If users don't see the value, especially during tough economic times, they might switch to cheaper options or cancel. People using DSL might not expect blazing speed, so they're more patient. DSL is often the only option in less populated areas, making churn less likely due to limited alternatives. This also might appeal more towards price-sensitive customers as they might prefer lower costs when it comes to their internet.

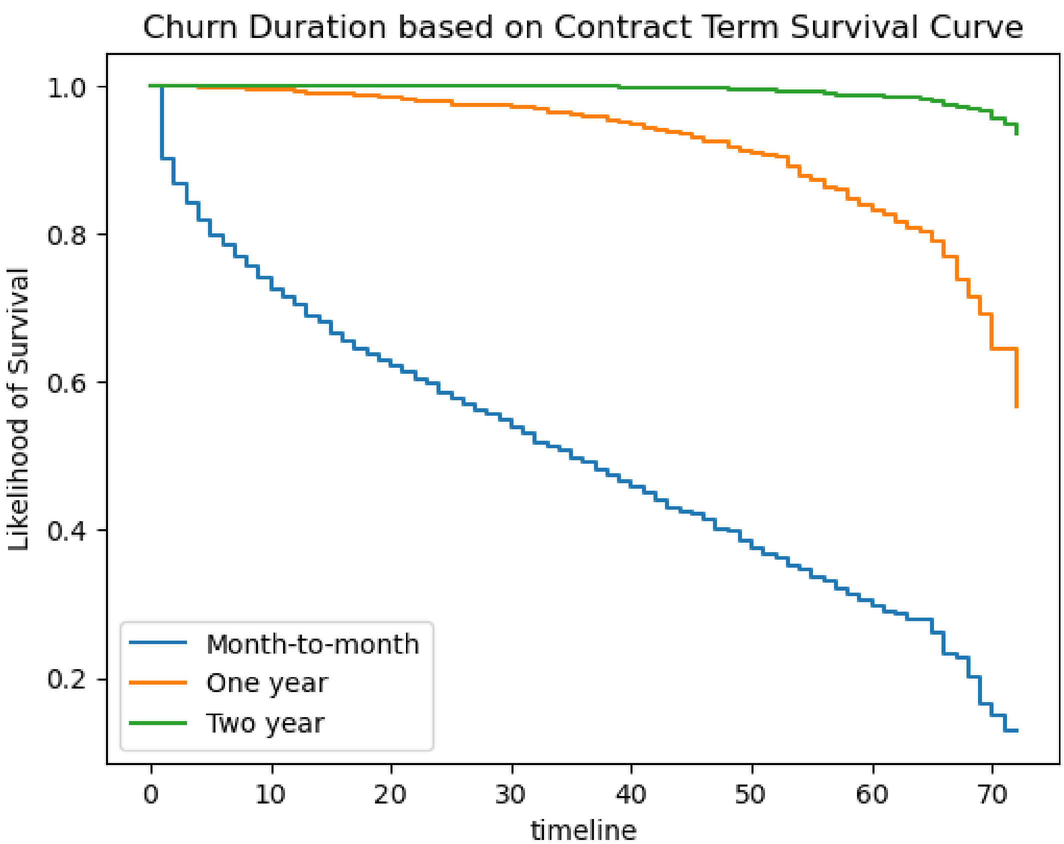
[35]:
```python
# Group 1: Bank transfer (automatic)
kmf_ch1 = KaplanMeierFitter()
T1 = df.loc[df['PaymentMethod'] == 'Bank transfer (automatic)', 'tenure']
E1 = df.loc[df['PaymentMethod'] == 'Bank transfer (automatic)', 'Churn']
kmf_ch1.fit(T1, E1, label='Bank transfer')
ax = kmf_ch1.plot(ci_show=False)

# Group 2: Credit Card
kmf_ch2 = KaplanMeierFitter()
T2 = df.loc[df['PaymentMethod'] == 'Credit card (automatic)', 'tenure']
E2 = df.loc[df['PaymentMethod'] == 'Credit card (automatic)', 'Churn']
kmf_ch2.fit(T2, E2, label='Credit card')
ax = kmf_ch2.plot(ci_show=False)

# Group 3: Electronic Check
kmf_ch3 = KaplanMeierFitter()
T3 = df.loc[df['PaymentMethod'] == 'Electronic check', 'tenure']
E3 = df.loc[df['PaymentMethod'] == 'Electronic check', 'Churn']
kmf_ch3.fit(T3, E3, label='Electronic check')
ax = kmf_ch3.plot(ci_show=False)

# Group 4: Mailed Check
kmf_ch4 = KaplanMeierFitter()
T4 = df.loc[df['PaymentMethod'] == 'Mailed check', 'tenure']
E4 = df.loc[df['PaymentMethod'] == 'Mailed check', 'Churn']
kmf_ch4.fit(T4, E4, label='Mailed check')
ax = kmf_ch4.plot(ci_show=False)

plt.title("Churn Duration based on Payment Method Survival Curve")
plt.ylabel('Likelihood of Survival');
```



This outcome is very similar to the bar chart that compared the no churn and churn by payment method. The bank transfer and credit card have very similar survival curves. The mailed check is slightly lower, which might be due to the fact that it is manual so customers might be quicker to drop the service. The electronic check is very similar in that fact, however there is a much higher proportion who have churned.

[36]:
```python
# Group 1: Month-to-month
kmf_ch1 = KaplanMeierFitter()
T1 = df.loc[df['Contract'] == 'Month-to-month', 'tenure']
E1 = df.loc[df['Contract'] == 'Month-to-month', 'Churn']
kmf_ch1.fit(T1, E1, label='Month-to-month')
ax = kmf_ch1.plot(ci_show=False)

# Group 2: One year
kmf_ch2 = KaplanMeierFitter()
T2 = df.loc[df['Contract'] == 'One year', 'tenure']
E2 = df.loc[df['Contract'] == 'One year', 'Churn']
kmf_ch2.fit(T2, E2, label='One year')
ax = kmf_ch2.plot(ci_show=False)
```

```python
# Group 3: Two year
kmf_ch3 = KaplanMeierFitter()
T3 = df.loc[df['Contract'] == 'Two year', 'tenure']
E3 = df.loc[df['Contract'] == 'Two year', 'Churn']
kmf_ch3.fit(T3, E3, label='Two year')
ax = kmf_ch3.plot(ci_show=False)

plt.title("Churn Duration based on Contract Term Survival Curve")
plt.ylabel('Likelihood of Survival');
```



The month-to-month contract has a very short likelihood of survival, the curve reaches 0% at around 70 months, and reaches 50% probability of survival around 35 months. While the two-year contract has a very high likelihood of survival since the customers who have the subscription for 2 years likely are satisfied with the service and are not going to churn. The one-year subscription drops a lot ater the 60 month mark, which shows that the length for the one-year is about half the length of survival and probability as those with the two-year subscription.

0.7 Data Processing

This portion compares the correlation of different variables with `Churn` and `tenure`.

[37]:
```python
# Turn categorical variables into numbers
df_copy = df.copy()
columns = df_copy.columns
label_encoder = LabelEncoder()
for col in columns:
    df_copy[col] = label_encoder.fit_transform(df_copy[col])
df_copy
```

[37]:
```
      Gender  Senior Citizen  Partner  Dependents  tenure  Phone Service  \
0          0               0        1           0       1              0
1          1               0        0           0      34              1
2          1               0        0           0       2              1
3          1               0        0           0      45              0
4          0               0        0           0       2              1
…      …               …       …          …      …             …
7038       1               0        1           1      24              1
7039       0               0        1           1      72              1
7040       0               0        1           1      11              0
7041       1               1        1           0       4              1
7042       1               0        0           0      66              1

      Multiple Lines  Internet Service  Online Security  Online Backup  \
0                  1                 0                0              2
1                  0                 0                2              0
2                  0                 0                2              2
3                  1                 0                2              0
4                  0                 1                0              0
…              …                 …                …              …
7038               2                 0                2              0
7039               2                 1                0              2
7040               1                 0                2              0
7041               2                 1                0              0
7042               0                 1                2              0

      Device Protection  Tech Support  Streaming TV  Streaming Movies  \
0                     0             0             0                 0
1                     2             0             0                 0
2                     0             0             0                 0
3                     2             2             0                 0
4                     0             0             0                 0
…                 …             …            …                 …
7038                  2             2             2                 2
7039                  2             0             2                 2
7040                  0             0             0                 0
```

```
7041                    0            0            0                 0
7042                    2            2            2                 2

      Contract  PaperlessBilling  PaymentMethod  MonthlyCharges  TotalCharges  \
0            0                 1              2             142            74
1            1                 0              3             498          3625
2            0                 1              3             436           536
3            1                 0              0             266          3571
4            0                 1              2             729           674
…          …               …             …              …            …
7038         1                 1              3             991          3701
7039         1                 1              1            1340          6305
7040         0                 1              2             137          1265
7041         0                 1              3             795          1157
7042         2                 1              0            1388          6151

      Churn
0         0
1         0
2         1
3         0
4         1
…     …
7038      0
7039      0
7040      0
7041      1
7042      0

[7043 rows x 20 columns]
```

[38]:

```python
# Find the correlation between Churn and other variables
correlation_matrix_churn = df_copy.corr()
churn_correlation = correlation_matrix_churn['Churn'].
 ↪sort_values(ascending=False)
print(churn_correlation)
```

```
Churn                1.000000
PaperlessBilling     0.191825
MonthlyCharges       0.183523
Senior Citizen       0.150889
PaymentMethod        0.107062
Multiple Lines       0.038037
Phone Service        0.011942
Gender              -0.008612
Streaming TV        -0.036581
Streaming Movies    -0.038492
```

```
Internet Service    -0.047291
Partner             -0.150448
Dependents          -0.164221
Device Protection   -0.178134
Online Backup       -0.195525
TotalCharges        -0.230754
Tech Support        -0.282492
Online Security     -0.289309
tenure              -0.352229
Contract            -0.396713
Name: Churn, dtype: float64
```

Monthly Charges (0.183523): * Monthly Charges out of the variables we analyzed has the highest correlation with churn * Customers might churn due to the fact that the monthly charges might be too high * This also might be associated with bundles, which comes with services that the customer doesn't use

Senior Citizens (0.150889): * Citizens that are also older will have a higher association and probability of churning * This might be because senior citizens are not as tech savvy and might not need as many subscriptions * They might be more price sensitive and not need the telecommunication services

Tenure (-0.352229): * df

Contract (-0.396713): * Many of the customers who do have the one-year or two-year contract are less likely to cancel their subscription since the contract goes for a full one or two years * If someone wants to cancel their subscription there also might be fees for cancelling earlier than their contract ends * Those on year-long contract might also have discounts and bundles that incentivizes them to stay

[39]:
```
# Find correlation between other variables with tenure
correlation_matrix_tenure = df_copy.corr()
tenure_correlation = correlation_matrix_tenure['tenure'].
 ↪sort_values(ascending=False)
print(tenure_correlation)
```

```
tenure               1.000000
TotalCharges         0.870526
Contract             0.671607
Partner              0.379697
Device Protection    0.371105
Online Backup        0.370876
Multiple Lines       0.343032
Online Security      0.325468
Tech Support         0.322942
Streaming Movies     0.296866
Streaming TV         0.289373
MonthlyCharges       0.268133
Dependents           0.159712
Senior Citizen       0.016567
```

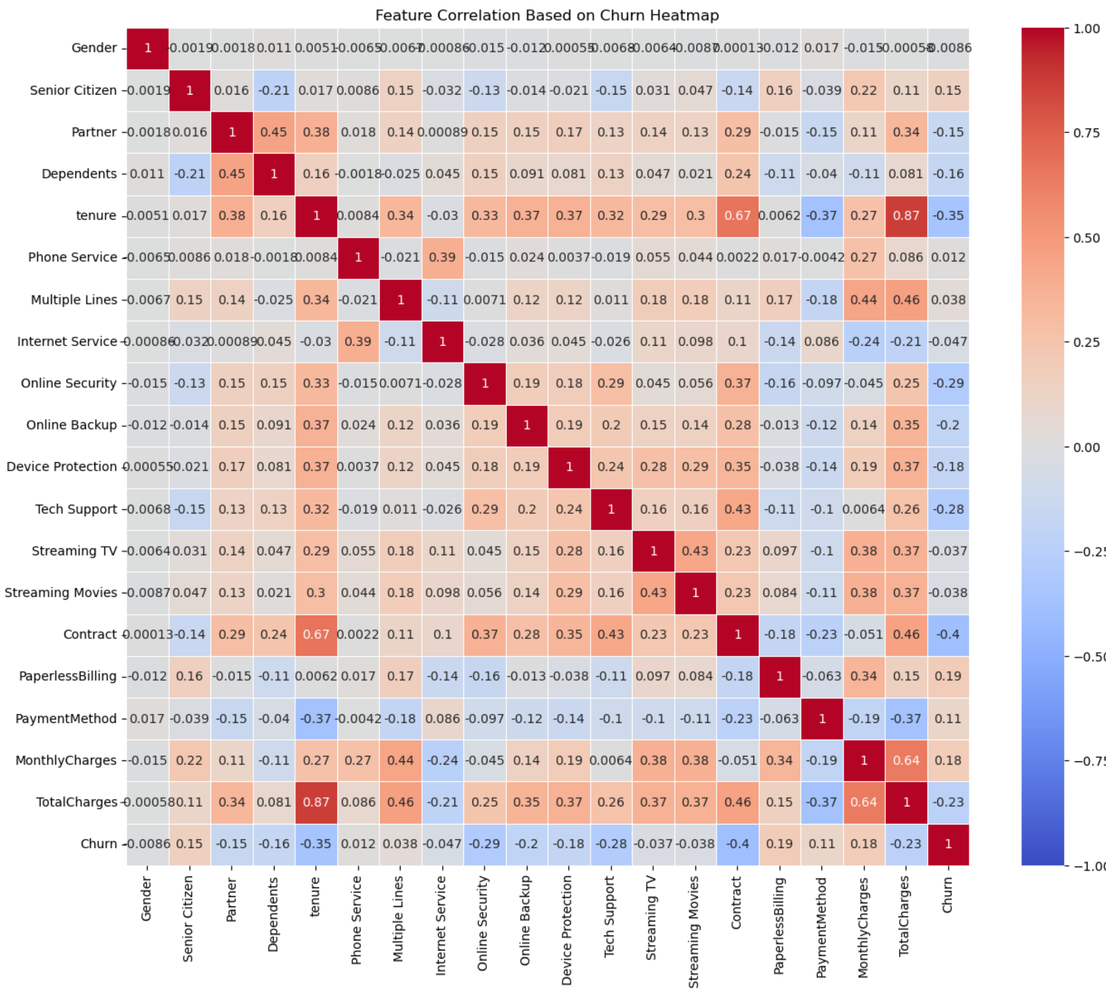
```
Phone Service        0.008448
PaperlessBilling     0.006152
Gender               0.005106
Internet Service    -0.030359
Churn               -0.352229
PaymentMethod       -0.370436
Name: tenure, dtype: float64
```

Total Charges (0.870526): * This has the highest correlation * Total Charges would depend on how long the customer stays with the company

Contract (0.671607): * The contract type also heavily depends on the tenure * The tenure would heavily depend on what type of contract they have * If someone is the month-to month contract type, then they would have a shorter tenure since it's by month * If someone has the one-year contract type, their tenure would be much longer since their subcription is making them stay for that long

Payment Method (-0.370436): * The payment method may favor certain types of tenure, but it is negatively correlated. * One might assume that payment method might be correlated with tenure since a customer's payment method (such as the manual type) might make them more inclined to cancel their subscription * The higher negative value might correspond to less reliable or manual payment methods * The manual payment types are favored by newer customers and are at greater risk of churn

[40]:
```python
# Visualize with a heat map
plt.figure(figsize=(15, 12))  # Adjust figure size
sns.heatmap(correlation_matrix_churn, annot=True, cmap='coolwarm', linewidths=0.
 ↪5, vmin = -1, vmax = 1)
plt.title('Feature Correlation Based on Churn Heatmap')
plt.show()
```



Split the data into the train and test set

[41]:
```
# Define features and target
X = df_copy.drop(columns=['Churn'])
y = df_copy['Churn']
X = pd.get_dummies(X, drop_first=True)

# Split the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
    random_state=42)
```

0.8 Machine Learning Models and Predictions

[42]:
```
# Train with Random Forest
random_forest = RandomForestClassifier(n_estimators=100, random_state=42)
random_forest.fit(X_train, y_train)
```

```python
y_pred_RF = random_forest.predict(X_test)

# Evaluate performance
accuracy = accuracy_score(y_test, y_pred_RF)
print(f"Accuracy: {accuracy * 100}%")
```

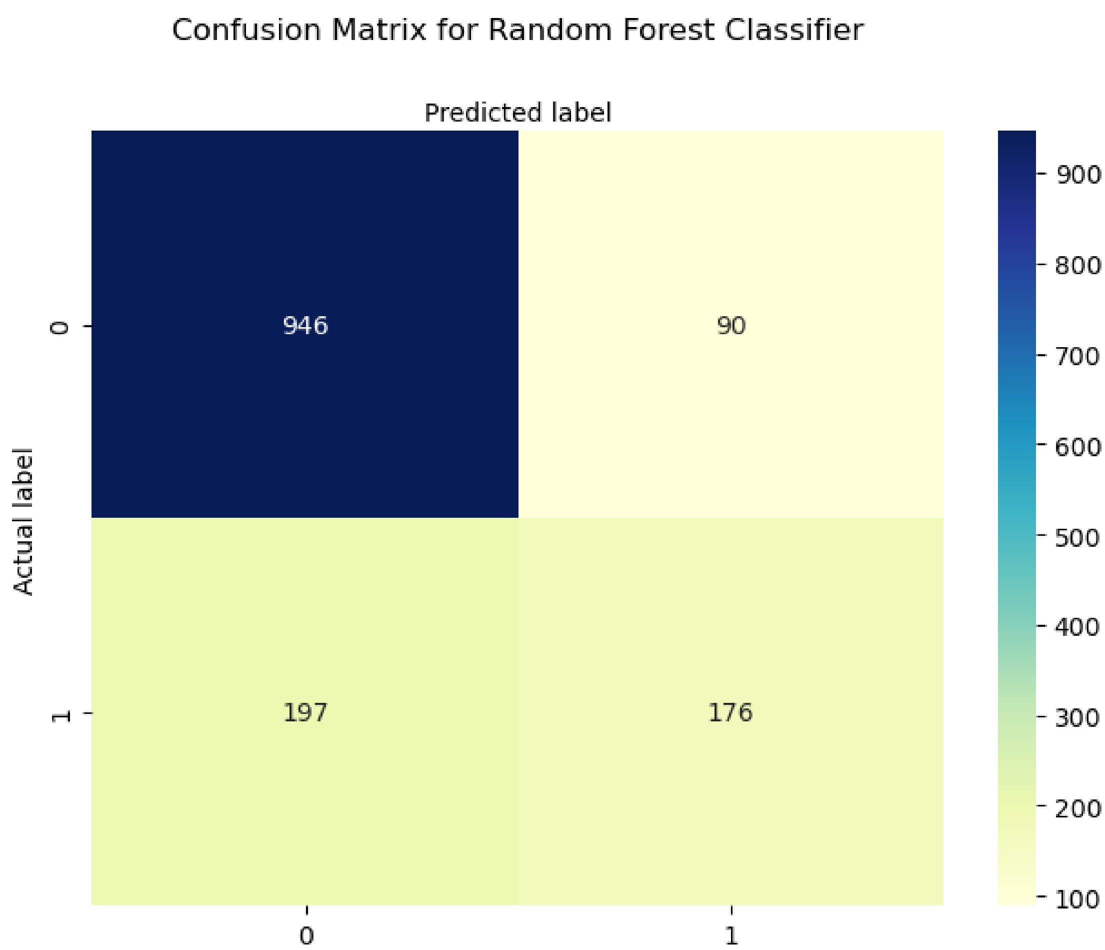
```
Accuracy: 79.63094393186657%
```

[43]:
```python
# Confusion matrix for Random Forest

confusion_matrix_RF = metrics.confusion_matrix(y_test, y_pred_RF)
confusion_matrix_RF
```

[43]:
```
array([[946,  90],
       [197, 176]])
```

[44]:
```python
# Create confusion matrix heat map for Logistic Regression
class_names=[0,1] # name  of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)

# create heatmap
sns.heatmap(pd.DataFrame(confusion_matrix_RF), annot=True, cmap="YlGnBu"␣
 ↪,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion Matrix for Random Forest Classifier', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

[44]:
```
Text(0.5, 427.9555555555555, 'Predicted label')
```

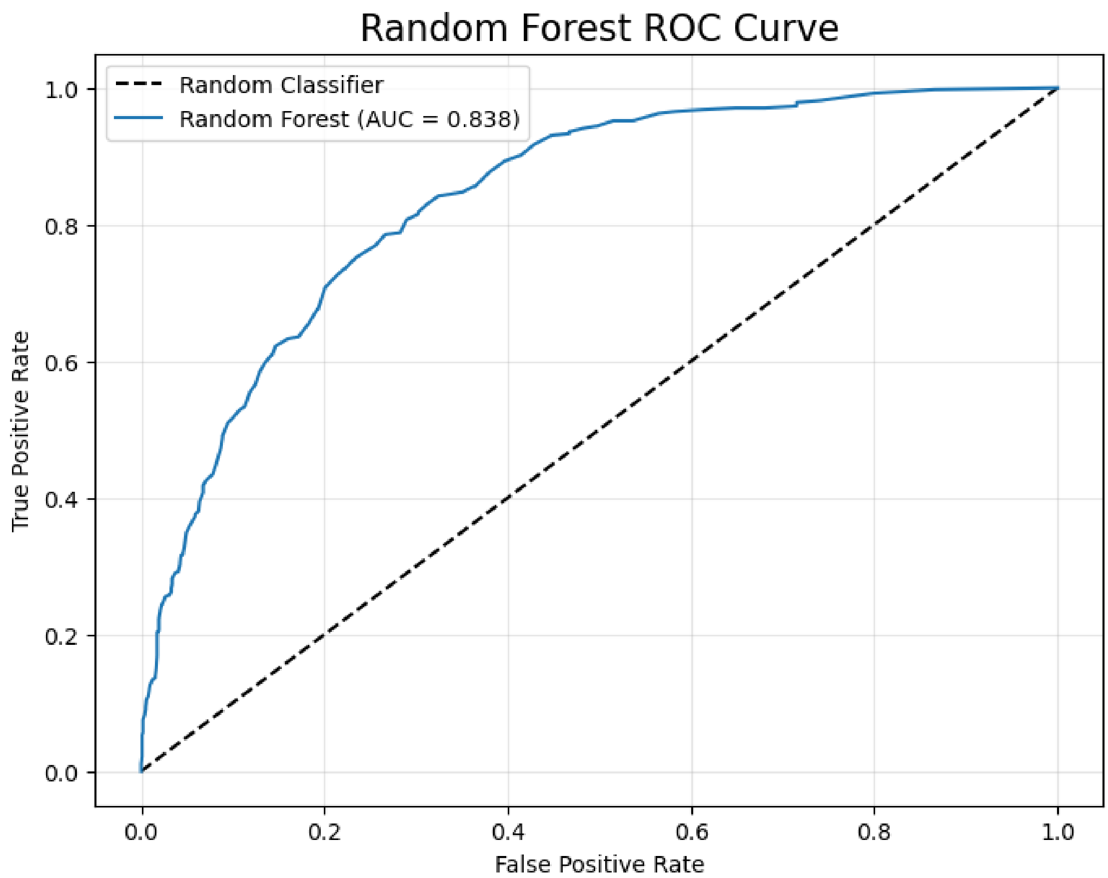


[45]:
```
target_names = ['No Churn', 'Churn']
print(classification_report(y_test, y_pred_RF, target_names=target_names))
```

```
              precision    recall  f1-score   support

    No Churn       0.83      0.91      0.87      1036
       Churn       0.66      0.47      0.55       373

    accuracy                           0.80      1409
   macro avg       0.74      0.69      0.71      1409
weighted avg       0.78      0.80      0.78      1409
```

[46]:
```
# Predict probabilities
y_probs = random_forest.predict_proba(X_test)[:, 1]
fpr_rf, tpr_rf, thresholds = roc_curve(y_test, y_probs)
auc = metrics.roc_auc_score(y_test, y_probs)
```

```
plt.figure(figsize=(8, 6))
plt.plot([0, 1], [0, 1], 'k--', label='Random Classifier')
plt.plot(fpr_rf, tpr_rf, label=f'Random Forest (AUC = {auc:.3f})')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Random Forest ROC Curve',fontsize=16)
plt.legend()
plt.grid(True, alpha=0.3)
plt.show();
```



The Receiver Operating Characteristic (ROC) curve plots the true positive rate against the false positive rate. It shows the difference between positive and negative classes.

[47]:
```
# Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Train logistic regression model
```

```
logisticRegr = LogisticRegression(max_iter=500)
logisticRegr.fit(X_train_scaled, y_train)

# Model evaluation
accuracy = logisticRegr.score(X_test_scaled, y_test)
y_pred_log = logisticRegr.predict(X_test_scaled)
print(f"Accuracy: {accuracy * 100}%")
```

```
Accuracy: 81.33427963094393%
```

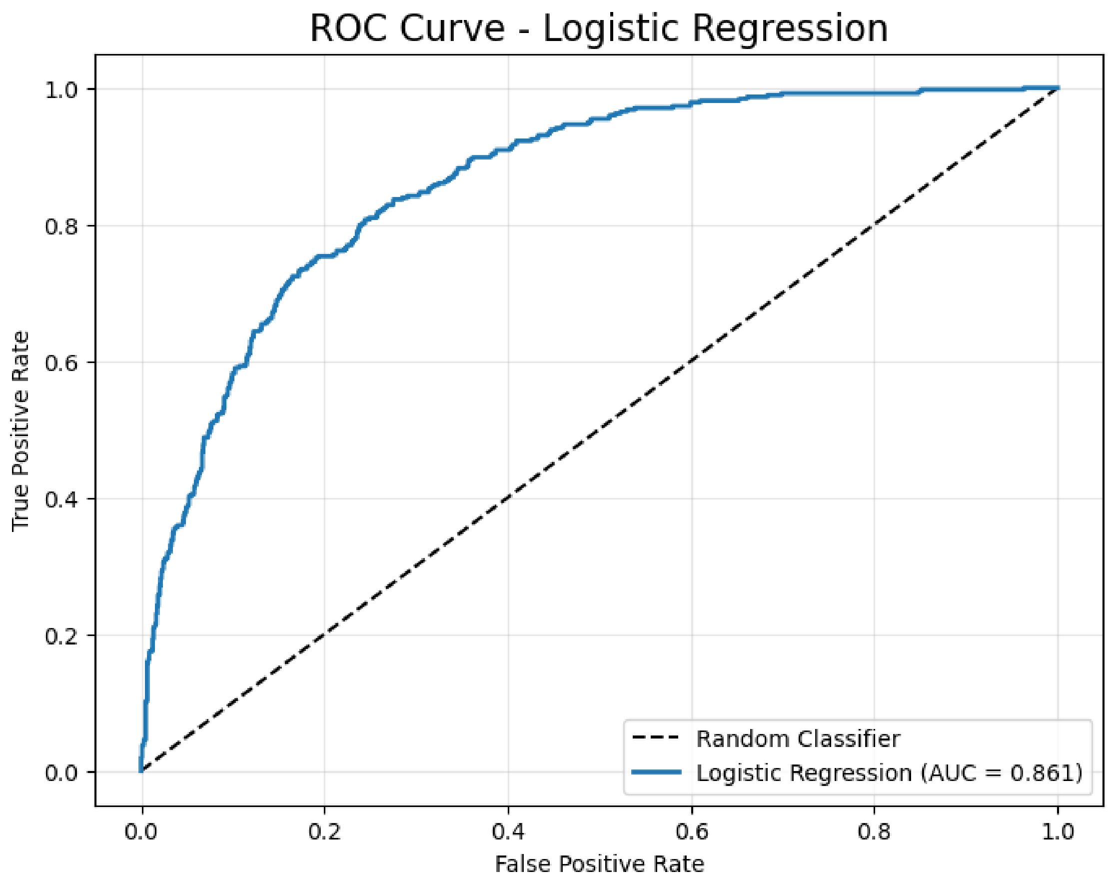
[48]:
```
# Create a regression table

# Fit logistic regression model
logit_model = sm.Logit(y, X)
result = logit_model.fit()

# Display the regression table
print(result.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.412298
         Iterations 7
                           Logit Regression Results
==============================================================================
Dep. Variable:                  Churn   No. Observations:                 7043
Model:                          Logit   Df Residuals:                     7024
Method:                           MLE   Df Model:                           18
Date:                Tue, 27 May 2025   Pseudo R-squ.:                  0.2874
Time:                        22:38:13   Log-Likelihood:                -2903.8
converged:                       True   LL-Null:                       -4075.1
Covariance Type:            nonrobust   LLR p-value:                     0.000
================================================================================
=====
                         coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
Gender                -0.0481      0.064     -0.755      0.450      -0.173
0.077
Senior Citizen         0.2351      0.085      2.778      0.005       0.069
0.401
Partner                0.0273      0.078      0.350      0.727      -0.126
0.180
Dependents            -0.1769      0.090     -1.974      0.048      -0.353
-0.001
tenure                 0.0114      0.006      1.912      0.056      -0.000
0.023
Phone Service         -1.0173      0.118     -8.622      0.000      -1.249
```

```
-0.786
Multiple Lines         0.0881      0.041      2.142      0.032       0.008
0.169
Internet Service       0.0946      0.064      1.479      0.139      -0.031
0.220
Online Security       -0.2578      0.041     -6.224      0.000      -0.339
-0.177
Online Backup         -0.1416      0.038     -3.700      0.000      -0.217
-0.067
Device Protection     -0.0739      0.040     -1.864      0.062      -0.152
0.004
Tech Support          -0.2465      0.042     -5.848      0.000      -0.329
-0.164
Streaming TV          -0.0054      0.042     -0.129      0.897      -0.088
0.077
Streaming Movies      -0.0005      0.042     -0.012      0.991      -0.082
0.081
Contract              -0.8389      0.079    -10.585      0.000      -0.994
-0.684
PaperlessBilling       0.3209      0.071      4.504      0.000       0.181
0.460
PaymentMethod          0.0110      0.031      0.360      0.719      -0.049
0.071
MonthlyCharges         0.0027      0.000     16.364      0.000       0.002
0.003
TotalCharges          -0.0006   7.79e-05     -8.299      0.000      -0.001
-0.000
================================================================================
=====
```

[51]:

```
y_probs_log = logisticRegr.predict_proba(X_test_scaled)[:, 1]
fpr_log, tpr_log, thresholds_log = roc_curve(y_test, y_probs_log)
auc_log = auc(fpr_log, tpr_log)

# Create the ROC curve plot
plt.figure(figsize=(8, 6))
plt.plot([0, 1], [0, 1], 'k--', label='Random Classifier')
plt.plot(fpr_log, tpr_log, label=f'Logistic Regression (AUC = {auc_log:.3f})',
 ↪linewidth=2)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - Logistic Regression', fontsize=16)
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()
```



[ ]:
```python
# Evaluate classification model for Logistical Regression Model

confusion_matrix = metrics.confusion_matrix(y_test, y_pred_log)
confusion_matrix
```

[ ]:
```python
# Create confusion matrix heat map for Logistic Regression
class_names=[0,1] # name  of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)

# create heatmap
sns.heatmap(pd.DataFrame(confusion_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix for Logistical Regression', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

[ ]:

```python
target_names = ['No Churn', 'Churn']
print(classification_report(y_test, y_pred_log, target_names=target_names))
```