Task_2_Exploratory_Data_Analysis_(EDA)

November 22, 2025

1 1. Loading the Dataset

1.1 Data From GitHub
1.2 Display First 5 Rows
1.3 Dataset Information

[15]:
```
# 1.1 Data From GitHub

import pandas as pd

# GitHub raw URL
url = 'https://raw.githubusercontent.com/abuthahir17/Dataset/main/
 ↪Telco_Customer_Churn_Dataset.csv'

# Read CSV file
data = pd.read_csv(url)

print("Dataset Loaded Successfully!")
```

```
Dataset Loaded Successfully!
```

[16]:
```
# 1.2 Display First 5 rows
print("First Five Rows in the Dataset: \n")
data.head()
```

```
First Five Rows in the Dataset:
```

[16]:

	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]
```

[17]:
```
# 1.3 Dataset Information
print("\nDataset Info:\n")
print(data.info())
```

```
Dataset 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
None
```

2 2. Handling Missing Values

2.1 Check the missing values
2.2 TotalCharges -> Numeric (Convert)
2.3 Fill with Median
2.4 Recheck Null (missing) values

[18]:
```
# 2.1 Check the missing values
data.replace(" ", None, inplace=True)
print("Missing Value: \n", data.isnull().sum())
```

```
Missing Value:
 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
```

[19]:
```
# 2.2 Convert TotalCharges to Numeric
data["TotalCharges"] = pd.to_numeric(data["TotalCharges"], errors="coerce")
```

[20]:
```
# 2.3 Fill the missing value with median
data["TotalCharges"] = data["TotalCharges"].fillna(data["TotalCharges"].
 ↪median())
```

[21]:
```
# 2.4 Also Check the " " value
data.replace(" ", None, inplace=True)
print("Missing Value after Cleaning: \n", data.isnull().sum())
```

```
Missing Value after Cleaning:
 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
```

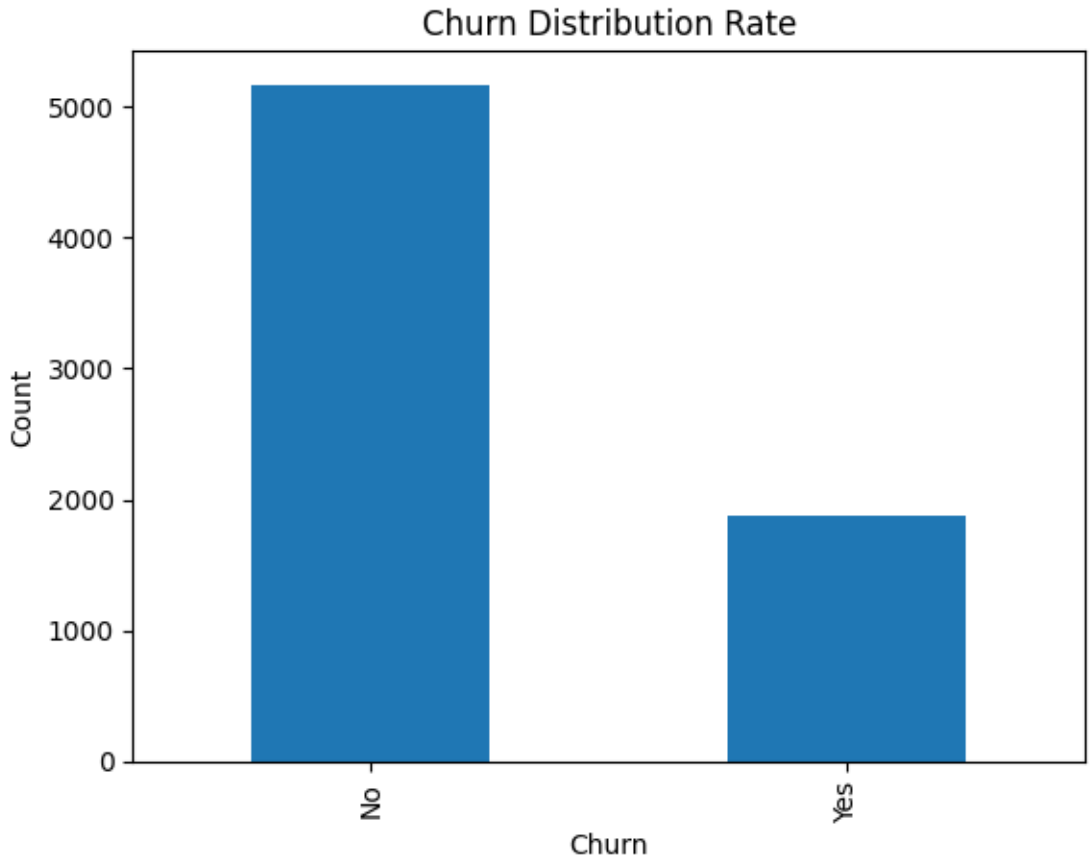
3 3. Calculate and visually represent the overall churn rate

3.1 Calculation for churn rate
3.2 Visual Representation

[22]:
```
# 3.1 Calculate churn rate
churn_rate = data['Churn'].value_counts(normalize=True) * 100
print("Overall Churn Rate in Percentage:")
print(churn_rate)
```

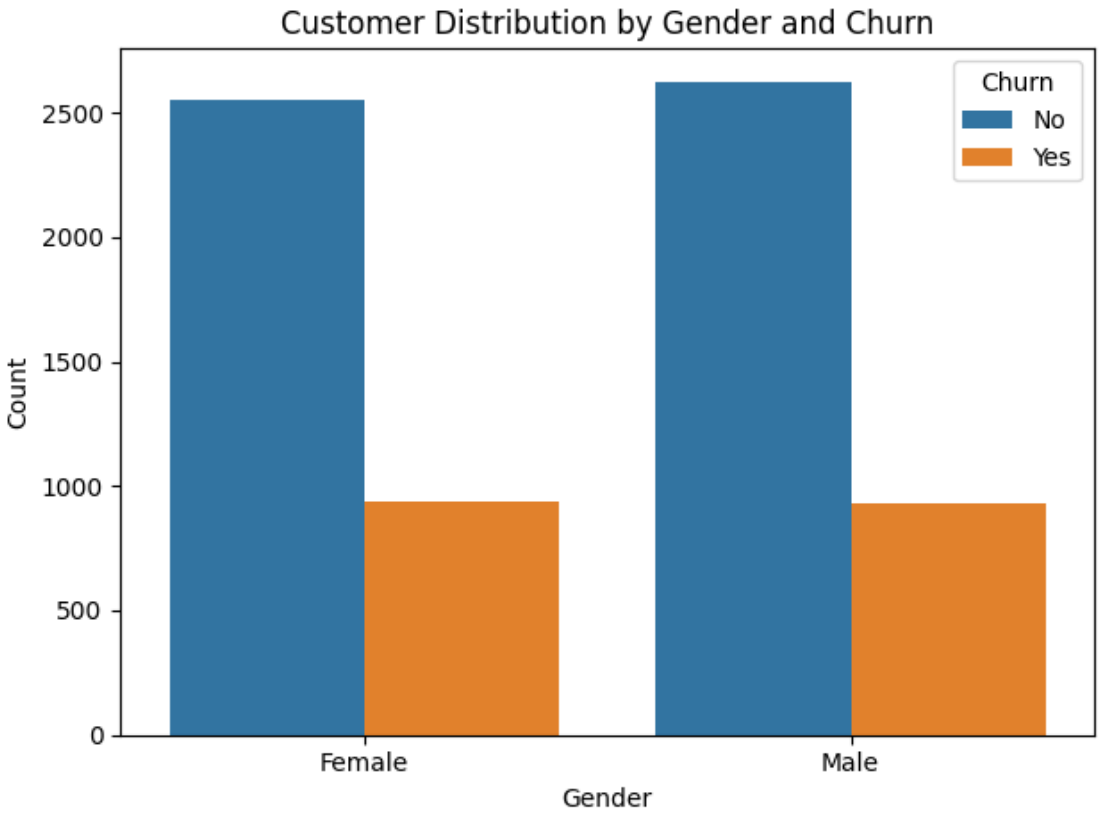
```
Overall Churn Rate in Percentage:
Churn
No     73.463013
Yes    26.536987
Name: proportion, dtype: float64
```

[23]:
```
# 3.2 Visual Representation for churn distribution Rate

import matplotlib.pyplot as plt

plt.figure()
data['Churn'].value_counts().plot(kind='bar')
plt.title("Churn Distribution Rate" )
plt.xlabel("Churn")
plt.ylabel("Count")
plt.show()
```



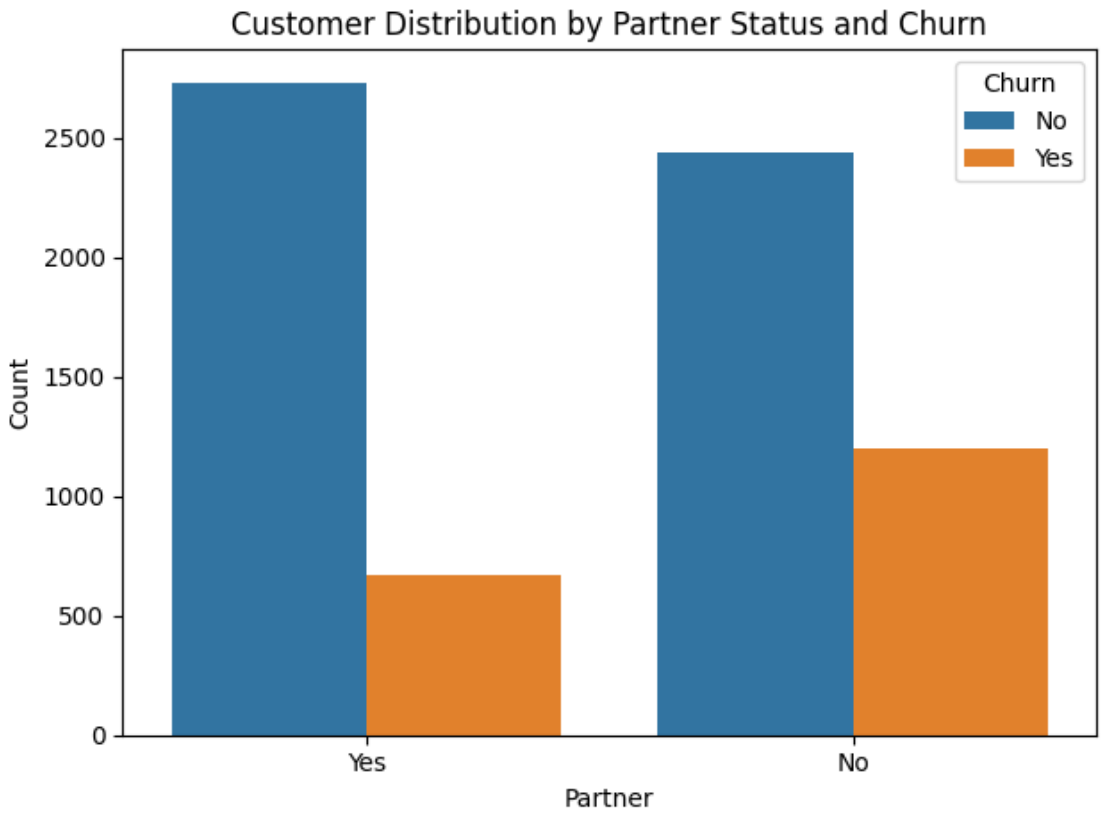
4 4. Explore customer distribution by gender, partner status, and dependent status.

[44]:
```
# 4.1 Gender vs Churn

# Plot the Graph

import seaborn as sns
plt.figure()
sns.countplot(data=data, x="gender", hue="Churn")
plt.title("Customer Distribution by Gender and Churn")
plt.xlabel("Gender")
plt.ylabel("Count")
plt.tight_layout()
plt.show()


# Gender_Churn_Rate
gender_churn = (
    data.groupby("gender")["Churn"]
    .value_counts(normalize=True)
    .unstack() * 100
).rename(columns={"Yes": "Churn_Yes", "No": "Churn_No"})

gender_churn.round(2)
```



[44]:
Churn	Churn_No	Churn_Yes
gender		
Female	73.08	26.92
Male	73.84	26.16

[45]:
```
# 4.2 Partner Status vs Churn

# Plot the Graph
plt.figure()
sns.countplot(data=data, x="Partner", hue="Churn")
plt.title("Customer Distribution by Partner Status and Churn")
plt.xlabel("Partner")
plt.ylabel("Count")
plt.tight_layout()
plt.show()

# Partner_Churn_Rate
partner_churn = (
    data.groupby("Partner")["Churn"]
    .value_counts(normalize=True)
    .unstack() * 100
).rename(columns={"Yes": "Churn_Yes", "No": "Churn_No"})

partner_churn.round(2)
```

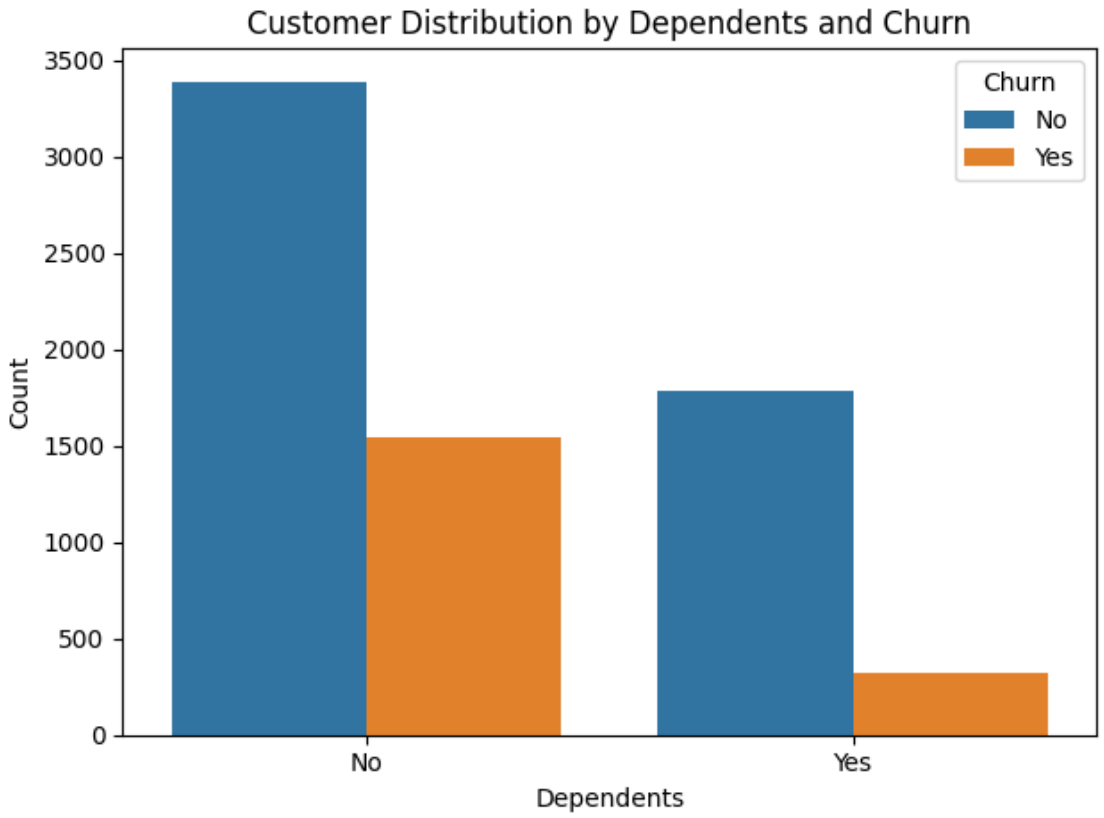


[45]:

Churn	Churn_No	Churn_Yes
Partner		
No	67.04	32.96
Yes	80.34	19.66

[46]:
```
# 4.3 Dependent Status vs Churn

# Plot the Graph
plt.figure()
sns.countplot(data=data, x="Dependents", hue="Churn")
plt.title("Customer Distribution by Dependents and Churn")
plt.xlabel("Dependents")
plt.ylabel("Count")
plt.tight_layout()
plt.show()

# Dependents_Churn_Rate
dependents_churn = (
    data.groupby("Dependents")["Churn"]
    .value_counts(normalize=True)
    .unstack() * 100
```

```
).rename(columns={"Yes": "Churn_Yes", "No": "Churn_No"})

dependents_churn.round(2)
```



[46]:

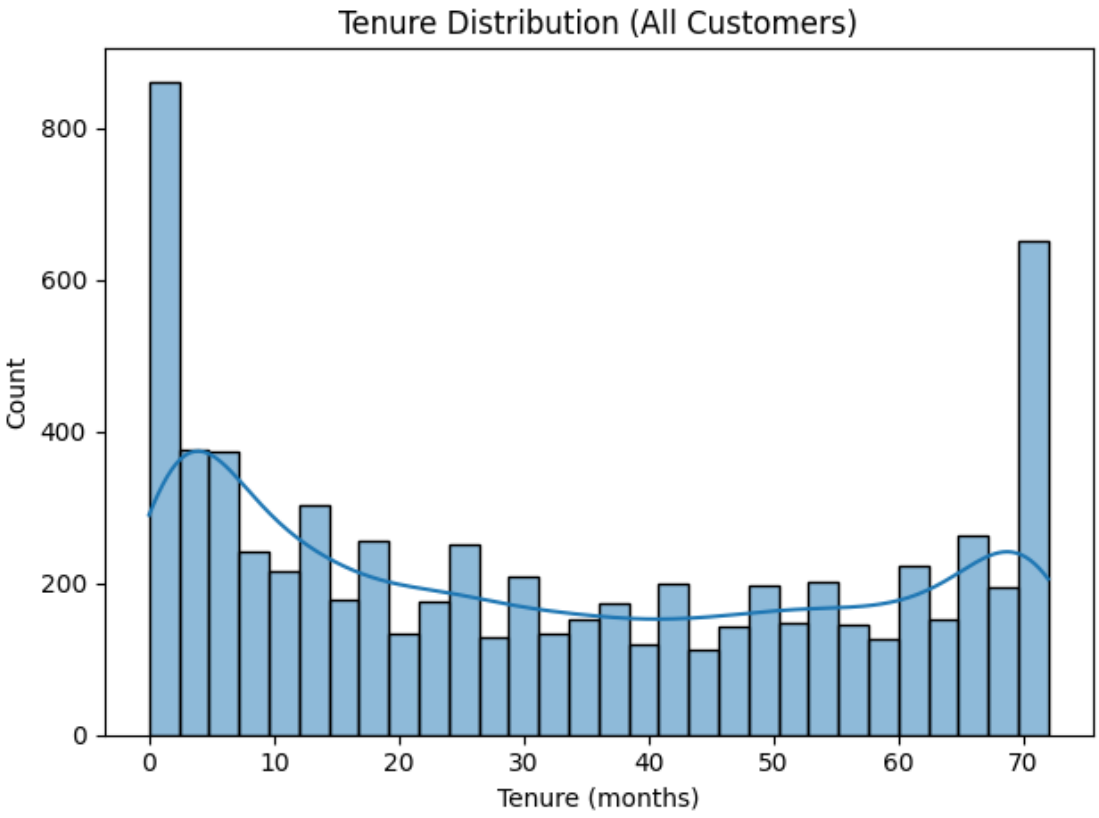
Churn	Churn_No	Churn_Yes
Dependents		
No	68.72	31.28
Yes	84.55	15.45

5 5. Analyze Tenure distribution and its relation with churn.

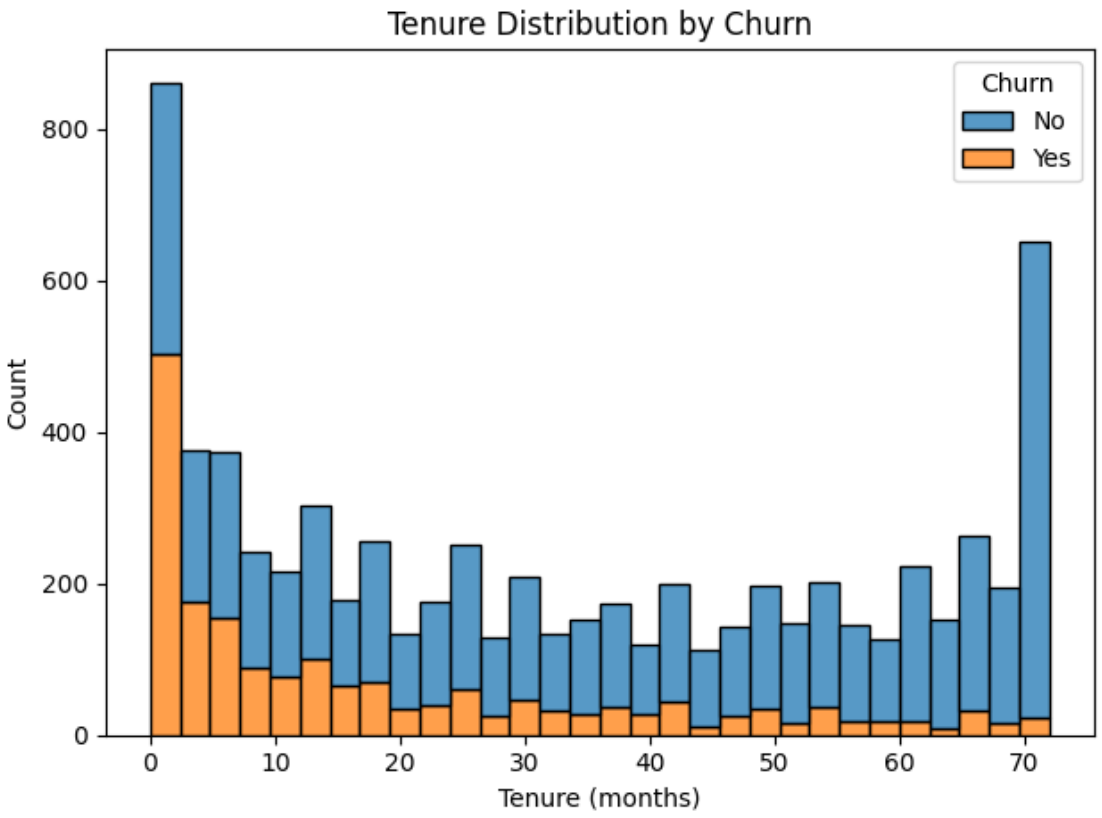
5.1 Overall tenure distribution
5.2 Tenure distribution split by churn
5.3 Boxplot - tenure vs churn
5.4 Summary statistics - tenure by churn

[33]:
```
# 5.1 Overall tenure distribution
plt.figure()
sns.histplot(data["tenure"], bins=30, kde=True)
plt.title("Tenure Distribution (All Customers)")
```

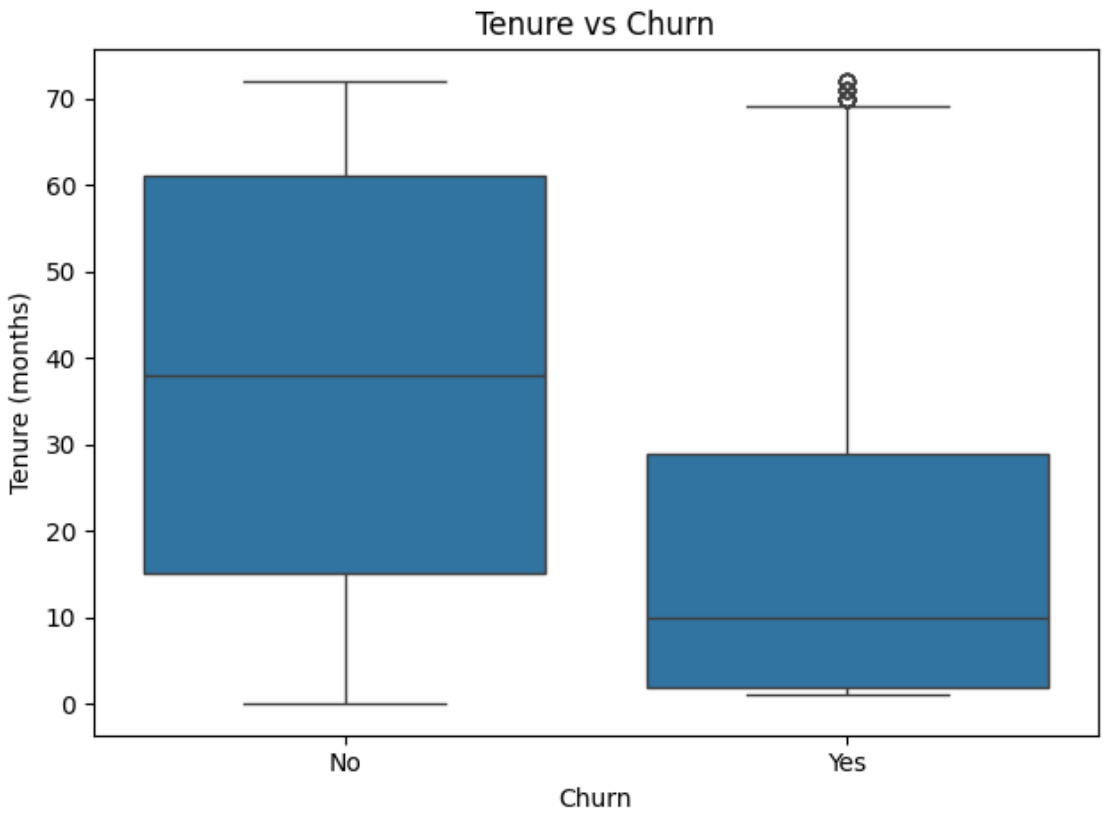
```
plt.xlabel("Tenure (months)")
plt.ylabel("Count")
plt.tight_layout()
plt.show()
```



[34]:
```
# 5.2 Tenure distribution split by churn
plt.figure()
sns.histplot(data=data, x="tenure", hue="Churn", bins=30, kde=False,␣
↪multiple="stack")
plt.title("Tenure Distribution by Churn")
plt.xlabel("Tenure (months)")
plt.ylabel("Count")
plt.tight_layout()
plt.show()
```



[35]:
```
# 5.3 Boxplot - tenure vs churn
plt.figure()
sns.boxplot(data=data, x="Churn", y="tenure")
plt.title("Tenure vs Churn")
plt.xlabel("Churn")
plt.ylabel("Tenure (months)")
plt.tight_layout()
plt.show()
```



[36]:
```
# 5.4 Summary statistics - tenure by churn
tenure_stats = data.groupby("Churn")["tenure"].describe()
print("\nTenure statistics by Churn:")
display(tenure_stats.round(2))
```

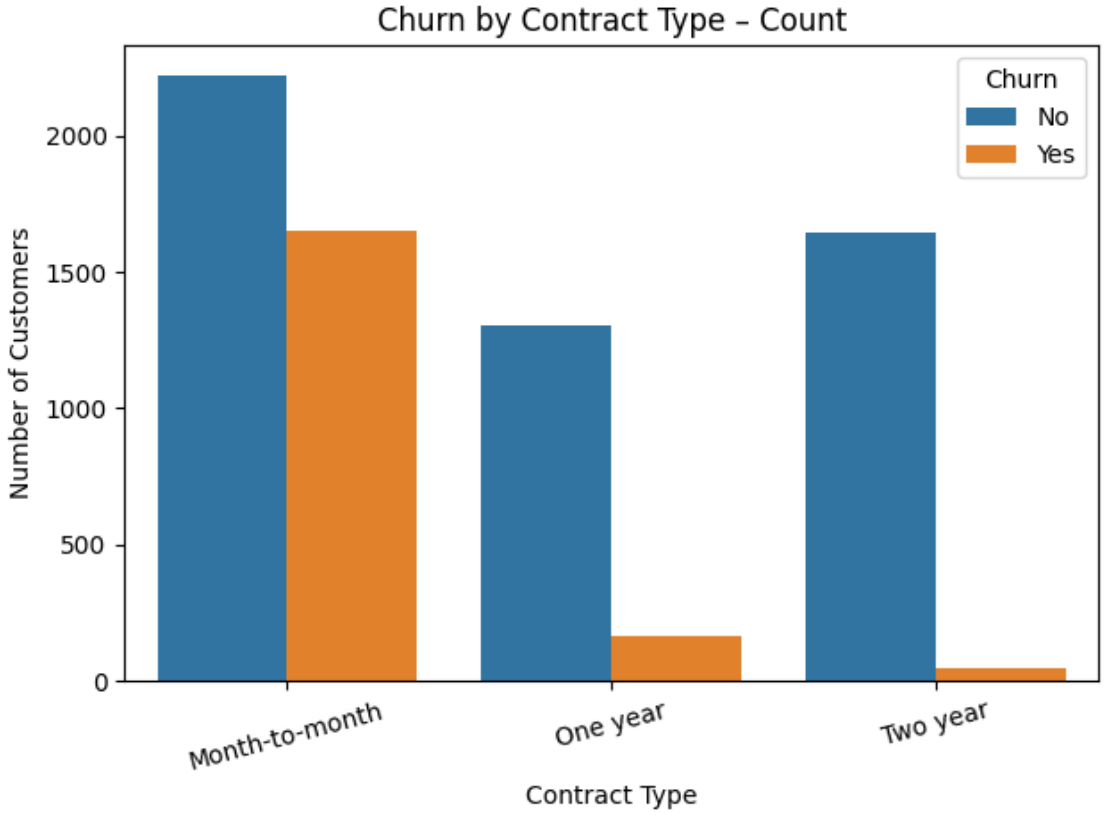
```
Tenure statistics by Churn:
```

Churn	count	mean	std	min	25%	50%	75%	max
No	5174.0	37.57	24.11	0.0	15.0	38.0	61.0	72.0
Yes	1869.0	17.98	19.53	1.0	2.0	10.0	29.0	72.0

6 6. How Churn varies across different Contract Types and Payment methods.

6.1 Churn vs Contract Type
6.2 Churn Rate by Contract
6.3 Churn vs Payment Method
6.4 Churn rate by Payment Method

[37]:
```
# 6.1 Churn vs Contract Type
plt.figure()
sns.countplot(data=data, x="Contract", hue="Churn")
plt.title("Churn by Contract Type - Count")
plt.xlabel("Contract Type")
plt.ylabel("Number of Customers")
plt.xticks(rotation=15)
plt.tight_layout()
plt.show()
```

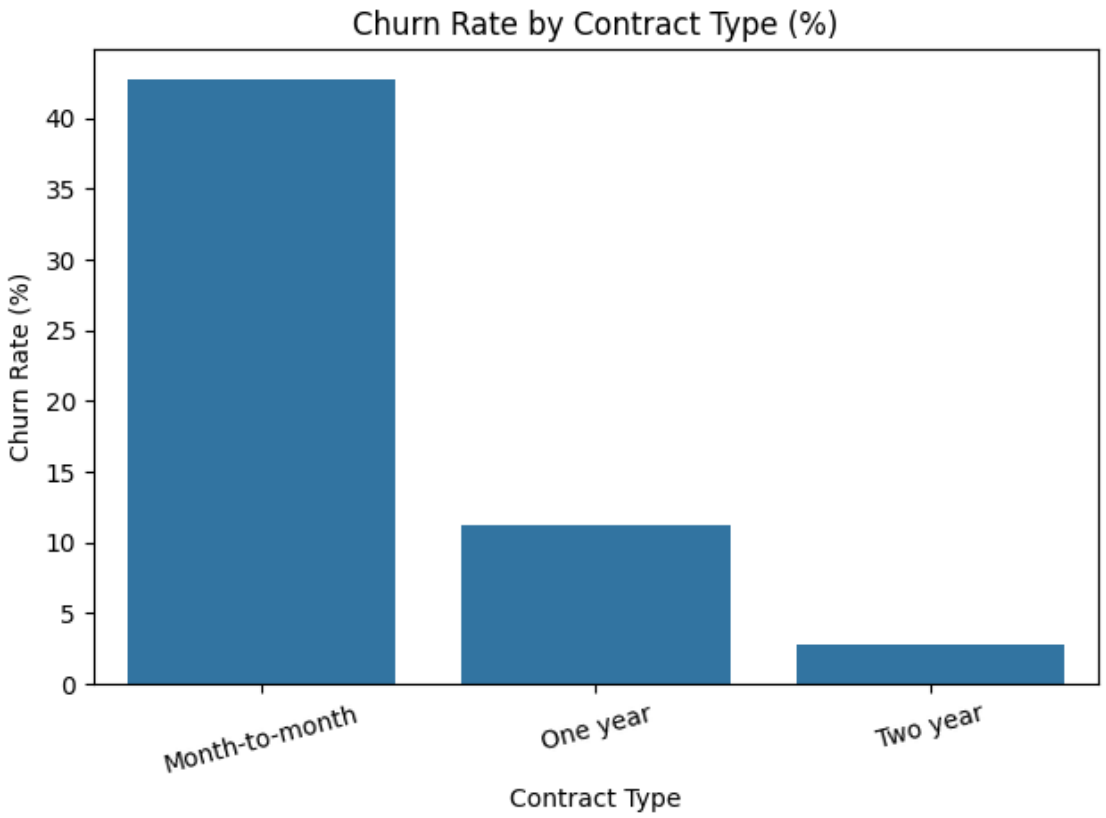


[41]:
```
# 6.2 Churn Rate by Contract
churn_by_contract = (
    data.groupby("Contract")["Churn"]
    .value_counts(normalize=True)
    .unstack()
    .rename(columns={"Yes": "Churn_Yes", "No": "Churn_No"}) * 100
)

print("\nChurn rate (%) by Contract type:")
display(churn_by_contract.round(2))
```

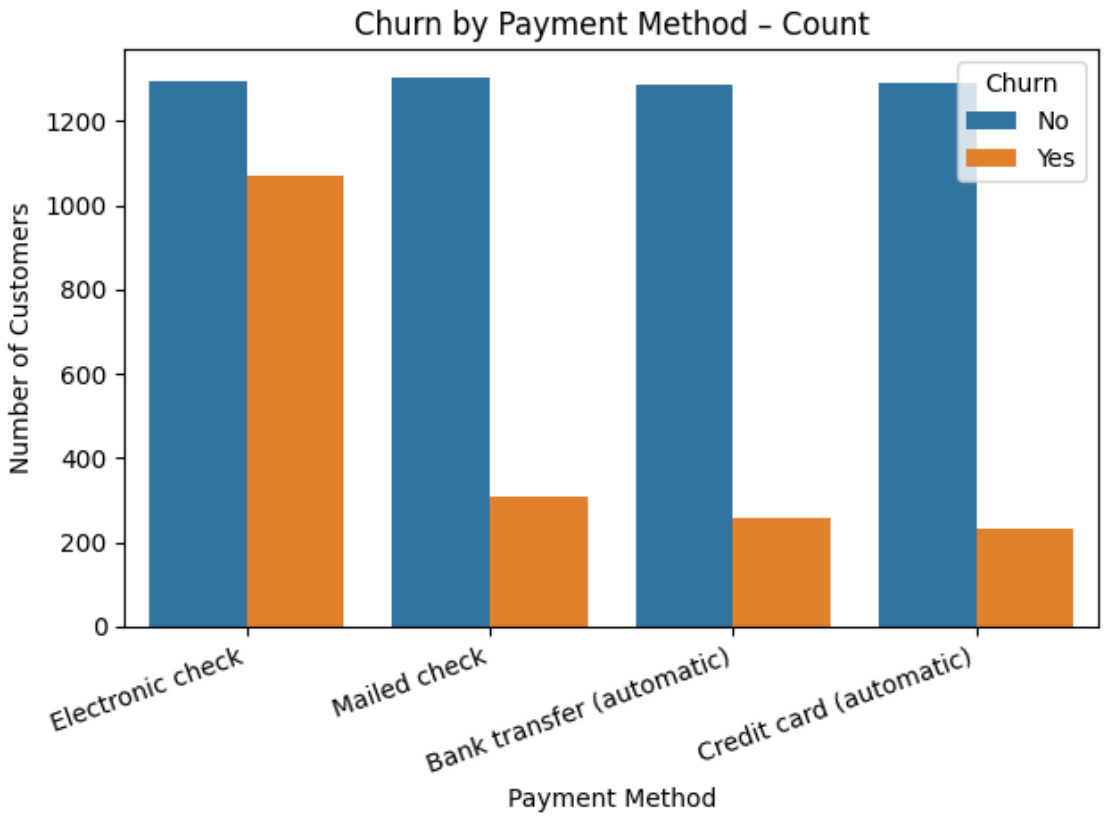
```
print("\n")


# For clear visualization of churn rate only (Yes)
plt.figure()
sns.barplot(
    x=churn_by_contract.index,
    y=churn_by_contract["Churn_Yes"]
)
plt.title("Churn Rate by Contract Type (%)")
plt.xlabel("Contract Type")
plt.ylabel("Churn Rate (%)")
plt.xticks(rotation=15)
plt.tight_layout()
plt.show()
```

```
Churn rate (%) by Contract type:
```

Churn	Churn_No	Churn_Yes
Contract		
Month-to-month	57.29	42.71
One year	88.73	11.27
Two year	97.17	2.83



[42]:
```
# 6.3 Churn vs Payment Method
plt.figure()
sns.countplot(data=data, x="PaymentMethod", hue="Churn")
plt.title("Churn by Payment Method - Count")
plt.xlabel("Payment Method")
plt.ylabel("Number of Customers")
plt.xticks(rotation=20, ha="right")
plt.tight_layout()
plt.show()
```



[43]:
```
# 6.4 Churn rate by Payment Method
churn_by_payment = (
    data.groupby("PaymentMethod")["Churn"]
    .value_counts(normalize=True)
    .unstack()
    .rename(columns={"Yes": "Churn_Yes", "No": "Churn_No"}) * 100
)

print("\nChurn rate (%) by Payment Method:")
display(churn_by_payment.round(2))
print("\n")


# For clear visualization of churn rate only (Yes)
plt.figure()
sns.barplot(
    x=churn_by_payment.index,
    y=churn_by_payment["Churn_Yes"]
)
plt.title("Churn Rate by Payment Method (%)")
```

```
plt.xlabel("Payment Method")
plt.ylabel("Churn Rate (%)")
plt.xticks(rotation=20, ha="right")
plt.tight_layout()
plt.show()
```

```
Churn rate (%) by Payment Method:
```

Churn	Churn_No	Churn_Yes
PaymentMethod		
Bank transfer (automatic)	83.29	16.71
Credit card (automatic)	84.76	15.24
Electronic check	54.71	45.29
Mailed check	80.89	19.11