

In [ ]: # 📊 Telco Customer Churn Analysis

This project explores and analyzes a telecom company's customer base to understand churn patterns, customer behavior,

```
In [5]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
sns.set(style="whitegrid")
plt.rcParams["figure.figsize"] = (7, 4)
```

```
In [4]: df = pd.read_csv("telco_customer_churn.csv")
df.head()
```

Out[4]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity
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0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No

5 rows × 21 columns



```
In [6]: df.shape
```

```
Out[6]: (7043, 21)
```

```
In [7]: 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
```

```
In [8]: df.describe()
```

```
Out[8]:
```

	SeniorCitizen	tenure	MonthlyCharges
<b>count</b>	7043.000000	7043.000000	7043.000000
<b>mean</b>	0.162147	32.371149	64.761692
<b>std</b>	0.368612	24.559481	30.090047
<b>min</b>	0.000000	0.000000	18.250000
<b>25%</b>	0.000000	9.000000	35.500000
<b>50%</b>	0.000000	29.000000	70.350000
<b>75%</b>	0.000000	55.000000	89.850000
<b>max</b>	1.000000	72.000000	118.750000

```
In [9]: df.nunique()
```

```
Out[9]: customerID      7043
gender                2
SeniorCitizen         2
Partner               2
Dependents            2
tenure                73
PhoneService          2
MultipleLines         3
InternetService       3
OnlineSecurity        3
OnlineBackup          3
DeviceProtection      3
TechSupport           3
StreamingTV           3
StreamingMovies       3
Contract              3
PaperlessBilling      2
PaymentMethod         4
MonthlyCharges       1585
TotalCharges         6531
Churn                 2
dtype: int64
```

```
In [10]: df["TotalCharges"].unique()[:10]
```

```
Out[10]: array(['29.85', '1889.5', '108.15', '1840.75', '151.65', '820.5',  
              '1949.4', '301.9', '3046.05', '3487.95'], dtype=object)
```

```
In [11]: df["TotalCharges"] = pd.to_numeric(df["TotalCharges"], errors="coerce")
```

```
In [12]: df.dropna(subset=["TotalCharges"], inplace=True)
```

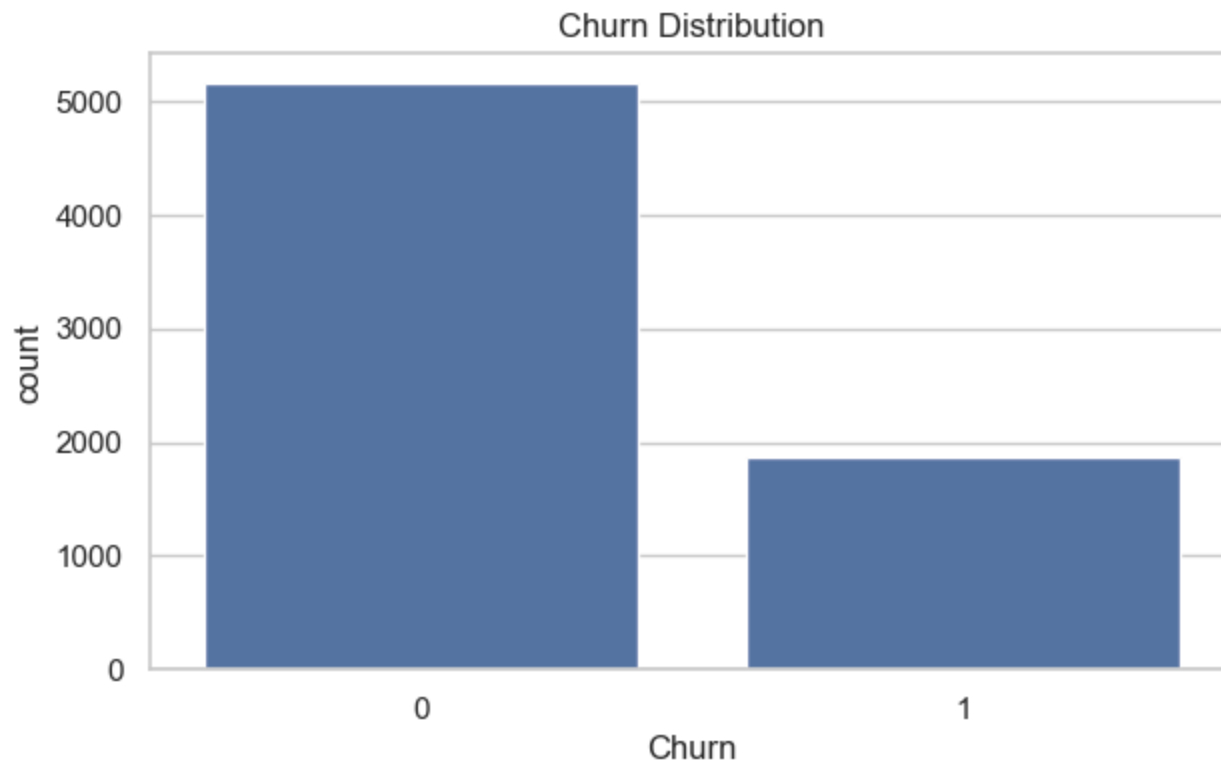
```
In [13]: df["SeniorCitizen"] = df["SeniorCitizen"].astype("category")
```

```
In [14]: df["Churn"].value_counts()
```

```
Out[14]: Churn  
No      5163  
Yes     1869  
Name: count, dtype: int64
```

```
In [15]: df["Churn"] = df["Churn"].map({"Yes": 1, "No": 0})
```

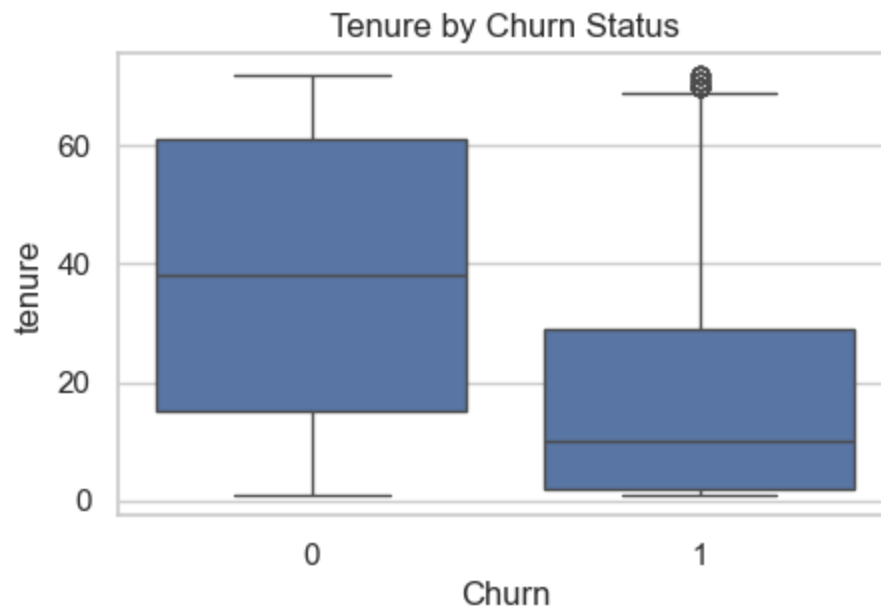
```
In [16]: sns.countplot(x="Churn", data=df)  
plt.title("Churn Distribution")  
plt.show()
```



```
In [17]: df.groupby("Churn")["tenure"].mean()
```

```
Out[17]: Churn
0      37.650010
1      17.979133
Name: tenure, dtype: float64
```

```
In [30]: plt.figure(figsize=(5, 3))
sns.boxplot(x="Churn", y="tenure", data=df)
plt.title("Tenure by Churn Status")
plt.show()
```



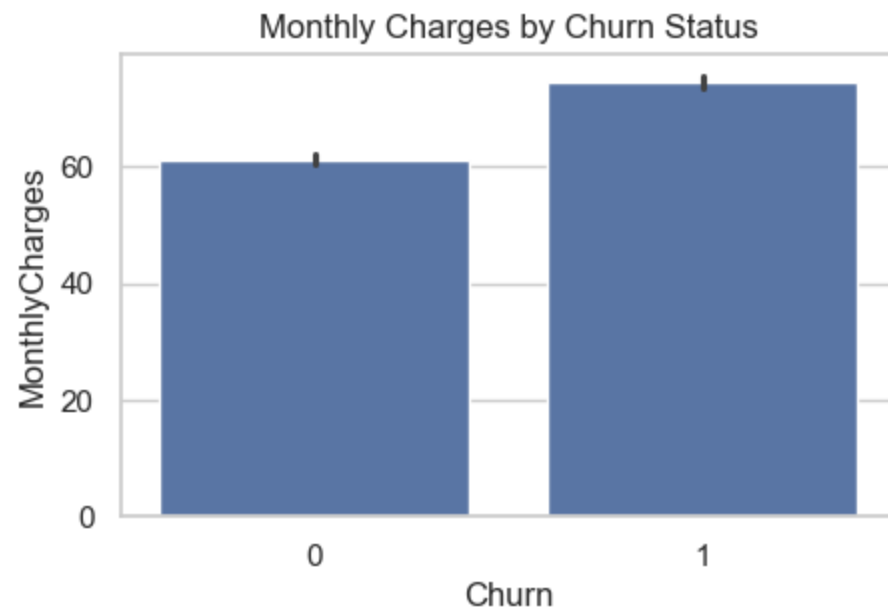
```
In [19]: df.groupby("Churn")[["MonthlyCharges", "TotalCharges"]].mean()
```

```
Out[19]:
```

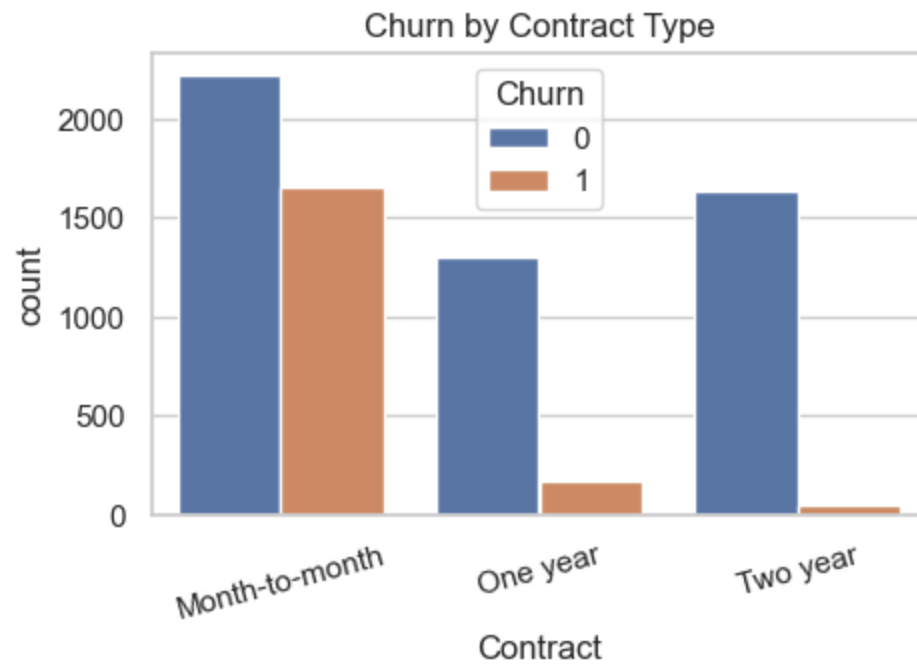
	MonthlyCharges	TotalCharges
Churn		

Churn		
0	61.307408	2555.344141
1	74.441332	1531.796094

```
In [29]: plt.figure(figsize=(5,3))
sns.barplot(x="Churn", y="MonthlyCharges", data=df)
plt.title("Monthly Charges by Churn Status")
plt.show()
```

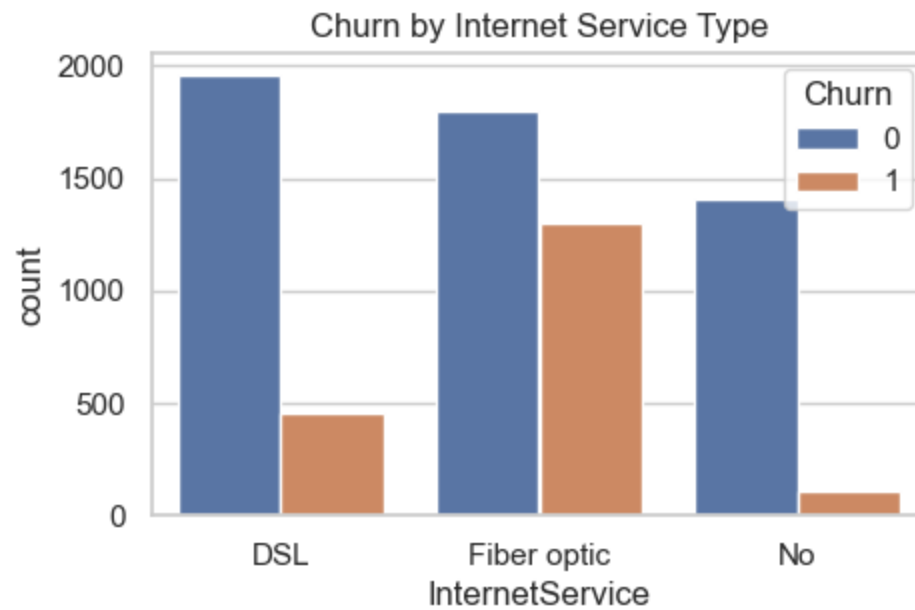


```
In [28]: plt.figure(figsize=(5, 3))
sns.countplot(x="Contract", hue="Churn", data=df)
plt.title("Churn by Contract Type")
plt.xticks(rotation=15)
plt.show()
```

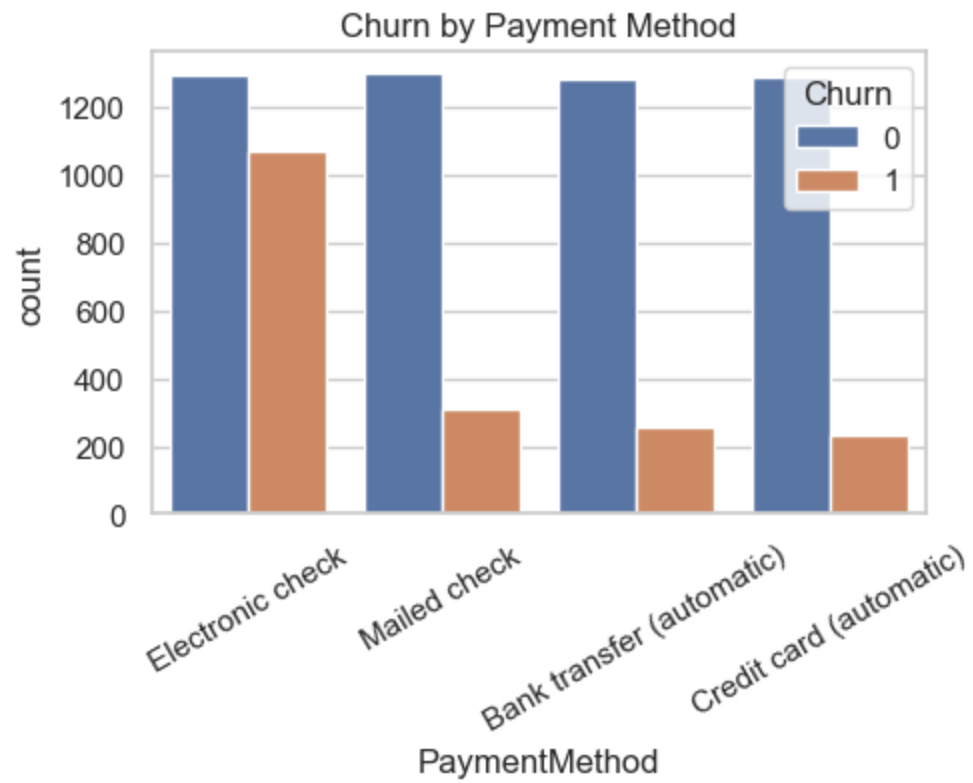


```
In [31]: plt.figure(figsize=(5,3))
sns.countplot(x="InternetService", hue="Churn", data=df)
plt.title("Churn by Internet Service Type")
plt.show()
```





```
In [32]: plt.figure(figsize=(5,3))
sns.countplot(x="PaymentMethod", hue="Churn", data=df)
plt.title("Churn by Payment Method")
plt.xticks(rotation=30)
plt.show()
```

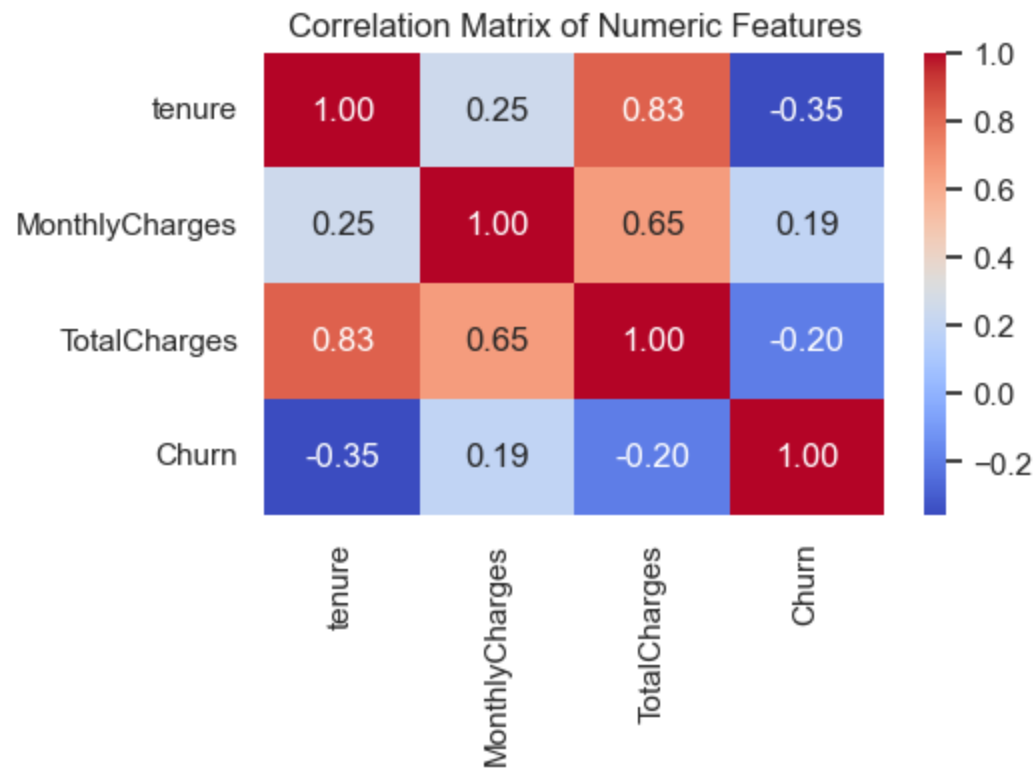


```
In [33]: plt.figure(figsize=(5,3))
sns.countplot(x="OnlineSecurity", hue="Churn", data=df)
plt.title("Churn by Online Security Service")
plt.show()
```



```
In [25]: numeric_df = df.select_dtypes(include=["float64", "int64"])
```

```
In [34]: plt.figure(figsize=(5, 3))
sns.heatmap(numeric_df.corr(), annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Matrix of Numeric Features")
plt.show()
```



In [ ]: *### Key Takeaways*

- Customers on month-to-month contracts show the highest churn rates.
- Those without online security or tech support are more likely to leave.
- Higher monthly charges and shorter tenure both correlate with churn.
- Long-term customers on yearly contracts rarely churn, even with high total charges.

*### Business Recommendations*

- Encourage long-term contracts with loyalty discounts.
- Bundle online security or tech support as retention incentives.
- Identify high-risk groups early based on billing and service patterns.