

Project Report
Introduction to Data Science
Semester - 2

“Telco Customer Churn dataset”

By

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GitHub link: [piyushT3003/IDS](https://github.com/piyushT3003/IDS)

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Project Overview

This project is a data analysis case study focused on customer churn prediction in a telecom company. Using the "Telco Customer Churn" dataset, the project explores the relationship between customer behavior and churn, aiming to identify patterns and visualize insights that could help reduce churn rates.

Introduction

Customer churn, or the loss of clients or subscribers, is a significant concern for subscription-based businesses such as telecom companies. The notebook begins by importing and cleaning the Telco Customer Churn dataset. This dataset includes customer demographic information, account details, and service usage statistics. The analysis provides a foundation for understanding which factors influence churn and helps businesses strategize better retention practices.

Project Goals

- To clean and prepare the dataset for analysis.
- To explore and visualize customer attributes and behavior.
- To identify key factors related to customer churn.
- To generate insights through visualizations (e.g., histograms, pie charts, box plots).
- To support decision-making for churn reduction strategies.

Challenges

- Missing and incorrect data: The TotalCharges column required conversion to numeric, which revealed missing or malformed entries.
- Data imbalances: As often seen in churn datasets, the number of customers who churned vs. those who didn't may be imbalanced, affecting visual clarity and any potential modeling.
- Feature interpretation: Some categorical variables required careful interpretation before visualization (e.g., contract type, payment method).
- Visualization complexity: Plotting meaningful graphs that convey insight without overcrowding the visuals.

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
df=pd.read_csv(r"C:\Users\piyus\Downloads\WA_Fn-UseC_-Telco-Customer-Churn
(1).csv")
```

```
df
```

	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-JJAZL	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]

1. Check for missing values and data types

Check for missing values

```
print("Missing Values:\n", df.isnull().sum())
```

Check data types

```
print("\nData Types:\n", df.dtypes)
```

Missing Values:

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

```

Data Types:

```

customerID        object
gender            object
SeniorCitizen     int64
Partner           object
Dependents        object
tenure            int64
PhoneService      object
MultipleLines     object
InternetService   object
OnlineSecurity    object
OnlineBackup      object
DeviceProtection  object
TechSupport       object
StreamingTV       object
StreamingMovies   object
Contract          object
PaperlessBilling  object
PaymentMethod     object
MonthlyCharges    float64
TotalCharges      object
Churn             object
dtype: object

```

1. A brief descriptive statistics overview

Summary statistics

df.describe(include='all')

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

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

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

	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	\
count	7043	7043	7043	7043.000000	
unique	3	2	4	NaN	
top	Month-to-month	Yes	Electronic check	NaN	
freq	3875	4171	2365	NaN	
mean	NaN	NaN	NaN	64.761692	
std	NaN	NaN	NaN	30.090047	
min	NaN	NaN	NaN	18.250000	
25%	NaN	NaN	NaN	35.500000	
50%	NaN	NaN	NaN	70.350000	
75%	NaN	NaN	NaN	89.850000	
max	NaN	NaN	NaN	118.750000	

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

max NaN NaN

[11 rows x 21 columns]

1. Convert 'TotalCharges' to numeric and handle non-numeric entries

Convert 'TotalCharges' to numeric, forcing errors to NaN

```
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors='coerce')
```

Check how many rows were affected

```
print("Missing values after conversion:", df['TotalCharges'].isnull().sum())
```

Fill or drop missing values

```
df = df.dropna(subset=['TotalCharges'])
```

Missing values after conversion: 11

1. Sort by 'tenure'

```
df = df.sort_values(by='tenure')
```

1. Check basic info

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
Index: 7032 entries, 0 to 3543
```

```
Data columns (total 21 columns):
```

#	Column	Non-Null Count	Dtype
0	customerID	7032 non-null	object
1	gender	7032 non-null	object
2	SeniorCitizen	7032 non-null	int64
3	Partner	7032 non-null	object
4	Dependents	7032 non-null	object
5	tenure	7032 non-null	int64
6	PhoneService	7032 non-null	object
7	MultipleLines	7032 non-null	object
8	InternetService	7032 non-null	object
9	OnlineSecurity	7032 non-null	object
10	OnlineBackup	7032 non-null	object
11	DeviceProtection	7032 non-null	object
12	TechSupport	7032 non-null	object
13	StreamingTV	7032 non-null	object
14	StreamingMovies	7032 non-null	object
15	Contract	7032 non-null	object
16	PaperlessBilling	7032 non-null	object
17	PaymentMethod	7032 non-null	object
18	MonthlyCharges	7032 non-null	float64
19	TotalCharges	7032 non-null	float64
20	Churn	7032 non-null	object

```
dtypes: float64(2), int64(2), object(17)
```

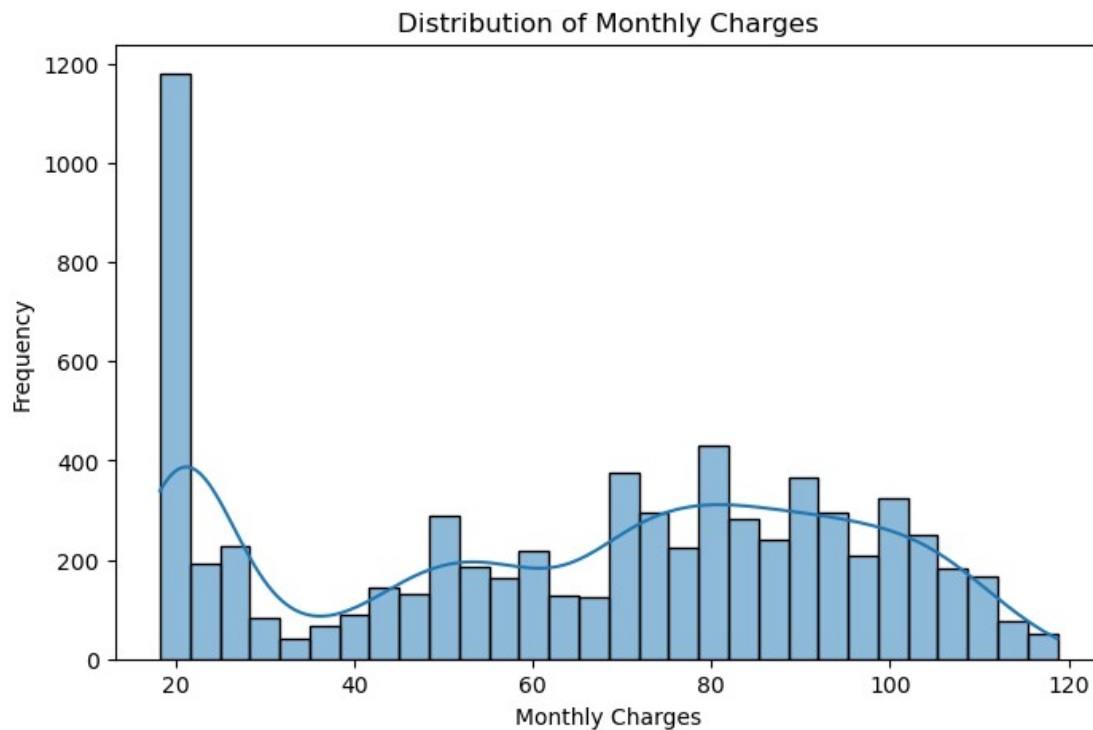
```
memory usage: 1.2+ MB
```

1. Visualizing the Data (requires matplotlib and seaborn)

```
import matplotlib.pyplot as plt
import seaborn as sns
```

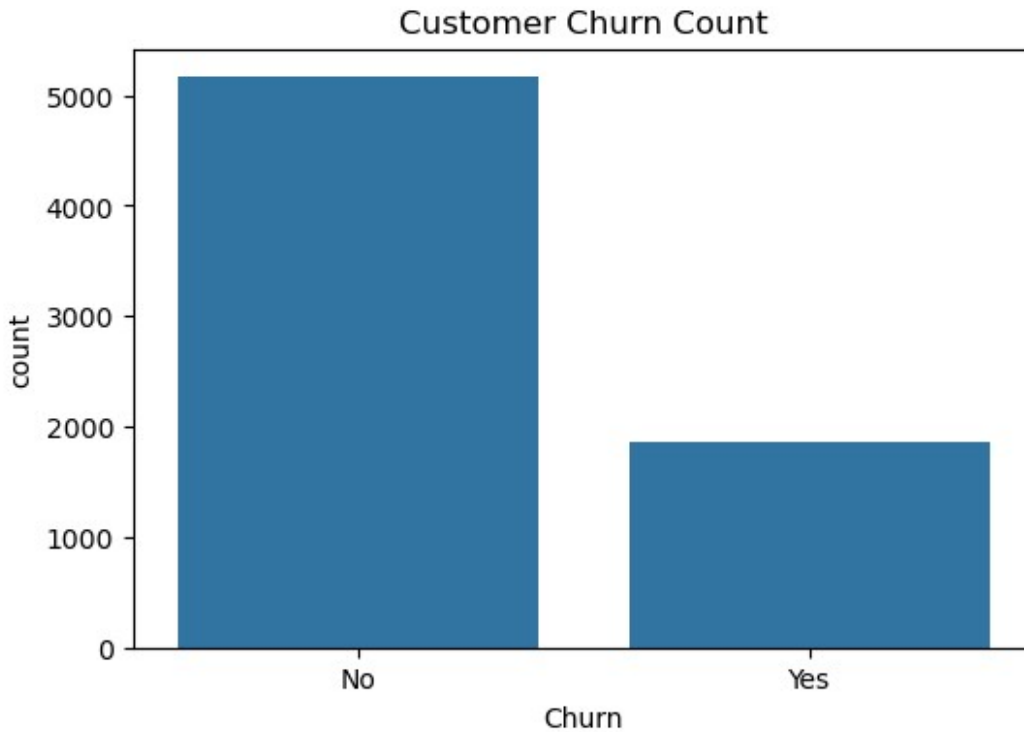
1. Histogram of 'MonthlyCharges'

```
plt.figure(figsize=(8, 5))
sns.histplot(df['MonthlyCharges'], bins=30, kde=True)
plt.title("Distribution of Monthly Charges")
plt.xlabel("Monthly Charges")
plt.ylabel("Frequency")
plt.show()
```



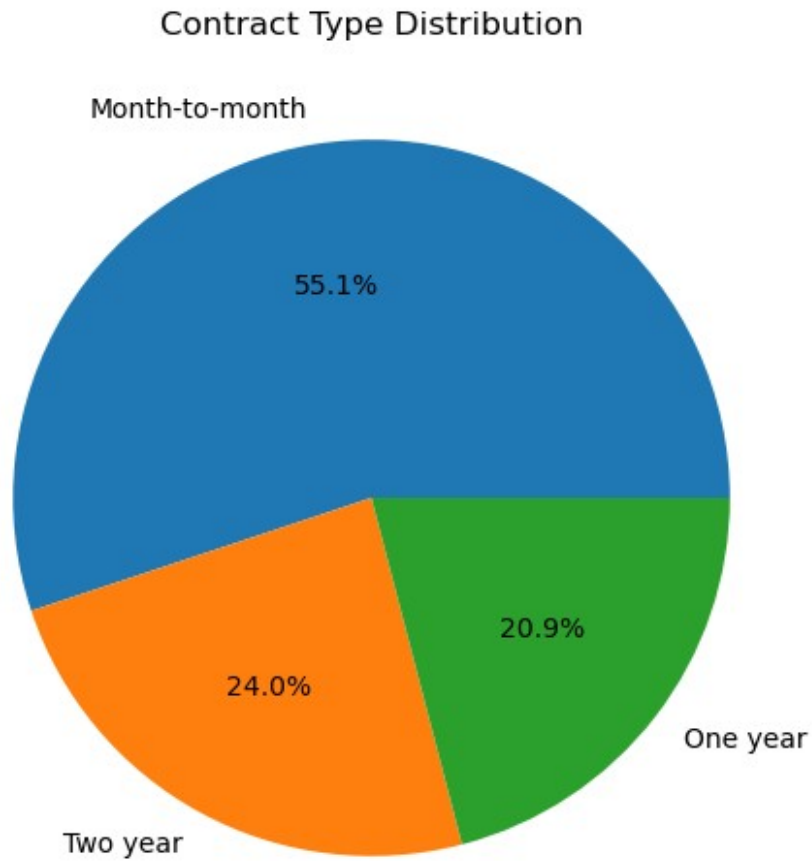
1. Bar plot: Churn count

```
plt.figure(figsize=(6, 4))
sns.countplot(x='Churn', data=df)
plt.title("Customer Churn Count")
plt.show()
```

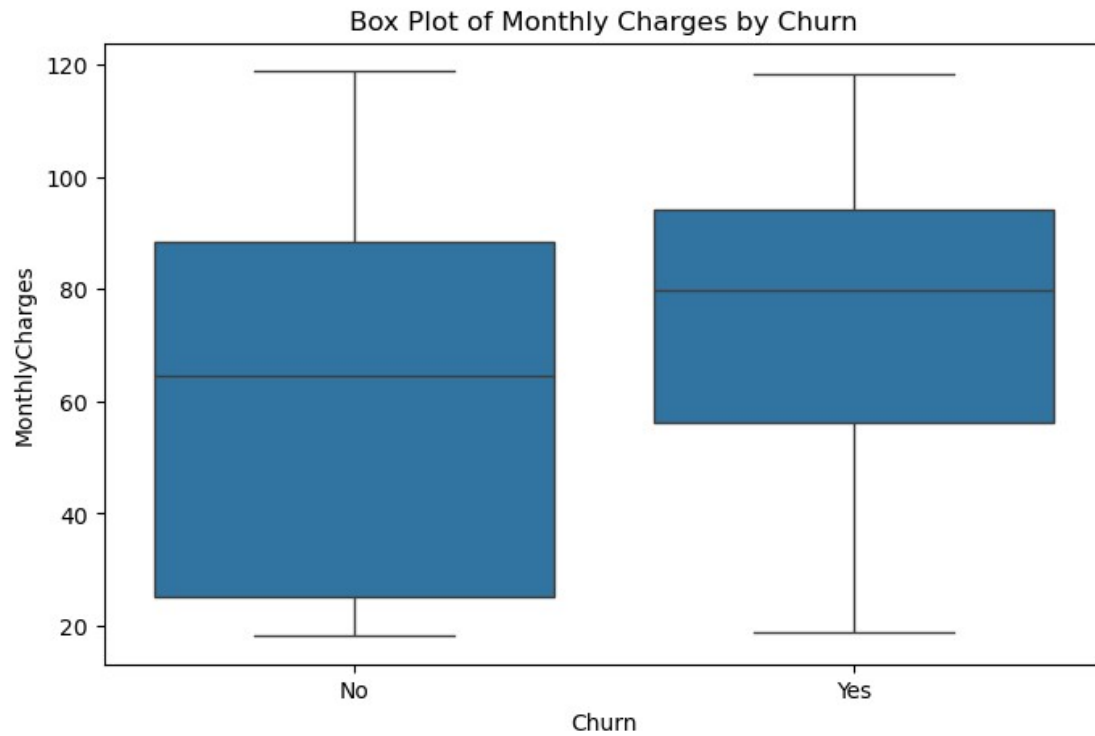
1. Pie chart of 'Contract' types

```
contract_counts = df['Contract'].value_counts()
plt.figure(figsize=(6, 6))
plt.pie(contract_counts, labels=contract_counts.index, autopct='%1.1f%%')
plt.title("Contract Type Distribution")
plt.show()
```



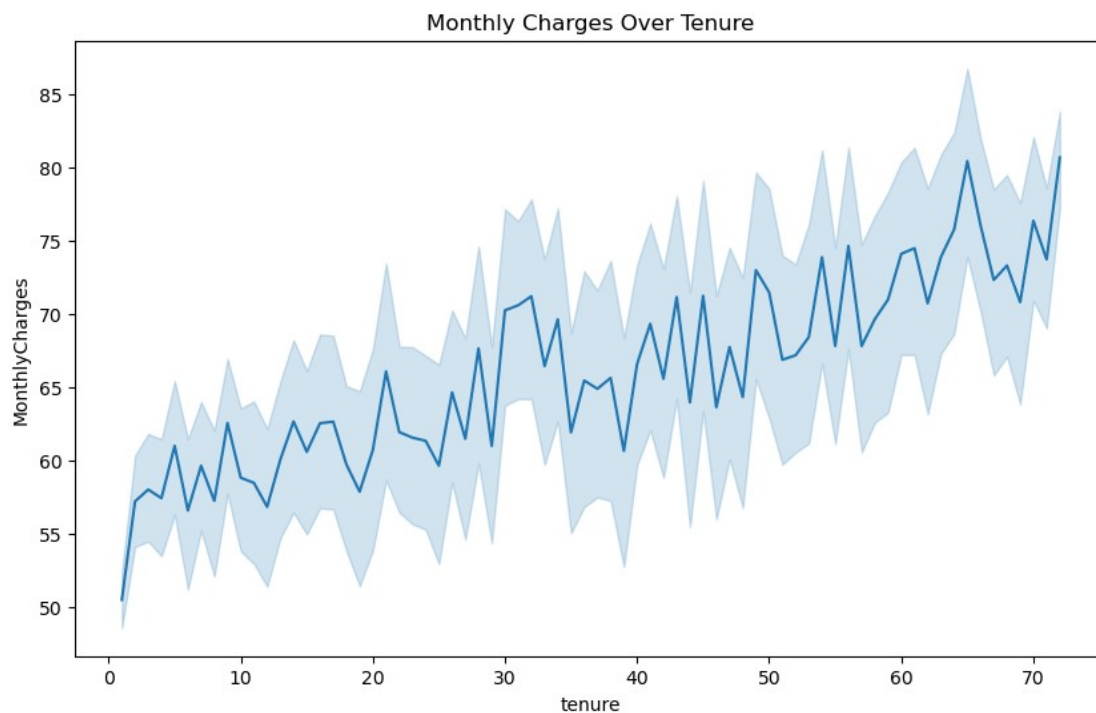
1. Creating a Box Plot (Monthly Charges by Churn)

```
plt.figure(figsize=(8, 5))
sns.boxplot(x='Churn', y='MonthlyCharges', data=df)
plt.title("Box Plot of Monthly Charges by Churn")
plt.show()
```



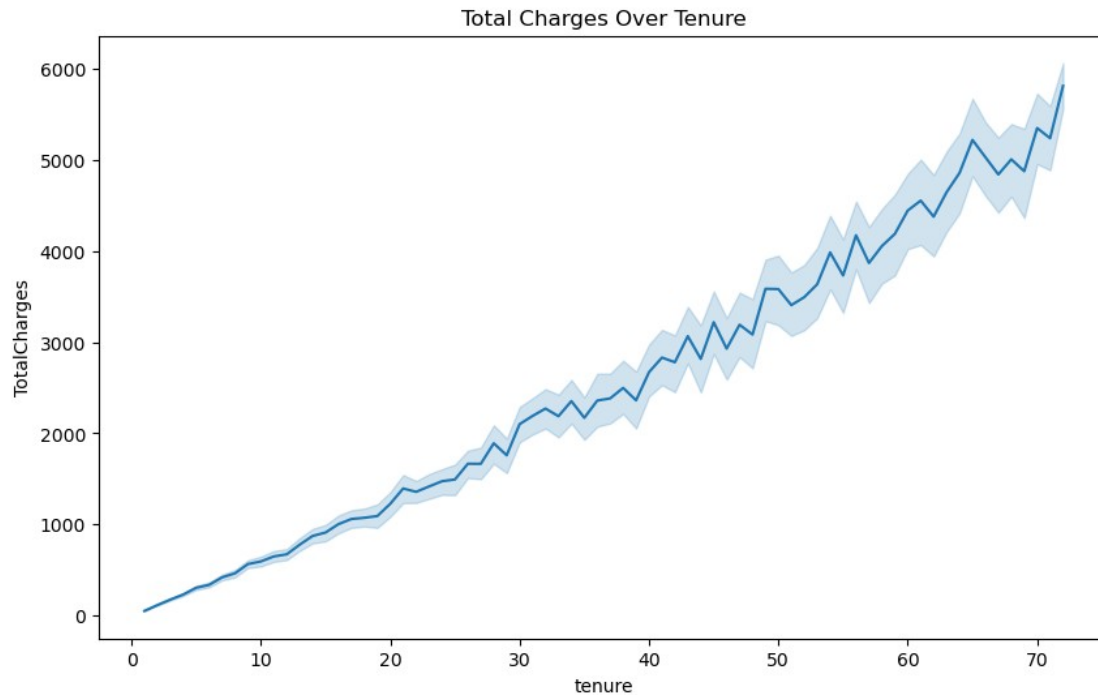
1. Plotting MonthlyCharges over Tenure

```
plt.figure(figsize=(10, 6))  
sns.lineplot(x='tenure', y='MonthlyCharges', data=df)  
plt.title("Monthly Charges Over Tenure")  
plt.show()
```



1. Displaying Volume trends — using 'tenure' as a time-like feature

```
plt.figure(figsize=(10, 6))
sns.lineplot(x='tenure', y='TotalCharges', data=df)
plt.title("Total Charges Over Tenure")
plt.show()
```



1. Creating log feature (log of TotalCharges)

```
import numpy as np
df['LogTotalCharges'] = np.log(df['TotalCharges'] + 1)
```

1. Creating Features and Target

```
features = df.drop(['customerID', 'Churn'], axis=1)
features = pd.get_dummies(features, drop_first=True)
target = df['Churn'].apply(lambda x: 1 if x == 'Yes' else 0)
```

1. Train-test split

```
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(features, target,
test_size=0.2, random_state=42)
```

1. Training a model (Logistic Regression)

```
from sklearn.linear_model import LogisticRegression
```

```
model = LogisticRegression(max_iter=1000)
model.fit(X_train, y_train)
```

```
c:\Users\piyus\anaconda3\Lib\site-  
packages\sklearn\linear_model\_logistic.py:469: ConvergenceWarning: lbfgs  
failed to converge (status=1):  
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max_iter) or scale the data as shown in:
<https://scikit-learn.org/stable/modules/preprocessing.html>
Please also refer to the documentation for alternative solver options:
https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

```
n_iter_i = _check_optimize_result(  

```

```
LogisticRegression(max_iter=1000)
```

1. Evaluating the model

```
from sklearn.metrics import accuracy_score, classification_report
```

```
y_pred = model.predict(X_test)  
print("Accuracy:", accuracy_score(y_test, y_pred))  
print("Classification Report:\n", classification_report(y_test, y_pred))
```

Accuracy: 0.8038379530916845

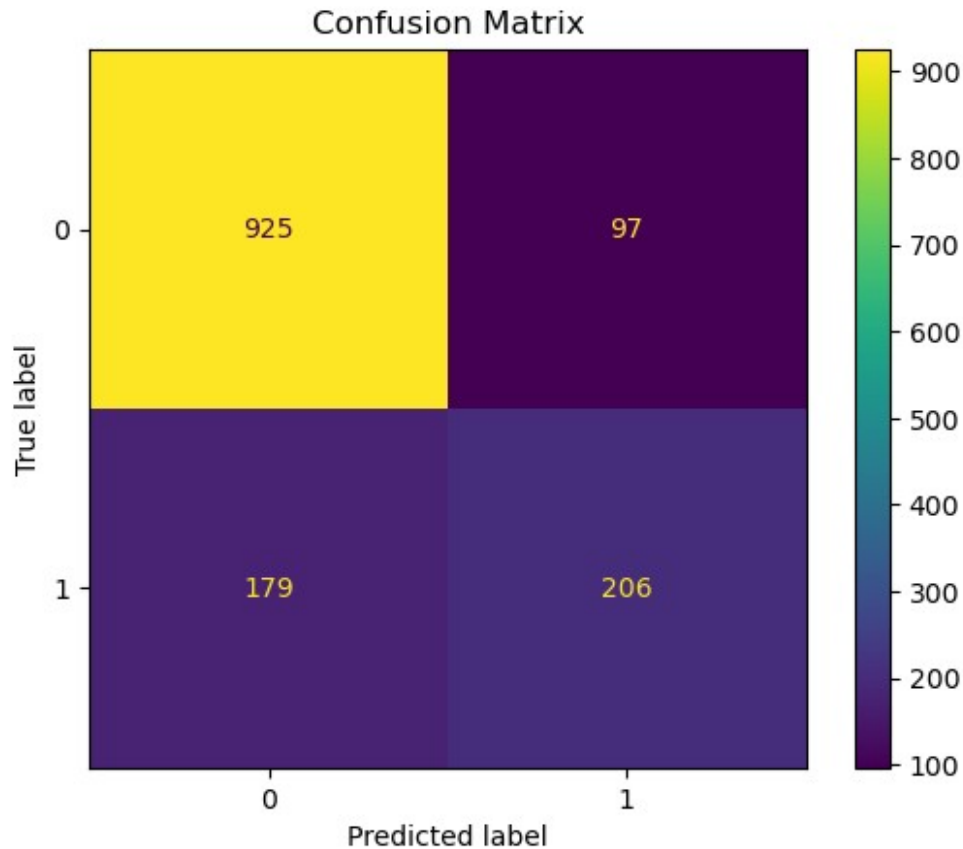
Classification Report:

	precision	recall	f1-score	support
0	0.84	0.91	0.87	1022
1	0.68	0.54	0.60	385
accuracy			0.80	1407
macro avg	0.76	0.72	0.73	1407
weighted avg	0.79	0.80	0.80	1407

1. Confusion Matrix

```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
```

```
cm = confusion_matrix(y_test, y_pred)  
ConfusionMatrixDisplay(confusion_matrix=cm,  
display_labels=model.classes_).plot()  
plt.title("Confusion Matrix")  
plt.show()
```



1. Creating a Correlation Heatmap

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset
df = pd.read_csv(r"C:\Users\piyus\Downloads\WA_Fn-UseC_-Telco-Customer-Churn(1).csv")

# Convert 'TotalCharges' to numeric, coercing errors to NaN
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors='coerce')

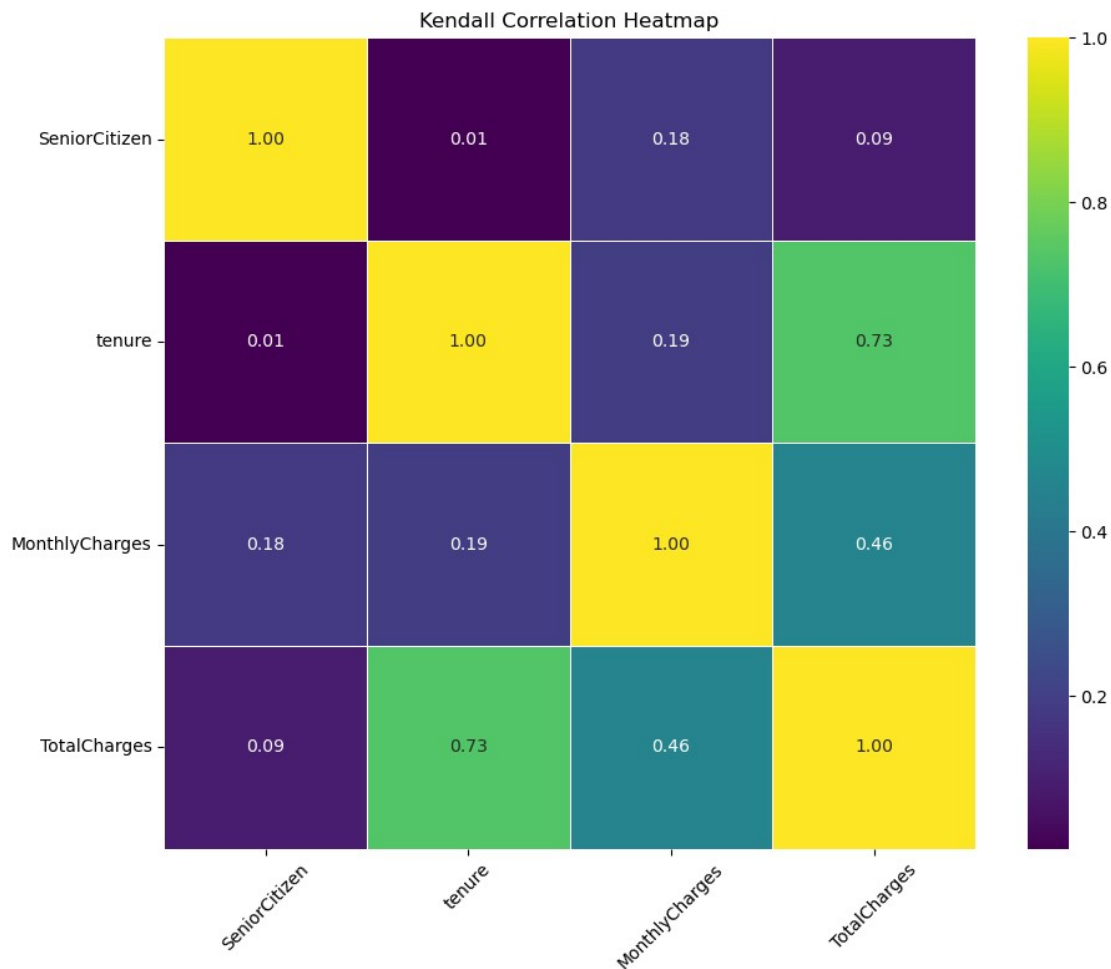
# Drop rows with missing values in 'TotalCharges'
df.dropna(subset=['TotalCharges'], inplace=True)

# Select only numeric columns
numeric_df = df.select_dtypes(include=['number'])

# Compute Kendall correlation matrix
corr_matrix = numeric_df.corr(method='kendall')

# Plot the heatmap
```

```
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap="viridis", square=True,
linewidths=0.5)
plt.title("Kendall Correlation Heatmap")
plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.tight_layout()
plt.show()
```



Conclusion

This exploratory analysis highlighted key trends in customer churn behavior. For instance, churn was more common among customers with month-to-month contracts and higher monthly charges. Visual tools like histograms, pie charts, and box plots helped simplify complex relationships, making the data easier to interpret. These insights can serve as a foundation for building predictive models or crafting customer retention strategies.

