ALLIANCE
UNIVERSITY
Alliance College of Engineering and Design

Project Report

Introduction to Data Science

Semester – 2

“Telco Customer Churn dataset”

By

PIYUSH TANDALE

Reg no: 2411021240006

GitHub link:

Department of Computer Application

Alliance University Chandapura — Anekal Main Road,

Anekal Bengaluru — 562 106

April 2025

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-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]
```

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')
```

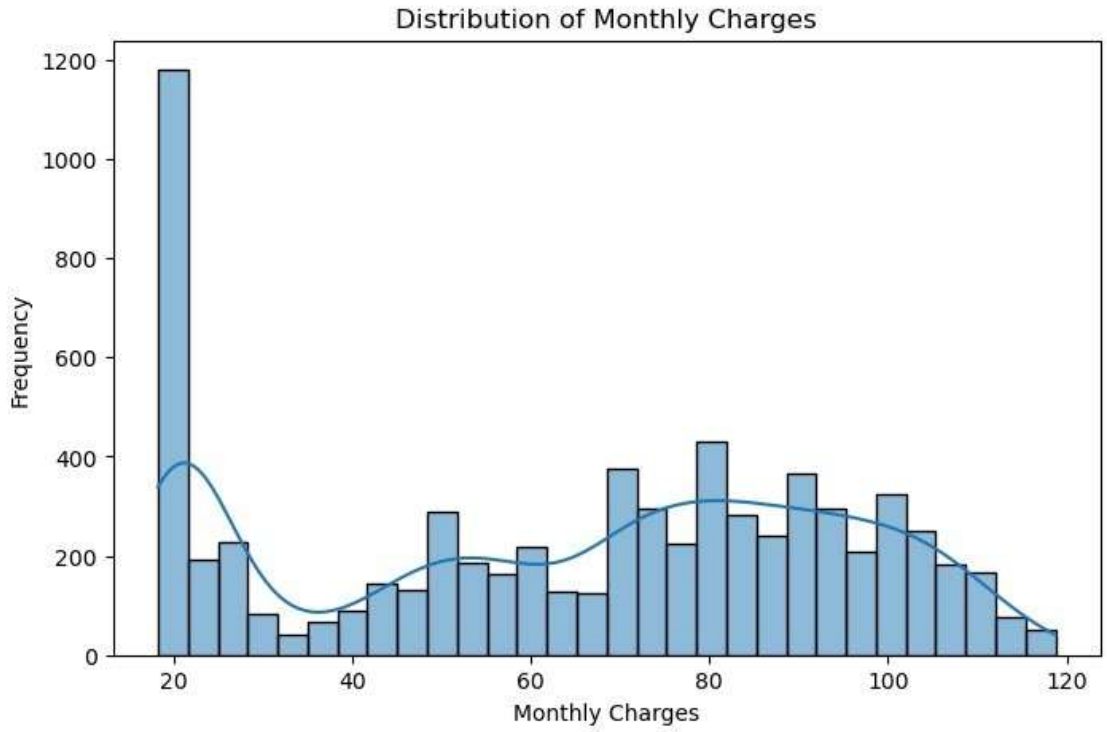
1. Check basic info df.info()

```
<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
```

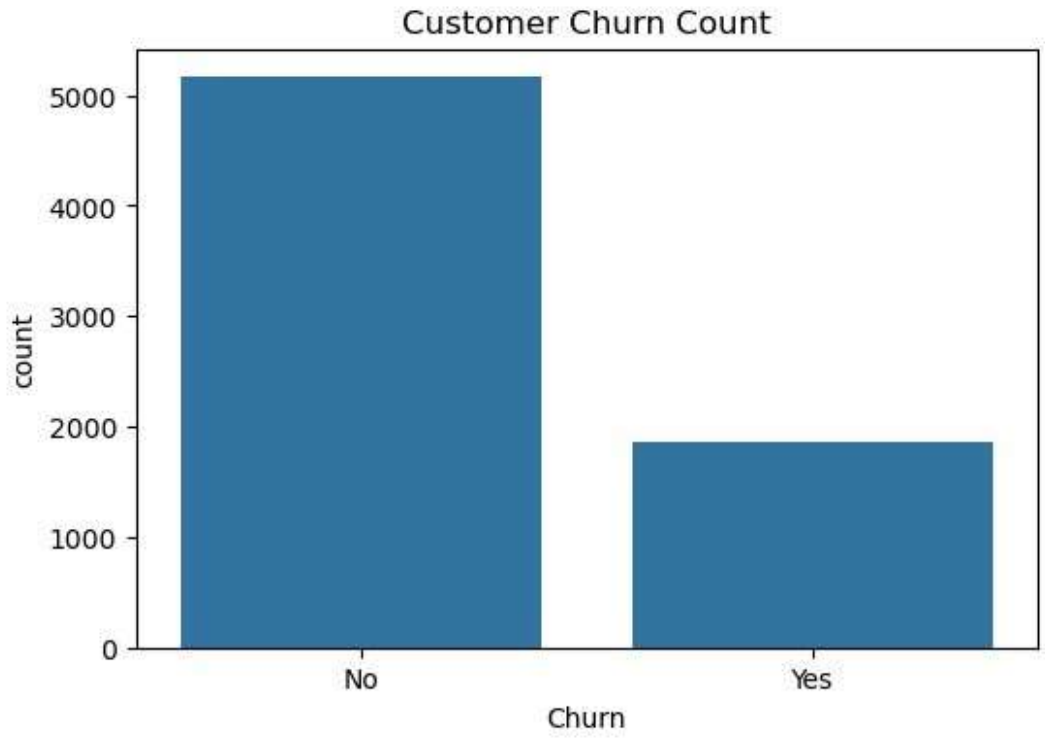
11 DeviceProtection 7032 non-null object
12 TechSupport 7032 non-null object
13 StreamingTV 7032 non-null object
14 StreamingMovies 7032 non-null object
15 Contract 7032 non-null object
16 PaperlessBilling 7032 non-null object
17 PaymentMethod 7032 non-null object
18 MonthlyCharges 7032 non-null float64
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

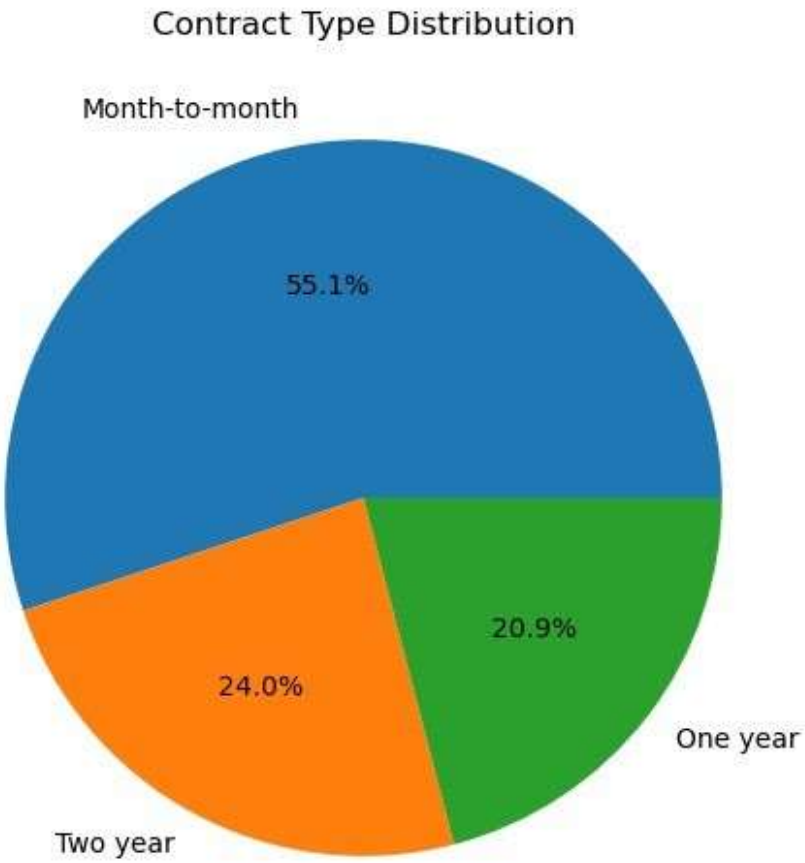
1. Histogram of 'MonthlyCharges' plt.figure(figsize=(8, 5)) sns.histplot(df['MonthlyCharges'], bins=30, kde=True) plt.title("Distribution of Monthly Charges") plt.xlabel("Monthly Charges") plt.ylabel("Frequency") plt.show()



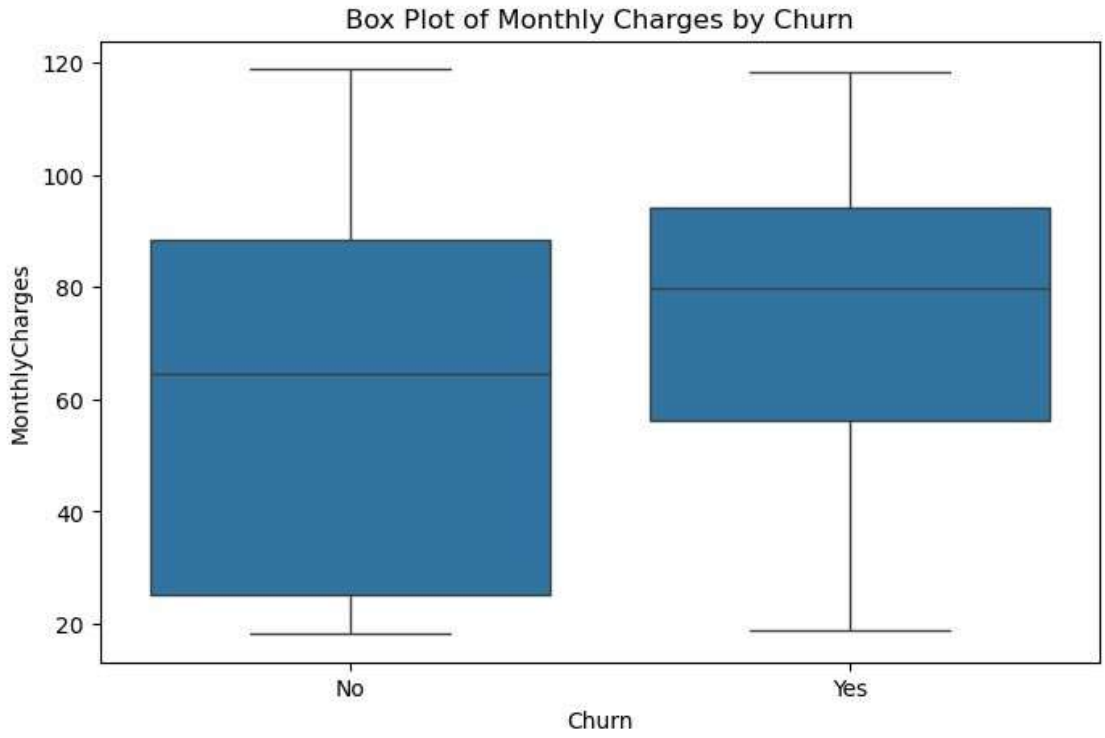
1. Bar plot: Churn count plt.figure(figsize=(6, 4)) sns.countplot(x='Churn', data=df) plt.title("Customer Churn Count") plt.show()



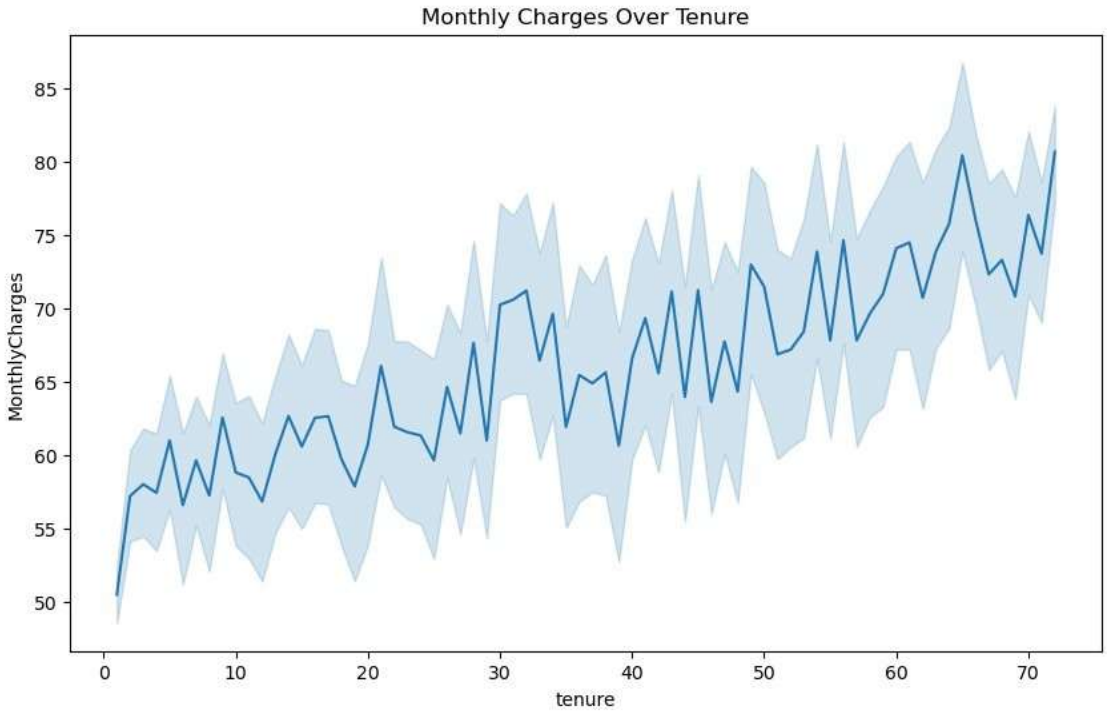
1. Pie chart of 'Contract' types contract_counts = df['Contract'].value_counts() plt.figure(figsize=(6, 6)) plt.pie(contract_counts, labels=contract_counts.index, autopct='%1.1f%%') plt.title("Contract Type Distribution") plt.show()



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()

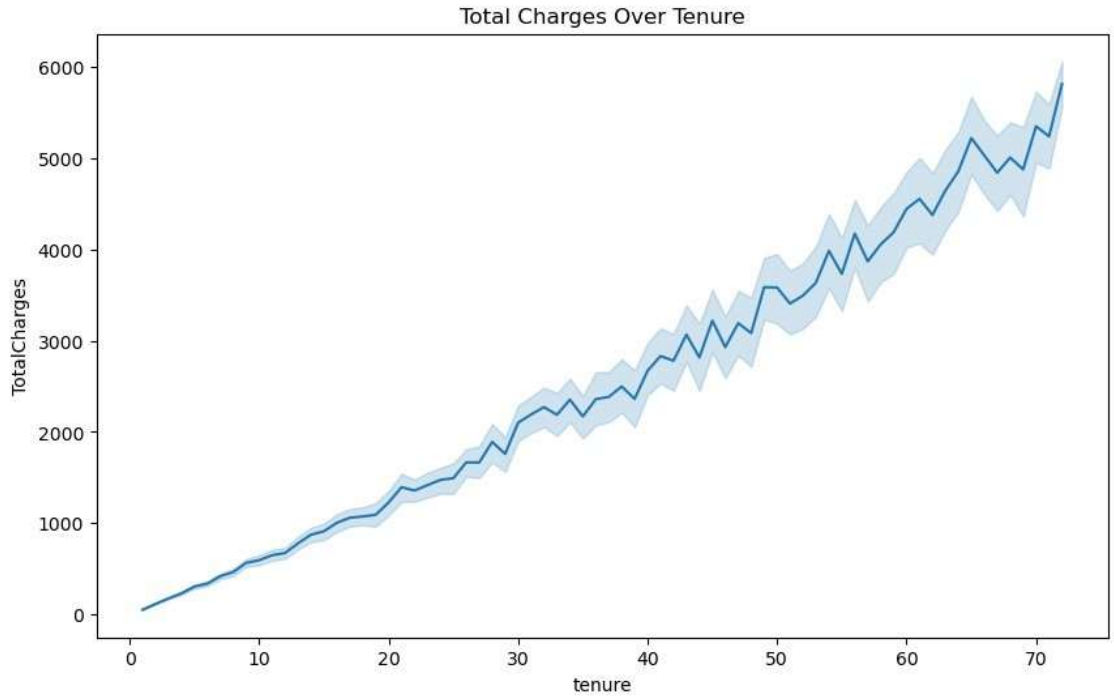


1. Plotting MonthlyCharges over Tenure plt.figure(figsize=(10, 6)) sns.lineplot(x='tenure', y='MonthlyCharges', data=df) plt.title("Monthly Charges Over Tenure") plt.show()



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#logisticregression n_iter_i = _check_optimize_result(

LogisticRegression(max_iter=1000)

1. Evaluating the model from sklearn.metrics import accuracy_score, classification_report

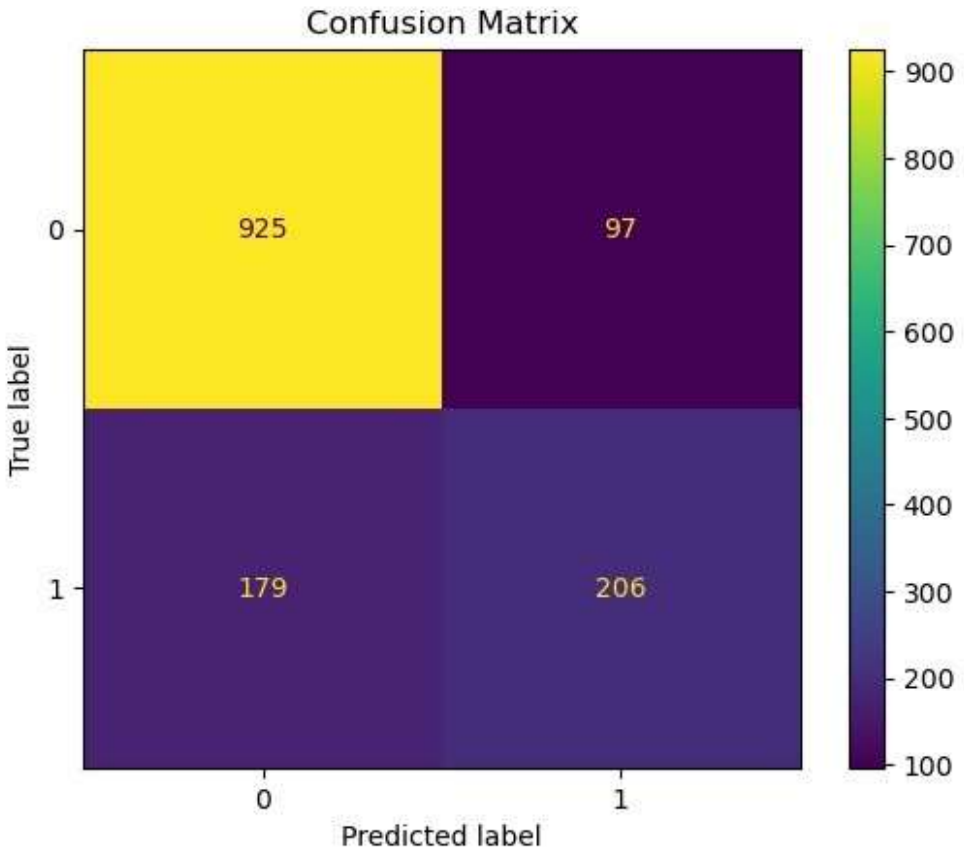
```
y_pred = model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred)) print("Classification Report:\n", classification_report(y_test, y_pred))
```

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

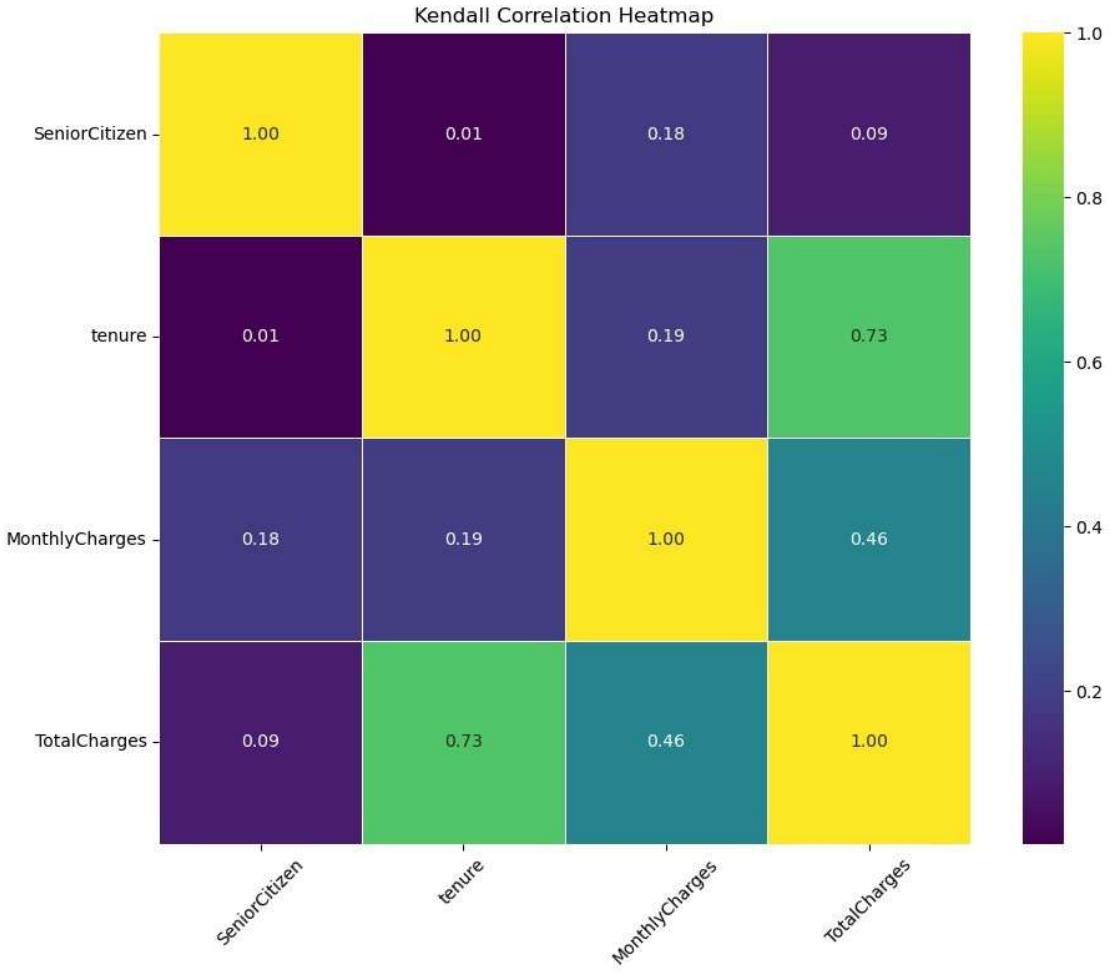
```
cm = confusion_matrix(y_test, y_pred)
ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=model.classes_).plot() plt.title("Confusion Matrix") plt.show()
```



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-tomonth 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.