Part B: Customer Churn Prediction

Analyze the provided customer data ("Customer_data") to build a machine learning model that predicts customer churn. The analysis should include data exploration, preprocessing (handling missing values, encoding, scaling), model training, and evaluation using metrics like accuracy, precision, recall, and F1 score. The goal is to identify customers at high risk of churning to inform retention strategies.

Load the data

Subtask:

Load the customer data from the specified file into a pandas DataFrame.

Reasoning: Import pandas and load the data into a DataFrame.

```
import pandas as pd

df = pd.read_csv('Customer_data.csv')
df.head()
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...
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

Explore and preprocess the data

Subtask:

Perform exploratory data analysis, handle missing values, encode categorical features, and scale numerical features to prepare the data for modeling.

Reasoning: Examine the data types and summary statistics, identify and handle missing values, identify and encode categorical features, and identify and scale numerical features to prepare the data for modeling.

```
# 1. Examine data types and summary statistics
display(df.info())
display(df.describe(include='all'))

# 2. Identify and handle missing values
# Check for missing values
display(df.isnull().sum())

# The 'TotalCharges' column has missing values.
# Since it's a numerical column, we can impute with the mean or median,
# or drop rows with missing values. Given the small number of missing values
# compared to the dataset size, dropping the rows is a reasonable approach.
df.dropna(inplace=True)

# Verify that missing values have been handled
display(df.isnull().sum())

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

# Drop rows where 'TotalCharges' became NaN after coercion (if any)
df.dropna(inplace=True)
```

```
# 3. Identify categorical features and apply one-hot encoding
categorical_features = df.select_dtypes(include='object').columns
# Exclude 'customerID' as it is an identifier
categorical_features = categorical_features.drop('customerID')

df = pd.get_dummies(df, columns=categorical_features, drop_first=True)

# 4. Identify numerical features and scale them
# Numerical features are now those that are not 'customerID' and are not boolean (from one-hot encoding)
numerical_features = df.select_dtypes(include=['int64', 'float64']).columns

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
df[numerical_features] = scaler.fit_transform(df[numerical_features])

display(df.head())
```

```
<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      7032 non-null   float64
 20  Churn             7043 non-null   object 
dtypes: float64(2), int64(2), object(17)
memory usage: 1.1+ MB
None
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineS
count	7043	7043	7043.000000	7043	7043	7043.000000	7043	7043	7043	
unique	7043	2	NaN	2	2	NaN	2	3	3	
top	3186-AJIEK	Male	NaN	No	No	NaN	Yes	No	Fiber optic	
freq	1	3555	NaN	3641	4933	NaN	6361	3390	3096	
mean	NaN	NaN	0.162147	NaN	NaN	32.371149	NaN	NaN	NaN	
std	NaN	NaN	0.368612	NaN	NaN	24.559481	NaN	NaN	NaN	
min	NaN	NaN	0.000000	NaN	NaN	0.000000	NaN	NaN	NaN	
25%	NaN	NaN	0.000000	NaN	NaN	9.000000	NaN	NaN	NaN	
50%	NaN	NaN	0.000000	NaN	NaN	29.000000	NaN	NaN	NaN	
75%	NaN	NaN	0.000000	NaN	NaN	55.000000	NaN	NaN	NaN	
max	NaN	NaN	1.000000	NaN	NaN	72.000000	NaN	NaN	NaN	

11 rows × 21 columns

	0
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

	0
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

	customerID	SeniorCitizen	tenure	MonthlyCharges	TotalCharges	gender_Male	Partner_Yes	Dependents_Yes	PhoneService_Yes
0	7590-VHVEG	-0.440327	-1.280248	-1.161694	-0.994194	False	True	False	False
1	5575-GNVDE	-0.440327	0.064303	-0.260878	-0.173740	True	False	False	True
2	3668-QPYBK	-0.440327	-1.239504	-0.363923	-0.959649	True	False	False	True
3	7795-CFOCW	-0.440327	0.512486	-0.747850	-0.195248	True	False	False	False
4	9237-HQITU	-0.440327	-1.239504	0.196178	-0.940457	False	False	False	True

5 rows × 32 columns

Split the data

Subtask:

Split the data into training and testing sets.

Reasoning: Split the data into training and testing sets using train_test_split.

```
from sklearn.model_selection import train_test_split

X = df.drop(['Churn_Yes', 'customerID'], axis=1)
y = df['Churn_Yes']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

print("Shape of X_train:", X_train.shape)
print("Shape of X_test:", X_test.shape)
print("Shape of y_train:", y_train.shape)
print("Shape of y_test:", y_test.shape)
```

```
Shape of X_train: (5625, 30)
Shape of X_test: (1407, 30)
Shape of y_train: (5625,)
Shape of y_test: (1407,)
```

Build and train a machine learning model

Subtask:

Choose a suitable classification model (e.g., Logistic Regression, Random Forest, or Gradient Boosting) and train it on the training data.

Reasoning: Import the LogisticRegression model, instantiate it, and train it using the training data.

```
from sklearn.linear_model import LogisticRegression

# Instantiate the Logistic Regression model
model = LogisticRegression(random_state=42)

# Train the model on the training data
model.fit(X_train, y_train)
```

```
▾ LogisticRegression
LogisticRegression(random_state=42)
```

Evaluate the model

Subtask:

Evaluate the trained model's performance on the testing data using appropriate metrics such as accuracy, precision, recall, and F1 score.

Reasoning: Evaluate the trained model's performance on the testing data using appropriate metrics such as accuracy, precision, recall, and F1 score and print the results.

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

# Use the trained model to predict churn on the test data
y_pred = model.predict(X_test)

# Calculate evaluation metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

# Print the evaluation metrics
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1 Score: {f1:.4f}")
```

```
Accuracy: 0.7875
Precision: 0.6206
Recall: 0.5160
F1 Score: 0.5635
```

Summary:

Data Analysis Key Findings

- The dataset initially contained 7043 entries and 21 columns.
- The 'TotalCharges' column had 11 missing values, which were handled by dropping the corresponding rows.
- Categorical features were successfully one-hot encoded, and numerical features ('SeniorCitizen', 'tenure', 'MonthlyCharges', and 'TotalCharges') were scaled using `StandardScaler`.
- The data was split into training (80%) and testing (20%) sets, resulting in 5625 training samples and 1407 testing samples.
- A Logistic Regression model was trained on the preprocessed training data.
- The trained model's performance on the test set was evaluated with the following metrics:
  - Accuracy: 78.75%
  - Precision: 62.06%
  - Recall: 51.60%
  - F1 Score: 56.35%

Insights or Next Steps

- The model demonstrates a reasonable overall accuracy, but the relatively lower recall suggests that it misses a significant portion of actual churn cases. For churn prediction, where identifying all potential churners is crucial for intervention, improving recall should be a focus.
- Further steps could involve experimenting with different classification models (e.g., Random Forest, Gradient Boosting), optimizing hyperparameters, or exploring techniques to handle the class imbalance if it exists in the churn data to potentially improve the recall and overall performance.

Visualize the data

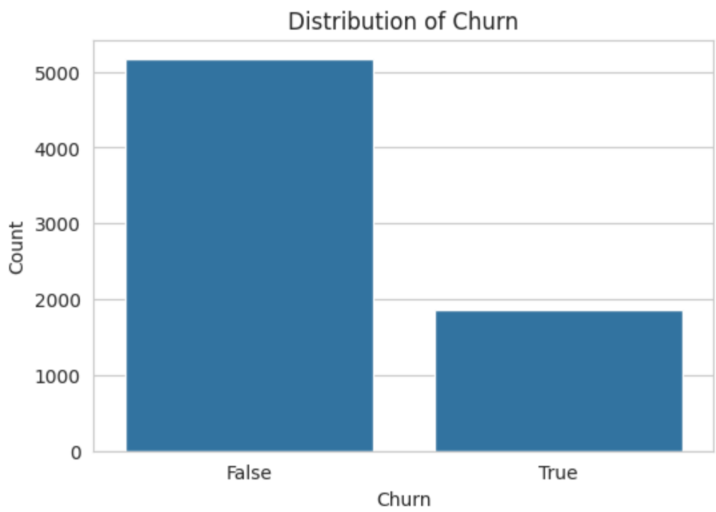
Subtask:

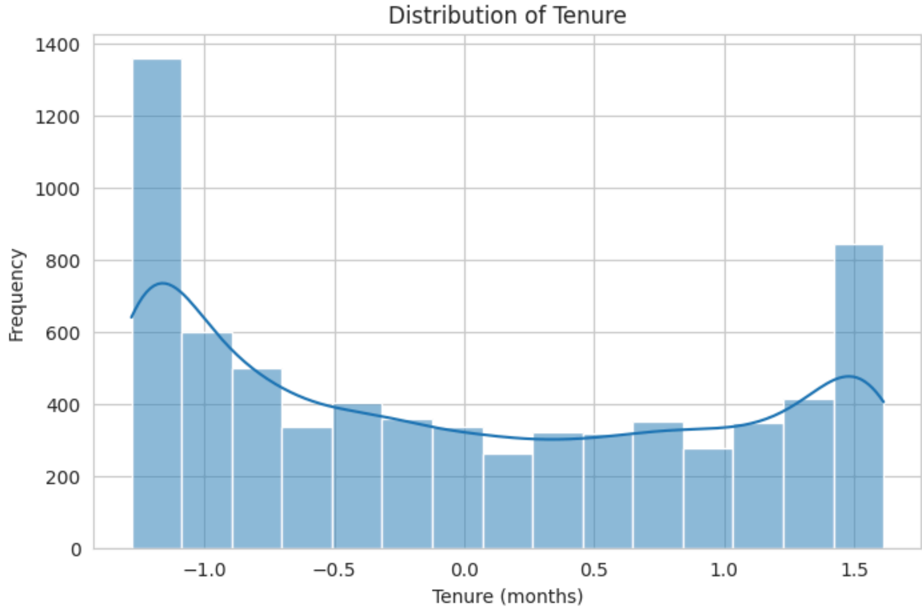
Create visualizations to explore the data and churn patterns.

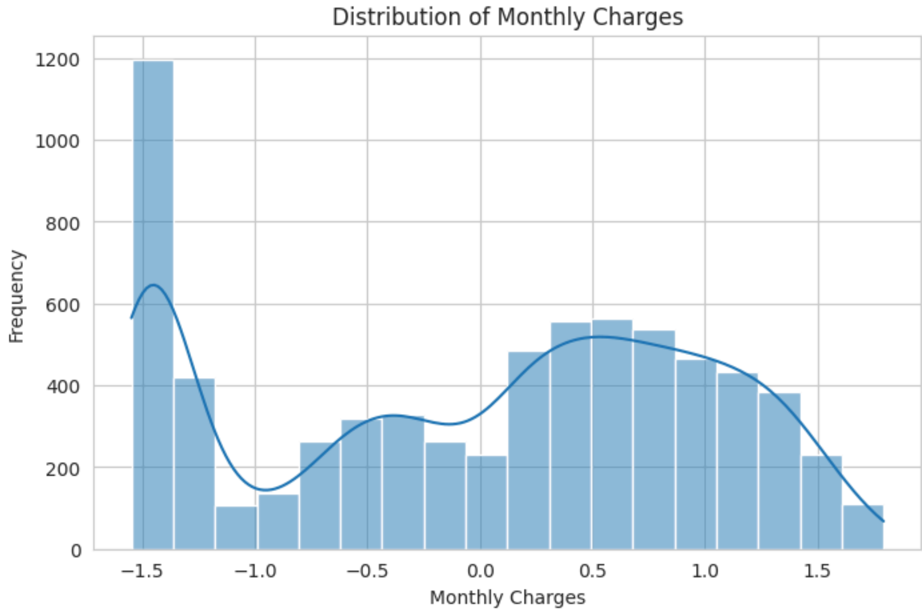
Reasoning: Visualize the distribution of the target variable and some key features, and the relationship between features and the target variable to gain insights about the data and churn patterns.

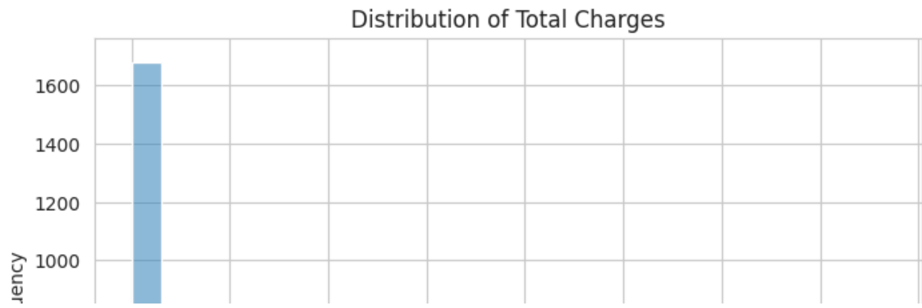
```
import matplotlib.pyplot as plt
import seaborn as sns

# Set the style for the plots
sns.set_style("whitegrid")

# Visualize the distribution of the target variable 'Churn_Yes'
plt.figure(figsize=(6, 4))
sns.countplot(x='Churn_Yes', data=df)
plt.title('Distribution of Churn')
plt.xlabel('Churn')
plt.ylabel('Count')
plt.show()

# Visualize the distribution of 'tenure'
plt.figure(figsize=(8, 5))
sns.histplot(data=df, x='tenure', kde=True)
plt.title('Distribution of Tenure')
plt.xlabel('Tenure (months)')
plt.ylabel('Frequency')
plt.show()

# Visualize the distribution of 'MonthlyCharges'
plt.figure(figsize=(8, 5))
sns.histplot(data=df, x='MonthlyCharges', kde=True)
plt.title('Distribution of Monthly Charges')
plt.xlabel('Monthly Charges')
plt.ylabel('Frequency')
plt.show()

# Visualize the distribution of 'TotalCharges'
plt.figure(figsize=(8, 5))
```

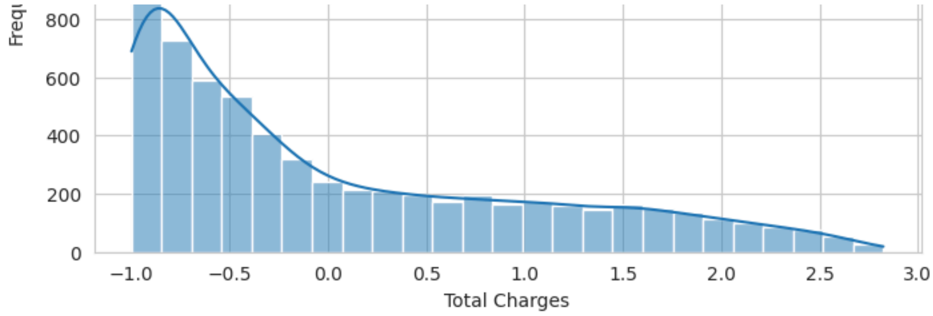
```
plt.figure(figsize=(8, 5))
sns.histplot(data=df, x='TotalCharges', kde=True)
plt.title('Distribution of Total Charges')
plt.xlabel('Total Charges')
plt.ylabel('Frequency')
plt.show()

# Visualize the relationship between 'tenure' and 'Churn_Yes'
plt.figure(figsize=(8, 5))
sns.boxplot(x='Churn_Yes', y='tenure', data=df)
plt.title('Churn vs. Tenure')
plt.xlabel('Churn')
plt.ylabel('Tenure (months)')
plt.show()

# Visualize the relationship between 'MonthlyCharges' and 'Churn_Yes'
plt.figure(figsize=(8, 5))
sns.boxplot(x='Churn_Yes', y='MonthlyCharges', data=df)
plt.title('Churn vs. Monthly Charges')
plt.xlabel('Churn')
plt.ylabel('Monthly Charges')
plt.show()

# Visualize the relationship between 'TotalCharges' and 'Churn_Yes'
plt.figure(figsize=(8, 5))
sns.boxplot(x='Churn_Yes', y='TotalCharges', data=df)
plt.title('Churn vs. Total Charges')
plt.xlabel('Churn')
plt.ylabel('Total Charges')
plt.show()

# Visualize the relationship between 'Contract' and 'Churn_Yes'
plt.figure(figsize=(8, 5))
sns.countplot(x='Contract_Two year', hue='Churn_Yes', data=df)
plt.title('Churn vs. Contract Type')
plt.xlabel('Contract Type (Two Year)')
plt.ylabel('Count')
plt.xticks(ticks=[0, 1], labels=['Month-to-month/One Year', 'Two Year'])
plt.show()

# Visualize the relationship between 'InternetService' and 'Churn_Yes'
plt.figure(figsize=(8, 5))
sns.countplot(x='InternetService_Fiber optic', hue='Churn_Yes', data=df)
plt.title('Churn vs. Internet Service Type')
plt.xlabel('Internet Service Type (Fiber Optic)')
plt.ylabel('Count')
plt.xticks(ticks=[0, 1], labels=['DSL/No internet service', 'Fiber Optic'])
plt.show()
```

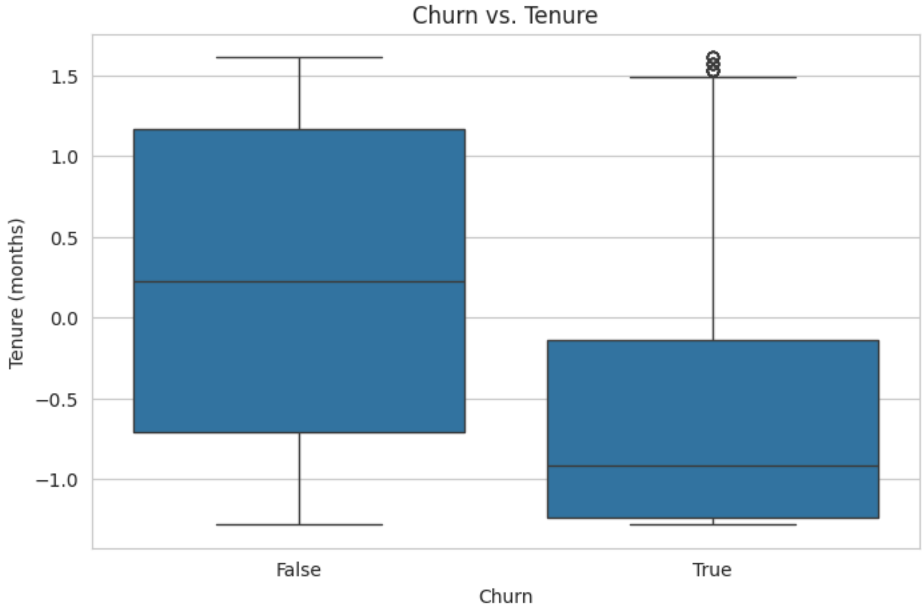

Distribution of Churn
Count
0
1000
2000
3000
4000
5000
False
True
Churn

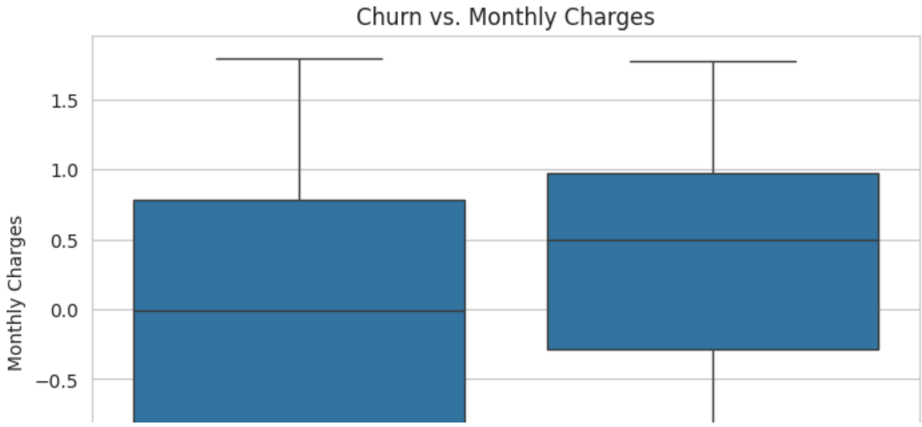

Distribution of Tenure
Frequency
0
200
400
600
800
1000
1200
1400
−1.0
−0.5
0.0
0.5
1.0
1.5
Tenure (months)


Distribution of Monthly Charges
Frequency
0
200
400
600
800
1000
1200
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
Monthly Charges


Distribution of Total Charges
1000
1200
1400
1600


Frequ
800
600
400
200
0
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Total Charges


Churn vs. Tenure
Tenure (months)
1.5
1.0
0.5
0.0
−0.5
−1.0
False
True
Churn


Churn vs. Monthly Charges
Monthly Charges
1.5
1.0
0.5
0.0
−0.5