```
In [24]:
           import pandas as pd
           import numpy as np
           import matplotlib.pyplot as plt
           import seaborn as sns
           from sklearn.preprocessing import LabelEncoder
           from sklearn.model_selection import train_test_split
           from sklearn.preprocessing import StandardScaler
           from sklearn.linear_model import LogisticRegression
           from sklearn.ensemble import RandomForestClassifier
           from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
           np.random.seed(42)
 In [3]:
           n_samples = 1000
           data = {
              'CustomerID': np.arange(1001, 1001 + n_samples),
              'Gender': np.random.choice(['Male', 'Female'], size=n_samples),
              'Age': np.random.randint(18, 80, size=n_samples),
              'ServiceLength': np.random.randint(1, 60, size=n_samples),
              'ContractType': np.random.choice(['Two-Year', 'One-Year', 'Month-to-Month'], size=n_samples),
              'MonthlyCharges': np.random.uniform(20, 120, size=n_samples),
              'TotalCharges': np.random.uniform(100, 5000, size=n_samples),
              'Churn': np.random.choice(['Yes', 'No'], size=n_samples)
           df = pd.DataFrame(data)
           df.to_csv('CommLink_Telecom_Customer_Data.csv', index=False)
In [12]:
           df.head()
Out[12]:
                           Gender
                                          ServiceLength ContractType
              CustomerID
                                    Age
                                                                       MonthlyCharges
                                                                                         TotalCharges Churn
           0
                     1001
                              Male
                                      71
                                                     23
                                                              Two-Year
                                                                              27.896916
                                                                                          3119.872381
                                                                                                          No
           1
                     1002
                            Female
                                      34
                                                     26
                                                             One-Year
                                                                              43.951017
                                                                                          2828.704372
                                                                                                          No
           2
                     1003
                                                     21
                                                              Two-Year
                                                                                          2137.298007
                              Male
                                      26
                                                                              99.457828
                                                                                                          Yes
                                                            Month-to-
           3
                     1004
                                      50
                                                     22
                              Male
                                                                              23.467027
                                                                                          2201.827234
                                                                                                          No
                                                                Month
           4
                     1005
                              Male
                                      70
                                                     58
                                                             One-Year
                                                                              78.280684
                                                                                          2750.434519
                                                                                                          No
           df[df["Churn"]=='Yes'].shape[0]
In [14]:
           518
Out[14]:
```

Encode Categorical Variables:

```
In [16]:
           label_encoder = LabelEncoder()
           df['Gender_encoded'] = label_encoder.fit_transform(df['Gender'])
```

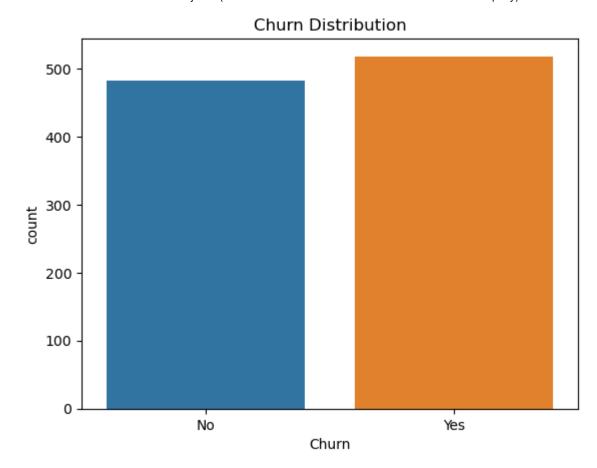
```
one_hot_encoded = pd.get_dummies(df['ContractType'], prefix='Contract')
 In [ ]:
           df = pd.concat([df, one_hot_encoded], axis=1)
In [19]:
           df.head()
Out[19]:
              CustomerID Gender
                                              ServiceLength ContractType MonthlyCharges TotalCharges Chur
                                          Age
                     1001
           0
                                     1.269334
                                                    -0.419836
                                                                                                   0.430072
                              Male
                                                                   Two-Year
                                                                                    -1.432829
                                                                                                                Ν
           1
                     1002
                                    -0.808227
                                                    -0.243434
                            Female
                                                                   One-Year
                                                                                    -0.877852
                                                                                                   0.222300
                                                                                                                Ν
           2
                     1003
                                                                   Two-Year
                                                                                     1.040972
                              Male
                                    -1.257430
                                                    -0.537437
                                                                                                   -0.271074
                                                                                                                Ye
                                                                  Month-to-
           3
                     1004
                              Male
                                     0.090177
                                                    -0.478636
                                                                                    -1.585966
                                                                                                   -0.225027
                                                                                                                Ν
                                                                      Month
           4
                     1005
                              Male
                                     1.213183
                                                     1.638182
                                                                   One-Year
                                                                                     0.308896
                                                                                                   0.166448
                                                                                                                Ν
```

Feature Scaling

```
In [18]:
           from sklearn.preprocessing import StandardScaler
            scaler = StandardScaler()
            scaled_features = scaler.fit_transform(df[['Age', 'ServiceLength', 'MonthlyCharges', 'TotalCharges']])
            df[['Age', 'ServiceLength', 'MonthlyCharges', 'TotalCharges']] = scaled_features
```

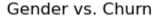
Churn distribution

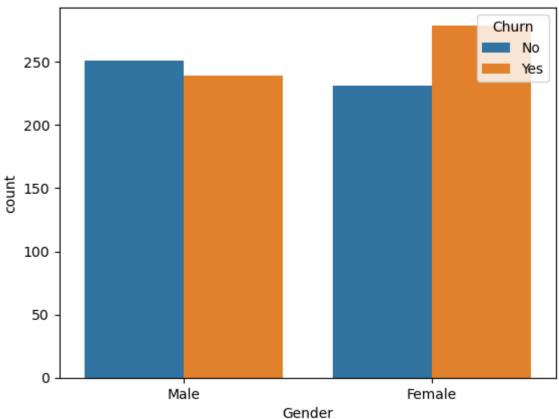
```
In [20]:
            sns.countplot(x='Churn', data=df)
            plt.title('Churn Distribution')
            plt.show()
```



Gender vs. Churn

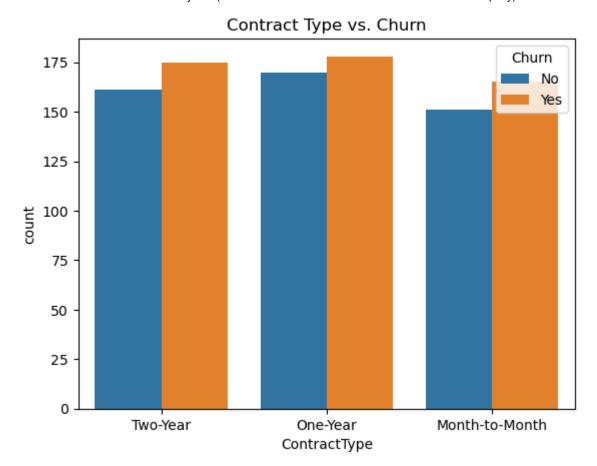
```
sns.countplot(x='Gender', hue='Churn', data=df)
In [21]:
           plt.title('Gender vs. Churn')
           plt.show()
```





Contract type vs. Churn

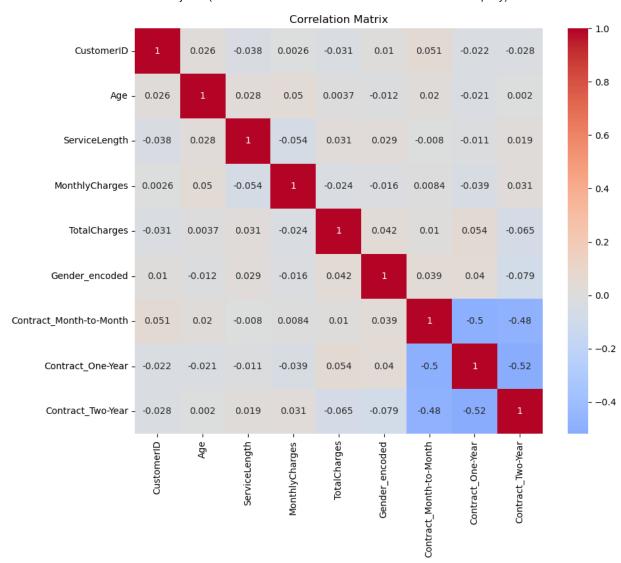
sns_countplot(x='ContractType', hue='Churn', data=df) In [22]: plt.title('Contract Type vs. Churn') plt.show()



Correlation matrix

```
In [23]:
           corr_matrix = df.corr()
           plt_figure(figsize=(10, 8))
            sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', center=0)
            plt.title('Correlation Matrix')
            plt.show()
```

C:\Users\Qurrat\AppData\Local\Temp\ipykernel_7968\3448318903.py:1: FutureWarning: The default value e of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning. corr_matrix = df.corr()



Churn Prediction(Logistic Regression, **Random Forest)**

```
features = ['Gender_encoded', 'Age', 'ServiceLength', 'MonthlyCharges', 'TotalCharges',
In [26]:
                    'Contract_One-Year', 'Contract_Two-Year', 'Contract_Month-to-Month']
            target = 'Churn'
            X = df[features]
            y = df[target]
            X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
            scaler = StandardScaler()
            X_train_scaled = scaler.fit_transform(X_train)
            X_test_scaled = scaler.transform(X_test)
            # Logistic Regression
            logreg_model = LogisticRegression()
            logreg_model.fit(X_train_scaled, y_train)
```

```
logreg_pred = logreg_model.predict(X_test_scaled)
          # Random Forest
          rf_model = RandomForestClassifier(random_state=42)
          rf_model.fit(X_train_scaled, y_train)
          rf_pred = rf_model.predict(X_test_scaled)
          # Model Evaluation
          print("Logistic Regression Results:")
          print("Accuracy:", accuracy_score(y_test, logreg_pred))
          print(classification_report(y_test, logreg_pred))
          print("\nRandom Forest Results:")
          print("Accuracy:", accuracy_score(y_test, rf_pred))
          print(classification_report(y_test, rf_pred))
          Logistic Regression Results:
          Accuracy: 0.545
                   precision
                             recall f1-score support
                No
                        0.58
                                0.37
                                         0.46
                                                  102
                        0.53
                                0.72
                Yes
                                        0.61
                                                  98
                                       0.55
                                                200
            accuracy
                          0.56
                                   0.55
                                           0.53
                                                    200
            macro avg
          weighted avg
                           0.56
                                    0.55
                                            0.53
                                                     200
          Random Forest Results:
          Accuracy: 0.45
                   precision recall f1-score support
                No
                        0.46
                                0.40
                                         0.43
                                                  102
                        0.45
                                0.50
                                                  98
                Yes
                                        0.47
                                       0.45
                                                200
            accuracy
                          0.45
                                   0.45
                                           0.45
                                                    200
            macro avg
          weighted avg
                           0.45
                                    0.45
                                            0.45
                                                     200
In [ ]:
```