In [1]:
```
import pandas as pd
import numpy as np
import pickle
import warnings
warnings.filterwarnings("ignore")
import scipy
import scipy.stats as stats
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:
```
data=pd.read_csv(r"C:\Users\reshma_koduri\OneDrive\Documents\Customer Churn Predicti
data
```

Out[2]:

| | Customer_ID | Age | Gender | Location | Tenure | ContractType | PaymentMethod | MonthlyCharges |
|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 18 | F | Village | 93 | One Month | Credit Card | 11.055215 |
| **1** | 1 | 32 | F | City | 65 | One Year | Debit Card | 5.175208 |
| **2** | 2 | 44 | F | Town | 129 | One Month | UPI | 12.106657 |
| **3** | 3 | 37 | M | City | 58 | One Year | UPI | 7.263743 |
| **4** | 4 | 31 | F | City | 88 | One Month | UPI | 16.953078 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... |
| **9995** | 9995 | 13 | M | Town | 18 | Three Months | Bank Transfer | 12.876577 |
| **9996** | 9996 | 37 | F | Town | 18 | One Month | UPI | 9.332120 |
| **9997** | 9997 | 26 | M | Town | 18 | One Month | Credit Card | 14.945345 |
| **9998** | 9998 | 41 | M | City | 18 | One Year | UPI | 16.109496 |
| **9999** | 9999 | 57 | F | City | 18 | One Month | UPI | 9.457105 |

10000 rows × 26 columns

In [3]:
```
data.head()
```

Out[3]:

| | Customer_ID | Age | Gender | Location | Tenure | ContractType | PaymentMethod | MonthlyCharges | T |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 18 | F | Village | 93 | One Month | Credit Card | 11.055215 | |
| **1** | 1 | 32 | F | City | 65 | One Year | Debit Card | 5.175208 | |
| **2** | 2 | 44 | F | Town | 129 | One Month | UPI | 12.106657 | |
| **3** | 3 | 37 | M | City | 58 | One Year | UPI | 7.263743 | |
| **4** | 4 | 31 | F | City | 88 | One Month | UPI | 16.953078 | |

5 rows × 26 columns

In [4]:
```
data.tail()
```

Out[4]:

| | Customer_ID | Age | Gender | Location | Tenure | ContractType | PaymentMethod | MonthlyCharges |
|---|---|---|---|---|---|---|---|---|
| **9995** | 9995 | 13 | M | Town | 18 | Three Months | Bank Transfer | 12.876577 |
| **9996** | 9996 | 37 | F | Town | 18 | One Month | UPI | 9.332120 |
| **9997** | 9997 | 26 | M | Town | 18 | One Month | Credit Card | 14.945345 |
| **9998** | 9998 | 41 | M | City | 18 | One Year | UPI | 16.109496 |
| **9999** | 9999 | 57 | F | City | 18 | One Month | UPI | 9.457105 |

5 rows × 26 columns

In [5]:
```
data.describe()
```

Out[5]:

| | Customer_ID | Age | Tenure | MonthlyCharges | TotalCharges | NumOfLogins | Supp |
|---|---|---|---|---|---|---|---|
| **count** | 10000.00000 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 | 10( |
| **mean** | 4999.50000 | 37.281600 | 55.285700 | 12.480065 | 740.833361 | 1.530200 | |
| **std** | 2886.89568 | 15.894382 | 41.631738 | 4.318035 | 525.435560 | 0.581654 | |
| **min** | 0.00000 | 10.000000 | 4.000000 | 4.991317 | 5.126487 | 1.000000 | |
| **25%** | 2499.75000 | 23.000000 | 14.000000 | 8.718597 | 320.705180 | 1.000000 | |

| | Customer_ID | Age | Tenure | MonthlyCharges | TotalCharges | NumOfLogins | Supp |
|---|---|---|---|---|---|---|---|
| **50%** | 4999.50000 | 37.000000 | 60.000000 | 12.496572 | 631.941232 | 1.000000 | |
| **75%** | 7499.25000 | 51.000000 | 94.000000 | 16.174508 | 1077.584225 | 2.000000 | |
| **max** | 9999.00000 | 64.000000 | 133.000000 | 19.988562 | 2352.584990 | 4.000000 | |

In [6]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 26 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   Customer_ID                  10000 non-null  int64  
 1   Age                          10000 non-null  int64  
 2   Gender                       10000 non-null  object 
 3   Location                     10000 non-null  object 
 4   Tenure                       10000 non-null  int64  
 5   ContractType                 10000 non-null  object 
 6   PaymentMethod                10000 non-null  object 
 7   MonthlyCharges               10000 non-null  float64
 8   TotalCharges                 10000 non-null  float64
 9   NumOfLogins                  10000 non-null  int64  
 10  SupportTickets               10000 non-null  int64  
 11  Complaints                   10000 non-null  int64  
 12  AvgFrequencyLoginDays        10000 non-null  float64
 13  AverageViewingDuration       10000 non-null  float64
 14  MultiDeviceAccess            10000 non-null  object 
 15  SubscriptionType             10000 non-null  object 
 16  DeviceRegistered             10000 non-null  object 
 17  ContentType                  10000 non-null  object 
 18  WatchlistSize                10000 non-null  int64  
 19  LoyaltyProgramParticipation  10000 non-null  object 
 20  GenrePreference              10000 non-null  object 
 21  CustomerSatisfactionScore    10000 non-null  int64  
 22  UserRating                   10000 non-null  float64
 23  CreditScore                  10000 non-null  int64  
 24  Feedback                     10000 non-null  object 
 25  Churn                        10000 non-null  object 
dtypes: float64(5), int64(9), object(12)
memory usage: 2.0+ MB
```

In [7]:
```
data.select_dtypes(include=['object']).head()
```

Out[7]:

| | Gender | Location | ContractType | PaymentMethod | MultiDeviceAccess | SubscriptionType | DeviceReg |
|---|---|---|---|---|---|---|---|
| **0** | F | Village | One Month | Credit Card | No | Platinum | |
| **1** | F | City | One Year | Debit Card | No | Premium | |
| **2** | F | Town | One Month | UPI | No | No | Cc |
| **3** | M | City | One Year | UPI | No | No | |

| | Gender | Location | ContractType | PaymentMethod | MultiDeviceAccess | SubscriptionType | DeviceReg |
|---|---|---|---|---|---|---|---|
| **4** | F | City | One Month | UPI | No | No | |

In [8]:
```
data.select_dtypes(include=[np.number]).head()
```

Out[8]:

| | Customer_ID | Age | Tenure | MonthlyCharges | TotalCharges | NumOfLogins | SupportTickets | Compla |
|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 18 | 93 | 11.055215 | 221.104302 | 1 | 5 | |
| **1** | 1 | 32 | 65 | 5.175208 | 294.986882 | 1 | 4 | |
| **2** | 2 | 44 | 129 | 12.106657 | 883.785952 | 3 | 0 | |
| **3** | 3 | 37 | 58 | 7.263743 | 232.439774 | 2 | 0 | |
| **4** | 4 | 31 | 88 | 16.953078 | 966.325422 | 1 | 0 | |

# Data Preprocessing

In [9]:
```
data.isna().sum()
```

Out[9]:
```
Customer_ID                0
Age                        0
Gender                     0
Location                   0
Tenure                     0
ContractType               0
PaymentMethod              0
MonthlyCharges             0
TotalCharges               0
NumOfLogins                0
SupportTickets             0
Complaints                 0
AvgFrequencyLoginDays      0
AverageViewingDuration     0
MultiDeviceAccess          0
SubscriptionType           0
DeviceRegistered           0
ContentType                0
WatchlistSize              0
LoyaltyProgramParticipation    0
GenrePreference            0
CustomerSatisfactionScore  0
UserRating                 0
CreditScore                0
Feedback                   0
Churn                      0
dtype: int64
```

# Correlation

In [10]:
```
cor=data.corr()
cor
```

Out[10]:

| | Customer_ID | Age | Tenure | MonthlyCharges | TotalCharges | NumOf |
|---|---|---|---|---|---|---|
| **Customer_ID** | 1.000000 | 0.013569 | -0.756206 | 0.012144 | 0.011981 | 0.( |
| **Age** | 0.013569 | 1.000000 | -0.004050 | -0.009121 | 0.006780 | 0.( |
| **Tenure** | -0.756206 | -0.004050 | 1.000000 | -0.017942 | -0.013285 | -0.( |
| **MonthlyCharges** | 0.012144 | -0.009121 | -0.017942 | 1.000000 | 0.489346 | -0.( |
| **TotalCharges** | 0.011981 | 0.006780 | -0.013285 | 0.489346 | 1.000000 | 0.( |
| **NumOfLogins** | 0.007246 | 0.012883 | -0.008234 | -0.001962 | 0.008225 | 1.( |
| **SupportTickets** | 0.038722 | -0.008715 | -0.021116 | 0.016616 | 0.010259 | -0.( |
| **Complaints** | -0.016957 | -0.009215 | 0.009174 | -0.011875 | -0.008107 | -0.( |
| **AvgFrequencyLoginDays** | 0.024949 | -0.005467 | -0.018139 | -0.003858 | -0.005956 | 0.( |
| **AverageViewingDuration** | -0.005577 | -0.009393 | 0.007605 | 0.005231 | 0.002495 | -0.( |
| **WatchlistSize** | 0.014756 | -0.007231 | -0.000870 | 0.003767 | -0.016316 | 0.( |
| **CustomerSatisfactionScore** | -0.012955 | -0.010204 | 0.009169 | 0.003408 | -0.013504 | 0.( |
| **UserRating** | -0.004056 | 0.016113 | 0.003304 | -0.002548 | -0.015137 | 0.( |
| **CreditScore** | 0.005840 | -0.024701 | -0.000427 | -0.017648 | -0.007623 | 0.( |

In [11]:

```
sns.heatmap(cor,linewidths='0.5',cmap='Purples',annot=True)
plt.show()
```


In [12]:

```
np.fill_diagonal(cor.values, np.nan)
max_correlation = cor.max().max()
best_pair = cor.stack().idxmax()
print(f"The best correlation is between {best_pair} with a value of {max_correlation
```

```
The best correlation is between ('MonthlyCharges', 'TotalCharges') with a value of 0.
4893463229671196
```

In [13]:
```
data['PaymentMethod'].unique()
```

Out[13]:
```
array(['Credit Card', 'Debit Card', 'UPI', 'Bank Transfer',
       'Mobile Payment'], dtype=object)
```

In [14]:
```
data['SubscriptionType'].unique()
```

Out[14]:
```
array(['Platinum', 'Premium', 'No', 'Gold', 'Silver', 'Basic'],
      dtype=object)
```

In [15]:
```
data['ContentType'].unique()
```

Out[15]:
```
array(['Both', 'Movies', 'TV Shows'], dtype=object)
```

In [16]:
```
data['GenrePreference'].unique()
```

Out[16]:
```
array(['Sci-Fi', 'Action', 'Fantasy', 'Drama', 'Comedy'], dtype=object)
```

In [17]:
```
data['DeviceRegistered'].unique()
```

Out[17]:
```
array(['Mobile', 'Tablet', 'Computer', 'TV'], dtype=object)
```

In [18]:
```
data['MultiDeviceAccess'].unique()
```

Out[18]:
```
array(['No', 'Yes'], dtype=object)
```

In [19]:
```
data['Churn'].unique()
```

Out[19]:
```
array(['No', 'Yes'], dtype=object)
```

In [20]:
```
data['ContractType'].unique()
```

Out[20]:
```
array(['One Month', 'One Year', 'Three Months'], dtype=object)
```

In [21]:
```
data['LoyaltyProgramParticipation'].unique()
```

Out[21]:
```
array(['Yes', 'No'], dtype=object)
```

In [22]:
```
data['Feedback'].unique()
```

Out[22]:
```
array(['Products always in Stock', 'Quality Customer Care',
       'Poor Website', 'No reason specified', 'Poor Product Quality',
       'Poor Customer Service', 'Too many ads', 'User Friendly Website',
       'Reasonable Price'], dtype=object)
```

In [23]:
```
data.groupby(['Gender']).count()
```

Out[23]:

| Gender | Customer_ID | Age | Location | Tenure | ContractType | PaymentMethod | MonthlyCharges | Tc |
|---|---|---|---|---|---|---|---|---|
| **F** | 5037 | 5037 | 5037 | 5037 | 5037 | 5037 | 5037 | |
| **M** | 4943 | 4943 | 4943 | 4943 | 4943 | 4943 | 4943 | |
| **Unknown** | 20 | 20 | 20 | 20 | 20 | 20 | 20 | |

3 rows × 25 columns

In [24]:
```
data.groupby(['PaymentMethod']).count()
```

Out[24]:

| PaymentMethod | Customer_ID | Age | Gender | Location | Tenure | ContractType | MonthlyCharges | Tota |
|---|---|---|---|---|---|---|---|---|
| **Bank Transfer** | 1755 | 1755 | 1755 | 1755 | 1755 | 1755 | 1755 | |
| **Credit Card** | 2017 | 2017 | 2017 | 2017 | 2017 | 2017 | 2017 | |
| **Debit Card** | 335 | 335 | 335 | 335 | 335 | 335 | 335 | |
| **Mobile Payment** | 799 | 799 | 799 | 799 | 799 | 799 | 799 | |
| **UPI** | 5094 | 5094 | 5094 | 5094 | 5094 | 5094 | 5094 | |

5 rows × 25 columns

In [25]:
```
data.groupby(['Location']).count()
```

Out[25]:

| Location | Customer_ID | Age | Gender | Tenure | ContractType | PaymentMethod | MonthlyCharges | Tota |
|---|---|---|---|---|---|---|---|---|
| **City** | 4911 | 4911 | 4911 | 4911 | 4911 | 4911 | 4911 | |
| **Town** | 3847 | 3847 | 3847 | 3847 | 3847 | 3847 | 3847 | |
| **Village** | 1242 | 1242 | 1242 | 1242 | 1242 | 1242 | 1242 | |

3 rows × 25 columns

In [26]:
```
data.groupby(['Churn']).count()
```

Out[26]:

| Churn | Customer_ID | Age | Gender | Location | Tenure | ContractType | PaymentMethod | MonthlyCharg |
|---|---|---|---|---|---|---|---|---|
| No | 4568 | 4568 | 4568 | 4568 | 4568 | 4568 | 4568 | 456 |
| Yes | 5432 | 5432 | 5432 | 5432 | 5432 | 5432 | 5432 | 543 |

2 rows × 25 columns

# Data Encoding/Data mapping

In [27]:

```
from sklearn.preprocessing import LabelEncoder
labelencoder_Feedback = LabelEncoder()
data['Feedback'] = labelencoder_Feedback.fit_transform(data.Feedback)
labelencoder_PaymentMethod = LabelEncoder()
data['PaymentMethod'] = labelencoder_PaymentMethod.fit_transform(data.PaymentMethod)
labelencoder_SubscriptionType = LabelEncoder()
data['SubscriptionType'] = labelencoder_SubscriptionType.fit_transform(data.Subscrip
labelencoder_Gender = LabelEncoder()
data['Gender'] = labelencoder_Gender.fit_transform(data.Gender)
labelencoder_Location = LabelEncoder()
data['Location'] = labelencoder_Location.fit_transform(data.Location)
labelencoder_MultiDeviceAccess = LabelEncoder()
data['MultiDeviceAccess'] = labelencoder_MultiDeviceAccess.fit_transform(data.MultiD
labelencoder_ContractType = LabelEncoder()
data['ContractType'] = labelencoder_ContractType.fit_transform(data.ContractType)
labelencoder_LoyaltyProgramParticipation = LabelEncoder()
data['LoyaltyProgramParticipation'] = labelencoder_LoyaltyProgramParticipation.fit_t
labelencoder_ContentType = LabelEncoder()
data['ContentType'] = labelencoder_ContentType.fit_transform(data.ContentType)
labelencoder_GenrePreference = LabelEncoder()
data['GenrePreference'] = labelencoder_GenrePreference.fit_transform(data.GenrePrefe
labelencoder_DeviceRegistered = LabelEncoder()
data['DeviceRegistered'] = labelencoder_DeviceRegistered.fit_transform(data.DeviceRe
```

In [28]:

```
data['Churn']=data['Churn'].map({'Yes':1,'No':0})
```

In [29]:

```
data
```

Out[29]:

| | Customer_ID | Age | Gender | Location | Tenure | ContractType | PaymentMethod | MonthlyCharges |
|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 18 | 0 | 2 | 93 | 0 | 1 | 11.055215 |
| 1 | 1 | 32 | 0 | 0 | 65 | 1 | 2 | 5.175208 |
| 2 | 2 | 44 | 0 | 1 | 129 | 0 | 4 | 12.106657 |
| 3 | 3 | 37 | 1 | 0 | 58 | 1 | 4 | 7.263743 |
| 4 | 4 | 31 | 0 | 0 | 88 | 0 | 4 | 16.953078 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 9995 | 9995 | 13 | 1 | 1 | 18 | 2 | 0 | 12.876577 |
| 9996 | 9996 | 37 | 0 | 1 | 18 | 0 | 4 | 9.332120 |
| 9997 | 9997 | 26 | 1 | 1 | 18 | 0 | 1 | 14.945345 |

| | Customer_ID | Age | Gender | Location | Tenure | ContractType | PaymentMethod | MonthlyCharges |
|---|---|---|---|---|---|---|---|---|
| **9998** | 9998 | 41 | 1 | 0 | 18 | 1 | 4 | 16.109496 |
| **9999** | 9999 | 57 | 0 | 0 | 18 | 0 | 4 | 9.457105 |

10000 rows × 26 columns

In [30]:
```
list(data)
```

Out[30]:
```
['Customer_ID',
 'Age',
 'Gender',
 'Location',
 'Tenure',
 'ContractType',
 'PaymentMethod',
 'MonthlyCharges',
 'TotalCharges',
 'NumOfLogins',
 'SupportTickets',
 'Complaints',
 'AvgFrequencyLoginDays',
 'AverageViewingDuration',
 'MultiDeviceAccess',
 'SubscriptionType',
 'DeviceRegistered',
 'ContentType',
 'WatchlistSize',
 'LoyaltyProgramParticipation',
 'GenrePreference',
 'CustomerSatisfactionScore',
 'UserRating',
 'CreditScore',
 'Feedback',
 'Churn']
```

# Feature Scaling

In [31]:
```
data1=data.drop(['Location','WatchlistSize','ContractType','Customer_ID','DeviceRegi
data1
```

Out[31]:

| | Age | Gender | Tenure | PaymentMethod | MonthlyCharges | TotalCharges | NumOfLogins | Support |
|---|---|---|---|---|---|---|---|---|
| **0** | 18 | 0 | 93 | 1 | 11.055215 | 221.104302 | 1 | |
| **1** | 32 | 0 | 65 | 2 | 5.175208 | 294.986882 | 1 | |
| **2** | 44 | 0 | 129 | 4 | 12.106657 | 883.785952 | 3 | |
| **3** | 37 | 1 | 58 | 4 | 7.263743 | 232.439774 | 2 | |
| **4** | 31 | 0 | 88 | 4 | 16.953078 | 966.325422 | 1 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **9995** | 13 | 1 | 18 | 0 | 12.876577 | 1364.917173 | 2 | |
| **9996** | 37 | 0 | 18 | 4 | 9.332120 | 839.890788 | 1 | |
| **9997** | 26 | 1 | 18 | 1 | 14.945345 | 478.251032 | 1 | |

| | Age | Gender | Tenure | PaymentMethod | MonthlyCharges | TotalCharges | NumOfLogins | Support |
|---|---|---|---|---|---|---|---|---|
| **9998** | 41 | 1 | 18 | 4 | 16.109496 | 434.956386 | 2 | |
| **9999** | 57 | 0 | 18 | 4 | 9.457105 | 416.112630 | 1 | |

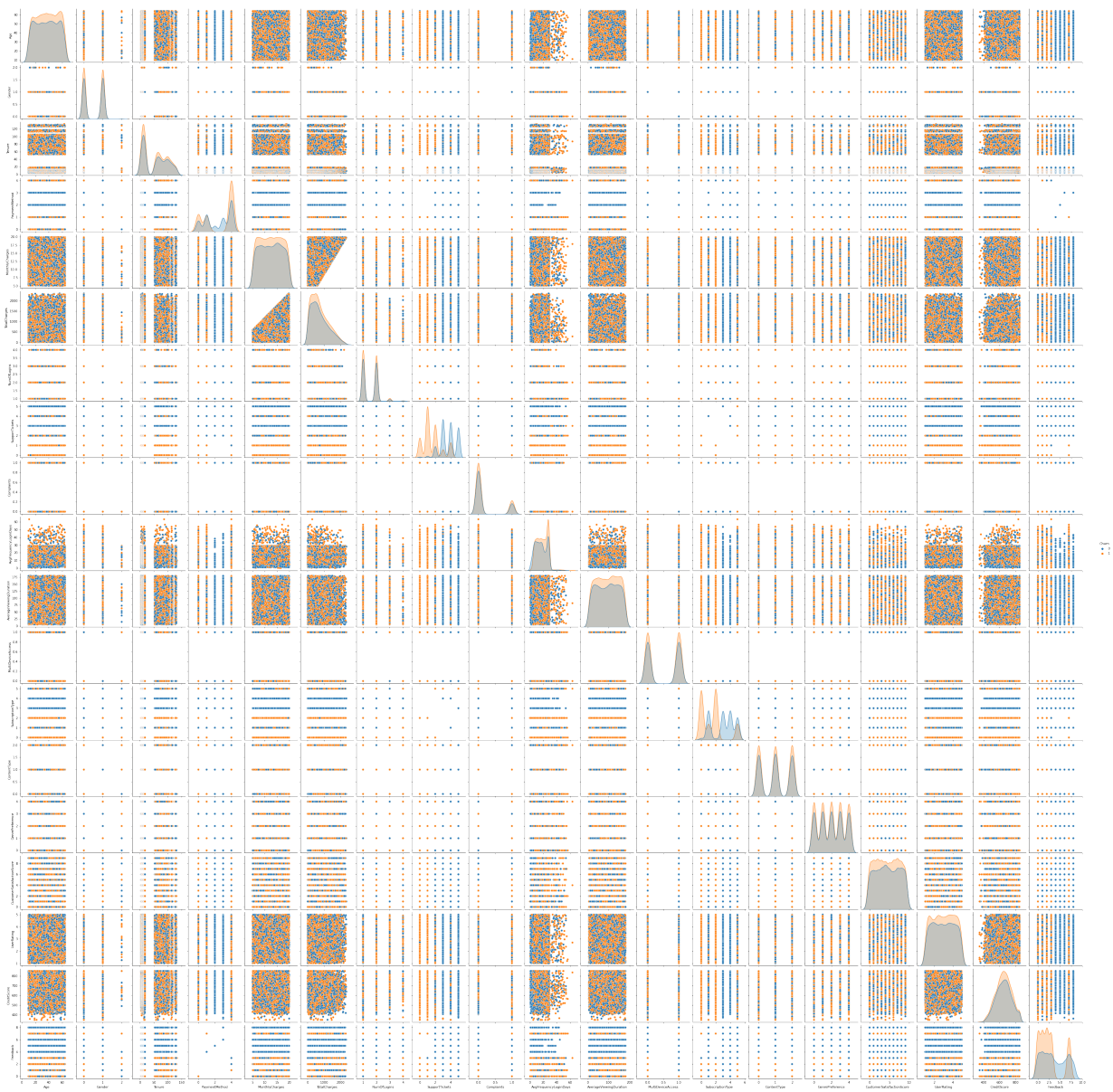
10000 rows × 20 columns

In [32]:
```
data1['Churn'].value_counts(normalize=True)
```

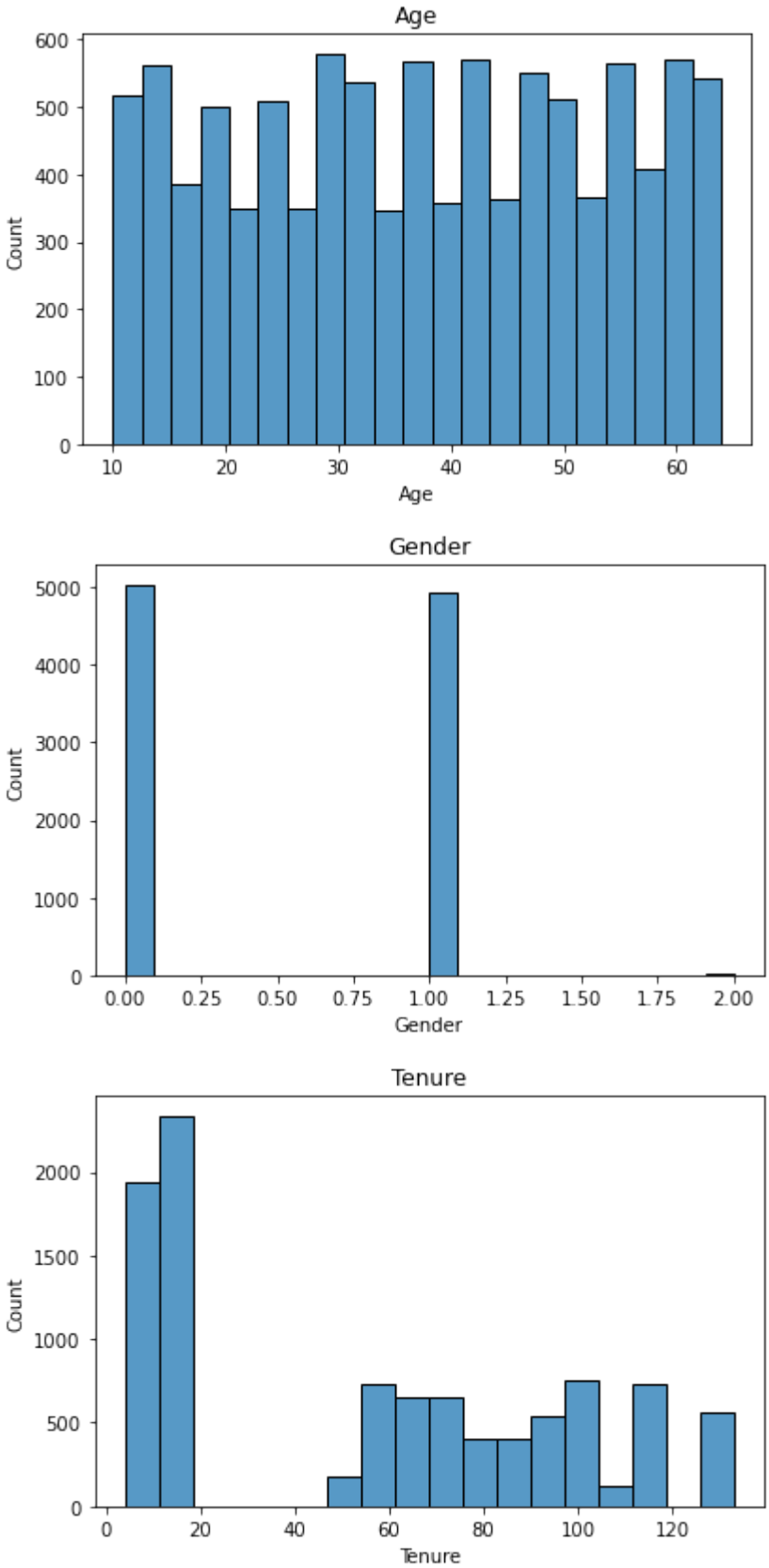
Out[32]:
```
1    0.5432
0    0.4568
Name: Churn, dtype: float64
```

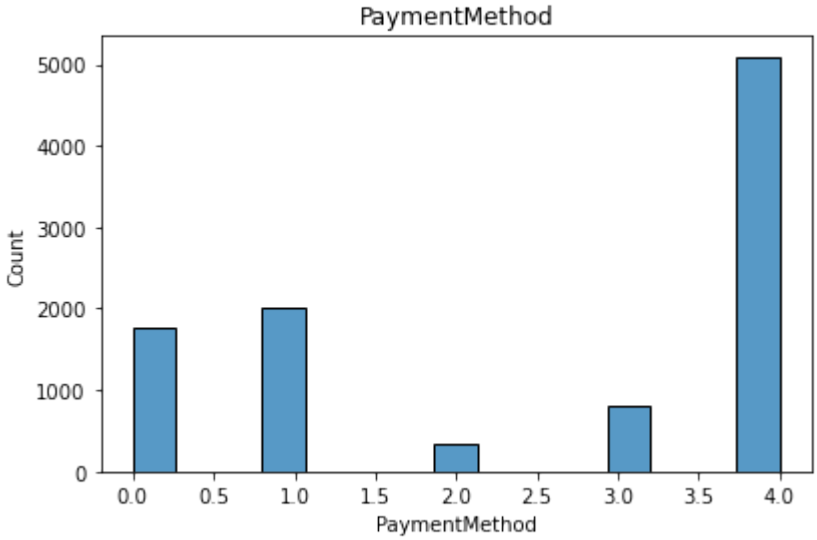
# Data Distribution

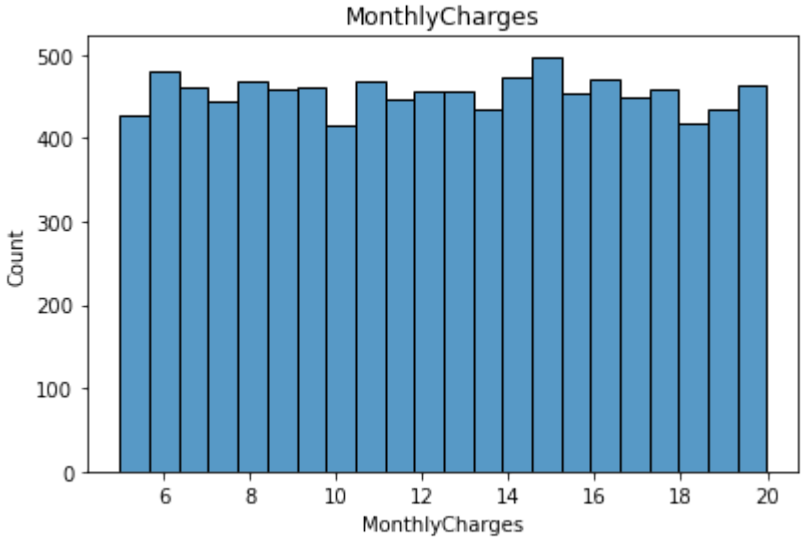
In [33]:
```
import seaborn as sns
import matplotlib.pyplot as plt
sns.pairplot(data1, hue='Churn')
plt.show()
```

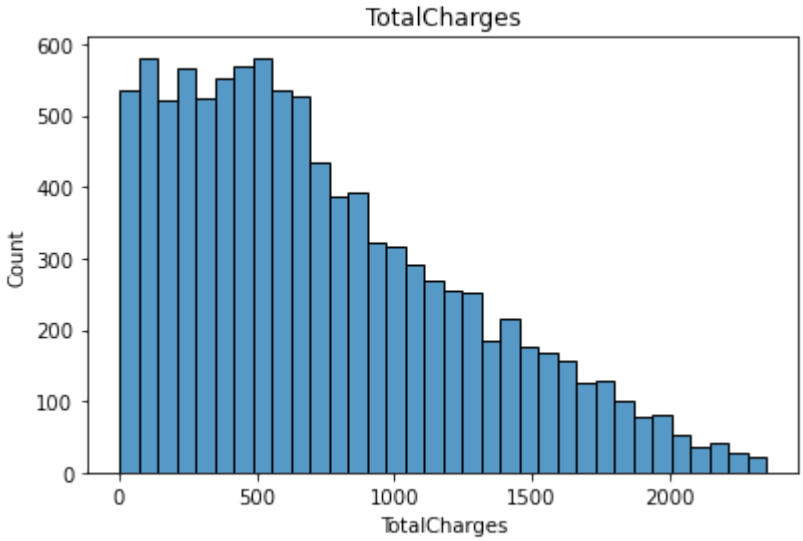


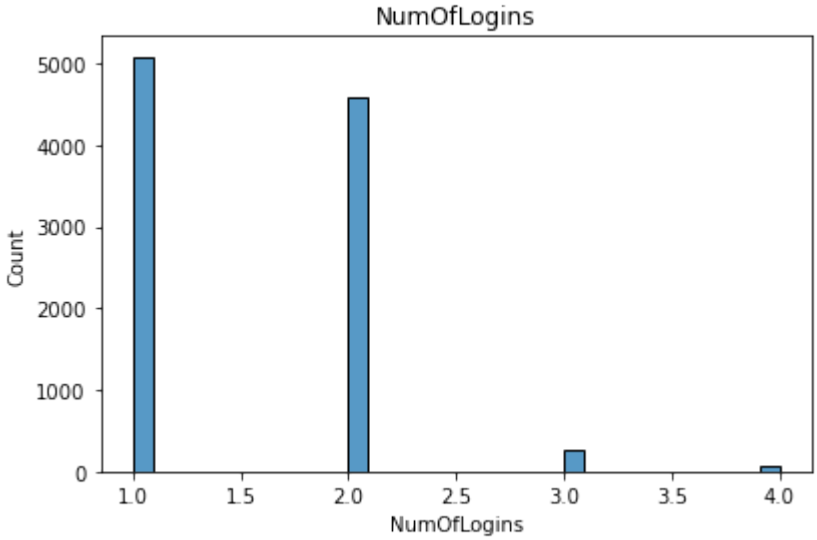
In [34]:
```
for column in data1:
    plt.figure(figsize = (14,4))
    plt.subplot(121)
    sns.histplot(data[column])
    plt.title(column)
```

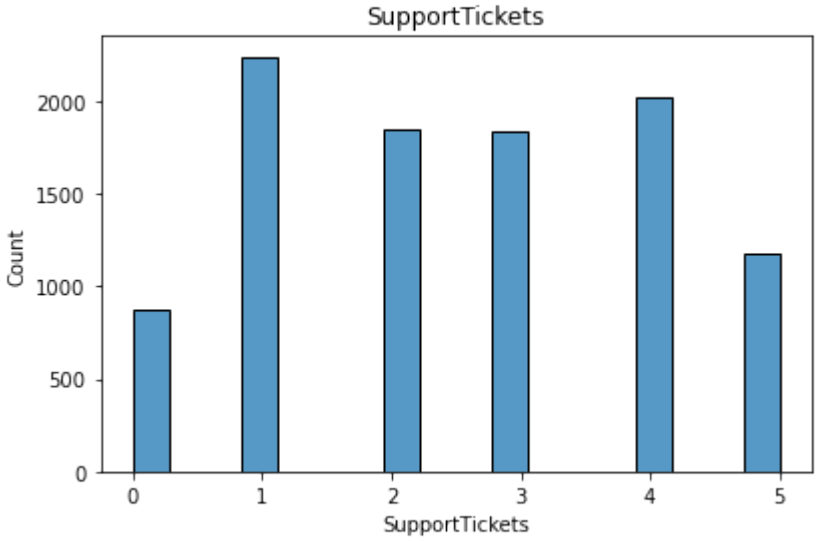


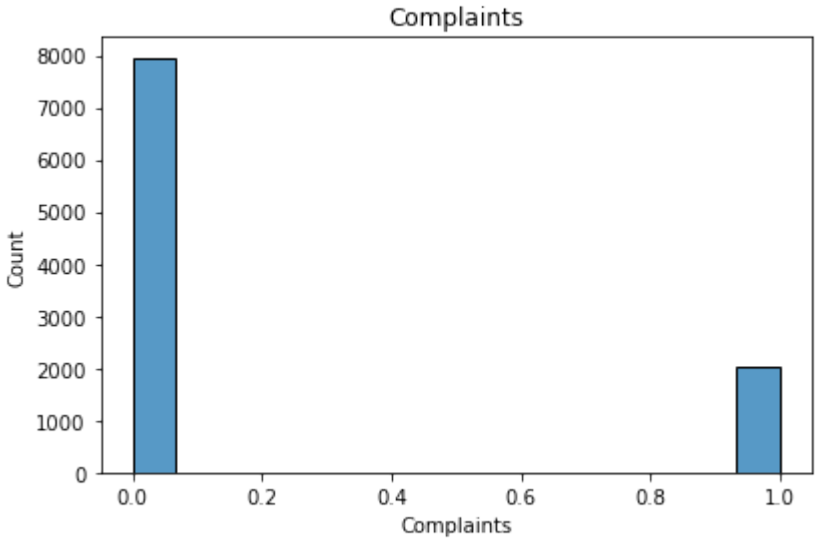

PaymentMethod
Count
PaymentMethod
0
1000
2000
3000
4000
5000
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0

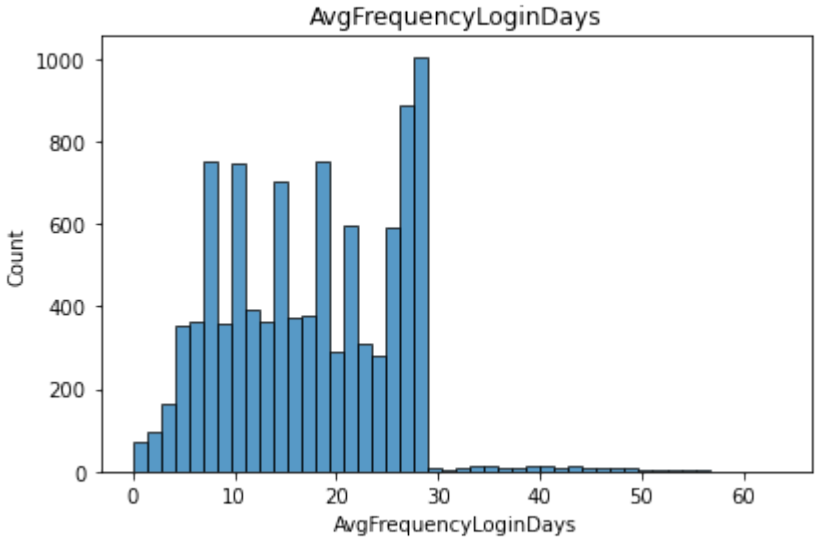

MonthlyCharges
Count
MonthlyCharges
0
100
200
300
400
500
6
8
10
12
14
16
18
20

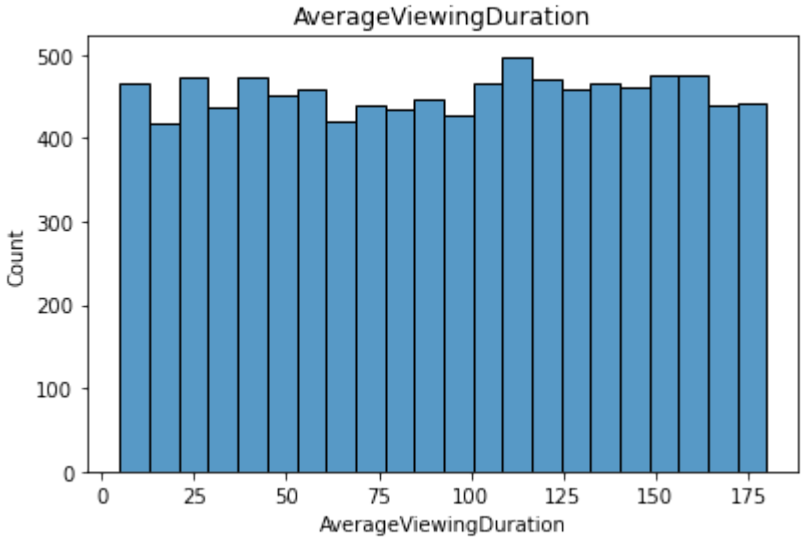

TotalCharges
Count
TotalCharges
0
100
200
300
400
500
600
0
500
1000
1500
2000

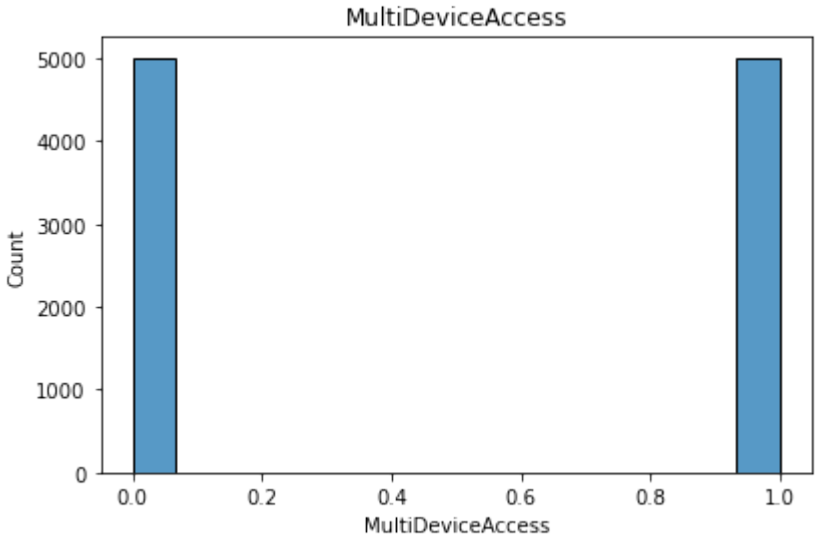

NumOfLogins
Count
5000
4000
3000
2000
1000
0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
NumOfLogins

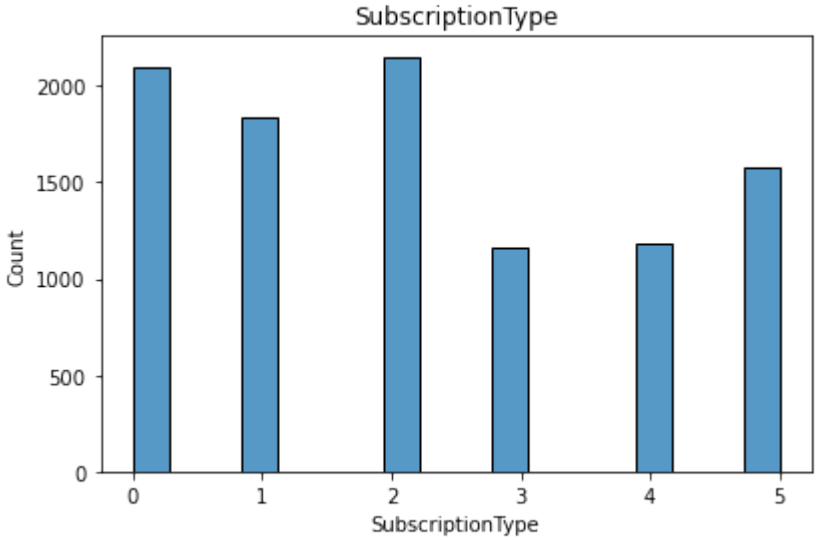

SupportTickets
Count
2000
1500
1000
500
0
0
1
2
3
4
5
SupportTickets

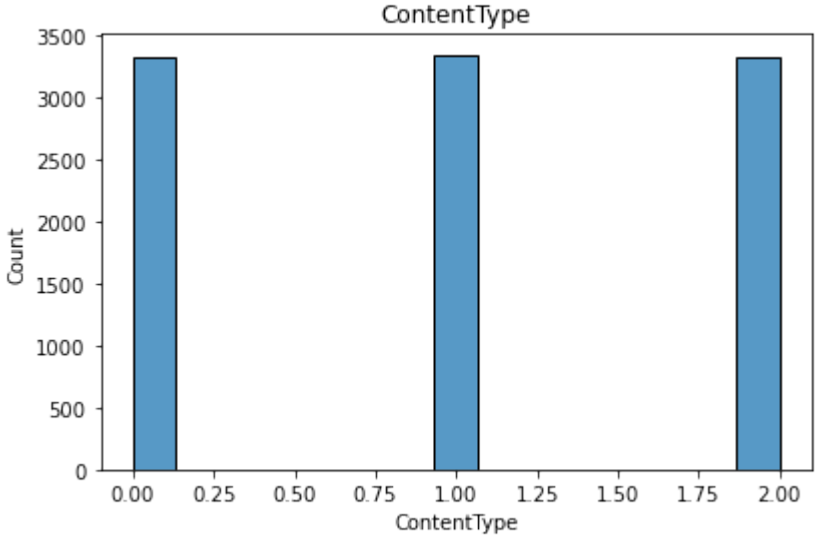

Complaints
Count
8000
7000
6000
5000
4000
3000
2000
1000
0
0.0
0.2
0.4
0.6
0.8
1.0
Complaints

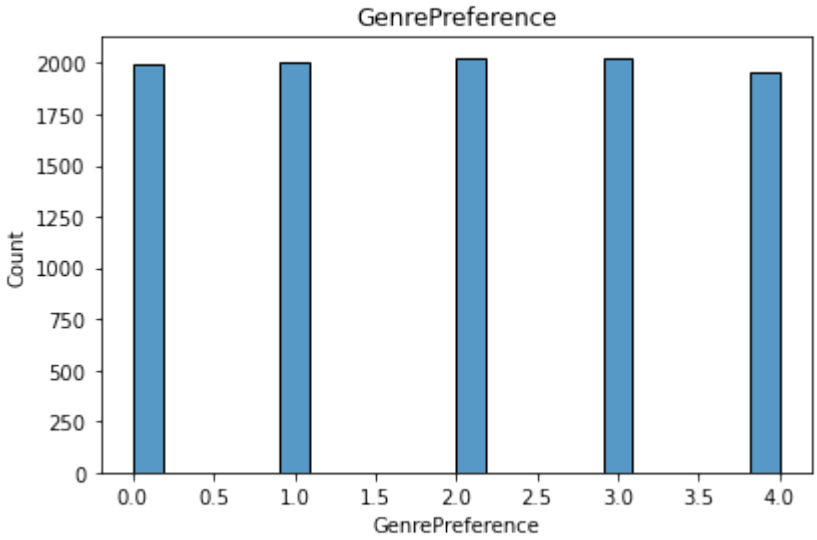

AvgFrequencyLoginDays
Count
AvgFrequencyLoginDays
0
200
400
600
800
1000
0
10
20
30
40
50
60


AverageViewingDuration
Count
AverageViewingDuration
0
100
200
300
400
500
0
25
50
75
100
125
150
175


MultiDeviceAccess
Count
MultiDeviceAccess
0
1000
2000
3000
4000
5000
0.0
0.2
0.4
0.6
0.8
1.0


SubscriptionType
Count
SubscriptionType
0
500
1000
1500
2000
0
1
2
3
4
5


ContentType
Count
ContentType
0
500
1000
1500
2000
2500
3000
3500
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00


GenrePreference
Count
GenrePreference
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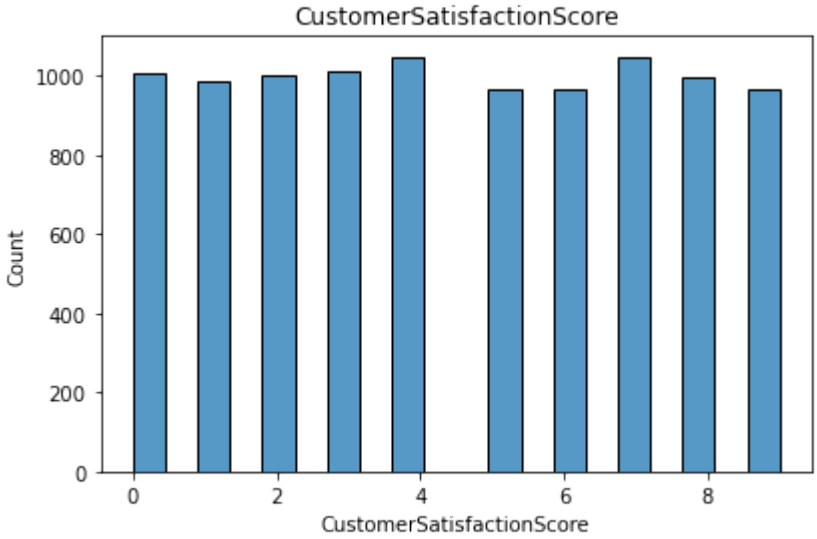
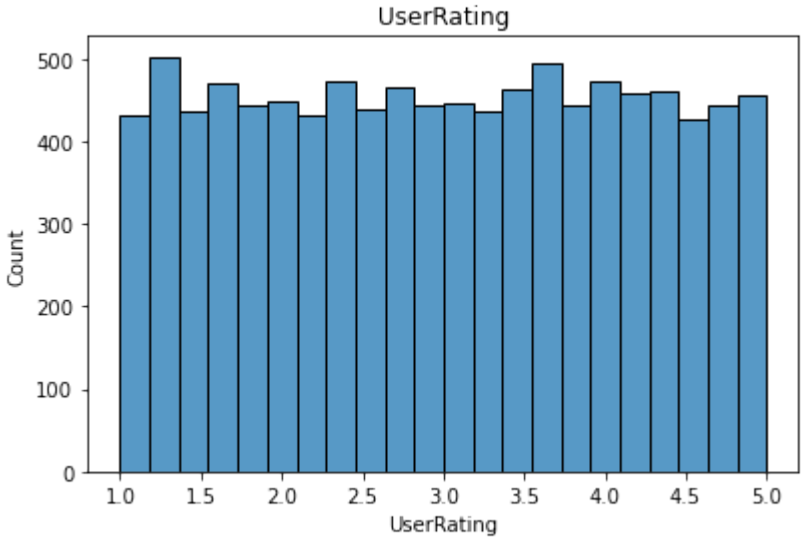
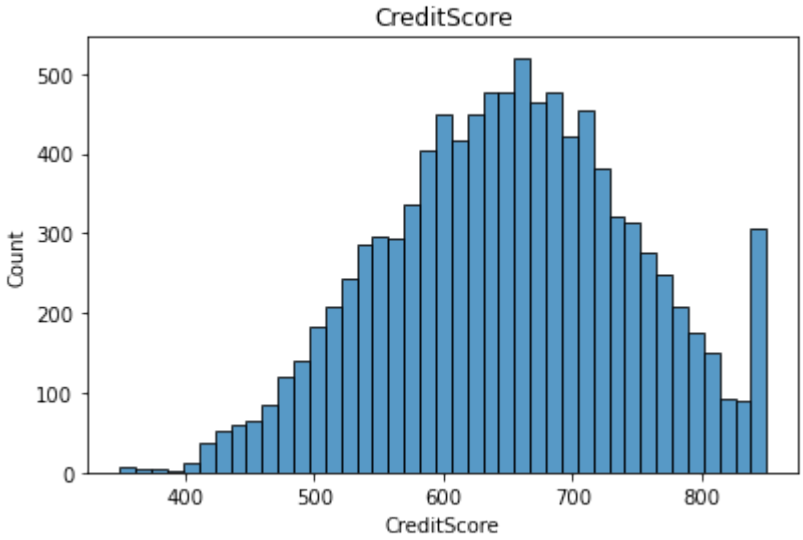
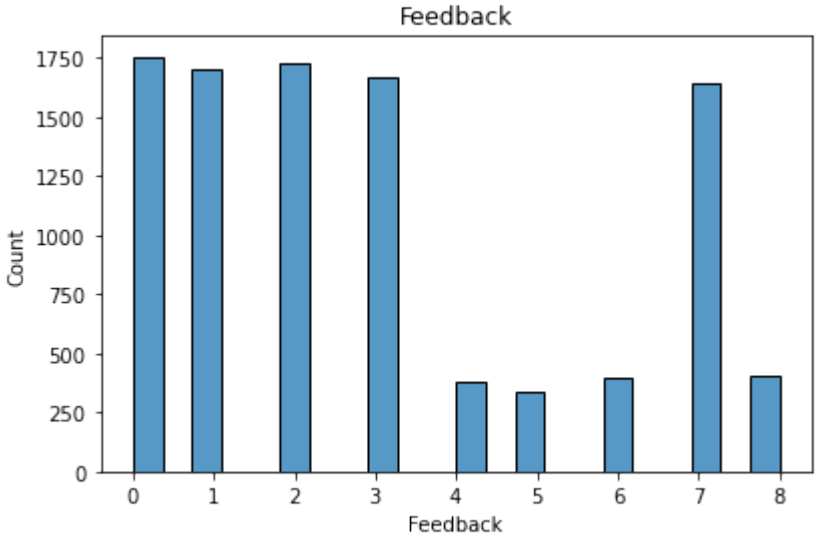
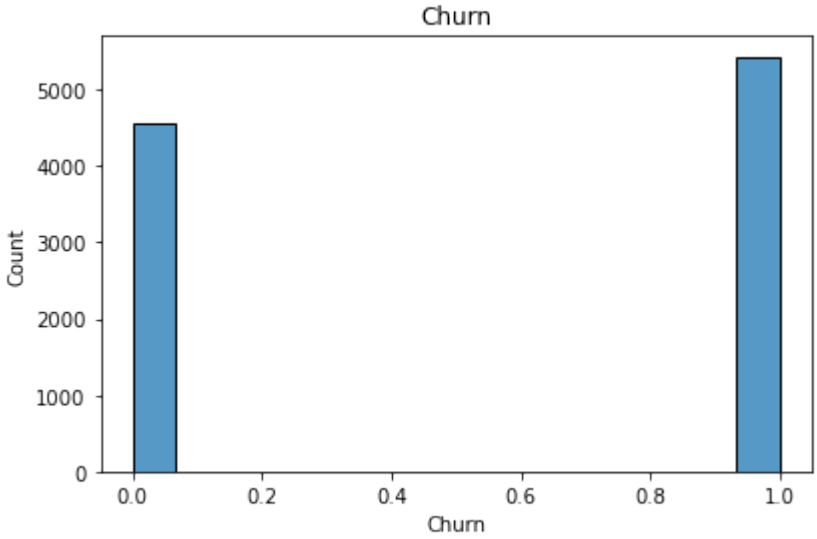
250
500
750
1000
1250
1500
1750
2000
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0


CustomerSatisfactionScore
Count
CustomerSatisfactionScore
0
200
400
600
800
1000
0
2
4
6
8


UserRating
Count
UserRating
0
100
200
300
400
500
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0

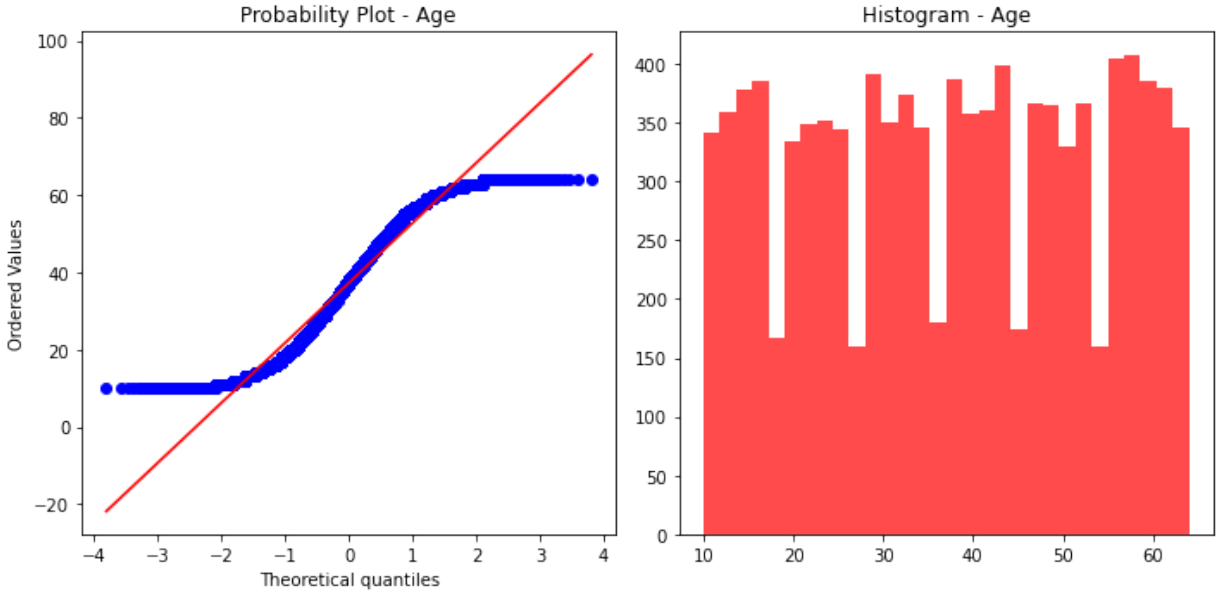

CreditScore
Count
CreditScore
0
100
200
300
400
500
400
500
600
700
800



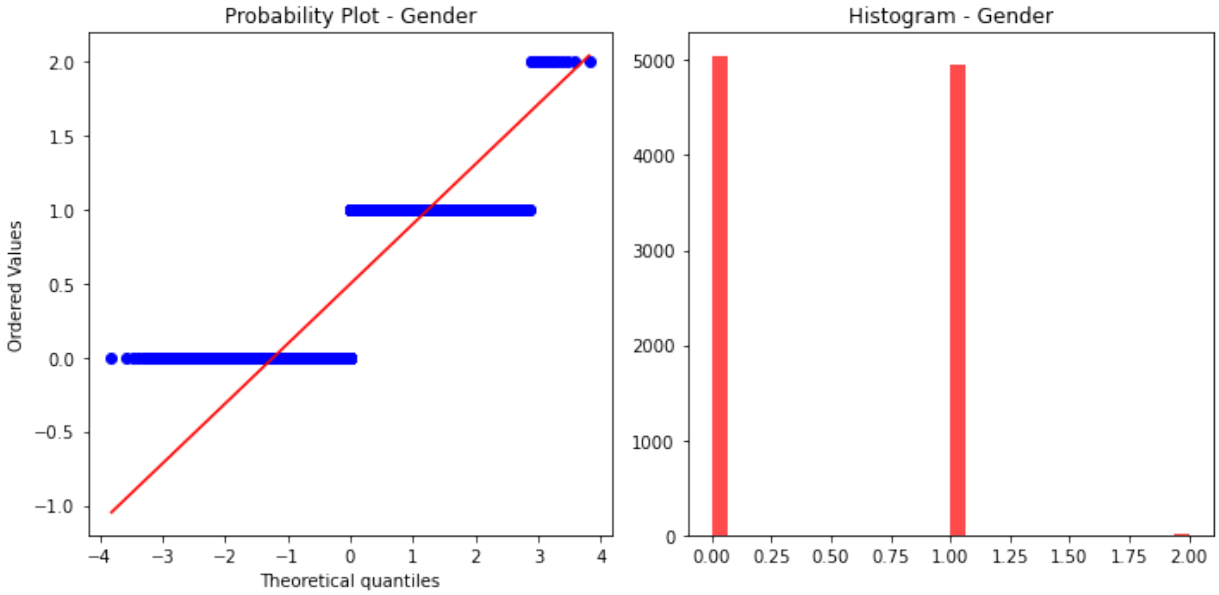




In [35]:

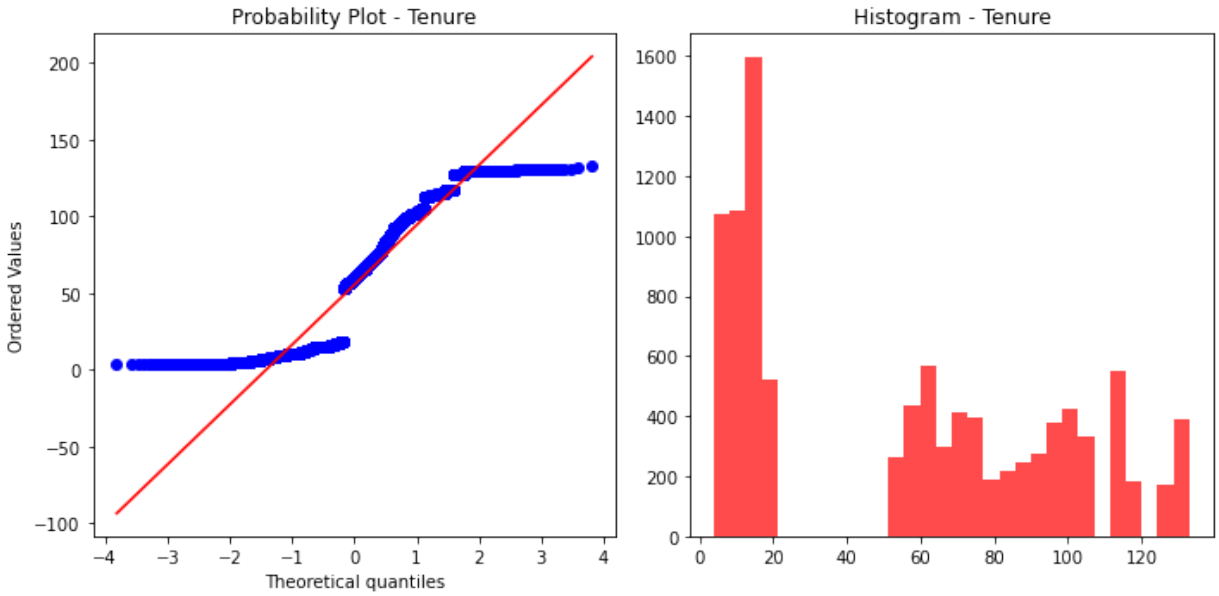
```
for column in data1.columns:
    plt.figure(figsize=(10, 5))
    plt.subplot(121)
    stats.probplot(data[column], dist='norm', plot=plt)
    plt.title(f'Probability Plot - {column}')
    plt.subplot(122)
    plt.hist(data[column], bins=30, alpha=0.7, color='red')
    plt.title(f'Histogram - {column}')
    plt.tight_layout()
    plt.show()
```


Probability Plot - Age
Ordered Values
Theoretical quantiles

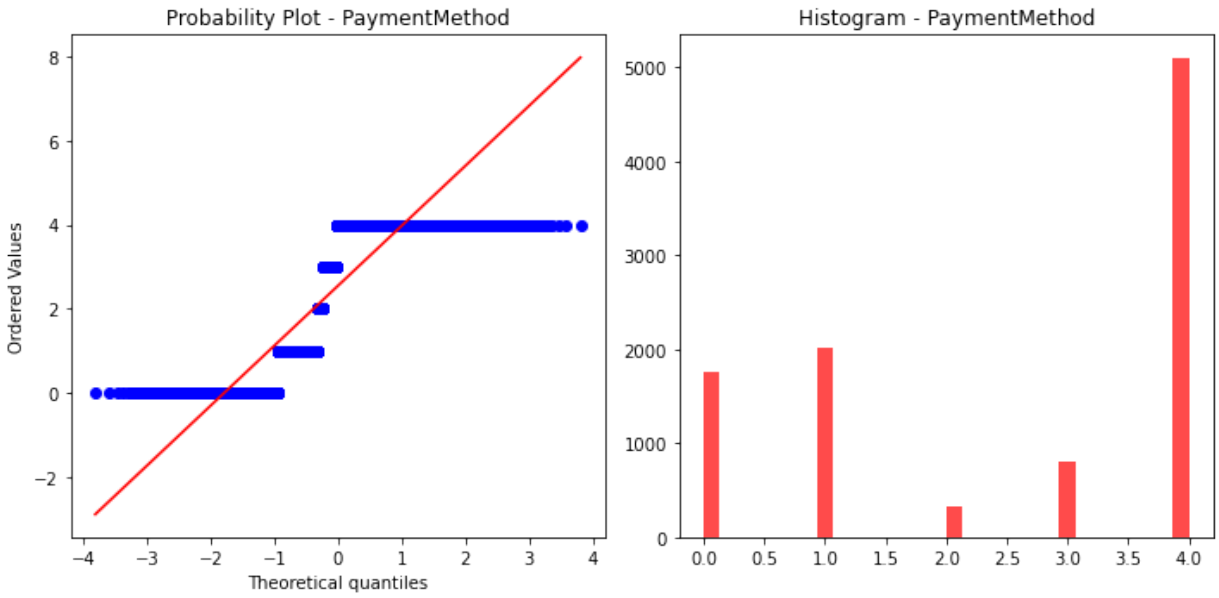

Histogram - Age


Probability Plot - Gender
Ordered Values
Theoretical quantiles

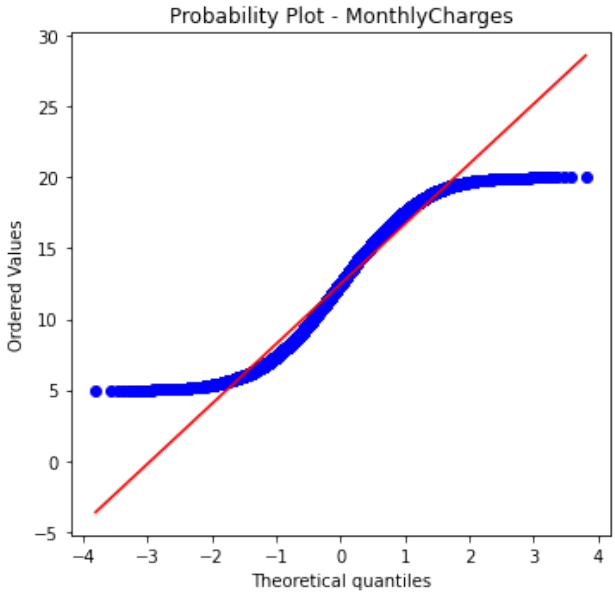

Histogram - Gender

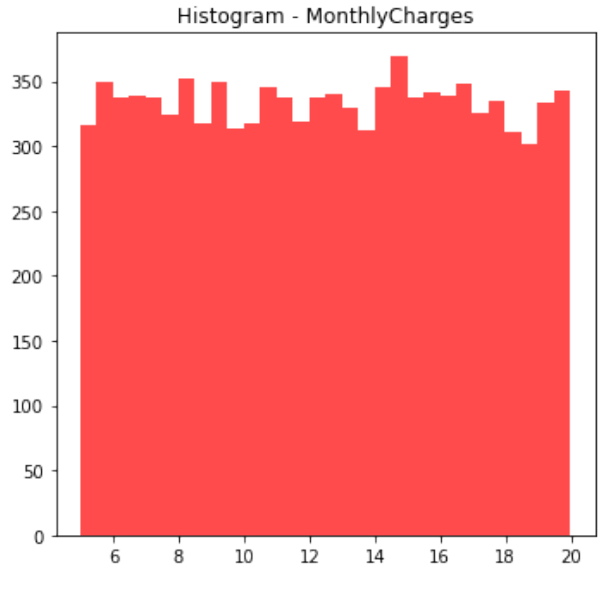

Probability Plot - Tenure
Ordered Values
Theoretical quantiles

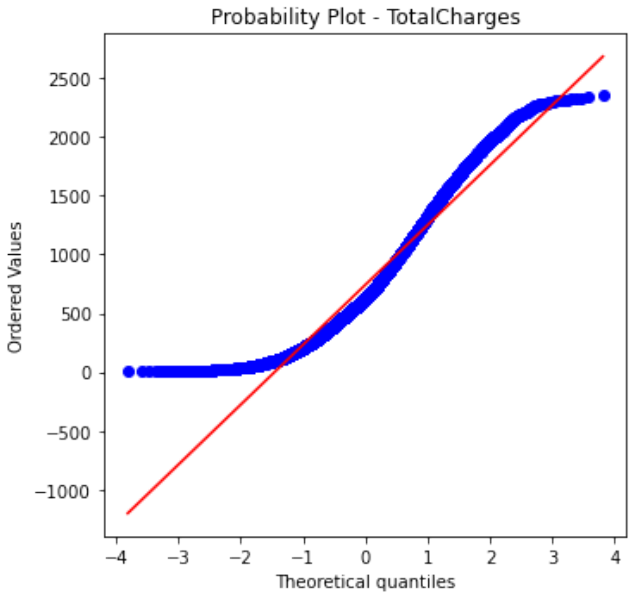

Histogram - Tenure


Probability Plot - PaymentMethod
Ordered Values
Theoretical quantiles

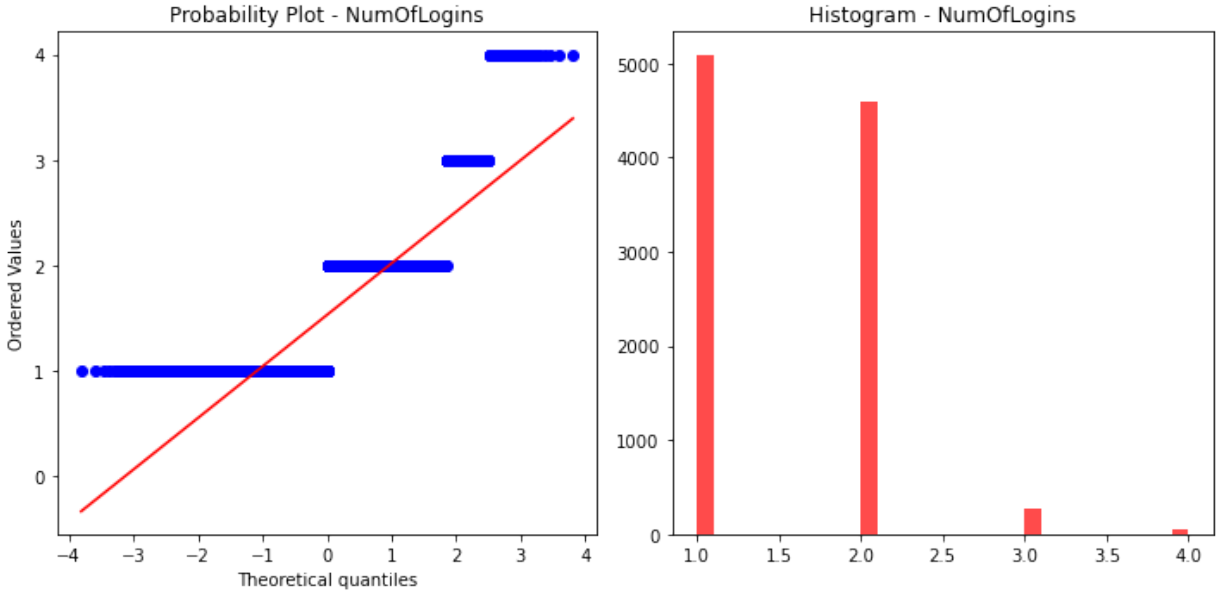

Histogram - PaymentMethod

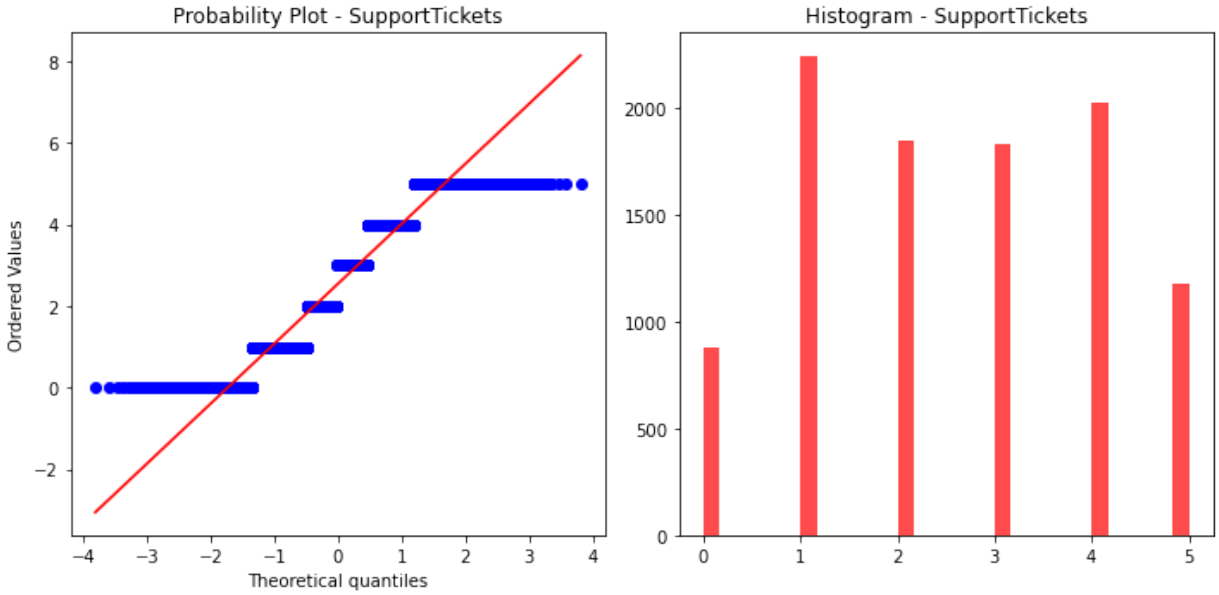

Probability Plot - MonthlyCharges
Ordered Values
Theoretical quantiles

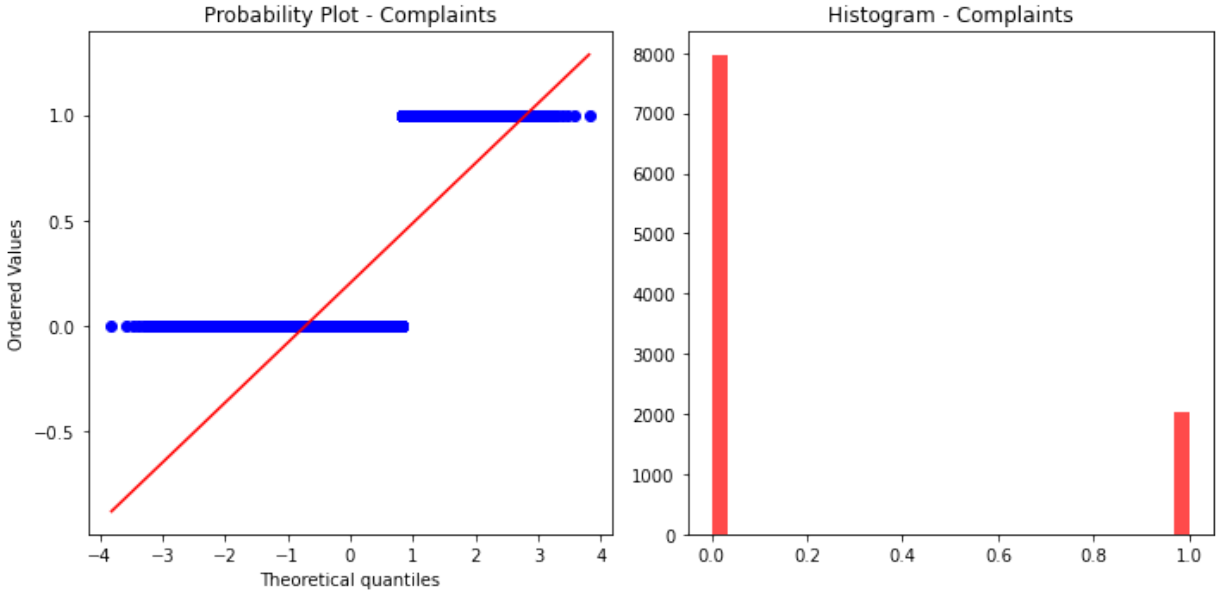

Histogram - MonthlyCharges

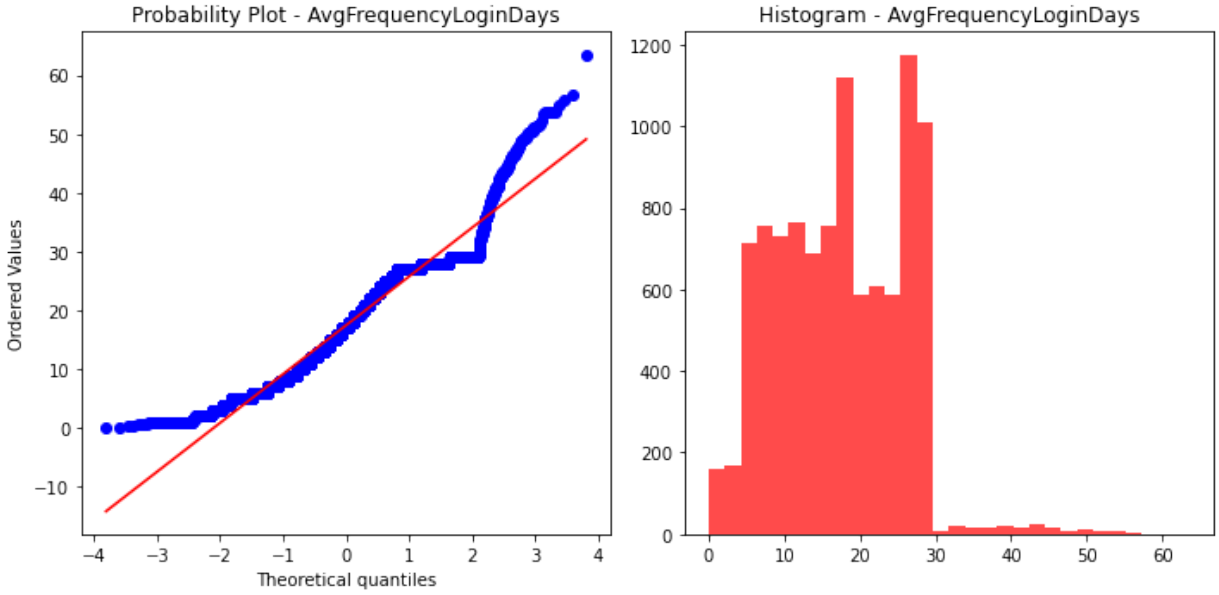

Probability Plot - TotalCharges
Ordered Values
Theoretical quantiles

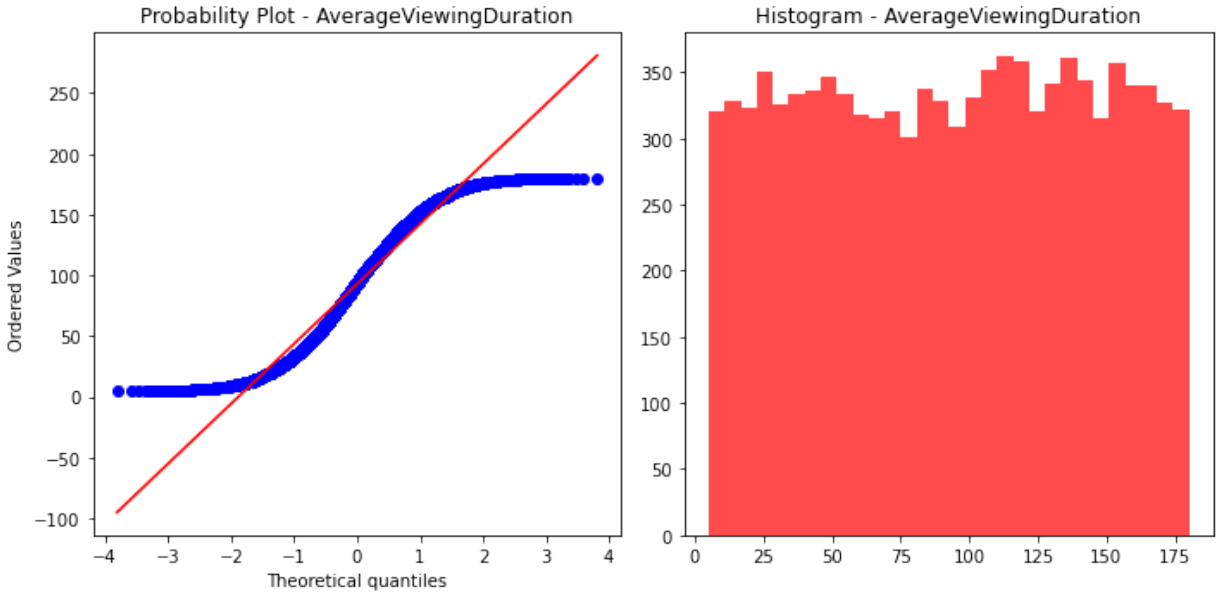

Histogram - TotalCharges

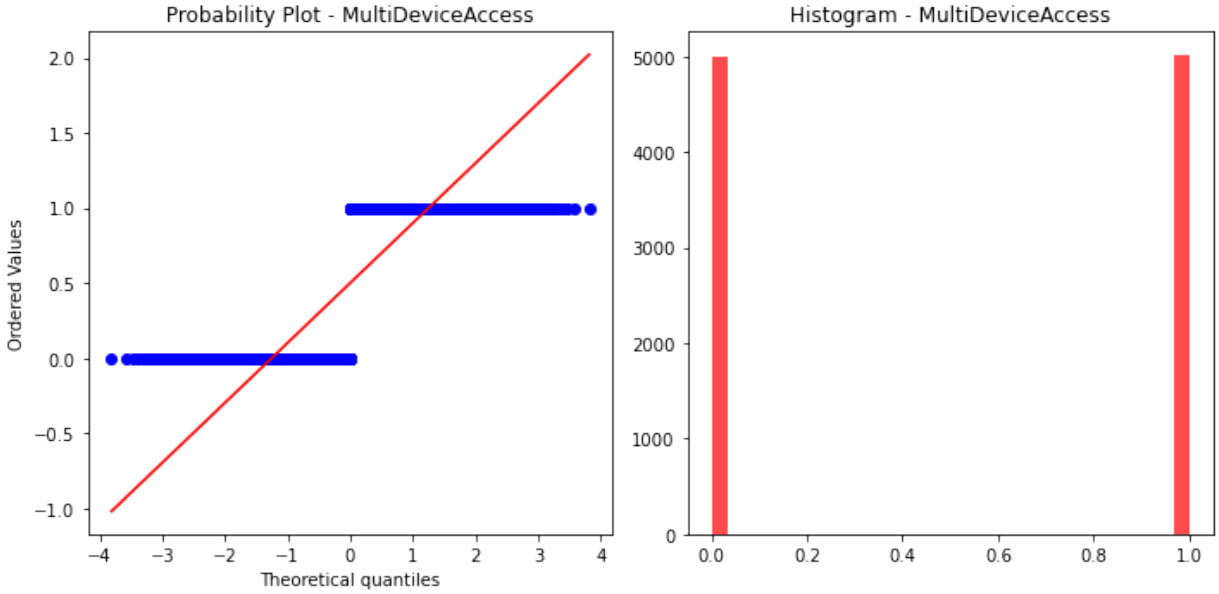

Probability Plot - NumOfLogins
Ordered Values
Theoretical quantiles
Histogram - NumOfLogins

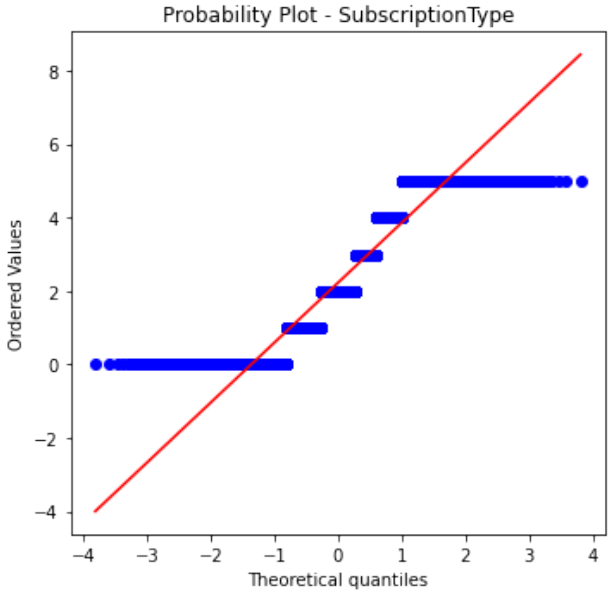

Probability Plot - SupportTickets
Ordered Values
Theoretical quantiles
Histogram - SupportTickets

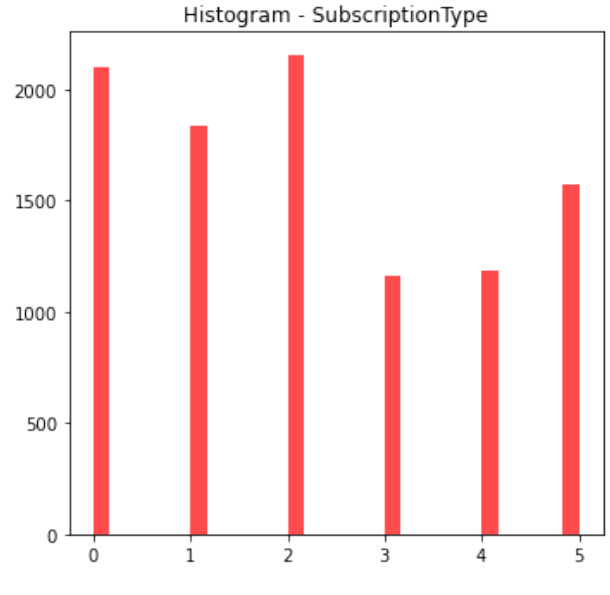

Probability Plot - Complaints
Ordered Values
Theoretical quantiles
Histogram - Complaints

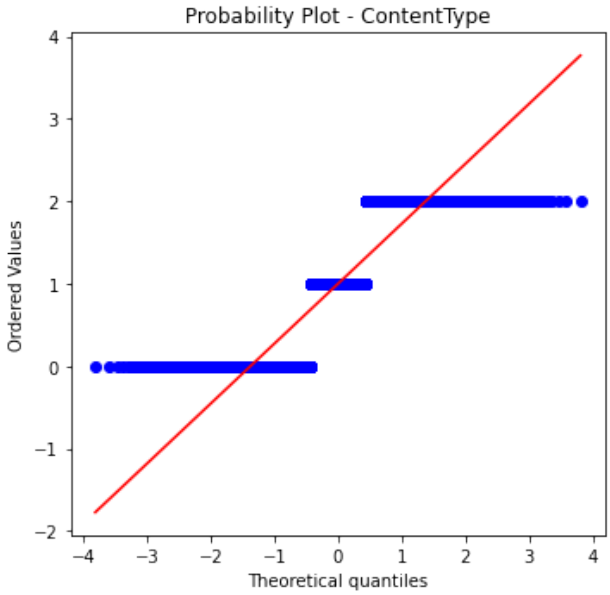

Probability Plot - AvgFrequencyLoginDays
Ordered Values
Theoretical quantiles
Histogram - AvgFrequencyLoginDays

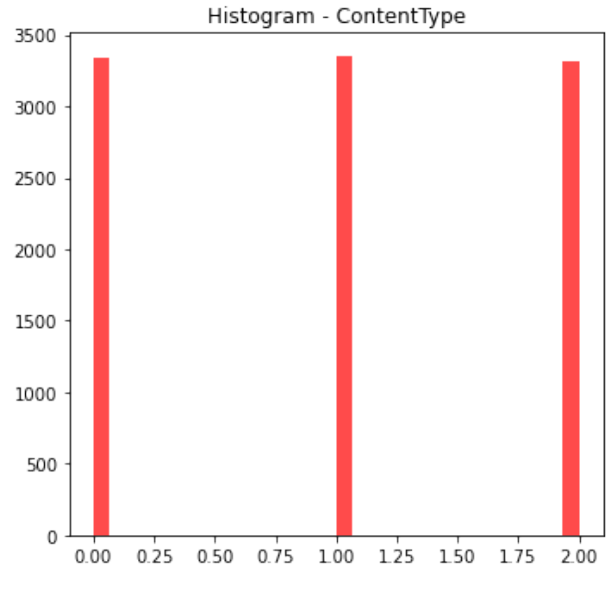

Probability Plot - AverageViewingDuration
Ordered Values
Theoretical quantiles
Histogram - AverageViewingDuration

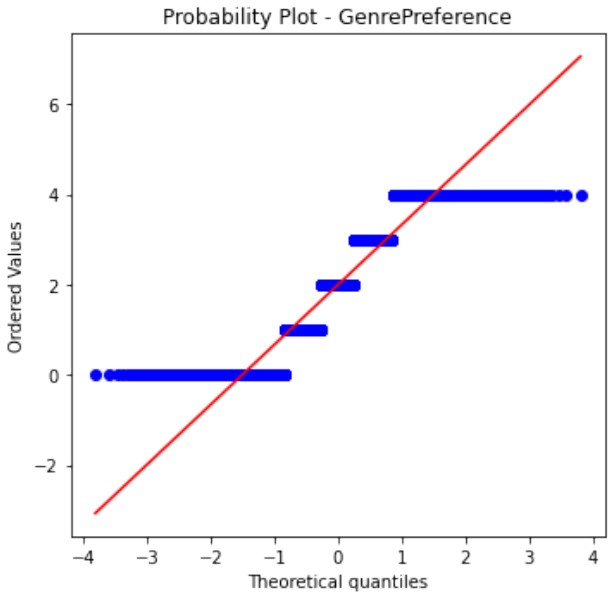

Probability Plot - MultiDeviceAccess
Ordered Values
Theoretical quantiles
Histogram - MultiDeviceAccess

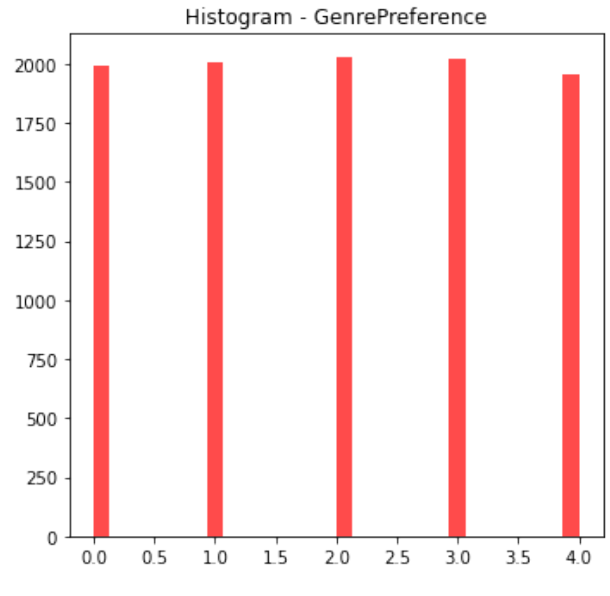

Probability Plot - SubscriptionType
Ordered Values
Theoretical quantiles

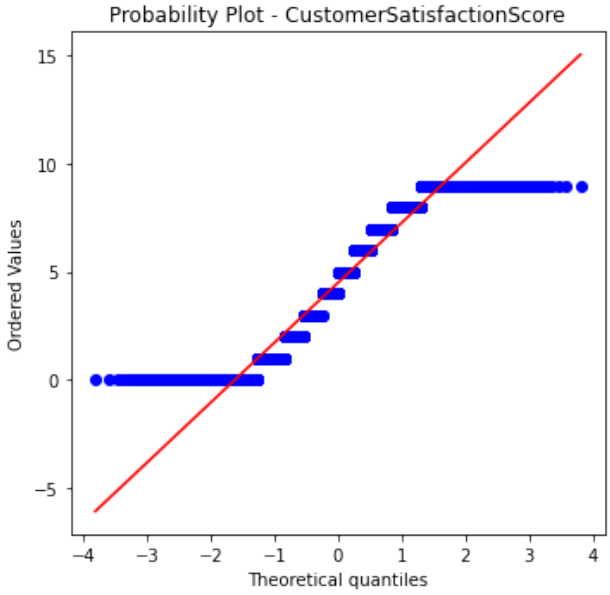

Histogram - SubscriptionType


Probability Plot - ContentType
Ordered Values
Theoretical quantiles

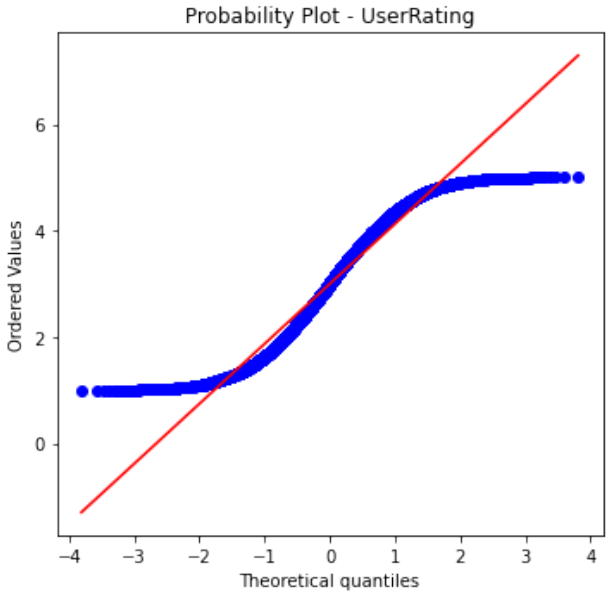

Histogram - ContentType

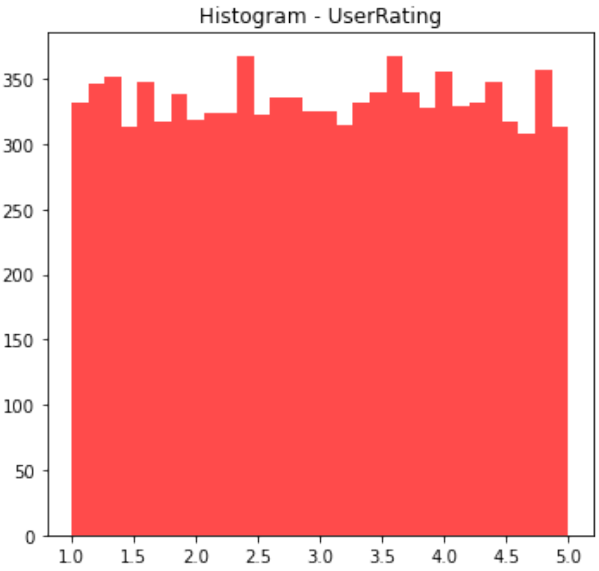

Probability Plot - GenrePreference
Ordered Values
Theoretical quantiles

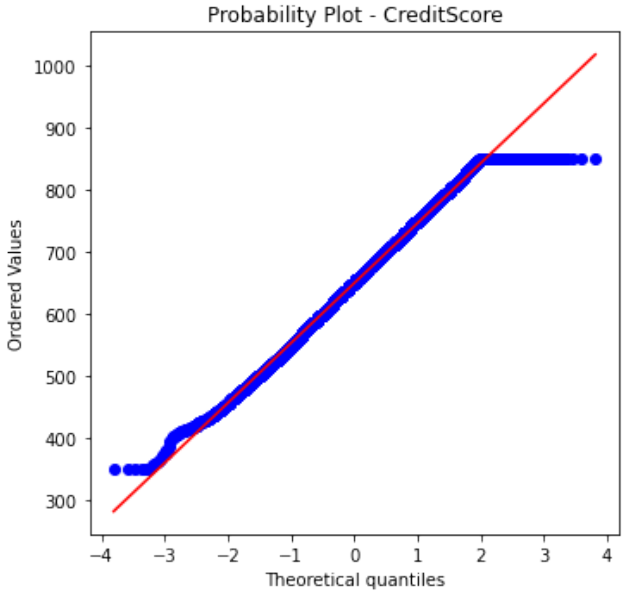

Histogram - GenrePreference

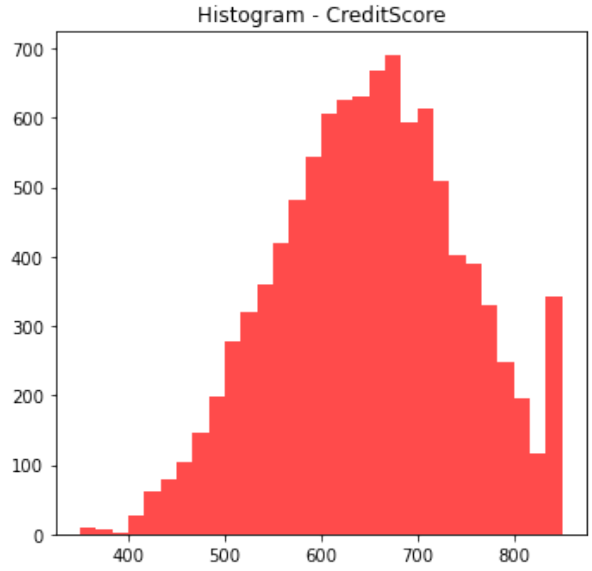

Probability Plot - CustomerSatisfactionScore
Ordered Values
Theoretical quantiles

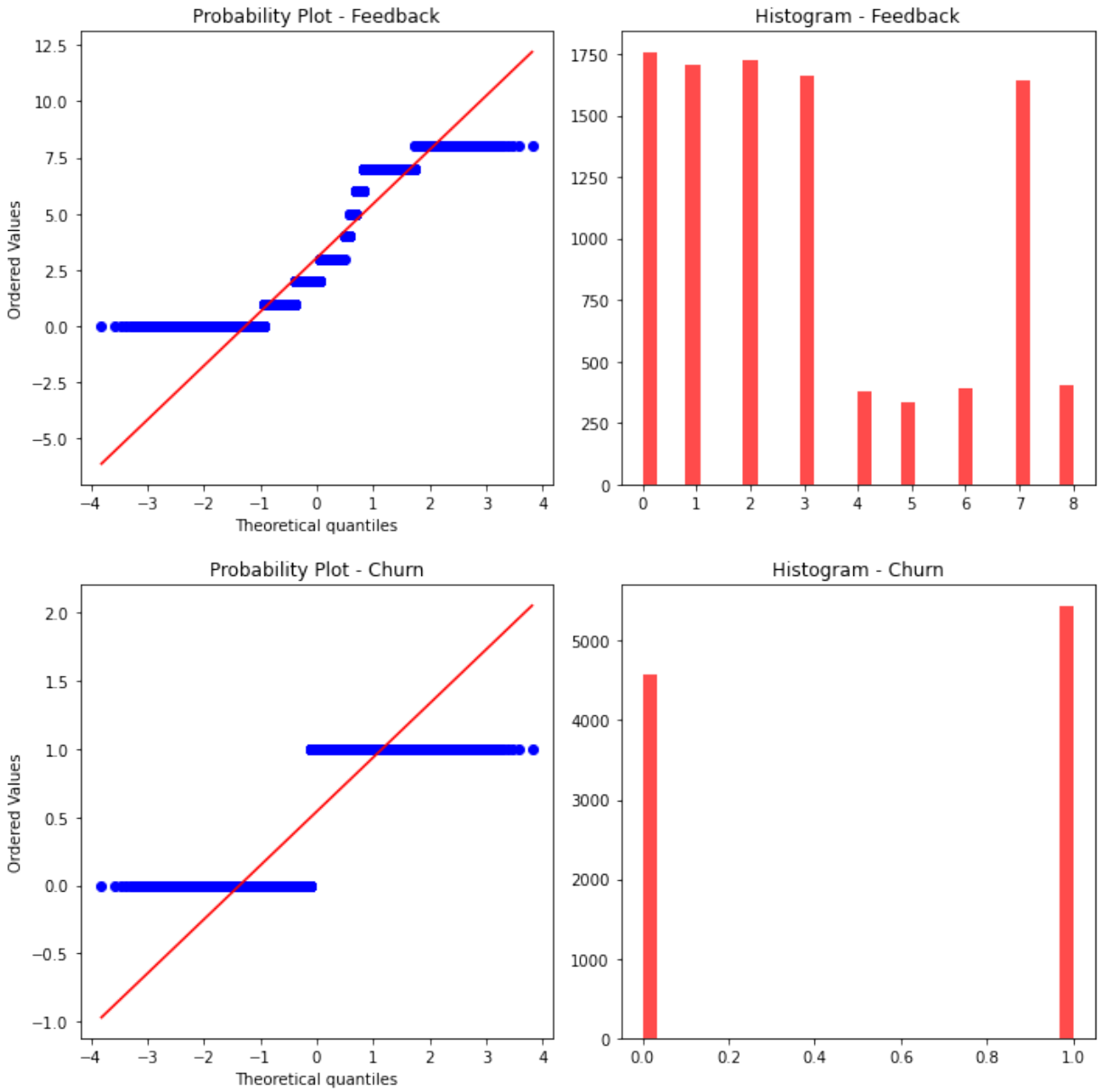

Histogram - CustomerSatisfactionScore


Probability Plot - UserRating
Ordered Values
Theoretical quantiles


Histogram - UserRating


Probability Plot - CreditScore
Ordered Values
Theoretical quantiles


Histogram - CreditScore




In [36]:

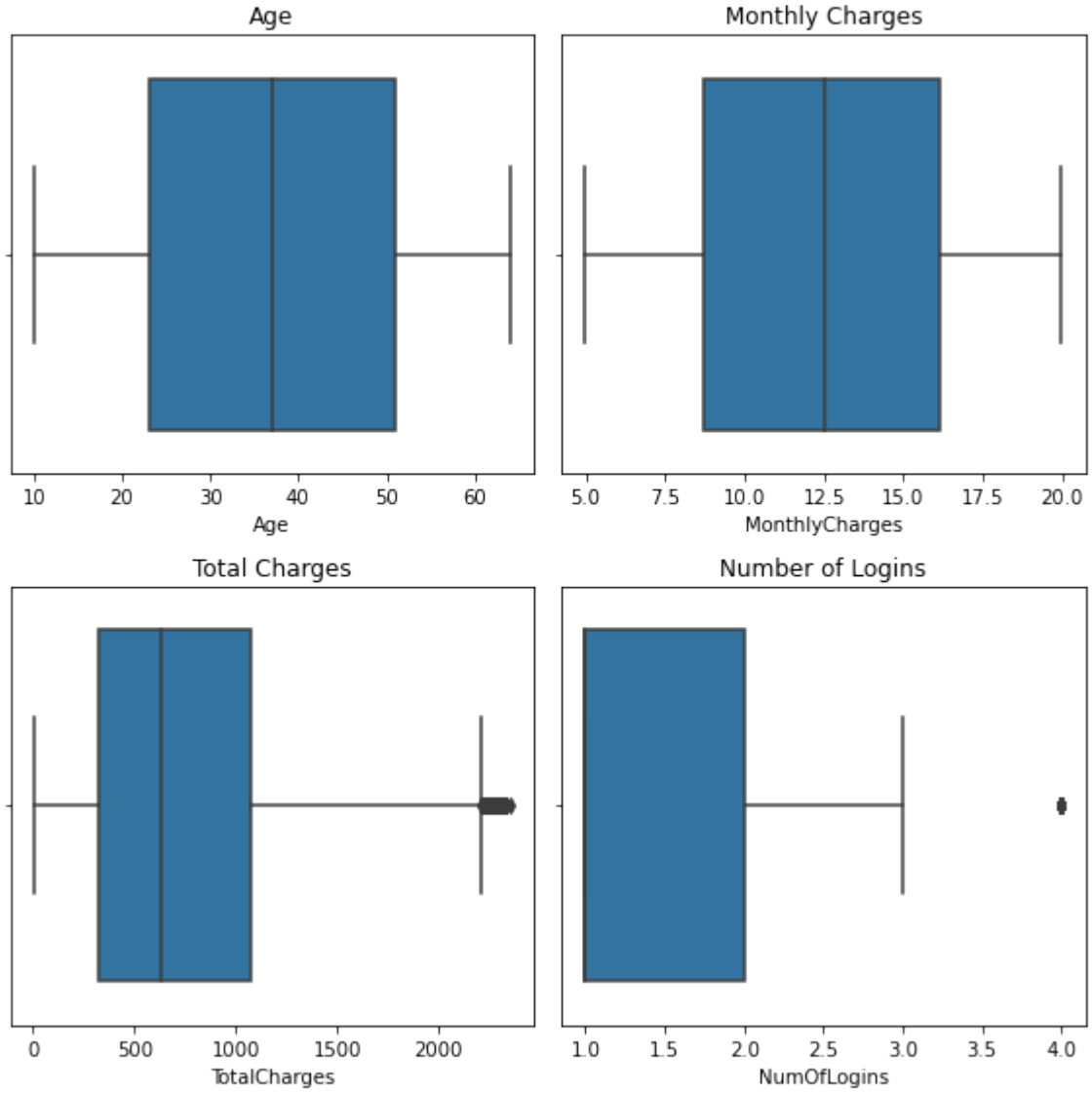
```
import matplotlib.pyplot as plt
import seaborn as sns
fig, ax = plt.subplots(nrows=2, ncols=2, figsize=(8, 8))
numerical_columns = [
    'Age', 'Tenure', 'MonthlyCharges', 'TotalCharges',
    'NumOfLogins', 'SupportTickets', 'Complaints', 'AvgFrequencyLoginDays',
    'AverageViewingDuration', 'WatchlistSize', 'CustomerSatisfactionScore', 'UserRat
    'CreditScore'
]
sns.boxplot(x=data1['Age'], orient="h", whis=1.5, ax=ax[0, 0])
ax[0, 0].set_title('Age')

sns.boxplot(x=data1['MonthlyCharges'], orient="h", whis=1.5, ax=ax[0, 1])
ax[0, 1].set_title('Monthly Charges')

sns.boxplot(x=data1['TotalCharges'], orient="h", whis=1.5, ax=ax[1, 0])
ax[1, 0].set_title('Total Charges')

sns.boxplot(x=data1['NumOfLogins'], orient="h", whis=1.5, ax=ax[1, 1])
ax[1, 1].set_title('Number of Logins')

# Adjust layout
plt.tight_layout()
plt.show()
```




# Model Evaluation

In [37]:
```
x=data1.drop(['Churn'],axis=1)
x
```

Out[37]:

| | Age | Gender | Tenure | PaymentMethod | MonthlyCharges | TotalCharges | NumOfLogins | Support |
|---|---|---|---|---|---|---|---|---|
| **0** | 18 | 0 | 93 | 1 | 11.055215 | 221.104302 | 1 | |
| **1** | 32 | 0 | 65 | 2 | 5.175208 | 294.986882 | 1 | |
| **2** | 44 | 0 | 129 | 4 | 12.106657 | 883.785952 | 3 | |
| **3** | 37 | 1 | 58 | 4 | 7.263743 | 232.439774 | 2 | |
| **4** | 31 | 0 | 88 | 4 | 16.953078 | 966.325422 | 1 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **9995** | 13 | 1 | 18 | 0 | 12.876577 | 1364.917173 | 2 | |
| **9996** | 37 | 0 | 18 | 4 | 9.332120 | 839.890788 | 1 | |
| **9997** | 26 | 1 | 18 | 1 | 14.945345 | 478.251032 | 1 | |
| **9998** | 41 | 1 | 18 | 4 | 16.109496 | 434.956386 | 2 | |
| **9999** | 57 | 0 | 18 | 4 | 9.457105 | 416.112630 | 1 | |

10000 rows × 19 columns

In [38]:
```
y=data1['Churn']
y
```

Out[38]:
```
0       0
1       0
2       1
3       1
4       1
       ..
9995    1
9996    0
9997    1
9998    0
9999    1
Name: Churn, Length: 10000, dtype: int64
```

In [39]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.33,random_state=42)
```

In [40]:
```
print(x_train.shape, x_test.shape, y_train.shape, y_test.shape)
```

```
(6700, 19) (3300, 19) (6700,) (3300,)
```

# Logistic Regression

In [41]:
```
from sklearn.linear_model import LogisticRegression
classifier=LogisticRegression()
classifier.fit(x_train, y_train)
```

Out[41]:
```
▾ LogisticRegression

LogisticRegression()
```

In [42]:
```
y_pred1=classifier.predict(x_test)
y_pred1
```

Out[42]:
```
array([1, 0, 1, ..., 0, 0, 0], dtype=int64)
```

In [43]:
```
from sklearn.metrics import accuracy_score
accuracy_score(y_test,y_pred1)
```

Out[43]:
```
0.8369696969696969
```

In [44]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test,y_pred1)
```

Out[44]:
```
array([[1308,  205],
       [ 333, 1454]], dtype=int64)
```

In [45]:
```
from sklearn.metrics import classification_report
report = classification_report(y_test, y_pred1)
print("Classification Report:")
print(report)
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.80      0.86      0.83      1513
           1       0.88      0.81      0.84      1787

    accuracy                           0.84      3300
   macro avg       0.84      0.84      0.84      3300
weighted avg       0.84      0.84      0.84      3300
```

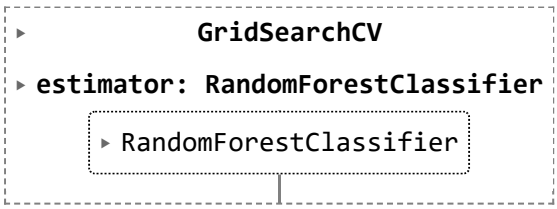
In [46]:
```
from sklearn.model_selection import cross_val_score
cv_scores = cross_val_score(classifier, x, y, cv=5, scoring='accuracy')
print("Cross-validation scores:", cv_scores)
print("Mean cross-validation score:", cv_scores.mean())
```

```
Cross-validation scores: [0.836  0.835  0.8615 0.839  0.847 ]
Mean cross-validation score: 0.8436999999999999
```

# Random Forest Classification

In [47]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
cls=RandomForestClassifier()
n_estimators=[25,50,75,100,125,150,175,200]
criterion=['gini','entropy']
max_depth=[3,5,10]
parameters={'n_estimators': n_estimators,'criterion':criterion,'max_depth':max_depth
RFC_cls = GridSearchCV(cls, parameters)
RFC_cls.fit(x_train,y_train)
```

Out[47]:

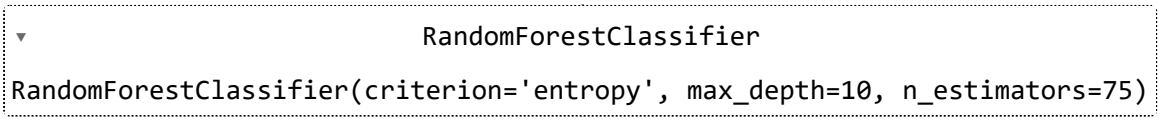



In [48]:
```
RFC_cls.best_params_
```

Out[48]:
```
{'criterion': 'entropy', 'max_depth': 5, 'n_estimators': 50}
```

In [49]:
```
cls=RandomForestClassifier(n_estimators=75,criterion='entropy',max_depth=10)
cls.fit(x_train,y_train)
```

Out[49]:



In [50]:
```
y_pred2=cls.predict(x_test)
y_pred2
```

Out[50]:
```
array([1, 0, 1, ..., 1, 1, 0], dtype=int64)
```

In [51]:
```
from sklearn.metrics import accuracy_score
accuracy_score(y_test,y_pred2)
```

Out[51]:
```
0.8527272727272728
```

In [52]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test,y_pred2)
```

Out[52]:
```
array([[1357,  156],
       [ 330, 1457]], dtype=int64)
```

In [53]:
```
from sklearn.metrics import classification_report
report2 = classification_report(y_test, y_pred2)
print("Classification Report:")
print(report)
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.80      0.86      0.83      1513
           1       0.88      0.81      0.84      1787

    accuracy                           0.84      3300
   macro avg       0.84      0.84      0.84      3300
weighted avg       0.84      0.84      0.84      3300
```

# DecisionTree Classification

In [54]:
```
from sklearn.tree import DecisionTreeClassifier
DTC_cls=DecisionTreeClassifier()
DTC_cls.fit(x_train,y_train)
```

Out[54]:
```
▾ DecisionTreeClassifier

DecisionTreeClassifier()
```

In [55]:
```
y_pred3=DTC_cls.predict(x_test)
y_pred3
```

Out[55]:
```
array([1, 0, 0, ..., 0, 0, 0], dtype=int64)
```

In [56]:
```
from sklearn.metrics import accuracy_score
accuracy_score(y_test,y_pred3)
```

Out[56]:
```
0.8306060606060606
```

In [57]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test,y_pred3)
```

Out[57]:
```
array([[1255,  258],
       [ 301, 1486]], dtype=int64)
```

In [58]:
```
from sklearn.metrics import classification_report
report2 = classification_report(y_test, y_pred3)
print("Classification Report:")
print(report)
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.80      0.86      0.83      1513
           1       0.88      0.81      0.84      1787

    accuracy                           0.84      3300
   macro avg       0.84      0.84      0.84      3300
weighted avg       0.84      0.84      0.84      3300
```

In [59]:
```
from sklearn.model_selection import cross_val_score
cv_scores = cross_val_score(DTC_cls, x, y, cv=5, scoring='accuracy')
print("Cross-validation scores:", cv_scores)
print("Mean cross-validation score:", cv_scores.mean())
```

```
Cross-validation scores: [0.816  0.838  0.793  0.8375 0.829 ]
Mean cross-validation score: 0.8227
```

# Support Vector Classification

In [60]:
```
from sklearn.svm import SVC
SVC_cls=SVC(kernel='linear', random_state=42)
SVC_cls.fit(x_train, y_train)
```

Out[60]:
```
SVC(kernel='linear', random_state=42)
```

In [61]:
```
y_pred4=SVC_cls.predict(x_test)
y_pred4
```

Out[61]:
```
array([1, 0, 1, ..., 0, 0, 0], dtype=int64)
```

In [62]:
```
from sklearn.metrics import accuracy_score
accuracy_score(y_test,y_pred4)
```

Out[62]:
```
0.8548484848484849
```

In [63]:
```
from sklearn.metrics import classification_report
report2 = classification_report(y_test, y_pred3)
print("Classification Report:")
print(report)
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.80      0.86      0.83      1513
           1       0.88      0.81      0.84      1787

    accuracy                           0.84      3300
   macro avg       0.84      0.84      0.84      3300
weighted avg       0.84      0.84      0.84      3300
```

In [64]:

```
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test,y_pred4)
```

Out[64]:

```
array([[1455,   58],
       [ 421, 1366]], dtype=int64)
```

In [65]:

```
from prettytable import PrettyTable
table=PrettyTable()
table.field_names = ["TEST_SIZE","0.33"]
table.add_row(["Logistic Regression",0.8369696969696969])
table.add_row(["Random Forest Classification",0.8527272727272728])
table.add_row(["DecisionTree Classification",0.8306060606060606])
table.add_row(["Support Vector Classification",0.8548484848484849])
print(table)
```

```
+-------------------------------+--------------------+
|           TEST_SIZE           |        0.33        |
+-------------------------------+--------------------+
|      Logistic Regression      | 0.8369696969696969 |
|  Random Forest Classification | 0.8527272727272728 |
|  DecisionTree Classification  | 0.8306060606060606 |
| Support Vector Classification | 0.8548484848484849 |
+-------------------------------+--------------------+
```

In [66]:

```
no_churn_examples = data1[data1['Churn'] == 1]
print(no_churn_examples)
```

```
      Age  Gender  Tenure  PaymentMethod  MonthlyCharges  TotalCharges  \
2      44       0     129              4       12.106657    883.785952
3      37       1      58              4        7.263743    232.439774
4      31       0      88              4       16.953078    966.325422
7      42       1     115              4        7.247550    181.188753
9      45       0      73              4       18.842934    263.801080
...   ...     ...     ...            ...             ...           ...
9991   16       0      18              1       19.770189   2016.559256
9994   32       0      18              0       15.975655     15.975655
9995   13       1      18              0       12.876577   1364.917173
9997   26       1      18              1       14.945345    478.251032
9999   57       0      18              4        9.457105    416.112630

      NumOfLogins  SupportTickets  Complaints  AvgFrequencyLoginDays  \
2               3               0           1                   22.0
3               2               0           0                    6.0
4               1               0           0                   16.0
7               4               0           1                   24.0
9               1               0           0                   28.0
...           ...             ...         ...                    ...
9991            1               1           1                   25.0
9994            2               2           0                   23.0
9995            2               1           0                   18.0
9997            1               1           1                   23.0
```

```
9999           1               2           0                   6.0

      AverageViewingDuration  MultiDeviceAccess  SubscriptionType  \
2                  57.364061                  0                 2
3                 131.537507                  0                 2
4                  45.356653                  0                 2
7                 154.521682                  0                 2
9                 122.012890                  0                 2
...                      ...                ...               ...
9991              171.817409                  0                 0
9994               39.400347                  1                 5
9995              135.005241                  1                 0
9997              144.020871                  1                 2
9999              118.508807                  0                 5

      ContentType  GenrePreference  CustomerSatisfactionScore  UserRating  \
2               1                3                          6    4.238824
3               2                2                          2    4.276013
4               2                1                          4    3.616170
7               2                3                          2    3.410221
9               1                1                          0    2.993441
...           ...              ...                        ...         ...
9991            1                2                          8    2.604131
9994            2                2                          7    2.306880
9995            2                1                          7    1.777635
9997            0                0                          4    3.986903
9999            1                2                          0    3.406803

      CreditScore  Feedback  Churn
2             502         3      1
3             699         3      1
4             850         3      1
7             376         2      1
9             684         1      1
...           ...       ...    ...
9991          597         7      1
9994          800         0      1
9995          771         0      1
9997          709         7      1
9999          792         1      1

[5432 rows x 20 columns]
```

In [67]:

```
no_churn_examples = data1[data1['Churn'] == 0]
print(no_churn_examples)
```

```
      Age  Gender  Tenure  PaymentMethod  MonthlyCharges  TotalCharges  \
0      18       0      93              1       11.055215    221.104302
1      32       0      65              2        5.175208    294.986882
5      13       1      68              0        7.295744    824.419081
6      21       1     129              0       12.340675    468.945639
8      44       1      69              4       19.803233    514.884050
...   ...     ...     ...            ...             ...           ...
9990   55       0      18              4       19.497260    740.895870
9992   37       1      18              1       13.493619    580.225636
9993   27       1      18              4       13.686193    875.916335
9996   37       0      18              4        9.332120    839.890788
9998   41       1      18              4       16.109496    434.956386

      NumOfLogins  SupportTickets  Complaints  AvgFrequencyLoginDays  \
0               1               5           1                   17.0
1               1               4           1                   10.0
5               2               4           1                   24.0
```

```
6              2               4           0                   28.0
8              2               3           0                   20.0
...          ...             ...         ...                    ...
9990           1               1           0                   24.0
9992           1               2           0                   25.0
9993           1               2           0                   27.0
9996           1               4           0                    5.0
9998           2               3           1                   20.0

      AverageViewingDuration  MultiDeviceAccess  SubscriptionType  \
0                  63.531377                  0                 3
1                  25.725595                  0                 4
5                  97.095746                  0                 1
6                  81.782993                  0                 1
8                  94.375211                  0                 5
...                      ...                ...               ...
9990              142.837598                  1                 2
9992               13.554846                  0                 5
9993               28.957209                  1                 5
9996              158.905447                  1                 1
9998              107.889809                  1                 4

      ContentType  GenrePreference  CustomerSatisfactionScore  UserRating  \
0               0                4                          4    2.176498
1               1                0                          8    3.478632
5               0                1                          8    3.721134
6               0                0                          9    4.090868
8               1                3                          0    2.679986
...           ...              ...                        ...         ...
9990            1                4                          0    1.331817
9992            1                2                          0    2.343996
9993            1                0                          6    4.419766
9996            1                1                          8    3.180864
9998            2                3                          8    3.851557

      CreditScore  Feedback  Churn
0             619         4      0
1             608         5      0
5             645         0      0
6             822         0      0
8             501         1      0
...           ...       ...    ...
9990          714         3      0
9992          726         7      0
9993          644         1      0
9996          516         1      0
9998          772         2      0

[4568 rows x 20 columns]
```

# Risk Prediction Of Customers Churn

In [68]:

```
new = x_test.iloc[0]
a = np.asarray(new)
a = a.reshape(1,-1)
p = cls.predict(a)
```

In [69]:

```
if (p[0] == 1):
    print("Yes, it is a churn")
else:
    print("No, it is not a churn")
```

```
Yes, it is a churn
```

In [70]:

```
if (p[0] == 0):
    print("Yes, it is a churn")
else:
    print("No, it is not a churn")
```

```
No, it is not a churn
```

In [ ]: