TELCO CUSTOMER CHURN CLASSIFICATION

1 Telco Customer Churn Classification

1.1 Problem Statement: In the dynamic telecommunications landscape, customers are presented with many options to fulfill their communication and internet needs. Customer satisfaction stands as a cornerstone in this domain, given that individuals often formulate holistic perceptions of a company based on singular interactions. The omnipresent role of communication services in daily routines renders even a brief maintenance lapse of just 30 minutes capable of inducing user anxiety, emphasizing the critical nature of these services. Against the backdrop of substantial expenses associated with customer acquisition, scrutinizing churn rates emerges as an imperative endeavor.

Churn rate, a pivotal performance metric, serves to quantify the volume of customers who have terminated or declined to renew their subscriptions with the company. A heightened churn rate invariably corresponds with a larger cohort of customers disengaging from patronage, thereby exerting a detrimental impact on revenue streams. Consequently, distilling actionable insights from churn analysis assumes paramount importance for companies aiming to craft strategic interventions, target precise market segments, and elevate service standards to enrich overall customer experiences and cultivate enduring trust.

Thus, the development of predictive modeling frameworks and the generation of exhaustive churn analysis reports serve as linchpins in propelling business expansion and fortifying market positioning.

1.2 Objective:

The objective of this initiative is to conduct binary classification on an imbalanced dataset to identify potential churn customers. This classification task will leverage a combination of numerical and categorical features to enhance the predictive accuracy and robustness of the model.

1.3 Dataset Attributes:

1. customerID: Unique identifier for each customer.
2. gender: Gender of the customer (Male, Female).
3. SeniorCitizen: Indicator for whether the customer is a senior citizen (1 for Yes, 0 for No).
4. Partner: Indicator for whether the customer has a partner (Yes, No).
5. Dependents: Indicator for whether the customer has dependents (Yes, No).
6. tenure: Number of months the customer has been with the company.
7. PhoneService: Indicator for whether the customer has a phone service (Yes, No).
8. MultipleLines: Indicator for whether the customer has multiple lines (Yes, No, No phone service).
9. InternetService: Type of internet service provider for the customer (DSL, Fiber optic, No).
10. OnlineSecurity: Indicator for whether the customer has online security (Yes, No, No internet service).
11. OnlineBackup: Indicator for whether the customer has online backup (Yes, No, No internet service).
12. DeviceProtection: Indicator for whether the customer has device protection (Yes, No, No internet service).
13. TechSupport: Indicator for whether the customer has tech support (Yes, No, No internet service).
14. StreamingTV: Indicator for whether the customer has streaming TV (Yes, No, No internet service).
15. StreamingMovies: Indicator for whether the customer has streaming movies (Yes, No, No Internet Service).
16. Contract: The contract term of the customer (Month-to-month, One

year, Two years).

17. PaperlessBilling: Indicator for whether the customer has paperless billing (Yes, No).

18. PaymentMethod: The payment method used by the customer (Electronic check, Mailed check, Bank transfer (automatic), Credit card (automatic)).

19. MonthlyCharges: The amount charged to the customer monthly.

20. TotalCharges: The total amount charged to the customer.

21. Churn: Indicator for whether the customer churned (Yes, No

Import the Necessary Libraries:

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
pd.options.display.float_format = '{:.2f}'.format
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
data = pd.read_csv('WA_Fn-UseC_-Telco-Customer-Churn.csv')
data.head()
```

[2]:
```
   customerID  gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  7590-VHVEG  Female              0     Yes         No       1           No
1  5575-GNVDE    Male              0      No         No      34          Yes
2  3668-QPYBK    Male              0      No         No       2          Yes
3  7795-CFOCW    Male              0      No         No      45           No
4  9237-HQITU  Female              0      No         No       2          Yes

      MultipleLines InternetService OnlineSecurity  ... DeviceProtection  \
0  No phone service             DSL             No  ...               No
1                No             DSL            Yes  ...              Yes
2                No             DSL            Yes  ...               No
```

```
3  No phone service          DSL             Yes  ...               Yes
4                No  Fiber optic              No  ...                No

  TechSupport StreamingTV StreamingMovies        Contract PaperlessBilling  \
0          No          No              No  Month-to-month              Yes
1          No          No              No        One year               No
2          No          No              No  Month-to-month              Yes
3         Yes          No              No        One year               No
4          No          No              No  Month-to-month              Yes

               PaymentMethod  MonthlyCharges  TotalCharges Churn
0           Electronic check           29.85         29.85    No
1               Mailed check           56.95        1889.5    No
2               Mailed check           53.85        108.15   Yes
3  Bank transfer (automatic)           42.30       1840.75    No
4           Electronic check           70.70        151.65   Yes

[5 rows x 21 columns]
```

[3]:
```
data.info()
```

```
<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      7043 non-null   object
 20  Churn             7043 non-null   object
dtypes: float64(1), int64(2), object(18)
```

```
memory usage: 1.1+ MB
```

[4]:
```
data.columns
```

[4]:
```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

[5]:
```
data.isnull().sum()
```

[5]:
```
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
```

No null values present in the data!

[6]:
```
data.describe().T
```

[6]:

	count	mean	std	min	25%	50%	75%	max
SeniorCitizen	7043.00	0.16	0.37	0.00	0.00	0.00	0.00	1.00
tenure	7043.00	32.37	24.56	0.00	9.00	29.00	55.00	72.00
MonthlyCharges	7043.00	64.76	30.09	18.25	35.50	70.35	89.85	118.75

The dataset has too many features with text data and are probably categorical features!

- Total Charges is a feature with numerical values but are stored in string datatype. First, we will convert this column into float.

[7]:
```python
#Converting DataFrame column elements from string to float using the following
↪code line :

#data['TotalCharges']  =  data['TotalCharges'].astype(float)

# Identify non-convertible values
non_convertible_values = data[data['TotalCharges'] == ' ']['TotalCharges']

# Print unique non-convertible values
print("Non-convertible values:", non_convertible_values.unique())

# Replace ' ' with NaN
data['TotalCharges'] = data['TotalCharges'].replace(' ', np.nan)

# Convert the column to float
data['TotalCharges'] = data['TotalCharges'].astype(float)

# Drop rows with ' ' in 'TotalCharges'
data = data[data['TotalCharges'] != ' ']

# Convert the column to float
data['TotalCharges'] = data['TotalCharges'].astype(float)

data.drop(columns = ['customerID'], inplace = True)
```

```
Non-convertible values: [' ']
```

While converting the TotalCharges to float, an error occurred with the message describing that it could not convert string to float.

This error message popped up because of the empty strings present.

As these elements were defined as string, they did not appear as Null values and hence the missing values did not display anything. E.g : a = ' '

We drop the customerID column as well!

Let's divide the features into numerical and categorical features.

We will also execute the label encoding transformation for categorical features.

[8]:
```python
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

df1 = data.copy(deep = True)
text_data_features = [i for i in list(data.columns) if i not in list(data.
↪describe().columns)]

print('Label Encoder Transformation')
for i in text_data_features :
```

```
    df1[i] = le.fit_transform(df1[i])
    print(i,' : ',df1[i].unique(),' = ',le.inverse_transform(df1[i].unique()))
```

```
Label Encoder Transformation
gender :  [0 1]  = ['Female' 'Male']
Partner :  [1 0]  = ['Yes' 'No']
Dependents :  [0 1]  = ['No' 'Yes']
PhoneService :  [0 1]  = ['No' 'Yes']
MultipleLines  : [1 0 2]  = ['No phone service' 'No' 'Yes']
InternetService  : [0 1 2]  = ['DSL' 'Fiber optic' 'No']
OnlineSecurity  : [0 2 1]  = ['No' 'Yes' 'No internet service']
OnlineBackup  :  [2 0 1]  = ['Yes' 'No' 'No internet service']
DeviceProtection  : [0 2 1]  = ['No' 'Yes' 'No internet service']
TechSupport : [0 2 1]   = ['No' 'Yes' 'No internet service']
StreamingTV : [0 2 1]   = ['No' 'Yes' 'No internet service']
StreamingMovies  : [0 2 1]  = ['No' 'Yes' 'No internet service']
Contract : [0 1 2] = ['Month-to-month' 'One year' 'Two year']
PaperlessBilling : [1 0] = ['Yes' 'No']
PaymentMethod  :  [2 3 0 1]  = ['Electronic check' 'Mailed check' 'Bank
transfer (automatic)'
 'Credit card (automatic)']
Churn :  [0 1]  = ['No' 'Yes']
```

We creating a deep copy of the orginal dataset and label encoding the text data.

Modifications in the original dataset will not be highlighted in this deep copy.

Hence, we use this deep copy of dataset that has all the features converted into numerical values for visualization & modeling purposes.

We now again the descriptive stats of the data.

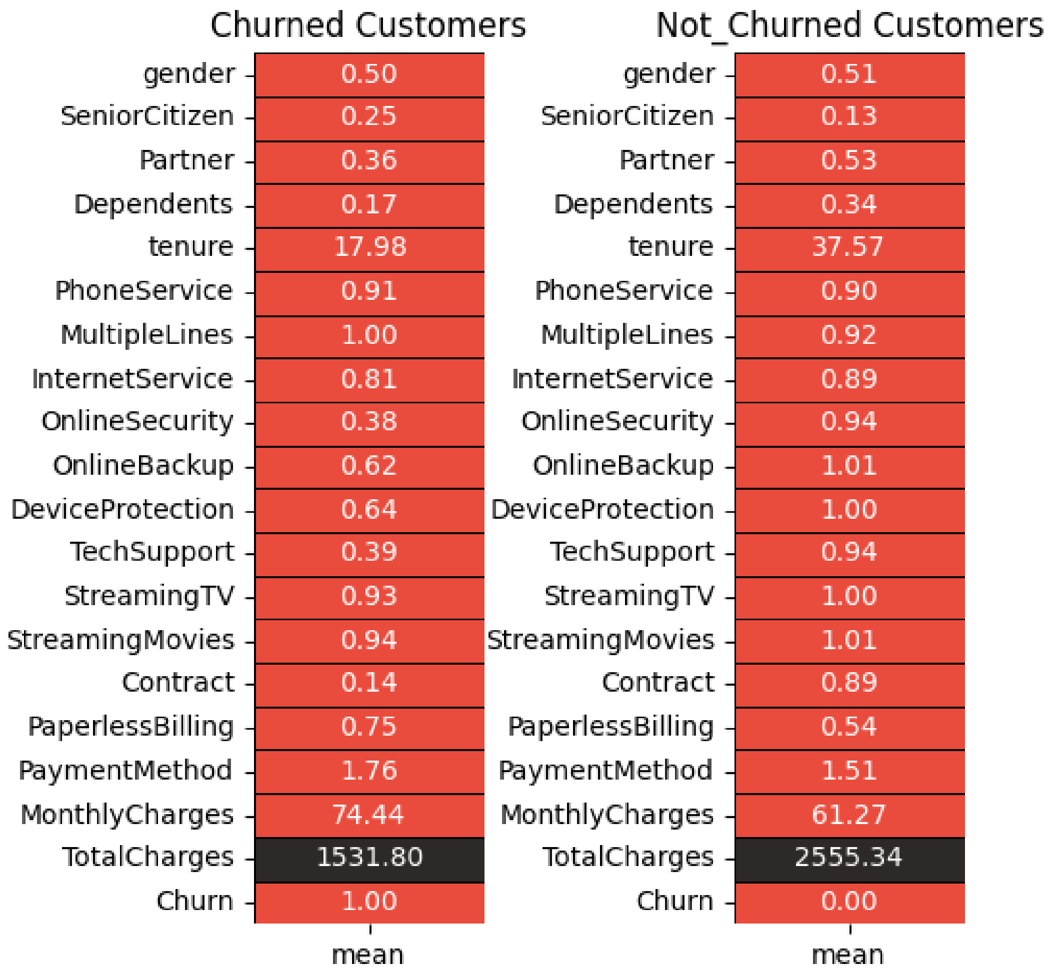
[9]:
```
df1.describe()
```

[9]:
```
       gender  SeniorCitizen  Partner  Dependents  tenure  PhoneService  \
count 7043.00        7043.00  7043.00     7043.00 7043.00       7043.00
mean     0.50           0.16     0.48        0.30   32.37          0.90
std      0.50           0.37     0.50        0.46   24.56          0.30
min      0.00           0.00     0.00        0.00    0.00          0.00
25%      0.00           0.00     0.00        0.00    9.00          1.00
50%      1.00           0.00     0.00        0.00   29.00          1.00
75%      1.00           0.00     1.00        1.00   55.00          1.00
max      1.00           1.00     1.00        1.00   72.00          1.00

       MultipleLines  InternetService  OnlineSecurity  OnlineBackup  \
count        7043.00          7043.00         7043.00       7043.00
mean            0.94             0.87            0.79          0.91
std             0.95             0.74            0.86          0.88
min             0.00             0.00            0.00          0.00
25%             0.00             0.00            0.00          0.00
```

```
50%               1.00            1.00           1.00           1.00
75%               2.00            1.00           2.00           2.00
max               2.00            2.00           2.00           2.00

      DeviceProtection  TechSupport  StreamingTV  StreamingMovies  Contract  \
count          7043.00      7043.00      7043.00          7043.00   7043.00
mean              0.90         0.80         0.99             0.99      0.69
std               0.88         0.86         0.89             0.89      0.83
min               0.00         0.00         0.00             0.00      0.00
25%               0.00         0.00         0.00             0.00      0.00
50%               1.00         1.00         1.00             1.00      0.00
75%               2.00         2.00         2.00             2.00      1.00
max               2.00         2.00         2.00             2.00      2.00

      PaperlessBilling  PaymentMethod  MonthlyCharges  TotalCharges    Churn
count          7043.00        7043.00         7043.00       7032.00  7043.00
mean              0.59           1.57           64.76       2283.30     0.27
std               0.49           1.07           30.09       2266.77     0.44
min               0.00           0.00           18.25         18.80     0.00
25%               0.00           1.00           35.50        401.45     0.00
50%               1.00           2.00           70.35       1397.47     0.00
75%               1.00           2.00           89.85       3794.74     1.00
max               1.00           3.00          118.75       8684.80     1.00
```

[10]:

```python
colors = ['#E94B3C','#2D2926']

churn = df1[df1['Churn'] == 1].describe().T
not_churn = df1[df1['Churn'] == 0].describe().T

fig,ax = plt.subplots(nrows = 1,ncols = 2,figsize = (5,5))
plt.subplot(1,2,1)
sns.heatmap(churn[['mean']],annot = True,cmap = colors,linewidths = 0.
    ↪4,linecolor = 'black',cbar = False,fmt = '.2f')
plt.title('Churned Customers');

plt.subplot(1,2,2)
sns.heatmap(not_churn[['mean']],annot = True,cmap = colors,linewidths = 0.
    ↪4,linecolor = 'black',cbar = False,fmt = '.2f',)
plt.title('Not_Churned Customers');

fig.tight_layout(pad = 0)
```



Mean values of all the features for churned and not-churned customers.

Clearly, the customers that churned had a low mean tenure of 17.98 months as compared to those who continued with an average tenure period of 37.57 months.

Mean values of OnlineSecurity, OnlineBackup, DeviceProtection and TechSupport are higher for not-churned customers than churn customers. This can serve as a good indicator or point to focus on!

Churned customer's Contract value is much smaller than those of not-churned customers.

Mean MonthlyCharges of the churn customers, 74.44, is more than that of not-churn customers, 61.27.

Not-churned customers TotalCharges, 2555.34, is higher than churn customers, 1531.80.

From these mean values, we can say that some of the features display a clear cut difference that can help to focus more churn customers to make sure they retain the services.

The dataset has too many categorical features, hence mean values of the features are present in the vicinity of 0.

We will now move on to the EDA section and look into the features with more detail!

2 Exploratory Data Analysis

[11]:
```python
#Dividing features into Numerical and Categorical :

col = list(df1.columns)
categorical_features = []
numerical_features = []
for i  in col:
    if len(df1[i].unique()) > 6:
        numerical_features.append(i)
    else:
        categorical_features.append(i)

print('Categorical Features :',*categorical_features)
print('Numerical Features :',*numerical_features)
```

```
Categorical Features : gender SeniorCitizen Partner Dependents PhoneService
MultipleLines InternetService OnlineSecurity OnlineBackup DeviceProtection
TechSupport StreamingTV StreamingMovies Contract PaperlessBilling PaymentMethod
Churn
Numerical Features : tenure MonthlyCharges TotalCharges
```

Here, categorical features are defined if the the attribute has less than 6 unique elements else it is a numerical feature.

Typical approach for this division of features can also be based on the datatypes of the elements of the respective attribute.

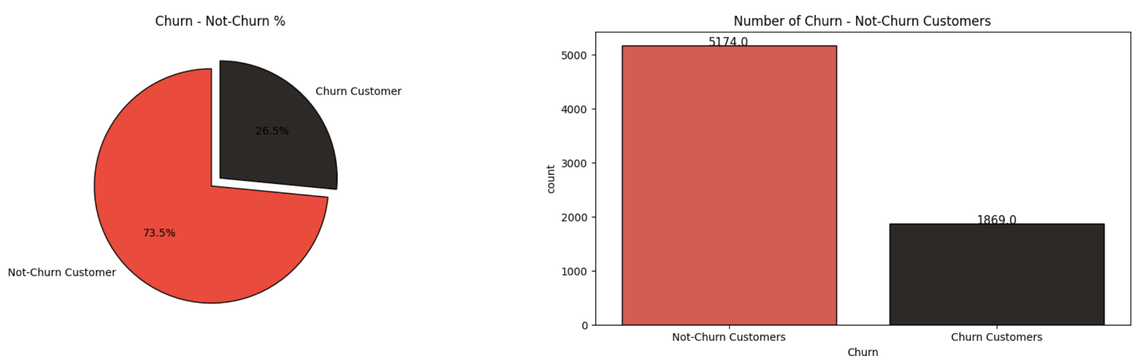
Eg : datatype = integer, attribute = numerical feature ; datatype = string, attribute = categorical feature

For this dataset, as the number of features are less, we can manually check the dataset as well.

2.1 Target Variable Visualization (Churn)

[12]:
```python
colors = ['#E94B3C','#2D2926']
# Assuming 'Churn' is a categorical variable with values 'Yes' and 'No'

l = list(df1['Churn'].value_counts())
circle = [l[0] / sum(l) * 100, l[1] / sum(l) * 100]

# Create subplots
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(20, 5))

# Pie chart
```

```
axes[0].pie(circle, labels=['Not-Churn Customer', 'Churn Customer'],
↪autopct='%1.1f%%', startangle=90, explode=(0.1, 0),
            colors=colors, wedgeprops={'edgecolor': 'black', 'linewidth': 1,
↪'antialiased': True})
axes[0].set_title('Churn - Not-Churn %')

# Countplot
ax = sns.countplot(x='Churn', data=df1, palette=colors, edgecolor='black')
for rect in ax.patches:
    ax.text(rect.get_x() + rect.get_width() / 2, rect.get_height() + 2, rect.
↪get_height(),
            horizontalalignment='center', fontsize=11)
ax.set_xticklabels(['Not-Churn Customers', 'Churn Customers'])

ax.set_title('Number of Churn - Not-Churn Customers')

plt.show()
```



The dataset is unbalanced in a near about 3 : 1 ratio for Not-Churn : Churn customers!

Due to this, predictions will be biased towards Not-Churn customers.

Visualizations will also display this bias!

2.2 Categorical Features vs Target Variable (Churn)

[13]:
```
categorical_features.remove('Churn')
```

We will remove Churn, target variable, from the categorical features list for visualization purposes.

[14]:
```
l1 = ['gender','SeniorCitizen','Partner','Dependents'] # Customer Information
l2 =
↪['PhoneService','MultipleLines','InternetService','StreamingTV','StreamingMovies',
      'OnlineSecurity','OnlineBackup','DeviceProtection','TechSupport'] #
↪Services Signed Up for!
```

```
l3 = ['Contract','PaperlessBilling','PaymentMethod'] # Payment Information
```

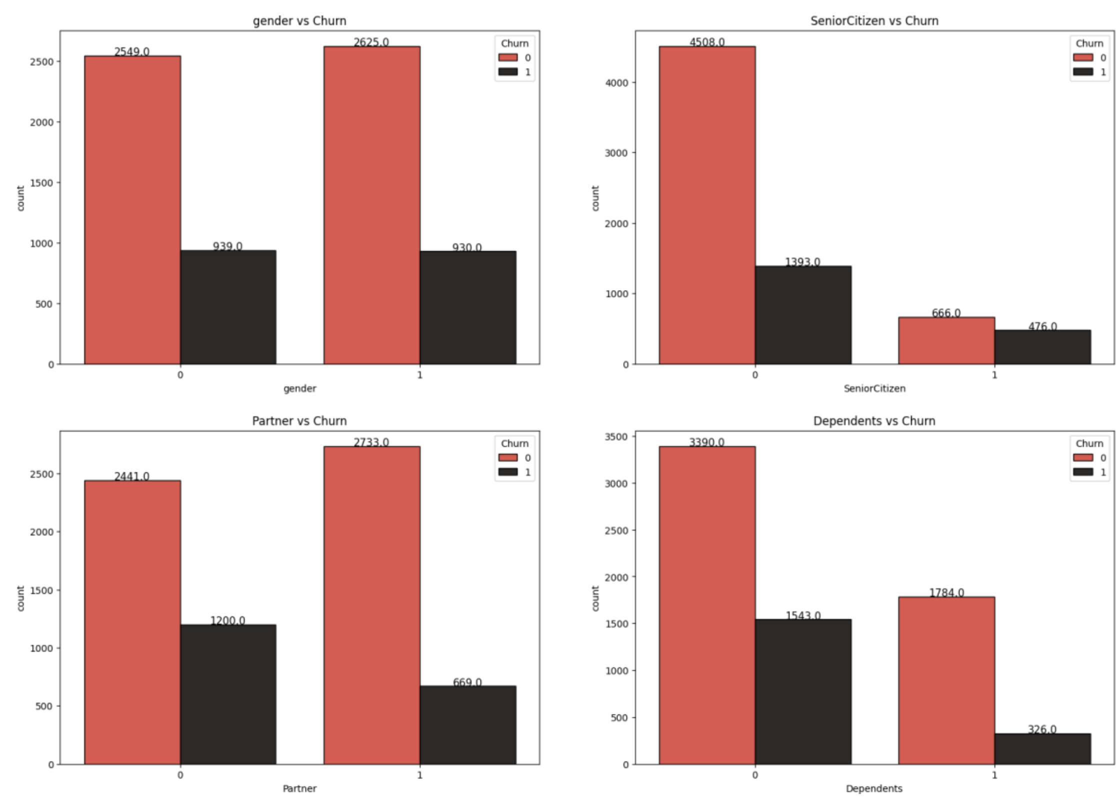
We have too many categorical features in this dataset!

We divide them into 3 groups depending on their values or based on the column name!

2.2.1 Group 1 : Customer Information :

gender | SeniorCitizen | Partner | Dependents |

[15]:
```
fig = plt.subplots(nrows = 2,ncols = 2,figsize = (20,14))
for i in range(len(l1)):
    plt.subplot(2,2,i+1)
    ax = sns.countplot(x=l1[i],data = df1,hue = "Churn",palette =␣
 ↪colors,edgecolor = 'black')
    for rect in ax.patches:
        ax.text(rect.get_x() + rect.get_width() / 2, rect.get_height() + 2,␣
 ↪rect.get_height(), horizontalalignment='center', fontsize = 11)
    title = l1[i] + ' vs Churn'
    plt.title(title);
```



Customer churning for male & female customers is very similar to each other!

Similarly, number of SeniorCitizen customers is pretty low! Out of that, we can observe a near about 40% churn of SeniorCitizen customers. It accounts for a total of 476 customers out of 1142 Senior Citizen customers.

Customers who are housing with a Partner churned less as compared to those not living with a Partner.

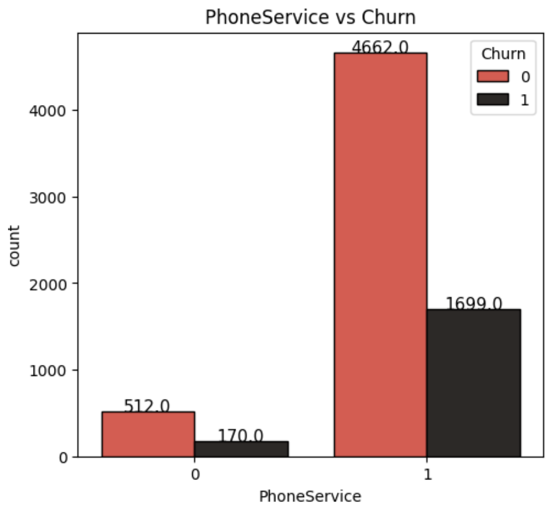
Similarly, churning is high for the customers that don't have Dependents with them!

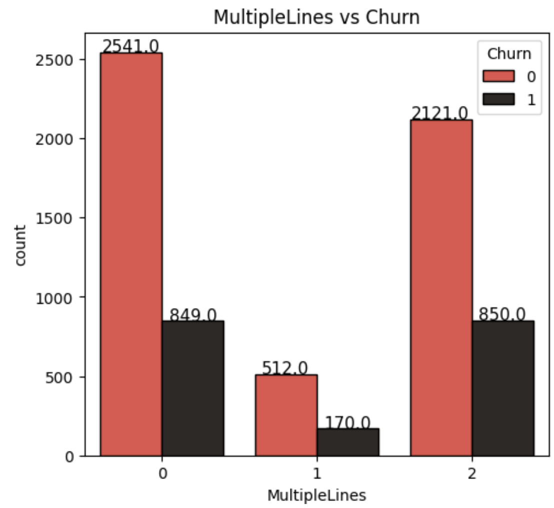
2.2.2 Group 2: Services Subscribed by the Customer :

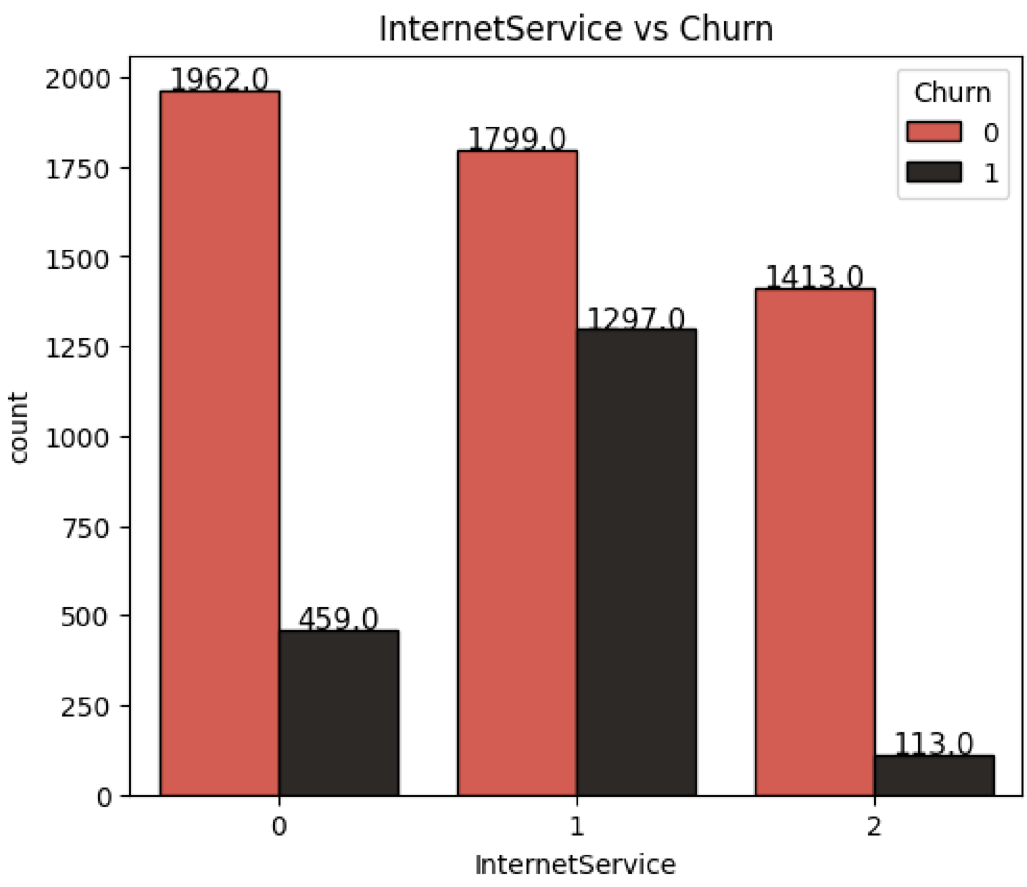
For visualization purposes, we will create 2 groups!

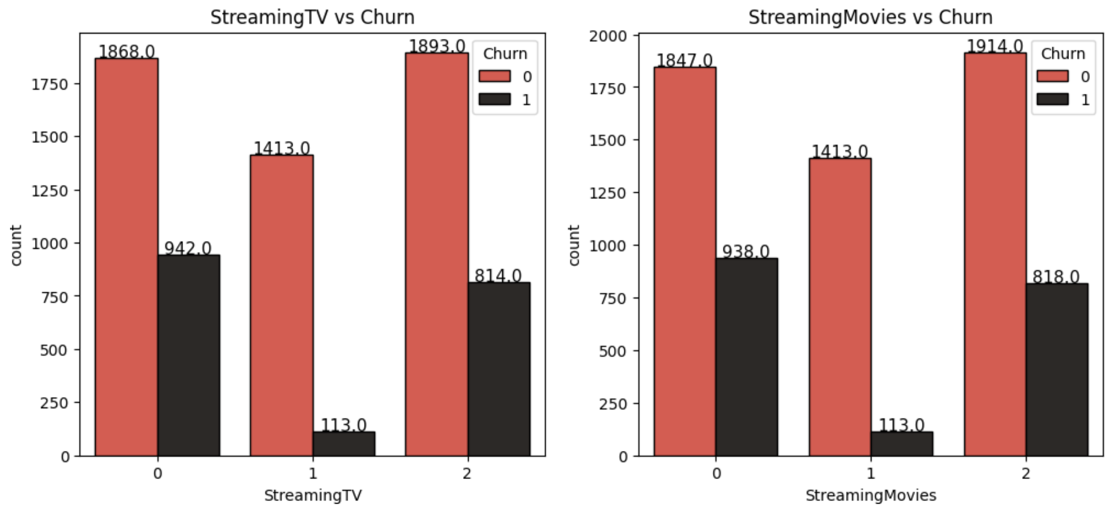
PhoneService | MultipleLines | InternetService | StreamingTV | StreamingMovies |

[16]:
```
fig = plt.subplots(nrows = 1,ncols = 2,figsize = (12,5))

for i in range(len(l2[0:2])):
    plt.subplot(1,2,i + 1)
    ax = sns.countplot(x=l2[i],data = df1,hue = "Churn",palette =␣
 ↪colors,edgecolor = 'black')
    for rect in ax.patches:
        ax.text(rect.get_x() + rect.get_width() / 2, rect.get_height() + 2,␣
 ↪rect.get_height(), horizontalalignment='center', fontsize = 11)
    title = l2[i] + ' vs Churn'
    plt.title(title);

fig = plt.subplots(nrows = 1, ncols = 1, figsize = (6,5))

plt.subplot(1,1,1)
ax = sns.countplot(x=l2[2],data = df1,hue = "Churn",palette = colors,edgecolor␣
 ↪= 'black')
for rect in ax.patches:
    ax.text(rect.get_x() + rect.get_width() / 2, rect.get_height() + 2, rect.
 ↪get_height(), horizontalalignment='center', fontsize = 11)
title = l2[2] + ' vs Churn'
plt.title(title);

fig = plt.subplots(nrows = 1,ncols = 2,figsize = (12,5))

for i in range(len(l2[3:5])):
    plt.subplot(1,2,i + 1)
    ax = sns.countplot(x=l2[i + 3],data = df1,hue = "Churn",palette =␣
 ↪colors,edgecolor = 'black')
    for rect in ax.patches:
        ax.text(rect.get_x() + rect.get_width() / 2, rect.get_height() + 2,␣
 ↪rect.get_height(), horizontalalignment='center', fontsize = 11)
    title = l2[i + 3] + ' vs Churn'
    plt.title(title);
```


PhoneService vs Churn
Churn
0
1
4662.0
1699.0
512.0
170.0
count
PhoneService
0
1
0
1000
2000
3000
4000


MultipleLines vs Churn
Churn
0
1
2541.0
849.0
512.0
170.0
2121.0
850.0
count
MultipleLines
0
1
2
0
500
1000
1500
2000
2500


InternetService vs Churn
Churn
0
1
1962.0
459.0
1799.0
1297.0
1413.0
113.0
count
InternetService
0
1
2
0
250
500
750
1000
1250
1500
1750
2000



For PhoneService, despite having no phone service, more customers were retained as compared to the number of customers who dropped the services.

In case of MultipleLines, churn rate in when the Multiplelines are present or not is the same.

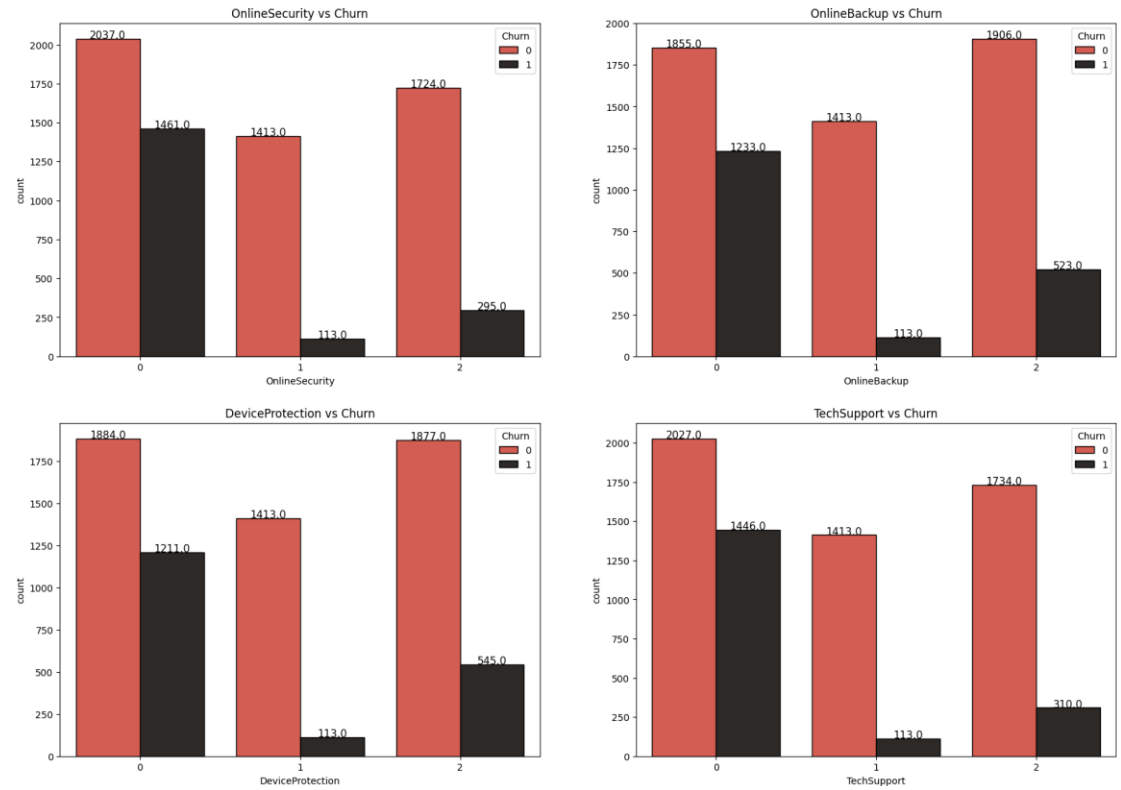
A high number of customers have displayed their resistance towards the use of Fiber optic cables for providing the InternetService. On the contrary, from the above graph, customers prefer using DSL for their InternetService!

StreamingTV and StreamingMovies display an identical graph. Irrespective of being subscribed to StreamingTV & StreamingMovies, a lot of customers have been churned. Looks like the streaming content was not entirely at fault!

2.2.3 Group 2: Services Subscribed by the Customer :

OnlineSecurity | OnlineBackup | DeviceProtection | TechSupport |

[17]:
```
fig = plt.subplots(nrows = 2,ncols = 2,figsize = (20,14))
for i in range(len(l2[-4:])):
    plt.subplot(2,2,i + 1)
    ax = sns.countplot(x=l2[-4 + i],data = df1,hue = "Churn",palette =␣
 ↪colors,edgecolor = 'black')
    for rect in ax.patches:
        ax.text(rect.get_x() + rect.get_width() / 2, rect.get_height() + 2,␣
 ↪rect.get_height(), horizontalalignment='center', fontsize = 11)
    title = l2[-4 + i] + ' vs Churn'
    plt.title(title);
```



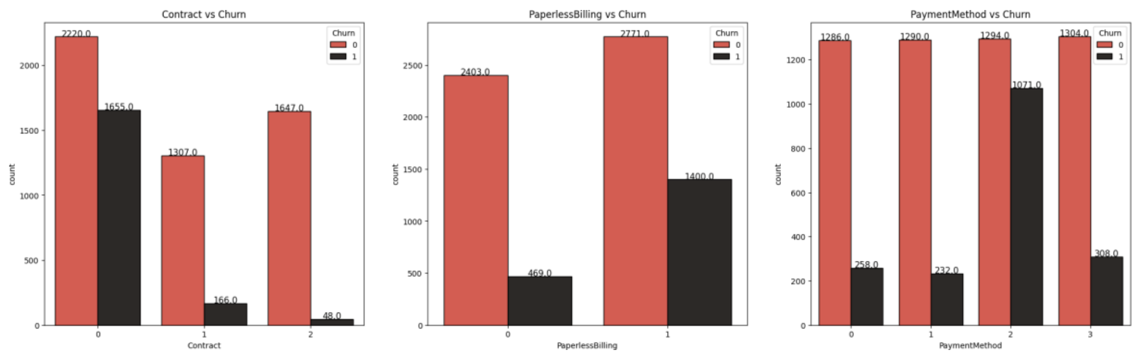
When it comes down to catering the customers, services w.r.t OnlineSecurity, OnlineBackup, DeviceProtection & TechSupport are crucial from the above visualizations!

A high number of customers have switched their service provider when it comes down poor services with the above mentioned features.

2.2.4 Group 3 : Contract | PaperlessBilling | PaymentMethod

[18]:
```
fig = plt.subplots(nrows = 1,ncols = 3,figsize = (25,7))

plt.subplot(1,3,1)
ax = sns.countplot(x=l3[0],data = df1,hue = "Churn",palette = colors,edgecolor
 ↪= 'black')
for rect in ax.patches:
    ax.text(rect.get_x() + rect.get_width() / 2, rect.get_height() + 2, rect.
 ↪get_height(), horizontalalignment='center', fontsize = 11)
title = l3[0] + ' vs Churn'
plt.title(title);

plt.subplot(1,3,2)
ax = sns.countplot(x=l3[1],data = df1,hue = "Churn",palette = colors,edgecolor
 ↪= 'black')
```

```
for rect in ax.patches:
    ax.text(rect.get_x() + rect.get_width() / 2, rect.get_height() + 2, rect.
↪get_height(), horizontalalignment='center', fontsize = 11)
title = l3[1] + ' vs Churn'
plt.title(title);

plt.subplot(1,3,3)
ax = sns.countplot(x=l3[2],data = df1,hue = "Churn",palette = colors,edgecolor␣
↪= 'black')
for rect in ax.patches:
    ax.text(rect.get_x() + rect.get_width() / 2, rect.get_height() + 2, rect.
↪get_height(), horizontalalignment='center', fontsize = 11)
title = l3[2] + ' vs Churn'
plt.title(title);
```



Customer churning for a Month-to-Month based Contract is quite high. This is probably because the customers are testing out the varied services available to them and hence, in order to save money, 1 month service is tested out!

Another reason can be the overall experience with the internet service, streaming service and phone service were not consistent. Every customer has a different priority and hence if one of the 3 was upto par, the entire service was cutoff!

PaperlessBilling displays a high number of customers being churned out. This is probably because of some payment issue or receipt issues.

Customers clearly resented the Electronic check PaymentMethod. Out of the 2365 number of bills paid using Electronic check, a staggering 1071 customers exited the pool of service due to this payment method. Company definitely needs to either drop Electronic check method or make it hassle-free and user-friendly

2.3 Categorical Features vs Positive Target Variable (Churn Cases) :

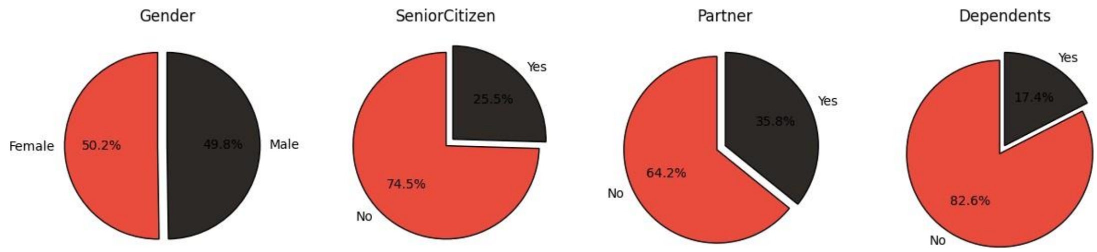
We will now point our attention directly towards to the churn customers!

3.3.1 Group 1 : Customer Information :

gender | SeniorCitizen | Partner | Dependents |

[19]:
```python
gender = df1[df1['Churn'] == 1]['gender'].value_counts()
gender = [gender[0] / sum(gender) * 100, gender[1] / sum(gender) * 100] #␣
↪Female / Male

seniorcitizen = df1[df1['Churn'] == 1]['SeniorCitizen'].value_counts()
seniorcitizen = [seniorcitizen[0] / sum(seniorcitizen) * 100,seniorcitizen[1] /␣
↪sum(seniorcitizen) * 100] # No - Yes

partner = df1[df1['Churn'] == 1]['Partner'].value_counts()
partner = [partner[0] / sum(partner) * 100,partner[1] / sum(partner) * 100] #␣
↪No - Yes

dependents = df1[df1['Churn'] == 1]['Dependents'].value_counts()
dependents = [dependents[0] / sum(dependents) * 100,dependents[1] /␣
↪sum(dependents) * 100] # No - Yes
```

[20]:
```python
ax,fig = plt.subplots(nrows = 1,ncols = 4,figsize = (15,15))

plt.subplot(1,4,1)
plt.pie(gender,labels = ['Female','Male'],autopct='%1.1f%%',startangle =␣
↪90,explode = (0.1,0),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('Gender');

plt.subplot(1,4,2)
plt.pie(seniorcitizen,labels = ['No', 'Yes'],autopct='%1.1f%%',startangle =␣
↪90,explode = (0,0.1),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('SeniorCitizen');

plt.subplot(1,4,3)
plt.pie(partner,labels = ['No','Yes'],autopct='%1.1f%%',startangle = 90,explode␣
↪= (0.1,0),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('Partner');

plt.subplot(1,4,4)
plt.pie(dependents,labels = ['No','Yes'],autopct='%1.1f%%',startangle =␣
↪90,explode = (0.1,0),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('Dependents');
```



We can observe a clear cut 50% - 50% split between the male and female customers that have switched their services. Hence, the reason for switching is something related to the service or some process which the customers reacted badly!

75% of the churned customers are not SeniorCitizen! This is a major info that the company needs to divert it's attention towards!

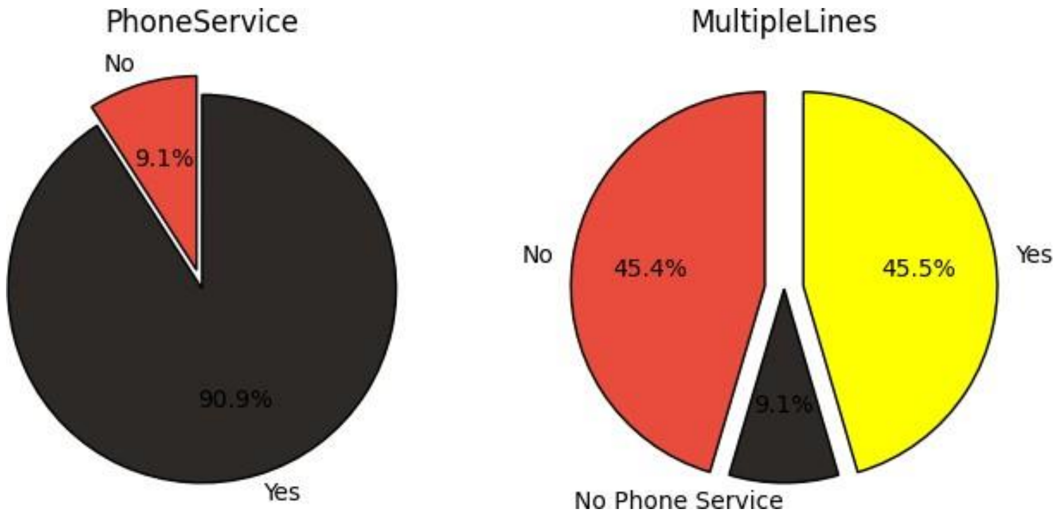
Customers living by themselves have cutoff the services. From Partners & Dependents data, average of 73.4% of customers churned out were living by themselves.

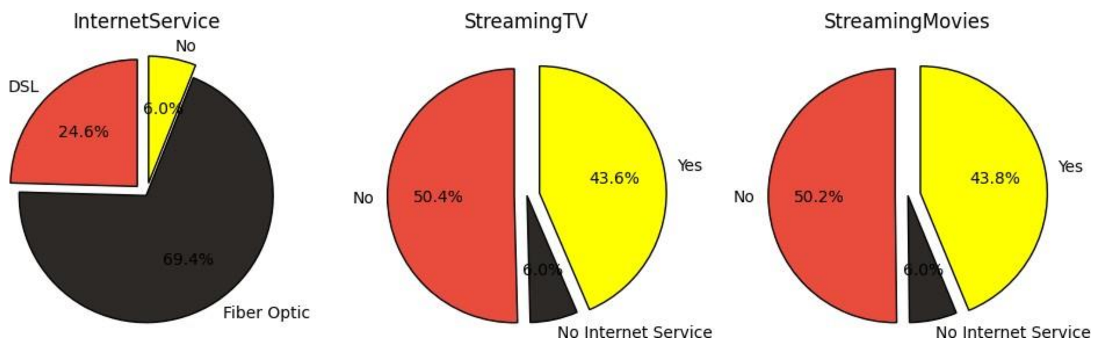
3.3.2 Group 2: Services Subscribed by the Customer :

PhoneService | MultipleLines | InternetService | StreamingTV | StreamingMovies |

[21]:
```
phoneservice = df1[df1['Churn'] == 1]['PhoneService'].value_counts()
phoneservice = [phoneservice[0] / sum(phoneservice) * 100, phoneservice[1] /
 ↪sum(phoneservice) * 100] # No - Yes

multiplelines = df1[df1['Churn'] == 1]['MultipleLines'].value_counts()
multiplelines = [multiplelines[0] / sum(multiplelines) * 100,multiplelines[1] /
 ↪sum(multiplelines) * 100, multiplelines[2] / sum(multiplelines) * 100] # No
 ↪- No Phone Service - Yes

internetservice = df1[df1['Churn'] == 1]['InternetService'].value_counts()
internetservice = [internetservice[0] / sum(internetservice) *
 ↪100,internetservice[1] / sum(internetservice) * 100, internetservice[2] /
 ↪sum(internetservice) * 100] # DSL - Fiber Optic - No

streamingtv = df1[df1['Churn'] == 1]['StreamingTV'].value_counts()
streamingtv = [streamingtv[0] / sum(streamingtv) * 100,streamingtv[1] /
 ↪sum(streamingtv) * 100, streamingtv[2] / sum(streamingtv) * 100] # No - No
 ↪Internet Service - Yes

streamingmovies = df1[df1['Churn'] == 1]['StreamingMovies'].value_counts()
streamingmovies = [streamingmovies[0] / sum(streamingmovies) *
 ↪100,streamingmovies[1] / sum(streamingmovies) * 100, streamingmovies[2] /
 ↪sum(streamingmovies) * 100] # No - No Internet Service - Yes
```

[22]:
```
colors = ['#E94B3C','#2D2926' , '#FFFF00' ]
ax,fig = plt.subplots(nrows = 1,ncols = 2,figsize = (8,8))

plt.subplot(1,2,1)
plt.pie(phoneservice,labels = ['No', 'Yes'],autopct='%1.1f%%',startangle =␣
↪90,explode = (0.1,0),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('PhoneService');

plt.subplot(1,2,2)
plt.pie(multiplelines,labels = ['No','No Phone Service','Yes'],autopct='%1.
↪1f%%',startangle = 90,explode = (0.1,0,0.1),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('MultipleLines');

ax,fig = plt.subplots(nrows = 1,ncols = 3,figsize = (12,12))

plt.subplot(1,3,1)
plt.pie(internetservice,labels = ['DSL', 'Fiber Optic','No'],autopct='%1.
↪1f%%',startangle = 90,explode = (0.1,0,0.1),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('InternetService');

plt.subplot(1,3,2)
plt.pie(streamingtv,labels = ['No', 'No Internet Service','Yes'],autopct='%1.
↪1f%%',startangle = 90,explode = (0.1,0,0.1),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('StreamingTV');

plt.subplot(1,3,3)
plt.pie(streamingmovies,labels = ['No', 'No Internet␣
↪Service','Yes'],autopct='%1.1f%%',startangle = 90,explode = (0.1,0,0.
↪1),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('StreamingMovies');
```





Despite providing PhoneService, a high percentage of customers have switched!

Similarly, availability of MultipleLines did not matter, as customer unsubscription was carried out regardless!

Customers definitely did not appreciate the approach of Fiber Optic cables for providing InternetService with a solid 70% opting out from the services!

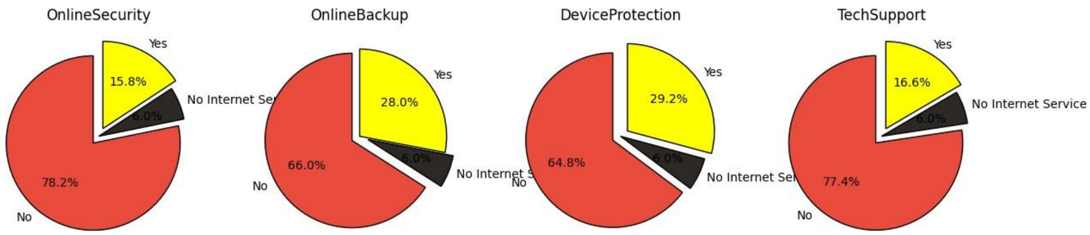
For StreamingTV & StreamingMovies, customers without these services definitely cancelled their subscription, however an average of 43.7% of customers switched despite consuming the streaming content.

3.3.3 Group 2: Services Subscribed by the Customer :

OnlineSecurity | OnlineBackup | DeviceProtection | TechSupport |

[23]:
```
onlinesecurity = df1[df1['Churn'] == 1]['OnlineSecurity'].value_counts()
onlinesecurity = [onlinesecurity[0] / sum(onlinesecurity) *
↪100,onlinesecurity[1] / sum(onlinesecurity) * 100, onlinesecurity[2] /
↪sum(onlinesecurity) * 100] # No - No Internet Service - Yes

onlinebackup = df1[df1['Churn'] == 1]['OnlineBackup'].value_counts()
onlinebackup = [onlinebackup[0] / sum(onlinebackup) * 100,onlinebackup[1] /
↪sum(onlinebackup) * 100, onlinebackup[2] / sum(onlinebackup) * 100] # No -
↪No Internet Service - Yes

deviceprotection = df1[df1['Churn'] == 1]['DeviceProtection'].value_counts()
deviceprotection = [deviceprotection[0] / sum(deviceprotection) *
↪100,deviceprotection[1] / sum(deviceprotection) * 100, deviceprotection[2] /
↪sum(deviceprotection) * 100] # No - No Internet Service - Yes

techsupport = df1[df1['Churn'] == 1]['TechSupport'].value_counts()
techsupport = [techsupport[0] / sum(techsupport) * 100,techsupport[1] /
↪sum(techsupport) * 100, techsupport[2] / sum(techsupport) * 100] # No - No
↪Internet Service - Yes
```

[24]:
```
colors = ['#E94B3C','#2D2926' , '#FFFF00' ]
ax,fig = plt.subplots(nrows = 1,ncols = 4,figsize = (15,15))

plt.subplot(1,4,1)
plt.pie(onlinesecurity,labels = ['No', 'No Internet Service','Yes'],autopct='%1.
↪1f%%',startangle = 90,explode = (0.1,0,0.1),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('OnlineSecurity');

plt.subplot(1,4,2)
plt.pie(onlinebackup,labels = ['No', 'No Internet Service','Yes'],autopct='%1.
↪1f%%',startangle = 90,explode = (0.1,0.1,0),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('OnlineBackup');

plt.subplot(1,4,3)
plt.pie(deviceprotection,labels = ['No', 'No Internet
↪Service','Yes'],autopct='%1.1f%%',startangle = 90,explode = (0.1,0,0.
↪1),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('DeviceProtection');

plt.subplot(1,4,4)
plt.pie(techsupport,labels = ['No', 'No Internet Service','Yes'],autopct='%1.
↪1f%%',startangle = 90,explode = (0.1,0,0.1),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('TechSupport');
```



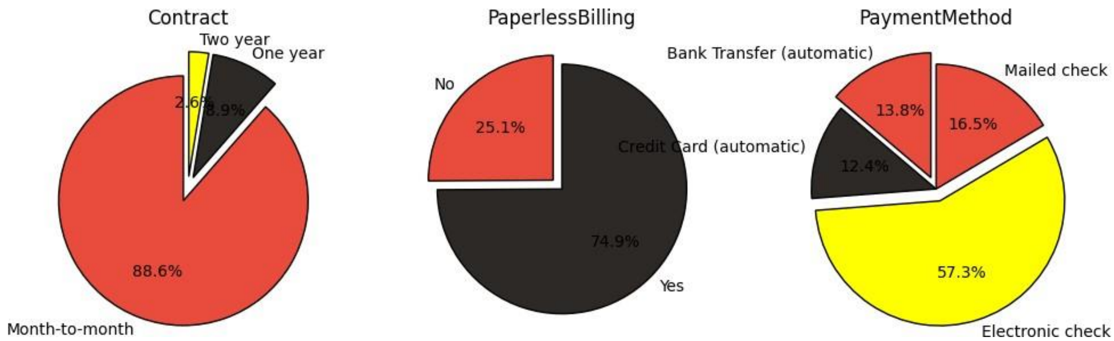
Above pie charts stress out the significance of providing OnlineSecurity, OnlineBackup, DeviceProtection & TechSupport as an average of 71.6% customers cutoff their services due to lack of these features!

3.3.4 Group 3 : Contract | PaperlessBilling | PaymentMethod |

[25]:
```
contract = df1[df1['Churn'] == 1]['Contract'].value_counts()
contract = [contract[0] / sum(contract) * 100, contract[1] / sum(contract) *
 ↪100, contract[2] / sum(contract) * 100] # Month-to-month - One year - Two
 ↪year

paperlessbilling = df1[df1['Churn'] == 1]['PaperlessBilling'].value_counts()
paperlessbilling = [paperlessbilling[0] / sum(paperlessbilling) *
 ↪100,paperlessbilling[1] / sum(paperlessbilling) * 100] # No - Yes

paymentmethod = df1[df1['Churn'] == 1]['PaymentMethod'].value_counts()
paymentmethod = [paymentmethod[0] / sum(paymentmethod) * 100, paymentmethod[1] /
 ↪sum(paymentmethod) * 100,
            paymentmethod[2] / sum(paymentmethod) * 100, paymentmethod[3] /
 ↪sum(paymentmethod) * 100]
            # Bank Transfer (automatic) - Credit Card (automatic) - Electronic
 ↪check - Mailed check
```

[26]:
```
colors = ['#E94B3C','#2D2926' , '#FFFF00' ]
ax,fig = plt.subplots(nrows = 1,ncols = 3,figsize = (12,12))

plt.subplot(1,3,1)
plt.pie(contract,labels = ['Month-to-month','One year','Two year'],autopct='%1.
 ↪1f%%',startangle = 90,explode = (0.1,0.1,0.1),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('Contract');

plt.subplot(1,3,2)
plt.pie(paperlessbilling,labels = ['No', 'Yes'],autopct='%1.1f%%',startangle =
 ↪90,explode = (0.1,0),colors = colors,
       wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('PaperlessBilling');
```

```
plt.subplot(1,3,3)
plt.pie(paymentmethod,labels = ['Bank Transfer (automatic)','Credit Card␣
↪(automatic)','Electronic check','Mailed check'],autopct='%1.1f%%',startangle␣
↪= 90,explode = (0.1,0,0.1,0),colors = colors,
        wedgeprops = {'edgecolor' : 'black','linewidth': 1,'antialiased' : True})
plt.title('PaymentMethod');
```



Month-to-Month Contract duration has the dominating share when it comes churning with a massive 88.6% customers!

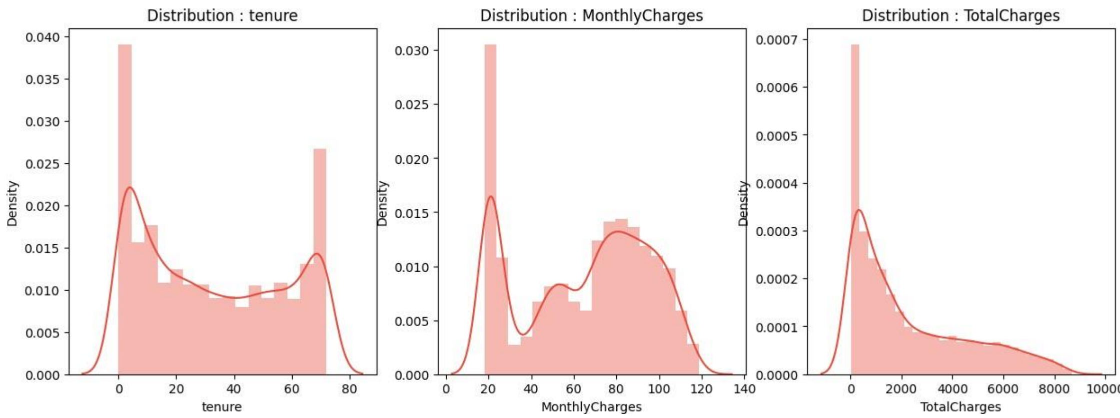
PaperlessBilling does not seemed to be appreciated by the customers!

Electronic check definitely needs to be sorted as it accounts for 57.3% of churn. It is then followed by Mailed check, Bank Transfer (automatic) & Credit Card (automatic)!

2.4 Numerical Features :

Distribution of Numerical Features :

[27]:
```
fig, ax = plt.subplots(nrows = 1,ncols = 3,figsize = (15,5))
for i in range(len(numerical_features)):
    plt.subplot(1,3,i+1)
    sns.distplot(df1[numerical_features[i]],color = colors[0])
    title = 'Distribution : ' + numerical_features[i]
    plt.title(title)
plt.show()
```

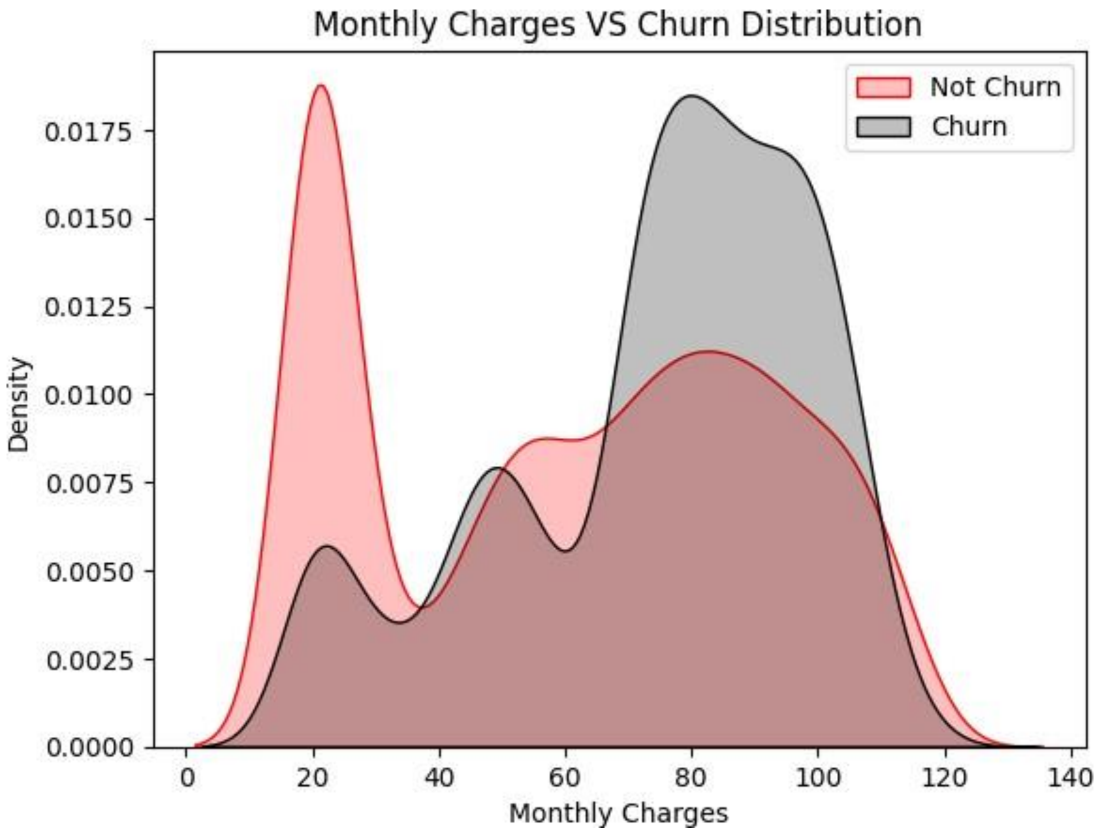


tenure and MonthlyCharges kind of create a bimodal distribution with peaks present at 0 - 70 and 20 - 80 respectively.

TotalCharges displays a positively or rightly skewed distribution.

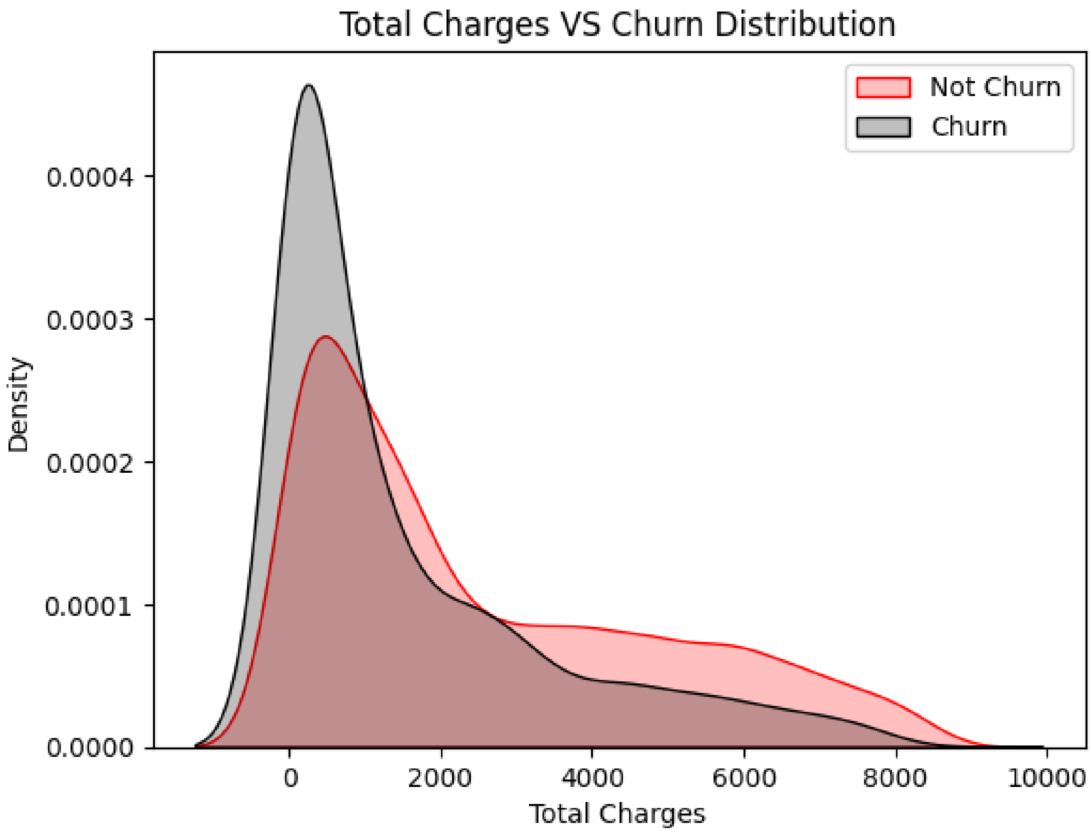
2.5 Numerical Features w.r.t Target Variable (Outcome) :

[28]:
```
ax = sns.kdeplot(df1.MonthlyCharges[(df1["Churn"] == 0) ],
                 color="Red", shade = True);
ax = sns.kdeplot(df1.MonthlyCharges[(df1["Churn"] == 1) ],
                 ax =ax, color="Black", shade= True);
ax.legend(["Not Churn","Churn"],loc='upper right');
ax.set_ylabel('Density');
ax.set_xlabel('Monthly Charges');
ax.set_title('Monthly Charges VS Churn Distribution');
```



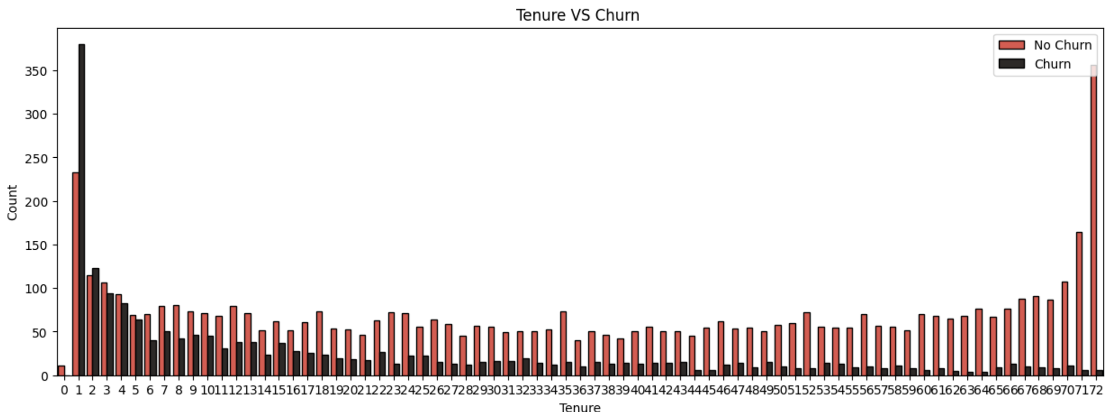
High Monthly Charges are also one of a reason which makes Customers more likely to churn

[29]:
```
ax = sns.kdeplot(df1.TotalCharges[(df1["Churn"] == 0) ],
                 color="red", shade = True);
ax = sns.kdeplot(df1.TotalCharges[(df1["Churn"] == 1) ],
                 ax =ax, color="black", shade= True);
ax.legend(["Not Churn","Churn"],loc='upper right');
ax.set_ylabel('Density');
ax.set_xlabel('Total Charges');
ax.set_title('Total Charges VS Churn Distribution');
```



High Total Charges are also one of a reason which makes Customers more likely to churn,there might be an issue with pricing system which needs to addressed

[30]:
```
plt.figure(figsize = (15,5))
sns.countplot(x="tenure", data=df1, hue="Churn", palette = colors,␣
 ↪edgecolor="black")
plt.title("Tenure VS Churn ")
plt.xlabel("Tenure")
plt.ylabel("Count")
plt.legend(["No Churn", "Churn"], loc="upper right")
plt.show()
```

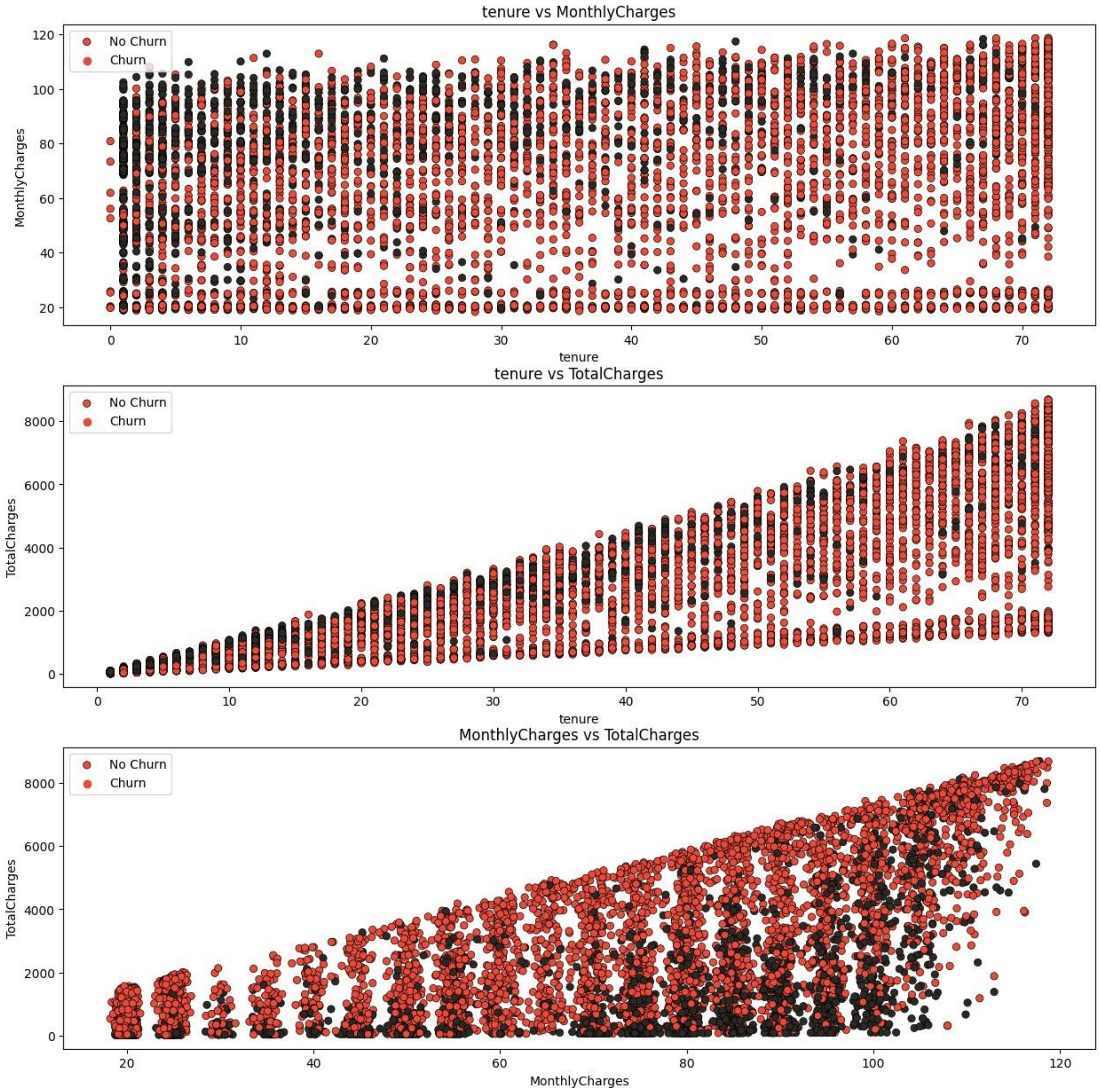


Considering tenure, a high number of customers have left after the 1st month. This high cancellation of services continues for 4 - 5 months but the churn customers have reduced since the 1st month. As the tenure increases, customers dropping out decreases.

This results in low customer churning as the tenure increases. It displays a symmetrical graph with the left side dominating with churn numbers and right side dominating with low churn numbers.

2.6 Numerical features vs Numerical features w.r.t Target variable (Churn) :

[31]:
```
a = 0
fig,ax = plt.subplots(nrows = 3,ncols = 1,figsize = (15,15))
for i in range(len(numerical_features)):
    for j in range(len(numerical_features)):
        if i != j and j > i:
            a += 1
            plt.subplot(3,1,a)
            sns.scatterplot(x = numerical_features[i],y =␣
↪numerical_features[j],data = df1,hue = "Churn",palette = colors,edgecolor =␣
↪"black");
            plt.legend(["No Churn","Churn"],loc = 'upper left',)
            title = numerical_features[i] + ' vs ' + numerical_features[j]
            plt.title(title)
```



For tenure of 0 - 20 months period, churning of customers quite at any MonthlyCharges values. For a tenure period from 20 - 60 months, customers at the top end of the MonthlyCharges values, 70 - 120, start to drop out from the services.

For TotalCharges vs tenure, as tenure increases, TotalCharges increase as well! Customers opting out from their plans are the ones who are charged the highest of their tenure period alongwith a few customers whose Total Charges rank in the middle!

Customers seemed to have decided to cancel their subscriptions when the MonthlyCharges reach 70 and above.

3 Summary Of EDA

Values of features for customer churn cases : Categorical Features (Order) :

gender : Male = Female

SeniorCitizen : No SeniorCitizen > SeniorCitizen

Partner : No Partner > Partner

Dependents : No Dependent > Dependent

PhoneService : PhoneService > No PhoneService

MultipleLines : MultipleLines > No MultipleLines > No PhoneService

InternetService : Fiber Optic > DSL > No InternetService

OnlineSecurity : Absent > Present > No InternetService

OnlineBackup : Absent > Present > No InternetService

DeviceProtection : Absent > Present > No InternetService

TechSupport : Absent > Present > No InternetService

StreamingTV : Absent > Present > No InternetService

StreamingMovies : Absent > Present > No InternetService

Contract : Month-to-Month > One year > Two year

PaperlessBilling : Present > Absent

PaymentMethod : Electronic check > Mailed check > Bank Transfer (automatic) > Credit Card (automatic)!

According to the EDA, these order / range of values results in customer churn!

4 Feature Engineering

4.1 Data Balancing using SMOTE :

In order to cope with unbalanced data, there are 2 options :

Undersampling : Trim down the majority samples of the target variable.

Oversampling : Increase the minority samples of the target variable to the majority samples.

After doing trial-error with undersampling & oversampling, we have decided to go with oversampling!

For data balancing, we will use imblearn.

[32]:
```
import imblearn
from collections import Counter
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
from sklearn.impute import SimpleImputer
```

[33]:
```
cols = list(df1.columns)
cols.remove("Churn")

x = df1.loc[:,cols]
y = df1.loc[:,"Churn"]


imputer = SimpleImputer(strategy="mean")
x = imputer.fit_transform(x)

over = SMOTE(sampling_strategy = 1)

x1,y1 = over.fit_resample(x,y)
print("Class distribution before SMOTE:", Counter(y))
print("Class distribution after SMOTE:", Counter(y1))
```

```
Class distribution before SMOTE: Counter({0: 5174, 1: 1869})
Class distribution after SMOTE: Counter({0: 5174, 1: 5174})
```

4.2 Data Leakage :

Data Leakage is the problem when the information outside the training data is used for model creation. It is one of the most ignored problem.

In order to create robust models, solving data leakage is a must! Creation of overly optimistic models which are practically useless & cannot be used in production have become common.

Thus, in order to avoid Data Leakage, it is advised to use train-test-split before any transformations. Execute the transformations according to the training data for the training as well as test data.

[34]:
```
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(x1, y1, test_size = 0.20,␣
↪random_state = 2)
```

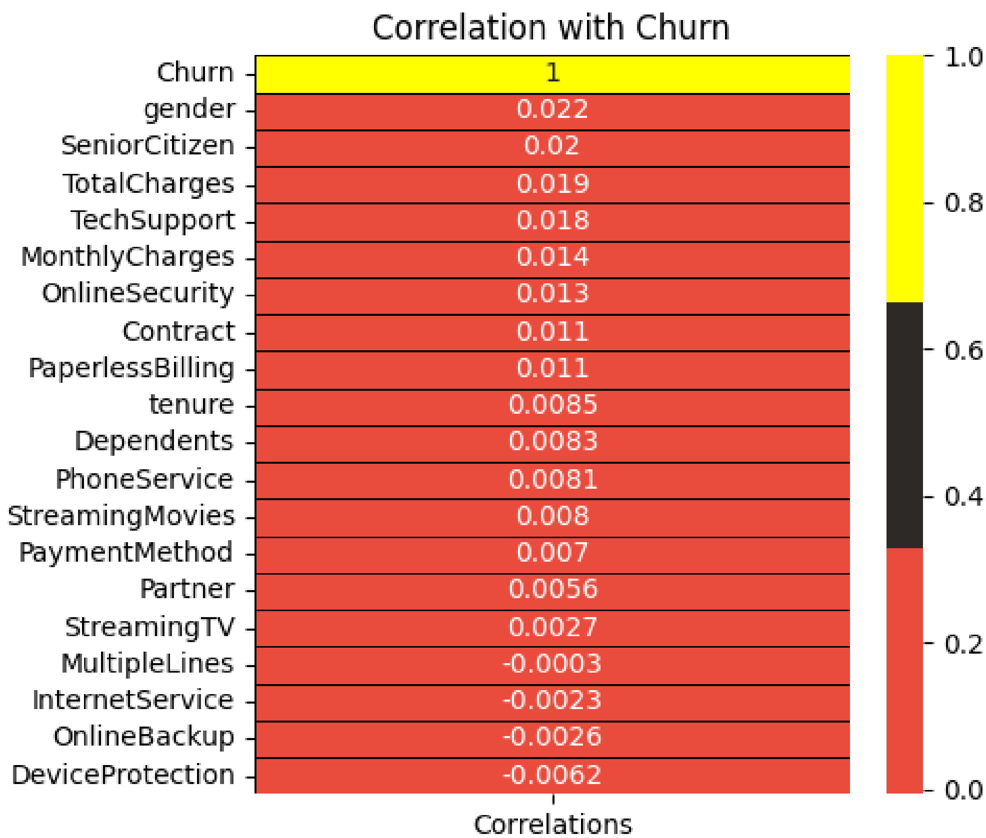
4.3 Correlation Matrix :

[35]:
```
# Creating a DataFrame from x_train
x_train_df = pd.DataFrame(x_train, columns=cols)

# Creating a DataFrame for y_train
y_train_df = pd.DataFrame({"Churn": y_train})

# Concatenate x_train_df and y_train_df along columns
x_train_test = pd.concat([x_train_df, y_train_df], axis=1)
```

In order to visualize the correlation matrix, we create a new dataframe that contains values from x_train & y_train.

Thus, we reject anything outside the training data to avoid data leakage.

[36]:
```
# Calculate correlation matrix
corr = x_train_test.corr()['Churn'].sort_values(ascending=False).to_frame()
corr.columns = ['Correlations']

# Plot heatmap
plt.subplots(figsize=(5, 5))
sns.heatmap(corr, annot=True, cmap=colors, linewidths=0.4, linecolor='black')
plt.title('Correlation with Churn')
plt.show()
```



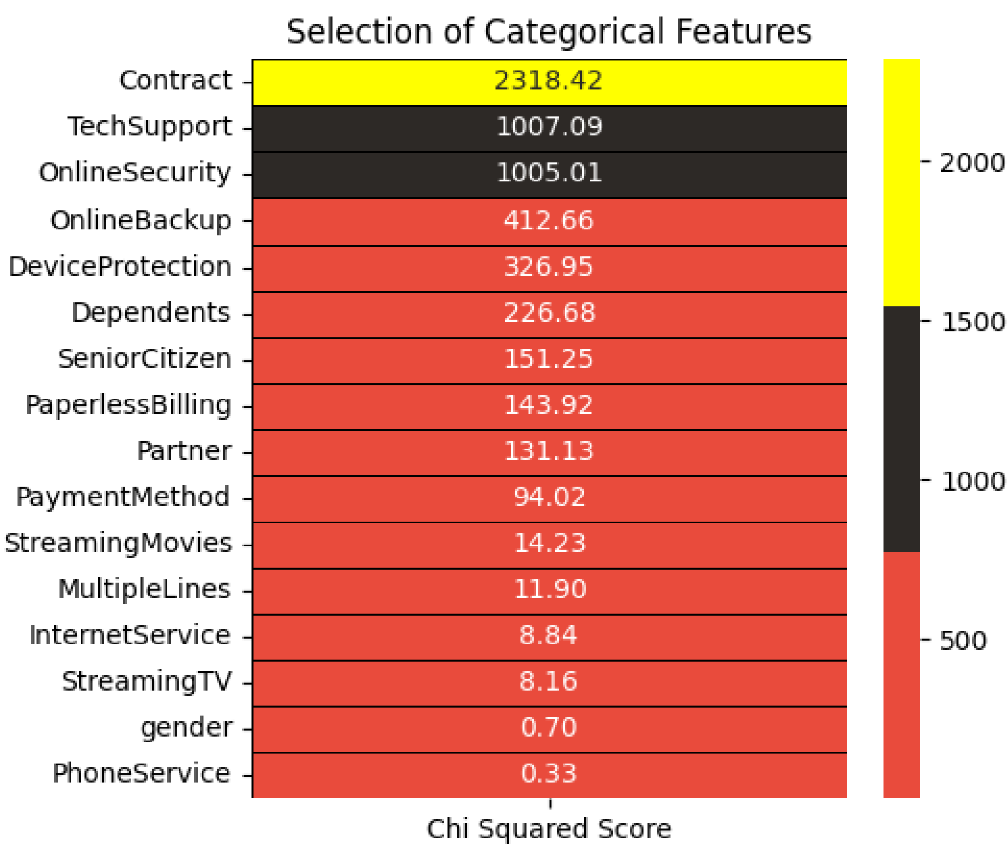
MulipleLines, PhoneService, gender, StreamingTV, StreamingMovies and InternetService does not display any kind of correlation. We drop the features with correlation coefficient.

Remaining features either display a significant positive or negative correlation.

4.3.1 Feature Selection for Categorical Features :

[37]:
```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
```

[38]:
```python
#Chi-Squared Test :

features = x_train_df.loc[:,categorical_features]
target = pd.DataFrame(y_train)

best_features = SelectKBest(score_func = chi2,k = 'all')
fit = best_features.fit(features,target)

featureScores = pd.DataFrame(data = fit.scores_,index = list(features.
↪columns),columns = ['Chi Squared Score'])

plt.subplots(figsize = (5,5))
sns.heatmap(featureScores.sort_values(ascending = False,by = 'Chi Squared␣
↪Score'),annot = True,cmap = colors,linewidths = 0.4,linecolor = 'black',fmt␣
↪= '.2f');
plt.title('Selection of Categorical Features');
```

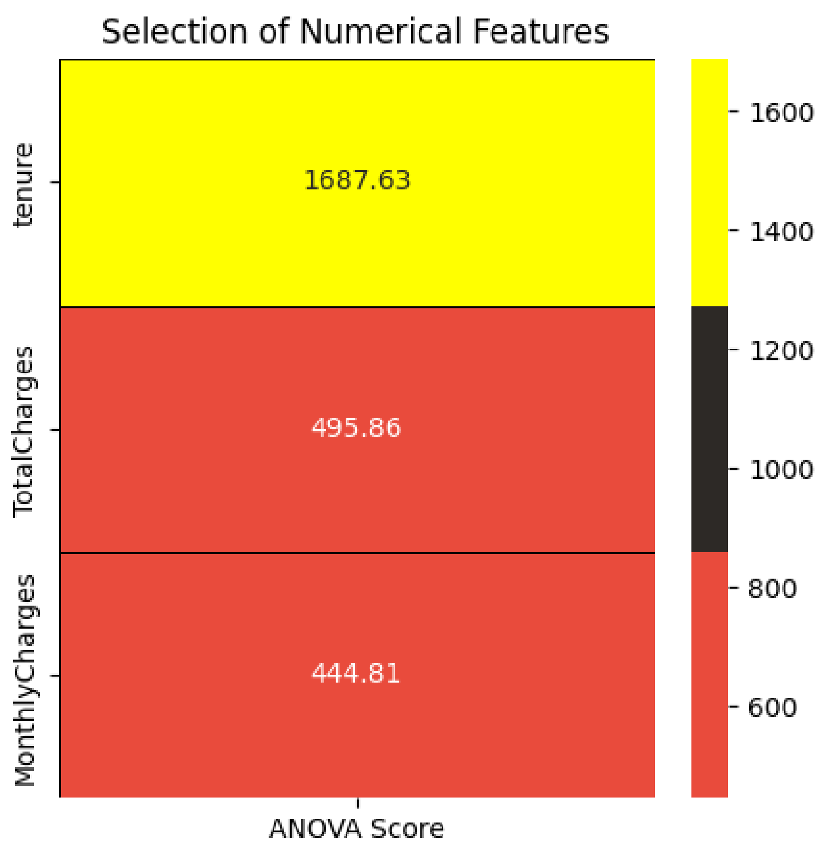


PhoneService, gender, StreamingTV, StreamingMovies, MultipleLines and InternetService display a very low relation with Churn.

4.3.2 Feature Selection for Numerical Features :

[39]:
```
from sklearn.feature_selection import f_classif
```

[40]:
```
#ANOVA Test :

from sklearn.feature_selection import f_classif

features = x_train_df.loc[:,numerical_features]
target = pd.DataFrame(y_train)

best_features = SelectKBest(score_func = f_classif,k = 'all')
fit = best_features.fit(features,target)

featureScores = pd.DataFrame(data = fit.scores_,index = list(features.
 ↪columns),columns = ['ANOVA Score'])

plt.subplots(figsize = (5,5))
sns.heatmap(featureScores.sort_values(ascending = False,by = 'ANOVA␣
 ↪Score'),annot = True,cmap = colors,linewidths = 0.4,linecolor = 'black',fmt␣
 ↪= '.2f');
plt.title('Selection of Numerical Features');
```



According to the ANOVA test, higher the value of the ANOVA score, higher the importance of the feature.

From the above results, we need to include all the numerical features for modeling.

[41]:
```
x_train=x_train_df.drop(columns = ['PhoneService',
 ↪'gender','StreamingTV','StreamingMovies','MultipleLines','InternetService'])
x_test_df = pd.DataFrame(x_test, columns=cols)
x_test=x_test_df.drop(columns = ['PhoneService',
 ↪'gender','StreamingTV','StreamingMovies','MultipleLines','InternetService'])
```

4.4 Data Scaling :

[42]:
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler

mms = MinMaxScaler() # Min-Max Scaling
ss = StandardScaler() # Standardization

columns_to_scale = ['tenure', 'MonthlyCharges', 'TotalCharges']

x_train[columns_to_scale] = mms.fit_transform(x_train[columns_to_scale])
x_test[columns_to_scale] = mms.transform(x_test[columns_to_scale])
```

Machine learning model does not understand the units of the values of the features. It treats the input just as a simple number but does not understand the true meaning of that value. Thus, it becomes necessary to scale the data.

Eg : Age = Years; FastingBS = mg / dl; Charges = Currency

We have 2 options for data scaling : 1) Normalization 2) Standardization. As most of the algorithms assume the data to be normally (Gaussian) distributed, Normalization is done for features whose data does not display normal distribution and standardization is carried out for features that are normally distributed where their values are huge or very small as compared to other features.

Normalization : tenure, MonthlyCharges and TotalCharges features are normalized as they displayed a right skewed and bimodal data distribution.

Standardization : None of the features are standardized for the above data.

5 Modeling

[43]:
```
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import cross_val_score
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report
```

```
from sklearn.metrics import accuracy_score
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.metrics import precision_recall_curve
```

Selecting the features from the above conducted tests and splitting the data into 80 - 20 train - test groups.

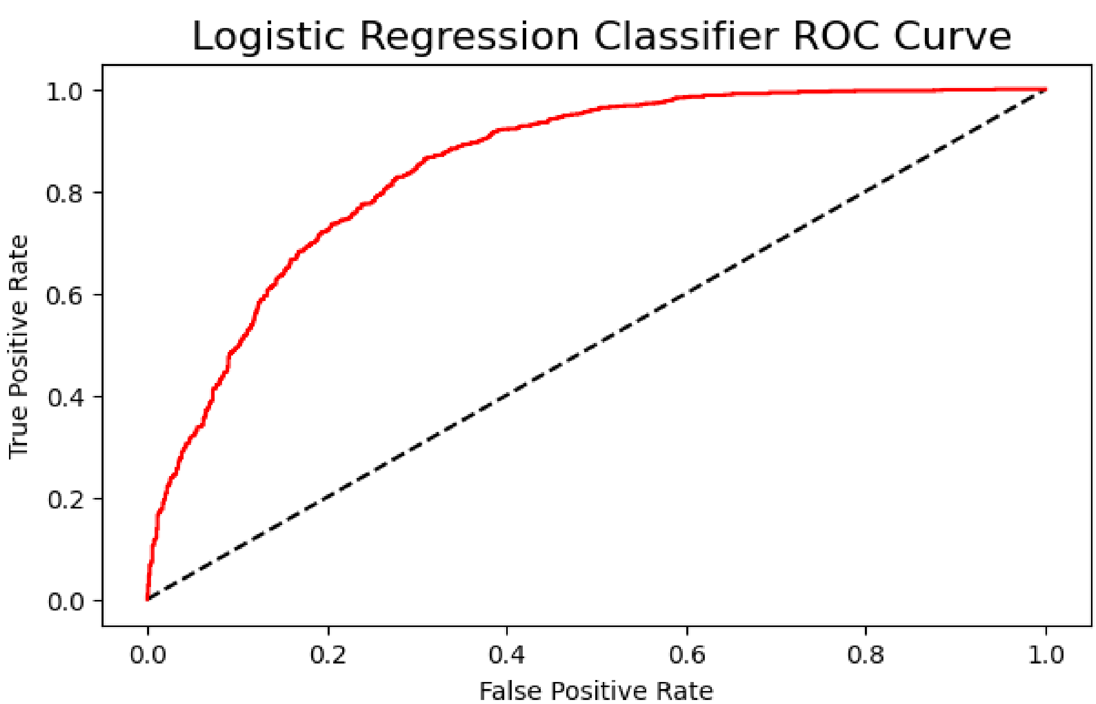
[44]:
```
def model(classifier,x_train,y_train,x_test,y_test):

    classifier.fit(x_train,y_train) prediction
    = classifier.predict(x_test)

    accuracy =classifier.score(x_test,y_test)
    print("Accuracy is :",accuracy)

    cv = RepeatedStratifiedKFold(n_splits = 10,n_repeats = 3,random_state = 1)

    print("Cross Validation Score : ",'{0:.2%}'.
↪format(cross_val_score(classifier,x_train,y_train,cv = cv,scoring =␣
↪'roc_auc').mean()))
    print("ROC_AUC Score : ",'{0:.2%}'.format(roc_auc_score(y_test,prediction)))



def model_evaluation(classifier,x_test,y_test):

    # Confusion Matrix
    plt.figure(figsize=(4,3))
    cm = confusion_matrix(y_test,classifier.predict(x_test))
    names = ['True Neg','False Pos','False Neg','True Pos']
    counts = [value for value in cm.flatten()]
    percentages = ['{0:.2%}'.format(value) for value in cm.flatten()/np.sum(cm)]
    labels = [f'{v1}\n{v2}\n{v3}' for v1, v2, v3 in␣
↪zip(names,counts,percentages)]
    labels = np.asarray(labels).reshape(2,2)
    sns.heatmap(cm,annot = labels,cmap = 'Blues',fmt ='')


    # Classification Report
    print(classification_report(y_test,classifier.predict(x_test)))
```

5.1 Logistic Regression Classifier

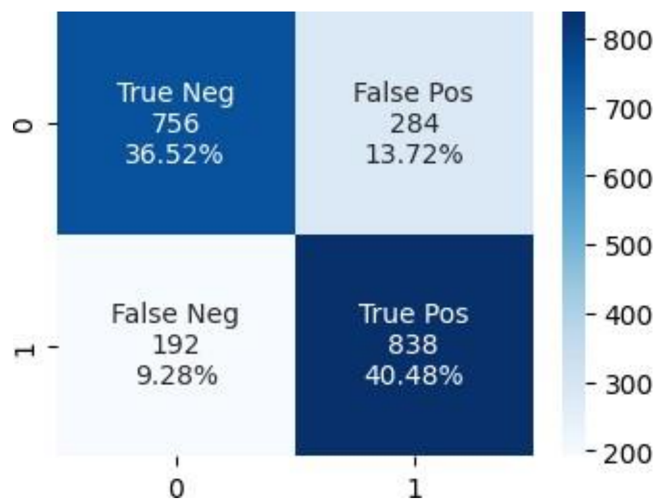
[45]:
```
from sklearn.linear_model import LogisticRegression

classifier_lr = LogisticRegression()
```

```
model(classifier_lr,x_train,y_train,x_test,y_test)

print('-'*80)

#plotting roc curve
y_pred_prob  =classifier_lr.predict_proba(x_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
plt.figure(figsize=(7, 4))

plt.plot([0, 1], [0, 1], 'k--' )
plt.plot(fpr, tpr, label='Logistic Regression Classifier',color = "r")
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title(' Logistic Regression Classifier ROC Curve',fontsize=16)
plt.show();

print('-'*80)

model_evaluation(classifier_lr,x_test,y_test)
```

```
Accuracy is : 0.770048309178744
Cross Validation Score :  84.67%
ROC_AUC Score :  77.03%
--------------------------------------------------------------------------------
```



```
--------------------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.80      0.73      0.76      1040
           1       0.75      0.81      0.78      1030

    accuracy                           0.77      2070
   macro avg       0.77      0.77      0.77      2070
weighted avg       0.77      0.77      0.77      2070
```

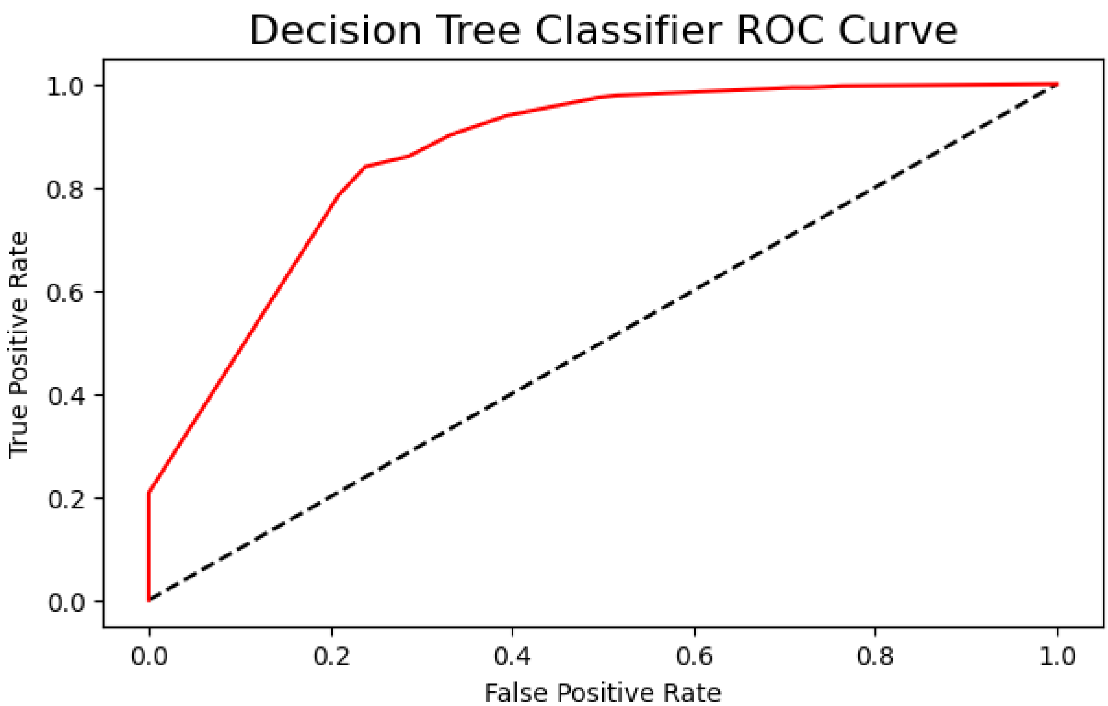


5.2 Decision Tree Classifier :

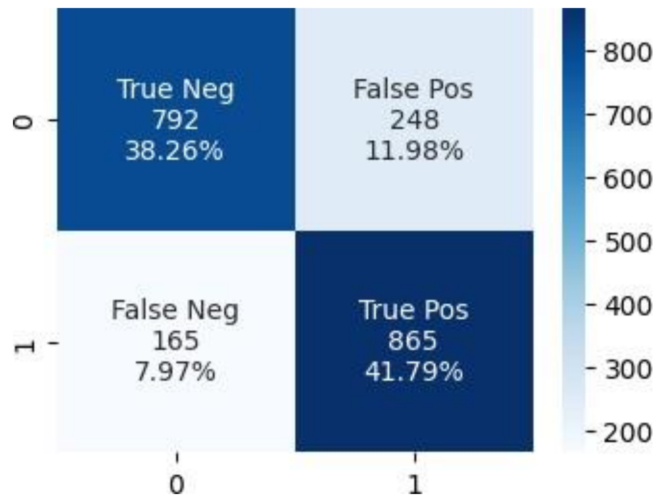
[46]:
```
from sklearn.tree import DecisionTreeClassifier

classifier_dt = DecisionTreeClassifier(random_state = 1000,max_depth =␣
↪4,min_samples_leaf = 1)

model(classifier_dt,x_train,y_train,x_test,y_test)

print('-'*80)

#plotting roc curve
y_pred_prob =classifier_dt.predict_proba(x_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
plt.figure(figsize=(7, 4))

plt.plot([0, 1], [0, 1], 'k--' )
plt.plot(fpr, tpr, label='Decision Tree Classifier',color = "r")
```

```
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Decision Tree Classifier ROC Curve',fontsize=16)
plt.show();

print('-'*80)

model_evaluation(classifier_dt,x_test,y_test)
```

```
Accuracy is : 0.8004830917874396
Cross Validation Score :  86.32%
ROC_AUC Score :  80.07%
--------------------------------------------------------------------------------
```



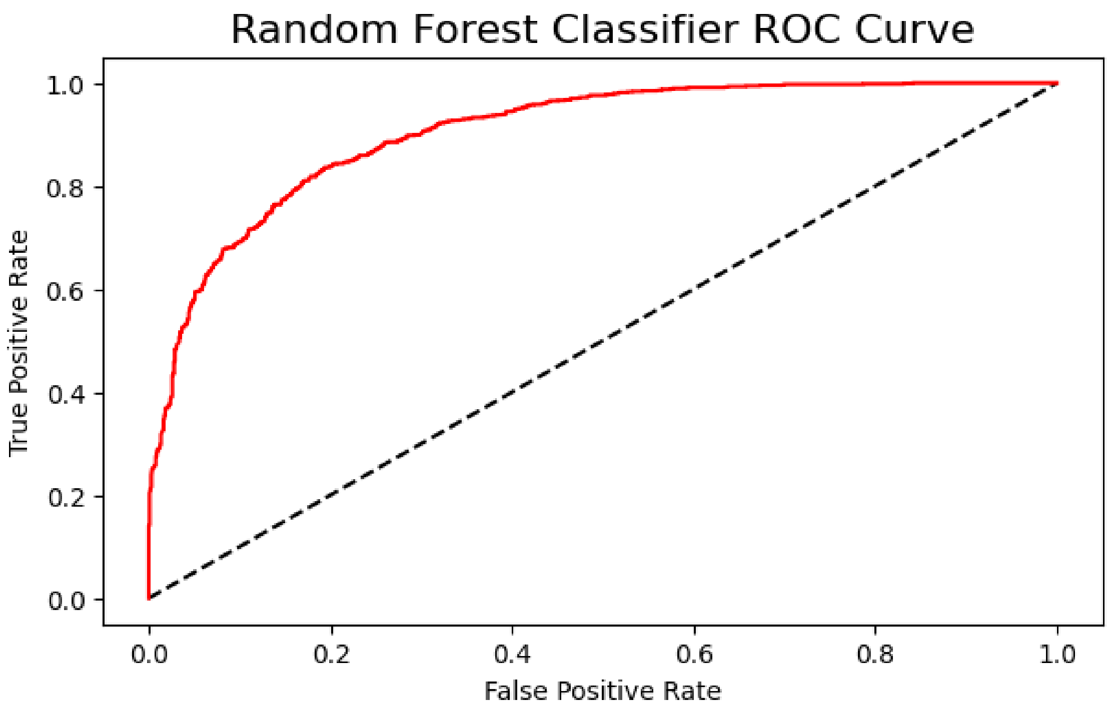

```
--------------------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.83      0.76      0.79      1040
           1       0.78      0.84      0.81      1030

    accuracy                           0.80      2070
   macro avg       0.80      0.80      0.80      2070
weighted avg       0.80      0.80      0.80      2070
```



5.3 Random Forest Classifier :

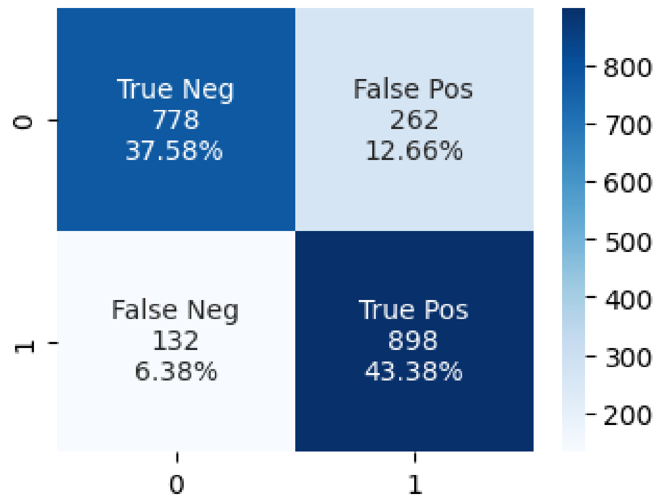
[47] :
```
from sklearn.ensemble import RandomForestClassifier

classifier_rf = RandomForestClassifier(max_depth = 4,random_state = 0)

model(classifier_rf,x_train,y_train,x_test,y_test)

print('-'*80)

#plotting roc curve
y_pred_prob =classifier_rf.predict_proba(x_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
plt.figure(figsize=(7, 4))

plt.plot([0, 1], [0, 1], 'k--' )
plt.plot(fpr, tpr, label='Random Forest Classifier',color = "r")
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Random Forest Classifier ROC Curve',fontsize=16)
plt.show();

print('-'*80)

model_evaluation(classifier_rf,x_test,y_test)
```

```
Accuracy is : 0.8096618357487922
Cross Validation Score :  89.79%
ROC_AUC Score :  81.00%
--------------------------------------------------------------------------------
```



---

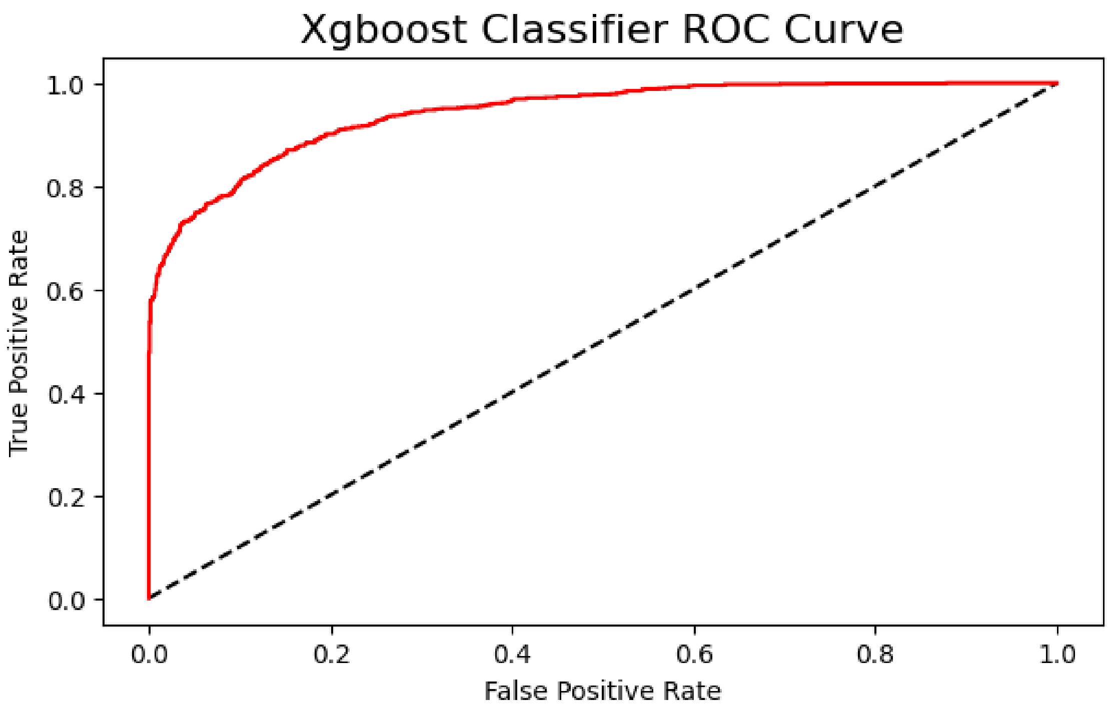
	precision	recall	f1-score	support
0	0.85	0.75	0.80	1040
1	0.77	0.87	0.82	1030
accuracy			0.81	2070
macro avg	0.81	0.81	0.81	2070
weighted avg	0.81	0.81	0.81	2070



5.4 Xgboost Classifier :

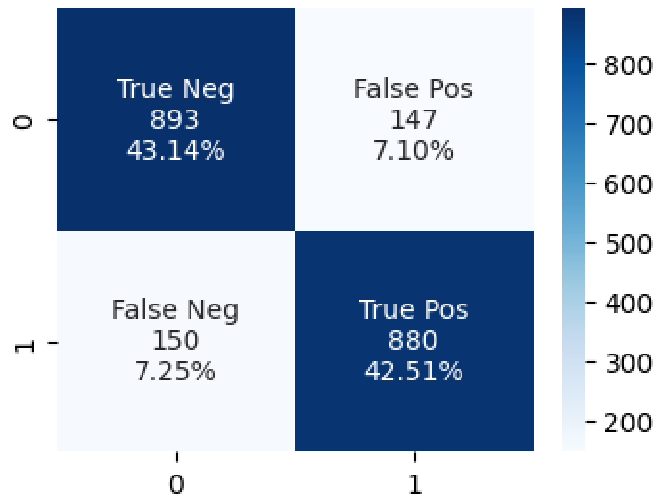
[48] :
```
from xgboost import XGBClassifier

classifier_xgb = XGBClassifier(learning_rate= 0.01,max_depth = 3,n_estimators =␣
↪1000)
model(classifier_xgb,x_train,y_train,x_test,y_test)

print('-'*80)

#plotting roc curve
y_pred_prob =classifier_xgb.predict_proba(x_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
plt.figure(figsize=(7, 4))

plt.plot([0, 1], [0, 1], 'k--' )
plt.plot(fpr, tpr, label='Xgboost Classifier',color = "r")
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Xgboost Classifier ROC Curve',fontsize=16)
plt.show();

print('-'*80)

model_evaluation(classifier_xgb,x_test,y_test)
```

```
Accuracy is : 0.8565217391304348
Cross Validation Score :  93.88%
ROC_AUC Score :  85.65%
--------------------------------------------------------------------------------
```



---

	precision	recall	f1-score	support
0	0.86	0.86	0.86	1040
1	0.86	0.85	0.86	1030
accuracy			0.86	2070
macro avg	0.86	0.86	0.86	2070
weighted avg	0.86	0.86	0.86	2070



6 Algorithm Results Table

[49]:
```
data = {
    'ML Algorithm': ['XGBClassifier', 'RandomForestClassifier',␣
↪'DecisionTreeClassifier', 'LogisticRegressionClassifier'],
    'Accuracy': [85.70, 81.01, 79.46, 77.43],
    'Cross Validation Score': [93.84, 89.91, 86.07, 84.70],
    'ROC AUC Score': [85.70, 81.04, 79.48, 77.46],
    'F1 Score (Churn)': [86, 82, 80, 78]
}

results_df = pd.DataFrame(data)
results_df
```

[49]:
```
                 ML Algorithm  Accuracy  Cross Validation Score  \
0               XGBClassifier     85.70                   93.84
1      RandomForestClassifier     81.01                   89.91
2      DecisionTreeClassifier     79.46                   86.07
3  LogisticRegressionClassifier   77.43                   84.70

   ROC AUC Score  F1 Score (Churn)
0          85.70                86
1          81.04                82
2          79.48                80
3          77.46                78
```

7. STRATEGIES FOR REDUCING CUSTOMER CHURN AND INCREASING REVENUE:

- **Targeting Specific Customer Segments:**
    - SeniorCitizen Segment: Despite being a minority, SeniorCitizen customers exhibit a willingness to pay premium rates. Therefore, it's crucial to tailor services to meet their high expectations.
    - Partnered and Solitary Customers: These segments prefer services with MonthlyCharges below $65, indicating a price sensitivity that should be considered in service offerings.
- **Building a Strong Customer Base:** Initial 6-Month Tenure Focus: During this critical period, prioritize features such as OnlineSecurity, OnlineBackup, DeviceProtection, and TechSupport to establish trust and loyalty. Efforts should aim to reduce churn between 40 to 50 months for these essential services.
- **Enhancing Affordable Streaming Services:** Streamlined Content and Payment: Make StreamingTV and StreamingMovies more accessible and appealing to diverse customer segments. Simplify payment processes to ensure seamless transactions and customer satisfaction.
- **Optimizing Payment Methods:** Payment Method Transformation: Phasing out Electronic check payments due to high churn rates and promoting Bank Transfer (automatic) and Credit Card (automatic) options. However, challenges lie in reducing the median churn tenure, which is currently double that of Electronic check payments.
- **Pricing Strategy:** Price-Consciousness Threshold: Recognize that customers become significantly more price-conscious once

MonthlyCharges exceed $70. Therefore, emphasize service quality as a primary differentiation factor to retain customers beyond this threshold.

These strategic initiatives aim to not only reduce churn but also enhance revenue streams through targeted customer engagement and service optimization.

9. Conclusion:

- **Utilizing Valuable Business Insights:** Leveraging the dataset presents a unique opportunity to tackle real-world business challenges using cutting-edge data science techniques. Insights derived from thorough Exploratory Data Analysis (EDA) serve as a cornerstone for evaluating existing systems and devising strategic improvement plans.

- **Implementing Effective Data Balancing Strategies:** Employing advanced techniques like SMOTE analysis for data balancing enhances the reliability and accuracy of predictive models. While initial attempts at undersampling were made, further exploration of alternative methods may yield even more optimized results.

- **Continuously Enhancing Model Performance:** Iterative refinement through meticulous feature engineering, hyperparameter tuning, and outlier detection is essential for maximizing the predictive power of models. Continued exploration of feature combinations holds promise for further improving model accuracy and robustness.

- **Addressing Business Challenges:** The insights garnered from the data analysis pave the way for addressing critical business challenges, particularly in customer churn prediction and revenue optimization. By leveraging data-driven strategies, businesses can adapt and thrive in dynamic market environments, ensuring sustained growth and competitiveness.

- **Fostering a Culture of Continuous Improvement:** Emphasizing the importance of ongoing evaluation and enhancement, businesses can cultivate a culture of continuous improvement. By embracing data-driven decision-making and actively seeking opportunities for innovation, organizations can stay ahead of the curve and achieve long-term success in the telecommunications industry.