CSCI - 6409 - Process of Data Science - Summer 2022

</center>

Assignment 2

</center>

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Import Files to Google Colab

In [1]:

```
from google.colab import files
# uploaded = files.upload()
```

Imports

In [2]:

```
import pandas as pd
import io
```

In [3]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [4]:

```
source_dataset = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/Telco-Customer-Churn.csv')
```

Shape of the dataframe

In [5]:

```
print(source_dataset.shape)
```

```
(7043, 20)
```

In [6]:

```
source_dataset.describe()
```

Out[6]:

	SeniorCitizen	MonthlyCharges	TotalCharges
count	7043.000000	7043.000000	7032.000000
mean	0.162147	64.761692	2283.300441
std	0.368612	30.090047	2266.771362
min	0.000000	18.250000	18.800000
25%	0.000000	35.500000	401.450000

	SeniorCitizen	MonthlyCharges	TotalCharges
50%	0.000000	70.350000	1397.475000
75%	0.000000	89.850000	3794.737500
max	1.000000	118.750000	8684.800000

1.A. Data quality report:

The data quality report consists of:

1. **Tabular report for continuous features**
2. **Tabular report for categorical features**
3. **Data visualizations of values in each feature**

Reference - [Brightspace Tutorial]

In [7]:

```
import warnings

pd.set_option("display.max_rows", None)
pd.set_option("display.max_columns", None)
pd.set_option('display.float_format', '{:.2f}'.format)
#Referred from Tutorial 2 of CSCI 6409 - [https://dal.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=fe8e7287-82c2-42bc-85ac-ae940127b726]
```

What are the features in the Telco-Customer-Churn Dataset ?

In [8]:

```
source_dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 20 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   PhoneService      7043 non-null   object 
 6   InternetService   7043 non-null   object 
 7   OnlineSecurity    7043 non-null   object 
 8   OnlineBackup      7043 non-null   object 
 9   DeviceProtection  7043 non-null   object 
 10  TechSupport       7043 non-null   object 
 11  StreamingTV       7043 non-null   object 
 12  StreamingMovies   7043 non-null   object 
 13  Contract          7043 non-null   object 
 14  PaperlessBilling  7043 non-null   object 
 15  PaymentMethod     7043 non-null   object 
 16  MonthlyCharges    7043 non-null   float64
 17  TotalCharges      7032 non-null   float64
 18  Churn             7043 non-null   object 
 19  Date              7043 non-null   object 
dtypes: float64(2), int64(1), object(17)
memory usage: 1.1+ MB
```

We can observe that all 20 columns of the dataset do not have any Null-records within them, since the total number of rows is 7043 and the number of non-null records in each column is also 7043.

Now let's peek at the first few rows of our data frame

In [9]:

```
source_dataset.loc[0]
```

Out[9]:

```
customerID                0002-ORFBO
gender                        Female
SeniorCitizen                      0
Partner                          Yes
Dependents                       Yes
PhoneService                     Yes
InternetService                  DSL
OnlineSecurity                    No
OnlineBackup                      No
DeviceProtection                  No
TechSupport                       No
StreamingTV                       No
StreamingMovies                   No
Contract                    One year
PaperlessBilling                 Yes
PaymentMethod       Electronic Check
MonthlyCharges                 65.60
TotalCharges                  593.30
Churn                             No
Date                    01 Jan, 2010
Name: 0, dtype: object
```

In [10]:

```
source_dataset.head(10)
```

Out[10]:

	customerID	gender	SeniorCitizen	Partner	Dependents	PhoneService	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Cl
0	0002-ORFBO	Female	0	Yes	Yes	Yes	DSL	No	No	No	No	No	No	One year	Yes	Electronic Check	65.60	593.30	
1	0003-MKNFE	Male	0	No	No	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Month-to-month	Yes	Mailed Check	59.90	542.40	
2	0004-TLHLJ	Male	0	No	No	Yes	DSL	No	No	No	No	No	No	Month-to-month	Yes	Credit card (automatic)	73.90	280.85	
3	0011-IGKFF	Male	1	Yes	No	Yes	DSL	No	No	No	No	No	No	Month-to-month	Yes	Credit card (automatic)	98.00	1237.85	
4	0013-EXCHZ	Female	1	Yes	No	Yes	DSL	Yes	Yes	No	No	No	No	Month-to-month	Yes	Electronic Check	83.90	267.40	
5	0013-MHZWF	Female	0	No	Yes	Yes	DSL	No	No	No	No	No	No	Month-to-month	Yes	Mailed Check	69.40	571.45	
6	0013-SMEOE	Female	1	Yes	No	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Two year	Yes	Credit card (automatic)	109.70	7904.25	
7	0014-BMAQU	Male	0	Yes	No	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Two year	Yes	Electronic Check	84.65	5377.80	
8	0015-UOCOJ	Female	1	No	No	Yes	DSL	No	No	No	No	No	No	Month-to-month	Yes	Bank transfer (automatic)	48.20	340.35	
9	0016-QLJIS	Female	0	Yes	Yes	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Two year	Yes	Electronic Check	90.45	5957.90	

Fit the best possible datatypes for columns of type object.

In [11]:

```
source_dataset = source_dataset.convert_dtypes()
source_dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 20 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   string
 1   gender            7043 non-null   string
 2   SeniorCitizen     7043 non-null   Int64
 3   Partner           7043 non-null   string
 4   Dependents        7043 non-null   string
 5   PhoneService      7043 non-null   string
 6   InternetService   7043 non-null   string
 7   OnlineSecurity    7043 non-null   string
 8   OnlineBackup      7043 non-null   string
 9   DeviceProtection  7043 non-null   string
 10  TechSupport       7043 non-null   string
 11  StreamingTV       7043 non-null   string
 12  StreamingMovies   7043 non-null   string
 13  Contract          7043 non-null   string
 14  PaperlessBilling  7043 non-null   string
 15  PaymentMethod     7043 non-null   string
 16  MonthlyCharges    7043 non-null   Float64
 17  TotalCharges      7032 non-null   Float64
 18  Churn             7043 non-null   string
 19  Date              7043 non-null   string
dtypes: Float64(2), Int64(1), string(17)
memory usage: 1.1 MB
```

In [12]:

```
source_dataset.columns
```

Out[12]:

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

Split the Datatypes into Numerical and Categorical attributes

Let's Segregate the columns with numerical values

In [13]:

```
source_dataset.describe(include=['number'])
```

Out[13]:

	SeniorCitizen	MonthlyCharges	TotalCharges
count	7043.00	7043.00	7032.00
mean	0.16	64.76	2283.30
std	0.37	30.09	2266.77
min	0.00	18.25	18.80
25%	0.00	35.50	401.45

	SeniorCitizen	MonthlyCharges	TotalCharges
50%	0.00	70.35	1397.47
75%	0.00	89.85	3794.74
max	1.00	118.75	8684.80

Let's Segregate the columns with categorical values

In [14]:

```
source_dataset.describe(exclude=['number'])
```

Out[14]:

	customerID	gender	Partner	Dependents	PhoneService	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	Churn	Date
count	7043	7043	7043	7043	7043	7043	7043	7043	7043	7043	7043	7043	7043	7043	7043	7043	7043
unique	7043	2	2	2	2	3	3	3	3	3	3	3	3	2	4	2	3346
top	0002-ORFBO	Male	No	No	Yes	Fiber optic	No	No	No	No	No	No	Month-to-month	Yes	Credit card (automatic)	No	04 Feb, 2011
freq	1	3555	3641	4933	5016	2917	3584	3543	3518	3547	3216	3241	3875	5019	1892	5174	7

Features in the Dataset:

Continuous Features:

SeniorCitizen, MonthlyCharges, TotalCharges

Categorical Features:

customerID, gender,Partner, Dependents, PhoneService, InternetService, OnlineSecurity, OnlineBackup, DeviceProtection, TechSupport, StreamingTV, StreamingMovies, Contract, PaperlessBilling, PaymentMethod, Churn, Date

1.B.Data Quality Report for Continuous Features:

Code refererred from [CSCI 6409 - Tutorial 2](#)

In [15]:

```
def build_continuous_features_report(data_df):

    """Build tabular report for continuous features"""

    stats = {
        "Count": len,
        "Miss %": lambda df: df.isna().sum() / len(df) * 100,
        "Card.": lambda df: df.nunique(),
        "Min": lambda df: df.min(),
        "1st Qrt.": lambda df: df.quantile(0.25),
        "Mean": lambda df: df.mean(),
        "Median": lambda df: df.median(),
        "3rd Qrt": lambda df: df.quantile(0.75),
        "Max": lambda df: df.max(),
        "Std. Dev.": lambda df: df.std(),
    }

    contin_feat_names = data_df.select_dtypes("number").columns
    continuous_data_df = data_df[contin_feat_names]

    report_df = pd.DataFrame(index=contin_feat_names, columns=stats.keys())

    for stat_name, fn in stats.items():
        # NOTE: ignore warnings for empty features
        with warnings.catch_warnings():
            warnings.simplefilter("ignore", category=RuntimeWarning)
            report_df[stat_name] = fn(continuous_data_df)
```

```
    return report_df
build_continuous_features_report(source_dataset)
```

Out[15]:

	Count	Miss %	Card.	Min	1st Qrt.	Mean	Median	3rd Qrt	Max	Std. Dev.
SeniorCitizen	7043	0.00	2	0.00	0.00	0.16	0.00	0.00	1.00	0.37
MonthlyCharges	7043	0.00	1585	18.25	35.50	64.76	70.35	89.85	118.75	30.09
TotalCharges	7043	0.16	6530	18.80	401.45	2283.30	1397.47	3794.74	8684.80	2266.77

Data Quality Report for Categorical Features:

Code refererred from [CSCI 6409 - Tutorial 2]

In [16]:

```
def build_categorical_features_report(data_df):

    """Build tabular report for categorical features"""

    def _mode(df):
        return df.apply(lambda ft: ft.mode().to_list()).T

    def _mode_freq(df):
        return df.apply(lambda ft: ft.value_counts()[ft.mode()].sum())

    def _second_mode(df):
        return df.apply(lambda ft: ft[~ft.isin(ft.mode())].mode().to_list())

    def _second_mode_freq(df):
        return df.apply(
            lambda ft: ft[~ft.isin(ft.mode())]
            .value_counts()[ft[~ft.isin(ft.mode())].mode()]
            .sum()
        )

    stats = {
        "Count": len,
        "Miss %": lambda df: df.isna().sum() / len(df) * 100,
        "Card.": lambda df: df.nunique(),
        "Mode": _mode,
        "Mode Freq": _mode_freq,
        "Mode %": lambda df: _mode_freq(df) / len(df) * 100,
        "2nd Mode": _second_mode,
        "2nd Mode Freq": _second_mode_freq,
        "2nd Mode %": lambda df: _second_mode_freq(df) / len(df) * 100,
    }

    cat_feat_names = data_df.select_dtypes(exclude="number").columns
    continuous_data_df = data_df[cat_feat_names]

    report_df = pd.DataFrame(index=cat_feat_names, columns=stats.keys())

    for stat_name, fn in stats.items():
        # NOTE: ignore warnings for empty features
        with warnings.catch_warnings():
            warnings.simplefilter("ignore", category=RuntimeWarning)
            report_df[stat_name] = fn(continuous_data_df)

    return report_df
```

In [17]:

```
build_categorical_features_report(source_dataset)
```

Out[17]:

	Count	Miss %	Card.	Mode	Mode Freq	Mode %	2nd Mode	2nd Mode Freq	2nd Mode %
customerID	7043	0.00	7043	[0002-ORFBO, 0003-MKNFE, 0004-TLHLJ, 0011-IGKF...	7043	100.00	[]	0	0.00
gender	7043	0.00	2	[Male]	3555	50.48	[Female]	3488	49.52
Partner	7043	0.00	2	[No]	3641	51.70	[Yes]	3402	48.30
Dependents	7043	0.00	2	[No]	4933	70.04	[Yes]	2110	29.96
PhoneService	7043	0.00	2	[Yes]	5016	71.22	[No]	2027	28.78
InternetService	7043	0.00	3	[Fiber optic]	2917	41.42	[DSL]	2708	38.45
OnlineSecurity	7043	0.00	3	[No]	3584	50.89	[Yes]	2041	28.98
OnlineBackup	7043	0.00	3	[No]	3543	50.31	[Yes]	2082	29.56
DeviceProtection	7043	0.00	3	[No]	3518	49.95	[Yes]	2107	29.92
TechSupport	7043	0.00	3	[No]	3547	50.36	[Yes]	2078	29.50
StreamingTV	7043	0.00	3	[No]	3216	45.66	[Yes]	2409	34.20
StreamingMovies	7043	0.00	3	[No]	3241	46.02	[Yes]	2384	33.85
Contract	7043	0.00	3	[Month-to-month]	3875	55.02	[Two year]	1695	24.07
PaperlessBilling	7043	0.00	2	[Yes]	5019	71.26	[No]	2024	28.74
PaymentMethod	7043	0.00	4	[Credit card (automatic)]	1892	26.86	[Bank transfer (automatic)]	1876	26.64
Churn	7043	0.00	2	[No]	5174	73.46	[Yes]	1869	26.54
Date	7043	0.00	3346	[04 Feb, 2011, 04 Jul, 2019, 06 Feb, 2018, 07 ...	70	0.99	[01 Dec, 2020, 01 May, 2020, 01 Sep, 2018, 02 ...	216	3.07

Visualization of Continuous Features

In [18]:

```
source_dataset.describe(include=['number'])
```

Out[18]:

	SeniorCitizen	MonthlyCharges	TotalCharges
count	7043.00	7043.00	7032.00
mean	0.16	64.76	2283.30
std	0.37	30.09	2266.77
min	0.00	18.25	18.80
25%	0.00	35.50	401.45
50%	0.00	70.35	1397.47
75%	0.00	89.85	3794.74
max	1.00	118.75	8684.80

Configuring Plot properties

In [19]:

```
from matplotlib import pyplot as plt
%matplotlib inline
plt.rcParams["figure.figsize"] = [12, 8]
plt.rcParams["font.size"] = 15
```

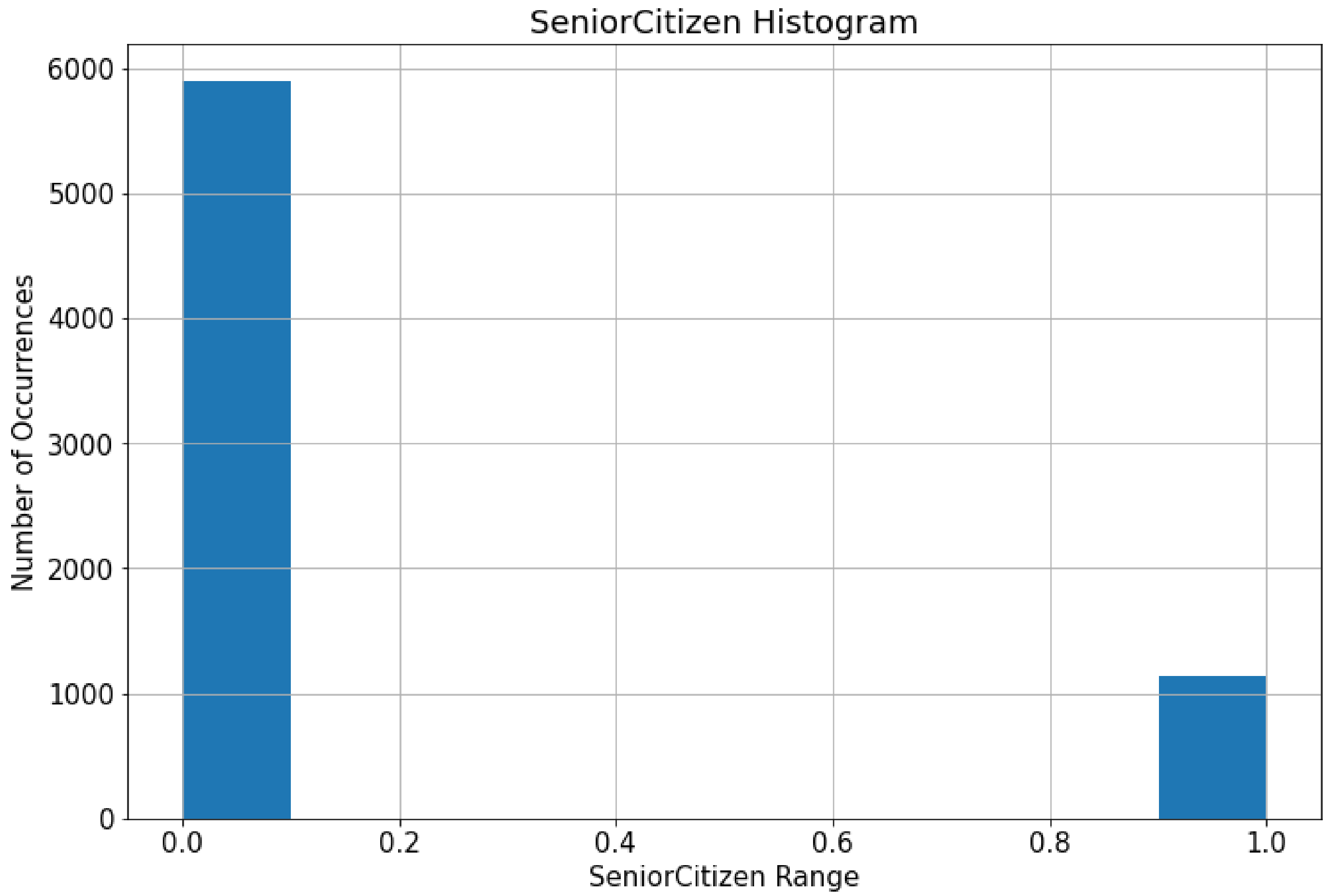
Histogram for the column - SeniorCitizen

In [20]:

```
source_dataset.hist(column=['SeniorCitizen'])
plt.xlabel('SeniorCitizen Range')
plt.ylabel('Number of Occurrences')
plt.title('SeniorCitizen Histogram')
```

Out[20]:

```
Text(0.5, 1.0, 'SeniorCitizen Histogram')
```



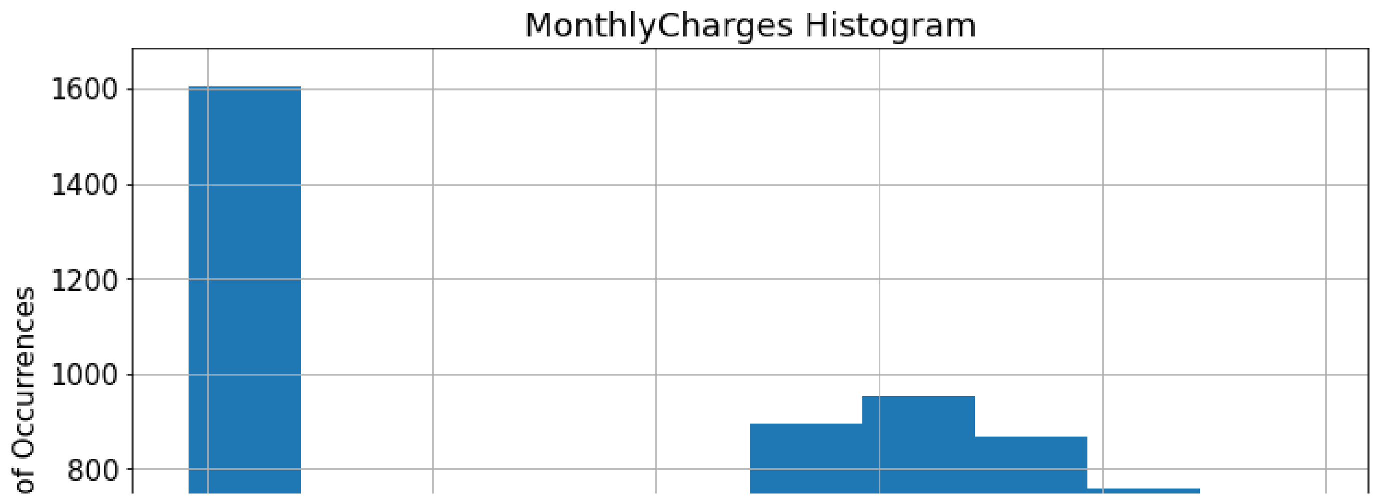
Histogram for the column - MonthlyCharges

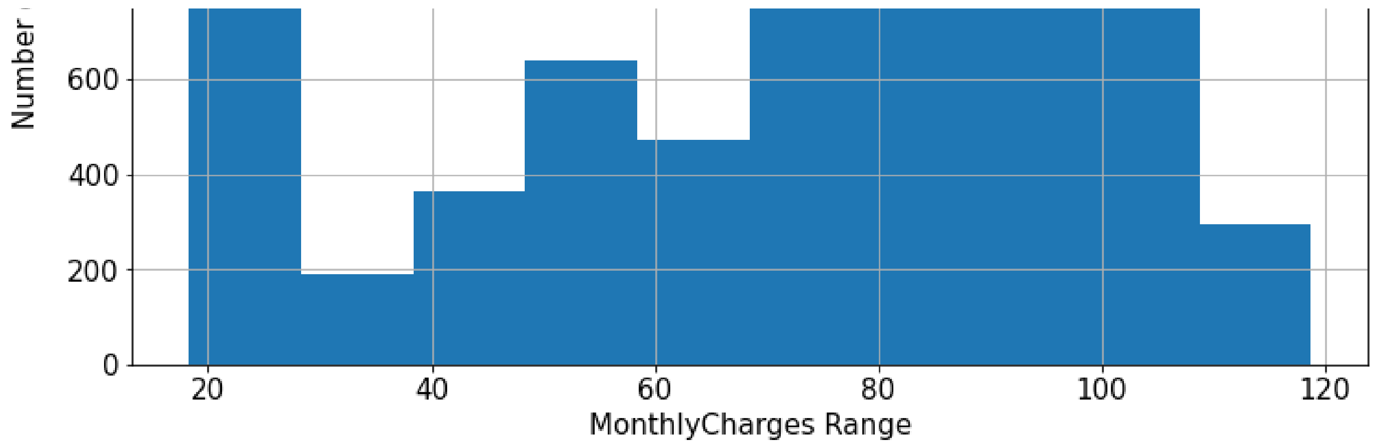
In [21]:

```
source_dataset.hist(column=['MonthlyCharges'])
plt.xlabel('MonthlyCharges Range')
plt.ylabel('Number of Occurrences')
plt.title('MonthlyCharges Histogram')
```

Out[21]:

```
Text(0.5, 1.0, 'MonthlyCharges Histogram')
```





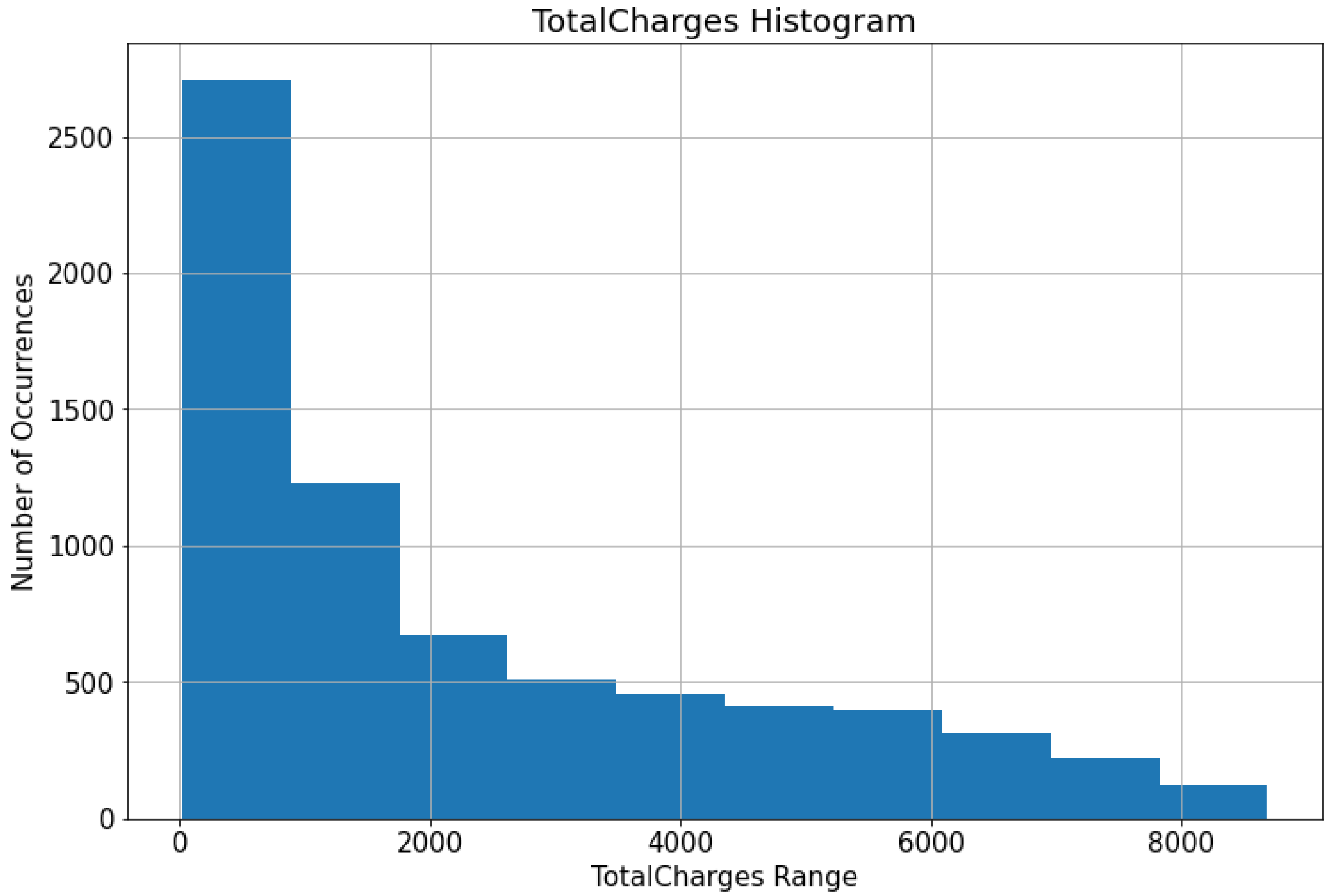
Histogram for the column - TotalCharges

In [22]:

```
source_dataset.hist(column=['TotalCharges'])
plt.xlabel('TotalCharges Range')
plt.ylabel('Number of Occurrences')
plt.title('TotalCharges Histogram')
```

Out[22]:

```
Text(0.5, 1.0, 'TotalCharges Histogram')
```



In [23]:

```
# continuous_features = source_dataset.describe(include=['number']).columns
# for col in continuous_features:
#   source_dataset.hist(column=['{}'.format(col)])
#   plt.xlabel('{} Range'.format(col))
#   plt.ylabel('Number of Occurrences')
#   plt.title('{} Histogram'.format(col))
```

In [23]:

Visualization of Categorical Features

In [24]:

```
source_dataset.describe(exclude=['number'])
```

Out[24]:

	customerID	gender	Partner	Dependents	PhoneService	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	Churn	Date
count	7043	7043	7043	7043	7043	7043	7043	7043	7043	7043	7043	7043	7043	7043	7043	7043	7043
unique	7043	2	2	2	2	3	3	3	3	3	3	3	3	2	4	2	3346
top	0002-ORFBO	Male	No	No	Yes	Fiber optic	No	No	No	No	No	No	Month-to-month	Yes	Credit card (automatic)	No	04 Feb, 2011
freq	1	3555	3641	4933	5016	2917	3584	3543	3518	3547	3216	3241	3875	5019	1892	5174	7

CustomerId

We are not going to find out the distribution of Customer Id, since we already know that each row corresponds to an unique customer and that the cardinality of the column is 7043.

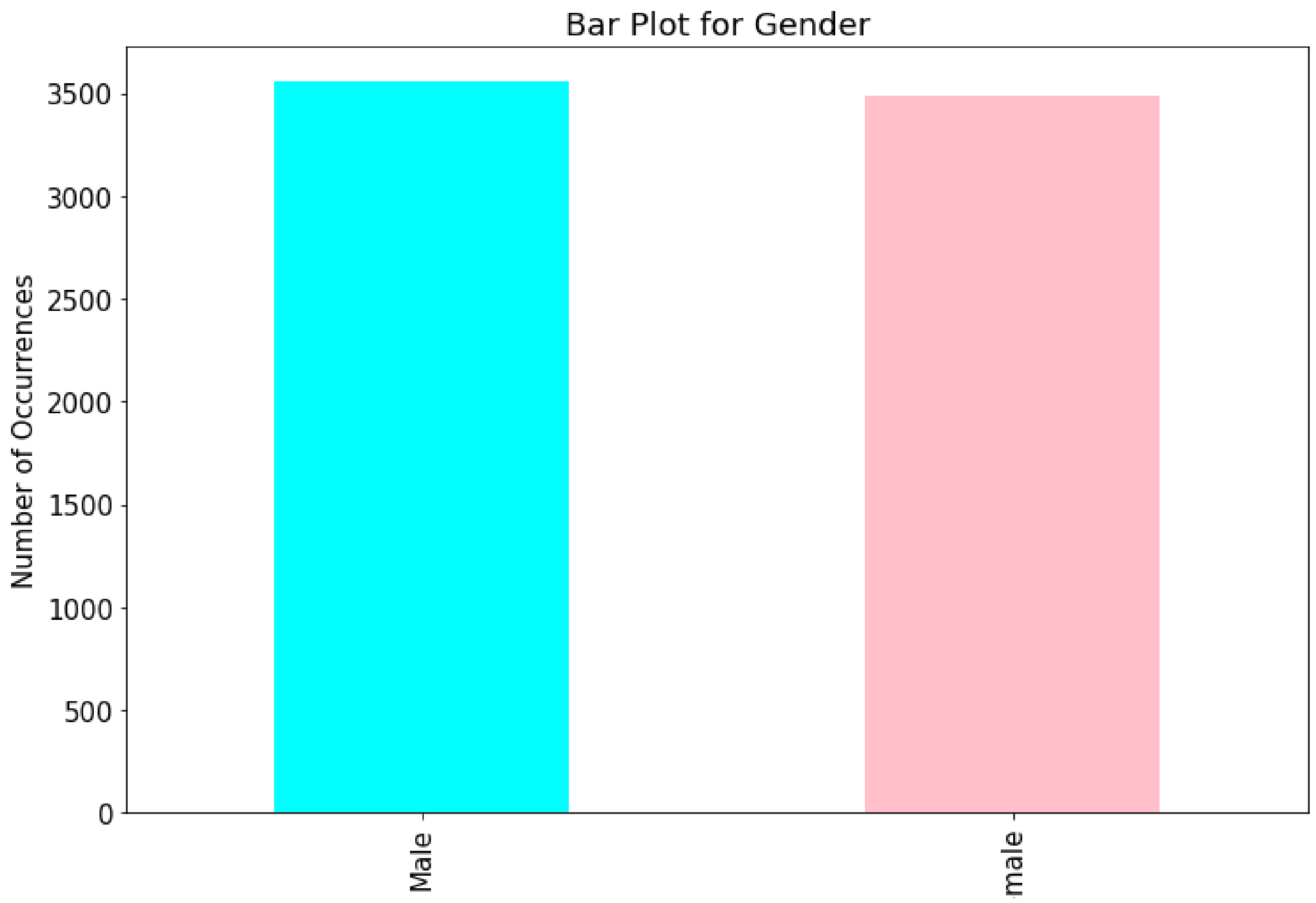
Frequencies of Male & Female for the Column - "Gender"

In [25]:

```
p1 = source_dataset['gender'].value_counts().plot.bar(color=['cyan', 'pink']);
plt.xlabel('Gender Categories')
plt.ylabel('Number of Occurrences')
plt.title('Bar Plot for Gender')
```

Out[25]:

```
Text(0.5, 1.0, 'Bar Plot for Gender')
```



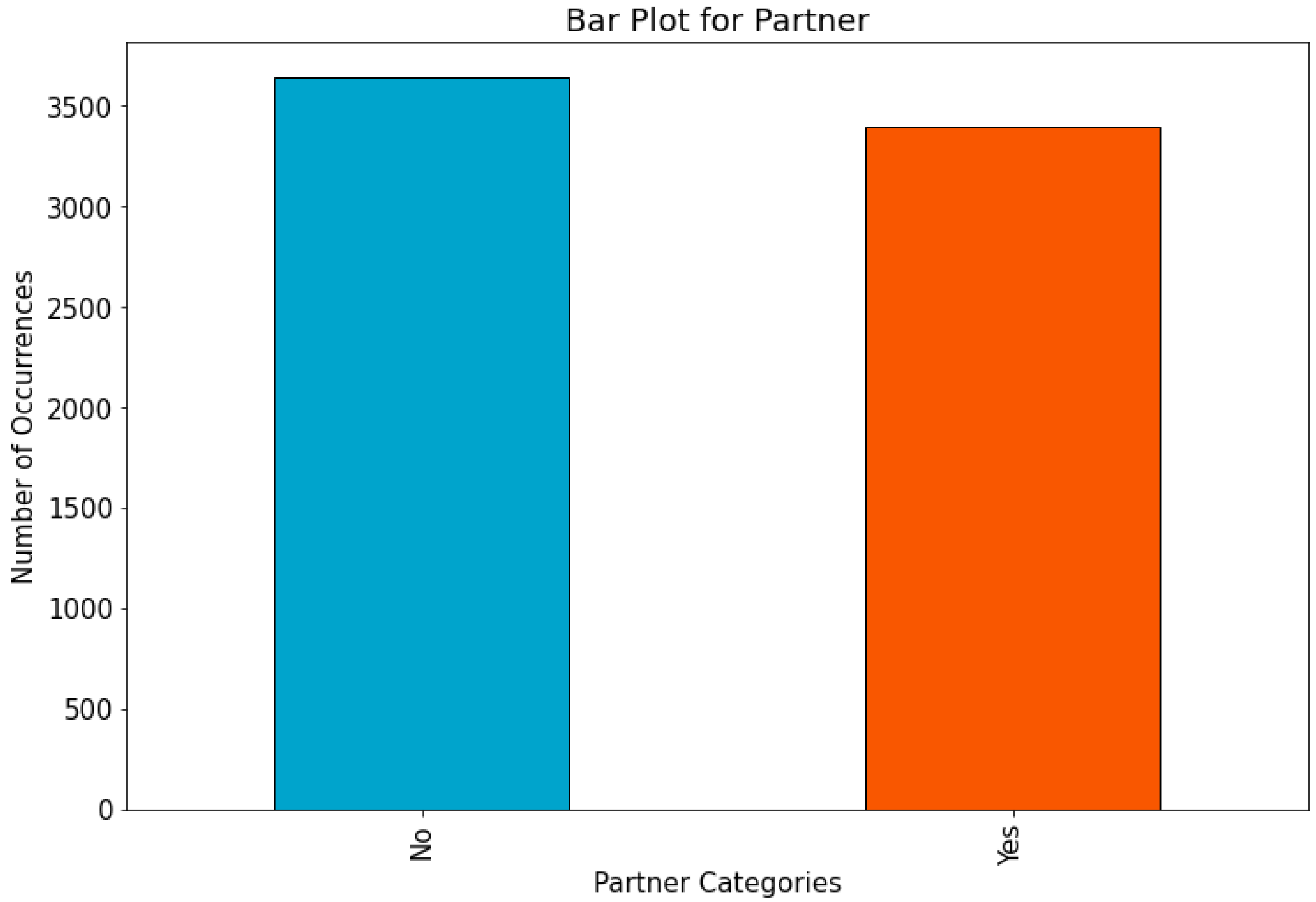
Frequency Distribution for the Column - "Partner"

In [26]:

```
p1 = source_dataset['Partner'].value_counts().plot.bar(color=['#00A4CCFF', '#F95700FF'],edgecolor='black');
plt.xlabel('Partner Categories')
plt.ylabel('Number of Occurrences')
plt.title('Bar Plot for Partner')
```

Out[26]:

```
Text(0.5, 1.0, 'Bar Plot for Partner')
```



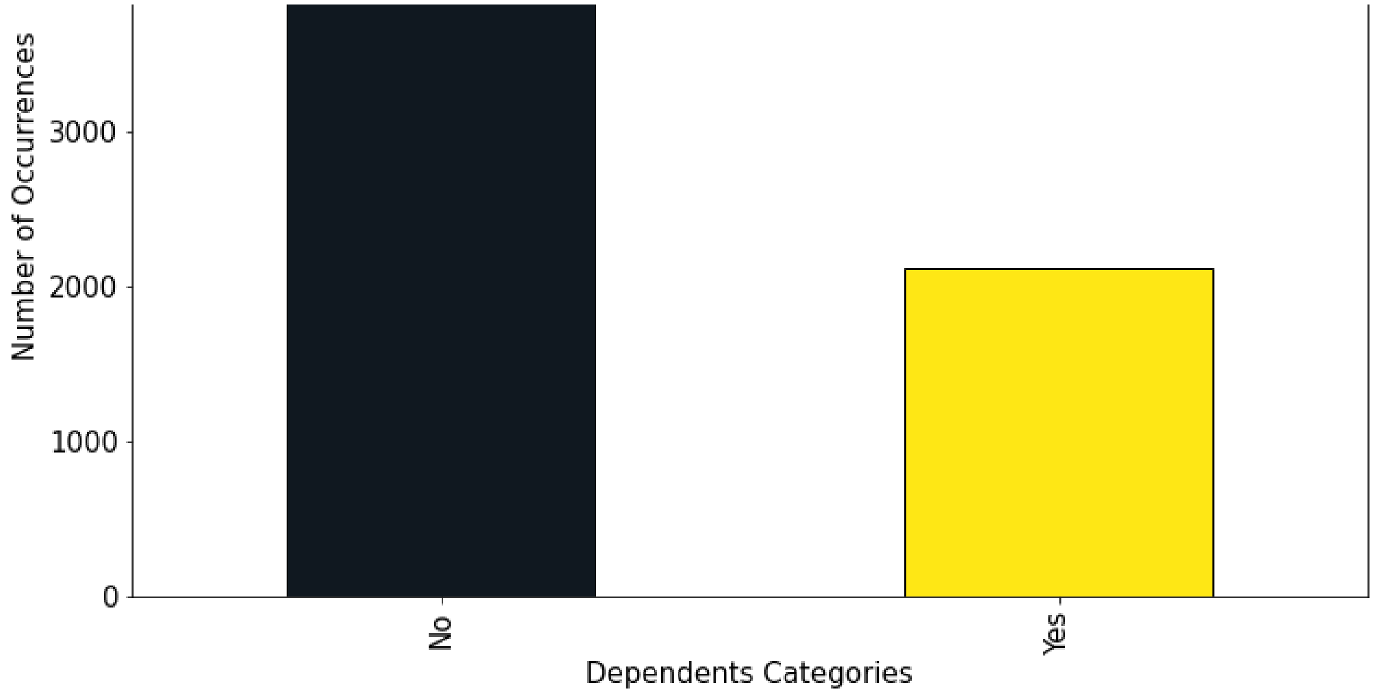
Frequency Distribution for the Column - "Dependents"

In [27]:

```
p1 = source_dataset['Dependents'].value_counts().plot.bar(color=['#101820FF', '#FEE715FF', 'brown'],edgecolor='black');
plt.xlabel('Dependents Categories')
plt.ylabel('Number of Occurrences')
plt.title('Bar Plot for Dependents')
```

Out[27]:

```
Text(0.5, 1.0, 'Bar Plot for Dependents')
```



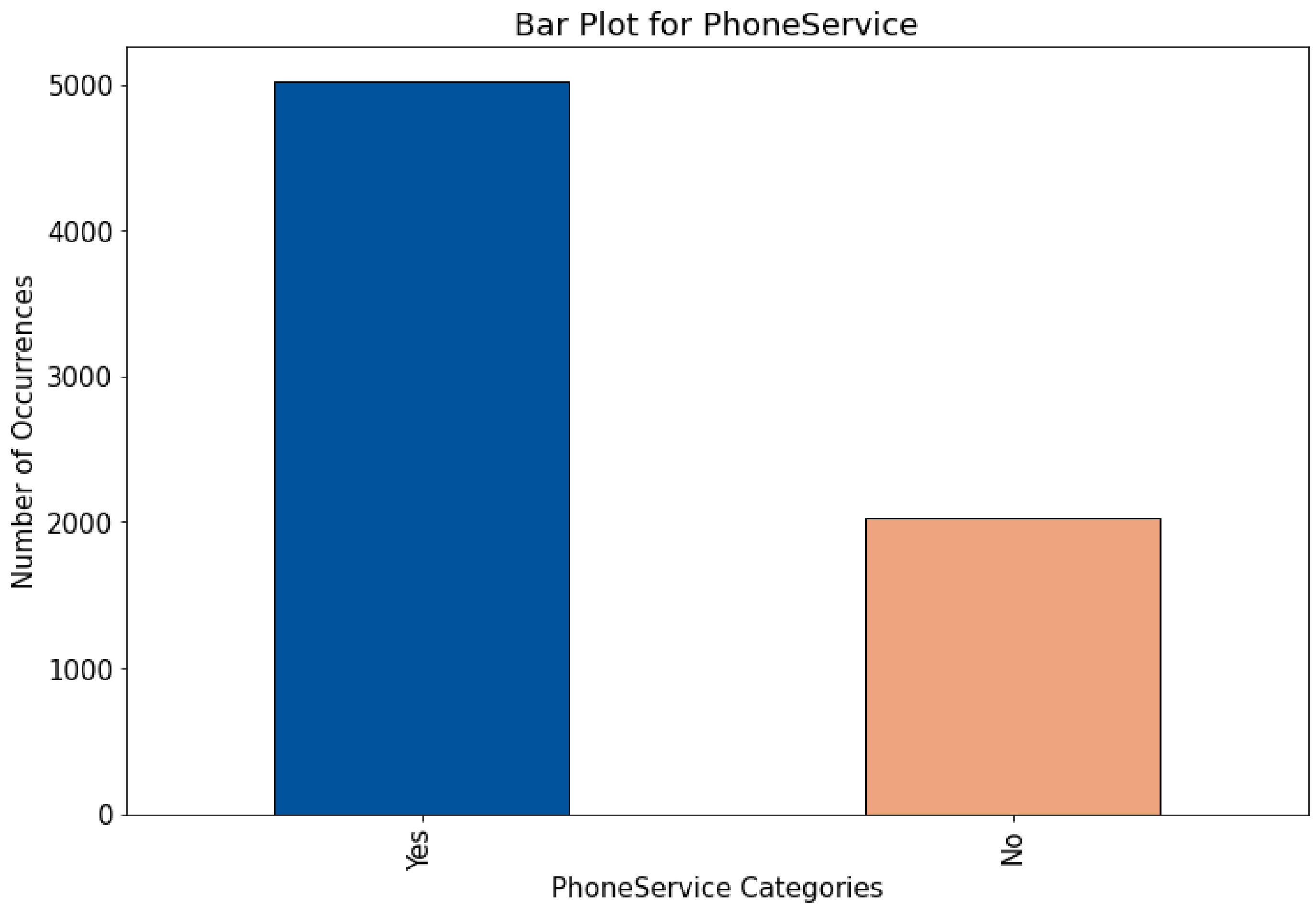
Frequency Distribution for the Column - "PhoneService"

In [28]:

```
p1 = source_dataset['PhoneService'].value_counts().plot.bar(color=['#00539CFF', '#EEA47FFF', 'brown'],edgecolor='black');
plt.xlabel('PhoneService Categories')
plt.ylabel('Number of Occurrences')
plt.title('Bar Plot for PhoneService')
```

Out[28]:

```
Text(0.5, 1.0, 'Bar Plot for PhoneService')
```



Frequency Distribution for the Column - "InternetService"

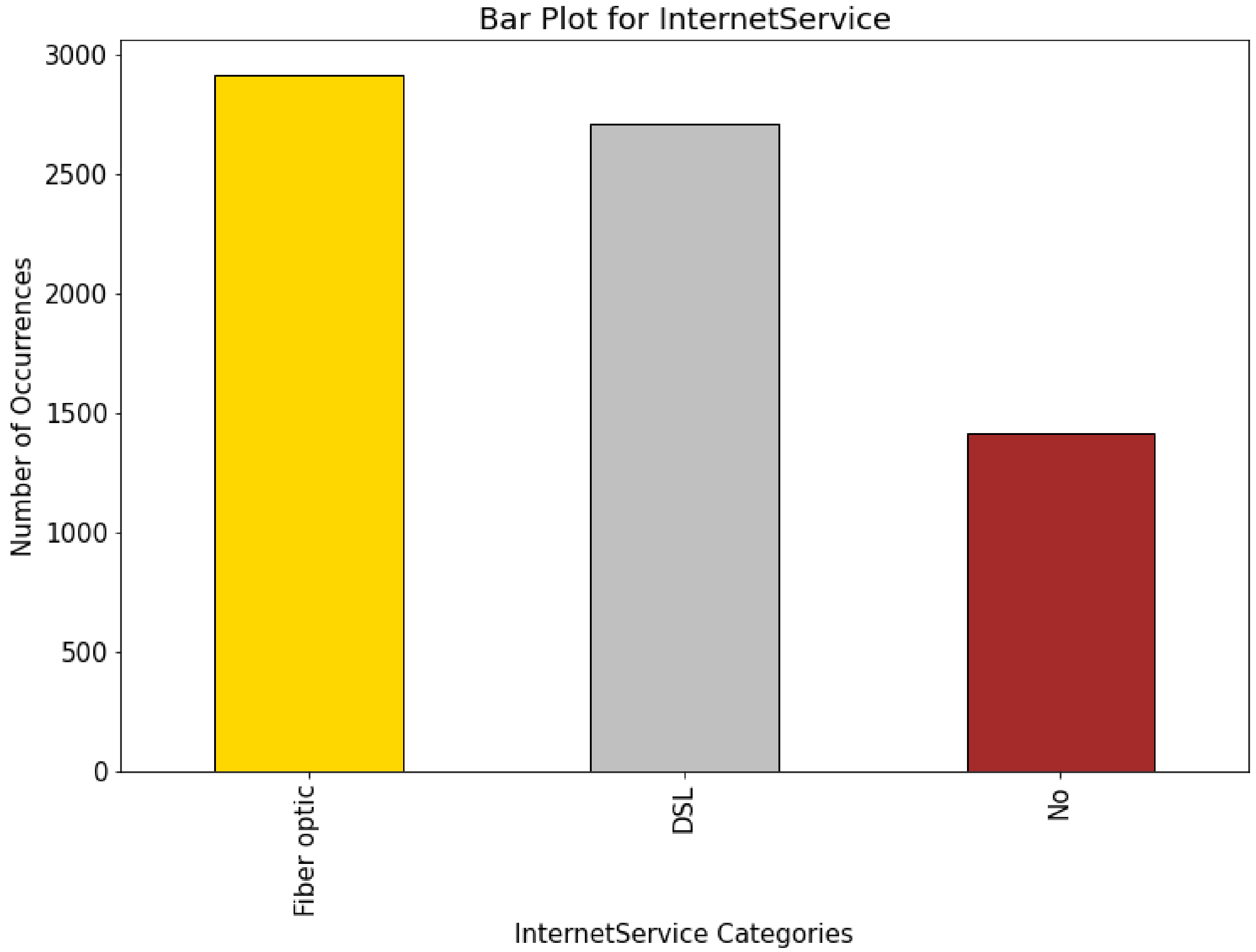
Frequency Distribution for the Column - "InternetService"

In [29]:

```
p1 = source_dataset['InternetService'].value_counts().plot.bar(color=['gold', 'silver', 'brown'],edgecolor='black');
plt.xlabel('InternetService Categories')
plt.ylabel('Number of Occurrences')
plt.title('Bar Plot for InternetService')
```

Out[29]:

```
Text(0.5, 1.0, 'Bar Plot for InternetService')
```



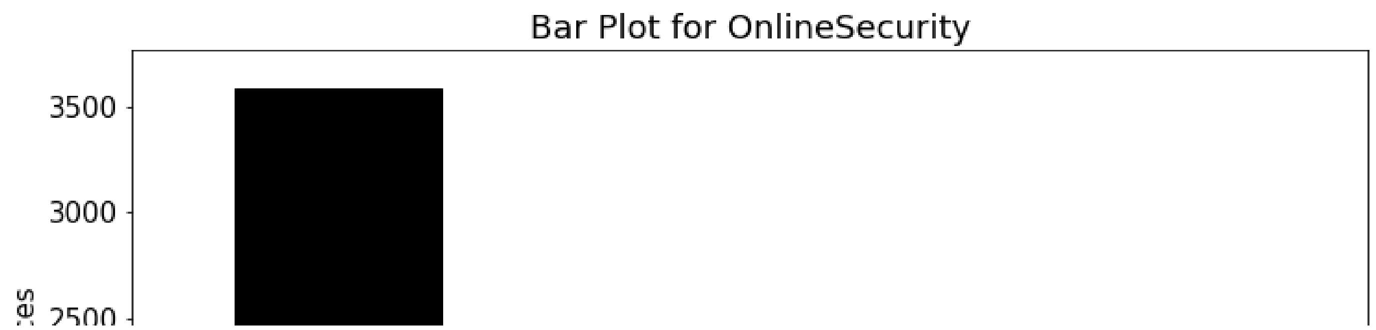
Frequency Distribution for the Column - "OnlineSecurity"

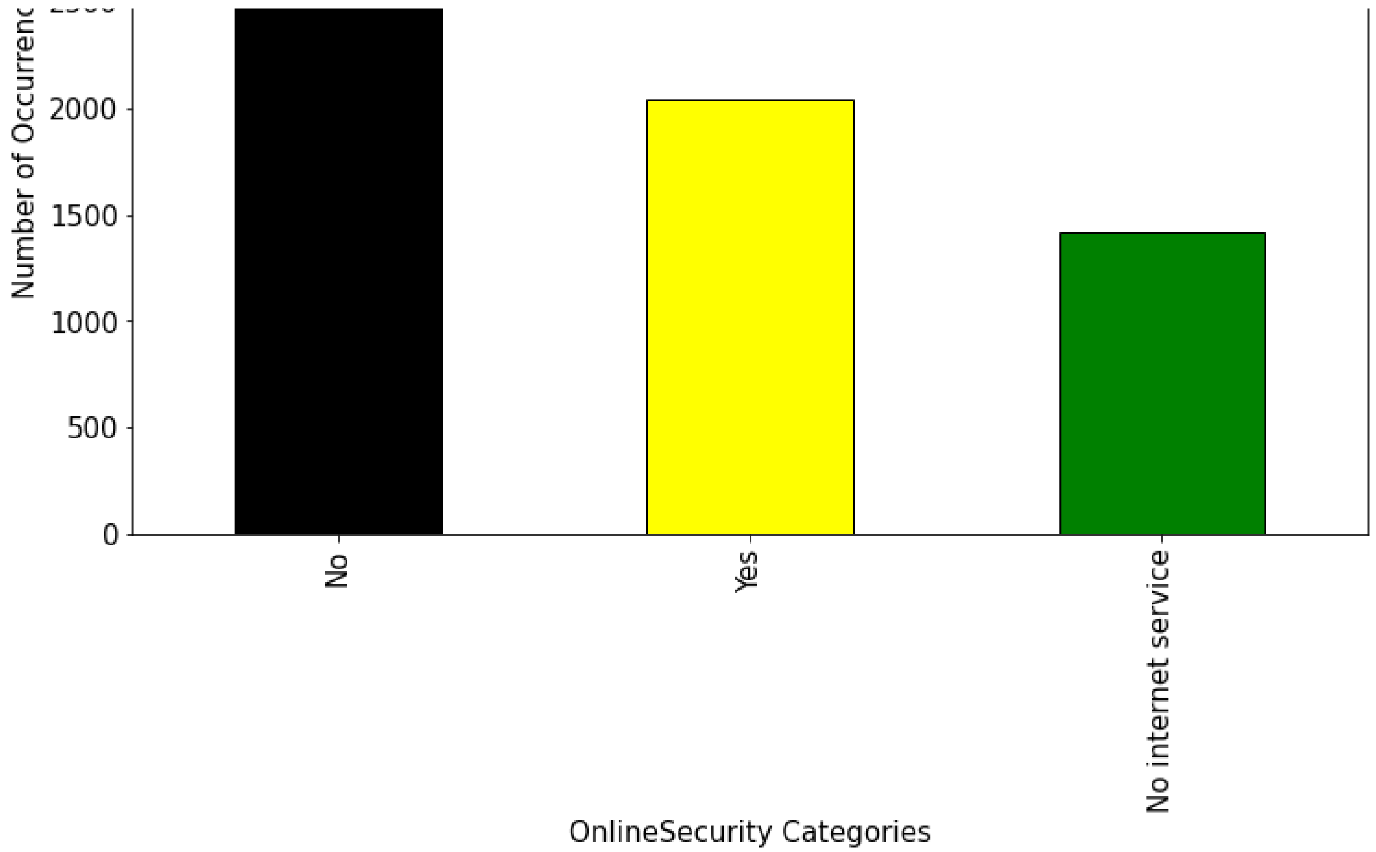
In [30]:

```
p1 = source_dataset['OnlineSecurity'].value_counts().plot.bar(color=['black', 'yellow', 'green', 'purple', 'cyan'],edgecolor='black');
plt.xlabel('OnlineSecurity Categories')
plt.ylabel('Number of Occurrences')
plt.title('Bar Plot for OnlineSecurity')
```

Out[30]:

```
Text(0.5, 1.0, 'Bar Plot for OnlineSecurity')
```





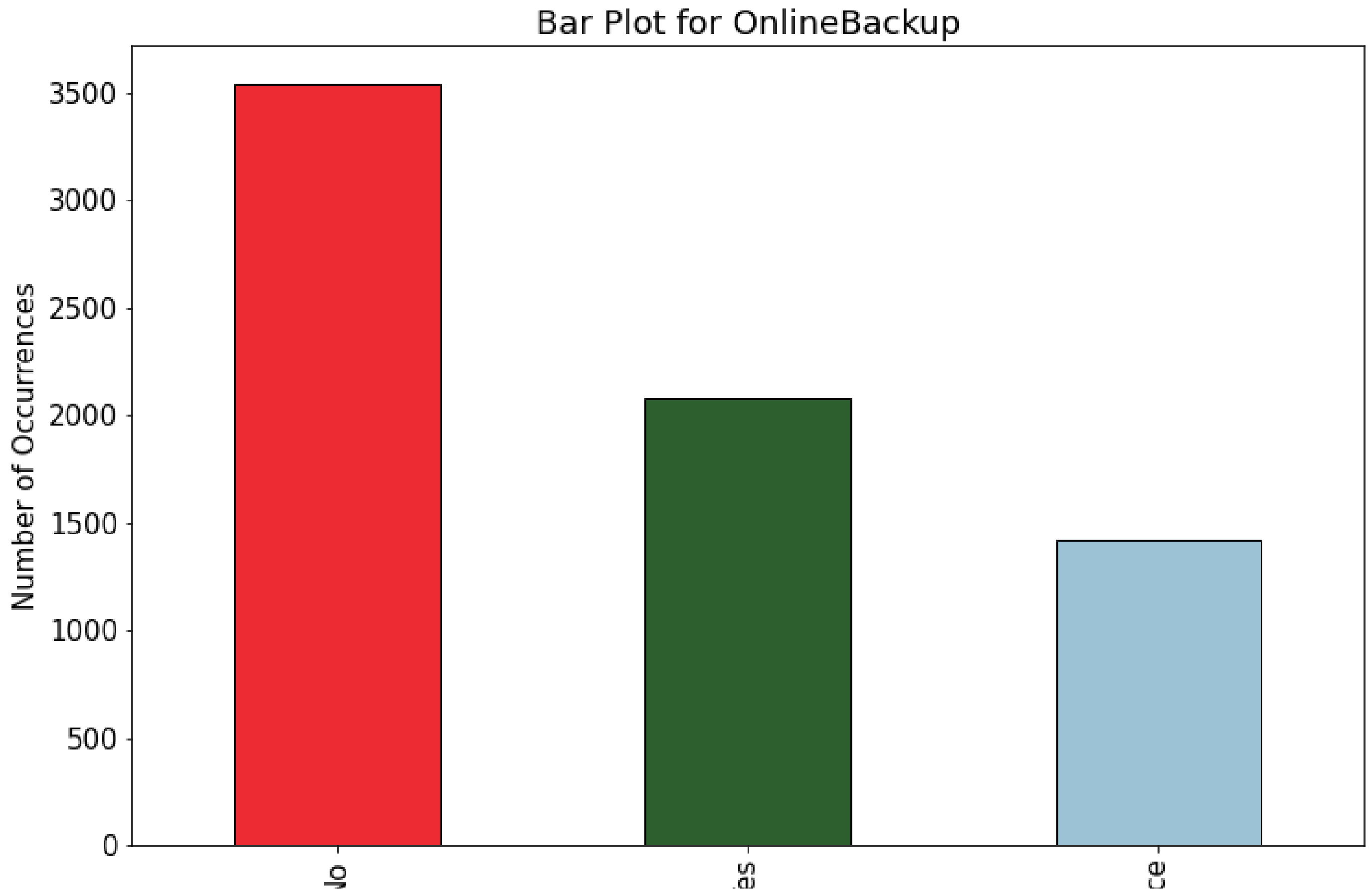
Frequency Distribution for the Column - "OnlineBackup"

In [31]:

```
p1 = source_dataset['OnlineBackup'].value_counts().plot.bar(color=['#ED2B33FF', '#2C5F2D','#9CC3D5FF'],edgecolor='black');
plt.xlabel('OnlineBackup Categories')
plt.ylabel('Number of Occurrences')
plt.title('Bar Plot for OnlineBackup')
```

Out[31]:

```
Text(0.5, 1.0, 'Bar Plot for OnlineBackup')
```



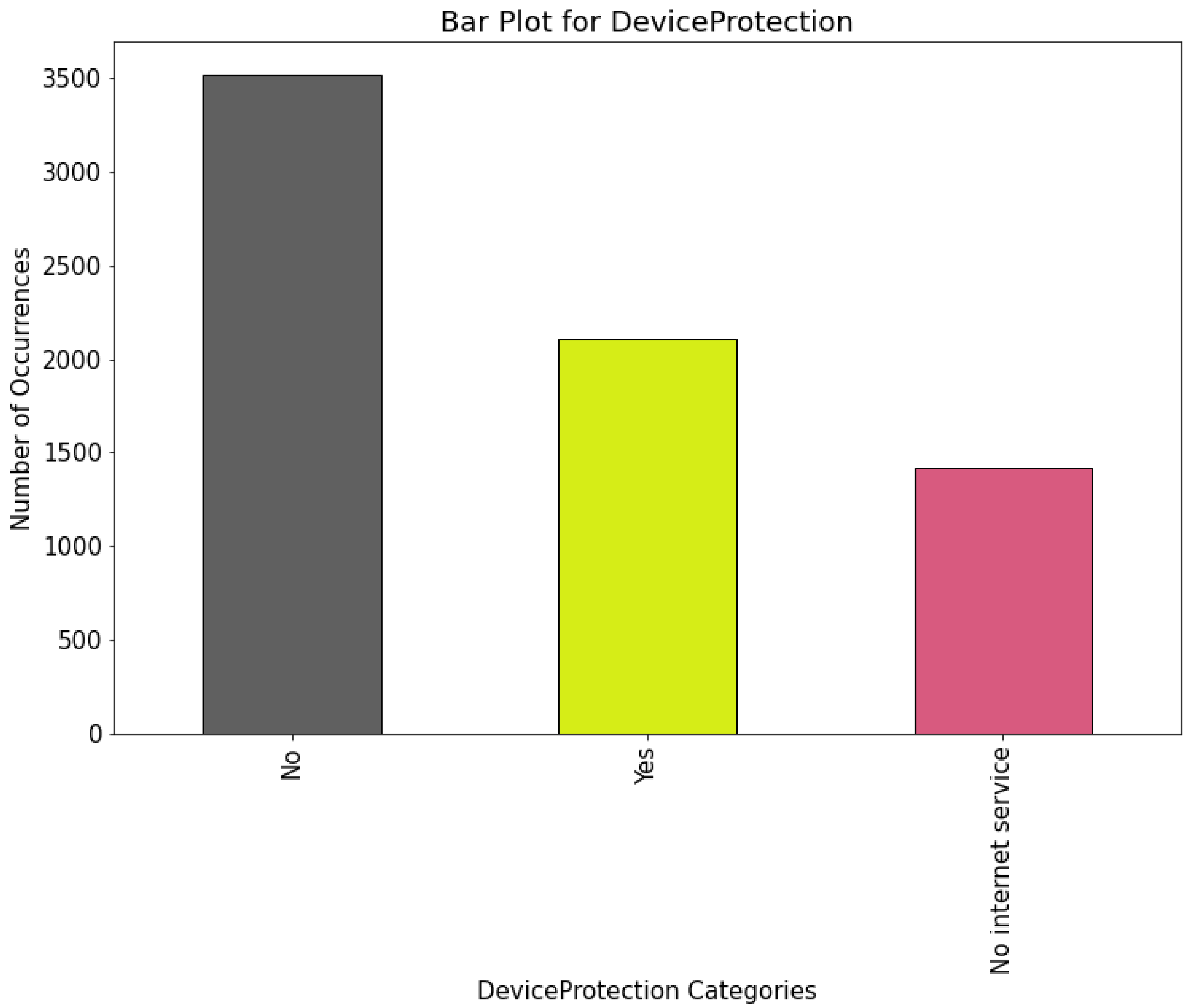
Frequency Distribution for the Column - "DeviceProtection"

In [32]:

```
p1 = source_dataset['DeviceProtection'].value_counts().plot.bar(color=['#606060FF', '#D6ED17FF','#D85A7FFF'],edgecolor='black');
plt.xlabel('DeviceProtection Categories')
plt.ylabel('Number of Occurrences')
plt.title('Bar Plot for DeviceProtection')
```

Out[32]:

```
Text(0.5, 1.0, 'Bar Plot for DeviceProtection')
```



Frequency Distribution for the Column - "TechSupport"

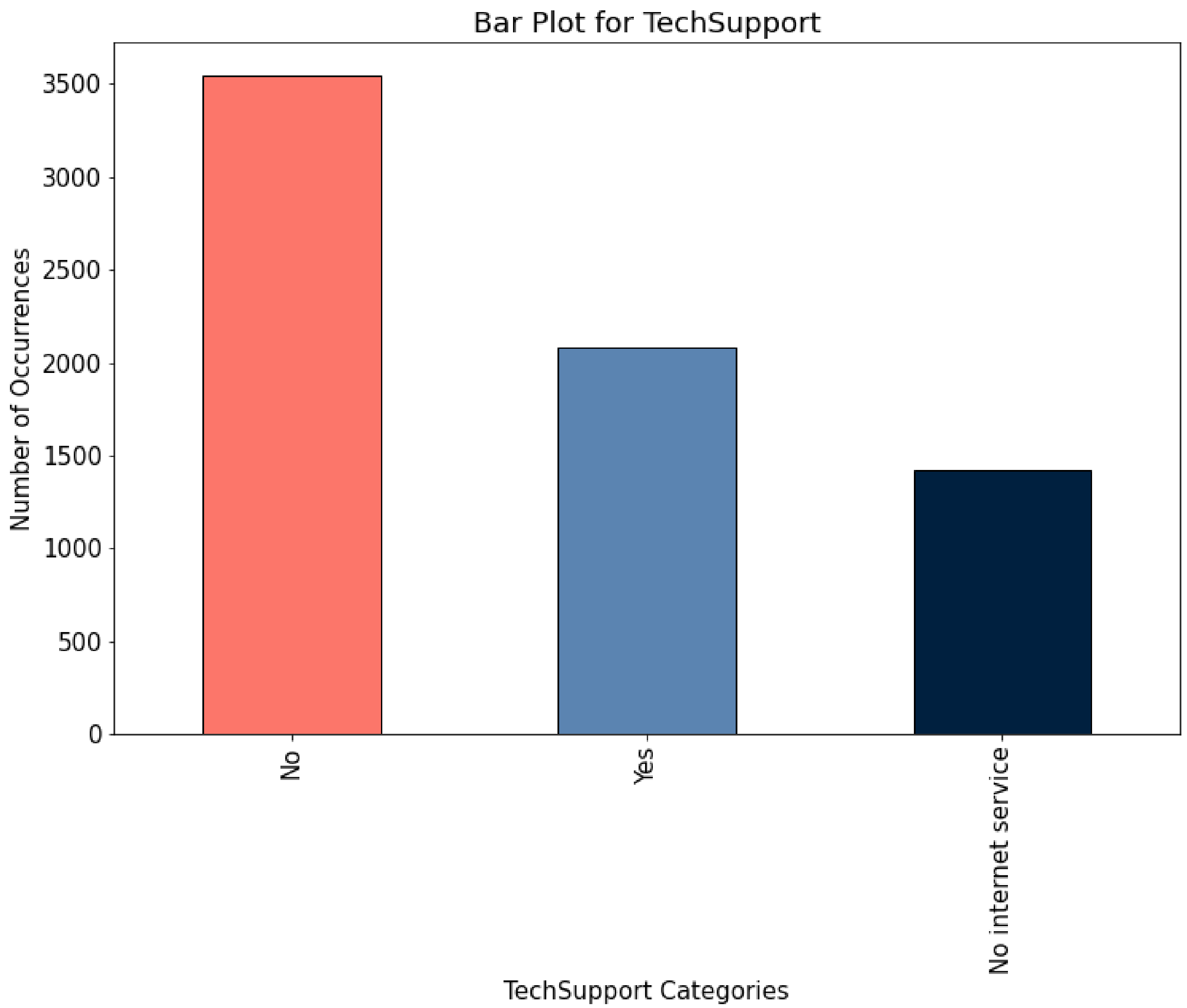
In [33]:

```
p1 = source_dataset['TechSupport'].value_counts().plot.bar(color=['#FC766A', '#5B84B1','#00203FFF'],edgecolor='black');
plt.xlabel('TechSupport Categories')
```

```
plt.ylabel('Number of Occurrences')
plt.title('Bar Plot for TechSupport')
```

Out[33]:

```
Text(0.5, 1.0, 'Bar Plot for TechSupport')
```



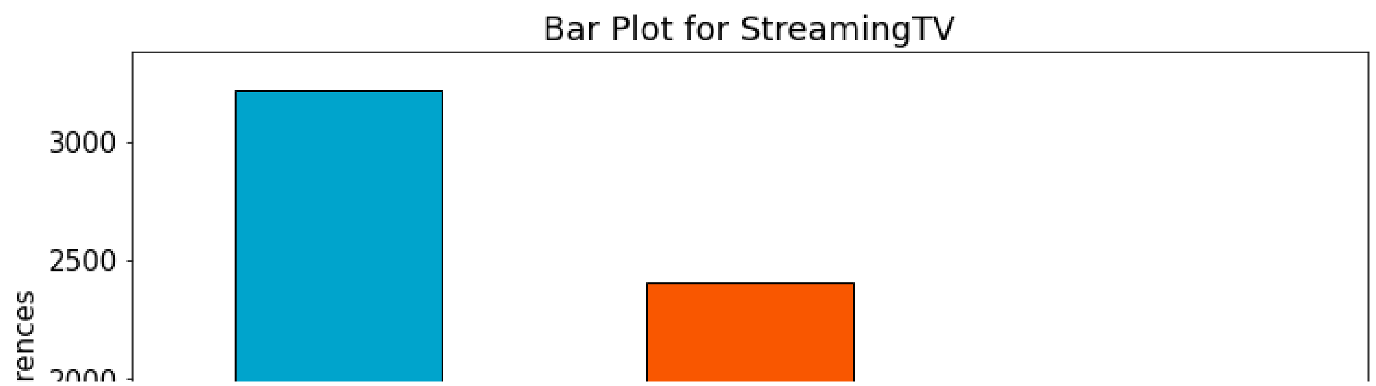
Frequency Distribution for the Column - "StreamingTV"

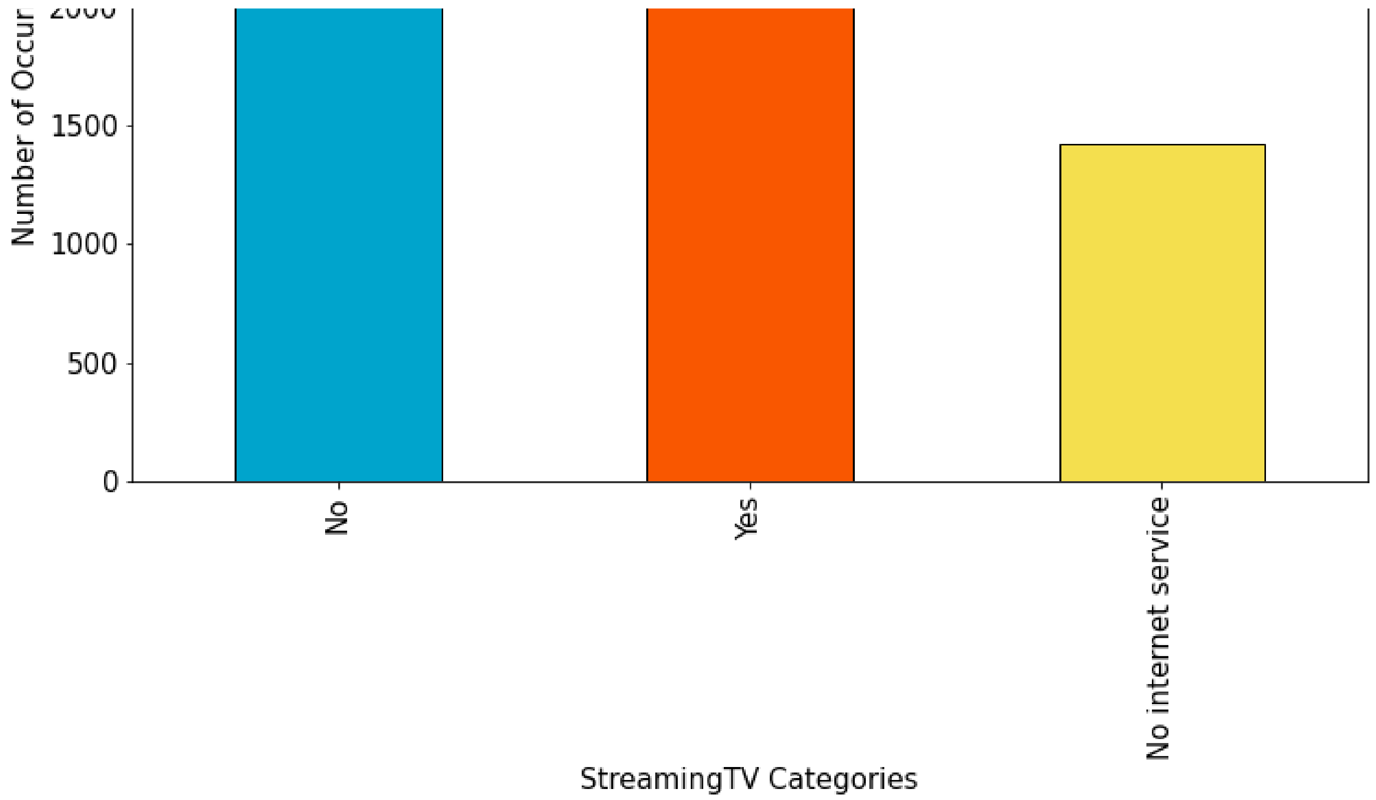
In [34]:

```
p1 = source_dataset['StreamingTV'].value_counts().plot.bar(color=['#00A4CCFF', '#F95700FF','#F4DF4EFF'],edgecolor='black');
plt.xlabel('StreamingTV Categories')
plt.ylabel('Number of Occurrences')
plt.title('Bar Plot for StreamingTV')
```

Out[34]:

```
Text(0.5, 1.0, 'Bar Plot for StreamingTV')
```





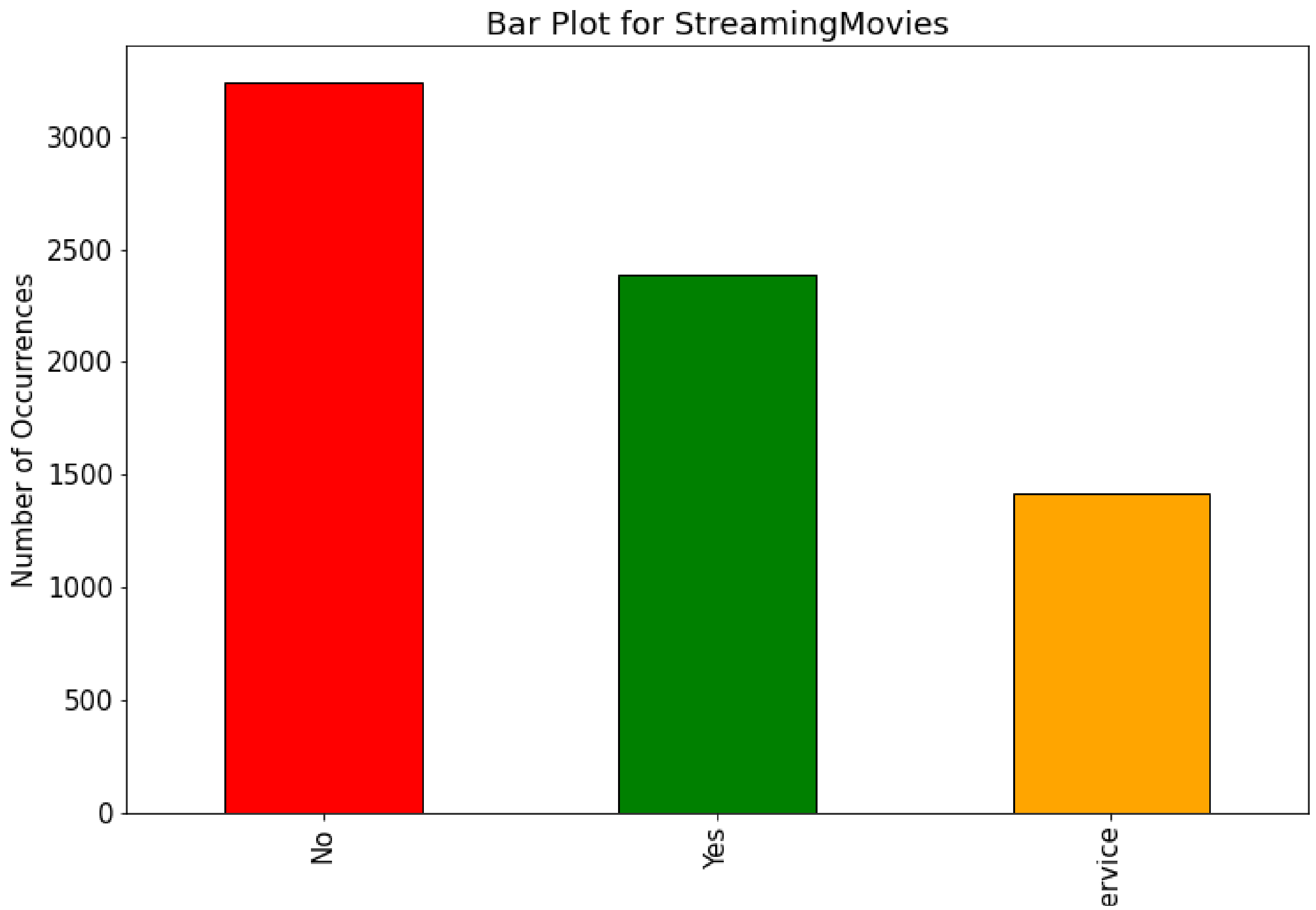
Frequency Distribution for the Column - "StreamingMovies"

In [35]:

```
p1 = source_dataset['StreamingMovies'].value_counts().plot.bar(color=['red', 'green', 'orange'],edgecolor='black');
plt.xlabel('StreamingMovies Categories')
plt.ylabel('Number of Occurrences')
plt.title('Bar Plot for StreamingMovies')
```

Out[35]:

```
Text(0.5, 1.0, 'Bar Plot for StreamingMovies')
```



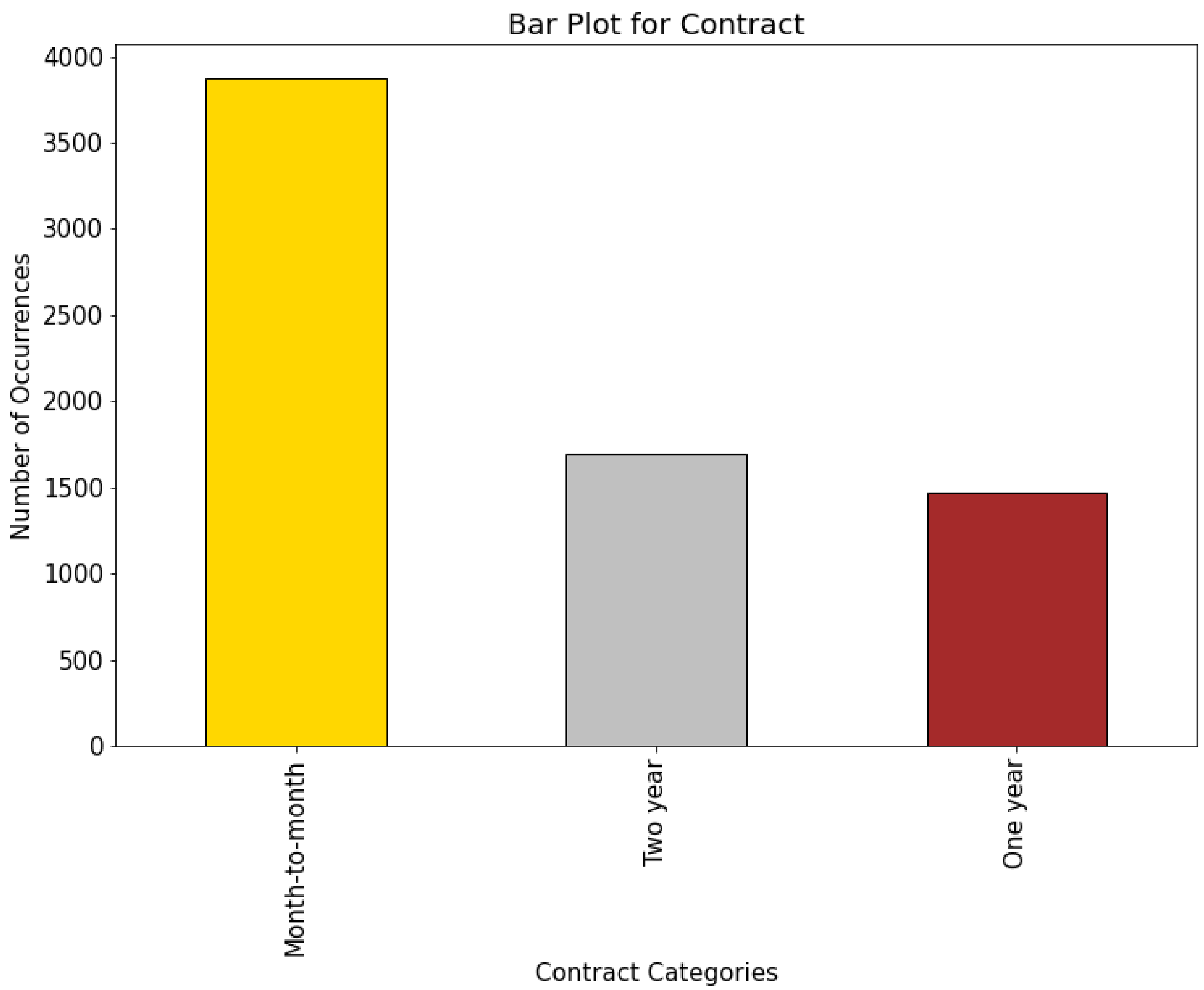
Frequency Distribution for the Column - "Contract"

In [36]:

```
p1 = source_dataset['Contract'].value_counts().plot.bar(color=['gold', 'silver', 'brown'],edgecolor='black');
plt.xlabel('Contract Categories')
plt.ylabel('Number of Occurrences')
plt.title('Bar Plot for Contract')
```

Out[36]:

```
Text(0.5, 1.0, 'Bar Plot for Contract')
```



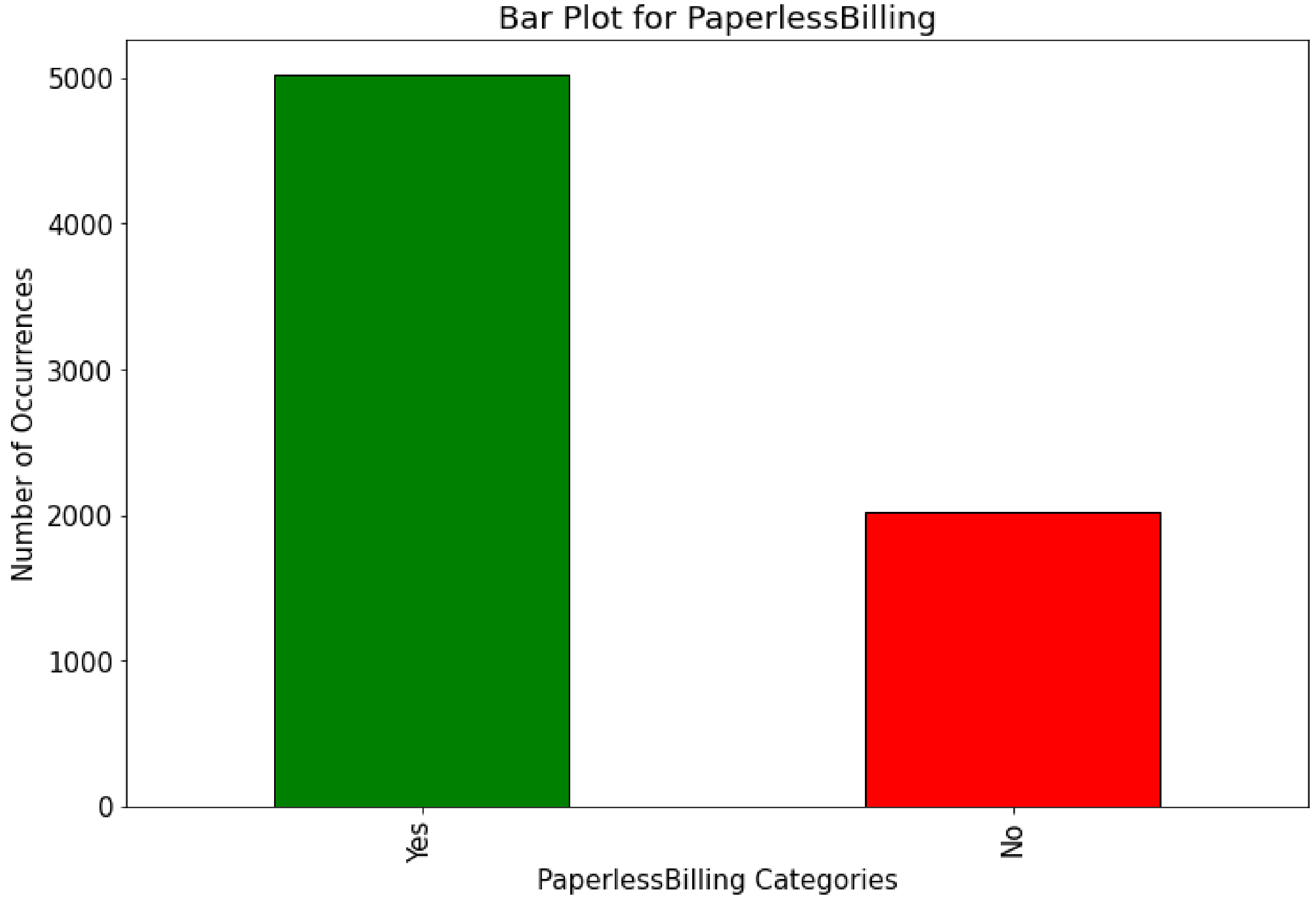
Frequency Distribution for the Column - "PaperlessBilling"

In [37]:

```
p1 = source_dataset['PaperlessBilling'].value_counts().plot.bar(color=['green', 'red', 'green', 'purple', 'cyan'],edgecolor='black');
plt.xlabel('PaperlessBilling Categories')
plt.ylabel('Number of Occurrences')
plt.title('Bar Plot for PaperlessBilling')
```

Out[37]:

Text(0.5, 1.0, 'Bar Plot for PaperlessBilling')



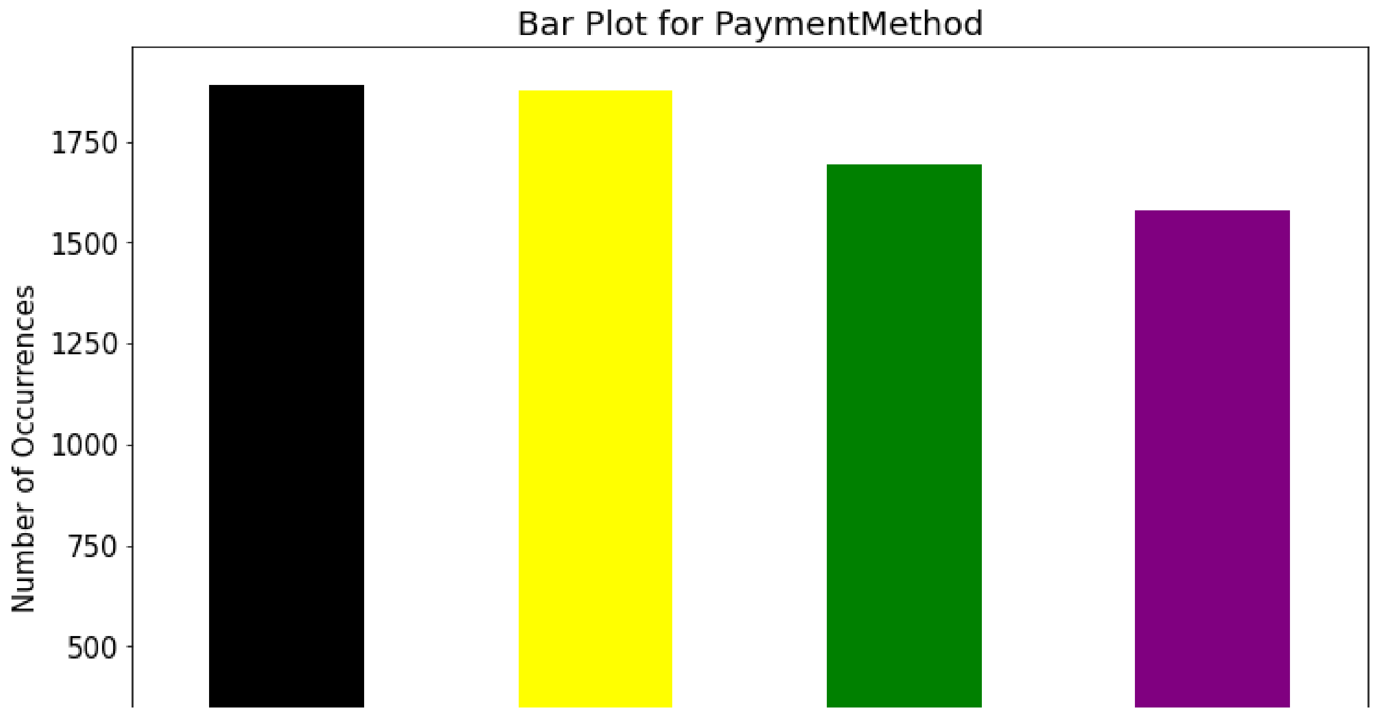
Frequency Distribution for the Column - "PaymentMethod"

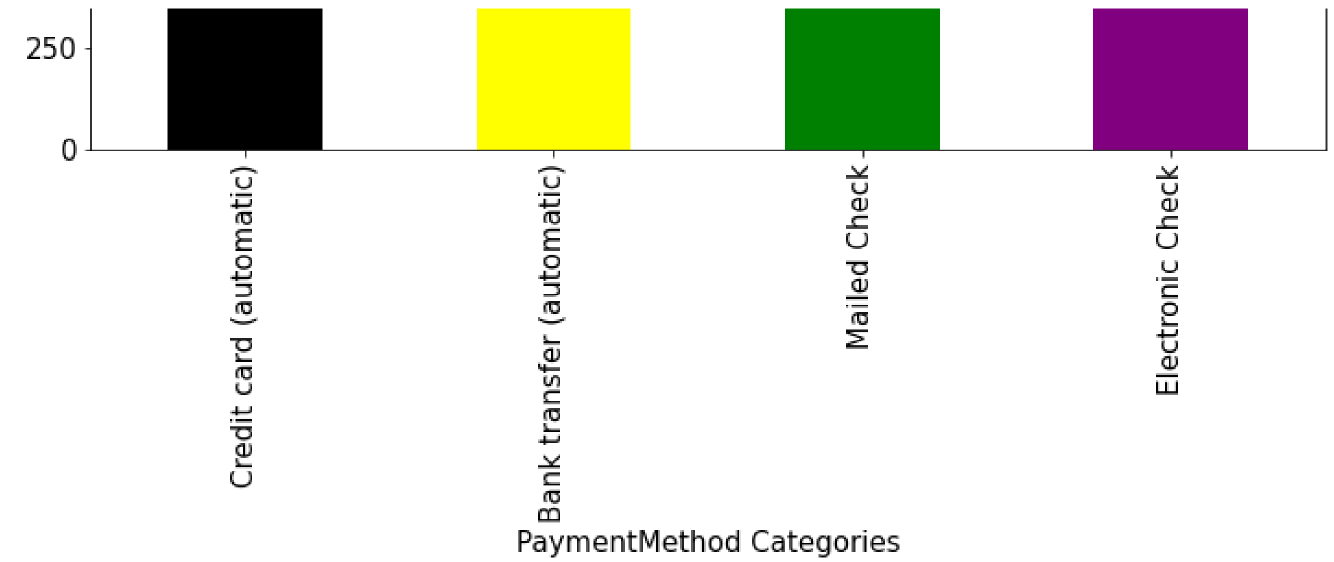
In [38]:

```
p1 = source_dataset['PaymentMethod'].value_counts().plot.bar(color=['black', 'yellow', 'green', 'purple', 'cyan']);
plt.xlabel('PaymentMethod Categories')
plt.ylabel('Number of Occurrences')
plt.title('Bar Plot for PaymentMethod')
```

Out[38]:

Text(0.5, 1.0, 'Bar Plot for PaymentMethod')





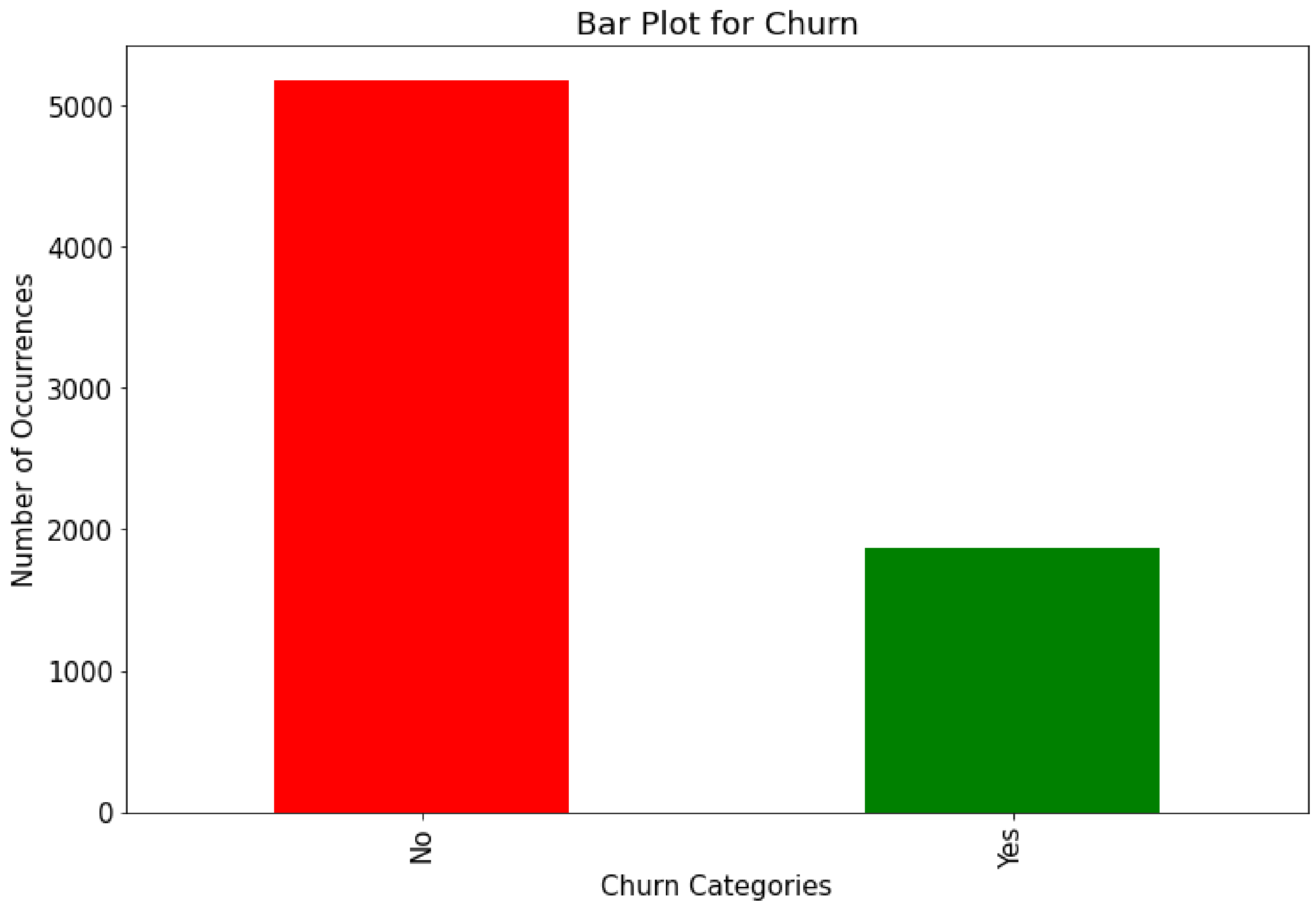
Frequency Distribution of values for the Column - "Churn"

In [39]:

```
p1 = source_dataset['Churn'].value_counts().plot.bar(color=['red', 'green'])
plt.xlabel('Churn Categories')
plt.ylabel('Number of Occurrences')
plt.title('Bar Plot for Churn')
# p1[0].set_color('r')
```

Out[39]:

```
Text(0.5, 1.0, 'Bar Plot for Churn')
```



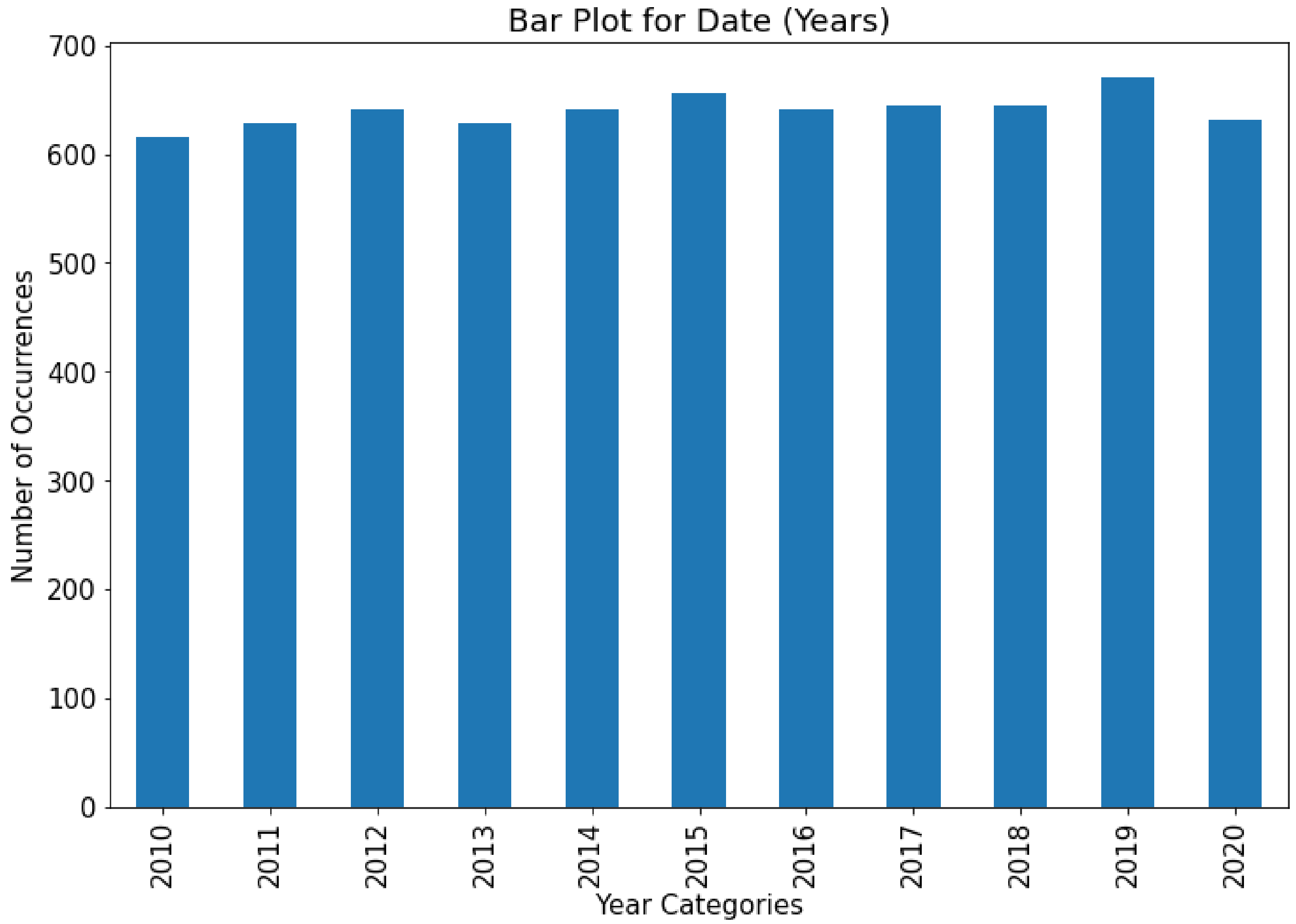
Frequencies of various Years for the Column - "Date"

In [40]:

```
source_dataset["Date"] =  pd.to_datetime(source_dataset["Date"])
source_dataset["Date"].groupby(source_dataset["Date"].dt.year).count().plot(kind="bar")
plt.xlabel('Year Categories')
plt.ylabel('Number of Occurrences')
plt.title('Bar Plot for Date (Years)')
```

Out[40]:

```
Text(0.5, 1.0, 'Bar Plot for Date (Years)')
```



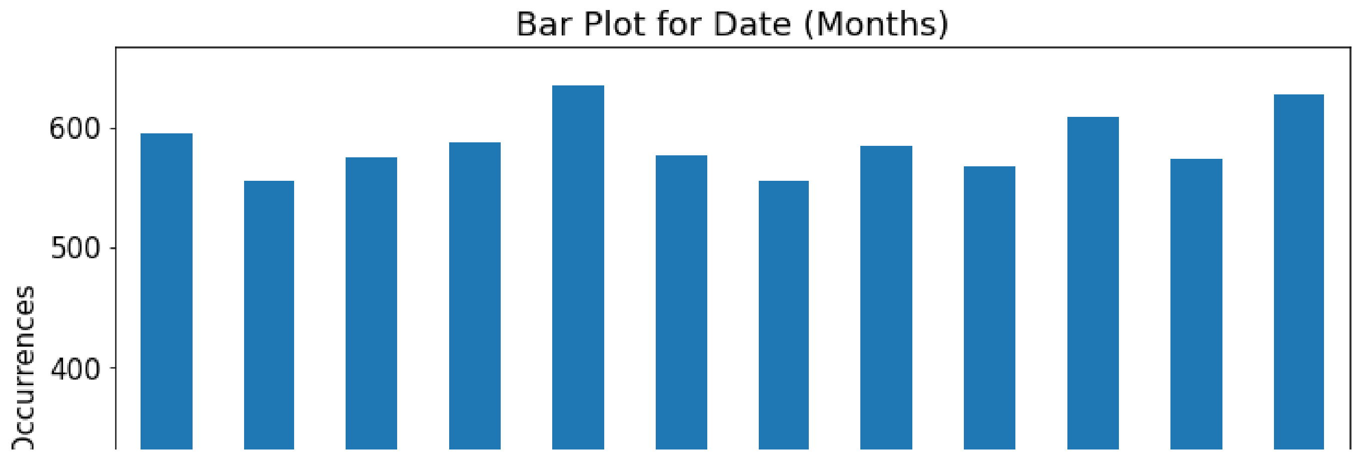
Frequencies of various Months for the Column - "Date"

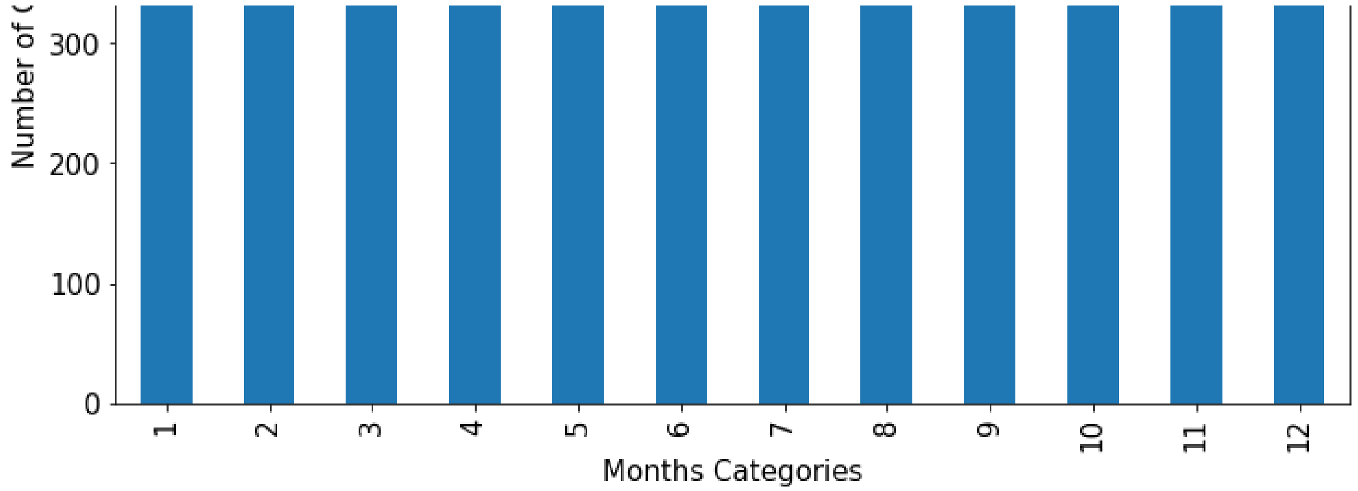
In [41]:

```
source_dataset["Date"] =  pd.to_datetime(source_dataset["Date"])
source_dataset["Date"].groupby(source_dataset["Date"].dt.month).count().plot(kind="bar")
plt.xlabel('Months Categories')
plt.ylabel('Number of Occurrences')
plt.title('Bar Plot for Date (Months)')
```

Out[41]:

```
Text(0.5, 1.0, 'Bar Plot for Date (Months)')
```





1.C.Data Quality Issues, Plan and Preprocessing

Missing values:

By referring to cells: [Data Quality Report -1]() and [Data Quality Report 2]() (Continuous and Categorical) we can notice that the percentage of missing values across all features is zero, save the column - 'TotalCharges', where 0.16% of records (~11 rows) are null.

In [42]:

```
source_dataset.isna().sum().sum()
```

Out[42]:

```
11
```

Rendering the 11 rows / customers whose TotaCharges is Null

In [43]:

```
source_dataset[source_dataset['TotalCharges'].isna()]
```

Out[43]:

	customerID	gender	SeniorCitizen	Partner	Dependents	PhoneService	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges
945	1371-DWPAZ	Female	0	Yes	Yes	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Two year	Yes	Bank transfer (automatic)	56.05	<NA>
1731	2520-SGTTA	Female	0	Yes	Yes	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Two year	Yes	Mailed Check	20.00	<NA>
1906	2775-SEFEE	Male	0	No	Yes	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Two year	Yes	Bank transfer (automatic)	61.90	<NA>
2025	2923-ARZLG	Male	0	Yes	Yes	Yes	DSL	No	No	No	No	No	No	One year	Yes	Credit card (automatic)	19.70	<NA>
2176	3115-CZMZD	Male	0	No	Yes	Yes	DSL	Yes	No	No	No	No	No	Two year	Yes	Electronic Check	20.25	<NA>
2250	3213-VVOLG	Male	0	Yes	Yes	Yes	Fiber optic	Yes	No	No	No	No	No	Two year	Yes	Electronic Check	25.35	<NA>
2855	4075-WKNIU	Female	0	Yes	Yes	Yes	Fiber optic	No	No	No	No	No	No	Two year	Yes	Electronic Check	73.35	<NA>
3052	4367-NUYAO	Male	0	Yes	Yes	Yes	DSL	No	Yes	No	No	Yes	Yes	Two year	Yes	Credit card (automatic)	25.75	<NA>
3118	4472-LVYGI	Female	0	Yes	Yes	Yes	Fiber optic	Yes	No	No	No	Yes	No	Two year	Yes	Electronic Check	52.55	<NA>
4054	5709-LVOEQ	Female	0	Yes	Yes	No	Fiber optic	No	Yes	No	Yes	No	Yes	Two year	Yes	Bank transfer (automatic)	80.85	<NA>

	customerID	gender	SeniorCitizen	Partner	Dependents	PhoneService	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges
5433	7644-OMVMY	Male	0	Yes	Yes	No	DSL	Yes	Yes	Yes	No	Yes	Yes	Two year	Yes	Credit card (automatic)	19.85	<NA>

Since we have only 11 rows that contain Null values for 'TotalCharges' we will eliminate these rows as we have assumed that these rows would not affect our analysis and predictions in a significant manner.

In [44]:

```
source_dataset.dropna(inplace = True)
```

In [45]:

```
source_dataset.isna().sum().sum()
```

Out[45]:

```
0
```

Irregular Cardinality

The column 'SeniorCitizen' has a cardinality of 2, which is odd for a continuous feature, therefore we will be treating this column as a categorical feature.

Churn

Let's convert the feature 'Churn' into numeric values

In [46]:

```
source_dataset['Churn'].replace(to_replace='Yes', value='1', inplace=True)
source_dataset['Churn'].replace(to_replace='No',  value='0', inplace=True)
source_dataset['Churn'] = source_dataset['Churn'].astype(int)
source_dataset.dtypes
```

Out[46]:

```
customerID                  string
gender                      string
SeniorCitizen                Int64
Partner                     string
Dependents                  string
PhoneService                string
InternetService             string
OnlineSecurity              string
OnlineBackup                string
DeviceProtection            string
TechSupport                 string
StreamingTV                 string
StreamingMovies             string
Contract                    string
PaperlessBilling            string
PaymentMethod               string
MonthlyCharges             Float64
TotalCharges               Float64
Churn                        int64
Date                datetime64[ns]
dtype: object
```

In [47]:

```
source_dataset.head(10)
```

Out[47]:

	customerID	gender	SeniorCitizen	Partner	Dependents	PhoneService	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Cl
0	0002-	Female	0	Yes	Yes	Yes	DSL	No	No	No	No	No	No	One	Yes	Electronic	65.60	593.30	

	customerID	gender	SeniorCitizen	Partner	Dependents	PhoneService	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Cl
1	0003-MKNFE	Male	0	No	No	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Month-to-month	Yes	Mailed Check	59.90	542.40	
2	0004-TLHLJ	Male	0	No	No	Yes	DSL	No	No	No	No	No	No	Month-to-month	Yes	Credit card (automatic)	73.90	280.85	
3	0011-IGKFF	Male	1	Yes	No	Yes	DSL	No	No	No	No	No	No	Month-to-month	Yes	Credit card (automatic)	98.00	1237.85	
4	0013-EXCHZ	Female	1	Yes	No	Yes	DSL	Yes	Yes	No	No	No	No	Month-to-month	Yes	Electronic Check	83.90	267.40	
5	0013-MHZWF	Female	0	No	Yes	Yes	DSL	No	No	No	No	No	No	Month-to-month	Yes	Mailed Check	69.40	571.45	
6	0013-SMEOE	Female	1	Yes	No	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Two year	Yes	Credit card (automatic)	109.70	7904.25	
7	0014-BMAQU	Male	0	Yes	No	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Two year	Yes	Electronic Check	84.65	5377.80	
8	0015-UOCOJ	Female	1	No	No	Yes	DSL	No	No	No	No	No	No	Month-to-month	Yes	Bank transfer (automatic)	48.20	340.35	
9	0016-QLJIS	Female	0	Yes	Yes	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Two year	Yes	Electronic Check	90.45	5957.90	

Tenure

The Feature 'Tenure' is calculated by determining the difference between a customer's 'join_date'/'Date' and a baseline Date. We have considered our baseline date to be `May-30-2021`.

Let's now add a new column - 'Tenure' to the dataframe

In [48]:

```
print(source_dataset["Date"].max())
print(source_dataset["Date"].min())
```

```
2020-12-30 00:00:00
2010-01-01 00:00:00
```

In [49]:

```
import datetime

end_date = datetime.date(2021, 5, 30)
print(end_date)
source_dataset["End_date"] = end_date
source_dataset.head(10)
```

```
2021-05-30
```

Out[49]:

	customerID	gender	SeniorCitizen	Partner	Dependents	PhoneService	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Cl
0	0002-ORFBO	Female	0	Yes	Yes	Yes	DSL	No	No	No	No	No	No	One year	Yes	Electronic Check	65.60	593.30	
1	0003-MKNFE	Male	0	No	No	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Month-to-month	Yes	Mailed Check	59.90	542.40	
2	0004-TLHLJ	Male	0	No	No	Yes	DSL	No	No	No	No	No	No	Month-to-month	Yes	Credit card (automatic)	73.90	280.85	

	customerID	gender	SeniorCitizen	Partner	Dependents	PhoneService	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Cl
3	0011-IGKFF	Male	1	Yes	No	Yes	DSL	No	No	No	No	No	No	Month-to-month	Yes	Credit card (automatic)	98.00	1237.85	
4	0013-EXCHZ	Female	1	Yes	No	Yes	DSL	Yes	Yes	No	No	No	No	Month-to-month	Yes	Electronic Check	83.90	267.40	
5	0013-MHZWF	Female	0	No	Yes	Yes	DSL	No	No	No	No	No	No	Month-to-month	Yes	Mailed Check	69.40	571.45	
6	0013-SMEOE	Female	1	Yes	No	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Two year	Yes	Credit card (automatic)	109.70	7904.25	
7	0014-BMAQU	Male	0	Yes	No	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Two year	Yes	Electronic Check	84.65	5377.80	
8	0015-UOCOJ	Female	1	No	No	Yes	DSL	No	No	No	No	No	No	Month-to-month	Yes	Bank transfer (automatic)	48.20	340.35	
9	0016-QLJIS	Female	0	Yes	Yes	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Two year	Yes	Electronic Check	90.45	5957.90	

In [50]:

```
source_dataset["Tenure"] = (pd.to_datetime(source_dataset.End_date) - pd.to_datetime(source_dataset.Date)).dt.days
source_dataset.tail(10)
```

Out[50]:

	customerID	gender	SeniorCitizen	Partner	Dependents	PhoneService	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges
7033	9975-SKRNR	Male	0	No	No	No	Fiber optic	Yes	No	Yes	No	Yes	Yes	Month-to-month	No	Bank transfer (automatic)	18.90	18.90
7034	9978-HYCIN	Male	1	Yes	Yes	Yes	Fiber optic	Yes	No	Yes	Yes	Yes	Yes	One year	No	Credit card (automatic)	84.95	4018.05
7035	9979-RGMZT	Female	0	No	No	Yes	Fiber optic	No	No	No	Yes	Yes	Yes	One year	No	Bank transfer (automatic)	94.05	633.45
7036	9985-MWVIX	Female	0	No	No	Yes	Fiber optic	Yes	Yes	Yes	Yes	No	Yes	Month-to-month	Yes	Credit card (automatic)	70.15	70.15
7037	9986-BONCE	Female	0	No	No	No	Fiber optic	Yes	Yes	Yes	No	Yes	No	Month-to-month	No	Bank transfer (automatic)	20.95	85.50
7038	9987-LUTYD	Female	0	No	No	No	Fiber optic	Yes	Yes	No	Yes	No	Yes	One year	No	Bank transfer (automatic)	55.15	742.90
7039	9992-RRAMN	Male	0	Yes	No	No	Fiber optic	Yes	Yes	Yes	Yes	Yes	Yes	Month-to-month	No	Credit card (automatic)	85.10	1873.70
7040	9992-UJOEL	Male	0	No	No	No	Fiber optic	No	Yes	Yes	Yes	Yes	No	Month-to-month	No	Credit card (automatic)	50.30	92.75
7041	9993-LHIEB	Male	0	Yes	Yes	No	Fiber optic	No	No	Yes	No	Yes	Yes	Two year	No	Credit card (automatic)	67.85	4627.65
7042	9995-HOTOH	Male	0	Yes	Yes	Yes	Fiber optic	Yes	Yes	No	No	Yes	Yes	Two year	No	Credit card (automatic)	59.00	3707.60

Note: We will be transforming the Dataframe after performing Exploratory Data Analysis by performing operations such as One-hot encoding.

Exploratory Data Analysis

Customer Attrition / Churn Distribution:

Let's visualize the percentage of customers who have retained their subscriptions or deactivated it. ***italicized text***

References: [Pie Charts with Plotly]

In [51]:

```
import plotly.express as px
fig = px.pie(source_dataset, names = 'Churn', template = 'seaborn',
            title = 'Churn')
fig.update_traces(rotation=90, pull = [0.1], textinfo = "percent+label")
fig.show()
```

Churn We can observe that 26.6% of the customers have deactivated their plans, which is around 1873 out of 7043 customers.

In [52]:

```
print(26.6/100*7043)
```

```
1873.438
```

Distribution of Senior Citizens

References: [Pie Charts with Matplotlib]

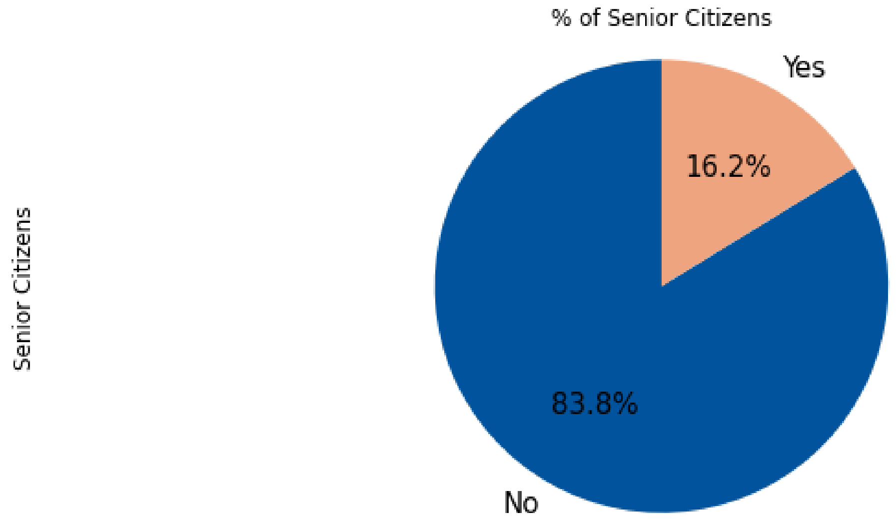
In [53]:

```
import matplotlib as mpl
colors = ['#00539CFF', '#EEA47FFF']
mpl.rcParams.update({'text.color' : "black"})
labels = 'No', 'Yes'
plt.figure(figsize = (12,5))
ax = ((source_dataset['SeniorCitizen'].value_counts()/len(source_dataset['SeniorCitizen']))*100).plot.pie(labels=labels, autopct='%1.1f%%', shadow=False, startangle=90, colors = colors)
ax.set_ylabel('Senior Citizens',fontsize = 12)
```

```
ax.set_title('% of Senior Citizens', fontsize = 12)
ax.axis('equal')
```

Out[53]:

```
(-1.1059512938819451,
 1.1065875007007335,
 -1.1055497655464688,
 1.1002643080914476)
```



We can observe that around 16% of customers are Senior Citizens whereas the rest are regular adults.

Distribution of Customers by Tenure

References: [Seaborn Distribution Plots]

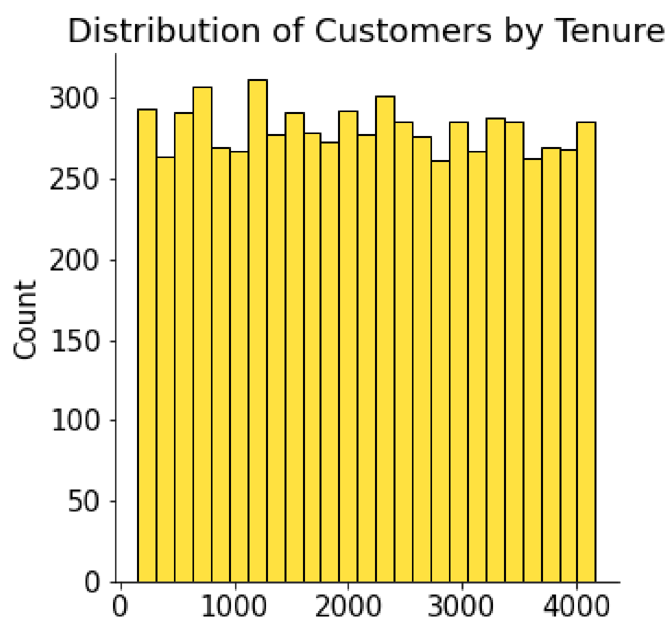
In [54]:

```
import seaborn as sb
colors = ['gold', 'silver']
sb.set_palette(sb.color_palette(colors))
plt.figure(figsize = (10,5))

ax = sb.displot(source_dataset["Tenure"], kde = False, bins = 25)
plt.title('Distribution of Customers by Tenure')
```

Out[54]:

```
Text(0.5, 1.0, 'Distribution of Customers by Tenure')
```

```
<Figure size 720x360 with 0 Axes>
```



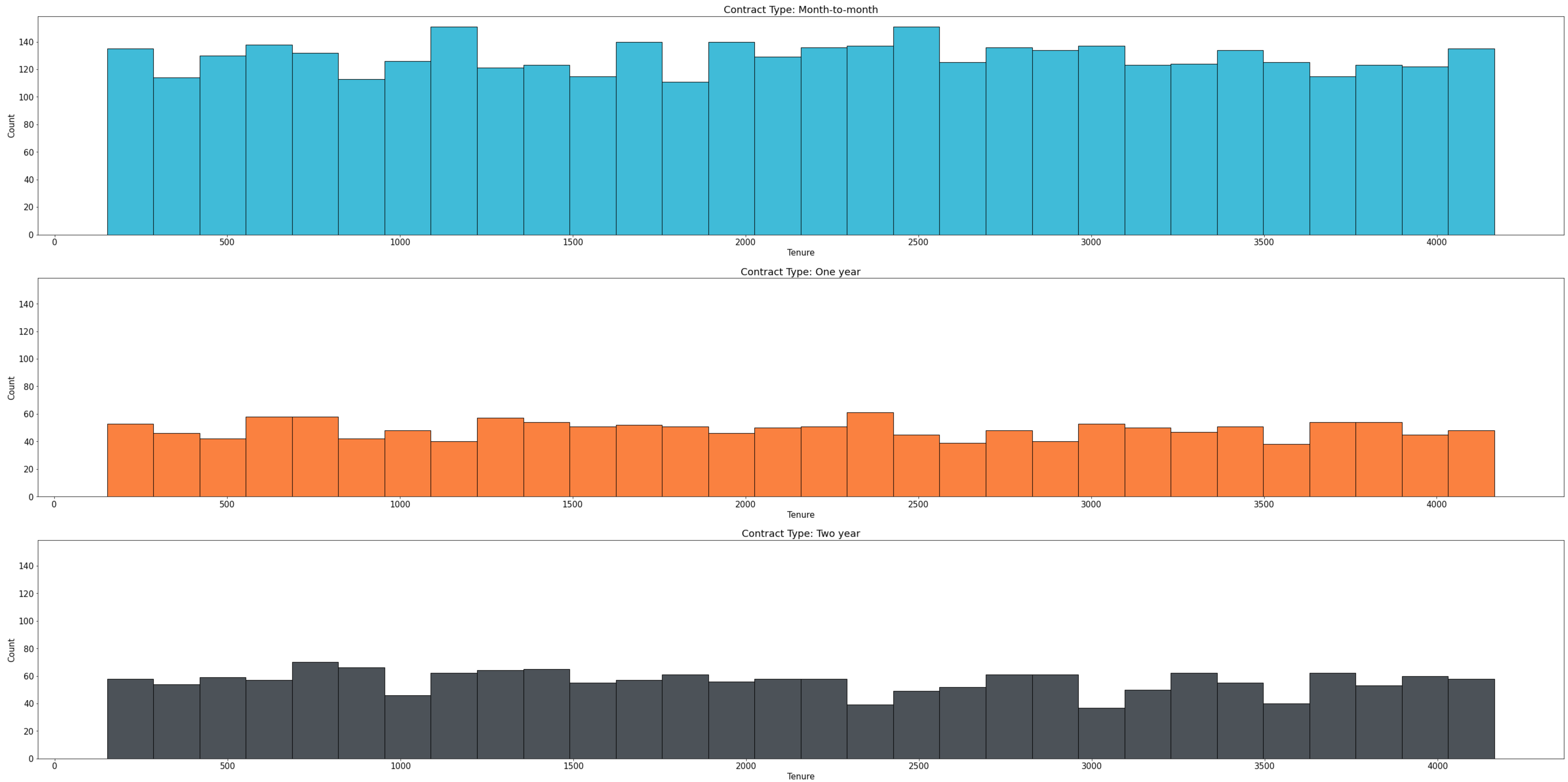
Tenure

Tenure Vs Contract Type

References: [Seaborn Histogram Plots]

In [55]:

```
fig, axs = plt.subplots(nrows = 3, ncols = 1, sharey = True, figsize=(50,25))

cols = ['Month-to-month', 'One year', 'Two year']
colors = ['#00A4CCFF', '#F95700FF','#101820FF']
for i, col in enumerate(cols):
    ax = sb.histplot(source_dataset[source_dataset['Contract'] == col]['Tenure'], kde = False, bins = 30, ax = axs[i], color = colors[i])
    ax.set_title('Contract Type: ' + col)
```



From the charts, we can observe that the number of customers with high tenure is predominant for the 'month-month' contract type.

Churn Vs Contract Type

O Refers to 'No' / which means that the Customer has an active subscription with the organization.

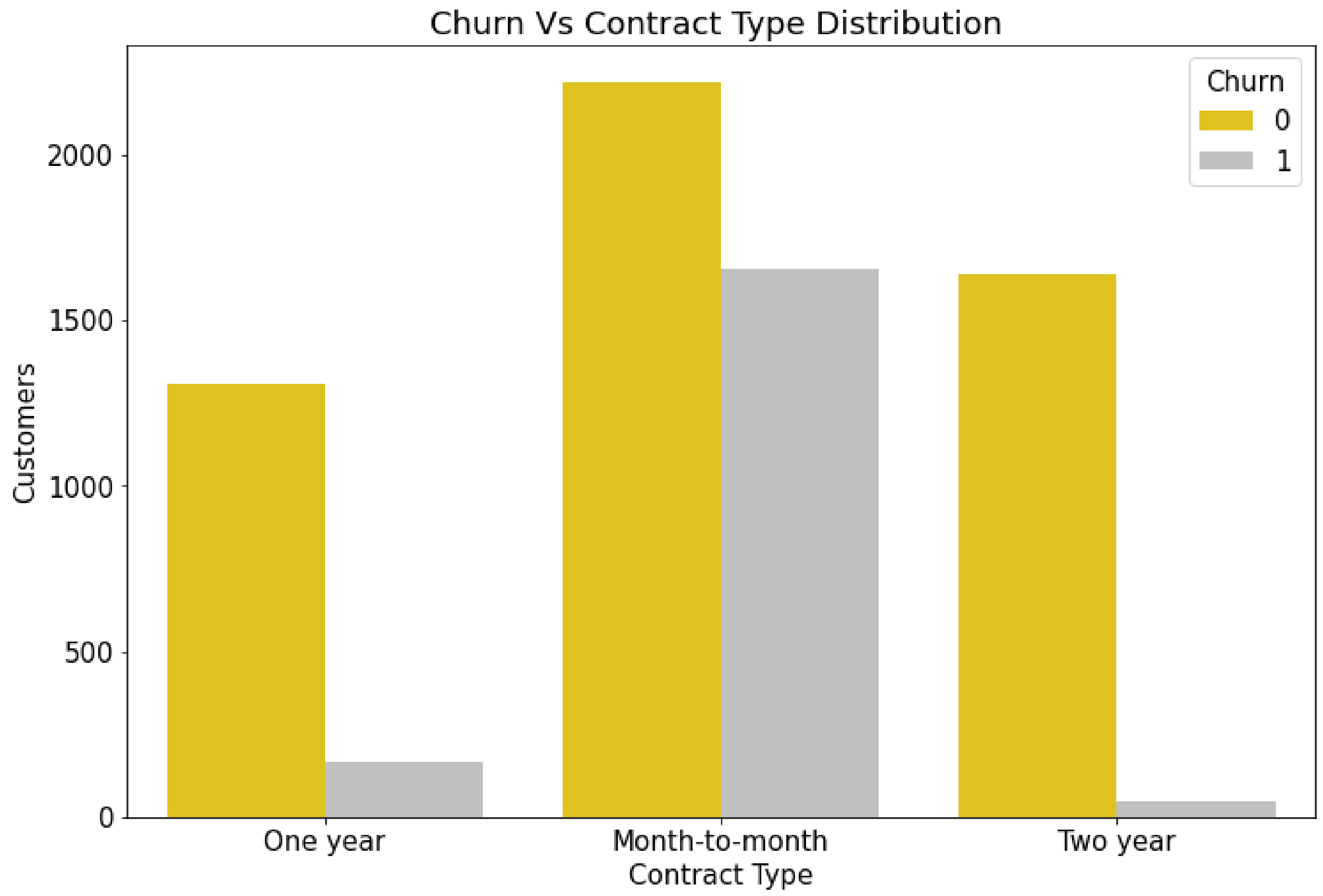
1 Refers to 'Yes' / which means that the Customer has unsubscribed from the origianization's plan.

In [56]:

```
ax = sb.countplot(data = source_dataset, x = 'Contract', hue = 'Churn')

ax.set_ylabel('Customers')
ax.set_xlabel('Contract Type')
ax.set_title('Churn Vs Contract Type Distribution ')
```

Out[56]:

```
Text(0.5, 1.0, 'Churn Vs Contract Type Distribution ')
```



From the graph, we can observe that 'Month-to-Month' contracts have the highest customer retention as well as highest cutomer attrition among all the contract types.

Churn Vs Total Charges and Monthly Charges

References: [Seaborn KDE Plots]

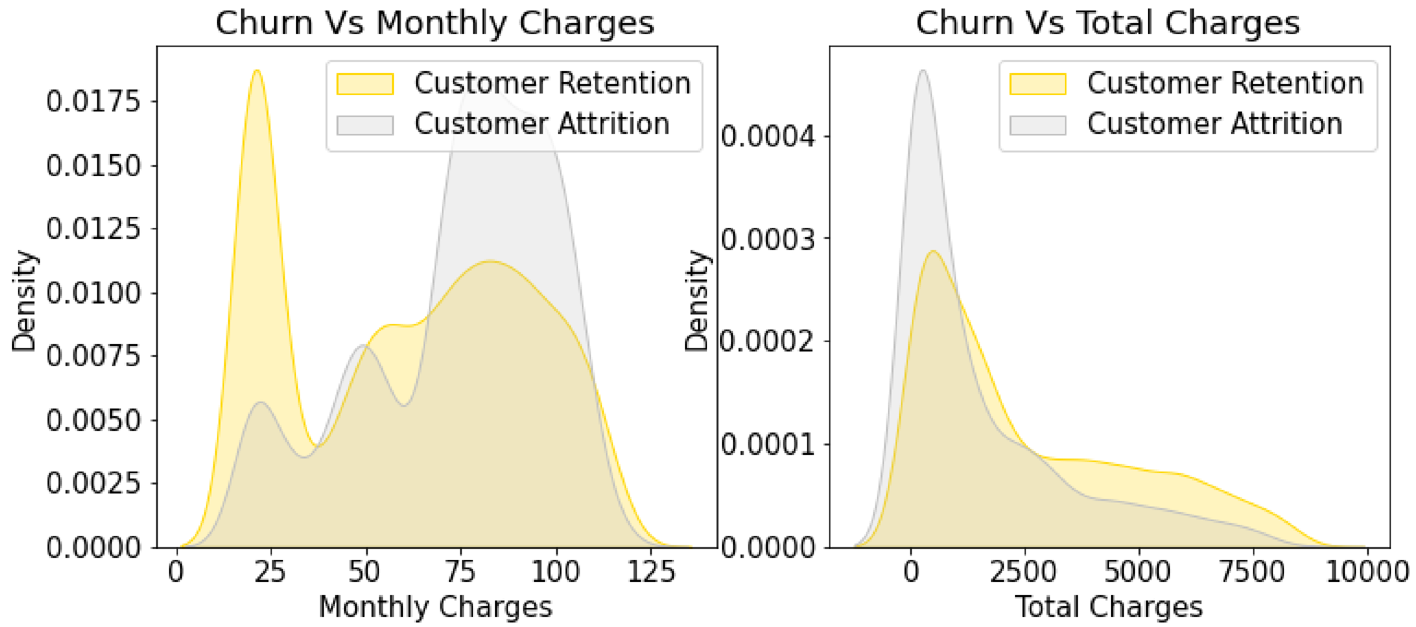
In [57]:

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


ax = sb.kdeplot(source_dataset.MonthlyCharges[(source_dataset["Churn"] == 0) ],
                ax = axs[0],shade = True)
ax = sb.kdeplot(source_dataset.MonthlyCharges[(source_dataset["Churn"] == 1) ],
                ax = axs[0], shade= True)

ax.legend(["Customer Retention","Customer Attrition"],loc='best')
ax.set_ylabel('Density')
ax.set_xlabel('Monthly Charges')
ax.set_title('Churn Vs Monthly Charges')
```

```
ax = sb.kdeplot(source_dataset.TotalCharges[(source_dataset["Churn"] == 0) ],
                ax = axs[1],shade = True)
ax = sb.kdeplot(source_dataset.TotalCharges[(source_dataset["Churn"] == 1) ],
                ax = axs[1], shade= True)

ax.legend(["Customer Retention","Customer Attrition"],loc='best')
ax.set_ylabel('Density')
ax.set_xlabel('Total Charges')
ax.set_title('Churn Vs Total Charges')
```

Out[57]:

```
Text(0.5, 1.0, 'Churn Vs Total Charges')
```



By observing the variations of the plot in both the graphs, we can come to a conclusion that the feature Monthly Charges is important for Determining Customer Churn or Attrition. The Feature Total Charges, however, doesn't represent much variation.

Distribution of customers for various services availed and comparison with the number of customers who cancelled their subscription (Churn)

Phone Service Vs Churn

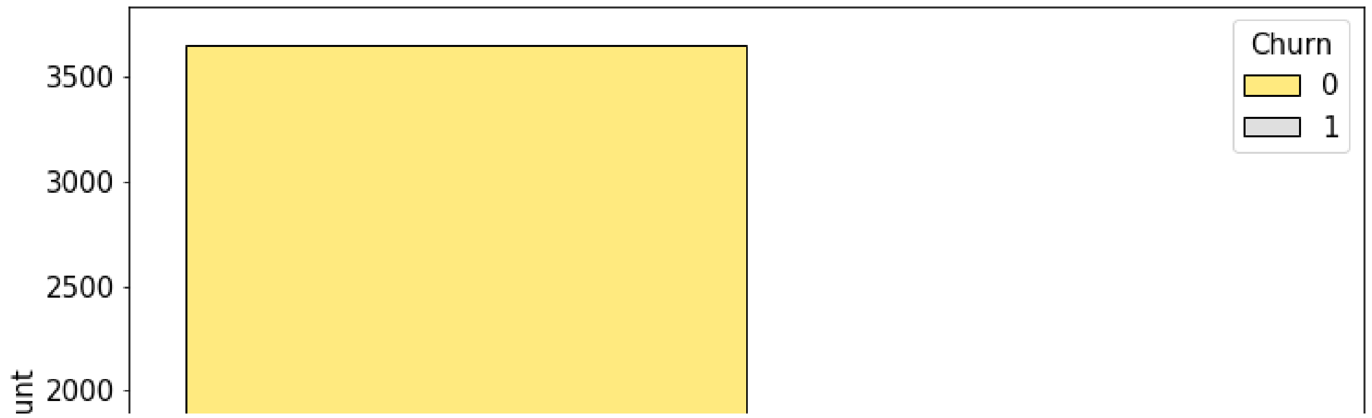
References: [Seaborn Histogram Plots]

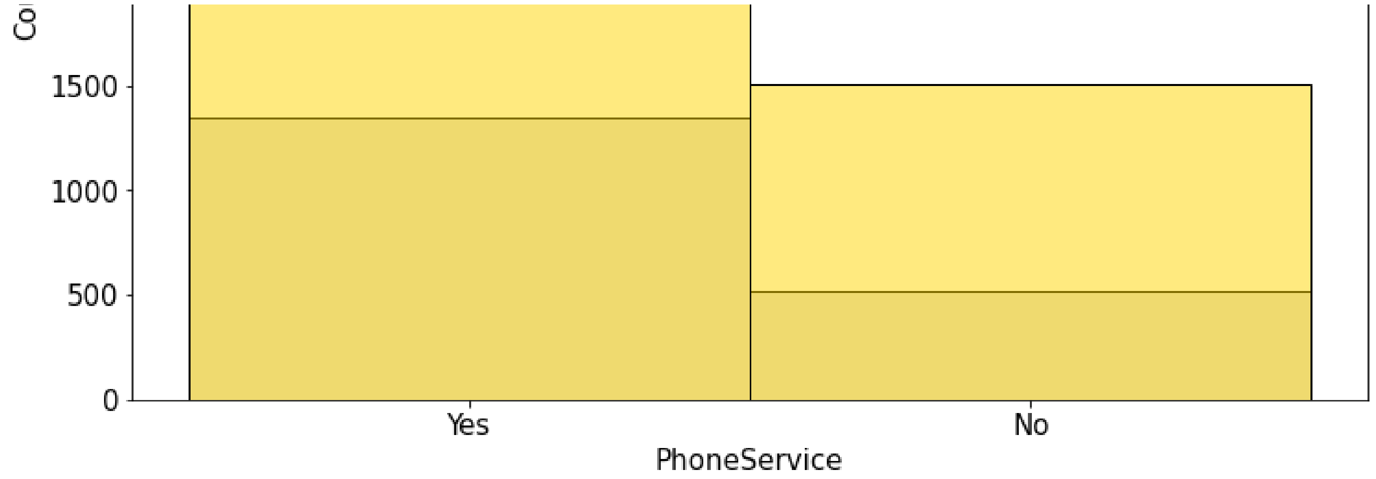
In [58]:

```
sb.histplot(data=source_dataset,x="PhoneService",hue='Churn')
```

Out[58]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8fd7334390>
```





From the graph above, we can observe that customers who had availed Phone Service are more in number than those who did not opt for Phone Service.

Internet Service Vs Churn

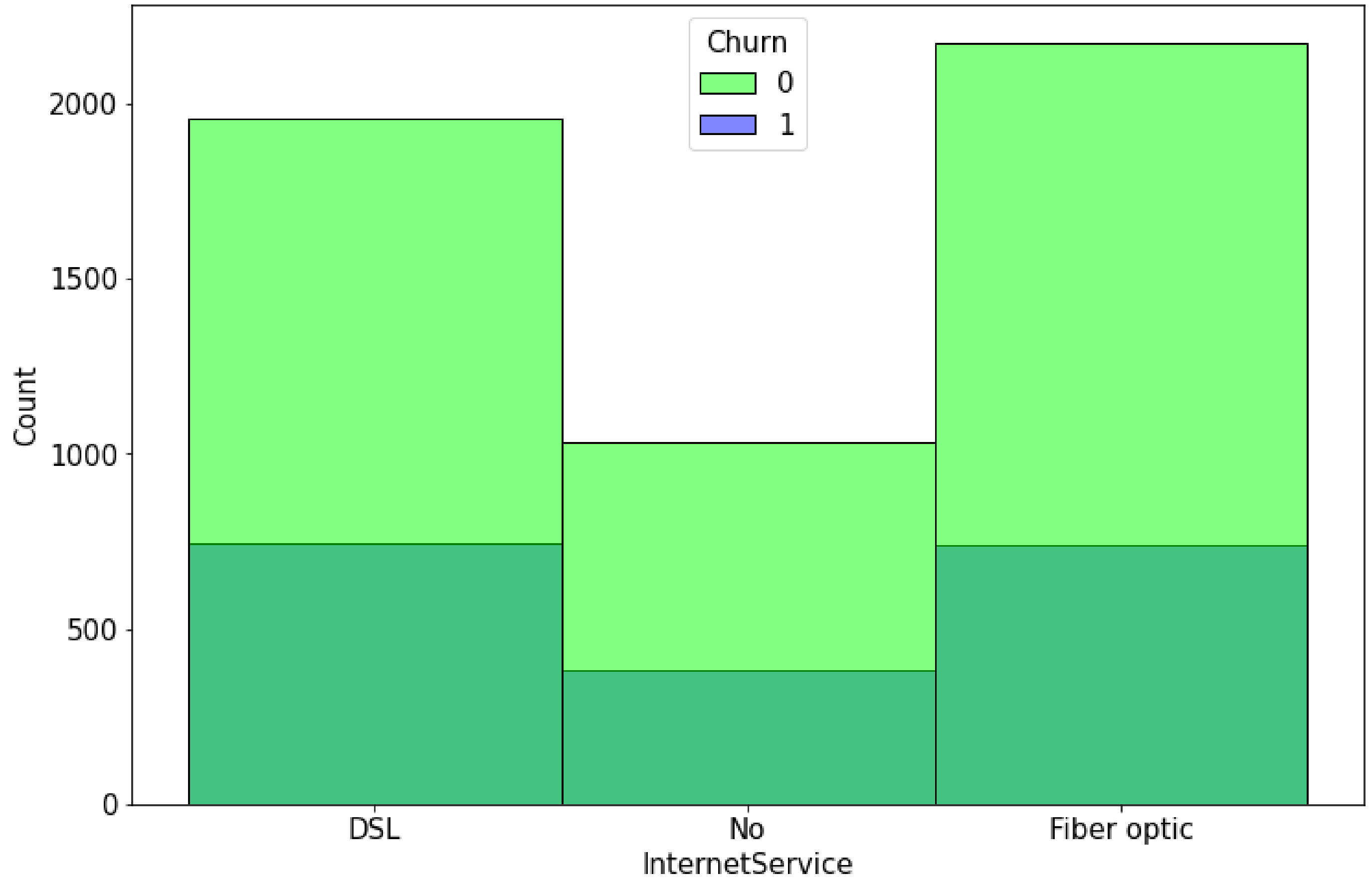
References: [Seaborn Histogram Plots]

In [59]:

```
sb.histplot(data=source_dataset,x="InternetService",hue='Churn', palette='hsv')
```

Out[59]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8fd070f510>
```



From the graph above, we can observe that customers who had availed Fibre Optic and DSL Service have a higher customer retention value than those who did not opt for Internet Service.

Online Service Vs Churn

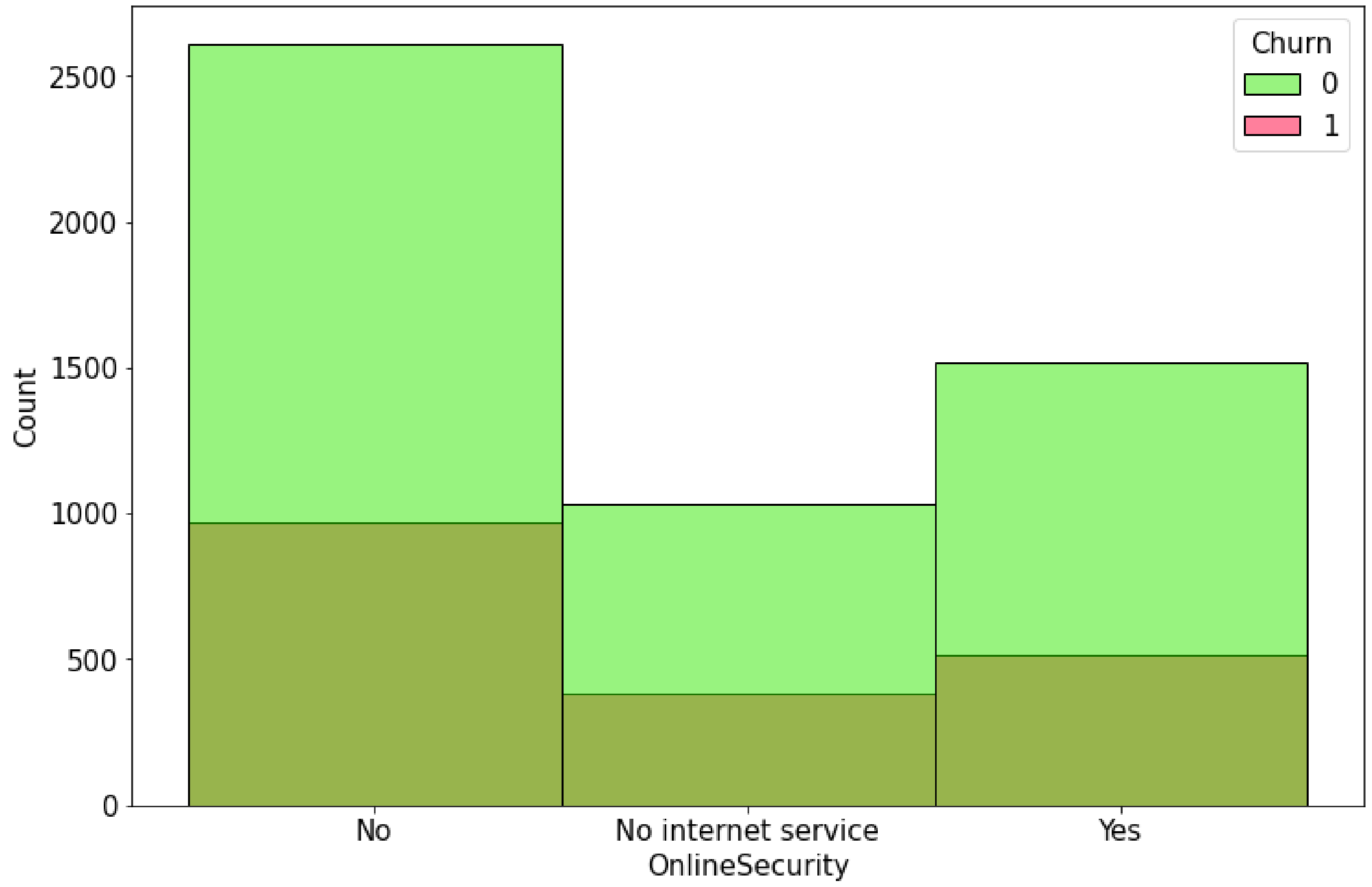
References: [Seaborn Histogram Plots]

In [60]:

```
sb.histplot(data=source_dataset,x='OnlineSecurity',hue='Churn', palette='prism')
```

Out[60]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8fd07a3c90>
```



From the graph above, we can observe that customers who didn't purchase Online Security features have lower churn values than those who did.

Internet Online Backup Service Vs Churn

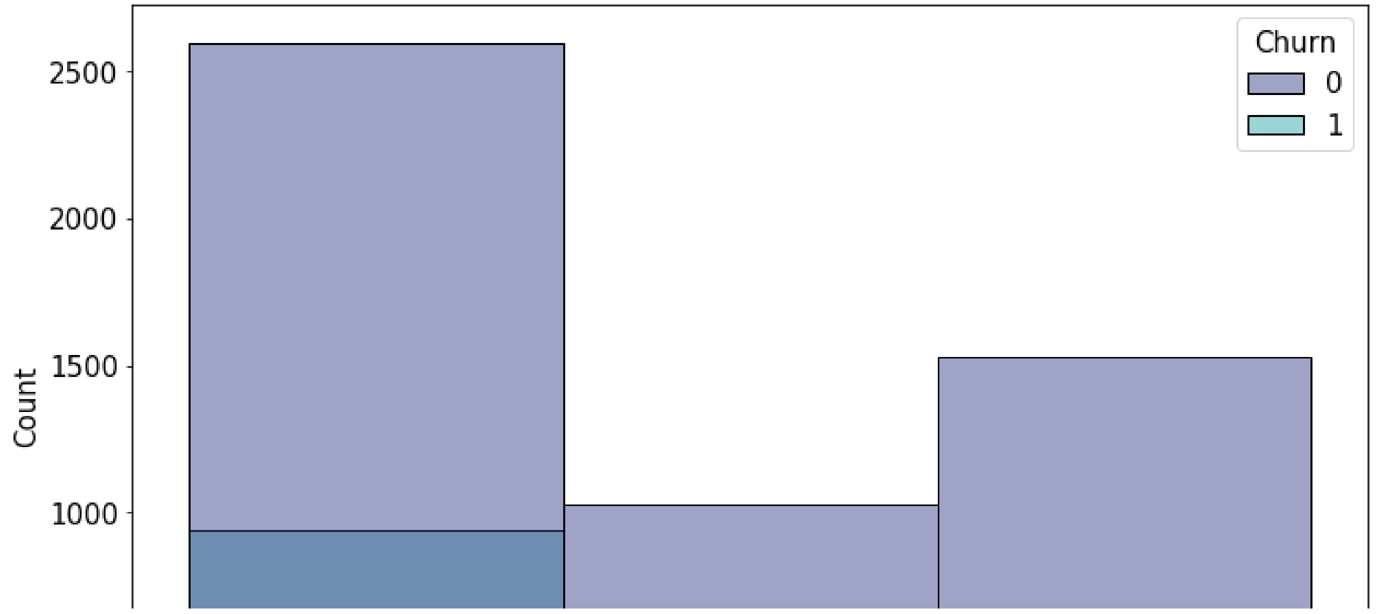
References: [Seaborn Histogram Plots]

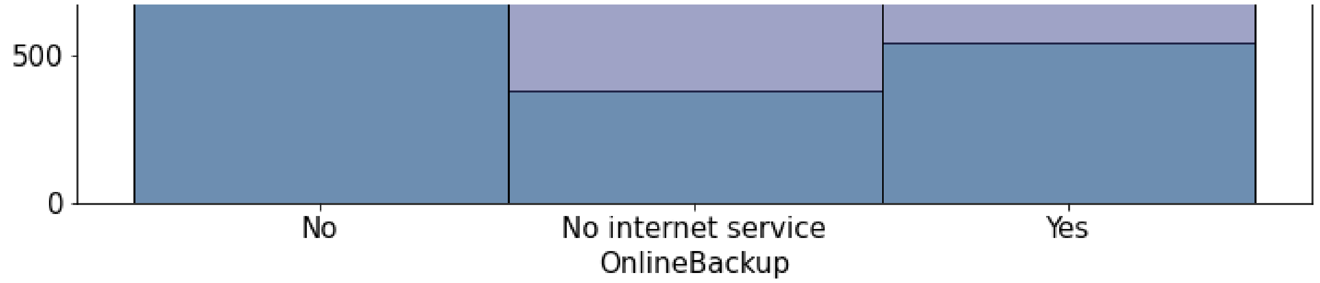
In [61]:

```
sb.histplot(data=source_dataset,x="OnlineBackup",hue='Churn', palette='mako')
```

Out[61]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8fd05faf10>
```





From the graph above, we can observe that customers who did not purchase Online Backup service tend to keep their subscriptions active than than those who did.

No Internet Service Vs Churn

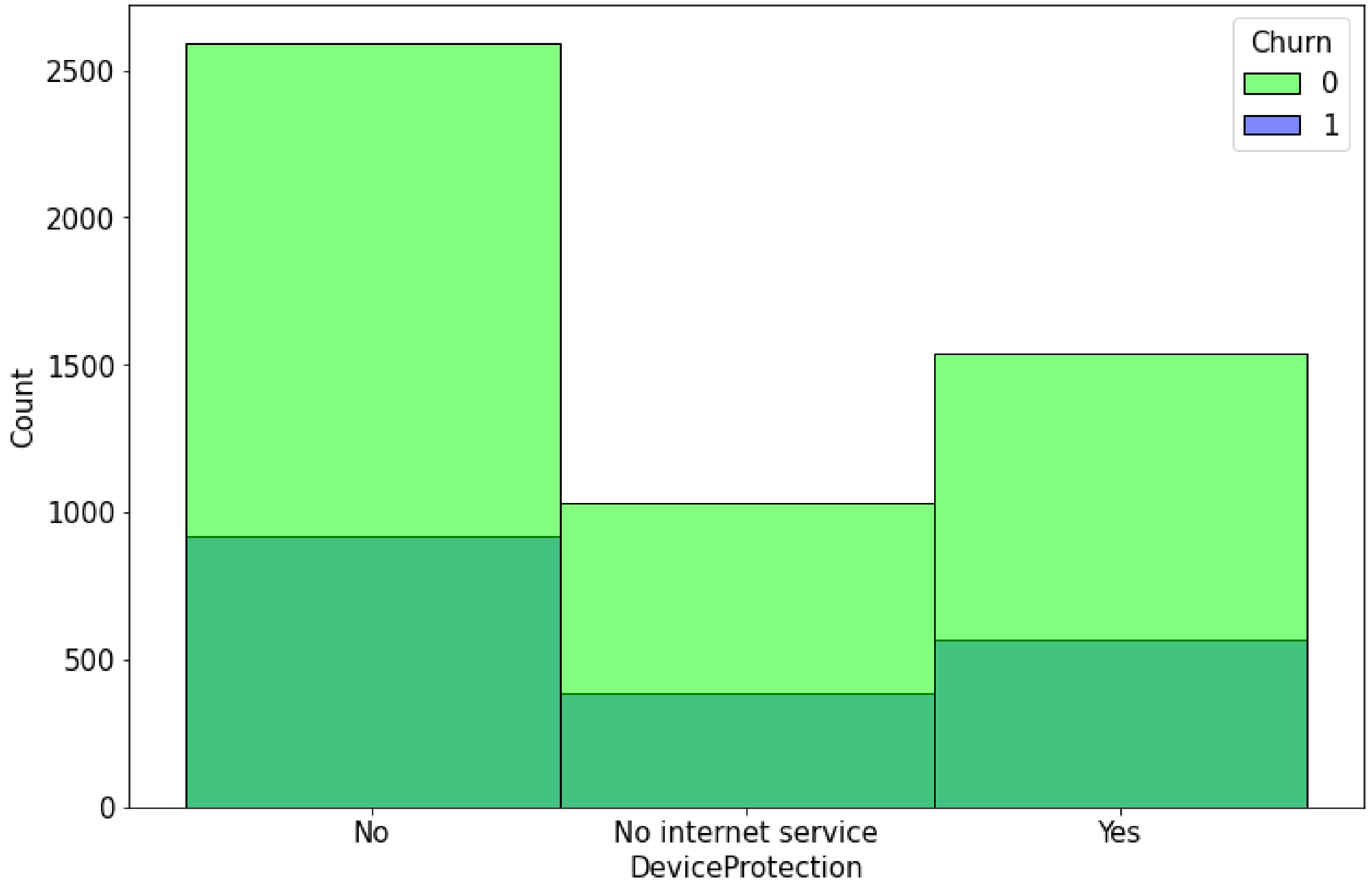
References: [Seaborn Histogram Plots]()

In [62]:

```
sb.histplot(data=source_dataset,x="DeviceProtection",hue='Churn', palette='hsv')
```

Out[62]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8fd0578a10>
```



From the graph above, we can observe that customers who did not purchase Device Protection service tend to keep their subscriptions active than than those who did.

Tech Support Vs Churn

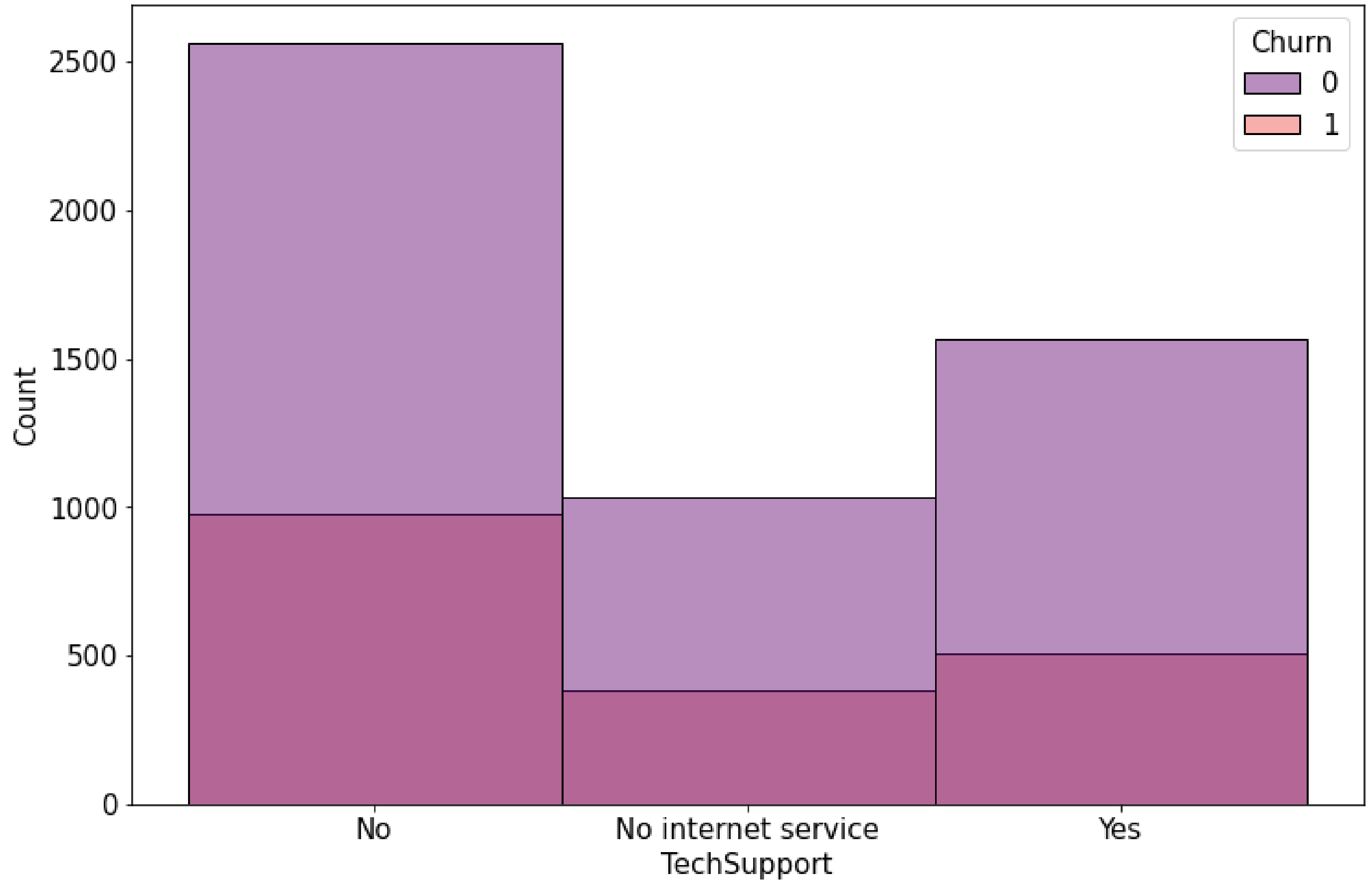
References: [Seaborn Histogram Plots]()

In [63]:

```
sb.histplot(data=source_dataset,x="TechSupport",hue='Churn', palette='magma')
```

Out[63]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8fd055f290>
```



From the graph above, we can observe that customers who did not purchase Device Protection service tend to keep their subscriptions active than than those who did.

Streaming TV Vs Churn

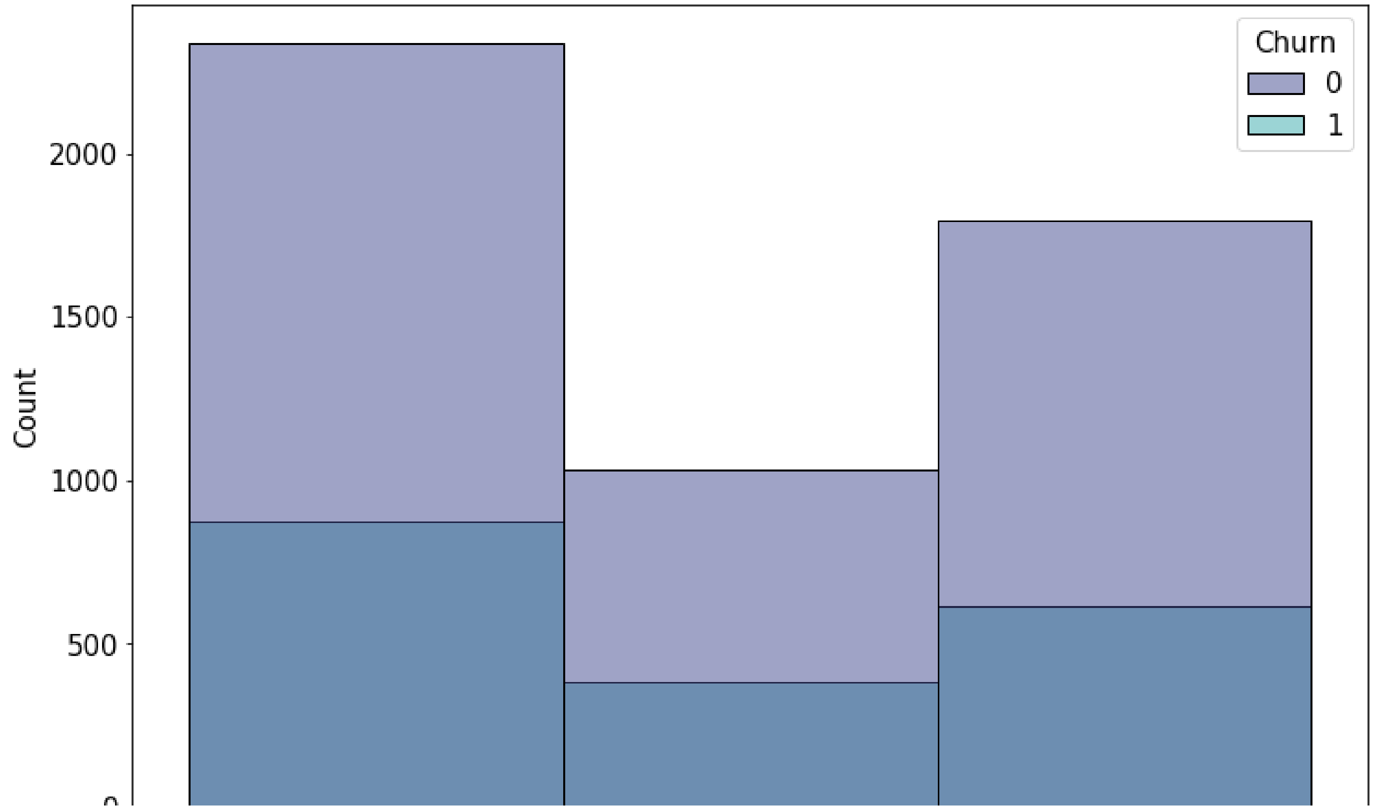
References: [Seaborn Histogram Plots]

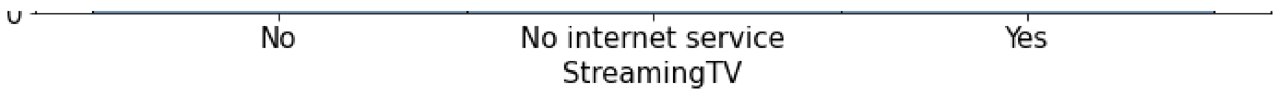
In [64]:

```
sb.histplot(data=source_dataset,x='StreamingTV',hue='Churn', palette='mako')
```

Out[64]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8fd0586250>
```





From the graph above, we can observe that customers who did not purchase Streaming TV service tend to keep their subscriptions active than than those who did.

Correlation Between the features in the dataset

Let's determine the correlation between all the features in the dataframe

In [65]:

```
source_dataset.head(10)
```

Out[65]:

	customerID	gender	SeniorCitizen	Partner	Dependents	PhoneService	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Cl
0	0002-ORFBO	Female	0	Yes	Yes	Yes	DSL	No	No	No	No	No	No	One year	Yes	Electronic Check	65.60	593.30	
1	0003-MKNFE	Male	0	No	No	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Month-to-month	Yes	Mailed Check	59.90	542.40	
2	0004-TLHLJ	Male	0	No	No	Yes	DSL	No	No	No	No	No	No	Month-to-month	Yes	Credit card (automatic)	73.90	280.85	
3	0011-IGKFF	Male	1	Yes	No	Yes	DSL	No	No	No	No	No	No	Month-to-month	Yes	Credit card (automatic)	98.00	1237.85	
4	0013-EXCHZ	Female	1	Yes	No	Yes	DSL	Yes	Yes	No	No	No	No	Month-to-month	Yes	Electronic Check	83.90	267.40	
5	0013-MHZWF	Female	0	No	Yes	Yes	DSL	No	No	No	No	No	No	Month-to-month	Yes	Mailed Check	69.40	571.45	
6	0013-SMEOE	Female	1	Yes	No	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Two year	Yes	Credit card (automatic)	109.70	7904.25	
7	0014-BMAQU	Male	0	Yes	No	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Two year	Yes	Electronic Check	84.65	5377.80	
8	0015-UOCOJ	Female	1	No	No	Yes	DSL	No	No	No	No	No	No	Month-to-month	Yes	Bank transfer (automatic)	48.20	340.35	
9	0016-QLJIS	Female	0	Yes	Yes	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Two year	Yes	Electronic Check	90.45	5957.90	

Let's perform 'one-hot encoding' to determine the correlation between features and subsequently build models to predict customer churn.

In [66]:

```
#categorical data
categorical_cols = ['gender',
 'SeniorCitizen',
 'Partner',
 'Dependents',
 'PhoneService',
 'InternetService',
 'OnlineSecurity',
 'OnlineBackup',
 'DeviceProtection',
 'TechSupport',
 'StreamingTV',
```

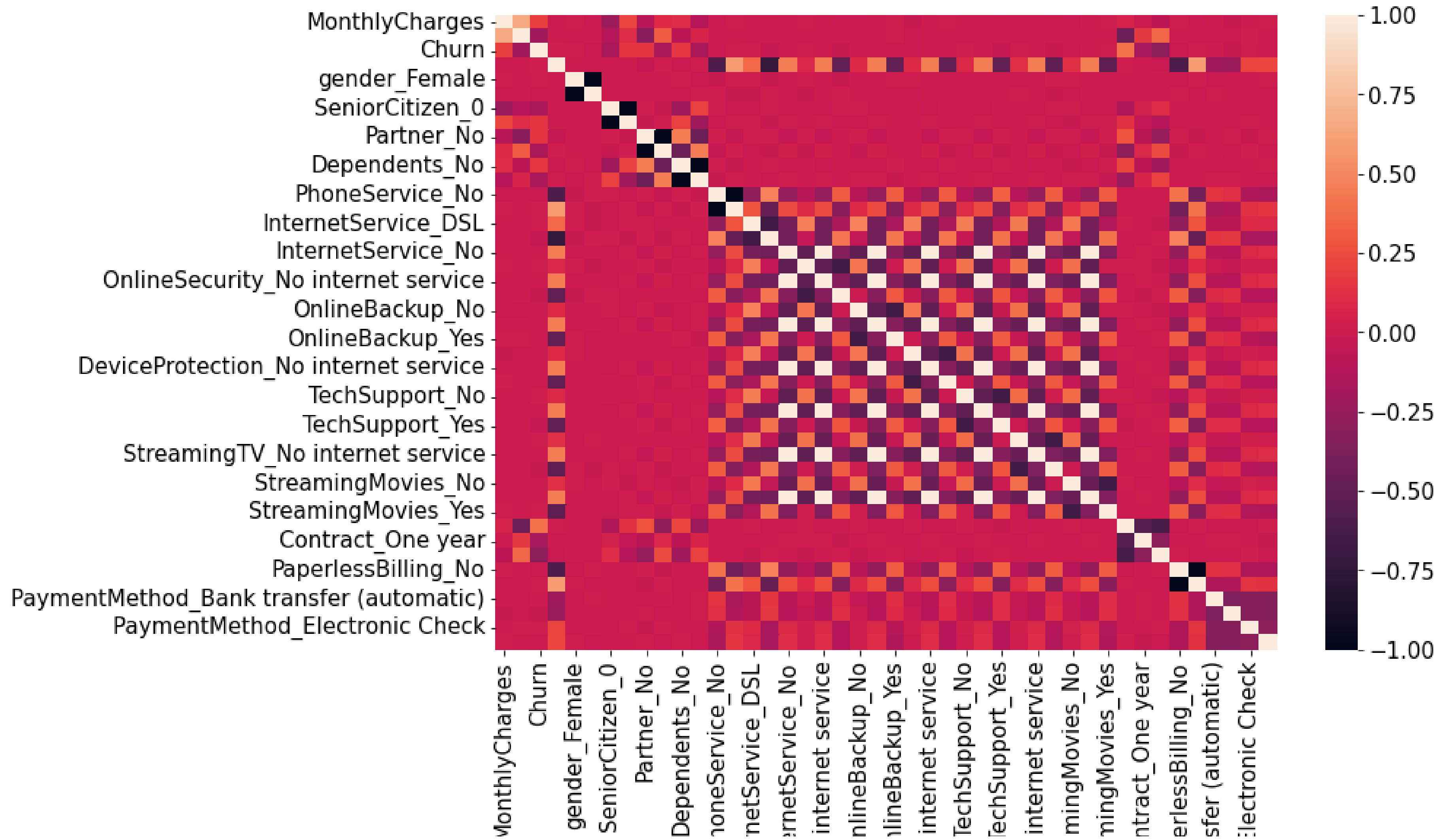
```
 'StreamingMovies',
 'Contract',
 'PaperlessBilling',
 'PaymentMethod']


#import pandas as pd
transformed_df = pd.get_dummies(source_dataset, columns = categorical_cols)
transformed_df.head(5)
```

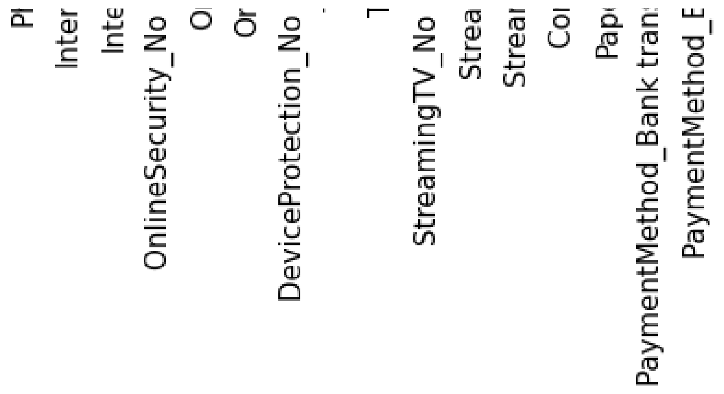
Out[66]:

	customerID	MonthlyCharges	TotalCharges	Churn	Date	End_date	Tenure	gender_Female	gender_Male	SeniorCitizen_0	SeniorCitizen_1	Partner_No	Partner_Yes	Dependents_No	Dependents_Yes	PhoneService_No	PhoneService_Yes	InternetService_DSL
0	0002-ORFBO	65.60	593.30	0	2010-01-01	2021-05-30	4167	1	0	1	0	0	1	0	1	0	1	1
1	0003-MKNFE	59.90	542.40	0	2010-01-01	2021-05-30	4167	0	1	1	0	1	0	1	0	0	1	0
2	0004-TLHLJ	73.90	280.85	1	2010-01-01	2021-05-30	4167	0	1	1	0	1	0	1	0	0	1	1
3	0011-IGKFF	98.00	1237.85	1	2010-01-02	2021-05-30	4166	0	1	0	1	0	1	1	0	0	1	1
4	0013-EXCHZ	83.90	267.40	1	2010-01-03	2021-05-30	4165	1	0	0	1	0	1	1	0	0	1	1

In [67]:

```
transformed_df.style
import matplotlib.pyplot as plt
import seaborn as sb
dataplot=sb.heatmap(transformed_df.corr())
plt.show()
```





Let's determine the correlation between 'Churn' and the other features in the dataframe

References:

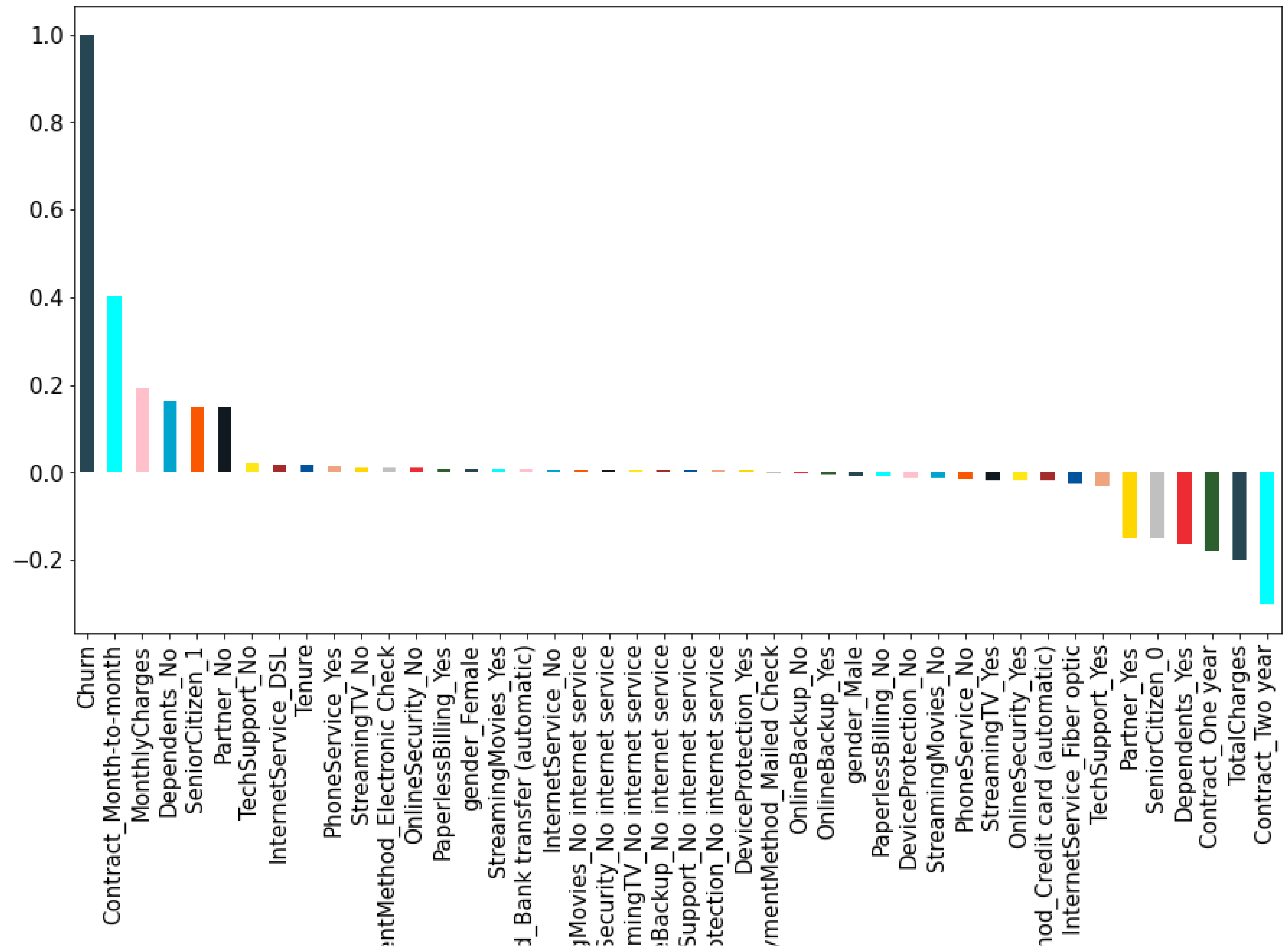
1. [Seaborn Histogram Plots]()
2. [Sort Bar Plots by a Column's values]()

In [68]:

```
plt.figure(figsize=(15,8))
colors = ['#264653','cyan', 'pink','#00A4CCFF', '#F95700FF','#101820FF', '#FEE715FF', 'brown','#00539CFF', '#EEA47FFF','gold', 'silver','#ED2B33FF', '#2C5F2D']
transformed_df.corr()['Churn'].sort_values(ascending = False).plot(kind = 'bar', color = colors)
```

Out[68]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8fcffe9790>
```



From the plots above, we can observe that the Correlation between Churn and the following features, is significant:

1. **Contract_Month_to_Month**
2. **Monthly_Charges**
3. **Dependents (No / Yes)**
4. **Senior Citizen (No / Yes)**
5. **Partner (No / Yes)**

Feature Transformation

In [69]:

```
transformed_df.head(5)
```

Out[69]:

	customerID	MonthlyCharges	TotalCharges	Churn	Date	End_date	Tenure	gender_Female	gender_Male	SeniorCitizen_0	SeniorCitizen_1	Partner_No	Partner_Yes	Dependents_No	Dependents_Yes	PhoneService_No	PhoneService_Yes	InternetService_DSL
0	0002-ORFBO	65.60	593.30	0	2010-01-01	2021-05-30	4167	1	0	1	0	0	1	0	1	0	1	1
1	0003-MKNFE	59.90	542.40	0	2010-01-01	2021-05-30	4167	0	1	1	0	1	0	1	0	0	1	0
2	0004-TLHLJ	73.90	280.85	1	2010-01-01	2021-05-30	4167	0	1	1	0	1	0	1	0	0	1	1
3	0011-IGKFF	98.00	1237.85	1	2010-01-02	2021-05-30	4166	0	1	0	1	0	1	1	0	0	1	1
4	0013-EXCHZ	83.90	267.40	1	2010-01-03	2021-05-30	4165	1	0	0	1	0	1	1	0	0	1	1

Before we perform feature selection let us drop columns that are obviously irrelevant to churn prediction as these features might have an adverse effect on the model.

Let's also seprarate the Target Feature (Churn) from the Input Features.

In [102]:

```
Y=transformed_df.Churn
X=transformed_df.drop(['Churn','customerID','Date','End_date'],axis=1).astype(float)
print(type(X))
X.head(5)
```

```
<class 'pandas.core.frame.DataFrame'>
```

Out[102]:

	MonthlyCharges	TotalCharges	Tenure	gender_Female	gender_Male	SeniorCitizen_0	SeniorCitizen_1	Partner_No	Partner_Yes	Dependents_No	Dependents_Yes	PhoneService_No	PhoneService_Yes	InternetService_DSL	InternetService_Fiber optic	InternetService_I
0	65.60	593.30	4167.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	0.
1	59.90	542.40	4167.00	0.00	1.00	1.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.
2	73.90	280.85	4167.00	0.00	1.00	1.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.
3	98.00	1237.85	4166.00	0.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	1.00	1.00	0.00	0.

	MonthlyCharges	TotalCharges	Tenure	gender_Female	gender_Male	SeniorCitizen_0	SeniorCitizen_1	Partner_No	Partner_Yes	Dependents_No	Dependents_Yes	PhoneService_No	PhoneService_Yes	InternetService_DSL	InternetService_Fiber optic	InternetService_N
4	83.90	267.40	4165.00	1.00	0.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	1.00	1.00	0.00	0.

In [103]:

```
Y.head(5)
```

Out[103]:

```
0    0
1    0
2    1
3    1
4    1
Name: Churn, dtype: int64
```

Most of our features have been transformed through one-hot encoding. However we still need to normalize 'Tenure', 'Monthly Charges' and 'Total Charges'.

We will use Min/Max Normalization to normalize these features.

In [104]:

```
X = (X-X.min()) / (X.max()-X.min())
X.head(5)
```

Out[104]:

	MonthlyCharges	TotalCharges	Tenure	gender_Female	gender_Male	SeniorCitizen_0	SeniorCitizen_1	Partner_No	Partner_Yes	Dependents_No	Dependents_Yes	PhoneService_No	PhoneService_Yes	InternetService_DSL	InternetService_Fiber optic	InternetService_N
0	0.47	0.07	1.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	0.0
1	0.41	0.06	1.00	0.00	1.00	1.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.0
2	0.55	0.03	1.00	0.00	1.00	1.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.0
3	0.79	0.14	1.00	0.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	1.00	1.00	0.00	0.0
4	0.65	0.03	1.00	1.00	0.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	1.00	1.00	0.00	0.0

2.Baseline Model

Feature Selection

References:

[Feature Selection with Chi-squared score function](#)

In [105]:

```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2

selector = SelectKBest(score_func=chi2, k=15)
selector.fit(X, Y)
# Get columns to keep and create new dataframe with the K best columns
cols = selector.get_support(indices=True)
X = X.iloc[:,cols]

print(X.shape)
print("\n")
print(X.columns)
print("\n")
print(Y.shape)
```

```
(7032, 15)
```

```
Index(['MonthlyCharges', 'TotalCharges', 'SeniorCitizen_0', 'SeniorCitizen_1',
       'Partner_No', 'Partner_Yes', 'Dependents_No', 'Dependents_Yes',
       'InternetService_Fiber optic', 'TechSupport_No', 'TechSupport_Yes',
       'Contract_Month-to-month', 'Contract_One year', 'Contract_Two year',
       'PaymentMethod_Credit card (automatic)'],
      dtype='object')
```

```
(7032,)
```

The following features are selected as the Input Columns for training and testing the model:

'MonthlyCharges',

'TotalCharges',

'SeniorCitizen_0',

'SeniorCitizen_1',

'Partner_No',

'Partner_Yes',

'Dependents_No',

'Dependents_Yes',

'InternetService_Fiber optic',

'TechSupport_No',

'TechSupport_Yes',

'Contract_Month-to-month',

'Contract_One year',

'Contract_Two year',

'PaymentMethod_Credit card (automatic)'

Training and evaluate the model on test data

In [106]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=101)
print(X_train.shape)
print(X_test.shape)
```

```
(5625, 15)
(1407, 15)
```

In [107]:

```
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import ShuffleSplit

ab = AdaBoostClassifier()
ab.fit(X_train, y_train)
```

```
ab_y_predict = ab.predict(X_test)
```

Confusion Matrix for our AdaBoost Model

References:

[Confusion Matrix - Python]

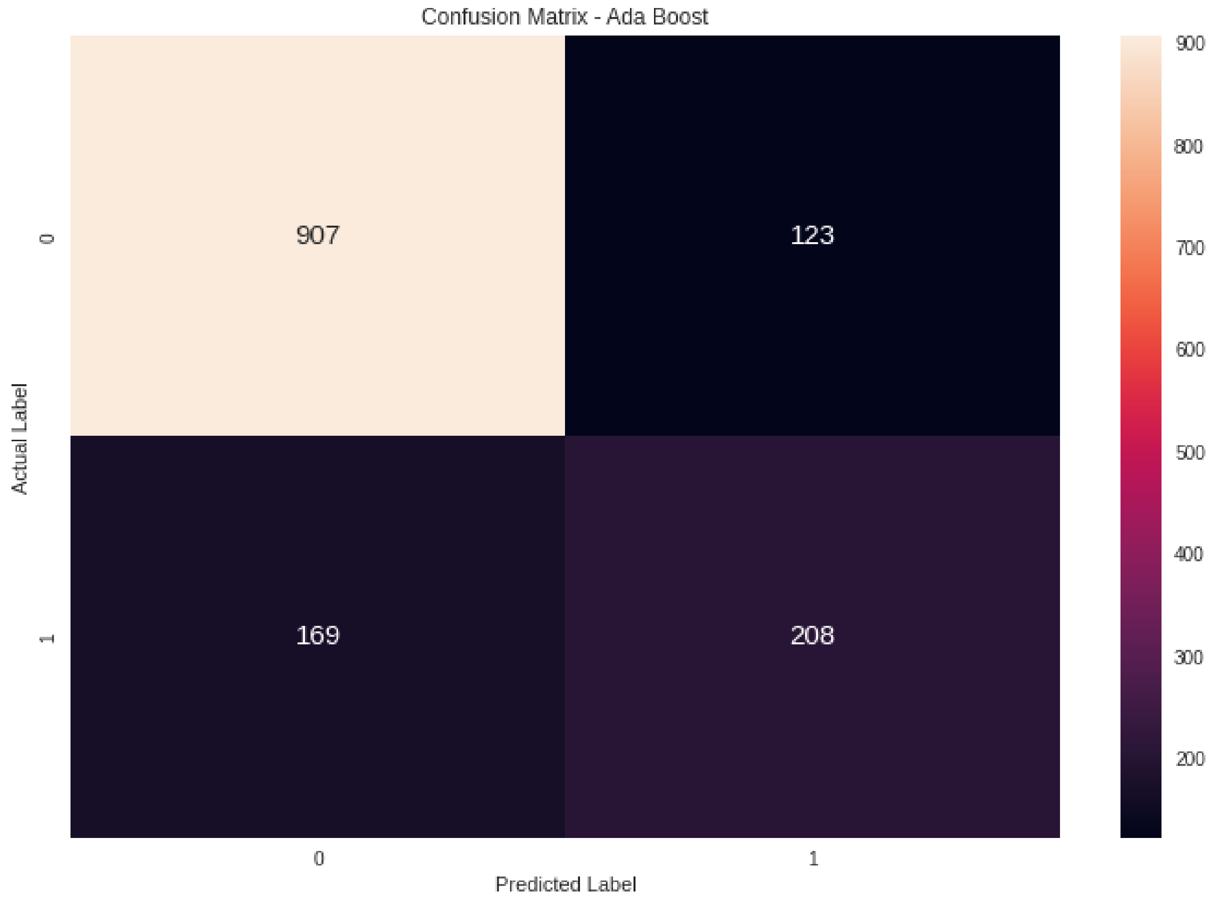
In [108]:

```
print('Accuracy: %.2f%%' % (accuracy_score(y_test, ab_y_predict) * 100 ))
print('Precision: %.2f%%' % (precision_score(y_test, ab_y_predict) * 100))
confusion_matrix_ab = confusion_matrix(y_test, ab_y_predict)
plt.figure(figsize=(12,8))
ax = plt.subplot()
sb.heatmap(confusion_matrix_ab, annot=True, fmt='g', ax = ax)
ax.set_xlabel('Predicted Label')
ax.set_ylabel('Actual Label')
ax.set_title('Confusion Matrix - AdaBoost')
ax.xaxis.set_ticklabels(['0','1'])
ax.yaxis.set_ticklabels(['0','1'])
```

```
Accuracy: 79.25%
Precision: 62.84%
Recall: 55.17%
F1_Score: 58.76%
```

Out[108]:

```
[Text(0, 0.5, '0'), Text(0, 1.5, '1')]
```



Hyperparameter Tuning

References:

[AdaBoost Hyperparameter Tuning]

In [80]:

```python
# Tuning Ada Boost
grid = {'n_estimators' : [50,100,500,1500,2000],
       'learning_rate' : [0.05,0.1,1.0,0.15,0.2,1.5,2.0]}

cv = ShuffleSplit()
adaboost = RandomizedSearchCV(AdaBoostClassifier(),
                             param_distributions = grid,
                             cv = cv,
                             n_iter = 10,
                             scoring = 'recall')
adaboost.fit(X_train, y_train)
```

Out[80]:

```
RandomizedSearchCV(cv=ShuffleSplit(n_splits=10, random_state=None, test_size=None, train_size=None),
                   estimator=AdaBoostClassifier(),
                   param_distributions={'learning_rate': [0.05, 0.1, 1.0, 0.15,
                                                          0.2, 1.5, 2.0],
                                        'n_estimators': [50, 100, 500, 1500,
                                                         2000]},
                   scoring='recall')
```

In [81]:

```python
adaboost.best_params_
```

Out[81]:

```
{'learning_rate': 0.2, 'n_estimators': 2000}
```

In [82]:

```python
tune_adaboost = AdaBoostClassifier(**adaboost.best_params_)
tune_adaboost.fit(X_train, y_train)
y_pred = tune_adaboost.predict(X_test)
```

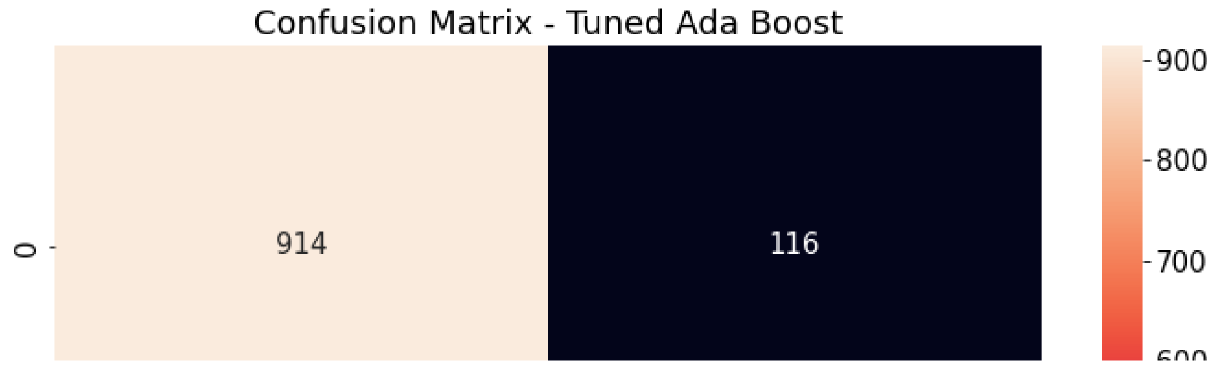
In [84]:

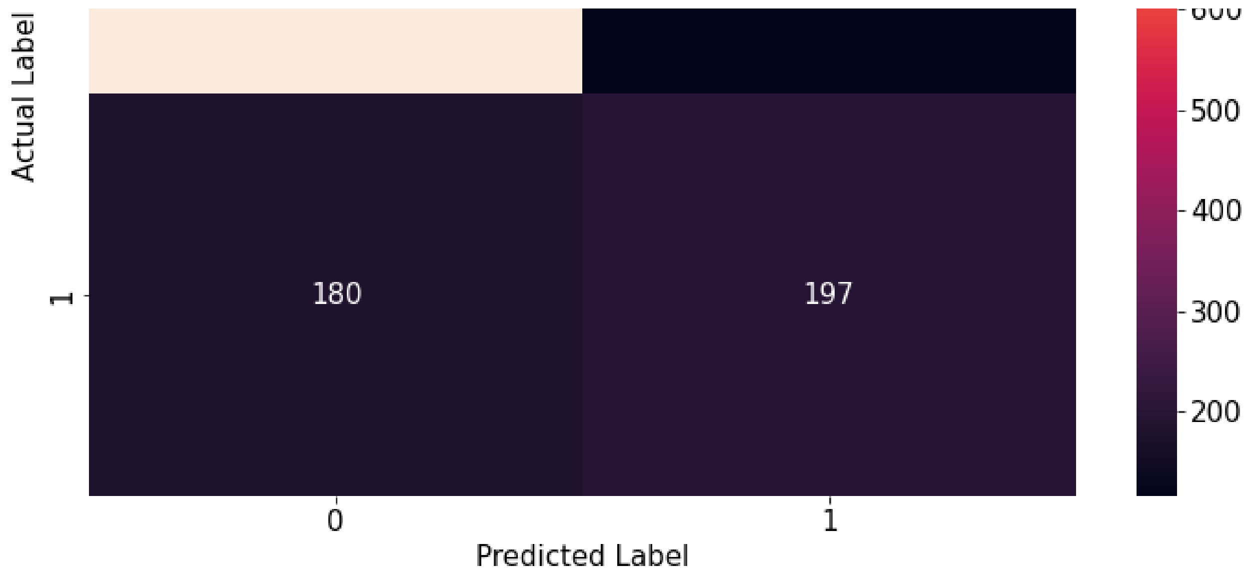
```python
print('Accuracy: %.2f%%' % (accuracy_score(y_test, y_pred) * 100 ))
print('Precision: %.2f%%' % (precision_score(y_test, y_pred) * 100))
print('Recall: %.2f%%' % (recall_score(y_test, y_pred) * 100))
print('F1_Score: %.2f%%' % (f1_score(y_test, y_pred) * 100))
confusion_matrix_tuned_adaboost = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(12,8))
ax = plt.subplot()
sb.heatmap(confusion_matrix_tuned_adaboost, annot=True, fmt='g', ax = ax)
ax.set_xlabel('Predicted Label')
ax.set_ylabel('Actual Label')
ax.set_title('Confusion Matrix - Tuned Ada Boost')
ax.xaxis.set_ticklabels(['0','1'])
ax.yaxis.set_ticklabels(['0','1'])
```

```
Accuracy: 78.96%
Precision: 62.94%
Recall: 52.25%
F1_Score: 57.10%
```

Out[84]:

```
[Text(0, 0.5, '0'), Text(0, 1.5, '1')]
```





Let us plot the learning curve for our AdaBoost model

References:

[Assignment -1]

In [116]:

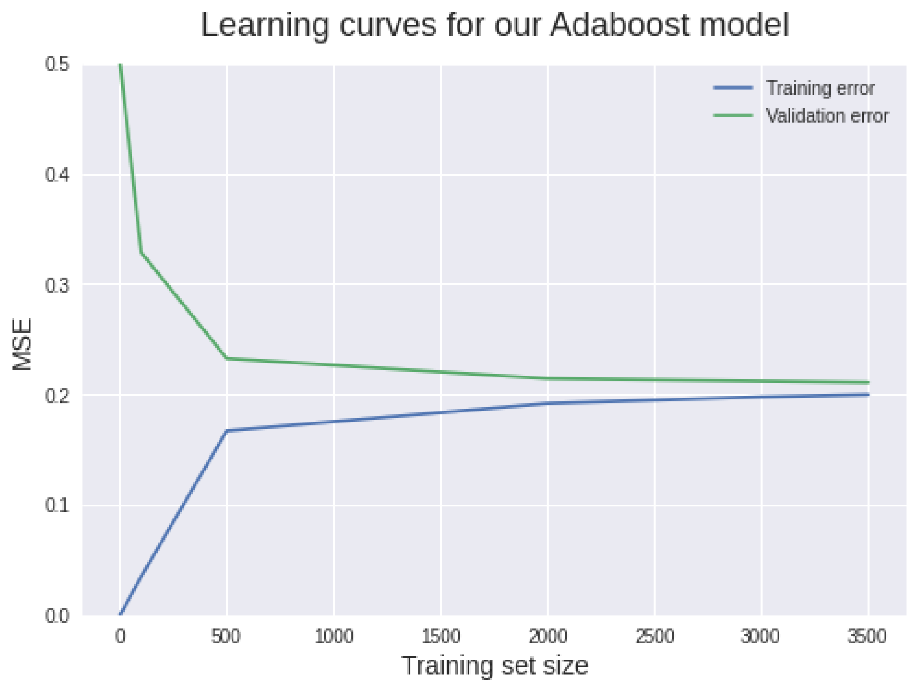
```
from sklearn.model_selection import learning_curve
train_sizes = [1, 100, 500, 2000, 3000,3500,]

train_sizes, train_scores, validation_scores = learning_curve(
estimator = ab,
X = X,
y = Y, train_sizes = train_sizes, cv = 2,
scoring = 'neg_mean_squared_error')

train_scores_mean = -train_scores.mean(axis = 1)
validation_scores_mean = -validation_scores.mean(axis = 1) #Changed the sign of the mean validation scores
print('Mean training scores\n\n', pd.Series(train_scores_mean, index = train_sizes))
print('\n', '-' * 20) # separator
print('\nMean validation scores\n\n',pd.Series(validation_scores_mean, index = train_sizes))

plt.style.use('seaborn')
plt.plot(train_sizes, train_scores_mean, label = 'Training error')
plt.plot(train_sizes, validation_scores_mean, label = 'Validation error')
plt.ylabel('MSE', fontsize = 14)
plt.xlabel('Training set size', fontsize = 14)
plt.title('Learning curves for our Adaboost model', fontsize = 18, y = 1.03)
plt.legend()
plt.ylim(0,0.5)
```

```
Mean training scores

 1      -0.00
100      0.03
500      0.17
2000     0.19
3000     0.20
3500     0.20
dtype: float64

 --------------------

Mean validation scores

 1      0.50
100     0.33
500     0.23
2000    0.21
3000    0.21
```

```
3000    0.21
3500    0.21
dtype: float64
```

Out[116]:

```
(0.0, 0.5)
```



3. Neural Networks Model

References:

[Churn Prediction with Neural Networks](#)

The task that we are solving is relevant to `Classification` where we will be training a model and testing it `(Supervised Learning)` to predict customer churn (whether a customer will choose to continue their subscription or cancel it, in this scenario).

Feature Selection

In [93]:

```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2

selector = SelectKBest(score_func=chi2, k=15)
selector.fit(X, Y)
# Get columns to keep and create new dataframe with the K best columns
cols = selector.get_support(indices=True)
X = X.iloc[:,cols]

print(X.shape)
print("\n")
print(X.columns)
print("\n")
print(Y.shape)
```

```
(7032, 15)


Index(['MonthlyCharges', 'TotalCharges', 'SeniorCitizen_0', 'SeniorCitizen_1',
       'Partner_No', 'Partner_Yes', 'Dependents_No', 'Dependents_Yes',
       'InternetService_Fiber optic', 'TechSupport_No', 'TechSupport_Yes',
       'Contract_Month-to-month', 'Contract_One year', 'Contract_Two year',
       'PaymentMethod_Credit card (automatic)'],
```

```
      dtype='object')
```

```
(7032,)
```

The following features are selected as the Input Columns for training and testing the model:

`MonthlyCharges`,

`TotalCharges`,

`SeniorCitizen_0`,

`SeniorCitizen_1`,

`Partner_No`,

`Partner_Yes`,

`Dependents_No`,

`Dependents_Yes`,

`InternetService_Fiber optic`,

`TechSupport_No`,

`TechSupport_Yes`,

`Contract_Month-to-month`,

`Contract_One year`,

`Contract_Two year`,

`PaymentMethod_Credit card (automatic)`

Training and evaluating the model on test data

In [96]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=101)
print(X_train.shape)
print(X_test.shape)
```

```
(5625, 15)
(1407, 15)
```

In [119]:

```
import tensorflow as tf
from tensorflow import keras

model = keras.Sequential([
    # input layer
    keras.layers.Dense(15, input_shape=(15,), activation='relu'),
    keras.layers.Dense(15, activation='relu'),
    keras.layers.Dense(10,activation = 'relu'),
    # we use sigmoid for binary output
    # output layer
    keras.layers.Dense(1, activation='sigmoid')
]
)
```

In [129]:

```
model.compile(optimizer = 'adam',
             loss = 'binary_crossentropy',
             metrics = ['accuracy'])
# now we fit our model to training data
history = model.fit(X_train,y_train,validation_data=(X_test, y_test),epochs=100)
```

```
Epoch 1/100
176/176 [==============================] - 2s 6ms/step - loss: 0.4023 - accuracy: 0.8078 - val_loss: 0.4360 - val_accuracy: 0.7953
Epoch 2/100
176/176 [==============================] - 1s 3ms/step - loss: 0.4019 - accuracy: 0.8071 - val_loss: 0.4393 - val_accuracy: 0.7918
Epoch 3/100
176/176 [==============================] - 1s 4ms/step - loss: 0.4025 - accuracy: 0.8044 - val_loss: 0.4385 - val_accuracy: 0.7903
Epoch 4/100
176/176 [==============================] - 1s 4ms/step - loss: 0.4022 - accuracy: 0.8041 - val_loss: 0.4390 - val_accuracy: 0.7910
Epoch 5/100
176/176 [==============================] - 1s 4ms/step - loss: 0.4024 - accuracy: 0.8053 - val_loss: 0.4387 - val_accuracy: 0.7932
Epoch 6/100
176/176 [==============================] - 1s 4ms/step - loss: 0.4008 - accuracy: 0.8096 - val_loss: 0.4409 - val_accuracy: 0.7896
Epoch 7/100
176/176 [==============================] - 1s 4ms/step - loss: 0.4017 - accuracy: 0.8064 - val_loss: 0.4415 - val_accuracy: 0.7953
Epoch 8/100
176/176 [==============================] - 1s 4ms/step - loss: 0.4005 - accuracy: 0.8062 - val_loss: 0.4389 - val_accuracy: 0.7903
Epoch 9/100
176/176 [==============================] - 1s 3ms/step - loss: 0.4021 - accuracy: 0.8053 - val_loss: 0.4458 - val_accuracy: 0.7925
Epoch 10/100
176/176 [==============================] - 1s 4ms/step - loss: 0.4011 - accuracy: 0.8048 - val_loss: 0.4377 - val_accuracy: 0.7896
Epoch 11/100
176/176 [==============================] - 1s 4ms/step - loss: 0.4013 - accuracy: 0.8060 - val_loss: 0.4362 - val_accuracy: 0.7903
Epoch 12/100
176/176 [==============================] - 1s 4ms/step - loss: 0.4000 - accuracy: 0.8044 - val_loss: 0.4395 - val_accuracy: 0.7903
Epoch 13/100
176/176 [==============================] - 1s 4ms/step - loss: 0.4027 - accuracy: 0.8034 - val_loss: 0.4386 - val_accuracy: 0.7918
Epoch 14/100
176/176 [==============================] - 1s 4ms/step - loss: 0.4012 - accuracy: 0.8062 - val_loss: 0.4402 - val_accuracy: 0.7918
Epoch 15/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3997 - accuracy: 0.8044 - val_loss: 0.4386 - val_accuracy: 0.7946
Epoch 16/100
176/176 [==============================] - 0s 2ms/step - loss: 0.4017 - accuracy: 0.8064 - val_loss: 0.4380 - val_accuracy: 0.7982
Epoch 17/100
176/176 [==============================] - 0s 2ms/step - loss: 0.4017 - accuracy: 0.8071 - val_loss: 0.4410 - val_accuracy: 0.7889
Epoch 18/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3999 - accuracy: 0.8078 - val_loss: 0.4386 - val_accuracy: 0.7960
Epoch 19/100
176/176 [==============================] - 0s 2ms/step - loss: 0.4016 - accuracy: 0.8048 - val_loss: 0.4395 - val_accuracy: 0.7946
Epoch 20/100
176/176 [==============================] - 0s 2ms/step - loss: 0.4009 - accuracy: 0.8057 - val_loss: 0.4481 - val_accuracy: 0.7790
Epoch 21/100
176/176 [==============================] - 0s 2ms/step - loss: 0.4007 - accuracy: 0.8066 - val_loss: 0.4390 - val_accuracy: 0.7910
Epoch 22/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3995 - accuracy: 0.8087 - val_loss: 0.4398 - val_accuracy: 0.7960
Epoch 23/100
176/176 [==============================] - 0s 2ms/step - loss: 0.4012 - accuracy: 0.8084 - val_loss: 0.4365 - val_accuracy: 0.7946
Epoch 24/100
176/176 [==============================] - 0s 2ms/step - loss: 0.4005 - accuracy: 0.8078 - val_loss: 0.4379 - val_accuracy: 0.7946
Epoch 25/100
176/176 [==============================] - 0s 2ms/step - loss: 0.4009 - accuracy: 0.8048 - val_loss: 0.4434 - val_accuracy: 0.7910
Epoch 26/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3992 - accuracy: 0.8096 - val_loss: 0.4363 - val_accuracy: 0.7960
Epoch 27/100
176/176 [==============================] - 0s 2ms/step - loss: 0.4013 - accuracy: 0.8064 - val_loss: 0.4384 - val_accuracy: 0.7967
Epoch 28/100
176/176 [==============================] - 0s 2ms/step - loss: 0.4002 - accuracy: 0.8073 - val_loss: 0.4391 - val_accuracy: 0.7967
Epoch 29/100
176/176 [==============================] - 0s 2ms/step - loss: 0.4006 - accuracy: 0.8078 - val_loss: 0.4372 - val_accuracy: 0.7903
Epoch 30/100
176/176 [==============================] - 0s 2ms/step - loss: 0.4013 - accuracy: 0.8046 - val_loss: 0.4380 - val_accuracy: 0.7946
Epoch 31/100
176/176 [==============================] - 0s 2ms/step - loss: 0.4004 - accuracy: 0.8059 - val_loss: 0.4369 - val_accuracy: 0.8031
Epoch 32/100
176/176 [==============================] - 0s 2ms/step - loss: 0.4017 - accuracy: 0.8018 - val_loss: 0.4420 - val_accuracy: 0.7889
```

```
Epoch 33/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3982 - accuracy: 0.8046 - val_loss: 0.4399 - val_accuracy: 0.7960
Epoch 34/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3992 - accuracy: 0.8034 - val_loss: 0.4390 - val_accuracy: 0.7953
Epoch 35/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3997 - accuracy: 0.8066 - val_loss: 0.4380 - val_accuracy: 0.7910
Epoch 36/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3990 - accuracy: 0.8053 - val_loss: 0.4421 - val_accuracy: 0.7918
Epoch 37/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3981 - accuracy: 0.8098 - val_loss: 0.4387 - val_accuracy: 0.7939
Epoch 38/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3994 - accuracy: 0.8069 - val_loss: 0.4408 - val_accuracy: 0.7903
Epoch 39/100
176/176 [==============================] - 0s 2ms/step - loss: 0.4005 - accuracy: 0.8057 - val_loss: 0.4404 - val_accuracy: 0.7889
Epoch 40/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3997 - accuracy: 0.8069 - val_loss: 0.4372 - val_accuracy: 0.7953
Epoch 41/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3990 - accuracy: 0.8030 - val_loss: 0.4435 - val_accuracy: 0.7910
Epoch 42/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3993 - accuracy: 0.8064 - val_loss: 0.4375 - val_accuracy: 0.7960
Epoch 43/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3999 - accuracy: 0.8060 - val_loss: 0.4387 - val_accuracy: 0.7953
Epoch 44/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3991 - accuracy: 0.8068 - val_loss: 0.4398 - val_accuracy: 0.7882
Epoch 45/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3984 - accuracy: 0.8073 - val_loss: 0.4395 - val_accuracy: 0.7918
Epoch 46/100
176/176 [==============================] - 0s 2ms/step - loss: 0.4011 - accuracy: 0.8071 - val_loss: 0.4398 - val_accuracy: 0.7967
Epoch 47/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3997 - accuracy: 0.8084 - val_loss: 0.4426 - val_accuracy: 0.7918
Epoch 48/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3993 - accuracy: 0.8048 - val_loss: 0.4401 - val_accuracy: 0.7953
Epoch 49/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3995 - accuracy: 0.8066 - val_loss: 0.4411 - val_accuracy: 0.7925
Epoch 50/100
176/176 [==============================] - 0s 2ms/step - loss: 0.4000 - accuracy: 0.8046 - val_loss: 0.4363 - val_accuracy: 0.7953
Epoch 51/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3991 - accuracy: 0.8078 - val_loss: 0.4417 - val_accuracy: 0.7868
Epoch 52/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3977 - accuracy: 0.8078 - val_loss: 0.4430 - val_accuracy: 0.7896
Epoch 53/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3988 - accuracy: 0.8050 - val_loss: 0.4419 - val_accuracy: 0.7939
Epoch 54/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3983 - accuracy: 0.8059 - val_loss: 0.4424 - val_accuracy: 0.7939
Epoch 55/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3986 - accuracy: 0.8094 - val_loss: 0.4422 - val_accuracy: 0.7882
Epoch 56/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3979 - accuracy: 0.8068 - val_loss: 0.4422 - val_accuracy: 0.7889
Epoch 57/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3972 - accuracy: 0.8060 - val_loss: 0.4455 - val_accuracy: 0.7811
Epoch 58/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3980 - accuracy: 0.8048 - val_loss: 0.4391 - val_accuracy: 0.7974
Epoch 59/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3983 - accuracy: 0.8060 - val_loss: 0.4445 - val_accuracy: 0.7925
Epoch 60/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3976 - accuracy: 0.8080 - val_loss: 0.4414 - val_accuracy: 0.7846
Epoch 61/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3983 - accuracy: 0.8068 - val_loss: 0.4428 - val_accuracy: 0.7925
Epoch 62/100
176/176 [==============================] - 0s 3ms/step - loss: 0.3968 - accuracy: 0.8073 - val_loss: 0.4400 - val_accuracy: 0.7868
Epoch 63/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3983 - accuracy: 0.8075 - val_loss: 0.4420 - val_accuracy: 0.7910
Epoch 64/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3974 - accuracy: 0.8055 - val_loss: 0.4413 - val_accuracy: 0.7925
Epoch 65/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3972 - accuracy: 0.8101 - val_loss: 0.4408 - val_accuracy: 0.7918
Epoch 66/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3980 - accuracy: 0.8082 - val_loss: 0.4435 - val_accuracy: 0.7910
Epoch 67/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3988 - accuracy: 0.8034 - val_loss: 0.4391 - val_accuracy: 0.7996
Epoch 68/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3986 - accuracy: 0.8076 - val_loss: 0.4411 - val_accuracy: 0.7910
```

```
Epoch 69/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3978 - accuracy: 0.8100 - val_loss: 0.4401 - val_accuracy: 0.7960
Epoch 70/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3983 - accuracy: 0.8082 - val_loss: 0.4402 - val_accuracy: 0.7967
Epoch 71/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3968 - accuracy: 0.8082 - val_loss: 0.4408 - val_accuracy: 0.7946
Epoch 72/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3978 - accuracy: 0.8048 - val_loss: 0.4400 - val_accuracy: 0.7953
Epoch 73/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3978 - accuracy: 0.8078 - val_loss: 0.4423 - val_accuracy: 0.7932
Epoch 74/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3966 - accuracy: 0.8100 - val_loss: 0.4423 - val_accuracy: 0.7825
Epoch 75/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3978 - accuracy: 0.8089 - val_loss: 0.4452 - val_accuracy: 0.7839
Epoch 76/100
176/176 [==============================] - 1s 4ms/step - loss: 0.3979 - accuracy: 0.8107 - val_loss: 0.4429 - val_accuracy: 0.7925
Epoch 77/100
176/176 [==============================] - 1s 6ms/step - loss: 0.3976 - accuracy: 0.8064 - val_loss: 0.4407 - val_accuracy: 0.7967
Epoch 78/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3976 - accuracy: 0.8071 - val_loss: 0.4424 - val_accuracy: 0.7918
Epoch 79/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3974 - accuracy: 0.8050 - val_loss: 0.4414 - val_accuracy: 0.7932
Epoch 80/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3973 - accuracy: 0.8066 - val_loss: 0.4426 - val_accuracy: 0.7896
Epoch 81/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3965 - accuracy: 0.8091 - val_loss: 0.4421 - val_accuracy: 0.7974
Epoch 82/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3963 - accuracy: 0.8076 - val_loss: 0.4425 - val_accuracy: 0.7910
Epoch 83/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3962 - accuracy: 0.8062 - val_loss: 0.4413 - val_accuracy: 0.7960
Epoch 84/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3964 - accuracy: 0.8037 - val_loss: 0.4405 - val_accuracy: 0.7932
Epoch 85/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3952 - accuracy: 0.8064 - val_loss: 0.4441 - val_accuracy: 0.7925
Epoch 86/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3957 - accuracy: 0.8062 - val_loss: 0.4424 - val_accuracy: 0.7996
Epoch 87/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3971 - accuracy: 0.8069 - val_loss: 0.4419 - val_accuracy: 0.7960
Epoch 88/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3951 - accuracy: 0.8078 - val_loss: 0.4446 - val_accuracy: 0.7839
Epoch 89/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3962 - accuracy: 0.8084 - val_loss: 0.4445 - val_accuracy: 0.7974
Epoch 90/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3946 - accuracy: 0.8050 - val_loss: 0.4436 - val_accuracy: 0.7861
Epoch 91/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3959 - accuracy: 0.8071 - val_loss: 0.4420 - val_accuracy: 0.7946
Epoch 92/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3961 - accuracy: 0.8089 - val_loss: 0.4470 - val_accuracy: 0.7818
Epoch 93/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3957 - accuracy: 0.8057 - val_loss: 0.4446 - val_accuracy: 0.7875
Epoch 94/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3959 - accuracy: 0.8092 - val_loss: 0.4439 - val_accuracy: 0.7875
Epoch 95/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3950 - accuracy: 0.8085 - val_loss: 0.4440 - val_accuracy: 0.7939
Epoch 96/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3950 - accuracy: 0.8092 - val_loss: 0.4439 - val_accuracy: 0.7903
Epoch 97/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3954 - accuracy: 0.8064 - val_loss: 0.4469 - val_accuracy: 0.7882
Epoch 98/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3955 - accuracy: 0.8112 - val_loss: 0.4438 - val_accuracy: 0.7903
Epoch 99/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3953 - accuracy: 0.8096 - val_loss: 0.4447 - val_accuracy: 0.7946
Epoch 100/100
176/176 [==============================] - 0s 2ms/step - loss: 0.3954 - accuracy: 0.8075 - val_loss: 0.4446 - val_accuracy: 0.7925
```

Evaluating the model on the test dataset

In [121]:

```
model.evaluate(X_test,y_test)
```

```
44/44 [==============================] - 0s 1ms/step - loss: 0.4287 - accuracy: 0.7925
```

Out[121]:

```
[0.42869895696640015, 0.7924662232398987]
```

Plots for Training Accuracy and Validation Accuracy

References:

[Training & Validation Accuracy for Neural Network Model](#)

In [130]:

```python
import matplotlib.pyplot as plt

history_dict = history.history
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']
accuracy = history_dict['accuracy']
val_accuracy = history_dict['val_accuracy']

epochs = range(1, len(loss_values) + 1)
fig, ax = plt.subplots(1, 2, figsize=(14, 6))
#
# Plot the model accuracy vs Epochs
#
ax[0].plot(epochs, accuracy, 'bo', label='Training accuracy')
ax[0].plot(epochs, val_accuracy, 'b', label='Validation accuracy')
ax[0].set_title('Training & Validation Accuracy', fontsize=16)
ax[0].set_xlabel('Epochs', fontsize=16)
ax[0].set_ylabel('Accuracy', fontsize=16)
ax[0].legend()
#
# Plot the loss vs Epochs
#
ax[1].plot(epochs, loss_values, 'bo', label='Training loss')
ax[1].plot(epochs, val_loss_values, 'b', label='Validation loss')
ax[1].set_title('Training & Validation Loss', fontsize=16)
ax[1].set_xlabel('Epochs', fontsize=16)
ax[1].set_ylabel('Loss', fontsize=16)
ax[1].legend()
```

Out[130]:

```
<matplotlib.legend.Legend at 0x7f8f5cc40ed0>
```

In [122]:

```
# predict the churn values
ypred = model.predict(X_test)
print(ypred)
# unscaling the ypred values
ypred_lis = []
for i in ypred:
    if i>0.5:
        ypred_lis.append(1)
    else:
        ypred_lis.append(0)
print(ypred_lis)
```

```
[[0.26455832]
 [0.57913214]
 [0.7634145 ]
 ...
 [0.07857111]
 [0.2118667 ]
 [0.42824316]]
[0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0,
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1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
```

In [123]:

```
data = {'orignal_churn':y_test, 'predicted_churn':ypred_lis}
df_check = pd.DataFrame(data)
df_check.head(10)
```

Out[123]:

	orignal_churn	predicted_churn
4256	0	0
2916	1	1
1565	1	1
5228	1	0
4429	0	0
5881	0	1
155	1	0
109	1	0
5025	0	0
5258	0	0

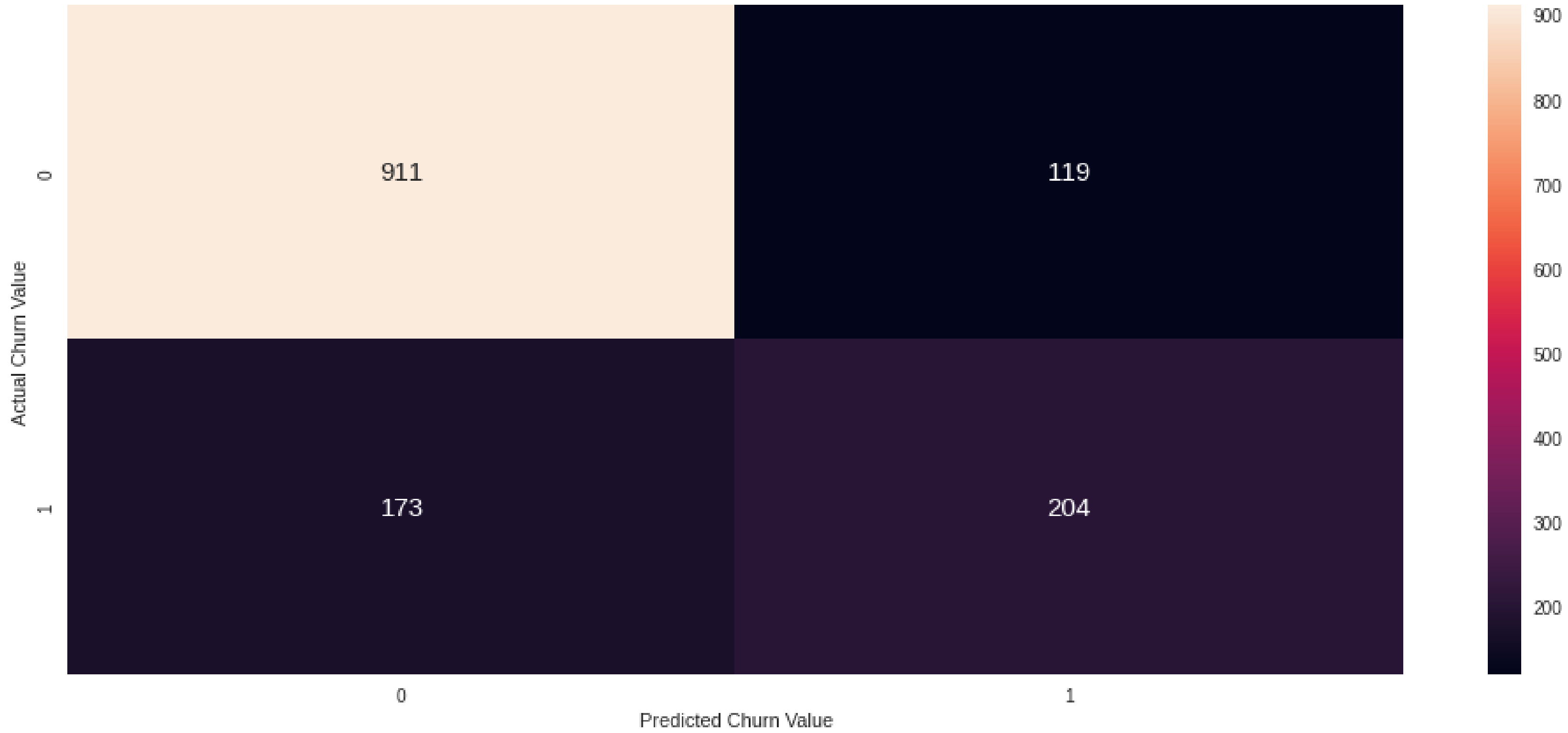
In [124]:

```
from sklearn.metrics import confusion_matrix, classification_report
#print classification_report
print(classification_report(y_test,ypred_lis))
# ploting the confusion metrix plot
conf_mat = tf.math.confusion_matrix(labels=y_test,predictions=ypred_lis)
plt.figure(figsize = (17,7))
sb.heatmap(conf_mat, annot=True,fmt='d')
plt.xlabel('Predicted Churn Value')
plt.ylabel('Actual Churn Value')
```

```
              precision    recall  f1-score   support

           0       0.84      0.88      0.86      1030
           1       0.63      0.54      0.58       377

    accuracy                           0.79      1407
   macro avg       0.74      0.71      0.72      1407
weighted avg       0.78      0.79      0.79      1407
```

Out[124]:

```
Text(132.0, 0.5, 'Actual Churn Value')
```



From the confusion matrix we can derieve the following observations:

True Negatives: 911 - This means that the model classified 911 instances where Churn is False, correclty.

True Positives: 204 - This means that the model classified 204 instances where Churn is True, correclty.

False Negatives: 173 - The model classified 173 instances as "False" when the Churn for those instances were actually "True"

False Positives: 119 - The model classified 119 instances as "True" when the Churn for those instances were actually "False"

4. Concept Drift Detection

“In predictive analytics and machine learning, concept drift means that the statistical properties of the target variable, which the model is trying to predict, change over time in unforeseen ways. This causes problems because the predictions become less accurate as time passes.”

For this Assignment, we have used ADWIN (ADaptive WINdowing) to detect Concept Drift.

References:

References:

1. [Concept drift]
2. [Tutorial 9]

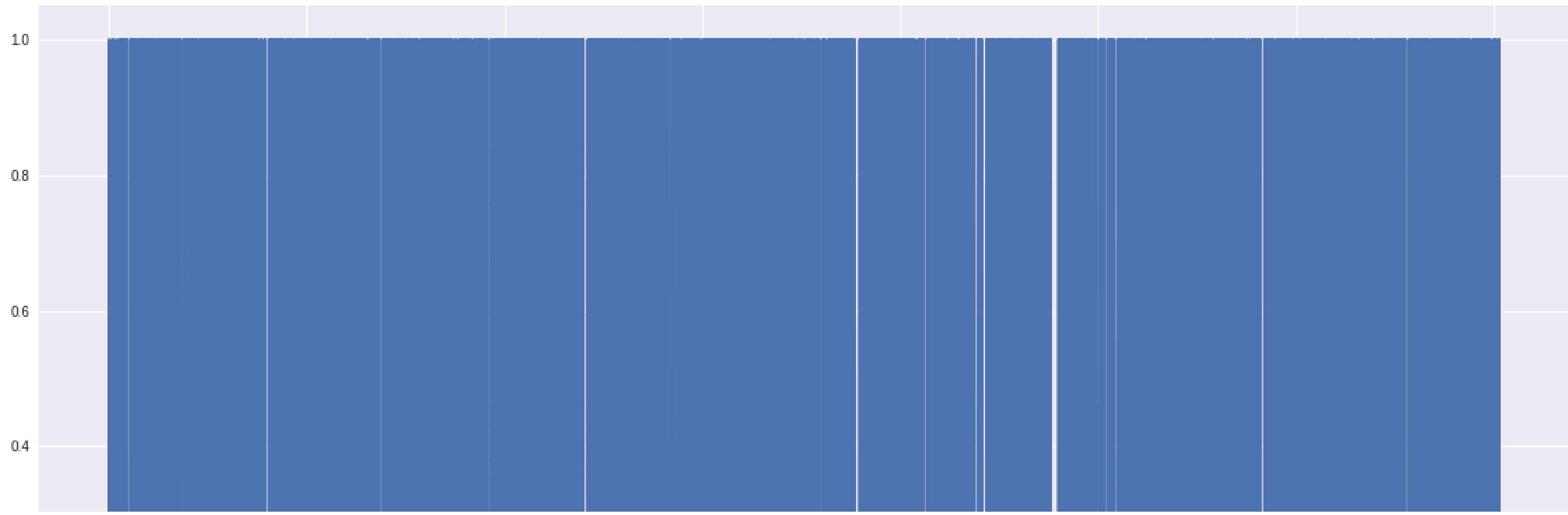
In [132]:

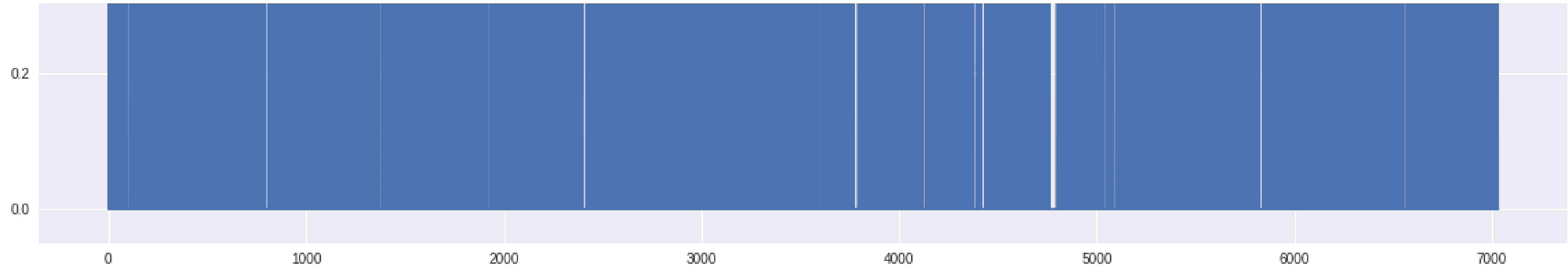
```
pip install scikit-multiflow
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting scikit-multiflow
  Downloading scikit_multiflow-0.5.3-cp37-cp37m-manylinux2010_x86_64.whl (1.1 MB)
     |████████████████████████████████| 1.1 MB 19.9 MB/s
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.7/dist-packages (from scikit-multiflow) (1.4.1)
Requirement already satisfied: pandas>=0.25.3 in /usr/local/lib/python3.7/dist-packages (from scikit-multiflow) (1.3.5)
Requirement already satisfied: matplotlib>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from scikit-multiflow) (3.2.2)
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.7/dist-packages (from scikit-multiflow) (1.21.6)
Requirement already satisfied: scikit-learn>=0.20 in /usr/local/lib/python3.7/dist-packages (from scikit-multiflow) (1.0.2)
Requirement already satisfied: sortedcontainers>=1.5.7 in /usr/local/lib/python3.7/dist-packages (from scikit-multiflow) (2.4.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=2.0.0->scikit-multiflow) (1.4.3)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=2.0.0->scikit-multiflow) (0.11.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=2.0.0->scikit-multiflow) (3.0.9)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=2.0.0->scikit-multiflow) (2.8.2)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/dist-packages (from kiwisolver>=1.0.1->matplotlib>=2.0.0->scikit-multiflow) (4.1.1)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-packages (from pandas>=0.25.3->scikit-multiflow) (2022.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (from python-dateutil>=2.1->matplotlib>=2.0.0->scikit-multiflow) (1.15.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.20->scikit-multiflow) (3.1.0)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.20->scikit-multiflow) (1.1.0)
Installing collected packages: scikit-multiflow
Successfully installed scikit-multiflow-0.5.3
```

In [138]:

```
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt

from skmultiflow.drift_detection import ADWIN

plt.figure(figsize=(20, 10))
plt.plot(Y.values.tolist())

adwin = ADWIN()

for i in range(Y.size):
    adwin.add_element(Y.values.tolist()[i])
    if adwin.detected_change():
        print('Change detected at index {}'.format(i))
```





From the Chart above, we can conclude that there's no change in the properties of the Target Feature over Time. Therefore there's no Concept Drift in the dataset.

Concept drift is significantly more likely to occur in a static machine learning process. A static model, which is often trained in an offline or local environment, won't adapt to altering environments or scenarios. A static algorithm created from historical data might deteriorate with time and become unreliable for models that deal with forecasting or predictions. To stay current with changing datasets and real-world settings, models that are considered to be at danger from idea drift should be routinely retrained and updated.

Reference:

Machine Learning & Concept Drift

Suppose the dataset exhibited Concept Drift,

Ideally in the case where the dataset exhibits Concept Drift, we would have implemented either of the following approaches to handle it:

1. We would update and train the model with samples of new training data. This would fine-tune the model and lower the risk of it becoming obsolete over time.
2. We would have manipulated the relative importance of different input data by assigning weights accordingly. For instance we would have applied a larger weightage for input which's more recent and lesser weights to historic data. This will emphasise the importance of new data within the algorithm, adding less weight to historic data which may be out-of-date.

References

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3. https://dal.brightspace.com/d2l/le/content/221741/viewContent/3023670/View
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