CSCI - 6409 - The Process of Data Science - Summer 2022

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Assignment 2

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1. Data understanding and feature engineering

1(a)Extract the numerical and categorical features from the dataset and build the data quality report.

Adding the below snippet to avoid future warnings in the result snippets

In [1]:
```
# import warnings filter
from warnings import simplefilter
import warnings
# ignore all future warnings
simplefilter(action='ignore', category=FutureWarning)

import warnings
warnings.filterwarnings('ignore')
```

Updating version of matplotlib to accomated axis labels used in this python notebook

In [2]:
```
# !pip install matplotlib==3.4
```

Importing essential libraries required for this assignment

In [3]:
```
import pandas as pd
import numpy as np
import seaborn as sb
import matplotlib as plt
import matplotlib.ticker as mtick

from sklearn.model_selection import train_test_split
```

Read the csv file provided for Customer Churn

In [4]:
```
telecom = pd.read_csv("/content/Telecom/telco.csv")
```

In [5]:
```
telecom
```

Out[5]:

	customerID	gender	SeniorCitizen	Partner	Dependents	PhoneService	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMe
0	0002-ORFBO	Female	0	Yes	Yes	Yes	DSL	No	No	No	No	No	No	One year	Yes	Electronic C
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 C
2	0004-TLHLJ	Male	0	No	No	Yes	DSL	No	No	No	No	No	No	Month-to-month	Yes	Credit (auton
3	0011-IGKFF	Male	1	Yes	No	Yes	DSL	No	No	No	No	No	No	Month-to-month	Yes	Credit (auton
4	0013-EXCHZ	Female	1	Yes	No	Yes	DSL	Yes	Yes	No	No	No	No	Month-to-month	Yes	Electronic C
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
7038	9987-LUTYD	Female	0	No	No	No	Fiber optic	Yes	Yes	No	Yes	No	Yes	One year	No	Bank tra (auton
7039	9992-RRAMN	Male	0	Yes	No	No	Fiber optic	Yes	Yes	Yes	Yes	Yes	Yes	Month-to-month	No	Credit (auton
7040	9992-UJOEL	Male	0	No	No	No	Fiber optic	No	Yes	Yes	Yes	Yes	No	Month-to-month	No	Credit (auton
7041	9993-LHIEB	Male	0	Yes	Yes	No	Fiber optic	No	No	Yes	No	Yes	Yes	Two year	No	Credit (auton
7042	9995-HOTOH	Male	0	Yes	Yes	Yes	Fiber optic	Yes	Yes	No	No	Yes	Yes	Two year	No	Credit (auton

7043 rows × 20 columns

Get Details of the data types and the columns present in the dataset

In [6]:
```
telecom.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
```

Describing the Data frame to visualize all the features and their value ranges

In [7]:
```
telecom.describe
```

Out[7]:
```
<bound method NDFrame.describe of       customerID  gender  SeniorCitizen Partner Dependents PhoneService  \
0     0002-ORFBO  Female              0     Yes        Yes          Yes
1     0003-MKNFE    Male              0      No         No          Yes
2     0004-TLHLJ    Male              0      No         No          Yes
3     0011-IGKFF    Male              1     Yes         No          Yes
4     0013-EXCHZ  Female              1     Yes         No          Yes
...          ...     ...            ...     ...        ...          ...
7038  9987-LUTYD  Female              0      No         No           No
7039  9992-RRAMN    Male              0     Yes         No           No
7040  9992-UJOEL    Male              0      No         No           No
7041  9993-LHIEB    Male              0     Yes        Yes           No
7042  9995-HOTOH    Male              0     Yes        Yes          Yes

     InternetService       OnlineSecurity         OnlineBackup  \
0                DSL                   No                   No
1                 No  No internet service  No internet service
2                DSL                   No                   No
3                DSL                   No                   No
4                DSL                  Yes                  Yes
...              ...                  ...                  ...
7038     Fiber optic                  Yes                  Yes
7039     Fiber optic                  Yes                  Yes
7040     Fiber optic                   No                  Yes
7041     Fiber optic                   No                   No
7042     Fiber optic                  Yes                  Yes

         DeviceProtection          TechSupport          StreamingTV  \
0                      No                   No                   No
1     No internet service  No internet service  No internet service
2                      No                   No                   No
3                      No                   No                   No
4                      No                   No                   No
...                   ...                  ...                  ...
7038                   No                  Yes                   No
7039                  Yes                  Yes                  Yes
7040                  Yes                  Yes                  Yes
7041                  Yes                   No                  Yes
7042                   No                   No                  Yes

          StreamingMovies        Contract PaperlessBilling  \
0                      No        One year              Yes
1     No internet service  Month-to-month              Yes
2                      No  Month-to-month              Yes
3                      No  Month-to-month              Yes
4                      No  Month-to-month              Yes
...                   ...             ...              ...
7038                  Yes        One year               No
7039                  Yes  Month-to-month               No
7040                   No  Month-to-month               No
7041                  Yes        Two year               No
7042                  Yes        Two year               No

                  PaymentMethod  MonthlyCharges  TotalCharges Churn  \
0              Electronic Check           65.60        593.30    No
1                  Mailed Check           59.90        542.40    No
2       Credit card (automatic)           73.90        280.85   Yes
3       Credit card (automatic)           98.00       1237.85   Yes
4              Electronic Check           83.90        267.40   Yes
...                         ...             ...           ...   ...
7038  Bank transfer (automatic)           55.15        742.90    No
7039    Credit card (automatic)           85.10       1873.70   Yes
7040    Credit card (automatic)           50.30         92.75    No
7041    Credit card (automatic)           67.85       4627.65    No
7042    Credit card (automatic)           59.00       3707.60    No
```

```
                Date
0     01 Jan, 2010
1     01 Jan, 2010
2     01 Jan, 2010
3     02 Jan, 2010
4     03 Jan, 2010
...            ...
7038  28 Dec, 2020
7039  29 Dec, 2020
7040  29 Dec, 2020
7041  30 Dec, 2020
7042  30 Dec, 2020

[7043 rows x 20 columns]>
```

Printing first row

In [8]:
```
telecom.iloc[0]
```

Out[8]:
```
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                  65.6
TotalCharges                   593.3
Churn                             No
Date                    01 Jan, 2010
Name: 0, dtype: object
```

In [9]:
```
telecom = telecom.convert_dtypes()
telecom.info()
```

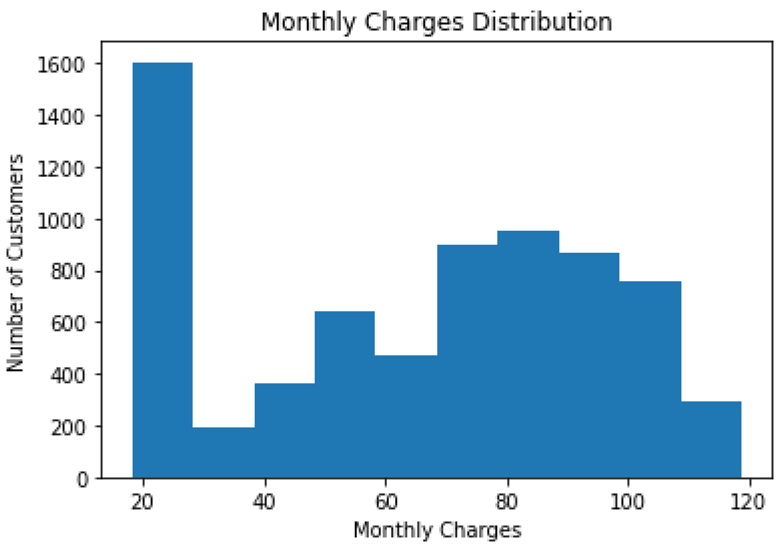
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 20 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        7043 non-null   string 
 1   gender            7043 non-null   string 
 2   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
```

Visualizations of contiguous features:

Monthly Charges

In [10]:
```python
import matplotlib.pyplot as plt

plt.hist(telecom['MonthlyCharges'])
plt.xlabel('Monthly Charges')
plt.ylabel('Number of Customers')
plt.title('Monthly Charges Distribution')
```

Out[10]:
```
Text(0.5, 1.0, 'Monthly Charges Distribution')
```

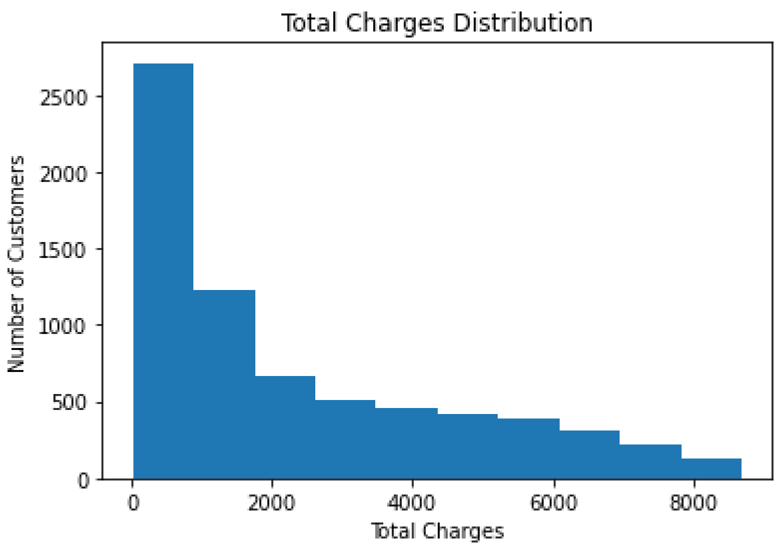


Total Charges

In [11]:
```python
import matplotlib.pyplot as plt
```

```
total_charges =telecom['TotalCharges'].dropna()

plt.hist(total_charges)

plt.xlabel('Total Charges')

plt.ylabel('Number of Customers')

plt.title('Total Charges Distribution')
```

Out[11]: Text(0.5, 1.0, 'Total Charges Distribution')



Continous features report

Continuous features report includes:

1. Min
2. 1st quartile
3. Mean
4. 2nd quartile - Median
5. 3rd quartile
6. Max
7. Standard deviation
8. Total num of instances
9. % missing values
10. Cardinality - num of distinct values for a feature

Using Pandas provides a function for generating data quality reports however it doesn't include all the statistics.

In [12]:
```
telecom.describe(include=['number'])
```

Out[12]:

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

Senior Citizen is a Categorical Feature, just 0 and 1 we can convert it into continous feature

In [13]:

```
import warnings
def build_continuous_features_report(telecom):

    """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 = telecom.select_dtypes("number").columns
    continuous_data_df = telecom[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
```

In [14]:

```
build_continuous_features_report(telecom)
```

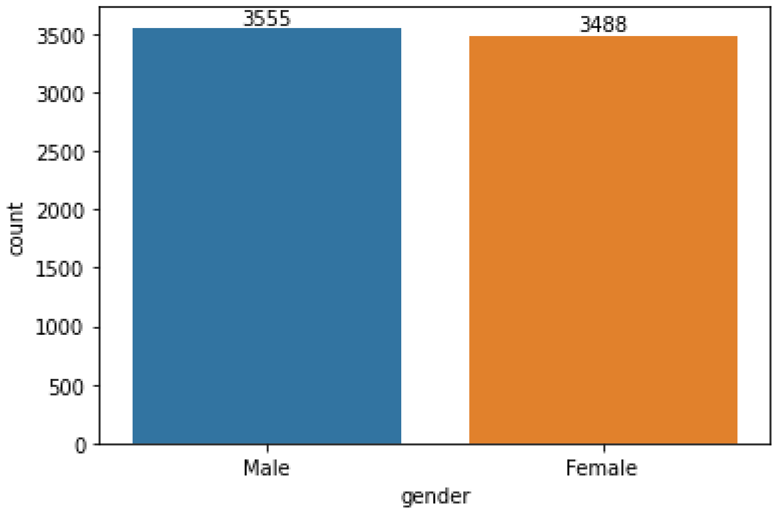
Out[14]:

	Count	Miss %	Card.	Min	1st Qrt.	Mean	Median	3rd Qrt	Max	Std. Dev.
SeniorCitizen	7043	0.000000	2	0.00	0.0	0.162147	0.000	0.0	1.00	0.368612
MonthlyCharges	7043	0.000000	1585	18.25	35.5	64.761692	70.350	89.85	118.75	30.090047
TotalCharges	7043	0.156183	6530	18.80	401.45	2283.300441	1397.475	3794.7375	8684.80	2266.771362

Visualizing Categorical features

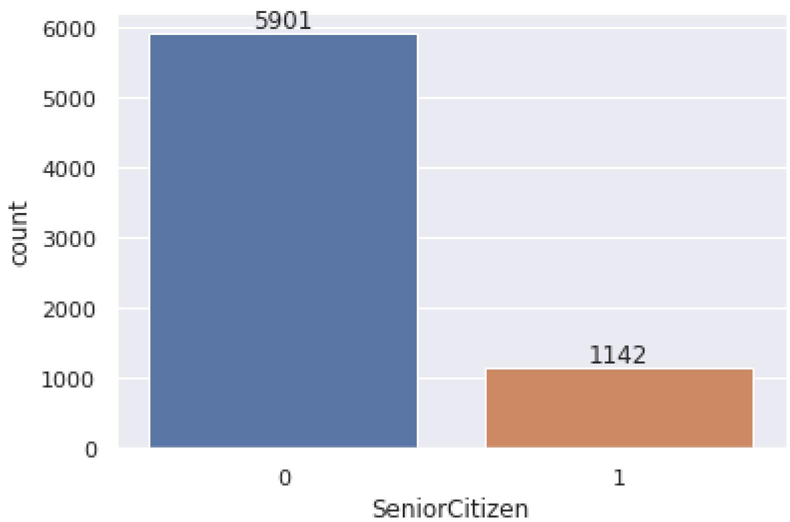
GENDER

In [15]:
```
import seaborn as sns
ax = sns.countplot(x=telecom['gender'],
                   order=telecom['gender'].value_counts(ascending=False).index);

abs_values = telecom['gender'].value_counts(ascending=False).values

ax.bar_label(container=ax.containers[0], labels=abs_values)
sns.set_theme(style="darkgrid")
```



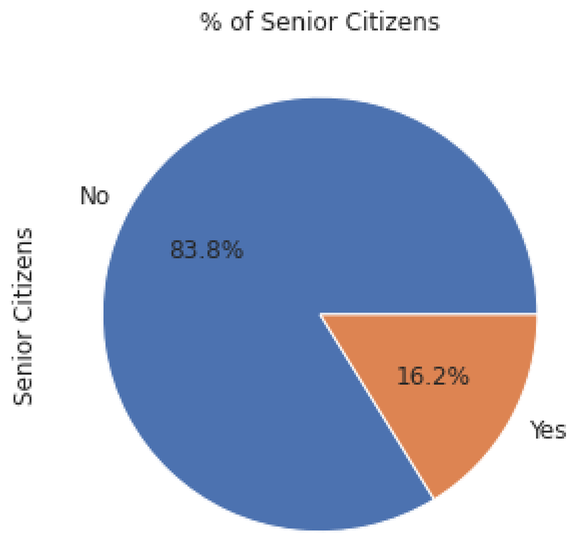
Senior Citizen

In [16]:
```
ax = sns.countplot(x=telecom['SeniorCitizen'],
                   order=telecom['SeniorCitizen'].value_counts(ascending=False).index);

abs_values = telecom['SeniorCitizen'].value_counts(ascending=False).values

ax.bar_label(container=ax.containers[0], labels=abs_values)
sns.set_theme(style="darkgrid")
```



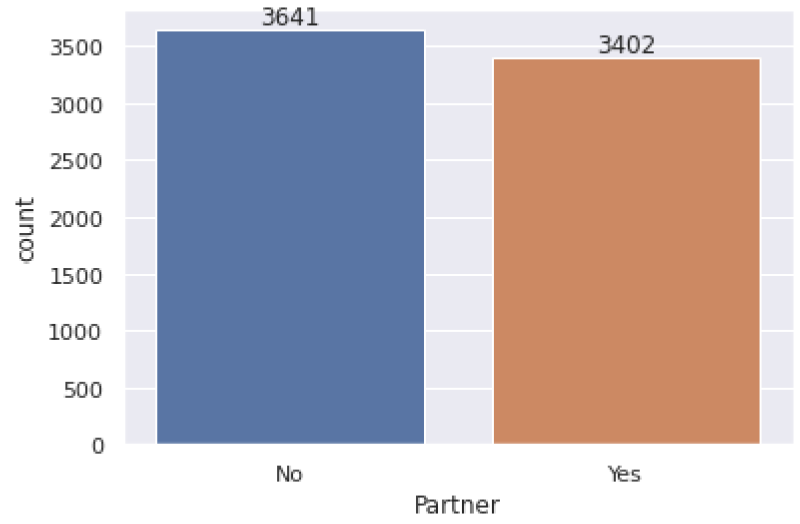
In [17]:
```
ax = (telecom['SeniorCitizen'].value_counts()*100.0 /len(telecom))\
.plot.pie(autopct='%.1f%%', labels = ['No', 'Yes'],figsize =(5,5), fontsize = 12 )
ax.yaxis.set_major_formatter(mtick.PercentFormatter())
ax.set_ylabel('Senior Citizens',fontsize = 12)
ax.set_title('% of Senior Citizens', fontsize = 12)
```

Out[17]: Text(0.5, 1.0, '% of Senior Citizens')



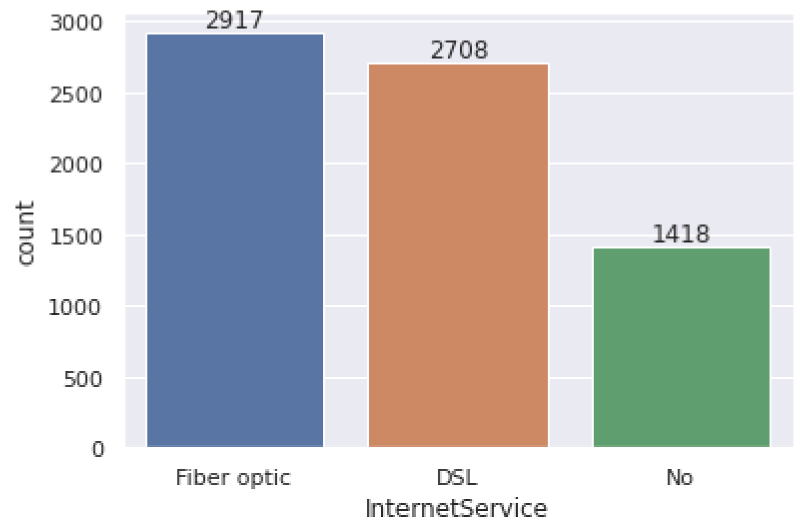
PARTNER

In [18]:
```
ax = sns.countplot(x=telecom['Partner'],
                   order=telecom['Partner'].value_counts(ascending=False).index);

abs_values = telecom['Partner'].value_counts(ascending=False).values

ax.bar_label(container=ax.containers[0], labels=abs_values)
sns.set_theme(style="darkgrid")
```



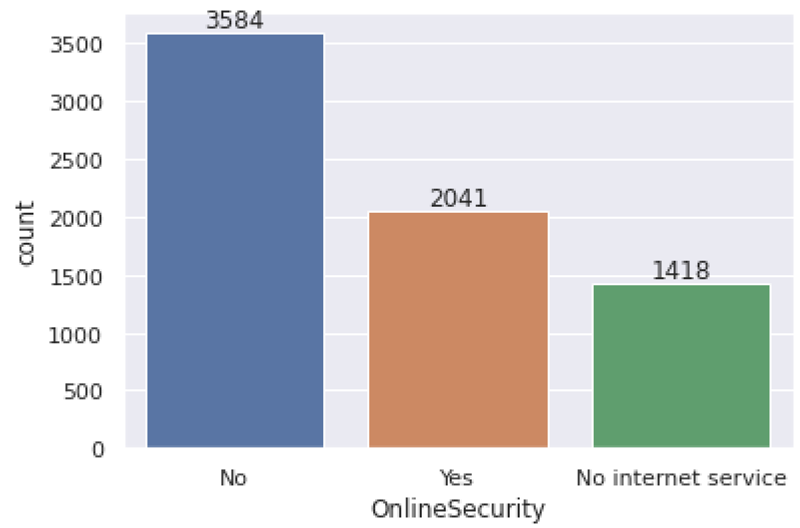
INTERNET SERVICE

In [19]:
```
ax = sns.countplot(x=telecom['InternetService'],
                   order=telecom['InternetService'].value_counts(ascending=False).index);

abs_values = telecom['InternetService'].value_counts(ascending=False).values

ax.bar_label(container=ax.containers[0], labels=abs_values)
sns.set_theme(style="darkgrid")
```



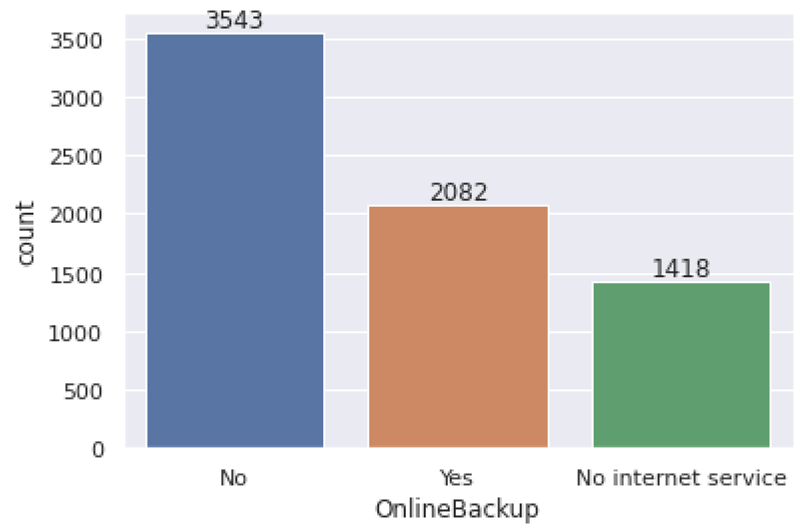
ONLINE SECURITY

In [20]:
```
ax = sns.countplot(x=telecom['OnlineSecurity'],
                   order=telecom['OnlineSecurity'].value_counts(ascending=False).index);

abs_values = telecom['OnlineSecurity'].value_counts(ascending=False).values

ax.bar_label(container=ax.containers[0], labels=abs_values)
sns.set_theme(style="darkgrid")
```



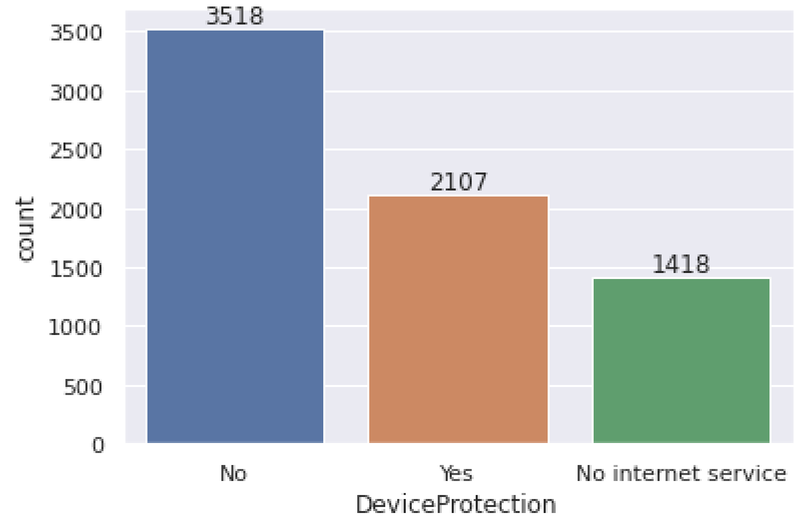
ONLINE BACKUP

In [21]:
```
ax = sns.countplot(x=telecom['OnlineBackup'],
                   order=telecom['OnlineBackup'].value_counts(ascending=False).index);

abs_values = telecom['OnlineBackup'].value_counts(ascending=False).values

ax.bar_label(container=ax.containers[0], labels=abs_values)
sns.set_theme(style="darkgrid")
```



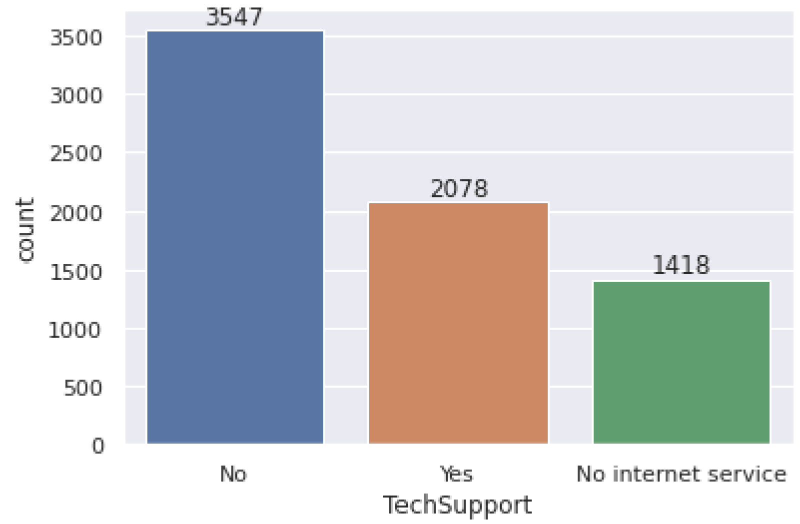
DEVICE PROTECTION

In [22]:
```
ax = sns.countplot(x=telecom['DeviceProtection'],
                   order=telecom['DeviceProtection'].value_counts(ascending=False).index);

abs_values = telecom['DeviceProtection'].value_counts(ascending=False).values

ax.bar_label(container=ax.containers[0], labels=abs_values)
sns.set_theme(style="darkgrid")
```



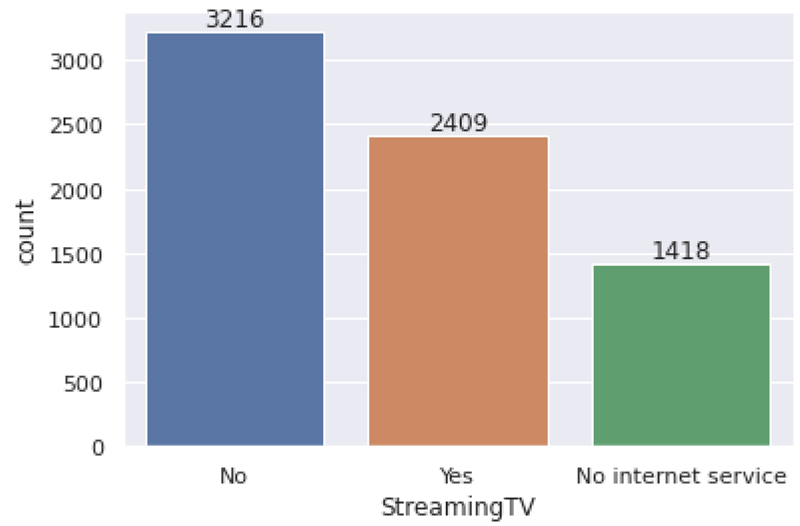
TECH SUPPORT

In [23]:
```
ax = sns.countplot(x=telecom['TechSupport'],
                   order=telecom['TechSupport'].value_counts(ascending=False).index);

abs_values = telecom['TechSupport'].value_counts(ascending=False).values

ax.bar_label(container=ax.containers[0], labels=abs_values)
sns.set_theme(style="darkgrid")
```



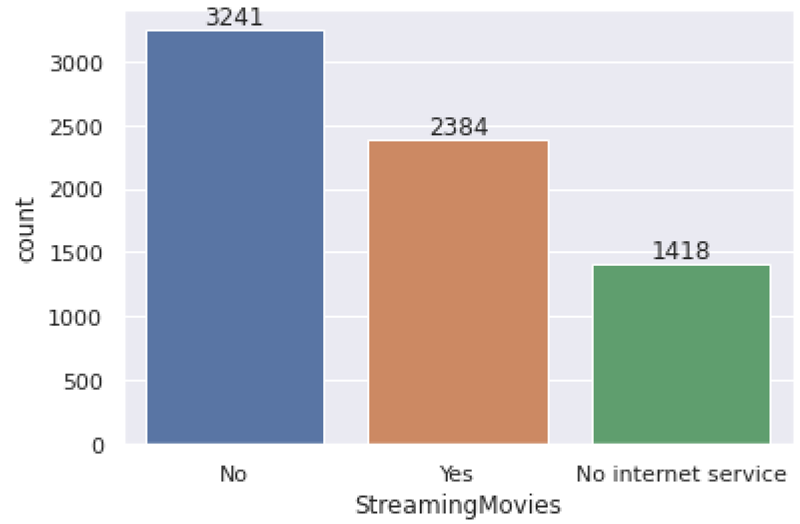
STREAMING TV

In [24]:
```
ax = sns.countplot(x=telecom['StreamingTV'],
                   order=telecom['StreamingTV'].value_counts(ascending=False).index);

abs_values = telecom['StreamingTV'].value_counts(ascending=False).values

ax.bar_label(container=ax.containers[0], labels=abs_values)
sns.set_theme(style="darkgrid")
```



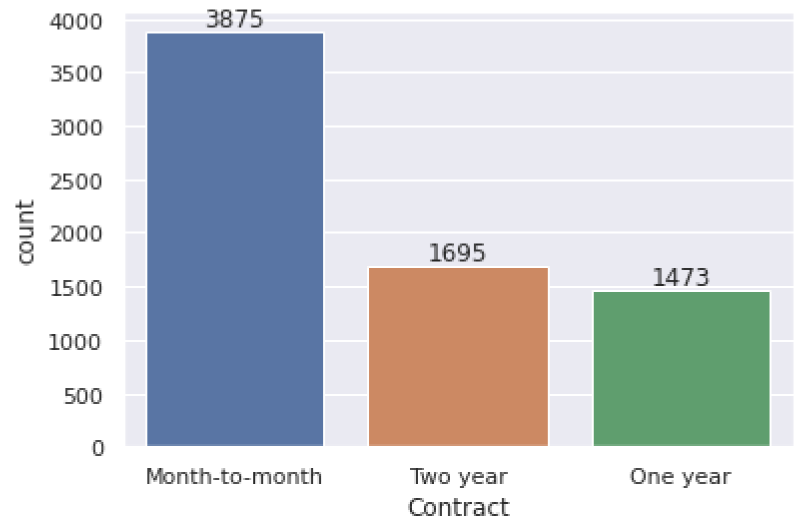
STREAMING MOVIES

In [25]:
```
ax = sns.countplot(x=telecom['StreamingMovies'],
                   order=telecom['StreamingMovies'].value_counts(ascending=False).index);

abs_values = telecom['StreamingMovies'].value_counts(ascending=False).values

ax.bar_label(container=ax.containers[0], labels=abs_values)
sns.set_theme(style="darkgrid")
```



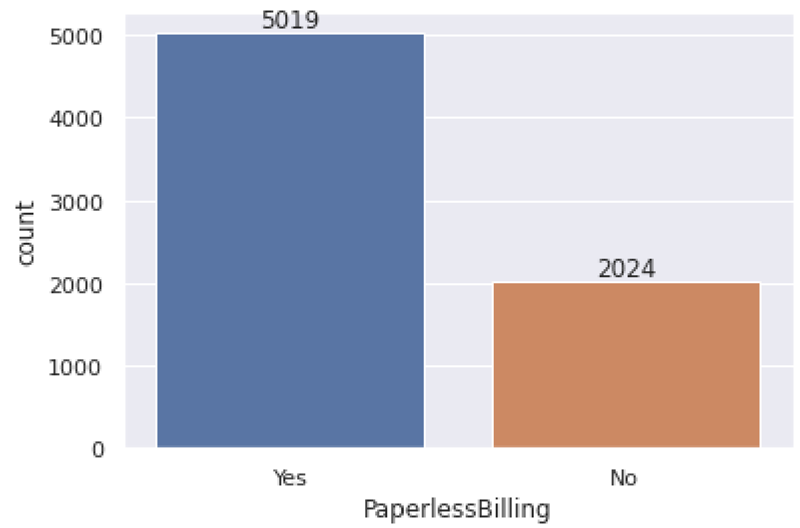
CONTRACT

In [26]:
```
ax = sns.countplot(x=telecom['Contract'],
                   order=telecom['Contract'].value_counts(ascending=False).index);

abs_values = telecom['Contract'].value_counts(ascending=False).values

ax.bar_label(container=ax.containers[0], labels=abs_values)
sns.set_theme(style="darkgrid")
```



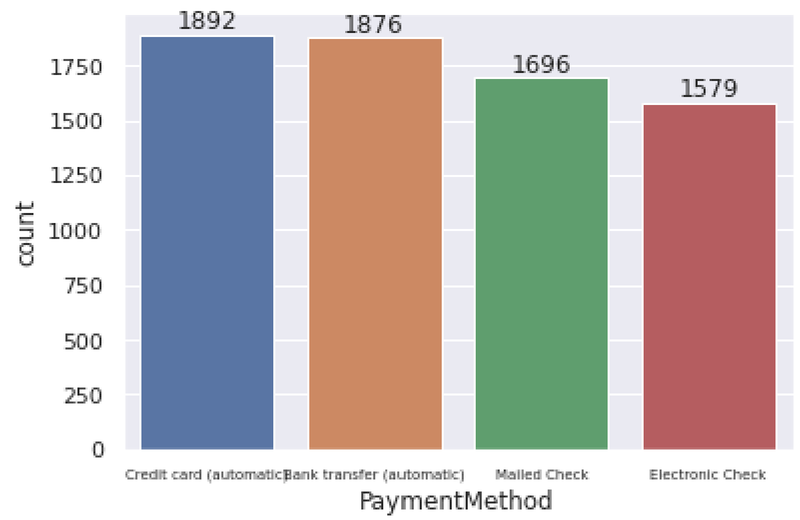
PAPERLESS BILLING

In [27]:
```
ax = sns.countplot(x=telecom['PaperlessBilling'],
                   order=telecom['PaperlessBilling'].value_counts(ascending=False).index);

abs_values = telecom['PaperlessBilling'].value_counts(ascending=False).values

ax.bar_label(container=ax.containers[0], labels=abs_values)
sns.set_theme(style="darkgrid")
```



PAYMENT METHOD

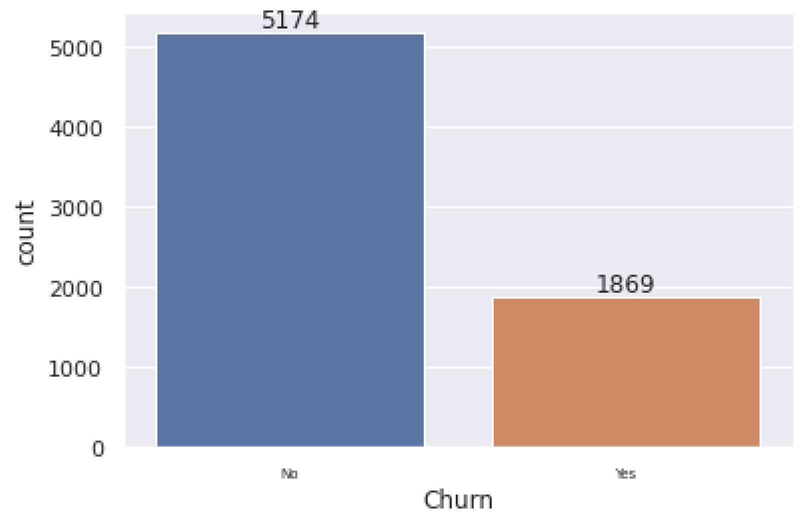
In [28]:
```
ax = sns.countplot(x=telecom['PaymentMethod'],
                   order=telecom['PaymentMethod'].value_counts(ascending=False).index);

abs_values = telecom['PaymentMethod'].value_counts(ascending=False).values

ax.bar_label(container=ax.containers[0], labels=abs_values)
sns.set_theme(style="darkgrid")
ax.tick_params(axis='x', labelsize=7)
```



CHURN-- THE TARGET VARIABLE

We can observe that the churn value is having unequal distribution, so if we use the same values while training the dataset it could lead to biased results

In [29]:
```
ax = sns.countplot(x=telecom['Churn'],
                   order=telecom['Churn'].value_counts(ascending=False).index);
abs_values = telecom['Churn'].value_counts(ascending=False).values

ax.bar_label(container=ax.containers[0], labels=abs_values)
sns.set_theme(style="darkgrid")
ax.tick_params(axis='x', labelsize=7)
```



Categorical features report

Categorical features report includes:

1. Mode - the most frequent value
2. 2nd mode - the second most frequent value
3. Frequency of mode
4. Proportion of mode in the dataset
5. Frequency of 2nd mode
6. Proportion of 2nd mode in the dataset
7. % missing values
8. Cardinality

Pandas provides a function for generating data quality reports however it doesn't include all the statistics.

In [30]:
```
telecom.describe(exclude=['number'])
```

Out[30]:

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

In [31]:
```
def build_categorical_features_report(telecom):

    """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 = telecom.select_dtypes(exclude="number").columns
    continuous_data_df = telecom[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 [32]:
```
build_categorical_features_report(telecom)
```

Out[32]:

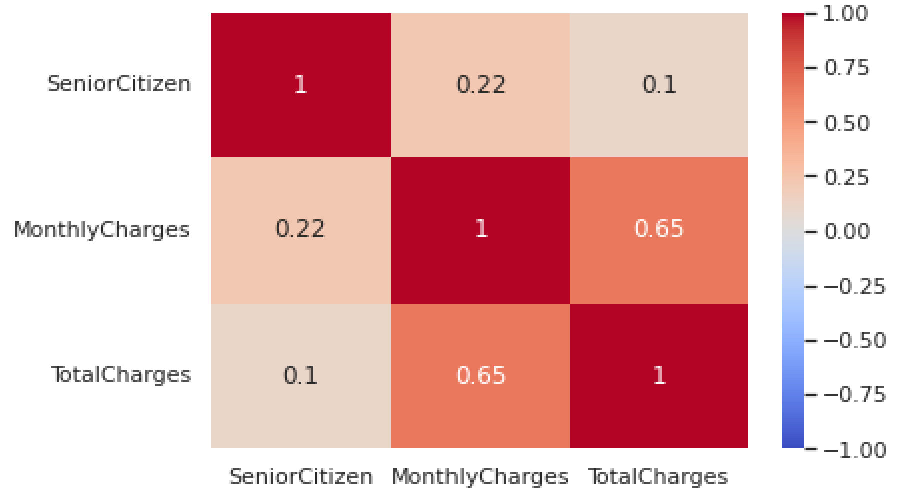
	Count	Miss %	Card.	Mode	Mode Freq	Mode %	2nd Mode	2nd Mode Freq	2nd Mode %
customerID	7043	0.0	7043	[0002-ORFBO, 0003-MKNFE, 0004-TLHLJ, 0011-IGKF...	7043	100.000000	[]	0	0.000000
gender	7043	0.0	2	[Male]	3555	50.475650	[Female]	3488	49.524350
Partner	7043	0.0	2	[No]	3641	51.696720	[Yes]	3402	48.303280
Dependents	7043	0.0	2	[No]	4933	70.041176	[Yes]	2110	29.958824
PhoneService	7043	0.0	2	[Yes]	5016	71.219651	[No]	2027	28.780349
InternetService	7043	0.0	3	[Fiber optic]	2917	41.417010	[DSL]	2708	38.449524
OnlineSecurity	7043	0.0	3	[No]	3584	50.887406	[Yes]	2041	28.979128
OnlineBackup	7043	0.0	3	[No]	3543	50.305268	[Yes]	2082	29.561267
DeviceProtection	7043	0.0	3	[No]	3518	49.950305	[Yes]	2107	29.916229
TechSupport	7043	0.0	3	[No]	3547	50.362062	[Yes]	2078	29.504473
StreamingTV	7043	0.0	3	[No]	3216	45.662360	[Yes]	2409	34.204174
StreamingMovies	7043	0.0	3	[No]	3241	46.017322	[Yes]	2384	33.849212
Contract	7043	0.0	3	[Month-to-month]	3875	55.019168	[Two year]	1695	24.066449
PaperlessBilling	7043	0.0	2	[Yes]	5019	71.262246	[No]	2024	28.737754
PaymentMethod	7043	0.0	4	[Credit card (automatic)]	1892	26.863552	[Bank transfer (automatic)]	1876	26.636377
Churn	7043	0.0	2	[No]	5174	73.463013	[Yes]	1869	26.536987
Date	7043	0.0	3346	[04 Feb, 2011, 04 Jul, 2019, 06 Feb, 2018, 07 ...	70	0.993895	[01 Dec, 2020, 01 May, 2020, 01 Sep, 2018, 02 ...	216	3.066875

In [33]:
```
telecom.isna().sum()
```

Out[33]:
```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
PhoneService        0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges       11
Churn               0
Date                0
dtype: int64
```

In [34]:
```
sb.heatmap(telecom.corr(),vmin = -1, vmax = +1, annot = True, cmap = 'coolwarm')
```

Out[34]:
```
<AxesSubplot:>
```



1(b) Identifying Data Quality Issues and Building a Data Quality Plan

The following data quality issues were identified

1. **Missing Values** : The feature 'Total Charges' has a total of 11 missing values
2. **Feature Values** : There is a high divergence in the values of Monthly Charges and Total Charges for some customers.
3. **Feature Type** :Senior Citizen is a categorial feature, having values 1 and 0 and hence should not be considered as a contionous feature
4. **Outliers:** We can identify if our dataset has Outliers by creating box-plots of the suspected feature. In the data quality report of continous features, we checked the outliers in Total Charges and Monthly Charges, but there was none found.

1(c) Preprocess your data according to the data quality plan

Preprocessing:-

1. Replacing the 11 missing values in the feature 'Total Charges' by mean of the column [1]
2. Convert data type of Senior Citizen from string to int (Yes/No) to (1/0) [2]
3. We thought of updating total charges where there would be a high variation by observing instances where the total charges are equal to monthly charges. There were 613 instances found where the the monthly charges and total charges are equal. We also used a scatter plot to visualize the variation in both the fetaures.

Updating the missing values with mean

In [35]:
```
telecom['TotalCharges'] = telecom['TotalCharges'].fillna(telecom['TotalCharges'].mean())
```

Checking the null values in the dataset after updation

In [36]:
```
telecom.isnull().sum()
```

Out[36]:
```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
PhoneService        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
Date                0
dtype: int64
```

Checking the instances where the monthly charges is equal to the total charges

In [37]:
```
df_check = telecom[telecom['MonthlyCharges']==telecom['TotalCharges']]
```

In [38]:
```
df_check
```

Out[38]:

	customerID	gender	SeniorCitizen	Partner	Dependents	PhoneService	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMe
17	0021-IKXGC	Female	1	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 c
19	0023-HGHWL	Male	1	No	No	Yes	DSL	No	No	No	No	No	Yes	Month-to-month	Yes	Mailed c
25	0032-PGELS	Female	0	Yes	Yes	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Month-to-month	Yes	Bank tra (auton
48	0082-LDZUE	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	Electronic c
63	0107-WESLM	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	Bank tra (auton
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
6980	9907-SWKKF	Female	1	No	No	No	Fiber optic	Yes	Yes	Yes	Yes	Yes	Yes	Month-to-month	Yes	Bank tra (auton
7007	9940-RHLFB	Female	0	No	No	No	Fiber optic	Yes	Yes	No	No	No	Yes	Month-to-month	No	Bank tra (auton
7021	9962-BFPDU	Female	0	Yes	Yes	No	Fiber optic	Yes	Yes	No	No	Yes	Yes	Month-to-month	No	Bank tra (auton
7033	9975-SKRNR	Male	0	No	No	No	Fiber optic	Yes	No	Yes	No	Yes	Yes	Month-to-month	No	Bank tra (auton
7036	9985-MWVIX	Female	0	No	No	Yes	Fiber optic	Yes	Yes	Yes	Yes	No	Yes	Month-to-month	Yes	Credit (auton

613 rows × 20 columns

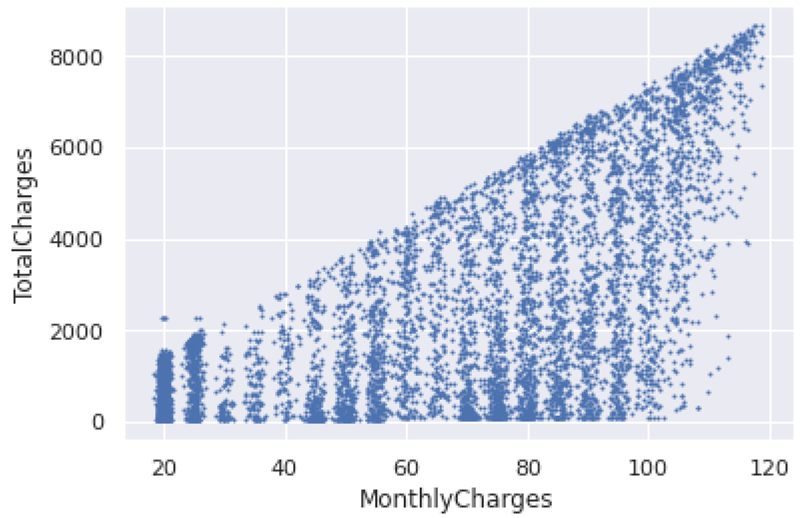
613 records are there where they are equal

Observing the variation of Total Charges and Monthly Charges [3]

In [39]:

```
telecom.plot.scatter(x = 'MonthlyCharges', y = 'TotalCharges', s = 1);
```

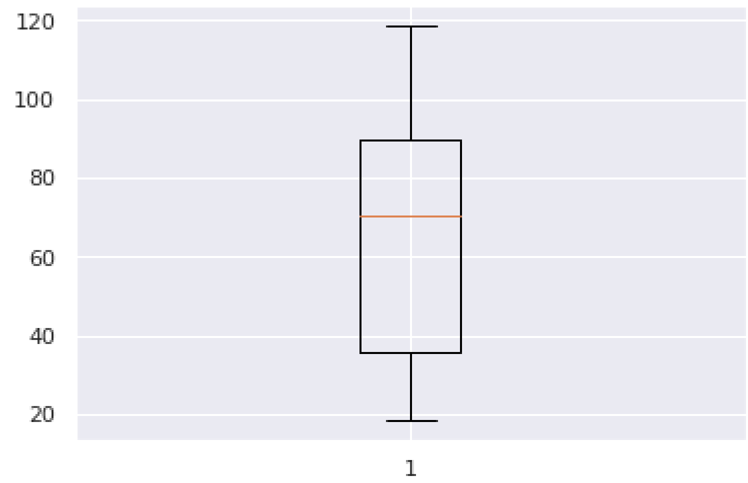
```
*c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its length matches with *x* & *y*.  Please use the *color* k
eyword-argument or provide a 2D array with a single row if you intend to specify the same RGB or RGBA value for all points.
```



Box plot for Monthly Charges

We can observe that there are no outliers for the feature 'Monthly Charges'

In [40]:
```
import matplotlib.pyplot as plt

#### Column: Monthly Charges

plt.boxplot(telecom['MonthlyCharges'])
fig = plt.figure(figsize =(10, 7))
plt.show()

# finding the 1st quartile
frp= telecom['MonthlyCharges']
q1 = np.quantile(telecom['MonthlyCharges'], 0.25)

# finding the 3rd quartile
q3 = np.quantile(telecom['MonthlyCharges'], 0.75)
med = np.median(telecom['MonthlyCharges'])

# finding the iqr region
iqr = q3-q1

# finding upper and lower whiskers
upper_bound = q3+(1.5*iqr)
lower_bound = q1-(1.5*iqr)
print(iqr, upper_bound, lower_bound)

outliers = frp[(frp <= lower_bound) | (frp >= upper_bound)]
print('The following are the outliers in the boxplot:{}'.format(outliers))
```

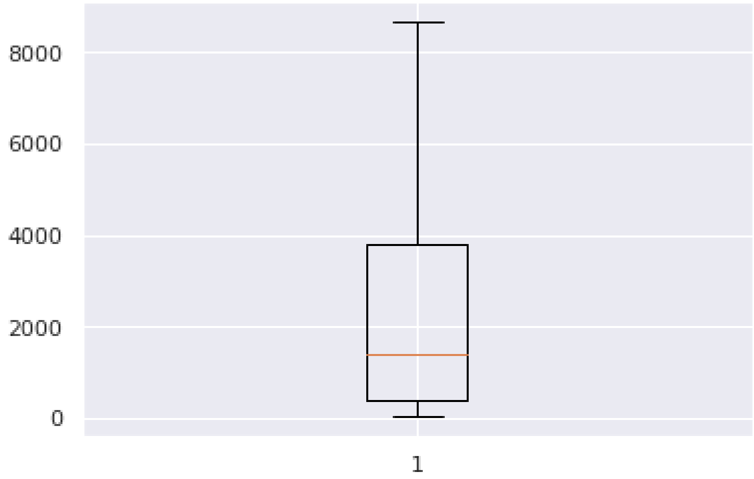



```
<Figure size 720x504 with 0 Axes>
54.349999999999994 171.375 -46.02499999999999
The following are the outliers in the boxplot:Series([], Name: MonthlyCharges, dtype: Float64)
```

Box Plot for Total Charges

We can observe that there are no outliers for the feature 'Total Charges'

In [41]:
```
#### Column: Total Charges

plt.boxplot(telecom['TotalCharges'])
fig = plt.figure(figsize =(10, 7))
plt.show()

# finding the 1st quartile
frp= telecom['TotalCharges']
q1 = np.quantile(telecom['TotalCharges'], 0.25)

# finding the 3rd quartile
q3 = np.quantile(telecom['TotalCharges'], 0.75)
med = np.median(telecom['TotalCharges'])

# finding the iqr region
iqr = q3-q1

# finding upper and lower whiskers
upper_bound = q3+(1.5*iqr)
lower_bound = q1-(1.5*iqr)
print(iqr, upper_bound, lower_bound)

outliers = frp[(frp <= lower_bound) | (frp >= upper_bound)]
print('The following are the outliers in the boxplot:{}'.format(outliers))
```




```
<Figure size 720x504 with 0 Axes>
3384.375 8863.1625 -4674.3375
The following are the outliers in the boxplot:Series([], Name: TotalCharges, dtype: Float64)
```

1(d) Extract the numerical and categorical features from the dataset and build the data quality report.

The general visualizations of the features are covered in part 1(a)

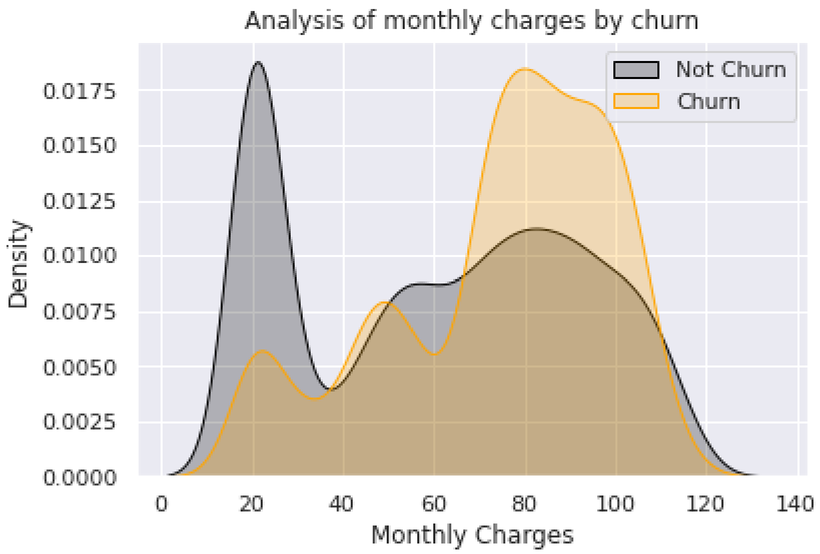
Churn by Monthly Charges: Higher % of customers churn when the monthly charges are high.

The churn is higher when the total charges are lower

Hypothesis : Churn is not dependent on the feature 'Monthly Charges'

In [42]:
```
ax = sns.kdeplot(telecom.MonthlyCharges[(telecom["Churn"] == 'No') ],
                color="Black", shade = True)
ax = sns.kdeplot(telecom.MonthlyCharges[(telecom["Churn"] == 'Yes') ],
                ax =ax, color="Orange", shade= True)
ax.legend(["Not Churn","Churn"],loc='upper right')
ax.set_ylabel('Density')
ax.set_xlabel('Monthly Charges')
ax.set_title('Analysis of monthly charges by churn')
```

Out[42]:
```
Text(0.5, 1.0, 'Analysis of monthly charges by churn')
```

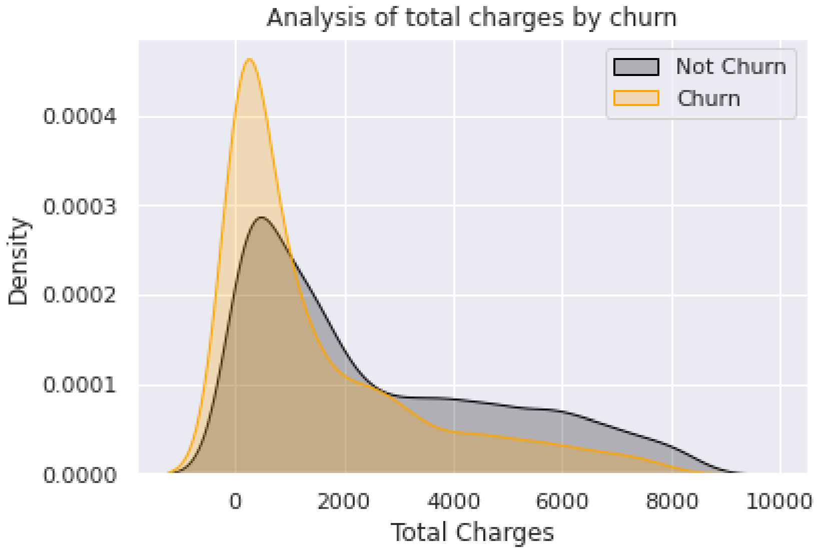


Hypothesis : Churn is not dependent on the feature 'Total Charges'

Churn is maximum when the total charges is in the range 0-1000 and it is similar in case when the customer is not churned out. Hence, total charges do not provide good potential point of comparison

In [43]:
```
ax = sns.kdeplot(telecom.TotalCharges[(telecom["Churn"] == 'No') ],
                color="Black", shade = True)
ax = sns.kdeplot(telecom.TotalCharges[(telecom["Churn"] == 'Yes') ],
                ax =ax, color="Orange", shade= True)
ax.legend(["Not Churn","Churn"],loc='upper right')
ax.set_ylabel('Density')
ax.set_xlabel('Total Charges')
ax.set_title('Analysis of total charges by churn')
```

Out[43]:
```
Text(0.5, 1.0, 'Analysis of total charges by churn')
```



Churn by Contract Type

Hypothesis : Churn is dependent on the type of contract customer

In [44]:
```
churn_contract = telecom.groupby(['Contract','Churn']).size().unstack()
churn_contract
```

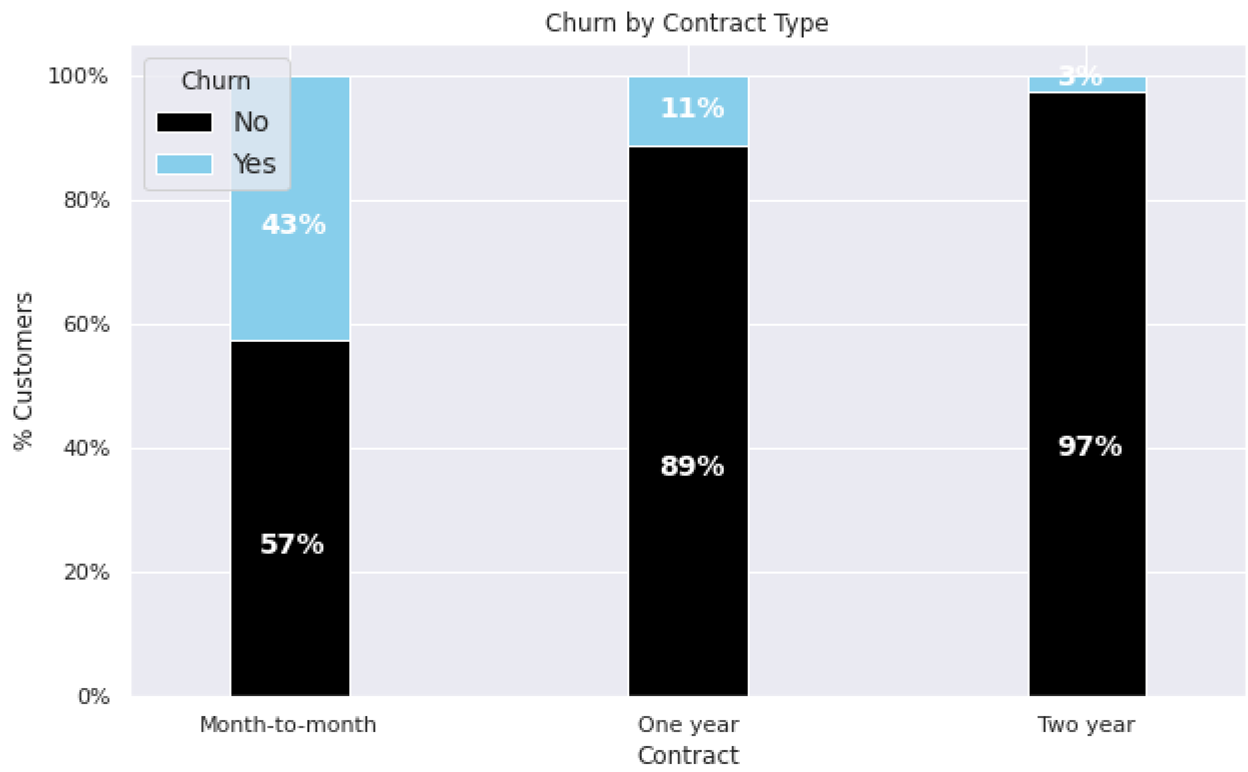
Out[44]:

Churn	No	Yes
Contract		
Month-to-month	2220	1655
One year	1307	166
Two year	1647	48

We can observe that the highest churn occurs in the case of "Month to Month" contract , followed by yearly , follwed by two year contract. Hence, it is benefical to keep the customers engaged in the long term contracts to avoid churn

In [45]:
```
ax = (churn_contract.T*100.0 / churn_contract.T.sum()).T.plot(kind='bar',
                                                                width = 0.3,
                                                                stacked = True,
                                                                rot = 0,
                                                                figsize = (10,6),
                                                                color = ['#000000','#87CEEB'])
ax.yaxis.set_major_formatter(mtick.PercentFormatter())
ax.legend(loc='best',prop={'size':14},title = 'Churn')
ax.set_ylabel('% Customers')
```

```
ax.set_title('Churn by Contract Type')

# Code to add the data labels on the stacked bar chart
for p in ax.patches:
    width, height = p.get_width(), p.get_height()
    x, y = p.get_xy()
    ax.annotate('{:.0f}%'.format(height), (p.get_x()+.25*width, p.get_y()+.4*height),
                color = 'white',
               weight = 'bold',
               size = 14)
```



In [46]:
```
from datetime import date
```

Convert the date column to date time

In [47]:
```
telecom['Date'] = pd.to_datetime(telecom['Date']).dt.date
```

Calculation of Tenure column

Tenure is a derived column for the calculating the duration the customer was there with the company. The date column in the dataset is the signup date, when the customer subscribed to the telecom company. Using this date we calculate the tenure by using the difference between today's date and signupdate. After this we convert the obtained value in months

We have also considered a scenario when the customer is churned out for that we have considered tenure as the above calclulation minus 1 month as the customer is not longer subscribed to the company.

In [48]:
```
telecom['tenure'] = np.where(telecom['Churn']=='No' ,((date.today()-telecom['Date'])/( np. timedelta64(1, 'M'))),((date.today()-telecom['Date'])/( np. timedelta64(1, 'M')))-1)
```

In [49]:
```
telecom['tenure']
```

Out[49]:
```
0       150.311095
1       150.311095
2       149.311095
3       149.278240
4       149.245385
           ...
7038     18.431590
7039     17.398735
7040     18.398735
7041     18.365880
7042     18.365880
Name: tenure, Length: 7043, dtype: float64
```

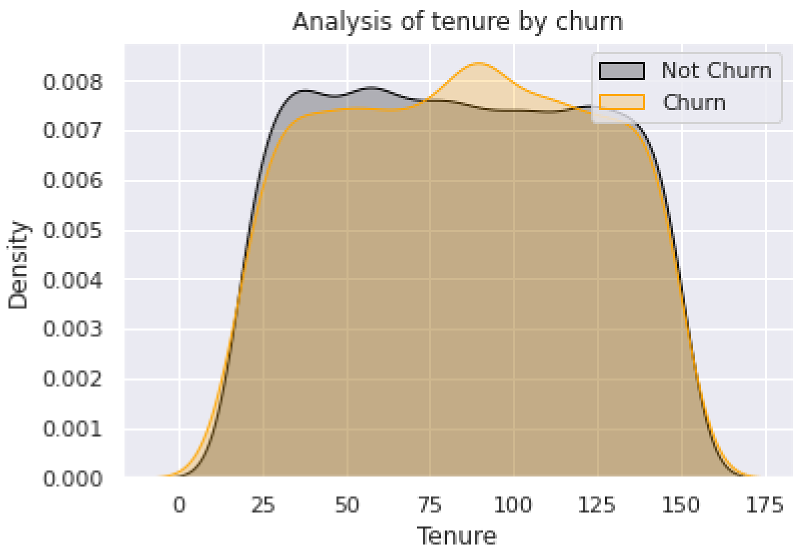
Churn by Tenure

Hypothesis : Churn is dependent on the tenure of the customer

We do not observe significant difference in the churn variable with respect to tenure

In [50]:
```
ax = sns.kdeplot(telecom.tenure[(telecom["Churn"] == 'No') ],
                color="Black", shade = True)
ax = sns.kdeplot(telecom.tenure[(telecom["Churn"] == 'Yes') ],
                ax =ax, color="Orange", shade= True)
ax.legend(["Not Churn","Churn"],loc='upper right')
ax.set_ylabel('Density')
ax.set_xlabel('Tenure')
ax.set_title('Analysis of tenure by churn')
```

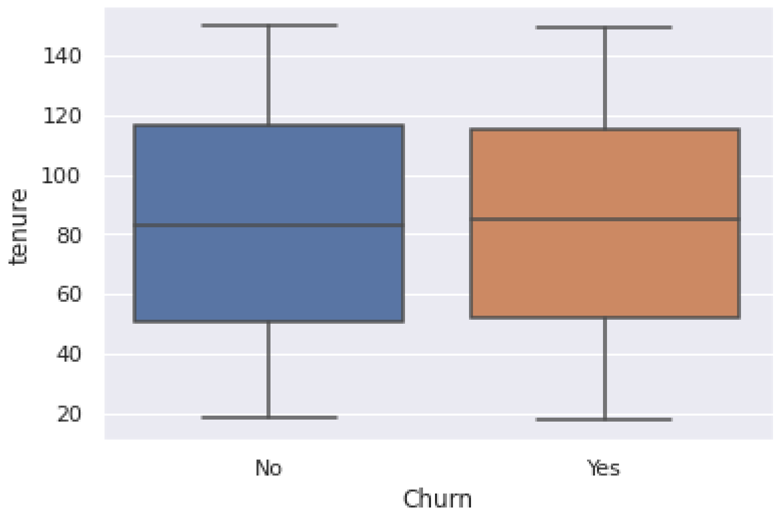
Out[50]:
```
Text(0.5, 1.0, 'Analysis of tenure by churn')
```



Box plot for tenure: We can observe from the box plot that tenure is almost similar for both churn and non churn scenarios

In [51]:
```
sns.boxplot(x = telecom.Churn, y = telecom.tenure)
```

Out[51]:
```
<AxesSubplot:xlabel='Churn', ylabel='tenure'>
```



One Hot Encoding of categorical features having more than 2 distinct values/categories

In [52]:
```
hot_encoded_df = telecom
hot_encoded_df = pd.get_dummies(hot_encoded_df, columns=['InternetService', 'Contract', 'PaymentMethod', 'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV', 'Stre

hot_encoded_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 40 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   PaperlessBilling                         7043 non-null   string 
 7   MonthlyCharges                           7043 non-null   Float64
 8   TotalCharges                             7043 non-null   Float64
 9   Churn                                    7043 non-null   string 
 10  Date                                     7043 non-null   object 
 11  tenure                                   7043 non-null   float64
 12  InternetService_DSL                      7043 non-null   uint8  
 13  InternetService_Fiber optic              7043 non-null   uint8  
 14  InternetService_No                       7043 non-null   uint8  
 15  Contract_Month-to-month                  7043 non-null   uint8  
 16  Contract_One year                        7043 non-null   uint8  
 17  Contract_Two year                        7043 non-null   uint8  
 18  PaymentMethod_Bank transfer (automatic)  7043 non-null   uint8  
 19  PaymentMethod_Credit card (automatic)    7043 non-null   uint8  
 20  PaymentMethod_Electronic Check           7043 non-null   uint8  
 21  PaymentMethod_Mailed Check               7043 non-null   uint8  
 22  OnlineSecurity_No                        7043 non-null   uint8  
 23  OnlineSecurity_No internet service       7043 non-null   uint8  
 24  OnlineSecurity_Yes                       7043 non-null   uint8  
 25  OnlineBackup_No                          7043 non-null   uint8  
 26  OnlineBackup_No internet service         7043 non-null   uint8  
 27  OnlineBackup_Yes                         7043 non-null   uint8  
 28  DeviceProtection_No                      7043 non-null   uint8  
 29  DeviceProtection_No internet service     7043 non-null   uint8  
 30  DeviceProtection_Yes                     7043 non-null   uint8  
 31  TechSupport_No                           7043 non-null   uint8  
 32  TechSupport_No internet service          7043 non-null   uint8  
 33  TechSupport_Yes                          7043 non-null   uint8  
 34  StreamingTV_No                           7043 non-null   uint8  
 35  StreamingTV_No internet service          7043 non-null   uint8  
 36  StreamingTV_Yes                          7043 non-null   uint8  
 37  StreamingMovies_No                       7043 non-null   uint8  
 38  StreamingMovies_No internet service      7043 non-null   uint8  
 39  StreamingMovies_Yes                      7043 non-null   uint8  
dtypes: Float64(2), Int64(1), float64(1), object(1), string(7), uint8(28)
memory usage: 873.6+ KB
```

We did Label Encoding of the fetaures where we had 2 uniques values in the feature. [2]

In [53]:
```
from sklearn.preprocessing import LabelEncoder

telecom_df = hot_encoded_df.drop(columns=['customerID'])

categorical_feature = telecom_df.dtypes=="string"
final_categorical_feature = telecom_df.columns[categorical_feature].tolist()


le = LabelEncoder()
telecom_df[final_categorical_feature] = telecom_df[final_categorical_feature].apply(lambda col: le.fit_transform(col))
telecom_df.head(5)
```

Out[53]:

	gender	SeniorCitizen	Partner	Dependents	PhoneService	PaperlessBilling	MonthlyCharges	TotalCharges	Churn	Date	...	DeviceProtection_Yes	TechSupport_No	TechSupport_No internet service	TechSupport_Yes	StreamingTV_No	Stream intern
0	0	0	1	1	1	1	65.6	593.3	0	2010-01-01	...	0	1	0	0	1	
1	1	0	0	0	1	1	59.9	542.4	0	2010-01-01	...	0	0	1	0	0	
2	1	0	0	0	1	1	73.9	280.85	1	2010-01-01	...	0	1	0	0	1	
3	1	1	1	0	1	1	98.0	1237.85	1	2010-01-02	...	0	1	0	0	1	
4	0	1	1	0	1	1	83.9	267.4	1	2010-01-03	...	0	1	0	0	1	

5 rows × 39 columns

Checking the data types of the features after one hot encoding and label encoding [2]

In [54]:
```
telecom_df.dtypes
```

Out[54]:
```
gender                                     int64
SeniorCitizen                              Int64
Partner                                    int64
Dependents                                 int64
PhoneService                               int64
PaperlessBilling                           int64
MonthlyCharges                           Float64
TotalCharges                             Float64
Churn                                      int64
Date                                      object
tenure                                   float64
InternetService_DSL                        uint8
InternetService_Fiber optic                uint8
InternetService_No                         uint8
Contract_Month-to-month                    uint8
Contract_One year                          uint8
Contract_Two year                          uint8
PaymentMethod_Bank transfer (automatic)    uint8
PaymentMethod_Credit card (automatic)      uint8
PaymentMethod_Electronic Check             uint8
PaymentMethod_Mailed Check                 uint8
OnlineSecurity_No                          uint8
OnlineSecurity_No internet service         uint8
OnlineSecurity_Yes                         uint8
OnlineBackup_No                            uint8
OnlineBackup_No internet service           uint8
OnlineBackup_Yes                           uint8
DeviceProtection_No                        uint8
DeviceProtection_No internet service       uint8
DeviceProtection_Yes                       uint8
TechSupport_No                             uint8
TechSupport_No internet service            uint8
TechSupport_Yes                            uint8
StreamingTV_No                             uint8
StreamingTV_No internet service            uint8
StreamingTV_Yes                            uint8
StreamingMovies_No                         uint8
StreamingMovies_No internet service        uint8
StreamingMovies_Yes                        uint8
dtype: object
```

Converting data types of the features

In [55]:
```
telecom_df= telecom_df.convert_dtypes()
telecom_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 39 columns):
 #   Column                                   Non-Null Count  Dtype  
---  ------                                   --------------  -----  
 0   gender                                   7043 non-null   Int64  
 1   SeniorCitizen                            7043 non-null   Int64  
 2   Partner                                  7043 non-null   Int64  
 3   Dependents                               7043 non-null   Int64  
 4   PhoneService                             7043 non-null   Int64  
 5   PaperlessBilling                         7043 non-null   Int64  
 6   MonthlyCharges                           7043 non-null   Float64
 7   TotalCharges                             7043 non-null   Float64
 8   Churn                                    7043 non-null   Int64  
 9   Date                                     7043 non-null   object 
 10  tenure                                   7043 non-null   Float64
 11  InternetService_DSL                      7043 non-null   UInt8  
 12  InternetService_Fiber optic              7043 non-null   UInt8  
 13  InternetService_No                       7043 non-null   UInt8  
 14  Contract_Month-to-month                  7043 non-null   UInt8  
 15  Contract_One year                        7043 non-null   UInt8  
 16  Contract_Two year                        7043 non-null   UInt8  
 17  PaymentMethod_Bank transfer (automatic)  7043 non-null   UInt8  
 18  PaymentMethod_Credit card (automatic)    7043 non-null   UInt8  
 19  PaymentMethod_Electronic Check           7043 non-null   UInt8  
 20  PaymentMethod_Mailed Check               7043 non-null   UInt8  
 21  OnlineSecurity_No                        7043 non-null   UInt8  
 22  OnlineSecurity_No internet service       7043 non-null   UInt8  
 23  OnlineSecurity_Yes                       7043 non-null   UInt8  
 24  OnlineBackup_No                          7043 non-null   UInt8  
 25  OnlineBackup_No internet service         7043 non-null   UInt8  
 26  OnlineBackup_Yes                         7043 non-null   UInt8  
 27  DeviceProtection_No                      7043 non-null   UInt8  
 28  DeviceProtection_No internet service     7043 non-null   UInt8  
 29  DeviceProtection_Yes                     7043 non-null   UInt8  
 30  TechSupport_No                           7043 non-null   UInt8  
 31  TechSupport_No internet service          7043 non-null   UInt8  
 32  TechSupport_Yes                          7043 non-null   UInt8  
 33  StreamingTV_No                           7043 non-null   UInt8  
 34  StreamingTV_No internet service          7043 non-null   UInt8  
 35  StreamingTV_Yes                          7043 non-null   UInt8  
 36  StreamingMovies_No                       7043 non-null   UInt8  
 37  StreamingMovies_No internet service      7043 non-null   UInt8  
 38  StreamingMovies_Yes                      7043 non-null   UInt8  
dtypes: Float64(3), Int64(7), UInt8(28), object(1)
memory usage: 1.0+ MB
```

Division of Dataset into Training , Test and Validation

Removing Churn and Date from the feature list on which model is to trained. Also, we are using the derived column Tenure. Hence removing Date is a logical choice.

In [56]:
```
X= telecom_df.drop(['Churn','Date'],axis=1)
y=telecom_df['Churn']
```

Diving Training and Test data into 40% and 60% respectively [4]

In [57]:
```
# Training data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.6, random_state=1)
```

Diving the Test data (60% of the original data) into 2 equal parts. So now our train data = 40% , test data =30% and validation data = 30%

In [58]:
```
# Testing an validation set
X_test, X_val, y_test, y_val = train_test_split(X_test, y_test, test_size=0.5, random_state=1)
```

Using Random Oversampler for oversampling so that we do not have the biased data [5]

In [59]:
```
from imblearn.over_sampling import RandomOverSampler
```

In [60]:
```
oversample = RandomOverSampler(sampling_strategy='minority')
```

In [61]:
```
from collections import Counter
```

In [62]:
```
print(Counter(y))
```

```
Counter({0: 5174, 1: 1869})
```

In [63]:
```
y_train= y_train.astype(int)
```

In [64]:
```
X_train_over, y_train_over = oversample.fit_resample(X_train, y_train)
```

2. Build a baseline model to predict customer churn

Division of Dataset into Training , Test and Validation

Removing Churn and Date from the feature list on which model is to trained. Also, we are using the derived column Tenure. Hence removing Date is a logical choice.

In [65]:
```
X= telecom_df.drop(['Churn','Date'],axis=1)
y=telecom_df['Churn']
```

Diving Training and Test data into 40% and 60% respectively

In [66]:
```
# Training data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.6, random_state=1)
```

Diving the Test data (60% of the original data) into 2 equal parts. So now our train data = 40% , test data =30% and validation data = 30%

In [67]:
```
# Testing an validation set
X_test, X_val, y_test, y_val = train_test_split(X_test, y_test, test_size=0.5, random_state=1)
```

As our training data is

Using Random Oversampler for oversampling so that we do not have the biased data [5]

In [68]:
```
from imblearn.over_sampling import RandomOverSampler
```

In [69]:
```
oversample = RandomOverSampler(sampling_strategy='minority')
```

In [70]:
```
from collections import Counter
```

In [71]:
```
print(Counter(y))
```

```
Counter({0: 5174, 1: 1869})
```

In [72]:
```
y_train= y_train.astype(int)
```

In [73]:
```
X_train_over, y_train_over = oversample.fit_resample(X_train, y_train)
```

2(a) Explain what the task you're solving is (e.g., supervised x unsupervised, classification x regression x clustering or similarity matching x, etc).

Since this data is labeled, we already know the target variable(Churn). Hence, this is a supervised learning problem. The target variable is a categorical variable. Hence, a classification model is the most suitable for this particular problem. We are performing classification to find out if there will be customer churn or not.

2(b) Use a feature selection method to select the features to build a model.

We are using recursive feature elimination(RFE) for selecting relevant features to train our model [6]

In [74]:
```
from sklearn.feature_selection import RFE
from sklearn.ensemble import RandomForestClassifier

rfe_selector = RFE(estimator=RandomForestClassifier(),n_features_to_select = 16, step = 1)
rfe_selector.fit(X, y.astype(int))
cols = rfe_selector.get_support(indices=True)
X_new = X.iloc[:,cols]
X_new.head()
```

Out[74]:

	gender	SeniorCitizen	Partner	PhoneService	MonthlyCharges	TotalCharges	tenure	Contract_Month-to-month	Contract_Two year	PaymentMethod_Bank transfer (automatic)	PaymentMethod_Mailed Check	OnlineSecurity_No	OnlineBackup_No	TechSupport_No
0	0	0	1	1	65.6	593.3	150.311095	0	0	0	0	1	1	1
1	1	0	0	1	59.9	542.4	150.311095	1	0	0	1	0	0	0
2	1	0	0	1	73.9	280.85	149.311095	1	0	0	0	1	1	1
3	1	1	1	1	98.0	1237.85	149.27824	1	0	0	0	1	1	1
4	0	1	1	1	83.9	267.4	149.245385	1	0	0	0	0	0	1

2(c) Select the evaluation metric. Justify your choice.

There are plenty of evaluation metrics available for classification tasks. [7]

Accuracy Score

The accuracy score is the ratio of correctly predicted output and the total number of predictions. [7]

Confusion Matrix

The confusion matrix is used to visualize the performance of a classification model. The matrix makes it easy to see if the model is confusing two classes. [7]

We are using the accuracy score for the evaluation of the model because we have used a random over sampler for balancing the data instances. Hence, the model will not train on a biased dataset.

Baseline Model: Random Forest Classifier

Random Forest Classifier is used in classification and regression problems. This algorithm is an ensemble method that trains multiple decision trees during training time [8]. For the classification problem, the output is calculated based on the voting process. The most voted class by the decision trees is chosen as the final class. In this data set, we are classifying whether there will be customer churn.

In [75]:
```
from sklearn.utils.validation import check_array
feature_data = X_train_over.iloc[:,cols]
target_data = y_train_over

# from sklearn.model_selection import train_test_split
from sklearn import datasets, linear_model, metrics

model_rf = RandomForestClassifier( n_estimators=12 , oob_score = True, n_jobs = -1,random_state =50, max_features = "auto", max_leaf_nodes = 50)

# train the model using the training sets
model_rf.fit(feature_data, target_data)
```

Out[75]:
```
RandomForestClassifier(max_leaf_nodes=50, n_estimators=12, n_jobs=-1,
                       oob_score=True, random_state=50)
```

In [76]:
```
X_val_fs = X_val.iloc[:,cols]
```

In [77]:
```
# Make predictions
prediction_test = model_rf.predict(X_val_fs)
```

In [78]:
```
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report

dt  = round(accuracy_score(y_val.astype(int), prediction_test.astype(int))*100, 2)
print(dt)
```

```
71.51
```

2(d) Perform hyperparameter tuning if applicable.

We are changing the values of max_leaf_nodes and estimators to get the model which best predicts the output on the test dataset. We are selecting the best model based on the highest accuracy score.

In [80]:
```
max_accuracy = 0
max_accuracy_model = None
optimum_estimator =0
optimum_leaf_node =0
X_plot=[]
Y_plot=[]
Z_plot=[]
for estimators in range(4, 14, 2):
  for max_leaf_nodes in range(50, 900, 50):
      model_rf = RandomForestClassifier( n_estimators=estimators , oob_score = True, n_jobs = -1,random_state =50, max_features = "auto",max_leaf_nodes = max_leaf_nodes)
      # train the model using the training set
      model_rf.fit(feature_data, target_data)
      prediction_test = model_rf.predict(X_val_fs)
      accuracy =round(accuracy_score(y_val.astype(int), prediction_test.astype(int))*100, 2)
      print(accuracy, max_leaf_nodes,estimators)
      X_plot.append(estimators)
      Y_plot.append(max_leaf_nodes)
      Z_plot.append(accuracy)
      if accuracy > max_accuracy:
            max_accuracy = accuracy
            optimum_estimator= estimators
            optimum_leaf_node=max_leaf_nodes
            max_accuracy_model = model_rf
```

```
71.37 50 4
73.31 100 4
73.64 150 4
73.97 200 4
74.96 250 4
74.59 300 4
74.4 350 4
74.21 400 4
74.16 450 4
74.11 500 4
74.87 550 4
74.92 600 4
74.68 650 4
74.68 700 4
74.68 750 4
74.68 800 4
74.68 850 4
71.89 50 6
74.25 100 6
74.59 150 6
75.2 200 6
75.44 250 6
75.72 300 6
75.49 350 6
75.72 400 6
75.53 450 6
75.49 500 6
75.77 550 6
76.01 600 6
75.53 650 6
75.58 700 6
75.58 750 6
75.58 800 6
75.58 850 6
71.94 50 8
74.02 100 8
74.21 150 8
74.96 200 8
75.06 250 8
75.15 300 8
75.25 350 8
74.96 400 8
75.2 450 8
74.82 500 8
75.86 550 8
76.53 600 8
76.53 650 8
76.48 700 8
76.48 750 8
76.48 800 8
76.48 850 8
71.6 50 10
73.54 100 10
73.92 150 10
75.06 200 10
75.63 250 10
75.67 300 10
76.15 350 10
75.82 400 10
75.91 450 10
75.82 500 10
76.34 550 10
76.34 600 10
76.48 650 10
```

```
76.53 700 10
76.53 750 10
76.53 800 10
76.53 850 10
71.51 50 12
73.54 100 12
73.36 150 12
75.11 200 12
75.3 250 12
75.91 300 12
76.19 350 12
76.24 400 12
76.19 450 12
76.24 500 12
77.19 550 12
77.09 600 12
76.9 650 12
76.86 700 12
76.86 750 12
76.86 800 12
76.86 850 12
```

Accuracy of the best model

In [82]:
```
print(max_accuracy, optimum_estimator,optimum_leaf_node)
```

```
77.19 12 550
```

2(e) Train and evaluate your model on test data.

Only picking the selected features

In [83]:
```
X_test_fs = X_test.iloc[:,cols]
```

In [84]:
```
prediction_test = max_accuracy_model.predict(X_test_fs)
```

In [85]:
```
accuracy = round(accuracy_score(y_test.astype(int), prediction_test.astype(int))*100, 2)
```

Accuracy of the Test Data

In [86]:
```
accuracy
```

Out[86]:
```
75.06
```

2(f) How do you make sure that your model is not overfitting the data?

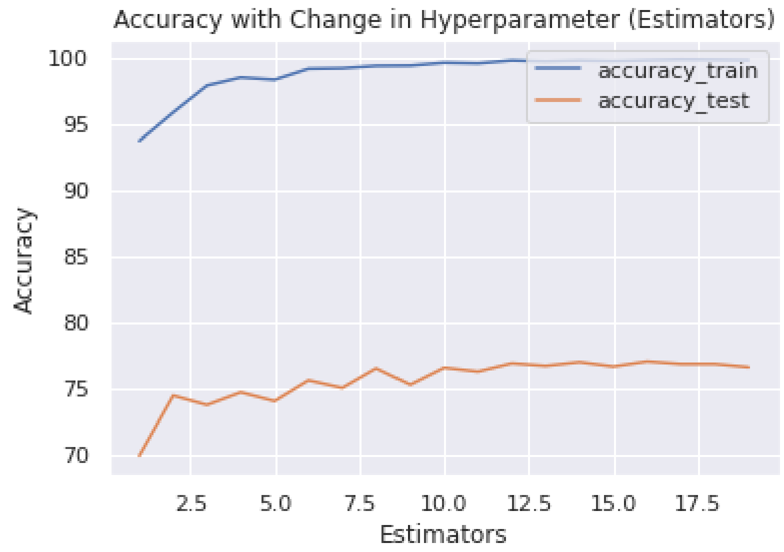
Unlike decision trees, the random forest is less likely to overfit the data because it's an ensemble method. In a decision tree, as the depth of the tree increases, so does the complexity of the model. Hence, there is a possibility of overfitting the data. However, in the case of random forests, it uses bootstrap aggregation with the ransom selection of features for a split. Also, it uses multiple decision trees. Thus the individual tree is strong but not correlated. Hence, the random forest does not need pruning [9].

2(g) Plot the learning curve. What can you conclude from this plot?

In [87]:
```
acc_train = []
acc_test = []
```

```
for estimators in range(1, 20):
    model_rf = RandomForestClassifier(n_estimators=estimators , oob_score = True, n_jobs = -1,random_state =50, max_features = "auto",max_leaf_nodes = 800)
    # train the model using the training set
    model_rf.fit(feature_data, target_data)
    prediction_train = model_rf.predict(feature_data)
    acc_train.append(round(accuracy_score(target_data.astype(int), prediction_train.astype(int))*100, 2))
    prediction_test = model_rf.predict(X_val_fs)
    acc_test.append(round(accuracy_score(y_val.astype(int), prediction_test.astype(int))*100, 2))
```

In [88]:
```
plt.plot(range(1, 20), acc_train, label='accuracy_train')
plt.plot(range(1, 20), acc_test, label='accuracy_test')
plt.legend(loc='upper right')
plt.xlabel("Estimators")
plt.ylabel("Accuracy")
plt.title("Accuracy with Change in Hyperparameter (Estimators)")
plt.show()
```



We have trained and tested the model by passing a different number of estimators. It can be seen that the accuracy of both training and testing data increases and saturates after a certain point. We have used two loops to find the best hyperparameter for the model. We have tuned estimators and max_leaf_nodes to find the best possible model with the highest accuracy.

3. Build a NN model to predict customer churn

Keras is an open-source library for building a deep neural network. It is built on top of TensorFlow. It provides a simple interface for modeling, training, and evaluating a complex neural network architecture. We are using Keras to simplify the process of creating a neural network architecture [10].

Importing Keras Library

In [89]:
```
from keras.models import Sequential
from keras import layers
from keras.layers.core import Dropout
```

The problem involves the classification of the customer churn. Hence, the target variable is a binary representation. The output of the neural network can be configured as a single neuron with a sigmoid function as the activation function. The output of the neural network denotes the probability of churn [11].

Creating function for building a model. The neural network input layer size is the same as the number of selected features in the dataset. Adding two hidden layers with 512 neurons in each layer. Each neuron is a "relu" activation function [11].

In each layer, the neurons are densely connected. For example, each neuron in the current layer receives input from all neurons from the previous layer [11].

In [90]:
```
def build_NN():
  model = Sequential()
  model.add(layers.Dense(512, input_shape=(feature_data.shape[1],), activation='relu'))
  model.add(Dropout(0.2))
  model.add(layers.Dense(512, activation='relu'))
  model.add(Dropout(0.2))
  model.add(layers.Dense(1, activation='sigmoid'))
  return model
```

What are you doing to avoid overfitting?

Since the neurons are densely connected, the model becomes fairly complex. Hence, there is a possibility of overfitting the training data. There are two ways to resolve the overfitting problem. Early stopping Dropout The early stopping method is done by constantly evaluating the model using the validation set to ensure that the accuracy of the validation set does not drop as compared to the training accuracy. The point where the testing accuracy drops and the training accuracy continues to increase is the point where the overfitting starts. The early stopping method stops the training of the model at the point where the testing accuracy starts decreasing. Another method to avoid overfitting the model is by using the dropout method. The dropout method randomly removes connections between neurons to avoid the building of an overly complex model. Thus, it avoids overfitting the data [12]. We have used the dropout method for avoiding overfitting the model. While training, the model drops 20% of the connections between layers to avoid the complexity of the model [12].

Building the model

In [91]:
```
nn_model = build_NN()
```

Using binary crossentropy loss function to calculate the loss of the model necessary for the gradient descent algorithm.

In [92]:
```
nn_model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

Summarizing the model

In [93]:
```
nn_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 512)               8704

 dropout (Dropout)           (None, 512)               0

 dense_1 (Dense)             (None, 512)               262656

 dropout_1 (Dropout)         (None, 512)               0

 dense_2 (Dense)             (None, 1)                 513

=================================================================
Total params: 271,873
Trainable params: 271,873
Non-trainable params: 0
_________________________________________________________________
```

The model feed-forwards the training dataset to calculate the error between the predicted output of the neural network and the actual output. The network error is very high initially. The backpropagation algorithm propagates the loss backward through the layers to update the weights of the network. In each epoch, the weights are updated to reduce the overall error produced by the network.

After experimenting with a few different models, we decided to go with two hidden layers and 512 neurons in each layer. We did not choose more number of layers because it causes a vanishing gradient problem. As a result, the training becomes very slow. Similarly, we found out that 512 neurons in each layer produce optimum results as compared to other lesser/greater numbers.

In [94]:
```
fit_nn = nn_model.fit(feature_data.astype(np.float32), target_data.astype(np.float32), epochs=80, verbose=True, validation_data=(X_val_fs.astype(np.float32), y_val.astype(np.float32)), batch_siz
```

```
Epoch 1/80
137/137 [==============================] - 2s 9ms/step - loss: 23.2001 - accuracy: 0.5857 - val_loss: 2.4250 - val_accuracy: 0.7643
Epoch 2/80
137/137 [==============================] - 1s 7ms/step - loss: 2.6473 - accuracy: 0.6140 - val_loss: 0.6363 - val_accuracy: 0.7643
Epoch 3/80
137/137 [==============================] - 1s 9ms/step - loss: 0.7380 - accuracy: 0.6306 - val_loss: 0.6250 - val_accuracy: 0.7577
Epoch 4/80
137/137 [==============================] - 1s 9ms/step - loss: 0.6872 - accuracy: 0.6357 - val_loss: 0.5897 - val_accuracy: 0.7496
Epoch 5/80
137/137 [==============================] - 1s 8ms/step - loss: 0.6876 - accuracy: 0.6494 - val_loss: 0.6496 - val_accuracy: 0.7383
Epoch 6/80
137/137 [==============================] - 1s 8ms/step - loss: 0.6463 - accuracy: 0.6523 - val_loss: 0.6508 - val_accuracy: 0.7440
Epoch 7/80
137/137 [==============================] - 1s 8ms/step - loss: 0.6319 - accuracy: 0.6687 - val_loss: 0.6070 - val_accuracy: 0.7317
Epoch 8/80
137/137 [==============================] - 1s 9ms/step - loss: 0.6291 - accuracy: 0.6802 - val_loss: 0.6745 - val_accuracy: 0.7572
Epoch 9/80
137/137 [==============================] - 1s 8ms/step - loss: 0.6253 - accuracy: 0.6746 - val_loss: 0.6894 - val_accuracy: 0.7473
Epoch 10/80
137/137 [==============================] - 1s 7ms/step - loss: 0.6211 - accuracy: 0.6777 - val_loss: 0.6032 - val_accuracy: 0.7487
Epoch 11/80
137/137 [==============================] - 1s 8ms/step - loss: 0.6243 - accuracy: 0.6846 - val_loss: 0.6855 - val_accuracy: 0.7544
Epoch 12/80
137/137 [==============================] - 2s 12ms/step - loss: 0.6083 - accuracy: 0.6934 - val_loss: 0.6867 - val_accuracy: 0.6294
Epoch 13/80
137/137 [==============================] - 2s 13ms/step - loss: 0.6170 - accuracy: 0.6882 - val_loss: 0.6269 - val_accuracy: 0.7501
Epoch 14/80
137/137 [==============================] - 1s 9ms/step - loss: 0.6037 - accuracy: 0.7007 - val_loss: 0.6275 - val_accuracy: 0.7605
Epoch 15/80
137/137 [==============================] - 1s 7ms/step - loss: 0.6053 - accuracy: 0.7061 - val_loss: 0.5597 - val_accuracy: 0.7549
Epoch 16/80
137/137 [==============================] - 1s 9ms/step - loss: 0.5974 - accuracy: 0.7002 - val_loss: 0.6195 - val_accuracy: 0.7629
Epoch 17/80
137/137 [==============================] - 1s 9ms/step - loss: 0.5990 - accuracy: 0.7068 - val_loss: 0.6684 - val_accuracy: 0.7459
Epoch 18/80
137/137 [==============================] - 1s 9ms/step - loss: 0.6062 - accuracy: 0.7043 - val_loss: 0.6322 - val_accuracy: 0.7605
Epoch 19/80
137/137 [==============================] - 1s 8ms/step - loss: 0.6019 - accuracy: 0.7000 - val_loss: 0.6396 - val_accuracy: 0.7525
Epoch 20/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5986 - accuracy: 0.7141 - val_loss: 0.5874 - val_accuracy: 0.7681
Epoch 21/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5954 - accuracy: 0.7002 - val_loss: 0.6060 - val_accuracy: 0.7506
Epoch 22/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5912 - accuracy: 0.7148 - val_loss: 0.5500 - val_accuracy: 0.7643
Epoch 23/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5874 - accuracy: 0.7141 - val_loss: 0.6149 - val_accuracy: 0.7619
Epoch 24/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5884 - accuracy: 0.7026 - val_loss: 0.5454 - val_accuracy: 0.7752
Epoch 25/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5883 - accuracy: 0.7070 - val_loss: 0.5930 - val_accuracy: 0.7511
Epoch 26/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5904 - accuracy: 0.7024 - val_loss: 0.5750 - val_accuracy: 0.7747
Epoch 27/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5854 - accuracy: 0.7166 - val_loss: 0.5496 - val_accuracy: 0.7799
Epoch 28/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5963 - accuracy: 0.7085 - val_loss: 0.5879 - val_accuracy: 0.7430
Epoch 29/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5806 - accuracy: 0.7109 - val_loss: 0.5761 - val_accuracy: 0.7506
Epoch 30/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5851 - accuracy: 0.7166 - val_loss: 0.6007 - val_accuracy: 0.7336
Epoch 31/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5758 - accuracy: 0.7236 - val_loss: 0.7046 - val_accuracy: 0.6801
Epoch 32/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5891 - accuracy: 0.7097 - val_loss: 0.5513 - val_accuracy: 0.7757
```

```
Epoch 33/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5841 - accuracy: 0.7090 - val_loss: 0.5618 - val_accuracy: 0.7719
Epoch 34/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5772 - accuracy: 0.7134 - val_loss: 0.5560 - val_accuracy: 0.7752
Epoch 35/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5785 - accuracy: 0.7180 - val_loss: 0.5495 - val_accuracy: 0.7743
Epoch 36/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5757 - accuracy: 0.7227 - val_loss: 0.5792 - val_accuracy: 0.7586
Epoch 37/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5777 - accuracy: 0.7175 - val_loss: 0.6530 - val_accuracy: 0.7321
Epoch 38/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5768 - accuracy: 0.7256 - val_loss: 0.5591 - val_accuracy: 0.7478
Epoch 39/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5759 - accuracy: 0.7102 - val_loss: 0.5603 - val_accuracy: 0.7601
Epoch 40/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5695 - accuracy: 0.7161 - val_loss: 0.7773 - val_accuracy: 0.5381
Epoch 41/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5800 - accuracy: 0.7129 - val_loss: 0.5432 - val_accuracy: 0.7690
Epoch 42/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5679 - accuracy: 0.7236 - val_loss: 0.6064 - val_accuracy: 0.7321
Epoch 43/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5665 - accuracy: 0.7253 - val_loss: 0.5583 - val_accuracy: 0.7279
Epoch 44/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5650 - accuracy: 0.7212 - val_loss: 0.5685 - val_accuracy: 0.7619
Epoch 45/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5671 - accuracy: 0.7183 - val_loss: 0.6060 - val_accuracy: 0.7577
Epoch 46/80
137/137 [==============================] - 1s 9ms/step - loss: 0.5667 - accuracy: 0.7339 - val_loss: 0.5466 - val_accuracy: 0.7790
Epoch 47/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5614 - accuracy: 0.7351 - val_loss: 0.5439 - val_accuracy: 0.7634
Epoch 48/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5560 - accuracy: 0.7375 - val_loss: 0.5319 - val_accuracy: 0.7714
Epoch 49/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5642 - accuracy: 0.7212 - val_loss: 0.5433 - val_accuracy: 0.7657
Epoch 50/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5569 - accuracy: 0.7263 - val_loss: 0.5373 - val_accuracy: 0.7799
Epoch 51/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5716 - accuracy: 0.7217 - val_loss: 0.5673 - val_accuracy: 0.7724
Epoch 52/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5635 - accuracy: 0.7251 - val_loss: 0.5113 - val_accuracy: 0.7842
Epoch 53/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5625 - accuracy: 0.7261 - val_loss: 0.5258 - val_accuracy: 0.7638
Epoch 54/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5576 - accuracy: 0.7312 - val_loss: 0.5254 - val_accuracy: 0.7795
Epoch 55/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5590 - accuracy: 0.7268 - val_loss: 0.5990 - val_accuracy: 0.7340
Epoch 56/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5540 - accuracy: 0.7358 - val_loss: 0.5015 - val_accuracy: 0.7799
Epoch 57/80
137/137 [==============================] - 1s 9ms/step - loss: 0.5735 - accuracy: 0.7253 - val_loss: 0.5522 - val_accuracy: 0.7520
Epoch 58/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5765 - accuracy: 0.7231 - val_loss: 0.5386 - val_accuracy: 0.7761
Epoch 59/80
137/137 [==============================] - 1s 9ms/step - loss: 0.5637 - accuracy: 0.7231 - val_loss: 0.5153 - val_accuracy: 0.7615
Epoch 60/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5688 - accuracy: 0.7258 - val_loss: 0.5332 - val_accuracy: 0.7823
Epoch 61/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5712 - accuracy: 0.7161 - val_loss: 0.5660 - val_accuracy: 0.7430
Epoch 62/80
137/137 [==============================] - 1s 9ms/step - loss: 0.5713 - accuracy: 0.7231 - val_loss: 0.5560 - val_accuracy: 0.7530
Epoch 63/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5668 - accuracy: 0.7273 - val_loss: 0.6267 - val_accuracy: 0.7283
Epoch 64/80
137/137 [==============================] - 2s 18ms/step - loss: 0.5436 - accuracy: 0.7336 - val_loss: 0.6110 - val_accuracy: 0.7056
```

```
Epoch 65/80
137/137 [==============================] - 1s 10ms/step - loss: 0.5505 - accuracy: 0.7356 - val_loss: 0.5523 - val_accuracy: 0.7539
Epoch 66/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5589 - accuracy: 0.7288 - val_loss: 0.5533 - val_accuracy: 0.7501
Epoch 67/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5574 - accuracy: 0.7214 - val_loss: 0.5593 - val_accuracy: 0.7487
Epoch 68/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5616 - accuracy: 0.7305 - val_loss: 0.5519 - val_accuracy: 0.7359
Epoch 69/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5965 - accuracy: 0.7214 - val_loss: 0.5675 - val_accuracy: 0.7530
Epoch 70/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5631 - accuracy: 0.7290 - val_loss: 0.5335 - val_accuracy: 0.7520
Epoch 71/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5627 - accuracy: 0.7268 - val_loss: 0.5602 - val_accuracy: 0.7657
Epoch 72/80
137/137 [==============================] - 1s 9ms/step - loss: 0.5482 - accuracy: 0.7314 - val_loss: 0.5385 - val_accuracy: 0.7700
Epoch 73/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5474 - accuracy: 0.7336 - val_loss: 0.5814 - val_accuracy: 0.7307
Epoch 74/80
137/137 [==============================] - 1s 9ms/step - loss: 0.5485 - accuracy: 0.7358 - val_loss: 0.5445 - val_accuracy: 0.7511
Epoch 75/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5543 - accuracy: 0.7397 - val_loss: 0.5463 - val_accuracy: 0.7496
Epoch 76/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5558 - accuracy: 0.7285 - val_loss: 0.5288 - val_accuracy: 0.7761
Epoch 77/80
137/137 [==============================] - 1s 8ms/step - loss: 0.5588 - accuracy: 0.7351 - val_loss: 0.5009 - val_accuracy: 0.7776
Epoch 78/80
137/137 [==============================] - 1s 9ms/step - loss: 0.5558 - accuracy: 0.7288 - val_loss: 0.5767 - val_accuracy: 0.7487
Epoch 79/80
137/137 [==============================] - 1s 9ms/step - loss: 0.5602 - accuracy: 0.7305 - val_loss: 0.5133 - val_accuracy: 0.7818
Epoch 80/80
137/137 [==============================] - 1s 7ms/step - loss: 0.5511 - accuracy: 0.7332 - val_loss: 0.5313 - val_accuracy: 0.7757
```

Training Accuracy

In [95]:
```
accuracy = nn_model.evaluate(feature_data.astype(np.float32), target_data.astype(np.float32))
print("Training Accuracy: {:.4f}".format(accuracy[1]))
```

```
128/128 [==============================] - 1s 4ms/step - loss: 0.5338 - accuracy: 0.7390
Training Accuracy: 0.7390
```

Testing Accuracy

In [96]:
```
X_test_fs=X_test.iloc[:,cols]
```

In [97]:
```
accuracy = nn_model.evaluate(X_test_fs.astype(np.float32), y_test.astype(np.float32))
print("Testing Accuracy: {:.4f}".format(accuracy[1]))
```

```
67/67 [==============================] - 0s 3ms/step - loss: 0.5273 - accuracy: 0.7615
Testing Accuracy: 0.7615
```

Learning Curve(Training and Testing Accuracy)

Because of the use of dropout, the model avoids overfitting. It can be seen from the learning curve that both training and testing accuracy improves with the epochs. Both testing and training accuracy converge at a certain point.

In [98]:
```
acc = fit_nn.history['accuracy']
val_acc = fit_nn.history['val_accuracy']
x = range(1, len(acc) + 1)
```

```
plt.plot(x, acc, 'b', label='Training acc')
plt.plot(x, val_acc, 'r', label='Testing acc')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Training and Testing accuracy')
plt.legend()
```

Out[98]: <matplotlib.legend.Legend at 0x7f3e5725b8d0>

Learning Curve(Training and Testing Loss)

Training and testing loss both drops dramatically in the initial epochs while training the model.

In [99]:
```
loss = fit_nn.history['loss']
val_loss = fit_nn.history['val_loss']
x = range(1, len(loss) + 1)
plt.plot(x, loss, 'b', label='Training loss')
plt.plot(x, val_loss, 'r', label='Testing loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training and Testing loss')
plt.legend()
```

Out[99]: <matplotlib.legend.Legend at 0x7f3ec4b38110>

Cross Validation of Random Forest CLassifier

In [100…
```
from sklearn.model_selection import cross_val_score

validation_random_forest= cross_val_score(max_accuracy_model, X.astype(int), y.astype(int), cv=5)
validation_random_forest
```

Out[100]:
```
array([0.76295245, 0.7707594 , 0.76863023, 0.76065341, 0.76349432])
```

Cross Validation of Neural Network

In [101…
```
from sklearn.model_selection import KFold
# define 5-fold cross validation test harness
kf = KFold(n_splits=5, random_state=None)
cvscores_nn = []
for train_index , test_index in kf.split(feature_data):
  X_train_nn , X_test_nn = feature_data.iloc[train_index,:],feature_data.iloc[test_index,:]
  y_train_nn , y_test_nn = target_data[train_index] , target_data[test_index]
        # create model
  model = Sequential()
  model.add(layers.Dense(512, input_shape=(feature_data.shape[1],), activation='relu'))
  model.add(Dropout(0.2))
  model.add(layers.Dense(512, activation='relu'))
  model.add(Dropout(0.2))
  model.add(layers.Dense(1, activation='sigmoid'))
        # Compile model
  model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
        # Fit the model
  model.fit(X_train_nn.astype(np.float32), y_train_nn.astype(np.float32), epochs=80, batch_size=30, verbose=0)
        # evaluate the model
  scores = model.evaluate(X_test_nn.astype(np.float32), y_test_nn.astype(np.float32), verbose=0)
  print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
  cvscores_nn.append(scores[1] * 100)

print("%.2f%% (+/- %.2f%%)" % (np.mean(cvscores_nn), np.std(cvscores_nn)))
```

```
accuracy: 75.98%
accuracy: 75.70%
accuracy: 70.94%
accuracy: 69.47%
accuracy: 58.00%
70.02% (+/- 6.53%)
```

Statistical Significance Test (Paired T test)

In [102…
```
from mlxtend.evaluate import paired_ttest_5x2cv
t, p = paired_ttest_5x2cv(estimator1=model_rf,
                          estimator2=nn_model,
                          X=feature_data.astype(int), y=target_data.astype(int),
                          scoring= 'neg_mean_squared_error',
                          random_seed=1)

print('t statistic: %.3f' % t)
print('p value: %5f' % p)

if p<=0.05:
    print('Null Hypothesis is rejected and we can conclude that both models do not perform equally well')
else:
    print('We cannot reject the null hypothesis since the p-value (p<0.001) is greater than 0.05.')
```

```
64/64 [==============================] - 1s 8ms/step - loss: 0.5462 - accuracy: 0.7344
64/64 [==============================] - 0s 8ms/step - loss: 0.5562 - accuracy: 0.7183
64/64 [==============================] - 1s 8ms/step - loss: 0.5424 - accuracy: 0.7378
64/64 [==============================] - 0s 8ms/step - loss: 0.5451 - accuracy: 0.7349
64/64 [==============================] - 0s 7ms/step - loss: 0.5393 - accuracy: 0.7324
64/64 [==============================] - 0s 8ms/step - loss: 0.5630 - accuracy: 0.7378
64/64 [==============================] - 1s 8ms/step - loss: 0.5516 - accuracy: 0.7383
64/64 [==============================] - 0s 8ms/step - loss: 0.5389 - accuracy: 0.7402
64/64 [==============================] - 1s 12ms/step - loss: 0.5541 - accuracy: 0.7188
64/64 [==============================] - 1s 11ms/step - loss: 0.5389 - accuracy: 0.7510
t statistic: 0.593
p value: 0.579081
We cannot reject the null hypothesis since the p-value (p<0.001) is greater than 0.05.
```

Box plot Comparison of Models

In [103…

```python
import scipy
scipy.stats.ttest_ind(validation_random_forest, [score / 100 for score in cvscores_nn])
```

Out[103]:

```
Ttest_indResult(statistic=1.9899899529218463, pvalue=0.0817742687043898)
```

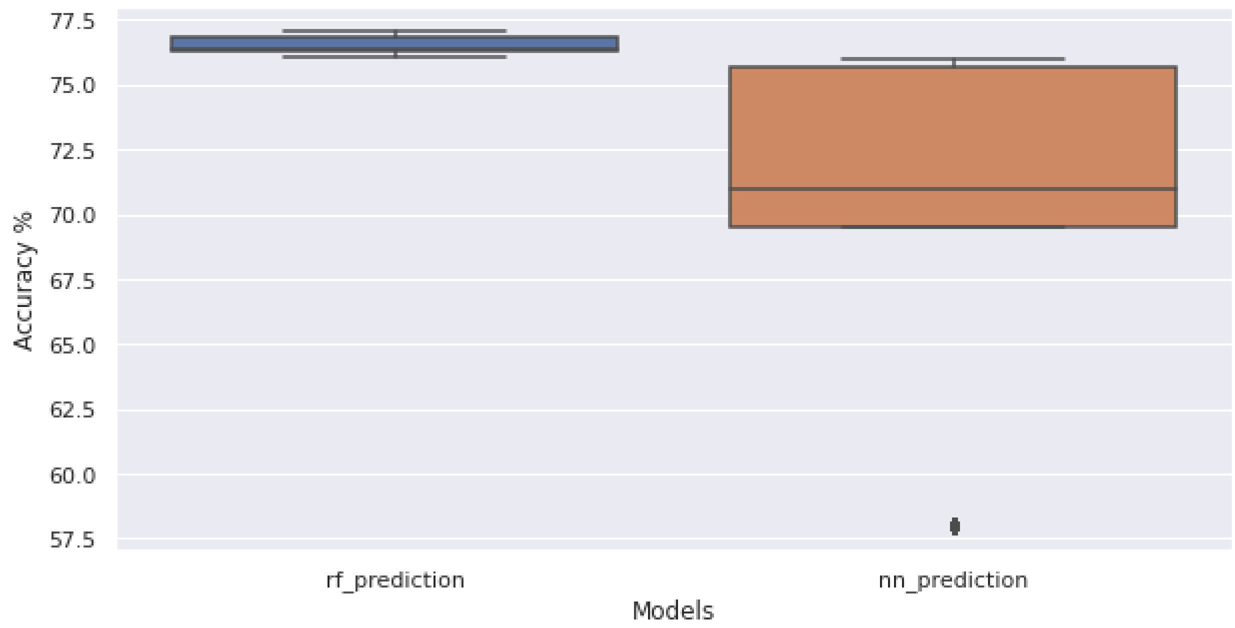
Box plot comparison of the cross validation done for both the models.

In [104…

```python
all_arr = [(validation_random_forest)*100, (cvscores_nn)*100]
fig = plt.figure(figsize =(10, 5))
ax=sns.boxplot(data=all_arr)
# ax.set_title('Box Plot Comparison of two models')
plt.xticks([0, 1], ['rf_prediction','nn_prediction'])
ax.set_xlabel('Models')
ax.set_ylabel('Accuracy %')
```

Out[104]:

```
Text(0, 0.5, 'Accuracy %')
```



4. Concept drift detection

We are checking concept drift for all the continous features. We have also checked for the target variable 'Churn' which is in the integer format (1/0). So the features we have checked the drift are:

1. Churn

2. Monthly Charges
3. Total Charges

We have not considered Tenure for checking the drift as it is a calculated feature and it is dependent on the target variable, hence checking drift for that feature would give us biased results.

Installing the required package for checking the concept drift

In [105…

```
!pip install scikit-multiflow
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: scikit-multiflow in /usr/local/lib/python3.7/dist-packages (0.5.3)
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.7/dist-packages (from scikit-multiflow) (1.5.4)
Requirement already satisfied: scikit-learn>=0.20 in /usr/local/lib/python3.7/dist-packages (from scikit-multiflow) (1.0.2)
Requirement already satisfied: matplotlib>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from scikit-multiflow) (3.4.0)
Requirement already satisfied: pandas>=0.25.3 in /usr/local/lib/python3.7/dist-packages (from scikit-multiflow) (1.3.5)
Requirement already satisfied: sortedcontainers>=1.5.7 in /usr/local/lib/python3.7/dist-packages (from scikit-multiflow) (2.4.0)
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.7/dist-packages (from scikit-multiflow) (1.21.6)
Requirement already satisfied: pyparsing>=2.2.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=2.0.0->scikit-multiflow) (3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=2.0.0->scikit-multiflow) (2.8.2)
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: pillow>=6.2.0 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=2.0.0->scikit-multiflow) (7.1.2)
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>=2.7->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)
```

Checking concept drift for the "Churn" variable

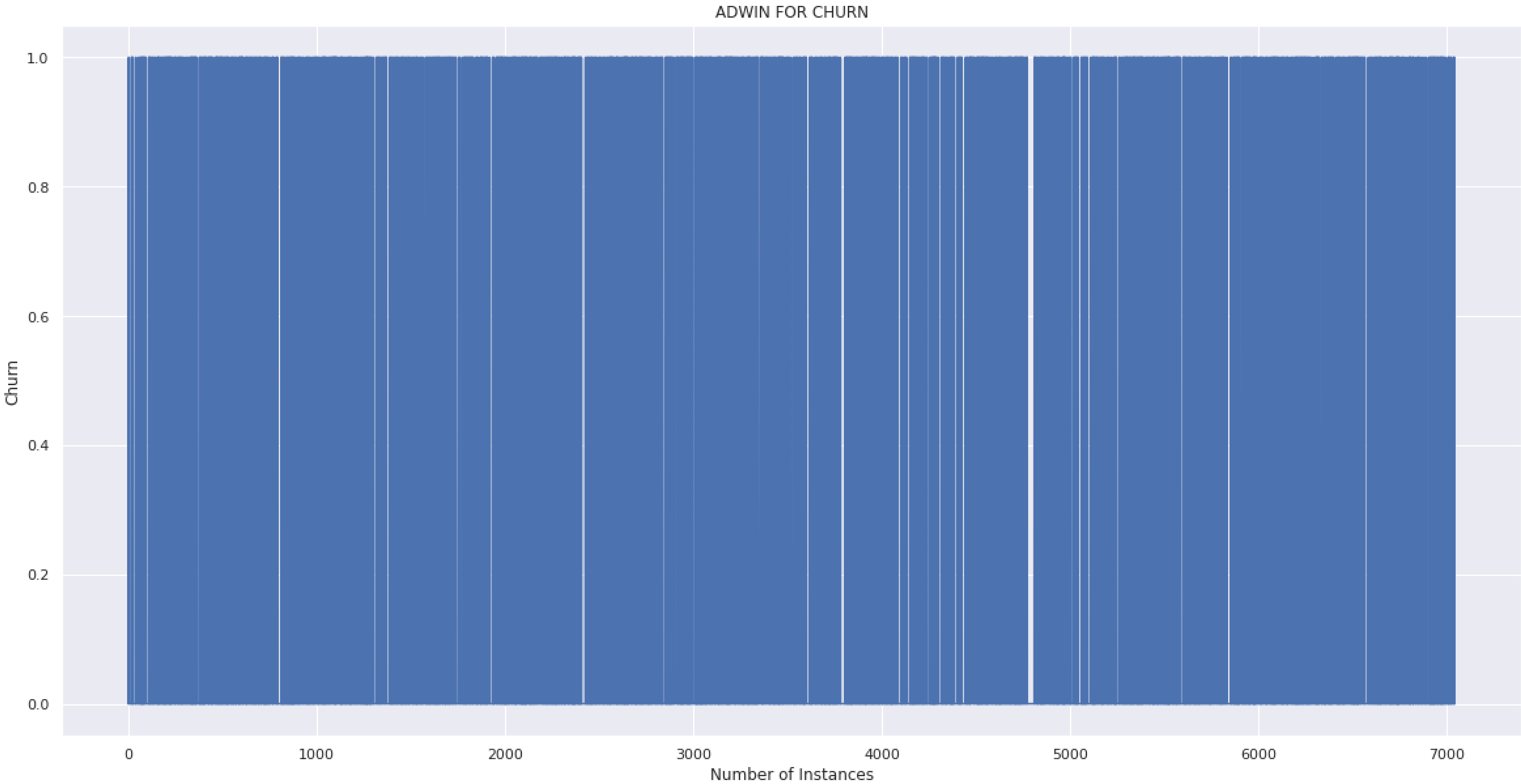
- We created a line chart of churn to check the variation over time
- Measured the change through ADWIN(Adaptive Windowing) an adaptive sliding window algorithm for detecting change, and keeping updated statistics about a data stream

There was no drift detected for the target variable 'Churn'

In [106…

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

# Import ADWIN
from skmultiflow.drift_detection import ADWIN

# Churn Variable
churn =np.array(y)


plt.figure(figsize=(20, 10))
plt.plot(churn)
plt.title('ADWIN FOR CHURN')
plt.ylabel('Churn')
plt.xlabel('Number of Instances')
# instantiate ADWIN object
adwin = ADWIN()

# for each data point in stream
for i in range(churn.size):
    # add a new point to adwin object
    adwin.add_element(churn[i])

    # if adwin detects change, print at what point in the stream
```

```
    # the change was detected
    if adwin.detected_change():
        print('Change detected at index {}'.format(i))
```



Checking concept drift for the "Total Charges" feature

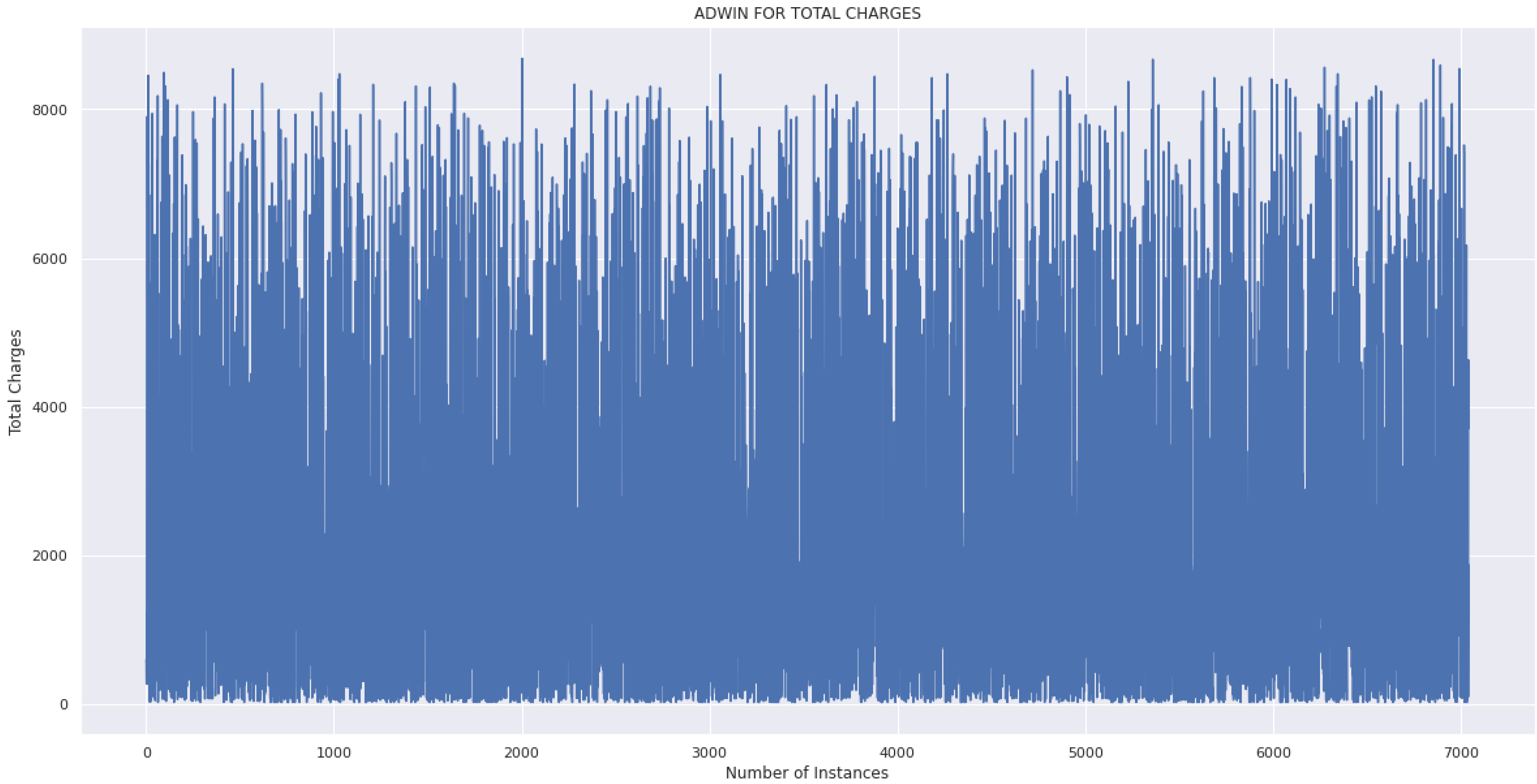
- We created a line chart of Total Charges to check the variation over time
- Measured the change through ADWIN(Adaptive Windowing) an adaptive sliding window algorithm for detecting change, and keeping updated statistics about a data stream

There was no drift detected for the feature 'Total Charges'

In [107…

```
#Total Charges
TotalCharges =telecom_df['TotalCharges']
TotalCharges=np.array(TotalCharges)

plt.figure(figsize=(20, 10))
plt.plot(TotalCharges)
plt.title('ADWIN FOR TOTAL CHARGES')
plt.ylabel('Total Charges')
plt.xlabel('Number of Instances')

# instantiate ADWIN object
adwin = ADWIN()
```

```
# for each data point in stream
for i in range(TotalCharges.size):
    # add a new point to adwin object
    adwin.add_element(TotalCharges[i])

    # if adwin detects change, print at what point in the stream
    # the change was detected
    if adwin.detected_change():
        print('Change detected at index {}'.format(i))
```



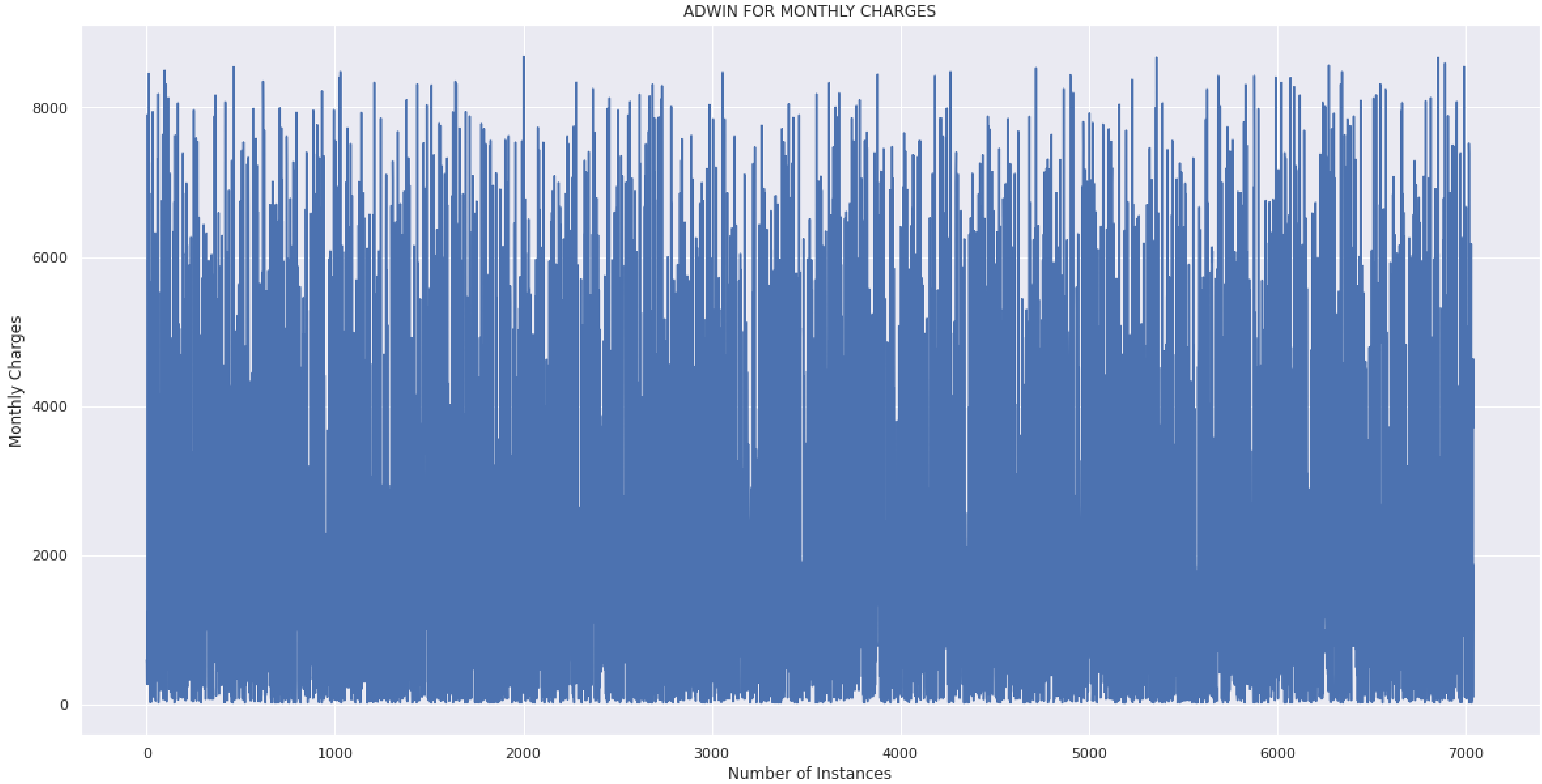
Checking concept drift for the "Monthly Charges" feature

- We created a line chart of Monthly Charges to check the variation over time
- Measured the change through ADWIN(Adaptive Windowing) an adaptive sliding window algorithm for detecting change, and keeping updated statistics about a data stream

There was no drift detected for the feature 'Monthly Charges'

In [108...
```
#Monthly Charges
MonthlyCharges =telecom_df['MonthlyCharges']
MonthlyCharges=np.array(MonthlyCharges)

plt.figure(figsize=(20, 10))
plt.plot(TotalCharges)
```

```
plt.title('ADWIN FOR MONTHLY CHARGES')
plt.ylabel('Monthly Charges')
plt.xlabel('Number of Instances')

# instantiate ADWIN object
adwin = ADWIN()

# for each data point in stream
for i in range(MonthlyCharges.size):
    # add a new point to adwin object
    adwin.add_element(MonthlyCharges[i])

    # if adwin detects change, print at what point in the stream
    # the change was detected
    if adwin.detected_change():
        print('Change detected at index {}'.format(i))
```



We did not find any type of Concept drift in the dataset by analyzing the above features!

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