DEVELOPMENT PHASE PART 2

Customer Churn Prediction Project

Date	**27-10-2023**
Team ID	**1288**
Project Name	**Customer Churn Prediction**

In this phase the various analysis, a predictive model and the interactive dashboards were developed with the help of jupyter and IBM Cognos platform.

A logistic regression predictive model is performed to the dataset. Logistic Regression has the more accuracy value compared to the Support Vector Machine, Random Forest Classifier, K-Nearest Neighbour and Decision Tree model.

In visualization part we did the churn rate, churn percentage, phone services, internet services and the payment methods from the dataset.

DATA PRE-PROCESSING

Jupyter platform is used for the data pre-processing phase. In that we initially imported the necessary python library files. The library files were

Pandas - used for working with data sets

Numpy - used for working with arrays

Sklearn - Used machine learning models and
statistical modelling

and some other important and necessary library for the visualization and the analysis were imported.

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Code JupyterLab Python 3 (ipykernel)

[126]:
```python
# 1.Data Information
# Loading libraries

import pandas as pd
import numpy as np
import missingno as msno
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import warnings
warnings.filterwarnings('ignore')
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn import svm
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from xgboost import XGBClassifier
from sklearn import metrics
from sklearn.metrics import roc_curve
from sklearn.metrics import recall_score, confusion_matrix, precision_score, f1_score, accuracy_score, classification_report
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

Then we imported the given data set “WA_Fn-UseC_-Telco-Customer-Churn.csv” and viewed the first 5 rows of the dataset.

[94]:
```python
# Load data

df = pd.read_csv('WA_Fn-UseC_-Telco-Customer-Churn (1).csv')
df
```

[94]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	DeviceProtection	TechSupport
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	...	No	No
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	...	Yes	No
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	...	No	No
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	...	Yes	Yes
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	...	No	No
...	...	...	...	...	...	...	...	...	...	...	...	...	...
7038	6840-RESVB	Male	0	Yes	Yes	24	Yes	Yes	DSL	Yes	...	Yes	Yes
7039	2234-XADUH	Female	0	Yes	Yes	72	Yes	Yes	Fiber optic	No	...	Yes	No
7040	4801-JZAZL	Female	0	Yes	Yes	11	No	No phone service	DSL	Yes	...	No	No
7041	8361-LTMKD	Male	1	Yes	No	4	Yes	Yes	Fiber optic	No	...	No	No
7042	3186-AJIEK	Male	0	No	No	66	Yes	No	Fiber optic	Yes	...	Yes	Yes

7043 rows × 21 columns

Some basic elementals were viewed such as shape of the dataset, columns of the dataset, values of the dataset and the information of the dataset.

```
[95]: df.shape

[95]: (7043, 21)

[96]: df.columns.values

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

[97]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   gender            7043 non-null   object
 2   SeniorCitizen     7043 non-null   int64
 3   Partner           7043 non-null   object
 4   Dependents        7043 non-null   object
 5   tenure            7043 non-null   int64
 6   PhoneService      7043 non-null   object
 7   MultipleLines     7043 non-null   object
 8   InternetService   7043 non-null   object
 9   OnlineSecurity    7043 non-null   object
 10  OnlineBackup      7043 non-null   object
 11  DeviceProtection  7043 non-null   object
 12  TechSupport       7043 non-null   object
 13  StreamingTV       7043 non-null   object
 14  StreamingMovies   7043 non-null   object
 15  Contract          7043 non-null   object
 16  PaperlessBilling  7043 non-null   object
 17  PaymentMethod     7043 non-null   object
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object
 20  Churn             7043 non-null   object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

From here the data pre-processing is initiated and the Customer ID is removed from the dataset.

```
•[98]: # 2.Data Preparation
       # Data manipulation

       df = df.drop(['customerID'], axis = 1)
       df.head()
```

[98]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	Stre
0	Female	0	Yes	No	1	No	No phone service	DSL	No	Yes	No	No	
1	Male	0	No	No	34	Yes	No	DSL	Yes	No	Yes	No	
2	Male	0	No	No	2	Yes	No	DSL	Yes	Yes	No	No	
3	Male	0	No	No	45	No	No phone service	DSL	Yes	No	Yes	Yes	
4	Female	0	No	No	2	Yes	No	Fiber optic	No	No	No	No	

In this step the Total Charges from the dataset is converted to numerical values and the missing value is checked if it is there.

```
[99]: # Convert 'Total Charges' into numerical values

df['TotalCharges'] = pd.to_numeric(df.TotalCharges, errors = 'coerce') # erros = 'coerce' is used if there are any non-numeric values in the 'TotalCharge

# Check for missing values

df.isnull().sum()
```

```
[99]: gender               0
SeniorCitizen        0
Partner              0
Dependents           0
tenure               0
PhoneService         0
MultipleLines        0
InternetService      0
OnlineSecurity       0
OnlineBackup         0
DeviceProtection     0
TechSupport          0
StreamingTV          0
StreamingMovies      0
Contract             0
PaperlessBilling     0
PaymentMethod        0
MonthlyCharges       0
TotalCharges        11
Churn                0
dtype: int64
```

Here, the missing values are calculated from the dataset.

```
[100]: # Calculate the missing values
def missing_values(n):
    df_m=pd.DataFrame()
    df_m["missing_values, %"]=df.isnull().sum()*100/len(df.isnull())
    df_m["missing_values, sum"]=df.isnull().sum()
    return df_m.sort_values(by="missing_values, %", ascending=False)
missing_values(df)
```

[100]:

	missing_values, %	missing_values, sum
TotalCharges	0.156183	11
gender	0.000000	0
SeniorCitizen	0.000000	0
MonthlyCharges	0.000000	0
PaymentMethod	0.000000	0
PaperlessBilling	0.000000	0
Contract	0.000000	0
StreamingMovies	0.000000	0
StreamingTV	0.000000	0
TechSupport	0.000000	0
DeviceProtection	0.000000	0
OnlineBackup	0.000000	0
OnlineSecurity	0.000000	0
InternetService	0.000000	0
MultipleLines	0.000000	0
PhoneService	0.000000	0
tenure	0.000000	0
Dependents	0.000000	0
Partner	0.000000	0
Churn	0.000000	0

The dataset is filtered to find the missing values in the rows of Total Charges.

[101]:
```python
# Filter df to find rows that have missing values in 'Total Charges'

df[np.isnan(df['TotalCharges'])]
```

[101]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport
488	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	No	Yes	Yes
753	Male	0	No	Yes	0	Yes	No	No	No internet service	No internet service	No internet service	No internet service
936	Female	0	Yes	Yes	0	Yes	No	DSL	Yes	Yes	Yes	No
1082	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	No internet service	No internet service	No internet service
1340	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	Yes	Yes	Yes
3331	Male	0	Yes	Yes	0	Yes	No	No	No internet service	No internet service	No internet service	No internet service
3826	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	No internet service	No internet service	No internet service
4380	Female	0	Yes	Yes	0	Yes	No	No	No internet service	No internet service	No internet service	No internet service
5218	Male	0	Yes	Yes	0	Yes	No	No	No internet service	No internet service	No internet service	No internet service
6670	Female	0	Yes	Yes	0	Yes	Yes	DSL	No	Yes	Yes	Yes
6754	Male	0	No	Yes	0	Yes	Yes	DSL	Yes	Yes	No	Yes

[102]:
```python
# Filter df to find the index positions of rows where the 'tenure' column has a value of 0

df[df['tenure'] == 0].index
```

[102]:
```
Index([488, 753, 936, 1082, 1340, 3331, 3826, 4380, 5218, 6670, 6754], dtype='int64')
```

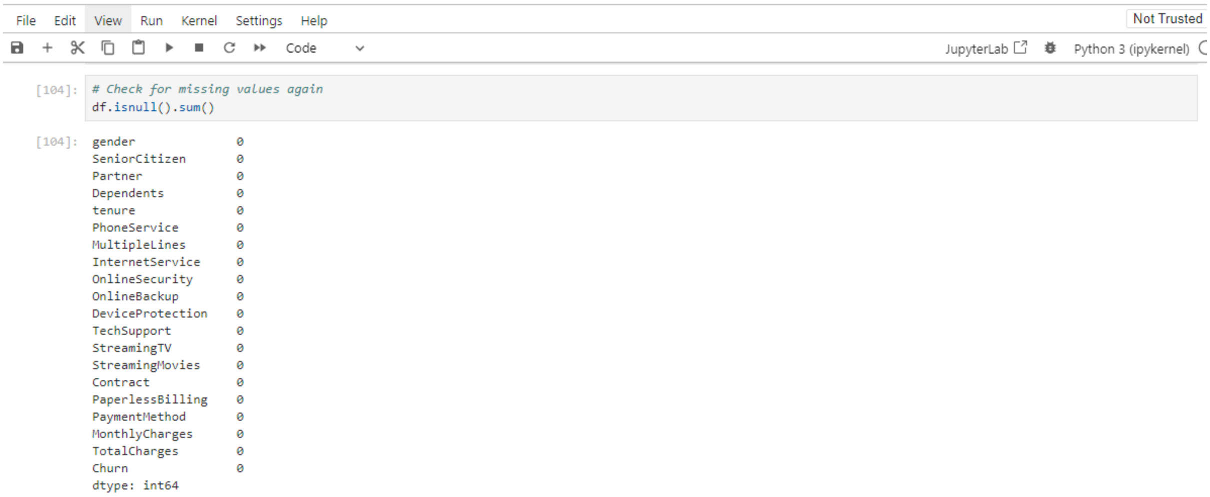
In this step the missing values are represented as the corresponding monthly charges.

[103]:
```python
# Impute missing values with corresponding monthly charges
df['TotalCharges'].fillna(df['TotalCharges'].mean(), inplace=True)
df[df['tenure'] == 0]
```

[103]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport
488	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	No	Yes	Yes
753	Male	0	No	Yes	0	Yes	No	No	No internet service	No internet service	No internet service	No internet service
936	Female	0	Yes	Yes	0	Yes	No	DSL	Yes	Yes	Yes	No
1082	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	No internet service	No internet service	No internet service
1340	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	Yes	Yes	Yes
3331	Male	0	Yes	Yes	0	Yes	No	No	No internet service	No internet service	No internet service	No internet service
3826	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	No internet service	No internet service	No internet service
4380	Female	0	Yes	Yes	0	Yes	No	No	No internet service	No internet service	No internet service	No internet service
5218	Male	0	Yes	Yes	0	Yes	No	No	No internet service	No internet service	No internet service	No internet service
6670	Female	0	Yes	Yes	0	Yes	Yes	DSL	No	Yes	Yes	Yes
6754	Male	0	No	Yes	0	Yes	Yes	DSL	Yes	Yes	No	Yes

The missing values were again checked in the customer dataset.




```
[104]: # Check for missing values again
       df.isnull().sum()

[104]: gender              0
       SeniorCitizen       0
       Partner             0
       Dependents          0
       tenure              0
       PhoneService        0
       MultipleLines       0
       InternetService     0
       OnlineSecurity      0
       OnlineBackup        0
       DeviceProtection    0
       TechSupport         0
       StreamingTV         0
       StreamingMovies     0
       Contract            0
       PaperlessBilling    0
       PaymentMethod       0
       MonthlyCharges      0
       TotalCharges        0
       Churn               0
       dtype: int64
```

There is no missing values in the dataset that means it is cleansed and the data preprocessing steps were completed.

Now, from this we can make analysis and create various visualization for the customer churn prediction.

ANALYSIS

It is the process of inspecting, cleansing, transforming, and modelling data with the goal of discovering useful information by informing conclusions and supporting decision making.

In the process of analysis the churn patterns, retention rates, and key factors influencing churn were discussed.

The analysis part makes us to easily understand the given dataset and makes us to provide a various solutions.

Initially the mean, standard deviation, count, minimum and maximum value for Tenure, Monthly Charges and Total Charges were found from the dataset.

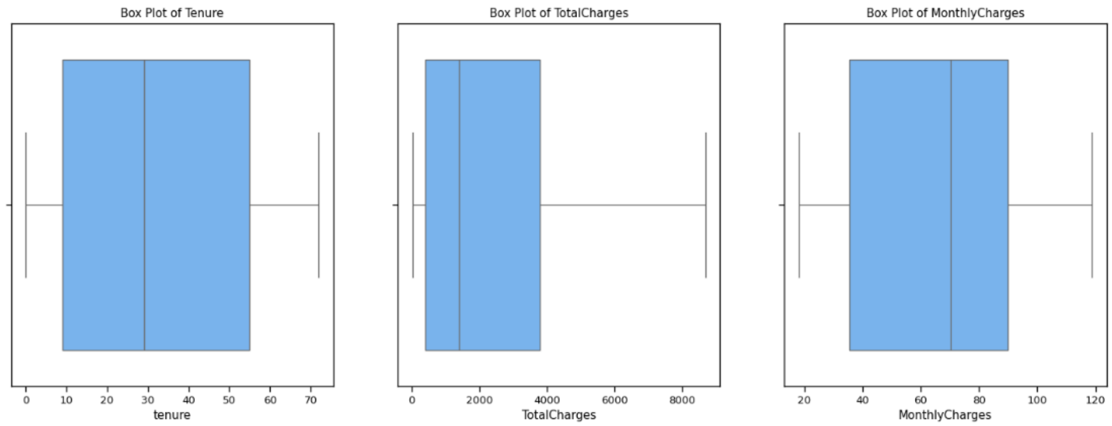
[105]:
```python
# Define numerical columns
numerical_cols = ['tenure', 'MonthlyCharges', 'TotalCharges']
df[numerical_cols].describe().T # Describing descriptive stats of the data
```

[105]:

	count	mean	std	min	25%	50%	75%	max
tenure	7043.0	32.371149	24.559481	0.00	9.000	29.00	55.00	72.00
MonthlyCharges	7043.0	64.761692	30.090047	18.25	35.500	70.35	89.85	118.75
TotalCharges	7043.0	2283.300441	2265.000258	18.80	402.225	1400.55	3786.60	8684.80

Then the visualization of box plot for the Tenure, Monthly Charges and Total Charges were implemented.

[106]:
```python
# Create separate box plots for 'tenure', 'TotalCharges', and 'MonthlyCharges'
plt.figure(figsize=(18, 6))

# Box Plot of 'tenure'
plt.subplot(131)  # 1 row, 3 columns, plot 1
sns.boxplot(x=df['tenure'], color='#66b3ff')
plt.title("Box Plot of Tenure")

# Box Plot of 'TotalCharges'
plt.subplot(132)  # 1 row, 3 columns, plot 2
sns.boxplot(x=df['TotalCharges'], color='#66b3ff')
plt.title("Box Plot of TotalCharges")

# Box Plot of 'MonthlyCharges'
plt.subplot(133)  # 1 row, 3 columns, plot 3
sns.boxplot(x=df['MonthlyCharges'], color='#66b3ff')
plt.title("Box Plot of MonthlyCharges")

plt.show()
```



For the informed encoding decision the unique values have to be found from the dataset.

```
[107]: # Check for unique values to be make informed encoding decision
unique_counts = df.nunique()
print("Unique Value Counts:")
print(unique_counts)
```

```
Unique Value Counts:
gender                 2
SeniorCitizen          2
Partner                2
Dependents             2
tenure                73
PhoneService           2
MultipleLines          3
InternetService        3
OnlineSecurity         3
OnlineBackup           3
DeviceProtection       3
TechSupport            3
StreamingTV            3
StreamingMovies        3
Contract               3
PaperlessBilling       2
PaymentMethod          4
MonthlyCharges      1585
TotalCharges        6531
Churn                  2
dtype: int64
```

In this step the data types of the dataset column values were displayed.

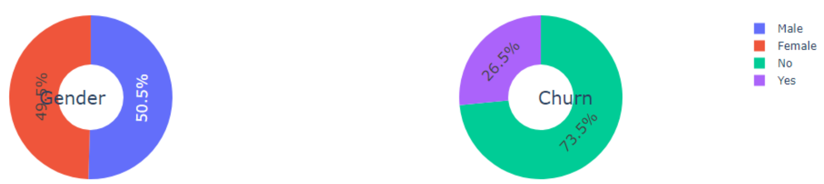
```
[108]: # Label-Encoding for Categorical Data
# Change data type for categorical data variables
cols = ['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'PhoneService', 'PaperlessBilling', 'Churn']

df[cols] = df[cols].astype('category')

# Label encoding for categorical data variables
for column in cols:
    df[column] = df[column].cat.codes

# Check data types of all columns
print(df.dtypes)
```

```
gender                 int8
SeniorCitizen          int8
Partner                int8
Dependents             int8
tenure                int64
PhoneService           int8
MultipleLines        object
InternetService      object
OnlineSecurity       object
OnlineBackup         object
DeviceProtection     object
TechSupport          object
StreamingTV          object
StreamingMovies      object
Contract             object
PaperlessBilling       int8
PaymentMethod        object
MonthlyCharges      float64
TotalCharges        float64
Churn                  int8
dtype: object
```

Here is the analysis from the dataset between the columns of churn and gender.

```
[109]:
# Data Analysis
g_labels = ['Male', 'Female']
c_labels = ['No', 'Yes']

# Create subplots: use 'domain' type for Pie subplot
fig = make_subplots(rows=1, cols=2, specs=[[{'type':'domain'}, {'type':'domain'}]])
fig.add_trace(go.Pie(labels=g_labels, values=df['gender'].value_counts(), name="Gender"),
              1, 1)
fig.add_trace(go.Pie(labels=c_labels, values=df['Churn'].value_counts(), name="Churn"),
              1, 2)

# Use `hole` to create a donut-like pie chart
fig.update_traces(hole=.4, hoverinfo="label+percent+name", textfont_size=16)

fig.update_layout(
    title_text="Gender and Churn Distributions",
    # Add annotations in the center of the donut pies.
    annotations=[dict(text='Gender', x=0.16, y=0.5, font_size=20, showarrow=False),
                 dict(text='Churn', x=0.84, y=0.5, font_size=20, showarrow=False)])
fig.show()
```

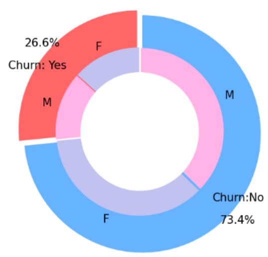
Gender and Churn Distributions



The analysis of churn distribution by gender.

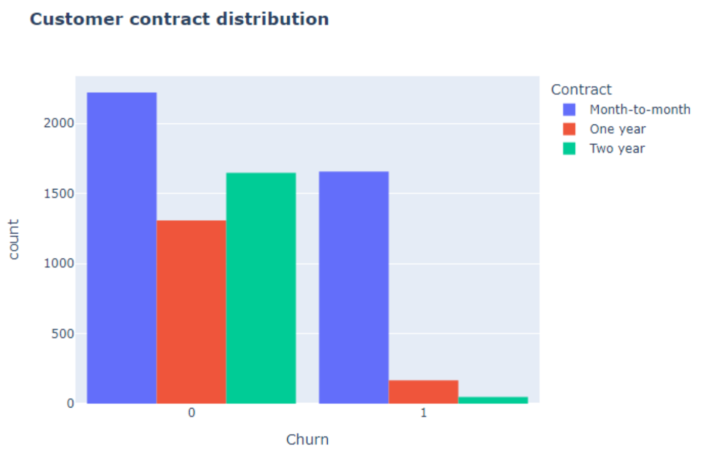
```
[34]:
plt.figure(figsize=(6, 6))
labels =["Churn: Yes","Churn:No"]
values = [1869,5163]
labels_gender = ["F","M","F","M"]
sizes_gender = [939,930 , 2544,2619]
colors = ['#ff6666', '#66b3ff']
colors_gender = ['#c2c2f0','#ffb3e6', '#c2c2f0','#ffb3e6']
explode = (0.3,0.3)
explode_gender = (0.1,0.1,0.1,0.1)
textprops = {"fontsize":15}
#Plot
plt.pie(values, labels=labels,autopct='%1.1f%%',pctdistance=1.08, labeldistance=0.8,colors=colors, startangle=90,frame=True, explode=explode,radius=10,
plt.pie(sizes_gender,labels=labels_gender,colors=colors_gender,startangle=90, explode=explode_gender,radius=7, textprops =textprops, counterclock = True
#Draw circle
centre_circle = plt.Circle((0,0),5,color='black', fc='white',linewidth=0)
fig = plt.gcf()
fig.gca().add_artist(centre_circle)

plt.title('Churn Distribution w.r.t Gender: Male(M), Female(F)', fontsize=15, y=1.1)

# show plot

plt.axis('equal')
plt.tight_layout()
plt.show()
```

Churn Distribution w.r.t Gender: Male(M), Female(F)



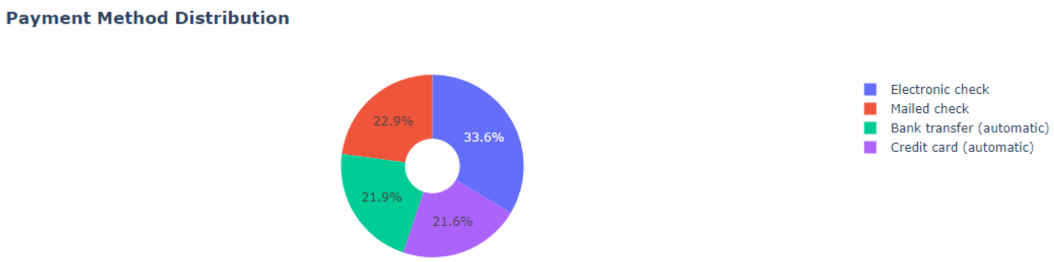
The analysis of customer contract distribution which is classified as Month to Month, One year and two year.

```
[83]: fig = px.histogram(df, x="Churn", color="Contract", barmode="group", title="<b>Customer contract distribution<b>")
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



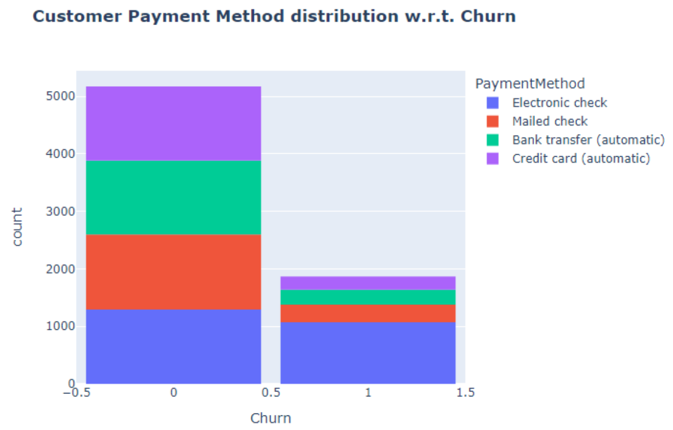
The analysis of payment method distribution which is classified as Electronic Check, Mailed Check, Bank Transfer [Automatic], Credit Card [Automatic].

```
[38]: labels = df['PaymentMethod'].unique()
values = df['PaymentMethod'].value_counts()

fig = go.Figure(data=[go.Pie(labels=labels, values=values, hole=.3)])
fig.update_layout(title_text="<b>Payment Method Distribution</b>")
fig.show()
```



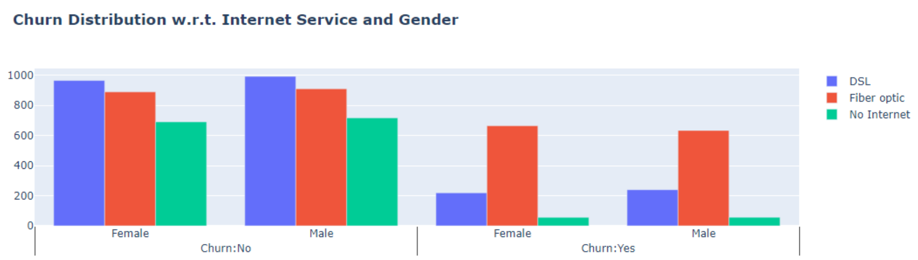
The analysis of customer payment method distribution with respect to churn.

[39]:
```
fig = px.histogram(df, x="Churn", color="PaymentMethod", title="<b>Customer Payment Method distribution w.r.t. Churn</b>")
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



The analysis of churn distribution with respect to internet service and gender.

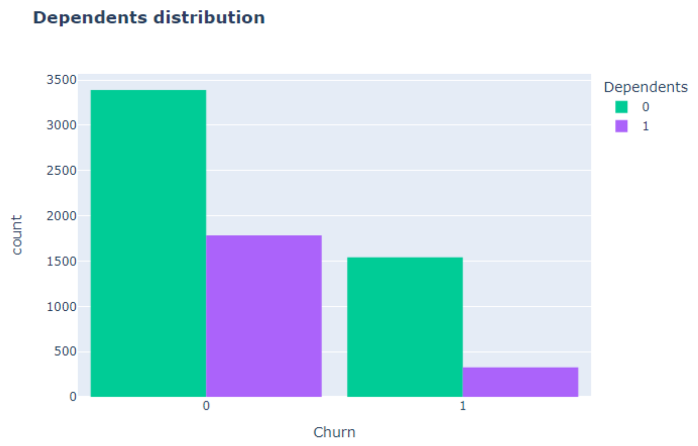
[40]:
```
fig = go.Figure()

fig.add_trace(go.Bar(
  x = [['Churn:No', 'Churn:No', 'Churn:Yes', 'Churn:Yes'],
       ["Female", "Male", "Female", "Male"]],
  y = [965, 992, 219, 240],
  name = 'DSL',
))

fig.add_trace(go.Bar(
  x = [['Churn:No', 'Churn:No', 'Churn:Yes', 'Churn:Yes'],
       ["Female", "Male", "Female", "Male"]],
  y = [889, 910, 664, 633],
  name = 'Fiber optic',
))

fig.add_trace(go.Bar(
  x = [['Churn:No', 'Churn:No', 'Churn:Yes', 'Churn:Yes'],
       ["Female", "Male", "Female", "Male"]],
  y = [690, 717, 56, 57],
  name = 'No Internet',
))

fig.update_layout(title_text="<b>Churn Distribution w.r.t. Internet Service and Gender</b>")

fig.show()
```



The analysis of dependents distribution which is in numerical values of 0’s and 1’s.

[41]:

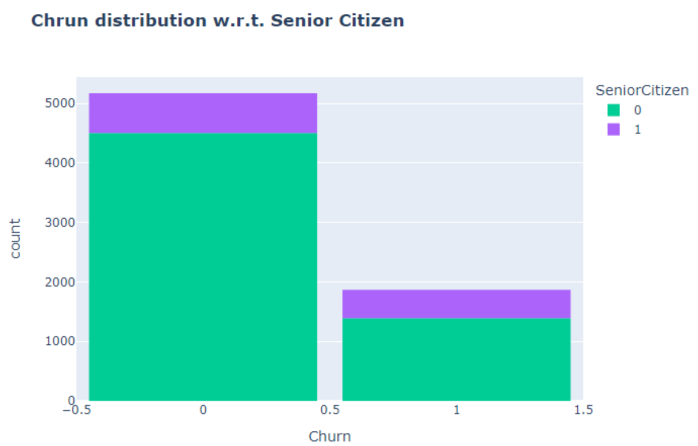
```
color_map = {"Yes": "#FF97FF", "No": "#AB63FA"}
fig = px.histogram(df, x="Churn", color="Dependents", barmode="group", title="<b>Dependents distribution</b>", color_discrete_map=color_map)
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



The analysis of churn distribution with respect to senior citizen.

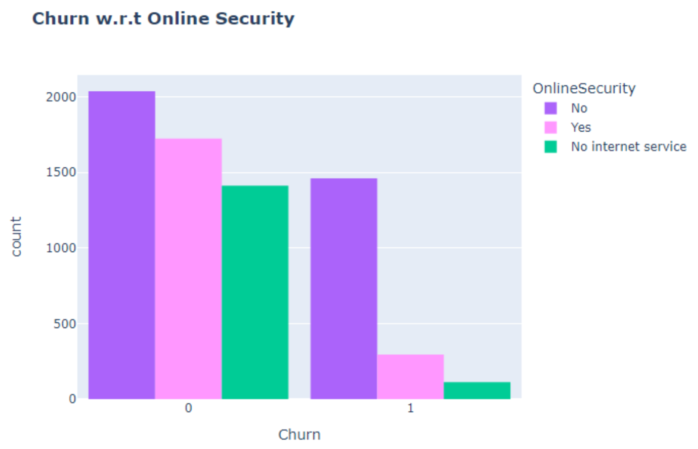
[42]:

```
color_map = {"Yes": '#00CC96', "No": '#B6E880'}
fig = px.histogram(df, x="Churn", color="SeniorCitizen", title="<b>Chrun distribution w.r.t. Senior Citizen</b>", color_discrete_map=color_map)
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



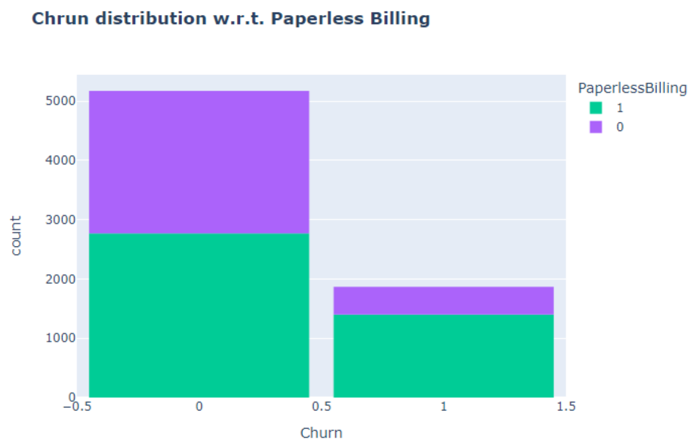
The analysis of churn rate with respect to online security.

```
[43]: color_map = {"Yes": "#FF97FF", "No": "#AB63FA"}
fig = px.histogram(df, x="Churn", color="OnlineSecurity", barmode="group", title="<b>Churn w.r.t Online Security</b>", color_discrete_map=color_map)
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



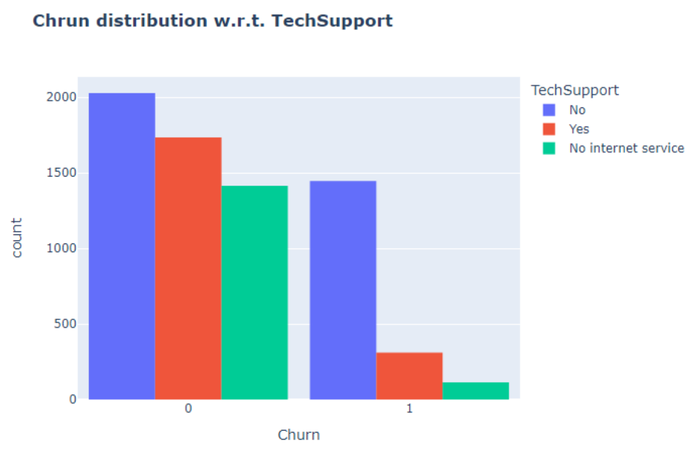
The analysis of churn distribution with respect to paperless billing.

```
[44]: color_map = {"Yes": '#FFA15A', "No": '#00CC96'}
fig = px.histogram(df, x="Churn", color="PaperlessBilling",  title="<b>Chrun distribution w.r.t. Paperless Billing</b>", color_discrete_map=color_map)
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



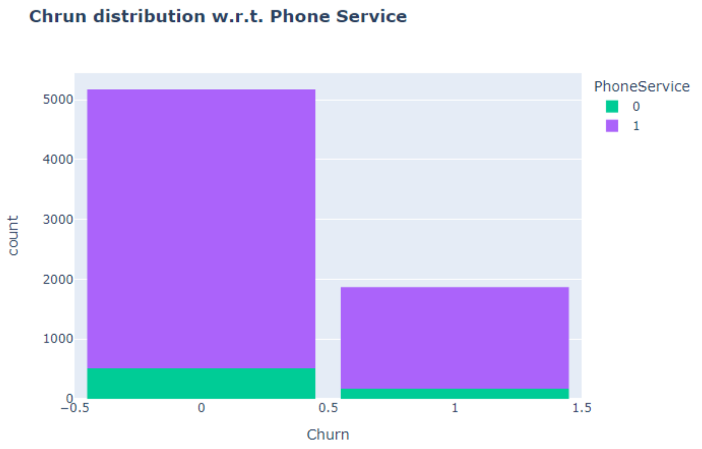
The analysis of churn distribution with respect to tech support.

```
[45]: fig = px.histogram(df, x="Churn", color="TechSupport",barmode="group",  title="<b>Chrun distribution w.r.t. TechSupport</b>")
      fig.update_layout(width=700, height=500, bargap=0.1)
      fig.show()
```



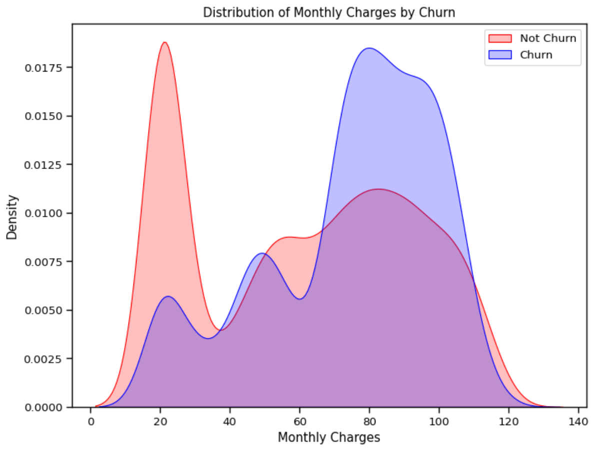
The analysis of churn distribution with respect to phone services.

```
[46]: color_map = {"Yes": '#00CC96', "No": '#B6E880'}
      fig = px.histogram(df, x="Churn", color="PhoneService", title="<b>Chrun distribution w.r.t. Phone Service</b>", color_discrete_map=color_map)
      fig.update_layout(width=700, height=500, bargap=0.1)
      fig.show()
```



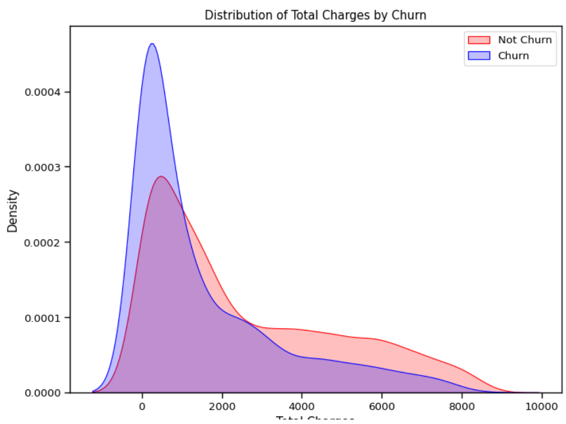
The analysis of Monthly charges distribution with respect to churn.

```
[47]:
sns.set_context("paper", font_scale=1.1)
plt.figure(figsize=(8, 6))

# Line plot for customers who do not churn (Churn = 0)
sns.kdeplot(df.MonthlyCharges[df['Churn'] == 0], color='red', label='Not Churn', shade=True)

# Line plot for customers who churn (Churn = 1)
sns.kdeplot(df.MonthlyCharges[df['Churn'] == 1], color='blue', label='Churn', shade=True)

plt.xlabel('Monthly Charges')
plt.ylabel('Density')
plt.title('Distribution of Monthly Charges by Churn')
plt.legend()

plt.show()
```



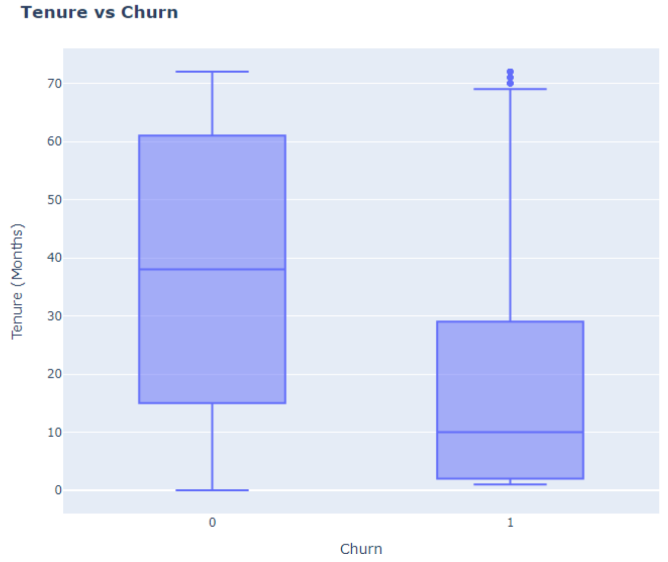
The analysis of Total charges distribution with respect to churn.

```
[48]:
sns.set_context("paper", font_scale=1.1)
plt.figure(figsize=(8, 6))

# Line plot for customers who do not churn (Churn = 0)
sns.kdeplot(df.TotalCharges[df['Churn'] == 0], color='red', label='Not Churn', shade=True)

# Line plot for customers who churn (Churn = 1)
sns.kdeplot(df.TotalCharges[df['Churn'] == 1], color='blue', label='Churn', shade=True)

plt.xlabel('Total Charges')
plt.ylabel('Density')
plt.title('Distribution of Total Charges by Churn')
plt.legend()

plt.show()
```



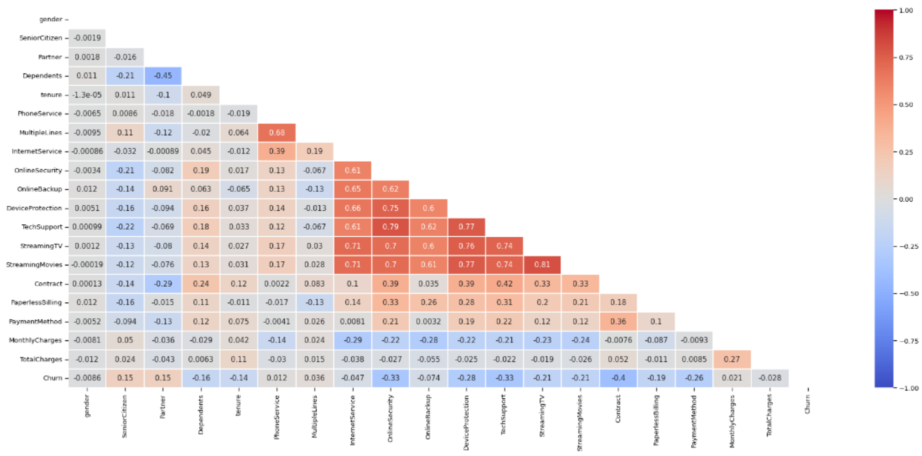
The analysis of box plot between Tenure and Churn.

```
[49]: fig = px.box(df, x='Churn', y = 'tenure')

# Update yaxis properties
fig.update_yaxes(title_text='Tenure (Months)', row=1, col=1)
# Update xaxis properties
fig.update_xaxes(title_text='Churn', row=1, col=1)

# Update size and title
fig.update_layout(autosize=True, width=750, height=600,
    title_font=dict(size=25, family='Courier'),
    title='<b>Tenure vs Churn</b>',
)

fig.show()
```



The analysis of Correlation between all variables.

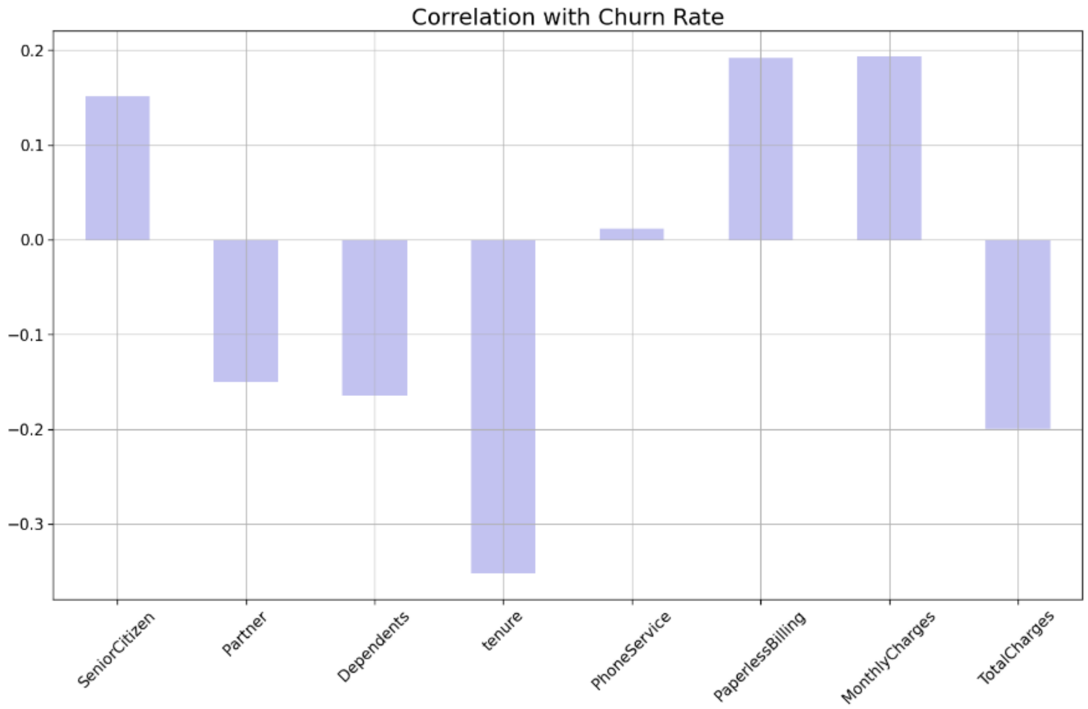
```
[50]: # Correlation between all variables

plt.figure(figsize=(25, 10))

corr = df.apply(lambda x: pd.factorize(x)[0]).corr()

mask = np.triu(np.ones_like(corr, dtype=bool))

ax = sns.heatmap(corr, mask=mask, xticklabels=corr.columns, yticklabels=corr.columns, annot=True, linewidths=.2, cmap='coolwarm', vmin=-1, vmax=1)
```



The analysis of correlation of churn with all variables.

[51]:
```
# Correlation between churn and selected boolean and numeric variables
plt.figure
ds_corr = df[['SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'PaperlessBilling',
        'MonthlyCharges', 'TotalCharges']]

correlations = ds_corr.corrwith(df.Churn)
correlations = correlations[correlations!=1]
correlations.plot.bar(
        figsize = (18, 10),
        fontsize = 15,
        color = '#c2c2f0',
        rot = 45, grid = True)

plt.title('Correlation with Churn Rate', horizontalalignment="center", fontstyle = "normal", fontsize = "22", fontfamily = "sans-serif")
```

[51]:
```
Text(0.5, 1.0, 'Correlation with Churn Rate')
```



The process of copying the dataset to maintain the original dataset in it’s actual format.

[52]:
```
# Copy data to new 'dataset' variable to conserve original values
dataset = df.copy()

# Hot-Encoding for categorical data
dataset = pd.get_dummies(dataset)
dataset.head()
```

[52]:

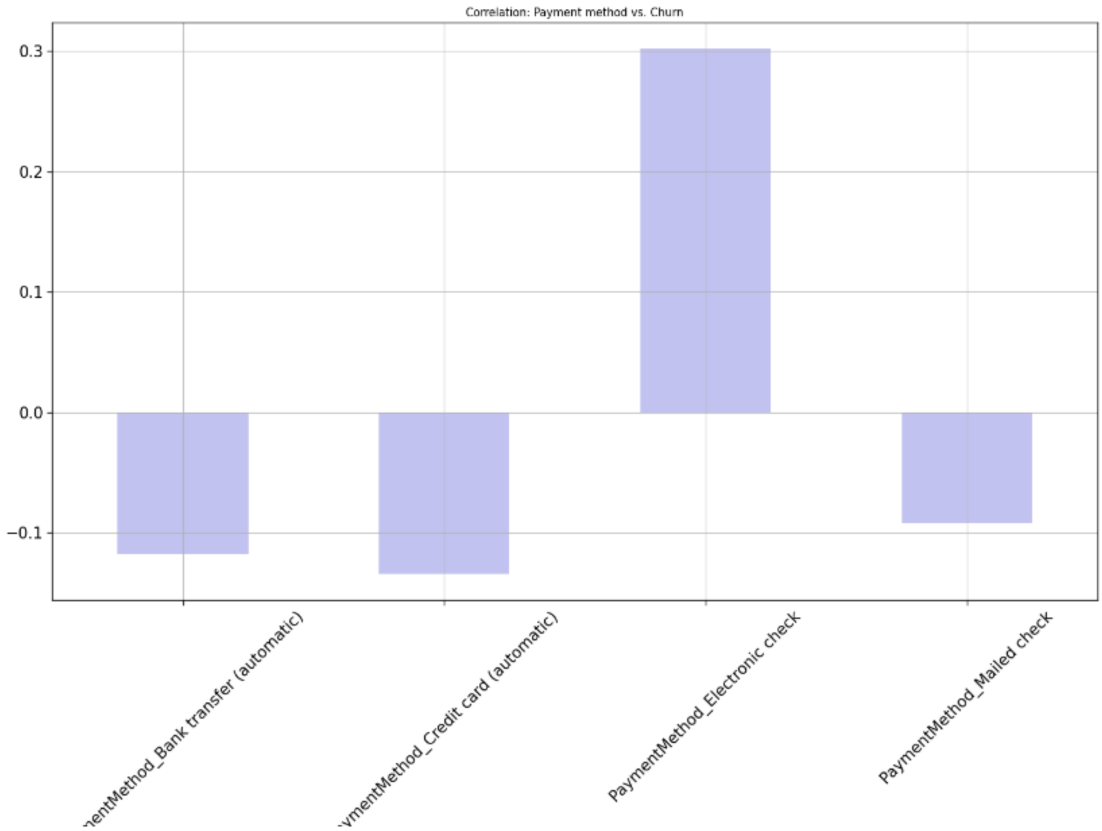
	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	PaperlessBilling	MonthlyCharges	TotalCharges	Churn	...	StreamingMovies_No	StreamingMovie internet se
0	0	0	1	0	1	0	1	29.85	29.85	0	...	True	
1	1	0	0	0	34	1	0	56.95	1889.50	0	...	True	
2	1	0	0	0	2	1	1	53.85	108.15	1	...	True	
3	1	0	0	0	45	0	0	42.30	1840.75	0	...	True	
4	0	0	0	0	2	1	1	70.70	151.65	1	...	True	

5 rows × 41 columns

The analysis of correlation between payment methods and churn rate.

```
[54]: # Correlation: PaymentMethod vs. Churn
plt.figure

ds_payment_method_corr = dataset[['PaymentMethod_Bank transfer (automatic)',
          'PaymentMethod_Credit card (automatic)',
          'PaymentMethod_Electronic check', 'PaymentMethod_Mailed check']]

correlations = ds_payment_method_corr.corrwith(dataset.Churn)
correlations = correlations[correlations!=1]

correlations.plot.bar(
        figsize = (18, 10),
        fontsize = 15,
        color = '#c2c2f0',
        rot = 45, grid = True)

plt.title('Correlation: Payment method vs. Churn')
```

```
[54]: Text(0.5, 1.0, 'Correlation: Payment method vs. Churn')
```



In this step the dataset is classified as features and target variable then it is splitted into train and test dataset.

Multicollinearity is implemented which is used to correleate several independent variables.

```
[55]: # Split the dataset into features (X) and target variable (y)
X = dataset.drop(columns=['Churn'])  # Features
y = dataset['Churn']  # Target variable

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42, stratify=y)
```

```
[111]: # Multicollinearity

from statsmodels.stats.outliers_influence import variance_inflation_factor

def calculate_vif(X):
# Calculate Variable Inflation Factors
    vif = pd.DataFrame()
    vif["variables"] = X.columns
    vif["Variable Inflation Factors"] = [variance_inflation_factor(X.values, i)
    for i in range(X.shape[1])]
    return(vif)

ds_vif = dataset[['gender', 'SeniorCitizen', 'Partner', 'Dependents',\
                  'tenure', 'PhoneService', 'PaperlessBilling', \
                  'MonthlyCharges','TotalCharges']]

vif = calculate_vif(ds_vif)
vif
```

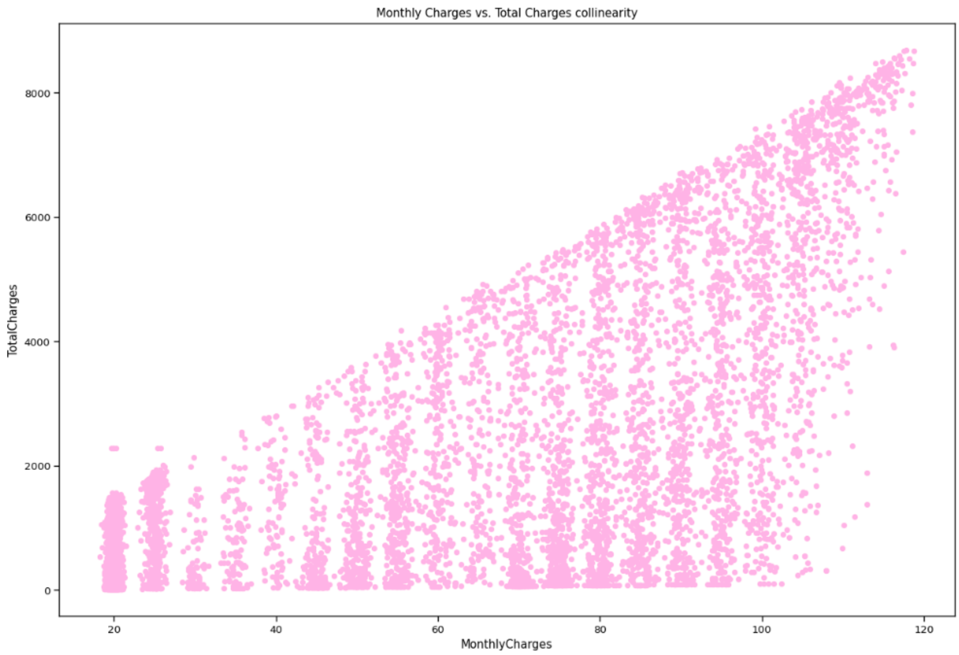
[111]:

	variables	Variable Inflation Factors
0	gender	1.921285
1	SeniorCitizen	1.327766
2	Partner	2.815272
3	Dependents	1.921208
4	tenure	10.549726
5	PhoneService	7.976437
6	PaperlessBilling	2.814154
7	MonthlyCharges	13.988695
8	TotalCharges	12.570370

The analysis of collinearity between Monthly charges and Total charges.

```
[113]:
ds_vif[['MonthlyCharges', 'TotalCharges']]\
           .plot.scatter(figsize = (15, 10),
                x ='MonthlyCharges',
                y='TotalCharges',
                color = '#ffb3e6')

plt.title('Monthly Charges vs. Total Charges collinearity')
```

```
[113]: Text(0.5, 1.0, 'Monthly Charges vs. Total Charges collinearity')
```



A PREDICTIVE MODEL

Logistic Regression

Logistic Regression is a statistical model. It is also known as logit model.

It is often used for classification and predictive analytics.

Logistic regression estimates the probability of an event occurring based on a given dataset of independent variables.

Since the outcome is a probability, the dependent variable is bounded between 0 and 1.

The model predicts dependent data variable by analyzing the relationship between one or more existing independent variables.

The dataset were re-splitted into train and test variables for the predictive model.

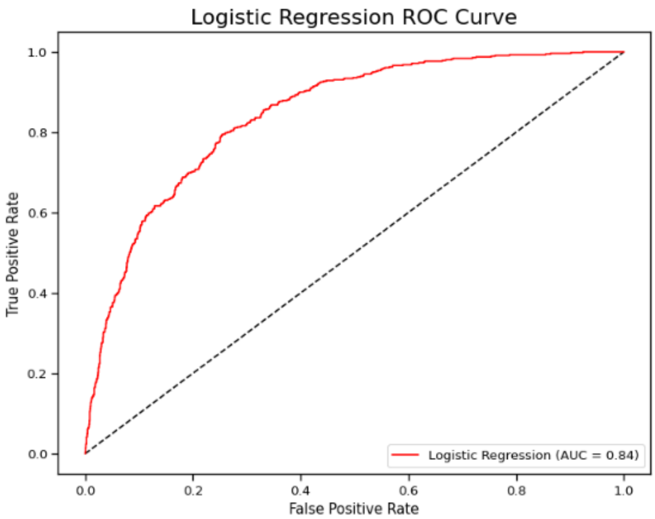
```
•[116]: # 4.Build Machine Learning Models
# Split the dataset into features (X) and target variable (y)
X = dataset.drop(columns=['Churn'])  # Features
y = dataset['Churn']  # Target variable

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42, stratify=y)
```

```
[117]: # Check for missing values in the training set
missing_train = X_train.isnull().sum()
print("Missing values in training set:")
print(missing_train[missing_train > 0])

# Check for missing values in the test set
missing_test = X_test.isnull().sum()
print("\nMissing values in test set:")
print(missing_test[missing_test > 0])
```

```
Missing values in training set:
Series([], dtype: int64)

Missing values in test set:
Series([], dtype: int64)
```

The predictive model is trained and it calculates the AUC [Area Under Curve] of the regression then it plots the ROC [Receiver Operating Characteristic]curve of the regression.

```
[64]: from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

# Train your Logistic Regression model (Logistic_regression_model) on X_train and y_train

# Assuming you've trained the model, you can proceed with calculating ROC and AUC
logistic_regression_model = LogisticRegression()
logistic_regression_model.fit(X_train, y_train)

y_pred_prob = logistic_regression_model.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)


# Calculate AUC
roc_auc_lr = auc(fpr, tpr)

# Plot the ROC curve
plt.figure(figsize=(8, 6))
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr, tpr, label=f'Logistic Regression (AUC = {roc_auc_lr:.2f})', color='r')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Logistic Regression ROC Curve', fontsize=16)
plt.legend(loc='lower right')
plt.show()
```



The accuracy of the regression is calculated.

```
[127]: from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

# Create and fit the Logistic Regression model (lr) to your data
lr = LogisticRegression(solver='liblinear')
lr.fit(X_telco, y_telco)

# Make predictions using the trained model
y_pred = lr.predict(X_telco)

# Calculate the accuracy of the model
accuracy = accuracy_score(y_telco, y_pred)

# Print or display the accuracy
print("Accuracy of Logistic Regression model: {:.2f}".format(accuracy))
```

```
Accuracy of Logistic Regression model: 0.80
```

VISUALIZATION

Data visualization is a graphical representation of data. It presents data as an image or graphic to make it easier to identify patterns and understand difficult concepts.

It allows users to interact with the data by changing the parameters to see more detail and create new insights.

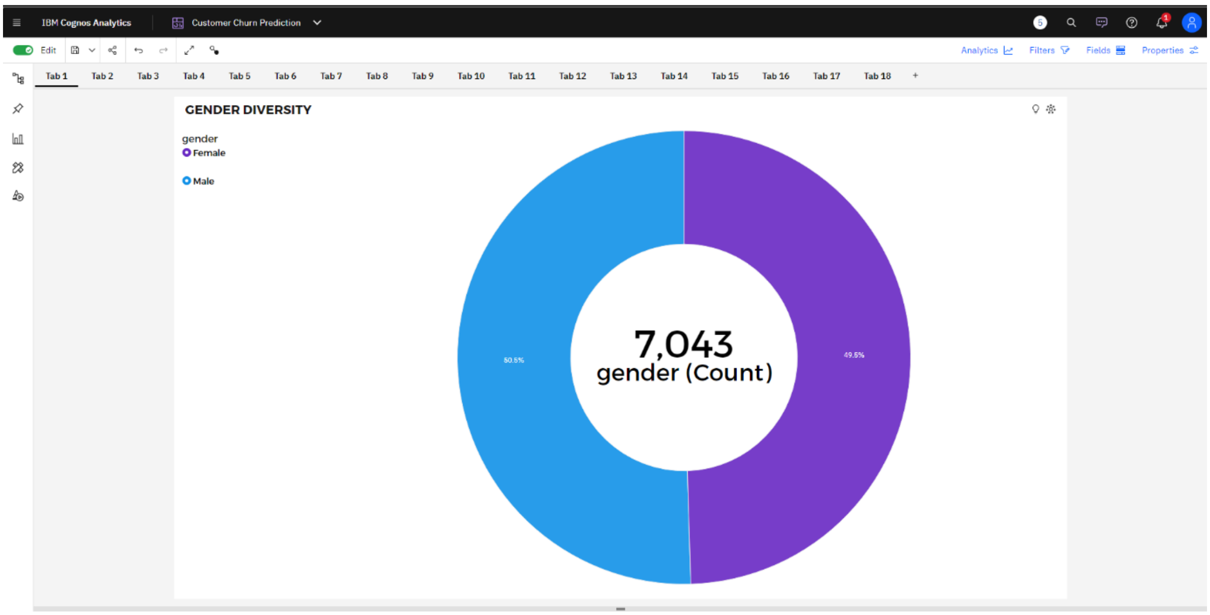
We used the IBM Cognos platform for the visualization to find more insights about the given dataset.

1.No of Customer

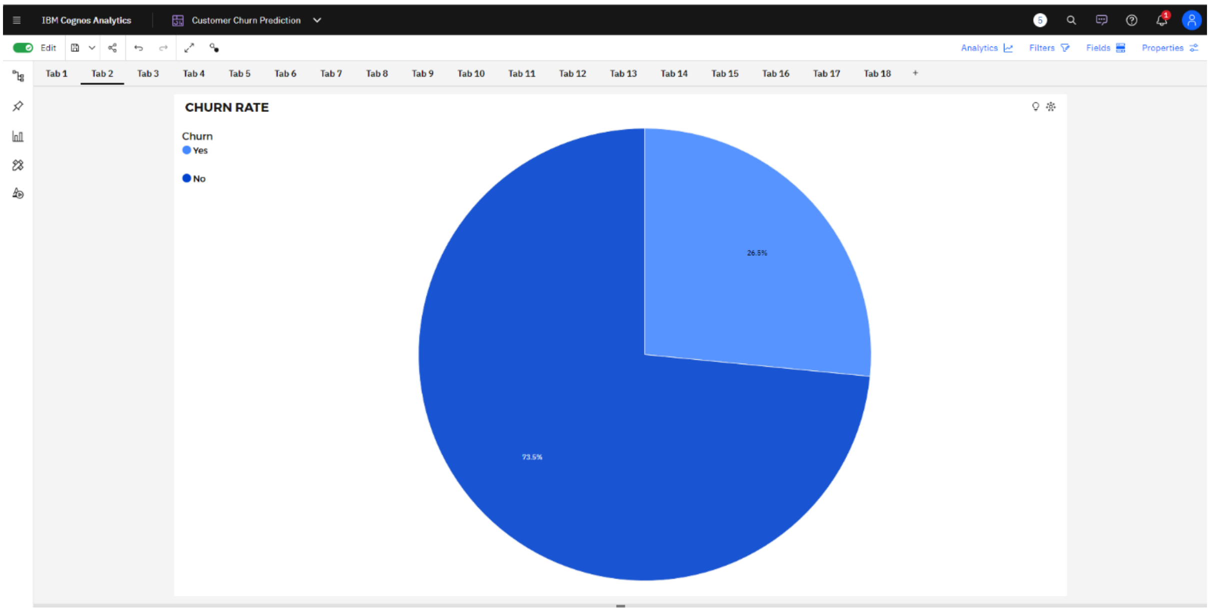
2.Customer Churned

3.Churn Rate Percentage

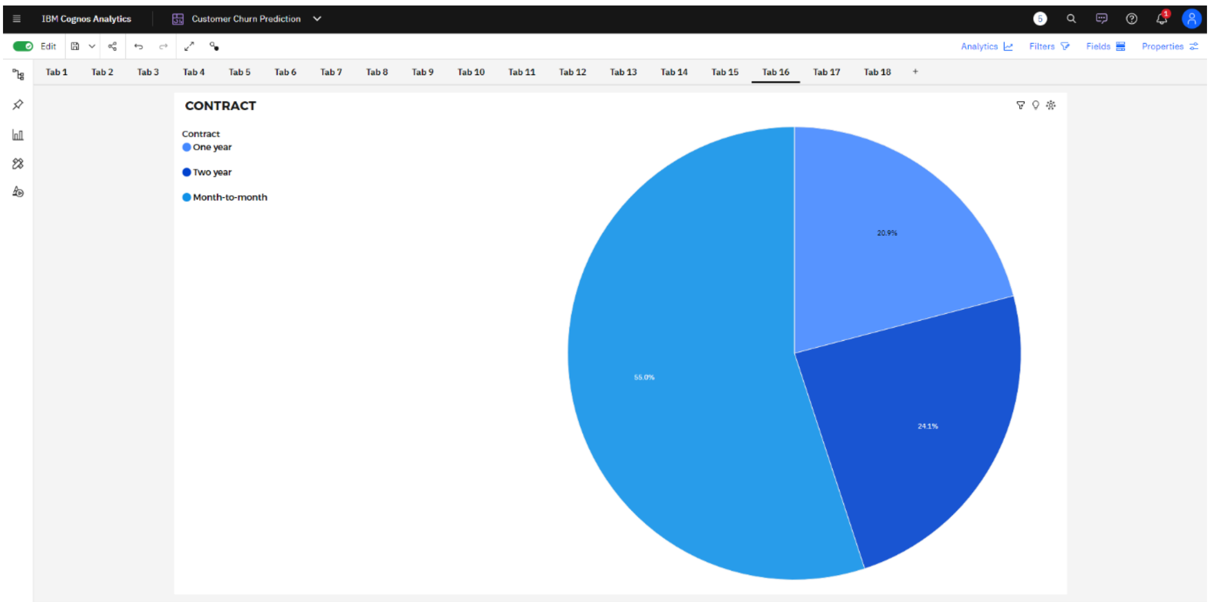
4.Gender Diversity



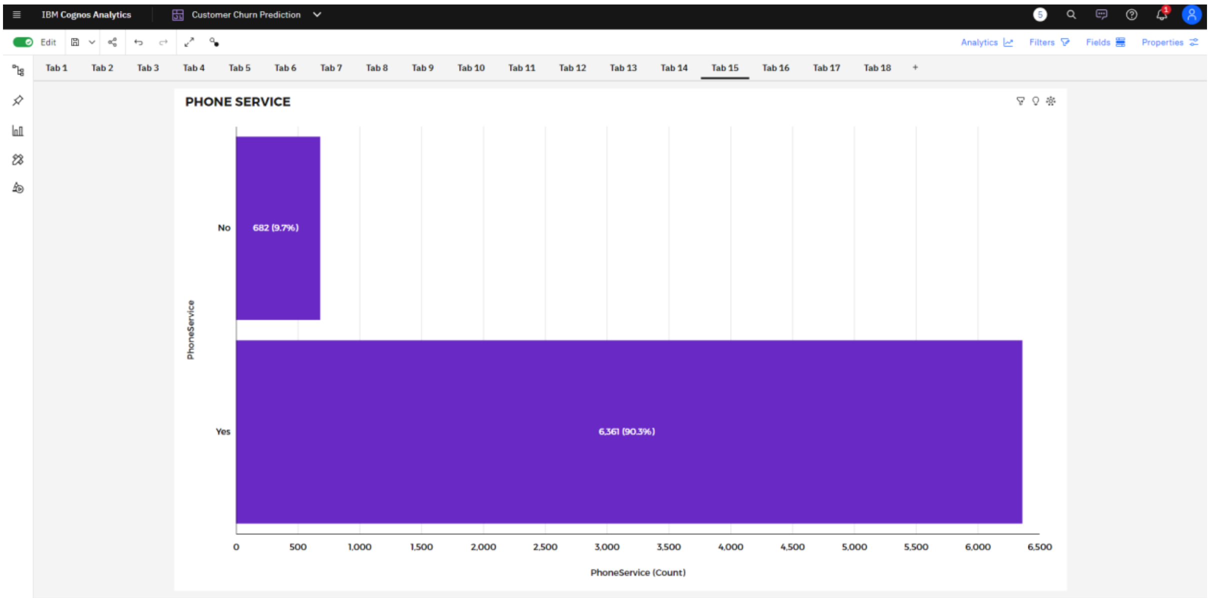
5.Churn Rate



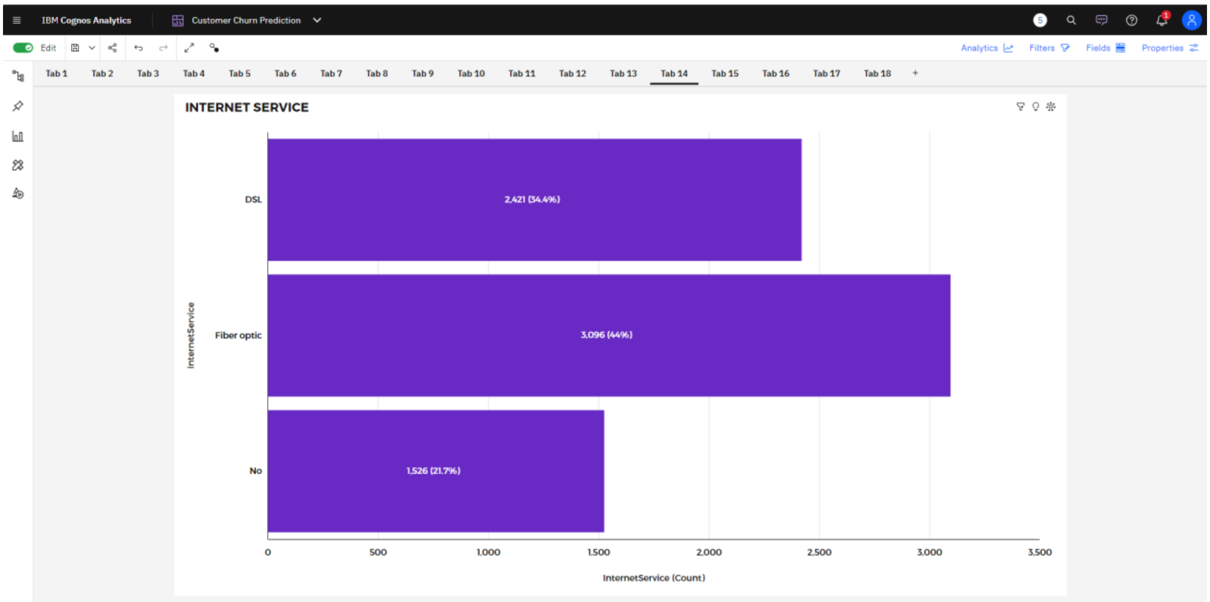
6.Contract



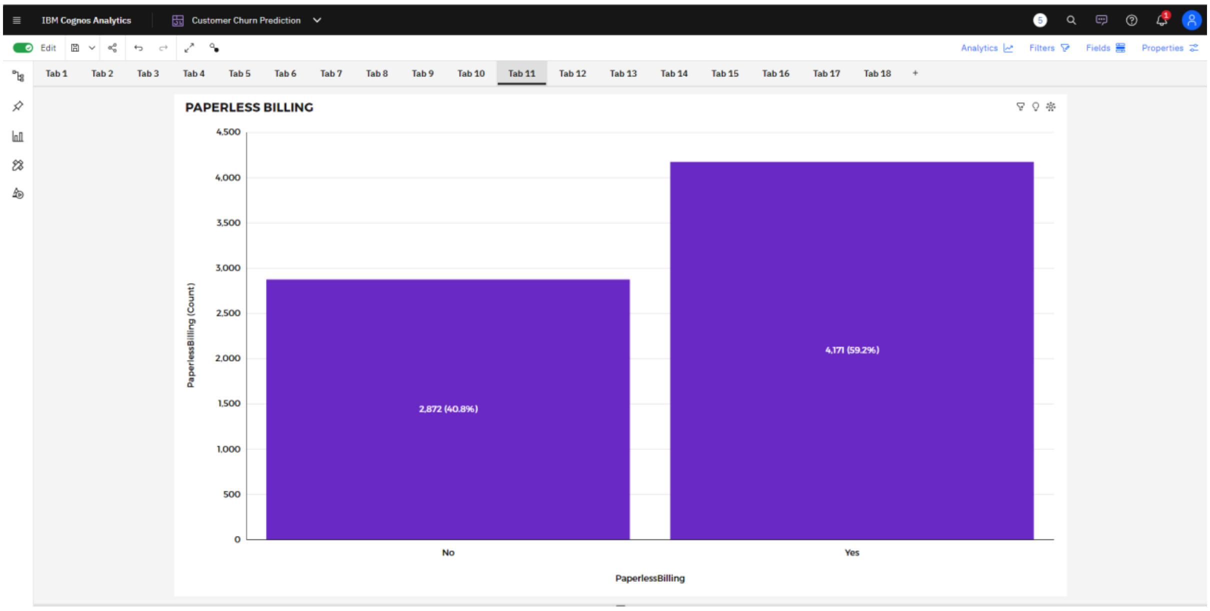
7.Phone Service



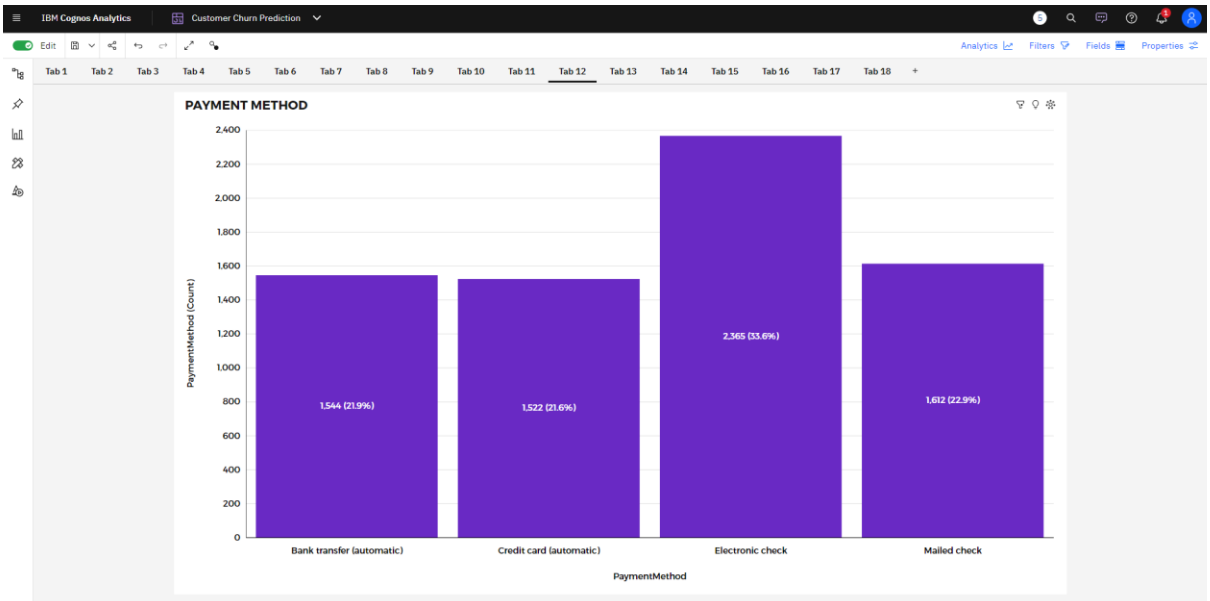
8.Internet Service



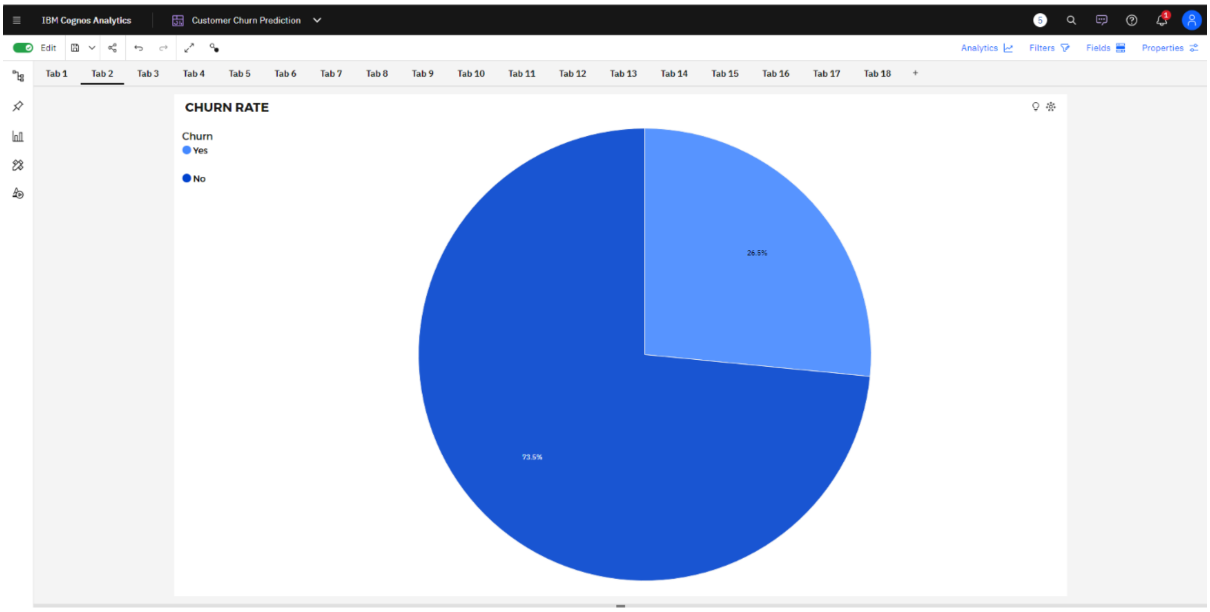
9.Paperles Billing



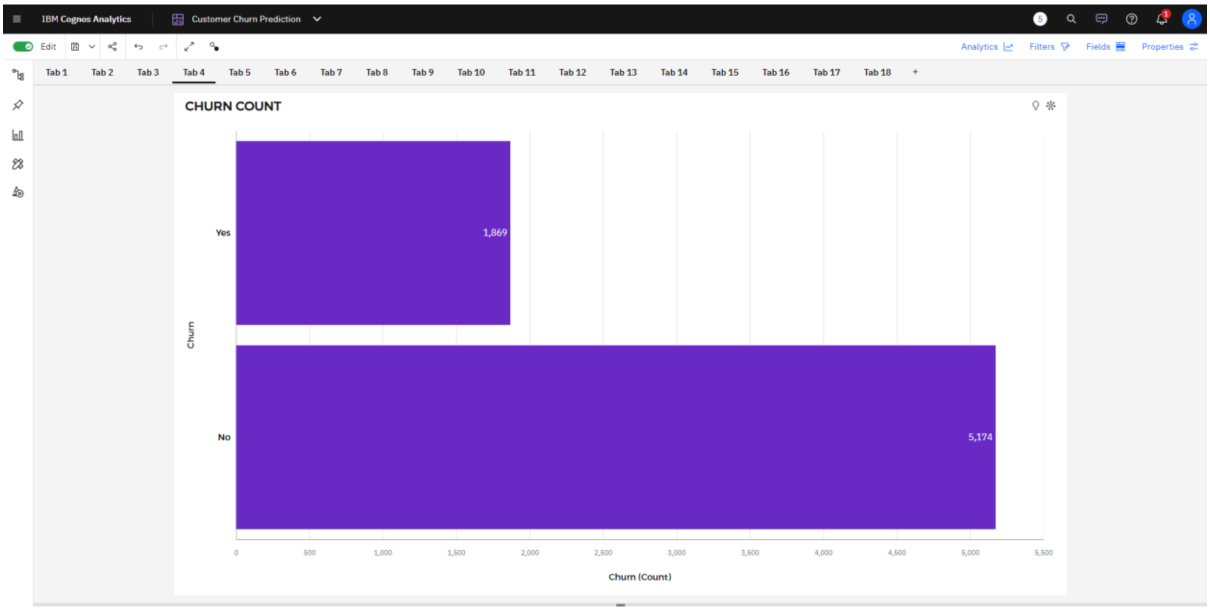
10.Payment Method



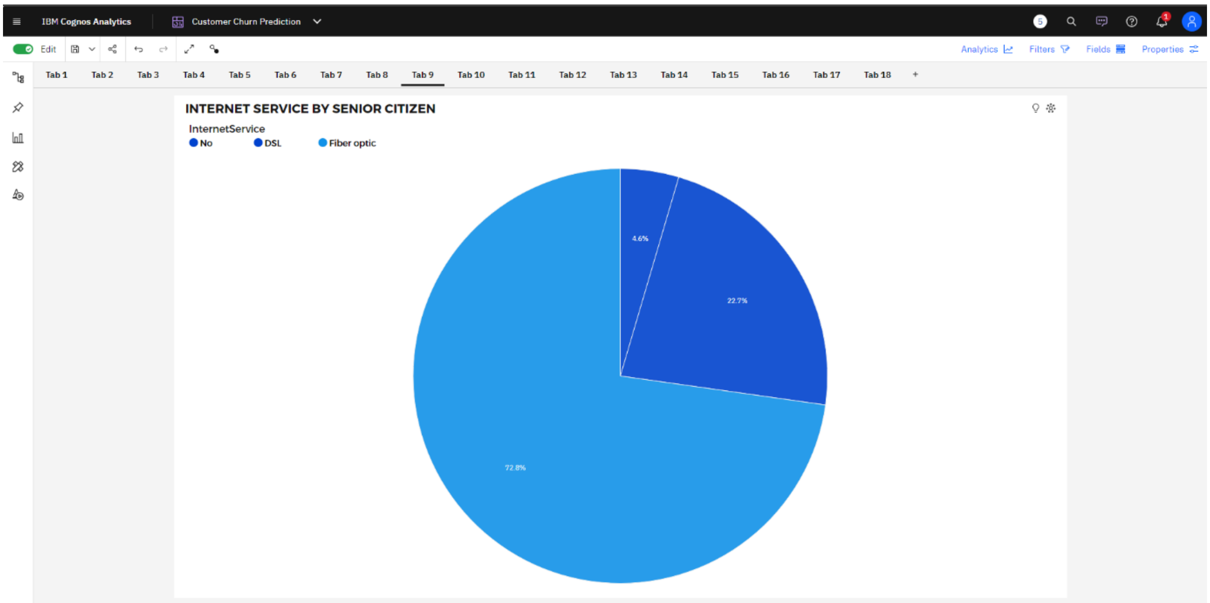
11.Churn Rate



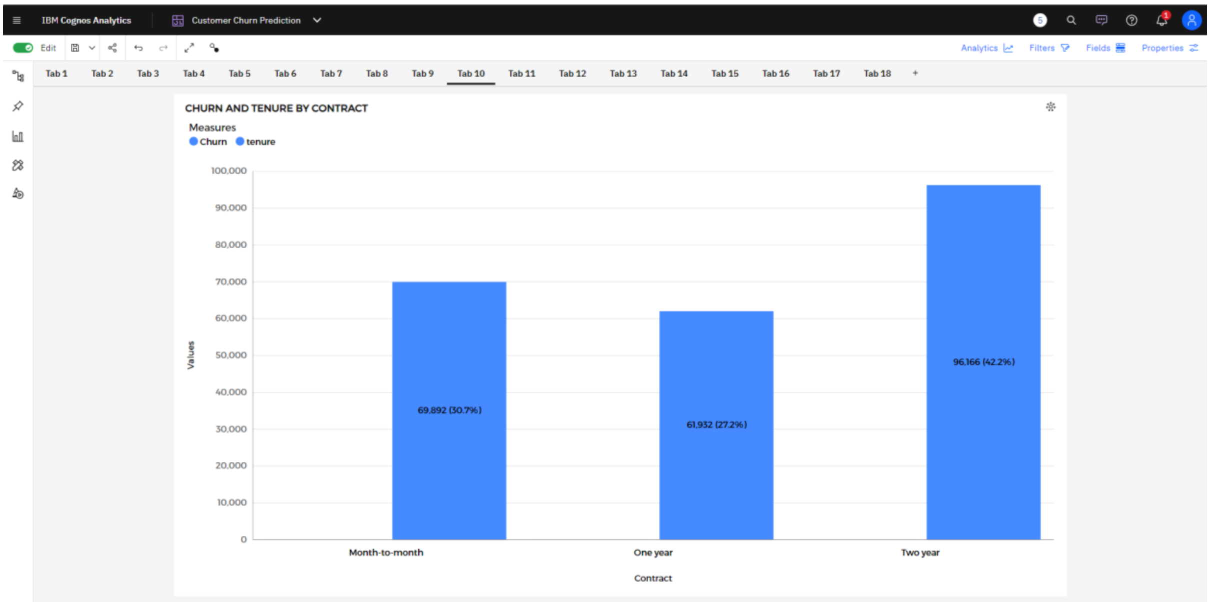
12.Churn Count



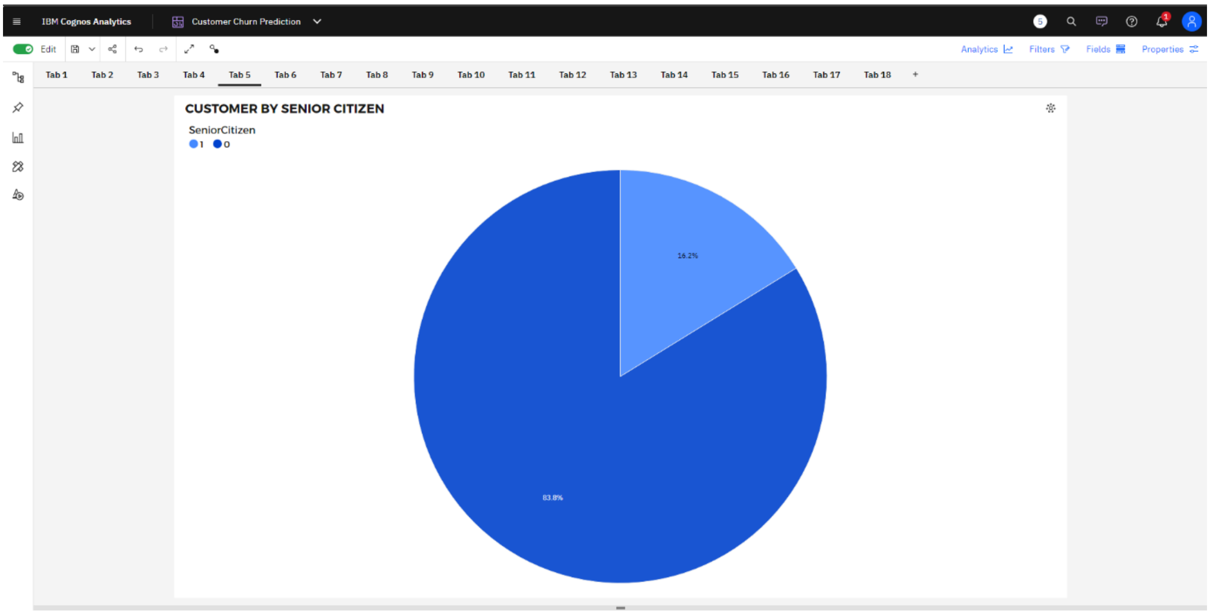
13.Internet Service By Senior Citizen



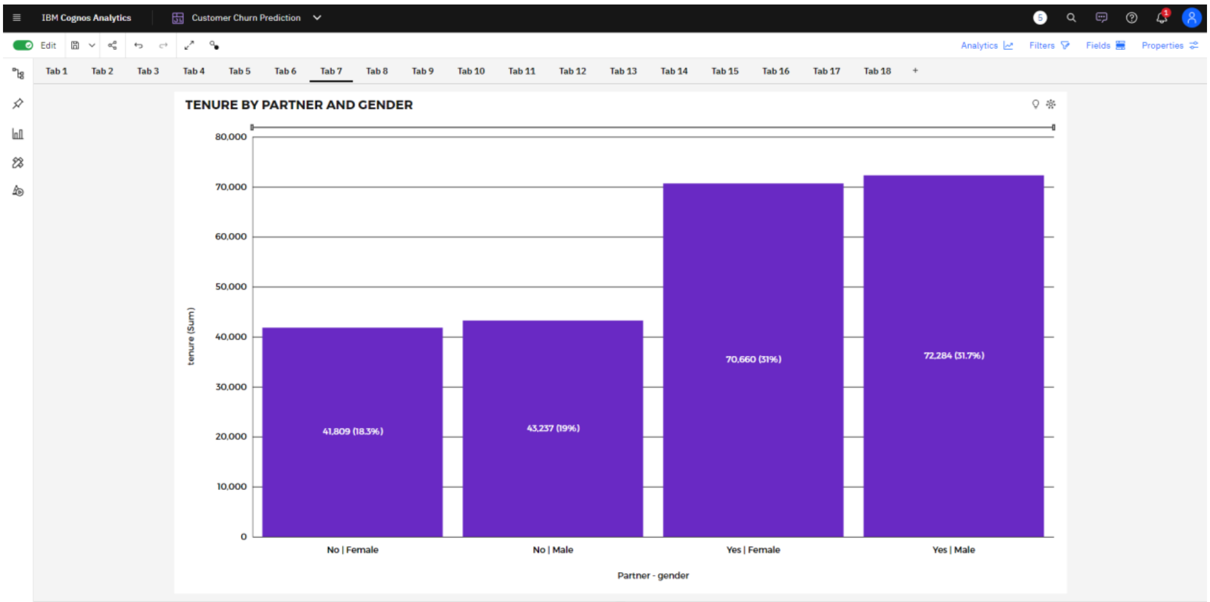
14.Churn And Tenure By Contract



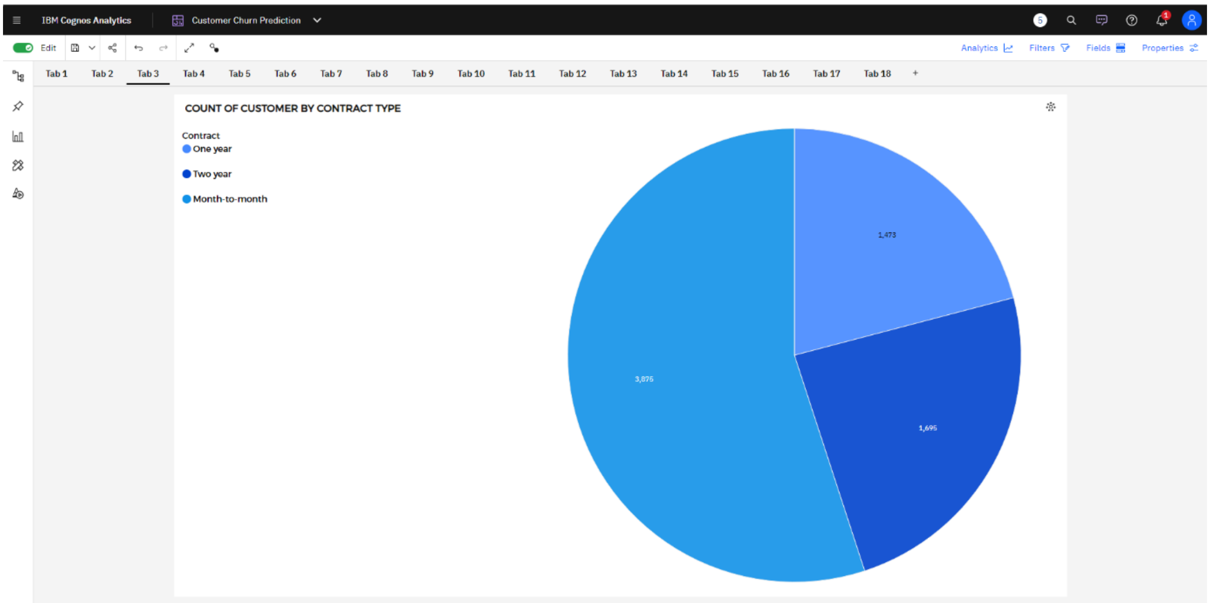
15.Customer By Senior Citizen



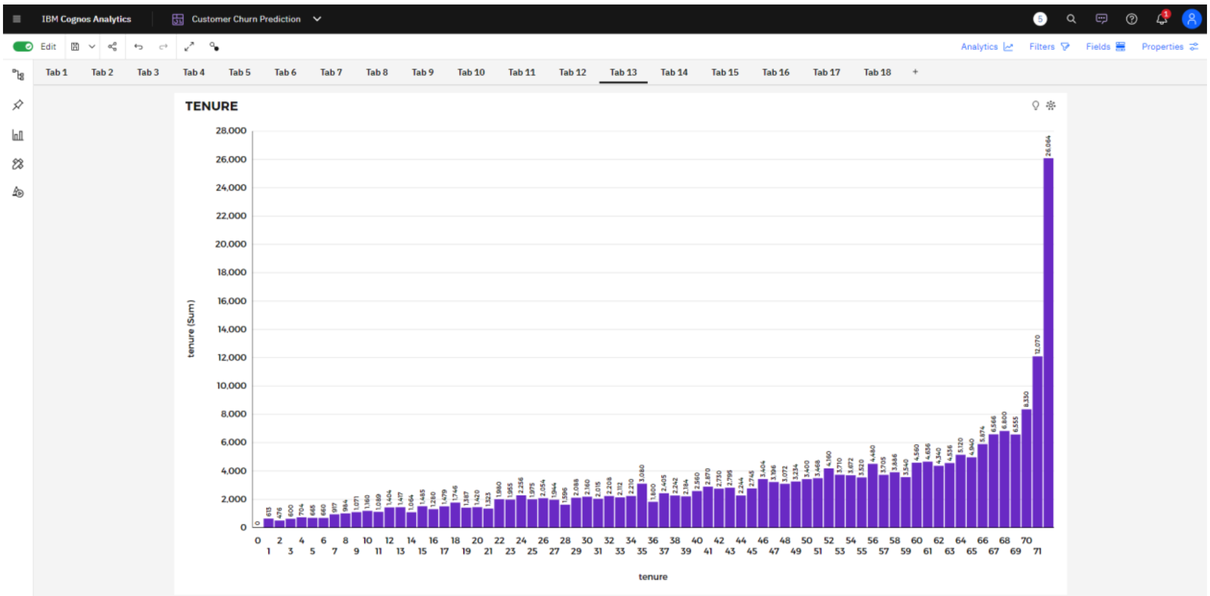
16.Tenure By Partner And Tenure



17.Count Of Customer By Contract Type

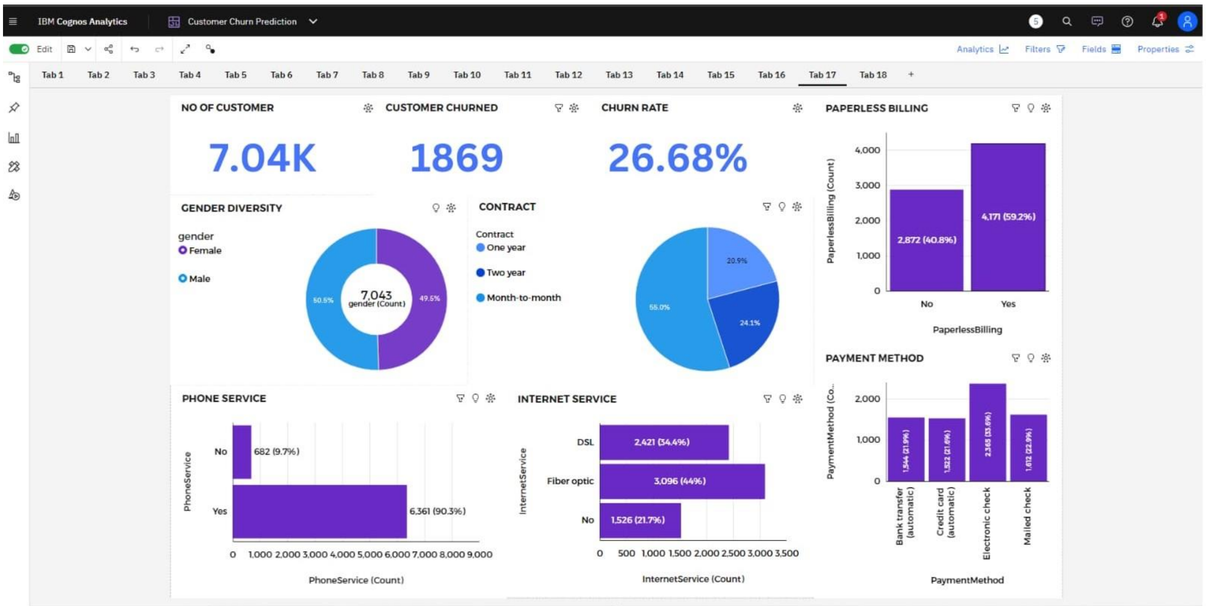


18.Tenure

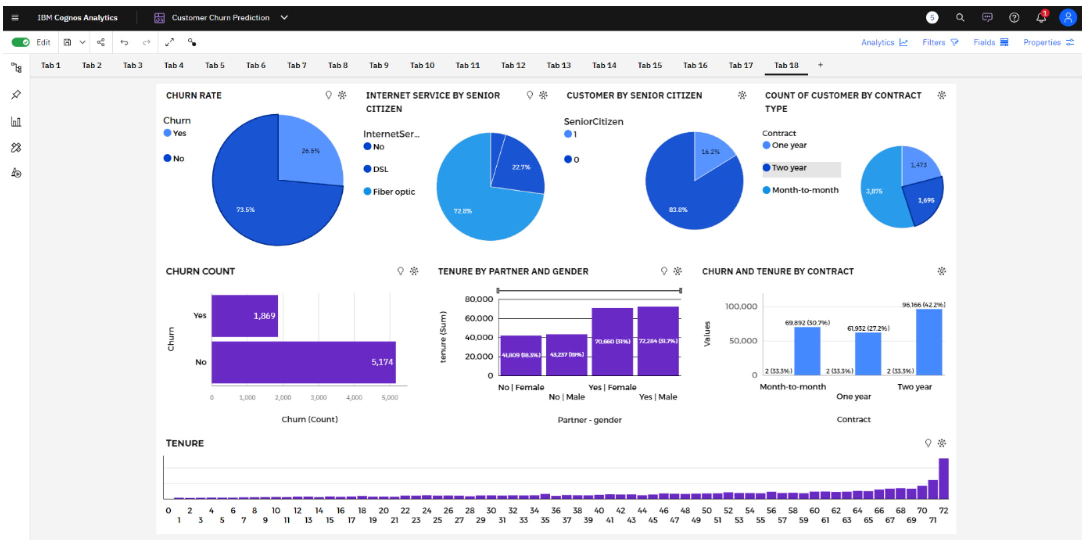


All the above individual visualization were incorporated as a single visualization known as Dashboard.

Dashboard 1



Dashboard 2



CONCLUSION

The document is concentrated on the analysis of customer churn rate, attrition rate and retention percentage of a given dataset. The analysis portions were implemented in the jupyter notebook and the utilization of python code which helped in the development of the Machine Learning model. The dashboard creation process is accomplished by IBM Cognos platform. The visualisation helps in understanding of the problem effectively. By analysing many ML models we concluded to a single predictive model with a high accuracy.