ML_Final_Assignment_2020-09-20

October 17, 2022

1 Business Problem Understanding

CCP (Churn Customer Prediction): following my experience and career in Telco Industry (MTN-Irancell), prediction on churn and how to increase the revenue of the company with different campaigns and make the customer more loyal is one of the most challenging problems which the baseline of all actions is to know the churn ratio on our products and our customers.

For this practice, a Dataset that has been chosen is from Kaggle which initially from the IBM (Telco customer churn (11.1.3+), 2022) is related to a telco industry with 7k records and 20 features "WA_Fn-UseC_-Telco-Customer-Churn.CSV"

As our target is to distinguish the churn customers which are identified with "Yes"/"No" in a specific field "Churn". we have a classification task in Machine Learning. for this purpose we tried different ML classification algorithms such as Decision Tree, SVM, Gaussian Naive Bayes, KNN, and Logistic Regression, each algorithm has its pros and cons; with different measurement criteria we will choose one of them and explain our hypothesis.

Download link for Dataset:

https://drive.google.com/drive/folders/1tVeHMCC-L7UBGAf5vRRHrLr8qhdkKtRs

2 Variable Description

1. customerID: Unique Values
2. gender: Whether the customer is a male or a female
3. SeniorCitizen: Indicates if the customer is 65 or older (1, 0)/: Yes, No
4. Partner: Whether the customer has a partner or not (Yes, No)
5. Dependents: Whether the customer has dependents or not (Yes, No)
6. Tenure: Number of months the customer has stayed with the company
7. PhoneService: Whether the customer has a phone service or not (Yes, No)
8. MultipleLines: Whether the customer has multiple lines or not (Yes, No, No phone service)
9. InternetService: Customer's internet service provider (DSL, Fiber optic, No)
10. OnlineSecurity: Whether the customer has online security or not (Yes, No, No internet service)
11. OnlineBackup: Whether the customer has online backup or not (Yes, No, No internet service)
12. DeviceProtection: Whether the customer has device protection or not (Yes, No, No internet service)
13. TechSupport: Whether the customer has tech support or not (Yes, No, No internet service)
14. StreamingTV: Whether the customer has streaming TV or not (Yes, No, No internet service)

15. StreamingMovies: Whether the customer has streaming movies or not (Yes, No, No internet service)
16. Contract: The contract term of the customer (Month-to-month, One year, Two year)
17. PaperlessBilling: Whether the customer has paperless billing or not (Yes, No)
18. PaymentMethod: The customer's payment method (Electronic check, Mailed check, Bank transfer (automatic), Credit card (automatic))
19. MonthlyCharges: The amount charged to the customer monthly
20. TotalCharges: The total amount charged to the customer
21. Churn: Customers who left within the last month, the column is called Churn (Yes or No)

3 1 Importing Libraries

Importing libraries such as: 1. pandas for data analysis. 2. numpy for working with arrays. 3. plotly and seaborn for representing graphs and plots 4. sklearn and sub-libraries for machine learning algorithms. 5. imblearn and LabelEncoder for Feature Engineering 6. beautifultable and termcolr for table creation

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from beautifultable import BeautifulTable
from termcolor import colored

import sklearn
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
from sklearn import linear_model
from sklearn import tree
from sklearn import neighbors
from sklearn.model_selection import GridSearchCV
from sklearn import preprocessing
from sklearn import model_selection
from sklearn import tree
import imblearn.over_sampling
```

4 2 Data Collection

5 Importing Data

Importing our dataset and indexing customerID as it is a unique ID, it is not a feature that we need to use for our model.

Represent first five rows as default

[2]:
```
df = pd.read_csv("WA_Fn-UseC_-Telco-Customer-Churn.csv")
df = df.set_index("customerID")
df.head()
```

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

               MultipleLines InternetService OnlineSecurity OnlineBackup  \
customerID
7590-VHVEG  No phone service             DSL             No          Yes
5575-GNVDE                No             DSL            Yes           No
3668-QPYBK                No             DSL            Yes          Yes
7795-CFOCW  No phone service             DSL            Yes           No
9237-HQITU                No     Fiber optic             No           No

           DeviceProtection TechSupport StreamingTV StreamingMovies  \
customerID
7590-VHVEG               No          No          No              No
5575-GNVDE              Yes          No          No              No
3668-QPYBK               No          No          No              No
7795-CFOCW              Yes         Yes          No              No
9237-HQITU               No          No          No              No

                  Contract PaperlessBilling              PaymentMethod  \
customerID
7590-VHVEG  Month-to-month              Yes           Electronic check
5575-GNVDE        One year               No               Mailed check
3668-QPYBK  Month-to-month              Yes               Mailed check
7795-CFOCW        One year               No  Bank transfer (automatic)
9237-HQITU  Month-to-month              Yes           Electronic check

            MonthlyCharges TotalCharges Churn
customerID
7590-VHVEG           29.85        29.85    No
5575-GNVDE           56.95       1889.5    No
3668-QPYBK           53.85       108.15   Yes
7795-CFOCW           42.30      1840.75    No
9237-HQITU           70.70       151.65   Yes
```

6 Preprocessing and Data Exploration

Observing the Data types of variables in the dataset.

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

```
<class 'pandas.core.frame.DataFrame'>
Index: 7043 entries, 7590-VHVEG to 3186-AJIEK
Data columns (total 20 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   gender            7043 non-null   object
 1   SeniorCitizen     7043 non-null   int64
 2   Partner           7043 non-null   object
 3   Dependents        7043 non-null   object
 4   tenure            7043 non-null   int64
 5   PhoneService      7043 non-null   object
 6   MultipleLines     7043 non-null   object
 7   InternetService   7043 non-null   object
 8   OnlineSecurity    7043 non-null   object
 9   OnlineBackup      7043 non-null   object
 10  DeviceProtection  7043 non-null   object
 11  TechSupport       7043 non-null   object
 12  StreamingTV       7043 non-null   object
 13  StreamingMovies   7043 non-null   object
 14  Contract          7043 non-null   object
 15  PaperlessBilling  7043 non-null   object
 16  PaymentMethod     7043 non-null   object
 17  MonthlyCharges    7043 non-null   float64
 18  TotalCharges      7043 non-null   object
 19  Churn             7043 non-null   object
dtypes: float64(1), int64(2), object(17)
memory usage: 1.1+ MB
```

As data explored "TotalCharges" field which contains a numeric value should be a float datatype by nature, but in our data set it is defined as an object after investigation we found some spaces in our values which it has been set to a null value.

[4]:
```
df["TotalCharges"] = df["TotalCharges"].replace(r"\s+", np.nan, regex=True)
df["TotalCharges"] = pd.to_numeric(df["TotalCharges"])
```

As expected the "TotalCharges" field is converted to float64.

[5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 7043 entries, 7590-VHVEG to 3186-AJIEK
Data columns (total 20 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   gender            7043 non-null   object
 1   SeniorCitizen     7043 non-null   int64
 2   Partner           7043 non-null   object
```

```
 3   Dependents        7043 non-null   object
 4   tenure            7043 non-null   int64
 5   PhoneService      7043 non-null   object
 6   MultipleLines     7043 non-null   object
 7   InternetService   7043 non-null   object
 8   OnlineSecurity    7043 non-null   object
 9   OnlineBackup      7043 non-null   object
 10  DeviceProtection  7043 non-null   object
 11  TechSupport       7043 non-null   object
 12  StreamingTV       7043 non-null   object
 13  StreamingMovies   7043 non-null   object
 14  Contract          7043 non-null   object
 15  PaperlessBilling  7043 non-null   object
 16  PaymentMethod     7043 non-null   object
 17  MonthlyCharges    7043 non-null   float64
 18  TotalCharges      7032 non-null   float64
 19  Churn             7043 non-null   object
dtypes: float64(2), int64(2), object(16)
memory usage: 1.1+ MB
```

The following lines indicated 11 null values and as it is Ignorable we drop them as part of the data cleaning process.

[6]:
```
df.isnull().sum()
```

[6]:
```
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
```

[7]:
```
df.dropna(inplace=True)
```

7 Duplicate Checking

The below duplication occurred due to indexing of CustomerID field, naturally, there is no duplication, therefore there is no action required and we will leave it as is.

[8]:
```
df.duplicated().sum()
```

[8]:
```
22
```

[9]:
```
duplicate = df[df.duplicated()]
print("Duplicate Rows except first occurrence based on all columns are:")
duplicate
```

```
Duplicate Rows except first occurrence based on all columns are:
```

[9]:
```
             gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
customerID
9117-SHLZX     Male              0      No         No       1          Yes
1934-SJVJK     Male              0      No         No       1          Yes
8605-ITULD   Female              0      No         No       1          Yes
9804-ICWBG     Male              0      No         No       1          Yes
3247-MHJKM     Male              0      No         No       1          Yes
5996-DAOQL     Male              0      No         No       1          Yes
2668-TZSPS     Male              0      No         No       1          Yes
2636-ALXXZ   Female              1      No         No       1          Yes
7096-UCLNH     Male              0      No         No       1          Yes
5356-RHIPP     Male              0      No         No       1          Yes
7434-SHXLS   Female              0      No         No       1          Yes
8048-DSDFQ     Male              0      No         No       1          Yes
8749-CLJXC     Male              0      No         No       1          Yes
9985-MWVIX   Female              0      No         No       1          Yes
0328-GRPMV   Female              0      No         No       1          Yes
2676-ISHSF     Male              0      No         No       1          Yes
1963-SVUCV     Male              0      No         No       1          Yes
1000-AJSLD     Male              0      No         No       1          Yes
7878-RTCZG   Female              0      No         No       1          Yes
7660-HDPJV   Female              0      No         No       1          Yes
0970-QXPXW   Female              0      No         No       1          Yes
6457-GIRWB     Male              0      No         No       1          Yes

           MultipleLines InternetService       OnlineSecurity  \
customerID
9117-SHLZX            No             DSL                   No
1934-SJVJK            No              No  No internet service
8605-ITULD            No              No  No internet service
9804-ICWBG            No     Fiber optic                   No
3247-MHJKM            No              No  No internet service
5996-DAOQL            No              No  No internet service
```

```
2668-TZSPS           No             No  No internet service
2636-ALXXZ           No    Fiber optic                   No
7096-UCLNH           No             No  No internet service
5356-RHIPP           No             No  No internet service
7434-SHXLS           No             No  No internet service
8048-DSDFQ           No             No  No internet service
8749-CLJXC           No             No  No internet service
9985-MWVIX           No    Fiber optic                   No
0328-GRPMV           No    Fiber optic                   No
2676-ISHSF           No             No  No internet service
1963-SVUCV           No            DSL                   No
1000-AJSLD           No             No  No internet service
7878-RTCZG           No             No  No internet service
7660-HDPJV           No    Fiber optic                   No
0970-QXPXW           No             No  No internet service
6457-GIRWB           No    Fiber optic                   No

                   OnlineBackup     DeviceProtection          TechSupport  \
customerID
9117-SHLZX                   No                   No                   No
1934-SJVJK  No internet service  No internet service  No internet service
8605-ITULD  No internet service  No internet service  No internet service
9804-ICWBG                   No                   No                   No
3247-MHJKM  No internet service  No internet service  No internet service
5996-DAOQL  No internet service  No internet service  No internet service
2668-TZSPS  No internet service  No internet service  No internet service
2636-ALXXZ                   No                   No                   No
7096-UCLNH  No internet service  No internet service  No internet service
5356-RHIPP  No internet service  No internet service  No internet service
7434-SHXLS  No internet service  No internet service  No internet service
8048-DSDFQ  No internet service  No internet service  No internet service
8749-CLJXC  No internet service  No internet service  No internet service
9985-MWVIX                   No                   No                   No
0328-GRPMV                   No                   No                   No
2676-ISHSF  No internet service  No internet service  No internet service
1963-SVUCV                   No                   No                   No
1000-AJSLD  No internet service  No internet service  No internet service
7878-RTCZG  No internet service  No internet service  No internet service
7660-HDPJV                   No                   No                   No
0970-QXPXW  No internet service  No internet service  No internet service
6457-GIRWB                   No                   No                   No

                    StreamingTV      StreamingMovies        Contract  \
customerID
9117-SHLZX                   No                   No  Month-to-month
1934-SJVJK  No internet service  No internet service  Month-to-month
8605-ITULD  No internet service  No internet service  Month-to-month
```

9804-ICWBG	No	No	Month-to-month
3247-MHJKM	No internet service	No internet service	Month-to-month
5996-DAOQL	No internet service	No internet service	Month-to-month
2668-TZSPS	No internet service	No internet service	Month-to-month
2636-ALXXZ	No	No	Month-to-month
7096-UCLNH	No internet service	No internet service	Month-to-month
5356-RHIPP	No internet service	No internet service	Month-to-month
7434-SHXLS	No internet service	No internet service	Month-to-month
8048-DSDFQ	No internet service	No internet service	Month-to-month
8749-CLJXC	No internet service	No internet service	Month-to-month
9985-MWVIX	No	No	Month-to-month
0328-GRPMV	No	No	Month-to-month
2676-ISHSF	No internet service	No internet service	Month-to-month
1963-SVUCV	No	No	Month-to-month
1000-AJSLD	No internet service	No internet service	Month-to-month
7878-RTCZG	No internet service	No internet service	Month-to-month
7660-HDPJV	No	No	Month-to-month
0970-QXPXW	No internet service	No internet service	Month-to-month
6457-GIRWB	No	No	Month-to-month

	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges \
customerID				
9117-SHLZX	Yes	Mailed check	45.70	45.70
1934-SJVJK	No	Mailed check	20.15	20.15
8605-ITULD	No	Mailed check	19.55	19.55
9804-ICWBG	Yes	Electronic check	69.90	69.90
3247-MHJKM	No	Mailed check	20.20	20.20
5996-DAOQL	Yes	Mailed check	20.45	20.45
2668-TZSPS	No	Mailed check	20.45	20.45
2636-ALXXZ	Yes	Electronic check	69.60	69.60
7096-UCLNH	No	Mailed check	20.05	20.05
5356-RHIPP	Yes	Mailed check	20.20	20.20
7434-SHXLS	No	Mailed check	20.90	20.90
8048-DSDFQ	No	Mailed check	20.20	20.20
8749-CLJXC	No	Mailed check	20.05	20.05
9985-MWVIX	Yes	Mailed check	70.15	70.15
0328-GRPMV	Yes	Electronic check	70.10	70.10
2676-ISHSF	No	Mailed check	20.30	20.30
1963-SVUCV	No	Electronic check	45.30	45.30
1000-AJSLD	Yes	Mailed check	20.10	20.10
7878-RTCZG	No	Mailed check	19.90	19.90
7660-HDPJV	Yes	Electronic check	69.20	69.20
0970-QXPXW	No	Mailed check	19.65	19.65
6457-GIRWB	Yes	Electronic check	69.35	69.35

	Churn
customerID	

```
9117-SHLZX   Yes
1934-SJVJK   Yes
8605-ITULD    No
9804-ICWBG   Yes
3247-MHJKM    No
5996-DAOQL    No
2668-TZSPS    No
2636-ALXXZ   Yes
7096-UCLNH    No
5356-RHIPP   Yes
7434-SHXLS   Yes
8048-DSDFQ    No
8749-CLJXC    No
9985-MWVIX   Yes
0328-GRPMV   Yes
2676-ISHSF    No
1963-SVUCV   Yes
1000-AJSLD   Yes
7878-RTCZG    No
7660-HDPJV   Yes
0970-QXPXW    No
6457-GIRWB   Yes
```

8 Missing Values

Presentation of Null Values, As it is sorted as Descending there are no missing values; the first 10 rows are selected.

[10]:
```
miss = df.isnull().sum().sort_values(ascending=False).head(10)
miss_per = round(miss / len(df) * 100, 2)
pd.DataFrame({"Null Values (Count)": miss, "Percentage (%)": miss_per.values})
```

[10]:

	Null Values (Count)	Percentage (%)
gender	0	0.0
SeniorCitizen	0	0.0
TotalCharges	0	0.0
MonthlyCharges	0	0.0
PaymentMethod	0	0.0
PaperlessBilling	0	0.0
Contract	0	0.0
StreamingMovies	0	0.0
StreamingTV	0	0.0
TechSupport	0	0.0

9 Data Exploration (Charts)

To get some insights from the above dataset, some charts and graphs are added:

All graphs show the total diversity and correlation of most features with our target label "Churn".

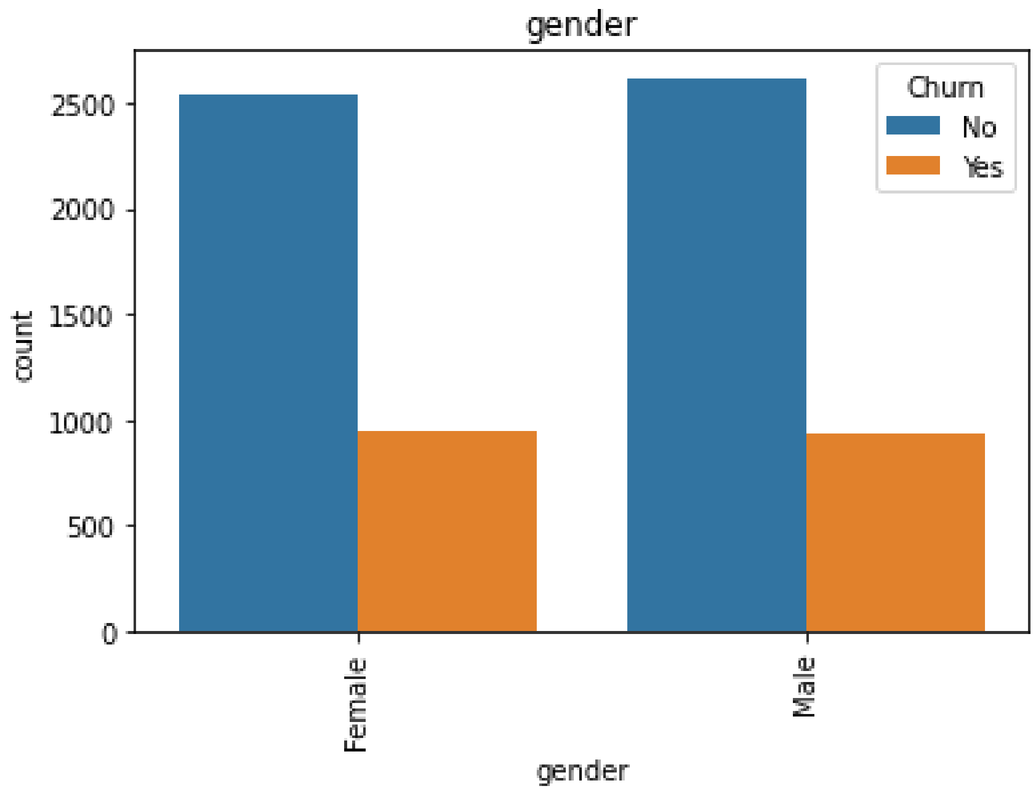
as an example distribution of Male and Female customers in churn is almost the same.

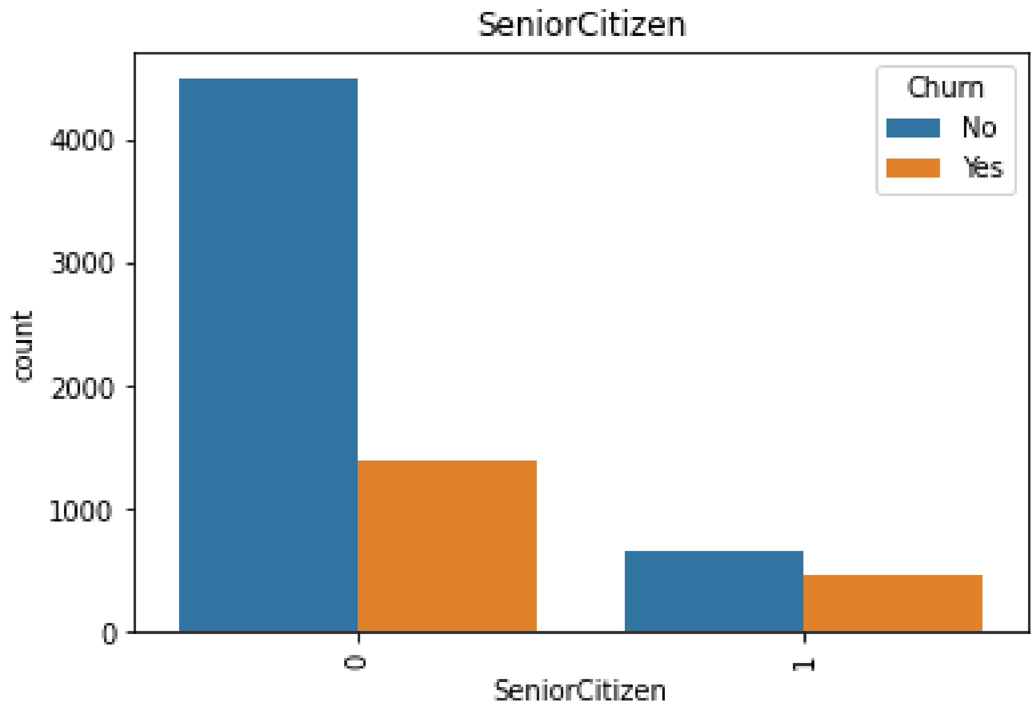
but senior citizens (those above 65 years old) significantly are low in the margin but in relation to churn rate is high.

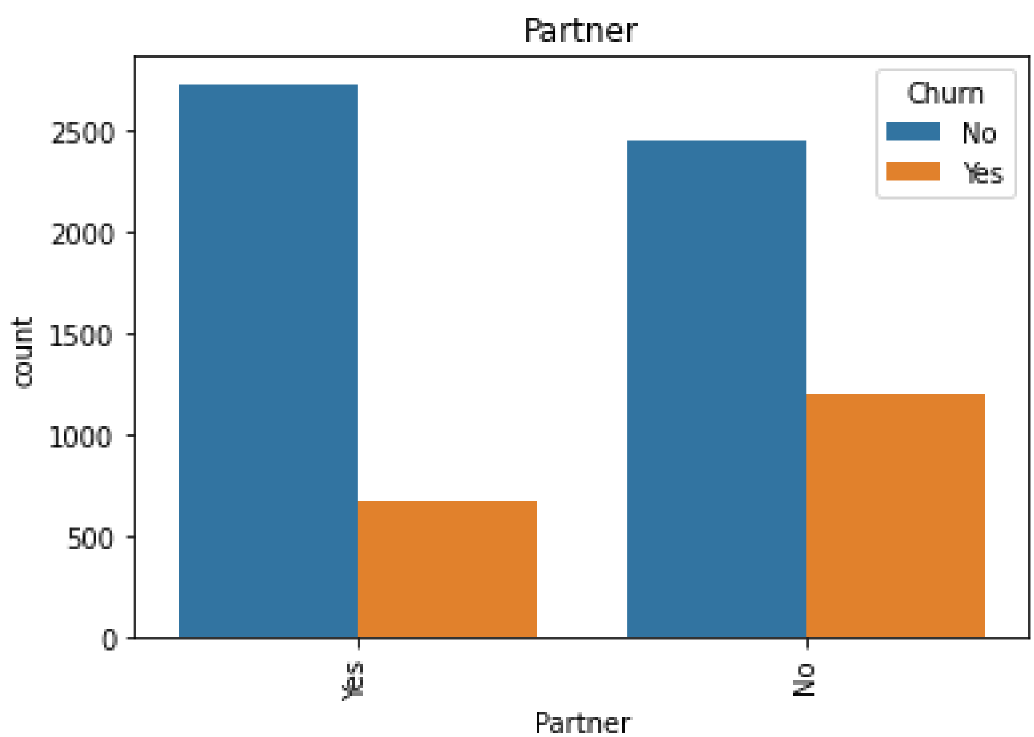
for each plot, we have a similar analysis and to avoid making long explanations we will keep going with the rest of the activities for the ML pipeline.

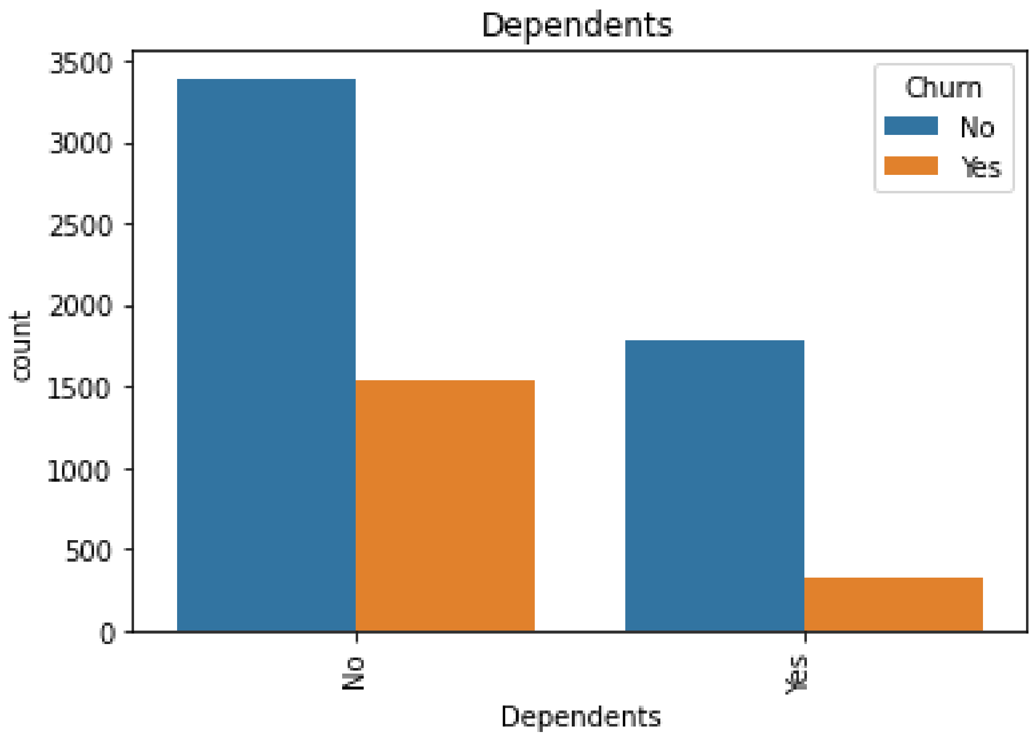
- To avoid repeating in coding, we get the column headers as text and put them in a for loop to generate for each column similar plot.

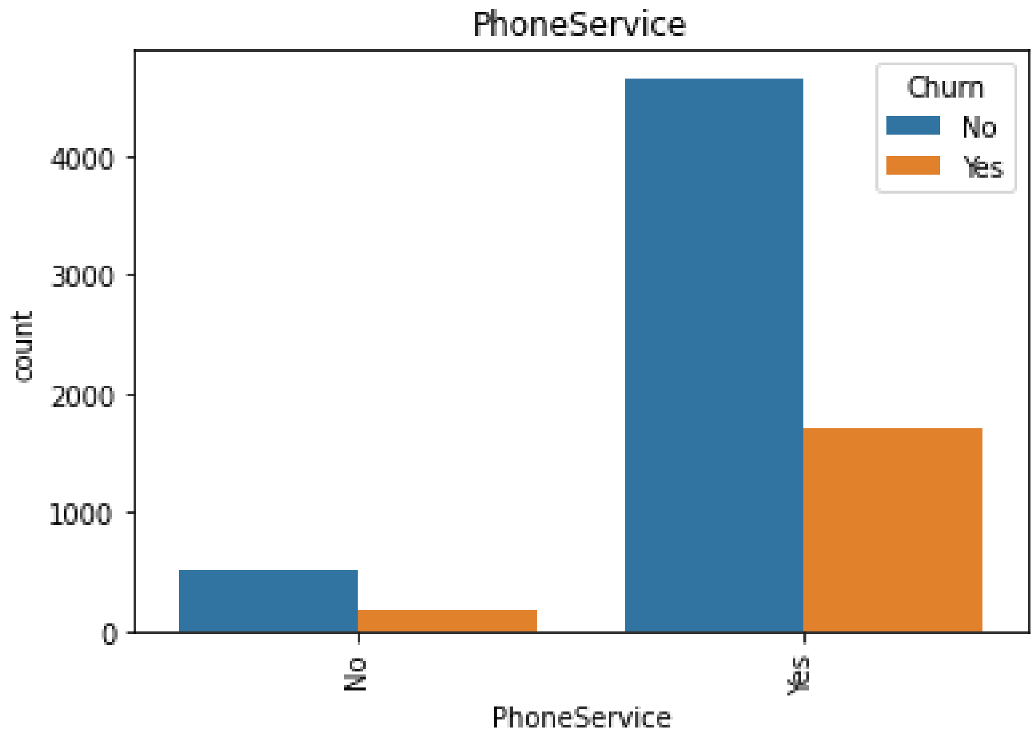
[11]:
```
df_column = """
    gender SeniorCitizen Partner Dependents  PhoneService
    MultipleLines InternetService OnlineSecurity OnlineBackup
    DeviceProtection TechSupport StreamingTV StreamingMovies
    Contract PaperlessBilling PaymentMethod
"""

plt_drw = df_column.split()
for word in plt_drw:
    sns.countplot(x=word, hue="Churn", data=df)
    plt1 = plt.xticks(rotation=90)
    plt1 = plt.title(word)
    plt.show()
    print("\n")
```

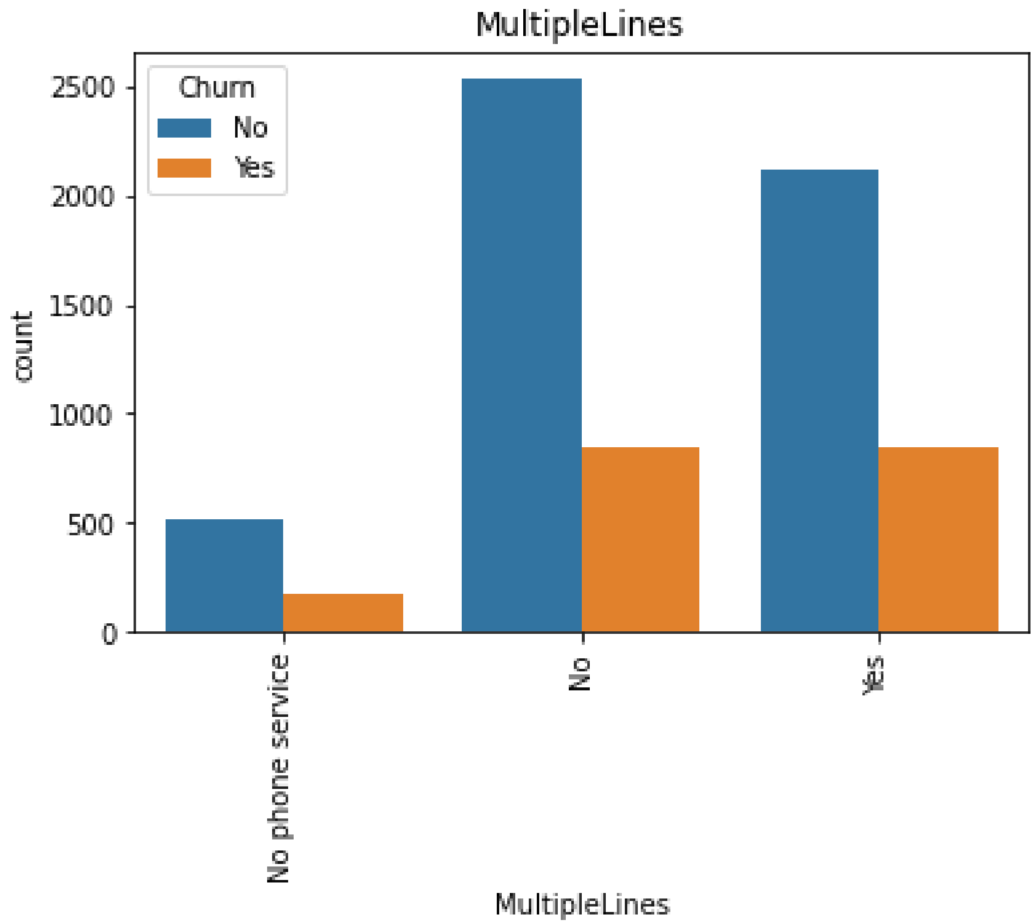

gender
Churn
No
Yes
2500
2000
1500
1000
500
0
count
Female
Male
gender

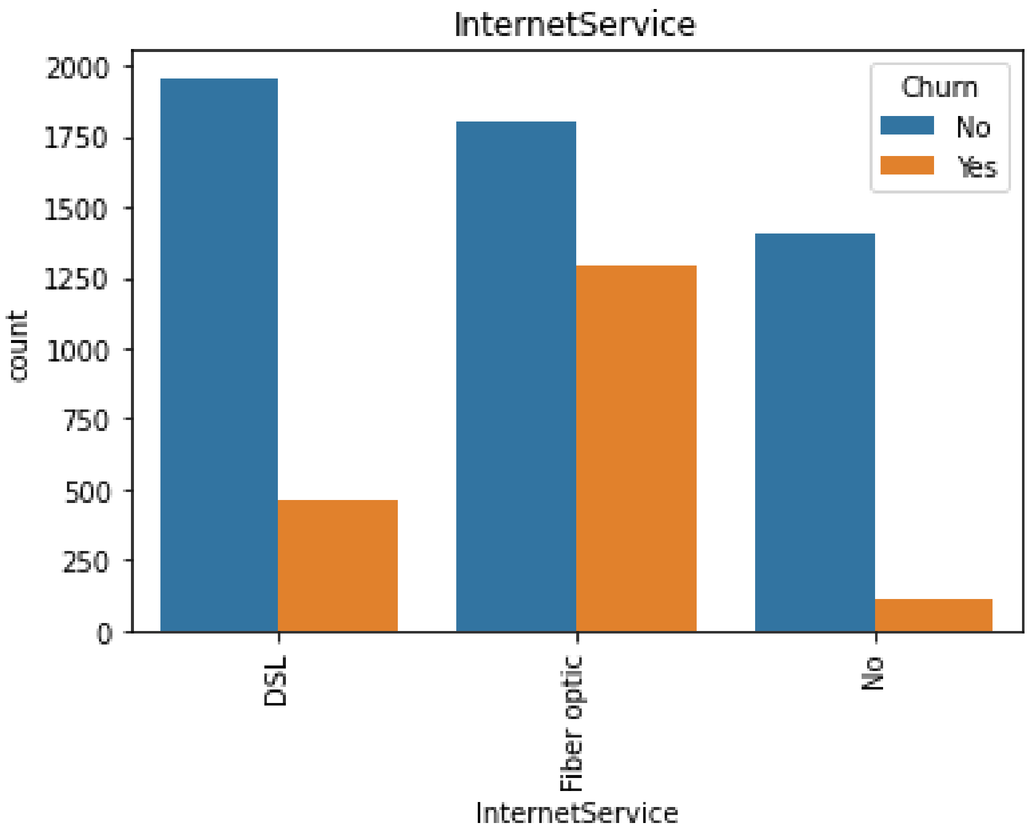

SeniorCitizen
Churn
No
Yes
count
0
1000
2000
3000
4000
0
1
SeniorCitizen

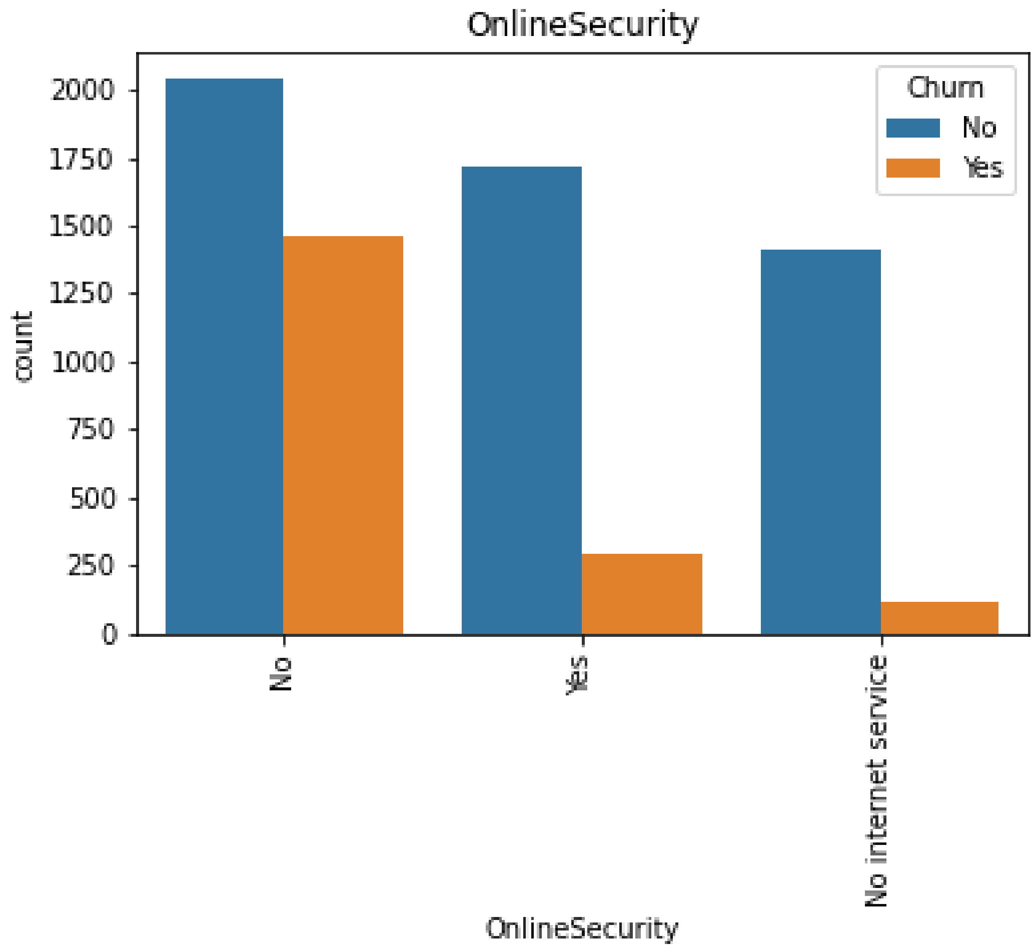

Partner
Churn
No
Yes
count
0
500
1000
1500
2000
2500
Yes
No
Partner

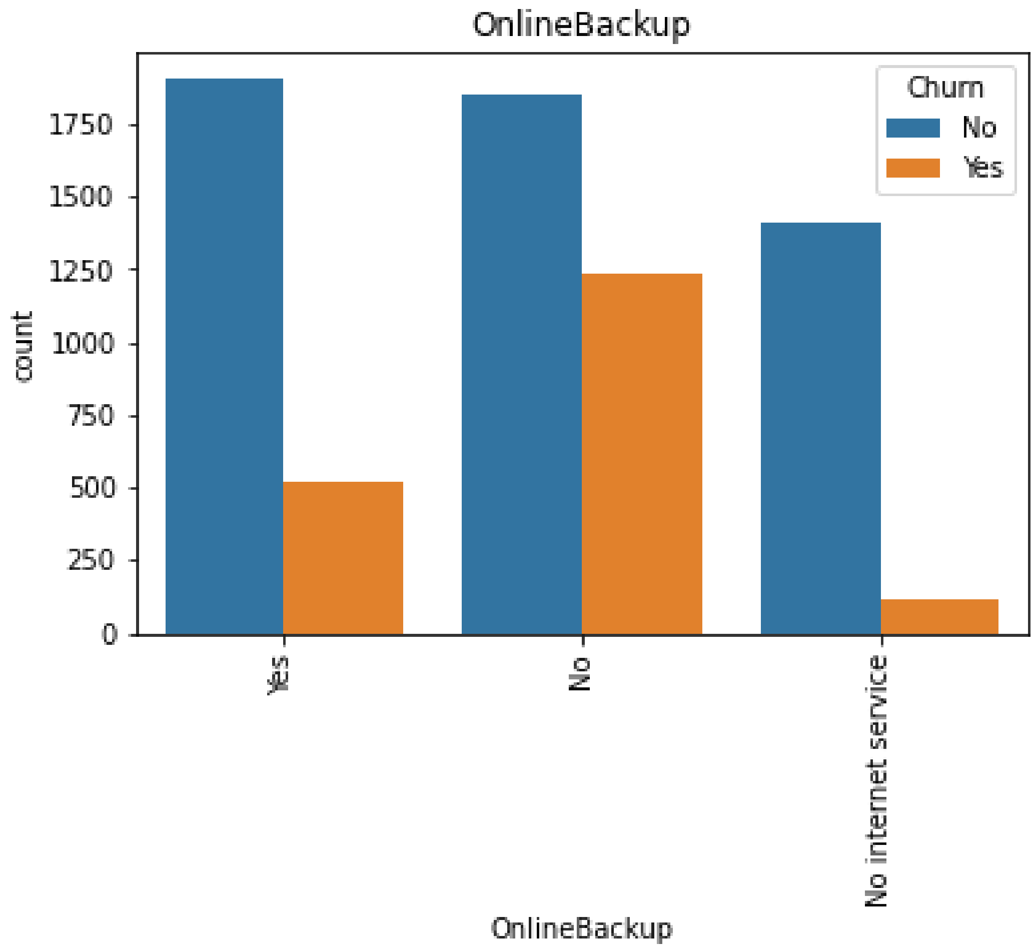

Dependents
Churn
No
Yes
3500
3000
2500
2000
1500
1000
500
0
count
No
Yes
Dependents

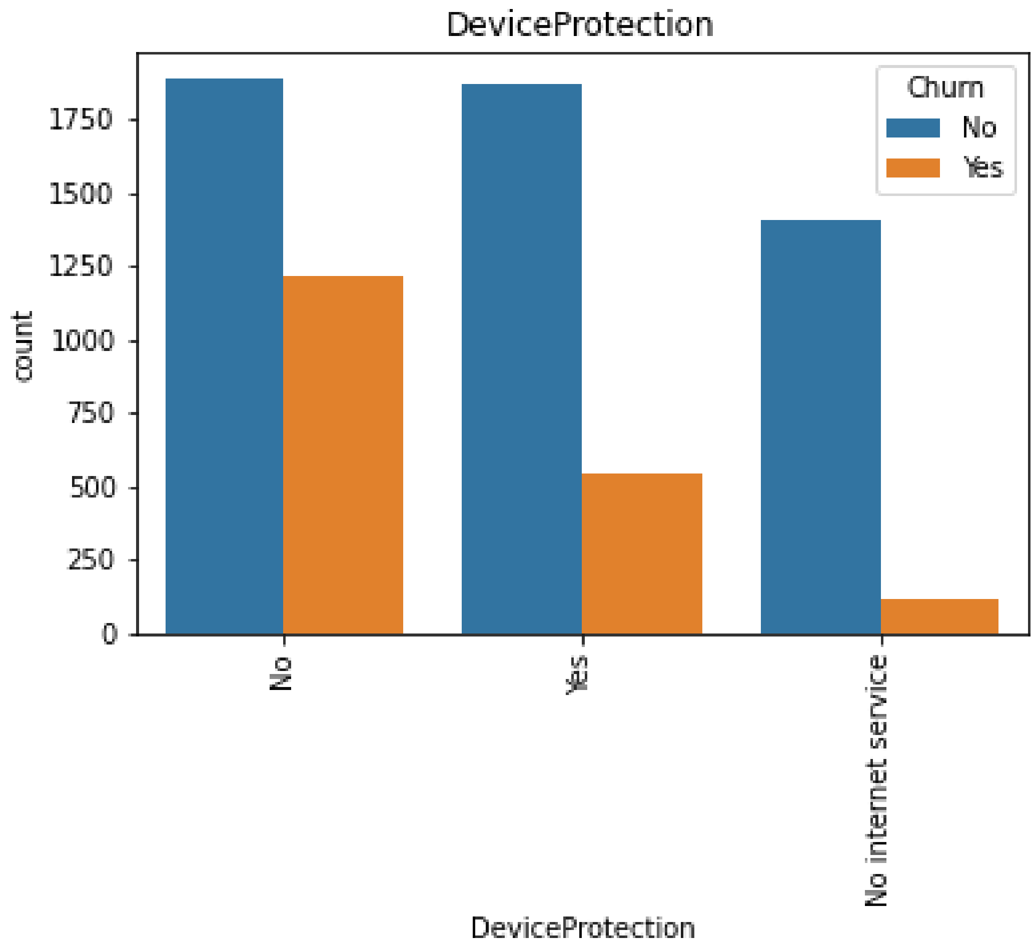

PhoneService
Churn
No
Yes
4000
3000
2000
1000
0
count
No
Yes
PhoneService

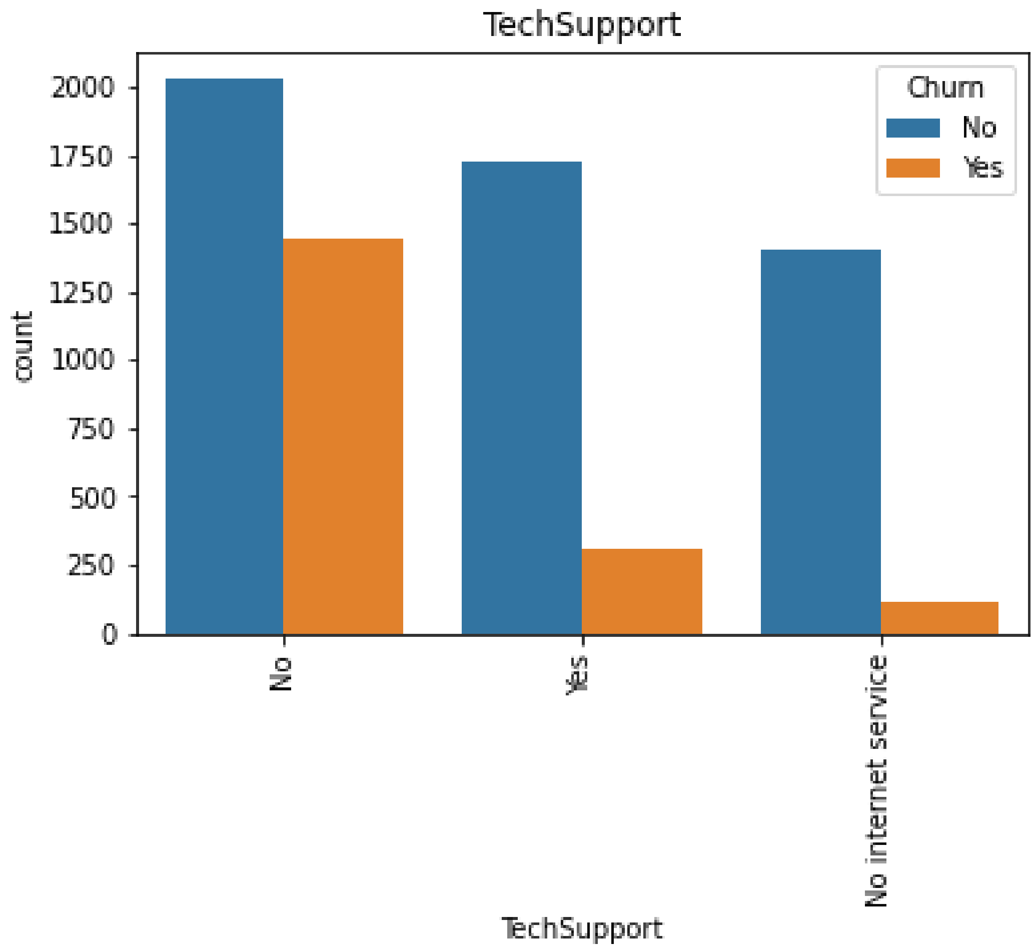

MultipleLines
Churn
No
Yes
2500
2000
1500
1000
500
0
count
No phone service
No
Yes
MultipleLines

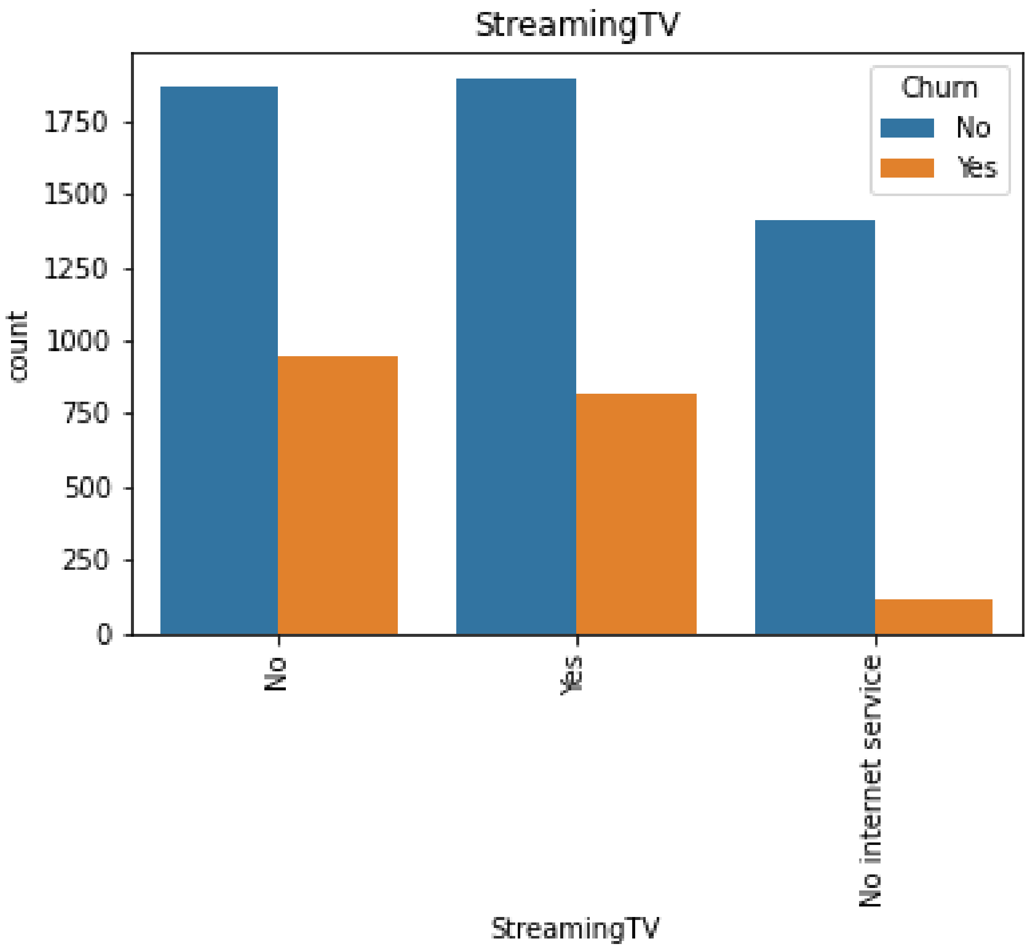

InternetService
2000
1750
1500
1250
1000
750
500
250
0
count
Churn
No
Yes
DSL
Fiber optic
No
InternetService

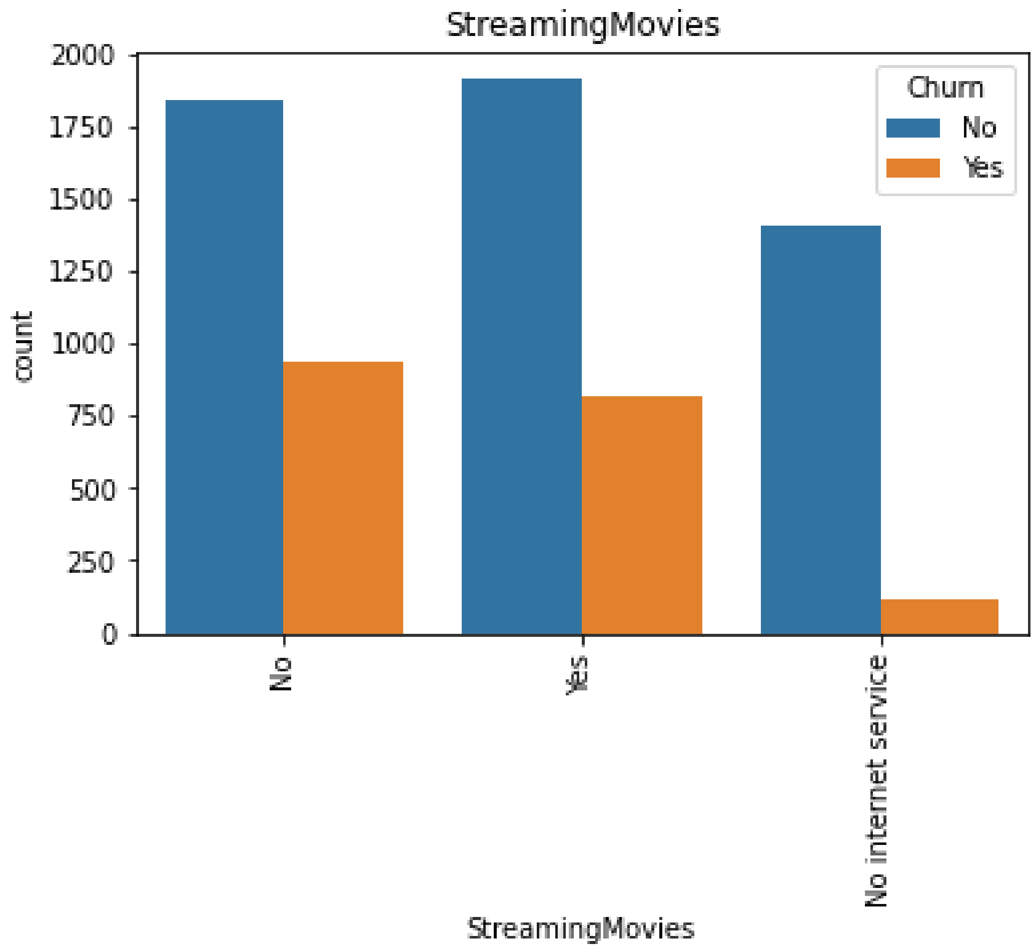

OnlineSecurity
Churn
No
Yes
2000
1750
1500
1250
1000
750
500
250
0
count
No
Yes
No internet service
OnlineSecurity

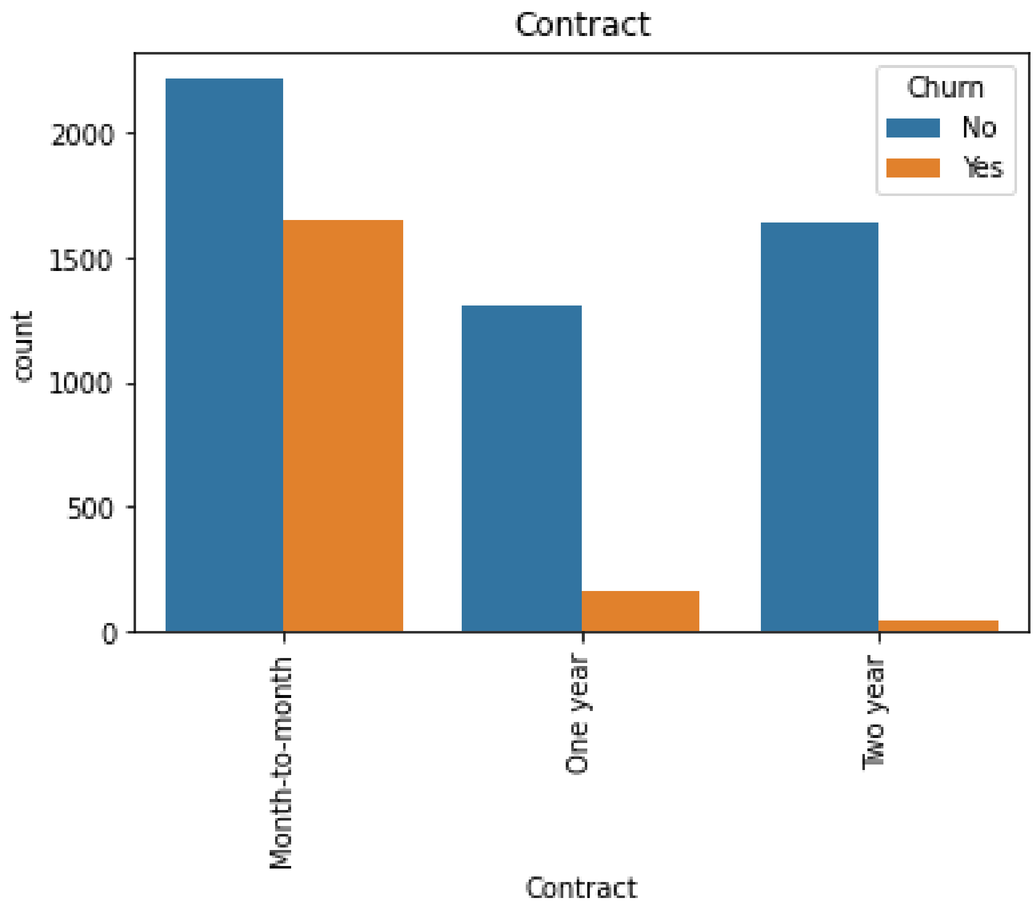

OnlineBackup
Churn
No
Yes
count
1750
1500
1250
1000
750
500
250
0
Yes
No
No internet service
OnlineBackup

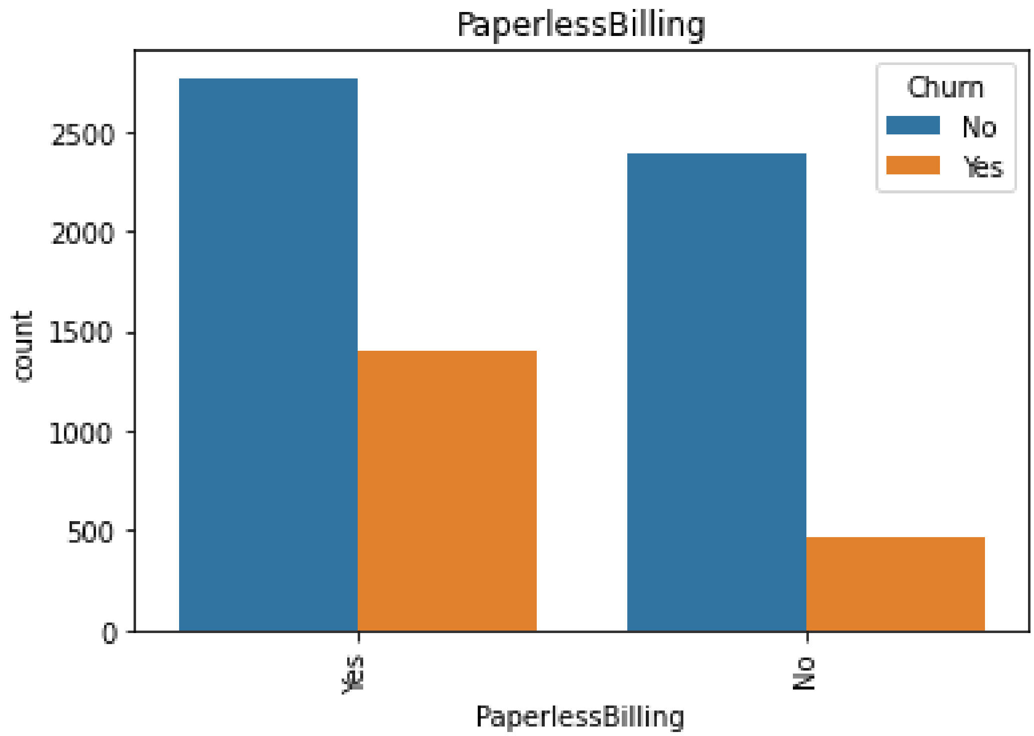

DeviceProtection
Churn
No
Yes
count
0
250
500
750
1000
1250
1500
1750
No
Yes
No internet service
DeviceProtection


TechSupport
Churn
No
Yes
count
2000
1750
1500
1250
1000
750
500
250
0
No
Yes
No internet service
TechSupport

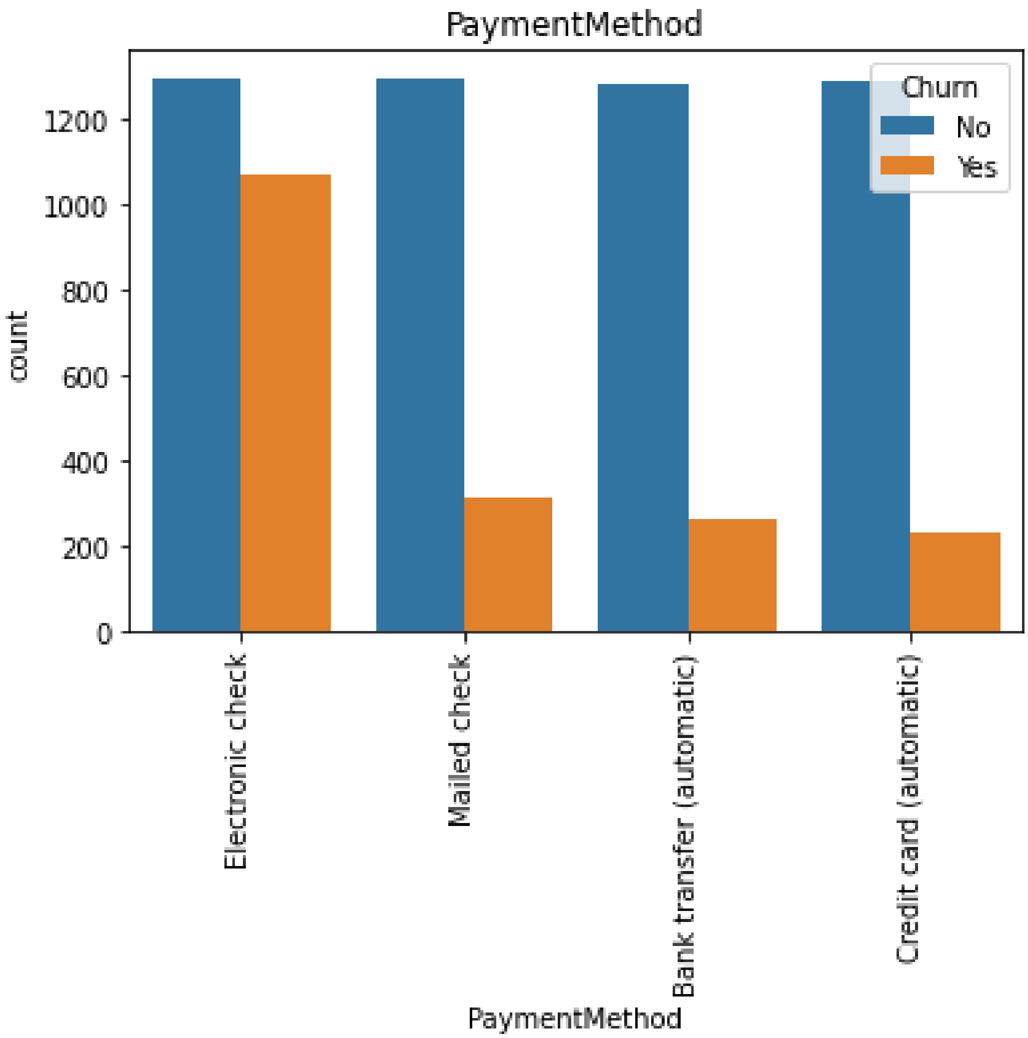

StreamingTV
Churn
No
Yes
1750
1500
1250
1000
750
500
250
0
count
No
Yes
No internet service
StreamingTV


StreamingMovies
2000
1750
1500
1250
1000
750
500
250
0
count
Churn
No
Yes
No
Yes
No internet service
StreamingMovies


Contract
Churn
No
Yes
count
2000
1500
1000
500
0
Month-to-month
One year
Two year
Contract



PaperlessBilling
Churn
No
Yes
2500
2000
1500
1000
500
0
count
Yes
No
PaperlessBilling



10 Spliting Dataset to Test and Train

Main dataset is splitted to Train and Test at the beggining with ratio of 30/70 before Feature Engineering

[12]:
```
training_data, testing_data = sklearn.model_selection.train_test_split(
    df, test_size=0.30, random_state=42
)
print(f"Train Dataset:{training_data.shape[0]:,}")
print(f"Test Dataset: {testing_data.shape[0]:,}")
```

```
Train Dataset:4,922
Test Dataset: 2,110
```

[13]:
```python
training_data.head()
```

[13]:
```
             gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
customerID
5154-VEKBL   Female              0      No         No       9           No
9052-DHNKM     Male              0      No         No      26          Yes
2988-PLAHS   Female              0      No         No       3          Yes
1196-AMORA     Male              0      No         No       7          Yes
6695-FRVEC     Male              0     Yes        Yes      67          Yes

                MultipleLines InternetService OnlineSecurity OnlineBackup  \
customerID
5154-VEKBL   No phone service             DSL            Yes           No
9052-DHNKM                Yes             DSL            Yes          Yes
2988-PLAHS                 No             DSL             No           No
1196-AMORA                Yes     Fiber optic             No           No
6695-FRVEC                 No             DSL            Yes           No

           DeviceProtection TechSupport StreamingTV StreamingMovies  \
customerID
5154-VEKBL              Yes         Yes         Yes             Yes
9052-DHNKM               No          No          No              No
2988-PLAHS              Yes          No         Yes             Yes
1196-AMORA               No          No          No              No
6695-FRVEC              Yes         Yes          No              No

                  Contract PaperlessBilling              PaymentMethod  \
customerID
5154-VEKBL   Month-to-month               No               Mailed check
9052-DHNKM         One year               No           Electronic check
2988-PLAHS         One year              Yes           Electronic check
1196-AMORA   Month-to-month               No           Electronic check
6695-FRVEC         Two year              Yes  Bank transfer (automatic)

             MonthlyCharges  TotalCharges Churn
customerID
5154-VEKBL            58.50        539.85   Yes
9052-DHNKM            61.55       1581.95    No
2988-PLAHS            69.95        220.45    No
1196-AMORA            73.60        520.00   Yes
6695-FRVEC            60.40       3953.70    No
```

Train and Test dataset information: (Shape, Dimension and Size)

[14]:
```
print("Training Dataset:")
print(f"Shape: {training_data.shape}")
print(f"Dimension: {training_data.ndim}")
print(f"Size: {training_data.size}", "\n")
print("Test Dataset:")
print(f"Shape:{testing_data.shape}")
print(f"Dimension:{testing_data.ndim}")
print(f"Size:{testing_data.size}")
```

```
Training Dataset:
Shape: (4922, 20)
Dimension: 2
Size: 98440

Test Dataset:
Shape:(2110, 20)
Dimension:2
Size:42200
```

Feature "Churn" is our target label which is dropped as part of train test split.

11 Feature Engineering

To Use ML algorithms all features must be converted to numeric, therefore we explore the data to investigate non-numeric features and convert them to numerical values based on existing methods.

Presentation of Numerical Columns

[15]:
```
df.describe()
```

[15]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges
count	7032.000000	7032.000000	7032.000000	7032.000000
mean	0.162400	32.421786	64.798208	2283.300441
std	0.368844	24.545260	30.085974	2266.771362
min	0.000000	1.000000	18.250000	18.800000
25%	0.000000	9.000000	35.587500	401.450000
50%	0.000000	29.000000	70.350000	1397.475000
75%	0.000000	55.000000	89.862500	3794.737500
max	1.000000	72.000000	118.750000	8684.800000

Presentation of Object Columns

[16]:
```
df.describe(include=["object"])
```

[16]:

	gender	Partner	Dependents	PhoneService	MultipleLines	InternetService \
count	7032	7032	7032	7032	7032	7032
unique	2	2	2	2	3	3
top	Male	No	No	Yes	No	Fiber optic
freq	3549	3639	4933	6352	3385	3096

```
       OnlineSecurity OnlineBackup DeviceProtection TechSupport StreamingTV  \
count            7032         7032             7032        7032        7032
unique              3            3                3           3           3
top                No           No               No          No          No
freq             3497         3087             3094        3472        2809

       StreamingMovies        Contract PaperlessBilling     PaymentMethod  \
count             7032            7032             7032              7032
unique               3               3                2                 4
top                 No  Month-to-month              Yes  Electronic check
freq              2781            3875             4168              2365

       Churn
count   7032
unique     2
top       No
freq    5163
```

The codes below indicate the unique count and values for each object feature.

[17]:
```
for i in df.select_dtypes(include="object"):
    print("Column", i, ":")
    print("Unique Values:", df[i].unique())
    print("Count of Unique values:", df[i].nunique(), "\n")
```

```
Column gender :
Unique Values: ['Female' 'Male']
Count of Unique values: 2

Column Partner :
Unique Values: ['Yes' 'No']
Count of Unique values: 2

Column Dependents :
Unique Values: ['No' 'Yes']
Count of Unique values: 2

Column PhoneService :
Unique Values: ['No' 'Yes']
Count of Unique values: 2

Column MultipleLines :
Unique Values: ['No phone service' 'No' 'Yes']
Count of Unique values: 3

Column InternetService :
Unique Values: ['DSL' 'Fiber optic' 'No']
```

```
Count of Unique values: 3

Column OnlineSecurity :
Unique Values: ['No' 'Yes' 'No internet service']
Count of Unique values: 3

Column OnlineBackup :
Unique Values: ['Yes' 'No' 'No internet service']
Count of Unique values: 3

Column DeviceProtection :
Unique Values: ['No' 'Yes' 'No internet service']
Count of Unique values: 3

Column TechSupport :
Unique Values: ['No' 'Yes' 'No internet service']
Count of Unique values: 3

Column StreamingTV :
Unique Values: ['No' 'Yes' 'No internet service']
Count of Unique values: 3

Column StreamingMovies :
Unique Values: ['No' 'Yes' 'No internet service']
Count of Unique values: 3

Column Contract :
Unique Values: ['Month-to-month' 'One year' 'Two year']
Count of Unique values: 3

Column PaperlessBilling :
Unique Values: ['Yes' 'No']
Count of Unique values: 2

Column PaymentMethod :
Unique Values: ['Electronic check' 'Mailed check' 'Bank transfer (automatic)'
 'Credit card (automatic)']
Count of Unique values: 4

Column Churn :
Unique Values: ['No' 'Yes']
Count of Unique values: 2
```

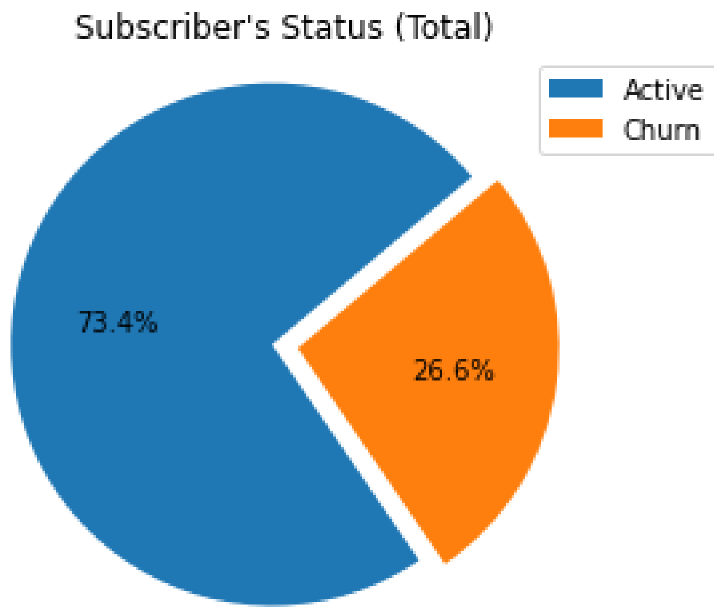
12 Total Churn Disstirbution

As our target:(Y) is the "Churn" column, therefore we explore a graphical distribution of churned and active customers as below to identify whether our data is balanced or not, in the case of imbalanced data we need to balance and normalize it.

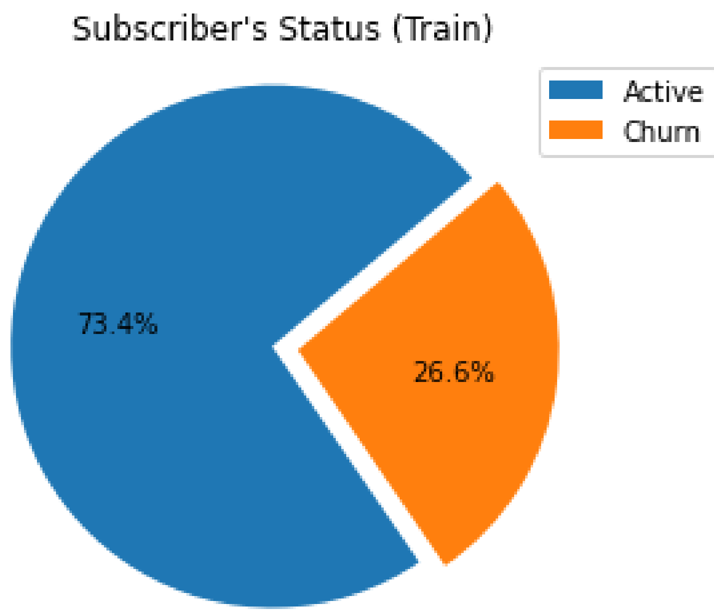
[18]:
```
active = df[(df["Churn"] == "No")].count()[1]
churn = df[(df["Churn"] == "Yes")].count()[1]

print("Active Subs: ", f"{active:,}")
print("Churn Subs: ", f"{churn:,}")

sizes = [active, churn]
labels = "Active", "Churn"
explode = (0, 0.1)
fig1, ax1 = plt.subplots()
ax1.pie(sizes, explode=explode, autopct="%1.1f%%", startangle=40)
ax1.axis("equal")
ax1.set_title("Subscriber's Status (Total)")
ax1.legend(labels)
plt.show()

active = training_data[(training_data["Churn"] == "No")].count()[1]
churn = training_data[(training_data["Churn"] == "Yes")].count()[1]
print("Active Subs: ", f"{active:,}")
print("Churn Subs: ", f"{churn:,}")

sizes = [active, churn]
labels = "Active", "Churn"
explode = (0, 0.1)
fig1, ax1 = plt.subplots()
ax1.pie(sizes, explode=explode, autopct="%1.1f%%", startangle=40)
ax1.axis("equal")
ax1.set_title("Subscriber's Status (Train)")

ax1.legend(labels)
plt.show()

active = testing_data[(testing_data["Churn"] == "No")].count()[1]
churn = testing_data[(testing_data["Churn"] == "Yes")].count()[1]
print("Active Subs: ", f"{active:,}")
print("Churn Subs: ", f"{churn:,}")

sizes = [active, churn]
labels = "Active", "Churn"
explode = (0, 0.1)
fig1, ax1 = plt.subplots()
ax1.pie(sizes, explode=explode, autopct="%1.1f%%", startangle=40)
```

```
ax1.axis("equal")
ax1.set_title("Subscriber's Status (Test)")

ax1.legend(labels)
plt.show()
```

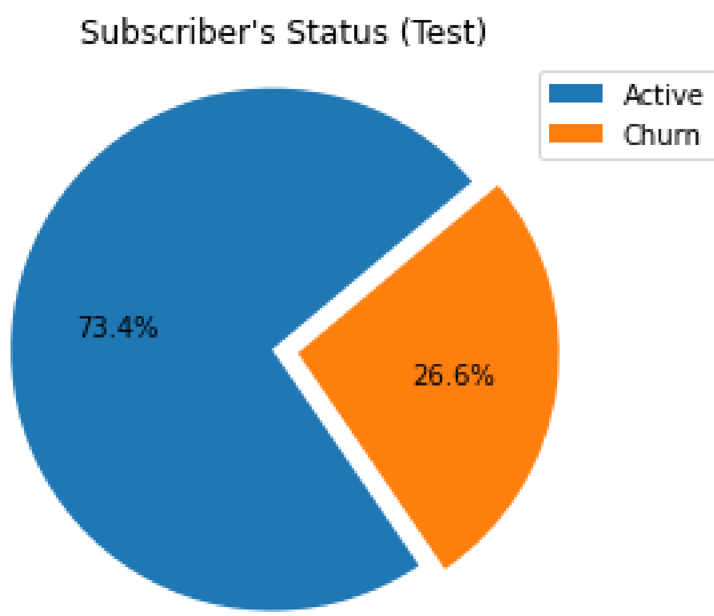
```
Active Subs:  5,163
Churn Subs:  1,869
```




```
Active Subs:  3,614
Churn Subs:  1,308
```




```
Active Subs:  1,549
Churn Subs:  561
```



13 Label Encoding

As "Churn" column is our target column we decided to encode it with labelEncoder to prevent header name changing

[19]:
```
lbl_train = LabelEncoder()
training_data["Churn"] = lbl_train.fit_transform(training_data["Churn"])
```

[20]:
```
training_data.head(3)
```

[20]:
```
            gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
customerID
5154-VEKBL  Female              0      No         No       9           No
9052-DHNKM    Male              0      No         No      26          Yes
2988-PLAHS  Female              0      No         No       3          Yes

               MultipleLines InternetService OnlineSecurity OnlineBackup  \
customerID
5154-VEKBL  No phone service             DSL            Yes           No
9052-DHNKM               Yes             DSL            Yes          Yes
2988-PLAHS                No             DSL             No           No

           DeviceProtection TechSupport StreamingTV StreamingMovies  \
customerID
5154-VEKBL              Yes         Yes         Yes             Yes
9052-DHNKM               No          No          No              No
2988-PLAHS              Yes          No         Yes             Yes

                  Contract PaperlessBilling     PaymentMethod  MonthlyCharges  \
customerID
5154-VEKBL  Month-to-month               No      Mailed check           58.50
9052-DHNKM        One year               No  Electronic check           61.55
2988-PLAHS        One year              Yes  Electronic check           69.95

            TotalCharges  Churn
customerID
5154-VEKBL        539.85      1
9052-DHNKM       1581.95      0
2988-PLAHS        220.45      0
```

[21]:
```
lbl_test = LabelEncoder()
testing_data["Churn"] = lbl_test.fit_transform(testing_data["Churn"])
```

[22]:
```
testing_data.head()
```

[22]:
```
            gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
customerID
6614-YWYSC    Male              1     Yes         No      61          Yes
```

```
9546-KDTRB  Female              0      No          No      19          Yes
0871-URUWO    Male              0     Yes          No      13          Yes
5151-HQRDG    Male              0     Yes          No      37          Yes
6624-JDRDS  Female              0      No          No       6           No

               MultipleLines InternetService       OnlineSecurity  \
customerID
6614-YWYSC               Yes              No  No internet service
9546-KDTRB               Yes              No  No internet service
0871-URUWO               Yes     Fiber optic                   No
5151-HQRDG               Yes             DSL                  Yes
6624-JDRDS  No phone service             DSL                  Yes

                   OnlineBackup     DevicePerotection          TechSupport  \
customerID
6614-YWYSC  No internet service  No internet service  No internet service
9546-KDTRB  No internet service  No internet service  No internet service
0871-URUWO                   No                  Yes                   No
5151-HQRDG                   No                   No                   No
6624-JDRDS                   No                   No                   No

                    StreamingTV      StreamingMovies        Contract  \
customerID
6614-YWYSC  No internet service  No internet service        Two year
9546-KDTRB  No internet service  No internet service  Month-to-month
0871-URUWO                  Yes                  Yes  Month-to-month
5151-HQRDG                   No                   No  Month-to-month
6624-JDRDS                   No                   No  Month-to-month

           PaperlessBilling              PaymentMethod  MonthlyCharges  \
customerID
6614-YWYSC               No  Bank transfer (automatic)           25.00
9546-KDTRB               No  Bank transfer (automatic)           24.70
0871-URUWO              Yes    Credit card (automatic)          102.25
5151-HQRDG              Yes               Mailed check           55.05
6624-JDRDS               No  Bank transfer (automatic)           29.45

            TotalCharges  Churn
customerID
6614-YWYSC       1501.75      0
9546-KDTRB        465.85      0
0871-URUWO       1359.00      1
5151-HQRDG       2030.75      0
6624-JDRDS        161.45      0
```

14 Get Dummies Encoding

For variables with equal or more than 2 categories, we used Get-Dummmies encoding. as we explored in the dataset, there is no priority between values for each feature, therefore, to prevent adding any weight to values we converted them with the Get-Dummies method.

[23]:
```python
training_data = pd.get_dummies(
    training_data,
    columns=[
        "gender",
        "Partner",
        "Dependents",
        "PhoneService",
        "MultipleLines",
        "InternetService",
        "OnlineSecurity",
        "OnlineBackup",
        "DeviceProtection",
        "TechSupport",
        "StreamingTV",
        "StreamingMovies",
        "Contract",
        "PaperlessBilling",
        "PaymentMethod",
    ],
)
```

To observe all features are converted to numerical values.

[24]:
```python
training_data.head(3)
```

[24]:
```
            SeniorCitizen  tenure  MonthlyCharges  TotalCharges  Churn  \
customerID
5154-VEKBL              0       9           58.50        539.85      1
9052-DHNKM              0      26           61.55       1581.95      0
2988-PLAHS              0       3           69.95        220.45      0

            gender_Female  gender_Male  Partner_No  Partner_Yes  \
customerID
5154-VEKBL              1            0           1            0
9052-DHNKM              0            1           1            0
2988-PLAHS              1            0           1            0

            Dependents_No  …  StreamingMovies_Yes  Contract_Month-to-month  \
customerID                 …
5154-VEKBL              1  …                    1                        1
9052-DHNKM              1  …                    0                        0
2988-PLAHS              1  …                    1                        0
```

```
            Contract_One year  Contract_Two year  PaperlessBilling_No  \
customerID
5154-VEKBL                  0                  0                    1
9052-DHNKM                  1                  0                    1
2988-PLAHS                  1                  0                    0

            PaperlessBilling_Yes  PaymentMethod_Bank transfer (automatic)  \
customerID
5154-VEKBL                     0                                        0
9052-DHNKM                     0                                        0
2988-PLAHS                     1                                        0

            PaymentMethod_Credit card (automatic)  \
customerID
5154-VEKBL                                      0
9052-DHNKM                                      0
2988-PLAHS                                      0

            PaymentMethod_Electronic check  PaymentMethod_Mailed check
customerID
5154-VEKBL                               0                           1
9052-DHNKM                               1                           0
2988-PLAHS                               1                           0

[3 rows x 46 columns]
```

As we encoded some features for our Train dataset with the same approach we will do it for the test dataset as well.

[25]:
```
testing_data = pd.get_dummies(
    testing_data,
    columns=[
        "gender",
        "Partner",
        "Dependents",
        "PhoneService",
        "MultipleLines",
        "InternetService",
        "OnlineSecurity",
        "OnlineBackup",
        "DeviceProtection",
        "TechSupport",
        "StreamingTV",
        "StreamingMovies",
        "Contract",
        "PaperlessBilling",
```

```
        "PaymentMethod",
    ],
)
```

To observe all features are converted to numerical values.

[26]:
```
testing_data.head(3)
```

[26]:
```
            SeniorCitizen  tenure  MonthlyCharges  TotalCharges  Churn  \
customerID
6614-YWYSC              1      61           25.00       1501.75      0
9546-KDTRB              0      19           24.70        465.85      0
0871-URUWO              0      13          102.25       1359.00      1

            gender_Female  gender_Male  Partner_No  Partner_Yes  \
customerID
6614-YWYSC              0            1           0            1
9546-KDTRB              1            0           1            0
0871-URUWO              0            1           0            1

            Dependents_No  …  StreamingMovies_Yes  Contract_Month-to-month  \
customerID                 …
6614-YWYSC              1  …                    0                        0
9546-KDTRB              1  …                    0                        1
0871-URUWO              1  …                    1                        1

            Contract_One year  Contract_Two year  PaperlessBilling_No  \
customerID
6614-YWYSC                  0                  1                    1
9546-KDTRB                  0                  0                    1
0871-URUWO                  0                  0                    0

            PaperlessBilling_Yes  PaymentMethod_Bank transfer (automatic)  \
customerID
6614-YWYSC                     0                                        1
9546-KDTRB                     0                                        1
0871-URUWO                     1                                        0

            PaymentMethod_Credit card (automatic)  \
customerID
6614-YWYSC                                      0
9546-KDTRB                                      0
0871-URUWO                                      1

            PaymentMethod_Electronic check  PaymentMethod_Mailed check
customerID
6614-YWYSC                               0                           0
9546-KDTRB                               0                           0
```

```
0871-URUWO                                          0                            0

[3 rows x 46 columns]
```

Split Training Data to test and train.

we did this approach to prevent any data leakage between our main test and train dataset.

[27]:
```
x1 = training_data.drop("Churn", axis=1)
y1 = training_data["Churn"]

x1_train, x1_test, y1_train, y1_test = train_test_split(
    x1, y1, test_size=0.30, random_state=42
)
print("X_train", len(x1_train))
print("X_test", len(x1_test))
print("y_train", len(y1_train))
print("y_test", len(y1_test))
```

```
X_train 3445
X_test 1477
y_train 3445
y_test 1477
```

[28]:
```
x2 = testing_data.drop("Churn", axis=1)
y2 = testing_data["Churn"]

x2_train, x2_test, y2_train, y2_test = train_test_split(
    x2, y2, test_size=0.30, random_state=42
)
print("X_train", len(x2_train))
print("X_test", len(x2_test))
print("y_train", len(y2_train))
print("y_test", len(y2_test))
```

```
X_train 1477
X_test 633
y_train 1477
y_test 633
```

15 Feature Engineering (Over Sampling)

As we explored our dataset previously, our target label which is "Churn" is imbalanced, therefore we need to balance our dataset.

For this purpose, we used SMOTE technic to generate some synthetic samples for the minority class.

[29]:
```
sm1 = imblearn.over_sampling.SMOTE()
x1_train, y1_train = sm1.fit_resample(x1_train, y1_train)
```

[30]:
```
sm2 = imblearn.over_sampling.SMOTE()
x2_train, y2_train = sm2.fit_resample(x2_train, y2_train)
```

16 Feature Engineering (Standardization)

As our features have different scales like gender and other categories most are boolean, but tenure is counting months, on the other hand, we have prices like Total Charges and Monthly charges which are money but there is no preferably among them and all features weight is same. therefore we use the standardization model to rescale our feature to prevent bias in our prediction.

We do standardization once for our training dataset and once for the test dataset.

x1_train and x1_test belong to the Training Dataset.

[31]:
```
scaler1 = sklearn.preprocessing.StandardScaler(with_mean=False)
scaler1.fit(x1_train)
x1_train = scaler1.transform(x1_train)
x1_test = scaler1.transform(x1_test)

print("x1_train Size", x1_train.shape)
print("x1_test size", x1_test.shape)
```

```
x1_train Size (5048, 45)
x1_test size (1477, 45)
```

Standardization for the test dataset.

x2_train and x2_test belong to the Testing Dataset.

[32]:
```
scaler2 = sklearn.preprocessing.StandardScaler(with_mean=False)
scaler2.fit(x2_train)
x2_train = scaler2.transform(x2_train)
x2_test = scaler2.transform(x2_test)

print("x_train size", x2_train.shape)
print("x_test size", x2_test.shape)
```

```
x_train size (2166, 45)
x_test size (633, 45)
```

17 Model Assessment

18 Model Selection and Hyperparameter Tunning

In the following steps, we will tune some Hyperparameters which were important according to Scikit-learn documentation.

below Classification algorithms are selected and tuned: 1. Decision Tree 2. Support vector machines (SVMs) 3. Gaussian Naive Bayes 4. K-Nearest Neighbour (KNN) 5. Logistic Regression

19 1. Decision Tree

[33]:
```python
parameters_grid = {
    "criterion": ["gini", "entropy"],
    "max_depth": range(1, 50, 2),
    "min_samples_split": range(2, 40, 2),
}
model_dt = sklearn.model_selection.GridSearchCV(
    sklearn.tree.DecisionTreeClassifier(),
    parameters_grid,
    scoring="accuracy",
    cv=5,
    verbose=2,
    n_jobs=-1,
)
model_dt.fit(x1_train, y1_train)
print("Accuracy of best Decision Tree classfier = {:.2f}".format(model_dt.
  ↪best_score_))
print(
    "Best found Hyperparameters of Decision Tree classifier ={}".format(
        model_dt.best_params_
    )
)
```

```
Fitting 5 folds for each of 950 candidates, totalling 4750 fits
Accuracy of best Decision Tree classfier = 0.83
Best found Hyperparameters of Decision Tree classifier ={'criterion': 'gini',
'max_depth': 9, 'min_samples_split': 26}
```

20 2. SVM

[34]:
```python
parameters_grid = {
    "kernel": ["rbf", "poly", "sigmoid"],
    "C": [ 0.01, 0.1, 1, 10,100,200,300]
}
model_svm = sklearn.model_selection.GridSearchCV(
    sklearn.svm.SVC(), parameters_grid, scoring="accuracy", cv=5, verbose=2,␣
  ↪n_jobs=-1
)
model_svm.fit(x1_train, y1_train)
print("Accuracy of best SVM classfier = {:.2f}".format(model_svm.best_score_))
print("Best found Hyperparameters of SVM classifier ={}".format(model_svm.
  ↪best_params_))
```

```
Fitting 5 folds for each of 21 candidates, totalling 105 fits
Accuracy of best SVM classfier = 0.83
Best found Hyperparameters of SVM classifier ={'C': 1, 'kernel': 'rbf'}
```

21 3. Gaussian Naive Bayes

[35]:
```
parameters_grid = {"var_smoothing": np.logspace(0, -9, num=100)}

model_naiveb = sklearn.model_selection.GridSearchCV(
    sklearn.naive_bayes.GaussianNB(),
    parameters_grid,
    scoring="accuracy",
    cv=5,
    verbose=2,
    n_jobs=-1,
)
model_naiveb.fit(x1_train, y1_train)
print(
    "Accuracy of best Naive Bayes classfier = {:.2f}".format(model_naiveb.
 ↪best_score_)
)
print(
    "Best found Hyperparameters of Naive Bayes classifier ={}".format(
        model_naiveb.best_params_
    )
)
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
Accuracy of best Naive Bayes classfier = 0.79
Best found Hyperparameters of Naive Bayes classifier ={'var_smoothing':
0.02310129700083159}
```

22 4. KNN

[36]:
```
parameters_grid = {
    "leaf_size": range(1, 10),
    "n_neighbors": range(1, 40),
    "p": [1, 2],
    "weights": ["uniform", "distance"],
    "metric": ["euclidean", "manhattan", "minkowski"],
}

model_knn = sklearn.model_selection.GridSearchCV(
    sklearn.neighbors.KNeighborsClassifier(),
    parameters_grid,
    scoring="accuracy",
```

```
    cv=5,
    verbose=2,
    n_jobs=-1,
)
model_knn.fit(x1_train, y1_train)
print("Accuracy of best KNN classfier = {:.2f}".format(model_knn.best_score_))
print("Best found Hyperparameters of KNN classifier ={}".format(model_knn.
 ↪best_params_))
```

```
Fitting 5 folds for each of 4212 candidates, totalling 21060 fits
Accuracy of best KNN classfier = 0.83
Best found Hyperparameters of KNN classifier ={'leaf_size': 1, 'metric':
'manhattan', 'n_neighbors': 10, 'p': 1, 'weights': 'uniform'}
```

23 5. Logistic Regression

[37]:
```
parameters_grid = {
    "solver": ["newton-cg", "lbfgs", "liblinear", "sag", "saga"],
    "penalty": ["l2"],
    "C": [
        1000,
        1100,
        1200,
        1300,
        1400,
        1500,
        1600,
        2000,
    ],
    "tol": np.logspace(0, -9, num=100),
}

model_lr = sklearn.model_selection.GridSearchCV(
    sklearn.linear_model.LogisticRegression(),
    parameters_grid,
    scoring="accuracy",
    cv=5,
    verbose=2,
    n_jobs=-1,
)
model_lr.fit(x1_train, y1_train)
print(
    "Accuracy of best Logistic Regression classfier = {:.2f}".format(
        model_lr.best_score_
    )
)
print(
```

```
    "Best found Hyperparameters of Logistic Regression classifier ={}".format(
        model_lr.best_params_
    )
)
```

```
Fitting 5 folds for each of 4000 candidates, totalling 20000 fits
Accuracy of best Logistic Regression classfier = 0.86
Best found Hyperparameters of Logistic Regression classifier ={'C': 1100,
'penalty': 'l2', 'solver': 'sag', 'tol': 0.1}
```

24 Training and Testing Models

25 1. Decision Tree

we will set all hyperparameters which are found in the above GridSearch Algorithm in the following models to train our model; then accordingly predict our test dataset. in our prediction we will represent four measures as below: * "Accuracy" * "Precision" * "Recall" * "F1"

[44]:
```
model_dt = sklearn.tree.DecisionTreeClassifier(
    criterion="gini", max_depth=9, min_samples_split=26
)
model_dt.fit(x1_test, y1_test)
```

[44]:
```
DecisionTreeClassifier(max_depth=9, min_samples_split=26)
```

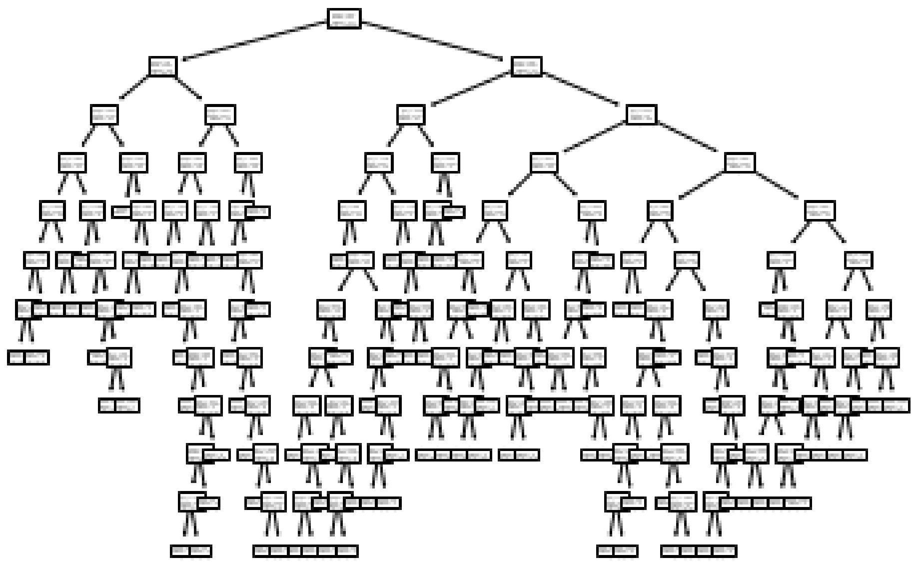
[45]:
```
y_predicted = model_dt.predict(x2_test)
accuracy_dt = sklearn.metrics.accuracy_score(y2_test, y_predicted)
accuracy_dt = round(accuracy_dt * 100, 2)
precision_dt = round(sklearn.metrics.precision_score(y2_test, y_predicted) *␣
 ↪100, 2)
recall_dt = round(sklearn.metrics.recall_score(y2_test, y_predicted) * 100, 2)
f1_dt = round(sklearn.metrics.f1_score(y2_test, y_predicted) * 100, 2)
# cm = sklearn.metrics.confusion_matrix(y2_test, y_predicted)

header = ["Accuracy", "Precision", "Recall", "F1"]
data_dt = np.array([accuracy_dt, precision_dt, recall_dt, f1_dt])
pd.DataFrame(data_dt, header)
# print(cm)
```

[45]:

	0
Accuracy	77.25
Precision	57.42
Recall	53.29
F1	55.28

Graphical view of Decision Tree

[46]:
```
tree.plot_tree(model_dt);
```



26 2. SVM

[48]:
```
model_svm = sklearn.svm.SVC(C=1, kernel="rbf")
model_svm.fit(x1_test, y1_test)
```

[48]: SVC(C=1)

[50]:
```
y_predicted = model_svm.predict(x2_test)
accuracy_svm = sklearn.metrics.accuracy_score(y2_test, y_predicted)
accuracy_svm = round(accuracy_svm * 100, 2)
precision_svm = round(sklearn.metrics.precision_score(y2_test, y_predicted) *
    100, 2)
recall_svm = round(sklearn.metrics.recall_score(y2_test, y_predicted) * 100, 2)
f1_svm = round(sklearn.metrics.f1_score(y2_test, y_predicted) * 100, 2)
# cm = sklearn.metrics.confusion_matrix(y2_test, y_predicted)
header = ["Accuracy", "Precision", "Recall", "F1"]
data_svm = np.array([accuracy_svm, precision_svm, recall_svm, f1_svm])
pd.DataFrame(data_svm, header)
# print(cm)
```

[50]:

	0
Accuracy	79.78
Precision	64.44
Recall	52.10
F1	57.62

27 3. Gaussian Naive Bayes

[53]:
```python
model_nb = sklearn.naive_bayes.GaussianNB(var_smoothing=0.02310129700083159)
model_nb.fit(x1_test, y1_test)
```

[53]:
```
GaussianNB(var_smoothing=0.02310129700083159)
```

[54]:
```python
y_predicted = model_nb.predict(x2_test)
accuracy_gnb = sklearn.metrics.accuracy_score(y2_test, y_predicted)
accuracy_gnb = round(accuracy_gnb * 100, 2)
precision_gnb = round(sklearn.metrics.precision_score(y2_test, y_predicted) *␣
↪100, 2)
recall_gnb = round(sklearn.metrics.recall_score(y2_test, y_predicted) * 100, 2)
f1_gnb = round(sklearn.metrics.f1_score(y2_test, y_predicted) * 100, 2)

header = ["Accuracy", "Precision", "Recall", "F1"]
data_gnb = np.array([accuracy_gnb, precision_gnb, recall_gnb, f1_gnb])
pd.DataFrame(data_gnb, header)
```

[54]:

	0
Accuracy	68.72
Precision	45.14
Recall	86.23
F1	59.26

28 4. KNN

[59]:
```python
model_knn = sklearn.neighbors.KNeighborsClassifier(
    leaf_size=1, n_neighbors=10, metric="manhattan", p=1, weights="uniform"
)
model_knn.fit(x1_test, y1_test)
```

[59]:
```
KNeighborsClassifier(leaf_size=1, metric='manhattan', n_neighbors=10, p=1)
```

[60]:
```python
y_predicted = model_knn.predict(x2_test)
accuracy_knn = sklearn.metrics.accuracy_score(y2_test, y_predicted)
accuracy_knn = round(accuracy_knn * 100, 2)
precision_knn = round(sklearn.metrics.precision_score(y2_test, y_predicted) *␣
↪100, 2)
recall_knn = round(sklearn.metrics.recall_score(y2_test, y_predicted) * 100, 2)
f1_knn = round(sklearn.metrics.f1_score(y2_test, y_predicted) * 100, 2)

header = ["Accuracy", "Precision", "Recall", "F1"]
data_knn = np.array([accuracy_knn, precision_knn, recall_knn, f1_knn])
pd.DataFrame(data_knn, header)
```

[60]:

	0
Accuracy	78.52
Precision	60.26
Recall	54.49
F1	57.23

29 5. Logistic Regression

[63]:
```
model_lr = sklearn.linear_model.LogisticRegression(
    C=1100, penalty="l2", solver="sag", tol= 0.1
)
model_lr.fit(x1_test, y1_test)
```

[63]: LogisticRegression(C=1100, solver='sag', tol=0.1)

[64]:
```
y_predicted = model_lr.predict(x2_test)
accuracy_lr = sklearn.metrics.accuracy_score(y2_test, y_predicted)
accuracy_lr = round(accuracy_lr * 100, 2)
precision_lr = round(sklearn.metrics.precision_score(y2_test, y_predicted) *␣
  ↪100, 2)
recall_lr = round(sklearn.metrics.recall_score(y2_test, y_predicted) * 100, 2)
f1_lr = round(sklearn.metrics.f1_score(y2_test, y_predicted) * 100, 2)

header = ["Accuracy", "Precision", "Recall", "F1"]
data_lr = np.array([accuracy_lr, precision_lr, recall_lr, f1_lr])
pd.DataFrame(data_lr, header)
```

[64]:

	0
Accuracy	80.57
Precision	67.19
Recall	51.50
F1	58.31

30 Model Selection

All the above results are integrated into the below table to have a better view and conclusion.

[66]:
```
result = BeautifulTable()
result.set_style(BeautifulTable.STYLE_RST)
result.column_headers = ["Model", "Accuracy", "Precision", "Recall", "F1"]
result.append_row(["Decision Tree", accuracy_dt, precision_dt, recall_dt,␣
  ↪f1_dt])
result.append_row(["SVM", accuracy_svm, precision_svm, recall_svm, f1_svm])
result.append_row(["Gaussian NB", accuracy_gnb, precision_gnb, recall_gnb,␣
  ↪f1_gnb])
result.append_row(["KNN",  accuracy_knn, precision_knn, recall_knn, f1_knn])
```

```
result.append_row(
    [
        colored("Logistic Regression", "blue"),
        accuracy_lr,
        precision_lr,
        recall_lr,
        f1_lr,
    ]
)
result.rows.sort("Accuracy", reverse=True)
print(result)
```

```
===================== ========== =========== ======== =======
        Model          Accuracy   Precision   Recall     F1
===================== ========== =========== ======== =======
 Logistic Regression     80.57       67.19      51.5    58.31
         SVM             79.78       64.44      52.1    57.62
         KNN             78.52       60.26     54.49    57.23
    Decision Tree        77.25       57.42     53.29    55.28
     Gaussian NB         68.72       45.14     86.23    59.26
===================== ========== =========== ======== =======
```

As it is observed, the Logistic Regression method has better "Accuracy" and "Precision" in comparison with other models.

Also worth mentioning all test scores are lower than train score which mean we probably didn't have data leakage and overfitting issues.

31 Analysis, Suggestion

In the end, according to some approaches from expert ML specialists: "The metrics alone aren't enough to determine if our model is usable in real-life scenarios. (The definitive guide to Accuracy, Precision, and Recall for product developers, 2022) we must establish a baseline score and compare our model's performance against that baseline score." In the future, we'll try to focus on this metric to assess how much these findings are practical with real data and similar datasets.

Since our model doesn't concentrate on fraudulent activity, higher precision might be not our main area of interest. However, we utilized the other measures, like "Recall" and "F1," to see how our model was behaving.

According to what was learned via practice, the "SVM" method is not very effective for comparable data since it takes too long and costs too much to calculate. However, "KNN" is an additional option after "Logistic Regression," which is quicker than "SVM."

Other classification methods, including "Random Forest Classification" and "Kernel SVM," that may be used in practice are those that have been explored.

As mentioned, testing certain ML algorithms for Classification is just getting started, and more tuning will be required to attain better outcomes.

32 Reference:

- Kaggle.com. 2022. Telco Customer Churn. [online] Available at: https://www.kaggle.com/datasets/blastchar/telco-customer-churn?select=WA_Fn-UseC_-Telco-Customer-Churn.csv [Accessed 19 August 2022].
- Community.ibm.com. 2022. Telco customer churn (11.1.3+). [online] Available at: https://community.ibm.com/community/user/businessanalytics/blogs/steven-macko/2019/07/11/telco-customer-churn-1113 [Accessed 19 August 2022].
- DEV Community . 2022. The definitive guide to Accuracy, Precision, and Recall for product developers. [online] Available at: https://dev.to/mage_ai/the-definitive-guide-to-accuracy-precision-and-recall-for-product-developers-4ahg [Accessed 20 September 2022].