In [ ]:
```
# import required libraries
```

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

In [ ]:
```

```

problem statement:

customer retention usecase in telecom and customer behaving attributes to know churning, so we have to predict whether the cutomer is churner or not churner.

In [ ]:
```
# as operators are losing there cutomers in todays market
# telecom domain contain most specifically the following churning:
#     Tarrif plan churn   >> rs.300 to rs.179
#     Service Churn       >> Weekly/Monthly Subscription
#     Product Churn       >> Postpaid/Prepaid
#     Usage Churn         >> Inactive /Zero balance

#     Which leads to Subscriber Churn
```

Data Gathering

In [3]:
```
telco_data = pd.read_csv("WA_Fn-UseC_-Telco-Customer-Churn.csv")
telco_data.head()
```

Out[3]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Int
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	
4	9237-HQITU	Female	0	No	No	2	Yes	No	

5 rows × 21 columns

In [ ]:
```

```

EDA

In [ ]:
```
# first we have to analyse the ratio of the customers who are getting churned with res
```

In [4]:
```
telco_data.shape
```

Out[4]:
```
(7043, 21)
```

In [5]:
```
telco_data.columns
```

Out[5]:
```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

In [6]:
```
telco_data.dtypes
```

Out[6]:
```
customerID           object
gender               object
SeniorCitizen         int64
Partner              object
Dependents           object
tenure                int64
PhoneService         object
MultipleLines        object
InternetService      object
OnlineSecurity       object
OnlineBackup         object
DeviceProtection     object
TechSupport          object
StreamingTV          object
StreamingMovies      object
Contract             object
PaperlessBilling     object
PaymentMethod        object
MonthlyCharges      float64
TotalCharges         object
Churn                object
dtype: object
```

In [7]:
```
# describe >> which will give us insights of mean,count,max,min,25%... ( desciptive st
```

In [8]:
```
telco_data.describe()
```

Out[8]:

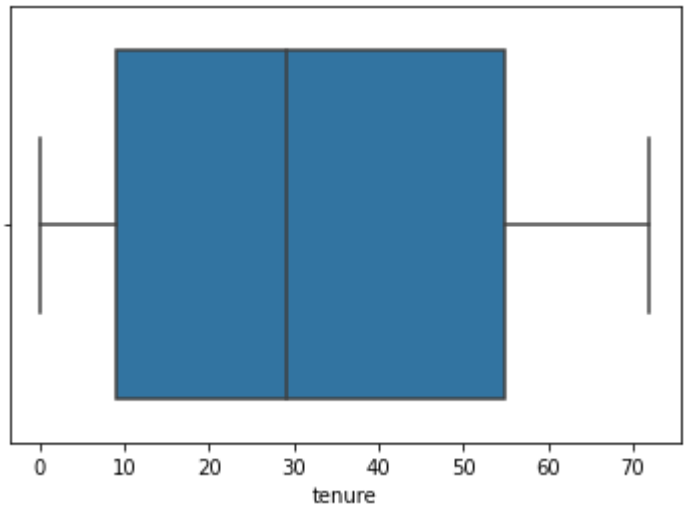
	SeniorCitizen	tenure	MonthlyCharges
count	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692
std	0.368612	24.559481	30.090047
min	0.000000	0.000000	18.250000
25%	0.000000	9.000000	35.500000
50%	0.000000	29.000000	70.350000
75%	0.000000	55.000000	89.850000
max	1.000000	72.000000	118.750000

Senior citizen columns is actually categorical hence 25%-50%-75% distribution is not proper. 75% of customers have tenure less than 55months. as mean of monthly charges is 64.76USD but the 75% customers have to pay 89.75USD pre month

lets check for outliers

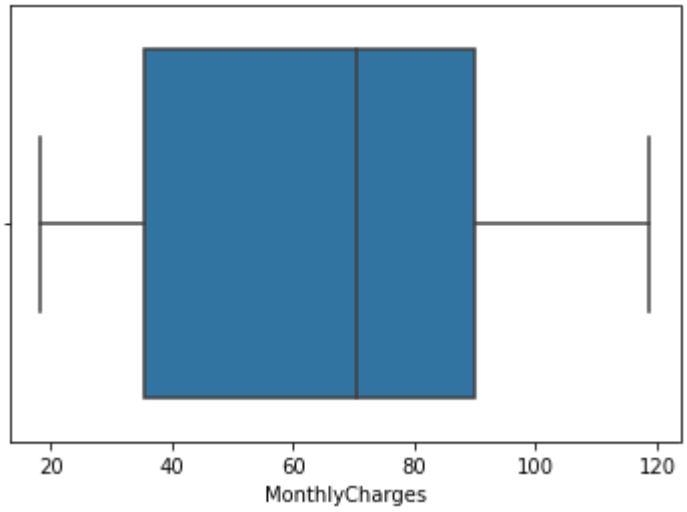
In [9]:
```
sns.boxplot(telco_data["tenure"])
```

Out[9]:
```
<AxesSubplot:xlabel='tenure'>
```



In [10]:
```
sns.boxplot(telco_data["MonthlyCharges"])
```

Out[10]:
```
<AxesSubplot:xlabel='MonthlyCharges'>
```



In [11]:
```
telco_data.info()
```

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

In [12]:
```
# lets check whether null value are present
```

In [13]:
```
telco_data.isnull().sum()
```

Out[13]:
```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

In [14]:
```
# lets identify the churners ratio
```

In [15]:
```
telco_data["Churn"].value_counts()
```

Out[15]:
```
No     5174
Yes    1869
Name: Churn, dtype: int64
```

In [16]:
```
(telco_data["Churn"].value_counts()/len(telco_data["Churn"]))*100
```

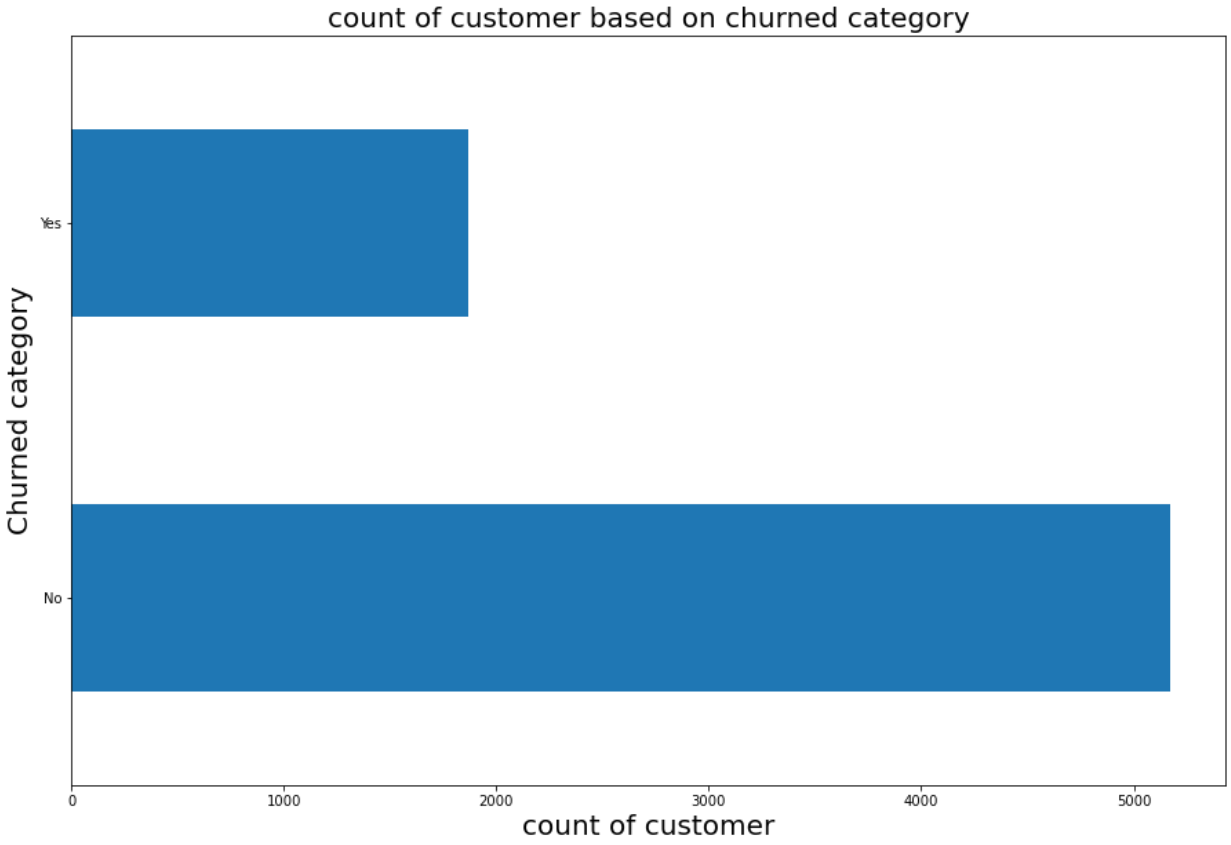
Out[16]:
```
No     73.463013
Yes    26.536987
Name: Churn, dtype: float64
```

There are 26.53 % churners and 73.46 % are non churners

In [17]:
```
# lets check plot
```

In [18]:
```
telco_data["Churn"].value_counts().plot(kind="barh",figsize=(15,10))
plt.xlabel("count of customer",fontsize=20)
plt.ylabel("Churned category",fontsize=20)
plt.title("count of customer based on churned category",fontsize=20)
```

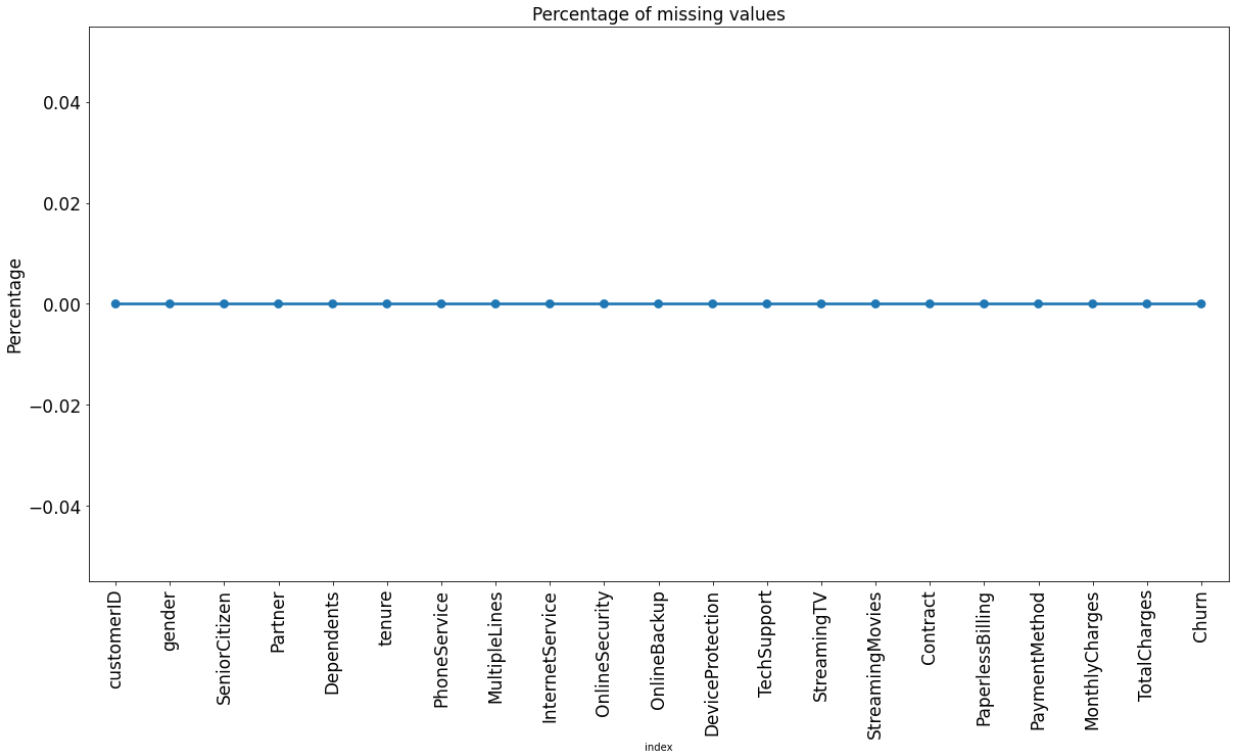
Out[18]:
```
Text(0.5, 1.0, 'count of customer based on churned category')
```



as data is highly imbalanced so we analysee the data with other features while taking target values seperately.

In [19]:
```
# lets check percentage of missing values in dataset
```

In [20]:
```
missing_values = pd.DataFrame((telco_data.isna().sum())*100/telco_data.shape[0]).reset
plt.figure(figsize=(20,10))
ax=sns.pointplot("index",0,data=missing_values)
plt.xticks(rotation=90,fontsize=17)
plt.yticks(fontsize=17)
plt.ylabel("Percentage",fontsize=17)
plt.title("Percentage of missing values",fontsize=17)
plt.show()
```



Data Engineering

In [21]:
```
telco_data.describe()
```

Out[21]:

	SeniorCitizen	tenure	MonthlyCharges
count	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692
std	0.368612	24.559481	30.090047
min	0.000000	0.000000	18.250000
25%	0.000000	9.000000	35.500000
50%	0.000000	29.000000	70.350000
75%	0.000000	55.000000	89.850000
max	1.000000	72.000000	118.750000

we will create copy of the data for the manupulation and processing so that original data should not get any problem

In [22]:
```
df1=telco_data.copy()
```

In [23]:
```
df1.head()
```

Out[23]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Int
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	
4	9237-HQITU	Female	0	No	No	2	Yes	No	

5 rows × 21 columns

In [24]:
```
df1.columns
```

Out[24]:
```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

In [25]:
```
df1["TotalCharges"].dtype
```

Out[25]:
```
dtype('O')
```

In [26]:
```
# total charges dtype should be numeric instead object so we will convert it into nume
```

In [27]:
```
df1.TotalCharges=pd.to_numeric(df1.TotalCharges,errors="coerce")
df1.isna().sum()
```

Out[27]:
```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges       11
Churn               0
dtype: int64
```

here we got to know that there are 11 null values in column>> TotalCharges

In [28]:
```
df1.loc[df1["TotalCharges"].isna()]
```

Out[28]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
488	4472-LVYGI	Female	0	Yes	Yes	0	No	No phone service
753	3115-CZMZD	Male	0	No	Yes	0	Yes	No
936	5709-LVOEQ	Female	0	Yes	Yes	0	Yes	No
1082	4367-NUYAO	Male	0	Yes	Yes	0	Yes	Yes
1340	1371-DWPAZ	Female	0	Yes	Yes	0	No	No phone service
3331	7644-OMVMY	Male	0	Yes	Yes	0	Yes	No
3826	3213-VVOLG	Male	0	Yes	Yes	0	Yes	Yes
4380	2520-SGTTA	Female	0	Yes	Yes	0	Yes	No
5218	2923-ARZLG	Male	0	Yes	Yes	0	Yes	No
6670	4075-WKNIU	Female	0	Yes	Yes	0	Yes	Yes
6754	2775-SEFEE	Male	0	No	Yes	0	Yes	Yes

11 rows × 21 columns

In [29]:
```
df1["TotalCharges"].isna().sum()
```

Out[29]:
```
11
```

As the percentage of isna() is very low so we will replace those values with mean

In [30]:
```
df1["TotalCharges"].mean()
```

Out[30]:
```
2283.3004408418697
```

In [31]:
```
df1.describe()
```

Out[31]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges
count	7043.000000	7043.000000	7043.000000	7032.000000
mean	0.162147	32.371149	64.761692	2283.300441
std	0.368612	24.559481	30.090047	2266.771362
min	0.000000	0.000000	18.250000	18.800000
25%	0.000000	9.000000	35.500000	401.450000
50%	0.000000	29.000000	70.350000	1397.475000
75%	0.000000	55.000000	89.850000	3794.737500
max	1.000000	72.000000	118.750000	8684.800000

In [32]:
```
df1["TotalCharges"] = df1["TotalCharges"].fillna(df1["TotalCharges"].mean())
df1["TotalCharges"].isna().sum()
```

Out[32]:
```
0
```

In [33]:
```
df1.head()
```

Out[33]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Int
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	
4	9237-HQITU	Female	0	No	No	2	Yes	No	

5 rows × 21 columns

In [34]:
```
df1.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   float64
 20  Churn             7043 non-null   object 
dtypes: float64(2), int64(2), object(17)
memory usage: 1.1+ MB
```

In [35]:
```
df1.shape
```

Out[35]:
```
(7043, 21)
```

In [36]:
```
df1["tenure"].value_counts()
```

Out[36]:
```
1     613
72    362
2     238
3     200
4     176
     ...
28     57
39     56
44     51
36     50
0      11
Name: tenure, Length: 73, dtype: int64
```

here tenure us having 73 values so analysing each with the churn will be more time consuming so for that we will convert those values into category so it will be helful to analyze that column with churn

In [37]:
```
# we will create groups to analyse better
# divude the customers into beans based on tenure e.g. for tenure<12 months , assign d
# for tenure between 1-2 years ,tenure group of 13-24: so on
```

In [38]:
```
print(df1["tenure"].max())
```

```
72
```

In [39]:
```
# here we can make 6 groups each  of 12 months
```

```
labels = ["{0} - {1}".format(i,i+11) for i in range(1,72,12)]
df1["tenure_group"]=pd.cut(df1.tenure,range(1,80,12),right=False,labels=labels)
df1["tenure_group"]
```

Out[39]:
```
0        1 - 12
1       25 - 36
2        1 - 12
3       37 - 48
4        1 - 12
          ...
7038    13 - 24
7039    61 - 72
7040     1 - 12
7041     1 - 12
7042    61 - 72
Name: tenure_group, Length: 7043, dtype: category
Categories (6, object): ['1 - 12' < '13 - 24' < '25 - 36' < '37 - 48' < '49 - 60' <
'61 - 72']
```

In [40]:
```
df1.head()
```

Out[40]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Int
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	
4	9237-HQITU	Female	0	No	No	2	Yes	No	

5 rows × 22 columns

Remove columns those are not required

In [41]:
```
df1.drop(columns=["customerID","tenure"],axis=1,inplace=True)
```

In [42]:
```
df1.head()
```

Out[42]:

	gender	SeniorCitizen	Partner	Dependents	PhoneService	MultipleLines	InternetService	OnlineS
0	Female	0	Yes	No	No	No phone service	DSL	
1	Male	0	No	No	Yes	No	DSL	
2	Male	0	No	No	Yes	No	DSL	
3	Male	0	No	No	No	No phone service	DSL	
4	Female	0	No	No	Yes	No	Fiber optic	

Lets analyse the data

In [43]:
```
# now lets take overview of churners based on each features we have
```

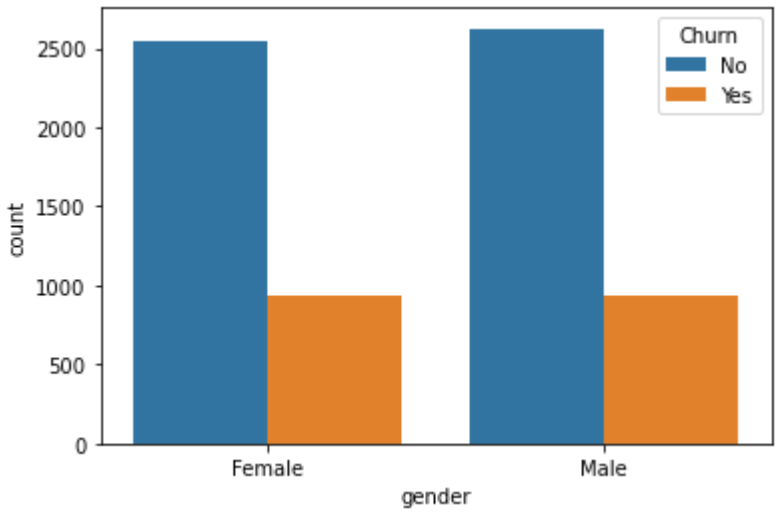
In [44]:
```
df1.columns
```

Out[44]:
```
Index(['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'PhoneService',
       'MultipleLines', 'InternetService', 'OnlineSecurity', 'OnlineBackup',
       'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies',
       'Contract', 'PaperlessBilling', 'PaymentMethod', 'MonthlyCharges',
       'TotalCharges', 'Churn', 'tenure_group'],
      dtype='object')
```

1.gender

In [45]:
```
sns.countplot(x=df1["gender"],hue=df1["Churn"])
```

Out[45]:
```
<AxesSubplot:xlabel='gender', ylabel='count'>
```



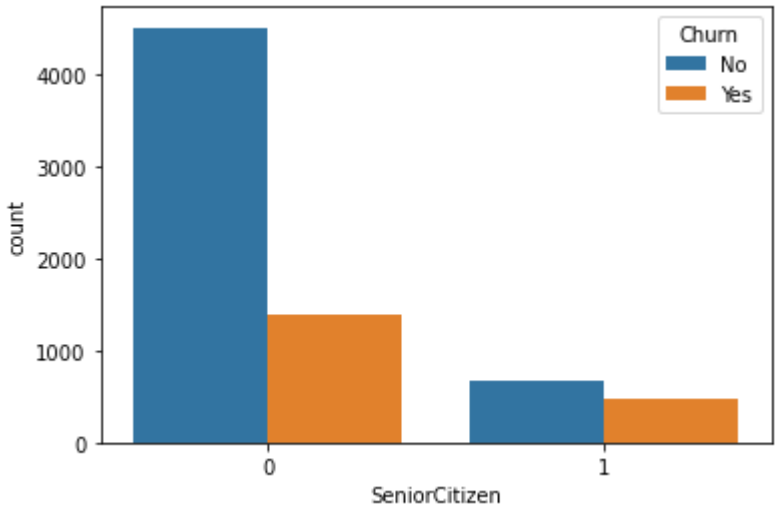
In [46]:
```
df1.groupby("gender")["Churn"].value_counts()
```

Out[46]:
```
gender  Churn
Female  No       2549
        Yes       939
Male    No       2625
        Yes       930
Name: Churn, dtype: int64
```

2.SeniorCitizen

In [47]:
```
sns.countplot(x=df1["SeniorCitizen"],hue=df1["Churn"])
```

Out[47]:
```
<AxesSubplot:xlabel='SeniorCitizen', ylabel='count'>
```



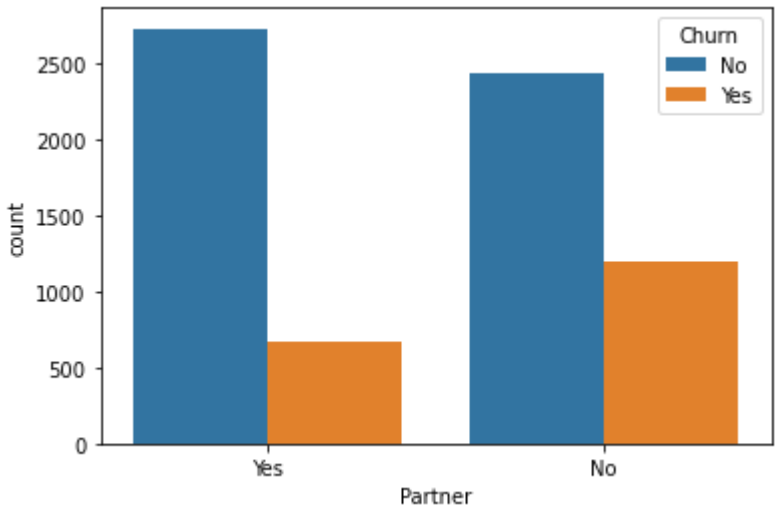
In [48]:
```
df1.groupby("SeniorCitizen")["Churn"].value_counts()
```

Out[48]:
```
SeniorCitizen  Churn
0              No       4508
               Yes      1393
1              No        666
               Yes       476
Name: Churn, dtype: int64
```

3.Partner

In [49]:
```
sns.countplot(x=df1["Partner"],hue=df1["Churn"])
```

Out[49]:
```
<AxesSubplot:xlabel='Partner', ylabel='count'>
```



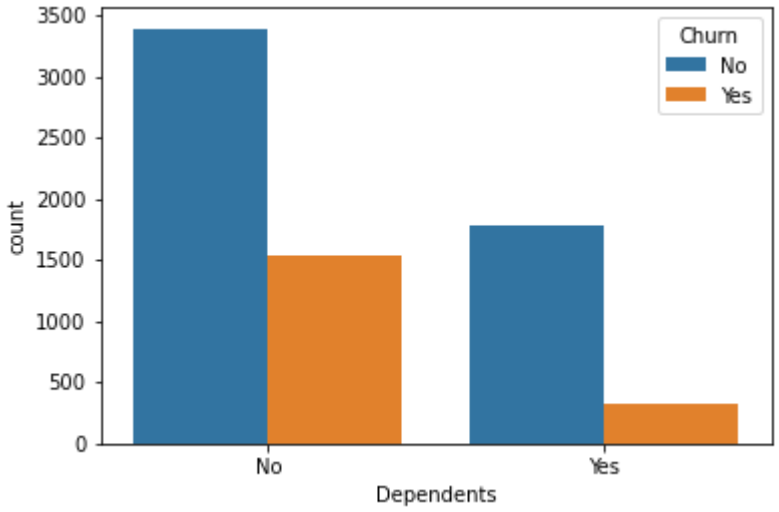
In [50]:
```
df1.groupby("Partner")["Churn"].value_counts()
```

Out[50]:
```
Partner  Churn
No       No       2441
         Yes      1200
Yes      No       2733
         Yes       669
Name: Churn, dtype: int64
```

4. Dependents

In [51]:
```
sns.countplot(x=df1["Dependents"],hue=df1["Churn"])
```

Out[51]:
```
<AxesSubplot:xlabel='Dependents', ylabel='count'>
```



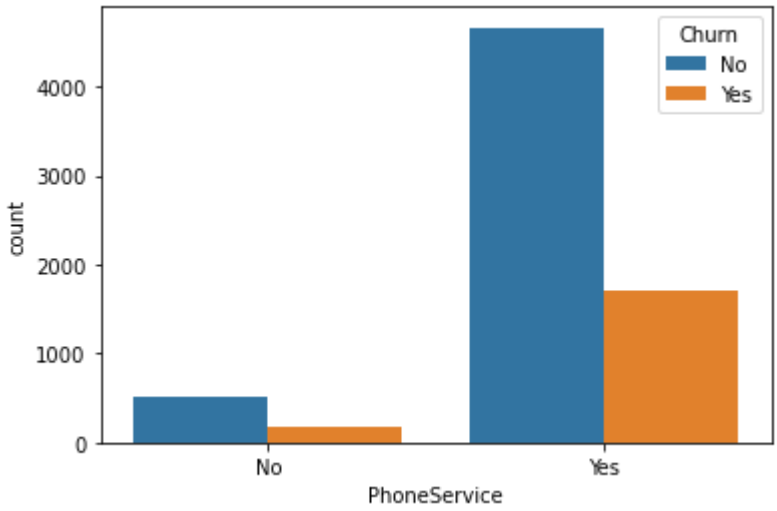
In [52]:
```
df1.groupby("Dependents")["Churn"].value_counts()
```

Out[52]:
```
Dependents  Churn
No          No       3390
            Yes      1543
Yes         No       1784
            Yes       326
Name: Churn, dtype: int64
```

5.PhoneService

In [53]:
```
sns.countplot(x=df1["PhoneService"],hue=df1["Churn"])
```

Out[53]:
```
<AxesSubplot:xlabel='PhoneService', ylabel='count'>
```



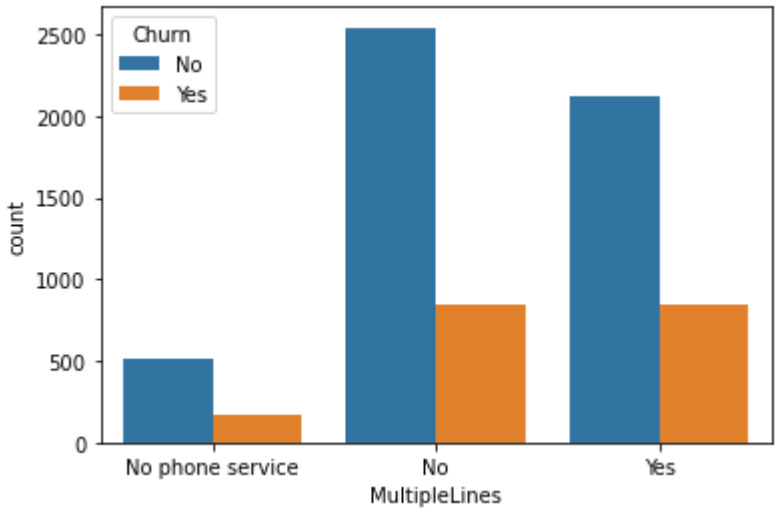
In [54]:
```
df1.groupby("PhoneService")["Churn"].value_counts()
```

Out[54]:
```
PhoneService  Churn
No            No        512
              Yes       170
Yes           No       4662
              Yes      1699
Name: Churn, dtype: int64
```

6.MultipleLines

In [55]:
```
sns.countplot(x=df1["MultipleLines"],hue=df1["Churn"])
```

Out[55]:
```
<AxesSubplot:xlabel='MultipleLines', ylabel='count'>
```



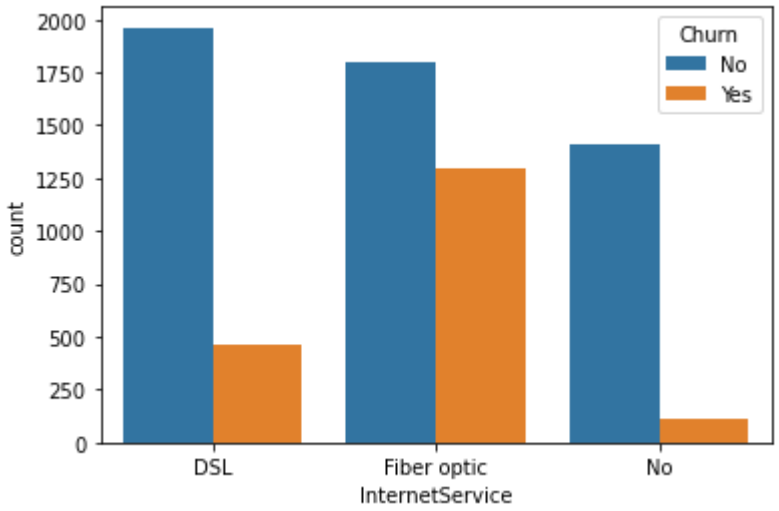
In [56]:
```
df1.groupby("MultipleLines")["Churn"].value_counts()
```

Out[56]:
```
MultipleLines     Churn
No                No       2541
                  Yes       849
No phone service  No        512
                  Yes       170
Yes               No       2121
                  Yes       850
Name: Churn, dtype: int64
```

7.InternetService

In [57]:
```
sns.countplot(x=df1["InternetService"],hue=df1["Churn"])
```

Out[57]:
```
<AxesSubplot:xlabel='InternetService', ylabel='count'>
```



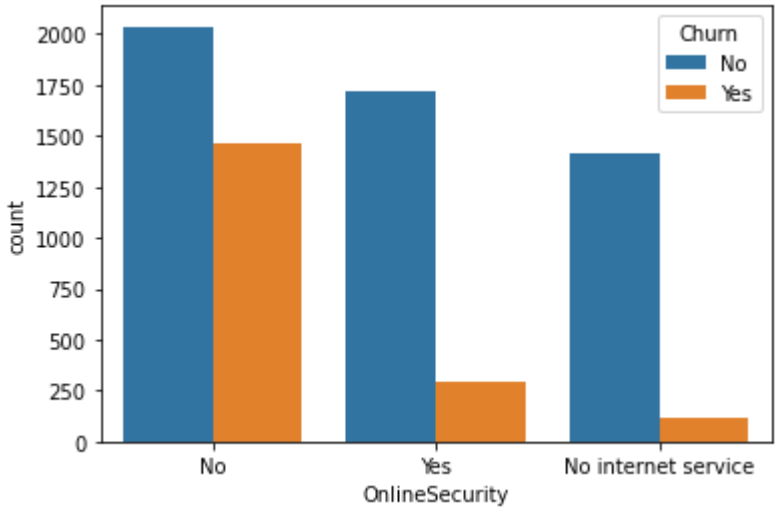
In [58]:
```
df1.groupby("InternetService")["Churn"].value_counts()
```

Out[58]:
```
InternetService  Churn
DSL              No       1962
                 Yes       459
Fiber optic      No       1799
                 Yes      1297
No               No       1413
                 Yes       113
Name: Churn, dtype: int64
```

8.OnlineSecurity

In [59]:
```
sns.countplot(x=df1["OnlineSecurity"],hue=df1["Churn"])
```

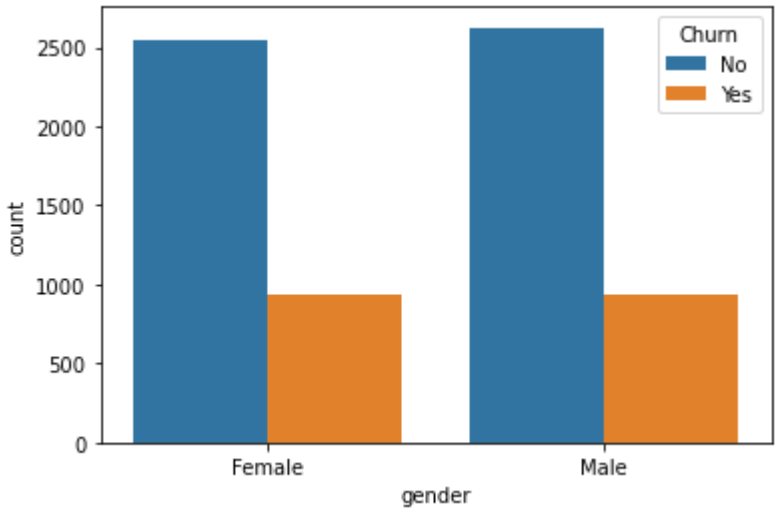
Out[59]:
```
<AxesSubplot:xlabel='OnlineSecurity', ylabel='count'>
```

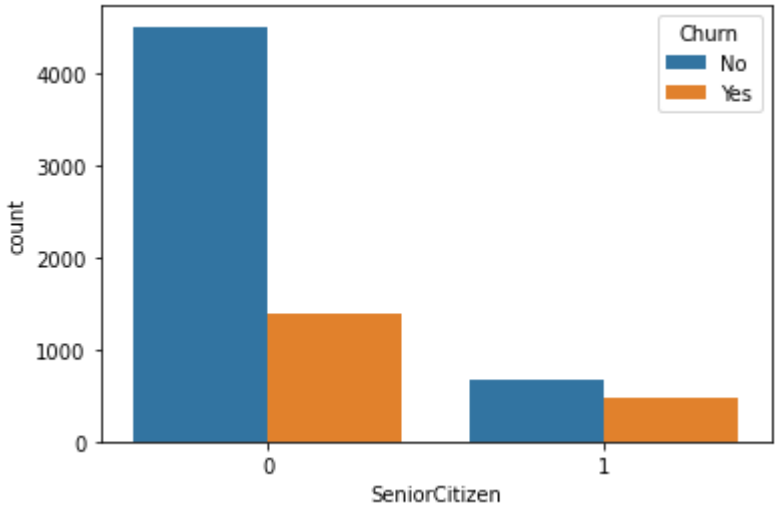


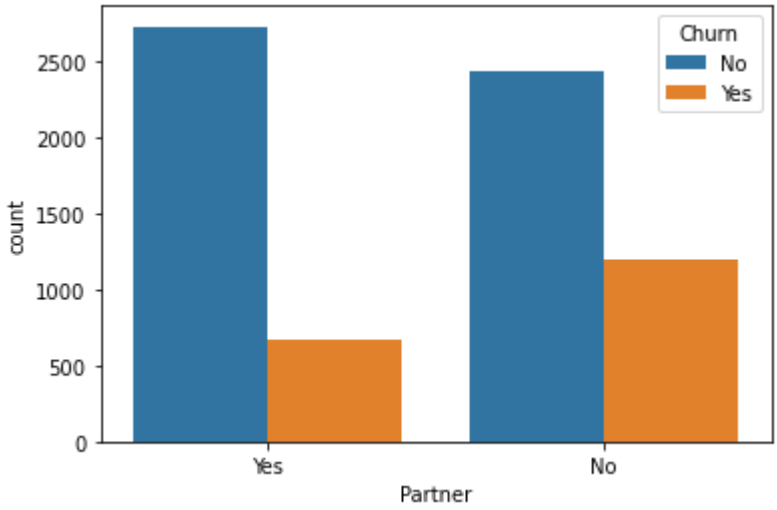
In [60]:
```
df1.groupby("OnlineSecurity")["Churn"].value_counts()
```

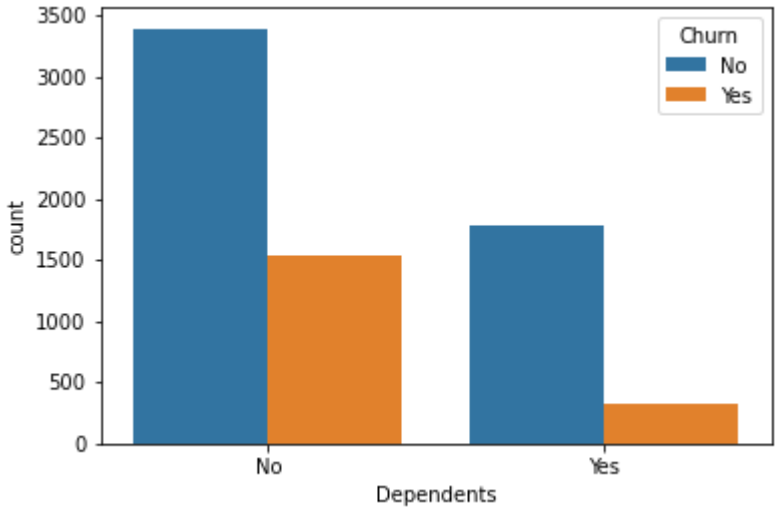
Out[60]:
```
OnlineSecurity       Churn
No                   No       2037
                     Yes      1461
No internet service  No       1413
                     Yes       113
Yes                  No       1724
                     Yes       295
Name: Churn, dtype: int64
```

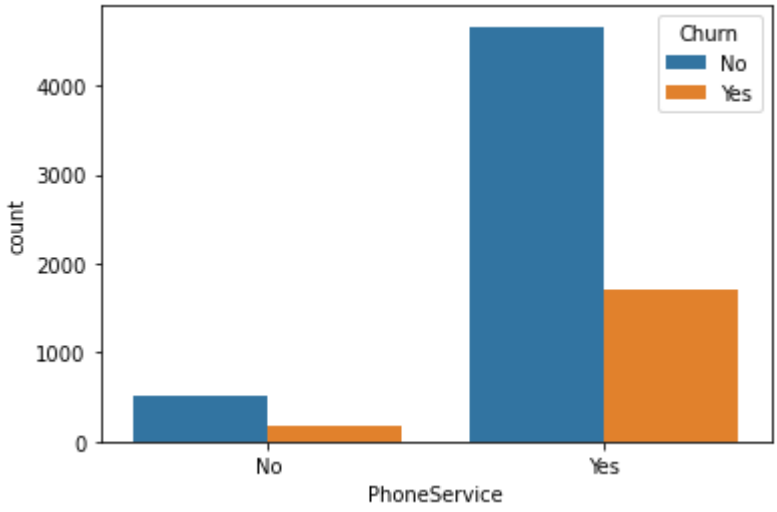
In [61]:
```
for i,predictor in enumerate(df1.drop(columns=['Churn', 'TotalCharges', 'MonthlyCharge
    plt.figure(i)
    sns.countplot(data=df1,x=predictor,hue=df1["Churn"])
```

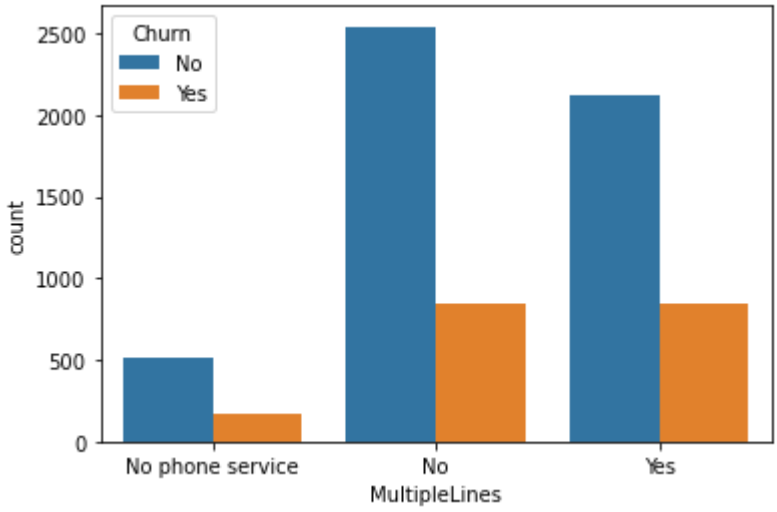


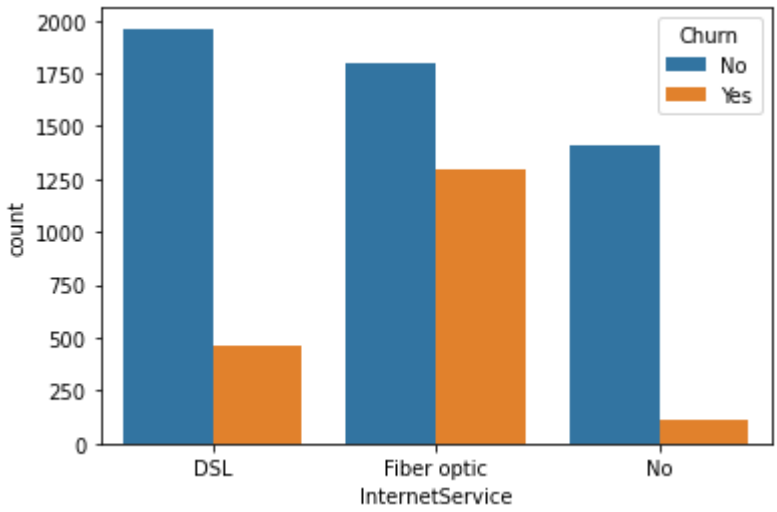

Churn
No
Yes
4000
3000
2000
1000
0
count
0
1
SeniorCitizen

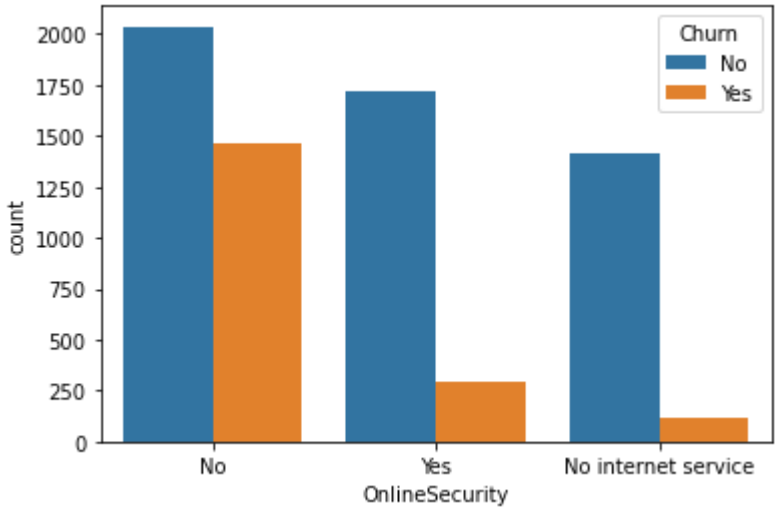

Churn
No
Yes
2500
2000
1500
1000
500
0
count
Yes
No
Partner

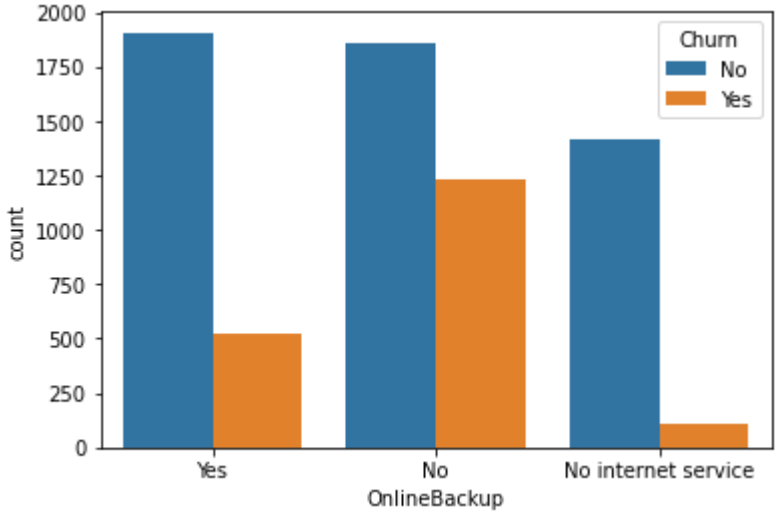

Churn
No
Yes
3500
3000
2500
2000
1500
1000
500
0
count
No
Yes
Dependents

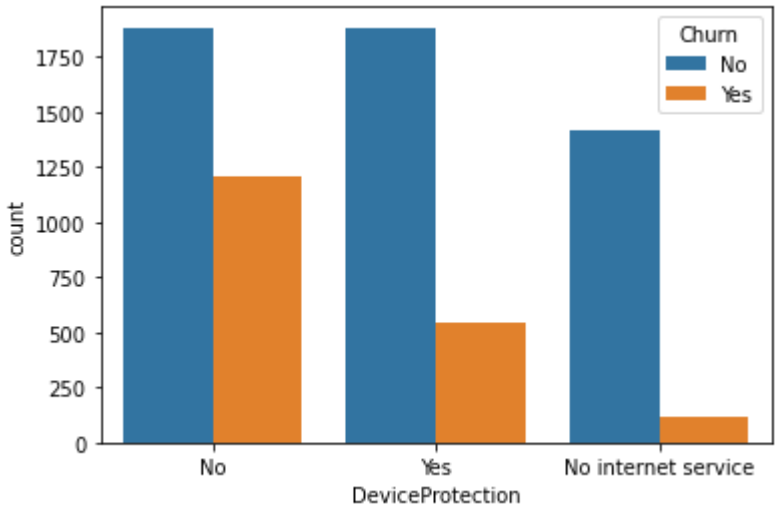

Churn
No
Yes
4000
3000
2000
1000
0
count
No
Yes
PhoneService

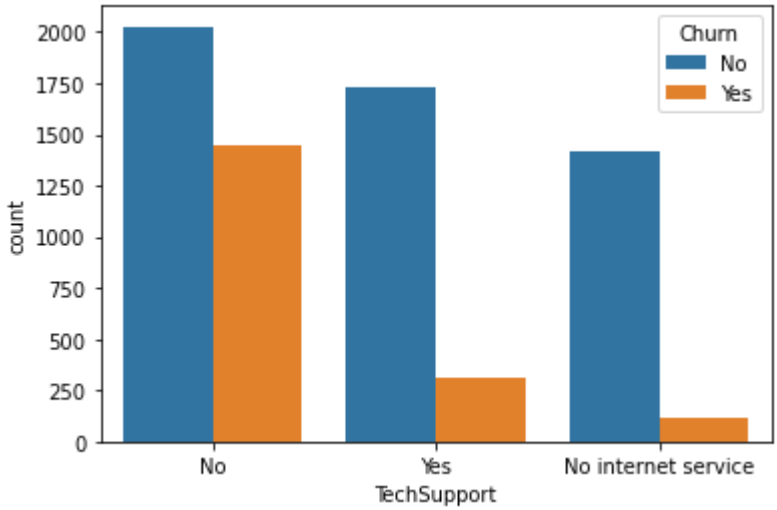

Churn
No
Yes
2500
2000
1500
1000
500
0
count
No phone service
No
Yes
MultipleLines

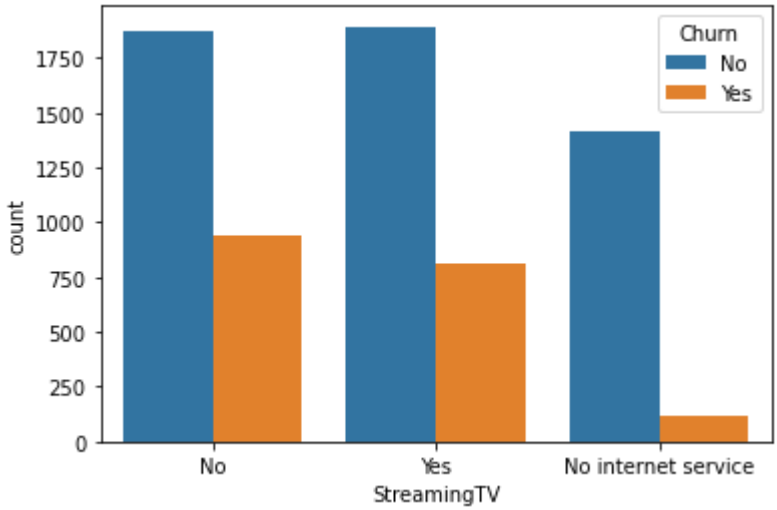

Churn
No
Yes
2000
1750
1500
1250
1000
750
500
250
0
count
DSL
Fiber optic
No
InternetService

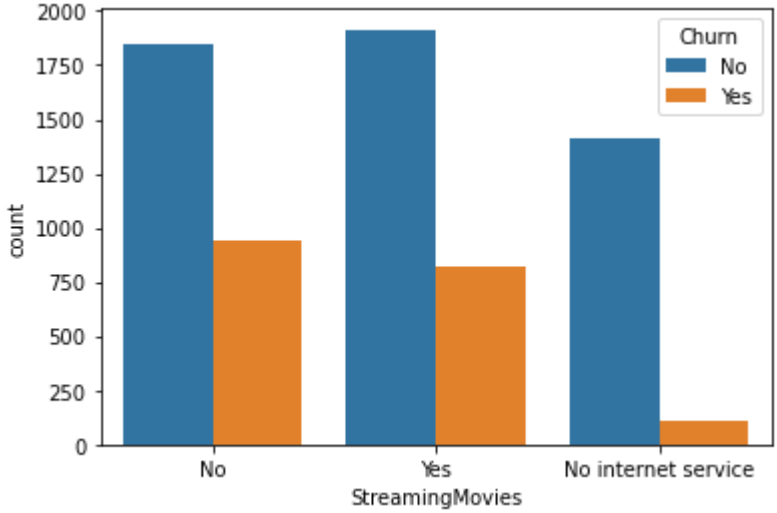

Churn
No
Yes
count
2000
1750
1500
1250
1000
750
500
250
0
No
Yes
No internet service
OnlineSecurity

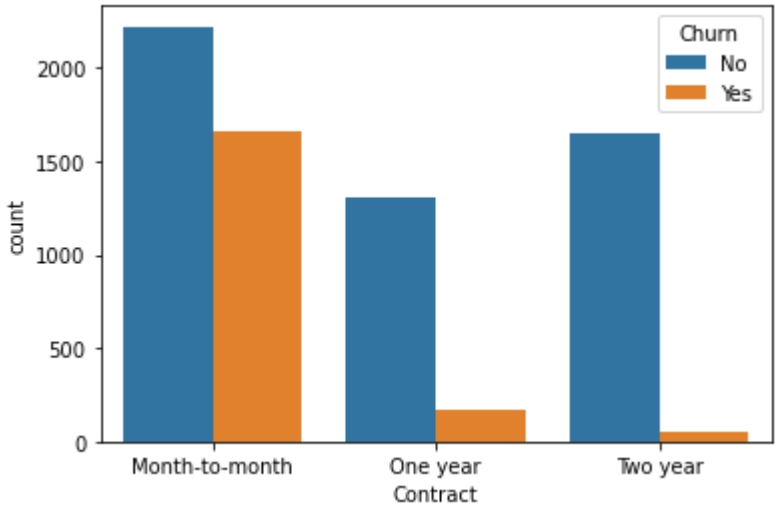

Churn
No
Yes
count
2000
1750
1500
1250
1000
750
500
250
0
Yes
No
No internet service
OnlineBackup

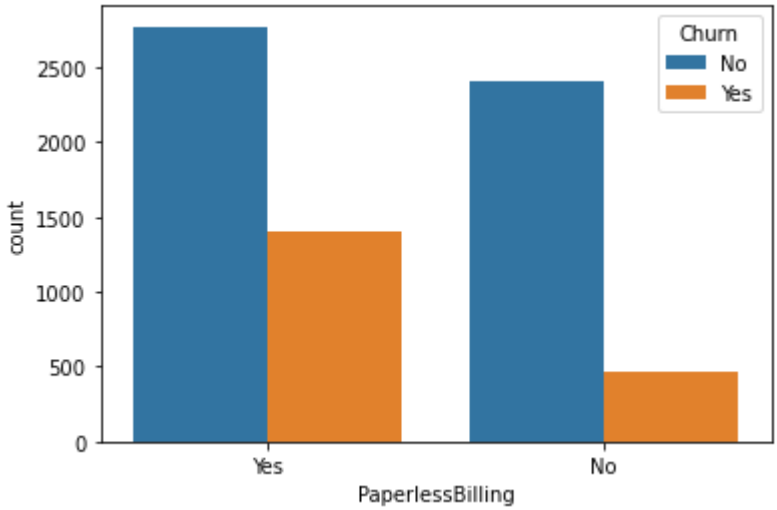

Churn
No
Yes
count
1750
1500
1250
1000
750
500
250
0
No
Yes
No internet service
DeviceProtection

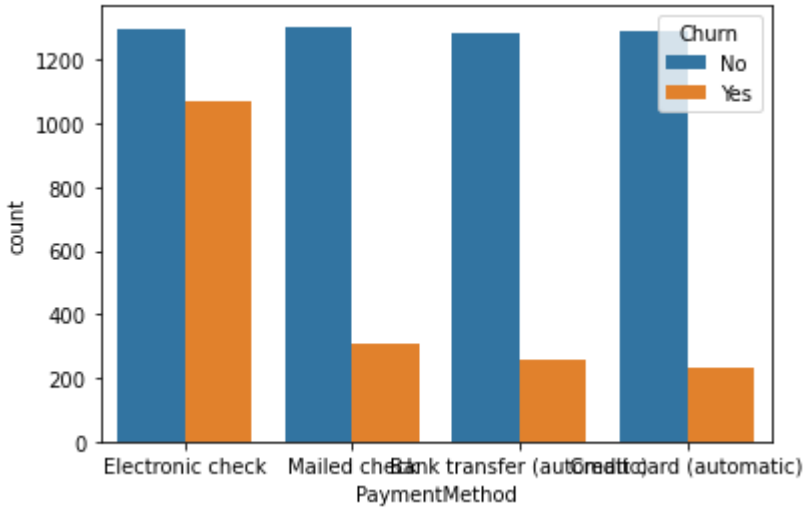

Churn
No
Yes
count
2000
1750
1500
1250
1000
750
500
250
0
No
Yes
No internet service
TechSupport

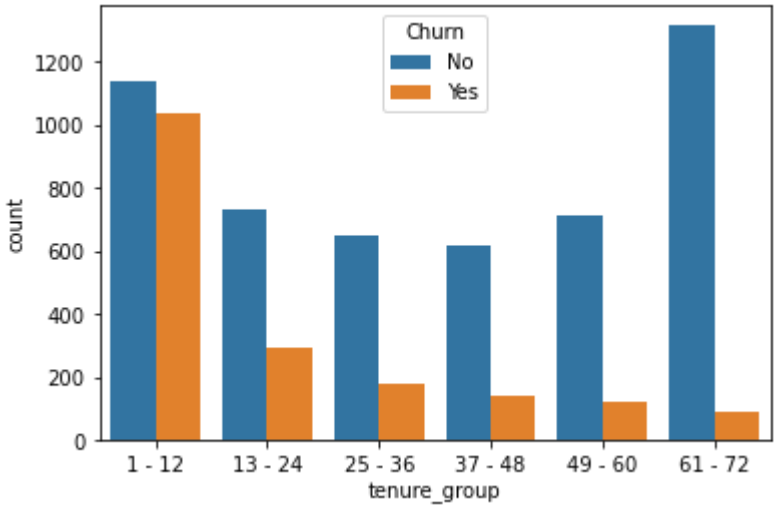

Churn
No
Yes
count
1750
1500
1250
1000
750
500
250
0
No
Yes
No internet service
StreamingTV


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


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


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


Churn
No
Yes
1200
1000
800
600
400
200
0
count
Electronic check
Mailed check
Bank transfer (automatic)
Credit card (automatic)
PaymentMethod



convert our target variable into binary numeric variables i.e Yes=1, No=0

In [62]:
```
df1["Churn"]=np.where(df1.Churn=="Yes",1,0)
```

In [63]:
```
df1.head()
```

Out[63]:

	gender	SeniorCitizen	Partner	Dependents	PhoneService	MultipleLines	InternetService	OnlineS
0	Female	0	Yes	No	No	No phone service	DSL	
1	Male	0	No	No	Yes	No	DSL	
2	Male	0	No	No	Yes	No	DSL	
3	Male	0	No	No	No	No phone service	DSL	
4	Female	0	No	No	Yes	No	Fiber optic	

convert all categorical variables into dummy variables

In [64]:
```
df1["gender"].nunique()
```

Out[64]:
```
2
```

In [65]:
```
df1["DeviceProtection"].nunique()
```

Out[65]:
```
3
```

In [66]:
```
df1=pd.get_dummies(df1)
df1.head()
```

Out[66]:

	SeniorCitizen	MonthlyCharges	TotalCharges	Churn	gender_Female	gender_Male	Partner_No	Pa
0	0	29.85	29.85	0	1	0	0	
1	0	56.95	1889.50	0	0	1	1	
2	0	53.85	108.15	1	0	1	1	
3	0	42.30	1840.75	0	0	1	1	
4	0	70.70	151.65	1	1	0	1	

5 rows × 51 columns

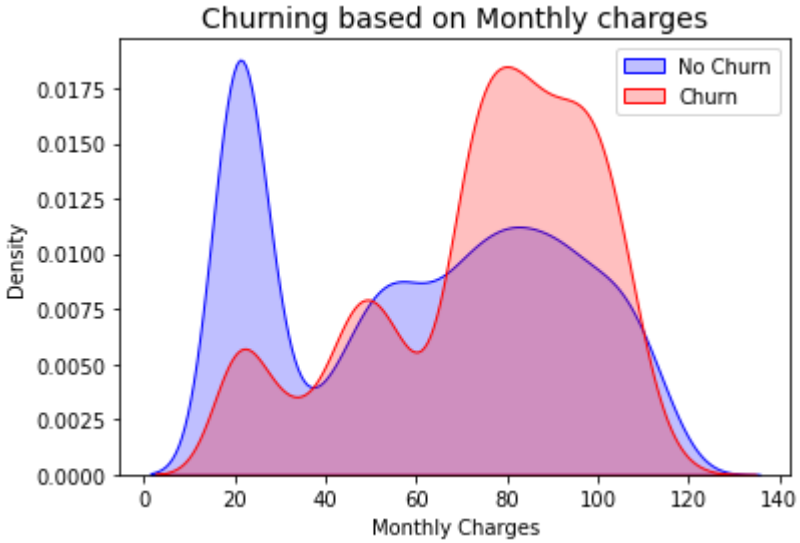
In [67]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 51 columns):
 #   Column                                   Non-Null Count  Dtype
---  ------                                   --------------  -----
 0   SeniorCitizen                            7043 non-null   int64
 1   MonthlyCharges                           7043 non-null   float64
 2   TotalCharges                             7043 non-null   float64
 3   Churn                                    7043 non-null   int32
 4   gender_Female                            7043 non-null   uint8
 5   gender_Male                              7043 non-null   uint8
 6   Partner_No                               7043 non-null   uint8
 7   Partner_Yes                              7043 non-null   uint8
 8   Dependents_No                            7043 non-null   uint8
 9   Dependents_Yes                           7043 non-null   uint8
 10  PhoneService_No                          7043 non-null   uint8
 11  PhoneService_Yes                         7043 non-null   uint8
 12  MultipleLines_No                         7043 non-null   uint8
 13  MultipleLines_No phone service           7043 non-null   uint8
 14  MultipleLines_Yes                        7043 non-null   uint8
 15  InternetService_DSL                      7043 non-null   uint8
 16  InternetService_Fiber optic              7043 non-null   uint8
 17  InternetService_No                       7043 non-null   uint8
 18  OnlineSecurity_No                        7043 non-null   uint8
 19  OnlineSecurity_No internet service       7043 non-null   uint8
 20  OnlineSecurity_Yes                       7043 non-null   uint8
 21  OnlineBackup_No                          7043 non-null   uint8
 22  OnlineBackup_No internet service         7043 non-null   uint8
 23  OnlineBackup_Yes                         7043 non-null   uint8
 24  DeviceProtection_No                      7043 non-null   uint8
 25  DeviceProtection_No internet service     7043 non-null   uint8
 26  DeviceProtection_Yes                     7043 non-null   uint8
 27  TechSupport_No                           7043 non-null   uint8
 28  TechSupport_No internet service          7043 non-null   uint8
 29  TechSupport_Yes                          7043 non-null   uint8
 30  StreamingTV_No                           7043 non-null   uint8
 31  StreamingTV_No internet service          7043 non-null   uint8
 32  StreamingTV_Yes                          7043 non-null   uint8
 33  StreamingMovies_No                       7043 non-null   uint8
 34  StreamingMovies_No internet service      7043 non-null   uint8
 35  StreamingMovies_Yes                      7043 non-null   uint8
 36  Contract_Month-to-month                  7043 non-null   uint8
 37  Contract_One year                        7043 non-null   uint8
 38  Contract_Two year                        7043 non-null   uint8
 39  PaperlessBilling_No                      7043 non-null   uint8
 40  PaperlessBilling_Yes                     7043 non-null   uint8
 41  PaymentMethod_Bank transfer (automatic)  7043 non-null   uint8
 42  PaymentMethod_Credit card (automatic)    7043 non-null   uint8
 43  PaymentMethod_Electronic check           7043 non-null   uint8
 44  PaymentMethod_Mailed check               7043 non-null   uint8
 45  tenure_group_1 - 12                      7043 non-null   uint8
 46  tenure_group_13 - 24                     7043 non-null   uint8
 47  tenure_group_25 - 36                     7043 non-null   uint8
 48  tenure_group_37 - 48                     7043 non-null   uint8
 49  tenure_group_49 - 60                     7043 non-null   uint8
 50  tenure_group_61 - 72                     7043 non-null   uint8
dtypes: float64(2), int32(1), int64(1), uint8(47)
memory usage: 516.0 KB
```

In [68]:
```
Mch= sns.kdeplot(df1.MonthlyCharges[(df1["Churn"]==0)],
```

```
                color="Blue",shade=True)

Mch=sns.kdeplot(df1.MonthlyCharges[(df1["Churn"]==1)],color="Red",shade=True)
Mch.legend(["No Churn","Churn"],loc="upper right")
Mch.set_xlabel("Monthly Charges")
Mch.set_title("Churning based on Monthly charges",fontsize=14)
```

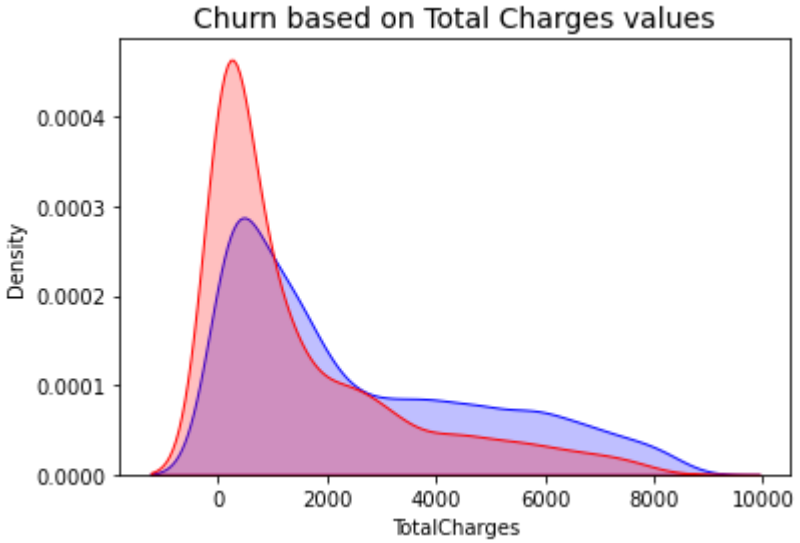
Out[68]:
```
Text(0.5, 1.0, 'Churning based on Monthly charges')
```



In [69]:
```
# here we can observe that churn value is high as monthly charges are high
```

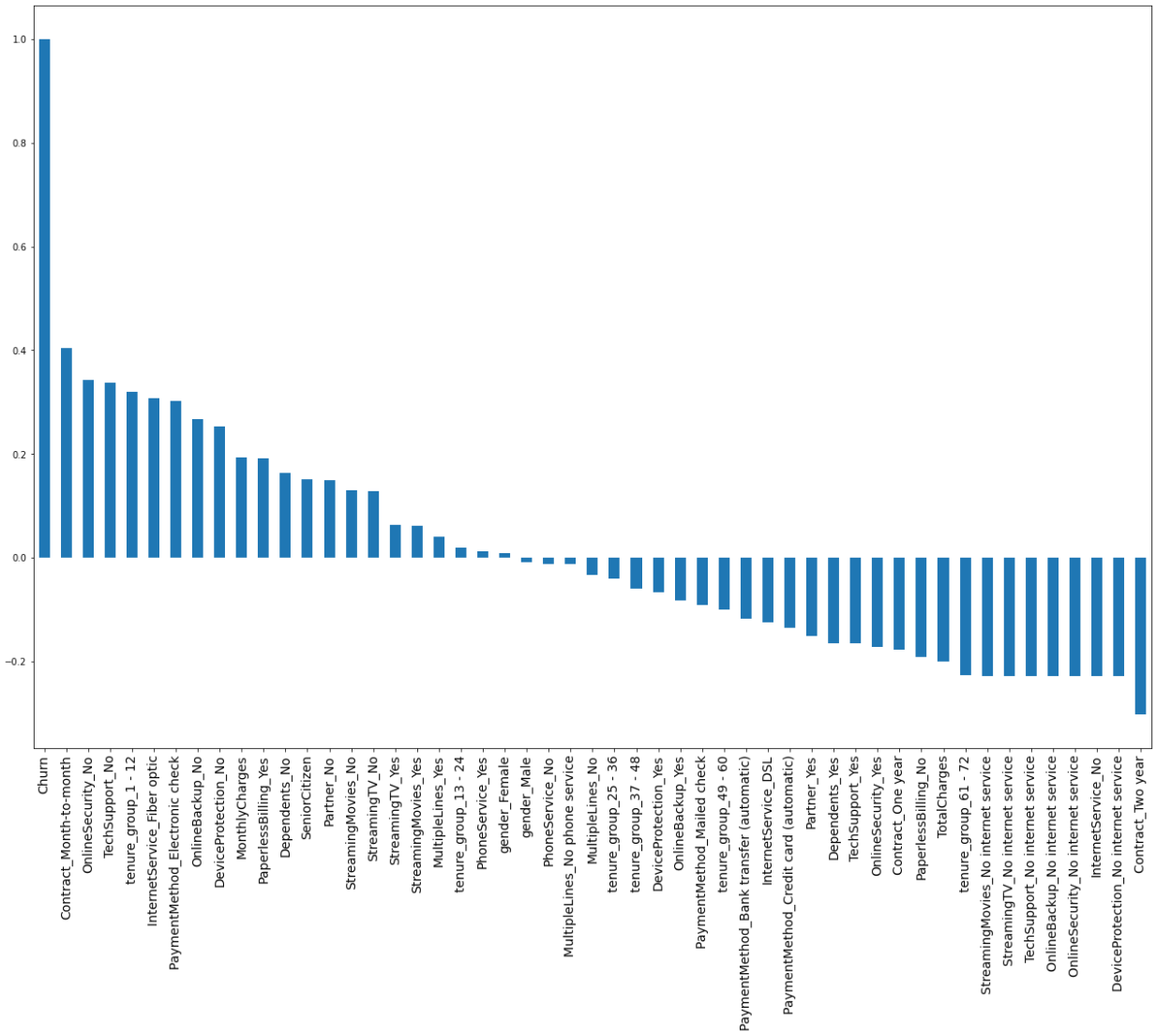
In [70]:
```
Tch = sns.kdeplot(df1.TotalCharges[(df1["Churn"]==0)],
                  color="Blue",shade=True)
Tch = sns.kdeplot(df1.TotalCharges[(df1["Churn"]==1)],
                  color="red",shade=True)
Tch.set_xlabel("TotalCharges")
Tch.set_title("Churn based on Total Charges values",fontsize=14)
```

Out[70]:
```
Text(0.5, 1.0, 'Churn based on Total Charges values')
```



Now lets get plot of which features are more likely to be giving more insights for the churning thing

In [71]:
```
plt.figure(figsize=(22,15))
df1.corr()["Churn"].sort_values(ascending=False).plot(kind="bar")
plt.xticks(fontsize=14)
plt.show()
```



HIGH Churn seen in case of Month to month contracts, No online security, No Tech support, First year of subscription and Fibre Optics Internet LOW Churn is seens in case of Long term contracts, Subscriptions without internet service and The customers engaged for 5+ years Factors like Gender, Availability of PhoneService and multiple lines have alomost NO impact on Churn

In [72]:
```
df1.to_csv("tel_churn.csv")
```

In [73]:
```
df1.describe()
```

Out[73]:

	SeniorCitizen	MonthlyCharges	TotalCharges	Churn	gender_Female	gender_Male	Part
count	7043.000000	7043.000000	7043.000000	7043.000000	7043.000000	7043.000000	7043.
mean	0.162147	64.761692	2283.300441	0.265370	0.495244	0.504756	0.
std	0.368612	30.090047	2265.000258	0.441561	0.500013	0.500013	0.
min	0.000000	18.250000	18.800000	0.000000	0.000000	0.000000	0.
25%	0.000000	35.500000	402.225000	0.000000	0.000000	0.000000	0.
50%	0.000000	70.350000	1400.550000	0.000000	0.000000	1.000000	1.
75%	0.000000	89.850000	3786.600000	1.000000	1.000000	1.000000	1.
max	1.000000	118.750000	8684.800000	1.000000	1.000000	1.000000	1.

8 rows × 51 columns

In [ ]:

Now lets move to Model building

In [74]:
```
import pandas as pd
import numpy as np

from sklearn.metrics import confusion_matrix,classification_report,accuracy_score
from sklearn.model_selection import train_test_split,GridSearchCV,RandomizedSearchCV
```

In [75]:
```
df=pd.read_csv("tel_churn.csv")
df.head()
```

Out[75]:

	Unnamed: 0	SeniorCitizen	MonthlyCharges	TotalCharges	Churn	gender_Female	gender_Male	Par
0	0	0	29.85	29.85	0	1	0	
1	1	0	56.95	1889.50	0	0	1	
2	2	0	53.85	108.15	1	0	1	
3	3	0	42.30	1840.75	0	0	1	
4	4	0	70.70	151.65	1	1	0	

5 rows × 52 columns

In [76]:
```
df.drop("Unnamed: 0",axis=1,inplace=True)
```

In [77]:
```
df.head()
```

Out[77]:

	SeniorCitizen	MonthlyCharges	TotalCharges	Churn	gender_Female	gender_Male	Partner_No	Pa
0	0	29.85	29.85	0	1	0	0	
1	0	56.95	1889.50	0	0	1	1	
2	0	53.85	108.15	1	0	1	1	
3	0	42.30	1840.75	0	0	1	1	
4	0	70.70	151.65	1	1	0	1	

5 rows × 51 columns

In [109…
```
df.shape
```

Out[109]:
```
(7043, 51)
```

In [110…
```
df["Churn"].value_counts()
```

Out[110]:
```
0    5174
1    1869
Name: Churn, dtype: int64
```

As we can see here that the dataset is imbalanced one so we will use SMOTE technique to make it balanced

In [80]:
```
from imblearn.over_sampling import SMOTE
```

In [81]:
```
df["Churn"].value_counts()
```

Out[81]:
```
0    5174
1    1869
Name: Churn, dtype: int64
```

In [87]:
```
x1=df.drop("Churn",axis=1)
```

In [88]:
```
y1=df["Churn"]
```

In [89]:
```
sm=SMOTE(k_neighbors=5,random_state=45)
x_sample,y_sample=sm.fit_resample(x1,y1)
```

In [90]:
```
y_sample.value_counts()
```

Out[90]:
```
0    5174
1    5174
Name: Churn, dtype: int64
```

In [93]:
```
x=x_sample
```

In [94]:
```
y=y_sample
```

In [95]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25,stratify=y)
```

Decision Tree Classifier

In [97]:
```
from sklearn.tree import DecisionTreeClassifier,plot_tree
```

Model Selection

In [111…
```
dt_clf=DecisionTreeClassifier()
dt_clf.fit(x_train,y_train)
```

Out[111]:
```
DecisionTreeClassifier()
```

Model Evaluation

In [112…
```
# training
y_pred_train = dt_clf.predict(x_train)

cnf_matrix = confusion_matrix(y_train,y_pred_train)
print("Confusion Matrix\n",cnf_matrix)

Accuracy = accuracy_score(y_train,y_pred_train)
print("ACCURACY",Accuracy*100)

cls_report = classification_report(y_train,y_pred_train)
print("CLASSIFICATION REPORT\n",cls_report)
```

```
Confusion Matrix
 [[3880    1]
 [   8 3872]]
ACCURACY 99.88403556242751
CLASSIFICATION REPORT
               precision    recall  f1-score   support

           0       1.00      1.00      1.00      3881
           1       1.00      1.00      1.00      3880

    accuracy                           1.00      7761
   macro avg       1.00      1.00      1.00      7761
weighted avg       1.00      1.00      1.00      7761
```

In [113…
```
# testing
y_pred_test = dt_clf.predict(x_test)

cnf_matrix = confusion_matrix(y_test,y_pred_test)
print("Confusion Matrix\n",cnf_matrix)

Accuracy = accuracy_score(y_test,y_pred_test)
print("ACCURACY",Accuracy*100)

clf_report = classification_report(y_test,y_pred_test)
print("CLASSIFICATION REPORT\n",clf_report)
```

```
Confusion Matrix
 [[1040  253]
 [ 249 1045]]
ACCURACY 80.59528411287205
CLASSIFICATION REPORT
              precision    recall  f1-score   support

           0       0.81      0.80      0.81      1293
           1       0.81      0.81      0.81      1294

    accuracy                           0.81      2587
   macro avg       0.81      0.81      0.81      2587
weighted avg       0.81      0.81      0.81      2587
```

In [ ]:

Hyper parameter Tuning

In [115…
```
dt_model = DecisionTreeClassifier()
hyper_para = {"criterion" :['gini',"entropy"],
"max_depth":np.arange(2,8),
"min_samples_split":np.arange(3,20),
"min_samples_leaf":np.arange(3,15),
}
rscv_dt_clf = RandomizedSearchCV(dt_model,hyper_para,cv=5)
rscv_dt_clf.fit(x_train,y_train)
```

Out[115]:
```
RandomizedSearchCV
estimator: DecisionTreeClassifier
DecisionTreeClassifier
```

In [116…
```
rscv_dt_clf.best_estimator_
```

Out[116]:
```
DecisionTreeClassifier(max_depth=6, min_samples_leaf=4, min_samples_split=1
3)
```

In [117…
```
dt_clf = DecisionTreeClassifier(max_depth=6, min_samples_leaf=4, min_samples_split=13)
dt_clf.fit(x_train,y_train)
```

Out[117]:
```
DecisionTreeClassifier(max_depth=6, min_samples_leaf=4, min_samples_split=1
3)
```

In [120…
```
#training
y_pred_train = dt_clf.predict(x_train)

cnf_matrix = confusion_matrix(y_train,y_pred_train)
print("Confusion matrix\n",cnf_matrix)
```

```
Accuaracy = accuracy_score(y_train,y_pred_train)
print("Accuracy",Accuracy)

clf_report = classification_report(y_train,y_pred_train)
print("Classification report\n",clf_report)
```

```
Confusion matrix
 [[3215  666]
 [ 653 3227]]
Accuracy 0.8059528411287206
Classification report
               precision    recall  f1-score   support

           0       0.83      0.83      0.83      3881
           1       0.83      0.83      0.83      3880

    accuracy                           0.83      7761
   macro avg       0.83      0.83      0.83      7761
weighted avg       0.83      0.83      0.83      7761
```

In [121…

```
#testing
y_pred_test = dt_clf.predict(x_test)

cnf_matrix = confusion_matrix(y_test,y_pred_test)
print("Confusion matrix\n",cnf_matrix)

Accuaracy = accuracy_score(y_test,y_pred_test)
print("Accuracy",Accuracy)

clf_report = classification_report(y_test,y_pred_test)
print("Classification report\n",clf_report)
```

```
Confusion matrix
 [[1065  228]
 [ 236 1058]]
Accuracy 0.8059528411287206
Classification report
               precision    recall  f1-score   support

           0       0.82      0.82      0.82      1293
           1       0.82      0.82      0.82      1294

    accuracy                           0.82      2587
   macro avg       0.82      0.82      0.82      2587
weighted avg       0.82      0.82      0.82      2587
```

In [ ]:

Random Forest classifier

In [123…

```
from sklearn.ensemble import RandomForestClassifier
```

Model training

In [125…
```
rf_clf= RandomForestClassifier()
rf_clf.fit(x_train,y_train)
```

Out[125]:
```
▾ RandomForestClassifier
RandomForestClassifier()
```

In [127…
```
#Training
y_pred_train = rf_clf.predict(x_train)

cnf_metrics = confusion_matrix(y_train,y_pred_train)
print("confusion metrics\n",cnf_metrics)

accuracy = accuracy_score(y_train,y_pred_train)
print("accuracy",accuracy*100)

clf_report = classification_report(y_train,y_pred_train)
print("clf_report\n",clf_report)
```

```
confusion metrics
 [[3873    8]
 [   1 3879]]
accuracy 99.88403556242751
clf_report
               precision    recall  f1-score   support

           0       1.00      1.00      1.00      3881
           1       1.00      1.00      1.00      3880

    accuracy                           1.00      7761
   macro avg       1.00      1.00      1.00      7761
weighted avg       1.00      1.00      1.00      7761
```

In [128…
```
#Testing
y_pred_test = rf_clf.predict(x_test)

cnf_metrics = confusion_matrix(y_test,y_pred_test)
print("confusion metrics\n",cnf_metrics)

accuracy = accuracy_score(y_test,y_pred_test)
print("accuracy",accuracy*100)

clf_report = classification_report(y_test,y_pred_test)
print("clf_report\n",clf_report)
```

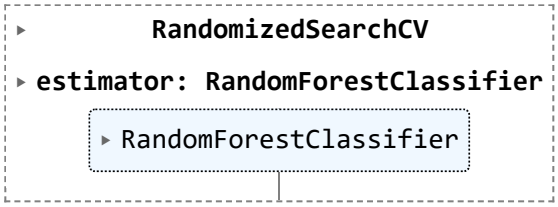
```
confusion metrics
 [[1153  140]
 [ 224 1070]]
accuracy 85.92964824120602
clf_report
              precision    recall  f1-score   support

           0       0.84      0.89      0.86      1293
           1       0.88      0.83      0.85      1294

    accuracy                           0.86      2587
   macro avg       0.86      0.86      0.86      2587
weighted avg       0.86      0.86      0.86      2587
```

In [ ]:

HyperParamter Tuning

In [133…
```
hyperparamter = {"n_estimators":np.arange(10,20),
"criterion":["gini","entropy"],
"max_depth" :np.arange(4,10),
"min_samples_split":np.arange(3,10),
"min_samples_leaf":np.arange(3,10),
"max_features":["sqrt", "log2"],
"random_state":[41,42,43,44,45],
"oob_score":[True]}
rdscv = RandomizedSearchCV(rf_clf,hyperparamter,cv=4)
rdscv.fit(x_train,y_train)
```

Out[133]:



In [134…
```
rdscv.best_estimator_
```

Out[134]:
```
RandomForestClassifier(max_depth=8, min_samples_leaf=4, min_samples_split=7,
                       n_estimators=13, oob_score=True, random_state=41)
```

In [135…
```
rf_clf= RandomForestClassifier(max_depth=8, min_samples_leaf=4, min_samples_split=7,
                       n_estimators=13, oob_score=True, random_state=41)
```

In [136…
```
rf_clf.fit(x_train,y_train)
```

Out[136]:
```
RandomForestClassifier(max_depth=8, min_samples_leaf=4, min_samples_split=7,
                       n_estimators=13, oob_score=True, random_state=41)
```

In [138…
```
# training
```

```
y_pred_train = rf_clf.predict(x_train)

cnf_matrix = confusion_matrix(y_train,y_pred_train)
print("Confusioin Matrix\n",cnf_matrix)

Accuracy=accuracy_score(y_train,y_pred_train)
print("Accuracy",Accuracy*100)

clf_report=classification_report(y_train,y_pred_train)
print("Classification report\n",clf_report)
```

```
Confusioin Matrix
 [[3164  717]
 [ 379 3501]]
Accuracy 85.87810849117382
Classification report
               precision    recall  f1-score   support

           0       0.89      0.82      0.85      3881
           1       0.83      0.90      0.86      3880

    accuracy                           0.86      7761
   macro avg       0.86      0.86      0.86      7761
weighted avg       0.86      0.86      0.86      7761
```

In [139…

```
# testing
y_pred_test = rf_clf.predict(x_test)

cnf_matrix=confusion_matrix(y_test,y_pred_test)
print("Confusion Matrix\n",cnf_matrix)

Accuracy=accuracy_score(y_test,y_pred_test)
print("Accuracy",Accuracy*100)

clf_report=classification_report(y_test,y_pred_test)
print("Classification report\n",clf_report)
```

```
Confusion Matrix
 [[1027  266]
 [ 158 1136]]
Accuracy 83.61035948975648
Classification report
               precision    recall  f1-score   support

           0       0.87      0.79      0.83      1293
           1       0.81      0.88      0.84      1294

    accuracy                           0.84      2587
   macro avg       0.84      0.84      0.84      2587
weighted avg       0.84      0.84      0.84      2587
```

SVM

In [140…

```
from sklearn.svm import SVC
```

In [141…

```
svc_model = SVC()
svc_model.fit(x_train,y_train)
```

Out[141]:
```
▾ SVC
SVC()
```

Evaluation

In [143…
```
#Training Data
y_pred_train = svc_model.predict(x_train)

cnf_metrix = confusion_matrix(y_train,y_pred_train)
print("confusion matrix\n",cnf_metrix)

accuracy = accuracy_score(y_train,y_pred_train)
print("accuarcy",accuracy*100)

clf_report = classification_report(y_train,y_pred_train)
print("classification report",clf_report)
```

```
confusion matrix
 [[2840 1041]
 [1703 2177]]
accuarcy 64.64373147790234
classification report               precision    recall  f1-score   support

           0       0.63      0.73      0.67      3881
           1       0.68      0.56      0.61      3880

    accuracy                           0.65      7761
   macro avg       0.65      0.65      0.64      7761
weighted avg       0.65      0.65      0.64      7761
```

In [144…
```
#Testing Data
y_pred = svc_model.predict(x_test)

cnf_metrix = confusion_matrix(y_test,y_pred)
print("confusion matrix\n",cnf_metrix)

accuracy = accuracy_score(y_test,y_pred)
print("accuarcy",accuracy*100)

clf_report = classification_report(y_test,y_pred)
print("classification report",clf_report)
```

```
confusion matrix
 [[927 366]
 [566 728]]
accuarcy 63.973714727483575
classification report               precision    recall  f1-score   support

           0       0.62      0.72      0.67      1293
           1       0.67      0.56      0.61      1294

    accuracy                           0.64      2587
   macro avg       0.64      0.64      0.64      2587
weighted avg       0.64      0.64      0.64      2587
```

In [ ]:

Adaboost classifier

In [146…
```
from sklearn.ensemble import AdaBoostClassifier
```

In [148…
```
ada_clf = AdaBoostClassifier()
ada_clf.fit(x_train,y_train)
```

Out[148]:
AdaBoostClassifier

AdaBoostClassifier()

In [150…
```
#training
y_pred_train = ada_clf.predict(x_train)

cnf_matrix = confusion_matrix(y_train,y_pred_train)
print("Confusion Matrix\n",cnf_matrix)

clf_report = classification_report(y_train,y_pred_train)
print("Classification Report\n",clf_report)

Accuracy = accuracy_score(y_train,y_pred_train)
print("ACCURACY",Accuracy*100)
```

```
Confusion Matrix
 [[3248  633]
 [ 487 3393]]
Classification Report
              precision    recall  f1-score   support

           0       0.87      0.84      0.85      3881
           1       0.84      0.87      0.86      3880

    accuracy                           0.86      7761
   macro avg       0.86      0.86      0.86      7761
weighted avg       0.86      0.86      0.86      7761

ACCURACY 85.56886999098055
```

In [151…
```
# testing
y_pred_test =ada_clf.predict(x_test)

cnf_matrix = confusion_matrix(y_test,y_pred_test)
print("Confusion Matrix\n",cnf_matrix)

clf_report = classification_report(y_test,y_pred_test)
print("Classification Report\n",clf_report)

Accuracy = accuracy_score(y_test,y_pred_test)
print("ACCURACY",Accuracy*100)
```

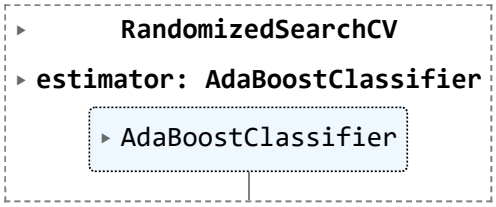
```
Confusion Matrix
 [[1086  207]
 [ 168 1126]]
Classification Report
              precision    recall  f1-score   support

           0       0.87      0.84      0.85      1293
           1       0.84      0.87      0.86      1294

    accuracy                           0.86      2587
   macro avg       0.86      0.86      0.86      2587
weighted avg       0.86      0.86      0.86      2587

ACCURACY 85.50444530344028
```

In [ ]:

Hyperparameter Tuning

In [153…
```
ada_clf=AdaBoostClassifier()
hyperparameter = {"n_estimators":np.arange(10,50),
                  "learning_rate":np.arange(0,2,0.001)}
rscv_adb = RandomizedSearchCV(ada_clf,hyperparameter,cv=5)
rscv_adb.fit(x_train,y_train)
```

Out[153]:



In [155…
```
rscv_adb.best_estimator_
```

Out[155]:

```
AdaBoostClassifier(learning_rate=1.733, n_estimators=35)
```

In [156…
```
ada_clf=AdaBoostClassifier(learning_rate=1.733, n_estimators=35)
ada_clf.fit(x_train,y_train)
```

Out[156]:

```
AdaBoostClassifier(learning_rate=1.733, n_estimators=35)
```

In [157…
```
#training
y_pred_train = ada_clf.predict(x_train)

cnf_matrix = confusion_matrix(y_train,y_pred_train)
print("Confusion Matrix\n",cnf_matrix)

clf_report = classification_report(y_train,y_pred_train)
print("Classification Report\n",clf_report)

Accuracy = accuracy_score(y_train,y_pred_train)
print("ACCURACY",Accuracy*100)
```

```
Confusion Matrix
 [[2980  901]
 [ 486 3394]]
Classification Report
              precision    recall  f1-score   support

           0       0.86      0.77      0.81      3881
           1       0.79      0.87      0.83      3880

    accuracy                           0.82      7761
   macro avg       0.83      0.82      0.82      7761
weighted avg       0.83      0.82      0.82      7761

ACCURACY 82.12859167633036
```

In [158…

```
# testing
y_pred_test =ada_clf.predict(x_test)

cnf_matrix = confusion_matrix(y_test,y_pred_test)
print("Confusion Matrix\n",cnf_matrix)

clf_report = classification_report(y_test,y_pred_test)
print("Classification Report\n",clf_report)

Accuracy = accuracy_score(y_test,y_pred_test)
print("ACCURACY",Accuracy*100)
```

```
Confusion Matrix
 [[ 978  315]
 [ 174 1120]]
Classification Report
              precision    recall  f1-score   support

           0       0.85      0.76      0.80      1293
           1       0.78      0.87      0.82      1294

    accuracy                           0.81      2587
   macro avg       0.81      0.81      0.81      2587
weighted avg       0.81      0.81      0.81      2587

ACCURACY 81.09779667568611
```

Lets see the accuracy we've got by the models

In [159…

```
ACCURACY_df = pd.DataFrame({"MODEL":["Decision tree","Decision tree with Hyperparamete
                                     "Random Forest","Random Forest with Hyperparameter","SVM",
                                     "Adaboost classifier","Adaboost classifier with Hyperparam
                            "Training Accuracy":[99.88,80.59,99.88,85.87,64.64,85.56,82.12],
                            "Testing Accuracy":[80.59,80.59,85.92,83.61,63.97,85.50,81.09],
                            })
ACCURACY_df
```

Out[159]:

	MODEL	Training Accuracy	Testing Accuracy
0	Decision tree	99.88	80.59
1	Decision tree with Hyperparameter	80.59	80.59
2	Random Forest	99.88	85.92
3	Random Forest with Hyperparameter	85.87	83.61
4	SVM	64.64	63.97
5	Adaboost classifier	85.56	85.50
6	Adaboost classifier with Hyperparameter Tuning	82.12	81.09

In [ ]: