1. Problem Statement

An E Commerce company or DTH (you can choose either of these two domains) provider is facing a lot of competition in the current market and it has become a challenge to retain the existing customers in the current situation. Hence, the company wants to develop a model through which they can do churn prediction of the accounts and provide segmented offers to the potential churners. In this company, account churn is a major thing because 1 account can have multiple customers. hence by losing one account the company might be losing more than one customer.

You have been assigned to develop a churn prediction model for this company and provide business recommendations on the campaign.

Your campaign suggestion should be unique and be very clear on the campaign offer because your recommendation will go through the revenue assurance team. If they find that you are giving a lot of free (or subsidized) stuff thereby making a loss to the company; they are not going to approve your recommendation.

Hence be very careful while providing campaign recommendation.

2. Data Collection

The Dataset is mentioned as below:

Customer Churn Data.xlsx

Dataset granted by: PARIKSHITH A

3. Data Ingestion

```
!pip install pandas numpy
!pip install seaborn matplotlib
!pip install sklearn
```

```
Requirement already satisfied: seaborn in /usr/local/lib/python3.10/dist-packages (0.12.2)
Requirement already satisfied: numpy!=1.24.0,>=1.17 in /usr/local/lib/python3.10/dist-packages (from seaborn) (1.22.4)
Requirement already satisfied: pandas>=0.25 in /usr/local/lib/python3.10/dist-packages (from seaborn) (1.5.3)
Requirement already satisfied: matplotlib!=3.6.1,>=3.1 in /usr/local/lib/python3.10/dist-packages (from seaborn) (3.7.1)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (0.1
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (8.
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seabo
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.25->seaborn) (2022.7.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib!=3.6.1,>=
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (3.7.1)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.1.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (4.41.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.4.4)
Requirement already satisfied: numpy>=1.20 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.22.4)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (23.1)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (8.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (3.1.0)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib) (1.16.0)
Collecting sklearn
  Downloading sklearn-0.0.post7.tar.gz (3.6 kB)
  Preparing metadata (setup.py) ... done
Building wheels for collected packages: sklearn
  Building wheel for sklearn (setup.py) ... done
  Created wheel for sklearn: filename=sklearn-0.0.post7-py3-none-any.whl size=2952 sha256=5f3eaf236055ced8eadcc6ef00f7abd50a2286ce9
  Stored in directory: /root/.cache/pip/wheels/c8/9c/85/72901eb50bc4bc6e3b2629378d172384ea3dfd19759c77fd2c
Successfully built sklearn
Installing collected packages: sklearn
Successfully installed sklearn-0.0.post7
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

```
cf=pd.read_excel('Customer Churn Data.xlsx',sheet_name='Data for DSBA') # reading the data set
```

```
cf.head() #top 5 rows get displayed
```

	AccountID	Churn	Tenure	City_Tier	CC_Contacted_LY	Payment	Gender	Service_Score	Account_user_count	account_segment	CC_Age
0	20000	1	4	3.0	6.0	Debit Card	Female	3.0	3	Super	
1	20001	1	0	1.0	8.0	UPI	Male	3.0	4	Regular Plus	
2	20002	1	0	1.0	30.0	Debit Card	Male	2.0	4	Regular Plus	
3	20003	1	0	3.0	15.0	Debit Card	Male	2.0	4	Super	
4	20004	1	0	1.0	12.0	Credit Card	Male	2.0	3	Regular Plus	

```
cf.tail() #last bottom 5 rows get displayed
```

	AccountID	Churn	Tenure	City_Tier	CC_Contacted_LY	Payment	Gender	Service_Score	Account_user_count	account_segment	CC_
11255	31255	0	10	1.0	34.0	Credit Card	Male	3.0	2	Super	
11256	31256	0	13	1.0	19.0	Credit Card	Male	3.0	5	HNI	
11257	31257	0	1	1.0	14.0	Debit Card	Male	3.0	2	Super	
11258	31258	0	23	3.0	11.0	Credit Card	Male	4.0	5	Super	
11259	31259	0	8	1.0	22.0	Credit Card	Male	3.0	2	Super	

4. Data Cleaning

Checking for null values and duplicate values

```
cf.dtypes # data types of each individual column get printed
```

```
AccountID                 int64
Churn                     int64
Tenure                   object
City_Tier               float64
CC_Contacted_LY         float64
Payment                  object
Gender                   object
Service_Score           float64
Account_user_count       object
account_segment          object
CC_Agent_Score          float64
Marital_Status           object
rev_per_month            object
Complain_ly             float64
rev_growth_yoy           object
coupon_used_for_payment  object
Day_Since_CC_connect     object
cashback                 object
Login_device             object
dtype: object
```

Here, there are 12 categorical characteristics in this list, 5 of which are float types and the remaining 7 are all integer types.

```
cf.isnull().sum() # checking each individual column that there are Null values or not|
```

```
AccountID                 0
Churn                     0
```

```
Tenure                    102
City_Tier                 112
CC_Contacted_LY           102
Payment                   109
Gender                    108
Service_Score              98
Account_user_count        112
account_segment            97
CC_Agent_Score            116
Marital_Status            212
rev_per_month             102
Complain_ly               357
rev_growth_yoy              0
coupon_used_for_payment     0
Day_Since_CC_connect      357
cashback                  471
Login_device              221
dtype: int64
```

In this case, we'll replace the column with NULL values with the median and mode, i.e., categorical by mode and numerical by mean.

```
cf.duplicated().sum() #there no duplicated rows
```

```
0
```

We are in the process of discarding the columns which satisfy neither our purposes nor those of our target.

```
cf.drop(['AccountID','Payment','Gender','Marital_Status','cashback','Login_device'],axis=1,inplace=True) #dropping the unwanted column
```

```
cf.drop(['coupon_used_for_payment'],axis=1,inplace=True)
```

```
cf.dtypes # data types of each individual column get printed
```

```
Churn                    int64
Tenure                  object
City_Tier              float64
CC_Contacted_LY        float64
Service_Score          float64
Account_user_count      object
account_segment         object
CC_Agent_Score         float64
rev_per_month           object
Complain_ly            float64
rev_growth_yoy          object
Day_Since_CC_connect    object
dtype: object
```

```
# Identify object columns except for 'Column1'
object_columns = cf.select_dtypes(include=['object']).columns.drop('account_segment')
```

```
# Convert object columns to float using pd.to_numeric()
cf[object_columns] = cf[object_columns].apply(pd.to_numeric, errors='coerce')
```

```
cf['Churn'] = cf['Churn'].astype(float) #converting int to float
```

```
cf.dtypes
```

```
Churn                  float64
Tenure                 float64
City_Tier              float64
CC_Contacted_LY        float64
Service_Score          float64
Account_user_count     float64
account_segment         object
CC_Agent_Score         float64
rev_per_month          float64
Complain_ly            float64
rev_growth_yoy         float64
Day_Since_CC_connect   float64
dtype: object
```

Let us now substitute mean and mode for the NULL values.

```
# cf = cf.fillna(cf.median()) #this is for numerical column

numeric_columns = cf.select_dtypes(include=['float', 'int']).columns
cf[numeric_columns] = cf[numeric_columns].fillna(cf[numeric_columns].median())


#now lets check again that there is null counts or not
cf.isnull().sum()
```

```
Churn                   0
Tenure                  0
City_Tier               0
CC_Contacted_LY         0
Service_Score           0
Account_user_count      0
account_segment        97
CC_Agent_Score          0
rev_per_month           0
Complain_ly             0
rev_growth_yoy          0
Day_Since_CC_connect    0
dtype: int64
```

```
#now lets fill object column null values with mode
object_columns = cf.select_dtypes(include=['object']).columns
cf[object_columns] = cf[object_columns].fillna(cf[object_columns].mode().iloc[0])


#now lets check again that there is null counts or not
cf.isnull().sum()
```

```
Churn                   0
Tenure                  0
City_Tier               0
CC_Contacted_LY         0
Service_Score           0
Account_user_count      0
account_segment         0
CC_Agent_Score          0
rev_per_month           0
Complain_ly             0
rev_growth_yoy          0
Day_Since_CC_connect    0
dtype: int64
```

```
# Check unique values in each column
for column in cf.columns:
    unique_values = cf[column].unique()
    print(f"Unique values in {column}: {unique_values}")
```

```
Unique values in Churn: [1. 0.]
Unique values in Tenure: [ 4.  0.  2. 13. 11.  9. 99. 19. 20. 14.  8. 26. 18.  5. 30.  7.  1. 23.
  3. 29.  6. 28. 24. 25. 16. 10. 15. 22. 27. 12. 21. 17. 50. 60. 31. 51.
 61.]
Unique values in City_Tier: [3. 1. 2.]
Unique values in CC_Contacted_LY: [  6.   8.  30.  15.  12.  22.  11.   9.  31.  18.  13.  20.  29.  28.
  26.  14.  10.  25.  27.  17.  23.  33.  19.  35.  24.  16.  32.  21.
  34.   5.   4. 126.   7.  36. 127.  42.  38.  37.  39.  40.  41. 132.
  43. 129.]
Unique values in Service_Score: [3. 2. 1. 0. 4. 5.]
Unique values in Account_user_count: [3. 4. 5. 2. 1. 6.]
Unique values in account_segment: ['Super' 'Regular Plus' 'Regular' 'HNI' 'Regular +' 'Super Plus' 'Super +']
Unique values in CC_Agent_Score: [2. 3. 5. 4. 1.]
Unique values in rev_per_month: [  9.   7.   6.   8.   3.   2.   4.  10.   1.   5. 130.  19. 139. 102.
 120. 138. 127. 123. 124. 116.  21. 126. 134. 113. 114. 108. 140. 133.
 129. 107. 118.  11. 105.  20. 119. 121. 137. 110.  22. 101. 136. 125.
  14.  13.  12. 115.  23. 122. 117. 131. 104.  15.  25. 135. 111. 109.
 100. 103.]
Unique values in Complain_ly: [1. 0.]
Unique values in rev_growth_yoy: [11. 15. 14. 23. 22. 16. 12. 13. 17. 18. 24. 19. 20. 21. 25. 26.  4. 27.
 28.]
Unique values in Day_Since_CC_connect: [ 5.  0.  3.  7.  2.  1.  8.  6.  4. 15. 11. 10.  9. 13. 12. 17. 16. 14.
 30. 46. 18. 31. 47.]
```

5. Exploratory Data Analysis (EDA)

```
cf.sample(6) #this line will randomly select any five column from dataset
```

	Churn	Tenure	City_Tier	CC_Contacted_LY	Service_Score	Account_user_count	a
8909	1.0	1.0	1.0	12.0	3.0	5.0	
3460	0.0	20.0	1.0	7.0	3.0	4.0	
4245	0.0	9.0	1.0	14.0	3.0	6.0	
973	0.0	13.0	1.0	14.0	3.0	3.0	
2892	0.0	8.0	1.0	17.0	3.0	4.0	

Attributes Information:

- churn: account churn flag (Target)
- Tenure:Tenure of account
- City_Tier:Tier of primary customer's city
- cc_contacted_Ly:How many time the customer of the account has contacted customer care in last 12months
- Service_Score:Satisfaction score given by customers of the account on service provided by company
- Account_user_count:Number of customers tagged with this account
- account_segment:Account segmentation on the basis of spend
- CC_Agent_Score:Satisfaction score given by customers of the account on customer care service provided by company
- rev_per_month:Monthly average revenue generated by account in last 12 months
- complain_ly:Any complaints has been raised by account in last 12 months
- rev_growth_yoy:revenue growth percentage of the account (last 12 months vs last 24 to 13month)
- Day_Since_CC_connect:Number of days since no customers in the account has contacted the customer care

.

```
cf.shape #{checking the number of rows and column}
```

```
(11260, 12)
```

```
cf.info() #{ checking the dataypes and count of null values if present}
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11260 entries, 0 to 11259
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Churn                 11260 non-null  float64
 1   Tenure                11260 non-null  float64
 2   City_Tier             11260 non-null  float64
 3   CC_Contacted_LY       11260 non-null  float64
 4   Service_Score         11260 non-null  float64
 5   Account_user_count    11260 non-null  float64
 6   account_segment       11260 non-null  object 
 7   CC_Agent_Score        11260 non-null  float64
 8   rev_per_month         11260 non-null  float64
 9   Complain_ly           11260 non-null  float64
 10  rev_growth_yoy        11260 non-null  float64
 11  Day_Since_CC_connect  11260 non-null  float64
dtypes: float64(11), object(1)
memory usage: 1.0+ MB
```

```
cf['Churn'].value_counts() # Here it can be seen that the number of 1's is very less as compared to number of 0's. So that dataset is imb
```

```
0.0    9364
1.0    1896
Name: Churn, dtype: int64
```

It can be seen that the number of 1s is much lower than the number of 0s. As a result, that dataset is imbalanced.

Separating Numerical and Categorical Features

```
num_feature= [fea for fea in cf.columns if cf[fea].dtype !=object]
cat_feature= [fea for fea in cf.columns if cf[fea].dtype==object]
```

```
print("We have {} Numerical features : {}".format(len(num_feature),num_feature))
print()
print("We have {} Categorical features : {}".format(len(cat_feature),cat_feature))
```

```
We have 11 Numerical features : ['Churn', 'Tenure', 'City_Tier', 'CC_Contacted_LY', 'Service_Score', 'Account_user_count', 'CC_Agen

We have 1 Categorical features : ['account_segment']
```

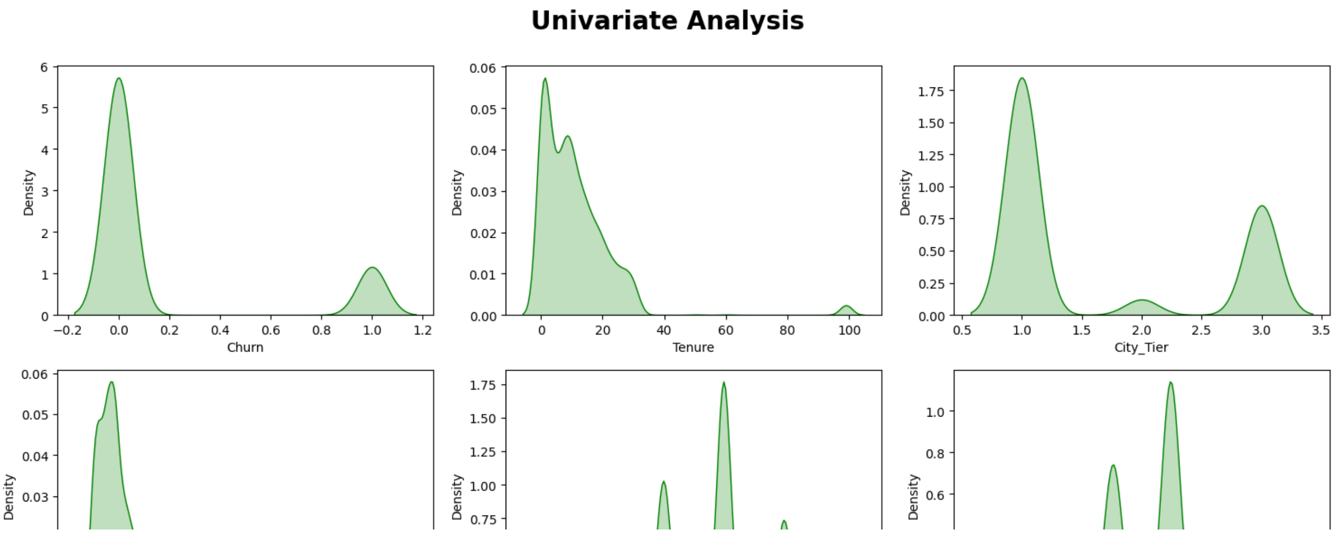
Statistical Description

```
cf.describe().T
```

	count	mean	std	min	25%	50%	75%	max
Churn	11260.0	0.168384	0.374223	0.0	0.0	0.0	0.0	1.0
Tenure	11260.0	10.985879	12.757534	0.0	2.0	9.0	16.0	99.0
City_Tier	11260.0	1.647425	0.912763	1.0	1.0	1.0	3.0	3.0
CC_Contacted_LY	11260.0	17.850178	8.814851	4.0	11.0	16.0	23.0	132.0
Service_Score	11260.0	2.903375	0.722476	0.0	2.0	3.0	3.0	5.0
Account_user_count	11260.0	3.704973	1.004383	1.0	3.0	4.0	4.0	6.0
CC_Agent_Score	11260.0	3.065808	1.372663	1.0	2.0	3.0	4.0	5.0
rev_per_month	11260.0	6.266874	11.488990	1.0	3.0	5.0	7.0	140.0
Complain_ly	11260.0	0.276288	0.447181	0.0	0.0	0.0	1.0	1.0
rev_growth_yoy	11260.0	16.193073	3.757271	4.0	13.0	15.0	19.0	28.0
Day_Since_CC_connect	11260.0	4.581261	3.649643	0.0	2.0	3.0	7.0	47.0

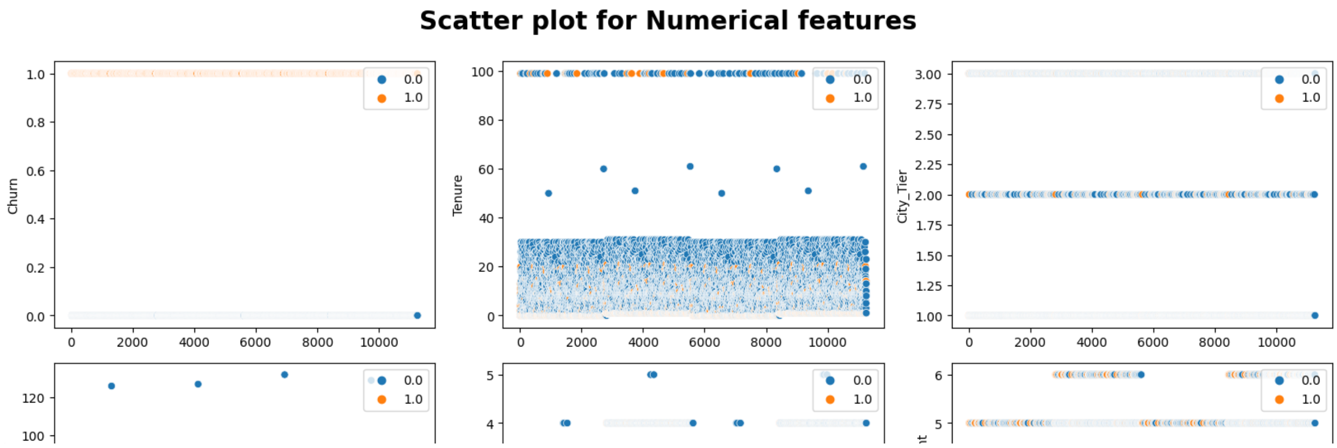
Univariate Analysis

```
plt.figure(figsize=(15,17))
plt.suptitle('Univariate Analysis',fontsize=20,fontweight='bold',y=1)

for i in range(0,len(num_feature)):
    plt.subplot(5,3,i+1)
    sns.kdeplot(x=cf[num_feature[i]],shade=True,color='g')
    plt.xlabel(num_feature[i])
    plt.tight_layout()
```

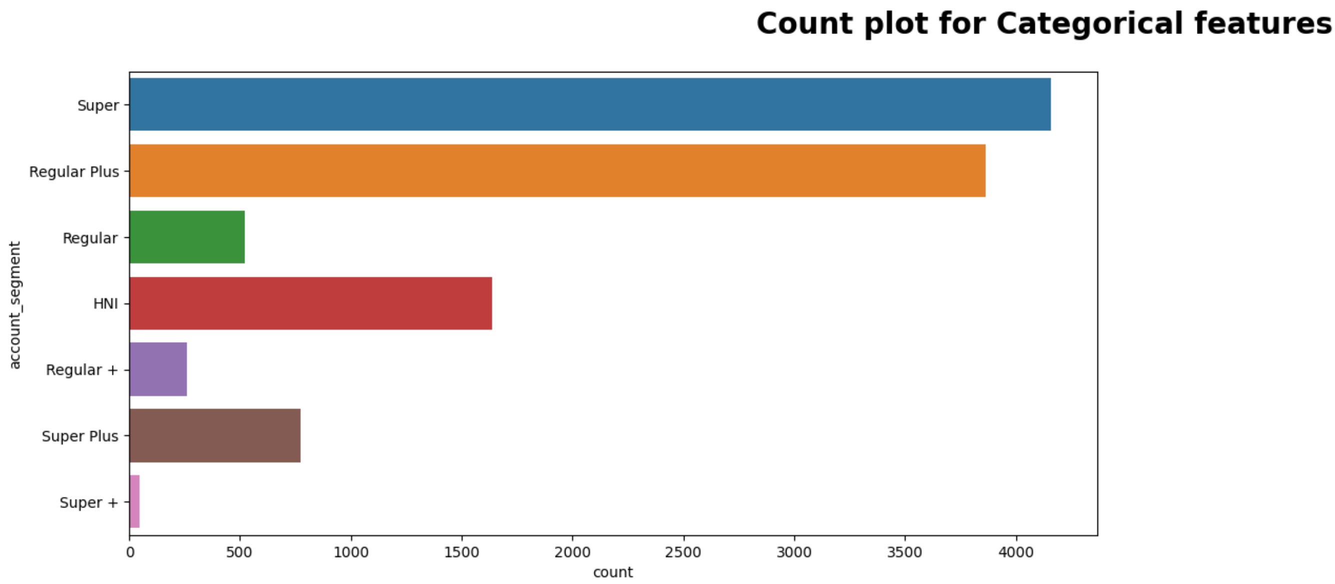


> Observations
>
> - CC_Agent_scored are normally distributed.
> - Tenure,Day_Since_CC_connect,rev_per_month,CC_Contacted_ly, is havily left skewed.
> - Almost 50% of the customefr are not active.

```
plt.figure(figsize=(15,17)) #fixing the size of graph
plt.suptitle('Scatter plot for Numerical features',fontsize=20,fontweight='bold',y=1) # placing at top of the graph heading.

for i in range(0,len(num_feature)):
    plt.subplot(5,3,i+1)
    sns.scatterplot(y=num_feature[i],x=cf.index,data=cf,color='b',hue='Churn')
    plt.legend(loc="upper right")
    plt.tight_layout()
```



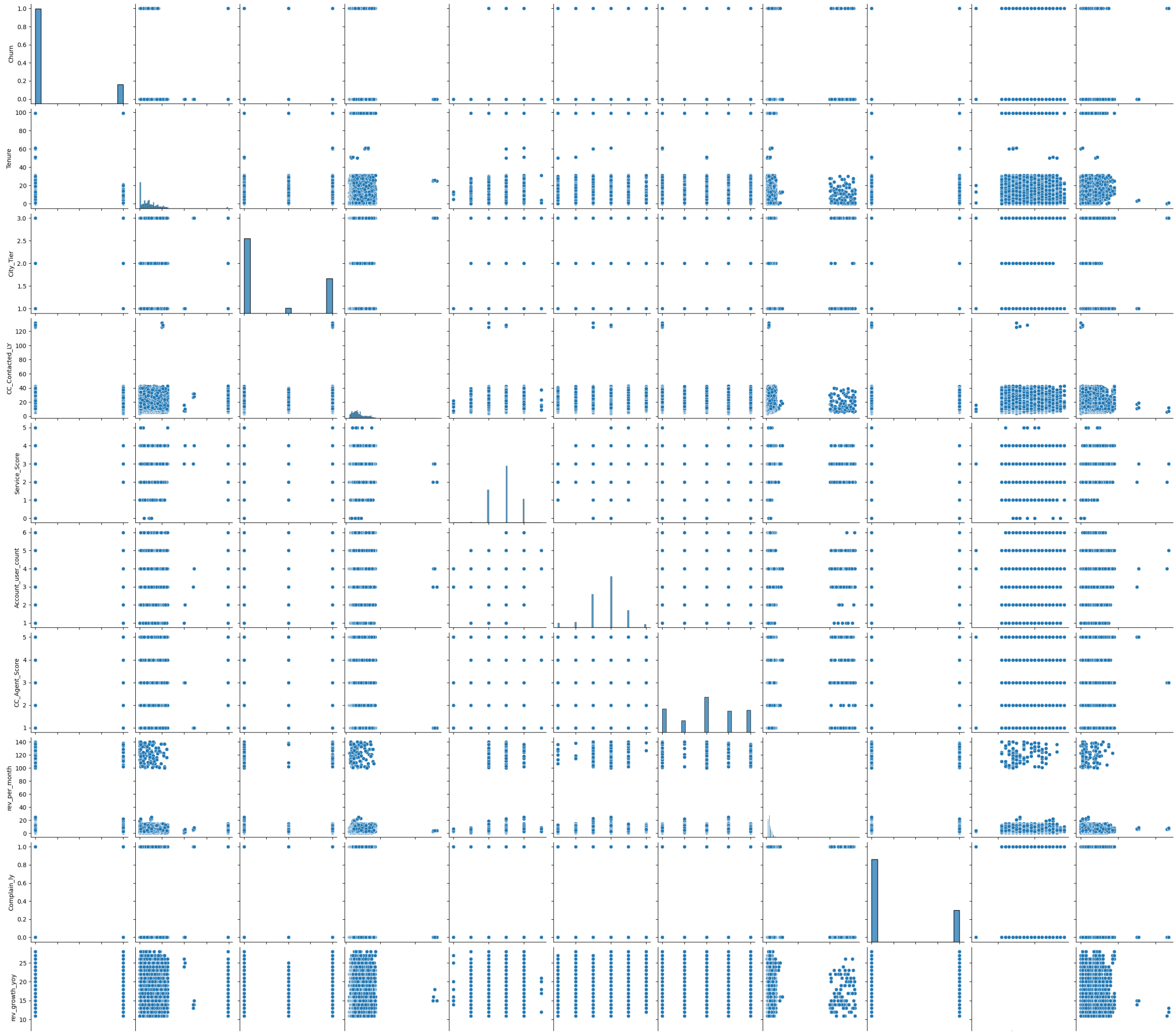

```
plt.figure(figsize=(20,40))
plt.suptitle('Count plot for Categorical features',fontsize=20,fontweight='bold',y=1)

for i in range(0,len(cat_feature)):
    plt.subplot(8,2,i+1)
    sns.countplot(y=cat_feature[i],data=cf)
    plt.tight_layout()
```



▾ Bivariate Analysis

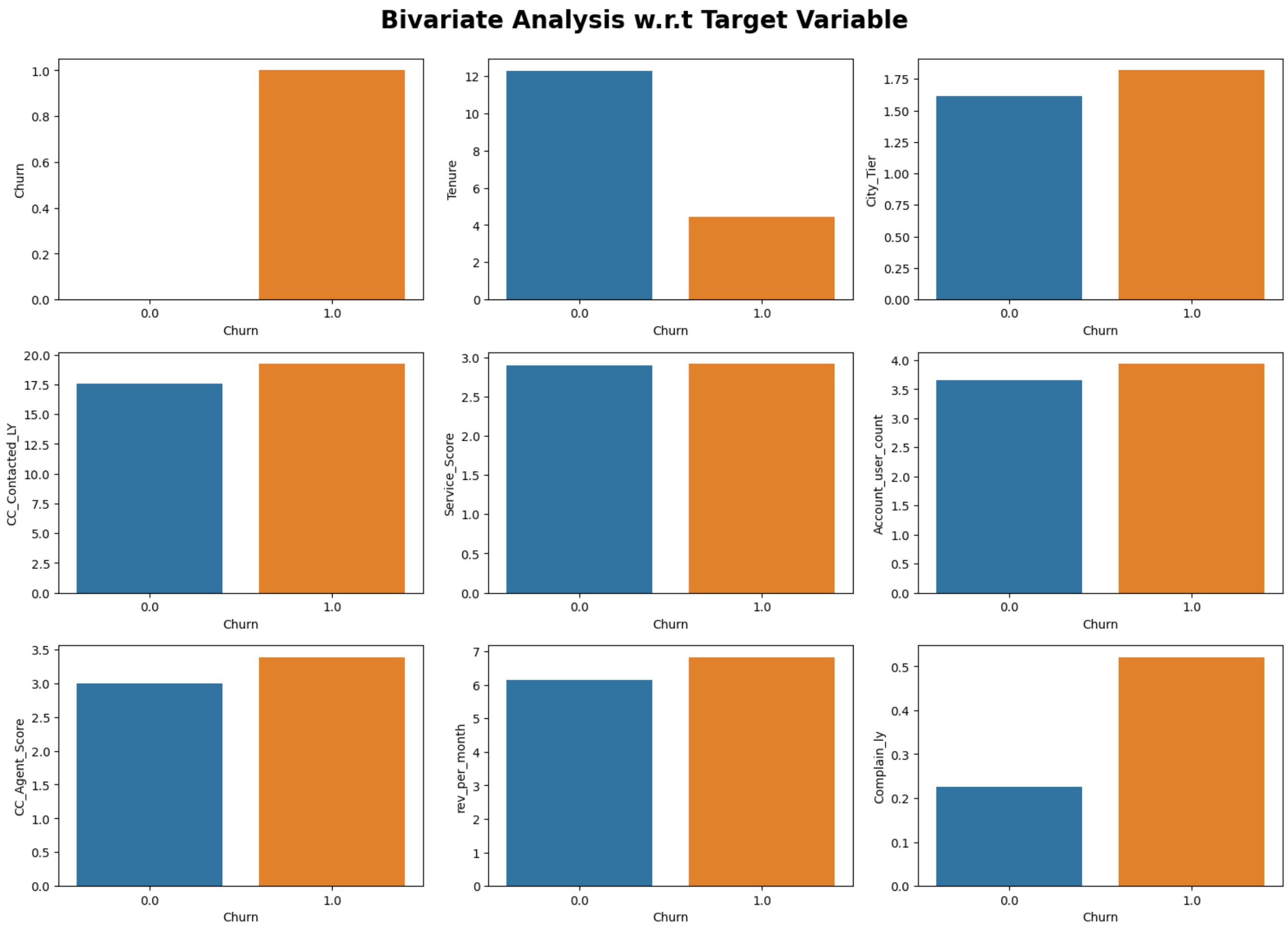
```
plt.figure(figsize=(10,20))
sns.pairplot(cf)
plt.show()
```

```
<Figure size 1000x2000 with 0 Axes>
```

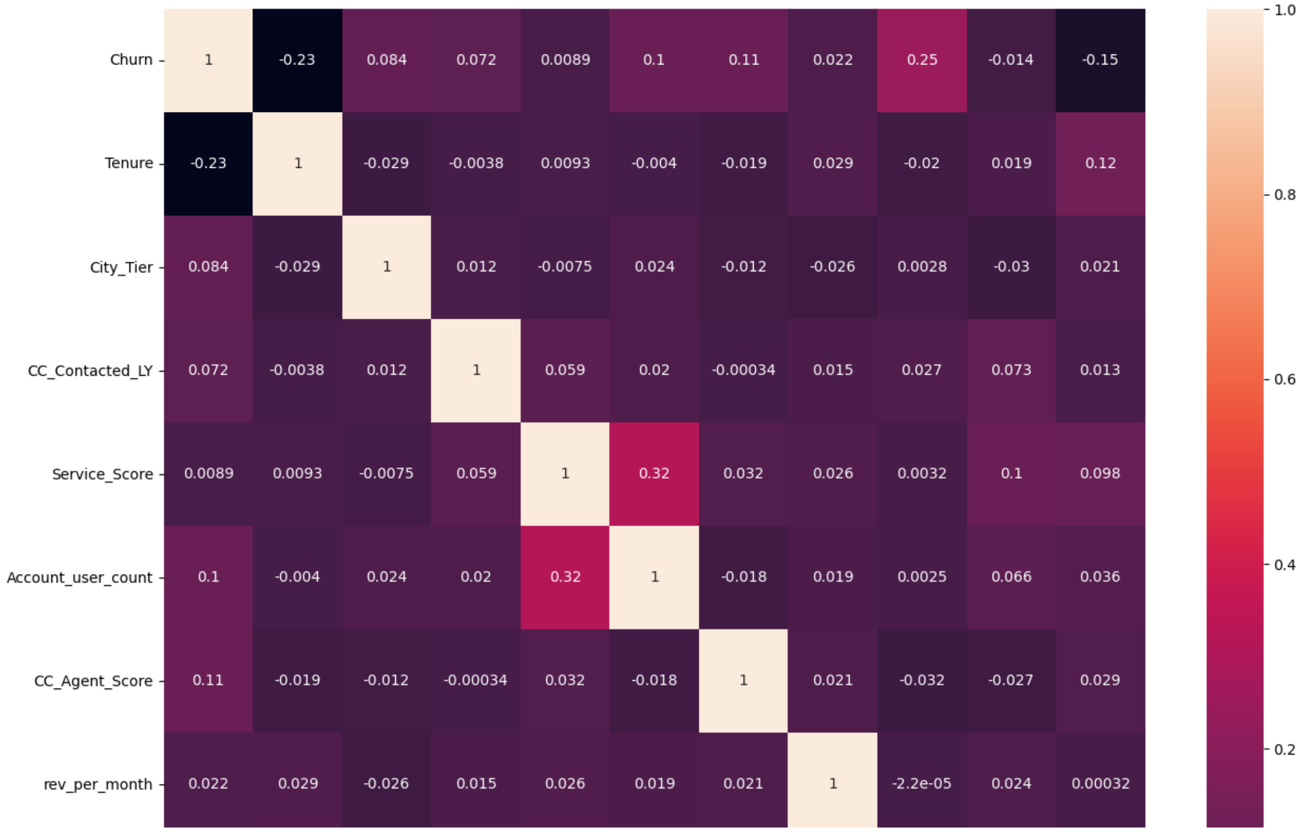


Bivariate Analysis w.r.t Target Variable

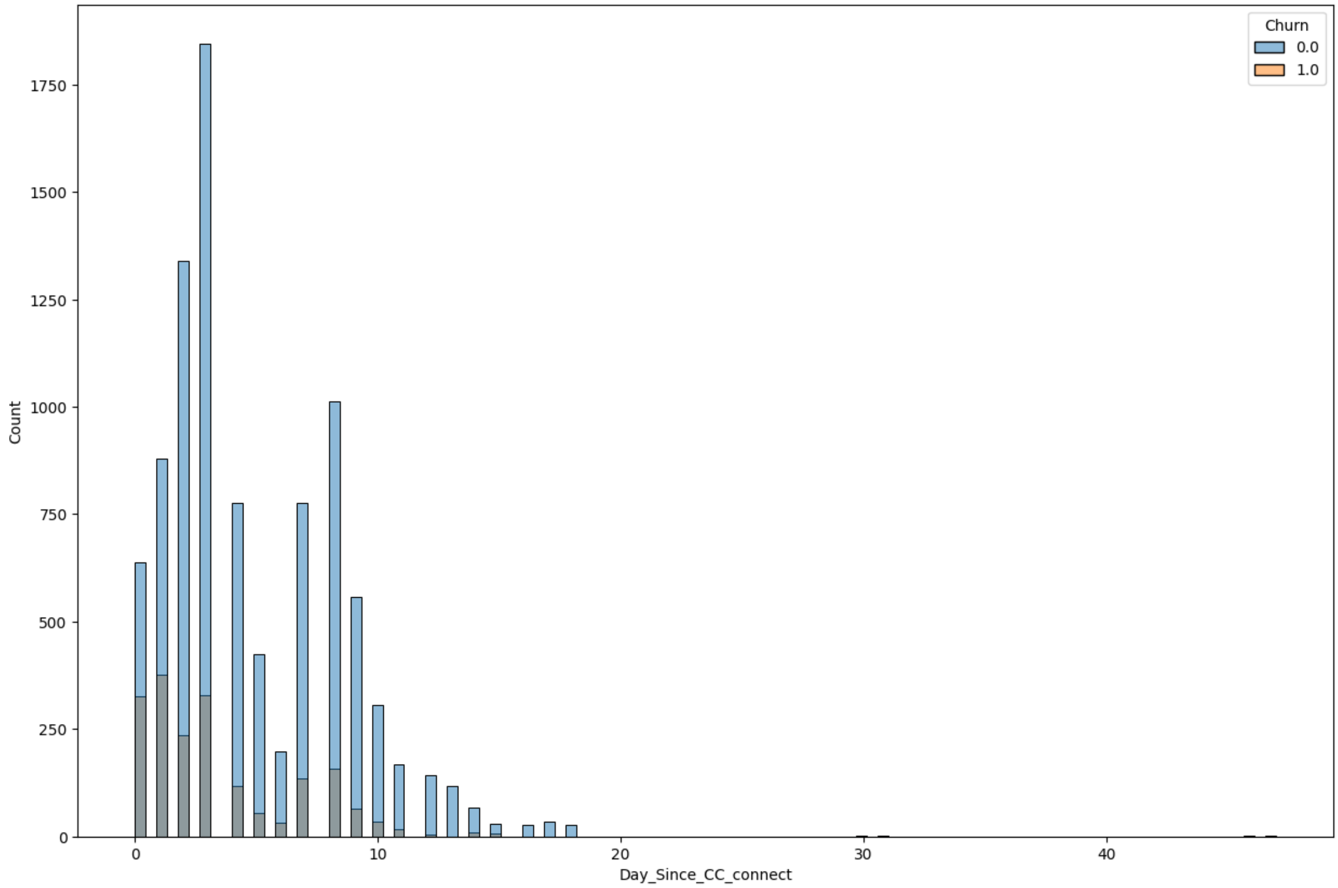
```
plt.figure(figsize=(15,17))
plt.suptitle('Bivariate Analysis w.r.t Target Variable',fontsize=20,fontweight='bold',y=1)

for i in range(0,len(num_feature)):
    plt.subplot(5,3,i+1)
    sns.barplot(y=num_feature[i],x='Churn',data=cf,ci=0)
    plt.tight_layout()
```



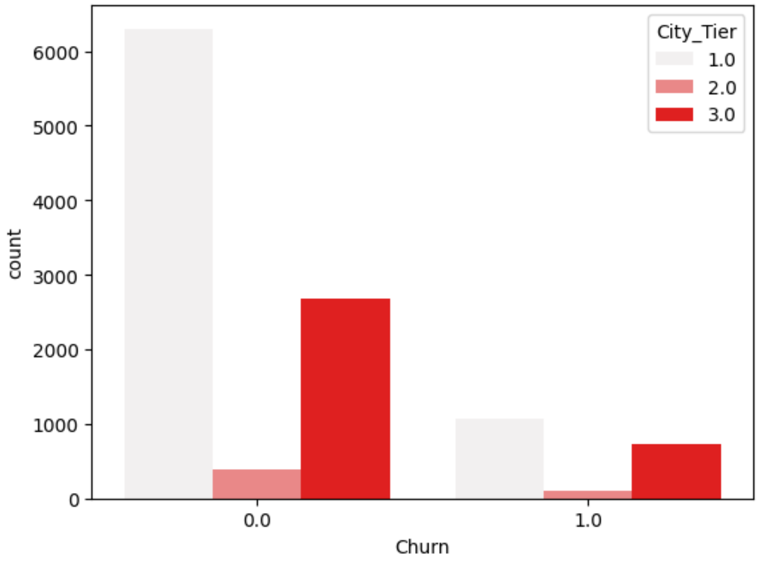

```
# Select only numeric columns
numeric_columns = cf.select_dtypes(include=['float', 'int'])

# Calculate the correlation matrix
corr_matrix = numeric_columns.corr()

# Plot the correlation matrix using a heatmap
plt.figure(figsize=(15, 14))
sns.heatmap(corr_matrix, annot=True)
plt.show()
```




```
plt.figure(figsize=(15,10))
sns.histplot(x='Day_Since_CC_connect',hue='Churn',data=cf)
plt.show()
```

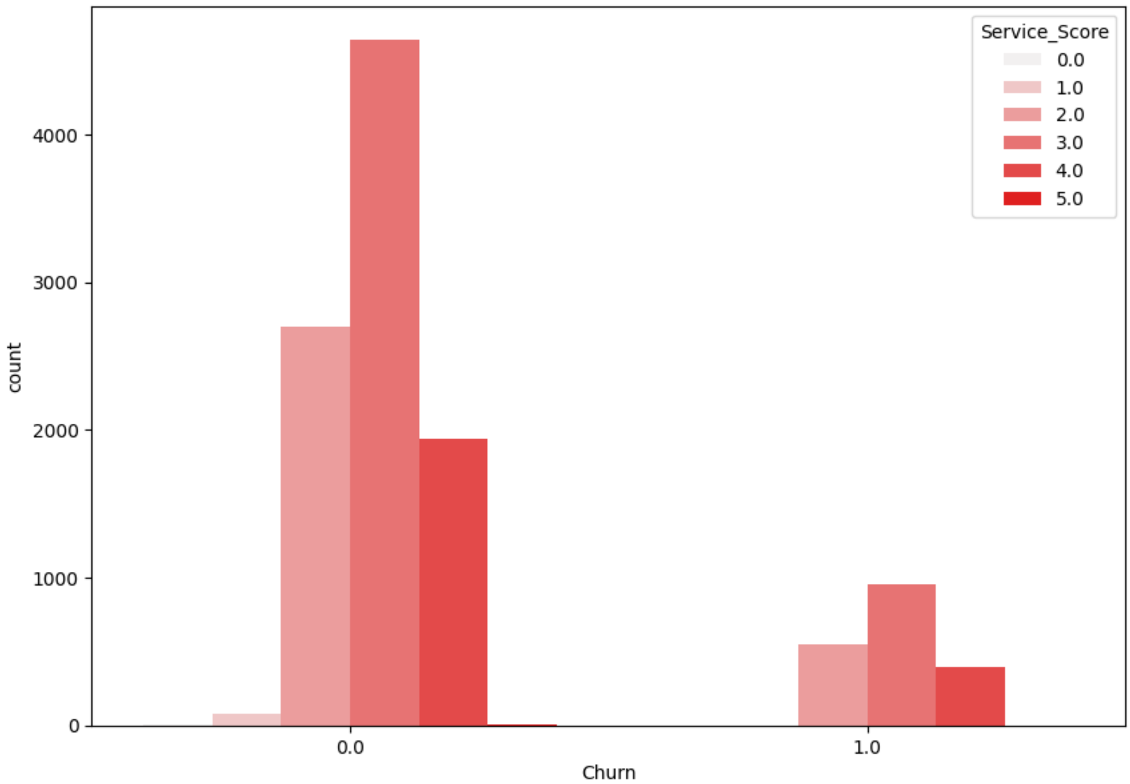


```
sns.countplot(x=cf.Churn,hue=cf.City_Tier,color='red')
plt.show()
```



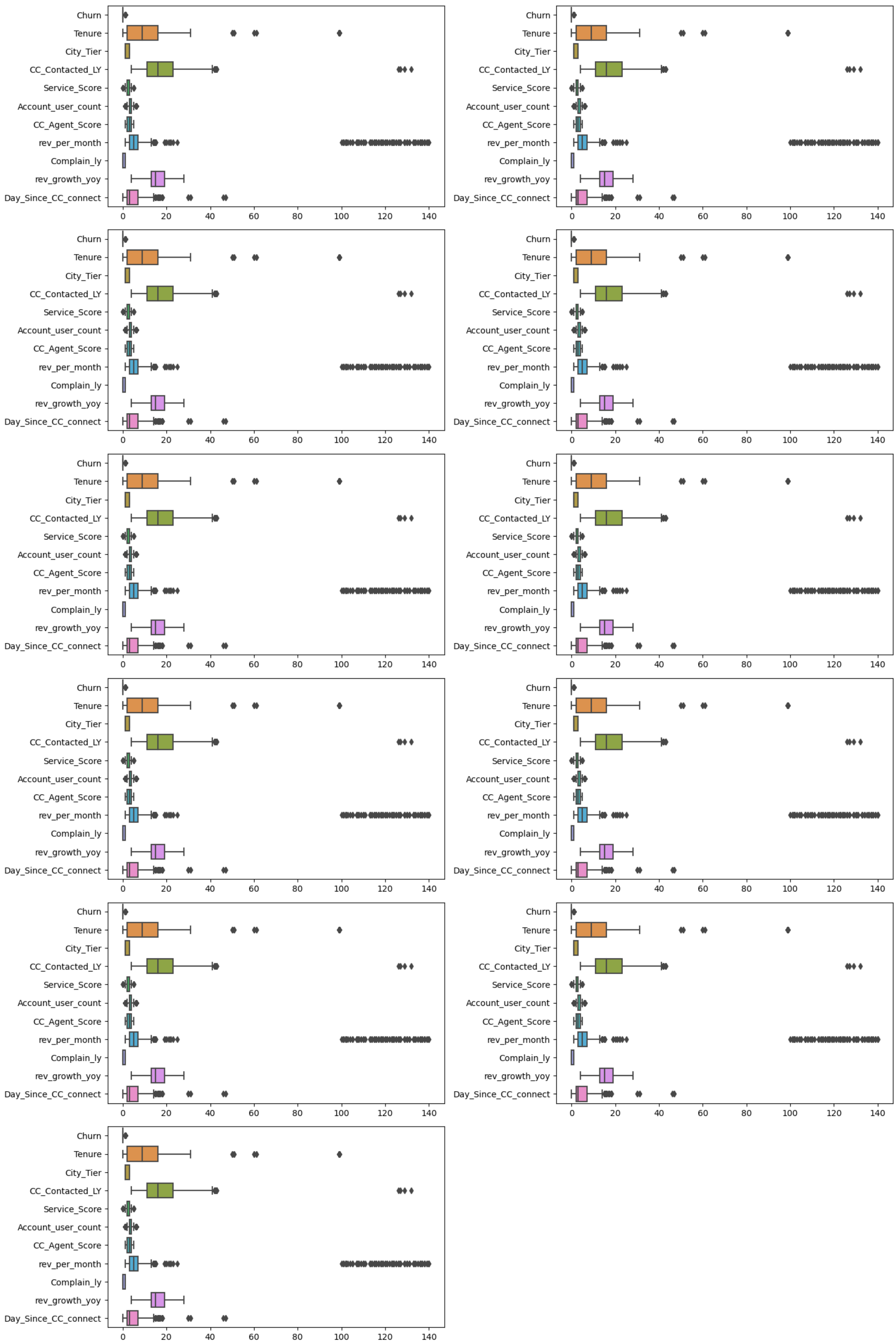

```
plt.figure(figsize=(10,7))
sns.countplot(x='Churn',hue='Service_Score',data=cf,color='red')
```

```
<Axes: xlabel='Churn', ylabel='count'>
```




```
plt.figure(figsize=(15,30))
plt.suptitle('BOX PLOT for all numerical feature',fontsize=20,fontweight='bold',y=1)

for i in range(0,len(num_feature)):
    plt.subplot(8,2,i+1)
    sns.boxplot(data=cf[num_feature],orient='h') # checking the outliers are present or not
    plt.tight_layout()
```

BOX PLOT for all numerical feature



6. Data Preprocessing

Feature encoding to convert the categorical features into numerical values

```
cf.head() #checking top 5 rows of the data set
```

	Churn	Tenure	City_Tier	CC_Contacted_LY	Service_Score	Account_user_count	account_segment	CC_Agent_Score	rev_per_month	Com
0	1.0	4.0	3.0	6.0	3.0	3.0	Super	2.0	9.0	
1	1.0	0.0	1.0	8.0	3.0	4.0	Regular Plus	3.0	7.0	
2	1.0	0.0	1.0	30.0	2.0	4.0	Regular Plus	3.0	6.0	
3	1.0	0.0	3.0	15.0	2.0	4.0	Super	5.0	8.0	
4	1.0	0.0	1.0	12.0	2.0	3.0	Regular Plus	5.0	3.0	

```
#Now doing one_hot_encoding to convert categorical features into numerical feature
cf1=pd.get_dummies(data=cf,columns=['account_segment'],drop_first=True)
```

```
cf1.head()
```

	Churn	Tenure	City_Tier	CC_Contacted_LY	Service_Score	Account_user_count	CC_Agent_Score	rev_per_month	Complain_ly	rev_gro
0	1.0	4.0	3.0	6.0	3.0	3.0	2.0	9.0	1.0	
1	1.0	0.0	1.0	8.0	3.0	4.0	3.0	7.0	1.0	
2	1.0	0.0	1.0	30.0	2.0	4.0	3.0	6.0	1.0	
3	1.0	0.0	3.0	15.0	2.0	4.0	5.0	8.0	0.0	
4	1.0	0.0	1.0	12.0	2.0	3.0	5.0	3.0	0.0	

Extracting the target column into separate vectors for training set and test set

```
X=cf1.drop(['Churn'],axis=1) #dropping the label
Y=cf1['Churn']
X.shape,Y.shape #checking shape
```

```
((11260, 16), (11260,))
```

```
X.head()
```

	Tenure	City_Tier	CC_Contacted_LY	Service_Score	Account_user_count	CC_Agent_Score	rev_per_month	Complain_ly	rev_growth_yoy
0	4.0	3.0	6.0	3.0	3.0	2.0	9.0	1.0	11.0
1	0.0	1.0	8.0	3.0	4.0	3.0	7.0	1.0	15.0
2	0.0	1.0	30.0	2.0	4.0	3.0	6.0	1.0	14.0
3	0.0	3.0	15.0	2.0	4.0	5.0	8.0	0.0	23.0
4	0.0	1.0	12.0	2.0	3.0	5.0	3.0	0.0	11.0

```
Y.head()
```

```
0    1.0
1    1.0
2    1.0
3    1.0
4    1.0
Name: Churn, dtype: float64
```

```
!pip install --upgrade imbalanced-learn
```

```
Requirement already satisfied: imbalanced-learn in /usr/local/lib/python3.10/dist-packages (0.11.0)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.10/dist-packages (from imbalanced-learn) (1.22.4)
Requirement already satisfied: scipy>=1.5.0 in /usr/local/lib/python3.10/dist-packages (from imbalanced-learn) (1.10.1)
Requirement already satisfied: scikit-learn>=1.0.2 in /usr/local/lib/python3.10/dist-packages (from imbalanced-learn) (1.3.0)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from imbalanced-learn) (1.3.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from imbalanced-learn) (3.1.0)
```

Balancing the dataset by using oversampling technique

```
from imblearn.combine import SMOTETomek
import matplotlib.pyplot as plt

smk = SMOTETomek()
X_res, Y_res = smk.fit_resample(X, Y)
%matplotlib inline
```

```
X_res.shape,Y_res.shape #after balancing the data set checking new shape
```

```
((18722, 16), (18722,))
```

Splitting the dataset into train and test data

```
from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test=train_test_split(X_res,Y_res,test_size=0.2,random_state=0)
```

Feature Scaling

```
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix

sc=StandardScaler()
X_train=sc.fit_transform(X_train)
X_test=sc.transform(X_test)
```

```
X_train
```

```
array([[ 0.93251743,  1.40805935, -0.61401581, ..., -0.63875643,
        -0.0510959 , -0.21992961],
       [-0.61684084,  1.40805935,  1.36771532, ..., -0.63875643,
        -0.0510959 , -0.21992961],
       [ 0.93251743, -0.77815845, -1.18081318, ...,  1.56554197,
        -0.0510959 , -0.21992961],
       ...,
       [-0.25818715, -0.77815845,  0.17950052, ...,  1.56554197,
        -0.0510959 , -0.21992961],
       [-0.57570838,  1.40805935, -0.95409423, ..., -0.63875643,
        -0.0510959 , -0.21992961],
       [-0.49632807, -0.77815845, -1.29417266, ...,  1.56554197,
        -0.0510959 , -0.21992961]])
```

```
X_test
```

```
array([[-0.41694776, -0.77815845, -0.61401581, ..., -0.63875643,
        -0.0510959 , -0.21992961],
       [-0.57570838, -0.77815845,  0.97301685, ..., -0.63875643,
        -0.0510959 , -0.21992961],
       [ 0.29747499, -0.77815845,  2.56004951, ...,  1.56554197,
        -0.0510959 , -0.21992961],
       ...,
       [-0.57570838, -0.77815845,  1.76653318, ..., -0.63875643,
        -0.0510959 , -0.21992961],
       [ 0.21809468,  1.40805935, -0.61401581, ..., -0.63875643,
        -0.0510959 , -0.21992961],
```

```
           [-0.57570838, -0.00570664,  0.44627254, ..., -0.63875643,
            -0.0510959 , -0.21992961]])
```

```
X_train.shape,X_test.shape,Y_train.shape,Y_test.shape
```

```
((14977, 16), (3745, 16), (14977,), (3745,))
```

```
Y_test.value_counts(normalize=True)*100
```

```
1.0    50.333778
0.0    49.666222
Name: Churn, dtype: float64
```

```
Y_train.value_counts(normalize=True)*100
```

```
0.0    50.083461
1.0    49.916539
Name: Churn, dtype: float64
```

```
model=LogisticRegression(max_iter=1000)
model.fit(X_train,Y_train)
Y_predict=model.predict(X_test)
type(model)
```

```
sklearn.linear_model._logistic.LogisticRegression
```

```
model_score=model.score(X_test,Y_test)
print('Accuracy score is',model_score*100)
```

```
Accuracy score is 80.37383177570094
```

```
confusion_mat = confusion_matrix(Y_test, Y_predict) # Calculate the confusion matrix

print("Confusion Matrix:\n", confusion_mat)  # Print the confusion matrix
```

```
Confusion Matrix:
 [[1470  390]
 [ 345 1540]]
```

Buiding the Model

```
!pip install --upgrade scikit-learn
```

```
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (1.3.0)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.22.4)
Requirement already satisfied: scipy>=1.5.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.10.1)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.3.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (3.1.0)
```

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report,confusion_matrix
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV
from sklearn.tree import export_graphviz
import matplotlib.pyplot as plt
import matplotlib.style
plt.style.use('classic')
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error,mean_squared_error
import statsmodels.formula.api as smf
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix
from sklearn import metrics
```

```
param_grid = {
'criterion': ['gini'],
'max_depth': [10],#[10,20,30,50]#[3,5,7,9]
'min_samples_leaf': [250],#[100,150,200,250]# 1-3% 50-150
'min_samples_split': [750]#[150,300,450,600,750] # 150 - 450
}
```

```
dtcl = DecisionTreeClassifier()
grid_search = GridSearchCV(estimator = dtcl, param_grid = param_grid, cv = 10)


grid_search.fit(X_train, Y_train)
print(grid_search.best_params_)
best_grid = grid_search.best_estimator_
best_grid
#{'criterion': 'gini', 'max_depth': 10, 'min_samples_leaf': 250, 'min_samples_split': 750}
```

```
{'criterion': 'gini', 'max_depth': 10, 'min_samples_leaf': 250, 'min_samples_split': 750}
▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=10, min_samples_leaf=250,
                       min_samples_split=750)
```

```
ytrain_predict = best_grid.predict(X_train)
ytest_predict = best_grid.predict(X_test)
```

Predicting on Training and Test dataset

```
ytest_predict
ytest_predict_prob=best_grid.predict_proba(X_test)
ytest_predict_prob
pd.DataFrame(ytest_predict_prob).head()
```

	0	1
0	0.567901	0.432099
1	0.038647	0.961353
2	0.934783	0.065217
3	0.946215	0.053785
4	0.048499	0.951501

Model Evaluation

Confusion Matrix for the Training Data

```
confusion_matrix(Y_train, ytrain_predict)
```

```
array([[6461, 1040],
       [1402, 6074]])
```

```
#Train Data Accuracy
cart_train_acc=best_grid.score(X_train,Y_train)
cart_train_acc
```

```
0.8369499899846431
```

```
print(classification_report(Y_train, ytrain_predict))
```

```
              precision    recall  f1-score   support

         0.0       0.82      0.86      0.84      7501
         1.0       0.85      0.81      0.83      7476

    accuracy                           0.84     14977
   macro avg       0.84      0.84      0.84     14977
weighted avg       0.84      0.84      0.84     14977
```

```
cart_metrics=classification_report(Y_train, ytrain_predict,output_dict=True)
cf1=pd.DataFrame(cart_metrics).transpose()
cart_train_precision=round(cf1.loc["1.0"][0],2)
cart_train_recall=round(cf1.loc["1.0"][1],2)
cart_train_f1=round(cf1.loc["1.0"][2],2)
print ('cart_train_precision ',cart_train_precision)
print ('cart_train_recall ',cart_train_recall)
print ('cart_train_f1 ',cart_train_f1)
```

```
cart_train_precision  0.85
cart_train_recall  0.81
```

```
cart_train_f1  0.83
```

Confusion Matrix for the Testing Data

```
confusion_matrix(Y_test, ytest_predict)
```

```
array([[1606,  254],
       [ 365, 1520]])
```

```
#Test Data Accuracy
cart_test_acc=best_grid.score(X_test,Y_test)
cart_test_acc
```

```
0.8347129506008011
```

```
print(classification_report(Y_test, ytest_predict))
```

```
              precision    recall  f1-score   support

         0.0       0.81      0.86      0.84      1860
         1.0       0.86      0.81      0.83      1885

    accuracy                           0.83      3745
   macro avg       0.84      0.83      0.83      3745
weighted avg       0.84      0.83      0.83      3745
```

```
cart_metrics=classification_report(Y_test, ytest_predict,output_dict=True)
cf1=pd.DataFrame(cart_metrics).transpose()
cart_test_precision=round(cf1.loc["1.0"][0],2)
cart_test_recall=round(cf1.loc["1.0"][1],2)
cart_test_f1=round(cf1.loc["1.0"][2],2)
print ('cart_train_precision ',cart_test_precision)
print ('cart_train_recall ',cart_test_recall)
print ('cart_train_f1 ',cart_test_f1)
```

```
cart_train_precision  0.86
cart_train_recall  0.81
cart_train_f1  0.83
```

Building a Random Forest Classifier

Grid Search for finding out the optimal values for the hyper parameters

Due to large volume of data, trying for different parameter values in the gridsearch with higher cv value will lead to performance issues and model will run for much longer time

```
param_grid = {#put a grid for hyperparameters
'max_depth': [8,9],
'max_features': [8,9],#[5,4,6],
'min_samples_leaf': [250,150],
'min_samples_split': [750,500],
'n_estimators': [100,150]#150,250
}
rfcl = RandomForestClassifier()
grid_search = GridSearchCV(estimator = rfcl, param_grid = param_grid, cv = 3)
```

```
grid_search.fit(X_train, Y_train)
```

```
▸ GridSearchCV
▸ estimator: RandomForestClassifier
  ▸ RandomForestClassifier
```

```
param_grid
```

```
{'max_depth': [8, 9],
 'max_features': [8, 9],
 'min_samples_leaf': [250, 150],
 'min_samples_split': [750, 500],
 'n_estimators': [100, 150]}
```

```
grid_search.best_params_
```

```
{'max_depth': 9,
 'max_features': 8,
 'min_samples_leaf': 150,
 'min_samples_split': 500,
 'n_estimators': 150}
```

```
best_grid = grid_search.best_estimator_
best_grid
```

```
▾                    RandomForestClassifier
RandomForestClassifier(max_depth=9, max_features=8, min_samples_leaf=150,
                       min_samples_split=500, n_estimators=150)
```

Predicting the Training and Testing data

```
ytrain_predict = best_grid.predict(X_train)
ytest_predict = best_grid.predict(X_test)
```

RF Model Perfotrmance Evaluation on Training data

```
confusion_matrix(Y_train,ytrain_predict)
```

```
array([[6482, 1019],
       [1066, 6410]])
```

```
rf_train_acc=best_grid.score(X_train,Y_train)
rf_train_acc
rf_test_acc=best_grid.score(X_test,Y_test)
rf_test_acc
```

```
0.8584779706275033
```

```
print(classification_report(Y_train,ytrain_predict))
```

```
              precision    recall  f1-score   support

         0.0       0.86      0.86      0.86      7501
         1.0       0.86      0.86      0.86      7476

    accuracy                           0.86     14977
   macro avg       0.86      0.86      0.86     14977
weighted avg       0.86      0.86      0.86     14977
```

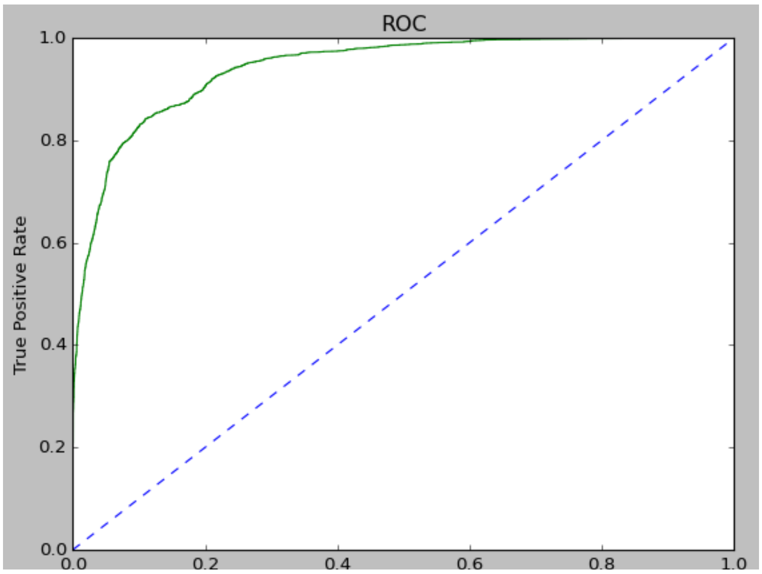
```
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
```

```
rf_metrics=classification_report(Y_train, ytrain_predict,output_dict=True)
cf1=pd.DataFrame(rf_metrics).transpose()
rf_train_precision=round(cf1.loc["1.0"][0],2)
rf_train_recall=round(cf1.loc["1.0"][1],2)
rf_train_f1=round(cf1.loc["1.0"][2],2)
rf_test_recall=round(cf1.loc["1.0"][1],2)
print ('rf_train_precision ',rf_train_precision)
print ('rf_train_recall ',rf_train_recall)
print ('rf_train_f1 ',rf_train_f1)
```

```
rf_train_precision  0.86
rf_train_recall  0.86
rf_train_f1  0.86
```

```
rf_train_fpr, rf_train_tpr,_=roc_curve(Y_train,best_grid.predict_proba(X_train)[:,1])
plt.plot(rf_train_fpr,rf_train_tpr,color='green')
plt.plot([0, 1], [0, 1], linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC')
rf_train_auc=roc_auc_score(Y_train,best_grid.predict(X_train))
print('Area under Curve is', rf_train_auc)
```

```
Area under Curve is 0.8607809131780467
```



Building a Neural Network Classifier

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train_scaled = sc.fit_transform(X_train)
X_test_scaled = sc.transform(X_test)
```

```
param_grid = {
'hidden_layer_sizes': [64,128],#[32,64,128], #Multiple layers(200,120)
'max_iter': [100,200,300],
'solver': ['adam','sgd'], #sgd
}
nncl = MLPClassifier(tol = 0.01)
grid_search = GridSearchCV(estimator = nncl, param_grid = param_grid, cv = 3)
```

```
grid_search.fit(X_train_scaled, Y_train)
#{'hidden_layer_sizes': 32, 'max_iter': 200, 'solver': 'adam', 'tol': 0.01}
```

```
GridSearchCV
estimator: MLPClassifier
MLPClassifier
```

```
best_grid = grid_search.best_estimator_
best_grid
```

```
MLPClassifier
MLPClassifier(hidden_layer_sizes=128, tol=0.01)
```

Predicting the Training and Testing data

```
ytrain_predict = best_grid.predict(X_train_scaled)
ytest_predict = best_grid.predict(X_test_scaled)
```

NN Model Performance Evaluation on Training data

```
confusion_matrix(Y_train,ytrain_predict)
```

```
array([[6508,  993],
       [ 828, 6648]])
```

```
nn_train_acc=best_grid.score(X_train_scaled,Y_train)
nn_train_acc
```

```
0.8784135674701209
```

```
print(classification_report(Y_train,ytrain_predict))
```

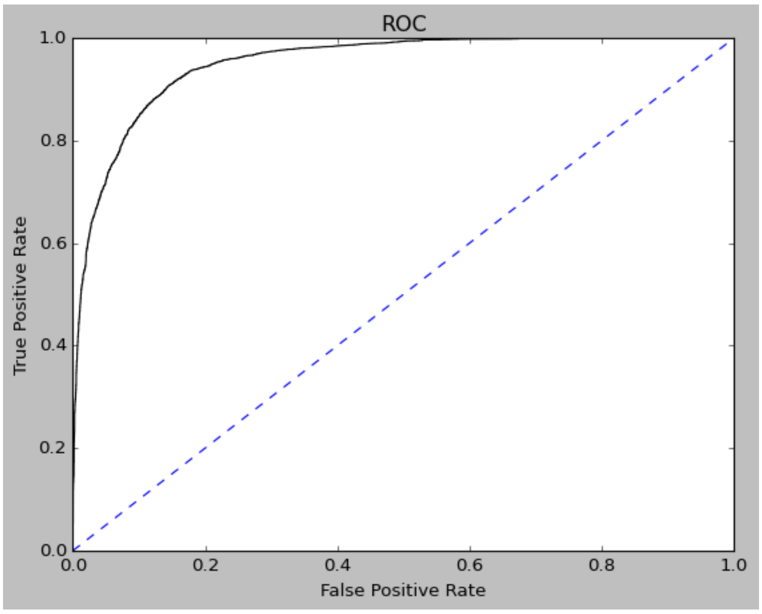
```
              precision    recall  f1-score   support

         0.0       0.89      0.87      0.88      7501
         1.0       0.87      0.89      0.88      7476

    accuracy                           0.88     14977
   macro avg       0.88      0.88      0.88     14977
weighted avg       0.88      0.88      0.88     14977
```

```
nn_metrics=classification_report(Y_train, ytrain_predict,output_dict=True)
cf1=pd.DataFrame(nn_metrics).transpose()
nn_train_precision=round(cf1.loc["1.0"][0],2)
nn_train_recall=round(cf1.loc["1.0"][1],2)
nn_train_f1=round(cf1.loc["1.0"][2],2)
print ('nn_train_precision ',nn_train_precision)
print ('nn_train_recall ',nn_train_recall)
print ('nn_train_f1 ',nn_train_f1)
```

```
nn_train_precision  0.87
nn_train_recall  0.89
nn_train_f1  0.88
```

```
nn_train_fpr, nn_train_tpr,_=roc_curve(Y_train,best_grid.predict_proba(X_train)[:,1])
plt.plot(nn_train_fpr,nn_train_tpr,color='black')
plt.plot([0, 1], [0, 1], linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC')
nn_train_auc=roc_auc_score(Y_train,best_grid.predict(X_train))
print('Area under Curve is', nn_train_auc)
```

```
Area under Curve is 0.8784316184273344
```



NN Model Performance Evaluation on Test data

```
confusion_matrix(Y_test,ytest_predict)
```

```
array([[1617,  243],
       [ 205, 1680]])
```

```
nn_test_acc=best_grid.score(X_test_scaled,Y_test)
nn_test_acc
```

```
0.8803738317757009
```

```
print(classification_report(Y_test,ytest_predict))
```

```
              precision    recall  f1-score   support

         0.0       0.89      0.87      0.88      1860
         1.0       0.87      0.89      0.88      1885
```

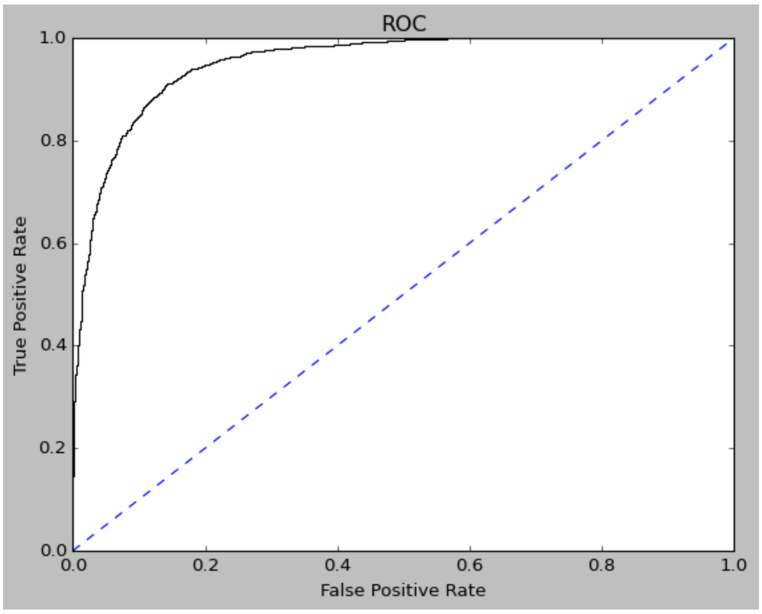
```
    accuracy                        0.88      3745
   macro avg       0.88      0.88      0.88      3745
weighted avg       0.88      0.88      0.88      3745
```

```
nn_metrics=classification_report(Y_test, ytest_predict,output_dict=True)
cf1=pd.DataFrame(nn_metrics).transpose()
nn_test_precision=round(cf1.loc["1.0"][0],2)
nn_test_recall=round(cf1.loc["1.0"][1],2)
nn_test_f1=round(cf1.loc["1.0"][2],2)
print ('nn_test_precision ',nn_test_precision)
print ('nn_test_recall ',nn_test_recall)
print ('nn_test_f1 ',nn_test_f1)
```

```
nn_test_precision  0.87
nn_test_recall  0.89
nn_test_f1  0.88
```

```
nn_test_fpr, nn_test_tpr,_=roc_curve(Y_test,best_grid.predict_proba(X_test)[:,1])
plt.plot(nn_test_fpr,nn_test_tpr,color='black')
plt.plot([0, 1], [0, 1], linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC')
nn_test_auc=roc_auc_score(Y_test,best_grid.predict(X_test))
print('Area under Curve is', nn_test_auc)
```

```
Area under Curve is 0.8803007615299051
```




```
best_grid.score
```

```
<bound method ClassifierMixin.score of MLPClassifier(hidden_layer_sizes=128, tol=0.01)>
```

```
index=['Accuracy','Recall','Precision','f1_Score']
data=pd.DataFrame({'CART Train':[cart_train_acc,cart_train_recall,cart_train_precision,cart_train_f1],
                   'CART Test':[cart_test_acc,cart_test_recall,cart_test_precision,cart_test_f1],
                   'Random forest train':[rf_train_acc,rf_train_recall,rf_train_precision,rf_train_f1],
                   'Neural Network train':[nn_train_acc,nn_train_recall,nn_train_precision,nn_train_f1],
                   'Neural Network test':[nn_test_acc,nn_test_recall,nn_test_precision,nn_test_f1]},index=index)
round(data,4)
```

	CART Train	CART Test	Random forest train	Neural Network train	Neural Network test
Accuracy	0.8369	0.8347	0.8608	0.8784	0.8804
Recall	0.8100	0.8100	0.8600	0.8900	0.8900
Precision	0.8500	0.8600	0.8600	0.8700	0.8700
f1_Score	0.8300	0.8300	0.8600	0.8800	0.8800

Based on the provided output from the dataset, here is an interpretation of the accuracy scores for different models:

1. Decision Tree (CART) Model:

- Train Data Accuracy: The decision tree model achieved a training accuracy of approximately 83.69% (0.8369). This indicates that the model correctly predicted the churn outcome for about 83.69% of the training data.
- Test Data Accuracy: The neural network model achieved a test accuracy of approximately 83.47% (0.8347). This suggests that the model correctly predicted the churn outcome for approximately 83.47% of the test data.

2. Random Forest Model:

- Train Data Accuracy: The random forest model achieved a training accuracy of around 86.08% (0.8608). This suggests that the model correctly predicted the churn outcome for approximately 86.08% of the training data.

3. Neutral Network Model:

- Train Data Accuracy: The neural network model achieved a training accuracy of approximately 87.84% (0.8784). This indicates that the model correctly predicted the churn outcome for around 87.24% of the training data.
- Test Data Accuracy: The neural network model achieved a test accuracy of approximately 88.04% (0.8804). This suggests that the model correctly predicted the churn outcome for approximately 88.04% of the test data.

Based on above observation our data set is good fit and good model

Based on these results, the neural network model seems to have the highest accuracy both on the training and test data, indicating its better performance compared to the decision tree and random forest models. However, it is important to consider other factors such as model complexity, interpretability, and potential overfitting when selecting the best model for your specific churnprediction task.

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