CAPSTONE PROJECT - CUSTOMER CHURN

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Content of Report

1. Introduction of the Business Problem

Problem Statement: -

An E-commerce company is facing a lot of competition in the current market and it has become a challenge to retain the existing customers in the current competitive situation. Hence, the DTH 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.

we have been assigned to develop a churn prediction model for this company and provide business recommendations on the campaign. The model or campaign has to be unique and has to sharp when offers are suggested. The offers suggested should have a win-win situation for company as well as customers so that company doesn't hit on revenue and on the other hand able to retain the customers.

Need of the study/project

This study/project is very essential for the business to **plan for future** in terms of product designing, sales or in rolling out different offers for different segment of clients. The outcome of this project will give a clear understanding where the firm stands now and what's the capacity it holds in terms for taking **risk**. It will also denote what's the future prospective of the organization and how they can make it even better and can plan better for the same and can help them **retaining customers** in a longer run.

Understanding business/social opportunity

This a case study of a e-commerce company where in they have customers assigned with unique account ID and a single account ID can hold many customers (like family plan) across gender and marital status, customers get flexibility in terms of mode of payment they want to opt for. Customers are again segmented across various types of plans they opt for as per their usage which also based on the device they use (computer or mobile) moreover they earn cashbacks on bill payment.

The overall business runs in customers loyalty and stickiness which in-turn comes from providing quality and value-added services. Also, running various promotional and festivals offers may help organization in getting new customers and also retaining the old one.

We can conclude that a customer retained is a regular income for organization, a customer added is a new income for organization and a customers lost will be a negative impact as a single account ID holds multiple number of customers i.e.; closure of one account ID means loosing multiple customers.

It's a great opportunity for the company as it's a need of almost every individual of family to have a DTH connection which in-turn also leads to increase and competition. Question arises how can a company creates difference when compared to other competitors, what are the parameter plays a vital role having customers loyalty and making them stay. All these social responsibilities will decide the best player in the market.

2. EDA and Business Implication

Data Report

Dataset of problem: - Customer Churn Data

Data Dictionary: -

- **AccountID --** account unique identifier
- **Churn --** account churn flag (Target Variable)
- **Tenure --** Tenure of account
- **City_Tier --** Tier of primary customer's city
- **CC_Contacted_L12m --** How many times all the customers of the account has contacted customer care in last 12months
- **Payment --** Preferred Payment mode of the customers in the account
- **Gender --** Gender of the primary customer of the account
- **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
- **Marital_Status --** Marital status of the primary customer of the account
- **rev_per_month --** Monthly average revenue generated by account in last 12 months
- **Complain_l12m --** 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 13 month)
- **coupon_used_l12m --** How many times customers have used coupons to do the payment in last 12 months
- **Day_Since_CC_connect --** Number of days since no customers in the account has contacted the customer care
- **cashback_l12m --** Monthly average cashback generated by account in last 12 months
- **Login_device --** Preferred login device of the customers in the account

Data Ingestion: -

Loaded the required packages, set the work directory and load the datafile.

Data set has 11,260 number of observations and 19 variables (18 independent and 1 dependent or target variable).

	AccountID	Churn	Tenure	City_Tier	CC_Contacted_LY	Payment	Gender	Service_Score	Account_user_count	account_segment	...
0	20000	1	4	3	6	1	1	3	3.0	1	...
1	20001	1	0	1	8	2	2	3	4.0	2	...
2	20002	1	0	1	30	1	2	2	4.0	2	...
3	20003	1	0	3	15	1	2	2	4.0	1	...
4	20004	1	0	1	12	3	2	2	3.0	2	...

Table 1 – glimpse of data-frame head with top 5 rows

Understanding how data was collected in terms of time, frequency and methodology

- data has been collected for random 11,260 unique account ID, across gender and marital status.
- Looking at variables “CC_Contacted_L12m”, “rev_per_month”, “Complain_l12m”, “rev_growth_yoy”, “coupon_used_l12m”, “Day_Since_CC_connect” and “cashback_l12m” we can conclude that the data has been collected for last 12 month.
- Data has 19 variables, 18 independent and 1 dependent or the target variable, which shows if customer churned or not.
- The data is the combination of services customers are using along with their payment option and also then basic individuals details as well.
- Data is mixed of categorical as well as continuous variables.

Visual inspection of data (rows, columns, descriptive details)

- Data has 11,260 rows and 19 variables.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11260 entries, 0 to 11259
Data columns (total 19 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   AccountID                11260 non-null  int64
 1   Churn                    11260 non-null  int64
 2   Tenure                   11158 non-null  object
 3   City_Tier                11148 non-null  float64
 4   CC_Contacted_LY          11158 non-null  float64
 5   Payment                  11151 non-null  object
 6   Gender                   11152 non-null  object
 7   Service_Score            11162 non-null  float64
 8   Account_user_count       11148 non-null  object
 9   account_segment          11163 non-null  object
 10  CC_Agent_Score           11144 non-null  float64
 11  Marital_Status           11048 non-null  object
 12  rev_per_month            11158 non-null  object
 13  Complain_ly              10903 non-null  float64
 14  rev_growth_yoy           11260 non-null  object
 15  coupon_used_for_payment  11260 non-null  object
 16  Day_Since_CC_connect     10903 non-null  object
 17  cashback                 10789 non-null  object
 18  Login_device             11039 non-null  object
dtypes: float64(5), int64(2), object(12)
memory usage: 1.6+ MB
```

Table 2:- Dataset Information

```
The shape of dataset is :(11260, 19)
```

Fig 1:- Shape of dataset

- Describing data: - This shows description of variation in various statistical measurements across variables which denotes that each variable is unique and different.

	count	unique	top	freq	mean	std	min	25%	50%	75%	max
AccountID	11260.0	NaN	NaN	NaN	25629.5	3250.62635	20000.0	22814.75	25629.5	28444.25	31259.0
Churn	11260.0	NaN	NaN	NaN	0.168384	0.374223	0.0	0.0	0.0	0.0	1.0
Tenure	11158.0	38.0	1.0	1351.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
City_Tier	11148.0	NaN	NaN	NaN	1.653929	0.915015	1.0	1.0	1.0	3.0	3.0
CC_Contacted_LY	11158.0	NaN	NaN	NaN	17.867091	8.853269	4.0	11.0	16.0	23.0	132.0
Payment	11151	5	Debit Card	4587	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Gender	11152	4	Male	6328	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Service_Score	11162.0	NaN	NaN	NaN	2.902526	0.725584	0.0	2.0	3.0	3.0	5.0
Account_user_count	11148.0	7.0	4.0	4569.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
account_segment	11163	7	Super	4062	NaN	NaN	NaN	NaN	NaN	NaN	NaN
CC_Agent_Score	11144.0	NaN	NaN	NaN	3.066493	1.379772	1.0	2.0	3.0	4.0	5.0
Marital_Status	11048	3	Married	5860	NaN	NaN	NaN	NaN	NaN	NaN	NaN
rev_per_month	11158.0	59.0	3.0	1746.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Complain_ly	10903.0	NaN	NaN	NaN	0.285334	0.451594	0.0	0.0	0.0	1.0	1.0
rev_growth_yoy	11260.0	20.0	14.0	1524.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
coupon_used_for_payment	11260.0	20.0	1.0	4373.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Day_Since_CC_connect	10903.0	24.0	3.0	1816.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
cashback	10789.0	5693.0	155.62	10.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Login_device	11039	3	Mobile	7482	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Table 3: - Describing Dataset

- Except variables “AccountID”, “Churn”, “rev_growth_yoy” and “coupon_used_for_payment” all other variables have null values present.

```
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
```

Table 4: - Showing Null Values in Dataset

- Data has “NIL” duplicate observations.
- With above understanding of data renaming of any of the variable is not required**.**
- we can move towards the EDA part where in we will understand the data little better along with treating bad data, null values and outliers.

Exploratory data analysis

Univariate analysis (distribution and spread for every continuous attribute, distribution of data in categories for categorical ones)

Univariate Analysis: -

- The variable shows outlier in data, which needs to be treated in further steps.

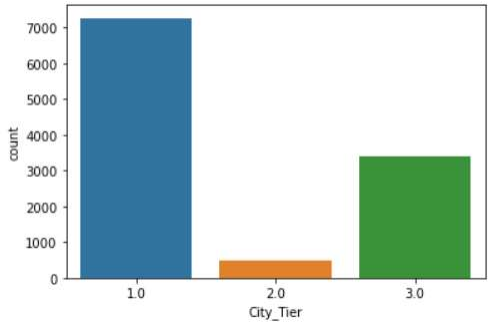
	outlier %
AccountID	0.00
Account_user_count	0.00
CC_Agent_Score	0.00
CC_Contacted_LY	0.37
Churn	16.84
City_Tier	0.00
Complain_ly	0.00
Day_Since_CC_connect	0.00
Gender	0.00
Login_device	0.00
Marital_Status	0.00
Payment	0.00
Service_Score	0.12
Tenure	0.00
account_segment	0.00
cashback	0.00
coupon_used_for_payment	0.00
rev_growth_yoy	0.00
rev_per_month	0.00

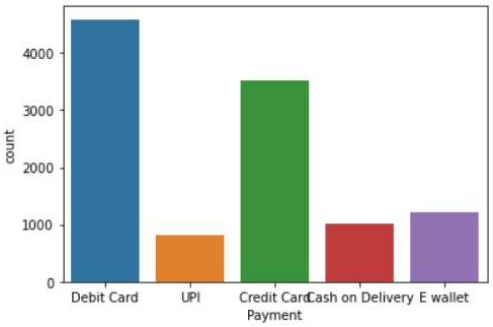
Table 5: - Showing Outliers in data

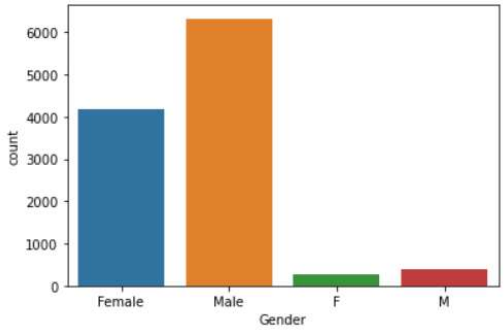
- None of the variables shows normal distribution and are skewed in nature.

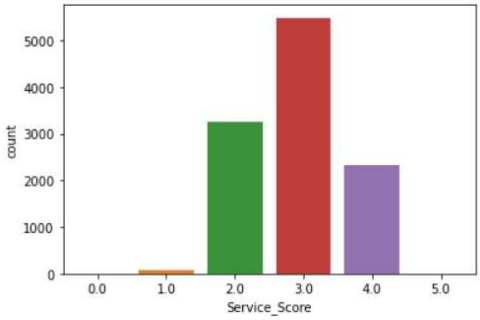
	Kurtosis	Skewness
AccountID	-1.20	0.00
Churn	1.14	1.77
City_Tier	-1.40	0.74
CC_Contacted_LY	8.23	1.42
Service_Score	-0.67	0.00
CC_Agent_Score	-1.12	-0.14
Complain_ly	-1.10	0.95

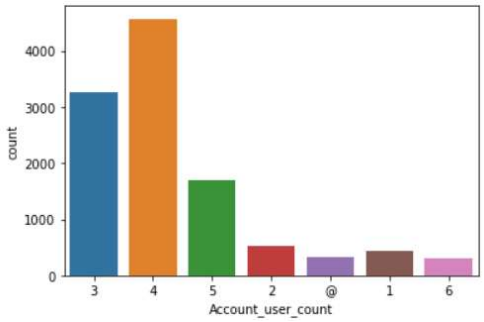
Table 6:- Showing skewness and kurtosis

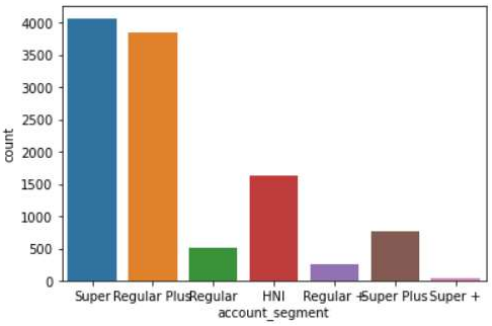

count
City_Tier
1.0
2.0
3.0

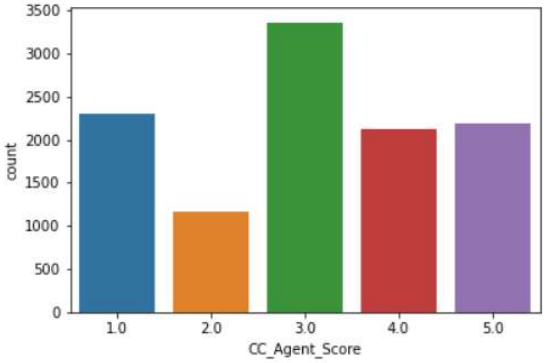

count
Payment
Debit Card
UPI
Credit Card
Cash on Delivery
E wallet

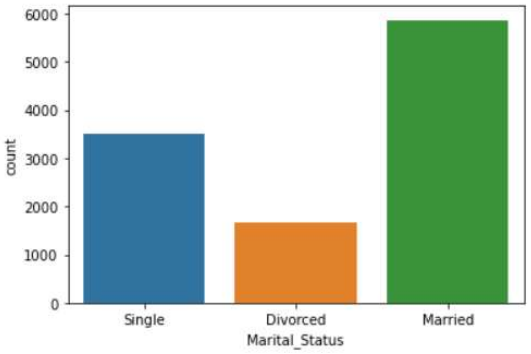

count
Gender
Female
Male
F
M


count
Service_Score


count
Account_user_count


count
account_segment
Super
Regular Plus
Regular
HNI
Regular +
Super Plus
Super +


count
CC_Agent_Score


count
Marital_Status
Single
Divorced
Married

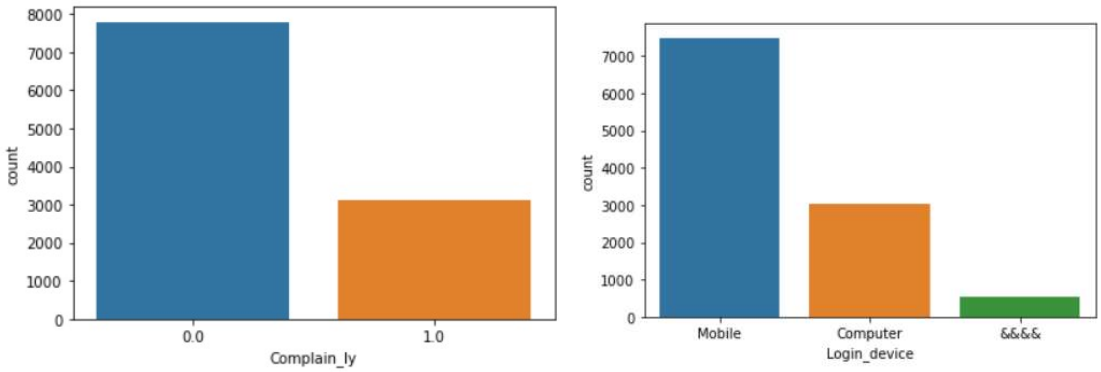
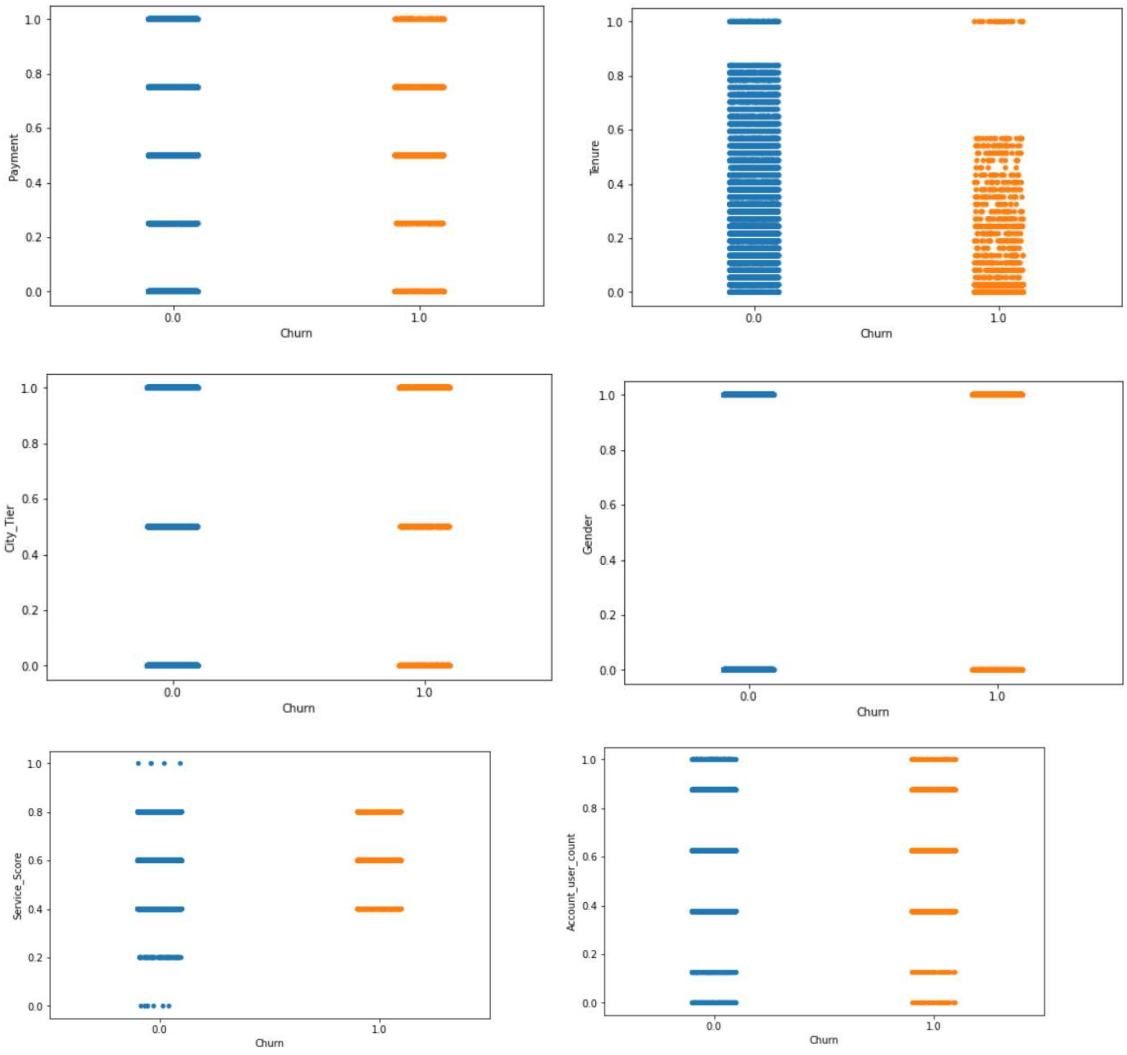


Fig 2: - Count plot of categorical variables



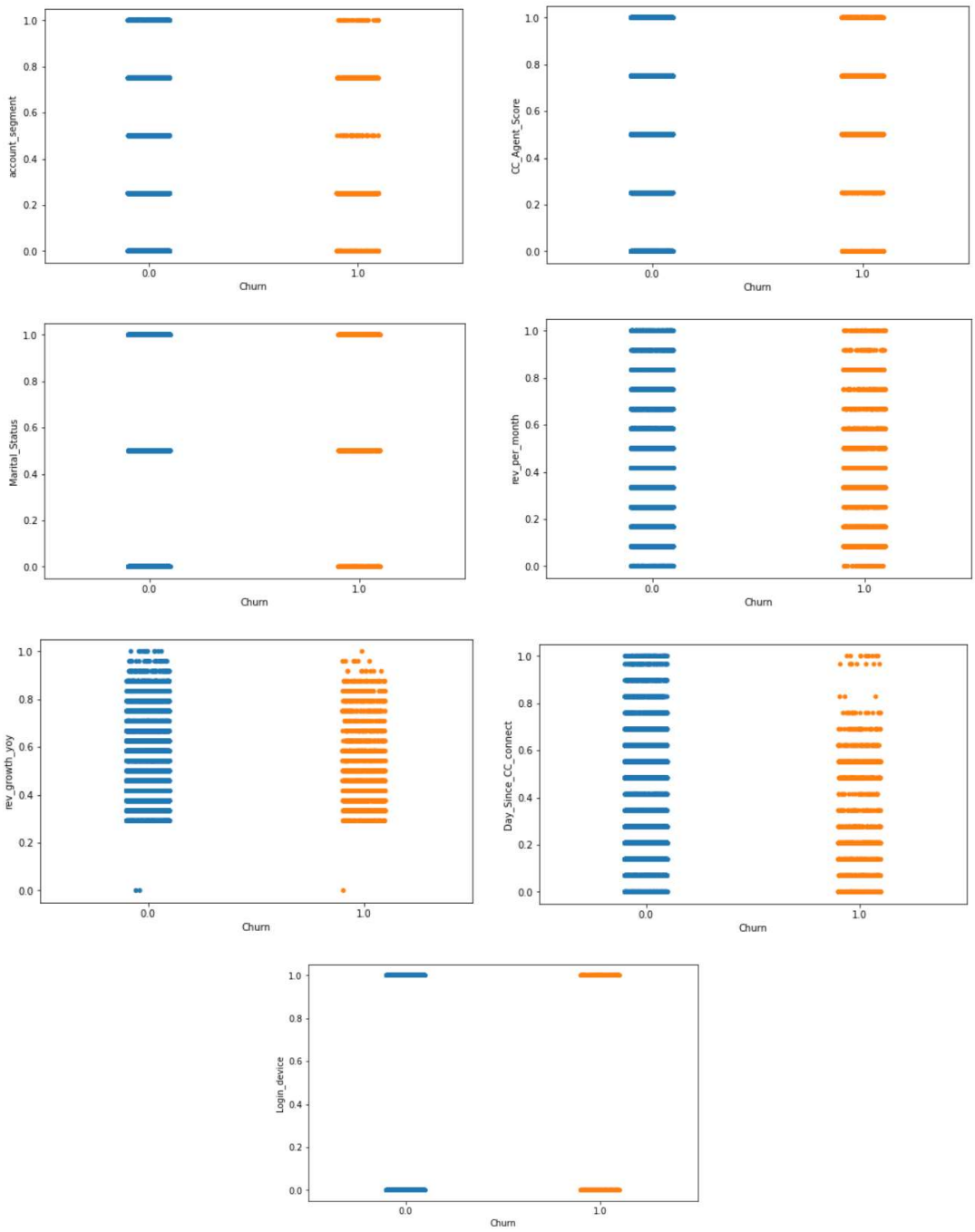


Fig 3: - Strip plot of across variables

Inferences from count plot: -

- Maximum customers are form city tire type “1”, which indicates the high number of population density in this city type.
- Maximum number of customers perfer debit and credit card as their preferred mode of payment.
- The ratio of male customers are higher when compared to female.

- Average service score given by a customer for the service provided is around “3” which shows the area of improvements.
- Most of the customers are into “Super+” segment and least number of customers are into “Regular” segment.
- Most of the customers availing servives are “Married”.
- Most of the customer perfer “Mobile” as the device to avail services.

Bi-variate Analysis: -

- Pair plot across all categorical data and its impact towards the target variable.

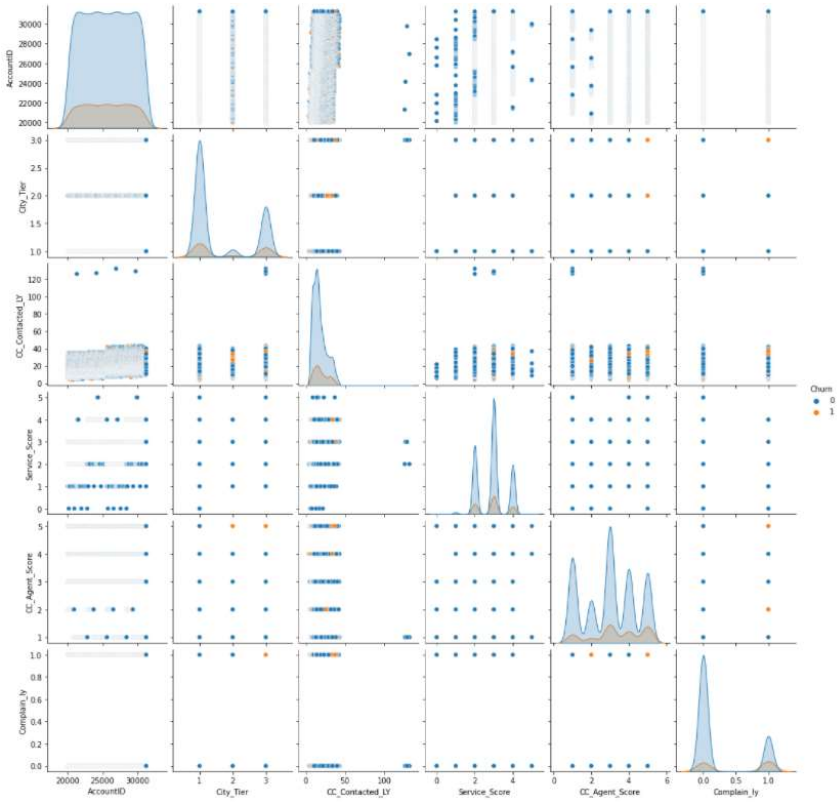
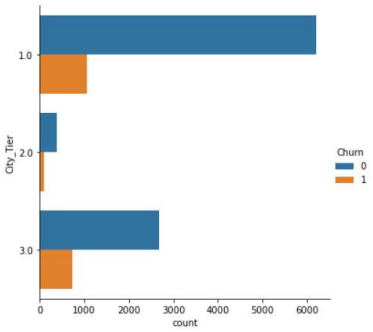
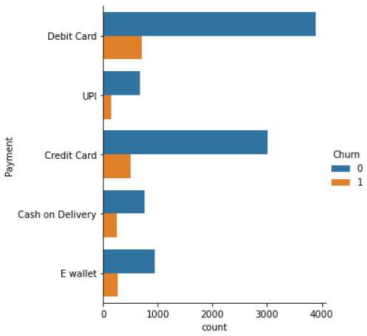
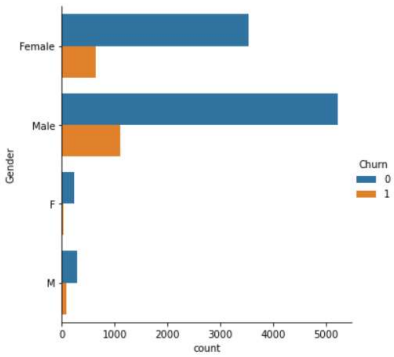


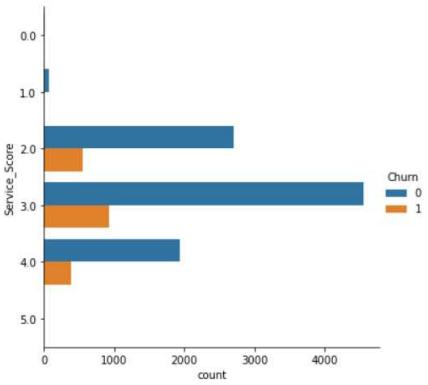
fig 4: - pairplot across categorical variables

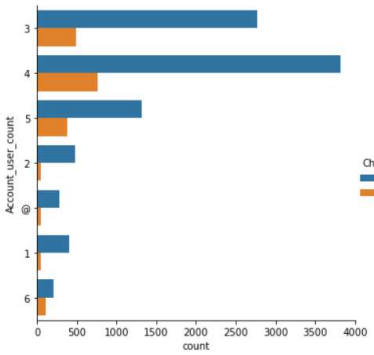
- The pair-plot shown above indiates that the independent variable are week or poor predictors of target variable as we the density of independent variable overlaps with the density of target variable.

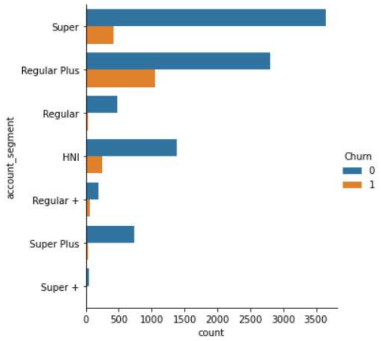

City_Tier
1.0
2.0
3.0
0
1000
2000
3000
4000
5000
6000
count
Churn
0
1

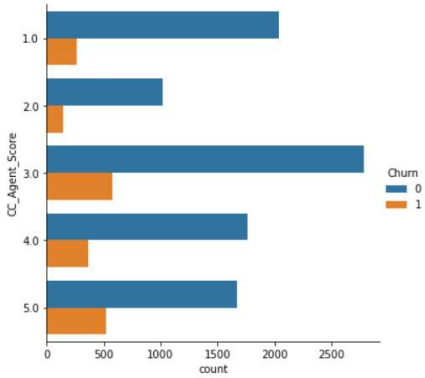

Payment
Debit Card
UPI
Credit Card
Cash on Delivery
E wallet
0
1000
2000
3000
4000
count
Churn
0
1

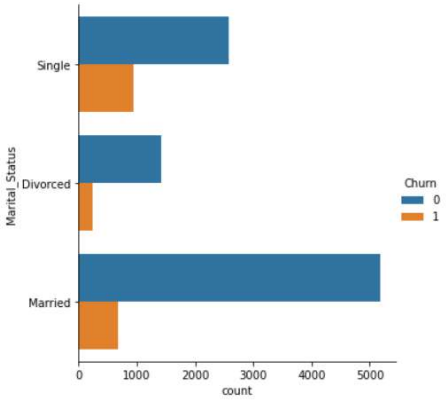

Gender
Female
Male
F
M
0
1000
2000
3000
4000
5000
count
Churn
0
1


Service_Score
0.0
1.0
2.0
3.0
4.0
5.0
0
1000
2000
3000
4000
count
Churn
0
1


Account_user_count
3
4
5
2
@
1
6
0
500
1000
1500
2000
2500
3000
3500
4000
count
Churn
0
1


account_segment
Super
Regular Plus
Regular
HNI
Regular +
Super Plus
Super +
0
500
1000
1500
2000
2500
3000
3500
count
Churn
0
1


CC_Agent_Score
1.0
2.0
3.0
4.0
5.0
0
500
1000
1500
2000
2500
count
Churn
0
1


Marital_Status
Single
Divorced
Married
0
1000
2000
3000
4000
5000
count
Churn
0
1

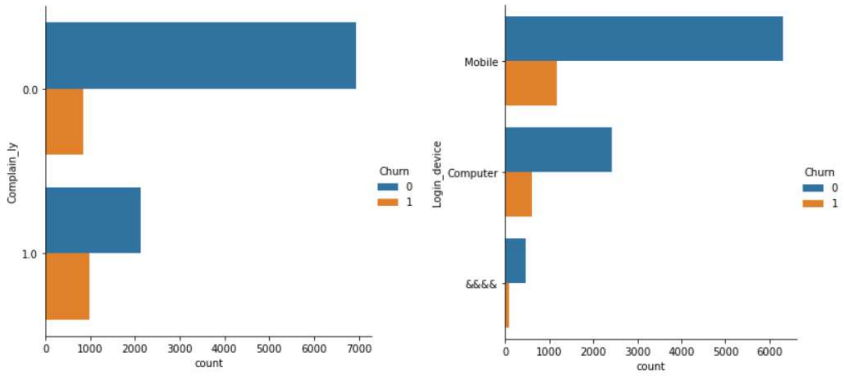


Fig 5: - Contribution of categorical variable towards chrun

- City_tier "1" has shown maximum churning when compared with "2" and "3".
- Customer with prefreffred mode of payment as "debit card" and "credit card" are more prone to churn.
- Customers with gender as "Male" are showing more Churn ratio as compared to female.
- Customers into "Regular Plus" segment showing more churn.
- Single customers are more tend to churn when compared with divorced and married.
- Customers using the service over mobile shows more churn.

Correlation among variable:-

We have performed correlation between variables after treatuing bad data and missing values. We have also converted into interger data types to check on correlation as data type as categorical wont show in the pictures below.

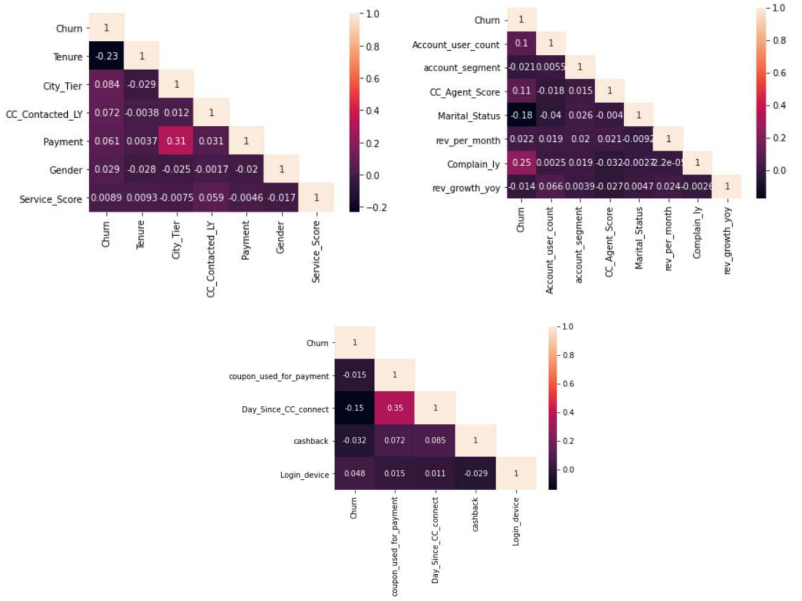


Fig 6: - Correlation among variables

Inferences from correlation: -

- Variable “Tenure” shows high co-relation with Churn.
- Variable “Marital Status” shows high co-relation with churn.
- Variable “complain_ly” shows high- correlation with churn.

Removal of unwanted variables: - After in-depth understanding of data we conclude that removal of variables is not required at this stage of project. We can remove the variable “AccountID” which denotes a unique ID assigned to unique customers. However, removing them will lead to 8 duplicate rows. Rest all the variables looks important looking at the univariate and bi-variate analysis.

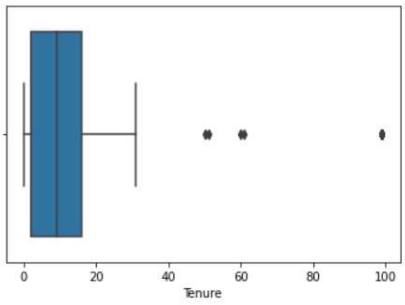
3. Data Cleaning and Pre-processing

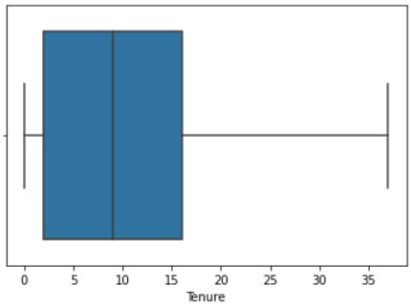
Outlier treatment: -

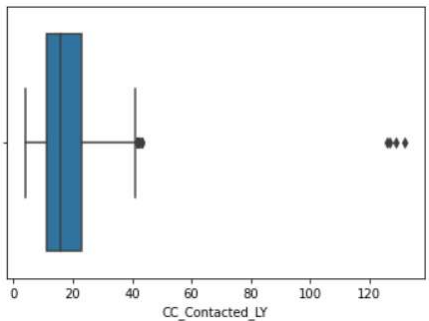
This dataset is the mix of continuous as well as categorical variables. It doesn’t make any sense if we perform outlier treatment on categorical variable as each category denotes a type of customer. So, we are performing outlier treatment only for variables continuous in nature.

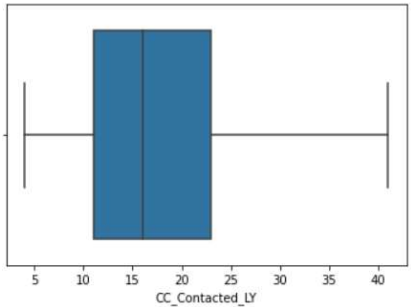
- We have 8 continuous variables in the dataset namely, “Tenure”, “CC_Contacted_LY”, “Account_user_count”, “cashback”, “rev_per_month”, “Day_Since_CC_connect”, “coupon_used_for_payment” and “rev_growth_yoy”.
- We have used upper limit and lower limit to remove outliers. Below is the pictorial representation of variables before and after outlier treatment.

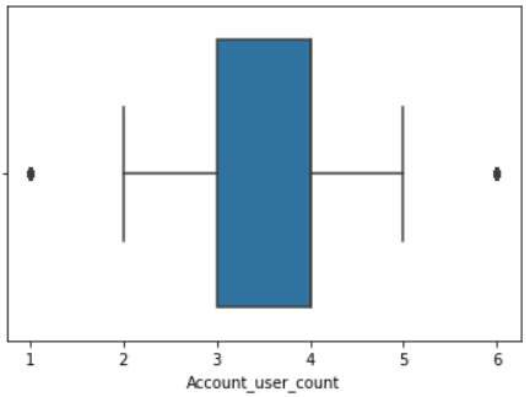
Before ***After***

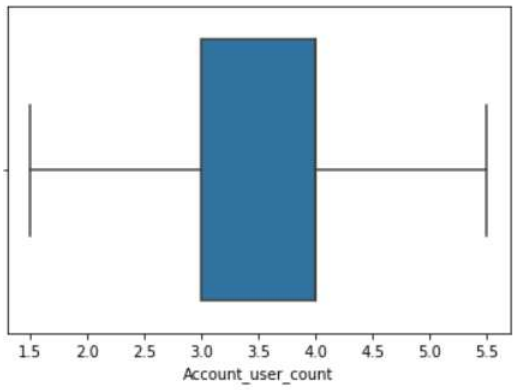


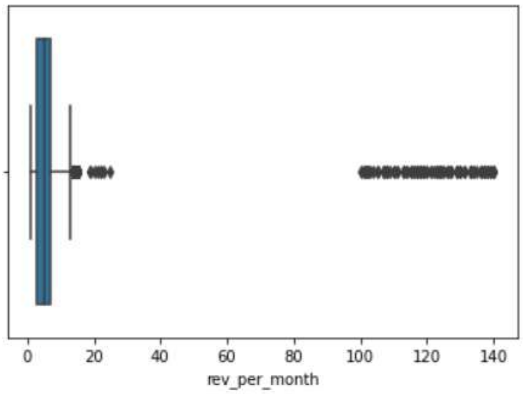


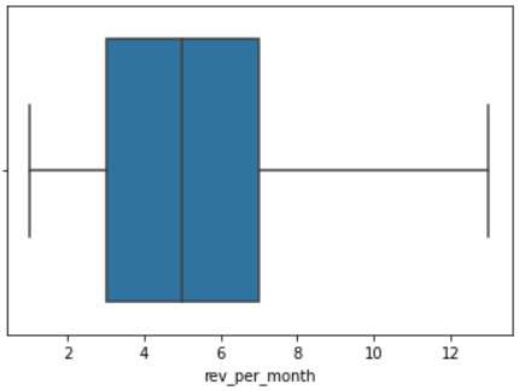


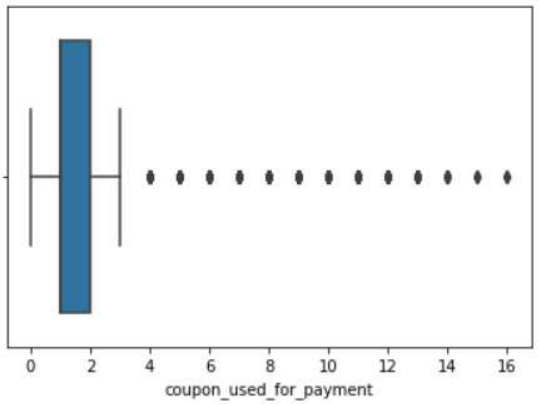


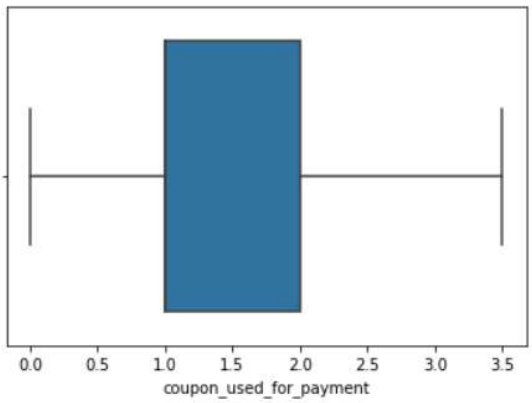

1
2
3
4
5
6
Account_user_count

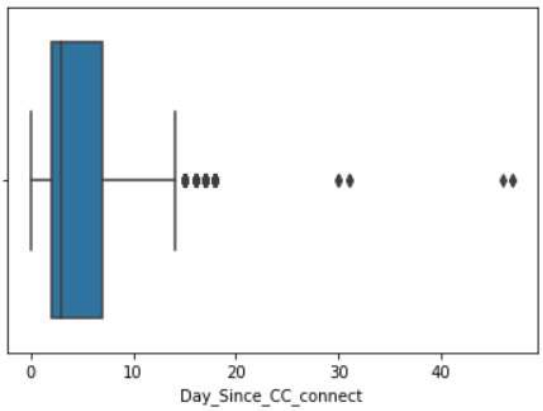

1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
5.5
Account_user_count

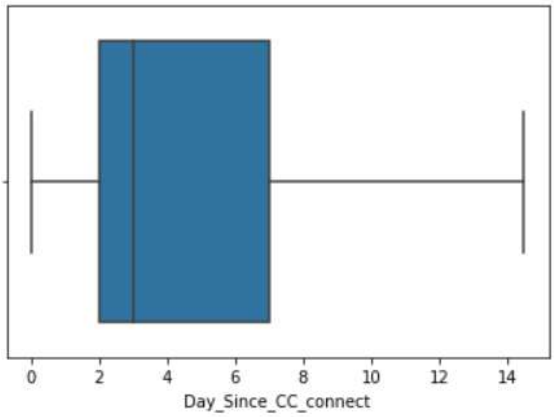

0
20
40
60
80
100
120
140
rev_per_month


2
4
6
8
10
12
rev_per_month


0
2
4
6
8
10
12
14
16
coupon_used_for_payment


0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
coupon_used_for_payment


0
10
20
30
40
Day_Since_CC_connect


0
2
4
6
8
10
12
14
Day_Since_CC_connect

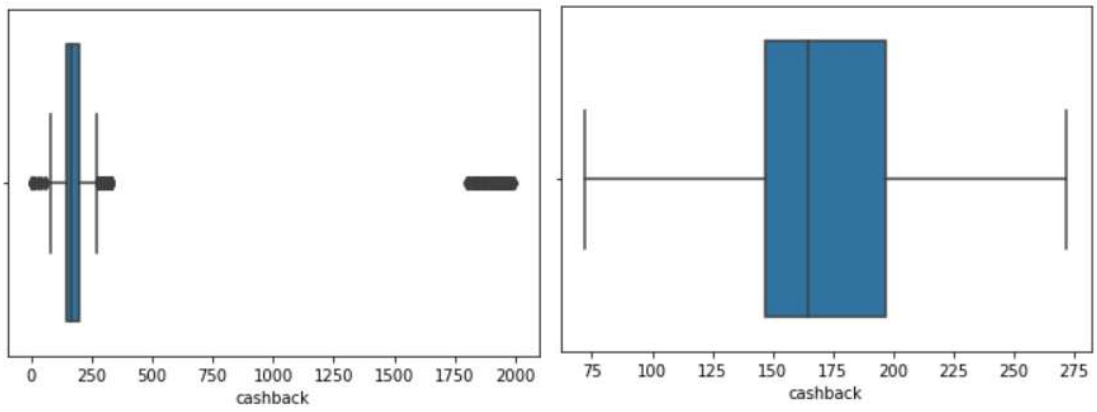


Fig 7: - Before and after outlier treatement

Missing Value treatment and variable transformation: -

- Out of 19 variables we have data anomalies present in 17 variable and null values in 15 variables.
- Using “Median” to impute null values where variable is continuous in nature because Median is less prone to outliers when compared with mean.
- Using “Mode: to impute null values where variables are categorical in nature.
- We have treated null values variable by variable as each and every variable is unique in its nature.

Treating Variable “Tenure”

- We look at the unique observations in the variable and see that we have “#” and “nan” present in the data. Where “#” is a anomaly and “nan” represents null value.

```
array([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, nan, 27, 12, 21, 17, 50,
       60, 31, 51, 61], dtype=object)
```

Fig 8: - before treatment

- Replacing “#” with “nan” and further we replace “nan” with calculated median of the variable and now we don’t see any presence of bad data and null values.
- Converted data type to integer, because IDE has recognized it as object data type due presence of bad data.

```
<IntegerArray>
[ 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]
Length: 37, dtype: Int64
```

Fig 9: - after treatment

Treating Variable “City_Tier”

- We look at the unique observations in the variable and see presence of null value as shown below.

```
array([ 3.,  1., nan,  2.])
```

Fig 10: - before treatment

- we are replacing “nan” with calculated mode of the variable and now we don’t see any presence of null values.
- Converted data type to integer, because IDE has recognized it as object data type due presence of bad data.

```
array([3., 1., 2.])
```

Fig 11: - after treatment

Treating Variable “CC_Contacted_LY”

- We look at the unique observations in the variable and see presence of null value as shown below.

```
array([  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., nan,  34.,   5.,   4., 126.,
         7.,  36., 127.,  42.,  38.,  37.,  39.,  40.,  41., 132.,  43.,
       129.])
```

Fig 12: - before treatment

- we are replacing “nan” with calculated Median of the variable and now we don’t see any presence of null values.
- Converted data type to integer, because IDE has recognized it as object data type due presence of bad data.

```
array([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, 41.0, 7, 36,
       38, 37, 39, 40], dtype=object)
```

Fig 13: - after treatment

Treating Variable “Payment”

- We look at the unique observations in the variable and see presence of null value as shown below.

```
array(['Debit Card', 'UPI', 'Credit Card', 'Cash on Delivery', 'E wallet',
       nan], dtype=object)
```

Fig 14: - before treatment

- we are replacing “nan” with calculated Mode of the variable and now we don’t see any presence of null values.
- Also performed label encoding for the observations. Where 1 = Debit card, 2 = UPI, 3 = credit card, 4 = cash on delivery and 5 = e-wallet. Then converting them to integer data type as it will be used for further model building.

```
array(['1', '2', '3', '4', '5'],
```

Fig 15: - after treatment

Treating Variable "Gender"

- We look at the unique observations in the variable and see presence of null value and multiple abbreviations of the same observations as shown below.

```
array(['Female', 'Male', 'F', nan, 'M'],
```

Fig 16: - before treatment

- we are replacing "nan" with calculated Mode of the variable and now we don't see any presence of null values.
- Also performed label encoding for the observations. Where 1 = Female card and 2 = Male. Then converting them to integer data type as it will be used for further model building.

```
array(['1', '2'],
```

Fig 17: - after treatment

Treating Variable "Service_Score"

- We look at the unique observations in the variable and see presence of null value as shown below.

```
array([ 3.,  2.,  1., nan,  0.,  4.,  5.])
```

Fig 18: - before treatment

- we are replacing "nan" with calculated Mode of the variable and now we don't see any presence of null values.
- Then converting them to integer data type as it will be used for further model building.

```
array([3., 2., 1., 0., 4., 5.])
```

Fig 19: - after treatment

Treating Variable "Account_user_count"

- We look at the unique observations in the variable and see presence of null value as well "@" as bad data, shown below.

```
array([3, 4, nan, 5, 2, '@', 1, 6]
```

Fig 20: - before treatment

- Replacing "@" with "nan" and further we replace "nan" with calculated median of the variable and now we don't see any presence of bad data and null values.
- Then converting them to integer data type as it will be used for further model building.

```
array([3., 4., 5., 2., 1., 6.])
```

Fig 21: - after treatment

Treating Variable "account_segment"

- We look at the unique observations in the variable and see presence of null value as well different denotations for the same type of observations, shown below.

```
array(['Super', 'Regular Plus', 'Regular', 'HNI', 'Regular +', nan,
       'Super Plus', 'Super +'], dtype=object)
```

Fig 22: - before treatment

- Replacing "nan" with calculated Mode of the variable and also labelled different account segments, where in 1 = Super, 2 = Regular Plus, 3 = Regular, 4 = HNI and 5 = Super Plus and now we don't see any presence of bad data and null values.
- Then converting them to integer data type as it will be used for further model building.

```
array(['1', '2', '3', '4', '5']
```

Fig 23: - after treatment

Treating Variable "CC_Agent_Score"

- We look at the unique observations in the variable and see presence of null value as shown below.

```
array([ 2.,  3.,  5.,  4., nan,  1.])
```

Fig 24: - before treatment

- Replacing "nan" with calculated Mode of the variable and now we don't see any presence of bad data and null values.
- Then converting them to integer data type as it will be used for further model building.

```
array([2., 3., 5., 4., 1.])
```

Fig 25: - after treatment

Treating Variable "Marital_Status"

- We look at the unique observations in the variable and see presence of null value as shown below.

```
array(['Single', 'Divorced', 'Married', nan],
```

Fig 26: - before treatment

- Replacing "nan" with calculated Mode of the variable and also labelled the observations. Where in 1 = Single, 2 = Divorced and 3 = Married and now we don't see any presence of bad data and null values.
- Then converting them to integer data type as it will be used for further model building.

```
array([1., 2., 3.])
```

Fig 27: - after treatment

Treating Variable "rev_per_month"

- We look at the unique observations in the variable and see presence of null value as well as presence of "+" which denoted bad data. shown below.

```
array([9, 7, 6, 8, 3, 2, 4, 10, 1, 5, '+', 130, nan, 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], dtype=object)
```

Fig 28: - before treatment

- Replacing "+" with "nan" and further we replace "nan" with calculated median of the variable and now we don't see any presence of bad data and null values.
- Then converting them to integer data type as it will be used for further model building.

```
array([  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.])
```

Fig 29: - after treatment

Treating Variable "Complain_ly"

- We look at the unique observations in the variable and see presence of null value as shown below.

```
array([ 1.,  0., nan])
```

Fig 30: - before treatment

- Replacing "nan" with calculated Mode of the variable and now we don't see any presence of null values.
- Then converting them to integer data type as it will be used for further model building.

```
array([1., 0.])
```

Fig 31: - after treatment

Treating Variable "rev_growth_yoy"

- We look at the unique observations in the variable and see presence of "$" which denoted bad data. shown below.

```
array([11, 15, 14, 23, 22, 16, 12, 13, 17, 18, 24, 19, 20, 21, 25, 26,
       '$', 4, 27, 28], dtype=object)
```

Fig 32: - before treatment

- Replacing "$" with "nan" and further we replace "nan" with calculated median of the variable and now we don't see any presence of bad data and null values.

- Then converting them to integer data type as it will be used for further model building.

```
array([11., 15., 14., 23., 22., 16., 12., 13., 17., 18., 24., 19., 20.,
       21., 25., 26.,  4., 27., 28.])
```

Fig 33: - after treatment

Treating Variable "coupon_used_for_payment"

- We look at the unique observations in the variable and see presence of "$", "*" and "#" which denoted bad data. shown below.

```
array([1, 0, 4, 2, 9, 6, 11, 7, 12, 10, 5, 3, 13, 15, 8, '#', '$', 14,
       '*', 16], dtype=object)
```

Fig 34: - before treatment

- Replacing "$", "*" and "#" with "nan" and further we replace "nan" with calculated median of the variable and now we don't see any presence of bad data and null values.
- Then converting them to integer data type as it will be used for further model building.

```
array([ 1.,  0.,  4.,  2.,  9.,  6., 11.,  7., 12., 10.,  5.,  3., 13.,
       15.,  8., 14., 16.])
```

Fig 35: - after treatment

Treating Variable "Day_Since_CC_connect"

- We look at the unique observations in the variable and see presence of "$" which denoted bad data and also the presence of null values. shown below.

```
array([5, 0, 3, 7, 2, 1, 8, 6, 4, 15, nan, 11, 10, 9, 13, 12, 17, 16, 14,
       30, '$', 46, 18, 31, 47], dtype=object)
```

Fig 36: - before treatment

- Replacing "$" with "nan" and further we replace "nan" with calculated median of the variable and now we don't see any presence of bad data and null values.
- Then converting them to integer data type as it will be used for further model building.

```
array([ 5.,  0.,  3.,  7.,  2.,  1.,  8.,  6.,  4., 15., 11., 10.,  9.,
       13., 12., 17., 16., 14., 30., 46., 18., 31., 47.])
```

Fig 37: - after treatment

Treating Variable "cashback"

- We look at the unique observations in the variable and see presence of "$" which denoted bad data and also the presence of null values. shown below.

```
array([159.93, 120.9, nan, ..., 227.36, '$', .91, 191.42]
```

Fig 38: - before treatment

- Replacing “$” with “nan” and further we replace “nan” with calculated median of the variable and now we don’t see any presence of bad data and null values.
- Then converting them to integer data type as it will be used for further model building.

```
array([159., 120., 165., 134., 129., 139., 122., 126., 272., 153., 133.,
       196., 157., 160., 149., 161., 203., 116., 206., 142., 172., 123.,
       189., 143., 208., 127., 194., 125., 124., 186., 130., 150., 111.,
       204., 131., 144., 195., 237., 267., 135., 152., 162., 168., 138.,
       166., 176., 121., 148., 193., 184., 199., 224., 235., 188., 221.,
        72., 179., 187., 132., 260., 137., 236., 164., 200., 209., 169.,
       268., 155., 140., 234., 218., 219., 156., 163., 145., 154., 147.,
       158., 114., 180., 136., 112., 220., 270., 175., 146., 174., 215.,
       171., 182., 259., 225., 167., 128., 266., 141., 243., 183., 265.,
       117., 241., 202., 190., 198., 232., 261., 118., 205., 254., 177.,
       110., 211., 248., 217., 178., 151., 216., 271., 263., 207., 238.,
       242., 197., 231., 239., 227., 233., 173., 119., 170., 185., 240.,
       247., 192., 113., 264., 115., 212., 201., 252., 229., 181., 257.,
       210., 269., 228., 214., 244., 253., 262., 191., 249., 213., 245.,
       250., 223., 230., 222., 256., 258., 246., 226.,  81., 251.])
```

Fig 39: - after treatment

Treating Variable “Login_device”

- We look at the unique observations in the variable and see presence of “&&&&” which denoted bad data and also the presence of null values. shown below.

```
array(['Mobile', 'Computer', '&&&&', nan]
```

Fig 40: - before treatment

- Replacing “&&&&” with “nan” and further we replace “nan” with calculated Mode of the variable. Also, labelling the observations where in 1= Mobile and 2 = Computer and now we don’t see any presence of bad data and null values.
- Then converting them to integer data type as it will be used for further model building.

```
array([1, 2]
```

Fig 41: - after treatment

Count of null values before and after treatment

Before

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

After

AccountID	0
Churn	0
Tenure	0
City_Tier	0
CC_Contacted_LY	0
Payment	0
Gender	0
Service_Score	0
Account_user_count	0
account_segment	0
CC_Agent_Score	0
Marital_Status	0
rev_per_month	0
Complain_ly	0
rev_growth_yoy	0
coupon_used_for_payment	0
Day_Since_CC_connect	0
cashback	0
Login_device	0

Fig 42: - Before and after null value treatment

- We see NIL null values across variable which indicated that the data is now cleaned and we can move further for data transformation of required.

Variable transformation: -

- We see that the different variable has different dimensions. Like variable “Cashback” denotes currency where as “CC_Agent_Score” denotes rating provided by the customers. Due to which they differ in their statistical rating as well.
- Scaling would be required for this data set which in turn will normalize the date and standard deviation will be close to “0”.
- Using MinMax scalar to perform normalization of data.

Standard Deviation Before and After Normalization: -

Before

standard deviation of variables	
AccountID	3250.626350
Churn	0.374223
City_Tier	0.915015
CC_Contacted_LY	8.853269
Service_Score	0.725584
CC_Agent_Score	1.379772
Complain_ly	0.451594

After

Churn	0.374223
Tenure	0.240241
City_Tier	0.456381
CC_Contacted_LY	0.231463
Payment	0.344845
Gender	0.488878
Service_Score	0.144495
Account_user_count	0.231069
account_segment	0.316751
CC_Agent_Score	0.343166
Marital_Status	0.447373
rev_per_month	0.239968
Complain_ly	0.447181
rev_growth_yoy	0.156553
coupon_used_for_payment	0.314928
Day_Since_CC_connect	0.240931
cashback	0.218847
Login_device	0.442952

Fig 43: - Before and after Normalization

- We see that the standard deviation of variables are now close to “0”.
- Also converted variables to int data type which will help in further model building process.

Addition of new variables: -

At the current stage we don’t see to create any new variable as such. May be required at further stage of model building and can be created accordingly.

4. Model Building

From the above visual and non-visual analysis, we can conclude that it's a case of classification model, where in the target variable needs to be classified into "Yes" or "No".

As a data analyst we have below algorithms to build the desired mechanism to predict if a given customer will churn or not: -

- **Logistic Regression --** Logistic Regression is a "Supervised machine learning" algorithm that can be used to model the probability of a certain class or event. It is used when the data is linearly separable and the outcome is binary or dichotomous in nature. That means Logistic regression is usually used for Binary classification problems.
- **Linear Discriminant Analysis (LDA) --** Linear Discriminant Analysis, or LDA for short, is a predictive modelling algorithm for multi-class classification. It can also be used as a dimensionality reduction technique, providing a projection of a training dataset that best separates the examples by their assigned class.
- **KNN --** KNN works by finding the distances between a query and all the examples in the data, selecting the specified number examples (K) closest to the query, then votes for the most frequent label (in the case of classification) or averages the labels (in the case of regression).
- **Naïve Bayes --** Naive Bayes is a kind of classifier which uses the Bayes Theorem. It predicts membership probabilities for each class such as the probability that given record or data point belongs to a particular class. The class with the highest probability is considered as the most likely class.
- **Bagging (Random Forest) --** Bagging, also known as bootstrap aggregation, is the ensemble learning method that is commonly used to reduce variance within a noisy dataset. In bagging, a random sample of data in a training set is selected with replacement—meaning that the individual data points can be chosen more than once.
- **Ada- Boosting --** The process of boosting involves improving the power of a machine learning program by adding more complex or capable algorithms. This process can reduce both bias and variance in machine learning, which helps to create more effective results.
- **Gradient Boosting --** Gradient boosting is a type of machine learning boosting. It relies on the intuition that the best possible next model, when combined with previous models, minimizes the overall prediction error. If a small change in the prediction for a case causes no change in error, then next target outcome of the case is zero
- **Support Vector Machine (SVM) --** SVM is a supervised machine learning algorithm which can be used for classification or regression problems. It uses a technique called the kernel trick to transform your data and then based on these transformations it finds an optimal boundary between the possible outputs.

Splitting Data into Train and Test Dataset: -

Following the accepted market practice, we have divided data into Train and Test dataset into 70:30 ratio and building various models on training dataset and testing for accuracy over testing dataset.

Below is the shape of Train and Test dataset: -

```
X_train (7882, 17)
X_test (3378, 17)
y_train (7882,)
y_test (3378,)
```

Fig 44: - Shape of training and test dataset

Treating im-balance nature of data

- Dataset provided is imbalance in nature. The categorical count of our target variable "Churn" shows high variation in counts. We have count of "0" as 9364 and count of "1" as 1896.

Churn	AccountID
0	9364
1	1896

Table 7: - Imbalanced dataset

- This imbalance in dataset can be performed using SMOTE technique will generates additional datapoints to balance the data.
- We need to apply SMOTE only on to train dataset not on test dataset. divided data into train and test dataset in 70:30 ratio as an accepted market practice (can be changed later as instructed).

Before SMOTE

```
X_train (7882, 17)
X_test (3378, 17)
y_train (7882,)
y_test (3378,)
```

After SMOTE

```
X_train_res (13112, 17)
y_train_res (13112,)
```

Table 8: - Before and after SMOTE

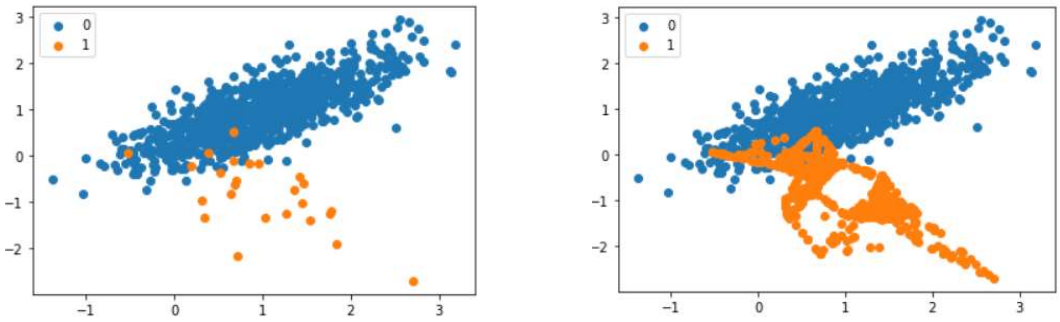


Fig 45: - Before and after SMOTE

- The increase in density of the orange dots indicates the increase in data points.

Approach is to observe model performance across various algorithms with their default parameters, then to check on model performance with tuning into different hyper-parameters. Also, will observe model performance on balanced data-set to check if that out performs over imbalanced data-set.

After building various models and analysing various parameters we conclude that "KNN" with default values out performs all other models built. We have concluded this basis Accuracy, F1 score, Recall, Precision and AUC score.

BUILDING KNN MODEL: -

Building model with default hyperparameters: -

Post splitting data into training and testing data set we fitted KNN model into training dataset and performed prediction on training and testing dataset using the same model. We made the first model with default hyperparameters with default value of n_neighbour as "5".

Below are the accuracy scores obtained from this model: -

```
Accracy of training dataset: 0.8572697284953058

accuracy for testing dataset 0.8404381290704559
```

Fig 46: - Accuracy Scores From KNN

Below are the confusion matrices obtained from this model: -

```
confusion matrix of training dataset
[[6312  244]
 [ 881  445]]
```

```
confusion matrix for testing dataset
[[2679  129]
 [ 410  160]]
```

Fig 47: - Confusion Matrix From KNN

Below are the classification Report obtained from this model: -

classificatoin report of training dataset

	precision	recall	f1-score	support
0.0	0.88	0.96	0.92	6556
1.0	0.65	0.34	0.44	1326
accuracy			0.86	7882
macro avg	0.76	0.65	0.68	7882
weighted avg	0.84	0.86	0.84	7882

classsification report for testing dataset

	precision	recall	f1-score	support
0.0	0.87	0.95	0.91	2808
1.0	0.55	0.28	0.37	570
accuracy			0.84	3378
macro avg	0.71	0.62	0.64	3378
weighted avg	0.81	0.84	0.82	3378

Fig 48: - Classification Report From KNN

Below are the AUC scores and ROC curves obtained from this model: -

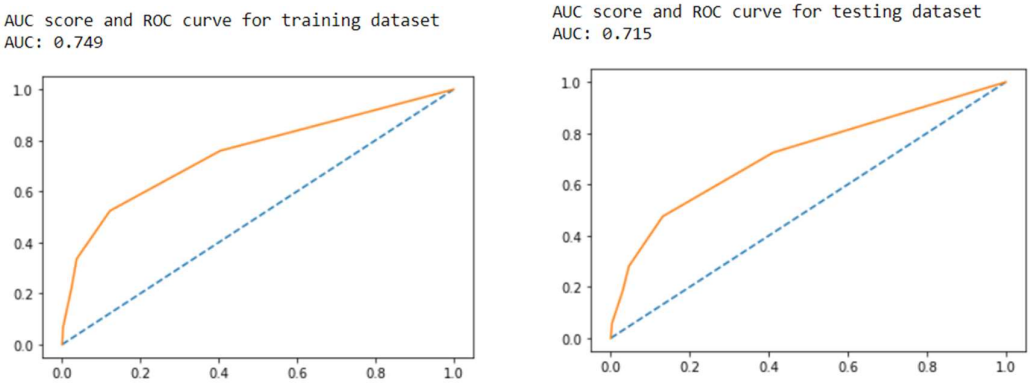


Fig 49: - ROC Curve and AUC Scores From KNN

Below are the 10-fold cross validation scores: -

```
cross validation scores for train dataset

array([0.83523447, 0.82129278, 0.84898477, 0.84771574, 0.84390863,
       0.8464467 , 0.84010152, 0.79568528, 0.84137056, 0.83883249])

cross validation scores for test dataset

array([0.83136095, 0.83136095, 0.83727811, 0.84023669, 0.82248521,
       0.82544379, 0.82544379, 0.82544379, 0.81305638, 0.80118694])
```

Fig 50: - Cross Validation Scores From KNN

we can observe that the cross validations scores are almost same for all the folds. Which indicates that the model built is correct.

Effort to improve model performance.

Find the right value of n_neighbor: -

It's very important to have the right value of n_neighbour's to fetch the best accuracy from the model. We can decide on the best value for n_neighbours based on MSE (mean squared error) scores. The value with least score of MSE indicated least error and will fetch the best optimized n_neighbours value.

Below are the MSE scores: -

```
[0.24304322084073415,
 0.17021906453522795,
 0.1595618709295441,
 0.16489046773238603,
 0.16015393724097093,
 0.16193013617525165,
 0.16341030195381878,
 0.16252220248667848,
 0.16370633510953225,
 0.16281823564239195]
```

Fig 51: - MSE Scores

Below is the graphical version of of MSE scores acorss numerous values of n_neighbors.

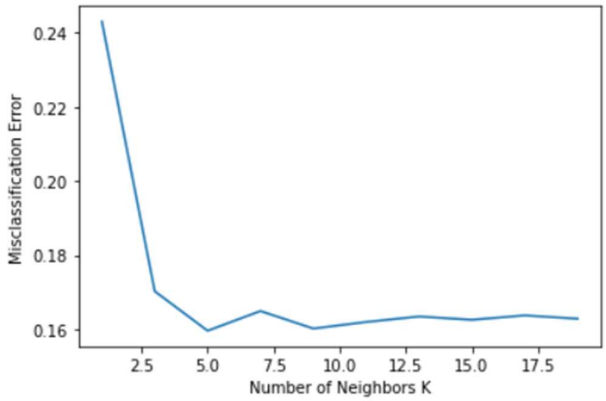


Fig 52: - Graphical Version Of MSE Score

From the above plotted graph we can see the n_neighbors with value "5" gives the least MSE score. With which we can proceed and build KNN model with n_neighbor value as "5" which is also the default n_neighbor. **Hence, different model building with correct number of n_nrighbor is not required as it's the same as default value if n_neighbor.**

Building model using GridSearchCV and getting the best hyperparameters: -

After building the model with its default values as shown above, we will try and find the best hyper parameters to check if we can outperform the accuracy achieved by the model built with default values of hyperparameter. From GridSearchCV we found that the best parameters are "ball-tree" as algorithm, "Manhattan" as metrics, "5" as n_neighbors and "distance" as weights.

Below are the accuracy scores obtained from this model using GridSearchCV: -

```
Accuracy of training dataset after gridsearchCV: 0.8582846993148947

Accuracy of testing dataset after gridsearchCV: 0.8416222616933097
```

Fig 53: - Accuracy From KNN with Hyperparamter Tuning

Below are the confusion matrices obtained from this model using GridSearchCV: -

```
confusuon matrix for training dataset

array([[6342,  214],
       [ 903,  423]], dtype=int64)
```

```
confusuon matrix for testing dataset

array([[2694,  114],
       [ 421,  149]], dtype=int64)
```

Fig 54: - Confusion Matrix From KNN with Hyperparamter Tuning

Below is the classification report obtained from this model using GridSearchCV: -

Classification report for train dataset

	precision	recall	f1-score	support
0.0	0.88	0.97	0.92	6556
1.0	0.66	0.32	0.43	1326
accuracy			0.86	7882
macro avg	0.77	0.64	0.68	7882
weighted avg	0.84	0.86	0.84	7882

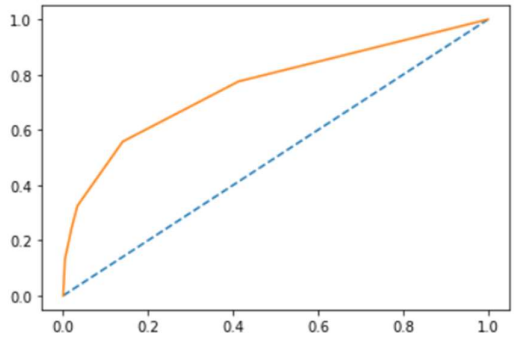
Classification report for test dataset

	precision	recall	f1-score	support
0.0	0.86	0.96	0.91	2808
1.0	0.57	0.26	0.36	570
accuracy			0.84	3378
macro avg	0.72	0.61	0.63	3378
weighted avg	0.81	0.84	0.82	3378

Fig 55: - Classification Report From KNN with Hyperparamter Tuning

Below are the AUC scores and ROC curves obtained from this model using GridSearchCV: -

AUC score and ROC curve for training dataset
AUC: 0.757



AUC score and ROC curve for testing dataset
AUC: 0.720

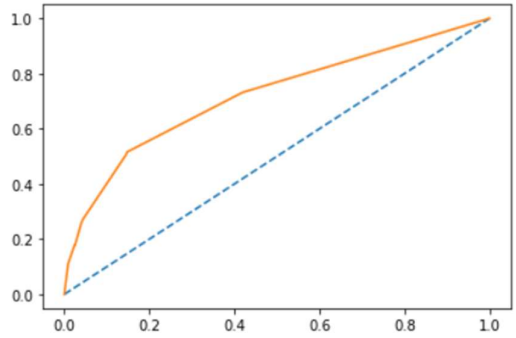


Fig 56: - ROC Curve and AUC Score From KNN with Hyperparamter Tuning

Below are the 10-fold cross validation scores: -

```
cross validation scores for train dataset

array([0.84537389, 0.83523447, 0.8464467 , 0.84010152, 0.83629442,
       0.85913706, 0.85025381, 0.81345178, 0.85406091, 0.85025381])

cross validation scores for test dataset

array([0.84319527, 0.82544379, 0.82840237, 0.83727811, 0.79289941,
       0.80177515, 0.83727811, 0.82544379, 0.83976261, 0.83086053])
```

Fig 57: Cross Validation Scores From KNN with Hyperparamter Tuning

we can observe that the cross validations scores are almost same for all the folds. Which indicates that the model built is correct.

Building model using SMOTE: -

From above descriptive analysis we can conclude that the original data provided is imbalance in nature and by using SMOTE technique we can balance the data to check if the model can outperform when data is balanced. We have applied SMOTE technique to oversample the data and to obtain a balanced dataset.

Below are the accuracy scores obtained from balanced dataset: -

```
Accuracy of training dataset: 0.713849908480781

Accuracy of testing dataset: 0.6669626998223801
```

Fig 58: Accuracy Score From KNN with SMOTE

Below are the confusion matrices obtained from balanced dataset: -

```
confusion matrix for training dataset

array([[4370, 2186],
       [1566, 4990]], dtype=int64)
```

```
confusion matrix for testing dataset

array([[1851,  957],
       [ 168,  402]], dtype=int64)
```

Fig 59: Confusion Matrix From KNN with SMOTE

Below are the classification reports obtained from balanced dataset: -

Classification report for train dataset

	precision	recall	f1-score	support
0.0	0.74	0.67	0.70	6556
1.0	0.70	0.76	0.73	6556
accuracy			0.71	13112
macro avg	0.72	0.71	0.71	13112
weighted avg	0.72	0.71	0.71	13112

Classification report for test dataset

	precision	recall	f1-score	support
0.0	0.92	0.66	0.77	2808
1.0	0.30	0.71	0.42	570
accuracy			0.67	3378
macro avg	0.61	0.68	0.59	3378
weighted avg	0.81	0.67	0.71	3378

Fig 60: Classification Reports From KNN with SMOTE

Below are the AUC scores and ROC curves obtained from balanced dataset: -

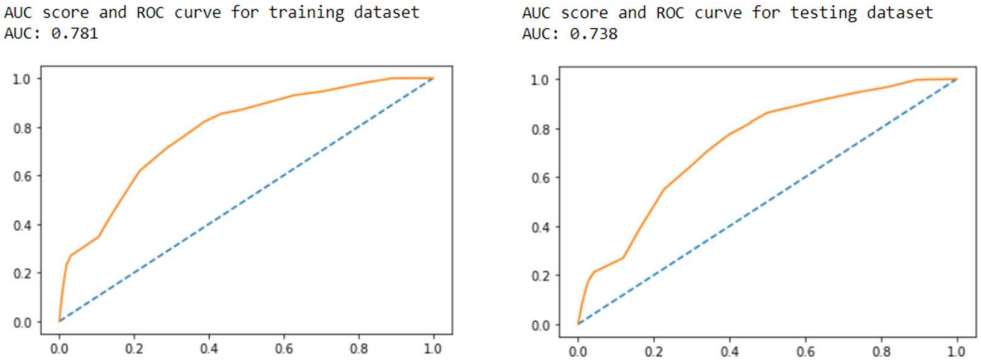


Fig 61: ROC Curve and AUC Scores From KNN with SMOTE

Below are the 10-fold cross validation scores: -

```
cross validation scores for train dataset

array([0.69588415, 0.71341463, 0.71167048, 0.72768879, 0.70480549,
       0.73150267, 0.70175439, 0.72006102, 0.73073989, 0.73302822])

cross validation scores for test dataset

array([0.84911243, 0.83431953, 0.84023669, 0.83431953, 0.83136095,
       0.82544379, 0.83136095, 0.82248521, 0.82492582, 0.83086053])
```

Fig 62: Cross Validation Scores From KNN with SMOTE

we can observe that the cross validations scores are almost same for all the folds. Which indicates that the model built is correct.

Inference/Conclusion from KNN Model: -

From the above we can conclude that the data is neither "Overfit" nor "Underfit" in nature. And we can also inference that the model built using grid search CV is best optimized model for prediction. However, we can see significant variations in accuracy score, F1 score, recall values, precision values, ROC curves and AUC scores when compared with default values of KNN and also with model built on balanced dataset. Model built on balance data set using SMOTE technique works well in training dataset however we can see a significant deplete in accuracy when it comes to testing dataset.

Inferences on final model: -

- From the above tabular representation of all the scores for training and testing dataset across various model we can conclude that the KNN model with default values of hyper-parameters is best optimized for the given dataset. (Highlighted in BOLD)
- There is marginal difference in accuracy for Logistic regression and LDA, but comparatively LDA had a little better performance than logistic regression.
- Model with bagging and boosting is also well optimized but difference in accuracy for training and testing dataset is little on the higher side as compared to KNN.
- Other model's namely Naïve Bayes, LDA and SVM worked well on training dataset but the accuracy came down when performed over testing dataset. Which indicates overfitting of data in that model.
- All models built on balances dataset showed overfitting.
- **We also understand that the accuracy and other measuring parameter of a model can be improved by trying various other combinations of hyper-parameter. Model building is an iterative process. Model performance both on training and testing dataset can be improves**

Similar approach like above have been used to create other models and below is the model comparison across parameter. However, we have showcased the result of KNN as we have concluded that it out performs all other models.

Overall Model Building Comparison across parameters: -

	Training Dataset (70%)								Test Dataset (30%)							
	Accuracy	Precision - 0	Recall - 0	F1 Score - 0	Precision - 1	Recall - 1	F1 Score - 1	AUC Score	Accuracy	Precision - 0	Recall - 0	F1 Score - 0	Precision - 1	Recall - 1	F1 Score - 1	AUC Score
Logistic Regression	83.91	0.85	0.99	0.91	0.62	0.11	0.19	0.75	83.98	0.85	0.98	0.91	0.62	0.13	0.21	0.75
Logistic Regression - CV	83.92	0.85	0.99	0.91	0.62	0.12	0.2	0.75	83.98	0.85	0.98	0.91	0.62	0.13	0.21	0.752
Logistic Regression - SM	68.21	0.69	0.67	0.68	0.68	0.7	0.69	0.751	67.67	0.92	0.67	0.77	0.3	0.71	0.43	0.748
LDA	84.21	0.85	0.98	0.91	0.61	0.17	0.27	0.748	83.62	0.85	0.98	0.91	0.55	0.15	0.24	0.748
LDA - CV	84.16	0.85	0.98	0.91	0.6	0.18	0.28	0.748	83.54	0.85	0.97	0.91	0.54	0.16	0.25	0.747
LDA - SM	68.66	0.69	0.67	0.68	0.68	0.7	0.69	0.752	67.85	0.92	0.67	0.78	0.31	0.72	0.43	0.748
KNN	**85.72**	**0.88**	**0.96**	**0.92**	**0.65**	**0.34**	**0.44**	**0.748**	**84.04**	**0.87**	**0.95**	**0.91**	**0.55**	**0.28**	**0.37**	**0.715**
KNN - 5	Same As Default								Same As Default							
KNN - CV	85.82	0.88	0.97	0.92	0.66	0.32	0.43	0.757	84.16	0.86	0.96	0.91	0.57	0.26	0.36	0.72
KNN - SM	71.38	0.74	0.67	0.7	0.7	0.76	0.73	0.781	66.69	0.92	0.66	0.77	0.3	0.71	0.42	0.738
Naïve Bayes	28.06	0.93	0.15	0.25	0.18	0.94	0.31	0.715	28.98	0.96	0.15	0.26	0.19	0.96	0.31	0.721
Naïve Bayes - SM	55.6	0.77	0.16	0.26	0.53	0.95	0.68	0.723	29.75	0.94	0.17	0.28	0.19	0.95	0.31	0.708
Bagging	86.24	0.87	0.98	0.92	0.73	0.29	0.41	0.833	84.28	0.86	0.97	0.91	0.59	0.22	0.32	0.794
Bagging - SM	74.5	0.75	0.74	0.74	0.74	0.75	0.75		71.81	0.92	0.72	0.81	0.34	0.69	0.45	0.785
Ada- Boosting	83.88	0.85	0.98	0.91	0.61	0.12	0.2	0.75	83.95	0.85	0.98	0.91	0.61	0.13	0.21	0.752
Ada- Boosting - SM	67.85	0.68	0.68	0.68	0.68	0.68	0.68	0.751	68.56	0.92	0.68	0.78	0.31	0.7	0.43	0.747
Gradient Boosting	84.77	0.85	0.98	0.91	0.69	0.17	0.27	0.782	84.13	0.85	0.98	0.91	0.61	0.16	0.25	0.774
Gradient Boosting - SM	71.77	0.71	0.74	0.72	0.73	0.7	0.71	0.785	71.78	0.92	0.73	0.81	0.33	0.67	0.44	0.769
SVM	85.29	0.86	0.99	0.92	0.74	0.19	0.31	0.75	84.31	0.85	0.98	0.91	0.64	0.16	0.26	0.754
SVM - CV	86.33	0.87	0.98	0.92	0.75	0.28	0.41	0.753	84.33	0.86	0.97	0.91	0.6	0.22	0.32	0.751
SVM - SM	74.09	0.74	0.75	0.74	0.74	0.74	0.74	0.753	71.99	0.92	0.73	0.81	0.34	0.68	0.45	0.75

Table 9: Comparison Across Various Models

Indicators/symbols for above tabular data: -

- CV : - indicates scores for model built on best params obtained from GridSearchCV with model name as prefix.
- SM: - indicates scores for model built on balanced dataset with model name as prefix.
- KNN-5: - Indicates KNN model built with N_neighbors as “5”.

Implication of final model on Business: -

- Using the model built above business can plan various strategies to make customers stick with them.
- They can roll out different Offers and discounts as family floater.
- They can give regular discount coupons if paid by their e-wallet platform.
- Discount vouchers of other vendors or on next bill can be provided based in minimum bill criteria.
- This model gives business an idea where they stand currently and what best they can do to improve on the same.

5. Model Validation

When it comes to model validation of a classification problem statement we cannot just get relied on accuracy, we need to look at various others parameter like F1 score, Recall, precision, ROC curve and AUC score, along with confusion matrix. The details of these parameters are described below: -

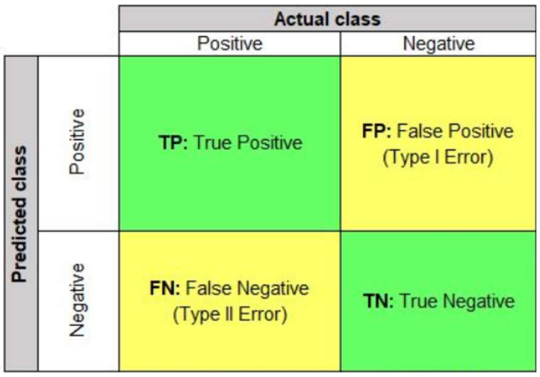


Fig :-63 – A look of confusion matrix

Confusion Matrix:

Confusion Matrix usually causes a lot of confusion even in those who are using them regularly. Terms used in defining a confusion matrix are TP, TN, FP, and FN.

True Positive (TP): - The actual is positive in real and at the same time the prediction was classified correctly.

False Positive (FP): - The actual was actually negative but was falsely classified as positive.

True Negative: - The actuals were actually negative and was also classified as negative which is the right thing to do.

False Negative: - The actuals were actually positive but was falsely classified as negative.

Various Components Of Classification Report: -

Accuracy: This term tells us how many right classifications were made out of all the classifications.

$$\text{Accuracy} = (TP + TN) / (TP + FP + TN + FN)$$

Precision: Out of all that were marked as positive, how many are actually truly positive.

$$\text{Precision} = TP / (TP + FP)$$

Recall or Sensitivity: Out of all the actual real positive cases, how many were identified as positive.

$$\text{Recall} = TP/ (TN + FN)$$

Specificity: Out of all the real negative cases, how many were identified as negative.

$$\text{Specificity} = TN/ (TN + FP)$$

F1-Score: As we saw above, sometimes we need to give weightage to FP and sometimes to FN. F1 score is a weighted average of Precision and Recall, which means there is equal importance given to FP and FN. This is a very useful metric compared to "Accuracy". The problem with using accuracy is that if we have a highly imbalanced dataset for training (for example, a training dataset with 95% positive class and 5% negative class), the model will end up learning how to predict the positive class properly and will not learn how to identify the negative class. But the model will still have very high accuracy in the test dataset too as it will know how to identify the positives really well.

$$\text{F1 score} = 2* (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$$

Area Under Curve (AUC) and ROC Curve: AUC or Area Under Curve is used in conjecture with ROC Curve which is Receiver Operating Characteristics Curve. AUC is the area under the ROC Curve. So, let's first understand the ROC Curve.

A ROC Curve is drawn by plotting TPR or True Positive Rate or Recall or Sensitivity (which we saw above) in the y-axis against FPR or False Positive Rate in the x-axis. FPR = 1-Specificity (which we saw above).

$$TPR = TP/ (TP + FN)$$

$$FPR = 1 – TN/ (TN+FP) = FP/ (TN + FP)$$

when we want to select the best model, we want a model that is closest to the perfect model. In other words, a model with AUC close to 1. When we say a model has a high AUC score, it means the model's ability to separate the classes is very high (high separability). This is a very important metric that should be checked while selecting a classification model.

6. Final interpretation / recommendation

Insights From Analysis: -

- Business have visibility in tier-1 city.
- Mostly customer rated “3” for the services provided by the business.
- Mostly customer rated “3” for the interactions they have customer care representatives.
- Transaction via UPI and e-wallet is very low.
- Maximum churn is from the account segment “Regular+”.
- Customers with marital status is “single” contributes max towards churn.
- Any complaints raised in last 12 months doesn’t show any impact toward churn.
- Tenure and cashback are directly proportional to each other.
- Computer usage is more in tier 1 city followed by tier 3 and tier 2 city.

Insights From Model Building: -

- From the above tabular representation of all the scores for training and testing dataset across various model we can conclude that the KNN model with default values of hyper-parameters is best optimized for the given dataset. (highlighted in BOLD)
- There is marginal difference in accuracy for Logistic regression and LDA, but comparatively LDA had a little better performance than logistic regression.
- Model with bagging and boosting is also well optimized but difference in accuracy for training and testing dataset is little on the higher side as compared to KNN.
- Other model’s namely Naïve Bayes, LDA and SVM worked well on training dataset but the accuracy came down when performed over testing dataset. Which indicates overfitting of data in that model.
- All models built on balances dataset showed overfitting.
- **We also understand that the accuracy and other measuring parameter of a model can be improved by trying various other combinations of hyper-parameter. Model building is an iterative process. Model performance both on training and testing dataset can be improves**

Recommendations: -

➢ Four Stages of Churn Management

- Introduce pre-defined customer segmentation and according to customers' needs and usage.
- Acquiring customers through different strategies

- Delighting customers in order to increase customers loyalty as compared to competitors.

- Preventing Customers from attrition through analyzing various churn signals and triggers

- Focus on saving customers from leaving the firm through several campaigns.

Other Recommendations: -

- Business can introduce referral drive for existing customers to acquire new customers.
- Business can be in joint with other life style vendors to provide vouchers to the new as well existing loyal customers.
- Business can internally bifurcate its customers based on spending pattern into deal seeker, tariff optimizer etc. and can have different acquisition strategy for each set of customers.
- Offering free cloud storage to loyal customers.
- Customized email response to priority customers basis segmentation for better customer interaction.

- Specialized team of customer service for Top notch customers to avoid waiting time and better customer experience and interaction.
- Understanding customers profile and sending small token of gift on special days.
- Thanking customers with hand written notes on invoices will create a good will factor.
- Follow-up in customers issues and taking regular feedbacks on the same.
- Conducting satisfaction survey to understand change in customers behavior.
- Business needs to make sure that all complaints and queries raised are resolve on time.
- Business can promote using their own e-wallet as payment option by giving certain discount over the bill.
- Business needs to come up with subsidized offers for customers who are single as they show high trend to churn.
- Business needs to introduce all-in-one family plan with extra services, it will make accessibility easier for customers.
- Business needs to increase in visibility in Tier-2 city for better customer acquisition.
- Business can promote payment via standing instruction in bank account or UPI which can be hassle free and safe for customers.

Customer Segment Approach: -

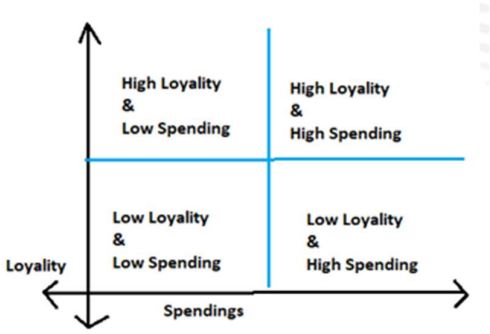


Fig 64: Graphical representation of customers division basis spending and loyalty

- Customers can divide into 4 sets as shown in figure.
- And at times business needs to take harsh decision of letting go the customers with “low on loyalty and Low on spending”.
- Customers under set of “High Loyalty & High Spending” can be retained by delighting them with various offers.

- Customers under “High Loyalty & Low Spending” can be offered with bundled family floater plan to increase on their spending’s.
- The 4th quadrant can be the major area of observation for business where in customers are “low on loyalty but high on spending’s”, they can be retained by increasing the service level index and with proper follow-up on running offers and subscriptions.

Appendix

Codes Snapshot: -

```
# importing libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
```

```
# loding data
churn  = pd.read_excel(r'C:\Users\abhay\Downloads\Customer Churn Data.xlsx', sheet_name = 'Data for DSBA')
```

```
# checking info of data
churn.info()
```

```
# checking shape of dataset
print("The shape of dataset is :{}".format(churn.shape))
```

```
# checking for duplicate values
print("Number of duplicate rows:",churn.duplicated().sum())
```

```
#checking for skewness
churn.hist(figsize=(20,15));
```

```
# kest check kurtosis and skewness of data
print("kurtosis and skewness of dataste is as below")
pd.DataFrame(data = [churn.kurtosis(), churn.skew()], index=['Kurtosis','Skewness']).T.round(2)
```

```
# plotting sns plot
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
# pair plot to check on data distribution and co-linearity
sns.pairplot(churn, hue = 'Churn', diag_kind='kde')
plt.show()
```

```
#checking if the data is balanced or not
churn.groupby(["Churn"]).count()
```

```
sns.countplot(churn["City_Tier"]);
```

```
sns.countplot(churn["Payment"]);
```

```
sns.countplot(churn["Gender"]);
```

```
sns.countplot(churn["Service_Score"]);
```

```
sns.countplot(churn["Account_user_count"]);
```

```
sns.countplot(churn["account_segment"]);
```

```
sns.countplot(churn["CC_Agent_Score"]);
```

```
sns.countplot(churn["Marital_Status"]);
```

```
sns.countplot(churn["Complain_ly"]);
```

```
sns.countplot(churn["Login_device"]);
```

```
sns.catplot(y="City_Tier", hue="Churn", kind="count", data=churn)
```

```
sns.catplot(y="Payment", hue="Churn", kind="count", data=churn)
```

```
sns.catplot(y="Gender", hue="Churn", kind="count", data=churn)
```

```
sns.catplot(y="Service_Score", hue="Churn", kind="count", data=churn)
```

```
sns.catplot(y="Account_user_count", hue="Churn", kind="count", data=churn)
```

```
sns.catplot(y="account_segment", hue="Churn", kind="count", data=churn)
```

```
sns.catplot(y="CC_Agent_Score", hue="Churn", kind="count", data=churn)
```

```
sns.catplot(y="Marital_Status", hue="Churn", kind="count", data=churn)
```

```
sns.catplot(y="Complain_ly", hue="Churn", kind="count", data=churn)
```

```
sns.catplot(y="Login_device", hue="Churn", kind="count", data=churn)
```

```
# plotting heatmap of correlation
cor = churn.corr()
mask = np.array(cor)
mask[np.tril_indices_from(mask)] = False
fig,ax= plt.subplots()
fig.set_size_inches(10,10)
sns.heatmap(cor, mask=mask, vmax=1, square=True, annot=True)
plt.show()
```

```
churn['account_segment'] = churn['account_segment'].replace('Super','1')
churn['account_segment'] = churn['account_segment'].replace('Regular Plus','2')
churn['account_segment'] = churn['account_segment'].replace('Regular +','2')
churn['account_segment'] = churn['account_segment'].replace('Regular','3')
churn['account_segment'] = churn['account_segment'].replace('HNI','4')
churn['account_segment'] = churn['account_segment'].replace('Super Plus','5')
churn['account_segment'] = churn['account_segment'].replace('Super +','5')
```

```
# lets check the percentage of outlier in each column
Q1 = churn.quantile(0.25)
Q3 = churn.quantile(0.75)
IQR = Q3 - Q1
pd.DataFrame((((churn < (Q1 - 1.5 * IQR)) | (churn > (Q3 + 1.5 * IQR))).sum()/churn.shape[0]*100),
             columns = ['outlier %'], index = None). round(2)
```

```
# kest check kurtosis and skewness of data
print("kurtosis and skewness of dataste is as below")
pd.DataFrame(data = [churn.kurtosis(), churn.skew()], index=['Kurtosis','Skewness']).T.round(2)
```

```
# lets check the percentage of outlier in each column
Q1 = churn.quantile(0.25)
Q3 = churn.quantile(0.75)
IQR = Q3 - Q1
pd.DataFrame((((churn < (Q1 - 1.5 * IQR)) | (churn > (Q3 + 1.5 * IQR))).sum()/churn.shape[0]*100),
             columns = ['outlier %'], index = None). round(2)
```

```
from sklearn.preprocessing import MinMaxScaler

churn['Scaled_Churn'] = MinMaxScaler().fit_transform(churn[['Churn']])
churn['Scaled_Tenure'] = MinMaxScaler().fit_transform(churn[['Tenure']])
churn['Scaled_City_Tier'] = MinMaxScaler().fit_transform(churn[['City_Tier']])
churn['Scaled_CC_Contacted_LY'] = MinMaxScaler().fit_transform(churn[['CC_Contacted_LY']])
churn['Scaled_Payment'] = MinMaxScaler().fit_transform(churn[['Payment']])
churn['Scaled_Gender'] = MinMaxScaler().fit_transform(churn[['Gender']])
churn['Scaled_Service_Score'] = MinMaxScaler().fit_transform(churn[['Service_Score']])
churn['Scaled_Account_user_count'] = MinMaxScaler().fit_transform(churn[['Account_user_count']])
churn['Scaled_account_segment'] = MinMaxScaler().fit_transform(churn[['account_segment']])
churn['Scaled_CC_Agent_Score'] = MinMaxScaler().fit_transform(churn[['CC_Agent_Score']])
churn['Scaled_Marital_Status'] = MinMaxScaler().fit_transform(churn[['Marital_Status']])
churn['Scaled_rev_per_month'] = MinMaxScaler().fit_transform(churn[['rev_per_month']])
churn['Scaled_Complain_ly'] = MinMaxScaler().fit_transform(churn[['Complain_ly']])
churn['Scaled_rev_growth_yoy'] = MinMaxScaler().fit_transform(churn[['rev_growth_yoy']])
churn['Scaled_coupon_used_for_payment'] = MinMaxScaler().fit_transform(churn[['coupon_used_for_payment']])
churn['Scaled_Day_Since_CC_connect'] = MinMaxScaler().fit_transform(churn[['Day_Since_CC_connect']])
churn['Scaled_cashback'] = MinMaxScaler().fit_transform(churn[['cashback']])
churn['Scaled_Login_device'] = MinMaxScaler().fit_transform(churn[['Login_device']])
```

```
churn_scaled = pd.DataFrame({
'Churn': churn['Scaled_Churn'] ,
'Tenure': churn['Scaled_Tenure'] ,
'City_Tier': churn['Scaled_City_Tier'] ,
'CC_Contacted_LY': churn['Scaled_CC_Contacted_LY'] ,
'Payment': churn['Scaled_Payment'] ,
'Gender': churn['Scaled_Gender'] ,
'Service_Score': churn['Scaled_Service_Score'] ,
'Account_user_count': churn['Scaled_Account_user_count'] ,
'account_segment': churn['Scaled_account_segment'] ,
'CC_Agent_Score': churn['Scaled_CC_Agent_Score'] ,
'Marital_Status': churn['Scaled_Marital_Status'] ,
'rev_per_month': churn['Scaled_rev_per_month'] ,
'Complain_ly': churn['Scaled_Complain_ly'] ,
'rev_growth_yoy': churn['Scaled_rev_growth_yoy'] ,
'coupon_used_for_payment': churn['Scaled_coupon_used_for_payment'] ,
'Day_Since_CC_connect': churn['Scaled_Day_Since_CC_connect'] ,
'cashback': churn['Scaled_cashback'] ,
'Login_device': churn['Scaled_Login_device'] })
churn_scaled
```

```
# plotting sns plot
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
# pair plot to check on data distribution and co-linearity
sns.pairplot(churn_scaled, hue = 'Churn', diag_kind='kde')
plt.show()
```

```
from numpy import where
import matplotlib.pyplot as plt

from collections import Counter
from sklearn.datasets import make_classification
from imblearn.over_sampling import SMOTE
```

```
X, y = make_classification(n_samples=1000, n_features=2, n_redundant=0, n_clusters_per_class=1, weights=[0.975], flip_y=0,
counter=Counter(y)
counter
```

```
from collections import Counter
for label, _ in counter.items():
    row_ix = where(y == label)[0]
    plt.scatter(X[row_ix, 0], X[row_ix, 1], label=str(label))
plt.legend()
plt.show()
```

Hyperparameters: -

```
# loading GridSearchCV and creating dataframe for parameters
from sklearn.model_selection import GridSearchCV
param_grid = {
    'solver': ['lbfgs','newton-cg', 'liblinear', 'sag', 'saga'],
    'penalty': ['l1','l2','none'],
    'tol':[0.0001,0.00001]
}

grid_search = GridSearchCV(estimator = lg, param_grid = param_grid, cv = 10, n_jobs=-1,scoring='f1')
```

```
# creating dataframe for GridSearchCV
from sklearn.model_selection import GridSearchCV
param_grid = {
    'solver': ['svd', 'lsqr', 'eigen'],
    'tol' : [0.0001,0.0002,0.0003],
    'shrinkage' : ['auto', 'float', 'None'],

}

grid_search = GridSearchCV(estimator = lda, param_grid = param_grid, cv = 10, n_jobs=-1,scoring='f1')
```

```
# getting the ideal number of value of "N"
# empty list that will hold accuracy scores
ac_scores = []

# perform accuracy metrics for values from 1,3,5....19
for k in range(1,20,2):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    # evaluate test accuracy
    scores = knn.score(X_test, y_test)
    ac_scores.append(scores)

# changing to misclassification error
MCE = [1 - x for x in ac_scores]
MCE
```

```
param_grid = {
    'n_neighbors': [5,7,9],
    'weights' : ['uniform','distance'],
    'metric' : ['euclidean', 'manhattan'],
    'algorithm' : ['auto', 'ball_tree', 'kd_tree', 'brute']

}

grid_search = GridSearchCV(estimator = knn, param_grid = param_grid, cv = 10, n_jobs=-1,scoring='f1')
```

```
from sklearn.ensemble import BaggingClassifier
Bagging=BaggingClassifier(base_estimator=rf,random_state=1)
Bagging.fit(X_train, y_train)
```

```
from sklearn.ensemble import AdaBoostClassifier


adb = AdaBoostClassifier(random_state=1)
adb.fit(X_train,y_train)
```

```
from sklearn.ensemble import GradientBoostingClassifier
gb = GradientBoostingClassifier(random_state=1)
gb.fit(X_train, y_train)
```

```
from sklearn import svm
SVM = svm.SVC()
SVM.fit(X_train, y_train)
```

----------END OF REPORT----------