CAPSTONE PROJECT NOTE – 1

DSBA

Content of Report

Introduction of the business problem

Problem Statement: -

An DTH company 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 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 client 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 DTH 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 ear 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.

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.

Understanding of attributes (variable info, renaming if required)

This project has 18 attributes contributing towards the target variable. Let’s discuss about these variables one after another.

1. **AccountID** – This variable represents a unique ID which represents a unique customer. This is of Integer data type and there is no null values present in this.
2. **Churn** – This is our target variable, which represents if customer has churned or not. This is categorical in nature will no null values. “0” represents “NO” and ”1” represents “YES”.
3. **Tenure** – This represents the total tenure of the account since opened. This is a continuous variable with 102 null values.
4. **City_Tier** – These variable segregates customer into 3 parts based on city the primary customer resides. This variable is categorical in nature and have 112 null values.
5. **CC_Contacted_L12m** – This variable represents the number of times all the customers of the account has contacted customer care in last 12months. This variable is continuous in nature and have 102 null values.
6. **Payment** – This variable represents the preferable mode of bill payment opted by customer. This is categorical in nature and have 109 null values.
7. **Gender** – This variable represents the gender of the primary account holder. This is categorical in nature and 108 null values.
8. **Service_Score** – Scores provided by the customer basis the service provided by the company. This variable is categorical in nature and have 98 null values.
9. **Account_user_count** – This variable gives the number of customers attached with an accountID. This is continuous in nature and have 112 null values.
10. **account_segment** – These variable segregates customers into different segment basis their spend and revenue generation. This is categorical in nature and have 97 null values.
11. **CC_Agent_Score** -- Scores provided by the customer basis the service provided by the customer care representative of the company. This variable is categorical in nature and have 116 null values.
12. **Marital_Status** – This represents marital status of the primary account holder. This is categorical in nature and have 212 null values.
13. **rev_per_month** – This represents average revenue generated per account ID in last 12 months. This variable is continuous in nature and have 102 null values.
14. **Complain_l12m** – This denotes if customer have raised any complaints in last 12 months. This is categorical in nature and have 357 null values.
15. **rev_growth_yoy** – This variable shows revenue growth in percentage of account for 12 months Vs 24 to 13 months. This is continuous in nature and doesn’t have any null values.

16. **coupon_used_l12m** – This represents the number of times customer's have used discount coupons for bill payment. This is continuous in nature and doesn't have any null values.
17. **Day_Since_CC_connect** – This represents the number of days since customer have contacted the customer care. Higher the number of days denotes better the service. This is continuous in nature and have 357 null values.
18. **cashback_l12m** – This variable represents the amount of cash back earned by the customer during bill payment. This is continuous in nature and have 471 null values.
19. **Login_device** – This variable represents in which device customer is availing the services if it's on phone or on computer. This is categorical in nature and have 221 null values.

- With above understanding of data renaming of any of the variable is not required**.**
- With the above understanding of data, 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.

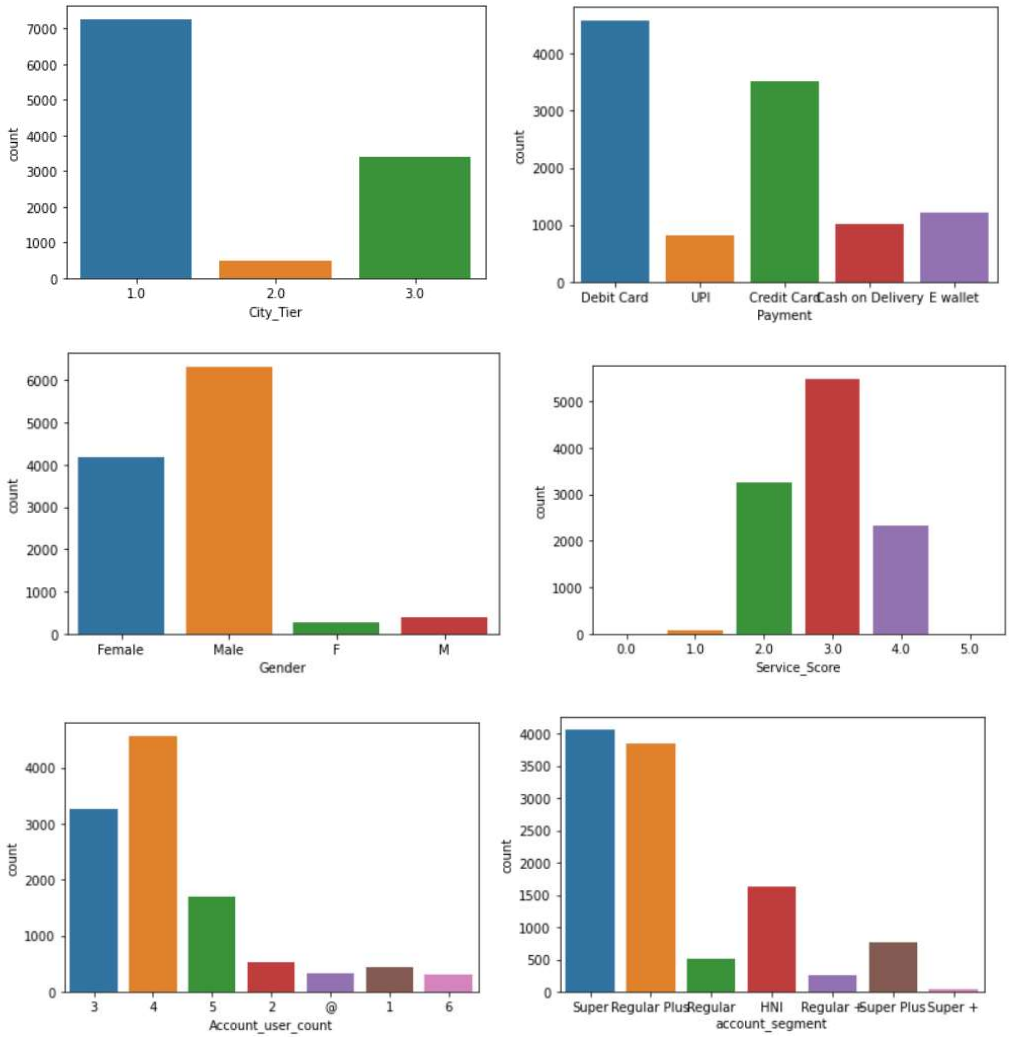
	outlier %
AccountID	0.00
Account_user_count	0.00
CC_Agent_Score	0.00
CC_Contacted_LY	0.37
Churn	16.84
City_Tier	0.00
Complain_ly	0.00
Day_Since_CC_connect	0.00
Gender	0.00
Login_device	0.00
Marital_Status	0.00
Payment	0.00
Service_Score	0.12
Tenure	0.00
account_segment	0.00
cashback	0.00
coupon_used_for_payment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



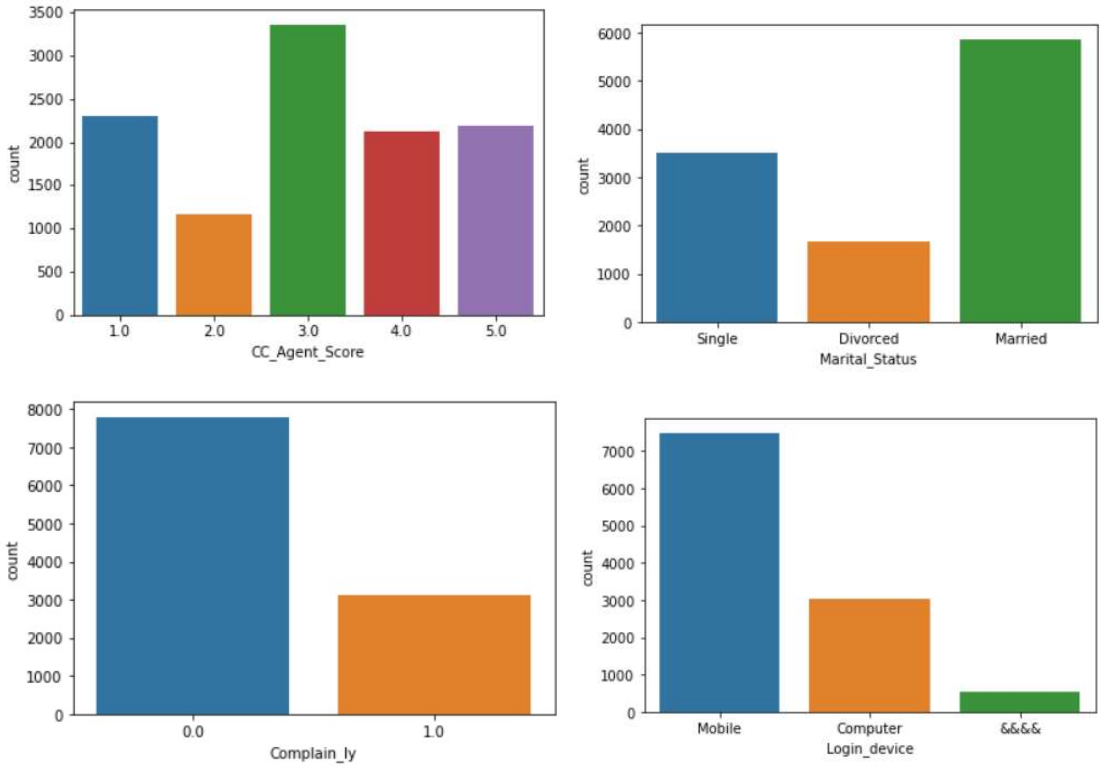
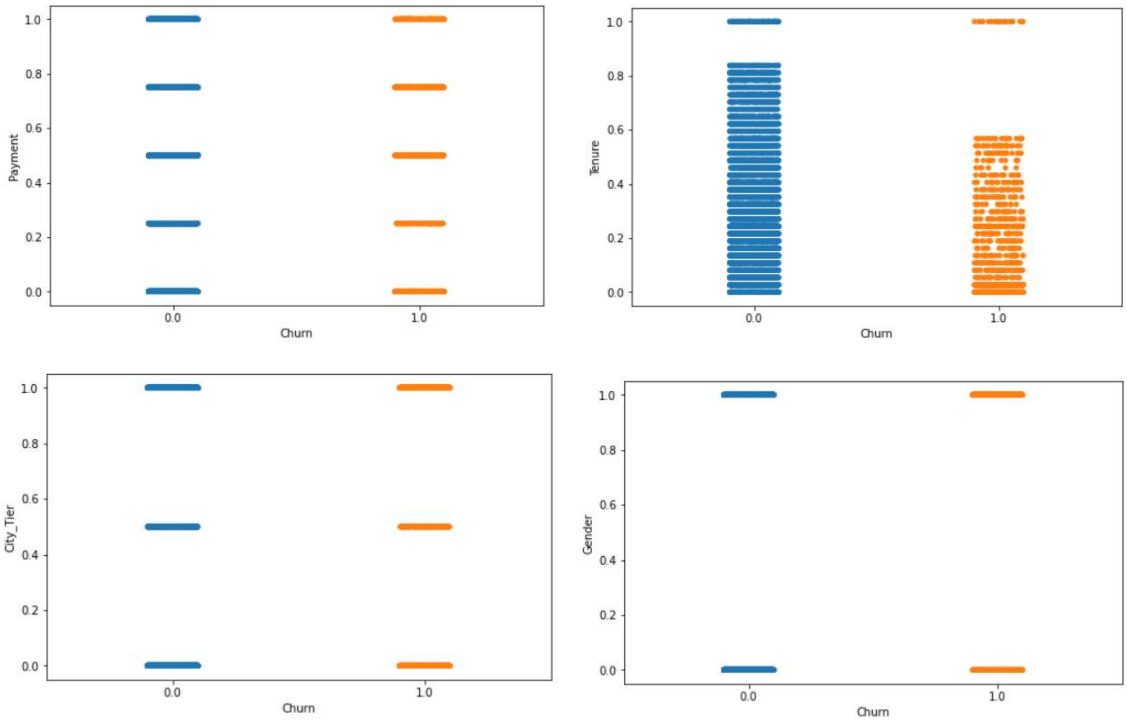


Fig 2: - Count plot of categorical variables



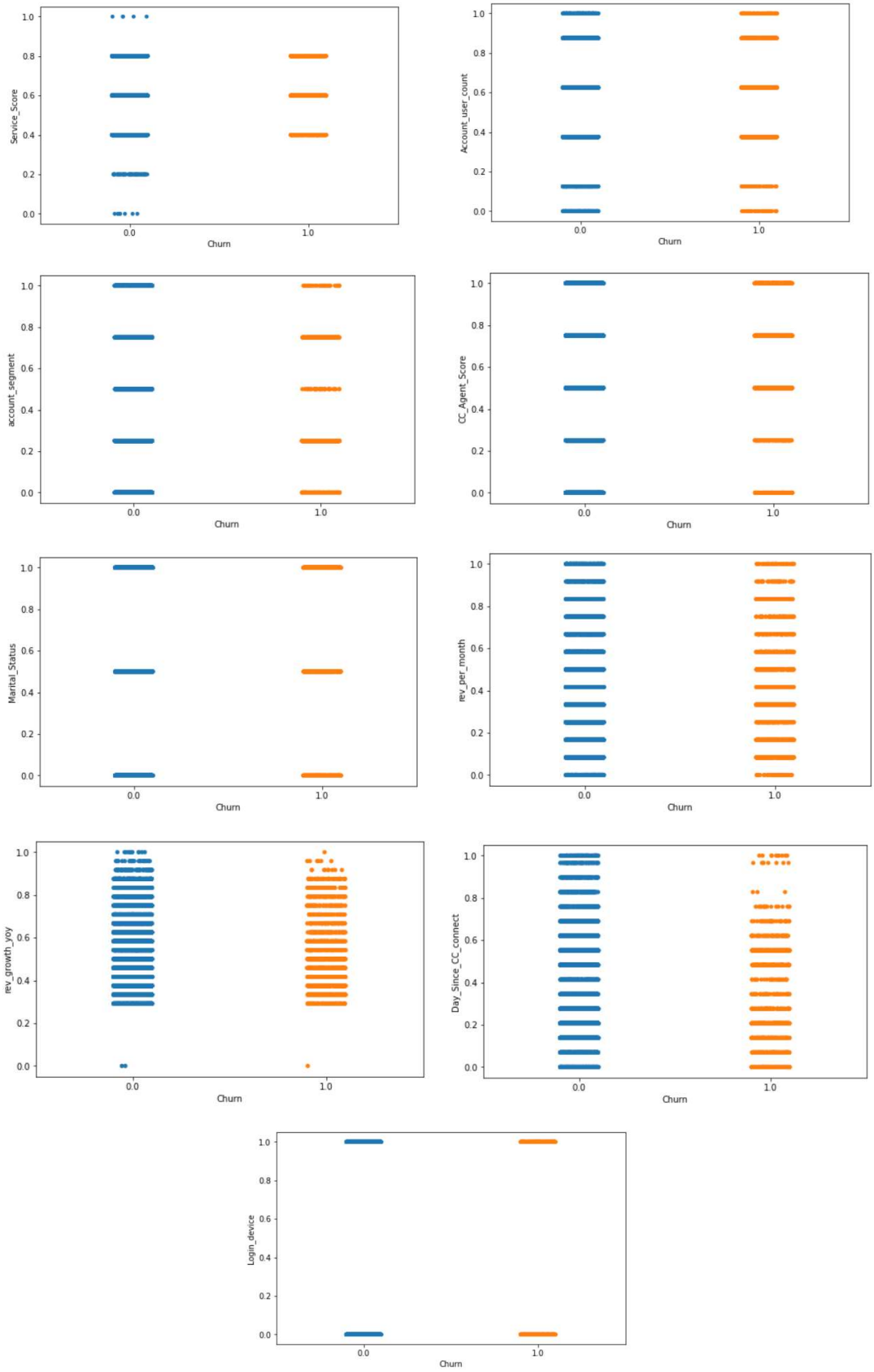


Fig 3: - Strip plot of across variables

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.

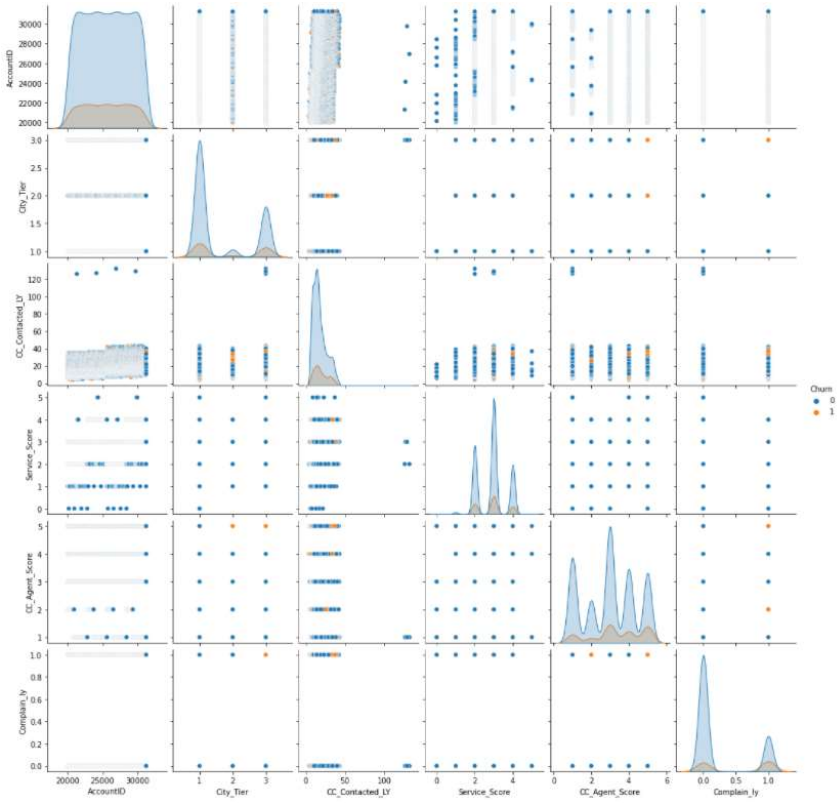
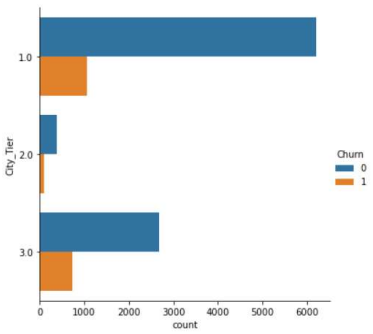
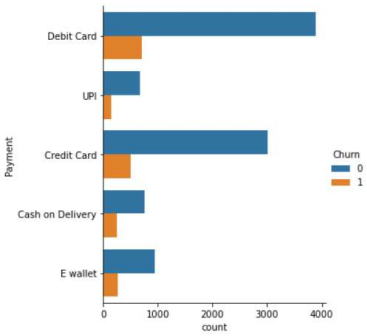
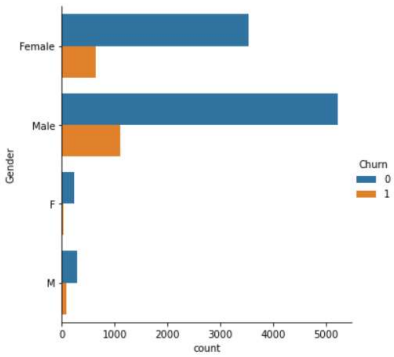


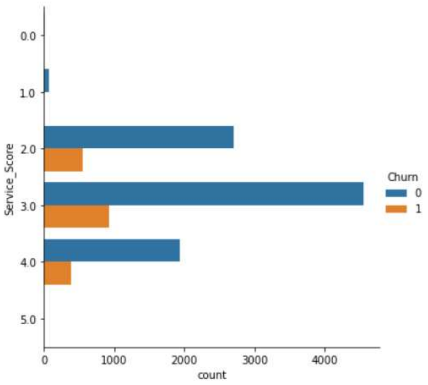
fig 4: - pairplot across categorical variables

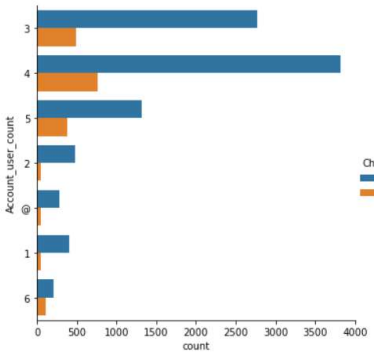
- The pair-plot shown above indiates that the independent variable are week or poor predictors of target variable as we the density of independent variable overlaps with the density of target variable.

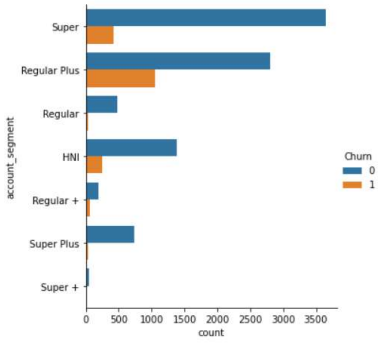

City_Tier
1.0
2.0
3.0
0
1000
2000
3000
4000
5000
6000
count
Churn
0
1

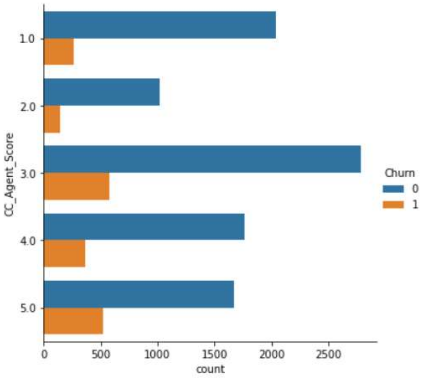

Payment
Debit Card
UPI
Credit Card
Cash on Delivery
E wallet
0
1000
2000
3000
4000
count
Churn
0
1

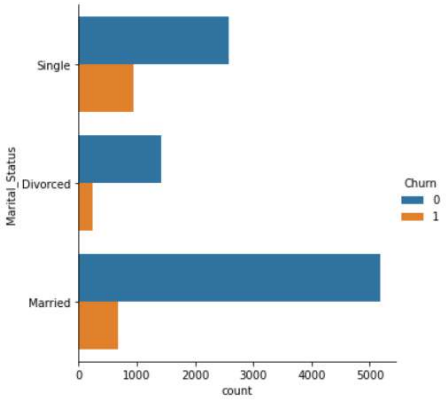

Gender
Female
Male
F
M
0
1000
2000
3000
4000
5000
count
Churn
0
1


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

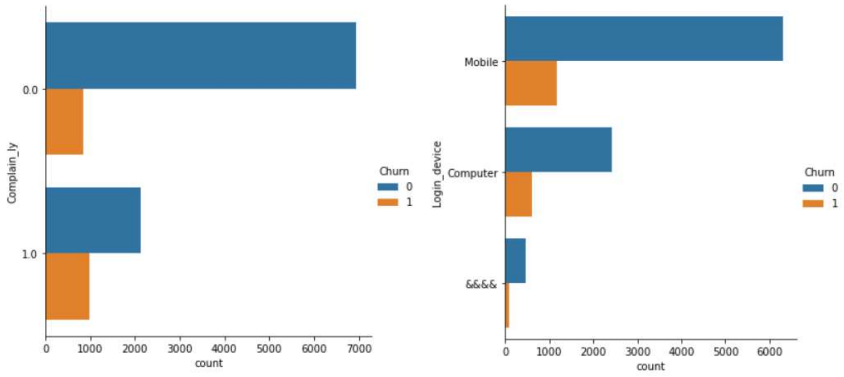


Fig 5: - Contribution of categorical variable towards chrun

- 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.

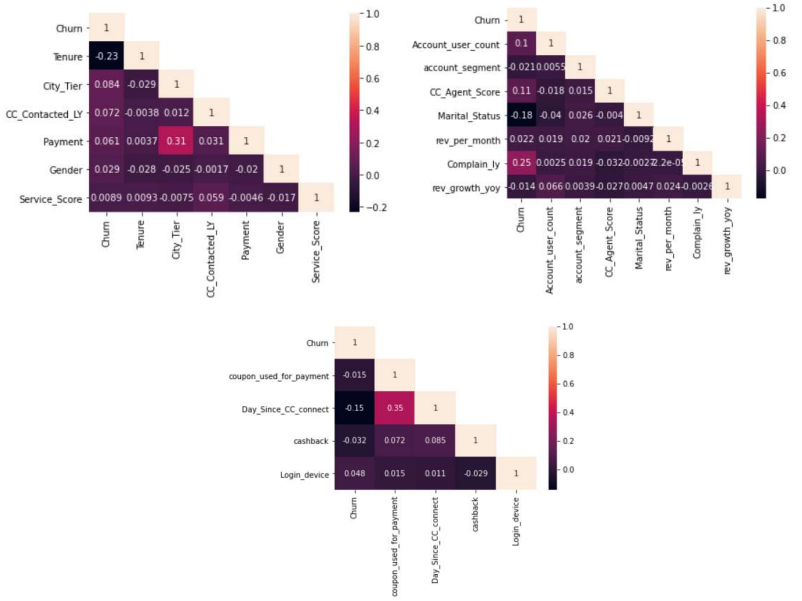


Fig 6: - Correlation among variables

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.

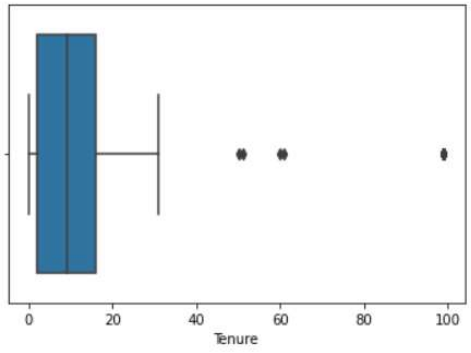
Removal of unwanted variables: - After in-depth understanding of data we conclude that removal of variables is not required at this stage of project. We can remove the variable “AccountID” which denotes a unique ID assigned to unique customers. However, removing them will lead to 8 duplicate rows. Rest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

Outlier treatment: -

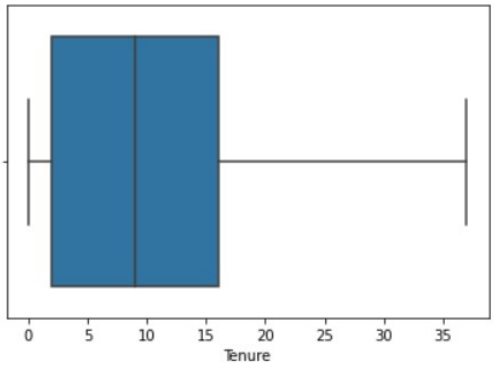
This dataset is the mix of continuous as well as categorical variables. It doesn’t make nay sense if we perform outlier treatment on categorical variable as each category denotes a type of customer. So, we are performing outlier treatment only for variables continuous in nature.

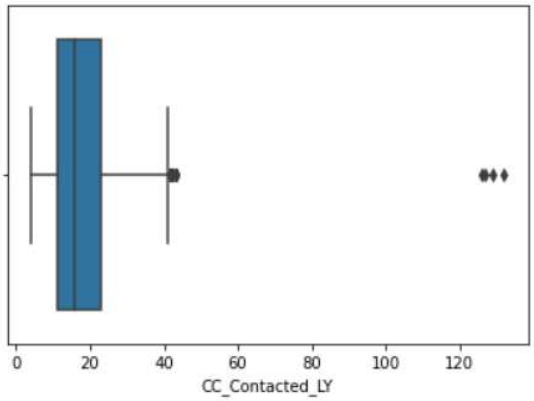
- Used box plot to determine the presence if outlier in a variable.
- The dots outside the upper limit of a quantile represents the outlier in the variable.
- We have 8 continuous variables in the dataset namely, “Tenure”, “CC_Contacted_LY”, “Account_user_count”, “cashback”, “rev_per_month”, “Day_Since_CC_connect”, “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.

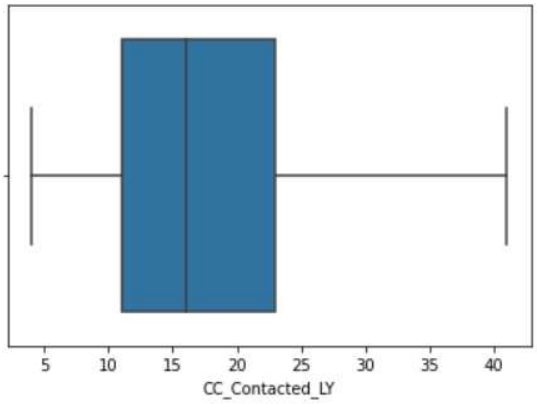
Before

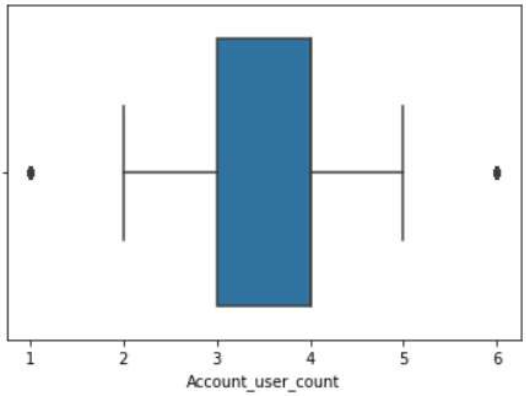


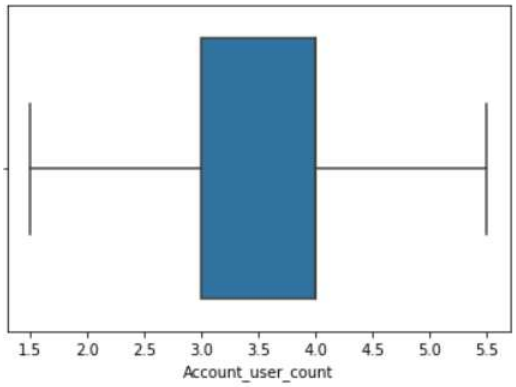
After

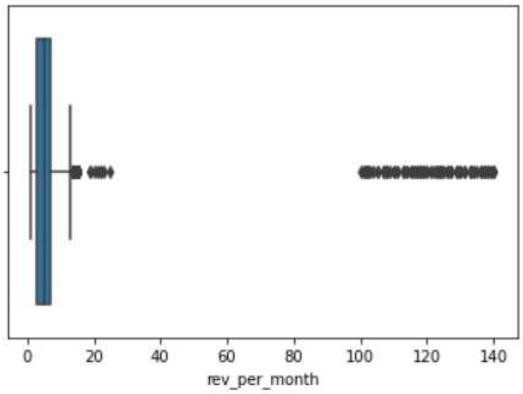


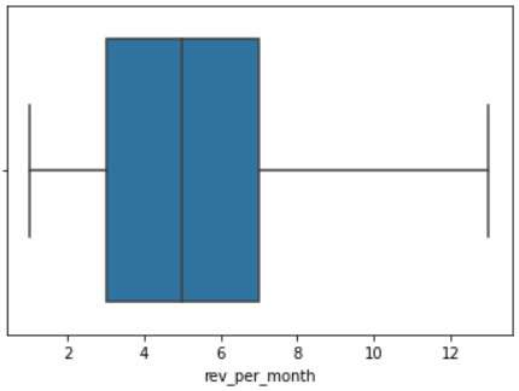

0
20
40
60
80
100
120
CC_Contacted_LY

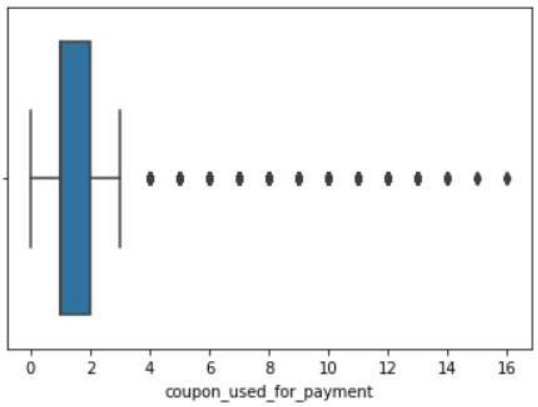

5
10
15
20
25
30
35
40
CC_Contacted_LY

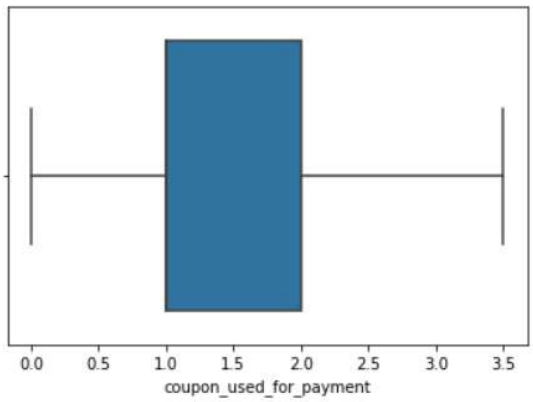

1
2
3
4
5
6
Account_user_count


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

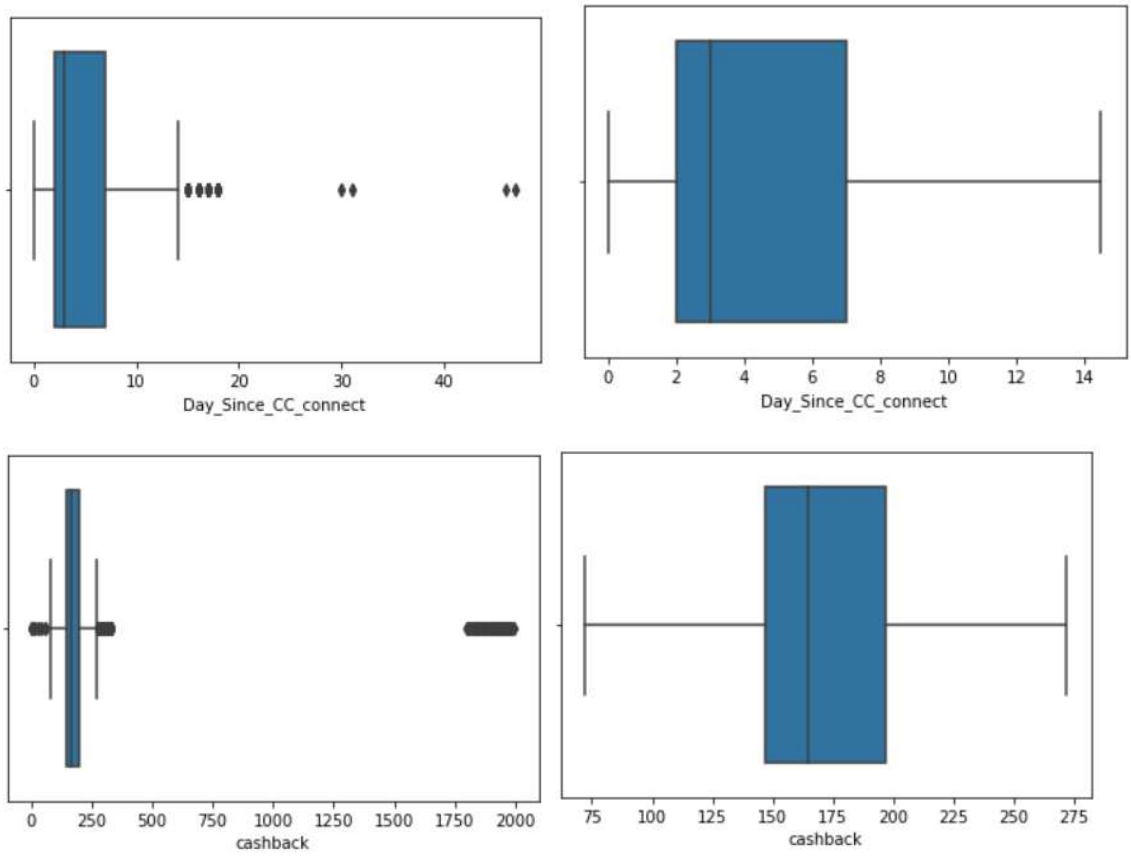


Fig 7: - Before and after outlier treatement

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		***After***	
AccountID	0	AccountID	0
Churn	0	Churn	0
Tenure	102	Tenure	0
City_Tier	112	City_Tier	0
CC_Contacted_LY	102	CC_Contacted_LY	0
Payment	109	Payment	0
Gender	108	Gender	0
Service_Score	98	Service_Score	0
Account_user_count	112	Account_user_count	0
account_segment	97	account_segment	0
CC_Agent_Score	116	CC_Agent_Score	0
Marital_Status	212	Marital_Status	0
rev_per_month	102	rev_per_month	0
Complain_ly	357	Complain_ly	0
rev_growth_yoy	0	rev_growth_yoy	0
coupon_used_for_payment	0	coupon_used_for_payment	0
Day_Since_CC_connect	357	Day_Since_CC_connect	0
cashback	471	cashback	0
Login_device	221	Login_device	0

Fig 42: - Before and after null value treatment

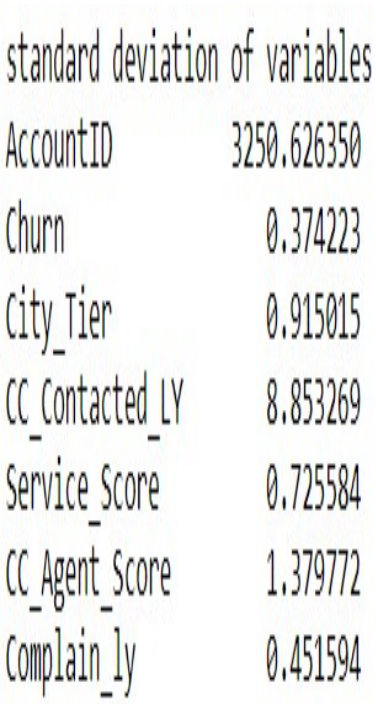
- We see NIL null values across variable which indicated that the data is now cleaned and we can move further for data transformation of required.

Variable transformation: -

- We see that the different variable have 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



After

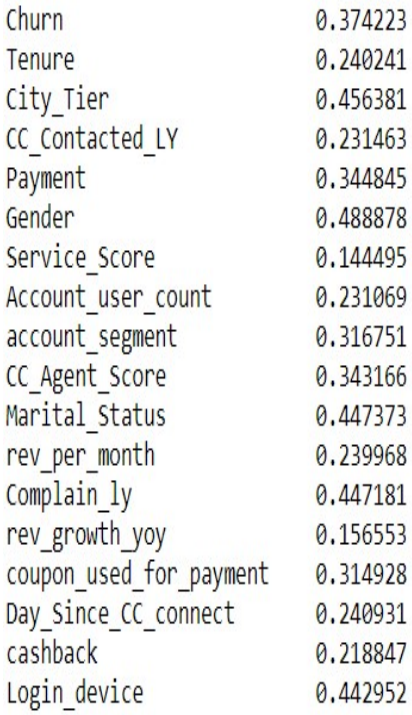


Fig 43: - Before and after Normalization

- 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 ay new variable as such. May be required at further stage of model building and can be created accordingly.

Business insights from EDA

Is the data unbalanced? If so, what can be done? Please explain in the context of the business

- 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 44: - 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 a 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

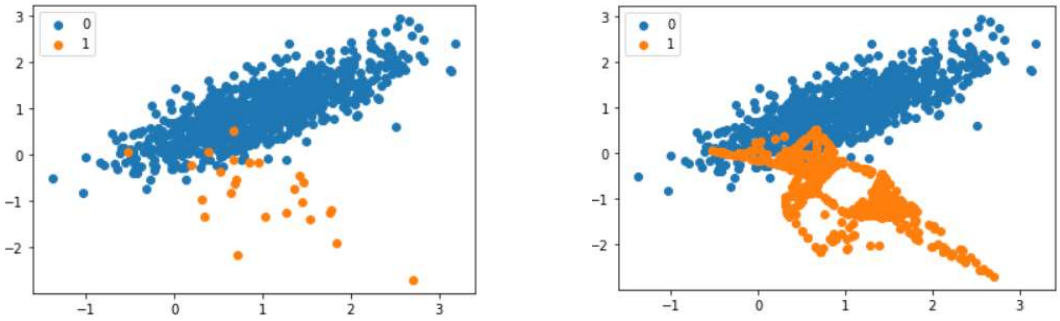


Fig 45: - Before and after SMOTE

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

Any business insights using clustering

- Created 3 clusters using K-means cluster and segmenting customers into these 3 segments.
- Decided as 3 number of clusters based upon the inertia value.
- Maximum counts of customers are in 2nd cluster and least in 3rd cluster.

Any other business insights

- We see decent variations in data collection with a mixture of services provided along with rating provided by the customer and also about customer profile.
- Business needs to increase its visibility in tier 2 city and can acquire new customers.
- Business can promote payment via standing instruction in bank account or UPI which can be hassle free and safe for customers.
- There is need of improvement in service scores and have a lot of grey area left over. Business and roll out a survey for better understanding of customer's expectations.
- Business can train their customer care executive to provide better customer experience which in turn will improve their feedback scores.
- Can have curated plans for customers not only based on the spend they have but also the tenure they have spent with the business.
- Can have curated plan for married people something like a family floater.

End of Project Note - 1

CAPSTONE PROJECT NOTE – II

DSBA

Model Building

In this part of capstone project, we will move towards various model building after EDA and data cleaning performed earlier followed by model tuning and assessing the performance over different metrics Accuracy, F1 Score, Recall, Precession, ROC curve, AUC score, Confusion matrix and classification report. We will choose the model which does not underfit or overfit along with the best accuracy in place.

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 46: - Shape of training and test dataset

Building Logistic Regression Model on Dataset: -

- **Building model with default hyperparameters: -**

Post splitting data into training and testing data set we fitted logistic regression 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 solver as Ibfgs. Below are the accuracy scores obtained from this model: -

```
Accuracy of training dataset: 0.8391271250951535

Accuracy of testing dataset: 0.8398460627590291
```

Fig 47: - Accuracy From Logistic Reression

Below is the confusion matrix obtained from this model: -

```
array([[6466,   90],
       [1178,  148]],

array([[2764,   44],
       [ 497,   73]],
```

Train **Test**

Fig 48: - Confusion Matrix From Logistic Reression

Below is the classification report obtained from this model: -

Classification report for train dataset

	precision	recall	f1-score	support
0.0	0.85	0.99	0.91	6556
1.0	0.62	0.11	0.19	1326
accuracy			0.84	7882
macro avg	0.73	0.55	0.55	7882
weighted avg	0.81	0.84	0.79	7882

Classification report for test dataset

	precision	recall	f1-score	support
0.0	0.85	0.98	0.91	2808
1.0	0.62	0.13	0.21	570
accuracy			0.84	3378
macro avg	0.74	0.56	0.56	3378
weighted avg	0.81	0.84	0.79	3378

Fig 49: - Clasification Report From Logistic Reression

Below is the AUC score and ROC curve obtained from this model: -

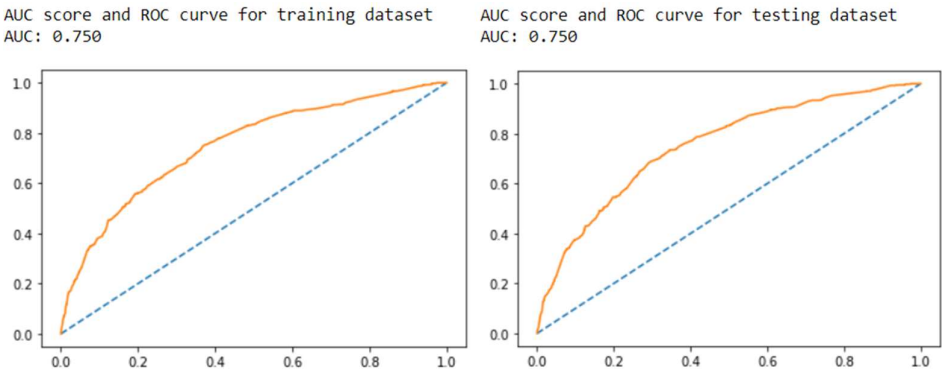


Fig 50: - ROC Curve & AUC Score From Logistic Reression

Below are the 10-fold cross validation for logistic regression with default values: -
Cross-validation is a process to check if the built model is correct or not. Below are the 10-fold cross validation scores: -

```
cross validation scroes for traning dataset

array([0.8365019 , 0.84030418, 0.84517766, 0.84010152, 0.83883249,
       0.84390863, 0.83629442, 0.8286802 , 0.83502538, 0.84010152])

cross calidation scores for testing dataset

array([0.82544379, 0.83727811, 0.83727811, 0.84615385, 0.84319527,
       0.82840237, 0.83727811, 0.83727811, 0.83679525, 0.83679525])
```

Fig 51: - Cross Validation Scores From Logistic Reression

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 GridSearchCV and analysing the best parameters: -

We use GridSearchCV to find an optimal combination of hyperparameters that minimizes a predefined loss function to give better results. Performed GridSearchCV with various hyper-parameters like “solver”, “penalty” and “tol” and we can find that “ibfgs” solver along with “none” penalty worked as best parameters for this dataset. However, we have also observed that the difference in accuracy for train and test dataset is very marginal and not much of significant.

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

```
Accuracy of training dataset after gridsearchCV: 0.8392539964476021

Accuracy of testing dataset after gridsearchCV: 0.8398460627590291
```

Fig 52: - Accuracy From Logistic Reression Using hyper-parameter

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

```
Classification report for train dataset
              precision    recall  f1-score   support

         0.0       0.85      0.99      0.91      6556
         1.0       0.62      0.12      0.20      1326

    accuracy                           0.84      7882
   macro avg       0.73      0.55      0.55      7882
weighted avg       0.81      0.84      0.79      7882

Classification report for test dataset
              precision    recall  f1-score   support

         0.0       0.85      0.98      0.91      2808
         1.0       0.62      0.13      0.21       570

    accuracy                           0.84      3378
   macro avg       0.74      0.56      0.56      3378
weighted avg       0.81      0.84      0.79      3378
```

Fig 53: - Classification Report From Logistic Reression Using hyper-parameter

Below is the confusion matrix obtained from this model using GridSearchCV: -

```
confusion matrix for train dataset

array([[6461,   95],
       [1172,  154]], dtype=int64)
```

```
confusion matrix for test dataset

array([[2764,   44],
       [ 497,   73]], dtype=int64)
```

Fig 54: - Confusion Matrix From Logistic Reression Using hyper-parameter

Below is the AUC score and ROC curve obtained from this model using GridSearchCV: -

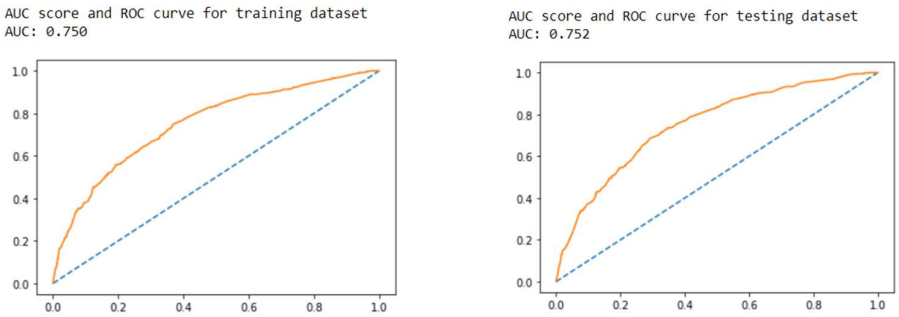


Fig 55: - ROC Curve and AUC Score From Logistic Reression Using hyper-parameter

Below are the 10-fold cross validation scores: -

```
cross validation score for training dataset

array([0.8365019 , 0.84030418, 0.84517766, 0.84137056, 0.83883249,
       0.84390863, 0.83629442, 0.8286802 , 0.83375635, 0.84137056])

cross calidation score for testing dataset

array([0.82248521, 0.83727811, 0.83431953, 0.84319527, 0.84615385,
       0.82840237, 0.84023669, 0.83727811, 0.83679525, 0.83976261])
```

Fig 56: - Cross Validation Scores From Logistic Reression Using hyper-parameter

Building model using SMOTE: -

In our previous analysis we have seen that the data is imbalanced in nature. We can use SMOTE technique to balance the data and then tried building model on the balanced data to check if we can see some significant improvement in accuracy for training and testing dataset. After building model on balanced dataset and checking on accuracy we can see that the performance is not that significant in terms of accuracy.

Below are the accuracy scores obtained from balanced data: -

```
Accuracy of training dataset: 0.6821995118974985

Accuracy of testing dataset: 0.6767317939609236
```

Fig 57: - Accuracy Score From Logistic Reression with SMOTE

Below is the confusion matrix obtained from balanced data: -

```
Confusion matrix for train dataset

array([[4369, 2187],
       [1980, 4576]], dtype=int64)
```

```
Confusion matrix for test dataset

array([[1880,  928],
       [ 164,  406]], dtype=int64)
```

Fig 58: - Confusion Matrix From Logistic Reression with SMOTE

Below is the classification report obtained from balanced data: -

Classification report for train dataset

	precision	recall	f1-score	support
0.0	0.69	0.67	0.68	6556
1.0	0.68	0.70	0.69	6556
accuracy			0.68	13112
macro avg	0.68	0.68	0.68	13112
weighted avg	0.68	0.68	0.68	13112

Classification report for test dataset

	precision	recall	f1-score	support
0.0	0.92	0.67	0.77	2808
1.0	0.30	0.71	0.43	570
accuracy			0.68	3378
macro avg	0.61	0.69	0.60	3378
weighted avg	0.82	0.68	0.72	3378

Fig 59: - Classification Report From Logistic Reression with SMOTE

Below are the AUC scores and ROC curve obtained from balanced data: -

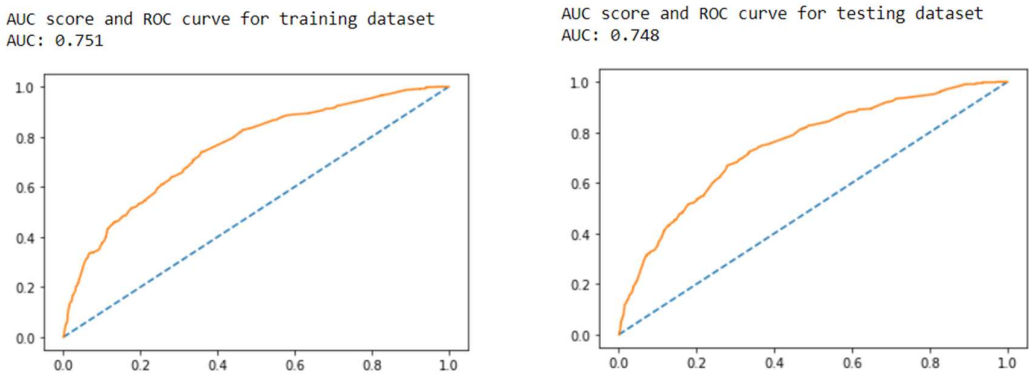


Fig 60: - ROC Curve & AUC Scores From Logistic Reression with SMOTE

Below are the 10-fold cross validation scores: -

```
cross validation score for balanced training dataset

array([0.67606707, 0.66920732, 0.68115942, 0.68115942, 0.668955  ,
       0.70633105, 0.6590389 , 0.68421053, 0.68954996, 0.70022883])

cross validation score for testing dataset

array([0.82544379, 0.83727811, 0.83727811, 0.84615385, 0.84319527,
       0.82840237, 0.83727811, 0.83727811, 0.83679525, 0.83679525])
```

Fig 61: - Cross Validation Scores From Logistic Reression 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 Logistic Regression 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 GridSearchCV is best optimized considering the best parameters obtained. However, the accuracy scores along with recall, precision, F1 values, ROC curve and AUC score are not that significant as compared with models built with default values and balanced data (SMOTE). Model built on balanced 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.

Building Linear Discriminant Analysis Model (LDA)

Building model with default hyperparameters: -

From the above split into training and testing dataset we are building Linear Discriminant Analysis (LDA) model to check it this can outperform Logistic regression model and we can choose form best for further predictions. Firstly, we are building model using default values of LDA. That is, solver as "svd" and shrinkage as "none".

Below are the accuracy scores obtained from this model: -

```
Accuracy score of training dataset: 0.8421720375539203

Accuracy score of testing dataset: 0.8362936648904677
```

Fig 62: - Accuracy From LDA

Below is the confusion matrix obtained from this model: -

```
Confusion matrix of training dataset
array([[6413,  143],
       [1101,  225]], dtype=int64)

Confusion matrix of testing dataset
array([[2738,   70],
       [ 483,   87]], dtype=int64)
```

Fig 63: - Confusion Matrix From LDA

Below is the classification report obtained from this model: -

```
Classification Report of the training data:
              precision    recall  f1-score   support

         0.0       0.85      0.98      0.91      6556
         1.0       0.61      0.17      0.27      1326

    accuracy                           0.84      7882
   macro avg       0.73      0.57      0.59      7882
weighted avg       0.81      0.84      0.80      7882


Classification Report of the test data:
              precision    recall  f1-score   support

         0.0       0.85      0.98      0.91      2808
         1.0       0.55      0.15      0.24       570

    accuracy                           0.84      3378
   macro avg       0.70      0.56      0.57      3378
weighted avg       0.80      0.84      0.80      3378
```

Fig 64: - Classification Report From LDA

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

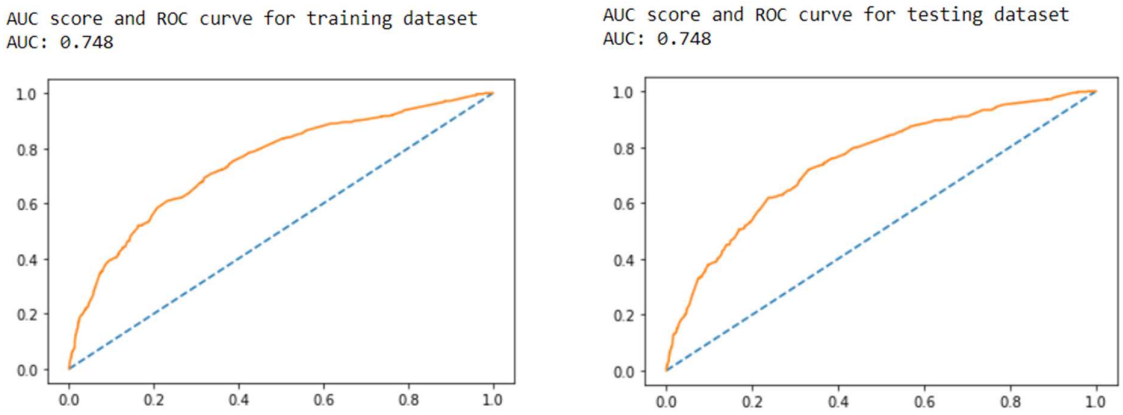


Fig 65: - ROC Curve and AUC Score From LDA

Below are the 10-fold cross validation scores: -

```
cross validation score for training dataset

array([0.83776933, 0.84157161, 0.84771574, 0.83375635, 0.83883249,
       0.84771574, 0.83629442, 0.82994924, 0.83629442, 0.85152284])

cross validation score for testing dataset

array([0.82840237, 0.83431953, 0.82840237, 0.84023669, 0.84615385,
       0.83136095, 0.84023669, 0.83431953, 0.83679525, 0.83086053])
```

Fig 66: - Cross Validation Score From LDA

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 GridSearchCV and analysing the best parameters: -

Using GridSearchCV function we tried finding the best parameters to further tune-in the above model for better accuracy and we have find that shrinkage as “auto”, solver as “lsqr” and tol value of “0.001” gives the best model considering accuracy, precision, recall, F1, ROC curve and AUC score.

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

```
Accuracy of training dataset after gridsearchCV: 0.8416645521441258

Accuracy of testing dataset after gridsearchCV: 0.8354055654233274
```

Fig 67: - Accuracy Score From LDA with Hypertuning

Below is the confusion matrix obtained from model built using GridSearchCV: -

```
confusuon matrix for training dataset

array([[6394,  162],
       [1086,  240]], dtype=int64)
```

```
confusuon matrix for testing dataset

array([[2728,   80],
       [ 476,   94]], dtype=int64)
```

Fig 68: - Confusion Matrix From LDA with Hypertuning

Below are the classification reports obtained from model built using GridSearchCV: -

Classification report for train dataset

	precision	recall	f1-score	support
0.0	0.85	0.98	0.91	6556
1.0	0.60	0.18	0.28	1326
accuracy			0.84	7882
macro avg	0.73	0.58	0.59	7882
weighted avg	0.81	0.84	0.80	7882

Classification report for test dataset

	precision	recall	f1-score	support
0.0	0.85	0.97	0.91	2808
1.0	0.54	0.16	0.25	570
accuracy			0.84	3378
macro avg	0.70	0.57	0.58	3378
weighted avg	0.80	0.84	0.80	3378

Fig 69: - Classification Report From LDA with Hypertuning

Below are the ROC curve and AUC scores obtained from model built using GridSearchCV: -

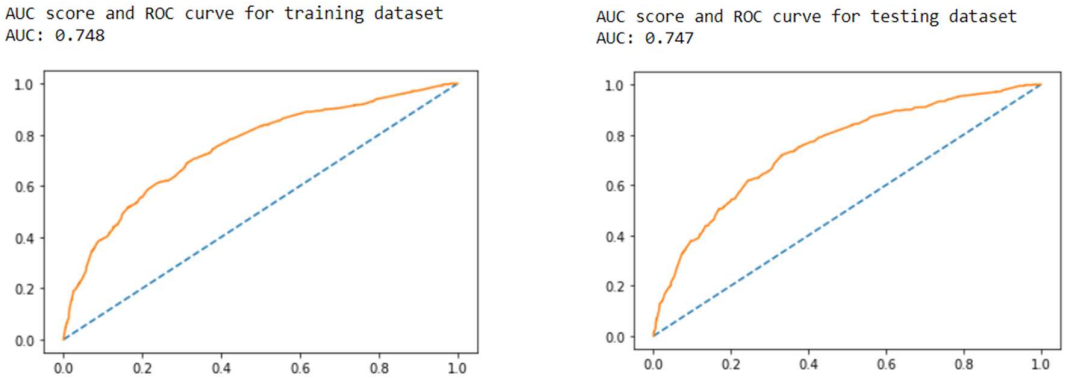


Fig 70: - ROC Curve and AUC Score From LDA with Hypertuning

Below are the 10-fold cross validation scores: -

```
cross validation scores for training dataset

array([0.83776933, 0.84157161, 0.84898477, 0.84010152, 0.83756345,
       0.85659898, 0.83883249, 0.8286802 , 0.83375635, 0.85152284])

cross validation scores from testing dataset

array([0.82840237, 0.83431953, 0.82840237, 0.84023669, 0.84615385,
       0.83136095, 0.84023669, 0.83431953, 0.83679525, 0.83086053])
```

Fig 71: - Cross Validartion Scores From LDA with Hypertuning

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

Building LDA 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: 0.6866229408175717

Accuracy of testing dataset: 0.6785079928952042
```

Fig 72: - Accuracy From LDA with SMOTE

Below is the confusion matrix obtained from balanced dataset: -

```
confusion matrix for training dataset
array([[4397, 2159],
       [1950, 4606]], dtype=int64)

confusion matrix for testing dataset
array([[1884,  924],
       [ 162,  408]], dtype=int64)
```

Fig 73: - Confusion Matrix From LDA with SMOTE

Below is the classification report obtained from balanced dataset: -

Classification report for train dataset

	precision	recall	f1-score	support
0.0	0.69	0.67	0.68	6556
1.0	0.68	0.70	0.69	6556
accuracy			0.69	13112
macro avg	0.69	0.69	0.69	13112
weighted avg	0.69	0.69	0.69	13112

Classification report for test dataset

	precision	recall	f1-score	support
0.0	0.92	0.67	0.78	2808
1.0	0.31	0.72	0.43	570
accuracy			0.68	3378
macro avg	0.61	0.69	0.60	3378
weighted avg	0.82	0.68	0.72	3378

Fig 74: - Classification Report From LDA with SMOTE

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

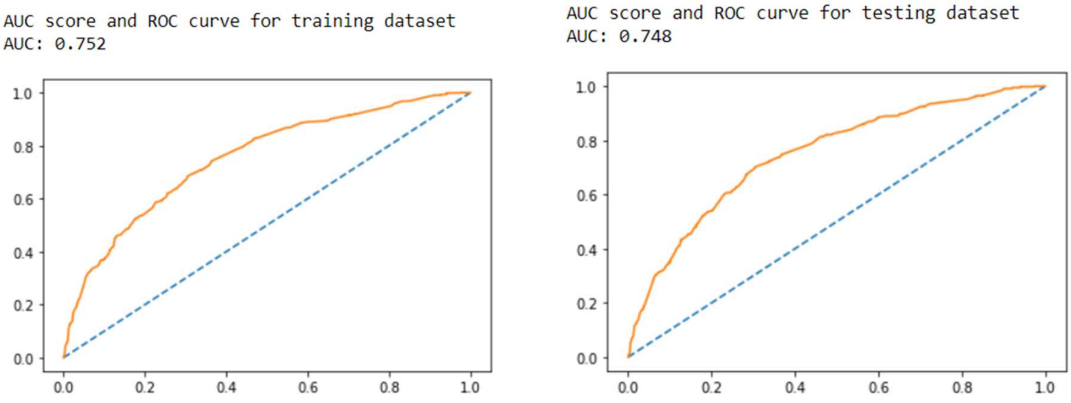


Fig 75: - ROC Curve and AUC Score From LDA with SMOTE

Below are the 10-fold cross validation scores: -

```
cross validation scores for training dataset

array([0.67682927, 0.67606707, 0.68421053, 0.68268497, 0.67276888,
       0.70861937, 0.66361556, 0.67963387, 0.68649886, 0.70480549])

cross validation scores for testing dataset

array([0.82840237, 0.83431953, 0.82840237, 0.84023669, 0.84615385,
       0.83136095, 0.84023669, 0.83431953, 0.83679525, 0.83086053])
```

Fig 76: - Cross Validation Scores From LDA 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 LDA 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 the parameters from GridSearchCV is best optimized. However, the accuracy scores along with recall, precision, F1 values, ROC curve and AUC score are not that significant as compared with models built with default values and model built using GridSearchCV. 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.

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 77: - 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 78: - 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 79: - Classification Report From KNN

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

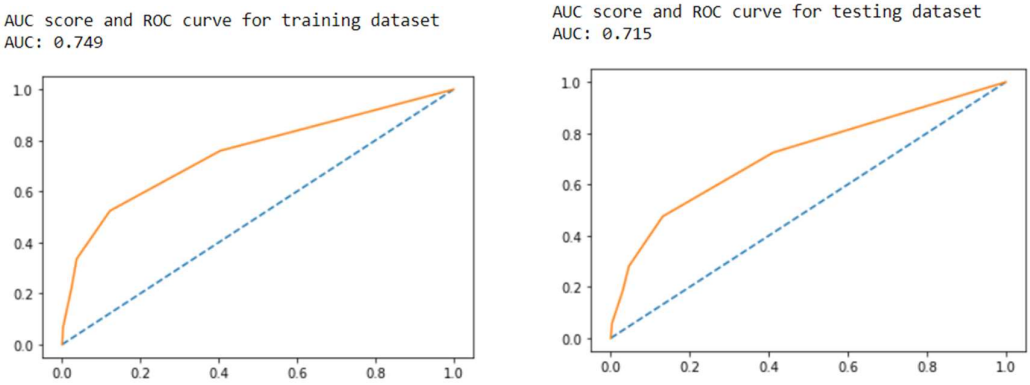


Fig 80: - ROC Curve and AUC Scores From KNN

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 81: - 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.

Find the right value of n_neighbor: -

Its very important to have the right value of n_neighbors to fetch the best accuracy from the model. We can decide on the best value for n_neighbors based on MSE (mean squared error) scores. The value with least score of MSE indicated least error and will fetch the best optimized n_neoghbors 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 82: - MSE Scores

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

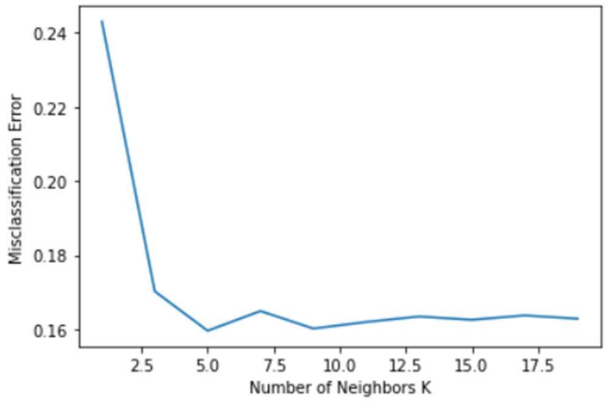


Fig 83: - Graphical Version Of MSE Score

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 84: - 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 85: - 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

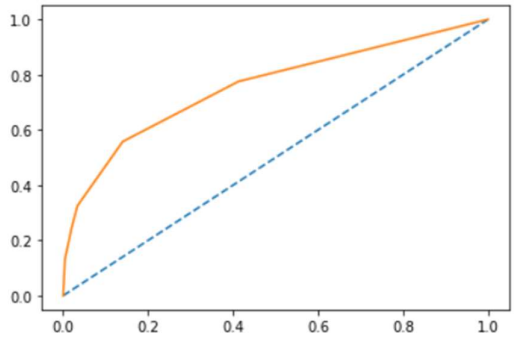
Classification report for test dataset

	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 86: - 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

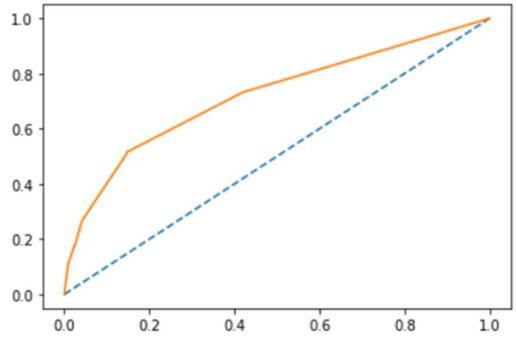


Fig 87: - ROC Curve and AUC Score From KNN with Hyperparamter Tuning

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 88: 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 89: 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 90: 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 91: Classification Reports From KNN with SMOTE

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

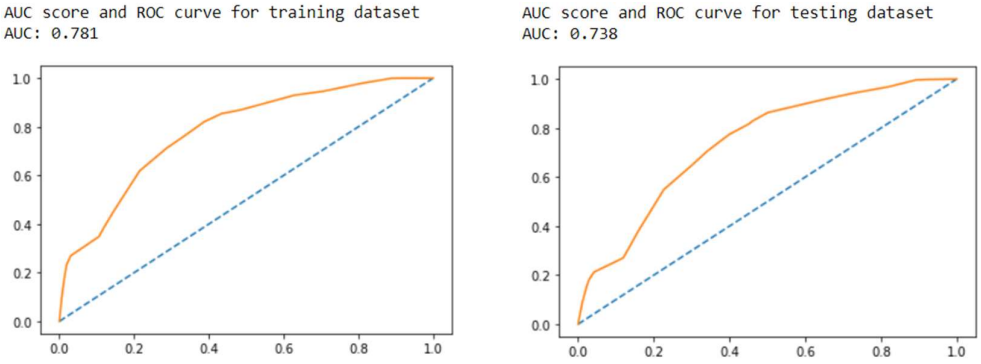


Fig 92: ROC Curve and AUC Scores From KNN with SMOTE

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 93: 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.

BUILDING NAÏVE BAYES MODEL: -

Post splitting data into training and testing we are now ready to build model using Naïve Bayes algorithm. Naïve bayes algorithm is based out of Bayes theorem of conditional probability. Considering that all events are independent of each other and then we find the probability of an event happening under the condition that one of the events has already occurred.

Below are accuracy scores using this model: -

```
Accracy of training dataset: 0.28063943161634103

Accracy of testing dataset: 0.2898164594434577
```

Fig 94: Training Scores From Naïve Bayes with SMOTE

Below are confusion matrices and classification reports using this model: -

```
Confusion matrix of train dataset
[[ 961 5595]
 [  75 1251]]
              precision    recall  f1-score   support

         0.0       0.93      0.15      0.25      6556
         1.0       0.18      0.94      0.31      1326

    accuracy                           0.28      7882
   macro avg       0.56      0.55      0.28      7882
weighted avg       0.80      0.28      0.26      7882
```

```
Confusion matrix of test dataset
[[ 429 2379]
 [  20  550]]
Classification report of test dataset
              precision    recall  f1-score   support

         0.0       0.96      0.15      0.26      2808
         1.0       0.19      0.96      0.31       570

    accuracy                           0.29      3378
   macro avg       0.57      0.56      0.29      3378
weighted avg       0.83      0.29      0.27      3378
```

Fig 95: Confusion Matrix And Classification Report From Naïve Bayes with SMOTE

Below are AUC scores and ROC curves using this model: -

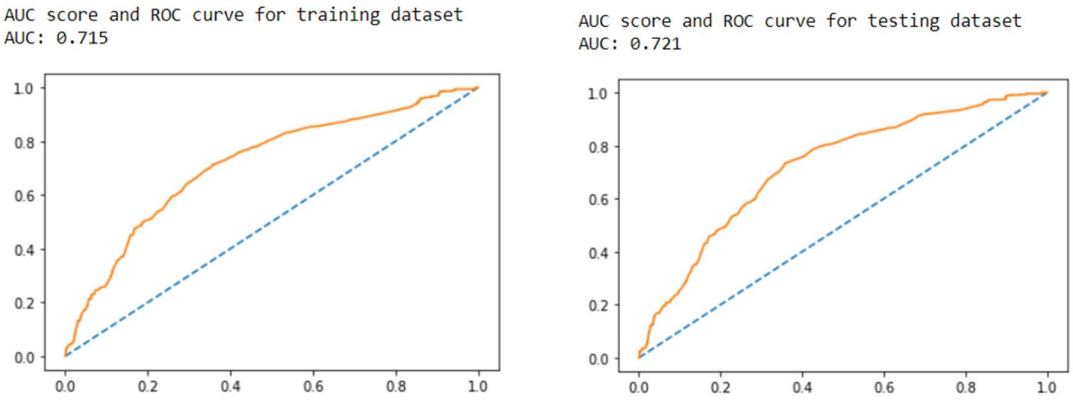


Fig 96: ROC Curve and AUC Scores From Naïve Bayes with SMOTE

Below are 10-fold cross validation scores using this model: -

```
cross validation scores for train dataset

array([0.2712294 , 0.25475285, 0.29187817, 0.26522843, 0.26903553,
       0.30076142, 0.27284264, 0.28172589, 0.26522843, 0.30964467])

cross validation scores for test dataset

array([0.29289941, 0.28994083, 0.28106509, 0.31656805, 0.28994083,
       0.26627219, 0.29881657, 0.27218935, 0.30563798, 0.27002967])
```

Fig 97: Cross Validation Scores From Naïve Bayes with SMOTE

Building Gaussian Naive Bayes over balanced data using SMOTE

After building naïve bayes model using original imbalanced data. Now, we can try and build the same model using balanced data to check if it outperforms in terms of accuracy and other measurement factors.

Below are the accuracy scores obtained using Naïve Bayes algorithm over balanced dataset: -

```
Accracy of training dataset: 0.5560555216595485

Accracy of testing dataset: 0.2975133214920071
```

Fig 98: Accuracay Scores From Naïve Bayes with SMOTE

Below are the confusion matrices and classification reports obtained using Naïve Bayes algorithm over balanced dataset: -

```
Confusion matrix of train dataset
[[1046 5510]
 [ 311 6245]]
              precision    recall  f1-score   support

         0.0       0.77      0.16      0.26      6556
         1.0       0.53      0.95      0.68      6556

    accuracy                           0.56     13112
   macro avg       0.65      0.56      0.47     13112
weighted avg       0.65      0.56      0.47     13112

Confusion matrix of test dataset
[[ 465 2343]
 [  30  540]]
Classification report of test dataset
              precision    recall  f1-score   support

         0.0       0.94      0.17      0.28      2808
         1.0       0.19      0.95      0.31       570

    accuracy                           0.30      3378
   macro avg       0.56      0.56      0.30      3378
weighted avg       0.81      0.30      0.29      3378
```

Fig 99: Confusion Matrix And Classification Report From Naïve Bayes with SMOTE

Below are the AUC scores and ROC curves obtained using Naïve Bayes algorithm over balanced dataset: -

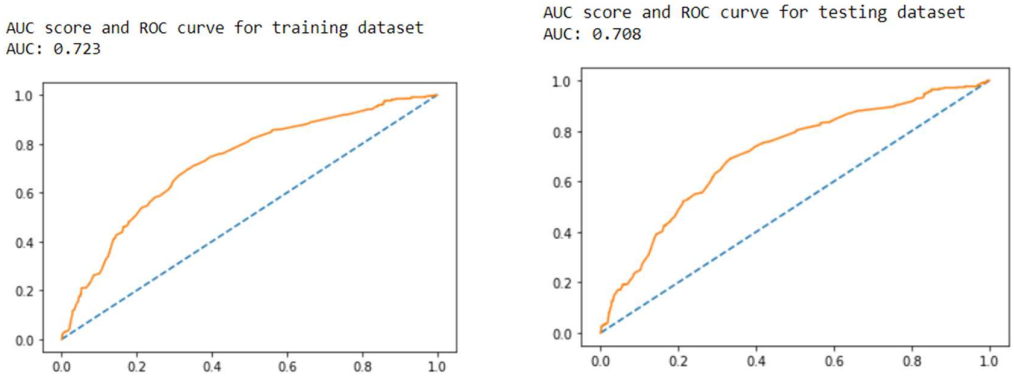


Fig 100: ROC Curve and AUC Scores From Naïve Bayes with SMOTE

Below are the 10-fold cross validation scores obtained using Naïve Bayes algorithm over balanced dataset: -

```
cross validation scores for train dataset

array([0.53887195, 0.52362805, 0.5682685 , 0.55682685, 0.5553013 ,
       0.57284516, 0.55301297, 0.55453852, 0.55758963, 0.58047292])

cross validation scores for test dataset

array([0.29289941, 0.28994083, 0.28106509, 0.31656805, 0.28994083,
       0.26627219, 0.29881657, 0.27218935, 0.30563798, 0.27002967])
```

Fig 101: Cross Validation Scores From Naïve Bayes with SMOTE

Inference/Conclusion from Naïve Bayes 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 original imbalanced data 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 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 training dataset.

BAGGING: -

Building Random Forest model: -

Firstly, let's build and random forest model for original dataset and balanced dataset and check the performance for the same.

Random Forest Built in original dataset: -

Below are the accuracy scores, confusion matrix and classification report for training and testing dataset: -

```
accuracy score for training dataset: 0.8633595534128394
confusion matrix for training dataset
[[6428  128]
 [ 949  377]]
classification report for training dataset
              precision    recall  f1-score   support

         0.0       0.87      0.98      0.92      6556
         1.0       0.75      0.28      0.41      1326

    accuracy                           0.86      7882
   macro avg       0.81      0.63      0.67      7882
weighted avg       0.85      0.86      0.84      7882


accuracy score for testing dataset: 0.8431024274718768
confusion matrix for testing dataset
[[2724   84]
 [ 446  124]]
classification report for testing dataste
              precision    recall  f1-score   support

         0.0       0.86      0.97      0.91      2808
         1.0       0.60      0.22      0.32       570

    accuracy                           0.84      3378
   macro avg       0.73      0.59      0.62      3378
weighted avg       0.81      0.84      0.81      3378
```

Fig 102: Accuracy Parameters From Random Forrest

Below are ROC Curve and AUC Score of train and test data set

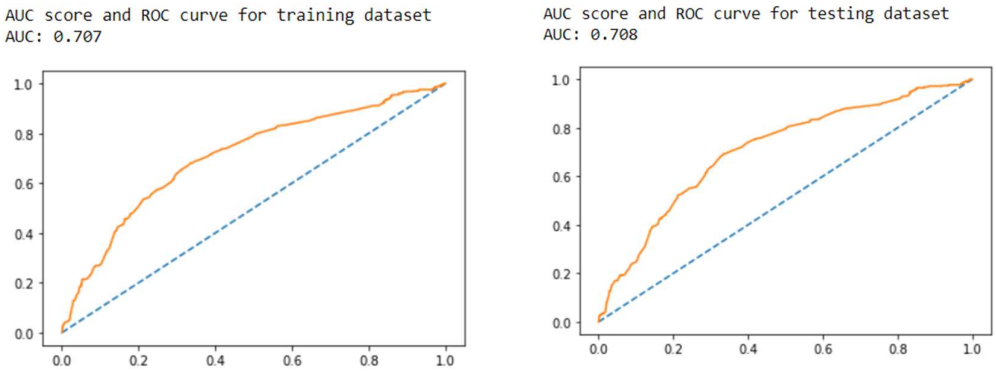


Fig 103: ROC Curve and AUC Scores From Random Forrest

Random Forest Built in balanced dataset: -

Below are the accuracy scores, confusion matrix and classification report for training and Tetsing dataset: -

```
accuracy score for training dataset: 0.7457291031116534
confusion matrix for training dataset
[[4763 1793]
 [1541 5015]]
classification report for training dataset
              precision    recall  f1-score   support

         0.0       0.76      0.73      0.74      6556
         1.0       0.74      0.76      0.75      6556

    accuracy                           0.75     13112
   macro avg       0.75      0.75      0.75     13112
weighted avg       0.75      0.75      0.75     13112


accuracy score for testing dataset: 0.7104795737122558
confusion matrix for testing dataset
[[1991  817]
 [ 161  409]]
classification report for testing dataste
              precision    recall  f1-score   support

         0.0       0.93      0.71      0.80      2808
         1.0       0.33      0.72      0.46       570

    accuracy                           0.71      3378
   macro avg       0.63      0.71      0.63      3378
weighted avg       0.83      0.71      0.74      3378
```

Fig 104: Accuracy Parameters From Random Forrest with SMOTE

Bagging on original dataset: -

Let's build bagging model using random forest and check if it can perform better than general random forest model.

Below are the accuracy scores, confusion matrix and classification report for training and Testing dataset: -

```
accuracy score or training dataset: 0.862471453945699
confusion report for training dataset
[[6417  139]
 [ 945  381]]
classification report for training dataset
              precision    recall  f1-score   support

         0.0       0.87      0.98      0.92      6556
         1.0       0.73      0.29      0.41      1326

    accuracy                           0.86      7882
   macro avg       0.80      0.63      0.67      7882
weighted avg       0.85      0.86      0.84      7882

Accuracy score for testing datatset: 0.8428063943161634
confusuion matrix for testing dataset
[[2720   88]
 [ 443  127]]
classification report for testing dataset
              precision    recall  f1-score   support

         0.0       0.86      0.97      0.91      2808
         1.0       0.59      0.22      0.32       570

    accuracy                           0.84      3378
   macro avg       0.73      0.60      0.62      3378
weighted avg       0.81      0.84      0.81      3378
```

Fig 105: Bagging On Original Dataset

Below is the AUC score and ROC curve for training and testing dataset: -

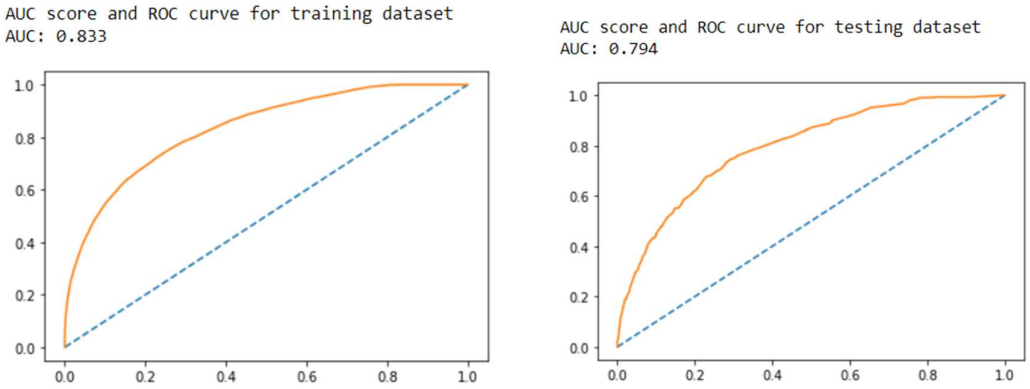


Fig 106: ROC Curve and AUC Score Bagging On Original Dataset

Bagging on Balanced dataset: -

Below are the accuracy scores, confusion matrix and classification report for training and Testing dataset:-

```
accuracy score or training dataset: 0.7450427089688835
confusion report for training dataset
[[4865 1691]
 [1652 4904]]
classification report for training dataset
              precision    recall  f1-score   support

         0.0       0.75      0.74      0.74      6556
         1.0       0.74      0.75      0.75      6556

    accuracy                           0.75     13112
   macro avg       0.75      0.75      0.75     13112
weighted avg       0.75      0.75      0.75     13112


Accuracy score for testing datatset: 0.7181764357608053
confusuion matrix for testing dataset
[[2032  776]
 [ 176  394]]
classification report for testing dataset
              precision    recall  f1-score   support

         0.0       0.92      0.72      0.81      2808
         1.0       0.34      0.69      0.45       570

    accuracy                           0.72      3378
   macro avg       0.63      0.71      0.63      3378
weighted avg       0.82      0.72      0.75      3378
```

Fig 107: Accuracy Parameters from Bagging On Balanced Dataset

Below is the AUC score and ROC curve for training and testing dataset: -

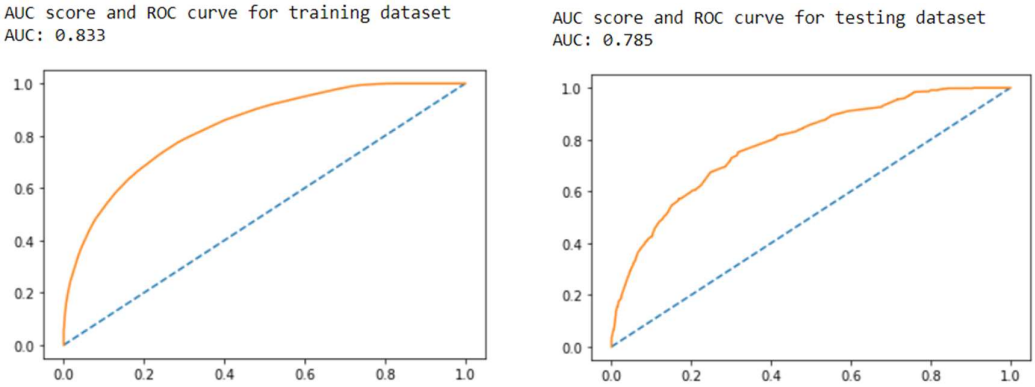


Fig 108: ROC Curve and AUC Scores from Bagging On Balanced Dataset

Building Ada-Boost Model on original dataset: -

Below are the accuracy scores, confusion matrix and classification reports for training and Tetsing dataset: -

```
Accuracy for training dataset: 0.8388733823902563
confusion matrix for training dataset
[[6453  103]
 [1167  159]]
classification report for training dataset
              precision    recall  f1-score   support

         0.0       0.85      0.98      0.91      6556
         1.0       0.61      0.12      0.20      1326

    accuracy                           0.84      7882
   macro avg       0.73      0.55      0.56      7882
weighted avg       0.81      0.84      0.79      7882

accuracy score for testing dataset: 0.8389579632918887
confusion matrix for testing dataset
[[2761   47]
 [ 497   73]]
classification report for testing dataset
              precision    recall  f1-score   support

         0.0       0.85      0.98      0.91      2808
         1.0       0.61      0.13      0.21       570

    accuracy                           0.84      3378
   macro avg       0.73      0.56      0.56      3378
weighted avg       0.81      0.84      0.79      3378
```

Fig 109: Accuracy Parameters from Ada-Boosting on Original Dataset

Below are the AUC scores and ROC curve for training and testing dataset: -

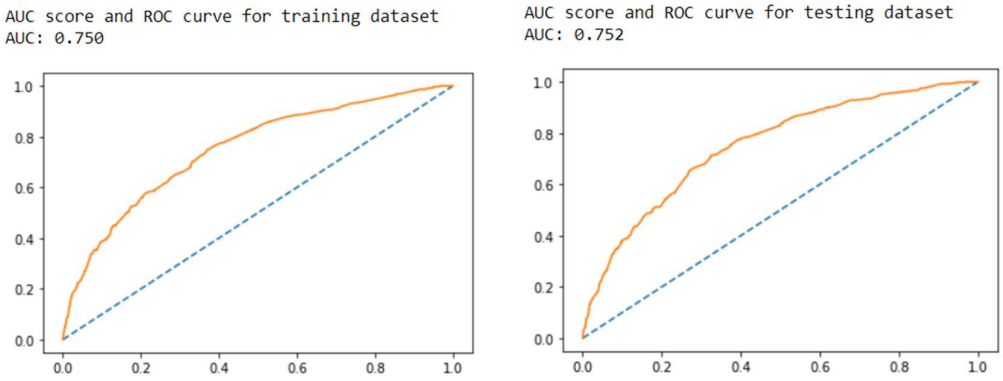


Fig 110: ROC curve and AUC score from Ada-Boosting on Original Dataset

Building Ada-Boost Model on balanced dataset: -

Below are the accuracy scores, confusion matrix and classification reports for training and Testing dataset: -

```
Accuracy for training dataset: 0.6785387431360586
confusion matrix for training dataset
[[4456 2100]
 [2115 4441]]
classification report for training dataset
              precision    recall  f1-score   support

         0.0       0.68      0.68      0.68      6556
         1.0       0.68      0.68      0.68      6556

    accuracy                           0.68     13112
   macro avg       0.68      0.68      0.68     13112
weighted avg       0.68      0.68      0.68     13112

 accuracy score for testing dataset: 0.6856127886323268
 confusion matrix for testing dataset
 [[1919  889]
  [ 173  397]]
 classification report for testing dataset
              precision    recall  f1-score   support

         0.0       0.92      0.68      0.78      2808
         1.0       0.31      0.70      0.43       570

    accuracy                           0.69      3378
   macro avg       0.61      0.69      0.61      3378
weighted avg       0.81      0.69      0.72      3378
```

Fig 111: Accuracy Parameter from Ada-Boosting on Balanced Dataset

Below are the AUC scores and ROC curve for training and testing dataset: -

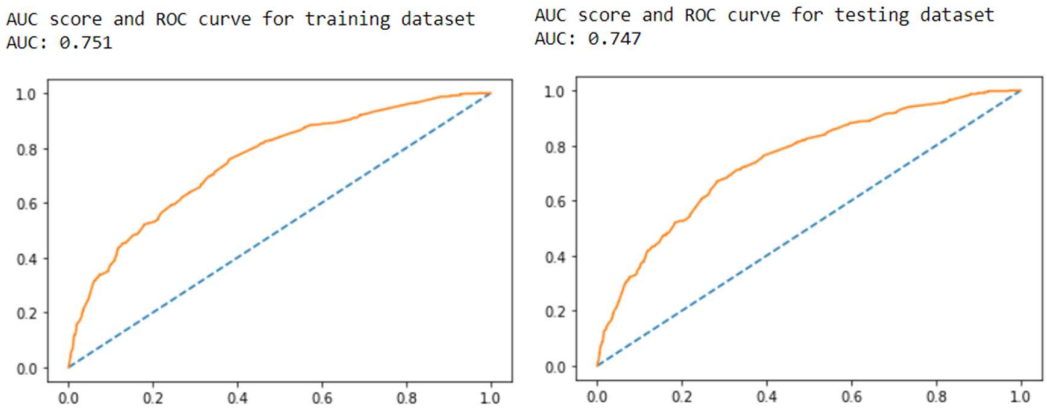


Fig 112: ROC Curve and AUC Score from Ada-Boosting on Balanced Dataset

Building Gradient Boosting Model on original dataset: -

Below are the accuracy scores, confusion matrix and classification reports for training and Testing dataset: -

```
accuracy for training dataset: 0.8477543770616595
confusion matrix for training dataset
[[6456  100]
 [1100  226]]
classification report for training dataset
              precision    recall  f1-score   support

         0.0       0.85      0.98      0.91      6556
         1.0       0.69      0.17      0.27      1326

    accuracy                           0.85      7882
   macro avg       0.77      0.58      0.59      7882
weighted avg       0.83      0.85      0.81      7882

accuracy score for testing dataset: 0.8413262285375962
confusuon matrix for testing dataset
[[2751   57]
 [ 479   91]]
classification report for testing dataset
              precision    recall  f1-score   support

         0.0       0.85      0.98      0.91      2808
         1.0       0.61      0.16      0.25       570

    accuracy                           0.84      3378
   macro avg       0.73      0.57      0.58      3378
weighted avg       0.81      0.84      0.80      3378
```

Fig 113: Accuracy Parameter from Gradient-Boosting on Original Dataset

Below are the AUC scores and ROC curve for training and testing dataset: -

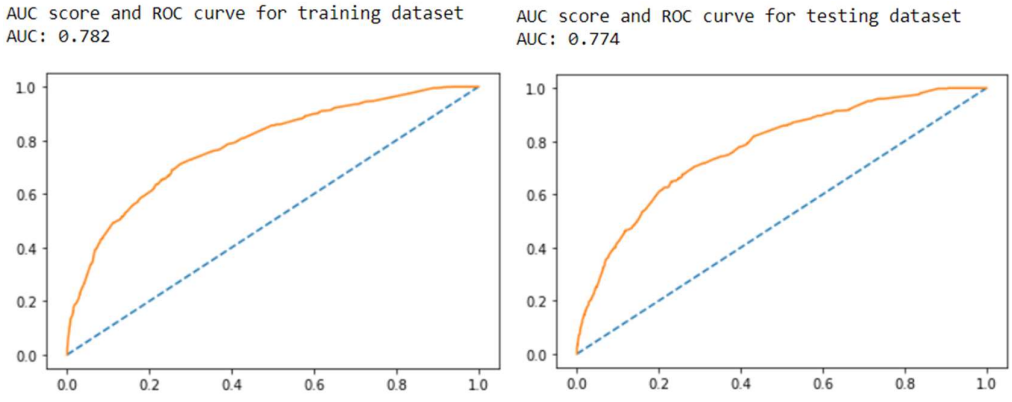


Fig 114: ROC Curve and AUC Score from Gradient-Boosting on Original Dataset

Building Gradient Boosting Model on balanced dataset: -

Below are the accuracy scores, confusion matrix and classification reports for training and Testing dataset: -

```
accuracy for training dataset: 0.7177394752898109
confusion matrix for training dataset
[[4840 1716]
 [1985 4571]]
classification report for training dataset
              precision    recall  f1-score   support

         0.0       0.71      0.74      0.72      6556
         1.0       0.73      0.70      0.71      6556

    accuracy                           0.72     13112
   macro avg       0.72      0.72      0.72     13112
weighted avg       0.72      0.72      0.72     13112


accuracy score for testing dataset: 0.7178804026050918
confusuon matrix for testing dataset
[[2043  765]
 [ 188  382]]
classification report for testing dataset
              precision    recall  f1-score   support

         0.0       0.92      0.73      0.81      2808
         1.0       0.33      0.67      0.44       570

    accuracy                           0.72      3378
   macro avg       0.62      0.70      0.63      3378
weighted avg       0.82      0.72      0.75      3378
```

Fig 113: Accuracy Parameter from Gradient-Boosting on Balanced Dataset

Below are the AUC scores and ROC curve for training and testing dataset: -

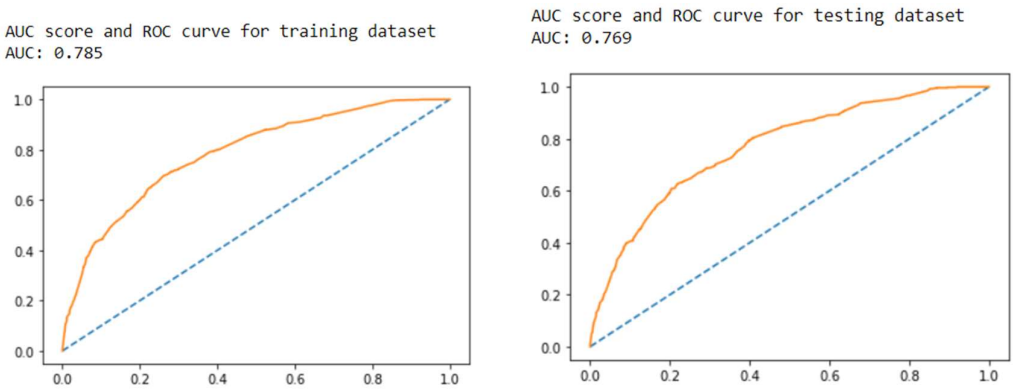


Fig 114: ROC Curve and AUC Score from Gradient-Boosting on Balanced Dataset

Inferences from Bagging and Boosting model: -

- Form both the model above we can notice that the model is still outfitted.
- When to comes to model performance over balanced dataset it performs well in training

dataset however the accuracy reduces when it comes to training dataset.

Building Support Vector Machine (SVM) Model on Original dataset: -

Below are the accuracy scores, confusion matrix and classification reports for training and Testing dataset: -

```
accuracy for training dataset: 0.8529561025120528
confusion matrix for training dataset
[[6466   90]
 [1069  257]]
classification report for training dataset
              precision    recall  f1-score   support

         0.0       0.86      0.99      0.92      6556
         1.0       0.74      0.19      0.31      1326

    accuracy                           0.85      7882
   macro avg       0.80      0.59      0.61      7882
weighted avg       0.84      0.85      0.82      7882

accuracy score for testing dataset: 0.8431024274718768
confusuon matrix for testing dataset
[[2754   54]
 [ 476   94]]
classification report for testing dataset
              precision    recall  f1-score   support

         0.0       0.85      0.98      0.91      2808
         1.0       0.64      0.16      0.26       570

    accuracy                           0.84      3378
   macro avg       0.74      0.57      0.59      3378
weighted avg       0.82      0.84      0.80      3378
```

Fig 115: Accuracy parameter Scores from SVM on Original Dataset

Building Support Vector Machine (SVM) Model on Original dataset Using Hyper-Parameter: -

Below are the accuracy scores, confusion matrix and classification reports for training and Testing dataset: -

```
Accuracy of training dataset after gridsearchCV: 0.8633595534128394

Accuracy of testing dataset after gridsearchCV: 0.8433984606275903

Classification report for train dataset
              precision    recall  f1-score   support

         0.0       0.87      0.98      0.92      6556
         1.0       0.75      0.28      0.41      1326

    accuracy                           0.86      7882
   macro avg       0.81      0.63      0.66      7882
weighted avg       0.85      0.86      0.84      7882
```

```
Classification report for test dataset
              precision    recall  f1-score   support

         0.0       0.86      0.97      0.91      2808
         1.0       0.60      0.22      0.32       570

    accuracy                           0.84      3378
   macro avg       0.73      0.60      0.62      3378
weighted avg       0.82      0.84      0.81      3378

confusuon matrix for training dataset
array([[6436,  120],
       [ 957,  369]], dtype=int64)

confusuon matrix for testing dataset
array([[2723,   85],
       [ 444,  126]], dtype=int64)
```

Fig 116: Accuracy parameter Scores from SVM on Original Dataset Using Hyper-Parameter

Building Support Vector Machine (SVM) Model on Balanced Dataset: -

Below are the accuracy scores, confusion matrix and classification reports for training and Testing dataset: -

```
accuracy for training dataset: 0.7409243441122636
confusion matrix for training dataset
[[4887 1669]
 [1728 4828]]
classification report for training dataset
              precision    recall  f1-score   support

         0.0       0.74      0.75      0.74      6556
         1.0       0.74      0.74      0.74      6556

    accuracy                           0.74     13112
   macro avg       0.74      0.74      0.74     13112
weighted avg       0.74      0.74      0.74     13112

accuracy score for testing dataset: 0.7199526346950859
confusuon matrix for testing dataset
[[2046  762]
 [ 184  386]]
classification report for testing dataset
              precision    recall  f1-score   support

         0.0       0.92      0.73      0.81      2808
         1.0       0.34      0.68      0.45       570

    accuracy                           0.72      3378
   macro avg       0.63      0.70      0.63      3378
weighted avg       0.82      0.72      0.75      3378
```

Fig 117: Accuracy parameter Scores from SVM on Balanced Dataset

Inferences from SVM 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 Balanced data 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 model built on imbalanced dataset. Model built on balance data set using SMOTE technique works well in training dataset and testing dataset.

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".

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 boostng 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**

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.

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)
```