Business Report

Project – FRA Project(Milestone-2)

Predicting Credit Risk for Company data

&

Predicting Market Risk

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Note: This is in continuation for Milestone -1 Project , in this week we have analyzed our model based on Logistic Regression, LDA and Random forest. Also, we have solved one more problem related to Market Risk analysis

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1. Credit Risk Dataset : Introduction

This report explains the business requirements and provide the detailed solution based on the data provided for each problem statement. given in the assignment. Also, the purpose of this exercise is to execute Stats Model supervised learning techniques on the given data, combine all predictions and find out the model with best prediction or accuracy. In supervised learning techniques, there are clearly defined X and Y variables. Supervised Learning is used to predict either a continuous response (as in regression) or a categorical response (as in classification). These are machine learning models for combining predictions from multiple separate models. Both regression and classification can be done using Ensemble Learning. Combining all the individual predictions can be done using either voting or averaging.

Problem statement :

Businesses or companies can fall prey to default if they are not able to keep up their debt obligations. Defaults will lead to a lower credit rating for the company which in turn reduces its chances of getting credit in the future and may have to pay higher interests on existing debts as well as any new obligations. From an investor's point of view, he would want to invest in a company if it is capable of handling its financial obligations, can grow quickly, and is able to manage the growth scale.

A balance sheet is a financial statement of a company that provides a snapshot of what a company owns, owes, and the amount invested by the shareholders. Thus, it is an important tool that helps evaluate the performance of a business.

Data that is available includes information from the financial statement of the companies for the previous year (2015). Also, information about the Networth of the company in the following year (2016) is provided which can be used to drive the labeled field.

Dataset for Problem 1: Company_Data2015-1.xlsx

To understand the problem, for Credit risk checking company has given sample of 3586 Company records collected data in the Company_Data2015-1.xlsx , which have financial information of the companies for previous year 3025 and we need to predict Company status based on next Year Networth.

Dependent variable - We need to create a default variable that should take the value of 1 when net worth next year is negative & 0 when net worth next year is positive.

Assumption:

Assume that the data follows a normal distribution. In reality, the normality assumption may not always hold if the sample size is small.

Step of understanding the data:

Import the data: Imported the data using Python notebooks and analyzed the effects of Education and Occupations over salary field.

1.1 Read the data as Dataframe in python and analyze the data.

This is how the data look like:

	Co_Code	Co_Name	Networth Next Year	Equity Paid Up	Networth	Capital Employed	Total Debt	Gross Block	Net Working Capital	Current Assets	Current Liabilities and Provisions	Total Assets/Liabilities	Gross Sales	Net Sales	Oi Inc
0	16974	Hind.Cables	-8021.60	419.36	-7027.48	-1007.24	5936.03	474.30	-1076.34	40.50	1116.85	109.60	0.00	0.00	
1	21214	Tata Tele. Mah.	-3986.19	1954.93	-2968.08	4458.20	7410.18	9070.86	-1098.88	486.86	1585.74	6043.94	2892.73	2892.73	4
2	14852	ABG Shipyard	-3192.58	53.84	506.86	7714.68	6944.54	1281.54	4496.25	9097.64	4601.39	12316.07	392.13	392.13	
3	2439	GTL	-3054.51	157.30	-623.49	2353.88	2326.05	1033.69	-2612.42	1034.12	3646.54	6000.42	1354.39	1354.39	22
4	23505	Bharati Defence	-2967.36	50.30	-1070.83	4675.33	5740.90	1084.20	1836.23	4685.81	2849.58	7524.91	38.72	38.72	

Shape of the data:

```
The number of rows (observations) is 3586
The number of columns (variables) is 67
```

Insights:

1. There are only 3586 Rows in sample, data , which are Companies previous year financial statements
2. We have given total 67 different fields for the data, so good amount of observation points.
3. Column names of the data:

```
'Co_Code', 'Co_Name', 'Networth Next Year', 'Equity Paid Up',, 'Networth', 'Capital
Employed', 'Total Debt', 'Gross Block ',, 'Net Working Capital ', 'Current Assets ',,
'Current Liabilities and Provisions ', 'Total Assets/Liabilities ',, 'Gross Sales',
'Net Sales', 'Other Income', 'Value Of Output',, 'Cost of Production', 'Selling
Cost', 'PBIDT', 'PBDT', 'PBIT', 'PBT',, 'PAT', 'Adjusted PAT', 'CP', 'Revenue
earnings in forex',, 'Revenue expenses in forex', 'Capital expenses in forex',, 'Book
Value (Unit Curr)', 'Book Value (Adj.) (Unit Curr)',, 'Market Capitalisation', 'CEPS
(annualised) (Unit Curr)',, 'Cash Flow From Operating Activities',, 'Cash Flow From
Investing Activities',, 'Cash Flow From Financing Activities', 'ROG-Net Worth (%)',,
'ROG-Capital Employed (%)', 'ROG-Gross Block (%)',, 'ROG-Gross Sales (%)', 'ROG-Net
Sales (%)',, 'ROG-Cost of Production (%)', 'ROG-Total Assets (%)', 'ROG-PBIDT (%)',,
'ROG-PBDT (%)', 'ROG-PBIT (%)', 'ROG-PBT (%)', 'ROG-PAT (%)',, 'ROG-CP (%)', 'ROG-
Revenue earnings in forex (%)',, 'ROG-Revenue expenses in forex (%)', 'ROG-Market
Capitalisation (%)',, 'Current Ratio[Latest]', 'Fixed Assets Ratio[Latest]',,
'Inventory Ratio[Latest]', 'Debtors Ratio[Latest]',, 'Total Asset Turnover
Ratio[Latest]', 'Interest Cover Ratio[Latest]',, 'PBIDTM (%)[Latest]', 'PBITM
(%)[Latest]', 'PBDTM (%)[Latest]',, 'CPM (%)[Latest]', 'APATM (%)[Latest]', 'Debtors
Velocity (Days)',, 'Creditors Velocity (Days)', 'Inventory Velocity (Days)',, 'Value
of Output/Total Assets', 'Value of Output/Gross Block'
```

1.2 Fixing messy column names (containing spaces) for ease of use :

We can also observe that above listed column names have multiple Special characters in it , example [, (,],), %, - white space etc.

In order to start analyzing them in out Python tool, we need to clear this clutter and modify Column names only.

After fixing column names, this is how the Column names look like:

'Co_Code', 'Co_Name', 'Networth_Next_Year', 'Equity_Paid_Up', 'Networth', 'Capital_Employed', 'Total_Debt', 'Gross_Block', 'Net_Working_Capital', 'Current_Assets', 'Current_Liabilities_and_Provisions', 'Total_Assets_by_Liabilities', 'Gross_Sales', 'Net_Sales', 'Other_Income', 'Value_Of_Output', 'Cost_of_Production', 'Selling_Cost', 'PBIDT', 'PBDT', 'PBIT', 'PBT', 'PAT', 'Adjusted_PAT', 'CP', 'Revenue_earnings_in_forex', 'Revenue_expenses_in_forex', 'Capital_expenses_in_forex', 'Book_Value_Unit_Curr', 'Book_Value_Adj_Unit_Curr', 'Market_Capitalisation', 'CEPS_annualised_Unit_Curr', 'Cash_Flow_From_Operating_Activities', 'Cash_Flow_From_Investing_Activities', 'Cash_Flow_From_Financing_Activities', 'ROG_Net_Worth_perc', 'ROG_Capital_Employed_perc', 'ROG_Gross_Block_perc', 'ROG_Gross_Sales_perc', 'ROG_Net_Sales_perc', 'ROG_Cost_of_Production_perc', 'ROG_Total_Assets_perc', 'ROG_PBIDT_perc', 'ROG_PBDT_perc', 'ROG_PBIT_perc', 'ROG_PBT_perc', 'ROG_PAT_perc', 'ROG_CP_perc', 'ROG_Revenue_earnings_in_forex_perc', 'ROG_Revenue_expenses_in_forex_perc', 'ROG_Market_Capitalisation_perc', 'Current_RatioLatest', 'Fixed_Assets_RatioLatest', 'Inventory_RatioLatest', 'Debtors_RatioLatest', 'Total_Asset_Turnover_RatioLatest', 'Interest_Cover_RatioLatest', 'PBIDTM_percLatest', 'PBITM_percLatest', 'PBDTM_percLatest', 'CPM_percLatest', 'APATM_percLatest', 'Debtors_Velocity_Days', 'Creditors_Velocity_Days', 'Inventory_Velocity_Days', 'Value_of_Output_by_Total_Assets', 'Value_of_Output_by_Gross_Block'

1.3 Data dictionary :

#	Field Name	Description	New Field Name
1	Co_Code	Company Code	Co_Code
2	Co_Name	Company Name	Co_Name
3	Networth Next Year	Value of a company as on 2016 – Next Year(difference between the value of total assets and total liabilities)	Networth_Next_Year
4	Equity Paid Up	Amount that has been received by the company through the issue of shares to the shareholders	Equity_Paid_Up
5	Networth	Value of a company as on 2015 – Current Year	Networth
6	Capital Employed	Total amount of capital used for the acquisition of profits by a company	Capital_Employed
7	Total Debt	The sum of money borrowed by the company and is due to be paid	Total_Debt
8	Gross Block	Total value of all of the assets that a company owns	Gross_Block
9	Net Working Capital	The difference between a company's current assets (cash, accounts receivable, inventories of raw materials and finished goods) and its current liabilities (accounts payable).	Net_Working_Capital
10	Current Assets	All the assets of a company that are expected to be sold or used as a result of standard business operations over the next year.	Curr_Assets
11	Current Liabilities and Provisions	Short-term financial obligations that are due within one year (includes amount that is set aside cover a future liability)	Curr_Liab_and_Prov
12	Total Assets/Liabilities	Ratio of total assets to liabailities of the company	Total_Assets_to_Liab
13	Gross Sales	The grand total of sale transactions within the accounting period	Gross_Sales
14	Net Sales	Gross sales minus returns, allowances, and discounts	Net_Sales
15	Other Income	Income realized from non-business activities (e.g. sale of long term asset)	Other_Income
16	Value Of Output	Product of physical output of goods and services produced by company and its market price	Value_Of_Output
17	Cost of Production	Costs incurred by a business from manufacturing a product or providing a service	Cost_of_Prod
18	Selling Cost	Costs which are made to create the demand for the product (advertising expenditures, packaging and styling, salaries, commissions and travelling expenses of sales personnel, and the cost of shops and showrooms)	Selling_Cost
19	PBIDT	Profit Before Interest, Depreciation & Taxes	PBIDT
20	PBDT	Profit Before Depreciation and Tax	PBDT
21	PBIT	Profit before interest and taxes	PBIT

22	PBT	Profit before tax	PBT
23	PAT	Profit After Tax	PAT
24	Adjusted PAT	Adjusted profit is the best estimate of the true profit	Adjusted_PAT
26	CP	Commercial paper , a short-term debt instrument to meet short-term liabilities.	CP
27	Revenue earnings in forex	Revenue earned in foreign currency	Rev_earn_in_forex
28	Revenue expenses in forex	Expenses due to foreign currency transactions	Rev_exp_in_forex
29	Capital expenses in forex	Long term investment in forex	Capital_exp_in_forex
30	Book Value (Unit Curr)	Net asset value	Book_Value_Unit_Curr
31	Book Value (Adj.) (Unit Curr)	Book value adjusted to reflect asset's true fair market value	Book_Value_Adj_Unit_Curr
32	Market Capitalisation	Product of the total number of a company's outstanding shares and the current market price of one share	Market_Capitalisation
33	CEPS (8nnualized) (Unit Curr)	Cash Earnings per Share, profitability ratio that measures the financial performance of a company by calculating cash flows on a per share basis	CEPS_annualised_Unit_Curr
34	Cash Flow From Operating Activities	Use of cash from ongoing regular business activities	Cash_Flow_From_Opr
35	Cash Flow From Investing Activities	Cash used in the purchase of non-current assets–or long-term assets– that will deliver value in the future	Cash_Flow_From_Inv
36	Cash Flow From Financing Activities	Net flows of cash that are used to fund the company (transactions involving debt, equity, and dividends)	Cash_Flow_From_Fin
37	ROG-Net Worth (%)	Rate of Growth – Networth	ROG_Net_Worth_perc
38	ROG-Capital Employed (%)	Rate of Growth – Capital Employed	ROG_Capital_Employed_perc
39	ROG-Gross Block (%)	Rate of Growth – Gross Block	ROG_Gross_Block_perc
40	ROG-Gross Sales (%)	Rate of Growth – Gross Sales	ROG_Gross_Sales_perc
41	ROG-Net Sales (%)	Rate of Growth – Net Sales	ROG_Net_Sales_perc
42	ROG-Cost of Production (%)	Rate of Growth - Cost of Production	ROG_Cost_of_Prod_perc
43	ROG-Total Assets (%)	Rate of Growth – Total Assets	ROG_Total_Assets_perc
44	ROG-PBIDT (%)	Rate of Growth- PBIDT	ROG_PBIDT_perc
45	ROG-PBDT (%)	Rate of Growth- PBDT	ROG_PBDT_perc
46	ROG-PBIT (%)	Rate of Growth- PBIT	ROG_PBIT_perc

47	ROG-PBT (%)	Rate of Growth- PBT	ROG_PBT_perc
48	ROG-PAT (%)	Rate of Growth- PAT	ROG_PAT_perc
49	ROG-CP (%)	Rate of Growth- CP	ROG_CP_perc
50	ROG-Revenue earnings in forex (%)	Rate of Growth - Revenue earnings in forex	ROG_Rev_earn_in_forex_perc
51	ROG-Revenue expenses in forex (%)	Rate of Growth - Revenue expenses in forex	ROG_Rev_exp_in_forex_perc
52	ROG-Market Capitalisation (%)	Rate of Growth – Market Capitalisation	ROG_Market_Capitalisation_perc
53	Current Ratio[Latest]	Liquidity ratio, company's ability to pay short-term obligations or those due within one year	Curr_Ratio_Latest
54	Fixed Assets Ratio[Latest]	Solvency ratio, the capacity of a company to discharge its obligations towards long-term lenders indicating	Fixed_Assets_Ratio_Latest
55	Inventory Ratio[Latest]	Activity ratio, specifies the number of times the stock or inventory has been replaced and sold by the company	Inventory_Ratio_Latest
56	Debtors Ratio[Latest]	Measures how quickly cash debtors are paying back to the company	Debtors_Ratio_Latest
57	Total Asset Turnover Ratio[Latest]	The value of a company's revenues relative to the value of its assets	Total_Asset_Turnover_Ratio_Latest
58	Interest Cover Ratio[Latest]	Determines how easily a company can pay interest on its outstanding debt	Interest_Cover_Ratio_Latest
59	PBIDTM (%)[Latest]	Profit before Interest Depreciation and Tax Margin	PBIDTM_perc_Latest
60	PBITM (%)[Latest]	Profit Before Interest Tax Margin	PBITM_perc_Latest
61	PBDTM (%)[Latest]	Profit Before Depreciation Tax Margin	PBDTM_perc_Latest
62	CPM (%)[Latest]	Cost per thousand (advertising cost)	CPM_perc_Latest
63	APATM (%)[Latest]	After tax profit margin	APATM_perc_Latest
64	Debtors Velocity (Days)	Average days required for receiving the payments	Debtors_Vel_Days
65	Creditors Velocity (Days)	Average number of days company takes to pay suppliers	Creditors_Vel_Days
66	Inventory Velocity (Days)	Average number of days the company needs to turn its inventory into sales	Inventory_Vel_Days
67	Value of Output/Total Assets	Ratio of Value of Output (market value) to Total Assets	Value_of_Output_to_Total_Assets
68	Value of Output/Gross Block	Ratio of Value of Output (market value) to Gross Block	Value_of_Output_to_Gross_Block

Description of the data elements:

	count	mean	std	min	25%	50%	75%	max
Co_Code	3586.0	16065.388734	19776.817379	4.00	3029.2500	6077.500	24269.5000	72493.00
Networth_Next_Year	3586.0	725.045251	4769.681004	-8021.60	3.9850	19.015	123.8025	111729.10
Equity_Paid_Up	3586.0	62.966584	778.761744	0.00	3.7500	8.290	19.5175	42263.46
Networth	3586.0	649.746299	4091.988792	-7027.48	3.8925	18.580	117.2975	81657.35
Capital_Employed	3586.0	2799.611054	26975.135385	-1824.75	7.6025	39.090	226.6050	714001.25
...	...	...	...	...	...	...	...	...
Debtors_Velocity_Days	3586.0	603.894032	10636.759580	0.00	8.0000	49.000	106.0000	514721.00
Creditors_Velocity_Days	3586.0	2057.854992	54169.479197	0.00	8.0000	39.000	89.0000	2034145.00
Inventory_Velocity_Days	3483.0	79.644559	137.847792	-199.00	0.0000	35.000	96.0000	996.00
Value_of_Output_by_Total_Assets	3586.0	0.819757	1.201400	-0.33	0.0700	0.480	1.1600	17.63
Value_of_Output_by_Gross_Block	3586.0	61.884548	976.824352	-61.00	0.2700	1.530	4.9100	43404.00

66 rows × 8 columns

Insights:

1. We can clearly see that data have different range of Min, max and Median.
2. We can Scale the data, based on our what prediction method we are using.

1.4 Create dependent variable:

Dependent variable – We need to create a default variable that should take the value of 1 when net worth next year is negative & 0 when net worth next year is positive.

Lets check for the proportion of the data:

```
1    3198
1    388
```

Now lets check for the summary of the “default” target data :

```
count    3586.000000
mean        0.108199
std         0.310674
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max         1.000000
Name: default, dtype: float64
```

Insights:

1. Target variable is 1, which denotes the Default companies
2. Value 0 denotes, non default company
3. Default companies data is very less as compare to Non-default company.
4. Ratio of the target variable is 10.8%

1.5 Data types of all variables:

```
Data columns (total 68 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   Co_Code                               3586 non-null   int64
 1   Co_Name                               3586 non-null   object
 2   Networth_Next_Year                    3586 non-null   float64
 3   Equity_Paid_Up                        3586 non-null   float64
 4   Networth                              3586 non-null   float64
 5   Capital_Employed                      3586 non-null   float64
 6   Total_Debt                            3586 non-null   float64
 7   Gross_Block                           3586 non-null   float64
 8   Net_Working_Capital                   3586 non-null   float64
 9   Current_Assets                        3586 non-null   float64
 10  Current_Liabilities_and_Provisions    3586 non-null   float64
 11  Total_Assets_by_Liabilities           3586 non-null   float64
 12  Gross_Sales                           3586 non-null   float64
 13  Net_Sales                             3586 non-null   float64
 14  Other_Income                          3586 non-null   float64
 15  Value_Of_Output                       3586 non-null   float64
 16  Cost_of_Production                    3586 non-null   float64
 17  Selling_Cost                          3586 non-null   float64
 18  PBIDT                                 3586 non-null   float64
 19  PBDT                                  3586 non-null   float64
 20  PBIT                                  3586 non-null   float64
 21  PBT                                   3586 non-null   float64
 22  PAT                                   3586 non-null   float64
 23  Adjusted_PAT                          3586 non-null   float64
 24  CP                                    3586 non-null   float64
 25  Revenue_earnings_in_forex             3586 non-null   float64
 26  Revenue_expenses_in_forex             3586 non-null   float64
 27  Capital_expenses_in_forex             3586 non-null   float64
 28  Book_Value_Unit_Curr                  3586 non-null   float64
 29  Book_Value_Adj_Unit_Curr              3582 non-null   float64
 30  Market_Capitalisation                 3586 non-null   float64
 31  CEPS_annualised_Unit_Curr             3586 non-null   float64
 32  Cash_Flow_From_Operating_Activities   3586 non-null   float64
 33  Cash_Flow_From_Investing_Activities   3586 non-null   float64
 34  Cash_Flow_From_Financing_Activities   3586 non-null   float64
 35  ROG_Net_Worth_perc                    3586 non-null   float64
 36  ROG_Capital_Employed_perc             3586 non-null   float64
 37  ROG_Gross_Block_perc                  3586 non-null   float64
```

```
 38  ROG_Gross_Sales_perc                 3586 non-null   float64
 39  ROG_Net_Sales_perc                   3586 non-null   float64
 40  ROG_Cost_of_Production_perc          3586 non-null   float64
 41  ROG_Total_Assets_perc                3586 non-null   float64
 42  ROG_PBIDT_perc                       3586 non-null   float64
 43  ROG_PBDT_perc                        3586 non-null   float64
 44  ROG_PBIT_perc                        3586 non-null   float64
 45  ROG_PBT_perc                         3586 non-null   float64
 46  ROG_PAT_perc                         3586 non-null   float64
 47  ROG_CP_perc                          3586 non-null   float64
 48  ROG_Revenue_earnings_in_forex_perc   3586 non-null   float64
 49  ROG_Revenue_expenses_in_forex_perc   3586 non-null   float64
 50  ROG_Market_Capitalisation_perc       3586 non-null   float64
 51  Current_RatioLatest                  3585 non-null   float64
 52  Fixed_Assets_RatioLatest             3585 non-null   float64
 53  Inventory_RatioLatest                3585 non-null   float64
 54  Debtors_RatioLatest                  3585 non-null   float64
 55  Total_Asset_Turnover_RatioLatest     3585 non-null   float64
 56  Interest_Cover_RatioLatest           3585 non-null   float64
 57  PBIDTM_percLatest                    3585 non-null   float64
 58  PBITM_percLatest                     3585 non-null   float64
 59  PBDTM_percLatest                     3585 non-null   float64
 60  CPM_percLatest                       3585 non-null   float64
 61  APATM_percLatest                     3585 non-null   float64
 62  Debtors_Velocity_Days                3586 non-null   int64
 63  Creditors_Velocity_Days              3586 non-null   int64
 64  Inventory_Velocity_Days              3483 non-null   float64
 65  Value_of_Output_by_Total_Assets      3586 non-null   float64
 66  Value_of_Output_by_Gross_Block       3586 non-null   float64
 67  default                              3586 non-null   int32
dtypes: float64(63), int32(1), int64(3), object(1)
```

Insights:

1. All of the data is in Numeric Format, except Co_Code and Co_Name, and these 2 fields are not required , so looks good to me.

1.6 Dropping unnecessary columns:

Drop the fields CO_Code and CO_name , since these are not required for our model. Also Drop column Networth_Next_Year, because we used this field to build the Dependent Field "default"

1.7 NULL Checks:

```
Equity_Paid_Up                     0
Networth                           0
Capital_Employed                   0
Total_Debt                         0
Gross_Block                        0
                                 ...
Creditors_Velocity_Days            0
Inventory_Velocity_Days          103
Value_of_Output_by_Total_Assets    0
Value_of_Output_by_Gross_Block     0
default                            0
```

Insights:

1. We checked that data have NULL values in all of these positional columns:
   `(array([26, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 61], dtype=int64),)`

2. Total NULL values in data set are : 103
3. Let's check how many percentage values are missing in each columns.
   if there are more than 30% of the values are missing, we will drop them

```
Inventory_Velocity_Days            0.028723
Book_Value_Adj_Unit_Curr           0.001115
Total_Asset_Turnover_RatioLatest   0.000279
CPM_percLatest                     0.000279
PBDTM_percLatest                   0.000279
                                     ...
ROG_Net_Worth_perc                 0.000000
Networth                           0.000000
PBIDT                              0.000000
Capital_Employed                   0.000000
default                            0.000000
```

No Column have values more than 30%, so we are good in this case, and no need to drop any field because of Missing values. Let's visually inspect the missing values in our data

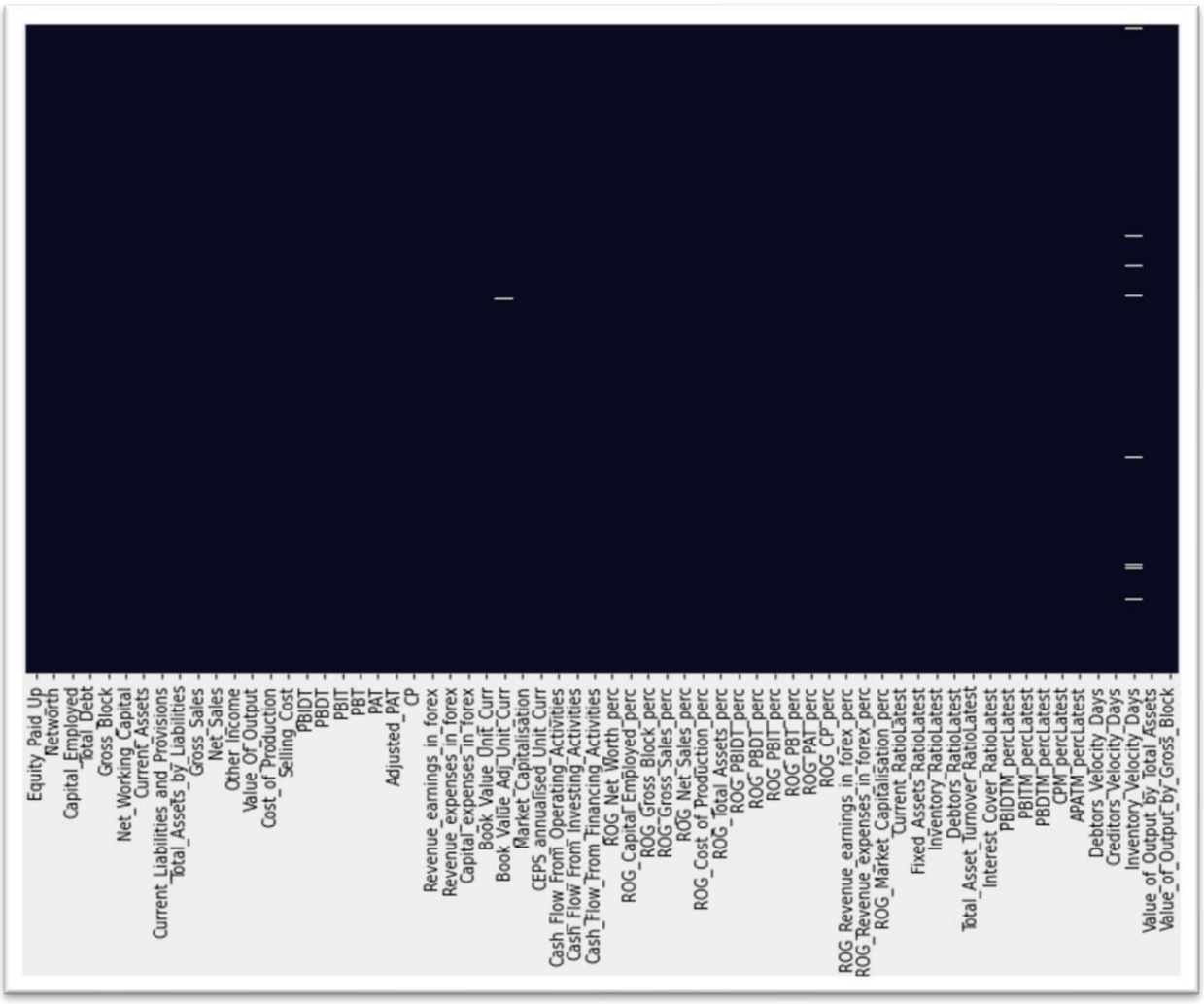


Figure 1 HeatMap

Insights:

1. We can see that data have NULL values in a few columns only, and that is spotted in white dashes in the data . This data is too less. And we can impute them
2. We can see that maximum percentage of missing are 2.8% in Column **Inventory_Velocity_Days**

1.8 Treat missing values:

There are many ways to Treat Missing values.

1. Either Replace them with Median
2. Impute them with any imputer

We will use both methods and analyze them separately . First of all we will impute missing values with Median value of that column:

Replace NULL with Median and this is how the data look like :

```
df.isnull().sum().sum()
```

```
0
```

1.9 Outlier detection:

Plot all data n box plot:

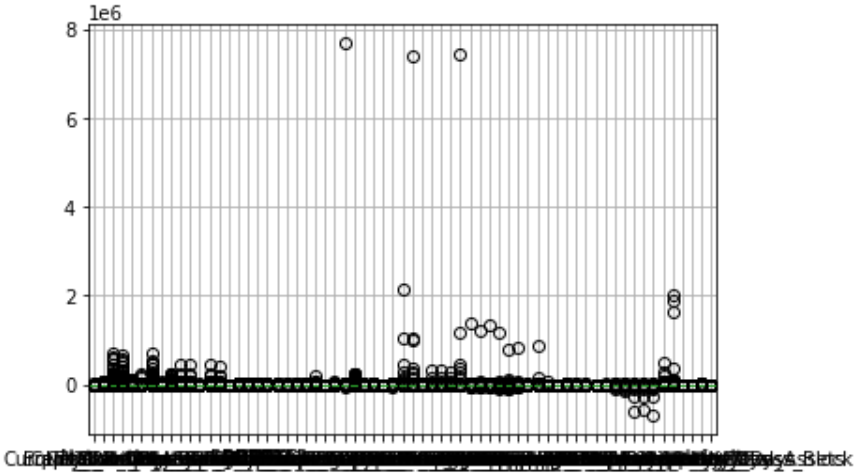


Figure 2 BoxPlot for all data elements

Insights:

1. Also individual box plot can not be draw in this document, as there are 65 box plot to draw, which wont fit into page.
2. But we can clearly see some bubbles in the above graph , which is depicting outliers in the data

1.10 Outlier Treatment:

We have created a function for checking upper and lower limit of the data and we will use that function for calculating, total no of records in each field, which are beyond this range.

List the total no of values in each column, which are above upper limit or less than lower limit of that column.

```
Equity_Paid_Up                    905
Networth                         1342
Capital_Employed                 1220
Total_Debt                       1247
Gross_Block                      1236
                                 ...
Debtors_Velocity_Days             738
Creditors_Velocity_Days           770
Inventory_Velocity_Days           719
Value_of_Output_by_Total_Assets   633
Value_of_Output_by_Gross_Block    984
Length: 64, dtype: int64
```

Insights:

1. There are total of 76984 records, which have values beyond upper and lower range of the value in that field.
2. There are many ways we can Treat Outliers ,
    a. Either we can replace Higher values to Upper Limit or very less value to Lower limit of outliers
    b. Or we can impute them to K Nearest neighbor Method.
    c. In our Case, we dont know Company Segmentations, and Companies can have different levels of Revenue, Profits and all can be Valid at same time. So we should Treat them with K nearest neighbor method , and Treat them same as we did for Missing values.
    d. Still I will be using both method for KNN as well as replacing higher values with Upper/lower values

First of all, we would replace the outlier data with upper and lower value.

Again , since data fields are too large, we can display the Box plot in the Business report.

1.11 Univariate analysis:

We will analyze this data with Distinct Counts, Distribution of the data and box plots with respect to dependent variables , its co-relations, Skewness , unique values, etc. We will use different methods plots for understanding this information.

1.12 Distinct Value Counts of each field:

```
Equity_Paid_Up:1586
Networth:2334
Capital_Employed:2512
Total_Debt:1557
Gross_Block:1877
Net_Working_Capital:2078
Current_Assets:2199
Current_Liabilities_and_Provisions:1698
Total_Assets_by_Liabilities:2565
Gross_Sales:2081
Net_Sales:2079
Other_Income:545
Value_Of_Output:2097
Cost_of_Production:1975
Selling_Cost:531
PBIDT:1418
PBDT:1179
PBIT:1327
PBT:969
PAT:885
Adjusted_PAT:883
CP:1129
Revenue_earnings_in_forex:431
Revenue_expenses_in_forex:528
Capital_expenses_in_forex:1
Book_Value_Unit_Curr:2540
Book_Value_Adj_Unit_Curr:2483
Market_Capitalisation:1469
CEPS_annualised_Unit_Curr:1315
Cash_Flow_From_Operating_Activities:1340
Cash_Flow_From_Investing_Activities:922
Cash_Flow_From_Financing_Activities:989
ROG_Net_Worth_perc:1725
ROG_Capital_Employed_perc:1972
ROG_Gross_Block_perc:1103
ROG_Gross_Sales_perc:2084
ROG_Net_Sales_perc:2085
ROG_Cost_of_Production_perc:2069
ROG_Total_Assets_perc:2107
ROG_PBIDT_perc:2208
ROG_PBDT_perc:2201
ROG_PBIT_perc:2216
ROG_PBT_perc:2150
ROG_PAT_perc:2097
ROG_CP_perc:2175
```

```
ROG_Revenue_earnings_in_forex_perc:1
ROG_Revenue_expenses_in_forex_perc:1
ROG_Market_Capitalisation_perc:1600
Current_RatioLatest:455
Fixed_Assets_RatioLatest:741
Inventory_RatioLatest:1134
Debtors_RatioLatest:1161
Total_Asset_Turnover_RatioLatest:352
Interest_Cover_RatioLatest:776
PBIDTM_percLatest:1835
PBITM_percLatest:1654
PBDTM_percLatest:1707
CPM_percLatest:1551
APATM_percLatest:1268
Debtors_Velocity_Days:241
Creditors_Velocity_Days:203
Inventory_Velocity_Days:225
Value_of_Output_by_Total_Assets:283
Value_of_Output_by_Gross_Block:764
default:2
```

insights:

1. These fields have distinct count of value as only 1

```
Column name is Capital_expenses_in_forex and its unique value count is : 1
Column name is ROG_Revenue_earnings_in_forex_perc and its unique value count is : 1
Column name is ROG_Revenue_expenses_in_forex_perc and its unique value count is : 1
```

2. Since these columns have only 1 value in it, we can not use it for our Predictions. So we should Drop these fields, as they are not going to contribute anything in Target variable prediction.
3. Individual Box plot and distribution of the data . Please refer Notebook for the diagram.
4. Data Skewness :

```
Equity_Paid_Up                    1.141900
Networth                          0.903328
Capital_Employed                  1.137131
Total_Debt                        1.197970
Gross_Block                       1.228742
                                    ...
Creditors_Velocity_Days           1.143302
Inventory_Velocity_Days           1.206446
Value_of_Output_by_Total_Assets   1.110709
Value_of_Output_by_Gross_Block    1.183618
default                           2.523672
```

5. Data is not normally distributed and it is Right skewed and left skewed in both directions for many fields.
6. Checking proportion of default

```
0    0.891801
1    0.108199
```

1.13 Correlation heatmap

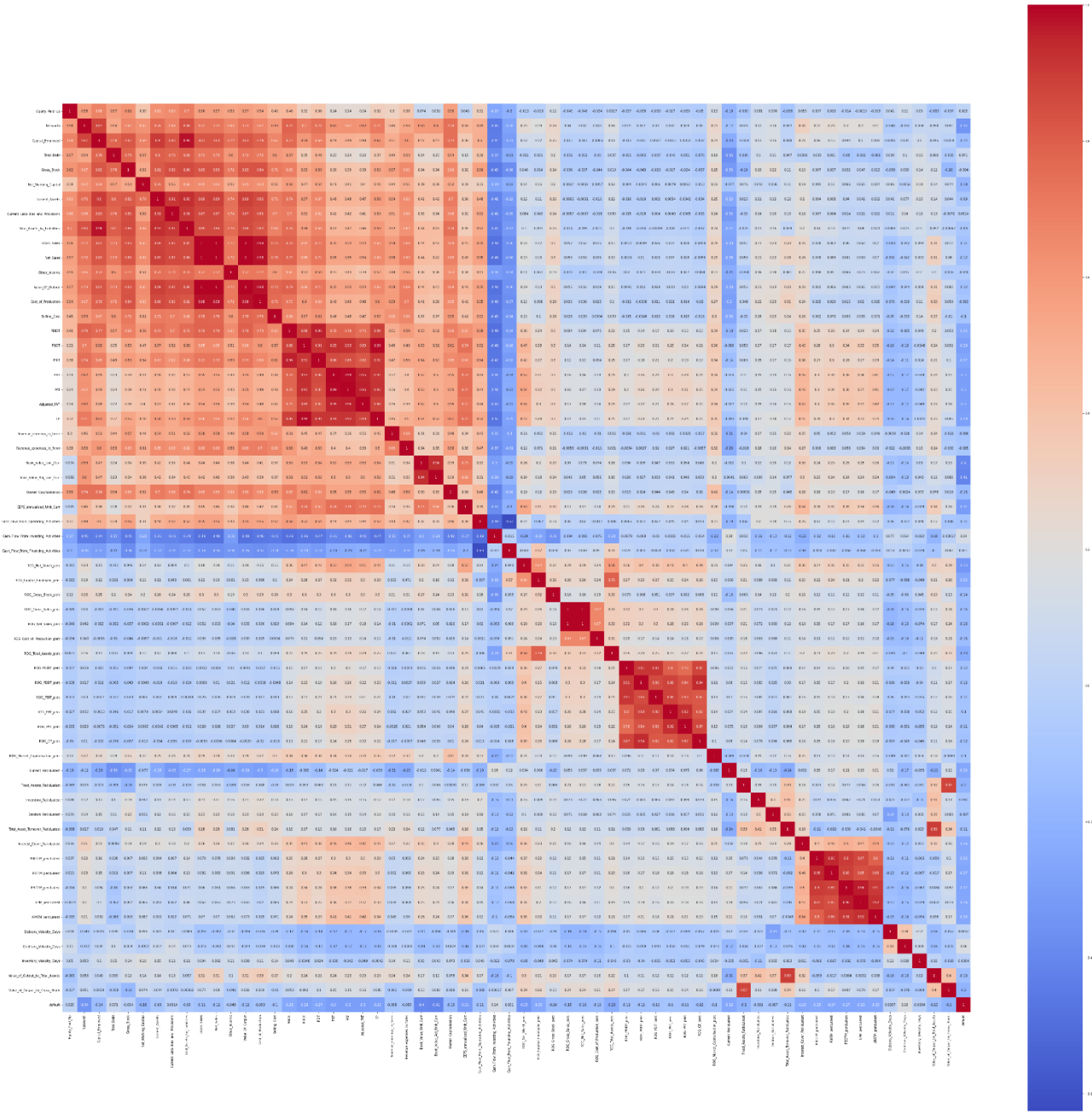


Figure 3 ScatterPlot

Insights:

1. We don't need to look at the Score of co-relation for each column, we can just look at the color coding and Dark Red and Dark Blue showing Strong Positive and negative co-relations, among fields. We can clearly see that there are many fields, which can be avoided for analyzing and building prediction models, because they have co-relation between them,

1.14 Model building using stats model:

Stats Model definitions:

We will use statsmodels module to implement Ordinary Least Squares(OLS) method of linear regression for predicting "Default " Companies based on the data provided for us.

Introduction :

A linear regression model establishes the relation between a dependent variable(y) and at least one independent variable(x) as:

$$\hat{y} = b_1 x + b_0$$

In OLS method, we have to choose the values of bi and b0 such that, the total sum of squares of the difference between the calculated and observed values of y, is minimized.
Formula for OLS:

$$S = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 = \sum_{i=1}^{n} (y_i - b_1 x_1 - b_0)^2 = \sum_{i=1}^{n} (\hat{\epsilon}_i)^2 = min$$

Where,
$\hat{y}_i$ = predicted value for the ith observation
y_i = actual value for the ith observation
ϵ_i = error/residual for the ith observation
n = total number of observations
To get the values of b0 and b1 which minimize S, we can take a partial derivative for each coefficient and equate it to zero.

Approach :

First of all we define the variables **x** and **y**. In the example below, the variables are read from a csv file using pandas. Next, We need to add the constant b0 to the equation using the **add_constant()** method.

The OLS() function of the statsmodels.api module is used to perform OLS regression. It returns an OLS object.
Then fit() method is called on this object for fitting the regression line to the data.

The summary() method is used to obtain a table which gives an extensive description about the regression results

1.15 Partitioning the data into train and test:

We divided the data into train and Test data set. With given parameters:

test_size = 0.33, random_state = 42, stratify = y

Test Size specify, what should be the size of train and test data set, in our case, train set will have 66 % of data and test will have about 33% of data elements

Random state given as 42.

Check the shape of the data :

Train size: (2402, 61)

Test Size : (1184, 61)

Why stratify = y?

Please note, because this data is highly imbalanced and could possibly result into different proportions in the y variable between train and test set.

Start with the model

This is how the final data looks like :

```
Company_imputed.head()
```

	Equity_Paid_Up	Networth	Capital_Employed	Total_Debt	Gross_Block	Net_Working_Capital	Current_Assets	Current_Liabilities_and_Provisions	Total_As
0	43.16875	-166.215	-320.90125	180.83	328.8825	-89.40625	40.50000	163.02625	
1	43.16875	-166.215	555.10875	180.83	328.8825	-89.40625	332.19375	163.02625	
2	43.16875	287.405	555.10875	180.83	328.8825	151.52375	332.19375	163.02625	
3	43.16875	-166.215	555.10875	180.83	328.8825	-89.40625	332.19375	163.02625	
4	43.16875	-166.215	555.10875	180.83	328.8825	151.52375	332.19375	163.02625	

Once the data is split into 4 parts : X_train, X_test, y_train, y_test

We need to Concatenate train data (X_train, y_train) with name as TRAIN and test data (X_test, y_test) as TEST separately, because Stats model work on Complete data, it does need Separation of independent variables into 2 form of train and test.

After concatenation of data, we have got these list of fields in Train data , which are all fields and all rows of independent variables:

```
Index(['Equity_Paid_Up', 'Networth', 'Capital_Employed', 'Total_Debt',
       'Gross_Block', 'Net_Working_Capital', 'Current_Assets',
       'Current_Liabilities_and_Provisions', 'Total_Assets_by_Liabilities',
       'Gross_Sales', 'Net_Sales', 'Other_Income', 'Value_Of_Output',
       'Cost_of_Production', 'Selling_Cost', 'PBIDT', 'PBDT', 'PBIT', 'PBT',
       'PAT', 'Adjusted_PAT', 'CP', 'Revenue_earnings_in_forex',
       'Revenue_expenses_in_forex', 'Book_Value_Unit_Curr',
       'Book_Value_Adj_Unit_Curr', 'Market_Capitalisation',
       'CEPS_annualised_Unit_Curr', 'Cash_Flow_From_Operating_Activities',
       'Cash_Flow_From_Investing_Activities',
       'Cash_Flow_From_Financing_Activities', 'ROG_Net_Worth_perc',
       'ROG_Capital_Employed_perc', 'ROG_Gross_Block_perc',
       'ROG_Gross_Sales_perc', 'ROG_Net_Sales_perc',
       'ROG_Cost_of_Production_perc', 'ROG_Total_Assets_perc',
       'ROG_PBIDT_perc', 'ROG_PBDT_perc', 'ROG_PBIT_perc', 'ROG_PBT_perc',
       'ROG_PAT_perc', 'ROG_CP_perc', 'ROG_Market_Capitalisation_perc',
       'Current_RatioLatest', 'Fixed_Assets_RatioLatest',
       'Inventory_RatioLatest', 'Debtors_RatioLatest',
       'Total_Asset_Turnover_RatioLatest', 'Interest_Cover_RatioLatest',
       'PBIDTM_percLatest', 'PBITM_percLatest', 'PBDTM_percLatest',
       'CPM_percLatest', 'APATM_percLatest', 'Debtors_Velocity_Days',
       'Creditors_Velocity_Days', 'Inventory_Velocity_Days',
       'Value_of_Output_by_Total_Assets', 'Value_of_Output_by_Gross_Block',
       'default'],
```

And similar fields will be part of Test data as well.

1.16 Model 1 (With all columns):

We have used all of the fields listed above and build our first model.

And this is the final result for our first model:

Logit Regression Results

Dep. Variable:	default	**No. Observations:**	2402
Model:	Logit	**Df Residuals:**	2340
Method:	MLE	**Df Model:**	61
Date:	Tue, 15 Nov 2022	**Pseudo R-squ.:**	0.6745
Time:	18:07:50	**Log-Likelihood:**	-268.02
converged:	True	**LL-Null:**	-823.47

Covariance Type:	nonrobust	LLR p-value:	1.198e-192			
	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-0.1885	0.258	-0.732	0.464	-0.693	0.316
Equity_Paid_Up	-0.0079	0.014	-0.585	0.559	-0.035	0.019
Networth	-0.0056	0.005	-1.215	0.224	-0.015	0.003
Capital_Employed	-0.0124	0.010	-1.294	0.196	-0.031	0.006
Total_Debt	0.0213	0.007	3.008	0.003	0.007	0.035
Gross_Block	0.0012	0.004	0.288	0.773	-0.007	0.009
Net_Working_Capital	-0.0040	0.010	-0.400	0.689	-0.023	0.015
Current_Assets	0.0053	0.008	0.640	0.522	-0.011	0.022
Current_Liabilities_and_Provisions	0.0010	0.013	0.081	0.935	-0.024	0.026
Total_Assets_by_Liabilities	0.0065	0.008	0.795	0.427	-0.010	0.023
Gross_Sales	-0.0114	0.010	-1.113	0.266	-0.031	0.009
Net_Sales	0.0203	0.022	0.939	0.348	-0.022	0.063
Other_Income	-0.0076	0.079	-0.097	0.923	-0.162	0.147
Value_Of_Output	-0.0188	0.014	-1.348	0.178	-0.046	0.009
Cost_of_Production	0.0065	0.013	0.510	0.610	-0.018	0.031
Selling_Cost	-0.0350	0.103	-0.340	0.734	-0.237	0.167
PBIDT	-0.0177	0.040	-0.438	0.661	-0.097	0.062
PBDT	-0.1551	0.145	-1.069	0.285	-0.440	0.129
PBIT	0.0184	0.050	0.368	0.713	-0.080	0.117
PBT	0.0480	0.212	0.226	0.821	-0.368	0.464
PAT	-0.0803	0.247	-0.325	0.745	-0.565	0.404
Adjusted_PAT	0.0038	0.077	0.050	0.960	-0.147	0.155
CP	0.1585	0.154	1.028	0.304	-0.144	0.461
Revenue_earnings_in_forex	-0.0277	0.037	-0.754	0.451	-0.100	0.044
Revenue_expenses_in_forex	0.0533	0.038	1.414	0.157	-0.021	0.127
Book_Value_Unit_Curr	-0.0215	0.035	-0.622	0.534	-0.089	0.046
Book_Value_Adj_Unit_Curr	-0.0684	0.036	-1.878	0.060	-0.140	0.003
Market_Capitalisation	-0.0043	0.004	-1.205	0.228	-0.011	0.003

CEPS_annualised_Unit_Curr	-0.0612	0.050	-1.218	0.223	-0.160	0.037
Cash_Flow_From_Operating_Activities	0.0100	0.027	0.375	0.707	-0.042	0.062
Cash_Flow_From_Investing_Activities	-0.0427	0.051	-0.834	0.404	-0.143	0.058
Cash_Flow_From_Financing_Activities	0.0023	0.043	0.053	0.958	-0.083	0.087
ROG_Net_Worth_perc	-0.0236	0.012	-1.899	0.058	-0.048	0.001
ROG_Capital_Employed_perc	0.0237	0.011	2.224	0.026	0.003	0.045
ROG_Gross_Block_perc	-0.0316	0.021	-1.476	0.140	-0.074	0.010
ROG_Gross_Sales_perc	0.0896	0.120	0.748	0.454	-0.145	0.325
ROG_Net_Sales_perc	-0.0914	0.119	-0.766	0.444	-0.325	0.143
ROG_Cost_of_Production_perc	-0.0060	0.004	-1.432	0.152	-0.014	0.002
ROG_Total_Assets_perc	-0.0256	0.010	-2.519	0.012	-0.046	-0.006
ROG_PBIDT_perc	-0.0058	0.006	-1.016	0.310	-0.017	0.005
ROG_PBDT_perc	0.0064	0.006	1.148	0.251	-0.005	0.017
ROG_PBIT_perc	0.0049	0.005	0.954	0.340	-0.005	0.015
ROG_PBT_perc	-0.0021	0.005	-0.435	0.663	-0.012	0.008
ROG_PAT_perc	0.0014	0.004	0.351	0.726	-0.006	0.009
ROG_CP_perc	-0.0042	0.004	-0.928	0.353	-0.013	0.005
ROG_Market_Capitalisation_perc	-0.0024	0.003	-0.799	0.424	-0.008	0.003
Current_RatioLatest	-0.5445	0.094	-5.763	0.000	-0.730	-0.359
Fixed_Assets_RatioLatest	-0.0015	0.112	-0.014	0.989	-0.221	0.218
Inventory_RatioLatest	-0.0678	0.026	-2.561	0.010	-0.120	-0.016
Debtors_RatioLatest	-0.0396	0.026	-1.523	0.128	-0.091	0.011
Total_Asset_Turnover_RatioLatest	-0.0678	0.207	-0.328	0.743	-0.473	0.337
Interest_Cover_RatioLatest	-0.1067	0.053	-2.023	0.043	-0.210	-0.003
PBIDTM_percLatest	0.0133	0.032	0.419	0.675	-0.049	0.076
PBITM_percLatest	-0.0783	0.040	-1.943	0.052	-0.157	0.001
PBDTM_percLatest	0.0095	0.054	0.177	0.859	-0.096	0.115
CPM_percLatest	-0.0490	0.068	-0.723	0.470	-0.182	0.084
APATM_percLatest	0.1252	0.069	1.802	0.072	-0.011	0.261
Debtors_Velocity_Days	-0.0042	0.002	-2.771	0.006	-0.007	-0.001

Creditors_Velocity_Days	0.0011	0.002	0.676	0.499	-0.002	0.004
Inventory_Velocity_Days	0.0015	0.002	0.827	0.408	-0.002	0.005
Value_of_Output_by_Total_Assets	0.7860	0.358	2.196	0.028	0.085	1.487
Value_of_Output_by_Gross_Block	-0.0875	0.111	-0.790	0.430	-0.305	0.130

Insights:

1. We can clearly see that results from our 1st Model have all 61 columns,,after removing unnecessary fields of Co_num, next_year_networth etc.
2. There are many columns with more than 0.05 P value, which denotes those fields are not required for predicting the Target field.
3. As per initial Heatmap, we already know, that data have multi collinearity in the data, so we don't need all of the columns for predicting target values

1.17 Removing multicollinearity using VIF:

What is VIF:

The Variance Inflation Factor (VIF) measures the severity of multicollinearity in regression analysis. It is a statistical concept that indicates the increase in the variance of a regression coefficient as a result of collinearity.

In ordinary least square (OLS) regression analysis, multicollinearity exists when two or more of the independent variables demonstrate a linear relationship between them. VIF can be calculated by the formula below:

$$VIF_i = \frac{1}{1 - R_i^2} = \frac{1}{Tolerance}$$

Where **Ri2** represents the unadjusted coefficient of determination for regressing the ith independent variable on the remaining ones. The reciprocal of VIF is known as **tolerance**. Either VIF or tolerance can be used to detect multicollinearity, depending on personal preference.

Interpreting the Variance Inflation Factor

Variance inflation factors range from 1 upwards. The numerical value for VIF tells you (in decimal form) what percentage the variance (i.e. the standard error squared) is inflated for each coefficient. For example, a VIF of 1.9 tells you that the variance of a particular coefficient is 90% bigger than what you would expect if there was no multicollinearity — if there was no correlation with other predictors.
A **rule of thumb** for interpreting the variance inflation factor:

- 1 = not correlated.
- Between 1 and 5 = moderately correlated.
- Greater than 5 = highly correlated.

Exactly how large a VIF has to be before it causes issues is a subject of debate. What is known is that the more your VIF increases, the less reliable your regression results are going to be. In general, a VIF above 10 indicates high correlation and is cause for concern. Some authors suggest a more conservative level of 2.5 or above.

Summary:

- Variance inflation factor (VIF) is used to detect the severity of multicollinearity in the ordinary least square (OLS) regression analysis.
- Multicollinearity inflates the variance and type II error. It makes the coefficient of a variable consistent but unreliable.
- VIF measures the number of inflated variances caused by multicollinearity.
- Eliminate fields with Greater than 5 , which means there is highly correlated. We should do it one by one for each field.

1.18 Model 2 with VIF threshold 4:

To Notice, since we have lot of independent fields, we should go and check for each single columns and check VIF multiple times.

Rather we have used a Loop function, its checking VIF in Iterations and remove one column in one iteration and calculate VIF again. This loop will run until we get all the fields with lesser value of VIF than threshold limit.

For this testing we will keep VIF threshold value as 5.

Keep VIF threshold value as 5:

After executing Loop function, we received 34 columns and about half of the fields are eliminated, which had very high co-relation in it.

Remained fields are:

```
Index(['Total_Debt', 'Net_Working_Capital', 'Other_Income', 'Selling_Cost',
       'Adjusted_PAT', 'Revenue_earnings_in_forex',
       'Revenue_expenses_in_forex', 'Book_Value_Adj_Unit_Curr',
       'Market_Capitalisation', 'CEPS_annualised_Unit_Curr',
       'Cash_Flow_From_Operating_Activities',
       'Cash_Flow_From_Investing_Activities',
       'Cash_Flow_From_Financing_Activities', 'ROG_Net_Worth_perc',
       'ROG_Capital_Employed_perc', 'ROG_Gross_Block_perc',
       'ROG_Net_Sales_perc', 'ROG_Cost_of_Production_perc',
       'ROG_Total_Assets_perc', 'ROG_PBIT_perc', 'ROG_CP_perc',
       'ROG_Market_Capitalisation_perc', 'Current_RatioLatest',
       'Inventory_RatioLatest', 'Debtors_RatioLatest',
       'Total_Asset_Turnover_RatioLatest', 'Interest_Cover_RatioLatest',
       'PBITM_percLatest', 'CPM_percLatest', 'Debtors_Velocity_Days',
       'Creditors_Velocity_Days', 'Inventory_Velocity_Days',
       'Value_of_Output_by_Gross_Block', 'default'],
```

We ran the stats Model on above listed field, and this is the Stats summary for same:

Dep. Variable:	default	**No. Observations:**	2402
Model:	Logit	**Df Residuals:**	2368
Method:	MLE	**Df Model:**	33
Date:	Tue, 15 Nov 2022	**Pseudo R-squ.:**	0.6546
Time:	18:08:40	**Log-Likelihood:**	-284.41
converged:	True	**LL-Null:**	-823.47
Covariance Type:	nonrobust	**LLR p-value:**	3.364e-205

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-0.2422	0.226	-1.072	0.284	-0.685	0.201
Total_Debt	0.0157	0.004	3.831	0.000	0.008	0.024
Net_Working_Capital	-0.0067	0.004	-1.643	0.100	-0.015	0.001
Other_Income	-0.0227	0.066	-0.341	0.733	-0.153	0.108
Selling_Cost	-0.0587	0.081	-0.725	0.469	-0.218	0.100
Adjusted_PAT	-0.0126	0.049	-0.259	0.796	-0.108	0.083
Revenue_earnings_in_forex	-0.0358	0.033	-1.084	0.278	-0.101	0.029
Revenue_expenses_in_forex	0.0480	0.034	1.433	0.152	-0.018	0.114
Book_Value_Adj_Unit_Curr	-0.1004	0.010	-10.195	0.000	-0.120	-0.081
Market_Capitalisation	-0.0081	0.003	-3.015	0.003	-0.013	-0.003
CEPS_annualised_Unit_Curr	-0.0670	0.037	-1.820	0.069	-0.139	0.005
Cash_Flow_From_Operating_Activities	0.0037	0.022	0.169	0.866	-0.039	0.047
Cash_Flow_From_Investing_Activities	-0.0143	0.041	-0.346	0.730	-0.095	0.067
Cash_Flow_From_Financing_Activities	0.0071	0.038	0.186	0.853	-0.067	0.082
ROG_Net_Worth_perc	-0.0267	0.012	-2.317	0.021	-0.049	-0.004
ROG_Capital_Employed_perc	0.0220	0.010	2.230	0.026	0.003	0.041

ROG_Gross_Block_perc	-0.0308	0.020	-1.512	0.131	-0.071	0.009
ROG_Net_Sales_perc	-0.0020	0.004	-0.474	0.636	-0.010	0.006
ROG_Cost_of_Production_perc	-0.0062	0.004	-1.551	0.121	-0.014	0.002
ROG_Total_Assets_perc	-0.0216	0.010	-2.231	0.026	-0.041	-0.003
ROG_PBIT_perc	0.0028	0.002	1.188	0.235	-0.002	0.008
ROG_CP_perc	-0.0016	0.002	-0.716	0.474	-0.006	0.003
ROG_Market_Capitalisation_perc	-0.0008	0.003	-0.290	0.772	-0.006	0.005
Current_RatioLatest	-0.5418	0.091	-5.931	0.000	-0.721	-0.363
Inventory_RatioLatest	-0.0537	0.023	-2.382	0.017	-0.098	-0.010
Debtors_RatioLatest	-0.0274	0.023	-1.186	0.236	-0.073	0.018
Total_Asset_Turnover_RatioLatest	0.2183	0.132	1.648	0.099	-0.041	0.478
Interest_Cover_RatioLatest	-0.0728	0.047	-1.547	0.122	-0.165	0.019
PBITM_percLatest	-0.0307	0.015	-2.040	0.041	-0.060	-0.001
CPM_percLatest	0.0044	0.017	0.251	0.802	-0.030	0.038
Debtors_Velocity_Days	-0.0042	0.001	-2.909	0.004	-0.007	-0.001
Creditors_Velocity_Days	0.0011	0.002	0.735	0.462	-0.002	0.004
Inventory_Velocity_Days	0.0011	0.002	0.689	0.491	-0.002	0.004
Value_of_Output_by_Gross_Block	-0.0515	0.044	-1.157	0.247	-0.139	0.036

Still we see lot of Columns have P value more than 0.05, so lets run VIF function one more time, and eliminate fields , which have VIF more than 4

1.19 Model 3 with VIF threshold 4:

We have observed that threshold limit 5 is not eliminating many fields, which have co-relations among them, so we have eliminated fields with threshold more than 4.

After adjusting threshold limit to 4 , we were successfully able to eliminate 3 more fields. Which means we have now below listed fields for our Third model:

```
Index(['Total_Debt', 'Net_Working_Capital', 'Other_Income', 'Adjusted_PAT',
       'Revenue_earnings_in_forex', 'Revenue_expenses_in_forex',
       'Book_Value_Adj_Unit_Curr', 'Market_Capitalisation',
       'Cash_Flow_From_Operating_Activities',
       'Cash_Flow_From_Investing_Activities',
       'Cash_Flow_From_Financing_Activities', 'ROG_Net_Worth_perc',
       'ROG_Capital_Employed_perc', 'ROG_Gross_Block_perc',
       'ROG_Net_Sales_perc', 'ROG_Cost_of_Production_perc',
       'ROG_Total_Assets_perc', 'ROG_PBIT_perc', 'ROG_CP_perc',
       'ROG_Market_Capitalisation_perc', 'Current_RatioLatest',
       'Inventory_RatioLatest', 'Debtors_RatioLatest',
       'Total_Asset_Turnover_RatioLatest', 'Interest_Cover_RatioLatest',
       'CPM_percLatest', 'Debtors_Velocity_Days', 'Creditors_Velocity_Days',
       'Inventory_Velocity_Days', 'Value_of_Output_by_Gross_Block', 'default']
```

We have also adjusted cut-off limit to 0.4, earlier it was 0.5, which means, items more than 0.5 predicted values will b e marked as 1, which is targeted value.
But we will consider Company as Default, even if there are 40% chances of this being Default, this will give us more ac curate results for getting targeted values.

Again, run the stats model on top of above listed columns.

Dep. Variable:	default	**No. Observations:**	2402
Model:	Logit	**Df Residuals:**	2371
Method:	MLE	**Df Model:**	30
Date:	Tue, 15 Nov 2022	**Pseudo R-squ.:**	0.6501
Time:	18:08:42	**Log-Likelihood:**	-288.13
converged:	True	**LL-Null:**	-823.47
Covariance Type:	nonrobust	**LLR p-value:**	5.990e-206

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Intercept	-0.2233	0.225	-0.993	0.321	-0.664	0.218

Total_Debt	0.0143	0.004	3.595	0.000	0.006	0.022
Net_Working_Capital	-0.0064	0.004	-1.687	0.092	-0.014	0.001
Other_Income	-0.0546	0.065	-0.843	0.399	-0.182	0.072
Adjusted_PAT	-0.0448	0.044	-1.021	0.307	-0.131	0.041
Revenue_earnings_in_forex	-0.0454	0.031	-1.457	0.145	-0.106	0.016
Revenue_expenses_in_forex	0.0477	0.033	1.463	0.143	-0.016	0.112
Book_Value_Adj_Unit_Curr	-0.1006	0.010	-10.439	0.000	-0.120	-0.082
Market_Capitalisation	-0.0079	0.003	-3.007	0.003	-0.013	-0.003
Cash_Flow_From_Operating_Activities	-0.0026	0.022	-0.119	0.905	-0.045	0.040
Cash_Flow_From_Investing_Activities	-0.0153	0.039	-0.388	0.698	-0.092	0.062
Cash_Flow_From_Financing_Activities	0.0049	0.037	0.132	0.895	-0.068	0.078
ROG_Net_Worth_perc	-0.0284	0.011	-2.531	0.011	-0.050	-0.006
ROG_Capital_Employed_perc	0.0197	0.010	2.033	0.042	0.001	0.039
ROG_Gross_Block_perc	-0.0265	0.020	-1.310	0.190	-0.066	0.013
ROG_Net_Sales_perc	-0.0022	0.004	-0.537	0.591	-0.010	0.006
ROG_Cost_of_Production_perc	-0.0060	0.004	-1.519	0.129	-0.014	0.002
ROG_Total_Assets_perc	-0.0229	0.010	-2.372	0.018	-0.042	-0.004
ROG_PBIT_perc	0.0025	0.002	1.049	0.294	-0.002	0.007
ROG_CP_perc	-0.0017	0.002	-0.769	0.442	-0.006	0.003
ROG_Market_Capitalisation_perc	-0.0008	0.003	-0.304	0.761	-0.006	0.005
Current_RatioLatest	-0.5498	0.091	-6.054	0.000	-0.728	-0.372
Inventory_RatioLatest	-0.0503	0.023	-2.224	0.026	-0.095	-0.006
Debtors_RatioLatest	-0.0281	0.023	-1.224	0.221	-0.073	0.017
Total_Asset_Turnover_RatioLatest	0.1895	0.130	1.458	0.145	-0.065	0.444
Interest_Cover_RatioLatest	-0.0896	0.047	-1.902	0.057	-0.182	0.003
CPM_percLatest	-0.0253	0.011	-2.345	0.019	-0.046	-0.004

Debtors_Velocity_Days	-0.0037	0.001	-2.616	0.009	-0.006	-0.001
Creditors_Velocity_Days	0.0010	0.001	0.689	0.491	-0.002	0.004
Inventory_Velocity_Days	0.0011	0.002	0.659	0.510	-0.002	0.004
Value_of_Output_by_Gross_Block	-0.0611	0.044	-1.392	0.164	-0.147	0.025

Check for VIF for all the fields in this model :

	variables	**VIF**
8	Cash_Flow_From_Operating_Activities	3.804148
7	Market_Capitalisation	3.769023
12	ROG_Capital_Employed_perc	3.671089
0	Total_Debt	3.620201
2	Other_Income	3.483271
5	Revenue_expenses_in_forex	3.418506
18	ROG_CP_perc	3.262816
17	ROG_PBIT_perc	3.251599
23	Total_Asset_Turnover_RatioLatest	3.135009
16	ROG_Total_Assets_perc	3.108078
3	Adjusted_PAT	3.033204
1	Net_Working_Capital	2.902452
4	Revenue_earnings_in_forex	2.872264
10	Cash_Flow_From_Financing_Activities	2.863477
11	ROG_Net_Worth_perc	2.719630
9	Cash_Flow_From_Investing_Activities	2.503964
6	Book_Value_Adj_Unit_Curr	2.460811
22	Debtors_RatioLatest	2.346833

	variables	VIF
26	Debtors_Velocity_Days	2.345360
29	Value_of_Output_by_Gross_Block	2.316941
24	Interest_Cover_RatioLatest	2.250516
21	Inventory_RatioLatest	2.221555
27	Creditors_Velocity_Days	2.180764
20	Current_RatioLatest	2.175016
14	ROG_Net_Sales_perc	2.081818
15	ROG_Cost_of_Production_perc	1.995917
28	Inventory_Velocity_Days	1.860591
25	CPM_percLatest	1.744019
19	ROG_Market_Capitalisation_perc	1.621405
13	ROG_Gross_Block_perc	1.477094
30	default	1.397951

We can see that all of the fields have less than 4 VIF value for this.

Validating the model on train set

Confusion Matrix for train data:

```
[[2094   48]
 [  55  205]]
```

Calculate Recall and other matrix:

```
              precision    recall  f1-score   support

           0       0.97      0.98      0.98      2142
           1       0.81      0.79      0.80       260

    accuracy                           0.96      2402
   macro avg       0.89      0.88      0.89      2402
weighted avg       0.96      0.96      0.96      2402
```

Validating the model on test set

Confusion Matrix for train data:

```
[[1027   29]
 [  27  101]]
```

Calculate Recall and other matrix:

```
              precision    recall  f1-score   support

           0       0.97      0.97      0.97      1056
           1       0.78      0.79      0.78       128

    accuracy                           0.95      1184
   macro avg       0.88      0.88      0.88      1184
weighted avg       0.95      0.95      0.95      1184
```

Insights:

1. We are more interested in RECALL value as it denotes, how much “default” value or Targeted value we are predicting correctly.
2. Recall value for train data and test data are 81% and 79% in sequence, which is not bad.
3. Still data is imbalanced, because our targeted values are very less in Sample data.

1.20 Model 4 - Balance data using SMOTE and threshold VIF as 4:

We will be using SMOTE functionality to generate data for target values, and we will upscaling the data for this case.

Steps:

1. Again, we will perform Smote on full sample data , so total fields are 62
2. Upscale data using imblearn.over_sampling library
3. We also run VIF function to check best features, which can be used for Stats model, after executing VIF calculation function, we found 31 fields and we kept threshold limit as 4 for eliminating features with High co-relation.
4. We generated the Stats model technique and following is the result for Stats model:

Dep. Variable:	default	**No. Observations:**	3748
Model:	Logit	**Df Residuals:**	3717
Method:	MLE	**Df Model:**	30
Date:	Tue, 15 Nov 2022	**Pseudo R-squ.:**	0.7452
Time:	18:08:45	**Log-Likelihood:**	-652.27
converged:	True	**LL-Null:**	-2559.5
Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	1.6931	0.162	10.462	0.000	1.376	2.010
Total_Debt	0.0240	0.003	7.305	0.000	0.018	0.030
Net_Working_Capital	-0.0053	0.003	-1.782	0.075	-0.011	0.001
Other_Income	-0.1006	0.050	-2.028	0.043	-0.198	-0.003
Adjusted_PAT	-0.0177	0.029	-0.602	0.547	-0.075	0.040
Revenue_earnings_in_forex	-0.0699	0.024	-2.966	0.003	-0.116	-0.024
Revenue_expenses_in_forex	0.0389	0.024	1.609	0.108	-0.008	0.086
Book_Value_Adj_Unit_Curr	-0.1220	0.007	-17.710	0.000	-0.135	-0.108
Market_Capitalisation	-0.0097	0.002	-4.788	0.000	-0.014	-0.006
Cash_Flow_From_Operating_Activities	-0.0262	0.016	-1.620	0.105	-0.058	0.006
Cash_Flow_From_Investing_Activities	-0.0400	0.031	-1.305	0.192	-0.100	0.020
Cash_Flow_From_Financing_Activities	-0.0079	0.028	-0.283	0.777	-0.062	0.047
ROG_Net_Worth_perc	-0.0340	0.008	-4.402	0.000	-0.049	-0.019

ROG_Capital_Employed_perc	0.0231	0.007	3.354	0.001	0.010	0.037
ROG_Gross_Block_perc	-0.0330	0.015	-2.201	0.028	-0.062	-0.004
ROG_Net_Sales_perc	-0.0058	0.003	-1.793	0.073	-0.012	0.001
ROG_Cost_of_Production_perc	-0.0070	0.003	-2.447	0.014	-0.013	-0.001
ROG_Total_Assets_perc	-0.0314	0.007	-4.631	0.000	-0.045	-0.018
ROG_PBIT_perc	0.0043	0.002	2.548	0.011	0.001	0.008
ROG_CP_perc	-0.0021	0.002	-1.300	0.194	-0.005	0.001
ROG_Market_Capitalisation_perc	-0.0027	0.002	-1.358	0.174	-0.007	0.001
Current_RatioLatest	-0.6289	0.056	-11.244	0.000	-0.739	-0.519
Inventory_RatioLatest	-0.0543	0.014	-3.784	0.000	-0.082	-0.026
Debtors_RatioLatest	-0.0576	0.016	-3.514	0.000	-0.090	-0.025
Total_Asset_Turnover_RatioLatest	0.3287	0.089	3.707	0.000	0.155	0.503
Interest_Cover_RatioLatest	-0.0856	0.034	-2.515	0.012	-0.152	-0.019
CPM_percLatest	-0.0507	0.008	-6.185	0.000	-0.067	-0.035
Debtors_Velocity_Days	-0.0059	0.001	-5.662	0.000	-0.008	-0.004
Creditors_Velocity_Days	0.0010	0.001	0.909	0.363	-0.001	0.003
Inventory_Velocity_Days	0.0005	0.001	0.414	0.679	-0.002	0.003
Value_of_Output_by_Gross_Block	-0.0945	0.028	-3.384	0.001	-0.149	-0.040

Validating the model on train set

Confusion Matrix for train data:

```
[[2009  133]
 [  84 1522]]
```

Calculate Recall and other matrix:

```
              precision    recall  f1-score   support

           0       0.96      0.94      0.95      2142
           1       0.92      0.95      0.93      1606

    accuracy                           0.94      3748
   macro avg       0.94      0.94      0.94      3748
weighted avg       0.94      0.94      0.94      3748
```

Validating the model on test set

Confusion Matrix for train data:

```
[[972  84]
 [ 11 117]]
```

Calculate Recall and other matrix:

	precision	recall	f1-score	support
0	0.99	0.92	0.95	1056
1	0.58	0.91	0.71	128
accuracy			0.92	1184
macro avg	0.79	0.92	0.83	1184
weighted avg	0.94	0.92	0.93	1184

Insights:

1. We are more interested in RECALL value as it denotes, how much “default” value or Targeted value we are predicting correctly.
2. Recall value for train data and test data are 95% and 91% in sequence, which is very good.
3. Accuracy on Train and Test data is also very good which is more than 92% with both train and test data.
4. Precision is Bad after SMOTE is implemented, because data was imbalanced, and we had to upscale data using SMOTE.

1.21 Perform Logistic Regression

We have used Sklearn's LogisticRegression library for building Logistic regression model . Logistic regression model works on Separate train and test data set. So we have used our split data for building model.

We are making some adjustments to the parameters in the Logistic Regression Class to get a better accuracy. We have used grid search method for identifying best parameters for Logit model.

Argument:

solver{'newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'}, default='lbfgs' Algorithm to use in the optimization problem.

For small datasets, 'liblinear' is a good choice, whereas 'sag' and 'saga' are faster for large ones.
For multiclass problems, only 'newton-cg', 'sag', 'saga' and 'lbfgs' handle multinomial loss; 'liblinear' is limited to one-versus-rest schemes.

'newton-cg', 'lbfgs', 'sag' and 'saga' handle L2 or no penalty
'liblinear' and 'saga' also handle L1 penalty
'saga' also supports 'elasticnet' penalty
'liblinear' does not support setting penalty='none'

Note that 'sag' and 'saga' fast convergence is only guaranteed on features with approximately the same scale.
You can preprocess the data with a scaler from sklearn.preprocessing.
New in version 0.17: Stochastic Average Gradient descent solver.
New in version 0.19: SAGA solver.
Changed in version 0.22: The default solver changed from 'liblinear' to 'lbfgs' in 0.22.

Reference : Article on Solvers

Following is list of parameters we have gathered after running Grid search:

```
{'penalty': 'l1', 'solver': 'liblinear', 'tol': 0.01}
```

Matrices for Logistic Regression Model on testing data

```
Accuracy of the Logistic Regression Model is  0.9527027027027027

Confusion Matrix
 [[1038   18]
 [  38   90]]

Classification Report
              precision    recall  f1-score   support

           0       0.96      0.98      0.97      1056
           1       0.83      0.70      0.76       128

    accuracy                           0.95      1184
   macro avg       0.90      0.84      0.87      1184
weighted avg       0.95      0.95      0.95      1184
```

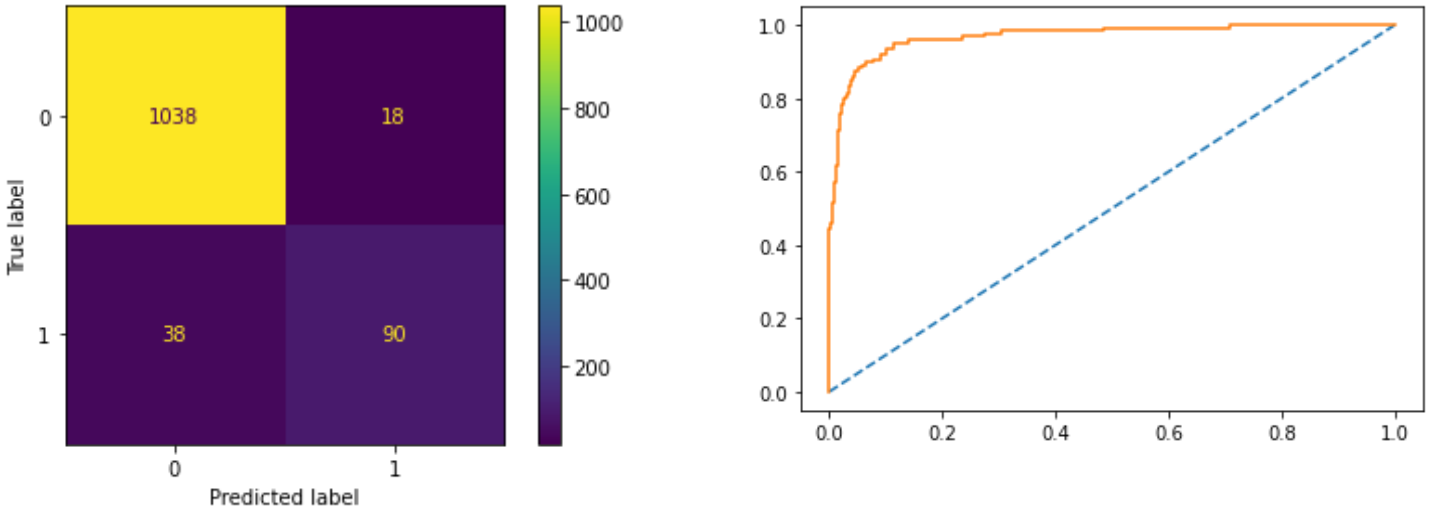


Figure 4 Confusion Matrix and AUC Curve for Train data using Logit model

Matrices for Logistic Regression Model on Training data:

```
Accuracy of the Logistic Regression Model is  0.9608659450457951

Confusion Matrix
 [[2114   28]
 [  66  194]]

Classification Report
              precision    recall  f1-score   support

           0       0.97      0.99      0.98      2142
           1       0.87      0.75      0.80       260

    accuracy                           0.96      2402
   macro avg       0.92      0.87      0.89      2402
weighted avg       0.96      0.96      0.96      2402
```

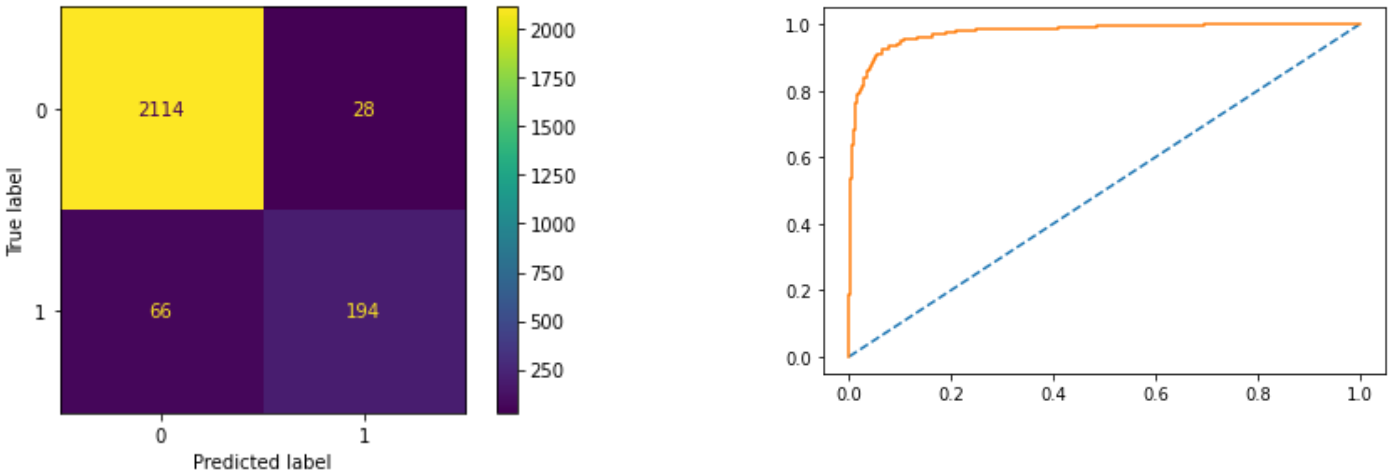


Figure 5Confusion Matrix and AUC Curve for Test data using Logit model

logit_train_precision 0.87
logit_train_recall 0.75
logit_train_acc 0.9608659450457951
logit_train_f1 0.8

logit_test_precision 0.83
logit_test_recall 0.7
logit_test_acc 0.9527027027027027
logit_test_f1 0.76

Insights:

1. Logistic regression model is not very bad on test and train both data sets in terms of predicting , its giving 70% True positive rate on Test data and 75% on train data, which means, 70% times on test data i ts predicting correct true positives, which is our targeted column.
2. Still there are chances of improvements.
3. There are about (18 out of 108 times), its Type 2 error, its predicting wrong for DEFAULT Companies and marking them as Non Default. It has to be eliminated , because we have very less data, that too, if it is pr edicting wrong, then its not good.

1.22 Building a Random Forest Classifier

Random Forest is a Supervised learning algorithm that is based on the ensemble learning method and many Decision Trees. Random Forest is a Bagging technique, so all calculations are run in parallel and there is no interaction between the Decision Trees when building them. RF can be used to solve both Classification and Regression tasks.

Some of the important parameters are highlighted below:

- n_estimators — the number of decision trees you will be running in the model
- criterion — this variable allows you to select the criterion (loss function) used to determine model outcomes. We can select from loss functions such as mean squared error (MSE) and mean absolute error (MAE). The default value is MSE.
- max_depth — this sets the maximum possible depth of each tree
- max_features — the maximum number of features the model will consider when determining a split
- bootstrap — the default value for this is True, meaning the model follows bootstrapping principles (defined earlier)
- max_samples — This parameter assumes bootstrapping is set to True, if not, this parameter doesn't apply. In the case of True, this value sets the largest size of each sample for each tree.
- Other important parameters are min_samples_split, min_samples_leaf, n_jobs, and others that can be read in the sklearn's

We have again used Grid search method for finding best parameters using in this model.

Following are the results from Grid search:

```
{'max_depth': 8,
 'max_features': 8,
 'min_samples_leaf': 50,
 'min_samples_split': 200,
 'n_estimators': 200}
```

Feature importance graph:

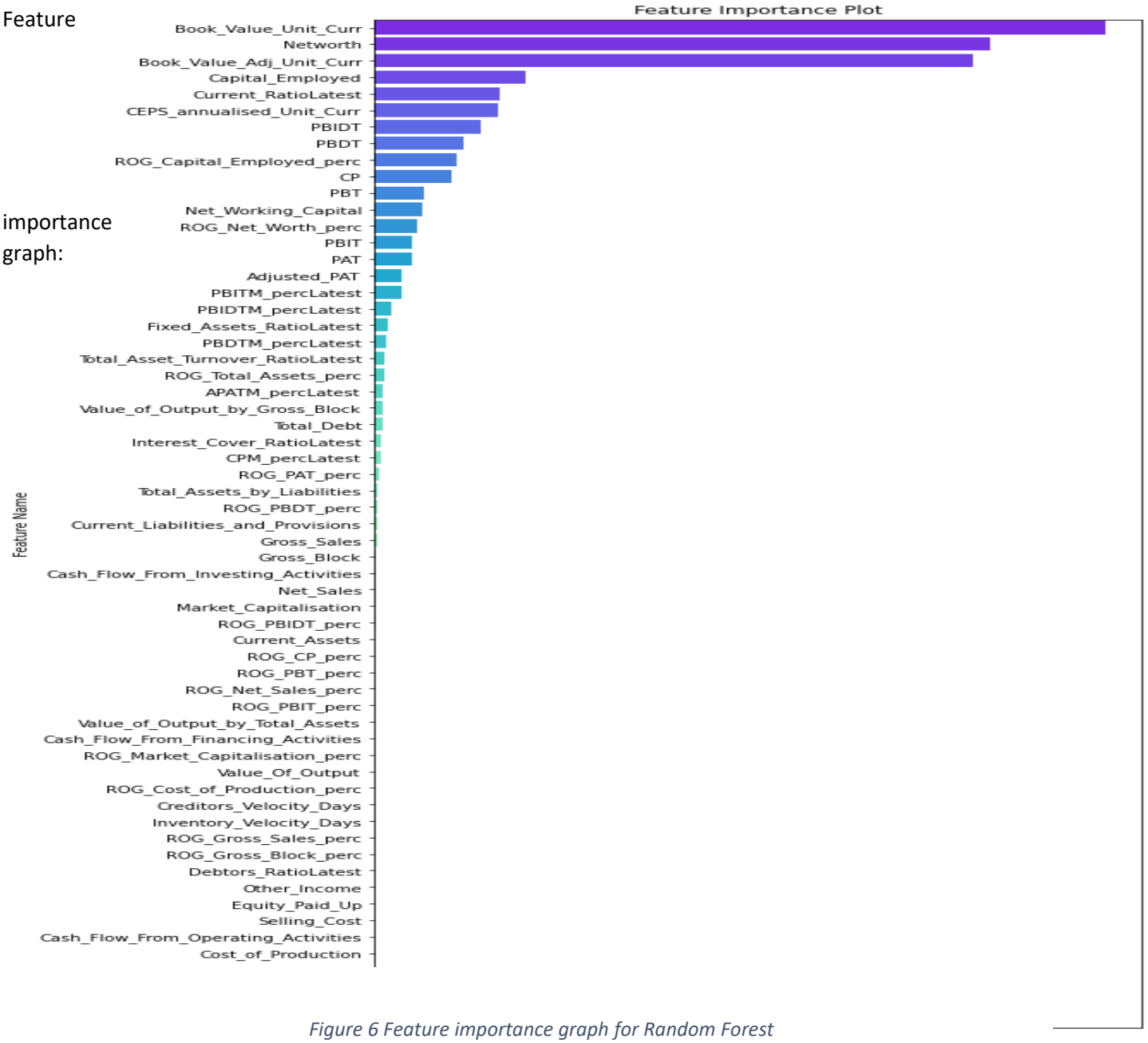


Figure 6 Feature importance graph for Random Forest

Following are importance of the features , used for building prediction models:

```
Book_Value_Unit_Curr        0.234250
Networth                    0.197338
Book_Value_Adj_Unit_Curr    0.192101
Capital_Employed            0.048405
Current_RatioLatest         0.040189
...                              ...
Cost_of_Production          0.000004
Debtors_Velocity_Days       0.000002
Revenue_expenses_in_forex   0.000002
Inventory_RatioLatest       0.000002
Revenue_earnings_in_forex   0.000000
```

RF Model Performance Evaluation on Training data set:

Classification report for Training data set is as follows :

	precision	recall	f1-score	support
0	0.99	0.99	0.99	2142
1	0.91	0.88	0.89	260
accuracy			0.98	2402
macro avg	0.95	0.94	0.94	2402
weighted avg	0.98	0.98	0.98	2402

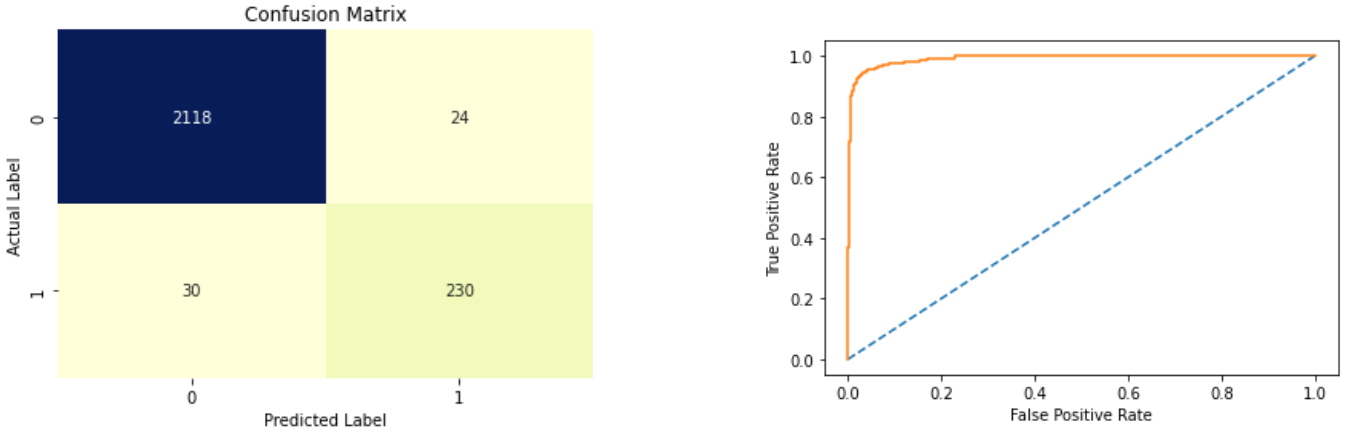


Figure 7 Confusion Metrix and AUC Curve on Train data for Random forest

RF Model Performance Evaluation on Testing data set

Classification report for test data set is as follows :

	precision	recall	f1-score	support
0	0.98	1.00	0.99	1056
1	0.96	0.87	0.91	128
accuracy			0.98	1184
macro avg	0.97	0.93	0.95	1184
weighted avg	0.98	0.98	0.98	1184

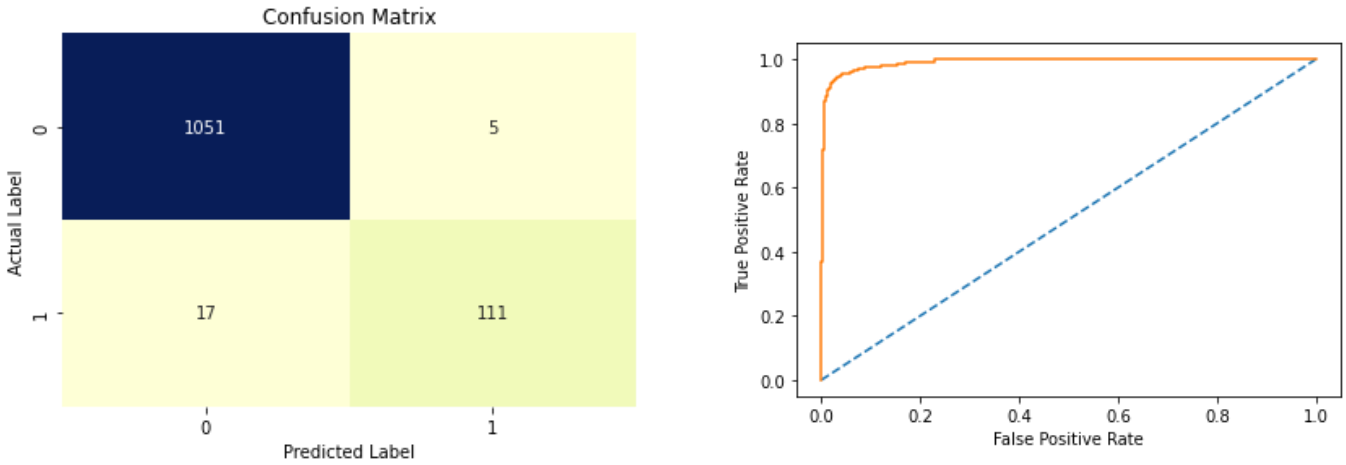


Figure 8 Confusion Metrix and AUC Curve on Test data for Random forest

rf_train_precision 0.91
rf_train_recall 0.88
rf_train_f1 0.89
rf_accuracy_train 0.98
rf_auc_train 0.99

rf_test_precision 0.96
rf_test_recall 0.87
rf_test_f1 0.91
rf_accuracy_test 0.98
rf_auc_test 0.99

Insights:

1. We have used all of the attributes of Sample data for building Random Forest model, but only a few fields are contributing in model predictions, list of those fields are with their weightage are:

Book_Value_Unit_Curr	0.234250
Networth	0.197338
Book_Value_Adj_Unit_Curr	0.192101

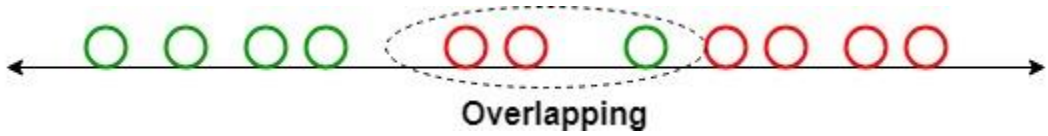
```
Capital_Employed            0.048405
Current_RatioLatest         0.040189
```

2. Random Forest is performing very good on train and test data set and it's recall value is 88% and 87% respectively on train and test data set.
3. Recall denotes Of all the positive cases, what percentage are predicted positive? And if this model is predicting 88% time correctly on test data, which is a very good model.
4. Accuracy measures how often the model is correct. And this is also very good for train and test data set , and giving accuracy of 98% on Train and test both data set.

1.23 Perform LDA

Linear Discriminant Analysis or **Normal Discriminant Analysis** or **Discriminant Function Analysis** is a dimensionality reduction technique that is commonly used for supervised classification problems. It is used for modelling differences in groups i.e. separating two or more classes. It is used to project the features in higher dimension space into a lower dimension space.

For example, we have two classes and we need to separate them efficiently. Classes can have multiple features. Using only a single feature to classify them may result in some overlapping as shown in the below figure. So, we will keep on increasing the number of features for proper classification.



We have used LinearDiscriminantAnalysis Library from Sklearn for performing LDA on our data. The assumptions made by an LDA model about your data:

- Each variable in the data is shaped in the form of a bell curve when plotted,i.e. Gaussian.
- The values of each variable vary around the mean by the same amount on the average,i.e. each attribute has the same variance.

Model Performance Evaluation on Test data set:

```
Accuracy of the LDA Model is  0.9366554054054054

Confusion Matrix
 [[1037   19]
 [  56   72]]

Classification Report
              precision    recall  f1-score   support

           0       0.95      0.98      0.97      1056
           1       0.79      0.56      0.66       128
```

```
    accuracy                           0.94      1184
   macro avg       0.87      0.77      0.81      1184
weighted avg       0.93      0.94      0.93      1184
```

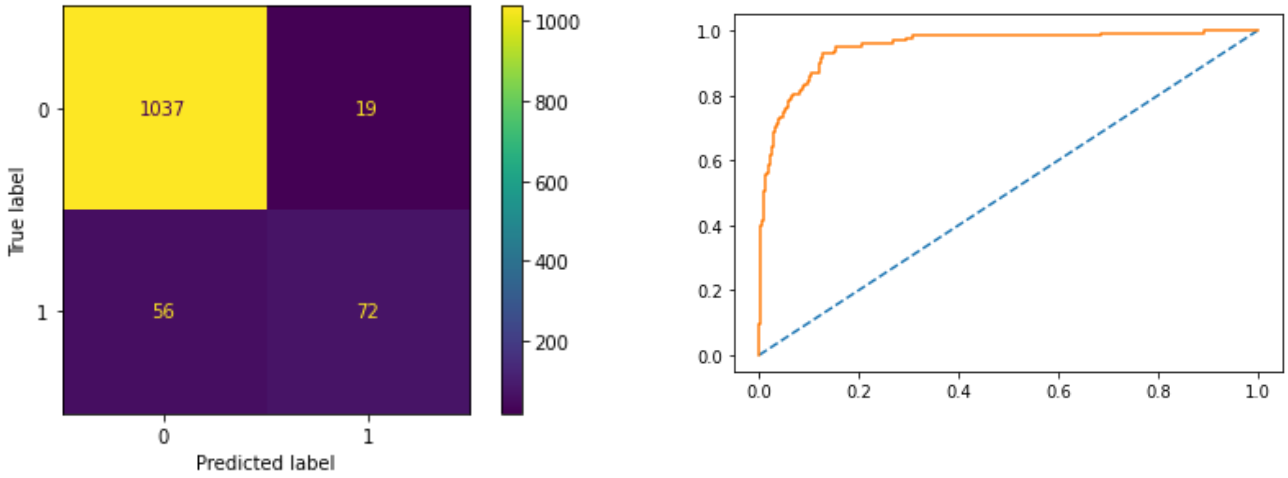


Figure 9 Confusion Metrix and AUC Curve on Test data for LDA

Model Performance Evaluation on Train data set:

```
Accuracy of the LDA Model is  0.9408825978351374

Confusion Matrix
 [[2110   32]
 [ 110  150]]

Classification Report
              precision    recall  f1-score   support

           0       0.95      0.99      0.97      2142
           1       0.82      0.58      0.68       260

    accuracy                           0.94      2402
   macro avg       0.89      0.78      0.82      2402
weighted avg       0.94      0.94      0.94      2402
```

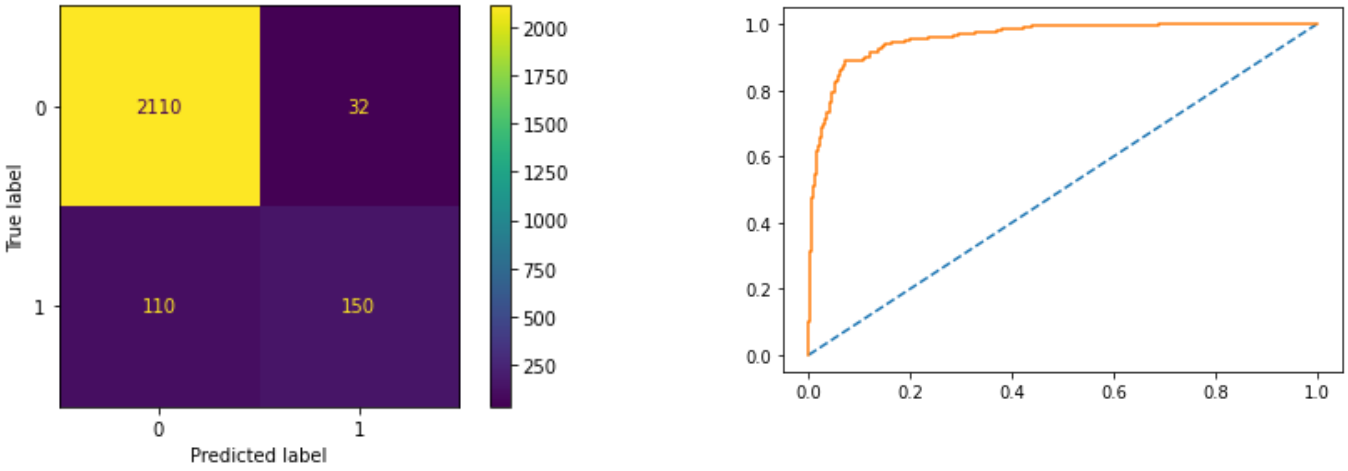


Figure 10 Confusion Metrix and AUC Curve on Train data for LDA

lda_train_precision 0.82
lda_train_recall 0.58
lda_train_acc 0.9408825978351374
lda_train_f1 0.68

lda_test_precision 0.79
lda_test_recall 0.56
lda_test_acc 0.9366554054054054
lda_test_f1 0.66

Insights:

1. This model is not working on our Sample data, its recall value is only 56% on test data and 58% on train data set.
2. Since LDA assumes that each input variable has the same variance, it is always better to standardize your data before using an LDA model. Keep the mean to be 0 and the standard deviation to be 1. And we can scale data for LDA analysis, that could be the reason, why we receive very less correct Recall value.

1.24 Compare the performances of Logistics, Radom Forest and LDA models (include ROC Curve)

We have evaluated multiple models and calculated its performance metrices .

We put them together in Tabular format for better side by side understanding and comparing different models.

This is how the data looks like for all the models, we have built so far:

	Accuracy	AUC	Recall	Precision	F1 Score
SM 4 Train	0.94	Not applicable	0.95	0.92	0.93
SM 4 Test	0.92	Not applicable	0.91	0.58	0.71
RF Train	0.98	0.99	0.88	0.91	0.89
RF Test	0.98	0.99	0.87	0.96	0.91
SM 3 Train	0.96	Not applicable	0.79	0.81	0.8
SM 3 Test	0.95	Not applicable	0.79	0.78	0.79
SM 1 Train	0.96	Not applicable	0.75	0.88	0.81
LR Train	0.960866	0.97619	0.75	0.87	0.8
SM 2 Train	0.96	Not applicable	0.73	0.87	0.79
SM 2 Test	0.95	Not applicable	0.72	0.83	0.77
SM 1 Test	0.95	Not applicable	0.7	0.81	0.75
LR Test	0.952703	0.96872	0.7	0.83	0.76
LDA Train	0.940883	0.959538	0.58	0.82	0.68
LDA Test	0.936655	0.951349	0.56	0.79	0.66

We have also compared Area under the curve for all the models on train and test data.

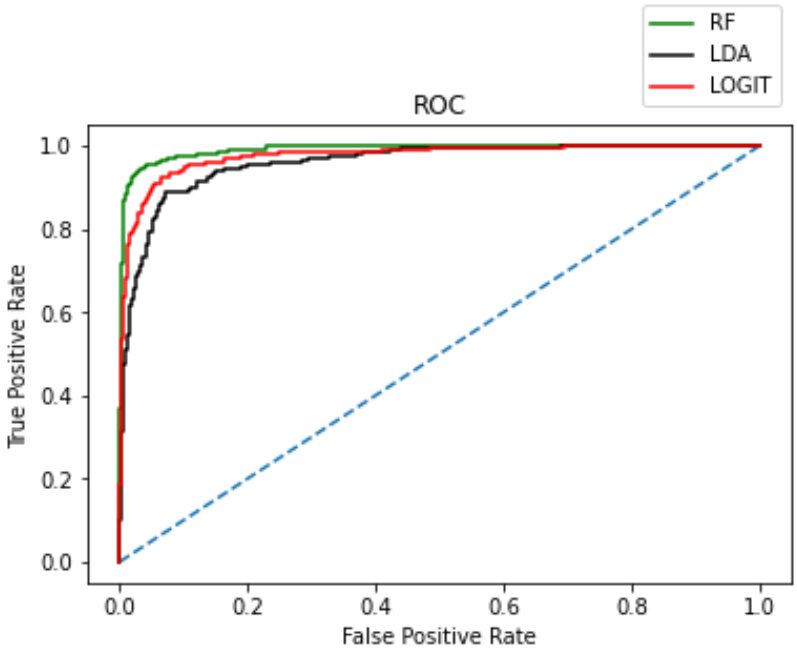


Figure 11 AUC Curve for all the models on Train data

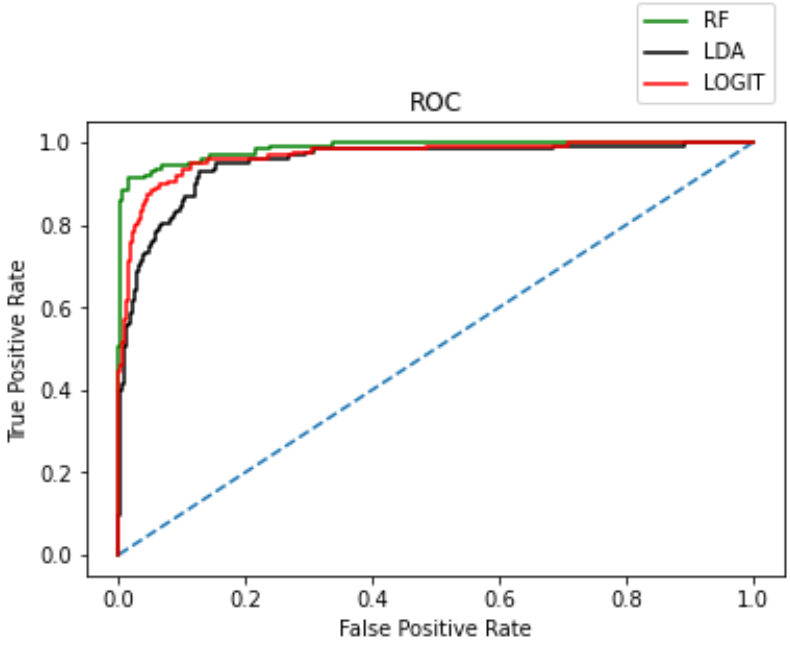


Figure 12 AUC Curve for all the models on Test data

Comparing all the models:

1. We have gathered stats from all the Models LDA, Logit, Random Forest, Stats Model and also done Smote data upscaling .
2. We arranged data from Descending order of Recall value, Recall denotes how accurately you are predicting True positives.
3. We have got the best Recall values from Stats Model with SMOTE upscaled data , with recall value of 91% on test data set
4. Second highest recall value is for Random forest Model and in this model have note upscaled data and data has been taken as it was given , (Only NULL value and Outliers imputed), it has given us Recall of 87%% on test data, which is very good.
5. Random Forest has also given very good Accuracy of 98% on both train and test data, which shows how good this model is in predicting correct data.
6. Random forest also has very good Precision and F1 Score is also about 90% for both Train and test data set.
7. I will consider Random Forest over Stats Model , even if SM-4 Model have slight better Recall value, because we have not done any data upscaling in Random forest and used data as it was given.

1.25 Conclusion and Recommendations from the above models:

1. Sample data had 3586 rows and 67 columns; total number of column values were not bad.
2. We have not given Company types, like Mid-Size, Small Size or Large capital companies.
3. We have not given revenue of the companies , so that we can segregate companies based on their revenue
4. We have not given industry type of companies like, IT, Manufacturing, Retail , Pharma, etc . We consider them all of same type and not taken any action based on what type company it is
5. Data have about 100+ NULL values in sample data, which we imputed by taking median.
6. Data was very large number of outliers , and for our modelling purpose, we treated outliers, using bringing them back to Normal Upper and Lower limits
7. NULL Values and Outlier treatment:
   Following methods were used in this exercise for treating NULL and outlier values:
   a. Impute NULL with Median and Impute Outlier by bringing them back to Normal range. This Method is used for this project submission, because it has the best RECALL and Accuracy score.

   b. I have also tested NULL values and Outlier treatment with KNN method of data imputations, but recall values and precision are very less in this case , so I switch back to above point a only . Following attached is notebook, where I have tested using KNN model as well, but RECALL values are very less. This is just for reference purpose.:

   Amit_Jain_Mileston e-1_KNN_Treatment.

   This is a Notebook file, in this Notebook, I have tested KNN treatment and calculated RECALL after KNN treatment of Missing values and Outliers.
8. Data was very imbalanced , and we upscale data using SMOTE feature, and Built Stats model on top of it.
   In the Final model , we have used 31 columns for deciding “DEFAULT” nature of companies, and there were total 67 features, were given.

9. We have found best model as Random forest for our analysis with best Recall , Accuracy and Precision on train and test both data set, and for building this model , we have not used any upscaling methodology , so this model is more close to real world scenarios and will not require too much of approval from managements.
10. According to Random forest model, only following features of data , contributing most in Model predictions and their weightage are as follows:

```
Book_Value_Unit_Curr       0.234250
Networth                   0.197338
Book_Value_Adj_Unit_Curr   0.192101
```

11. I would also like to Emphasize on following results,

	Accuracy	AUC	Recall	Precision	F1 Score
SM 4 Train	0.94	Not applicable	0.95	0.92	0.93
SM 4 Test	0.92	Not applicable	0.91	0.58	0.71
RF Train	0.98	0.99	0.88	0.91	0.89
RF Test	0.98	0.99	0.87	0.96	0.91
SM 3 Train	0.96	Not applicable	0.79	0.81	0.8
SM 3 Test	0.95	Not applicable	0.79	0.78	0.79

Stats Model 3, which was created , after removing highly co-related attributes , is also a very good model after random forest, in terms of Recall , Accuracy and Precision model, on Train and test both data set.

2. Market Risk Analysis: Introduction

This report explains the business requirements and provide the detailed solution based on the data provided for each problem statement. given in the assignment. Also, the purpose of this exercise is to understand Market risks, given stock prices for different Stock prices for certain Time period, Calculating Mean and standard deviation of Stocks and calculate returns of those Stocks in longer terms.

Problem statement :

The dataset contains 1 year of Stock information about 10 Stocks from Indian stock exchange . It has Stock price listed for all weekdays, whenever Market opens.

This is how the data look like:

	Date	Infosys	Indian_Hotel	Mahindra_&_Mahindra	Axis_Bank	SAIL	Shree_Cement	Sun_Pharma	Jindal_Steel	Idea_Vodafone	Jet_Airways
0	31-03-2014	264	69	455	263	68	5543	555	298	83	278
1	07-04-2014	257	68	458	276	70	5728	610	279	84	303
2	14-04-2014	254	68	454	270	68	5649	607	279	83	280
3	21-04-2014	253	68	488	283	68	5692	604	274	83	282
4	28-04-2014	256	65	482	282	63	5582	611	238	79	243

Shape of the data:

```
The number of rows (observations) is 314
The number of columns (variables) is 11
```

Insights:

4. There are only 314 Rows (About a year worth of Stock prices , whenever Market opens) in sample, data
5. We have given total 10 Stock prices
6. Stocks given are :

```
'Infosys', 'Indian_Hotel', 'Mahindra_&_Mahindra', 'Axis_Bank',
       'SAIL', 'Shree_Cement', 'Sun_Pharma', 'Jindal_Steel', 'Idea_Vodafone',
       'Jet_Airways'
```

2.1 Data dictionary :

	count	mean	std	min	25%	50%	75%	max
Infosys	314.0	511.340764	135.952051	234.0	424.00	466.5	630.75	810.0
Indian_Hotel	314.0	114.560510	22.509732	64.0	96.00	115.0	134.00	157.0
Mahindra_&_Mahindra	314.0	636.678344	102.879975	284.0	572.00	625.0	678.00	956.0
Axis_Bank	314.0	540.742038	115.835569	263.0	470.50	528.0	605.25	808.0
SAIL	314.0	59.095541	15.810493	21.0	47.00	57.0	71.75	104.0
Shree_Cement	314.0	14806.410828	4288.275085	5543.0	10952.25	16018.5	17773.25	24806.0
Sun_Pharma	314.0	633.468153	171.855893	338.0	478.50	614.0	785.00	1089.0
Jindal_Steel	314.0	147.627389	65.879195	53.0	88.25	142.5	182.75	338.0
Idea_Vodafone	314.0	53.713376	31.248985	3.0	25.25	53.0	82.00	117.0
Jet_Airways	314.0	372.659236	202.262668	14.0	243.25	376.0	534.00	871.0

Checking data types of all columns:

```
#   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Date                  314 non-null    object
 1   Infosys               314 non-null    int64
 2   Indian_Hotel          314 non-null    int64
 3   Mahindra_&_Mahindra   314 non-null    int64
 4   Axis_Bank             314 non-null    int64
 5   SAIL                  314 non-null    int64
 6   Shree_Cement          314 non-null    int64
 7   Sun_Pharma            314 non-null    int64
 8   Jindal_Steel          314 non-null    int64
 9   Idea_Vodafone         314 non-null    int64
 10  Jet_Airways           314 non-null    int64
```

Data is given in correct format for us.

All stock prices are in Numeric format and Date field on which Stock price is captured is in Object format.

2.2 Draw Stock Price Graph(Stock Price vs Time) for any 2 given stocks with inference

Lets us plot & see price trend over time for different companies . For the purpose of this exercise, we have asked to do analysis for Any 2 Stocks. For this exercise, we would Consider "Infosys" and "Jet_Airways" Stocks for plotting Price against time.

This is how data looks like:

	Infosys	Jet_Airways	Date
0	264	278	31-03-2014
1	257	303	07-04-2014
2	254	280	14-04-2014
3	253	282	21-04-2014
4	256	243	28-04-2014

Jet airways over the year:

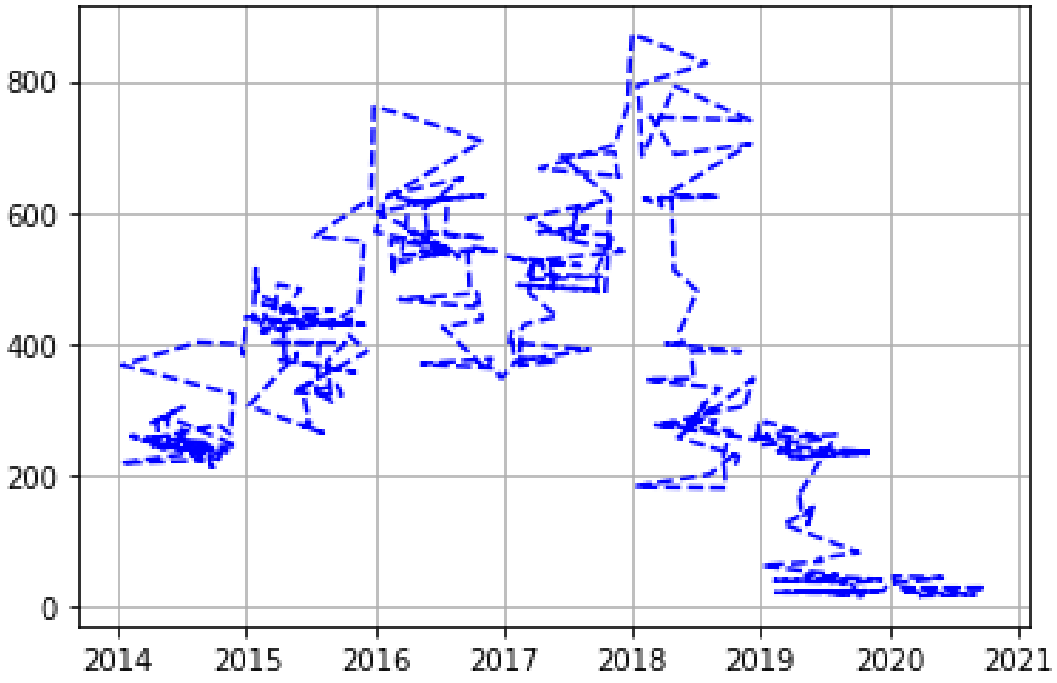


Figure 13 Jet_Airways Stock LinePlot

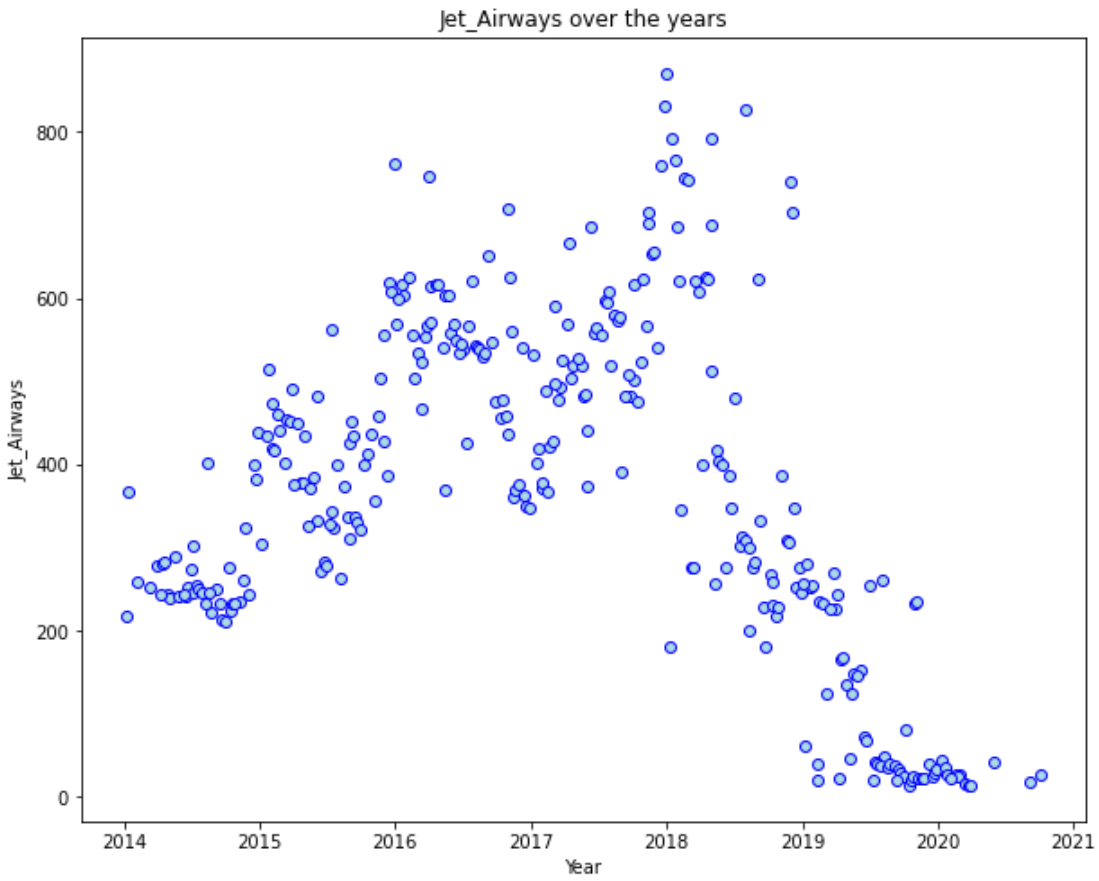


Figure 14 Jet Airways Stock Scatter plot

Insights:

1. JetAirways share grown up in year 2017-18 period,
2. It came down eventually after year 2019 and a big loss for the company,
3. It reached to all time low level from year 2019 to 2021 and collapse completely.

Infosys Stock Prices over the year:

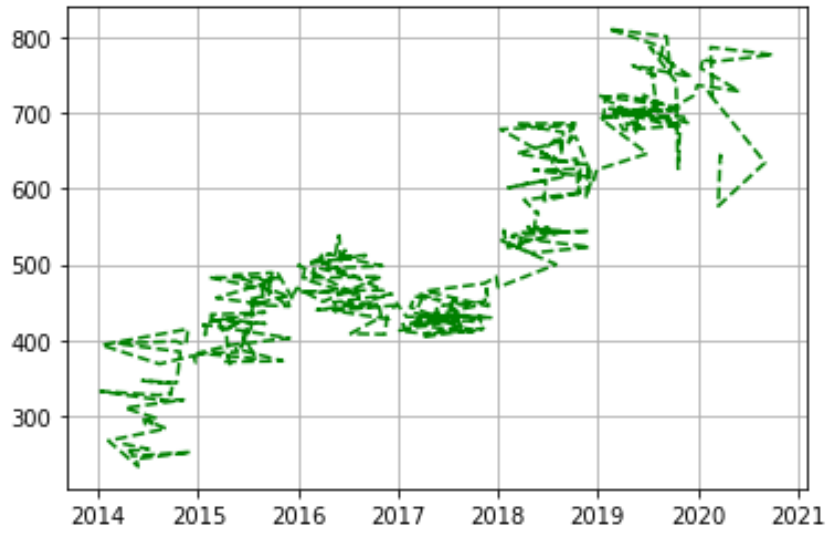


Figure 15 Infosys Stock Line Plot

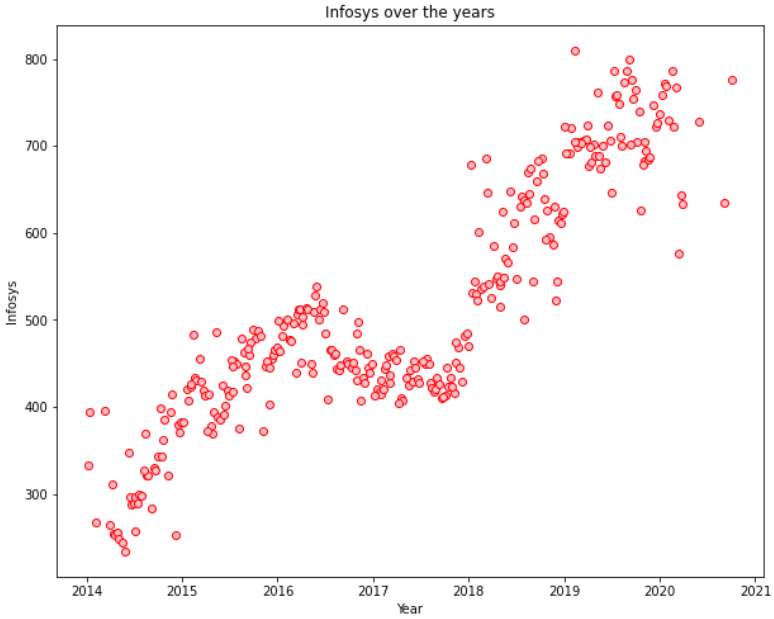


Figure 16 Infosys Stock Scatter Plot

Insights:

1. Infosys Stocks are going high every year,
2. There is always a positive trend in Infosys stocks
3. This is a safe Stock in Long term investment and can be trusted.
4. It is on it's highest level in year 2019-20

2.3 Calculate Returns for all stocks with inference

There are 2 ways we can calculate Returns of the Stocks :

Logarithmic returns

Athematic returns

The difference between a logarithmic and arithmetic chart scale can be seen on the vertical axis, which is the y axis. An arithmetic scale shows equal spacing between the chart units.

A semi-logarithmic scale, on the other hand, is set up to measure price distances in percentage terms. This means a 10% advance from 60 to 66 looks the same as a 10% advance from 100 to 110, even though the first advance is six Dollars and the second advance is ten Dollars.

So which scaling system is best? Both systems have their advantages and disadvantages. One's preference largely depends on analysis style and timeframe. Traders looking to capture short-term price movements or analyze trading ranges may prefer arithmetic scales for price purity. Chartists interested in trends and long-term price histories will likely prefer log scaling. Notice that a log scale is best used when prices have moved a significant amount, up or down. Chartists can switch between arithmetic and log scaling by using the "log scale" check box in the Chart Attributes sector under the SharpChart.

For our exercise purpose, we have chosen Logarithmic returns.

Steps for calculating returns from prices:

Take logarithms

Take differences

Stock Price at time T *minus* Stock price at time (T-1) will give returns of that Stock at T point of time.

We have taken differences of the prices and taken log of the data. This is how the data looks like :

	Infosys	Indian_Hotel	Mahindra_&_Mahindra	Axis_Bank	SAIL	Shree_Cement	Sun_Pharma	Jindal_Steel	Idea_Vodafone	Jet_Airways
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	-0.026873	-0.014599	0.006572	0.048247	0.028988	0.032831	0.094491	-0.065882	0.011976	0.086112
2	-0.011742	0.000000	-0.008772	-0.021979	-0.028988	-0.013888	-0.004930	0.000000	-0.011976	-0.078943
3	-0.003945	0.000000	0.072218	0.047025	0.000000	0.007583	-0.004955	-0.018084	0.000000	0.007117
4	0.011788	-0.045120	-0.012371	-0.003540	-0.076373	-0.019515	0.011523	-0.140857	-0.049393	-0.148846

Describer returns of all the Stocks:

	count	mean	std	min	25%	50%	75%	max
Infosys	313.0	0.002794	0.035070	-0.167300	-0.014514	0.004376	0.024553	0.135666
Indian_Hotel	313.0	0.000266	0.047131	-0.236389	-0.023530	0.000000	0.027909	0.199333
Mahindra_&_Mahindra	313.0	-0.001506	0.040169	-0.285343	-0.020884	0.001526	0.019894	0.089407
Axis_Bank	313.0	0.001167	0.045828	-0.284757	-0.022473	0.001614	0.028522	0.127461
SAIL	313.0	-0.003463	0.062188	-0.251314	-0.040822	0.000000	0.032790	0.309005
Shree_Cement	313.0	0.003681	0.039917	-0.129215	-0.019546	0.003173	0.029873	0.152329
Sun_Pharma	313.0	-0.001455	0.045033	-0.179855	-0.020699	0.001530	0.023257	0.166604
Jindal_Steel	313.0	-0.004123	0.075108	-0.283768	-0.049700	0.000000	0.037179	0.243978
Idea_Vodafone	313.0	-0.010608	0.104315	-0.693147	-0.045120	0.000000	0.024391	0.693147
Jet_Airways	313.0	-0.009548	0.097972	-0.458575	-0.052644	-0.005780	0.036368	0.300249

Insights:

- We can see that maximum returns gained was from 'Idea Vodafone' Stocks with 69% growth in any time period.
- We have added a new Row with Total in Stock data frame and calculated in total Returns of each Stock as compared to first value of Stock prices and this is how Total value looks like:

	310	311	312	313	Total
Shree_Cement	-0.081183	-0.119709	-0.067732	-0.006816	1.152290
Infosys	-0.139625	-0.094207	0.109856	-0.017228	0.874521
Axis_Bank	-0.145324	-0.284757	-0.173019	0.051432	0.365382
Indian_Hotel	-0.051293	-0.236389	-0.182322	0.000000	0.083382
Sun_Pharma	-0.043319	-0.050745	-0.076851	0.040585	-0.455337
Mahindra_&_Mahindra	-0.093819	-0.285343	-0.091269	-0.031198	-0.471323
SAIL	-0.095310	-0.105361	-0.251314	0.090972	-1.084013
Jindal_Steel	-0.187816	-0.141830	-0.165324	-0.081917	-1.290374
Jet_Airways	-0.200671	-0.117783	-0.133531	0.000000	-2.988564
Idea_Vodafone	0.693147	-0.693147	0.000000	0.000000	-3.320228

As per above data, we can see that maximum percentage returns from Sample data, given by Shree_Cement Stock, which game 115% returns , followed by Infosys Stocks, which gave 87% returns.

Least returns given by Idea_Vodafone, which ran into Loss for 332% Stocks down.

2.4 Means & Standard Deviations of these returns

Stock Means: Average returns that the stock is making on a week to week basis

Stock Standard Deviation : It is a measure of volatility meaning the more a stock's returns vary from the stock's average return, the more volatile the stock

Calculating stock means:

```
Infosys                 0.002794
Indian_Hotel            0.000266
Mahindra_&_Mahindra    -0.001506
Axis_Bank               0.001167
SAIL                   -0.003463
Shree_Cement            0.003681
Sun_Pharma             -0.001455
Jindal_Steel           -0.004123
Idea_Vodafone          -0.010608
Jet_Airways            -0.009548
```

Calculating stock standard deviation

```
Infosys                 0.035070
Indian_Hotel            0.047131
Mahindra_&_Mahindra     0.040169
Axis_Bank               0.045828
SAIL                    0.062188
Shree_Cement            0.039917
Sun_Pharma              0.045033
Jindal_Steel            0.075108
Idea_Vodafone           0.104315
Jet_Airways             0.097972
```

Lets frame both mean and Standard deviation in a data frame and this is how, it look like in a combined manner:

	Average	Volatility
Shree_Cement	0.011009	0.135825
Infosys	0.008355	0.104582
Axis_Bank	0.003491	0.061553
Indian_Hotel	0.000797	0.047984
Sun_Pharma	-0.004350	0.068222
Mahindra_&_Mahindra	-0.004503	0.066553
SAIL	-0.010357	0.137027
Jindal_Steel	-0.012328	0.163605
Jet_Airways	-0.028553	0.350688
Idea_Vodafone	-0.031722	0.388369

Insights:

1. Best Stock from sample data is Shree_cement, which is giving average returns of 11% from each previous Stock value.
2. Worst Stock is Idea_vodafone, which is going down every time and average price decline by 3.1% on an average.
3. Jet_airways and Idea_Vodafone remains the highly volatile Stocks, which are unpredicted with Max Standard deviation of 35-36% each.
4. Indian Hotels are highly consistent in performance, though their returns are not good .
5. Similarly Sun_pharma and Mahindra_&Mahindra are also least risk volatile Stocks, with consistent performance of about 4.3 to 4.5 % returns on average.

2.5 Draw a plot of Stock Means vs Standard Deviation and state your inference:

We have not given column for Sensex values, so we have calculated Mean for both Average and Volatility. And we will plot each Stock's Average and Volatility against this mean of all stock's and see , how that is performing against other Stocks from Sample data.

```
Mean for Averages of all the stocks from Sample data is :  -0.004544117653834371
Mean for Volatility of all the stocks from Sample data is :  0.09334834662321471
```

Let us now plot each Stock against above means:

We have taken Volatility on X -axis and Average prices on Y axis and seen Volatility/Average of each stocks against means.

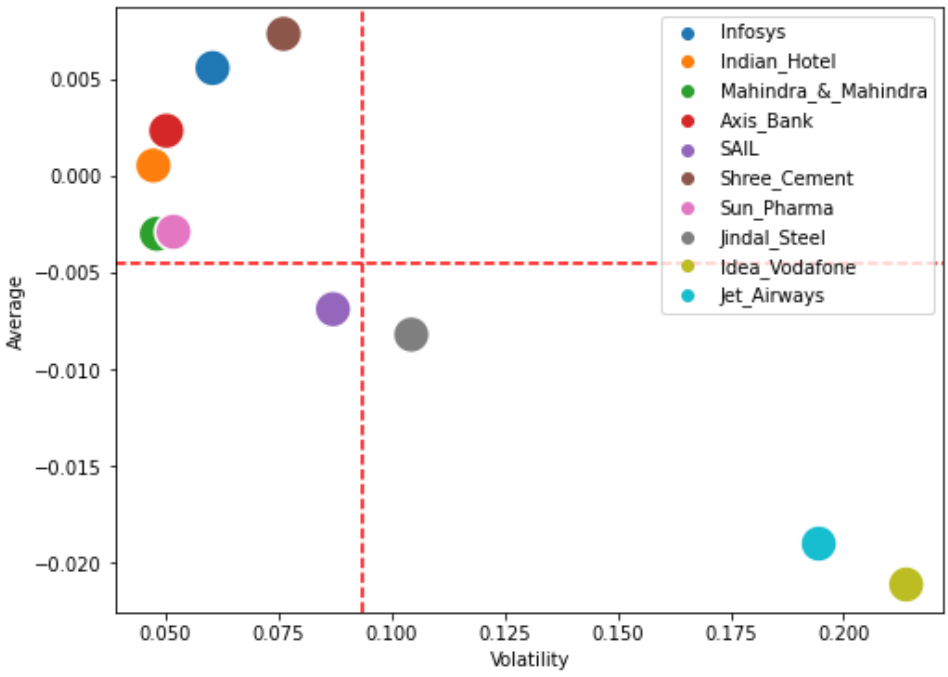


Figure 17Mean and Std Dvt for Stock returns

Insights:

1. We can see that Volatility us very high for Idea_Vodafone, at the same time, it is giving consistent loss for it's stocks
2. Same thing High Volatility and least profit with Jet_airways as well after Idea_vodafone
3. Jindal_steel and SAIL are also giving average negative returns as well as High in Volatility.
4. Shree_cement and Infosys remain the best Stocks for giving very good returns , but little volatile as well. In Long terms, they are always beneficiaries .

2.6 Conclusion and Recommendations

1. There are only 314 Rows (About a year worth of Stock prices , whenever Market opens) in sample, data
2. We have given total 10 Stock prices
3. Stocks given are :

```
'Infosys', 'Indian_Hotel', 'Mahindra_&_Mahindra', 'Axis_Bank', 'SAIL', 'Shree_Cement'
, 'Sun_Pharma', 'Jindal_Steel', 'Idea_Vodafone',       'Jet_Airways'
```

4. JetAirways and Idea_vodafone mong the least performing Stocks and its prices going down always. These Stocks are very risky and Suggestions would be not buy these Stocks, unless there is any Magic happens, acquisition or some other Policy launches. Those are Sinking ships.
5. Infosys and Shree_cement are the best Stocks, for giving consistent returns and these are Rocket stocks.
6. In Long terms investments, **Infosys** and **Shree_cements** are best Stocks to purchase, which might give consistent returns of about 8-11% average returns, but they are volatile as well, so these Stocks are a very good suggestion for **Long term traders**.
7. "**Indian_Hotel**" is least risky Stocks for Intra-day traders. Because those are least Volatile. But the profit is also very le ss for it.
8. "Mahindra_&_mahindra" stocks are also among least Volatile Stock, but this is not a profit making Stock, average returns is in **negative 4%**.
9. Axis_bank is Safe stock with Least Volatility and giving Positive returns of average 2% always, so I would suggest to buy Axis_bank stock for **Intra-day traders**.