FINANCE AND RISK ANALYTICS

MILESTONE PROJECT-1

-REKHA WANKHEDE

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INTRODUCTION

This report consists of Classification modelling of Company Financials using Logistic Regression. It is expected to find whether a given company is in good financial health and will it have a positive Net-worth for the next year.

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.

Explanation of data fields available in Data Dictionary, 'Credit Default Data Dictionary.xlsx'
Data Description :

Co_Code	Company Code
Co_Name	Company Name
Networth_Next_Year	Value of a company as on 2016 - Next Year(difference between the value of total assets and total liabilities)
Equity_Paid_Up	Amount that has been received by the company through the issue of shares to the shareholders
Networth	Value of a company as on 2015 - Current Year
Capital_Employed	Total amount of capital used for the acquisition of profits by a company
Total_Debt	The sum of money borrowed by the company and is due to be paid

Variable	Description
Co_Code	Company Code
Co_Name	Company Name

Networth_Next_Year	Value of a company as on 2016 - Next Year(difference between the value of total assets and total liabilities)
Equity_Paid_Up	Amount that has been received by the company through the issue of shares to the shareholders
Networth	Value of a company as on 2015 - Current Year
Capital_Employed	Total amount of capital used for the acquisition of profits by a company
Total_Debt	The sum of money borrowed by the company and is due to be paid
Gross_Block	Total value of all of the assets that a company owns
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).
Curr_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_Liab_and_Prov	Short-term financial obligations that are due within one year (includes amount that is set aside cover a future liability)
Total_Assets_to_Liab	Ratio of total assets to liabailities of the company
Gross_Sales	The grand total of sale transactions within the accounting period
Net_Sales	Gross sales minus returns, allowances, and discounts
Other_Income	Income realized from non-business activities (e.g. sale of long term asset)
Value_Of_Output	Product of physical output of goods and services produced by company and its market price
Cost_of_Prod	Costs incurred by a business from manufacturing a product or providing a service
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)
PBIDT	Profit Before Interest, Depreciation & Taxes
PBDT	Profit Before Depreciation and Tax
PBIT	Profit before interest and taxes
PBT	Profit before tax
PAT	Profit After Tax
Adjusted_PAT	Adjusted profit is the best estimate of the true profit
CP	Commercial paper , a short-term debt instrument to meet short-term liabilities.
Rev_earn_in_forex	Revenue earned in foreign currency
Rev_exp_in_forex	Expenses due to foreign currency transactions
Capital_exp_in_forex	Long term investment in forex
Book_Value_Unit_Curr	Net asset value
Book_Value_Adj_Unit_Curr	Book value adjusted to reflect asset's true fair market value
Market_Capitalisation	Product of the total number of a company's outstanding shares and the current market price of one share

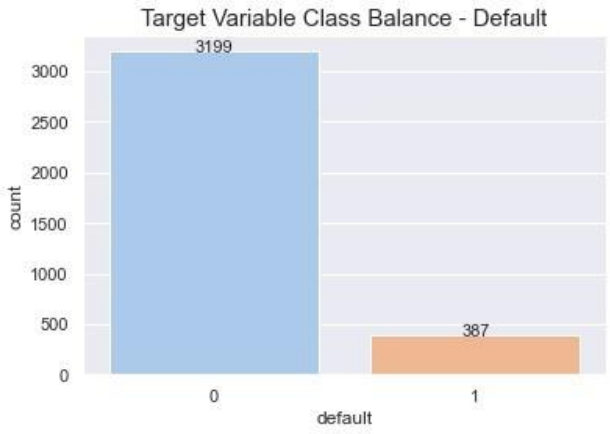
Variable	Description
CEPS_annualised_Unit_Curr	Cash Earnings per Share, profitability ratio that measures the financial performance of a company by calculating cash flows on a per share basis
Cash_Flow_From_Opr	Use of cash from ongoing regular business activities
Cash_Flow_From_Inv	Cash used in the purchase of non-current assets–or long-term assets– that will deliver value in the future
Cash_Flow_From_Fin	Net flows of cash that are used to fund the company (transactions involving debt, equity, and dividends)
ROG_Net_Worth_perc	Rate of Growth - Networth
ROG_Capital_Employed_perc	Rate of Growth - Capital Employed
ROG_Gross_Block_perc	Rate of Growth - Gross Block
ROG_Gross_Sales_perc	Rate of Growth - Gross Sales
ROG_Net_Sales_perc	Rate of Growth - Net Sales
ROG_Cost_of_Prod_perc	Rate of Growth - Cost of Production
ROG_Total_Assets_perc	Rate of Growth - Total Assets
ROG_PBIDT_perc	Rate of Growth- PBIDT
ROG_PBDT_perc	Rate of Growth- PBDT
ROG_PBIT_perc	Rate of Growth- PBIT
ROG_PBT_perc	Rate of Growth- PBT
ROG_PAT_perc	Rate of Growth- PAT
ROG_CP_perc	Rate of Growth- CP
ROG_Rev_earn_in_forex_perc	Rate of Growth - Revenue earnings in forex
ROG_Rev_exp_in_forex_perc	Rate of Growth - Revenue expenses in forex
ROG_Market_Capitalisation_perc	Rate of Growth - Market Capitalisation
Curr_Ratio_Latest	Liquidity ratio, company's ability to pay short-term obligations or those due within one year
Fixed_Assets_Ratio_Latest	Solvency ratio, the capacity of a company to discharge its obligations towards long-term lenders indicating
Inventory_Ratio_Latest	Activity ratio, specifies the number of times the stock or inventory has been replaced and sold by the company
Debtors_Ratio_Latest	Measures how quickly cash debtors are paying back to the company
Total_Asset_Turnover_Ratio_Latest	The value of a company's revenues relative to the value of its assets
Interest_Cover_Ratio_Latest	Determines how easily a company can pay interest on its outstanding debt
PBIDTM_perc_Latest	Profit before Interest Depreciation and Tax Margin
PBITM_perc_Latest	Profit Before Interest Tax Margin
PBDTM_perc_Latest	Profit Before Depreciation Tax Margin

CPM_perc_Latest	Cost per thousand (advertising cost)
APATM_perc_Latest	After tax profit margin
Variable	**Description**
Debtors_Vel_Days	Average days required for receiving the payments
Creditors_Vel_Days	Average number of days company takes to pay suppliers
Inventory_Vel_Days	Average number of days the company needs to turn its inventory into sales
Value_of_Output_to_Total_Assets	Ratio of Value of Output (market value) to Total Assets
Value_of_Output_to_Gross_Block	Ratio of Value of Output (market value) to Gross Block

Table 1 - Data description of all variables of raw data

OBSERVATION:

1. Total Number of Companies (observations) = 3586
2. Total Number of Variables = 67 (1 target and 66 predictors)
3. Target Variable -
   - We create a target variable - 'default'
   - Where, if Net-worth next year is zero or positive —> default = 0
   - If Net-worth next year is negative —> default = 1
   - Default = 1 —> 387 Companies in the data



4. Number of Duplicates = 0
5. Missing Value Treatment -
   - Less than 1% missing values present
   - We impute these missing values by using KNN Imputer (`n_neighbors=10`)
6. Zero Values -

- Large amount of zero values present (total = 15.1 %)

- We drop columns with more than 30% of zero values (9 columns)

- We found that 164 out of total 387 defaulting companies had more than 5 zero values in their rows

—-> We conclude, more the missing or zero values, higher is the probability of default

- For the rest of columns —> we convert zeros to Missing Nan values

  - Impute all these missing values using KNN Imputer

(`n_neighbors=10`)

7. Outlier Treatment -

   - IQR and Z-Score methods - used separately to identify and treat outliers
   - Different Logistic Regression models fitted and tested using both
   - Z-Score outlier treatment was found to give better results on Test Data

8. Scaling - We use Z-score Standard scaling

9. Multi-Collinearity -

   - Many variables in the data are extracts of each other
   - Hence, there is a high correlation between many of them
   - This causes Multi-Collinearity and can harm a model's interpretability
   - Also, these columns don't add any more value to predictions by regression
   - Variance Inflation Factor method is used to check and drop columns causing Multi-Collinearity
   - Recursively, one-by-one, columns with VIF > 5 are dropped

10. Feature Engineering -

    - We start with large number of 66 predictor variables
    - There are various methods employed to extract the best features
    - Methods and Steps taken for all modelling -
    - Drop unique identifiers which add no value to predictions - Company Code and name —> 64 vars left
    - Drop variables with zeros > 30% (9 cols dropped) —> 55 vars left
    - Drop vars one-by-one with VIF > 5 —> 27 vars left after IQR outliers
      —> 23 vars left after Zscore outliers

- Also, for some models, we test by dropping insignificant variables for prediction (vars with p-values > 0.05) at 95% confidence
- For Model #7 - we use Recursive Feature Elimination (RFE) technique to select 15 best features for modelling

11. We choose Model #8 as the best model for deployment -

- This has the best combination of Recall and Precision for default=1

- This model -

Outlier treatment —> Z-score with values capped to ±3 std dev

RFE —> with top 15 features

Oversampling method —> SMOTE with 50-50 balance of 0 & 1

Choosing Optimum Threshold = 0.5

- Metrics for default = 1 —>

Recall = 95%, Precision = 78%, Accuracy = 96%, f1-score = 86%

1.1 Outlier Treatment

- Outlier treatment is necessary for any regression model
- In Regression, outliers pull the regression line towards itself thereby affecting its slope. This distorts the reality and leads to faulty predictions
- We employ 2 types of Outlier detection and treatments in this case study
- Inter-Quartile Range (IQR) Treatment
- Z-score treatment
- We show box plots of 15 variables before and after Outlier treatment. We scale these variables for better comparison
- These 15 vars are finally chosen as the best predictors for Logistic Regression
- IQR Treatment -
- Q1 = 25th percentile, Q3 = 75th percentile
- IQR = Q3 - Q1

- Outlier = any value which lies beyond 1.5 times of IQR from Q1 and Q3 on either side
- We cap all outliers to this upper or lower level

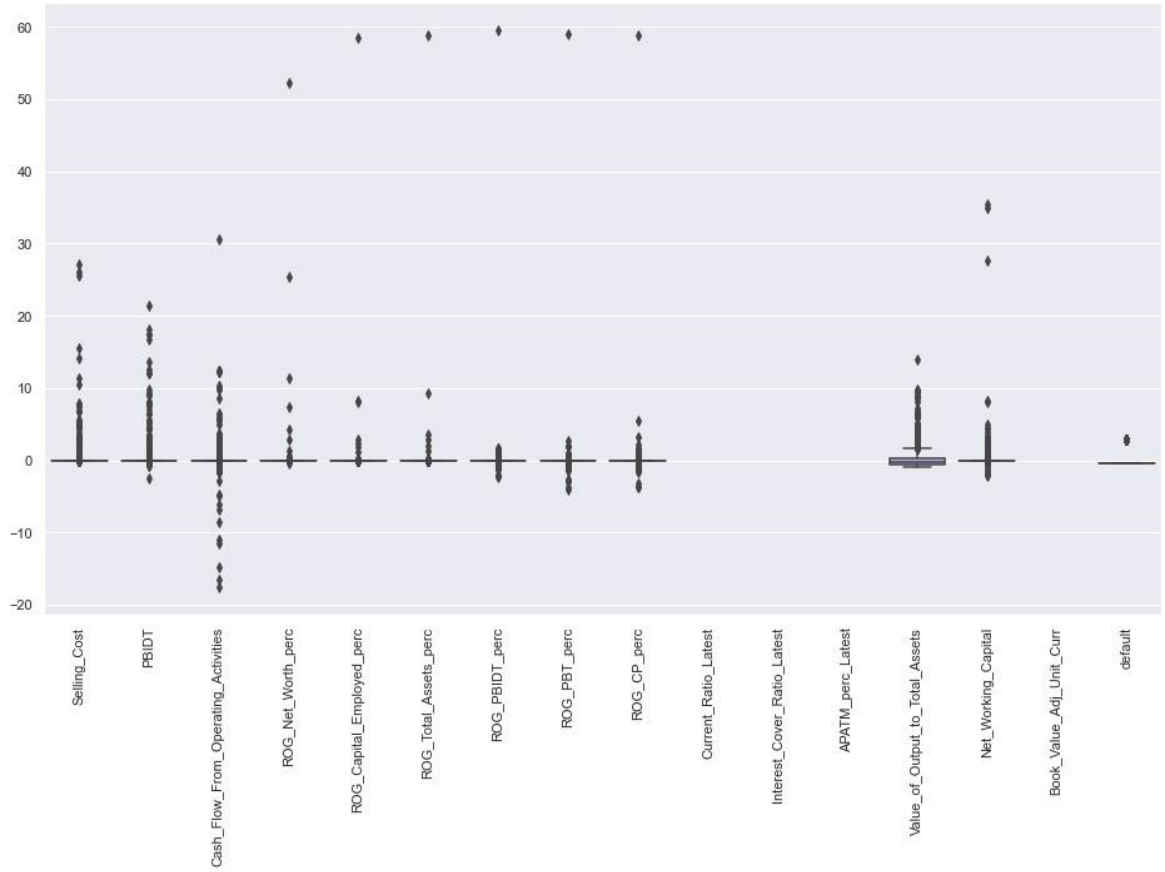


Fig 2 - Boxplot before Outlier Treatment - Top 15 predictors - Z-scaled

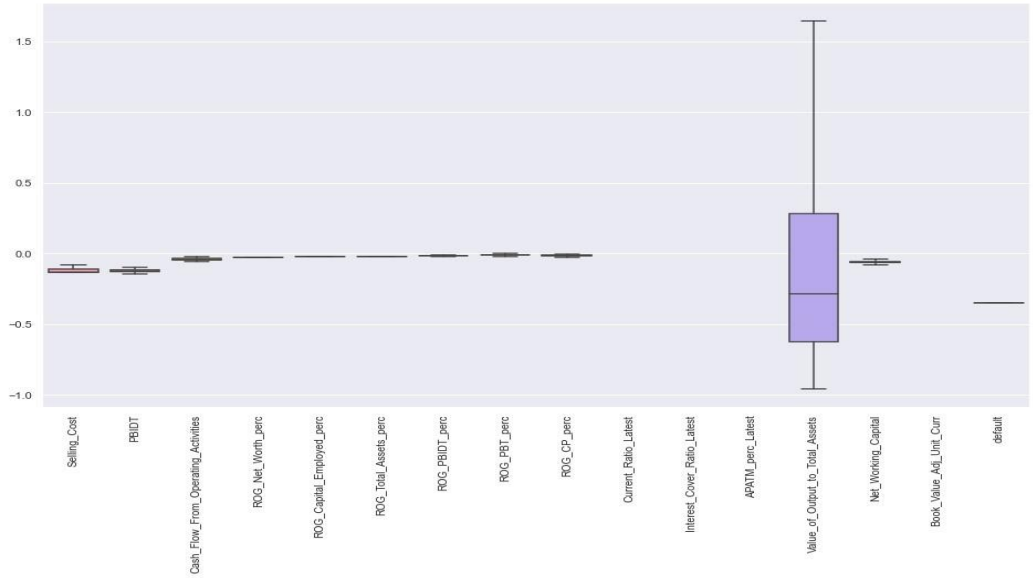


Fig 3 - Boxplot after IQR Treatment - Top 15 predictors - Z-scaled

- Z-score Treatment -

$$z - score = \frac{value - mstedandeovf\ feature}{}$$

- We find z-score of each value of the feature
- Outlier = any value with z-score < -3 or > 3
- We cap outliers to ±3 on either side

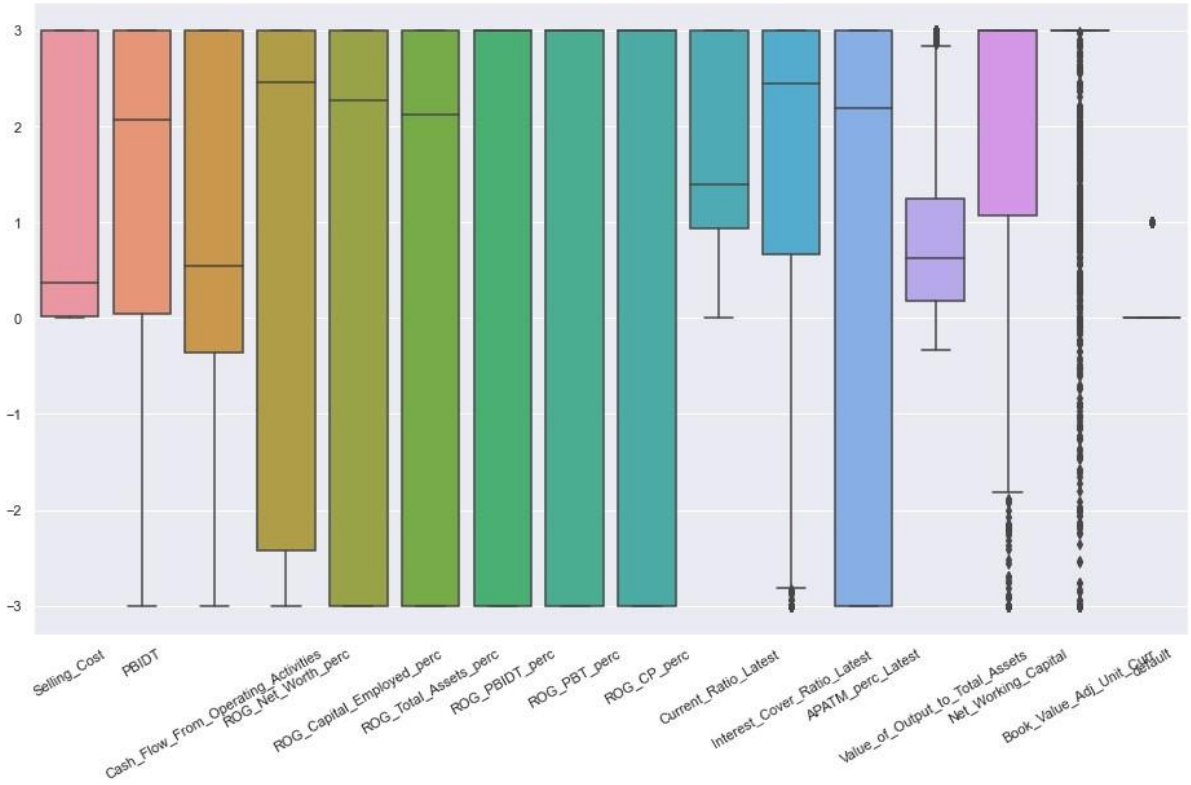


Fig 4 - Boxplot after Z-score Treatment - Top 15 predictors - Z-scaled

1.2 Missing Value Treatment

- Missing values in the raw data are very less, about 0.05%
- But there are large number of zero values, which are mostly placeholders for missing values, about 15%
- Also, these zero values add no more value to predictions
- But also mainly, large number of zero values in any feature cause ‘Linear Algebra Error’ while using StatsModel

- Hence, it is of paramount importance to treat these zero values
- Firstly, we drop all those features with zero values greater than 30%
- Then, we convert all other zero values to Missing Values (Nan values)
- These transformed and original missing values together are imputed using KNN Imputer (`n_neighbors=10`)
- A visual of all these missing values is give below - after dropping vars

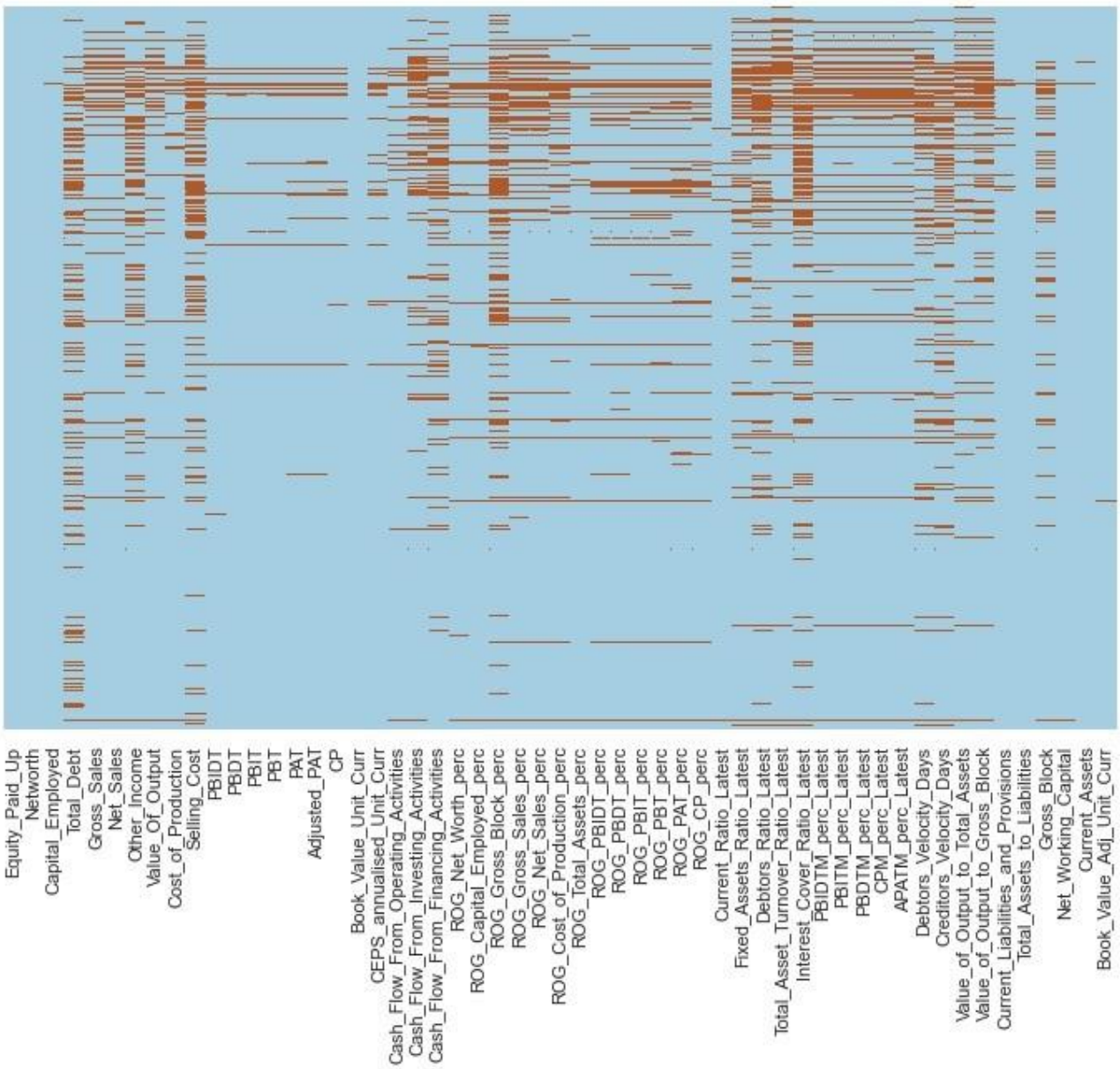


Fig 5 - Missing Values visualised - Raw data (55 vars)

1.3 Transform Target variable into 0 and 1

- We check the financial health of companies

- We'll base our prediction on Company's health on whether they will have a positive Net-worth next year or negative
- Hence, We consider 'Networth Next Year' as our Default Variable
- So, we call negative values as Default = 1
- And, zero or positive values as Default = 0
- We convert accordingly - Below is the sample

default	Networth_Next_Year
1	-8021.6
1	-3986.19
1	-3192.58
1	-3054.51
1	-2967.36

Table 2 - Target Variable - First 5

default	Networth_Next_Year
0	72677.77
0	79162.19
0	88134.31
0	91293.7
0	111729.1

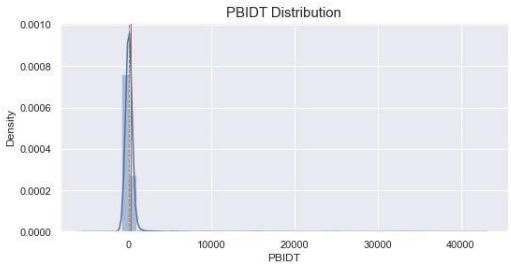
Table 3 - Target Variable - Last 5

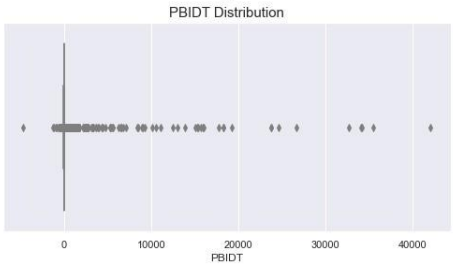
1.4 Univariate (4 marks) & Bivariate (6marks) analysis with proper interpretation. (You may choose to include only those variables which were significant in the model building)

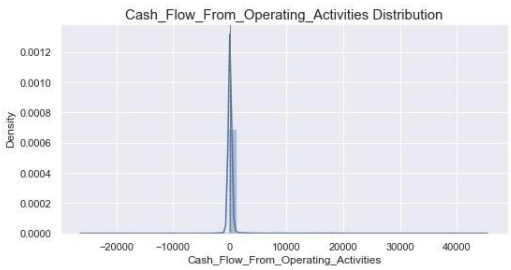
UNIVARIATE ANALYSIS

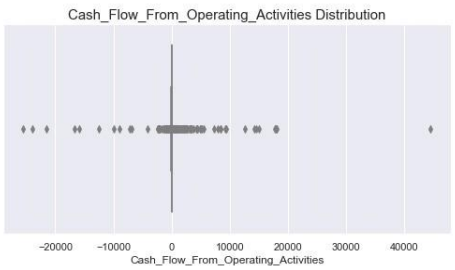

Selling_Cost Distribution
Density
Selling_Cost

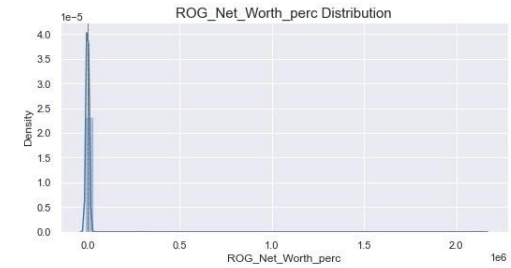

Selling_Cost Distribution
Selling_Cost

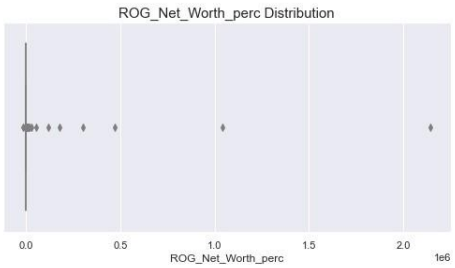

PBIDT Distribution
Density
PBIDT

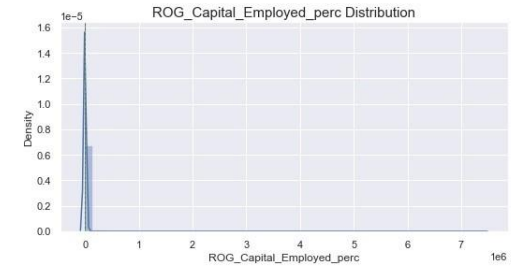

PBIDT Distribution
PBIDT

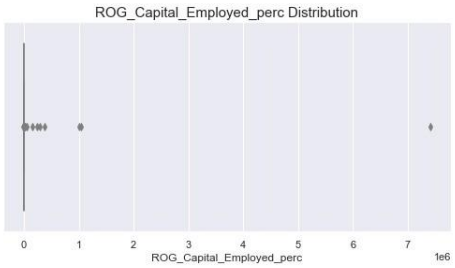

Cash_Flow_From_Operating_Activities Distribution
Density
Cash_Flow_From_Operating_Activities

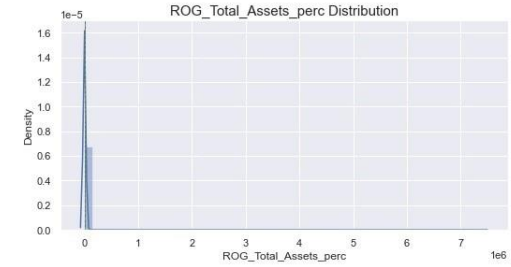

Cash_Flow_From_Operating_Activities Distribution
Cash_Flow_From_Operating_Activities

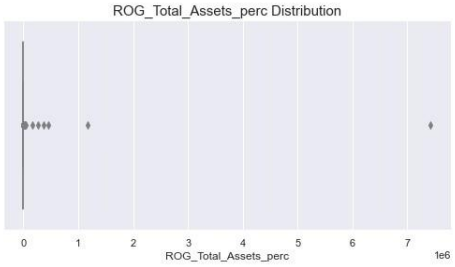

ROG_Net_Worth_perc Distribution
1e−5
Density
ROG_Net_Worth_perc
1e6

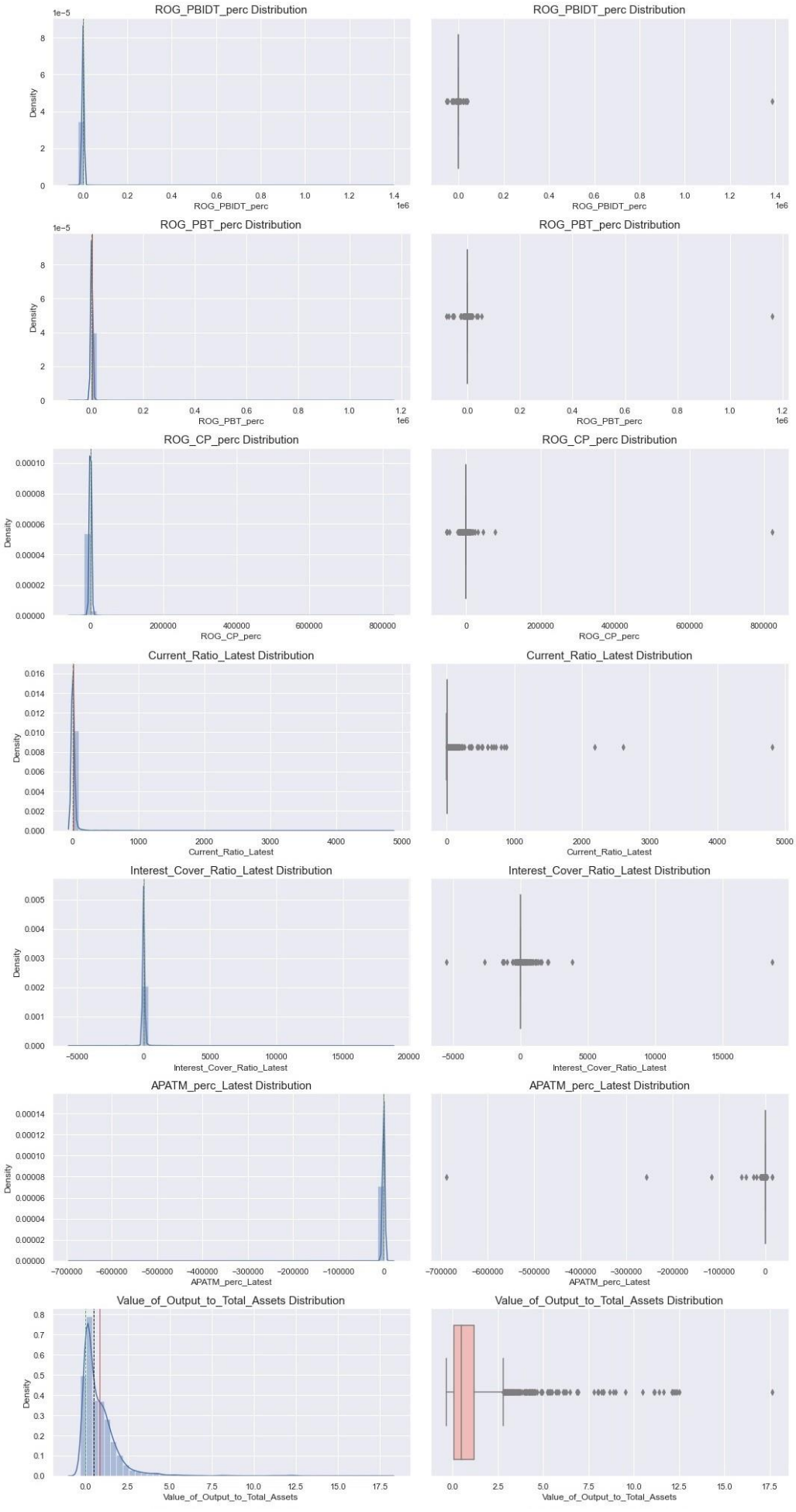

ROG_Net_Worth_perc Distribution
ROG_Net_Worth_perc
1e6


ROG_Capital_Employed_perc Distribution
1e−5
Density
ROG_Capital_Employed_perc
1e6


ROG_Capital_Employed_perc Distribution
ROG_Capital_Employed_perc
1e6


ROG_Total_Assets_perc Distribution
1e−5
Density
ROG_Total_Assets_perc
1e6


ROG_Total_Assets_perc Distribution
ROG_Total_Assets_perc
1e6


ROG_PBIDT_perc Distribution
ROG_PBIDT_perc Distribution
ROG_PBT_perc Distribution
ROG_PBT_perc Distribution
ROG_CP_perc Distribution
ROG_CP_perc Distribution
Current_Ratio_Latest Distribution
Current_Ratio_Latest Distribution
Interest_Cover_Ratio_Latest Distribution
Interest_Cover_Ratio_Latest Distribution
APATM_perc_Latest Distribution
APATM_perc_Latest Distribution
Value_of_Output_to_Total_Assets Distribution
Value_of_Output_to_Total_Assets Distribution
Density
ROG_PBIDT_perc
ROG_PBT_perc
ROG_CP_perc
Current_Ratio_Latest
Interest_Cover_Ratio_Latest
APATM_perc_Latest
Value_of_Output_to_Total_Assets
1e6
1e−5

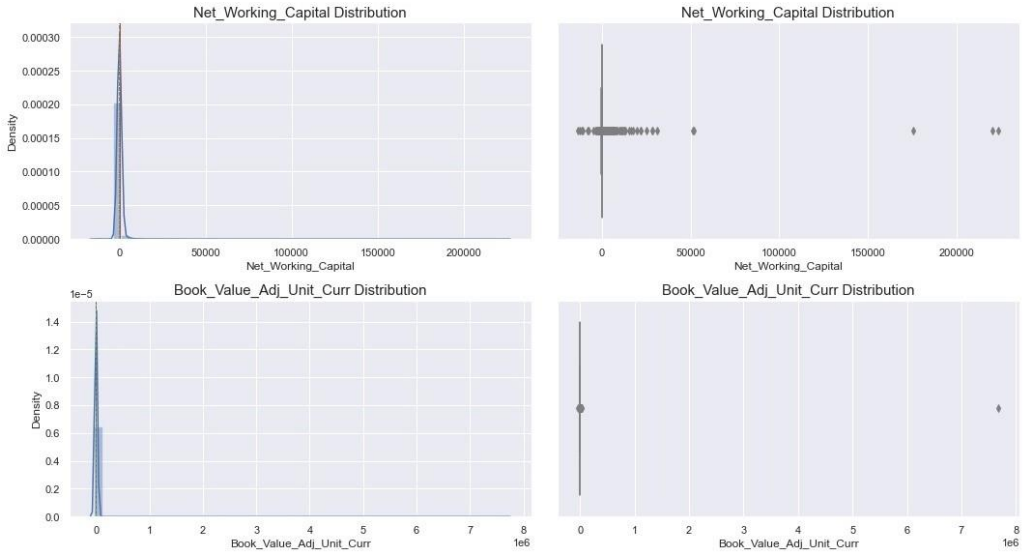


Fig 6 - Distribution of top 15 vars - Z-Scaled

- Distribution of Z-Scaled data of top 15 variables given
- Coloured vertical lines in the distribution indicate central tendencies
- Mean by Red - Median by Black - Mode by Green
- 'Selling Cost' - has max companies around its mean. They have Right Skew with outliers on higher side.
- 'PBIDT' - 'Profit before Int Depreciation and Tax' - max companies are around the mean with a prominent right skew. This indicates that there are still many companies with high PBIDT - 'Cash Flow from Operating Activities' - normal distribution with max companies lying around the mean
- 'ROG Networth', 'ROG Capital Employed', 'ROG Total Assets', 'ROG PBIDT', 'ROG PBT (Profit Before Tax)', 'ROG CP', 'Current ratio Latest', 'Interest Cover Ratio Latest', 'Value of Output to Total Assets', 'Net Working Capital', 'Book Value Adjusted' - these variables have max density of companies around its mean with right skew. This indicates outliers on the higher side.
- 'APATM (After Tax Profit Margin)' - has max density around its mean and a prominent left skew. This indicates that there are many companies have their Net Profit on the lower side of the distribution - Possible indication of default
- Largely, it is observed that there are many companies with good margin and financials before tax and all other costs. But, after costs are considered, they slide to the lower half - Shows they need to work on their costs and bottom line <u>BIVARIATE ANALYSIS</u>

- Correlation Heat-map is given below of 55 variables (after dropping vars with zeros>30%)

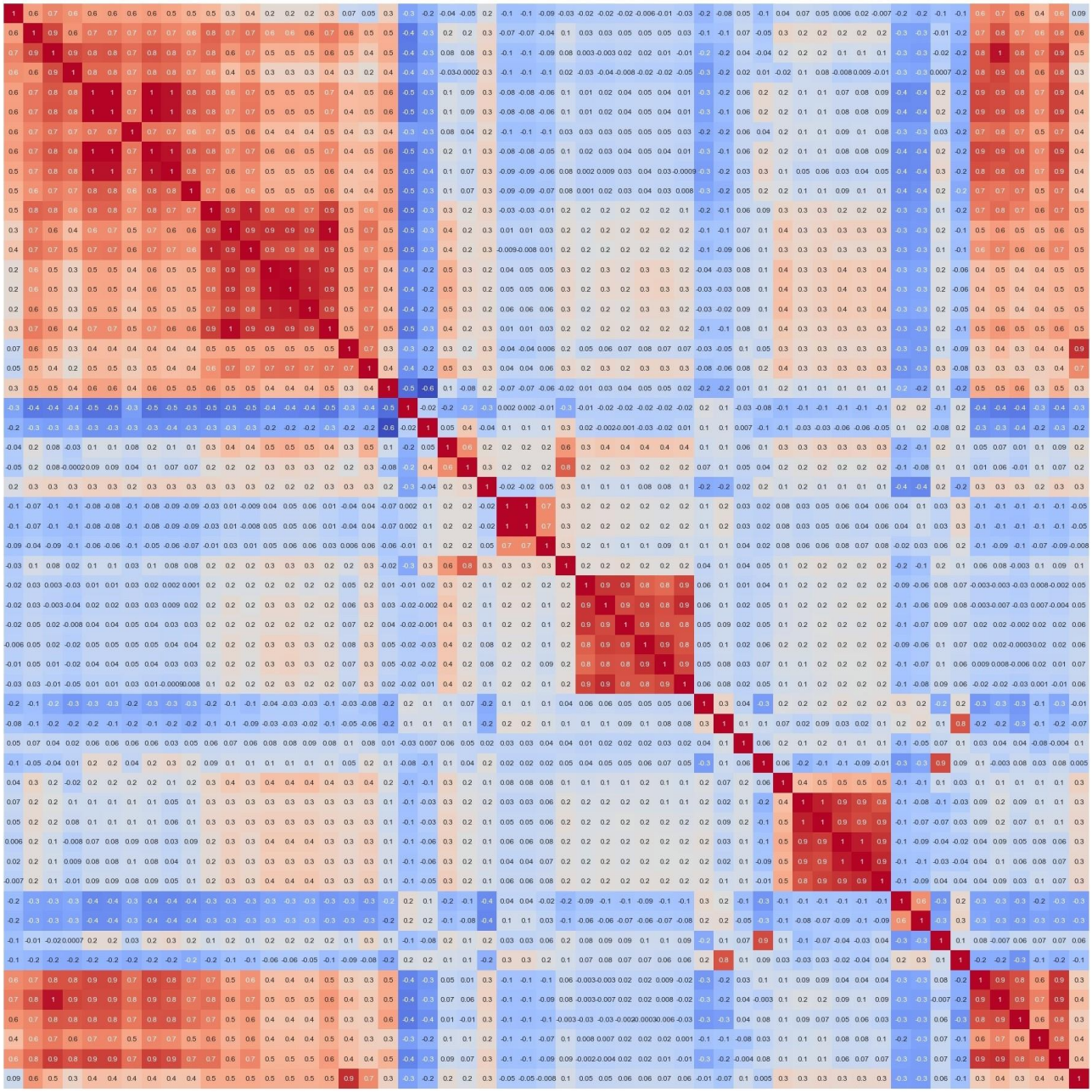


Fig 7 - Correlation Heatmap - 55 Variables

- There are a lot of red patches seen. This indicates high correlation between many variables

- Highly correlated features cause Multi-Collinearity which affect the interpretability of Logistic Regression model. They are best removed.

- We use Variance Inflation factor method and remove all variables with VIF > 5. This is done recursively, one-by-one

- Correlation heat-map of top 15 predictors and 1 Target, used to get the best model is given below-

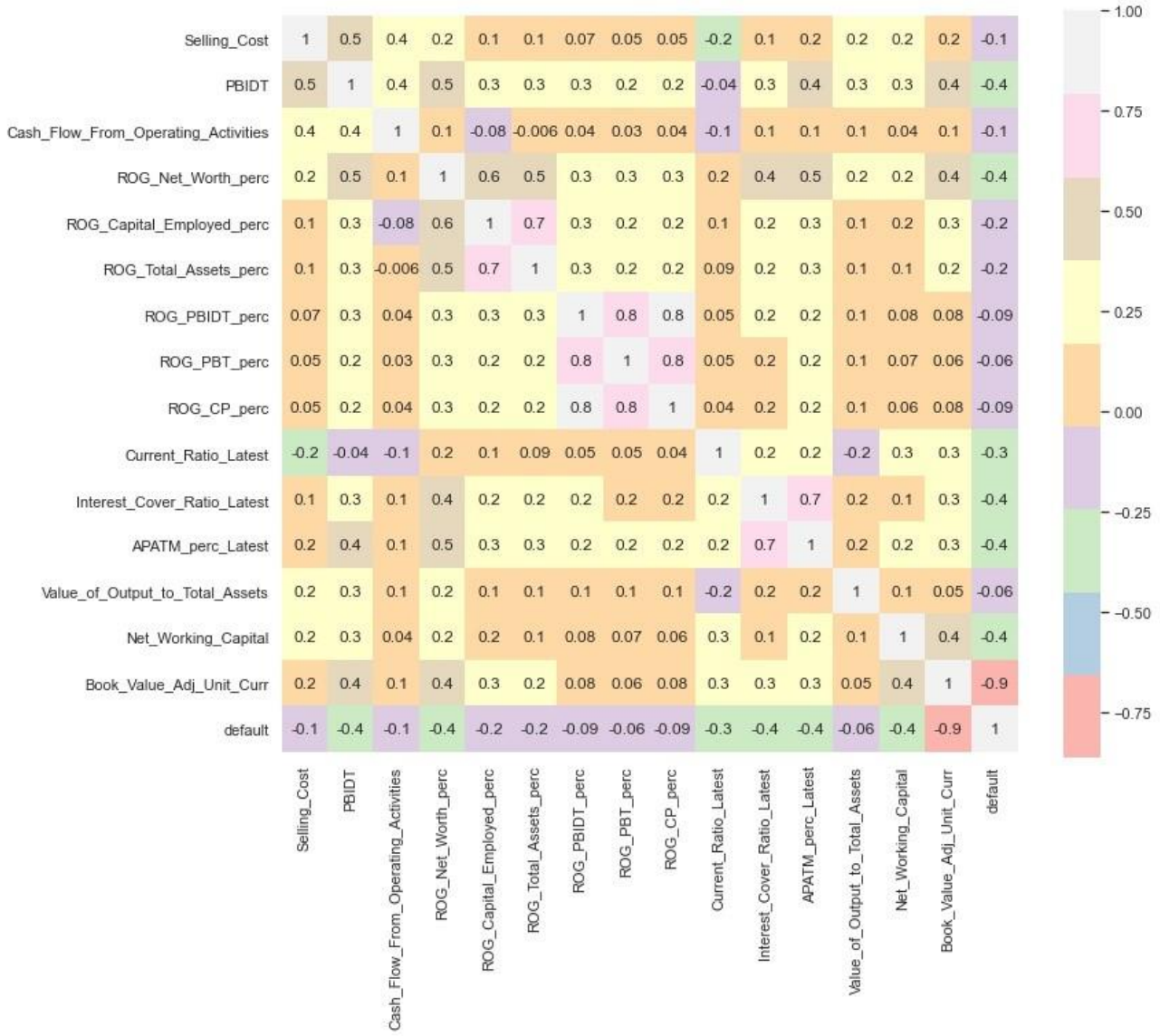


Fig 8 - Correlation Heatmap of top 15 vars

- ‘ROG-Capital Employed and ROG-Total Assets’ — ‘ROG-PBT and ROG-PBIDT’ —

‘ROG-CP and ROG-PBIDT’ — ‘ROG-CP and ROG-PBT’

- the above pairs of features show high correlation
- it looks obvious as they seem derived or direct functions of each other
- Target variable ‘default’ has high negative correlation with ‘Book Value Adj’
- this indicates as Book Value rises, Probability of Default falls

1.5 Train Test Split

- We use `train_test_split` function from scikit-learn library to split the data into train and validation sets

- We split in the ratio of 67-33 - 67% in Training Set and 33% in Testing (Validation) Set

- We seed this split at random_state=42

- So after split, Out of Total 3586 —> Train Set has 2402 observations

  Test Set has 1184 observations

1.6 Build Logistic Regression Model (using stats model library) on most important variables on Train Dataset and choose the optimum cutoff. Also showcase your model building approach

PREPROCESSING DATA FOR ALL MODELS

- We had large number of 66 predictor variables in the raw data

- 2 unique identifiers - Company Code and Name - were dropped

- There are large number of zero values in the data. We drop all variables with zeros > 30% (9 vars)

- Highly correlated features exist in the data, which cause Multi-Collinearity. This indicates existence of redundant features

- We perform Outlier treatments using IQR and Z-score methods

- We drop all features recursively one-by-one with VIF > 5 (VIF - Variance Inflation Factor)

- We are left with - 27 variables after IQR Outlier treatment

- 23 variables after Z-score treatment

LOGISTIC REGRESSION MODELS

- We build multiple Logistic Regression models with different approaches and strategies. We test each model on Test set and fine-tune to improve Recall and Precision of default=1

- We use StatsModel and SciKitLearn libraries to build and test these models
- Model 1 :
- 27 vars, IQR Outlier treated
- Model 2 :
- From 27 vars - insignificant vars dropped with p-values > 0.05 (final 10 vars)
- IQR Outlier treatment
- Model 3 :
- 23 vars, Z-score Outlier treatment
- Model 4 :
- From 23 vars - insignificant vars dropped with p-values > 0.05 (final 9 vars)
- Z-score Outlier treatment
- Model 5 :
- Above 9 vars, Z Score treatment
- Regularising the model by Hyper-parameter tuning with GridSearch over 10 folds over following -

```
{'penalty':['l2','none', 'l1'],
'solver':['lbfgs', 'liblinear', 'sag', 'saga', 'newton-cg'],
'tol':[0.0001,0.00001]}
```

- Best Parameters were found as follows -

`{'penalty': 'none', 'solver': 'lbfgs', 'tol': 0.0001}` - Model 6 :

- From 23 vars - insignificant vars dropped with p-values > 0.05 (final 9 vars)
- Z-score Outlier treatment
- Check for optimum threshold to get max Recall for default=1
- This is obtained by maximising the difference between True Positivity rate and False Positivity rate `(tpr - fpr)`
- Optimum Threshold = 0.084
- Model 7 :
- 23 vars, Z-score Outlier treatment
- Extracting top 15 features using Recursive Feature Elimination (RFE)
- Model 8 :

- 23 vars, Z-score Outlier treatment
- Extracting top 15 features using Recursive Feature Elimination (RFE)
- Balancing default labels (0s and 1s) 50-50 using Over Sampling technique - SMOTE
- This model gave the best metrics on Test Set
- StatsModel report of Model 9 given below -
- We note that 'Book_Value_Adj_Unit_Curr' has the highest negative coefficient
- suggesting that this variable has the highest negative impact on Probability of Default
- Also, 'Selling_Cost' has the highest positive coefficient
- suggesting that this variable has the highest positive impact on Probability of Default

	coef	std err	z	P>|z|	[0.025	0.975]
Other_Income	0.3180	0.101	3.145	0.002	0.120	0.516
Selling_Cost	**0.6835**	0.119	5.754	0.000	0.451	0.916
PBIDT	-0.3132	0.056	-5.553	0.000	-0.424	-0.203
ROG_Net_Worth_perc	-0.4148	0.049	-8.388	0.000	-0.512	-0.318
ROG_Capital_Employed_perc	0.4119	0.054	7.656	0.000	0.306	0.517
ROG_Gross_Block_perc	0.0368	0.047	0.790	0.429	-0.055	0.128
ROG_Total_Assets_perc	-0.2154	0.055	-3.939	0.000	-0.323	-0.108
ROG_PBIDT_perc	0.2171	0.057	3.835	0.000	0.106	0.328
ROG_CP_perc	-0.1513	0.057	-2.677	0.007	-0.262	-0.041
Current_Ratio_Latest	-0.3419	0.107	-3.199	0.001	-0.551	-0.132
Interest_Cover_Ratio_Latest	-0.3591	0.059	-6.077	0.000	-0.475	-0.243
APATM_perc_Latest	-0.2973	0.055	-5.371	0.000	-0.406	-0.189
Value_of_Output_to_Total_Assets	-0.0817	0.177	-0.461	0.645	-0.429	0.266
Value_of_Output_to_Gross_Block	0.2140	0.092	2.329	0.020	0.034	0.394

Book_Value_Adj_Unit_Curr	-1.6181	0.071	-22.933	0.000	-1.756	-1.480

Table 4 - StatsModel Summary Report of Model #8

- **Model 9 :**

- 23 vars, Z-score Outlier treatment
- Extracting top 15 features using Recursive Feature Elimination (RFE)
- Balancing default labels (0s and 1s) 50-50 using Over Sampling technique - SMOTE
- Check for optimum threshold to get max Recall for default=1
- This is obtained by maximising the difference between True Positivity rate and False Positivity rate `(tpr - fpr)`
- Optimum Threshold = 0.4246 - Model 10 :
- Z-Score Outlier treatment, Top 15 features through RFE
- Class balancing 50-50 using SMOTE
- Optimum Threshold = 0.5
- Dropping insignificant vars with p-values > 0.05

1.7 Validate the Model on Test Dataset and state the performance matrices. Also state interpretation from the model

- Performance Metrics of all models on Test Dataset is given below

MODEL NAME	RECALL FOR 1 (in %)	PRECISION FOR 1 (in %)	ACCURACY (in %)	F-1 FOR 1 (in %)
Model 1	99	23	61	38
Model 2	99	23	60	37
Model 3	88	90	97	89
Model 4	88	89	97	88
Model 5	88	89	97	88
Model 6	95	71	95	81
Model 7	87	89	97	88

Model 8	95	78	96	86
Model 9	95	75	96	84
Model 10	92	78	96	85

Table 5 - All Model Performance Comparison

	precision	recall	f1-score	support
0	0.99	0.96	0.98	1042.00
1	0.78	0.95	0.86	142.00
accuracy	0.96	0.96	0.96	0.96
macro avg	0.89	0.96	0.92	1184.00
weighted avg	0.97	0.96	0.96	1184.00

Table 6 - Classification Report of Model 8

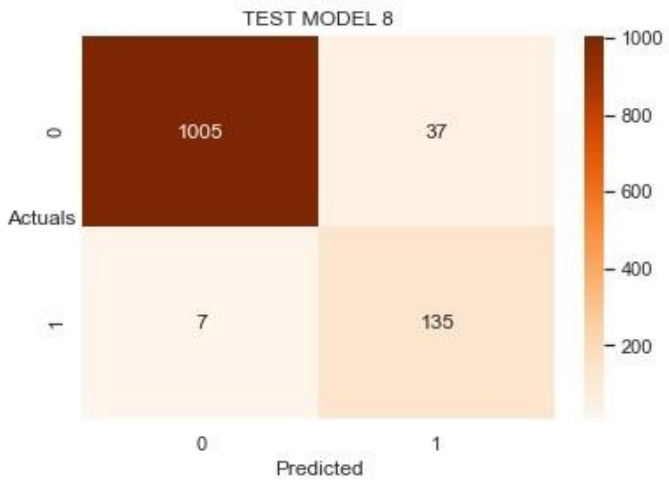


Fig 9 - Confusion Matrix of Model 8

- We have Models 1 and 2 with Best Recall of 99% but very poor Precision, hence we ignore these models
- We choose Model 8 for deployment, because of its best combination scores of Recall and Precision

INTERPRETATION

- Recall of 95% means - 95% of Actual Defaults were Predicted Correctly
- Precision of 78% means - 78% of Predicted Defaults were Actual

- For this modelling, we needed to predict as many of Actual Defaults as possible and minimise Type 2 errors foremost
- Hence Recall and then Precision were considered in choosing the best model
- In Table 4 above, coefficients of all variables indicate the weightage of that variable in predicting Default

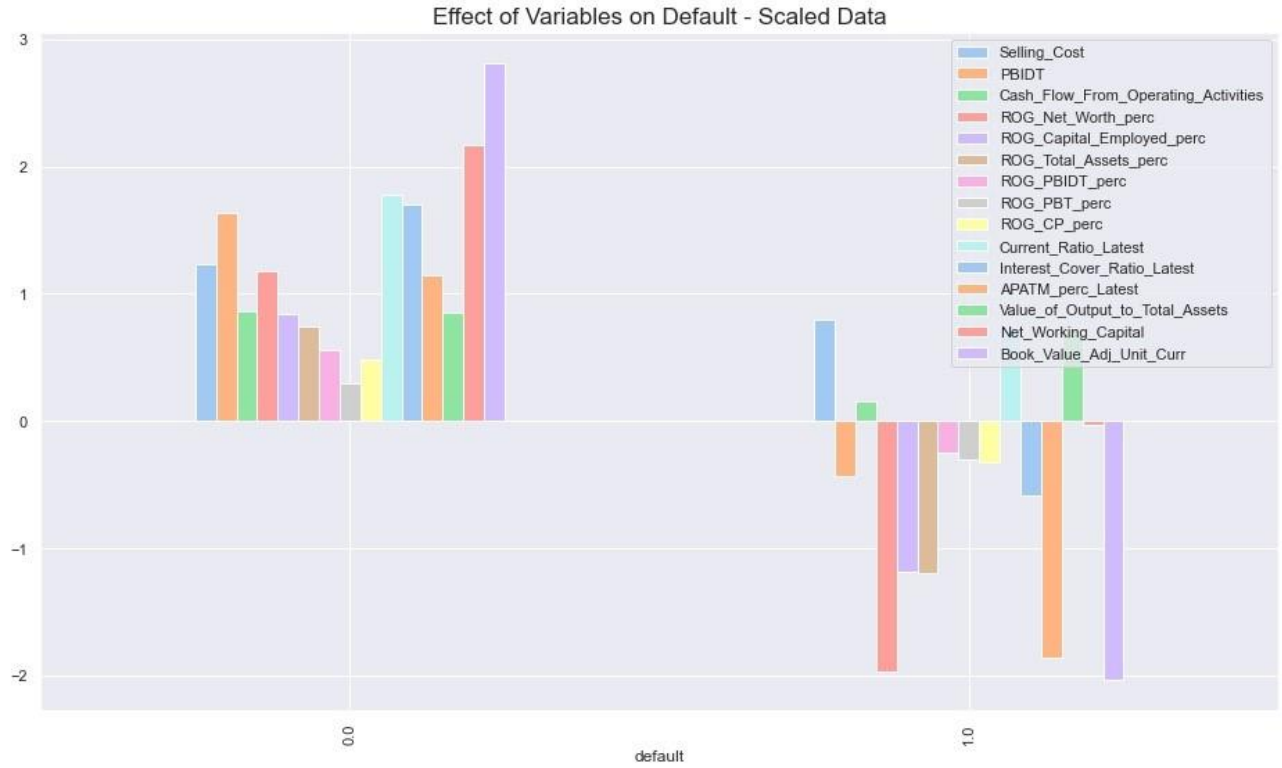


Fig 10 - Effect of Variables on Default

- Positive coefficient means, if all else is equal, then higher value of this variable will lead to higher likelihood of default
- Negative coefficient means, if all else is equal, then higher value of this variable will lead to lower likelihood of Default
- In figure 9 above, we see the effect of various features on Default
- We note that highest negative value is of - 'Book_Value_Adj_Unit_Curr'
- suggesting if all else is same, then as Book Value of a Company increases, then the Probability of Default by that Company decreases - Also, highest positive coefficient is of - 'Selling_Cost'
- suggesting if all else is same, then as Selling Cost of a Company increases, then the Probability of Default by that Company increases
- From Multi-variate Analysis, we observed that many companies had good profit margins before considering taxes, interests and other costs

- But once all costs are considered along-with taxes and depreciation, majority of these companies slide to the bottom half in Profitability
- These companies should focus on optimising their bottom line.