FRA Project(Milestone-1)

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.

Questions:

1.1 Outlier Treatment

1.2 Missing Value Treatment

1.3 Transform Target variable into 0 and 1

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

1.5 Train Test Split

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

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

Quality of Business report.(Please refer to the Evaluation Guidelines for Business report checklist. Marks in this criteria are at the moderator's discretion).

In [1]:
```
#Importing libraries

import numpy as np, pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import sklearn.metrics as metrics
```

```
color = sns.color_palette()
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
#Loading dataset
df = pd.read_excel(r'D:\SHUBHANK !\GL\12. TOPIC 11 - FRA\Milestone 1 project\Company_Da
```

In [3]:
```
#Reading dataset
df.head()
```

Out[3]:

	Co_Code	Co_Name	Networth Next Year	Equity Paid Up	Networth	Capital Employed	Total Debt	Gross Block	Net Working Capital	Current Assets
0	16974	Hind.Cables	-8021.60	419.36	-7027.48	-1007.24	5936.03	474.30	-1076.34	40.50
1	21214	Tata Tele. Mah.	-3986.19	1954.93	-2968.08	4458.20	7410.18	9070.86	-1098.88	486.86
2	14852	ABG Shipyard	-3192.58	53.84	506.86	7714.68	6944.54	1281.54	4496.25	9097.64
3	2439	GTL	-3054.51	157.30	-623.49	2353.88	2326.05	1033.69	-2612.42	1034.12
4	23505	Bharati Defence	-2967.36	50.30	-1070.83	4675.33	5740.90	1084.20	1836.23	4685.81

5 rows × 67 columns

In [4]:
```
#Renaming the columns for better readability

df.columns = ['Co_Code','Co_Name','Networth_Next_Year','Equity_Paid_Up','Networth','Cap
              'Total_Debt','Gross_Block','Net_Working_Capital','Curr_Assets','Curr_Liab
              'Gross_Sales','Net_Sales','Other_Income','Value_Of_Output','Cost_of_Prod'
              'PBIT','PBT','PAT','Adjusted_PAT','CP','Rev_earn_in_forex','Rev_exp_in_fo
              'Book_Value_Unit_Curr','Book_Value_Adj_Unit_Curr','Market_Capitalisation'
              'Cash_Flow_From_Opr','Cash_Flow_From_Inv','Cash_Flow_From_Fin','ROG_Net_W
              'ROG_Capital_Employed_perc','ROG_Gross_Block_perc','ROG_Gross_Sales_perc'
              'OG_Cost_of_Prod_perc','ROG_Total_Assets_perc','OG_PBIDT_perc','ROG_PBDT_
              'ROG_PAT_perc','ROG_CP_perc','ROG_Rev_earn_in_forex_perc','ROG_Rev_exp_in
              'ROG_Market_Capitalisation_perc','Curr_Ratio_Latest','Fixed_Assets_Ratio_
              'Debtors_Ratio_Latest','Total_Asset_Turnover_Ratio_Latest','Interest_Cove
              'PBITM_perc_Latest','PBDTM_perc_Latest','CPM_perc_Latest','APATM_perc_Lat
              'Creditors_Vel_Days','Inventory_Vel_Days','Value_of_Output_to_Total_Asset
```

In [5]:
```
#Checking Shape
df.shape
```

Out[5]:
```
(3586, 67)
```

In [6]:
```
#Checking Size
df.size
```

Out[6]:
```
240262
```

In [7]:
```
#Checking the duplicates

dups = df.duplicated()
print('Number of duplicate rows = %d' % (dups.sum()))
```

```
Number of duplicate rows = 0
```

In [8]:
```
#Checking the basic info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3586 entries, 0 to 3585
Data columns (total 67 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   Curr_Assets                     3586 non-null   float64
 10  Curr_Liab_and_Prov              3586 non-null   float64
 11  Total_Assets_to_Liab            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_Prod                    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  Rev_earn_in_forex               3586 non-null   float64
 26  Rev_exp_in_forex                3586 non-null   float64
 27  Capital_exp_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_Opr              3586 non-null   float64
 33  Cash_Flow_From_Inv              3586 non-null   float64
 34  Cash_Flow_From_Fin              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  OG_Cost_of_Prod_perc               3586 non-null   float64
 41  ROG_Total_Assets_perc              3586 non-null   float64
 42  OG_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_Rev_earn_in_forex_perc         3586 non-null   float64
 49  ROG_Rev_exp_in_forex_perc          3586 non-null   float64
 50  ROG_Market_Capitalisation_perc     3586 non-null   float64
 51  Curr_Ratio_Latest                  3585 non-null   float64
 52  Fixed_Assets_Ratio_Latest          3585 non-null   float64
 53  Inventory_Ratio_Latest             3585 non-null   float64
 54  Debtors_Ratio_Latest               3585 non-null   float64
 55  Total_Asset_Turnover_Ratio_Latest  3585 non-null   float64
 56  Interest_Cover_Ratio_Latest        3585 non-null   float64
 57  PBIDTM_perc_Latest                 3585 non-null   float64
 58  PBITM_perc_Latest                  3585 non-null   float64
 59  PBDTM_perc_Latest                  3585 non-null   float64
 60  CPM_perc_Latest                    3585 non-null   float64
 61  APATM_perc_Latest                  3585 non-null   float64
 62  Debtors_Vel_Days                   3586 non-null   int64
 63  Creditors_Vel_Days                 3586 non-null   int64
 64  Inventory_Vel_Days                 3483 non-null   float64
 65  Value_of_Output_to_Total_Assets    3586 non-null   float64
 66  Value_of_Output_to_Gross_Block     3586 non-null   float64
dtypes: float64(63), int64(3), object(1)
memory usage: 1.8+ MB
```

In [9]:

```
#Dropping the company code column (Co_Code) because that is not very useful for our ana

df.drop(['Co_Code','Co_Name'], axis = 1, inplace = True)

#Checking the df.describe

pd.set_option('display.float_format', lambda x: '%.2f' % x) #Keeping the decimal points

df.describe()
```

Out[9]:

	Networth_Next_Year	Equity_Paid_Up	Networth	Capital_Employed	Total_Debt	Gross_Block	Net_
count	3586.00	3586.00	3586.00	3586.00	3586.00	3586.00	
mean	725.05	62.97	649.75	2799.61	1994.82	594.18	
std	4769.68	778.76	4091.99	26975.14	23652.84	4871.55	
min	-8021.60	0.00	-7027.48	-1824.75	-0.72	-41.19	
25%	3.98	3.75	3.89	7.60	0.03	0.57	
50%	19.02	8.29	18.58	39.09	7.49	15.87	
75%	123.80	19.52	117.30	226.60	72.35	131.90	
max	111729.10	42263.46	81657.35	714001.25	652823.81	128477.59	

8 rows × 65 columns

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.

In [10]:
```
#Creating a 'Default' Variable with the below conditions

#Creating a list of our conditions:

conditions = [(df['Networth_Next_Year'] < 0), (df['Networth_Next_Year'] > 0)]

#Creating a list of the values that we have to assign for each condition
values = ['1', '0']

#Now, Creating a new column named 'Default'
#Using np.select to assign values to this new variable using the lists (conditions and

df['Default'] = np.select(conditions, values)
```

In [81]:
```
#Let's look at the head after created the default variable.

df[['Networth_Next_Year','Default']].head()
```

Out[81]:

	Networth_Next_Year	Default
0	-8021.60	1
1	-3986.19	1
2	-3192.58	1
3	-3054.51	1
4	-2967.36	1

In [82]:
```
#Let's look at the tail after created the default variable.

df[['Networth_Next_Year','Default']].tail()
```

Out[82]:

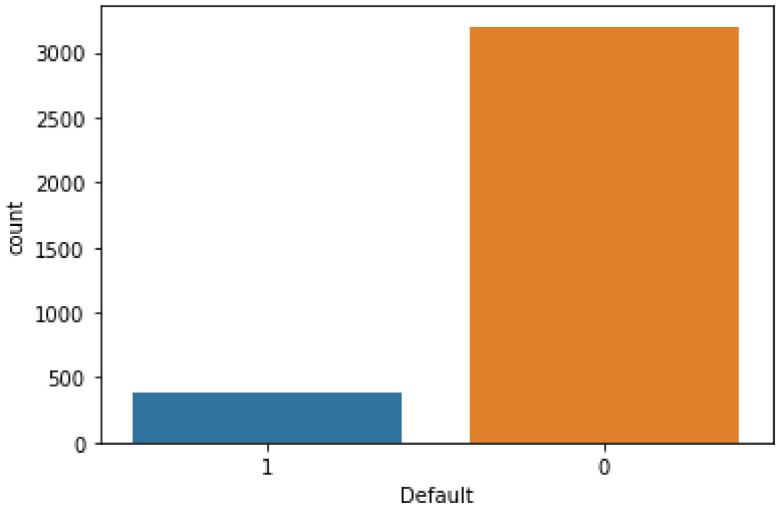
	Networth_Next_Year	Default
3581	72677.77	0
3582	79162.19	0
3583	88134.31	0
3584	91293.70	0
3585	111729.10	0

In [11]:
```
df['Default'].value_counts()
```

Out[11]:
```
0    3199
1     387
```

```
Name: Default, dtype: int64
```

In [12]:
```
ax = sns.countplot(x="Default", data=df)
```



In [13]:
```
df_x = df.drop('Default', axis =1)
df_y = df['Default']
```

In [14]:
```
df_x.head()
```

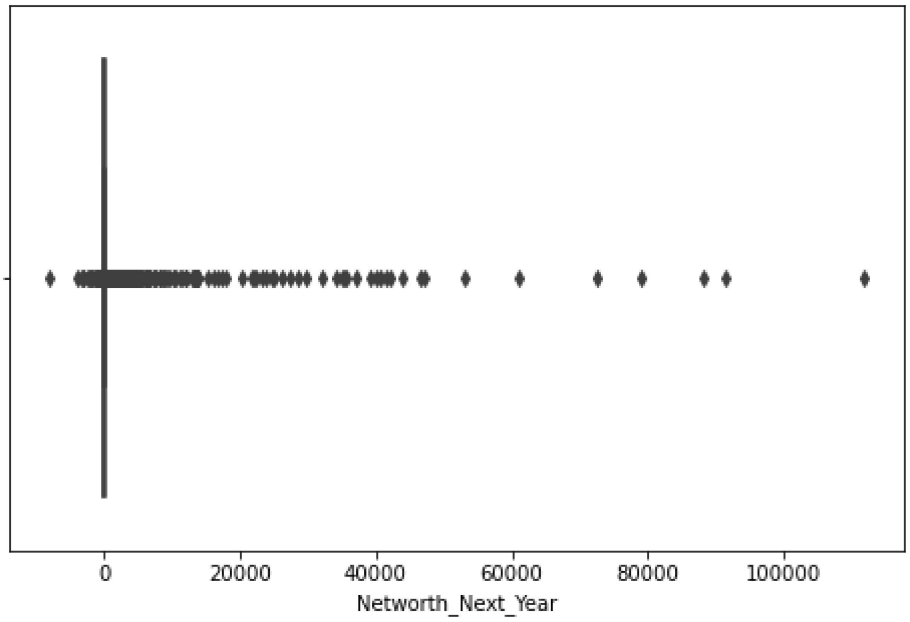
Out[14]:

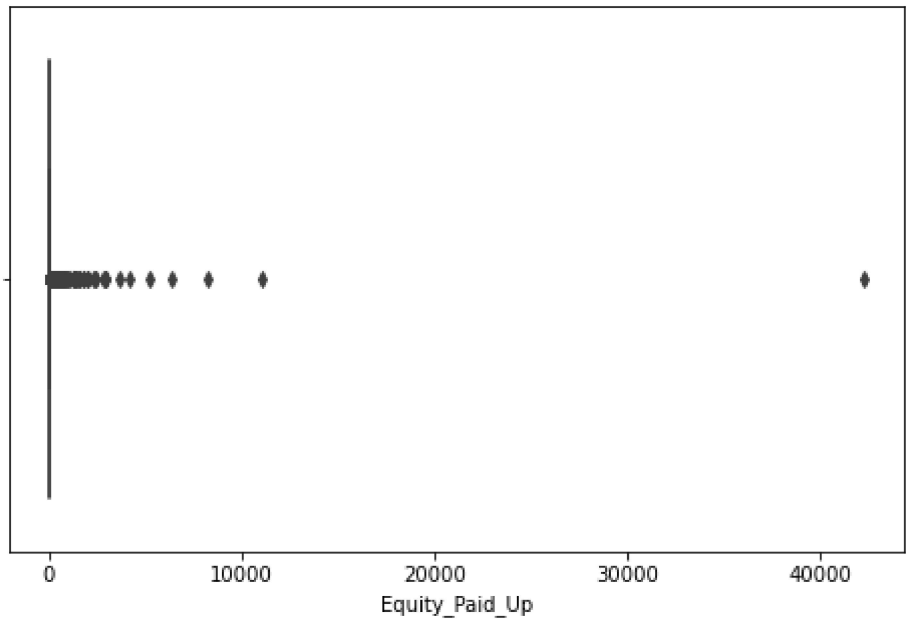
	Networth_Next_Year	Equity_Paid_Up	Networth	Capital_Employed	Total_Debt	Gross_Block	Net_Wor
0	-8021.60	419.36	-7027.48	-1007.24	5936.03	474.30	
1	-3986.19	1954.93	-2968.08	4458.20	7410.18	9070.86	
2	-3192.58	53.84	506.86	7714.68	6944.54	1281.54	
3	-3054.51	157.30	-623.49	2353.88	2326.05	1033.69	
4	-2967.36	50.30	-1070.83	4675.33	5740.90	1084.20	

5 rows × 65 columns

In [15]:
```
#Checking outliers

for x in df_x.columns:
    plt.figure(figsize=(8,5))
    sns.boxplot(df[x])
    plt.show()
```


0
20000
40000
60000
80000
100000
Networth_Next_Year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30000
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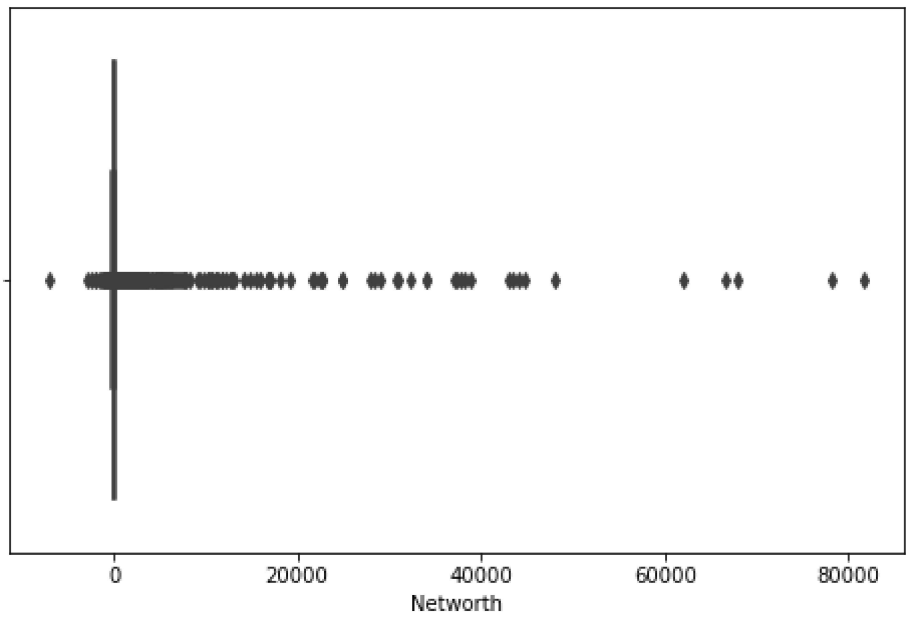
Equity_Paid_Up


0
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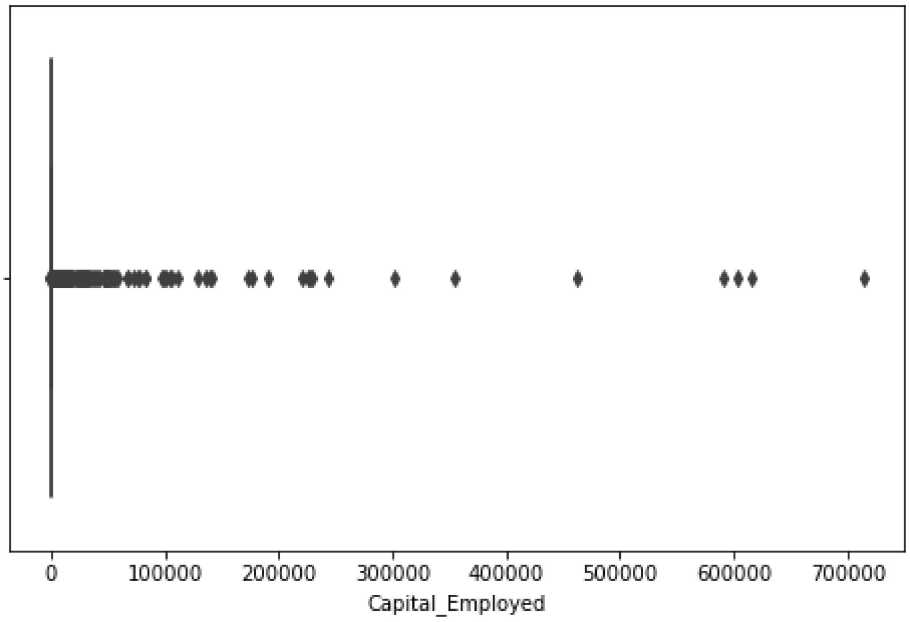
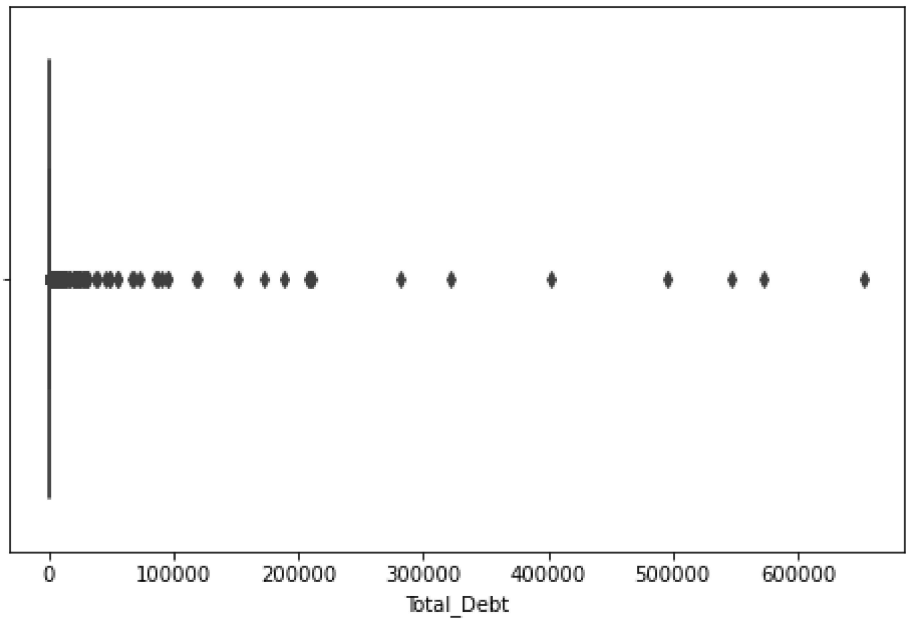
40000
60000
80000
Networth


0
100000
200000
300000
400000
500000
600000
700000
Capital_Employed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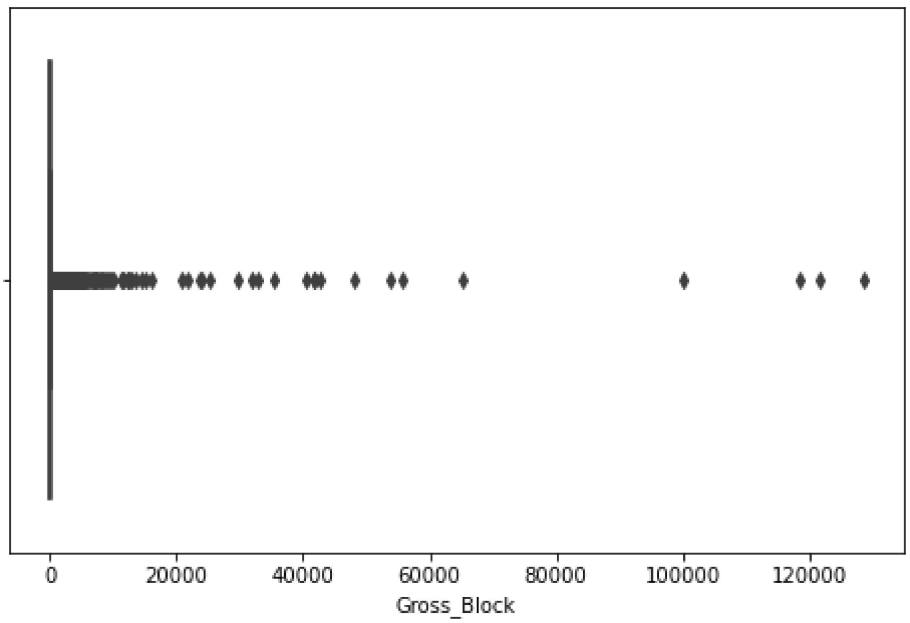
500000
600000
Total_Debt


0
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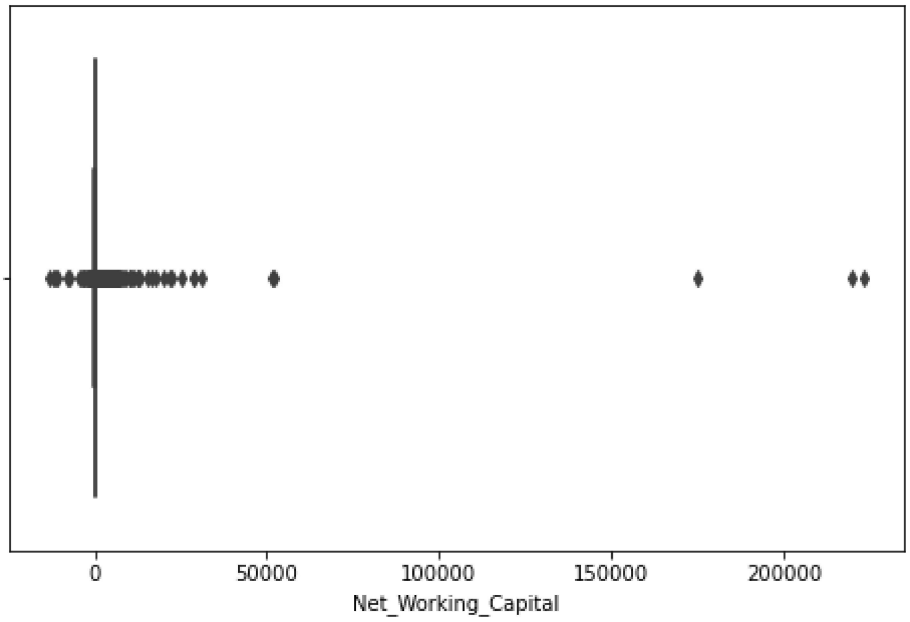
80000
100000
120000
Gross_Block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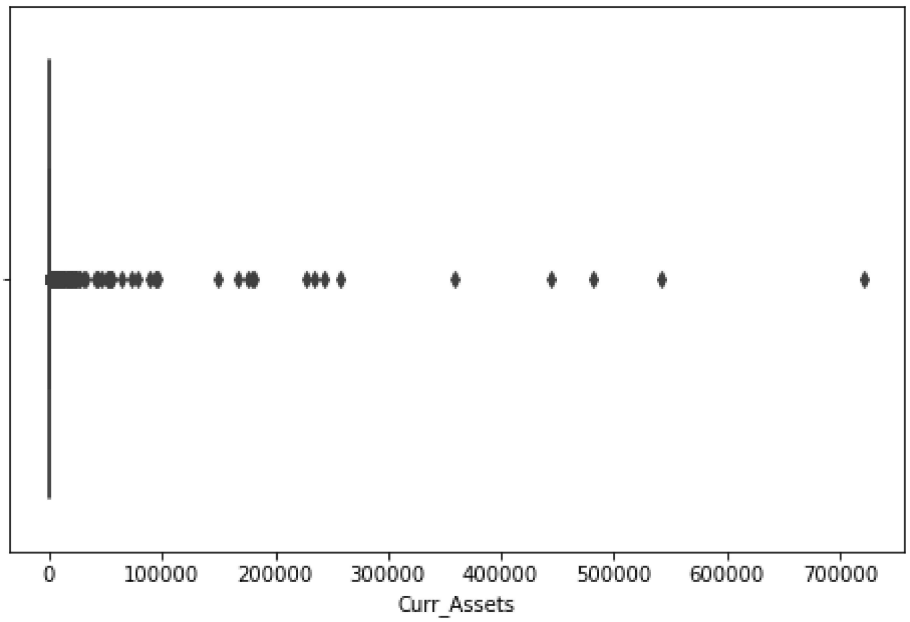
200000
Net_Working_Capital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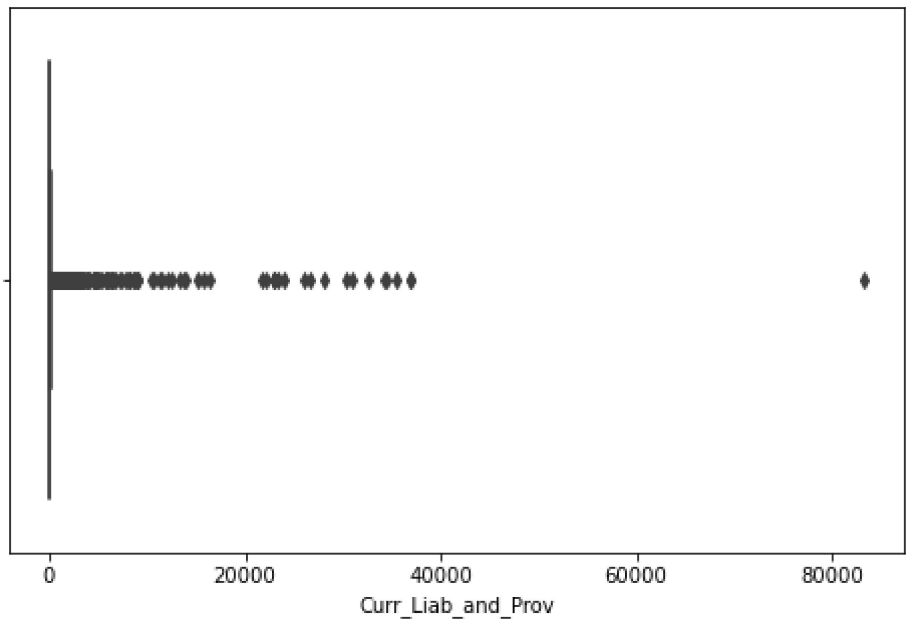
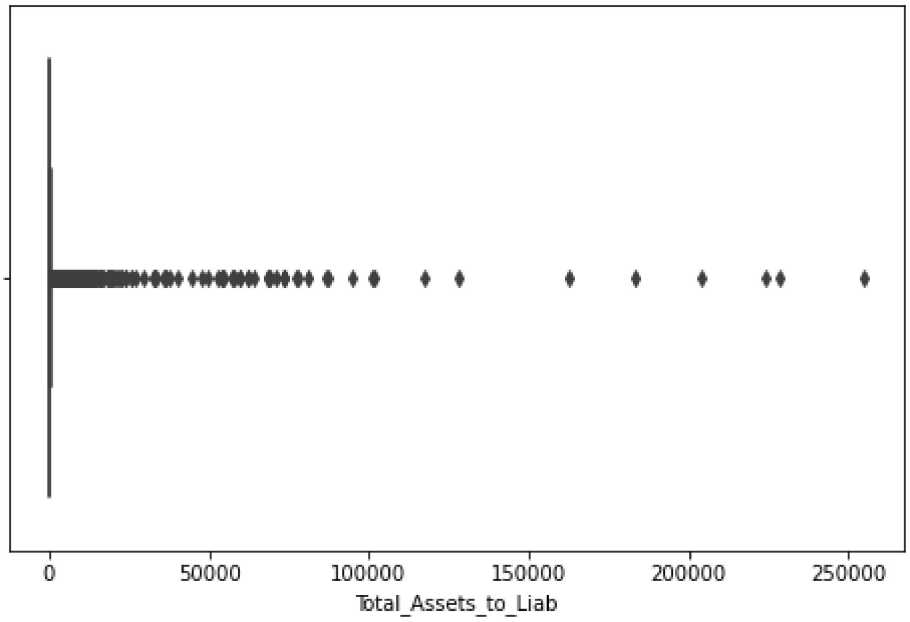
500000
600000
700000
Curr_Assets


0
20000
40000
60000
80000
Curr_Liab_and_Prov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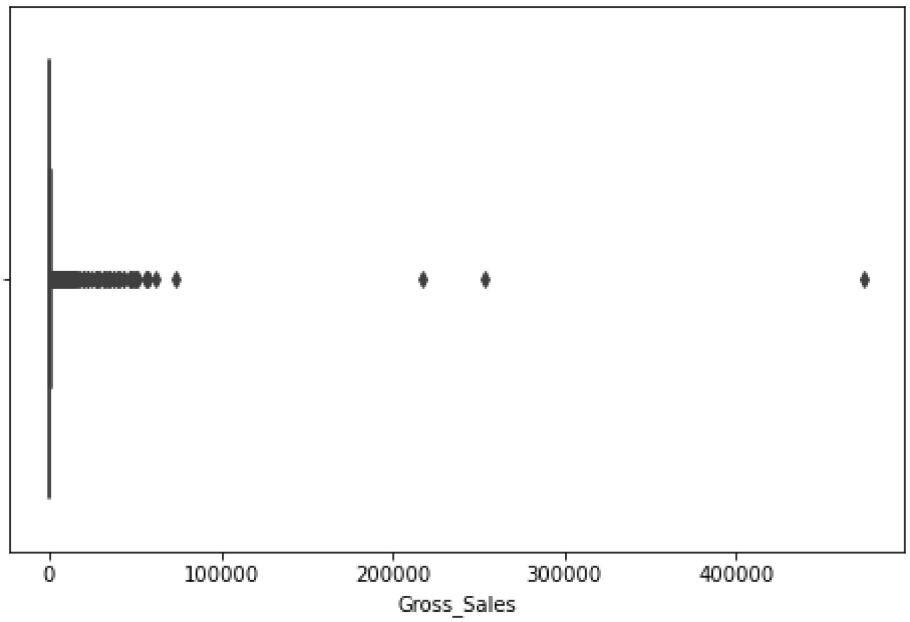
Total_Assets_to_Liab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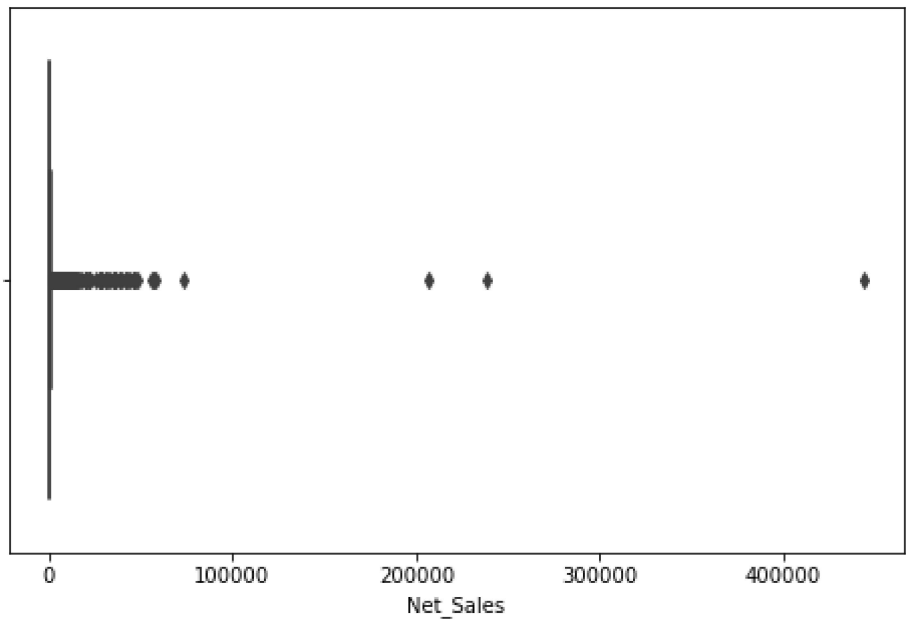
Gross_Sales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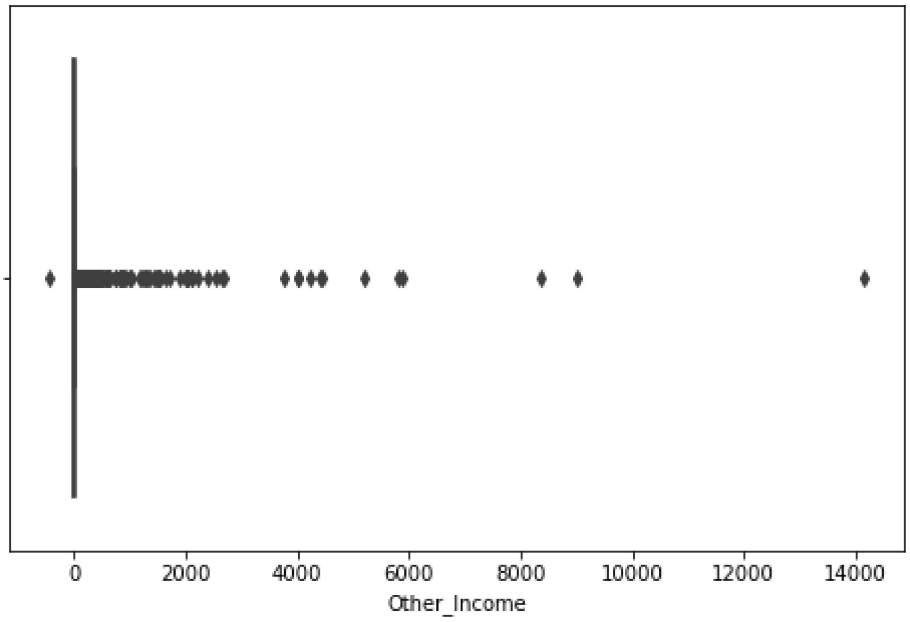
Net_Sales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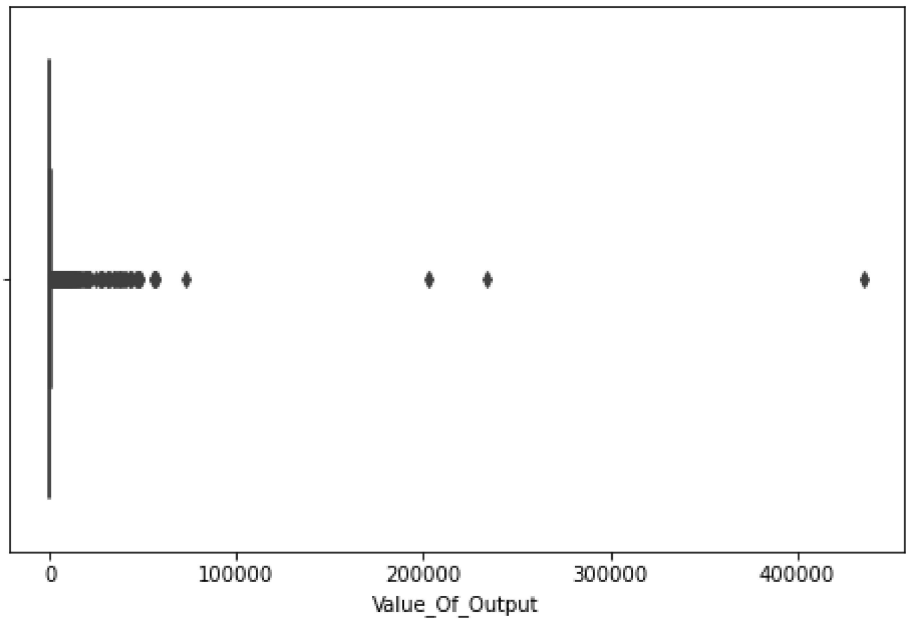
14000
Other_Income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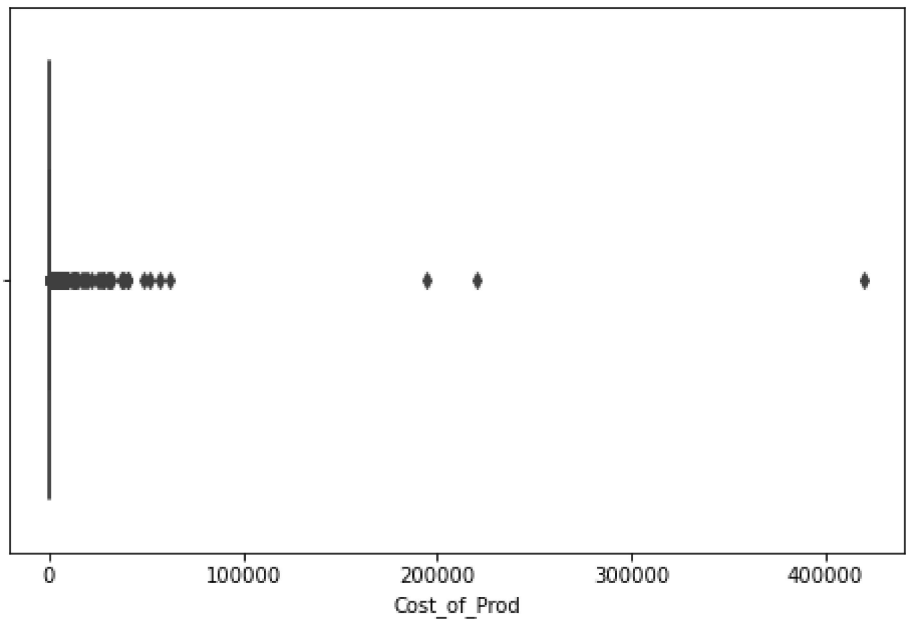
Value_Of_Output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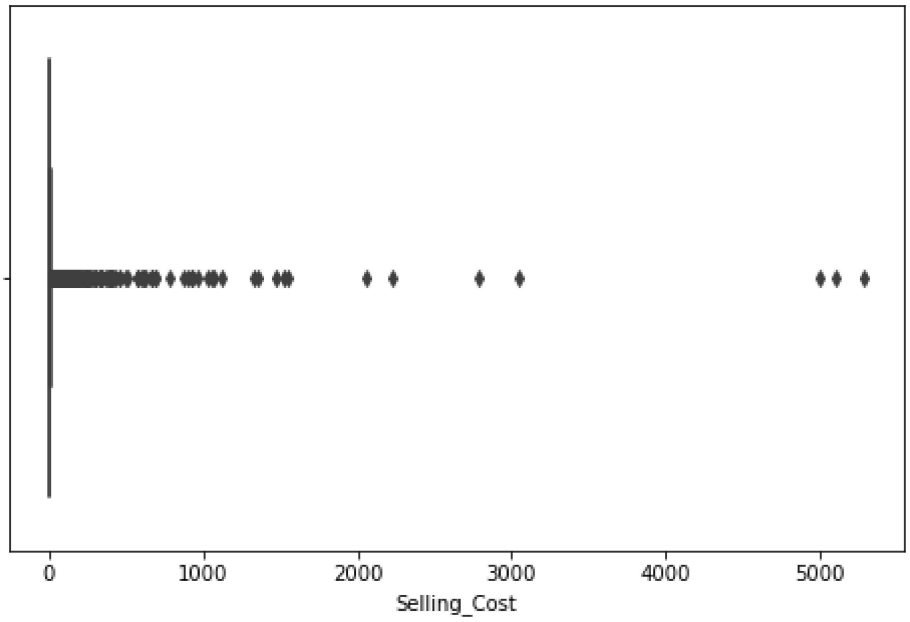
Cost_of_Prod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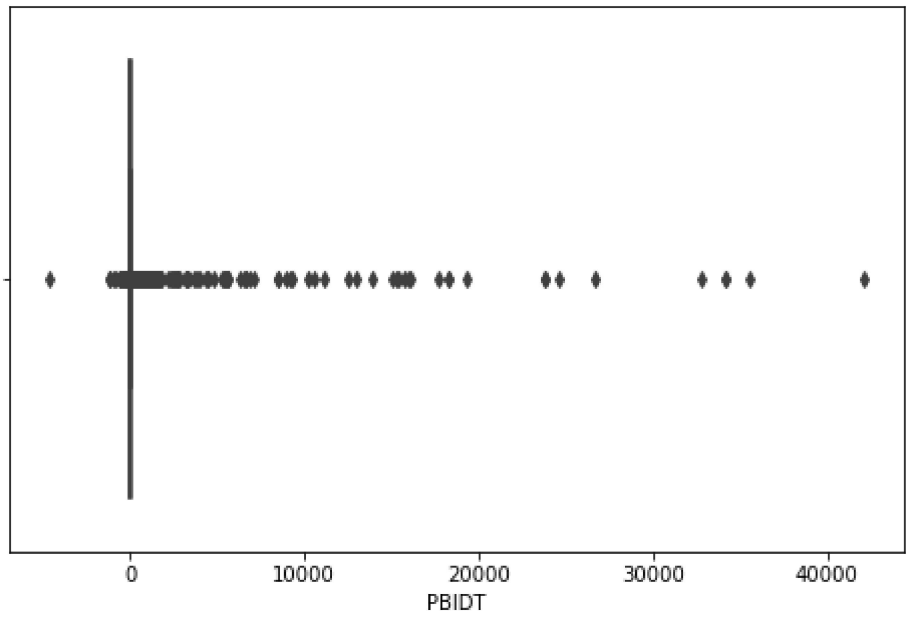
Selling_Cost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30000
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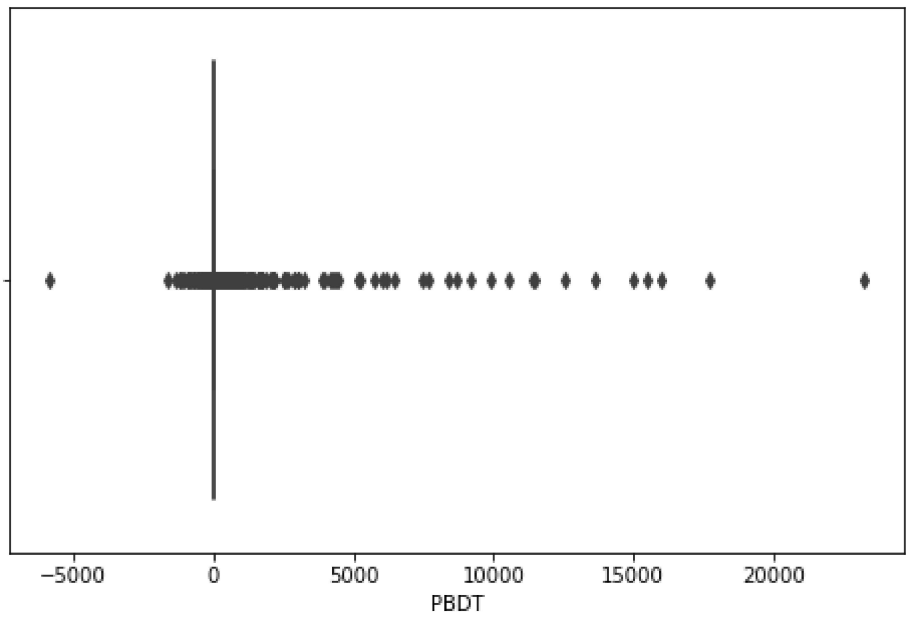
PBIDT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0
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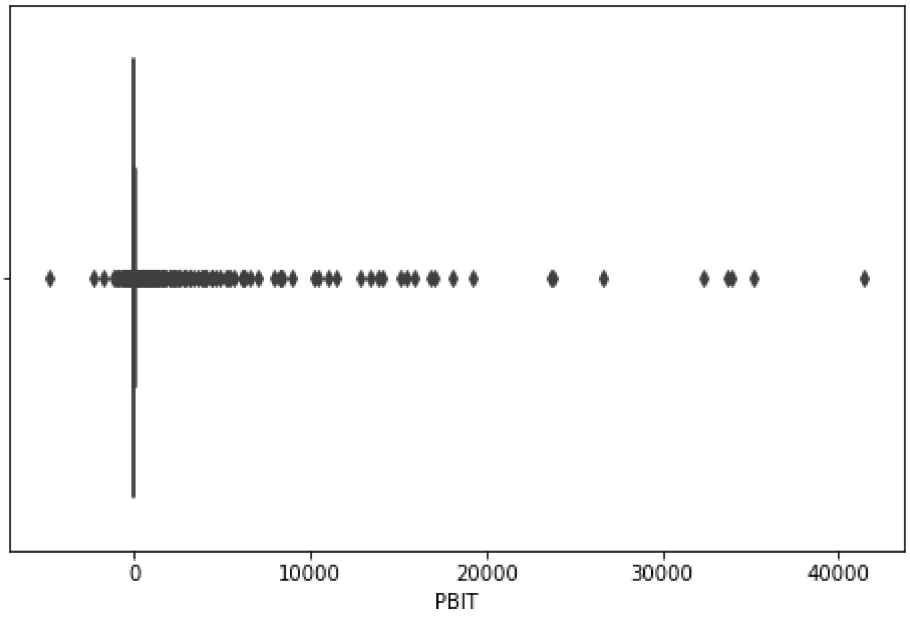
10000
15000
20000
PBDT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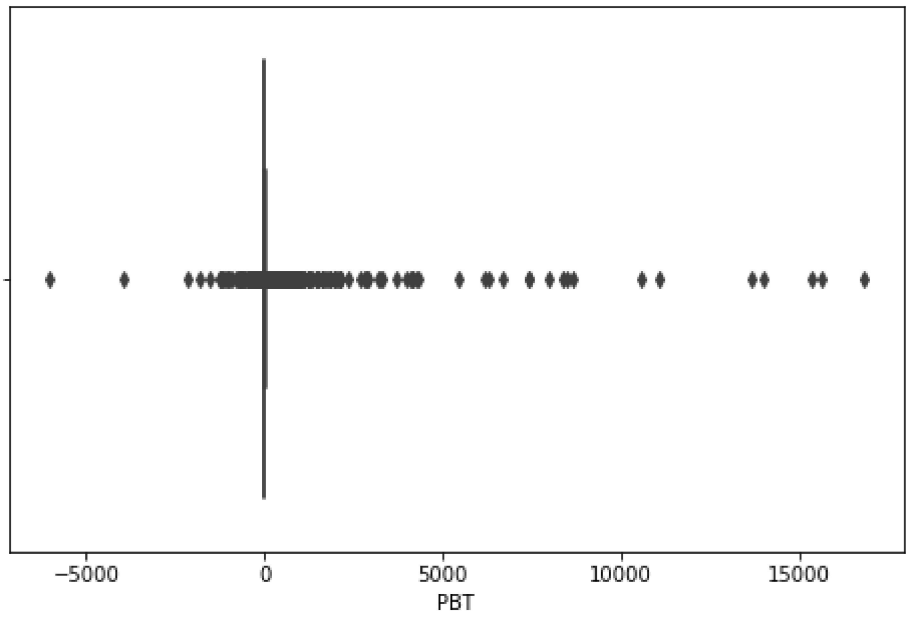
10000
20000
30000
40000
PBIT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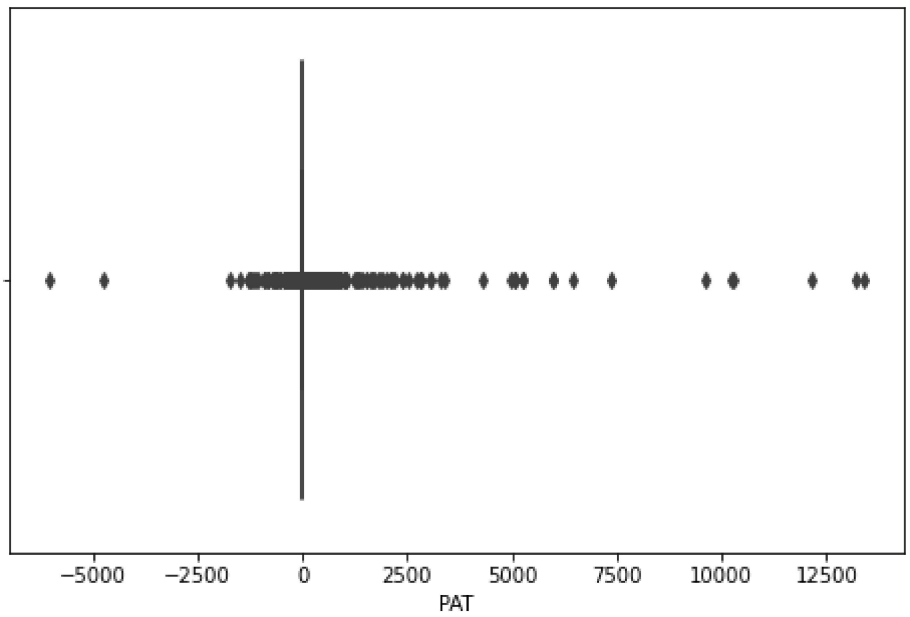
5000
10000
15000
PBT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−2500
0
2500
5000
7500
10000
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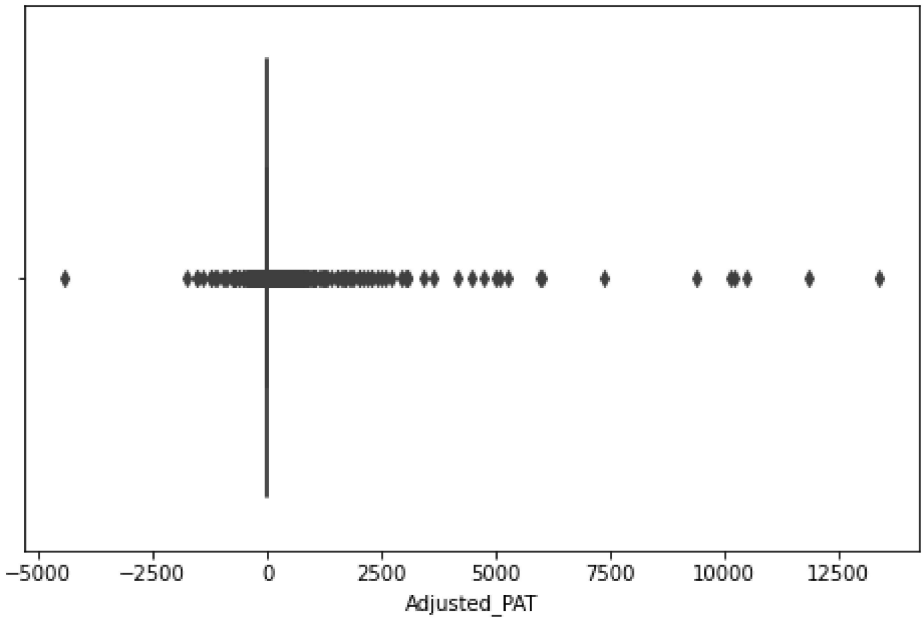
PAT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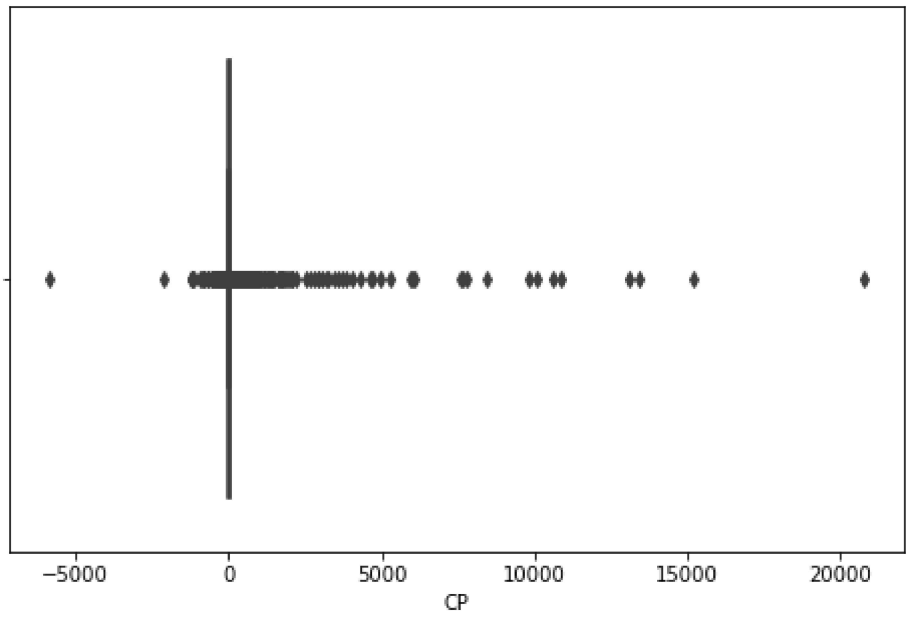
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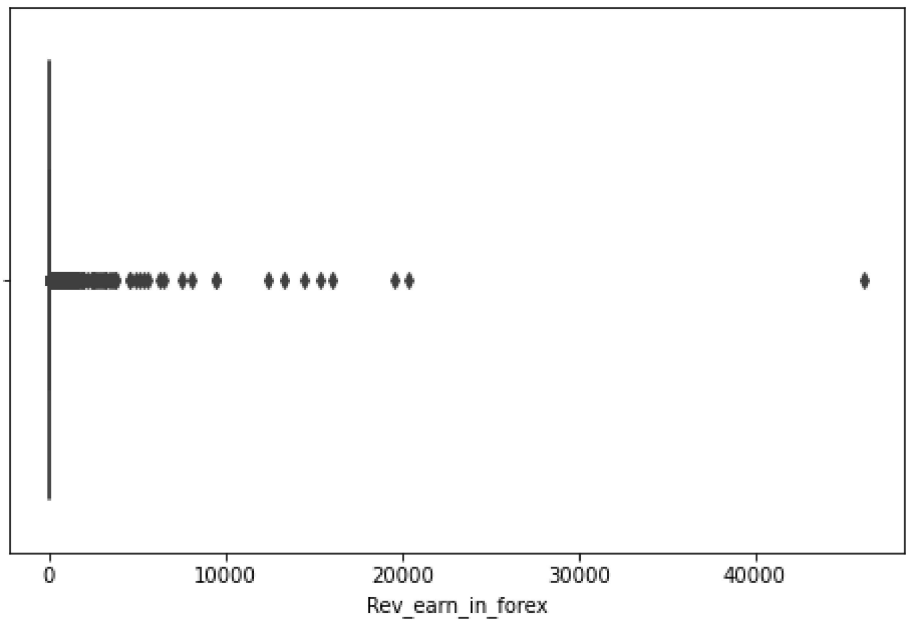
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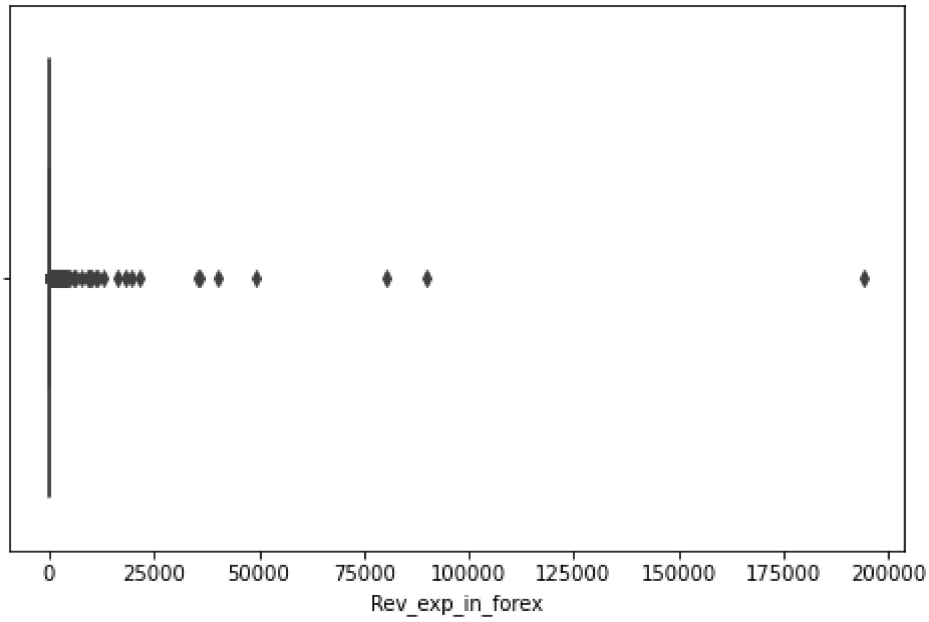
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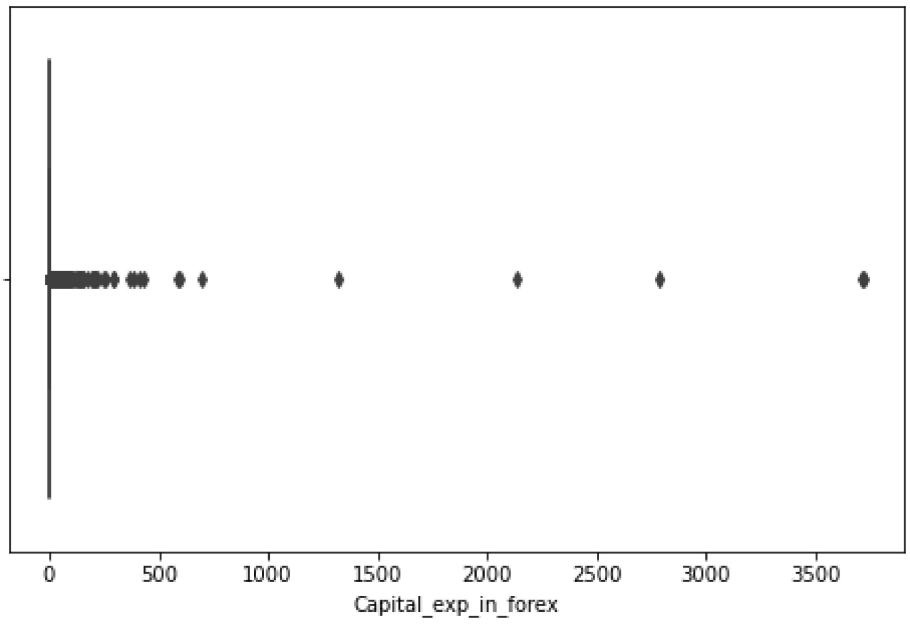
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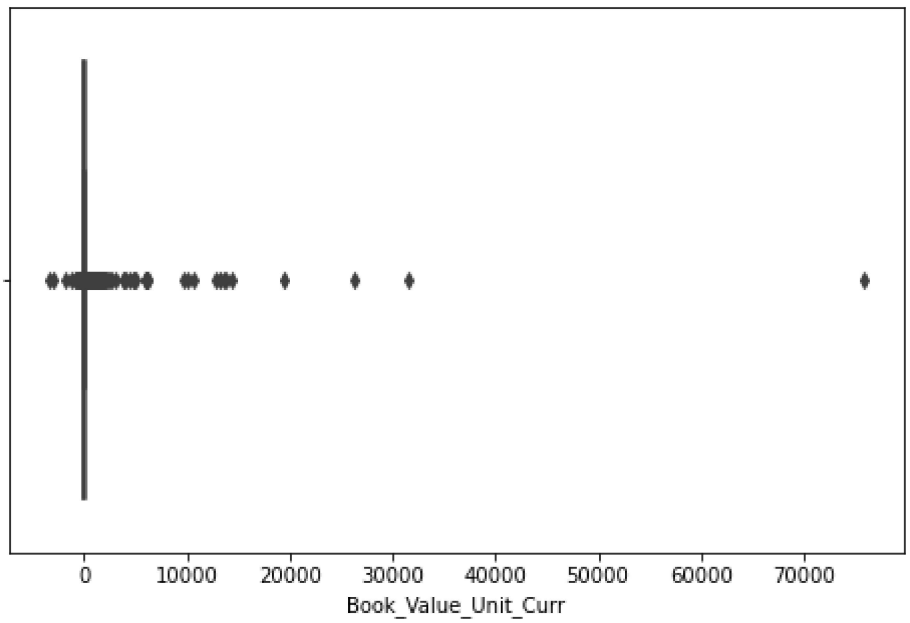
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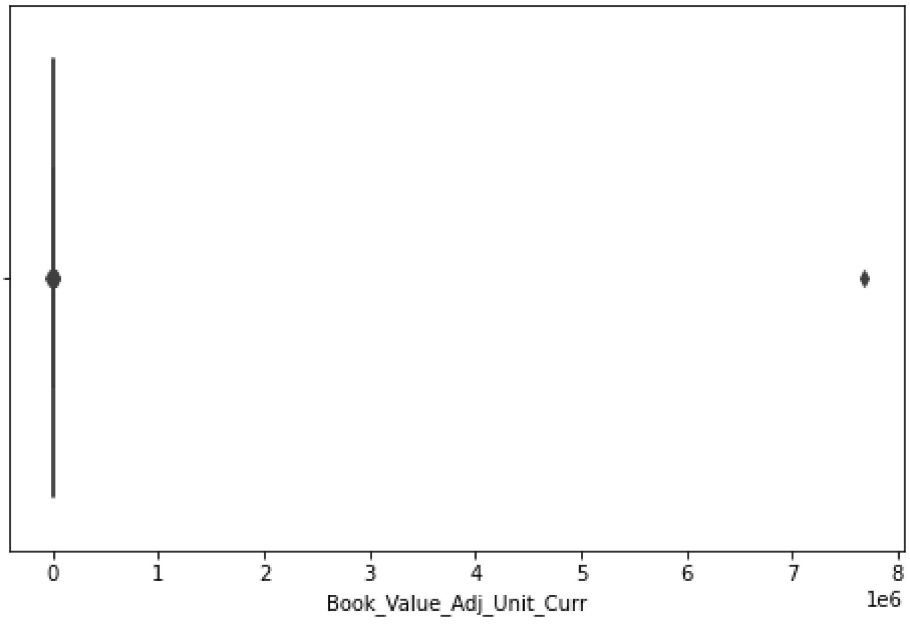
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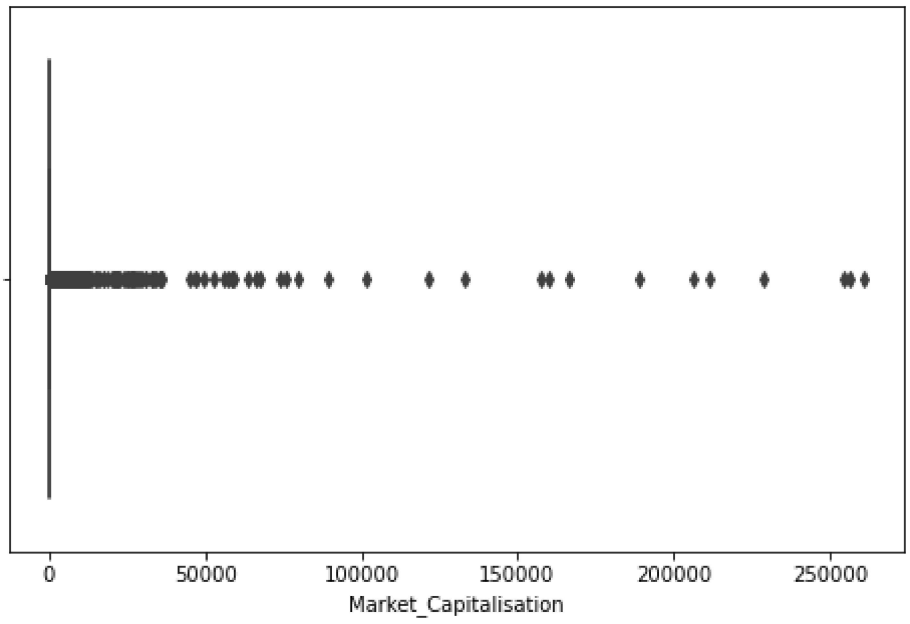
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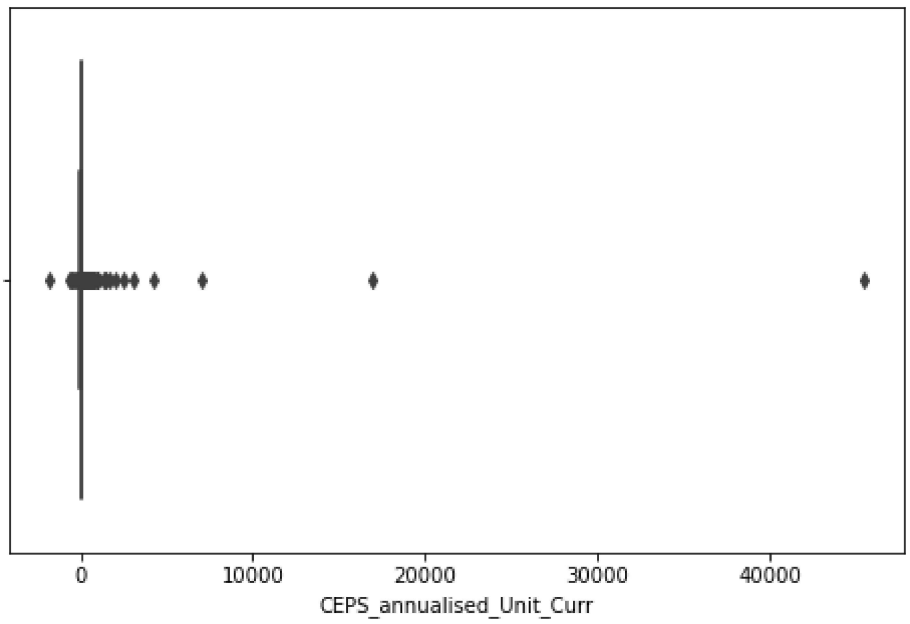
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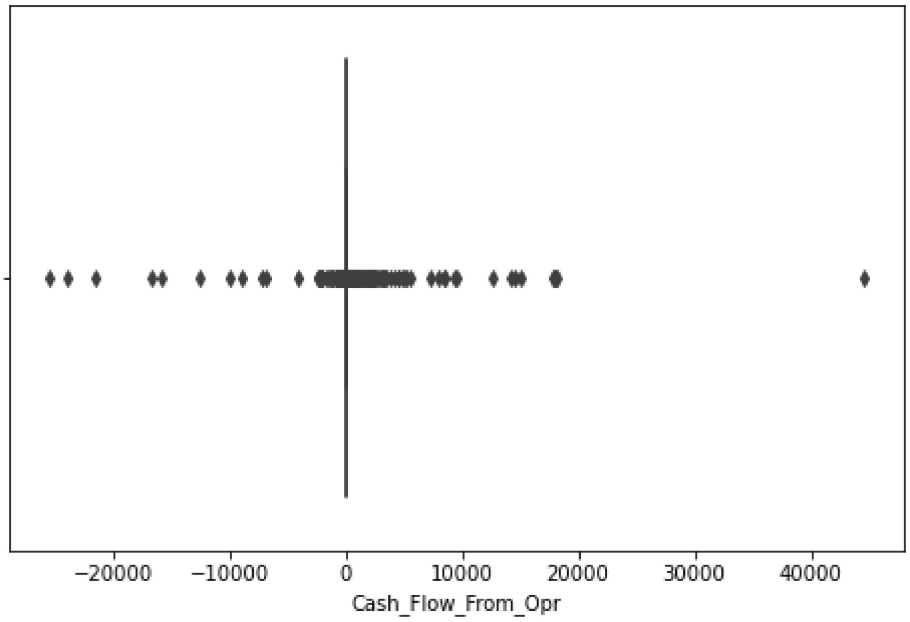
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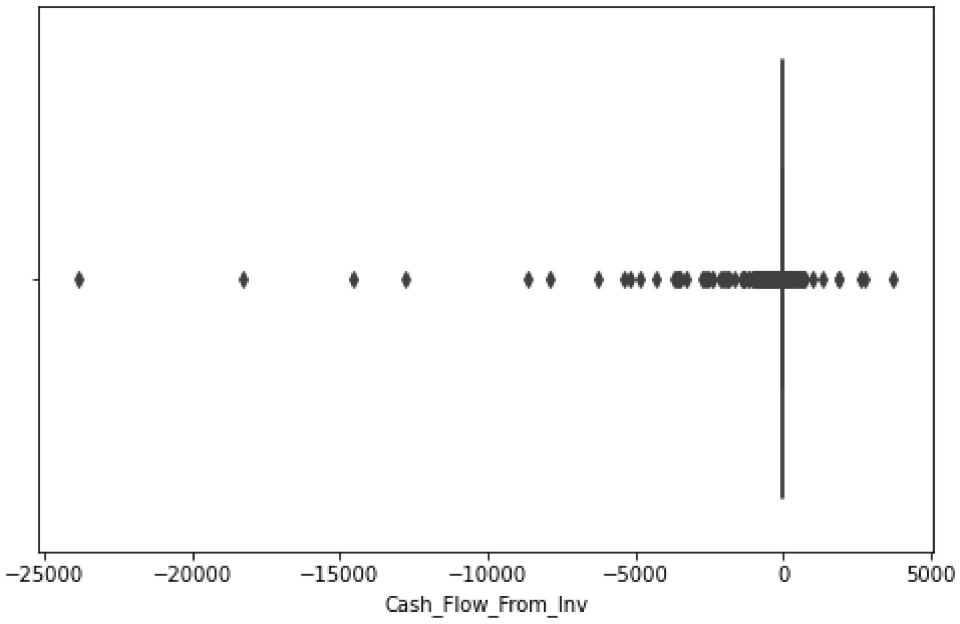
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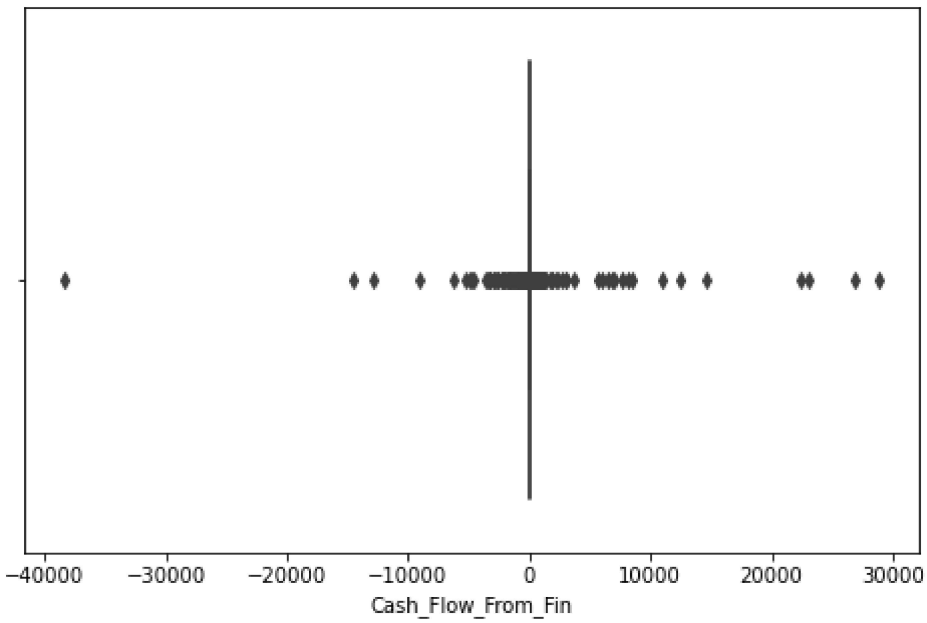
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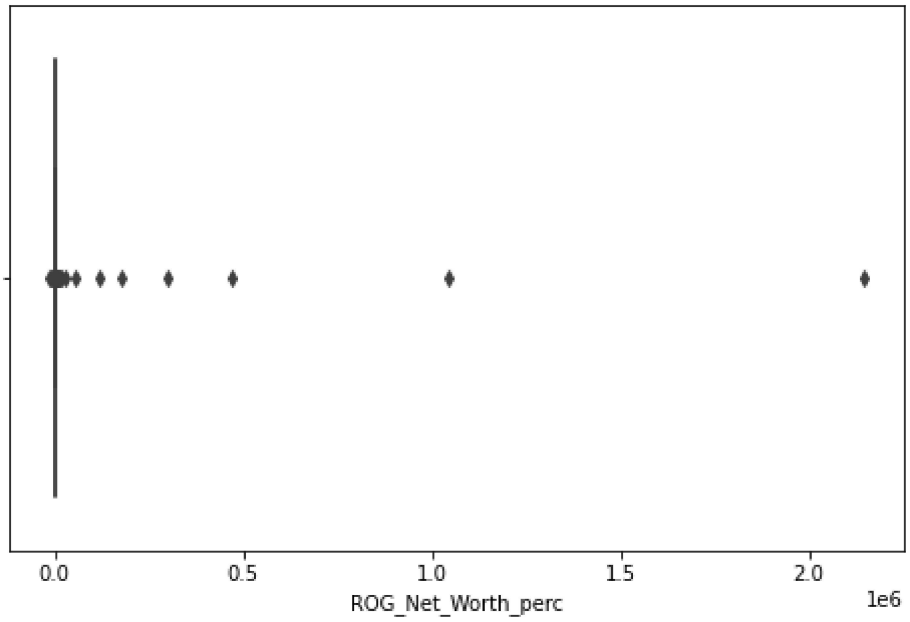
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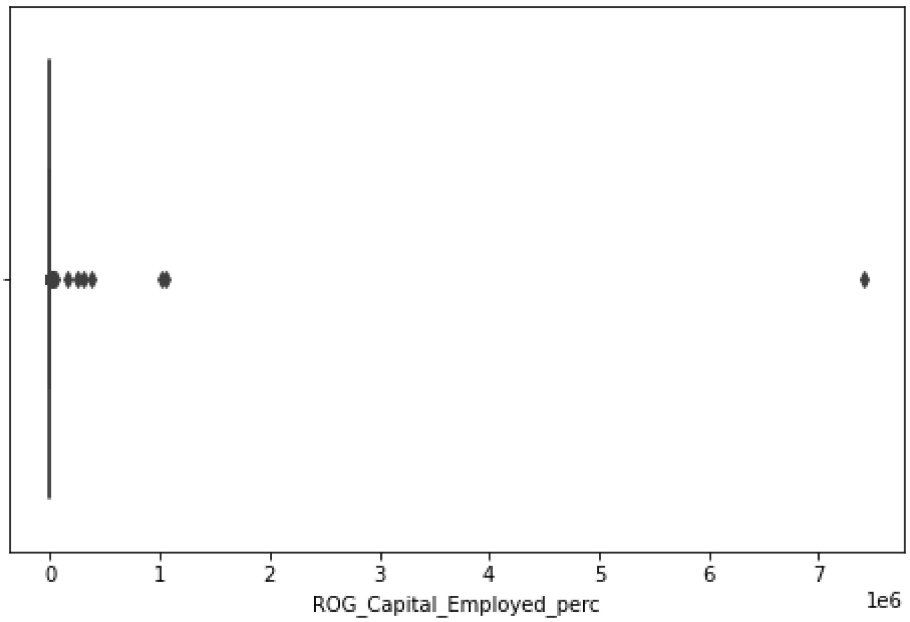
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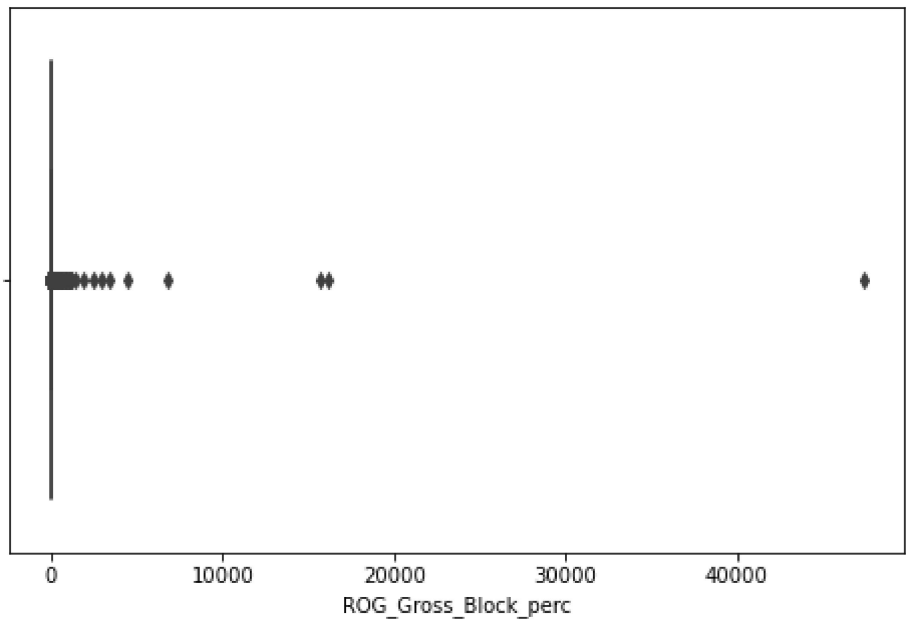
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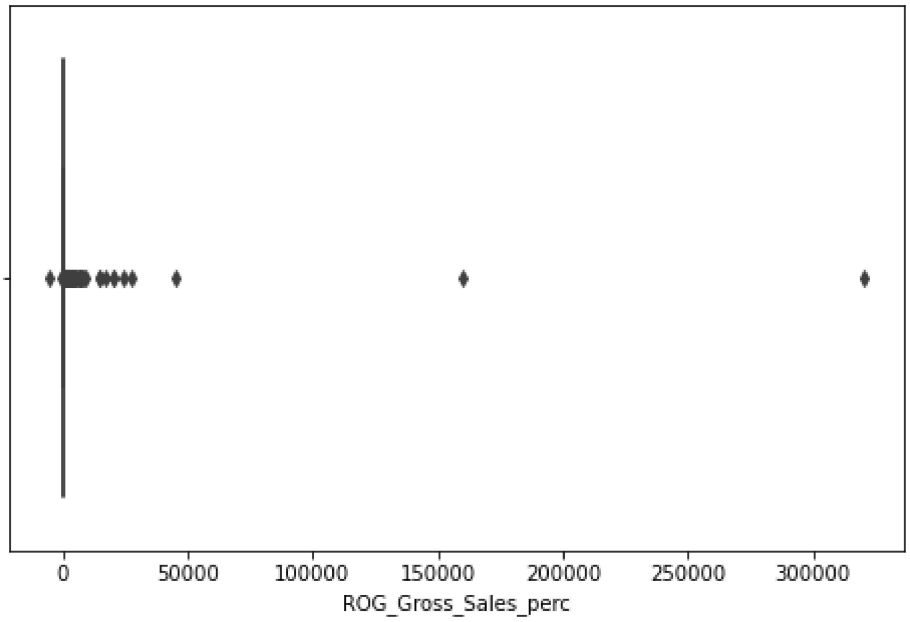
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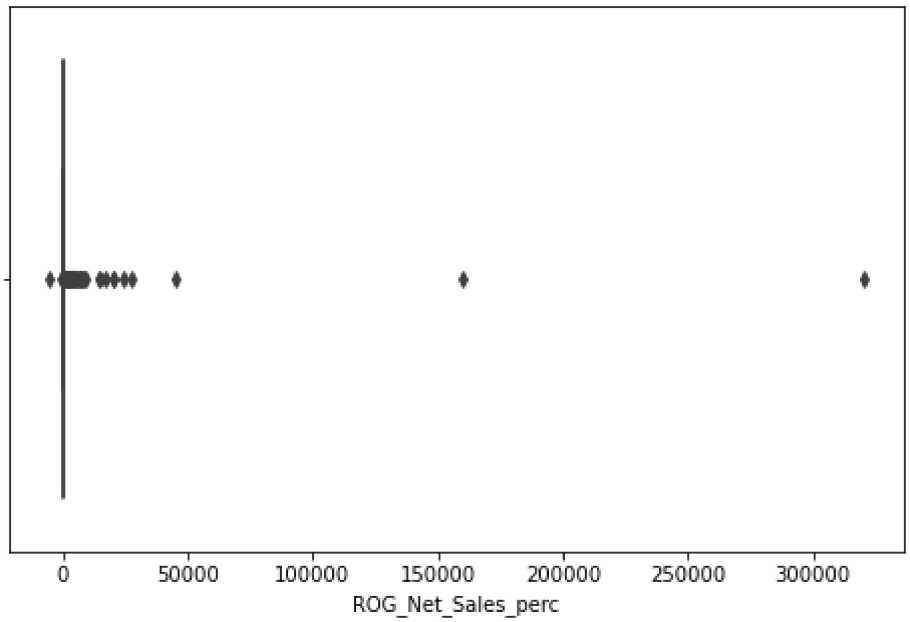
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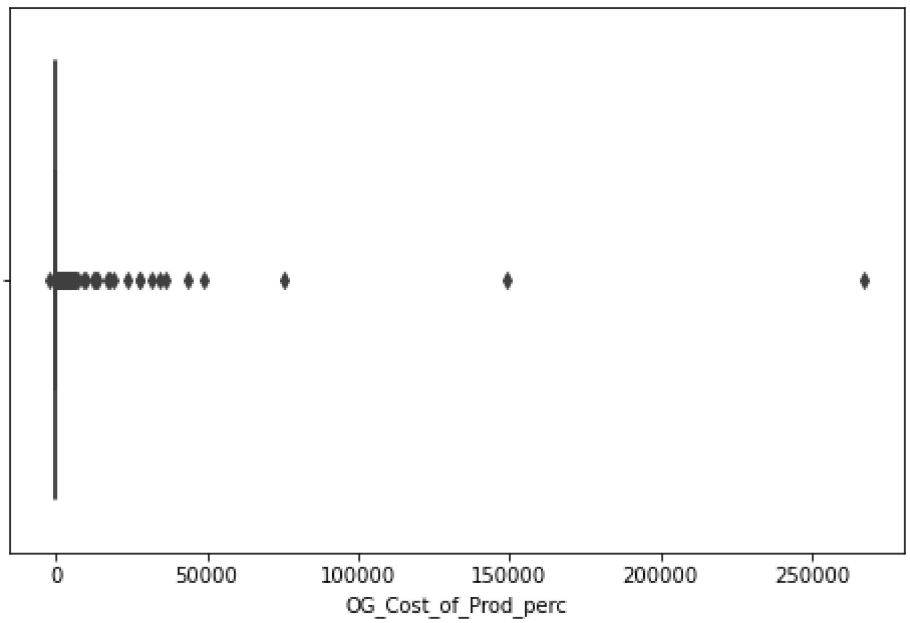
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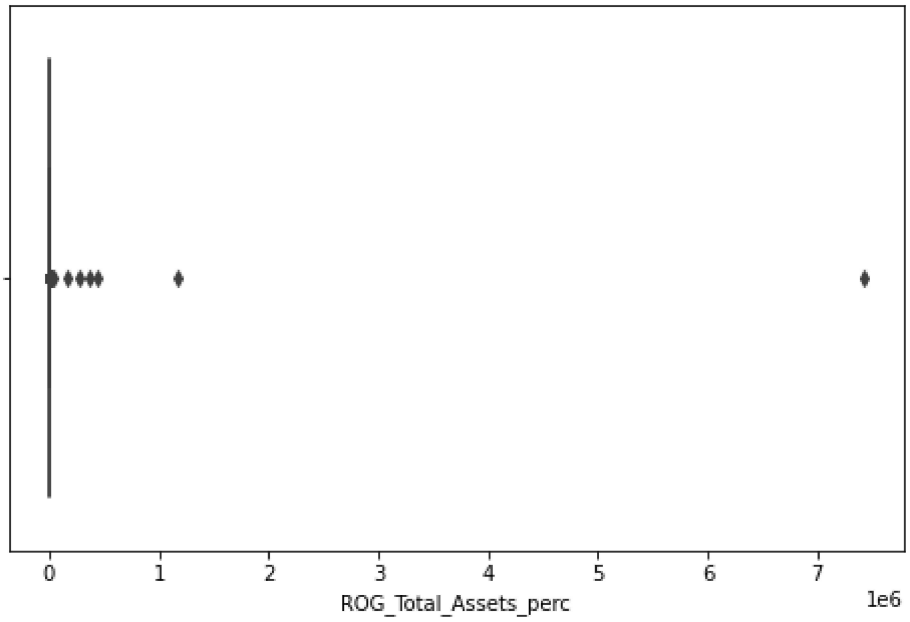
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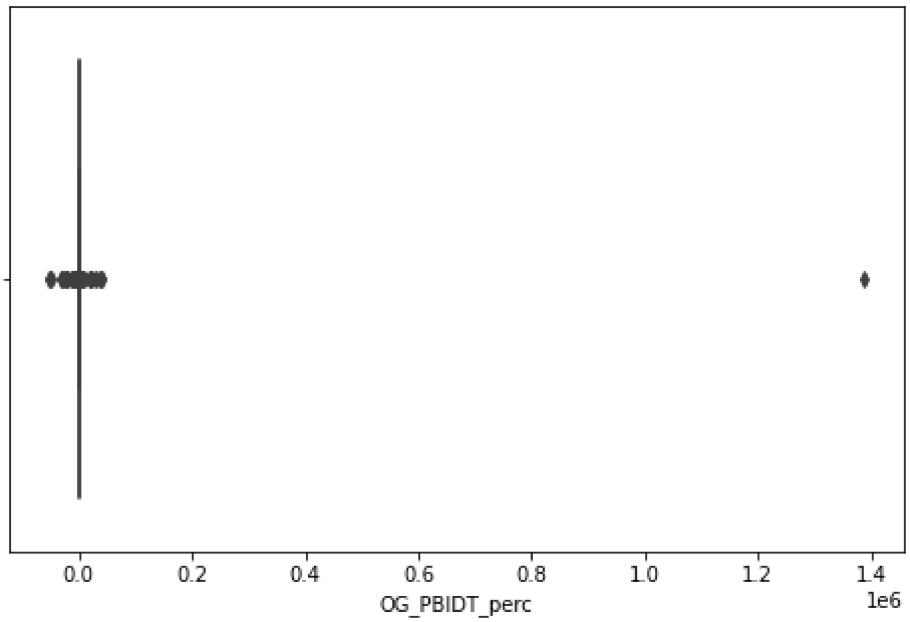
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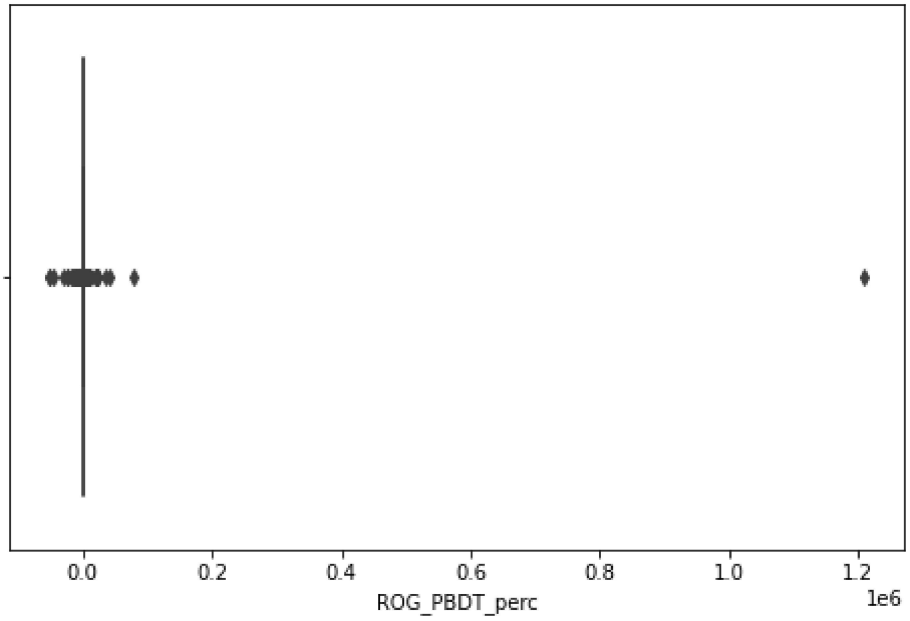
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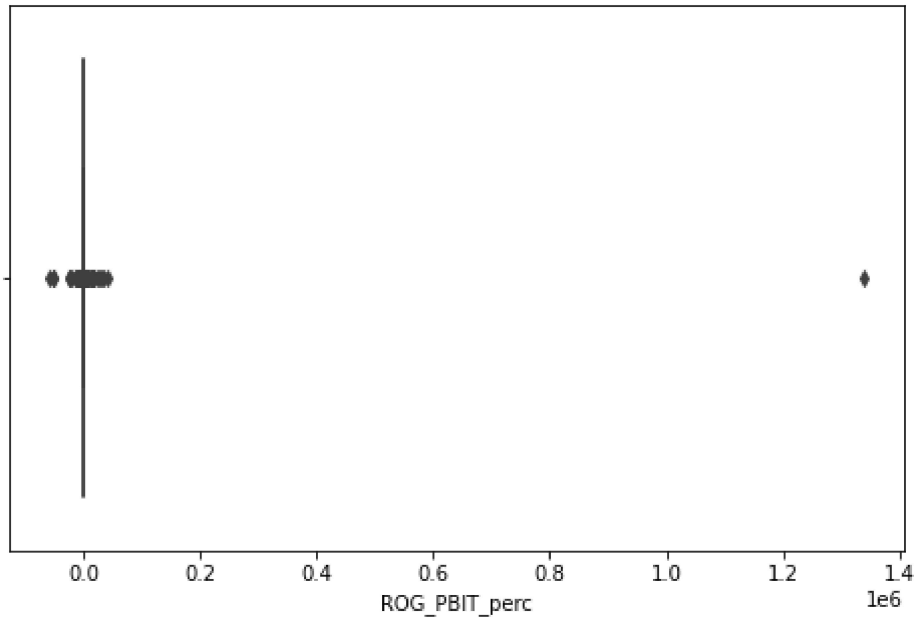
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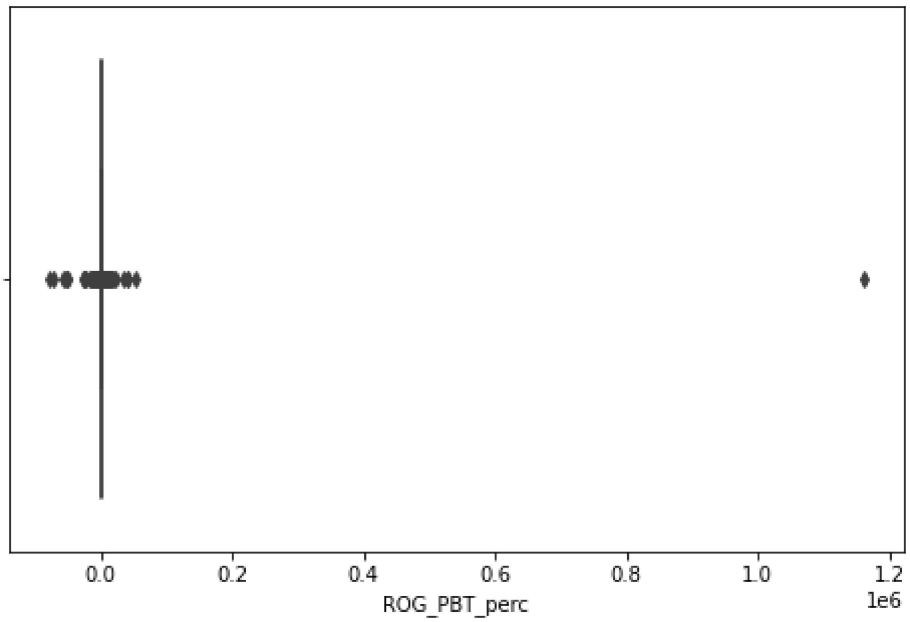
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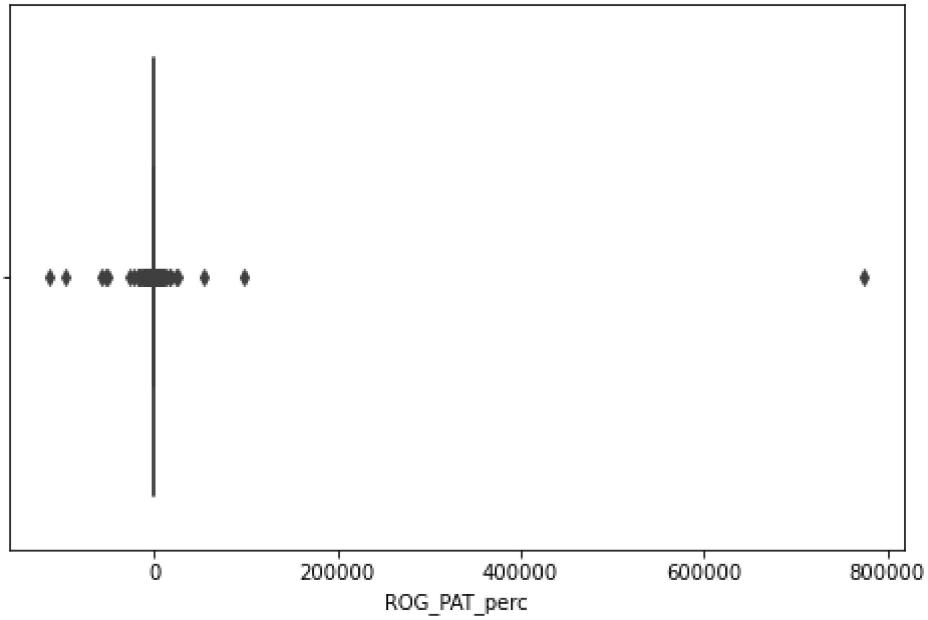
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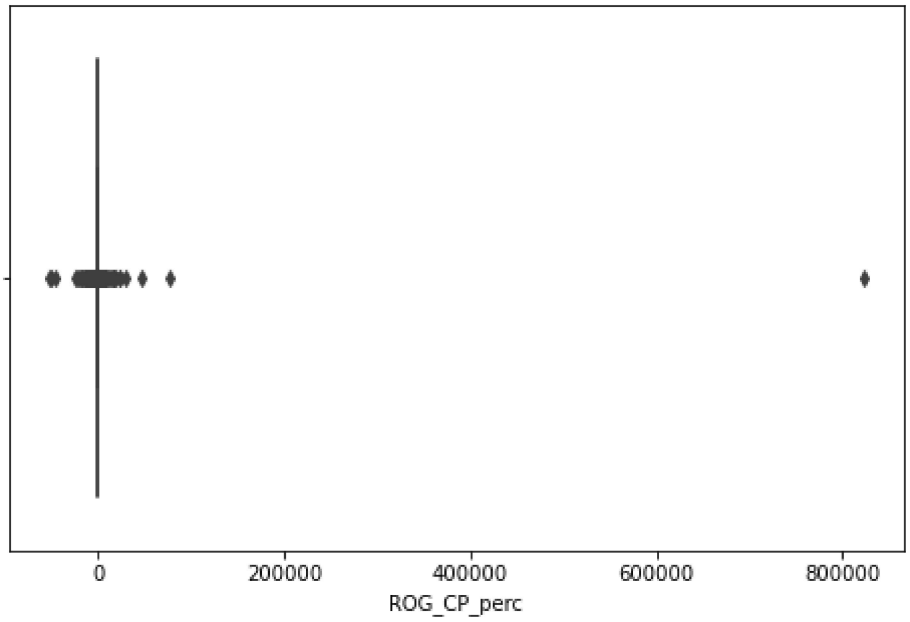
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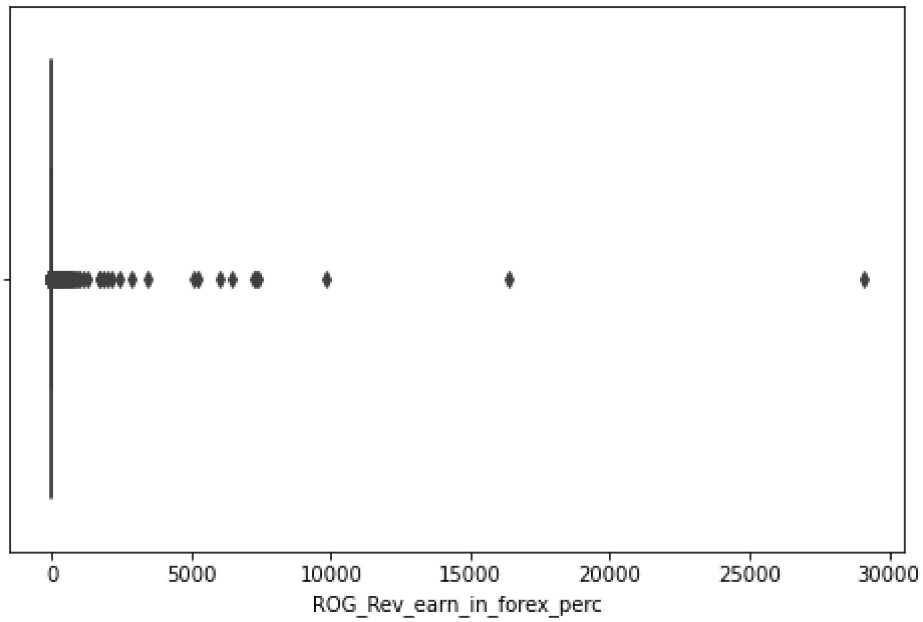
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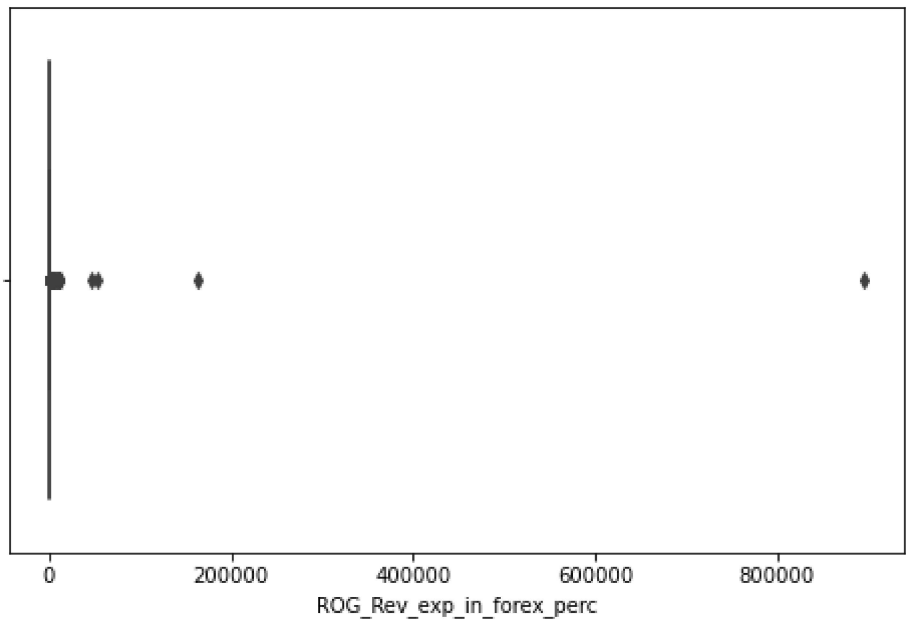
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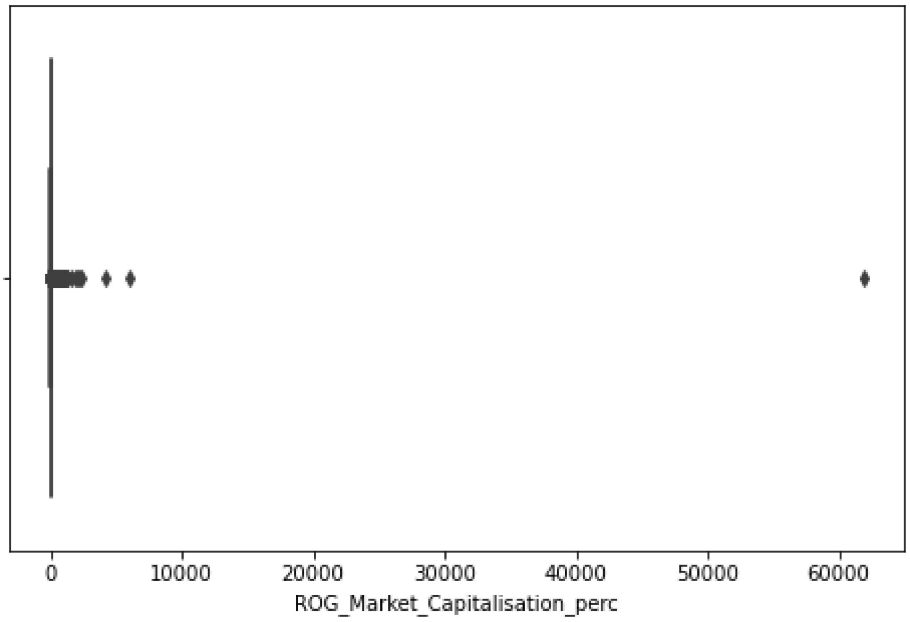
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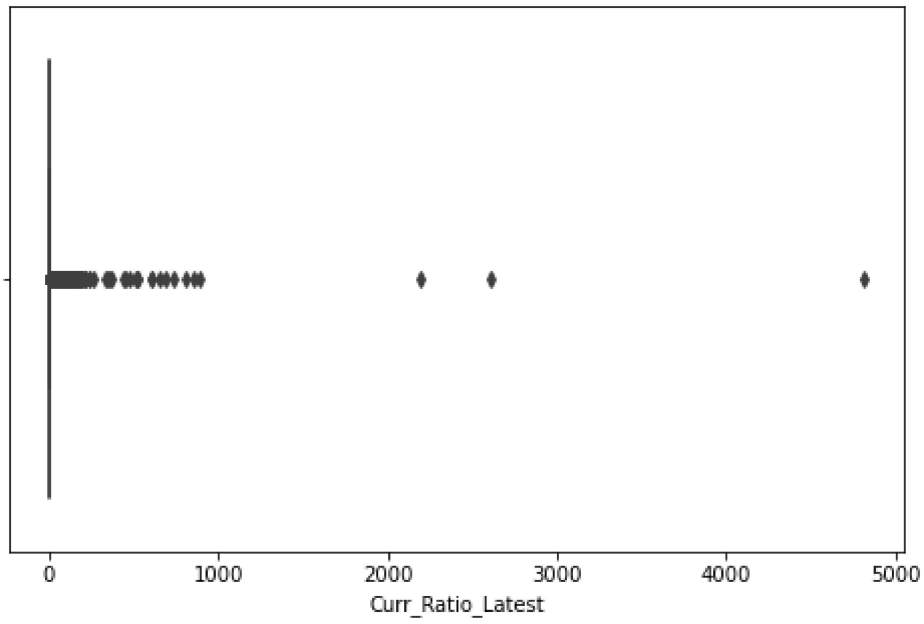
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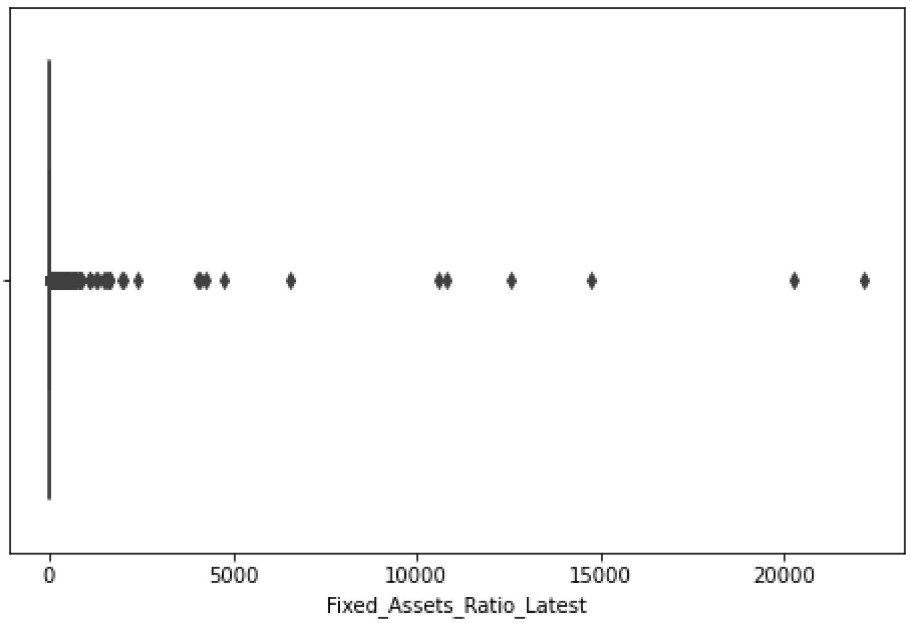
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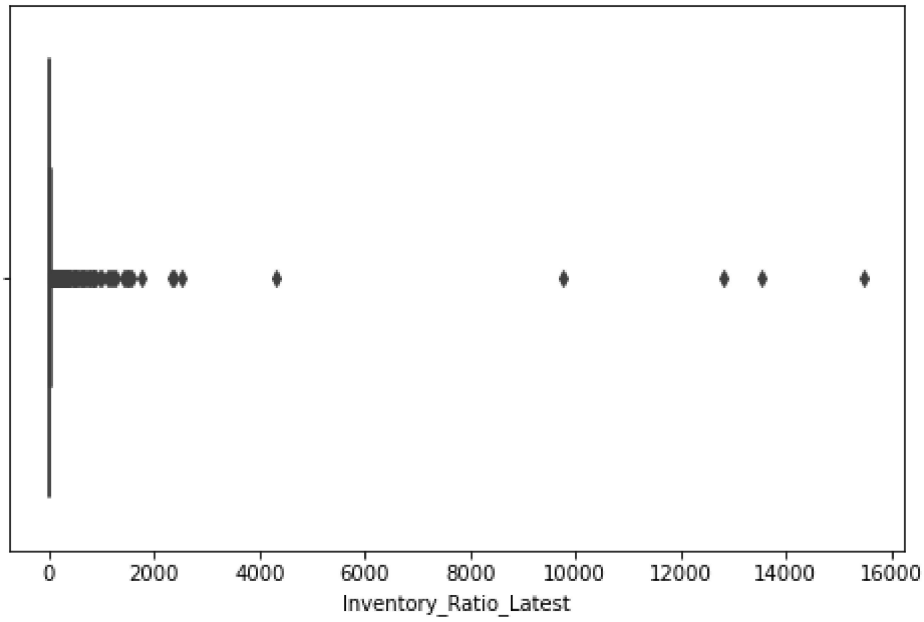
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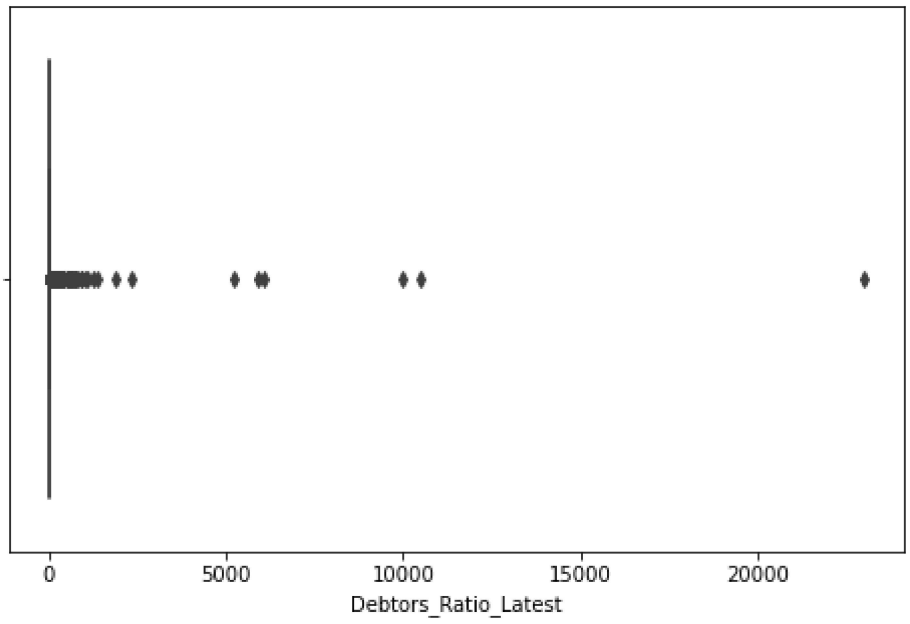
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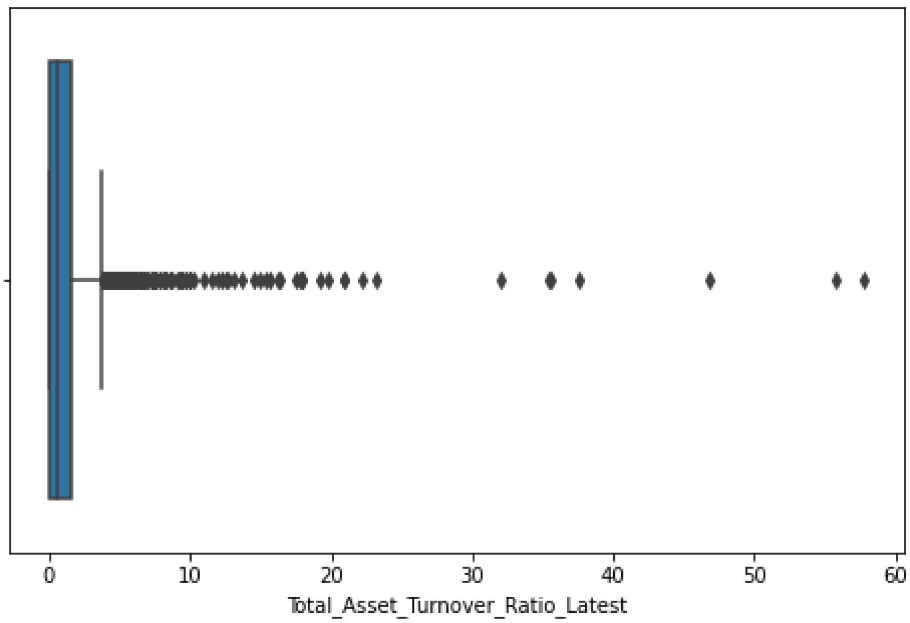
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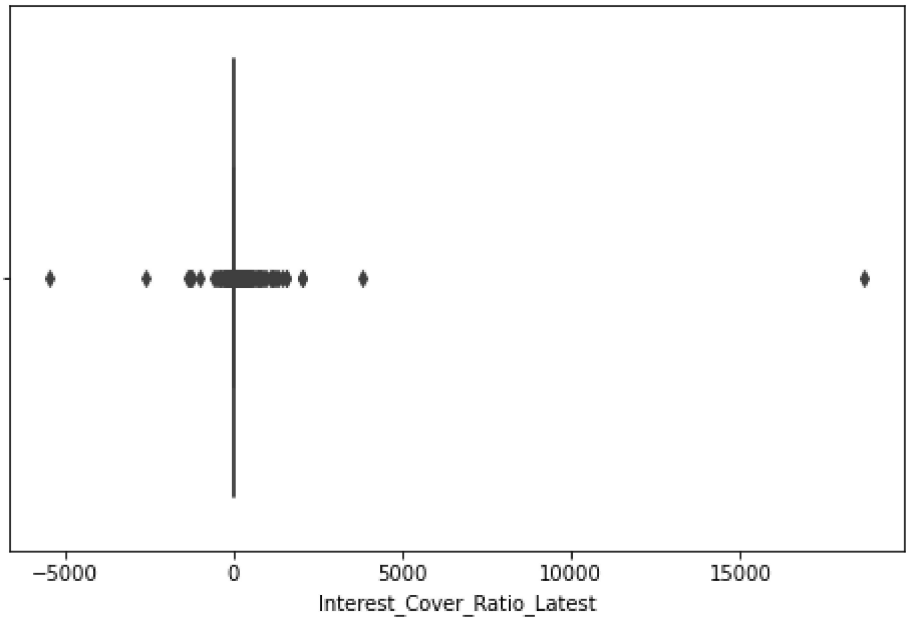
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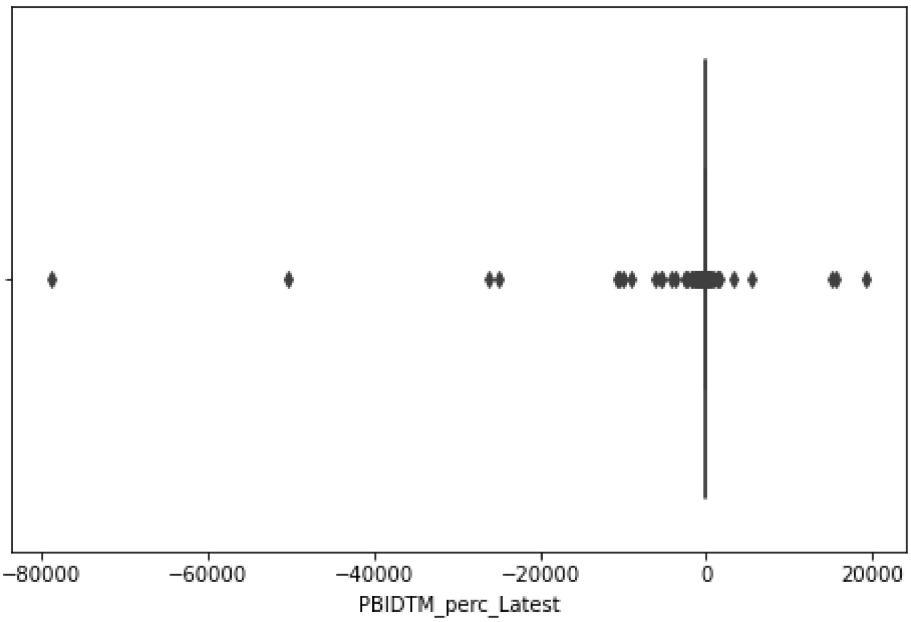
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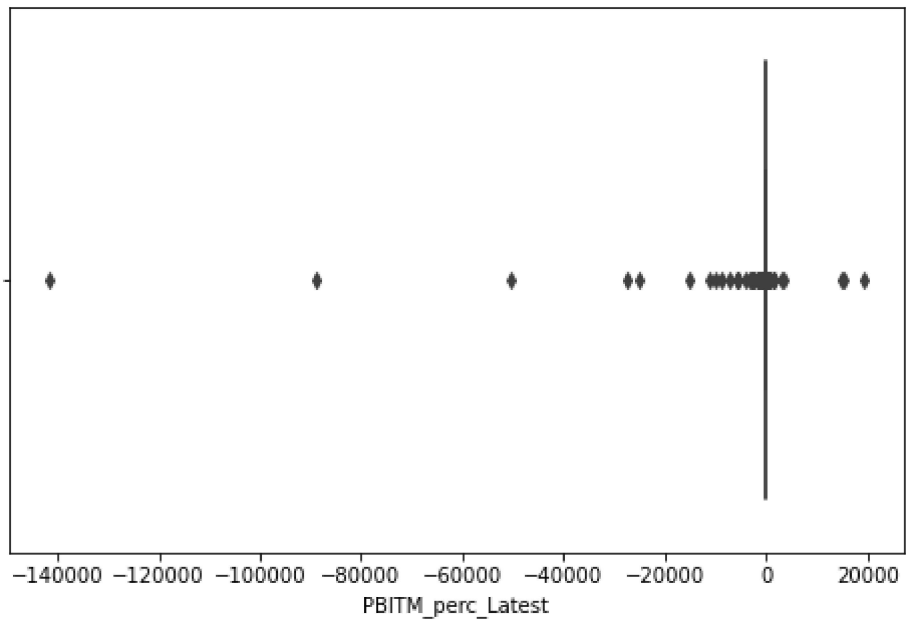
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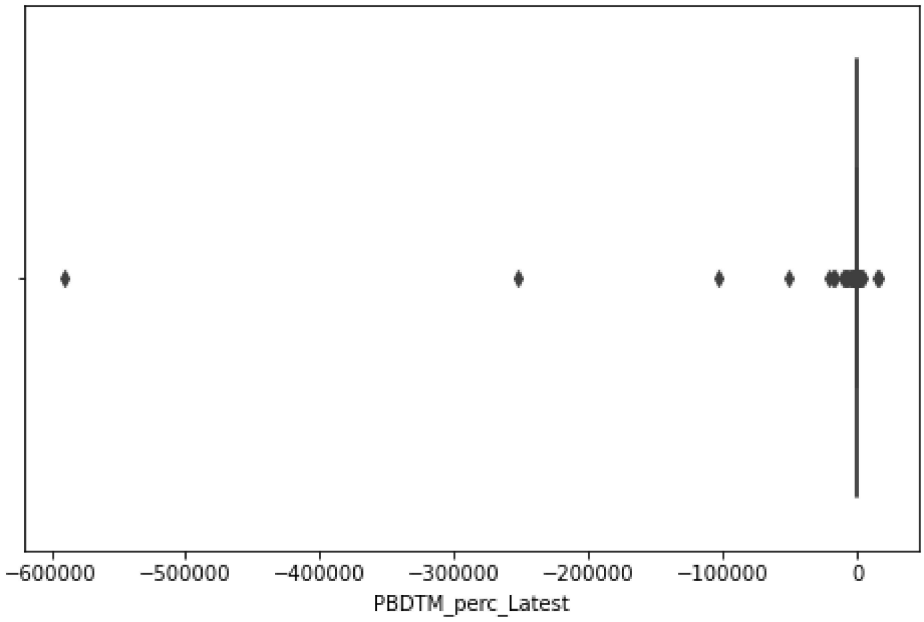
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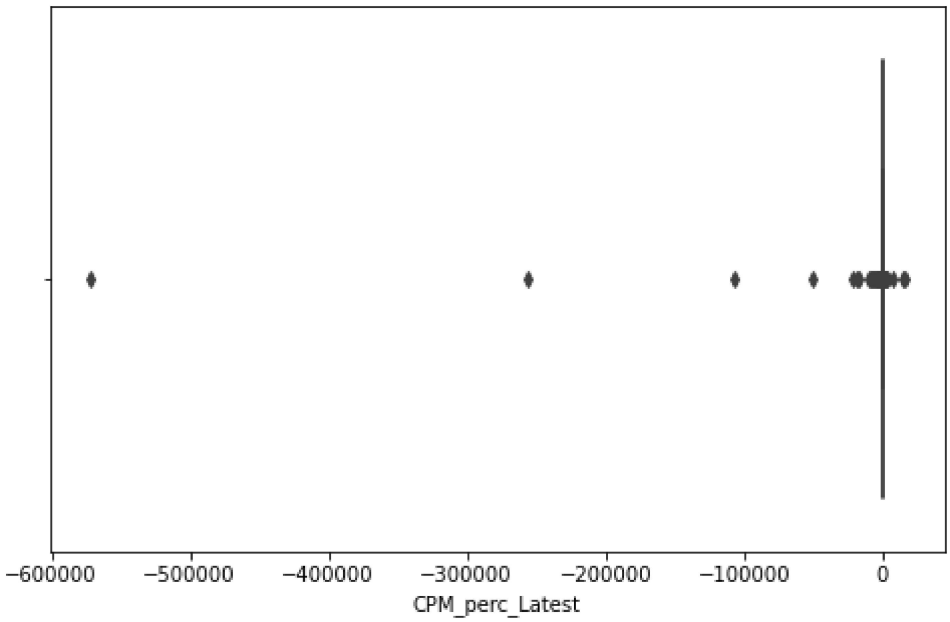
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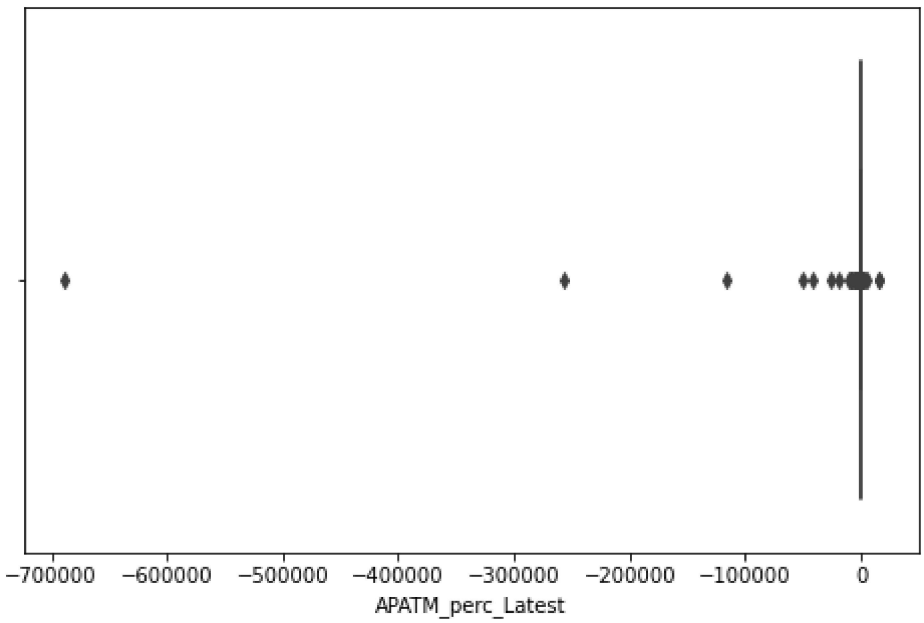
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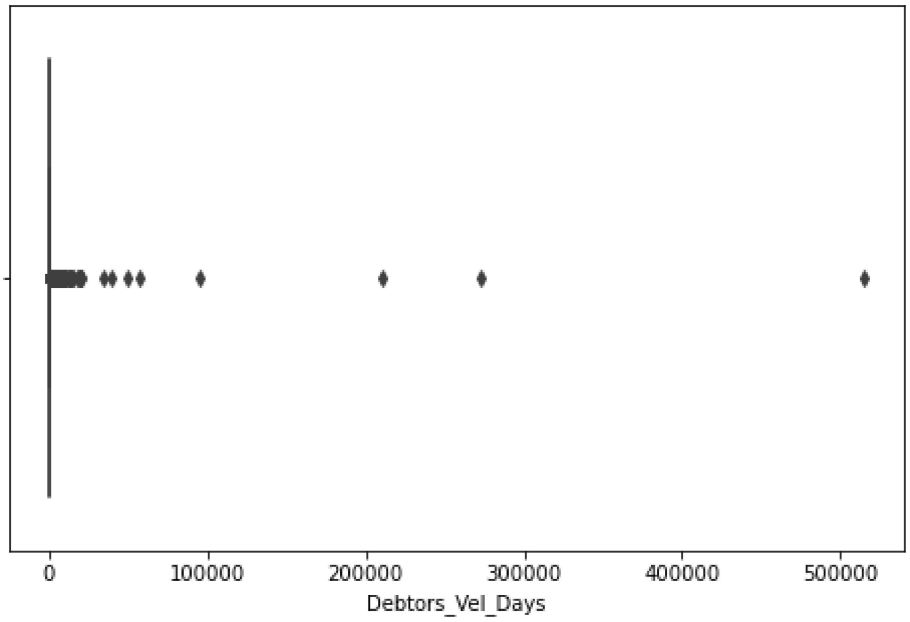
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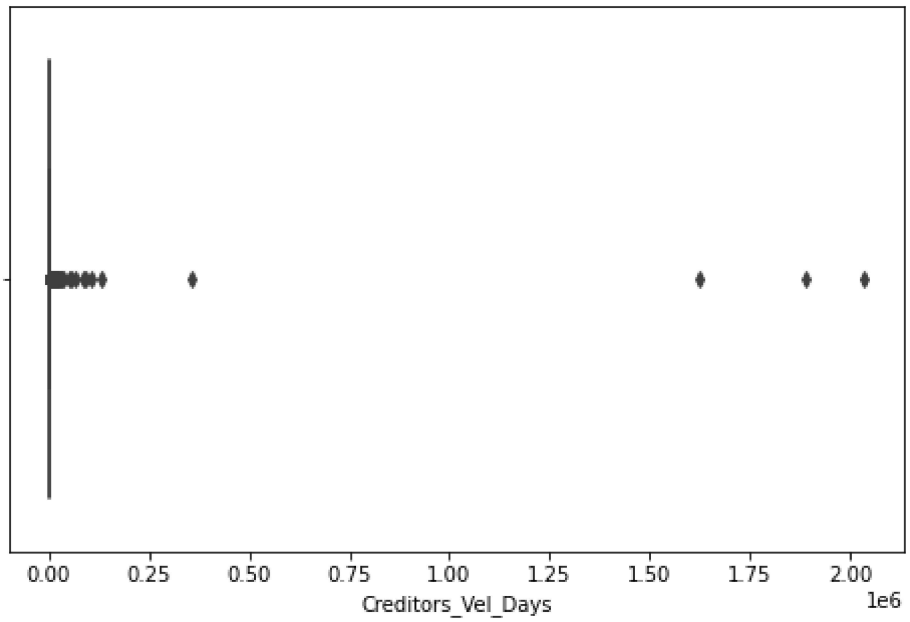
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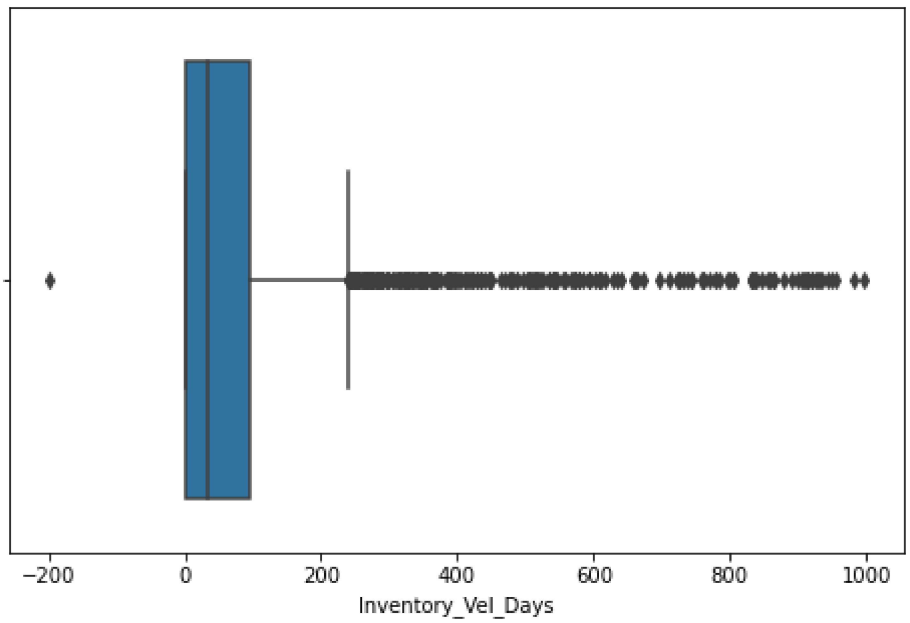
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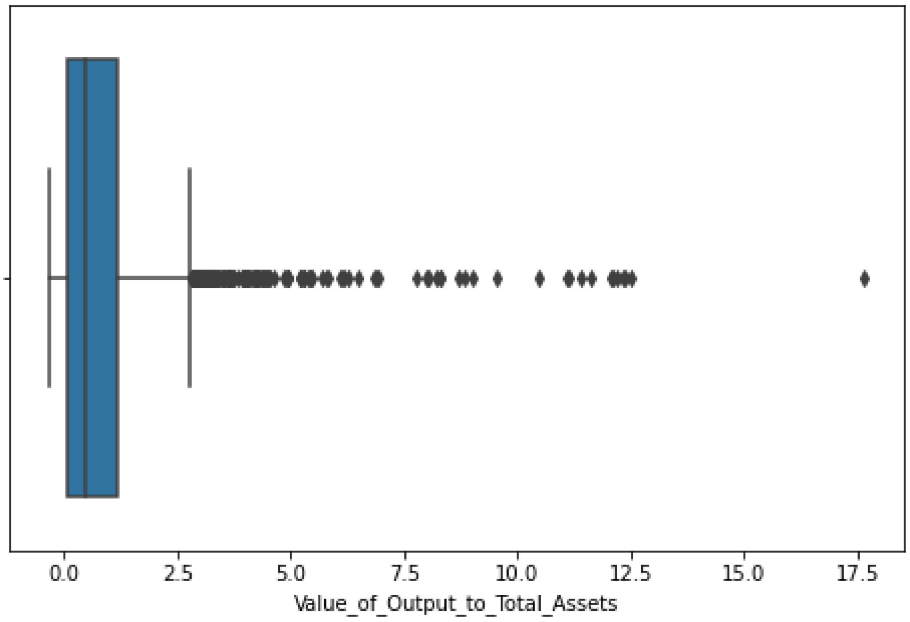
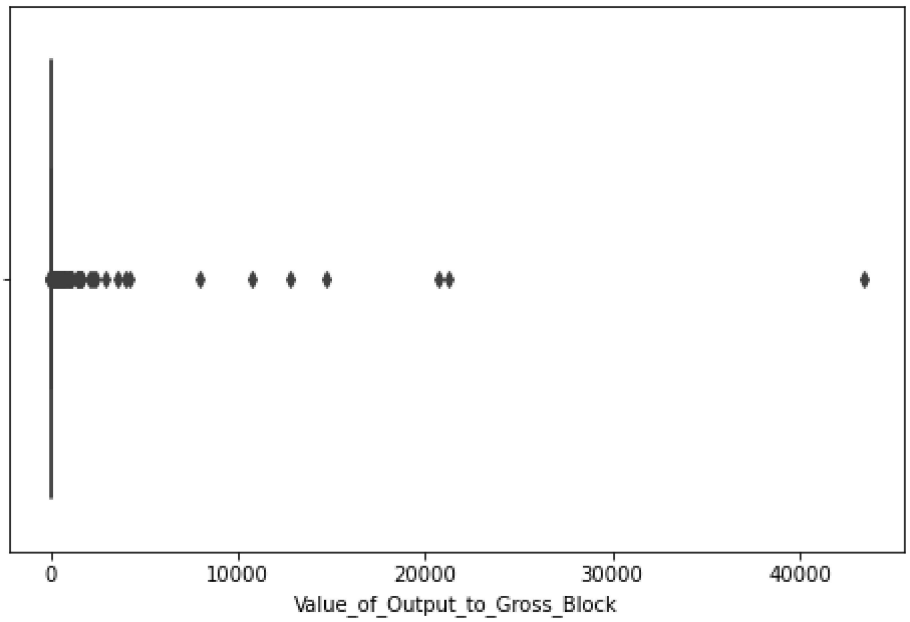
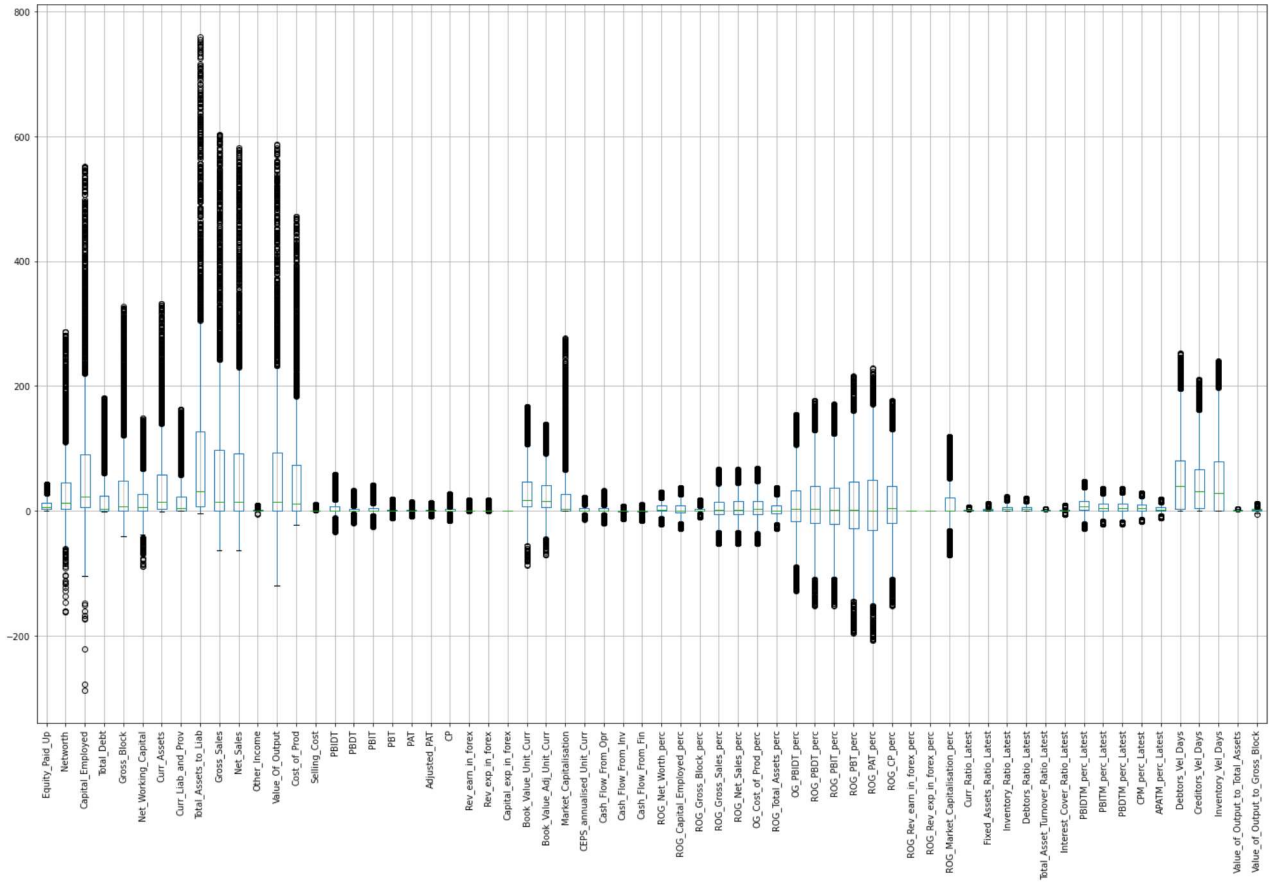
Inventory_Vel_Days





In [75]:
```
df_x.boxplot(figsize=(25, 15), rot=90)
```

Out[75]: <AxesSubplot:>



In [16]:
```
Q1 = df_x.quantile(0.25)
Q3 = df_x.quantile(0.75)
IQR = Q3 - Q1
UL = Q3 + 1.5*IQR
LL = Q1 - 1.5*IQR
```

In [17]:
```
#Sum of outliers in each column
pd.options.display.max_rows = None
((df_x > UL) | (df_x < LL)).sum()
```

Out[17]:

Networth_Next_Year	676
Equity_Paid_Up	448
Networth	650
Capital_Employed	596
Total_Debt	583
Gross_Block	540
Net_Working_Capital	625
Curr_Assets	577
Curr_Liab_and_Prov	581
Total_Assets_to_Liab	574
Gross_Sales	554
Net_Sales	556
Other_Income	603
Value_Of_Output	559
Cost_of_Prod	560
Selling_Cost	605
PBIDT	671
PBDT	815
PBIT	720

```
PBT                                941
PAT                                959
Adjusted_PAT                       954
CP                                 816
Rev_earn_in_forex                  738
Rev_exp_in_forex                   693
Capital_exp_in_forex               694
Book_Value_Unit_Curr               485
Book_Value_Adj_Unit_Curr           486
Market_Capitalisation              639
CEPS_annualised_Unit_Curr          602
Cash_Flow_From_Opr                 801
Cash_Flow_From_Inv                 876
Cash_Flow_From_Fin                1005
ROG_Net_Worth_perc                 747
ROG_Capital_Employed_perc          572
ROG_Gross_Block_perc               830
ROG_Gross_Sales_perc               671
ROG_Net_Sales_perc                 667
OG_Cost_of_Prod_perc               675
ROG_Total_Assets_perc              483
OG_PBIDT_perc                      611
ROG_PBDT_perc                      628
ROG_PBIT_perc                      616
ROG_PBT_perc                       611
ROG_PAT_perc                       598
ROG_CP_perc                        637
ROG_Rev_earn_in_forex_perc        1317
ROG_Rev_exp_in_forex_perc         1615
ROG_Market_Capitalisation_perc     497
Curr_Ratio_Latest                  565
Fixed_Assets_Ratio_Latest          495
Inventory_Ratio_Latest             375
Debtors_Ratio_Latest               371
Total_Asset_Turnover_Ratio_Latest  201
Interest_Cover_Ratio_Latest        725
PBIDTM_perc_Latest                 595
PBITM_perc_Latest                  717
PBDTM_perc_Latest                  695
CPM_perc_Latest                    720
APATM_perc_Latest                  933
Debtors_Vel_Days                   398
Creditors_Vel_Days                 391
Inventory_Vel_Days                 262
Value_of_Output_to_Total_Assets    150
Value_of_Output_to_Gross_Block     481
dtype: int64
```

In [18]:
```
#Total outliers
((df_x > UL) | (df_x < LL)).sum().sum()
```

Out[18]:
```
42031
```

As we can see there are so many outliers available. So for going ahead with the logistic regression, we have to treat the outliers in a much better way than we treated them every time in the past. So here we are replacing the outliers with Nan.

In [19]:

```
df_x[((df_x > UL) | (df_x < LL))] = np.nan
```

After converting outliers with nan, now we will treat those missing values.

In [20]:
```
#Now checking the missing values
df_x.isnull().sum()
```

Out[20]:

Networth_Next_Year	676
Equity_Paid_Up	448
Networth	650
Capital_Employed	596
Total_Debt	583
Gross_Block	540
Net_Working_Capital	625
Curr_Assets	577
Curr_Liab_and_Prov	581
Total_Assets_to_Liab	574
Gross_Sales	554
Net_Sales	556
Other_Income	603
Value_Of_Output	559
Cost_of_Prod	560
Selling_Cost	605
PBIDT	671
PBDT	815
PBIT	720
PBT	941
PAT	959
Adjusted_PAT	954
CP	816
Rev_earn_in_forex	738
Rev_exp_in_forex	693
Capital_exp_in_forex	694
Book_Value_Unit_Curr	485
Book_Value_Adj_Unit_Curr	490
Market_Capitalisation	639
CEPS_annualised_Unit_Curr	602
Cash_Flow_From_Opr	801
Cash_Flow_From_Inv	876
Cash_Flow_From_Fin	1005
ROG_Net_Worth_perc	747
ROG_Capital_Employed_perc	572
ROG_Gross_Block_perc	830
ROG_Gross_Sales_perc	671
ROG_Net_Sales_perc	667
OG_Cost_of_Prod_perc	675
ROG_Total_Assets_perc	483
OG_PBIDT_perc	611
ROG_PBDT_perc	628
ROG_PBIT_perc	616
ROG_PBT_perc	611
ROG_PAT_perc	598
ROG_CP_perc	637
ROG_Rev_earn_in_forex_perc	1317
ROG_Rev_exp_in_forex_perc	1615
ROG_Market_Capitalisation_perc	497
Curr_Ratio_Latest	566
Fixed_Assets_Ratio_Latest	496

```
Inventory_Ratio_Latest                376
Debtors_Ratio_Latest                  372
Total_Asset_Turnover_Ratio_Latest     202
Interest_Cover_Ratio_Latest           726
PBIDTM_perc_Latest                    596
PBITM_perc_Latest                     718
PBDTM_perc_Latest                     696
CPM_perc_Latest                       721
APATM_perc_Latest                     934
Debtors_Vel_Days                      398
Creditors_Vel_Days                    391
Inventory_Vel_Days                    365
Value_of_Output_to_Total_Assets       150
Value_of_Output_to_Gross_Block        481
dtype: int64
```

In [21]:
```
#Total missing values
df_x.isnull().sum().sum()
```

Out[21]:
```
42149
```

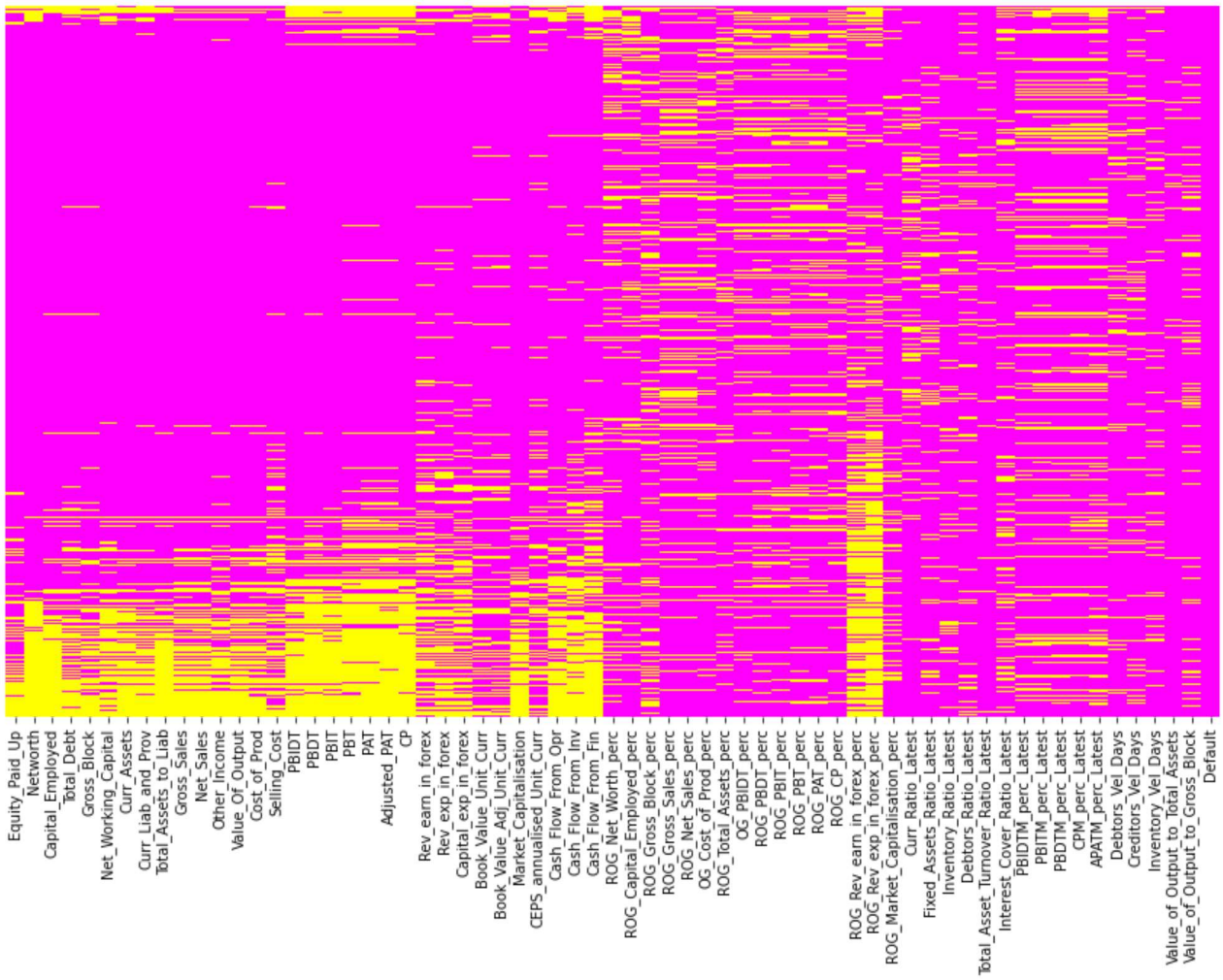
In [22]:
```
df_x = df_x.drop(['Networth_Next_Year'], axis = 1) #since this we have already converte
```

In [23]:
```
df_concat = pd.concat([df_x, df_y], axis = 1)
```

In [24]:
```
### Now let's see the heatmap for missing values

plt.figure(figsize = (15,9))
sns.heatmap(df_concat.isnull(), cbar = False, cmap = 'spring', yticklabels = False)
```

Out[24]:
```
<AxesSubplot:>
```



Yellow color here represent the data points which are missing, that we can see that there are many missing data in columns in dataset.

In [25]:
```
##Now here we will also check total missing values in each row (Row Wise missing values
##To get which are the companies has most missing values


df_concat.isnull().sum(axis = 1)
```

Out[25]:
```
0       19
1       34
2       43
3       36
4       35
5        9
6       37
7       34
8       24
9       27
10      20
11      34
12      21
13      35
14      27
15      35
16      34
17      31
```

18	12
19	22
20	23
21	16
22	33
23	38
24	28
25	21
26	14
27	11
28	14
29	33
30	27
31	22
32	21
33	15
34	30
35	28
36	22
37	30
38	11
39	25
40	25
41	27
42	16
43	4
44	23
45	21
46	34
47	27
48	29
49	10
50	28
51	28
52	16
53	35
54	31
55	20
56	17
57	17
58	10
59	12
60	23
61	20
62	29
63	15
64	19
65	16
66	32
67	26
68	15
69	17
70	23
71	16
72	9
73	11
74	34
75	18
76	21
77	26

78	20
79	18
80	20
81	5
82	23
83	10
84	22
85	21
86	14
87	14
88	24
89	23
90	26
91	29
92	17
93	13
94	16
95	3
96	4
97	16
98	6
99	20
100	25
101	15
102	24
103	0
104	15
105	5
106	21
107	17
108	8
109	15
110	5
111	20
112	12
113	6
114	9
115	10
116	18
117	12
118	13
119	9
120	6
121	20
122	14
123	25
124	10
125	23
126	9
127	12
128	19
129	20
130	7
131	7
132	24
133	13
134	20
135	27
136	8
137	5

138	6
139	7
140	12
141	18
142	31
143	11
144	1
145	7
146	14
147	4
148	2
149	1
150	8
151	5
152	6
153	15
154	14
155	14
156	6
157	27
158	3
159	7
160	9
161	6
162	6
163	13
164	17
165	5
166	6
167	15
168	8
169	12
170	6
171	1
172	19
173	15
174	11
175	9
176	6
177	9
178	1
179	10
180	30
181	11
182	3
183	4
184	5
185	2
186	22
187	6
188	13
189	0
190	9
191	17
192	13
193	11
194	16
195	12
196	1
197	4

198	3
199	11
200	19
201	13
202	4
203	7
204	8
205	0
206	3
207	4
208	3
209	20
210	4
211	4
212	2
213	7
214	8
215	7
216	1
217	1
218	2
219	0
220	12
221	13
222	7
223	4
224	9
225	14
226	10
227	2
228	0
229	10
230	2
231	8
232	8
233	6
234	1
235	11
236	19
237	12
238	1
239	11
240	0
241	16
242	1
243	0
244	11
245	9
246	6
247	8
248	17
249	10
250	6
251	8
252	6
253	5
254	5
255	3
256	2
257	9

258	11
259	6
260	4
261	3
262	5
263	1
264	8
265	10
266	6
267	9
268	7
269	1
270	8
271	7
272	1
273	13
274	3
275	6
276	17
277	6
278	4
279	2
280	13
281	7
282	2
283	8
284	16
285	7
286	0
287	0
288	13
289	7
290	5
291	11
292	7
293	2
294	1
295	4
296	4
297	1
298	15
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300	0
301	14
302	8
303	5
304	5
305	8
306	0
307	9
308	3
309	16
310	3
311	0
312	3
313	7
314	5
315	0
316	5
317	10

318	6
319	11
320	8
321	1
322	5
323	9
324	1
325	12
326	4
327	5
328	5
329	14
330	10
331	8
332	2
333	4
334	2
335	3
336	1
337	7
338	6
339	4
340	10
341	17
342	7
343	8
344	5
345	4
346	4
347	9
348	4
349	5
350	4
351	8
352	7
353	5
354	1
355	9
356	9
357	4
358	0
359	2
360	2
361	2
362	4
363	27
364	1
365	0
366	9
367	1
368	7
369	7
370	13
371	12
372	0
373	4
374	11
375	10
376	12
377	12

```
378      2
379      9
380      1
381      5
382      3
383      2
384     11
385      3
386      0
387      0
388      3
389     11
390     10
391      3
392      4
393      7
394      5
395      5
396      7
397      1
398      0
399      2
400      0
401      1
402      4
403      1
404      6
405      1
406      5
407     11
408      1
409     12
410      1
411      1
412      0
413     10
414      9
415      0
416      0
417      9
418      9
419      2
420      5
421      4
422      2
423     12
424      3
425      0
426      2
427      6
428     10
429      4
430      3
431      5
432      9
433      0
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435      3
436      5
437      5
```

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445	3
446	10
447	7
448	7
449	12
450	1
451	3
452	1
453	9
454	11
455	4
456	0
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458	0
459	0
460	2
461	5
462	4
463	7
464	4
465	10
466	3
467	4
468	8
469	9
470	5
471	9
472	2
473	5
474	11
475	1
476	8
477	16
478	9
479	4
480	5
481	4
482	7
483	17
484	12
485	0
486	13
487	6
488	7
489	1
490	2
491	1
492	6
493	2
494	4
495	3
496	10
497	7

498	10
499	5
500	5
501	1
502	2
503	4
504	13
505	5
506	0
507	6
508	6
509	10
510	5
511	14
512	8
513	9
514	9
515	7
516	5
517	5
518	8
519	7
520	5
521	10
522	1
523	12
524	2
525	4
526	18
527	3
528	10
529	0
530	0
531	7
532	6
533	6
534	11
535	10
536	2
537	10
538	7
539	6
540	10
541	4
542	3
543	9
544	11
545	4
546	12
547	15
548	12
549	2
550	1
551	12
552	1
553	5
554	1
555	1
556	5
557	6

558	3
559	3
560	3
561	15
562	9
563	5
564	18
565	6
566	6
567	6
568	0
569	17
570	6
571	10
572	7
573	2
574	14
575	13
576	5
577	8
578	0
579	1
580	10
581	6
582	12
583	5
584	7
585	0
586	1
587	4
588	2
589	6
590	6
591	5
592	0
593	5
594	13
595	1
596	4
597	0
598	2
599	9
600	7
601	7
602	0
603	10
604	2
605	10
606	9
607	2
608	1
609	3
610	3
611	5
612	10
613	4
614	4
615	0
616	13
617	2

618	4
619	1
620	0
621	6
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623	12
624	2
625	23
626	5
627	1
628	14
629	3
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631	9
632	10
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647	4
648	12
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650	4
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654	6
655	1
656	12
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658	5
659	7
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663	7
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668	11
669	10
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671	9
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674	7
675	9
676	2
677	3

678	0
679	5
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681	1
682	6
683	9
684	1
685	12
686	8
687	7
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689	11
690	7
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692	6
693	2
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696	7
697	3
698	4
699	9
700	1
701	9
702	12
703	3
704	1
705	9
706	6
707	7
708	14
709	1
710	10
711	7
712	1
713	0
714	6
715	9
716	5
717	3
718	6
719	4
720	7
721	2
722	5
723	2
724	9
725	2
726	13
727	7
728	3
729	5
730	12
731	6
732	2
733	0
734	8
735	4
736	3
737	5

```
738     11
739      2
740      8
741      3
742      4
743      5
744      9
745      5
746      2
747      3
748      5
749      0
750      3
751      7
752      4
753      2
754      1
755      4
756      6
757     13
758      7
759     10
760      1
761      6
762      3
763     13
764     10
765      5
766      6
767      4
768      1
769      0
770      4
771      9
772      6
773      2
774      7
775      3
776      7
777      2
778     11
779      7
780      4
781      3
782      4
783      3
784      1
785      2
786      9
787      7
788      8
789      8
790      3
791      3
792      5
793      1
794      6
795     14
796      5
797      4
```

```
798     13
799      9
800      4
801     14
802      8
803      6
804     10
805      8
806     10
807      2
808      3
809      2
810      1
811      3
812      2
813     12
814      2
815      2
816      8
817      1
818      7
819      6
820     11
821      5
822      9
823     11
824     13
825      6
826      3
827      6
828      2
829     11
830     10
831      2
832      3
833      9
834      4
835     10
836      2
837     14
838      2
839      0
840      9
841      4
842      4
843      1
844      4
845      6
846     14
847      1
848      6
849      7
850     15
851      4
852     10
853      7
854      8
855     10
856      1
857      9
```

858	2
859	9
860	5
861	3
862	2
863	0
864	3
865	3
866	5
867	1
868	4
869	5
870	0
871	3
872	4
873	4
874	8
875	0
876	13
877	2
878	14
879	8
880	4
881	7
882	4
883	6
884	10
885	3
886	6
887	5
888	1
889	2
890	6
891	8
892	3
893	17
894	7
895	0
896	14
897	3
898	8
899	15
900	7
901	8
902	1
903	3
904	4
905	7
906	30
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908	5
909	12
910	2
911	6
912	10
913	13
914	5
915	9
916	12
917	6

918	8
919	11
920	10
921	5
922	1
923	6
924	2
925	4
926	5
927	4
928	4
929	13
930	11
931	0
932	8
933	3
934	2
935	8
936	3
937	11
938	7
939	19
940	3
941	10
942	6
943	6
944	0
945	2
946	6
947	0
948	6
949	5
950	5
951	12
952	7
953	11
954	11
955	11
956	10
957	2
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959	14
960	10
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965	10
966	3
967	4
968	7
969	5
970	5
971	15
972	4
973	14
974	3
975	11
976	6
977	5

978	7
979	0
980	4
981	0
982	13
983	13
984	1
985	5
986	9
987	9
988	3
989	7
990	6
991	6
992	10
993	5
994	7
995	1
996	16
997	2
998	2
999	7
1000	0
1001	7
1002	10
1003	5
1004	3
1005	1
1006	21
1007	7
1008	8
1009	7
1010	11
1011	14
1012	1
1013	8
1014	2
1015	13
1016	1
1017	8
1018	4
1019	11
1020	2
1021	4
1022	4
1023	5
1024	12
1025	4
1026	15
1027	1
1028	8
1029	3
1030	8
1031	7
1032	6
1033	1
1034	5
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2412	6
2413	15
2414	6
2415	4
2416	10
2417	5

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3317    25
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3577    35
3578    19
3579    29
3580    35
3581    30
3582    36
3583    34
3584    30
3585    36
dtype: int64
```

In [26]:
```
##Let's now get only those records where number of missing values are less than 10%

df_concat_z = df_concat[df_concat.isnull().sum(axis = 1) <=6]
```

In [27]:
```
#Now let's check shape
df_concat_z.shape
```

Out[27]:
```
(1460, 65)
```

In [28]:
```
#Now, let see the default counts

df_concat_z['Default'].value_counts()
```

Out[28]:
```
0    1320
1     140
Name: Default, dtype: int64
```

Now we can see that out of 387 defaults initially, now when we filtered out only those records which has at least 90% of the data is filled then we only left with 140 defaults.

In [29]:
```
df_concat['Default'].value_counts()
```

Out[29]:
```
0    3199
1     387
Name: Default, dtype: int64
```

In [30]:
```
#That means if we calculate, we will get what percentage of defaults we have covered in

140/387
```

Out[30]:
```
0.36175710594315247
```

We will only drop records with more than 25% of the data missing

In [31]:
```
###Now first lets see which are the records has more than 25% missing data

df_concat.isnull().sum().sort_values(ascending = False)/df_concat.index.size
```

Out[31]:
```
ROG_Rev_exp_in_forex_perc          0.45
ROG_Rev_earn_in_forex_perc         0.37
Cash_Flow_From_Fin                 0.28
PAT                                0.27
Adjusted_PAT                       0.27
PBT                                0.26
APATM_perc_Latest                  0.26
Cash_Flow_From_Inv                 0.24
ROG_Gross_Block_perc               0.23
CP                                 0.23
PBDT                               0.23
Cash_Flow_From_Opr                 0.22
ROG_Net_Worth_perc                 0.21
Rev_earn_in_forex                  0.21
Interest_Cover_Ratio_Latest        0.20
CPM_perc_Latest                    0.20
PBIT                               0.20
PBITM_perc_Latest                  0.20
PBDTM_perc_Latest                  0.19
Capital_exp_in_forex               0.19
Rev_exp_in_forex                   0.19
OG_Cost_of_Prod_perc               0.19
ROG_Gross_Sales_perc               0.19
PBIDT                              0.19
ROG_Net_Sales_perc                 0.19
Networth                           0.18
Market_Capitalisation              0.18
ROG_CP_perc                        0.18
ROG_PBDT_perc                      0.18
Net_Working_Capital                0.17
ROG_PBIT_perc                      0.17
ROG_PBT_perc                       0.17
OG_PBIDT_perc                      0.17
Selling_Cost                       0.17
Other_Income                       0.17
CEPS_annualised_Unit_Curr          0.17
ROG_PAT_perc                       0.17
PBIDTM_perc_Latest                 0.17
Capital_Employed                   0.17
Total_Debt                         0.16
Curr_Liab_and_Prov                 0.16
Curr_Assets                        0.16
Total_Assets_to_Liab               0.16
ROG_Capital_Employed_perc          0.16
Curr_Ratio_Latest                  0.16
Cost_of_Prod                       0.16
```

```
Value_Of_Output                    0.16
Net_Sales                          0.16
Gross_Sales                        0.15
Gross_Block                        0.15
ROG_Market_Capitalisation_perc     0.14
Fixed_Assets_Ratio_Latest          0.14
Book_Value_Adj_Unit_Curr           0.14
Book_Value_Unit_Curr               0.14
ROG_Total_Assets_perc              0.13
Value_of_Output_to_Gross_Block     0.13
Equity_Paid_Up                     0.12
Debtors_Vel_Days                   0.11
Creditors_Vel_Days                 0.11
Inventory_Ratio_Latest             0.10
Debtors_Ratio_Latest               0.10
Inventory_Vel_Days                 0.10
Total_Asset_Turnover_Ratio_Latest  0.06
Value_of_Output_to_Total_Assets    0.04
Default                            0.00
dtype: float64
```

In [32]:
```
#So after getting the above results we are removing these below features

df_concat_new = df_concat.drop(['ROG_Rev_exp_in_forex_perc','ROG_Rev_earn_in_forex_perc
                ,'Adjusted_PAT','PBT','APATM_perc_Latest'], axis = 1)
```

In [33]:
```
df_concat_new.shape
```

Out[33]:
```
(3586, 58)
```

Now we will do scaling

In [34]:
```
#### But first let's separate predictors and response

predictors = df_concat_new.drop('Default', axis = 1)
response = df_concat_new['Default']
```

In [35]:
```
from sklearn.preprocessing import StandardScaler
SS = StandardScaler()
predictors_scaled = pd.DataFrame(SS.fit_transform(predictors), columns = predictors.col
```

In [36]:
```
df_z = pd.concat([predictors_scaled, response], axis = 1)
```

In [37]:
```
df_z.head()
```

Out[37]:

	Equity_Paid_Up	Networth	Capital_Employed	Total_Debt	Gross_Block	Net_Working_Capital	Curr_Ass
0	NaN	NaN	NaN	NaN	NaN	NaN	-(
1	NaN	NaN	NaN	NaN	NaN	NaN	N
2	NaN	NaN	NaN	NaN	NaN	NaN	N

	Equity_Paid_Up	Networth	Capital_Employed	Total_Debt	Gross_Block	Net_Working_Capital	Curr_Ass
3	NaN	NaN	NaN	NaN	NaN	NaN	N
4	NaN	NaN	NaN	NaN	NaN	NaN	N

5 rows × 58 columns

In [38]:
```
## Now imputing the other remaining missing values using KNN Imputer


from sklearn.impute import KNNImputer

imputer = KNNImputer(n_neighbors = 10)
```

In [39]:
```
df_imputed = pd.DataFrame(imputer.fit_transform(df_z), columns = df_z.columns)
```

In [40]:
```
#Now checking null values

df_imputed.isnull().sum()
```

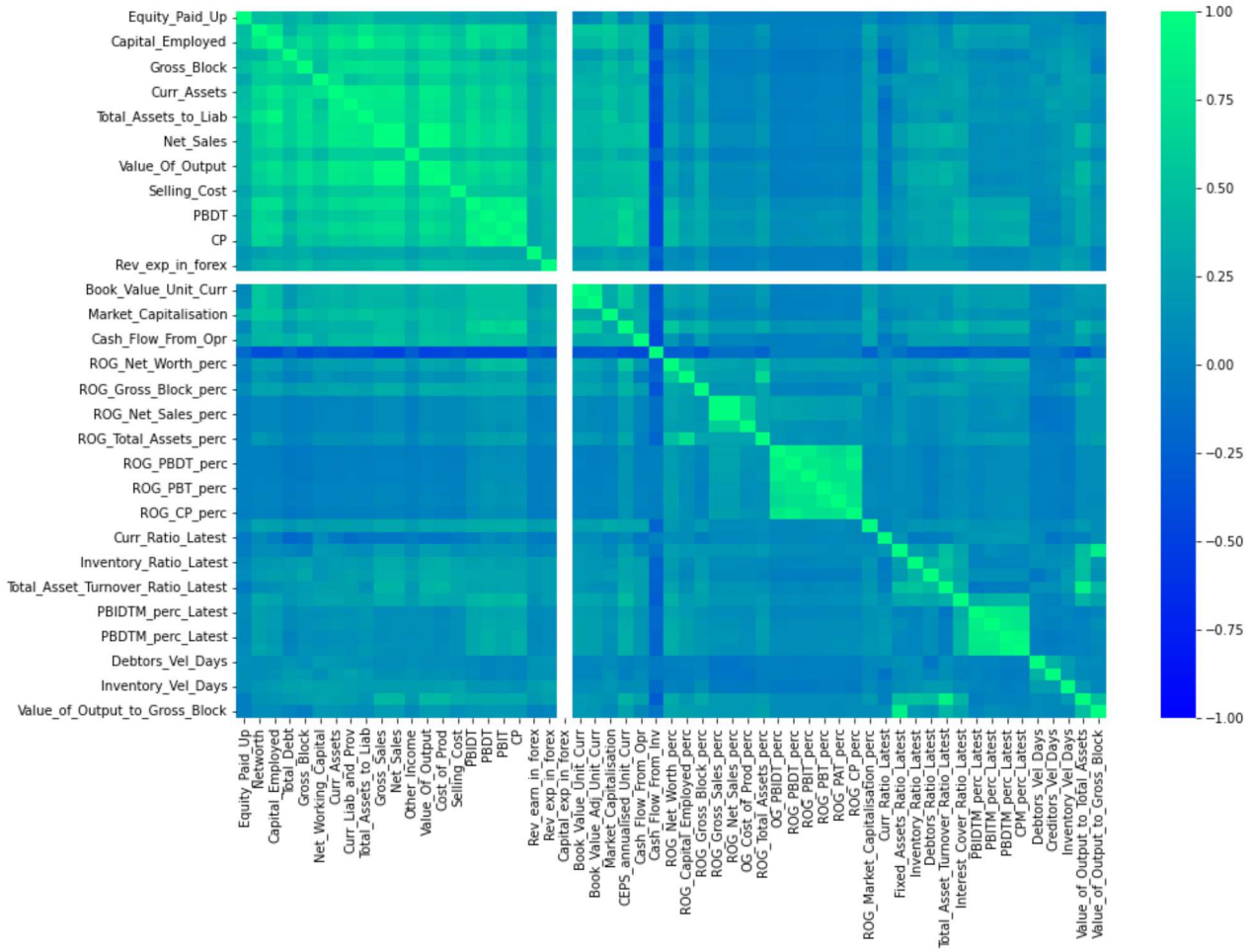
Out[40]:
```
Equity_Paid_Up                0
Networth                      0
Capital_Employed              0
Total_Debt                    0
Gross_Block                   0
Net_Working_Capital           0
Curr_Assets                   0
Curr_Liab_and_Prov            0
Total_Assets_to_Liab          0
Gross_Sales                   0
Net_Sales                     0
Other_Income                  0
Value_Of_Output               0
Cost_of_Prod                  0
Selling_Cost                  0
PBIDT                         0
PBDT                          0
PBIT                          0
CP                            0
Rev_earn_in_forex             0
Rev_exp_in_forex              0
Capital_exp_in_forex          0
Book_Value_Unit_Curr          0
Book_Value_Adj_Unit_Curr      0
Market_Capitalisation         0
CEPS_annualised_Unit_Curr     0
Cash_Flow_From_Opr            0
Cash_Flow_From_Inv            0
ROG_Net_Worth_perc            0
ROG_Capital_Employed_perc     0
ROG_Gross_Block_perc          0
ROG_Gross_Sales_perc          0
ROG_Net_Sales_perc            0
```

```
OG_Cost_of_Prod_perc                0
ROG_Total_Assets_perc               0
OG_PBIDT_perc                       0
ROG_PBDT_perc                       0
ROG_PBIT_perc                       0
ROG_PBT_perc                        0
ROG_PAT_perc                        0
ROG_CP_perc                         0
ROG_Market_Capitalisation_perc      0
Curr_Ratio_Latest                   0
Fixed_Assets_Ratio_Latest           0
Inventory_Ratio_Latest              0
Debtors_Ratio_Latest                0
Total_Asset_Turnover_Ratio_Latest   0
Interest_Cover_Ratio_Latest         0
PBIDTM_perc_Latest                  0
PBITM_perc_Latest                   0
PBDTM_perc_Latest                   0
CPM_perc_Latest                     0
Debtors_Vel_Days                    0
Creditors_Vel_Days                  0
Inventory_Vel_Days                  0
Value_of_Output_to_Total_Assets     0
Value_of_Output_to_Gross_Block      0
Default                             0
dtype: int64
```

Now after treating the outliers and missing values, lets look at the correlation

In [41]:
```
plt.figure(figsize = (15,10))
correlation = df_imputed.drop('Default', axis=1).corr()
sns.heatmap(correlation, cmap = 'winter', vmin = -1, vmax = 1)
```

Out[41]:
```
<AxesSubplot:>
```



In [42]:
```
predictors = df_imputed.drop('Default', axis = 1)
response = df_imputed['Default']
```

Now we will split the dataset into train and test set

In [43]:
```
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import RFE #Recursive Feature Elimination
from sklearn.linear_model import LogisticRegression
```

In [44]:
```
#split should be done in 67:33 and random_state = 42 as given already

X_train, X_test, y_train, y_test = train_test_split(predictors, response, test_size = 0
```

In [86]:
```
#shape of X_train

X_train.shape
```

Out[86]: (2402, 57)

In [87]:
```
#shape of X_test

X_test.shape
```

Out[87]: (1184, 57)

In [45]:
```
#After splitting we are using Logistic Regression as a model with recursive feature eli


LR = LogisticRegression()
selector = RFE(estimator = LR, n_features_to_select = 20, step = 1)

selector = selector.fit(X_train, y_train)

selector.n_features_
```

Out[45]: 20

In [46]:
```
#Now let see ranking

selector.ranking_
```

Out[46]:
```
array([25,  1,  1,  2,  1,  7,  1,  1,  1,  1, 21,  6,  1,  1, 18,  1,  1,
        1,  1, 33, 10, 38,  1,  1,  9, 34, 35, 17,  1,  1, 29, 14, 15, 16,
        1, 36, 31, 23, 26, 22, 37, 32,  1,  3, 12, 27,  5,  1, 20, 13, 28,
       19, 24, 11,  8,  4, 30])
```

In [47]:
```
#Now let see which are those 20 best features

df_new = pd.DataFrame({'Feature':predictors_scaled.columns, 'Rank':selector.ranking_})
```

In [48]:
```
df_new[df_new['Rank']==1] #features at Rank 1
```

Out[48]:

	Feature	Rank
1	Networth	1
2	Capital_Employed	1
4	Gross_Block	1
6	Curr_Assets	1
7	Curr_Liab_and_Prov	1
8	Total_Assets_to_Liab	1
9	Gross_Sales	1
12	Value_Of_Output	1
13	Cost_of_Prod	1
15	PBIDT	1
16	PBDT	1
17	PBIT	1
18	CP	1
22	Book_Value_Unit_Curr	1

	Feature	Rank
23	Book_Value_Adj_Unit_Curr	1
28	ROG_Net_Worth_perc	1
29	ROG_Capital_Employed_perc	1
34	ROG_Total_Assets_perc	1
42	Curr_Ratio_Latest	1
47	Interest_Cover_Ratio_Latest	1

In [49]:
```
#### Validating the model on test and train
```

In [50]:
```
from sklearn.metrics import confusion_matrix, classification_report
```

In [51]:
```
train_predictor = selector.predict(X_train)
test_predictor = selector.predict(X_test)
```

In [67]:
```
print(confusion_matrix(y_train, train_predictor))
```

```
[[2137   20]
 [  96  149]]
```

In [53]:
```
print(classification_report(y_train, train_predictor))
```

```
              precision    recall  f1-score   support

         0.0       0.96      0.99      0.97      2157
         1.0       0.88      0.61      0.72       245

    accuracy                           0.95      2402
   macro avg       0.92      0.80      0.85      2402
weighted avg       0.95      0.95      0.95      2402
```

In [54]:
```
print(confusion_matrix(y_test, test_predictor))
```

```
[[1028   14]
 [  48   94]]
```

In [55]:
```
print(classification_report(y_test, test_predictor))
```

```
              precision    recall  f1-score   support

         0.0       0.96      0.99      0.97      1042
         1.0       0.87      0.66      0.75       142

    accuracy                           0.95      1184
   macro avg       0.91      0.82      0.86      1184
```

```
weighted avg       0.95      0.95      0.94      1184
```

The recall score is not so good. Maybe the data is still imbalance. We will balance the data using SMOTE

In [56]:
```
from imblearn.over_sampling import SMOTE
SM = SMOTE(random_state=33)
X_res, y_res = SM.fit_resample(X_train, y_train)
```

In [57]:
```
selector_smote = selector.fit(X_res, y_res)
```

In [58]:
```
selector_smote.n_features_
```

Out[58]:
```
20
```

In [59]:
```
train_predictor_smote = selector_smote.predict(X_res)
test_predictor_smote = selector_smote.predict(X_test)
```

In [60]:
```
print(classification_report(y_res, train_predictor_smote))
```

```
              precision    recall  f1-score   support

         0.0       0.93      0.91      0.92      2157
         1.0       0.91      0.93      0.92      2157

    accuracy                           0.92      4314
   macro avg       0.92      0.92      0.92      4314
weighted avg       0.92      0.92      0.92      4314
```

In [61]:
```
print(classification_report(y_test, test_predictor_smote))
```

```
              precision    recall  f1-score   support

         0.0       0.99      0.87      0.93      1042
         1.0       0.50      0.94      0.65       142

    accuracy                           0.88      1184
   macro avg       0.74      0.91      0.79      1184
weighted avg       0.93      0.88      0.89      1184
```

Now our recall has been improved so much for both test and train.

CONCLUSION:

1. We got better recall of 94% for 1, that means 94% of the actual value of defaults are the right prediction.
2. Precision of 50% means 50% of the predicted defaults are actual.

__END__