

PROJECT REPORT - TEAM 6

LoanStats – Data Preprocessing

Team Members

Aravind Senthil Kumar

Mohit Kumar Dhiman

Anjani Korkonda Bhattar

Poojith Routhu

Sneha Jyotindrakumar

Note: “The work contained and presented here is our team’s work and our team’s work alone.”

Contents

1.0	Executive Summary.....	3
2.0	Sampling.....	4
3.0	Key Observations	5
4.0	Data Preprocessing	6
4.1	Changing variable types	6
4.2	Data Cleaning	7
4.2.1	Missing Values.....	7
4.2.2	Resolve inconsistencies.....	12
4.2.3	Outlier Detection & Analysis	13
4.3	Data Reduction.....	27
4.3.1	Correlation	27
4.3.2	Principal Component Analysis.....	28
5.0	Updated Data dictionary	30
6.0	Appendix	31

1.0 Executive Summary

We started our data pre-processing by obtaining the random sample data set “loan_sample_final” of size 30000 from the main data table “LoanStats modified fall 2018 Group Project 1” where we first checked the data type of all variables in JMP and made necessary corrections.

We then used **Summary table** to find missing data across all fields and found that it constituted less than 5% of the total sample. We also used various combinations of **Missing Data Pattern** and found out that 1089 rows were missing data in 8 fields in the dataset. We further analyzed other missing data in the fields. We then retained, modified or deleted the rows as applicable and saved the new version of the sample as “loan_sample_final_v2”.

We tried different methods for modifying the data like contingency tables and distributions for each variable, recoding the necessary variables and formatting them to be used for analysis, and applying formulas for creating new columns.

We tried to take actions on the observed inconsistencies in the data. We also tried to check for various outlier methods like univariate and multivariate outlier analysis to see for the potential outliers. We transformed some variables to best fit the data using Shash transform, Johnson Si transform, etc.

For data reduction we performed bivariate and multivariate correlation analysis between the fields and took necessary actions based on the insights from the analysis for the data preparation.

We also performed the Principal Component Analysis for finding the cumulative percentages of information captured by the principal components. From the observations of PCA we decided to retain 18 Principal Components for modeling purposes for 98% information retain.

Finally, we have two data sets, one with the Principal Components and one with the original continuous fields. We have decided to keep both data sets and try modeling on both data sets to see which provides more accurate results.

2.0 Sampling

1. Open the data table LoanStats modified fall 2018 Group Project 1
2. Go to **Row** → **Row selection** → **Select Randomly**
3. Enter the sample size value as 30000

	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7	Column 8	Column 9	Column 10	Column 11	Column 15	Col
1	member_id	loan_amnt	funded_amnt	term	int_rate	installment	grade	emp_title	emp_length	annual_inc	is_inc_v	loan
2	11981032	7550	7550	36 months	16.24%	266.34	C	Special Order Fulfillment Clerk	3 years	28000	Not Verified	Curr
3	12000897	27050	27050	36 months	10.99%	885.46	B	Team Leadern Customer Ops & Systems	10+ years	55000	Verified	Curr
4	12001118	28000	28000	36 months	7.62%	872.52	A	Area Sales Manager	5 years	325000	Source Verified	Fully
5	11971211	11500	11500	60 months	22.90%	323.54	E	Secretary	4 years	32760	Verified	Curr
6	12001033	4800	4800	36 months	10.99%	157.13	B	Surgical Technician	2 years	39600	Source Verified	Curr
7	11981122	20800	20800	36 months	13.53%	706.16	B	Operations Manager	10+ years	81500	Verified	Curr
8	12011167	15000	15000	36 months	8.90%	476.3	A	aircraft maintenance engineer	2 years	63000	Not Verified	Curr
9	11999781	12000	12000	36 months	7.62%	373.94	A	Systems Engineer	3 years	96500	Not Verified	Curr
10	11971241	12000	12000					LTC	10+ years	130000	Source Verified	Curr
11	12001108	8000	8000					PARTS MANAGER	2 years	33000	Not Verified	Curr
12	12086734	11100	11100					Teacher	10+ years	90000	Not Verified	Curr
13	12011200	9750	9750					Medical Assistant	1 year	26000	Not Verified	Curr
14	1319523	12000	12000					MANAGER INFORMATION DELIVERY	10+ years	105000	Not Verified	Curr
15	11941167	20000	20000					Senior Underwriter	3 years	72000	Verified	Curr
16	11961207	10000	10000					Associate	2 years	60000	Verified	Curr
17	11970773	30000	30000	60 months	14.47%	705.38	C	School Administrator	10+ years	72524	Verified	Curr
18	10389317	10000	10000	60 months	13.98%	232.58	C	electronic mapper	5 years	25000	Source Verified	Curr
19	11951188	18450	18450	36 months	13.98%	630.4	C	LPN nurse	10+ years	65000	Not Verified	Curr
20	11931181	14825	14825	36 months	18.25%	537.83	D	Manager	< 1 year	175000	Verified	Curr
21	11970403	10000	10000	36 months	9.67%	321.13	B	machinist	9 years	45000	Not Verified	Fully
22	11927267	6000	6000	36 months	9.67%	192.68	B	IT Analyst	1 year	70000	Not Verified	Fully
23	11961248	20000	20000	36 months	13.98%	683.36	C	Alarm Technician	10+ years	80000	Source Verified	Curr
24	11929803	17475	17475	60 months	21.48%	477.49	E	Probation Officer	10+ years	42494	Source Verified	Curr
25	11961187	4500	4500	36 months	19.22%	165.46	D	Senior Network Engineer	10+ years	105000	Not Verified	Curr
26	11961279	8325	8325	36 months	15.61%	291.09	C	data analyst	10+ years	65000	Source Verified	Curr
27	11971186	31825	31825	60 months	20.50%	852.05	E	Technician support specialist	10+ years	70000	Verified	Curr
28	11667635	16000	16000	36 months	7.62%	498.59	A	Senior Software Engineer	< 1 year	112000	Not Verified	Curr

4. When the sample rows are highlighted, go to **Rows** → **Row selection** → **Invert Row Selection**
5. Go to **Rows** → **Hide and Exclude**

1	11981032	7550	7550	36 months	16.24%	266.34	C	Special Order ...	3 years	28000	Not Verified	Current	debt_consolidation	1	160
2	12000897	27050	27050	36 months	10.99%	885.46	B	Team Leadern ...	10+ years	55000	Verified	Current	debt_consolidation	3	16473
3	12001118	28000	28000	36 months	7.62%	872.52	A	Area Sales ...	5 years	325000	Source Verified	Fully Paid	debt_consolidation	6	13901
4	11971211	11500	11500	60 months	22.90%	323.54	E	Secretary	4 years	32760	Verified	Current	debt_consolidation	9	2689
5	12001033	4800	4800	36 months	10.99%	157.13	B	Surgical Technician	2 years	39600	Source Verified	Current	home_improvem...	0	21564
6	11981122	20800	20800	36 months	13.53%	706.16	B	Operations ...	10+ years	81500	Verified	Current	debt_consolidation	9	6811
7	12011167	15000	15000	36 months	8.90%	476.3	A	aircraft ...	2 years	63000	Not Verified	Current	debt_consolidation	3	2969
8	11999781	12000	12000	36 months	7.62%	373.94	A	Systems Engineer	3 years	96500	Not Verified	Current	debt_consolidation	4	2441
9	11971241	12000	12000	36 months	11.99%	398.52	B	LTC	10+ years	130000	Source Verified	Current	debt_consolidation	4	3567
10	12001108	8000	8000	36 months	10.99%	261.88	B	PARTS MANAGER	2 years	33000	Not Verified	Current	debt_consolidation	2	2255
11	12086734	11100	11100	36 months	14.98%	384.68	C	Teacher	10+ years	90000	Not Verified	Current	other	2	1016
12	12011200	9750	9750	36 months	13.98%	333.14	C	Medical Assistant	1 year	26000	Not Verified	Current	debt_consolidation	2	1752
13	1319523	12000	12000	36 months	6.62%	368.45	A	MANAGER ...	10+ years	105000	Not Verified	Current	debt_consolidation	4	39432
14	11941167	20000	20000	60 months	16.24%	488.92	C	Senior Underwriter	3 years	72000	Verified	Current	debt_consolidation	3	6797
15	11961207	10000	10000	60 months	14.98%	237.8	C	Associate	2 years	60000	Verified	Current	major_purchase	10	5317
16	11970773	30000	30000	60 months	14.47%	705.38	C	School ...	10+ years	72524	Verified	Current	credit_card	3	18096
17	10389317	10000	10000	60 months	13.98%	232.58	C	electronic mapper	5 years	25000	Source Verified	Current	debt_consolidation	6	709
18	11951188	18450	18450	36 months	13.98%	630.4	C	LPN nurse	10+ years	65000	Not Verified	Current	debt_consolidation	5	11329
19	11931181	14825	14825	36 months	18.25%	537.83	D	Manager	< 1 year	175000	Verified	Current	small_business	3	27360
20	11970403	10000	10000	36 months	9.67%	321.13	B	machinist	9 years	45000	Not Verified	Fully Paid	debt_consolidation	4	8279
21	11927267	6000	6000	36 months	9.67%	192.68	B	IT Analyst	1 year	70000	Not Verified	Fully Paid	credit_card	4	3149
22	11961248	20000	20000	36 months	13.98%	683.36	C	Alarm Technician	10+ years	80000	Source Verified	Current	debt_consolidation	5	3083
23	11929803	17475	17475	60 months	21.48%	477.49	E	Probation Officer	10+ years	42494	Source Verified	Current	debt_consolidation	2	130
24	11961187	4500	4500	36 months	19.22%	165.46	D	Senior Network ...	10+ years	105000	Not Verified	Current	other	1	1338
25	11961279	8325	8325	36 months	15.61%	291.09	C	data analyst	10+ years	65000	Source Verified	Current	debt_consolidation	7	508
26	11971186	31825	31825	60 months	20.50%	852.05	E	Technician ...	10+ years	70000	Not Verified	Current	debt_consolidation	6	6605
27	11667635	16000	16000	36 months	7.62%	498.59	A	Senior Software ...	< 1 year	112000	Not Verified	Current	debt_consolidation	3	51254
28	11930310	3000	3000	36 months	19.97%	111.45	D	Claimsadjuster	10+ years	110000	Source Verified	Current	other	7	1513
29	11921243	5000	5000	36 months	13.53%	169.75	B	Dispatcher	10+ years	70000	Not Verified	Current	other	8	5854
30	11951257	4000	4000	36 months	16.24%	141.11	C	Teacher	10+ years	84000	Source Verified	Fully Paid	other	3	2676
31	12030851	9800	9800	36 months	10.99%	320.8	B	sales merchandiser	10+ years	40000	Not Verified	Current	debt_consolidation	1	4294
32	12020895	14575	14575	36 months	13.53%	494.82	B	Administrative ...	10+ years	41600	Source Verified	Fully Paid	debt_consolidation	4	17698
33	12021092	11200	11200	36 months	13.53%	380.24	B	Customer ...	5 years	38000	Source Verified	Current	house	9	11827
34	11971062	11000	11000	36 months	7.90%	344.2	A	Teacher	1 year	38000	Not Verified	Current	credit_card	3	3416
35	11971152	14000	14000	36 months	7.90%	438.07	A	Tooling Engineer	7 years	87500	Not Verified	Current	credit_card	6	8674
36	12021016	30000	30000	60 months	13.40%	705.70	F	Administrative ...	10+ years	134000	Source Verified	Current	debt_consolidation	7	4669

6. Export this data to excel to remove the headers 'Column1', 'Column2' etc.
7. Import it back to JMP and save the sample as loan_sample_final

3.0 Key Observations

Below are the highlights of our initial observations

1. *loan_amnt* and *funded_amnt* have a correlation of 0.9997
2. There are 1447 rows with no data in any column – 4.84% of the total data
3. The variables *int_rate*, *emp_length*, *revol_util* are displayed as nominal variables
4. *mnths_since_last_delinq* has 17,932 missing values
5. *revol_balance* has an extreme outlier value '1746716' in Row 2699
6. The following fields have the same set of 1089 values missing
 - a. *acc_open_past_24mnths*
 - b. *bc_open_to_buy*
 - c. *percent_bc_gt_75*
 - d. *bc_util*
 - e. *mort_acc*
 - f. *total_bal_ex_mort*
 - g. *num_rev_accts*
 - h. *total_cur_bal*

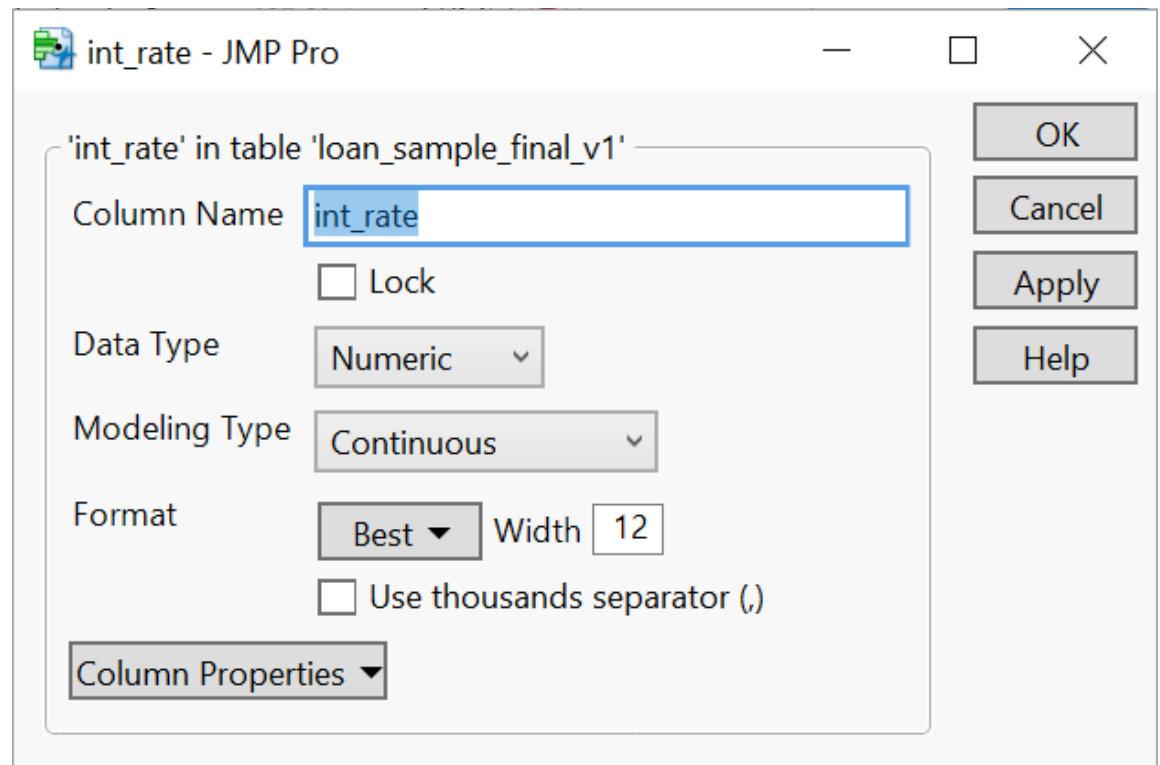
Note: The above data are just the highlights of our initial observations. For detailed analysis and modifications information, please refer to the [Data Preprocessing](#) section

4.0 Data Preprocessing

4.1 Changing variable types

The variables *int_rate*, *emp_length*, *Revol_util* are displayed as nominal variables and need to be changed to continuous variables for further analysis.

1. *emp_length*
 - a. To change this variable to continuous, the term 'years' has to be removed from the values.
 - b. The word 'years' was eliminated using **Recode** and the resultant data was saved in a new column 'emp_length2'
 - c. By this, the variable *emp_length* was changed to continuous
2. *int_rate*
 - a. Each value in this variable contains the percentage sign (%)
 - b. The symbol was removed by accessing **Columns** → **Column Info**, changing the Data Type to 'Numeric' and Modeling Type to 'Continuous'




3. *revol_util*
 - a. Every value in this variable also contains the percentage sign (%)
 - b. Similarly, the symbol was removed by accessing **Columns** → **Column Info**, changing the Data Type to 'Numeric' and Modeling Type to 'Continuous'

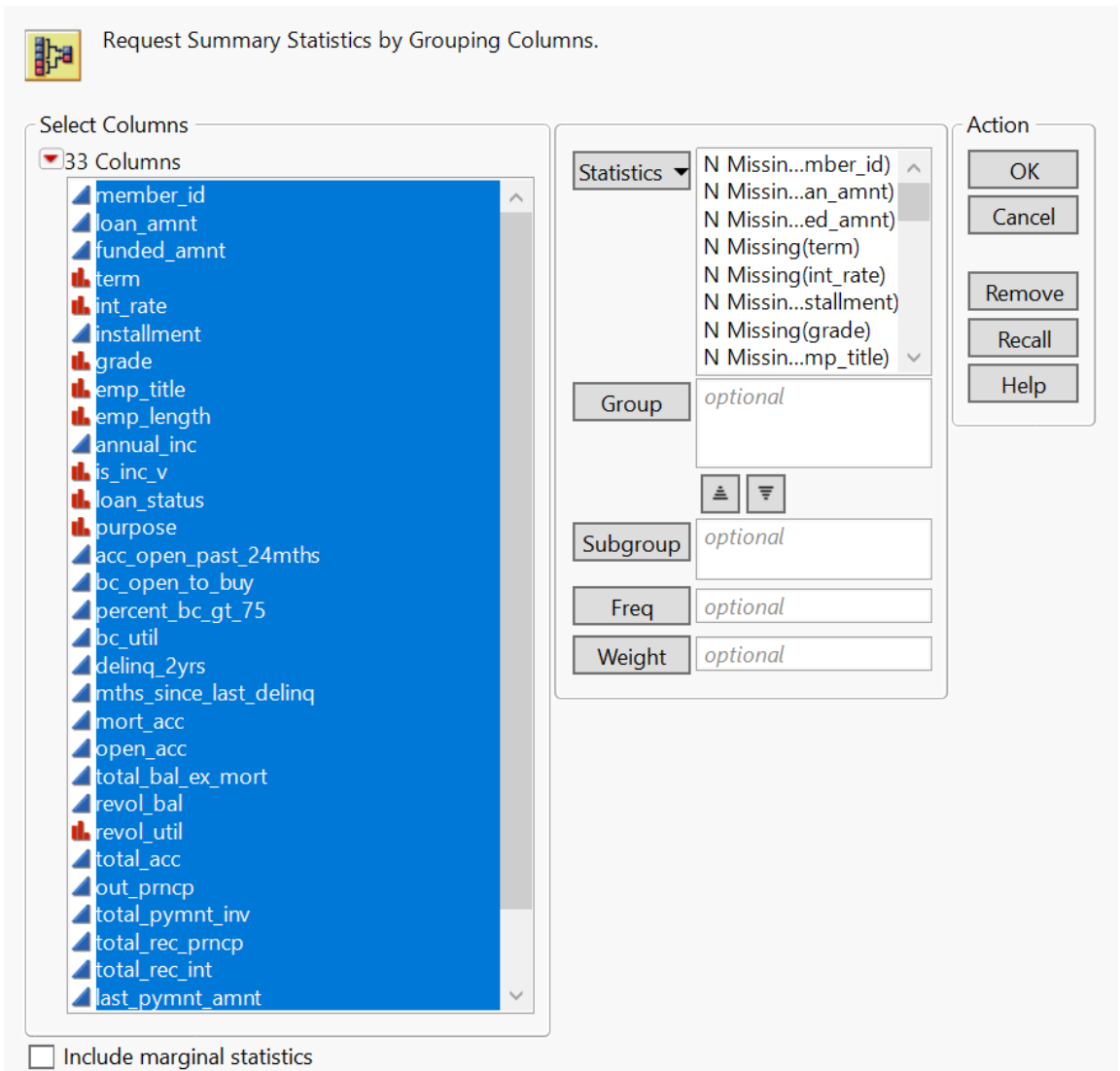
4.2 Data Cleaning

4.2.1 Missing Values

4.2.1.1 Observations

1. Missing data across all fields was identified using **Tables → Summary**
2. All the fields in the left pane were selected under the Statistics 'N missing'

 Summary - JMP Pro



3. From the obtained Summary table, it was observed that 1447 rows were completely blank and contained no value for any variable.

	32/0 Cols		member_id	loan_amnt	term	int_rate	installment	grade	emp_title	emp_length	annua
		29974			
		29975			
		29976			
		29977			
		29978			
		29979			
		29980			
		29981			
		29982			
		29983			
		29984			
		29985			
		29986			
		29987			
		29988			
		29989			
		29990			
		29991			
		29992			
		29993			
		29994			
		29995			
		29996			
		29997			
		29998			
		29999			
		30000			

4. On further analysis using various combinations of missing data patterns (**Tables → Missing Data Pattern**), it was observed that all the below variables were missing data in 1089 common rows:
- acc_open_past_24mnth*
 - bc_open_to_buy*
 - percent_bc_gt_75*
 - bc_util*
 - mort_acc*
 - total_bal_ex_mort*
 - num_rev_accts*
 - total_cur_bal*

Missing Data Pattern - JMP Pro

File Edit Tables Rows Cols DOE Analyze Graph Tools Add-Ins View Window Help

Missing Data Pattern

Source
Treemap
Cell Plot

Columns (11/0)

Count
Number of columns missing
Patterns
acc_open_past_24mths
bc_open_to_buy
percent_bc_gt_75
bc_util
mort_acc
total_bal_ex_mort
num_rev_accts
tot_cur_bal

	Count	Number of columns missing	Patterns	acc_open_past_24mths	bc_open_to_buy	percent_bc_gt_75	bc_util	mort_acc	total_bal_ex_mort	num_rev_accts	tot_cur_bal
1	24207	0	00000000	0	0	0	0	0	0	0	0
2	3001	2	00000011	0	0	0	0	0	0	1	1
3	15	1	00010000	0	0	0	1	0	0	0	0
4	3	3	00010011	0	0	0	1	0	0	1	1
5	200	3	01110000	0	1	1	1	0	0	0	0
6	38	5	01110011	0	1	1	1	0	0	1	1
7	1089	8	11111111	1	1	1	1	1	1	1	1

4.2.1.2 Deletion

- Based on the above observations, the 1447 rows that were missing data for all the variables were deleted as they provide no information and constitute less than 5% of the total sample. The updated version of the sample was saved as loan_sample_final_v1
- The 1089 rows that were commonly missing the values for the below 8 variables were also deleted. The updated version of the sample was saved as loan_sample_final_v2
- The below table clearly depicts the count of missing values in the
 - initial sample
 - sample after deleting the 1447 blank rows across all variables and
 - sample after deleting the 1089 rows that were commonly missing in 8 variables

Variable	Missing Values		
	Initial Sample	Sample after deleting the 1447 rows with no data	Sample after deleting the 1089 rows commonly missing in the 8 variables listed above in Page 9
member_id	1447	0	0
loan_amnt	1447	0	0
funded_amnt	1447	0	0
term	1447	0	0
int_rate	1447	0	0
installment	1447	0	0
grade	1447	0	0
emp_title	3231	1784	1784
emp_length	1447	0	0
annual_inc	1447	0	0
is_inc_v	1455	8	8
loan_status	1447	0	0

purpose	1447	0	0
acc_open_past_24mths	2536	1089	0
bc_open_to_buy	2774	1327	238
percent_bc_gt_75	2774	1327	238
bc_util	2792	1345	256
delinq_2yrs	1447	0	0
mths_since_last_delinq	17,932	16,485	16,485
mort_acc	2536	1089	0
open_acc	1447	0	0
total_bal_ex_mort	2536	1089	0
revol_bal	1447	0	0
revol_util	1474	27	27
total_acc	1447	0	0
out_prncp	1447	0	0
total_pymnt_inv	1447	0	0
total_rec_prncp	1447	0	0
total_rec_int	1447	0	0
last_pymnt_amnt	1447	0	0
num_rev_accts	5578	4131	3042
tot_cur_bal	5578	4131	3042
policy_code	1447	0	0

4.2.1.3 Modification

For the remaining missing data, the respective steps taken are provided in the below table.

Field Name	Missing Values	Steps Taken
emp_title	1784	<ul style="list-style-type: none"> • These are nominal data with no values in common • Some values are invalid employee titles • Since there is no additional data available from the source, this variable may not be of any use for data analysis or modeling • Hence, no modifications were made to this field
is_inc_v	8	<ul style="list-style-type: none"> • We tried to predict the missing values in this field using the contingency tables by checking with the variables <i>loan_status</i> and <i>purpose</i> • No relation could be found between these variables and we replaced them with the nominal value “Unknown” so that we can perform analysis in the future using this nominal variable
bc_open_to_buy	238	<ul style="list-style-type: none"> • Values missing in same rows as <i>percent_bc_gt_75</i> • We did not impute this field since mean and median were too far and there was no significant correlation with any other field

percent_bc_gt_75	238	<ul style="list-style-type: none"> • A new column 'percent_bc_gt_75 2' was added and the median(value=50) was used to fill the missing values using Recode • The median is used since the distribution is slightly right skewed • Values were missing in same rows as <i>bc_open_to_buy</i> • The screenshots and steps of this process are provided below
bc_util	256	<ul style="list-style-type: none"> • A new column 'bc_util2' was added and the median (value=72.2) was used to fill the missing values using Recode • The median is used since distribution is right skewed • The screenshots and steps of this process are provided below
mths_since_last_delinq	16,485	<ul style="list-style-type: none"> • This variable is missing more than 55% of data from the sample • No additional data being available from the source, no modifications were made to this variable
revol_util	27	<ul style="list-style-type: none"> • A new column 'revol_util2' was added and the median (0.604) was used to fill the missing values using Recode • The median is used since the distribution is skewed • The screenshots and steps of this process are provided below
num_rev_accts	3042	<ul style="list-style-type: none"> • A new column 'num_rev_accts 2' was added and the median (64) was used to fill the missing values using Recode • The median is used since the distribution is right skewed • The screenshots and steps of this process are provided below
tot_cur_bal	3042	<ul style="list-style-type: none"> • Upon analysis, it was observed that if the number of mortgage accounts is 0, total balance except mortgage will be the same as the total current balance • Hence, the below formula was applied to get the missing values for total current balance field in the additional column created as 'tot_cur_bal_calc' <ul style="list-style-type: none"> ○ If mort_acc ==0 => total_bal_ex_mort ○ Else => tot_cur_bal

4.2.2 Resolve inconsistencies

The below inconsistencies were observed in the data set.

1. In the variable '*term*',
 - a. 1 record marked as 'NA' was replaced with the most occurring value '36 months' using **Recode**
 - b. The value '45' was changed to '45 months' for data consistency using **Recode**

The screenshot shows the 'Recode' dialog for the variable 'term'. The 'In Place' checkbox is checked. The 'Name' field is set to 'term'. The 'Count' column shows the frequency of each value. The 'Old Values (5)' column lists the original values, and the 'New Values (4)' column lists the new values. The 'Latest change' is '45 months -> .'. The 'Group controls' section has 'View Groups' checked. The 'Recode' button is highlighted.

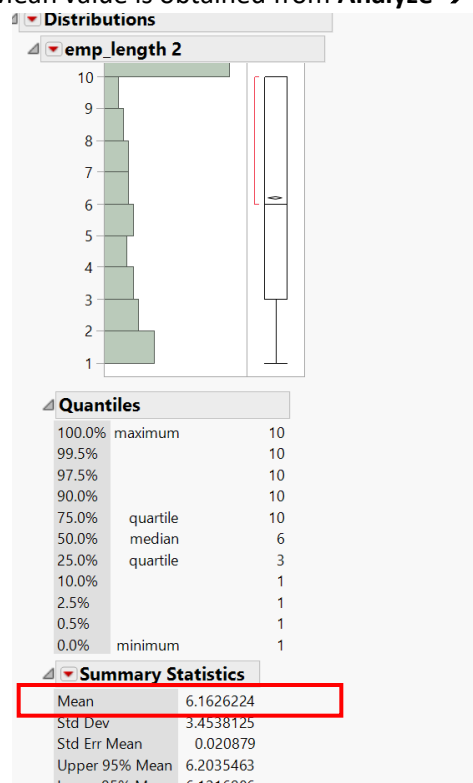
Count	Old Values (5)	New Values (4)
21899	36 months	36 months
1	36 months	36 months
1	45 months	45 months
6652	60 months	60 months
1447	.	.

Latest change: 45 months -> .

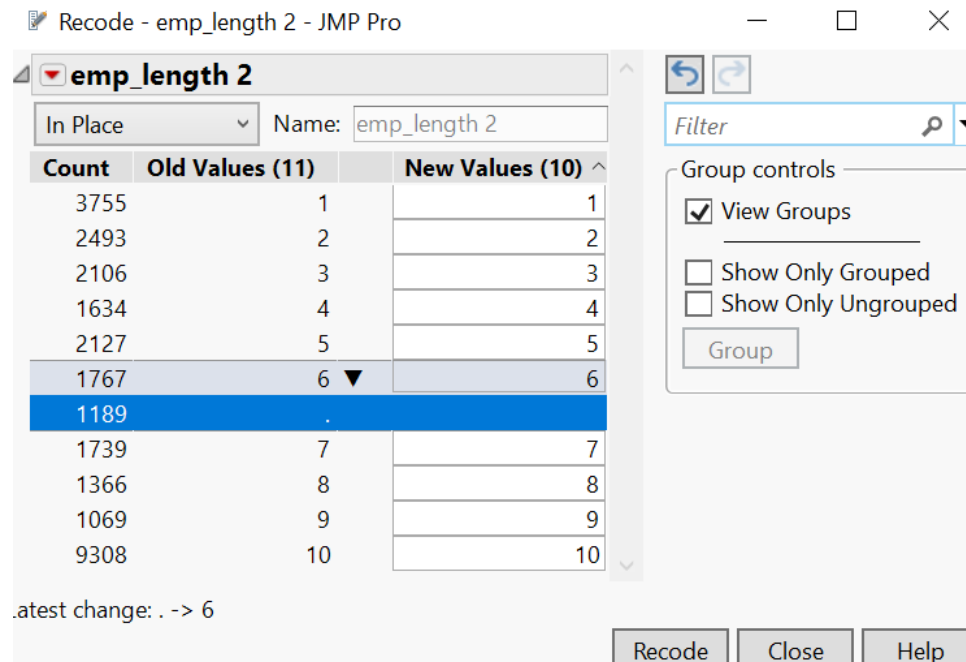
Buttons: Recode, Close, Help

2. In the variable '*policy*', there was a record with value '22'. As per data dictionary, the valid value for policy is either 1 or 2. Assuming '22' to be a typo, we replaced it with '2'.
3. In the variable '*emp_length 2*', the '.' Values were replaced with the mean

- a. Mean value is obtained from **Analyze** → **Distribution**



- b. Replace '.' value by Mean value using **Cols** → **Recode**



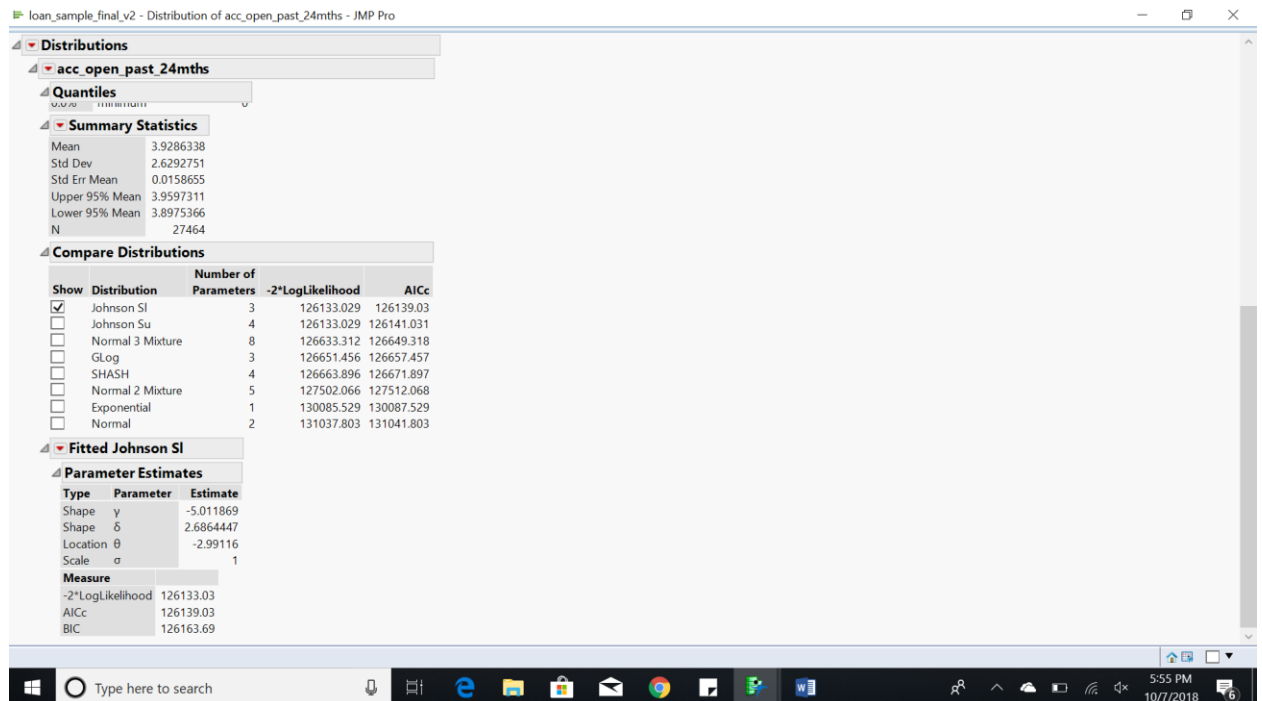
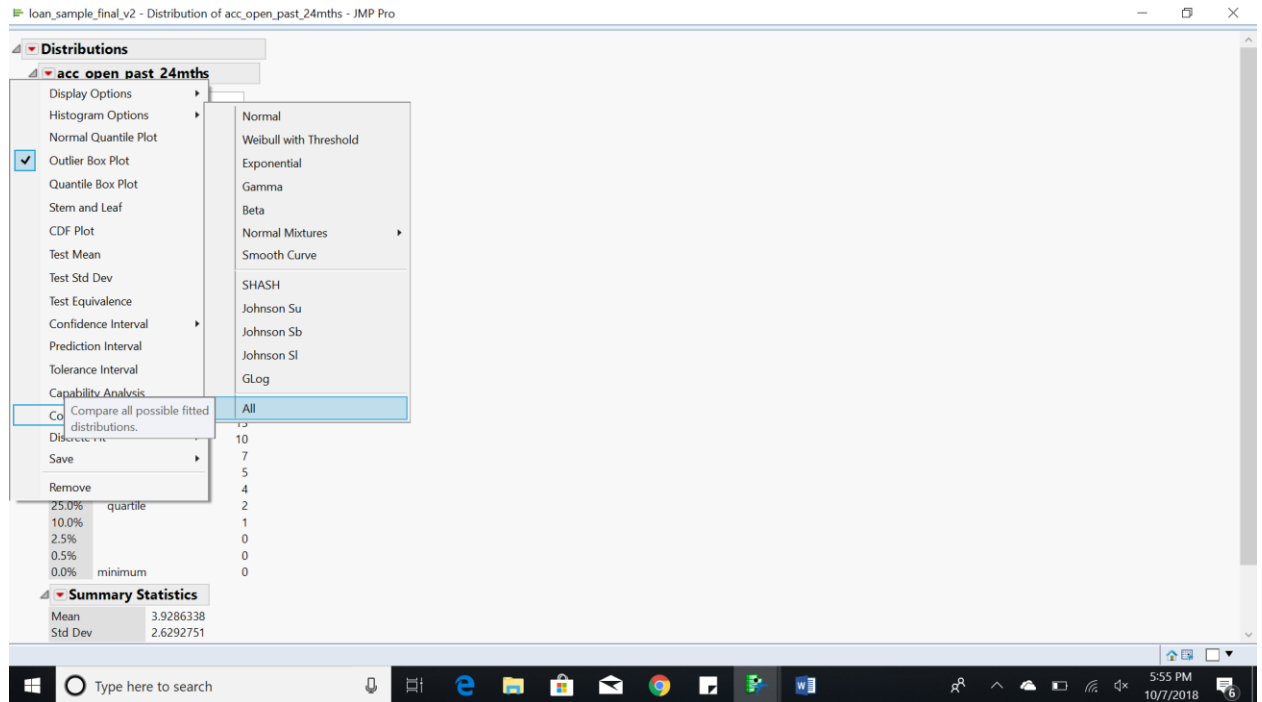
4.2.3 Outlier Detection & Analysis

We analyzed the distribution on each continuous field to determine the number of outliers. Below are a few fields that we modified because of the presence of too many outliers.

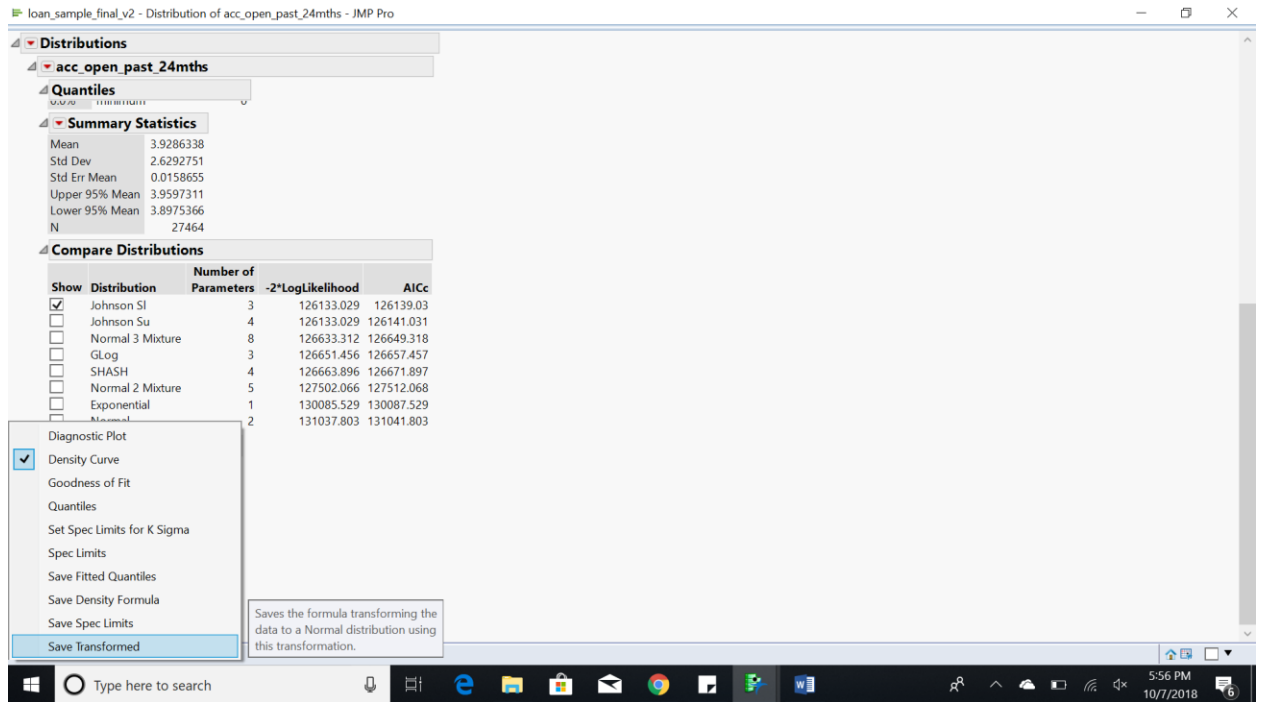
Field Name	Outlier Analysis & Transformation
installment	<ul style="list-style-type: none"> Applied continuous fit and Saved Standardized - Gamma Distribution as new column '<i>Standardized installments</i>' The screenshots and steps of transformation are provided below
bc_open_to_buy	<ul style="list-style-type: none"> Applied continuous fit and Saved SHASH transform as new column '<i>SHASH Transform bc_open_to_buy</i>' The screenshots and steps of transformation are provided below
total_acc	<ul style="list-style-type: none"> Applied continuous fit and Saved Johnson SI transform as new column '<i>Johnson SI Transform total_acc</i>' The screenshots and steps of transformation are provided below
total_pymnt_inv	<ul style="list-style-type: none"> Applied continuous fit and Saved Johnson SI transform as new column '<i>Johnson SI Transform total_pymnt_inv</i>' The screenshots and steps of transformation are provided below
total_rec_prncp	<ul style="list-style-type: none"> Applied continuous fit and Saved Generalized Logarithm transform as new column '<i>Generalized Logarithm Transform total_rec_prncp</i>' The screenshots and steps of transformation are provided below
total_rec_int	<ul style="list-style-type: none"> Applied continuous fit and Saved Johnson SI transform as new column '<i>Johnson SI Transform total_rec_int</i>' The screenshots and steps of transformation are provided below
last_pymnt_amnt	<ul style="list-style-type: none"> Applied continuous fit and Saved Johnson SU transform as new column '<i>Johnson SU Transform last_pymnt_amnt</i>' The screenshots and steps of transformation are provided below

Steps for analyzing outlier and transforming the data to the distribution that fits the best

1. Select a column and click on **Analyze** → **Distribution**
2. Click the Red arrow and select **Continuous Fit** → **All**

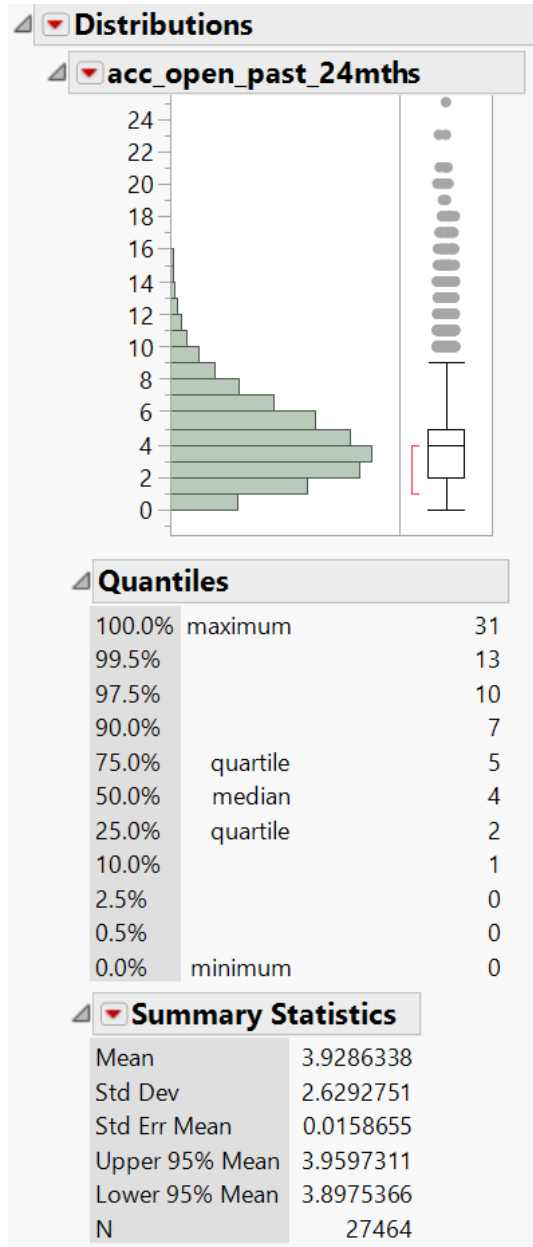


3. Save the selected fit

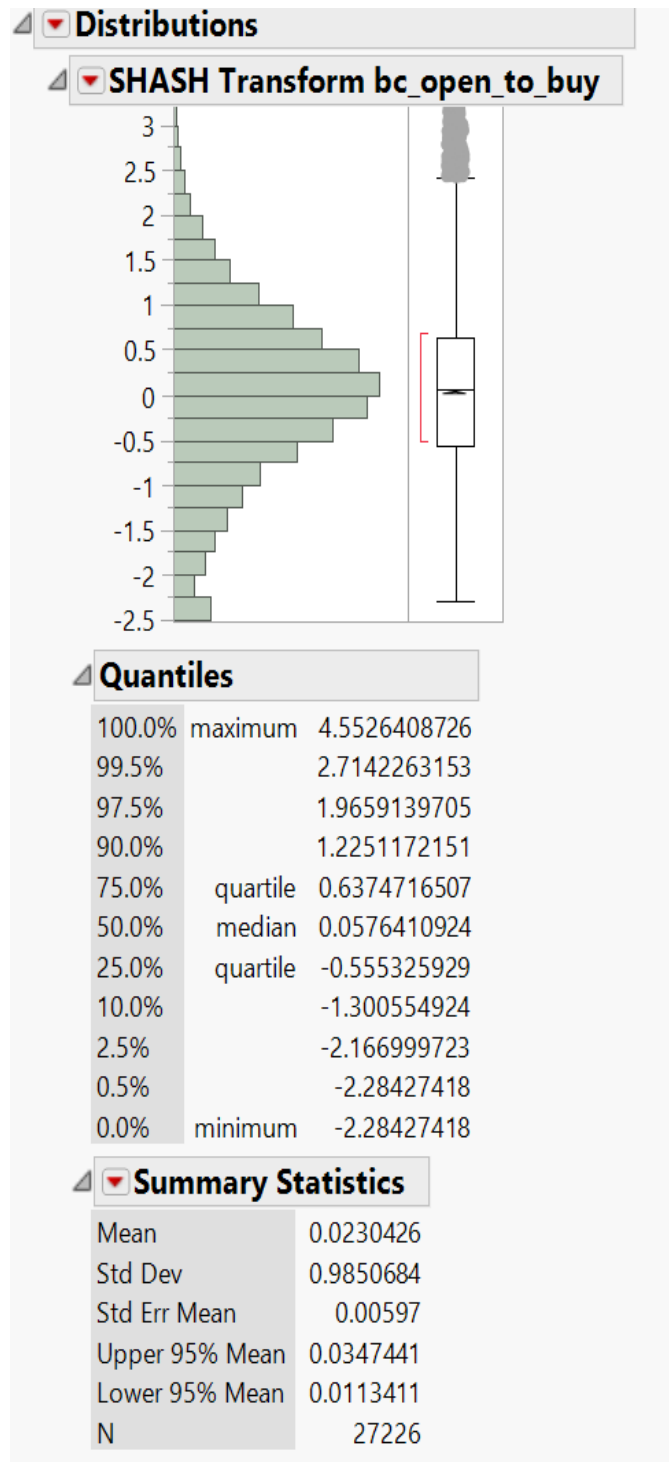


Screenshots for outlier analysis and transformations

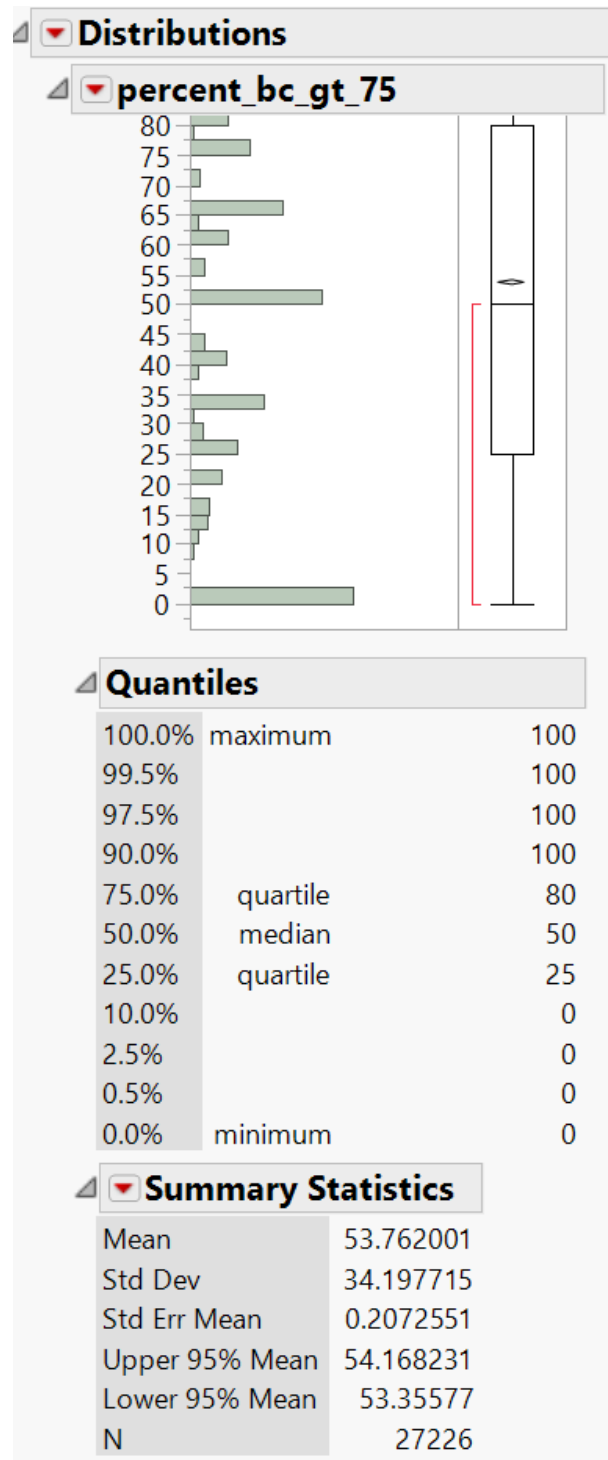
1. *Acc_open_past_24months*: Box-whisker plot



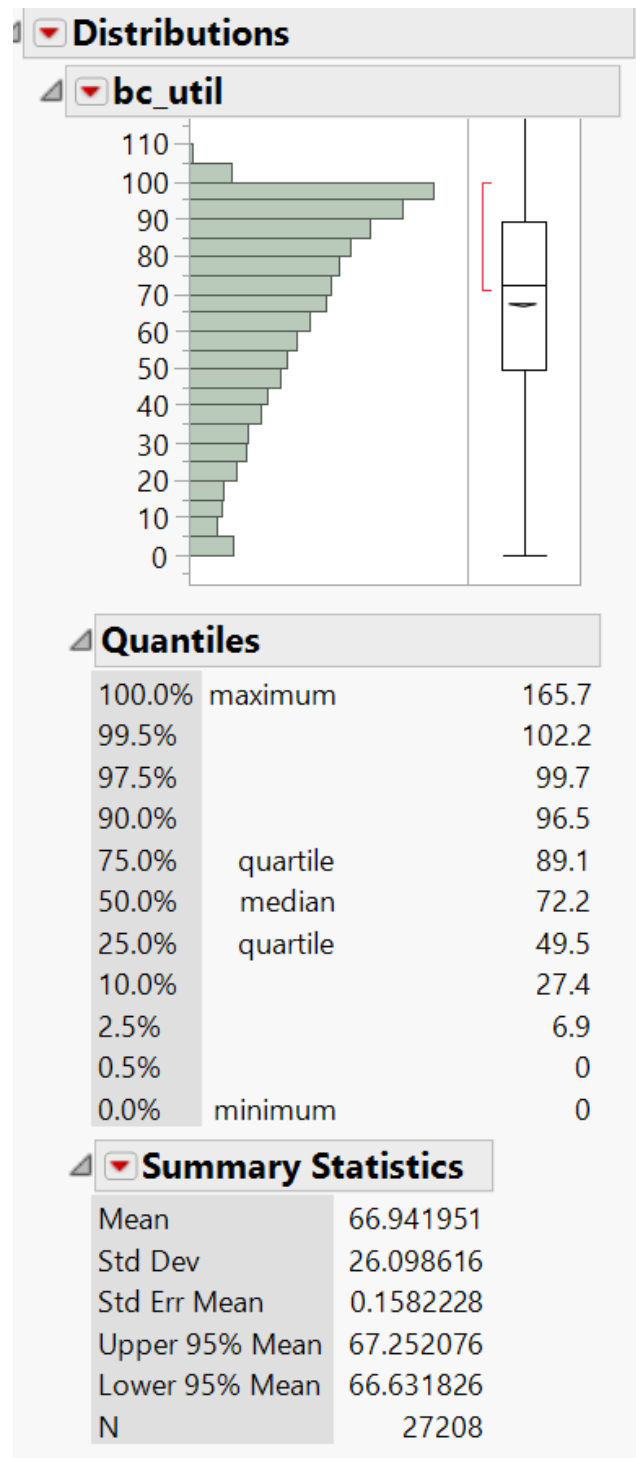
2. *bc_open_to_buy*: SHASH Transform Box-whisker plot



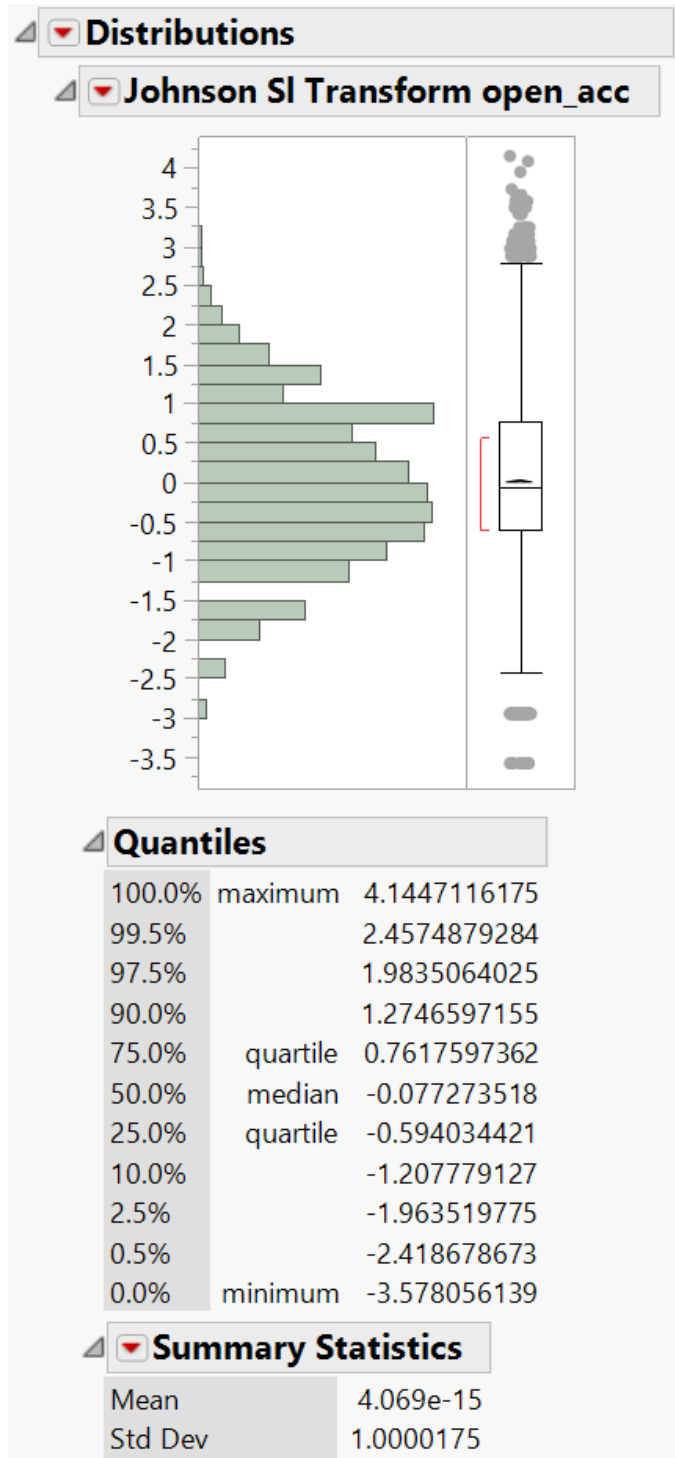
3. *percent_bt_gt_75*: Box-whisker plot



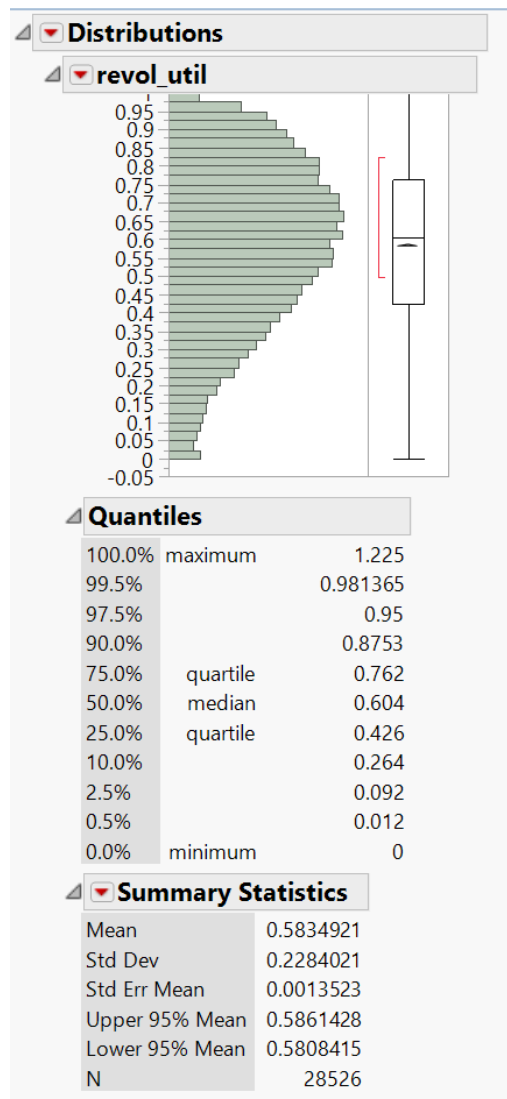
4. *bc_util*: Box-whisker plot



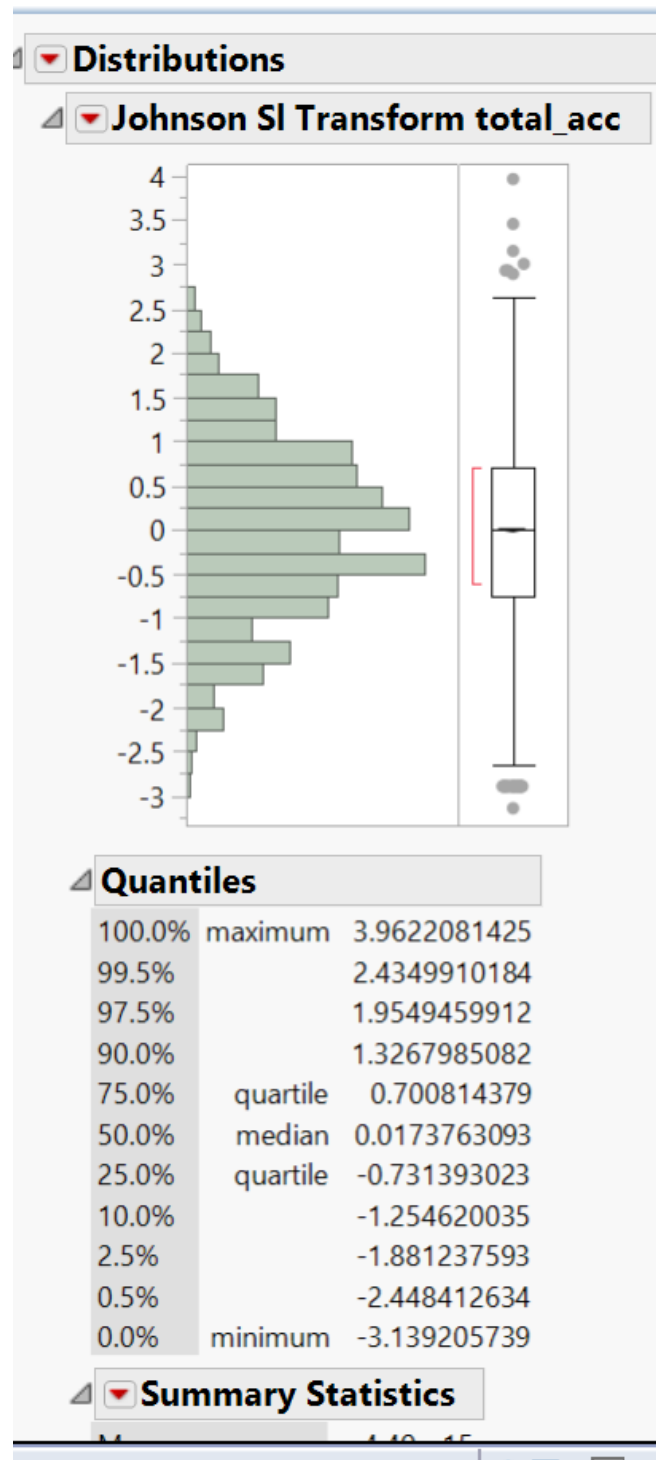
5. *open_acc*: Johnson SI Transform Box-whisker plot



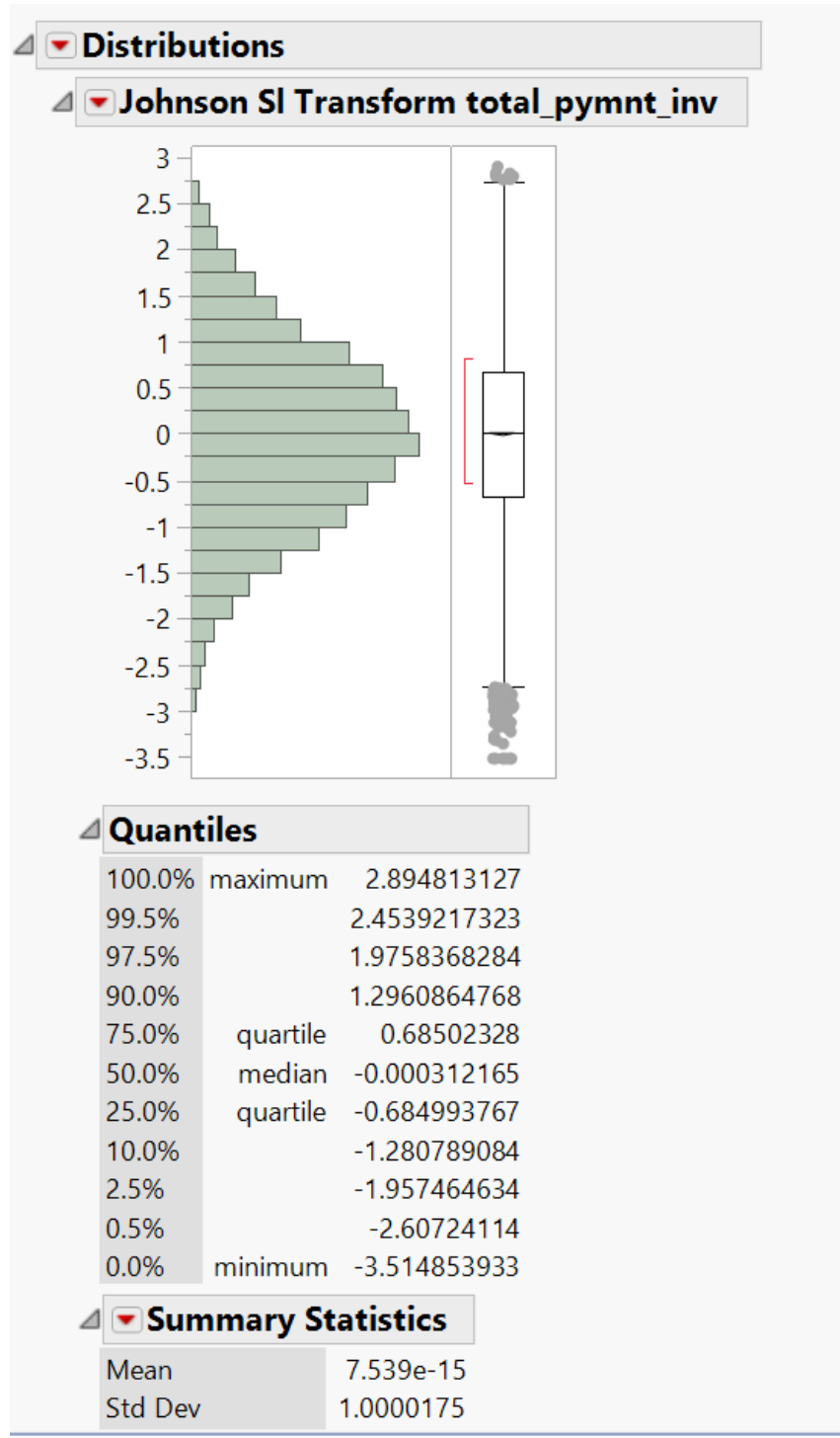
6. *revol_util*: Box-whisker plot



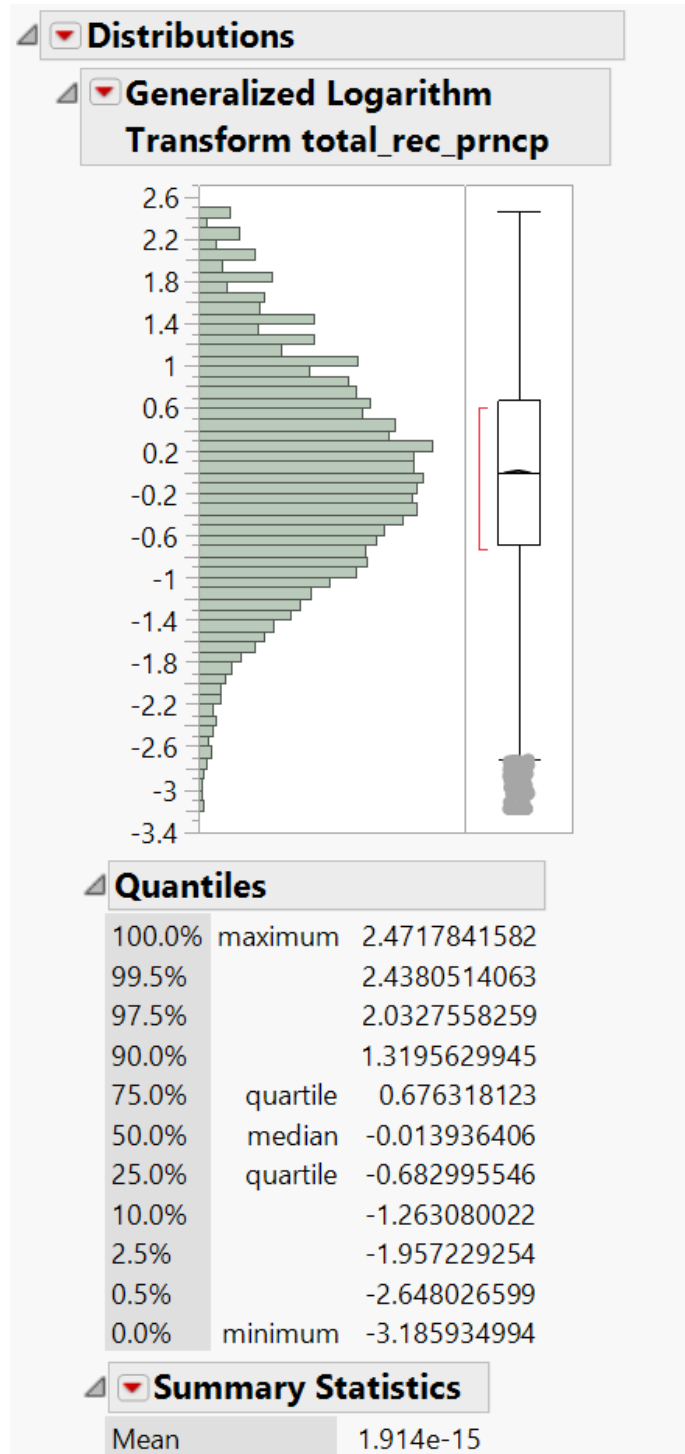
7. *total_acct*: Johnson SI Transform Box-whisker plot



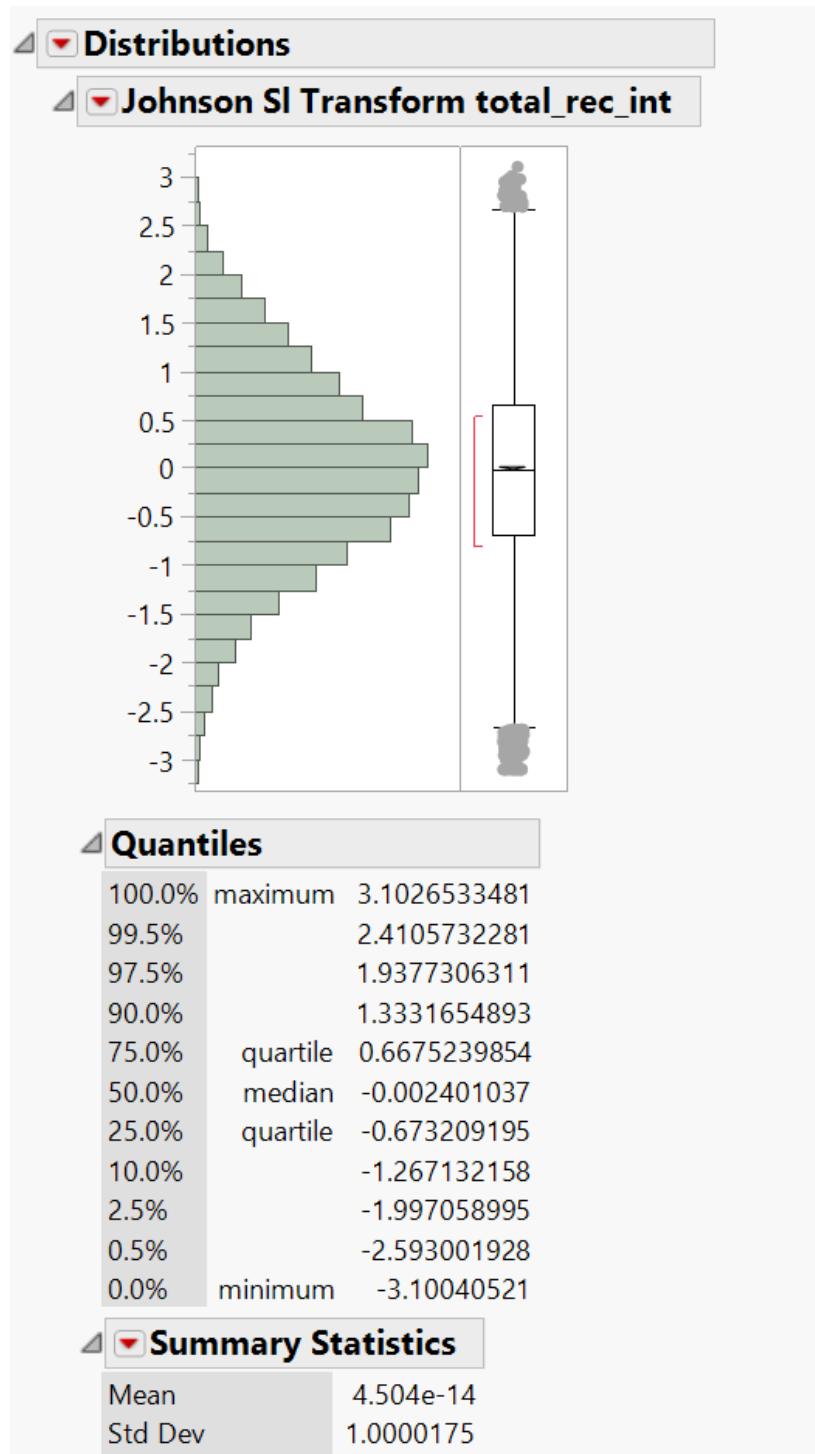
8. *total_pymnt_inv*: Johnson SI Transform Box-whisker plot



9. *Total_rec_prncp*: Generalized Logarithm Transform Box-whisker plot



10. *total_rec_int*: Johnson SI Transform Box-whisker plot

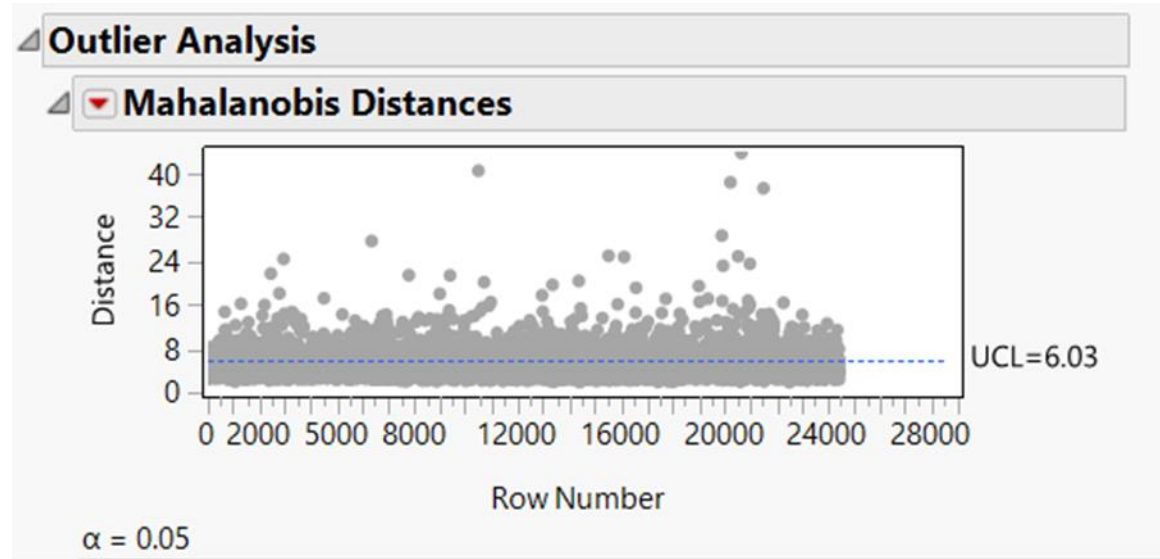


Multivariate Outlier Analysis

To consider the potential outliers with respect to other variables we have done multivariate outlier analysis. We used Mahalanobis Distances to check for the potential outliers.

We included all continuous variables except the variables member_id and policy_code for the analysis.

We can see that the points above the UCL can be considered as potential outliers. But we have to analyze various other parameters to actually eliminate them which depends on other factors and depends on the impact of the variable that we need to predict. So, we haven't excluded any of these from our dataset.



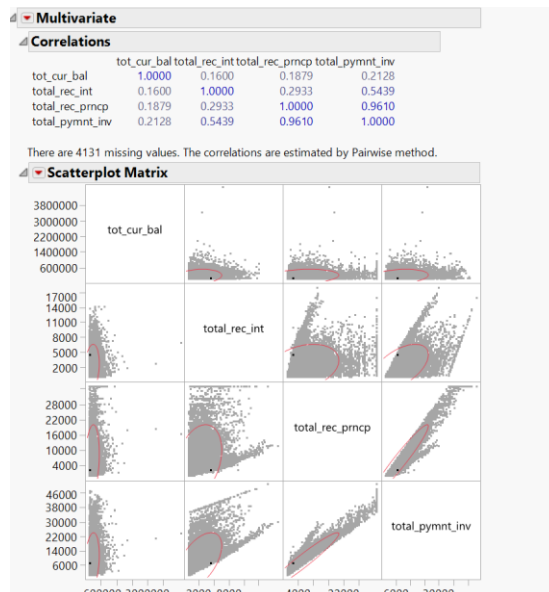
4.3 Data Reduction

4.3.1 Correlation

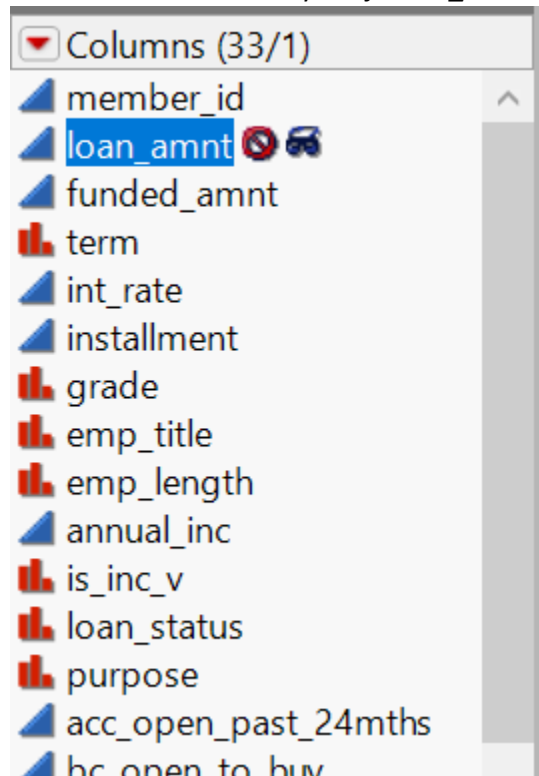
- The Multivariate Correlation was analyzed for all the continuous variables using **Analyze → Multivariate Methods → Multivariate**.
- The correlation matrix obtained is displayed below

Row	member_i	loan_amn	funded_ai	installmer	annual_in	acc_open	bc_open	percent_b	bc_util	delinq_2y	mths_sinc	mort_acc	open_acc	total_bal	revol_bal	total_acc	out_prncp	total_pym	total_rec	total_rec	last_pym	num_rev
member_i	1	0.035204	0.035666	0.019122	0.01645	0.005085	-0.00314	-0.01415	-0.00378	0.051286	-0.05715	0.036668	0.023712	0.020711	-0.00465	0.030779	0.346569	-0.35566	-0.32998	-0.22063	-0.10434	-0.01705
loan_amn	0.035204	1	0.999697	0.954852	0.419536	-0.00716	0.189127	0.001631	0.030875	0.016215	-0.04097	0.238367	0.200949	0.280554	0.317395	0.241547	0.680699	0.635963	0.48026	0.738688	0.230492	0.192785
funded_ai	0.035666	0.999697	1	0.955214	0.419468	-0.00724	0.189038	0.001715	0.030894	0.016198	-0.04072	0.238219	0.200874	0.280402	0.317475	0.241324	0.681302	0.635737	0.480022	0.738494	0.230026	0.192696
installmer	0.019122	0.954852	0.955214	1	0.416077	0.003343	0.150531	0.032969	0.067775	0.026882	-0.03916	0.19745	0.196317	0.272237	0.313482	0.222291	0.59643	0.661363	0.527144	0.682449	0.231008	0.186368
annual_in	0.01645	0.419536	0.419468	0.416077	1	0.046757	0.200223	-0.04379	-0.02629	0.087035	-0.07823	0.323142	0.182724	0.425191	0.35223	0.266972	0.262423	0.29809	0.253199	0.262878	0.125409	0.141436
acc_open	0.005085	-0.00716	-0.00724	0.003343	0.046757	1	0.056149	-0.11044	-0.11694	-0.0621	0.121088	0.066934	0.437191	0.163022	-0.03387	0.379094	-0.03812	0.016121	0.009864	0.02183	0.056364	0.290013
bc_open	-0.00314	0.189127	0.189038	0.150531	0.200223	0.056149	1	-0.48356	-0.59754	-0.03633	-0.02655	0.151311	0.255989	0.11335	0.204709	0.211052	0.090792	0.138385	0.163771	-0.01981	0.080441	0.288223
percent_b	-0.01415	0.001631	0.001715	0.032969	-0.04379	-0.11044	-0.48356	1	0.832625	-0.02563	0.041574	-0.04729	-0.09716	0.04306	0.078444	-0.08406	0.030255	-0.00592	-0.05486	0.145626	-0.03246	-0.14328
bc_util	-0.00378	0.030875	0.030894	0.067775	-0.02629	-0.11694	-0.59754	0.832625	1	-0.0162	0.042921	-0.04463	-0.09123	0.067251	0.111896	-0.08086	0.059361	0.006238	-0.04863	0.169076	-0.03699	-0.14658
delinq_2y	0.051286	0.016215	0.016198	0.026882	0.087035	-0.0621	-0.03633	-0.02563	-0.0162	1	-0.60712	0.106049	0.055412	0.047602	-0.02184	0.133455	0.038744	-0.0136	-0.02757	0.035546	-0.00607	0.090904
mths_sinc	-0.05715	-0.04097	-0.04072	-0.03916	-0.07823	0.121088	-0.02655	0.041574	0.042921	-0.60712	1	-0.09504	-0.03007	-0.0407	-0.01863	-0.06459	-0.05949	0.006241	0.020487	-0.03776	0.004291	-0.04876
mort_acc	0.036668	0.238367	0.238219	0.19745	0.323142	0.066934	0.151311	-0.04729	-0.04463	0.106049	-0.09504	1	0.132286	0.160393	0.1922	0.426387	0.170097	0.141934	0.122179	0.118946	0.077764	0.220646
open_acc	0.023712	0.200949	0.200874	0.196317	0.182724	0.437191	0.255989	-0.09716	-0.09123	0.055412	-0.03007	0.132286	1	0.397503	0.220627	0.664781	0.146607	0.117687	0.089167	0.135776	0.050587	0.614058
total_bal	0.020711	0.280554	0.280402	0.272237	0.425191	0.163022	0.11335	0.04306	0.067251	0.047602	-0.0407	0.160393	0.397503	1	0.55327	0.422153	0.190671	0.177517	0.139285	0.187966	0.073865	0.115714
revol_bal	-0.00465	0.317395	0.317475	0.313482	0.35223	-0.03387	0.204709	0.078444	0.111896	-0.02184	-0.01863	0.1922	0.220627	0.55327	1	0.197997	0.211652	0.198939	0.158187	0.205301	0.053702	0.20313
total_acc	0.030779	0.241547	0.241324	0.222291	0.266972	0.379094	0.211052	-0.08406	-0.08086	0.133455	-0.06459	0.426387	0.664781	0.422153	0.197997	1	0.152886	0.164103	0.139925	0.143068	0.099237	0.767786
out_prncp	0.346569	0.680699	0.681302	0.681302	0.59643	0.262423	-0.03812	0.090792	0.030255	0.059361	0.038744	-0.05949	0.170097	0.146607	0.190671	0.211652	0.152886	1	-0.01769	-0.20502	0.581379	-0.34792
total_pym	-0.35566	0.635963	0.635737	0.661363	0.29809	0.016121	0.138385	-0.00592	0.006238	-0.0136	0.006241	0.141934	0.117687	0.177517	0.198939	0.164103	-0.01769	1	0.961014	0.543853	0.713802	0.143373
total_rec	-0.32998	0.48026	0.480022	0.527144	0.253199	0.009864	0.163771	-0.05486	-0.04863	-0.02757	0.020487	0.122179	0.089167	0.139285	0.158187	0.139925	-0.20502	0.961014	1	0.293311	0.803302	0.1257
total_rec	-0.22063	0.738688	0.738494	0.682449	0.262878	0.02183	-0.01981	0.145626	0.169076	0.035546	-0.03776	0.118946	0.135776	0.187966	0.205301	0.143068	0.581379	0.543853	0.293311	1	0.029855	0.110374
last_pym	-0.10434	0.230492	0.230026	0.231008	0.125409	0.056364	0.080441	-0.03246	-0.03699	-0.00607	0.004291	0.077764	0.050587	0.073865	0.053702	0.099237	-0.34792	0.713802	0.803302	0.029855	1	0.064538
num_rev	-0.01705	0.192785	0.192696	0.186368	0.141436	0.290013	0.288223	-0.14328	-0.14658	0.090904	-0.04876	0.220646	0.614058	0.115714	0.20313	0.767786	0.116432	0.143373	0.1257	0.110374	0.064538	1
tot_cur_b	-0.00115	0.315994	0.315949	0.28307	0.550163	0.091973	0.170841	-0.01381	0.000938	0.084359	-0.08672	0.528805	0.242224	0.498818	0.419478	0.321912	0.207573	0.212802	0.187878	0.160027	0.09581	0.137084
policy_coc	0.01075	0.011946	0.011953	0.009002	-0.0003	0.004754	0.00427	-0.00731	-0.00447	-0.00207	0	-0.00223	0.009042	0.004565	0.000609	0.006155	0.016749	-0.00214	-0.00388	0.004511	-0.00166	0.007858

- From the above matrix, it can be observed that *loan_amnt* and *funded_amnt* have a correlation of 0.9997
- *bc_util* and *percent_bc_gt_75* have a correlation of 0.8326
- *total_rec_prncp* and *total_pymnt_inv* have a correlation of 0.9610



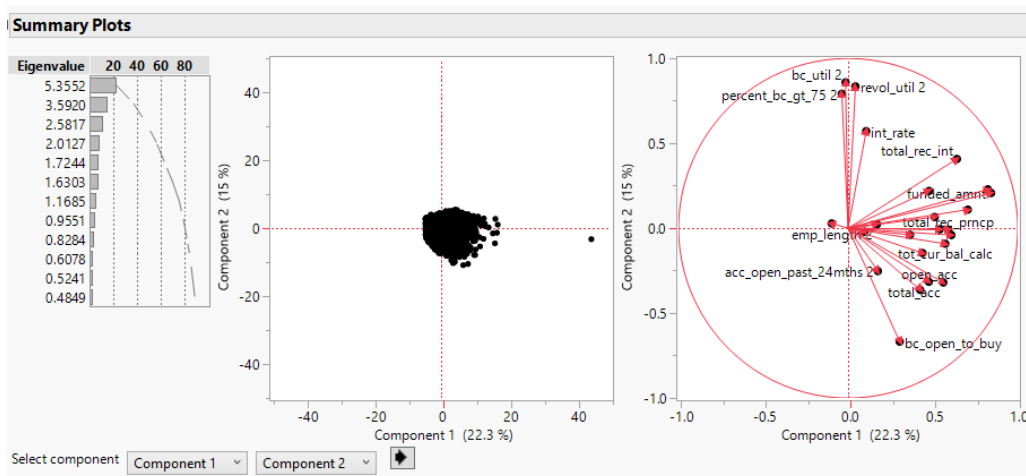
1. Between *loan_amnt* and *funded_amnt*, we decided to hide and exclude the *loan_amnt* column and retain only the *funded_amnt* column



2. Though *percent_bc_gt_75* and *bc_util* have a correlation of 0.8326, we decided to retain both the fields and reduce dimensionality using Principal Component Analysis

4.3.2 Principal Component Analysis

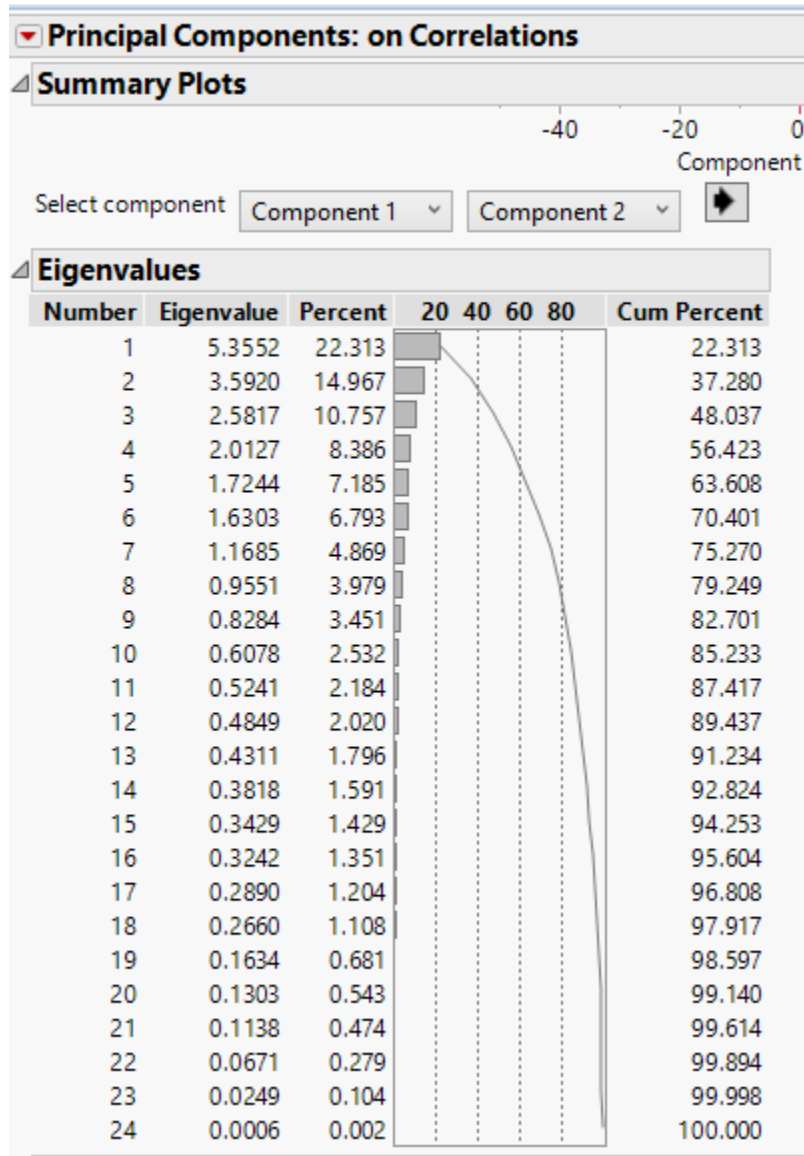
- We performed principle component analysis for the cleaned dataset. The screenshots of the Summary Plots and Eigen Values are provided below.



We excluded the following fields from the analysis

- *member_id*: This variable is excluded as it doesn't provide any information for building the model since this is unique at row level. (all unique records)

- policy_code: This variable had only one record with value 2 and all other rows are all value 1. So this is considered very insignificant for PCA.
- mths_since_last_delinq: This variable has almost 60% of data missing. So this is excluded from the PCA analysis since this would impact the analysis and cause missing values.



The above analysis shows the cumulative percentages of information captured by the principal components. We can actually go ahead and use these principal components to build our model. Though the question of how many components are to be included is always there and completely depends on the expected accuracy and business needs, we would recommend to use 18 variables as they constitute almost 98% of the available information from all the original continuous variables.

5.0 Updated Data dictionary

In the updated loan_data_dictionary we have updated the column “BrowseNotesFile”. In this we have stated whether the variable is included in the dataset or not.

We have also added some extra variables in the dataset and their respective descriptions.

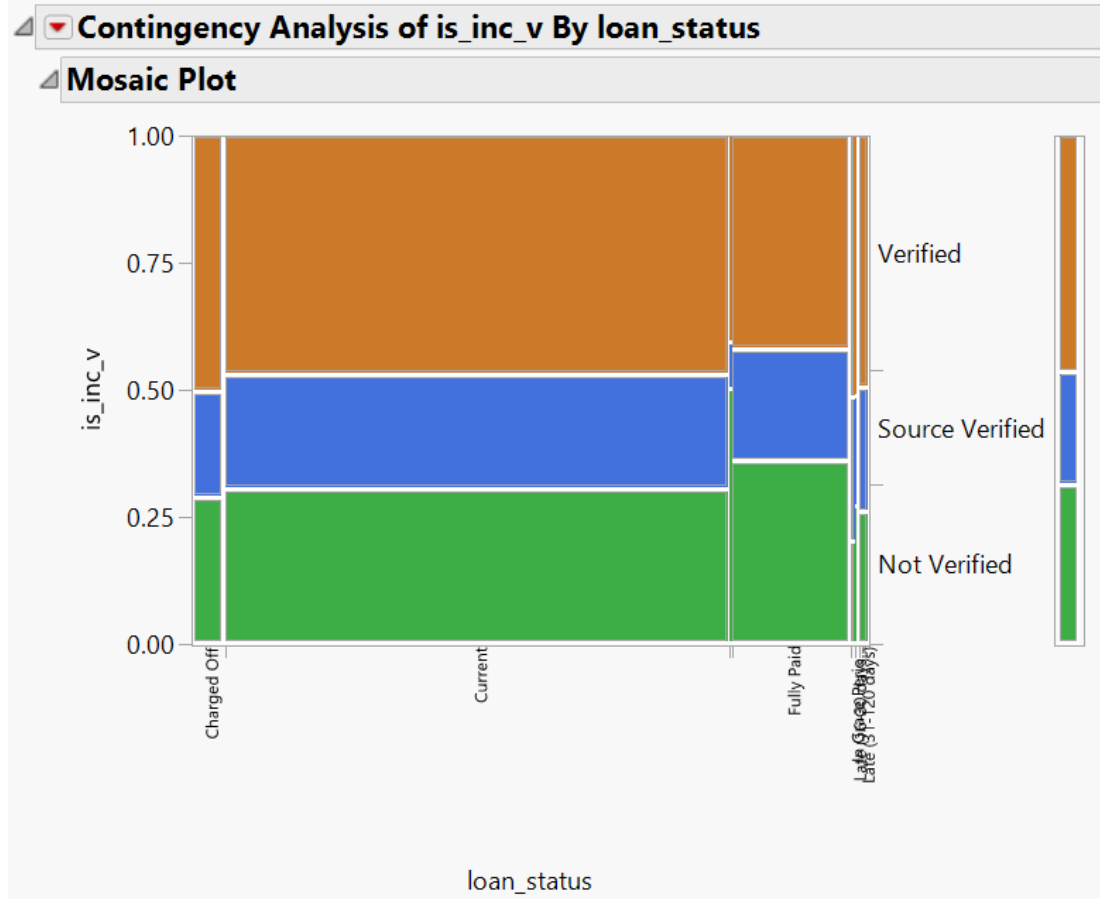
Added variables in the data set:

Field added	Field Description
acc_open_past_24mths 2	Imputed column for acc_open_past_24mths
bc_util 2	Included column for bc_util
emp_length 2	Imputed column for emp_length
num_rev_accts 2	Imputed column for num_rev_accts
percent_bc_gt_75 2	Imputed column for percent_bc_gt_75
revol_util 2	Imputed column for revol_util
tot_cur_bal_calc	Imputed column for tot_cur_bal
SHASH Transform bc_open_to_buy	Transformed variable for bc_open_to_buy
Johnson SI Transform open_acc	Transformed variable for open_acc
Johnson SI Transform total_acc	Transformed variable for total_acc
Generalized Logarithm Transform total_rec_prncp	Transformed variable for total_rec_prncp
Johnson SI Transform total_rec_int	Transformed variable for total_rec_int
Johnson SI Transform total_pymnt_inv	Transformed variable for total_pymnt_inv
Johnson Su Transform last_pymnt_amnt	Transformed variable for last_pymnt_amnt
Std installment	Standerdized column for installment

6.0Appendix

This section includes trials that did not prove fruitful in our analysis

1. We tried to predict the missing values in this field using the contingencies tables by checking with the variables loan_status and the variable purpose
 - a. Is_inc_v & loan status – Mosaic plot – no relation



- b. Is_inc_v & purpose – Mosaic plot – no actual relation

Contingency Analysis of is_inc_v By purpose

Mosaic Plot

