

4. Association Rule Mining implementation in R and SAS EM

We begin with importing our dataset to both R programming and SAS Enterprise Miner. We will go through both approaches one at a time.

A. Association Rule Mining with R

Firstly, we take deeper into our data and its type using str function in R Output ¹.

```
> str(transactions)
'data.frame': 25 obs. of 20 variables:
 $ SPIRITS      : Factor w/ 2 levels "NO","YES": 2 2 2 2 2 2 2 2 2 2 ...
 $ CANDY        : Factor w/ 2 levels "NO","YES": 2 2 2 2 2 2 2 2 2 2 ...
 $ BEVERAGES     : Factor w/ 2 levels "NO","YES": 2 2 2 2 2 2 2 2 2 2 ...
 $ HEALTH.AIDS  : Factor w/ 2 levels "NO","YES": 2 2 2 2 2 2 2 2 2 2 ...
 $ WINE         : Factor w/ 2 levels "NO","YES": 2 2 2 2 2 2 2 2 2 2 ...
 $ TOBACCO      : Factor w/ 2 levels "NO","YES": 2 2 2 2 2 2 2 2 2 1 ...
 $ HOUSEHOLD.CLEANING: Factor w/ 2 levels "NO","YES": 2 2 2 2 2 2 2 2 2 2 ...
 $ PERSONAL.CARE : Factor w/ 2 levels "NO","YES": 2 2 2 2 2 2 2 2 2 2 ...
 $ BEAUTY.CARE   : Factor w/ 2 levels "NO","YES": 2 2 2 2 2 2 2 2 2 2 ...
 $ BEER         : Factor w/ 2 levels "NO","YES": 2 2 2 2 2 2 2 2 2 2 ...
 $ PET.SUPPLIES  : Factor w/ 2 levels "NO","YES": 2 2 2 2 2 2 2 2 2 2 ...
 $ AMERICAN.GREETINGS: Factor w/ 2 levels "NO","YES": 2 2 2 2 2 2 2 2 2 2 ...
 $ GENERAL.GROCERIES : Factor w/ 2 levels "NO","YES": 2 2 2 2 2 2 2 2 2 2 ...
 $ TOYS         : Factor w/ 2 levels "NO","YES": 2 2 2 2 2 2 2 2 2 2 ...
 $ BABY.CARE     : Factor w/ 2 levels "NO","YES": 1 2 2 2 2 2 2 2 2 2 ...
 $ SUNGLASSES   : Factor w/ 2 levels "NO","YES": 2 1 1 2 2 2 2 2 2 1 ...
 $ BATTERIES     : Factor w/ 2 levels "NO","YES": 2 1 1 2 2 2 2 1 2 2 ...
 $ BATH         : Factor w/ 2 levels "NO","YES": 2 2 1 1 2 2 2 2 2 2 ...
 $ BEDDING      : Factor w/ 2 levels "NO","YES": 2 2 2 1 2 1 2 2 2 2 ...
 $ GIFTS        : Factor w/ 2 levels "NO","YES": 1 1 1 1 1 1 1 1 1 1 ...
```

Output ¹

We compute sum of columns with item purchase status of “Yes” or “No” and we create a data frame to calculate the sum and frequency of occurrences of such instances as shown in Output ².

```
> #colsums() function computes the sums of columns.
> YES <- colsums(transactions == "YES")
> YES
      SPIRITS      CANDY      BEVERAGES      HEALTH.AIDS      WINE      TOBACCO
      15         19         20         18         16         14
HOUSEHOLD.CLEANING  PERSONAL.CARE  BEAUTY.CARE      BEER  PET.SUPPLIES AMERICAN.GREETINGS
      18         16         17         15         17         18
GENERAL.GROCERIES    TOYS      BABY.CARE  SUNGLASSES  BATTERIES      BATH
      15         15         13         12         9         10
      BEDDING      GIFTS
      11         1

> NO <- colsums(transactions=="NO")
> NO
      SPIRITS      CANDY      BEVERAGES      HEALTH.AIDS      WINE      TOBACCO
      10         6         5         7         9         11
HOUSEHOLD.CLEANING  PERSONAL.CARE  BEAUTY.CARE      BEER  PET.SUPPLIES AMERICAN.GREETINGS
      7         9         8         10         8         7
GENERAL.GROCERIES    TOYS      BABY.CARE  SUNGLASSES  BATTERIES      BATH
      10         10         12         13         16         15
      BEDDING
      14         24
```

Output ²

Now we combine both frequency into one data frame and view the data together as in output ³.

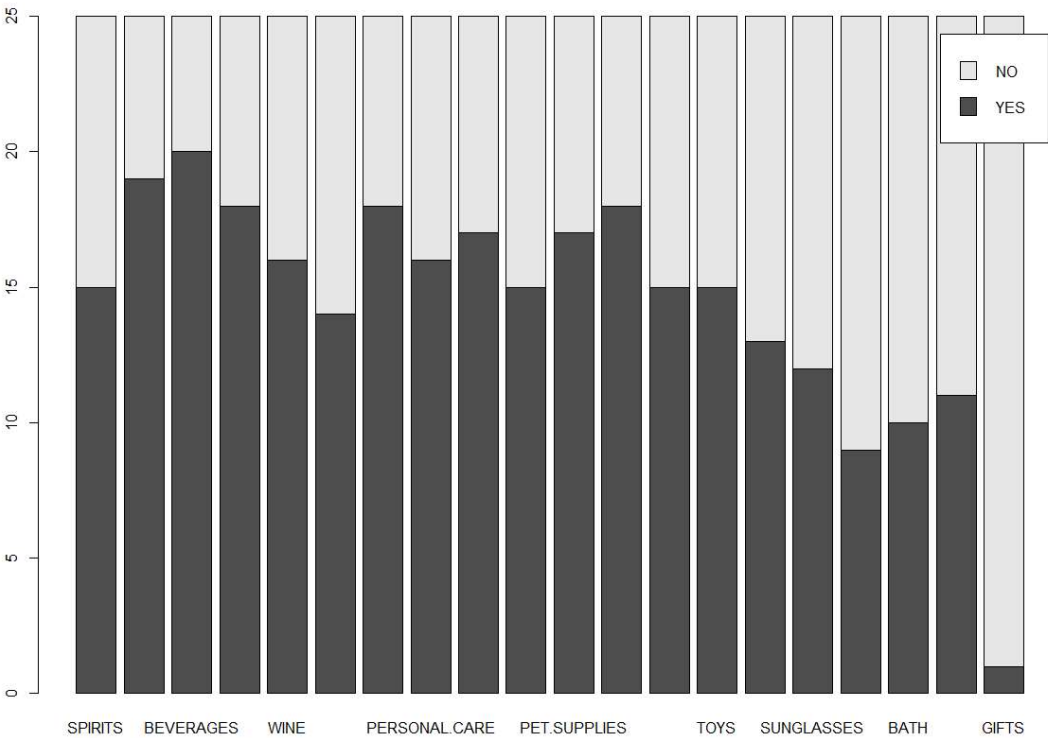
```
> visited <- rbind(YES,NO)
> visited
```

	SPIRITS	CANDY	BEVERAGES	HEALTH.AIDS	WINE	TOBACCO	HOUSEHOLD.CLEANING	PERSONAL.CARE	BEAUTY.CARE	BEER	PET.SUPPLIES
YES	15	19	20	18	16	14	18	16	17	15	17
NO	10	6	5	7	9	11	7	9	8	10	8

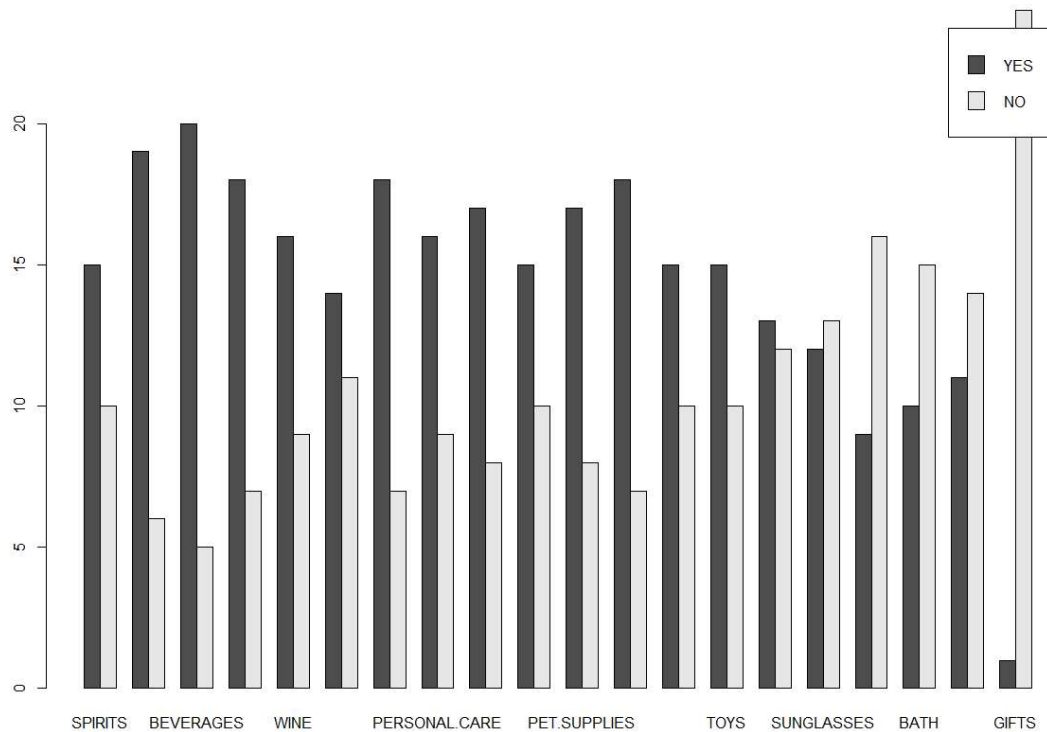
	AMERICAN.GREETINGS	GENERAL.GROCERIES	TOYS	BABY.CARE	SUNGLASSES	BATTERIES	BATH	BEDDING	GIFTS
YES	18	15	15	13	12	9	10	11	1
NO	7	10	10	12	13	16	15	14	24

Output ³

We show our data statistics using bar plot, bar plot ¹ shows the frequency of items and bar plot ² shows the purchase frequency of the items in our data.



bar plot ¹



bar plot ²

Using arules package and Apriori function call we create an association rule and out from first summary of rules we get 1 rule with 5 item and 226598 rules. Upon further inspection of rules, we get all the associations in our results, in our case we had to set the max limit to minimize overall rules creation.

We use apriori again to create rules with 95% confidence level as show in output ⁴.

```
> rules <- apriori(transactions, parameter =list(minlen=2,maxlen=3, conf = 0.95))
Apriori

Parameter specification:
 confidence minval  smax  arem  aval originalSupport  maxtime support minlen maxlen target  ext
  0.95      0.1     1 none FALSE          TRUE         5     0.1      2     3 rules  TRUE

Algorithmic control:
 filter tree heap memopt load sort verbose
  0.1 TRUE TRUE  FALSE TRUE    2    TRUE

Absolute minimum support count: 2
```

Output ⁴

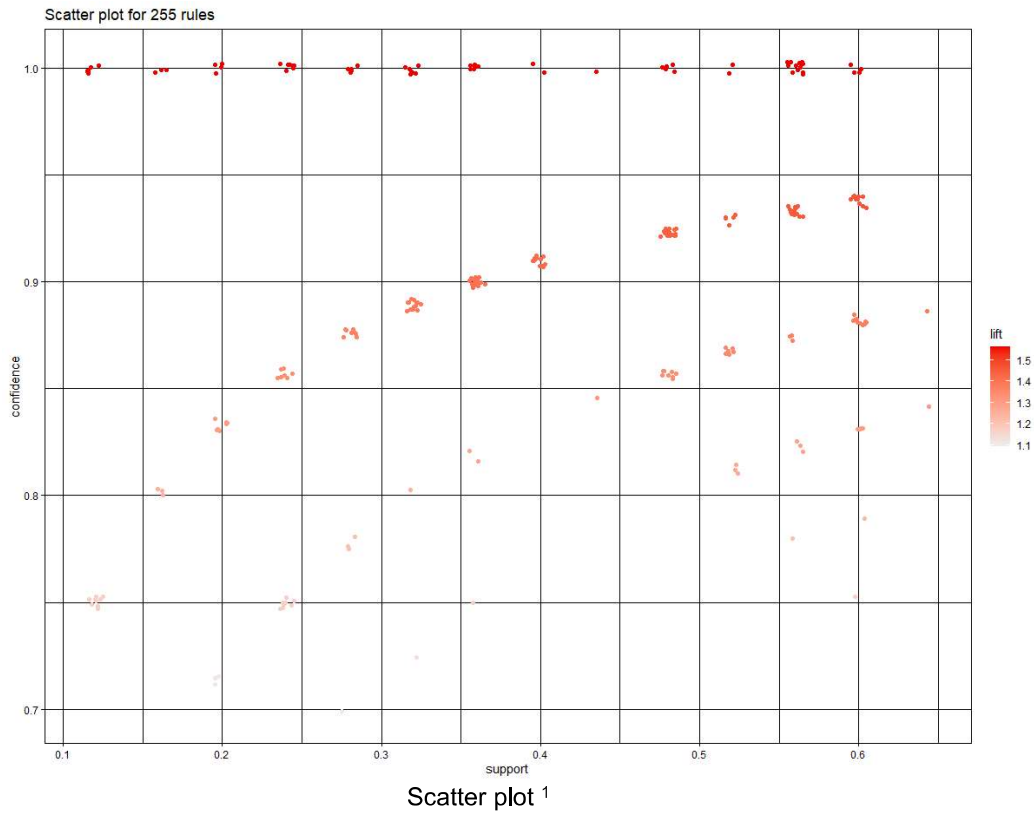
We will inspect the rules created and now we can see the list of items with related item association as in output ⁵.

```
> inspect(rules)
```

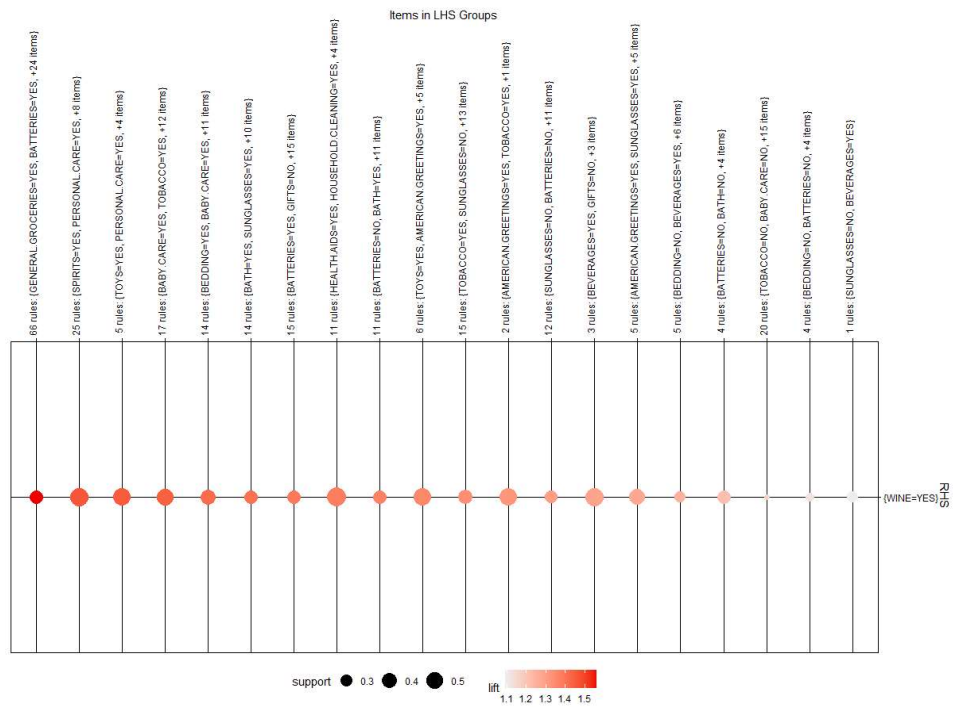
	lhs	rhs	support	confidence	coverage	lift	count
[1]	{BEVERAGES=NO}	=> {SPIRITS=NO}	0.20	1	0.20	2.500000	5
[2]	{BEVERAGES=NO}	=> {BEER=NO}	0.20	1	0.20	2.500000	5
[3]	{BEVERAGES=NO}	=> {TOBACCO=NO}	0.20	1	0.20	2.272727	5
[4]	{BEVERAGES=NO}	=> {BABY.CARE=NO}	0.20	1	0.20	2.083333	5
[5]	{BEVERAGES=NO}	=> {BEDDING=NO}	0.20	1	0.20	1.785714	5
[6]	{BEVERAGES=NO}	=> {BATTERIES=NO}	0.20	1	0.20	1.562500	5
[7]	{BEVERAGES=NO}	=> {GIFTS=NO}	0.20	1	0.20	1.041667	5
[8]	{CANDY=NO}	=> {PERSONAL.CARE=NO}	0.24	1	0.24	2.777778	6
[9]	{CANDY=NO}	=> {WINE=NO}	0.24	1	0.24	2.777778	6
[10]	{CANDY=NO}	=> {SPIRITS=NO}	0.24	1	0.24	2.500000	6
[11]	{CANDY=NO}	=> {TOYS=NO}	0.24	1	0.24	2.500000	6
[12]	{CANDY=NO}	=> {GENERAL.GROCERIES=NO}	0.24	1	0.24	2.500000	6
[13]	{CANDY=NO}	=> {BEER=NO}	0.24	1	0.24	2.500000	6
[14]	{CANDY=NO}	=> {BABY.CARE=NO}	0.24	1	0.24	2.083333	6
[15]	{CANDY=NO}	=> {BEDDING=NO}	0.24	1	0.24	1.785714	6
[16]	{CANDY=NO}	=> {BATH=NO}	0.24	1	0.24	1.666667	6
[17]	{CANDY=NO}	=> {GIFTS=NO}	0.24	1	0.24	1.041667	6
[18]	{AMERICAN.GREETINGS=NO}	=> {BATH=NO}	0.28	1	0.28	1.666667	7
[19]	{AMERICAN.GREETINGS=NO}	=> {BATTERIES=NO}	0.28	1	0.28	1.562500	7
[20]	{AMERICAN.GREETINGS=NO}	=> {GIFTS=NO}	0.28	1	0.28	1.041667	7
[21]	{HOUSEHOLD.CLEANING=NO}	=> {HEALTH.AIDS=NO}	0.28	1	0.28	3.571429	7
[22]	{HEALTH.AIDS=NO}	=> {HOUSEHOLD.CLEANING=NO}	0.28	1	0.28	3.571429	7
[23]	{HOUSEHOLD.CLEANING=NO}	=> {PET.SUPPLIES=NO}	0.28	1	0.28	3.125000	7
[24]	{HOUSEHOLD.CLEANING=NO}	=> {BEAUTY.CARE=NO}	0.28	1	0.28	3.125000	7
[25]	{HOUSEHOLD.CLEANING=NO}	=> {PERSONAL.CARE=NO}	0.28	1	0.28	2.777778	7
[26]	{HOUSEHOLD.CLEANING=NO}	=> {SPIRITS=NO}	0.28	1	0.28	2.500000	7
[27]	{HOUSEHOLD.CLEANING=NO}	=> {TOYS=NO}	0.28	1	0.28	2.500000	7
[28]	{HOUSEHOLD.CLEANING=NO}	=> {BEER=NO}	0.28	1	0.28	2.500000	7
[29]	{HOUSEHOLD.CLEANING=NO}	=> {TOBACCO=NO}	0.28	1	0.28	2.272727	7
[30]	{HOUSEHOLD.CLEANING=NO}	=> {BABY.CARE=NO}	0.28	1	0.28	2.083333	7
[31]	{HOUSEHOLD.CLEANING=NO}	=> {BEDDING=NO}	0.28	1	0.28	1.785714	7
[32]	{HOUSEHOLD.CLEANING=NO}	=> {BATH=NO}	0.28	1	0.28	1.666667	7
[33]	{HOUSEHOLD.CLEANING=NO}	=> {BATTERIES=NO}	0.28	1	0.28	1.562500	7
[34]	{HOUSEHOLD.CLEANING=NO}	=> {GIFTS=NO}	0.28	1	0.28	1.041667	7
[35]	{HEALTH.AIDS=NO}	=> {PET.SUPPLIES=NO}	0.28	1	0.28	3.125000	7
[36]	{HEALTH.AIDS=NO}	=> {BEAUTY.CARE=NO}	0.28	1	0.28	3.125000	7

Output ⁵

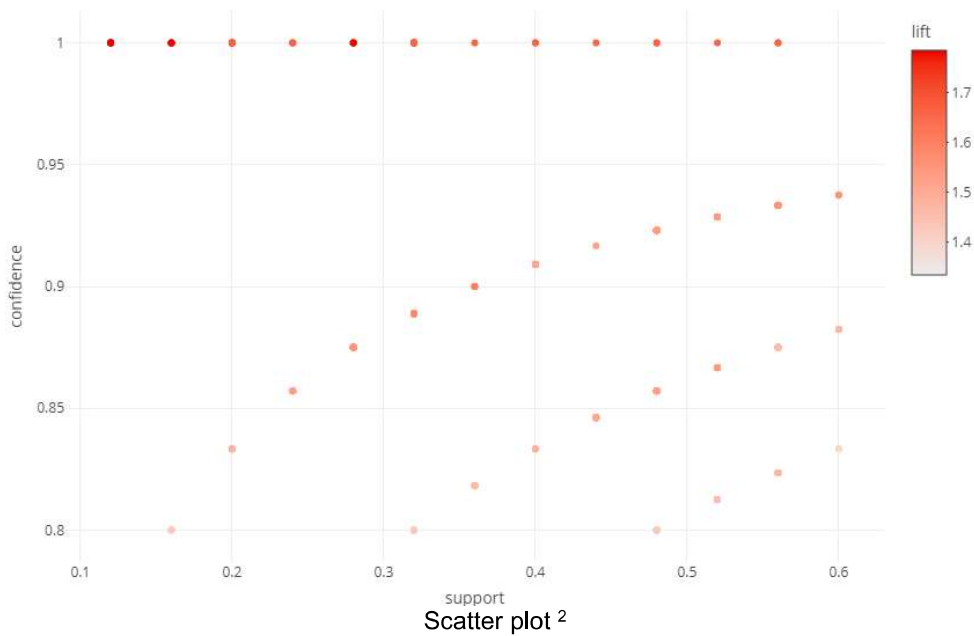
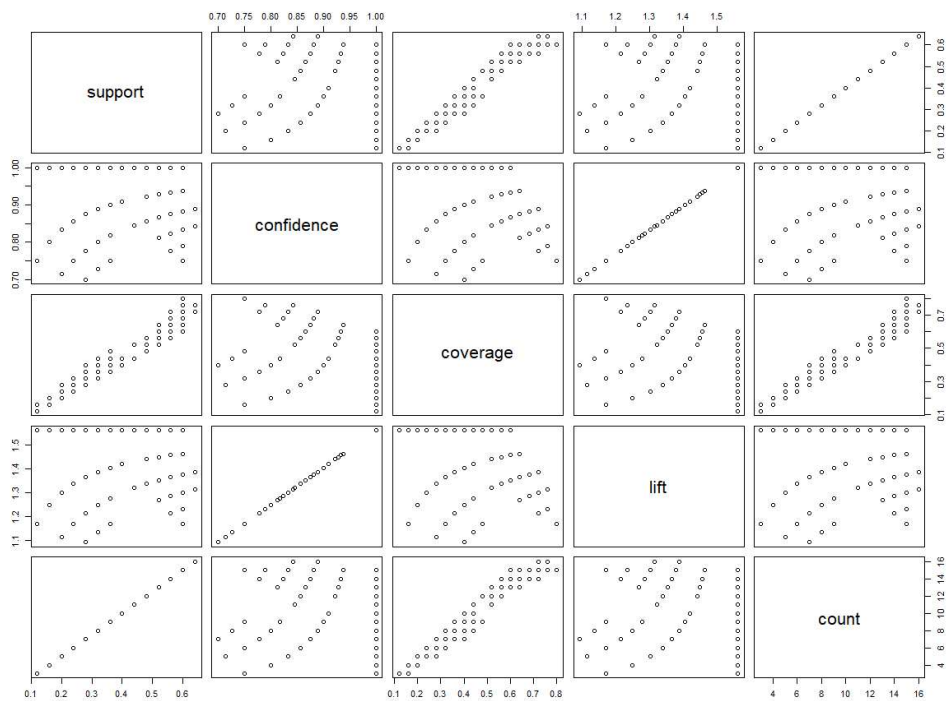
Plotting will enable us in finding custom association relation model of our data as show in scatter plot ¹, here we are trying to find all rules associated to Wine with condition purchased is Yes.



And the RHS and LHS rules quality and support measure are plotted together with lift parameter as show in plot ¹.



Now we test the same by creating 3rd rule for tobacco with purchase condition to Yes with apriori and show the results in statistics of confidence, support, coverage, lift and count.



Scatter plot ² show the confidence, support, and lift intercepts on our rule 3.

We can use shiny dashboard and explore our created rules or default rules association and show the relations of our data as shown in Figure 1.

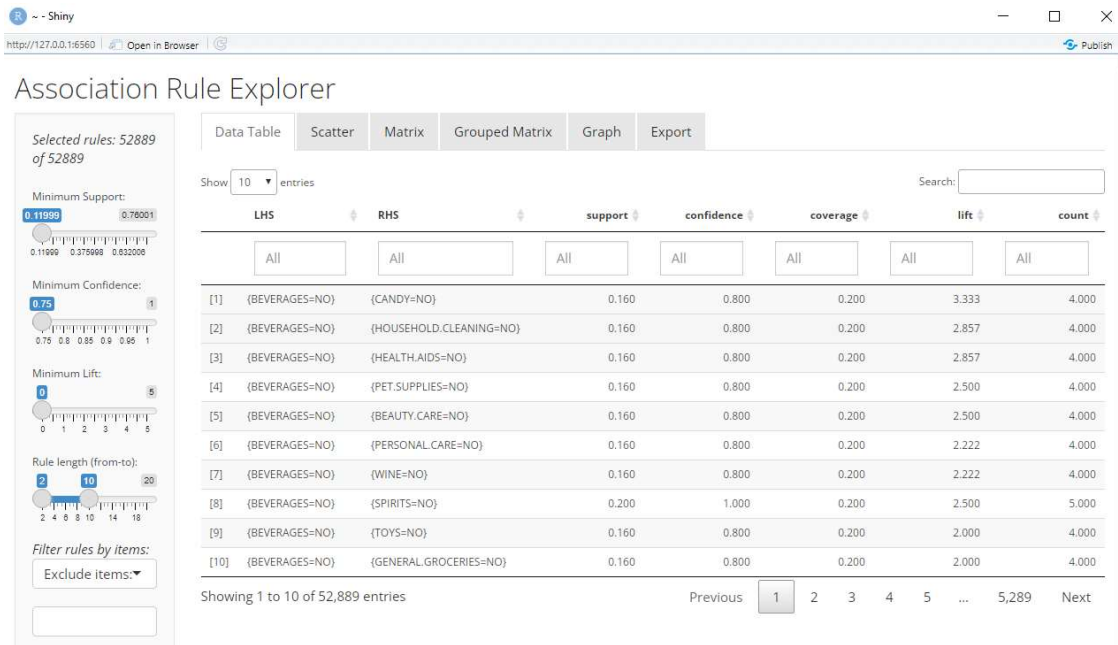


Figure 1

Appendix for Association Rule Mining in R

```

1 transactions <- read.csv("C:/Users/Phani/Documents/Transactions.csv",header=T, colclasses="factor")
2 setwd("C:/Users/Phani/Documents")
3 names(transactions)
4 head(transactions)
5 tail(transactions)
6 summary(transactions)
7 str(transactions)
8 dim(transactions)
9 #colSums() function computes the sums of columns.
10 YES <- colSums(transactions == "YES")
11 YES
12 NO <- colSums(transactions=="NO")
13 NO
14 visited <- rbind(YES,NO)
15 visited
16 barplot(visited,legend=rownames(visited)) #Plot 1
17 barplot(visited, beside=T,legend=rownames(visited))# Plot 2
18 #arules package is a powerful tool for mining associative rules in transactional databases. The most
19 #install.packages("arules") # install "arules" package.
20 library(arules) # activate "arules" package
21 #The apriori() function from the arules package implements the
22 #Note that, by default, the apriori() function executes all the
23 #usage of apriori() function
24 rules <- apriori(transactions, maxlen = 5)
25 summary(rules)
26 #The result tells you that there was 2 rules with 3 item and 255 rules
27 inspect(rules, maxlen=20)
28 #inspect function prints the internal representation of an R object
29 # when the max len parameter is not set, the algorithm continues
30 #set the minlen=2,maxlen=3 and confident = 0.95
31 rules <- apriori(transactions, parameter =list(minlen=2,maxlen=3, conf = 0.95))
32 summary(rules)
33 inspect(rules)
34 #Plotting could be the easiest way to find the most visited
35 rules <- apriori(transactions, parameter = list(minlen=2, maxlen=3, conf = 0.95), appearance= list(rhs=c("WINE=YES"),default="lhs"))
36 barplot(visited, beside=T,legend=rownames(rules))
37 #random variable selection
38 rules <- apriori(transactions,
39   parameter = list(minlen=2, maxlen=3,conf = 0.70),
40   appearance= list(rhs=c("WINE=YES"),default="lhs"))
41 summary(rules)
42 inspect(rules)
43 install.packages("arulesviz") # install "arulesviz"
44 library(arulesviz) # activate "arules" package
45 plot(rules)
46 plot(rules, jitter=0)
47 plot(rules, method="grouped")
48 plot(rules@quality)
49
50 rules3 <- apriori(transactions, parameter = list(minlen=2,maxlen=3, conf = 0.80), appearance =list(rhs=c("TOBACCO=YES","BEER=YES"),default="lhs"))
51 summary(rules3)
52 inspect(rules3)
53 barplot(visited, beside=T,legend=rownames(visited))

```



```

54
55 library(plotly)
56 install.packages("arulesviz")
57 library(arulesviz)
58 plot(rules3, engine = "plotly")
59 #removing jitter
60 plot(rules3, engine = "plotly", jitter = 0)
61 plot(rules3, measure = c("support", "lift"), shading = "confidence", engine = "plotly")
62
63
64
65 rules2 <- apriori(transactions, parameter = list(minlen=2, maxlen=5, conf = 0.6),
66                  appearance = list(rhs=c("BABY.CARE=YES"),lhs=c("BATTERIES=YES", "BEDDING=YES", "GIFTS=YES", "CANDY=YES", "BEVERAGES=YES",
67                                     "HOUSEHOLD.CLEANING=YES", "AMERICAN.GREETINGS=YES", "SUNGLASSES=YES"), default="none"))
68 inspect(rules2)
69 rules_ex <- apriori(transactions,
70                    parameter = list(minlen=2, maxlen=4, conf=0.75))
71 #Explore association rules using interactive manipulations and
72 ruleExplorer(rules_ex)

```

B. Association Rule Mining with SAS Enterprise Miner

Before to the initial step of importing data, we transform the data with only transaction and item set list as show below.

	A	B	C	D
1	pos_txn	Dept		
2	16120100160021008773	HOSIERY		
3	16120100160021008773	VITAMINS & HLTH AIDS		
4	16120100160021008775	SMALL ELECTRICS		
5	16120100160022004679	SPIRITS		
6	16120100160023004356	SPORTS NUTRITION		
7	16120100160023004356	SEASONAL		
8	16120100160023004356	PET SUPPLIES		
9	16120100160023004357	FITNESS/EXERCISE		
10	16120100160023004358	FITNESS/EXERCISE		
11	16120100160023004359	MISC CUSTOM SERVICES		
12	16120100160023004359	TOBACCO		
13	16120100160023004360	TOBACCO		
14	16120100160023004361	GIRLS ACCESSORIES		
15	16120100160023004361	TOYS		

As our initial step we import our dataset to SAS EM library to perform association rule mining technique. Once import is complete, we will have to assigned role our input data to be transaction type as show in Figure 2.

Property	Value
Notes	
Train	
Variables	
Import File	C:\Users\Phani\Dow...
Maximum Rows to Imp	1000000
Maximum Columns to	10000
Delimiter	,
Name Row	Yes
Number of Rows to Sk	0
Guessing Rows	500
File Location	Local
File Type	xlsx
Advanced Advisor	No
Rerun	No
Score	
Role	Transaction
Report	
Summarize	No

Figure 2

Now, set the variable roles of our dataset as shown in figure 3. Transaction ids to be ID and itemset to be Target variable.

(none) ☐ not Equal to ☐

Columns: ☐ Label ☐ Mining

Name	Role	Level	Report	Order	Drop
C	Rejected	Nominal	No		No
Dept	Target	Nominal	No		No
pos_txn	ID	Nominal	No		No

Figure 3

Our next step would be drag and drop association icon on to diagram platform and run association mining to get our rules formed by association of items in our data as shown in Figure 4.

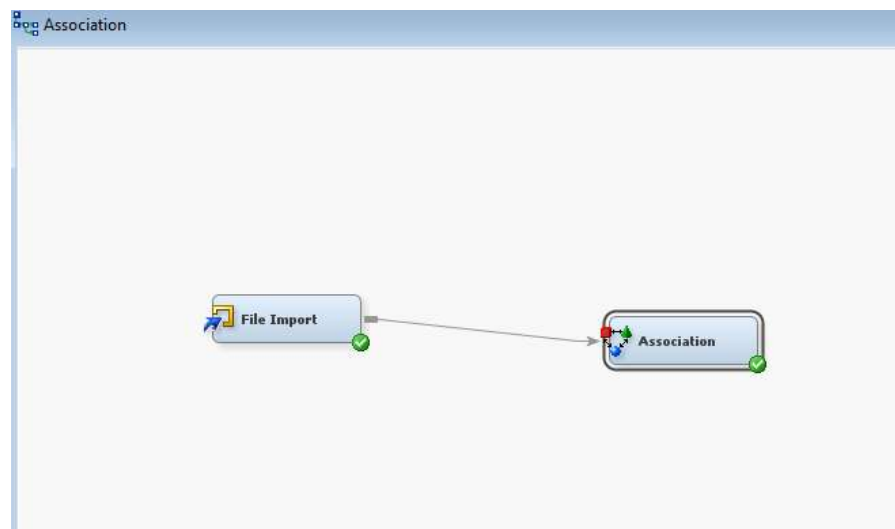
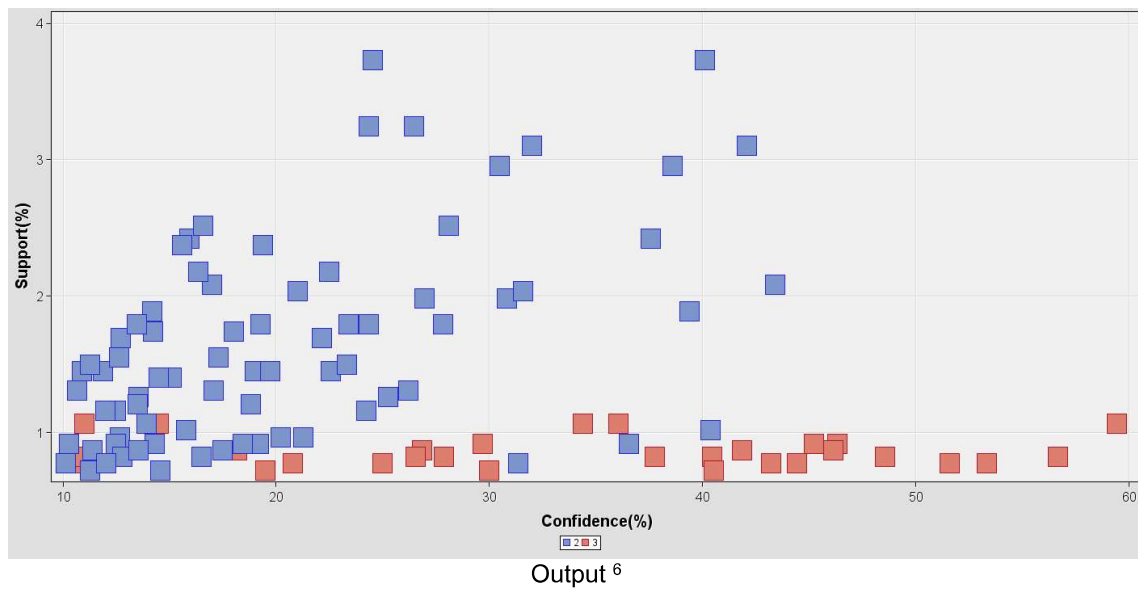
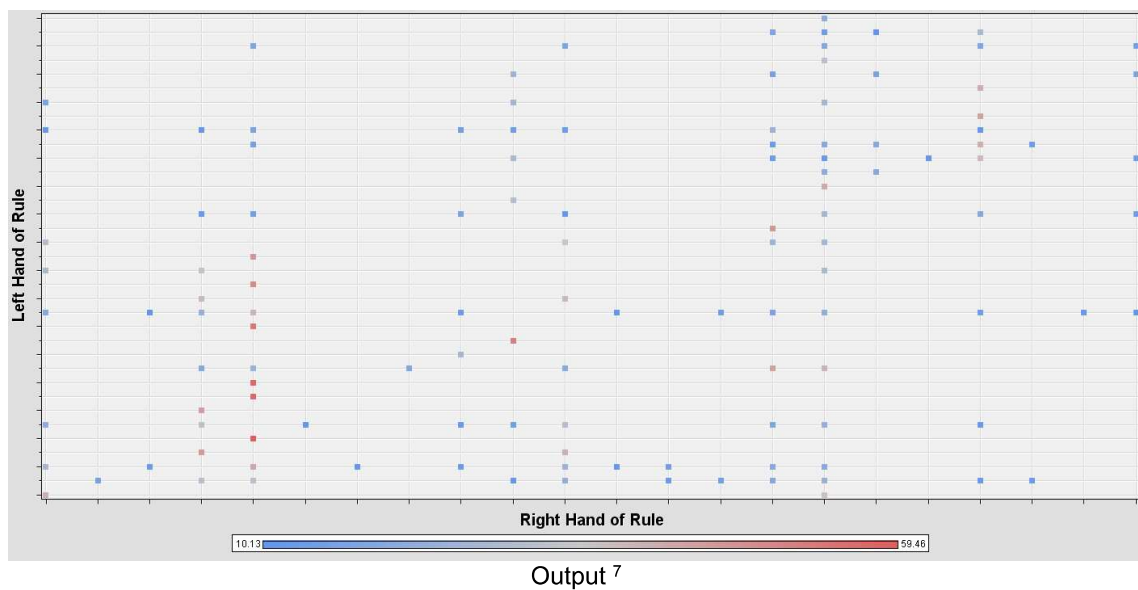


Figure 4

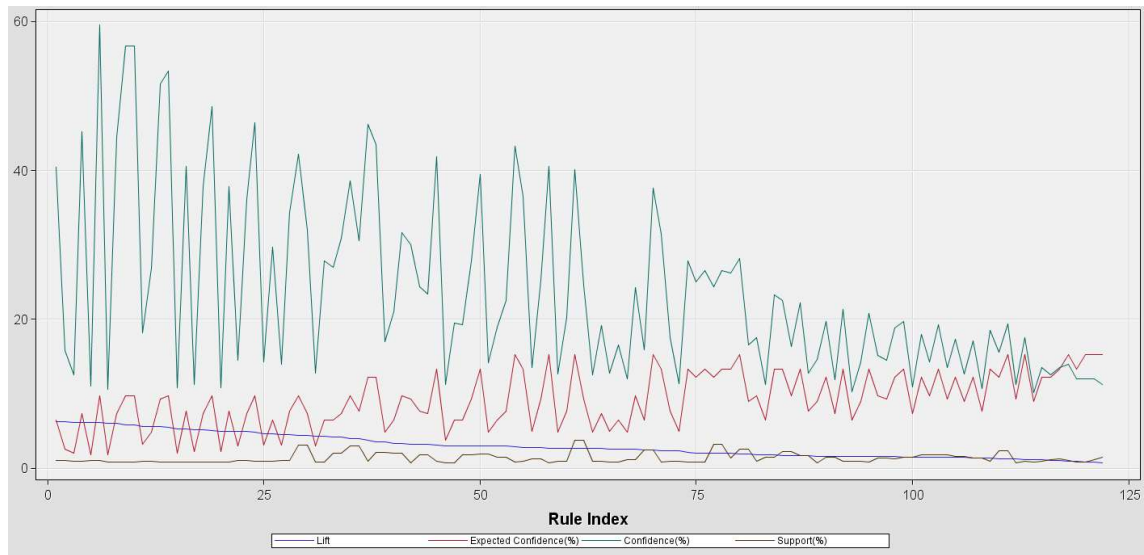
SAS Enterprise Miner now computes and create association rules among our itemset and we get our results as follows.



In output ⁶, we get the support of confident matrix table of individual rules which are created from our dataset.



Output ⁷, gives the RHS AND LHS comparison of individual item set and their confidence level.



Output ⁸

Output ⁸, show the line graph of confidence interval, support and lift of rules that got created and their rule index values.

Output

```

1  *-----*
2  User:      Phani
3  Date:      14 January 2022
4  Time:      14:22:13
5  *-----*
6  * Training Output
7  *-----*
8
9
10
11
12 Variable Summary
13
14
15 Role      Measurement      Frequency
16           Level            Count
17 ID        NOMINAL          1
18 TARGET    NOMINAL          1
19
20
21
22
23 Association Report
24
25
26
27 Relations      Expected      Confidence      Support      Lift      Transaction      Rule
                Confidence      (%)            (%)            (%)            Count
28
29 2              6.44         40.38         1.02         6.27         21.00         MASS COSMETICS ==> BEAUTY CARE
30 2              2.52         15.79         1.02         6.27         21.00         BEAUTY CARE ==> MASS COSMETICS
31 3              2.03         12.50         0.92         6.14         19.00         PERSONAL CARE ==> HEALTH AIDS & BEAUTY CARE
32 3              7.36         45.24         0.92         6.14         19.00         HEALTH AIDS & BEAUTY CARE ==> PERSONAL CARE
33 3              9.69         59.46         1.07         6.14         22.00         PERSONAL CARE & HOUSEHOLD CLEANING ==> HEALTH AIDS
34 3              1.79         11.00         1.07         6.14         22.00         HEALTH AIDS ==> PERSONAL CARE & HOUSEHOLD CLEANING
35 3              1.74         10.53         0.78         6.04         16.00         PERSONAL CARE ==> HEALTH AIDS & BEVERAGES
36 3              7.36         44.44         0.78         6.04         16.00         HEALTH AIDS & BEVERAGES ==> PERSONAL CARE
37 3              9.69         56.67         0.82         5.85         17.00         PERSONAL CARE & CANDY ==> HEALTH AIDS
38 3              9.69         56.67         0.82         5.85         17.00         HOUSEHOLD CLEANING & BEAUTY CARE ==> HEALTH AIDS
39 3              3.25         18.18         0.87         5.60         18.00         GENERAL GROCERIES ==> CANDY & BEVERAGES
40 3              4.80         26.87         0.87         5.60         18.00         CANDY & BEVERAGES ==> GENERAL GROCERIES

```

Left Hand of Rule

MASS COSMETICS
BEAUTY CARE
PERSONAL CARE
HEALTH AIDS & BEAUTY CARE
PERSONAL CARE & HOUSEHOLD CLEANING
HEALTH AIDS
PERSONAL CARE
HEALTH AIDS & BEVERAGES
PERSONAL CARE & CANDY
HOUSEHOLD CLEANING & BEAUTY CARE
GENERAL GROCERIES
CANDY & BEVERAGES

41	3	9.30	51.61	0.78	5.55	16.00	SPIRITS & CANDY ==> WINE	SPIRITS & CANDY
42	3	9.69	53.33	0.78	5.50	16.00	PERSONAL CARE & BEVERAGES ==> HEALTH AIDS	PERSONAL CARE & BEVERAGES
43	3	2.03	10.76	0.82	5.29	17.00	HOUSEHOLD CLEANING ==> HEALTH AIDS & BEAUTY CARE	HOUSEHOLD CLEANING
44	3	7.66	40.48	0.82	5.29	17.00	HEALTH AIDS & BEAUTY CARE ==> HOUSEHOLD CLEANING	HEALTH AIDS & BEAUTY CARE
45	3	2.18	11.18	0.82	5.13	17.00	PERSONAL CARE ==> HEALTH AIDS & CANDY	PERSONAL CARE
46	3	7.36	37.78	0.82	5.13	17.00	HEALTH AIDS & CANDY ==> PERSONAL CARE	HEALTH AIDS & CANDY
47	3	9.69	48.57	0.82	5.01	17.00	HOUSEHOLD CLEANING & CANDY ==> HEALTH AIDS	HOUSEHOLD CLEANING & CANDY
48	3	2.18	10.76	0.82	4.94	17.00	HOUSEHOLD CLEANING ==> HEALTH AIDS & CANDY	HOUSEHOLD CLEANING
49	3	7.66	37.78	0.82	4.94	17.00	HEALTH AIDS & CANDY ==> HOUSEHOLD CLEANING	HEALTH AIDS & CANDY
50	3	2.96	14.47	1.07	4.90	22.00	PERSONAL CARE ==> HOUSEHOLD CLEANING & HEALTH AIDS	PERSONAL CARE
51	3	7.36	36.07	1.07	4.90	22.00	HOUSEHOLD CLEANING & HEALTH AIDS ==> PERSONAL CARE	HOUSEHOLD CLEANING & HEALTH AIDS
52	3	9.69	46.34	0.92	4.78	19.00	PERSONAL CARE & BEAUTY CARE ==> HEALTH AIDS	PERSONAL CARE & BEAUTY CARE
53	3	6.44	29.69	0.92	4.61	19.00	PERSONAL CARE & HEALTH AIDS ==> BEAUTY CARE	PERSONAL CARE & HEALTH AIDS
54								
55								
56								
57	Right Hand of Rule		Rule Item 1	Rule Item 2	Rule Item 3	Rule Item 4	Rule Item 5	Rule Index
58								
59	BEAUTY CARE	MASS COSMETICS	=====>	BEAUTY CARE				1
60	MASS COSMETICS	BEAUTY CARE	=====>	MASS COSMETICS				2
61	HEALTH AIDS & BEAUTY CARE	PERSONAL CARE	=====>	HEALTH AIDS	BEAUTY CARE			3
62	PERSONAL CARE	HEALTH AIDS	=====>	BEAUTY CARE	PERSONAL CARE			4
63	HEALTH AIDS	PERSONAL CARE	=====>	HOUSEHOLD CLEANING	HEALTH AIDS			6
64	PERSONAL CARE & HOUSEHOLD CLEANING	HEALTH AIDS	=====>	PERSONAL CARE	HOUSEHOLD CLEANING			5
65	HEALTH AIDS & BEVERAGES	PERSONAL CARE	=====>	HEALTH AIDS	BEVERAGES			7
66	PERSONAL CARE	HEALTH AIDS	=====>	BEVERAGES	PERSONAL CARE			8
67	HEALTH AIDS	PERSONAL CARE	=====>	CANDY	HEALTH AIDS			9
68	HEALTH AIDS	HOUSEHOLD CLEANING	=====>	BEAUTY CARE	HEALTH AIDS			10
69	CANDY & BEVERAGES	GENERAL GROCERIES	=====>	CANDY	BEVERAGES			11
70	GENERAL GROCERIES	CANDY	=====>	BEVERAGES	GENERAL GROCERIES			12
71	WINE	SPIRITS	=====>	CANDY	WINE			13
72	HEALTH AIDS	PERSONAL CARE	=====>	BEVERAGES	HEALTH AIDS			14
73	HEALTH AIDS & BEAUTY CARE	HOUSEHOLD CLEANING	=====>	HEALTH AIDS	BEAUTY CARE			15
74	HOUSEHOLD CLEANING	HEALTH AIDS	=====>	BEAUTY CARE	HOUSEHOLD CLEANING			16
75	HEALTH AIDS & CANDY	PERSONAL CARE	=====>	HEALTH AIDS	CANDY			17
76	PERSONAL CARE	HEALTH AIDS	=====>	CANDY	PERSONAL CARE			18
77	HEALTH AIDS	HOUSEHOLD CLEANING	=====>	CANDY	HEALTH AIDS			19
78	HEALTH AIDS & CANDY	HOUSEHOLD CLEANING	=====>	HEALTH AIDS	CANDY			20
79	HOUSEHOLD CLEANING	HEALTH AIDS	=====>	CANDY	HOUSEHOLD CLEANING			21
80	HOUSEHOLD CLEANING & HEALTH AIDS	PERSONAL CARE	=====>	HOUSEHOLD CLEANING	HEALTH AIDS			22
81	PERSONAL CARE	HOUSEHOLD CLEANING	=====>	HEALTH AIDS	PERSONAL CARE			23
82	HEALTH AIDS	PERSONAL CARE	=====>	BEAUTY CARE	HEALTH AIDS			24
83	BEAUTY CARE	PERSONAL CARE	=====>	HEALTH AIDS	BEAUTY CARE			26
84								
85								
86								
87								
88	Rule Statistics							
89								
90	The MEANS Procedure							
91								
92	Variable	Label	Minimum	Maximum	Mean			
93								
94	EXP_CONF	Expected Confidence(%)	1.7441860	15.2131783	9.1311634			
95	CONF	Confidence(%)	10.1265823	59.4594595	23.6447400			
96	SUPPORT	Support(%)	0.7267442	3.7306202	1.3685030			
97	LIFT	Lift	0.7409644	6.2672065	2.9782965			
98								
99								
100								
101								
102	Sequence Report							
103								
104	The FREQ Procedure							
105								
106		Relations						
107								
108								
109	SET_SIZE	Frequency	Percent	Cumulative Frequency	Cumulative Percent			
110								
111	2	83	68.03	83	68.03			
112	3	39	31.97	122	100.00			
113								
114								
115	*-----*							
116	* Score Output							
117	*-----*							
118								
119	*-----*							
120								

Output ⁹

In our final output, (Output ⁹) we get variable summary, Association report of all items in dataset, RHS, LHS rule index. Also, some Rule Statistics such as The MEANS Procedure, Frequency Procedure reports are computed.

Upon more inspection we explore rules table we see 122 rules with relations in LHS vs RHS association rule format Output ¹⁰.

Rule Index	Relations	Expected Confidence (%)	Confidence (%)	Support (%)	Lift	Transaction Count	Rule	Left Hand of Rule	Right Hand of Rule	Rule Item 1	Rule Item 2	Rule Item 3	Rule Item 4	Rule Item 5	Transpose Rule
1	2	6.44	40.38	1.02	6.27	21.00	MASS C...	MASS C...	BEAUTY...	MASS C...	=====	BEAUTY...			1
2	2	2.52	15.79	1.02	6.27	21.00	BEAUTY...	BEAUTY...	MASS C...	MASS C...	=====	MASS C...			1
3	3	2.03	12.50	0.92	6.14	19.00	PERSO...	PERSO...	HEALTH...	PERSO...	=====	HEALTH...	BEAUTY...		1
4	3	7.36	45.24	0.92	6.14	19.00	HEALTH...	HEALTH...	PERSO...	HEALTH...	=====	PERSO...	BEAUTY...		1
6	3	9.69	59.46	1.07	6.14	22.00	PERSO...	PERSO...	HEALTH...	PERSO...	HOUSEH...	=====	HEALTH...		1
5	3	1.79	11.00	1.07	6.14	22.00	HEALTH...	HEALTH...	PERSO...	HEALTH...	=====	PERSO...	HOUSEH...		1
7	3	1.74	10.53	0.78	6.04	16.00	PERSO...	PERSO...	HEALTH...	PERSO...	=====	HEALTH...	BEVERA...		1
8	3	7.36	44.44	0.78	6.04	16.00	HEALTH...	HEALTH...	PERSO...	HEALTH...	BEVERA...	=====	PERSO...		1
9	3	9.69	56.67	0.82	5.85	17.00	PERSO...	PERSO...	HEALTH...	PERSO...	CANDY...	=====	HEALTH...		1
10	3	9.69	56.67	0.82	5.85	17.00	HOUSEH...	HOUSEH...	HEALTH...	HOUSEH...	BEAUTY...	=====	HEALTH...		1
11	3	3.25	18.18	0.87	5.60	18.00	GENERA...	GENERA...	CANDY...	GENERA...	=====	CANDY...	BEVERA...		1
12	3	4.80	26.87	0.87	5.60	18.00	CANDY...	CANDY...	GENERA...	CANDY...	BEVERA...	=====	GENERA...		1
13	3	9.30	51.61	0.78	5.55	16.00	SPIRITS...	SPIRITS...	WINE...	SPIRITS...	CANDY...	=====	WINE...		1
14	3	9.69	53.33	0.78	5.50	16.00	PERSO...	PERSO...	HEALTH...	PERSO...	BEVERA...	=====	HEALTH...		1
15	3	2.03	10.76	0.82	5.29	17.00	HOUSEH...	HOUSEH...	HEALTH...	HOUSEH...	=====	HEALTH...	BEAUTY...		1
16	3	7.66	40.48	0.82	5.29	17.00	HEALTH...	HEALTH...	HOUSEH...	HEALTH...	BEAUTY...	=====	HOUSEH...		1
17	3	2.18	11.18	0.82	5.13	17.00	PERSO...	PERSO...	HEALTH...	PERSO...	=====	HEALTH...	CANDY...		1
18	3	7.36	37.78	0.82	5.13	17.00	HEALTH...	HEALTH...	PERSO...	HEALTH...	CANDY...	=====	PERSO...		1
19	3	9.69	48.57	0.82	5.01	17.00	HOUSEH...	HOUSEH...	HEALTH...	HOUSEH...	CANDY...	=====	HEALTH...		1
20	3	2.18	10.76	0.82	4.94	17.00	HOUSEH...	HOUSEH...	HEALTH...	HOUSEH...	=====	HEALTH...	CANDY...		1
21	3	7.66	37.78	0.82	4.94	17.00	HEALTH...	HEALTH...	HOUSEH...	HEALTH...	CANDY...	=====	HOUSEH...		1
22	3	2.96	14.47	1.07	4.90	22.00	PERSO...	PERSO...	HOUSEH...	PERSO...	=====	HOUSEH...	HEALTH...		1
23	3	7.36	36.07	1.07	4.90	22.00	HOUSEH...	HOUSEH...	PERSO...	HOUSEH...	HEALTH...	=====	PERSO...		1
24	3	9.69	46.34	0.92	4.78	19.00	PERSO...	PERSO...	HEALTH...	PERSO...	BEAUTY...	=====	HEALTH...		1
26	3	6.44	29.69	0.92	4.61	19.00	PERSO...	PERSO...	BEAUTY...	PERSO...	HEALTH...	=====	BEAUTY...		1
25	3	3.10	14.29	0.92	4.61	19.00	BEAUTY...	BEAUTY...	PERSO...	BEAUTY...	=====	PERSO...	HEALTH...		1
28	3	7.66	34.38	1.07	4.49	22.00	PERSO...	PERSO...	HOUSEH...	PERSO...	HEALTH...	=====	HOUSEH...		1
27	3	3.10	13.92	1.07	4.49	22.00	HOUSEH...	HOUSEH...	PERSO...	HOUSEH...	=====	PERSO...	HEALTH...		1
29	2	9.69	42.11	3.10	4.35	64.00	PERSO...	PERSO...	HEALTH...	PERSO...	=====	HEALTH...			1
30	2	7.36	32.00	3.10	4.35	64.00	HEALTH...	HEALTH...	PERSO...	HEALTH...	=====	PERSO...			1
32	3	6.44	27.87	0.82	4.32	17.00	HOUSEH...	HOUSEH...	BEAUTY...	HOUSEH...	HEALTH...	=====	BEAUTY...		1
31	3	2.96	12.78	0.82	4.32	17.00	BEAUTY...	BEAUTY...	HOUSEH...	BEAUTY...	=====	HOUSEH...	HEALTH...		1
33	2	6.44	26.97	1.99	4.19	41.00	PERSO...	PERSO...	BEAUTY...	PERSO...	=====	BEAUTY...			1
34	2	7.36	30.83	1.99	4.19	41.00	BEAUTY...	BEAUTY...	PERSO...	BEAUTY...	=====	PERSO...			1
35	2	9.69	38.61	2.96	3.98	61.00	HEALTH...	HEALTH...	HOUSEH...	HEALTH...	=====	HEALTH...			1
36	2	7.66	30.50	2.96	3.98	61.00	HEALTH...	HEALTH...	HOUSEH...	HEALTH...	=====	HOUSEH...			1

Output ¹⁰

5. Conclusion and Output Comparison of R and SAS EM

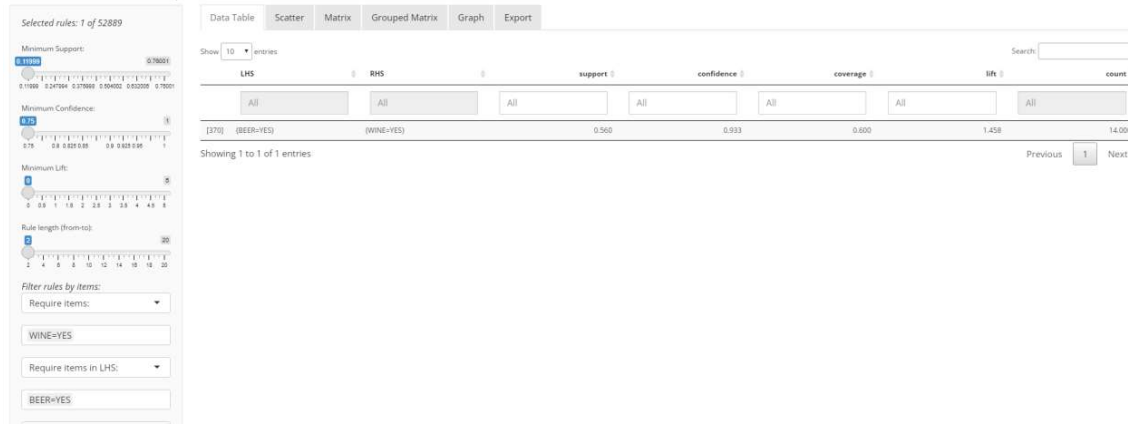
From R programming output we have rule explorer which enables us easy approach in finding associated rules between the selected items from our dataset. So, we take association rule SAS Enterprise miner and check the support, confidence, and lift of that rules with R programming computed rule explorer.

From the Rule Table Output ¹⁰, we pick WINE ==> BEER Output ¹¹ as our rule to compare with R programming rule explorer we set WINE in LHS and BEER in RHS we get out initial support lift and confidence values. We are had change rule length to 2 since are testing only two items from our data set Output ¹².

SET_SIZE	EXP_CON	CONF	SUPPORT	LIFT	COUNT	RULE	_LHAND	_RHAND	ITEM1	ITEM2	ITEM3	ITEM4	ITEM5	index	Transpo
2	9.30	27.82	1.79	2.99	37.00	BEER ==> WINE	BEER	WINE	BEER	=====	WINE			49	

Output ¹¹

Association Rule Explorer



Output ¹²

Comparing the default values of both R results and SAS Enterprise Miner results, we get differences in count, support, lift and confidence as well, if we could tune minimum support and minimum lift in rule explorer, we can achieve same results as of from SAS Miner. By this, we came to conclusion that R programming and SAS EM although may have difference in execution, but we may achieve similar statistical values.

References

1. Agrawal R, Imielinski T, Swami A. Mining association rules between sets of items in large databases. In: Proceedings of ACM SIGMOD conference on management of data (SIGMOD 1993). New York: ACM; 1993. p. 207-216.
2. Fayyad U, Piatetsky-Shapiro G, Smyth P. Knowledge discovery and data mining: Towards a unifying framework. In: Proc. KDD-96: Second International Conference on Knowledge Discovery & Data Mining Menlo Park, CA: AAAI Press, 1996, pp.82–88.
3. Sanmiquel L, Rossell JM, Vintro C. Study of Spanish mining accidents using data mining techniques. Saf Sci. 2015;75:49–55.
4. Hussein, N., Alashqur, A. and Sowan, B., 2015. Using the interestingness measure lift to generate association rules. Journal of Advanced Computer Science & Technology, 4(1), p.156.
5. A. Agresti. Categorical Data Analysis. John Wiley & Sons, 1990.
6. https://data.world/zipencer/transaction-itemset/workspace/file?filename=transactions_by_dept.csv