Association Rules for Purchase Dependency of Grocery Items

S. Sarifah Radiah Shariff, Zurriyati Bakri, Paezah Hamzah

Centre for Statistical and Decision Science Studies,
Faculty of Computer and Mathematical Sciences,
Universiti Teknologi MARA,
40450 Shah Alam, Selangor, MALAYSIA.
E-mail: radiah@tmsk.uitm.edu.my

ABSTRACT

Customer purchasing behaviour is reflected in the choice of products consumers purchased. An item that a customer purchases sometimes depends on the purchase of another item. Retailers can use purchasing dependencies for planning replenishment of inventory to avoid stock-outs. However, such dependencies are usually not visible. This study uses the data mining approach in finding associations between products purchased by customers from a supermarket and four retail shops. Primary data were obtained from 130 single-sales transactions made over a seven days period by customers of the supermarket and retail stores. Association rules for purchase dependencies were mined using two different algorithms, Apriori and Carma, on IBM SPSS Modeller 15. Results indicated that for retail shops, the purchase of grocery products depends on the availability of fresh food items with 83.33% confidence, and 40% of the customers tend to purchase both items within one transaction. For the supermarket, customers are 27.06% more frequent to buy grocery products together with health beauty products and fresh foods items with 96.66% confidence.

Keywords: *purchase dependency, association rules, apriori model, carma model*

INTRODUCTION

In the current competitive retail environments, there is a need for all organisations to look for opportunities to be ahead of others. For retailers, the need is mainly based on their ability to optimise the use of available resources, through minimising operation costs and maximising profit. A possible good strategy is minimising lost sales due to stock-out. Lost sales occur not only because of stock-outs of a particular product, but it can also be due to stock-out of related products. This is the effect of customer purchase dependency behaviour. Purchase dependency effect is observed when a customer purchases a certain product according to the availability of another product (Bala, 2008a). With a better understanding of purchase dependencies, retailers can design a better replenishment policy for their inventory items to avoid stock-out. The objective of this study is to identify product categories with positive purchase dependencies. The study involved customers of four retail shops and one supermarket.

The paper is structured as follows: Section II gives some insight on studies related to purchase dependencies and customers purchase behaviours. Section III details the methodology used to achieve the objective. Section IV presents the results, and discusses the main findings. Finally, Section V gives the conclusions and suggestions for future research.

LITERATURE REVIEW

Purchase dependency exists when a purchase of an item from a category depends on the purchase of an item from another category. Bala (2008a) studied purchase dependency in grocery products by exploring various forms of purchase dependency in retail sale. The study on sales transactions from 45 grocery stock keeping units (SKUs) in a retail store in India found that items which showed positive purchase dependencies are raisins and basmati, coffee and Nescafe as well as Maggi noodle and Maggi tomato sauce with MDH chicken masala. Bala (2012) also extended his research by comparing different applicable inventory replenishment policies in multi-item inventory with a large number of items on the items that have interdependent demand. Another study of purchase dependencies in the retail store was by Park and Seo (2013) who introduced the purchase dependency on the inventory operations practice of spare parts at Hyundai Engine Europe Service Centre (HEESC).

Seetharaman and Narasimhan (2012) emphasised that in order to understand the demand inter-relationships between product offerings in related product categories, it is necessary to understand demand inter-relationships with other brands in those categories as well. Leingpibul et al. (2013) studied the relationship between retailers and manufacturers towards brand purchase behaviour of customers. 87 usable samples were analysed using structural equation modelling to test the hypothesis and the results indicated that retailer's brand has greater influence on consumer's brand purchase behaviour. Nevertheless, the results might be biased since there were only two grocery products purchased from a single retailer and the respondents had purchased the items from that retailer.

In another study, Heitz-Spahn (2013) analysed the phenomenon of cross-channel free-riding on customers purchased behaviour. The goal is to gain better insight on cross-channel free-riding in a multichannel retailing environment. 741 French respondents participated in the online survey to answer the questions related to channels and retailers selections as well as the questions to determine whether the respondents are free-riders or retention consumers. Logistic regression is applied and the results indicated that free-riding is higher when customers adopt cross-channel. However, cross-channel free-riding is different across products.

Jackson (2008) defined association rules as relationships between the attributes of known group of entities that have one or more aspects of those entities, which allow predictions to be made about aspects of other entities that are not in the group but having the same attributes. With various items or products offered in the market, in order to find the relationship among items which have depicted purchase dependency conditions, data mining approach has been widely used by the researchers. Basically, there are two methods for clustering various items to see a clear pattern of dependency among items. One is association rules which can provide patterns for insightful interpretation (Bala, 2008b) while another data mining method that can be applied is the Artificial Neural Network (ANN) that gives various classifications such as pattern recognition and genetic algorithms (Kumar & Bala, 2013).

METHODOLOGY

This study employs a data mining approach to meet the objective of the study which is to identify positive purchase dependencies. It was done in three phases: (i) data collection, (ii) data analysis, and (iii) application of step by step data mining procedures to obtain association rules.

In this study, data were collected from customer sales receipts done in single transactions. A total of 130 sales receipts were obtained from customers visiting the supermarket and retail stores over a seven day period. 85 sales receipts were collected from the supermarket customers and the remaining 45 were from the retail shop customers. Items purchased by the customers were grouped into nine categories according to sections or departments in the supermarket and retail shops as shown in Table 1.

Table 1: Product categories

Product Category	Items
Health and beauty	Hair care, oral care, bath toiletries, skin care, cosmetics, feminine care and health care.
Cloth and apparels	Women's clothing, men's clothing and shoes.
Grocery	Rice, cooking oil, noodles, pasta, cooking ingredients, seasonings, pastries, canned food, dried food, cereals, chocolate, sweets, snacks, creamer, sugar, salt and flour.
Fresh foods	Fruits, vegetables, eggs, fish and seafood, meat and chicken.
Drinks	3-in-1, tea, coffee, mineral water, milk, soya, malt, chocolate, carbonated drink, juice, cordial, and yogurt.
Chilled and frozen items	Frozen food, butter, margarine, cheese, mayonnaise and ice-cream.
Household	Detergents, softener, insect repellent, garbage bags, air freshener and tissues.
Baby	Diapers, baby wipes, baby toiletries, milk powder, baby's food bottles and warmer.
Learning tools	Books and stationeries.

Association Rules for Purchase Dependency

Association analysis on the data is done for determining what products are most likely to be purchased together. An association rule simply means a statement in the form of (*Item set A*) Þ (*Item set B*). *Item set A* is the antecedent while *Item set B* is the consequent. There are two methods for evaluating the association rules, by Market Basket Analysis and by IBM SPSS Modeller 15 software.

A Market Basket Analysis determines which of the items are associated with one another and then calculates the association rules comprising of ***support, confidence, expected confidence*** and ***lift***.

Support measures how frequently the items occurred in the market basket (or in the total number of customer transactions being studied). The higher the percentage obtained from the support measures, the more frequent the items being purchased together by the customers. It can be calculated as follows:

$$Support = \frac{n(A \cap B)}{n(T)} \times 100\% \qquad (1)$$

Confidence measures the strength of an association between the products. Confidence indicates the percentage of cases in which consequent appears given that the antecedent has occurred. Highest confidence measures indicate strong associations between the products. It can be calculated as follows:

$$Confidence = \frac{n(A \cap B)}{n(A)} \times 100\% \qquad (2)$$

Expected confidence measures the associations between the items set in the consequent transactions with the total number of transactions being studied. The higher the percentage of expected confidence, the more strongly is the associations between the consequent items in the overall total number of transactions. It can be calculated as follows:

$$Expected\ Confidence = \frac{n(B)}{n(T)} \times 100\% \qquad (3)$$

Lift is a factor in which the likelihood of the consequent increases given an antecedent. There are three measures of lift; positive correlation (when the value of lift is greater than 1), negative correlation (when the value of lift is less than 1) and zero correlation (when lift value equal to one). Higher value of lift indicates stronger associations between the products. It can be calculated as follows:

$$Lift = \frac{Confidence}{Expected\ Confidence} \qquad (4)$$

IBM SPSS Modeller 15 has three different algorithms for generating association rules. These are Apriori, Carma and Sequential algorithms. However, this study only formulates the association rules based on only two algorithms which are Apriori and Carma. The difference between these two algorithms is only in the format of the input data. As for Apriori algorithm, the input data must be categorical while the input data for Carma algorithm can either be categorical consequents or numeric inputs. Apriori is essential in extracting association rules in a very efficient manner since it has the advantage of having options that provide choices in the criterion measurement used to guide the rules. Unlike Apriori, Carma offers options for rule detection that includes support for both the antecedent and consequence. It allows data in transaction format and allows rules with multiple consequents or final outcome that is not restricted to only categorical data.

In any decision making process, there may be four conditions at any point of time while considering an association rules, X Þ Y. The four situations are:

1. Both X and Y are available.
2. X is in stock but Y is not available.
3. X is not in stock but Y is available.
4. Both X and Y are not available.

In this study, the focus is only on condition (iii) in which item X is not in stock but item Y is available. Under this condition, the customers with demand for both items X and Y will most probably not purchase item Y although it is in stock. Hence it will result in lost sales for both items since the purchase of item Y is dependent on the purchase of item X.

Firstly, we presented primary data and data profiles for each of the related category used in this study. Next, we run the data in IBM SPSS Modeller 15 to show the association rules for categories in the retail shop and the supermarket that has depicted purchase dependencies.

Data profiles

Table 2 shows the profiles for the primary data collected in the retail shop and supermarket respectively. The classifications of the items or products purchased by the customers following the categories being assigned previously and their respective total weekly demand, total selling price, average selling price and average unit cost are summarised.

Table 2: Sales transaction profiles

	Retail Shop Customers		Supermarket Customers	
Product Category	**Daily Purchase (units)**	**Total Sales (RM)**	**Daily Purchase (units)**	**Total Sales (RM)**
Baby (B)	3	59.5	18	412.41
Cloth Apparel (CA)	1	17.5	38	532.59
Chilled/ Frozen (CF)	16	90.68	61	402.24
Drinks (D)	51	352.10	166	988.49
Fresh Foods (FF)	94	561.97	200	2810.45
Grocery (G)	110	351.00	335	1541.56
Household (HH)	10	82.23	101	1401.71
Health/Beauty (HB)	18	183.67	101	978.18
Learning Tools (LT)	3	11.2	19	76.39

The data were stored in a SPSS data file. The sample consists of 45 customer sales transactions from the retail shops while 85 customer sales transactions from the supermarket. There are no missing values for both data sets. Hence, we can continue with the modelling stage.

Data modelling

Figures 1 and 2 show the predictive modelling flow for customer sales transaction from the retail shops and supermarket, respectively. The data source was connected to the data partition node. The data was partitioned as training samples by using 70% and 30% as testing or evaluation samples, respectively. To extract sets of association rules from the data, the Carma node and Apriori node were connected to the type node. The web node was also connected to the type node to have a graphical view of the associations rules obtained from the data.

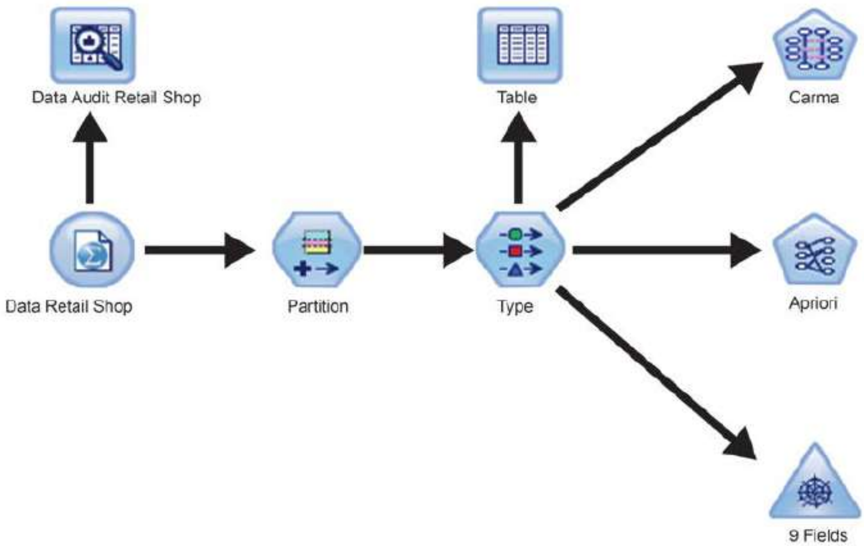

Figure 1: Predictive modelling flow for customer sales transaction in the retail shops

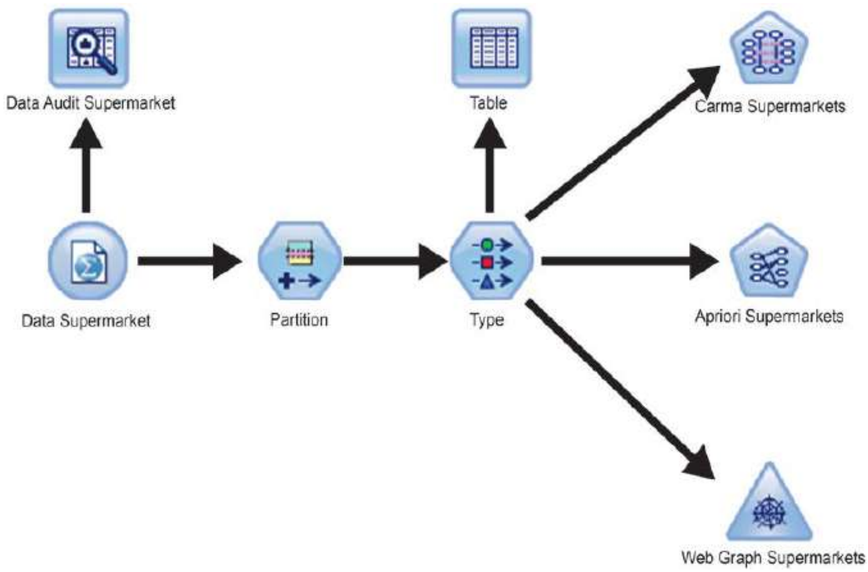

Figure 2: Predictive modelling flow for customer sales transaction in the supermarket

For the Apriori model, the association rules have been mined by selecting a maximum of five numbers of antecedents for the combinations of the derived fields containing binary data for threshold values of 10% as minimum antecedent support and 80% as minimum confidence.

Overall, in mining association rules using Apriori model for customer sales transactions in the retail shops, we found that only one rule satisfied the condition being set up. The minimum support obtained is 40% while the maximum confidence is 83.33%. Another relevant condition is lift ratio in which both the maximum and minimum lift is 1.103 since only one rule is obtained.

As for the mining association rules using Apriori model for customer sales transactions in the supermarket, we found that there are 37 rules which satisfied the threshold values of 10% support and 80% confidence. The minimum support obtained is 10.59% while the maximum rule support is 68.24%. The minimum and maximum confidence is 80% and 100% respectively. The minimum lift ratio obtained is 0.986 while the maximum lift ratio is 1.889. Table 3 shows the details result from the Apriori model.

Table 3: Results from Apriori model

(i) Retail Store

No of Rule	Consequent	Antecedent	Support %	Confidence %	Rule Support %	Lift
1	G	FF	40	83.333	33.333	1.103

(ii) Supermarket

No of Rule	Consequent	Antecedent	Support %	Confidence %	Rule Support %	Lift
1	D	CA and FF	11.765	90	10.588	1.319
2	D	CA, FF and G	10.588	88.889	9.412	1.303
3	D	HH and FF	18.824	81.25	15.294	1.191
4	D	HH, FF and G	17.647	80	14.118	1.172
5	D	CF, FF and G	29.412	80	23.529	1.172
6	FF	CA and D	10.588	100	10.588	1.771
7	FF	CF, HB and D	15.294	84.615	12.941	1.498
8	FF	CF, D and G	28.235	83.333	23.529	1.476
9	FF	CF, HB, D and G	14.118	83.333	11.765	1.476
10	FF	CA and G	12.941	81.818	10.588	1.449
11	FF	CF and D	31.765	81.481	25.882	1.443
12	G	HB and FF	27.059	95.652	25.882	1.178
13	G	CF and HB	21.176	94.444	20	1.163
14	G	HB, FF and D	21.176	94.444	20	1.163
15	G	HH and FF	18.824	93.75	17.647	1.155
16	G	CF, HB and FF	16.471	92.857	15.294	1.144
17	G	HH, FF and D	15.294	92.308	14.118	1.137
18	G	CF, HB and D	15.294	92.308	14.118	1.137
19	G	HH, HB and FF	14.118	91.667	12.941	1.129
20	G	CF, FF and D	25.882	90.909	23.529	1.12
21	G	CF, HB, FF and D	12.941	90.909	11.765	1.12

22	G	CA and FF	11.765	90	10.588	1.109
23	G	FF	56.471	89.583	50.588	1.104
24	G	FF and D	44.706	89.474	40	1.102
25	G	CF and FF	32.941	89.286	29.412	1.1
26	G	CF	42.353	88.889	37.647	1.095
27	G	CA and D	10.588	88.889	9.412	1.095
28	G	CF and D	31.765	88.889	28.235	1.095
29	G	CA, FF and D	10.588	88.889	9.412	1.095
30	G	HH, HB, FF and D	10.588	88.889	9.412	1.095
31	G	HB and D	31.765	85.185	27.059	1.049
32	G	HB	44.706	84.211	37.647	1.037
33	G	D	68.235	82.759	56.471	1.019
34	G	HH and CF	12.941	81.818	10.588	1.008
35	G	HH and HB	23.529	80	18.824	0.986
36	G	HH, HB and D	17.647	80	14.118	0.986
37	HH	LT	11.765	80	9.412	1.889

Unlike the Apriori model, Carma model offers options for rule detection that includes support for both the antecedent and the consequence. Moreover, it allows data in transaction format and not limited to only categorical data. The format of the output is identical to the Apriori model however for Carma model we have set the same value for minimum rule support and rule confidence which is 20% while the maximum rule size we set as 10. Table 4 shows the detail results from Carma model.

Table 4: Results from Carma model

(i) Retail Store

No of Rules	Consequent	Antecedent	Support %	Confidence %	Rule Support %	Lift
1	G	FF	40	83.333	33.333	1.103
2	G	D	51.111	73.913	37.778	0.978
3	D	G	75.556	50	37.778	0.978
4	FF	G	75.556	44.118	33.333	1.103

(ii) Supermarket

No of Rules	Consequent	Antecedent	Support %	Confidence %	Rule Support %	Lift
1	CF	G, FF and D	40	58.824	23.529	1.389
2	CF	FF	56.471	58.333	32.941	1.377
3	CF	G and FF	50.588	58.14	29.412	1.373
4	CF	FF and D	44.706	57.895	25.882	1.367
5	CF	HB and G	37.647	53.125	20	1.254
6	CF	G and D	56.471	50	28.235	1.181
7	CF	HB	44.706	47.368	21.176	1.118
8	CF	D	68.235	46.552	31.765	1.099
9	CF	G	81.176	46.377	37.647	1.095
10	D	G, FF and CF	29.412	80	23.529	1.172
11	D	FF	56.471	79.167	44.706	1.16
12	D	G and FF	50.588	79.07	40	1.159
13	D	FF and CF	32.941	78.571	25.882	1.151
14	D	HB and FF	27.059	78.261	21.176	1.147
15	D	HB, G and FF	25.882	77.273	20	1.132
16	D	CF	42.353	75	31.765	1.099
17	D	G and CF	37.647	75	28.235	1.099
18	D	HB and G	37.647	71.875	27.059	1.053
19	D	HB	44.706	71.053	31.765	1.041
20	D	G	81.176	69.565	56.471	1.019
21	D	G and HH	30.588	65.385	20	0.958

22	D	HH	42.353	63.889	27.059	0.936
23	D and CF	G and FF	50.588	46.512	23.529	1.464
24	D and CF	FF	56.471	45.833	25.882	1.443
25	D and CF	G	81.176	34.783	28.235	1.095
26	D and HH	G	81.176	24.638	20	0.911
27	FF	G, D and CF	28.235	83.333	23.529	1.476
28	FF	D and CF	31.765	81.481	25.882	1.443
29	FF	G and CF	37.647	78.125	29.412	1.383
30	FF	CF	42.353	77.778	32.941	1.377
31	FF	HB, G and D	27.059	73.913	20	1.309
32	FF	G and D	56.471	70.833	40	1.254
33	FF	HB and G	37.647	68.75	25.882	1.217
34	FF	HB and D	31.765	66.667	21.176	1.181
35	FF	D	68.235	65.517	44.706	1.16
36	FF	G	81.176	62.319	50.588	1.104
37	FF	HB	44.706	60.526	27.059	1.072
38	FF and CF	G and D	56.471	41.667	23.529	1.265
39	FF and CF	D	68.235	37.931	25.882	1.151
40	FF and CF	G	81.176	36.232	29.412	1.1
41	FF and D	G and CF	37.647	62.5	23.529	1.398
42	FF and D	CF	42.353	61.111	25.882	1.367
43	FF and D	HB and G	37.647	53.125	20	1.188
44	FF and D	G	81.176	49.275	40	1.102
45	FF and D	HB	44.706	47.368	21.176	1.06
46	FF, D and CF	G	81.176	28.986	23.529	1.12
47	G	HB and FF	27.059	95.652	25.882	1.178
48	G	HB and CF	21.176	94.444	20	1.163
49	G	HB, FF and D	21.176	94.444	20	1.163
50	G	FF, D and CF	25.882	90.909	23.529	1.12
51	G	FF	56.471	89.583	50.588	1.104
52	G	FF and D	44.706	89.474	40	1.102
53	G	FF and CF	32.941	89.286	29.412	1.1
54	G	CF	42.353	88.889	37.647	1.095

55	G	D and CF	31.765	88.889	28.235	1.095
56	G	HB and D	31.765	85.185	27.059	1.049
57	G	HB	44.706	84.211	37.647	1.037
58	G	D	68.235	82.759	56.471	1.019
59	G	D and HH	27.059	73.913	20	0.911
60	G	HH	42.353	72.222	30.588	0.89
61	G and CF	FF and D	44.706	52.632	23.529	1.398
62	G and CF	FF	56.471	52.083	29.412	1.383
63	G and CF	HB	44.706	44.737	20	1.188
64	G and CF	D	68.235	41.379	28.235	1.099
65	G and D	HB and FF	27.059	73.913	20	1.309
66	G and D	FF and CF	32.941	71.429	23.529	1.265
67	G and D	FF	56.471	70.833	40	1.254
68	G and D	CF	42.353	66.667	28.235	1.181
69	G and D	HB	44.706	60.526	27.059	1.072
70	G and D	HH	42.353	47.222	20	0.836
71	G, D and CF	FF	56.471	41.667	23.529	1.476
72	G and FF	D and CF	31.765	74.074	23.529	1.464
73	G and FF	CF	42.353	69.444	29.412	1.373
74	G and FF	HB and D	31.765	62.963	20	1.245
75	G and FF	D	68.235	58.621	40	1.159
76	G and FF	HB	44.706	57.895	25.882	1.144
77	G, FF and CF	D	68.235	34.483	23.529	1.172
78	G, FF and D	CF	42.353	55.556	23.529	1.389
79	G, FF and D	HB	44.706	44.737	20	1.118
80	G and HH	D	68.235	29.31	20	0.958
81	HB	HH	42.353	55.556	23.529	1.243
82	HB	G and CF	37.647	53.125	20	1.188
83	HB	G and FF	50.588	51.163	25.882	1.144
84	HB	CF	42.353	50	21.176	1.118
85	HB	G, FF and D	40	50	20	1.118
86	HB	FF	56.471	47.917	27.059	1.072
87	HB	G and D	56.471	47.917	27.059	1.072

88	HB	FF and D	44.706	47.368	21.176	1.06
89	HB	D	68.235	46.552	31.765	1.041
90	HB	G	81.176	46.377	37.647	1.037
91	HB and CF	G	81.176	24.638	20	1.163
92	HB and D	G and FF	50.588	39.535	20	1.245
93	HB and D	FF	56.471	37.5	21.176	1.181
94	HB and D	G	81.176	33.333	27.059	1.049
95	HB and FF	G and D	56.471	35.417	20	1.309
96	HB and FF	G	81.176	31.884	25.882	1.178
97	HB and FF	D	68.235	31.034	21.176	1.147
98	HB,FF and D	G	81.176	24.638	20	1.163
99	HB and G	CF	42.353	47.222	20	1.254
100	HB and G	FF	56.471	45.833	25.882	1.217
101	HB and G	FF and D	44.706	44.737	20	1.188
102	HB and G	D	68.235	39.655	27.059	1.053
103	HB, G and D	FF	56.471	35.417	20	1.309
104	HB, G and FF	D	68.235	29.31	20	1.132
105	HH	HB	44.706	52.632	23.529	1.243
106	HH	D	68.235	39.655	27.059	0.936
107	HH	G	81.176	37.681	30.588	0.89
108	HH	G and D	56.471	35.417	20	0.836

Association Rules Mined from Sales Transactions Data in the Retail Shops

Association rules have been mined from 45 sale transactions of nine categories in the retail shops at various threshold values for support and confidence. Some of the rules mined are as follows:

1. Fresh foods => Grocery with 40% support, 83.33% confidence and lift ratio of 1.103

2. Drinks => Grocery with 51.11% support, 73.91% confidence and lift ratio of 0.978

It is expected that an association rule will depict purchase dependency. However, the most reliable association rule should have higher percentage of confidence and at least with value of lift ratio greater than 1. It shows that there is a positive correlation in the purchase of fresh foods items and grocery products since the lift value is greater than 1. Moreover, a strong association is shown based on the percentage of confidence (83.33%) and 40% of customers tend to purchase both fresh food items and grocery products in one transaction.

Hence, we have considered that the purchase of grocery products depends on the availability of fresh food items. As a result, customers with demand for both fresh foods items and grocery products will not purchase grocery products in the absence of fresh food items. This is how lost sale for both fresh food items and grocery products occurs in the retail shops.

Association Rules Mined from Sale Transactions Data in the Supermarkets

Association rules have been mined from 85 sale transactions of nine categories in the supermarket at various threshold values for support and confidence. Some of the rules mined are as follows:

1. Cloth Apparel and Drinks => Fresh Foods with 10.59% support, 100% confidence and lift ratio of 1.771

2. Health Beauty and Fresh Foods => Grocery with 27.06% support, 95.66% confidence and lift ratio of 1.178

3. Chilled Frozen and Health Beauty => Grocery with 21.18% support, 94.44% confidence and lift ratio of 1.163

4. Household and Fresh Foods => Grocery with 18.82% support, 93.75% confidence and lift ratio of 1.155

In the supermarket, there is positive correlation between fresh food items with cloth apparels and drinks as the lift ratio is 1.771. This indicates that customers who purchased fresh food items are about twice more likely to purchase cloth and apparel and drinks with 100% confidence. However, customers are not frequents in buying this three products together in one transaction as the support value is only 10.59%.

Hence, this study considered the association between health beauty products and fresh food items with grocery products. There is a positive correlation in the purchase of health beauty and fresh food items with grocery products since the lift ratio indicates the value of 1.178 which is greater than 1. In addition, a strong association between these three items purchased in one transaction with 96.66% of confidence and customers are 27.06% more frequent to buy these three items altogether.

The purchase of grocery products depends on the availability of health beauty products and fresh food items. As a result, the stock outs of health beauty products and fresh food items will lead to non-purchase of grocery products. We believe that this is how lost sale for health beauty products, fresh food items and grocery products may occur in the supermarket.

CONCLUSION

This paper describes the study with the identification of the existence of purchase dependence in grocery products in retail shops and supermarkets, with the purpose of minimising the lost sale by incorporating purchase dependence elements in the inventory model. In this study, primary data obtained from a total of 130 customer's sales transactions in the retail shops and the supermarket is used to conduct the association's analysis. The purpose of association analysis is to study the relationship between product's category in the retail shops and the supermarket. The output from the association analysis is used to simulate the inventory model using Excel spreadsheets. The simulation results indicated that the extended inventory models incurred lower average total inventory cost than the inventory model that ignored purchase dependencies. Similarly, the inventory model that considered purchase dependencies has resulted in the reduction in values of profit and lost sales as compared with the inventory model that ignored purchase dependencies which incurred higher value in profits and lost sales. Moreover, there is a significant difference between the associated inventory costs when considering as well as when ignoring purchase dependencies in the inventory model based on Wilcoxon signed-ranks test. Hence, the study can conclude that by incorporating purchase dependence elements, total inventory cost as well as lost and profit cost can be minimised.

REFERENCES

Bala, P.K. (2008a, October). *Exploring Various Forms of Purchase Dependency in Retail Sale.* Paper presented at Proceedings of the World Congress on Engineering and Computer Science (WCECS) 2008, San Francisco.

Bala, P.K (2008b). Mining Association Rules for Selective Inventory Control. *Journal of Academy of Business & Economics, 8*(2), 75-85.

Bala, P.K. (2012). An Inventory Replenishment Model under Purchase Dependency in Retail Sale. *International Journal of Computer Applications*, *37*(10), 43-48.

Heitz-Spahn, S. (2013). Cross-channel Free-Riding Consumer Behaviour in a Multichannel Environment: An Investigation of Shopping Motives, Socio-demographics and product categories. *Journal of Retailing and Consumer Services, 20*(6), 570-578.

Jackson, J. (2008). Data Mining: A Conceptual Overview. *Communications of the Association for Information Systems*, *8*(19), 267-296.

Kumar, B. and Bala, P.K. (2013). Data Mining Approach for Multi-Item Inventory Replenishment Model Under Purchase Dependency. *International Journal of Business Research*, *13*(2), 29-34.

Leingpibul T., Broyles S.A and Kohli, C. (2013). The Comparative Influence of Manufacturer and Retailer Brands on Customers' Purchase Behaviour. *Journal of Product & Brand Management*, *22*(3), 208-217.

Park, C. and Seo, J. (2013). Consideration of Purchase Dependence in Inventory Management. *Computer & Industrial Engineering*, *66*(2), 274-285.

Seetharaman, P.B. and Narasimhan, C. (2012). Modelling Dependencies in Brand Choice Outcomes across Complementary Categories. *Journal of Retailing*, *88*(1), 47-62.