

The Digitally Associated Display Model For Convenience Stores: A Case Study

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The digitally associated display model for convenience stores: a case study

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Abstract:

Commodity display is one of the important means to improve customer shopping experience and enhance competitiveness in the convenience. Previous research only based on the characteristics of the commodities, but did not consider the importance of customers to display of commodities. Therefore, this paper presents the digitally associated display model that combines customer group concepts and digital means to mine customer and commodities information. First, analyze the preliminary association rules of commodities by Apriori algorithms, to provide data support, and check whether the data is true and feasible. Second, apply RFM model to analyze customers to get the importance of customers. Finally, construct a digital display model that combines customer group concepts and digital means to mine customer and commodities information. The research showed that: (1) the digitally associated display model can provide a scientific basis for the community convenience store to optimize the way of commodity display; (2) the digitally associated display model can optimize the layout of commodities to bring great room for profit growth for convenience stores. (3) the digitally associated display model can provide a reference for optimizing customer management methods, which is conducive to enhancing customers' shopping experience and satisfaction.

Key words: digitization; customer group; association rules; commodity display; convenience store

1.Introduction

According to the 2017 Smart Supply Chain High Score Forum, 2020-2040 will be a golden 20 years for the development of convenience stores. The number of convenience stores is expected to reach 600,000 nationwide in 2020. Convenience store is a new type of retail business, which is formed after the mature development of large stores and supermarkets. In past research, convenience stores were defined as stores with the certain size and brand, rather than simple mom-and-pop stores. The main function of convenience store is to provide convenient services to nearby customers [1]. Although there are many types of convenience stores, show obvious homogeneity in merchandise display and merchandise service methods, rather than truly providing customers with "facilitation." In other words, there is a general lack of substantial "facilitation" features [2]. As a key link to improve convenience, commodity display is very urgent for in-depth research.

Commodity display is a part of the convenience store's business that directly faces consumers,

and affects the convenience store's business performance and its value image in the minds of consumers [3]. In practice, consumer service demand is studied by many scholars, due to market segmentation marketing concepts and consumer retail demand increases are widely used. Van (2012) proposed that the focus of retail research is on customer service experience to improve customer satisfaction [4]. Hollebeek (2014) pointed out that how to establish long-term cooperative relationships with the most valuable customers is the core of customer relationship marketing [5], and Keller (2016) more precisely stated that customer value has become the center and focus of customer relationship marketing [6]. The mining of customer value is based on improving customer experience, so enhancing customer experience is key to effective marketing. Olfa (2013) realizes that the customer experience is deeply influenced by the in-store logistics [7]. Therefore, there are three urgent problems to be solved for the survival of brick-and-mortar stores following as: how to scientifically display goods in stores, optimize in-store logistics and improve customer experience. This requires us to use consumer big data analysis, according to consumer demand preferences, consumption level, etc., to achieve the targeted product layout of different stores, timely update and adjust the product varieties operated by the store, and provide differentiated products and services. Use digital means to explore the characteristics of convenience store consumers and improve the phenomenon of convenience stores [8]. The digital associated display model uses digital means to excavate the characteristics of convenience store consumers and improve the phenomenon of convenience stores [9].

Community convenience store is the home life service entity store, which has the characteristics of relatively fixed customer group, clear targets of shopping in the store and short stay in the store [10]. With the rapid development of the retail industry, community convenience stores are facing the fierce competitive environment. The key to their survival is how to enable customers to achieve the purpose of purchasing in the shortest time, and to enhance the sense of experience. However, the digitally associated display of commodities is the key measure to enhance customer experience. Therefore, the digitally display of convenience store commodity is considered to be a key issue in the research field based on customer group. Customer group and commodity associated display are combined insights in this paper, the related display analysis method of community convenience stores is proposed based on customer groups. This method can be used to guide the scientific display of community convenience stores, and promote the improvement of customer experience.

The overall structure of this article is as follows. Section 2 includes a brief review of customer value, commodity association and the application of these concepts in convenience stores. Section 3 describes the construction of the digitally associated display model. First, the data is excavated to construct the preliminary association model. Then the RFM model is constructed. At last, the preliminary association model and the RFM model are merged to realize the construction of the digitally associated display model. Section 4 is a case study. We choose one convenient store as the case study to verify the feasibility and practicability of the model. Finally, the conclusions and prospects are presented in Section 5.

2. Literature Review

2.1 Customer value

The existing researches on customer value mainly focus on three aspects following as: the value of enterprises to customers, the value of customers to enterprises and the value exchange between

customers and enterprises. However, the research on customer value focuses on the value of customers to enterprises in retail industry. Firstly, customer value applied to relationship marketing. Kotler (2000) proposed that the focus of relationship marketing between customers and enterprises lies in how to establish long-term and stable relationship with valuable customers [11]. Then Wyner (1994) pointed out that 80% of corporate profits come from 20% of its important customers, while the remaining 20% of profits require 80% of the company's marketing expenses [12]. Therefore, it is of great significance to find out valuable customers for the formulation of enterprise marketing strategy and long-term development.

Compared with them, Verhoef (2010) combed the relationship between customer engagement, customer marketing and customer experience in terms of the diversity of marketing channels [13], the importance of customer engagement and customer experience satisfaction to help companies adopt better marketing strategies, aiming to achieve precision marketing. In order to enhance customer experience, Han (2012) proposed a customer segmentation method based on customer life cycle, and identified valuable customers through five decision-making models: current value, historical value, long-term value, credit degree and loyalty prediction model [14]. As a result, Customer experience plays an important role in the research of customer value. Based on this, Nikhashemi (2016) redefined customer experience from four aspects following as: customer satisfaction, customer management, service quality and relationship marketing, and established a complete customer experience view [15]. Thus, customer value research with customer experience as the core was produced. In order to improve customer experience satisfaction, Khajvand (2011) and Lin (2011) adopted the RFM model to formulate targeted marketing strategies by calculating the potential value of customers [16,17]. When studying customer value, Ma (2011) and Ye (2016) also used RFM model to determine a more detailed customer segmentation method [18,19], which not only identified customer value but also provided a method for analyzing customer behavior. Most of the RFM models are used to study customer value, and can fit to represent customer experience view.

By combing the previous research on customer value, we can know customer experience plays an important role in customer value research. And research on customer experience mostly adopts RFM model. Therefore, this paper will study customer value based on RFM model through customer clustering. According to the results of clustering, different levels of customers are maintained and managed to obtain specific needs of customers, which deeply affects the related display analysis of commodities.

2.2 Commodity Association

Association rule method is one of the most commonly used research methods in data mining. It can be used to find the relationship between things, and the earliest is to find the relationship between different commodities in the supermarket transaction database. The famous application of association rules is Wal-Mart supermarkets. In the case, association rules have conducted a detailed analysis of the original transaction data in the data warehouse for more than a year, and found that diapers and beer are often purchased together. Accordingly, the shelf position is adjusted and diapers and beer were sold side by side, greatly increasing the sales. Therefore, a series of researches on mining association rules between commodities are triggered (Qian&Ji,2020) [20].

Association rule analysis was firstly proposed by Agrawal. Association rule reflects the interdependence and correlation between one thing and other things. If there is a certain correlation between two or more things, one of them can be predicted by other things (Agrawal &Swami.1993)

[21]. Since Agrawal proposed the association rule method, people have carried on the massive research to the association rule analysis. Some scholars focus on the optimization of correlation algorithms. For example, Cheung (1996) apply hashing technology to algorithm improvement, and introduce transaction compression, division, sampling, parallel ideas, in order to improve the efficiency of algorithm operation [22]. Zaki (2000) improved the efficiency of the sequential correlation vertical research algorithm [23]; Giannella (2006) proposed a mining algorithm based on data flow, whose principle is to improve the defects of Apriori algorithm by increasing the time sensitivity of word scanning [24], so as to improve the operating efficiency of association rules; Chon (2018) used Bit Map technology to compress the representation data to improve the speed of Apriori candidate set generation and support count [25]. In addition, some scholars mine association rules in different fields, apply them to the wider range of services, and constantly emphasize the importance of customers in association rules. Chen (2020) applied the mining of association rules to medical data analysis, analyzed sample data sets, and provided the new idea for medical diagnosis [26]. Zhou (2020) applied association rules to the analysis of electric energy substitution data, and mined implicit conclusions through association rules to guide electric energy substitution policies [27].

In conclusion, some scholars pay attention to the optimization of algorithm, and some have incorporated customer value into association relations and applied to different research fields. However, it is rarely to use association rule analysis which integrates customer value into convenience store commodity listing. Therefore, this paper puts forward the method of association display based on customer group, and applies it to commodity display in convenience stores. The purpose is to provide the method that is feasible and provides the selection basis for commodity display layout in the logistics link of the store.

3. Model construction

This paper takes the shopping receipt data of the historical sales of convenience stores as a sample. The preliminary association rules are mined to obtain the preliminary correlation between commodities, based on the correlation principle of displayed commodities. Because the core of digital analysis is the customer group concept, the RFM model is used to analyze customers. There are four factors to get the characteristics of various customers, that is R, F, M scores and RFM value scores. The results of digitally associated model are combined with preliminary association analysis and RFM for mining association rules again. Combined with magnet point theory to select layout of commodity display, and provide guidance and reference for improvement of commodity display methods in convenience stores.

3.1 Mining preliminary relationships

Apriori algorithm is an association rule analysis method, which focuses on finding out the occurrence of some specific events in the database, to find out those credible and representative rules. It is very practical for the analysis of commodity correlation in convenience stores.

It is known that the commodities sold in a certain community fresh convenience retail store during a period of time, including M shopping baskets and N kinds of commodities. The M shopping baskets in the data transaction are analyzed through the Apriori algorithm to obtain the association relationship all the kinds of commodities. And customers buy goods at high frequency (also known as frequent item sets). In this algorithm, there are two key indicators, respectively:

- (1) Support

The degree of support is the percentage of transactions involving items on the left and right sides of the association rule, indicating the importance of the whole combination (Xin, Cong&Guo,2019) [28]. Generally speaking, this is the number of times the item appears in the total transaction data that is the percentage of transactions that support the rule. The formula expression (D is complete set of data) is:

$$S(X) = P(X) = \frac{Support(X)}{D} \quad (1)$$

(2) Confidence

The degree of confidence is percentage of the number of combinations containing both item set X and item set Y in the total number of combinations containing x in the data set, reflecting the reliability of the rule (Xin, Cong&Guo,2019) [28]. This is the percentage of the number of times a product appears in all transactions in which it was purchased. The formula expression is:

$$C(X) = P(X|Y) = \frac{Sup(X \cup Y)}{Sup(X)} \quad (2)$$

In SPSS MODELER software, the calculation of formula 1 and formula 2 requires some analysis steps to get the indicators.

Step 1, audit data field type. Generally, the data audit is to check whether the field role is arbitrary and whether the measurement is arbitrary.

Step 2, perform network diagram analysis. There is an analysis about network diagram and strong and weak links. And the relationship all sub-categories can be obtained. Result is the molecular data in formula 2.

Step 3: analyze sub-category distribution. Support of various commodities is obtained. And confidence level can be calculated by combining strong links and the results of the distribution analysis.

Due to minimum support and minimum confidence are important measurement indicators for association analysis, their setting can be based on the calculation results of confidence and support. In the association rule results, strong association rule is a combination in which both support and confidence are greater than the set minimum. Strong association rule is the final association result through the continuous deletion of frequent item sets, which is the main reference basis for the association display and guides display of commodity.

3.2 Customer group analysis

Customer-oriented development has become the wind vane of modern enterprise development, so customer management is particularly important. In general, customer management focuses on the analysis of customer contribution, while RFM emphasizes customer behavior to distinguish customers. The purpose of this analysis is to group customers through their buying behavior. RFM model is mainly suitable for companies that provide a variety of commodities. In the company, the unit prices of these commodities are relatively low or are complementary to each other. And it is necessary for multiple repeated purchases. These characteristics meet the data characteristics of this analysis, so the RFM model is selected for customer group analysis. Data is analyzed by RFM value. Analysis flow is shown in Figure 1.

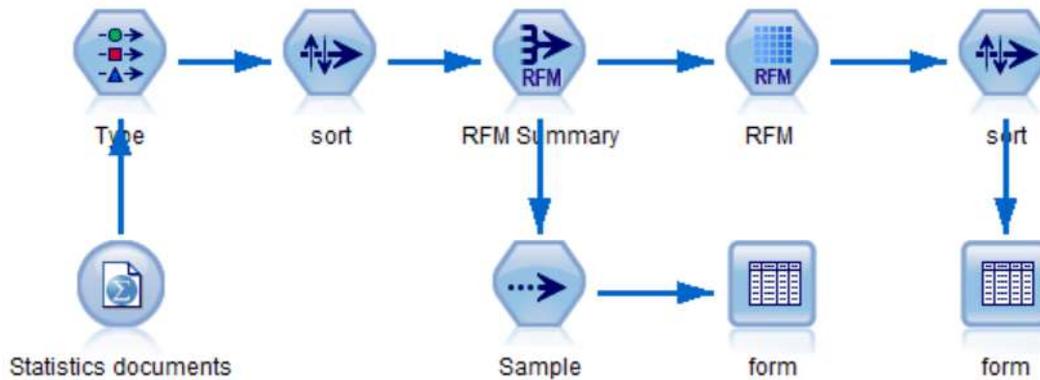


Figure 1 RFM analysis flow

The principle of RFM model is as follows: (1) R represents the time interval between the last purchase of the customer. Generally speaking, customer with the closest consumption time should be the better customer. (2) F represents frequency of purchases by customers over a period of time. For the purchase of commodity, the higher consumption frequency is, the higher customer satisfaction and loyalty is. (3) M represents amount of consumption in a period of time, indicating that the purchasing power of customer is an important factor that affects customer management method. Regarding index weight of RFM variables, Hughes (1994) [29], Zong (2019) believed that the weights of RFM in measuring a problem are consistent [30], so they didn't give different weights. Through empirical analysis of credit cards, Stone (1995) believed that the weights of various indicators are not same [31], and that indicators should be given different weights, namely $F > R > M$. Through the investigation of the actual situation, this paper did not set different weights for indicators of R, F, and M. In the research, R indicator is measured as the number of days between the last purchase and the first purchase of customer in the current month; F indicator is the number of transactions of customer this month; and M indicator is consumption amount of customer in the current month. Usually, the raw data for RFM analysis should include three fields following as: namely customer ID, consumption amount and consumption date. Original data was imported into SPSS Modeler for RFM node analysis to obtain the RFM value, proximate cause score, frequency score and currency score. According to these values, customers are graded and managed. The RFM model divides customers into eight levels as follows: important value customers, important retention customers, important development customers, important retention customers, general value customers, general retention customers, general development customers, and general retention customers. Combined with precision marketing, customers are divided into four levels: important customers to maintain, important customers to develop, important customers to retain and general customers.

There is the basis for dividing the customer group: (1) important maintain customers also known as diamond customers: $RFM \geq 500$, and $R < 3$, $F \geq 3$, $M \geq 3$; (2) important development customers are also called growth customers: $400 \leq RFM \leq 500$, $R < 3$, $F \geq 3$, $M < 3$; (3) Important retention customers: $300 \leq RFM \leq 400$, $R \geq 3$, $F \geq 3$, $M \geq 3$; (4) general customers: $RFM \leq 300$, $R \geq 3$, $F < 3$, $M < 3$.

3.3 Analysis of Apriori algorithm integrating customer groups

This paper conducts an analysis of commodity association relationship based on the concept of customer group. The purpose is to better explore correlation all commodities, and speculate characteristics of market demander. Meanwhile, by mining associations, we can formulate more

suitable for the development of market business strategy, and put forward further development direction for the improvement of logistics performance in supermarket industry.

In the experiment, Apriori algorithm in SPSS modeler is used for node processing, and analysis flow results are as shown in Figure 2. Association rule 1 is preliminary association analysis, and association rule 2 is association rule analysis result integrated into customer group. It can be seen that the results of association rule 1 can be combined with the analysis results of RFM model by merging nodes. Association rule 2 is obtained by merging association rule 1 with the analysis result of the RFM model. The process is as follows: first add the type node, then set each field, filter out the useless fields, and finally add the Apriori node. Through Apriori node, the association rules of integrated customer group are obtained. The exported data shows R-score, F-score and M-score. On this basis, association results can be divided into various customer groups for data analysis, to obtain the associated commodities of various customer groups.

Magnet point theory refers to the place where the customer's attention can be most attracted in the store [32]. Appropriate products are configured to promote sales and can guide customers to visit the entire store to increase the proportion of customers' impulsive purchases [33]. In the digitally associated model, use magnet point theory to match customer importance and commodity display [34]. As follows: (1) important maintain customer's association commodity is placed at the first magnet point; (2) important development customer's association commodity is placed at the section magnet point; (3) important retention customer's association commodity is placed at the third magnet point; (4) general customer's association commodity is placed at the fourth magnet point. According to the results of final association rules, we can guide display layout of commodities in convenience store. The final effect can be obtained through practice [35].

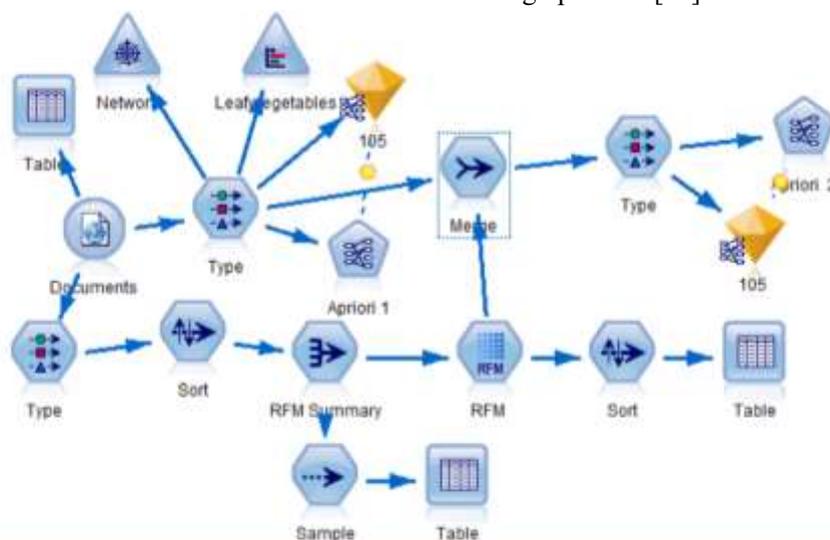


Figure 2 Association rule analysis flow fusing RFM

4. Case study

4.1 Data collection and preprocessing

Different from supermarkets and boutique stores, convenience stores are usually located in residential areas, schools and other places with large customer flow. They are small stores with the first purpose of satisfying demand for convenience, and have characteristics of relatively stable consumer customer group. This paper will take a chain convenience store as an example. Chain convenience stores have the following: business area is about 200 square meters, business time is

12-18 hours, convenience store mostly sells fresh food. Similarly, convenience stores have characteristics of timely consumption, small capacity and emergency. The monthly turnover is stable, and the operating condition is good. This paper selects one of the stores to analyze the transaction data of October, 2019 as an example. The store's monthly turnover reached RMB 300,000 in October, 2019. Average daily sales volume is about RMB 10,000. There are 2,431 types of goods in operation, which are divided into 531 sub-categories. At last, 85 sub-categories with sales in October were selected for the association study.

The sales data of retail enterprises is an important basis to reflect correlation between consumers' shopping behavior and commodities in the current period. Sales data is also called shopping basket data, which is usually customer data and transaction data of retail enterprises. In this paper, shopping basket data refers to transaction data and represents sales receipts of customers. This association rule analysis takes October sales data of the community convenience store as an example, divides customers into groups, and analyzes commodity purchased at the same time in one transaction. Because customers need to be numbered to group customers. Customers with integral numbers are selected for analysis, and transaction data without integral numbers are excluded. Part of the transaction data is shown in Table 1.

Table 1 Convenience Store Transaction Data

Sales Date	Sales number	Cashier number	Commodity code	Commodity name	Subclass code	Subclass name	Commodity price	Sales Amount
10-04-2019	579xx	6001	87xx	Fresh eggs	11013x	Bulk eggs	13.96	11.67
10-04-2019	579xx	6001	4xx	Cabbage	11030x	Leafy vegetables	4.38	1.69
10-18-2019	665xx	6001	2200x	Squeezed peanut oil	12570x	peanut oil	169.9	169.9
10-08-2019	604xx	6001	4xx	Cabbage	11030x	Leafy vegetables	3.95	1.36
10-08-2019	6044x	6001	6xx	Lettuce Tip	12520x	Leafy vegetables	3.96	2.55
10-05-2019	589xx	6001	1563x	Jiatianxia dumplings	12520x	Meat dumplings	7.5	7.5
10-05-2019	589xx	6001	1563x	Lettuce	11030x	Root vegetables	4.38	3.5

However, the transaction data in this form cannot meet data requirements of association analysis. The data form of association analysis is as follows: each row represents a customer, and the following field represents the name of commodities. In data table, it can be intuitively seen whether the customer has purchased commodity. Therefore, the data has been preliminarily improved to the T/F (T for purchase of the item, F for non-purchase of the item) form common in basket analysis. Because of concept of customer group is added to the association analysis, and main analysis method of customer group was RFM model analysis. The data were further processed to obtain the R, F and M values of each customer (R represents the interval days between the last purchase and the first purchase of a customer in the month; F represents the total frequency of the customer's purchase in the month; M represents the total amount of money spent by the customer in that month). The results are shown in Table 2.

Table 2 TF Data

Reward card number	R	F	M	Sales Date	Sales number	Bulk eggs	Leafy vegetables	peanut oil	Raisins	Cooking meat dumplings
1300231xxxx		1	13.36	10-04-2019	5799x	T	T	F	F	F
1300233xxxx		1	169.9	10-18-2019	6656x	F	F	T	F	F

1300234xxxx	1	3.91	10-08-2019	6044x	F	T	F	F	F
1300236xxxx	3	3	26	10-05-2019	5896x	F	F	F	F
1300236xxxx	3	3	26	10-08-2019	6063x	F	F	F	F
1300238xxxx	1	6.65	10-14-2019	6436x	F	T	F	F	F
1300238xxxx	1	29.56	10-03-2019	5743x	F	F	F	T	F
1300831xxxx	1	2.56	10-14-2019	6447x	F	T	F	F	F
1301235xxxx	6	2	9.53	10-10-2019	6158x	F	F	F	F
1301235xxxx				10-16-2019	6569x	F	T	F	F
1301831xxxx	13	2	104.4	10-01-2019	5666x	F	F	F	F
1301831xxxx				10-14-2019	6449x	F	T	F	F
1301832xxxx	15	2	55.51	10-01-2019	5652x	T	T	F	F
1301832xxxx				10-16-2019	6564x	F	F	F	F

4.2 Data analysis

The first step is preliminary analysis of association rules. Pre-processed data contains 85 items from the 2,877 transactions of 1,178 users, and the data is imported into MODELER for operation according to model construction steps. Review the data first, aiming to compare the audit result with source data table, after success of the audit, network diagram analysis, 85 kinds of commodities import analysis field, running Figure 3. It can see the relationship between the various commodities. Through the strong link table available formula 2 molecular data, it generates a strong link table at the same time, preparing for the confidence of computation.

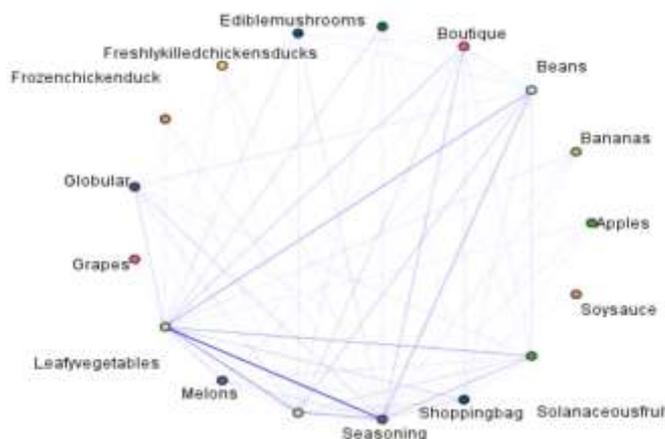


Figure 3 Association analysis network diagram

According to node strength of the network graph, distribution analysis for the hot-selling sub-categories is performed, and support of the hot-selling sub-categories can be obtained by applying formula 1, and confidence level can be calculated by combining the link strength obtained in previous step. By analogy, support and confidence of each type of commodity can be obtained, and the analysis of calculation results can provide support for determining the minimum support and the minimum confidence.

Before finally association rules analysis, scholars usually set a 5% minimum support, minimum

confidence level of 60%, based on the above analysis result set a 3% minimum support, minimum confidence level of 45%, the largest number prediction is 3, the largest number is referred to in preceding paragraph 5, run to draw correlation table, total of 17 group strong association rules. The first seven groups of association rules are shown in Table 3. It can be seen that association rules of the first three groups are all about seasoning commodities, and seasoning commodities are post-transaction items. It is known that commodity associations centered on seasoning commodities, includes correlation between flavoring and leafy vegetables, fine food and globular. Starting from the fourth set of association relationships, taking leafy vegetables as the post item of transaction, the result is commodity association centered on leafy vegetables. That is, leafy vegetables, melons, root vegetables, boutique, solanum fruits and beans can be based on these association relationships for the display of commodities. In the last, all kinds of goods will be re-placed on the shelves.

Table 3 Association Table

	After the transaction	Front the transaction	Support	Confidence
1	Seasoning	Shopping Bag Leafy vegetables	3.549	56.863
2	Seasoning	Boutique Leafy vegetables	3.688	56.604
3	Seasoning	Globular Leafy vegetables	3.619	53.846
4	Leafy vegetables	Melons Seasoning	3.062	53.409
5	Leafy vegetables	Root Vegetables Seasoning	6.402	52.717
6	Leafy vegetables	Solanaceous fruit Seasoning	4.593	51.515
7	Leafy vegetables	Beans Seasoning	5.393	49.677

The second step is RFM analysis. According to steps of model construction, three indicators should be summarized by RFM first, among which the identification value is score card number, the date is the sales date, and the value is sales amount. Summary results are analyzed by RFM, and new data are generated through analysis. After export, four columns are added to original table, as shown in Table 4, which are proximate R- score, F- score, M- score, and RFM score. Table 4 shows the ranking of some customers by RFM value.

Table 4 RFM Customer Analysis

	Reward card number	R	F	M	R- Score	F- Score	M- Score	RFM- Score
1	15823xxxxxx	123	235	20263.400	5	5	5	555
2	13075xxxxxx	123	7	303.700	5	4	5	545
3	18702xxxxxx	123	6	165.040	5	4	5	545
4	8801173xxxxxx	124	6	157.320	5	4	5	545
5	6900037xxxxxx	124	4	116.100	5	4	5	545
6	15922xxxxxx	124	5	97.390	5	4	5	545
7	13657xxxxxx	123	8	565.220	5	4	5	545
8	8801178xxxxxx	123	14	383.080	5	4	5	545

After the analysis, number of important development customers and important maintaining customers is more than 12%. Important management of these two types customers is required in order to bring more profits to the store. It is important to maintain customers (diamond customers), which is an important force for enterprises to obtain profits and facilitate their future development. Enterprises should try their best to maintain these customers and avoid transferring to competitors. At the same time, relationship between them and enterprises is the most stable and they do not need to invest too much energy. Important development customers (growth customers), these customers have high loyalty to enterprise, but due to various reasons, the current consumption is not high, so we need to understand potential needs of such customers, develop personalized solutions for them, and promote their transformation to diamond customers.

Finally, the preliminary association results are combined with customer group for Apriori algorithm analysis. Carry out the analysis flow operation in model construction, and finally set the minimum support degree of the model as 3%, the minimum confidence degree as 45%, the

maximum prediction number as 3, and the maximum number of preceding items as 5. The result is 40 sets of association transactions.

The resulting association rules are exported, and association rule diagram is obtained in Ucinet, as Figure 4. Based on the analysis of R-score, F-score and M-score, it can be seen that important maintain customers buy leafy vegetables, root vegetables, seasonings, and solanaceous fruits. Therefore, these customers pay attention to vegetable commodity. According to the RFM model, information should be kept unblocked for such customers, and business policies should be adjusted timely to adapt to customer needs. Combining the magnet point theory, place the associated commodity at the first magnet point position, that is, the store's main channel. The results show that important development customers mainly buy globular, leafy vegetables, solanaceous fruit and seasoning. According to theory of RFM model, it is necessary to have an in-depth understanding of such customers, formulate sales strategies in line with the individual, and enhance the potential value of customers. Combining with the magnet point theory, place the related products customer at the second magnet point, at the top of the aisle and the innermost part of the store. Finally, we analyzed the important retention customers and general customers, found that association results of important retention customers and general customers were similar. They were related to melons, solanum fruits, leafy vegetables and seasoning. The common characteristics of these two types customers are low loyalty and satisfaction [36]. Therefore, correct strategies should be adopted for these two types customers to enhance the competitiveness of enterprises and improve customer loyalty and satisfaction at the same time. According to the magnet point theory, the related products of these customers are placed in the remaining magnet points.

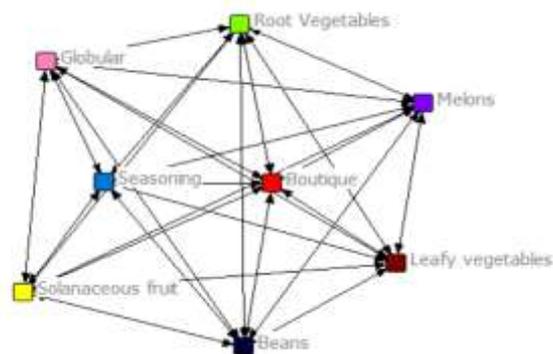


Figure 4 Association Rule Graph

In the convenience store, digitally associated display analysis model is applied to change commodity display, and commodities are displayed according to association rules. Adjusted layout is shown in Figure 5. Meanwhile, different management strategies are adopted for different customer groups. After adjustment, the store's sales volume has been greatly improved. Taking the monthly sales volume of one month as an example, the monthly sales volume has reached RMB 530,000 and the average daily sales volume is RMB 17,000. It has been proved that the model is effective.

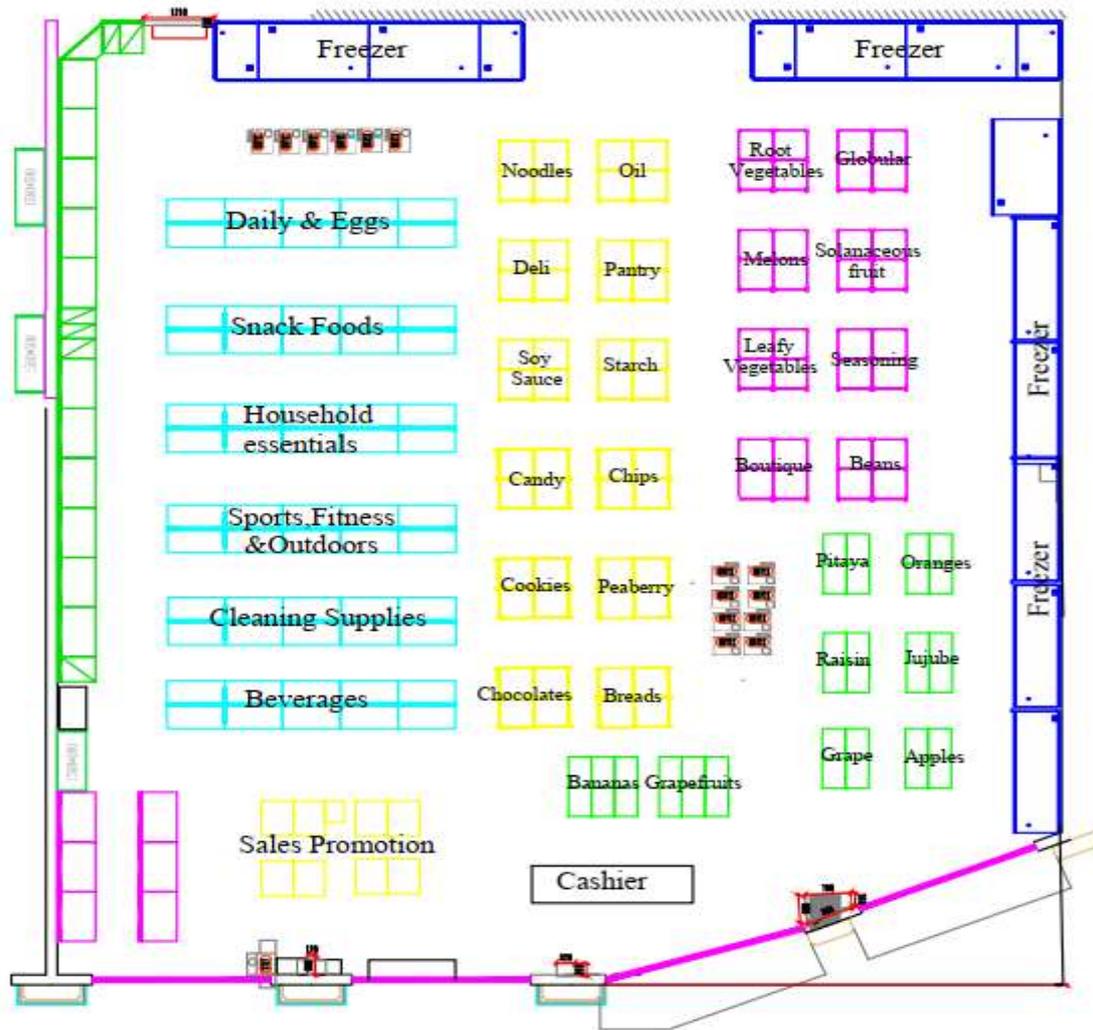


Figure 5 Commodity display

5. Conclusions

Digitally associated display of commodity is a key means to optimize in-store logistics and enhance the competitiveness of convenience stores. In this paper, there are the commodity association display models that have been constructed based on customer groups. The model combines the RFM model for customer base analysis with the Apriori algorithm for association rule analysis. According to the application of RFM-Apriori model, we can find the association rules of commodities and guide display of convenience stores. This can verify that the RFM-Apriori is scientific, and the RFM-Apriori will be widely applied in other convenience stores. The research results show that the following: (1) the digitally associative display model enriches commodity display methods and optimizes the way of commodity display. In the past, commodity display was mainly based on simple analysis of commodity relationship, lacking of analysis of customer group. This paper proposes the RFM-Apriori model based on the concept of customer base, which complements the existing commodity display methods. (2) the digitally associated display model results in a sharp increase in the enterprise's turnover. By taking the historical customer receipt data of a convenience store as the sample, the product display mode was improved according to this model. The monthly sales increased from RMB 300,000 to RMB 500,000. The daily sales increased from RMB 10,000

to RMB 17,000. The percentage increase in daily operating profit was 70%. (3) the digitally associated display model can improve customer's satisfaction and loyalty, and provide sufficient preparation for the long-term development of enterprises. At the same time, it will help the stores to formulate scientific and reasonable business strategies to meet the needs of customers.

However, the current research data has the shortcoming of short cycle, so more data can be selected in future studies while ensuring the credibility of the data. Future studies can conduct in-depth studies on other aspects that affect logistics performance, so as to gradually reduce the low benefits caused by logistics performance.

CRedit authorship contribution statement

Shuwei Jing: Conceptualization, Methodology, Investigation. Mingxia Li: Validation, Formal analysis, Writing. Qian Zhang: Supervision, Project administration Fudong Yang: Supervision, Funding acquisition, Data curation.

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Declaration of Competing Interest

The author declares that there is no conflict of interest regarding the publication of this manuscript. We also confirm that the mentioned received grants in the "Acknowledgments" section did not lead to any conflicts of interest regarding the publication of this manuscript.

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Figures

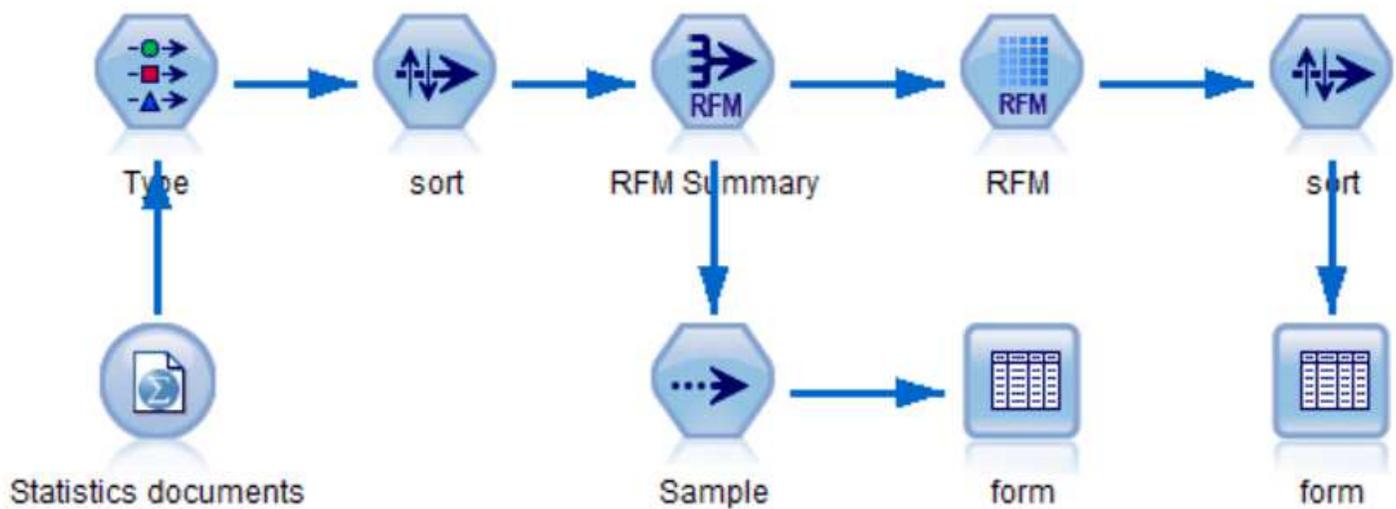


Figure 1

RFM analysis flow

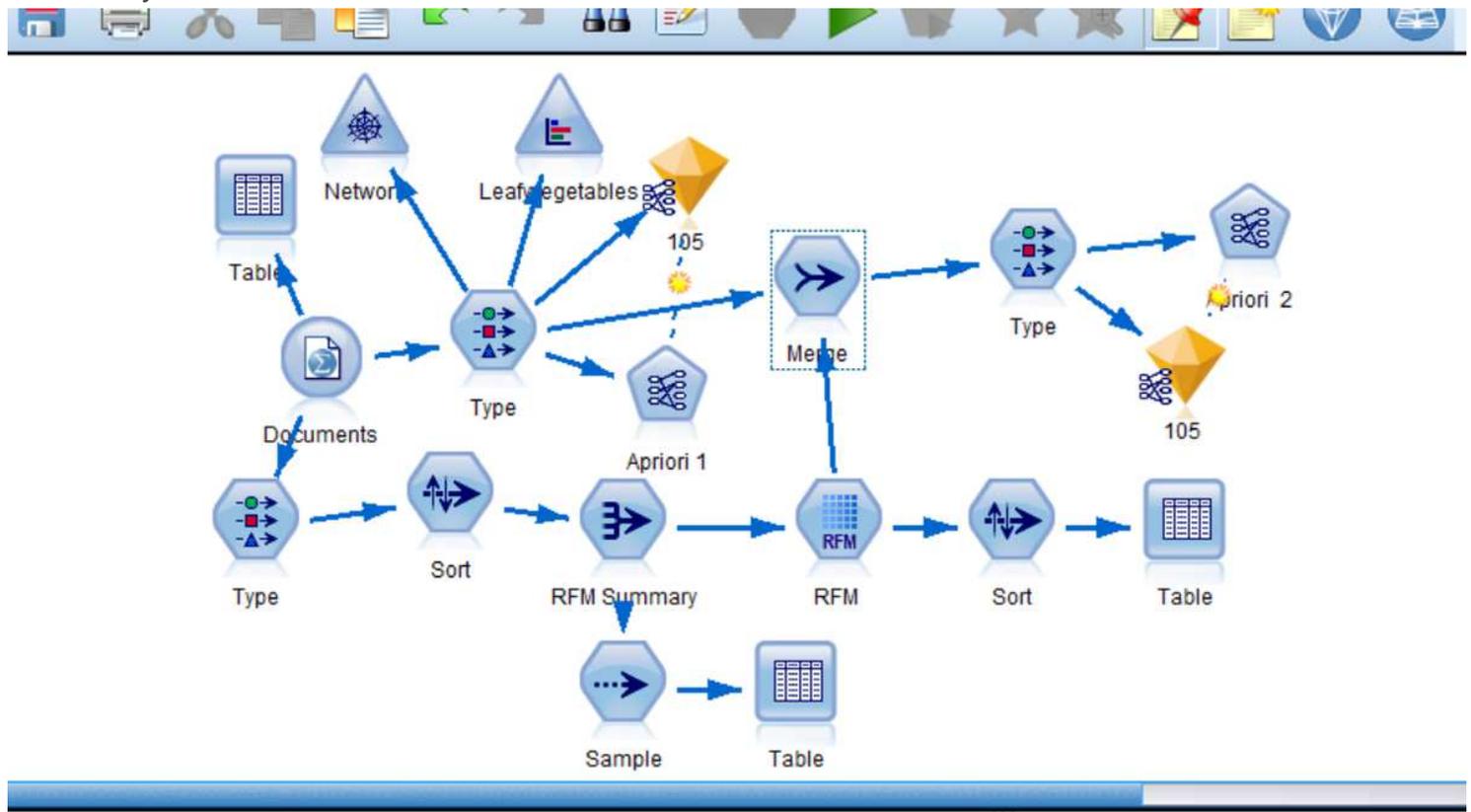


Figure 2

Association rule analysis flow fusing RFM

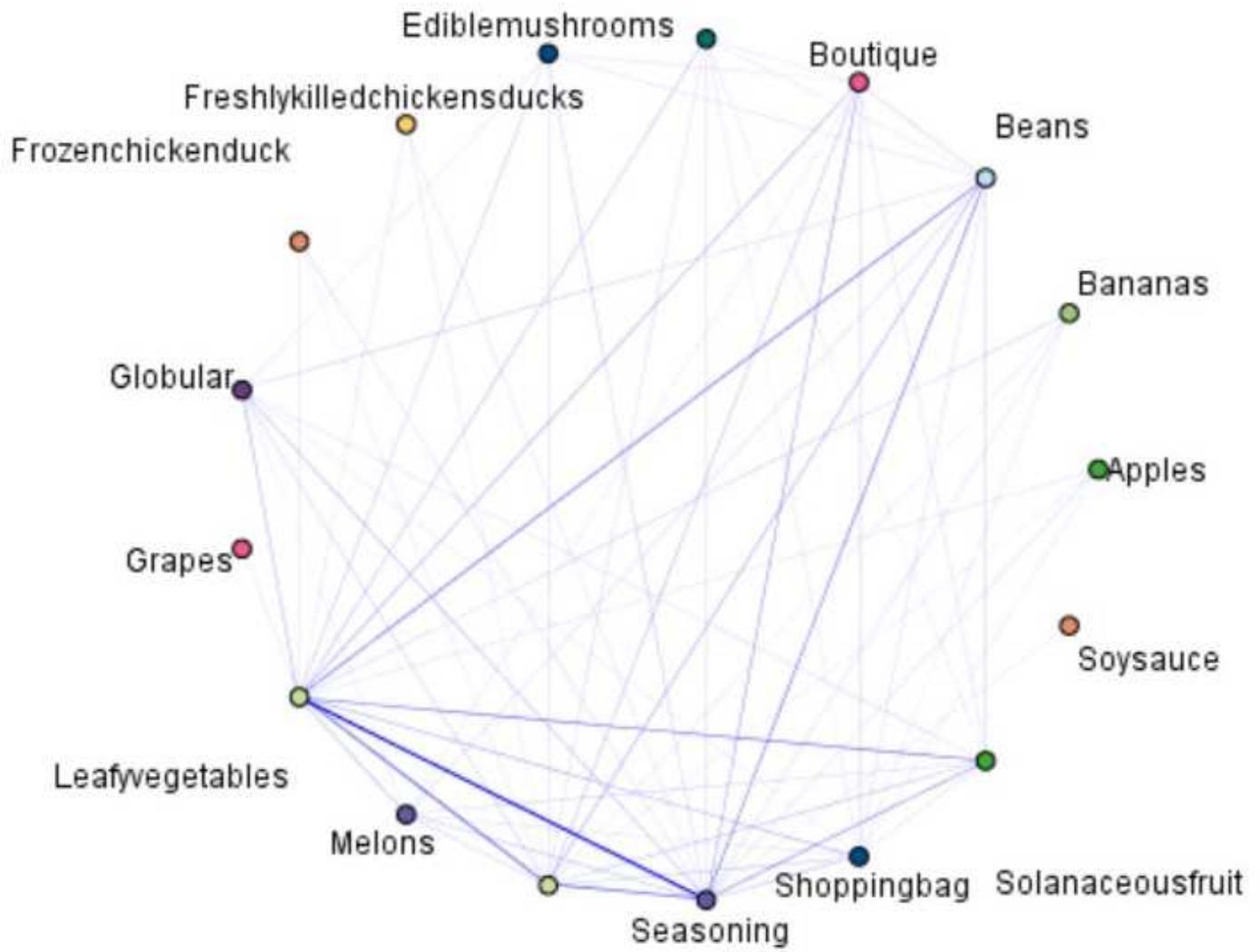


Figure 3

Association analysis network diagram

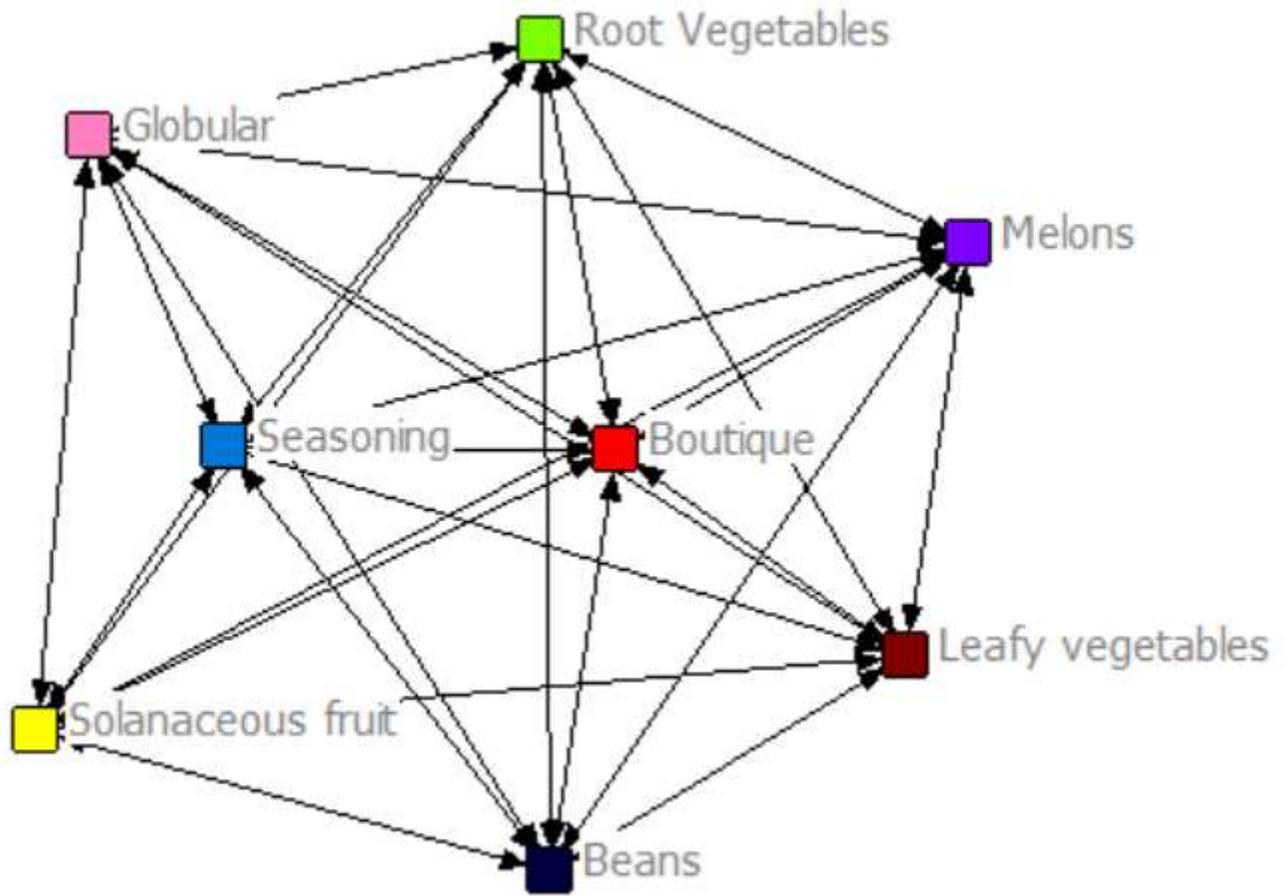


Figure 4

Association Rule Graph

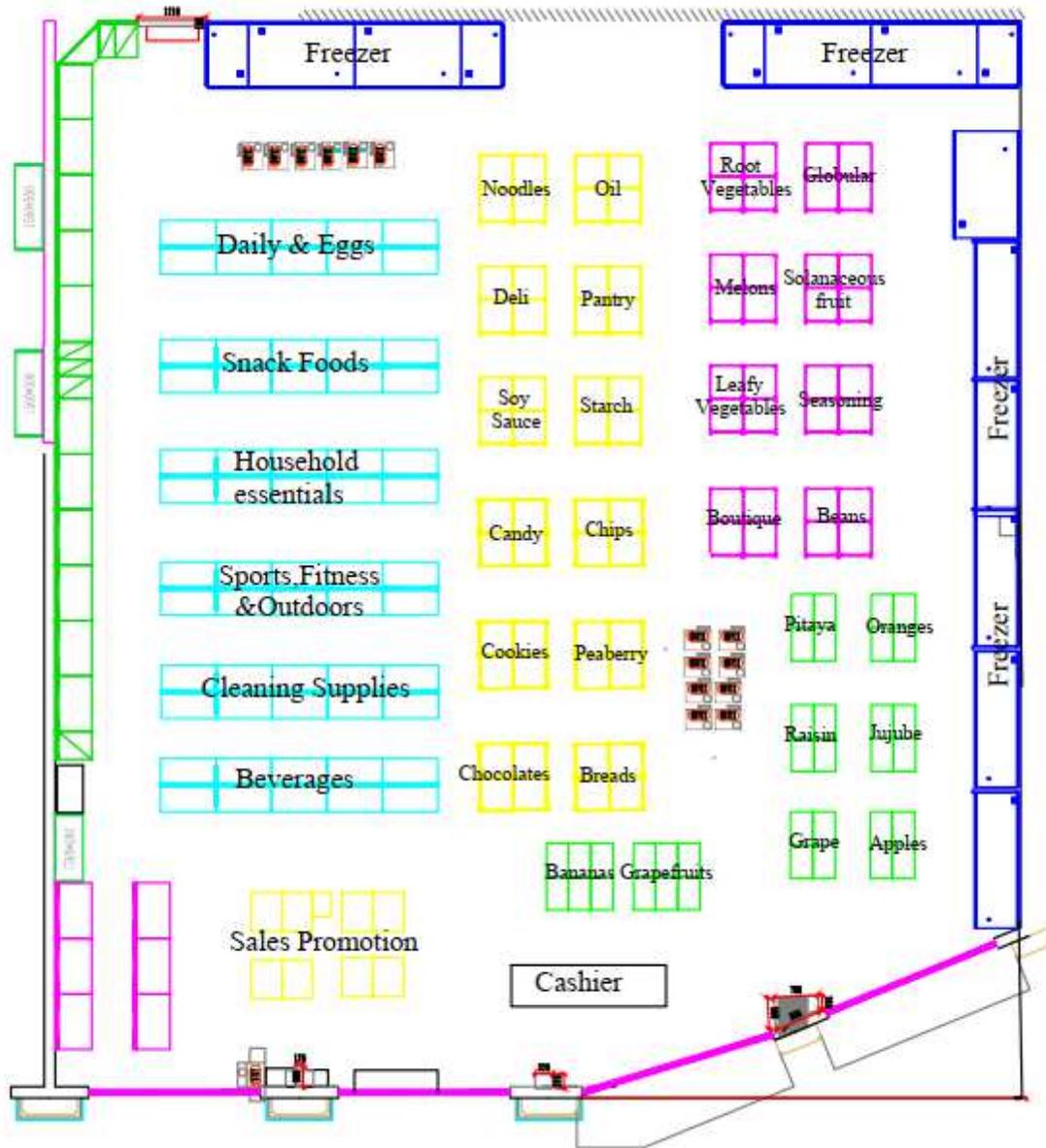


Figure 5

Commodity display