Decision Support Applications by Coordinate Purchase Association Graph in Retailing

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***Abstract*—For the decision support in retailing, Coordinate Purchase Association (CPA) graph is proposed as a coordinatized visualization of the purchase association rules for the retail transaction data. From the viewpoint of retailing, data association is focused on the purchase associations of products, whose visualization will be very informative through graph-based techniques. This paper analyzes nine Graph Design (GD) principles of three categories, GD-Layout principles, GD-Element principles, and GD-Elaboration principles, for the construction of a CPA graph, which places all the product sets and their purchase associations on a coordinate plane. Moreover, four Decision Support (DS) principles of CPA graphs are proposed to figure out several important decision support points in retailing. To prove the practical, several CPA graphs are constructed for a real furniture commerce. The proposed DS principles are concretely utilized to compare the purchase associations between two customer groups and to evaluate new product development.**

***Index Terms*—Coordinate graph, data association, data visualization, retail transaction**

I. Introduction

When big data is applied for retailers, "retail analytics" is possible to integrate information to get solutions and generate growth (The Nielsen Company, 2018). As the new science is introduced to retailing, the sales data can be mined to identify missing opportunities, improve store-level execution, create flexible supply chains, and so on. Formally, the Journal of Retailing suggests five key topics: (1) technology and tools to facilitate decision making, (2) visual displays and merchandise offers decisions, (3) consumption and engagement, (4) big data collection and usage, and (5) analytics and profitability (Grewal *et al.*, 2017). Following these directions, this paper tries to provide a visualized data analysis tools for decision support in retailing.

In definition, the revenue in retailing means the income of this business from normal commercial activities, usually through the sales of products or services. Commercially, such revenue can be formulated from two indicators: *customer volume* and Average Transaction Value (ATV), i.e., revenue = (customer volume) × ATV. When a shop wants to get a revenue of US$100,000 each month and this shop has about "customer volume" 1000 persons/month, this means each customer must contribute US$100 on average (ATV=100), that is, revenue = US$100,000 = (customer volume 1000) × (ATV 100).

The ways to increase the revenue of a business can be (1) to increase customer volume or (2) to increase ATV. The increase of customer volume can be done by many commercial operations, like advertisement, visual merchandising, salesman promotion, which is not the focal point of this paper. On the other hand, ATV means the average amount of a customer in purchasing products/services. The increase of ATV will be greatly affected by our research spotlight—purchase association, which is formally defined as the associated purchase rate, i.e., the rate of customers who buy more than two products/services. The increase of associated purchase rate is an important emphasis in practical retailing, which is related to selling techniques, the closing of transaction and the visual display of products. From the viewpoint of data analytics, the association rule can provide a scientific tool for such increase, especially through its visualization. Thus, for the applications of retailing, it is possible to develop some elaborate visualization of association rules for the use of commercial operations.

For the knowledge search process of data mining, visualization techniques can facilitate the understanding of extracted knowledge by identifying structures, characteristics, tendencies, anomalies and relationships among data (Ajibade and Adediran, 2016). Especially for managerial objective, data visualization can help decision making in a rapid and efficient way (Umesh and Kagan, 2015). More precisely, data visualization is defined to present data graphically or pictorially, for the clear and efficient information communication with users (Brigham, 2016). Its main goal is not only focused on sophisticated, beautiful or gorgeous looks, but on the effective convey of key ideas or insights within rather sparse or complex data sets in more intuitive ways.

As a standard data mining method, association rule introduces rule-based machine learning to discover interesting relations among variables in a large database (Piatetsky-Shapiro, 1991). For large-scale transaction databases in retailing, a set of strong association rules with form "if A then B" can be derived under some interestingness measures, such as support and confidence (Agrawal and Imielinski *et al.*, 1993). A similar technique, called Market Basket Analysis (MBA) or called affinity analysis, focuses on the co-occurrence relationships among activities recorded for some specific individuals or groups. Research reveals these two kinds of approaches, can create the same rules (Nengsih, 2015). Here, our purchase association problem begins through the data association of retail transaction database.

Manuscript received December 27, 202; revised February 20, 2023; accepted April 9, 2023.

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doi: 10.18178/joebm.2023.11.3.747

II. Retail Transaction Database and Its Purchase Association

A basic retail transaction database can be represented as a transaction database **D** of m transactions (Agrawal and Imielinski *et al.*, 1993) **D** = {d_1, d_2, ..., d_i, ..., d_m}, the items d_i's in which are collected as an item set (called product set in this paper) **P** of n items (products here) **P** = {p_1, p_2, ..., p_j, ..., p_n}. Each transaction $d_i = p_i$ = {p_{i1}, p_{i2}, …} ⊆ **P** contains a subset of products of product set **P**. Such transaction database **D** is generally recorded by Point-of-Sale (POS) systems in supermarkets, in which items may correspond to retailing products (Agrawal and Imielinski *et al.*, 1993). A demonstrative example database of 9835 transactions and 169 products can be obtained as: **D** = {d_1 = {p_1=citrus fruit, p_2=semi-finished bread, p_3=margarine, p_4=ready soups}, d_2 = {p_5=tropical fruit, p_6=yogurt, coffee}, ..., d_{9835} = {chicken, p_5=tropical fruit, other vegetables, vinegar, p_{169} = shopping bags}}, which is 1 month (30 days) real POS transaction data from a local grocery outlet (Hahsler and Hornik *et al.*, 2006).

To discover the association regularities between items/products in transaction database **D**, Agrawal and Imielinski *et al.* (1993) proposed Apriori algorithm. These associations are represented in an implication form (rule): **A** ⇒ **B**, where **A**, **B** ⊆ **P** are both subsets of the product set **P** and **A** ∩ **B** = ∅ (empty set). In such association rule, the product-subsets **A** and **B** are called antecedent (Left-Hand-Side or LHS) and consequent (Right-Hand-Side or RHS), respectively. From the viewpoint of data mining, these extracted rules (knowledge) may be duplicated, intuitive or meaningless; hence, need to be filtered by some criteria of measures, called interest or interestingness (Klemettinen and Mannila *et al.*, 1994). The measures of rule interestingness measures are divided into two categories: objective and subjective. The former (objective interests) are based on the rule structure and statistical significance of the patterns in data processing, such as support and confidence. On the other hand, the latter (subjective interests) are based on the subjectivity of the user evaluation, such as novelty, actionability unexpectedness (Havel and Gupta *et al.*, 2022). For the objective interestingness, the support of a product subset **A** is defined as the proportion of transactions {d_i: d_i in **D**, d_i ⊆ **A** ⊆**P**} in the database **D**, i.e., supp(**A**) = n(d_i) / n(**D**), where n(•) denotes the number of elements in the set. Then the confidence of a rule **A** ⇒ **B** means the proportion of the transactions **B** which are also contained in **A**: conf(**A** ⇒ **B**) = supp(**A**∩**B**) / supp(**A**).

For the above demonstrative example, the settings of support= 0.01 and confidence= 0.5 can give association rules in Table I. In retailing, each association rules means the probability (confidence) for customers buying product A to buy product B, i.e., the probability of *purchase association*. With big purchase association, the application of marketing effort can easily increase the ATV of customers. Therefore, when applied to retailing, these data associations become a kind of purchase association.

After the computation of association rules by objective interestingness, more integrated picture of these extracted rules may be depicted by subjective measures, especially visualization techniques. Many researchers made much effort on the visualization of general data association, including scatter plots, Doubledecker plot, matrix visualizations graphs, Mosaic plots, parallel coordinate plots, and so on (Bayardo and Agrawal, 1999; Hahsler and Chelluboina, 2017). Moreover, graph-based techniques are commonly used with the products are represented as vertices to try to make these rules more interpretative (Han and An *et al.*, 2000; Yang, 2003). However, the researcher comments these visualization techniques are not suitable to display large rule sets (Hahsler and Chelluboina, 2017). To make purchase association meet practical commercial use, some more sophisticate designs are needed in retailing, as the following derived.

TABLE I: Purchase Association Rules of the Demonstrative Example through Apriori Algorithm

rules	LHS => RHS	support	confidence
$Rule_1$	{p_8=curd, p_6=yogurt} => {p_7=whole milk}	0.01006609	0.5823529
$Rule_2$	{p_{167}=other vegetables, p_9=butter} => {p_7=whole milk}	0.01148958	0.5736041
…	…	…	…
$Rule_{15}$	{p_{167}=other vegetables, p_6=yogurt} => {p_7=whole milk}	0.02226741	0.5128806

III. Purchase Association Visualization and Graph Design Principles

For one association result after processing, there are two parts: the association rule **A** ⇒ **B** and its interest measures. Both rule components of the LHS/RHS of the association rule are a combination of products (or product sets), and the inference rule connects them. For the example Rule1 of Table I: {p_8=curd, p_6=yogurt} ⇒ {p_7=whole milk}, the LHS contains two components (p_8 and p_6) which form an intersection operation, the consequent (p_7) in the RHS is definitely a single component. Besides, the most popular interest measures are support and confidence, in which the support is a proportion measure of product set **A** and confidence provides the strength of the connection of the rule to product set **B**.

For the above-mentioned visualization techniques of general data association, scatter plot and Doubledecker plot focus on the visualization of interest measures to show the proportions of rules or their product sets (Bayardo and Agrawal, 1999; Hofmann and Siebes *et al.*, 2000). On the other hand, graph-based techniques put the emphasis on the relationships among rule components (product sets), which are treated as the vertices of a graph, and the rules will be directed edges from LHS to RHS (Han and An *et al.*, 2000; Yang, 2003). Then a series of rules can form sequential orderings, from one product set to another product set sequentially. Such association rules form a partial-ordering which represents overall relationship among these product sets (vertices) (Han and An *et al.*, 2000).

For retailing, the purchase association rule **A** ⇒ **B** refers one product set **A** to another product set **B**, which is a standard action of product promotion in commerce. Thus, more elaborate visualization can be designed from the viewpoint of retailing. Such design follows the previous graph-based techniques of data association but with some more practical considerations. For an information visualization, there are three kinds of elements: (1) **spatial**

substrate: two-dimensional space of visualization; (2) **graphical elements**: points and lines and their properties; and (3) **graphical properties**: the attributes of points and lines, e.g., point sizes/colors, line lengths/orientation, and so on (Midway, 2020). These three aspects will be introduced as graph design principles (**GD**s) of the proposed Coordinate Purchase Association Graph (CPA graph). These **GD** principles are classified into three categories: GD-Layout principles, GD-Element principles, and GD-Elaboration principles.

Graph Design (GD) Principles

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(1) **GD-Layout principles**: The first category of GD principles come from the spatial substrate of information visualization, including:

- **(GD1)** A CPA graph is arranged on a layout of two-dimensional (x,y)-plane.
- **(GD2)** The x-coordinate of a CPA graph is often nominal (has better be ordinal) product categories.
- **(GD3)** The y-coordinate of a CPA graph comes from marketing factors, such as product-subcategories, prices, places and persons.

(2) **GD-Element principles**: Researches describe the graphical elements are points, lines, surfaces, and volumes (Midway, 2020). Here four properties are sophisticatedly designed as follows:

- **(GD4)** The points of a CPA graphs are shown as vertices and their labels, which denote the product sets of association rule (LHSs/RHSs in A⇒B).
- **(GD5)** The volumes of the corresponding vertices in a CPA graph symbolize the number/proportion (then the support) of product sets fitting the rules.
- **(GD6)** The lines in a CPA graph are exactly directed edges (from LHSs to RHSs) of association rules A ⇒ B, which are a visualization of product association (promotion).
- **(GD7)** Then, the labels which denote the strength of directed edges can be naturally used to show the confidences.

(3) **GD-Elaboration principles:** The graphical properties are the properties which can be applied to the graphical elements to make more notable or to show more valuable (Midway, 2020). Since CPA graphs are used for business strategies, the settings of graphical properties may be very helpful, as the following principles suggested.

- **(GD8)** From the retailing viewpoint, the colors, label fonts and shapes of points can be used to represent different kinds of products categories (in x-direction) or to represent different levels of prices, different places, or different groups of persons (in y-direction). Such settings can make decision makers keep intuitive ideas, then make decisions easier.
- **(GD9)** More generally, the colors, label fonts, edge types and widths of the edges, or even the width of the directed edges, can be used as the visual keys to attention; for example, different numbers of supports/confidences can be set different color levels to represent different attention levels.

IV. PURCHASE ASSOCIATION GRAPH

From the design principles discussed previously and purchase association problem in Section II, the formulation of CPA graph (purchase association graph) can be easily derived.

Algorithm of Coordinated Purchase Association (CPA) Graph

Given a transaction database D, the corresponding Coordinate Purchase Association (CPA) graph CPA can be obtained through the following steps:

(1) The derived (purchase) association rules A ⇒ B within this transaction database D can be found as Section II discussed.

(2) The vertex set V(CPA) includes all the one-product LHS/RHS set in rules A ⇒ B are collected, with coordinates (x(V), y(V)) assigned by (GD1-3).

(3) The points as well as the corresponding volumes of all vertices in V(CPA) are determined by (GD4-5).

(4) Subsequently, (GD6) gives all edges of (purchase) association rules A⇒B represented as the edges in E(CPA), with confidence labels as (GD7) indicated.

(5) Then, the coordinated purchase graph CPA (V,E) is accomplished with vertex set V and edge set E.

(6) As graph shown pictorially, the principles (GD8) and (GD9) and other GDs can be applied to make the whole picture more intuitively.

As the construction of the CPA graph of the previous demonstrative example, the above 169 products are too detailed and will be replaced by 7 categories and 55 subcategories for data association. And a setting of support = 0.04 and confidence = 0.5 can generate 15 association rules as IF {eggs} THEN {dairy product}. Then the corresponding CPA graph can illustrate more complete association picture, as Fig. 1 shown. In Fig. 1, the 13 product subcategories of 7 product categories are distributed (**GD5**) on a product plane of x-axis as product category (**GD2**) and y-axis as product subcategory (**GD3**), all the 15 inference rules (**GD6**) are represented directed edges between product set vertices, which depicts the possibility of promotion in marketing.

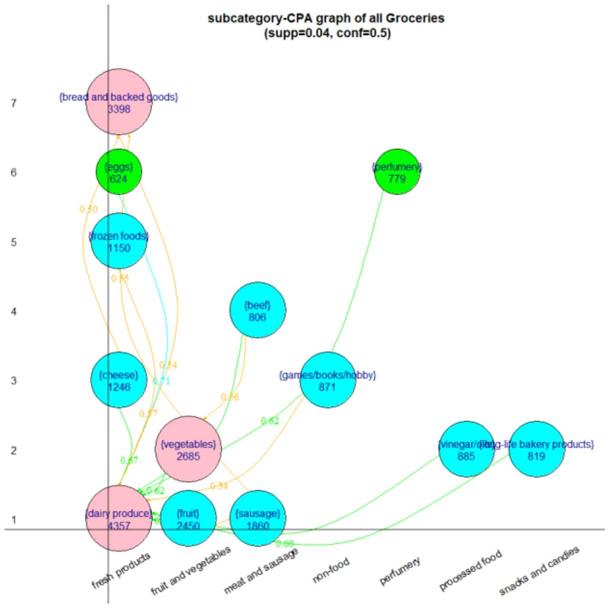


Fig. 1. Category-subcategory CPA graph of the demonstrative example over product plane.

Each vertex of the CPA graph in Fig. 1 has a unique (x,y)-coordinate pair, which should possess its commercial meaning in retailing, such as (fresh products, cheese).To make the graph easy to read, those vertices involving more transactions possess larger sizes and obvious colors. (**GD5**) Furthermore, the resultant CPA graph shown in Fig. 1 is a directed graph, with directed edges denoting association rules. (**GD6**) For examples, the association rule 5: {beef}⇒{vegetables} is denoted as an orange arrow with labels showing the confidence 0.56. (**GD7**) Note that the confidence values are not only labelled but painted in different colors to show their importance levels. As discussed, Fig. 1 only utilizes the colors and volumes of vertices to represent the transaction counts/supports of product subcategories; and only the colors of directed edges are used for rule confidences. There still leave many graphical properties can be utilized in later applications.

In the marketing of a brand, a promotion means one kind of marketing communication to inform or persuade target audiences of the merits of products/services, and so on. The purpose of a promotion is to increase sales, to make customers accept new products, to create brand equity, positioning, and then corporate image, and so on (2022 Global Marketing Trends). Such promotion can present products' information and their differentiation among customer groups. For those customers buying product set A in rule **A** ⇒ **B**, CPA graph provides a whole picture for a brand to promote another (purchase) associated product set **B**. From this whole picture, some important commercial targets can be focused by the following decision support principles (**DS**s).

Decision Support (DS) Principles

- **(DS1: extrema principle)** Those vertices (product sets) with larger volumes (supports) and those edges (purchase association rules) with larger weights (confidence) are more important.
- **(DS2: average principle)** The average volumes of vertices or the average values of edges denote the distribution of the products and the average interactions between product sets.
- **(DS3: marginal principle)** Those vertices (product sets) in the marginal area (e.g., with larger price intervals or with special categories) have great opportunity to become the focus.
- **(DS4: cross-edge principle)** Those edges upwards or cross-wards may have special commercial meanings, such as up-selling or cross-selling.

With these DS principles, these purchase associations in CPA graph provide more precise directions to commercial operations, as discussed in the following section.

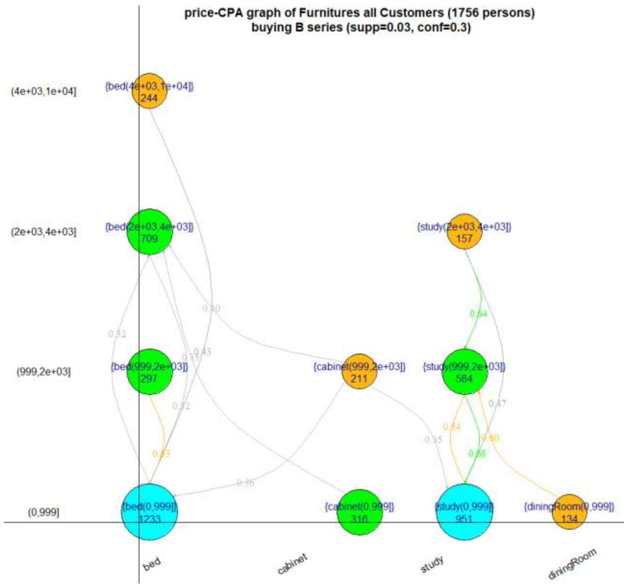
V. Practical Applications of CPA Graph

The basic marketing elements includes four P's: product, price, place, and promotion (Ngugi and Mcharo *et al.*, 2020). The first three ones can be used in the construction of CPA graph and the whole picture of CPA graph is used to illustrate the purchase promotion. Here, the price factor will be used to build up practical CPA graphs. This real application comes from a Great China furniture company of about thirty years and over hundreds of cities. The experiment data is from 28600 transactions of two product series B and K in one city during half-a-year.

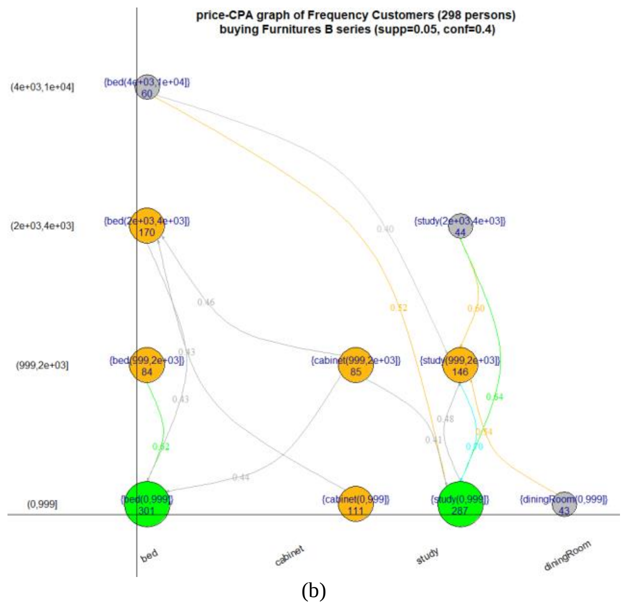
A. Comparison of the Purchase Associations between two Customer Groups

As shown in Fig. 2(a) and 2(b), the association rules are illustrated over a (product-category, price) plane. The x-coordinate are the furniture (product) categories {dressing, bed, pad, cabinet, study, dining Room, living Room, others}. On the other direction, the y-coordinate are the price intervals of furniture, {(0, 999), (999, 2e+03), (2e+03, 4e+03), (4e+03, 1e+04)}, which are all in scientific notations and valued in RMB. In the half-year, Series B own 1756 customers in totals (all customers) and 298 frequent customers (visit more than once), whose purchase associations are shown in Fig. 2(a) and 2(b).

Several observations can be made by the previous decision support principles: (**DS1**) The most frequent products are the low price (0-999) bed and study furniture; whereas, the greatest-confidence associations occur for the association from (study, (999, 2e+03)) furniture to (study, (0, 999)) furniture. (**DS2**) The most frequent distributions are bed furniture of RMB 0–4000, study furniture of RMB 0–2000 and cabinet furniture of RMB 0–999. (**DS3**) The highest price intervals appear in bed furniture and then study furniture, which brings more revenue than others. (**DS4**) For the up-selling case, (0, 999) bed furniture has the probability (confidence) 0.32 to up-sell (2e+03, 4e+03) bed furniture in Fig. 2(a), which can be used for more profitable sale, to recommend more expensive items or upgrade other add-ons. For the cross-selling case, (0, 999) dining Room furniture has the probability (confidence) 0.54 to cross-sell (999, 2e+03) study furniture in Fig. 2(b). Moreover, for down-selling case, (2e+03, 4e+03) study furniture has the confidence 0.64 to down-sell (0, 999) study furniture, which may get higher chances of acceptance. It is notable that CPA graphs should not be over-estimated for product recommendation, which needs more elaborate designs; however, CPA graphs still provides primary clues.



(a)



(b)

Fig. 2. (a) CPA graphs of all customers buying B series; (b) CPA graphs of frequent customers buying B series.

B. CPA Graph Applications to Product Development

Besides product recommendation, CPA graphs can also be used for product development. For any brand, it is important to evolve its product series for the growing and new-incoming customers. This experiment furniture company continuously keeps developing decades of series over several decades of years. Here, Series B is a long-selling furniture series in the last decade; whereas, Series K is a new-developed furniture series in these two years. The comparison of Fig. 2(b) and Fig. 3 for the frequent customers of Series B / Series K shows their differences.

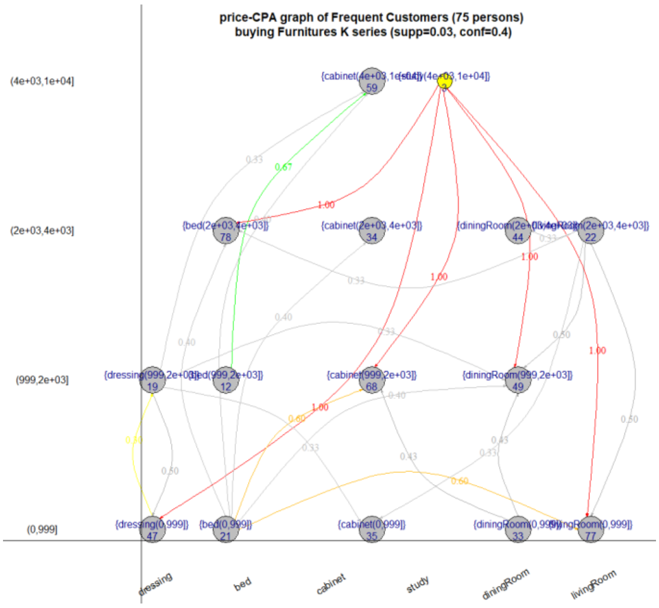


Fig. 3. The CPA graph of frequent customers buying brand K.

Once again, the decision support principles point out several notable foci in CPA graph: (**DS1**) The number of frequent customers of Series B is 298, about 17% of all its customers (1756); however, the number of frequent customers of Series K is 75, about 28.3% of all its customers (298, not shown in these figures). This implies that Series K keeps a higher customer retention rate. (**DS2**) There are many high associations (confidence > 0.9) among high-price furniture, which means that Series K can attract more customers to carry out more high-price associations (to purchase high-price products). (**DS3**) Series K possesses two high-price (over 6000RMB) product categories (cabinet and study); on the other hand, Series B keeps only one. Not restricted to these three observations, the comparison of CPA graphs can be carried out for different product series, and it is possible to design new product series, even their pricing.

VI. Conclusion

For the transaction data in retailing, this paper proposes a coordinatized visualization method for the purchase association rules, called Coordinate Purchase Association (CPA) graph to support the decision making. After a brief introduction of retailing, data association and its visualization in Section II, Section II reviews the formulation of general data association, the derived inference rules and the corresponding visualization methods. In order to visualize the retail purchase associations in a coordinate plane, Section III encircles three kinds of graph elements to propose nine graph design (**GD**) principles, which can be applied to build up the CPA graph. For such CPA graph, Section IV proposes four decision support (**DS**) principles, which can be utilized to explore several emphases for the support of commercial decisions.

To prove our idea, this approach is used in a real furniture commerce to construct several CPA graphs and the DS principles are applied for the comparison of purchase associations between two customer groups and for the evaluation of new product development. In the future, more advanced analysis tools and decision support principles can be developed by other data analytics, such as clustering and supervised learning, which can integrate more domain (retailing) knowledge to accomplish BDA+retailing or AI+retailing researches.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contributions

Shein-Yung Cheng and Meng-Yen Tom Lin analyzed the data; Yung-Tzu Joyce Lin and Chuan-Yi Chang conduct the research and wrote the paper. All authors had approved the final version of this paper.

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