Shelf Layout With Integrating Data Mining And Multi-Dimensional Scaling

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Abstract

Thanks to information, communication and technological improvements in these days, data mining method are used to obtain significant results from very large data sets. In terms of businesses, decision-making in product design, placement, layout and so on issues are of vital importance. Association rules taking part in data mining topic is used so much especially in marketing research in the market basket. The Multi-Dimensional scaling (MDS) method is also frequently used for the positioning of products in the marketing field. MDS is measured similarities between products, units and so on according to the method of Euclidean space. Relations between products or units are visualized in two or three dimensions using MDS method according to the purpose. The aim of this study is to determine the product shelf layout using association rules according to the relationship map of the products generated by MDS. Together with the association rules (conviction ratios) used in data mining field, proximity coefficients between products were calculated and used in MDS analyze. Product groups were created by using MDS and proximity coefficient combinations made up between products. Shelf layout ensuring similar products in line with side by side was determined with the help of association rules. The applicability of the proposed method for products and alternative shelf layout was presented visually. 750 shopping and customers who purchase products in the same shelf made up the data of this study. In this study, placement of the products designed to maximize the benefit level for customers in terms of time and convenience.

Keywords: Data Mining, Apriori Algorithm, Association Rules, Multidimensional Scaling, Market Basket Analysis, Shelf Layout.

Introduction

Data mining is used for extracting hidden predictive information from big databases and is used in many disciplines of engineering and science applications. Prediction and classification, association rule analysis, clustering, regression analysis, decision tree and the combination of these techniques are the most used data mining methods in the literature (Rathod and Garg, 2016: 368).

Marketing strategies, such as brand positioning, market segmentation, market basket analysis, new product development and pricing are developed based on market structure research (Chen et al., 2015: 59). The market basket analysis can be used for a department, shelf or product advertising.

The ultimate goal of market basket analysis with association rules is finding the products that customers often purchase together. The stores can use this information by putting these products in close proximity coefficient or conviction values of each other and making them more visible and accessible for customers or products selling fewer to sell more at the time of shopping. These assortments can affect and direct customer behavior and promote the sales for complement or substitution items. The other utilizing of this information is to decide about the layout of catalogs, shelves or departments and put the items with strong association together in sales catalogs shelves or departments (Olson and Delen, 2008: 56). In this study, integrated data mining and Multi-Dimensional Scaling analysis (MDS) is discussed for products shelf layout.

Data Mining Analysis and Apriori Algorithm

Thanks to technological advances of information and the need for extracting useful information to managers from the large dataset, data mining, its techniques and integrated methods with other techniques are appeared to achieve the goal (Al-Maolegi and Arkok, 2014: 21) which can be related to the business.

A dataset usually contains a large amount of data, commonly referred to as “big data”. Data mining techniques can be effectively applied to any discipline, including physics, biology, engineering, finance, environmental sciences, and so on (Sanctis et al., 2016: 24).

Data mining uses different approaches such as clustering, classification and association rules and builds different models depending upon the type of data and objectives. Data mining methods are usually classified as predictive and descriptive. Classification techniques can be defined as the predictive method and descriptive method covers association rules and clustering (Rathod and Garg, 2016: 368).

Association rule mining is one of the most used and useful research techniques of data mining. ARM is one of the most important pillars of data mining. Agrawal et al. (1993) were first introduced ARM. ARM aims to make sense of interesting correlations, frequent patterns, association or informal structures between the set of items, units, department or database or other data repositories. The ARM technique is used in market basket analysis to explain the meaning a set of products that customers frequently purchase together. Retailers or anyone related sales are using association mining technique to investigate customers buying habits. ARM comprises several algorithms such as Apriori, ECLAT and FP-Growth algorithms. Apriori Algorithm is one of the best ARM algorithm (Ingle and Suryavanshi, 2015: 37-38).

ARM is a substantial data mining approach that can uncover consumer purchasing behaviors from transaction databases. Agrawel defined ARM as results of all the rules from transaction data that satisfy the minimum confidence and minimum support constraints. The two indicator, minimum support and minimum confidence, are used to utilize frequent itemsets and association rules, respectively (Weng, 2016: 518).

Apriori Algorithm is easy to execute and very simple, is used to mine all frequent itemsets in the database (Al-Maolegi ve Arkok, 2014: 22). Apriori Algorithm was first introduced by Agrawal and Srikant (1994).

The Apriori Algorithm can be used to discover boolean association rules. The main idea of the Apriori Algorithm is to gradually produce frequent itemsets by increasing the number of items as long as those itemsets appear sufficiently often in the dataset (Sanctis et al., 2016: 25).

The Apriori Algorithm has been widely used to generate all the frequent itemsets contained in a transaction database. Frequent itemsets mining algorithms are classified into three categories according to the data types they can tackle: ordinal data, and quantitative data and nominal/Boolean data (Weng, 2016: 519).

The validity of the rules can be evaluated by item's or unit's support, confidence and lift values. Support is explained as the proportion of cases in which the association occurs divided by the total number of cases (i.e. number of shopping). Support is briefly a measure of how frequently the rule occurs throughout the analyzed period. The confidence is explained as the proportion of cases in which the association which includes at least two conditions about units or products occurs divided by the number of cases containing the premise (Ahlameyer-Stubbe and Coleman, 2014: 157).

Support and confidence formula can be shown as below (Ingle and Suryavanshi, 2015: 38).

$$A \Rightarrow B \left\langle \begin{array}{l} Support = \dfrac{freq(A,B)}{N} \\ Confidence = \dfrac{freq(A,B)}{freq(A)} \end{array} \right. \quad (1)$$

Minimum support and confidence were used to control association rule modeling. Minimum support value is a constraint requiring at least the expressed number of cases be present in the training set. A low minimum support will yield too many rules. The confidence value is the accuracy of a rule as measured by the correct classification of cases (Olson and Delen, 2008: 26).

A lift value which is smaller than 1 indicates the negative relationship between antecedent and consequent, a value that equals to 1 indicates independence, and a value greater than 1 indicates the positive relationship. A higher lift value indicates stronger associations (Weng et al., 2016: 48).

The interest of A, B is explained as P(A,B)/P(A)P(B) and units in both P(A) and P(B); essentially it is a measure of departure from independence. However, it only measures co-occurrence, not an implication, in that it is completely symmetric. To fill the gap, Brin et al. defined conviction as below (Brin et al., 1997: 260).

$$Conviction = \frac{P(A)P(\neg B)}{P(A,\neg B)} \quad (2)$$

Market-basket analysis considers to techniques studying the composition of a shopping basket of products purchased throughout a single shopping event. This technique has been extensively applied to grocery store operations (as well as other retailing operations, markets, to include restaurants or other similar companies). Market basket data in its rawest form would be the transactional list of purchases by customer, indicating only the items or products purchased together (with their prices). This data is interesting because of numerous features (Olson and Delen, 2008: 55): A very large number of cases (often millions of transactions per day), Intermittence (each market basket contains only a small portion of items carried), Heterogeneity (customers tends to purchase a specific subset of items).

Ay and Cil (2008) proposed an alternative layout by using Apriori Algorithm and MDS analysis with confidence values between departments within the market. Aksarayli and Altuntas (2009) made a new simulation model approach to compare with each other basic workbench shapes and products placement for factory layout. Chauhan and Chauhan (2014) analyzed air data set with using Weka program and Apriori Algorithm. Ingle and Suryavanshi (2015) introduced an improved Apriori Algorithm based on minimum support values that provide time and number of scans saving.

Sulianta et al. (2013) applied association rules using Apriori Algorithm for reduction of multidimensional and time series data in the food industry. Yang et al. (2009) established association rules with Apriori Algorithm for fault diagnosis of power transformers. Al-Maolegi and Arkok (2014) improved an Apriori Algorithm more efficient and less time consuming. Weng (2016) introduced a new model with improved Apriori Algorithm in terms of time-related to specific later-marketed consequent association rules.

Weng et al. (2016) presented a paper which investigated work zone casualty characteristics and contributory factors - by using data mining approach - association rules with different values of support and confidence. Rathod and Garg (2016) carried out association rule analysis to form association rules on electricity consumption in Sangli city to describe the result of the physical distance between natural geographic objects and various regions with using association rule building.

Multi-Dimensional Scaling Analysis

MDS is a long-established and commonly used statistical method for finding a spatial representation of a set of units, depends on the similarities between those units (Okada and Lee, 2016: 35).

Researchers define a MDS analysis through three key factors: selecting the goals that will be analyzed, deciding whether similarities, dissimilarities or preference is to be analyzed and finally choosing whether the analysis will be applied to the group or individual level (Esmalifalak et al., 2015: 8394).

The basic problem that MDS explores may be explained as follows. For a set of observed similarities between every possible bipartite of n items, find the least number of dimensions such that the inter-point distances of n items, indicated along the dimensions, closely correspond to the original similarities (Safizadeh and McKenna, 1996: 55).

For the goal of visualizing data by means of a two-dimensional map (or p-dimensional as the case may require) the MDS model provides to a very advantageous multivariate analysis procedure. MDS method either takes as input a matrix of dissimilarity or similarity data or may compute this proximity data from the input (Akkucuk, 2011: 24).

Richardson (1938) discovered the first metric procedure for MDS, Young and Householder (1938), suggested a method for constructing the configuration from the given (Euclidean) distances among the points, by a method closely related to factor analysis. Torgerson (1958) rediscovered this method and extended it. Coombs (1964), suggested the first procedure for nonmetric MDS (Kruskal & Wish, 1978: 22-23, Kruskal, 1964: 2).

Torgerson (1952, 1958) developed a method for MDS, now named CMDS (Metric or Classical ing). Assume that the dissimilarity measure, δ_{ij}, is the distance between objects *i* and *j* a *p*-dimensional Euclidean space, i.e.;

$$\delta_{ij} = \sqrt{\sum_{k=1}^{p} \left(x_{ik} - x_{jk}\right)^2} \qquad (3)$$

where x_{ik} is the *k*th element of x_i. The elements x_{ik} are unknown, and the purposes of MDS is to transform them from the dissimilarity data (Oh and Raftery, 2001: 1032).

MDS models differ in the representation function that is used to approximate distances $d_{ij}(X)$ to converted (dis)similarities $f(p_{ij})$. The sum of the squared error of representation over all bipartite of units yields a badness of fit measure which is explained raw Stress σ_r (standardized residual sum of squares) for a given dimension (Richter and Keuchel, 2012: 668):

$$\sigma_r = \sigma_r\left(X\right) = \sum_{(i,j)} \left[f(p)_{ij} - d_{ij}(X) \right]^2 \qquad (4)$$

Detailed mathematical derivations concerning the PROXSCAL algorithm can be found in Commandeur and Heiser (1993).

Marketing researchers who have the domain knowledge can infer some features from the two-dimensional plane in directional manners (horizontal, vertical, or tilted). Then they can interpret the composite features of certain markets and do the segmentation jobs or units based upon customers' preferences (Cha et al., 2009: 4885).

Safizadeh and McKenna (1996) applied MDS for cost limited and three-dimensional factory layout to minimize the interactions between departments. Oh and Raftery (2001) proposed a Bayesian framework model for object configuration with using Markov chain Monte Carlo algorithm. Okada and Lee (2016) introduced Bayesian approach for the K-INDSCAL extension of the standard MDS model which the data had been taken the form of three-way observed dissimilarities between pairs of I stimuli judged by H subjects.

A case study visualizing the market structure of mobile phones was conducted by using integrate topic modeling, TOPSIS, and multi-dimensional scaling approaches by Chen et al. (2015). Tsekouras (2016) proposed a novel approach for the development of highly accurate and interpretable fuzzy models with Gaussian fuzzy sets, under the framework of non-linear constrained optimization and MDS. Witten and Tibshirani (2011) proposed supervised MDS explored in a simulation article, as well as on a prostate cancer gene expression data set and on a handwritten digits data set for visualization, classification, and bipartite ranking.

Sagarra et al. (2016) explored the efficiency of Mexican universities with integrating Data Envelopment Analysis (DEA) and MDS to see how

"Educational Modernisation Programme" plan has affected efficiency in teaching and research at Mexico's universities and to visualize the results and make them accessible to policy makers. Ouyang et al. (2015) developed the integrated fuzzy analytical hierarchy process (AHP) with MDS approach to improving current decision-making methods for determining the optimal alternative.

Johnson et al. (2013) explored whether wine experts would group Shiraz wines from the same region together, following ortho and retronasal assessments of the wines with MDS, cluster and descriptive analyses. Cha et al. (2009) introduced an application of MDS for marketing-mix modification of products at the maturity stage of product life cycle. Cil (2012) proposed a methodological framework for the use of the knowledge discovery process and its visualization to improve store layout and has been used the buying association measure to create a category correlation matrix and has applied the MDS technique to display the set of products in the store space.

Esmalifalak et al. (2015) addressed to the feasibility and benefits of two visual data interpretation methods, based on MDS and cluster analysis, in GSM integration context. Machado et al. (2011) proposed a graphical method to visualize possible time-varying correlations between fifteen stock market values with applying MDS techniques.

Olatunji et al. (2015) introduced a study which employed Profile Analysis via MDS (PAMS), a procedure for extracting dimensions, in order to identify core eating disorder symptoms in a clinical sample. Pawliczek and Dzwinel (2013) developed novel SUBSET algorithm of a lower complexity, which is competitive with the best, currently used, MDS algorithms in terms of efficiency and accuracy. Alt (2015) assessed science students' perceptions of the learning environment as a function of individual experiences of the teachers' just (TJ) behavior with Structural Equation Modeling (SEM) and MDS.

Application

Studies data covers 16 biscuit products from a store in the same shelf and covers 750 customers who bought at least two products throughout the period of one month. The frequency distribution of 16 product sales is shown in Figure 1.

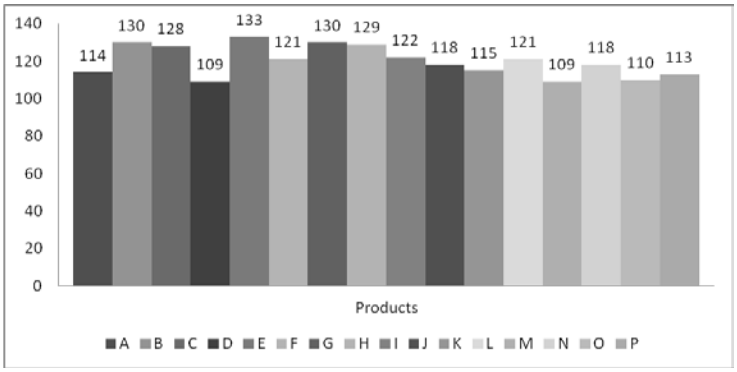

Figure 1. Sales amount of products.

Sales data are arranged in the Notepad++ program with using nominal scale (coding with 0 and 1). Weka program was used for Apriori Algorithm. Established model and results for association rules are shown in Figure 2.

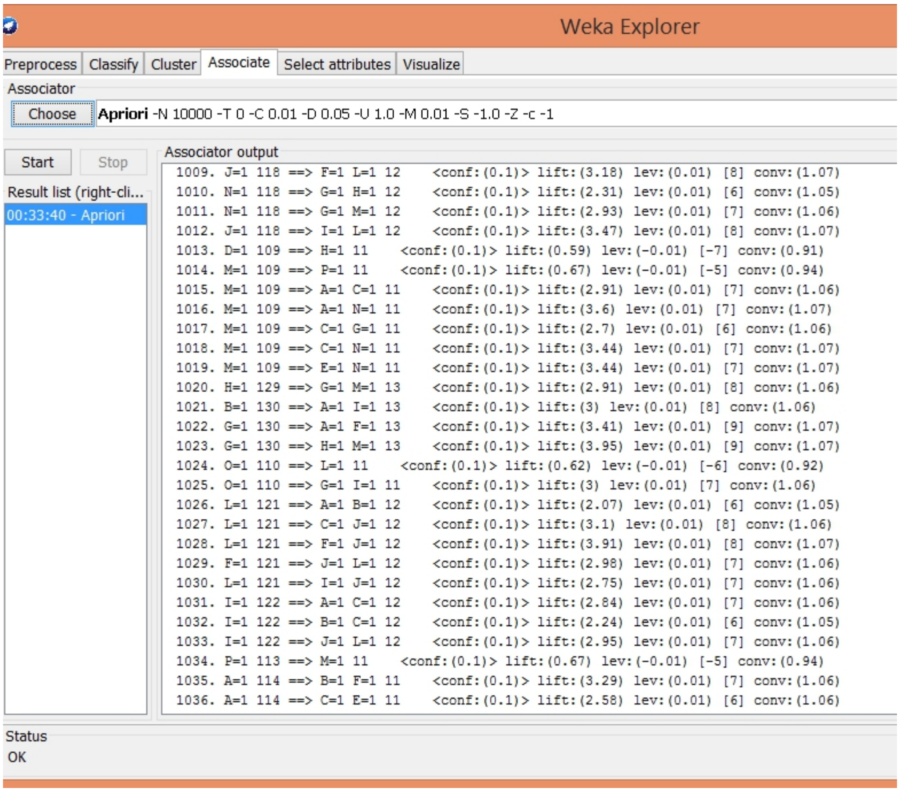

Figure 2. Apriori Algorithm results.

Association rules and conviction rates were obtained from Apriori Algorithm. Bipartite conviction rates for 16 products are shown in Table 1.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
A	-	1.19	1.06	0.98	0.98	1.03	1.12	1	1.06	0.99	1.04	1.02	1.06	1.02	1	1.01
B	1.16	-	1.1	0.91	0.94	1	1	1.02	1.01	1	0.99	1.03	0.99	1	0.99	0.97
C	1.05	1.1	-	1.05	1.06	1.02	1.05	0.96	1.01	1.03	0.99	1	1.01	1.01	0.96	0.97
D	0.98	0.89	1.06	-	1	0.96	0.98	0.91	0.98	0.99	0.97	0.95	0.96	0.94	0.96	0.97
E	0.98	0.94	1.04	1	-	1.01	1	0.98	0.97	0.95	1.01	0.95	1.01	1	0.95	0.96
F	1.03	1	1.02	0.97	1.02	-	1.09	0.99	0.98	0.99	0.99	1.04	0.99	1.01	0.96	0.94
G	1.1	1	1.05	0.98	1	1.08	-	1.1	1.03	1.02	0.99	1	1.06	1.03	1.06	0.99
H	1	1.02	0.96	0.93	0.98	0.99	1.1	-	1	0.95	0.97	1.01	0.99	1.07	0.97	0.94
I	1.06	1.01	1.01	0.98	0.97	0.98	1.03	1	-	1.07	0.97	1.01	0.98	1.02	0.98	0.99
J	0.99	1	1.03	0.99	0.94	0.99	1.03	0.95	1.07	-	1	1.05	0.99	1	1.01	0.94
K	1.02	0.99	0.98	0.97	1.01	0.98	0.99	0.96	0.97	1	-	1.04	0.96	0.96	1.04	1.01
L	1.02	1.03	1	0.96	0.95	1.04	1	1.01	1.01	1.05	1.03	-	0.99	0.99	0.93	1.06
M	1.06	0.99	1.02	0.96	1.01	0.99	1.07	0.99	0.98	0.99	0.96	0.99	-	1.09	0.99	0.94
N	1.02	1	1.01	0.94	1	1.01	1.04	1.07	1.02	1	0.96	0.99	1.08	-	0.97	0.97
O	1	0.99	0.95	0.96	0.93	0.95	1.07	0.97	0.98	1.01	1.05	0.92	0.99	0.97	-	0.91
P	1.01	0.96	0.97	0.98	0.95	0.94	0.99	0.94	0.99	0.93	1.01	1.06	0.94	0.97	0.91	-

Table 1. Conviction values for products.

The conviction values that the Apriori Algorithm results are used for MDS. These values were analyzed to determine the shelf layout of products with SPSS 21 program. Data are considered as proximity coefficient and one source matrix for MDS model.

MDS model parameters; the shape is the full matrix, proximity transformations are the interval, the dimension is 2 and proximities are similarities. Minimum normalized raw stress value is obtained by selecting Torgerson method as Initial Configuration. Iteration criteria values for MDS model are selected as Stress convergence=0.0001, Minimum stress=0.0001 and Maximum iterations=100. The product points in two dimensions that the result of MDS analyze is shown in Figure 3.

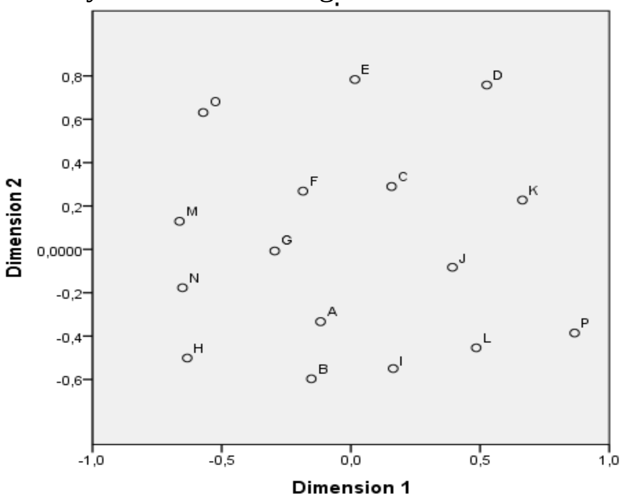

Figure 3. Product points in two dimensions.

The normalized raw stress value was found to be appropriate in an acceptable level of 0.08309. The result of the study, available shelf layout is designed to be side by side the products sold together and shown in Table 2.

Available					Recommended			
A	B	C	D		O	F	E	D
E	F	G	H		M	G	C	K
I	J	K	L		N	A	I	J
M	N	O	P		H	B	L	P

Table 2. Shelf layout.

Conclusion

Firstly the methods which were used and literature review are mentioned in the study. Therefore, Apriori Algorithm and MDS is briefly described and examples are given to fields of use. In the application section, association rules were calculated by using Apriori Algorithm. Shelf layout is determined by products bipartite conviction values with MDS analysis.

The method used in the study can be done a similar way to be provided ease of finding products in terms of customers and to provide customers spend a longer time in the market in terms of the company.

The effect of shelf layout changes in a number of sales can be analyzed in similar or next studies and a number of product sales can be directed. But often shelf layout changes may adversely affect customer loyalty.

One of the major drawbacks of this method is the data is derived from the bipartite buying behavior for MDS. Also by forming groups of products and taking into account all sales of the products, shelf layout can be arranged to the most purchased products and the most glamorous place.

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