How shoppers buy a specific product category in retail stores? The case of face care products

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Abstract

Customer satisfaction is the key of the success of any retail store or business and has an effect on their profitability. Companies have identified the importance to gain insights on their customer's behavior, so as to better satisfy their needs. Both retailers and suppliers have understood the need to cooperate in order to combine their data, gain knowledge and improve the offered services and customer satisfaction. Additionally, they have realized the potential mutual benefits if they combine their individual knowledge and expertise. Nowadays, the advent of business analytics, aids this cooperation. Thus, data mining techniques could be utilized to analyze the vast amount of data both retailers and suppliers have, to extract knowledge and support data-driven decision-making. However, not enough research has been conducted to analyze such data in order to investigate consumers' behavior regarding a specific product category. This study presents an effort to fill this gap by introducing a Data Mining-based framework, which could be used to discover sales affinities in customers' visits in a supermarket related to a specific product category, and extract behavioral insights. The utility of this framework has been evaluated by applying it in real data of two representative supermarket stores of a Greek retailer. The proposed approach is useful for both an academic and business perspective. It gives retailers the opportunity to extract how shoppers buy specific categories when they visit their stores, while it also enriches the suppliers' knowledge about their shoppers. This knowledge can be used to support the decision-making process for all stakeholders in the retail domain, and improve their relationships with shoppers.

Keywords: Data Mining (DM), Clustering, Retail Analytics

1. Introduction

Consumers' behavior and expectations for service have changed dramatically in recent years, as they have become far more demanding. In the ever-changing world, many businesses have identified the need to become more customer-centric, respond to the ever increasing demands of consumers, and cope with the global competition. As a consequence, Customer Relationship Management (CRM) has risen to the agenda of many organizational strategies. At the same time, many companies have collected and stored a vast amount of data concerning their customers. However, they are unable to transform these data into valuable knowledge. Here comes to contribute business analytic techniques that have been developed, and enable broader and deeper analysis than previously possible. Businesses seek to leverage their data, to extract knowledge about their shoppers and gain insights. Thus, there is a growing enthusiasm for data-driven decision-making. Retailers have realized the importance of applying these new technological trends to sense their shoppers, support decision-making and offer them appropriate services to satisfy their needs.

Major companies, like Metro and Wal-Mart, have recognized the need of data-driven decision-making; thus they aim to analyse the vast amount of transactional data they have to understand and satisfy their shoppers. However, in the literature there is limited research looking into how we can utilize data derived from the actual shoppers' purchases and focus on a specific product category, to gain behavioral insights. There are researchers that focus on the whole product assortment that retailers have, and examine the associations among all products, or product categories using association rule mining, apriori and nearest neighbor algorithms etc. Moreover, there are researches that focus on specific categories or products, but they do so utilizing perceived data, such as data derived from focus groups or questionnaires, and no actual data (e.g. real data from shoppers' purchases).

Motivated by both business needs and literature gaps, our research provides a clustering-based framework for the exploitation of the point-of-sale (POS) data collected by customer purchases in the retail stores, in order to gain insights about shoppers' behavior regarding a specific product category. Our framework allows the transformation of the common retail POS data, into knowledge about the shoppers' purchasing behavior. This research empowers retailers and suppliers to identify how shoppers purchase a specific product category, and take advantage of these insights to plan targeted marketing actions and increase customer satisfaction.

The remainder of the paper is organized as follows. Section 2 explores the research area, analyzes the literature, and points out the research gap. Next, Section 3 presents the proposed framework, while its evaluation is given in Section 4. Finally, Section 5 overviews the main outcomes of the paper, and presents the theoretical contribution and the practical implications of the proposed framework. Moreover, further research is highlighted.

2. Background

Customer satisfaction is the key of the success of any business, thus, CRM has risen to the agenda of many organizational strategies (Bull, 2003; Jeevananda, 2011). As any other business, so do retailers have realized that customer satisfaction has an effect on their profitability. As a consequence, they seek to embrace a more customer-centric focus and find out innovative ways to, understand their customers, support CRM strategies, and improve their relationships (Anderson, Jolly, & Fairhurst, 2007; Linoff & Berry, 2011). In the meantime, business analytic techniques have been developed that can connect large datasets to enable broader and deeper analysis than previously possible (Phan and Vogel, 2010; Provost and Fawcett, 2013), and there is growing enthusiasm for the notion of Big Data. Big Data research looks at how to analyze data in different domains in a way that generates deeper knowledge and adds value to the decision-making process in businesses (Sharda et al., 2013). Big data analytics now drive nearly every aspect of our modern society, including retail industry, financial services etc., and affect global economy (Bertino et al.,2011; McKinsey Global Institute, 2011). Since, big data analytics are now everywhere, the key to success for any firm is to support data-driven decision-making. Nowadays, businesses that leveraging their data, extract hidden knowledge using several data mining (DM) techniques, and use this knowledge to support decision-making, have a higher performance (Wang & Zhou, 2013).

As a consequence, nowadays, business analytics tools are used to assist CRM systems (Phan & Vogel 2010). As, many companies have collected and stored useful data, the application of DM tools in CRM is an emerging trend in global economy (Ngai et al. 2009). DM applied to CRM enables in-depth analysis of datasets, and allows extracting hidden customer characteristics, and behaviors of large volumes of data (Liao et al. 2012; Ngai et al. 2009). By discovering patterns in customers' behaviors, enterprise's decision making could also be empowered (Wang & Zhou 2012). Hence, DM-enhanced CRM could help retailers and suppliers, patronage shoppers' behavior, gain insights, and retain customers that really add value to the business (Min, 2006).

In the literature, there are plenty of papers that use DM-enhanced CRM to satisfy their customers. More specifically, some researchers seek to identify the associations among products, or product categories in retail stores using real POS data to support decision making. For example, Cil (2012) and Borges (2003) use association rules and apriori algorithms to identify sales affinities among categories using POS data of a Turkish and a French supermarket respectively. There is also, another group of papers (Ahn, 2012; Raorane, Kulkarni, & Jitkar, 2012; Shrivastava & Sahu, 2007) which use market-basket analysis to generate a set of rules that link two or more products together. In these cases, apriori and nearest neighbor algorithms are used to identify the hidden associations between products, in order to gain shopper insights, and interpret customer's behavior in supermarkets. However, in all the aforementioned researches they do not focus on specific product categories, or products; they examine the whole variety of products the retail stores have. Furthermore, there are some researches that focus on specific/focal product categories (Broniarczyk et al. 1998); nonetheless their findings are based on perceived and not actual data.

Although, as we presented above, there are papers that use real POS data to extract how shoppers buy all products that a retailer has in his assortment, or other papers that use perceived data derived from focus groups or questionnaires to extract some finding about a focal category; in the literature, there is a lack of papers that utilize data derived from the actual shoppers' purchases and focus on a specific product category, to identify (a) how shoppers purchase this category, (b) with what other products this category is co-purchased, and (c) how we can gain from meaningless transactional data, behavioral insights about the shoppers that buy this focal category. Hence, taking advantage of big data capabilities, we propose a clustering based framework, which shows how we can exploit real data derived from actual transactions to examine a focal category, gain insights, and satisfy shoppers. To the best of our knowledge there is no other framework, which gives specific steps and guidelines to analyze POS retail data per shopping visit and extract how shoppers buy a focal category, by identifying correlations in the purchased products. Moreover, in contrast to the relevant works that are using association rule mining, apriori and nearest neighbor algorithms to identify the correlations between products, this research utilizes clustering, as data mining model to reach its goal.

3. *Framework*

This research adopted the "Design Science" approach (Henver et. al, 2004). An artifact has been developed; it is a DM-based framework (Figure 1) that draws on CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology (Chapman et al., 2000) and includes four phases: (a) Business and Data Understanding, sub-steps of which are: Data Preparation, Data modelling and Data Sampling, (b) Data Mining Modelling, (c) Evaluation, and (d) Deployment. The proposed framework has been implemented in practice, in order to evaluate its ability to solve a real business problem. More specifically, we extracted how shoppers buy a focal category from two stores of a major Greek retail chain. The following subsections summarize each framework's phase.

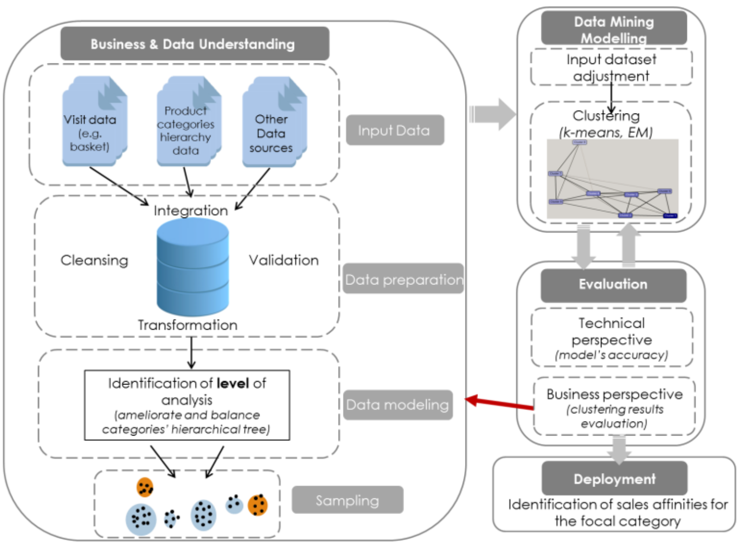

Figure 1: Data Mining Framework

3.1. Business and Data Understanding

The initial phase focuses on obtaining, exploring and preparing the dataset according to the business objective, which is to understand how shoppers buy a specific category, i.e. sales affinities of the focal category with other categories. The necessary data concern the consumers' daily purchases collected from the POS /cashiers in the retail stores. These data need to come with additional information about the receipt/ basket they belong to. Additionally, we need data about the product categories hierarchy, as well as the barcodes the retailer uses, but also data provided by the suppliers, concerning the focal category we want to examine; for example, barcodes that constitutes the focal category, data about the competitive brands, and qualitative data about how suppliers handle the focal category (e.g. promotion plan). Moreover, we could enrich the framework by asking for additional data, such as shoppers' loyalty cards data. Having the latter dataset, we can better profile the shopper, e.g. by extracting additional information, such as demographic characteristics, about each resulting shopping behavior.

3.1.1. Data preparation

This phase covers all the activities to construct the final dataset, which will be used in the DM modelling phase. More particularly, the basic tasks in this phase include (a) data integration, (b) data cleansing and (c) data transformation.

The data integration phase includes combining data from different sources. It is common that the retailer sends the POS data in batches, concerning months, or quarters, etc. A basic task is to integrate all these data in a table that will concern all the POS data. Additionally, we need to match the POS data with the product hierarchy data, and the data the suppliers provide us. As it is legit, the collected data cannot be used for analysis immediately, but they need to be cleaned. Therefore, the data cleansing phase involves detecting and correcting or removing errors, wrong entries and inconsistencies of the data so as to improve data quality. In this phase, we also remove irrelevant data according to the analysis purposes.

Next, we proceed with the data transformation phase which includes the transformation of the cleansed data in a more useful representation for the forthcoming analysis. One basic transformation task is to represent them in a proper unit of analysis. More specifically, in retail data, the unit of analysis is the basket and thus, we need to transform the transactions to baskets. Additionally, in this phase we may produce all meta-data that serve the purpose of the analysis. For example, from the date-time field of the transaction, we may extract the day of the week or even the period of the day (e.g. morning) the transaction was performed.

3.1.2. Data modelling

Within the data modelling phase we proceed with the transformation of the product hierarchy provided from the retailer, so that new customized categories are generic enough to describe similar products, while keeping the proper level of detail that will support the analysis of sales affinities. Here we need to combine retailer's product hierarchy with information from the supplier, in order to better define the focal category. Next, we create some descriptive statistics about the dataset, i.e. the baskets, such as the total number of products per basket (basket volume), the total number of different categories (basket variety) etc. Comparing the results for all baskets with the ones related to the focal category, we may get some first insights about how the typical customer differs from the customer that purchases also a product from the focal category.

3.1.3. Data sampling

Taking into consideration the purpose of the research, i.e. the identification of sales affinities related to the focal category, we proceed with the isolation of the baskets that contain at least one item from this category. Moreover, this subset contains also outliers and more specifically there are baskets with products of only one category. Such baskets cannot provide insights about category affinities, and thus cannot lead to a concrete conclusion. So, from the above selected baskets that contain the focal category, we proceed with omitting the ones' with only this category included.

3.2. Data Mining Modelling

3.2.1. Input Dataset Adjustment

A DM precondition is the integration of the database tables into one. This new table (named as fact table) includes all the information about the database tables in basket level and serves as the training dataset of the model. Each row will represent a basket, having as columns all basket attributes, as well as the product categories from the customized product taxonomy. All columns that concern the product categories will be filled with a binary value of (1) if the basket contained products of this product category or (0) if not. Figure 2 represents the structure of this table.

Attributes from Basket table — Categories we have created

Basket id	Basket size	...	Basket variety	Bread	...	Face care

Figure 2. Fact table structure

3.2.2. Model implementation

The proposed DM technique for understanding customer behavior regarding the focal category is clustering, with k-means or expectation – maximization (EM) algorithm. Clustering is the task of segmenting the objects into groups called clusters, so that the objects within a cluster are "similar" to another and "dissimilar" to objects in other clusters. Similarity is defined as how close the objects are in space, based on a distance function (Phan & Vogel, 2010). Before executing the model, we need to generate a procedure or mechanism to test the model's quality, validity and accuracy. Therefore, we split the dataset into training and testing sets. The training set will be used to implement the clustering, and the testing set to estimate its quality and accuracy (Chapman et al., 2000). The proposed percentage of training and testing set is seventy (70%) and thirty (30%) percent respectively. Moreover, it is proposed to avoid indicating the actual number of clusters, but leave the algorithm propose the optimal case heuristically, especially at the early stages of the research. This is the case, because on the one hand there isn't any predefined optimal number of shopping patterns, while on the other hand a better fit between the model and the data is expected.

3.3. Evaluation

This phase includes the evaluation of the DM results in both business and technical terms. Concerning the business evaluation, in cooperation with industry's people that are experts in this domain, we will examine whether the results meet the reality, and assess if re-execution of the previous phase with changes in the input dataset is needed. In order to evaluate the results, we make a first identification of how the focal category is purchased within a single visit. Specifically, the results of the modeling phase would be groups/clusters of product categories, where each resulting cluster describes a shopping pattern. By studying which categories have been grouped together, we can identify the shopping behavior. For example, if the milk is purchased with cereals, coffee and sugar, this indicates that the shopper was looking for "breakfast". Moreover, as mentioned above, changes in the input dataset may be necessary so as to proceed with the re-execution of the previous phase. Such changes may include deleting and /or merging of some product categories. Merging contiguous product categories attributes is followed as a practice to increase the internal consistency of a cluster and deliver recognizable shopping behaviors to the experts. In more detail, the task is to derive potential shopping profiles from the available clusters and we realized that it is more effective to identify them based on generic product categories. A generic product category is formed through the merging operation of two or more product categories that usually have the same parent node. To this end the evaluation process forms a dialectic process between the experts and the data mining techniques. The role of the researcher is to balance the cluster model, in order to both satisfy important data mining metrics, and deliver an understandable representation of the reality to the experts. Regarding the technical evaluation, we have to evaluate the DM model we created in the previous phase in terms of validity and accuracy according to the training and testing sets.

3.4. Deployment

This is the final phase of the framework, which includes the in-depth analysis of the final and verified modeling results. In particular, this phase includes the final identification of the shopping patterns taking place and extraction of the conclusions that retailers can use to support their marketing actions. As in the evaluation phase, we examine the product categories, and their contribution in each cluster. It is helpful to calculate the average basket size (baskets volume) and the average number of unique product categories (baskets variety) of the baskets contained in each cluster. These two factors, among others, will support the analysis and the characterization of the final shopping profiles.

4. Framework Evaluation: The case of face care products

The proposed framework is used in practice in order to evaluate if it manages to solve the original business problem. One of the biggest retail chains in Greece, in terms of both turnover and number of stores, provided us with retail data, in order to understand how shoppers buy the face care category, while one of the biggest suppliers in the respective industry provided us with insights about this category.

4.1. Business and Data Understanding

The retailer extracted from the corporate database the product categories, the barcodes and the POS data from July 2014 to July 2015, from two representative stores in the Attica region. The stores had common characteristics and belonged to the same store type; they were both supermarkets. Except for the retail data, the supplier also provided us with detailed barcodes of products that belong to the focal category. Having completed the cleansing and transformation processes, we have resulted with 946.317 baskets (7.207.009 transactions). Next, we combined the supplier's input about the categories with the product taxonomy provided by the retailer and defined the focal category, as well as the affiliated ones. For example, the face care category has as affiliated categories the maquillage, body care, hair care etc. Editing the product hierarchy, 110 new-customized categories had been created. Next, we proceeded with the isolation of the targeted category, i.e. the face care. Extracting all baskets that contain at least one product from this category. The resulted dataset included 3.377 baskets, from which 222 baskets where omitted because they contained products only from this category.

4.2. Data Mining Modelling

In order to integrate all useful data, namely data from different stores of the same store type, different time periods as well as the custom categories, we implemented Java code. The data mining method used was clustering, while the non-scalable k-means and non-scalable EM had been used. Implementing the meta-heuristic versions of these algorithms, i.e. with no predefined number of resulting clusters, we resulted with two different models.

4.3. Evaluation

According to the first clustering results, industry people realized that the results provide more business value, namely better understanding how shoppers buy the face care category, if this category is split in two subcategories, which are the face care and the face cleansing. Moreover, the model was proved valid, since it scored 91% to 99% accuracy.

4.4. Deployment

The final cluster diagram is shown in Figure 3. The more densely populated clusters have darker color. The intensity of the line's shading that connects one cluster to another represents the strength of cluster similarity of nodes. The average basket size, and the average unique product categories (basket variety) each cluster contained, had been calculated to help with the analysis and specifically with the results' interpretation. For instance, baskets that belong to cluster number 5, have on average twelve products from eight different product categories.

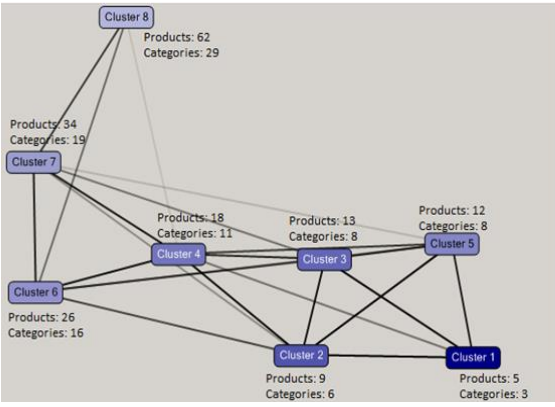

Figure 3. Cluster Diagram

Studying each cluster separately, we observe that cluster number 1 contains many categories which are related to the face care one (focal category), like haircare, clothing, face cleansing, body care, sanitary products etc. So, this cluster indicates that the shopper may be a woman that cares about her face, body, and her total personal hygiene. Additionally, she may look for clothing or products about the house, especially decorative products. Thus, the visit could be characterized as "Beauty, household and clothing". Alike, in cluster 2 we observe that the shopper buys the face care products with milk, fresh fruit and vegetables, baked goods, as well as pet food and healthy food. Such baskets could be purchased by women that look after health and wellness while having a pet. Similarly, in cluster 3 most baskets include products related to face care, hair care, toiletries, household cleansing, oral care and detergents, as well as baby care products, leading us to the assumption that the shopper may be a new mother, that cares both for her baby and herself. In such cases, the shopping visit to the supermarket may be her break to relax and look after herself. Next, cluster 4 seems to be bought from women that indulge into sweets or dessert ingredients, while balancing their choice with face and personal care products. In cluster 5 we observe that the shopper buys the face care category with the ingredients of the main meal and dessert, like fresh fruits and vegetables, baked goods, milk, meat, cans, pasta. Cluster 6 contains the face care category, as well as milk, fresh fruit, baked goods, haircare, chocolate and snack, and kids food like crèmes and yogurts, nuts, butter, cheese and ham etc. So, we may assume that this shopper is a mother that looks after her child's food, as well as her personal face care. Cluster 7 is a more abstract cluster which contains multiple categories such as face care, toiletries, cans, baked goods, coffee, milk, detergents, pasta etc. which can be characterized as a stock visit, which includes personal care products (including the face care ones). Last but not least, cluster 8 represents the most abstract cluster as it represents the big stock visit for fresh food, like fruits and vegetables, milk, cheese and other products like face care, baked goods, cans, pasta, chocolate and candies, biscuits etc.

Studying the shopping behavior for the face care category, we observed how it is bought in different stages of the woman life cycle. Starting from the young woman that looks after her health and wellness, continuing with the young month that looks for 360^{o} self-care solutions, we have also identified the housewife that may indulge to some sweets and candies but on the same time will try to balance it with face care products.

5. *Conclusions & Discussion*

We proposed a DM-based framework which could be used to investigate how shoppers buy a specific product category in retail stores. This approach can change/improve the nature of retailer-supplier-shopper relationships, by giving both retailers and suppliers the opportunity to gain behavioral insights about the shoppers that buy this specific category, and use this knowledge to support data-driven decision making to satisfy their customers. From the literature review, derived that there are researches that examine how shoppers buy all products that a retailer have in his assortment applying DM techniques on POS data, or other papers that use perceived data derived from focus groups or questionnaires to extract findings about a focal category. To the best of our knowledge there is no other framework, which gives specific steps and guidelines to analyze actual POS retail data per shopping visit and extract how shoppers buy a focal category, by identifying correlations in the purchased products. Moreover, in contrast to the relevant studies that are using association rule mining, apriori and nearest neighbor algorithms to identify the correlations between products, this research utilizes clustering, as data mining model to reach its goal.

From a practical point of view, the results of our research empower retailers and suppliers to identify how shoppers purchase a specific product category, and take advantage of these insights to plan targeted marketing actions and increase customer satisfaction. In essence, we can utilize the knowledge extracted to enable effective decision-making in order to grow the penetration of the focal category in terms of units sold, and acquire a larger market share. More specifically, the extracted knowledge may support commercial decision making in retailing e.g. design of new marketing campaigns and promotions for the specific category, according to the derived sale affinities. One more implication is that the framework's results can help marketers to increase customer loyalty, as they could design cross-coupon programs, regarding the focal category. Furthermore, we can use this knowledge to find the appropriate in store placement of the specific product category, by placing it for example in nearby store aisles with those categories that is highly correlated, in order to satisfy the shoppers that don't want to spend a lot of time in the store searching for the products they want to purchase. Increasing both sales and customer satisfaction, by performing the aforementioned actions, both suppliers and retailers will gain benefits.

Further research could be conducted to apply other data mining techniques, such as association rules, and compare the results with those that had been derived from clustering. Moreover, it would be of great interest to compare the results of loyal to those of non-loyal customers.

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