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Intelligent Marketing and Merchandising Techniques for an Internet Shopping Mall

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Abstract

In this paper, intelligent marketing and merchandising methods utilizing data mining and Web mining techniques are proposed for online retailers to survive and succeed in gaining competitive advantage in a highly competitive environment.
The first part of this paper explains the procedures of one-to-one marketing based on customer relationship management (CRM) techniques and personalized recommendation lists generation. The second part illustrates Web merchandising methods utilizing data mining techniques, such as association and sequential pattern mining. We expect that our Web marketing and merchandising methods will both provide a currently operating Internet shopping mall with more selling opportunities and give more useful product information to customers.

Keyword: Electronic commerce; Customer relationship management; Data mining; Web mining; Internet Marketing and Merchandising.

1. Introduction

Nowadays, the explosive growth and rapid adoption of the Internet as a commercial medium have generated retailers' significant interests in establishing a business on the Internet. Its high approval and use by the retail industry may be largely attributed to two factors.

First, it provides both retailers and consumers with unprecedented levels of market transparency. In the marketplace for goods and services, the concept of transparency manifests itself in four primary dimensions: Price transparency, Availability transparency, Supplier transparency, and Product transparency. Price transparency means that the trading participants can get the market price or the price they have come to expect, and know nearly perfect information on price variation by geographic region or by size of supplier (or buyer). Availability transparency implies that the consumer who needs a certain product now can get the information on who has it. Supplier transparency is about that who else out there makes this product. Product transparency indicates whether there is a substitute, alternative product or not. Having sufficient information in all four of these dimensions by utilizing the Internet can substantially change the behavior of the consumers to do shopping and hence the way of the retailers' doing business with them.

Second, the widespread availability of the Internet and the Web technologies enable consumers to efficiently search for and online purchase a wide variety of goods directly from retailers, thereby reducing the costs of commercial activity that retailers and consumers would normally incur. Retailers and consumers divide and take all the benefits of reducing the transaction costs among them. By these reasons, they have the incentive to use the Internet.

With such a large benefit, so many physical retailers jump into online business, therefore it

results in a lot of competition toward profitability. In the end, the online retailer who services its customers better than both its bricks-and mortar and online competitors will win out. Thus, the rise of e-CRM in business-to-consumer electronic commerce (B2C EC) is mainly attributed to the willingness of online retailers to survive and succeed in gaining competitive advantage in such a competitive environment.

CRM allows online retailers to manage customer relationships at every point of contact, and to acquire and build loyalty among those customers considered most profitable. The essential components for successful building of e-CRM are summarized as rapid customer acquisition and increased customer loyalty, and higher customer retention through online interactive customer support and one-to-one marketing. In order to get successful e-CRM solution, the data mining, with other techniques such as collaborative filtering and multidimensional analytical profiling, can be used to perform predictive modeling of online customer behavior. The capability of collecting customer behavior data, which includes searching for and purchasing a wide variety of goods during his or her online session, has provided the Internet retailer with huge amount of data to analyze, transform intelligently and automatically into useful information and knowledge. In this context, data mining has been an interesting issue in the related research fields on the B2C EC.

Data mining, which is also referred to as knowledge discovery in databases, is an emerging science of applying modern statistical and artificial intelligence technologies to the problem of extracting valid, previously unknown, comprehensible, and actionable information from the large sets of data and of using it to make crucial business decisions (Fayyad et al., 1996). Combined with real-time campaign management and personalization applications, it allows the retailers to identify a customer, predict and understand the customer buying pattern, identify an appropriate offer, and deliver it in a personalized format directly to the customer during his or her online session, through hand-held mobile devices (M-commerce), or via e-mails or direct mails.

This paper focuses on development of one-to-one marketing strategies based on CRM and of personalized recommendation lists utilizing data mining techniques, such as clustering, sequential pattern generation, and Web log analysis. In addition, this paper also concentrates on implementing the Web merchandising methods utilizing sequential patterns and association rules.

2. Literature review

In general, online retailers analyze their site's effectiveness from two perspectives: marketing and merchandising. Web marketing is broadly defined as the activities used to acquire customers to online stores and retain them (Schafer et al., 2001). Techniques for online marketing include the use of database marketing, one-to-one marketing, and ad targeting (offer targeting). Database marketing is an attempt by businesses to provide more personal service to their customers. It divides customers into segments based on demographic characteristics such as ZIP code, income, and occupation, and marketed to each segment as a group. One-to-one marketing (Peppers and Rogers, 1997) attempts to overcome the impersonal nature of marketing by using technology to assist businesses in treating each customer individually. Recommendation systems help retailers implement an one-to-one marketing strategy. A number of Web-based personalized recommendation systems have been proposed recently (Resnick and Varian, 1997; Konstan et al., 1997; Borchers et al., 1998;

Aggarwal et al., 1999). Personalization works by filtering a candidate set of items such as products or Web pages through some representation of a personal profile. There are two main approaches for the filtering: content-based and collaborative filtering. A content-based filtering system recommends items based on their similarity to what a given person has liked in the past. Typically, both items and profiles are represented as vectors in the space of features and their similarity is computed via a standard distance metric such as Euclidean distance. Collaborative filtering aims to recommend items that other people, who are similar to the target person, have liked. It uses the information about a group, which can be the whole population of users or a cluster, in order to produce individual recommendations. Ad targeting (offer targeting) is an attempt to identify which consumers should be made an offer based on their prior behavior.

The area of analyzing Web marketing is relatively well understood, while useful metrics and analysis tools for Web merchandising lag behind. Merchandising consists of the activities involved in acquiring particular products and making them available at the right places, right time, and right prices and in the right quantity to enable a retailer to reach its goals: to survive and to sustain competitive advantage (Berman and Evans, 1998). There are generally four areas for Web merchandising analysis: product assortment, merchandising cues, shopping metaphor, and Web design features (Lee et al., 2000). The first analysis area, product assortment deals with whether the products in an online store appeal to the visitors or not. Merchandising cues are techniques for presenting and grouping products to motivate purchase in online stores. Examples include cross-sells, up-sells, promotions and recommendations. Shopping metaphors in an online store are the means that shoppers use to find products of interest. Examples of shopping metaphors are browsing through the product catalog hierarchy, various forms of searching, and configuration for build-to-order type products. The Web design features include media type (e.g., image or text), font, size, color, and location of hyperlinks.

In an e-commerce environment, analyzing such information embedded in click-stream data is critical to improve the effectiveness of Web marketing and merchandising in online stores. As part of such efforts, recently there have been many researches on Web server log analysis from both industry and academia. Some of these efforts show how data mining techniques can be used to characterize and model Web site access patterns in electronic commerce scenarios (Buchner and Mulvenna, 1998; Cooley et al., 1999).

3. A Method of One-to-One Web Marketing

Figure 1 provides an overview of the analysis involved in the one-to-one Web marketing. The process of establishing e-commerce marketing strategies begins with the identification of customers of a retailer and the construction of a customer purchase database from online customer history of purchases. The raw input data for this analysis contain 8 months of product-level transaction data for 2,036 customers of an online shopping mall located in South Korea.

Once the customer purchase database has been built on the enterprise Intranet, the lightly summarized data – *Recency*, *Frequency*, and *Monetary* (RFM) values – as training and testing data for mining tools are extracted from the customer information of the database. More generally, data mining has two phases: the learning phase and the use phase. In the learning phase, the data mining system analyzes the RFM data and builds a model of customer

behavior. This phase is often very time consuming and may require the assistance of human analysts. After the model is built, the system enters a use phase where the model can be rapidly and easily applied to customer situations. RFM measures provide information on what customers do: when they buy, how often they buy, and how much they buy products and services. Clearly any system based on customer behavior is much more likely to be accurate in analyzing customer's buying patterns, and in predicting future customer behavior than any possible combination of demographic information (Hughes, 1996).

[Figure 1] Procedure for one-to-one Web marketing
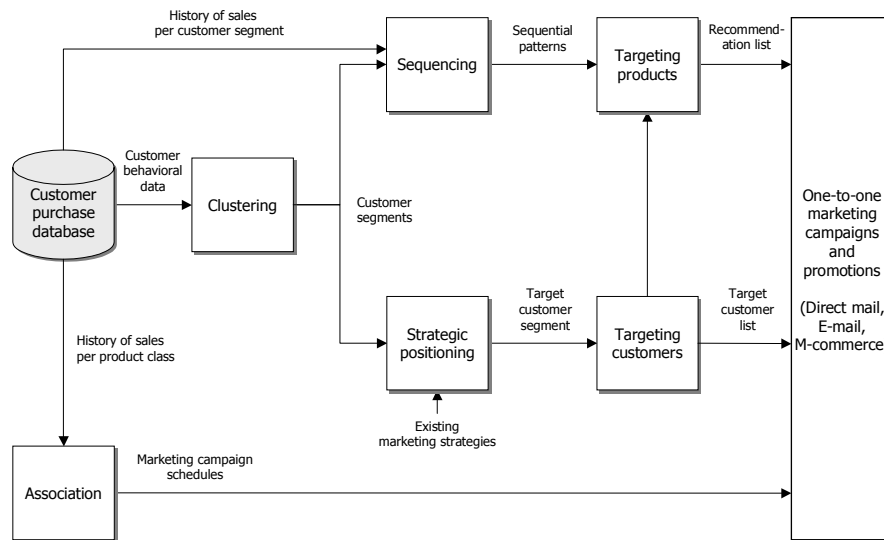
For some more explanations about the RFM information, refer to (Bult and Wansbeek, 1995).

- Recency measures include the time period since the last purchase.
- Frequency measures include the number of purchases made in a certain time period.
- Monetary measures include the amount of money spent during a certain period of time.

3.1. Clustering (Segmentation) analysis

Given a large number of database records, clustering can be used for identifying a small number of customer stereotypes, which represent dominant characteristics or features present in the input customer purchase data (Michaud, 1997). Some of the common algorithms used to perform clustering include Kohonen feature maps (also known as self-organizing map) and K-means algorithm. Among them, the self-organizing map (SOM) is chosen to divide the customers of a retailer into a number of clusters of similar customers with similar RFM values, and assign each customer to the resulting customer clusters. This particular type of neural network, SOM, can be used as a decision support tool for supporting strategic decisions involving identifying and targeting market segments (Mangiameli et al., 1996).

SOM uses an unsupervised learning scheme to train the neural network (Sestito and Dillon, 1994; Berry and Linoff, 1997). Unsupervised learning is comprised of those techniques for which the resulting actions or desired outputs for the training sequences are not known. The

network is only told the input vectors, and the network self-organizes these inputs into categories. SOM uses competitive learning. When an input pattern is imposed on the network, one output node is selected from among all the output nodes as having the smallest Euclidean distance between the presented input pattern vector and its weight vector. This output unit is declared the winner in the competition among all the neurons in the output layer. Only the winning neuron generates an output signal from the output layer. All the other neurons have a zero output signal.

The input and weight vectors are usually normalized in a SOM so that they have values between 0 and 1 inclusive. If the dot products between the normalized input vector $\hat{X}$ and a normalized set of weight vectors $\hat{W}_j$ are determined, the neuron with the largest dot product (the one with the smallest Euclidean distance) is declared to be the winner. Thus the winner is the vector obtained from the expression:

$$\max_j \left(\hat{X}^t \hat{W}_j \right)$$

where $\hat{X}^t$: Normalized input vector, $\hat{W}_j$: Normalized weight vector. As learning involves adjustment of weight vectors, learning with this particular input pattern is restricted to lateral interconnections with immediately neighboring units of the winning neuron in the output layer. Adjusting their weights closer to the input vector carries out learning for the nodes within the neighborhood. The size of the neighborhood is initially chosen to be enough large to include all units in the output layer. However, as learning proceeds, the size of the neighborhood is progressively reduced to a pre-defined limit. Thus during these stages, fewer neurons have their weights adjusted closer to the input vector. Lateral inhibition of weight vectors that are distant from a particular input pattern may also be carried out.

Table 1 summarizes the 9 clusters, which are derived from a 3 by 3 SOM produced by the neural clustering method, showing the fraction of total customers assigned to each cluster, as well as the most significant characteristics – average values of recency, frequency, and monetary – that make the clusters unique.

(Table 1: Summary of customer cluster characteristics)

Cluster	Fraction of customers (%)	Characteristic vector (Centroid)		
		Average Recency	Average Frequency	Average Monetary
1	5.7	83.78	3.60	1617.45
2	12.3	436.16	1.22	545.55
3	27.8	162.43	1.27	471.88
4	6.9	295.19	2.14	1590.79
5	8.1	278.58	1.45	570.62
6	4.7	87.53	6.01	3278.25
7	14.1	68.87	1.44	544.02
8	6.4	112.78	3.37	2600.83
9	14.0	167.25	1.66	1351.65
Total Average		190.88	1.91	1031.90

Each row represents a cluster, with the largest cluster containing 27.8% (567 out of 2,036) of the customers, the smallest 4.7% (95 out of 2,036). The "average recency (frequency, or

monetary)" of a cluster is defined as the ratio of the total of recency (frequency, or monetary) values of customers in a cluster to the customer population who is in that cluster. The information on customer segments identified is then used to perform the sequential pattern mining and later targeting products.

3.2. Sequential pattern mining

Given a customer purchase database where each sequence is a list of transactions ordered by transaction time and each transaction consists of a set of items (products or product categories), sequential pattern mining finds all sequential patterns with a pre-defined minimum support, where the support is defined as the fraction of total customers who support this sequence.

Sequential pattern mining, which discovers frequent sequential patterns in a customer purchase database, was first introduced by Agrawal and Srikant (1995). In this study, it is used to produce lists of the most popular products for each customer cluster being identified above, and then the cluster-specific list of popular products is used as input to the generation of recommendations for a customer in that particular cluster. Generating the recommendation lists per each customer cluster reflects the premise that similar customers in the same customer cluster share common characteristics (purchasing behavior patterns). Differentiating between customers via market segmentation much helps retailers understand their needs and cross-sell an incremental product to an existing customers by matching products and levels of service more closely to customer expectations.

Products are divided into 9 product classes (categories) in the online shopping mall. Examples of these classes are "Fashion and Notions", "Cosmetics and Perfumes", "Book and Music", "Computer and Communication", "Sports and Leisure", "Electronics", "Home and Living", "Cakes and Flowers", and "Kids and Education". Each product class contains subclasses, which contain fewer than 50 products. For example, a product class, "Computer and Communication", has several subclasses, such as "Storage/Media", "Game driver", "Desktop", "Video/Audio card", and so on. It is worth noting that the product taxonomy used here is strictly a characteristic of the individual online retailer's preferences and it is conceivable that other retailers can use different hierarchies to represent retail product catalogs.

Instead of using "support" as a common measure of interestingness in sequential patterns, a metrics, called the correlation score, is used to represent the degree of strength of sequential patterns among the product lists for each customer cluster. Hence, the correlation score between product m and product n is defined as:

$$correlation\ score(m \Rightarrow n) = \frac{C_{m \cap n}}{C_m}$$

where C_m is the number of customers who have spent in product m, ($C_m \geq 1$) and $C_{m \cap n}$ is the number of customers who have spent in product n, given that they have bought product m. In general, a correlation score indicates the strength of the sequential patterns. The value ranges from 0 to +1. 0 indicates no relationship, and +1 indicates a perfect relationship, meaning that a customer who has bought product m always bought product n some time later.

Table 2 shows a subset of sequential patterns computed at product-subclass levels for the customer cluster 1.

[Table 2] Sample sequential patterns computed at product-subclass level for customer cluster 1

Correlation scores	Sequential patterns	Average period (days)
0.31	(Storage/Media) (Digital camera)	65
0.29	(Digital camera) (Storage/Media)	61
0.28	(Desktop) (Operating system)	43
0.27	(Desktop) (Monitor)	80
0.27	(Game driver) (CD title)	35
0.26	(MP3 player) (Digital camera)	73
0.25	(Digital camera) (Video/Audio card)	61
0.23	(Video/Audio card) (Scanner)	74
0.23	(Desktop) (Office software)	26
0.22	(Operating system) (Office software)	47
0.20	(Monitor) (CD recorder)	53
0.19	(Storage/Media) (Desktop)	68
0.16	(Desktop) (Notebook)	114
0.15	(Digital camera) (Office software)	135

Although complex patterns are possible, only simple sequential patterns containing a single item are computed. The reasons include clarity of understanding as well as computational complexity. A threshold on the correlation score can be chosen to achieve this filtering, after experimenting with different limits on this parameter and inspecting the resulting sequences. Although heuristic, this choice produces a reasonable number of sequential patterns (when setting the threshold to 0.1, about 90 sequences are produced). The textual format of the first sequential pattern is "31% of customers who belong to the specific customer cluster 1 and buy "Storage/Media", also buy "Digital camera" within average 65 working days". 65 days of average period represent the arithmetic mean time that it takes to purchase "Digital camera" after purchasing "Storage/Media".

3.3. Strategic positioning of customer segments

Target customer clusters are chosen via a strategic positioning of the customer clusters, to which some marketing campaigns and promotions will be applied. The strategic positioning of the customer clusters is to plot the characteristics of average member, such as average RFM values, of each customer cluster in the same graph. The current marketing strategies can be considered as an important decision-making factor that can influence target cluster decision.

Centroids (average RFM values) of each cluster are compared with the total average RFM values of all clusters. If each average is bigger than overall mean, an up-headed arrow ↑ is given to that value. If the opposite case occurs, a down-headed arrow ↓ is given. Superimposing these comparisons on the strategic positioning of customer clusters from the RM point of view in Figure 2 shows another important implication. Clusters 2 and 5 in quadrant 2 have characteristics R↑F↓M↓ and cluster 4 in quadrant 1 has R↑F↑M↑. They are likely to represent vulnerable segments, based on above-average value in recency. Clusters 3 and 7 in quadrant 3, having R↓F↓M↓, appear to represent "new comers", given minor figures in frequency. Clusters 1, 6, and 8 in quadrant 4 can be considered as loyal segments, which contain frequent and big shoppers. Customers of cluster 9 in quadrant 4 are promising ones who could become the loyal customers in the future.
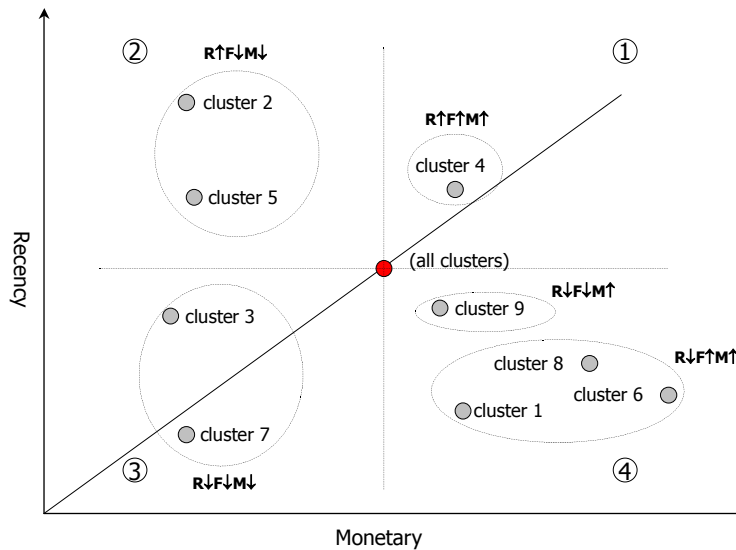
[Figure 2] Identification of target segments

Table 3 summarizes some characteristics of customer cluster and corresponding marketing strategies.

[Table 3] Customer cluster characteristics and corresponding marketing strategies

Cluster	Characteristics	Marketing strategy
2, 5	R↑F↓M↓	Customer reactivation
4	R↑F↑M↑	
3, 7	R↓F↓M↓	Customer maturity
9	R↓F↓M↑	
1, 6, 8	R↓F↑M↑,	Customer retention

Customer reactivation strategy can be applied to customers who belong to segments that have some types of vulnerable patterns. Vulnerable customers are likely to leave for a competitor sooner or later. Some marketing actions have to be taken to get those customers back because doing so is usually far less expensive than acquiring a new customer. Customer maturity strategy focuses on increasing customer loyalty to the higher degree, which enhances existing relationships with customers and extends their duration. Customer retention strategy maintains customer loyalty at the highest level over a period in time, which keeps profitable customers longer.

The next step is to select target customers who will receive some marketing promotional offerings with the aid of direct mails and e-mails. Suppose that segments 1, 6, and 8 are selected as the target according to the 80:20 rule stating that 80 percent of profits come from 20 percent of customers [Hughes 1996]. Then all of customers who belong to those segments become target customers for direct mailings or e-mailings.

3.4. Targeting products

The final step in the one-to-one marketing process is to target products, that is, to select the

candidate products for a specific target customer. For explanation, when we choose a target customer, 019503001, who belongs to one of target segments (i.e., segment 1), product purchase sequences for the cluster 1 are revealed like Table 2 above. According to the sequential patterns, the target customer who recently bought "Digital camera" will receive marketing promotional offers or campaigns on "Storage/Media" with the first priority, followed by "Video/Audio card" and "Office software" in sequence. However, the sequential patterns discovered can be refined further by mining the product search and Web page navigation patterns of customers – Web mining – after their purchasing "Digital camera".

Web mining has been used in two distinct ways (Cooley et al., 1997). The first, called *Web content mining*, is the process of information discovery from sources across the WWW. In recent years, it has prompted researchers to develop more intelligent tools for information retrieval, and to extend data mining techniques to provide a higher level of organization for semi-structured data available on the Web. The second, called *Web usage mining*, is the process of the automatic discovery of customer browsing and access patterns from Web servers. Retailers, which run online shopping mall sites, collect large volumes of data, generated automatically by Web servers and collected in server access logs. Analyzing such data can help retailers determine the life time value of customers, cross marketing strategies across products, and effectiveness of a promotional campaigns. It can also provide information on how to restructure a Web site to create a more effective Web site presence, and shed light on more effective management of customer communication and Web server infrastructure.

Before extracting access histories, on which the mining algorithms can be run, of a customer, a number of data preprocessing issues, such as data cleaning and transaction identification, have to be addressed. The major preprocessing task is data cleaning [Cooley et al. 1999]. Techniques to clean a server log to eliminate irrelevant items are of importance for this type of Web log analysis. Elimination of irrelevant items can be reasonably accomplished by checking the suffix of a file name in the uniform resource locator (URL). We can remove all log entries with filename suffixes such as gif, jpeg, GIF, and JPEG, which indicate graphic files. Identifying individual customers and their sessions can be done relatively easily because the system keeps login histories of each customer. For more details about the problem of transaction identification, refer to Chen, Park, and Yu (1996) and Cooley et al. (1997).

Once customer access histories have been identified, there are several kinds of access pattern mining, such as path analysis, discovery of association rules and sequential patterns, and clustering and classification. For targeting products, we perform clustering analysis of Web page traversal, which can be formed by customers themselves as they search products and navigate Web pages that contain information of each product. In order to obtain traversal histories between the purchase of "Digital camera" and the subsequent purchase for 89 customers who reside in customer segment 1 and make a purchase of "Digital camera", the following data are computed at product-class level (in this case, there are 9 product classes):

- Customer number or customer id that belongs to customer segment 1;
- How long it has been since each customer made a last visit to the Web page (Recency view);
- How many times each customer has made a visit to the Web page (Frequency view);

After that, traversal histories are segmented by a SOM to discover customers with similar

access patterns. Figure 3 shows the resulting customer access segments listed as a 3 by 3 SOM. Each cell represents a cluster, which contains the number of customers who share similar Web page access patterns in the center of each cell.

[Figure 3] Clustering analysis of Web page traversal

1 10	2 8	3 6
4 7	5 14	6 18
7 3	8 12	9 11

The target customer, 019503001, who just bought "Digital camera" has been showing similar access patterns with customer access segment 6 ever since. Then for predicting subsequent purchase and recommending appropriate products, it is plausible to investigate the purchase patterns of 18 customers in customer access segment 6: 36% of the 18 customers made a purchase of "Storage/Media", 41% of the 18 customers made a purchase of "Video/Audio card", and 18% of the 18 customers made a purchase of "Office software". Based on this result, the recommendation sequence for the target customer, 019503001, is changed as follows: "Video/Audio card" -> "Storage/Media" -> "Office software". Notice that this recommendation sequence reflects the customer's Web access patterns and is slightly different from product sequential patterns in Table 2. Also notice that recommendations are generated on a daily basis, and the list and sequence of candidate products can be updated daily.

4. A Method of Web Merchandising

Figure 4 illustrates a procedure of the analysis involved in the Web merchandising.

[Figure 4] Procedure for Web merchandising
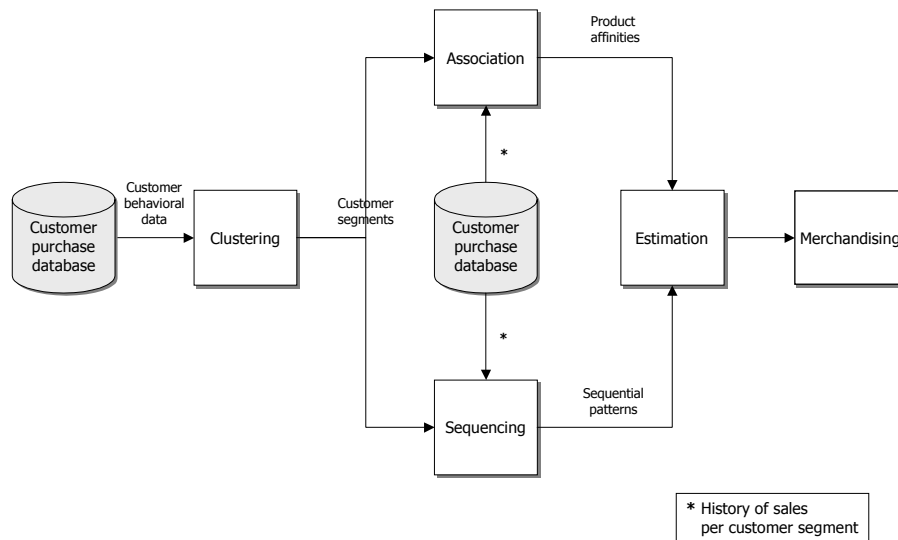
4.1. Associations mining

Generating the Web merchandising model per each customer cluster, in essence, reflects the fact that some customers are more profitable than others, meaning that the 80:20 rule remains valid. Acquiring particular products and making them available at the right places, right time, and right prices for these profitable customers enables a retailer to satisfy the needs of customers to certainly survive and succeed in gaining competitive advantage.

With purchase sequence information derived from sequential pattern mining, association mining is performed as prerequisite for Web merchandising. Given a database of customer purchase transactions, discovering association rules is to find all associations and correlations among items (products or product classes) such that the presence of some items in a transaction will imply the presence of other items in the same transaction [Chen, Han, and Yu 1996]. An association rule is an implication of the form $X \Rightarrow Y$, where X and Y are set of items. The most common measures of interestingness in current association rule discovering algorithms are the *support* and *confidence*. Each association rule has an associated support and confidence, where support is the probability that a transaction satisfies both X and Y, and confidence is the probability that a transaction satisfies Y, given that it satisfies X. The rule $X \Rightarrow Y$ has support s in the transaction set if s% of transactions in transaction set contain $X \cap Y$. The rule $X \Rightarrow Y$ holds in the transaction set with confidence c if c% of transactions in a transaction set that contain X also contain Y. Such rules with high confidence and support are referred to as strong rules. The task of mining association rules is essentially to discover strong association rules in large databases.

Table 4 shows a subset of association rules computed at the product-subclass level for customer cluster 1.

[Table 4] Sample associations computed at the product-subclass level for customer cluster 1

Support	Confidence	Product subclass	Relevant affinities
0.04	0.51	Storage/Media	=> Digital camera

0.11	0.49	Digital camera	=> Storage/Media
0.24	0.47	Desktop	=> Operating system
0.16	0.43	Game driver	=> CD title
0.05	0.39	Digital camera	=> Video/Audio card
0.17	0.35	Desktop	=> Office software
0.10	0.32	Operating system	=> Office software
0.02	0.21	Storage/Media	=> Desktop
0.02	0.20	Digital camera	=> Office software

As well as the sequential patterns, only simple association rules are discovered. A combination of thresholds on the support and confidence of a rule is used to achieve this filtering: minimum support above 2% and minimum confidence above 20%.

Association rules give several managerial implications on one-to-one marketing strategies and Web merchandising strategies:

- According to these association rules, the interrelation between products can be analyzed. They are helpful in determining locations and hyperlinks between interrelated products within the mall. The more associative the products are, the closer is the location so that customers can access them easier and quicker. The association rules can also be used for determining the timing and the type of marketing promotion offers for each product. The associative products had better not simultaneously make similar sales promotion offers such as a bargain sale, since customers who are led by a bargain sale of an item are likely to purchase other interrelated items too.
- It is a good practice to determine the timing of inventory assessment and the inventory level of the interrelated products according to the degree of association. For example, if there exists 50% of associations between products, maintain the inventory level at that degree, namely 50%, too. If a retailer knows the degree of the association between two products, he or she may estimate the change in sales amount of them. When the degree of association is high, the sales increase (or decrease) in a product gives much impact on the sales increase (or decrease) in the other product.

4.2. Implementation of Web merchandising

In order to implement Web merchandising, the following procedures are involved:

1. Determine product inventory levels by using sequential patterns.
An experiment shows that 34 customers in customer cluster 1 made a purchase of MP3 players and 53 customers made purchase of Storage/Media during the analysis period. It also shows that if a customer in that cluster tries to purchase "Digital camera", he or she purchases on the average 1.12 units at a time, and if "Desktop", he or she purchases on the average 1.45 units at a time. Then product inventory levels can be calculated by using correlation score of sequential patterns as following Table 5:

[Table 5] Sequential patterns and calculation of product inventory levels

Product subclass	Product sequence	Correlation score	Average purchase per customer	Predicted sales volume (Proper inventory level)
MP3 player	Digital camera	0.26	1.12 (units)	$(34 \times 0.26) \times 1.12 = 9.9$ (*units*)
Storage/Media	Digital camera	0.31	1.12 (units)	$(53 \times 0.31) \times 1.12 = 18.4$ (*units*)

| | Desktop | 0.19 | 1.45 (units) | $(53 \times 0.19) \times 1.45 = 14.6$ (*units*) |

Table 5 indicates that about 10 units out of 29 units of "Digital camera" will be needed on the average within 73 days, while about 19 units within 65 days. About 15 units of "Desktop" will be needed on the average within 68 days.

2. Determine products affinities and their inventory levels by using association rules.
In this step, the highly associative products with "Digital camera" and "Desktop" are selected and their inventory levels are calculated by using confidence factors of association rules as following Table 6:

[Table 6] Product affinities and their inventory levels computed by using association rules

Product subclass	Product affinities	Confidence	Predicted sales volume (Proper inventory level)
Digital camera	Storage/Media	0.49	$10 \times 0.49 = 4.9$ (*units*) $19 \times 0.49 = 9.3$ (*units*)
	Video/Audio card	0.39	$10 \times 0.39 = 3.9$ (*units*) $19 \times 0.39 = 7.4$ (*units*)
	Office software	0.20	$10 \times 0.2 = 2.0$ (*units*) $19 \times 0.2 = 3.8$ (*units*)
Desktop	Operating software	0.47	$15 \times 0.47 = 7.1$ (*units*)
	Office software	0.35	$15 \times 0.35 = 5.3$ (*units*)

Table 6 shows that 4.9 units of "Storage/Media", 3.9 units of "Video/Audio card", and 2 units of "Office software" will be needed on the average within 73 days, while 9.3 units of "Storage/Media", 7.4 units of "Video/Audio card", and 3.8 units of "Office software" within 65 days. About 8 units of "Operating software" and about 6 units of "Office software" will be needed on the average within 68 days.

3. Repeat from step 1 for the remaining product subclasses of which customers in customer cluster one make a purchase. If a retailer wants to prepare total merchandising for the shopping mall, aggregate the merchandising plans for each customer cluster.

5. Conclusion

CRM is essential to compete effectively in today's marketplace including the electronic commerce. It has helped retailers improve the profitability of their interactions with customers, at the same time, make the interactions appear friendlier through individualization. The more effectively retailers can use information about customers to meet their needs, the more profitable the retailers will be. To be successful with CRM, retailers need to match products and campaigns to prospects and customers – in other words, to intelligently manage the customer life cycle. In the Internet era, its importance never decreases. However, the sheer volumes of customer information and increasingly complex interactions with customers have propelled data mining to the forefront of making customer relationships profitable. Data mining is a process that uses a variety of data analysis and modeling techniques to discover patterns and relationships in data that are used to understand what customers want and predict what they will do. Data mining can help retailers select the right customers on whom to focus, offer the right additional products to the existing customers and identify vulnerable customers who may be about to leave. This results in improved revenue because of a greatly improved

ability to respond to each individual contact in the best way and reduced costs due to properly allocated resources. In this paper, one-to-one Web marketing and Web merchandising strategies to increase the sales amount of the target online store as well as to improve customer satisfaction were explained from the CRM and data mining perspectives.

A clustering tool, SOM, was applied to customer lists of the online shop in order to segment its own customers according to their buying patterns and to provide them with different sales promotion offers. After customers having been clustered, target customers were identified through the strategic positioning of customer clusters and then customized offers could be made via direct mails or e-mails. Strategic positioning of customer clusters also gave a retailer helpful hints for linking customer clusters to corresponding marketing strategies, such as customer reactivation, customer retention, and customer maturity strategies. In order to generate recommendation lists, sequential pattern mining was used to find all sequential patterns with a pre-defined minimum correlation score. However, the sequential patterns discovered could be refined further by mining the product search and Web page navigation patterns of customers – Web usage mining. Through the Web usage mining of the customer's Web access patterns, the recommendation sequence for the target customer could be changed. With purchase sequence information derived from sequential pattern mining, association mining was performed for Web merchandising. Through generating the effective Web merchandising methods, acquiring particular products and making them available at the right places, right time, and right prices for these profitable customers enabled a retailer to satisfy the needs of customers in order to certainly survive and succeed in gaining competitive advantage.

The work presented in this paper can be extended in several ways for future research. First, the clustering analysis used for segmenting customers can be extended to include richer information. The current clustering analysis uses RFM values as base variables for customer segmentation. Although they did perform well, it leaves some room for improvement. In particular, attention should be given to alternative set of features with the better predictive performance than the RFM values. If it were possible to significantly improve predictive accuracy by using the alternative, it would provide the basis for future research in this kind of analysis. Second, though the concept of buying-behavior-based CRM was advanced several decades ago, virtually little application of the dynamic (longitudinal) CRM has been reported to date. The traditional CRM studies are mainly focused on CRM in specific point of time. The static CRM and derived knowledge of customer behavior could help general marketers to redirect marketing resources for profit gain at the given point in time. But, as time goes on, the static knowledge becomes obsolete. Therefore, application of dynamic CRM to electronic commerce should be a new challenging problem. Finally, more empirical studies need to be performed covering a long time range (e.g., one year), and over different types of online stores. Such work will help validate various speculations about Web marketing and merchandising strategies in a rigorous way. Also, it will help understand the effectiveness of an online store with minimal effort.

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