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Zhiyuan Yao
Åbo Akademi University

Peter Sarlin
Åbo Akademi University

Tomas Eklund
Åbo Akademi University

Barbro Back
Åbo Akademi University

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Yao, Zhiyuan, Åbo Akademi University, Turku Centre for Computer Science (TUCS), Joukahainengatan 3-5, 20520 Åbo, Finland, Zhiyuan.Yao@abo.fi

Sarlin, Peter, Åbo Akademi University, Turku Centre for Computer Science (TUCS), Joukahainengatan 3-5, 20520 Åbo, Finland, Peter.Sarlin@abo.fi

Eklund, Tomas, Åbo Akademi University, Turku Centre for Computer Science (TUCS), Joukahainengatan 3-5, 20520 Åbo, Finland, Tomas.Eklund@abo.fi

Back, Barbro, Åbo Akademi University, Turku Centre for Computer Science (TUCS), Joukahainengatan 3-5, 20520 Åbo, Finland, Barbro.Back@abo.fi

Abstract

Customer Relationship Management (CRM) is a central part of Business Intelligence, and sales campaigns are often used for improving customer relationships. This paper explores customer behavior during sales campaigns. We provide a visual, data-driven and efficient framework for customer segmentation and campaign-response modeling. First, the customers are grouped by purchasing behavior characteristics using a self-organizing map. To this behavioral segmentation model, we link segment migration patterns using feature plane representations. This enables visual monitoring of the customer base and tracking customer behavior before and during sales campaigns. In addition to the general segment migration patterns, this method provides the capability to drill down into each segment to visually explore the dynamics. The framework is applied to a department store chain with more than one million customers.

Keywords: Business intelligence, Customer relationship management (CRM), Visual analytics, Customer segmentation, Campaign response modeling.

1 Introduction

For a long time, the focus of modern companies has been shifting from being product-oriented to customer-centric (Shah, et al., 2006). In recent years, this change has been particularly rapid due to the increasing interest in Business Intelligence (BI) in general, and Customer Relationship Management (CRM) in particular. In the industry and the CRM literature, it is commonly held that maintaining and improving existing customer relationships is more cost-effective than attracting new ones (Berry, 2002).

Sales campaigns, one of the most commonly used customer-facing activities, provide a good means for improving customer relationships. Although sales campaigns have been widely used to improve ROI, they have traditionally been more bottom-line focused than customer-focused (Day, 1997). One of the reasons for this is a lack of understanding of customer behavior and requirements. Previous research has shown the importance of using customer data for better understanding of customers' needs and behavior, especially in customer-facing activities (Jayachandran, Sharma, Kaufman and Raman, 2005; Kumar, Venkatesan and Reinartz, 2008). The availability of large amounts of customer data in data warehouses is providing companies with ample opportunity to analyze data patterns and extract knowledge for building better customer relationships.

Customer segmentation is an effective approach for evaluating the value of the customers and understanding their behavior. Customer segmentation divides the customer base into distinct and internally homogeneous groups. Effective segmentation enables companies to interact with customers in each segment collectively, and allocate limited resources to various customer segments according to corporate strategies. A range of data mining techniques have been used for customer segmentation, e.g., decision trees (Kim, Wei and Ruys, 2003), self-organizing maps (SOMs) (Holmbom, Eklund and Back, 2011; Mo, Kiang, Zhou and Li, 2010; Yao, Holmbom, Eklund and Back, 2010), k-means clustering (Dennis, Marsland and Cockett, 2001; Hosseini, Maleki and Gholamian, 2010), and combinations of different methods (Kuo, Ho and Hu, 2002; McCarty and Hastak, 2007). These studies have successfully demonstrated the usefulness of customer segmentation in a variety of industries. However, the solutions are often stand-alone analytical models, derived based on a specific time frame, and thereby often disregard connections with marketing campaigns (Chan, 2008). This static snapshot of the customer base might overlook possible dynamics. For example, customers may exhibit different purchasing behavior before and during campaigns, and accordingly migrate among segments. Previous research (Basu, Basu and Batra, 1995; Piatetsky-Shapiro and Masand, 1999) on response modeling focuses on estimation of response rate and campaign profitability, often ignoring the possible customer heterogeneity in terms of response patterns. Song (2001) and Chen (2005) approach response pattern modeling by categorizing and quantifying changes in customer behavior, which are summarized by a set of rules. However, customer rules provide fragmented information regarding customer behavior, and large rule sets are also difficult to manage.

In this paper, we apply a BI approach to model campaign response among customers in different segments. First, we create a demographics and purchasing behavior-based customer segmentation model, using a method for visual segmentation, the Self-Organizing Map. Then, we connect information about customers' responses to a number of sales campaigns based upon transition probabilities, to 1) model which customer segments react to campaigns, and 2) to identify differences in purchasing behavior during campaign/non-campaign periods. This model is expected to create a more effective analytical CRM system that is able to consolidate the patterns in customers' purchasing behavior and their underlying dynamics in one view, and thus provide actionable marketing information.

The remainder of this paper is organized as follows. Section two introduces the methodology behind the framework. Section three introduces the framework for conducting visual customer segmentation and campaign-driven segment migration pattern analysis. Section four documents the application of the framework, the analysis of the results, and discussion of managerial implications. In section five, conclusions are drawn by presenting our key findings.

2 Methodology

This section introduces the SOM and transition probabilities on the SOM, as well as describes the data used in this study.

2.1 Self-Organizing Maps

Clustering algorithms have been widely used to approach customer segmentation tasks. From about the turn of the century, visualization techniques have gained in popularity for understanding and assessing clustering results (Oliveira and Levkowitz, 2003). Visual clustering, in particular, consists of techniques capable of conducting clustering tasks and a multivariate visual display of the clustering results. These techniques provide simultaneously visual representations of the underlying data structures, therefore facilitating the exploration of useful patterns in the data.

The Self-Organizing Map (SOM) (Kohonen, 2001) is a well-known and widely used method for visual clustering. Unlike most traditional clustering algorithms that require post-processing for understanding cluster structures, the SOM is a unique technique for data and dimensionality reduction through its simultaneous clustering and projection capabilities. The SOM projects relationships between high-dimensional data onto a two-dimensional display, where similar input records are located close to each other. Conceptually, serial or parallel combinations of stand-alone clustering and projection methods come close to what the SOM performs. However, common motivations for using the SOM over alternative methods are the interaction between the two tasks of clustering and projection, the pre-defined grid structure for linking visualizations, flexibility for missing data and computational efficiency (see e.g., Vesanto, 1999). In addition, the SOM has previously been shown to be an efficient and easy-to-interpret tool for customer segmentation (Kim, Wei and Ruys, 2003; Holmbom, Eklund and Back, 2011; Yao, Holmbom, Eklund and Back, 2010; Vellido, Lisboa and Meehan, 1999; Lee, Suh, Kim and Lee, 2004; Lee, Xiang and Jing, 2005; Lingras, Hogo, Snorek and West, 2005).

The functioning of the SOM can be split into two stages: (1) matching data records to their best-matching units, and (2) updating each unit towards the attracted data, including those in adjacent locations. The individual units of a SOM can be treated as separate clusters. However, when performing visualization, detail through a larger number of units is often preferred. Instead, a larger number of units can be grouped to second-level clusters for performing clustering. The dataset is first projected onto a two-dimensional display using the SOM, and the resulting SOM is then clustered. The two-level SOM (Vesanto and Alhoniemi, 2001) has in previous studies shown to be effective, in particular Li (2005) shows superiority of the combinatorial approach of the SOM and Ward's (1963) hierarchical clustering over some classical clustering algorithms. Ward's clustering starts with each unit being treated as a separate cluster. Then, the two clusters (or units) with the minimum distance are merged in each step until there is only one cluster left on the map. Then, a suitable cut-off (number of clusters) is chosen for analysis. In order to take into account the ordering of the SOM, Ward’s clustering is limited to agglomerate only adjacent units.

The second-level clustering of the SOM is shown using contour lines, such as those shown in Figure 3 where we have five clusters denoted S1-S5. While the SOM represents a high-dimensional space on a two-dimensional output space, the multidimensionality can be described using feature planes (Vesanto, 1999). They are views of individual variables on the same SOM grid structure and aid in understanding the characteristics of the SOM model. This paper uses heat map coloring for illustrating low (blue colors) to high values (red colors). For instance, Figure 3 displays five feature planes, and the first feature plane in Figure 3 shows high values (elderly customers) for the lower right part of the SOM grid and low values for the mid-right part (young customers).

2.2 Transition Probabilities on the SOM

While the SOM is an ideal tool for data and dimensionality reduction, identifying temporal movements in a SOM model is not a simple process (see Sarlin (2011) for a review of time in SOMs). Previously, trajectories have been a common means to illustrate temporal movements of individual data records on the SOM grid (see e.g., Eklund, Back, Vanharanta and Visa, 2003; Sarlin and Marghescu, 2011). The use of trajectories suffers, however, from the deficiency that they can only be used on a limited set of data in order not to clutter the display, and give no indications of overall patterns and their strengths. Recently, it has been shown that transition probabilities can be used for producing a probabilistic model of the temporal variations in a SOM model (Sarlin, Yao and Eklund, 2012). Probabilities are computed for movements on the two-dimensional SOM grid and can model transitions to a specified region, such as segments. In CRM terms, this would translate to segment migration analysis.

Given a SOM model, the location for each data record at each point in time is derived by assigning them to their best-matching unit. Then, we can summarize the segment migrations by computing probabilities of belonging to each segment in the following period, given their current characteristics. We compute migration from unit i (where i=1,2,…,M) to segment s (where s=1,2,…,S) one period ahead using p_{is}(t+1):

$$p_{is}(t+1) = \frac{n_{is}(t+1)}{\sum_{s=1}^{S} n_{is}(t+1)}$$

where n_{is} is the number of customers migrating from unit i to segment s and t is a time coordinate. That is, the migration probability from unit i to segment s equals the number of customers switching from unit i to segment s divided by the sum of customer movements from unit i to every other segment. In a SOM model with four segments, this could in practice mean that for, say, unit 1 the probability of being in segments s=1,2,...,4 in period t+1 could be 0.5, 0.2, 0.2 and 0.1, respectively.

As the migration probabilities are associated to each of the units of the SOM model, they can be linked to the SOM visualization. Migration probabilities for units can be visualized on feature planes, where one unique point represents the same unit on the previously presented SOM grid. This shows the probability to migrate to a particular segment for each unit on own feature plane, such that the color code of each unit represents its probability to migrate to that particular segment. Thereby, the structure of the migrations between segments can be directly identified by studying the underlying migration probability feature planes.

2.3 Data

The data used in this study are from a department store chain that belongs to a large, multiservice Finnish corporation. Through a loyalty card system, the corporation provides customers with various discounts and rewards based on the loyalty points accumulated. Personal information about the cardholders is collected when they apply for the card, and their transactions are recorded in the system. The dataset containing a total of 1,271,433 customers was obtained through the loyalty card system. It contains aggregated sales information from all branches of the department store chain in Finland, for the period of 2007-09. Customers with spending amounts of less than 50 € in total from the department store chain during the two-year period were excluded from the dataset. The dataset consists of twenty variables that fall into three bases: *demographic variables*, *purchasing behavior variables*, and *product mix variables*.

The demographic variables show background data about the customers.

- Age
- Gender: 0 for male and 1 for female.

- Estimated probability of children: The higher the value of this variable is, the more likely there are children living in the household. The value ranges from 1 to 10.
- Estimated income level: The higher the value, the wealthier the household is considered to be. Possible values are 1, 2 and 3.
- Customer tenure: The number of years the customer has been a cardholder.

The purchasing behavior variables are summarized from a massive daily database to quarterly aggregates per customer. A level of aggregation on a quarterly basis was assessed to avoid or mitigate problems related to irregular short-term behavior and canceling fluctuations in behavior over time. Hence, each customer has eight corresponding records, i.e., one for each quarter during the period 2007-09.

- Basket size: Average number of items per transaction.
- Average item value: Average value per item purchased.
- Average transaction value: Average value per purchase transaction.
- Working time transaction: The percentage of purchases made during Mon - Fri, 9am – 5pm.
- Number of categories: Average total number of distinct product groups purchased in each transaction.
- Spending amount: Average daily spending amount.
- Purchase frequency: Average number of transactions per day.

The product mix variables measure the percentage of spending amount of each customer in each department during each quarter, i.e., the mix of products that they tend to buy. This set of variables enables us to identify the quarterly purchasing preferences of each customer.

3 A Framework for Customer Segmentation and Response Modeling

In this section, we discuss how we apply the database retrieved from a loyalty card system for a visual combined customer segmentation and response modeling approach. Figure 1 summarizes the entire process. First, the training data are created by integrating all the customer information, i.e., the demographic, purchasing behavior, and product mix variables. Customers are divided into distinct segments using SOM-Ward clustering, and the revealed segments are profiled with the help of feature plane visualization. The response modeling dataset is created by summarizing customer purchasing behavior and product mix patterns for the periods before and during the campaign. The response modeling dataset is applied to the customer segmentation model, i.e., each of the data records of the response modeling dataset is assigned to a best-matching unit on the customer segmentation model. The unit-to-segment migrations are computed and visualized using feature plane representations. Finally, by combining the information from the customer segmentation model and campaign response model, behavioral profiles of the campaign responders are created.

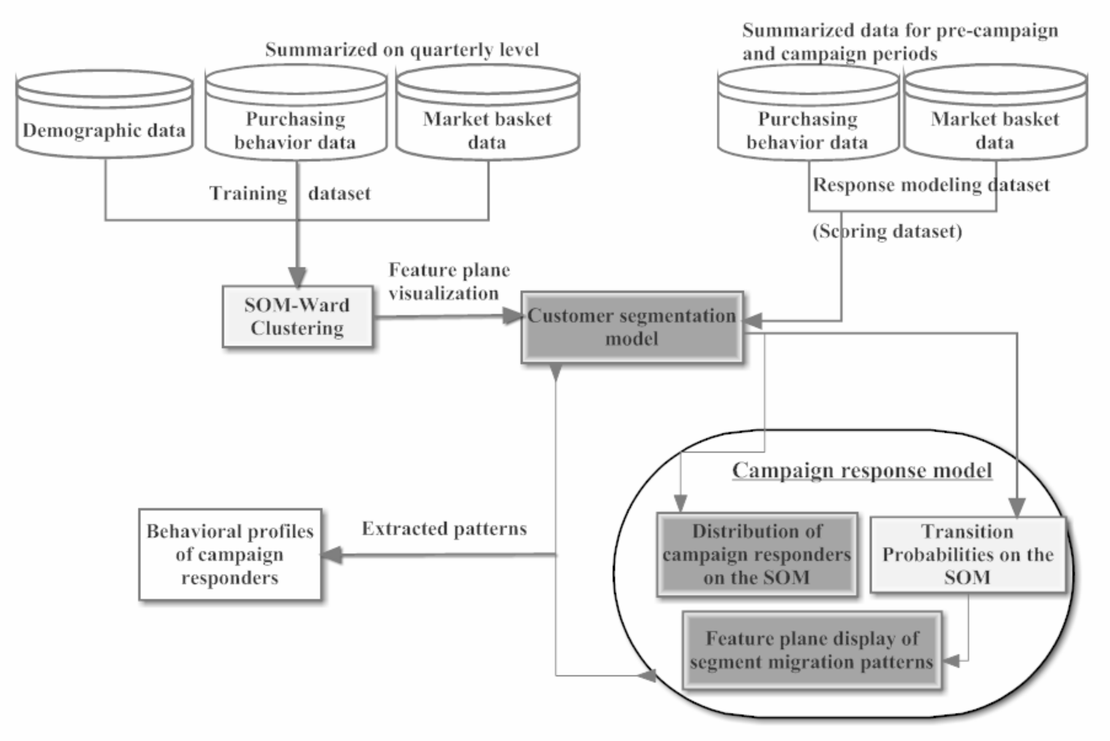


Figure 1. The customer segmentation and campaign response modeling approach used in this study.

3.1 Performing Customer Segmentation

The Viscovery SOMine package was used for computing the SOM model. Ward clustering was used to conduct two-level clustering on the SOM. This eliminates the need for subjective identification of clusters, as is needed when using the U-matrix method (Vesanto and Alhoniemi, 2000).

All the variables included in the training process were pre-processed using a z-score transformation in order to normalize their weight in training and post-processed in order to have original values when interpreting models. However, for normalizing the influence of categorical variables, their weights have been divided by the number of categories. For demographic variables not used in building the customer segmentation model, the weight is set to zero. They hence have no influence on training, but enable interpretation of the demographics of segments that are based primarily upon purchasing behavior. In addition to the facilitating heuristics provided by SOMine, the SOM has been parametrized to create a model suitable for both data and dimensionality reduction. In particular, for more detailed visualization, the number of SOM units is chosen to be larger than the expected number of customer segments. Then, a built-in heuristic indicator is used for finding the suitable number of customer segments through the second-level clustering in SOMine. The final SOM model has 76 units and 5 customer segments.

3.2 Performing Response Modeling

The sales campaign is an event of the department store chain, organized twice a year and lasting approximately one week at a time. Figure 2 shows the average daily revenue of the four campaign periods during the period 2007-09, as well as the rest of the pre- and post- campaign periods.

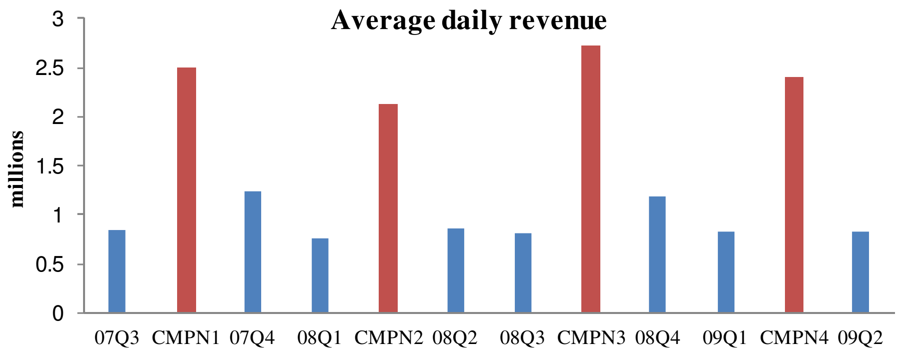


Figure 2. The average daily revenue per quarter and campaign period.

The response modeling dataset contains the same variables as the ones used for training the SOM model, i.e., the behavior and product mix variables introduced in section 2.3. We summarized each customer's purchasing behavior and product mix variables for each of the four campaign periods and their corresponding pre-campaign periods (i.e., 2007Q3, 2008Q1, 2008Q3 and 2009Q1). These data can be located to their best-matching units on the SOM model, and thus migration patterns can be computed. For a customer that made no purchases during a period, we assign a missing value for working time transaction.

4 Results and Analysis

In this section, we present the results of the study. First, we present the customer segmentation model created according to the framework in Figure 1. Then, we apply the response modeling approach and associate the results with the segmentation model.

4.1 Visual Customer Segmentation

The resulting SOM model consists of five segments (S1-S5). The feature planes (Figures 3-5) show the distributions of each variable across the map, on which the color scale visualizes the distribution of each variable over different segments, i.e., warm colors indicate high values and cold colors low values as described in Section 2.1. For example, the feature planes in Figure 4 show that high-spending customers can be found in S3, while the customers in S1 tend to buy products from a number of different categories. The key figures and important characteristics of each segment are summarized in Table 1. The table reveals that customers belonging to S3 are the most valuable customers, whose spending contributed to about 70% of the total revenue. They are a group of female customers who exhibit high spending amounts, purchase more items, and shop frequently. Customers belonging to S5 should draw management's attention. They are a group of relatively old, high-income male customers, who purchase expensive products, but shop less frequently than average customers. The customers belonging S2 are likely pensioners, who have time to go shopping during working hours. Customers belonging to the S1 and S4 are low-value customers for the company.

The feature plane representation and the table summarizing the key findings provide an overview of the customer value, shopping behavior, product preferences and demographics for each segment. However, this segmentation model is based on customers' characteristics during normal periods, and provides little information regarding their responsiveness to campaigns. In the following section, we will apply the framework introduced in Section 3, in order to link the information from the visual customer segmentation model and the campaign response model.

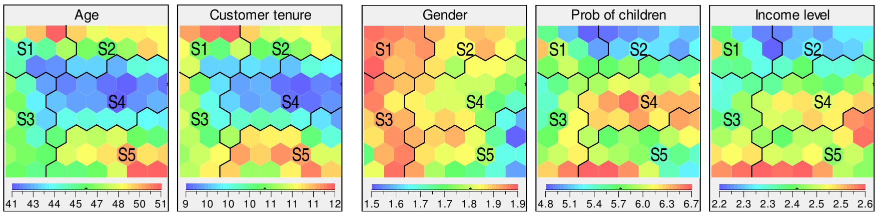


Figure 3. *Demographic profile.*

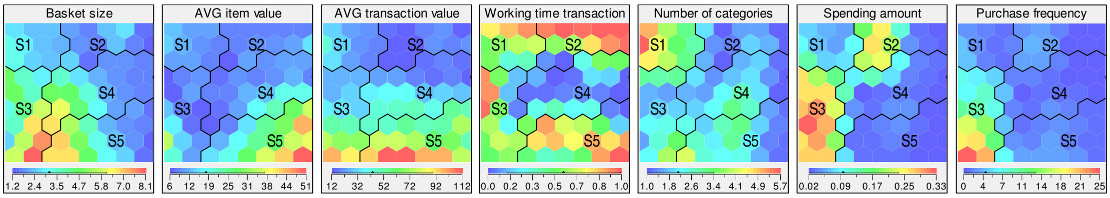


Figure 4. *Purchasing behavior profile.*

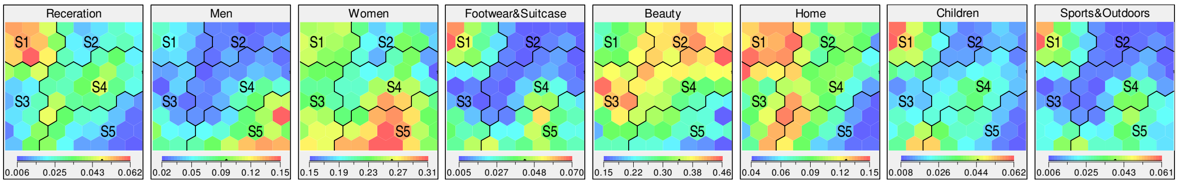


Figure 5. *Product mix profile.*

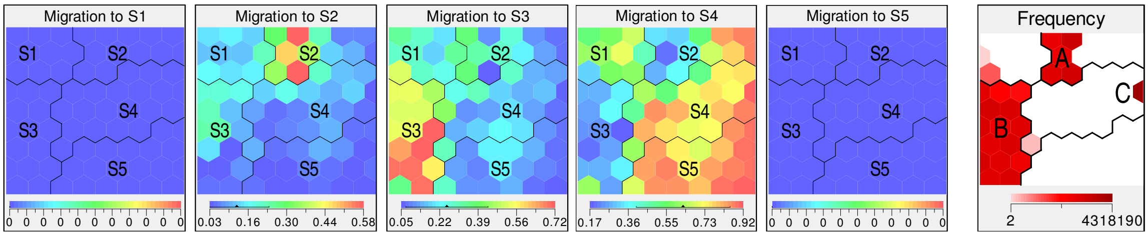
Segment Size (%)	**CTOR** (%)	**Behavioral Profile**	**Product Mix**	**Demographics**
S1 14	6.6	Purchase from different categories of products.	Recreation, footwear & suitcase, home, children, and sports & outdoors	Female customers with a low estimated income level.
S2 22	7.8	Most transactions were made during working time.	Beauty and home	Low probability of having children, low estimated income level, relatively old customers.
S3 16	69.7	High spending amount. High purchasing frequency. Large basket size.	No special product preferences.	Female customers with average demographic characteristics.
S4 21	4.0	Low value customers.	Recreation and beauty	High probability of having children, young and new customers.
S5 27	12.0	Purchase expensive items. High-value transactions.	Men, women, footwear & suitcase, and sports & outdoors	Relatively old, male customers with high estimated income level.

Note: Size refers to the percentage of all customers in the segment. CTOR refers to the contribution to the overall revenue, i.e., the proportion of revenue of the respective segment in the total revenue.

Table 1. *Segment profiles of the customer segmentation model.*

4.2 Visual Response Modeling

The response modeling is performed using migration patterns on the SOM. We compute unit-to-segment patterns and use feature plane representations for linking the visualization to the SOM segmentation. The segment migration patterns are shown in Figure 6, where the first five feature planes represent the per unit probability of moving to a particular segment. The last feature plane, i.e., the frequency picture, was created by projecting the data concerning only the campaign periods (i.e., excluding the pre-campaign data from the response-modeling dataset) to the customer segmentation model. The color shades on the last feature plane represent the number of data records matching each unit. The darker the red of the unit, the higher is the frequency of matches. Units with no matches are white.



Note: The color scales of the first five feature planes represent migration probabilities.

Figure 6. A feature plane visualization of segment migration probabilities and the frequency of migration patterns.

The analysis of segment migration on the SOM and the frequency of migration reveal several interesting patterns regarding the campaign-driven segment migration. S5 (i.e., the male customers who under normal campaign periods purchase expensive products) is the segment of customers that is least likely to be activated by the campaign, as is indicated by the warm color of the nodes of S5 on the fourth feature plane in Figure 6. Moreover, almost all customers in S1 and S5 changed their purchasing behavior and moved to other segments during the campaign period, as is indicated by the white area in S1 and S5 in the frequency map in Figure 6. Customers in the left part of S2 have high probabilities of staying in the same segment, i.e., do not change their regular behavior during the campaign. These customers display rather stable purchasing patterns, with low value but often recurring purchases, which continue even during the campaign. The customers in S3 are also stable, but display considerably higher value purchases. The rest of the customers tended to move to S4 during the campaign period. While the migrations on the SOM show the unit-to-segment patterns of the campaign effect, the frequency picture pinpoints the location each customer resides in during the campaign periods. The frequency picture reveals three categories of responses: Area A (left part of S2), B (S3), and C (one single unit in S4). Using the feature plane visualization of the customer segmentation model and the results of the response model, Table 2 summarizes the three types of campaign responses.

Categories	**CTSR (%)**	**Size (%) and Sources (No.)**			**Behavioral Profile**	**Product Mix**
A *Response*	9.2	5.5	Stay in: Migrate to: Migrate out:	1,411 1,417 282,659	Purchased small items during the campaigns.	Beauty and home
B *Response*	90.8	9.5	Stay in: Migrate to: Migrate out:	6,709 478,272 5,994	Made several shopping visits and purchased expensive items during the campaigns.	No particular preference of product.
C *No response*	0	85	Stay in: Migrate to: Migrate out:	1,977,075 2,340,516 200,152	Made no purchases.	None

Note: CTSR refers to contribution to segment revenue and size to the percentage of all response data.

Table 2. Customer profiles of the campaign response types.

Table 2 shows that customers already in or moving to S3 during the campaign account for 90.8% of the campaign revenue. Customers belonging to S3 have high probabilities of remaining in the segment during the campaign. An interesting pattern is that while there is migration from S3 to other segments during a campaign, very little is to the no response area C. This indicates that the customers in S3 are loyal, high-value customers. In addition to these customers, many customers in S1 also show high probabilities of moving to S3. Figure 4 indicates that these customers are characterized by the diversity of their market baskets, which can be seen as a sign of customer loyalty and high switching costs (Reinartz and Kumar, 2003). At the same time, significantly changing purchasing patterns as indicated by the shift to Segment three (area B) indicate a strong campaign response. Most of the customers in area A are the ones belonging to that area of the segmentation model, i.e., a sub-section of S2. These customers would also appear to be quite 'loyal', as very few of them change their behavior during the campaign. This loyalty is, however, of questionable real value as they exhibit very low spending amounts. The patterns provided by the model, while not being entirely unexpected, would provide the company with actionable information through a better understanding of profiles of the responders to this campaign, in particular when combined with a customer segmentation model.

5 Conclusion

In this paper, we have developed a framework for detecting changes in customer behavior during a sales campaign. For this purpose, we first divided customers into distinct groups based on purchasing behavior characteristics. The revealed segments were profiled using feature plane visualization. We then computed the unit-to-segment migrations by applying the customer segmentation model to the response modeling dataset. Finally, the segment migration patterns were visualized using feature plane representations.

We demonstrate the usefulness of the framework on a case company's customer dataset, containing more than one million customers. The result shows that the framework provides a holistic view of the patterns of customer purchase behavior and the underlying dynamics, and it enables the efficient identification of campaign-driven segment migration patterns and within-segment heterogeneity in terms of campaign response propensity. Additionally, the integration of customer segmentation, campaign response and segment migration modeling provides decision makers with an effective analytical CRM for better campaign management. Future work should focus on addressing the changing nature of customer segments by attempting visual temporal clustering, something that the Self-Organizing Time Map (Sarlin, 2011) holds promise for.

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