Intelligent Decision Making for Customer Dynamics Management Based on Rule Mining and Contrast Set Mining

A Segmentation Analysis Perspective

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Abstract In real world situations, customer needs and preferences are changing over time and induce segment instability. The aim of this paper is to explore the patterns of customer segments' structural changes. This study examines how businesses can gain better insight and knowledge through using data mining techniques to support intelligent decision making in customer dynamics management. Up to now, no attempt was done to describe and explain segments' structural changes or to investigate the impact of customer dynamics on these changes. In this paper, a general method is presented based on rule mining and contrast set mining to describe and explain this issue. This method provides explanatory and predictive analytics to enlarge the opportunities for intelligent decision making in this area. The method is implemented on two different data sets for more generalizability. The results show that the method is capable in this domain. Based on the findings, a new concept is developed in the domain of customer dynamics as "structure breakers" that represents a group of customers whose dynamic behavior causes structural changes. The results provide knowledge through some if-then rules which would improve the decision making ability of marketing managers.

Keywords Customer segmentation · Structural changes · Data mining · Sequential rule mining · Contrast set mining · Intelligent decision making

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1 Introduction

With the advent and growth of information technology, intelligent decision making has reached greater significance and has proved to have a particularly large potential in many administrative, social, economic, business and medical issues. Intelligent Decision support systems (IDSS) are a specific class of computerized information systems that support business and organizational decision making activities. Intelligent expert systems, rule-based systems and business intelligence tools are some examples. These systems are developed with the goal of guiding users through some of the decision making phases and tasks [1–4].

On the other hand, data mining technology extends the possibilities for intelligent decision support by discovering and extracting hidden patterns and knowledge in data through an inductive approach. Data mining techniques are capable in analyzing a large amount of data to extract useful knowledge, and introduced as an important component in designing intelligent decision support systems (IDSS) [3, 5]. In this regard, this paper examines how data mining technology can support intelligent decision making and can enlarge the opportunities for intelligent decision support systems in customer relationship management (CRM).

The competitive business environment is continuously changing over time and forces companies to analyze and understand customer needs, preferences and behavior [6–8]. Organizations need to have a deeper understanding and more complete view of customer behavior in order to gain a competitive advantage. One of the most important issues that should be considered while analyzing customer behavior is "customer dynamics" [9–14]. Actually, in today's competitive business environment, customer behavior is often complex and uncertain. In fact, because of the influence of psychosocial and environmental factors, customer behavior and preferences are changing over time. Facing such a dynamic situation, it is necessary to understand the changes of customer behavior and consider this dynamism in different business-related activities to develop effective marketing strategies [15–18].

One of the most important and strategic marketing activities that should be conducted by considering the dynamic nature of customer behavior, is customer segmentation. In fact, in real world situations, customer needs and preferences are changing and induce segment instability [9–12, 14, 16]. Based on [14, 18], customer segments can change in several ways over time. New segments can appear, disappear, merge, move, shrink or grow. The focus of this paper is on the changes in the type and composition of segments. These changes are very important and introduced as segments' structural changes. For example, a segment may disappear over time; conversely, a new group might appear. Two segments can be merged into one group or a segment may split into two or more ones [19].

This paper focuses on analyzing dynamic customer behavior and investigating its impact on segments' structural changes. This study examines how businesses can gain better insight and knowledge through using data mining techniques to support intelligent decision making in customer dynamics management. This paper is a revised and extended version of our paper [20] published in IRI 2015. The main aim is to explore the patterns of customer segments' structural changes. The main question is how and in which manner segments' structural changes occur. In other words, are there any patterns or trends that can describe the structural changes? We answered to these questions in our paper [20] published in IRI 2015. Our suggestion was to use the sequential rule mining technique to extract such patterns and trends.

These rules can provide us with a good insight about patterns of segments' structural changes. Furthermore, one of the main advantages and benefits of such rules is to support intelligent decision making which is discussed in the current paper. The intelligent agents and systems usually rely on a knowledge base containing a set of rules. Accordingly, the focus of this study is to present a general method to provide knowledge through some if-then rules to support intelligent decision making for customer dynamics analytics and management. This method provides explanatory and predictive analytics to enlarge the opportunities for intelligent decision making in this area. The method is developed based on data mining techniques including rule mining and contrast set mining.

Up to now, there has been no research on describing and explaining the manner of segments' structural changes. The researches have been conducted, extracted only the types of segments over time to see if there is any change or not. No attempt was done to describe and explain the structural changes or to investigate the impact of dynamic customer behavior on segments' structural changes. As the best of our knowledge, our research is the first to develop a general method based on rule mining techniques to approach this problem. A new concept is also developed in this study in the domain of customer dynamics as "structure breakers". We implement our method on two different data sets to validate this concept and the proposed method. This would allow for more generalizability of the new concept and method.

The structure of the paper is as follows: In Sect. 2, the related literature is briefly reviewed. Section 3 explains the proposed method. The analysis of results is presented for two different data sets in Sect. 4. Section 5 discusses the potential usefulness of results in intelligent decision making. Finally, Sect. 6 deals with the conclusion.

2 Literature Review

2.1 Customer Relationship Management

Customer relationship management (CRM) has been identified as an important business concept. All of the existing definitions consider it as a comprehensive process of acquiring and retaining customers integrating with business intelligence concepts in order to maximize the customer value [6, 18, 21].

CRM cycle includes four dimensions: customer identification, customer attraction, customer retention, and customer development. This cycle begins with customer identification that has two elements: "customer segmentation" and "target customer analysis" [10, 14]. Accordingly, customer segmentation has critical importance as the first phase of CRM process [6, 22].

2.2 Customer Segmentation

Customer segmentation is introduced as a strategic marketing and CRM activity [6, 23]. It is defined as the process of dividing customers into distinct and meaningful groups of homogeneous customers. It helps companies to build differentiated and adopted strategies according to each group's characteristics and to identify the most profitable group of customers [6, 24].

One important issue in customer segmentation is the criteria and attributes on which segmentation is performed. The RFM (Recency, Frequency and Monetary) model is a common and well-known method for customer segmentation. RFM values are defined as follows:

- R stands for "Recency" and relates to the time of the last purchase. This attribute shows the time interval between the last purchase and the target time of analysis;
- F represents "Frequency", indicating the number of purchases in a particular period; and
- M stands for "Monetary", showing the consumption of money during a certain period

A segment of customers with higher values of "Frequency" and "Monetary" and lower value of "Recency" is considered as the most valuable group [25].

Reference [26] proposed TFM model for customer segmentation in telecommunication industry based on RFM model. Time and frequency respectively, show the "average time" and "frequency" of using application services. Monetary indicates the total amount generated for using different application services. As telecommunication applications users may subscribe to applications every few minutes, the Recency variable is not meaningful in these cases. It has proved that heavy and valuable customers in telecommunication industry are the users who accumulate a greater volume of service time (T), purchase services frequently (F) and amass large billing amounts per month (M) [26].

2.3 Segment Instability

In real world situations, customer needs and preferences are changing over time and induce segment instability [9–12, 14, 16]. Tracking the changes of customer segments is very important for companies to develop effective marketing strategies [27].

Reference [19] can be considered as the major study in this field that addressed comprehensively the issue of dynamic segments in a review work. The basic related theories are conceptually explored and a comprehensive review of literature is performed [18]. It is notable that the focus of this study is on segment instability in business-to-business markets. The authors defined segment instability as below:

"Segment instability refers to a state of change in customers' needs and what they value within identified market segments, as well as changes in segment membership, as triggered by internal to the customer and external to the customer change drivers, and reflected by changes in segment contents and segment structure".

One important issue emphasized in this paper is investigating the relation between customer value change and segment instability. Developing tools that are capable of forecasting the direction of segment changes integrating the theories of customer value was recommended by these researchers.

Reference [10] also discussed the changing customer needs from the view point of product development in a review research. They discussed different related subjects including segment instability that was extensively documented. Some other researchers, who have empirically investigated segments' changes, are [9, 14, 27]. They have used the frequent item sets and association rule mining to mine the changes of segments [18].

Investigating the published papers show that most of them have considered only the content changes of segments. However, in real world situations, segments can change in several ways: new groups can appear, disappear, merge, move, shrink or grow over time [14, 18]. Accordingly, one of the challenging research areas can be modeling the complex nature of structural changes of segments. The researches have been conducted in this domain, extracted only the types of segments over time to see if there is any change or not. No attempt was done to describe and explain the structural changes.

2.4 Intelligent Decision Support Systems

Intelligent Decision support systems (IDSS) are a specific class of computerized information systems that support business and organizational decision making activities. These systems are developed with the goal of guiding users in some of the decision making phases and tasks. Intelligent expert systems, rule-based systems and business intelligence tools are some examples [1–4]. The use of intelligent decision support systems allows to decrease the time for decision making and to improve the quality and efficiency of decisions [28].

An IDSS has a data base, knowledge base, and model base. This paper is related to the knowledge base as a key component in these systems. The knowledge base holds problem knowledge, such as guidance for selecting decision alternatives or advice in interpreting possible outcomes. A large number of applications of IDSSs are based on the knowledge bases which have capabilities to maintain information and knowledge in the form of rules (i.e. if-then rules, decision trees etc.). If information about different scenarios is stored in these systems, it can provide a basis for taking any suitable action in many unexpected circumstances [1, 28, 29].

2.5 Clustering

Clustering is an unsupervised data mining method that divides data into groups such that the objects in each cluster are very homogenous but dissimilar to the objects in other clusters [30]. We use the K-means algorithm in this study which is the most common clustering method for customer segmentation.

This algorithm firstly selects K objects randomly as the initial centers of clusters. Next, the remaining objects are assigned to the closest clusters based on the distance between the object and the center of cluster. Then, the update and assign steps are run repeatedly until the criterion function converges [30].

We use the Davies–Bouldin index for clustering validation in this study. It is one of the most popular indexes and considers both the cohesion and separation concepts [19]. The value of K that minimizes this index is selected as the optimal number of clusters. This index is calculated as the following:

$$DB_{nc} = \frac{1}{n_c} \sum\nolimits_{i=1}^{n_c} R_i \tag{1}$$

$$R_i = \max_{i=1,\ldots,n_n, i \neq j} R_{ij}, \tag{2}$$

$$\mathrm{R_{ij}} = (S_i + S_j)/d \tag{3}$$

R_{ij} is a similarity measure between cluster C_i and C_{j}. S_i and d_{ij} are two measures for the dispersion of a cluster and the dissimilarity between two clusters, respectively [31].

2.6 Sequential Rule Mining

Sequential pattern mining which extracts the frequent subsequences in a set of sequences was first proposed by Agrawal and Srikant (1995) [32–34]. This technique is not able to make predictions. To overcome this shortcoming, the sequential rule mining technique is developed that can address the prediction issues [33].

A sequential rule is an expression of the form X→Y with two measures including support and confidence. This rule indicates that if event X occurs, event Y is likely to occur following the occurrence of X with high confidence or probability. The support and confidence measures are used to quantify the significance of the rule. The support implies the probability that the rule may occur in the sequence database. The confidence indicates the support of the rule over the support of the antecedent (X). When sequential patterns are extracted, sequential rules can be generated by using a minimum confidence threshold [33, 35].

In this paper, we use the generalized sequential pattern (GSP) algorithm, which is a basic and well-known sequential pattern mining technique. It is the generalized form the algorithm proposed by [32]. The priority and advantage of this algorithm is considering time constraints and sliding time window. This algorithm adopts an Apriori-like candidate set generation-and-test approach consisting of two main phases: candidate generation and support counting. In the first pass, all frequent single items (1-sequences) are extracted. The candidate 2-sequences are then formed based on these single frequent sequences. After calculating the support of these candidates and selecting the frequent ones, the candidate 3-sequences are generated, accordingly. This process is repeated until no more frequent sequences are found [18, 36–39].

2.7 Contrast Set Mining

A special data mining task which is developed to find differences between contrasting groups is contrast set mining [40]. Comparing groups to find differences between them can be very useful in many applications [39]. Contrast set mining can be performed by using different techniques; for example decision tree induction, rule learning and mining frequent item sets [40]. In this paper, we use distinguishing sequential rules and emerging patterns that are explained in the following two sub-sections.

Distinguishing sequential rules.

There are four types of distinguishing sequential patterns: site-characteristic, site-class-characteristic, class-characteristic and surprising. This paper is in the domain of the third type. In this field, a distinguishing sequential rule is defined as below based on [18]:

"Given two sequence sets A and B, a distinguishing sequential rule contrasting A from B, is a strong rule from A that does not match with the sequences of B with high strength. In other words, the sequences of B do not approve the occurrence of this sequential rule; in fact, this rule would be considered as a weak rule in B. The strength and interestingness of such rules change significantly from one group of customers to another."

These rules are helpful for mining useful contrast knowledge and also for prediction purposes [18, 34]. Reference [18] presented a framework for finding minimal distinguishing sequential rules as below:

"Given two groups of sequences pos (positive) and neg (negative), two support thresholds α_1 and α_2 ($\alpha_1 < \alpha_2$), and three confidence thresholds β_1, β_2 and β_3($\beta_1 < \beta_2 < \beta_3$), a sequential rule (r) is defined as a minimal distinguishing sequential rule if and only if the following conditions are satisfied:

- **High strength condition**: $r \in L$ where L is the set of top-k sequential rules of positive group that are extracted based on the following definition proposed by [41]. The min confidence is set equal to β_2.
  Reference [41] defined mining top-k sequential rules as "discovering a set L containing k rules such that for each rule $r_m \in L$, $conf(r_m) \geq$ min conf and there exists

no rule $r_n \notin L$ such that $\sup(r_n) > \sup(r_m)$ and $\mathrm{conf}(r_n) \geq$ min conf. In fact, k rules are discovered that have the highest support such that their confidence is higher than the confidence threshold.

- **Low strength condition**: conf_{neg} (r) $< \beta_1$ or supp_{neg} (r) $< \alpha_2$
  Each of the above two options indicates low strength condition. In each case, we face a weak rule with low strength and poor reliability. In the first one, we consider only the confidence threshold, because the rules with low confidence are poor, even if their support is high. The rules with supp_{neg} (r) $< \alpha_2$ are considered as weak rules with one exception mentioned in Note 1.
- **Non-redundancy condition**: r is a Non-redundant rule.
  Assume r and r′ are two rules with the same support and confidence values that satisfy the above both conditions. Sequential rule r: $a \rightarrow b$ is redundant with respect to another rule r′: $a' \rightarrow b'$ if and only if it can be inferred by rule r′. In other words, rule r is redundant if and only if conf (r) = conf (r′) and supp(r) = supp(r′) and $a' \subseteq a$ and $b \subseteq b'$.
  The redundancy condition was derived from [41, 42] that discussed the non-redundant sequential rules.

Note1: The mentioned exception in low strength condition is the rule satisfying both $\alpha_1 \leq \mathrm{supp}_{neg}$ (r) $< \alpha_2$ and Conf_{neg} (r) $\geq \beta_3$ conditions, because the rules with low support and very high confidence are often interesting and provide new insights. Actually, these rules indicate small groups in the negative group that behave the same as the positive group members with a high confidence. Obviously, this affects the strength of distinguishing rules and may reduce the accuracy of decisions and predictions. The minimum threshold (α_1) for supp_{neg} is considered to remove the rare items that may be noise or outliers.
Note 2: Considering that time constraints are essential to find more interesting rules and to efficiently aid decision making [37], we suggest these constraints for mining distinguishing sequential rules".

Emerging patterns.

Emerging patterns are defined as item sets whose support values change significantly from one data set to another. They can be used to find the emerging trends in time stamped databases or to extract useful and interesting contrasts between different classes and groups [9, 43]. Emerging patterns cover a wide range of techniques including decision tree, frequent item sets, association rules, classifiers and etc. The main idea is comparing two sets of patterns from two splits of data [14, 43].

Emerging patterns can be defined based on [43, 44] as below:

Rule r_j^{t+k} is called an emerging pattern with respect to rule r_j^t, if the following two conditions are met:

1. The antecedent and consequent parts of the rules r_j^{t+k} and r_j^t are the same.
2. Supports of two rules are significantly different.

3 The Proposed Method

The aim of this study is to present a general method to explore the patterns of customer segments' structural changes and to provide knowledge to support intelligent decision making for customer dynamics management in segmentation analysis.

The proposed method is developed based on clustering, distinguishing sequential rules and emerging patterns. This method includes 6 main steps. These steps are explained in details below:

Step 0: **Data collection and preprocessing**.

This step includes data collection and preprocessing which is discussed in details later.

Step 1: **Detecting customer segments in each period and identification of structural changes**.

This step includes three sub-steps as follows:

1. Clustering the customers based on TFM/RFM model in each period
   Firstly, customer segments are identified in each period by using the K-means algorithm. It is notable that the initial centers influence the results of the K-means algorithm. In this regard, the initial centers are selected randomly in this paper which is the common approach to choose the initial centroids. One technique that is commonly used to address the problems of choosing initial centroids by random is to perform multiple runs with a different set of randomly chosen initial centroids and selecting the set of clusters with the minimum SSE or Davies–Bouldin [30]. Accordingly, we performed the algorithm 70 runs with a different set of randomly chosen initial centroids for each K to select the optimum clusters. Normalizing the TFM/RFM attributes is performed by the Min-Max normalization method. The Davies–Bouldin index is used for the evaluation of the clustering results.
2. Analyzing and labeling the clusters
   Analyzing and labeling the clusters are performed based on the model proposed by [30] in the following manner:
   The average of T/R and F variables in each cluster are calculated and compared with their total average of all customers in the corresponding period. If the average of T/R (F) variable in a cluster is greater or less than the overall average T/R (F), the High (H) or Low (L) label is assigned to the corresponding variable, respectively. For the M variable, three labels are considered including High1 (H1), High2 (H2) and Low (L). The thresholds for the monetary categorization were chosen based on the first 20 and 30 % of customers with higher values of monetary [16]. We also assign the label "Inactive" to a customer when he/she does not have any transactions during a period.
3. Identification of structural changes
   The identification of structural changes is performed by comparing the types of segments obtained in different periods.

Step 2: **Extracting the transition sequences**.

In this step, an individual sequence is built for each customer indicating the history of his/her membership to different segments over time. We name this sequence as "transition sequence". In this step, the transition sequences of all customers are extracted.

Step 3: **Categorizing the transition sequences of dynamic customers into two groups**.

In this step, the corresponding transition sequences to dynamic customers are selected, firstly. Dynamic customers are those who do not remain stable or relatively stable in one specific segment over time. Then, these sequences are classified into two groups. The first group includes the transition sequences indicating the identified structural changes. The transition sequences that include at least one state referring to the structural changes are assigned to this group. The remaining sequences are considered as the second group.

Step 4: **Mining the distinguishing sequential rules of each group**.

In this step, the distinguishing sequential rules of each group are extracted. To mine the sequential rules, the sequential patterns are firstly extracted by using the GSP algorithm. The sequential patterns are the ones that satisfy the minimum support threshold and time constraints on the minimum and the maximum gap between two adjacent items. Then, sequential rules are extracted from the set of obtained sequential patterns by using a minimum confidence threshold. To find the distinguishing sequential rules, the framework of [18] is used.

In fact, there may be some identical and similar patterns relating to these two groups which cannot provide any additional and special information about them. In other words, this kind of rules cannot indicate the differences between the customers' behavior of two groups and are not able to classify them. In contrast to these rules, there may be some distinguishing rules that differentiate these two groups from each other. These sequential rules capture what makes one group different from another one and indicate their special characteristics. They can be also used for prediction purposes.

In this step, by analyzing the rules of the first group that relates to identified structural changes, we can understand how these changes occur. In other words, these rules are representing the patterns of structural changes. The distinguishing rules of the second group help us to understand the behavior of the customers of this group and the difference between these two groups better. In fact, we obtain three categories of rule: rules that distinguish group 1 from other customers, rules that differentiate the second group from the first one and identical rules between two groups. These three groups of rules firstly provide the marketing managers with a good insight about the behavior of dynamic customers. Second, these rules can be very helpful for prediction purposes and help the marketing managers to classify a new customer into these two groups and to predict his/her behavior.

Step 5: **Mining emerging patterns in each group**.

In this step, we try to find the contrast characteristics of these two groups by using the definition presented in Sect. 2.7 and mining the frequent item sets. At this stage, different characteristics of customers depend on the type of case and the aim of study can be used. In this paper, we use the demographic features which are available such as age, gender and etc. Based on the results of the previous step, a group of customers is identified as "structure breakers" whose behavior causes structural changes. The other group is named as "non-structure breakers". This group includes dynamic customers who switch between different segments over time but do not cause any structural changes. The aim of this stage is to find the characteristics that differentiate "structure breakers" from "non-structure breakers" or vice versa by mining the frequent item sets of these two groups and finding the contrast sets. If the difference between the support values of a frequent set in two groups is more than α, this frequent set is detected as a contrast set. The parameter α is set by the user. The obtained knowledge of this step can be very helpful for intelligent decision making.

4 Results

Here, we present the implementation of the proposed method and analysis of results. Firstly, we discuss the results of dataset 1 in details. Next, the results analysis of data set 2 is presented more briefly.

4.1 *Results Analysis of Data Set 1*

Data collection and preprocessing.

Among different businesses, the telecommunication industry and specially the mobile telecommunication are the best examples of a dynamic market; the customer behavior is very dynamic and complex in this industry. In this regard, we implemented our method on a data of a telecommunication service provider, firstly.

The data source has been the database of this company. It includes approximately 150 fields and 400 million records for three years. These fields provide us with detailed information about the usage of different services by customers; we know that each customer used which kinds of services, when and in what amount. The duration of using every service and obtained monetary value are available. The discount amount for using each service is also identified.

The target population was selected randomly composed of 165,800 customers. In this step, the data preprocessing was also performed including handling noise and missing values, deleting duplicate data, and feature selection.

Detecting customer segments in each period and identification of structural changes.

The data includes 18 two-month periods. The length of time window to analyze the users' usage in this company was set to two months. Customer segments were identified in each period by using the TFM model and K-means algorithm. The Davies–Bouldin index was used to find the optimum number of clusters; the K values of 2–12 were tested in each period.

It is notable that finding the best moment to perform a new analysis is very important and challenging. Selecting the time intervals and the length of time window depend on the type of business and the specific case study. Some businesses are very dynamic and changing very rapidly over time while some are not. The experts' opinion and domain knowledge can be also very helpful to find the best moment. As mentioned above, the time window is set to two months in this paper; because this company analyzes the users' usage every two months. This relates to the characteristics of business and the dynamic nature of customers' behavior in this area. Furthermore, these two-month periods are meaningful based on cultural issues and special events in the related country that affect customer changing behavior.

Based on the results, six different groups of customers were obtained during 18 periods including HHH1, HHH2, HLH2, LHH2, HLL and LLL. For example, label LHH2 implies a group of customers with a lower average of T and greater average of F comparing to the total average. The average of M variable for these customers has been between the average of this variable for the first 20 and 30 % of customers. Or segment HLH2 indicates a group of customers with a greater average of T and lower average of F comparing to the total average. The value of M variable for these customers is the same as segment LHH2 which explained above.

The clustering results of the second period are shown as sample in Table 1. Cluster_0, cluster_1 and cluster_2 are described as LLL, HHH2 and HHH1, respectively.

Table 2 shows the structure of segments over 18 periods. Value 1 indicates that the segment appeared in the corresponding period, while a zero value shows that it did not appear.

As shown, segments HHH1, HHH2 and LLL appeared in all periods. Segment LHH2 was present only three times. Segment HLH2 and HLL were created and stabled after the seventh and twelfth periods, respectively. Accordingly, the main structural changes occurred during the 18 periods include creating segments HLH2 and HLL.

Table 1 The centers of clusters (T_2)

ID	Cluster	T_Mean	F_Mean	M_Mean	Number of customers
1	cluster_2	93.90	2715.29	1114845.55	13,270
2	cluster_1	78.12	1053.77	460211.51	45,620
3	cluster_0	70.86	289.28	145947.09	99,088

Table 2 The structure of segments over 18 periods

Period	Segment					
	HHH1	HHH2	LLL	HLH2	LHH2	HLL
T_1	1	1	1	1	1	1
T_2	1	1	1	0	0	0
T_3	1	1	1	0	0	0
T_4	1	1	1	0	0	0
T_5	1	1	1	0	0	0
T_6	1	1	1	0	0	0
T_7	1	1	1	1	1	1
T_8	1	1	1	1	0	0
T_9	1	1	1	1	0	0
T_{10}	1	1	1	1	0	0
T_{11}	1	1	1	1	0	0
T_{12}	1	1	1	1	0	1
T_{13}	1	1	1	1	1	1
T_{14}	1	1	1	1	0	0
T_{15}	1	1	1	1	0	1
T_{16}	1	1	1	1	0	1
T_{17}	1	1	1	1	0	1
T_{18}	1	1	1	1	0	1

It is notable that the structure of segments in periods 1, 7 and 13 are the same and different from their neighbor periods. This is because of the changes in customers' behavior in these three periods relating to a specific holiday. Based on the marketing experts' opinions of this company, most of customers use services for their businesses; so, their behavior changes in these periods. Hereafter, we do not consider these three periods in our analysis; because the corresponding structural changes relate to a special reason.

Extracting the transition sequences.

In this step, the transition sequences of all customers were extracted. Six samples are shown in Fig. 1.

Categorizing the transition sequences of dynamic customers into two groups.

In this case, we defined the "static customer" and "dynamic customer" as below.

A customer is a "static customer" if he/she remained in one segment at least 13 times over 15 periods; otherwise, the customer is dynamic.

Accordingly, 44,462 customers were identified as "dynamic customers". The number of the transition sequences indicating the identified structural changes was equal to 22,037. The remaining sequences composed of 22,425 records were considered as the second group.

LLL→ LLL → Inactive → LLL→ LLL→ LLL→ LLL→ LLL→ LLL → LLL→ LLL→ LLL→ LLL→ LLL→ LLL
HHH2→ HHH1→ HHH2→ HHH2→ HHH2→ HHH2→ HHH2→ LLL→ LLL→ LLL→ LLL→ LLL→ LLL→ LLL→ LLL
HHH2→ HHH1→ HHH2→ HHH2→ HHH2→ LHH2→ HHH2→ HHH2→ HLH2→ HLH2→ HLH2→ HLL→ HLL→ HLL→ HLL
HHH2→ HHH2→ LLL→ LLL→ LLL→ LLL→ LLL→ LLL→ LLL→ LLL→ LLL→ LLL→ LLL→ LLL→ LLL
HHH1→ HHH1→ HHH1→ HHH1→ HHH1→ HHH1→ HHH1→ HHH1→ HHH1→ HHH1→ HHH1→ HHH1→ HHH1→ HHH1→ HHH1
HHH2→ LLL→ LLL→ HHH2→ LLL→ LLL→ LLL→ LLL→ LLL → HLH2→ LLL → HLH2→ HLH2→ HLL→ HLL

Fig. 1 Samples of transition sequences

Mining the distinguishing sequential rules of each group.

To find the distinguishing rules, the proposed framework in Sect. 3 step 4 was used by the following parameters:

$\alpha_1 = 1\,\%, \alpha_2 = 4\,\%, \beta_1 = 50\,\%, \beta_2 = 70\,\%$ and $\beta_3 = 90\,\%$.

There are 92 rules that distinguish these two groups from each other. 48 rules belong to the first group and 52 rules relate to the second group. 27 rules are identified as "not-distinguishing" rules. Seven samples are shown in Table 3. The last two rows show 2 samples of not-distinguishing rules. In these two cases, the support and confidence values for the both groups are shown.

For example, the second rule implies a group of customers who were in segment HHH2 and then migrated to HLH2. In fact, the frequency variable of these customers decreased over time and led to create a new behavioral pattern with H, L and H2 values for T, F and M variables, respectively. This new behavioral pattern formed segment HLH2. In other words, the changes in the behavior of these customers caused to form a new segment named in HLH2.

In this section, we analyzed all the obtained distinguishing and not-distinguishing rules. Accordingly, two groups of customers are identified as "structure breakers" and "non-structure breakers" as the following:

"**Structure breakers**": There is a group of customers whose behavior and the dynamism of their behavior caused to form segments HLH2 or HLL. We name these customers as "structure breakers".

The analysis of obtained rules indicates two groups of customers whose changing behavior causes to form segment HLH2: The customers with a high relative stability in segment HHH2 and a group of customers with a high relative stability in segment LLL. The first group includes the customers whose behavior also causes creating segment HLL. In fact, when the frequency variable of these customers decreases, the monetary variable will fall after some periods. The second group contains the customers whose average time of using services and monetary values increased over time.

Table 3 Distinguishing and not-distinguishing rules

ID	Group	Antecedent	Consequent	Rule support (%)	Confidence (%)
1	Group 1	HHH2 then HHH2 then HHH2 then HHH2 then HLH2 then HLH2 then HLH2 then HLH2 then HLH2	HLL	15.62	80.95
2	Group 1	HHH2 then HHH2 then HHH2 then HHH2 then HHH2 then HHH2 then HHH2 then HHH2 then HHH2 then HHH2 then HHH2 then HLH2	HLH2	9.08	95.81
3	Group 1	HHH1 then HHH1 then HHH1 then HHH2 then HHH2 then HHH2 then HHH2	HHH2	5.48	85.92
4	Group 2	HHH2 then HHH2 then HHH2 then HHH2 then HHH2 then HHH2 then LLL then LLL then LLL	LLL	36.96	71.68
5	Group 2	LLL then LLL then LLL then Inactive then LLL then LLL then Inactive then Inactive then Inactive	Inactive	15.05	90.45
6	Not-distinguishing	HHH2 then HHH2 then HHH2 then HHH2 then HHH2 then HHH2 then HHH2 then HHH2	HHH2	31.28	89.14
				39.72	91.27
7	Not-distinguishing	LLL then LLL then LLL then LLL then LLL then LLL then LLL	LLL	16.31	70.04
				22.47	81.23

Distinguishing rules of the structure breakers show that all the customers with a high relative stability in segment HHH2 are not structure breakers. But, the customers who were firstly in segment HHH1 and then migrated to HHH2 are structure breakers with a high confidence. These customers will migrate to segment HLH2 and then HLL over time. The customers, who shift between segments HHH1 and HHH2 with a higher relative stability in HHH2, also follow this behavior. These rules help us to detect the structure breakers more accurately. If a customer behavior is similar to these patterns, he/she will be a structure breaker with high probability. It is notable that every customer who belongs to segment LLL with a high relative stability, may be a structure breaker or not.

"**Non-structure breakers**": The obtained rules from the second group imply another group of dynamic customers who switch between different segments over time but do not cause any structural changes. We name this group as "non-structure breakers". Analyzing the distinguishing sequential rules of these customers indicate three sub-groups: a group of customers who were relatively stable in segment LLL and sometimes migrated to the inactive status; these customers finally churned. The second group includes the customers who switched between segments HHH2 and LLL with a higher relative stability in segment HHH2, but finally migrated to LLL. The third group of customers was in segment HHH2 and then migrated to LLL over time.

Mining emerging patterns in each group.

In this step, we tried to find the contrast characteristics of "structure breakers" and "non-structure breakers" by using the method presented in Sect. 3 step 5. We had access to four attributes of customers including age, gender, job and geographical region. For the age variable, we defined five categories based on the experts' opinions of this company. The job attribute is also classified into three categories: "jobless", "private jobs" and "governmental jobs". The minimum support to find the frequent item sets was considered equal to 5 %. The parameter α was set to 20 %. The extracted contrast frequent sets are shown in Table 4.

Based on the experts' opinions of this company, the first contrast set of "structure breakers" which is shown in the first row of Table 4, implies the students who partially churned to one of competitors because of special promotions that were launched

Table 4 Contrast frequent item sets of "structure breakers" and "non-structure breakers"

ID	Group	Frequent item set	$\text{Support}_{\text{structurebreakers}}$ (%)	$\text{Support}_{\text{non-structurebreakers}}$ (%)
1	"Structure breakers"	18 <= Age < 25 and Job = jobless	54.37	29.41
2	"Structure breakers"	45 <= Age < 60 and Job = "private jobs" and Gender = "male"	8.43	–
3	"Non-structure breakers"	Age >= 60	1.52	23.76

by that company. This frequent item set is probably related to the customers who migrated from HHH2 to HLH2 and HLL. The experts of this company believe that the second frequent item set refers to the men who use the services for their job; they are the customers who migrated from HHH1 to HHH2. It is notable that the difference between the support values of this frequent set is less that 20 %. As the support of this frequent set for "non-structure breakers" is too low, we considered this item set as a contrast one. We run the algorithm by a minimum support of 1 %; accordingly, the support of this frequent item set in "non-structure breakers" group is surely less than 1 %.

The third contrast set implies that 23.76 % of "non-structure breakers" are older than 60 years old. Based on the experts' opinions, these customers use these types of services infrequently, not only the services of this company. In other words, the demand for using these services decreased gradually over time in this group. Based on the obtained rules of "non-structure breakers", these customers migrated from HHH2 to LLL or from LLL to inactive status that admits this idea. The obtained contrast sets can be used to improve marketing decisions; they can be also implemented for prediction purposes to predict the behavior of a customer based on his/her characteristics.

4.2 Results Analysis of Data Set 2

We applied the proposed method on the customer data of a private bank. The related data contains detailed information about customers' transactions during two years including these attributes: customer ID, date, type of product/account, amount, channel and branch. 20000 customers were selected randomly.

We used the RFM model to detect customer segments over 8 three-month periods. Based on the results, four different groups of customers were obtained during 8 periods including HLL, LLL, LHH1 and LHH2. Segments HLL, LLL and LHH1 appeared in all periods. Segment LHH2 was present only two times at periods 6 and 7. Accordingly, the structural changes in this case include creating segments LHH2.

Similar to the previous case which was discussed in the previous sub-section, steps 3 and 4 of the proposed method were implemented on the both categories of transition sequences including 3893 and 5673 records, respectively. It is notable that most of the customers in this case follow a static behavior. In this case, we defined a customer as "static customer", if he/she remained in one segment at least 6 times over 8 periods.

Based on the results, two groups of customers are identified:

"**Structure breakers**": the customers who were in segment LHH1 in the first periods and then migrated to segment LHH2. In fact, the behavior of this group and the changes in the behavior of these customers cause the formation of segment LHH2 in periods 6 and 7.

"**Non-structure breakers**": this group includes the customer who switched between segments LLL and HLL with a higher relative stability in segment HLL and finally migrated to HLL.

In this case, we did not access to the demographics or any other features of the customers to implement step 5.

5 The Potential Usefulness of Results in Intelligent Decision Making

The focus of this study is to present a general method to provide knowledge through some if-then rules to support intelligent decision making for customer dynamics analytics and management. In this section, we discuss how the obtained results and rules can enlarge the opportunities for intelligent decision making. The obtained results provide a good insight about customers' changing behavior and the patterns of structural changes. This would help the marketing managers to improve marketing decisions.

For example, as a result of the telecommunication case study, a group of customers were detected whose changing behavior causes to create segments HLH2 and HLL over time. As the obtained rules imply, customers partially churn gradually, not instantaneously and the movement from segment HHH2 to HLL happens gradually. In fact, firstly, the frequency variable of these customers decreases and then the monetary variable falls after some periods. This implies that changing customer behavior in this manner is a warning signal indicating a fall in the monetary value. By using the obtained rules and the knowledge achieved about the distinguishing and contrast characteristics of this group, the marketing experts can identify the potential structure breakers at the first steps. Here, there is a good opportunity for the marketing managers to avoid the fall in the monetary values of these customers by using appropriate marketing strategies.

As a main result, three categories of rules are obtained by using the proposed method: "rules that distinguish structure breakers from non-structure breakers", "rules that differentiate non-structure breakers from structure breakers" and "identical rules between two groups". These rules can provide the knowledge required to design the knowledge base of an intelligent decision support system. To support intelligent decision making, the intelligent agents and systems must maintain a knowledge base. This knowledge base usually relies on a set of rules. In this regard, these rules can be very effective and provide good capabilities.

These rules and the obtained contrast characteristics can be very helpful for prediction purposes. This can help the marketing managers to classify a new customer into the mentioned two groups. The obtained rules are also helpful to predict his/her behavior. If a target customer's membership history is similar to the conditional part of a rule, then his/her switching behavior is deemed the consequent part of the rule.

Accordingly, an intelligent expert system can be designed based on the obtained rules and the contrast characteristics. This system can support intelligent decision making and suggest the type of customer and the future behavior based on the trail of his/her previous switches between different segment and his/her profile.

6 Conclusion

This study proposed a general method to investigate the impact of customer dynamics on segments' structural changes and to explore the patterns of these changes for the first time. This method provides explanatory and predictive analytics through some if-then rules to provide knowledge for intelligent decision making in customer dynamics management. The proposed method was successfully implemented on the customer data of a telecommunication service provider and also a private bank.

According to the results, we defined a new concept in the domain of customer dynamics as "structure breakers". Structure breakers are the customers whose changing behavior causes structural changes. Identifying these customers is very important; because they cause segment instability which is a difficult challenge in customer segmentation analysis. Another group of dynamic customers is also identified as "non-structure breakers" who switch between different segments over time but do not cause any changes in the structure of segments. The distinguishing rules and contrast sets of these two groups provide accurate knowledge about the behavior and characteristics of these two types of customers. The findings provide a good insight about customers' dynamic behavior that helps the marketing managers to improve marketing decisions and strategies.

One of the main advantages of the results is to enlarge the opportunities for intelligent decision making for dynamic customer management. Three groups of if-then rules are extracted: "distinguishing rules of structure breakers", "distinguishing rules of non-structure breakers" and "not-distinguishing and identical rules between these two groups". These rules and the emerging patterns can be used for prediction purposes. We can identify the group that a new customer may belong to; we can also predict the behavior of a customer based on these rules. The obtained rules are relatively easy to interpret and use and so strengthen the practicality of results.

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References

1. Fasihfar, Z., Mehrabifard, M., Rivandi, J., Al-Hosseini, M.S.: Design of a fuzzy expert system as an intelligent assistant for thesis supervisor's educational counseling. Cum. Sci. J. **36**, 1372–1376 (2015)
2. Phillips-Wren, G., Mora, M., Forgionne, G.A., Gupta, J.N.: An integrative evaluation framework for intelligent decision support systems. Eur. J. Oper. Res. **195**, 642–652 (2009)
3. Kaklauskas, A.: Biometric and Intelligent Decision Making Support. Springer International Publishing, Switzerland (2015)

4. Khademolqorani, S., Hamadani, A.Z.: An adjusted decision support system through data mining and multiple criteria decision making. Procedia Soc. Behav. Sci. **73**, 388–395 (2013)
5. Yang, Y., Tan, W., Li, T., Ruan, D.: Consensus clustering based on constrained self-organizing map and improved Cop-Kmeans ensemble in intelligent decision support systems. Knowl. Based Syst. **32**, 101–115 (2012)
6. Ngai, E.W.T., Xiu, L.I., Chau, D.C.K.: Application of data mining techniques in customer relationship management: a literature review and classification. Expert Syst. Appl. **36**, 2592–2602 (2009)
7. Liu, D.R., Shih, Y.Y.: Integrating AHP and data mining for product recommendation based on customer lifetime value. Inf. Manage. **42**, 387–400 (2005)
8. Lee, ShL: Commodity recommendations of retail business based on decision tree induction. Expert Syst. Appl. **37**, 3685–3694 (2010)
9. Chen, M.C., Chiu, A.L., Chang, H.H.: Mining changes in customer behavior in retail marketing. Expert Syst. Appl. **28**, 773–781 (2005)
10. Chong, Y.T., Chen, C.H.: Customer needs as moving targets of product development: a review. Int. J. Adv. Manuf. Technol. **48**, 395–406 (2010)
11. Kim, J.K., Song, H.S., Kim, T.S., Kim, H.K.: Detecting the change of customer behavior based on decision tree analysis. Expert Syst. **22**, 193–205 (2005)
12. Song, H.S., Kim, J.K., Kim, S.: Mining the change of customer behavior in an internet shopping mall. Expert Syst. Appl. **21**, 157–168 (2001)
13. Liu, D.R., Lai, ChH, Lee, W.J.: A hybrid of sequential rules and collaborative filtering for product recommendation. Inf. Sci. **179**, 3505–3519 (2009)
14. Böttcher, M., Spott, M., Nauck, D., Kruse, R.: Mining changing customer segments in dynamic markets. Expert Syst. Appl. **36**, 155–164 (2009)
15. Ha, S.H., Bae, S.M.: Keeping track of customer life cycle to build customer relationship. In: Li, X., Zaïane, O.R., Li, Z.H. (eds.) Advanced Data Mining and Applications, vol. 4093, pp. 372–379. Springer, Heidelberg (2006)
16. Tan, H., Xu, J., Zhao, B.: Research on index system of dynamic customer segmentation: based on the case study of China telecom. In: 9th IEEE International Conference on Information Management and Engineering, pp. 441–445. IEEE Press, Kuala Lumpur (2009)
17. Ha, S.H.: Applying knowledge engineering techniques to customer analysis in the service industry. Adv. Eng. Inf. **21**, 293–301 (2007)
18. Akhondzadeh-Noughabi, E., Albadvi, A.: Mining the dominant patterns of customer shifts between segments by using Top-K and distinguishing sequential rules. Manag. Decis. **53**, 1976–2003 (2015)
19. Blocker, C.P., Flint, D.J.: Customer segments as moving targets: integrating customer value dynamism into segment instability logic. Ind. Mark. Manage. **36**, 810–822 (2007)
20. Akhond Zadeh Noughabi, E., Albadvi, A., Far, B.H.: How can we explore patterns of customer segments' structural changes? a sequential rule mining approach. In: IEEE International Conference on Information Reuse and Integration, pp. 273–280. IEEE Press, San Francisco (2015)
21. Becker, J.U., Greve, G., Albers, S.: The impact of technological and organizational implementation of CRM on customer acquisition, maintenance, and retention. Int. J. Res. Mark. **26**, 207–215 (2009)
22. Parvatiyar, A., Sheth, J.N.: Customer relationship management: emerging practice, process, and discipline. J. Econ. Soc. Res. **3**, 1–34 (2001)
23. Dibb, S.: Market segmentation: strategies for success. Mark. Intell. Plann. **16**, 394–406 (1998)
24. Tsiptsis, K., Chorianopoulos, A.: Data Mining Techniques in CRM: Inside Customer Segmentation. Wiley, UK (2009)
25. Cheng, C.H., Chen, Y.S.: Classifying the segmentation of customer value via RFM model and RS theory. Expert Syst. Appl. **36**, 4176–4184 (2009)
26. Cheng, L.C., Sun, L.M.: Exploring consumer adoption of new services by analyzing the behavior of 3G subscribers: an empirical case study. Electron. Commer. Res. Appl. **11**, 89–100 (2012)

27. Wang, Z., Lei, X.: Study on customer retention under dynamic markets. In: 2th IEEE International Conference on Networks Security Wireless Communications and Trusted Computing, pp. 514–517. IEEE Press, Wuhan (2010)
28. Wriggers, P., Kultsova, M., Kapysh, A., Kultsov, A., Zhukova, I.: Intelligent Decision Support System for River Floodplain Management. In: Kravets, A., Shcherbakov, M., Kultsova, M., Iijima, T. (eds.) Knowledge-Based Software Engineering. CCIS, vol. 466, pp. 195–213. Springer International Publishing (2014)
29. Ur-Rahman, N.: Textual data mining for next generation intelligent decision making in industrial environment: a survey. Eur. Sci. J. **11**, 346–377 (2015)
30. Tan, P.N., Steinbach, M., Kumar, V.: Introduction to Data Mining. Pearson Education Inc., USA (2006)
31. Davies, D.L., Bouldin, D.W.: A cluster separation measure. IEEE Trans. Pattern Anal. Mach. Intell. **1**, 224–227 (1979)
32. Agrawal, R., Srikant, R.: Mining sequential patterns. In: 11th IEEE International Conference on Data Engineering, pp. 3–14. IEEE Press, Taipei (1995)
33. Fournier-Viger, P., Faghihi, U., Nkambou, R., Nguifo, E.M.: CMRules: mining sequential rules common to several sequences. Knowl. Syst. **25**, 63–76 (2012)
34. Dong, G., Pei, J.: Sequence data mining. In: Ahmed, A.K., Elmagarmid, K. (eds.) Advances in Database Systems Advances in Database Systems, vol. 33, pp. 1–148. Springer, New York (2007)
35. Tang, H., Liao, S.S., Sun, S.X.: A prediction framework based on contextual data to support mobile personalized marketing. Decis. Support Syst. **56**, 234–246 (2013)
36. Pei, J., Han, J., Wang, W.: Constraint-based sequential pattern mining: the pattern-growth methods. J. Int. Inf. Syst. **28**, 133–160 (2007)
37. Masseglia, F., Poncelet, P., Teisseire, M.: Efficient mining of sequential patterns with time constraints: reducing the combinations. Expert Syst. Appl. **36**, 2677–2690 (2009)
38. Srikant, R., Agrawal, R.: Mining sequential patterns: generalizations and performance improvements. In: Apers, P., Bouzeghoub, M., Gardarin, G. (eds.) Extending Database Technology: Advances in Database Technology, vol. 1057, pp. 25–29. Springer, Heidelberg (1996)
39. Deng, K., Zaiane, O.R.: Contrasting sequence groups by emerging sequences. In: Li, X., Zaïane, O.R., Li, Z.H.H. (eds.) Discovery Science, vol. 5808, pp. 377–384. Springer, Heidelberg (2009)
40. Kralj, P., Lavrač, N., Gamberger, D., Krstačić, A.: Contrast set mining for distinguishing between similar diseases. In: Bellazzi, R., Abu-Hanna, A., Hunter, J. (eds.) Artificial Intelligence in Medicine. LNCS, vol. 4594, pp. 109–118. Springer, Heidelberg (2007)
41. Fournier-Viger, P., Tseng, V.S.: TNS: mining Top-k non-redundant sequential rules. In: 28th Annual ACM Symposium on Applied Computing, pp. 164-166. Coimbra (2013)
42. Lo, D., Khoo, S.C., Wong, L.: Non-redundant sequential rules—theory and algorithm. Inf. Syst. **34**, 438–453 (2009)
43. Song, H.S., kyeong Kim, J., Kim, S.H.: Mining the change of customer behavior in an internet shopping mall. Expert Syst. Appl. **21**, 157–168 (2001)
44. Dong, G., Li, J.: Efficient mining of emerging patterns: discovering trends and differences. In: 5th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 43–52. ACM, New York (1999)