RESEARCH ARTICLE OPEN ACCESS

Using Data Mining Techniques in Customer Segmentation

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ABSTRACT
Data mining plays important role in marketing and is quite new. Although this field expands rapidly, data mining is still foreign issue for many marketers who trust only their experiences. Data mining techniques cannot substitute the significant role of domain experts and their business knowledge. In the other words, data mining algorithms are powerful but cannot effectively work without the active support of business experts. We can gain useful results by combining these techniques and business expertise. For instance ability of a data mining technique can be substantially increased by combining person experience in the field or information of business can be integrated into a data mining model to build a more successful result. Moreover, these results should always be evaluated by business experts. Thus, business knowledge can help and enrich the data mining results. On the other hand, data mining techniques can extract patterns that even the most experienced business people may have missed. In conclusion, the combination of business domain expertise with the power of data mining techniques can help organizations gain a competitive advantage in their efforts to optimize customer management. Clustering algorithms, a group of data mining technique, is one of most common used way to segment data set according to their similarities. This paper focuses on the topic of customer segmentation using data mining techniques. In the other words, we theoretically discuss about customer relationship management and then utilize couple of data mining algorithm specially clustering techniques for customer segmentation. We concentrated on behavioral segmentation.

Keywords - Clustering, Customer Relationship Management, Customer Segmentation, Data Mining.

I. INTRODUCTION

Customers are the most important property of an organization. There cannot be any business prospects without satisfied customers who remain loyal and develop their relationship with the organization. That is why an organization should employ a certain strategy for treating customers. The main goal of every industry is understand each customer individually and use that to make it easier for the customer to do business with them rather than with competitors. The subject of many books topics is Customer relationship management (CRM). CRM naturally focuses on established customers. CRM is the strategy for building, managing, and strengthening loyal and long-lasting customer relationships. CRM should be a customer centric approach based on customer insight [1].

Many companies often use data mining techniques for CRM, which helps provide more customized, personal service addressing individual customer's needs, instead of mass marketing. By studying purchasing and link patterns on web, companies can make advertisements and promotions to customer profiles, so that customers are less likely to be annoyed with unwanted requests like junk mail. These actions can result in substantial cost savings for companies. The customers further benefit in that they are more likely to be notified of offers that are actually of interest, resulting in less waste of personal time and greater satisfaction [2].

There are several CRM software packages and used to track interactions with customers, including the management of marketing campaigns and call centers. These packages typically support processes in sales, marketing, and customer service, automating communications and interactions with the customers. They record contact history and store valuable customer information. However, these packages are tools in which should be used to support the strategy of effectively managing customers [3].

Organizations need to gain insight into customers, their needs, and wants through data analysis to succeed with CRM. In other words, organizations analyze customer information to better address the CRM objectives and deliver the right message to the right customer [4]. It involves the use of data mining methods in order to assess the value of the customers, understand, and predict their behavior. They analyze patterns to extract knowledge to optimize customer relationships. The role of data mining methods in marketing is quite new. Although this field expands rapidly, data mining is still foreign issue for many marketers who trust only their experiences.

Data mining techniques cannot substitute the significant role of domain experts and their business knowledge. We can gain useful results by combining data mining techniques and business expertise. For instance, we may combine person experience in the field or information of business with a data mining model to build more successful results. Moreover, these results should always be evaluated by business experts. Thus, business knowledge can help and enrich the data mining results [5][6].

On the other hand, data mining techniques can discover patterns that even the most experienced business people may have missed. As a result, the combination of business domain expertise with the power of data mining techniques can help organizations to gain a competitive advantage in their efforts to optimize customer management.

This paper focuses on the topic of customer segmentation using data mining techniques. The next section is dedicated to data mining modeling techniques. This section provides a brief introduction to the main modeling concepts. The second one goes a step further and focuses on the techniques used for CRM. Customer segmentation by data mining techniques is topic of forth section. Section 5 specifies some recommendations for planning and carrying out a segmentation project and finally we conclude paper in sixth section.introduction of the paper should explain the nature of the problem, previous work, purpose, and the contribution of the paper. The contents of each section may be provided to understand easily about the paper.

II. DATA MINING TECHNIQUES

A. *Knowledge Discovery and Data Mining*

Data mining is considered the most important step in the knowledge discovery process. Data mining is the process of extracting interesting patterns from large amounts of data [7]. Data mining is about solving problems by analyzing data already present in datasets. It provides tools for automated learning from historical data and developing models to predict future trends and behaviors. The essence of data mining is the nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data. Data mining functionalities are used to specify the kind of patterns to be found in data mining tasks [8].

In general, data mining tasks can be classified into two categories: descriptive and predictive. Descriptive data mining models try to extract useful patterns that can describe the mined data and explore its properties and characterize the general properties of the data in the database. Predictive mining tasks perform inference on the current data in order to make predictions, in other words, try to predict unknown values or future trends or behaviors depending on other variables or historical values presented in the mined database [7].

Data mining is widely used by different companies and organizations especially in the field of medical, retail, marketing, finance, communication, and science. It enables these companies to gain information about diseases, sales behavior, customer satisfaction, and corporate profits. Using data mining, organizations can increase the profitability of their interactions with patients, customers, and improve risk management in marketing. The extracted patterns using data mining help organizations to have better decisions. In the following section, we examine a number of different data mining tasks.

B. *Data Mining Tasks*

Using data mining task depends on the application domain and the structure of the patterns that are expected to be extracted. We should know that there is no single method which is appropriate for all possible problems. The universal method is an idealistic fantasy. There are some basic data mining tasks such as association rules, sequential pattern, clustering and classification.

The discovery of frequent patterns, association, and correlation relationships among huge amounts of data are useful in many applications. Association rule mining algorithms employ one of two common approaches: Breadth First Search approach (BFS), and Depth First Search approach (DFS). Many efficient and scalable algorithms have been developed for rule mining, from which association and correlation rules can be derived. Mining sequential patterns is highly similar with mining association rules. The main difference between the sequential patterns and the association rules is that the time element is taken into account (order of events). Sequential patterns indicate the correlation between transactions while association rules represent intra transaction relationships. Sequential patterns can be widely used in different areas, such as mining user access patterns for the web sites, using the history of symptoms to predict certain kind of disease, also by using sequential pattern mining, the retailers can make their inventory control more efficient. Clustering divides a dataset into different groups. The process of grouping objects into clusters such that the objects from the same cluster are similar and objects from different clusters are dissimilar. Most efforts to produce a rather simple group structure from a complex data necessarily require a measure of closeness or similarity. In clustering data objects have no class label and when we start clustering we do not know what the resulted clusters will be. For this reason, clustering is also called unsupervised learning. Clustering is used in many areas, including artificial intelligence, biology, CRM, image processing, machine learning, marketing, medicine, and statistics. Clustering has many different methods and techniques such as Partitioning Methods, Hierarchical Methods, Density based Methods, Grid based Methods, and Model based

Methods. Each of them includes some parameters in which users can set them and gain different results.
Classification and prediction are two forms of data analysis that can be used to extract models describing important data classes or to predict future data trends. Classification also known as supervised learning is the process of finding a set of models or functions that describe and distinguish data classes or concepts where the models derived based on a set of training data. Decision tree classifiers, Bayesian classifiers and rule based classifiers are basic and well known techniques for data classification. There are some complex classification algorithms such as support vector machine (SVM).

III. DATA MINING IN CRM

We are able to use data mining techniques to analyze customer information but clustering and association rules mining are most popular in this field. The main idea of data mining for CRM is that data from the past can contains information that will be useful in the future. It works because customer behaviors captured in corporate data are not random, but reflect the differing needs, preferences, propensities, and treatments of customers. The goal of data mining is to extract patterns in historical data. The task is not easy, because the patterns are not always strong, and the signals sent by customers are noisy and confusing. Separating signal from noise is an important and difficult role of data mining. For example, data mining can help to show distinct customer segments, facilitating the development of customized new products and product offerings which better address the specific priorities of the customers. Data mining can provide customer insight, which is vital to make an effective CRM strategy. It can help to personalized interactions with customers and hence increased satisfaction and profitable customer relationships through data analysis. It can support an optimized customer management throughout all the phases of the customer lifecycle, from the acquisition and establishment of a strong relationship to the prevention of attrition and the winning back of lost customers. In simple words, they are responsible for getting, developing, and keeping the customers. Data mining models can help in all these tasks, as shown in Table I. Depend on our requests, we select several applications.

Table I: Data mining tasks and CRM

Modeling Task	**Modeling Techniques**	**Example of Application**
Association	Apriority, FP-Growth	Market Basket Analysis
Sequence Mining	Apriority, FP-Growth	Web Usage Analysis
Clustering	K-means, Hierarchical Models…	Segmentation
Classification	Decision Trees, Neural Networks, Regression, SVM, …	Prediction

Marketers use direct marketing campaigns to communicate a message to their customers through mail, the Internet, e-mail, phone, and other direct channels. The stages of direct marketing campaigns are illustrated in Fig. 1 and explained below [1]:

1. Collect and clean the necessary data from different sources.
2. Customer analysis and segmentation (clustering) into different groups.
3. Development of targeted marketing campaigns in order to select the right customers.
4. Campaign execution by choosing the appropriate channel, the appropriate time, and the appropriate offer for each campaign.
5. Campaign evaluation through the use of test and control groups. The evaluation involves the partition of the population into test and control groups and comparison of the positive responses.
6. Analysis of campaign results in order to improve the campaign for the next round in terms of targeting, time, offer, product, communication, and so on.

Data mining can play a significant role in all these stages, particularly in identifying the right customers to be contacted. Data mining projects are not simple. They usually start with high expectations but may end in business failure if the engaged team is not guided by a clear methodological framework. The CRISP-DM process model charts the steps that should be followed for successful data mining implementations [9].

Fig. 1: The stages of direct marketing campaigns

These steps are as follows:

1. **Business understanding:** The data mining project should start with an understanding of the business objective and an assessment of the current situation and also problems. The project's parameters should be considered, including resources and limitations. The business objective should be translated into a data mining goal. Success criteria should be defined and a project plan should be developed.
2. **Data understanding:** This phase involves considering the data requirements for properly addressing the defined goal and an investigation of the availability of the required data. This phase also includes initial data collection and exploration with summary statistics and visualization tools to understand the data and identify potential problems in availability and quality.
3. **Data preparation:** The data to be used should be identified, selected, and prepared for inclusion in the data mining model. This phase involves the collection, integration, and formatting of the data according to the needs of the project. The consolidated data should then be cleaned and properly transformed according to the requirements of the algorithm to be applied. New aggregation fields such as sums, averages, ratios, flags, and so on should be derived from the raw fields to enrich customer information, to better summarize customer characteristics, and therefore to enhance the performance of the models.
4. **Modeling:** The prepared dataset are then used for model training. Analysts should select the appropriate modeling technique for the particular business objective. Before the training of the models and especially in the case of predictive modeling, the modeling dataset should be partitioned so that the model's performance is evaluated on a separate dataset. This phase involves the examination of alternative modeling algorithms and parameter settings and a comparison of their fit and performance in order to find the one that yields the best results. Based on an initial evaluation of the model results, the model settings can be revised and fine-tuned.
5. **Evaluation:** The generated models are then formally evaluated not only in terms of technical measures but also, more importantly, in the context of the business success criteria set out in the business understanding phase. The project team should decide whether the results of a given model properly address the initial business objectives. If so, this model is approved and prepared for deployment.
6. **Deployment:** The project's findings and conclusions are summarized in a report, but this is hardly the end of the project. Even the best model will turn out to be a business failure if its results are not deployed and integrated into the organization's everyday marketing operations. A procedure should be designed and developed to enable the scoring of customers and the updating of the results. The deployment procedure should also enable the distribution of the model results throughout the enterprise and their incorporation in the organization's databases and operational CRM system. Finally, a maintenance plan should be designed and the whole process should be reviewed. Lessons learned should be taken into account and the next steps should be planned.

IV. CUSTOMER SEGMENTATION AND DATA MINING

Customer segmentation is the process of dividing customers into distinct, meaningful, and homogeneous subgroups based on various attributes and characteristics. It is used as a differentiation marketing tool. It enables organizations to understand their customers and build differentiated strategies [3].

Traditionally organizations, regardless of the industry they operate in, tend to use market segmentation schemes that are based on demographics and value information. Over the past few decades organizations have been deciding their marketing activities and developing their new products and services based on these simple, business rule segments.

One of the big challenges with traditional survey-based market research is that it provides a lot of information about a few customers. However, to use the results of market research effectively often requires understanding the characteristics of all customers. That is, market research may find interesting segments of customers. These then need to be projected onto the existing customer base using available data. Behavioral data can be particularly useful for this; such behavioral data is typically summarized from transaction and billing histories. One requirement of the market research is that customers need to be identified so the behavior of the market research participants is known.

In today's competitive markets, this approach is not sufficient and efficient. On the contrary, organizations need to have a complete view of their customers in order to gain a competitive advantage. They also need to focus on their customers' needs, wants, attitudes, behaviors, preferences, and perceptions, and to analyze relevant data to identify the underlying segments. The identification of groups with unique characteristics will enable the organization to manage and target them more effectively with, among other things, customized product offerings and promotions.

Customer segmentation is a popular application of data mining with established customers. A segmentation project starts with the definition of the business objectives and ends with the delivery of differentiated marketing strategies for the segments. There are many different segmentation types based on the specific criteria or attributes used for segmentation. Specifically, customers can be segmented according to their value. The type of segmentation used depends on the specific business objective [1].

There are various segmentation types according to the segmentation criteria used. Particularly, customers can be segmented according to their value, socio-demographic and life-stage information, and their behavioral, need/attitudinal, and loyalty characteristics. The type of segmentation used depends on the specific business objective and your target. Different criteria and segmentation methods are appropriate for different situations and business objectives.

In behavioral segmentation, customers are grouped by behavioral and usage characteristics. Although behavioral segments can be created with business rules, this approach has inherent disadvantages. It can efficiently handle only a few segmentation fields and its objectivity is questionable as it is based on the personal perceptions of a business expert. Data mining on the other hand can create data-driven behavioral segments. Clustering algorithms can analyze behavioral data, identify the natural groupings of customers, and suggest a solution founded on observed data patterns. Provided the data mining models are properly built, they can uncover groups with distinct profiles and characteristics and lead to rich segmentation schemes with business meaning and value.

In general, the application of a cluster model is required to reveal the segments, particularly if we need to combine a large number of segmentation attributes. As opposed to business rules, a cluster model is able to manage a large number of attributes and reveal data-driven segments which are not known in advance.

Data mining can also be used for the development of segmentation schemes based on the current or expected value of the customers. These segments are necessary in order to prioritize customer handling and marketing interventions according to the importance of each customer.

Moreover, since a vital part of a segmentation project is insight into the derived clusters and an understanding of their meaning, we will also propose ways for profiling the clusters and for outlining their differentiating characteristics.

One way to find behavioral segments is to use the clustering techniques described in [8]. This methods lead to clusters of similar customers but it may be hard to understand how these clusters relate to the business.

More typically, a business would like to perform a segmentation that places every customer into some easily described segment. Often, these segments are built with respect to a marketing goal such as subscription renewal or high spending levels. Decision tree techniques described in [10] are ideal for this sort of segmentation.

Segmentation in marketing can be used for the following [3]:

• Greater understanding of customers to support the identification of new marketing opportunities.

• Design and development of new products/services and product bundles tailored to each segment's characteristics rather than the mass market.

• Design of customized product offering strategies to existing customers according to each segment's identified wants and needs.

• Offering tailored rewards and incentives.

• Selecting the appropriate advertising and communication message and channel.

• Selecting the appropriate sales and service channel.

• Determining the brand image and the key product benefits to be communicated based on the specific characteristics of each segment.

• Differentiation in customer service according to each segment's importance.

• More effective resource allocation according to the potential return from each segment.

• Prioritization of the marketing initiatives which aim at customer retention and development according to each segment's importance and value.

There are various criteria for customer segmentation that can be used to optimize consumer marketing. As mentioned earlier, different segmentation types are used for different business situations.

The following segmentation types are most widely used [1]:

1. **Value based:** In value-based segmentation customers are grouped according to their value. This is one of the most important segmentation types since it can be used to identify the most valuable customers and to track value and value changes over time. It is also used to differentiate the service delivery strategies and to optimize the allocation of resources in marketing initiatives.

Value-based segmentation is the process of dividing the customer base according to value. It should be emphasized that this is not a one-off task. It is vital for the organization to be able to track value changes across time. The organization should monitor and, if possible, intervene in order to prevent downward and encourage upward migrations.

A prerequisite for this segmentation scheme is the development of an accurate and credible procedure for determining the value of each customer, on a periodic basis, preferably at least monthly, using day-to-day inputs on revenues and costs. Value-based segmentation is developed through simple computations and does not involve the application of a data mining model. Specifically, the identification of the value segments involves order customers according to their value and their binning in groups of equal size. These groups are the basis for the development of value segments of the form low *n*%, medium *n*%, top *n*%.

2. **Behavioral:** This is a very efficient and useful segmentation type. It is also widely used since it presents minimal difficulties in terms of data availability. The required data include product ownership and utilization data which are usually stored and available in the organization's databases. Customers are divided according to their identified behavioral and usage patterns. This type of segmentation is typically used to develop customized product offering strategies and for new product development, and the design of loyalty schemes.

In behavioral segmentation the segments are identified with the application of appropriate clustering models on usage/behavioral data that usually reside in the organization's data warehouse or data marts. Thus behavioral segmentation can be implemented with a high degree of confidence and relatively low cost. Attributes that can be used for behavioral segmentation include product ownership and utilization, volume/type/frequency of transactions, payment and revenue history, and so on. Because behavioral segmentation is useful segmentation type, detailed methodological approach for behavioral segmentation is presented in the next section.

3. **Propensity based:** In propensity-based segmentation customers are grouped according to propensity scores, such as churn scores, cross-selling scores, and so on, which are estimated by respective classification (propensity) models. This type of segmentation involves simple computations and the binning of customers in groups according to their propensity scores. For instance, customers can be divided into groups of bad, good, and very good.

Propensity scores can also be combined with other segmentation schemes to better target marketing actions. For instance, the value-at-risk segmentation scheme is developed by combining propensities with value segments to prioritize retention actions.

Propensity-based segmentation utilizes the results of classification models such as churn or cross- and up-selling models. This type of segmentation involves simple computations and the binning of customers in groups according to their propensity scores.

Cluster analysis can be applied to the respective propensity scores in order to reveal the segments of customers with similar future needs for specific product. Analysts can combine multiple propensity models and scores to create compound segmentation schemes. This procedure typically requires the application of a clustering model. Once the propensity scores are estimated by the relevant models, they can be used as inputs fields in the clustering model.

4. **Loyalty based:** Loyalty segmentation involves the investigation of the customers' loyalty status and the identification of loyalty-based segments such as

loyal and switchers/migrators. Retention actions can then be focused on high value customers with a disloyal profile whereas cross-selling on prospectively loyal customers.

Loyalty segmentation is used to identify different groupings of customers according to their loyalty status and to separate loyal from migrators/switchers. The segments are created by the application of simple business rules and/or cluster models on survey or database information.

Loyalty segments can be associated with specific usage behaviors and customer database attributes. To achieve this, an organization can start with a market survey to reveal the loyalty segments and then build a classification model with the loyalty segments' field as the target [1].

5. **Socio-demographic and life-stage:** This type reveals different customer groupings based on socio-demographic and/or life-stage information such as gender, race, age, social status, education, occupation, income, and marital status. This type of segmentation is appropriate for promoting specific life-stage-based products as well as supporting life-stage marketing.

In demographic segmentation customers are grouped according to their demographics. It is a widely used segmentation since demographics are considered to have a strong influence on the customers' needs, preferences, and consuming/usage behaviors. We should point out, though, that in many cases people in the same demographic group may have different wants and needs as customers.

6. **Needs/attitudinal:** This segmentation type is typically based on market research data and identifies customer segments according to their needs, wants, attitudes, preferences, and perceptions pertaining to the company's services and products. It can be used to support new product development and to determine the brand image and key product features to be communicated.

Needs/attitudinal-based segmentation is used to investigate customers' needs, wants, attitudes, perceptions, and preferences. Relevant information can only be collected through market surveys and the segments are typically identified by the application of a cluster model on gathered questionnaire responses.

In the data mining framework, needs/attitudinal segmentation is mainly used in combination with behavioral and value-based segments to enrich the profile of the revealed segments, provide insight into their qualitative characteristics, and hence support:

• New product design/development

• The communication of the product features/brand image important for each segment

• Tailored communication messages

• New promotions

V. BEHAVIOURAL SEGMENTATION METHODOLOGY

The methodology for behavioral segmentation includes the following main steps [1]:

1. Business understanding and design of the segmentation process. This phase starts with understanding the project requirements from a business perspective. It involves knowledge-sharing meetings and close collaboration between the data miners and marketers involved in the project to assess the situation, clearly define the specific business goal, and design the whole data mining procedure.

Tasks in this step include definition of business objective, selection of appropriate segmentation criteria, determination of segmentation population, and determination of segmentation level.

2. Data understanding, preparation, and enrichment. The investigation and assessment of the available data sources is followed by data acquisition, integration, and processing for the needs of segmentation modeling. The data understanding and preparation phase is probably the most time-consuming phase of the project

Tasks in this step include but not limited data source investigation, defining the data to be used, data integration and aggregation, data validation and cleaning, data transformation and enrichment, and data reduction.

3. Identification of the segments with cluster modeling. Customers are divided into distinct segments by using cluster analysis. The clustering fields, typically the component scores, are fed as inputs into a cluster model which assesses the similarities between the records/customers and suggests a way of grouping them. Data miners should try a test approach and explore different combinations of inputs, different models, and model settings before selecting the final segmentation scheme.

Different clustering models will most likely produce different segments and this should not come as a surprise. Expecting a unique and definitive solution is a sure recipe for disappointment. Usually the results of different algorithms are not identical but similar. They seem to converge to some common segments.

Analysts should evaluate the agreement level of the different models and examine which aspects disagree. In general, a high agreement level between many different cluster models is a good sign for the existence of discernible groupings.

The modeling results should be evaluated before selecting the segmentation scheme to be deployed. This takes us to the next stage of the behavioral segmentation procedure.

4. Evaluation and profiling of the revealed segments. In this phase the modeling results are evaluated and the segmentation scheme that best addresses the needs of the organization is selected for deployment. Data miners should not blindly trust the solution suggested by one algorithm. They should explore different solutions and always seek guidance from the marketers for selecting the most effective segmentation.

Tasks in this step include technical evaluation of clustering solution, profiling of the reveal segments, cluster profiling with supervised model, using marketing research information to evaluate and enrich the behavioral segments, and labeling the segments based on their identified profiles.

5. Deployment of the segmentation solution, design, and delivery of the differentiated strategies. The segmentation project concludes with the deployment of the segmentation solution and its use in the development of differentiated marketing strategies and segmented marketing.

There are usually three tasks that doing in this step: building the customer scoring model for updating the segments, building a decision tree for scoring segments, and distribution of the segmentation information.

In contrast to behavioral segmentation, which is multi-attribute since it typically involves the examination of multiple segmentation dimensions, value-based segmentation is one dimensional as customers are grouped on the basis of a single measure, the customer value. The most difficult task in such a project is the computation of a valid value measure for dividing customers, rather than the segmentation itself.

VI. SOME RECOMMENDATIONS

The following tips should be taken into account when planning and carrying out a segmentation project [1]:

• Take into account the core industry segments before proceeding with the segmentation project and then decide which core segments need further analysis.

• Clean your data set from obvious segments (e.g., inactive customers) before proceeding with the segmentation analysis.

• Always keep in mind that eventually the resulting model will be deployed. In other words, it will be used for scoring customers and for supporting specific marketing actions. Thus, when it comes to selecting the population to be used for model training, do not forget that this is the same population that will be scored and included in a marketing activity at the end. So sometimes it is better to start with the end in mind and consider who we want to score, segment, or classify at the end: the entire customer base, consumer customers, only high-value customers, and so on. This deployment-based approach can help us to resolve ambiguities about selection of the modeling dataset population.

• Select only features relevant to the specific business objective and the particular behavioral aspects you want to investigate. Avoid mixing all available inputs in an attempt to build a magic segmentation that will cover all aspects of a customer's relationship with the organization (e.g., phone usage and payment behavior).

• Avoid using demographic features in a behavioral segmentation project. Mixing behavioral and demographical information may result in ambiguous behavioral segments since two customers with identical demographic profiles may have completely different behaviors.

• Consider the case of a father who has activated a mobile phone line for his teenage son. In a behavioral segmentation solution, based only on behavioral data, this line would most likely be assigned to the ''Young – SMS users'' segment, along with other teenagers and young technophile users. Therefore we might expect some ambiguities when trying to examine the demographic profile of the segments. In fact, this hypothetical example also outlines why the use of demographic inputs should be avoided when the main objective is behavioral separation.

• Use aggregation function to your data set. Prefer to use monthly averages, percentages, ratios, and other summarizing functions that are based on more than one month of data.

• A general recommendation on the time frame of the behavioral data to be used is to avoid using less than 6 months and more than 12 months of data in order to avoid founding the segments on unstable/volatile or outdated behaviors.

• Try different combinations of input variables and explore different models and model settings. Build numerous solutions and pick the one that best addresses the business goal.

• Labeling the segments needs extra care. Keep in mind that this label will characterize the segments, so a hasty naming will misguide all recipients/users of this information. A simple label will unavoidably be a kind of derogation, as it is impossible to incorporate all the differentiating characteristics of a segment. Yet, a carefully chosen name may simply and successfully communicate the unique characteristics of the segments to all subsequent users.

• Always prefer supervised to unsupervised models when your business problem concerns the classification of customers into categories known in advance. Predicting events (e.g., purchase of a product, churn, defaulting) is a task that can be addressed much more efficiently by classification models. A decision tree that estimates the event's propensities will produce better results than any unsupervised model.

• Customers that do not fit well to their segment should be set apart and assigned to an ''unclassified'' segment in order to improve the homogeneity and quality of the segments. For instance, a customer with a very low amount in stocks and a stocks-only product portfolio, even if classified as an ''Investor'' by a clustering algorithm, should be identified and assigned either to the ''Unclassified'' or to the ''Passive/Inactive'' group.

VII. CONCLUSION

In this paper we outlined how data mining can help an organization to better address the CRM objectives and achieve individualized and more effective customer management through customer insight. The following list summarizes some of the most useful data mining applications in the CRM framework [1]:

• Customer segmentation:

– Value-based segmentation: Customer ranking and segmentation according to current and expected/estimated customer value.

– Behavioral segmentation: Customer segmentation based on behavioral attributes.

– Value-at-risk segmentation: Customer segmentation based on value and estimated voluntary churn propensity scores.

• Targeted marketing campaigns:

– Voluntary churn modeling and estimation of the customer's likelihood/propensity to churn.

– Estimation of the likelihood/propensity to take up an add-on product, to switch to a more profitable product, or to increase usage of an existing product.

– Estimation of the lifetime value (LTV) of customers.

Customer segmentation is the process of identifying groups that have common characteristics. The main objective of customer segmentation is to understand the customer base and gain customer insight that will enable the design and development of differentiated marketing strategies.

The following outlines the main steps that segmentation should follow to develop an effective marketing strategy based on behavioral segments:

Step 1: Identify the customer segments in the database

Step 2: Evaluate and position the segments

Step 3: Perform cost-benefit analysis to prioritize actions per segment

Step 4: Build and deliver differentiated strategies

Clustering is a most popular way to identify segments not known in advance and split customers into groups that are not previously defined. The identification of the segments should be followed by profiling the revealed customer groupings. Profiling is necessary for understanding and labeling the segments based on the common characteristics of the members.

The criteria used to divide customers (behavioral, demographic, value or loyalty information, needs/attitudinal data) define the segmentation type. Finally in this paper we specify some recommendations for planning and carrying out a segmentation project in which described in [1].

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