One Approach to the Client-Oriented Marketing Based on Artificial Intelligence

A. Hilbert
Fakultät Wirtschaftswissenschaften
Technische universität Dresden
Dresden, Germany
e-mail: hilbert@wiid.wiwi.tu-dresden.de

D. R. Bogdanova
Department of computer science and robotics
Ufa state aviation technical university
Ufa, Russia
e-mail: dianochka7bog@mail.ru

N. V. Sholokhova
Department of computer science and robotics
Ufa state aviation technical university
Ufa, Russia
e-mail: nadya_88@inbox.ru

Abstract[1]

In this paper will be described two approaches that take into account uncertain information on clients and their individual preferences. RFMR is based on a scoring approach provide the foundation for the quantification of customer behaviour. The proposed conceptual approach to the operational service management is based on individual preferences in domain-specific complex of models. It is hoped that this discussion assists marketers in forging a solid base for understanding and executing customer segmentation.

1. Introduction

Client-oriented marketing is the part of marketing directed on your "best customers" – those who make your basic profit.

As well as in many aspects of marketing, there is no «correct way» or «a wrong way» for marketing: what is necessary to do will depend on the purposes you wish to reach. The purposes are always the same: to increase quantity of "the best customers" and profit, brought by them. It is simple idea, but till now many companies lose huge profits without giving a proper attention to the constant clients.

One of the methods of client-oriented approach is to create the constant program of loyalty:

The given method assumes the use of the program of loyalty for creation of base of constant clients, their segmentation into groups, and then use of different marketing strategies for each segment. This approach allows you to learn your clients in more details, to use target marketing, and you will have an information how to modify your business according to the desires of customers [1].

Performing marketing research, it often appears a problem of processing the great volume of the qualitative (i.e. subjective, uncertain) information on clients. To solve such problems can be used methods of fuzzy logic which refer to methodology of an artificial intelligence.

In this paper will be described two of these methods.

RFMR method

RFMR is a scoring approach which assesses recency, frequency and monetary ratio of a customer's purchases along an interval scale and aggregates the results to a single customer value score. This score can be used to define customer segments and develop marketing plans.

- Recency is the time that has elapsed since the customer made his most recent purchase. A customer who made his most recent purchase last month will receive a higher recency score than a customer who made his most recent purchase three years ago.
- Frequency is the total number of purchases that a customer has made within a designated period of time. A customer who made six purchases in the last three years would receive a higher frequency score than a customer who made one purchase in the last three years.
- Monetary Ratio is each customer's average purchase amount. A customer who averages a $100 purchase amount would receive a higher monetary ratio score

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than a customer who averages a \$20 purchase amount (average purchase amount = total dollars spent on purchases in last three years / total number of purchases in last three years) [5].

The purpose of RFMR scoring is to drive better segmentation decisions by valuing customers along an interval scale. The most common approach is to sort customers in descending order (best to worst). Customers are broken into five equal groups (quintiles). The best receive a score of 5, the worst a score of 1. For recency, customers are sorted by days since last purchase, the lower number of days – the higher the score. For frequency, customers are sorted by number of purchases, the higher number of purchases the higher the score. For monetary ratio, customers are sorted by the amount spent. The higher amount the higher the score. Each time customers are scored, a new relative segmentation scheme is created. This has the advantage of quantifying customer behaviour which can be projected into the future. The relatively best customers would always fall into the 5, 5, 5 category. It is necessary to identify where the cut-off points fall, because they automatically change with every new customer. This kind of sorting can be applied if one deals with quantitative variables [3]. However, in case of fuzzy sets related to linguistic variables, sorting by membership function value should be applied.

For example:

1. Customer 1: Recency (R) - $\mu_{1high} = 0.8$, $\mu_{1low} = 0.3$;
   Frequency (F) - $\mu_{2high} = 0.6$, $\mu_{2low} = 0.5$;
   Monetary R. (MR) - $\mu_{3high} = 0.7$, $\mu_{3low} = 0.4$.
2. Customer 2: Recency (R) - $\mu_{1high} = 0.4$, $\mu_{1low} = 0.6$;
   Frequency (F) - $\mu_{2high} = 0.5$, $\mu_{2low} = 0.4$;
   Monetary R. (MR) - $\mu_{3high} = 0.8$, $\mu_{3low} = 0.3$.
3. Customer 3: Recency (R) - $\mu_{1high} = 0.9$, $\mu_{1low} = 0.2$;
   Frequency (F) - $\mu 2_{high} = 0.3$, $\mu_{2low} = 0.4$;
   Monetary R. (MR) - $\mu_{3high} = 0.1$, $\mu_{3low} = 0.6$.

Then, by means of the function max (μhigh, μlow), the highest membership function value is selected.

Customer 1: Recency (R) – $\mu_{1high} = 0.8$;
Frequency (F) - $\mu_{2high} = 0.6$;
Monetary R. (MR) - $\mu_{3high} = 0.7$.

Customer 2: Recency (R) – $\mu_{1low} = 0.6$;
Frequency (F) - $\mu_{2high} = 0.5$;
Monetary R. (MR) - $\mu 3_{high} = 0.8$.

Customer 3: Recency (R) – $\mu_{1high} = 0.9$;
Frequency (F) - $\mu_{2low} = 0.7$;
Monetary R. (MR) - $\mu_{3low} = 0.9$.

Now, all customers can be sorted by each indicator separately (R in ascending order, F in descending order, MR in descending order). The following sequence will result:

Recency (R): Customer 2 ($\mu_{1high} = 0.6$);
Customer 1 ($\mu_{1high} = 0.8$);
Customer 3 ($\mu_{1high} = 0.9$).

Frequency (F): Customer 1 ($\mu_{2high} = 0.6$);
Customer 2 ($\mu_{2high} = 0.5$);
Customer 3 ($\mu_{2low} = 0.4$).

Monetary R. (MR): Customer 2 ($\mu_{3high} = 0.8$);
Customer 1 ($\mu_{3high} = 0.7$);
Customer 3 ($\mu_{3low} = 0.6$).

As an example, two parameter values of the indicators (high and low) were used, and actually there could be more parameter values (very high, high, middle, low, very low etc.). The customer quintile method has the advantage of yielding equal numbers of customers in each segment. There are five equally-sized groups for recency, frequency and monetary ratio (according to a principle of Pareto, 20 % of customers bring 80 % of profit, hence, quintiles are used), generating 125 segments overall (cells would have definitions like: 4, 3, 5 or 2, 3, 3) [3]. Borders of each segment are calculated by dividing the ordered list of the customers into the desirable number of quantiles (n, usually five). Then, a score from 1 to n is assigned to the different segments. As an example, 3 segments are defined:

Recency (R): Customer 2 – 3 points;
Customer 1 – 2 points;
Customer 3 – 1 point.

Frequency (F): Customer 1 – 3 points;
Customer 2 – 2 points;
Customer 3 – 1 point.

Monetary R. (MR): Customer 2 – 3 points;
Customer 1 – 2 points;
Customer 3 – 1 point.

Since past behaviour can be regarded as the best predictor of future behaviour, recency is typically considered as the most powerful of the three variables. Many direct marketing decisions are solely based on recency. Unlike frequency and monetary ratio, customers reset themselves. A three-year-long reordering customer who has purchased an average amount only once, for example, moves up from 1 to 2 regarding frequency and monetary ratio, whereas regarding recency, he may move from 1 to 5. Customers that order regularly may hardly have anything other than a 5 score. At the core of recency is the idea that most of the customers fall into two groups:

hot and dead. With relational, database-driven marketing databases becoming more common, most marketers can select RFMR scores independently. However, aggregating the scores allows for an overall segmentation of the customers based on a combination of different characteristics. When working with linguistic variables, one alternative for the aggregation would be simply to add together the RFMR scores discussed above. The best customers would have a composite score of 15 (5+5+5) and the worst customers would have a minimum score of 3 (1+1+1). Many of the customers would have a score of 7 or 8 and it would be difficult to put them into an order. Moreover, the experience of direct mail marketing suggests that the most recent customers are of greater value than those who have ignored more than a few repeated mailings. To enhance the aggregation, the scores are often multiplied with different weights, e. g. Rx3, Fx2 and MRx1. This would give the best customers a composite score of 30 (5x3 + 5x2 + 5x1). This not only draws more attention to the most recent activities, it also gives a bit of a boost to frequency. The idea behind weighting frequency is that if two customers have equal recency, spent the same amount but one ordered several times and the other only once, the more frequent buyer is much more likely to respond. One additional enhancement is often employed by creating a composite score using the weighting factors 9.9, 6.6 and 3.3 instead of 3, 2 and 1. This yields a range of composite scores between 99 and 19.8 and preserves the approximately 3x weighting of R, while it also creates more of a 100 point scale.

Operational management of services based on individual preferences of customers

In an ever increasing competition and customers' raised requirements there arises a problem of enhancing operational management efficiency of services provided, which is a multifactor task.

The need to take into account individual preferences and technological limitations predetermines its multi-criterion nature. The completion of such a task would be impossible without the application of intelligence information technologies.

The paper looks at the two basic constituents of operational service management. First, formalization of a domain-specific scheduling problem of industry in the necessity to use semantically expressive means for the description of technological limitations and customers' preferences. Second, more and more improving network and multi-core technologies put even in the ordinary personal computers allow to solve scheduling problems at a new technological level. These aspects are reflected in the technologies of ontological knowledge bases and multi-agent systems, related to the area of the distributed artificial intelligence.

According to the provisions of economic theory the mission of the operational management is ensuring a stable process of the primary activity of an organization.

A customer turns to an organization having certain goals and individual preferences. During the dialog with the manager there occurs an assignment of a complex service from a set of standard services rendered by the organization. In other words, a complex service is a reflection of the client's aims on a set of standard services rendered by the organization.

We are set a task of operational service management. So, what are the parameters in this process that we can manage? The controlled variables on the part of the customer in the process of providing services are the ones which describe the desired state of the client. Uncontrollable variables are the beginning and the end of the possible consumption of services, the initial state and physiological features, financial position and status of the client. The effectiveness parameters are the subjective perception of services and preferences.

Controllable variables in operational service management on the part of the service are temporal periods of availability of a service, the information about the mechanism of doing services. Uncontrollable variables are the service location, exploited resources, natural environment, history of doing services, requirements of the technological process and factors of the production environment. The effectiveness parameters are quality criteria and subjective perception of the service by the client.

The proposed conceptual approach to the operational service management is based on a domain-specific complex of models as well as on the chart of an identification type adaptive management. The main acting persons in the service provision process are service user and manager [2].

The mathematical problem model of assigning services to clients is formulated in terms of the integer programming and is decided by the method of dynamic programming and allows to take into account the economic aspects of providing services and to ground pricing in an organization.

The mathematical model of service scheduling is formulated in terms of game theory with non-contrary interests as a game with the concerted vector of interests with the forbidden situations, and allows to take into account the formalized technological features of the service provision process, individual strategies of customers' behavior, and also behavioral strategies common for all the participants involved in the process.

Presence of non-protuberant area of feasible solutions makes it impossible to solve the given problem by mathematical programming methods.

The method of intellectual decision support is based on:

- an iterative process of the adaptive planning and making possible administrative decisions;
- the rules of management decision-making;
- the agent paradigm of artificial intelligence.

All this provides a theoretical basis for realization of the proposed approach.

Conclusion

In this paper have been described two approaches that take into account uncertain information on clients and their individual preferences. RFMR is based on a scoring approach provide the foundation for the quantification of customer behavior. The proposed conceptual approach to the operational service management is based on individual preferences in domain-specific complex of models. It is hoped that this discussion assists marketers in forging a solid base for understanding and executing customer segmentation.

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