

COSTUMER BEHAVIOR METRICS IN DATABASE MARKETING

Cristina Romanciuc,
Babes-Bolyai University of Cluj-Napoca
Email: cristina_romanciuc@econ.ubbcluj.ro

Keywords: CRM, Data, Database marketing, Consumer behavior, Descriptive model, Predictive model.

Abstract:

Data gathering and processing is very important for every business. Database and especially, Database Marketing is an instrument which is gaining more and more territory. This instrument is used in different fields of economy, but especially in marketing, playing an important role in processing data about costumers. Areas such as costumer behavior and customer relationship are strongly related to database marketing. Two types of model can be used for determining consumer behavior: descriptive model and predictive model.

1. INTRODUCTION

Today in digital era, huge amount of data is generated every day. Gathering this information may be an elaborate process, but deriving meaningful information, from this data is more important. Data can be generated by the marketer's activities (sales, surveys) and supplemented by data purchased from other sources. Databases are an important instrument for every business. Most of the times, Databases are defined as a collection of related data. Database marketing applications can be divided logically between those marketing programs that reach existing customers and those that are aimed at prospective customers. Corporations maintain all their important records in databases. They represent the data gathered from different types of sources. Although organizations of any size can employ database marketing, it is particularly well-suited to companies with large numbers of customers.

The importance of database comes from a body of knowledge and technology that has developed over several decades and is embodied in several software programs, called database management systems, or DBS, or more colloquially a database system.

The present paper emphasizes the importance of Database Marketing for consumer behavior metrics. The second chapter presents basic information about data in economy – data types and data sources. The third chapter is focused more on data processing using databases and specific elements of database marketing. In the fourth chapter consumer behavior characteristics are analyzed. Specialists from different areas are trying to understand human behavior and to use that knowledge to understand consumer behavior. In the next two chapters two models are described: Descriptive Model and Predictive Model. Characteristics and particularities of these two types of models are presented in chapter five, chapter six. Withdrawn conclusions are included in chapter seven.

2. DATA IN ECONOMY

Data may be collected from past purchases, such as items purchased, and the recency, frequency, and monetary value of purchases, or it may be no purchase related, such as income, education level, and age. Data are the facts and figures related to the problem, and are divided into two main parts: secondary data and primary data.

Primary data: information that is developed or gathered by the researcher specifically for the research project at hand. Secondary data: information that has previously been gathered by someone other than the researcher and/or for some other purpose than the research project at hand.

Primary data are the facts and figures that are newly collected for a project. Sources of primary data are: Surveys, Focus groups, Questionnaires, Personal interviews, Experiments and observational study. Types of Primary Data are: Demographic/Socioeconomic (Age, Sex, Income, Marital Status, Occupation), Psychological/Lifestyle (Activities, Interests, and Personality Traits), Attitudes/Opinions (Preferences, Views, Feelings, and Inclinations), Awareness/Knowledge (Facts about product, features, price, and uses), Intentions (Planned or Anticipated Behavior), and Motivations, Behavior (Purchase, Use, Timing, and Traffic Flow) [1].

Secondary data are the facts and figures that have already been recorded before the project at hand. The source of secondary can be internal or external. Internal secondary data are data that have been collected within the firm such as sales records, purchase requisitions, and invoices.

Internal secondary data is used for database marketing.

Database marketing is the process of building, maintaining customer (internal) databases and other (internal) databases for the purpose of contacting, transacting, and building relationships. External Secondary Data are data collected from sources outside the company. Published external secondary data are sources of information prepared for public distribution and normally found in libraries or a variety of other entities such as trade or Governmental organizations. Syndicated Services Data are data provided by firms that collect data in a standard format and make them available to subscribing firms, highly specialized and not available in libraries.

Secondary data have many uses in marketing research and sometimes the entire research project may depend on the use of secondary data. Applications include economic-trend, forecasting, corporate intelligence, international data, public opinion, and historical data.

From the economical point of view data can be divided into two types: consumer data, and business data. Marketing to prospects relies extensively on third-party sources of data. In most developed countries, there are a number of providers of such data. Such data is usually restricted to name, address, and telephone, along with demographics, some supplied by consumers, and others inferred by the data compiler. Companies may also acquire prospect data directly through the use of sweepstakes, contests, on-line registrations, and other lead generation activities.

For business-to-business companies the relationships with customers will often rely on intermediaries, such as salespeople, agents, and dealers and the number of transactions per customer may be small. As a result, business-to-business marketers may not have as much data at their disposal as business-to-consumer marketer is accustomed [2].

Sources of customer data often come from the sales force employed by the company and from the service engineers. Increasingly, online interactions with customers are providing B2B marketers with a lower cost source of customer information. For prospect data, businesses can purchase data from compilers of business data, as well as gather information from their direct sales efforts, on-line sites, and specialty publications.

3. DATABASE MARKETING

Databases are an important instrument for every business. Most of the times, Databases are defined as a collection of related data. Databases are used to prospects, to target offers, to deepen loyalty, to reactivate customers, to avoid mistakes Logical Structure for database is tree structures, relational structures, and network structures. The most common relational DBMS is Microsoft access and oracle, Components of DBMS are: Data, Hardware, Software, Users [3]. Types of Database usefull in marketing are:

- Operational database
- Analytical database

- Data warehouse
- Distributed database
- End-user database
- External database
- Hypermedia databases on the web
- Navigational database
- In-memory databases
- Document-oriented databases
- Real-time databases
- Relational Database

Although database marketing was invented in the late 1970s, it did not take hold immediately. It only began to take root actively in major American corporations in the late 1980s, as a result of decreasing costs of computer storage and retrieval [4]. Database Marketing is the use of customer database to enhance marketing productivity through more effective acquisition, retention and development of customers (R.C. Blattberg, 2008) [5]. Database Management System (DBMS) is a software package/system to facilitate the creation and maintenance of a computerized database [6]. Database System is the DBMS software together with the data itself. Sometimes, the applications are also included. A DBMS is a powerful tool for creating and managing large amounts of data efficiently and allowing it to persist over long period of time, safely. These systems are among the most complex types of software available [7].

In fact, Forrester Research reports that many DBMS customers must manage nine such vendors and those two thirds of these would like to consolidate. Of the group surveyed, just 20 percent for Fortune 500 firms indicated a desire to consolidate vendors, a relatively low figure no doubt due to the difficulty in reducing supplier dependencies. This trend promises to continue given that many DBMS provider customers have requirements that are maturing beyond single channel direct marketing. Customers of DBMS providers typically fund these efforts at more than \$1 M USD each year, despite this significant investment, marketers often require additional services, not all of which can be sourced from their primary providers. Data appending is one such service that helps marketers better understand the attributes of customer segments, or can be used as an input to models for predicting churn or cross/up sell propensities. Industry-specific analytical and marketing services are another component of many customers' database marketing strategy to; for example, develop best practice lifetime value models, for focusing marketing dollars on most valuable customers. Many providers also offer business services around the execution of direct marketing programs, such as creative, fulfillment and telephone follow-up.

Long period database marketing has been dominated by direct marketers, more recently, mass marketers are beginning to understand and use it as well. It is used to lead customers or potential customers to generate personalized communications for marketing purposes. The method of communication can be any addressable medium, as in direct marketing. Many say that it generates junk mail or spam, if it's unwanted by the addressee. On the other hand direct and database marketing organizations, on the other hand, argue that a targeted letter or e-mail to a customer, who wants to be contacted about offerings that may interest the customer, benefits both the customer and the marketer [8].

Database marketing is an important field. It allows a business to take advantage of names of individuals who may be interested in their products. These databases of people are often some of the best potential customers out there because they have already made purchases or shown interest in the products and services that you are providing. But not everyone likes these options and not everyone likes database marketing.

4. CUSTOMER BEHAVIOR ANALITYCS

For many organizations, both business to consumer and business to business, database marketing services (DBMS) providers have become trusted and valued partners to their marketing departments. Firms lacking the technical, marketing and analytical skills necessary to develop a database for customer or prospect marketing have turned to DBMS providers to not only develop, host and maintain these databases, but also provide insight into distinct segments to target for achieving a greater return on direct marketing investments.

Companies with large databases of customer information risk being "data rich and information poor." As a result, a considerable amount of attention is paid to the analysis of data. For instance, companies often segment their customers based on the analysis of differences in behavior, needs, or attitudes of their customers. A common method of behavioral segmentation is RFM, in which customers are placed into sub segments based on the recency, frequency, and monetary value of past purchases. Van den Poel gives an overview of the predictive performance of a large class of variables typically used in database-marketing modeling [9].

The differences from descriptive and predictive have different approaches. If we are trying to predict someone's behavior in a given situation then our prediction must be one of the actions that it would be rational, in the action-guiding sense, for the agent to perform. In fact, as proponents of the simulation approach to "theory of mind" have emphasized, one way of securing such a prediction is to think oneself into an approximation of the psychological profile of the person whose behavior one is trying to predict and then to ask oneself the action-guiding question from the first-person perspective (Gordon 1986; Heal 1986) [10]. The predictive/explanatory dimension can be understood, however, in a way that is neutral between particular models of how explanation and prediction are achieved.

5. DESCRIPTIVE MODEL

Descriptive and predictive models work with decision making theories. Scientific psychologists, in contrast, have typically approached the question from the opposite direction, taking it as given that a theory of rationality must provide a descriptively and predicatively adequate account of decision-making and then working backwards from a descriptive model of choice to a theory of rationality [11]. Kahneman and Tversky themselves distinguish the explanatory/predictive project from the normative and action-guiding projects, arguing that no single theory can do all three jobs because the best normative theory is hopeless from a descriptive point of view. But other authors have tried to bring the normative and the descriptive into harmony.

Customer Based Value Metrics. Strategic Customer Value Analysis process is focused on examining customers and marketplace. Customer value analysis develops a quantitative picture of the markets.

RFM is one of the most used methods for analyzing customer behavior and defining market segments. It is commonly used in database marketing and direct marketing and has received particular attention in retail.

- a) RFM - Recency, Frequency and Monetary Value-applied on historical data tracks customer behavior over time in a state-space

Recency - how long it has been since a customer last placed an order with the company

Frequency - how often a customer orders from the company in a certain defined period

Monetary value – is the amount that a customer spends on an average transaction.

To create an RFM analysis, one creates categories for each attribute. For instance, the Recency attribute might be broken into three categories: customers with purchases within the last 90 days; between 91 and 365 days; and longer than 365 days. Such categories may be arrived at by applying business rules, or using a data mining technique, such as CHAID, to find meaningful breaks.

Once each of the attributes has appropriate categories defined, segments are created from the intersection of the values. If there were three categories for each attribute, then the resulting matrix would have twenty-seven possible combinations (one well-known commercial approach uses five bins per attributes, which yields 125 segments). Companies may also decide to collapse certain sub segments, if the gradations appear too small to be useful. The resulting segments can be ordered from most valuable (highest recency, frequency, and value) to least valuable (lowest recency, frequency, and value). Identifying the most valuable RFM segments can capitalize on chance relationships in the data used for this analysis. For this reason, it is highly recommended that another set of data be used to validate the results of the RFM segmentation process.

Advocates of this technique point out that it has the virtue of simplicity: no specialized statistical software is required, and the results are readily understood by business people. In the absence of other targeting techniques, it can provide a lift in response rates for promotions.

b) Past Customer Value

$$\text{Past Customer Value of a customer} = \sum_{n=1}^n GC_{in} * (1+r)^n$$

I = number representing the customer, r = applicable discount rate

n = number of time periods prior to current period when purchase was made

GC_{in} = Gross Contribution of transaction of the i^{th} customer in the n^{th} time period

c) Lifetime Value metrics (Net Present Value models)

LTV is a measure of a single customer's worth to the firm used for pedagogical and conceptual purposes.

$$\text{Calculation of Lifetime Value: Simple Definition } LTV = \sum_{t=1}^T CM_t \left(\frac{1}{1+\delta} \right)^t$$

LTV = lifetime value of an individual customer in \$,

CM = contribution margin,

δ = interest rate, t = time unit, Σ = summation of contribution margins across time periods

d) Customer Equity

CE is the sum of the lifetime value of all the customers of a firm

$$\text{Customer Equity, } CE = \sum_{i=1}^I \sum_{t=1}^T CM_{it} \left(\frac{1}{1+\delta} \right)^t$$

Other Customer Based Value Metrics are based on amount of sales made by a consumer and the likelihood to buy a product.

a) Size-of-wallet

$$\text{Size-of-wallet (\$) of customer in a category} = S_j \sum_{j=1}^J$$

S_j = sales to the focal customer by the firm j

j = firm, Σ = summation of value of sales made by all the J firms that sell a category of products to the focal customer

b) Share of Category Requirement

$$\text{SCR (\%) of firm or brand in category} = \sum_{i=1}^I V_{ij} / \sum_{i=1}^I \sum_{j=1}^J V_{ij}$$

j = firm, V = purchase volume, i = those customers who buy brand

$\sum_{i=1}^I$ = Summation of volume purchased by all the I customers from a firm j,

$\sum_{j=1}^J \sum_{i=1}^I$ = Summation of volume purchased by all I customers from all j firms

c) Share-of-Wallet (SW)

Individual Share-of-Wallet of firm to customer (%) = $S_j / \sum_{j=1}^J S_j$

S = sales to the focal customer, j = firm, $\sum_{j=1}^J$ = summation of value of sales made by all the J firms that sell a category of products to a buyer

d) Aggregate Share-of-Wallet (ASW) (brand or firm level)

Aggregate Share-of-Wallet of firm (%)

$ASW = \sum_{i=1}^I$ Individual Share-of-Wallet j_i / number of customers

$ASW = \sum_{i=1}^I S_i / \sum_{j=1}^J \sum_{i=1}^I S_{ij}$

S = sales to the focal customer, j = firm, i = customers who buy brand

e) Transition Matrix

TM characterizes a customer's likelihood to buy over time or a brand's likelihood to be bought.

6. PREDICTIVE MODEL

Predictive modeling is used extensively in analytical customer relationship management and data mining to produce customer-level models that describe the likelihood that a customer will take a particular action. The actions are usually sales, marketing and customer retention related. For example, a large consumer organization such as a mobile telecommunications operator will have a set of predictive models for product cross-sell, product deep-sell and churn. It is also now more common for such an organization to have a model of solvability using an uplift model.

Today's Customer Relationship Management (CRM) systems use the stored data not only for direct marketing purposes but to manage the complete relationship with individual customer contacts and to develop more customized product and service offerings. However, a combination of CRM, content management and business intelligence tools are making delivery of personalized information a reality.

Main tasks for CRM are to: identify prospects and customers, differentiate customers by needs and value to company, interact to improve knowledge, customize for each customer. Four important steps are involved in building profiles and profiting from them:

- Collecting and analyzing the data so that conclusions can be drawn.
- Gaining insight through defining the groups, and classifying all customers into the correct group after they have been with the store for six months or more.
- Managing customer relationships—changing your behavior toward customers based on what you know about them.
- Tracking the impact of your strategies and tactics on each segment to be sure that what you are doing is actually affecting customer behavior and company profits.

Strategies to accomplish the goals are: reduce rate of defection, increase longevity, enhance share-of-wallet, terminate low-profit customers, and focus more effort on high-value customers.

Other models are based on understanding the human behavior, and predicting its behavior as a consumer. Consumer perception about the product is a very important criterion in buying decision process. Product perception and preferences are very important for consumer when they are evaluating a product.

Perceptual measurement basics are beliefs about products (perceptions) can be measured directly by asking consumers how much of a feature they perceive a certain product to contain, or they can be inferred, by asking consumers how similar certain products are and then inferring what discriminates between different products.

The two analytical approaches most frequently used to derive evaluation criteria and build perceptual maps are decomposition methods, based on multidimensional scaling (MDS), and compositional methods, based on factor analysis (FA). MDS procedures infer dimensions that discriminate between consumers' evaluation of different products based on brand interrelationships, while FA methods take explicit attribute data and distill them into underlying dimensions or factors.

Multidimensional scaling

Multidimensional scaling covers a variety of techniques, it become popular and has extended into areas other than its traditional place in the behavioral sciences. Many statistical computer packages now include multidimensional scaling.

MDS is a set of procedures in which a reduced space depicting product alternatives reflects perceived similarities and dissimilarities between products by the inter product distances. Different types of multidimensional scaling may be distinguished on the basis of the type of data input to the model, the number of dimensions on which the data are collected (modes), and the geometric model used to analyze the data (Kotler & Moorthy 1997). The idea behind MDS is to create a map representing the product stimuli or consumer references, but it is not only about reconstructing maps, but can be used on a wide range of dissimilarities arising from various situations.

A wider definition of multidimensional scaling can subsume several techniques of multivariate data analysis.

Several types of data lend themselves to analysis by multidimensional scaling. Behavioral scientists have adopted several terms relating to data which often are not familiar to others: Types of data, Nominal scale, Ordinal scale, Interval scale, Ratio scale [12].

Issues that must be considered with multidimensional scaling include the number of products needed, the determination of the dimensions, and the validity of the process. Green & Wind (1973) suggest that the number of dimensions should be less than one-third of the number of products. In practice, the consideration set size provides an upper bound on the number of brands that can be evaluated. Tests of the reliability and validity of MDS have produced encouraging results and the methods are reasonably robust with respect to measurement error.

Factor analysis

Factor analysis has been used in economics to derive a set of uncorrelated variables for further analysis when the use of highly inter correlated variables may yield misleading results in regression analysis. Psychologists and educators have used the technique to determine how people perceive different "stimuli" and categorize them into different response sets, e.g., how different elements of language are interrelated.

Factor analysis was originally developed in connection with efforts to identify the major factors making up human intelligence. Since then, it has been applied to many other problems and is a frequently used technique in performing product-evaluation analyses in marketing. A fundamental principle inherent in any application of factor analysis is that a factor analysis model is not an exact representation of real-world phenomena. Such a model, at least in any parsimonious form, is always wrong to some degree, even in the population. There is a variety of ways in which such models may be incorrect. For example, most factor analysis models specify a linear influence of latent variables on measured variables, when in fact that relationship may be nonlinear in the real world. Factor analysis models also attempt to account for relationships among measured variables using a small number of common factors and are not capable of fully representing the undoubtedly large number of minor common factors that influence measured variables and account in part for their inter correlations. There are many other sources of error in such models. At best, a factor analysis model is an approximation of real-world phenomena. An alternative form to common-factor analysis is principal-components factor analysis. Studies comparing principal-components and common-factor analysis generally find similar results.

Both the number and the names of factors are important issues in performing a factor analysis. The number of factors used is often chosen based on the magnitude of the given value of the last factor chosen and the interpretability of the solution. An examination of factor loadings, supplemented by market knowledge, generally leads to reasonable names or interpretations for factors.

Several other methods have been applied to modeling perceptual spaces, particularly multiple discriminant analysis and correspondence analysis. Multiple discriminant analysis (MDA) is a method of determining which variables explain the groups to which different stimuli belong (Albaum & Hawkins, 1983). Correspondence analysis is a method that summarizes both the rows and columns of categorical data in a lower-dimensional. The flexibility of data format is achieved at a cost of not being able to interpret interpoint distances (Hoffman & Franke, 1986)

Preferential basics

Basic models of attitude formation are either compensatory or non-compensatory. In a compensatory model, the weakness of a brand or product on one dimension can be compensated for by strength on another, and those strengths or weaknesses are combined to determine an attitude toward the brand. In non-compensatory models, usually only a small number of attributes are used to evaluate a brand, and shortcomings on one attribute cannot be overcome by favorable levels of another.

A basic compensatory model is belief-importance model (Bass & Talarzyk's, 1972), building on theory of attitude formation. In the belief-importance model, the attitude toward the brand is a function of the beliefs about the attributes possessed by the brand weighted by the importance of each attribute.

In general, non-compensatory models require individuals to process information by attribute across brands, while compensatory models require consumers to process information within brand across attributes. Since evaluations are simpler and faster in non-compensatory models, it is likely that they are better representations of decision processes for low-involvement goods or for the screening phase when there are many brands, while compensatory models more accurately describe brand evaluations for high-involvement products in more complex decision-making. A third alternative is where both types of rules are used in sequence, called a phased-decision rule (Wright & Barbour, 1977).

7. CONCLUSIONS

Database marketing and customer behavior metrics are high valued instruments used to understand customers and its behavior. These are tools that provide management with customer information. That information is used in various ways to increase customer retention and increase customer acquisition rates—the essence of business strategy.

In the chapter above 2 different methods are presented. Although it implies approaching different strategies, consumers are the same.

Some of the companies chose descriptive model to understand the impact of a campaign and to measure the impact. Others need to predict the consumer behavior in certain situation. No matter what method is chosen, important decision relay on the information resulted. From data gathering, to data processing, everything relates to the chosen method. This process is very important, because after all, understanding customer gets us one step closer to them. From the customer's point of view, database marketing could be a ways of making customers happy—of providing them with recognition, service, friendship, and information for which, in return, they will reward you with loyalty, retention, and increased sales. Genuine customer satisfaction is the goal of satisfactory database marketing.

References:

1. R. Elmasri, M. Park, “Fundamentals of Database Systems”, 1994, Calif,
2. A. Tapp, “Principles of direct and database marketing”, 2005, New York.
3. “Best practices for a Data, Warehouse on Oracle Database”, 2008
4. A. Hughes - "Strategic Database Marketing"
5. R. C. Blattberg, B. Kim, S. A. Neslin, “Database marketing: analyzing and managing customers”, Springer, 2008, New York.
6. R. M. Stair, G.Reynolds, “Principles of Information Systems”, 2010, Boston, USA
7. J. Ullman, J. Widom, “Database Systems: The Complete Book”. 2008.
8. E. L. Nash, “Direct marketing: strategy, planning, execution”, 2000, New York
9. W. Buckinx, D. Van den Poel, “Predicting Online Purchasing Behavior”, 2003
10. R. Gordon, P. Hammond, “Folk psychology as simulation, mind and language”, 1986.
11. D. Kahneman, A.Tversky, “Choices, values, and frames”, 2002, Sage, New York Russell
12. D.R. Cox, V. Isham, N. Keiding, “ Monographs on statistics and applied probability” , 2001