A STUDY ON USING BUSINESS INTELLIGENCE FOR IMPROVING MARKETING EFFORTS

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Abstract

A major success criteria for the marketing department of the company is the understanding of the consumers and the success of the campaigns. Based on the outputs of certain data mining tasks, a marketer would be able to chalk out his strategy. But the major barrier against proper utilization of business intelligence is that often the marketer is unable to see the actual benefits the system can provide him in meeting his objective. Firstly this article provides a basic knowledge of the various data-mining tasks which can create value to the marketer. A major concern becomes, even if the marketer is convinced of the benefits to be obtained, he is unaware of the process involved to get it done. The data requirements are huge for a business intelligence system. This article also provides some insights on what kind of data requirements the data-mining system would require to perform such business intelligence tasks. Thirdly, this article maps how business intelligence can be collaborated with marketing strategy to create value in each stage of the product development life cycle following Kotler's product life cycle framework. The entire paper provides these conceptualizations based on theoretical understanding of the areas under discussion.

***Key Words*:** Business Intelegence, Business Success, Cluster Analysis, Pattorn Association, Link Analysis, Task Discussion.

1. Introduction

A major expense associated with the marketing department is that from advertisements. Total global advertising expenditure reached US$290 billion in 1999, an increase of over US$15 billion on 1998. In real terms, global ad-spend increased by more than 3% from 1998 onwards. It has been established empirically and mathematically that investment on advertising improves consumer knowledge about the product and hence affects product sales positively. Kaldor and Silverman (1948) established that advertising as a percentage of sales is remarkably similar by product in the U.S. and U.K. Telser (1 961) established that advertising affects the profitability of firms and a firm maximizing profit spends an amount on advertising and chooses a price such that the price elasticity of the demand for its product equals the value of the marginal sales effect of advertising. Multiple studies starting as early as late 1960s (Comanor and Wilson, 1967) established the relationship between profit performance, advertising intensity.

and market structure. Advertisement has a huge spiraling cost as has already been indicated. Due to the huge nature of the possible number of consumers, it makes sense to understand which advertisement would impact which consumer the most. Knowing this would not only help in serious cost cutting of advertisement expenditure, but also improve the take up rates of advertising campaigns. This is where information technology plays a crucial role by processing information and thus providing key business intelligence for the marketer by providing key insights. This paper talks about some of the business intelligence techniques which help to do so and provides insight on which technique may be most optimally used under which conditions.

2. Theoretical Discussion

Traditional views of marketing, like that of Kotler and Kelly (2006) have mainly focused on the physical and human aspects or the organization. The information view of marketing started getting conceptualized with contributions from Haeckel and Nolan (1993). Naude and Holland (1995). Rayport and Sviokla (1995). More recently Holland and Naude (2004) argued that marketing should increasingly be viewed as information handling problem rather than the classical transaction driven or the relationship driven approach. The management approach to the study of marketing, can be traced to such concepts as the marketing concept, marketing mix, product life cycle and market segmentation. According to Moller (1994). this management approach can be characterized as trying to solve the problem of "how to develop an optimal marketing mix consisting of Product. 'Place*. Price and Promotion solutions for the competing preferences of a chosen target segment of consumers, households or organizational buyers". The concept of the marketing mix focuses on the need for marketing managers to view the marketing task as the process of mixing or integrating several different functions simultaneously, as was postulated by Sheth, Gardner and Garett (1988). To improve the -fit between the 4 Ps, understanding the customers become crucial, for which not only data is needed on the customers, but what can be done with the information which can deliver key insights on marketing. This focus on the mentioned problem domain has opened up a new area of study, known as database marketing. This offers benefits from increased revenue to the marketer from two areas, increase in revenue by better targeting and increase in revenue from better understanding of customer needs and hence designing more suitable promotions. It has been established by Webster (1988) and Gronroos (1990) that marketing can no longer be an area of the marketing specialists but that everyone in the organization must be charged with responsibility for customers and contributing to developing and delivering value for them. According to Webster (1992), this customer focus may require increasingly large investments in information management and information technology. The next frontier of automation will be marketing and sales functions as was argued by Moriarty and Swartz (1989). Brooks (1989) argued that these functions are likely to receive the largest investment of technological resources in the future. It is also evident that many companies have started, or are planning to build, marketing related IS. It is essential now to study and classify these systems in more detail so as to be able to design better and more cost- effective IS in marketing for the future.

There are various data mining or business intelligence techniques which are used in marketing as a tool to reduce marketing expenditure and increase the take up rate of campaigns. These techniques are used individually or are clubbed to do certain tasks. The challenge for ever customer-oriented organization consists of identifying potential customers and satisfying and retaining existing customer.This necessitates a detailed understanding of the people's needs and expectations. Adequately addressing these needs and at the right time is crucial to grow and maintain a long-lasting and mutually profitable relationship. In applying data mining methods to marketing problems, there are several critical issues within the knowledge discovery process, from Business Understanding over Data Preparation and Modeling to Deployment of the model in a marketing environment , pattern association, summarization, predictive modeling, link analysis and social network analysis. These tools have been classified under query tools. descriptive statistics, visualization tools, regression type models, association rules, decision trees, case based reasoning, genetic algorithms and graph theory. In this paper, a brief introduction has been provided on how the following data mining tasks can help to reduce marketing expenditure and increase the take up rate of campaigns. While there are multiple studies in the area of each of these -tasks in data mining, there is no study which dictates how these tasks can be used effectively by the marketer at different stages of the product life cycle, based on which, promotion strategies are actually taken. This paper strives to bridge this gap. In the following part, a brief description of the major tasks of data mining is provided with the description of their possible application for a marketer.

Cluster analysis

Clustering or cluster analysis is the process of grouping the data into classes or clusters, so that objects within a cluster have high similarity in comparison to one another but are very dissimilar to objects in other clusters (Han and Kamber, 2006). Clustering is a method of unsupervised learning, and a common technique for statistical data analysis. Data clustering algorithms may be hierarchical which find successive clusters using previously established clusters. These algorithms can be either agglomerative (also called bottom-up) or divisive (also called top-down). Agglomerative algorithms begin with each element as a separate cluster and merge them into successively larger clusters.

The data-mining tasks who are used for the purpose are clustering, classification, Divisive algorithms begin with the whole set and proceed to divide it into successively smaller clusters. Partition algorithms typically determine all clusters at once, but can also be used as divisive algorithms in the hierarchical clustering. Density-based clustering algorithms are devised to discover arbitrary-shaped clusters. In this approach, a cluster is regarded as a region in which the density of data objects exceeds a threshold. Clustering may typically be used in marketing, for advertisements when the customers are yet to be segmented. After running a cluster analysis, the clusters may be examined for characteristics based on which advertisement campaigns may be directed at the customer base. After segmentation, based on the characteristics of the clusters, product positioning, product repositioning and product development may be done, to improve its fit with the targeted customers. Cluster analysis may also be done to selecting test markets.

Classification

Classification essentially mapping an input pattern, A pattern classification problem is represented as an input vector, to a particular class or category. Thus given a database D={t1,t2...tn} and a set of classes C={C1....Cn}, the classification problem is to define a mapping:D-C where each ti is assigned to one class (Dunham, 2006). Traditionally classification (Duda, Hart and Stork, 2001) has been studied using Bayesian decision theory and parameter estimation, non-parametric techniques, linear discriminant functions, multi-layer neural networks, stochastic method and non-metric methods.

Pattern classification may he used efficiently in marketing and advertisements by first segmenting the entire customer base and then delivering selective advertisements to specific classes of customers which the latter would be able to relate to better, and thus in the process, increase the t t rate and the success of such advertisement campaigns.

Pattern Association

From the early 1970s, pattern association was primarily studied in the context of market research development. Pattern Association is used to predict patterns based on past patterns or data sequences on which er the tool has been trained upon. Perhaps the most common precursors to the exploration of the associative relationship between two variables in marketing involve the use of bivariate cross-tabulations or multivariate analysis (DeSarbo and Hildebrand 1980: Green 1478: Perreault and Barksdale1980).). Several alternative measures are available for assessing the extent of association in a contingency table. Current pattern association studies in data mining started developing from 1993. Agrawal, Imielinski, and Swami (1993): Holsheimer. Kersten and Mannila(1995): Houtsma and Swami (1995); is studied association in mining approaches and are highly cited works. Pattern association may be extensively used to predict customer preferences when very little data about the customer is available to the marketer. Focus for pattern association would help a marketer to predict which product or advertisement the customer may be interested in solely by the current buying behaviour of the customer and matching it with the buying behaviour or similar customers (who bought similar products) even when no information is available for the customer.

Summarization

Summarization refers to methods that collapse large amounts of data into the summary measures that provide general description of variables and their relationships (Peacock,1998) Summarization maps data into subsets with associated simple descriptions (Dunham, 2003). Simple cross tabs, counts, averages, graphs, pie charts and descriptive statistics provide summarization. Summarization maps data into subsets with associated simple descriptions like characterization and generalization. Summarization can help marketers identify the profitability of segments and then focus resources accordingly, such that segments with higher profitability receive for advertisement efforts. BY this task, those segments which are non-profitable may be neglected thus saving a lot of advertisement expenses. Also. using this task. those segments may he identified for who the take up rate of campaigns are faster, and also push new products to early adopters.

Predictive modeling

Predictive modeling is the process by which a model is created or chosen to try to best predict the probability of an outcome. In many cases the model is chosen on the basis of detection theory to try to guess the probability of a signal given a set amount of input data. Predictive modeling is assuming an increasing role in the database marketing (DBM) industry to analyze customers' response and drive the decision process. The range of predictive modeling covers a variety of models, including statistical models and artificial intelligence-based models (such as neural networks). Predictive modeling is typically used to predict some type of a response measure for each customer, as a function of a set of explanatory variables (predictors). If the response level exceeds a certain cut-off point, the customer is selected for the promotion; otherwise the customer is rejected. In most practical applications, the response is measured by a discrete, often a binary yes/ no variable, such as buy/do not buy, pay/do not pay, Loyal/non-loyal, and the likes. But in many cases, the response is continuous, with a degree of belongingness to both responses. This task enables careful selection of-customers for targeted advertising, and thus brings down overall ad-spend considerably.

Social network analysis / Link analysis

From the point of view of data mining, a social network is a heterogeneous and multi-relational data set represented by a graph. The graph is typically very large, with nodes corresponding to objects and edges corresponding to links representing relationships or interactions between objects and both nodes and links have attributes. Social Network Analysis or link Analysis is a methodology for mapping and measuring the information flows through interactions among people in groups, represented as nodes on the graph. Social network analysis is a set of scientific techniques for modeling and assessing social relationships which depicts nodes and the types and strengths of links between them. Marketers use it to gain a detailed understanding of how people in groups interact. Software tools are emerging that simplify the process of creating the link analysis diagrams. The task uses graph theory to analyze social networks. Using this task, the marketer is able to isolate early adopters and influencers from a group, to push new campaigns. Also, the marketer is able to identify thought leaders and influencers in a social group, who if takes up a campaign, will influence others in their social network to do the same. This task may also be used effectively for low cost but highly effective viral marketing. Also. the same may be used to identify potential churners and thus impact the cost of customer acquisition. Thus Social network analysis can help a company save a lot on their marketing expenditure from advertisement campaigns.

Task discussion summary

Each of the tasks described earlier has a very specific data requirement. The following matrix summarizes few possible utilities of each task and when they can be used, by the marketer, based on the preceding discussions. Also the data requirements of each task are also provided in the same. This matrix has been drawn from conceptual understanding of the theory in the area.

Table 1. Mapping of task., Data requirement and Utility to the marketer

Task	Type of customer information needed	Utility to marketer
Cluster analysis	Psychographics, demographics, product preferences	Segment identification. Need identification
Classification	Psychographics, demographics, product preferences, other related data	Segmentation of customer, and future purchase prediction
Pattern association	Purchase behaviour records, basket data information	Predicting future purchase
Summarization	Segment purchase detail, customer detail	Profitable and non profitable segment identification
Predictive modeling	Psychographics, demographics, past trends in behaviour, acceptance of campaign/new product	Predict campaign take-up, loyalty
Social network analysis	Social network with whom the customer interacts	Identifying early adopters, product launches, viral marketing.

Proposition

As has been argued and established in previous studies, information and how it is mined plays a crucial role in marketing, especially in the success of campaigns, promotions and advertisements. Based on the insights developed from the study made on the various tasks used to meet various marketing utilities, a matrix is being proposed for mapping which task would create value for the marketer for which type of product or at which stage of the product life cycle the same is. The proposition is entirely conceptual in nature and aims to help marketer lower the huge expenses incurred in advertising. The product life cycle framework being used is to further develop the information needs based on the task is as depicted by Kotler and kelly (2006). They presented a comprehensive strategy based on product lifecycle, for each product, but the same did not focus on information needs being extremely crucial, as it is in the current information age. information can he used by a marketer in many ways using the previously mentioned tasks. Identification of early adopters can be done by link analysis, predictive modeling and summarization. This can help a firm kick-start the campaign of a new product. Similarly identifying influencers can help a company focus their marketing efforts on those few people who if accepts the product will make the campaign successful by influencing others to take it up as well. Similarly, identifying needs and thus the basis for segmentation is one of the crucial tasks of a marketer which may be done by a cluster analysis, and then customers may be mapped to their segment by a classification tool, and then more focused campaigns may be possible. Similarly, clustering may help to identify the gap between expected benefits and perceived of a product and this help the marketer to reposition his product. Again, if nothing is known about the customer, just on the basis of mining his immediate shipping pattern, it is possible to predict Future purchases, through association rule mining, and then create an immediate campaign based on generated rules, thus increasing sales by cross-selling of multiple products. The list of tasks and outputs are not comprehensible, but the matrix given in the following part gives a good indication of the data-mining tasks and their business impact. The matrix identifies which task can have what type of impact at which stage of the product life cycle. The proposed outputs have been developed based on the suggested classical strategies for the different stages of the product life cycle which can be impacted by information processing, as has been mentioned in Kotler and Kelly (2006). The same has been chosen due to the comprehensive nature or the framework in covering all aspects of the product life cycle. As is evident in the following matrix, various tasks can help to provide various benefits for the company based on the stage of the product in the product development life cycle. The tasks can be used to identify the segments for a focused targeting and also predict which customers belong to which segment, thus automating the entire process. Mining data can help a company position and reposition their products based on the needs of their customer. Also the tasks may help to improve the products and even extend the product line by better understanding of customers' needs. The tasks may also be used to identify which customers should actually be targeted by campaigns to derive higher returns on the huge marketing expenditure made by the firm. Also. it may help to identify potential churners and help prevent loss of revenue for the client and also help to reduce cost of customer acquisition by better targeted campaigning.

Table 2. Mapping of Tasks, Product life cycle and utility to the marketer.

Link analysis	Identify innovators, early adopters	Identify early adopters & influencers	Identify influencers & laggards	Identify churners & laggards	Identify churners
Predictive modeling	Identify innovators, early adopters	Identify early adopters & influencers	Identify profitable and loyal customers	Identify loyal customers calculation of CLTV	
Summarization	Identify early adopters	Identify new customer segment	Identify profitable customer segment	Identify profitable customer segment	
Pattern association		Identify potential associated	Identify potential associated	Identify potential associated	Identify possible product line

		purchase	purchase	purchase	diversification
Classification	Push product to target segment	Push product to target segment	Push product to target segment	Push product to target segment	Push product to target segment
Clustering	Identify segment and size, market needs	Identify product extentions	Identify product extentions	Reposition based on segment need if needed	Reposition based on segment needs if needed
Task ↑ Stage →	**Introduction**	**Growth**	**Maturity**	**Saturation**	**Decline**
Product life cycle (increasing maturity)					

The mapping of the task can have important implications of how a practitioner may use the information available to him, at each stage of the product life cycle,to fulfill the business needs. Knowing which task can fulfil the business need and what sort of data would be needed to do so, would enable a practitioner chalk out a plan or action to implement a business strategy. This mapping has been conceptualised by studying the theory in the related discipline.

3. Conclusion

Information plays a major role in the current times in improving business processes. To become produtively engaged in knowledge discovery activities, marketing managers should possess a good understanding of what these activities consist of, For doing the same, there has to be a good understanding of the various task, . their requirements and their outputs, to be able to appreciate their relevance in the business context.

This paper provides a basic understanding of the various tasks and indicates how each task can provide value to the marketer based on theoretical understanding of both areas under discussion. It also maps the data-mining tasks with the product life-cycle stages and also provides insights of a few possible business benefits that may be extracted by engaging in the tasks. The focus has been on the product life cycle as various strategies actually depend on the stage of the product in the PLC curve, with which the data-mining tasks have been mapped. This paper also provides a keen insight on how information technology can be used to enable business processes and strategies better by using the keen insights developed from processing information.

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