Retail analytics in the context of 'Segmentation, Targeting, Optimisation' of the operations of convenience store franchises

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Abstract

Retail analytics is seen as an essential instrument for improving retail business performance under the pressure of increased competition. Segmentation is beneficial, insightful, instructive and inventive but the real zeal is in implementing it. This paper presents a methodology and implementation of segmentation for a convenience store franchise based on the drinks sold at each store. The purpose of the segmentation of stores is the minimisation of time for organising cooler sections for drinks, so that management can keep popular drinks in larger number and less popular will acquire less room. Clustering models are created based on sales variables enriched with small number of selected demographics as opposed to just demographic variables as such models performed better. Results are currently used by retailers in one state of Australia.

Introduction

Retail analytics provides organisations with essential business intelligence for making smarter decisions and manage business more effectively. This allows organisations to get the most out of their existing management information system without the risk of committing to significant investments. There is increasing competition in retail analytics as the current business focus has moved from mass marketing to target marketing. Target marketing, also referred as micro marketing, requires slicing potential market into segments. It helps businesses to promote right product and service to the right market, hence saving efforts, space and costs of targeting the section of customers who may never be interested in buying. However, doing that effectively requires reliable customer intelligence and actions aligned with that intelligence.

Customer transaction data is one of the sources that can reveal important information about customers. With the appropriate methods this information then can be converted into an actionable knowledge about customers. Businesses use these data to trace the buying behaviour of their customers. Based on extracted typical behaviours the pool of customers is then partitioned into different segments, where each segment reflects a particular customer profile. However, transaction data on its own provides a relatively surface knowledge, consisting mainly of associations between products. Moreover, the nature of the business usually provides essential additional background knowledge to the customer analytics process.

This paper presents an original technique for segmentation of convenience store franchises built on a combination of data mining techniques for extracting complementary pieces of information from a linked collection of data sets. The technique adapts the 'Segmentation, Targeting, Positioning' (STP) approach from marketing to the optimisation of franchise store operation, hence we label it 'Segmentation, Targeting, Optimisation' (STO). This is based on the value disciplines model (Treacy & Wiersema, 1995), where we consider store optimisation in terms of operational excellence with elements of customer intimacy. Segments are expressed as *store profiles*. Next section provides the relevant background on segmentation from the perspectives of market segmentation and as a technique in customer analytics.

Segmentation – Identify targets and stay focussed

Segmentation is a technique used in customer analytics across industries, including banking, insurance, telecommunications, government agencies (ATO, Centrelink, Medicare), airlines, tourism, for different analysis tasks, such as credit risk, marketing, churn prevention. Usually the purpose of the segmentation is to divide a population of objects (individuals, stores, companies) in groups that exhibit similar characteristics. Within the STP framework, segmentation is a key to marketing success (Weinstein, 2004b). Behavioural segmenting and clustering help to generate customer shareholder value, demographic clustering within behaviour segment helps tactical marketing campaigns (Kelly, 2006). In retail chains (e.g. WalMart in the US, Tesco in the UK), segmentation has been deployed to identify the specific customer-buying patterns corresponding to particular stores in the chain. For instance, to do that, WalMart captures point-of-sale transactions from over 2,900 stores in six countries and transmits this data to its data warehouse. Analytical techniques are used to extract information about the consumer patterns, which then are used to manage local store inventory and identify new merchandising opportunities. Other examples in retail analytics include, shoe manufacturers use the data to: predict fashion trends and future demands; have the right kind of shoes in stock at the right location.

Market segmentation

Market segmentation is the process of dividing a market into subsets with potential buyers (Punj & Stewart, 1983). The major categories of consumer characteristics used for market segmentation are: Demographical (age, family, size, life cycle, occupation); Geographical (states, regions, countries); Behaviour (product knowledge, usage, attitudes, responses); Psychographic (lifestyle, values, personality) (Schiffman et al., 2008).

Cluster-based market segmentation has become increasingly popular in marketing since 1970's. Customer clustering and segmentation are frequently used data mining techniques in marketing and customer relationship management(Kelly, 2006; Saarenvirta, 1998) Popular practical segmentation (classification) systems are PRIZMNE in the US and MOSAIC in Australia. Both tools provide demographic and lifestyle clustering service (*Prizm NE The new evolution segmentation snapshots*, 2003)(Inc, 2003; Schiffman et al., 2008). Such clustering techniques, provided by external companies, do not necessarily provide the deeper and specific insights for an individual company to achieve significant competitive advantage. That's the reason these days businesses require market segmentation based on their own data. It is more expensive but the resultant factors are worthwhile (McDonald & Dunbar, 2004).

There are 4 criteria for evaluation of the quality of segmentation – measurability, substantiality, accessibility and actionability (Speed & Smith, 1992). As a business is required to develop separate marketing plan for each market segment, the segments should not be too granular as there has to be a solid customer base for each segment and the market segments should be accessible to the business. Market segmentation is useful to design marketing strategies (Saarenvirta, 1998) and quite significant for marketing planning (Myers, 1996).

In marketing science segmentation is considered both as science and an art (Weinstein, 2004a). There are several ways market segmentation is classified, two major type of classification schemes used as background for segmentation efforts are *customer* based versus *service* or *product* based and *a priori* versus *post hoc* or *cluster* based segmentation. The customer based approach explores customers specific characteristics while product or service based approach is all about physical features of products or services themselves and their

benefit to customers (Myers, 1996). In a priori segmentation the analysts selects the basis for segmentation, such as demographic and socioeconomic characteristics, while cluster-based method is based on a similarity, identified by an algorithm chosen by the analyst (Speed & Smith, 1992). The next section presents an example of cluster based segmentation using fastclus clustering algorithm.

Micro marketing is the specialised technique in market segementation that focus on prospects as it is easier to attract attention of interested people and discover niche market. Niche marketeer target speciality market to promote products and services as a result they are more effective with better results as compare to mass marketeer. The concept of micromarketing even helps with relationship marketing as it helps enhancing relationship with current customer base (Storbacka, 1997).

The benefits of such segmentation to businesses help them plan responsive products, develop efficient promotional scheme and campaigns, measure competitive arrangement and fine-tune current marketing programmes though implementation of such segmentation strategies is more expensive than mass marketing (Weinstein, 2004a).

Retail analytics in Australian context

The pressure on Australian retail industries by the increasing competition on the Australian retail market (for example Aldi and Costco moving into Australian market) has led retailers to focus on getting deeper understanding of Australian consumers. This level of consumer insights is becoming the new benchmark in many retail channels as the two main grocery retailers acquire businesses in these channels. The demand is also driven by increased competitive and industry data availability through third-party sources (for example, Synovate Aztec).

Retailers want to enhance their business by driving strategic insights via data analysis. In particular, many Australian retailers are interested in segmenting their stores into groups that represent similar customer needs and purchase behaviour with the objective to optimise their sales, market share, ranging, cost, and staff performance.

Segmentation is beneficial, insightful, instructive and inventive but the real zeal is in implementing segmentation (Weinstein, 2004a). In the next section we provide an example of implementation of a successful application of advanced segmentation techniques for a project completed by Synovate Aztec for a major international retailer.

Case study of the application of retail analytics to convenience store franchise in Australia

This section presents a study of creating segments for a convenience store based on data about sales of drinks. Many cluster analysis projects have been done primarily based on demographic data. In this case the segmentation is solely based on the *sales variables*.

Data. The data is collected from 106 stores located in a single state in Australia. The total number of attributes in the collected dataset is 151. These include sales information of store products; store features such as number of cooler doors, competition intensity, inbound or outbound; geo demographic data for each postcode; annual sales figures for all drinks. In the dataset about 800 SKU's were classified into 11 groups as Sugar CSD Take Home, Sugar CSD Single Serve, Diet CSD Single Serve, Diet CSD Take Home, Water, Energy, Sports,

Juice, Milk, Slushee and Other. The sales data given by client is on an annual level not on monthly level, hence seasonal analysis is not done in this project.

Methodology. The flowchart of the methodology is presented in Figure 1 (the overlaid layers provide the standard data mining stages). The data from all the stores has been integrated and enriched with demographics data. The data set structure is of a 'wide data set' with 151 variables and 106 stores. In addition to this fact, the data set has been analysed in terms of its information content. We applied correlation analysis with SAS Enterprise Guide ("SAS") to remove some redundant information, i.e. to identify the variables, which were highly correlated to each other and could be removed from the analysis. This step reduced the dimensionality to 79 attributes. In order to decrease the impact of noise and insignificant variables on partitioning, we performed variable selection procedures with these 79 attributes. Salford systems TreeNet and Random Forest algorithms, which utilise information-based splitting criteria were used to determine the importance of each variable. A total of 32 variables were selected based on Tree Net HuberM method, among these 32 variables, 13 variables ~~(all these 13 variables~~ were sales variables of store~~)~~ and were used to form clusters. An array of clustering techniques including fastclus, SOM and others clustering algorithms in SAS and Random Forest clustering approach were then used to generate 6 store clusters. The clusters were then profiled on soft drink sales.

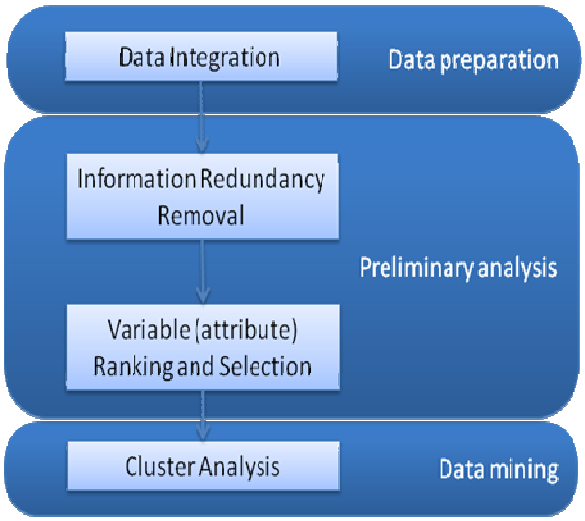

Figure 1: Methodology

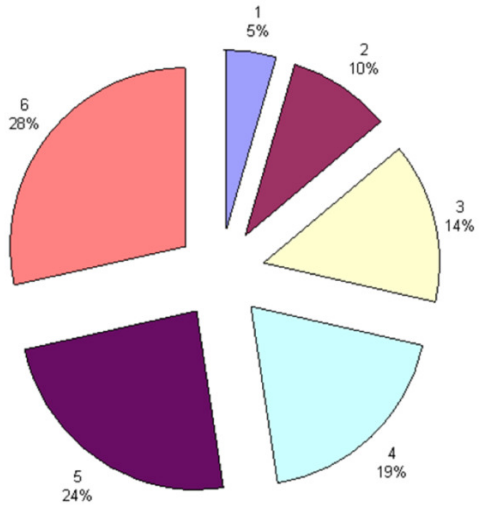

Figure 2: Identified segments

Results. A number of segmentation models has been created with geodemographic, store characteristics and sales figures, but the model results based on the sales values enhanced by the most relevant demographics factors such as population income, geographic location, proximity to main roads, % of blue vs white collar workers etc performed best, hence, the final segmentation is done based on drinks sales values only. Figure 2 shows the partitioning of the stores into six segments with the following characteristics:

(1) Stores with commuter fuel stations, these fuel stations are mostly close to major arterial roads and motorways;

(2) Stores in higher income suburban night entertainment, located in suburbs with clubs, cinemas, cafes or fuel stations on the way to or from these suburbs in higher income areas;

(3) Stores based in inner city area (in Central Business Districts) with high number of people working in the area, many offices, universities etc;

(4) Stores in diverse sub-central dwellings such as inner city and central area, where there are diverse areas with population from backpackers to affluent professionals;

(5) Stores in less affluent areas such as areas with lower income and high percentage of rented and mortgaged properties;.

(6) Stores in lower income suburban night entertainment such as stores in suburbs with clubs, cinemas, cafes or fuel stations on the way to or from these suburbs in higher income areas.

Each segment has a specific consumption profile in terms of the types of the drinks, their brands and quantities. As a result for each segment there has been designed specific store organisation in order to minimise time for organising cooler section for drinks, so that management keep popular drinks in larger number and less popular acquire less room, that is actionable knowledge and also comply with substantiality criteria. Test and control studies were performed based on the results of the project estimating the effect of the applying clusters-based approach and the stores where recommendations based on the study were used, had a significant sales growth in beverages, which satisfies measurability criteria. The study results were easily accessible and it satisfies our third criteria of accessibility. Hence, as discussed in the market segmentation section 4 criteria for evaluation of the quality of segmentation – measurability, substantiality, accessibility and actionability (Speed & Smith, 1992), our case study results have complied with all 4 criteria's at end of the STO process.

Conclusion

We presented an original technique for segmentation of convenience store franchises that adapts the STP framework to the optimisation of store layout in order to serve respective segments. It integrates a set of data mining techniques for variable selection and clustering in order to achieve high quality partitions, based on the sales data enhanced by demographics as opposed to the usual use of primarily demographics data. The purpose of the segmentation was to get deeper understanding of consumer segments so that the stores can be optimised in terms of keeping popular drinks in larger number and provide easier access to them, as well as to minimise the space, occupied by less popular drinks. The approach was tested on retailers in one state of Australia. The future work includes testing the work on data from different states.

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First, stores are segmented in 5 clusters using a hierarchical clustering method and then association rules are applied for each cluster. Keywords. Clustering Association rules Market basket analysis Segmentation. This is a preview of subscription content, log in to check access. Appendix. Table 5. Frequent item - 2 itemsets - 3itemsets for the entire data and each cluster. Open image in new window. Table 6. Association rules with support and confidence measures, for the entire transaction data and for each cluster.Â Kolyshkina, I., Nankani, E.: Retail analytics in the context of segmentation, targeting, optimisation of the operations of convenience store franchises. In: Anzmac 2010Google Scholar. 8. Mendes, A., Cardoso, M.: Clustering supermarkets: the role of experts. J. Retail. Consum. Analytics in Retail: A Historical Context. Retail is a data-intensive industry. We serve millions of customers, move hundreds of thousands of items, stock thousands of SKUs in hundreds of stores, in pursuit of that one goal â€“ a profitable relationship with customers. For decades retailers have focused on data and its analysis to drive improvements in core business pro-cesses and to improve operational decision-making.Â â€¢ Improve marketing effectiveness through micro-targeting, personalization and delivery of context and channel sensitive promotions and offers that increase the likelihood of purchase. â€¢ Optimize the supply chain to ensure the most profitable outcome in terms of demand fulfillment balanced against cost of carrying excess inventory. Retail - Business Operations. Retail Management - Space. Retail Selling.Â Market segmentation is very useful for the marketing force of the retail organization to create a custom marketing mix for specific groups. For example, Venus is in the business of retailing organic vegetables. She would prefer to invest her money for advertising to reach out to working and health conscious people who have monthly income of more than say, $10,000. Market segmentation can also be conducted based on customerâ€™s gender, age, religion, nationality, culture, profession, and preferences. Types of Retail Markets. There are two types of retails âˆ’ Organized Retail and Unorganized Retail. Organized ... The analysis of the internal environment of the company is the analysis of strengths and weaknesses, as well as the assessment of the potential that the company can count on in the competitive struggle to achieve its goals.Â After you finished the Environmental Analysis, it is time to go to the internal analysis of your company. The analysis of the internal environment of the company is the analysis of strengths and weaknesses, as well as the assessment of the potential that the company can count on in the competitive struggle to achieve its goals. The main objectives of the analysis are to determine the factors and causes of the strengths and weaknesses of the organization. One of the tools for internal analysis is ABC analysis.