

New Opportunities in Marketing Data Mining

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INTRODUCTION

Data mining has been widely applied in many areas over the past two decades. In marketing, many firms collect large amount of customer data to understand their needs and predict their future behavior. This chapter discusses some of the key data mining problems in marketing and provides solutions and research opportunities.

BACKGROUND

Analytics and data mining are becoming more important than ever in business applications, as described by Davenport and Harris (2007) and Baker (2006). Marketing analytics have two major areas: market research and database marketing. The former addresses strategic marketing decisions through survey data analysis and the latter handles campaign decisions through analysis of behavioral and demographic data. Due to the limited sample size of a survey, market research is normally not considered data mining. This chapter will focus on database marketing where data mining is used extensively by large corporations and consulting firms to maximize marketing return on investment.

The simplest tool is RFM where historical purchase recency (R), frequency (F), and monetary (M) value are used for targeting. Other tools include profiling by pre-selected variables to understand customer behavior, segmentation to group customers with similar characteristics, and association rules to explore purchase relationships among products, see Rud (2001); Berry and Linoff (2000). More advanced marketing involves predictive modeling to improve targeting and maximize returns. For examples, marketing-mix analysis has been around for three decades to optimize advertising dollars, see Dekimpe and Hanssens (2000); attrition modeling is used to identify customers at risk of attrition, see Rud (2001); and long-term value is used to prioritize marketing and services, see Peppers and Rogers (1997,1999).

To improve 1:1 marketing campaigns (e.g. direct mails, outbound), response modeling to identify likely responders is now a standard practice in larger corporations. As summarized in Figure 1, a previous campaign provides data on the 'dependent variable' (responded or not), which is merged with individual characteristics. A response model is developed to predict the response rate given the characteristics. The model is then used to score the population to predict response rates for all individuals. Finally, the best list of individuals will be targeted in the next campaign in order to maximize effectiveness and minimize expense.

Response modeling can be applied in the following activities via any marketing channel, see Rud (2001); Berry and Linoff (1997):

1. **Acquisition:** Which prospects are most likely to become customers.
2. **Development:** Which customers are mostly likely to purchase additional products (cross-selling) or add monetary value (up-selling).
3. **Retention:** Which customers are most retainable; this can be relationship or value retention.

MAIN FOCUS

In this chapter, we describe highly important problems that are infrequently mentioned in academic literature but frequently faced by marketing analysts. These problems are embedded in various components of the campaign process, from campaign design to response modeling to campaign optimization, see Figure 2. Each problem will be described in the Problem-Solution-Opportunity format.

CAMPAIGN DESIGN

The design of a marketing campaign is the starting point of a campaign process. It often does not receive enough attention in data mining. A poorly designed campaign

Figure 1. Response modeling process

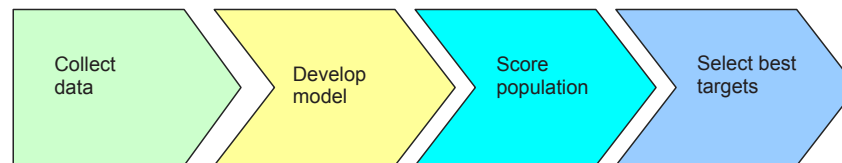
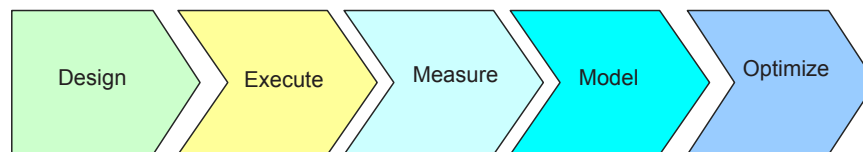


Figure 2. Database marketing campaign process



could make learning infeasible while a scientifically designed one can maximize learning opportunities.

The design process includes activities such as sample size determination for treatment and control groups (both have to be sufficiently large such that measurement and modeling, when required, are feasible), sampling methods (pure or stratified random sampling), and cell design structure (testing various offers and also by age, income, or other variables). We will focus on the latter here.

Problem 1: Classical designs often test one variable at a time. For example, in a cell phone direct mail campaign, we may test a few price levels of the phone. After launching the campaign and the price level that led to the highest revenue is uncovered, another campaign can be launched to test monthly fee and a third campaign will test the mail message, etc. A more efficient way is to structure the cell design such that all these variables are testable in one campaign. Consider an example, a credit card company would like to determine the best combination of treatments for each prospect, and the treatment attributes and attribute levels are summarized in Table 1 (channel is incorporated as an attribute). The number of all possible combinations = $4^4 \times 2^2 = 1024$ cells, which is not practical to test.

Solution 1: To reduce the number of cells, a fractional factorial design can be applied (full factorial refers to the design that includes all possible combinations), see Montgomery (1991) and Almquist and Wyner (2001). Two types of fractional factorial are: 1) orthogonal design where all attributes are made orthogonal (uncorrelated) with each other; and 2) optimal design where criterion related to the covariance matrix of parameter estimates is optimized, see Kuhfeld (1997,2004) for the applications of SAS PROC FACTEX and PROC OPTEX in market research (Kuhfeld's market research applications are applicable to database marketing).

For the credit card problem above, an orthogonal fractional factorial design using PROC FACTEX in SAS with estimable main effects, all two-way interaction effects, and quadratic effects on quantitative variables generates a design of 256 cells, which may still be considered large. An optimal design using PROC OPTEX with the same estimable effects generates a design of 37 cells only, see Table 2.

Fractional factorial design has been used in credit card acquisition but is not widely used in other industries for marketing. Two reasons are: (1) lack of experimental design knowledge and experience; (2) business process

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