Advanced Database Marketing
Innovative Methodologies and Applications for Managing Customer Relationships

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Introduction

The aim of marketing is to know and understand the customer so well the product or service fits him and sells itself.

(Peter F. Drucker, 1973)

1 The Brave New World of Database Marketing

The origins of database marketing can be traced to the fields of direct marketing and relationship marketing. Direct marketing brought to the forefront the importance of customer data, concepts such as recency, frequency, and monetary value (RFM), predictive modeling, and the need for accountability in marketing efforts. Relationship marketing, introduced by Leonard Berry (Berry, 1983), broadened the scope of database marketing to consider the customer relationship, exemplified by concepts such as customer acquisition, retention, and development, and the unifying theme of customer lifetime value. The result of this fusion between direct marketing and relationship marketing is what we know as customer relationship management (CRM). Database marketing can be seen as the analytical side of CRM, and is sometimes called analytical CRM.

Blattberg et al. (2008: 4) considered these developments in developing a definition of database marketing, namely:

*Database marketing is the use of customer databases to enhance marketing productivity through more effective acquisition, retention, and development of customers.*

This definition indeed captures the importance of analyzing customer data, making the analysis accountable (*enhance marketing productivity*) while focusing on the the importance of the customer relationship (*acquisition, retention, and development*).

This definition still applies today. However, there are four recent trends that substantially amplify this definition. These trends are:

1. the greater variety of data available;
2. the availability of a broader set of methodologies beyond standard statistical tools;
3. the desire to develop not only actions but *insights* from the data; and
4. the ability to implement these targeted actions quickly and in real time.

The proliferation of data available today is due in part to advances in data processing, collection, and management, but perhaps most strikingly due to the diffusion and harnessing of the Internet. The Internet provides traditional transactional data such as customer purchases, but much more, including product search behavior,
the formulation as well as use of recommendations, participation in social media, exposure to advertising, and the modern form of direct mail, namely email. Even more important is that companies are starting to merge these data with offline data, creating a “360-degree view” of the customer. Indeed the proliferation of Internet data is why we find ourselves with five chapters strongly related to database applications involving the Internet.

The “tried and true” methodologies of simple RFM analysis and regression are still widely used in database marketing. But new, more powerful methods are making their way into modern database marketing. The distinction of these methods is they draw on several disciplines, including computer science, operations research, computational linguistics, sociology, economics, as well as statistics. This is why methods such as machine learning, dynamic programming, text mining, Bayesian analysis, and consumer choice models make their way into this book.

One criticism of database marketing is that it has been “black-box;” it prescribes actions that work in the sense of increased response rates and profits, but in today’s world of database marketing there is more emphasis on insight. The de-mystification of database marketing has become important for two key reasons. First, as database marketing has become a more significant investment, senior marketing management pays more attention to it, and marketing managers want to understand why they are contacting customer A but not customer B, and why they are recommending certain products to certain customers. They want to make sure the activities of the database marketing group are consistent with the positioning and target group strategy of the brand. Second, new tools are becoming available for deriving insights. This is particularly evident in the rules-based learning chapter.

Finally, database marketing’s emphasis on implementation and accountability has been enhanced by modern-day capabilities. Companies can now implement the recommendations prescribed by statistical models. They can do so in real time on the Internet. They can conduct field tests of recommendation engines, search advertising copy, and banner advertising. In general, companies’ ability to implement and evaluate the actions prescribed by sophisticated models can be tested more easily today than ever before.

In summary, the definition of database marketing hasn’t changed – it’s still about analyzing customer data and using it to improve marketing productivity by managing the customer relationship. But the meaning of the definition has become more vivid and more exciting due to the greater variety of data, the increasingly multidisciplinary analytical “toolkit,” the drive for insights in addition to financial performance, and the capability to implement and evaluate more effectively. The reader will see these themes emerge in the chapters we have assembled for this book.

2 Book Contents

The contributions within this book are structured along the two dimensions – methodology and application. Part I describes the methodological advances, while Part II summarizes innovative applications areas in the database marketing field. Below you will find a detailed overview of the different chapters in the book.
2.1 PART I: METHODS

During the last few decades, methods for tracking consumer behavior became more sophisticated, and there has been a move from describing historical customer information to predicting consumers’ future behavior. Predictive modeling has established itself as a popular tool in database marketing. The true utility of a predictive model depends on the decisions made in:

1. assembling data;
2. modeling; and
3. implementation.

Part I is structured along these three stages of the predictive modeling process. Chapter 1 addresses data preprocessing, a necessary and vital step that has to take place before any modeling activity can be initiated. Data preprocessing greatly influences the degree to which pattern extraction is feasible and successful. The chapter strives to increase the awareness that data preprocessing is an important part of predictive analytics and a potential leverage to increase performance. Core preprocessing tasks and techniques are reviewed and some guidelines are provided on how to choose among alternative procedures. Furthermore, an empirical case study is undertaken to explore the relationship between prediction method, preprocessing, and forecasting accuracy. The results confirm a significant accuracy impact for certain preprocessing techniques and evidence that their effectiveness differs across prediction methods.

Chapter 2 zooms in upon text mining, a technique for assembling data when the data are in text format. The increasing amount of textual customer information that is stored in customer data warehouses leads to increased challenges and opportunities for marketing managers to better grasp the underlying customer behavior. However, marketing analytics often neglect this valuable type of information as it requires additional knowledge and effort to convert the text into a numeric representation suitable for subsequent processing. This chapter discusses the text mining process, and zooms into:

1. the text preprocessing phase that convert the textual consumer data into a high dimensional term-by-document matrix;
2. the dimension reduction techniques singular value decomposition and non-negative matrix factorization that group together related terms and projects them into a semantic space of lower dimensionality that could be used in traditional marketing analysis; and
3. the text mining applications published in top-tier marketing journals.

Chapter 3 shifts the focus to the actual model building process. Bayesian networks are popular within the fields of artificial intelligence and data mining due to their ability to support probabilistic reasoning from data with uncertainty. They can represent the correlated relationships among random variables and the conditional probabilities of each variable from a given data set. With a network structure at hand, people can conduct probabilistic inference to predict the outcome of some variables based on the values of other observed ones. The objective of the direct marketing modeling problem is to predict and rank potential buyers from the buying records of previous customers. The
customer list will be ranked according to each customer’s likelihood of purchase. Bayesian networks can estimate the probability of a customer belonging to certain class(es) and are therefore suitable for many database marketing applications. For example, by assuming the estimated probability to be equal to the likelihood of purchase or response, they are suitable to handle the direct marketing problem. However, the databases containing the buying records of customers may contain missing values. This chapter gives an introduction to Bayesian networks and proposes a system for discovering Bayesian networks from incomplete databases in the presence of missing values. The authors apply it to a real-world direct marketing modeling problem, and compare the performance of the discovered Bayesian networks with other models obtained by other methods. In the comparison, the Bayesian networks learned by the proposed system outperform other models.

Chapter 4 discusses quantile regression and its relevance for database marketing. The simple yet well-performing and easily interpretable statistical methods such as linear and logistic regression account as gold standard methods in predictive modeling for marketing in both academic literature and business usage. In regression, an equation is sought describing the relationship between a number of independent variables and the mean of the dependent variable conditional upon the independent variables’ values. Unfortunately, a mean is a strong simplification of reality as it is unable to unveil other characteristics of the underlying data distribution and might lead to incomplete or flawed conclusions when the conditional distribution is for instance highly skewed or contains outliers. Quantile regression is a generic approach that extends the mean regression model to a model specifying the relationship between covariates and any conditional quantile of the response variable of interest.

This chapter introduces the topic of quantile regression. A distinction is made between the frequentist and the Bayesian approach to estimate such models. Further, special attention is given to a recent development within this family of methods: binary quantile regression. Then, an elaborate section discusses the potential usage and advantages of quantile regression for database marketing through two case studies on customer lifetime value and customer churn prediction.

Chapter 5 sheds light upon the advantages of letting predictive models in database marketing join forces, whereby several models are combined into new, more flexible, and more powerful models. These so-called ensemble learners or multiple classifier systems have consistently emerged as winning entries in data mining contests, such as the Teradata/Duke CRM competition, KDD Cup or the Netflix Prize since many years. However, despite their strength and intuitive nature, their applications in real-life business are still scarce. This chapter untangles the topic of ensemble learning by first explaining their common structure, shared by the numerous algorithms that have been proposed within this category of statistical learners over recent years. Three intuitive arguments are presented to explain the potential of these methods to predict more accurately. The chapter continues with an elaborate overview of a selection of the most prominent and relevant ensemble learning algorithms for classification. Subsequently, it provides an overview and discussion of the academic literature on real-life database marketing applications in which ensemble learning was deployed, while a practical example is used to illustrate several concepts throughout the chapter. Special attention is given to two more advanced topics: (1) diversity, a key ingredient of any successful ensemble learner, and how it can be measured and assured; and (2) model interpretability.
The final chapter of the first part of this book (Chapter 6) shifts the focus to implementation by focusing on interpreting and operationalizing predictive models. Various different data mining techniques for marketing purposes are recently discussed in literature and have proven their excellence performance in a day-to-day business setting. Besides the search for optimal prediction performance, classification models should be intuitively correct and in accordance with the experts’ knowledge. This chapter focuses on rule-based methods, that is, techniques which supplement the superior performance of black-box models with a set of insightful and comprehensible rules. These techniques open up these black-box models. The chapter summarizes the state-of-the-art rule-based models, describes the use of decision tables to visualize the extracted rules and concludes with an application in a churn prediction setting.

2.2 PART II: APPLICATIONS

Part II describes new applications in which the principles of database marketing can be applied in companies. Chapter 7 presents an integrated, comprehensive discussion of recommender systems. Recommender systems are software systems and statistical procedures used by firms to suggest (“recommend”) products to their customers. A recommender system consists of data, a user model, and a selection model. A recommender system utilizes customer and product data to predict what product the customer is likely to prefer or purchase, and uses this prediction to select the product to be recommended to the customer. The data used to compute these predictions can pertain to the user, the product, or the user/product dyad. The chapter builds a general structure that shows how all three types of predictor data can be integrated into a “hybrid latent factor model.” The model incorporates observed as well as unobserved user, product, and dyad data. It combines content-type user models that rely on observed predictors and collaborative filtering models that rely just on observed preferences or purchases. The chapter shows how the general model can be extended to binary preferences, missing data, unary data, buying context, and preference evolution. It then includes a discussion of estimation and selection models and closes with an overview of future research topics.

Chapter 8 examines strategic goals, tactics, and research issues related to marketing via mobile devices. The strategic goals examined include advertising and promotion, targeting, branding, and sales. The tactics that help achieve these goals include mobile web and applications (“apps”), mobile social media and social networks, location-based services, and mobile commerce. Mobile devices enhance the potential of companies to market to customers in real time more so than ever before. The chapter discusses these marketing tactics and reviews academic research relevant to them. This research provides key insights on how consumers use mobile devices, how consumers generate and consume user-generated content, how consumers select and use apps, how consumers use mobile devices as social media, the relevance of geography, and complementarity/substitution between mobile and non-mobile channels. While there is much more that needs to be learned, and the mobile platform is evolving, research to-date reveals the tremendous potential of mobile devices to enhance marketing effectiveness.

In Chapter 9, online display advertising and its targeting strategies are addressed. Online display advertising, or banner advertising, while being one of the earliest forms of advertising on the Internet, is still highly relevant today as expenditures have been consistently on the rise. Simultaneously however, this form of online advertising has
been troubled by steadily decreasing effectiveness in terms of click-through rates, a phenomenon often described as banner blindness. However, over the years, as strategies have been developed to gather increasing amounts of data and establish better metrics and analytics, online marketers have developed and refined their ability to target display ads to the most promising prospects. This chapter first provides an overview of metrics that are commonly used to evaluate the effectiveness of online display ads. Thereby, initially, a distinction is made between metrics that measure short-term and long-term effects. Further, the chapter discusses models that take into account immediate and long-term response simultaneously, and models that formally incorporate the multi-channel effect of online advertising. Finally, targeting strategies are discussed that deploy individual information to match ads and their most likely responders. Subsequently, targeting based upon user characteristics, geographical targeting, contextual targeting, and behavioral targeting are discussed.

Chapter 10 discusses paid search advertising, where Internet advertisers reach customers in the midst of their product search process. The chapter addresses the direct and indirect impacts of paid search. The direct effect is the immediate impact of a paid search ad, whereas indirect effects are longer term. The chapter reviews the history of paid search advertising and institutional issues such as the bidding process for ad placement. It then turns to a summary of empirical studies and models pertaining to direct effects, including the determinants of click-through rates and conversion. The chapter next discusses indirect effects including the impact of generic search on future branded search, the impact of click-through visits on future visits, the value of search advertising as a customer acquisition channel, and search ad copy design. The chapter concludes with a discussion of emerging topics such as the long tail in paid search, and the relationship between organic search and paid search click-throughs.

Chapter 11 summarizes how the firm can manage online social interactions. First, it describes the why and what of social interactions. That is, the chapter discusses what motivates consumers to share product recommendations and what product characteristics result in more word of mouth. The chapter then discusses issues related to social media metrics and data collection. It next proceeds to summarize existing research on the three roles that the firm can play in the management of social interactions:

1. observer;
2. influencer; and
3. participant.

Existing research suggests that the firm can measure the impact of social media interactions and successfully influence these interactions. While there is growing literature related to the role of the firm as observer and as influencer, the role of the firm as participant has not been studied extensively. Hence, the opportunities for impactful new research are greatest in this area.

Dynamic customer optimization models, discussed in Chapter 12, combine customer response models and optimization to determine what types of marketing to target to which customers at what time in order to maximize customer lifetime value. The fundamental premise of dynamic customer optimization is that marketing activities targeted in the current period should take into account the implications of these actions for marketing in subsequent periods. This chapter reviews the dynamic elements of
customer response models that come to play in dynamic customer optimization, and then discusses the fundamentals of dynamic optimization techniques. The chapter next reviews the evolution of the customer optimization field, starting with its roots in sales force management, proceeding to modern applications in catalogs, to more recent applications involving marketing tactics such as emails, sampling, and coupons, and free shipping. The last section of the chapter reviews several research papers, discussing the customer response model, the optimization, and the application. We conclude with a discussion of the promise and challenges of dynamic customer optimization models.

Chapter 13 focuses on how direct marketing practices in the non-profit sector differ from traditional direct marketing activities in the public and private sector. Using real-life case studies throughout the chapter, the author illustrates several direct marketing activities along the customer lifecycle, that is, donor acquisition, retention, and reactivation. Understanding charitable giving in its stage of the customer lifecycle is of crucial importance to optimize the donor database. More specifically, three questions are crucial: “To whom should the non-profit organizations send a donor invitation?”; “How to optimize or personalize the content of the mailing campaign?” and “Via which channels should the direct marketer target its donors?” This chapter concludes with an explanation of numerous campaign evaluation keywords.

References