An Approach for Selecting Optimum Marketing Strategies across Customers

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Abstract

The advancements and adoption of technologies such as Customer Relationship Management (CRM) have now enabled firms to use data driven approaches to manage their marketing strategies. These strategies can be about different marketing processes such as those related to the acquisition of customers (advertising) and the retention of customers (loyalty program). In the Customer Lifetime Value paradigm, marketers are suggested to consider customers as assets, and to use their Lifetime value (future profitability) to decide the appropriate engagement level with them. This paper extend that line of thought by presenting a model that selects the optimum marketing strategies for the marketer. This approach maximizes the expected future profitability from the customers while maintaining the associated revenue related uncertainty at a given level (set by marketer). The paper shows that the proposed optimization problem is in the NP-hard computational class and is a general version of multiple choice knapsack problem. It also shows that the approach requires solving a problem, which is a generalized version of a version (linear rather than quadratic) of the classical portfolio selection problem. The complete paper will have the experiments on time required to solve the different instance sizes of the problem on Fico Xpress 7.9. Optimization software.

Key words: Marketing strategies, Portfolio selection problem, Customer Lifetime Value
Introduction

The advancements in web and the Internet technologies have transformed the marketing choices that are now available to businesses and marketers. These tools allow markets to engage with customers on a scale that has never existed before. In addition to traditional marketing (direct mailers, radio, TV, magazine, etc.), businesses can now engage with their customers on Social media (Mangold and Faulds 2009), Daily deal websites, and through various websites/platforms. This facilitates businesses to gather and use vast amount of individual level data of existing and potential customers from different data sources for developing its marketing strategy.

In the traditional Marketing framework, the strategy of a marketer is conceptualized as marketing choices in four different domains, popularly known called 4Ps: Price, Promotion, Product, and Placement (McCarthy1964). Because of the advancement in web technologies and adaptation of technologies such as Customer Relationship Management (CRM), now it is possible for marketers to measure the impact (costs/benefits) of using different marketing strategies on different customer segments on a real time basis. These strategies can be conceptualized across Price, Promotion, Product and Placement, and the Information System of the business can provide a unified view of the impact of the different business strategies (which spans over all 4Ps) on different customers’ profiles/segments (current and potential).

In order to develop highly personalized strategies, marketers can segment their customers on the basis of rules that can be provided by the marketer. A list of criteria (rules), which can be calculated for every customer daily, or even in real time, can be the basis of customer segmentation. This allows for the possibility to categorize customers on such a fine level that each segment can potentially even have one or two customers on any given time. The criteria that can be used for customer segmentation may include factors such as:

- Longevity (length of time customer is in the database)
- Spending patterns (amount, frequency)
- Specific website/app that the customer visited, customers’ activities/behavior on those sites
- Social media activities and views on social media
- Brand loyalty, Product preferences/affinities
- Response history to previous campaigns
- Predicted customer lifetime value and propensity to churn

Figure 1 below shows how a business can microsegment its customers and use personalized marketing strategies that can even change on a daily basis.
Even in this environment of abundance of technology and data it is noteworthy that many businesses still do not employ any quantitative strategy for measuring the impact of their marketing spending. According to the 2013 Chief Marketing Officers (CMOs) survey (Monier et. al. 2013) only 36 percent of CMOs have quantitatively proven the short-term impact of their marketing spending, and for demonstrating long-term impact, this figure drops to 32 percent. That is, almost two out of three CMOs are using qualitative measures to show impact, or aren’t measuring impact at all. This lack of quantitative approach of measuring marketing impact can also cause a barrier between marketing and finance functions of businesses. As one financial services CMO has pointed out about how CFOs typically perceive his function (Monier et. al. 2013):

“We’re going to give a certain amount of dollars to those guys. They’re going to make ads and do whatever it is they do. And let’s hope it generates demand.”

This paper provides a data driven, analytical approach from the perspective of CMO (marketer). The optimization model selects the optimum set of strategies from a set of possible strategies that can be created from the inputs of the marketer. The integer programming model maximizes the expected future profitability of the company while maintaining the risks (uncertainty of future expected revenue) to a desired level, which can be set by the marketer. The model finds the set of strategies that provide the optimum level of marketing engagement for each possible customer/customer segment. The problem considered in this paper is shown to be in NP-hard complexity class. The problem is a generalized version of a version (linear rather than quadratic) of classic portfolio selection problem (Elton and Gruber 1995; Keller et al 2004).

One part of this study, which has not been completed yet, is to test how much time such a problem of instance size, say, 1 million customers, will take to solve. To answer this question the plan is to be run the proposed model on Fico Xpress 7.9 software (FICO 2015). The objective is
to demonstrate that the suggested approach can be scaled to large size and that the optimization can be executed on a daily basis.

**Relevant Literature**

In the Customer Lifetime Value (Berger, P. D. and Nasr, N. I. 1998) paradigm of marketing literature, the objective of a firm’s CRM/Marketing strategy is to optimize each individual customer’s profitability over time (Reinartz and Kumar 2000, 2003). (Kumar 2008) suggests that managing customers for loyalty does not necessarily means managing them for profitability. Customer Lifetime Value (CLV) metrics is proposed for measuring and managing the future probability of the customers. I argue, in this paper, that the objective of the firm’s marketing strategy should be not only to maximize the profitability from each individual customer, but it should also consider the “risk” in terms of the uncertainty of the expected revenue, while making marketing spending related decisions. The proposed approach in a sense consider marketing spending as an investment instead of just a cost.

A vast amount of marketing literature has been focused on studying different marketing activities/processes. For example, there is a great deal of work that consider issues in the areas of advertising (customer acquisition) (Gönül, F. and M. Shi 1998; Gharkanlu et. al. 2014), loyalty programs (customer retention) (Lacey R. and Sneath J. Z. 2006), and Customer Relationship Management (the related technologies). There is also a great deal of work that aims at estimating the future profitability of the customers based on their past transactions and demographic data. Marketing metrics such as RFM (Recency of purchases, Frequency of purchases, and Monetary value of purchases), PCV (Past Customer Value), and SOW (Share of Wallet) are proposed for measuring the future profitability of a customer. Rust and Verhoef (2005) considers a setting where a marketer is optimizing the Marketing Interventions Mix in Intermediate-Term CRM. They presents a model that outperformed models based on RFM, or finite mixture segmentation in predicting the effectiveness of intermediate-term CRM.

There has been some work that use linear programming in the domain of advertising (Douglas B. Brown and Martin R. Warshaw, 1965). These models maximizes advertising matrices such as reach, frequency, and quality of exposure in a media campaigns. Similarly, the optimization models in computer sciences/online advertising literature (Danaher et. al. 2010) also typically maximize the effectiveness of advertisement campaigns by using customer response data on marketing metrics such as Click though Rate (CTR). This paper, on the other hand, considers a broader setting where the marketer is optimizing the overall marketing spending across activities that may include activities such as advertising, promotion, etc.

As (Hanssens 2003) suggests: “The more challenging task is to assess long run marketing effectiveness and to allocate the overall marketing budget across the key activities that generate customer equity...For any given set of business and customer response parameters, there is an optimal level of customer acquisition and retention which translates into optimal acquisition and retention spending levels.”

This paper suggests the firm’s marketing strategy should not only focus on engaging the
customers based on their profitability, but also consider the risk (of revenue uncertainty) associated with making those marketing choices. The proposed model maximizes the expected profitability from the marketing strategies while maintaining the risk associated with spending (uncertainty in the expected revenue) to a level (L), which can be decided by the marketer.

One advantage of the proposed approach is that it does not solely rest on lifestyle predictions of customer behavior or pooled data. Instead, a data warehouse of actual transactions by the organization’s own customers, and information from other sources such as social media, can forms the basis for decision making. In the longer term, because of potentially sophisticated rules of segmentations, the model is expected to become more effective and can become the foundation of targeted automated campaigns that are both cheaper and more effective than traditional scattered approaches.

The Proposed 0-1 Integer Programming Model:

The model assumes that the marketer has used any of the prediction models from the literature to estimate the expected profitability and standard deviation in the profitability of using different strategies on all possible customer segments. The following notation are used for formulating the marketer’s problem:

$I$: The set contains the indexes of all the customers (existing and potential customers)
$S_i$: The set contains the indexes of the strategies available or being considered for individual $i$
$p_{ij}$: The expected profit from using strategy $j$ on individual $i$
$\sigma_{ij}$: A measure of risk (the standard deviation of the potential profitability of customer $i$) if strategy $j$ is used on customer $i$

$B$: The total budget to be distributed on marketing strategies
$L$: Allowable limit on total risk (set by the marketer)

Decision Variables:

$x_{ij} = 1$, if strategy $j$ is selected for customer $i$

$=0$, otherwise.

The optimum selection of marketing strategies can be formulated as:
\[ P: \text{Max} \sum_{i \in I} \sum_{j \in S_i} P_{ij} x_{ij} \]

\[ \sum_{i \in I} \sum_{j \in S_i} c_{ij} x_{ij} \leq B \] (The total cost of selected strategies must be less than the allowable budget)

\[ \sum_{i \in I} \sum_{j \in S_i} \sigma_{ij} x_{ij} \leq L \] (The total uncertainty in profitability must be maintained/contained)

\[ \sum_{j \in S_i} x_{ij} = 1 \quad \forall i \in I \] (One strategy must be selected for each customer/segment)

\[ x_{ij} = \{0,1\} \]

**Observation 1:** The problem \( P \) given above is in the computational class NP. 
Proof: Observe that the above problem reduces to Multiple Choice Knapsack problem (Keller et al. 2004) if standard deviation related constraints is removed.

**Observation 2:** The formulation is a variation of a simple version (linear rather than quadratic) (Keller et al 2004) of classic portfolio selection problem (Elton and Gruber 1995) of finance. The classic portfolio selection problem the choices are in one dimension; either an “item” is selected from a portfolio or not. In the problem given above the choices are with the relationship between two entities: “customers” and “strategies.”

**The Current Status of Manuscript:**

The work is in preliminary stage and currently suitable for a poster session format.

**References**


Kumar. V. 2008. Customer Lifetime Value: The Path to Profitability


