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A new marketing strategy map for direct marketing

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ABSTRACT

Direct marketing is one of the most effective marketing methods with an aim to maximize the customer's lifetime value. Many cost-sensitive learning methods which identify valuable customers to maximize expected profit have been proposed. However, current cost-sensitive methods for profit maximization do not identify how to control the defection probability while maximizing total profits over the customer's lifetime. Unfortunately, optimal marketing actions to maximize profits often perform poorly in minimizing the defection probability due to a conflict between these two objectives. In this paper, we propose the *sequential* decision making method for profit maximization under the given defection probability in direct marketing. We adopt a Reinforcement Learning algorithm to determine the sequential optimal marketing actions. With this finding, we design a marketing strategy map which helps a marketing manager identify sequential optimal campaigns and the shortest paths toward desirable states. Ultimately, this strategy leads to the ideal design for more effective campaigns.

1. Introduction

Direct marketing is one of the most effective marketing methods with an aim to maximize the expected profits [13]. A number of cost-sensitive learning methods which focus on predicting profitable customers have been proposed for direct marketing [2,3,13,15]. However, a common objective of these methods is to only maximize the short-term profit associated with each marketing campaign. They ignore the interactions among decision outcomes when sequences of marketing decisions are made over time. These independent decision-making strategies cannot guarantee the maximization of total profits generated over a customer's lifetime because they often inundate profitable customers with frequent marketing campaigns or encourage radical changes in customer behavior [10]. This approach can decrease customer profitability because of the annoyance factor or their budgetary limits per unit time.

Some researchers have recognized the importance of sequential decision making to overcome the limitations of isolated decision making. For example, Pednault et al. [10] and Abe et al. [1] proposed sequential cost-sensitive learning methods for direct marketing. These sequential cost-sensitive methods, however, fail to consider the cost generated from customer defections. Although a primary objective of direct marketing is to maximize total profit, it is also important to control the probability of customer defection, keeping it under a desirable or acceptable level because the occurrence of a customer defection brings about tangible and intangible loss, (i.e., an increase of acquisition cost of a new customer, loss of word-of-mouth effects, and loss of future cash flows and profits). Since customer switching costs are much lower in e-commerce marketplaces, a company always needs to pay more attention to customer defection. However, current sequential cost-sensitive methods for maximizing profit do not indicate how to control the probability of customer defection while maximizing total profits over the customer's lifetime. Unfortunately, optimal marketing actions designed to maximize profits often perform poorly in minimizing the probability of customer defection due to a conflict between a profit maximization and defection probability minimization. For example, an optimal marketing action for profit maximization is liable to give up unprofitable customers who are most likely to defect but are profitable from a *long-term* perspective. In contrast, an optimal marketing action for the minimization of defection probability is apt to unnecessarily sacrifice loyal customers' profit with excessive marketing cost.

To overcome this conflict, we regard the customer defection probability as a constraint and try to control it under the given threshold because, in general, controlling defection probability under the threshold is more cost effective than completely avoiding customer defection with 0%. We also think that most companies have more interest in a strategy which guarantees the maximization of total profits while the defection probability is bounded by a desirable or acceptable level.

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In this paper, we have developed a sequential decision-making methodology for profit maximization under the given defection probability constraint. For effective sequential learning, we have adopted the Reinforcement Learning algorithm. We have also suggested the concept of a marketing strategy map which visualizes the results of learning such as an optimal marketing action in each state and customer's behavior dynamics according to suggested marketing actions. This marketing strategy map can help a company identify sequential optimal campaigns and the shortest paths toward desirable states. Ultimately, this strategy leads to the ideal design for more effective campaigns.

The rest of this paper is organized in the following manner: In Section 2, a Self-Organizing Map and Reinforcement Learning that are prerequisites for our study are briefly introduced. Section 3 details our method for direct marketing and Section 4 reports experimental results with real-world data sets. Section 5 describes a marketing strategy map and its applications. Finally, Section 6 summarizes our works and contributions.

2. Background

The proposed method adopts a Self-Organizing Map (SOM) and Reinforcement Learning for effective sequential learning and its visualization.

2.1. Self-Organizing Map (SOM)

The SOM [8,11] is a sophisticated clustering algorithm in terms of the visualization of its clustering results. It clusters high-dimensional data points into groups and represents the relationships between the clusters onto a map that consists of a regular grid of processing units called "neurons." Each neuron is represented by an n-dimensional weight vector, $\mathbf{m} = [m_1, m_2, \ldots, m_n]$ where n is equal to the dimension of the input features. The weight vector of each neuron is updated during iterative training with input data points. The SOM tends to preserve the topological relationship of the input data points so the similar input data points are mapped onto nearby output map units. This topology-preserving property of SOM facilitates the ability to design the marketing strategy map in our proposed method. In our method below, we define the possible customer states using SOM, and with the output map of SOM, we design the marketing strategy map.

2.2. Reinforcement learning

Reinforcement Learning [9,12] is characterized by goal-directed learning from interaction with its environment. At each discrete time t, the learning agent observes the current *state* $s_t \in S$, where S is the set of possible states in a system and selects an action $a_t \in A(s_t)$, where $A(s_t)$ is the set of actions available in state s_t. As a consequence of its action a_t in state s_t, the agent receives an immediate positive or negative*reward* r_{t+1}, and next state s_{t+1}. Based on these interactions, the agent attempts to learn a policy $\pi{:}S \rightarrow A$ which is a function of mapping states to actions to maximize the expected sum of its immediate rewards, $R = \sum_{t=0}^{\infty} \gamma^t r_t$ [where γ (i.e.,$0 \leqslant \gamma < 1$) is *a discount rate*]. Thus, Reinforcement Learning is particularly well suited to multi-step decision problems where the decision criteria can be represented in a recursive way as a function of the immediate numerical value [4].

3. The proposed method

We suggest the following method for profit maximization under the control of defection probability in direct marketing. As shown in Fig. 1, we prepared customer episodes with campaigns and the response history data and adopted the Reinforcement Learning algorithm to determine an optimal policy. We then design a marketing strategy map. To provide more simple and practical business intelligence, we designed a method for segmentation marketing instead of for individualized marketing.

3.1. Definition of states and actions

States are representations of the environment that the agent observes and are the basis on which agent's decisions are made. In this method, states would be represented as customer segments which have similar purchase patterns and response behaviors against promotion (e.g., recency, frequency, and monetary value) at the time of each campaign. In the rest of the paper, the following terms are used interchangeably: "state" and "customer segment." Thus,

$$S = \{s1, s2, \ldots, sN\}$$

where S is the set of states, N is the total number of states.

The actions are defined as all of the marketing campaigns conducted in a company. As the number of campaigns increases, companies feel the need to analyze the effects of diverse competing campaigns in each state (e.g., customer segments) in a systematic way. Thus,

$$A = \{a1, a2, \ldots, aM\}$$

where A is the set of actions, M is the total number of actions (i.e. campaigns)

3.2. Definition of profit and defection probability

The agent achieves both profit and defection probability as immediate rewards at each transition. An immediate profit P is the net profit which is computed as the purchase amount minus the cost of action. An immediate defection probability D is computed as the probability of falling into a fatal state (i.e., defection state). The concept of fatal state was first introduced by Geibel [5,6] who noted that processes, in general, have a dangerous state which the agent wants to avoid by the optimal policy. For example, a chemical plant where temperature or pressure exceeds some threshold may explode. Thus, the optimal strategy of operating a plant is not to completely avoid the fatal state when considering the related control costs, but to control the probability of entering a fatal state (i.e., an exploration) under a threshold.

In this method, a fatal state means the status of customer defection. Like an exploration in a chemical plant, customer defection is fatal to a company and brings about tangible and intangible loss. However, it is difficult to reflect both the tangible and intangible loss from defection to the reward of profit. It is also impossible and cost-ineffective to completely avoid customer defection, but customer defection could be controlled under the threshold – an acceptable or desirable level for a company. The defection probability means the customer defection rate of each state as well as the defection probability of a customer in each state. The immediate defection probability D on transition from s to s' under action a is defined by:

$$D(s, a, s') = \begin{cases} 1 & \text{if} \quad s \text{ is a non-fatal state, } s' \text{ is a fatal state} \\ 0 & \text{else} \end{cases} \tag{1}$$

If the agent enters a fatal state from a non-fatal state, the immediate defection probability is 1 and the immediate profit is 0. It is natural to consider a fatal state as a final state (i.e., an absorbing state) in which the agent ends its learning with the current sequence (i.e., a sequence of (s, a, r) sets).