Multi-campaign Assignment Problem and Optimizing Lagrange Multipliers*

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Customer relationship management is crucial in acquiring and maintaining royal customers. To maximize revenue and customer satisfaction, companies try to provide personalized services for customers. A representative effort is one-to-one marketing. The fast development of Internet and mobile communication boosts up the market of one-to-one marketing. A personalized campaign targets the most attractive customers with respect to the subject of the campaign. So it is important to expect customer preferences for campaigns. Collaborative Filtering (CF) and various data mining techniques are used to expect customer preferences for campaigns. Especially, since CF is fast and simple, it is widely used for personalization in e-commerce. There have been a number of customer-preference estimation methods based on CF. As personalized campaigns are frequently performed, several campaigns often happen to run simultaneously. It is often the case that an attractive customer for a specific campaign tends to be attractive for other campaigns. If we perform separate campaigns without considering this problem, some customers may be bombarded by a considerable number of campaigns. We call this overlapped recommendation problem. The larger the number of recommendations for a customer, the lower the customer interest for campaigns. In the long run, the customer response for campaigns drops. It lowers the marketing efficiency as well as customer satisfaction. Unfortunately, traditional methods only focused on the effectiveness of a single campaign and did not consider the problem with respect to the overlapped recommendations. In this paper, we define the multi-campaign assignment problem (MCAP) considering the overlapped recommendation problem and propose a number of methods for the issue including a genetic approach. We also verify the effectiveness of the proposed methods with field data.

Let N be the number of customers and K be the number of campaigns. The MCAP is to find customer-campaign assignments that maximizes the effects of campaigns. The main difference with independent campaigns lies in that the customer response for campaigns is influenced by overlapped recommendations. More detailed description is omitted by space limit. In case of overlapped campaign recommendations, the customer response rate drops as the number of recommendations grows. We introduce the response suppression function for

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Table 1. Comparison of Algorithms

Method	Independent	Random	CAA†	LM-GA
Fitness	26452.75	25951.19	66473.63	**66980.76**

† Starting at the situation that no customer is recommended any campaigns, we iteratively assign campaigns to customers by a greedy method. We call this algorithm Constructive Assignment Algorithm (CAA). We use an AVL tree for the efficient management of real-valued gains. The time complexity of the algorithm is $O(NK^2 logN)$.

the response-rate degradation with overlapped recommendations. We used the response suppression function derived from Gaussian function.

Since the MCAP is a constraint optimization problem, it can be solved using Lagrange Multipliers (LMs). But, since it is a discrete problem which is not differentiable, it is formulated to a restricted form. The LM method guarantees optimal solutions. The suboptimality of heuristic algorithms can be measured by using the optimality of the LM method. By using LM method, the problem of finding the optimum campaign assignment matrix becomes that of finding a K-dimensional real vector with LMs. The LM method takes $O(NK2^K)$ time. It is more tractable than the original problem. Roughly, for a fixed number K, the problem size is lowered from $O(N^{K+1})$ to $O(N)$. We also propose a genetic algorithm (GA) for optimizing LMs. Our GA provides an alternative search method to find a good campaign assignment matrix by optimizing K LMs instead of directly dealing with the campaign assignment matrix. A typical steady-state genetic algorithm is used in our GA. In the following, we describe each part of the GA. A real encoding is used for representing a solution. A gene corresponding to a LM has a real value. The GA first creates 100 real vectors at random. We use a proportional selection scheme and the uniform crossover. After the crossover, mutation operator is applied to the offspring. We use a variant of Gaussian mutation that we devised. Our evaluation function is to find a LM vector that has high fitness satisfying the constraints as *much* as possible.

We used the preference values estimated by CF from field data with 48,559 customers and 10 campaigns. We examined the Pearson correlation coefficient of preferences for each pair of campaigns. Thirty three pairs (about 73%) out of the totally 45 pairs showed higher correlation coefficient than 0.5. This property of field data provides a good reason for the need of MCAP modeling. Table 1 shows the performance of the independent campaign and various multi-campaign algorithms in the multi-campaign formulation. The figures in the table represent the fitness values. The result of "Independent" campaign is from 10 independent campaigns without considering their relationships with others. Although the independent campaign was better than the "Random" assignment in multi-campaign formulation, it was not comparable to the other multi-campaign algorithms. The solution fitness of CAA heuristic was more than 2.5 times higher than that of the independent campaign. When LMs are optimized by a genetic algorithm (LM-GA), we found the best-quality solution satisfying all the constraints. Our LM method is fast and outputs optimal solutions. But, it is not easy to find LMs satisfying all constraints. When combined with the genetic algorithm, we could find high-quality LMs.