Assortment Optimization for Boundedly Rational Customers

Mahsa Farhani, Prof. Caspar. G. Chorus, and Dr.Yousef Maknoon

Delft University of Technology, Netherlands

1. Introduction

Assortment optimization addresses the problem of finding the optimal subset (i.e., assortment) of potential alternatives to offer to consumers in order to maximize the expected profits of firms. It has grown towards being a flourishing research area of Revenue Management (RM). Accurate predictions of consumers' choices from the offered choice-set is fundamental in the assortment optimization. The value of representing consumer demand using discrete choice models has been extensively studied (e.g., (Talluri and Van Ryzin(2004), alluri and Van Ryzin(2004)) and (Strauss et al.(2018)Strauss, Klein, and Steinhardt, trauss et al.(2018)Strauss, Klein, and Steinhardt)), and applying more realistic customer behavior models is an active area of research in assortment optimization.

Assortment optimization has been developed for various parametric and non-parametric choice models. Parametric choice models formulate choice probabilities by a parametric function that describes the customer choice behavior as a function of the offered set of alternatives. Assortment optimization is initiated by van Ryazin and Mahajan in their seminal paper that uses the multinomial logit (MNL) model which is the most extensively studied parametric choice model ((Ryzin and Mahajan(1999), yzin and Mahajan(1999))). It has further developed for other parametric choice models such as mixture of MNLs (MMNL) (Rusmevichientong et al.(2010)Rusmevichientong, Shmoys, and Topaloglu, usmevichientong et al.(2010)Rusmevichientong, Shmoys, and Topaloglu), Nested Logit (NL) (Davis et al.(2014)Davis, Gallego, and Topaloglu, avis et al.(2014)Davis, Gallego, and Topaloglu), Generalized Attraction Model (GAM) (Gallego et al.(2015)Gallego, Ratliff, and Shebalov, allego et al.(2015)Gallego, Ratliff, and Shebalov), and Paired Combinatorial Logit (PCL) model (Zhang et al.(2020)Zhang, Rusmevichientong, and Topaloglu, hang et al.(2020)Zhang, Rusmevichientong, and Topaloglu). Non-parametric choice models estimate choice probabilities using a general distribution over different rankings of alternatives. The rankings are known as preference lists which order alternatives according to their utility, and each preference list is associated with one consumer type. Among others, (Rusmevichientong et al.(2006)Rusmevichientong, Van Roy, and Glynn, usmevichientong et al.(2006)Rusmevichientong, Van Roy, and Glynn), (Farias et al.(2013)Farias, Jagabathula, and Shah, arias et al.(2013)Farias, Jagabathula, and Shah), (van Ryzin and Vulcano(2015), an Ryzin and Vulcano(2015)), (Bertsimas and Mišic(2015), ertsimas and Mišic(2015)), and (Berbeglia(2018), erbeglia(2018)) have studied assortment optimization using the non-parametric choice models. For a comprehensive review of assortment optimization under different choice models see (Kök et al.(2008)Kök, Fisher, and Vaidyanathan, ök et al.(2008)Kök, Fisher, and Vaidyanathan) and (Gallego et al.(2019)Gallego, Topaloglu, et al., allego et al.(2019)Gallego, Topaloglu, et al.) textbook.

Although assortment optimization has been extensively studied in the recent years, choice-set composition effects have been overlooked in this research area. This research proposes an assortment optimization model which incorporates the impacts of choice set compositions on individual preferences while keeps the mathematical tractability of formulations.

2. Methodology

In this research, we employ the Generalized Random Regret Minimization (G-RRM) model proposed by (Chorus(2014), horus(2014)) to model customer choice behavior. We aim to select the optimal assortment of alternatives from the given universal set Ω including N alternatives so that the expected profit per customer is maximized. In our problem setting, alternative i is defined by the bundle of M attributes $(x_1^i,\ldots,x_M^i)$. The random regret of alternative i is composed out of a systematic regret R_i and an i.i.d. random error ε_i, $RR_i = R_i + \varepsilon_i$. The systematic regret of alternative i is defined as the sum of the binary regrets that are associated with bilaterally comparing the attributes of alternative i with each of the other alternatives in the choice set. Thus, the systematic regret of alternative i in assortment s is written as below:

$$R_i(s) = \sum_{j\in s,\ j\neq i} \sum_{m=1}^{M} \left(\ln\left(\gamma + \exp\left[\beta_m.(x_m^j - x_m^i)\right]\right) - \ln(1+\gamma)\right) \tag{1}$$

Where β_m and γ denote the weight of attribute m and the regret weight, respectively. It has been revealed that the RRM model (1) captures the compromise effect as one of the most important and robust choice set composition effects (e.g., (Guevara and Fukushi(2016), uevara and Fukushi(2016)) and (Chorus and Bierlaire(2013), horus and Bierlaire(2013))).

Under the RRM model, the choice probability of alternative i is defined by Equation (2), where V_0 denotes the constant attraction value of the no-purchase option.

$$\pi_i(s) = \frac{\exp\left(-R_i(s)\right)}{V_0 + \sum_{j\in s} \exp\left(-R_j(s)\right)} \tag{2}$$

Let p_i denote the associated profit of alternative i. Therefore, the assortment optimization problem is formulated as follows.

$$\max_{s\subseteq\Omega} \sum_{i\in s} p_i.\pi_i(s) \tag{3}$$

3. Solution method and findings

We have proposed an efficient algorithm to solve Problem (3). We have tested our algorithm for micromobility services. The results show that our proposed algorithm can find the optimal solution for all studied instances. Moreover, we have compared the planned assortments against the widely used multinomial logit model to examine the implications of the compromise effect on the assortment decisions. Our results indicate that this behavioral phenomenon has significant impacts on the optimal choice set, so they need to be taken into account by those who want to offer a menu of options to their customers.

REFERENCES

Kalyan Talluri and Garrett Van Ryzin. Revenue management under a general discrete choice model of consumer behavior. *Management Science*, 50(1):15–33, 2004.

Arne K Strauss, Robert Klein, and Claudius Steinhardt. A review of choice-based revenue management: Theory and methods. *European Journal of Operational Research*, 271(2):375–387, 2018.

Garrett van Ryzin and Siddharth Mahajan. On the relationship between inventory costs and variety benefits in retail assortments. *Management Science*, 45(11):1496–1509, 1999.

Paat Rusmevichientong, David Shmoys, and Huseyin Topaloglu. Assortment optimization with mixtures of logits. Technical report, Tech. rep., School of IEOR, Cornell University, 2010.

James M. Davis, Guillermo Gallego, and Huseyin Topaloglu. Assortment Optimization Under Variants of the Nested Logit Model. *Operations Research*, 62(2):250–273, 2014.

Guillermo Gallego, Richard Ratliff, and Sergey Shebalov. A general attraction model and sales-based linear program for network revenue management under customer choice. *Operations Research*, 63(1):212–232, 2015.

Heng Zhang, Paat Rusmevichientong, and Huseyin Topaloglu. Assortment optimization under the paired combinatorial logit model. *Operations Research*, 68(3):741–761, 2020.

Paat Rusmevichientong, Benjamin Van Roy, and Peter W Glynn. A nonparametric approach to multiproduct pricing. *Operations Research*, 54(1):82–98, 2006.

Vivek F Farias, Srikanth Jagabathula, and Devavrat Shah. A nonparametric approach to modeling choice with limited data. *Management science*, 59(2):305–322, 2013.

Garrett van Ryzin and Gustavo Vulcano. A market discovery algorithm to estimate a general class of nonparametric choice models. *Management Science*, 61(2):281–300, 2015.

Dimitris Bertsimas and Velibor V Mišic. Data-driven assortment optimization. *Operations Research Center, MIT*, 2015.

Gerardo Berbeglia. The generalized stochastic preference choice model. *arXiv preprint arXiv:1803.04244*, 2018.

A Gürhan Kök, Marshall L Fisher, and Ramnath Vaidyanathan. Assortment planning: Review of literature and industry practice. In *Retail supply chain management*, pages 99–153. Springer, 2008.

Guillermo Gallego, Huseyin Topaloglu, et al. *Revenue management and pricing analytics*, volume 209. Springer, 2019.

Caspar G Chorus. A generalized random regret minimization model. *Transportation research part B: Methodological*, 68:224–238, 2014.

C Angelo Guevara and Mitsuyoshi Fukushi. Modeling the decoy effect with context-rum models: Diagrammatic analysis and empirical evidence from route choice sp and mode choice rp case studies. *Transportation Research Part B: Methodological*, 93: 318–337, 2016.

Caspar G Chorus and Michel Bierlaire. An empirical comparison of travel choice models that capture preferences for compromise alternatives. *Transportation*, 40(3):549–562, 2013.