UNIVERSITY OF MANNHEIM
Business School

CHAIR OF SERVICE OPERATIONS MANAGEMENT
Prof. Dr. Cornelia Schön

Master Thesis Proposal

Designing Better Recommendations: Integrating Choice-Based Optimization and Recommender Systems

In today's digital environments, users face an overwhelming number of choices – whether selecting a product on Amazon, content to consume on Netflix, or following a new account on Instagram. Recommender Systems (RS) have emerged as vital tools for helping users navigate this abundance by filtering and ranking items based on inferred preferences. In parallel, econometric choice models, though simpler but grounded in theory instead of data, have long been used to predict consumer behavior and optimize managerial decisions such as pricing, product design, and assortment planning. As both fields increasingly address similar problems (selecting and presenting items to users or customers) there is a growing intersection between both research fields. At their core, both RS and choice-based optimization aim to solve a selection problem e.g. deciding which subset of items to present from a larger pool of alternatives. In choice-based optimization, this selection is typically guided by clearly defined business objectives (e.g., maximizing expected revenue) and subject to explicit constraints (e.g. shelf space, inventory, or marketing budgets). In contrast, RS focus on identifying and ranking items based on their predicted appeal to individual users. These systems optimize for user-centric goals like engagement, satisfaction, or retention, which are not always directly aligned with firm-side goals. Furthermore, RS often incorporate additional design criteria, such as diversity, novelty, and catalogue coverage, to enhance the quality of recommendations. However, these criteria are not included explicitly as constraints but implicitly during model training. Some researchers therefore view RS as a form of assortment personalization system, where each user is dynamically offered a tailored subset of the full catalogue, similar in spirit to assortment optimization but driven by different objectives and techniques. Despite these conceptual overlaps, the relationship between RS and choice-based optimization remains underexplored. While it is often acknowledged in the literature, it is rarely analyzed in depth. This gap presents a compelling opportunity to bring together insights from both fields and to explore how their integration can create more effective, user-aware, and business-aligned decision-making systems.

This thesis will critically examine the relationship between RS and choice-based optimization, with a particular focus on how these fields can complement and inform one another, especially in the context of personalization. To this end, the thesis will begin by introducing the fundamentals of discrete choice models and choice-based optimization, alongside a comprehensive overview of RS, including collaborative filtering, content-based filtering, and hybrid approaches. Literature at the intersection of RS and choice-based optimization will be critically reviewed to assess the conceptual and methodological relationships between the two fields, evaluating their respective strengths and weaknesses, and areas of divergence and convergence. Following this it will be discussed how deeper integration might benefit both fields. To illustrate the benefits of this integration in practice, a suitable approach integrating RS and choice-based methods, will be explained in detail and implemented using a publicly available real-world dataset (e.g. Expedia Hotel Recommendations, H&M Personalized Fashion, OTTO Recommender System, Santander Financial Product Recommendation, …). Finally, the thesis will identify open research gaps at the intersection of these domains and outline promising directions for future work.

The objectives of the thesis are to:

- Introduce the theoretical foundations of RS and choice-based optimization.
- Critically review literature at the intersection of RS and choice-based optimization.
- Discuss the potential benefits of deeper integration between RS and choice-based optimization, particularly in the context of personalization.
- Choose a suitable model that combines elements of both fields and explain it in detail before implementing it using a publicly available real-world dataset.
- Identify open research gaps and outline future research directions.

Requirements

- OPM 781
- Profound knowledge in Operations Research
- Excellent analytical skills and an ability to transform real-world business problems into Operations Research models

Administrative information for writing a master thesis at the Chair of Service Operations Management can be found here.

Selected Literature Recommendations

Besbes, O., Gur, Y., & Zeevi, A. (2016). Optimization in Online Content Recommendation Services: Beyond Click-Through Rates. *Manufacturing & Service Operations Management*, *18*(1), 15–33.

Chen, X., Ma, W., Simchi-Levi, D., & Xin, L. (2024). Assortment Planning for Recommendations at Checkout Under Inventory Constraints. *Mathematics of Operations Research*, *49*(1), 297–325.

Chen, S.-S., Choubey, B., & Singh, V. (2021). A neural network based price sensitive recommender model to predict customer choices based on price effect. *Journal of Retailing and Consumer Services*, *61*, 102573.

Danaf, M., Becker, F., Song, X., Atasoy, B., & Ben-Akiva, M. (2019). Online discrete choice models: Applications in personalized recommendations. *Decision Support Systems*, *119*, 35–45.

Ettl, M., Harsha, P., Papush, A., & Perakis, G. (2020). A Data-Driven Approach to Personalized Bundle Pricing and Recommendation. *Manufacturing & Service Operations Management*, *22*(3), 461–480.

Feldman, J., Zhang, D. J., Liu, X., & Zhang, N. (2022). Customer Choice Models vs. Machine Learning: Finding Optimal Product Displays on Alibaba. *Operations Research*, *70*(1), 309–328.

Ferreira, K. J., Parthasarathy, S., & Sekar, S. (2022). Learning to Rank an Assortment of Products. *Management Science*, *68*(3), 1828–1848.

Kallus, N., & Udell, M. (2020). Dynamic Assortment Personalization in High Dimensions. *Operations Research*, *68*(4), 1020–1037.

Lü, L., Medo, M., Yeung, C. H., Zhang, Y.-C., Zhang, Z.-K., & Zhou, T. (2012). Recommender systems. *Physics Reports*, *519*(1), 1–49.

Miao, S., & Chao, X. (2022). Online Personalized Assortment Optimization with High-Dimensional Customer Contextual Data. *Manufacturing & Service Operations Management*, *24*(5), 2741–2760.

Jiang, H., Qi, X., & Sun, H. (2014). Choice-Based Recommender Systems: A Unified Approach to Achieving Relevancy and Diversity. *Operations Research*, *62*(5), 973–993.

Ricci F, Rokach L, Shapira B (2011). Introduction to recommender systems handbook. Ricci F, Rokach L, Shapira B, Kantor PB, eds. *Recommender Systems Handbook* (Springer, Boston), 1–35.

Roy, D., & Dutta, M. (2022). A systematic review and research perspective on recommender systems. *Journal of Big Data*, *9*(1), 59.