



DEPARTMENT OF INFORMATICS

TECHNISCHE UNIVERSITÄT MÜNCHEN

Master's Thesis in Informatics

# **Item Combination in Destination Recommendation Systems**

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## **Kombination von Items in Empfehlungssystemen für Reiseziele**

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I confirm that this master's thesis in informatics is my own work and I have documented all sources and material used.

Munich, November 29, 2021

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## Acknowledgments

# Abstract

# Kurzfassung

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# 1. Introduction

Recommender Systems (RSs) can be described as systems that produce individualized recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful items in a large space of possible options [1]. Given an input of users preferences, recommendation algorithms generate one or more recommended item(s). A RS typically focuses on a specific item type. Amazon.com [2] uses recommendation algorithms to personalize the online store for each customer, for example showing programming titles to a software engineer and baby toys to a new mother. Netflix [3] also use sophisticated recommendation algorithms to suggest movies to users based on user profile and behavior. These real world examples intuitively suggest that recommendation algorithms can find valuable use cases in tourism. Travel recommendation and tourist trip planning is a popularly researched area with different proposed systems [4, 5, 6, 7, 8] and commercial destination recommendation tools (e.g. Triparoti<sup>1</sup>, Tripzard<sup>2</sup>, Besttripchoices<sup>3</sup>).

Designing travel recommender systems is a difficult task because of the amount of possible destinations, as well as the complex and multi-layered nature of the preferences and needs of tourists. Recommending a combination of destinations is an even more complex task. To illustrate the challenge of designing recommender systems for composite trips, consider the following scenario: A person wants to travel for a 3 weeks holiday in March, and she has a budget of 1500€; her preferred activities include going to the beach, shopping and visiting cultural attractions. The recommender system has to recommend a combination of destinations from a large space of possible destinations while respecting her time and budget limitations. The traveller would derive more satisfaction if the recommender system suggests stay duration for each recommended destination. Furthermore, her preferred activities must be taken into account by recommender system, such that she doesn't miss out on any of her preferred activities during the total trip. Additionally, for maximum value, the recommender system should take factors like weather of the chosen time of the year, security of the regions, and proximity of the destinations per composite trip sequence of recommendation into account.

We can distinguish RSs based on the issues they focus on and the techniques they use. *Content-based* recommendation systems try to recommend items similar to those a given user has liked in the past, whereas systems designed according to the *collaborative* recommendation approach identify users whose preferences are similar to those of the given user and recommend

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<sup>1</sup>[www.triporati.com](http://www.triporati.com)

<sup>2</sup>[www.tripzard.com](http://www.tripzard.com)

<sup>3</sup>[www.besttripchoices.com](http://www.besttripchoices.com)

items they have liked [9]. *Hybrid approaches* [10] combine collaborative and content-based methods. *Knowledge-based* systems [11] depend on knowledge models of the object domain for effective item recommendation. They are based on the needs and preferences that the user provides. Depending on the recommendation technique employed, destination recommendation systems can be classified as content-based, collaborative or knowledge based.

Travel recommender system design can be described as a Tourist Trip Design Problem (TTDP) [12]. A TTDP model typically consists of a set of candidate Point of Interests (POIs) each associated with a number of attributes (e.g. activities, location, etc), and a *score* of each POI, calculated as a weighted function of the objective and/or subjective value of each POI. The objective of solving the TTDP is to maximize the collected score of each sequence of ordered visits to the POIs while respecting user constraints related to travel cost and POI attributes [13]. The Orienteering Problem (OP) may be used to model variants of the TTDP. The term OP, similar the TTDP, seeks to maximize the total collected profit by visiting selected nodes (i.e POI) under a given value [14]. In this problem, not all available nodes can be visited due to the limited time budget. Thus, a standard OP can be interpreted as a combination between the *Knapsack Problem* and the Traveling Salesman Problem (TSP) [15].

Existing TTDP variants focus on optimizing for best routes between POIs (i.e route planning) under POI attributes constraints without or within a time frame. Deriving optimal routes between nodes is a classical TSP problem. The TTDP presented by this thesis does not include optimizing for routes between POIs (i.e order of visit to the chosen destinations will not be recommended). Thus, our TTDP is a special case of the OP that can be formulated as a type of knapsack problem. The objective of a knapsack problem in its basic form, is to maximize the value of the items placed in a knapsack without going over a weight limit or capacity. Intuitively, the sequence of trips to be recommended by our recommender system can be described as the knapsack, while the items to be placed in the knapsack are the single POIs (i.e destination). The weight limit enforced by the knapsack can be thought of as the budget and time constraint, while the value to be maximized by the knapsack problem is the score of each POI with respect to given user preferences and POI attributes.

In this thesis, we shall be investigating various state-of-the-art algorithms that is been used in research to solve the OP in TTDPs. The problem of finding the best possible combination of trips is modeled as a special case of the Multiple Choice Knapsack Problem (MCKP). MCKPs are generalizations of the standard knapsack problem which has been proven to be a *NP-Hard* problem [16]. At the time of this thesis, the data that we have collated is not voluminous enough for us to consider deep learning techniques that could be applied to the TTDP. Hence, we will not be researching on deep learning algorithms or techniques to use.

The main contributions of this thesis are as follows.

- A formal definition of the composite trip recommendation problem as an optimization problem modelled as a special case of the Multiple Choice Knapsack Problem MCKP
- Empirical research into how current state-of-the-art algorithms used for solving Orien-

teering Problems OPs can be extended to our MCKP

- ... ([**(TODO: name the algorithms)**]) to obtain sequence of candidate solutions that satisfy user constraints in a destination recommendation system
- A working prototype that implements the algorithms and results of comparison of algorithms by evaluating performance through users perspective

Subsequent parts of this thesis is structured as follows. In section 2 we shall review the available literature on various state-of-the-art approaches to travel recommendation. In section 3 we formally define the composite trip recommendation problem as a special case of the MCKP and provide empirical research into possible algorithmic approaches for solving TTDP and how if and how they can be applied to the MCKP. In section 4 we describe our algorithms to identify candidate solutions to the MCKP and describe the implementation. We evaluate the results of our implementation in section 5. Finally, the results are discussed and possible paths for future research are proposed in section 6.

## **2. Literature Review**

## 3. Analysis

### 3.1. Orienteering Problems

### 3.2. Knapsack Problems

[(TODO: Write mathematical formulation of general knapsack problem her to buff it up)]

#### 3.2.1. Types of Knapsack problem

### 3.3. Problem Formulation

[(TODO: Mathematical formulation of problem as a Multiple Choice Knapsack Problem)]

### 3.4. Algorithmic Approaches

#### 3.4.1. Greedy Heuristics

#### 3.4.2. Dynamic Programming

#### 3.4.3. Branch and Bound

#### 3.4.4. Constraint Programming

#### 3.4.5. Genetic Algorithms

#### 3.4.6. Simulated Annealing

#### 3.4.7. Ant Colony Optimization

## 4. Prototype Implementation

### 4.1. Data Model

[(NOTE: Current thinking: child regions with same parents are within the same proximity)]

[(TODO: Research traveller type and categorize preferences under classes for the multiple choice knapsack classes)]

## **5. Evaluation**

### **5.1. Procedure of the study**

### **5.2. Algorithm Comparison**

### **5.3. Results**

## **6. Conclusion**

### **6.1. Limitations**

### **6.2. Future Research**



## **A. General Addenda**

If there are several additions you want to add, but they do not fit into the thesis itself, they belong here.

### **A.1. Detailed Addition**

Even sections are possible, but usually only used for several elements in, e.g. tables, images, etc.

## B. Figures

### B.1. Example 1

✓

### B.2. Example 2

✗

## List of Figures

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# Bibliography

- [1] R. Burke. "Hybrid Recommender Systems : Survey and and Experiments. User Modelling and User-Adapted Interaction". In: *User Modeling and UserAdapted Interaction* 12 (2002). ISSN: 09241868.
- [2] G. Linden, B. Smith, and J. York. "Amazon.com recommendations: Item-to-item collaborative filtering". In: *IEEE Internet Computing* 7.1 (2003). ISSN: 10897801. DOI: 10.1109/MIC.2003.1167344.
- [3] X. Amatriain. "Big & personal: Data and models behind Netflix recommendations". In: *Proc. of 2nd Int. Workshop on Big Data, Streams and Heterogeneous Source Mining: Algorithms, Systems, Programming Models and Applications, BigMine 2013 - Held in Conj. with SIGKDD 2013 Conf.* 2013. DOI: 10.1145/2501221.2501222.
- [4] W. Wörndl. "A web-based application for recommending travel regions". In: *UMAP 2017 - Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization*. Association for Computing Machinery, Inc, July 2017, pp. 105–106. ISBN: 9781450350679. DOI: 10.1145/3099023.3099031.
- [5] D. Herzog and W. Wörndl. *A Travel Recommender System for Combining Multiple Travel Regions to a Composite Trip*. Tech. rep. 2014. URL: <http://en-corporate.canada.travel/resources->.
- [6] P. Thiengburanathum. "An intelligent destination recommendation system for tourists". In: *PQDT - UK & Ireland* March (2018).
- [7] Y. M. Arif, H. Nurhayati, F. Kurniawan, S. M. S. Nugroho, and M. Hariadi. "Blockchain-Based Data Sharing for Decentralized Tourism Destinations Recommendation System". In: *International Journal of Intelligent Engineering and Systems* 13.6 (2020). ISSN: 21853118. DOI: 10.22266/ijies2020.1231.42.
- [8] H. Alrasheed, A. Alzeer, A. Alhowimel, N. Shameri, and A. Althyabi. "A Multi-Level Tourism Destination Recommender System". In: *Procedia Computer Science*. Vol. 170. Elsevier B.V., 2020, pp. 333–340. DOI: 10.1016/j.procs.2020.03.047.
- [9] M. Balabanović and Y. Shoham. "Content-Based, Collaborative Recommendation". In: *Communications of the ACM* 40.3 (1997). ISSN: 00010782. DOI: 10.1145/245108.245124.
- [10] G. Adomavicius and A. Tuzhilin. *Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions*. 2005. DOI: 10.1109/TKDE.2005.99.
- [11] R. Burke. *Knowledge-based recommender systems*. Tech. rep. 2000, p. 180. URL: <http://www.personallogic.com/>.

- [12] P. Vansteenwegen and D. V. Oudheusden. "The Mobile Tourist Guide: An OR Opportunity". In: *OR Insight* 20.3 (2007), pp. 21–27. DOI: 10.1057/ori.2007.17. URL: <https://www.tandfonline.com/doi/abs/10.1057/ori.2007.17>.
- [13] D. Gavalas, C. Konstantopoulos, K. Mastakas, and G. Pantziou. "A survey on algorithmic approaches for solving tourist trip design problems". In: *Journal of Heuristics* 20.3 (2014), pp. 291–328. ISSN: 15729397. DOI: 10.1007/s10732-014-9242-5.
- [14] T. T. "Heuristic Methods Applied to Orienteering". In: *Journal of Operational Research Society* 35 (1984), p. 797.
- [15] A. Gunawan, H. C. Lau, and P. Vansteenwegen. *Orienteering Problem: A survey of recent variants, solution approaches and applications*. Dec. 2016. DOI: 10.1016/j.ejor.2016.04.059.
- [16] H. Kellerer, U. Pferschy, and D. Pisinger. "The Multiple-Choice Knapsack Problem". In: *Knapsack Problems*. 2004. DOI: 10.1007/978-3-540-24777-7{\\_}11.