Advancing Personalized Event Recommendations for Social Networking and Event Planning Platforms

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LITERATURE REVIEW

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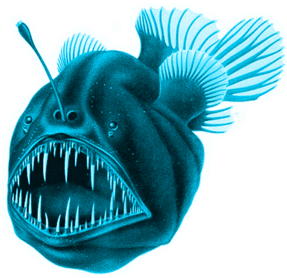
Scientific environment (optional)

This study is carried out at the . . . Institute, University of Bergen. The work is supported by the. . . . Fill this out if you are working on a project and put their logo in here. The ones below are just for example so please replace or remove them



Acknowledgements

Thank someone

Your Name
Place, Date

Abstract

. . . partial- couple of sentences about motivation / task

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Chapter 1

Introduction

In an age of information abundance, the demand for tailored and personalized experiences has never been more pronounced. Online platforms, ranging from e-commerce websites to content streaming services, strive to anticipate user preferences and present them with recommendations that resonate on a personal level. This quest for precision has fueled the development of advanced recommendation systems, which act as the behind-the-scenes orchestrators of user interactions, subtly guiding them through a vast array of choices. Among the diverse array of recommendation techniques, collaborative filtering and content-based filtering have stood out as two prominent methodologies, each harnessing distinct strengths to offer recommendations.

Fundamentally, recommendation systems revolve around two primary components: users and items. In this context, users assign ratings (or preference scores) to items (or products). User ratings are typically gathered using implicit or explicit techniques. Implicit ratings are indirectly collected based on user interactions with items. In contrast, explicit ratings involve users directly assigning values from a finite point scale or labeled interval values *Roy and Dutta* (2022). Among the well-known methods for making recommendations, content-based filtering stands out as a prominent approach *Basu et al.* (1998). This technique leverages connections between previously interacted-with jobs and shared attributes found within new job prospects, often gleaned from textual data. Conversely, collaborative filtering offers an alternative method for making suggestions *Breese et al.* (2013). This strategy capitalizes on the observation that users drawn to the same item generally share similar preferences for other items. Notably, integrating both sources of information holds the promise of a more potent recommendation system, prompting the development of model-based hybrid recommenders *Basilico and Hofmann* (2004). While effective, these systems often demand substantial feature manipulation to render this fusion operationally viable.

This research embarks on an exploration of a compelling avenue: the creation of hybrid recommendation systems that transcend the boundaries of collaborative and content-based filtering. By synergizing the inherent strengths of these two approaches, a potent opportunity arises to elevate the accuracy, relevance, and comprehensiveness of recommendations. This study delves into the mechanisms that underlie this synergy, aiming to unravel how collaborative and content-based filtering can harmonize to produce a recommendation system that optimizes personalized experiences for users.

Chapter 2

Background and Related Work

2.1 Introduction

In this chapter we discuss ...

2.2 Types of recommender systems

In today's digital era, where choices abound and information overload is a constant challenge, recommender systems stand as essential tools in guiding users through the sea of options. These systems, also known as recommendation engines, form the backbone of personalized experiences across diverse domains. Within this landscape lies a spectrum of recommender system types, each a unique approach to tailoring suggestions to individual preferences. From collaborative filtering to content-based strategies and hybrids that meld multiple techniques, these types collectively shape the art of offering tailored recommendations. In this exploration, we delve into the core concepts of these types, unveiling how they intricately fuse data, algorithms, and user inclinations to create a symphony of personalized suggestions. Figure 2.1 illustrates a visual depiction showcasing the various types of recommender systems *Roy and Dutta* (2022).

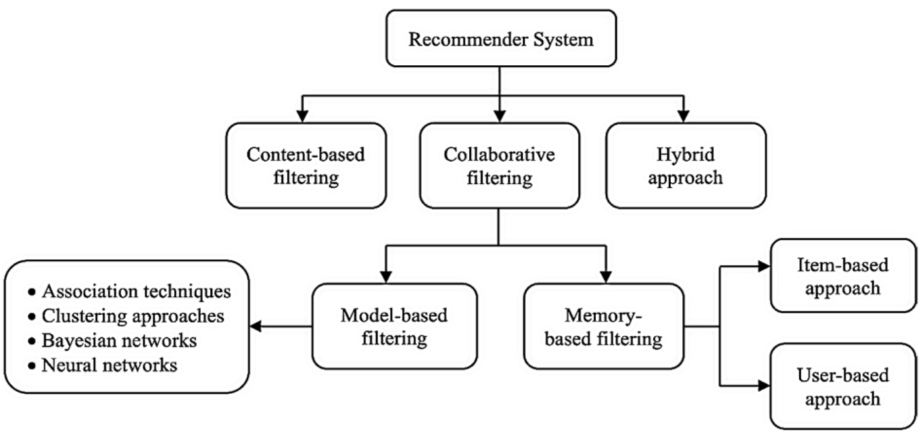

Figure 2.1: Types of recommender systems

2.2.1 Content-based recommender system

2.2.2 Collaborative filtering-based recommdender system

Two primary methods exist for collaborative filtering: Model Based and Memory Based. This paper will discuss Memory Based collaborative filtering, as user-based and item-based filtering. These two approaches diverge in their considerations during recommendation calculations. In item-based collaborative filtering, recommendations stem from identifying similarity patterns among items. Conversely, user-based filtering identifies akin users and offers recommendations based on the preferences of other individuals with comparable consumption behaviors *Yu* (2015). The core principle underlying these methods is to assess the similarities between users or items based on the user-item rating matrix. This computation of similarities facilitates the process of generating recommendations. Collaborative filtering algorithms typically encompass the following sequential steps:

1. **Building the user-item rating matrix:** Collecting user ratings or browsing data, and processing, transforming, and inputting the information results in the user-item rating matrix. This matrix serves as the foundational data for collaborative filtering algorithms.

2. **Finding the nearest neighbor set of users (or items):** Similarities between the target user (or item) and others are computed using the user-item rating matrix. The top k users (or items) are selected to create the nearest neighborhood set.

3. **Predicting item ratings:** Approximating the current user's rating for an item involves calculating the product of the rating and the corresponding user (or item) similarity for each neighbor. The average of these products yields the predicted rating for the item.

4. **Generating the recommendation list:** After predicting ratings for all unrated items for the target user, the top N items are chosen to create a recommendation list. This list is presented to users as the final recommendation outcome.

The majority of recommendation systems acquire user feedback in various ways, encompassing explicit and implicit methods. This user-provided input, manifested as ratings, is organized within a matrix that juxtaposes users and items, commonly referred to as the user-item rating matrix or the utility matrix, as exemplified in Table 2.1. This matrix frequently exhibits gaps due to incomplete data. The central challenge in recommender systems revolves around the task of inferring and completing the absent values within the utility matrix.

Memory-based collaborative methods propose novel items for users by considering the preferences of their neighboring users. These approaches directly utilize the utility matrix to make predictions. The initial phase of this strategy involves constructing a model, which essentially corresponds to a function that takes the utility matrix as its input:

$$Model = f(\text{utility matrix}) \tag{2.1}$$

	Item 1	Item 2	Item 3	...	Item N
User 1	5	-	3	...	-
User 2	-	4	-	...	2
User 3	-	-	-	...	-
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
User N	2	-	1	...	4

Table 2.1: Utility Matrix with Missing Values

Subsequently, recommendations are generated through a function that takes both the model and the user's profile into account. Notably, this process enables recommendations solely for users whose profiles are already encompassed within the utility matrix. Consequently, when intending to provide suggestions for a new user, the user's profile must be integrated into the utility matrix. Additionally, the similarity matrix necessitates recalculation, rendering this technique computationally intensive.

$$\text{Recommendation} = f(\text{defined model}, \text{user profile}) \quad \text{where user profile} \in \text{utility matrix} \tag{2.2}$$

Model-based systems leverage diverse data mining and machine learning algorithms to construct predictive models for estimating user ratings on items they haven't rated. Unlike relying on the entire dataset during recommendation calculations, these systems extract features from the data to build a model, which substantiates their moniker as "model-based" techniques. This methodology entails a two-step process for prediction: first, the model is constructed, and then a function f is employed, taking the model from the initial step and the user profile as inputs.

$$\text{Recommendation} = f(\text{defined model}, \text{user profile}) \quad \text{where user profile} \notin \text{utility matrix} \tag{2.3}$$

Notably, model-based techniques obviate the necessity of introducing a new user's profile into the utility matrix before generating predictions. Recommendations can be offered to users not originally part of the model. These techniques exhibit superior efficiency for group recommendations, swiftly suggesting sets of items utilizing pre-trained models. The efficacy of this approach heavily depends on the proficiency of the underlying learning algorithm employed for model creation. Model-based techniques hold the capacity to mitigate conventional issues in recommender systems, such as sparsity and scalability, through the integration of dimensionality reduction methods *Burke* (2002) and model learning techniques.

2.2.3 Hybrid filtering recommdender system

Chapter 3

Methodology

3.1 Design Science - if that is what you did

No.	Guidelines	Compliance
1	Design science research must produce a workable, practical artefact in the form of a construct, model, method, or instantiation	It can be used according to the original purpose, by the intended users. Be careful not to over promise. Be careful to promise the right things.
2	Ensure that the artefact produced is relevant and important	Has anyone tried to solve it before? Why hasn't it been solved before? How important can it be? Is it too difficult?
3	Rigorously evaluate the artefact produced	How do you know you accomplished what you wanted? Don't just ask people if they like it. Analytically using a mathematical model. Empirically using field study or experiment
4	Produce an artefact that makes a research contribution.	Solve a previously unsolved problem. Show that an artefact can be produced when it was previously unclear that this is possible.
5	Follow rigorous construction methods.	The method must be rigorous and replicable
6	Show the artefact is the outcome of a search process	This is done after you're finished
7	Clearly communicate the research process and outcome	Say a little about your thesis, any conference papers planned

Table 3.1: The seven guidelines for rigorous design science and how the work reported in this thesis fulfils them.

This is an example of how you can cross reference anything marked with a label 1

3.2 Experimental design

What was your design, how did you select subjects/participants

3.2.1 Threats to validity

3.3 Analytical study

Did you derive your results through mathematical proof? How do you know it is correct? Will it generalise to a class of problems?

3.3.1 Case Study

Did you do a case study?

Chapter 4

Methods

What you actually did

4.1 Implementation

4.2 Evaluation

Chapter 5

Results and Discussion

This will depend entirely on what you did in 4

5.1 Results and Analyses

What did you find?

5.2 Discussion

Did your findings support your hypothesis? Why? Why not?

Chapter 6

Conclusions and Future Work

This Chapter concludes the thesis by summarizing the findings from the study, the contributions and possible limitations of the approach. It can also identify issues that were not solved, or new problems that came up during the work, and suggests possible directions going forward. *Foldvik et al.* (1985)

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