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MASTER THESIS

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Fairness in group recommender systems

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I declare that I carried out this master thesis independently, and only with the cited sources, literature and other professional sources. It has not been used to obtain another or the same degree.

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Dedication.

Title: Fairness in group recommender systems

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Contents

1	Introduction	3
1.1	Problem statement	3
1.2	Research objective	4
1.3	Thesis structure	4
2	Recommender systems	5
2.1	Recommender systems	5
2.2	Group recommender systems	6
3	Fairness	7
3.1	General	7
3.2	Long-term fairness	7
3.3	Evaluation	7
4	Related work	8
4.1	Aggregating member preferences	8
4.2	Aggregation methods	8
4.3	Direct model methods	8
5	Datasets	9
5.1	Main datasets	9
5.2	Group datasets	9
5.3	Creating of artificial groups	9
6	Our work	10
6.1	EP-FuzzyD'Hondt	10
7	Offline experiments	11
7.1	Our work	11
7.2	Proceedings	11
8	Application	12
8.1	Design requirements	12
8.2	Architecture and design choices	12
8.3	Cold start problem	12
8.4	User manual	12
9	User study	13
9.1	Methodology	13
9.2	Results	13
9.3	Discussion	13
10	Conclusion	14
	Conclusion	15
	Bibliography	16

List of Figures	17
List of Tables	18

1. Introduction

Most of us interact with many recommender systems daily. Even if seemingly indirectly. The proliferation of this technology is astounding. Almost every interaction with today's web is in some way personalised. From the search results, shopping, listening to music, to reading news, browsing social media and many more. It has become quite unavoidable.

We can view recommender systems from a very simple perspective - they are algorithms that recommend items to users. Where items and users can be many different things, items for example being movies, news articles, more complex object or even entire systems. And users being, real people or other entities that exhibits some sort of preference on which the algorithm can decide.

One of the variants of recommender systems are those where the recommendation result is shared among more users based on their shared (aggregated) preferences. This is a subset called group recommender systems. They are not used as widely as the non-group variants due to the nature of the usage of most of the aforementioned technologies. We mostly use the web, listen to music and read the news as individuals. At least from the perspective of those systems. But for some of the domains there are valid use cases. We often listen to music and watch movies in groups. Select a restaurant and other public services not just for us. And that's where the group recommenders come handy.

tady je trochu moc velky skok - nejdriv asi neco o tom jak group RS funguji. Spis nez evaluation zminit primo fairness, nebo obecneji co ma byt cilem skupinoveho doporuzeni

But how to approach the evaluation? It starts to become harder than just simply rating the results based on a single feedback, now we have multiple users with possibly very different personal experiences. We want to be fair towards all individuals in the group. But the fairness property can be tricky to describe and evaluate due to the subjective nature of preference perception and distribution among the group members.

Classical recommendation systems has been studied for quite a long time, but the group variant and more soft-level (meaning evaluation on other than classical parameters) thinking about them is quite recent. With the rise of social dilemmas around recommender systems appears the fairness-ensuring topic more and more in many different shapes and sizes. And with that, there is a growing popularity towards recommender systems that are trained (and therefore evaluated) with these novel requirements in mind.

1.1 Problem statement

The current research on the topic of group recommender systems is lacking. There are no standardized data sets that would offer evaluation of the research without using various methods of data augmentation and artificial data creation. And the definition of fairness is not unified. It can mean many different things and be evaluated with many different methods.

With these two aforementioned problems goes hand in hand the very subjec-

tive nature of user preference.

Mozna merge obou kapitol dohromady?

1.2 Research objective

We would like to study how fairness can be defined in the context of the recommender systems, how it can be measured and eventually used to improve recommendations in the group setting. And explore different variants of fairness such as long-term fairness and different distribution of fairness among group members.

The primary goal of this thesis is to research and design novel group recommender system algorithm that would keep fairness as its primary optimization objective. If we could adapt fairness preserving methods such as voting systems from other fields to group recommendation problem. And evaluating the new algorithm with already existing approaches in the domain of group recommender systems.

Additionally we would like to research and contribute to data sets that could be used for the group setting. Expanding single user data sets with data augmentation that would generate synthetic groups' information and creating a web application in a movie domain that would serve as a platform for online evaluation of group recommender algorithms and provided us with real-user group recommendation data.

1.3 Thesis structure

We start with an introduction to recommender systems and specifically to group recommender systems in chapter: 2. Then we will continue with the definitions and evaluation methods for fairness in chapter Fairness. Next we will introduce few algorithms that are used in the group recommender field in chapter Related work. **TODO: check out other works and decide what should be here. This can be nice from the reading perspective, but is it really necessary?**

2. Recommender systems

In this chapter we will briefly introduce in general what recommender systems are (hereinafter referred to as RS) and then continue with description of the group variant of recommender systems and introduce common approaches and methods they employ.

2.1 Recommender systems

Broadly speaking, recommender systems are algorithms that are trying to suggest items to its users or from other perspective they aim to predict how would a user rate (like) an unseen item. They are used in variety of settings, from e-commerce, media consumption, social networks, expert systems, search engines and many others.

We can generally divide them by their approach as stated in [1] into:

- **Collaborative filtering** (CF)
Solely based on ratings of items from users (user-item interactions). Trying to recommend unseen items that were liked by users which have similar taste for other items that they both rated. And thus exploiting data of users with similar preferences.
- **Content-based filtering** (CB)
Relies on additional information about users and items. For example parameters of the items together with provided or mined preferences of users. We are essentially building a model based on available features both for items and users.

The popularity of these two approaches vary from domain to domain. Some domains naturally contain item specific data which allows to use the *content-based filtering* for example product parameters in e-shops, but other domains do not. Then it is more beneficial to use the *collaborative filtering* techniques or a mix of the two.

There are benefits and drawbacks for both, CF is able to extract latent meaning from the data that would remain inaccessible to CB that relies on hard data about the items. But at the same time it can cause problems to rely only on user-item interactions, because we need a lot of data in order to make a precise recommendations. There will be nothing to recommend if we cannot find a similar enough other user that already rated some unseen items. This problem is called *cold-start problem*.

Some of the classical and more advanced methods include:

- User-based and item-based nearest neighbor similarity [2][3][4]
- Matrix Factorisation techniques[5]
- Keyword-based Vector Space Models
- Linear Classifiers, Rule mining

- Explicit decision models
- Neural collaborative filtering
- Graph Convolutional Neural Networks

2.2 Group recommender systems

3. Fairness

3.1 General

3.2 Long-term fairness

3.3 Evaluation

4. Related work

4.1 Aggregating member preferences

4.2 Aggregation methods

4.3 Direct model methods

5. Datasets

5.1 Main datasets

5.2 Group datasets

5.3 Creating of artificial groups

6. Our work

6.1 EP-FuzzyD'Hondt

7. Offline experiments

7.1 Our work

7.2 Proceedings

8. Application

8.1 Design requirements

8.2 Architecture and design choices

8.3 Cold start problem

8.4 User manual

9. User study

9.1 Methodology

9.2 Results

9.3 Discussion

10. Conclusion

Future work

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List of Figures

List of Tables