<u>ResponsibleRecs</u>

Fairness, Diversity and Transparency in Recommender Systems

Kostas Stefanidis Tampere University, Finland

konstantinos.stefanidis@tuni.fi



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recommendations

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Total price from: € 119





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Very good - 8.5/10

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Recommender Systems

Recommender systems aim at suggesting to users data items of potential interest to them

Two main steps:

- Estimate a rating for each item and user
- <u>Recommend</u> to the user the item(s) with the highest rating(s)

Data for and about people



The data is here!

Data for and about people

The potential benefits of recommenders are well-accepted

• The importance of using such techniques in a fair, diverse and transparent manner is only recently considered

Our objective: create new algorithms for generating responsible recommendations for individual users and groups

• Ensure fairness, diversity and transparency

Design and develop algorithms for both offline and online scenarios:

- All data items are available before any selections have to be made
- Not all data items are available at once; classify each individual item as presented, into the selected ones or not for recommendations

Apply to many domains, from traditional products recommendations to health-related recommendations

The promise of Big Data

With the growing complexity of the available online information, users find themselves overwhelmed by the mass of choices available

• Recommender systems provide suggestions on data items of potential interest to the users

Big data technology comes with the promise to improve people's lives towards this direction by enhancing the discovery of interesting information, and provide results tailored to users' profiles

• Remember the power!: Enormous datasets, Enormous computational power, Massively parallel processing

However!

The same technology, if not used responsibly, may lead to <u>discrimination</u>, <u>amplify biases in the original</u> <u>data</u>, <u>restrict transparency</u> and <u>strengthen unfairness</u>

• Recommendations may play an important role in guiding users' decisions and forming their opinions

E.g., consider scenarios in which models based on biased data can abet violence, increase diversity issues, have an impact on economy policies, or even amplify discrimination in the justice system

Fairness

By fairness, we typically mean lack of bias

Is it correct to assume that insights achieved via computations on data are unbiased simply because data was collected automatically or processing was performed algorithmically?

• Bias may come from the algorithm, reflecting, e.g., commercial or other preferences of its designers, or even from the actual data, e.g., if a survey contains biased questions

So far: recommenders consider the notion of fairness *indirectly*

- No explicit models and algorithms
- For group recommendations, there are approaches that consider disagreements [1] and social relationships [2] among group members, or use fairness to measure the quality of a set of items for a group [3]

Our goal is to model and formally define fairness, as well as to introduce algorithms that directly optimize it

Diversity

Diversity ensures that different kinds of data items are represented in the output of an algorithmic process

• E.g., in a news recommender, suggest news from several political parties and not only from the user's favourite one

There is considerable work on search result diversification:

• Diverse keyword database search using preferences [4] / Assess the topical diversity of recommendation lists using order-independent intra-list similarity measures [5] / ...

Our goal here is to consider a family of diversity constraints that can express <u>coverage-based</u>, in addition to distance-based (relying on the pairwise similarity between items), diversity.

Re-define the measures of fairness

Fairness is related to diversification: when considering that a fair set of data items is likely to include items that represent different, or even all, categories of data items, or when considering groups, that satisfy different users

Transparency

Users many times want to know and control both what is being recorded about them, and how this piece of information is being used, e.g., to recommend content or for target advertising

We skip privacy for now

A transparent data analysis framework requires suggestions that can be easily understood by the users

• Can we explain the output of the algorithm?

Our goal is to suggest explainable items along with explanations — <u>Provide the WHY!</u>

- A user-based explanation is based on similar users
- An item-based explanation presents the items that had the highest impact on the recommender's decision

We aim at an integrated approach that considers explanations in the recommendation process rather than separating the explanation from the recommendation process

• <u>Recommendations along with their associated explanations will form graph-based summaries that include data items that ensure fairness and diversity</u>

Online Recommendations

But, all data items are available for evaluation at once?

• Many times, items appear one at a time, with a decision to be made on the specific item instantaneously

Online scenario / Streaming data / Sequential recommendations, i.e., suggestions in rounds, by exploiting newly added data items

The idea: Process items incrementally, maintaining a valuable recommendations set at any point in time

- [6] considers a fixed window of recent items, posing a problem for items not generated at a fixed rate
- [7] proposes algorithms to diversify a stream of results using a jumping window approach

<u>Our goal</u>: Provide a fair, diverse and transparent set of items considering the whole item set, rather than a fixed number of recent items

• Allow actively withdrawing items from the recommendations set, instead of simply dropping items as they leave the window

To our knowledge, combing fairness, diversity and transparency, especially in an online setting has not been considered

Research Agenda

The focus is on set-based selections: Both fairness and diversity are set-based concepts

- It makes no sense to talk about an individual item as being diverse
- Currently, most algorithmic decision-making approaches are based on individual items, where a utility score is associated with each item typically computed with respect to the values of the item

Group Recommendations: Even more so than in traditional recommendations for individual users, identifying data items of high relevance to a group is challenging, especially for cases where group members disagree on their dearest items

- We focus on developing novel data analysis methods that ensure **fairness**, **diversity** and **transparency** in *set selection for recommendations*
- We aim to design and develop algorithms that generate recommendations for **individual users** and **groups**, for both when data items are available before any selections have to be made and the **online case**

Generating responsible recommendations is timely due to the available big data technologies and the current discussions on bias and discrimination in algorithmic processing and decision making, yet is not enough supported by existing models and algorithms

Objective - Fairness & Diversity

Previous work focused *separately* on fairness or diversity in query processing and recommender systems

• This is a useful basis but must be significantly extended to bring in both fairness and diversity

Preliminary: Fairness can be defined as the proportional representation of the values of attributes of particular concern, and diversity as the existence of such values

How fairness and diversity can be combined with respect to the users preferences as expressed by the users' ratings?

Objective - Transparency & Explainability

Recommend items based on their explainability: Integrate recommendation and explanation to improve transparency

NOT! Data employed for producing recommendations can be different from the data used in generating the explanations, leading to explanation generation modules that are separate from the recommender system

E.g., consider "black boxes" in machine learning

Provide explainable recommendations through summaries: produce an abridged version of results

- We do not focus on providing the data items with the maximum utility score, but on summaries consisting of explainable items that exhibit fairness and diversity
- We aim to handle efficiently exploratory operations, like zoom-in and zoom-out, providing granular information access to the user

Objective - Individual User & Group Recommendations

Special focus on group recommendations!

New definitions for fairness and diversity applicable to groups

Fairness for groups via *envy-freeness*: A user considers a set of items fair for him/her, if there are items for which the user does not feel jealous, i.e., the presented items have utility scores within the range of scores of the best items for him/her

Diversity for groups via *coverage*: Rely on the existence of a number of items for all group members

+ Integration of items' explainability

Objective - Static & Online Processing

The static case solves the problem making the assumption that all data items are available at processing time

• Fairness, diversity and transparency constraints will direct the process; return the items with the highest utility computed with respect to our constraints

In the online case, not all items are available at once

- Classify each individual item, as presented, into the selected or not selected ones based on the fairness, diversity and transparency constraints
- How? Extend the K-choice Secretary Problem [8] to design online methods for picking items, presented in random order independently to their utility, subject to fairness, diversity and transparency constraints

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