

# FRecs - Fairness, Diversity and Transparency in Health Recommenders: Challenges & Objectives

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**Abstract.** With the growing complexity of the available online information, users find themselves overwhelmed by the mass of choices available. To facilitate users, recommender systems provide suggestions on interesting data items to them. Big data technology promises to improve people's lives in this direction, by enhancing the discovery of interesting information. However, this technology, if not used responsibly, may lead to discrimination and amplify biases in the original data; so, recommendations may play an important role in guiding users' decisions and forming opinions. In this paper, we focus on providing useful resources to patients that is essential in achieving the vision of participatory medicine. Specifically, the objective of FRecs is to create new algorithms for generating responsible recommendations, i.e., recommendations that ensure fairness, diversity and transparency. Producing responsible recommendations is timely due to the huge growth of big data technologies and the current debate on fairness and transparency in algorithmic decision making, yet is not well enough supported by existing models and algorithms.

## 1 Introduction

Nowadays, there is a big number of people who search online for health and medical information. To facilitate the user selection process, given the growing complexity of the available online information, recommender systems provide suggestions on resources of potential interest to the users, like news articles and other sources. The interest of a user for a suggested data item is inferred typically, from the user's health background and interests in paper, electronic, or mental records.

At the same time, 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. However, the same technology, if not used responsibly, may lead to discrimination, amplify biases in the original data, restrict transparency and strengthen unfairness; this way,

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recommendations may play an important role in guiding users’ decisions and forming their opinions. For example, consider scenarios in which models based on biased data can increase diversity issues, or have an impact on access policies. While 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.

Recommender systems have attracted extensive research attention and have been deployed in a wide range of applications. Recently there are also examples coming from the health domain (e.g., [25, 24]). A recommender system consists typically of a set of data items, data sources in the form of documents in our case, a set of users and the ratings of users for certain documents. Typically, the cardinality of the document set is very high and users rate only a few documents. For the documents unrated by the users, recommender systems estimate a relevance score, following for example the collaborative filtering approach [19], where the relevance scores predicted for a user produced based on the ratings of other similar users, or the content-based approach [15], where the system recommends documents with features similar to documents a user likes. In FRecs, apart from recommendations for individual users, we pay special attention to recommendations for groups, for supporting cases in which a group of people participates in an activity, e.g., a group therapy session, targeting at best satisfying the preferences of all the group members [1, 13]. We next point out recommenders systems state of the art in areas related to FRecs.

***Background in fairness in recommender systems.*** By fairness, we typically mean lack of bias [17, 16, 18]. It is not 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, for example, commercial or other preferences of its designers, or even from the actual data, for example, if a survey contains biased questions. Previous works in recommenders consider the notion of fairness only indirectly, without guaranteeing it via explicit models and algorithms [9, 14, 24, 25]. In the context of group recommendations, there are approaches that introduce additional factors into the model, such as agreement [1] or social relationships [11] among group members, but still without directly tackling the concept of fairness. More recently, [20] uses the concept of fairness for expressing the notion of quality of a set of items for a group. FRecs aims to model and formally define fairness, as well as to introduce algorithms that directly optimize it.

***Background in diversity in recommender systems.*** Diversity ensures that different kinds of data items are represented in the output of an algorithmic process. For example, in a news recommender, instead of suggesting only news from user’s favourite political party, an approach would be to also display news from other political parties to break out of user’s internet bubble. This is a general term used to capture the quality of a set of items, with regards to the variety of its constituent elements. There is considerable work on search result diversification

(for surveys, see at [32, 10]). For example, [21] proposes diverse keyword database search that utilizes user preferences, [33] introduces an order-independent intra-list similarity measure to assess the topical diversity of recommendation lists, while [27] focuses on diversifying the recommended items with respect to user interests. The work in FRecs differs from prior work in the sense that we consider a family of diversity constraints that can express coverage-based, in addition to distance-based (relying on the pairwise similarity between documents), diversity. We will take into account these constraints in order to define measures of fairness. Fairness is related to diversification, for instance, when considering that a fair set of documents is likely to include documents that represent different, or even all, categories of documents, or when considering groups, that satisfy different users.

***Background in transparency in recommender systems.*** Users many times want to know and control both what is being recorded about them, and how this piece of information is being used, for example, to recommend content or for target advertising. While privacy is clearly related to this, here we focus on the concept of transparency that plays an important role as well. A transparent data analysis framework requires suggestions that can be easily understood by the users. That is, transparency contrasts with the concept of “black box” systems, where even the data scientist or algorithm designer cannot explain the output of an algorithm. In FRecs, we envision providing explainable documents along with explanations. There are different ways of classifying explanation styles. A user-based explanation is based on similar users [29], while an item-based explanation presents the items that had the highest impact on the recommender’s decision [28]. In all styles, the input data employed for producing recommendations, may be different from the input data used for generating the explanation [8, 23], leading to explanation generation modules that are separate from the recommender system. However, building recommendations based on the items’ explainability, thus integrating recommendation and explanation, may improve transparency by suggesting interpretable items to the user. Recently, [31] proposes a model-based collaborative filtering approach to generate explainable recommendations based on item features and sentiment analysis of user reviews, in addition to the ratings data. In our approach, we aim at an integrated approach that considers explanations in the recommendation process rather than separating the explanation from the recommendation process. Recommendations along with their associated explanations will form graph-based summaries that include documents that ensure fairness and diversity.

***Background in online recommendations.*** In practice, even though a set of suggestions has to be selected, not all data items in the set is available for evaluation at once. Rather, items may appear one at a time, with a decision to be made on the specific item instantaneously. Such situations motivate us to consider an online scenario, which is sometimes referred to as streaming. In such scenario, we need to process items incrementally, maintaining a valuable recommendations set at any point in time. Previous works in this line, e.g., [5],

consider a fixed window of recent items, posing a problem for items that are not generated at a fixed rate. More recently, [4] proposes algorithms to diversify a stream of results using a jumping window approach. FRecs aims to start at the beginning of the stream, providing a fair, diverse and transparent set of documents considering the whole document set, rather than a fixed number of recent documents. This will allow our algorithm to actively withdraw documents from the recommendations set, instead of simply dropping documents as they leave the window. To our knowledge, combing fairness, diversity and transparency, especially in an online setting has not been considered.

We will use the prominent collaborative filtering recommender model. In collaborative filtering, users preferences are represented by a ratings matrix. It is based on the idea that people who agreed in their evaluation of certain data items in the past are likely to agree again in the future. A key advantage of collaborative filtering is that it is capable of accurately recommending, even complex, data items without requiring an understanding of the item itself. Our goal is to extend the flexible collaborative filtering model by integrating fairness, diversity and transparency into the recommender system.

## 2 The FRecs Challenges & Objectives

Given that both fairness and diversity are set-based concepts (e.g., it makes no sense to talk about an individual item as being diverse), in FRecs, we focus on set-based selections, unlike most algorithmic decision-making approaches that are based on individual items, where a utility score is associated with each item typically computed with respect to the values of the item. Even more so than in traditional recommendations for individual users, identifying documents of high relevance to a group is challenging, especially for cases where group members disagree on their favorite items.

We focus on developing novel data analysis methods that ensure fairness, diversity and transparency in set selection for recommendations. In addition to produce traditional recommendations, we consider the online case, in which not all documents are available at once, and we have to classify each individual document as presented, into the selected ones or not for recommendations. Our aim is on both recommendations for individual users and on recommendations for groups. Producing responsible recommendations is timely due to the huge growth of big data technologies and the current debate on fairness and transparency in algorithmic decision making, yet is not well enough supported by existing models and algorithms.

The objective of FRecs is to create new algorithms for responsible recommendations for individual users and groups of users, i.e., recommendations that ensure fairness, diversity and transparency. The algorithms will cover both cases in which we make the assumption that all documents are available before any selections have to be made, as well as we decide whether to accept, reject or defer a document in an online manner as the documents appear. We translate the aforementioned challenges into research objectives, described below:

**Fairness and diversity.** Previous work focused separately on either fairness or diversity in query processing and recommender systems [14, 5, 25, 10]; it is a useful basis but must be significantly extended to bring in both fairness and diversity. We consider fairness as the proportional representation of the values of attributes of particular concern, and diversity as the existence of such values. In this line, we will study how fairness and diversity can be combined with respect to the users preferences as expressed by their ratings. We will pay special attention on allowing combinations of attributes of particular concern, so as to capture attribute dependencies.

**Transparency and explainability.** In all explanation styles, data employed for producing recommendations, can be different from the data used in generating the explanations [8, 28, 13], leading to explanation generation modules that are separate from the recommender system. Performing the recommendation task based on the items' explainability, thus integrating recommendation and explanation, can improve transparency by suggesting interpretable documents to the user, while preserving the powerful prediction of the collaborative filtering approach. Moving forward, we target at building upon our previous work on summary-driven data exploration [26, 22], in order to provide explainable recommendations through summaries. Recommendation summaries will be defined as the process of distilling knowledge from the whole result set in order to produce an abridged version. We do not focus on providing only the most important documents, i.e., the ones with the maximum utility score, but on summaries consisting of explainable documents that exhibit fairness and diversity. We aim to handle efficiently exploratory operations, like zoom-in and zoom-out, on both data models, providing granular information access to the user.

**Individual user and group recommendations.** In addition to individual user recommendations, FRecs focuses also on recommendations for groups. Based on the useful insights produced by previous work on group recommendations [24, 25], we will provide new definitions for fairness and diversity applicable to groups. Regarding fairness, in addition to proportional representation, we consider also envy-freeness, in which intuitively, a user considers a set of documents fair for him/her, if there are documents for which the user does not feel jealous, i.e., the presented documents have utility scores within the range of scores of the best documents for him/her. Coverage-based diversity for groups rely on the existence of a number of documents for all group members. Furthermore, our early work on the effective presentation of group recommendations [13, 23], will be extended by integrating documents' explainability into the group recommendation process. We envision a definition for FRecs group recommendations in which all fairness, diversity and transparency aspects play a crucial role.

**Static and online processing.** For locating the recommendations to be presented to the user/group, we consider two cases. First, in the static case, we solve the problem making the assumption that we have access to all documents. Fairness, diversity and transparency constraints will direct the process; the goal is to return the set of documents with the highest utility computed with respect to these constraints. In addition, we consider the online case, in which not all

documents in the set are available at once. This way, we exploit our previous work in online settings [5] to classify each individual document, as presented, into the selected or not selected box based on the fairness, diversity and transparency constraints. The focus here is on extending the K-choice Secretary Problem [2], in order to design and develop online methods for picking a set of documents, presented in random order - independently to their utility, subject to fairness, diversity and transparency constraints.

### 3 Research Methods

In FRecs, we extend state of the art work on fairness, diversity and transparency in set selection, explanations for recommendations, group recommendations and online set selection.

**Fairness and diversity in recommender systems.** The basic problem setting is that we have a set of documents, each with associated attributes. From this set, we wish to select  $K$  documents to maximize a utility score. The utility score of the  $K$  documents can be computed based on the documents individual utility scores (as obtained, for example, by a recommendation algorithm), or based on more complex functions that take into account co-existence of documents. Let us now turn to fairness and diversity constraints. Among the attributes associated with documents, we assume that one attribute is of particular concern. Our notions of fairness and diversity are defined with respect to the value of this attribute. In practice, there may be multiple such attributes, rather than just one. If combinations of multiple attributes are of concern, or if dependencies between the attributes need to be captured explicitly, we could represent such combinations as a single Cartesian product attribute of concern. Attributes may also have associated privacy concerns, and so may need to be converted to noisy histograms, e.g., to enforce differential privacy. We assume that documents are partitioned on the value of the attribute of concern. Let there be  $d$  distinct values of the attribute of concern. Our requirement is to choose  $k_i$  elements for each distinct value  $i$  in  $[1, \dots, d]$  with each  $k_i \in [0, K]$  and  $Sum(k_i) = K$ . This begs the question of what the  $k_i$  values should be. We next briefly consider several notions of fairness and diversity that will be exploited towards producing recommendations in FRecs.

For achieving fairness, we will start by considering the proportional representation of the values of the attribute of concern. Namely, proportional representation requires that the desired size  $K$  of the selected documents set be prorated among the  $d$  categories. Another potentially appropriate fairness metric is the normalized difference: the mean difference normalized by the rate of positive outcomes, which in our case corresponds to being selected among the top-k [34, 3]. Proportional representation can be extended, so as to be used for producing fair recommendations for groups. In this case, we say that a user is satisfied by a document, if the document is ranked in the top documents for the user. Intuitively, this means that the user considers the top- $K$  recommendations fair for him/her, if there are at least a particular number of documents that the user

likes. As an alternative, we consider fair group recommendations by counting the envy of the users in a group. This way, we say that a user is satisfied by a specific document, if the utility score of the document for the user is among the top scores of the users in the group for this document. Intuitively, in this definition, the user considers the package fair for him/her, if there are at least a particular number of documents for which the user does not feel envious. With respect to proportional representation and envy-freeness concepts, the goal is to define measures for counting the fairness of a set of documents.

FRecs considers both distance-based and coverage-based (differently to previous approaches) definitions for diversity. Distance-based diversity rely on a pairwise distance measure between two documents appearing in the resulting set. Given such a measure, the diversity of a set of documents is expressed by using an aggregation function of the pairwise distances between the documents in the set [21]. Maximizing the minimum (resp., average) diversity is known as MaxMin (resp., MaxSum) diversification [6]. Assuming that we have a set of categories, and that each document belongs to one or more categories, coverage-based diversity aims to represent every category in the selected set [32]. Whether this is possible depends on how  $K$ , the number of documents selected in total, compares to  $d$ , the number of categories of documents. This way, the diversity of a set of documents is expressed as the extent to which the documents in the set cover the categories.

Summarizing the scenarios considered above, our focus is on designing and developing algorithms that allow us to treat combinations between fairness and diversity. Namely, we formulate the problem as follows: Given a collection of documents, a fairness measure and a set of categories (resp., a distance measure), locate the set of documents that maximizes fairness, and includes  $y$  documents from each category (resp., and all pairs of documents in the set have distance greater than a threshold). Since the problem of identifying the diverse set of documents with the maximum fairness is NP-hard, for enhancing the efficiency of our approach, we opt to start with greedy algorithms, like for example, add the document to the output set, in each round of the algorithm, that maximizes fairness and covers a category that does not exist in the already selected documents. More sophisticated algorithms will be designed in order to ensure the satisfaction of all constraints dictated by fairness and diversity.

**Transparency via explanations in recommender systems.** It has been shown that explanations in recommender systems can help users make more accurate decisions; hence, improving user satisfaction and acceptance of recommendations [8]. The typical flow of most recommenders is to generate explanations for the recommendations produced [30]. In FRecs, we propose integrating explanations with recommendations. For doing so, we need to be able to quantify the explainability of a documents, so as to combine explainability with the utility score of the document. Considering, for instance, the user-based collaborative filtering case, explainability can be formulated with respect to the ratings of the users that are similar to a user in question. If many similar users have rated an document, this can provide a basis upon which to explain the docu-

ment, which in turn means that the document can be considered as explainable. Our goal is to propose novel algorithms for producing recommendations that, in addition to the utility score of a document, consider the explainability score of the document. We formulate this as an optimization problem that outputs the set of documents with a maximum score that is defined by combining documents utility and explainability.

Given the growing complexity of the available online information, databases are becoming increasingly difficult to understand and use. To facilitate users, FRecs builds upon our previous work [26] and provides, in an effective way, overviews of recommendations, forming graph-based summaries that include the most valuable documents for a user or group, subject to fairness, diversity and explainability. To create an explainable summary, we include in the graph, nodes that represent both documents and users, along with their connections, so as to highlight interesting associations and enable a decent understanding of the provided information. Moving forward, although exploration operators over summaries have already been identified as useful (e.g., [12]), the available approaches, even in different domains, are limited, working with predefined taxonomies on documents. Here, we introduce exploration operators on recommendation summaries, that can be used iteratively, to allow focusing on a specific subgraph of the initial summary, providing granular information access to the user. Zoom-in and zoom-out operators are defined in order to be able to promote either fairness, diversity or both at the same time.

**Online recommendations.** In practice, even though a set of documents has to be selected, not all documents in the set may be available for evaluation at once. Rather, they may appear one at a time, with a decision to be made on the specific document instantaneously. This means that we have to select or not each individual document, as presented, subject to the utility, fairness, diversity and explainability criteria in our problem statement.

The problem of designing an online algorithm to optimize the probability of selecting the document with the maximum utility in a randomly-ordered sequence has been studied extensively [7], and is known as the Secretary Problem. In this problem, the goal is to hire one secretary from a pool of  $N$  candidates, where candidates arrive in random order. When a candidate is interviewed, the decision must be made to hire or reject the candidate, and this decision is irreversible. A generalization of this problem, called the  $K$ -choice Secretary Problem [7], is stated as follows: design an online algorithm for picking  $K$  out of  $N$  documents presented in random order, to maximize their expected sum. In FRecs, we target at designing online algorithms for picking  $K$  out of  $N$  documents, each with an associated utility score, presented in random order. Specifically, the goal is to select documents to recommend that maximize their expected aggregated utility, subject to fairness, diversity and explainability. Intuitively, we start with the basic idea of solving the  $K$ -choice Secretary Problem separately for each concept, aiming to satisfy all of them. In addition, we will study other interesting variants, like how to work when documents are partially ordered.



## 4 Conclusions

FRecs aims to develop novel algorithms for selecting sets of documents, in both a static and online setting, optimized for providing fair, representative and explainable recommendations in the health domain, as well as for recommendations comprehension. The key insight is that fairness, diversity and transparency should not be analyzed in isolation, but together. The approach advances the state of science in realizing a holistic treatment of fairness, diversity and transparency through different stages of the data management and analysis life-cycle, namely, data processing, selection, ranking, and result interpretation. The work also concerns enabling incremental maintenance of the responsible properties of a set of recommendations.

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