Ensuring Fairness in Group Recommendation

Recommender systems have the general goal of proposing items (e.g., movies, restaurants, hotels) to a user based on her preferences [1]. In many real-world settings however, there is a need to recommend items for a group of users rather than a single user, e.g., department members going out to a festive dinner or friends planning to watch a movie. In addition, with the success of social networking, there is a recently emerging trend, where people form groups and participate together in activities. This calls for effective techniques for group recommendation.

Research on group recommendation discerns two main kinds of groups: persistent and occasional groups [2]. Persistent groups refer to groups with consistent structure and information about the group-item preferences [3, 4], in this case, each group can be treated as a virtual user and personalized recommendation techniques are applied, while in occasional groups, only the individual preferences are available [5, 6], and recommendations must be done on this basis, i.e., by aggregating the individual preferences of group members.

In the vast majority of work on group recommendation, the main objective is to maximize the group's overall satisfaction with the recommended list of items. The major drawback of this approaches is that they usually recommend items which are highly liked by some group members and highly disliked by others. However, more recently, there has been great interest in making recommendations that are fair to each group member [7, 8, 9, 10, 11]. In this context, fairness attempts to minimize the feeling of dissatisfaction within group members.

Research agenda. The goal of this thesis research is to deal with the problem on fairness in group recommendation by proposing effective models and efficient algorithms aggregating the preferences of group members. In this context, there is a broad range of research questions that one can pose. The plan is to delve into a few select highly focused research directions, which nicely compliment each other. The planned research necessitates the interplay of modern data science techniques. To achieve this goal, the planned research may be structured as follows.

1. *Fair group recommendation.* The first contribution is to introduce an effective model capturing the fairness of a list of items to a group defining the ranking criterion on the candidate items. Then dividing efficient algorithms to quickly identify the list of relevant items to the group by employing optimization techniques.

2. *Diversify of the recommendations.* To present more meaningful recommendations in personalization systems, we need to take into account the notion of diversity within results. Briefly, the main goal is to increase the utility of the set of items presented to the group, so that it includes relevant and at the same time dissimilar to each other, better capturing the users' intent.

3. *Contextual fair recommendation.* Context-ware recommendations refer to the need to take into account additional information in serving content to users [12]. Context refers to many different dimensions, for example, geographical (at home or at work), companion (alone, friends or family), mode (happy, sad or active), etc. The objective in this line of work is to make a fair group recommendation while taking into account the notion of the context.

Candidate Profile. The desired candidate must have a certain ease with the concepts of optimization and data science. Knowledge of Python is essential, and familiarity with relevant libraries is a plus; among these libraries, we can cite pandas and scikit-learn.

Do not censor yourself if you do not have precisely all of the stated skills; a part of the thesis will be dedicated to upgrading the successful candidate in the fields indicated.

Supervisors information. The thesis will take place at LIRIS–CNRS, and will be supervised by Prof. Youssef Amghar (INSA de Lyon) and Dr. Karim Benouaret (Université Claude Bernard Lyon 1).

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