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# Long-term effects of user preference-oriented recommendation method on the evolution of online system

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## HIGHLIGHTS

- With consideration of heterogeneity of real user, we propose a novel personalized recommendation method based on the user preference.
- Our main focus is on evaluating the health state of ecosystem in the long-term evolution by building an evolution model, which simulates the mutual feedback between user choices and recommender system.
- We find that there is a good trade-off between short- and long-term performances of recommendation if online system allows multiple recommenders work simultaneously and assigns the optimal recommender to each user in the individual level.

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## ABSTRACT

As the explosion growth of Internet economy, recommender system has become an important technology to solve the problem of information overload. However, recommenders are not one-size-fits-all, different recommenders have different virtues, making them be suitable for different users. In this paper, we propose a novel personalized recommender based on user preferences, which allows multiple recommenders to exist in E-commerce system simultaneously. We find that output of a recommender to each user is quite different when using different recommenders, the recommendation accuracy can be significantly improved if each user is assigned with his/her optimal personalized recommender. Furthermore, different from previous works focusing on short-term effects on recommender, we also evaluate the long-term effect of the proposed method by modeling the evolution of mutual feedback between user and online system. Finally, compared with single recommender running on the online system, the proposed method can improve the accuracy of recommendation significantly and get better trade-offs between short- and long-term performances of recommendation.



## 1. Introduction

The last decade has witnessed an explosion of development in the area of Internet economy: there are ten thousands of movies and books, and billions of web pages. As a result, it forces us to live in an information overload society: the amount of information, especially on Internet, is increasing far quickly than our ability to process it. In this context, most popular web sites such as Amazon, Netflix and YouTube provide the recommender system, which attempts to facilitate user navigation

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by suggesting user new possibly relevant items and thus increases customers satisfaction and their profits [1,2]. Namely, recommender systems seek to predict users' non-considered preference typically according to their historical activities. Until now, numerous recommenders based on different ideas and concepts have been proposed, including collaborative filtering [3–5], the content-based method [6], spectral analysis [7,8], latent semantic models and Dirichlet allocation [9,10], iterative self-consistent refinement [11,12] as well as topology adaptation method [13].

Although recommenders have been greatly developed, there still are a lot of rooms for improvement. The traditional method supports the recommendation services for all users by adopting single recommender and always ignores the heterogeneity between users. It is well-understood that different recommenders, even ones that have quantitatively similar behavior on common accuracy metrics, produce recommendations that differ in ways that users can perceive and that may impact their ability to meet different user needs, or the needs of different users [14]. One way of making use of the advantage of different algorithms to improve recommendation is through hybrid recommender. For example, hybrid method combining heat conduction and probability spreading algorithm (HHP) is proposed to achieve better recommendation performance [15]. With a tunable hybrid parameter, the HHP method provides a smooth yet non-trivial transition from one method to the other. Besides, each real system is shown to have its own optimal hybrid parameter. Guan et al. propose UHHP, a advanced HHP, that apply HHP in individual level, namely each user has his/her own personalized hybrid parameter to adjust [16]. In order to improve higher accuracy than standard collaborative filtering (CF), Liu et al. [17] introduce a modified collaborative filtering algorithm by using the second-order correlations. Zhu et al. [18] adopt mutual correction of forward and backward similarity estimations to design personalized recommender. By considering the users' similarity direction and the second-order correlations to depress the influence of mainstream preferences, Guo et al. [19] propose the directed second-order CF (HDCF) algorithm specifically to address the challenge of accuracy and diversity of the CF algorithm. Furthermore, for solving the accuracy–diversity dilemma, the directed random walks method was proposed [20]. In the aspect of user heterogeneity, based on a weighted projection of the user–object bipartite network, it studies the effects of user tastes on the mass-diffusion-based personalized recommendation algorithm [21]. Furthermore, Shang et al. [22] analysis the structure and evolution of web-based user–object networks in an empirical way. In addition, those existing methods put considerable attentions on short-term effects such as recommendation accuracy and user privacy, the long-term mutual feedback between user and recommender system has been neglected so far. Zeng et al. [23] propose a model of network evolution to study the complex dynamics induced by this feedback, and remark that item diversity can be enhanced by sacrificing a small fraction of recommendation's short-term accuracy in exchange for higher long-term diversity. Zhao et al. [24] also analysis the long-term effects of different recommenders on the evolution of online systems.

In this paper, we explore another approach to solve the personalized recommendation problem. Based on the heterogeneity of real users, we propose a novel personalized recommendation method running on the individual level, where each user can have his/her special recommender. The designed recommender system supports more than one recommender simultaneously. Meanwhile, with consideration of the recommendation results affect the growth of the user–item network, and the change of the network meanwhile influences the future recommendation outcome, we study the co-evolution of the users decision and the recommender system. With this incentive, we make a close study about the users' optimal personalized recommendation algorithm. We consider two benchmark datasets (*Movielens* and *Netflix*) and find that there is a significant enhancement for recommendation performance if all users are assigned with their optimal recommenders. Hence, we design a recommender system that supports multiple recommenders. Moreover, in order to understand the long-term impact of recommender systems, we model the co-evolution of the decisions of users and the recommender system by a rewiring process, and use the structure properties (e.g., Gini coefficient, cluster coefficient) to evaluate long-term diversity of evolution network. Finally, our work highlights that there is a good trade-off between short- and long-term performances of recommendation if online system allows multiple recommenders work at the same time and assigns the optimal recommender to each user in the individual level.

## 2. Methods and model

### 2.1. Methods

In this part, we first introduce several well-known recommenders in this work, and then we present the user preference-oriented recommendation method.

*Popularity-based recommendation* (PR): PR is a classic represent of no-personalized recommendation method, which recommends items to each user based on item popularity. First, it makes statistics on the degree of each item, then sorts the item according to degree in a descend way, and excludes off items that the user have selected. After that, it recommends other products to the user.

*User-based collaborative filtering* (UCF): The basic idea of UCF is that similar users like similar items. The UCF algorithm follows this process: First, the similarities between the target user and the rest of the users are calculated. Then, the recommendation scores of uncollected items for user $i$ is calculated by

$$P_{i,a} = \sum_{j=1}^{N} s(i,j) a_{j,a} \tag{1}$$