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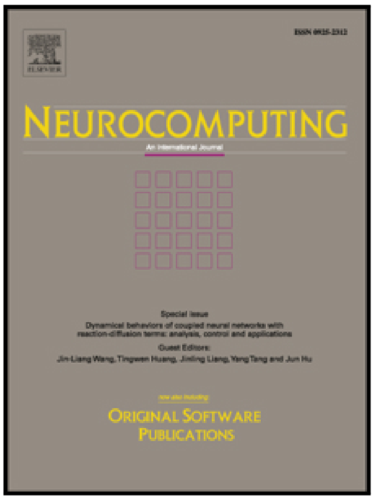

Long-term Performance of Collaborative Filtering Based Recommenders in Temporally Evolving Systems

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***Abstract*—Recommender systems benefit people at every moment in their daily life. Considerable attentions have been drawn by performance in one-step recommendation and static user-item network, while the performances of recommenders on temporally evolving systems remain unclear. To address this issue, this paper first describes an online commercial system by using a bipartite network. On this network, a recommendation-based evolution method is proposed to simulate the temporal dynamics between a recommender and its users. Then the long-term performance of three state-of-the-art collaborative filtering (CF)-based recommenders, i.e., the user-based CF (UCF), item-based CF (ICF) and latent factor-based model (LFM), is evaluated on the generated temporally evolving networks. Experimental results on two large, real datasets generated by industrial applications demonstrate that 1) optimization-based CF models like the LFM enjoy their high-prediction accuracy in one-step recommendation; and 2) entity relationship-based CF models like the ICF benefit the recommendation diversity, as well as the system health on a temporally evolving network. It turns out that in a temporally evolving system, an efficient recommender should consider both the one-step and long-term effects to generate satisfactory recommendations. Thus, it is necessary to adopt heterogeneous models, e.g., trade-off between optimization-based model and entity relationship-based model, in real systems to grasp various users' behavior patterns to improve their experiences.**

***Index Terms*—Learning System, Recommender System, One-step Recommendation, Long-term Effect, Temporally Evolving System, Bipartite Network**

I. Introduction

In the last two decades, people have witnessed the rapid development of the information technologies (especially the artificial intelligence [1-6]) and the Internet economy, nowadays there are a massive numbers of resources (e.g., pictures, videos, goods and etc.) on the Internet [7-8]. As a result, people are often overwhelmed with information overload that available information is too much to fit out the key part. In such context, various information filtering and optimization tools have been emerged [9-14]. Among them, recommender systems, which predict the user's potentially interesting items via analyzing user historical behaviors, are considered as a promising way to extract valuable data [15-16]. Therefore, they have become attractive for many fields. For example, Amazon, Netflix and YouTube, adopt recommender systems to gain a better user satisfaction and user experience to benefit their profits further [17-20].

In the last two decades, different kinds of recommenders have been proposed based on various ideas and concepts. Among them, collaborative filtering (CF) is one of the most popular and effective recommender [21-23]. The research on the CF recommenders with varying ideas can be divided into the Neighborhood Based Model (NBM) and the Latent Factor Model (LFM) respectively. For the NBM, it is a kind of entity relation-based method. It focuses on building the neighborhoods of target entity (i.e., user or item) based on the similarity between different entities, then makes commendations according to the historical behaviors of target's neighbors. It further includes two different types of forms that the user-oriented (U-NBM) and item-oriented (I-NBM) recommendation [20].

Compared with NBM, LFM is one of numerical optimization method, it first maps both users and items into a joint latent factor space, then trains this user-item model with feature factors by using the known ratings, after that the unknown ratings is estimated by calculating the inner products of corresponding user-factor and item-factor vectors pair [24]. Motivated by Netflix prize, matrix factorization (MF)-based techniques for latent factor (LF) analysis on sparse matrices arise and become the most successful approach for LFM . The existing literature on this topic embodies a variety of approaches, including the singular value decomposition (SVD) ++ model [25], probabilistic MF model [26], Nonnegative MF [27] (NMF) and nonparametric MF model [28]. In summary, these two kinds of models (i.e., NBM and LMF) can be employed in different occasions depending on detailed requirements.

Regarding for designing the healthy recommender system, most prior works focus on evaluating the one-step

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