Chapter 16
Social Recommendations:
Mentor and Leader Detection to Alleviate the Cold-Start Problem in Collaborative Filtering

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ABSTRACT

Recommender systems aim at suggesting to users items that fit their preferences. Collaborative filtering is one of the most popular approaches of recommender systems; it exploits users' ratings to express preferences. Traditional approaches of collaborative filtering suffer from the cold-start problem: when a new item enters the system, it cannot be recommended while a sufficiently high number of users have rated it. The quantity of required ratings is not known a priori and may be high as it depends on who rates the items.

In this chapter, the authors propose to automatically select the adequate set of users in the network of users to address the cold-start problem. They call them the "delegates", and they correspond to those who should rate a new item first so as to reliably deduce the ratings of other users on this item.

They propose to address this issue as an opinion poll problem. The authors consider two kinds of delegates: mentors and leaders. They experiment some measures, classically exploited in social networks, to select the adequate set of delegates.

The experiments conducted show that only 6 delegates are sufficient to accurately estimate ratings of the whole set of other users, which dramatically reduces the number of users classically required.

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INTRODUCTION

With the democratization of the Internet, users often need to be assisted in their search of information or search of items. Recommender systems have been proposed in the beginning of the 90's (Goldberg *et al*, 1992), with the aim to fulfill this need. Indeed, the volume of items that users can access is now so huge that they cannot get the information they want within a small amount of time; users are thus unsatisfied. This consequence can be dramatic for e-commerce services for example, that aim at increasing their sales and at developing customers' loyalty. As a consequence, recommender systems are increasing in popularity and are no more of secondary importance; they are becoming mandatory in many e-services.

Recommender systems are not simple information delivery systems; they recommend and display personalized information or pertinent items to users. They are a way to cope with the classical "one size fits all" characteristic of many information delivery systems, such as classical search engines (Allan *et al.*, 2003).

Recommender systems take into consideration the users' specific characteristics, represented under the form of users' profile (Adomavicius & Tuzhilin, 2005). An item is the minimal unit that a recommender system can manage. For example, an item can be a book, a movie, a web page, etc. Recommender systems are now exploited in many application domains, such as e-commerce (Paolino *et al*., 2009), e-learning (Zhuhadar *et al*., 2009), restaurants (Hosseini-Pozveh *et al*., 2009), news (Tintarev & Masthoff, 2006), etc.

Recommender systems generally fall into three categories: content-based systems which compute recommendations from the semantic content of items (Pazzani & Billsus, 2007); knowledge-based systems where recommendations rely on the knowledge about the domain, the users and pre-established heuristics (Burke *et al*, 1996); and at last collaborative filtering systems (Adomavicius & Tuzhilin, 2005) which compute recommendations by examining users' preferences on items.

The users' preferences managed by a collaborative filtering (CF) system are often expressed under the form of ratings and stored in users' profiles. The structure of such a system can be represented under the form of a graph, with nodes being the users and links being the similarity of preferences among them. This graph can be viewed as a social network (Brun & Boyer, 2010), where the links are not social relations but preference relations. To compute recommendations for an active user *a,* a classical CF system exploits the known preferences of the users linked to *a* in the social network, as well as the values of the links.

In CF, *a* implicitly requests the preferences from his like-minded users about some items: he asks them for some recommendations. The ratings of the items *a* has not rated yet are then inferred from these recommendations. The items with the highest ratings are then recommended to *a.*

A collaborative filtering recommender system is thus a social process: not only the active user is involved in the recommendation process; other users are also. In CF, *a*'s like-minded users are called his neighbors. Two main approaches are used to select *a*'s neighbors: the memory-based approach and the model-based approach. In the memory-based approach, the set of neighbors is specific to each user; in the model-based approach, the set of neighbors can be specific to each class of users.

The search of the best set of neighbors has attracted much attention in the literature (Breese *et al*, 1998, Herlocker *et al*, 2004, Kim & Yang, 2007, Castagnos & Boyer, 2007). Classically the number of neighbors required to get high quality recommendations is about several dozens (Shardanand & Maes, 1995, Brun *et al,* 2009).

In the literature, the set of neighbors is only selected according to their similarity with the active user. These neighbors are then used as recommenders. However, we argue that these neighbors may be bad recommenders despite their

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