Recommender Technologies and Emerging Applications

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INTRODUCTION

A *recommender system* (or *recommendation system*) is a software application that provides users with personalized recommendations of goods, services or other potentially relevant and interesting information, and thus helps users find useful items in the information overload (Aggarwal, 2016; Resnick & Varian, 1997; Ricci, Rokach, & Shapira, 2015). The field of recommender systems is highly interdisciplinary and based on various technologies. Though relatively new, recommender technologies have made significant progress for the last decade.

A variety of recommender systems have been developed and used mainly in e-commerce application domains, including Amazon.com, BarnesandNoble.com, Netflix.com, mystrands.com, and Yahoo.com (Konstan et al., 1997; Sarwar, Karypis, Konstan, & Riedl, 2000; Schafer, Konstan, & Riedl, 2001). Over the last decade, recommender systems have proven very useful in increasing sales and retaining consumers, and are considered an effective personalization tool in the e-commerce environment (Adomavicius & Tuzhilin, 2005; Goy, Ardissono, & Petrone, 2007; Jannach, Zanker, Felfernig, & Friedrich, 2011; Ricci et al., 2015; Sarwar et al., 2000; Schafer et al., 2001;). One illustration is the famous Netflix competition (2006-2009), which offered a one million dollar prize in exchange for an algorithm to enhance the recommendation accuracy (i.e., movie rating prediction) of its recommender systems (Bell, Koren, & Volinsky, 2010).

This chapter presents an overview of the field of recommender technologies and their emerging application domains. We characterize current major recommender system approaches in a unifying model and describe emerging applications of recommender technologies beyond traditional e-commerce. We conclude with emerging and future trends and topics, as well as additional readings in the area of recommender technologies and applications.

BACKGROUND

Since the first major recommender systems emerged in the mid-1990s (Resnick & Varian, 1997), a large number of recommender systems have been developed and used in a wide range of e-commerce environments and improved by continuing research.

A typical recommender system provides users with *personalized* recommendations of items such as goods, services or information to guide users to find items that are relevant to them. Recommendations are based on past and present profiles of users with respect to items. The *personalized recommendation problem* can be described as follows:

Given a target user, produce personalized recommendations of items relevant to the target user.

To solve this recommendation problem, a recommender system generally uses three types of data—data about the users (*U_data*), data about the items such as goods, services or information (*I_data*), and data about the relevance (such as rating, evaluation, purchase, or interest) relation between the users and the items (*R_data*):

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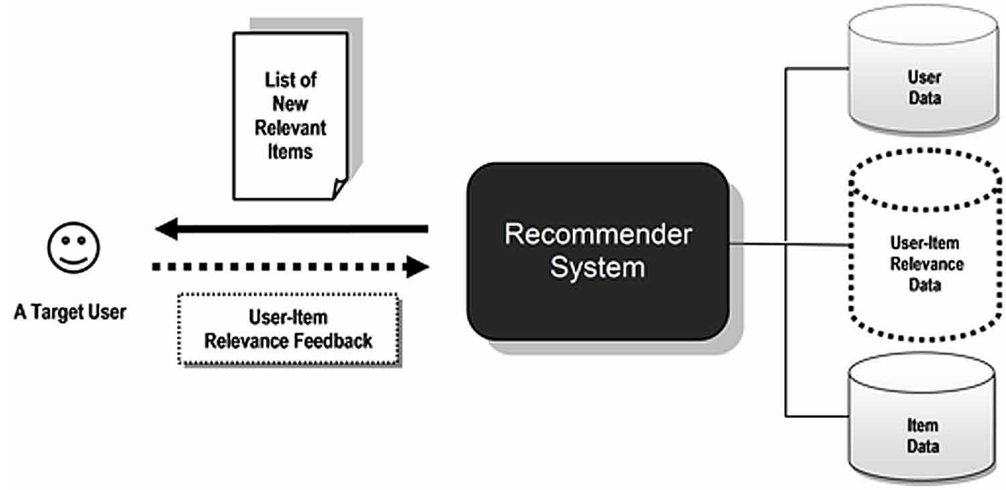
Figure 1. A model for recommender systems



- *U_data* contains a set of all users and some optional additional information about all users.
- *I_data* contains a set of all items and some optional additional information about all items.
- *R_data* contains relevance information (such as rating, evaluation, purchase, or interest) of the item to the user. Such information can be viewed and represented as a partial function (or matrix) that maps a pair of user and item into a relevance value.

As shown in Figure 1, a recommender system can be modeled as follows:

Given a target user, a recommender system recommends a list of new items that are most relevant to the target user by using U_data, I_data, and R_data.

The user data is constructed for all existing users and the item data is constructed for all existing items. The user-item relevance data is constructed over time and can be obtained either explicitly from user participation (*explicit relevance feedback*), inferred implicitly from user behavior (*implicit relevance feedback*), or both.

In order to find items that are relevant to the target user, recommender systems are premised on the *similarity* between users or between items. A number of similarity metrics are used to represent the degree of similarity between users or items. *Pearson Correlation* and *Cosine Similarity* are among most widely used metrics in recommender systems.

The recommendation process typically consists of two phases – the prediction phase and the suggestion phase. First, the recommended list of most relevant and new items for the target user is determined by predicting the unknown relevance values of new items by the target user. The predicted relevance value of a new item is estimated from the relevance values of the item from some of the most similar users (i.e., nearest user neighbors) or the relevance values of some of the most similar items (i.e., nearest item neighbors) using some prediction algorithm such as the weighted sum. Second, the recommender system typically recommends a list of top *n* items with the highest predicted relevance values.

The quality of recommender systems is evaluated in many ways (Herlocker, Konstan, Terveen, & Riedl, 2004). The accuracy of the recommended items is the most frequently evaluated measure. Popular accuracy metrics include *mean absolute error* (MAE, or the average of absolute differences