Advanced Recommender Systems

D

Young Park
Bradley University, USA

INTRODUCTION

It is increasingly difficult to find the right information on the Web in the age of explosive information overload. Recommender systems provide users with personalized suggestions of goods, services, or information and thus help them find the most relevant and interesting goods, services, or information for them. Over the last two decades since the first major recommender systems emerged in the mid-1990s (Konstan et al., 1997; Resnick & Varian, 1997), numerous recommender systems have been developed and used in various application domains including e-commerce, education, and engineering (Aggarwal, 2016; Jannach, Zanker, Felfernig, & Friedrich, 2011; Manouselis, Drachsler, Verbert, & Santos, 2014; Ricci, Rokach, & Shapira, 2015; Robillard, Maalej, Walker, & Zimmermann, 2014). Recommender systems have also proven very useful in various application domains.

A basic personalized recommender system suggests a list of items that seem to be most relevant for a given single target user without considering the context that the user is in by using users' ratings of items on a single overall criterion where both users and items are in a single domain (Jannach et al., 2011). The basic recommender system can be extended in several ways. There are four major extensions, i.e., suggesting items for a group of target users rather than a single user (group recommendations), suggesting items by considering a specific context of the target user (context-aware recommendations), suggesting items using ratings on multiple criteria rather than a single overall criterion (multi-criteria recommendations), and suggesting items by using users and items in multiple domains rather than a single domain (multiple-domain recommendations).

In this chapter, we present a brief and systematic overview of four major advanced recommender systems — *group* recommender systems, *context-aware* recommender systems, *multi-criteria* recommender systems, and *cross-domain* recommender systems. We characterize and compare them within a unifying model as extensions of the basic recommender systems. Future research topics and directions in the area of advanced personalized recommendations are discussed.

BACKGROUND

Recommender Systems (RS)

A *recommender system (RS)* is a software-intensive system that provides a given target users with personalized recommendations of items such as goods, services, or information to guide the user to find the most relevant items (Aggarwal, 2016; Jannach et al., 2011; Ricci et al., 2015). The personalized recommendations are made by using profiles of the target user and other users with respect to items.

A typical recommender system generally uses the following three types of data — data about the users (U), data about the items such as goods, services, or information (I), and data about the relevance (such as rating, evaluation, purchase, or interest) information between the users and the items (R) where

- U contains a set of all existing users.
- I contains a set of all existing items.

DOI: 10.4018/978-1-5225-2255-3.ch151

- *R* contains relevance ratings of items to users that are represented as a matrix that maps a user-item pair into a relevance value and are constructed over time either explicitly, inferred implicitly, or both.

Given a target user *T*, a recommender system recommends a list of new items that are likely to be most relevant to the target user by using *U, I,* and *R*. The personalized recommendation process generally uses two phases: the prediction phase and the suggestion phase. The prediction phase predicts the unknown relevance values of new items by the target user based on the *similarity* between users or between items. There are a number of similarity metrics including *Pearson correlation* and *Cosine similarity* to represent the degree of similarity between users or items (Jannach et al., 2011). The suggestion phase generates a list of top *n* items with the highest predicted relevance values. Various metrics such as *mean absolute error* (MAE), *mean square error* (MSE), *root mean squared error* (RMSE), *precision* and *recall* are used for evaluating the accuracy of the recommended items (Herlocker, Konstan, Terveen, & Riedl, 2004; Jannach et al., 2011).

There are a number of different approaches for generating personalized recommendations. Three major approaches for personalized recommendations are *collaborative recommender*, *content-based recommender* and *hybrid recommender*. For recommending relatively complex items there is an approach called *knowledge-based recommender* that is based on deep domain *knowledg*e about users and items.

Collaborative filtering-based recommendation is based on *user collaborations* and is the most widely used and proven method of providing recommendations (Ekstrand, Riedl, & Konstan, 2011; Schafer, Frankowski, Herlocker, & Sen, 2007). There are two types of collaborative filtering: *neighborhood-based collaborative filtering* such as user-based collaborative recommender and item-based collaborative recommender (Linden, Smith, & York, 2003) and *model-based collaborative filtering* (Koren, Bell, & Volinsky, 2009). The collaborative filtering-based recommenders, however, have the relevance feedback sparsity problem and the new item problem. Content-based recommendation is based on the *content* of items (Lops, Gemmis, & Semeraro, 2011; Pazzani & Billsus, 2007). The content-based recommender recommends a list of items with similar content to the items that the target user gave good ratings. But, content-based recommendation has limitations such as the item overspecialization problem and the new user problem. Hybrid recommendation recommends items via *hybridization*, i.e., by combining the content-based recommendation and the collaborative filtering-based recommendation together (Burke, 2007).

Basic Recommendation

We will use a model of basic personalized recommendation to characterize advanced recommendations as extensions of the basic model. We define the *basic recommender system* (BRS) as a collaborative recommender system that recommends a list of items:

- For a single target user,
- In a single context,
- By using users' ratings of items on a single overall relevance criterion,
- where both users and items are in a single domain.

Figure 1 depicts the overall architecture of our basic personalized recommender system that is represented as *single target user, single context, single relevance criterion & single domain*.

ADVANCED RECOMMENDATIONS

There are four major advanced recommendations, i.e., group recommendation, context-aware recommendation, multi-criteria recommendation, and cross-domain recommendation. We comparatively