Chapter 5
Advances in Collaborative Filtering

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Abstract
The collaborative filtering (CF) approach to recommenders has recently enjoyed much interest and progress. The fact that it played a central role within the recently completed Netflix competition has contributed to its popularity. This chapter surveys the recent progress in the field. Matrix factorization techniques, which became a first choice for implementing CF, are described together with recent innovations. We also describe several extensions that bring competitive accuracy into neighborhood methods, which used to dominate the field. The chapter demonstrates how to utilize temporal models and implicit feedback to extend models accuracy. In passing, we include detailed descriptions of some the central methods developed for tackling the challenge of the Netflix Prize competition.

5.1 Introduction

Collaborative filtering (CF) methods produce user specific recommendations of items based on patterns of ratings or usage (e.g., purchases) without need for ex-

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ogenous information about either items or users. While well established methods work adequately for many purposes, we present several recent extensions available to analysts who are looking for the best possible recommendations.

The Netflix Prize competition that began in October 2006 has fueled much recent progress in the field of collaborative filtering. For the first time, the research community gained access to a large-scale, industrial strength data set of 100 million movie ratings—attracting thousands of scientists, students, engineers and enthusiasts to the field. The nature of the competition has encouraged rapid development, where innovators built on each generation of techniques to improve prediction accuracy. Because all methods are judged by the same rigid yardstick on common data, the evolution of more powerful models has been especially efficient.

Recommender systems rely on various types of input. Most convenient is high quality *explicit feedback*, where users directly report on their interest in products. For example, Netflix collects star ratings for movies and TiVo users indicate their preferences for TV shows by hitting thumbs-up/down buttons.

Because explicit feedback is not always available, some recommenders infer user preferences from the more abundant *implicit feedback*, which indirectly reflects opinion through observing user behavior [22]. Types of implicit feedback include purchase history, browsing history, search patterns, or even mouse movements. For example, a user who purchased many books by the same author probably likes that author. This chapter focuses on models suitable for explicit feedback. Nonetheless, we recognize the importance of implicit feedback, an especially valuable information source for users who do not provide much explicit feedback. Hence, we show how to address implicit feedback within the models as a secondary source of information.

In order to establish recommendations, CF systems need to relate two fundamentally different entities: items and users. There are two primary approaches to facilitate such a comparison, which constitute the two main techniques of CF: *the neighborhood approach* and *latent factor models*. Neighborhood methods focus on relationships between items or, alternatively, between users. An item-item approach models the preference of a user to an item based on ratings of similar items by the same user. Latent factor models, such as matrix factorization (aka, SVD), comprise an alternative approach by transforming both items and users to the same latent factor space. The latent space tries to explain ratings by characterizing both products and users on factors automatically inferred from user feedback.

Producing more accurate prediction methods requires deepening their foundations and reducing reliance on arbitrary decisions. In this chapter, we describe a variety of recent improvements to the primary CF modeling techniques. Yet, the quest for more accurate models goes beyond this. At least as important is the identification of all the signals, or features, available in the data. Conventional techniques address the sparse data of user-item ratings. Accuracy significantly improves by also utilising other sources of information. One prime example includes all kinds of tem-

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