

presented by most of the competitors, including the winners (Töscher *et al.*, 2009; Koren, 2009).

Beyond these bilinear models with distributed representations, one of the first uses of neural networks for collaborative filtering is based on the RBM undirected probabilistic model (Salakhutdinov *et al.*, 2007). RBMs were an important element of the ensemble of methods that won the Netflix competition (Töscher *et al.*, 2009; Koren, 2009). More advanced variants on the idea of factorizing the ratings matrix have also been explored in the neural networks community (Salakhutdinov and Mnih, 2008).

However, there is a basic limitation of collaborative filtering systems: when a new item or a new user is introduced, its lack of rating history means that there is no way to evaluate its similarity with other items or users (respectively), or the degree of association between, say, that new user and existing items. This is called the problem of cold-start recommendations. A general way of solving the cold-start recommendation problem is to introduce extra information about the individual users and items. For example, this extra information could be user profile information or features of each item. Systems that use such information are called **content-based recommender systems**. The mapping from a rich set of user features or item features to an embedding can be learned through a deep learning architecture (Huang *et al.*, 2013; Elkahky *et al.*, 2015).

Specialized deep learning architectures such as convolutional networks have also been applied to learn to extract features from rich content such as from musical audio tracks, for music recommendation (van den Oörd *et al.*, 2013). In that work, the convolutional net takes acoustic features as input and computes an embedding for the associated song. The dot product between this song embedding and the embedding for a user is then used to predict whether a user will listen to the song.

12.5.1.1 Exploration Versus Exploitation

When making recommendations to users, an issue arises that goes beyond ordinary supervised learning and into the realm of reinforcement learning. Many recommendation problems are most accurately described theoretically as **contextual bandits** (Langford and Zhang, 2008; Lu *et al.*, 2010). The issue is that when we use the recommendation system to collect data, we get a biased and incomplete view of the preferences of users: we only see the responses of users to the items they were recommended and not to the other items. In addition, in some cases we may not get any information on users for whom no recommendation has been made (for example, with ad auctions, it may be that the price proposed for an