Abstract:

Recommendation systems provide personalized service to users and aim at suggesting to them items that they may prefer. There is an increasing requirement of next-item recommendation systems to infer a user’s next favor item based on his/her historical selection of items.

In this work, we study the next-item recommendation under the cold-start situation, where the users in the system share no interaction with the new items. Specifically, we seek to handle the problem from the perspective of zero-shot learning (ZSL), which classifies samples whose classes are unseen during training. To this end, we first crystallize the relationship and setting from ZSL to the cold-start next-item recommendation. Then, we propose a novel model called User-Item Matching and Auto-encoders (UIMA), which learns the latent embeddings for both users and items by exploiting user historical preferences and item attributes. Concretely, UIMA consists of three components, i.e., two auto-encoders for learning user and item embeddings and a matching network to explore the relationship between the learned user and item embeddings. We perform extensive experiments to demonstrate the performance of the proposed UIMA method is better than that of the other testing methods for the cold-start next-item recommendation.