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Enhanced Recommender Systems with Deep Neural Networks

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Certificate of Original Authorship

I, Ruiping Yin, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Engineering and Information Technology at the University of Technology Sydney.

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Abstract

Recommender system is an intelligent decision making system that adopts machine learning technology to recommend relevant contents to users based on the analysis of users' interests and preferences. It can help users find appropriate contents within a reasonable time and has been proved to be an effective means to deal with the problem of information overload. At present, although the recommender system has been widely used in various social fields, there are still many problems in the existing recommender system. For example, data sparsity, cold start, long tail items are difficult to be recommended, and graph structure data cannot be effectively processed, resulting in low recommendation performance and poor user experience, which restricts the development of personalized recommender system. In recent years, with the rapid development of the theory and technology of deep learning, the study on personalized recommendation on deep neural networks has been paid more and more attention by the industry and academia. How to use the principles and techniques of deep learning to alleviate and overcome the problems in the existing personalized recommender system, so as to improve the performance of the recommender system, is a topic worthy of research.

The main work of this thesis for deep learning-based personalized recommendation methods is as follows:

To model the conception of fashion and visual factors on the fashion recommendation task, we propose a cross-domain recommendation method based on visual collocation knowledge transfer. First, we extract visual collocation knowledge of fashion items from images on a popular fashion website and even street photography, and incorporate the learnt knowledge to the recommender system through transfer learning. By collecting cross-domain information and updating visual collocation knowledge, the accuracy of clothing recommendation is improved.

To overcome the difficulty of accurately extracting latent features of new users and non-popular products, we propose a recommendation method based on deep graph convolutional neural network. Different with the conventional methods which consider the low-order similarity only, we learn the representation of users and items from the high-order similarity between users and items. We treat the recommendation task as an edge prediction problem on a bipartite graph. It inherits the advantages of graph convolutional neural network to quickly combine local information on the graph, so that we can obtain the node embedding which consists of the node's information, neighbors' information and local structure information. At the same time, for the over-smoothing problem caused by the multi-layer graph convolutional neural network, we propose an information propagation method based on the attention mechanism, which can effectively alleviate the over-smoothing problem when the graph convolutional neural network is too deep.

To solve the problem that the user's preference is affected by the environment and changes with time, we propose a recommendation method based on the user's long-term and short-term preference. In one session, the products browsed by the user have a certain continuity. This method models the user's current shopping intention through the items that the user has browsed in the current session. At the same time, the method also combines the user's long-term stable preferences contained in the user's historical records to provide users with in-time recommendations. The method can quickly adapt to the changes of the user's current interests caused by changes of the context and improve users' stickiness to shopping websites.

To solve the problem of data sparsity, we propose a recommendation method based on generative adversarial strategy. The algorithm generates a user's latent feature vector by training a generator network with a denoising autoencoder, which generates recommendations for the user accordingly, while training a discriminant network to distinguish the recommendation prediction generated by the generating network from the user's real transaction records. The adversarial training between the discriminating network and the generating network helps to push recommendation predictions closer to the real transaction records. Through continuous iterative adversarial training between generation network and discriminant network, the two networks are mutually promoted. Therefore, the final recommendation is improved.

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