Yong-ping Du, Chang-qing Yao, Shu-hua Huo, Jing-xuan Liu, 2017. A new item-based deep network structure using a restricted Boltzmann machine for collaborative filtering. *Frontiers of Information Technology & Electronic Engineering*, **18**(5):658-666. http://dx.doi.org/10.1631/FITEE.1601732

A new item-based deep network structure using a restricted Boltzmann machine for collaborative filtering

Key words: Restricted Boltzmann machine; Deep network structure; Collaborative filtering; Recommendation system

Corresponding author: Chang-qing Yao
E-mail: yaocq@istic.ac.cn

Motivation

- With the explosive growth of information, the application of recommender systems has attracted increasing attention. Despite the development of the CF technique, some problems still exist, such as data sparsity and cold start.
- With the appearance of the RBM fast-learning algorithm known as contrastive divergence, RBMs have attracted an increasing amount of attention in the field of machine learning.
- The existing RBM-based CF algorithms are primarily user based; thus, they treat each user as a single RBM.

Main idea

- **Deep structure built by RBM**

Based on the two-layer RBM, we add multiple hidden layers in the network, and the connections exist only between adjacent layers that compose the deep RBM.

- **Deep network structure for CF**

The paper proposes an item-based RBM for CF and uses the deep structure of a multi-RBM for parameter learning. The final rating data is predicted by the more accurate features obtained from the deep structure of RBM.

Method

- The deep RBM structure model can learn the internal representations, which capture the complicated structure in the higher layers.

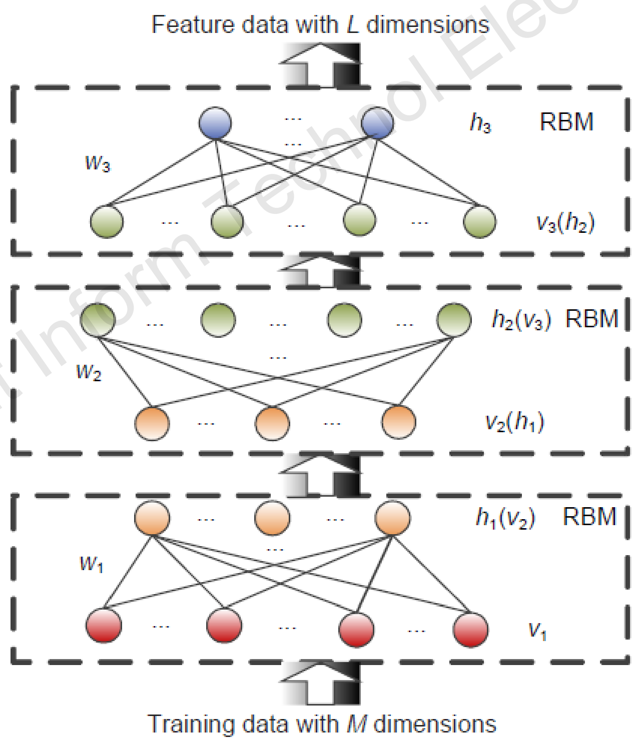
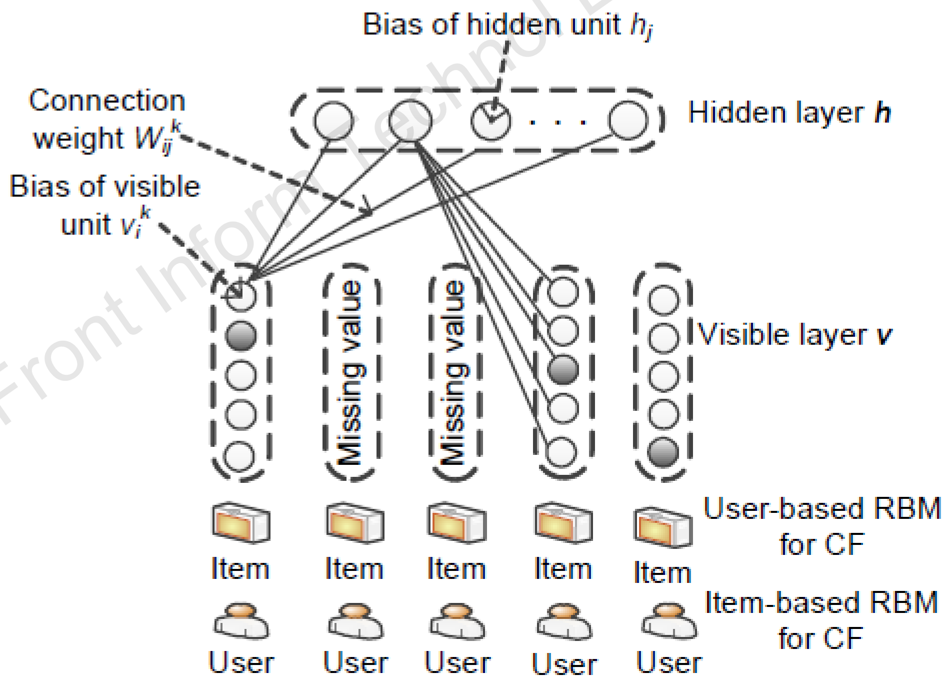


Fig. 2 Pretraining phase of the deep Boltzmann machine

Method

- Restricted Boltzmann machine (RBM) for collaborative filtering (CF), in which the visible layer can represent the item that denotes the user-based RBM for CF and, on the other hand, it represents the user, which denotes the item-based RBM for CF.



Major results

- Item-based RBM achieved better performance than user-based RBM with a different number of hidden units.

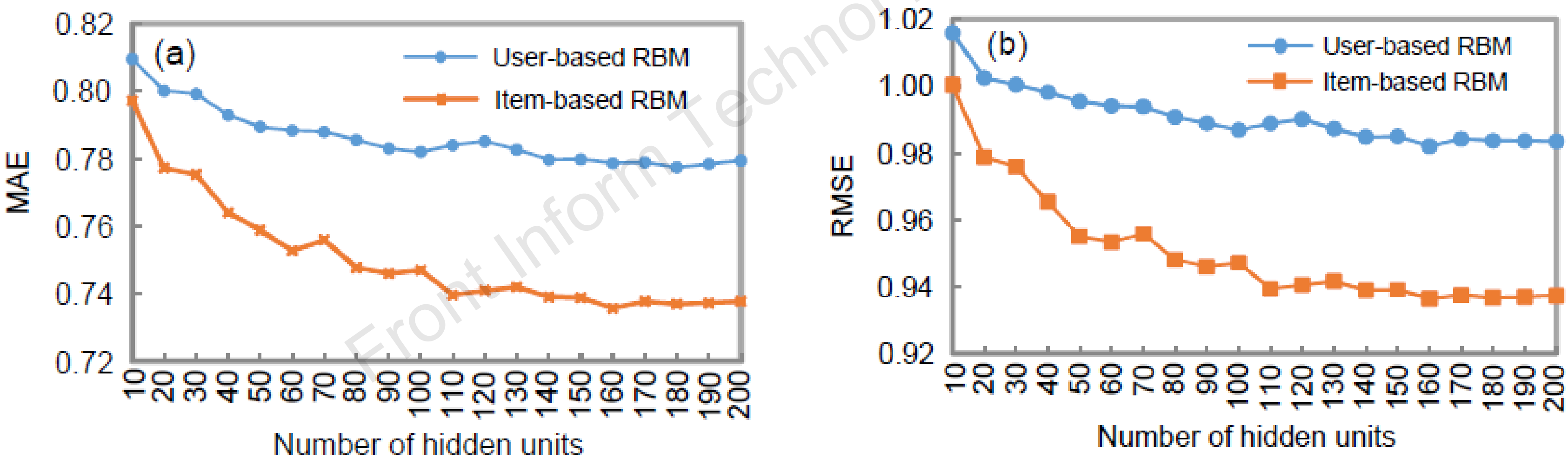


Fig. 6 Performance comparison of user-based RBM and item-based RBM on MovieLens-100k: (a) MAE; (b) RMSE

Major results (Cont'd)

- We implemented the rating prediction using the item-based multilayer RBM. *L* denotes the feature vector dimension after reduction by the multilayer RBM.

Table 3 Performances of deep structure on two Movie-Lens data sets

L	MAE		RMSE	
	Movie-Lens-100k	Movie-Lens-1M	Movie-Lens-100k	Movie-Lens-1M
30	0.6874	0.6734	0.8546	0.8159
50	0.6733	0.6556	0.8457	0.8064
70	**0.6721**	0.6558	**0.8416**	0.7892
90	0.6725	0.6457	0.8418	0.7849
110	0.6821	**0.6424**	0.8454	**0.7843**
130	0.6779	0.6453	0.8452	0.7845

L: feature vector dimension

Conclusions

- We proposed a new item-based approach to apply RBM for collaborative filtering, and the multilayer deep structure was trained for rating prediction.
- The stochastic gradient descent method with minibatch was used to update the parameters. All the parameters were learned layer by layer in the deep RBM structure.
- The experimental results on the MovieLens data set show that item-based RBM outperforms user-based RBM significantly.