

Faculty of Engineering and Information Technology  
University of Technology Sydney

# **Learning Complex Relations for Session-based Recommendations**

A thesis submitted in partial fulfillment of  
the requirements for the degree of  
**Doctor of Philosophy**

by

Shoujin Wang

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## CERTIFICATE OF AUTHORSHIP/ORIGINALITY

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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# Dedication

*To my parents and elder sisters for their love and support*



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# List of Publications

## Papers Published

- **Shoujin Wang**, Wei Liu, Jia Wu, Longbing Cao, Qinxue Meng and Paul J. Kennedy (2016), Training Deep Neural Networks on Imbalanced Data Sets. *in 'Proceedings of the 29th International Joint Conference on Neural Networks (IJCNN2016)'* , pp. 4368-4374.
- Liang Hu, Longbing Cao, **Shoujin Wang** (2017), Diversifying Personalized Recommendation with User-session Context. *in 'Proceedings of the 26th International Joint Conference on Artificial Intelligence (IJCAI2017)'*, pp. 1858-1864.
- **Shoujin Wang**, Longbing Cao (2017), Inferring Implicit Rules by Learning Explicit and Hidden Item Dependency. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 10.1109/TSMC.2017.2768547.
- **Shoujin Wang**, Liang Hu, Longbing Cao (2017), Perceiving the Next Choice with Comprehensive Transaction Embeddings for Online Recommendation. *in 'Proceedings of the 15th Joint European Conference on Machine Learning and Knowledge Discovery in Databases (ECML-PKDD2017)'*, pp.285-302.
- **Shoujin Wang**, Liang Hu, Longbing Cao, Xiaoshui Huang, Defu Lian and Wei Liu (2018), Attention-based Transactional Context Embedding for Next-Item Recommendation. *in 'Proceedings of the 32nd*

## LIST OF PUBLICATIONS

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*AAAI Conference on Artificial Intelligence (AAAI2018)*, pp.2532-2539.

### Papers to be Submitted/Under Review

- **Shoujin Wang**, Longbing Cao, and Liang Hu (2018), HATE: Jointly Modeling Intra- and Inter-transaction Dependencies with Hierarchical Attentive Transaction Embeddings. *IEEE Transactions on Knowledge and Data Engineering*.
- **Shoujin Wang**, Longbing Cao, and Liang Hu (2018), A Survey on Session-based Recommender Systems. *ACM Computing Surveys*.

# Abstract

In the era of big data, recommender systems (RSs) are a powerful engine to promote intelligent life by helping humans to make decisions concerning their daily necessities (e.g., food, clothes, and houses) much more efficiently and effectively, selecting from a large number of choices. Of the various types of recommender systems, session-based (SB) ones are of great value and significance, but they are not well studied.

The value of session-based recommender systems comes from two fold. From the research perspective, a SBRS takes a session as the basic unit for data organization and thus keeps the intrinsic nature of the original transaction-like data. As a result, the system effectively retains and models the rich information (e.g., intra-session dependency) embedded in a session structure to produce a more reliable recommendation. This modelling cannot be achieved by other types of recommender systems because they usually break down the original session data into multiple pair-wised user-item interactions to fit the models. From the business perspective, session data for session-based recommender systems is much more readily available than either the rating data or the item attribute data required by other recommender systems including content-based or collaborative filtering ones. This actually makes session-based RSs much more applicable in real-world business.

Though valuable, SBRSs are quite challenging. Generally, a hierarchical architecture consisting of five levels (cf. Figure 1.1) is built from the low-level feature values till to the high-level sessions in session data, as demonstrated

in Chapter 1. The challenge arises mainly comes from three considerations: the heterogeneity of the elements in each level (e.g., there are both categorical and numerical features), the complex dependency within each level (e.g., the implicit inter-item relations), and the interactions between different levels (e.g., the inter-session dependency may affect the item occurrence). From my observation, the existing works mainly focus on the general item-level dependency modelling for session-based recommendations while ignoring other level relations as demonstrated in Chapter 3.

To bridge the huge gaps between the existing works and great challenges mentioned above, I build a systematic framework consisting of dependency modelling from the three core levels, i.e., feature-level, item-level and session-level (cf. Figure 1.1), for session-based recommendations. To the best of my knowledge, this is the first framework to systematically address various levels of challenges in session-based recommendations. Particularly, due to the limitations regarding space, I address one or two critical challenges in each level, as shown below.

In Chapter 4, to capture the implicit inter-item relations ignored by existing rule-based approaches, I proposed an implicit rule-based RS that first infers implicit rules and then applies the resultant rules for reliable rule-based recommendations, a basic approach for session-based recommendations.

In Chapter 5, I continue to work on item-level dependency modelling and focus on the issue of item heterogeneity, referring to different items with different levels of relevance to the next choice of an item. To this end, I build an attentive transaction-embedding model to discriminatively integrate multiple items in a transaction context into a unified context-embedding for next-item recommendations.

In Chapter 6, the feature-level dependency and feature-item interactions are modelled by a shallow neural network which takes both contextual items in a session and their corresponding features as the input. Accordingly, the cold-start issue in SBRs has been well addressed.

In Chapter 7, the session-level (i.e., transaction-level) dependency and

session-item interactions are modelled. A hierarchical attentive transaction embedding model is built to jointly model the intra-session (item-level) and inter-session (session-level) dependency. Accordingly, the influence from previous sessions on a current session is incorporated for more accurate next-item recommendations.

All these models are applied to real-world transaction data, like Tmall and Tafang and they clearly outperform other representative SBRs. More importantly, this thesis proposes a systematic framework to explore the driving force behind SBRs, which provides some insights into both the researchers and engineers in this domain.

