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NON-IID RECOMMENDER SYSTEMS: A MACHINE LEARNING APPROACH

by

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Certificate of Original Authorship

I, Liang Hu declare that this thesis, submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Advanced Analytics Institute at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This thesis is the result of a research candidature conducted jointly with Shanghai Jiao Tong University as part of a collaborative Doctoral degree.

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ABSTRACT

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A recommender system (RS) comprises the core software, tools, and techniques that effectively and efficiently cope with information overload as well as locate information that is genuinely required. As one of the most widely used artificial intelligence (AI) systems, RSs have been integrated into daily life over the past two decades. In recent decade, the machine learning approach has dominated AI research in almost all areas. Therefore, modeling advanced RSs using the machine learning approach forms the basic methodology of this thesis.

Current RSs suffer from many problems, such as data sparsity and cold start, because they fail to consider the non-IIDness in data, which includes the heterogeneities and coupled relations within and between users and items, as well as their interactions. Thus, we propose non-IID recommender systems by modeling the non-IIDness in recommendation data with the machine learning approach. Specifically, we study non-IID RS modeling techniques from three perspectives: users, items, and interactions. This research not only promotes the design of new machine learning models and algorithms in theory, but also extensively influences the evolution of technology and society.

To construct the non-IID RS from a user perspective, we jointly model two aspects: (1) the heterogeneities of users and (2) the coupling between users. Specifically, we study the non-IID user modeling in two representative RSs: (1) a group-based RS (GBRS) and (2) a social network-based RS (SNRS). First, we perform an in-depth analysis of existing GBRSs and demonstrate their deficiencies in modeling

the heterogeneity and coupling between group members for making group decisions. A deep neural network is designed to learn a group preference representation, which jointly considers all members' heterogeneous preferences. Second, we model an SNRS by modeling the influential contexts that embed the influence of relevant users and items, because a user's selection is largely influenced by other users with social relationships.

To construct the non-IID RS from an item perspective, we target two modeling aspects: (1) the heterogeneities of items and (2) the coupling between items. Specifically, we study the non-IID item modeling in two representative RSs: (1) a cross-domain RS (CDRS) and (2) a session-based RS (SBRS). First, existing CDRSs may fail to conduct cross-domain transfer because of domain heterogeneity; thus, we propose an irregular tensor factorization model, which can more effectively capture the coupling between heterogeneous domains with learning the domain factors for each domain. Second, we construct an effective and efficient personalized SBRS to more effectively capture the couplings between items by modeling intra- and inter-session contexts.

To construct the non-IID RS from an interaction perspective, we target two modeling aspects: (1) the heterogeneities of interactions and (2) the coupling between interactions. Specifically, we study the non-IID interaction modeling in two representative RSs: (1) a multi-objective RS (MORS) and (2) an attraction-based RS (ABRS). First, we study an MORS to tackle the challenges of recommendation for users and items in the long tail. Subsequently, a coupled regularization model is proposed to jointly optimize two objectives: the credibility and specialty. Existing content-based RSs can recommend new content according to similarity; however, they are not capable of interpreting the attraction points in user-item interactions. Therefore, to construct an interpretable content-based RS, we propose attraction modeling to learn and track user attractiveness.

In the last section, we summarize the contributions of our work and present the future directions that can improve and extend the non-IID RS.

Dedication

To my parents, my wife, and my son.

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List of Publications

Journal Papers

J-1. Hu, L., Chen, Q, Jian, S., Cao, L., and Cao, J. Neural Cross-session Filtering: Next-item Prediction under Intra- and Inter-session Context. IEEE Intellegent System, vol. 33, pp. 57-67, 2018.

J-2. Hu, L., Cao, L., Cao, J., Gu, Z., Xu, G., and Wang, J. Improving the Quality of Recommendations for Users and Items in the Tail of Distribution. ACM Trans. Inf. Syst. 35, 3, 1-37, 2017.

J-3. Hu, L., Cao, L., Cao, J., Gu, Z., Xu, G., and Yang, D. Learning Informative Priors from Heterogeneous Domains to Improve Recommendation in Cold-Start User Domains. ACM Trans. Inf. Syst. 35, 2, 1-37, 2016.

J-4. Hu, L., Cao, J., and Gu, Z. . Service Discovery and Recommendation in Rough Hierarchical Granular Space. Advanced Science Letters, 7(1), 135-139, 2012.

J-5. Yang, D., Guo, J., Wang, Z.-J., Wang, Y., Zhang, J., Hu, L., Yin, J., and Cao, J. FastPM: An approach to pattern matching via distributed stream processing. Information Sciences 453, 263-280, 2018.

J-6. Cao, J., Xu, W., Hu, L., Wang, J. and Li, M.. A social-aware service recommendation approach for mashup creation. International Journal of Web Services Research (IJWSR), 10(1), pp.53-72, 2013.

J-7. Hu, L., Jian, S., Cao, L., and Chen, Q.. Attraction Modeling: Enhancing Content-based Recommender Systems with Statistical Interpretability. (To be submit to AIJ)

Conference Papers

C-1. Hu, L., Jian, S., Cao, L., Chen, Q., and Z. Gu, "HERS: Modeling Influential Contexts with Heterogeneous Relations for Sparse and Cold-start Recommendation," in AAAI-19, 2019.

C-2. Hu, L., Jian, S., Cao, L., and Chen, Q. Interpretable Recommendation via Attraction Modeling: Learning Multilevel Attractiveness over Multimodal Movie Contents. In Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI-18, 3400-3406, 2018.

C-3. Hu, L., Cao, L., Wang, S., Xu, G., Cao, J., and Gu, Z. Diversifying Personalized Recommendation with User-session Context. In Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI-17, 1858–1864, 2017.

C-4. Hu, L., Cao, W., Cao, J., Xu, G., Cao, L., and Gu, Z. Bayesian Heteroskedastic Choice Modeling on Non-identically Distributed Linkages. In Data Mining (ICDM), 2014 IEEE International Conference on, 851-856, 2014.

C-5. Hu, L., Cao, J., Xu, G., Cao, L., Gu, Z., and Cao, W. Deep Modeling of Group Preferences for Group-Based Recommendation. In Twenty-Eighth AAAI Conference on Artificial Intelligence, 1861-1867, 2014.

C-6. Hu, L., Cao, J., Xu, G., Cao, L., Gu, Z. and Zhu, C. Personalized recommendation via cross-domain triadic factorization. In Proceedings of the 22nd international conference on World Wide Web (pp. 595-606). ACM, 2013.

C-7. Hu, L., Cao, J., Xu, G., Wang, J., Gu, Z. and Cao, L. Cross-domain collaborative filtering via bilinear multilevel analysis. In International Joint Conference on Artificial Intelligence. IJCAI-13, 2013.

C-8. Hu, L., Cao, J., Xu, G. and Gu, Z.. Latent Informative Links Detection. In KES (pp. 1233-1242), 2012.

C-9. Hu, L., Cao, J. and Gu, Z.. Service Discovery and Recommendation in Rough Hierarchical Granular Computing. In Services Computing Conference (APSCC), 2010 IEEE Asia-Pacific (pp. 191-198). IEEE, 2010, December.

C-10. Jian, S., Hu, L., Cao, L., Lu, K., and Gao H., "Evolutionarily Learning Multi-aspect Interactions and Influences from Network Structure and Node Content," in AAAI-19, 2019.

C-11. Jian, S., Hu, L., Cao, L., and Lu, K. Metric-Based Auto-Instructor for Learning Mixed Data Representation. In AAAI-18, 2018.

C-12. Wang, S., Hu, L., Cao, L., Huang, X., Lian, D. and Liu, W.. Attention-based transactional context embedding for next-item recommendation. AAAI, 2018.

C-13. Wang, S., Hu, L., and Cao, L. Perceiving the Next Choice with Comprehensive Transaction Embeddings for Online Recommendation. In Machine Learning and Knowledge Discovery in Databases: European Conference, ECML PKDD 2017, Skopje, Macedonia, September 1822, 2017.

C-14. Cao, W., Hu, L., and Cao, L. Deep Modeling Complex Couplings within Financial Markets. In Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence, 2518-2524, 2015.

C-15. Chen, Q., Hu, L., Xu, J., Liu, W., and Cao, L. Document similarity analysis via involving both explicit and implicit semantic couplings. In Data Science and Advanced Analytics (DSAA), 2015. 36678 2015. IEEE International Conference on, 1-10, 2015.

C-16. Xu, W., Cao, J., Hu, L., Wang, J. and Li, M., June. A social-aware service recommendation approach for mashup creation. In 2013 IEEE 20th International Conference on Web Services (pp. 107-114). IEEE, 2013.

C-17. You, Y., Huang, G., Cao, J., Chen, E., He, J., Zhang, Y. and Hu, L.. Geam: A general and event-related aspects model for twitter event detection. In International Conference on Web Information Systems Engineering (pp. 319-332). Springer, Berlin, Heidelberg, 2013, October.

C-18. Shangguan, Q., Hu, L., Cao, J. and Xu, G.. Book Recommendation Based on Joint Multi-relational Model. In Cloud and Green Computing (CGC), 2012 Second International Conference on (pp. 523-530). IEEE, 2012, November.

Contents

List of Figures

Abbreviation

RS - Recommender System

AI - Artificial Intelligence

CF - Collaborative Filtering

CBF - Context-based Filtering

NLP - Natural Language Processing

CV - Computer Vision

CNN - Convolutional Neural Networks

RNN - Recurrent Neural Networks

TSA - Time Series Analysis

CDRS - Cross-domain Recommender Systems

SNRS - Social Network-based Recommender Systems

CARS - Context-aware Recommender Systems

MORS - Multi-objective Recommender Systems

SBRS - Session-based Recommender Systems

GBRS - Gruop-based Recommender Systems

ABRS - Attraction-based Recommender Systems

MF - Matrix Factorization

TF - Tensor Factorization

RBM - Restricted Boltzmann Machines

GRU - Gated Recurrent Units

LSTM - Long Short-Term Memory

MAE - Mean Absolute Error

RMSE - Root Mean Square Error

AP - Average Precision

MRR - Mean Reciprocal Rank

nDCG - Normalized Discounted Cumulative Gain

AUC - Area Under the ROC Curve

Nomenclature and Notation

$(.)^\top$ denotes the transpose operation.

$\mathbf{I}$ is the identity matrix.

$\mathbb{R}$, $\mathbb{R}^+$ denote the field of real numbers, and the set of positive reals, respectively.

$\mathcal{X}$ denotes a tensor (boldface script letter)

$\mathcal{X}^{I\times J\times K}$ denotes The dimensionality of each mode

$\mathbf{X}$ denotes a matrix (boldface capital letter)

$\mathbf{X}_{i,:}$ denotes the ith row of matrix $\mathbf{X}$

$\mathbf{X}_{:,j}$ denotes the jth column of matrix $\mathbf{X}$

$\mathbf{X}_{i,j}$ denotes the entry (i,j) of matrix $\mathbf{X}$

$\mathbf{x}$ denotes a vector (boldface lower-case letter)

$\mathbf{X}_{(n)}$ denotes mode-n matricization of a tensor

$\otimes$ denotes Kronecker product

$\odot$ denotes Khatri-Rao product

$\cdot^*$ denotes Hadamard product

$\cdot^/$ denotes element-wise division

$\circ$ denotes outer product

$\|\mathcal{X}\|$ denotes the norm of a matrix or a tensor $\mathcal{X}$

$\mathcal{X} = [\![\mathbf{A}, \mathbf{B}, \mathbf{C}]\!]$ denotes the factorization form of a tensor

$vec\mathbf{X}$ denotes vectorization of matrix