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NON-IID RECOMMENDER SYSTEMS:
A MACHINE LEARNING APPROACH

by

Liang Hu

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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.
Acknowledgements

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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 - Group-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 \(i\)th row of matrix \(\mathbf{X}\)

\(\mathbf{X}_{:,j}\) denotes the \(j\)th 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

\(-\ast\) denotes Hadamard product

\(-/\) denotes element-wise division

\(\circ\) denotes outer product

\(\|\mathcal{X}\|\) denotes the norm of a matrix or a tensor \(\mathcal{X}\)
$\mathbf{X}' = [\mathbf{A}, \mathbf{B}, \mathbf{C}]$ denotes the factorization form of a tensor

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