Beyond Probability Ranking Principle: Modeling the Dependencies among Documents

Liang Pang
Institute of Computing Technology, Chinese Academy of Sciences
Beijing, China
pangliang@ict.ac.cn

Qingyao Ai
The University of Utah, USA
aiqy@cs.utah.edu

Jun Xu
Gaoling School of Artificial Intelligence, Renmin University of China
junxu@ruc.edu.cn

ABSTRACT

Probability Ranking Principle (PRP) [30], which assumes that each document has a unique and independent probability to satisfy a particular information need, is one of the fundamental principles for ranking. Traditionally, heuristic ranking features and well-known learning-to-rank approaches have been designed by following the PRP principle. Recently, neural IR models, which adopt deep learning to enhance the ranking performances, also obey the PRP principle. Though it has been widely used for nearly five decades, in-depth analysis shows that PRP is not an optimal principle for ranking, due to its independent assumption that each document should be independent of the rest candidates. Counter examples include pseudo relevance feedback [24], interactive information retrieval [45], search result diversification [10] etc. To solve the problem, researchers recently proposed to model the dependencies among the documents during the designing of ranking models. A number of ranking models have been proposed and state-of-the-art ranking performances have been achieved. This tutorial aims to give a comprehensive survey on these recently developed ranking models that go beyond the PRP principle. The tutorial tries to categorize these models based on their intrinsic assumptions: assuming that the documents are independent, sequentially dependent, or globally dependent. In this way, we expect the researchers focusing on ranking in search and recommendation can have a novel angle of view on the designing of ranking models, and therefore can stimulate new ideas on developing novel ranking models.

The material of this tutorial can be found in https://github.com/pl8787/wsdm2021-beyond-prp-tutorial.

CCS CONCEPTS

• **Information systems** → **Retrieval models and ranking**; • **Computing methodologies** → **Neural networks**.

KEYWORDS

Learning to rank; Deep Learning; Probability Ranking Principle

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1 MOTIVATION AND INTRODUCTION

Ranking is at the core of many AI applications such as web search [25], recommendation [38], question answering [11], and dialogue system [19]. In general, the goal of ranking is to sort result candidates into a special sequence so that the utility of the final ranked list could be maximized. For example, in Information Retrieval, one of the most famous ranking theory is the **Probability Ranking Principle (PRP)** which assumes that the effectiveness of a ranking system to its users will be optimized if it can present documents/items in order of the decreasing probabilities of relevance. In other words, the utility of a ranked list with respect to a user can be maximized as long as we score and rank documents according to their intrinsic relevance to user's information need.

In the last decades, considerable retrieval models and ranking systems have been proposed under the vanilla form of the Probability Ranking Principle. Proposed by Robertson in 1977 [29], PRP assumes that each document has a unique probability to satisfy a particular information need. To obtain the best ranked lists under PRP, the ranking scores of documents should align with their probabilities of relevance and can be assigned independently to each other. Thus, previous work on ranking function developments mostly focus on predicting the relevance between queries and documents using a univariate scoring function that score each query-document pair separately. For instances, traditional retrieval models such as TF-IDF [23], BM25 [31], and language modeling approaches [43] build heuristic ranking functions using the exact match signals of query and document words to determine each document's relevance with respect to a query; Learning-to-rank algorithms, despite their pointwise [15], pairwise [7, 21], or listwise [5, 6, 9, 35] loss functions, combine features from different information sources to score each query-document pair and rank them accordingly; More recently, Neural IR models, e.g. representation learning models [16, 18], matching function learning models [17, 26, 27, 33], and their combination [12], bridge the semantic gap between query and document using deep learning methods and predict the relevance of each query-document pair automatically from their raw text.

Despite widely adopted, the power of PRP-based ranking models, however, have been found limited in recent studies [1, 3, 20]. First, PRP argues that each document has an intrinsic probability of relevance for each query, which essentially assume that the relevance scores of each document could or should be estimated independently. Such independent scoring paradigms prevent traditional learning-to-rank models from modeling cross-document interactions and capturing local context information. As shown by previous studies on pseudo relevance feedback [24] and query-dependent learning-to-rank [8], incorporating local context information such as query-level document feature distributions can significantly improve the effectiveness of modern ranking systems. Second, as pointed by Robertson [30], PRP works document-by-document while the results of ranking should be evaluated request-by-request. Behavior analysis on search engine users manifest that user's interactions with information retrieval systems show strong *comparison* patterns [22, 41]. In practice, search engine users often compare multiple documents on a result page before generating a click action. Studies on query-document relevance annotations show that information from other documents in the same ranked list could affect an annotator's decision on the current document [32, 40], which challenge the basic hypothesis that relevance should be modeled independently on each document for a single information request.

Aware of those problems, a new group of ranking models [1, 3, 14, 28, 34, 37, 39, 42] constructed beyond PRP has emerged and attracted more and more attention in recent literature. Instead of scoring each query-document pair independently, they model the dependencies among documents in order to incorporate cross-document and request-level context for the evaluation and prediction of ranking scores. Generally speaking, existing work on ranking beyond PRP can be categorized into two groups: (1) the models with sequential dependency assumptions on document ranking, such as MMR and their variations [10, 36], and (2) the models with global dependency assumptions, such as query-dependent learning-to-rank [8] and multivariate learning-to-rank functions [1]. As information retrieval tasks and applications are growing much more complex today, those models constructed without the document independence assumption inherited from PRP have been shown to be promising and have great potential for online ranking systems [3, 4]

With growing popularity and potential impact of ranking algorithms beyond PRP, this tutorial aims to increase the general understanding and awareness of these techniques in our community. The people involved in this proposal have followed the studies of ranking models for a long period, and are actively working on research projects in this area. We will first introduce the well-known underlying principles used in existing ranking models as well as their characteristics in ranking practices. We will illustrate the limitations of PRP principle with real examples and formally discuss recent advances on ranking models that designed to model the dependencies among documents beyond the assumption of PRP. Overall, this tutorial aims to attract more people to look at the problem and design ranking models that better suit the need of modern AI applications. It will provide important guidance for the design of ranking systems and inspire future studies on related research topics.

2 OBJECTIVES

In this tutorial, we want to introduce the recent advances of ranking models that go beyond probability ranking principle to a broader audience. For better understanding, we first introduce the fundamental probability ranking principle and the ranking models follow this principle as the background knowledge. After that, we discuss the limitations of PRP principle, and provide a brief survey of recent advanced ranking models that break the PRP principle. The ultimate goal of this tutorial is to tell the audience that PRP is not the optimal, that many ranking task do not satisfied this assumption. Besides, the mentioned ranking models that break PRP may provide a new trend of learning-to-rank techniques and inspire future studies on the related topics.

3 OUTLINE AND SCHEDULE

The outline of the proposed tutorial is as follows. After briefly introducing the ranking problem and describing the important probability ranking principle, it will make audience better understand the design principle of recent ranking models. In Part I, we will recapitulate traditional ranking models, including feature based ranking models and neural IR models. In Part II, we will discuss the limitations of current PRP principle using heuristic examples and need of advanced ranking tasks. To extend independent ranking models, a new branch of ranking models are proposed to model the dependencies among documents. It can be categorized into sequential dependency and global dependency for ranking. Lastly, we will summarize the tutorial and discuss the future directions.

4 TARGET AUDIENCE

This tutorial focuses on introducing the new type of ranking models which go beyond probability ranking principle. They have a great importance and significant potential in a variety of information retrieval tasks, such as diversity ranking, interactive IR or personal search, and recommendation tasks. Therefore, it will be relevant and interesting to the audience of WSDM 2021 who work on search or recommendation problems. It is optional but recommended for the audience to have some basic knowledge of deep learning model and learning to rank. For example, it would be good to know the basic concepts of neural networks (e.g., fully-connected networks, transformer structures, recurrent structures, convolution structures, etc.) and ranking loss functions (e.g., pointwise, pairwise, and listwise loss functions, etc.) before attending this tutorial. Some knowledge of the machine learning techniques, reinforcement learning techniques would also help the audience better understand the content and impacts of this tutorial.

5 SUPPLEMENTAL MATERIALS

The tutorial materials to be supplied to the attendees include

Slides: tutorial slides will be made publicly available on the lecturers' personal homepages.

Bibliography: a list of references will cover all the work discussed in the tutorial and provide a good resource for further study.

Several wonderful tutorials were given at related conferences: Jun Xu, Xiangnan He and Hang Li for Deep Learning for Matching in Search and Recommendation, at SIGIR 2018, WWW 2018,

Table 1: The schedule of the tutorial (starting from 9:30 am UTC+2 or 15:30 pm UTC+8).

Half Day (9:30 am - 12:30 am)	Time (UTC+2)	Time (UTC+8)	Speaker	Slides
Part I: Introduction 1. Introduction 2. Ranking with Probability Ranking Principle (PRP) 3. Limitations of PRP Principle	9:30-10:10	15:30-16:10	Qingyao Ai	Part1.pdf
5min break				
Part II: Ranking with Sequential Dependency 4. Ranking with Sequential Dependency 4.1 Heuristic Sequential Ranking Models 4.2 Learning Sequential Ranking Models 4.3 Challenges	10:15-11:05	16:15-17:05	Jun Xu	Part2.pdf
5min break				
Part III: Ranking with Global Dependency 5. Ranking with Global Dependency 5.1 List Inputted Global Ranking Models 5.2 Set Inputted Global Ranking Models 6. Conclusion	11:10-12:20	17:10-18:20	Liang Pang	Part3.pdf
7. Q&A and Open Discussions	12:20-12:30	18:20-18:30	Liang Pang Qingyao Ai Jun Xu	

WSDM 2019; Bhaskar Mitra and Nick Craswell, Neural Text Embeddings for Information Retrieval, at WSDM 2017; Kyomin Jungj, Byoung-Tak Zhan, and Prasenjit Mitra, Deep Learning for the Web, at WWW 2015; Tom Kenter et al., Neural Networks for Information Retrieval (NN4IR), at SIGIR 2017; Hang Li and Zhengdong Lu, Deep Learning for Information Retrieval, at SIGIR 2016; Ganesh Venkataraman et al., Deep Learning for Personalized Search and Recommender Systems, at KDD 2017; Alexandros Karatzoglou et al., Deep Learning for Recommender Systems, at Recsys 2017. This tutorial is significantly different from the previous tutorials in the sense that it focuses on the semantic matching problem in search and recommendation.

6 PRESENTERS' BIOGRAPHY

• Dr. **Liang Pang** is an Assistant Professor at Institute of Computing Technology, Chinese Academy of Sciences. Liang Pang's research interests focus on designing deep models for text matching and learning-to-rank in information retrieval. He has published about 30 papers at top international journals and conferences, including SIGIR, CIKM, ACL, AAAI, IJCAI etc. His work on information retrieval has received the Best Paper Runner-up of ACM CIKM 2017. He is very active in the research communities and has served or is serving top international conferences as PC member, including SIGIR, WWW, NIPS, AAAI, IJCAI, CIKM etc.

• Dr. **Qingyao Ai** is an Assistant Professor at School of Computing, University of Utah. His research mainly focuses on developing intelligent retrieval systems with machine learning techniques. He actively works on applying deep learning techniques on IR problems including ad-hoc retrieval, product search/recommendation and learning to rank. He has published more than 40 papers on top international journals or conferences such as SIGIR, CIKM, WWW, TOIS, etc. He has organized multiple tutorials/workshops [2, 13, 44, 46] and served as the senior/ordinary PC member of top-tier IR conferences including SIGIR, CIKM, WSDM, WWW, AAAI, etc.

• Dr. **Jun Xu** is a Professor at Gaoling School of Artificial Intelligence, Renmin University of China. Jun Xu's research interests focus on applying machine learning to information retrieval and recommendation. He has published more than 50 papers and 2 monographs at top international journals and conferences, including TKDE, TOIS, JMLR, SIGIR, CIKM, ACL, EMNLP etc. His work on information retrieval has received the Test of Time Award Honorable mention of ACM SIGIR 2019, Best Paper Runner-up of ACM CIKM 2017, and Best Paper Award of AIRS 2010. He has served or is serving top international conferences as Senior PC members, including SIGIR, ACML, CIKM, AAAI, and top international journal of JASIST as an editorial board member, and ACM TIST as an associate editor. He has given tutorials at top conferences like SIGIR, WSDM, TheWebConf (WWW) on the topic of deep learning for semantic matching in search and recommendation.

7 ACKNOWLEDGEMENT

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REFERENCES

[1] Qingyao Ai, Keping Bi, Jiafeng Guo, and W Bruce Croft. 2018. Learning a deep listwise context model for ranking refinement. In *Proceedings of the 41st ACM SIGIR*. ACM, 135–144.

[2] Qingyao Ai, Jiaxin Mao, Yiqun Liu, and W Bruce Croft. 2018. Unbiased learning to rank: Theory and practice. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*. 2305–2306.

[3] Qingyao Ai, Xuanhui Wang, Nadav Golbandi, Michael Bendersky, and Marc Najork. 2019. Learning groupwise scoring functions using deep neural networks. In *Proceedings of the ACM ICTIR*.

[4] Irwan Bello, Sayali Kulkarni, Sagar Jain, Craig Boutilier, Ed Chi, Elad Eban, Xiyang Luo, Alan Mackey, and Ofer Meshi. 2018. Seq2slate: Re-ranking and slate optimization with rnns. *arXiv preprint arXiv:1810.02019* (2018).

[5] Sebastian Bruch, Shuguang Han, Michael Bendersky, and Marc Najork. 2020. A Stochastic Treatment of Learning to Rank Scoring Functions. In *Proceedings of the 13th WSDM*. ACM, 61–69.

[6] Sebastian Bruch, Masrour Zoghi, Michael Bendersky, and Marc Najork. 2019. Revisiting Approximate Metric Optimization in the Age of Deep Neural Networks. In *Proceedings of the 42nd International ACM SIGIR*. ACM, 1241–1244.

[7] Chris Burges, Tal Shaked, Erin Renshaw, Ari Lazier, Matt Deeds, Nicole Hamilton, and Greg Hullender. 2005. Learning to rank using gradient descent. In *Proceedings of the 22nd ICML*. ACM, 89–96.

[8] Ethem F Can, W Bruce Croft, and R Manmatha. 2014. Incorporating query-specific feedback into learning-to-rank models. In *Proceedings of the 37th ACM SIGIR*. ACM, 1035–1038.

[9] Zhe Cao, Tao Qin, Tie-Yan Liu, Ming-Feng Tsai, and Hang Li. 2007. Learning to rank: from pairwise approach to listwise approach. In *Proceedings of the 24th ICML*. ACM, 129–136.

[10] Jaime Carbonell and Jade Stewart. 1999. The Use of MMR, Diversity-Based Reranking for Reordering Documents and Producing Summaries. *SIGIR Forum (ACM Special Interest Group on Information Retrieval)*. https://doi.org/10.1145/290941.291025

[11] Danqi Chen, Adam Fisch, Jason Weston, and Antoine Bordes. 2017. Reading Wikipedia to Answer Open-Domain Questions. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Association for Computational Linguistics, Vancouver, Canada, 1870–1879. https://doi.org/10.18653/v1/P17-1171

[12] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics*. 4171–4186.

[13] Yixing Fan, Qingyao Ai, Zhaochun Ren, Liangjie Hong, Dawei Yin, and Jiafeng Guo. 2019. DAPA: The WSDM 2019 Workshop on Deep Matching in Practical Applications. In *Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining*. 844–845.

[14] Yue Feng, Jun Xu, Yanyan Lan, Jiafeng Guo, Wei Zeng, and Xueqi Cheng. 2018. From Greedy Selection to Exploratory Decision-Making: Diverse Ranking with Policy-Value Networks. In *The 41st International ACM SIGIR Conference on Research and Development in Information Retrieval* (Ann Arbor, MI, USA) *(SIGIR '18)*. Association for Computing Machinery, New York, NY, USA, 125âĂŞ134. https://doi.org/10.1145/3209978.3209979

[15] Jerome H Friedman. 2001. Greedy function approximation: a gradient boosting machine. *Annals of statistics* (2001), 1189–1232.

[16] Jiafeng Guo, Yixing Fan, Qingyao Ai, and W Bruce Croft. 2016. A deep relevance matching model for ad-hoc retrieval. In *Proceedings of the 25th ACM CIKM*. ACM, 55–64.

[17] Baotian Hu, Zhengdong Lu, Hang Li, and Qingcai Chen. 2014. Convolutional neural network architectures for matching natural language sentences. In *NIPS*. 2042–2050.

[18] Po-Sen Huang, Xiaodong He, Jianfeng Gao, Li Deng, Alex Acero, and Larry Heck. 2013. Learning deep structured semantic models for web search using clickthrough data. In *Proceedings of the 22nd ACM CIKM*. ACM, 2333–2338.

[19] Michimasa Inaba and Kenichi Takahashi. 2016. Neural Utterance Ranking Model for Conversational Dialogue Systems. In *Proceedings of the 17th Annual Meeting of the Special Interest Group on Discourse and Dialogue*. Association for Computational Linguistics, Los Angeles, 393–403. https://doi.org/10.18653/v1/W16-3648

[20] Ray Jiang, Sven Gowal, Timothy A Mann, and Danilo J Rezende. 2018. Beyond greedy ranking: Slate optimization via List-CVAE. *arXiv preprint arXiv:1803.01682* (2018).

[21] Thorsten Joachims. 2006. Training linear SVMs in linear time. In *Proceedings of the 12th ACM SIGKDD*. ACM, 217–226.

[22] Thorsten Joachims, Laura A Granka, Bing Pan, Helene Hembrooke, and Geri Gay. 2005. Accurately interpreting clickthrough data as implicit feedback. In *SIGIR*, Vol. 5. 154–161.

[23] Karen Sparck Jones. 1972. A statistical interpretation of term specificity and its application in retrieval. *Journal of documentation* (1972).

[24] Victor Lavrenko and W Bruce Croft. 2017. Relevance-based language models. In *ACM SIGIR Forum*, Vol. 51. ACM, 260–267.

[25] Tie-Yan Liu. 2009. Learning to rank for information retrieval. *Foundations and Trends in Information Retrieval* 3, 3 (2009), 225–331.

[26] Liang Pang, Yanyan Lan, Jiafeng Guo, Jun Xu, Shengxian Wan, and Xueqi Cheng. 2016. Text matching as image recognition. In *Thirtieth AAAI Conference on Artificial Intelligence*.

[27] Liang Pang, Yanyan Lan, Jiafeng Guo, Jun Xu, Jingfang Xu, and Xueqi Cheng. 2017. Deeprank: A new deep architecture for relevance ranking in information retrieval. In *Proceedings of the 2017 ACM CIKM*. ACM, 257–266.

[28] Liang Pang, Jun Xu, Qingyao Ai, Yanyan Lan, Xueqi Cheng, and Jirong Wen. 2020. SetRank: Learning a Permutation-Invariant Ranking Model for Information Retrieval. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval* (Virtual Event, China) *(SIGIR '20)*. Association for Computing Machinery, New York, NY, USA, 499âĂŞ508. https://doi.org/10.1145/3397271.3401104

[29] Stephen E Robertson. 1977. The probabilistic character of relevance. *Information Processing & Management* 13, 4 (1977), 247–251.

[30] Stephen E Robertson. 1977. The probability ranking principle in IR. *Journal of documentation* 33, 4 (1977), 294–304.

[31] Stephen E Robertson and Steve Walker. 1994. Some simple effective approximations to the 2-poisson model for probabilistic weighted retrieval. In *SIGIR*. Springer-Verlag New York, Inc., 232–241.

[32] Falk Scholer, Andrew Turpin, and Mark Sanderson. 2011. Quantifying test collection quality based on the consistency of relevance judgements. In *Proceedings of the 34th ACM SIGIR*. ACM, 1063–1072.

[33] Shengxian Wan, Yanyan Lan, Jun Xu, Jiafeng Guo, Liang Pang, and Xueqi Cheng. 2016. Match-SRNN: modeling the recursive matching structure with spatial RNN. In *Proceedings of the 25th IJCAI*. 2922–2928.

[34] Zeng Wei, Jun Xu, Yanyan Lan, Jiafeng Guo, and Xueqi Cheng. 2017. Reinforcement Learning to Rank with Markov Decision Process. In *Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval* (Shinjuku, Tokyo, Japan) *(SIGIR '17)*. Association for Computing Machinery, New York, NY, USA, 945âĂŞ948. https://doi.org/10.1145/3077136.3080685

[35] Fen Xia, Tie-Yan Liu, Jue Wang, Wensheng Zhang, and Hang Li. 2008. Listwise approach to learning to rank: theory and algorithm. In *Proceedings of the 25th ICML*. ACM, 1192–1199.

[36] Long Xia, Jun Xu, Yanyan Lan, Jiafeng Guo, and Xueqi Cheng. 2015. Learning maximal marginal relevance model via directly optimizing diversity evaluation measures. In *Proceedings of the 38th international ACM SIGIR conference on research and development in information retrieval*. 113–122.

[37] Long Xia, Jun Xu, Yanyan Lan, Jiafeng Guo, Wei Zeng, and Xueqi Cheng. 2017. Adapting Markov Decision Process for Search Result Diversification. In *Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval* (Shinjuku, Tokyo, Japan) *(SIGIR '17)*. Association for Computing Machinery, New York, NY, USA, 535âĂŞ544. https://doi.org/10.1145/3077136.3080775

[38] Jun Xu, Xiangnan He, and Hang Li. 2018. Deep Learning for Matching in Search and Recommendation. In *The 41st International ACM SIGIR Conference on Research and Development in Information Retrieval* (Ann Arbor, MI, USA) *(SIGIR '18)*. Association for Computing Machinery, New York, NY, USA, 1365âĂŞ1368. https://doi.org/10.1145/3209978.3210181

[39] Jun Xu, Zeng Wei, Long Xia, Yanyan Lan, Dawei Yin, Xueqi Cheng, and Ji-Rong Wen. 2020. Reinforcement Learning to Rank with Pairwise Policy Gradient. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval* (Virtual Event, China) *(SIGIR '20)*. Association for Computing Machinery, New York, NY, USA, 509âĂŞ518. https://doi.org/10.1145/3397271.3401148

[40] Ziying Yang. 2017. Relevance Judgments: Preferences, Scores and Ties. In *Proceedings of the 40th ACM SIGIR*. ACM, 1373–1373.

[41] Emine Yilmaz, Manisha Verma, Nick Craswell, Filip Radlinski, and Peter Bailey. 2014. Relevance and effort: An analysis of document utility. In *Proceedings of the 23rd ACM CIKM*. ACM, 91–100.

[42] Wei Zeng, Jun Xu, Yanyan Lan, Jiafeng Guo, and Xueqi Cheng. 2018. Multi Page Search with Reinforcement Learning to Rank. In *Proceedings of the 2018 ACM SIGIR International Conference on Theory of Information Retrieval* (Tianjin, China) *(ICTIR '18)*. Association for Computing Machinery, New York, NY, USA, 175âĂŞ178. https://doi.org/10.1145/3234944.3234977

[43] Chengxiang Zhai and John Lafferty. 2001. A Study of Smoothing Methods for Language Models Applied to Ad Hoc Information Retrieval *(SIGIR '01)*. Association for Computing Machinery, New York, NY, USA, 334âĂŞ342. https://doi.org/10.1145/383952.384019

[44] Yongfeng Zhang, Jiaxin Mao, and Qingyao Ai. 2019. WWWâĂŹ19 Tutorial on Explainable Recommendation and Search. In *Companion Proceedings of The 2019 World Wide Web Conference*. 1330–1331.

[45] Yinan Zhang and Chengxiang Zhai. 2015. Information Retrieval as Card Playing: A Formal Model for Optimizing Interactive Retrieval Interface. In *Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval* (Santiago, Chile) *(SIGIR '15)*. Association for Computing

Machinery, New York, NY, USA, 685âĂŞ694. https://doi.org/10.1145/2766462.2767761
[46] Xiaoqiang Zhu, Kuang-chih Lee, Guorui Zhou, Biye Jiang, Liang Xiong, Junlin Zhang, Zhe Wang, Zheng Wen, Haitian Liu, Kan Ren, Qingyao Ai, Shandian Zhe, and Weinan Zhang. 2020. DLP-KDD: The 2nd International Workshop on Deep Learning Practice for High-Dimensional Sparse Data. In *Proceedings of the 26th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*.