Tutorial: Data Denoising Metrics in Recommender Systems

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ABSTRACT

Recommender systems play a pivotal role in navigating users through vast reservoirs of information. However, data sparseness can compromise recommendation accuracy, making it challenging to improve recommendation performance. To address this issue, researchers have explored incorporating multiple data types. Yet, this approach can introduce noise that impairs the recommendations' accuracy. Therefore, it is crucial to denoise the data to enhance recommendation quality. This tutorial highlights the importance of data denoising metrics for improving the accuracy and quality of recommendations. Four groups of data denoising metrics are introduced: feature, item, pattern, and modality level. For each group, various denoising methods are presented. The tutorial emphasizes the significance of selecting the right data denoising methods to enhance recommendation quality. It provides valuable guidance for practitioners and researchers implementing reliable data denoising metrics in recommender systems. Finally, the tutorial proposes open research questions for future studies, making it a valuable resource for the research community.

CCS CONCEPTS

• **Information systems** → **Recommender systems**.

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CIKM '23, October 21–25, 2023, Birmingham, United Kingdom

ACM ISBN 979-8-4007-0124-5/23/10…$15.00
https://doi.org/10.1145/3583780.3615297

KEYWORDS

Recommender Systems; Data Denoising; Data Sparsity

ACM Reference Format:
Pengfei Wang, Chenliang Li, Lixin Zou, Zhichao Feng, Kaiyuan Li, Xiaochen Li, Xialong Liu, and Shangguang Wang. 2023. Tutorial: Data Denoising Metrics in Recommender Systems. In *Proceedings of the 32nd ACM International Conference on Information and Knowledge Management (CIKM '23), October 21–25, 2023, Birmingham, United Kingdom.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3583780.3615297

1 INTRODUCTION

The recommender system aims to provide a limited number of relevant and high-quality items for users to avoid information overload. Due to its great effects, now it becomes an indispensable and ubiquitous system that is widely applied in the domain of e-platform. In this scenario, recommender systems often suffer poor performance due to data spareness problems. This is particularly evident in large e-commerce like Amazon or Alibaba, where user interactions cover only encompass a small portion of the vast items. As a result, limited data makes it difficult for recommender to learn effective representations and in turn leads to a significant drop in the quality of recommendations.

To alleviate this problem, many early works investigate to fuse more information to enhance recommendation performance. For example, multi-behavior modeling[9, 16], feature engineering[10, 28], multi-modal representation[11, 38, 47] and knowledge graph recommendation[48]. Although effective, we believe that introducing more information inevitably brings in some noise that misleads the recommender system, thereby decreasing its performance.

This tutorial aims to address the challenge of data denoising in recommender systems, with a focus on classifying various types of noise and exploring corresponding denoising metrics. Specifically, we will delve into this topic into four groups:

- **Feature level**: The feature-level deniosing metrics include make denoising for individual [15, 17, 25, 29, 40, 49] and interactive features [3–5, 19, 23, 24, 31, 45] respectively. Individual features refer to characteristics of users and items, encompassing aspects such as user profiles and item metadata. For example, when buying daily necessities such as chairs and tables, the gender of the user may not be very important for prediction. The other type of noise is mainly related to interactive features. For example, middle-aged male users may have similar preferences, but the combination of gender and login website may not have too much significance. One way to solve this problem is through manual feature engineering, which involves manually selecting effective individual features and feature combinations. However, this manual approach can often incur significant human resource expenses. Therefore, how to automatically select proper features has become a highly concerning issue.

- **Item level**: From the item-level perspective, noise primarily hides in user interaction [1, 8, 21, 32] and item relevance [6, 13, 26, 27, 33, 46, 53]. Specifically, noise in user interaction data is mainly caused by the ambiguity of implicit feedback, such as when a user clicks an item but doesn't like it, or likes it but forgets to click. The goal of denoising from this level is to identify these noise signals using user information and filter high-quality user interaction data for recommendation. On the other hand, item relevance may be inconsistent, and not all pairs of items in user-item interaction data are correlated. For example, an Apple earphone has a strong dependency on iPhone but has a weak correlation with other brands of phones. Therefore, identifying the significance of dependencies between items, and filtering out noise from the item level is the main goal of this topic.
- **Pattern level**: For the pattern level, noise is regarded as a set of items, like a mined association rule, or one path obtained from the knowledge graph [7, 12, 14, 34–37, 39, 43, 44, 50, 52, 54]. For example, with a massive amount of user interactions, we can extract complex patterns based on designed rules. However, not all patterns are trustworthy, so it is necessary to denoise them and extract high-value patterns for recommendations. The problem is getting more complex when fusing knowledge graphs for recommendation, usually, a set of paths are provided, making it more crucial to identify relevant patterns. To summarize, denoising from the pattern level mainly focuses on how to automatically and accurately find these relevant patterns.
- **Modality level**: For the modality perspective, the noise can be mainly divided into two aspects: intra-modal noise [2, 22, 30] and inter-modal noise [18, 20, 41, 42, 51] respectively. Intra-modal noise refers to the presence of irrelevant elements within a particular modality. For example, when it comes to visual information, users only focus on some elements or areas in the image, while for textual information, users only focus on some interesting aspects in the item description or reviews. The goal of intra-modal denoising is removing irrelevant properties inside the modality to enhance the recommendation performance. In contrast, Inter-modal noise refers to the noise generated in the process of combining various modal information. For example, when buying a dress, a woman may pay more attention to the visual information of the dress style in the images, whereas when purchasing a skincare product, she may focus more on the textual information such as product description and reviews. Therefore, inter-modal denoising aims to select which modal information is truly helpful. To summarize, How to identify the intra-modal and inter-modal noise and only fuse valuable modal information is the main issue at this level.

2 TABLE SHEET

2.1 TITLE

Tutorial: Data Denoising Metrics in Recommender Systems

2.2 LENGTH

The estimated duration of the speech is three hours, and a detailed schedule of the timing will be described in section 6.

2.3 FORMAT

All presenters will give their reports in person.

2.4 INTENDED AUDIENCE AND PREREQUISITE KNOWLEDGE

In recent years, denoising metrics for recommender systems have attracted the attention of researchers in related fields, including data mining and information retrieval. Therefore, anyone interested in recommender systems, data mining, and information retrieval can obtain valuable information from this tutorial.

Audience members are expected to have a basic understanding of machine learning, deep learning, and recommender systems, as this will help them better understand the ideas we convey. We also maintain a list[1] of papers to help readers keep up with the latest work on denoising in recommender systems.

2.5 PRESENTERS

Pengfei Wang(wangpengfei@bupt.edu.cn): Pengfei Wang is an Associate Professor at the School of Computer Science, Beijing University of Posts and Telecommunications. His research focuses on recommender systems, service computing and satellite computing. He has published over 60 research papers in top international academic journals and conferences, including more than 20 first-author or corresponding-author papers in top-tier academic conferences and journals, including SIGIR, WWW, CIKM, and IJCAI. He has been invited to serve as a reviewer for various high-profile international academic conferences and journals. He has contributed as a core leader to the development of RecBole, a well-known open-source recommendation algorithm library in the field, which has received over 2700 stars on GitHub. Website: https://teacher.bupt.edu.cn/wangpengfei/

Chenliang Li(cllee@whu.edu.cn): Chenliang Li is a Professor at School of Cyber Science and Engineering, Wuhan University. His research interests include information retrieval, recommender systems, natural language processing, and social media analysis. He has published over 90 research papers on leading academic conferences and journals such as SIGIR, ACL, WWW, IJCAI, AAAI, TKDE

[1]https://github.com/WHUIR/cikm2023_DenoisingRec_tutorial

and TOIS. He has served as Associate Editor / Editorial Board Member for ACM TOIS, ACM TALLIP, IPM and JASIST. His research won the SIGIR 2016 Best Student Paper Honorable Mention and TKDE Featured Spotlight Paper. Website: http://lichenliang.net/

Lixin Zou(zoulixin@whu.edu.cn): Lixin Zou is an Associate Professor at the School of Cyber Science and Engineering, Wuhan University. Prior to his current position, he served as a Staff Algorithm Engineer at Baidu Search Science team from Jul. 2020 to Nov. 2022. He earned the Ph.D. in Computer Science I& Technology from Tsinghua University in 2020. He had led a team and won the runner-up award in KDD Cup 2019. His research interests include information retrieval, recommender systems, and reinforcement learning. He has published over 20 research papers in top-tier academic conferences and journals, including SIGIR, KDD, WWW, NeurIPS, WSDM, IJCAI, TWeb, and CIKM. Website: https://www.zoulixin.site/.

Kaiyuan Li(tsotfsk@bupt.edu.cn): Kaiyuan Li is a master's student at Beijing University of Posts and Telecommunications. His research interests include recommender systems, reinforcement learning, and graph machine learning. He has published papers in related fields, such as SIGIR, WWW, and CIKM. He has also contributed as a core developer to the development of RecBole, a well-known open-source recommendation algorithm library in the field, which has received over 2700 stars on GitHub. He has also been invited by companies such as Meituan and Alibaba to speak about denoising in recommender systems.

Zhichao Feng(fengzc@bupt.edu.cn): Zhichao Feng is a master's student at Beijing University of Posts and Telecommunications. His research interest includes recommender systems. He has published papers in related fields, such as TOIS and CIKM. He has also contributed as a core developer to the development of RecBole, a well-known open-source recommendation algorithm library in the field, which has received over 2700 stars on GitHub.

3 MOTIVATION AND OBJECTIVES

In recent years, data denoising in recommender systems has received considerable attention. To mitigate data sparsity while avoiding noise interference, many attempts have been made in this area and achieved state-of-the-art performance. Therefore, this tutorial can help researchers and practitioners in the recommender system field better understand and recognize this new research area.

Although there has been a lot of work related to data denoising metrics, these works are often scattered across different sub-fields, such as feature selection, multi-modal fusion, and pattern mining, which lack a unified description and classification. This tutorial takes a global perspective to sort and classify these works, helping beginners to better understand their intrinsic meaning.

4 RELEVANCE TO THE INFORMATION RETRIEVAL COMMUNITY

Recommender systems are an essential component of many information retrieval systems, and their performance depends heavily on the quality of the data they receive. However, data collected from various sources often contain noise, which can negatively impact the accuracy and effectiveness of recommender systems. Therefore, developing effective methods to remove noise from data is critical to improving the performance of recommender systems.

This tutorial aims to provide valuable insights and practical guidance to researchers and practitioners in the information retrieval community. This tutorial will cover various metrics for data denoising, including four aspects: feature level, item level, pattern level, and modality level, and will provide examples of their applications in recommender systems. Researchers in these sub-fields can also extract valuable information from this tutorial.

5 REFERENCE TO TUTORIALS IN THE SAME AREA AT CIKM / RELATED CONFERENCES

We have not found any similar tutorial information at relevant conferences. To the best of our knowledge, this is the first tutorial that provides a comprehensive summary of data denoising metrics for recommender systems. However, there may be similar tutorials on specific techniques, which focus on a specific sub-field but may not cover the concept of data denoising.

6 DETAILED SCHEDULE OF THE TUTORIAL

This tutorial is organized as follows:

(1) Introduction and Background [20 mins]
   (a) Introduction and Background of recommender System:
   (b) Data Sparsity Phenomenon
   (c) Brief Overview for Current work
(2) Motivations and Challenges of Data Denoising [20 mins]
   (a) Motivations
   (b) Challenges
(3) Data Denoising Trick [120 mins]
   (a) Feature-level denoising: individual feature denoising and interactive feature denoising
   (b) Item-Level denoising: user-item interactions denoising and item-item dependency denoising
   (c) Pattern-Level denoising: statistic rules-based denoising and expert-guided denoising
   (d) Modality-Level denoising: intra-modality denoising and inter-modality denoising
(4) Conclusion [20 mins]
   (a) Summary of the tutorial
   (b) Open problem and future works

7 SUPPOTR MATERIALS

We will release the slides for our tutorial, and in addition, we maintain a list of papers at https://github.com/WHUIR/cikm2023_DenoisingRec_tutorial to help readers keep up-to-date with the latest advancements in the field.

REFERENCES

[1] Zhi Bian, Shaojun Zhou, Hao Fu, Qihong Yang, Zhenqi Sun, Junjie Tang, Guiquan Liu, Kaikui Liu, and Xiaolong Li. 2021. Denoising User-aware Memory Network for Recommendation. In *RecSys*. 400–410.

[2] Xu Chen, Yongfeng Zhang, Hongteng Xu, Yixin Cao, Zheng Qin, and Hongyuan Zha. 2018. Visually Explainable Recommendation. *CoRR* abs/1801.10288 (2018).

[3] Yifan Chen, Pengjie Ren, Yang Wang, and Maarten de Rijke. 2019. Bayesian Personalized Feature Interaction Selection for Factorization Machines. In *SIGIR*. 665–674.

[4] Yifan Chen, Pengjie Ren, Yang Wang, and Maarten de Rijke. 2019. Bayesian Personalized Feature Interaction Selection for Factorization Machines. In *SIGIR*. 665–674.

[5] Maurizio Ferrari Dacrema, Fabio Moroni, Riccardo Nembrini, Nicola Ferro, Guglielmo Faggioli, and Paolo Cremonesi. 2022. Towards Feature Selection for Ranking and Classification Exploiting Quantum Annealers. In *SIGIR*. 2814–2824.

[6] Qihan Du, Li Yu, Huiyuan Li, Youfang Leng, and Ningrui Ou. 2022. Denoising-Oriented Deep Hierarchical Reinforcement Learning for Next-Basket Recommendation. In *ICASSP*. 4093–4097.

[7] Shaohua Fan, Junxiong Zhu, Xiaotian Han, Chuan Shi, Linmei Hu, Biyu Ma, and Yongliang Li. 2019. Metapath-guided Heterogeneous Graph Neural Network for Intent Recommendation. In *KDD*. 2478–2486.

[8] Yunjun Gao, Yuntao Du, Yujia Hu, Lu Chen, Xinjun Zhu, Ziquan Fang, and Baihua Zheng. 2022. Self-Guided Learning to Denoise for Robust Recommendation. In *SIGIR*. 1412–1422.

[9] Yulong Gu, Zhuoye Ding, Shuaiqiang Wang, Lixin Zou, Yiding Liu, and Dawei Yin. 2020. Deep Multifaceted Transformers for Multi-objective Ranking in Large-Scale E-commerce Recommender Systems. In *CIKM*. 2493–2500.

[10] Huifeng Guo, Ruiming Tang, Yunming Ye, Zhenguo Li, and Xiuqiang He. 2017. DeepFM: A Factorization-Machine based Neural Network for CTR Prediction. In *IJCAI*. ijcai.org, 1725–1731.

[11] Ruining He and Julian McAuley. 2016. Ups and downs: Modeling the visual evolution of fashion trends with one-class collaborative filtering. In *WWW*. 507–517.

[12] Binbin Hu, Chuan Shi, Wayne Xin Zhao, and Philip S. Yu. 2018. Leveraging Meta-path based Context for Top- N Recommendation with A Neural Co-Attention Model. In *KDD*. 1531–1540.

[13] Yunfan Hu, Zhaopeng Qiu, and Xian Wu. 2022. Denoising Neural Network for News Recommendation with Positive and Negative Implicit Feedback. In *NAACL-HLT (Findings)*. 2320–2329.

[14] Jin Huang, Wayne Xin Zhao, Hongjian Dou, Ji-Rong Wen, and Edward Y. Chang. 2018. Improving Sequential Recommendation with Knowledge-Enhanced Memory Networks. In *SIGIR*. 505–514.

[15] Tongwen Huang, Zhiqi Zhang, and Junlin Zhang. 2019. FiBiNET: combining feature importance and bilinear feature interaction for click-through rate prediction. In *RecSys*. 169–177.

[16] Bowen Jin, Chen Gao, Xiangnan He, Depeng Jin, and Yong Li. 2020. Multi-behavior Recommendation with Graph Convolutional Networks. In *SIGIR*. ACM, 659–668.

[17] Noam Koenigstein and Ulrich Paquet. 2013. Xbox movies recommendations: variational bayes matrix factorization with embedded feature selection. In *RecSys*. 129–136.

[18] Kaiyuan Li, Pengfei Wang, and Chenliang Li. 2022. Multi-Agent RL-based Information Selection Model for Sequential Recommendation. In *SIGIR*. 1622–1631.

[19] Bin Liu, Chenxu Zhu, Guilin Li, Weinan Zhang, Jincai Lai, Ruiming Tang, Xiuqiang He, Zhenguo Li, and Yong Yu. 2020. AutoFIS: Automatic Feature Interaction Selection in Factorization Models for Click-Through Rate Prediction. In *KDD*. 2636–2645.

[20] Fan Liu, Zhiyong Cheng, Changchang Sun, Yinglong Wang, Liqiang Nie, and Mohan S. Kankanhalli. 2019. User Diverse Preference Modeling by Multimodal Attentive Metric Learning. In *ACM Multimedia*. 1526–1534.

[21] Yiyu Liu, Qian Liu, Yu Tian, Changping Wang, Yanan Niu, Yang Song, and Chenliang Li. 2021. Concept-Aware Denoising Graph Neural Network for Micro-Video Recommendation. In *CIKM*. 1099–1108.

[22] Songyin Luo, Xiangkui Lu, Jun Wu, and Jianbo Yuan. 2021. Review-Aware Neural Recommendation with Cross-Modality Mutual Attention. In *CIKM*. 3293–3297.

[23] Yuanfei Luo, Mengshuo Wang, Hao Zhou, Quanming Yao, Wei-Wei Tu, Yuqiang Chen, Wenyuan Dai, and Qiang Yang. 2019. AutoCross: Automatic Feature Crossing for Tabular Data in Real-World Applications. In *KDD*. 1936–1945.

[24] Yuanfei Luo, Mengshuo Wang, Hao Zhou, Quanming Yao, Wei-Wei Tu, Yuqiang Chen, Wenyuan Dai, and Qiang Yang. 2019. AutoCross: Automatic Feature Crossing for Tabular Data in Real-World Applications. In *KDD*. 1936–1945.

[25] Xueyu Mao, Saayan Mitra, and Viswanathan Swaminathan. 2017. Feature Selection for FM-Based Context-Aware Recommendation Systems. In *ISM*. 252–255.

[26] Qi Pi, Guorui Zhou, Yujing Zhang, Zhe Wang, Lejian Ren, Ying Fan, Xiaoqiang Zhu, and Kun Gai. 2020. Search-based User Interest Modeling with Lifelong Sequential Behavior Data for Click-Through Rate Prediction. In *CIKM*. 2685–2692.

[27] Yuqi Qin, Pengfei Wang, and Chenliang Li. 2021. The World is Binary: Contrastive Learning for Denoising Next Basket Recommendation. In *SIGIR*. 859–868.

[28] Steffen Rendle. 2010. Factorization Machines. In *ICDM*. IEEE Computer Society, 995–1000.

[29] Royi Ronen, Noam Koenigstein, Elad Ziklik, and Nir Nice. 2013. Selecting content-based features for collaborative filtering recommenders. In *RecSys*. 407–410.

[30] Sungyong Seo, Jing Huang, Hao Yang, and Yan Liu. 2017. Interpretable Convolutional Neural Networks with Dual Local and Global Attention for Review Rating Prediction. In *RecSys*. 297–305.

[31] Weiping Song, Chence Shi, Zhiping Xiao, Zhijian Duan, Yewen Xu, Ming Zhang, and Jian Tang. 2019. AutoInt: Automatic Feature Interaction Learning via Self-Attentive Neural Networks. In *CIKM*. 1161–1170.

[32] Changxin Tian, Yuexiang Xie, Yaliang Li, Nan Yang, and Wayne Xin Zhao. 2022. Learning to Denoise Unreliable Interactions for Graph Collaborative Filtering. In *SIGIR*. 122–132.

[33] Xiaohai Tong, Pengfei Wang, Chenliang Li, Long Xia, and Shaozhang Niu. 2021. Pattern-enhanced Contrastive Policy Learning Network for Sequential Recommendation. In *IJCAI*. 1593–1599.

[34] Hongwei Wang, Fuzheng Zhang, Jialin Wang, Miao Zhao, Wenjie Li, Xing Xie, and Minyi Guo. 2018. RippleNet: Propagating User Preferences on the Knowledge Graph for Recommender Systems. In *CIKM*. 417–426.

[35] Hongwei Wang, Fuzheng Zhang, Xing Xie, and Minyi Guo. 2018. DKN: Deep Knowledge-Aware Network for News Recommendation. In *WWW*. 1835–1844.

[36] Hongwei Wang, Fuzheng Zhang, Miao Zhao, Wenjie Li, Xing Xie, and Minyi Guo. 2019. Multi-Task Feature Learning for Knowledge Graph Enhanced Recommendation. In *WWW*. 2000–2010.

[37] Pengfei Wang, Hanxiong Chen, Yadong Zhu, Huawei Shen, and Yongfeng Zhang. 2019. Unified Collaborative Filtering over Graph Embeddings. In *SIGIR*. 155–164.

[38] Xi Wang, Iadh Ounis, and Craig Macdonald. 2021. Leveraging Review Properties for Effective Recommendation. In *WWW*. ACM / IW3C2, 2209–2219.

[39] Xiang Wang, Dingxian Wang, Canran Xu, Xiangnan He, Yixin Cao, and Tat-Seng Chua. 2019. Explainable Reasoning over Knowledge Graphs for Recommendation. In *AAAI*. 5329–5336.

[40] Yejing Wang, Xiangyu Zhao, Tong Xu, and Xian Wu. 2022. AutoField: Automating Feature Selection in Deep Recommender Systems. In *WWW*. 1977–1986.

[41] Yinwei Wei, Xiang Wang, Liqiang Nie, Xiangnan He, and Tat-Seng Chua. 2020. Graph-Refined Convolutional Network for Multimedia Recommendation with Implicit Feedback. In *ACM Multimedia*. 3541–3549.

[42] Yinwei Wei, Xiang Wang, Liqiang Nie, Xiangnan He, Richang Hong, and Tat-Seng Chua. 2019. MMGCN: Multi-modal Graph Convolution Network for Personalized Recommendation of Micro-video. In *ACM Multimedia*. 1437–1445.

[43] Yikun Xian, Zuohui Fu, S. Muthukrishnan, Gerard de Melo, and Yongfeng Zhang. 2019. Reinforcement Knowledge Graph Reasoning for Explainable Recommendation. In *SIGIR*. 285–294.

[44] Yikun Xian, Zuohui Fu, S. Muthukrishnan, Gerard de Melo, and Yongfeng Zhang. 2019. Reinforcement Knowledge Graph Reasoning for Explainable Recommendation. In *SIGIR*. 285–294.

[45] Jun Xiao, Hao Ye, Xiangnan He, Hanwang Zhang, Fei Wu, and Tat-Seng Chua. 2017. Attentional Factorization Machines: Learning the Weight of Feature Interactions via Attention Networks. In *IJCAI*. 3119–3125.

[46] Sicong Xie, Qunwei Li, Weidi Xu, Kaiming Shen, Shaohu Chen, and Wenliang Zhong. 2022. Denoising Time Cycle Modeling for Recommendation. In *SIGIR*. 1950–1955.

[47] Zixuan Yi, Xi Wang, Iadh Ounis, and Craig MacDonald. 2022. Multi-modal Graph Contrastive Learning for Micro-video Recommendation. In *SIGIR*. ACM, 1807–1811.

[48] Fuzheng Zhang, Nicholas Jing Yuan, Defu Lian, Xing Xie, and Wei-Ying Ma. 2016. Collaborative Knowledge Base Embedding for Recommender Systems. In *KDD*. 353–362.

[49] Junlin Zhang, Tongwen Huang, and Zhiqi Zhang. 2019. FAT-DeepFFM: Field Attentive Deep Field-aware Factorization Machine. In *ICDM*. 43–57.

[50] Yongfeng Zhang, Qingyao Ai, Xu Chen, and Pengfei Wang. 2018. Learning over Knowledge-Base Embeddings for Recommendation. *CoRR* abs/1803.06540 (2018).

[51] Jiawei Zheng, Qianli Ma, Hao Gu, and Zhenjing Zheng. 2021. Multi-view Denoising Graph Auto-Encoders on Heterogeneous Information Networks for Cold-start Recommendation. In *KDD*. 2338–2348.

[52] Jiayin Zheng, Juanyun Mai, and Yanlong Wen. 2022. Explainable Session-based Recommendation with Meta-path Guided Instances and Self-Attention Mechanism. In *SIGIR*. 2555–2559.

[53] Guorui Zhou, Xiaoqiang Zhu, Chengru Song, Ying Fan, Han Zhu, Xiao Ma, Yanghui Yan, Junqi Jin, Han Li, and Kun Gai. 2018. Deep Interest Network for Click-Through Rate Prediction. In *KDD*. 1059–1068.

[54] Qiannan Zhu, Xiaofei Zhou, Jia Wu, Jianlong Tan, and Li Guo. 2020. A Knowledge-Aware Attentional Reasoning Network for Recommendation. In *AAAI*. 6999–7006.