

A Brief History of Recommender Systems

Zhenhua Dong¹, Zhe Wang^{2,3}, Jun Xu⁴, Ruiming Tang¹, Jirong Wen⁴

¹ Huawei Noah's Ark Lab; ² ByteDance Ltd; ³ Tsinghua University

⁴ Gaoling School of Artificial Intelligence, Renmin University of China, China

{dongzhenhua,tangruiming}@huawei.com; zhe.wangz@bytedance.com; zhewang06@tsinghua.edu.cn;
{junxu,jrwen}@ruc.edu.cn

ABSTRACT

Soon after the invention of the World Wide Web, the recommender system emerged and related technologies have been extensively studied and applied by both academia and industry. Currently, recommender system has become one of the most successful web applications, serving billions of people in each day through recommending different kinds of contents, including news feeds, videos, e-commerce products, music, movies, books, games, friends, jobs etc. These successful stories have proved that recommender system can transfer big data to high values. This article briefly reviews the history of web recommender systems, mainly from two aspects: (1) recommendation models, (2) architectures of typical recommender systems. We hope the brief review can help us to know the dots about the progress of web recommender systems, and the dots will somehow connect in the future, which inspires us to build more advanced recommendation services for changing the world better.

CCS CONCEPTS

• Information systems → Recommender systems.

KEYWORDS

recommender system, recommendation model, architecture

ACM Reference Format:

Zhenhua Dong¹, Zhe Wang^{2,3}, Jun Xu⁴, Ruiming Tang¹, Jirong Wen⁴. 2022. A Brief History of Recommender Systems. In *Proceedings of ACM Conference (Conference'17)*. ACM, New York, NY, USA, 9 pages. <https://doi.org/10.1145/nnnnnnnn.nnnnnnnn>

1 INTRODUCTION

In 1992, Belkin and Croft [5] analyzed and compared information filtering and information retrieval, where the information retrieval is the fundamental technology of search engine, and the recommender system is mainly based on the technology of information filtering. In the same year, Goldberg et al. [25] proposed Tapestry system which is the first information filtering system based on collaborative filtering through human evaluation. Inspired by the study, some researchers from Massachusetts Institute of Technology (MIT) and University of Minnesota (UMN) developed the news

recommendation service, named GroupLens [64], whose key component is a user-user collaborative filtering model. Prof. John Riedl founded a research lab at UMN, also named GroupLens, which is the pioneer of recommender system studies. For music and video, similar recommendation technologies have been applied by the Ringo system [75] and Video Recommender [35], respectively. Along with the emergence of e-commerce, the industry realized the business value of recommendation. Net Perceptions [89], the first company that focuses on offering the marketing recommender engine, was found in 1996. The customers include Amazon, Best Buy, and JC Penney etc. Schafer et al. [72] explained how recommender systems help E-commerce sites to increase sales through analyzing six web sites, from three aspects such as interfaces, recommendation model, and user inputs. Since then, the academic studies and industrial practical applications became the two wheels of the progress of recommender system technologies. In the fall of 1997, the GroupLens research lab launched the MovieLens [30] project and trained the first version of the recommender model with the EachMovie dataset. After that, several MovieLens datasets were continuously released during 1998 to 2019, and became one of the most popular datasets for recommendation studies.

From the perspective of recommendation models, collaborative filtering technologies dominated the recommender system applications and studies before 2005, such as user-user collaborative filtering [7, 34], item-item collaborative filtering [50, 69] and Singular Value Decomposition (SVD) based collaborative filtering [71]. Inspired by the Netflix Prize during 2006 to 2009, the matrix factorization models had been extensively studied [41, 42]. In the same period, some researchers began to propose informal arguments that the evaluation of the recommender systems should move from the conventional accuracy metrics to the user-centric evaluation [55].

Because of the fast development of basic research and commercial applications in recommender system, the community decided to hold the first ACM Recommender Systems Conference [40] at UMN in 2007. Currently, ACM RecSys has become one of the most important annual academic conference that focuses on the study of recommender system. In the same year, Richardson et al. [67] presented a logistic regression (LR) model that achieved a 30% reduction in term of the error in click-through rate estimation. Since then, LR models were continuously improved from different aspects, including optimizing methods [26, 54], automatic feature engineering [33] etc. In 2010, Rendle [63] proposed the Factorization Machines (FMs) which combines the advantages of Support Vector Machines (SVM) and factorization models. Based on FMs, Juan et al. [38] proposed Field-aware Factorization Machines (FFMs) which considers the fields of features when modeling the weight of each feature pair. In the meantime, more and more studies pay attention to the user experiences in recommender system. Pu et al. [59, 60]

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
Conference'17, July 2017, Washington, DC, USA

© 2022 Association for Computing Machinery.
ACM ISBN 978-x-xxxx-xxxx-x/YY/MM...\$15.00
<https://doi.org/10.1145/nnnnnnnn.nnnnnnnn>

proposed a user-centric evaluation framework for recommender systems; Konstan and Riedl [39] appeal the evolution of the recommender system study from research concentrated purely on algorithms to research concentrated on user experience.

Since 2016, recommendation models based on deep neural networks have emerged in both academia and industry. As for the industrial recommendation models, the **Wide&Deep** model [11] and **DeepFM** [29] had been deployed for improving the App recommendations. **YouTubeDNN** [13] and **correct-sfx** [94] were used for increasing the accuracy of video recommendation. **DIN** [105] and **DIEN** [104] were proposed for modeling the sequential information like user interests with attention mechanism. Wang et al. proposed **DCN** [83] and **DCN-V2** [84] to automatically and efficiently learn bounded-degree predictive feature interactions. In academia, researchers also proposed important deep recommendation models, such as **FNN** [100], **PNN** [61], **NeuralCF** [32], **NFM** [31], **CVAE** [46]. To address the issue of reproducibility in recommendation model studies [14, 48], [106] developed an open benchmark for CTR prediction, named **FuxiCTR**. Sun et al. [78] created benchmarks, like reproducible and fair evaluation metrics, for implicit-feedback based top-N recommendation algorithms. [102] proposed a unified framework to develop and reproduce recommendation algorithms for the research purpose. There are also some other open source recommendation models which largely advanced the progress of recommender system studies [22, 28, 90].

In recent years, for addressing the biases in recommender systems, there are increasingly studies on causal inference inspired recommendation [19, 96]. Schnabel et al. [73] provided an approach to handling the selection biases by adapting models and estimations from causal inference. Thorsten taught a course named counterfactual machine learning [17] in 2018. Most of the course content was based on examples from information retrieval and recommender systems. In this paper, we do not attempt to give a comprehensive review of all aspects of recommender systems, such as human computer interaction [12, 79], evaluation [4, 15, 59], privacy [2, 98], attacking [44], user experiences [39, 59], fairness [21] etc. There have been a number of thorough surveys about these related research topics. In the rest of the studies, we mainly review two aspects of recommender systems based on our research and industrial experiences, including practical recommendation models and the architectures of typical recommender systems, corresponding to Section 2, 3. Finally, we will briefly discuss some ideas about the future recommender system.

2 RECOMMENDATION MODELS

There have been a number of surveys and books focusing on the recommendation models [23, 65, 99], in this session, we will introduce five kinds of practical recommendation models chronologically. The models are selected mainly based on two principles: the model has important effect on the progress of recommender system, and the model has been successfully deployed on the products.

2.1 Collaborative Filtering

Most of early recommendation models belong to collaborative filtering technologies, K-Nearest-Neighbor (KNN) models predict the user neighbors of a target user u through computing a similarity

between u 's prior preferences and the preferences of other users, then the preferences of the neighbors assigned to a target item i can be as a prediction for u to i [34], this classic recommendation model is known as user-user based collaborative filtering. With the similar way, item-item based collaborative filtering predicts a user's preference to an item i based on the user's preferences on the neighbors of i . When the number of users is more than that of items, item-item based collaborative filtering model is faster than the user-user one [69]. Some studies [82] combine the two kinds of collaborative filtering approaches. To improve the efficiency of recommendation based on big data, the commercial recommender systems applied SVD [70] for reducing the dimensionality of user-item preference matrix to a latent taste dimensions. During the Netflix Prize, the Matrix Factorization (MF) models [43] had been deeply studied for rating prediction task, the MF is another kind of collaborative filtering technology, which is better than the classic KNN models by considering factors like implicit feedback and temporal information. It is interesting to find that the Netflix product did not really use the winner's solution, which uses the ensemble approach for combining different models, too large engineering effort for implementation is one reason [66]. Many recommender systems can only collect positive user feedbacks, so several one-class collaborative filtering models [56, 76] are proposed for such recommendation scenarios, where some missing samples as negative. Yu et al. [95] develop efficient optimization techniques to model "full" samples, where all missing entries as negative samples.

Collaborative filtering based recommendation model is easy to implement and deploy, but there are also some problems, like cold start issues for both user and item, low computing efficiency when the numbers of users and items are huge.

2.2 Linear models

Linear models can mitigate the cold start problem through considering the side information, such as user demographic, historic behaviors, item attributes, contextual information. Logistic regression is one of the most practical linear models for recommendation, especially for the click-through rate (CTR) task [33]. Since it can naturally model the value of CTR between 0 and 1. Given a data set with n instances (y_i, x_i) , $i = 1, \dots, m$, where y_i is the label and x_i is the feature vector, and the model w can be obtained by learning the following optimization:

$$\min_w \frac{\lambda}{2} \|w\|_2^2 + \sum_{i=1}^n \log(1 + \exp(-y_i \phi(w, x_i))), \quad (1)$$

where λ is the regularization parameter and the $\|w\|_2^2$ term is used to avoid overfitting data. The second term in (1) is an approximate sum of training errors by using the logistic loss. The ϕ function is important. Traditionally, a linear model (LM) is considered with $\phi(w, x) = w^T x$. Since every feature corresponds to an individual weight of w , the jointly weight between features is not taken into account. So a sort of feature engineering technologies are proposed for modeling the feature pair conjunction. Beside artificial feature interactions, degree-2 polynomial (*Poly2*) [9] is a widely adopted model, which learns a weight for every possible feature pair. Decision tree plus LR is another practical automatic feature engineering approach, Facebook [33] designs a hybrid model structure, where

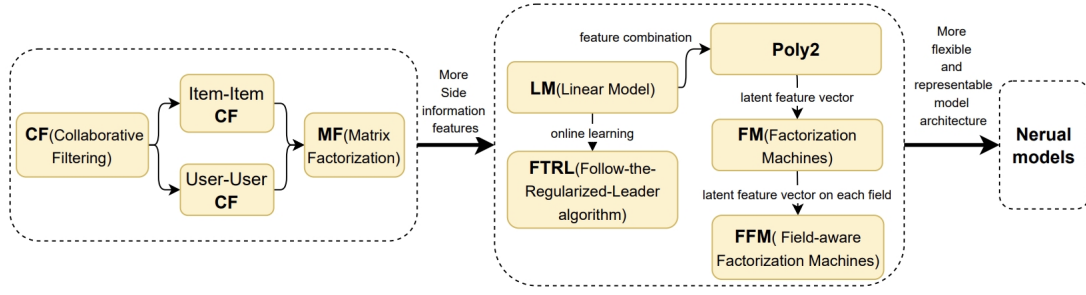


Figure 1: Evolution graph of classic recommendation models

boosted decision tree transforms the input features, and the output of each individual tree can be as the input feature to a logistic linear classifier. There are some important progresses about optimizing algorithms for LR, [26] learns the LR with Bayes optimization for improving the Ads CTR estimator of Microsoft Bing. McMahan et. al. [53] propose the Follow-the-Regularized-Leader (FTRL) algorithm, and then implement an FTRL-Proximal online learning algorithm for improving the accuracy of CTR prediction task [54].

Logistic regression model is practical for industry recommender system, since it is good at modeling the side information and easy to extend. But LR can not model features conjunction by itself, the conjunction operation always depends on artificial feature engineering or other models, like *Poly2* or boost decision trees, so features conjunction and model optimization are two isolate stages.

2.3 Low rank models

Generalized low rank models [80] can approximate a tabular data set by a low rank representation. Matrix factorization and Factorization Machines (FMs) are two popular low rank models, the former one had been introduced in the previous section, while the FMs [63] provides another feature conjunction method, which can decomposes one weight of *Poly2* for each feature pair into the inner product of two k dimensional latent vectors corresponding to each feature in the pair, and the ϕ function in (1) is as following:

$$\phi_{FM}(\mathbf{w}, \mathbf{x}) = \sum_{j_1=1}^n \sum_{j_2=j_1+1}^n (\mathbf{w}_{j_1} \cdot \mathbf{w}_{j_2}) x_{j_1} x_{j_2}, \quad (2)$$

where j_1 (or j_2) are feature indexes, \mathbf{w}_{j_1} (or \mathbf{w}_{j_2}) $\in \mathbb{R}^k$. Because \mathbf{w}_{j_1} and \mathbf{w}_{j_2} are not solely decided by the co-occurrence of feature pair x_{j_1} and x_{j_2} , so FMs can mitigate the issue of insufficiently learning of rare feature pairs. Field-aware Factorization Machines [38] groups features to several fields, and each feature has different latent vector for each field, and the ϕ is as following:

$$\phi_{FFM}(\mathbf{w}, \mathbf{x}) = \sum_{j_1=1}^n \sum_{j_2=j_1+1}^n (\mathbf{w}_{j_1, f_1} \cdot \mathbf{w}_{j_2, f_1}) x_{j_1} x_{j_2}, \quad (3)$$

where f_1 and f_2 are the fields of j_1 and j_2 respectively. When deciding the weight for $x_{j_1} x_{j_2}$, we use j_1 's corresponding latent vector on j_2 's field and j_2 's corresponding latent vector on j_1 's field. FFM won some CTR prediction competitions, like Criteo and Avazu Kaggle competitions. [8] indicated that *Poly2 tends to be good*

at modeling the dense features, while the FM/FFM are useful for sparse ones, so a model-based feature conjunction method named AutoConjunction has been proposed.

Fig.1 summarizes the evaluation of the above classic recommendation models. Feature conjunction is important to the accuracy of recommendation estimator. Although the above models can automatically learn the first and second order feature conjunctions efficiently, it is still hard to extend them to model the combined features more than two. So researchers began to study the neural recommendation models, whose structure are more flexible for advanced feature conjunction.

2.4 Neural models

Since 2016, deep neural network based recommendation model has received rapidly growing attention. It not only became research hotspot in academia, but also dominated development of industry recommender system and brought huge commercial value. Starting from general Multi-layer Perceptron, Fig.2 illustrates main evolution process of deep learning recommendation model which includes the following directions.

Classic deep neural network. Deep Crossing [74] is an early-stage deep learning recommendation model, while its architecture is classic and has been inherited by many following models. Deep Crossing has three main components, such as embedding layer, stacking layer and residual layers. The function of embedding layer is to transform sparse categorical features into dense embeddings. Stacking layer is used for concatenating embedding and other continuous features. The last residual layers consisting of residual units automatically combine features to produce a superior model. YouTubeDNN [13] is another influential model with similar architecture as Deep Crossing. The main difference is that YouTubeDNN uses ReLU neurons instead of residual units as the feature crossing layers. The most valuable thing of YouTubeDNN is that it discloses some details of industry recommendation model, such as feature processing, specific methods of model training and serving.

Two-tower neural network. Since the nature of recommendation is to calculate a user interest to a specific item, two-tower neural network containing user tower and item tower becomes a straight forward solution for recommendation model. CF based matrix factorization is a classic and the simplest two-tower model using dot product to calculate similarity between item and user. NeuralCF [31] replaces dot product with MLP to enhance feature crossing capacity

of the model. Some follow-up studies like YouTube Neural Retrieval Model [94] and Embedding-based Retrieval model of Facebook Search [36] add more features to each tower in the basic two-tower structure. The most important benefit of two-tower structure for industry application is highly efficient model serving. By making use of ANN (Approximate Nearest Neighbor) search in user and item embedding space, recommender system can fetch hundreds of relevant items from millions level candidates pool with a constant time complexity, which is necessary for industry online system.

Shallow and deep model. This type of model mainly refers to the Wide&Deep model [11] and its subsequent variants, such as Deep&Cross [83], DeepFM [29], AFM [92] etc. The main idea is to combine two or more deep learning networks with different advantages to enhance model capability. The original Wide&Deep model is composed of LR and DNN, so it has both advantages of strong memorization of LR and generalization of DNN. To strengthen capability of feature crossing, DeepFM replaces LR with FM as a new wide component, while cross layer takes the place of LR in Deep&Cross. On the other hand, AFM and NFM [31] improve deep component by adding attention net and bi-interaction layers.

Natural Language Processing (NLP) inspired neural model. There are some NLP key technologies have been applied for improving the performance of recommender system. DIN [105] introduces attention mechanism into recommendation model to learn relevance between user historically interactive items and target item. DIEN [104] uses sequence model to learn the evolution trend of user interest. Transformer models, like BERT [16], have achieved great successes for NLP tasks, they are also quickly applied in the field of sequential recommendation, like BERT4Rec [77] and SSE-PT [91].

Deep Reinforcement learning. The environment of online recommender system is a dynamic feedback loop. The user's interactive behaviors are collected in real time and used to the model training process. Reinforcement learning is good at modeling this kind of continuously changing environment. Some early studies on Exploration and Exploitation (E&E), like LinUCB [45], try to use real-time rewards to improve model. Some studies combine deep learning and reinforcement learning, and enhances the recommendation performance by letting the recommendation model learn user rewards in real time. Among these studies, DRN (Deep Reinforcement Learning Network) [103] is a deep Q-Learning based recommendation framework, whose main innovation is to explore model parameter online by using dueling bandit gradient descent. NICF (Neural Interactive Collaborative Filtering) [107] is another typical model which can quickly catch the user's interests through representing the exploration policy with a two-tower neural network.

Graph neural network. Much of internet data is in the form of graphs like knowledge graph, social network and user-item bipartite graph, so how to efficiently use graph structure data has become a key research direction for providing more accurate, diverse, and explainable recommendation. Some random walk based graph embedding approaches, like DeepWalk [58] and Node2vec [27] make initial trails on this direction. In recent years, different methods of graph neural network have been proposed to directly build a recommendation model on the graph structure. RippleNet [81] starts from selected seeding nodes and recursively propagates the embeddings from a node's neighbors to refine the node's embedding. Furthermore, KGAT (Knowledge Graph Attention Network) [87]

adds user-item interaction links into graph and employs an attention mechanism to discriminate the importance of the neighbors based on RippleNet.

2.5 Causality inspired methods

Recently, the researchers in recommender system community have realized the importance of technology evolution from association learning to causal inference, which can not only improve the accuracy but also have potential to benefit the recommendation in a broader scope of perspectives, such as debias, transparency, fairness, evaluation, robustness, etc. Beyond modeling with the statically observed data, the causality based methods can actively explore new situations through intervention, or build and learn the unobserved world with **counterfactual learning methods**. For intervention technologies, [6] makes use of uniform data to handle the bias problems through **Inverse Propensity Score (IPS)**, **Doubly Robust (DR)**, joint learning. [37, 86] apply swap intervention approach to improve the ranking tasks. [1, 24] propose several debiasing methods with natural intervention data, and prove their efficiency for mitigating the position bias of information system. For counterfactual learning, [19] summarizes some counterfactual approaches for modeling three kinds of data, such as observed biased data, observed unbiased data and unobserved data. The counterfactual approaches mainly include **counterfactual data learning**, **the correcting biased observed data** and **doubly robust methods**. The basic idea of counterfactual data learning is that we counterfactually assume that each user expresses his or her preferences to each item, and construct the counterfactual samples. The full information data through combining the factual and counterfactual data has potential to learn a more unbiased model. [10, 96, 97] propose efficient methods to learn the parameters of recommendation model from the whole data (including all missing data). Yang et al. [93] counterfactually simulate user ranking-based preferences to handle the data scarce problem with Pearl's causal inference framework. IPS [73] is the most popular method of the correcting biased data approach, it is defined as the conditional probability of receiving the treatment given pre-treatment covariate [68], but IPS method should satisfy the prerequisite about overlap and unconfoundedness [3], which are not easy to achieve in recommendation scenario when candidates number is large. The doubly robust methods have IPS part and direct method part, corresponding to the first two counterfactual approaches. Dudik et al. [20] prove the DR can yields accurate prediction when either part is a consistent estimator for policy evaluation and learning.

Structural Causal Model (SCM) [57] and Potential Outcome Model (POM) [51] are two mainstream causal frameworks, most of the current causality inspired recommendation studies [52, 85, 101] try to analyze the problems (e.g. biases) with SCM, and a few studies [88] begin to frame recommendation with POM for developing the deconfounded recommender.

3 TYPICAL RECOMMENDER SYSTEMS

Beyond models, the practical recommender systems need other important components. In this section, we will introduce typical recommender systems and their architectures.

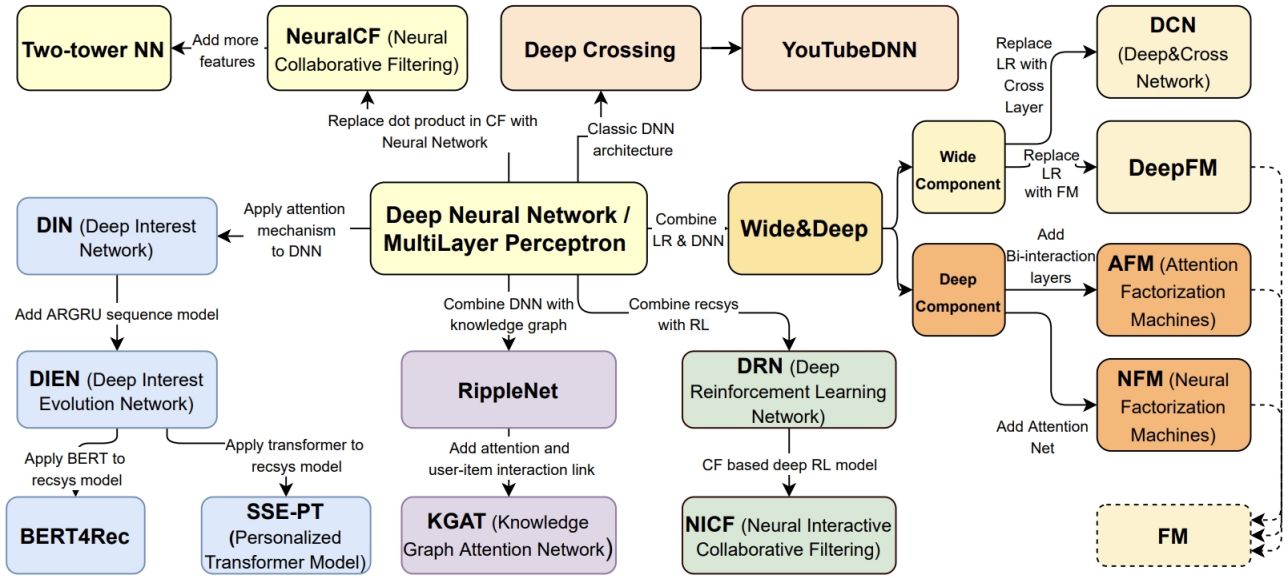


Figure 2: Evolution graph of deep learning recommendation models

Collaborative Filtering based Recommender System. Tapestry [25] is the earliest collaborative filtering based recommender system, which relied on the opinions of people in a small community. The Fig2. in [25] describes the flows of information through the major architectural components of Tapestry, including *Indexer*, *Document store*, *Annotation store*, *Filterer*, *Little box*, *Remailer*, *Appraiser*, *Reader/Browser*. The collaborative filtering of Tapestry can not server large communities, since we can not assume each user knows each others, so the *neighbors* mechanism had been implemented by GroupLens [64] news recommender system, whose architecture is illustrated by the Fig2. in [64] and Fig2. in [71], where the *Better Bit Bureau* is plugged entity to the netnews architecture, it can collect the user preferences from clients, predict the recommendation scores, and send the score to clients. The core components include *WWW Server*, *Dynamic HTML Generator* and *Recommender System*.

Two-layer Recommender System. Bambini et. al. [65] describes how to integrate a recommender system into a real production environment of one IP Television (IPTV) providers. The Fig 9.2 in [65] describes the architecture of the IPTV recommender system, and the Fig 9.3 illustrates the model training in *batch* stage and prediction in *real-time* stage. As far as we know, it is the first public recommender system whose architecture is two-stage architecture. The IPTV recommender system integrates both collaborative filtering models and content-based models for satisfying different kinds of recommendation scenarios. Hulu's technology blog [47] proposes their recommender system architecture, which includes online and offline parts, the former one is in charge of generating recommendation results and contains five main modules, like *User profile builder*, *Recommendation Core*, *Filtering*, *Explanation* and *Ranking*, as shown in Fig 1 in [47]. While the online components rely on offline system, whose components include *Data Center*, *Related Table Generator*, *Topic Model*, *Feedback Analyzer* and *Report Generator*, as shown in Fig 2 in [47].

Three-layer Recommender System. Amatriain and Basilico [66] describe a generic three-layer architecture of recommender system at Netflix, where the *Online Computation* can respond better to recent events, user interaction, and requests in real-time, like generating the recommendation results. The *Offline Computation* has more time to execute more complex computation with more data, like model training. While the *Nearline Computation* is an intermediate between these two computations which can perform online-like computations but not in real-time, like user features updating. The main components of the three-layer architecture have been shown in Fig.11.10 in [66]. Dong [18] introduces a general three-layer architecture diagram for industrial recommender systems, and describes its key components. As shown in Fig.3, there are mainly three layers, named *Offline Module*, *Online Service* and *Nearline Updating*. The *Offline Module* is in charge of model training. It extracts features from *Offline Data Service*, then generate the samples through *Feature Extractor*, and the recommendation model can be learned through the *Modeling* component with batch learning mechanism. After the offline evaluation by *Analyzer*, we select the best model and upload it to the *Predictor* in *Online Service*. The extracted features are also synchronized to the *Indexer* of *Online Service*. The *Online Service* receives and distributes the user's recommendation requirement through *Router*. After parsing the requirement and acquire the user ID, we can get the feature vector x through the *Indexer* and *Feature Extractor*, finally, the *Predictor* computes the recommendation score and generate the recommendation list. The *Nearline Updating* is in charge of updating the features in real-time by *Feature updating*, and updating the recommendation model according to specific scenario through *Model updating*.

4 ABOUT FUTURE

The future is very hard to predict, especially for the fast developing recommender systems and their widely applications. However, we

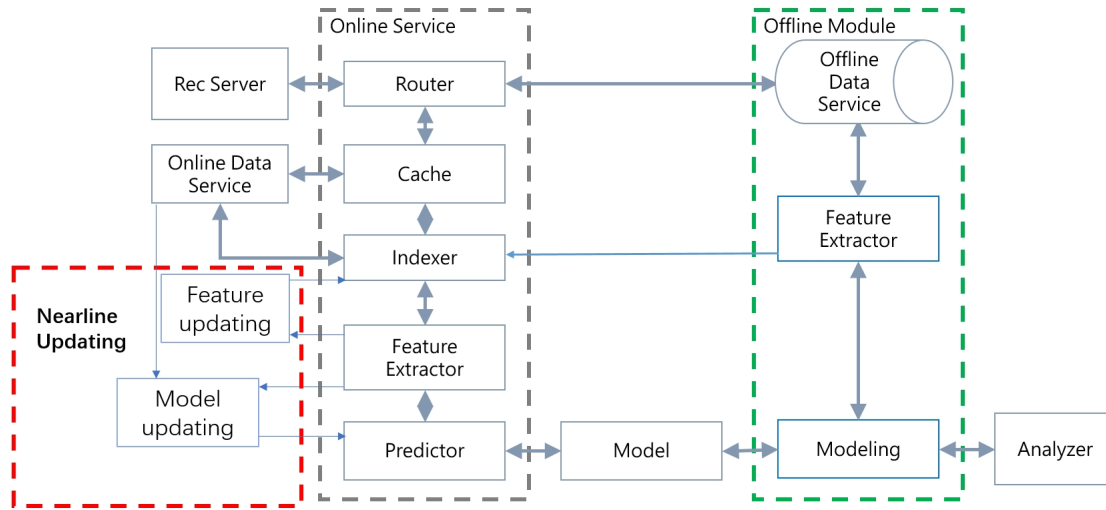


Figure 3: A general three-layer architecture diagram for industrial recommender systems.

hope to summarize some thoughts about the trends of recommendation based on the above history of web recommendation and our practical experiences. We think that the evolution of recommender systems mainly come from two driving forces, technological innovations and valuable industrial applications.

From the perspective of technological paradigm, the large pre-trained model is learned with big data based on self-supervised learning methods. It has potential to make use more past information to learn more efficient recommendation model. On the one hand, the recommender system can make use of the knowledge in the pre-trained model to improve the system efficiency; on the other hand, we also need to explore novel pre-training methods for recommendation tasks through improving the structure and objectives of the classic pre-train models. Human understands and interacts with the world through multimodal information, recommender system also needs to make use of the multimode technologies to model user, item and context. There are some studies [49, 62] about how to learn multimodal pre-train model. Most of the previous recommendation work studied how to learn the associations with delicately complicated models through fitting the observed data. Although the association based learning methods achieve many successes, the disadvantages gradually emerge, such as the performance is unstable in out-of-distribution conditions, the complex models are nontransparent, the prediction result is less responsible. We think the neural science, causal inference and knowledge-enhanced methods have potential to inspire new solutions to handle the problems.

From the perspective of applications, recommender systems serve users, so more intelligent and user-centric applications will emerge, like naturally conversational recommender system and general intelligent assistants, would be the next mainstream recommendation applications. On the one hand, the future recommender system likes the British butler, who is well trained and serves people based on his knowledge and long serving experiences with the master; on the other hand, it also likes a knowledgeable teacher, who can help us to discover new useful information and benefit

our lifelong growth. In the mean time, the user-centric and responsible evaluations would be future studied, we hope the future recommender system can provide more accurate, fair, accountable, knowledgeable, transparent and useful services for improving the user experiences in both long and short term.

ACKNOWLEDGMENTS

Special thanks to Prof. John Riedl for his great and pioneering research in area of recommender systems, and his wonderful conversations with Zhenhua Dong about GroupLens, MovieLens, Net Perception during 2010 to 2011, there is no this work without him. Thanks to the colleagues of Huawei Noah's Ark Lab, there is no this work without their fabulous work in both recommender system applications and academic studies in the past 10 years.

REFERENCES

- [1] Aman Agarwal, Ivan Zaitsev, Xuanhui Wang, Cheng Li, Marc Najork, and Thorsten Joachims. 2019. Estimating position bias without intrusive interventions. In *Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining*. 474–482.
- [2] Esma Aïmeur, Gilles Brassard, José M Fernandez, and Flavien Serge Mani Onana. 2008. A lambic: a privacy-preserving recommender system for electronic commerce. *International Journal of Information Security* 7, 5 (2008), 307–334.
- [3] Peter C Austin. 2011. An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate behavioral research* 46, 3 (2011), 399–424.
- [4] Joeran Beel, Stefan Langer, Marcel Genzmehr, Bela Gipp, Corinna Breiter, and Andreas Nürnberger. 2013. Research paper recommender system evaluation: a quantitative literature survey. In *Proceedings of the International Workshop on Reproducibility and Replication in Recommender Systems Evaluation*. 15–22.
- [5] Nicholas J. Belkin and W. Bruce Croft. 1992. Information filtering and information retrieval: two sides of the same coin? *Communications of The ACM* 35, 12 (1992), 29–38.
- [6] Stephen Bonner and Flavian Vasile. 2018. Causal embeddings for recommendation. In *Proceedings of the 12th ACM conference on recommender systems*. 104–112.
- [7] John S. Breese, David Heckerman, and Carl Kadie. 1998. Empirical analysis of predictive algorithms for collaborative filtering. In *UAI'98 Proceedings of the Fourteenth conference on Uncertainty in artificial intelligence*. 43–52.
- [8] Chih-Yao Chang, Xing Tang, Bo-Wen Yuan, Jui-Yang Hsia, Zhirong Liu, Zhenhua Dong, Xiuqiang He, and Chih-Jen Lin. 2020. AutoConjunction: Adaptive Model-based Feature Conjunction for CTR Prediction. In *2020 21st IEEE International Conference on Mobile Data Management (MDM)*. IEEE, 202–209.
- [9] Yin-Wen Chang, Cho-Jui Hsieh, Kai-Wei Chang, Michael Ringgaard, and Chih-Jen Lin. 2010. Training and testing low-degree polynomial data mappings via linear SVM. *Journal of Machine Learning Research* 11, 4 (2010).
- [10] Chong Chen, Min Zhang, Yongfeng Zhang, Yiqun Liu, and Shaoping Ma. 2020. Efficient neural matrix factorization without sampling for recommendation. *ACM Transactions on Information Systems (TOIS)* 38, 2 (2020), 1–28.
- [11] Heng-Tze Cheng, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, Hrishi Aradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Ispir, Rohan Anil, Zakaria Haque, Lichan Hong, Vihan Jain, Xiaobing Liu, and Hemal Shah. 2016. Wide & Deep Learning for Recommender Systems. In *Proceedings of the 1st Workshop on Deep Learning for Recommender Systems*. 7–10.
- [12] Dan Cosley, Shyong K Lam, Istvan Albert, Joseph A Konstan, and John Riedl. 2003. Is seeing believing? How recommender system interfaces affect users' opinions. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. 585–592.
- [13] Paul Covington, Jay Adams, and Emre Sargin. 2016. Deep Neural Networks for YouTube Recommendations. In *Proceedings of the 10th ACM Conference on Recommender Systems*. 191–198.
- [14] Maurizio Ferrari Dacrema, Paolo Cremonesi, and Dietmar Jannach. 2019. Are we really making much progress? A worrying analysis of recent neural recommendation approaches. In *Proceedings of the 13th ACM Conference on Recommender Systems*. 101–109.
- [15] Félix Hernández Del Olmo and Elena Gaudioso. 2008. Evaluation of recommender systems: A new approach. *Expert Systems with Applications* 35, 3 (2008), 790–804.
- [16] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805* (2018).
- [17] Zhenhua Dong. 2018. Counterfactual Machine Learning. <http://www.cs.cornell.edu/courses/cs7792/2018fa/>. [Online; Fall 2018].
- [18] Zhenhua Dong. 2019. Recommender System for Real Mobile Applications: Two Case Studies. https://www.comp.hkbu.edu.hk/mdm2019/files/slides/ind_dong.pdf. [Online; accessed 13-June-2019].
- [19] Zhenhua Dong, Hong Zhu, Pengxiang Cheng, Xinhua Feng, Guohao Cai, Xiuqiang He, Jun Xu, and Jirong Wen. 2020. Counterfactual learning for recommender system. In *Fourteenth ACM Conference on Recommender Systems*. 568–569.
- [20] Miroslav Dudík, John Langford, and Lihong Li. 2011. Doubly robust policy evaluation and learning. *arXiv preprint arXiv:1103.4601* (2011).
- [21] Michael D Ekstrand, Robin Burke, and Fernando Diaz. 2019. Fairness and discrimination in recommendation and retrieval. In *Proceedings of the 13th ACM Conference on Recommender Systems*. 576–577.
- [22] Michael D Ekstrand, Michael Ludwig, Jack Kolb, and John T Riedl. 2011. LensKit: a modular recommender framework. In *Proceedings of the fifth ACM conference on Recommender systems*. 349–350.
- [23] Michael D Ekstrand, John T Riedl, and Joseph A Konstan. 2011. *Collaborative filtering recommender systems*. Now Publishers Inc.
- [24] Zhichong Fang, Aman Agarwal, and Thorsten Joachims. 2019. Intervention harvesting for context-dependent examination-bias estimation. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*. 825–834.
- [25] David Goldberg, David Nichols, Brian M. Oki, and Douglas Terry. 1992. Using collaborative filtering to weave an information tapestry. *Communications of The ACM* 35, 12 (1992), 61–70.
- [26] Thore Graepel, Joaquin Q. Candela, Thomas Borchert, and Ralf Herbrich. 2010. Web-Scale Bayesian Click-Through rate Prediction for Sponsored Search Advertising in Microsoft's Bing Search Engine. In *Proceedings of the 27th International Conference on Machine Learning*. 13–20.
- [27] Aditya Grover and Jure Leskovec. 2016. node2vec: Scalable feature learning for networks. In *Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining*. 855–864.
- [28] Guibing Guo, Jie Zhang, Zhu Sun, and Neil Yorke-Smith. 2015. Librec: a Java library for recommender systems. In *Workshop on the 23rd Conference on User Modeling, Adaptation, and Personalization, UMAP 2015*, Vol. 1388.
- [29] Huifeng Guo, Ruiming Tang, Yunming Ye, Zhenguo Li, Xiuqiang He, and Zhenhua Dong. 2018. DeepFM: An End-to-End Wide & Deep Learning Framework for CTR Prediction. *arXiv preprint arXiv:1804.04950* (2018).
- [30] F. Maxwell Harper and Joseph A. Konstan. 2015. The MovieLens Datasets: History and Context. *Ksii Transactions on Internet and Information Systems* 5, 4 (2015), 19.
- [31] Xiangnan He and Tat-Seng Chua. 2017. Neural Factorization Machines for Sparse Predictive Analytics. In *Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 355–364.
- [32] Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. 2017. Neural Collaborative Filtering. In *Proceedings of the 26th International Conference on World Wide Web*. 173–182.
- [33] Xinran He, Junfeng Pan, Ou Jin, Tianbing Xu, Bo Liu, Tao Xu, Yanxin Shi, Antoine Atallah, Ralf Herbrich, Stuart Bowers, and Joaquin Quiñero Candela. 2014. Practical Lessons from Predicting Clicks on Ads at Facebook. In *Proceedings of the Eighth International Workshop on Data Mining for Online Advertising*. 1–9.
- [34] Jonathan L. Herlocker, Joseph A. Konstan, Al Borchers, and John Riedl. 1999. An algorithmic framework for performing collaborative filtering. In *Proceedings of the 22nd annual international ACM SIGIR conference on Research and development in information retrieval*, Vol. 51. 230–237.
- [35] Will Hill, Larry Stead, Mark Rosenstein, and George Furnas. 1995. Recommending and evaluating choices in a virtual community of use. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 194–201.
- [36] Jui-Ting Huang, Ashish Sharma, Shuying Sun, Li Xia, David Zhang, Philip Pronin, Janani Padmanabhan, Giuseppe Ottaviano, and Linjun Yang. 2020. Embedding-based retrieval in facebook search. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 2553–2561.
- [37] Thorsten Joachims, Adith Swaminathan, and Tobias Schnabel. 2017. Unbiased learning-to-rank with biased feedback. In *Proceedings of the Tenth ACM International Conference on Web Search and Data Mining*. 781–789.
- [38] Yuchin Juan, Yong Zhuang, Wei-Sheng Chin, and Chih-Jen Lin. 2016. Field-aware Factorization Machines for CTR Prediction. In *Proceedings of the 10th ACM Conference on Recommender Systems*. 43–50.
- [39] Joseph A. Konstan and John Riedl. 2012. Recommender systems: from algorithms to user experience. *User Modeling and User-adapted Interaction* 22, 1 (2012), 101–123.
- [40] Joseph A. Konstan, John Riedl, and Barry Smyth. 2007. Proceedings of the 2007 ACM conference on Recommender systems. In *Proceedings of the 2007 ACM conference on Recommender systems*.
- [41] Yehuda Koren. 2008. Factorization meets the neighborhood: a multifaceted collaborative filtering model. In *Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining*. 426–434.
- [42] Yehuda Koren. 2010. Collaborative filtering with temporal dynamics. *Communications of The ACM* 53, 4 (2010), 89–97.
- [43] Yehuda Koren, Robert Bell, and Chris Volinsky. 2009. Matrix factorization techniques for recommender systems. *Computer* 42, 8 (2009), 30–37.
- [44] Shyong K Lam and John Riedl. 2004. Shilling recommender systems for fun and profit. In *Proceedings of the 13th international conference on World Wide Web*. 393–402.
- [45] Lihong Li, Wei Chu, John Langford, and Robert E Schapire. 2010. A contextual-bandit approach to personalized news article recommendation. In *Proceedings of the 19th international conference on World wide web*. 661–670.
- [46] Xiaopeng Li and James She. 2017. Collaborative Variational Autoencoder for Recommender Systems. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. 305–314.
- [47] Hang Li Liang Xiang, Hua Zheng. 2011. Hulu's Recommendation System. <https://www.cnblogs.com/zhenjing/articles/hulu-recommendation-system.html>. [Online; 2011].
- [48] Jimmy Lin. 2019. The Neural Hype and Comparisons Against Weak Baselines. *international acm sigir conference on research and development in information retrieval* 52, 2 (2019), 40–51.
- [49] Junyang Lin, Rui Men, An Yang, Chang Zhou, Ming Ding, Yichang Zhang, Peng Wang, Ang Wang, Le Jiang, Xianyan Jia, et al. 2021. M6: A chinese multimodal

- pretrainer. *arXiv preprint arXiv:2103.00823* (2021).
- [50] G. Linden, B. Smith, and J. York. 2003. Amazon.com recommendations: item-to-item collaborative filtering. *IEEE Internet Computing* 7, 1 (2003), 76–80.
 - [51] Roderick J Little and Donald B Rubin. 2000. Causal effects in clinical and epidemiological studies via potential outcomes: concepts and analytical approaches. *Annual review of public health* 21, 1 (2000), 121–145.
 - [52] Dugang Liu, Pengxiang Cheng, Hong Zhu, Zhenhua Dong, Xiuqiang He, Weike Pan, and Zhong Ming. 2021. Mitigating Confounding Bias in Recommendation via Information Bottleneck. In *Fifteenth ACM Conference on Recommender Systems*. 351–360.
 - [53] H. Brendan McMahan. 2011. Follow-the-Regularized-Leader and Mirror Descent: Equivalence Theorems and L1 Regularization. In *Proceedings of the Fourteenth International Conference on Artificial Intelligence and Statistics*. 525–533.
 - [54] H. Brendan McMahan, Gary Holt, D. Sculley, Michael Young, Dietmar Ebner, Julian Grady, Lan Nie, Todd Phillips, Eugene Davydov, Daniel Golovin, Sharat Chikkerur, Dan Liu, Martin Wattenberg, Arnar Mar Hrafnkelsson, Tom Boulos, and Jeremy Kubica. 2013. Ad click prediction: a view from the trenches. In *Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining*. 1222–1230.
 - [55] Sean M. McNee, John Riedl, and Joseph A. Konstan. 2006. Being accurate is not enough: how accuracy metrics have hurt recommender systems. In *CHI '06 Extended Abstracts on Human Factors in Computing Systems*. 1097–1101.
 - [56] Rong Pan, Yunhong Zhou, Bin Cao, Nathan N Liu, Rajan Lukose, Martin Scholz, and Qiang Yang. 2008. One-class collaborative filtering. In *2008 Eighth IEEE International Conference on Data Mining*. IEEE, 502–511.
 - [57] Judea Pearl. 2009. *Causality*. Cambridge university press.
 - [58] Bryan Perozzi, Rami Al-Rfou, and Steven Skiena. 2014. Deepwalk: Online learning of social representations. In *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining*. 701–710.
 - [59] Pearl Pu, Li Chen, and Rong Hu. 2011. A user-centric evaluation framework for recommender systems. In *Proceedings of the fifth ACM conference on Recommender systems*, Vol. 612. 157–164.
 - [60] Pearl Pu, Li Chen, and Rong Hu. 2012. Evaluating recommender systems from the user's perspective: survey of the state of the art. *User Modeling and User-adapted Interaction* 22, 4 (2012), 317–355.
 - [61] Yanru Qu, Han Cai, Kan Ren, Weinan Zhang, Yong Yu, Ying Wen, and Jun Wang. 2016. Product-Based Neural Networks for User Response Prediction. In *2016 IEEE 16th International Conference on Data Mining (ICDM)*. 1149–1154.
 - [62] Wasifur Rahman, Md Kamrul Hasan, Sangwu Lee, Amir Zadeh, Chengfeng Mao, Louis-Philippe Morency, and Ehsan Hoque. 2020. Integrating multimodal information in large pretrained transformers. In *Proceedings of the conference. Association for Computational Linguistics. Meeting*, Vol. 2020. NIH Public Access, 2359.
 - [63] Steffen Rendle. 2010. Factorization Machines. In *2010 IEEE International Conference on Data Mining*. 995–1000.
 - [64] Paul Resnick, Neophytos Iacovou, Mitesh Suchak, Peter Bergstrom, and John Riedl. 1994. GroupLens: An Open Architecture for Collaborative Filtering of Netnews. *Research Papers in Economics* (1994).
 - [65] Francesco Ricci, Lior Rokach, and Bracha Shapira. 2011. Introduction to recommender systems handbook. In *Recommender systems handbook*. Springer, 1–35.
 - [66] Francesco Ricci, Lior Rokach, and Bracha Shapira. 2015. Recommender systems: introduction and challenges. In *Recommender systems handbook*. Springer, 1–34.
 - [67] Matthew Richardson, Ewa Dominowska, and Robert Ragno. 2007. Predicting clicks: estimating the click-through rate for new ads. In *Proceedings of the 16th international conference on World Wide Web*. 521–530.
 - [68] Paul R Rosenbaum and Donald B Rubin. 1984. Reducing bias in observational studies using subclassification on the propensity score. *Journal of the American statistical Association* 79, 387 (1984), 516–524.
 - [69] Badrul Sarwar, George Karypis, Joseph Konstan, and John Riedl. 2001. Item-based collaborative filtering recommendation algorithms. In *Proceedings of the 10th international conference on World Wide Web*. 285–295.
 - [70] Badrul Sarwar, George Karypis, Joseph Konstan, and John Riedl. 2002. Incremental singular value decomposition algorithms for highly scalable recommender systems. In *Fifth international conference on computer and information science*, Vol. 1. Citeseer, 27–8.
 - [71] Badrul Sarwar, George Karypis, Joseph Konstan, and John T. Riedl. 2000. Application of Dimensionality Reduction in Recommender System - A Case Study. citeseer.ist.psu.edu/sarwar00application.html (2000).
 - [72] J. Ben Schafer, Joseph Konstan, and John Riedl. 1999. Recommender systems in e-commerce. In *Proceedings of the 1st ACM conference on Electronic commerce*. 158–166.
 - [73] Tobias Schnabel, Adith Swaminathan, Ashudeep Singh, Navin Chandak, and Thorsten Joachims. 2016. Recommendations as treatments: Debiasing learning and evaluation. In *international conference on machine learning*. PMLR, 1670–1679.
 - [74] Ying Shan, T Ryan Hoens, Jian Jiao, Haijing Wang, Dong Yu, and JC Mao. 2016. Deep crossing: Web-scale modeling without manually crafted combinatorial features. In *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*. 255–262.
 - [75] Upendra Shardanand and Pattie Maes. 1995. Social information filtering: algorithms for automating “word of mouth”. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 210–217.
 - [76] Vikas Sindhwani, Serhat S Bucak, Jianying Hu, and Aleksandra Mojsilovic. 2010. One-class matrix completion with low-density factorizations. In *2010 IEEE international conference on data mining*. IEEE, 1055–1060.
 - [77] Fei Sun, Jun Liu, Jian Wu, Changhua Pei, Xiao Lin, Wenwu Ou, and Peng Jiang. 2019. BERT4Rec: Sequential recommendation with bidirectional encoder representations from transformer. In *Proceedings of the 28th ACM international conference on information and knowledge management*. 1441–1450.
 - [78] Zhu Sun, Di Yu, Hui Fang, Jie Yang, Xinghua Qu, Jie Zhang, and Cong Geng. 2020. Are We Evaluating Rigorously? Benchmarking Recommendation for Reproducible Evaluation and Fair Comparison. In *Fourteenth ACM Conference on Recommender Systems*. 23–32.
 - [79] Kirsten Swearingen and Rashmi Sinha. 2001. Beyond algorithms: An HCI perspective on recommender systems. In *ACM SIGIR 2001 workshop on recommender systems*, Vol. 13. Citeseer, 1–11.
 - [80] Madeleine Udell. 2015. *Generalized low rank models*. Stanford University.
 - [81] Hongwei Wang, Fuzheng Zhang, Jialin Wang, Miao Zhao, Wenjie Li, Xing Xie, and Minyi Guo. 2018. RippletNet: Propagating user preferences on the knowledge graph for recommender systems. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*. 417–426.
 - [82] Jun Wang, Arjen P De Vries, and Marcel JT Reinders. 2006. Unifying user-based and item-based collaborative filtering approaches by similarity fusion. In *Proceedings of the 29th annual international ACM SIGIR conference on Research and development in information retrieval*. 501–508.
 - [83] Ruoxi Wang, Bin Fu, Gang Fu, and Mingliang Wang. 2017. Deep & Cross Network for Ad Click Predictions. In *Proceedings of the ADKDD'17*. 12.
 - [84] Ruoxi Wang, Rakesh Shivanna, Derek Cheng, Sagar Jain, Dong Lin, Lichan Hong, and Ed Chi. 2021. DCN V2: Improved Deep & Cross Network and Practical Lessons for Web-scale Learning to Rank Systems. In *Proceedings of the Web Conference 2021*. 1785–1797.
 - [85] Wenjie Wang, Fuli Feng, Xiangnan He, Hanwang Zhang, and Tat-Seng Chua. 2021. Clicks can be cheating: Counterfactual recommendation for mitigating clickbait issue. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 1288–1297.
 - [86] Xuanhui Wang, Nadav Golbandi, Michael Bendersky, Donald Metzler, and Marc Najork. 2018. Position bias estimation for unbiased learning to rank in personal search. In *Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining*. 610–618.
 - [87] Xiang Wang, Xiangnan He, Yixin Cao, Meng Liu, and Tat-Seng Chua. 2019. Kgat: Knowledge graph attention network for recommendation. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 950–958.
 - [88] Yixin Wang, Dawen Liang, Laurent Charlin, and David M Blei. 2020. Causal inference for recommender systems. In *Fourteenth ACM Conference on Recommender Systems*. 426–431.
 - [89] Contributing Writer. 2013. Fine Tuning the Social Web: John Riedl. <https://research.umn.edu/inquiry/post/fine-tuning-social-web-john-riedl>. [Online; accessed 19-July-2008].
 - [90] Contributing Writer. 2020. Fine Tuning the Social Web: John Riedl. <https://research.umn.edu/inquiry/post/fine-tuning-social-web-john-riedl>.
 - [91] Liwei Wu, Shuqing Li, Cho-Jui Hsieh, and James Sharpnack. 2020. SSE-PT: Sequential recommendation via personalized transformer. In *Fourteenth ACM Conference on Recommender Systems*. 328–337.
 - [92] 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. *arXiv preprint arXiv:1708.04617* (2017).
 - [93] Mengyue Yang, Quanyu Dai, Zhenhua Dong, Xu Chen, Xiuqiang He, and Jun Wang. 2021. Top-N Recommendation with Counterfactual User Preference Simulation. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*. 2342–2351.
 - [94] Xinyang Yi, Ji Yang, Lichan Hong, Derek Zhiyuan Cheng, Lukasz Heldt, Aditee Kumthekar, Zhe Zhao, Li Wei, and Ed Chi. 2019. Sampling-bias-corrected neural modeling for large corpus item recommendations. In *Proceedings of the 13th ACM Conference on Recommender Systems*. 269–277.
 - [95] Hsiang-Fu Yu, Mikhail Bilenko, and Chih-Jen Lin. 2017. Selection of negative samples for one-class matrix factorization. In *Proceedings of the 2017 SIAM International Conference on Data Mining*. SIAM, 363–371.
 - [96] Bowen Yuan, Jui-Yang Hsia, Meng-Yuan Yang, Hong Zhu, Chih-Yao Chang, Zhenhua Dong, and Chih-Jen Lin. 2019. Improving Ad Click Prediction by Considering Non-displayed Events. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management*. 329–338.
 - [97] Bowen Yuan, Yaxu Liu, Jui-Yang Hsia, Zhenhua Dong, and Chih-Jen Lin. 2020. Unbiased Ad click prediction for position-aware advertising systems. In *Fourteenth ACM Conference on Recommender Systems*. 368–377.

- [98] Justin Zhan, Chia-Lung Hsieh, I-Cheng Wang, Tsan-Sheng Hsu, Churn-Jung Liao, and Da-Wei Wang. 2010. Privacy-preserving collaborative recommender systems. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)* 40, 4 (2010), 472–476.
- [99] Shuai Zhang, Lina Yao, Aixin Sun, and Yi Tay. 2019. Deep learning based recommender system: A survey and new perspectives. *ACM Computing Surveys (CSUR)* 52, 1 (2019), 1–38.
- [100] Weinan Zhang, Tianming Du, and Jun Wang. 2016. Deep learning over Multi-Field categorical Data - A case study on user response prediction. In *ECIR*. 45–57.
- [101] Yang Zhang, Fuli Feng, Xiangnan He, Tianxin Wei, Chonggang Song, Guohui Ling, and Yongdong Zhang. 2021. Causal Intervention for Leveraging Popularity Bias in Recommendation. *arXiv preprint arXiv:2105.06067* (2021).
- [102] Wayne Xin Zhao, Shanlei Mu, Yupeng Hou, Zihan Lin, Kaiyuan Li, Yushuo Chen, Yujie Lu, Hui Wang, Changxin Tian, Xingyu Pan, Yingqian Min, Zhichao Feng, Xinyan Fan, Xu Chen, Pengfei Wang, Wendi Ji, Yaliang Li, Xiaoling Wang, and Ji-Rong Wen. 2020. RecBole: Towards a Unified, Comprehensive and Efficient Framework for Recommendation Algorithms. *arXiv: Information Retrieval* (2020).
- [103] Guanjie Zheng, Fuzheng Zhang, Zihan Zheng, Yang Xiang, Nicholas Jing Yuan, Xing Xie, and Zhenhui Li. 2018. DRN: A deep reinforcement learning framework for news recommendation. In *Proceedings of the 2018 World Wide Web Conference*. 167–176.
- [104] Guorui Zhou, Na Mou, Ying Fan, Qi Pi, Weijie Bian, Chang Zhou, Xiaoqiang Zhu, and Kun Gai. 2019. Deep Interest Evolution Network for Click-Through Rate Prediction. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 33. 5941–5948.
- [105] Guorui Zhou, Xiaoqiang Zhu, Chenru 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 *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery; Data Mining*. 1059–1068.
- [106] Jieming Zhu, Jinyang Liu, Shuai Yang, Qi Zhang, and Xiuqiang He. 2020. Fuxi-CTR: An Open Benchmark for Click-Through Rate Prediction. *arXiv preprint arXiv:2009.05794* (2020).
- [107] Lixin Zou, Long Xia, Yulong Gu, Xiangyu Zhao, Weidong Liu, Jimmy Xiangji Huang, and Dawei Yin. 2020. Neural interactive collaborative filtering. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*. 749–758.