Table 1. The categorization of experimental settings in the collected papers. (Part one)

Aspect	Factors	Options	Papers
Evaluation metrics	Metrics incorporated in evaluation	Recall	[32] [93] [23] [66] [25] [74] [67] [82] [64] [70] [48] [16] [40] [4] [86] [85] [29] [44] [53]
		NDCG	[23] [66] [7] [25] [74] [20] [15] [67] [76] [21] [82] [59] [70] [13] [72] [75] [84] [30] [12] [48] [16] [45] [1] [40] [46] [4] [85] [42] [77] [53]
		AUC	[7] [48]
	Sampled metrics	Sampled	[32] [23] [15] [76] [21] [59] [72] [84] [12] [45] [1] [87] [46] [44] [42] [77]
		Non-sampled	[93] [10] [66] [7] [25] [20] [67] [64] [70] [88] [13] [75] [30] [81] [16] [4] [86] [29] [85] [53]
Dataset construction	Number of used datasets	≥ 3	[10] [23] [66] [74] [20] [15] [67] [82] [64] [59] [70] [88] [75] [84] [30] [12] [48] [18] [16] [45] [1] [40] [46] [4] [86] [42]
		<3	[32] [93] [7] [25] [76] [21] [13] [72] [81] [87] [85] [29] [44] [77] [53]
	Dataset filtering	*n*-core filtering	[32] [93] [66] [7] [25] [67] [20] [21] [82] [59] [88] [13] [72] [84] [81] [12] [18] [16] [1] [40] [4] [86] [85] [29] [42] [77]
		Original or neglection	[23] [74] [15] [76] [64] [70] [75] [30] [48] [45] [87] [46] [44] [53]
	Dataset splitting	RO_RS	[23] [66] [25] [74] [67] [82] [64] [70] [30] [81] [16] [40] [87] [4] [86] [85] [29] [44] [42]
		RO_LS	[32] [10] [20] [76] [88] [48] [18] [45] [46] [53]
		TO_RS	[93] [7] [74]
		TO_LS	[15] [20] [76] [21] [59] [13] [72] [75] [84] [12] [1]
Model optimization	Objective function	BPR-based	[66] [7] [25] [20] [15] [67] [76] [82] [59] [70] [13] [75] [81] [48] [1] [4] [85] [29] [44] [77] [53]
		BCE-based	[93] [10] [23] [74] [21] [64] [84] [30] [12] [45] [86] [42]
	Hyper-parameters	Reported	[32] [10] [7] [74] [67] [64] [88] [30] [81] [16] [1] [40] [85] [29]
		Not reported	[93] [23] [66] [25] [20] [21] [76] [15] [82] [59] [70] [13] [75] [72] [84] [12] [48] [45] [46] [4] [86] [44] [42] [77] [53]

Table 2. The categorization of experimental settings in the collected papers. (Part two)

Aspect	Factors	Options	Papers
Evaluation metrics	Metrics incorporated in evaluation	Recall	[57] [63] [41] [68] [73] [22] [43] [3] [63] [5] [39] [65] [14] [31] [34] [51] [60] [92] [49] [37] [90] [47] [52] [62] [58] [38] [71]
		NDCG	[41] [6] [78] [2] [68] [43] [3] [80] [39] [36] [91] [9] [26] [19] [79] [17] [65] [83] [33] [34] [69] [24] [51] [60] [49] [37] [11] [35] [52] [58] [38] [71]
		AUC	[89] [73] [55] [54] [61] [33] [27] [50]
	Sampled metrics	Sampled	[41] [8] [43] [80] [9] [26] [79] [83] [69] [24] [11] [71]
		Non-sampled	[68] [22] [3] [39] [19] [17] [61] [31] [60] [90] [58] [28]
Dataset construction	Number of used datasets	≥ 3	[63] [41] [8] [68] [73] [22] [63] [5] [55] [80] [36] [9] [26] [54] [65] [14] [61] [31] [34] [69] [60] [92] [37] [11] [52] [50] [62] [58] [28] [38] [71]
		<3	[57] [89] [6] [78] [2] [43] [3] [39] [91] [19] [17] [83] [33] [24] [51] [56] [49] [90] [27] [47] [35]
	Dataset filtering	*n*-core filtering	[41] [6] [78] [68] [22] [43] [5] [80] [39] [36] [9] [26] [79] [92] [11] [47] [35] [50] [58] [28] [38] [71]
		Original or neglection	[57] [63] [89] [2] [8] [73] [63] [91] [17] [65] [14] [83] [61] [31] [34] [69] [24] [51] [60] [56] [49] [37] [90] [27] [52] [62]
	Dataset splitting	RO_RS	[57] [41] [2] [68] [22] [3] [63] [5] [36] [19] [17] [65] [14] [61] [31] [34] [69] [24] [92] [49] [90] [47] [52] [62] [38]
		RO_LS	[8] [28]
		TO_RS	[91] [56] [27] [58] [71]
		TO_LS	[6] [78] [43] [80] [9] [26] [79] [83] [11]
Model optimization	Objective function	BPR-based	[89] [6] [78] [68] [22] [43] [3] [63] [5] [55] [33] [92] [49] [11] [27] [47]
		BCE-based	[57] [63] [41] [8] [80] [36] [9] [26] [19] [79] [54] [65] [34] [69] [24] [56] [50] [62] [58] [38] [71]
	Hyper-parameters	Reported	[63] [41] [8] [68] [63] [22] [39] [79] [54] [65] [14] [33] [69] [90] [47] [38]
		Not reported	[57] [89] [6] [78] [2] [73] [43] [3] [5] [55] [80] [36] [91] [9] [26] [19] [17] [83] [61] [31] [34] [24] [51] [60] [92] [56] [49] [37] [11] [27] [35] [52] [50] [62] [58] [28] [71]

1 PAPER COLLECTION AND OPTION CATEGORIZATION

REFERENCES

[1] Oren Barkan, Yonatan Fuchs, Avi Caciularu, and Noam Koenigstein. 2020. Explainable Recommendations via Attentive Multi-Persona Collaborative Filtering. In *Fourteenth ACM Conference on Recommender Systems* (Virtual Event, Brazil) *(RecSys '20)*. Association for Computing Machinery, New York, NY, USA, 468–473. https://doi.org/10.1145/3383313.3412226

[2] Rocío Cañamares and Pablo Castells. 2018. Should I follow the crowd? A probabilistic analysis of the effectiveness of popularity in recommender systems. In *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval*. 415–424.

[3] Yixin Cao, Xiang Wang, Xiangnan He, Zikun Hu, and Tat-Seng Chua. 2019. Unifying knowledge graph learning and recommendation: Towards a better understanding of user preferences. In *The world wide web conference*. 151–161.

[4] Chong Chen, Min Zhang, Yiqun Liu, and Shaoping Ma. 2019. Social Attentional Memory Network: Modeling Aspect- and Friend-Level Differences in Recommendation. In *Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining* (Melbourne VIC, Australia) *(WSDM '19)*. Association for Computing Machinery, New York, NY, USA, 177–185. https://doi.org/10.1145/3289600.3290982

[5] Chih-Ming Chen, Chuan-Ju Wang, Ming-Feng Tsai, and Yi-Hsuan Yang. 2019. Collaborative similarity embedding for recommender systems. In *The World Wide Web Conference*. 2637–2643.

[6] Jingyuan Chen, Hanwang Zhang, Xiangnan He, Liqiang Nie, Wei Liu, and Tat-Seng Chua. 2017. Attentive collaborative filtering: Multimedia recommendation with item-and component-level attention. In *Proceedings of the 40th International ACM SIGIR conference on Research and Development in Information Retrieval*. 335–344.

[7] Yihong Chen, Bei Chen, Xiangnan He, Chen Gao, Yong Li, Jian-Guang Lou, and Yue Wang. 2019. λ Opt: Learn to Regularize Recommender Models in Finer Levels. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (Anchorage, AK, USA) *(KDD '19)*. Association for Computing Machinery, New York, NY, USA, 978–986. https://doi.org/10.1145/3292500.3330880

[8] Yifan Chen, Pengjie Ren, Yang Wang, and Maarten de Rijke. 2019. Bayesian personalized feature interaction selection for factorization machines. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*. 665–674.

[9] Weiyu Cheng, Yanyan Shen, Yanmin Zhu, and Linpeng Huang. 2018. DELF: A Dual-Embedding based Deep Latent Factor Model for Recommendation.. In *IJCAI*, Vol. 18. 13–19.

[10] Evangelia Christakopoulou and George Karypis. 2018. Local Latent Space Models for Top-N Recommendation. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (London, United Kingdom) *(KDD '18)*. Association for Computing Machinery, New York, NY, USA, 1235–1243. https://doi.org/10.1145/3219819.3220112

[11] Felipe Soares da Costa and Peter Dolog. 2019. Collective embedding for neural context-aware recommender systems. In *Proceedings of the 13th ACM Conference on Recommender Systems*. 201–209.

[12] Zhi-Hong Deng, Ling Huang, Chang-Dong Wang, Jian-Huang Lai, and Philip S. Yu. 2019. DeepCF: A Unified Framework of Representation Learning and Matching Function Learning in Recommender System. *Proceedings of the AAAI Conference on Artificial Intelligence* 33, 01 (Jul. 2019), 61–68. https://doi.org/10.1609/aaai.v33i01.330161

[13] Jingtao Ding, Guanghui Yu, Yong Li, Xiangnan He, and Depeng Jin. 2020. Improving Implicit Recommender Systems with Auxiliary Data. *ACM Trans. Inf. Syst.* 38, 1, Article 11 (Feb. 2020), 27 pages. https://doi.org/10.1145/3372338

[14] Trong Dinh Thac Do and Longbing Cao. 2018. Coupled poisson factorization integrated with user/item metadata for modeling popular and sparse ratings in scalable recommendation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 32.

[15] Travis Ebesu, Bin Shen, and Yi Fang. 2018. Collaborative Memory Network for Recommendation Systems. In *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval* (Ann Arbor, MI, USA) *(SIGIR '18)*. Association for Computing Machinery, New York, NY, USA, 515–524. https://doi.org/10.1145/3209978.3209991

[16] Ehtsham Elahi, Wei Wang, Dave Ray, Aish Fenton, and Tony Jebara. 2019. Variational Low Rank Multinomials for Collaborative Filtering with Side-Information. In *Proceedings of the 13th ACM Conference on Recommender Systems* (Copenhagen, Denmark) *(RecSys '19)*. Association for Computing Machinery, New York, NY, USA, 340–347. https://doi.org/10.1145/3298689.3347036

[17] Wenqi Fan, Tyler Derr, Yao Ma, Jianping Wang, Jiliang Tang, and Qing Li. 2019. Deep adversarial social recommendation. *arXiv preprint arXiv:1905.13160* (2019).

[18] Evgeny Frolov and Ivan Oseledets. 2019. HybridSVD: When Collaborative Information is Not Enough. In *Proceedings of the 13th ACM Conference on Recommender Systems* (Copenhagen, Denmark) *(RecSys '19)*. Association for Computing Machinery, New York, NY, USA, 331–339. https://doi.org/10.1145/3298689.3347055

[19] Guibing Guo, Enneng Yang, Li Shen, Xiaochun Yang, and Xiaodong He. 2019. Discrete Trust-aware Matrix Factorization for Fast Recommendation.. In *IJCAI*. 1380–1386.

[20] Xiangnan He, Zhankui He, Xiaoyu Du, and Tat-Seng Chua. 2018. Adversarial Personalized Ranking for Recommendation. In *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval* (Ann Arbor, MI, USA) *(SIGIR '18)*. Association for Computing Machinery, New York, NY, USA, 355–364. https://doi.org/10.1145/3209978.3209981

[21] Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. 2017. Neural Collaborative Filtering *(WWW '17)*. International World Wide Web Conferences Steering Committee, Republic and Canton of Geneva, CHE, 173–182. https://doi.org/10.1145/3038912.3052569

[22] Cheng-Kang Hsieh, Longqi Yang, Yin Cui, Tsung-Yi Lin, Serge Belongie, and Deborah Estrin. 2017. Collaborative metric learning. In *Proceedings of the 26th international conference on world wide web*. 193–201.

[23] 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 *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (London, United Kingdom) *(KDD '18)*. Association for Computing Machinery, New York, NY, USA, 1531–1540. https://doi.org/10.1145/3219819.3219965

[24] Liang Hu, Songlei Jian, Longbing Cao, Zhiping Gu, Qingkui Chen, and Artak Amirbekyan. 2019. Hers: Modeling influential contexts with heterogeneous relations for sparse and cold-start recommendation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 33. 3830–3837.

[25] Shuyi Ji, Yifan Feng, Rongrong Ji, Xibin Zhao, Wanwan Tang, and Yue Gao. 2020. Dual Channel Hypergraph Collaborative Filtering. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (Virtual Event, CA, USA) *(KDD '20)*. Association for Computing Machinery, New York, NY, USA, 2020–2029. https://doi.org/10.1145/3394486.3403253

[26] Junyang Jiang, Deqing Yang, Yanghua Xiao, and Chenlu Shen. 2020. Convolutional Gaussian embeddings for personalized recommendation with uncertainty. *arXiv preprint arXiv:2006.10932* (2020).

[27] Zhengshen Jiang, Hongzhi Liu, Bin Fu, Zhonghai Wu, and Tao Zhang. 2018. Recommendation in heterogeneous information networks based on generalized random walk model and bayesian personalized ranking. In *Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining*. 288–296.

[28] Wang-Cheng Kang and Julian McAuley. 2019. Candidate generation with binary codes for large-scale Top-N recommendation. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management*. 1523–1532.

[29] Dung D. Le and Hady W. Lauw. 2017. Indexable Bayesian Personalized Ranking for Efficient Top-k Recommendation. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management* (Singapore, Singapore) *(CIKM '17)*. Association for Computing Machinery, New York, NY, USA, 1389–1398. https://doi.org/10.1145/3132847.3132913

[30] DongSheng Li, Chao Chen, Qin Lv, Li Shang, Stephen Chu, and Hongyuan Zha. 2017. ERMMA: Expected Risk Minimization for Matrix Approximation-based Recommender Systems. https://aaai.org/ocs/index.php/AAAI/AAAI17/paper/view/14625

[31] Jingjing Li, Mengmeng Jing, Ke Lu, Lei Zhu, Yang Yang, and Zi Huang. 2019. From zero-shot learning to cold-start recommendation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 33. 4189–4196.

[32] 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*. Association for Computing Machinery, New York, NY, USA, 305–314. https://doi.org/10.1145/3097983.3098077

[33] Chen Lin, Xiaolin Shen, Si Chen, Muhua Zhu, and Yanghua Xiao. 2019. Non-compensatory psychological models for recommender systems. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 33. 4304–4311.

[34] Chenghao Liu, Xin Wang, Tao Lu, Wenwu Zhu, Jianling Sun, and Steven Hoi. 2019. Discrete social recommendation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 33. 208–215.

[35] Dugang Liu, Chen Lin, Zhilin Zhang, Yanghua Xiao, and Hanghang Tong. 2019. Spiral of silence in recommender systems. In *Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining*. 222–230.

[36] Han Liu, Xiangnan He, Fuli Feng, Liqiang Nie, Rui Liu, and Hanwang Zhang. 2018. Discrete factorization machines for fast feature-based recommendation. *arXiv preprint arXiv:1805.02232* (2018).

[37] Huafeng Liu, Jingxuan Wen, Liping Jing, and Jian Yu. 2019. Deep generative ranking for personalized recommendation. In *Proceedings of the 13th ACM Conference on Recommender Systems*. 34–42.

[38] Ninghao Liu, Yong Ge, Li Li, Xia Hu, Rui Chen, and Soo-Hyun Choi. 2020. Explainable Recommender Systems via Resolving Learning Representations. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*. 895–904.

[39] Yong Liu, Lifan Zhao, Guimei Liu, Xinyan Lu, Peng Gao, Xiao-Li Li, and Zhihui Jin. 2018. Dynamic Bayesian Logistic Matrix Factorization for Recommendation with Implicit Feedback.. In *IJCAI*, Vol. 18. 3463–3469.

[40] Chen Ma, Peng Kang, Bin Wu, Qinglong Wang, and Xue Liu. 2019. Gated Attentive-Autoencoder for Content-Aware Recommendation. In *Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining* (Melbourne VIC, Australia) *(WSDM '19)*. Association for Computing Machinery, New York, NY, USA, 519–527. https://doi.org/10.1145/3289600.3290977

[41] Chen Ma, Liheng Ma, Yingxue Zhang, Ruiming Tang, Xue Liu, and Mark Coates. 2020. Probabilistic Metric Learning with Adaptive Margin for Top-K Recommendation. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 1036–1044.

[42] Jingwei Ma, Jiahui Wen, Mingyang Zhong, Liangchen Liu, Chaojie Li, Weitong Chen, Yin Yang, Hongkui Tu, and Xue Li. 2019. DBRec: Dual-Bridging Recommendation via Discovering Latent Groups. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management* (Beijing, China) *(CIKM '19)*. Association for Computing Machinery, New York, NY, USA, 1513–1522. https://doi.org/10.1145/3357384.3357892

[43] Weizhi Ma, Min Zhang, Yue Cao, Woojeong Jin, Chenyang Wang, Yiqun Liu, Shaoping Ma, and Xiang Ren. 2019. Jointly learning explainable rules for recommendation with knowledge graph. In *The World Wide Web Conference*. 1210–1221.

[44] Lei Mei, Pengjie Ren, Zhumin Chen, Liqiang Nie, Jun Ma, and Jian-Yun Nie. 2018. An Attentive Interaction Network for Context-Aware Recommendations. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management* (Torino, Italy) *(CIKM '18)*. Association for Computing Machinery, New York, NY, USA, 157–166. https://doi.org/10.1145/3269206.3271813

[45] Athanasios N. Nikolakopoulos, Dimitris Berberidis, George Karypis, and Georgios B. Giannakis. 2019. Personalized Diffusions for Top-n Recommendation. In *Proceedings of the 13th ACM Conference on Recommender Systems* (Copenhagen, Denmark) *(RecSys '19)*. Association for Computing Machinery, New York, NY, USA, 260–268. https://doi.org/10.1145/3298689.3346985

[46] Athanasios N. Nikolakopoulos and George Karypis. 2019. RecWalk: Nearly Uncoupled Random Walks for Top-N Recommendation. In *Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining* (Melbourne VIC, Australia) *(WSDM '19)*. Association for Computing Machinery, New York, NY, USA, 150–158. https://doi.org/10.1145/3289600.3291016

[47] Wei Niu, James Caverlee, and Haokai Lu. 2018. Neural personalized ranking for image recommendation. In *Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining*. 423–431.

[48] Rasaq Otunba, Raimi A. Rufai, and Jessica Lin. 2017. MPR: Multi-Objective Pairwise Ranking. In *Proceedings of the Eleventh ACM Conference on Recommender Systems* (Como, Italy) *(RecSys '17)*. Association for Computing Machinery, New York, NY, USA, 170–178. https://doi.org/10.1145/3109859.3109903

[49] Shan Ouyang, Lin Li, Weike Pan, and Zhong Ming. 2019. Asymmetric Bayesian personalized ranking for one-class collaborative filtering. In *Proceedings of the 13th ACM Conference on Recommender Systems*. 373–377.

[50] Wenjie Pei, Jie Yang, Zhu Sun, Jie Zhang, Alessandro Bozzon, and David MJ Tax. 2017. Interacting attention-gated recurrent networks for recommendation. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*. 1459–1468.

[51] Dimitrios Rafailidis and Fabio Crestani. 2017. Learning to rank with trust and distrust in recommender systems. In *Proceedings of the Eleventh ACM Conference on Recommender Systems*. 5–13.

[52] Ilya Shenbin, Anton Alekseev, Elena Tutubalina, Valentin Malykh, and Sergey I Nikolenko. 2020. RecVAE: A new variational autoencoder for Top-N recommendations with implicit feedback. In *Proceedings of the 13th International Conference on Web Search and Data Mining*. 528–536.

[53] Rui Sun, Xuezhi Cao, Yan Zhao, Junchen Wan, Kun Zhou, Fuzheng Zhang, Zhongyuan Wang, and Kai Zheng. 2020. Multi-Modal Knowledge Graphs for Recommender Systems. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management* (Virtual Event, Ireland) *(CIKM '20)*. Association for Computing Machinery, New York, NY, USA, 1405–1414. https://doi.org/10.1145/3340531.3411947

[54] Zhu Sun, Jie Yang, Jie Zhang, and Alessandro Bozzon. 2017. Exploiting both vertical and horizontal dimensions of feature hierarchy for effective recommendation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 31.

[55] Zhu Sun, Jie Yang, Jie Zhang, Alessandro Bozzon, Yu Chen, and Chi Xu. 2017. MRLR: Multi-level Representation Learning for Personalized Ranking in Recommendation.. In *IJCAI*. 2807–2813.

[56] Zhu Sun, Jie Yang, Jie Zhang, Alessandro Bozzon, Long-Kai Huang, and Chi Xu. 2018. Recurrent knowledge graph embedding for effective recommendation. In *Proceedings of the 12th ACM Conference on Recommender Systems*. 297–305.

[57] Xiaoli Tang, Tengyun Wang, Haizhi Yang, and Hengjie Song. 2019. AKUPM: Attention-enhanced knowledge-aware user preference model for recommendation. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 1891–1899.

[58] Thanh Tran, Kyumin Lee, Yiming Liao, and Dongwon Lee. 2018. Regularizing matrix factorization with user and item embeddings for recommendation. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*. 687–696.

[59] Thanh Tran, Xinyue Liu, Kyumin Lee, and Xiangnan Kong. 2019. Signed Distance-Based Deep Memory Recommender. In *The World Wide Web Conference* (San Francisco, CA, USA) *(WWW '19)*. Association for Computing Machinery, New York, NY, USA, 1841–1852. https://doi.org/10.1145/3308558.3313460

[60] Daniel Valcarce, Alejandro Bellogín, Javier Parapar, and Pablo Castells. 2018. On the robustness and discriminative power of information retrieval metrics for top-n recommendation. In *Proceedings of the 12th ACM Conference on Recommender Systems*. 260–268.

[61] Chengwei Wang, Tengfei Zhou, Chen Chen, Tianlei Hu, and Gang Chen. 2019. Camo: a collaborative ranking method for content based recommendation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 33. 5224–5231.

[62] 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 *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*. 417–426.

[63] Hongwei Wang, Fuzheng Zhang, Mengdi Zhang, Jure Leskovec, Miao Zhao, Wenjie Li, and Zhongyuan Wang. 2019. Knowledge-aware graph neural networks with label smoothness regularization for recommender systems. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 968–977.

[64] Hongwei Wang, Fuzheng Zhang, Miao Zhao, Wenjie Li, Xing Xie, and Minyi Guo. 2019. Multi-Task Feature Learning for Knowledge Graph Enhanced Recommendation. In *The World Wide Web Conference* (San Francisco, CA, USA) *(WWW '19)*. Association for Computing Machinery, New York, NY, USA, 2000–2010. https://doi.org/10.1145/3308558.3313411

[65] Menghan Wang, Xiaolin Zheng, Yang Yang, and Kun Zhang. 2018. Collaborative filtering with social exposure: A modular approach to social recommendation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 32.

[66] 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* (Anchorage, AK, USA) *(KDD '19)*. Association for Computing Machinery, New York, NY, USA, 950–958. https://doi.org/10.1145/3292500.3330989

[67] Xiang Wang, Xiangnan He, Meng Wang, Fuli Feng, and Tat-Seng Chua. 2019. Neural Graph Collaborative Filtering. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval* (Paris, France) *(SIGIR'19)*. Association for Computing Machinery, New York, NY, USA, 165–174. https://doi.org/10.1145/3331184.3331267

[68] Xiang Wang, Hongye Jin, An Zhang, Xiangnan He, Tong Xu, and Tat-Seng Chua. 2020. Disentangled Graph Collaborative Filtering. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*. 1001–1010.

[69] Xiang Wang, Dingxian Wang, Canran Xu, Xiangnan He, Yixin Cao, and Tat-Seng Chua. 2019. Explainable reasoning over knowledge graphs for recommendation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 33. 5329–5336.

[70] Xiang Wang, Yaokun Xu, Xiangnan He, Yixin Cao, Meng Wang, and Tat-Seng Chua. 2020. Reinforced Negative Sampling over Knowledge Graph for Recommendation. In *Proceedings of The Web Conference 2020* (Taipei, Taiwan) *(WWW '20)*. Association for Computing Machinery, New York, NY, USA, 99–109. https://doi.org/10.1145/3366423.3380098

[71] Yifan Wang, Suyao Tang, Yuntong Lei, Weiping Song, Sheng Wang, and Ming Zhang. 2020. DisenHAN: Disentangled Heterogeneous Graph Attention Network for Recommendation. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*. 1605–1614.

[72] Zengmao Wang, Yuhong Guo, and Bo Du. 2018. Matrix completion with Preference Ranking for Top-N Recommendation. In *Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI-18*. International Joint Conferences on Artificial Intelligence Organization, 3585–3591. https://doi.org/10.24963/ijcai.2018/498

[73] Ze Wang, Guangyan Lin, Huobin Tan, Qinghong Chen, and Xiyang Liu. 2020. CKAN: Collaborative Knowledge-aware Attentive Network for Recommender Systems. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*. 219–228.

[74] Ga Wu, Maksims Volkovs, Chee Loong Soon, Scott Sanner, and Himanshu Rai. 2019. Noise Contrastive Estimation for One-Class Collaborative Filtering. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval* (Paris, France) *(SIGIR'19)*. Association for Computing Machinery, New York, NY, USA, 135–144. https://doi.org/10.1145/3331184.3331201

[75] Xin Xin, Bo Chen, Xiangnan He, Dong Wang, Yue Ding, and Joemon Jose. 2019. CFM: Convolutional Factorization Machines for Context-Aware Recommendation. In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI-19*. International Joint Conferences on Artificial Intelligence Organization, 3926–3932. https://doi.org/10.24963/ijcai.2019/545

[76] Xin Xin, Xiangnan He, Yongfeng Zhang, Yongdong Zhang, and Joemon Jose. 2019. Relational Collaborative Filtering: Modeling Multiple Item Relations for Recommendation. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval* (Paris, France) *(SIGIR'19)*. Association for Computing Machinery, New York, NY, USA, 125–134. https://doi.org/10.1145/3331184.3331188

[77] Fengli Xu, Jianxun Lian, Zhenyu Han, Yong Li, Yujian Xu, and Xing Xie. 2019. Relation-Aware Graph Convolutional Networks for Agent-Initiated Social E-Commerce Recommendation. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management* (Beijing, China) *(CIKM '19)*. Association for Computing Machinery, New York, NY, USA, 529–538. https://doi.org/10.1145/3357384.3357924

[78] Qidi Xu, Fumin Shen, Li Liu, and Heng Tao Shen. 2018. Graphcar: Content-aware multimedia recommendation with graph autoencoder. In *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval*. 981–984.

[79] Yanan Xu, Yanmin Zhu, Yanyan Shen, and Jiadi Yu. 2019. Learning Shared Vertex Representation in Heterogeneous Graphs with Convolutional Networks for Recommendation.. In *IJCAI*. 4620–4626.

[80] Hong-Jian Xue, Xinyu Dai, Jianbing Zhang, Shujian Huang, and Jiajun Chen. 2017. Deep Matrix Factorization Models for Recommender Systems.. In *IJCAI*, Vol. 17. Melbourne, Australia, 3203–3209.

[81] Lu Yu, Chuxu Zhang, Shichao Pei, Guolei Sun, and Xiangliang Zhang. 2018. WalkRanker: A Unified Pairwise Ranking Model With Multiple Relations for Item Recommendation. https://aaai.org/ocs/index.php/AAAI/AAAI18/paper/view/16520

[82] Wenhui Yu, Huidi Zhang, Xiangnan He, Xu Chen, Li Xiong, and Zheng Qin. 2018. Aesthetic-Based Clothing Recommendation. In *Proceedings of the 2018 World Wide Web Conference* (Lyon, France) *(WWW '18)*. International World Wide Web Conferences Steering Committee, Republic and Canton of Geneva, CHE, 649–658. https://doi.org/10.1145/3178876.3186146

[83] Jing Zhang, Bowen Hao, Bo Chen, Cuiping Li, Hong Chen, and Jimeng Sun. 2019. Hierarchical reinforcement learning for course recommendation in MOOCs. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 33. 435–442.

[84] Shuai Zhang, Lina Yao, Lucas Vinh Tran, Aston Zhang, and Yi Tay. 2019. Quaternion Collaborative Filtering for Recommendation. In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI-19*. International Joint Conferences on Artificial Intelligence Organization, 4313–4319. https://doi.org/10.24963/ijcai.2019/599

[85] Yongfeng Zhang, Qingyao Ai, Xu Chen, and W. Bruce Croft. 2017. Joint Representation Learning for Top-N Recommendation with Heterogeneous Information Sources. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management* (Singapore, Singapore) *(CIKM '17)*. Association for Computing Machinery, New York, NY, USA, 1449–1458. https://doi.org/10.1145/3132847.3132892

[86] Yuan Zhang, Xiaoran Xu, Hanning Zhou, and Yan Zhang. 2020. Distilling Structured Knowledge into Embeddings for Explainable and Accurate Recommendation. In *Proceedings of the 13th International Conference on Web Search and Data Mining* (Houston, TX, USA) *(WSDM '20)*. Association for Computing Machinery, New York, NY, USA, 735–743. https://doi.org/10.1145/3336191.3371790

[87] Yan Zhang, Hongzhi Yin, Zi Huang, Xingzhong Du, Guowu Yang, and Defu Lian. 2018. Discrete Deep Learning for Fast Content-Aware Recommendation. In *Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining* (Marina Del Rey, CA, USA) *(WSDM '18)*. Association for Computing Machinery, New York, NY, USA, 717–726. https://doi.org/10.1145/3159652.3159688

[88] Feipeng Zhao and Yuhong Guo. 2017. Learning Discriminative Recommendation Systems with Side Information. In *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI-17*. 3469–3475. https://doi.org/10.24963/ijcai.2017/485

[89] Jun Zhao, Zhou Zhou, Ziyu Guan, Wei Zhao, Wei Ning, Guang Qiu, and Xiaofei He. 2019. Intentgc: a scalable graph convolution framework fusing heterogeneous information for recommendation. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 2347–2357.

[90] Qi Zhao, Yongfeng Zhang, Yi Zhang, and Daniel Friedman. 2017. Multi-product utility maximization for economic recommendation. In *Proceedings of the Tenth ACM International Conference on Web Search and Data Mining*. 435–443.

[91] Wei Zhao, Benyou Wang, Jianbo Ye, Yongqiang Gao, Min Yang, and Xiaojun Chen. 2018. PLASTIC: Prioritize Long and Short-term Information in Top-n Recommendation using Adversarial Training.. In *Ijcai*. 3676–3682.

[92] Lei Zheng, Chun-Ta Lu, Fei Jiang, Jiawei Zhang, and Philip S Yu. 2018. Spectral collaborative filtering. In *Proceedings of the 12th ACM conference on recommender systems*. 311–319.

[93] Han Zhu, Xiang Li, Pengye Zhang, Guozheng Li, Jie He, Han Li, and Kun Gai. 2018. Learning Tree-Based Deep Model for Recommender Systems. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (London, United Kingdom) *(KDD '18)*. Association for Computing Machinery, New York, NY, USA, 1079–1088. https://doi.org/10.1145/3219819.3219826