



Enhanced Recommendation Systems: A Survey on the Impact of Auxiliary Information

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Abstract

In the age of big data, recommendation systems have become a critical tool for helping users navigate the overwhelming amount of online information. Enhanced recommendation systems take this one step further, leveraging the latest algorithms and data-driven insights to deliver highly personalized and relevant recommendations. This research paper provides a comprehensive overview of the recent progress in enhanced recommendation systems, covering the current state-of-the-art techniques and discussing the opportunities and challenges practitioners face. The article explores a range of approaches, including deep learning techniques and hybrid models that integrate both user and item data, and presents the essential concepts, methods, and applications driving the advancement of recommendation systems. We recognize the pressing hurdles in the field as sparsity and diversity, thereby focusing on intent-based models that exploit the additional/auxiliary information by aggregating implicit feedback from user-item interactions. We have gone one step further by compiling the benchmarks in the field, enabling new researchers to explore and innovate at a much more thoughtful and faster pace.

1. Introduction

With the inevitable rise in available information, concocting effective techniques for filtering and organizing data is imperative. Enhanced recommendation systems offer a promising solution, leveraging advanced reinforcement learning algorithms and data-driven insights to deliver personalized, relevant recommendations to users (Afsar, Crump, and Far). However, with the rapid evolution of technology and the increasing availability of data, recommendation systems are also rapidly advancing, leading to the development of enhanced recommendation systems.

The first recommendation system dates back to 1979 when Rich and Waters developed the

”Grundy” system that asked users questions as an input mechanism and classified them (Rich). A downside to the proposed method was that users of the same group received the same recommendations, leading to criticism of the approach due to the authenticity of the feedback provided by the user. Nisbett and Wilson (Nisbett and Wilson) inferred that describing one’s cognitive state is improper, and people often fall prey to their subconscious stereotypes. In 1992, Belkin and Croft (Belkin and Croft) mentioned that the fundamentals of search engines are information filtering and retrieval systems. Such developments led to the diversification of the field into Collabora-

tive Filtering (CF) (Breese, Heckerman, and Kadie), Content-based Filtering (CbF) (Mooney and Roy), and Hybrid systems (Balabanović and Shoham). Further advancements in the CF segment occurred in the same year when Goldberg et al. (Goldberg et al.) proposed the Tapestry system, which filters the information using document relationships. Inspired by the Tapestry system, Resnick et al. (Resnick) presented the GroupLens architecture in 1994. This architecture followed collaborative filters by including ratings and scores aimed at mining reactions from news articles.

Over time, the prevalence of content-based recommendation systems came to rise. The main aim of CbF systems is the identification of similar items. A few content-based systems from the germination stage of the field are PSUN (Sorensen and Mcelligott), NewsDude (Billisus and Pazzani), NewT (Sheth and Maes), LIBRA (Mooney and Roy), and PANDORA. Some latest works include the JUMP system (Basile), News@hand (Cantador, Bellogín, and Castells), Publication Recommendation System (D. Wang et al.), LPRS (Dwivedi, Kant, and Bharadwaj), LTRS (Nabizadeh et al.), and the system proposed by Albatayneh et al. (Albatayneh and Ahmad). Content-based systems have also seen massive growth, from learning short-term and long-term profiles using the Nearest Neighbour and Naive Bayesian Classifiers to n-gram and vector representation works. The hybrid systems developed from collaborative and content-based filtering techniques are also worth mentioning. The first hybrid systems were FAB (Balabanović and Shoham), P-Tango (Claypool), PTV (Smyth and Cotter), Content boosted Collaborative Filtering (Melville et al.), and Cinema Screen (Salter and Antonopoulos). Hybreed (Hussein et al.), THOR (Sabet and Alireza), and the hybrid course recommendation system (Perez and Sanguino) are some of the initial works in the field.

With the dominance of neural networks in computer science, recommendation tasks have benefited from deep learning architectures' excellent pattern recognition properties. Ruihui Mu (Mu) conducted a comprehensive survey that explains the advantages of using deep neural nets for recommendation tasks. It is seen that non-linear and non-trivial information can be easily captured using deep neural networks, which opens up the possibility of solving sparsity

issues. The survey (Mu) categorizes the pioneering methods into four classes: Autoencoders, Boltzmann machine learning-based models, Recurrent Neural Networks (RNNs), and General Adversarial Networks (GANs). For collaborative filtering (CF), the authors mention state-of-the-art (SOTA) models such as ACF (Sedhain), CDAE (Strub, Mary, and Philippe), RBM (Salakhutdinov, Mnih, and Hinton), RNN-based system (C. Wu et al.), and IRGAN (J. Wang).

Wu et al. (L. Wu et al.) recently conducted a more detailed study comparing neural net systems, with accuracy as the primary parameter for comparison. The authors mention various models, such as NAIS (He et al.), built upon item-based CF and achieve significant results on datasets like MovieLens (Harper, Maxwell, and Konstan) and Pinterest (Geng et al.). The authors also differentiate models into four categories: Classical Matrix Factorization, History Attention, Autoencoder models, and Graph Learning Models. With future directions to explore long-term and short-term temporal features, the authors mention the latest models like MA-GNN (Ma et al.), HyperRec (J. Wang et al.), IMfOU (Guo, Shi, and C. Liu), KGAT (X. Wang), and KGIN (X. Wang et al.). The authors also concluded that GNNs capture user-item interactions at different granularities, making them suitable for exploring temporal features using GNN architectures for sequential learning in recommendations.

In addition to the advancements in recommendation systems, there has been significant progress in multi-objective optimization. The traditional approach to multi-objective optimization involves weighing the objectives and finding a single optimal solution. However, this approach has several limitations, such as requiring the user to specify the weightings and only finding a single optimal solution. In recent years, there has been a shift towards using Pareto optimization, which aims to find optimal solutions for multiple objectives without requiring the user to specify weights. Several approaches have been proposed for incorporating Pareto optimization into recommendation systems, including P-MOIA-RS (Chai, Y. Li, and S. Zhu), PE-LTR (X. Lin et al.), and AESM² (Zou et al.). These approaches attempt to improve recommendation quality and diversity by taking into account numerous objectives such as accuracy, diversity,

novelty, and serendipity (Kaminskas and Bridge).

1.1. Scope and Organization of the Survey

This paper is organized as follows: Section 2 comprises of the latest models in the field, along with the references to relevant datasets used in each work. The benchmark metrics are also mentioned in the corresponding subsection itself. Section 3 provides the compiled view of the popular benchmark datasets, and Section 4 gives the conclusion of this work.

2. Recommendation Models

The use of auxiliary information has been a boon to the existence of recommendation systems. Supplementary information has boosted how models roll out user recommendations in various domains. Knowledge graphs, reinforcement learning, and meta-learning have surpassed the previously known limits to recommendations. The reasons for using supplementary information are straightforward and can be seen from past trends and setbacks in recommendation systems.

The trends from the last two decades showcase the urgent need to address Sparsity and Diversity. Huang et al. (Huang, H. Chen, and Zeng), and Papagelis et al. (Papagelis, Plexousakis, and Kutsuras) first addressed the sparsity problem in collaborative filtering models. They define sparsity as the lack of similarity between users implicitly originating due to limited ratings from a given user. They emphasize that a given user can only rate so many items, resulting in the user-item matrix with many empty user-item pairs. The inclusion of additional information has been observed to overcome inefficiencies in CF models caused by the above cold start problem (I Schein et al.).

The second major hindrance faced by collaborative filtering models is diversity. Although Smyth and McClave (Smyth and McClave) introduced diversity as a significant issue in content-based systems, the problem is observed in modern collaborative filtering models. Diversity or Temporal Diversity refers to the characteristic of a model to recommend new items to users despite an abundance of a specific set of items as training recommendations. Lathia (Lathia and Kiritkumar) stated that Temporal Diversity is dangerous to collaborative filtering models as it can lead to loss of interest due to stagnant recommendations. Over the years, a solu-

tion to both sparsity and diversity is the exploration of hidden patterns that can be made more apparent to the model using auxiliary information.

This section presents the latest works contributing unique outlooks and tackling diversity and sparsity issues. The following subsections present the latest works involving Improved Matrix Factorization (MF), Distance Based models, Graph Convolution Networks (GCNs), Graph Neural Networks (GNNs), Knowledge Graphs (KGs), and Causal Graphs (CGs). Some models do not include auxiliary information, but these models have given intense competition to the ones using auxiliary information. Thus, we categorize the section into more sections than required, enabling a more straightforward understanding for future researchers. A compilation of all the latest works is also presented by Table 1.

2.1. Matrix Factorization

Matrix Factorization (MF) has been the most prominent technique in CF. The root cause of sparsity arose in the matrix factorization technique due to the lack of user-item pairs. Despite this, many enhanced MF-based models have proven efficient, showing conventional CF models' power.

Lian et al. (Lian et al.) presented Product Quantized Collaborative Filtering (pQCF) in 2020. The pQCF architecture employs a latent space that separates users and items into low-dimensional Cartesian dot product subspaces, allowing for the learning of clustered representations within each subspace. The authors use the Block Coordinate Descent Algorithm for training the model on various datasets, such as Yelp, Amazon, Netflix, MovieLens, Gowalla, and LastFM. The algorithm ensures that convergence is theoretically guaranteed (Tseng). The architecture continues with hashing and index-based lookups for recommending the learned items. Given the efficient indexing, the authors achieve a leveled trade-off between the accuracy of the model and the low memory cost associated with fast item retrieval. An asymmetric pQCF version dubbed QCF is also presented, reaching elevated metrics values. The results for QCF on implicit and explicit feedback datasets are comparable or elevated for all metrics (Normalized Discounted Cumulative Gain@50 [NDCG@50], Recall@50, AUC) compared to SOTA models.

2.2. Distance-Based Models

The recommendations from a model are based on the similarity between the user interests. This property opens a new exploration space for the recommendation models to advance based on distance comparison. Distance-based methods have shown prevalence in the field over the past decade. However, the most prominent work was proposed in 2017 by Hsieh et al. (Hsieh et al.) named Collaborative Metric Learning (CML).

The approach adopted the triplet loss structure and aimed at increasing the distance between negative recommendation items and the user while reducing the same between positive items and users. According to the literature, CML suffered from two main problems: it employed a static margin value for all users and needed to account for the dissimilarity between positive and negative items. As Li et al. (M. Li et al.) proposed, the first issue arises due to the variance in the number of item interactions for every user. The first issue with CML pertains to the use of a static margin, which can lead to a biased model that is less expressive. The second challenge concerns the need for improved representation of user-item triplets to account for the varying degrees of similarity between positive and negative items, as opposed to just between positive items and users. This can often lead to incorrect recommendations leading to poor results. To solve the two obstacles, the authors introduce Symmetric Metric Learning (SML) (M. Li et al.), wherein an adaptive margin mechanism enables the model to make better decisions.

$$L_{AM} = - \left(\frac{1}{|U|} \sum_u m_u + \frac{1}{|J|} \sum_v n_v \right) \quad (1)$$

This adaptive margin can be formulated using Equation (1). The resulting loss function is given as Equation (2); where u denotes user, $(v^-, v^+]$ denote negative and positive items, $d(u, v)$ represents the distance between u and v , $(m_u, n_v]$ denote the adaptive margins for user and item respectively and l is the bound to prevent the margin from being too large.

$$\sum_{(u,v) \in \zeta} \sum_{(u,v^-) \notin \zeta} ([d(u, v) - d(u, v^-) + m_u] + \lambda [d(u, v) - d(u, v^-) + n_v]_+) + \gamma L_{AM} \quad (2)$$

such that.

$$m_u \in (0, l], n_v \in (0, l];$$

The authors tested their experiments on the Amazon Instant Video Dataset, Yelp, and the IMDB Dataset and compared their results using three widely used metrics: Precision@K, Hit Ratio@K, and Normalized Discounted Cumulative Gain (NDCG@K).

In 2020, Ma et al. (M. Chen et al.) introduced a metric learning model that incorporates a probabilistic approach and features an adaptive margin. The authors targeted Top-K recommendations as an output of the architecture. The use of Wasserstein distance for interactions, followed by an adaptive margin generation module, yields a 4.00% to 22.45% improvement in the Recall@10 metric and a 4.23% to 31.46% improvement in NDCG@10. The Amazon Books, Electronics, and CDs dataset, the GoodReads Comics dataset (Wan and McAuley), and the Gowalla dataset were used for experimentation. A bilevel optimization with approximate gradient optimization further improves the adaptive margins.

2.3. Graph Convolution Networks

In 2020, Sun et al. (Jianing et al.) proposed Neighbor interaction aware graph convolution networks (NIA-GCN). The NIA-GCN model leverages relational information from neighboring nodes to capture the heterogeneity of the user-item bipartite graph. They utilize three main modules: a Pairwise Neighborhood Aggregation graph convolution layer (PNA layer), Parallel GCNs, and a Cross-Depth Ensemble layer. The prevalent issue in the field is the incorrect consideration of the negative samples as unobserved user-item interactions. This issue is resolved by the Bayesian Graph Convolutional Neural Network framework (BGCF) proposed by Sun et al. (Sun et al.). The authors implement the Neighborhood Copying Graph Generative Model to distribute the interaction graph effectively. The authors adopt a joint training approach that involves both the observed and sampled graphs after the copying and redistribution stages. This work aims at resolving the uncertainty associated with the user-item interaction graphs.

To improve the recommendations by GCNs, Wu et al. Wu et al. (J. Wu et al.) proposed Self-supervised Graph Learning (SGL) in 2021. The SGL framework employs an augmentation architecture to generate different views of each node in the interaction graph. The augmented graph is used

as an input for contrastive learning, followed by a multitasking strategy. The authors used the Yelp, Amazon-Book, and Alibaba-iFashion datasets. The variations presented by the authors reach double-digit improvements for Recall and NDGC metrics. In the same year, Xu et al. (Xu) proposed Causal Collaborative Filtering (CCF). The work aims at estimating causal relations in the user-item interactions, using do-calculus. The paper describes basic notations such as Structural Causal Models, Causal Graphs, Intervention, the Causal Effect Rule, Backdoor Criterion, and the Counterfactual term. The causal graph aims to transform the arbitrary recommendation system into an unbiased user preference estimation, revealing the users' real preferences. Using benchmark datasets such as MovieLens, Amazon baby, Yahoo!R3, and Coat Shopping dataset, the authors achieve up to 166% improvement in the Hit@1 metric and up to 46% improvement in NDGC@10 metric.

In 2022, Zhang et al. (Zhang) proposed IA-GCN: Interactive Graph Convolutional Network. Using an interaction guidance mechanism, the IA-GCN architecture builds explicit interactions between the user and item graphs. The root guides the user/item tree aggregators to emphasize the importance of the children nodes similar to the target user/item pair. Such guidance encodes higher-order features containing target-specific features, strengthening the user's preference. The results on the Gowalla, Yelp, and Amazon-Book datasets are comparable with many benchmark results, demonstrating faster training than Light-GCN (He).

After involving intent and enhanced graph structure, Lin et al. (Z. Lin et al.) presented Neighborhood-enriched Contrastive Learning (NCL) for improving graph-based applications in CF. The core idea of the improvement remains the same; improvement of interaction structure, although the approach shifts to a new structure-contrastive objective that generates positive contrastive pairs based on users/items and their structural neighbors. The idea boils down to a multi-task learning strategy that captures the representations of homogeneous neighborhoods from even layer outputs of the GNN model. This, however, introduces noise information in the contrastive pairs. To address the problem of noise, the approach employs a prototype-contrastive

objective that seeks to identify semantic neighbors. The authors use the LightGCN (He) model as the backbone GNN model. The authors use multiple significant benchmark datasets with improvements on Recall@K and NDGC@K metrics ranging from as low as 0.83% to 12.81%.

2.4. Graph Neural Networks

Wang et al. (Xiang et al.) proposed the work on Disentangled graph collaborative filtering (DGCF) yielding disentangled representations with the help of intent-aware graph networks. The architecture involves the graph disentangling module and the independence modeling module. After slicing them into chunks, the disentangling module couples the user-item vectors with intent. The GNN model in the module includes a unique neighbor routing mechanism in the propagation path for the embeddings. This mechanism distinguishes the different importance levels of interactions between users and items in the interaction graphs. The authors use cross-intent embedding propagation to further enhance the interaction graph's intent learning. The second module involves mutual information and a distance correlation term that allow the factor-aware representations to be independent. The model parameters are optimized using the BPR Loss (Rendle). The architecture improves benchmark metrics like Recall and NGDC by approximately 4%, 5%, and 12% for the Gowalla, Yelp, and Amazon-Book Dataset. This work is beneficial for providing insights into the role of users' intent in recommender systems.

Another important work in the GNN workspace was proposed by Yang et al. (Yang et al.) in 2021. The authors present the enhanced graph learning network (EGLN) for collaborative filtering via mutual information maximization. According to the authors, relying on a fixed graph structure can result in negative and unknown positive preferences mixed up with users' unobserved behaviors. To mitigate this issue, their model improves upon the user-item bipartite graph by adding a residual graph structure learned iteratively alongside the node embedding graph. the EGLN architecture achieves an approximate 7% improvement in both Hit Ratio@10 and NDGC@10 for the MovieLens-1M and Amazon-Video Games Dataset. The authors improve the metrics by 3% and 5%, respectively, for the Pinterest

Dataset.

2.5. Knowledge Graphs

Sang et al. (Sang et al.) proposed Knowledge Graph enhanced Neural Collaborative Filtering with Residual Recurrent Network (KGNCF-RNN) in 2022. The architecture uses a knowledge graph (KG) to extract path embeddings for relations between entities in the KG. A path is formulated such that $p = \left(e_1 \xrightarrow{r_1} e_2 \xrightarrow{r_2} \dots \xrightarrow{r_{L-1}} e_L \right)$, where $e_1 \in I, e_L \in I$; (e_l, e_r, e_{l+1}) is a triplet, and I is the Interaction Graph. Such paths of different lengths can be created for every user/item pair and are denoted by p_i . These path embeddings are fed to a Recurrent Residual Network (RRN) for contextual learning. The output embedding obtained from the RRN module is given by $(h'_1, h'_2, \dots, h'_s)$. This is then applied to the self-attention model resulting in Equation (3), where f is the attention function.

$$f(h'_i, h'_j) = W\sigma(W_1h'_i + W_2h'_j)$$

$$E^1_{i,j} = \frac{\exp(f(h'_i, h'_j))}{\sum_{j=1}^s \exp(f(h'_i, h'_j))} \quad (3)$$

The Correlation matrix or the interaction matrix E^2 is formulated as given in Equation 4. These two matrices are passed as an input to a CNN model, resulting in feature recommendations.

$$E^2 = k_u \otimes j_i = k_u j_i^T \quad (4)$$

The authors of KGNCF-RNN improve on the benchmark results on the MovieLens, Book Crossing, and LastFM datasets.

Another significant work from 2022 was proposed by Wang et al. (X. Wang et al.). The authors present Knowledge Graph-based Intent Network (KGIN), where they aim to learn the intents behind interactions in KGs. They also devise an information aggregation scheme for GNNs for accumulating long-range connectivity from relational paths. The architecture involves creating an intent graph using intent representations obtained from representation learning. In order to remove the redundancy of intent learned, an independence modeling module is implemented. An aggregation layer is devised that first goes over the intent graph and

then the original knowledge graph. This allows the model to aggregate the knowledge from both graphs, improving the capture of relational paths. This work also shows a significant contribution in the Amazon-Book, Alibaba-iFashion, and LastFM datasets.

3. Benchmark Datasets

The following section provides a comprehensive overview of the benchmark datasets available in the recommendation systems domain. Research and private organizations, including universities, non-profit organizations, and product-based companies like Amazon and Netflix, have published these datasets. The datasets are classified for future researchers to quickly understand and pick the dataset that best matches their field of study. The list is non-exhaustive, although it comprises all the benchmark datasets used for experimenting and publishing the results of recommendation system models.

3.1. Movie Datasets

3.1.1. MovieLens-25M Dataset:

This is one of the most used movie rating datasets provided by GroupLens Research. The dataset comprises approximately 25 million ratings and one million tags collected from 162,000 users and 62,000 movies. The movies are rated by users and classified into various genres. First published by Harper and Konstan (Harper, Maxwell, and Konstan) in 2015, the dataset is available in sizes 1M, 20M, and 25M.

3.1.2. Netflix \$1M Prize Dataset:

Netflix released this dataset to motivate researchers to develop improvised recommendation models. Introduced by Bennett et al. (Bennett and Lanning) in 2007, the dataset contains 17,770 movies and ratings from 480,189 users. The competition encouraged participants to improve their RMSE score for a grand prize of 1 million dollars.

3.1.3. Flixster Dataset:

Zafarani and Liu (Zafarani and H. Liu) from Arizona State University published the dataset in 2009. The dataset contains 2,523,386 nodes as users from the website Flixster, making 9,197,338 edges, indicating the friendship between users. The dataset is available on the ASU Data Repository.

3.2. Music Datasets

3.2.1. Million Song Dataset:

The Million Song Dataset is a cluster of complementary datasets the community contributes for research purposes. A collaborative effort by The Echo Nest and LabROSA (Bertin-Mahieux), the most famous subset is the Last.FM dataset. This song corpus includes song tags and similarity attributes for the Million Song Dataset, with 522,366 unique tags and 56,506,688 (track - similar track) pairs.

3.2.2. Yahoo! Music Dataset:

This dataset aggregates around 136 thousand songs rated by 1.8 million users. The 717 million ratings were scraped from the Yahoo! Music Website. The songs are collected between 2002 and 2006, with genre attributes and genre hierarchy.

3.3. Product-based Datasets

3.3.1. Amazon Product Review Dataset:

First Released in 2014, the Amazon Review Data contains reviews from product metadata such as description, price, and brand information. Jianmo at UCSD (Ni, J. Li, and McAuley) published the dataset with 233.1 million reviews containing ratings, text, and helpfulness votes, along with reviews from product categories like Books, Video-Games, CDs, Movies, Beauty, and many more. The per-category data is also available for domain-specific tasks.

3.3.2. GoodBooks-10k Dataset:

Introduced by FastML (Zajac), this book's dataset contains 6 million ratings for the most popular ten thousand books. Available on FastML, the dataset contains explicit ratings and implicit feedback markers for researchers to experiment. The authors have also created tags for the books, enabling a more extensive metadata study to be conducted.

3.3.3. Alibaba-iFashion:

Chen et al. (W. Chen et al.) published the Alibaba-iFashion dataset in 2019. Clicks behaviors and events from 3.57 million users and 4.75 million items make it the largest Fashion Product recommendation domain dataset.

3.4. Image and Video Datasets

3.4.1. Pinterest Dataset:

Geng et al. (Geng et al.) published this dataset by sampling users from 468 categories on Pinterest. The pinned images and additional information indi-

cating categories from 1 million users were crawled from the Pinterest Website. The dataset is available on the Xue@Alphabeta Website.

3.4.2. Steam Dataset:

Pathak et al. (Pathak, Gupta, and McAuley) published the Steam Video Game Dataset by compiling Steam Video Gaming Platform reviews. It contains 7,793,069 reviews from over 2.5 million users and 15 thousand items. It has metadata attributes like purchases, plays, pricing information, and likes.

3.4.3. Miscellaneous Datasets

Given the rise of e-commerce, many other domain-specific datasets are available for researchers to use. Among these, the most common ones are mentioned in this section. The MICROSOFT NEWS Dataset (MIND) published by Wu et al. (F. Wu et al.) in 2020, is a large-scale dataset captured from Microsoft News. The Gowalla Dataset (Cho et al.) available on the SNAP Stanford Repository is a location-based social networking dataset with 196,591 nodes and 950,327 edges. The Douban Dataset is a high sparsity dataset crawled by Zhu et al. (F. Zhu) from the Douban Website. It contains user and item interactions from various categories like movies, books, and music. Similarly, the Yelp Dataset contains business reviews, including over 200 thousand images and around 1.2 million attributes from businesses including parking, hours, ambiance and availability.

4. Conclusion

This paper presents the evolution of recommendation systems, particularly collaborative filtering systems. Our focus remains on using auxiliary/implicit information and its impact on the existing architectures. As seen from the recent works, a significant improvement is delivered by the systems capturing the hidden intent of users. Often, this hidden intent is learned using knowledge graphs, node neighborhood similarity matching, and mutual information. For future researchers to understand the field, this work can serve as a consolidated, non-exhaustive compilation that summarizes the eventual use of additional information in the recommender system space.

TABLE 1. Comparison of Latest Enhanced Recommendation Systems

Model Type	Architecture Name	Year	Algorithms	Datasets	Metrics
MF Distance- Based	Product Quantized Collaborative Filtering (pQCF)	2021	Block Coordinate Descent Algorithm, Hashing and Indexing	Yelp2018, Amazon Review, Netflix, MovieLens, Gowalla, LastFM	NDCG@KRecall @KAUC(K=50)
	Symmetric Metric Learning (SML)	2020	Adaptive Margin, SML over Collaborative Metric Learning	Amazon Instant-Video, Yelp2018, IMDB	Precision@KHit Ratio@KNDCG @K(K=5,10)
	Probabilistic Metric Learning	2020	Adaptive Margin, Probabilistic Approach, Bilevel Optimization using Approximate Gradient Descent	Amazon Review, GoodReads Comics, Gowalla	NDCG@KRecall @K(K=50)
GCN	Neighbor Interaction Aware Graph Convolution Networks (NIA-GCN)	2020	Pairwise Neighborhood Aggregation Convolution Layer, Parallel GCNs, and a Cross-Depth Ensemble Layer.	Gowalla, Amazon Review, Industrial Data	NDCG@KRecall @KAUC(K=20)
	Bayesian Graph Convolutional Neural Networks (BGCF)	2020	Neighborhood Copying Graph Generative Model using Joint Training	Amazon Review	NDCG@KRecall @KSerendipity @K(K=10,20)
	Self-supervised Graph Learning (SGL)	2021	GCN with Multi-task learning and Contrastive Learning	Yelp2018, Amazon-Book, Alibaba-iFashion	NDCG@KRecall @K(K=20)
	Causal Collaborative Filtering (CCF)	2021	Structural Causal Models, Intervention, Backdoor Criterion, Lagrange optimization for counterfactual reasoning in discrete space	MovieLens-100K, Amazon Baby, Yahoo R3, Coat Shipping	Hit Ratio@1NDCG@10

Continued on next page

Table 1 continued

GNN	Interactive Graph Convolutional Network (IA-GCN)	2022	2 Tree GCN approach with guiders for focusing on target specific features	Gowalla, Yelp2018, Amazon-Book	NDCG@KRecall @K(K=20)
	Disentangled Graph Collaborative Filtering (DGCF)	2020	Graph Disentangling, Independence Modeling, BPRLoss	Yelp2018, Gowalla, Amazon Book	NDCG@K ² Recall @K(K=20)
	Enhanced Graph Learning Network (ELGN)	2021	Similarity Calculation, Residual Graph, Node Embedding Learning	MovieLens-1M, Amazon-Video Games, Pinterest	Hit Ratio@KNDCG @K(K=5,10,15,20,25,30)
KG	Neighborhood-enriched Contrastive Learning (NCL)	2022	Contrastive Learning with Structural and Semantic Neighbors	Yelp2018, Amazon-Book	NDCG@KRecall@K(K=10, 20, 50)
	Knowledge Graph enhanced Neural Collaborative Filtering with Residual Recurrent Network (KGNCF-RNN)	2021	KG, RRN, Noise-Contrastive Estimation, Convolution NCF	MovieLens, Book Crossing, LastFM	NDCG@KRecall@K(K=20)
	Knowledge Graph-based Intent Network (KGIN)	2021	KG based entity-relation-entity triplets + User-intent-item triplets using intent representation, BPR Loss for optimization)	Amazon-Book, LastFM, Alibaba-iFashion	AUCF1

Further, it is clear from the challenges researchers face in the field that diversity and sparsity can hinder recommender systems' performance. Such issues can lead to redundant recommendations or a complete lack of reliability in the system. For future architectures to understand the implicit interests of users, graph networks with supporting information can prove to be highly efficient, both in terms of results and learning capabilities. These issues will increase given the vast amount of data flowing into the databases, although an effort to reduce them can be made by following the current works presented in the paper.

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