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Explainable AI and deep learning models for recommender systems: State of the art and challenges

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Abstract: Recommender systems have a pivotal function in delivering customized and pertinent suggestions to clients on the basis of their preferences and activities. The present paper presents a thorough overview of deep learning-based recommender systems, explores their application to enhance performance, and overcomes limitations. The survey encompasses fundamental models of recommender systems; moreover, it also delves into key deep learning models.
This discussion focuses on the effective integration of deep learning techniques into recommender systems. Real-world applications highlight the effectiveness of these approaches in capturing complex and nonlinear patterns from large-scale data.
This paper concludes by reflecting on challenges encountered in this research field and outlines potential future directions, offering valuable insights for academics and professionals in the field of recommender systems based on deep learning.

Keywords: Recommender systems, deep learning, XAI, benchmark dataset
Categories: H.3.3, H.3.5, H.2.8, I.2.6, I.5.1, I.2.8
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List of abbreviations:

Abbreviation	Full Form
AE	Autoencoder
AN	Adversarial Network
AUC	Area Under the Curve
CA	Context-Aware
CB	Content-Based
CNN	Convolutional Neural Network

CF	Collaborative Filtering
DL	Deep Learning
DNN	Deep Neural Network
DRL	Deep Reinforcement Learning
GAN	General Adversarial Network
Hyb	Hybrid
MAE	Mean Absolute Error
MF	Matrix Factorization
MAP	Mean Average Precision
MAPE	Mean Absolute Percentage Error
MAR	Mean Average Recall
ML	Machine Learning
MLP	Multi-Layer Perceptron
MPR	Mean Percentage Ranking
MRR	Mean Reciprocal Rank
MSE	Mean Squared Error
NA	Neural Attention
NADE	Neural Autoregressive Density Estimation
NCF	Neural Collaborative Filtering
nDCG	Normalized Discounted Cumulative Gain
RBM	Restricted Boltzmann Machine
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
RS	Recommender System

1 Introduction

RSs are essential software applications that offer users personalized suggestions for items or services aligned with their preferences or needs [Konstan, 12]. By extracting key information fragments from large volumes of dynamically generated data based on users' preferences, interests, or observed behavior related to items, they ensure that users receive recommendations that are both relevant and timely [Chenguang, 10]. Widely employed across diverse fields such as e-commerce, healthcare, entertainment, education and social media, these systems significantly impact the user experience and satisfaction [Konstan, 12]. Notable examples include Netflix, which recommends movies based on viewing history; YouTube, which suggests videos tailored to user interests; and Amazon, which proposes products informed by purchase history and browsing patterns. Such instances underscore how RSs enhance user engagement, loyalty, and service provider revenue.

DL, a branch of machine learning, employs multilayered artificial neural networks to glean insights from vast datasets and execute complex tasks. Speech recognition, natural language processing, and computer vision are some fields that have achieved breakthroughs through DL which enabled capabilities previously deemed unattainable.

For instance, it excels at facial and object recognition in images, generates text captions and summaries, facilitates language translation, and synthesizes speech. The employment of DL in RSs represents a burgeoning research area aimed at augmenting the efficiency and quality of recommendations. DL-based models can learn from diverse data types, including user ratings, reviews, profiles, and behavior logs, enabling the capture of intricate connections between customers and objects. Moreover, these models address challenges like data sparsity, cold start issues, scalability, diversity, and explainability within RSs.

This paper delves into the challenges and opportunities linked to integrating DL into RSs, exploring topics such as data sparsity, cold start, scalability, and diversity. It covers key types and architectures of DL-based models tailored for RSs, encompassing MF, AE, NCF and DNN. Empirical results and evaluations of different models and techniques are presented to offer insights into performance and effectiveness. Finally, the paper summarizes the principal findings and provides recommendations for practitioners and researchers seeking to leverage or enhance DL in RSs.

2 Recommender systems

RSs, often referred to as engines, serve a crucial function in delivering personalized suggestions to customers, encompassing products, movies, articles, services, and more. These information filtering systems are designed to improve user experiences across diverse tasks, from shopping to movie nights and service exploration. Leveraging various data sources such as past purchases, search history, and demographic information, RSs strive to offer the most relevant suggestions (Figure 1).

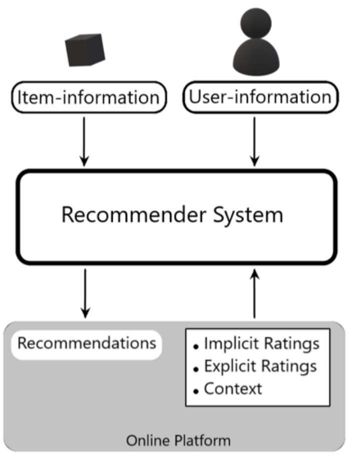

Figure 1: Recommender system

Different architectural approaches exist for RSs, encompassing CB filtering, CF, context filtering, and hyb RSs. Content-based filtering relies on item attributes and features, collaborative filtering draws inspiration from other users' preferences, and context filtering tailors recommendations on the basis of users' current situations. Every model presents distinct strengths and weaknesses, making hybrid filtering models valuable in scenarios where multiple techniques are employed simultaneously.

The impact of RSs extends beyond enhancing user experiences; they contribute to increased customer satisfaction, business revenue, and customer loyalty by delivering enhanced value to users. The importance of RSs spans different domains, like e-commerce, content platforms, etc. In e-commerce, these systems drive sales and revenue for online retailers by providing personalized and relevant product or service suggestions to potential and existing customers. Examples of e-commerce platforms employing RSs include Amazon, eBay, and Alibaba. Content platforms, which offer diverse content types like movies, TV shows, and music, utilize RSs to increase user engagement and retention. Netflix, Spotify, Goodreads, and The New York Times are notable examples. Social networks like Facebook leverage RSs to enhance user involvement, retention, and contentment by providing tailored and pertinent content or people.

2.1 Recommender system techniques

RSs employ diverse models and techniques on the basis of available data and specific objectives. They are primarily categorized into three model types: CB RSs, CF RSs, and hyb RSs.

An additional type is the context-filtering RS, which relies on additional side information. Figure 2 illustrates these models.

Within collaborative filtering, two main models are prominent: memory-based systems, which encompass user-based and item-based approaches, and model-based systems, which include clustering [Ubukata, 20], association [Lourenco, 20], Bayesian networks [Dai, 19], and neural networks [Chakrabarti, 19]. These variations demonstrate the adaptability of RSs to different scenarios, with each model type calling for distinct advanced techniques such as MF, ML, and DL models.

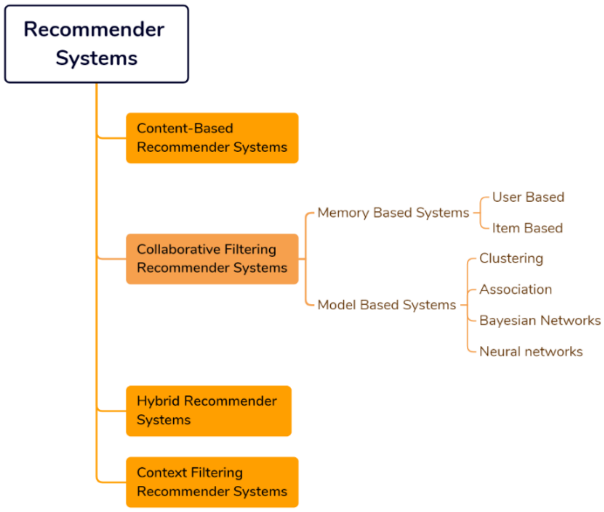

Figure 2: Recommender system models

A. Content-based recommender system

CB RSs operate on the premise that users interested in specific products will likely prefer similar ones. These systems leverage features or attributes of items, such as price, category, and description, to measure similarity and suggest objects that align with the user's habits or past purchases.

For instance, Amazon employs CB RSs to recommend products comparable to items the user has already viewed or bought. The prediction of user preferences is represented by equation (1).

$$\hat{r}_{ui} = \text{sim}(u, i) = \sum_k \text{tf} - \text{idf}_{uk} \cdot \text{tf} - \text{idf}_{ik} \quad (1)$$

$\hat{r}_{ui}$ represents the predicted preference or rating of user *u* for item *i*.
sim(*u, i*) is the similarity between user *u* and item *i*. It is computed using the cosine similarity between the user's and item's term frequency-inverse document frequency (tf-idf) vectors.
$\sum_k$ is a summation over all terms (*k*) in the vector space.
$\text{tf} - \text{idf}_{uk}$ represents the term frequency-inverse document frequency of term *k* for user *u*. It measures how important term *k* is to user *u*.
$\text{tf} - \text{idf}_{ik}$ is the term frequency-inverse document frequency of term *k* for item *i*. It measures the importance of the term k for the item *i*.

B. Collaborative filtering

CF RSs are built upon the concept that users with similar tastes or preferences will probably enjoy the same objects. These systems utilize user–item engagements, which may be characterized by purchases, clicks, and views, to gauge the similarity between users and items and recommend objects liked by users with comparable tastes. eBay, for example, employs collaborative filtering RSs to suggest products favored by users who have bought or bid on similar products as the target user.
The user-user similarity is given by equation (2):

$$sim(u, v) = \frac{\sum_{i \in I_u \cap I_v} r_{ui} \cdot r_{vi}}{\sqrt{\sum_{i \in I_u} r_{ui}^2 \cdot \sum_{i \in I_v} r_{vi}^2}} \quad (2)$$

$sim(u, v)$ is the similarity between the users *u* and *v*.
$\sum_{i \in I_u \cap I_v}$ is the summation over items that both users *u* and *v* have interacted with (items at the intersection of their item sets).
r_{ui} and r_{vi} represent the ratings of users *u* and *v* for item *i*, respectively.

The item-item similarity is given by equation (3):

$$sim(i, j) = \frac{\sum_{u \in U_{ij}} r_{ui} \cdot r_{uj}}{\sqrt{\sum_{u \in U_{ij}} r_{ui}^2 \cdot \sum_{u \in U_{ij}} r_{uj}^2}} \quad (3)$$

$sim(i, j)$: The similarity between items *i* and *j*.
$\sum_{u \in U_{ij}}$: The summation is over users who have interacted with both items *i* and *j* (users at the intersection of their user sets).
r_{ui} and r_{uj}: The ratings of user *u* for items *i* and *j*, respectively.

C. Hybrid

Hybrid RSs combine different recommendation systems to enhance the effectiveness and accuracy of recommendations. These systems incorporate a mix of CB and CF techniques or other approaches, such as demographic or knowledge-based methods, to offer comprehensive and diverse recommendations. Alibaba employs hybrid RSs to suggest products according to both user choices and behavior, and item features, and popularity.

D. Matrix factorization

Matrix factorization is a versatile technique applicable to CB or CF RSs. The user–item matrix, which contains interactions between users and items, is broken into two low-dimensional matrices that symbolize latent factors or embeddings of users and items. MF reduces data dimensionality, addresses sparsity, and uncovers hidden patterns and relationships between users and items. Netflix, which uses MF, predicts movie ratings for users according to their previous ratings and preferences.

The matrix factorization (model-based collaborative filtering) is given by:

$$R \approx P \times Q^T \tag{4}$$

R: user-item rating matrix, which represents the ratings that users give to items.
P: user-feature matrix, which captures the characteristics of users.
Q: item-feature matrix, which captures the characteristics of items.
Matrix multiplication with superscript *T* indicates the transposition of *Q*.

E. Context-aware recommendations

Context-aware recommendations recognize that recommendations should be based on the user's and/or item's current contexts, including time, location, mood, device, categories, etc., in addition to user preferences. These recommendations incorporate contextual information to filter or adjust suggestions according to the user's needs or goals in a specific context. For instance, Uber utilizes context-aware recommendations to suggest rides or drivers suitable for the user's current location, destination, time, and traffic conditions. Within this realm, Gasmi et al. [Gasmi, 21a] explored the enhancement of context-aware RSs by combining LDA with PSO. In another examination, the authors improved predictions based on evolutionary collaborative filtering algorithms [Gasmi, 21b].

2.2 Recommender system data types

Various RS models have been designed with the primary goal of delivering highly accurate recommendations. These recommendations are derived from the intricate analysis of diverse inputs, each contributing to the model's predictive capabilities. These inputs encompass a spectrum of data types, including user-profile information, explicit and implicit ratings, as well as other explicit data sources.

- **User-Profile Data:** This type of data delves into the features and preferences of each user. Information such as historical behavior, previous interactions, and user-provided preferences contribute to creating a personalized comprehension of the tastes of the user.

- **Explicit and Implicit Ratings:** RSs consider both explicit ratings, in which users explicitly offer feedback on items, and implicit ratings, which are inferred from user behavior. Explicit ratings might include user-generated reviews or numerical ratings, whereas implicit ratings involve actions like clicks, views, or purchase history.
- **Knowledge-Based Data:** Knowledge-based data incorporates information about the items themselves. This could include attributes like genre, category, author, or any relevant metadata associated with the items being recommended. This type of data helps the RS make informed suggestions based on the intrinsic properties of the items.
- **Community Data:** Community data involves insights gained from the collective behavior of a group of users. It can encompass trends, popular choices, or collaborative filtering techniques, where recommendations are grounded on the preferences of users sharing the same tastes.
- **Contextual Data:** Contextual data takes into account the situational and environmental factors that might influence a user's preferences. For instance, the time of day, location, or current trends can be considered to tailor recommendations based on the specific context in which a user is making choices.
- **Demographic Data:** Demographic information provides a broader understanding of users by considering characteristics such as age, gender, location, and other socioeconomic factors. These data help create more generalized but still relevant recommendations for users with similar demographic profiles.

Table 1 presents a comparison of the previously mentioned models, highlighting how each model incorporates diverse data inputs to optimize recommendation accuracy.

Input	CB	CF	Hyb	MF	CA
User-Profile	Yes	Yes	Yes	Yes	Yes
Explicit Ratings	Yes	Yes	Yes	Yes	Yes
Implicit Ratings	Yes	Yes	Yes	Yes	Yes
Knowledge-Based	Yes	No	Yes	No	Yes
Community Data	No	No	Yes	No	Yes
Contextual Data	No	No	Yes	No	Yes
Demographic Data	No	No	Yes	No	Yes

Table 1: Recommender System Models and Input Types

3 Deep learning-based recommender systems: Main models

A branch of machine learning is deep learning, which emulates the human brain mechanism for processing information. This entails the training of multiple layers of artificial neural networks to predict, make decisions, and classify data, which is achieved through extensive training on large datasets [Fu, 23].

A. Multilayer perceptron (MLP):

A foundational architecture in deep learning is the multilayer perceptron (MLP). Comprising interconnected nodes organized in layers—input, one or multiple concealed layers, along with an output layer—MLPs demonstrate proficiency in grasping intricate patterns and relationships [Ramchoun, 17].

Widely applicable in fields like healthcare, entertainment, safety, and security, MLPs are adept at understanding relationships between items and users and providing accurate recommendations [Alghofaily, 20]. MLPs are commonly used for classification and regression and are capable of approximating complex nonlinear functions. They are extensively used for simulating user-item interactions within RSs, as they can grasp intricate non-linear relationships between user profiles, item features, and user preferences to generate personalized recommendations. MLPs have been applied to tasks such as CF, CB filtering, and hyb recommendation models.

MLP4Rec, as developed by Li et al. [Li, 22], is an innovative architecture for sequential RSs utilizing MLP blocks to identify sequential dependencies within user-item interactions. The architecture employs a tri-directional fusion mechanism to efficiently capture sequential, cross-channel, and cross-feature relationships in user historical data. By using MLP blocks instead of self-attention mechanisms, MLP4Rec simplifies the model architecture, reduces computational complexity, and requires fewer parameters while outperforming current state-of-the-art techniques on benchmark datasets.

Wang et al. [Wang, 21a] presented a novel framework called AMEIR, which utilizes NAS to enhance the conception of RSs. AMEIR automates the process of creating recommendation models by dividing it into three phases: behavior modeling, interaction exploration, and MLP investigation. This approach involves a novel search space that includes tailored subspaces for each stage, enabling the identification of optimal architectures without extensive manual intervention. AMEIR progressively conducts one-shot random searches within these subspaces, ultimately assembling the search results to form a complete recommendation model. Test results show that AMEIR achieves superior performance compared to existing manual and NAS-based methods, offering a more efficient, effective, and robust solution for personalized recommendations in various scenarios.

B. Autoencoder (AE):

An unsupervised learning artificial neural network is the autoencoder. It excels in dimensionality reduction and feature learning. Consisting of an encoder to compress input data and a decoder to reconstruct the low-dimensional representation, autoencoders efficiently encode and decode data. Valued for image denoising, anomaly detection, and RSs. They are a versatile tool in the deep learning arsenal [Xia, 21].

AE have been employed to learn low-dimensional representations of user preferences and item features, which can then be used for recommendation tasks. They can capture latent patterns in user-item interactions and provide effective representations for collaborative filtering and content-based recommendation models.

AutoRec++ [Liang, 22], an enhanced model designed by Liang et al. to enhance RS performance by addressing inherent biases. AutoRec++ builds on the autoencoder framework of the original AutoRec model, integrating Preprocessing Bias (PB) and Training Bias (TB) techniques to increase the accuracy and efficiency of deep neural network (DNN)-based systems. Extensive experiments on five reference datasets show that using the optimal combination of PB and TB significantly enhances prediction accuracy and computational efficiency, allowing AutoRec++ to outperform existing developed models. The outstanding design of debiasing is crucial to improving RSS's reliability and effectiveness.

C. Convolutional neural networks (CNNs):

CNNs use convolutional layers to learn spatial hierarchies of features from grid-like input such as photos and videos. Proven effective in computer vision, CNNs have extended their influence on RSs. Notable models like LeNet-5 [Lecun, 98] and AlexNet [Krizhevsky, 17] paved the way, whereas deeper architectures like VGG [Simonyan, 15] and ResNet [He, 16a] further pushed the boundaries. In healthcare, CNNs have found applications in medical image analysis [Prakash, 23].

An example of the use of CNN in RSs is illustrated in Figure 3, which demonstrates a RS where user and item data are first preprocessed and embedded into dense vectors. These embeddings are passed through fully connected layers to pull user and item attribute characteristics. The features are combined in a prediction layer to generate recommendations, ultimately producing a ranked list of top N items for the user based on the predicted likelihood of interaction.

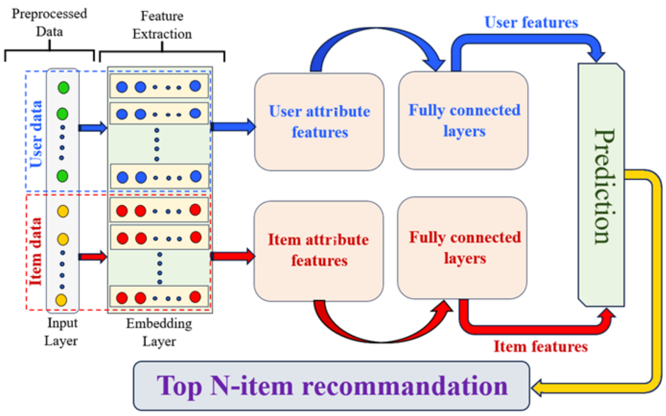

Figure 3: Convolutional Neural Network (CNN) example

CNNs have been used in RSs to learn features from different data types, including images, text, and audio. They can capture spatial and time-based dependencies in input data, which aids in tasks like item feature extraction, multimodal recommendation, and session-based recommendation.

Yang et al. presented a novel RS called TC-PR [Yang, 19], which integrates time context information into a CNN framework to enhance personalized recommendations. The authors emphasize the significance of temporal dynamics in user preferences and propose a method to capture these dynamics, leading to improved recommendation accuracy. Through comprehensive investigations on real datasets, they reveal that TC-PR outperforms traditional RSs, particularly in handling the cold-start issue and achieving higher precision and strength as dataset sizes increase. Overall, the study highlights the crucial role of time context in developing effective RSs.

Another application of CNNs in RSs was presented by Dharne et al. [Dharne, 23] by exploring the development of an Emotion-driven Music RS leveraging Viola-Jones and CNN. The system is built to suggest songs aligned with the user's emotional mood by analyzing their facial expressions in real-time. It employs the Viola-Jones approach for facial detection and CNNs to identify emotions. Users can input the singer's name, language, and their emotional state, enabling the system to search for suitable music tracks on platforms such as YouTube Music. Furthermore, the system includes features aimed at enhancing positive moods and alleviating negative emotions through carefully selected music.

In e-commerce field, Hong et al. [Hong, 24] introduced an innovative approach called the ROP-CNN model to tackle the issue of information overload in the e-commerce market. This research focuses on developing a RS that employs CNNs to pull semantic features from user reviews and incorporate these characteristics to understand intricate user-item interactions. By integrating user preference information from reviews, the ROP-CNN model aims to improve recommendation performance over existing baseline models. This study offers a theoretical and methodological perspective on recommendation research, highlighting the significance of rich user-item interaction data in enhancing RSs.

Selamat et al. [Selamat, 24] proposed a novel approach for personalized recommendations in social networks that utilizes CNN and integrates tagging and contextual features to improve recommendation accuracy. The method attempts to address the problem of sparse data by using DL approaches in conjunction with contextual information to provide users with more accurate and relevant suggestions in social networks.

D. Recurrent neural networks (RNNs):

Tailored for sequential data, Recurrent Neural Networks (RNNs) maintain an internal memory or hidden state [Cai, 02]. Suitable for processing natural language, recognizing speech, and predicting time series, RNNs capture patterns in data sequences. Variants such as LSTM [Hochreiter, 97], and GRU [Cho, 14] find application in RSs for journals [Hemila, 23].

RNNs have been employed in RSs to model user behavior and preferences over time. They are commonly used in tasks such as session-based recommendation, sequential recommendation, and next-item prediction. RNNs can effectively identify the temporal dynamics of user-item interactions and generate personalized suggestions grounded on a user's past actions.

A knowledge-based recommendation system (KBRS) was developed by Sunitha et al. [Sunitha, 23], which integrates sentiment analysis and advanced DL methods. The system's goal is to improve the effectiveness of RSs by specifying users who may be experiencing stress or depression on online social networks. Through the analysis of the engagement of the user and sentiment data, the KBRS provides personalized recommendations to improve users' emotional well-being. The study emphasizes the importance of incorporating additional user profile variables, ontology concepts, and advanced sentiment analysis techniques to achieve greater accuracy than existing studies. The research underscores the value of using ontology and focused sentiment analysis in RSs to enhance user experience and emotional well-being.

Siet et al. [Siet, 24] introduced a novel recommendation approach utilizing a RNN built on social networks to tackle the issue of sparsity in RSs while improving their accuracy and diversity in complex scenarios. This study focuses on delivering personalized recommendation services in response to the issue of information overload, which has been intensified by rapid advancements in information technology and the expansion of the Internet. The main goal of the system is to boost user engagement and satisfaction by providing personalized movie recommendations that align with users' interests.

E. Restricted Boltzmann Machines (RBM):

RBMs, a type of neural network for unsupervised learning, capture complex patterns and relationships within data. Comprising visible and hidden layers, RBMs model the input data’s probability distribution, proving effective in dimensionality reduction, feature learning, and CF for RSs.

They can learn latent representations of user-item interactions and product features, which can then be applied to generate personalized suggestions.

Sattar et al. created a RS established on RBM by leveraging latent features to boost the accuracy and efficiency of recommendations, focusing on analyzing user ratings and preferences to provide personalized recommendations effectively [Sattar, 21]. The methodology employs RBM to process vast datasets, demonstrating impressive performance with over 1 million ratings, where it achieves efficient training times (CPU-time) and reduced error rates. Applications of this system extend to various real-time scenarios, such as managing advertisements and even enhancing public safety by analyzing user preferences. The study includes comprehensive technical details on the dataset, which features user demographics and movie ratings, as well as the RBM model's architecture and implementation. By capturing complex user-item interactions, the RBM approach significantly boosts recommendation accuracy, contributing substantially to advancements in RSs.

F. Neural Autoregressive Density Estimation (NADE):

Neural autoregressive density estimation (NADE) is a probabilistic model and generative neural network architecture intended to calculate the conditional probability of an element in a sequence based on previous elements. Renowned for generating complex, high-dimensional data samples and density estimation, NADE finds applications in collaborative filtering and implicit feedback RSs [Chen, 22], where it effectively captures the dependencies between user-item interactions to generate accurate recommendations in item-to-item RSs.

Implicit CF-NADE, which is a collaborative filtering with neural autoregressive distribution estimator, was introduced by Zheng et al. [Zheng, 16] to tackle the challenges tied to implicit feedback in RSs. While traditional RSs often depend on explicit feedback like ratings, implicit feedback, such as clicks and viewing behavior, is more prevalent but harder to interpret. This approach involves transforming implicit feedback into a "like" vector and a confidence vector, which are then used to predict user preferences using a neural autoregressive model. This model captures complex relationships and sequential patterns in user interactions by maximizing a weighted negative log-likelihood during training. In experimental evaluations, implicit CF-NADE significantly outperforms traditional matrix factorization methods, demonstrating its effectiveness in processing and leveraging implicit feedback to improve recommendation accuracy.

G. Neural attention (NA):

Neural attention is a DL mechanism that dynamically targets specific sections of the input data when making predictions. This architecture, capable of weighing the importance of different elements in input sequences, enhances the handling of variable-length sequences. Effective in multimedia recommendation and hashtag recommendation [Jianfeng, 23][Wang, 21b][Zhang, 23][Li, 21][Hanafi, 22], neural attention mechanisms offer improved performance in RSs.

These mechanisms have been employed in RSs to model complex user-item interactions, capture contextual information, and provide personalized recommendations. They have been applied to various tasks, including session-based recommendation, multi-task recommendation, and knowledge-aware recommendation.

A sentiment-aware deep RS was explored by D a'u et al. [Da'u, 19]. It integrates a semi-supervised topic model into a DL framework using a neural attention mechanism. This system aims to effectively grasp domain-specific features of products along with user sentiments, thus improving RSs' performance. The proposed approach includes several key components: an LSTM encoder for capturing word dependencies, a semi-supervised topic model for deriving aspects and sentiment lexicons, a co-attention mechanism for learning the significance of various aspects, and a prediction layer for estimating user ratings on items. The study highlights the model's contributions, such as improved recommendation performance, efficient sentiment-aware learning for user/item representations, and a better understanding of user-item interactions.

H. Adversary network (AN):

Adversary networks, especially generative adversarial networks (GANs), comprise a generator and a discriminator trained simultaneously through adversarial techniques (Figure 4). GANs find applications in generating different types of data, from images to texts, and have been extended to domains such as healthcare and RSs [Goodfellow, 20][Isola, 17][Reed, 16][Zhu, 22][Shafqat, 22].

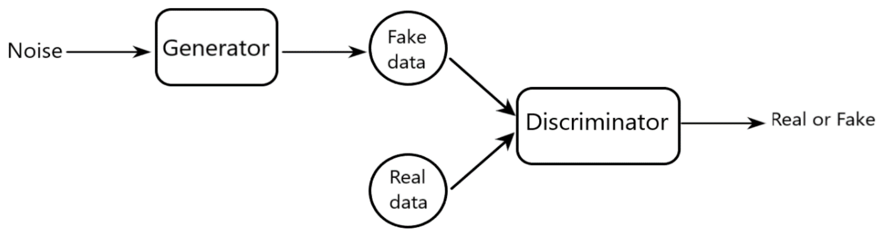

Figure 4: Generative adversarial network (GAN)

Adversarial networks have been utilized in RSs to enhance diversity and recommendation quality, as well as to address common challenges such as sparse data and cold-start issues. These networks are utilized for generating synthetic user-item interactions, learning robust representations, and enhancing the performance of recommendation models.

An innovative method for personalized citation recommendation within heterogeneous bibliographic networks was presented by Cai et al. [Cai, 18]. The proposed model integrates network structure and vertex content information to enhance the precision and relevance of citation recommendations for researchers. By utilizing generative adversarial networks and deep network representation techniques, the model aims to provide tailored and effective suggestions for reference papers based on the similarity scores among various objects in the network, such as manuscripts, scientific papers, and authors. The study evaluates the model's performance using two bibliographic datasets and underscores the importance of personalized citation recommendations in boosting research productivity and improving information retrieval in academic contexts.

The adversarial neural collaborative filtering (ANCF) model presented by Gao et al. [Gao, 23], which combines matrix factorization and CNNs to increase the robustness of RSs against adversarial attacks. ANCF addresses the vulnerabilities of traditional neural collaborative filtering models by explicitly modeling correlations between embedding dimensions through the external product method, as opposed to relying on conventional inner product or concatenation techniques. Through adversarial training, the model learns to generate more resilient user–item interactions, thereby enhancing both the accuracy and security of the recommendation process. The experimental results prove that ANCF outperforms existing models on multiple public datasets, showcasing its effectiveness in strengthening RS robustness.

I. Deep reinforcement learning (DRL):

Deep reinforcement learning (DRL), exemplified by deep Q-Network (DQN) merges deep neural networks with reinforcement learning methods. By enabling agents to learn from interactions with an environment, DRL networks make decisions on the basis of expected cumulative rewards [Bahi, 23]. Applications like AlphaGo and AlphaZero demonstrate DRL's success in game-playing tasks [Wu, 19][Mnih, 15][Sun, 19][Liu, 18][Chen, 21].

DRL has been applied to RSs to effectively model the interactive and sequential nature of user–item interactions. It is employed to develop optimal recommendation strategies and understand long-term user preferences and generate personalized recommendations that maximize user engagement or satisfaction.

Building on this application of DRL, Du et al. explored how adversaries can exploit DRL-based RSs by injecting carefully crafted user–system interaction records [Du, 24]. The authors introduce a three-phase mechanism called PARL, which is designed to maximize the hit ratio while avoiding detection. PARL aims to improve the rating of a specific item without altering the rankings of other items. Experiments on actual datasets demonstrate PARL's effectiveness in manipulating RSs and its ability to bypass detection techniques. This paper underscores the importance of defending against such poisoning attacks to preserve the integrity and reliability of RSs.

Similarly, to address vulnerabilities in RSs, Keat et al. [Keat, 22] tackled the limitations of current recommendation methods by proposing a novel approach using DRL for multi-objective optimization. This study attempts to enhance the accuracy, novelty, and diversity of recommendations by optimizing these key metrics simultaneously. By leveraging DRL techniques, the research introduces innovative strategies to enhance the performance of RSs, ultimately providing users with more personalized and diverse recommendations.

Another approach in this area was presented by Ma et al. [Ma, 23], who propose a recommendation framework called SGNR, which utilizes Social Graph Neural Networks to improve interactive RSs on e-commerce platforms. This study investigates how incorporating multi-hop social relationships among users can successfully tackle the user cold-start problem and outperform existing recommendation schemes. Comprehensive tests on real datasets showcase SGNR's superiority over traditional approaches, showcasing its ability to optimize long-term user benefits in e-commerce settings.

In the field of travel recommendations, Wang and Hu [Wang, 23] extended the application of DRL by investigating route planning using deep reinforcement learning. Their research focused on achieving autonomous route planning in unfamiliar environments utilizing visual observation and global map analysis within a 3D visual framework. This study addresses the challenges of feature extraction from visual inputs and decision-making complexities by applying intensive training on a large dataset of maps. CNNs are employed for image processing and end-to-end training, which are highlighted as promising techniques. The methodology involves updating value functions and positioning parameters using historical data, with the results section providing insights into experimental data collection and model verification based on traffic and tourist destination information.

J. Hybrid Models:

Hybrid models combine various statistical models, ML algorithms, and DL networks to improve overall performance. By incorporating CF with other DL models for image recommendations [Lei, 16] or integrating CF and content-based approaches, as seen in collaborative recurrent autoencoders for RSs [Wang, 16], hybrid models aim to leverage diverse models for accurate predictions. Another illustration of hybrid models is the user-item multi-criteria collaborative filtering algorithm, which utilizes multi-criteria ratings to recommend appropriate restaurants, tackling the challenge of sparse rating data [Shambour, 23].

The development of a personalized sleep RS using a hyb DL approach was presented by Park et al. [Park, 23]. The system is designed for personalized analysis of non-standardized sleep data, address the cold start problem in service recommendations, and improve the accuracy of hyb RSs for personalized sleep services. The customized deep recommender system (CDSRS) gathers data by utilizing move mattresses, constructs user shapes, and incorporates user feedback assessments. It aims to provide tailored recommendations to enhance sleep quality. The system collects various types of user data, such as sleep duration, movement, sound, and snoring data, to create personalized sleep recommendation content, ultimately improving the user experience and sleep quality.

In a similar vein of enhancing RS accuracy, Guo et al. explored the creation and implementation of a hyb RS that combines autoencoders and latent feature analysis to boost recommendation accuracy and efficiency [Guo, 23]. The system addresses the limitations of traditional linear models by leveraging the complex (non-linear) relationships between users and items. By utilizing autoencoders for feature learning and latent feature analysis to project users and items into a shared low-dimensional space, the hybrid RS can effectively estimate missing entries in the data. Additionally, the study highlights the scalability and efficiency of the presented approach, particularly in industrial settings. The integration of autoencoders and latent feature analysis offers a promising approach to enhancing RSs by capturing complex user–item interactions to boost overall recommendation performance.

Meanwhile, in the healthcare sector, hybrid RSs have been utilized for detecting mental illness on social media, utilizing DL techniques by Ahmed et al. [Ahmad, 23]. The study focuses on employing RSs to analyze user behavior patterns on social media platforms to identify signs of mental illness. By incorporating DL algorithms, the system aims to improve the accuracy of identifying individuals who may be experiencing mental health issues. This research explores the potential of leveraging technology to support mental health awareness and provide timely interventions for those in need.

Table 2 presents a detailed comparison of different ML models across diverse domains, shedding light on their performance metrics on different datasets. Each row in the table corresponds to a specific model's evaluation in a particular domain, utilizing a specific dataset and reporting various performance metrics, with corresponding references for further exploration.

Model	**Domain**	**Dataset**	**Metrics**	**Ref**
RBM	Entertainment	Movies' collected data	Accuracy	[Sattar, 21]
AN	E-commerce, Entertainment	CIAO, WATCHA, MovieLens	Precision, Recall, NDCG, MRR	[Chae, 19]
AN	E-commerce	Real e-commerce dataset	NDCG, MAP	[Gao, 19]
AN	Entertainment	DBpedia, Douban	Avg, Precision, NDCG	[Yang, 18]
AN	Tech	Programmableweb	Precision, Recall, MRR, NDCG	[Xie, 19]
RNN	Psychology	MBTI Personality	Accuracy, Sensitivity, Specificity, Precision, F-Measure	[Maheswara Rao, 23]
RNN	Science	Physics (PH), Chemistry (CH), Biology (BIO)	Accuracy	[Hemila, 23]
RNN	Entertainment	Million songs	Recall, Precision, F1-score	[Mesghali, 22]
RBM, AE, DNN	Entertainment	MovieLens ml-latest-small	RMSE, MAE	[Raghavendra, 22]

MLP, AE	Entertainment	MovieLens-100k, MovieLens-1M	RMSE, MAE	[Yengikand, 21]
MLP	Healthcare, Entertainment, Safety/Security	390 datasets	Precision, Recall, F1-score	[Alghofaily, 20]
AE	Entertainment	MovieLens-100K	RMSE, MAE	[Mecheri, 22]
AE	Entertainment	Netflix 3 months	RMSE	[Srikanth, 21]
AE	E-commerce, Entertainment	MovieLens-1M, MovieLens-100K, MovieLens-HetRec, Yahoo, Douban	RMSE, MAE	[Liang, 22]
CNN	E-commerce	Fashion products	Accuracy	[Kumar, 23]
CNN	Healthcare	Eye disease images	Accuracy, Precision, Recall	[Prakash, 23]
CNN	E-commerce	Fashion products	Accuracy, Precision, Recall, F1-score	[Suvarna, 22]
RNN, CNN	Multitask	YouTube data	AUC, RMSE	[Tang, 23]
AE	Entertainment	MovieLens-1M, MovieLens-10M, Netflix prize data, Foursquare, Yelp	RMSE, NDCG@K, Precision@K	[Xia, 21]
NADE	Entertainment	Collected data (watch behaviors)	MPR	[Zheng, 16]
AN	Entertainment	Yelp, Pinterest, MovieLens-1M	HR@K, NDCG@K	[Gao, 23]
DRL	Entertainment	Pantry, Yahoo, MovieLens-1M	Hit Ratio	[Du, 24]
NA	E-commerce, Entertainment	Amazon datasets, Yelp	MSE	[Da'u, 19]
Hybrid	Entertainment	MovieLens-1M, MovieLens-100K, MovieLens-HetRec, Yahoo, Douban	RMSE, MAE	[Guo, 23]

Table 2: Comparative Analysis of Models in Various Domains

In the entertainment domain, the restricted boltzmann machine (RBM) is evaluated using movies' collected data, with a focus on the metric of accuracy [Sattar, 21]. Autoencoder networks (AN) are versatile, demonstrating their effectiveness in both e-commerce and entertainment domains. The evaluation involves datasets such as CIAO, WATCHA, and MovieLens, with metrics including metrics such as precision, recall, NDCG, and MRR [Chae, 19]. The study presented by Chae et al. addresses the problem of improving the accuracy of RSs by proposing a novel framework that combines adversarial training and autoencoder-based collaborative filtering [Chae, 19]. This framework aims to provide more accurate suggestions to users according to their preferences and actions. The suggested approach, as illustrated in the study, surpasses various state-of-the-art algorithms in terms of recommendation accuracy.

AN is further assessed in e-commerce using an authentic e-commerce dataset, emphasizing NDCG and MAP metrics [Gao, 19]. In a subsequent work by Gao et al., DRCGR, a deep reinforcement learning framework, was introduced to tackle the dynamic interactive recommendation challenge. The DRCGR model incorporates CNN and GAN frameworks to autonomously learn the optimal recommendation strategy for modeling a recommended session. The results from the experiments presented in the paper show that the DRCGR model outperforms other contemporary recommendation models across various metrics, including MAP, NDCG, and other widely used measures.

In the entertainment domain, AN performance is measured against datasets such as DBpedia and Douban, with precision, average precision, and NDCG as key metrics [Yang, 18]. Additionally, in the tech domain, AN is applied to programmable web data, which are evaluated on the basis of precision, recall, mean reciprocal rank (MRR), and NDCG [Xie, 19].

Recurrent neural networks (RNN) exhibit versatility across psychology, science, and entertainment domains. Evaluated on datasets such as MBTI Personality, Physics, Chemistry, Biology, and Million Songs, RNN's metrics include accuracy, sensitivity, specificity, precision, and F-measure [Maheswara Rao, 23][Mesghali, 22]. In their study [Maheswara Rao, 23], the authors sought to forecast the personalities of Twitter users by employing the Myers-Briggs Type Indicator (MBTI) framework. They analyzed social behavior and linguistic patterns on the Twitter platform to achieve this goal. The researchers created an RNN-LSTM learning model for personality prediction using MBTI data and assessed its effectiveness in comparison to other machine learning classifiers. The results confirmed that the suggested RNN-LSTM model exhibited remarkable accuracy in predicting personality traits. Furthermore, the model offered personalized career recommendations on the basis of the predicted personality, aligning with the overarching objective of the research.

Hemila et al. [Hemila, 23] addressed the problem of journal RSs within the scientific disciplines of physics (PH), chemistry (CH), and biology (BIO). The authors set out to assess the efficacy of their system and determine the classification system that produces the most reliable recommendations. Furthermore, they explored whether there was a noteworthy variation in the effectiveness of the classification systems across three distinct scientific disciplines. The study yields encouraging and practical outcomes, particularly in the field of physics, making a major breakthrough in developing journal RSs.

Within the field of RSs (RS), the focus is on the entertainment sector, specifically movie recommendations utilizing datasets such as MovieLens ml-latest-small. Evaluation metrics include RMSE and MAE [Raghavendra, 22].

MLP and AE techniques are deployed in the entertainment domain for movie recommendations using datasets such as MovieLens-100K and MovieLense-1M, with evaluation metrics of RMSE and MAE [Yengikand, 21]. The challenge solved by Yengikand et al. [Yengikand, 21] is the improvement of RSs' performance. This study addresses the challenge of accurately predicting users' ratings for items in RSs. By comparing various recommendation methods and evaluating their performance using RMSE and MAE metrics, this research aims to pinpoint the optimal method for making accurate predictions. Compared with other baseline models, the proposed Deep-MSR model achieves superior performance, thus addressing the challenge of enhancing RS accuracy.

MLPs have also been applied across healthcare, entertainment, and safety/security domains using 390 datasets, with measures like precision, recall, and F1-score [Alghofaily, 20]. Convolutional neural networks (CNN) prove valuable in classifying fashion products in e-commerce datasets and diagnosing eye diseases in healthcare datasets, with evaluation methods encompassing accuracy, precision, recall, and F1-score [Prakash, 23] [Kumar, 23][Suvarna, 22]. Autoencoders (AEs) are employed in healthcare, but the specific dataset and evaluation metrics are not explicitly mentioned [Ubukata, 20].

In multitask scenarios, both RNN and CNN are applied to YouTube data, and their performance is evaluated using AUC and RMSE metrics [Tang, 23]. Tang et al. aimed to address the issue of training instability in recommendation models, specifically in a practical multitask ranking model applied for YouTube recommendations [Tang, 23]. The Google team discussed the difficulties in reproducing and detecting loss divergence during training, as well as the absence of viable methods to address this issue. This paper aims to disseminate its discoveries and optimal strategies for enhancing the training stability of recommendation models.

AE demonstrates its applicability across multiple domains, including collaborative filtering, with evaluation metrics such as RMSE, NDCG at K, and precision at K, using datasets like MovieLens-1M, MovieLens-10M, Netflix prize data, Foursquare, and Yelp [Xia, 21].

Table 3 offers a comprehensive examination of recommendation techniques approximations employed by various platforms across diverse categories. The platforms span multiple fields such as e-commerce and content platforms, and social media, each utilizing distinct strategies to enhance user experiences and engagement.

Within the domain of e-commerce, Amazon adopts a multifaceted approach, combining content-based, collaborative filtering, and DL techniques to tailor recommendations. eBay employs a sophisticated integration of modal data, multimodal embedding, graphs, and factorization machines to enhance its RS. On the other hand, Alibaba leverages a graph embedding framework to optimize its recommendation processes. Uber Eats innovatively combines content-based and collaborative filtering methods for restaurant tips, incorporating natural language processing to ensure balanced satisfaction in recommendations.

Content platforms like Netflix employ matrix factorization, deep neural networks, and filters for quality and freshness in their RSs, showcasing a holistic approach to content suggestion. Spotify utilizes collaborative filtering for playlist-based song suggestions and integrates natural language processing and content-based methods for song recommendations.

Goodreads focuses on content-based book recommendations, considering genres, keywords, and authors, while providing users with options to join groups, follow authors, and explore book lists. YouTube employs DL for user and video embeddings, NLP, computer vision for video metadata, and heuristic filters for quality and safety in recommendations. In the social media category, Instagram, Twitter, and Facebook all employ social graph analysis and content-based filtering to enhance user experience and engagement.

It is crucial to emphasize that the particular specifics of these methodologies are often proprietary and confidential to each company, rendering the provided insights as approximations. The real intricacies of these RSs are typically closely guarded secrets within the industry, reflecting the proprietary nature of the algorithms and methodologies employed by these platforms.

Platform	Category	Techniques
Amazon	E-commerce	Combine content-based, collaborative filtering, and deep learning.
eBay	E-commerce	Integrate modal data with multimodal embedding, graphs, and factorization machines.
Alibaba	E-commerce	Graph embedding framework.
Uber Eats	E-commerce	Combine content-based and collaborative filtering for restaurant tips. Optimize with natural language processing for balanced satisfaction.
Netflix	Content Platform	Matrix factorization for users and items. Deep neural networks for embeddings. Filters for quality and freshness in recommendations.
Spotify	Content Platform	Collaborative filtering for playlist-based song suggestions. Use NLP and content-based methods for song recommendations.
Goodreads	Content Platform	Hybrid approach: Content-based book recommendations (genres, keywords, authors), collaborative filtering (User options: join groups, follow authors, explore book lists).
YouTube	Content Platform	Deep learning for user and video embeddings. NLP and computer vision for video metadata. Use heuristics and filters for quality and safety in recommendations.
Instagram	Social Media	Social graph Analysis, Content Based Filtering
Twitter	Social Media	Social graph Analysis, Content Based Filtering
Facebook	Social Media	Social graph Analysis, Content Based Filtering

Table 3: Example Table with Platforms, Categories, and Techniques

4 Evaluation of the success of recommender systems: Common metrics

When assessing the performance and effectiveness of RSs, several key metrics are used. These metrics offer insights into various aspects of the system's capabilities and its ability to provide valuable and relevant suggestions. Predictive accuracy metrics are essential for evaluating the accuracy and performance of predictive models, including RSs. The commonly used predictive accuracy metrics, along with their formulas, include the following:

- **Mean absolute error (MAE):**

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|actual_i - predicted_i| \quad (5)$$

Each pair of $\boldsymbol{actual_i}$ and $\boldsymbol{predicted_i}$ corresponds to one data point (user-item interaction), and *n* is the total number of such pairs.

The MAE evaluates the average absolute deviation between predicted and actual values. In RSs, it is commonly used to evaluate the accuracy of rating predictions, where the goal is to predict how a user will rate a particular item. A lower MAE indicates better performance, as it means that the predictions are closer to the true values.

- **Root mean squared error (RMSE):**

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(actual_i - predicted_i)^2} \quad (6)$$

The RMSE is similar to the MAE, but it places more emphasis on larger errors. It is computed as the square root of the average squared difference among the expected and actual values. The RMSE is also widely used in RSs to assess the overall accuracy of rating predictions, with lower RMSE values indicating better performance.

- **Accuracy:**

$$Accuracy = \frac{NCP}{TPred} \quad (7)$$

NCP: Number of correct predictions.
TPred: Total number of predictions.

Accuracy is the overall measure of how well the RS performs, considering both true positives and true negatives. In the context of RSs, accuracy may not be the most relevant metric, as it can be influenced by class imbalance (e.g., the number of recommended vs. not recommended items). It is more beneficial when false positive and false negative costs are comparable, which may not always be the case in RSs.

- **Precision:**

$$Precision = \frac{TP}{TP + FP} \quad (8)$$

TP: true positives.
FP: false positives.

Precision is the proportion of true positives among the items the RS has recommended. It is particularly important in RSs, as it reflects the system's ability to make relevant recommendations.

High precision is crucial in situations where the expense of false positives (e.g., recommending irrelevant items) is high, such as in product recommendations, where users have limited time and attention. In multimedia recommendations (e.g., music, movies, TV shows), precision may be less crucial, as users may be more willing to explore a broader range of recommendations.

- **Recall:**

$$Recall\ (Sensitivity) = \frac{TP}{TP + FN} \tag{9}$$

FN: false negatives.

Recall is the proportion of true positives that the RS has correctly identified among all the relevant items.

This is important in scenarios where the cost of false negatives (e.g., failing to recommend relevant items) is high, such as in multimedia recommendations, where users may expect the system to provide a comprehensive set of relevant options.
In product recommendations, where the number of items is often more limited, recall may be less critical, as users may be satisfied with a few highly relevant recommendations.

- **F1-score:**

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{10}$$

The F1-score, as the harmonic mean of precision and recall, offers a balanced assessment of both. It is especially useful when balancing precision and recall is essential, depending on the particular needs of the RS. In product recommendations, where precision is often more important, the F1-score may put more emphasis on precision. In multimedia recommendations, where recall is more crucial, the F1-score may be more balanced between precision and recall.

These metrics deliver a quantitative evaluation of model predictive accuracy, enabling a thorough evaluation of their performance across different domains.

MAP@K evaluates precision for the top K recommendations, considering the average precision of relevant items up to rank K. Similarly, **MAR@K** assesses recall for the top K recommendations, measuring how well relevant items are captured within the first K. The formulas are as follows:

$$MAP@K = \frac{1}{|Q|}\sum_{q=1}^{|Q|}\frac{1}{min(K,R_q)}\sum_{k=1}^{K}P@K(q,k)\cdot R(q,k) \tag{11}$$

$$MAR@K = \frac{1}{|Q|}\sum_{q=1}^{|Q|}\frac{1}{R_q}\sum_{k=1}^{K}R@K(q,k)\cdot R(q,k) \tag{12}$$

Here, *Q* is the set of queries, *P@K(q, k)* is the precision at standing K for query *q*, *R@K(q, k)* is the recall at standing K for query *q*, *R(q, k)* is a binary indicator of relevance, and R_q is the number of relevant items for query *q*.

- **Mean reciprocal rank (MRR):**

MRR is a ranking measure that assesses the effectiveness of a RS on the basis of the inverse of the rank of the first relevant item. The formula for MRR is as follows:

$$MRR = \frac{1}{|Q|}\sum_{q=1}^{|Q|}\frac{1}{rank_q} \quad (13)$$

Here, $rank_q$ is the ranking of the first pertinent item in the list of recommendations for query q.

- **Normalized discounted cumulative gain (NDCG):**

NDCG is a ranking measure that takes into account both the relevance and the position of items in the recommendation list. The formula for NDCG is as follows:

$$NDCG@K = \frac{1}{|Q|}\sum_{q=1}^{|Q|}\frac{1}{DCG@K(q)}\sum_{k=1}^{K}\frac{2^{R(q,k)}-1}{\log_2(k+1)} \quad (14)$$

In this equation, DCG@K(q) is the discounted cumulative gain at position *K* for query q, and *R(q, k)* is a binary indicator of relevance.

These ranking metrics, MRR and NDCG, provide valuable insights into how well a RS performs in terms of presenting relevant items and their positions in the recommendation list.

- **Mean absolute percentage error (MAPE):**

The MAPE is a metric used to measure a forecasting model's accuracy. It represents the average absolute discrepancy between estimated and real values, shown as a percentage of the real values. The formula for MAPE is given as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - F_i}{A_i}\right| \times 100 \quad (15)$$

A_i : The actual value.
F_i : The forecasted value.
n : The number of observations.

The MAPE provides an easy-to-understand way to measure how accurate a forecast is, which makes it helpful for comparing how different models perform across various datasets or scales. However, the MAPE can sometimes give misleadingly large errors when dealing with very small actual values. In RSs, the MAPE measures how accurately the predicted ratings or preferences match the actual user ratings by calculating the average percentage difference between them. This metric is useful because it shows errors as percentages, making it simple to compare results across different datasets. Despite that, it can be problematic when the actual ratings are near zero, as this can result in unusually high percentage errors.

- **Mean squared error (MSE):**

The MSE is a widely used metric for assessing the accuracy of a model's predictions by measuring the mean squared deviation between predicted and actual values. The formula for the MSE is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(A_i - F_i)^2 \quad (16)$$

The MSE emphasizes larger errors because it squares discrepancies between predicted and actual values, making it prone to outliers. This characteristic helps measure how much predictions vary from actual outcomes, which is why MSE is frequently applied in regression tasks to gauge model performance. In RSs, the MSE calculates the accuracy of predicted ratings by averaging the squared differences between what the system predicts and what users actually rate. This provides an overall sense of how well the system predicts user preferences, highlighting significant mismatches. However, MSE's sensitivity to large errors can sometimes lead to a skewed evaluation, as it heavily penalizes outliers, potentially pushing models to favor safer predictions rather than exploring diverse recommendations.

As a result, within RS applications, MAE and RMSE are more commonly used than the MAPE and the MSE for the following reasons:

1. **Rating prediction**: In RSs, the goal is often to forecast the rating or preference score a user might assign to an item. The MAE and the RMSE are well-suited for this task, as they directly measure the predicted ratings' accuracy.
2. **Interpretability**: The MAE and RMSE have the same unit as the target variable (e.g., rating scores), which makes them more intuitive to interpret than the MAPE and MSE.
3. **Sensitivity to outliers**: RSs may be more sensitive to large errors, as extreme mistakes can significantly impact the user experience. RMSE's sensitivity to outliers can be beneficial in this context.
4. **Widespread adoption**: MAE and RMSE are widely used and well-understood metrics in the RSs literature, making them more commonly reported and easier to compare across different studies and models.

While the MAPE and MSE can also be used in RSs, the nature of the task and the preference for interpretable metrics often make MAE and RMSE the more prevalent choices for evaluating of recommender models' performance.

Therefore, the choice of evaluation metrics for RSs depends upon the particular demands and details of the domain.

Table 4 provides a clear and concise comparison of the different metrics, highlighting their key characteristics and suitability for various scenarios. Additionally, the trade-offs between the metrics are shown.

Metric	User Experience Alignment	Sensitivity to Dataset Biases	Suitability
MAP@K	Prioritizes pertinent items at the forefront of the recommendation list.	Sensitive to the distribution of relevant items across users and items.	Suitable for scenarios where users are primarily interested in the top-ranked recommendations (e.g., e-commerce product recommendations, news article recommendations).
MRR	Focuses on the placement of the first relevant item, which aligns with quick satisfaction.	Less sensitive to dataset biases as it only considers the first relevant item.	Suitable for scenarios where users are primarily interested in finding a single relevant item (e.g., question-answering systems, product search).

NDCG	Captures the idea that users value relevant items higher when they appear at the leading position of the recommendation list.	More sensitive to dataset biases as it considers the entire recommendation list.	Suitable for scenarios where users expect a comprehensive set of relevant recommendations (e.g., content discovery, multimedia recommendations).

Table 4: Comparison of Commonly Used Ranking Recommendation Metrics

5 Challenges of Deep Learning-Based Recommender Systems

Deep learning-based RSs leverage neural networks to enhance the quality and efficiency of recommendations by learning from extensive datasets and handling complex tasks. These systems can address various challenges and opportunities in RSs, including data sparsity, the cold start problem, scalability issues, diversity considerations, and the need for explainability.

A. Data sparsity:

In the context of RSs, data sparsity refers to the property where most elements in the user–item interaction matrix have zero values, indicating a lack of user–item interactions. Matrix factorization techniques, such as those employed by autoencoders, can address this challenge by breaking down the user-item matrix into low-dimensional latent factors. Autoencoders, in particular, perform matrix factorization by encoding and compressing the user-item matrix into latent factors, effectively handling implicit interactions such as clicks and views. Additionally, autoencoders can integrate auxiliary data, such as user profiles or item attributes, to further improve performance [Cui, 23].

B. Cold start:

The cold start issue occurs when a RS encounters a new person or object with limited interaction data. DL models, such as Neural Collaborative Filtering, can mitigate this challenge by incorporating auxiliary data. Neural collaborative filtering combines matrix factorization with neural network layers to learn interactions between user and item features, effectively leveraging side information to find similarities with existing users or items [Woo, 22].

C. Scalability:

Scalability becomes a concern when addressing large and dynamic datasets. DL models address scalability challenges by employing parallel processing techniques, allowing for the efficient use of multiple cores, processors, or GPUs. Distributed computing frameworks further contribute to scalability by distributing data and computations across various devices, such as cloud or edge services. Deep neural networks, owing to their ability to learn complex functions, are well-suited for parallel and distributed computing systems, employing techniques such as mini-batch training and stochastic gradient descent [Tandon, 08].

D. Diversity:

Maintaining diversity in recommendations is crucial for user satisfaction and avoiding filter bubble effects. DL models, including those using multi-objective optimization and reinforcement learning, strike a balance between relevance and diversity. Techniques such as sampling from different regions of the latent space, as seen in generative adversarial networks (GANs), contribute to generating diverse recommendations [Yang, 23].

E. Explainability:

Explainable AI (XAI) pertains to the creation of artificial intelligence systems that not only provide precise forecasts but also offer clear and understandable justifications for their actions. The goal is to enhance trust and comprehension, allowing users to interpret and trust AI outputs, especially in critical applications where accountability and interpretability are essential (Figure 5).

Providing explainable recommendations enhances user trust and satisfaction. Attention mechanisms, saliency maps, and natural language generation are instrumental in achieving explainability. Attention mechanisms assign weights to input data, highlighting important features, whereas saliency maps visualize high-gradient regions. Natural language generation ensures that recommendations are accompanied by textual descriptions, aiding in their interpretability [Vultureanu-Albişi, 21].

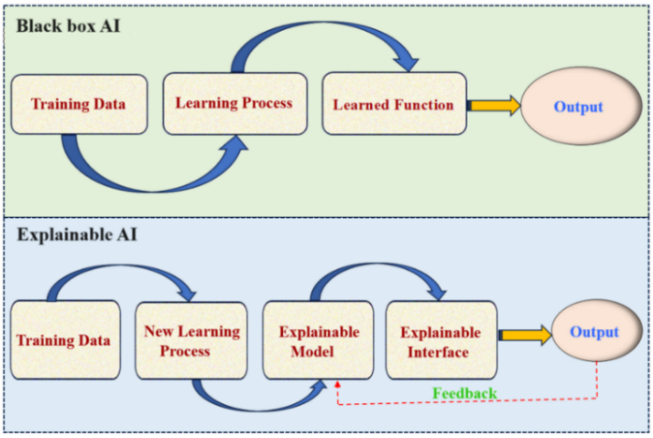

Figure 5: Explainable AI (XAI) Concept

6 Benchmark datasets for recommender systems

The delivery of accurate recommendations spans different fields like healthcare, education, entertainment, and e-commerce. To develop precise RSs, researchers often construct datasets tailored to the specific type or field of recommendation. This involves creating synthetic datasets to enrich existing benchmarks or collecting data by crawling different sources. The following is a compilation of several commonly used datasets for RSs:

- **Ciao Dataset:** Introduced by Tang et al. [Tang, 12], this dataset contains user ratings for items along with item category details, derived from the Epinions dataset.
- **Amazon Product Data:** As presented by He et al. [He, 16b], this dataset comprises reviews and metadata of products from Amazon. The collected data from May 1996 to July 2014 consists of 142.8 million reviews.

- **Pinterest Dataset:** As described by Geng et al. [Geng, 15], over one million images allied with Pinterest users who have "pinned" them are collected in this dataset.
- **Microsoft News Dataset (MIND):** As presented by Wu et al [Wu, 20], MIND includes around 160,000 English news articles and over 15 million impression logs. This dataset is designed for research in news recommendation.
- **ReDial (Recommendation Dialogues):** Curated by Li et al. [Li, 18], ReDial is a dataset of dialogues where users suggest movies to each other, featuring over 10,000 conversations.
- **Douban Conversation Corpus:** As presented by Wu et al. [Wu, 17], this dataset is tailored for retrieval-based chatbots and includes training, development, and test sets.
- **Yahoo Dataset:** Introduced in the Yahoo! Learning to Rank Challenge [Chapelle, 10], this dataset contains 709,877 documents characterized by 700 features, extracted from Yahoo! search engine query logs.
- **WeChat Dataset:** Presented by Wang et al. [Wang, 20], this dataset for fake news detection includes over 20,000 news instances categorized as either fake or authentic.
- **MovieLens Datasets:** Introduced by Harper et al. [Harper, 15], MovieLens datasets document individuals' stated movie preferences through a 0–5 star rating system, submitted through the MovieLens website for personalized movie recommendations.
- **Netflix Prize Dataset:** This dataset comprises approximately one hundred million ratings assigned to 17,770 movies by 480,189 users, serving as the basis for the Netflix Prize competition [Bennett, 07].
- **Million Song Dataset (MSD):** Compiled by Bertin-Mahieux et al. [Bertin-Mahieux, 16], the MSD contains audio features and metadata for one million popular contemporary music tracks.
- **Spotify Podcast Dataset:** Introduced by Clifton et al. [Clifton, 20], this dataset includes around 100,000 podcast episodes with raw audio files and corresponding ASR transcripts.
- **Yelp2018 Dataset [1]:** Derived from the 2018 Yelp Challenge, this dataset treats local businesses such as restaurants and bars as items, maintaining a consistent 10-core setting.
- **Gowalla Dataset:** Gowalla is a social networking platform centered around location, comprising check-ins and friendship interactions, introduced by Cho et al. [Cho, 11].

Figure 6 offers a comprehensive overview of common datasets in RS research spanning from 2019 to 2023. In this chart, it is evident that the most frequently utilized dataset for research purposes is MovieLens.

[1] https://www.yelp.com/dataset

Table 5 compiles the highest-ranked results, providing a showcase of the forefront achievements. This compilation provides a key resource for grasping the cutting-edge performance in this evolving field.

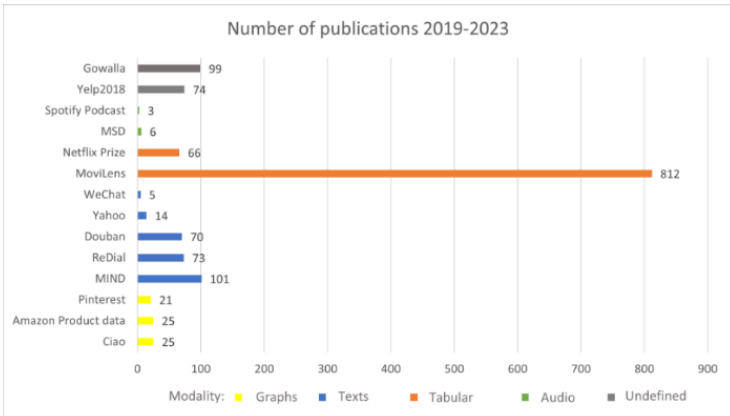

Figure 6: Recommender Systems' common datasets

Dataset	Model	Metrics	Results	Year	Ref
Amazon Product Dataset	TLSAN	AUC	0.9773	2021	[Zhang, 21]
	SLI-Rec	AUC	0.8494	2019	[Yu, 19]
Pinterest	TransCF	Hits@10	0.5504	2019	[Park, 18]
		Hits@20	0.8108		
		nDCG@10	0.258		
		nDCG@20	0.3242		
MIND	Glove+NRMS	AUC	0.7221	2022	[Abdulhussein, 22]
		MRR	0.3572		
		nDCG@5	0.4445		
		nDCG@10	0.3805		
	DKN	AUC	0.6436	2018	[Wang, 18]
		MRR	0.3128		
		nDCG@5	0.3371		
		nDCG@10	0.3908		
	LSTUR	AUC	0.6356	2019	[An, 19]
		MRR	0.3098		
		nDCG@5	0.3345		
		nDCG@10	0.4137		
	Wide&Deep	AUC	0.6216	2016	[Cheng, 16]
		MRR	0.2931		
		nDCG@5	0.3128		
		nDCG@10	0.3712		
ReDial	CRFR	Recall@1	0.04	2021	[Zhou, 21]
		Recall@10	0.202		
		Recall@50	0.399		

	CR-Walke	Recall@1	0.04	2021	[Ma, 21]
		Recall@10	0.187		
		Recall@50	0.376		
Douban	DGRec	NDCG	0.195	2019	[Song, 19]
		Recall@20	0.1861		
	I-CFN	RMSE	0.6911	2016	[Strub, 16]
	U-CFN	RMSE	0.7049		
MSD	EASE	nDCG@100	0.389	2019	[Steck, 19]
		Recall@20	0.333		
		Recall@50	0.428		
	RecVAE	nDCG@100	0.326	2020	[Shenbin, 20]
		Recall@20	0.276		
		Recall@50	0.374		
MovieLens 20M	VADP	nDCG@100	0.448	2021	[Vančura, 21]
		Recall@20	0.414		
		Recall@50	0.552		
	H+Vamp Gated	nDCG@100	0.445	2019	[Kim, 19]
		Recall@20	0.413		
		Recall@50	0.551		
Netflix	H+Vamp Gated	nDCG@100	0.40861	2019	[Kim, 19]
		Recall@20	0.37678		
		Recall@50	0.46252		
	RecVAE	nDCG@100	0.394	2020	[Shenbin, 20]
		Recall@20	0.361		
		Recall@50	0.452		
Gowalla	STAN	Recall@5	0.3016	2021	[Luo, 21]
		Recall@10	0.3998		
Ciao	TransCF	Hits@10	0.2292	2019	[Park, 18]
		Hits@20	0.374		
		nDCG@10	0.1167		
		nDCG@20	0.1525		

Table 5: Benchmark Table: Highest-Ranked Results in Recommender Systems Using Common Datasets

This table delineates a comprehensive benchmark of the highest-ranked results in RSs across diverse datasets. Each entry in the table encompasses details about the dataset, the specific model utilized, the metrics assessed, the reported results, the corresponding year of publication, and the reference for further exploration.

Within the Amazon Product dataset category, TLSAN achieves a notable AUC of 0.9773 in 2021, whereas SLI-Rec follows closely with an AUC of 0.8494 in 2019 [Zhang, 21][Yu, 19]. In the Pinterest dataset, TransCF stands out with results including Hits@10 (0.5504) and Hits@20 (0.8108) in 2019 [Park, 18]. For the MIND dataset, Glove+NRMS and DKN perform competitively in terms of AUC, MRR, and nDCG metrics, providing insights into the evolving landscape of recommendation techniques [Abdulhussein, 22][Wang, 18]. Similarly, in the ReDial dataset, CRFR and CR-Walker excel on Recall@1, Recall@10, and Recall@50 metrics in 2021 [Zhou, 21][Ma, 21].

Douban's DGRec and I-CFN, U-CFN models exhibit their prowess NDCG, Recall@20, and RMSE metrics, providing a nuanced understanding of the diverse evaluation criteria applied to RSs in 2019 and 2016, respectively [Song, 19][Strub, 16]. The MSD dataset shows the capabilities of the EASE and RecVAE models in the nDCG@100, Recall@20, and Recall@50 metrics, offering insights into RSs applied to large-scale music datasets in 2019 and 2020 [Steck, 19][Shenbin, 20].

Moving to MovieLens 20M, VASP and H+Vamp Gated models exhibit competitive results in nDCG@100, Recall@20, and Recall@50, elucidating their efficacy in movie recommendation scenarios in 2021 and 2019 [Vančura, 21][Kim, 19]. Similarly, in the context of Netflix, H+Vamp Gated and RecVAE models showcase their effectiveness in nDCG@100, Recall@20, and Recall@50 metrics, providing a nuanced understanding of their performance in 2019 and 2020, respectively [Kim, 19][Shenbin, 20].

The Gowalla dataset, explored in 2021, showcases STAN as a notable model, achieving impressive Recall@5 and Recall@10 results [Luo, 21]. Finally, in the Ciao dataset, TransCF emerges as a prominent model, achieving noteworthy results in Hits@10, Hits@20, nDCG@10, and nDCG@20 metrics in 2019 [Park, 18]. A comprehensive overview of model performance across multiple metrics is presented in Figure 7.

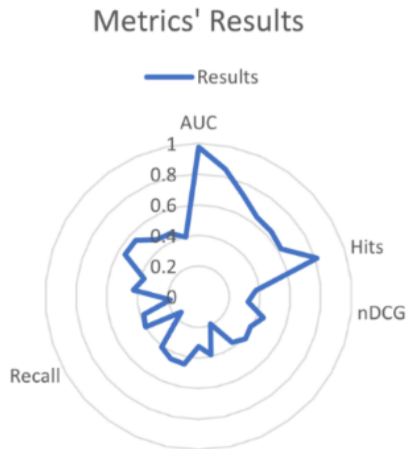

Figure 7: Metrics' Results

In terms of the AUC (area under the curve), TLSAN distinguishes itself as the leading model, demonstrating a notable score of 0.9773, indicating strong performance. SLI-Rec closely follows, contributing a respectable AUC score of 0.8494. On the other hand, models such as Glove+NRMS, DKN, LSTUR, and Wide\&Deep exhibit comparatively lower AUC scores.

Shifting focus to Hits at 1, TransCF takes the lead with a score of 0.8108, suggesting effectiveness in capturing relevant items. However, other models, including Glove+NRMS, DKN, LSTUR, and Wide\&Deep, have lower Hits scores of 1.

When the nDCG (Normalized Discounted Cumulative Gain) is examined, TransCF stands out with a noteworthy score of 0.3242. While other models like Glove+NRMS, DKN, LSTUR, and Wide\&Deep demonstrate varying nDCG scores, TransCF leads in this particular metric.

In terms of Recall, VASP and H+VampGated emerge as the top performers, both achieving scores of approximately 0.55. Conversely, models such as CRFR, CR-Walker, DGRec, EASE, RecVAE, and STAN exhibit lower Recall scores.

7 Future Directions

In the ever-evolving landscape of information and technology, RSs stand as pivotal tools, shaping the way users discover content, products, and experiences. As sights are set on the future, several intriguing directions emerge, promising to improve the efficacy and user interaction with RSs.

- **Personalization Pioneered by AI and Machine Learning:**

The advancement of RSs depends on harnessing the power of sophisticated artificial intelligence (AI) and ML algorithms. These systems delve deeper into user actions, preferences, and context to provide hyper-personalized recommendations. By leveraging neural networks and DL techniques, RSs can be adept at understanding intricate patterns and nuances in individual user choices.

- **Explainability and trustworthiness:**

As RSs become more sophisticated, the need for transparency and explainability becomes paramount. Users are increasingly concerned about the "black box" nature of complex algorithms. Future RSs prioritize explainability, offering clear insights into the rationale behind recommendations. This not only builds trust but also allows users to have a better understanding of how their preferences are being interpreted.

- **Cross-Domain recommendations:**

The boundaries between different domains, such as music, movies, books, and products, are blurring. Future RSs will transcend these silos, providing users with holistic recommendations that span multiple domains. This cross-domain approach offers users a more comprehensive and interconnected experience, reflecting the multifaceted nature of their interests.

- **Context-Aware recommendations:**

The integration of contextual information will be a cornerstone of future RSs. These systems can adapt suggestions by considering various features, including time, location, etc. For example, they might suggest a different type of content during a commute compared with a lazy weekend at home. This contextual knowledge ensures that recommendations are personalized, timely and relevant.

- **Interactive and user-driven recommendations:**

Empowering users to actively participate in the recommendation procedure is a key trend. Future RSs will facilitate more user feedback, allowing individuals to express preferences, provide ratings, and offer explicit input. This user-driven approach not only refines recommendations but also ensures a more engaging and collaborative user experience.

- **Ethical considerations and diversity:**

Addressing ethical concerns and promoting diversity in recommendations will be a focal point. Future systems will be designed to avoid reinforcing biases and ensure fair representation of content across diverse demographics. Striking a balance between personalization and avoiding algorithmic discrimination is crucial in shaping the ethical framework of RSs.

- **Decentralized and privacy-preserving solutions:**

With increasing concerns over privacy of user data, future RSs will explore decentralized approaches. Implementing techniques for privacy preservation, including federated learning and homomorphic encryption, will allow recommendations to be generated while safeguarding user privacy. This shift is consistent with an increasing focus on data security and user autonomy.

8 Conclusion

This paper delves into the evolutionary trajectory and the profound impact of DL techniques on RSs. Beginning with an exploration of traditional methods including CF, CB filtering, and hybrid strategies, the narrative shifts to the transformative influence of DL methodologies. These advancements have exhibited significant promise in increasing recommendation accuracy and effectively addressing the challenges inherent in conventional methods.

The survey underscores notable contributions within the realm of RSs based on DL. It also sheds light on benchmark datasets crucial for algorithm testing and fostering a thriving research environment. Additionally, this paper discusses the evaluation methods employed to gauge the success of RSs. The amalgamation of DL with RSs is an ever-evolving narrative, and this article serves as a snapshot, capturing the essence of a field in perpetual motion.

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