



Deep learning approaches to address cold start and long tail challenges in recommendation systems: a systematic review

Manisha Jangid¹ · Rakesh Kumar¹

Received: 28 June 2023 / Revised: 23 July 2024 / Accepted: 11 September 2024 /

Published online: 16 October 2024

© The Author(s), under exclusive licence to Springer Science+Business Media, LLC, part of Springer Nature 2024

Abstract

Recommendation systems (RS) have become prevalent across different domains including music, e-commerce, e-learning, entertainment, and social media to address the issue of information overload. While traditional RS approaches have achieved significant success in delivering recommendations, they still face issues including sparse data, diversity, cold start, and long tail problem. The emergence of deep learning as a prominent and extensively studied topic has shown significant potential in addressing these challenges in RS. Deep learning captures intricate patterns of interaction and precisely reflects user preferences, allowing for encoding complex abstractions in data representation and enhancing information processing capabilities. This paper provides an extensive survey of the existing literature on recommendation systems. We will begin by providing a foundational understanding of the core concepts and terminology of recommendation systems and significance of deep learning. Secondly, we talk about the original studies being conducted on deep learning methods and solutions to address “Cold start and long tail” challenges in recommendation. Thirdly, we examine the potential future directions of research pertaining to deep learning-based recommender systems (DLRS). Our review provides valuable insights for both researchers and practitioners in using deep learning to address challenges in recommendation and in developing effective and efficient recommendation systems.

Keywords Recommendation System · Deep Learning · Cold Start · Long Tail · Deep learning-based recommendation systems

1 Introduction

Data explosions have become more frequent and severe in recent years, primarily driven by the rapid advancement of sensors, storage devices, computers, and networks [1]. However, the growing availability of data presents the problem where individuals

✉ Manisha Jangid
mishajangid1@gmail.com

Rakesh Kumar
raakeshthiman@gmail.com

¹ Department of Computer Science & Engineering, Central University of Haryana, Haryana, India

struggle to make decisions when choosing items of interest. The best known term for this type of problem is "information overload" [2]. A challenge often seen in big data analysis [3] is to find a way to leverage artificial intelligence methodologies for extracting valuable information from vast amounts of data, thereby converting it into actionable knowledge. The demand for recommendation systems has increased in recent years due to the surge in unmanageable amounts of information. By analyzing a user's previous actions and preferences, recommender systems aim to construct a model that can automatically suggest relevant goods or products tailored specifically to the user. Subsequently, the user gets a personalized list curated based on their individual preferences [4]. The recommendation systems possess the capability to provide suggestions not only based on the preferences of users and similarities with other users, but also to suggest unfamiliar items that may be of interest to them, even in cases where the user has not explicitly expressed any preferences. These issues can be alleviated by recommender systems, which do an efficient job of identifying the prospective requirements of users and select appropriate items from large quantity of candidate material. The difficulty of collecting user details has increased in tandem with the growing awareness among Internet users regarding the need to protect their personal information. It is unable to produce suggestions for newly introduced items that lack user ratings.

Meanwhile, deep learning technology has been rapidly evolving over the past several years, making it an exciting new area of study for data miners and ML experts [5]. Some of the earliest uses of deep learning yielded the most impressive outcomes in audio recognition, natural language processing, and image recognition [6]. For training a complicated multivariate function, deep learning utilizes a network structure. To do this, a nonlinear, multilayered, interconnected network structure is built. This allows deep learning to learn intrinsic features of the dataset by using a huge volume of unlabeled training data. It is a relatively new study area which is being analyzed and its purpose is to explore methods for automatically extracting feature representations at multiple levels from data. The underlying principle is to generate more meaningful and complex representations of data by combining basic attributes, thereby addressing the challenge of manually crafting features, a common obstacle in traditional machine learning [7]. The recommendation architecture has been through a significant transformation thanks to deep learning, which also brings with it new potential to boost the performance of recommendation system. Recent developments in DLRS have attracted a lot of interest thanks to their ability to overcome the challenges posed by traditional models and achieve a high level of suggestion quality. In data representation, the higher layers of a deep neural network are better equipped to capture non-linear correlations between products and users [8–20]. In addition to this, it analyses the intricate associations that exist within the data itself, accessed from various widely available sources of data including visual, textual, and contextual knowledge.

The research objectives of the paper are as follows:

1. To provide a comprehensive overview of existing literature on deep learning approaches within recommendation systems, highlighting key advancements, methodologies, and application domains.
2. To conduct comparative analysis of different DLRS to evaluate their performances for improving the recommendation process.
3. To attain a thorough understanding of deep learning approaches employed in recent studies, emphasizing their significance in addressing challenges like the "Cold Start" and "Long Tail" problems.

4. To provide valuable insights about prevailing trends and issues in the field of recommendation systems aiming to identify potential paths for future research and advancement.

1.1 Motivation

The efficacy of recommendation systems depends substantially on the quality and amount of accessible data, which can be affected by various factors including sparse data, long tail, heterogeneity, and the cold-start problem. DLRS have emerged as a promising solution to tackle challenges of traditional recommendation systems, and they have been actively used in variety of applications, such as Spotify, Netflix, Amazon, YouTube. Therefore, this review intent is to offer an extensive overview of recent studies focusing deep learning approaches to address challenges in recommender systems and indicate gaps and future research possibilities.

1.2 Article organization

The organization of this article is as follows: Section 2 includes an overview of previous surveys on recommendation systems. Section 3 outlines survey approach used to identify relevant research papers, including the chosen search criteria, information sources, and the process for assessing the quality of the selected papers. Section 4 identifies the main challenges faced by traditional recommendation systems, and how deep learning can help overcome these challenges. Section 5.1 examines DLRS for handling cold start and long tail problem. Section 6 analyzes different evaluation metrics for recommendation systems. Section 7 and 8 discusses further research directions involving deep learning techniques and conclusion respectively.

2 Related studies

Previous studies have explored various aspects of recommendation systems and incorporation of deep learning methods. By leveraging deep learning models ability in extracting hidden features and associations, alternative solutions have been provided by the researchers to handle recommendation issues including diversity, data sparsity, long tail, and cold-start problem. Social networks have proven to be a valuable resource for determining user preferences and gathering information. Camacho et al. [21] surveyed collaborative filtering-based RS that use social networking information about users to address cold-start issue. Similarly, Qin [22] provides review on various techniques and approaches used in recommending long-tail items. This study categorizes the existing recommendation methods into different groups including clustering approaches, graph-based methods, etc.

Deep learning methods have shown remarkable achievement in addressing complex problems such as decision making [23] and visual understanding [24], leading to their utilization in building recommendation systems for more accurate and improved recommendations. While some studies [23] have provided a review of DLRS, their scope has been limited to a few specific architectures, thus lacking comprehensiveness. Other studies [25, 26] have conducted reviews and classification methods, but their analysis was based on a small number of publications, limiting the depth of insights into emerging approaches. Recently [27] conducted a survey on of deep learning models that scrutinized and categorized over 100 papers. However, these studies basically focused

on structural categorization of techniques and ignored practical implementation concerns while evaluating the publications. In order to explore different methods in DLRS, a recent survey [28] conducted a thorough review that identified existing challenges and proposed remedies. The authors analyzed various challenges posed by existing approaches and provided solutions to address each of these challenges. The growing popularity of deep architectures necessitates a thorough study and analysis of previous research findings for adaption of these models in different domains of recommendation systems.

The following gaps have been identified in the literature review:

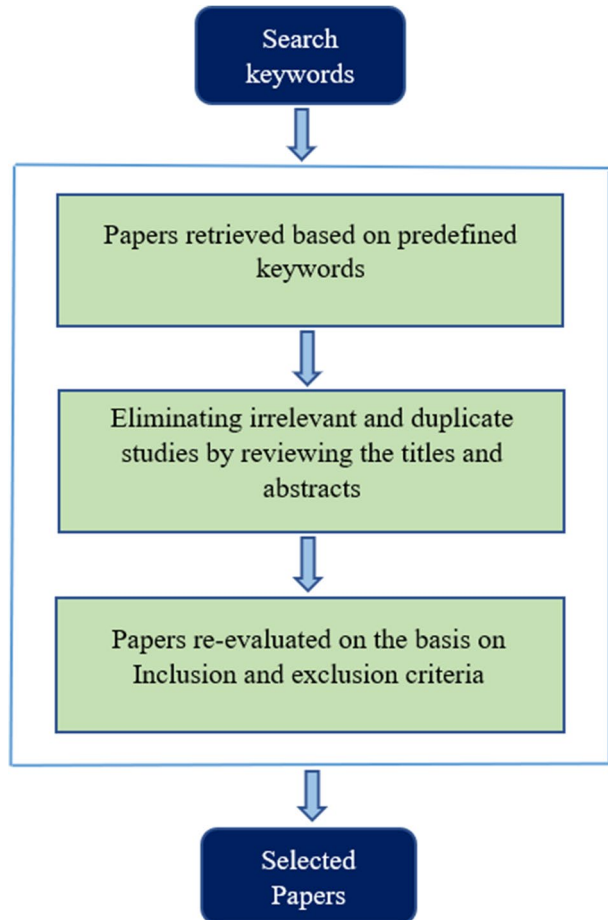
- The existing studies lacks an exhaustive survey specifically addressing how deep learning techniques can mitigate the Cold Start and Long Tail problem.
- While many studies have explored specific aspects of recommendation systems, there is a need for a comprehensive review that integrates these diverse approaches.
- This entails identifying and exploring these emerging techniques, which is crucial for the continued advancement of the recommendation system.

3 Survey technique

This section examines research paper information sources, paper selection criteria, assessing quality, and results obtained after evaluation. In Table 1, we have listed a set of research questions that will guide the preparation of our survey on various deep learning models and assist us to explore current issues in recommendation systems. The sequential phases of the article search and identification method based on the inclusion–exclusion criteria is depicted in Fig. 1.

Table 1 List of Review Questions

Research Questions	Motivation
RQ1: What types of deep learning approaches are employed for developing recommendation systems and how do they differ from traditional methods?	The primary objective is to conduct a comprehensive review of deep learning models to address challenges in traditional RS. Its advancement emphasizes importance of identifying and analyzing relevant studies and articles published over time, showing their significance in tackling the challenges faced by recommender systems
RQ2: What are the major challenges faced by traditional recommendation systems and how do deep learning approaches address these challenges?	
RQ3: In what domains are deep learning-based recommender systems commonly applied, and which datasets are commonly used to assess their performance?	
RQ4: What metrics have been used to assess the efficacy of DLRS?	
RQ5: Does deep learning improve recommendation in “Cold start” scenarios?	To identify how deep learning approaches offer potential solutions to cold start situations and long tail problem
RQ6: Does deep learning improve long tail item recommendations?	
RQ7: What are the current concerns and potential avenues for further research in the advancement of DLRS?	To explore innovative solutions and enhance the capabilities of DLRS

Fig. 1 Paper selection process

3.1 Source of information

This extensive research is conducted across multiple databases for selecting conference and journal research papers. In our search, we used the following databases:

- ACM Digital Library (<https://www.acm.org/digital-library>)
- Springer (<https://link.springer.com>)
- ScienceDirect (<http://www.sciencedirect.com>)
- IEEE Xplore (<http://ieeexplore.ieee.org>)
- Google Scholar (<https://scholar.google.co.in>)
- Scopus (<https://www.scopus.com>)

Distribution of reviewed publications from different sources can be seen in Fig. 2.

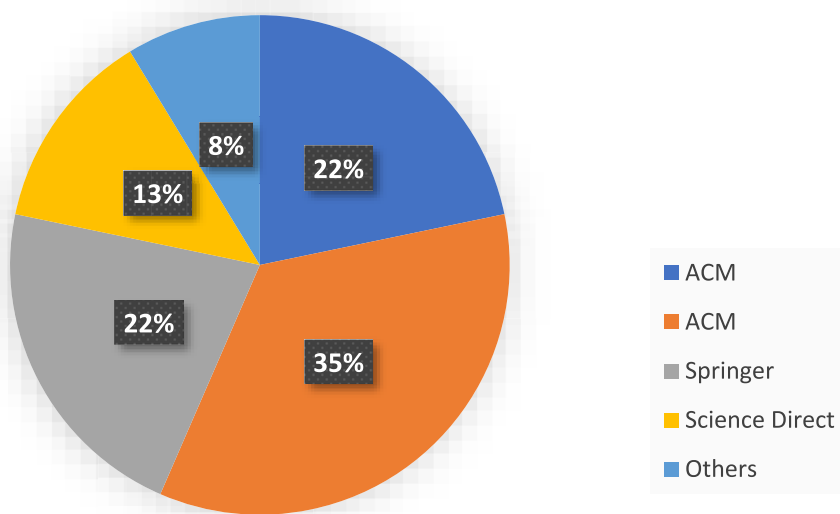


Fig. 2 Percentage of surveyed papers on deep learning based recommendation systems

3.2 Search criteria

Firstly, search terms are defined in the aforementioned databases. We included "deep learning," "recommendation systems," and "challenges" in our search query. To ensure that we captured all relevant studies, we also included related keywords such as "cold start," "long tail". We refined our search query to ensure precise results and then it is applied it to research paper titles and abstracts. Our study focused on the period between January 2014 to December 2022 to come up with in-depth analysis of the latest advancements in the field. we have prepared a set of pertinent questions that served as criteria for selecting the most relevant and important research papers for review. By categorizing these papers, we aim to provide answers to these questions and shed light on the advancements made in this domain.

3.3 Quality assessment

We conducted a thorough search of various databases and sources, including Science Direct, IEEE Xplore, Springer and ACM, using basic keywords, resulting in 1,060 articles. Using our pre-defined inclusion and exclusion criteria outlined in Table 2, articles were eliminated based on their titles and abstract that did not satisfy our criteria. For this systematic review, we selected 55 research papers that met our inclusion criteria, after screening the remaining papers and conducting a complete review of each article.

Table 2 Criteria for Paper selection

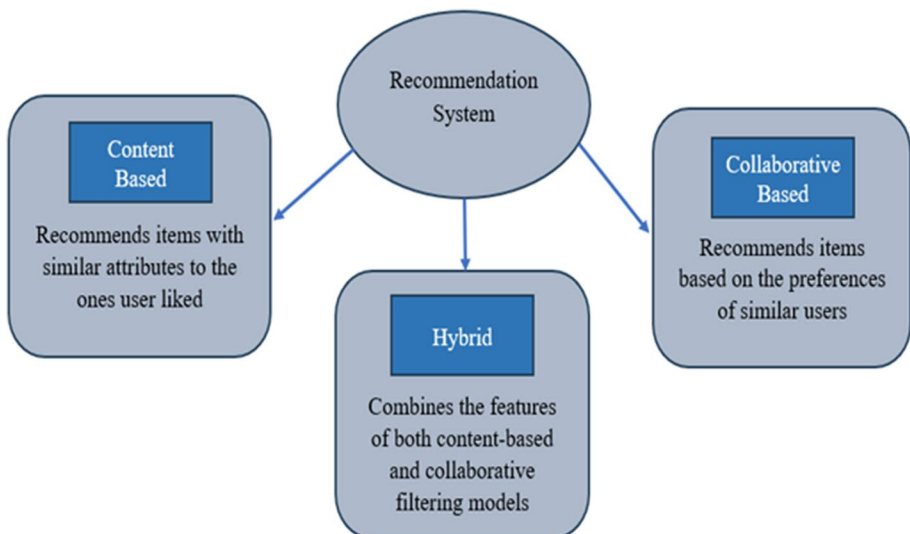
Criteria	
Inclusion	1. Specifically investigate deep learning techniques for tackling various issues in traditional RS 2. Published in the field of Recommendation System 3. Papers published in reputable conferences and journals 4. Written in English language and are peer-reviewed
Exclusion	1. Papers that do not emphasize on DLRS 2. Papers that are not peer-reviewed

4 Overview of recommender systems

This section highlights fundamental concepts and terms related to recommendation systems and deep learning technology. We study the key features of deep learning methodologies, emphasizing their significance and usefulness in the context of recommendation systems.

4.1 Recommendation system

A recommendation system is a filtering mechanism which analyzes the consumer's preferences and suggests possibly captivating content to them. A recommendation system's primary purpose is to offer customers with personalized suggestions based on prior interactions, preferences, and behavior. To anticipate which things the user is most likely to engage with, the system analyses data including user behavior, attributes of products/items, and information about context. Traditional recommendations systems are broadly categorized into three types: Content-based [29], Collaborative-based [30], and Hybrid RS [31] Fig. 3.

**Fig. 3** Recommendation system approaches

4.1.1 Content-based

A content-based recommendation system works on the idea that if a customer has showed interest in particular products in the past, they are probably to be fascinated by similar products. The contents of objects are analyzed to identify the points of similarity between the items. The user profile is obtained after analyzing a substantial amount of products that the user has expressed an interest in. The system would then be able to scan through the database and select appropriate products in accordance with the consumer's profile [32].

The challenge presented by these algorithms is to identify user's preferences on the basis of the information included in products. Data mining and machine learning are two topics that have seen a lot of development in recent years as potential solutions to this challenge [33]. For instance, a recommender system will first collect all of the books that a particular reader has already read and then perform an in-depth content analysis on those books in order to determine which articles to suggest to that reader. By employing text mining techniques, it is possible to retrieve key terms from the provided text. A multi-dimensional vector may be used to represent a book once all of the important words and their associated weights have been included into the equation. Specialized clustering techniques [34] could be utilized to identify the centroids of these vectors, which depict the reader's interests, and subsequently implement these procedures.

4.1.2 Collaborative-based

Collaborative filtering (CF) is a popular recommendation method that is commonly utilized in the recommendation process. Unlike content-based techniques, CF is entirely dependent on the item ratings provided by individual users. The underlying concept behind CF is that individuals who have rated certain products in a similar manner are likely to have similar choices[35]. This process involves recommending products based on the interests of other users who exhibit similar tastes or identifying similar item/products to those that the target user has already rated. This approach utilizes statistical methods to calculate similarity between item vectors and user vectors. CF methods can be categorized into two main types: Memory-Based and Model-Based CF Techniques [36].

4.1.3 Hybrid-based

Monolithic, parallel, and pipeline are the three categories that fall under the umbrella of hybrid recommendation systems [37]. In a monolithic hybrid recommendation approach [38], different recommendation techniques are combined into a single unified model. The remaining two hybrid types requires utilization of at least two different recommendation approaches, which are then combined. The input information is used to drive the operation of the parallel hybrid recommendation system, which results in each component individually producing a list of recommendations, which are then merged using the output data to provide the whole set of recommendations. One such design is the pipeline hybrid recommendation, in which output of one serves as the input for another.

Hybrid recommender systems can be employed for one of two purposes: either to boost the performance of current RS in the context of a certain data modality [39], or to exploit the potential of various data sources. There are recommender systems that do better when they are built from the ground, and there are others that do better when they are given

access to a large quantity of data [40]. Hybrid recommender systems make an effort to capitalize on the complimentary characteristics that these systems provide in order to produce a system that is more resilient overall [41].

4.2 Challenges faced by traditional recommendation approaches

1. **Cold start problem:** The RS faces difficulty because of addition of new user or products/item in the system without any available data regarding their preferences. Traditional RS approaches rely on previous data interactions to generate recommendations, which makes it difficult to produce useful suggestions when such data is unavailable. Deep learning approaches, on the other hand, provides solution by generating suggestions in such cases by using auxiliary data such as item metadata, user demographics, and social networks.
2. **Sparsity problem:** The sparsity problem is usually seen when the available data is insufficient for generating accurate recommendations. Traditional recommendation approaches utilize user-item matrix method, which contains user preferences for each item. However, this matrix is often sparse, with many missing entries. Deep learning approaches can solve this problem by using matrix factorization techniques that can fill in missing values and generate recommendations.
3. **Novelty and diversity:** Traditional recommendation approaches struggle to provide unique recommendations to its users, often suggesting items that users have already witnessed before. Deep learning approaches can address this issue by employing techniques such as item embedding, which recommends items having similar embeddings to the user, ensuring that diverse and novel items are recommended.
4. **Long Tail:** The long tail refers to a catalog which contains huge number of items with low popularity (often referred as niche items) or with limited number of user interactions. Traditional recommendation systems often struggle to recommend long-tail items because they tend to recommend popular items to its customers. DLRS can address the long-tail problem using advanced neural network architectures that can capture complex relationships between users, items, and features for suggesting diverse recommendations for both popular and long-tail items.

4.3 Machine learning vs. Deep learning for recommendation system

Machine learning algorithms in the domain of recommendation systems have been employed to monitor user preferences and provide personalized recommendations. Recent research work in recommendation systems has explored the application of SVM, Decision trees, Naive Bayes, Random forest and regression models for tasks such as personalized ranking, preference prediction, item classification, sentiment analysis, and user behavior modeling [42–44].

Zelaya et al. [45] have adopted machine learning techniques including random forest and classification trees to tackle cold start issue in recommendation system by extracting user's implicit information from social stream. Matrix factorization method, like singular value decomposition (SVD) are used to solve data sparsity issues. The rating matrix which is decomposed into lower-dimensional latent factors, represent underlying patterns in the data. Matrix factorization allows estimation of missing ratings and can handle large sparse matrices more efficiently [46].

Table 3 Traditional Recommendation system approaches vs. Deep learning

Category	Traditional RS	Deep learning-based RS
Data Requirements	Requires sufficient user-item interactions	Can handle sparse and implicit data
Scalability	Limited scalability to large datasets	Can handle large-scale datasets
Complexity	Simple and interpretable	High Complexity
Recommendation accuracy	Limited ability to capture non-linear patterns	Ability to capture complex non-linear patterns

Machine learning requires manual feature engineering which is quite time consuming and is unable to handle high dimensional data. In recent years, deep learning has had a substantial influence on the field of recommendation systems, sweeping through the machine intelligence industry. Several substantial factors have led to the growing popularity of this domain. To begin, deep learning models excel in handling complicated patterns and correlations in large-scale and high-dimensional data, which is important aspect in recommendation systems. These models can identify user preferences and item attributes by automatically extracting important features and capturing nonlinear relationships, resulting in more accurate and personalized suggestions. Additionally, deep learning also has the potential to learn hierarchical data representations. This capability is critical in the context of recommendation systems because it allows the model to find latent characteristics and identify important associations between users and items. Deep learning models acquire a richer knowledge of user-item interactions by capturing multiple levels of abstraction, resulting in increased recommendation quality.

Overall, the rise of deep learning in this domain is due to its capability to handle complex patterns, learn hierarchical representations, process diverse data types, scale efficiently, leverage transfer learning, and excel in sequential and session-based recommendations. These advancements have propelled recommendation systems towards more accurate and personalized recommendations, ultimately enhancing user experiences and driving user engagement. The summarized comparison is shown in Table 3.

4.4 Deep learning architecture

The investigation of artificial neural networks led to the advancement of deep learning. [47]. Deep learning structures consist of things like multilayer perceptrons that have numerous hidden layers. Hinton et al. [48] introduced the idea of deep learning to the scientific world in 2006. For the optimization challenge associated with deep structure, they presented an unsupervised greedy method. Following that, they proposed a deep structure for a multi-layer autoencoder [49]. In addition, Lecun et al. [50] suggested using a convolutional neural network. This strategy, the first of its kind, enhances training performance by lowering the number of parameters through the use of spatial relative relations, and it does so without sacrificing accuracy. Deep learning combines simple features into more generalized characteristics that may be used to locate representations of data in a distributed fashion [51].

Deep learning is a novel area emerging within the realm of machine learning [52]. This is achieved by modelling its operations after those used by the human brain to interpret visual, audio, and textual information [53]. Both supervised and unsupervised learning may be used to the deep learning methodology [54], much like the machine learning strategy.

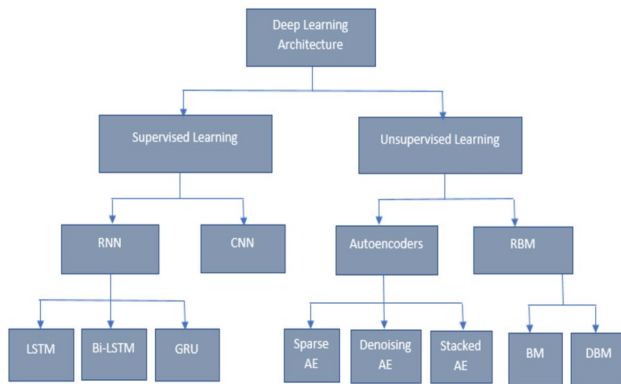


Fig. 4 Classification of Deep Learning Models

Supervised learning demands training model using labelled data, in order to learn a mapping function that can precisely estimate the correct output label for unobserved input data. It is often used for tasks such as classification, regression, and sequence labeling, where the desired output is known and explicitly provided during training. Unsupervised learning, on the other hand, seeks to identify patterns, structures, and relationships in unlabeled data without explicit instruction or target labels. This method is especially beneficial in situations when labelled data is insufficient or unavailable, since it can reveal hidden patterns and give insights on data distribution. Unsupervised learning techniques, including autoencoders, generative adversarial networks (GANs), and self-organizing maps (SOMs), have found applications in anomaly detection, dimensionality reduction, data visualization, and generative modeling.

This section explores commonly employed deep learning models. Firstly, we will explore the autoencoders (AE). Next, we will examine the convolutional neural network (CNN), then recurrent neural network (RNN) and after that Restricted Boltzmann machine (RBM). Finally, we will conclude by discussing the deep belief network (DBN). Figure 4 represents classification of deep learning models.

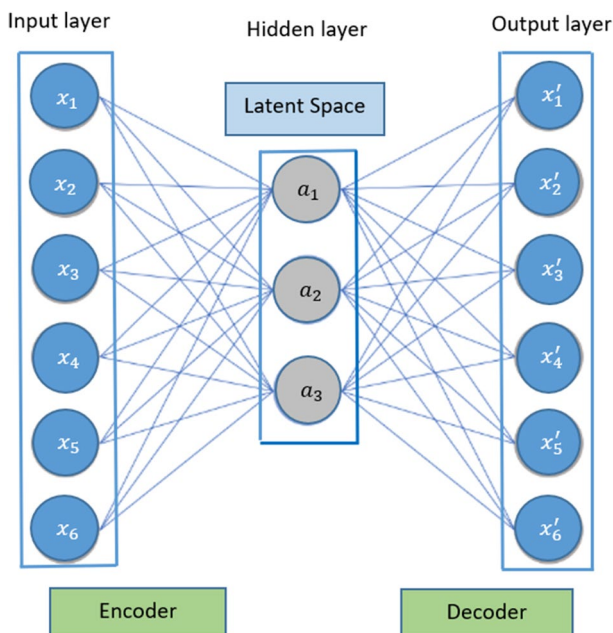
4.4.1 Autoencoder

An autoencoder (AE) is designed to learn efficient representations of input data by reconstructing it through an encoder-decoder process. In most cases, the bottleneck layer or latent space (the one in the middle of the hierarchy) is used to represent the incoming data with a conspicuous characteristic. Based on the work of Rumelhart et al. [55], the autoencoder may be seen as a variation on the standard multi-layer perceptron.

The input data is encoded into a lower-dimensional representation and then decode it back to the original input dimensions. Figure 5 depicts the construction in its entirety.

In the autoencoder, there are three distinct networks operating together. The output layer contains an equivalent number of neurons as in the input layer of the autoencoder. However, the intermediate layer has fewer neurons compared to the combined total of the other two layers. During the training process, each training sample generates a distinct signal at the output layer. This signal is propagated and transmitted throughout the network. When training a network, accuracy is measured by how well the output signal matches the input

Fig. 5 Autoencoder



signal. The reconstruction mistake exemplifies this connection between the two objects. Cascaded training and training on a layer-by-layer basis allow autoencoder to produce deep structures. Fine tuning may be achieved by letting the whole network reconstitute the input signal after training the deep model by optimizing each layer in turn. This step is taken following the learning of the deep model. Denoising autoencoder, marginalization denoising autoencoder [56], stacked denoising autoencoder (SDAE) [57], and variational autoencoder (VAE) are only a few examples of the various types of autoencoders.

In context of a recommendation system, autoencoder may be used in one of two ways: either to learn lower-dimensional feature representation in the latent space or to fill in the missing entries or gaps of the interaction matrix in the reconstruction layer. The recommendation job is applicable to nearly all autoencoder variations [58–62], including the VAE, the denoising autoencoder, and the marginalized autoencoder.

4.4.2 Convolutional neural network

A CNN is a feedforward neural network especially intended for processing visual data having convolution layers and pooling operations [63]. It is able to take into account both global and local characteristics, considerably improving both the efficiency and accuracy of the process. It works very well when processing data with a structure similar to a grid. Its architecture is generally composed of one or more convolutional layers, which sometimes involve a subsampling phase, followed by one or more fully connected layers, which are comparable to those seen in a standard multilayer neural network. The multi-layer perceptron is the fundamental unit of every CNN. In recent years, CNNs have garnered a lot of interest, especially in the field of image interpretation.

In comparison with traditional multi-layer perceptrons, CNNs are more robust because they employ a pooling technique that reduces spatial dimension while keeping important

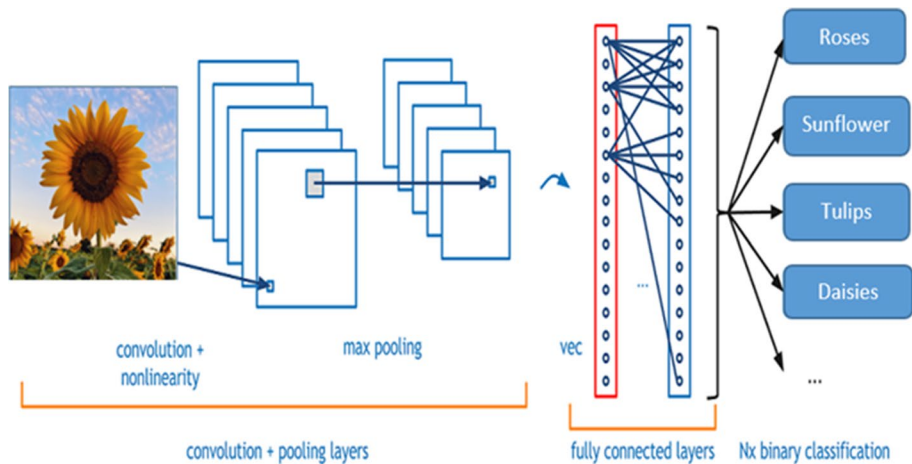


Fig. 6 Convolutional neural network

data. Furthermore, the number of parameters in the model may be reduced because of CNN's shared-weights architecture, making the model simpler and increasing its generalisation ability. CNN's principal use case is the processing of two-dimensional image data. The building blocks of a CNN is shown in Fig. 6.

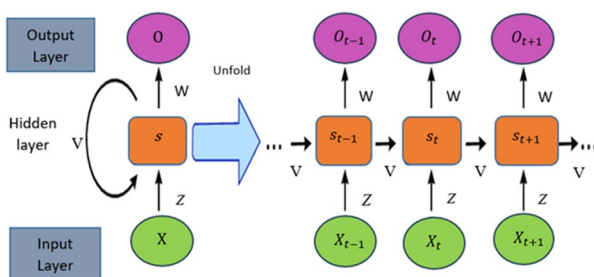
CCNs are extremely useful for the processing of unstructured multimedia data thanks to the convolution and pooling functions they provide. They are used for feature extraction in the vast majority of recommendation models [64–69].

4.4.3 Recurrent neural network

For modelling time-dependent data, the Recurrent Neural Network (RNN) excels. In contrast to feedforward neural networks, which do all calculations in one single pass, recurrent neural networks use loops and memory to look back on and refine earlier results. Three areas where RNNs have found substantial usage include machine translation [70], speech recognition [71], and label construction [72].

While RNNs have the theoretical capacity to represent an arbitrary number of successive data points, but practically it is considered that the present state is only influenced by the state of the immediately preceding time period. Therefore, the complexity of the model is reduced. RNN perform well in modeling sequences of arbitrary length. In a recurrent neural architecture, there are input, output, and hidden units as seen in Fig. 7. RNNs have the ability to remember the information that they have received in the past, which allows them to perform the calculation that determines the current output of the hidden layer.

There are many different RNN models available to accommodate the needs of different programmes, including long short-term memory (LSTM) [73], neural turing machines (NTM)[74], gated recurrent unit (GRU) [75]and so on. LSTM is well suited for the processing and prediction of significant events in time series that have relatively large intervals and delays. By combining short-term memory with long-term memory through nuanced gate control, LSTM offers a partial solution to the issue of gradient disappearance. The addition of a "processor" to the method is what distinguishes LSTM from RNN. This "processor" evaluates the information to determine whether or not it is valuable.

Fig. 7 Recurrent neural network

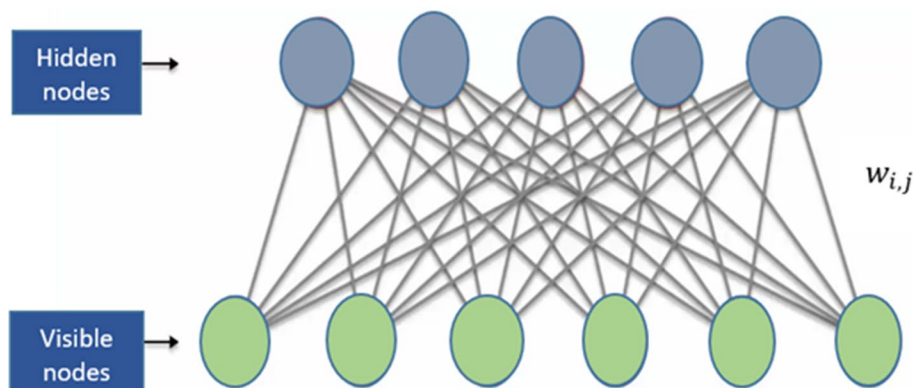
RNNs excel at processing data in a certain, sequential order [76–81]. Therefore, it becomes a natural choice for managing additional content that includes sequential signals (such as audio, texts, and so on), as well as the sequential patterns of user behaviour. In their paper, Chen et al. [82] argued that location-based social networks might benefit from incorporating suggestions of sites of interest.

4.4.4 Restricted Boltzmann machine

Restricted Boltzmann Machine (RBM) [83] is an extended form of the Boltzmann machine and belongs to family of neural networks. It is made up of two layers: a hidden one and a visible one. The RBM is considered as an early artificial neural network capable of learning intrinsic representations from input data, allowing it to solve complex learning problems. A distinctive feature of RBMs is the restricted connection between the visible and hidden layers, implying that there is no direct communication in both ways. This constraint improves learning efficiency tremendously. They are useful for developing deep architectures because they can be simply stacked together to form deep networks. Figure 8 is an illustration of the constrained Boltzmann machine's internal construction.

The following equation may be used to describe the combined probability distribution of the visible layer and the hidden layer:

$$P(v, h) = 1Ze - (aTv + bTh + hTwv) \quad (1)$$

**Fig. 8** Restricted Boltzmann machine

The maximum likelihood estimation serves as the basis for this model's optimization aim, which is as follows:

$$\operatorname{argmax} \sum_{v \in V} \log P(v, h) \quad (2)$$

The RBM model is particularly quick in comparison to other models such as the sparse Autoencoder, and it just needs a straightforward forward encoding procedure to function. However, if we try to solve the problem by employing the conventional sampling approach, the number of iterations would be excessive, and the efficiency will be poor. In attempt to find a solution to this issue, Smolensky [84] and Hinton [85] came up with the idea of a quick method that they named contrastive divergence (CD).

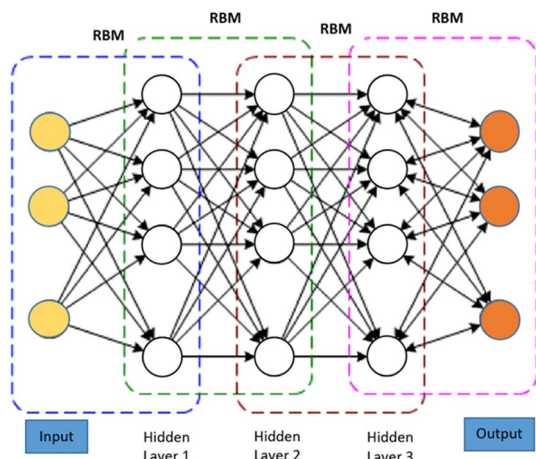
The formation of a deep structure is possible by the cascading of numerous models of single-layer limited Boltzmann machines. This means that the layer that was buried in the layer below it is utilised as the layer that is visible in the one above it. A method of optimization that works on a layer-by-layer basis is used for the optimization of the network. Various extended models have improved the structure and probability distribution of the RBM to incorporate more complicated probability distributions. This is done in order to improve the model's predictive power. RBM-based recommender systems were suggested by Salakhutdinov et al. [86], Truyen et al. [87], and Georgiev and Nakov [88].

4.4.5 Deep belief network

Deep Belief Network, or DBN, is an example of a generative model in which individual nodes are built using Restricted Boltzmann Machines (RBMs). A DBN is trained sequentially, layer by layer. In this process, the data vector is employed to determine the corresponding hidden layer at each stage, and the resulting output from that hidden layer serves as the data vector for the subsequent, higher layer. The diagram of its assembly is depicted in Fig. 9.

It is possible to think of the structure of DBN as being composed of a number of constrained Boltzmann machine stacks. When travelling from one RBM to the next in the network, the hidden layer of the RBM preceding it is the visible layer of network. This feature simplifies DBN training process as each RBM can learn from the output of the previous one, unlike traditional neural networks. Developing a deep neural network often involves

Fig. 9 Deep belief network



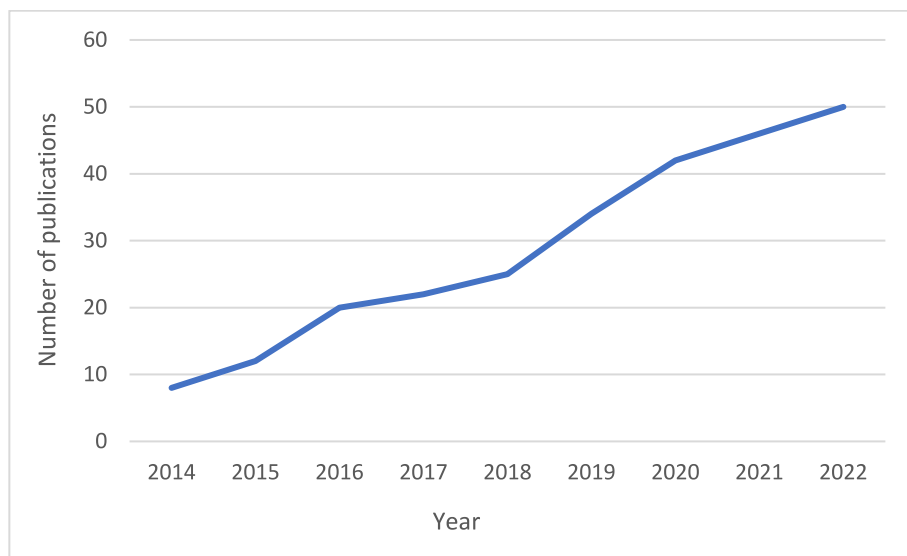


Fig. 10 Publications in DLRS over the years

increasing the number of hidden layers and the nodes within those layers. Deep neural networks are commonly used to refer to fully linked neural networks. These neural network models are often employed to extract meaningful feature representations in tasks such as music recommendation [89], picture and speech recognition, and other comparable tasks. The entire connection neural network model's depth and breadth of structure are limited by the large number of parameters. The number of publications related to DLRS is shown in Fig. 10 and Table 4 outlines publications exploring various deep learning models.

5 Deep learning-based recommendation systems

This section examines the emergence of deep learning in addressing the challenges encountered by traditional recommendation system approaches i.e. Cold start and Long tail. The summary of the publications is provided in Tables 5 and 6.

5.1 Deep learning based cold start recommendation

Cold start recommendations refer to the challenge of generating personalized suggestions for new items or users having no information about them. Deep learning models have been explored to cope up with this issue by leveraging various sources of information to make informed recommendations. For instance, it could use contextual information including user's current location to recommend nearby restaurants or events. Wei et al. [125] utilized two different recommendation models to handle cold start problem in case of newly added items. The models adopt the combination of collaborative filtering and neural network which is termed as SADE, that extracts content attributes of the items. The CF model, timeSVD++ , is modified to predict ratings for cold start items using content features.

Table 4 Publications on various deep learning Models

Deep learning model		Learning scenario	UseCase	Advantages	Publications
Autoencoder	Unsupervised	Dimensionality reduction	Non-linear feature learning, Dimensionality reduction for large-scale data	Zuo et al.[90], Zhuang et al.[91], Unger et al.[92], Deng et al.[93], Zhao et al.[94], Wang et al.[95], Jiang et al.[96],Tahmasebi et al.[97], Noshad et al.[98], Yu et al.[99]	
CNN	Supervised	Image classification	Can capture spatial and temporal features, handle variable-length input sequences	Kim et al.[100], Shu et al.[101],Wu et al.[102], Da'u et al.[103], Zhang et al.[104], Khan et al.[105], Lee et al.[106]	
RNN	Supervised	Natural language processing	Can handle sequential data and capture long-term dependencies	Caihua et al.[107], Gunawan et al. [108], Katarya et al. [109], Chen et al.[110], Vedavathi et al. [111], Bansal et al.[112]	
RBM	Unsupervised	Pattern recognition	Efficient learning of complex data distributions, can handle high-dimensional data effectively	Xiaomeng et al.[113], Weizhu et al.[114], Du et al.[115], Pujahari et al.[116],Chen et al. [117], Biswal et al.[118], Kumar et al.[119], Jha et al.[120]	
DBN	Unsupervised	Transfer Learning	Captures hierarchical representations of data, allows unsupervised pre-training for better performance	Wakita et al.[121], Chen et al.[122],Venkatesh et al.[123], Mehbodniya et al.[124]	

Table 5 Publications focusing on Cold Start problem

Author	DL model	Dataset	Evaluation metrics	Advantages
Wei et al. [125]	SDAE	Netflix	RMSE, MAE	Significant improvement in rating prediction for cold start items
Da'u et al. [126]	CNN	Amazon, Yelp	Precision, Recall, and F1-score, RMSE, MAE	Combines CNN and mutual attention network techniques for learning adaptive user/item representations
Kiran et al. [127]	DNIN	Book-Crossing	RMSE, MSE, MAE, and R-squared	Model learns non-linear latent factors achieving better predictive accuracy
Qian et al. [128]	GNN	MovieLens, Yelp	RMSE, MAE	AGNN can learn embeddings for both users and item simultaneously and capture complex relationship between them through attribute graph
Hazrati et al. [129]	RBM	MovieLens, Youtube	NRMSE, Precision, Diversity	Incorporates visual features with collaborative filtering technique to address cold start issue in case of addition of new item
Ahmed et al. [136]	Autoencoder	AliExpress	Precision, NDGC Hit ratio, and MAP	Creates users' profiles based on sentiment analysis, considers temporal activity in computing recommendations

Table 6 Publications focusing on Long Tail problem

Author	DL model	Dataset	Evaluations Metrics	Advantage
Sreepada et al. [136]	Siamese network	MovieLens, Netflix	Precision, Long-Tail Coverage Recall, F1 Score, Weighted Long-Tail Coverage Tail of the Tail Coverage	Model can learn non-linear associations among input features and similarity metric, that can capture complex user item associations
Qin et al. [138]	CNN	MovieLens, BookCrossing	Recall, Coverage, Diversity	It can be trained with a small number of instances Effectively extract informative features from item metadata, leading to more accurate and representative item representations for recommendation
Liu et al. [139]	GRU Encoder, Attention mechanism	YOUCHOOSE, 30MUSIC	Recall, MRR, coverage, tail_coverage	Captures the temporal dynamics and dependencies within sessions, allowing for more accurate and personalized recommendations considering customer's current session context
Bai et al. [133]	SDAE	ProgrammableWeb.com	Recall, Diversity	Caters diverse needs and preferences of users by effectively capturing complex patterns and representations between user-item
Krishnan et al. [140]	NCF	MovieLens, Ask-Ubuntu Stack Exchange	Recall, NDGC	Employs an adversarial training process to adapt the item embeddings for long-tail items resulting in more diverse recommendations

In [126], the authors presented a method to tackle cold start scenario in recommendation systems by utilizing two parallel CNN architectures. These architectures were designed to better model the latent features of items and users from the textual content of reviews provided by the users. Word embeddings were utilized by the model to map the content into a lower dimensional space while retaining contextual information. The features extracted were then passed through convolutional layers. The two parallel networks' outputs were combined and provided to a prediction layer, which used factorization machines to estimate user ratings for items.

A hybrid RS based on deep learning is proposed by Kiran et al. [127] to tackle the cold start situation by incorporating side information related to users and items in a deep neural network. To improve the model's accuracy, a lowering learning rate and increasing weight decay technique were used, with their values cyclically modified over epochs. A framework named as Attribute Graph Neural Networks (AGNN) proposed by Qin et al. [128] learns embeddings for the strict scenario of user/item cold start issue. Hazrati et al. [129] addresses new item cold start problem by incorporating visual features with restricted Boltzmann machines. This approach improved the accuracy of recommendations and provide better user experience.

In [130], Ahmed et al. proposes a deep learning-based strategy to tackle the cold-start problem. The method uses hypergraphs to represent user-item interactions, an adversarial autoencoder for learning shared representation, and domain adaptation to address cold-start situations faced by RS. The AAE is trained on the source domain to learn a shared representation, and then the weights of the generator network are fine-tuned using a domain adaptation loss that encourages the generator to produce similar representations for source and target domains.

5.2 Deep learning based long tail item recommendation

With the explosive growth of e-commerce platforms and the abundance of options available to consumers, the "long tail" phenomenon has become increasingly prevalent. The long tail refers to the large number of niche products that have relatively low sales volume individually but collectively account for a significant portion of total sales. As a result, accurately recommending these long-tail products to customers is becoming a critical challenge for e-commerce platforms. Long-tail item recommendation focuses on identification and recommendation of niche products to its customers, thus helping to increase customer satisfaction.

Deep learning methods exhibit enhanced representation capabilities, particularly in handling textual and visual data. Hong et al. have presented a model named miniGCN (Mini-batch Graph Convolutional Network) model, which combines the strengths of both GCN (Graph Convolutional Networks) as well as CNN (Convolutional Neural Networks) for image classification. This method has been shown to have stronger representation abilities compared to the individual GCN or CNN models [131]. Moreover, Hong et al. have also introduced a multimodal deep learning (MDL) framework for image classification and utilized multiple sources of information (i.e., multimodal data) to enhance variety of information available for image classification tasks [132].

Deep learning has become an important technique for user profiling in recommendation systems, outperforming traditional methods and improving the accuracy of the results. Recently, Deep learning is utilized for long-tail item suggestions, which focuses on items that are rarely recommended but could be appealing to certain users. For instance, Bai et al. [133] presented an online long-tail item recommendation system named DLTSR based on

stacked denoising autoencoders (SDAE) technology [134]. This concept is used for web service suggestions and it comprises of two key aspects: (1) leveraging knowledge from popular services in SDAE and (2) employing a specialized approach to gather developers' preferences based on long-tail item ratings. Similarly, Kumar et al. [135] suggested a few-shot learning approach for recommending long-tail products/items.

A few-shot learning method employed by Sreepada and Patra [136] addresses the challenge associated with long-tail product recommendation. They utilized OCCF (One Class Collaborative Filtering Technology) [137] for constructing matrix of user preferences. Prior to calculating user preferences, the original rating matrix was transformed into a binary rating, where scoring values were set to 1. Within each cluster, the items selected by users were categorized into liked, long-tail, and disliked item lists. A Siamese network was used to measure the similarity between user profile and product description to recommend appropriate items to customers.

Qin et al. [138] presented a recommendation framework utilizing Convolutional Neural Networks (CNN) to handle the long-tail issue prevalent in nearest neighbor recommendation methods. Their proposed approach mitigates the issue of frequent item recommendations, thereby enhancing the coverage and diversification of the outcomes generated. Additionally, Liu and Zheng [139] introduced TailNet, a neural network and attention-based framework for long-tail item suggestion using session data. The performance of their method is evaluated using three metrics: coverage, tail coverage, and tail. Coverage measures the total number of items suggested, tail coverage quantifies the number of long-tail items in the result list, and tail indicates the average number of long-tail items within each recommendation list. The experimental results demonstrate that TailNet outperforms traditional recommendation methods and has better coverage.

A novel adversarial training approach is presented by Krishnan et al. [140] to improve long-tail suggestions for users with the help of Neural Collaborative Filtering (NCF) model. The adversarial network learns the implicit correlation with the items in the feedback data, resulting in improved long-tail performance Table 7.

The distribution of studies addressing long tail, cold start and other issues is shown in Fig. 11. The details of commonly used datasets is provided in Table 7.

We summarize points that will be helpful for new researchers on how deep learning models can effectively encode and utilize additional contextual factors such as temporal, location, and social information to address challenges like cold start and long tail problems in several ways:

- **Feature Embeddings:** By embedding temporal, location, and social signals into a common feature space, deep learning models can learn representations that capture both the inherent structure of these signals and their interactions with other features. For example, representing temporal signals as time embeddings or using geographical coordinates as spatial embeddings allows the model to learn patterns specific to different contexts.
- **Attention Mechanisms:** Attention mechanisms in deep learning models enable them to focus on relevant contextual signals at different stages of processing. For instance, in natural language processing tasks, self-attention mechanisms can dynamically weight the importance of words or phrases based on contextual relevance, thereby incorporating temporal dependencies or social context.
- **Hybrid Architectures:** Combining deep learning with traditional machine learning models or rule-based systems can leverage the strengths of each approach. For instance, using deep learning for feature extraction from contextual signals and combining it

Table 7 Commonly used datasets in recommendation systems

Dataset name	Description	Type of data	Domain	Data format	Users	Items
MovieLens 10 M	Movie ratings, user-item interactions, movie metadata	Explicit	Movie	CSV	71,567	10,681
Amazon Reviews	Product information, reviews, ratings, metadata	Explicit	E-Commerce	JSON	6,643,669	2,441,053
Last.fm	User listening histories, music tags, artist information	Implicit	Music	CSV	992,931	92,834
Book-Crossing	Book ratings, user information, book metadata	Explicit	Book	CSV	278,858	271,379
Netfix	Movie ratings, user-item interactions	Explicit	Movie	CSV	480,189	17,770
Spotify Million playlist	Playlist information, track listings, metadata	Implicit	Music	JSON	1,000,000	226,229
Yelp	User reviews and ratings	Explicit	Restaurants	JSON	1,326,101	192,609

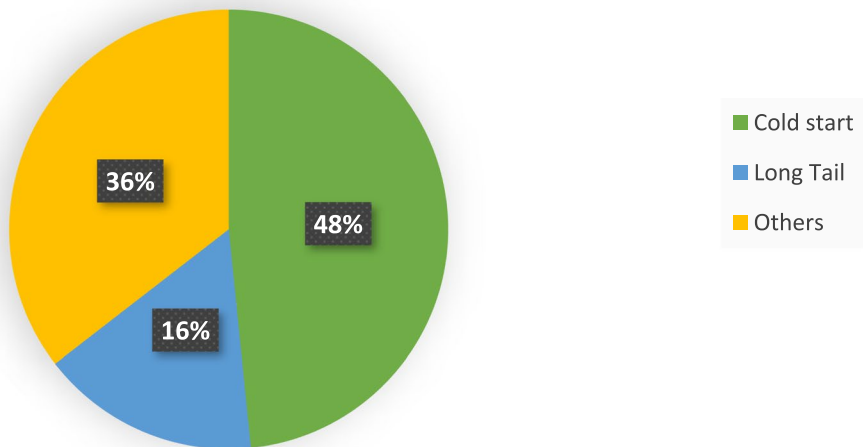


Fig. 11 Percentage of DLRS papers for long tail, cold start & other issues

with a rule-based system that handles specific edge cases can provide robustness in scenarios where data is sparse or novel.

- **Transfer Learning:** Pre-training models on large-scale datasets that include diverse contextual signals can improve generalization to new contexts encountered during cold start scenarios. Fine-tuning these models on smaller, task-specific datasets further adapts them to utilize specific contextual signals effectively.
- **Meta-Learning:** Meta-learning techniques empower models to swiftly adapt to new tasks or environments with minimal data. By training on a variety of tasks that involve different contextual signals, meta-learning enhances the model's ability to generalize to new contexts encountered in long tail scenarios.
- **Reinforcement Learning:** In scenarios where exploration of novel contextual signals is necessary, reinforcement learning techniques can guide the model's decisions by rewarding exploration of new contexts while leveraging existing knowledge from observed signals.

While addressing cold start and long tail challenges in DLRS, users often face privacy issues. The following techniques could be employed for preserving user privacy and data ownership along with deep learning models:

- **Federated Learning:** This technique allows numerous decentralized devices to jointly train a model while keeping the data localized on each device. Each client trains a local model and sends the model updates to a central server, which aggregates these updates to improve the global model.

Benefits:

1. Enables the model to learn from a varied group of users without compromising the privacy of new users.

2. Utilizes the collective knowledge from various users to recommend niche items without centralizing sensitive data.
3. **Differential privacy:** This technique ensures individual data points cannot be distinguished within a dataset, even if an adversary has access to the model outputs. It introduces noise to the data or the learning process to provide strong privacy guarantees.

Benefits:

1. Protects the data of new users by adding noise, ensuring that their contributions do not lead to privacy breaches.
2. Ensures that rare and unique user preferences do not compromise privacy by applying noise to the relevant data.

We can adopt the following strategies for implementation of DLRS in real-world applications:

- **Deep Transfer Learning (DTL):** Utilize pre-trained models and fine-tune them on specific industrial datasets. This reduces the need for extensive labeled data and computational resources, which are often a barrier in industrial settings.
- **Optimize data utilization:** Implement dynamic selection of hyper-parameters and network structures based on the changing data patterns to improve model performance and applicability.
- **Utilize Hybrid and Ensemble Models:** Combine generative and discriminative models to benefit from both approaches. Effective hybridization can enhance performance and handle uncertainty better, which is crucial for high-risk industrial applications.
- **Use Established DL Libraries:** Frameworks like TensorFlow and PyTorch provide robust tools and pre-trained models that can be adapted for specific industrial applications, reducing development time and resources.
- **Address Hardware Dependencies:** Secure access to high-performance computing resources, like GPU-enabled servers, to handle the large computational demands of deep learning model.

6 Evaluation metrics

Evaluation metrics are crucial in determining the efficacy and quality of recommendation systems. This section analyses commonly used metrics in recommendation systems, focusing on precision, recall, F1 score, mean squared error (MSE), mean absolute error (MAE), root mean squared error (RMSE), and normalized discounted cumulative gain (NDCG). The distribution of evaluation metrics used is shown in Fig. 12.

a. Precision: The number of relevant item recommendations obtained is divided by the total number of irrelevant and relevant item recommendations obtained corresponding to different categories.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

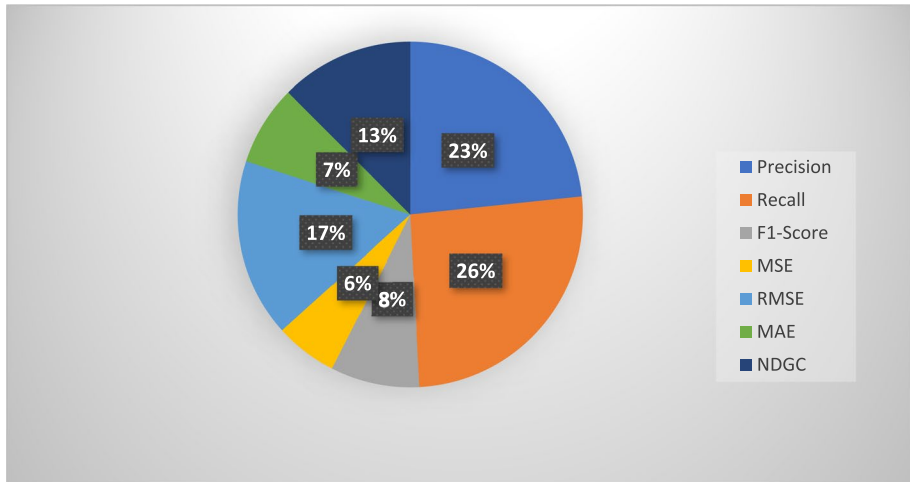


Fig. 12 Evaluation metrics used in papers

b. Recall: The number of relevant items that were correctly recommended divided by the total number of relevant items corresponding to different categories.

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

c. F1 Score: It is a measure which computes harmonic mean of accuracy and recall.

$$F1Score = \frac{2 * (Precision * Recall)}{Precision + Recall}$$

d. MSE: It is a metric used to determine the accuracy of the predicted rating.

$$MSE = \frac{1}{n} * \sum_{i=0}^n |y_i - \bar{y}_i|^2 \text{ where } y_i = \text{actual value}, \bar{y}_i = \text{predicted value}$$

e. MAE: It measures how much the estimated value differs from the actual value. Lower value of MAE indicates more accurate results.

$$MAE = \frac{1}{n} * \sum_{i=0}^n |y_i - \bar{y}_i| \text{ where } y_i = \text{actual value}, \bar{y}_i = \text{predicted value}$$

f. RMSE: It is calculated as the square root of the average squared difference between predicted and actual ratings.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=0}^n |y_i - \bar{y}_i|^2} \text{ where } y_i = \text{actual value}, \bar{y}_i = \text{predicted value}$$

g. NDCG: It is a ranking metric that takes into account both the relevance and position of suggested items. It evaluates the suggestion list's quality Fig. 12.

$$NDCG = \frac{DCG_p}{IDCG_p} \text{ where } DCG_p = \sum_{i=1}^p \frac{2^{rel_i} - 1}{\log_2(i+1)} \text{ and } IDCG_p = \sum_{i=1}^{REL_p} \frac{2^{rel_i} - 1}{\log_2(i+1)}$$

7 Future research directions

With the evolution of Recommendation system, there are plenty of promising future research paths that might further improve the efficacy of deep learning-based techniques. This section discusses prospective areas for further study in this topic.

- a. **Explainable DLRS:** Although deep learning models are extremely popular in recommendation systems, but it suffers from lack of transparency. There are two ways to include explainability in DLRS. The first strategy is to present consumers with clear forecasts, allowing them to grasp the elements that influence the system's suggestions. This can be achieved by giving suitable explanations that why the system considers what is being suggested as reasonable. The second method focuses on making the model more understandable to practitioners. The weights and activation functions of the model are analyzed to gain better understanding of the generated recommendations. Attention mechanism, for example, might be used to acquire a better understanding of how specific items are suggested. By adopting these strategies, future study might look into ways to make DLRS more transparent and interpretable [141, 142].
- b. **Personalized recommendation systems:** Delivering personalization content is considered to be one of the important features exhibited by recommendation system which suggests most suitable articles according to specific individual interests. Graph neural networks, for example, could be used to represent user-item interactions as a graph and learn representations that capture their relationships and interactions. Transfer learning could be applied to handle the “cold-start” problem and improve suggestion quality for new users or items. Attention mechanisms, commonly used in natural language processing tasks, could be leveraged to concentrate on key aspects of user behavior and preferences, thereby improving the recommendation process. However, there remains significant potential for advancement, and future research could focus on developing more effective personalized recommendation models that can provide more relevant and accurate recommendations [143, 144].
- c. **Multi-modal recommendation systems:** The majority of current deep learning-based recommendation systems rely on a single modality, such as text or images. Many real-world recommendation scenarios, on the other hand, combine multiple modalities, such as employing text for enhancing image-based suggestions. To overcome the data imbalance problem, adversarial learning can also be used to produce synthetic data for underrepresented modalities. Overall, these research paths present interesting prospects for advancing the field of multimodal recommendation systems that employ deep learning techniques [145, 146].
- d. **Fairness and bias in DLRS:** Bias and fairness issues are often seen in recommendation systems which uses popularity-based recommendation algorithms to suggest new items. Methods for detecting and reducing bias in recommendation systems have been investigated by researchers. Another approach might be to create diverse and inclusive

assessment criteria to analyze the fairness of the system and its efficacy, such as metrics that measure user happiness, engagement, and access to a wider range of suggestions. Finally, including user feedback and making diversity and fairness explicit goals in system design might assist in ensuring that suggestions are not just fair, but also interesting and relevant to users. Researchers may assist in promoting fairer and more effective recommendation systems that benefit all users by using a holistic approach that incorporates the complex interplay between data, algorithms, and user demands [147, 148].

8 Conclusion

The exponential rise in data which is generated by electronic and automated equipment has resulted in the development of techniques for storing, processing, retrieving, and analyzing these data for the benefit of users. DLRS could be seen as a promising solution to these difficulties. These systems are ideal tools to facilitate the process of searching for information more quickly. Through this survey, we emphasized the importance of deep learning approaches in improving recommendation system performance. These algorithms analyse massive volumes of data to identify latent representations, allowing for more accurate and personalized suggestions. In comparison to previous approaches, DLRS has advantages such as the capacity to integrate heterogeneous data from numerous sources, predict sequence patterns, and capture diverse user preferences. The review has shed light on several problems that standard recommender systems face, as well as how deep learning techniques handle them. Furthermore, the study outlines prospective future research avenues in the area. These include integrating multimodal data, addressing concerns of fairness and diversity, and investigating innovative designs. These directions pave the path for future improvements and provide chances for innovative ideas. This overview was written with the expectation that researchers may find it helpful in understanding how DLRS came into being. It serves as a comprehensive resource for understanding the current challenges, and explore further research scope. By leveraging these techniques, we can continue to enhance recommendation systems, offering users more accurate and personalized suggestions.

Author's contribution Ms. Manisha Jangid and Dr. Rakesh Kumar have equally contributed in this research paper.

Funding No funding was received for conducting this study.

Data availability Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

Declaration

Conflict of interests The authors declare that there is no conflict of interest.

References

1. Zhang Q, Yang LT, Chen Z, Li P (2018) A survey on deep learning for big data. *Inf Fusion* 42:146–157
2. Najafabadi MM, Villanustre F, Khoshgoftaar TM, Seliya N, Wald R, Muharemagic E (2015) Deep learning applications and challenges in big data analytics. *J big data* 2:1–21

3. Adomavicius G, Tuzhilin A (2005) Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Trans Knowl Data Eng* 17(6):734–749
4. Wang H, Wang N, Yeung D-Y (2015) Collaborative deep learning for recommender systems. In: *Proceedings of the 21th ACM SIGKDD international conference on knowledge discovery and data mining*. ACM, Sydney, pp 1235–1244
5. LeCun Y, Bengio Y, Hinton G (2015) Deep learning. *Nature* 521:436–444
6. Peng Y-x et al (2017) Cross-media analysis and reasoning: advances and directions. *Frontiers Inf Technol Electronic Eng* 18(1):44–57
7. Karatzoglou A et al (2016) RecSys' 16 workshop on deep learning for recommender systems (DLRS). In: *Proceedings of the 10th ACM conference on recommender systems*. Boston, pp 415–416
8. Covington P, Adams J, Sargin E (2016) Deep neural networks for Youtube recommendations. In: *Proceedings of the 10th ACM conference on recommender systems*. Boston, pp 91–198
9. Cheng H-T et al (2016) Wide & deep learning for recommender systems. In: *Proceedings of the 1st workshop on deep learning for recommender systems (DLRS)*. Boston, pp 7–10
10. Song K, Ji M, Park S, Moon IC (2019) Hierarchical context enabled recurrent neural network for recommendation. In: *Proceedings of the AAAI conference on artificial intelligence* 33(1):4983–4991
11. Elkahky AM, Song Y, He X (2015) A multi-view deep learning approach for cross domain user modeling in recommendation systems. In: *Proceedings of the 24th international conference on world wide web*, Florence, pp 278–288
12. Song Y, Elkahky AM, He X (2016) Multi-rate deep learning for temporal recommendation. In: *Proceedings of the 39th international ACM SIGIR conference on Research and Development in information retrieval*. ACM, pp 909–912
13. Vasile F, Smirnova E, Conneau A (2016) Meta-prod2vec: product embeddings using side-information for recommendation. In: *Proceedings of the 10th ACM conference on recommender systems*, Boston, pp 225–232
14. Grbovic M et al (2015) E-commerce in your inbox: product recommendations at scale. In: *Proceedings of the 21th ACM SIGKDD international conference on knowledge discovery and data mining*. Sydney, pp 1809–1818
15. Hsieh C-K, Yang L, Cui Y, Lin T-Y, Belongie S, Estrin D (2017) Collaborative metric learning. In: *Proceedings of the 26th international conference on world wide web*. Perth, pp 193–201
16. Roy S, Guntuku SC (2016) Latent factor representations for cold-start video recommendation. In: *Proceedings of the 10th ACM conference on recommender systems*. Boston, pp 99–106
17. Li S, Kawale J, Fu Y (2015) Deep collaborative filtering via marginalized denoising auto-encoder. In: *Proceedings of the 24th ACM international on conference on information and knowledge management*. CIKM, Melbourne, pp 811–820
18. Xi WD, Huang L, Wang CD, Zheng YY, Lai JH (2021) Deep rating and review neural network for item recommendation. *IEEE Trans Neural Netw Learn Syst* 33(11):6726–6736
19. Liu H, Wang Y, Peng Q, Wu F, Gan L, Pan L, Jiao P (2020) Hybrid neural recommendation with joint deep representation learning of ratings and reviews. *Neurocomputing* 374:77–85
20. Wu Y, DuBois C, Zheng AX, Ester M (2016) Collaborative denoising auto-encoders for top-n recommender systems. In: *Proceedings of the ninth ACM international conference on web search and data mining (WSDM)*, pp 153–162
21. Camacho LAG, Alves-Souza SN (2018) Social network data to alleviate cold-start in recommender system: a systematic review. *Inf Process Manage* 54(4):529–544
22. Qin J (2021) A Survey of long-tail item recommendation methods. *Wirel Commun Mob Comput* 2021:1–14
23. Betru BT, Onana CA, Batchakui B (2017) A survey of state-of-the-art: deep learning methods on recommender system. *Int J Comput Appl* 162:10
24. Guo Y, Liu Y, Oerlemans A, Lao S, Wu S, Lew MS (2016) Deep learning for visual understanding: a review. *Neurocomputing* 187:27–48
25. Batmaz Z, Yurekli A, Bilge A, Kaleli C (2019) A review on deep learning for recommender systems: challenges and remedies. *Artif Intell Rev* 52:1–37
26. Zhang S, Yao L, Sun A, Tay Y (2019) Deep learning based recommender system: a survey and new perspectives. *ACM Comp Surv (CSUR)* 52(1):1–38
27. Liu J, Wu C (2017) Deep learning based recommendation: a survey. In: *Proceedings of information science and applications (ICISA)*, lecture notes in electrical engineering, vol 424. Springer, p 451–458
28. Liu W, Wang Z, Liu X, Zeng N, Liu Y, Alsaadi FE (2017) A survey of deep neural network architectures and their applications. *Neurocomputing* 234:11–26

29. Mooney RJ, Roy L (2000) Content-based book recommending using learning for text categorization. In: Proceedings of the fifth ACM Conference on Digital Libraries, ACM, Texas, pp 195–204
30. Breese JS, Heckerman D, Kadie C (1998) Empirical analysis of predictive algorithms for collaborative filtering. In: Proceedings of the fourteenth conference on uncertainty in artificial intelligence(UAI), Madison, pp 43–52
31. Balabanović M, Shoham Y (1997) Fab: content-based, collaborative recommendation. *Commun ACM* 40(3):66–72
32. Schafer JB, Konstan J, Riedl J (1999) Recommender systems in e-commerce. In: Proceedings of the 1st ACM conference on electronic commerce. ACM, pp 158–166
33. Bhatt CA, Kankanhalli MS (2011) Multimedia data mining: state of the art and challenges. *Multimed Tools Appl* 51:35–76
34. Noia T, Di MR, Ostuni VC, Romito D, Zanker M (2012) Linked open data to support content-based recommender systems. In: Proceedings of the 8th international conference on semantic systems(I-SEMANTICS), Graz, pp 1–8
35. Bobadilla J, Hernando A, Ortega F, Bernal J (2011) A framework for collaborative filtering recommender systems. *Expert Syst Appl* 38(12):14609–14623
36. Sharaf M, Hemdan EED, El-Sayed A, El-Bahnasawy NA (2022) A survey on recommendation systems for financial services. *Multimed Tools Appl* 81(12):16761–16781
37. Burke R (2002) Hybrid recommender systems: survey and experiments. *User modeling and user-adapted interaction*.12:331–370
38. Hussein T, Linder T, Gaulke W, Ziegler J (2014) Hybreed: a software framework for developing contextaware hybrid recommender systems. *User Model User-Adap Inter* 24:121–174
39. Li X, Wang M, Liang T-P (2014) A multi-theoretical kernel-based approach to social network-based recommendation. *Decis Support Syst* 65:95–104
40. Alhamid MF, Rawashdeh M, Al Osman H, Hossain MS, El Saddik A (2015) Towards context-sensitive collaborative media recommender system. *Multimed Tools Appl* 74:11399–11428
41. Kosmides P, Remoundou C, Demestichas K, Loumiotis I, Adamopoulou E, and Theologou M(2014) A location recommender system for location-based social networks. *Proceedings of IEEE international conference on mathematics and computers in sciences and in industry*. IEEE. Varna, Bulgaria, p 277–280
42. Ren L, Wang W (2018) An SVM-based collaborative filtering approach for Top-N web services recommendation. *Futur Gener Comput Syst* 78:531–543
43. Lika B, Kolomvatsos K, Hadjiefthymiades S (2014) Facing the cold start problem in recommender systems. *Expert Syst Appl* 41(4):2065–2073
44. Karimi R, Nanopoulos A, Schmidt-Thieme L (2015) A supervised active learning framework for recommender systems based on decision trees. *User Model User-Adap Inter* 25:39–64
45. Herce-Zelaya J, Porcel C, Bernabé-Moreno J, Tejeda-Lorente A, Herrera-Viedma E (2020) New technique to alleviate the cold start problem in recommender systems using information from social media and random decision forests. *Inf Sci* 536:156–170
46. Aleksandrova M, Brun A, Boyer A, Chertov O (2017) Identifying representative users in matrix factorization-based recommender systems: application to solving the content-less new item cold-start problem. *J Intell Inf Syst* 48(2):365–397
47. Silver D et al (2016) Mastering the game of Go with deep neural networks and tree search. *Nature* 529:484–489
48. Hinton GE, Osindero S, Teh Y-W (2006) A fast learning algorithm for deep belief nets. *Neural Comput* 18(7):1527–1554
49. Krizhevsky A, Hinton GE (2011) Using very deep autoencoders for content-based image retrieval. *Proceed Eur Symp Art Neural Networks* 1:2
50. LeCun Y et al (1989) Backpropagation applied to handwritten zip code recognition. *Neural Comput* 1(4):541–551
51. Shan Y, Hoens TR, Jiao J, Wang H, Yu D, Mao J (2016) Deep crossing: web-scale modeling without manually crafted combinatorial features. In: Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining, San Francisco, pp 255–262
52. Shan Y, Hoens T R, Jiao J, Wang H, Yu D, Mao J (2016) Deep crossing: web-scale modeling without manually crafted combinatorial features. In: Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining. ACM, San Francisco, pp 255–262
53. Guo H, Tang R, Ye Y, Li Z, He X (2017) DeepFM: a factorization-machine based neural network for CTR prediction. In: Proceedings of the 26th International Joint Conference on Artificial Intelligence(IJCAI), Melbourne, pp 1725–1731

54. Zhou G et al (2018) Deep interest network for click-through rate prediction. In: Proceedings of the 24th ACM SIGKDD international conference on knowledge Discovery & Data Mining. London, pp 1059–1068
55. Rumelhart DE, Hinton GE, Williams RJ (1986) Learning representations by back-propagating errors. *Nature* 323:533–536
56. Wei P, Ke Y, Goh CK (2018) Feature analysis of marginalized stacked denoising autoencoder for unsupervised domain adaptation. *IEEE Trans Neural Netw Learn Syst* 30(5):1321–1334
57. Vincent P, Larochelle H, Bengio Y, Manzagol P-A (2008) Extracting and composing robust features with denoising autoencoders. In: Proceedings of the 25th international conference on machine learning (ICML), Helsinki, pp 1096–1103
58. Sedhain S, Menon AK, Sanner S, Xie L (2015) Autorec: autoencoders meet collaborative filtering. In: Proceedings of the 24th international conference on world wide web, Florence, pp 111–112
59. Li X, She J (2017) Collaborative variational autoencoder for recommender systems. In: Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining. Halifax, p 305–314
60. Dai T, Zhu L, Wang Y, Carley KM (2019) Attentive stacked denoising autoencoder with bi-lstm for personalized context-aware citation recommendation. *IEEE/ACM Trans Audio Speech Lang Process* 28:553–568
61. Dong B, Zhu Y, Li L, Wu X (2020) Hybrid collaborative recommendation via dual-autoencoder. *IEEE Access* 8:46030–46040
62. Liu Y, Wang S, Khan MS, He J (2018) A novel deep hybrid recommender system based on auto-encoder with neural collaborative filtering. *Big Data Min Anal* 1(3):211–221
63. Krizhevsky A, Sutskever I, Hinton GE (2017) Imagenet classification with deep convolutional neural networks. *Commun ACM* 60(6):84–90
64. Chen M, Ma T, Zhou X (2022) CoCNN: co-occurrence CNN for recommendation. *Expert Syst Appl* 195:116595
65. Putzu L, Piras L, Giacinto G (2020) Convolutional neural networks for relevance feedback in content based image retrieval: a content based image retrieval system that exploits convolutional neural networks both for feature extraction and for relevance feedback. *Multimed Tools Appl* 79(37):26995–27021
66. Kim D, Park C, Oh J, Lee S, Yu H (2016) Convolutional matrix factorization for document context-aware recommendation. In: Proceedings of the 10th ACM conference on recommender systems, pp 233–240
67. Rawat YS, Kankanhalli MS (2016) ConTagNet: exploiting user context for image tag recommendation. In: Proceedings of the 24th ACM international conference on multimedia, Amsterdam, pp 1102–1106
68. Lei C, Liu D, Li W, Zha Z-J, Li H (2016) Comparative deep learning of hybrid representations for image recommendations. In: Proceedings of international conference on computer vision and pattern recognition. IEEE, pp 2545–2553
69. Wang S, Wang Y, Tang J, Shu K, Ranganath S, Liu H (2017) What your images reveal: exploiting visual contents for point-of-interest recommendation. In: Proceedings of the 26th international conference on world wide web, Perth, pp 391–400
70. Vathsala MK, Holi G (2020) RNN based machine translation and transliteration for twitter data. *Int J Speech Technol* 23(3):499–504
71. Graves A and Jaitly N (2014) Towards end-to-end speech recognition with recurrent neural networks. In: Proceedings of international conference on machine learning. PMLR 32(2):1764–1772.
72. Karpathy A, Fei-Fei L (2015) Deep visual-semantic alignments for generating image descriptions. In: Proceedings of international conference on computer vision and pattern recognition. IEEE, pp 3128–3137
73. Hochreiter S, Schmidhuber J (1995) Long short-term memory. *Neural Comput* 9(8):1735–1780
74. Graves A, Wayne G, Danihelka I (2014) Neural turing machines. Preprint at <https://arxiv.org/abs/1410.5401>
75. Mohsen S (2023) Recognition of human activity using GRU deep learning algorithm. *Multimed Tools Appl* 82(30):47733–47749
76. De Boom C, Agrawal R, Hansen S, Kumar E, Yon R, Chen CW, ... Dhoedt B (2018) Large-scale user modeling with recurrent neural networks for music discovery on multiple time scales. *Multimed Tools Appl* 77:15385–15407
77. Liu Q, Wu S, Wang L (2017) Multi-behavioral sequential prediction with recurrent log-bilinear model. *IEEE Trans Knowl Data Eng* 29(6):1254–1267

78. Yang C, Sun M, Zhao WX, Liu Z, Chang EY (2017) A neural network approach to jointly modeling social networks and mobile trajectories. *ACM Trans Inf Syst (TOIS)* 35(4):1–28
79. Hidasi B, Karatzoglou A (2018) Recurrent neural networks with top-k gains for session-based recommendations. In: *Proceedings of the 27th ACM international conference on information and knowledge management*. Torino, pp 843–852
80. Tan YK, Xu X, Liu Y (2016) Improved recurrent neural networks for session-based recommendations. In: *Proceedings of the 1st workshop on deep learning for recommender systems*, Boston, pp 17–22
81. Dai H, Wang Y, Trivedi R, Song L (2016) Recurrent coevolutionary latent feature processes for continuous time recommendation. In: *Proceedings of the 1st workshop on deep learning for recommender systems*, Boston, pp 29–34
82. Chen C, Meng X, Xu Z, Lukasiewicz T (2017) Location-aware personalized news recommendation with deep semantic analysis. *IEEE Access* 5:1624–1638
83. Hinton GE, Sejnowski TJ (1986) Learning and relearning in Boltzmann machines. *Parallel Distributed Process: Explor Microstruct Cog* 1:282–317
84. Smolensky P (1986) Information processing in dynamical systems: foundations of harmony theory, vol 1. Colorado University at Boulder Department of Computer Science, pp 194–284
85. Hinton GE (2012) A practical guide to training restricted Boltzmann machines. *Neural networks: tricks of the trade*, vol 7700, 2nd edn (Lecture Notes in Computer Science). Springer, Berlin, pp 599–619
86. Salakhutdinov R, Mnih A, Hinton G (2007) Restricted Boltzmann machines for collaborative filtering. In: *Proceedings of the 24th international conference on machine learning (ICML)*, Corvallis, pp 791–798
87. Truyen TT, Phung DQ, Venkatesh S (2009) Ordinal Boltzmann machines for collaborative filtering. In: *Proceedings of the twenty-fifth conference on uncertainty in artificial intelligence*, Montreal, pp 548–556
88. Georgiev K and Nakov P (2013) A non-iid framework for collaborative filtering with restricted Boltzmann machines. In: *Proceedings of international conference on machine learning*. PMLR 28(3):1148–1156
89. Wang X, Wang Y (2014) Improving content-based and hybrid music recommendation using deep learning. In: *Proceedings of the 22nd ACM international conference on multimedia*, MM '14. ACM, Orlando Florida, pp 627–636
90. Zuo Y, Zeng J, Gong M, Jiao L (2016) Tag-aware recommender systems based on deep neural networks. *Neurocomputing* 204:51–60
91. Zhuang F, Zhang Z, Qian M, Shi C, Xie X, He Q (2017) Representation learning via dual-autoencoder for recommendation. *Neural Netw* 90:83–89
92. Unger M, Bar A, Shapira B, Rokach L (2016) Towards latent context-aware recommendation systems. *Knowl-Based Syst* 104:165–178
93. Deng S, Huang L, Xu G, Wu X, Wu Z (2016) On deep learning for trust-aware recommendations in social networks. *IEEE Trans Neural Netw Learn Syst* 28(5):1164–1177
94. Zhao J et al (2019) Attribute mapping and autoencoder neural network based matrix factorization initialization for recommendation systems. *Knowl-Based Syst* 166:132–139
95. Wang K, Xu L, Huang L, Wang C-D, Lai J-H (2019) SDDRS: stacked discriminative denoising autoencoder based recommender system. *Cogn Syst Res* 55:164–174
96. Jiang J, Li W, Dong A, Gou Q, Luo X (2020) A Fast Deep AutoEncoder for high-dimensional and sparse matrices in recommender systems. *Neurocomputing* 412:381–391
97. Tahmasebi H, Ravanmehr R, Mohamadzaei R (2021) Social movie recommender system based on deep autoencoder network using Twitter data. *Neural Comput Appl* 33:1607–1623
98. Noshad Z, Bouyer A, Noshad M (2021) Mutual information-based recommender system using autoencoder. *Appl Soft Comput* 109:107547
99. Yu M, Quan T, Peng Q, Yu X, and Liu L (2022) A model-based collaborate filtering algorithm based on stacked AutoEncoder. *Neural computing and applications* 1–9
100. Kim D, Park C, Oh J, Yu H (2017) Deep hybrid recommender systems via exploiting document context and statistics of items. *Inf Sci* 417:72–87
101. Shu J, Shen X, Liu H, Yi B, Zhang Z (2018) A content-based recommendation algorithm for learning resources. *Multimedia Syst* 24(2):163–173
102. Wu H, Zhang Z, Yue K, Zhang B, He J, Sun L (2018) Dual-regularized matrix factorization with deep neural networks for recommender systems. *Knowl-Based Syst* 145:46–58
103. Da'u A, Salim N, Rabi'u I, Osman A (2020) Recommendation system exploiting aspect-based opinion mining with deep learning method. *Inf Sci* 512:1279–1292

104. Zhang X, Liu H, Chen X, Zhong J, Wang D (2020) A novel hybrid deep recommendation system to differentiate user's preference and item's attractiveness. *Inf Sci* 519:306–316
105. Khan ZY, Niu Z (2021) CNN with depthwise separable convolutions and combined kernels for rating prediction. *Expert Syst Appl* 170:114528
106. Lee S, Kim D (2022) Deep learning based recommender system using cross convolutional filters. *Inf Sci* 592:112–122
107. Wu C, Wang J, Liu J, Liu W (2016) Recurrent neural network based recommendation for time heterogeneous feedback. *Knowl-Based Syst* 109:90–103
108. Gunawan AA, Suhartono D (2019) Music recommender system based on genre using convolutional recurrent neural networks. *Procedia Comp Sci* 157:99–109
109. Katarya R, Arora Y (2020) Capsmf: a novel product recommender system using deep learning based text analysis model. *Multimed Tools Appl* 79:35927–35948
110. Chen H, Wang S, Jiang N, Li Z, Yan N, Shi L (2021) Trust-aware generative adversarial network with recurrent neural network for recommender systems. *Int J Intell Syst* 36(2):778–795
111. Vedavathi N, Anil Kumar KM (2021) An efficient e-learning recommendation system for user preferences using hybrid optimization algorithm. *Soft Comput* 25(14):9377–9388
112. Bansal S, Baliyan N (2022) Remembering past and predicting future: a hybrid recurrent neural network based recommender system. *J Ambient Intell Humaniz Comput* 14:1–12
113. Liu X, Ouyang Y, Rong W, Xiong Z (2015) Item category aware conditional restricted Boltzmann machine based recommendation. In: *Proceedings of neural information processing: 22nd international conference, ICONIP 2015*. Springer, Istanbul, pp 609–616
114. Xie W, Ouyang Y, Ouyang J, Rong W, Xiong Z. User occupation aware conditional restricted Boltzmann machine based recommendation. In: *Proceedings of IEEE international conference on internet of things (iThings) and IEEE green computing and communications (GreenCom) and IEEE cyber, physical and social computing (CPSCom) and IEEE smart data (SmartData)*. IEEE, Chengdu, pp 454–461
115. Du Y-p, Yao C-q, Huo S-h, Liu J-x (2017) A new item-based deep network structure using a restricted Boltzmann machine for collaborative filtering. *Frontiers Inf Technol Electronic Eng* 18(5):658–666
116. Pujahari A, Sisodia DS (2019) Modeling side information in preference relation based restricted Boltzmann machine for recommender systems. *Inf Sci* 490:126–145
117. Chen Z, Ma W, Dai W, Pan W, Ming Z (2020) Conditional restricted Boltzmann machine for item recommendation. *Neurocomputing* 385:269–277
118. Biswal A, Borah MD, Hussain Z (2021) Music recommender system using restricted Boltzmann machine with implicit feedback. *Proceed Adv Comp* 122:367–402
119. Kumar RR, Apparao G, Anuradha S (2022) Deep scalable and distributed restricted Boltzmann machine for recommendations. *Int J Syst Assur Eng Manag* 15:161–173
120. Jha GK, Gaur M, Ranjan P, Thakur HK (2023) A trustworthy model of recommender system using hyper-tuned restricted Boltzmann machine. *Multimed Tools Appl* 82(6):8261–8285
121. Wakita Y, Oku K, Kawagoe K (2016) Toward fashion-brand recommendation systems using deep-learning: preliminary analysis. *Int J Knowl Eng* 2(3):128–131
122. Chen R-C (2019) User rating classification via deep belief network learning and sentiment analysis. *IEEE Trans Comput Soc* 6(3):535–546
123. Venkatesh M, Sathyalaksmi S (2022) Memetic swarm clustering with deep belief network model for e-learning recommendation system to improve learning performance. *Concurr Comput Pract Exp* 34(18):7010
124. Mehdodniya A, Rao MV, David LG, Nigel KGJ, Vennam P (2022) Online product sentiment analysis using random evolutionary whale optimization algorithm and deep belief network. *Pattern Recogn Lett* 159:1–8
125. Wei J, He J, Chen K, Zhou Y, Tang Z (2017) Collaborative filtering and deep learning based recommendation system for cold start items. *Expert Syst Appl* 69:29–39
126. Da'u A, Salim N, and Idris R, (2021) An adaptive deep learning method for item recommendation system. *Knowl-Based Syst* 213:106681
127. Kiran R, Kumar P, Bhasker B (2020) DNNRec: a novel deep learning based hybrid recommender system. *Expert Syst Appl* 144:113054
128. Qian T, Liang Y, Li Q, Xiong H (2020) Attribute graph neural networks for strict cold start recommendation. *IEEE Trans Knowl Data Eng* 34(8):3597–3610
129. Hazrati N, Elahi M (2021) Addressing the New Item problem in video recommender systems by incorporation of visual features with restricted Boltzmann machines. *Expert Syst* 38:12645
130. Ahmed A, Saleem K, Khalid O, Gao J, Rashid U (2022) Trust-aware denoising autoencoder with spatial-temporal activity for cross-domain personalized recommendations. *Neurocomputing* 511:477–494

131. Hong D, Gao L, Yao J, Zhang B, Plaza A, Chanussot J (2020) Graph convolutional networks for hyper-spectral image classification. *IEEE Trans Geosci Remote Sens* 59(7):5966–5978
132. Hong D et al (2020) More diverse means better: multimodal deep learning meets remote-sensing imagery classification. *IEEE Trans Geosci Remote Sens* 59(5):4340–4354
133. Bai B, Fan Y, Tan W, Zhang J (2017) DLTSR: a deep learning framework for recommendations of long-tail web services. *IEEE Trans Serv Comput* 13(1):73–85
134. Vincent P, Larochelle H, Lajoie I, Bengio Y, Manzagol P-A, Bottou L (2010) Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. *J Mach Learn Res* 11:3371–3408
135. Kumar Y et al (2020) Harnessing gans for zero-shot learning of new classes in visual speech recognition. *Proc AAAI Conf Art Intel* 34(3):2645–2652
136. Sreepada RS, Patra BK (2020) Mitigating long tail effect in recommendations using few shot learning technique. *Expert Syst Appl* 140:112887
137. Pan R et al (2008) One-class collaborative filtering. *Proceedings of Eighth IEEE international conference on data mining*. IEEE, Pisa, Italy, p 502–511
138. Qin J, Zhang Q, Wang B (2020) Recommendation method with focus on long tail items. *J Comput Appl* 40(2):454
139. Liu S, Zheng Y (2020) Long-tail session-based recommendation. In: *Proceedings of the 14th international conference on recommender systems, RecSys '20, Brazil*. ACM, pp 509–514
140. Krishnan A, Sharma A, Sankar A, Sundaram H (2018) An adversarial approach to improve long-tail performance in neural collaborative filtering. In: *Proceedings of the 27th ACM international conference on information and knowledge management, CIKM '18*. ACM, Torino, pp 1491–1494
141. Vultureanu-Albiși A, Bădică C (2021) Recommender systems: an explainable AI perspective. In: *Proceedings of international conference on INnovations in intelligent SysTems and applications (INISTA)*. IEEE, pp 1–6
142. Samih A, Adadi A, Berrada M (2019) Towards a knowledge based explainable recommender systems. In: *Proceedings of the 4th international conference on big data and internet of things, BDIOT'19*. ACM, Rabat, pp 1–5
143. Cui Z et al (2020) Personalized recommendation system based on collaborative filtering for IoT scenarios. *IEEE Trans Serv Comput* 13(4):685–695
144. Hui B, Zhang L, Zhou X, Wen X, Nian Y (2021) Personalized recommendation system based on knowledge embedding and historical behavior. *Appl Intell* 52:954–966
145. Li G et al (2021) Multi-modal visual adversarial Bayesian personalized ranking model for recommendation. *Inf Sci* 572:378–403
146. Li X et al (2020) Adversarial multimodal representation learning for click-through rate prediction. In: *Proceedings of the web conference 2020*. ACM, pp 827–836
147. Chen J, Dong H, Wang X, Feng F, Wang M, He X (2023) Bias and debias in recommender system: a survey and future directions. *ACM Trans Inf Syst* 41(3):1–39
148. Rahmani HA, Deldjoo Y, Tourani A, Naghiaei M (2022) The unfairness of active users and popularity bias in point-of-interest recommendation. In: *Proceedings of advances in Bias and fairness in information retrieval: third international workshop, BIAS 2022*. Springer, Stavanger, pp 56–68

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.