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Machine Learning and Deep Learning Techniques for Recommendation Systems: A Comprehensive Review

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Abstract
In the current era, our digital lives are driven by data. Recommendation engines have become part and parcel of our digital lives and help us to make decisions about products, content, and services to buy. The evolving landscape of deep learning-based recommendation systems has been extensively discussed in this paper. The main focus is on key advancements in recommendation system evaluation, personalized recommendation techniques, and the integration of various data sources. Furthermore, it discusses the ethical and privacy concerns associated with recommendation systems. A critical analysis of the current state of recommendation systems has been presented to give valuable insights for future advancements in this area.

Keywords: Recommendation systems; Deep learning; Machine Learning; Recommendation; E-commerce; Personalization

1. Introduction

Information overload is a potential issue that may arise from the rapid increase of digital information accessible and Internet users. This phenomenon can make it challenging to locate engaging content on the Internet quickly. Information retrieval systems like Google, Altavista, and DevilFinder have addressed this issue to a significant extent, however, there remained a lack of prioritization and personalization of the available content (the process by which a system aligns accessible content with a user's interests and preferences). E-commerce is currently being used more and more as a result of the advancements made in smart computing and the internet [1][2]. Because of this, there is now a greater need for recommendation systems. The concept of recommendation has added all new doors and dimensions to the user experience. When a user is looking at a particular product the system automatically gets an alert and starts suggesting similar items and engaging the customer to get more interested in that type of product he wants. Recommendation systems (RS) use Artificial Intelligence (AI) and Machine Learning (ML) algorithms to offer suggestions to different users. The context is related to the user's query and the results are produced according to the user's liking and search criteria. An example that illustrates this system is that an online movie website shall apply Machine Learning and Deep Learning techniques to produce movie show searches based on genre and then recommend similar shows to the users.

To mitigate the information overloading problem [3], recommendation systems pick key information fragments from vast volumes of dynamically generated data depending on user preferences, observed behavior, or interests in a particular item [4]. Recommendation systems can determine whether or not the user will find a given item appealing, based on their profile. One of the most useful features of recommendation systems is that they can analyze user behavior, preferences, and needs to produce personalized recommendations [5]. They identified user preferences based on the stored information about users and products and accordingly, products will be suggested for shopping[65]. All users' data have been grouped into separate categories to form neighbors that are harmonious substitutes for searching the entire user space. Hence the scalability of the system increases [6]. They have been used in e-commerce websites like Amazon, and Netflix to recommend books, movies, music, news articles, CDs, etc. Users and E-Commerce organizations both get benefits from recommendation systems [7] i.e., they not only assist users but also increase the company's profitability by selling more items.

Types of Recommendation Systems

Since the 1990s, many studies have been used to develop recommendation systems. Various fields like cognitive science, information retrieval, approximation theory, and so on are applied to design recommendation systems. Traditionally, there are three categories of recommendation systems based on their implementation methods:

Content-based recommendation systems: They look for products, services, or content that are comparable to those that the user has already examined. User feedback (which can be gathered in a variety of methods) is critical in these systems. The fundamental principles of these systems are: 1) determine a user's preferences by analyzing the product description that he or she prefers and store in a user profile. 2) match each product's features with the user profile and recommend those that are the most similar to the user profile [8]. CB Recommendation system is the most used recommendation technique in various fields like academic resource recommendation, information acquisition, and so on.

Collaborative Filtering (CF) recommendation systems: This technique relies on finding similarities between the users by collecting the preferences, likes, and dislikes of different users[9]. Likewise, there are two users- A and B. The similarity features of A are proven useful for B in making decisions wisely because both are neighbors to each other. It is termed a collaborative approach. The memory-based recommends new items to the new user by taking the preferences of the neighbor. It takes the utility matrix as input and then makes suggestions using the similarity matrix.

Hybrid recommendation systems: They combine the best aspects of more than one recommendation approach to enhance recommendation quality and mitigate the shortcomings of conventional recommendation systems[10].

The evolution of the recommendation system from 1992 till date is depicted diagrammatically in figure 1.

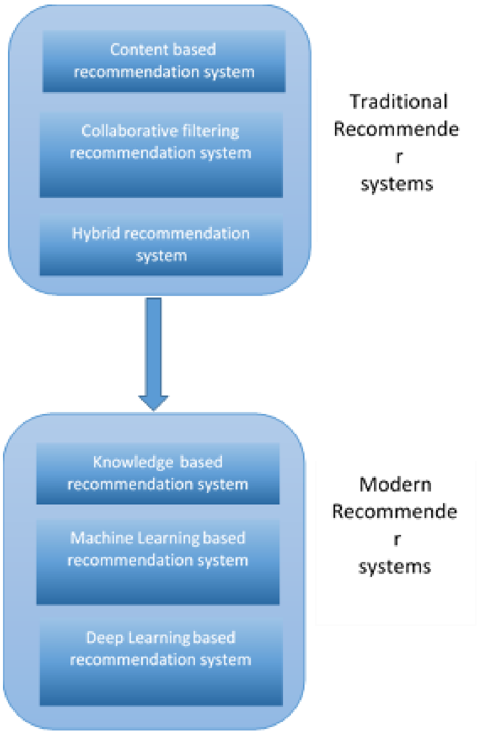

Figure 1. Evolution of Recommendation system

Applications of Recommendation Systems:

Recommendation systems were widely used by big tech companies in various areas, like entertainment, e-commerce, and social media, to enhance user engagement and satisfaction as depicted in figure 2.

E-commerce Services:

Amazon: Amazon uses recommendation systems to recommend products to users according to their browsing and purchase history. They also employ recommendation engines in their Prime Video service to suggest movies and TV shows. According to McKinsey, 35% of Amazon purchases are made possible by recommendation algorithms.

Alibaba: Alibaba uses recommendation systems to personalize product recommendations for users on its e-commerce platforms, like Tmall and Taobao.

Entertainment and Streaming Services:

Netflix: Netflix is well-known for its recommendation algorithms. According to users' viewing tastes and history, they make movie and TV show recommendations using machine learning algorithms. As per the recently mentioned McKinsey analysis, 75% of Netflix viewing is attributed to suggestions. Netflix holds data science competitions called Prizes, where a $1,000,000 prize is awarded to the best accurate movie recommendation system winner.

Spotify: Spotify employs recommendation algorithms to provide users with music selections and playlists based on their listening preferences and past selections. For every subscriber, Spotify generates a new, customized playlist called "Discover Weekly" every week. This playlist consists of 30 songs chosen specifically for each user based on their individual musical preferences. They succeeded in creating a music recommendation after acquiring Echo Nest, a firm that specializes in music intelligence and data analytics.

Social Media:

Facebook: Facebook uses recommendation systems to personalize users' news feeds, suggesting posts, articles, and content from friends and pages that align with a user's interests and engagement history.

Instagram: Instagram employs recommendation algorithms to surface content, including photos and videos, in users' feeds and Explore sections.

Travel and Hospitality:

Airbnb: Airbnb uses recommendation systems to offer users lodging recommendations based on past reservations and preferences.

Booking.com: This platform uses recommendation systems to suggest hotels and accommodations based on user preferences and browsing history.

Figure 2. Applications of Recommendation Systems

Retail and Fashion:

Zara: Zara, a fashion retailer, uses recommendation systems to provide clothing and accessory recommendations to online shoppers based on their style and browsing patterns.

ASOS: ASOS employs recommendation algorithms to suggest fashion items and accessories to its customers.

Video Games:

Steam: Steam uses recommendation systems to suggest games to users as per their tastes and gaming history.

Epic Games Store: The Epic Games Store employs recommendation algorithms to suggest games and content to users.

Food Delivery:

Uber Eats & Door Dash: Uber Eats uses recommendation systems to offer restaurant and food options to customers based on previous orders and preferences.

Personalized Advertising:

Google: Google uses recommendation algorithms to personalize the ads shown to users on its platforms, including Google Search, YouTube, and other services.

News and Content Aggregation:

Flipboard & Google News: The apps like Flipboard and Google News provide users with personalized news articles tailored to their interests and reading habits.

Financial Services:

Robo-advisors: Robo-advisors and financial institutions use recommendation systems to suggest investment opportunities and portfolio allocations based on a user's financial goals and risk tolerance.

Table 1 categorizes different research papers into various domains of recommendation systems.

Table 1: Domain-specific Recommendation Systems

Citation (reference)	Hotel based	Health-based	Online product based	Online course	E-learning	Movie based	Music based	Tourism based
García et al. [16]								▲
Chen et al. [21]		▲						
Hsu et al. [22]				▲				
Gemmell et al. [23]			▲					
Choi et al. [24]			▲					
Garibaldi et al. [25]	▲							
Lobo et al. [27]				▲				
Lucas et al. [29]								▲
Liu et al. [30]								▲
Wang et al. [31]						▲		
Chen et al. [36]						▲		
Nikou et al. [41]		▲						
Ayata et al. [42]							▲	
Santhi et al. [45]					▲			
Toivanen et al. [46]		▲						
Cai et al. [49]				▲				
Bhalse et al. [51]						▲		

He et al. [54]						▲		
Mondal et al. [60]		▲						

Issues and Challenges in RS:

The evolution of recommendation systems has seen several difficulties and challenges. Some of the critical challenges encountered during recommendation system deployment are specified below:

- **Sparse RSs:** Think of recommendation systems as trying to guess what you want to watch or buy based on what other people like. If there's not much data on your preferences or on what others like, it's like trying to complete a puzzle with missing pieces.
- **Cold-start problem:** When you're new to a platform, or when a new product is introduced, the system may struggle to make accurate recommendations because it doesn't have enough data about your preferences or the new item.
- **Scalability Problem:** For platforms with a lot of users and items (like Amazon or YouTube), it's a big challenge to process all that data quickly and efficiently to provide good recommendations.
- **Privacy Issue:** Recommendation systems collect data about your preferences. Sometimes, this data needs to be kept private and secure. People worry about their data being used in ways they don't like, which can be a challenge for these systems.
- **Robustness of RSs:** Resisting attacks is a significant challenge faced by RSs. A performance metric for RSs is robustness. Based on several attack models, such as Push/Nuke Attacks to increase or decrease the popularity of particular target products, an attacker may create fictitious user profiles to benefit. These types of assaults are often known as profile injection or shilling attacks.
- **Recommenders in Mobile Devices:** Users may look for various recommendations, particularly when traveling between cities, hotels, eateries, retail establishments, etc. This kind of situation necessitates the development of mobile user interfaces and computational solutions that can make optimal use of the restricted resources at hand, such as the computer power and screen size of mobile devices.
- **Feedback Loop:** When a system recommends popular items because they have lots of ratings, it can create a feedback loop. These items get even more popular, and niche or new items can get overlooked.
- **Algorithm Bias:** Sometimes, the algorithms used in recommendation systems can unintentionally favor certain groups of people or content. This can lead to unfair or biased recommendations.
- **Filter Bubbles:** These systems tend to show you things similar to what you've liked before. While this can be nice, it can also create a "filter bubble," where you only see a narrow set of content and miss out on new and diverse things.
- **Diversity of Items:** Recommendation systems should offer a variety of options. If they keep suggesting the same type of content, it can get boring. It's like a music player that only plays one genre of music.

The rest of the paper is organized in the following sections. Section 2 gives the related work of product recommendation systems. Section 3 describes the role of machine learning and deep learning in recommendation systems. Section 4 concludes the article followed by references.

2. Literature Review

A lot of work has been done in the field of recommendation systems. This section reviews some previous work related to this area. The recommendation system proposed by Garcia et al. [11] relates to correspondence education through the Internet. Its target is steering e-books to students after going through user data. Castellano et al. [12] evolved a "NEuro-fuzzy WEb Recommendation (NEWER)" system to estimate user preferences based on computational intelligence. Two diverse tools in a unique combination were implemented by Wang et al. [13]

in assisting personalized learning facilitation. Lin et al. [14] came up with a recommendation system crafted for computerized vending appliances based on 'Bayesian Network' (BN), Decision Tree (DT), k-means, and Genetic algorithm (GA). It focuses on local items with the help of hybrid model methods (that were – 'statistical, classification, clustering, and meta-heuristic methods). Hussain et al. [15] while working towards the enhancement of a service-concept recommendation system came up with an innovative model. García-Crespo et al. [16] developed the concept of a "semantic hotel" recommendation system that was based on adopting a fuzzy logic approach. Bazzan et al. [17] made strides in the hospitality industry and ended up in an "assumption-based multi-agent" system that was able to suggest travel calendars based on user preferences. It was capable of generating and customizing travel schemes based on the scheduling of the users. Li et al. [18] in knowledge management systems crafted a Fuzzy linguistic modeling-based RS. Huang et al. [19] with the help of collaborative filtering and a rough set model created a context-aware recommendation system. Chandrasekaran et al. [20] developed the "Ontology-driven bee's foraging approach (ODBFA)" to guess the online sites and posts probably popular among users. It is a self-adaptive system that deploys a scoring technique to perform comparisons. Chen et al. [21] applied "Semantic Web Rule Language (SWRL) and Java Expert System Shell (JESS) in the context of the healthcare system. It assisted in finding formulas for the patients. Hsu et al. [22] move a step forward and bring to the table a "personalized auxiliary material" RS keeping in mind particular topics; personalized learning choices, and the complex nature of auxiliary materials. Gemmell et al. [23] explored the grounds of social annotation systems and proposed a remedial tool for problems of resource recommendation. A novel model based on the linear-weighted hybrid method was born with the skill to contribute recommendations under various factors. Choi et al. [24] in their work "Hybrid Online-Product Recommendation (HOPE) System" performed memory-based filtering by analyzing user preferences and ratings. Garibaldi et al. [25] proposed a fuzzy logic inference-based model for user reviews and ratings. They wanted to underpin the variability of users. This model found its use in making positive choices of treatment in females suffering from breast cancer after the conduction of the operation. Salehi et al. [26] invented an e-learning material RS "modeling of materials in a multidimensional space of material's attribute" using content and collaborative filtering. Lobo et al. [27] proposed a mining and rule-based recommendation system using K-means clustering. Kardan et al. [28] performed segregation of users before the recommendation process based on filtering and operations. Lucas et al. [29] proposed a travel-based model by using association rules and fuzzy logic. Liu et al. [30] in the tourism sector came up with tailor-made real-time recommendations for self-driven tourists to curtail queuing time and traffic in tourist destinations. User preference was deployed for recommendations. Bakshi et al. [31] applied similarities in combination with technology for exploring international allies. Kim et al. [32] on social media platforms presented a recommendation system on the concept of "latent Dirichlet allocation using probabilistic modeling for Twitter". Kolomvatsos et al. [33] based on optimal stopping theory came up in the field of entertainment that gave ideas and suggestions regarding books/music. Zahálka et al. [34] gave birth to the "City Melange", a venue recommender. The sector of share market model given by Sankar et al. [35] proposed a mutual funding system. The movie recommendation system of Chen et al. [36] uses an AI-based collaborative filtering mechanism. It uses a similarity estimation formula for the movie recommendation process. A tag recommendation system was devised by Wu et al. [37]. Li, Zhao, et al. [38, 39] used audience feedback from microblogs and social networks to create a movie recommendation system. Lee WP et al. [40] came up with the concept of a music-related recommendation system whose foundation was on smartphone usage frequency. A system created by Nikou et al. [41] enabled its clients to undertake healthy actions to enhance their physical well-being. The type of bodily activity of the use along with its preferences was considered to make recommendations. Another music-related RS was crafted by Ayata et al. [42] and was based on the unique element of user emotions secured by wearable physiological sensors. Another movie-related RS was brought forward by Zhao et al. [43] as a social learning model. It presented a remarkable solution to the sparsity problem of RS. In the field of social network recommendation systems, Mouline S et al. [44] unveiled a hybrid initialization method. Whereas Santhi et al. [45] invented a hybrid, trust-based e-learning RS. The integrated recommender model of Toivanen et.al [46] was founded on collaborative filtering. Their model was capable of integrating recommendation systems that proved beneficial in making decisions for the proper management of the disease. Kang et al. [47] deployed a tree model to make personal advertisement recommendations to be used in Online Broadcasting. In the domain of online purchasing, Ullahet al. [48] have developed an image-based model for service recommendation that makes use of convolutional neural networks (CNN) and random forests. Cai et al. [49] used an evolutionary algorithm to perform recommendations. Dhelim et al. [50] developed a discovery path recommendation model based on the interests of the user. A cinema-based system developed by Bhalse et al. [51] rests on 'Collaborative filtering, Singular Value Decomposition (SVD), and cosine similarity (CS')' which concerns about sparsity issue of recommendation systems. It propounded movie details after exploring the content information of movies. Table 2 summarizes key insights from selected papers.

Table 2: Insights from literature survey

Citation (reference)	Description	Limitations	Approach Used
Garcia et al. [11]	Suitable for education platforms	Not suitable for big data	Learning objects
Castellano et.al [12]	Combines computational intelligence and user reviews	Not suited for real-time applications	Feedbacks
Wang et al. [13]	Enhanced learning process	Does not consider user behavior	Learning graphs
Lin et al. [14]	Hybrid method to cluster items	Not much efficient	Learning paths
Hussain et al. [15]	Uses ontology concepts	Not validated by simulation	Learning paths
García-Crespo et al. [16]	Use feature extraction techniques	Unable to handle large datasets	Learning paths
Bazzan et al. [17]	Works on the assumed dataset by computing similarity measure	Low accuracy	Feedbacks
Li et al. [18]	Knowledge management system	Does not consider the user's previous preferences	Learning paths
Huang et al. [19]	Organize sets of data based on user reviews	Low accuracy	Learning objects
Chandrasekaran et al. [20]	Self-adaptive system	Does not consider user dynamic preferences	Learning graphs
Chen et al. [21]	The model acts as a blood repository system	Unable to handle large datasets of patients	Learning paths
Hsu et al. [22]	Better execution time	Less accuracy and more complex	Feedbacks

Gemmell et al. [23]	Does annotations of user-based preferences	Involves high memory	Weighted graphs
Choi et al. [24]	High accuracy and precision	Consumes time	Learning paths
Garibaldi et al. [25]	Better recommendations for breast cancer	Unable to handle sparse datasets	Learning paths
Lobo et al. [27]	Online courses recommendation to students	Works with limited datasets	Learning graphs
Kardan et al. [28]	Segregation of posts based on groups	Does not involve ranking of algorithm	Learning paths
Lucas et al. [29]	Mitigates problems like grey sheep, and cold start. Sparsity	Does not store the user's previous preferences	Learning paths
Liu et al. [30]	Prevent tourists from traffic and longer queues	Platform dependent	Learning paths
Bakshi et.al [31]	Address the issue of scalability and sparse datasets	Datasets are chosen randomly	Feedbacks
Kim et.al [32]	Based on social platform preferences	Highly complex	Feedbacks
Zahálka et al. [34]	Describes features from visual domains	Requires feature extraction techniques	Weighted space model
Chen et al. [36]	Performs movie recommendation process based on a hybrid approach	Cold start issue, memory capacity issue	Learning paths
Li et al. [38]	Perform frequent patterns and sorting of reviews	Cold start issue, memory capacity issue	Learning graphs
Wu et al. [39]	Extracts user information related to social networks	Highly complex	Learning graphs
Ayata et al. [42]	Shows fluctuations in signals by sensors	Not dynamic	Learning graphs
Mouline et al. [44]	Creates perceptron with inputs and outputs	Does not involve real dataset	Learning paths
Toivanen [46]	Performs filtering of reviews based on medical history	Unable to handle real datasets	Learning paths
Santhi et al. [45]	Shows activities by online clients	Not suitable for wide-domain applications	Learning paths
Cai et al. [49]	Handles datasets and provides recommendations to university students	Cold start issue	Learning paths
Bhalse et al. [51]	Solves sparsity issues	Unable to handle complex data	Linear sets
Lian et al. [53]	Handles activities over multiple networks	Low searching process	Feedbacks

He et.al [54]	Removes data sparsity issue	Highly complex with large variables	Feedbacks
Mondal et al. [60]	Good precision on medical datasets	Unable to handle complex datasets	Learning graphs

3. Machine Learning and Deep Learning based techniques for Recommendation Systems

Machine Learning and Deep Learning are the two most commonly used techniques for recommendation systems. Earlier researchers were working on Machine Learning techniques. With the passage of time, they move towards Deep Learning techniques for better efficiency[1][66]. In this section, we are going to discuss various Machine Learning and Deep Learning-based approaches to be used in recommendation systems.

Machine Learning

Machine Learning (ML) enhances human learning by permitting systems to establish and gain real-world information and revamp the performance of tasks according to the newly acquired knowledge. In present times, ML algorithms have wide applications in businesses [15], advertising [26], movies [54], and health care [55]. Learning is a mechanism that results from acquiring knowledge. Human's tendency to find the cause/reason leads to learning from an acquaintance**.** Today exists a wide array of ML algorithms whose nomenclature is based on the type of learning approach used by them. Basic classifications comprise: 'supervised, unsupervised, semi-supervised, and reinforcement learning'. In Supervised learning, algorithms are supplied with a training set that consists of training data and correct answers. ML algorithm assists in learning according to training data, and in applying knowledge obtained from real data. Simplifying with this example, suppose a bookstore uses an ML learning algorithm for book categorization. A training set that may comprise a table provides information regarding every book under a particular classification. This can be anything ranging from a book/author name, word/a set of words contained in books. The ML algorithm learns in the company of the training set. After the arrival of a new stock of books, the algorithm will classify it under the light of knowledge about book classification attained by it.

In Unsupervised learning, there is no training set. Instead, they are fed certain data regarding the real world, and by putting that data to use they are expected to self-learn. Such systems aim to detect hidden materials in data. The algorithm in this type of system categorically divides its users based on personality traits – introvert/extrovert that informs platforms of Social media sites to tailor advertising to explicit user groups. Yet another type of ML algorithm is semi-supervised where algorithms deal with training sets having insufficient information, but are liable to learn from it. E.g. ML algorithm dealing with movie ratings.

ML algorithms can also contain a reinforcement learning approach. Here algorithms learn through extrinsic feedback that may be provided by a thinking entity/ environment. It is similar to training a pet to sit or jump. Each time the pet carries out an order in the correct fashion it gains a small treat (positive feedback). Nothing is bagged for an incorrect activity (negative feedback). E.g. in the computer field, ML algorithms participate in playing games with an opposing party. ML is receiving rapid growth and acceptance because of processor speed and memory size.

Deep Learning

This subsection contains, a series of DL-based architectural paradigms used for RS.

- Multilayer Perceptron (MLP) consists of a neural network consisting of input and output layers. It has a perceptron that signifies non-linear transformations and features.
- Auto-encoder (AE) is defined as a model to transform input data into its output layer. Auto-encoders are available in a multitude of varieties including 'denoising auto-encoder, marginalized denoising auto-encoder, sparse auto-encoder, contractive auto-encoder, and variational auto-encoder (VAE) [15, 45]. Auto-encoders are available in a multitude of varieties.

- Convolutional Neural Network (CNN) ~~[45] is a~~ neural network with a combination of layers and pooling operations.
- Recurrent Neural Network (RNN) ~~[45]~~ performs excellently in modeling sequential data. ~~As opposed to a feedforward neural network, it~~It contains loops and memories ~~in RNN~~ to gather earlier computations.
- Restricted Boltzmann Machine (RBM) is a double-layered network in which one layer is the visible layer and the other is the hidden layer. The communication between both layers is absent.
- Deep Reinforcement Learning (DRL) ~~[95]~~ framework generally constitutes the list of the following elements: 'agents, states, environments, ~~states,~~ actions and rewards'. ~~Deep neural networks bring~~It brings to the knowledge of agent info from raw data that outcome in representations even in the absence of features and domain heuristics.

Table 3 classifies various papers into approach-based recommendation systems.

Table 3: Classification of RS

Citation (reference)	Web-based	Social based	Collaborative based	Cloud-based	Hybrid	Context-aware	CNN based	Ontology-based	Deep learning based	Sensor-based
Garcia et al. [11]			▲							
Castellano et al. [12]	▲									
Wang et al. [13]						▲				
Lin et al. [14]					▲					
Hussain et al. [15]								▲		
Li et al. [18]									▲	
Huang et al. [19]						▲				
Chandrasekaran et al. [20]								▲	▲	
Kardan et al. [28]				▲						
Zahálka et al. [34]							▲			
Li et al. [38]		▲								
Wu et al. [39]		▲								
Ayata et al. [42]										▲
Mouline S et al. [44]									▲	
Lian et al. [53]							▲			

Why Deep Neural Networks for Recommendation?

Throughout the past few years, a large number of deep recommendation systems have been introduced. It should be understood why so many kinds of it are needed and what is the use of neural networks. Besides this it is a wise thing to do to explain each architecture and where would it fit in best. The two distinctive features of neural networks are their ability to (1) support distinct inductive biases based on the type of input data, and (2) be end-to-end differentiable. Because of their flexibility, deep neural networks can be taught end-to-end by compacting several neural building blocks into a single differentiable function. Working with a content-based recommendation demonstrates its virtue. When modeling online persons or goods with multi-modal data, it is essential. CNNs and RNNs are neural building blocks, for example, if we look at textual data (tweets [56], etc.) and visual data (social postings, product photographs). Therefore, the recommendation system cannot leverage joint (end-to-end) representation learning, and traditional alternatives are not important. Remember that developments in recommendation systems share platform research with similar modalities (e.g., language or vision communities). For instance, expensive pre-processing (such as key phrase extraction, topic modeling, etc.) is necessary to digest reviews, while emerging deep learning-based techniques may absorb entire information texts. Thus, deep learning techniques can present text, graphics, and interactivity inside a single, integrated framework [58]. When it comes to interaction-only problems, the general idea is that deep neural networks function best in conditions that are overwhelming or when they have a large number of training examples.

• Non-linear Transformation- Unlike linear models, deep neural networks can sustain the modeling of non-linearity in data by using nonlinear activations. It avoids complex user-item interaction patterns. It makes it suitable to handle complex interaction patterns and accordingly reflect the user's preference.

• Representation Learning- Under normal scenarios, real-world applications have detailed information about items and clients. When this information is put to good use, it leads to a better recommender due to the interpretation of items and users. Deep learning networks are becoming more and more popular in the processing of multimedia data, and they can be used to represent learning from a variety of sources.

• Sequence Modelling- Deep neural networks are now a fundamental component of many applications involving sequential modeling, such as chatbots, machine translation, natural language processing, speech recognition, and more. Two components of RNN and CNN are mandatory here. RNN utilizes it with internal memory states in contrast CNN carries it out through filters sliding along with time.

5. Conclusion and future research aspects

The applications of recommendation systems are diversified including e-commerce[64], social networks, healthcare, and many more. It employs algorithms that maintain interaction between humans and machines and comes under the sub-category of artificial intelligence. ML is composed of a mosaic of algorithms having varied features. The literature seems ambiguous algorithms sub-classes and their most-suited environment in which they are most suitable. Thus, exercising judgment on the election of ML algorithm for RSs becomes taxing. In addition, researchers in RSs are unaware of recent ML trends/ algorithm usage. The current article describes a deep and thorough understanding of studies and description of recommendation systems thereby providing future research directions to fellow researchers and academicians.

Researchers and academicians are talking about recommendation systems all the time. In this work, research papers on recommendation systems with a variety of applications that were published between 2011 and 2023 are identified and reviewed. To achieve this, a variety of information has been gathered for this assessment, including the issues faced by recommendation systems and the various application fields, techniques used, and applications that have been focused on. In addition, the difficulties and research gaps were presented to examine the recommendation system research outlook for the future. The following insights can be considered for tapping the unlimited potential of recommendation systems in the future :

Exploring the unexplored in deep learning

Tremendous research and innovation are going on related to deep learning and AI. It necessitates inferences by visual representation of the input dataset. A similarity between recommendation and reasoning (e.g., question answering) is that they serve as information retrieval problems [40].

Cross Domain Recommendation with Deep Neural Networks

Many businesses today showcase a wide range of goods and services to prospective clients. For instance, Google provides mobile apps, the most recent news, and search engines on its plate. You may buy clothing and household necessities on Amazon. Single-domain recommendation systems ignore user preferences about other domains in favor of just one, leading to sparsity and cold start problems [62]. A valuable answer to such challenges is provided by cross-domain recommendation systems. Transfer learning, whose goal is to enhance learning tasks in one domain by using knowledge transferred from other domains, is a highly researched issue in cross-domain recommendation [62]. It is therefore a worthwhile but unexplored region that requires exploration.

Scalability of Deep Neural Networks for Recommendation

In this big data time, data volume is magnifying and multiplying various challenges to real-world applications. Thereupon, scalability is mandatory for recommendation models' versatility and serviceability in real-world systems, also a feature of time complexity dominates the choice of models. Deep learning is promising when talking about big data analytics [63], particularly in light of computation power. The process of making a flawless recommendation is a long journey. A somewhat untapped but intriguing area of this study involves knowledge distillation to help build small/compact models for inference in recommendation systems.

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