ARTIFICIAL INTELLIGENCE BASED RECOMMENDER SYSTEMS

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ABSTRACT
Recommender systems anticipate customers' present preferences for certain items based on their past behavior, offering individualized service support to users. The evolution of recommender systems has naturally included artificial intelligence (AI), notably computational intelligence and machine learning techniques and algorithms to enhance prediction precision and resolve issues with cold start and data sparsity. This paper methodically examines the fundamental approaches and current practices in recommender systems.

Keywords: Artificial Intelligence, Recommender Systems, Deep Learning

1. INTRODUCTION

In a cutthroat industry, it can be difficult for companies to provide goods and services that appeal directly to consumers' certain requirements. One significant issue that is addressed by personalised e-services is information overload thus improving user experience and simplifying the decision-making process for clients. When these personalized e-services were originally introduced twenty years ago, the recommender systems that power them were created using user profiling and preference finding techniques and ideas from other artificial intelligence (AI) domains.

The number of successful AI-driven applications has increased significantly in the last few years. The self-driving automobile, Deepmind's AlphaGo, an AI-driven programme that notably defeated a professional human player in the game of Go, and other advancements in computer vision and speech recognition are examples of successes. Recommender systems are primarily designed to help people who lack experience or understanding navigate the wide range of options that are available to them. [1]

In order to improve user pleasure and experience, recommender systems have more recently incorporated a variety of AI approaches. AI makes recommendations that are of a higher caliber than those possible with traditional recommendation techniques. With the creation of sophisticated insights into the connections
between people and products, the display of increasingly intricate data representations, and the discovery of extensive information in demographic, textural, virtual, and contextual data, this has ushered in a new era for recommender systems.

The aim of this paper is to review the theoretical and practical contributions to the field and to indicate new research directions in the development of Artificial Intelligence in recommender systems. In this paper, the improvements AI has made to recommender systems is reviewed such as the inclusion of natural language processing, neural networks and deep learning, computer vision, fuzzy techniques and active learning.

2. RECOMMENDER SYSTEMS WITH ARTIFICIAL INTELLIGENCE

Several artificial intelligent techniques have been developed and applied to recommender systems to meet the growing recommendation demands of the big data information explosion. In this section, five artificial intelligence techniques have been discussed that have improved recommender systems.

2.1 Deep neural networks in recommender systems

In recommender systems, neural networks are infrequently employed because the recommendation task involves item ranking rather than categorization. Aside from Truven et al. work, who expanded this research by examining RBM with the parameterization choices in recommendation [2], this method garnered a lot of interest during the Netflix Prize competition held in 2009.[3]. Further, speech recognition, computer vision, and natural language processing have all availed advantages from deep learning [4].

Further we explore deep learning techniques in recommender systems according to the various kinds of deep neural networks contributed in recommender systems.

2.1.1 Use of Auto Encoder in Recommender Systems

Authors in [5] used an autoencoder AutoRec integrate with matrix factorization in order to learn non-liner latent representations of items or users. Authors in [6] upgraded AutoRec through enhancing its strength by using denoising techniques and blending additional information as user-contributed tags or item content [6]. For the purpose of user profiling and item representation in recommender system this technique serves as a fundamental unit for representation learning.
2.1.2 Use of Multi-layer perceptron in recommender systems

Factorization machines use multilayer perceptrons to support for the feature engineering process. Since the suggested factorization machines may be trained leaving behind the need for feature engineering, researchers upgraded the extensive and deep model in [7]. In contrast to matrix factorization, which is used to describe the linear relationship, use of neural collaborative filtering method is suggested to represent the non-linear relationship among items and users [8].

2.1.3 Use of Convolutional neural network in recommender systems

DeepCoNN unitedly models items and users by connecting a common layer used though factorization machines. with the help of reviews this method integrates two parallel neural networks, and then cooperatively models users and [9]. The two convolutional networks are related by a common layer simplified with factorization machines. For the hashtag recommendation task attention mechanism convolutional neural network has also been facilitated in Microblogging.[10]

2.1.4 Use of Recurrent neural network in recommender systems

RNN is primarily used to model and analyse the progression of client interests or item features because it is appropriate for sequential data. To show interaction among clients and items a co-evolutionary latent feature method is presented to simulate the temporal dynamics.[11]. In order to forecast whether or not to carry forward current user behaviour in the future, authors employed an LSTM-based model to record the dynamics of client behaviour [12].

Session-based recommender systems, also called sequential recommender systems, are a new approach utilizing RNNs in which real-time recommendations are improved based on previous sequential data [13]. In order to forecast the subsequent item that might pique consumers' attention, [14] models the most current states using an RNN. In [15], the user selection is improved in the near run, and user selection drift is also examined.

2.1.5 Use of Graph neural network in recommender systems

RS are basically interested in GNNs' capacity to learn features for nodes from the neighborhood data in the graph, since user-item connections are typically represented as bipartite graphs. In [16], the random walk and GNN feature embedding are included,
and Pinterest proposes and uses a very scalable and effective recommendation system. In [17], a generalized GNNs'-based collaborative filtering framework is presented, whereby information is propagated through an attention-based massage-passing technique. In order to model component sequences as graphs, Graph neural network is also well-suited for sequential recommender systems [18].

Recently deep neural networks are being used in RS to handle increasingly complex scenarios, including dynamic settings, various data sources, and diverse data representations.

2.2 Active learning(AL) in RS

In RS, each user-product correlation is important for user preference profiling and has a significant impact on system performance, especially if the system is founded on clear-cut ratings or latent interactions between items and users. The problem of data sparsity in RS demonstrates that a system's performance in making recommendations improves with the quantity of user evaluations it has received.

In order to assist RS in choosing the most classical items and presenting them for user rating, active learning has been populazied [19]. Thus, choosing products whose ratings are most likely to reveal the most about the user's preferences is one of AL's goals. AL techniques come in various kinds including rating impact analysis [21], bootstrapping [22], and decision trees [23].

2.3 Reinforcement learning in RS

According to reinforcement learning, using a RS involves an interactive method with a sequence of states and actions among the user and the system. Reinforcement learning based RS strive to maximise users' engagement with happiness over the long term, in comparison to traditional recommender systems, which often consider forecasting users' interests at a certain time point.

The balance between exploitation and exploration also referred to as bandit problems—is the primary subject of the early research [24]. In order to recommend the following item with the previously k used items, a direct implementation of Markov decision processes to recommender systems without taking the balance into account is suggested in [25]. Deep reinforcement learning based RS development is going to be trendy topic, with industrial applications driving the majority of its development. Alibaba and YouTube [27,28] are the major applications of RL techniques in industrial recommender systems.
2.4 Fuzzy techniques in RS

In Recommender systems, item attributes and user behaviours are typically ambiguous, subjective, and incomplete. It is possible to address information uncertainty issues with fuzzy set, which are also applicable to RS. [29]. Considering the classification of RS methods, three classes of fuzzy recommendation techniques are discussed.

2.4.1 Use of fuzzy techniques in Content-based RS:

In content-based RS, the matching of suitable items phases uses fuzzy techniques. Many RS with fuzzy tree have already been created for e-commerce, business-to-business e-services and e-learning systems because product information frequently takes the hierarchical tree-structured content information form and because user preferences are hazy and unclear.

2.4.2 Use of fuzzy techniques in Memory-based CF RS:

In memory-based CF recommender systems Fuzzy set theories are utilised to characterise the degree of uncertainty in user preferences [31]. These techniques can increase accuracy in some situations by reducing the inherent noise of uncertainty and matching consumer desires with the services offered [32].

2.4.3 Use of fuzzy techniques in Model-based CF RS:

By merging Bayesian networks, soft computing, and CF approaches, authors modelled uncertainty using the probability of the description of ratings and related users [33]. Fuzzy approaches work well with knowledge descriptions, user preference profiles that build up gradually, and rough user preference descriptions (like language phrases).

2.5 Natural language processing (NLP) in RS

The use of natural language and vision in recent advances in deep NN, particularly in RNN, CNN, and GNN-based techniques. This section describe how NLP and computer vision can be incorporated to enhance recommender systems via unification of free text, such as reviews, and visual imagery, such as photos of things.

In [34] authors improved recommendation using product experience and feature sentiment to deliver better items in response to user query with the help of users reviews. Comparable consumers with a comparable degree of experience are probably going to react to the same item similarly, according to an analysis of user expertise through online evaluation [35]. In information extraction two methods Entity and relationship extraction in which from
unstructured text organised information is extracted.[36]. Text summarization evaluates each sentence's significance before assigning a score and choosing the best few sentences to include in the summary.

NLP techniques will be crucial in the advancement of an interactive RS with voice feedback, as digital voice systems like Siri and Google Home continue to advance in sophistication.

2.6 Computer vision in RS

The advancement in technologies of computer vision has been beneficial to recommender systems, particularly in the domains of fashion analysis and things that are highly connected with looks, such as apparel, jewellery, and pictures. Image recommendation is its direct application. In order to map user preferences and images, a duel-net deep network which integrates computer vision directly to image recommendation was presented in [37]. Using deep NNs to extract features from photos, early efforts in various e-commerce recommendation domains combine these features with pre-existing techniques for clothing suggestion [38].

Jaradat suggested utilizing two CNNs one for images and one for text to transfer knowledge among domains in order to get benefit from user preferences that are hidden on social media platforms such as Instagram [39]. To fully model user preferences, recommender systems require applications of multi-task learning and multi-model fusion. Future fashion recommender systems will highly desire new features like cloth design and collocation.

3. FUTURE DIRECTIONS

There is radical advancement in recommender systems center on offering extensive metadata connected to objects, photos, social networks, and user-contributed evaluations to improve decision-making. We have examined the several branches of AI that incorporate these types of systems and tracked their evolution in this study.

3.1 Long tail in recommender systems

Long tail items are uncommon and not very popular with users. Recommender systems ought to give long-tail items more consideration in order to facilitate user discovery. Because less data is gathered on long-tail items, people are less likely to notice them exactly, which leads to both customers and e-commerce companies forgetting about these items.

However, when properly utilized, long-tail products can benefit businesses and consumers greatly [40]. Because cross-
domain RS may substitute knowledge from associated but distinct data from one type of field to another, even in situations when data is scarce, they present a viable solution to the long tail problem.

3.2 Visualization of Recommender System

Several recommender systems lack sufficient explanation, instead concentrating on techniques and accuracy. Despite recommender systems' excellent efficacy, it is not an easy task for people to trust them due to their security and privacy issues. In recommender systems it is a difficult constraint especially when mixed with sophisticated AI methods like natural language processing or deep learning.

To support future efforts on recommender system visualization, systems must have a more thorough depiction of the workflow and improved user interactivity.

3.3 Concept drift detection

While RS have been quite effective in the last decades, but to manage the complex and dynamic properties of large data RS are not well suited. [41]. it is assumed that user preferences set out as constant over time so in traditional RS Users' historical records are weighted. In contrast, user preferences shift as a consequence of the slow development of unique preferences, life experiences, or effects based on popularity.

4. SUMMARY

In this paper, we evaluate five areas of artificial intelligence, describe how they are employed in recommender systems and suggest future directions in this field of study. This paper intends to guide researchers in the domain of recommender systems by highlighting the ways in which AI approaches might improve recommender systems.

5. REFERENCES

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