ЖАРАТЫЛЫСТАНУ ЖӘНЕ ТЕХНИКАЛЫҚ ҒЫЛЫМДАР

NATURAL AND TECHNICAL SCIENCES

IRSTI 55.01.01

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A COMPREHENSIVE REVIEW OF APPROACHES, CHALLENGES IN CAREER RECOMMENDATION SYSTEMS

Abstract. This research presents an extensive investigation into recommendation systems pertinent to career guidance, encompassing job matching, education, and skill development applications. The study rigorously examines methodologies, algorithms, and data sources integral to these systems, evaluating their strengths and limitations. It thoroughly explores evaluation metrics, real-world case studies, and emerging trends, emphasizing challenges like data sparsity, scalability, and fairness.

Furthermore, the paper provides a comprehensive analysis of machine learning (ML), deep learning (DL), and reinforcement learning (RL) algorithms within recommender systems. By illuminating their strengths, applications, and constraints, the study highlights the intricate interplay of these algorithms within recommendation systems. It addresses challenges including cold-start issues, the stability-plasticity balance, and user satisfaction, offering insights into navigating these complexities.

This research serves as an indispensable guide for researchers and practitioners alike, providing comprehensive insights into machine learning, deep learning, and reinforcement learning algorithms' roles within career recommendation systems. It underscores the significance of overcoming inherent limitations and advocates for innovative solutions to enhance these systems' effectiveness and applicability in real-world scenarios.

Keywords: collaborative filtering, content-based filtering, hybrid-based recommendation systems, k-nearest neighbors, decision trees, random forests, reinforcement learning, deep neural networks, convolutional neural networks.

I. Introduction

The contemporary employment and education landscape is undergoing a profound transformation, driven by the confluence of technological innovation, evolving job markets, and shifting workforce dynamics. In this dynamic milieu, the need for effective career guidance and recommendations has never been more pronounced. Career recommendation systems, underpinned by the principles of data science and artificial intelligence, have emerged as instrumental tools in connecting individuals with opportunities that resonate with their skills, interests, and career aspirations. As individuals seek to navigate the labyrinth of career choices and development paths, these recommendation systems serve as guiding beacons, offering tailored insights and suggestions that facilitate informed decision-making [1].

In this survey paper, we embark on a comprehensive exploration of the field of career recommendation systems. We categorize and dissect the various approaches, methodologies, and algorithms that drive these systems. Data, as the linchpin of recommendation engines, assumes a central role in our analysis, as we investigate the diverse sources and their impact on system performance. Personalization, an essential hallmark of effective recommendations, is scrutinized in depth, with a particular focus on privacy and ethical concerns.

Furthermore, we delve into the nuances of evaluating the performance of career recommendation systems, exploring the metrics that illuminate their effectiveness and the inherent challenges in assessing their impact. The challenges facing these systems, from data sparsity to scalability and fairness, are articulated, providing a holistic view of the obstacles that must be surmounted.

Real-world case studies and success stories highlight the practical implications of career recommendation systems, offering invaluable insights into best practices and lessons learned. Looking forward, we examine emerging trends and the integration of cutting-edge technologies such as artificial intelligence and natural language processing as potential solutions to the field's persistent challenges.

In the quest for meaningful and impactful career recommendations, this survey paper serves as a guiding compass, navigating the complexities, opportunities, and future horizons of career recommendation systems. By comprehensively reviewing the approaches and challenges that define this field, we endeavor to provide a roadmap for researchers, practitioners, and stakeholders, ensuring that individuals are equipped with the guidance needed to embark on fulfilling and successful career journeys.

The remaining sections of the paper are structured as follows: Section 2 is about Methodology. Section 3 delves into Common Approaches of Recommender Systems. Section 4 focuses on the Challenges in Educational Recommender Systems. Sections 5 and 7 comprehensively cover Machine Learning and Deep Learning Approaches of Recommender Systems, respectively. Meanwhile, sections 6 and 8 delve into the Limitations of Popular

Machine Learning Algorithms and Deep Learning Algorithms in Recommender Systems. In Section 9, we explore Reinforcement Learning algorithms employed in recommender systems. Section 10 presents an analysis of Key Studies, and lastly, Section 11 provides a discussion on the conclusion.

II. Methodology

The primary aim of this research is to comprehensively explore and analyze the landscape of recommender systems, focusing on their applicability in educational and career guidance domains. The methodology is structured to investigate prevalent recommender system approaches, challenges faced in educational contexts, and the efficacy of machine learning and reinforcement learning models within these domains. The *approach identification* involves conducting a literature review to identify key recommender system methodologies like Collaborative Filtering, Content-based Filtering, Hybrid strategies, Machine Learning, Deep Learning, and Reinforcement Learning algorithms. This is followed by an *in-depth analysis* of each approach, examining their workings, advantages, limitations, and applications in educational and career guidance, drawing insights from relevant literature. The research then focuses on understanding challenges encountered by Educational Recommender Systems (ERS), such as the "cold start" problem, adapting to diverse user profiles, etc. Proposed solutions from contemporary research are explored to mitigate these challenges within ERS. Furthermore, the research involves the *evaluation of models*, including machine learning algorithms like K-Nearest Neighbors, Decision Trees, Random Forests, and Deep Learning models, to assess their effectiveness in improving recommendation accuracy. Additionally, the potential of Reinforcement Learning algorithms within recommender systems is analyzed. Finally, a *comparative analysis* is conducted to understand the distinctive attributes and limitations of each recommendation system approach. This includes synthesizing key research studies in recommender systems to provide an overview of methodologies and performance metrics used. For a visual representation of our research approach, please refer Figure 1.

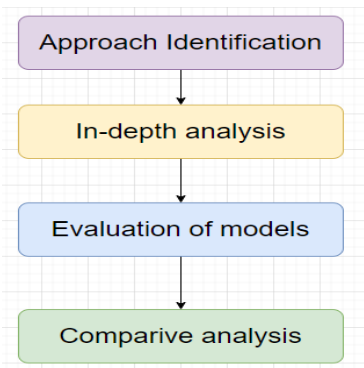

Figure 1. Methodology flowchart

III. Common Approaches of Recommender Systems

Numerous methodologies have been developed for recommender systems, with some of the most prevalent approaches, as indicated in reference [2], including collaborative filtering, content-based filtering, hybrid-based strategies. It is noteworthy that a significant portion of scholarly works and publications in the recommender systems domain predominantly focus on the algorithms mentioned earlier.

III.1 Collaborative filtering filtering approach

Collaborative Filtering, a commonly utilized technique in the creation of recommender systems, holds a central position within the realm of education and career counseling, as referenced in [3]. Collaborative filtering relies on the collection and analysis of substantial data related to user behaviors, activities, and preferences. It leverages this data to predict a user's preferences by identifying similarities between that user and others [4], [5]. Notably, collaborative filtering does not depend on the decomposition of machine-generated data, which makes it adept at accurately recommending complex items. This characteristic represents a significant benefit of the collaborative filtering method.

In the domain of education and career development, collaborative filtering recommendation systems excel at offering personalized guidance. They select recommended educational or career-related objects based on the collective past evaluations of a large user group \cite{B2}. This user-centric approach ensures that the recommendations provided are tailored to the individual's specific educational or career needs. This aspect is crucial in helping users make informed decisions and discover opportunities that align with their goals. You can see in Figure 2, how collaborative filtering-based recommendation systems work. [2].

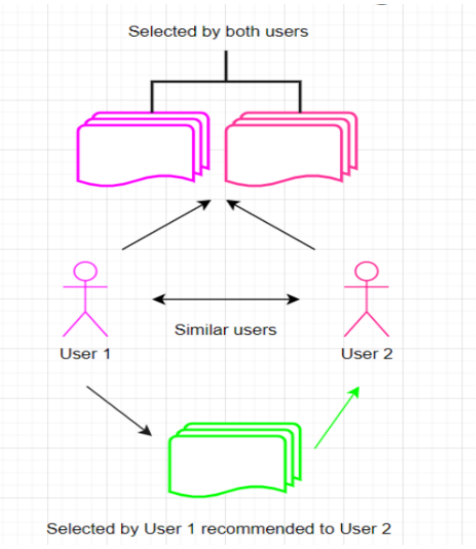

Figure 2. Collaborative Filtering-based Recommendation System

III.2 Content-based filtering approach

Content-based recommender systems, an extensively used technique in the field of information retrieval, offer personalized recommendations by analyzing and manually assigning terms to items. This process involves selecting a method to compare terms in user profile information and applying a learning algorithm to generate suitable results [5].

Content-based filtering (CBF) is a technique that recommends courses based on the similarities between previously selected courses and attributes of available courses [1]. Key terms are employed for item descriptions, and a user profile is generated to propose items aligning with their preferences. In essence, these algorithms strive to suggest items that closely resemble the user's prior selections, making it easier to recommend items akin to those the user has previously reviewed or is presently exploring [7].

Content-based recommender systems offer several advantages, including transparency, independence, and the ability to provide recommendations for unclassified entities. However, they come with limitations such as the potential lack of serendipity, partial content analysis, and the risk of over-specialization [8]. Figure 3, shows, how works content-based recommendation System

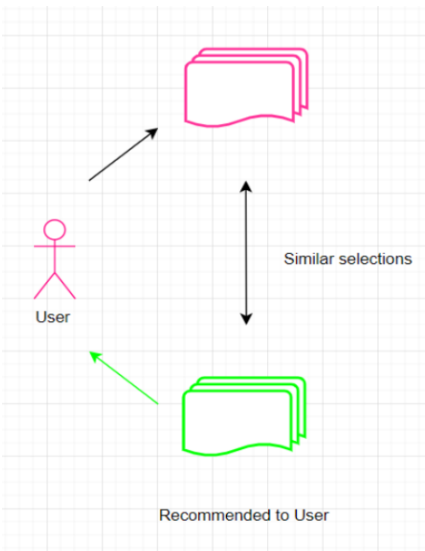

Figure 3. Content-based Recommendation System

III.3 Hybrid-based approach

Hybrid recommendation systems are designed to harness the strengths of various recommendation techniques while mitigating the potential shortcomings of conventional systems [9]. Seven core hybrid recommendation strategies, as identified in [10], encompass weighted, mixed, switching, feature combination, feature augmentation, cascade, and meta-level methods, as detailed in references

[11] and [12]. Among these, the most commonly utilized approach involves the integration of collaborative filtering recommendation techniques with alternative recommendation methods like content-based or knowledge-based techniques.

This integration is instrumental in tackling issues associated with data sparsity, scalability, and the cold-start problem [13] , [14] , [15]. In essence, hybrid systems offer a versatile and robust approach to enhance the accuracy and effectiveness of recommendation systems by synergizing different methodologies.

IV. Challenges in Educational Recommender Systems

Educational recommender systems have immense potential to enhance learning outcomes and elevate the educational experience for students. However, they encounter significant challenges in realizing these goals. These include the cold start problem, dealing with data sparsity, and addressing the unique needs of users who do not conform to standard user profiles. Overcoming these challenges is essential for these systems to fulfill their educational objectives effectively.

IV.1 Cold start problem

The "cold start" challenge poses a notable problem for educational recommender systems (ERS). The ERS aim to deliver customized learning experiences designed to match the specific preferences and requirements of each individual user. Nonetheless, the "cold start" problem occurs in situations where there is insufficient user information, rendering it challenging for the system to produce precise recommendations. To address this issue, educational data can be converted into a format suitable for enhancing the effectiveness of interaction-based recommender systems, as indicated in reference [16]. Additionally, one of the primary hurdles encountered by ERS pertains to comprehending the user's interests and the domain's objectives, which are crucial for generating pertinent recommendations, as discussed in reference [17]. Overfitting stands out as another challenge in ERS, manifesting when the model excessively tailors its learning to the training data, leading to reduced accuracy and skewed predictions, as detailed in reference [18]. To address these challenges, researchers have conducted comprehensive reviews of state-of-the-art practices for ERS, including requirements, challenges, advantages, and disadvantages [19]. Such reviews can provide insights into best practices and help developers create more effective and efficient ERS. Finally, there are opportunities for merging recommender systems with personalized health education, which can further improve the performance of ERS, but also present new challenges [20].

IV.2 Sparsity

Educational recommender systems (ERS) are faced with the challenge of understanding the user's preferences and comprehending the domain's objectives [17]. However, the performance of ERS can be affected by sparsity, which is a common problem in recommendation systems. Sparsity occurs when data sets have a low density of ratings or interactions. Predictions that use numerical ratings and review texts are biased and have lower accuracy.In response to this challenge, researchers have investigated methods for transforming educational data with the goal of enhancing interaction-based recommender systems' performance [16]. Moreover, research has explored the obstacles and potential advantages of integrating recommender systems with personalized health education, as referenced in [20]. A thorough evaluation of state-of-the-art recommendation systems was undertaken to offer insights into the most recent approaches for ERS [21].Overfitting is another common challenge in machine learning, including recommendation systems, wherein a model excessively tailors its learning to the training data, resulting in reduced capacity for generalization, as mentioned in [18]. Hence, further research should focus on developing more effective methods for overcoming sparsity and overfitting in ERS to improve their accuracy and efficiency.

IV.3 Grey sheep

Recommender systems are becoming increasingly popular in various domains, including movies, music, books, news, tourism, and education [21]. The ERS have gained popularity in the realm of teaching and learning by offering tailored recommendations to students according to their learning preferences, interests, and requirements. Nonetheless, the utilization of recommender systems in the educational sphere brings forth a number of recognized problems and hurdles, as noted in reference [19]. One of the main challenges is dealing with "grey sheep" students who do not fit into any specific category. These students have diverse interests and learning styles that cannot be easily predicted by the ERS algorithms. This poses a challenge for ERS as it struggles to provide personalized recommendations that cater to their unique learning needs. Another challenge is the absence of comprehension regarding the user's preferences and the domain's objectives, as mentioned in reference [16].

V. Machine Learning Approaches of Recommender Systems

In recent years, Machine Learning (ML) algorithms have made significant inroads into the domain of educational recommendation systems, offering personalized and data-driven guidance to students and educators.

V.1 K-Nearest Neighbors (KNN) Algorithm in Educational Recommendation Systems

The K-Nearest Neighbors (KNN) algorithm stands as a fundamental component within educational recommendation systems. KNN leverages the concept of similarity to provide recommendations. It measures the likeness between students or educational resources based on various attributes, such as learning styles, academic performance, and preferences. When applied to recommend courses, textbooks, or supplementary materials to students, KNN takes into account the preferences and learning profiles of similar students. This approach helps in tailoring educational content to individual needs, thereby improving student engagement and learning outcomes [25].

V.2 Decision Trees in Educational Recommendation Systems

Moreover, decision trees and random forests have also found application in educational recommendation systems. Decision tree algorithms have several advantages, including ease of use, easy interpretability, high accuracy, and strong predictive capabilities. Various studies have successfully employed decision trees in the education domain. For example, in the study [26], a model for assessing educational grants was proposed using a C4.5 decision tree. Decision trees have also been applied to address issues related to employment courses and training professionals, providing solutions for bridging the gap between training plans and enterprise needs [27].

V.3 Random Forests in Educational Recommendation Systems

Random forests are considered an effective machine learning method, particularly for addressing issues like overfitting, which decision trees can encounter. RF leverages an ensemble learning approach by constructing multiple decision trees during training and determining results through voting. Unlike individual decision trees, where nodes are split based on the best attribute, RF splits nodes using a random subset of predictors as shown in Figure 4. This approach has found success in educational settings. For example, RF has been used to predict whether students will obtain an undergraduate degree by analyzing their performance in the first two semesters of courses [28]. In the study cited in [29], Random Forest (RF) was employed to forecast the academic performance of a freshman student in a university in Bangladesh. This prediction was based on various factors such as note-taking habits, adaptation to campus life, and self-assuredness, which were collected through a questionnaire survey.

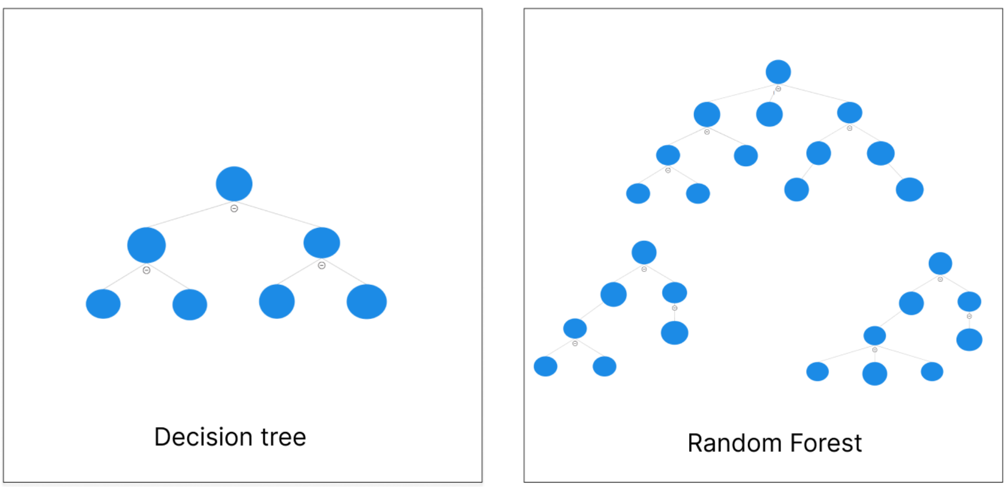

Figure 4. Decision tree vs Random Forest

VI. Limitations of Machine Learning-Based Recommender System Algorithms

Although Decision Tree, K-Nearest Neighbors (KNN), Random Forest are widely recognized machine learning algorithms frequently applied in recommender systems, they also come with their own set of disadvantages. For instance, KNN requires a large amount of memory and computational power, which can be a challenge for large datasets. Furthermore, the performance of KNN heavily depends on the selection of the similarity metric and the number of nearest neighbors chosen [22]. In contrast, Random Forest may encounter overfitting issues when the forest comprises an excessive number of trees. Additionally, Random Forest struggles when it comes to handling imbalanced datasets and can result in biased predictions. This is because the algorithm tends to favor majority classes and under-predict minority classes [23].Lastly, Decision Trees are susceptible to overfitting and can be highly responsive to minor data variations, leading to diverse tree structures. Furthermore, Decision Trees can be biased towards features that have a larger number of categories or levels [23]. Notwithstanding these constraints, these algorithms continue to be extensively utilized in recommender systems because of their straightforwardness and ease of interpretation. Other advanced techniques like neural networks and deep learning-based methods also have a large scope of research in developing recommender systems [24]. However, researchers must carefully consider the benefits and shortcomings of each algorithm before selecting the most appropriate one for their specific use case.

VII. Deep Learning Approaches of Recommender Systems

Deep learning has emerged as a dominant force in the field of recommender systems in recent years, promising to improve the accuracy and personalization of recommendations. Deep learning approaches make use of neural networks with several hidden layers in order to grasp intricate patterns and relationships in data. Deep learning is increasingly being used in career recommendation systems to address the inherent difficulties of the domain [30].

VII.1 Neural Collaborative Filtering (NCF)

NCF represents a significant leap in the evolution of collaborative filtering-based recommendation systems. This approach combines the strengths of matrix factorization and multi-layer perceptrons. By employing neural networks, NCF is capable of modeling both explicit and implicit user-item interactions. This enables it to learn more nuanced patterns, enhancing the quality of job recommendations and career guidance [30].

Neural Collaborative Filtering (NCF) is a popular deep learning approach that combines matrix factorization and multi-layer perceptrons to model user-item interactions. NCF captures both the latent factors of users and items and their nonlinear interactions.

VII.2 Deep Content-Based Filtering

Deep learning is leveraged in content-based recommendation systems to better understand the textual and contextual information associated with jobs, skills, and user profiles. Deep content-based filtering uses techniques such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs) to capture the semantic meaning of textual data. This enables more accurate matching of users with job listings, online courses, and skill development resources that align with their specific requirements[31].

VII.2.1 Deep Neural Networks (DNN)

Deep Neural Networks (DNN) have been widely used in recommender systems to learn high-level representations of users and items. DNNs consist of multiple layers of interconnected artificial neurons, enabling the model to capture intricate patterns in the input data [31].

VII.2.2 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are commonly used in recommender systems to extract local patterns and features from user-item interaction data. CNNs utilize convolutional layers to capture spatial relationships within the input data [31].

VII.3 Hybrid Models

The integration of deep learning into hybrid recommendation models, which combine collaborative and content-based approaches, has gained traction. Hybrid models use deep neural networks to fuse information from various sources, such as user profiles, item descriptions, and historical interactions. This allows for a more comprehensive understanding of user preferences, leading to more relevant career recommendations [32].

Moreover, as career recommendations often involve sensitive personal data, the ethical considerations surrounding user privacy and transparency become more critical when deep learning techniques are employed. It is imperative to ensure that recommendations generated by these models are not only accurate but also fair and unbiased.

As career recommendation systems continue to evolve, deep learning will likely play an increasingly prominent role in shaping their capabilities. Researchers and practitioners are exploring innovative architectures, attention mechanisms, and reinforcement learning techniques to further refine the accuracy and personalization of career guidance.

The integration of deep learning approaches into career recommendation systems represents a promising avenue for improving the precision and relevance of recommendations. However, it also necessitates a nuanced understanding of the challenges and ethical considerations associated with these advanced techniques. In the following sections, we delve deeper into these challenges, ethical concerns, and emerging trends in the field of career recommendation systems.

Deep learning approaches, such as NCF, DNNs, and CNNs, have demonstrated promising results in recommender systems by effectively modeling complex user-item interactions and capturing high-level representations. These techniques enable recommender systems to generate personalized recommendations that align with user preferences and needs [33].

VIII. Reinforcement Learning algorithms

Reinforcement learning (RL) algorithms can be adapted and applied to recommender systems to learn optimal recommendation policies [34]. Here are a few types of RL algorithms commonly used in recommender systems:

Q-Learning: Q-Learning is a model-free RL algorithm that learns an action-value function, known as the Q-function, to estimate the expected cumulative rewards of taking a particular action in a given state. In the context of recommender systems, the state can represent the user's current preferences or the system's knowledge about the user, and the action can represent the recommendation made to the user. Q-Learning can be used to learn an optimal policy for making recommendations based on maximizing the long-term rewards [34].

Deep Q-Network (DQN): DQN is an extension of Q-Learning that uses deep neural networks to estimate the Q-function. DQN combines RL with deep learning techniques, allowing for more complex and high-dimensional state representations. In recommender systems, DQN can be used to learn the optimal policy by taking into account various user and item features, historical interactions, and contextual information [34].

Actor-Critic Methods: Actor-Critic methods combine policy-based and value-based RL approaches. The actor component learns the policy that selects actions, while the critic component estimates the value function to evaluate the expected rewards. This two-component architecture allows for more stable learning and faster convergence. Actor-Critic methods can be used in recommender systems to learn the optimal policy for making recommendations by considering both exploration and exploitation [34].

Proximal Policy Optimization (PPO): PPO is a policy optimization algorithm that aims to find the best policy by iteratively improving the current policy while ensuring a smooth policy update. PPO has been applied to recommender systems to learn the optimal recommendation policy by considering user feedback and interaction data. PPO can handle continuous and discrete action spaces, making it suitable for various recommendation scenarios [34].

Multi-Armed Bandit (MAB) Algorithms: MAB algorithms are a class of RL algorithms that address the exploration-exploitation trade-off by selecting actions based on estimated rewards and uncertainties. These algorithms are particularly useful in scenarios where the recommender system needs to continuously explore different options to learn user preferences while providing good recommendations. MAB algorithms, such as Upper Confidence Bound (UCB) or Thompson Sampling, can be adapted to recommender systems to learn the optimal recommendation strategy [34].

It's worth noting that the choice of RL algorithm depends on the specific requirements of the recommender system, such as the nature of the recommendation task, available data, and computational constraints. Additionally, hybrid approaches that combine RL with other recommendation techniques, such as collaborative filtering or content-based filtering, can also be explored to leverage the strengths of different algorithms and mitigate their limitations.

IX. Limitations of Reinforcement Learning-Based Recommender System Algorithms

Reinforcement learning (RL) has gained attention as a promising approach for building recommender systems. RL algorithms learn to make sequential decisions by interacting with an environment to maximize a reward signal. While RL-based recommender systems have shown promising results, they also come with certain limitations that need to be considered. In this section, we discuss some of the key limitations of RL-based recommender system algorithms [35].

Reinforcement learning (RL) algorithms, crucial components in recommender systems, present intricate challenges that require careful examination. The diverse realm of RL, including algorithms like Proximal Policy Optimization (PPO) and Deep Q Networks (DQN), demands thoughtful selection based on contextual appropriateness[36], [37]. The scalability issue introduces obstacles, encompassing difficulties in managing extensive datasets and variations in scalability among approaches such as Trust Region Policy Optimization (TRPO) and Asynchronous Advantage Actor-Critic (A3C). Tackling the "cold start" problem in scenarios with limited data involves a nuanced comparative analysis, acknowledging algorithmic distinctions [38]. The challenge of interpretability persists, with RL models often lacking transparency, impacting their suitability for user-facing applications. Training time complexity adds a layer of computational intensity and efficiency differences across RL algorithms, such as Deep Deterministic Policy Gradients (DDPG) and Dueling DQN. Despite these hurdles, continuous exploration endures due to the potential advantages of RL algorithms, emphasizing the dynamic nature of recommender systems and the necessity for ongoing developments to address identified limitations [39], [40].

X. Key Studies Analysis

In our comparative analysis of recommendation systems, we find that each system offers distinct advantages and challenges. Table 1 provides a detailed breakdown of these systems, highlighting their key attributes.

Table 1. Strengths and Weaknesses of Recommendation Systems

Key Points	CF	CB	DG	RF	KNN	Q	DQN	ACM	PPO	MAB
Strengths										
Identification of diverse niches	+	+								+
Independence from domain knowledge requirement	+	+	+	+		+	+	+	+	
Adaptability with quality enhancement over time	+	+	+			+	+	+	+	
Adequacy of implicit feedback utilization	+	+					+	+	+	
Resilience to cold-start user issues	+	+	+	+	+					+
Resilience to cold-start item issues	+	+	+	+	+	+	+	+	+	
Sensitivity to changing preferences	+	+			+			+	+	
Incorporation of non-product features	+	+				+	+	+	+	+
Alignment of user needs with product recommendations		+					+		+	
Transparency in recommendation processes		+			+	+	+	+	+	
Establishment of trust, scrutiny, and persuasiveness						+	+	+	+	

Weaknesses										
Challenges with new users	+	+	+	+		+	+	+	+	+
Challenges with new items	+			+	+	+	+	+	+	+
Addressing the "gray sheep" problem	+	+	+	+		+	+	+	+	+
Dependency on extensive historical datasets for quality	+	+	+	+		+	+	+	+	+
Balancing stability and plasticity is a challenge	+	+	+	+		+	+	+	+	+
Limited capability for static suggestions	+	+	+	+		+	+	+	+	+
Dependence on knowledge engineering for some approaches			+	+				+		

Collaborative Filtering (CF) excels in identifying diverse niches and adapting over time but faces challenges with new users and dependencies on historical datasets. Content-Based (CB) systems demonstrate independence from domain knowledge and resilience to cold-start item issues, yet grapple with challenges related to the "gray sheep" problem and user input of utility functions. Decision Trees (DG) and Random Forest (RF) prioritize transparency and resilience to cold-start issues but must contend with challenges surrounding new items and the delicate balance between stability and plasticity. K-Nearest Neighbors (KNN) stands out for its resilience to cold-start user and item issues, sensitivity to changing preferences, and trust establishment, but faces similar challenges as decision tree-based approaches. Reinforcement learning models, such as Q-learning and Deep Q Network (DQN), exhibit strengths in transparency and resilience, with challenges related to the "gray sheep" problem and stability-plasticity balance. Actor-Critic Model (ACM), Proximal Policy Optimization (PPO), and Multi-Armed Bandit (MAB) also showcase strengths and challenges, emphasizing the nuanced landscape of recommender systems in balancing effectiveness and adaptability.

The Appendix provides a comprehensive overview of key research papers in the realm of recommender systems, offering insights into the data collections used, approaches applied, and performance measures employed for evaluating recommendation algorithms. These studies encompass a diverse range of application domains, from educational platforms to online forums and job recommendation systems. The table serves as a valuable resource for researchers, practitioners, and enthusiasts in the field, showcasing the breadth and depth of recommender system research.

As we delve into the contents of Appendix , we acquire insights into the various challenges and advancements within the realm of recommender systems. The selection of datasets, the array of approaches, and the assessment criteria underscore the multifaceted character of recommendation tasks. Researchers have employed a wide range of techniques, including machine learning, deep learning, common traditional approaches, and natural language processing, to address the complexities of different recommendation scenarios.

XI. Conclusion

The landscape of career recommendation systems is a dynamic and evolving one, shaped by technological advancements, shifting workforce dynamics, and the quest for more meaningful and personalized career guidance. In this comprehensive survey paper, we have undertaken an in-depth exploration of the diverse approaches and formidable challenges that characterize this burgeoning field.

Our review began by categorizing career recommendation systems based on their purpose, which includes job matching, career path planning, education, and skill development recommendations. We investigated the methodologies, algorithms, and data sources that underpin these systems, shedding light on their strengths and limitations. The importance of personalization, driven by the adoption of deep learning and other advanced techniques, was underscored as a pivotal theme, accompanied by ethical concerns and user privacy considerations.

To assess the performance of these systems, we dissected the evaluation metrics commonly used and revealed the inherent challenges in gauging their impact. Challenges in this field, such as data sparsity, scalability, and fairness, were articulated, emphasizing the obstacles that must be overcome.

Real-world case studies and success stories demonstrated the practical implications of career recommendation systems, offering invaluable insights into best practices and lessons learned. In anticipation of the future, we examined emerging trends and the integration of cutting-edge technologies, such as artificial intelligence and natural language processing, as potential solutions to the challenges facing these systems.

The field of career recommendation systems stands at a crossroads, as it embraces technological advancements and confronts the complexities of guiding individuals through their professional journeys. This survey paper has illuminated the path from existing approaches to future possibilities, addressing the multifaceted aspects of this field.

As we look to the future, it is evident that career recommendation systems will continue to play an integral role in the ever-evolving landscape of employment and education. The integration of deep learning and other advanced techniques promises to deliver more accurate and personalized recommendations, enhancing user experiences and outcomes. However, it is crucial to strike a balance between innovation and ethical considerations, ensuring that privacy, fairness, and transparency remain paramount in the development and deployment of these systems.

The challenges that have been dissected in this survey are not insurmountable but rather opportunities for growth and refinement. The collaborative efforts of researchers, practitioners, and stakeholders will be pivotal in addressing these challenges and realizing the full potential of career recommendation systems.

In closing, this survey paper serves as a guiding compass for the field, offering a holistic understanding of the approaches and challenges that define career recommendation systems. By providing insights into the past, present, and future of this domain, we aim to empower individuals with the guidance needed to embark on fulfilling and successful career journeys, ensuring that the synergy between human potential and technology remains at the heart of this transformative endeavor.

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МАНСАПТЫҚ ҰСЫНЫСТАР ЖҮЙЕСІНДЕГІ ТӘСІЛДЕР МЕН ҚИЫНДЫҚТАРҒА ШОЛУ.

Аңдатпа. Бұл зерттеу жұмыс іздеу, білім беру және дағдыларды дамыту қосымшаларын қамтитын мансаптық бағдарға қатысты ұсыныстар жүйесін кеңінен зерттеуді қамтамасыз етеді. Зерттеу осы жүйелерге қажетті әдістемелерді, алгоритмдерді және деректер көздерін мұқият зерттейді, олардың артықщылықтарымен шектеулерін бағалайды. Ол деректердің аздығы, ауқымдылығы және әділдігі сияқты мәселелерге ерекше назар аудара отырып, бағалау көрсеткіштерін, жағдайлық зерттеулерді және дамып келе жатқан үрдістерді мұқият зерттейді.

Сонымен қатар, мақалада кеңес беру жүйелеріндегі машиналық оқыту , терең оқыту және күшейтілген оқыту алгоритмдерінің жан-жақты талдауы берілген. Олардың артықшылыұтарын, қолданбаларын және шектеулерін көрсету арқылы зерттеу бұл алгоритмдердің кеңес беру жүйелеріндегі күрделі өзара әрекеттесуін көрсетеді. Ол суық іске қосу проблемалары, тұрақтылық пен икемділікті теңестіру және пайдаланушының қанағаттанушылығы сияқты мәселелерді қарастырады және осы қиындықтарды жеңу идеяларын ұсынады.

Бұл зерттеу мансапты ұсыну жүйелеріндегі машиналық оқытудың, тереңдетіп оқытудың және күшейтетін оқыту алгоритмдерінің рөлі туралы жан-жақты түсінік беру арқылы зерттеушілер мен практиктер үшін таптырмас нұсқаулық ретінде қызмет етеді. Ол олардың тән шектеулерін еңсерудің маңыздылығын атап көрсетеді және осы жүйелердің нақты тәжіребиеде тиімділігі мен қолданылуын жақсарту үшін инновациялық шешімдерді жақтайды.

Түйін сөздер: бірлескен фильтрация, мазмұнды фильтрация, гибридті кеңес беру жүйелері, k-ең жақын көршілер, шешім ағаштары, кездейсоқ орман, ынталы оқыту, терең нейрондық желілер, конволюциялық нейрондық желілер.

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ОБЗОР ПОДХОДОВ И ВЫЗОВОВ В СИСТЕМАХ РЕКОМЕНДАЦИЙ КАРЬЕРЫ.

Аннотация. Это исследование представляет собой обширное исследование систем рекомендаций, имеющих отношение к профориентации, охватывающих приложения для поиска работы, образования и развития навыков. В исследовании тщательно изучаются методологии, алгоритмы и источники данных, необходимые для этих систем, оцениваются их сильные стороны и ограничения. В нем тщательно рассматриваются показатели оценки, практические примеры и возникающие тенденции, подчеркивая такие проблемы, как разреженность данных, масштабируемость и справедливость.

Кроме того, в статье представлен всесторонний анализ алгоритмов машинного обучения (ML), глубокого обучения (DL) и обучения с подкреплением (RL) в рекомендательных системах. Освещая их сильные стороны, области применения и ограничения, исследование подчеркивает сложное взаимодействие этих алгоритмов в рекомендательных системах. В нем рассматриваются такие проблемы, как проблемы холодного запуска, баланс стабильности и пластичности, а также удовлетворенность пользователей, а также предлагаются идеи по преодолению этих сложностей.

Это исследование служит незаменимым руководством как для исследователей, так и для практиков, предоставляя всестороннее представление о роли алгоритмов машинного обучения, глубокого обучения и обучения с подкреплением в системах рекомендаций по карьере. Он подчеркивает важность преодоления присущих им ограничений и выступает за инновационные решения для повышения эффективности и применимости этих систем в реальных сценариях.

Ключевые слова: коллаборативная фильтрация, контентная фильтрация, гибридные рекомендательные системы, k-ближайшие соседи, деревья решений, случайные леса, обучение с подкреплением, глубокие нейронные сети, сверточные нейронные сети.

Appendix

Recommender System Studies Overview

Authors	**Dataset**	**Approaches**	**Measures**
[41] Odiete O. et al.	Stack Overflow	Gephi, NetworkX, Centrality Measures, Badges, Weighted In-Degree	Degree Centrality, Closeness Centrality
[42] Adaji I. et al.	Allrecipes.com	LIWC Tool, Network Graph	Two-Way Mixed ANOVA
[43] Orji F. A. et al.	924 university students' data	Decision Tree, Linear Regression, Random Forest, K-Nearest Neighbors, Support Vector Machine	MAE, accuracy, F1-score, precision, and recall
[44] Thai-Nghe N. et al.	Educational Data Sets Algebra 2008-2009 and Bridge to Algebra 2008-2009	Collaborative Filtering, Matrix Factorization, Logistic Regression	RMSE
[45] Dwivedi S. et al.	Different schools of Central Board of	Collaborative filtering, Crab- A	RMSE

	Secondary Education (CBSE)	Recommender framework in Python	
[46] Lalitha T. et al.	E-Learning Materials	KNN	N/A
[47] Zheng Y. et al.	Graduate students data collected using questionnaire	Multi-Label Classification, Regression	Accuracy, RMSE
[48] Bourkoukou O. et al.	E-Learning Recommender	Collaborative filtering, KNN	MAE, Accuracy
[49] Mazhoud O. et. al.	Student's t-test	Data Mining, NLP, Machine Learning	Mean, std dv.
[50] Phuwadol V. et al.	Online Questionnaire	GBT Algorithm	Accuracy Precision
[51] Ryan G. et al.	Personality Cafe forum	Logistic regression, XGBoost, Linear Support Vector Classification, Stochastic Gradient Descent, Random Forest, CatBoost	F1 score

[52] Manar Q. et al.	High-school	Fuzzy recommender system	N/A
[53] Yusen W. et al.	Session data	GRU4REC, NARM, SR-GNN, AIGNN	Recall, Mean Reciprocal Rank
[54] John I. et al.	Data collected through Google Forms	Naïve Bayes, Support Vector Machine, Decision Tree, K-Nearest Neighbors Bagging	Accuracy, Error Rate, Precision, Recall, F1 Score
[55] Ghislain W. et al.	Nigam and Minajobs	Naive Bayes, Decision tree	Precision, MRR, MAP
[56] Elsafty A. et al.	Own dataset scrapped from their website	TF-IDF, Word2Vec, Doc2Vec	Precision at 10 (P@10)
[57] Padmaja S. et al.	N/A	Artificial neural networks	Accuracy
[58] Shuo Y. et al.	N/A	Relational Dependency Networks (RDNs), Relational Functional Gradient Boosting (RFGB),	FPR FNR Precision Recall

		Collaborative filtering, Content-based filtering, Hybrid filtering	Accuracy AUC-ROC
[59] Sushma K.N. et al.	• courses after 10th • courses after 12th • courses after under graduation	Content-based and Collaborative filtering, Hybrid filtering	N/A
[60] Séguéla J. et al.	N/A	TF-IDF, Latent Semantic Analysis (LSA), Partial Least Squares regression (PLS-R)	Mean Absolute Error (MAE)
[61] Brijmohan D. et al.	Our dataset consists of 18,000 entries from students	Artificial neural networks	Accuracy
[62] Roshan G.B. et al.	Tab-separated files (TSV),	Collaborative filtering, Content-based filtering	RMSE, precision, recall
[63] Mulay A. et al.	N/A	Cosine similarity, Content-based and Collaborative filtering	Precision, recall, F1 measure

[64] Hmood A.D. et al.	2,255 IT sector professionals in Saudi Arabia.	K-Nearest Neighbors, Bagging, Decision Tree, Gradient Boosting, XGBoost	Accuracy
[65] Qing W. et al.	Collected from the employment guidance platform for college students.	Hybrid convolutional neural network model	Recall rate, F1-Score
[65] Suleiman A.A. et al.	Scraping jobs description from Indeed from major cities in Saudi Arabia (Dammam, Jeddah, and Riyadh)	NLP techniques, Cosine similarity, Jaccard similarity	Precision, recall, F1-score, accuracy
[67] Meddi Afsar. et al.	MovieLens [110] and Million Song dataset	Q-learning, SARSA, Deep Q-Networks (DQN), Actor-Critic, Deep Deterministic Policy Gradient (DDPG)	Precision, recall, F1-score, and mean average precision (MAP)
[68] Xinshi Chen. et al.	MovieLens	DQN algorithm	N/A
[69] Zefang Liu	MovieLens	N/A	Recall

[70] Ramkumar R. et al.r	MovieLens dataset	Deep reinforcement learning	Recall
[71] Lucas Farris	Trivago tracking data	Deep reinforcement learning	Accuracy, Coverage, Confidence, Novelty, Serendipity, Diversity, Robustness, Stability, and Scalability
[72]Aleem Akhtar	Student records, course information	Learning rank and Deep learning (Artificial Neural Networks)	Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE)
[73]Daniel F. et al.	MBTI test	N/A	N/A
[74] Xin X. et al.	RC15 and RetailRocket.	Self-Supervised Q-learning (SQN) and Self-Supervised Actor-Critic (SAC)	HR (Hit Ratio) and NDCG (Normalized Discounted Cumulative Gain).

[75] Ioannis P. et al.	Employee profiles on the web	Supervised machine learning algorithms	Decision tree naive Bayes (DTNB) models.
[76] Xingsheng G. et al.	Real-world, open source dataset	Content-based and case-based approaches to job recommendation	Precision and recall at rank position N, where N ranges from 1 to 5
[77] Amin B. et al.	User-item interactions	Content-based filtering, collaborative filtering	Include precision, recall, accuracy, and mean average precision
[78] Maria Augusta Silveira Netto Nunes	User preferences, characteristics of items, and psychological attributes of users	Recommender systems, classifiers, and algorithms such as horting	GPI inventory and NEO-PI-R
[79] Alexandra Roshchina et.al	TWIN Personality-based Recommender System	Content-based and collaborative filtering	Cosine similarity