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OPTIMIZE TEXTILE BOOK RECOMMENDATION SYSTEM USING DEEP LEARNING ALGORITHMS

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Abstract

The research aims to optimize the recommendation system for textile books by applying deep learning algorithms. The textile industry, rich in content and material variation, requires a system of recommendations that can accurately accommodate the diverse needs of its users. Deep learning, with its sophistication in processing large and complex data, offers solutions in improving the quality of recommendations. The study explores the use of deep learning models in interpreting user preferences and book characteristics, with the hope of producing more relevant and personal predictions. Research methods that literature conducts systematically through the collection of data from scientific sources such as journals, conferences, and related articles published in the last decade. The results show that deep learning algorithms such as Convolutional Neural Networks (CNN) and Recurrent Neural Network (RNN) have been successfully applied in improving the accuracy of book recommendation systems, including in textile contexts. These models are able to understand and process textile information and user preferences more deeply than traditional algorithms. The research also revealed important factors that influence model performance, such as data quantity and quality, model architecture, and parameter setting. Although there are limitations associated with resource use and the need for large datasets, the use of deep learning algorithms in recommendation systems for textile books shows significant potential in improving personalization and user satisfaction.

Keywords: Optimization, Recommendation Systems, Textile Books, Deep Learning Algorithms.

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Introduction

The digital age has revolutionized many aspects of human life, changing the way we communicate, learn, work, and even interact with the world around us. (Ding, L., & Wu, S. 2024). With the advent of the Internet, social media, mobile technology, and smart algorithms, we now live in an environment that is constantly connected and where information is available in unlimited quantities at our fingertips. This transformation not only brings ease and efficiency but also new challenges and questions about privacy, information security, and digital gaps. (Indrawati, S. M., & Kuncoro, A. 2021).

One of the most significant changes brought by the digital age is in the way we communicate (Gulson, K. N. (Ed.). 2024). Social media, instant messaging apps, and video call platforms have enabled faster and easier communication across geographical and time zones. The concept of community and social networking has evolved, enabling people to share ideas, collaborate, and build relationships without having to face up physically. (Williamson et al., 2023).

The digital age also marked the beginning of the information revolution, where access to knowledge and information became easier and more affordable. Internet search engines, online encyclopedias, and digital libraries have broadened the horizons of learning and research, reducing geographical and economic constraints in access to education (Håkansson Lindqvist et al., 2024). Faced with the digital age, humans are faced with an unprecedented paradox of information and connectivity. On the one hand, there are huge opportunities for innovation, learning, and collaboration. On the other, there is significant challenges related to privacy, security, and information integrity. (Education, E., & Hammoda, B. 2023).

Thus, since technological changes in human life, ease of access to information has brought its own challenge in finding relevant and quality content. One area that is experiencing this problem is in the context of reading materials in the textile industry. Although there are many books and references available, finding the right book and relevant to the needs of the reader is not easy (Gabriel, M., & Luque, M. L. D. 2020).

The presence of textiles in the book industry reflects the fact that textiles have a wide range of applications in different sectors. Although their influence in the books industry is relatively small compared to other industries such as clothing or furniture, textiles still add value in terms of aesthetics and functionality to book products. Therefore, an effective and efficient textile book recommendation system is urgently needed. (Abbate et al., 2024).

Recommendation systems in general have been extensively developed and used on various platforms, such as film recommendations on Netflix or product recommendation on Amazon. In the digital entertainment industry, Netflix uses technology to provide film recommendations tailored to user preferences. Netflix uses a sophisticated recommendation system that learns from user behavioral data, covering what is watched, when viewed, and the extent to which users watch movies or TV shows. With this system, whenever we finish watching a movie or series, Netflix's algorithms use that data to train its predictive models and provide recommendations for new content that matches our preferences (Abbate et al., 2024).

The same is true of Amazon, which has achieved great success in selling through the web, largely thanks to its sophisticated product recommendation system. This system provides recommendations based on user purchasing history, products that are often purchased or viewed, as well as preferences and purchases of other users with similar patterns. This product recommendation not only facilitates a more personalized shopping experience, but also promotes increased sales and customer retention (Catrysse, P. B., & Fan, S. 2024).

In today's digital world, recommendation systems are a key component of many online platforms' business strategies. With the huge and ever-increasing volume of information, having a sophisticated recommendation system is a must to guide users through a variety of content or products, helping them find what they are looking for or maybe something new, which they have not realized before. (Purushothama, B. 2024). These systems play an important role in increasing user engagement, improving user experience, and ultimately driving business growth. However, the application of the recommendation system to textile books is still relatively rare and not optimal. Furthermore, traditional methods in recommendation systems such as collaborative filtering and content-based filtering may be less accurate in this context. (Putri, H. D., & Faisal, M. 2023; Praditya et al., 2021). Therefore, this research is designed to find a more accurate method of recommendation using deep learning technology. (LeCun et al., 2015).

Deep Learning is a part of Machine Learning that uses a duplicate neural network with more than two levels. This algorithm can identify complex patterns and produce more accurate predictions in a particular context, which makes it an interesting choice for a book recommendation system. In this study, we want to explore how deep learning can be used to improve the accuracy of textile book recommendations systems. (Goodfellow et al., 2016).

By understanding the needs of readers and applying advanced technology, we hope to design a better textile book recommendation system to help readers find the book that best suits their interests and needs. Furthermore, this research also contributes to the development of knowledge about how deep learning can be used in a recommending system.

Research Method

The method of research carried out in this research is using literature studies. Literature research method is a series of activities related to the method of collecting data from library sources, including reading, recording, and managing research materials. (Punch, 2013; Adhabi & Anozie, 2017; Champe & Kleist, 2003). There are several ways to do literary research, including searching for relevant keywords in catalogues, indexes, and search engines. (Tharenou et al., 2007).

The study of literature is a study that collects a number of books, magazines that relate to the problems and purposes of such research. This process involves the collection, identification, organization, and analysis of the various data found. (Basrowi, 2008; Zed, 2004; Sugiyono, 2010)

Result and Discussion

Basic Theory of Recommendation Systems

Basic theory is a concept or set of concepts that describes patterns of behavior, events or phenomena observed. Basic a theory usually has a broad coverage and is the basis for a more specific theory or hypothesis (da Silva et al., 2023). Basic an theory provides a framework for understanding and explaining observed phenomenon and is often used as a basis for conducting scientific experiments and research. In addition, basic theories are also useful in formulating questions for further research and in developing new theories. (da Silva et al., 2023).

Recommendation systems are a sophisticated and vital tool in today's digital environment, with the primary purpose of helping users find the most relevant products, content, or services based on user preferences, behaviors, and interactions. Recommended systems are widely used, ranging from e-commerce platforms, video streaming, music, to news services and social media. (Maphosa, V., & Maphosa, M. 2023).

The main component of the Recommendation System, consists of; 1) Users: primary data sources about preferences, search behavior, and interaction with the system. 2) Items: Product or content recommended. 3) Feedback: Information from users related to the item, which can be ratings, reviews, or click behaviour. (Atalla et al., 2023).

Recommendation systems typically implement one of the following three approaches or a combination of several of them: 1) Content-Based Filtering: Items are recommended based on feature similarities between items and user preferences. For example, if a user likes action movies, the system will tend to recommend movies with similar genres. 2) Collaborative Filtering: Using data and behavior from a large user set to recommend items. There are two main types: (a) Memory-Based: Uses an entire dataset to calculate similarities between users or items in real-time and (b) Model-based: Builds predictive models of user data. 3) Knowledge-Based Recommendation: Recommends items based on explicit knowledge of user needs, preferences, and characteristics of items. Suitable for items purchased not often, such as cars or houses (Atalla et al., 2023; Maphosa, V., & Maphosa, M. 2023).

Advantages and Challenges, among which the advantages include: 1) Increase user satisfaction by offering personalized recommendations; 2) Encourage sales and engagement by exposing users to items they may be interested in; 3) Can help users find products or content that they may not even be aware of before. Meanwhile, the challenge consists of; 1) Cold start problems: How to handle recommendations for new users or new items that have not had adequate ratings or interactions; 2) Privacy and security of user data. 3) Avoid bubble filters, where recommendations consistently support a narrow interest bubble (Zhao et al., 2023; Atalla et al., 2023; Sharma et al., 2023).

Recommendation systems are a key element in personalizing digital experiences, giving users what they want even before they realize it. Like all technology, this system has huge potential but also faces challenges that must be done wisely.

The basic theory of a recommendation system focuses on the development of methods to predict preferences or ratings that users will give to an item, so that they can select the items that are most relevant or interesting to recommend.

The main concepts of basic theory that are often used in making recommendation systems, consist of; 1) User Ratings. The recommendation system depends on data about how users rate items, either explicitly (direct ratings) or implicitly. (melalui perilaku pengguna, seperti klik, pembelian, atau waktu yang dihabiskan). This data is used to understand user preferences and make predictions about which items they might be valuing high. 2) Content-Based Filtering (Content-based Filtering). This method recommends items by looking at attributes of items that have been evaluated by users in the past. If a user reviews a particular item positively, the system will likely recommend a similar item. To this, it takes modeling or feature extraction techniques to understand the characteristics of the item. 2) Collaborative Filtering. Colaborative filtering works by using ratings patterns from multiple users to make recommendations. There are two main approaches: (a) Memory-based: calculating similarities between users or items based on existing rating data; and (b) Model- based: using data mining and machine learning techniques to predict user ratings on unassessed items. 3) Hybrid recommendation systems. Hybrid approaches combine content-based filtration, collaborative filtration and other methods to reduce the constraints of each approach and improve the accuracy of recommendations. This approach can often solve the problem of a cold start for a new user or item. 4) Matrix Factorization. One popular technique in recommendation systems, especially in model-based collaborative filtering approaches, is matrix factorization. This technique aims to compose the user-item interaction matrix into two lower dimensional factor matrix, which represents hidden or latent features of users and items. Methods such as Singular Value Decomposition (SVD) are often used in this context. Evaluation of recommendation systems is an important part of development. Metrics such as prediction accuracy (e.g., RMSE, MAE), precision, recall, and F1 scores are often used.

Besides, aspects such as novelty, diversity, and serendipity of recommendations are also important to ensure a satisfactory user experience (Sharma et al., 2023; Paun et al., 2023; Mauro, N., Hu, Z. F., & Ardissono, L. 2023).

The basic theory of recommendation systems continues to evolve with advances in data science and machine learning, with the aim of making recommendations that are increasingly accurate, relevant, and personalized. Further development and research in this field is still very open, given the dynamics and diversity of user preferences as well as the challenges that exist in the processing and analysis of large-scale data.

Deep Learning in Recommendation Systems

Deep Learning is a subfield of machine learning that uses algorithms called neural networks to mimic the way the human brain works in learning and making decisions. This concept has gained much attention because of its remarkable ability to recognize patterns and trends in very large and complex data, which is often difficult or impossible to explicitly program by humans. (Shlezinger et al., 2023).

Deep learning has been used in a wide range of applications such as: 1) Image recognition: for facial recognition, object detection, and image classification. 2) Natural Language Processing (NLP): for language translation, text generation, and sentiment analysis. 3) System recommendations: Personalizing content for users in e-commerce and streaming. 4) Voice and Audio processing: voice identification, automatic writing, and natural language understanding. 5) Automatic control: Autonomous cars and drones utilize deep learning for navigation and environmental identification. (Shlezinger et al., 2023; Xu et al., 2023).

Deep Learning is a powerful technology that has the potential to transform the way we interact with the digital world. Despite having challenges, such as the need for big data and high computing power, its advances in recent years promise breakthroughs in a variety of fields (Xu et al., 2023).

Deep learning algorithms have had a significant impact on the development and improvement of recommendation systems. A deep learning-based recommendation system utilizes the capabilities of a simulated neural network algorithm to capture complex non-linear features and interactions on user data and items, which may not be detected by traditional methods. (Minaee et al., 2023).

How to apply deep learning in a recommendation system: 1) Embedding Features. Deep learning algorithms can be used to produce representations of dens or embedding for both users and items. This embedding represents a latent feature that is rich in information and can better explain the preferences and characteristics of the user or item. 2) Collaborative Filtering with Deep Learning. Deep learning algorithms such as Multilayer Perceptron (MLP) can be used to study non-linear interactions between user features and items. Models like Neural Collaborative Filtering (NCF) have shown improved performance compared to traditional collaborative filtering algorithms. 3)

SEQ2SEQ Model. A sequence-to-sequence model (SEQ2SeQ), as used in natural language processing tasks, can be applied to a recommendation system to process sequence data, such as purchase history or browsing history, in order to produce recommendations that are relevant to the user context. 4) RNN/CNN in Recommendation. Recurrent Neural Networks (RNN) and Convolutional Neural Network (CNN) are used to understand the sequence of clicks or interactions of users, which can be used to make recommendations for the next product or content. CNN is also effective in analyzing product images to give recommendations based on visual aspects. 5) Deep Reinforcement Learning. Techniques such as reinforcement learning, in particular the variants that use deep learning, are used to develop dynamic adaptive recommendation systems, in which models learn to make recommendations based on the rewards received from user interactions. 6) Hybrid Systems. Hybrid recommendation systems that integrate deep learning with other methods such as collaborative or content-based filtering can help overcome a variety of constraints, including cold starts and data sparsity. 7) Deep Learning for Feature Extraction. In a content-based recommendation system, deep learning can be used to automatically extract features from complex content, such as text, images, or videos, enabling more accurate recommendations based on deep content similarities. (Minaee et al., 2023; Xu et al., 2023; Menghani, G. 2023).

To implement deep learning algorithms in a recommendation system, it is usually necessary: Collection and pre-processing of relevant big data, Production of suitable simulated neural network models, including architectural selection and activation functions, Model training with techniques such as gradient descent and backpropagation and Balancing between recommendation accuracy and overhead computing (Minaee et al., 2023).

The application of deep learning algorithms in recommendation systems has shown promising results, in improving the accuracy and relevance of recommendations, as well as handling data in large volumes and a variety of formats. However, its use also presents challenges such as the need for large computing resources and potential difficulties in model interpretation.

There are some deep learning algorithms that are widely used in a variety of applications. The four most common algorithms are Convolutional Neural Network or CNN, Recurrent Neural network or RNN, Long Short Term Memory Network or LTSM, and Self Organizing Maps or SOM. Each has its own strengths and weaknesses, so developers should choose the type of algorithm that best suits their needs. (Minaee et al., 2023; Lu et al., 2023).

Textile Industry and Textile Book Context

The textile book market, often known as the textbook or textbook market, sees a number of important dynamics that may affect future prospects and business opportunities, among them; 1) Digitalization. In this digital age, many textbooks are moving from printed to digital formats. E-books, online textbooks, and interactive learning resources are becoming increasingly popular. In addition, the online learning platform also provides access to a variety of learning materials. 2) New Learning Methods. Some educational institutions are now switching to more interactive and innovative learning methods. Through such methods, the emphasis is no longer on textbooks but more on practical and project-based activities. Textbooks are often expensive, and this has resulted in a continuous search for cheaper alternatives, such as textbook rentals, used textbooks, and free online resources. 4) Self-publishing. With technological advances, self-publishing textbooks has become easier and more affordable. As a result, more writers and educators are able to distribute their own material. 5) Education regulations and policies. Education policies and regulations, especially at the government level, can have a major impact on the textbook market. For example, policies that encourage or require the use of digital resources in schools can affect the demand for printed textbooks (Satya et al., 2018; Pratiwi, D. R. 2020).

The readers' preferences and needs in finding text or textile reading materials, which are often found in the context of learning, research, or professional work related to the textile industry, can vary significantly. Some important aspects include: 1) Information Accuracy and Sustainability. Readings must contain accurate and up-to-date information. The textile industry is constantly expanding and using new technologies, so it is important for readers to gain access to the latest and reliable information. 2) Specialization and Subject Details. The reading material should offer a specialization that matches the interests or needs of the reader. Some readers may be looking for very specific or technical information about certain aspects of the textile industry, while others may be searching for a broad overview or introduction to the topic. 3) Format and Readability. Readers' preferences may also include the format of the reading material. Some readers may prefer traditional printed textbooks, while others may prefer digital or audio formats. Plus, readability and information presentation are also important. Structures, diagrams, photos, and illustrations can be very helpful in understanding and absorbing information. 4) Accessibility and Price. Readings must be easily accessible and affordable. Whether it's through libraries, publishers, or online platforms. 5) Additional Resources. Readers may also be looking for additional resources such as quizzes, case studies, and practical exercises that can help them apply what they have learned. 6) Author/Publisher Reputation. Author or publisher reputation may affect reading choices. The reader may be more confident of a recognised source in his field (Prabandani, E. A. (2020; Silaban, E. 2020).

Conclusion

In the context of optimizing a recommendation system for textile books using deep learning algorithms, the main conclusions that can be drawn are as follows: 1) Increased recommendation accuracy: With the implementation of deep learning techniques, recommendation systems can study user preferences in greater depth to provide more accurate and personalized advice. 2) Complex Data Processing Capacity: Deep learning algorithms are capable of processing and extracting complex features of big data, which include text, images, and user interactions, to improve the quality of recommendations. 3) Enhanced Personalization: Since deep learning can be enhanced usually rely on large amounts of data for 'learning', optimized recommendation systems can be better at capturing and understanding the individual preferences of each user. 4) More dynamic and adaptive: Recommendation systems that use deep learning tend to be more flexible and adaptable to changing trends and user preferences over time. 5) Resource Investment: Although these techniques promise better results, building and training a deep learning model for a recommendation system requires significant investments in terms of time, expertise, and computing resources.

Deep learning algorithms have the potential to significantly improve textile book recommendation systems by providing more accurate and personalized advice to users. This technology enables complex data analysis and provides results that are more adaptive to user needs and preferences. Nevertheless, this requires a sufficient commitment in resources and technical expertise to develop and manage efficient systems.

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