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Shusheng Yin

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Systemic construction of a machine learning-based tourist attraction recommendation model for tourism demand

Shusheng Yin

Jiangsu Vocational College Agriculture and Forestry,
School of Economics and Humanities,
Zhenjiang, 212499, China

and

Center for Studies of Marine Economy and Sustainable Development,
Key Research Base of Humanities and Social Sciences
of the Ministry Education,
Liaoning Normal University,
Dalian, 116029, China
Email: yinshusheng01@163.com

Abstract: As the internet continues to advance, the volume of data generated daily has grown exponentially, posing challenges for traditional search engines to fully meet modern user needs. In response, recommendation systems have emerged as a transformative solution, evolving into a multidisciplinary field aimed at addressing the complexities of big data while enhancing user experiences. Over the years, recommendation systems have become indispensable in information filtering and retrieval, with widespread applications in social networks, e-commerce, and news delivery, yielding substantial economic and social benefits. The concept of 'slow living' offers a thoughtful counterbalance to the pressures of modern life, emphasising individual well-being amidst time constraints. This paper introduces a tourist attraction recommendation model, leveraging machine learning algorithms to cater to the 'slow living' preferences of tourists. The proposed model achieves an 18% performance improvement over traditional algorithms, showcasing its potential for extensive real-world applications.

Keywords: slow living; machine learning algorithm; tourist attraction recommendation model.

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Biographical notes: Shusheng Yin is affiliated with Jiangsu Vocational College of Agriculture and Forestry and the Center for Studies of Marine Economy and Sustainable Development at Liaoning Normal University. His research focuses on marine economy, sustainable development, and regional economic transformation. He has participated in multiple research projects supported by national and provincial foundations and published papers in journals related to marine resources and ecological economics.

1 Introduction

With the advancement of modern society and rapid developments in computing, human life is undergoing profound transformations (Cheng, 2021). The exponential growth of data generated by computers has become a hallmark of our era, with vast amounts of information being produced every second. A major challenge today is how to effectively harness this massive influx of data to benefit humanity (Xu et al., 2018). In daily life, individuals are confronted with an overwhelming variety of choices in goods and services, shaped by their unique personalities, upbringing, and education (Malik and Kim, 2019). As data complexity and user preferences continue to grow, traditional search engines are increasingly unable to meet modern demands. This gap has given rise to personalised recommendation systems, a cornerstone of the internet age, designed to analyse user data, capture individual preferences, and recommend relevant information or products (Ge, 2018).

Recommendation systems, typically powered by machine learning algorithms, have significantly benefited from the widespread adoption of cloud computing. Cloud technologies enable the rapid deployment of these algorithms, greatly enhancing the efficiency and accuracy of recommendation systems (Augusto et al., 2021). Historically, limited computational resources constrained the effective utilisation of large-scale data. However, advancements in computing technologies, particularly in distributed and parallel systems, now enable the efficient management and processing of vast datasets (Chen et al., 2020). These systems collect and analyse diverse user data, including demographic information (age, occupation, gender, etc.), item attributes (price, origin, popularity, etc.), and user interactions (browsing, clicking, purchasing, rating, reviewing, etc.), to build machine learning models that predict user interests and preferences (Malik, 2019). E-commerce companies have increasingly recognised the strategic value of recommendation systems, utilising user profiling to study behaviour and meet the diverse needs of different customer groups. By categorising individuals based on factors such as age, gender, and occupation, companies can tailor recommendations to varying demand levels (Chen and Wang, 2021). Breakthroughs in big data management have further empowered scientists to address the challenges posed by large-scale data. Distributed systems enable the efficient storage and retrieval of vast datasets, while parallel systems accelerate the execution of complex algorithms (Bin et al., 2019). These technological innovations allow computers to perform tasks previously requiring extensive human intervention with greater speed and efficiency (Zhu et al., 2021).

Machine learning, a technology enabling computers to learn from data and improve over time, has become the backbone of modern recommendation systems. As these systems continue to evolve, they have transformed how users discover information, shifting from basic search functions to personalised content delivery (Logesh, 2019). By analysing user behaviour, social networks, textual information, and contextual data, recommendation systems can infer user needs and interests, even when these are not explicitly defined (Lyu et al., 2020). As technical tools, recommendation systems allow users to efficiently navigate vast datasets, reducing the time and effort required to find relevant information.

From a business perspective, recommendation systems offer numerous advantages, such as identifying potential customers, increasing product visibility, extending user engagement, driving website traffic, and improving overall satisfaction and sales (Li et al., 2018). Traditional statistical methods often struggle to predict outcomes in complex, incomplete, or irregular datasets. In contrast, machine learning techniques, such as neural networks, excel in handling these challenges, providing more accurate and reliable predictions (Wang, 2020). For example, by analysing factors like household size, per capita disposable income, loan interest rates, and urbanisation levels, machine learning models can offer more precise insights into consumer behaviour (Alexandridis et al., 2019).

Significant contributions to recommendation algorithm development have been made in recent years. For instance, Li proposed an incremental matrix factorisation (IMF) model optimised for real-time applications, enabling efficient updates to feature vectors without compromising accuracy when user-item interaction data changes (Huang et al., 2020). Wang introduced a mapping function based on kernel functions and KKT condition solutions to enhance cross-domain recommendations (Shafqat and Byun, 2020). Alexandridis developed a weighted clustering method to address data sparsity in dynamic collaborative filtering, offering rapid computation and cost-effectiveness (Renjith et al., 2020). Huang applied matrix decomposition techniques to manage latent user/item vectors, mitigating data sparsity challenges (Logesh et al., 2019). Shafqat extended the traditional Pure SVD algorithm with the EIGENREC model, integrating multiple recommendation strategies to address long-tail distributions and cold-start issues (Zhang et al., 2021). Renjith proposed a cross-domain recommendation model leveraging user-item-domain ternary relationships to improve accuracy (Li et al., 2019). Logesh utilised a Boolean kernel to address data sparsity in collaborative filtering, achieving high computational efficiency and effectiveness (Chen et al., 2018).

This study introduces a tourist attraction recommendation model based on machine learning algorithms, tailored to the 'slow living' preferences of tourists. The proposed model demonstrates an 18% improvement in recommendation accuracy compared to traditional approaches. As data challenges intensify, this paper underscores the critical role of machine learning and data mining techniques in advancing personalised recommendations. Key innovations include the integration of the 'slow living' concept, the application of cutting-edge machine learning algorithms for efficient data processing, and the development of personalised recommendation systems that adapt to user preferences. The paper is organised to provide an overview of related research, theoretical foundations, methodology, and experimental results, concluding with insights into the practical applications and benefits of the proposed model.

2 Construction of tourist attractions recommendation model based on machine learning algorithm under the 'slow living' demand of tourists

2.1 Slow living

In recent years, the 'Slow Movement' has experienced significant growth, attracting over 800,000 members across 55 countries. As urban life becomes increasingly fast-paced, a growing number of people are seeking an alternative to the efficiency-driven culture that defines modern society. The persistent feeling of 'time scarcity' has led many to re-evaluate their lifestyles, with 'slow living' emerging as a compelling response. This philosophy encourages individuals to slow down in areas such as eating, thinking, breathing, and relaxing – not in a literal sense of moving sluggishly, but in pursuit of balance. Comparable to the musical concept of Tempo Giusto, 'slow living' emphasises the importance of knowing when to accelerate and when to decelerate.

In the realm of tourism, this concept manifests as 'slow travel', which prioritises meaningful, immersive experiences over hurried sightseeing. Rather than merely extending the duration of trips, 'slow travel' encourages deeper connections with destinations, allowing tourists to fully engage with their surroundings. This approach resonates with the psychological needs of modern individuals, offering an escape from the pressures of daily life and fostering a sense of tranquility and stability.

The growing popularity of 'slow living' reflects a broader societal shift toward a more balanced and intentional way of life. It underscores the importance of well-being, social ethics, and mental health in shaping modern lifestyles. 'Slow travel', in particular, hinges on two key factors: sufficient time and enriching experiences. Tourists with ample time seek diverse and engaging activities, while immersive and meaningful tourism offerings require more time and attention to be appreciated.

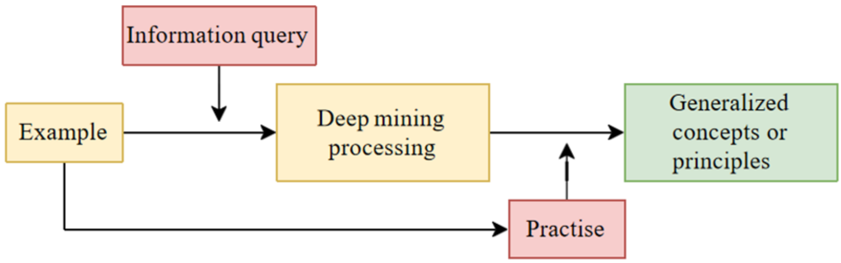
Importantly, the philosophy of 'slow living' is not a nostalgic retreat to simpler times but an effort to infuse modern life with greater meaning, care, and enjoyment. As this value system permeates various aspects of contemporary living, it encourages a redefinition of social relationships and personal priorities, ultimately promoting a more thoughtful and balanced approach to life.

2.2 Machine learning algorithm

In recent years, the continuous decline in computer terminal prices, advancements in performance, the widespread adoption of smartphones, and the improvement of both computer and mobile internet infrastructures have significantly enhanced the ease of information dissemination and sharing. Simultaneously, storage costs have dropped dramatically. Since the advent of computers, humanity has entered the information age, characterised by unprecedented growth in the information industry and an exponential increase in data generation. This era has introduced terms like 'Hadoop', reflecting the massive flow of data and the increasing demand for deep data mining. As industries transform and enterprises evolve, machine learning algorithms have emerged as indispensable tools for processing large-scale information and driving societal progress.

Machine learning algorithms provide robust solutions to the challenges of data mining. By leveraging advanced artificial intelligence techniques and mathematical models, these algorithms can effectively process and analyse vast datasets, uncovering valuable insights. Studying machine learning algorithms within the Hadoop environment carries significant practical implications, as it enables the extraction of meaningful knowledge from complex and dynamic databases. In the context of exponential data growth, large volumes of information are stored across the hardware infrastructures of various organisations. The need for systems capable of analysing and processing this data to generate actionable insights or facilitate automation has become widespread. However, the scale of these datasets often exceeds the capacity of human processing and, in many cases, even the computational capabilities of a single machine. This has necessitated the adoption of distributed systems, comprising hundreds of computing terminals, to perform efficient data analysis and processing. In today's Hadoop environment, data analysis has become a critical focus for industries worldwide. Machine learning, with its ability to rapidly assimilate knowledge and adapt, plays a pivotal role in enhancing technological capabilities and improving processing efficiency. The key challenge lies in adopting effective learning techniques within the Hadoop framework to optimise its potential. As a result, machine learning has gained widespread recognition as a powerful and increasingly popular tool for applications ranging from learning to service delivery. Figure 1 provides a visual representation of the machine learning process.

Figure 1 Machine learning process (see online version for colours)



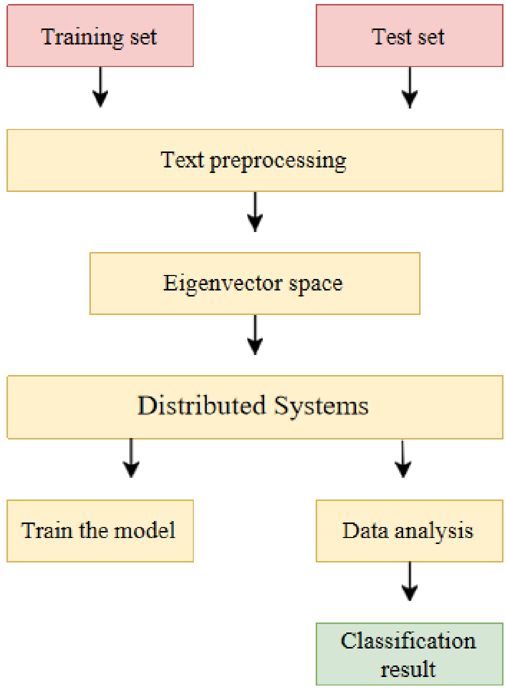
This integration of machine learning with Hadoop continues to drive advancements across industries, ensuring that the vast amounts of data generated are transformed into meaningful insights, thereby propelling innovation and societal progress.

With the advent and rapid evolution of the internet, humanity has fully entered the information age, where everyday life is increasingly intertwined with the online world. Today, the internet serves as an essential platform for communication, information retrieval, and the creation, processing, publication, and dissemination of knowledge. Its ubiquity has made it an indispensable tool, underscoring the rising prominence of big data research. Big data, characterised by its vast volume, dynamic nature, uncertainty, and fluidity, has become a cornerstone of the modern 'Internet Plus' era and the ongoing wave of big data innovation. As society continues to integrate more deeply with big data, traditional data mining techniques are reaching their limits, driving the need for more sophisticated methods to uncover actionable insights. In this context, machine learning algorithms have emerged as vital tools for efficiently processing massive datasets and performing complex analyses. Machine learning not only enables automation of tasks that surpass human capability but also facilitates the extraction of deep insights from large and complex datasets. By employing well-designed algorithms, machines can identify patterns, trends, and relationships within data, unlocking insights that would otherwise remain inaccessible.

The importance of machine learning lies in its ability to transform raw data into valuable knowledge, making it a critical component of modern data mining and knowledge discovery processes. The flexibility and scalability of machine learning make it particularly well-suited for handling the challenges posed by big data. Figure 2 illustrates the flow chart of classification tasks in machine learning, showcasing the structured process by which machines categorise and analyse data.

As the world becomes increasingly data-driven, the integration of machine learning with big data processing is reshaping industries and fostering innovation. These advancements are not only solving complex problems but also paving the way for new opportunities in research, business, and technology, further solidifying the role of machine learning as a cornerstone of the information age.

Figure 2 Flow chart of classification tasks in machine learning (see online version for colours)



The core of machine learning lies in its ability to learn. Learning, a uniquely human trait, involves improving performance through interactions with the external environment. The goal of machine learning research is to enable machines to mimic this process, enhancing their problem-solving capabilities through experience. Machine learning algorithms have significant practical value in both academic and industrial fields. The process of machine learning can be described as a transition from the unknown to the known, where machines, equipped with learning programs, improve their performance over time as they solve more problems. This ability to learn from experience is what defines machine learning.

In the current Hadoop environment, the volume and diversity of data have significantly increased, and data is being generated at an accelerating pace. Additionally, the emergence of new data types presents greater analytical challenges. Machine learning allows systems to leverage accumulated data to improve automatically and enhance performance. The foundations of machine learning can be traced back to statistical learning and optimisation theory, which originated with the advent of computers. Since then, numerous algorithms have been developed to address problems across various disciplines.

Machine learning improves the performance of machines, particularly in the field of pattern recognition, which focuses on classifying different objects into distinct categories. The integration of machine learning algorithms into pattern recognition systems enhances their classification abilities, making these systems more robust and accurate.

3 Methods and experimental results

With the widespread use of the internet and the rapid improvement of message technique, the internet is playing an increasingly important role in people's lives. In daily life, it is more and more common for people to use the internet to engage in activities such as study, shopping, entertainment and so on. The internet first appeared in 1969, and it originated in USA. The internet can be seen as a global network formed by connecting some computers that communicate with each other by using some common rules. It is a carrier for public message and services. At first, it was only provided to computer experts and scientists. Later, it was gradually opened to the public and oriented to e-commerce.

Mean absolute error is also the MAE that is most commonly used when we evaluate recommendation algorithms. MAE Easy to understand and simple in calculation, the calculation formula is as follows:

$$MAE = \frac{\sum_{I}^{N} |P_i - V_i|}{N} \tag{1}$$

Among them, P_i is the prediction score of the recommendation system, V_i is the real score of users in the test set, and N is the number of predictions or tests.

Normalised mean absolute error, referred to as $NMAE$ for short, is calculated as follows, where $R_{\max}$ and $R_{\min}$ are the maximum and minimum values of the user scoring interval, respectively.

$$NMAE = \frac{MAE}{R_{\max} - R_{\min}} \tag{2}$$

Average square error, referred to as MSE. The smaller the value of MSE, it means that the predicted score is closer to the actual score and has better accuracy. The calculation formula is as follows:

$$RMSE = \sqrt{\frac{\sum_{i}^{N} (p_i - v_i)^2}{N}} \tag{3}$$

The accuracy rate is calculated as follows:

$$P = \frac{N_{11}}{N_{1m}} \tag{4}$$

With the advent of the era of Hadoop in today's society, the amount of message data on the internet has been saturated all over the world, and it has gradually become an explosive trend. As the number of internet users has gradually increased, various message resources in the internet are rapidly increasing. These message resources not only have complex structures, various types and varieties, but also are accompanied by the phenomenon of 'message overload'. Network applications such as search engines, portals, professional data indexes, etc. have solved this problem to some extent. These applications are essentially a means of message filtering, helping users to filter out things unrelated to their needs in specific domains or using specific keywords. Users need to actively seek relevant message that is useful or interesting to them in these filtering results, but these network applications still can't solve the problem of 'overload' well when there is a large amount of message.

In practical application, personalised recommendation system can produce good economic benefits for enterprises to a certain extent. The task of e-commerce recommendation system is to contact users and papers, which can not only make the papers that users are interested in appear in front of users, but also enable users to find the papers they need and prefer, thus realising a win-win situation for users and internet companies. When the internet first appeared, due to the number of webpages and the small amount of message contained in the webpages, the main way for users to browse network message was to browse the webpages through navigation functions, and navigation websites mainly provided message retrieval classes for users. However, with the emergence of a large number of websites and the increase of message, the navigation websites based on simple message classification have gradually failed to provide users with effective services in message retrieval. The diversification and quantification of message resources make the majority of users become aimless and disoriented. It is very difficult for users to dig out the real message data they need, which leads to the phenomenon that users spend a lot of time and energy searching step by step. However, they cannot be clear about their needs and interests, and sometimes even forget their original goals and needs.

Let $\hat{w}(i,u)$ represent the weight of the item i consumed by the user u, V the total number of items, N the total number of users, $tf(i,u)$ the number of the same item consumed by the user, and $df(i)$ the measure of the popularity of item i. The standard $TF-IDF$ calculation formula is as follows:

$$\hat{w}(i,u)=\frac{\lg\left(tf(i,u)\right)\cdot\lg\left(\frac{N}{df(i)}+0.01\right)}{\sqrt{\sum_{i=1}^{V}\left(\lg\left(tf(i,u)\right)\cdot\lg\left(\frac{N}{df(i)}+0.01\right)\right)^2}} \tag{5}$$

The value of $TF-IDF$ is used to represent the measure of the effectiveness of the third factor item in the feedback weight. Combine the other two factors into the above formula. The improved formula is as follows:

$$W(u,i)=\hat{w}(u,i)\cdot f(i) \tag{6}$$

$$f(i)=e^{\alpha\cdot time(i)+\beta\cdot grade(i)} \tag{7}$$

On the basis of feedback, *Gibbs* samples are re-sampled, and the improved calculation formula is as follows:

$$P\left(t_n=k\middle|i_n,\alpha,\beta,T_{-n}\right)\propto\frac{W(u,i)C_{k,-n}^{MK}+\alpha}{\sum_{v=1}^{K}W(u,i)C_{v,-n}^{MK}+K\alpha}\cdot\frac{W(u,i)C_{k,i,-n}^{NK}+\beta}{\sum_{j=1}^{N}W(u,i)C_{k,j,-n}^{NK}+N\beta} \tag{8}$$

Therefore, through further analysis and deduction of the above formula, a new user interest distribution formula is obtained as shown below:

$$\tilde{\theta}_{i,j} = P\left(t_i \middle| u_j, \alpha\right) = \frac{W(u,i)C_{i,j}^{MK} + \alpha}{\sum_{k=1}^{K} W(u,i)C_{i,k}^{MK} + K\alpha} \tag{9}$$

$$\tilde{\varphi}_{q,p} = P\left(i_p \middle| t_q, \beta\right) = \frac{W(u,i)C_{q,p}^{NK} + \beta}{\sum_{j=1}^{N} W(u,i)C_{q,j}^{NK} + N\beta} \tag{10}$$

Personalised recommendation research utilises either pre-provided user data or data mining techniques to extract user preferences from historical records. This process aims to help users obtain relevant and interesting information while addressing the challenge of information overload on the internet. For users, recommendation systems offer several advantages: they provide personalised services by recommending preferred items in real time, save time spent searching for desired goods, and enhance the overall user experience.

Unlike recommendation systems, search engines primarily operate on passive queries, requiring users to input specific keywords to generate results. This approach reveals several limitations. When users cannot accurately define the keywords for their desired information, or when their input only partially reflects their current needs, search engines struggle to infer related preferences or predict future ones. Additionally, search engines are unable to distinguish the unique demands of different users through detailed analysis. This limitation arises due to the randomness of user queries, the brevity of keyword inputs, and the restricted capacity of search engines to process and utilise this limited information. As a result, search engines are unable to accurately understand users' real needs or provide personalised recommendations.

Recommendation systems, on the other hand, can deliver high-quality, tailored services that significantly improve user satisfaction, enhance loyalty, and reduce user attrition. As an essential tool for information retrieval and processing, personalised recommendation systems have become a core component of internet technical services, with their quality now serving as a critical metric for evaluating online services.

In recent years, the rapid growth of the internet has resulted in an exponential increase in the volume of online information. However, the challenge of efficiently identifying the most useful information continues to frustrate web users. Recommender Systems (RS) have proven to be an effective solution to the problem of information overload, achieving notable success across various industries. Deep neural networks, as one of the most advanced machine learning methods, have been widely applied to solve diverse tasks such as machine translation, image classification, and image generation. Despite their success, traditional deep neural networks are limited by their reliance on all data being presented simultaneously for learning. This limitation poses a significant challenge to their adaptability. The effectiveness of recommendation systems depends on two primary factors: algorithm performance and the richness of input data features. When a new task is introduced, deep neural networks often overwrite previously learned knowledge, a phenomenon referred to as 'catastrophic forgetting' in cognitive science. This limitation not only increases computational demands but also prevents the effective utilisation of time-series information acquired earlier.

Traditional collaborative filtering techniques, while successful in recommending items like movies and music, rely primarily on interest-based variables and ignore other critical individual characteristics. For instance, factors such as users' long-term online shopping habits or personal financial situations are often overlooked. These characteristics, however, can be mined from users' historical data to provide more accurate and comprehensive recommendations.

As shown in Figures 3–6, the algorithm presented in this study outperforms traditional algorithms. The corresponding values for the dataset demonstrate a steady increase with the number of iterations and eventually converge to a value significantly higher than the initial baseline. These results highlight the advantages of the proposed algorithm in delivering superior recommendation performance compared to conventional approaches.

Figure 3 Comparison of roc curves (see online version for colours)

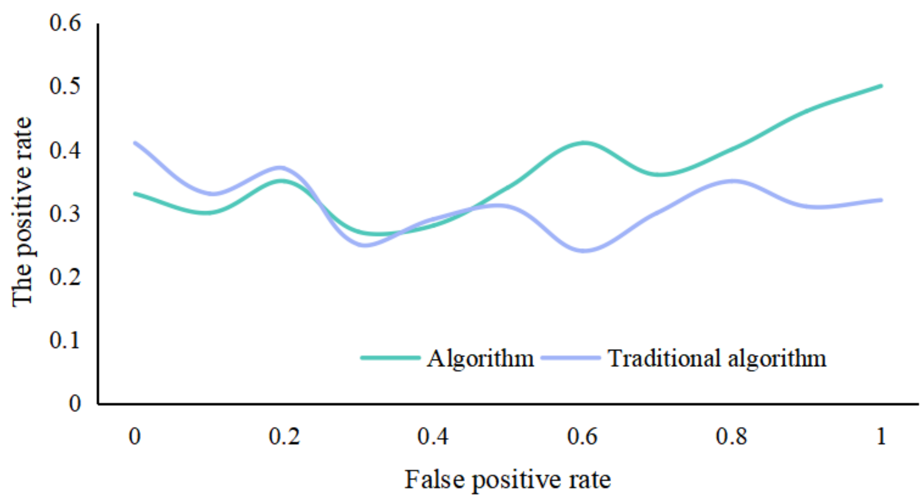


Figure 4 Convergence analysis (see online version for colours)

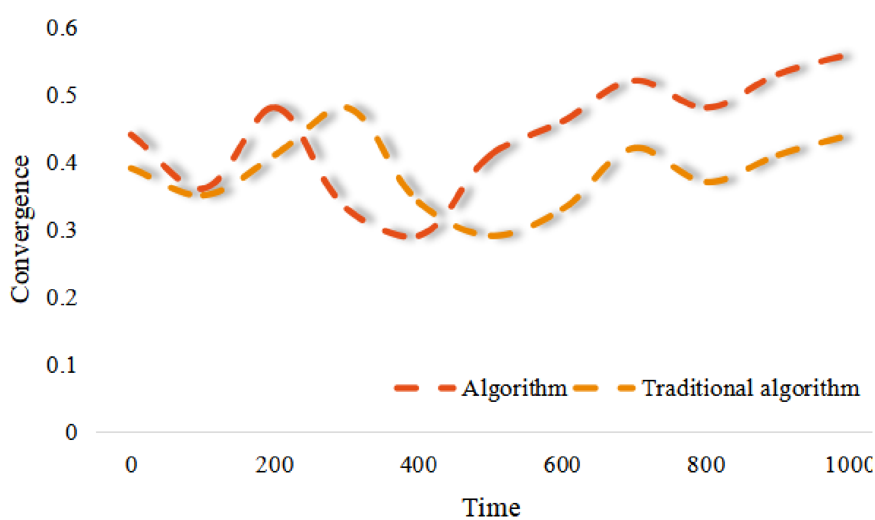


Figure 5 User distribution status project distribution status (see online version for colours)

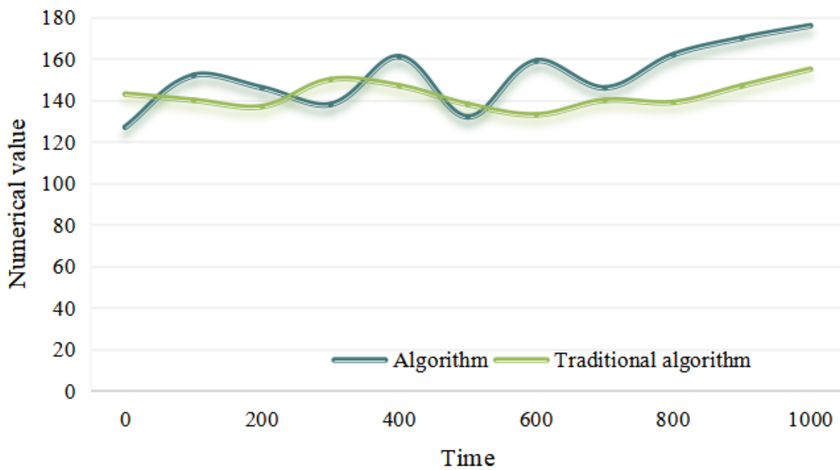
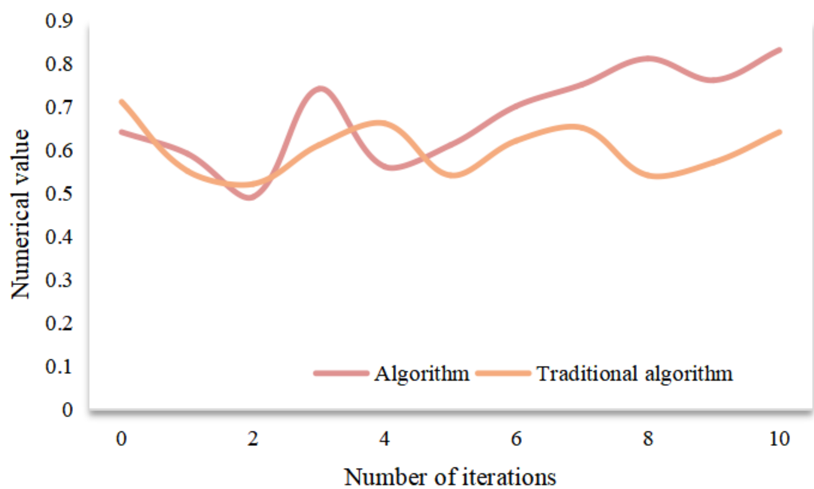


Figure 6 Changes of dataset values with iteration times (see online version for colours)



In the real world, users typically focus on a small subset of the vast number of available items, and they make choices based on their personal interest preferences. Therefore, recommendation methods that are driven by interest preferences can effectively address the problem of data sparsity and deliver more accurate recommendations. Among the various algorithms used in recommendation systems, collaborative filtering stands out for its ability to recommend items to groups of users with similar interests. The collaborative filtering method assumes that if two users have shared preferences in the past, they are likely to be interested in the same products in the future. However, the products purchased by users are not always the ones they are most interested in; often, they select items that offer the best balance between cost and benefit.

As a result, data modelling methods based on machine learning have become a preferred approach in many e-commerce recommendation systems, especially when working with labelled sample sets. As shown in Tables 1 and 2 and Figures 7 and 8, the algorithm presented in this study outperforms traditional algorithms by approximately 18%. Additionally, the issue of imbalanced data classification can be mitigated through the use of data hierarchy and algorithm hierarchy techniques, further enhancing the performance of the recommendation system.

Figure 7 Influence of the number of interest preferences on recommendation results (see online version for colours)

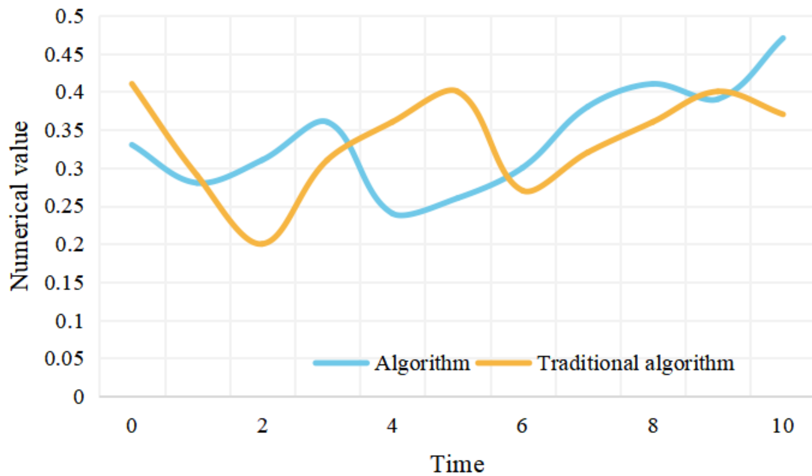


Figure 8 Purchase conversion rate (see online version for colours)

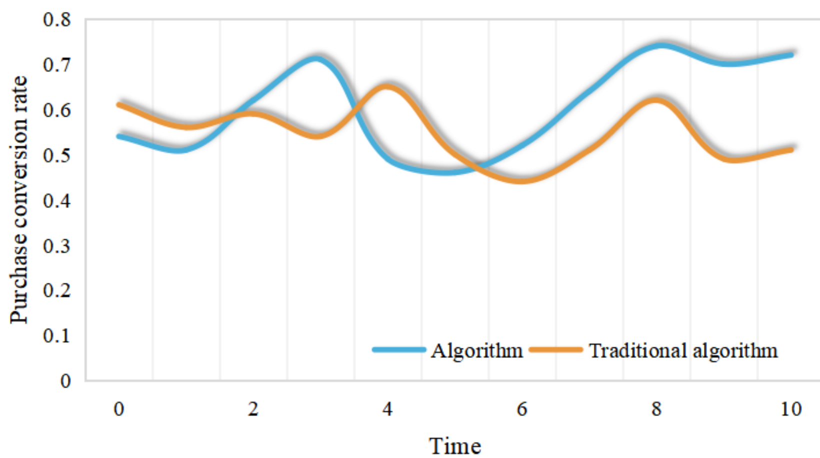


Table 1 Influence of the number of interest preferences on recommendation results

	0	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Algorithm	0.33	0.28	0.31	0.36	0.24	0.26	0.30	0.38	0.41	0.39	0.47
Traditional algorithm	0.41	0.29	0.20	0.31	0.36	0.40	0.27	0.32	0.36	0.40	0.37

Table 2 Purchase conversion rate

	0	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Algorithm	0.54	0.51	0.62	0.71	0.49	0.46	0.52	0.64	0.74	0.70	0.72
Traditional algorithm	0.61	0.56	0.59	0.54	0.65	0.50	0.44	0.51	0.62	0.49	0.51

User comments provide a rich and valuable source of data for training recommendation system models. The ‘user-interest-comment’ model is particularly significant in practical applications, as it leverages users’ decision-making processes, which are often guided by their personal preferences. By capturing and analysing these preferences, recommendation systems can enhance both their interpretability and stability, leading to more accurate and reliable predictions.

Collaborative filtering, one of the most commonly used techniques in recommendation systems, is categorised into two main types: in-memory and model-based approaches. In-memory collaborative filtering directly utilises the entire database of user-item interactions to generate predictions, making it heavily dependent on real-time data. In contrast, model-based collaborative filtering involves constructing a user preference model prior to making recommendations. This approach employs probabilistic calculations to predict a user’s potential interest in other items, using collaborative filtering techniques to estimate expected preferences.

To build these models, various machine learning algorithms are employed, including Bayesian networks, clustering techniques, and rule-based methods. The fundamental principle of collaborative filtering lies in its ability to predict what a user may be interested in based on the historical behaviours or preferences of other users. Remarkably, this approach requires minimal information about users or products, relying instead on behavioural patterns to make accurate predictions.

Collaborative filtering algorithms serve as a bridge between users and products – entities that are inherently different – by uncovering patterns in user behaviour and preferences. This capability allows the system to provide personalised and relevant recommendations, enhancing user satisfaction and driving engagement. By incorporating user comments and preferences into the recommendation process, collaborative filtering systems can achieve higher levels of personalisation and efficiency, further solidifying their role as a cornerstone of modern recommendation technologies.

4 Conclusions

With the rapid advancement of the internet, the cost of data collection and computation has significantly decreased, ushering in the era of Hadoop and big data. Both e-commerce companies and research institutions worldwide are increasingly leveraging data to provide personalised recommendations, addressing the pervasive challenge of ‘information overload’. Recommendation systems have emerged as a popular and effective solution, garnering widespread attention from both academia and industry. However, traditional recommendation algorithms face persistent challenges, including data sparsity, cold start issues, low accuracy, and limited coverage. These limitations have remained a focal point of research as scholars and practitioners work to overcome them. The design of effective recommendation systems requires a clear alignment between product needs and machine learning methodologies. Translating product requirements into machine learning problems enables researchers to tailor algorithms and methods to the specific demands of the system. By applying domain-specific algorithms, the performance and accuracy of recommendation systems can be significantly enhanced. This approach not only optimises the system's design but also improves the efficiency and adaptability of the underlying machine learning models.

In this paper, we propose a tourist attraction recommendation model driven by machine learning algorithms, specifically designed to address the 'slow living' preferences of tourists. By focusing on the unique needs of this demographic, the model achieves an 18% improvement in recommendation accuracy compared to traditional algorithms. The results highlight its practicality and potential for widespread application, offering a robust solution for personalised recommendations in the tourism industry.

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