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An Analysis of the Effectiveness of Personalised Recommender Systems in Movie Recommendation

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Abstract
The arrival of the digital era has greatly promoted the innovation of the entertainment industry, and personalised recommendation system has become one of the core technologies in the field of movie recommendation in this context. This study aims to deeply explore the application of personalised recommendation system in movie recommendation, assess the challenges and opportunities it faces, and propose corresponding optimisation strategies. Through literature review and case studies, this study comprehensively examines key topics such as the effectiveness of recommendation algorithms, the cold-start problem, the data sparsity problem, the accuracy and diversity of recommendation results, and the protection of user privacy. It is found that although personalised recommendation systems play a positive role in enhancing user experience and satisfaction, there are still some pressing issues that need to be addressed. To cope with these challenges, this paper proposes a series of solutions to provide theoretical support and practical guidance for the future development of movie recommender systems, aiming to promote the wider application and in-depth development of personalised recommender systems in the movie field.

Keywords: *Personalised recommender systems; film domain; recommendation algorithms; user privacy; technological innovation*

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I. INTRODUCTION

1.1 Definition of personalised recommendation system

Personalized recommender system is a system that automatically recommends items or information to users that meet their individual needs based on their interests and behavioural history, through algorithmic analysis. In the field of movie recommendation, personalised recommendation system mines users' preferences and interests by analysing their viewing records, ratings, search history, social relationships and other data, and then recommends movies that may be of interest to users. This recommendation process aims to reduce the problem of information overload when users are faced with a huge number of film choices, and to improve their viewing experience and satisfaction.

1.2 Classification of Personalised Recommender Systems

1.2.1 Content-based recommender system

The content-based recommender system mainly relies on the user's historical behaviour and interest preferences, and recommends content with similar characteristics to the user by analysing the characteristics of the content the user liked in the past[1]. The system needs to collect the descriptions of the user's interests and the descriptions of the items, and make recommendations by comparing the similarities between the two. Content-based recommender systems are simple and intuitive, but their results may not be satisfactory when dealing with complex and unstructured data.

1.2.2 Collaborative Filtering Recommender System

Collaborative filtering recommender system is a recommendation method based on user behaviour data. It is divided into two types: user collaborative filtering and item collaborative filtering. User collaborative filtering finds other users with similar interests to the target user by calculating the similarity between users, and then recommends items that these users like to the target user. Item collaborative filtering, on the other hand, finds other items similar to the items preferred by the target user by analysing the user's evaluation and feedback on the items, and then recommends them to the target user. Collaborative filtering recommender systems are adaptive and can handle complex, unstructured data, but may not perform well when dealing with cold start problems (i.e., problems with new users or new items)[2].

1.2.3 Deep Learning-based Recommender Systems

Deep learning-based recommender systems make use of deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to perform more sophisticated extraction and modelling of user and item features. This type of system is capable of handling large-scale, high-dimensional data and automatically learning the complex relationships between users and items. Deep learning-based recommender systems have powerful learning and generalisation capabilities and can provide more accurate and personalised recommendation results. However, this class of systems requires a large amount of training data and computational resources, and its interpretability is poor.

1.3 Characteristics of Movie Recommender Systems

1.3.1 Personalisation and Customisation

The core feature of personalised recommendation system is that it can provide customised services according to users' individual needs. In the field of movie recommendation, this feature is manifested in the system's ability to deeply analyse the user's viewing history, rating records, search behavior and other data, to explore the user's interest preferences and viewing habits, and then recommend movies that meet the user's tastes. This kind of personalised recommendation can effectively meet the user's demand for diversified and differentiated information, and improve the user's movie watching satisfaction.

1.3.2 Data-driven and real-time update

The personalised recommendation system relies on a large amount of user data and movie data to provide recommendation services. These data include not only explicit feedback data such as users' viewing history and rating records, but also implicit feedback data such as users' search behaviour and click rate. By analysing and mining these data, the system is able to more accurately understand users' needs and interests and update the recommendation results in real time. In addition, the system is able to adjust the recommendation strategy according to the film's release time, box office performance and other data, making the recommendation results more in line with the current market environment and user needs.

1.3.3 Diversity and richness

The personalised recommendation system can provide users with diverse and rich movie recommendations. By exploring the differences and commonalities of interests between different users, the system can recommend films of different types, styles and countries to meet the users' needs for diversified information. At the same time, the system can also recommend films with similar interests or other works of actors based on the user's viewing history and rating records, enriching the user's viewing choices.

II. PERSONALISED MOVIE RECOMMENDATION TECHNIQUE

2.1 Collaborative Filtering Techniques

Collaborative filtering technique is one of the most classic methods in recommender systems, which predicts the items that users may be interested in based on their historical behaviours or preferences. This technique is mainly divided into two implementations: user-based and item-based, and generates recommendations by calculating the similarity between users or items.

Collaborative filtering has the advantage of being able to leverage the collective intelligence of the user community to recommend items to users that are liked by other users with similar interests to theirs. However, it also has some limitations such as the cold start problem, the data sparsity problem, and the difficulty in explaining the reasons for the recommendations.

2.2 Content-based recommendation methods

Content-Based Filtering (CBF) focuses on analysing the attributes of the items themselves, such as the genre, director, and actors of a movie, to predict the movies that users may be interested in.

The advantage of CBF is that it provides highly explanatory recommendations and works better for new users and new films. However, it may ignore the diversity and dynamics of user preferences and is difficult to deal with the recommendation of long-tail items.

2.3 Deep Learning Methods in Film Recommendation

Deep learning methods, especially neural network technologies that have emerged in recent years, such as convolutional neural networks (CNN), recurrent neural networks (RNN) and self-encoders, have been widely used in the field of film recommendation.

Deep learning methods are capable of automatically extracting higher-order features of film content, dealing with nonlinear relationships, and learning effectively on large-scale datasets. In addition, they excel in handling complex user behaviour patterns and sequential data.

III. CASE STUDIES

3.1 Case Study of Existing Movie Recommender System

Take the Netflix movie recommendation system as an example, which successfully applies collaborative filtering technology to movie recommendation and has achieved remarkable results.Netflix uses collaborative filtering algorithms to recommend similar movies for users by analysing their browsing and rating records. Through continuous learning and optimisation, the system is able to automatically adapt to changes in user interests and update the recommendation results in real time. This intelligent recommendation method enables Netflix to provide accurate and informative film recommendations, which greatly enhances the user's viewing experience.

In addition, the Netflix movie recommendation system also incorporates a content-based recommendation algorithm that takes into account the content, actors, directors and other characteristics of the film, further improving the accuracy and diversity of the recommendations. This diverse recommendation strategy enables users to not only discover films with similar interests to their own, but also explore different genres, increasing the fun and richness of movie watching.

3.2 User Satisfaction Survey

The China Movie Audience Satisfaction Survey provides powerful data on the user satisfaction of the movie recommendation system. Conducted by China Film Art Research Centre in conjunction with Yien Data, the survey adopts methods such as on-site sampling in cinemas, online surveys by frontline practitioners and experts, and big data capture and analysis, to comprehensively evaluate domestic films by three indices: ornamental, ideological, and dissemination[3]. The survey results show that a number of films received high scores in terms of satisfaction, such as 85.2 points for "Keep You Safe" and 82.8 points for "More Than Restless". These highly satisfied films not only represent the audience's recognition of the film content, but also reflect the important role of the film recommendation system in enhancing the user experience.

Through the user satisfaction survey, we can find that the effectiveness of the film recommendation system is not only reflected in the accuracy of the recommendation results, but also in the user's satisfaction with the recommendation results. A successful movie recommendation system should be able to accurately understand users' interests and needs, and provide users with movie recommendations that meet their tastes, so as to enhance users' viewing experience and satisfaction.

3.3 System Optimisation Suggestions

(1) Data update and real-time:

It is crucial to keep the data of the film recommendation system up-to-date. Newly released movies, user behaviour data and user evaluations should be incorporated into the system's calculations and analysis in a timely manner[4]. Through real-time data updating, the system can more accurately reflect users' interests and needs, and provide more accurate and tailored film recommendations.

(2) Application of deep learning technology:

The application of deep learning technology in the film recommendation system has made significant progress. Deep learning algorithms are able to discover hidden patterns and features from massive data, and improve the accuracy and personalisation level of recommendations. It is suggested that the system introduces deep learning models for movie feature extraction and user modelling, thus improving the performance of the recommendation system.

(3) Multi-source data fusion:

In addition to the user's rating and film viewing history data, other data sources can be considered for fusion, such as the user's social network information, geographic location information, and so on. This information can provide the system with a richer and more comprehensive user profile, further improving the accuracy and personalisation of recommendations.

(4) Diversity and richness of recommendation results:

In order to meet users' needs for different types and styles of films, the system should be able to provide diversified and enriched recommendation results. This can be achieved by adjusting the strategies and parameters of the recommendation algorithm or introducing new recommendation methods.

IV. CHALLENGES AND OPPORTUNITIES FOR PERSONALISED RECOMMENDER SYSTEMS

4.1 Cold Start Problem

The cold start problem is one of the important challenges faced by personalised recommender systems. It is mainly divided into three categories: user cold start, item cold start and system cold start. In the case of user cold start, the lack of historical behavioural data after a new user registers makes it difficult for the system to accurately make personalised recommendations[5]. Item cold start, on the other hand, involves how to recommend new items to users who may be interested in them, and in the case of system cold start, the entire recommendation system lacks any historical data.

To cope with the cold-start problem, existing strategies include providing non-personalised recommendations (e.g., popularity rankings), using user registration information or social network data for coarse-grained personalised recommendations, and asking users to give feedback on some items to collect preference information. While these approaches can alleviate the cold-start problem to a certain extent, further research and optimisation are needed.

4.2 Data sparsity problem

Data sparsity is another challenge, which refers to the fact that the interaction data between users and items is very sparse, i.e., each user interacts with only a small number of items while most of the items are not interacted with. The MovieLens dataset, for example, has a sparsity of only 4.5%, while real-world systems such as Taobao may face a sparsity of one in a million or less.

To cope with the data sparsity problem, methods such as content-based recommendation, popular item recommendation, user or item similarity calculation, and model-based recommendation can be used. In addition, hybrid recommendation techniques and reinforcement learning have been shown to be effective solutions. These methods are able to improve the accuracy and diversity of recommendations by integrating user behaviour data, item attribute information and social relationships.

4.3 User Privacy Protection

With the wide application of personalised recommendation systems, user privacy protection has become an issue that cannot be ignored. Personalised recommendation systems need to collect and analyse users' personal information in order to provide accurate recommendations, but at the same time, they also bring the risk of privacy leakage such as data abuse, data loss and user profile construction.

In order to protect user privacy, methods such as anonymisation, differential privacy and privacy agreement with user right to know can be adopted. Anonymisation reduces the risk of privacy leakage by separating user information from personal identity. Differential privacy protects privacy by adding noise to user information while maintaining data availability. Privacy agreements and the user's right to information require the system to clearly inform the user of the purpose of data collection and use, and to obtain the user's explicit consent.

V. CONCLUSIONS AND FUTURE WORK

5.1 Research Summary

This paper provides an in-depth discussion of the effectiveness of personalised recommender systems in movie recommendation, with a special focus on the application of collaborative filtering technology. Through the detailed description and case study of collaborative filtering technology, we can see that the technology plays an important role in movie recommendation, and is able to provide movie recommendations that match the user's interests based on his or her historical behaviours and preferences. However, personalised recommendation systems also face a series of challenges, such as the cold-start problem, data sparsity problem and user privacy protection[6]. To address these challenges, this paper proposes some solutions and strategies, such as utilising user registration information, adopting deep learning techniques and enhancing privacy protection measures.

In addition, this paper analyses the prospects of new technologies in movie recommendation systems, including deep learning and multimodal data fusion. The development of these new technologies provides more possibilities for the personalised recommendation system, enabling the system to more accurately mine the interests and needs of users and provide more accurate and personalised recommendation services.

In summary, personalised recommendation system has important application value in film recommendation, but at the same time, it also needs to constantly face and solve various challenges. With the continuous development and innovation of technology, we have reason to believe that the personalised recommendation system will play a more important role in the future and provide users with a better movie watching experience.

5.2 Future Research Directions

In the research of personalised recommendation system, the following directions can be explored and researched in depth in the future:

(1) The application of deep learning in the recommendation system:

Deep learning technology has achieved remarkable results in many fields, and its application in recommendation systems also presents great potential. The application of deep learning technology in feature extraction, user modelling and recommendation algorithms can be further explored in the future to improve the accuracy and personalisation of recommendations.

(2) Multimodal data fusion:

With the development of the Internet of Things and mobile Internet, user-generated data presents diverse characteristics. In the future, it is possible to study how to effectively fuse multimodal data such as text, image, audio, etc. into the recommender system in order to more comprehensively understand the interests and needs of users and improve the accuracy and diversity of recommendations.

(3) User privacy protection and data security:

With the increasing concern of users about privacy protection, how to provide high-quality recommendation services while protecting user privacy has become an important research direction. More effective privacy protection techniques and data security techniques can be explored in the future to ensure the security and privacy of user data.

(4) Cross-domain recommendation:

Personalised recommendation system can not only be applied in the field of movie recommendation, but also be extended to other fields, such as music recommendation, commodity recommendation and so on. In the future, cross-domain recommendation technology can be studied to integrate knowledge and data from different fields to provide users with more comprehensive and personalised recommendation services.

(5) Interpretable recommendation:

In order to improve the user's trust and satisfaction with the recommendation results, explainable recommendation technology can be studied in the future. By showing users the process and basis for generating recommendation results, it increases users' trust in the recommendation results and helps them better understand their interests and needs.

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