The Investigation and Discussion Related to Recommendation Systems in Video Social Platforms

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Abstract. With the increasing popularity of video social platforms, recommendation systems play a crucial role on these platforms. They can recommend content of interest to users based on their interests and preferences, greatly improving their content browsing experience. This article provides an in-depth analysis of the recommendation algorithms for the two popular video social platforms, Bilibili and TikTok. This study first introduced the key implementation steps of recommendation algorithms for these two platforms, including user behavior modeling, content feature extraction, and personalized recommendation. Through the analysis of existing algorithms, this study has identified some noteworthy issues, such as the possibility that overly precise personalized recommendations may cause the "information cocoon" effect and reduce the user's content contact surface; Recommendation algorithms may have certain biases that affect the fairness of content creation; And issues such as user privacy protection. In response to these issues, it is possible to look forward to the future development direction of recommendation algorithms, including enhancing algorithm interpretability, building more fair recommendation systems, and adopting technologies such as federated learning and differential privacy to protect user privacy. Overall, this article provides a comprehensive analysis of the current status and future trends of recommendation algorithms on video social platforms, providing valuable references for research in this field.

Keywords: Recommendation system, bilibili, tiktok, algorithm, AI

1 Introduction

A recommendation system in video websites is a technology that suggests or recommends videos to users based on their preferences [1-3], viewing history, and other relevant factors. Its goal is to enhance the user experience by providing personalized and relevant content that aligns with the user's interests. Recommendation systems in video websites offer several benefits, both for users and for the platform itself. Recommendation systems improve the user experience by providing personalized content recommendations. Users are more likely to find videos that align with their interests and preferences, increasing their satisfaction and engagement with the platform. It saves users time and effort in searching for relevant videos, as the system curates a tailored selection for them. By suggesting relevant and interesting videos, recommendation systems

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help keep users engaged on the platform for longer periods. This increased engagement can lead to more frequent visits, longer viewing sessions, and a higher likelihood of users returning to the website. In addition, recommendation systems expose users to a wider range of subjects, including videos they may not have discovered on their own. This promotes content discovery and serendipitous exploration, introducing users to new genres, channels, creators, or topics they might be interested in. It can help users break out of their viewing habits and discover fresh and exciting content. Moreover, of course, it has a deep relationship with people's life and achieve significant progresses in real application. Take the example of the beloved video-watching platform Youtube, it employed content-based filtering algorithms to analyze the characteristics of videos, such as metadata, titles, descriptions, and tags, to understand their content and context. By comparing these characteristics to a user's viewing history and preferences, the system can recommend similar videos that align with the user's interests.

Collaborative filtering [4, 5] use algorithms to analyze patterns of user behavior and identify users with similar interests or viewing habits. By leveraging this information, the system can recommend videos that have been popular among users with similar tastes, even if those videos are not directly related to the user's previous viewing history.

Deep learning techniques, such as neural networks [6, 7], are used to process large amounts of data and extract meaningful patterns and relationships. These techniques are employed to understand user preferences, identify similarities between videos, and make personalized recommendations based on complex user behavior patterns.

AI algorithms can use reinforcement learning to optimize the recommendation system's performance. By continuously evaluating user feedback, such as watch time, likes, and shares, the system can learn which recommendations are most effective in engaging and satisfying users. It then adjusts its recommendations accordingly to maximize user engagement. AI algorithms can adapt and update recommendations in real-time based on user interactions. For example, if a user watches a video, likes it, and shares it, the system can promptly adjust its recommendations to include similar content that aligns with the user's interests.AI algorithms can take into account contextual information, such as the user's location, device type, and time of day. This information helps tailor recommendations to the user's specific circumstances and preferences, providing a more personalized and relevant experience.

This paper will discuss some basic algorithms within popular video platforms and how they work in terms of recommending the preferred content for the vast number of its users. The drawbacks of the mentioned algorithms and future prospects will be discussed. Lastly, the whole paper will be summarized.

2 Methods

2.1 The Mechanism of Video Recommendation System

The recommendation system in video platforms first collects user data and video metadata. Next, it selects suitable algorithms, such as collaborative filtering or content-based filtering, which are trained using machine learning techniques and historical user behavior data. This process allows the system to make informed recommendations tailored to individual user tastes and interests [8].

When users access the platform, their personal information will be analyzed in real-time and their history will be viewed. The trained model compares such information to generate personalized recommendations. The system uses metrics such as click through rate and user feedback to evaluate recommendations. It conducts A/B testing to compare different recommendation strategies and optimize performance, iterating and improving its algorithm based on the results.

Overall, recommendation systems use artificial intelligence to analyze user data, extract features, train models, and generate personalized video recommendations to increase user engagement and satisfaction.

2.2 Video Recommendation System Based on the TikTok

TikTok is a popular social media platform known for its short-form videos [9]. It utilizes a recommendation system to suggest videos to its users. The recommendation system of TikTok is designed to provide a personalized and engaging content experience.

When interacting with content on TikTok, various signals are sent to the recommendation system. These signals help the recommendation system understand the types of content users may like. It uses these signals to create prediction scores for different videos. This score is an estimate of the likelihood of users' interaction with each video, ensuring a tailored and engaging user experience.

TikTok's content recommendation algorithm is a personalized recommendation system based on deep learning. It can analyze various behavioral data on the platform, such as clicks, browsing, likes, comments, etc., to learn users' interests, preferences, and behavioral habits. Based on this information, it can recommend the most suitable video for users. This system mainly includes the following three steps:

Data collection: This forms the foundation of the recommendation system, with TikTok collecting various behavioral data on the platform, including which videos have been watched, the duration of viewing, and whether there are likes, comments, shares, etc. This data can reflect the level of interest in videos, as well as preferences and styles.

Feature extraction: This is the core of recommendation systems, and TikTok will extract features from the collected data, representing users and the video using vectors to form the user profile and video features. This vectorized representation enables TikTok to better understand the similarities and differences between users and the video

Model training: This is the key to recommendation systems, and TikTok utilizes deep learning models such as neural networks to match the features of user profile and video, calculating the similarity score between each pair of users and the video. These scores will determine which videos should be recommended to user, as well as the order and frequency of recommendations.

2.3 Video Recommendation System Based on the Bilibili

The recommendation system in a well-known video website called Bilibili in China is quite interesting [10]. Here are some mechanisms behind the scenes: Entering Bilibili, there is a clear first level navigation area divided by content type, such as animation, music, dance, technology, etc. Taking the technology area as an example, it can also be expanded into second level navigation areas such as science popularization, social sciences and humanities, public speaking courses, etc. When choosing the science popularization column, users can also see subcategories such as environment, science, biology, and meteorology.

On the submission page, it is noted that users can fill in five fields after uploading a video: section, title, type, tag, and introduction. Tags can be chosen from customized options, recommended sources, or related to specific activities. If a video is profiled before and after submission, the creator's relevant information and content information can be classified as static data. In contrast, specific data performance, which changes over time, is classified as dynamic data.

The recording of playback history allows users to easily track what videos they watched at what time, but users often do not pay attention to where they saw. Instead, they primarily care about whether they can skip the played part the next time they click in.

But the playback time ratio is an important criterion for evaluating video quality: short playback time, users may only be attracted by the number of views or titles to come in and take a look, but they do not actually prefer such content; Medium playback time, users may prefer this type of content, but video duration or quality can affect viewing completeness; The long playback time reflects that this type of content may be of interest to the user. In addition, users' likes, favorites, or dislikes of content on the video details page also reflect their personal preferences; As text data, comments can also reflect the user's preference for content based on their length, emotional bias, and readability.

The above behaviors that can be clearly perceived by users are classified as explicit behaviors, while another type of operations that are not easily perceived by users, such as screen operation trajectory and dwell time, are called implicit behaviors. The latter can not only be used to build user profiles, but also to stimulate explicit behavior, such as triggering the sharing icon to turn into a brightly colored WeChat icon when the duration of stay on Bilibili's video detail page reaches a certain level.

3 Discussion

However, there are many other limitations incorporated when applying AI.

1) The problem of poor interpretability of AI: This is mainly due to the fact that most recommendation systems use complex machine learning algorithms, such as deep learning, which make it difficult to explain and elucidate the internal principles and decision-making processes of these models. In the future, more interpretable methods such as rule-based Expert systems and causal relationship based graph models can be attempted, while incorporating visualization techniques to enhance user understanding.

2) Data privacy and model security issues: User privacy protection is an important challenge that requires the adoption of technologies such as encryption, anonymization, and federated learning to protect user privacy. At the same time, strengthening the security of model training and deployment processes to prevent models from being exploited by hackers and leaking user privacy.

3) Model universality and training cost issues: Currently, most recommendation systems are customized and trained for specific fields or application scenarios, and their universality is poor. In the future, it is possible to develop universal pre training models and use transfer learning and other technologies to reduce training costs for new scenarios while optimizing the model architecture and training algorithms, improving the ability to share parameters and quickly adapt to new environments.

4) Other issues: Recommendation systems are prone to issues such as overfitting and filter bubbles, resulting in a lack of diversity and freshness in recommendation results.

It is possible to explore techniques such as reinforcement learning and diversity optimization to balance the needs of personalized recommendations and increasing diversity.

4 Conclusion

This article provides a comprehensive analysis of recommendation algorithms for social platforms Bilibili and TikTok. Bilibili and TikTok, as popular social platforms nowadays, both use advanced personalized recommendation algorithms. The implementation of recommendation algorithms for these two platforms mainly includes: User behavior modeling: By analyzing user browsing history, likes, shares, and other behavioral data, establish a model of user interests and preferences. Content feature extraction: Extract features from videos, articles, and other content on the platform, including the titles, tags, and content themes of the videos and articles. Personalized recommendation: Based on user models and content characteristics, collaborative filtering, content filtering and other algorithms are used for personalized recommendation to recommend content of interest to users. Feedback learning: By monitoring user feedback on recommended content (clicks, viewing time, etc.), continuously optimizing and adjusting recommendation algorithms. Overall, the recommendation algorithms of both platforms can effectively capture user preferences and recommend content of interest to users. But it can be also found some shortcomings: User experience: overly precise personalized recommendations may create an "information cocoon" that hinders users from accessing fresh and interesting content. Meanwhile, excessive recommendations may also affect the user's content browsing experience. Algorithm fairness: Recommendation algorithms may generate some biases, such as overly focusing on hot content and ignoring obscure content creators, thereby affecting the fairness of content creation. Privacy protection: These platforms collect a large amount of user data for personalized recommendations, and the issue of user privacy protection is worth paying attention to. In the future, the mainstream trends are Enhanced algorithm interpretability: Adopting rule-based recommendation methods to improve algorithm interpretability and enhance user trust in recommendation results. Building a fair recommendation system: Introducing fairness constraints into recommendation algorithms, balancing the exposure of popular and unpopular content, and safeguarding the interests of content creators. Protecting user privacy: By adopting technologies such as federated learning and differential privacy, personalized recommendation services can still be provided while protecting user privacy. In summary, the recommendation algorithms of Bilibili and TikTok have achieved certain results, but further optimization is still needed to improve user experience, ensure algorithm fairness, and strengthen privacy protection to make the recommendation system more comprehensive.

References

1. Zhao, Y.: A Video Resource Recommendation System Based on Deep Learning. In: Intelligent Computing Technology and Automation 2024, pp. 49-58. IOS Press (2024).
2. Gurung, M.I., Bhuiyan, M.M., Al-Taweel, A., Agarwal, N.: Decoding YouTube's Recommendation System: A Comparative Study of Metadata and GPT-4 Extracted Narratives. In: Companion Proceedings of the ACM on Web Conference 2024, pp. 1468-1472 (2024).
3. Zhou, R., Khemmarat, S., Gao, L.: The impact of YouTube recommendation system on video views. In: Proceedings of the 10th ACM SIGCOMM Conference on Internet Measurement, pp. 404-410 (2010).
4. Su, X., Khoshgoftaar, T.M.: A survey of collaborative filtering techniques. Advances in Artificial Intelligence 2009 (2009).
5. Herlocker, J.L., Konstan, J.A., Riedl, J.: Explaining collaborative filtering recommendations. In: Proceedings of the 2000 ACM Conference on Computer Supported Cooperative Work, pp. 241-250 (2000).
6. Landman, T., Nissim, N.: Deep-Hook: A trusted deep learning-based framework for unknown malware detection and classification in Linux cloud environments. Neural Networks 144, 648-685 (2021).
7. Qiu, Y., Wang, J., Jin, Z., Chen, H., Zhang, M., Guo, L.: Pose-guided matching based on deep learning for assessing quality of action on rehabilitation training. Biomedical Signal Processing and Control 72, 103323 (2022).
8. Ko, H., Lee, S., Park, Y., Choi, A.: A survey of recommendation systems: recommendation models, techniques, and application fields. Electronics 11(1), 141 (2022).
9. Wang, P.: Recommendation algorithm in TikTok: Strengths, dilemmas, and possible directions. International Journal of Social Science Studies 10, 60 (2022).
10. Yang, Z., Lin, Z.: Interpretable video tag recommendation with multimedia deep learning framework. Internet Research 32(2), 518-535 (2022).