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Research on Personalized Course Recommendation for Online MOOC Platforms Based on Emotion Recognition

Bing LI[a,b,c,1], Yuqi HOU[a] and Biao YANG[d]
[a] *School of software, Jiangxi Normal University, Nanchang 330022, Jiangxi*
[b] *Research Centre for Management Science and Engineering, Jiangxi Normal University, Nanchang 330022, Jiangxi*
[c] *Jiangxi Provincial Engineering Research Center of Blockchain Data Security and Governance, Nanchang 330022, Jiangxi*
[d] *School of digital Industries, Jiangxi Normal University, Nanchang 330022, Jiangxi*
ORCiD ID: Bing LI https://orcid.org/0000-0002-5246-796X

Abstract. In the era of smart education, online courses as the avant-garde force in the educational field are leading the way in innovating teaching methods. Although online learning platforms provide students with convenient channels for learning, issues such as course quality, personalized service, and learning motivation still exist. This study, based on China University MOOC, proposes a personalized online course recommendation method based on emotion recognition, aimed at deeply understanding students' emotional states to enhance the accuracy and personalization of course recommendations. Initially, this paper collected a dataset of course user comments from China University MOOC and built an emotional dictionary in the education domain to analyze users' emotional states. Combining emotion analysis, user characteristics, and course features, the SAFM and SDFM models were proposed, incorporating a negative sampling method to generate personalized course recommendations. The experiments prove that this method effectively enhances students' learning motivation and participation, offering new insights for the development of online education platforms.

Keywords. Personalized recommendation, smart education, data mining, sentiment analysis, China University MOOC

1. Introduction

In the wave of digitization and intelligence, smart education driven by technology and data has become a new force in education, opening up unprecedented possibilities [1]. Countries are adapting their education policies to this trend, emphasizing the importance of STEM education, personalized learning and online education [2-4]. Online courses, as an important part of smart education, offer more flexible and personalized learning through digital technology, and MOOC platforms, as the main bearers of online education, are favored for their rich course resources and flexible learning time [5-7].

[1] Corresponding Author: Bing LI, E-mail: 004970@jxnu.edu.cn.

However, with the growth in the number of courses and learners on MOOC platforms, the problem of course selection is becoming more pronounced. MOOC recommender systems aim to meet the diverse needs of learners by taking into account learner preferences and past behaviors to recommend relevant courses. Despite the continuous efforts of recommender systems to improve their effectiveness, the complexity of review data and the problem of mismatch between ratings and review sentiment suggest the need for more comprehensive consideration of user feedback. In recent years, integrating sentiment analysis into recommender systems has become a key direction to improve the quality of recommendations. Haojun et al. (2023) proposed a multilayered interactive deep recommendation model that deepens the understanding of user needs through sentiment analysis [8]. The studies of Li Shuzhi et al. (2022) and Hsu et al. (2019) further demonstrate the value of deep sentiment analysis in improving personalized recommendation accuracy [9-10]. The work of Guerreiro and Rita (2020) and Kumar et al. (2020) demonstrates the potential of applying sentiment analysis in recommender systems in different domains [11-12]. The research of Liu and Zhao (2023) and Karn et al. (2023) explores new ways of combining sentiment analysis with other recommender techniques, especially in the e-commerce domain to provide users with more personalized services [13-14]. Together, these studies emphasize the important role of sentiment analysis in improving recommender system performance and user experience. However, current research in online educational recommendation faces the challenge of limited datasets, especially in acquiring high-quality sentiment labeling data. To address these issues, a multi-layer interactive deep recommendation model incorporating sentiment analysis is proposed.

In this paper, based on a large amount of data from MOOC platforms, we propose a multi-layer interactive deep recommendation model that integrates user-course integration and emotion recognition, aiming to solve the multiple challenges in recommendation systems. The main innovations and contributions of this study include:

- Sentiment analysis and user-course integration: By crawling data from MOOC platforms and developing an education review sentiment dictionary, we deeply analyze users' emotional tendencies towards courses.
- Innovative design of recommendation models: Based on deep learning technology, we constructed two new types of online course recommendation models, which are more precisely adapted to users' learning needs and emotional states, and significantly improve the personalization and accuracy of recommendations.
- Extensive empirical support: Utilizing a large amount of data from MOOC platforms, we verified the validity of the models to ensure the reliability and applicability of the research results.

2. Related work

2.1. Data collection

Currently, MOOC platform data are mostly private and rarely disclosed by the owners, which limits the in-depth analysis of platform behavior and learning trends; the disclosed data are often not comprehensive and representative enough, and the differences in the format and structure of the data between different platforms further hinder cross-platform research [15-18]. In this study, we gathered course information from major universities through the MOOC platform's school portal and utilized Python web crawling techniques to simulate user interactions, such as clicking and page-flipping, to collect user, course, and comment data, as shown in Tables 1 to 3. The dataset includes 4,347 courses, 534,291 users, and 747,253 comments, providing new insights into the status and challenges of MOOC education.

Table 1. Partial course information.

Course Name	University	Number of Sessions	Participants	Number of Reviews	Category	Rating
Introduction to Algorithms	Peking University	2	5,527	33	Computer Science	4.8
Recommendation Systems	Peking University	4	1,497	34	Computer Science	4.6
English Reading	Peking University	5	19,010	176	Foreign Languages	4.7

Table 2. Partial user information.

Username	Occupation	Following	Followers	Study Hours	Topic Replies	Likes Received
Luyuanfanglyf	Student	0	0	32	0	0
Group1Class6-Zhang Qiao	Student	0	0	342	6	0
S19181920 Duan Rong	Employed	0	0	473	7	0

Table 3. Partial user comments.

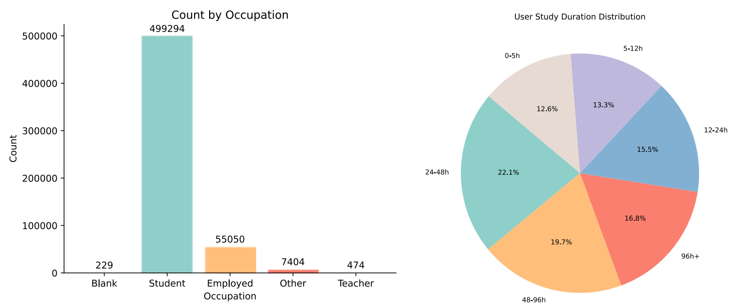
Comment	Comment Date	Likes	Session Number	Rating	Course Name
The content is good, covering many basic algorithms, suitable for an introductory course	2023-01-08 00:00:00	0	2nd Offering	4	Introduction to Algorithms
Very good, just that there are too few courses taught by Teacher Li!	2023-01-06 00:00:00	0	2nd Offering	5	Introduction to Algorithms
Expanded my thinking	2023-01-05 00:00:00	0	2nd Offering	3	Introduction to Algorithms

2.2. Data cleansing

After crawling the data, we performed a comprehensive data cleansing process, which first dealt with missing values, used appropriate padding strategies or deleted some records to fit the data characteristics. Then, we identified and handled outliers, converted and standardized the format and type of all data to ensure data accuracy and ease of analysis. In addition, we performed data de-duplication and removed duplicate records to improve the quality of the dataset. Finally, the scope and distribution of the data were adjusted through data normalization to make the data suitable for subsequent analysis. Regarding the comment data, there were input errors and arbitrariness, which resulted in some redundant and worthless comment texts. Therefore, we specifically performed comment de-weighting, mechanical compression de-wording, and phrase filtering, which significantly improved the data quality and analysis effectiveness.

2.3. Data visualizations

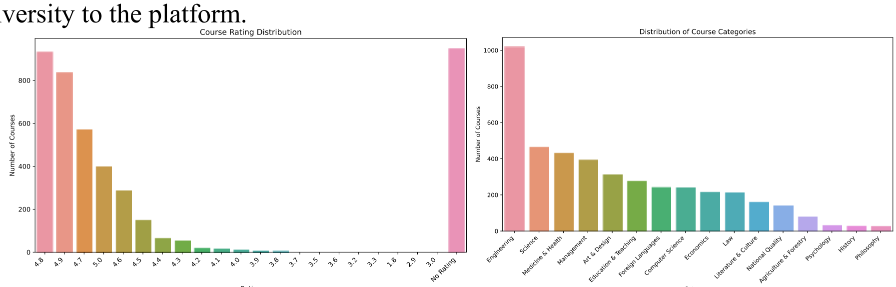
This study analyzes the user behaviors on MOOC platforms and finds, as depicted in Figure 1, that the platform is predominantly used by students and professionals who exhibit diversity in the time they devote to learning. Most users spend more than 24 hours on courses, indicating a willingness to deeply engage with specific subjects, while those studying for "12-24 hours" and "5-12 hours" tend to adopt a more balanced approach. Users who spend "0-5 hours" might only have a preliminary interest or casually browse courses. These insights highlight the need for MOOC platforms to tailor courses to meet different learning preferences and emphasize the importance of personalized services.



(a) Occupation statistics chart. (b) Study duration distribution chart.

Figure 1. Visualization of user behavior data.

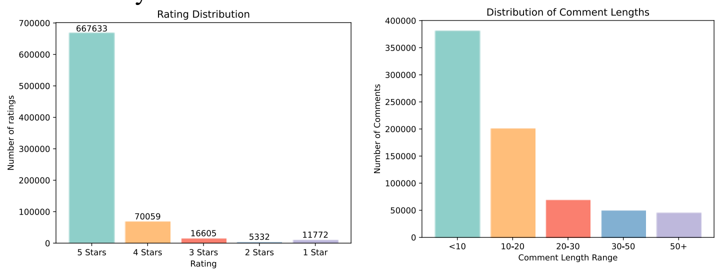
Figure 2 further demonstrates the visualization of course information, with generally high course ratings, particularly concentrated in the 4.8 to 4.9 range, reflecting high user satisfaction with the courses. Engineering courses lead the way in terms of number, highlighting their importance in online education, while science and medical and health courses also have a significant proportion, attesting to the popularity of STEM education. Although courses in Humanities, Economics and Law are lower in number, they provide diversity to the platform.



(a) Distribution of course ratings chart. (b) Distribution of course categories chart.

Figure 2. Course information visualization.

The review system serves as a crucial feedback mechanism for MOOC courses, enhancing the recommendation algorithms through detailed analysis of user reviews, as highlighted in Figure 3. It shows that users are generally satisfied, with a majority giving 5-star reviews and fewer low scores, reflecting positive feedback. Additionally, the average review length is around 18 characters, suggesting that users prefer to express their opinions concisely.



(a) Visualization of rating distribution. (b) Visualization of comment length.

Figure 3. Visualization of comment information.

This study analyzes user reviews by constructing sentiment labels (positive, negative, and neutral) on a MOOC platform, aiming to help the platform fully understand user sentiment and improve course quality and user satisfaction. Four sentiment analysis methods are used: TextBlob library [19], Snownlp library [20], universal sentiment dictionary [21] and self-built thesaurus [22]. TextBlob is good at recognizing neutral sentiments, while Snownlp performs well in the Chinese context but is sensitive to complex semantics. Generalized sentiment dictionaries are widely applicable but may not be precise enough, while self-built thesauri can better reflect domain-specific sentiment but need to be continuously updated. Selecting a sentiment analysis method should be based on application needs and data traits. The analysis in Figure 4 shows that most MOOC users provide positive feedback, with significantly more positive than negative comments. However, a thorough understanding requires considering factors like review content, course diversity, and user characteristics.

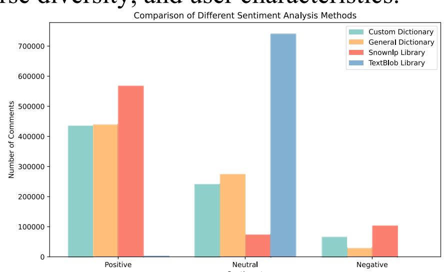


Figure 4. Comparison of different sentiment analysis methods.

3. Multi-layer interactive deep recommendation model

3.1. Overall framework

In this study, we collected data from MOOC platforms using web crawling techniques and created an education-based sentiment dictionary. In addition, we integrated sentiment analysis into the recommender system and applied deep learning models such as DeepFM [23] and AFM [24], which improved the accuracy of the sentiment analysis and strengthened the model's ability to understand the connection between user sentiment and course features. This integration strategy greatly optimizes the online learning experience and provides MOOC users with more accurate course recommendations. The framework is shown in Figure 5.

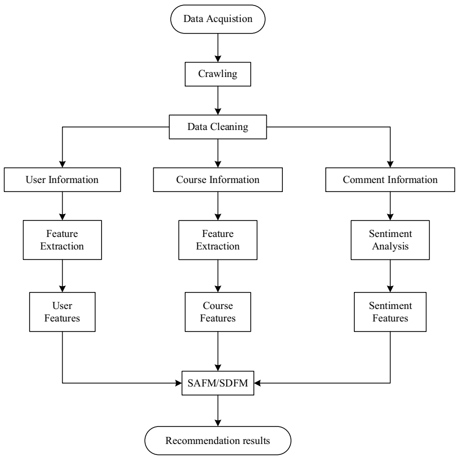


Figure 5. Overall framework diagram.

3.2. SDFM model

The SDFM model is a further innovation based on DeepFM, which combines the advantages of Factorization Machine (FM) and Deep Neural Network (DNN) to effectively capture the low-order and high-order interactions in the data so as to deeply parse the complex data relationships. Its structure is shown in Figure 6. In SDFM, sentiment labels such as 'positive', 'neutral', and 'negative' are encoded as 1, 0, and -1, respectively, and are converted into dense vectors through the embedding layer. Specifically, $\mathrm{V_u}$, $\mathrm{V_c}$, $\mathrm{V_s}$ denote the embedding vectors of user features, course features, and sentiment label features, respectively.

$$\begin{cases} \mathrm{V_u} = \mathrm{Embedding(User\ Feature)} \\ \mathrm{V_c} = \mathrm{Embedding(Course\ Feature)} \\ \mathrm{V_s} = \mathrm{Embedding(Sentiment\ Feature)} \end{cases} \tag{1}$$

The FM part of the model is responsible for computing the first-order and second-order interactions between the features, while the DNN part processes these embedding vectors through a multilayer fully-connected network to introduce nonlinear transformations. Ultimately, the model makes predictions by integrating the outputs of the FM and DNN parts.

$$FM(V_u, V_c, V_s) = \sum_{i=1}^{k} \sum_{j=i+1}^{k} \langle V_{ui}, V_{ci}, V_{si} \rangle \tag{2}$$

$$\mathrm{V_{concat}} = \mathrm{Concatenate}(\mathrm{V_u}, \mathrm{V_c}, \mathrm{V_s}) \tag{3}$$

$$\mathrm{DNN\ Output} = \mathrm{DNN}(\mathrm{V_{concat}}) \tag{4}$$

$$\mathrm{Final\ Output} = \mathrm{FM}(\mathrm{V_u}, \mathrm{V_c}, \mathrm{V_s}) + \mathrm{DNN\ Output} \tag{5}$$

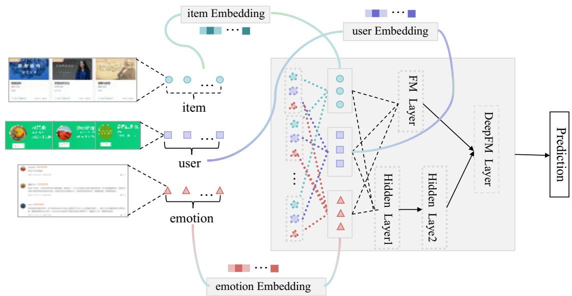


Figure 6. Schematic diagram of SDFM structure.

3.3. SAFM model

The SAFM model is an improvement of the traditional Attention Factorization Machine (AFM) model by introducing sentiment analysis to enhance the understanding and prediction accuracy of users' emotional attitudes. Its structure is shown in Figure 7. In SAFM, sentiment labels such as 'positive', 'neutral', and 'negative' are similarly encoded as 1, 0, and -1 and converted into dense vector form through the embedding layer.

$$\begin{cases} \mathrm{V_u} = \mathrm{Embedding(User\ Feature)} \\ \mathrm{V_c} = \mathrm{Embedding(Course\ Feature)} \\ \mathrm{V_s} = \mathrm{Embedding(Sentiment\ Feature)} \end{cases} \tag{6}$$

The model specifically utilizes the attention mechanism to compute the attention weights between different features, especially the weights of the sentiment labels, which allows the model to focus on the features that have a significant impact on the prediction results. Ultimately, the model utilizes the AFM part of the output for final prediction by calculating the interaction weights of the sentiment labels with other features, a process that significantly enhances the model's ability to utilize sentiment information and its prediction performance.

$$a_i = \frac{\exp(V_s \cdot V_i)}{\sum_{j=1}^{n}(V_s \cdot V_i)} \tag{7}$$

$$AFM\ Output = \sum_{i=1}^{n} \sum_{j=i+1}^{n} a_i a_j \langle V_i, V_j \rangle \tag{8}$$

$$\mathrm{Final\ Output} = \mathrm{AFM\ Output} + \mathrm{Other\ Components} \tag{9}$$

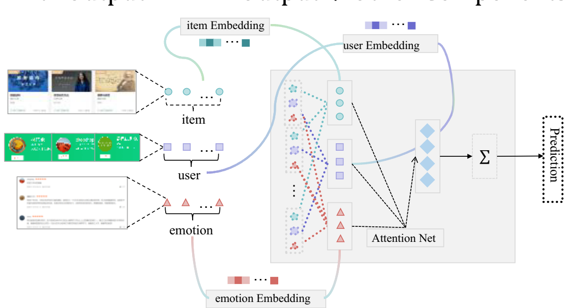


Figure 7. Schematic diagram of SAFM structure.

By integrating sentiment analysis into these models, we enhance accuracy in capturing feature interactions and gain deeper insights into user emotions, enabling more personalized and emotionally-aligned recommendations.

4. Experimentation and evaluation

4.1. Dataset

In this study, we cleaned and preprocessed the self-crawled MOOC dataset, including handling missing and outliers, de-duplication, and text cleaning. We binaryized the user ratings and performed negative sampling to increase data diversity. We then divided the dataset into a training set (80%) and a test set (20%) and saved it in CSV format to prepare it for model training and testing. Through these steps, we ensured the quality of the dataset and built a solid foundation for the sentiment analysis model.

4.2. Assessment of indicators

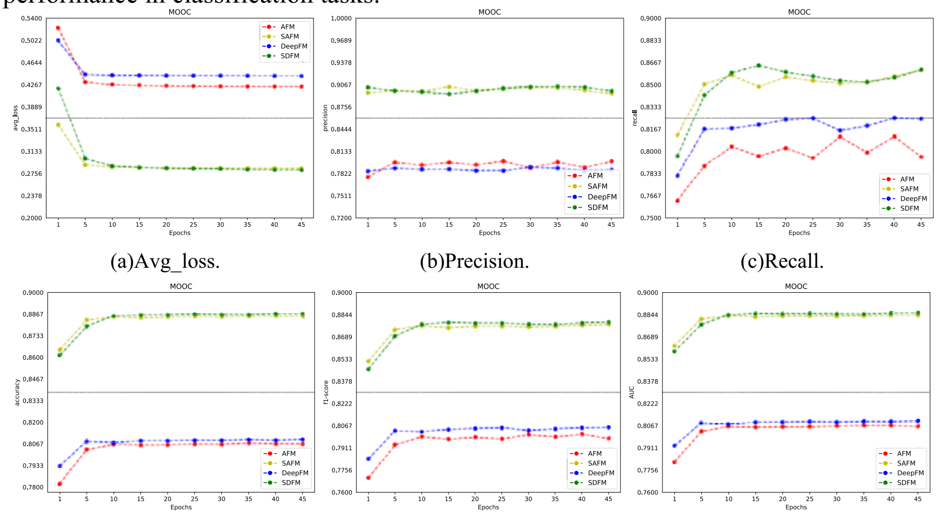
In recommendation tasks, commonly used metrics to evaluate model performance include average loss (a measure of how close the prediction is to the true label), precision (the proportion of actual positive classes that are predicted to be positive), recall (the proportion of actual positive classes that are correctly predicted), accuracy (the proportion of correctly categorized samples), F1 scores (a reconciled average of precision and recall, balancing the performance of the two), and the AUC value (the dichotomous model area under the ROC curve, reflecting classification ability). These metrics combine to reflect the performance of the model in different aspects, which helps in the overall evaluation and optimization of the model.

4.3. Sentiment analysis

In this study, MOOC user comments were analyzed in depth using a Chinese sentiment analysis tool based on the HowNet lexicon. First, text was extracted from the MOOC and Tencent Classroom comment dataset, using a lexical segmentation technique and sorted according to word frequency, so as to filter out the key words that express emotions. Words with insignificant emotional tendencies were manually eliminated and categorized into positive and negative sentiment lexicons, respectively. In the process of sentiment analysis, the effects of adverbs and negatives were taken into account, and the sentiment tendency was determined by calculating the sentiment score of the sentence. This approach not only improves the accuracy of sentiment analysis in the field of education, but through the continuous optimization of the sentiment lexicon, we can understand the emotional responses of MOOC users more effectively, which provides valuable data support for the improvement of educational services.

4.4. Analysis of experimental results

This section analyzes the advantages and performance improvements of the new model by comparing the experimental results shown in Figure 8 and Table 4. First, the average loss of the new model during the training process is significantly lower than that of the old model, which indicates that the new model has a higher training effect. Second, the accuracy of the new model was significantly improved in the testing stage, which not only showed its higher prediction accuracy, but also reflected its reliability in practical applications. In addition, the new model significantly outperforms the old model in the test F1 score, especially in dealing with sample imbalance. Finally, the new model also performs superiorly on the test AUC values, further demonstrating its all-round performance in classification tasks.



(a)Avg_loss. (b)Precision. (c)Recall.

(d)Accuracy. (e)F1-score. (f)AUC.

Figure 8. Comparison chart of experimental results.

Table 4. Schematic diagram of the course information section.

Model	Average Loss	Precision	Recall	Accuracy	F1 Score	AUC
AFM	0.4238	0.8013	0.8111	0.8069	0.8111	0.8071
SAFM	0.2851	0.9088	0.8640	0.8855	0.8783	0.8845
DEEPFM	0.4422	0.7936	0.8332	0.8097	0.8056	0.8103
SDFM	0.2816	0.9044	0.8530	0.8864	0.8792	0.8851

Based on the analysis of experimental results, the SDFM and SAFM models performed the best in precision, recall, accuracy, F1 score, and AUC, achieving precision rates of 0.9044 and 0.9088 respectively. They also scored high in other metrics, demonstrating excellent performance. Although the DeepFM model exhibited intermediate performance in most metrics, it still showed acceptable performance. On the other hand, the AFM model performed the worst across all metrics. Overall, the SDFM and SAFM models may have an advantage in handling recommendation system tasks, as they can better address the feature interactions of multi-source data.

In summary, through comparisons of average loss, test accuracy, test F1 score, and test AUC value, this study concludes that the new model performs better in this task. This finding will contribute to further improvements and optimizations in model design, enhancing its performance and applicability in various domains.

5. Concluding remarks

By exploring the frontier of online course recommendation and sentiment analysis, this study successfully proposes a framework for an intelligent and personalized learning system that integrates deep learning techniques. The system aims to accurately identify and classify learners' emotional tendencies and topics of concern by analyzing course reviews on MOOC platforms and constructing a sentiment lexicon and a review text analysis model, so as to provide course recommendations that are more in line with learners' needs and emotional states. The results of the study show that this recommendation system based on sentiment analysis can provide educators with practical teaching references and learners with timely emotional support to help them effectively face and overcome challenges in the learning process.

However, the study also faces the challenges of data collection and annotation, and future work needs to explore these areas more deeply in order to apply sentiment analysis to MOOC recommendation systems more comprehensively and accurately, and to enhance the system's personalized recommendation level. Despite the limited focus and sample coverage of this study, it provides valuable insights and foundations for the continuous optimization of online education systems and the development of the education field. In conclusion, by continuously improving the level of intelligence and personalization of online course recommendations, this study expects to provide a solid theoretical and practical foundation for achieving high-quality online learning experiences and support, and to contribute to the innovation and progress in the field of education.

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