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ACADEMIC PERFORMANCE RECOMMENDATION SYSTEM

HỆ THỐNG GỢI Ý NÂNG CAO HIỆU SUẤT HỌC TẬP

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ABSTRACT

In today's education system, grades are considered a measure to evaluate they may struggle to identify which subjects align with their abilities. Recommendation systems are currently being widely applied in various fields, especially in e-commerce. Recently, many researchers have started to focus on the field of education. Although there are numerous recommendation algorithms, I will utilize the Biased Matrix Factorization (BMF) algorithm to predict students' academic performance, helping them choose subjects that suit their abilities. The research will focus on studying the model of the primary BMF algorithm.

Keywords. *Biased matrix factorization, matrix factorization, recommender systems.*

TÓM TẮT

Trong hệ thống giáo dục ngày nay, điểm số được coi là một thước đo để đánh giá năng lực học tập của sinh viên. Tuy nhiên, nhiều sinh viên có thể gặp khó khăn trong việc xác định các môn học phù hợp với khả năng của mình. Các hệ thống gợi ý hiện đang được ứng dụng rộng rãi trong nhiều lĩnh vực, đặc biệt là thương mại điện tử. Gần đây, nhiều nhà nghiên cứu đã bắt đầu tập trung vào lĩnh vực giáo dục. Mặc dù có nhiều thuật toán gợi ý khác nhau, nghiên cứu này sẽ sử dụng thuật toán Biased Matrix Factorization - BMF để dự đoán kết quả học tập của sinh viên, từ đó hỗ trợ họ lựa chọn môn học phù hợp với năng lực cá nhân. Nghiên cứu sẽ tập trung vào việc phân tích mô hình của thuật toán BMF cơ bản.

Từ khóa: *Phân rã ma trận có thiên vị, phân rã ma trận, hệ thống gợi ý.*

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1. INTRODUCTION

In the current educational landscape, there is growing attention to personalized support, course counseling, and study path planning. This is particularly relevant in university programs with a credit-based system, where students can choose their courses. While this flexibility is beneficial, it can also lead to challenges if students enroll in classes that do not align with their abilities. This misalignment can result in low grades, negatively impacting both their academic performance and confidence.

Advising students on course selection and study paths requires experienced and dedicated instructors who can analyze and evaluate the curriculum to recommend appropriate courses. This process demands significant time, effort, and resources from universities. Despite the availability of various learning management tools, most do not offer personalized recommendation features, leading to inefficiencies in guiding students through their academic journeys.

Recommendation systems have been extensively developed and utilized, particularly in e-commerce, where they suggest products based on user preferences. Popular recommendation algorithms include content-based filtering, collaborative filtering, and hybrid approaches. However, these algorithms have a common limitation: they rely on user and item features for making recommendations, which makes accurate predictions difficult when those features are sparse or unavailable. While some research has investigated predicting academic performance, these approaches often focus on general evaluations instead of personalized assessments for individual students.

To address these limitations and improve the accuracy of academic performance recommendations, a new academic recommendation system and an innovative recommendation algorithm are proposed. This paper suggests employing the Biased Matrix Factorization (BMF) algorithm to predict students' academic performance. Based on these predictions, the system offers tailored recommendations to help students effectively plan their study paths.

2. RELATED WORK

Recommendation systems have been thoroughly researched and applied in various fields, particularly in education. These systems are essential for personalizing recommendations for users, including suggestions for products, study materials, and academic courses.

Matrix Factorization (MF) is a popular technique used in recommendation systems, known for its effectiveness in handling sparse datasets and improving recommendation accuracy. Koren's seminal work in 2009 introduced the Biased Matrix Factorization (BMF) algorithm, which enhances traditional MF by incorporating bias parameters like user preferences and product attributes. This innovation significantly increased the precision of recommendation systems. Subsequent studies, such as the one by Zhong and Shi-Ting in 2022, have applied BMF to recommend courses for students by analyzing their academic performance and learning histories.

One significant advantage of BMF is its ability to manage sparse and incomplete datasets, a common challenge in educational settings where student data may be irregular or fragmented. By integrating bias parameters, the algorithm improves the predictive accuracy of recommendation systems, especially for students who have not completed all available courses. As a result, BMF is particularly well-suited for educational recommendation systems, where personalization and accuracy are crucial.

This study builds upon previous research on BMF by implementing the algorithm to develop a learning outcome recommendation system for students. The proposed system utilizes existing academic performance data while addressing the issue of data sparsity through the integration of bias parameters for both students and courses. The ultimate goal is to provide accurate and highly personalized predictions to support student learning and academic success.

3. DATA

3.1. Data preparation

To develop any recommendation system, the availability of high-quality data for model training is fundamental. Consequently, data collection represents a critical phase in the construction of such systems. The dataset utilized in this study was obtained from Hanoi University of Industry for the academic year 2022/2023. It comprises student demographic information, a catalog of courses, and students' final grades in each course, assessed on a 10-point scale. The objective is to leverage this dataset to train a recommendation system capable of predicting and suggesting optimal learning outcomes for students. However, the initial dataset may include incomplete fields, such as students who have not enrolled in certain courses, as well as missing or invalid data values.

3.2. Data processing

During the data preprocessing phase, the dataset is refined by eliminating instances containing anomalous values, as real-world data is often incomplete and inconsistent. The collected data undergoes a rigorous cleaning process to identify and address missing values and resolve inconsistencies.

Given the complexity of university databases, the dataset was transformed into a standardized format required by the Biased Matrix Factorization (BMF) algorithm, which involves three key components: users, items, and ratings. The data preprocessing process was conducted in three main steps:

- Conversion of student data into users
Student IDs were converted into integer format to optimize memory usage.

- Conversion of course data into items
Similarly, course IDs were converted into integer format to maintain consistency with the user representation.

- Conversion of grade data into ratings

Final course grades, measured on a 10-point scale, were used as the evaluation metric. For students without recorded final grades, missing values were marked with a "?" and subsequently estimated using bias parameters, including student bias (b_s) and course bias (b_i).

4. METHODOLOGY

The BMF algorithm is a technique in the group of recommendation algorithms based on latent factor models. BMF is an improvement of the Matrix Factorization (MF) algorithm [1], which is a method of decomposing a matrix X into two smaller matrices such that the original matrix X can be reconstructed from these two matrices. The improvement in the BMF algorithm involves incorporating bias values into the matrix factorization model, which allows for more accurate recommendations by taking into account individual biases, such as user preferences or item characteristics.

		Items			
		1	2	3	4
Students	1	9.5	0	8.5	?
	2	10	5	4.5	7.5
	3	?	8	?	5.5
	4	?	?	8	7
	5	5	?	?	?

X matrix

-0.86	0.95
1.08	1.26
-0.17	-1.09
-0.25	-0.06
-0.45	-0.95

W

x

0.45	0.28	-1.27	0.16	K
1.41	-1.24	-0.56	0.79	

H

Figure 1. The matrix factorization model decomposes the matrix X into two matrices W and H based on latent features K

4.1. Matrix Factorization

Decomposing the matrix X into two smaller matrices W and H such that X can be reconstructed from these two matrices, as described in [1]:

$W \approx XH^T$

Where K is the talent feature, and K << |S|; K << |I|

The training process using the BMF algorithm is carried out according to the following formula:

Where $W \in R^{SxK}$ and $H \in R^{IxK}$

Prediction formula, as explained in [1]:

$\hat{p}_{si} = \sum_{k=1}^{K} w_{sk}h_{ik} = w_s h_i^T$

In the Matrix Factorization algorithm, we perform training to find the two optimized parameters, W and H. The method involves initializing two matrices with random values based on a normal distribution, with a standard deviation of 0.01. The error function is calculated as follows, as mentioned in [1]:

$O^{MF} = \sum_{(s,i,p) \in D^{train}} e^2{}_{si}$

Where:

$e^2{}_{si} = (p_{si} - \hat{p}_{si}) = (p_{si} - \sum_{k=1}^{K} w_{sk}h_{ik})^2$

Next, we aim to minimize this error and update the values of W and H iteratively using the Gradient method, as described in [2]:

$$\frac{\partial}{\partial w_{sk}} e_{si}{}^2 = -2e_{si}h_{ik} = -2(p_{si} - \hat{p}_{si})\, h_{ik}$$

$$\frac{\partial}{\partial w_{ik}} e_{si}{}^2 = -2e_{si}h_{sk} = -2(p_{si} - \hat{p}_{si})\, h_{wk}$$

After obtaining the gradient values, we update the values of w_{sk} and h_{ik} with the learning rate β, as mentioned in [2]:

$$w'_{sk} = w_{sk} - \beta\frac{\partial}{\partial w_{sk}} e_{si}{}^2$$

$$= w_{sk} + 2\beta e_{si}h_{ik} = w_{sk} + 2\beta(p_{si} - \hat{p}_{si})h_{ik}$$

$$h'i_k = wi_k - \beta\frac{\partial}{\partial w_{ik}} e_{si}{}^2$$

$$= hi_k + 2\beta e_{si}w_{sk} = h_{ik} + 2\beta(p_{si} - \hat{p}_{si})w_{sk}$$

We repeat the process of updating the values of W and H until the error reaches an acceptable level or the specified number of iterations is reached.

To address overfitting, we use the regularization term, as explained in [2]:

$w'_{sk} = w_{sk} + \beta(2e_{si}h_{ik} - \lambda w_{sk})$

$h'_{ik} = w_{ik} + \beta(2e_{si}w_{sk} - \lambda h_{ik})$

4.2. Improve the MF technique to the Biased Matrix Factorization algorithm

As mentioned in the introduction, due to various factors such as differing levels of difficulty and requirements of the course, or influences from students such as being talented, smart, or lazy, the recommendations can be skewed. To address this issue, I added a bias term to the prediction model, transforming Standard Matrix Factorization into Biased Matrix Factorization.

To predict the ability of student s for course i, the following formula is used:

$\hat{p}_{si} = \mu + b_s + b_i + \sum_{k=1}^{K} \omega_{sk}h_{ik}$

With the value μ representing the global average, which is the score of all students across all courses with the training dataset.

$\mu = \frac{\sum (s,i,p) \in D^{train}\, P}{|D^{train}|}$

The value b_s represents the bias of the student (the average value of a student compared to the global average μ).

$$b_s = \frac{\sum (s', i, p) \in D^{train} \mid s' = s(p - \mu)}{|\{(s', i, p) \in D^{train} \mid s' = s\}|}$$

The value b_i represents the bias of the course (the average value of a course compared to the global average μ).

$$b_i = \frac{\sum (s, i', p) \in D^{train} \mid i' = i(p - \mu)}{|\{(s, i', p) \in D^{train} \mid i' = i\}|}$$

Since there are changes in the bias values of both the student and the course, the error rate also changes according to the following formula:

$$O^{BMF} = \sum_{(s,i,p) \in D^{train}} \left(p_{si} - \mu - b_s - b_i - \sum_{k=1}^{K} \omega_{sk} h_{ik}\right)^2 + \lambda(||W||_F^2 + ||H||_F^2 + b_s{}^2 + b_i{}^2)$$

4.3. Pseudocode

Begin Biased-Matrix Factorization (D_train, K, β, λ, iter)

// Initialize the global bias μ as the mean of all ratings in D_train

μ ← Sum of all scores p_si in D_train / Number of elements in D_train

// Compute student bias

for each student s in S:

b_s[s] ← Sum (p_si - μ) for (s, i, p_si) ∈D_train where s == student / Number of ratings for s

// Compute item bias

for each item i in I:

b_i[i] ← Sum (p_si - μ) for (s, i, p_si) ∈D_train where i == item / Number of ratings for i

// Initialize latent matrices W and H with random values from a normal distribution N(0,σ^2)

W ← Random(N(0,σ^2))

H ← Random(N(0,σ^2))

// Training loop

for iter times or until convergence:

(s, i, p_si) ← Randomly select a pair (s, i, p_si) from D_train

// Predict the rating

*p_hat ← μ + b_s[s] + b_i[i] + Sum(W[s][k] * H[i][k]) for k ∈[0, K)*

// Compute the prediction error

e_si ← p_si - p_hat

// Update global bias

*μ ← μ + β * e_si*

// Update student and item biases

*b_s[s] ← b_s[s] + β * (e_si - λ * b_s[s])*

*b_i[i] ← b_i[i] + β * (e_si - λ * b_i[i])*

// Update latent factors W and H

for k in range(K):

*W[s][k] ← W[s][k] + β * (e_si * H[i][k] - λ * W[s][k])*

*H[i][k] ← H[i][k] + β * (e_si * W[s][k] - λ * H[i][k])*

return (W, H, b_s, b_i)

End

5. RECOMMENDATION

Based on the processed dataset, which includes tables for users, items, scores, and the W and H matrices decomposed from the X matrix, I proceeded to train the model using the BMF algorithm. This was done to optimize the W and H matrices, as well as the bias values. The training results indicate that the model is highly effective, as the error function (15) continues to converge with each iteration.

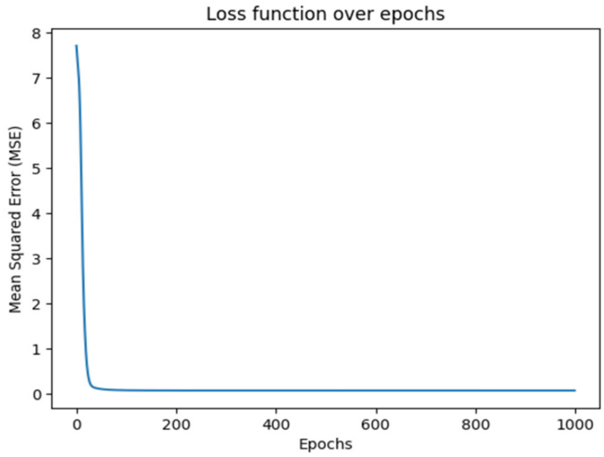

Figure 2. The error function value increasingly converges

After the training process, we obtain the two matrices W and H and the optimized bias values. I then proceed to predict the scores of students corresponding to courses with a score of 0. The process of predicting the score of a student is as follows:

The prediction formula for the score of student s in course i is: $\hat{p}_{si} = \mu + b_s + b_i + w_s h_i{}^T$

		Items			
		1	2	3	4
Students	1	9.5	5.6	8.5	7.8
	2	10	5	4.5	7.5
	3	6.21	8	7.95	5.5
	4	8.11	7.07	8	7
	5	5	6.44	7.02	4.56

X matrix

-0.86	0.95
1.08	1.26
-0.17	-1.09
-0.25	-0.06
-0.45	-0.95

W

x

0.45	0.28	-1.27	0.16
1.41	-1.24	-0.56	0.79

H

K

P33 = 7.08 + -0.05 + 0.09 + (-0.17 * -1.27 + -1.09*-0.56) = 7.95

Figure 3. The predicted score for student 3 in course 3

6. EVALUATION

Several methods have been implemented to evaluate the quality (performance) of a recommendation system. The most common method for evaluation is Root Mean Squared Error (RMSE), which measures the difference between actual and predicted values. The smaller the RMSE value, the more accurate the predictions of the recommendation system. The formula for RMSE is as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{|D^{test}|}\sum_{(u,i,y)\in D^{test}}(y_{ui} - \hat{y}_{ui})}$$

The RMSE value of the BMF model after training on an initial training dataset is 0.276, while for MF it is 0.473. This value demonstrates the superior effectiveness of the BMF model in predicting student grades.

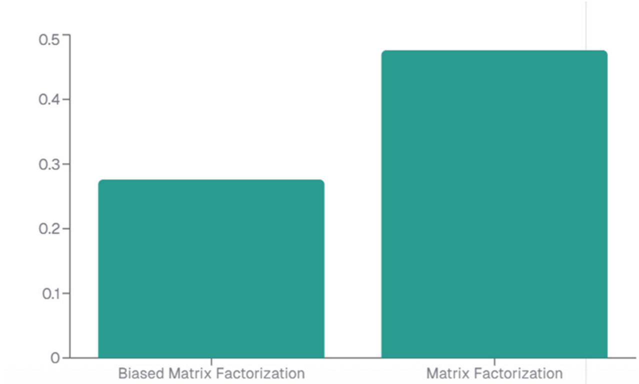

Figure 4. Comparison of Biased Matrix Factorization and Matrix Factorization

7. CONCLUSION AND FUTURE WORK

This report outlines a method for predicting academic performance and offering appropriate course recommendations. The proposed algorithm, called Biased Matrix Factorization (BMF), shows superior performance compared to other recommendation algorithms, such as traditional Matrix Factorization. Experimental results demonstrate that the BMF model effectively addresses the limitations of these alternative algorithms, confirming its effectiveness in assisting students with course selection, improving academic performance, and boosting their confidence. The system not only aims to recommend courses but also helps optimize school resources by reducing the reliance on lecturers for advice.

In future research, I plan to address the cold-start problem. The current system depends on student score data and learning history. To enhance applicability for new students or courses that lack data, future studies will incorporate additional recommendation system techniques, such as Collaborative Filtering and Content-based Filtering. Furthermore, we will use personalized data, including individual preferences, career goals, and students' learning abilities, to improve the personalization and quality of recommendations.

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