Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 129 (2018) 449–453

Procedia Computer Science

www.elsevier.com/locate/procedia

2017 International Conference on Identification, Information and Knowledge in the Internet of Things

Intelligent Recommendation System for Course Selection in Smart Education

Jinjiao Lin[a,b,*], Haitao Pu[c], Yibin Li[b] Jian Lian[c]

[a] School of Control and Engineering, Shandong University
[b] School of Management Science and Engineering, Shandong University of Finance and Economics
[c] Shandong University of Science and Technology

Abstract

Being an essential component of smart education, we propose a novel recommendationsystem for course selection in the specialty of information management inChinese Universities.To implement this system, we firstly collect the course enrollment data-set for specific group of students. The sparse linear method (SLIM) is introduced in our framework to generate the top-N recommendations of courses appropriate to the students. Meanwhile, aL_0 regularization term isexploited as the optimization strategywhich is established on the observation of the course items in the current recommendation system. The comparison experiments betweenstate-of-the-art methods and our approachare conducted to evaluate the performance of our method. Experimental results of different topics and number of courses both show that our proposed method outperforms state-of-the-art methods both in accuracy and efficiency.

Keywords: Course Recommendation System; Sparse Linear Method;Smart Education

1. Introduction

Smart education is the conception to describe the brand new learning process in the information era[1]. It has attracted plenty of attention from experts of various researching fields for recent decades. As learning could be

* Corresponding author. Tel.: +86-531-8699-0201 ; fax:+86-531-8699-0201.
E-mail address: linjj112@163.com

10.1016/j.procs.2018.03.023

undertaken anytime, anywhere in the smart education context by using the intelligent devices and the number of courses in the framework of smart education has greatly increased, the corresponding course selection issue is playing a significant role in the process of modern education and has transferred into the determination of the curriculum that are suitable for the students accurately and efficiently. In the past, a plethora of methods and algorithms[2,3] for course selection have been proposed to deal with course recommendation problem. However, none of them was specifically designed for the requirements of smart education.

A great deal of the methods proposed for the course selection in recommendation systems can be categorized into three different groups, which are collaborative[8], content-based[7], and knowledge-based[5,8]. They all have been applied in different fields such as in [4] a collaborative filtering based artificial immune system was implemented in the course recommendation for college students and the rating results acquired from the teachers were considered as the ground truth of the evaluation outcomes.

According to the requirement of course selection for intelligent recommendation in smart education and inspired by the idea presented in [4, 9], we propose a sparse linear based technique for top-N course recommendation through both adding the expert knowledge and sparseness regularization in the computation. The presented method could extract the inner structure and information of the courses existed in the education management system from the student/course relationship by constraining the newly proposed regularization term optimized calculation. The characteristics of sparseness was introduced to diminish the complexity (or the feature space dimension) of the course recommendation matrix. Sparse linear method (SLIM)[9] was also introduced to our top-N recommendation system, which is hardly exploited in smart education before. According to the characteristics of course recommendation system in Chinese Universities, the technique that we proposed mainly focuses on the accuracy of course recommendation comparing with the ground truth that we collected with experts' discussion. It differs from the original SLIM based methods[6,9], which is mainly used to addresses the applications of top-N course recommendation in real time.

Base on our previous researches on the regular recommendation system computation, most of the entries in course selection matrix are assigned with the same initial value (zero), while the gradients of adjacent entries also have the same assigned values. Therefore, the sparse strategy through the introduction of L_0 regularization term was initially taken as the optimization framework of SLIM. The L_0 terms can globally constrain the non-zero values of entries and the gradients in the recommendation system matrix, which is also treated as the primary contribution of our proposed method. Different from the other commonly used regularization terms (e.g., the L1 and L2 terms), the L_0 regulation term can maintain the interior and subtle relationship between the pair of entries in the course selection matrix while controlling the sparseness.

After the process of data gathering, comparison experiments between state-of-the-art methods and our method are carried out. Both the experimental results of state-of-the-art methods and our method are evaluated with the course recommendations presented by several educational experts

2. Our method

In the following sections, t_j and s_i are used to represent every course and every student in the proposed course recommendation system, respectively. The intact student-course relationship will be calculated with a matrix A (size of $m \times n$), in which the entry is either 1 or 0 (where 1 denotes the student has taken the course, and 0 denotes that the student has not taken the course).

In the proposed framework, a sparse linear method is used to implement the course selection pipeline. In our method, a score of course recommendation on each empty entry with a course t_j and a student s_i is computed with the sparseness aggregation strategy, the general process is shown in Eq.(1).

$$\overline{a_{ij}} = a_i^T w_j \qquad (1)$$

where a is the initial course selection of a specific student and w_j is the sparse vector of aggregation coefficients. The model of SLIM in the form of matrix is modified into:

$$\overline{A} = \underline{A}W \qquad (2)$$

Where $\underline{A}$ denotes the firstly given value for the initial matrix, A denotes the potential binary student-course matrix, W denotes the $n \times n$ sparse matrix of aggregation coefficients, in which j - th column corresponds to w_j as in Eq.(1), and each row of $C(c_i)$ is the course recommendation scores about the selected courses for student s_i. The final course recommendation result of each student is finished by arranging the non-taken courses in a decreasing sequence, and the first N courses in the queue are the final recommendation result.

The initial student/course matrix is extracted from the learning management system of a specific University in China. With the extracted student/course matrix of size $m \times n$, the sparse matrix W size of $n \times n$ in Eq.(2) is iteratively optimized by using the alternative minimization procedure. Different from the objective function previously proposed in[9] shown in Eq.(3),

$$\min_{W\geq 0}\frac{1}{2}\|A-AW\|_2^2+\frac{\beta_2}{2}|W\|_F^2+\lambda_2\|A\|_0+\mu|\nabla A|_0 \qquad (3)$$

our proposed method is listed as follows in Eq.(4):

$$\min_{W\geq 0}\frac{1}{2}\|A-AW\|_2^2+\frac{\beta_1}{2}|W\|_F^2+\lambda_1\|A\|_1 \qquad (4)$$

Where $\|.\|_F$ denotes the Frobenius norm, $\|W\|_1$ is the L_1 norm operator, $\|W\|_0$ denotes the entry-wise L_0 norm used to constrain the number of zero entries in a matrix. The data term $\|A - AW\|$ is presented to measure the difference between the generated outcome and the training data-set. The $L_F - norm$, $L_1 - norm$, and $L_0 - norm$ are integrated to control the entries characteristics of the coefficient matrix W, A,and ∇A, respectively. The parameters $\beta_1, \beta_2, \lambda_2$, and μ are used to balance the weights for regularization terms in the objective function.

In the final form of our objective function, the L_F norm is mainly exploited to transfer the optimization problem to diminish the over-fitting of the learning process. Moreover, the L_1 norm in Eq.(3) is adapted to the L_0 norm in the final objective function. The new L_0 norm is introduced to express both the sparseness of the matrix A and ∇A.

Furthermore, the final objective function in Eq.(4) could be decoupled into a set of objective functions because the orthogonality of any pair of columns in matrix W,:

$$\min_{w_j\geq 0, w_j, j=0}\frac{1}{2}\|a_j-a_jw_j\|_2^2+\frac{\beta_2}{2}|w_j\|_F^2+\lambda_2\|a_j\|_0+\mu|\nabla a_j|_0 \qquad (5)$$

where a_j is the j column of matrix A, w_j denotes j column of matrix W. We propose to use the alternate minimization strategy to calculate the outcome.

3 Experimental Results

3.1 Data-sets

To evaluate the performance of our method, comparison experiments between state-of-the-art recommendation methods and our method were carried out at the same time.

Table 1. The initial data obtained from the students (Ci denotes each course)

No.	C1	C2	C3	C4	C5	C6
1	1	1	1	0	1	0
2	0	1	1	0	1	0
3	0	1	1	0	1	1
4	0	1	1	0	1	1
5	1	1	1	1	1	0
6	1	1	1	1	1	0
7	0	1	1	1	1	0
8	1	1	1	1	1	1
9	1	1	1	0	1	1
10	1	1	1	0	1	1
11	0	1	1	0	1	0
12	0	1	1	0	1	1
13	0	1	1	1	1	0
14	1	1	1	1	1	1
15	1	1	1	1	1	1
16	0	1	1	0	1	1
17	1	1	1	1	1	1

3.2 Measurement

We both use the hit rate (HR) and the average reciprocal Hit-Rank (ARHR) in to measure the corresponding calculation results. The two measuring metrics are shown in Eq.(6) and Eq.(7), respectively.

$$HR = \frac{\#hits}{\#students} \qquad (6)$$

where*#hits* denotes the number of students whose course in the testing set is practically selected, and *#students* denotes the number of students covered in the data-set.

$$ARHR = \frac{1}{\#\text{students}} \sum_{i=1}^{\#hits} \frac{1}{p_i} \qquad (7)$$

Where p_i is the course selection's queue.

3.3 Experimental Results

Table 2 shows the comparison results of state-of-the-art methods and our method for top-N course selection in this study.

Table 2. The performance of the comparing methods

	HR_1	$ARHR_1$	HR_2	$ARHR_2$
kNN	0.18	0.13	0.19	0.14
Itemprob	0.21	0.15	0.19	0.16
P-SVD	0.09	0.11	0.10	0.12
SLIM	0.24	0.16	0.17	0.18
ours	0.27	0.17	0.19	0.17

where HR_i, $ARHR_i$ denotes the performance forstudents in $class_i$.

To exhibit the performance of our proposed method with different quantity of courses and topics, we carried out two other comparison experiments. The experimental results show in Fig.1 and a increasing trend of accuracy is obtained when more courses are added.

4 Conclusion

To improve the availability and effectiveness for the intelligence of smart education, we propose an optimization framework based approach for course recommendation system. To evaluate the performance of our method, comparison experiments on students between state-of-the-art methods and our method are conducted. The experimental results of hit rate, average reciprocal Hit-Rank all show that our method outperforms the other methods. Furthermore， we use the accuracy of different number of courses and themes of courses to evaluate the effectiveness of our method, and the results again support the optimum of out approach.

Acknowledgments

This work was financially supported by the Teaching ReformResearch Project of Undergraduate Colleges and Universities of ShandongProvince (2015M111, 2015M110，2015M136，Z2016Z036) and the Teaching Reform Research Projectof Shandong University of Finance and Economics (2891470，jy201438), SDUST Young Teachers Teaching Talent Training Plan(BJRC20160509); SDUST Excellent Teaching Team Construction Plan; Teachingresearch project of Shandong University of Science and Technology (JG201509 and qx2013286); Shandong Province Science and Technology Major Project (No.2015ZDXX0801A02) and National Nature Science Foundation of China (Grant No. 71402084).

References

[1] Zhu Z, Yu M, Riezebos P, et al.(2016) "A research framework of smart education" *Smart Learning Environments* 3(1).

[2] Babad E, Tayeb A. (2003) "Experimental analysis of students' course selection" *British Journal of Educational Psychology* 73(3): 373-393.

[3] Gil A B, Garciapenalvo F J. (2008) "Learner Course Recommendation in e-Learning Based on Swarm Intelligence"*Journal of Universal Computer Science*: 2737-2755.

[4] Chang, P., Lin, C., Chen, M. (2016)"A hybrid course recommendation system by integrating collaborative filtering and artificial immune systems. " *Algorithms* 9(3): 47.

[5] Chen, Y., Cheng, L., Chuang, C. (2008)"A group recommendation system with consideration of interactions among group members." *Expert Systems With Applications* 34(3): 2082-2090 .

[6] Chris, E., Karypis, G.(2014)"Hoslim: Higher-order sparse linear method for top-n recommendation systems": 38-49 .

[7] Kim, E., Kim, M., Ryu, J.(2004)"Collaborative filtering based on neural networks using similarity. International symposium on neural networks ": 355-336 .

[8] Mclaughlin, M., Herlocker, J.L.(2004)"A collaborative filtering algorithm and evaluation metric that accurately model the user experience": 329-336 .

[9] Ning, X., Karypis, G.(2011)"Slim: Sparse linear methods for top-n recommendation systems": 497-506 .

Fig.1 Accuracy of our proposed method