Machine learning-based classification of academic performance via imaging sensors

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***Abstract*—Teaching is the primary component of the educational process for college students. To achieve the training objectives of different subjects, every University has arranged various types of courses. The ultimate purpose of teaching activities for these courses consists of improving the students' knowledge level, ability level, and quality level. However, most of the current teaching activities only focus on the evaluation system and performance evaluation method for each course, thus lacking an overall academic performance and evaluation pipeline designed for the influence of different courses on students' future development. Bearing the above-mentioned analysis in mind, we introduced machine learning-based techniques into students' academic performance analysis and leveraged the learning-based approaches of rank models to establish a framework for students learning ability analysis. By employing imaging sensors, the capability of multiple media including image and video has also been embedded into the proposed architecture. Meanwhile, we exploited the pipeline for different students academic performance to reveal the academic commonality among students and the different influence of the primary courses for students' future development between different groups.**

***Index Terms*—classification, machine learning, ranking learning, education data.**

I. Introduction

Academic performance is the primary indicator of academic achievement evaluation, it is also the core content of higher education evaluation. The student achievement evaluation plays a vital role in reflecting the practical situation of teaching,can be exploited to improve the teaching quality and promote teaching reform. Besides, the evaluation of students' learning effectiveness is of great significance to the inspection and improvement of teaching quality and the optimization of students' management. Specifically, the ministry of education in China has paid great attention to the students' learning effectiveness in the latest undergraduate teaching evaluation, which has become a hot issue in higher education theory and practice. Furthermore, the academic performance of college students is an important indicator to reflect the achievements and potentials of the students' professional development. It is also an important basis for the selection of students by colleges and universities. The scientific and rigorous evaluation of academic performance is relative to the authority and fairness of the teaching and management in the universities.

Academic performance not only can provide the basic function for evaluation and diagnosis and forecast the students ability, but also has great guiding function [1]. For example, the review of scholarship requires comprehensive evaluation according to the course grade statistics, the postgraduaterecommendation needs to provide the professional ranking of core courses, and studying abroad requires computing the average grade point [2]. In addition, the academic performance evaluation has a significant influence on the teaching content, methods, and management.

However, due to the influence of many factors for highereducation in China, there are undesirable tendencies or disadvantages of the following aspects in the practice of academic performance evaluation [3][4]: 1) credit reference is given priority to the evaluation, the form is too simple or confined, attaching great importance to the set of the evaluation and ignoring the feedback of students' development; 2) neglecting the development of a variety of students, general motors, and the single evaluation rules, can not reflect the different students' ability with categorical discrepancy; 3) some teachers tend to adopt the paper examination as the primary testing pattern. However, the pure testing scores in the curriculum can not reflect the practical ability of the students, while the sorting result might conflict with the comparison of the corresponding activities; 4) rareness of the evaluation on the academic performance itself, it requires of the assessment of the feedback information to promote teaching activities, relative management departments should be inspected, reflected and enhanced, periodically.

The ranking is a popular researching area in information retrieval and machine learning. It refers to solving the sorting problem by using machine learning algorithms to train the dataset and generate the sorting model automatically. Compared with the traditional sorting method with numerous fixed parameters, the advantage of ranking includes that the embedded features can be integrated and optimized, and a large number of corresponding parameters can be learned automatically. Finally, a more efficient, accurate and optimized sorting model can be obtained. This kind of method is very suitable for the academic performance ranking evaluation problem with feedback ability.

Above all, an intelligent sorting method with better performance for academic performance evaluation is provided. Meanwhile, the evaluation result can not only reflect the reality of the students learning ability but also can be used to

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estimate the teachers teaching situation according to academic performance. In this study, we present a learning to rank-based evaluation approach for academic performance analysis and classification, which can change this bad situation and improve the comprehensive academic performance evaluation system. To guarantee the precision of the proposed framework, the imaging sensors were employed to capture the students academic performance. To be specific, digital cameras were leveraged to record the details of the students presentation and examination process. Accordingly, their academic performance can be evaluated and by the instructors with assigned scores.

This paper introduced our machine learning technology in students' academic performance analysis. Contributions are included as learning to rank for analysis of students' academic performance, and our framework for academic difference analysis among different students. First, the learning to rank model is used to build a framework for students' learning ability analysis. Second, a framework is proposed for different students academic difference analysis in order to find academic commonality among students and the different influence of the main courses for students' future development between different groups.

The organization of the paper is as follows: Section II presents the related work of analysis and classification of academic performance of students involvement. Section III introduces our learning to rank model and framework to make analysis and classification of academic performance based on machine learning. Section IV presents the experimental result. Conclusions and future work are outlined in the last section.

II. Related work

A. Evaluation of Student Learning

Evaluation of student learning is a hot research area in computer science courses [5]. Evaluation and assessment require thoughtful planning and implementation to support the learning process and to inform teaching. All evaluations of student achievement must be based on the outcomes in the provincial curriculum. There are a lot of commercial and academic student grading systems [6][7][8]. These systems provide support for the submission of student deliverables and artifacts. Most of the teaching activities only focus on the evaluation system and performance evaluation method of each course. However, it lacks analysis of students' overall academic performance and evaluation of the influence of different courses on students' future development [9]. These systems were created primarily for classroom use and are not tools used in the industry. Compared with current methods and systems, we introduce machine learning technology in students' academic performance analysis, use the learning to rank model to build a framework for students' learning ability analysis [10]. Evaluation involves the systematic collection of information about student learning with respect to achievement of curriculum outcomes, effective teaching strategies, and student self-reflection on learning.

B. Predication of Academic Performance

In China's education, the evaluation of students' academic performance depends on standardized tests and the evaluation system [11]. It includes the test grade, the test score, whether the test score is passed or not, whether the first time to take the test is passed or not. Limited by the implementation of standardized tests, on-campus paper-and-pencil tests, course papers, classroom learning evaluation, professional practice constitute the main links of student learning evaluation [12]. School examination is the core of the evaluation, with some advantagessuch as simple, time-saving, economy, strong adaptability, but the drawback is that the many courses in universities have no unified syllabus, have no teaching quality evaluation system, teachers' proposition subjectivity is very strong, they could hardly balance the reliability, validity, difficulty, and degree of the examination questions.

Traditionally, many teachers have evaluated their students by giving examinations and homework, often only at the middle and end of the semester [13]. As a result, a professor lecturing to a large introductory class might not recognize until final exams are finished that students consistently confused two important and closely related ideas. On the other hand, the score is not the object for student learning, and helping students gaining the ability is the essential purpose for student learning.

C. Sorting in information retrieval

In information retrieval, the traditional sorting models mainly includes relevance sorting model and importance sorting model, such as HITS[14], TrustRank[15], BrowseRank[16], ClickRank[17] and so on. The process of constructing the traditional sorting models usually adjusts some parameters involved in the sorting model manually based on experience, but these empirical parameters are difficult to adjust and easy to produce overfitting. On the other hand, although the different sorting models generally make sorting result in obtaining a certain performance improvement, how to sort different models together to build a better uniform sorting model is not easy. At the same time, as the available features that affect the performance are increasing, there have been hundreds of sorting features, traditional sorting models are no longer suitable for handling such multidimensional and complicated sort features.

Kleinberg developed the HITS algorithm [14], being aimed at rate web pages. There are for two types of pages in the algorithm: hubs and authorities. In the HITS algorithm, a hub refers to many authorities, and authority is a page with many incoming links from different hubs. Deguchi et al. [18] can calculate the values of the weighted HITS hub and authority for each country in a conjugate way. They showed the time evolution of world trade in terms of hub-authority, and they found that some of the typical behaviors are consistently explained by changes in countries and international relations. Zhang et al. [19] generalize the similarity of web pages and propose a query-induced similarity describing how a webpage is similar to another on a query topic and provide a new improved weighted hits-based (I-HITS) algorithm by assigning appropriate weights to links with the similarity and popularity of web pages. Yang et al. [20] improved the HITS algorithm has enhanced the correlation of search results and limited the occurrence of topic drift to some degree. Radu Soricut et al [15] describe TrustRank with a capability to rank the quality of translation output from good to bad. They quantify the gains they obtain in translation quality, and show that their solution works in a wide variety of domains and language pairs. Zou et al [21] develop a recommended system based on TrustRank which handles the Cold-start problem in user trust network which is commonly available for e-commerce applications. They devise an iterative computation algorithm of the original personalized TrustRank which can incrementally compute trust vectors for Cold-Start users. They conduct extensive experiments to demonstrate the consistent improvement provided by our proposed algorithm over the existing algorithms on the accuracy of Cold-Strat users.

D. learning to rank

Machine Learning-based method can automatically adjust the parameters, the result from the fusion of multiple models through the way of regulation to avoid overfitting. In such a context, there are a large number of research work using different machine learning techniques to train sorting model to solve the ranking problems in information retrieval. That led to a hot research field in the intersection of information retrieval and machine learning [22][23]. Learning to rank is to use machine learning methods to learn on the training dataset, automatically generate sorting model to solve rank problems. Compared with traditional models, the advantage of the learning methods lies in the combination and optimization of many features, which need a large number of parameters that need to be optimized automatically and end up with high precision.

Learning to rank (L2R) for information retrieval has been received a lot of attention from the research community. Recently, there are new methods. A new ranking approach for information retrieval is proposed where the diversity among queries was taken into consideration [24]. The authors treated the probability distribution of retrieved documents by relaxing assumption. A Bayesian learning approach is proposed to promoting diversity for information retrieval in biomedicine and a re-ranking model to improve retrieval performance in the biomedical domain [25]. The problem of retrieving images relying on a content-based approach is proposed based on genetic programming and association rules [26]. In document summarization, RankNet [27] and single document [28] is used to rank by features.

III. OUR METHOD

A. Problem setting

Suppose X is a set of students and $\mathcal{X}_i$ is one studentin the data samples. In this model, a data record contains several features as $x_i = (x_{i,1}, x_{i,2}, x_{i,3} \ldots)$. And y_i is the corresponding students status or so-called label. With thedefinition, we have the training data samples:

$$\mathrm{D} = \{(x_1, y_1), (x_2, y_2), (x_3, y_3) \ldots\} \quad (1)$$

By training on the dataset D, we continue to leverage a sorting function $f(x)$ to implement the ranking for all of the students sequentially.

$$f(x) = \omega^T x \quad (2)$$

where ω denotes the set of weighting coefficients and T represents the transpose operator for a matrix.

B. The basic framework of learning to rank

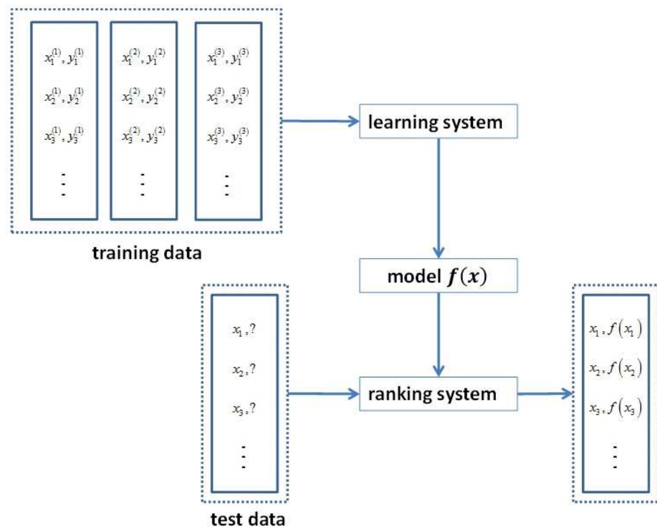

Fig. 1. The basic framework of learning to rank

Learning to rank equals to leverage the machine learning-based algorithms to extract the features suitable for sorting from the dataset, along with modifying the parameters and optimizing the evaluation metrics during the sorting process. Figure 1 illustrates a typical framework for learning rank [23], which investigates the primary content of machine learning, including the datasets, methods, and evaluation metrics. The training set is used to improve the training performance while the validation set is exploited to determine the prediction model. Notable that if there is no validation set at the beginning, the training set can be used to yield the sorting framework. Afterward, a testing set is supposed to evaluate the sorting performance of the presented algorithm. The dataset for learning to rank consists of a set of sorting characteristics and the corresponding annotations with correlation levels assigned. The feature x denotes the representation of the paired query-document. Correlation annotation y represents the relationship between the document and one specific query, such as two-level annotations (0 and 1) or multi-level annotations (0, 1, 2, 3, and 4).

C. learning to rank-based academic performance

Pairwise is one of the most popular learning to rank methods. Better than this type of algorithms, it emphasizes sequential processing, simultaneously converts the ranking problem to a binary classification problem, which is much easier to be processed. Both the SVM and neural network-based pipelines can be used to address this issue.

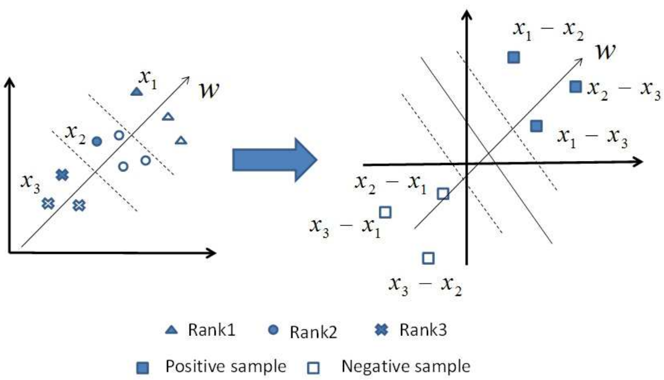

Fig. 2. An example of getting the training data

In the same student category, we first randomly select two students. According to their academic performance and level annotations, we can obtain a training instance (y_i, y_j). If $y_i > y_j$, the $+1$ label is assigned. Otherwise, the 1 label is obtained. Accordingly, the training dataset for the binary classifier can be achieved by a sequence of random selections. The toy example is shown in Figure 2.

Then, as long as the instances of all the students in the category can be produced according to the same selecting method for processing, we can get all the students' academic partial order associations. And the partial order relations can be used to train learning to rank model, the essence of the model is to sort the student list inthe premiseofnot having the wrong partial order relation, increasing the correct partial order relation, ultimately achieve convergence of the model training.

With the order relations, we can use Ranking SVM to train a sorting model. It can is equivalent to a quadratic convex optimization problem.

$$\min_{\omega} \frac{1}{2} \|\omega\|^2 \tag{3}$$

$$\text{s.t.} \quad y_i \langle \omega, x_i - x_j \rangle \geq 1 \tag{4}$$

This is equivalent to the following unconstrained optimization problem

$$\min_{\omega} \sum_{i=1}^{m} [1 - y_i \langle \omega, x_i - x_j \rangle] + \lambda \|w\|^2 \tag{5}$$

In order to improve classification errors in the hard linear margins, Ranking SVM can be formulated as the following QP problem:

$$\min_{\omega, \xi} \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^{m} \xi_i \tag{6}$$

$$\text{s.t.} \quad y_i \langle \omega, x_i - x_j \rangle \geq 1 - \xi_i, and \tag{7}$$

$$\xi_i \geq 0 \quad \text{i} = 1, \ldots, \text{m} \tag{8}$$

Among them,x_i andx_j are the first and second eigenvectors in the eigenvector pairs, m represents the number of training samples. $C > 0$ is a coefficient.

D. Academic variance analysis for different student categories

In the previous section, we can use the graduate students academic performance and the their label of the development situation construct the partial order relation between the s-tudents, then use the data to train a learning to rank model to achieve the intelligent ranking of the students academic performance.

However, the future development of our students have more than one direction, such as some students passed the examinationfor thegraduate program, some students entered the enterprise work, some students admitted to civil servants institution, etc., this is equivalent to that the students can be further divided into different categories.

The development of the students after graduation is the externalization form of their different academic performance. Different categories have different learning objectives, naturally their course emphasis will also have certain differences, eventually make students having different trajectories after graduation. Therefore, it is necessary to study academic behavior differences of different students, promote the diversity of curriculum system construction. This is an important aspect in the teaching development of highschools.

Asdiscussedabove, we can build different ranking models to investigate the different influence of the main courses for students' future development in different group, shown in Figure 3.

IV. Experiments

A. Dataset

TABLE I
THE BASIC STATISTICS OF THE DATA

Description	Number
Student	142
Class	4
Course	9
Group	3

The data is from the students in the computer science major of the University of Jinan. The students come from grade 2013-2014. The basic statistics of the data is showed in Table I.

B. Metrics

In our experiments, we use two popular ranking metrics-Precision@N and Recall@N to evaluate the models.

Precision@N is the fraction of the top-N students that are appeared in the test dataset.

Precision $@N = \frac{|\{\text{ top } -N \text{ students }\} \cap \{\text{ students that are appeared }\}|}{|\{\text{ top } -N \text{ students }\}|}$

Recall@N is the fraction of the items that are selected by a group that are successfully recommended in the top-N items.

$$\text{Recall } @N = \frac{|\{\text{top} -N \text{ students }\} \cap \{\text{ all appeared items }\}|}{|\{\text{ all appeared items }\}|} \tag{9}$$

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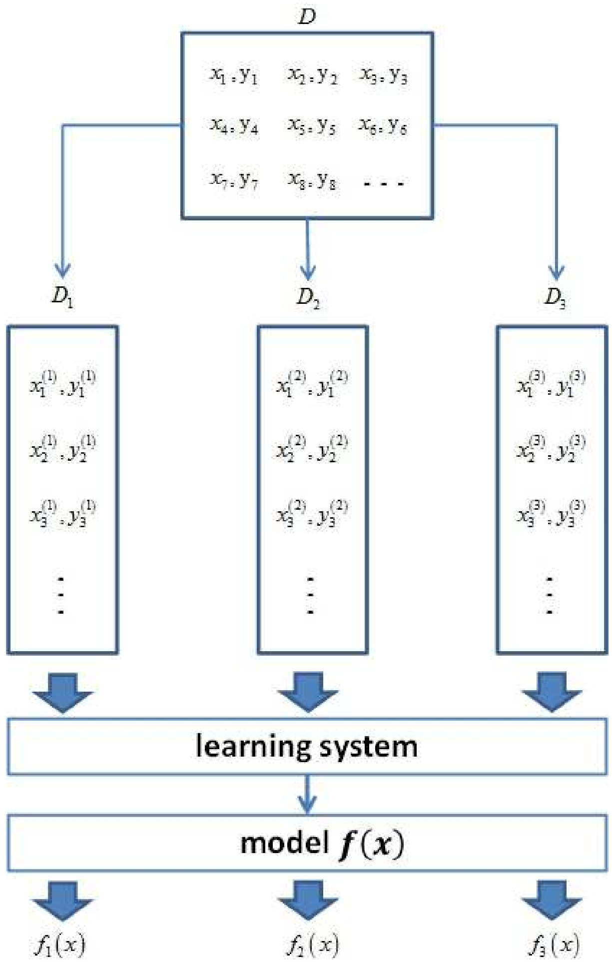

Fig. 3. Build different ranking models for different groups

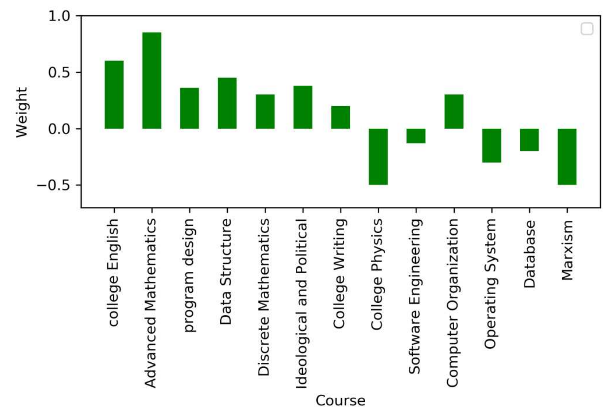

Fig. 4. The weights of the model in the group of becoming a postgraduate

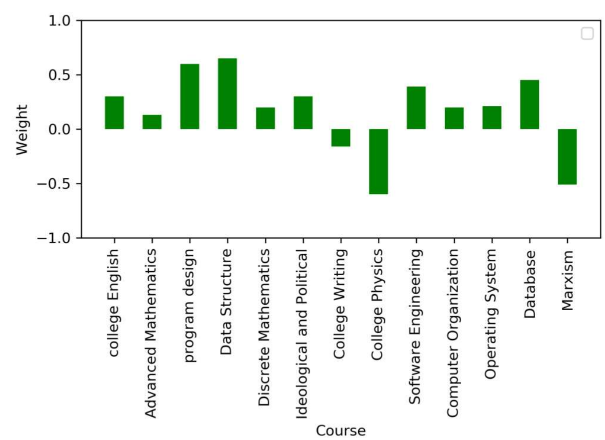

Fig. 5. The weights of the model in the group of looking?for a?job

Precision@N considers only the top most results returned by the system, while Recall@N considers all the students who teachers are concerned. We average Precision@N and Recall@N in the test set as the final prediction. The larger Precision@N or Recall@N value means better performance.

C. Performance comparison

In this section, we analyze how the changes of the parameters (the weights of the main courses) in our model affect the performance. We aim to find the different influence of the course grade on the students' learning ability. Besides, we investigate the different influences of the main courses on students' future development in different groups.

Figure 4 The weights of the model in the group of becoming a postgraduate.

Figure 5 shows the ranking results of different directions, such as becoming a postgraduate, looking for a job, and passing a civil servant. In the models of each direction, we observe that the weight of the courses is different: some weights are positive, meaning that the courses positively affect the students in the direction; some weights are negative, meaning that the courses do little to enhance the students learning ability in the direction.

Figure 6 The weights of the model in the group of looking for a job.

The results in the figures can be used for further analysis to determine whether there are different weights for the same courses in a different direction. We observe that the weights are different: in the group of becoming a postgraduate, the weights of 'Advanced Mathematics' and 'college English' are fairly large; in the group of looking for a job, the weights of 'program design', 'Database' and 'Data Structure' are fairly large; in the group of admitting to civil servants, the weights of 'ideology and politics' and 'College Writing' are fairly large. This illustrates different groups have different learning objectives, naturally, their course emphasis has certain differences.

Figure 7 The ranking results of different models on different groups.

Finally, we compare the ranking results of different models in different groups. Figure 4 shows the ranking results. We

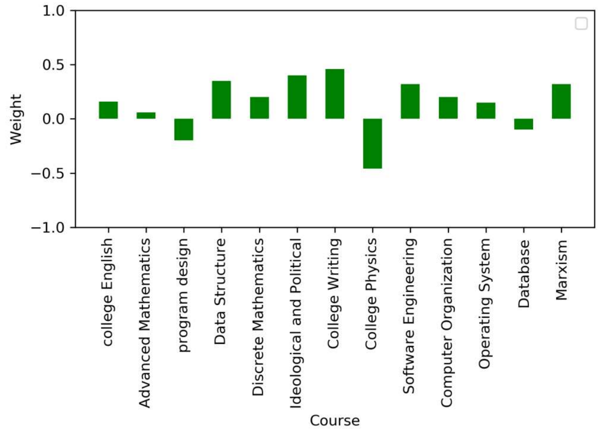

Fig. 6. The weights of the model in the group of looking?for a?job

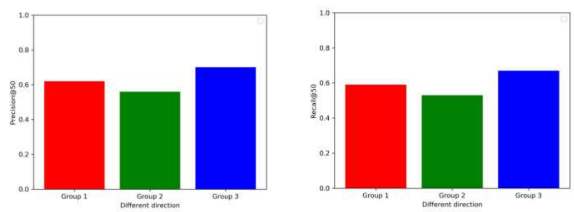

Fig. 7. The ranking results of different models on different groups

can observe that the models can achieve good performance for different groups of students.

V. Conclusion

In this paper, we study academic performance problem in teaching by exploiting the students' feedback information to infer the real ability of students. A key characteristic of our work is to use learning to rank-based model for academic performance analysis and classification. Then, different ranking models are used to investigate the different influences of the main courses on students' future development in different groups. Experimental results show that our model can improve the comprehensive academic performance evaluation.

In future work, we are going to expand the field of investigation for the students in order to make the results more reliable. At the same time, the students from different majors in the same field should be taken into account in order to study the differences between different majors. We need to collect more feedback data about the students' development trajectory. If we have more data, we can train better models in sorting. Finally, we should consider the reasonableness of the score for different courses.

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