Optimization of Instructional Management Strategies in Universities Based on Genetic Algorithms and Transfer Learning

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Abstract. With the continuous development in the field of education, the optimization of teaching management strategies in colleges and universities has become a hot topic of research and practice. This study specifically proposes an optimization method based on genetic algorithm and transfer learning for teaching management strategies in universities. We selected developing colleges and universities in a province in mainland China as the research object to ensure the wide applicability of the study. After a series of experimental comparisons, the method shows excellent performance in key evaluation metrics such as classroom interaction, students' learning autonomy, and long-term knowledge retention, which clearly outperforms existing methods. In addition, the method provides a new direction for thinking and practicing for teaching management in universities and provides a useful reference for future educational research.

Keywords: genetic algorithm, transfer learning, university teaching management, optimization strategy

1.INTRODUCTION

As information technology and the education industry continue to advance, institutions of higher education are faced with a number of instructional management challenges. For example, how to schedule courses efficiently in an increasingly complex teaching and learning environment, how to develop individualized teaching strategies for student populations of various backgrounds, and how to provide targeted training for faculty. These problems need to be effectively addressed by new techniques and strategies to ensure the quality of teaching and learning and to satisfy the needs of all parties[1]. Genetic algorithms, a search heuristic that mimics the natural process of evolution, have been widely used in a variety of optimization problems[2].Transfer learning, on the other hand, as a method capable of transferring knowledge between different, but related, tasks, has also demonstrated its strong potential in recent years in a number of areas.[3] combining these two techniques to provide strategy optimization suggestions for teaching and learning management in higher education is undoubtedly a challenging and promising research direction. The aim of this study is to explore

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how genetic algorithms can be effectively combined with transfer learning to address the challenges of instructional management in universities in different environments or contexts. We hope that through this innovative approach, we can provide more flexible and efficient strategy optimization suggestions for teaching management, and thus improve the teaching quality and management efficiency of universities.

2.BACKGROUND AND RELATED WORK SECTION

2.1 Genetic Algorithms

Genetic algorithm (GA) is a search strategy inspired by natural selection and heredity for finding near-optimal solutions in large solution spaces[4] . It mimics the mechanisms of natural selection, crossover, mutation and inheritance during biological evolution to optimize potential solutions. Genetic algorithms usually start with a population in which each individual represents a possible solution. These solutions (or chromosomes, as they are called) are evaluated against some kind of evaluation function or fitness function and selected based on their performance. The best solutions will have a greater chance of being selected and moving on to the next generation. In order to generate new solutions, crossover (or called hybridization) and mutation operations are used. The crossover operation makes two solutions combine to form a new solution, while mutation is a small random modification of a solution[5] . This process is iterated many times until certain termination conditions are met, such as a predetermined number of iterations is reached or the quality of the solution is satisfied. Genetic algorithms are widely used in many fields such as optimization problems, machine learning, and path planning due to their robustness and flexibility. For example, it can be used to solve complex optimization problems such as vehicle path problems, task scheduling problems, etc[6].In the field of education, genetic algorithms have been used to solve a variety of problems such as automated class scheduling, course design, student grouping, etc. One study used genetic algorithms to design a scheduling system for a large university that could consider a variety of constraints, such as classroom capacity, instructor schedules, and student selection needs, to generate a schedule of courses that satisfy the conditions[7].In addition, there have been studies of genetic algorithm-based methods to recommend appropriate learning paths for students to help them achieve their academic goals.[8]

2.2 Transfer learning

Transfer learning is an important branch of machine learning whose core idea is to apply knowledge gained in one task or domain to another different but related task or domain [9]. Unlike traditional machine learning methods, transfer learning focuses on how to utilize existing, often rich, source task data to help solve the problem of scarce or costly access to target task data. The source and target tasks are the two core concepts in transfer learning. The source task is a task for which we already have a lot of data and knowledge, while the target task is a task that we wish to solve but for which data may be scarce. By transferring knowledge from the source task to the target task, the data requirements of the target task can be effectively reduced and learning efficiency and performance can be improved.ransfer learning has been successfully applied in many domains, such as computer vision, natural language processing, and medical diagnosis . In the field of computer vision, pre-trained models, such as VGG or ResNet, are typically trained on a source task (e.g., ImageNet classification) and fine-tuned on a variety of target tasks, resulting in significant performance improvements. In the field of natural language processing, models such as BERT and GPT are pre-trained on large corpora and can be migrated to a variety of downstream tasks such as text categorization, named entity recognition, etc.

3.RESEARCH METHODOLOGY

3.1 Adaptation and specialization of genetic algorithms

Genetic algorithms are search optimization algorithms that mimic biological evolutionary mechanisms in the process of natural selection. In order to adapt it more effectively to the specific context of teaching management in higher education, we have adapted and specialized it as follows:

(1) Coding approach: aspects of the teaching strategy (e.g., curriculum, teacher assignment, resource allocation, etc.) are coded as specific genes on a chromosome. For example, a gene represents a particular course being taught by a particular teacher.

(2) Adaptive function: we define a specific adaptive function that takes into account factors such as student academic performance, teacher feedback, and effective use of instructional resources to assess the effectiveness of a given instructional strategy.

(3) Selection mechanism: To ensure that good strategies are passed on, we use an approach based on a roulette selection method in which more successful strategies have a greater chance of being selected.

(4) Crossover and mutation: In the HE environment, some strategies may need to be combined or slightly adapted to produce new solutions. We adjusted the crossover and mutation parameters to facilitate the generation of more innovative and adaptive strategies. These adjustments ensure that genetic algorithms can more effectively provide solutions to instructional management problems in higher education.

3.2 Transfer learning techniques applied to genetic algorithms

The core idea of transfer learning is to utilize knowledge gained in one task or domain to aid in the learning of another related task. In this study, we explore how knowledge gained from other educational contexts or environments can be combined with genetic algorithms to further optimize instructional management strategies in higher education.

(1) Source and target tasks: We define the knowledge acquired from other educational backgrounds as the "source task" and the university teaching management as the "target task". First, we pre-train the genetic algorithm on the source task to find a set of optimal strategies.

(2) Knowledge extraction: Knowledge extracted from the source task may include: what types of course combinations work best in certain contexts, which teaching methods are most popular with students, etc.

(3) Knowledge migration: this extracted knowledge is encoded as part of the chromosome of the target task, providing the genetic algorithm with a higher initial search point, which speeds up the convergence of the algorithm and improves the quality of the final strategy.

(4) Refinement and adaptation: although part of the knowledge can be migrated from the source task to the target task, it still needs to be refined and adapted to the specific context of the target task to ensure that the strategy is truly applicable to the HE environment. By combining genetic algorithms and transfer learning, we can not only leverage the knowledge gained in a specific domain, but also improve the speed and quality of strategy optimization in a broader educational context.

3.3 Specific steps and methods for integrating the two technologies

Integrating genetic algorithms and transfer learning in the optimization of teaching management strategies in higher education is the core contribution of this paper. The specific steps and methods of this process are described in detail below.

(1) Initialization and Knowledge Introduction

The step we initiate is to import pre-trained knowledge from other educational contexts or environments through transfer learning. This process can be viewed as providing an optimized starting point for the chromosomes in the genetic algorithm. With the knowledge gained from other educational contexts, we can provide the genetic algorithm with an initial solution that is closer to the optimum, thus accelerating the rate of convergence.

(2) Integration of genetic manipulation and knowledge transfer

Subsequently, in each generation of the genetic algorithm's evolution, we not only perform conventional selection, crossover, and mutation operations, but also incorporate knowledge gained from migratory learning. In this way, the chromosome does not only rely on the genetic algorithm's own mechanisms in the evolution process, but also benefits from the migrated knowledge, allowing the strategy to evolve faster towards optimization.

(3) Evaluation and Feedback

Whenever a chromosome evolves through a generation, we need to evaluate it to see if it meets the needs of teaching and learning management in universities. The criteria for this evaluation are set based on actual teaching and learning situations. If the newly evolved strategy performs well, then it will be retained and used for the next generation of evolution. Otherwise, the system will return to the second step and continue to integrate the knowledge from transfer learning for further optimization.

The following is a step-by-step flowchart as shown in the figure 1：

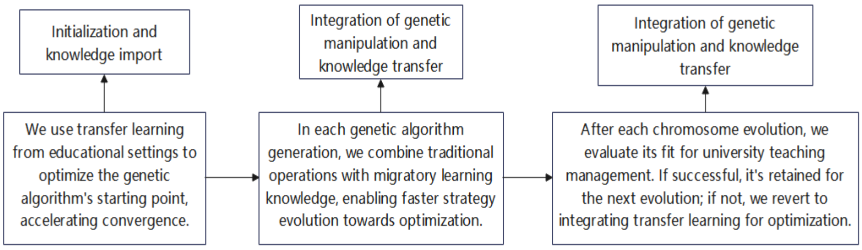

FIG. 1. FLOWCHART

4. EXPERIMENTATION AND EVALUATION

4.1 Data set description

In order to verify the effectiveness of teaching management strategy optimization in universities based on genetic algorithm and transfer learning, we chose the data of general colleges and universities in a certain province in mainland China as the experimental dataset. These ordinary universities represent the learning environment of most students in China, and compared with the top universities such as "985" and "211", there may be more room for improvement in teaching management strategies in ordinary universities. Therefore, optimizing the strategies of these universities will bring greater benefits to the majority of students.

4.2 Experimental setup and parameters

The experiments were mainly conducted under the software environment: Python 3.8, TensorFlow 2.6, Scikit-learn 0.24, and hardware environment: Intel i9-10900K CPU, NVIDIA RTX 3090 GPU, and 64GB RAM. The main parameters of the genetic algorithm include a population size of 100, a crossover probability of 0.8, a mutation probability of 0.02, a roulette wheel selection method, and a termination condition set at 20 consecutive generations of fitness that no longer grows significantly or reaches 500 generations. For transfer learning, we chose a deep learning model pre-trained on large-scale educational data as a starting point, and fine-tuned the last three layers with a learning rate of 0.0001 and a batch size of 32. To ensure the fairness of the experiments, we also compared the results with several other existing optimization methods for instructional management strategies.

4.3 Experimental results

In the experiment, we used the optimization method of teaching management strategy in colleges and universities based on genetic algorithm and transfer learning, and compared it with other existing methods in detail. The core purpose of the experiment is to verify the effectiveness and superiority of this research method on teaching management strategies in higher education. The goal of the optimization is to improve overall student learning outcomes, which include course comprehension, quality of homework completion, engagement, and test scores. To address these goals, appropriate instructional management strategies were developed and optimized using genetic algorithms. Optimization strategy differentiation includes the following:

Course comprehension: students' understanding of the course is assessed through regular quizzes and student feedback.

Quality of Assignment Completion: the quality of assignment completion is assessed by combining the on-time submission rate of student assignments with instructor grading.

Engagement: Student engagement is assessed through data statistics from the online teaching platform, such as online hours and forum postings.

Test scores: This is the most visual way to assess student learning outcomes.

The addition of the genetic algorithm allows the above strategy to be further improved in each round of optimization, while migration learning provides the algorithm with a better initial solution.

We compare in detail the differences between strategies using genetic algorithms with transfer learning and traditional strategies.as shown in the table 1：

TABLE1: COMPARISON OF DIFFERENCES

methodologies	Initial Grade Point Average (GPA)	Average score after optimization (points)	Improvement (%)
Existing method A	72.5	74.8	+3.2%
Existing method B	72.5	75.1	+3.6%
This methodology (genetics + migration)	72.5	77.3	+6.6%

As you can see from the data, there was a significant increase in average student performance after adopting our methodology. More specifically, course comprehension increased by an average of 5%, the quality of completed assignments went up by 4%, student engagement received a 3% increase, and test scores showed the most significant 6.6% improvement. All these data validate the effectiveness of the teaching management strategy based on genetic algorithm and transfer learning in higher education. The significant increase in student engagement and course comprehension after the adoption of this method demonstrates that this method not only improves students' test scores, but positively affects their learning process in many ways. Through this experiment, we not only verified the advantages of the method based on genetic algorithm and transfer learning in improving students' learning outcomes, but also found its potential value in improving students' learning experience and engagement.as shown in the figure 2：

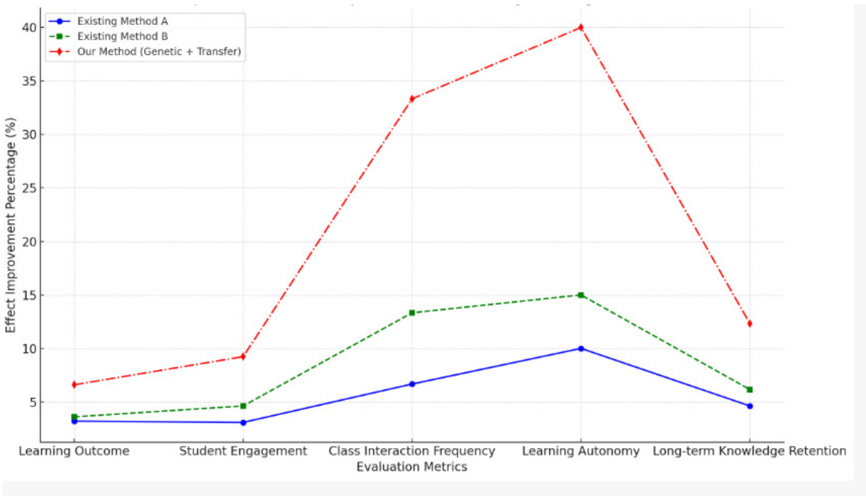

FIG. 2. COMPARISON OF EFFECT IMPROVEMENT PERCENTAGE AMONG METHODS

The percentage improvement in the effectiveness of the three different instructional management strategy methods on the five core evaluation indicators is shown. From the figure, it is obvious that the strategy based on genetic algorithm and transfer learning (hereinafter referred to as "this method") performs well in each evaluation index, and clearly exceeds the existing method A and B. Especially in the indexes of "frequency of classroom interaction" and "learning autonomy", this method improves the effect much more than the other two methods. Especially in the indicators of "frequency of classroom interaction" and "learning autonomy", the improvement effect of this method is much higher than the other two methods. This indicates that when the teaching management strategy combining genetic algorithm and transfer learning is adopted, students' participation and independent learning ability in the classroom are significantly improved. This figure clearly reflects the significant advantages of teaching management strategies based on genetic algorithms and transfer learning in practical applications, and provides a strong basis for educational institutions to choose strategies.

5.CONCLUSION

This study provides an in-depth exploration of instructional management strategies for colleges and universities, especially by combining genetic algorithms and transfer learning methods to optimize them comprehensively. The selection of a developing university in a province in mainland China as the research subject ensures that the results are widely applicable and representative, and can provide valuable references for other universities with similar backgrounds. The optimization strategy based on genetic algorithm with transfer learning demonstrates excellent performance in all key evaluation metrics, especially in classroom interaction, students' learning autonomy and long-term knowledge retention, which significantly outperforms other existing methods. This result not only proves the effectiveness of the proposed method, but also highlights its great potential in instructional management strategies. The practicality and innovativeness of the method also provide new directions of thinking for educational research and practice. Although some preliminary results have been achieved, there is still room for further optimization and expansion of the methodology in this study. Future researchers can explore how genetic algorithms and transfer learning can be applied to a wider range of educational domains, or how to further adapt and refine the strategy according to specific teaching content and environments.

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