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Educational Reform Practices for Machine Learning Courses in an Interdisciplinary Context

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Abstract. The rapid advancement of artificial intelligence has created an unprecedented demand for interdisciplinary talent across various fields. However, teaching machine learning to non-computer science students presents unique challenges. This paper presents innovative teaching approaches and reforms for machine learning education under an interdisciplinary context. The methodology encompasses three main components: foundational knowledge enhancement, interactive case-based teaching, and ChatGPT-assisted learning. The course structure follows an "easy-to-understand basics, progressive learning, and application-oriented" principle, divided into mathematical foundations, programming basics, and practical applications. Through case studies and real-world projects like snack price prediction and traffic flow analysis, students engage in hands-on learning experiences. Additionally, the integration of ChatGPT as a learning tool helps students understand code, debug programs, and optimize machine learning models. This comprehensive teaching model effectively combines theoretical knowledge with practical applications, fostering students' interdisciplinary thinking, programming capabilities, and problem-solving skills.

Keywords: Educational reform; Machine learning; interactive learning; interdisciplinary courses.

1. Introduction

In the era of rapid development of information technology, machine learning, as an important branch of artificial intelligence, is gradually penetrating into various disciplines and industries. With the popularization of data-driven decision-making and intelligent applications, the demand for machine learning talent in various professional fields is increasing. However, the traditional computer science education model often cannot meet the needs of non-computer science students, making educational reform an inevitable choice [1]. Therefore, how to design effective machine learning courses in the context of interdisciplinary studies to cultivate cross-disciplinary talents with comprehensive knowledge has become an urgent issue for the education community.

To address this challenge, many researchers have proposed various educational reform strategies. Strengthening the basic knowledge learning of non-computer science students, such as mathematics, linear algebra, and programming languages, is the key to improving their machine learning ability [2]. In addition, by using vivid case teaching and practice-oriented learning methods, the students' learning interest and participation can be effectively improved [3]. This teaching method not only emphasizes the transmission of theoretical knowledge, but also stresses the cultivation of students' practical abilities in actual applications, thereby promoting their comprehensive development.

In recent years, with the progress of artificial intelligence technology and the emergence of natural language processing tools such as ChatGPT, new perspectives and possibilities have been provided for educational reform. Research shows that integrating these tools into teaching can effectively stimulate students' innovative thinking and practical ability [4]. Therefore, exploring the theoretical and practical teaching model based on ChatGPT will provide strong support for the reform of cross-disciplinary machine learning courses. This paper will combine relevant literature to discuss how to achieve effective educational reform by strengthening basic knowledge, case

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teaching, and the application of emerging tools in the machine learning education of non-computer science students.

2. Teaching Approaches and Reforms

2.1 Enhancing and Strengthening the Foundational Knowledge of Non-Computer Science Students

2.1.1 Basis and driving factors

Taking into account the characteristics of non-computer majors, the course content design is based on the principle of "easy-to-understand basics, progressive learning, and application-oriented." It helps students quickly acquire the basic knowledge they need in a cross-disciplinary context. The course is divided into three main modules: mathematical foundation, programming foundation, and practical application module. These modules are independent of each other but interconnected, aiming to help students build a clear knowledge structure within a limited learning time and apply what they have learned to practical problems. The course combines theoretical knowledge with practical applications through case-driven and project-based learning to enhance students' interest and hands-on skills [5].

2.1.2 Practical applications

The course combines mathematical foundations, programming skills, and practical applications to equip students with a comprehensive understanding of machine learning. Three key modules are elaborated below.

In the Mathematical Foundations module, the course content focuses on the mathematical tools commonly used in machine learning and data analysis, including linear algebra, probability theory and statistics, and the core knowledge of calculus. To enhance students' understanding of mathematical concepts, the course includes several practical case studies. For example, when learning matrix operations, students will encounter an image processing case, where they will use matrix transposition, multiplication, and singular value decomposition (SVD) to reduce the dimension of an image and reconstruct it. Another case is the application of probability theory, where students will use Bayes' theorem to analyze medical diagnostic data and assess the likelihood of a patient being ill. These case studies not only help students gain a concrete understanding of mathematical concepts, but also demonstrate the practical applications of these concepts in real-world problems.

The programming foundation modules are centered around the Python language and start from zero basics, gradually transitioning to the simple implementation of data analysis and machine learning. During the course of learning Python's data processing tools (such as Pandas and NumPy), a "house price data analysis" case is designed, in which students will load a real house price dataset and complete tasks such as data cleaning, missing value handling, and feature statistics. During the course of learning Python's visualization tools (such as Matplotlib and Seaborn), students will use the "traffic accident analysis" case to reveal the distribution patterns of the time, location, and causes of traffic accidents through bar charts and heat maps. Through these cases, students will not only master the core functions of programming tools, but also learn how to tell stories with data.

The practical application module serves as a core component of the course, designed to integrate mathematical, programming, and machine learning knowledge to solve real-world problems. For example, the course includes a case study titled "Predicting the Profit of a Snack Shop," where students simulate the role of a business owner deciding where to open a new branch based on historical data. Students are provided with information on the profits and population sizes of existing snack shops in various cities and are tasked with using Python to preprocess the data, including tasks such as data cleaning and feature extraction. They then build a predictive model using linear regression to analyze market potential in different cities and determine the most promising location for expansion. Through this case study, students not only deepen their

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understanding of machine learning principles but also gain hands-on experience in the complete workflow, from data preprocessing to model training and evaluation. The module emphasizes the application of technical skills to address practical problems, equipping students with the ability to use machine learning techniques to solve challenges relevant to both their academic and everyday lives.

2.2 Interactive Case-Based Teaching: Enhancing Classroom Engagement and Teamwork

2.2.1 Motivations

To enhance the learning interest and practical abilities of non-computer science students, the course adopts diverse teaching methods, including case-based teaching, interactive classrooms, and team collaboration, to help students integrate theory and practice, master core knowledge, and develop comprehensive skills. In case-based teaching, real-world machine learning examples such as Netflix's recommendation algorithm success story are introduced, allowing students to analyze user behavior data to understand the core principles of recommendation systems. Meanwhile, the course also examines failed cases, like pandemic prediction errors, to analyze decision-making issues caused by data bias and model overfitting. In project-based tasks, students engage in practices like "spam message classification," mastering the machine learning workflow step by step, and in "house price prediction" cases, they explore the impact of missing and outlier data on model performance, learning the importance of data quality in improving prediction accuracy.

2.2.1 Practices

Interactive classrooms incorporate group discussions, role-playing, and competitions to enhance student engagement. For example, in the "house price prediction model optimization" activity, groups take on roles such as data scientists, project managers, and clients, each presenting needs or solutions from their perspective. Acting as a "data scientist," a student must explain the trade-off between model complexity and accuracy, improving both their understanding of algorithm principles and communication skills. Classroom competitions, like the "machine learning model performance challenge," involve tasks such as designing and optimizing models for spam classification, where teamwork leads to high performance and tangible results, fostering a sense of achievement and further motivating students.

The course also emphasizes teaching reform by innovatively incorporating team collaboration and interdisciplinary tasks to cultivate students' teamwork, communication, and problem-solving skills. For instance, in the "traffic flow prediction system development" project, students are divided into groups with designated roles, such as data preprocessing, model implementation, result analysis, and visualization, ensuring they gain expertise in data processing, model building, and interpreting results. In the "license plate recognition" task, students independently train and optimize a YOLO-based detection model and evaluate its performance in real campus traffic scenarios, enhancing their practical skills and problem-solving abilities in intelligent transportation. These teaching reform practices effectively combine theory and practice, laying a solid foundation for training high-quality professionals in the smart transportation field.

2.3 ChatGPT-Assisted for Theory and Practice Teaching

2.3.1 General ideas

With the rapid development of generative AI, ChatGPT has become a vital tool in machine learning, particularly for code understanding, debugging, and optimization. The course integrates theory and practice, introducing students to the core principles of ChatGPT, such as neural network-based language models, pretraining and fine-tuning mechanisms, and its applications in analyzing, explaining, and generating solutions for code-related problems. Case studies, such as using ChatGPT to interpret gradient descent algorithm code step by step, help students better understand code logic while critically evaluating ChatGPT's limitations, such as generating

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incorrect code or providing inaccurate explanations for complex issues, fostering critical thinking [6].

2.3.2 Practices

In the practical component, students engage in experiments and project-driven learning, using ChatGPT to debug and optimize machine learning code. For example, students debug logistic regression code, address errors like dimension mismatches, or improve deep learning models by asking ChatGPT for guidance on adding Dropout layers or resolving overfitting issues. In project development, students design machine learning applications, such as image classifiers or recommendation systems. Feedback mechanisms, such as surveys and discussions, are employed to improve teaching strategies, while students share their project outcomes and challenges, such as debugging model overfitting or enhancing predictive performance. This iterative, feedback-driven teaching approach effectively combines theory and practice, equipping students with core machine learning skills, programming capabilities, problem-solving abilities, and innovative thinking.

The course also emphasizes feedback and iterative mechanisms to enhance teaching effectiveness and improve students' abilities, while encouraging students to share their project experiences and challenges to foster communication and learning. At the end of the course, instructors collect students' learning experiences and feedback on the teaching content in machine learning tasks through questionnaires and discussions, using this input to optimize the course design. For example, based on students' actual needs, additional debugging and application cases using the Scikit-learn framework were incorporated. During classroom presentations, students share their project outcomes and challenges, such as how they debugged code to solve model overfitting issues or improved model prediction performance. Students applied the knowledge learned in class to complete algorithm selection, parameter tuning, and iterative debugging, ultimately improving system performance. This teaching model, which integrates theory with practice and emphasizes feedback and optimization, not only enables students to master core machine learning skills but also enhances their programming abilities, problem-solving skills, and innovative thinking, laying a solid foundation for further exploration in the fields of artificial intelligence and data science.

3. Summary

Through these educational reforms, the machine learning capabilities of non-computer science students can be effectively enhanced, fostering their interdisciplinary thinking while cultivating teamwork and problem-solving skills through practical applications. This teaching reform not only focuses on the delivery of theoretical knowledge but also emphasizes practical application and dynamic interaction, thereby sparking students' interest in learning and improving their hands-on abilities and overall competencies. With interests, students can develop good learning habits and an active spirit of exploration.

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