Journal of Education and Educational Research
ISSN: 2957-9465 | Vol. 12, No. 3, 2025

Teaching Reform and Practice of the Machine Learning Course in the Context of Professional Certification

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Abstract: The engineering education accreditation framework, recognized as a pivotal quality assurance mechanism under the Washington Accord, has achieved worldwide adoption since its establishment. Chinese higher education institutions have strategically aligned their curricula with professional accreditation standards in recent years, systematically implementing outcome-based evaluation to cultivate globally competent engineering professionals. Using the machine learning course as a case study, this paper investigates teaching reform and practice under the framework of professional certification. The outlined student-centered pedagogical innovation process encompasses four constitutive phases: precise definition of outcome-based teaching objectives, backward-designed modularized teaching content, implementation of problem-oriented didactic methodologies integrated with case-practice immersion modules, and deployment of an evaluation enabling real-time learning analytics and formative feedback loops across instructional cycles. These strategies serve as a reference for advancing course-level reforms within the engineering education professional certification framework, offering actionable insights for related disciplines.

Keywords: Engineering Education Accreditation; Student-centered; Outcome-based Education; Continuous Improvement.

1. Introduction

Engineering education accreditation serves as an internationally recognized quality assurance mechanism for engineering education [1]. In recent years, Chinese universities have progressively aligned with global standards by implementing this accreditation system to cultivate competent engineering professionals. Exploring curriculum and pedagogical reforms under engineering education accreditation standards holds critical significance, particularly in addressing three key research questions: defining course objectives that demonstrably align with graduation requirements; establishing curricular implementation strategies that operationalize this alignment; and developing systematic assessment methods to validate the achievement of such alignment. Resolving these issues is essential for enhancing the quality of talent development and ensuring the smooth passing of professional certification.

Traditional machine learning pedagogy exhibits the following limitations: Overemphasis on instructional delivery rather than measurable student learning outcomes; Teacher-dominated classroom dynamics with students as passive recipients, lacking structured mechanisms for deep learner engagement; Monolithic evaluation by instructors only, without cyclical, evidence-based feedback for continuous instructional improvement. To address these challenges, we implement a teaching reform focused on holistic talent development, guided by the core principles of engineering education accreditation standards. Through systematically reforms across four key dimensions: defining instructional objectives, structuring curricular content, innovating pedagogical approaches, and building evaluation systems—we aim to achieve the following outcomes: enhancing instructional efficacy, fostering students' self-directed learning competencies, cultivating problem-solving abilities for complex engineering challenges, and sustaining improvements in talent cultivation quality.

2. Pedagogical Innovation Strategies

2.1. Outcome-Based Development of Teaching Objective

With the advancement of the AI era and continuous breakthroughs in science and technology, machine learning-driven artificial intelligence has emerged as a pivotal component of national strategic development. The profound societal impact of AI technologies across industries necessitates urgent enhancements in AI talent cultivation across all educational tiers and disciplines. As the cornerstone course of AI education, machine learning provides foundational theories and methodologies for advanced courses such as deep learning, computer vision, and natural language processing.

In recent years, many university faculty members have conducted valuable explorations into the reform of machine learning course instruction, addressing prominent pedagogical challenges while considering their institutions' specific contexts. However, significant variations persist across higher education institutions in terms of talent development objectives, educational paradigms, distinctive features of academic programs, instructional resources, and practical support infrastructure. Consequently, the curricular goals, content selection criteria, and development priorities for machine learning courses differ substantially among institutions. Given these circumstances, it becomes imperative to develop a tailored approach to machine learning course reform that aligns with both institutional realities and pedagogical needs. This approach should be grounded in engineering education accreditation standards while maintaining congruence with student learning profiles. Such reform efforts aim to enhance learning outcomes, elevate talent cultivation quality, support the fulfillment of program-

specified graduation requirements, and ultimately ensure successful compliance with professional accreditation standards for engineering education.

The Computer Science and Technology program at our university cultivates application-oriented engineering professionals capable of responding to socioeconomic development demands and regional industrial needs. These professionals achieve well-rounded development encompassing moral, intellectual, physical, aesthetic, and labor education, while attaining mastery in mathematical foundations, natural sciences, and computer science core competencies. Equipped with strong engineering practice capabilities and professional ethics, graduates demonstrate proficiency in software/hardware systems development, technical research, and operational management within computing-related fields. In accordance with engineering education accreditation standards, our graduation requirements encompass twelve core competency indicators. Course objectives must demonstrate explicit alignment with these program-level indicators, and it can effectively guide pedagogical implementation through precisely articulated statements. Within the machine learning curriculum, we decompose the prescribed graduation indicators into measurable course-specific outcomes. These outcomes are systematically mapped to specific instructional modules and assessment components, creating an evidence-based framework for achievement verification. Formalized through syllabus documentation, this approach ensures standardized implementation across teaching practices. Table 1 shows the precise mapping relationships between machine learning course outcomes and their associated graduation requirement indicators.

Table 1. Course Objectives

Graduation Requirement Indicators	Course Objective
Problem Formulation Model Construction	C01
Experimental Analysis	C02
Leverage Modern Toolkits	C03
Engineering and Society	C04

The Machine Learning course mandates the attainment of specific pedagogical objectives, encompassing the following dimensions.

C01: Students will demonstrate the capacity to properly apply methodologies including data preprocessing, model evaluation, and hyper parameter tuning to tackle regression, classification, and clustering tasks using mainstream machine learning algorithms. They will be capable of analyzing and critically evaluating conclusions obtained, while exhibiting integrative problem-solving competencies through data science approaches. (Accounts for 30% of the total weight)

C02: Students will demonstrate the ability to select and evaluation diverse machine learning models through comparative experimentation based on specific datasets and practical requirements. They will critically analyze algorithmic strengths and limitations, while exhibiting discernment in model evaluation and selection. (Accounts for 20% of the total weight)

C03: Students will demonstrate proficiency in utilizing integrated development environments such as Jupyter Notebook and PyCharm, while exhibiting hands-on competencies in implementing machine learning algorithms through the Scikit-learn framework. (Accounts for 40% of the total weight)

C04: Students will recognize the significance and implications of applying disciplinary knowledge to address societal challenges, while cultivating an ethical framework for the responsible deployment of machine learning technologies. They will demonstrate collaborative competencies in peer-assisted problem-solving, systematically fulfilling team-assigned responsibilities through structured coordination. (Accounts for 10% of the total weight)

2.2. Backward-Designed Modular Curriculum Components

The machine learning curriculum is systematically constructed using backward design principles, aligning with defined learning outcomes. The instructional architecture encompasses five core technical domains: regression, classification, clustering, data preprocessing, and model evaluation. Course development focuses on classic machine learning algorithm and implementations including k-Nearest Neighbors (k-NN), linear regression with polynomial extensions, logistic regression, Support Vector Machines (SVM), decision tree, Random Forest, k-Means clustering, and DBSCAN density-based clustering. Content organization follows a progressive learning trajectory beginning with regression, advancing through classification, and culminating in unsupervised clustering approaches. Data preprocessing and model evaluation competencies are strategically embedded within practical case studies across instructional units, ensuring contextualized application of these fundamental skills.

The curriculum systematically integrates value-oriented educational components through multifaceted pedagogical design. Integrating cutting-edge machine learning technologies and achievements can help students build scientific and technological confidence and inspire their patriotic feelings and mission of serving the country through science and technology; discussing the challenges faced by machine learning in the intelligent era to strengthen students' engineering ethics awareness and enhance their sense of social responsibility; adjusting hyper parameters to continuously optimize the model and guide students to cultivate the spirit of craftsmanship of striving for excellence in practice; comparing individual learning with ensemble learning, educating students on group wisdom and cultivating students to brainstorm and collaborate in innovation.

2.3. A Problem-Driven Pedagogical Framework with Case-Based Practice

The key to implementing the course objectives is to solve the problem of "how the course can support graduation requirements" [2]. Goal-oriented learning aims to stimulate students' proactive engagement in the learning process and ensure the attainment of measurable competencies, with its efficacy fundamentally dependent on well-structured pedagogical design. The core principle of instructional design requires the systematic integration of competency development throughout the educational process. In our machine learning curriculum implementation, we have developed a problem-driven, case-based pedagogical model to achieve course objectives. This framework strategically

guides students through autonomous thinking, problem exploration, analytical reasoning, and solution development, enabling knowledge construction through seeking solutions to real-world problems. The model emphasizes learner agency and it is a student-centered pedagogical approach. The problem-oriented classroom teaching design is shown in Figure 1.

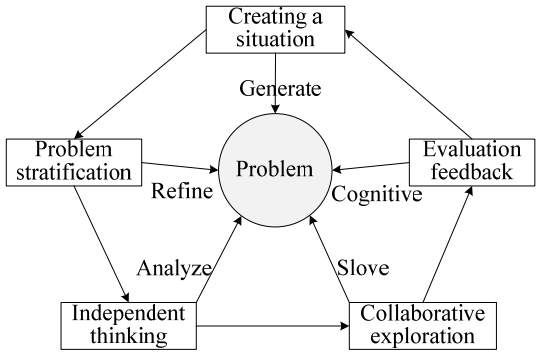


Figure 1. The Problem-oriented Classroom Teaching

The foremost task lies in the meticulous selection and refinement of classroom instructional content. This selection and refinement process strategically employs typical application cases as pedagogical vehicles, implementing problem-driven instruction through key issues identified during content condensation [3]. We employ cognitively optimized techniques to construct empathic resonance scenarios where students encounter familiar yet unexplored knowledge domains from both academic and quotidian perspectives. Such strategic contextualization achieves dual catalytic effects: immediate cognitive engagement and sustained epistemic curiosity, effectively stimulating learners' intrinsic motivation through deliberate epistemic tension. Teachers implement a pedagogical framework whereby complex algorithmic problems undergo stratified refinement through systematic decomposition and targeted questioning. This methodology guides learners through a gradual cognitive progression from foundational exploration to in-depth analysis and ultimate problem resolution. Under teachers' guidance, students engage in self-directed problem analysis, perspective articulation through peer dialogue, collaborative inquiry, and cooperative problem-solving. On the basis of full communication and discussion, teachers should summarize and give full positive evaluation to students' cognitive innovations emerging from collaborative learning processes. For the thinking deviations in the process of learning and communication, the reasons for them should be rationally analyzed, the crux should be found, and the correct understanding and cognition should be listed for comparative analysis. Teachers employ problem-driven teaching to conduct systematic deconstruction through multidimensional interrogation, so that students can deeply understand the ideas expressed in the classroom teaching content.

Under the guidance of teachers and driven by case tasks, students can master theoretical knowledge through case practice while truly understanding how to apply machine learning theory to practice, thereby achieving a deeper understanding and mastery of knowledge. Through active immersion in pedagogical processes, students deploy autonomous cognitive agency, thereby enabling systematic enhancement of analytical problem-solving competencies as well as their practical skills. The curriculum embeds praxis-oriented cases encompassing predictive modeling (e.g., beverage delivery volume forecasting for retail chains), pattern recognition (e.g., MNIST-style handwritten digit classification), and unsupervised learning (e.g., cold tolerance clustering in Prunus serrulata cultivars), each rigorously aligned with computing curricular guidelines for applied machine learning pedagogy. When engaging with these practical project, students are required to proactively investigate data quality, identifying prevalent issues including class imbalance, missing value patterns, and significant noise contamination. Given that multifaceted challenges in authentic implementations inevitably compromise model performance, students must synthesize knowledge through exploratory experimentation, empirical validation, comparative analysis, and iterative optimization to achieve solutions.

3. Multi-Dimensional Evaluation Framework with Real-Time Processual Guidance

Assessment and evaluation mainly solve the problem of "how can the course prove its support for graduation requirements" [4]. In the machine learning course, a tripartite evaluative ecosystem has been constructed, comprising teacher-student, student-to-student, and student-teacher feedback dimensions. Through systematic integration of objective competency metrics from direct assessments and perceptual data from indirect feedback channels, the course establishes evidence-based enhancement strategies, thereby operationalizing an iterative feedback mechanism following the 'evaluation → revision → implementation' cycle. The course teaching evaluation system is shown in Figure 2.

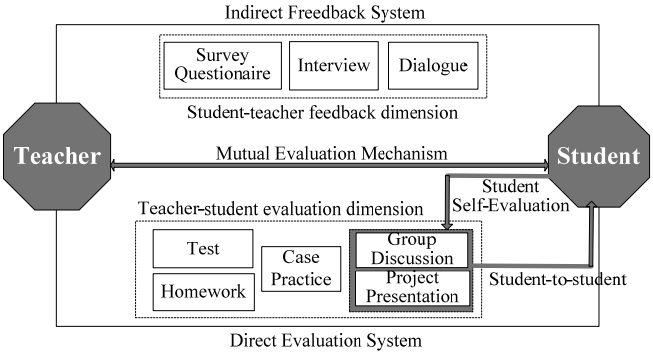


Figure 2. Teaching Evaluation Framework

The design principle of course assessment centers on curricular objectives, systematically evaluating each instructional component. Each course objective should correspond to an appropriate assessment method with corresponding weighting. The machine learning course assessment comprises five modalities: tests, homework assignments, case practices, group discussions, and project presentations. The assessment matrix with weighting allocations is shown in Table 2.

The percentage allocation of assessment modalities within the final course grade is determined through weighted alignment between course objective priorities and their corresponding evaluation instruments. As delineated in the syllabus, each assessment modality including its weighting coefficient and scoring rubric is explicitly specified. For collaborative learning components—specifically group discussions and project presentations— peer evaluation

metrics are implemented. These metrics systematically quantify group performance across three dimensions: instructional engagement process, defense presentation quality, and final report rigor. Student-generated evaluations are subsequently integrated with instructor assessments via weighted synthesis, forming a multidimensional evaluation framework. The final course achievement metric is computed utilizing a validated scoring matrix, ensuring validity and reliability.

Table 2. Course Assessment Modalities

Evaluation Methods	Weight Allocation			
	C01	**C02**	**C03**	**C04**
Test	0.4	0	0.25	0
Homework Assignment	0.33	0.15	0.25	0
Case Practice	0.17	0.75	0.25	0
Group Discussion	0	0	0	0.5
Project Presentation	0.1	0.1	0.25	0.5
Total Weight	1	1	1	1

We build MOOC of the course via the Chaoxing Smart Classroom Platform, integrating didactic videos and an item bank. This digital infrastructure provides support for transformative pedagogical innovation.

Within each instructional cycle, students complete standardized evaluation measuring both course objective attainment levels and instructional process satisfaction indices. To In order to facilitate the comparison of the evaluation results, the survey data undergo rigorous quantification using metrics. Concurrently, qualitative analysis of course efficacy is conducted through focus group discussions and post-instructional interviews. This approach culminates in a comprehensive indirect feedback ecosystem integrating quantitative survey, discourse analytics, and interview data.

To enable real-time monitoring and formative intervention in student learning trajectories, the machine learning course has architected an integrated processual feedback system through the Chaoxing Smart Platform's advanced data analytics infrastructure. This system captures multi-dimensional learning data including video engagement patterns and automated assessment performance, while facilitating pedagogical refinement via synchronized student self-evaluation and instructor mediation mechanisms.

4. Conclusion

The pedagogical reformation of Machine Learning courses under the Engineering Education Accreditation framework effectively embodies the principles of student-centered pedagogy, outcome-based orientation, and continuous improvement, which holds significant referential value for instructional innovations across other disciplines within professional accreditation systems for engineering education.

Acknowledgments

This work was financially supported by Undergraduate Education and Teaching Foundation of Dalian Polytechnic University. (No. JGLX2023030, No. JGLX 2023102).

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