

Construction of Machine Learning Classroom Knowledge System and Intelligent Guidance Practice under the Dual-Driven Concept

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Abstract: With the full arrival of the artificial intelligence era, machine learning has gradually become a core compulsory course for majors such as computer science, big data, and artificial intelligence in universities. It also acts as a key hub connecting basic theories with industrial implementation. Traditional machine learning classrooms have long adopted the one-way indoctrination teaching mode. Prominent problems, including fragmented knowledge systems and homogenized teaching adaptation, make it difficult to meet the personalized, intelligent, and practical talent-training demands of the new era. The “dual-driven concept” mentioned in this paper refers to machine-learning-oriented teaching reform jointly supported by a course knowledge graph and an intelligent agent. The knowledge graph undertakes structural organization, relationship presentation, and dynamic updating of course knowledge, while the intelligent agent is responsible for teaching interaction support, Q&A assistance, learning-situation analysis, and personalized recommendation. The two form a collaborative linkage through the loop of “knowledge supply–behavioral feedback–iterative optimization.”

Keywords: Dual-driven concept; Machine learning classroom; Construction of knowledge system; Intelligent guidance; Practice

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1. Core value of machine learning classroom teaching reform under the dual-driven concept

1.1. Empowering the reconstruction of curriculum system and realizing the transformation of knowledge teaching from fragmentation to systematization

The dual-driven concept can effectively solve the problem of students’ fragmented learning. Based on the underlying logic of machine learning discipline, it reorganizes the course knowledge context, breaks the inherent chapter barriers of textbooks, integrates multiple contents including prerequisite mathematical

foundations and core algorithm principles, and eliminates obsolete and redundant knowledge points. In this way, a closed-loop knowledge system with progressive and interlocking contents is gradually constructed. Driven by intelligent technology practice, practical scenarios are provided for the implementation of the knowledge system. Abstract theoretical knowledge points are deeply bound with practical projects and industrial cases, so that every theoretical knowledge item has a corresponding practical application ^[1]. The two empower each other bidirectionally and effectively break the dilemma of separation between theory and practice as well as fragmented and isolated knowledge points. Machine learning courses are transformed from a simple accumulation of knowledge points into a systematic and structured three-dimensional knowledge teaching system, which greatly improves the scientific nature, logicity, and practicality of course contents.

1.2. Optimizing talent training modes and realizing the upgrade of competence cultivation from singularity to compound orientation

The dual-driven talent training mode effectively breaks the shackles of singular cultivation and constructs a compound talent training logic of “theory-based foundation + practice-driven empowerment.” Systematic theoretical drive consolidates students’ core disciplinary literacy, helps them gain an in-depth understanding of the underlying principles of machine learning, master core logic such as the advantages, disadvantages, and applicable scenarios of algorithms, and cultivates students’ rigorous mathematical thinking and disciplinary cognitive competence. Driven by intelligent technology practice, intelligent guidance platforms, cloud-based practical training, and simulation scenarios provide students with all-weather and personalized practical training environments, helping students rapidly convert theoretical knowledge into engineering practical capabilities and problem-solving skills ^[2]. This bidirectional-driven training mode avoids the hollowing-out problem caused by overemphasizing theory while ignoring practice, and also solves the superficial drawback of valuing operation over principles. It gives consideration to the cultivation of students’ basic literacy and innovative ability, so as to more accurately satisfy the core demands of the artificial intelligence industry for compound and innovative talents.

1.3. Promoting classroom teaching innovation and realizing the transition of talent training modes from homogenization to precision

The dual-driven concept offers a brand-new path for intelligent and precise classroom innovation, and effectively pushes the shift of teaching modes from traditional experience-driven mode to data-intelligence-driven mode. The systematic knowledge system provides standardized content support for precise guidance and makes personalized tutoring targeted rather than aimless. Empowered by intelligent technologies, big-data-based AI guidance systems collect full-dimensional learning situation data, including students’ prior performance and classroom interactions in real time, so as to accurately assess every student’s knowledge gaps, learning weaknesses, and competence levels ^[3]. Based on dynamic analysis of learning situation data, classroom teaching can flexibly adjust its rhythm and contents, and guidance services can realize hierarchical resource push, personalized Q&A, and targeted special training, completely getting rid of the drawbacks of homogenized teaching. Such teaching innovation enables classrooms to truly adapt to individual student differences, better achieve all-student coverage and hierarchical cultivation, and greatly enhance the pertinence and efficiency of machine learning classroom teaching. It also provides replicable practical paradigms for intelligent teaching reform of science and engineering majors in universities ^[4].

2. Prominent problems in current machine learning classroom teaching and guidance practice

2.1. Disordered construction of knowledge system and disintegration between theory and practice

The knowledge system constitutes the core foundation of classroom teaching. At present, obvious arbitrariness and fragmentation exist in the construction of knowledge frameworks in many machine learning classrooms, lacking scientific top-level design. Some teachers teach strictly according to textbook arrangements, delivering knowledge chapter by chapter, and ignore internal correlations and hierarchical logic among knowledge points^[5]. Interleaved presentation of basic mathematical knowledge and algorithm principles results in poor connection between new and prior knowledge. Consequently, students can hardly build complete knowledge networks or achieve mastery through comprehensive study of knowledge. Severe disconnection between theory and practice represents another prominent shortcoming in knowledge-system construction. Many classrooms separate theoretical teaching from practical teaching. Theoretical classes focus on formula derivation and concept explanation, whose abstract and tedious content is hard for students to understand. Besides, practical classes merely involve code reproduction and model application, where students only perform mechanical operations without understanding underlying principles. Lacking effective connecting links between the two, a common phenomenon appears among students: they “understand theories yet cannot conduct practical operations, and can operate without knowing relevant principles”^[6].

2.2. Formalized intelligent guidance practice and insufficient precision-oriented talent-training effectiveness

At present, many universities have introduced various intelligent teaching platforms, and teachers attempt to carry out intelligent guidance practice. Nevertheless, actual teaching outcomes are unsatisfactory, and intelligent guidance mostly stays at the level of superficial tool application. In many classrooms, intelligent platforms are only used for courseware display and assignment release, without constructing systematic guidance systems supported by platforms. The core strengths of intelligent technologies in data analysis and precise push are not brought into full play^[7]. Moreover, existing guidance modes mostly adopt unified resource push and homogenized exercise training without hierarchical adaptation according to individual learning situation differences. Platforms fail to conduct in-depth mining of students’ learning data, making it hard to accurately locate students’ knowledge gaps, learning difficulties, and competence weaknesses, nor can they offer data support for teachers to adjust teaching strategies. Furthermore, intelligent guidance lacks a full-process closed-loop service. Most intelligent guidance only focuses on after-class assignment tutoring, ignoring full-process coverage of pre-class preview guidance, in-class targeted Q&A, and after-class expansion and improvement. Fragmented guidance contents and fragmented guidance procedures cannot form complete closed-loop guidance covering pre-class, in-class, and after-class stages, and thus can hardly satisfy students’ core demands for personalized learning^[8].

2.3. Absence of dual-driven integration mechanism and lack of systematic support for teaching reform

The essence of dual-driven teaching lies in the collaborative empowerment of systematic theoretical systems and intelligent technology-supported practice. However, teaching reform in many classrooms shows a state of “bidirectional separation,” without sound dual-driven integration mechanisms. Some teachers overemphasize

the construction of theoretical systems, stick to traditional lecture-based modes, and ignore the empowering value of intelligent technologies, resulting in dull and rigid classroom teaching as well as severe deficiencies in practical teaching and personalized guidance. Some other classrooms blindly pursue intelligent forms and introduce various intelligent teaching tools without the support of systematic knowledge systems^[9]. Intelligent guidance resources are disorganized and disconnected from core course knowledge points. Some intelligent operations deviate from theoretical foundations. As a result, technological empowerment becomes superficial. Although teaching forms appear diversified, knowledge-transmission efficiency remains low, and students' core abilities are not effectively improved. Deficiencies also exist in teachers' competence, and backward evaluation systems greatly restrict the implementation of dual-driven integration. Most professional teachers possess solid theoretical foundations yet lack competence in intelligent technology application and intelligent teaching design. Some young teachers are familiar with intelligent tools but weak in sorting out disciplinary theoretical systems. The traditional singular assessment-evaluation system only attaches importance to final scores while neglecting comprehensive evaluation of learning processes, competence improvement, and practical innovation. It can hardly satisfy talent training requirements of the dual-driven teaching mode, making teaching reform hard to deepen and implement sustainably^[10].

3. Practical paths for constructing machine learning classroom knowledge system and implementing intelligent guidance under the dual-driven concept

3.1. Reconstructing hierarchical knowledge system to realize in-depth integration of theory and practice

Systematic reconstruction of knowledge systems serves as the fundamental prerequisite for dual-driven teaching. We should break the fragmented compilation logic of traditional textbooks and build a knowledge system of "core-knowledge layer + frontier-expansion layer" oriented toward disciplinary core literacy, so as to achieve bidirectional unification of theoretical logic and application logic.

The first layer is the basic foundation layer. We focus on underlying supporting knowledge indispensable for machine learning, integrate prerequisite knowledge including advanced mathematics, linear algebra, and probability theory, and sort out internal correlations of basic knowledge points combined with basic machine-learning concepts and core elements, solving students' problems of weak foundations and difficult entry-level learning^[11]. In teaching, isolated explanation of single knowledge points should be abandoned. Mathematical formulas shall be interpreted together with algorithm principles, helping students better understand the physical meanings and application scenarios behind formulas and consolidate disciplinary theoretical foundations.

The second layer is the core advancement layer. We construct the main knowledge framework centered on core machine-learning algorithms, sort out core modules such as supervised learning and unsupervised learning by category, clarify principles and applicable scenarios of various algorithms, break chapter barriers, and establish a logical network with horizontally-associated and vertically-progressive knowledge points. It helps students master the core logic of algorithm iteration and model optimization and develop their algorithm-oriented thinking.

The third layer is the practical implementation layer. Real industrial cases and engineering practical projects are adopted to convert all theoretical knowledge points into practical tasks. Corresponding data sets and practical-operation procedures are matched for each type of core algorithm to build an integrated

teaching chain. It thoroughly solves the problem of separation between theory and practice and realizes the practical transformation of knowledge^[12].

3.2. Building a full-process intelligent guidance system and implementing targeted teaching in accordance with students' aptitudes

Supported by hierarchical knowledge systems, we can build a pre-class, in-class, and after-class closed-loop intelligent guidance system relying on big-data and artificial-intelligence technologies. It overcomes the drawbacks of fragmentation and homogenization in traditional guidance and realizes precise and personalized talent training based on learning-situation data.

For pre-class intelligent preview guidance, we focus on laying prerequisite knowledge foundations and warming up new-lesson content. Based on the course knowledge graph and Q&A knowledge base, the Agent identifies questions, retrieves associated knowledge, and generates differentiated responses for concept interpretation, code debugging, and case analysis. Generated responses shall be compared against standard expressions in the knowledge graph. Teachers will conduct verification in case of inconsistencies. For instance, students with weak foundations receive materials sorting out prerequisite knowledge and micro-lectures on basic concepts, while advanced students are pushed with expanding new-lesson cases and cutting-edge technical documents^[13]. The platform automatically counts preview data and generates learning-situation reports, providing data support for teachers to precisely adjust classroom teaching rhythm and content. For in-class real-time intelligent guidance, we focus on breaking through key and difficult points and providing real-time Q&A. During classroom teaching, teachers carry out real-time quizzes and in-class tests via intelligent interactive platforms to dynamically collect classroom learning data. For knowledge points where most students make mistakes, the platform automatically pushes explanatory micro-lectures and knowledge-point interpretations. Teachers adjust teaching rhythm in real time according to data feedback and give priority to tackling common difficulties.

For after-class intelligent expansion guidance, based on pre-class and in-class learning-situation data, the platform accurately locates knowledge gaps and generates personalized error sets and consolidation exercises for students. Meanwhile, differentiated expansion resources are pushed according to students' competence levels: students at the basic level focus on consolidation of basic exercises and review of practical operation procedures; advanced students focus on model optimization and algorithm improvement training.

3.3. Deepening dual-driven synergy and integration and constructing integrated theory-practice teaching mode

To better solve the separation problem of dual-driven elements, we should break integration barriers between systematic theories and intelligent-technology-oriented practice, apply intelligent technologies throughout knowledge-system construction and classroom-teaching implementation, and build an integrated teaching mode of "theory-based foundation and technology-driven empowerment"^[14].

At the teaching-design level, we take the systematic knowledge framework as the core to reconstruct intelligent teaching contents. The three-tier hierarchical knowledge system is split into several modular teaching units. Each unit is equipped with theoretical objectives, practical objectives, and guidance objectives. Intelligent platforms are utilized to integrate teaching resources including micro-lecture videos, theoretical courseware, practical operation tutorials, and exercises, forming a modular, intelligent, and adaptable teaching resource library. Intelligent guidance resources are fully aligned with course knowledge

logic to avoid disordered and disconnected resources.

At the classroom-implementation level, the “three-stage progressive plus full-process” teaching mode is promoted. In the first half of the class, core theories are elaborated to clarify knowledge-point logic and core principles and consolidate students’ theoretical foundations. In the second half of the class, real-time practical training is conducted on intelligent practical training platforms. Students verify theoretical knowledge through practical operations and finish model training, debugging, and optimization simultaneously. Throughout the whole teaching procedure, the intelligent guidance system monitors learning situation data in real time, offers timely Q&A, and pushes resources. In this way, theoretical learning, practical training, and intelligent guidance advance simultaneously and achieve in-depth integration^[15].

At the scenario-expansion level, immersive practical scenarios are built with intelligent technologies. Virtual simulation platforms and cloud-based practical training environments break the restrictions of hardware equipment, site and time-space conditions, and provide all-weather machine learning practical-training scenarios for students. Combined with real industrial projects, multi-level practical tasks are set: from reproduction of basic algorithms and simple model application to algorithm optimization and innovative model construction, students’ engineering practical abilities are improved step by step, so that systematic theoretical knowledge can be fully implemented in intelligent practical scenarios.

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