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Demand-Driven and AI-Enabled: Exploration and Practice of Teaching Reform in the "Statistical Modeling" Course for Applied Undergraduate Education

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Abstract

In response to the new demand for applied statistics professionals driven by the digital transformation of the modern service industry, the "Statistical Modeling" teaching team at Sichuan University of Science and Engineering has implemented a profound pedagogical reform. By analyzing the bottlenecks of traditional teaching models such as the decoupling of theory and practice and simplistic evaluation methods, this paper proposes a "four-in-one" reform path: "real-world problem driving, deep industry-education integration, AI-enabled teaching, and curriculum-competition integration". Practice has proven that this approach effectively enhances students' ability to solve complex problems and their statistical literacy, providing a replicable model for the construction of applied brand courses.

Keywords: Statistical modeling; applied courses; industry-education integration; AI empowerment; teaching reform

I. Introduction

With the rapid development of Big Data and Artificial Intelligence, the modern service industry is undergoing a profound digital transformation, which poses some new challenges to statistics education. In this context, the industry's demand for statistical talent has shifted from simple "data processing" to "decision support in complex scenarios". However, traditional "Statistical Modeling" courses often focus
on mathematical derivations and standard algorithms. Common issues include a disconnect between teaching content and industrial needs, a lack of real business scenarios, and a rift between tool operation and statistical thinking, where students can operate software but struggle to explain the business logic behind models.
Furthermore, lagging evaluation systems fail to measure students' innovation and their ability to solve non-standard problems. To address these inherent issues, our team has systematically restructured the course based on the positioning of applied talent cultivation, focusing on industry-education integration and pedagogical innovation to cultivate composite statistical talents capable of serving regional economic development.

II. Restructuring the Curriculum System

Traditional teaching often teaches"Regression Analysis, Cluster Analysis, and
Classification Algorithms"as isolated chapters, leading to students' inability to choose appropriate methods when facing real-world problems. The reformed course establishes a five-level progressive structure: "Basic Knowledge-Core Methods - Case Analysis - Comprehensive Practice - Expansion and Innovation", emphasizing full-process modeling training. The curriculum no longer pursues the depth of algorithms in isolation but emphasizes the "full life cycle" of modeling. The concepts of "problem formulation, data processing, model construction, evaluation, optimization, result interpretation, and achievement expression" are integrated throughout. For example, when teaching regression analysis, the focus is no longer solely on significance testing but on the business basis for variable selection, improvement plans for model diagnosis, and the economic significance of regression coefficients in actual business. The content is organized into five modules: Regression, Clustering, Classification & Ensemble Learning, Principal Component Analysis (PCA), and Model Evaluation & Optimization. By comparing different methods (e.g., Hierarchical Clustering vs. K-means), students shift from "only knowing one method" to "selecting the optimal method based on the scenario".

III. Deep Integration of Industry and Education

The course constructs a“Course-Competition-Research”collaborative education model. By collaborating with enterprises such as Miaochen Technology Co., Ltd., the team solved the problem of“outdated or fictional”teaching resources. Real horizontal projects (e.g.,“Economic Census Project, “Power Battery Industry Cluster Analysis”) were de-identified and transformed into teaching cases. The following is the specific implementation details

(a) RFM Model Case

Using real transaction data from retail enterprises to perform customer profiling,
helping students master clustering algorithms via “Precision Marketing” problems.

(b) Market Prediction

Conducting demand forecasting modeling based on modern service industry operating data to strengthen predictive accuracy evaluation skills.

(c) Competition Integration

Incorporating topics from the“National Tertiary Students Statistical Modeling Contest”into daily teaching through a path of “Case→Project→Competition Training”. In the past two years, students have won 6 national awards in subject competitions, significantly enhancing their engineering practice capabilities.

IV. Innovation in Teaching Paradigms

Under the wave of Generative AI, statistics education faces both the risk of being“replaced”and the opportunity of“empowerment”. The course explores a new paradigm of“Teacher-led, Student-centered, and AI-collaborative”teaching.

(a) Lowering the Barrier

Combining Python practice with Generative AI tools allows AI to assist in code
debugging and result interpretation. Students use AI to generate base code, allowing them to focus more on validating model assumptions and analyzing statistical significance.

(b) AI Trap

Teachers intentionally set“AI traps”, requiring students to independently audit and critique AI-generated statistical conclusions to foster a scientific spirit of not following tools blindly.

(c) AI Tutor System

A system based on a course knowledge graph is being developed to provide 24-hour knowledge retrieval and modeling suggestions, shifting from “uniform

teaching" to "personalized guidance".

V. Reform of the Evaluation System

To solve the problem of "high scores but low ability", the course built a multidimensional system: "Process Evaluation + Outcome Evaluation + Multi-subject
Evaluation".

(a) Process Tracking

Formative assessment weight increased to 40%. Students must submit"modeling logs"recording failed attempts and improvement processes to evaluate their scientific thinking.

(b) Comprehensive Final

The traditional written exam is replaced by a"Comprehensive Modeling Project". Students must complete the entire workflow from data cleaning to reporting on an unknown industry dataset within a specified time.

(c) Ethical Criteria

Evaluation standards go beyond R square or accuracy; they now include assessments of the student's consideration of data privacy, algorithmic fairness, and model interpretability.

VI. Achievements and Reflections

Practice shows the reform is highly welcomed, with a student teaching evaluation rating of 91.49%. The proportion of"double-qualified"(academic and industry-certified) teachers reached 61.5%. In the future, the team will further integrate"statistical integrity"and "data ethics"into modeling tasks and explore a brand course cluster with local industrial characteristics.

VII. Conclusion

The reform of the"Statistical Modeling"course is a proactive response to digital transformation. By being "demand-driven" and "AI-enabled", the course has successfully transitioned from"knowledge transmission"to "capability shaping", enhancing students' employment competitiveness and providing a reference for the construction of other applied professional courses.

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