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From Black Box to Explainability: An AI-Integrated and Value-Oriented Pedagogical Reform for Undergraduate Applied Stochastic Processes in Statistics Programs

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Abstract: The rapid advancement of artificial intelligence is reshaping higher education, while value-oriented education (curriculum-based ideological and political education) has become a fundamental requirement for talent cultivation in the new era. Applied Stochastic Processes, a core course for statistics majors, is characterized by abstract theory, intensive mathematical derivations, and broad applications. Traditional teaching methods face three structural dilemmas: heavy emphasis on mathematical derivations with little connection to real-world applications, focus on computational techniques at the expense of conceptual understanding, and rigid model assumptions without fostering critical thinking. This paper proposes a dual-driven pedagogical reform framework integrating AI and value-oriented education, using "explainability" as the cognitive bridge that organically connects stochastic process theory with AI methods while embedding value guidance. Utilize AI visualization tools to lower the cognitive threshold of stochastic processes, introduce large language model-assisted programming accompanied by a 'critical programming' strategy to prevent over-reliance; integrate the spirit of scientists into teaching to enhance cultural confidence; and use Markov chains and the PageRank algorithm as a case study to embed data ethics and social responsibility education into the explanation of algorithm principles. Teaching practice demonstrates that this reform effectively enhances students' conceptual understanding, programming skills, and dialectical thinking abilities, achieving an organic unity of knowledge transmission, competency development, and value cultivation.

Keywords: Applied stochastic processes; Artificial intelligence; Value-oriented education; Pedagogical reform; Explainability

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1. Introduction

Stochastic processes-mathematical tools describing random phenomena evolving over time-form the theoretical foundation of modern statistics, financial engineering, and machine learning. From Brownian motion to stock price fluctuations, from queuing theory to Markov decision processes, the theory and methods of stochastic processes have permeated every corner of natural and social sciences. For undergraduate statistics majors, Applied Stochastic Processes not only serves as a bridge connecting probability theory and mathematical statistics but also represents a necessary pathway to the frontiers of data science. However, in practice, this course faces three persistent dilemmas.

First dilemma: the tension between mathematical derivation and student anxiety. Stochastic processes involve highly abstract mathematical concepts including measure-theoretic foundations, conditional expectations, and martingale theory. Traditional teaching typically follows a "definition–theorem–proof–example" sequence, and students easily lose direction amidst dense formula derivations, struggling to develop intuitive understanding. As one student remarked, "I know the formula for a Poisson process, but I don't know what it 'looks like'."

Second dilemma: the disconnect between classical theory and modern technology. Stochastic process theory was largely developed in the first half of the 20th century, creating a significant "translation" gap with today's AI boom. The Markov chains students learn in class have evolved into core tools such as hidden Markov models, Markov decision processes, and diffusion models in AI, but textbooks and instruction often fail to establish these connections, leading students to believe stochastic processes are "outdated mathematics mistakenly."

Third dilemma: the separation of value guidance and professional education. Value-oriented education requires integrating ideological and political education throughout the teaching process, yet "forced insertion" of such content in stochastic processes courses is common-either awkwardly adding policy propaganda before class or mechanically attaching moral lectures afterward. This "two-skin" approach not only fails to achieve educational goals but may also trigger student resistance.

To address these dilemmas, a natural question arises: Can AI technologies help solve the pedagogical challenges of stochastic processes? Furthermore, can value guidance be naturally embedded within this technological empowerment?

This paper proposes a dual-driven pedagogical reform framework integrating AI and value-oriented education. The cognitive bridge of this framework is explainability-a concept that represents a frontier issue in current AI research (the explainability of "black box" algorithms), an inherent characteristic of stochastic process theory (stochastic processes provide explainable mathematical models for random phenomena), and a goal of value-oriented education (cultivating students' ability to explain social phenomena critically).

Specifically, the framework integrates three dimensions: The first one is the technological dimension: Using AI tools (e.g., large language models, visualization programming) to assist stochastic process teaching, lowering cognitive barriers and stimulating learning interest. Secondly, the cognitive dimension: Revealing the role of stochastic processes as the "underlying logic" of AI algorithms, helping students develop knowledge transfer skills from "classical theory to modern applications". The last one is the value dimension: Embedding data ethics education in algorithm principle instruction, cultivating critical thinking in model assumption discussions, and enhancing cultural confidence through narratives of Chinese scientists' contributions.

Recent years have seen various explorations of pedagogical reforms for stochastic processes courses. In value-oriented education, some scholars have examined pathways for excavating value-oriented elements in stochastic processes courses at a macro level [1,2], while others have proposed blended teaching instructional designs [3–5]. Regarding AI-empowered teaching, research has explored using Matlab/Python for Wiener process simulation demonstrations [6,7], and some reform projects have focused on "new paradigms of probability and statistics experimental teaching empowered by AI" [8,9]. Internationally, some universities have attempted interdisciplinary integration of probability theory with robotics education [10].

However, existing research has two notable shortcomings: first, AI technology and value-oriented education dimensions are often discussed separately, lacking a unified integration framework; second, most reforms remain at the "tool assistance" level without re-examining the nature of stochastic process teaching from an epistemological perspective. This paper's innovation lies in proposing "explainability" as the cognitive bridge connecting AI empowerment and value guidance, achieving organic integration at the operational level rather than simple superposition.

2. Pathways for integrating AI and value-oriented education

The abstraction of stochastic processes largely stems from their "dynamic" nature-students see static formulas on paper, but stochastic processes are essentially "stories" unfolding over time. Visualization technologies in the AI era provide powerful tools to address this challenge.

Take teaching Wiener processes (Brownian motion) as an example. In traditional teaching, instructors define Wiener processes through formulas $W(t) \sim N(0,t)$ and independent increment properties, making it difficult for students to develop an intuitive feel. Using Python's Matplotlib library or more advanced interactive tools (such as Plotly, Bokeh), instructors can generate sample paths of Wiener processes in real time during class, dynamically adjusting parameters (such as step size, simulation duration, number of samples). Students can intuitively observe key features: the continuity but non-differentiability of sample paths, linear growth of variance over time, self-similarity across different time scales, and more.

Going further, one can introduce "large language model-assisted programming" sessions. Instructors assign tasks like: "Please use Python to simulate a Wiener process and compute its first passage time $T_a = \inf\{t>0: W(t)=a\}$ distribution." Students can use GitHub Copilot or ChatGPT to assist in writing code, but they must understand the mathematical meaning of each step and verify the generated results. This approach lowers programming barriers while preventing "code black box" problems.

While AI-assisted teaching brings convenience, it also harbors risks. The most prominent issue is that students may become overly dependent on large language models to complete programming assignments, abandoning independent thinking. To address this, instructors should adopt a "critical programming" strategy:

(1) Process assessment: Require students to submit an "AI contribution statement" alongside their code, indicating which parts were generated by AI, which parts were modified by themselves, what problems were encountered, and how they were solved

(2) Variation training: Set "variation problems" in class exercises that AI cannot easily generate directly, such as "change the Euler method in the Wiener process simulation to the Milstein method and compare the convergence rates of both"

(3) Reverse engineering: Provide AI-generated "buggy code" and require students to identify and fix errors, understanding the code logic in the process

The history of stochastic process development is an epic of relay exploration by scientists from China and abroad, rich with educational resources on the spirit of scientists.

The discovery and research of Brownian motion is a typical case. In 1827, British botanist Brown, while observing pollen particles under a microscope, discovered the ceaseless random motion of particles. This phenomenon attracted the attention of many physicists over the following nearly century-from Wiener (who proposed molecular vibration hypotheses in 1863) to Einstein (who provided quantitative explanations using statistical physics methods in 1905), from Perrin (who experimentally verified Einstein's theory) to Wiener (who mathematically abstracted it as a stochastic process). Instructors can guide students to reflect: scientific discovery often begins with "accidental observation," but transforming observation into theory requires the ability to cross disciplinary boundaries (Brown was a botanist, Einstein a physicist, Wiener a mathematician), as well as the perseverance to "sit on a cold bench."

Regarding Chinese scientists' contributions, one can introduce the pioneering work of Pao-Lu Hsu in probability theory and mathematical statistics. Hsu was the founder of probability theory in China, making world-class contributions to hypothesis testing theory in mathematical statistics and multivariate analysis. In recent years, Chinese scholars have also achieved remarkable accomplishments in cutting-edge fields such as random matrix theory and high-dimensional statistical inference. These stories can be integrated "silently" into teaching, enhancing students' national pride and academic aspirations.

At the operational level, AI empowerment and value guidance may seem to belong to separate domains, but they are deeply unified at the epistemological level—with "explainability" as the core concept.

From an AI perspective, "explainability" addresses the question: Can humans understand the predictions made by machine learning models? From the "black box" problem of deep learning to the "right to explanation" clause in the EU's General Data Protection Regulation, explainability has become a central issue in AI ethics. From a value-oriented education perspective, "explainability" addresses: Can the regularities described by mathematical models be understood within a broader social context? A "black box" model is not only technically unexplainable but also ethically irresponsible.

3. Teaching case designs

3.1. Markov chains and web ranking-from mathematical theorems to algorithmic ethics

(1) Knowledge points: Transition matrices of Markov chains, stationary distributions, limit theorems

(2) AI connection: Mathematical principles of the Google PageRank algorithm

(3) Value integration: Ethical examination of algorithmic power

3.2. Teaching design

(1) Problem introduction: In the early Internet era, how could we determine which web pages were more important? (Intuitive idea: pages linked to by more pages are more important)

(2) Mathematical modeling: Treat web pages as states, links between pages as transitions, defining the transition matrix PP. The core idea of PageRank: a page's importance equals the stationary probability of a random surfer visiting that page.

(3) Theoretical deepening: Explain the conditions under which an irreducible, aperiodic Markov chain has a unique stationary distribution, and the convergence guarantee of the power iteration method.

(4) Ethical discussion: Is PageRank truly "objective"? (1) Matthew effect: already highly-ranked pages more easily obtain new links; (2) Manipulation possibilities: SEO "black hat" techniques;

(5) Algorithmic bias: whose links are being "voted" on? Instructors guide students to reflect: every choice in algorithm design (such as the damping factor value, initial ranking settings) contains value judgments, and once deployed, algorithms reshape what they measure-this is the dialectic of "description" and "prescription."

(6) Assessment: Write an 800-word essay analyzing the social impact of a specific algorithm (such as

recommendation algorithms, rating algorithms), applying stochastic process concepts learned in this class.

4. Teaching evaluation and reflection

This study has several limitations. First, the reform plan was implemented at a single university with limited sample representativeness, so the generalizability of the findings needs further testing. Second, due to course cycle constraints, "long-term educational effects" are difficult to assess—can the ethical awareness and social responsibility developed during the course persist into the workplace? This requires longitudinal research. Third, the introduction of AI tools brings new challenges: how to prevent over-reliance on large language models? How to assess the boundary between "AI assistance" and "independent thinking"? These issues require continued exploration in future teaching.

Future reform directions include: (1) developing knowledge graph-based personalized learning systems that recommend learning paths based on students' cognitive levels; (2) building an "stochastic processes + X" interdisciplinary case library covering finance, healthcare, transportation, environment, and other fields; (3) exploring "project-based learning" models where students comprehensively apply stochastic process knowledge and reflect on ethical issues with real-world data projects; (4) conducting longitudinal studies to assess the long-term educational effects of value-oriented integration.

5. Conclusion

The pedagogical reform of Applied Stochastic Processes is, on the surface, an update of technical tools (introducing AI tools) and an expansion of content boundaries (integrating value-oriented elements), but in essence, it represents a deep transformation in educational philosophy-from "knowledge transmission" to "holistic education."

The introduction of AI technology is not for "showing off" or "following trends," but to help students better "see" stochastic processes, more deeply "understand" stochastic processes, and more consciously "apply" stochastic processes. The integration of value-oriented elements is not for "completing political tasks," but to cultivate "statisticians with warmth"-people who not only master advanced data analysis tools but also possess critical thinking, ethical awareness, and social responsibility. When students can both simulate Brownian motion paths with Python and tell the relay story of scientific discovery from Brown to Einstein to Wiener; both derive the stationary distribution of a Markov chain and reflect on the social impact of the PageRank algorithm; both understand the mathematical definition of a martingale and identify the deception in "sure-win gambling" schemes-only then can we say: this course has truly fulfilled its mission.

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References

[1] Cai L, Li Y, Ding N, 2021, Exploration of Teaching Reform of "Stochastic Process" Course under the Background of Emerging Engineering Education. Education and Teaching Forum, (45): 75–78.

[2] Wang M, Gao T, 2024, Research on the Construction Methods and Realization Approaches of Ideological and Political Education in University Courses—Taking Applied Stochastic Process as an Example. Modern Commercial Industry, 45(2): 251–252.

[3] Bai Y, Sun Y, 2024, Teaching Design for Course Ideology and Politics Based on Blended Learning—A Case Study of "Law of Total Probability and Bayes' Theorem". Advances in Education, 14(5): 963–968.

[4] Li W, Qu J, Gao Y, Yang Y, 2024, Teaching Reform and Practice of "Stochastic Process" Course Integrating Ideological and Political Elements. Journal of Hebei GEO University, (2): 126–129.

[5] Liu X, Zhao J, Li N, 2020, A Preliminary Study on the Integration Cases of Ideological and Political Elements in Stochastic Process Course. University Mathematics, 36(5): 28–32.

[6] Cao J, Xu X, 2023, Practical Exploration of AI-Enabled Ideological and Political "Golden Course" Construction. Ideological and Political Education Research, 39(6): 74–78.

[7] Zhang J, Zhao Y, Shi X, et al., 2024, Teaching Environment Construction under the Digital Background—Taking "Applied Stochastic Process" Course as an Example. Journal of Lanzhou Institute of Technology, 31(4): 136–139.

[8] Li C, Tian B, Fang R, 2025, Discussion on Teaching Design of Stochastic Process Course: "Ergodicity". University Mathematics, 41(4): 106–113.

[9] Wang S, Zhu W, 2024, Data-Driven, Smart Ideological and Political Education—Integration of Big Data Application and Ideological and Political Education Based on "Applied Stochastic Process". Journal of Hefei University (Natural Science Edition), (2): 130–134.

[10] Oruc O, 2026, An Integrated Approach to AI, Probability and Robotics Education for Mechanical Engineering Students. ASEE Annual Conference, Tennessee.