Construction and Practice of Teaching Resources for University Computer Courses Based on Large AI Models

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Abstract: *Traditional university computer courses use textbook, static courseware, and standard laboratory environment which guarantee the stability of teaching content in case of slow update of knowledge but have become increasingly prominent with regard to knowledge lag and rigid structure under the knowledge ecology where computer technology updates at a frequency. With the ability of large AI models to generate content, it will change from pre-packaging to on-demand generation of resource construction. We analyzed the structural limitation of the traditional resource system; clarified the redefinition of the generation mechanism by large AI models raising three types of theoretical questions (interpretability, controllability, and adaptability boundaries); constructed a large AI model adaptation mechanism for computer course resource generation involving semantic modeling of the knowledge system, teaching adaptation control, and computable quality evaluation; designed a resource construction framework based on multi-stage generation process, multi-source knowledge fusion, and a dynamic evolution mechanism working together aiming to provide theoretical analysis and technical path reference for the large AI model driving construction of teaching resources for computer courses.*

Keywords: *large AI models; teaching resource construction; computer courses; resource generation mechanism; knowledge fusion; adaptation control*

Introduction

The frequent iteration of knowledge in computer science and quick updates of technology stacks impose great pressure on the timeliness and adaptability of course teaching resources because of the limitation of textbook publishing cycle and the workload of manual revisions, with no uniform mode of providing resources meeting diverse needs of learners' cognitive paths and knowledge reserves. The arrival of large AI models brings us new technical conditions to solve these problems: it can not only generate structured teaching content according to teaching objectives directly, but also achieve generation precision control and knowledge supplementation through prompt engineering and retrieval augmentation. This change will cause profound changes in various levels including resource generation logic, quality evaluation standard, and system construction methods, requiring systematic response at both theoretical and methodological levels. Based on the context of computer courses and starting from the analysis of paradigm transformation, in this paper, we explore the adaptation mechanism and dynamic construction path between large models and teaching resources aim to provide a reference framework for further research in this field.

1. Paradigm Transformation in the Construction of Teaching Resources for University Computer Courses

1.1 Structural Characteristics and Limitations of the Traditional Teaching Resource System

The traditional teaching resources in university computer courses are mainly textbooks, static courseware, preset cases, and standard laboratory environment: organized according to a linear logic of the course knowledge graph that has been written by an expert with peer review and unified release, with strict update rhythms (annual or semi-annual) – all these have obvious advantages on content stability and teaching controllability under slow knowledge updating[1] .

At what speed is knowledge evolving in computer science? Updates on programming language versions and replacing functions in development framework happen constantly. Traditional resources have inherent problems like prominent knowledge lag, rigid content structure, and one form of resource. Textbook revisions can't keep up with technology updating rates, fixed modules cannot easily adapt to different learning path, and static texts and illustrations do not completely reflect the dynamics of algorithms and state transition relationships. All these point out a mismatched structure between the pre-packaged resource providing mode and the fast-evolving computer knowledge.

1.2 Redefinition of the Teaching Resource Generation Mechanism by Large AI Model Technology

With large-scale parametric knowledge representation, cross-task context understanding ability and generative language output capability, large AI models are able to generate structured explanatory texts, executable code examples or step-by-step algorithm derivations based on teaching objective description directly for resource generation (from pre-production then retrieval to on-demand instant production and delivery) which greatly accelerate resource response and with the attention mechanism it automatically extract implicit association between knowledge points embeds cross-knowledge-point integration work requiring a large amount of professional time in the generation process.

Moreover, the structure of main entities involved in resource production also underwent great changes: Traditionally, almost all course resources were created by course instructors or dedicated writing team; after the intervention of large models, it changed to a human-machine collaboration mode that teachers decide on the generation goal and quality constraint while the model generates content based on these constraints which is then screened and revised by teachers. The new technology shortens the pedagogical transformation cycle of frontier knowledge from an annual level to a daily response, narrowing down the time gap between resource content and the disciplinary development frontier. It enables large models to generate various difficulty versions of the same knowledge unit simultaneously, offering a feasible resource-level foundation for differentiation instruction. We are no longer just replacing tools now, we do a full-chain reconstruction from resource production efficiency and content organization methods to the form of supply, with the internal logic of resource generation undergoing a fundamental paradigm shift[2].

1.3 Key Theoretical Issues in the Transformation of the Resource Construction Model

The widespread use of large AI models generating teaching resources has greatly improved the generation efficiency as well as the freshness of the content. Facing such technological changes, there should be systematic responses to some theoretical problems. The extent to which they can be solved determines the actual usability of resources generated by large AI models in course teaching. Interpretability of resource is the main theoretical problem. The generation process of large AI models relies on a probabilistic prediction mechanism with massive parameters which output results lack explicit traceability chain of knowledge sources. If a model generates an explanatory text about the principle of algorithms or programming specifications, we cannot guarantee that the specific basis of the content comes from an authoritative textbook, a technical community post or noisy information in the training corpus. For computer courses, the definition of concepts needs high precision whereas correctness of code examples requires accuracy; if the generated content lacks traceable knowledge foundation, it will find difficulty gaining the recognition of course instructors and learners.

The knowledge modules in computer courses are quite diverse: Basic grammar requires memorizing rules; algorithm design calls for logical reasoning; system-oriented courses emphasize component interactions and architectural rationality. Adaptation validity of large AI models for different types of knowledge varies. Lack of interpretability exacerbate difficulty in control which blur the boundary of determinations of adaptability due to lack of controllability. All these three sets of problems are interrelated as a theoretical frontier that needs urgent attention at the time of paradigm transformation with a clear problem orientation for our further discussions regarding adaptation mechanisms and construction paths.

2. Large AI Model Adaptation Mechanism for Computer Course Resource Generation

2.1 Semantic Modeling and Input Representation of the Course Knowledge System

The quality of teaching resources generated from large AI models depends on accurately describing

the course knowledge structure in the inputs. The knowledge system for computer courses has complex features like hierarchical nesting and multidimensional associations; three levels: basic knowledge, core principles, and frontier extensions does not progress linearily but there exists cross references and prerequisites between each other. We need a machine-understandable semantic representation scheme which makes the implicit knowledge structure embedded in the course syllabus explicit as an input form percevable by the model[3].

Specifically, each knowledge unit needs to be decomposed into different multidimensional semantic elements such as concept definition, operation procedure, logical derivation, or code implementation based upon which it corresponds with different generation emphasis and expression constraint. For input organization, we construct a hierarchical prompt template structure in order to present the whole course objective, chapter position, and detailed description on specific knowledge point to the model sequentially from coarse to fine; we annotate the dependency among knowledge units so that the generation has a global knowledge perspective instead of focusing on individual knowledge points, thereby ensuring the cohesion/coherence of the generated contents within the knowledge system and their logical self-consistency.

2.2 Teaching Adaptation Control Strategies for Generated Content

The content produced by native from large models is fluent in language, but it doesn't mean teaching usability. Some requirements exist on difficulty positioning, expression precision, and cognitive load for computer course resources that require systematical deviation with model output to be controlled. Different control schemes were designed respectively according to the need of concept explanation, process demonstration, and exercise design in this section.

For concept explanation resources: We utilize difficulty-graded prompts and analogy guidance to constrain the depth of explanations and levels of abstraction explicitly specified for the target cognitive level; Process demonstration resources concentrate on the granularity of step decomposition and details of state annotation and improve the teaching value of visual presentation by specifying the format requirement in prompts. For exercise design resources: We utilize Bloom's taxonomy of cognitive objectives to build up an instruction system so that generated exercises can be designed with targeting coverage over different cognitive dimensions (e.g., memory, understanding, application, analysis) -- a common design idea among all control strategies is embedding adjustable teaching constraint parameters under the condition of keeping the flexibility of model generation transforming the implicit teaching requirements from course objectives into operational instructions which the model could accurately perform, improving the matching precision between generated contents and real classroom needs[4].

2.3 Computable Evaluation Dimensions of Resource Quality

Quality evaluation for resources produced by large models is different than traditional courseware review; it does not depend on experts' subjective scoring, but a clearly quantified path and operable evaluation system. In this section we construct evaluation indicators based on three aspects – semantic accuracy, structural completeness, and teaching expressiveness. Semantic accuracy evaluation aims at identifying knowledge errors, concept confusion or logic break in generated content which obtains preliminary automatic screening assisted by knowledge graph alignment and consistency verification algorithms.

Structural completeness checks whether all the constitutive parts are contained in the generated resources by quantifying the structural matching degree of a preset content skeleton (the less missing items, the higher completeness), Teaching expressiveness is about the clarity of language, typicality of examples and rationality of cognitive load distribution that obtains quantitative indicators through combining text readability calculation tool with cognitive difficulty analysis tools; The results obtained from the above three aspects will be converged into a multidimensional profile of resource quality which can make screening decision on one generation of content as well as accumulate evaluation data to optimize and adjust the prompt for next-generation generations so as to create a closed loop of quality control based on quantitative evaluation.

3. Dynamic Construction Path of Computer Teaching Resources Based on Large Models

3.1 Multi-Stage Process Design for Course Resource Generation

In order to build up large model-driven resources, we need to establish a novel operation process which differs from the traditional development model so as to achieve an equilibrium between generation efficiency and output quality. In the traditional model, the resource development has been simplified as a one-way linear "writing—review—release". However, with the introduction of large models, we have the ability to design processes with multiple stages of decomposition and feedback intervention points. We designed a four-stage resource generation process: Objective parsing parses the teaching requirements in the course syllabus into the generation objective description understandable to the model (knowledge scope, difficulty positioning, and output format); Knowledge retrieval retrieves relevant reference materials on the generation objectives from external knowledge bases as knowledge anchor for the model's generation to avoid hallucinated output; Structured generation calls large models to generate initial resource drafts module by module according to a preset content framework, every module being individually generated together with its annotation of their generation basis; Quality screening checks the initial draft item by item based on the evaluation dimensions proposed in Chapter 2, if it does not meet the threshold, it will be regenerated or marked for manual revision[5].

Our process design transforms the resource generation from "one-time completion" to "phased advancement", where every phase has a specific input/output standard, which makes the generation process traceable and local-optimizable. The first two phases (objective parsing and knowledge retrieval) have dual constraints for next-generation: not only what to generate but what to generate based on in order to minimize the randomness and uncertainty of generated content at its source. Information transfer between all four stages uses structured data format so that it can correctly parse the output of one stage by another; this whole process is operatable, repeatable and debuggable.

3.2 Resource Enhancement Strategy through Multi-Source Knowledge Fusion

The inevitable time lag and domain coverage limitation regarding the parametric knowledge of large models can not meet the immediate need of computer courses for new technology content by relying solely upon its internal memory for generating resources. In this section we propose a strategic integration of multiple source external knowledge to improve the quality of resource generation. External knowledge sources include structured electronic version of course textbooks, API reference library of mainstream technical documentation, code repository from open-source community as well as algorithm description paragraph from academic paper. There are format heterogeneity and difference in expression style among different knowledge sources: textbook language emphasizes normativity and systematicity; technical documentation emphasizes operability and precision while open-source code contains real engineering context[6].

Using retrieval-augmented generation technology to retrieve external text fragments related to the current knowledge unit in each generation and injecting it into the model's input as generation context. We choose textbooks as our knowledge skeleton to guarantee its systematic completeness, technical documentation provides the functional description of the latest versions which compensate for the lack of timeliness of textbooks while open-source code serves as a case source giving the generated examples with an authentic engineering character. In terms of allocation of fusion weights, textbooks and official technical documentation are prioritized to ensure their authority, while community code and academic papers serve as supplements to extend coverage. Our fusion strategy guarantees balance between the three aspects (systematic rigor, technical standardization, engineering freshness) of generated resources without being too narrow by relying on just one knowledge source.

3.3 Dynamic Evolution and Continuous Updating Mechanism of the Resource Repository

Obviously, the effectivity of teaching resources for computer courses will decay over time due to the release of new technologies or updates of frameworks as well as the evolution of programming paradigmes constantly changing the scope of applicability of course contents. It is impossible to adapt the traditional resource repository's static storage mode to these changes; building a dynamic evolution mechanism which can update itself becomes a prerequisite to maintain the long-term value of resources. We build a resource evolution mechanism by establishing a feedback loop based on different kind of signals derived from the process of resource usage (e.g., the distribution of learners' dwell time on resource pages, the result of clustering questions content in the dimension of high-frequency words),

and the correlation strength of resource content against course assessment results to make decision about its update in this section.

Once the accumulated signals exceed the threshold triggered by the system, an automatic resource revision request is sent to the large model along with some prompts on revision direction. Apart from supplementing content and correcting errors, there are also adjustments in difficulty (expression style) as well as adapting the runtime environment for example code included in the evolution operations. Version record matrix records the generation time, revision history and difference between versions of each resource unit providing data support for traceability and backtracking of the evolution process. The resource repository turns into a responsive living system that is not only a collection of finished products but drives its own evolution rhythm based on the real needs generated during the process of teaching use instead of a preset timetable: its updating behavior has problem orientation and resource efficiency.

3.4 Structural Integration and Synergistic Relationships of the Resource Construction Framework

Analysis on the generation process, knowledge fusion, and evolution mechanism as shown above in the previous three sections forms a synergistic structure with hierarchy instead of just serial/parallel relationship: Multi-stage generation process offers an operation framework over time dimensions that define the whole lifecycle of resources from demand to output; multi-source knowledge fusion contributes information increments along content dimension during the generation stage of this process providing knowledge foundation and source support for model output; Dynamic evolution mechanism creates a feedback loop between the end and the beginning of the process giving the resource construction system characteristics of a closed loop rather than one way, one time operations.

For system functions, we have the synergistic effect between the three as follows: The signal data acquired through the evolution mechanism is used to optimize the accuracy of input description when it parses objectives; Retrieval library for knowledge fusion evolves along with the resource repository so as to achieve synchronous update; Classified statistics of quality screening result can be used to adjust process parameters. For multi-layer interaction, the overall effectiveness of our framework relies not only on the technical implementation level of one link, but also on the efficiency of information transfer and collaboration adjustment ability among these three subsystems (process, knowledge, feedback). Organic integration of the three has formed a systemic feature different from traditional resource construction models, which provides an extensible reference architecture for similar research.

Conclusion

According to the structural contradiction between the rapid iteration of knowledge in computer science and the rigid structure of resource supply model, exploring the potential paradigm change brought about by the participation of large AI models in teaching resource construction, including three kinds of theoretical problems raised (interpretability, controllability, and adaptability boundaries), focusing on three main links: semantic modeling and input representation of course knowledge system, teaching adaptation control of generated content, and computable evaluation of resource quality, we design a large AI model adaptation mechanism for computer course resource generation which provides a technical way to exactly match the model's output and course needs; designing a resource construction framework composed of a multi-stage generation process, multi-source knowledge fusion strategy, and dynamic evolution mechanism, showing their synergism and transform resource construction from static one-time development into a continuous evolution process with closed-loop feedback capability. The framework theoretically solves the key issues encountered when generating resources through large AI models as well as providing an methodology operable systematic solution to efficiently constructing teaching resources for computer courses. We will continue this line of future works such as long-term effect tracking of generated resources, differentiation of adaptation strategies for courses at different levels, applying multimodal large models in experimental resource generation, and automatically improve quality evaluation frameworks.

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