

UniEDU: Toward Unified and Efficient Large Multimodal Models for Educational Tasks

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Abstract

Education materials for K-12 students often consist of multiple modalities, such as text and images, posing challenges for models to fully understand nuanced information in these materials. In this paper, we propose a unified and efficient large multimodal model UniEDU designed for various educational applications, including knowledge recommendation, knowledge tracing, time cost prediction, and user answer prediction, all within a single model. Unlike conventional task-specific models, UniEDU offers a unified solution that excels across multiple educational tasks while maintaining strong generalization capabilities. Its adaptability makes it well-suited for real-world deployment in diverse learning environments. Furthermore, UniEDU is optimized for industry-scale deployment by significantly reducing computational overhead—achieving approximately a 3× increase in efficiency—while maintaining competitive performance with minimal degradation compared to fully fine-tuned models. This work represents a significant step toward creating versatile AI systems tailored to the evolving demands of education.

1 Introduction

The incorporation of artificial intelligence (AI) significantly enhances the quality of K-12 education by enabling more personalized learning experiences, improving student engagement (Chen and Leitch, 2024; Adetayo et al., 2024), and providing educators with valuable insights to tailor instruction to individual needs (Bhowmik et al., 2024; Zheng et al., 2025). For example, knowledge recommendation systems leverage AI to suggest relevant learning materials based on students’ past performance and preferences (Wang et al., 2024b; Chu

et al., 2025), while knowledge tracing techniques track students’ understanding over time, allowing for real-time adjustments to learning paths (Li et al., 2024; Shen et al., 2024; Yang et al., 2024b).

Despite these advancements, previous research has primarily focused on plain text modality, while real-world K-12 scenarios often involve multimodal data, such as text and images in question stems. Furthermore, the significant differences between tasks pose a challenge in designing a unified model that can effectively handle diverse input types. However, since user profiles remain consistent across tasks, a unified approach could facilitate seamless knowledge transfer among them. For example, while knowledge recommendation is typically framed as a ranking problem and knowledge tracing as a binary classification task, both rely on a shared understanding of student learning behaviors and knowledge states. These disparities underscore the need for a unified model capable of handling the complexities of multimodal scenarios and supporting diverse task types within the context of educational AI assistance.

Large Multimodal Models (LMMs) (Liu et al., 2023b,a; Chen et al., 2024) emerge as a promising solution due to their proficiency in handling multimodal data. Furthermore, by leveraging the flexibility of natural language, LMMs can reframe tasks in a generative format and tailor input descriptions to effectively support a wide range of distinct tasks. However, the computational cost of processing long input contexts remains a significant challenge. Since user interaction histories often span extended periods—up to 300 interactions in our study, with a maximum length reaching 45,000 tokens—retaining all interactions would substantially increase token costs, thereby escalating both training and inference expenses. A detailed analysis of these computational costs is provided in Section 3.4. While directly truncating such data may risk losing important information, educational

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user profiles are largely constructed from interaction histories, which makes them more amenable to compression. Unlike other domains that may require precise memory of all events, educational contexts often tolerate approximate representations, as not all historical details are equally critical for capturing learning behaviors and knowledge states (Rendle and Zhang, 2023; Purificato et al., 2024; Chu et al., 2024).

To address these challenges and accommodate the unique demands of educational settings, we propose **UniEDU**—a unified large multimodal model optimized for efficient deployment in educational assistant systems. UniEDU compresses student interaction histories into a compact set of tokens for efficient feature extraction and reformulates diverse real-world educational tasks within a generative framework. Comprehensive experiments demonstrate that UniEDU achieves strong performance across real-world tasks, outperforming task-specific models while delivering approximately a 300% improvement in computational efficiency.

2 Related Work

To provide students with support tailored to their abilities and preferences, it is essential to develop an effective AI assistant for K-12 learning. At the outset of AI integration in education, improving e-learning quality was a primary focus (Murtaza et al., 2022; Rahayu et al., 2022; Xu et al., 2025b), with techniques such as recommendation systems for personalized learning and adaptive learning platforms playing a central role in tailoring educational content to individual student needs (Zaiane, 2002; Ali et al., 2022). While these systems are effective, most are designed for specific tasks, such as knowledge tracing (Li et al., 2024; Shen et al., 2024), and lack generalization across diverse educational contexts.

With the development of LLMs (OpenAI, 2022, 2023; Dubey et al., 2024; Yang et al., 2024a), which leverage superior understanding and generation capabilities, e-learning assistants have made significant strides in expanding their generalization. These assistants can now serve both as teaching assistants (Xu et al., 2024; Guo et al., 2024; Abu-Rasheed et al., 2024; Xu et al., 2025a) and student support (Park et al., 2024; Liu et al., 2024; Scarlatos et al., 2025; Yan et al., 2024), reducing teachers’ workloads while offering personalized responses tailored to each student’s needs. However, since

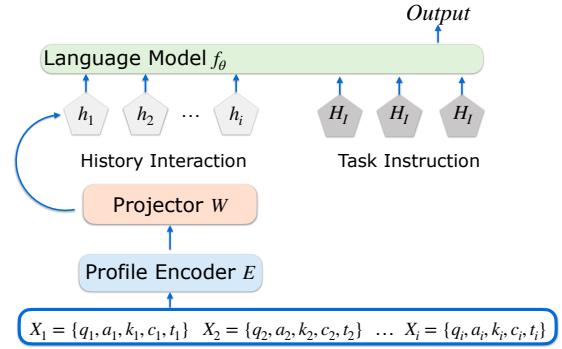


Figure 1: The architecture of UniEDU. The profile encoder processes history interactions with multimodal information, while the language model integrates compressed history interactions and task instructions to generate the output.

LLMs are typically trained on general-domain data, they often struggle to adapt to the multimodal inputs and long-context scenarios common in modern e-learning environments. This highlights the need for a unified model capable of effectively handling these complexities.

3 Methodology

3.1 Model Architecture

UniEDU comprises two main modules: the **Profile Encoder** and the **Language Model**. As illustrated in Figure 1, the **Profile Encoder** is for extracting features from the user’s interaction history, while the **Language Model** is used to generate task-specific responses.

The **Profile Encoder** is designed for compressing the user’s interaction history into a compact representation that the **Language Model** can efficiently process. Formally, let $S = \{X_1, X_2, \dots, X_n\}$ represent a sequence of user interactions, where each interaction X_i is defined as $X_i = \{q_i, a_i, k_i, c_i, t_i\}$. These components are chosen for their relevance to downstream tasks and are representative of common inputs in real-world educational systems (See Section 4.1). Each component of X_i is characterized as follows: q_i denotes the question stem, a_i represents the user’s response, k_i corresponds to the knowledge concept associated with the question, c_i indicates the correctness of the user’s response, and t_i denotes the time taken by the user to complete the interaction. q_i could be multimodal, encompassing both visual information (e.g., figures associated with the question) and textual content. Please refer to Appendix A.2 for the demonstration of interaction history. Given the se-

Variable	Definition
a	number of attention heads
b	batch size
d	hidden dimension size
l	number of transformer layers
s	sequence length
t	tensor parallel size
v	vocabulary size

Table 1: Definitions of the variables.

quence S , the **Profile Encoder** compresses it into a feature matrix of shape $|S| \times m \times h$, where $|S|$ is the sequence length, m is a hyperparameter that determines the number of tokens used to represent each interaction, and h is the hidden state dimension expected by the language model. To ensure compatibility, we apply a **Projector**—a linear layer that projects the encoder output to the hidden size of the **Language Model**.

By processing S through the **Profile Encoder** and **Projector**, we obtain $|S| \times m$ compressed profile embeddings, denoted as $H_p = \{h_1, \dots, h_{m|S|}\}$. These embeddings, together with the uncompressed task instruction embeddings H_i , are then processed by the **Language Model**, which generates responses for different tasks.

3.2 Training Objective

To enable multi-task learning, UniEDU is trained to generate task-specific outputs conditioned on the user’s interaction history and task instructions. In particular, given a sequence of user interactions S and a task instruction $\mathbf{X}_{\text{inst}}$, the model generates the corresponding target output $\mathbf{X}_t$. The training process employs the standard auto-regressive training objective, formally defined as:

$$p(\mathbf{X}_t | S, \mathbf{X}_{\text{inst}}) = \prod_{i=1}^{|\mathbf{X}_t|} p_{\theta}(x_i | S, \mathbf{X}_{\text{inst}}, \mathbf{X}_{t, < i}), \quad (1)$$

where θ represents the trainable parameters, and $\mathbf{X}_{\text{inst}}$ and $\mathbf{X}_{t, < i}$ denote the instruction tokens and the generated target tokens preceding the current prediction token x_i , respectively. In Section 4, we discuss the education tasks we considered in detail.

3.3 VRAM Computation

In this section, we provide a detailed analysis of why UniEDU is VRAM-efficient for both training and inference. We compare UniEDU’s VRAM requirements with general fine-tuning demands, focusing on two key components: parameters-loaded

VRAM ($VRAM_{para}$) and activation memory ($VRAM_{activation}$). In Table 1, we list all the definitions of the variables used in this section.

Assuming both model parameters and activations are stored in a 16-bit floating point format, each element requires 2 bytes of storage. During the training stage, in addition to S_{model} for model loading, additional memory is required for storing optimizer states and gradients. Specifically, the Adam optimizer maintains two sets of moment estimates—first-order (mean of past gradients) and second-order (variance of past gradients)—for each model parameter, effectively doubling the memory required for optimization. As a result, the optimizer states require $2S_{\text{model}}$. Additionally, gradient storage requires S_{model} . Thus, the total VRAM for loading the parameters in the training stage is:

$$VRAM_{para}^{\text{train}} = 4 \times 2S_{\text{model}} = 8S_{\text{model}}. \quad (2)$$

During inference, the only VRAM requirement is for loading the model itself, as no optimizer states or gradient storage are needed. Therefore, the VRAM required for inference is given by:

$$VRAM_{model}^{\text{infer}} = 2S_{\text{model}}. \quad (3)$$

Following the VRAM computation from NVIDIA, the activation memory required for Transformer is given by:

$$VRAM_{activation-blocks} = \frac{s b d l}{t} \left(34 + 5 \frac{a s}{d} \right). \quad (4)$$

In addition to activations within Transformer blocks, there are activation memory requirements before and after these blocks. The token and position embeddings before the first block require:

$$VRAM_{activation-embedding} = 4 b s d. \quad (5)$$

After passing through the Transformer blocks, the output tensors are typically stored in float32, even if the model was loaded at lower precision, as it often casts outputs to float32 by default (Smirnov, 2023). During training, probabilities that are the same size as the output tensor also need to be stored, contributing additional memory overhead. This results in the following VRAM usage:

$$VRAM_{activation-output} = \begin{cases} 8 b s v, & \text{training} \\ 4 b s v, & \text{inference} \end{cases} \quad (6)$$

To further optimize VRAM consumption, we employ Flash Attention (Dao et al., 2022), which reduces attention memory complexity from quadratic

	Model Size	$VRAM_{para}$	$VRAM_{activation}$			$VRAM_{total}$
			Embedding	Blocks	Output	
Training						
Qwen2-VL-2B	2B	14.9GB	0.3GB	61.3GB	50.9GB	127.4GB
Qwen2-VL-7B	7B	52.2GB	0.3GB	143.0GB	50.9GB	246.4GB
UniEDU-5B	5B	37.3GB	1.8MB	1.1GB	0.4GB	38.8GB
Inference						
Qwen2-VL-2B	2B	3.7GB	0.1GB	2.2GB	25.5GB	31.5GB
Qwen2-VL-7B	7B	13GB	0.3GB	5.1GB	25.5GB	43.9GB
UniEDU-5B	5B	9.3GB	1.8MB	25MB	0.2GB	9.5GB

Table 2: VRAM Usage Comparison Across Different Models. The results assume $b = 1$ and $t = 1$, with other parameters set according to their respective models. For UniEDU, $s = 300$ due to compression, while for the other models, $s = 45,000$, representing the maximum number of history interaction tokens. For clarity, token counts for task instructions are omitted, resulting in slight discrepancies in real VRAM usage.

to linear with respect to the sequence length. Given that the sequence length in our setting (up to 45K) is significantly larger than the number of attention heads a , the activation memory in the training stage can be approximated as:

$$VRAM_{activation} \approx 34 \frac{sbd}{t} + (4d + 8v)bs. \quad (7)$$

For inference, the activation memory cost depends on the maximum single activation memory in blocks (i.e., the activation memory of each layer), as intermediate parameters for updates are not stored. Therefore, the inference cost is:

$$VRAM_{activation} \approx 34 \frac{sbd}{t} + 4bsv. \quad (8)$$

3.4 Efficiency Analysis

In Table 2, we present the VRAM requirements for Qwen2-VL-2B and 7B (Wang et al., 2024a), as well as our UniEDU. Due to the long context required for recommendation tasks (up to 45K tokens in our dataset) and the large vocabulary size of modern LLMs, activation memory consumes a substantial amount of VRAM, leading to high computational costs during both training and inference. However, after compression, UniEDU significantly reduces VRAM usage compared to traditional models, achieving over a 3× reduction even relative to the smaller Qwen2-VL-2B in both training and inference stages. This substantial decrease in memory consumption offers a significant advantage for real-world deployment, enabling the model to process larger batches and handle more data within the same timeframe.

4 Experiments

4.1 Education Tasks

Our system primarily focuses on the subject of mathematics. During training, we use the same user interaction history across tasks while varying task instructions to avoid data leakage. Below, we detail the formulation of each task, with corresponding training examples provided in Appendix A.2.

Knowledge Recommendation. This task aims to recommend relevant knowledge concept based on a user’s interaction history. In the educational assistant context, the model identifies a student’s weak areas and provides targeted recommendations, including both foundational knowledge to address weaknesses and advanced knowledge for further development. For example, if a student consistently struggles with questions involving quadratic equations, the model may recommend reviewing the fundamentals of factoring and completing the square. Conversely, if the student performs well on basic algebraic manipulation, the system might suggest more advanced topics such as functions or inequalities to support continued growth. Specifically, we define the data format as a triplet (S, Y, C) , where S represents the user’s interaction history (as detailed in Section 3), Y denotes the ground truth knowledge concepts that reflect the student’s weak areas, obtained from real-world exam history. C comprises candidate knowledge concepts, including both the ground truth concepts Y and distractors. To construct C , we sample K candidate concepts, where $K \in \{5, 10, 25, 50\}$, including one

ground truth and $K - 1$ distractors. The model needs to rank the candidate set C based on its modeling of the student’s ability. Task performance is measured using Precision@1, where a prediction is considered correct only if the ground truth concept is ranked first among the K candidates.

Knowledge Tracing. This task aims to predict whether a student can correctly answer a given question. The model must capture the user’s profile, identifying both strengths and weaknesses, to make an accurate prediction. Specifically, given a sequence of the user’s interaction history S and a question Q , the model is expected to predict a binary outcome: [True] or [False], where the ground truth is derived from the student’s actual answer. The performance of this task is evaluated based on prediction accuracy.

Time Cost Prediction. The goal of this task is to predict the time a student needs to solve a given question. The task requires the model to understand both the student’s learning path and the inherent difficulty of the task. Specifically, similar to Knowledge Tracing, given a sequence of the user’s interaction history S and a question Q , the model is expected to predict an integer value representing the time required, with the ground truth derived from the student’s actual time spent. We evaluate the model’s performance using Mean Absolute Error (MAE).

User Answer Prediction. The User Answer Prediction task aims to predict the user’s possible answer to a given question based on their interaction history and learning profile. If the model thinks that the student can successfully answer the question, it needs to predict the correct answer (Liu et al., 2022). However, if the student is unlikely to succeed, the model needs to predict an answer that aligns with the student’s profile, reflecting a potentially incorrect response. This task requires the model to capture the student’s strengths, weaknesses, and learning paths to generate realistic answers. Specifically, given a sequence of the user’s interaction history S and a question Q , the model predicts the most probable answer, with the ground truth being the student’s actual response. We use exact match (EM) to evaluate the performance.

4.2 Implementation Details

Datasets. We collect our dataset from real student exercise data on a widely used e-learning platform and construct the training data for each task. The statistics of the dataset are shown in Table 3. Each

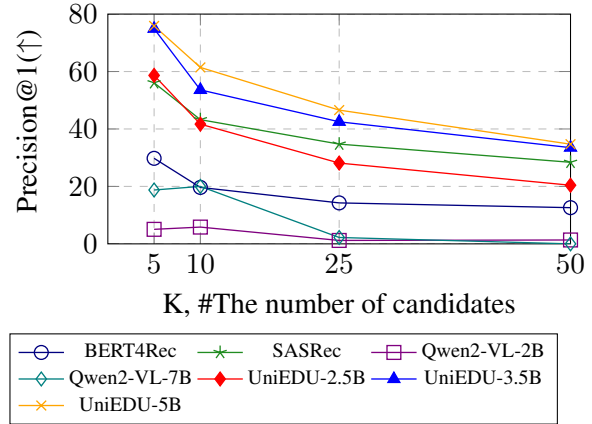


Figure 2: Performance comparison of seven models on the Knowledge Recommendation task.

# of students	13,239
# of knowledge	8,247
# of questions	235,687
# of interactions	3,892,084

Table 3: Dataset statistics.

student’s history sequence exceeding 300 interactions is truncated into multiple segments. As a result, although we processed 13,239 students, the total number of sequences exceeds this count.

Baselines. To assess UniEDU’s effectiveness, we compare it against two representative baselines for each task. Specifically, for knowledge recommendation, we evaluate two widely adopted models: SASRec (Kang and McAuley, 2018) and Bert4Rec (Sun et al., 2019). For the knowledge tracing task, we consider extraKT (Li et al., 2024) and reKT (Shen et al., 2024). For time cost prediction, we utilize N-BEATS (Oreshkin et al., 2020) and Prophet (Meta, 2023). For user answer prediction, a generative task requiring the model to produce responses in natural language, we employ Qwen2-VL-2B and Qwen2-VL-7B (Wang et al., 2024a). Additionally, these two models, without fine-tuning, are included as baselines for the three aforementioned tasks.

All experiments are conducted using the same training and test sets. The maximum length of interaction history is 300, with a maximum token cost of 45,000, based on the Qwen tokenizer. For baseline models that require indexing specific users and items, we follow their official guidelines to complete this process.

Backbone Models. We fine-tune UniEDU on

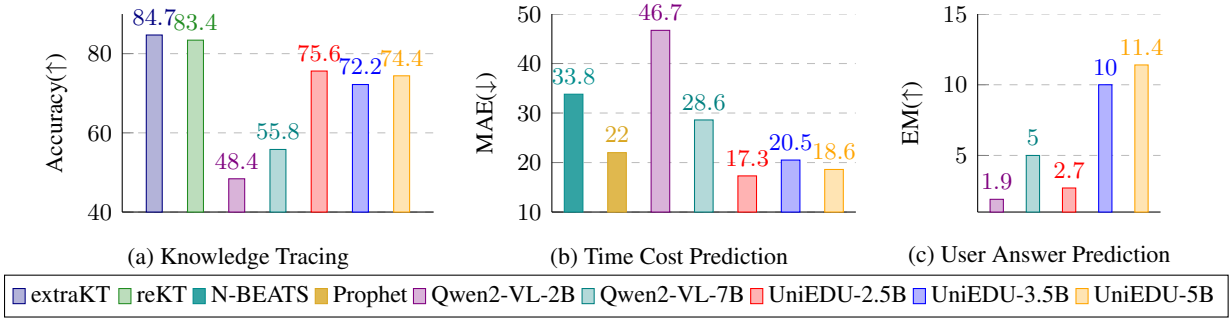


Figure 3: Performance comparison of UniEDU and baseline models on Knowledge Tracing, Time Cost Prediction, and User Answer Prediction.

the four tasks outlined in Section 4.1. For each task, we use 24,504 sequences for training, with 5% of the data randomly selected as a validation set, and 2,784 sequences for testing. For UniEDU, we fix the encoder model as Qwen2-VL-2B and vary the language model size by using Qwen2.5-0.5B, Qwen2.5-1.5B, and Qwen2.5-3B. These configurations form UniEDU-2.5B, UniEDU-3.5B, and UniEDU-5B, enabling us to assess the impact of model size on performance.

4.3 Results

We compare the performance of baselines and UniEDU with various parameter sizes on four tasks. The results are reported in Figure 2 and Figure 3.

First, **UniEDU demonstrates strong performance across four tasks**. Except for knowledge tracing, UniEDU outperforms task-specific models in Knowledge Recommendation, Time Cost Prediction, and User Answer Prediction. Notably, it achieves performance gains of approximately 30% and 20% over the best baselines in knowledge recommendation and time cost prediction, respectively. While UniEDU performs competitively in knowledge tracing, it slightly lags behind specialized models like extraKT and reKT, which are better suited for simpler discriminative tasks. However, these models struggle with unseen items, whereas UniEDU handles them effectively through natural language descriptions.

Second, **model size significantly affects generative tasks but has limited impact on discriminative ones**. For Knowledge Tracing and Time Cost Prediction, performance remains relatively stable across model sizes. In contrast, for Knowledge Recommendation and User Answer Prediction, larger models like UniEDU-5B show clear advantages over smaller variants. This suggests that tasks requiring longer or more complex generation benefit more from increased language model capacity.

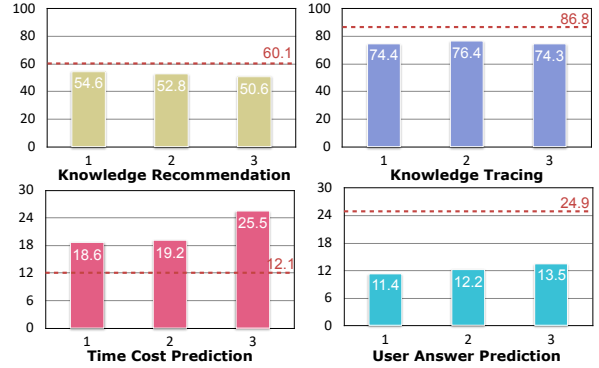


Figure 4: Performance of UniEDU-5B with different numbers of compression tokens. The red dashed line indicates Qwen2-VL-2B with full fine-tuning.

4.4 Analysis of Compression Tokens

To evaluate the impact of compression ratio on performance, we vary the number of compression tokens (i.e., m , as defined in Section 3.1) to 1, 2, 3, meaning each history interaction X_i is compressed into 1, 2, 3 hidden states. We conduct this analysis on UniEDU-5B and use Qwen2-VL-2B as an upper bound, excluding the 7B variant due to its high computational cost.

Results in Figure 4 show that increasing the number of compression tokens slightly degrades performance in Knowledge Recommendation and Knowledge Tracing, likely due to noise from excessive historical context. In contrast, User Answer Prediction benefits from additional context, as it requires modeling both historical interactions and candidate questions. Overall, our compression approach provides substantial efficiency gains with minimal performance loss, except in the more complex generative setting of User Answer Prediction. Furthermore, compared to the fully fine-tuned model, our compression technique achieves significant improvements in training and inference efficiency with minimal performance degradation, except for the User Answer Prediction task.

5 Conclusion

In this paper, we propose UniEDU, a unified generative model for education that effectively handles various multimodal tasks while being computationally efficient. Unlike task-specific models, UniEDU not only achieves better performance but also generalizes well across different educational challenges, making it suitable for real-world deployment. Extensive experiments validate its effectiveness, showing that compared to fully fine-tuned models, UniEDU reduces computation costs by approximately 300% while incurring minor performance drops. Overall, UniEDU represents a promising step toward integrating LMMs into industrial education applications, offering a scalable and efficient approach to personalized learning.

Limitations

While UniEDU shows strong performance and efficiency across multiple educational tasks, several limitations remain. First, its generalizability beyond mathematics to other subjects and task types (e.g., essay grading) has not been explored. Second, the compression strategy, though effective for reducing VRAM, introduces minor performance drops in complex generative tasks, with trade-offs between efficiency and fidelity requiring further study. Third, the interaction-history-based profile modeling may overlook latent learner traits like motivation or learning style; incorporating richer signals could improve personalization.

Broader Impact Statement

UniEDU has the potential to significantly improve personalized learning by providing targeted knowledge recommendations based on students' interaction histories. This can enhance student engagement, support educators in curriculum design, and scale AI-driven education to a wider audience. Furthermore, our computationally efficient design in UniEDU makes it accessible to institutions and companies with limited computational resources, while maintaining competitive performance with minimal trade-offs.

However, training large models on student data poses potential risks to student privacy. To mitigate these concerns, our dataset is constructed from real student interactions, but all personally identifiable information is strictly anonymized. Only interaction data relevant to learning behaviors is retained, while sensitive details such as names, user IDs, and

other personal attributes are carefully masked to ensure privacy and compliance with ethical data usage standards.

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A Appendix

A.1 VRAM Calculation

In the NVIDIA paper (Korthikanti et al., 2023), the hidden size is increased to $4h$ and then reduced back to h across layers. This varies in models like Qwen2-VL-7B, where the hidden size is 1,576, and the intermediate size is 8,960. For consistency, we adopt the evaluation strategy provided by NVIDIA, which may introduce a minor discrepancy in the real memory costs for models with different configurations.

A.2 Example Demonstration

We provide examples of the four tasks mentioned in Section 4.1. Let $S = \{X_1, X_2, \dots, X_n\}$ denote a sequence of user interactions, where each interaction is defined as $X_i = \{q_i, a_i, k_i, c_i, t_i\}$, consisting of the question q_i , the user’s response a_i , associated knowledge k_i , response correctness c_i , and response time t_i . The question q_i may be

multimodal, incorporating both textual content and visual elements (e.g., figures).

Interaction History:

Interaction 1:
Question: The difference between 4.6 and 3.26 is ___ less than their sum.
User’s Response: ["6.52"]
Correct: True
Response Time: 61s
Knowledge Concept: Three-step word problems with decimal addition and subtraction

Interaction 2:
Question: Shape A is translated ___ by ___ units to get Shape B.
Image: <image>
User Answer: ["down", "5"]
Correct: True
Response Time: 22s
Knowledge Concept: Identifying the direction and distance of translation

Interaction 3:
Question: Xiao Pang’s electricity usage in the first quarter was: 105 kWh, 150 kWh, and 99 kWh. The average monthly electricity usage in the first quarter is ___ kWh.
User Answer: ["118"]
Correct: True
Response Time: 71s
Knowledge Concept: Calculating average basic level

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Interaction n:
Question: Teacher Hu rode a bicycle to the library and crossed a 1500-meter bridge. On the way there, it took 300 seconds to cross the bridge, and on the way back, it took 200 seconds. Then the average speed over the round trip on the bridge is ___ meters/second.
User Answer: ["6"]
Correct: True
Response Time: 69s
Knowledge Concept: Calculating average speed round trip

Knowledge Recommendation:

Based on the user’s past problem-solving history, select 1 knowledge concept from the following list that the user is likely to make mistakes on.

Candidate Knowledge Concepts:
Properties of opposite numbers, absolute values, and reciprocals-evaluating algebraic expressions, Solving average problems using equations, Decomposition and

composition of numbers within 10 (including 0), Midpoint of a line segment-identifying relationships involving sum, difference, and multiples, Applications of ratio-given the total, Figures obtained by rotation followed by translation, Translation of figures in coordinate systems, Calculations of the form $(\alpha + \beta)/2$, Applications of linear equations-relationships between points on a number line, Calculating averages-pie chart interpretation, Finding the value represented by a point given the distance between two points, Simplified decimal addition and subtraction, Weighted averages-weights in percentage form, Identifying rotated figures-pattern problems, Weighted averages-weights in ratio form, Corresponding elements of congruent triangles-methods of geometric transformation, Translation drawing on a grid, Translating the rectangular coordinate system, Applications of common factors-finding the number in each group, Word problems with two-digit divisors-constant total amount

Hyperparameter	Value
Encoder Layers	28
Encoder Heads	12
Encoder Hidden Size	1536
Projector Hidden Size	1536->2048
Language Model Layers	36
Language Model Heads	16
Language Model Hidden Size	2048
Max History Window	300
# Compression Tokens	1/2/3
Optimizer	AdamW
Learning Rate	2.0e-6
Scheduler	Cosine
Batch Size per GPU	4
Training Steps	6000

Table 4: Hyperparameter setting for UniEDU-5B.

A.3 Training Details

In Table 4, we introduce the hyperparameter configuration used to train UniEDU-5B.

Knowledge Tracing:

Based on the user’s past problem-solving history, determine whether the following question can be answered correctly.
Question: Based on the picture, write two complete equations: ___ (separate with a comma)
Knowledge Concept: Addition and subtraction within 10
Image: <image>

Time Cost Prediction

Based on the user’s past problem-solving history, estimate how long the user will take to answer the following question (in seconds).
Question: The area of the figure below is ___ square meters.
Knowledge Concept: Area units comparing sizes
Image: <image>

User Answer Prediction:

Based on the user’s past problem-solving history, predict the answer the user is likely to give for the following question.
Question: Look at the picture and write the equation. The complete equation is ____.
Knowledge Concept: Advanced addition with carrying-adding to 7
Image:<image>