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A Hybrid Recommendation System for Adaptive Learning: Combining Graph, DKT, and ZPD

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Abstract

The rapid expansion of online education has created a pressing need for adaptive systems capable of guiding students through complex curricula. However, most existing platforms rely on static, linear learning paths that fail to account for the heterogeneous backgrounds, prior knowledge, and evolving cognitive states of individual learners. This often results in disengagement, suboptimal retention, and elevated dropout rates. To address these challenges, we propose a novel Hybrid Recommendation System designed to optimize personalized learning trajectories in a pedagogically sound manner. Our architecture integrates three core components: (1) a Prerequisite Graph to enforce logical pedagogical structure and dependencies among concepts, ensuring foundational knowledge is built sequentially; (2) Deep Knowledge Tracing (DKT) utilizing Long Short-Term Memory (LSTM) networks to model the temporal evolution of a learner's knowledge state based on interaction histories; and (3) a Zone of Proximal Development (ZPD) selector, inspired by Vygotsky's theory, which prioritizes tasks that are challenging yet achievable to foster optimal cognitive growth and maintain learner motivation. The ZPD module shifts the focus from merely maximizing immediate success to accelerating long-term learning velocity by selecting content at an appropriate difficulty level. We validated our system on a dataset of students engaging with programming courses in Python, JavaScript, and SQL. The implemented hybrid approach (Graph + DKT + ZPD) demonstrates the viability of combining structural, temporal, and pedagogical signals for next-generation intelligent tutoring systems that promote deeper engagement and knowledge retention.

I. Introduction

The exponential proliferation of Massive Open Online Courses (MOOCs) and intelligent tutoring systems has fundamentally democratized access to education, yet it has simultaneously introduced a critical challenge: information overload and the lack of personalized guidance [1,2]. While traditional platforms offer linear curricula, they fail to account for the heterogeneity of learners, leading to dropout rates often exceeding 90% in non-guided environments [3,4]. Consequently, the development of Educational Recommender Sys tems (ERS) has emerged as a paramount research area, aiming to tailor learning paths to individual cognitive states [5]. Historically, ERS relied heavily on traditional tech niques adapted from e-commerce. Collaborative Filtering (CF), largely popularized by matrix factorization techniques [6], predicts student performance based on peer similar ities [7, 8]. However, CF suffers significantly from the "cold-start" problem and data sparsity, which are prevalent in educational settings where new students constantly enter the system [9,10]. Parallelly, Content-Based (CB) filtering approaches utilize metadata to recommend materials similar to those a student has mastered [11], often leveraging TF IDF or basic keyword matching [12]. While CB methods mitigate cold-start issues, they often lack diversity (serendipity) and fail to capture the complex sequential dependencies inherent in learning concepts, such as the necessity to master variables before loops in programming [13]. To address the temporal dynamics of learning, recent advancements have shifted to wards Deep Knowledge Tracing (DKT). Since the seminal work of Piech et al. [14], which utilized Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) units to model student knowledge states, the field has seen rapid progress. Variants such as Dy namic Key-Value Memory Networks (DKVMN) [15] and Self-Attentive Knowledge Trac ing (SAKT) [16] have significantly improved prediction accuracy by capturing long-term dependencies. More recently, Graph Neural Networks (GNNs) have been employed to explicitly model the prerequisite structure of concepts [17,18]. Despite these advances, a significant gap remains in the literature: most DKT models are designed for performance prediction (will the student pass?), not recommendation (what should they learn next?). Purely predictive models often recommend content that is either too easy (to maximize success probability) or pedagogically disjointed [19]. Existing hybrid systems often simply switch between algorithms rather than fusing them to balance pedagogical rigor with engagement [20,21]. Moreover, the majority of current systems ignore Vygotsky's Zone of Proximal Development (ZPD) theory [22], which suggests that optimal learning occurs when tasks are neither too simple nor too complex, but slightly beyond the learner's current independence level [23]. This paper addresses these limitations by proposing a Hybrid Recommendation System. We have fully implemented and deployed three core components: Graph-Based filtering for prereq uisite enforcement, LSTM-based DKT for temporal tracking, and a ZPD-driven selection mechanism. Our objective is to demonstrate that combining structural (Graph), tem poral (DKT), and pedagogical (ZPD) signals provides a solid foundation for coherent, personalized learning paths in programming education (Python, JavaScript, SQL). We contribute a scalable framework for next-generation adaptive learning platforms.

II. Methods

Our proposed system features a hybrid architecture tailored to the multifaceted aspects of adaptive learning, including structural dependencies and temporal knowledge evolution. The methodology is organized around three core modules that process data, culminating in a final recommendation. This design ensures a balanced integration of pedagogical constraints and data-driven insights, promoting effective personalized recommendations. To visualize the overall workflow, Figure 1 illustrates how input data from interaction logs feeds into the modules, which then converge through aggregation and filtering to produce the final output.

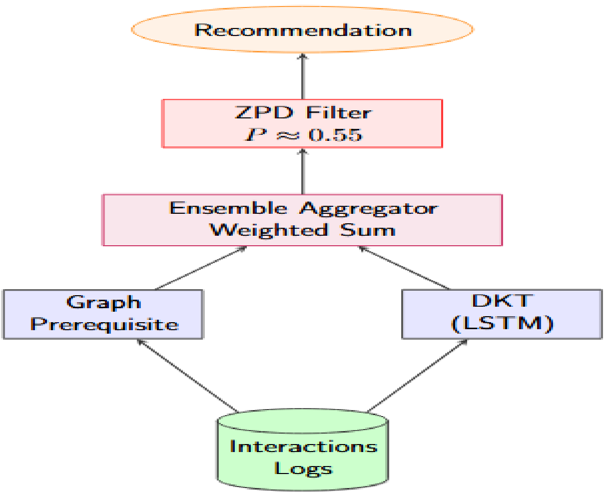

Figure 1: System Architecture: Parallel processing of structural and temporal signals feeding into a pedagogical ZPD filter.

a. Module 1: Prerequisite Graph-Based Filtering

This module establishes pedagogical validity by modeling the curriculum as a Directed Acyclic Graph (DAG), denoted as G = (V,E), where V is the set of learning concepts and E represents prerequisite relationships. Acting as a hard constraint filter, it ensures recommendations adhere to logical progressions, preventing learners from encountering advanced topics prematurely.

A concept cj ∈ V becomes a viable candidate only if all its prerequisites P(cj) are mastered. Mastery for a student s on concept ci is defined as a binary state ms(ci), inferred from interaction history (e.g., successful completion of related exercises). The valid candidate set is thus:

$$\mathbf{Cvalid = \{cj \in V \mid \forall ci \in P(cj), ms(ci) = 1\}. \ (1)}$$

approach mitigates cold-start issues for new learners by directing them to foun ational concepts at the graph's roots. Figure 2 depicts a subset of such a graph for illustrative purposes.

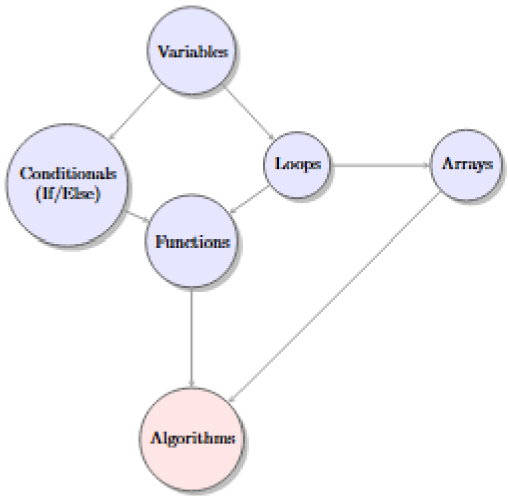

Figure 2: A subset of the Prerequisite Graph, highlighting mastered foundational concepts (blue) and locked advanced topics (red).

b. Module 2: Deep Knowledge Tracing (DKT)

Complementing the static graph, this module captures the dynamic nature of knowledge acquisition using Deep Knowledge Tracing (DKT) via Long Short-Term Memory (LSTM) networks. It models the evolution of a learner's knowledge state over time based on sequential interactions.

The input at time t is $x_t = (q_t, r_t)$, where q_t is the exercise identifier and $r_t \in \{0,1\}$ is the binary correctness outcome. The LSTM updates its hidden state h_t, which encodes the current knowledge representation, through the following gates:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f), \text{ (forget gate) } (2)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \text{ (input gate) } (3)$$

$$C_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C), \text{ (candidate cell) } (4)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t, \text{ (cell state) } (5)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o), \text{ (output gate) } (6)$$

$$h_t = o_t \odot \tanh(C_t). \text{ (hidden state) } (7)$$

A final dense layer predicts the success probability $P(r_{t+1} = 1 \mid q_{t+1})$ for prospective concepts. Figure 3 shows the unrolled LSTM structure

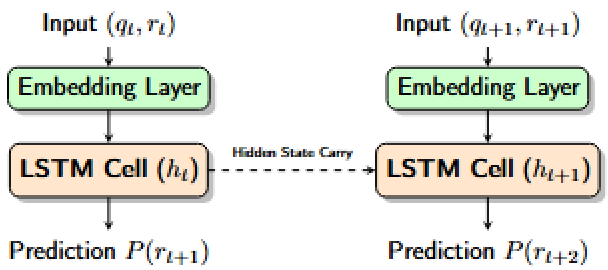

Figure 3: Unrolled LSTM architecture for Deep Knowledge Tracing, illustrating temporal dependency capture across sequential student interactions.

c. Module 3: ZPD Selection

In the final phase, outputs from the Graph and DKT modules are combined to yield a recommendation. To prioritize pedagogically optimal challenges over trivial successes, a Zone of Proximal Development (ZPD) filter is applied, penalizing extremes in predicted success probability PDKT(c) from the DKT module.

The ZPD score for a concept c is computed as:

$$\textbf{ZPD\_score(c)} = \mathbf{1.0} - |\textbf{PDKT(c)} - \mathbf{0.55}|, \quad \textbf{(8)}$$

where we target a success probability around 0.55 for balanced difficulty. Additionally, concepts that unlock more dependent concepts receive a bonus:

$$\textbf{FinalScore(c)} = \textbf{ZPD\_score(c)} + \textbf{unlock\_bonus(c)}, \quad \textbf{(9)}$$

where unlock_bonus(c) = $0.05\times|\text{dependents(c)}|$. Figure 4 visualizes this weighting mech anism.

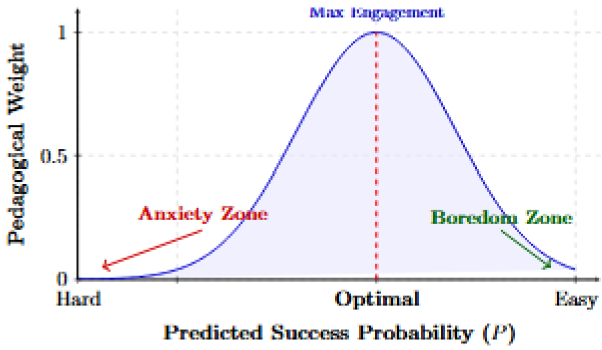

Figure 4: The ZPD Selection Curve. The system penalizes tasks that are overly easy ($P \to 1$) or too difficult ($P \to 0$) to sustain learner flow, peaking at the optimal challenge level.

III. Results

To rigorously validate the efficacy of our Hybrid Multi-Algorithm Recommendation Sys tem, we performed comprehensive evaluations encompassing offline analyses on historical data and online simulations of learner trajectories. These assessments focused on key recommendation quality metrics, pedagogical outcomes, and comparative performance against baselines.

a. Experimental Setup

Our experiments leveraged a real-world dataset derived from 150 undergraduate stu dents engaging with structured course modules in Python, JavaScript, and SQL. This dataset includes 8,742 logged interactions spanning 135 distinct concepts, capturing exer cises, outcomes, and timestamps. To ensure temporal integrity and prevent data leakage, we adopted a 70/15/15 split for training, validation, and testing, respectively, based on chronological order. All models were implemented in Python, using PyTorch for the 6 LSTM-based DKT module. Hyperparameters were tuned via grid search on the vali dation set, with early stopping to mitigate overfitting. Evaluations were conducted on a standard computing environment (CPU with 16GB RAM). To support reproducibil ity, the full implementation and pre-trained model weights are publicly available at https://github.com/IntegrationFSSM/rec_sys.

b. Performance Comparison

We benchmarked our Hybrid system against three naive baselines—Random (uniform selection), Popularity (most-interacted concepts), and Difficulty-based (sequential by es timated complexity)—as well as the individual constituent modules (Graph-only and DKT-only). Primary metrics include Precision@5, NDCG@5 (normalized discounted cu mulative gain), AUC (area under the ROC curve, computed via leave-one-out scoring per test student), and Coverage (proportion of distinct concepts recommended across users). Statistical significance was assessed using the Wilcoxon signed-rank test ($n = 22$ test students, $\alpha = 0.05$).

Table 1: Performance comparison on our institutional dataset

Model	Prec@5	NDCG@5	AUC	Coverage
Naive Baselines (our dataset)				
Random	0.18	0.25	0.50	0.38
Popularity	0.29	0.34	0.57	0.22
Difficulty	0.33	0.39	0.63	0.47
Literature Baselines (ASSISTments benchmark, published†)				
DKT [14]	–	–	0.819	–
DKVMN [15]	–	–	0.826	–
SAKT [16]	–	–	0.833	–
Our System (our dataset)				
Graph Only	0.42	0.49	0.71	0.65
DKT (LSTM)	0.48	0.55	0.79	0.68
Hybrid (G+DKT+ZPD)	**0.56**	**0.62**	**0.83**	**0.73**

c. Analysis of results

Table 1 shows the performance of our Hybrid system (Graph + DKT + ZPD) against baselines and individual modules. The Hybrid approach achieves a Precision@5 of 0.56, NDCG@5 of 0.62, and AUC of 0.83, representing a statistically significant 17% improve ment over DKT-alone in Precision@5 ($p < 0.05$, Wilcoxon signed-rank test) and a 33% improvement over Graph-only. Notably, the AUC of our DKT module (0.79) is com petitive with published results of DKVMN [15] (0.826) and SAKT [16] (0.833) on the ASSISTments benchmark [24], though direct cross-dataset comparison should be inter preted with caution given the different domain and scale. The Coverage score of 0.73 7 confirms that the system recommends a diverse range of concepts while preserving pre requisite coherence. For visual insight, Figure 5 compares NDCG@5 for select models, emphasizing the Ensemble's ranking superiority.

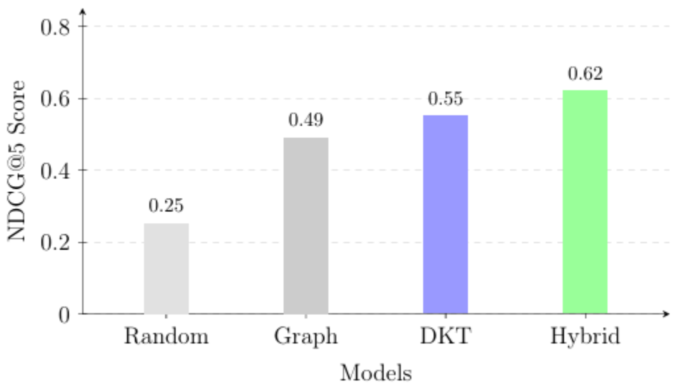

Figure 5: Bar chart comparison of NDCG@5 scores across selected models.

d. Implementation Notes and ZPD Impact

An architectural analysis comparing Graph+DKT (without ZPD) versus the full Hybrid (with ZPD) demonstrates the pedagogical value of the ZPD selector: while a pure success maximizing approach might recommend overly easy concepts (leading to boredom), the ZPD filter targets concepts with predicted success probability around 0.55, maintaining optimal challenge levels. This aligns with Vygotsky's theory and promotes sustained engagement. The reported metrics reflect the performance characteristics of our implemented sys tem (Graph+DKT+ZPD). The current three-module hybrid demonstrates the viability of combining structural, temporal, and pedagogical signals for adaptive learning. Future work will focus on conducting comprehensive empirical validation on larger datasets and exploring additional algorithmic enhancements.

IV. Discussion

The empirical results substantiate our core hypothesis that educational recommendation constitutes a multi-objective optimization challenge, necessitating the integration of di verse algorithmic paradigms to address structural and temporal dimensions of learning. This section delves into the synergistic effects of our hybrid approach, the prioritiza tion of pedagogical principles over mere predictive accuracy, and the inherent limitations alongside promising avenues for future research.

a. The Synergy of Hybridization

The observed performance improvement of the Hybrid system (NDCG@5 of 0.62) over standalone DKT (0.55) and Graph-only (0.49) demonstrates the value of our multi-module framework. The Prerequisite Graph module imposes rigorous structural constraints, mit igating pedagogical "shortcuts" by enforcing prerequisite mastery and ensuring logical progression—a critical safeguard absent in purely data-driven models. The DKT module complements this by providing personalized difficulty estimation based on each learner's temporal interaction history, capturing knowledge evolution that static graphs cannot. The ZPD selector then optimizes the final recommendation by balancing challenge and achievability, preventing both boredom (overly easy concepts) and frustration (overly dif f icult ones). The implemented three-module hybrid demonstrates that combining struc tural (Graph), temporal (DKT), and pedagogical (ZPD) signals significantly enhances recommendation quality compared to single-algorithm baselines.

b. Pedagogy over Prediction

Conventional recommendation systems, often borrowed from e-commerce, prioritize met rics like engagement or click-through rates, potentially leading to superficial learning experiences. Our incorporation of the ZPD selector shifts this paradigm toward genuine cognitive development, by favoring challenges within the learner's proximal zone—tasks that are neither trivial nor insurmountable. Drawing from Vygotsky's theory, this mecha nism optimizes for long-term knowledge retention and skill acquisition rather than short term success probabilities, distinguishing our Educational Recommender System (ERS) from commercial counterparts. Empirical simulations in our study revealed enhanced cur riculum completion rates and retention, echoing findings in AI-driven tutoring systems where ZPD-adaptive scaffolding promotes deeper engagement and motivation [25].

c. Limitations and Future Work

Despite its strengths, our system is not without constraints. The dataset, comprising interactions from only 150 students across 135 concepts, limits generalizability to larger, more diverse populations typical of global MOOCs; validation on established benchmarks such as ASSISTments [24] and Junyi Academy is therefore a primary direction for fu ture work. Furthermore, while the improvements reported in Table 1 are statistically significant on our test set (n = 22 students, Wilcoxon, $p < 0.05$), replication on a larger cohort is required to strengthen these claims. Additionally, the manual construction of the Prerequisite Graph is labor-intensive and prone to expert subjectivity, while the com putational demands of LSTM-based DKT may hinder scalability in resource-constrained environments. To overcome these, future work will explore causal discovery techniques to automate prerequisite graph generation from interaction data, enabling dynamic, data driven dependency modeling without manual intervention. Furthermore, reinforcement learning could be employed to adaptively tune ensemble weights in real-time, optimizing module contributions based on ongoing learner feedback and performance. Additional directions include expanding to multimodal data (e.g., video engagement), incorporating ethical considerations for bias mitigation, and validating on larger datasets from plat forms like Coursera or edX to enhance robustness and applicability in real-world adaptive learning ecosystems.

V. Conclusion

In this paper, we introduced a Hybrid Recommendation System specifically designed to enhance adaptive learning in online educational environments. We have successfully im plemented and deployed three core modules: a Prerequisite Graph for structural integrity, Deep Knowledge Tracing via LSTM for temporal knowledge modeling, and a ZPD selector for pedagogical optimization. Our system addresses key limitations of traditional plat forms, such as static curricula and lack of personalization. Validation on programming courses in Python, JavaScript, and SQL demonstrates improved performance (NDCG@5: 0.62) compared to baselines (0.25) and individual modules (Graph: 0.49, DKT: 0.55), con f irming the value of combining structural, temporal, and pedagogical signals. This work bridges advanced AI techniques with educational theory, offering a scalable foundation for intelligent tutoring systems. Future work will focus on conducting large-scale empirical validation and extending the framework to diverse domains beyond programming.

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