Learning Semantic and Structure Aware Representation with Large Language Models for Concept Recommendation

Extended Abstract

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ABSTRACT

Concept recommendation aims to suggest the next concept aligned with both the learner's state and the educational knowledge system. However, existing methods often overlook concept semantics, leading to recommendations that lack semantic relevance and structural consistency. To address this, we propose **SSRec**, a novel **S**emantic and **S**tructure aware representation learning framework. SSRec leverages Large Language Models (LLMs) to capture concept semantics and introduces a graph-based adapter. This adapter not only integrates structural relationships but also transforms anisotropic text encodings into a smooth representation space. Extensive experiments on real-world datasets demonstrate that SSRec significantly outperforms state-of-the-art baselines in delivering accurate and consistent recommendations.

KEYWORDS

Large Language Models; Online Education

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1 INTRODUCTION

Online education relies heavily on personalized content recommendations to engage and retain learners [5, 7]. A seamless learning experience requires recommendations that align not only with the learner's knowledge state—often estimated via knowledge tracing [1, 6]—but also with the overarching educational knowledge system. While prior approaches have utilized concept graphs to model structural relationships (e.g., prerequisites) [2, 8], they frequently overlook the intrinsic *semantic* meanings of concepts. This oversight limits the model's ability to capture deeper connections, resulting in recommendations that lack semantic relevance and structural consistency.

To bridge this gap, we propose **SSRec** (**S**emantic- and **S**tructure-aware representation learning for concept **Rec**ommendation), a framework that injects open-world semantic knowledge from Large Language Models (LLMs) into structured educational graphs. SSRec tackles *concept ambiguity* (e.g., "Table" as furniture vs. data) by prompting an LLM to produce *neighbor-conditioned* concept interpretations, leveraging prerequisite and subsequent concepts as disambiguating context. To make LLM text embeddings effective for recommendation—which are often anisotropic and misaligned with the graph structure—we further introduce a **graph-based adapter**. Instead of a generic MLP, our adapter is trained with *self-supervised contrastive learning* on the concept graph, pulling together representations of structurally/semantically related concepts while separating unrelated ones, thereby mapping text embeddings into a smooth space that jointly captures semantic meaning and educational structure.

Finally, we combine these enhanced representations with the learner's knowledge state to predict the next concept. Extensive experiments on real-world datasets demonstrate that SSRec significantly outperforms state-of-the-art baselines, providing recommendations that are both semantically relevant and structurally consistent.

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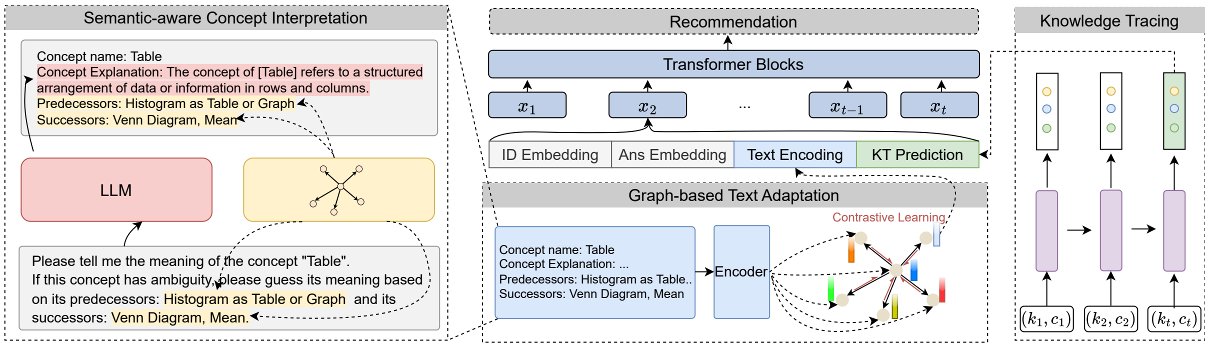

Figure 1: The overall framework of SSRec. It integrates semantic-aware interpretation (left), graph-based text adaptation (bottom), and knowledge tracing (right) for next-concept recommendation.

2 METHODOLOGY

We propose a framework that integrates the educational knowledge system with the learner's state, as illustrated in Figure 1. The framework consists of three key components:

Semantic-aware Concept Interpretation. To address the ambiguity of concept names (e.g., "Table"), we utilize LLMs to generate context-aware definitions. We prompt the LLM with the concept's name alongside its *predecessors* and *successors* from the concept graph. This structural context ensures the generated explanation $\tilde{w}^k$ is educationally relevant. We then use a pre-trained LM (e.g., BART) to encode $\tilde{w}^k$ into an initial semantic vector T^k.

Graph-based Text Adaptation. Directly using LM embeddings is suboptimal due to their anisotropic nature. We design a graph-based adapter to transform these embeddings into a smooth, structure-aware space. We initialize node features with $h_k^0 = T^k$ and apply a Graph Convolutional Network (GCN):

$$h_k^l = \mathrm{Combine}(H(h_k^{l-1}), \mathrm{Agg}(\{H(h_i^{l-1}) \mid i \in \mathcal{N}_k\})) \tag{1}$$

where $\mathcal{N}_k$ denotes the neighbors of concept k. To ensure the adapter captures structural dependencies, we employ *contrastive learning*. We generate two graph views via edge dropout and optimize the InfoNCE loss to maximize the similarity between the same node's representations across views:

$$\mathcal{L}_{ssl}^G = -\sum_{k \in \mathcal{K}} \log \frac{e^{\mathrm{sim}(h_k^{(1)}, h_k^{(2)})/\tau}}{\sum_{i \in \mathcal{K}, i \neq k} e^{\mathrm{sim}(h_k^{(1)}, h_i^{(2)})/\tau}} \tag{2}$$

Recommendation & Training. We track the learner's knowledge state s_t using Deep Knowledge Tracing (DKT) [6]. The final input representation x_t combines the concept ID i_{k_t}, answer correctness a_{c_t}, the graph-adapted semantic embedding h_{k_t}, and the knowledge state s_t:

$$x_t = i_{k_t} \oplus a_{c_t} \oplus h_{k_t} \oplus s_t \tag{3}$$

A Transformer-based architecture then processes the sequence $x_{1:t}$ to predict the next concept. The model is trained in two stages: (1) **Pre-training** with the graph contrastive loss $\mathcal{L}_{ssl}^G$, knowledge tracing loss, and sequence self-supervised tasks; (2) **Fine-tuning** end-to-end on the next-concept prediction task.

3 EXPERIMENTS

We evaluate our method and baseline approaches across three distinct real-world datasets: *Junyi*, *ASSIST12*, and *ASSIST09*, following standard sequential recommendation settings. We compare SSRec against a comprehensive set of baselines, including ID-based methods (e.g., SASRec [4]), text-enhanced models (e.g., UniSRec [3]), and graph-based approaches (e.g., GCARec [8]). Experimental results demonstrate that SSRec significantly outperforms other state-of-the-art baselines across all metrics (HR@1, NDCG@5, and MRR). Specifically, SSRec achieves substantial improvements over the strongest ID-Text baselines, highlighting the distinct advantages of our proposed graph-based adapter in capturing both the semantic nuances and structural dependencies of educational concepts.

Further ablation studies validate the necessity of each component in our framework. We observe that removing either the LLM-enhanced concept interpretations or the graph-based contrastive learning module leads to a marked decline in performance. This confirms that addressing the anisotropy of text embeddings via graph adaptation is crucial for effective recommendation. Beyond accuracy, we assessed the quality of recommendations using GPT-4 evaluations and a structural consistency metric (*Matching Ratio*). The results indicate that SSRec generates recommendations that are not only semantically more relevant but also adhere more strictly to the prerequisite relationships defined in the educational knowledge graph. Finally, quantitative analysis using the Davies-Bouldin Index (DBI) confirms that our method successfully transforms non-smooth text encodings into a better-clustered representation space (reducing DBI from > 2.0 to < 0.7 on ASSIST09).

4 CONCLUSION

We introduced **SSRec**, a novel framework that bridges the gap between open-world semantic knowledge and structured educational systems. Our work demonstrates that effectively integrating LLMs into concept recommendation requires addressing two critical challenges: resolving concept ambiguity through structural context and adapting anisotropic text encodings for downstream tasks. By employing a graph-based adapter with contrastive learning, SSRec successfully learns representations that are both semantically rich and structurally consistent. Experiments confirm that our approach significantly outperforms state-of-the-art baselines, offering a more precise and coherent learning path for students.

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