Have We Designed Generalizable Structural Knowledge Promptings? Systematic Evaluation and Rethinking

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https://github.com/zjukg/SUBARU

Abstract

Large language models (LLMs) have demonstrated exceptional performance in text generation within current NLP research. However, the lack of factual accuracy is still a dark cloud hanging over the LLM skyscraper. Structural knowledge prompting (SKP) is a prominent paradigm to integrate external knowledge into LLMs by incorporating structural representations, achieving state-of-the-art results in many knowledge-intensive tasks. However, existing methods often focus on specific problems, **lacking a comprehensive exploration of the generalization and capability boundaries of SKP**. This paper aims to evaluate and rethink the generalization capability of the SKP paradigm from four perspectives including **Granularity, Transferability, Scalability, and Universality**. To provide a thorough evaluation, we introduce a novel multi-granular, multi-level benchmark called SUBARU, consisting of 9 different tasks with varying levels of granularity and difficulty. Through extensive experiments, we draw key conclusions regarding the generalization of SKP, offering insights to guide the future development and extension of the SKP paradigm.

1 Introduction

Large language models (LLMs) (Zhao et al., 2023) have sparked a new wave in the natural language processing (NLP) field. By pre-training on massive corpus with billion-scale decoder transformers (Vaswani et al., 2017), LLMs achieve exceptional capabilities in text generation, and are widely used in current researches and applications (Zhang et al., 2024a; Chen et al., 2024; Yin et al., 2023).

However, the lack of factual accuracy in LLMs (Zhang et al., 2023) remains a significant issue, leading to unreliable and untrustworthy outputs that limit their applications. To address this, external knowledge bases are widely used (Gao et al., 2023) to incorporate reliable knowledge into LLMs for a fact-grounded generation. Among these, knowledge graphs (KGs) (Liang et al., 2024; Zhang et al., 2025) are a specialized form of semi-structured knowledge base, organizing vast amounts of factual knowledge as triples within graph structures. Numerous works (Wen et al., 2024) propose different KG-oriented methods to incorporate the KGs into the LLMs for specific tasks such as question answering (Tian et al., 2024), knowledge graph reasoning (Zhang et al., 2024b). As illustrated in Figure 1, structural knowledge prompting (SKP) is a widely used paradigm that integrates pre-trained structural information in the KGs to the LLMs with an adapter. The structural information is learned in the structural encoder, while the adapter is an extra neural network to bridge the representation gap. This approach is consistent with many Multi-modal LLMs (MLLMs) (Yin et al., 2023), where a pre-trained encoder is used to bridge the non-textual information to the textual representation space of the LLMs.

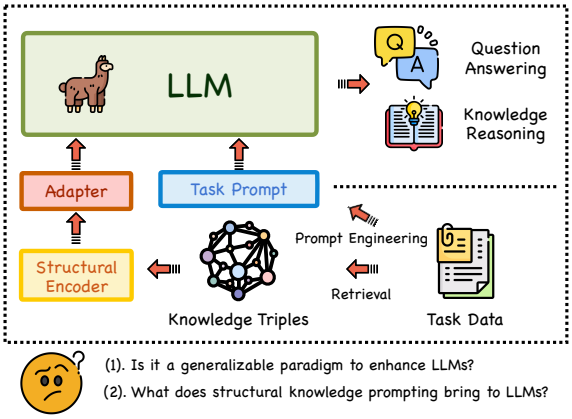

Figure 1: An intuition of the structural knowledge prompting paradigm in current LLM research.

However, existing SKP methods typically adapt the paradigm directly to specific tasks with the ready-to-use principle, without thoroughly examining the paradigm itself. This raises several im-

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portant questions: What makes SKP successful on specific tasks? What level of knowledge granularity does SKP provide to LLMs, and how can it enhance generalization across tasks of varying difficulty? Furthermore, it is crucial to re-assess the full spectrum of SKP methods to better guide the future development of this research field.

To fill the gaps in current research, we explore the generalization capability of the SKP paradigm in this paper. We first construct a new **S**tr**U**ctural Prompting **B**enchm**A**rk with **R**easoning and **U**nderstanding tasks (SUBARU for short), consisting of 9 tasks with varying granularity and difficulty, which are captured from large-scale encyclopedic knowledge graphs. We design a complete training evaluation protocol to adequately assess the generalization of SKP across four dimensions: **Granularity, Transferability, Scalability, Universality**. Finally, we conduct extensive experiments with 16 different SKP settings, exploring these four dimensions and drawing key conclusions to explain the success of current SKP methods, while offering insights to guide future developments aimed at enhancing the factual accuracy of LLMs. Our contribution can be summarized as:

- We examine the widely used SKP paradigm in current LLM research. Rather than applying it to specific tasks, we provide a systematic evaluation and explore its generalization potential.
- We introduce a new benchmark, SUBARU, consisting of 9 tasks with varying granularity and difficulty levels, designed to assess the generalization of the SKP paradigm.
- We conduct a comprehensive evaluation on the generalization of existing SKP modules from four dimensions, exploring the granularity, transferability, scalability, and universality. We make several interesting conclusions after the explorations.

2 Related Works

The combination of KGs and LLMs (Zhang et al., 2024b; Guo et al., 2024a,b; Gutiérrez et al., 2024; Lyu et al., 2024) is an important topic in nowadays research. In addition to the factual knowledge contained in KGs, many methods try to augment the LLMs with the rich structural information present in the KG to achieve knowledge infusion capabilities. DrugChat (Liang et al., 2023) and GNP (Tian et al., 2024) employ a graph neural network to extract structural information from the retrieved knowledge subgraph to enhance the question-answering (QA) ability of LLMs. KoPA (Zhang et al., 2024b) incorporates the pre-trained structural knowledge embeddings into LLMs with a project layer to enhance the knowledge graph completion (KGC) ability of LLMs. Their paradigm lies in the use of various structural encoders to extract non-textual features and for enhancing the textual inference capability of LLM, a concept borrowed from multi-modal LLMs. While adaptations are made for specific tasks, there is a lack of in-depth exploration on the rationale of this paradigm. In this paper, we provide a comprehensive evaluation and analysis of its generalization ability.

3 Preliminary

In this paper, we focus on the evaluation of the structural knowledge promptings (SKP) in the LLMs. The LLM is denoted as $\mathcal{M}$. and the general prediction process of the LLM can be denoted as:

$$\mathcal{A}^* = \max_{\mathcal{A}} P_{\mathcal{M}}(\mathcal{A}|\mathcal{Q}) \tag{1}$$

where $\mathcal{A}$ is the answer to the question $\mathcal{Q}$, and $\mathcal{A}^*$ is the optimal answer decoded by the LLMs.

Many recent works aim to enhance the reasoning ability of LLMs by incorporating structural knowledge. A common approach involves retrieving relevant entities and relations from an external KG, extracting and embedding them as prompt tokens for the LLM. We denote an external KG as $\mathcal{KG} = (\mathcal{E}, \mathcal{R}, \mathcal{T})$, where $\mathcal{E}, \mathcal{R}, \mathcal{T}$ are the entity set, relation set and triple set respectively. A triple (h, r, t) means that there is a relation r between head entity h and tail entity t. An entity or a relation would be treated as one basic element s_i in such a SKP process. For a given element e_i, the input prompt token can be denoted as:

$$\mathcal{S}(e_i) = \mathcal{P}(\texttt{ENC}(e_i|\mathcal{KG})) \tag{2}$$

where $\texttt{ENC}(e_i|\mathcal{KG})$ is the structural encoder learned self-supervisedly on the given $\mathcal{KG}$ and $\mathcal{P}$ is the adapter for bridging two representation spaces of the structural embeddings and LLMs. Several classic implementations of the adapter $\mathcal{P}$ exist, such as a simple MLP (Tian et al., 2024), Qformer (Li et al., 2023), etc. Depending on the specific task, the SKP tokens would be organized as a sequence $\mathcal{S} = (\mathcal{S}_1, \ldots, \mathcal{S}_n)$, which can represent a single

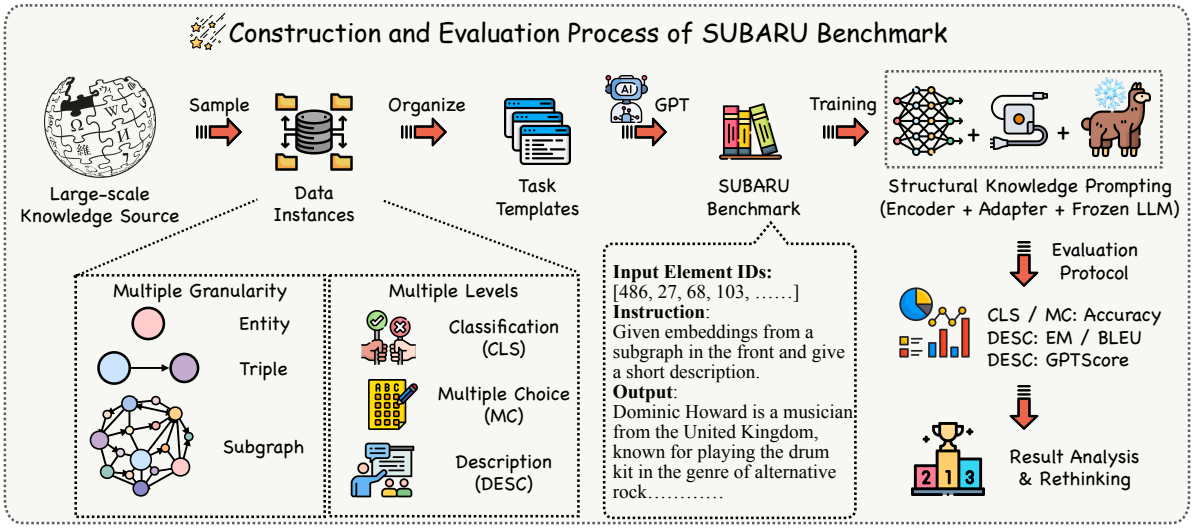

Figure 2: An overview of the construction pipeline of SUBARU benchmark and the evaluation process. In SUBARU, we construct 9 different tasks with multiple granularity (entity/triple/subgraph) and multiple difficulty levels for comprehensive evaluation of the generalization capability of the structural knowledge prompting paradigm.

entity, a triple, or a subgraph. It is further concatenated with the input tokens of the LLMs, resulting in the final prediction process:

$$\mathcal{A}^* = \max_{\mathcal{A}} P_{\mathcal{M}}(\mathcal{A}|\mathcal{Q}, \mathcal{S}) \tag{3}$$

Such basic setting and formulation for SKP are widely used in existing works. However, current approaches often utilize this paradigm directly to specific downstream tasks **without a deeper exploration of the paradigms themselves**. In this paper, we will dive deep into this problem by conducting a comprehensive evaluation with our proposed benchmark to address this gap.

4 Our Evaluation Framework

4.1 The General Motivation

In the previous section, we introduce the basic paradigm of SKP, which is widely used by current KG-enhanced LLM applications. While these methods have achieved state-of-the-art results in knowledge-intensive tasks such as QA and KGC, the generalization capabilities of the SKP paradigm remain under-explored. In this paper, we will explore the following four research questions (RQ) about the generalization ability of SKP:

- **RQ1. Granularity**: What levels of structural knowledge from KGs can the SKP paradigm integrate to LLMs?
- **RQ2. Transferability**: Is the SKP paradigm transferable across different tasks? Can SKP process new elements haven't seen before?

Table 1: The statistical information of SUBARU. We have 3 granularity and 3 levels resulting in 9 tasks.

Task		# Train	# Valid	# Test
Entity (EG)	CLS	32122	4016	4016
	MC	16096	2012	2013
	DESC	16061	2008	2008
Triple (TG)	CLS	371168	20620	20622
	MC	185584	10310	10311
	DESC	185584	10310	10311
Subgraph (SG)	CLS	29454	3998	5142
	MC	14727	1999	2571
	DESC	7453	931	939

- **RQ3. Scalability**: Does the SKP paradigm exhibit scaling laws?
- **RQ4. Universality**: Can the SKP paradigm be applied to different LLMs?

Existing SKP methods lack the exploration of the above four questions, and no suitable benchmarks exist for such exploration. To facilitate a more thorough investigation, we start by introducing a new benchmark containing various new datasets and tasks to facilitate better nature exploration in the experimental section.

4.2 The SUBARU Benchmark

To better explore the mentioned four key RQs about the SKP paradigm. We propose the **S**tr**U**ctural Prompting **B**enchm**A**rk with **R**easoning and **U**nderstanding tasks (SUBARU for short). In this section, we briefly introduce SUBARU, outlining its general principles and the process of its

construction. An overview of the SUBARU framework is presented in Figure 2.

4.2.1 General Principle of SUBARU

Existing SKP applications typically target the specific tasks requiring varying granularity of structural knowledge from KGs. For instance, the QA task needs subgraph-level knowledge, while the KGC task only requires triple-level knowledge. Although these applications have made significant progress using the same paradigm, they **do not fully capture the capabilities of SKP**. In the SUBARU framework, we aim to evaluate the SKP paradigm more comprehensively by designing tasks with different levels of structural knowledge granularity. These include entity-granularity (EG), triple-granularity (TG), and subgraph-granularity tasks (SG), which assess the model's ability to reason and understand entities, triples, and subgraphs from KGs.

Additionally, depending on the difficulty of reasoning and comprehension, we introduce three more difficulty levels in our SUBARU: binary classification (CLS), multiple choice (MC), and description (DESC). These tasks correspond to the model's ability to perform binary classification, answer multiple-choice questions, or generate detailed descriptions based on the input structural prompts. By combining the three granularity with three levels of difficulty, we create **9 different tasks** as shown in Figure 2. Next, we describe how our dataset was constructed.

4.2.2 Construction Process of SUBARU

We present an overview of the SUBARU in Table 1. We employ CoDeX (Safavi and Koutra, 2020), a large-scale KG extract from WikiData (Vrandecic and Krötzsch, 2014) as our data source. CoDeX contains approximately 110K triples. The construction process involves two key steps:

Instance Sampling. First, we sample entity/triple/-subgraph instances at different granularity from the KG to prepare for different tasks. For the EG task, we sample approximately 20K entities with adequate descriptions with an 8:1:1 split. For the TG task, we employ the split of CoDeX-M triples to build the datasets. For the SG task, we start with the entities selected in the EG task and then randomly sample their 1-hop and 2-hop neighborhoods to construct the subgraphs. Meanwhile, each task has specific settings. For the CLS task, we treat an entity ID with its real short name as a positive instance. For TG and SG, we consider each triple and subgraph sampled from the existing KG as positive instances. We further generate negative samples maintaining a 1:1 ratio by random perturbing. In the MC task, we sample four choices for each instance: for EG, we predict the entity name, and for TG and SG, we predict the missing entity. The missing entity prediction in TG-MC is similar to the traditional KGC task to predict the missing tail entity in the given query $(h, r, ?)$. For SG, the query provides a subgraph with one core entity missing and ask for the missing entity in the subgraph. For the DESC task, the entity, triple, and subgraph descriptions serve as the target for generation. Entity and triple descriptions are taken directly from the CoDeX dataset, while subgraph descriptions are generated using *GPT-3.5-turbo*. Due to the page limit, we present a more detailed description of the 9 tasks in Appendix A.1.

Task Prompt Template in SUBARU

Input: <Structural Knowledge Promptings $\mathcal{S}$>, <Task-specific Prompt Q_{task}>
Output: Task-specific Answers $\mathcal{A}$

Figure 3: A general prompt template for all tasks.

Prompt Generation. After sampling from the CoDeX KG, we create task-specific instances by applying a hand-crafted instruction prompt, $\mathcal{I}_{task}$, for each task, transforming the instances into the text format for further evaluation. Following the existing paradigms, we put the SKP in the front of the input sequence to inform the LLMs with structural information from KGs. To objectively assess the model's ability to utilize these SKPs, we remove the important textual information of the relevant elements in the instruction template, **allowing the model to complete the tasks using mainly the SKPs rather than the texts to assess the utilization of the SKPs.** We present a general prompt template used in our evaluation in Figure 3. Here we present a general prompt template during our evaluation. We present the detailed prompt templates and data samples in Appendix A.2.

4.2.3 The Evaluation Process of SUBARU

In the following experiments section, we provide a comprehensive evaluation of the four generalization properties of the SKP paradigm using the SUBARU. As SKP is an external module added to knowledge-intensive task adaption, it must be

Table 2: The main experiment results on the 9 tasks of SUBARU benchmark. We colored the top-3 results under each task with a different green color from shallow to deep.

Method		Entity Granularity			Triple Granularity			Subgraph Granularity			
		L-1 (Acc)	L-2 (Acc)	L-3 (EM)	L-1 (Acc)	L-2 (Acc)	L-3 (EM)	L-1 (Acc)	L-2 (Acc)	L-3 (B-4)	L-3 (GPT)
Random Choice		50.00	25.00	-	50.00	25.00	-	50.00	25.00	-	-
FC	**TransE**	55.85	39.49	0.00	55.41	87.42	2.77	82.43	57.95	9.85	14.97
	DistMult	52.61	34.02	0.00	47.23	89.60	21.21	87.10	78.99	4.32	35.42
	RotatE	57.34	51.16	0.00	55.59	66.77	6.88	70.12	62.54	2.12	22.20
	R-GCN	52.44	41.97	0.00	52.53	90.50	27.90	86.75	54.49	5.64	19.57
MLP	**TransE**	84.76	91.01	0.00	53.92	86.51	41.83	91.71	89.34	12.67	45.61
	DistMult	57.71	61.84	0.00	55.64	93.53	97.91	65.46	90.35	26.72	55.56
	RotatE	85.43	54.94	0.00	53.71	88.21	83.74	89.14	90.43	24.74	55.80
	R-GCN	66.85	44.46	0.00	53.68	90.45	94.59	76.70	91.05	16.08	49.25
MoE	**TransE**	58.66	38.89	0.00	65.24	92.07	19.72	88.46	80.32	19.50	46.93
	DistMult	55.35	27.37	0.00	54.49	92.92	8.38	86.98	81.60	9.75	35.57
	RotatE	56.47	29.30	0.00	59.47	89.09	7.32	90.31	88.44	19.68	47.05
	R-GCN	54.23	38.15	0.00	53.59	92.09	27.46	54.90	78.91	4.04	20.39
Q-former	**TransE**	59.48	92.50	0.00	54.77	94.42	38.90	78.97	27.14	11.32	41.19
	DistMult	75.34	60.40	0.00	52.95	94.11	17.77	78.59	37.53	9.25	32.74
	RotatE	82.96	79.50	0.00	50.84	94.02	6.23	80.35	26.33	14.43	42.41
	R-GCN	81.77	41.11	0.00	51.18	93.94	16.23	73.60	27.42	4.73	21.82

trained on the training set before its performance can be evaluated on the test set. The training process, based on classic next-word prediction, is defined as:

$$\mathcal{L}_{SKP} = -\log P_{\mathcal{M}}(\mathcal{A}|\mathcal{Q}_{task}, \mathcal{S}) \tag{4}$$

where $\mathcal{Q}, \mathcal{A}$ is an question-answering pair from the training data. $\mathcal{S}$ is the corresponding structural prompt for the given question, which can be an entity, a triple, or a sequential subgraph. During training, the LLM $\mathcal{M}$ is frozen, and the adapter $\mathcal{P}$ is trained to bridge the pre-trained structural encoder $\texttt{ENC}()$ and the LLM. Meanwhile, for the four RQs, we will present the detailed evaluation protocols and implementation in the next section.

5 Evaluation Results

In this section, we first introduce the experimental setup, including implementation details and the evaluation protocol. Then, we present the results of the experiments to explore the four significant RQs (mentioned in Section 4.1) about the Granularity, Transferability, Scalability, and Universality of the SKP paradigm. We further provide some intuitive cases to explore the capability boundary of SKP.

5.1 Experimental Setup

Implementation Details. TransE (Bordes et al., 2013), DistMult (Yang et al., 2015), RotatE (Sun et al., 2019), and R-GCN (Schlichtkrull et al., 2018). We implement the structural encoders based on NeuralKG (Zhang et al., 2022). Among these structural encoders, R-GCN is a graph neural network method and others are classic KG embedding methods. For the adapter $\mathcal{P}$, we choose 4 mainstream architectures used by recent works, including single **fully-connected layer (FC)** (Zhang et al., 2024b), **multi-layer perceptron (MLP)** (Liang et al., 2023), **MoE** (Ma et al., 2024), and **Qformer** (Li et al., 2023). For LLMs, we mainly employ Llama3-8B-Instruct (Dubey et al., 2024) as the backbone model for experiments. We also evaluate the performance of other LLMs (Touvron et al., 2023) on the SUBARU in further exploration. All the experiments are conducted on a Linux server with NVIDIA A800 GPUs. We set the LLMs in FP16 precision and optimized the SKP with AdamW (Loshchilov and Hutter, 2019) optimizer. For detailed backbone selection, hyperparameter settings, and training efficiency of all the tasks, we present a summary in Appendix B.2.

Evaluation Protocol. For the CLS and MC tasks, we use the accuracy (ACC) for evaluation. For the description tasks, we use different metrics for different granularity levels. For the entity-level and triple-level tasks, we use the exact match (EM) rate as the evaluation metric, which needs the LLMs to generate the exact entity name and triple information. For the subgraph-level description, we use BLEU-4 (B-4) (Papineni et al., 2002) and GPTScore as the evaluation metrics. BLEU is a traditional metric for text generation evaluation. GPTScore follows the LLM-as-a-judge paradigm (Li et al., 2024) and employs *GPT-3.5-turbo* as the judger to score the generated descriptions against

the golden answer. A more detailed introduction of our evaluation protocol and the prompt template for GPT scoring can be found in Appendix B.3.

5.2 Multi-Granularity Knowledge Evaluation (RQ1)

The main evaluation results are presented in Table 2. Based on these results, we make the following observations regarding the granularity of structural knowledge learned by the models:

Observation 1. Simple MLP is surprisingly effective. Despite recent efforts to use complex adapters for SKP, the simple MLP architecture achieves the best performance on most tasks in SUBARU. As presented in Table 2, the MLP-based results dominate in most of the colored cells compared to other adapters. Complex SKP architectures like Qformer and MoE don't perform well on certain tasks like SG.

Observation 2. SKP excels in coarse-grained reasoning tasks. The three granularities in SUBARU correspond to progressively coarser reasoning tasks (MC). For EG, LLMs must precisely understand the input SKP to make the correct choice. However, for TG and SG, the MC task becomes more coarse-grained, with the LLM only needing to grasp the correlation between the input SKP and the options, as the SKP provides more semantic richness and auxiliary information. We can observe that SKP performs well in the MC tasks of TG and SG than EG. This suggests that SKP demonstrates some coarse-grained reasoning ability, but lacks sufficient fine-grained understanding for EG.

Observation 3. SKP struggles to understand new entities accurately, failing in the EG DESC task. As we mentioned before, the smallest elements in SKP are entities or relations. Therefore, in the EG task, all the tasks require LLMs to understand the unseen entities during training and make predictions or descriptions. We observe that SKP performs poorly in the EG task, especially in the DESC task. This suggests that SKP struggles to accurately understand new entities and **lacks inductive reasoning ability at EG**. This is because the current SKP modeling approach is still relatively lacking in extrapolation capabilities. The encoder's characterization ability is inadequate for effective extrapolation when bridged with the LLM, highlighting a gap between SKP and classical MLLM in terms of generalization.

Based on these observations, we conclude that current SKP methods are **not perfect across all granularities and have their limitations**. However, mainstream SKP applications typically focus on triple or subgraph reasoning tasks, where these methods excel. The format of these downstream tasks closely resembles the TG/SG MC tasks. Additionally, to better understand the description ability of SKP models, we further conduct a case study in Figure 5.6.

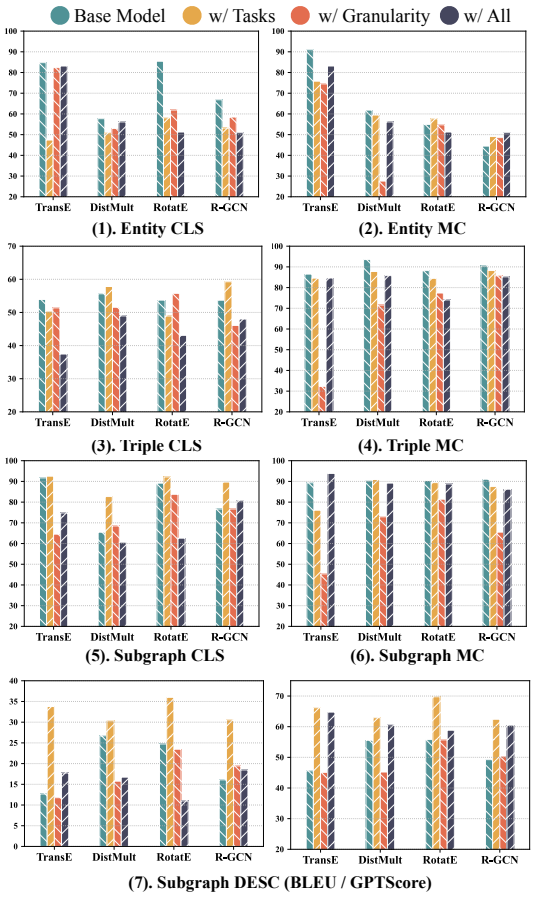

Figure 4: The transferability experiments among different granularities and levels with MLP adapter.

5.3 Transferability Evaluation (RQ2)

To further validate the transferability of SKP methods, we conduct an additional evaluation to answer the following two sub-issues: (1). Can SKP learn positive transfer from the tasks in different granularities and levels? (2). How well does SKP handle new entities under different scenarios? These issues relate to the **transferability of SKP across tasks and elements**.

5.3.1 Transferability among Tasks

Settings. We conduct four sets of experiments to explore this issue by training SKP models with the dataset from the single task (Base), all tasks in the same level, same granularity, and whole benchmark

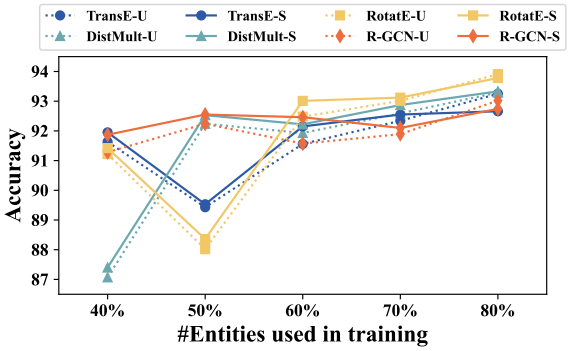

Figure 5: The inductive transfer experiments.

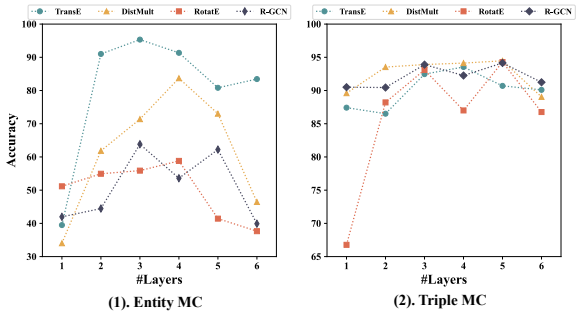

Figure 6: The scalability experiments on the entity / triple MC tasks. We use MLP as the adapter.

(w/ Tasks, w/ Granularity, w/ All). The model's performance is then evaluated on each task to investigate whether it benefits from knowledge transfer across tasks.

Analysis. The results are shown in Figure 4 reveal that SKP does not exhibit strong transferability on CLS and MC tasks. In most cases,training on tasks across different granularities or difficulty levels does not yield a significant improvement in model performance on the target task. However, SKP models perform better on the DESC task when trained with additional data, likely due to the nature of the task. SG DESC is a relatively coarse-grained generation task that can benefit from extra training data containing more structural information.

Overall, this experiment suggest that the current SKP architecture faces challenges in transferability.

5.3.2 Transferability in New Elements

To explore SKP's ability to handle new entities, we conduct experiments in an inductive transfer scenario for TG tasks. As we mentioned before, the entity is the basic element in SKP, making EG tasks naturally inductive. While SG Task will inevitably have overlapping elements, TG is the best scenario for inductive experiments.

Settings. We re-split the datasets by preserving a certain ratio (%) of entities in the training set. In the test set, there will be some unseen entities. This allows us to further divide the test triples into two categories: triples with unseen entities (U) and those without (S). We evaluate the model's performance on these two subsets separately.

Analysis. The results in Figure 5 suggest that SKP performs well with new entities in the TG MC task. Specifically, the performance on the unseen triples is nearly identical to that on the seen triples. Besides, training on more entities can improve the model's ability to inductive reasoning. This raises an interesting question: why does SKP perform better in terms of transferability on TG tasks compared to EG tasks? We believe this is due to a combination of task difficulty and granularity. The SKPs in TG and SG tasks provide more structural context, which reduces the difficulty for the model in understanding the key elements, making it easier to generate correct predictions.

5.4 Scalability Evaluation (RQ3)

To verify the scalability, we conducted the following experiment.

Settings. We dedicate research to the MLP adapter, constantly deepening its layers from 1 to 6 for experiments on the SUBARU benchmark.

Analysis. The results presented in Figure 6 reveal that adapters in SKP models undergo an upward and then downward change in performance. An MLP with 3-4 layers is strong enough to achieve state-of-the-art performance. This law is confirmed on different structural encoders. Of course, the scalability of the adapter is also related to the amount of data required for training, which is currently limited, and the scalability at larger data volumes needs to be further explored.

5.5 Universality Evaluation (RQ4)

Settings. To further evaluate the universality of SKP, we conduct experiments with more different LLM backbones such as Llama2-7B-chat (Touvron et al., 2023), Llama3.1-8B-Instruct (Dubey et al., 2024), and Mistral-7B (Jiang et al., 2023). We report the results of them on the MLP adapter.

Analysis. As shown in Figure 7, we can find that SKP is a universal framework that can be adapted in various decoder LLMs. The performance variation across different backbones on the same task is minimal, and a consistent trend is observed across models. However, there is a slight performance drop when combining certain backbones, likely due to differences in the LLM architectures. More

Table 3: A case study for subgraph description task. We colored the key words of the sentence.

(Golden Answer) Franz Grashof was a university teacher in the field of mechanics, who spoke, wrote, or signed in German. He was buried at Hauptfriedhof Karlsruhe.
(Good Prediction) Friedrich Ernst Petersen was a German engineer who worked in the field of engineering. He was employed at the University of Göttingen, where he was also educated. Friedrich Ernst Petersen spoke, wrote, or signed in German. **(GPTScore: 90)**
(Neutral Prediction) Friedrich August von Hayek was a university teacher who specialized in the field of economics. He was fluent in German, which he spoke, wrote, and signed. After his death, he was buried in the cemetery of the village of Zermatt. **(GPTScore: 60)**
(Bad Prediction) Karl-Heinz Rummeny, a notable alpine skier, was born in Garmisch-Partenkirchen. He was also a member of the German Alpine Club and was also a member of the German Ski Association. **(GPTScore: 25)**

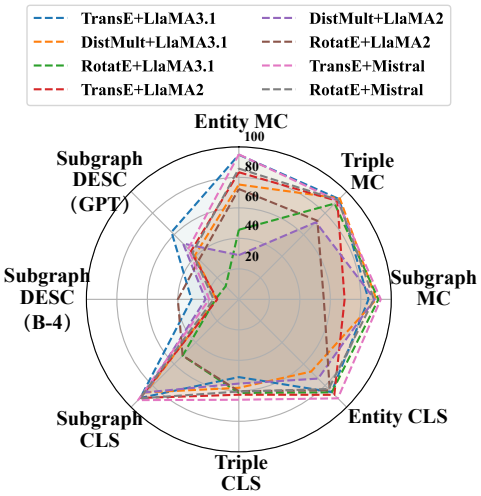

Figure 7: Experiments on more different LLMs.

additional results about LlaMA2 and LlaMA3.1 are presented in Appendix B.5.

5.6 Case Study and Further Analysis

In the three difficulty levels we designed in SUBARU benchmark, the CLS and MC tasks provide clear answers and quantitative metrics, allowing for precise comparisons of model performance. However, for the task of subgraph DESC, assessing the quality of generated text is more subjective. Therefore, we conduct case studies in this section to analyze the ability of the SKP model to describe the subgraph structures. **The goal of this case study is not to compare the differences in the performance of different SKP models, but to identify the commonalities that exist in descriptions.** As shown in Figure 3, we present a simple case with a golden answer and several predictions from different SKP models, which would be a personal description. We can observe the following two points:

(1). None of the SKP models were able to accurately identify the central entity, highlighting the **inability to include particularly precise and personalized information** in the SKPs. This also explains why all the SKP models fail in the EG DESC task in Table 2, which requires precise entity identification.

(2). **The SKP models demonstrate an understanding of some coarse-grained entities and relations** in the input SKP, capturing their connections and reflecting semantic understanding in the generated text. A good prediction can understand more hidden information encoded in SKP such as profession, major, nationality, and skills.

Combining these insights, we can conclude that SKP can inform LLMs coarse-grained information for understanding some subgraph structures roughly, but struggles with detailed information like specific names, places, or specialized terms. While SKP excels at recognizing broad knowledge such as entity attributes, it lacks the cognitive ability to handle finer details. As text generation and deep-level understanding are key capabilities for LLMs, we think that **future improvements to SKP should focus on activating more precise and detailed information through additional prompt tokens**.

6 Conclusion

In this paper, we investigate a popular paradigm SKP which aims to integrate external structural knowledge into LLMs. We conduct a thorough evaluation of its generalization capabilities using a new benchmark, SUBARU, which encompasses multiple levels of granularity and difficulty. We detail the construction process and evaluation protocol of SUBARU. After conducting sufficient experiments in four perspectives, we draw several insightful conclusions. Our findings suggest that SKP effectively provides LLMs with coarse-grained information across different granularities and task types. However, **achieving fine-grained, precise factual awareness remains a significant challenge**. This evaluation will guide the future development of the SKP to incorporate multiple granularity structural knowledge and task-solving abilities into LLMs.

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Limitations

In this paper, we make a deep exploration of the generalization of the structural knowledge prompting paradigm. Our work has the following three limitations:

The scale of the SUBARU benchmark. The benchmark constructed by us has some limitations in terms of scale. SUBARU does not consist of million-scale training and evaluation data, which limits the exploration of the scalability.

The exploration on larger LLMs. Due to the limited computational resources, we mainly conduct experiments on LLMs with 7B-8B parameters. Though most of the SKP works are based on LLMs with the same scale, our exploration lacks results on larger LLMs such as 13B and 70B LlaMA.

Lack of explanation of internal mechanisms. We mainly evaluate the SKP paradigm by the tasks and metrics defined by the SUBARU benchmark, lacking further exploration of the internal mechanisms in LLMs, such as the layer-wise attention weights analysis.

More diverse structural knowledge in different data types. There is a very diverse amount of structured data and LLM combinations to be explored in addition to KG, such as tables, and relational databases. Research into a unified approach to structured data representation is also of great interest to the NLP community. The main topic of our paper is still KG, and we will follow up with a more in-depth investigation around the unified representation of KG and other structured data, as well as the union with LLM in the future.

We will continue to solve these limitations.

Ethical Considerations

In this paper, all of our research and experiments are conducted on publicly available open-source datasets and models. We construct our evaluation benchmark from open-source data and we will release them for open research. Therefore, there is no ethical consideration in this paper.

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A Details in SUBARU benchmark

A.1 Detailed Task Settings

In this section, we provide a detailed description of the 9 task settings in the SUBARU benchmark. Note that we have 3 different granularity (EG/TG/SG) and 3 different levels (CLS/MC/DESC) in the SUBARU benchmark.

- **Task 1: EG CLS.** This task needs the LLM to predict the true or false of a given question about whether a given embedding and an entity name are a pair.
- **Task 2: EG MC.** This task needs the LLM to select the true answer in the given 4 options to answer the question about a given entity embedding.
- **Task 3: EG DESC.** This task needs the LLM to generate a short entity name to answer what the entity is based on the input SKP.
- **Task 4: TG CLS.** This task needs the LLM to predict the true or false of a given question about whether the SKP of the triple is a positive one.
- **Task 5: TG MC.** This task needs the LLM to select the true answer in the given 4 options to complete the given query in the form of SKP. The query can be a head prediction $(?, r, t)$, a relation prediction $(h, ?, t)$, or a tail prediction $(h, r, ?)$. Here, we denote $?$ as the missing entity/relation that needs to be completed by the model.
- **Task 6: TG DESC.** This task needs the LLM to generate the head/tail entity name and the relation to answer what the triple is based on the input SKP.
- **Task 7: SG CLS.** This task needs the LLM to predict the true or false of a given question about whether the SKP of the subgraph is a positive one.
- **Task 8: SG MC.** This task needs the LLM to select the true answer in the given 4 options to complete the given query in the form of SKP. The query is a subgraph that removes a key entity, which should be predicted by the model.
- **Task 9: SG DESC.** This task needs the LLM to generate a paragraph to describe what the SKP is in the given input. The subgraph is extracted from the KGs by random sampling.

Note that, for CLS tasks, an entity-short name pair/triple/subgraph sampled from the KG is regarded as a positive sample. We generate negative samples by randomly replacing the positive samples in a 1:1 manner. For the EG DESC and TG DESC tasks, the golden label for each entity and relation is their short name in the given KG. For the SG task, we employ GPT-3.5 to generate golden answers. The prompt template we used is presented in Figure 8. We manually verified the generated results and found that the generated golden answer is of acceptable quality and can be used to train models of around 7B.

A.2 The Prompt Templates

We present the prompt templates we used in the SUBARU benchmark in Figure 10 to Figure 18. For each task, the instruction is consistent and the input would be changed by different data instances. We present one case for each task.

B Experiments

B.1 The choice of the datasets

There are no current LLM benchmarks that are perfect for our motivation. As we mentioned in the paper, we aim to make a comprehensive evaluation of the generalization capability of the SKP paradigm with diverse granularity and task formats.

This requires not only a diversity of tasks and data but also a relatively reliable external KG for support. Our focus in this paper is not on the accuracy of the RAG or anything like that, but on whether LLM can achieve generalization through structural information when the correct external knowledge is already available.

However, we find that existing datasets such as QA do not meet our requirements, on the one hand, they do not have enough data granularity and diversity of tasks, on the other hand, they often do not have accurate structured external knowledge, but need to do some additional RAG.

So we satisfy both of these requirements by constructing a new benchmark SUBARU by ourselves, and we build evaluation data from KG, which satisfies the diversity of tasks through multi-granularity sampling and multi-level task setting. On the other hand, building the data from KG also ensures the

Prompt for Golden Answer Generation

Given several triples in an extracted subgraph from a knowledge graph, you need to organize them into text paragraphs to describe the information contained in this graph.
The given triple:
<head_1, relation_1, tail_1>
<head_2, relation_2, tail_2>
. . . . . .
<head_n, relation_n, tail_n>
Your Answer:

Figure 8: The prompt template used to generate the golden answer of SG DESC task.

GPT Evaluation Prompt Template

Score the given model-generated text against the ground truth on a scale from 0 to 100, focusing on the alignment of meanings rather than the formatting.
The ground truth text: <Golden Label>
The model output: <Model Prediction>
Provide your score as a number and do not provide any other text in the response.

Figure 9: The prompt template used for GPT evaluation.

accuracy of external knowledge, thus achieving our evaluation purpose. It should be noted that this is also the difference between us and other benchmarks for LLM fact accuracy and knowledgeability.

B.2 Experimental Details

In our experiments, we implement the training and evaluation process with PyTorch (Paszke et al., 2019) and hugging-face transformers (Vaswani et al., 2017) library. We train 3 epochs for each SKP model with a fixed context length of 384. The batch size is set to 16. We tune the learning rate in $\{1e^{-4}, 3e^{-4}, 5e^{-4}\}$.

For the structural encoders, we set the embedding dimensions of four different backbones to 512. We implement them using NeuralKG (Zhang et al., 2022), with a 3000 epoch training until coverage. The KG embedding methods (TransE/DistMult/RotatE/RGCN) are classic backbones to train structural embedding for a given KG. Besides, R-GCN (Schlichtkrull et al., 2018) employs a relational graph convolution layer for message aggregation in the KG. The training process is self-supervised. The training objective can be denoted as:

$$\mathcal{L} = \frac{1}{|\mathcal{T}|} \sum_{(h,r,t)\in\mathcal{T}} \Big(-\log \sigma(\gamma - \mathcal{F}(h,r,t)) - \sum_{i=1}^{K} p_i \log \sigma(\mathcal{F}(h'_i, r'_i, t'_i) - \gamma) \Big) \tag{5}$$

where $(h, r, t) \in \mathcal{T}$ is a positive triple. σ is the sigmoid function and γ is a margin hyper-parameter. p_i is the self-adversarial training weights proposed by RotatE (Sun et al., 2019). $\mathcal{F}$ is the score function defined specifically by different methods. For example, the score function of TransE is:

$$\mathcal{F}(h,r,t) = -||\mathbf{h} + \mathbf{r} - \mathbf{t}||_1 \tag{6}$$

For the four kinds of adapters, we implement them with the following setting:

- **FC**. It is implemented by a single linear layer in PyTorch in the form of $d_e \times d_l$, where d_e is the structural embedding dimension and d_l is the token embedding dimension of LLMs.
- **MLP**. It is implemented by several linear layers with ReLU (Glorot et al., 2011) as an activation function. The intermediate dimension of the MLPs is $3 \times d_e$. In most of the experiments, we use a two-layer MLP. In the scalability experiments, we explore deeper MLPs.

- **MoE**. We follow the implementation in XRec (Chen et al., 2024) for the MoE adapter layers. We set the expert number to 4 with adaptive gated fusion.
- **Qformer**. We follow the implementation in BLIP-2 (Li et al., 2023). The number of transformer layers in Qformer is set to 2 with 2 attention heads. The readout layer is set to be a two-layer MLP.

Now we can explain why we chose these four kinds of adapters in our evaluation. Note that the paradigm of SKP and MLLMs have certain ideas in common, which is **bridging heterogeneous information into LLM with adapters and employing texts as a core expression to solve different tasks**. Therefore, existing SKP models are heavily informed by MLLMs.

Overall, they are all popular architectures used by existing methods. FC and MLP are fundamental neural networks used by GNP (Tian et al., 2024) and KoPA (Zhang et al., 2024b). MoE network is used by XRec, a work that attempts to inform LLMs with the structural information in user-item interaction graphs. Though different from the structural information in KGs, it is also worth a try. Qformer is a classic adapter widely used in Multimodal LLMs such as BLIP-2, which is more complex than vanilla FC and MLP. Though no current work employs Qformer, we think Qformer is a representative design with amazing ideas. Therefore, we also evaluate it in our experiments.

The training process task about 20 to 30 minutes for EG and SG tasks in our experiment environment while TG takes about 4 hours. Some of our code implementation is under the help of AI assitant like ChatGPT.

B.3 Evaluation Details

In our evaluation protocol, we have several different metrics for different tasks. The CLS tasks and MC tasks have deterministic results, which can be measured by the quantitative accuracy metric. For the DESC, the situation becomes more complex. This is caused by the different settings in the DESC tasks. For EG DESC, we expect the model to generate a precise entity name. For TG DESC, we expect the model to generate the entities and relations properly in the given triple. For the SG DESC, the target is to create a paragraph to describe the given subgraph context. We can find that among these tasks, EG and TG require high accuracy and need to use Exact Match (EM) as an evaluation metric. SG, although also requires high accuracy, is not suitable for EM due to the generation of long text, so we adopt the current model of combining BLEU and GPTScore to evaluate the semantic similarity of the generated texts and the golden labels. The prompt template we used in the GPT evaluation is presented in Figure 9.

Table 4: A further exploration on the influence of textual query in the TG MC task. We use the MLP as the adapter for SKP.

Method	w/ text	w/o text
TransE	86.51	49.09
DistMult	97.91	90.94
RotatE	83.74	83.51
R-GCN	94.59	78.45

Table 5: Results on LlaMA3.1-8B.

Method		Entity MC	Triple MC	Subgraph MC
FC	**TransE**	51.86	88.26	49.35
	DistMult	30.15	90.25	78.10
	RotatE	35.67	72.65	46.28
	R-GCN	40.04	89.12	65.61
MLP	**TransE**	94.83	93.04	85.05
	DistMult	75.31	93.67	90.19
	RotatE	45.65	88.84	91.59
	R-GCN	67.81	93.78	90.93
MoE	**TransE**	44.16	89.94	78.56
	DistMult	37.31	91.50	76.93
	RotatE	61.00	91.60	81.83
	R-GCN	46.24	90.54	68.84
Q-former	**TransE**	88.47	90.95	20.34
	DistMult	75.21	93.14	44.18
	RotatE	72.67	92.67	28.54
	R-GCN	69.64	92.83	22.59

B.4 The influence of textual query in TG-MC task.

As we presented in the task definitions of SUBARU, we provide text-based descriptions of the given

Table 6: Results on LlaMA2-7B-chat.

Method		Entity MC	Triple MC	Subgraph MC
FC	**TransE**	34.72	46.77	43.29
	DistMult	26.08	61.75	70.75
	RotatE	23.00	67.21	52.66
	R-GCN	18.18	64.62	50.91
MLP	**TransE**	83.38	91.32	69.38
	DistMult	29.01	71.51	89.03
	RotatE	72.37	72.88	55.73
	R-GCN	37.06	89.01	79.19
MoE	**TransE**	42.42	60.62	63.78
	DistMult	42.37	61.05	71.64
	RotatE	25.73	58.37	62.15
	R-GCN	22.75	63.04	64.56
Q-former	**TransE**	77.20	62.73	31.73
	DistMult	37.04	89.93	40.80
	RotatE	39.84	91.96	22.83
	R-GCN	40.73	87.41	25.86

Table 7: Efficiency of different SKPs.

Method	Entity MC	Triple MC	Subgraph MC
None	12.1min	180.1min	13.5min
FC	12.6min	187.6min	14.2min
MLP	12.7min	190.1min	14.4min
MoE	12.8min	196.5min	15.4min
QFormer	13.1min	198.8min	15.9min

query in the TG MC task. For example, *([MASK] | occupation | romanist)* in Figure 14. Besides, the options are also in the form of texts which means many questions can make text-based predictions without SKP as well. To better investigate LLM's ability to understand SKP on the task TG MC, we performed some additional implementations to validate the experiments in the absence of text. As shown in Figure 4, it is obvious that the model performs better in the presence of text, because the query present in the form of text greatly simplifies LLM's understanding of the problem and makes the whole thing easier. But on the other hand, in the absence of text, the LLM still has some SKP comprehension and it can make the right choices relying on SKP alone.

B.5 Additional results on LlaMA3.1 and LlaMA2

We present more detailed experimental results in Figure 5 and Figure 6 about the SUBARU benchmark of LlaMA3.1-8B-Instruct and LlaMA2-7B-chat. These results are complementary to the universality experiment. We can observe that the model based on LlaMA3.1 performs relatively better in general compared to the model based on LlaMA2.

B.6 Efficiency of different SKPs

We compare the training efficiency of different SKP methods under the same conditions, and the results are presented in Table 7: Note that "None" means we do not add any SKPs in the training stage. With this setup, structural information can not be incorporated into LLMs. From these results, we can find that SKPs can efficiently incorporate external structural information into LLMs with a few more tokens. The time latency is tolerable for LLM training as the main workload is still the LLM rather than the adapter.

Table 8: Additional results on LLaMA2-13B.

Method	Entity MC	Triple MC
Entity CLS	88.24	74.10
Entity MC	43.83	58.46
Triple CLS	63.26	59.65
Triple MC	91.92	90.69
Subgraph CLS	90.33	55.63
Subgraph MC	75.84	86.25

B.7 Results on larger LLMs

All we have shown in the current paper are indeed results on models around 7B. To better illustrate the generalization ability of our method on larger models, we performed additional experiments on the LLaMA2-13B model with the following results:

Entity Classification (EG-CLS)

<Structural Knowledge Prompting $\mathcal{S}_e$ >
Instruction: Given an entity embedding in the front and answer the following question.
Question: Is this entity Bonnie Owens?
Output: Yes.

Figure 10: The prompt template for EG-CLS.

Entity Multiple Choice (EG-MC)

<Structural Knowledge Prompting $\mathcal{S}_e$ >
Instruction: Given an entity embedding in the front and select the true answer.
Question: Which is the possible type of entity? A. bell tower B. congestive heart failure C. academic major D. wall hanging
Output: Your Answer is: D

Figure 11: The prompt template for EG-MC.

Entity Description (EG-DESC)

<Structural Knowledge Prompting $\mathcal{S}_e$ >
Instruction: Given an entity embedding in the front and describe this entity.
Output: Bonnie Owens. ### Dessctiption: Bonnie Owens , born Bonnie Campbell, was an American country music singer who was married to Buck Owens and later Merle Haggard.

Figure 12: The prompt template for EG-DESC.

Triple Classification (TG-CLS)

<Structural Knowledge Prompting $\mathcal{S}_h$, $\mathcal{S}_r$, $\mathcal{S}_t$ >
Instruction: Given the embeddings of an knowledge triple in the front. Please answer the following question.
Question: Is this a positive triple?
Output: No

Figure 13: The prompt template for TG-CLS.

Triple Multiple Choice (TG-MC)

<Structural Knowledge Prompting $\mathcal{S}_r$, $\mathcal{S}_t$ > # Note that the masked answer does not appear in SKP
Instruction: Given the embeddings of a query and four candidates in the front. Select a correct answer to fill the [MASK] and complete the triple.
Question: ([MASK] | occupation | romanist) A. László András B. Rebekah Brooks C. Franz Konwitschny D. Francisco Rodríguez Marín
Output: A

Figure 14: The prompt template for TG-MC.

Triple Description (TG-DESC)

<Structural Knowledge Prompting $\mathcal{S}_h, \mathcal{S}_r, \mathcal{S}_t$ >
Instruction: Given the embeddings of an knowledge triple in the front and describe the head entity, relation, and tail entity of the triple.
Output: Billy Idol###languages spoken, written, or signed###English

Figure 15: The prompt template for TG-DESC.

Subgraph Classification (SG-CLS)

<Structural Knowledge Prompting $\mathcal{S}_h, \mathcal{S}_{r_1}, \mathcal{S}_{t_1}, \cdots, \mathcal{S}_{r_k}, \mathcal{S}_{t_k}$>
Instruction: Given embeddings from a subgraph in the front and answer the following question.
Question: Is there any anomaly in this subgraph?
Output: No

Figure 16: The prompt template for SG-CLS.

Subgraph Multiple Choice (SG-MC)

<Structural Knowledge Prompting $\mathcal{S}_{r_1}, \mathcal{S}_{t_1}, \cdots, \mathcal{S}_{r_k}, \mathcal{S}_{t_k}$> # The center entity does not appear.
Instruction: Given an entity embedding in the front and select the true answer.
Question: Which is the center entity descripted by this subgraph? A. The Lord of the Rings: The Fellowship of the Ring B. Christian Reimers C. Harry Fett D. Manuel Acevedo
Output: Your Answer is: D

Figure 17: The prompt template for SG-MC.

Subgraph Description (SG-DESC)

<Structural Knowledge Prompting $\mathcal{S}_h, \mathcal{S}_{r_1}, \mathcal{S}_{t_1}, \cdots, \mathcal{S}_{r_k}, \mathcal{S}_{t_k}$>
Instruction: Given embeddings from a subgraph in the front and answer the following question.
Output: Dominic Howard is a musician from the United Kingdom, known for playing the drum kit in the genre of alternative rock. He primarily works in the field of music.

Figure 18: The prompt template for SG-DESC.