# Unlock the Power of Frozen LLMs in Knwoledge Graph Completion

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# **Abstract**

Traditional knowledge graph completion (KGC) methods rely solely on structural information, struggling with the inherent sparsity of knowledge graphs (KGs). By contrast, Large Language Models (LLMs) encapsulate extensive world knowledge and exhibit powerful context modeling capabilities, making them promising for mitigating the limitations of traditional methods. However, direct fine-tuning of LLMs for KGC, though effective, imposes substantial computational and memory overheads, while utilizing non-finetuned LLMs is efficient but yields suboptimal performance. In this work, we propose a novel framework that synergizes the strengths of LLMs with robust knowledge representation to enable effective and efficient KGC. We extract the context-aware hidden states of knowledge triples from the intermediate layers of LLMs, thereby capturing rich semantic and relational nuances. These representations are then utilized to train a data-efficient classifier tailored specifically for KGC tasks. To bridge the semantic gaps between LLMs and KGs, we employ subgraph sampling on KGs to generate model-friendly entity descriptions. We further adopt sliced mutual information (SMI) as a principled metric to quantify the task-specific information encoded in these representations. Extensive experiments on standard benchmarks validate the efficiency and effectiveness of our approach. We achieve a 47% relative improvement over previous methods based on non-fine-tuned LLMs and, to our knowledge, are the first to achieve classification performance comparable to fine-tuned LLMs while enhancing GPU memory efficiency by 188× and accelerating training and inference by 26.11×.

#### **CCS Concepts**

• Computing methodologies → Reasoning about belief and knowledge; *Information extraction*; Neural networks; Supervised learning by classification.

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# **Keywords**

Knowledge Graph Completion, Large Language Models

#### **ACM Reference Format:**

# 1 Introduction

Knowledge graph completion has become a crucial endeavor to improve the application of knowledge graphs [5], which aims to complete the knowledge graph and expand its scale by predicting the potential relationship between existing entities and discovering new relational facts [24]. Traditional knowledge graph embedding methods only utilize structure information from the knowledge graph [3, 28, 31], which is vulnerable to the sparseness of KGs [39]. Leveraging the powerful contextual modeling capabilities and the implicit world knowledge encoded in LLMs, recent works have demonstrated the potential to effectively mitigate these issues and enhance KGC performance [34].

These approaches generally fall into two types: using non-finetuned LLMs with prompting techniques and fine-tuned LLMs specifically for KGC. The first type leverages LLMs with prompt techniques, such as in-context learning. These techniques enable models to perform KGC directly through natural language outputs [34, 38, 40], harnessing the pre-trained knowledge embedded within these models without additional training. While this approach offers computational efficiency, it may not fully capture the task-specific nuances required for optimal KGC performance. In contrast, the latter type involves fine-tuning the LLMs using supervised techniques to adapt models specifically for KGC tasks. This method involves fine-tuning LLMs, such as LLaMA, through the use of training samples [40], which can lead to improved performance by aligning the models more closely with the KGC objectives [40, 41]. However, fine-tuning demands significant increases in time and resource expenditure. This dichotomy between computational efficiency and task-specific performance raises a fundamental question: How can we harness LLMs for effective and efficient KGC without incurring the high costs associated with fine-tuning?

Answering this question necessitates a deeper understanding of why fine-tuned LLMs outperform their non-fine-tuned counterparts. Non-fine-tuned LLMs, while cost-effective, risk generating

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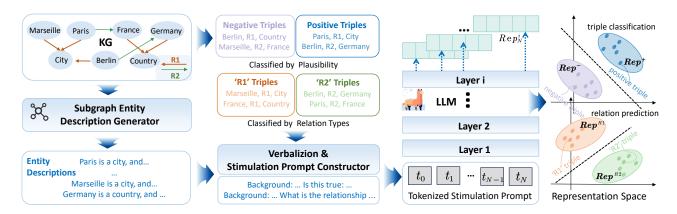


Figure 1: The overall architecture of our method for KGC involves categorizing triples based on the type of task, followed by their verbalization. This is combined with entity descriptions, which are generated by the subgraph entity description generator, to produce the stimulation prompt. Finally, the internal representation (hidden states) of the LLM obtained from the stimulation prompt is used to train a classifier, thereby completing the KGC. The only component that needs training in the entire architecture is the data-efficient classifier, making the method easy to train and cheap to deploy.

misleading outputs in the form of hallucinations [42] and underutilizing their latent knowledge [33]. Moreover, the intricate relational structures and semantic subtleties embedded in KGs compound the challenge, since LLMs are not inherently designed to parse or disambiguate complex entity linkages [15]. Crucially, fine-tuning mitigates hallucinations [43] and aligns LLM representations with KG semantics through supervised parameter updates.

Motivated by this insight, we propose a novel framework that reconciles these competing demands by fully exploiting the knowledge representation capabilities of LLMs without fine-tuning, as shown in Figure 1. Our method strategically extracts intermediate hidden states from LLMs to capture rich, context-aware representations of knowledge triples, which are then used to train a lightweight, data-efficient classifier specifically tailored for KGC. To better align LLMs with KG semantics, we introduce a novel subgraph sampling technique that generates model-friendly entity descriptions, facilitating the interpretation and disambiguation of relational patterns and thereby enhancing knowledge representation. Furthermore, we introduce Sliced Mutual Information (SMI) as a principled information-theoretic measure to quantify the task-specific information encoded within these representations. By systematically integrating these techniques, our framework effectively reduces hallucinations and semantic misalignment commonly observed in frozen LLMs, achieving accuracy comparable to fine-tuned counterparts while significantly reducing computational overhead.

Extensive experiments demonstrate that our framework not only outperforms existing non-fine-tuned LLM-based methods by 47% relative improvement but also achieves classification performance comparable to fine-tuned LLMs. Our approach enhances GPU memory efficiency by a factor of  $188\times$  and accelerates both training and inference processes by  $26.11\times$ . Our contributions can be summarized as follows:

• We propose, to the best of our knowledge, the first framework that directly leverages the intermediate representation space of frozen LLMs for KGC tasks. To facilitate semantic alignment between LLM representations and KG entities,

- we introduce a novel subgraph-based entity description generator, providing LLMs with rich, model-friendly textual contexts to effectively bridge the semantic gap.
- We provide an in-depth analysis to reveal the underlying reasons behind the superior performance of fine-tuned LLMs.
   We further employ SMI to quantify task-specific information encoded in LLM representations. Guided by these insights, we propose novel optimization strategies that, for the first time, enable frozen LLMs to match the KGC performance of their fine-tuned counterparts.
- We conduct comprehensive experiments across standard KGC datasets to validate the effectiveness and efficiency of our proposed method. These substantial improvements highlight the scalability and practicality of our method, making it a viable solution for large-scale KGC applications under resource-constrained scenarios.

#### 2 Method

Our method is proposed in face of the limitations of non-fine-tuned LLMs on KGC. In Section 2.2, we present how to precisely extract context-aware representation of knowledge from intermediate layers of LLMs. In Section 2.3 we tackle complex relationships in KGs, by the generation of model-friendly entity descriptions through subgraph sampling. Furthermore, in Section 2.4, we employ SMI as a principled information-theoretic metric to quantify the task-specific information encoded within the extracted representations, providing deeper insights into their effectiveness.

#### 2.1 Formulation and Notations

A knowledge graph, G, comprises a set of entities, E, and relations, R. It can be represented as a set of triples  $G = \{(h, r, t)\}$ , where  $h \in E$  is the head entity,  $t \in E$  is the tail entity, we collectively refer to the head entity and tail entity as e, and  $r \in R$  represents the relation between them. D is the set of long descriptions for each entity and relation. We denote D(e), D(r) as the long textual description

of each entity and each relation (hereafter simply referred to as descriptions). Additionally, we define EN(e) as the entity name of an entity e. For instance, given the entity '00952182', its entity name is EN('00952182') = 'voice', and its description D('00952182') can be 'utter with vibrating vocal chords'.

For triple classification, the task is to assess the plausibility of a given knowledge triple, determining whether the triple is true or not. As for relation prediction and entity prediction, they aim to predict the missing relation and entity in a triple, respectively.

# **Extracting Knowledge Representations**

 $PT_1$ : Is this true: Verbalize(  $\{EN(h)\}\{EN(r)\}\{EN(t)\}$ )?

 $PT_2$ : Background: 1.{D(h)}2.{D(t)}\n

Question: Is this true: Verbalize(EN(h)) EN(r) EN(t)?

 $PT_3$ : What is the relationship between  $\{EN(h)\}\$  and  $\{EN(t)\}$ ? Please choose your answer from:  $\{r1\}|\{r2\}|...|\{r_n\}$ .

 $PT_4$ : Background: 1.{D(h)}2.{D(t)}\n

Question: What is the relationship between {EN(h)} and  $\{EN(t)\}$ ? Please choose your answer from:  $\{r1\}|\{r2\}|...|\{r_n\}$ .

**Figure 2: Prompt templates to stimulate the LLM.** Knowledge graphs comprise numerous triples encoding complex relational and semantic information. However, directly prompting pre-trained, frozen LLMs, despite their extensive world knowledge, frequently results in hallucinations or incorrect responses. Although fine-tuning effectively mitigates this issue by optimizing the model's parameters to produce KG-consistent outputs, it incurs significant computational overhead. Motivated by recent findings [18, 44] that accurate relational knowledge is often internally encoded within LLMs yet not reliably reflected in their outputs, we propose directly probing intermediate layer representations as a principled alternative to fine-tuning. This approach leverages the internal semantic encoding capabilities of frozen LLMs, thereby mitigating the computational overhead and hallucination problems associated with direct textual generation.

First, we construct specialized prompt templates designed to stimulate the LLM to generate the necessary classification information within its intermediate layers. For triple classification, where the objective is to determine the plausibility of KG triples, we employ a prompt template  $PT_1$  to construct positive and negative sample pairs for training, as illustrated in Figure 2. Notably, the prompt avoids explicitly describing the positivity or negativity of triples.

Subsequently, we construct positive samples  $S^+$  from existing KG triples, and employ the negative sampling technique [39] to generate negative samples  $S^-$ . This process results in a training dataset containing N samples. Each training sample is tokenized and fed into the LLM to obtain representations from its intermediate layers. Specifically, we capture plausibility information and extract hidden states for positive samples  $s^+ \in S^+$  as follows:

$$Rep_{j}^{l}(s^{+}) = \{M_{1:l}(s^{+})[j], 0 < l < L, 0 < j < N\},$$
 (1)

where M represents the language model,  $M_{1:I}$  represents the first *l* layers of the model, [*j*] refers to the hidden state corresponding to the *j*th token, L and N represent the number of layers in the model and the number of tokens resulting from tokenizing s<sup>+</sup>, respectively. Consistent with findings in [44], we utilize the representation of the last token in each input text, as it is more conducive to information extraction due to the autoregressive nature of causal language models. Negative samples are processed similarly to ensure consistency in representation extraction.

The extracted representations  $Rep_i^l(s^+)$  and  $Rep_i^l(s^-)$  serve as input features to train a lightweight classifier. This classifier distinguishes plausible from implausible triples by learning a decision boundary that effectively separates positive and negative samples in the representation space. Although the classifiers employed—such as multilayer perceptrons (MLPs) and logistic regression models-are inherently simple, their effectiveness is significantly amplified by the quality and richness of the intermediate layer representations, thereby enhancing the ability to make accurate predictions without the computational overhead associated with fine-tuning the entire LLM.

For relation prediction, we extend our binary classification framework to a multi-class setting, where the classifier predicts the specific relationship types within the KG. Utilizing the PT<sub>3</sub> shown in Figure 2, we stimulate the LLM to generate hidden states that capture the characteristics of different relation types. This approach ensures that the classifier can effectively learn to differentiate between multiple relationship categories from the model's internal processing, enhancing the accuracy of KGC.

> User: The entity description is a description of the entity name. Given the entity name: '{EN(e)}'; at the same time, '{EN(e)}' satisfies the constraints: {D\_1(e)}. Please generate an entity description that satisfies the constraints for '{EN(e)}'. Assistants:

Figure 3: Prompt used for generating model-friendly entity descriptions via LLM rephrasing. In-context examples omitted for brevity.

#### **Subgraph Entity Description Generator**

Entities in a KG often exhibit semantic ambiguity, posing significant challenges for frozen LLMs that rely solely on entity names. Finetuning alleviates this ambiguity by aligning LLM entity representations with KG entities. However, for frozen LLMs, achieving such semantic alignment without parameter updates remains challenging. To bridge this gap, we propose a principled subgraph-besed approach that generates rich, context-aware entity descriptions from local subgraph contexts. These descriptions provide rich semantic context, enabling frozen LLMs to achieve semantic alignment comparable to fine-tuned models, without costly parameter updates. Specifically, we achieve this by extending the prompt template constructed in Section 2.2. We focus on aligning the language model's

internal entity understanding with those in the KG. Therefore, we construct new prompts  $PT_2$  and  $PT_4$ , as shown in Figure 2.

Most KGs do not contain explicit entity descriptions that can be directly used as D(e), or provide only limited and incomplete descriptions. Therefore, we propose a method to generate comprehensive and informative entity descriptions D(e). Unlike the approach in [38], which generates the entity description using only a single triple, our method constructs a more comprehensive and precise D(e) by incorporating richer subgraph contexts in two distinct ways. For the first approach, following [41], we construct  $D_1(e)$  by concatenating the verbalized triples within the one-hop subgraph around the entity e:

$$D_1(e) = \text{CONCAT} \left( \{ \text{Verbalize}(EN(h_i), EN(r_i), EN(t_i)), \\ (h_i, r_i, t_i) \in \text{Subgraph}(e) \} \right),$$
 (2)

where Subgraph(·) is a function that automatically retrieves a specified number of triples in the one-hop subgraph where the entity resides; Verbalize(·) is a function that transform the triple into its textual string, in this work, we use the linear verbalization [1]; and  $CONCAT(\cdot)$  joins each verbalized triple statement with a separator.

However, presenting information explicitly as structured triples may hinder effective knowledge retrieval by LLMs [2], since the structure of these subgraph triples substantially deviates from the textual data encountered during pre-training. Motivated by this limitation, we propose a second, more model-friendly approach, denoted as  $D_2(e)$ , which employs a language model to rephrase these verbalized triples into a narrative format that is more comprehensible to the LLM. Specifically, we employ an in-context learning approach, where a small set of carefully selected examples are prepended to the prompt to guide the LLM to generate high-quality, narrative-like descriptions. For brevity, Figure 3 illustrates only the core instruction of our prompt, omitting the in-context examples. This approach produces more refined and model-friendly entity descriptions, enabling the LLM to more effectively retrieve and leverage knowledge during the KGC task.

By leveraging the subgraph entity description generator, we align the LLM's internal understanding of entities with their counterparts in the KG, similar to an entity linking process. This approach addresses semantic ambiguity, achieving alignment comparable to fine-tuning while significantly reducing computational overhead.

# 2.4 Representation Evaluation via Sliced Mutual Information

To quantitatively assess the task-specific information encoded in the frozen-LLM representations, we adopt sliced mutual information (SMI), which scales more effectively to high-dimensional data compared to mutual information [8, 35]. Let the random variable X denote the representations extracted from the intermediate layers, where  $x_k = Rep_j^l(s_k) \in \mathbb{R}^d$  corresponds to the representation of the k-th sample  $s_k$ . Let the random variable Y denote the corresponding discrete KGC labels. Since labels Y are discrete, the SMI is defined as the expectation of mutual information between the labels Y and one-dimensional random projections of X, where these projections are sampled uniformly at random from the d-dimensional unit

sphere (denoted  $\mathbb{S}^{d-1}$ ). We estimate SMI via Monte-Carlo sampling combined with a scalar MI estimator [14]:

$$\widehat{SMI}(X;Y) = \frac{1}{m} \sum_{i=1}^{m} \hat{I}(\{\theta_{i}^{\top} x_{k}\}_{k=1}^{n}; \{y_{k}\}_{k=1}^{n}), \quad \theta_{i} \sim \text{Unif}(\mathbb{S}^{d-1}).$$

Here n represents the number of samples, m represents the number of projections, and  $\hat{I}(\cdot;\cdot)$  is the mutual information estimated via the KSG estimator with k=3 nearest neighbors. This metric quantifies the task-specific information contained in our extracted LLM representations for KGC prediction. We thus use SMI as a principled measure to verify whether the frozen-LLM representations retain a level of label-relevant information comparable to that of fine-tuned counterparts.

# 3 Experiments

In the experiments, our objective is to answer the following research questions (RQs):

- RQ1: Can LLMs with our method effectively achieve performance on par with their fine-tuned counterparts?
- **RQ2**: How does our method perform across different language models and classification models?
- RQ3: What are the data efficiency and computation efficiency of our proposed method for KGC?

#### 3.1 Datasets

Dataset	E	$ \mathbf{R} $	# Train	# Valid	# Test
FB13	75,043	13	316,232	5,908	23,733
WN11	38,696	11	112,581	2,609	10,544
FB15K-237N	13,104	93	87,282	14,082	16,452
WN18RR	40,943	11	86,835	6,068	6,268
UMLS	135	46	5,216	1,304	1,322
YAGO3-10	123,182	37	1,079,040	5,000	5,000

Table 1: Statistical information of datasets.

In our experiments, we employ five widely-used KG datasets for triple classification: FB13 [27], WN11 [27], FB15K-237N [17], WN18RR [6], and UMLS [39]. For relation prediction, we adopt the YAGO3-10 dataset [6], and for entity prediction, we use WN18RR. Specifically, WN11 and WN18RR are subsets of WordNet, while FB13 and FB15K-237 [30] are subsets of Freebase. The FB15K-237N dataset is a modified version of FB15K-237. Additionally, UMLS is a medical semantic network comprising semantic types (entities) and semantic relations.

To address incomplete or low-quality entity descriptions in some KGs, we propose two systematic approaches to generate entity descriptions from local subgraph structures, as detailed in Section 2.3 (hereafter referred to as *generated entity descriptions*). Specifically, for the first approach in Section 2.3, we construct entity descriptions by concatenating ten randomly sampled triples from each entity's one-hop subgraph, employing linear verbalization [1]; we denote these as *generated descriptions (Tri)*. For the second approach, we further utilize GPT-3.5-turbo to rephrase these concatenated triples into coherent, model-friendly descriptions via in-context learning; we denote these as *generated descriptions (GPT)*.

To assess the quality and effectiveness of our generated entity descriptions, we also utilize existing entity descriptions (provided by the original datasets or external authoritative sources) as reference baselines, hereafter referred to as *non-generated descriptions*. Specifically, for FB13, entity descriptions are obtained from corresponding Wikipedia; for FB15K-237N, we adopt the descriptions provided by [36]; for WN18RR, we utilize synset definitions from [39]; and for UMLS, we employ the entity descriptions included in the original dataset.

# 3.2 Experimental Settings

Following the experimental settings in [41], we compare our method with four widely-used structure information-based methods: TransE [3], DistMult [37], ComplEx [31] and RotatE [28]. Additionally, we compare against seven additional information-based methods: KG-LLAMA [40], KG-BERT [39], KG-T5 [22], LLaMA-7B, Alpaca-7B, LLaMA-7B-ICL and Alpaca-7B-ICL [41]. KG-LLAMA, KG-BERT and KG-T5 fine-tune the language models on the full training set. LLaMA-7B and Alpaca-7B use frozen LLMs directly for predictions. LLaMA-7B-ICL and Alpaca-7B-ICL perform predictions via in-context learning [41]. Since our method aims to fully exploit the capabilities of LLMs alone, we do not compare against hybrid methods such as KoPA [41], which fine-tunes LLMs and additionally incorporates external structural methods (e.g., TransE). Such hybrid approaches incorporate additional structural information, and thus fall outside the scope of our current investigation. We give priority to using the results reported in the official baseline paper. For structure information-based methods, we reproduce the results with OpenKE [9]. For additional information-based methods, we reproduce results using official implementations. Please refer to Section 4.1 for detailed introductions of these baseline methods.

Since existing KGs typically contain only positive triples, we follow standard practice [39] and generate negative samples by corrupting head or tail entities within positive triples for training. All training sets used in subsequent experiments thus contain equal number of positive and negative triples. For evaluation, we generate negative test triples equal in number to positive test triples on WN18RR, and UMLS datasets, while directly utilizing the original test splits containing balanced positive and negative triples for WN11, FB13 and FB15K-237N. For the intermediate layer selection, we determine the optimal layer via validation set performance.

For the MLP classifier, we adopt a two-layer perceptron structure with PReLU activation and a softmax output layer. Specifically, we set the batch size to 64 and employ the AdamW optimizer with a learning rate of 3e-5. For the SVM classifier, we set the regularization parameter C=0.5 with a squared L2 penalty term and adopt the radial basis function (RBF) kernel. For the logistic regression classifier, we also set the regularization parameter C=0.5 and employ an L2 penalty term.

# 3.3 Main Results (For RQ1)

As shown in Table 2, LLAMA-MLP-DES (NG) and LLAMA-MLP-DES (GPT), using only a limited subset (3k/10k) of the training samples, achieve comparable performance to KG-LLAMA-7B, which requires fine-tuning on the entire training set. Moreover, under

equal-sized training subsets, LLAMA-MLP-DES (NG) and LLAMA-MLP-DES (GPT) significantly outperform KG-LLAMA-SAMPLED, the existing state-of-the-art approach that relies exclusively on LLaMA for KGC, with an average improvement of 17.15% and 18.16%.

The experimental results presented in Table 2 also validate the effectiveness of the approaches proposed in Section 2.2 and Section 2.3. Specifically, LLAMA-MLP-DES (NG) and LLAMA-MLP-DES (GPT) outperform LLAMA-MLP, demonstrating the effectiveness of using subgraph entity description generator to improve the LLM's understanding of entities in the KG, as proposed in Section 2.3. Furthermore, LLAMA-MLP demonstrates superior performance compared to LLAMA-7B and LLAMA-7B-ICL, affirming the effectiveness of stimulation method proposed in Section 2.2. Thus, the experimental results substantiate the effectiveness of our proposed methodology. Additionally, our results clearly demonstrate that non-fine-tuned LLMs can achieve comparable KGC performance to their fine-tuned counterparts.

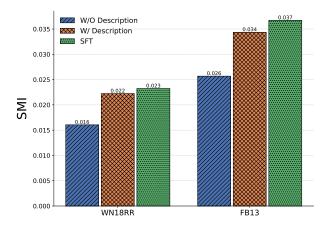


Figure 4: SMI Values of Intermediate Layer Representations in the LLaMA Model Across Different Methods. W/O Description uses LLAMA-7B with  $PT_1$  for stimulus generation; W/Description uses LLAMA-7B with  $PT_2$  for stimulus generation; SFT uses KG-LLAMA with  $PT_1$  for supervised fine-tuning.

Notably, the performance on the UMLS dataset exhibits a distinct pattern, where generated entity descriptions negatively impact classification accuracy, and non-generated descriptions yield worse results than not using descriptions as well. We hypothesize that this discrepancy arises from the highly specialized and domain-specific nature of entity names in the UMLS dataset, which are often precise medical terms with limited room for multiple interpretations. The entities in the knowledge graph have well-aligned with the internal entities of the LLM. Meanwhile, using entity descriptions may be affected by noisy description text, and descriptions generated by GPT-3.5-turbo may be influenced by hallucination, thereby affecting the classification effectiveness of the induced hidden states. Meanwhile, our method shows slightly lower performance (3.8% and 2.2% lower, respectively) on the WN11 and FB15K237N datasets compared to KG-LLAMA, which was fine-tuned on the full training set. This discrepancy may stem from the fact that the pretrained

Method	Pred	Samples	FB13	WN11	15K237N	WN18RR	UMLS
TransE	S-F	ALL	0.815	0.759	0.697	0.884	0.845
DistMult	S-F	ALL	0.862	0.871	0.587	0.851	0.864
ComplEx	S-F	ALL	0.857	0.862	0.657	0.841	0.871
RotatE	S-F	ALL	0.819	0.847	0.685	0.882	0.877
KG-BERT	L-MLP	ALL	0.899	0.935	0.560	0.916	0.773
KGT5	N-L	ALL	0.663	0.728	-	-	-
LLAMA-7B	N-L	0	0.699	0.661	0.573	0.458	0.658
LLAMA-7B-ICL	N-L	2	0.501	0.500	0.578	0.502	0.538
KG-LLAMA-7B	N-L	ALL	0.892	0.955	0.748	0.921	0.858
KG-LLAMA-SAMPLED	N-L	3k/10k	0.727	0.682	0.614	0.574	0.834
LLAMA-MLP	H-MLP	3k/10k	0.855	0.872	0.674	0.858	0.882
LLAMA-MLP-DES (NG)	H-MLP	3k/10k	0.901	-	0.738	0.934	0.862
LLAMA-MLP-DES (Tri)	H-MLP	3k/10k	0.842	0.755	0.671	0.779	0.782
LLAMA-MLP-DES (GPT)	H-MLP	3k/10k	0.912	0.917	0.726	0.924	0.860
LLAMA-MLP-DES (NG)	H-MLP	ALL	0.920	-	0.753	0.943	0.863

Table 2: The main experiment results (accuracy) of triple classification. In the 'Pred' column, S-F uses score function, L-MLP uses MLP on last layer hidden states, N-L uses natural language, and H-MLP uses MLP on intermediate layer hidden states to predict. 'Samples' indicates training sample counts, with 3k/10k indicating 10k samples for the UMLS dataset and 3k for others. LLAMA-MLP uses LLaMA-7B with MLP for hidden state classification and  $PT_1$  for stimulus generation; LLAMA-MLP-DES (NG) combines non-generated descriptions with  $PT_2$  for stimulus generation; LLAMA-MLP-DES (Tri)/(GPT) uses generated descriptions (Tri)/(GPT) with  $PT_2$  for stimulus generation. Top three results per dataset are bolded.

LLM did not acquire knowledge of certain triples in the KG during its pretraining phase, resulting in incorrect predictions even when probing is conducted.

Pred	Samples	YAGO3-10
L-MLP	ALL	0.6816
N-L	ALL	0.5714
N-L	0	0.0658
N-L	ALL	0.5662
N-L	0	0.0348
N-L	0	0.0040
N-L	ALL	0.7028
H-MLP	6996	0.5968
H-MLP	6996	0.6824
H-MLP	ALL	0.7015
	L-MLP N-L N-L N-L N-L N-L N-L H-MLP	L-MLP ALL N-L 0 N-L ALL N-L 0 N-L ALL N-L 0 N-L ALL H-MLP 6996 H-MLP 6996

Table 3: The experiment results (Hits@1) of relation prediction.

Method	Pred	Samples	WN18RR
KG-BERT	L-MLP	ALL	0.1102
StAR	L-MLP	ALL	0.2430
KGT5	N-L	ALL	0.1011
KG-ChatGLM-6B	N-L	ALL	0.1613
LLaMA-7B	N-L	0	0.0849
LLaMA-13B	N-L	0	0.0991
KG-LLaMA-7B	N-L	ALL	0.2415
LLAMA-MLP-7B	H-MLP	10k	0.2108
LLAMA-MLP-DES (GPT)	H-MLP	10k	0.2433
LLAMA-MLP-DES (GPT)	H-MLP	ALL	0.2495

Table 4: The experiment results (Hits@1) of entity prediction.

In addition to the triple classification, we also validate the effectiveness of the proposed probing method on the relation prediction task as shown in Table 3. The experimental results similarly demonstrate that the probing method can achieve the nearly same performance as full training set fine-tuning, even when using only 0.6% of the training data. For entity prediction, we obtain the plausibility confidence scores of the triples through the classifier and rank them accordingly. Table 4 also displays similar results, showing that after using model-friendly descriptions, the LLAMA-MLP-DES (GPT) method improves the performance of LLAMA-MLP-7B and surpasses its fine-tuned counterparts.

We further investigate the effectiveness of our method by evaluating the SMI values of representations extracted from intermediate layers, as illustrated in Figure 4. Notably, incorporating modelfriendly entity descriptions (W/ Description) leads to substantial improvements in the SMI values compared to representations obtained without entity descriptions (W/O Description), yielding an average relative increase of 34.1% across the two datasets. This improvement substantiates that our subgraph entity description generator effectively aligns the LLM's internal semantic comprehension with KGs' entities, thereby yielding more precise intermediate representations that better predict triple plausibility. Moreover, representations enhanced by entity descriptions achieve SMI values comparable to those obtained from supervised fine-tuned (SFT) LLMs. This observation suggests that fine-tuning primarily aligns the LLM's internal entity understanding with KG entities, rather than substantially augmenting the model's intrinsic knowledge from the training set. These findings further underscore the feasibility and effectiveness of leveraging frozen LLMs for efficient and accurate KGC. These results further demonstrate the feasibility and effectiveness of leveraging frozen LLMs' representations, combined

with our proposed subgraph-based entity description generator, to achieve efficient and accurate KGC performance comparable to fine-tuned models.

# 3.4 Ablation Study (For RQ2)

Through the analysis depicted in the left portion of Figure 5, it is observed that with an increase in the index of the intermediate layer, the efficacy of hidden states for triple classification demonstrates an initial incline followed by a subsequent decline. Intermediate layers closer to natural language text output generally exhibit better prediction performance compared to the lowest layers. This observation aligns with the findings of [7], suggesting that language models encode knowledge differentially across Transformer layers, where higher layers integrate information from lower layers. During pretraining, the lower layers may not have stored certain knowledge, thus failing to produce hidden states informative for triple classification. Furthermore, the prediction performance of the layers closer to the natural language text output is generally worse than those in the middle layers. This phenomenon may be attributed to the fact that intermediate layers appear to strike a balance between retaining sufficient information (avoiding overcompression) and discarding low-level noise, thus effectively preserving task-specific features while filtering out irrelevant details [12, 44]. Similar trends can be observed on the right side of Figure 5 for the Mistral model, which employs an architecture distinct from LLaMA. Our empirical results are consistent with recent studies [12, 18, 25, 26], highlighting the general advantage of intermediate layers over the final layers for downstream tasks. Meanwhile, as observed in Table 6, our method demonstrates strong versatility across different backbone models, achieving performance comparable to full dataset fine-tuning.

We further compare different classifiers, including MLP, SVM, and Logistic Regression, with results summarized in Table 5. Results indicate that MLP consistently outperforms the other two classifiers across all three datasets, while Logistic Regression also exhibits results close to MLP. This underscores the efficacy of our stimulus methodology, whereby the model inherently encodes discriminative features for KGC tasks, making hidden states easily distinguishable in high-dimensional space and allowing straightforward classification boundaries to emerge without the need for complex, nonlinear decision functions.

Method	FB13	WN11	FB15K-237N
LLAMA-SVM	0.821	0.866	0.594
LLAMA-LR	0.839	0.860	0.662
LLAMA-MLP	0.855	0.872	0.674

Table 5: The variation in KGC prediction performance across different datasets using SVM, Logistic Regression, MLP as classification models. All these methods use LLaMA-7B as the base model, and generate stimuli using  $PT_1$ .

# 3.5 Efficiency Study (For RQ3)

As illustrated in Figure 6, our method outperforms both KG-LLAMA and KG-BERT on the FB13 when trained with only 100 samples, as opposed to the 3000 samples used by the latter methods. For the

Model	Method	FB13	WN11
	KG-LLAMA-7B	0.892	0.955
LLaMA	LLAMA-MLP	0.855	0.872
LLaMA	LLAMA-MLP-DES (NG)	0.901	-
	LLAMA-MLP-DES (GPT)	0.912	0.917
	KG-MISTRAL-7B	0.891	0.962
Mistral	MISTRAL-MLP	0.846	0.901
	MISTRAL-MLP-DES (NG)	0.880	-
	MISTRAL-MLP-DES (GPT)	0.893	0.925
Gemma	KG-GEMMA-7B	0.897	0.944
	GEMMA-MLP	0.806	0.893
	GEMMA-MLP-DES (NG)	0.891	-
	GEMMA-MLP-DES (GPT)	0.867	0.917
Qwen2.5	KG-Qwen-7B	0.913	0.961
	Qwen-MLP	0.864	0.908
	Qwen-MLP-DES (NG)	0.904	-
	Qwen-MLP-DES (GPT)	0.916	0.935

Table 6: The variation in KGC prediction performance across different datasets using LLaMA, Mistral [11], Gemma [29] and Qwen2.5 [19] as base models (which have different backbones).

UMLS, the performance of KG-LLAMA and KG-BERT with 3000 training samples is comparable to that of LLAMA-MLP-DES (NG) trained with only 500 samples. Additionally, combining the results from Table 2, for the FB13 dataset, our method attains 97.2% of the performance achievable with the full training set, utilizing only 500 samples, which constitutes a mere 0.079% of the total training samples. In contrast, KG-LLAMA and KG-BERT achieve only 78.7% and 63.1% of the maximum performance, respectively. For the UMLS, with 9.58% of the training set, our method reaches 90.6% of the full training set performance. These results validate the capability of our method to effectively leverage the language model's internal representations, highlighting its potential for data-efficient KGC scenarios.

In addition to data efficiency, we investigate the computational efficiency of our method. Table 7 presents a detailed comparison between our approach with parameter-efficient fine-tuning, demonstrating substantial improvements in resource utilization. Specifically, GPU memory usage is measured using 'torch.cuda.memoryallocated' to record peak memory consumption per step. For a fair comparison, the KG-LLAMA baseline utilizes LoRA combined with 8-bit quantization techniques during supervised fine-tuning. As shown in Table 7, the time labeled as 'Probing' refers to the total inference duration required to extract representations for both training and test samples. Since this step involves only forward passes without gradient computations, we categorize it under the inference procedure. Compared to the fine-tuned 7B LLM baseline, our method improves GPU memory efficiency by 188× during training and achieves an overall speedup of 26.11×. Notably, the training overhead of our method lies solely in the classifier, which is independent of the LLM size. Therefore, when scaling LLMs to larger sizes, such as 70B, the substantial overhead associated with backpropagation in fine-tuning becomes increasingly burdensome. In these scenarios, the advantages of our method in terms

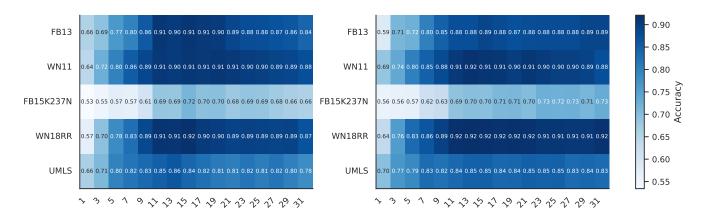


Figure 5: Differences in KGC performance across different layers of the LLAMA-MLP-DES (GPT) [left] and Mistral-MLP-DES (GPT) [right]. The horizontal axis represents the position of the intermediate layers in LLaMA or Mistral, and the vertical axis represents the dataset.

Method	Procedure	GPU Memory	Time
KG-LLAMA	Training (LLM:1 epoch)	14.68G (LLM Parameters+LoRA+Gradient etc)	83h (Forward+Backward)
	Inference (LLM:Generation)	12.94G (LLM Parameters+LoRA)	2h50min (Forward)
LLAMA-MLP	Training (MLP:10 epoch)	0.078G (MLP Parameters+Gradient etc)	33min (Forward+Backward)
	Inference (LLM:Probing+MLP)	12.82G+0.018G (LLM Parameters+MLP Parameters)	2h44min+15s (Probing+MLP Forward)

Table 7: Efficiency Comparsion between KG-LLAMA-7B and LLAMA-MLP on the WN11 full dataset. The 'Procedure' column represents several key steps of these methods.

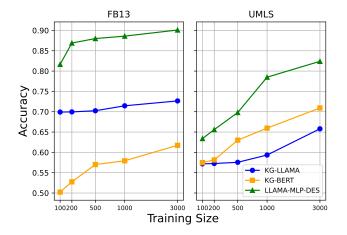


Figure 6: The prediction performance of KG-LLAMA, KG-BERT, and LLAMA-MLP-DES (NG) on triple classification varies with the size of the training dataset. The horizontal axis represents the number of training samples used, with an equal number of positive and negative samples.

of GPU memory usage and time consumption become even more pronounced.  $\,$ 

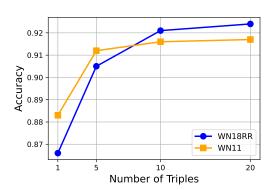


Figure 7: Performance of LLAMA-MLP-DES (GPT) versus the number of sampled triplets.

# 3.6 Additional Analysis

We investigate how varying the number of sampled triples affects the performance of LLAMA-MLP-DES (GPT). As shown in Figure 7, increasing the number of sampled triples consistently improves accuracy. For example, on WN18RR, the accuracy increases from 86.6% to 92.4% as the number of triples grows from 1 to 20. This improvement highlights that richer subgraph information facilitates more precise entity descriptions, thus better aligning the LLM's internal entity understanding with the KG semantics. Nonetheless, we also observe diminishing returns with increasing triples, indicating that additional subgraph information only marginally improves semantic alignment once sufficient context is captured. Meanwhile, as shown in Table 2, LLAMA-MLP-DES (Tri) consistently underperforms LLAMA-MLP-DES (GPT), exhibiting an average accuracy decrease of 10.5% across all evaluated datasets. Surprisingly, LLAMA-MLP-DES (Tri) even falls short of LLAMA-MLP, which does not incorporate any form of entity description, resulting in an average accuracy decline of 6.24%. This suggests that naively concatenating verbalized triples with separators as entity descriptions does not facilitate-and may even impair-the LLM's reasoning capabilities for KGC. A plausible explanation is that the structure of verbalized triples deviate significantly from the natural language distributions encountered by LLMs during pre-training, thereby introducing ambiguous stimulation information. In contrast, transforming these triples into a more natural, narrative-style format substantially alleviates this issue. Specifically, as demonstrated in Table 2, LLAMA-MLP-DES (GPT) achieves an average accuracy improvement of 3.96% compared to LLAMA-MLP. This improvement underscores the effectiveness of generating model-friendly entity descriptions, enabling LLMs to retrieve and leverage relevant knowledge more precisely for KGC tasks.

Additionally, to investigate the generalization capabilities of our approach, we conduct cross-dataset evaluation experiments where classifiers trained on one knowledge graph are tested on others. As shown in Figure 8, the classifier demonstrates strong generalization capabilities, particularly between datasets from similar knowledge sources. For instance, a classifier trained on FB13 achieves an accuracy of 0.75 when tested on FB15K237N, matching its indomain performance. This substantial transfer performance can be attributed to the fact that both FB13 and FB15K237N are subsets of Freebase, sharing similar entity and relation structures. Classifiers trained on semantically distinct datasets, such as WN18RR (derived from WordNet) and UMLS, exhibit relatively weaker transfer performance when evaluated on Freebase-derived datasets. Nevertheless, these classifiers still achieve respectable performance, underscoring that representations probed from intermediate layers of LLMs encode generalizable and task-agnostic relational knowledge, enabling effective transfer across diverse knowledge graph contexts.

# 4 Related Work

# 4.1 Knowledge Graph Completion

Knowledge graphs are inherently incomplete, necessitating effective approaches for knowledge graph completion [10]. Prevailing KGC methodologies generally fall into two categories: structure information-based methods and additional information-based methods [24]. Structure information-based methods leverage the inherent structural patterns of knowledge graphs. Representative methods such as TransE [3], DistMult [37], COMPGCN [32], ConvE

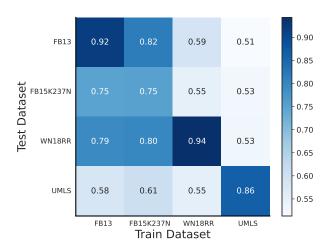


Figure 8: Generalization across Datasets, LLAMA-MLP-DES (NG). The horizontal axis represents the training set, and the vertical axis represents the test set.

[6] and RotatE [28] primarily use scoring functions defined in a latent embedding space to infer missing information. Additional information-based methods incorporate a variety of supplementary data to enrich the knowledge graphs. Representative methods include KG-BERT [39] and LASS [23], which represent entities, relations, and triples as textual sequences, reformulating KGC as a sequence classification problem solvable via encoder-only language models. Meanwhile, KG-S2S [4] and KGT5 [22] leverage encoder-decoder language models to perform KGC in a generative manner. Recently, decoder-only large language models have shown great promise in KGC tasks. KoPA [41] integrates structural embeddings with LLMs to jointly leverage the structural information of KGs and their powerful contextual modeling capabilities. More recently, KG-LLAMA [40] frames KGC as an instruction-based question-answering task, applying parameter-efficient fine-tuning techniques to LLMs. Unlike hybrid approaches that combine LLMs with external structural embeddings, KG-LLAMA solely relies on the intrinsic capabilities of LLaMA, aligning closely with the core motivation of our proposed framework.

#### 4.2 Large Language Models

Several studies have explored the mechanisms through which Large Language Models process, interpret, and generate factual knowledge. As demonstrated by [21], LLMs serve as implicit knowledge bases, encoding extensive world knowledge within their parameters. This intrinsic capability positions LLMs as promising tools for knowledge-intensive tasks such as knowledge graph completion, by effectively leveraging their embedded factual representations. To examine the extent and quality of factual knowledge encoded in LLMs, recent works have employed probing methods. For instance, [20] conducted evaluations across multiple LLMs to assess their knowledge of world geography using probing. Similarly, [13] analyzed the conceptual abstraction capabilities of different model layers, revealing hierarchical encoding patterns within the intermediate representations. Furthermore, [16] investigated the potential

existence of a universal truthfulness hyperplane in LLMs via probing. Notably, recent probing analyses [25, 26] have indicated that intermediate layers often yield more informative representations for downstream tasks than the final layers. These findings align closely with our approach of leveraging intermediate representations from LLMs to achieve effective and efficient KGC.

#### 5 Conclusion

This paper proposes a novel framework that leverages the latent representation space of LLMs to improve KGC. By integrating subgraph-based entity descriptions, our approach bridges the semantic gap between LLMs and KGs, enabling LLMs to achieve performance on par with their fine-tuned counterparts. Simultaneously, our method enhances data efficiency and saves a significant amount of GPU memory and time compared to parameter-efficient fine-tuning. This work explores the potential of LLMs in KGC tasks with both efficacy and efficiency. Compared to fine-tuning, we hit the core of KGC problem in a better way.

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