

Prompted Meta-Learning for Few-shot Knowledge Graph Completion

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Abstract

Few-shot knowledge graph completion (KGC) has obtained significant attention due to its practical applications in real-world scenarios, where new knowledge often emerges with limited available data. While most existing methods for few-shot KGC have predominantly focused on leveraging relational information, rich semantics inherent in KGs have been largely overlooked. To address this gap, we propose a novel prompted meta-learning (PromptMeta) framework that seamlessly integrates meta-semantics with relational information for few-shot KGC. PromptMeta has two key innovations: (1) a Meta-Semantic Prompt (MSP) pool that captures and consolidates high-level meta-semantics, enabling effective knowledge transfer and adaptation to rare and newly emerging relations. (2) a learnable fusion prompt that dynamically combines meta-semantic information with task-specific relational information tailored to different few-shot tasks. Both components are jointly optimized with model parameters within a meta-learning framework. Extensive experiments on two benchmark datasets demonstrate the effectiveness of our approach. We will release our code and datasets to facilitate future research.

1 Introduction

Knowledge Graphs (KGs) represent knowledge facts in the form of triplets (h, r, t) , where each triplet indicates a relationship r between a head entity h and a tail entity t . Large-scale KGs such as Wikidata (Vrandečić and Krötzsch, 2014), NELL (Mitchell et al., 2018), YAGO (Suchanek et al., 2007), and Freebase (Bollacker et al., 2008) provide strong inference capabilities for a myriad of AI-empowered applications, including question answering (Yao and Van Durme, 2014), web search (Eder, 2012), and recommender systems (Wang et al., 2019). Despite their great potential, KGs are highly incomplete due to their

semi-automatic construction from unstructured data source. This incompleteness is further exacerbated by the long-tail problem, where the majority of relations are associated with only a few triplets, leading to severe data sparsity. This sparsity poses a significant challenge in predicting missing triplets, especially for rare or long-tail relations.

To circumvent this issue, few-shot KGC methods have emerged over the past decade. Given an unseen relation and only a few support triplets, the task of few-shot KGC is to predict the missing tail entity for query triplets. The core challenge lies in effectively learning from the limited support triplets and adapting to the query set. Most current few-shot KGC methods adopt a meta-learning framework (Chen et al., 2019; Jiang et al., 2021; Niu et al., 2021; Wu et al., 2023), where the model is pretrained on meta-training tasks and then fine-tuned to predict for unseen relations with only a few support triplets.

Although meta-learning based methods have achieved state-of-the-art KGC results, they predominantly rely on KG embedding models like TransE (Bordes et al., 2013) or DistMult (Yang et al., 2015) to exploit relational information in KGs. These approaches typically embed entities and relations into a latent vector space and optimize a scoring function based on structural relations, *e.g.*, $h + r \approx t$, to learn a few-shot model. However, this structure-based focus alone is insufficient, as it often neglects the rich semantic contexts inherently present in KGs (*e.g.*, the learned relational embedding of h can be irrelevant to its semantic meaning). While prior works (Chen et al., 2019; Cornell et al., 2022a) have acknowledged this limitation, how to effectively incorporate semantic information into few-shot KGC remains largely under-explored.

To fill this gap, we propose a novel prompted meta-learning framework, called **PromptMeta**, for few-shot KG completion. PromptMeta seamlessly integrates meta-semantic knowledge with relational

information inherent in KGs to enhance the model’s ability to generalize to rare or newly emerging relations. Inspired by the recent success of prompting techniques in retrained language models (Zhou et al., 2022; Yu et al., 2023), PromptMeta incorporates prompting learning into the meta-representation learning of few-shot tasks, offering a distinctive approach for improving knowledge transfer. Our novelty lies in two key innovations: First, we propose a Meta-Semantic Prompt (MSP) pool that captures and consolidates high-level meta-semantics that are shared across few-shot tasks. This allows for effective knowledge transfer and adaptation to newly emerging relations. Second, we introduce a learnable fusion prompt that effectively integrates meta-semantic information with task-specific relational information, tailored to individual few-shot tasks. Both types of prompts are jointly optimized with model parameters within a meta-learning framework. Our contributions can be summarized as follows:

- We present **PromptMeta**, a novel prompted meta-learning framework that synergistically combines meta-semantics with relational information for effective few-shot KGC, addressing a critical research gap in the field.
- Extensive experiments and analyses on benchmark datasets demonstrate that PromptMeta significantly outperforms state-of-the-art methods, validating its superior adaptation capability.
- We construct and release pretrained semantic entity embeddings on widely used KG datasets, creating valuable resources that open new avenues for advancing future research on few-shot KGC.

2 Related Works

2.1 Few-Shot KG Completion

Existing few-shot KGC methods generally fall into metric learning based and meta-learning based approaches. Metric learning based methods aim to learn a metric that can effectively capture the similarities between support and query triplets. As a seminal work, GMatching (Xiong et al., 2018) addresses the problem of one-shot KGC using a neighbor encoder to aggregate one-hop neighbors of any given entity and a matching processor to compare similarity between query and reference entity pairs. FSRL (Zhang et al., 2020) generalizes to few-shot settings and investigates how to

integrate the information learned from multiple reference triplets for fast adaptation to new tasks. FAAN (Sheng et al., 2020) proposes a dynamic attention mechanism to improve the aggregation of one-hop neighbors. CSR (Huang et al., 2022) employs subgraph matching as a bridge to adapt from the support triplets to the query set.

Most current few-shot KGC methods fall into the regime of meta-learning (Finn et al., 2017), which focuses on quickly adapting to new few-shot relations by pre-training on prior tasks to obtain better initialization for unseen relations. MetaR (Chen et al., 2019) learns relation-specific meta-information for knowledge transfer, but it simply generates meta-representation by averaging the representations of all support triplets. MetaP (Jiang et al., 2021) introduces a meta-pattern learning framework for predicting new facts of relations under one-shot settings. GANA (Niu et al., 2021) integrates meta-learning with TransH (Wang et al., 2014) and devises a gated and attentive neighbor aggregator that better handles sparse neighbors to learn informative entity embeddings. HiRe (Wu et al., 2023) further exploits multi-granularity relational information in KGs to learn meta-knowledge that better generalizes to unseen few-shot relations. However, while these methods predominantly utilize relational information, they largely overlook rich semantic information in KGs, leaving a critical gap in how to effectively integrate rich semantics with relational information for few-shot KGC.

2.2 Prompt Learning on Graphs

Inspired by the recent success in fine-tuning retrained language models in natural language processing (NLP), prompting techniques have attracted a surge of attention for graph learning tasks.

Hard text prompts, widely used in NLP tasks (Zhou et al., 2022; Yu et al., 2023), serve as handcrafted instruction that are prepended to an input text, guiding the model to extract relevant task-specific knowledge for downstream tasks. This is often achieved through using masked language modeling as a task template. G-Prompt (Huang et al., 2023) uses hard text prompts to extract task-relevant node features, which are then fed into a learnable graph neural network (GNN) layer for few-shot node classification on text-attributed graphs. TAPE (He et al., 2024) prompts an LLM to retrieve textual explanations as features to enrich node vector representations for boosting downstream GNNs. The effectiveness of these works

reply on the quality of constructed prompts.

Recently, learnable prompts have emerged as an alternative to handcrafted prompts, alleviating the high engineering costs in prompt design. By optimizing prompt representations alongside task learning objectives, the aim is to better align the task with the retrained model to achieve faster adaptation. ProG (Sun et al., 2023) reformulates node-level and edge-level tasks to graph-level tasks, and employs meta-learning to learn a better initialization for a prompt graph under multi-task settings. GraphPrompt (Liu et al., 2023) employs subgraph similarity as a task template and designs learnable prompts as the parameters of the READOUT operation, offering different aggregation schemes for node and graph classification. HGPrompt (Yu et al., 2024) extends GraphPrompt to address few-shot learning on heterogeneous graphs, where an additional heterogeneity prompt is introduced to modify the input to the aggregation layer. Despite promising results achieved, prompt-based methods have yet been explored in the context of KGs with intrinsic semantic and relational information. Our work is proposed to fill this research gap by introducing a novel prompt-based meta-learning framework for few-shot KGC, enabling more effective model adaptation to predicting unseen relations.

3 Problem Formulation

A knowledge graph (KG) can be represented as a collection of factual triplets $\mathcal{G} = \{(h, r, t) \in \mathcal{E} \times \mathcal{R} \times \mathcal{E}\}$, where \mathcal{E} and \mathcal{R} denote the entity set and the relation set, respectively. Each triplet $(h, r, t) \in \mathcal{TP}$ indicates a relationship r between a head entity h and a tail entity t .

Definition: Few-shot KG Completion. Given a relation $r \in \mathcal{R}$ and its K -shot support set $\mathcal{S}_r = \{(h_i, r, t_i) \in \mathcal{TP}\}$, where $|\mathcal{S}_r| = K$ denotes the number of support triplets, the K -shot KGC task aims to predict the true tail entity for each triplet from the query set $\mathcal{Q}_r = \{(h'_j, r, ?)\}$ based on the knowledge learned from the support set \mathcal{S}_r . For each query triplet $(h'_j, r, ?) \in \mathcal{Q}_r$, given a set of candidates $\mathcal{C}_{h'_j, r}$ for the missing tail entity, the objective is to rank the true tail entity highest among the candidates $\mathcal{C}_{h'_j, r}$.

As defined above, few-shot KGC is a relation-specific task. The goal of a few-shot KGC model is to accurately predict new triplets associated with a relation r , when only a few triplets are provided for training. Thus, the model is trained based on

the unit of tasks, where each task \mathcal{T}_r is to predict new triplets associated with a specific relation r . The objective is to optimize the model based on a set of meta-training tasks $\mathcal{D}_{train} = \{\mathcal{T}_i\}_{i=1}^I$, where each meta-training task \mathcal{T}_r , corresponding to a specific relation r , consists of a support set \mathcal{S}_r and a query set \mathcal{Q}_r , i.e. $\mathcal{T}_r = \{\mathcal{S}_r, \mathcal{Q}_r\}$. During testing, the model is required to infer new triplets for unseen relations in the test set $\mathcal{D}_{test} = \{\mathcal{T}_j\}_{j=1}^J$, given a corresponding few-shot support set. The relations in the test set are unseen during training, i.e., $\mathcal{R}_{train} \cap \mathcal{R}_{test} = \emptyset$.

4 The Proposed Method

In this section, we present our proposed learning framework in detail. As previously discussed, the core challenge in few-shot KGC is two-fold: (1) enabling model adaptation from the support set—where task-specific information is present but highly limited—to the query set; (2) learning transferable knowledge from the training set to predict for unseen relations. To address these two challenges, our proposed **PromptMeta** learning framework integrates meta-semantic prompts to enhance meta-relation representations. This integration allows the meta-relation representation to encapsulate both relational and meta-semantic knowledge, enabling more effective few-shot KGC. Our approach consists of three key components: (1) an attentive neighbor aggregator for relational information learning, (2) a learnable meta-semantic prompt pool for knowledge transfer, and (3) knowledge fusion for integrating relational and meta-semantic information.

4.1 Attentive Neighbor Aggregator for Relational Information Learning

As demonstrated by prior studies (Xiong et al., 2018; Niu et al., 2021), local relational information plays an important role in improving the representation learning of entities in KGs. In light of this, we propose an attentive neighbor aggregator which captures the local relational information of a given entity and imbues the embedding of the target entity with such information.

Formally, given an entity e , the set of its neighboring relation-entity tuples is denoted as $\mathcal{N}_e = \{(r_i, t_i) \mid (e, r_i, t_i) \in \mathcal{TP}\} \cup \{(h_i, r_i) \mid (h_i, r_i, e) \in \mathcal{TP}\}$. Our attentive neighbor aggregator aims to enrich the embedding of e with its local relational information obtained from \mathcal{N}_e . Specif-

ically, a neighboring tuple $(r_i, e_i) \in \mathcal{N}_e$ (for simplicity, both the head and tail entities are uniformly denoted as e_i) is first encoded as the concatenation of relational embeddings of relation r_i and entity e_i , denoted as $\mathbf{n}_{ri} = [\mathbf{r}_{ri}; \mathbf{e}_{ri}]$. The relational embedding \mathbf{e}_r of entity e is updated by aggregating the information from its local neighborhood:

$$\mathbf{e}'_r = f_n\left(\sum_{i=1}^{|\mathcal{N}_e|} a_i \mathbf{n}_{ri}\right) + \mathbf{e}_r, \quad (1)$$

where $\mathbf{e}_r \in \mathbb{R}^{1 \times d}$ denotes the relational embedding of the target entity e , and a_i is the attention weight that measures the importance of tuple embedding \mathbf{n}_{ri} based on its correlation with the target entity e , and f_n is a two-layer MLP. Tuples with higher correlations would contribute more towards the embedding of e and provide more relational knowledge to the learning of local information.

The attention weight a_i of the neighboring tuple (r_i, e_i) to the target entity e is computed by:

$$\alpha_i = g_n(\mathbf{e}_{ri} \mathbf{W}_q, \mathbf{n}_{ri} \mathbf{W}_k), \quad (2)$$

$$a_i = \frac{\exp(\alpha_i)}{\sum_{j=1}^{|\mathcal{N}_e|} \exp(\alpha_j)}, \quad (3)$$

where $\mathbf{n}_{ri} \in \mathbb{R}^{1 \times 2d}$ denotes the relational embedding of i -th tuple, $\mathbf{W}_q \in \mathbb{R}^{d \times d_k}$, $\mathbf{W}_k \in \mathbb{R}^{2d \times d_k}$ denotes the projection parameter matrices. $|x|$ denotes the size of set x . g_n performs *cross-attention* using the target entity embedding \mathbf{e}_r as query on neighboring tuples, implemented as a single-layer MLP with LeakyReLU as activation function. The original attention weights α_i are normalized via Eq. 3 to serve as the final attention weights for local information aggregation.

4.2 Learnable Meta-Semantic Prompt Pool for Knowledge Transfer

KGs, as structured representations of real-world knowledge, contain rich textual information that has however been overlooked in existing few-shot KGC methods. Relying solely on relational information has proven to be suboptimal, especially in few-shot settings where the scarcity of training data further exacerbates this issue (Cornell et al., 2022b). This underscores the necessity of leveraging both relational and semantic information to effectively generalize the fused meta-representation from the support set to the query set. In addition, current methods lack an effective mechanism

for explicitly learning transferable semantic knowledge from the training set to predict for unseen relations. To fill this gap, we propose a Meta-Semantic Prompt (MSP) pool that serves as a repository for high-level semantic patterns, capturing transferable knowledge from previously seen tasks. The MSP pool is randomly initialized and consolidated during meta-training to organize meta-knowledge. For a given few-shot task, we first aggregate its task-semantic embedding and then retrieve its relevant meta-semantic prompt from the pool to enrich the representation of the task relation and achieve rapid adaptation to unseen relations.

Task-Semantic Embedding Aggregation. Given a K -shot task \mathcal{T}_r , we first construct a task-semantic embedding for relation r , denoted as \mathbf{s}_r , by aggregating semantic information from the support set. This embedding is generated using a *self-attention* mechanism that captures pairwise interactions among support triplets, allowing more representative triplets to contribute more significantly to \mathbf{s}_r . Formally, the task-semantic embedding \mathbf{s}_r is computed as follows:

$$\mathbf{s}_r = f_{sa}(\{[\mathbf{h}_{si}; \mathbf{t}_{si}]\}_{i=0}^K), \quad (4)$$

where $[\mathbf{h}_{si}; \mathbf{t}_{si}]$ indicates the concatenated semantic embeddings for the head and tail entities for each support triplet (h_i, r, t_i) . f_{sa} is a *self-attention* function that aggregates the embeddings of K support triplets, assigning higher weights to more representative triplets in the task-semantic embedding.

Meta-Semantic Prompt Retrieval. After aggregating task-semantic embeddings, we retrieve relevant meta-knowledge from the meta-semantic prompt (MSP) pool. Formally, let $\mathbf{P} \in \mathbb{R}^{M \times D_s}$ denote the MSP pool with M components. Each component $\mathbf{p}_z \in \mathbb{R}^{1 \times D_s}$ denotes a meta-semantic prompt vector of dimension D_s . The knowledge maintained in the MSP pool \mathbf{P} constitutes more abstract, high-level semantic patterns, such as Person-Location or Person-Person relationships, which are crucial for better adapting to unseen relations that follow similar semantic patterns. For example, predicting a new relation between *Obama* and *Washington* would benefit from the Person-Location pattern, as it provides abstract meta-knowledge about how people and places are commonly related. Such meta-knowledge would facilitate knowledge transfer in few-shot KGC.

Given the task-semantic embedding \mathbf{s}_r , we retrieve a corresponding meta-semantic prompt \mathbf{p}_r

from the MSP pool based on:

$$\mathbf{p}_r = \max_{j \in \{1, 2, \dots, M\}} \eta(\mathbf{s}_r, \mathbf{p}_j), \quad (5)$$

where η is a score function based on cosine similarity between \mathbf{s}_r and pool components \mathbf{p}_j . The meta-semantic prompt \mathbf{p}_j with the largest similarity is retrieved as the meta-semantic prompt to provide high-level semantic cues related to the current task.

The MSP pool is dynamically updated after each meta-training task, continuously refining and retaining high-level semantics for effective knowledge transfer across few-shot tasks and model generalization to unseen relations.

Pool Tuning. To optimize the learnable knowledge in the MSP pool, we formulate a pool tuning objective based on the observation that the support triplets associated with the same relation r should retrieve similar meta-semantic prompts, while the triplets from different relations should retrieve more distant ones. To this end, we introduce a contrastive learning-based approach to regularize the prompt retrieval process. For a given relation r , its support triplets and the retrieved meta-semantic prompt \mathbf{p}_r are treated as positive pairs, encouraging their embeddings to be close in the semantic space. Conversely, meta-semantic prompts retrieved for different relations are treated as negative pairs, pushing their embeddings to be farther apart. This approach ensures that meta-semantic prompts are coherently organized in a semantic space. As a result, the model can leverage them as transferable knowledge to enhance adaptation to few-shot tasks and unseen relations.

Formally, the loss for pool tuning is defined as:

$$\mathcal{L}_{\text{pt}} = \frac{1}{K} \sum_{i=1}^K -\log \frac{\exp(\text{sim}(\mathbf{p}_r, [\mathbf{h}_{si}; \mathbf{t}_{si}])/\tau)}{\sum_{n=0}^N \exp(\text{sim}(\mathbf{p}_r, \mathbf{p}_{r'n})/\tau)}, \quad (6)$$

where N is the number of meta-semantic prompts for a different relation r' from the same batch, τ denotes the temperature parameter, $\text{sim}(x, y)$ measures the cosine similarity between x and y .

4.3 Fusing Relational and Meta-Semantic Information

For a given few-shot task \mathcal{T}_r , two primary sources of knowledge are utilized: the relational information conveyed by the head and tail embeddings, \mathbf{h}_r and \mathbf{t}_r , which are further enhanced by the attentive

neighbor aggregator, and the task-relevant meta-semantic information encapsulated by the meta-semantic prompt \mathbf{p}_r . To effectively integrate these two sources of information, we introduce a fusion prompt \mathbf{fp}_r , which acts as a flexible intermediary for fusing meta-semantic knowledge from \mathbf{p}_r with task-specific relational information inherent in the head and tail entities. Formally, the fused meta-representation \mathbf{mr}_r for task \mathcal{T}_r is generated by:

$$\mathbf{mr}_r = \Phi_{\text{fuse}}(\mathbf{r}_r, \mathbf{p}_r, \mathbf{fp}_r), \quad (7)$$

where Φ_{fuse} is a fusion function taking task-relational embedding, meta-semantic prompt and the task-specific fusion prompt as input, implemented as a two-layer MLP. \mathbf{r}_r denotes task-relational embedding obtained using the self-attention function f_{sa} in Eq. 4 with shared parameters, given by:

$$\mathbf{r}_r = f_{\text{sa}}(\{[\mathbf{h}_{ri}; \mathbf{t}_{ri}]\}_{i=0}^K). \quad (8)$$

The task-specific fusion prompt is designed to offer a flexible fusion scheme, tailored to the current few-shot task, ensuring a cohesive and fused meta-representation.

4.4 Training Objective and Model Optimization

After obtaining fused meta-representation \mathbf{mr}_r on the support set, we adopt the idea of MTransD (Wu et al., 2023) to optimize model parameters and then adapt the learned \mathbf{mr}_r to the query set. Specifically, for a target relation r and its support set \mathcal{S}_r , we first calculate a score for each entity pair $(h_i, t_i) \in \mathcal{S}_r$ by projecting the embeddings of head/tail entity into a latent space determined by its corresponding entities and relation simultaneously. Mathematically, the projection process and the score function can be formulated as:

$$\mathbf{h}_{pi} = \mathbf{r}_{pi} \mathbf{h}_{pi}^T \mathbf{h}_i + \mathbf{I}^{m \times n} \mathbf{h}_i, \quad (9)$$

$$\mathbf{t}_{pi} = \mathbf{r}_{pi} \mathbf{t}_{pi}^T \mathbf{t}_i + \mathbf{I}^{m \times n} \mathbf{t}_i, \quad (10)$$

$$\text{score}(h_i, t_i) = \|\mathbf{h}_{pi} + \mathbf{mr}_r - \mathbf{t}_{pi}\|_2, \quad (11)$$

where $\|\mathbf{x}\|_2$ represents the ℓ_2 norm of vector \mathbf{x} , \mathbf{h}_i and \mathbf{t}_i are the head and tail entity embeddings generated by $\mathbf{h}_i = \mathbf{h}_{ri} + \mathbf{h}_{si}$, $\mathbf{t}_i = \mathbf{t}_{ri} + \mathbf{t}_{si}$. \mathbf{h}_{pi} and \mathbf{t}_{pi} are their corresponding projection vectors. \mathbf{r}_{pi} is the projection vector of \mathbf{mr}_r , and $\mathbf{I}^{m \times n}$ is an identity matrix (Ji et al., 2015). Consider the entire support set, we can further define a loss function as

follows:

$$\mathcal{L}(\mathcal{S}_r) = \sum_{(h_i, t_i) \in \mathcal{S}_r} \max\{0, \text{score}(h_i, t_i) + \gamma - \text{score}(h_i, t'_i)\}, \quad (12)$$

where γ is a hyper-parameter that determines the margin to separate positive pairs from negative pairs. $\text{score}(h_i, t'_i)$ calculates the score of a negative pair (h_i, t'_i) which results from negative sampling of the positive pair $(h_i, t_i) \in \mathcal{S}_r$, i.e. $(h_i, r, t'_i) \notin \mathcal{G}$.

The fused meta-representation \mathbf{mr}_r can be refined based on the gradient of $\mathcal{L}(\mathcal{S}_r)$:

$$\mathbf{mr}'_r = \mathbf{mr}_r - l_r \nabla_{\mathbf{mr}_r} \mathcal{L}(\mathcal{S}_r), \quad (13)$$

where l_r indicates the learning rate. Furthermore, for each few-shot task \mathcal{T}_r , the projection vectors \mathbf{h}_{pi} , \mathbf{r}_{pi} and \mathbf{t}_{pi} are also optimized in the same manner to enable the model’s generalization to the query set. With the updated parameters, each entity pair (h_j, t_j) from the query set \mathcal{Q}_r is projected and scored following the same scheme as support set. The loss function on query set $\mathcal{L}(\mathcal{Q}_r)$ can be derived as:

$$\text{score}(h_j, t_j) = \|\mathbf{h}_{pj} + \mathbf{mr}'_r - \mathbf{t}_{pj}\|_2, \quad (14)$$

$$\mathcal{L}(\mathcal{Q}_r) = \sum_{(h_j, t_j) \in \mathcal{Q}_r} \max\{0, \text{score}(h_j, t_j) + \gamma - \text{score}(h_j, t'_j)\}, \quad (15)$$

where (h_j, t'_j) is also a negative triplet generated similarly as (h_i, t'_i) . The optimization objective for training the whole model is to minimize $\mathcal{L}(\mathcal{Q}_r)$ and \mathcal{L}_{pt} together, given by:

$$\mathcal{L} = \mathcal{L}(\mathcal{Q}_r) + \lambda \mathcal{L}_{pt}, \quad (16)$$

where λ is a trade-off hyper-parameter.

5 Experiments

5.1 Datasets and Metrics

We evaluate our method using two popular few-shot KGC datasets, Nell-One and Wiki-One (Xiong et al., 2018), following the standard setup used by GMatching (Xiong et al., 2018). To be specific, relations associated with more than 50 but less than 500 triplets are selected as few-shot relations. A background graph is constructed by excluding the few-shot relations from training/validation/test sets to provide the neighborhood graph for our proposed method. For each few-shot relation, we use the candidate entity set provided by GMatching to ensure a fair comparison. We follow the common splits of

Table 1: Statistics of benchmark KG datasets.

Dataset	# Relations	# Entities	# Triplets	# Tasks
Nell-One	358	68,545	181,109	67
Wiki-One	822	4,838,244	5,859,240	183

51/5/11 on Nell-One and 133/16/34 on Wiki-One for training/validation/testing, respectively. The statistics of both datasets are provided in Table 1.

For evaluation, we adopt two widely used metrics, MRR (mean reciprocal rank) and Hits@ N ($N = 1, 5, 10$) on both datasets for the evaluation of performance. MRR indicates the mean reciprocal rank of the correct tail entities, and Hits@ N indicates the ratio of the correct tail entities that rank in top N . We compare the proposed method against other baseline methods under the most common 1-shot and 5-shot settings.

5.2 Baseline Methods

We compare our proposed method against two groups of state-of-the-art baselines:

Conventional KGC methods: This category of methods focus on modeling relational structures in KGs to learn entity/relation embeddings. We adopt four representative methods as baselines, including TransE (Bordes et al., 2013), TransH (Wang et al., 2014), DistMult (Yang et al., 2015), and ComplEx (Trouillon et al., 2016). We use OpenKE (Han et al., 2018) to reproduce the results of these models with hyper-parameters reported in the original papers. We also compare with KG-BERT (Yao et al., 2019) which combines relational and semantic information in KGs to facilitate KGC. We use the code released by authors to reproduce the results. All results are obtained after training the models using all triplets from background relations (Xiong et al., 2018) and training relations, as well as relations from all reference sets.

Few-shot KGC methods: These methods are specifically designed for few-shot KGC with competitive results, including GMatching (Xiong et al., 2018), MetaR (Chen et al., 2019), FAAN (Sheng et al., 2020), FSRL (Zhang et al., 2020), GANA (Niu et al., 2021) and HiRe (Wu et al., 2023). For MetaR (both In-Train and Pre-Train) and FAAN, we directly report results from the original papers. For GMatching, we report the results provided by Chen et al. (2019) for both 1-shot and 5-shot settings. As FSRL was originally evaluated using a much smaller candidate set, we report the results re-implemented by Sheng et al. (2020) under the same setting with other methods. The

Table 2: Comparison against state-of-the-art methods on Nell-One and Wiki-One. MetaR-I and MetaR-P indicate the In-train and Pre-train of MetaR (Chen et al., 2019), respectively.

Methods	Nell-One								Wiki-One							
	MRR		Hits@1		Hits@5		Hits@10		MRR		Hits@1		Hits@5		Hits@10	
	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot
TransE	0.105	0.168	0.041	0.082	0.111	0.186	0.226	0.345	0.036	0.052	0.011	0.042	0.024	0.057	0.059	0.090
TransH	0.168	0.279	0.127	0.162	0.160	0.317	0.233	0.434	0.068	0.095	0.027	0.047	0.060	0.092	0.133	0.177
DistMult	0.165	0.214	0.106	0.140	0.174	0.246	0.285	0.319	0.046	0.077	0.014	0.035	0.034	0.078	0.087	0.134
ComplEx	0.179	0.239	0.112	0.176	0.212	0.253	0.299	0.364	0.055	0.070	0.021	0.030	0.044	0.063	0.100	0.124
KG-BERT	0.191	0.238	0.122	0.172	0.224	0.257	0.303	0.388	0.062	0.088	0.028	0.040	0.046	0.071	0.125	0.159
GMatching	0.185	0.201	0.119	0.143	0.260	0.264	0.313	0.311	0.200	-	0.120	-	0.272	-	0.336	-
MetaR-I	0.250	0.261	0.170	0.168	0.336	0.350	0.401	0.437	0.193	0.221	0.152	0.178	0.233	0.264	0.280	0.302
MetaR-P	0.164	0.209	0.093	0.141	0.238	0.280	0.331	0.355	0.314	0.323	0.266	0.270	0.375	0.385	0.404	0.418
FSRL	-	0.184	-	0.136	-	0.234	-	0.272	-	0.158	-	0.097	-	0.206	-	0.287
FAAN	-	0.279	-	0.200	-	0.364	-	0.428	-	0.341	-	0.281	-	0.395	-	0.436
GANa	0.265	0.295	0.163	0.202	0.357	0.394	0.453	0.473	0.290	0.302	0.250	0.259	0.336	0.341	0.379	0.384
HiRe	0.288	0.306	0.184	0.207	0.403	0.439	0.472	0.520	0.322	0.371	0.271	0.319	0.383	0.419	0.433	0.469
PromptMeta	0.291	0.327	0.189	0.233	0.405	0.442	0.473	0.522	0.338	0.386	0.280	0.327	0.388	0.426	0.434	0.473

Table 3: Ablation study of the components in PromptMeta under 3-shot and 5-shot settings on Nell-One benchmark.

Ablation on	3-shot				5-shot			
	MRR	Hits@1	Hits@5	Hits@10	MRR	Hits@1	Hits@5	Hits@10
PromptMeta (Ours)	0.318	0.219	0.428	0.510	0.327	0.233	0.442	0.522
w/o Semantic	0.281	0.185	0.380	0.461	0.294	0.205	0.383	0.471
w/o MSP pool - Task-Semantic	0.315	0.209	0.424	0.502	0.320	0.225	0.429	0.515
w/o Fusion Prompt	0.304	0.202	0.414	0.485	0.314	0.212	0.421	0.500
w/o Pool Tuning	0.311	0.211	0.419	0.494	0.315	0.219	0.418	0.508

results of GANA (Niu et al., 2021) and HiRe (Wu et al., 2023) are reproduced using the code released by authors. All reported results are produced under the same settings for fair comparisons.

5.3 Implementation Details

Settings of our method: For fair comparison, we use the entity and relation embeddings pretrained by TransE on both datasets, released by GMatching, for relational embedding initialization. Following the literature, the embedding dimension is set to 100 and 50 for Nell-One and Wiki-One, respectively. We apply drop path to avoid overfitting with a drop rate of 0.2. The maximum number of neighbors for a given entity is set to 50, the same as in prior works. For all experiments except for the sensitivity test on the trade-off parameter λ in Eq. 16, λ is set to 0.05. The margin γ in Eq. 12 is set to 1. We apply mini-batch gradient descent to train the model with a batch size of 1,024 for both datasets. Adam optimizer is used with a learning rate of 0.001. Our proposed method is evaluated on the validation set every 1,000 steps, and the best model within 80,000 steps is chosen based on MRR for testing. All models are implemented by PyTorch and trained on 1 Tesla V100 GPU.

Pretrained semantic entity embeddings: To ensure consistency with the conventional initializa-

tion methods that incorporate relational information, we generated a corresponding set of initialization parameters based on semantic information for the Nell-One and Wiki-One datasets. Specifically, we processed and generated text descriptions for each entity in Nell-One based on the original entity names. For Wiki-One, we enriched the text descriptions for entities following the methodology proposed by Cornell et al. (2022b). Subsequently, we derived an initialization vector for each entity in both datasets using pretrained weights from GloVe (Pennington et al., 2014) followed by Smooth Inverse Frequency embeddings (Arora et al., 2017) for compact representation generation. To maintain alignment with relational embeddings, the vectors for Nell-One were set to 100 dimensions, and for Wiki-One, 50 dimensions. We will release the pretrained semantic entity embedding to facilitate future research in few-shot KGC.

5.4 Few-Shot KGC Results

Table 2 compares our method with baseline methods on the Nell-One and Wiki-One datasets under both 1-shot and 5-shot settings. Traditional KGC methods, *e.g.*, TransE (Bordes et al., 2013), TransH (Wang et al., 2014), and ComplEx (Trouillon et al., 2016), are designed for scenarios with

λ	5-shot			Samples	5-shot			MSP	5-shot		
	MRR	H@1	H@10		MRR	H@1	H@10		MRR	H@1	H@10
0	0.315	0.219	0.508	0	0.315	0.219	0.508	0	0.294	0.205	0.471
0.01	0.322	0.229	0.513	256	0.322	0.225	0.518	32	0.319	0.227	0.511
0.05	0.327	0.233	0.522	512	0.327	0.230	0.521	64	0.327	0.233	0.522
0.10	0.319	0.226	0.518	1024	0.327	0.233	0.522	128	0.312	0.215	0.508

(a) Pool tuning weight.

(b) Number of negative samples.

(c) Size of the MSP pool.

Table 4: Ablation on a) prompt tuning weight; b) the number of negative samples in contrastive loss; c) the size of MSP pool. 5-shot setting on Nell-One are reported. Default settings are marked in gray.

abundant training data and perform significantly worse in few-shot settings. In contrast, our method, PromptMeta, outperforms state-of-the-art few-shot KGC methods like GANA (Niu et al., 2021) and HiRe (Wu et al., 2023) across both datasets and settings. For example, on Nell-One, our method surpasses the second-best approach in terms of MRR and Hits@1 by +0.3% and +0.5% in the 1-shot setting, and by +2.1% and +2.6% in the 5-shot setting. Notably, as the number of support triplets increases from 1-shot to 5-shot, our method demonstrates even greater performance gains compared to previous approaches. This improvement is attributed to our meta-semantic prompt pool, which effectively captures and leverages shared meta-semantic information across different few-shot tasks. 0200

5.5 Ablation Studies

To investigate the contributions of each component in PromptMeta, we conduct a thorough ablation study on Nell-One dataset under 3-shot and 5-shot settings, as shown in Table 3.

- **w/o Semantic:** To evaluate the importance of semantic information, we remove \mathbf{p}_r and \mathbf{fp}_r from Eq 7, utilizing only the task-relational embedding to generate the meta-representation. The removal of both MSP pool and fusion prompt results in a profound performance drop under both settings, highlighting the critical role of semantic information in few-shot KGC.
- **w/o MSP pool - Task-Semantic:** To further assess the efficacy of the MSP, we replace the selected meta-semantic prompt \mathbf{p}_r in Eq 7 with \mathbf{s}_r from Eq 4, directly using the task-semantic embedding to provide semantic information. The observed performance drop indicates that MSP is crucial for the model to learn high-level, generalizable semantic knowledge, which is essential for predicting unseen relations in few-shot scenarios.
- **w/o Fusion Prompt:** The ablation of the fusion prompt \mathbf{fp}_r from Eq 7 also leads to a significant performance decline under both settings. This outcome underscores the importance of the fu-

sion prompt in bridging the gap between task-relational embedding and meta-semantic prompt, ensuring effective information fusion.

- **w/o Pool-tuning:** The performance drop resulted from ablating the pool tuning loss \mathcal{L}_{pt} from Eq. 16 confirms the necessity of optimizing the learnable MSP during training, as it enhances the cohesiveness and distinctiveness of the meta semantic knowledge provided.

5.6 Hyperparameter Analysis

We conduct three sensitivity tests, including the trade-off parameter λ in Eq. 16, the number of negative samples N in Eq. 6, and the size M of the MSP pool on Nell-One as shown in Table 4.

Considering different scales of the supervised margin loss and pool tuning loss, we study the impact of different values of λ between 0 and 0.1. As Table 4a shows, PromptMeta achieves the best performance when $\lambda = 0.05$. Consistently, PromptMeta achieves better performance when $\lambda > 0$, validating the efficacy of our contrastive learning based pool tuning.

We set N from 0 to 1024 in Table 4b. PromptMeta performs the best when $N = 1024$. As N increases, the performance increases accordingly, suggesting different meta-semantics are becoming more effectively differentiated from one another.

We set the size of the MSP pool M as 0, 32, 64, 128 in Table 4c. The best performance is achieved when $M = 64$ for Nell-One. When M increases to 128, the significant performance drop suggests that the semantic information indeed exhibits shared patterns essential for knowledge transfer.

6 Conclusion

This paper presents PromptMeta, a novel prompted meta-learning framework for few-shot KGC. By injecting meta-semantic knowledge with relational information, PromptMeta is equipped with more effective knowledge transfer and adaptation abilities for predicting unseen relations. Experimental results on two commonly used benchmark datasets

show that PromptMeta consistently outperforms state-of-the-art methods, demonstrating its efficacy for few-shot KGC. The ablation analysis and hyperparameter sensitivity study verify the significance of the key components of PromptMeta.

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