Adapting Meta Knowledge Graph Information for Multi-Hop Reasoning over Few-Shot Relations

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Abstract

Multi-hop knowledge graph (KG) reasoning is an effective and explainable method for predicting the target entity via reasoning paths in query answering (QA) task. Most previous methods assume that every relation in KGs has enough training triples, regardless of those few-shot relations which cannot provide sufficient triples for training robust reasoning models. In fact, the performance of existing multi-hop reasoning methods drops significantly on few-shot relations. In this paper, we propose a meta-based multi-hop reasoning method (Meta-KGR), which adopts meta-learning to learn effective meta parameters from high-frequency relations that could quickly adapt to few-shot relations. We evaluate Meta-KGR on two public datasets sampled from Freebase and NELL, and the experimental results show that Meta-KGR outperforms the current state-of-the-art methods in few-shot scenarios. Our code and datasets can be obtained from https://github.com/THU-KEG/MetaKGR.

1 Introduction

Recently, large-scale knowledge graphs (KGs) have been demonstrated to be beneficial for many NLP tasks like query answering (QA). A triple query for QA is generally formalized as $(e_s, r_q, ?)$, where e_s is the source entity and r_q is the query relation. For example, given a language query "*What is the nationality of Mark Twain?*", we can transform it into $(Mark\ Twain, nationality, ?)$ and then search the target entity *America* from KGs as the answer. However, as many KGs are constructed automatically and face serious incompleteness problems (Bordes et al., 2013), it is often hard to directly get target entities for queries.

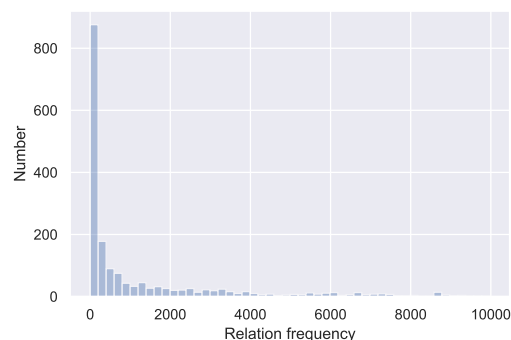To alleviate this issue, some knowledge graph embedding methods (Bordes et al., 2013;

Figure 1: The histogram of relation frequency in the real-world knowledge graph Wikidata.

Dettmers et al., 2018) have been proposed to embed entities and relations into semantic spaces to capture inner connections, and then use the learned embeddings for final predictions. Although these embedding-based methods have shown strong abilities in predicting target entities for queries, they only give answers and lack interpretability for their decisions (Lin et al., 2018). In order to make models more intuitive, Das et al. (2018) and Lin et al. (2018) propose multi-hop reasoning methods, which leverage the symbolic compositionality of relations in KGs to achieve explainable reasoning results. For example, when queried with $(Mark\ Twain, nationality, ?)$, multi-hop reasoning models can give not only the target entity *America* but also multi-hop explainable paths $(Mark\ Twain, bornIn, Florida) \wedge (Florida, locatedIn, America)$ as well.

Most previous work assumes that there are enough triples to train an effective and robust reasoning models for each relation in KGs. However, as shown in Figure 1, a large portion of KG relations are actually long-tail (Xiong et al., 2018; Han et al., 2018) and only contain few triples, which can be called few-shot relations. Some pilot experiments show that the performance of

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previous multi-hop reasoning models, e.g., MINERVA (Das et al., 2018) and MultiHop (Lin et al., 2018), on these few-shot relations will drop significantly. Note that, there are some knowledge graph embedding models (Xiong et al., 2018; Shi and Weninger, 2018; Xie et al., 2016) that can deal with zero-shot or one-shot relations, but they still have two main drawbacks: (1) they are embedding-based models and lack interpretability; (2) they focus on zero-shot or one-shot relations, which is a little far away from real-world scenes. In fact, even for people, it is hard to grasp new knowledge with almost no examples. Therefore, few-shot multi-hop reasoning is a quite important and practical problem that has not yet been fully resolved.

In this paper, we propose a meta-based algorithm for multi-hop reasoning (Meta-KGR) to address the above problems, which is explainable and effective for few-shot relations. Specifically, in Meta-KGR, we regard triple queries with the same relation r in KGs as a task. For each task, we adopt reinforcement learning (RL) to train an agent to search target entities and reasoning paths. Similar to previous meta-learning method MAML (Finn et al., 2017), we use tasks of high-frequency relations to capture meta information, which includes common features among different tasks. Then, the meta information can be rapidly adapted to the tasks of few-shot relations, by providing a good starting point to train their specific reasoning agents. In experiments, we evaluate Meta-KGR on two datasets sampled from Freebase and NELL, and the experimental results show that Meta-KGR outperforms the current state-of-the-art multi-hop reasoning methods in few-shot scenarios.

2 Problem Formulation

We formally define a KG $\mathcal{G} = \{\mathcal{E}, \mathcal{R}, \mathcal{F}\}$, where $\mathcal{E}$ and $\mathcal{R}$ denote the entity and relation sets respectively. $\mathcal{F} = \{(e_s, r, e_o)\} \subseteq \mathcal{E} \times \mathcal{R} \times \mathcal{E}$ is the triple set, where $e_s, e_o \in \mathcal{E}$ are entities and $r \in \mathcal{R}$ is a relation between them. In this paper, if the number of triples mentioning a relation r is smaller than the specific threshold K, r is considered as a few-shot relation, otherwise, it is a normal relation.

Given a query $(e_s, r_q, ?)$, where e_s is the source entity and r_q is the few-shot relation, the goal of few-shot multi-hop reasoning is to predict the right entity e_o for this query. Different from the previ-

ous knowledge graph embedding work, multi-hop reasoning also gives a reasoning path from e_s to e_o over $\mathcal{G}$ to illustrate the whole reasoning process.

3 Related Work

Knowledge Graph Embedding (Bordes et al., 2013; Yang et al., 2015; Dettmers et al., 2018) aims to embed entities and relations into low-dimensional spaces, and then uses embeddings to define a score function $f(e_s, r, e_o)$ to evaluate the probability that a triple is true. Recently, several models (Xie et al., 2016; Shi and Weninger, 2018) incorporate additional entity descriptions to learn embeddings for unseen entities, which can be seen as zero-shot scenarios. Xiong et al. (2018) predict new facts under a challenging setting where only one training triple for a given relation r is available, which can be seen as a one-shot scenario. Although these models are effective, they lack interpretability for their decisions.

Multi-Hop Reasoning over KGs aims to learn symbolic inference rules from relational paths in $\mathcal{G}$ and has been formulated as sequential decision problems in recent years. DeepPath (Xiong et al., 2017) first applies RL to search reasoning paths in KGs for a given query, which inspires much later work (e.g., MINERVA (Das et al., 2018) and DIVA (Chen et al., 2018)). Because it is hard to train an RL model, Reinforce-Walk (Shen et al., 2018) proposes to solve the reward sparsity problem using off-policy learning. MultiHop (Lin et al., 2018) further extends MINERVA with reward shaping and action dropout, achieveing the state-of-the-art performance. These reasoning methods are intuitive and explainable. However, all of them have a weak performance in few-shot scenarios. In addition to multi-hop reasoning over KGs, there are also some multi-hop QA methods in recent years. Yang et al. (2018) proposes a high quality dataset, which greatly promotes the development of this field. After that, many methods like CogQA (Ding et al., 2019) and DFGN (Xiao et al., 2019) are also proposed.

Meta-Learning tries to solve the problem of "fast adaptation on a new training task". It has been proved to be very successful on few-shot task (Lake et al., 2015; Gu et al., 2018). Previous meta-learning models mainly focus on computer vision and imitation learning domains. In this paper, we propose a new model (Meta-KGR) using the meta-learning algorithm MAML (Finn et al., 2017) for
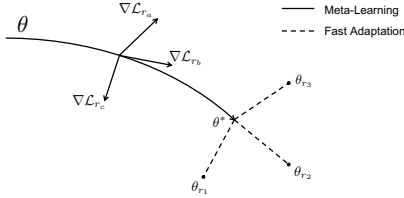
Figure 2: Meta-learning.

few-shot multi-hop reasoning. To the best of our knowledge, this work is the first research on few-shot learning for multi-hop reasoning.

4 Model

The main idea of MAML is to use a set of tasks to learn well-initialized parameters θ^* for a new task with few training examples. When applied to few-shot multi-hop reasoning, triple queries with the same relation r are considered as a task $\mathcal{T}_r$. We use triples with normal relations to find well-initialized parameters θ^* and train new models on triples with few-shot relations from the found initial parameters. As shown in Figure 2, we can easily fast adapt to new models with parameters θ_{r_1}, θ_{r_2} or θ_{r_3} for few-shot relation r_1, r_2 or r_3.

The learning framework of Meta-KGR can be divided into two parts: (1) relation-specific learning; (2) meta-learning. Relation-specific learning aims to learn a REINFORCE model with parameters θ_r for a specific relation r (task) to search target entities and reasoning paths. Meta-learning is based on relation-specific learning and is used to learn a meta-model with parameters θ^*. We will introduce these two parts in the following sections.

4.1 Relation-Specific Learning

For each query relation $r_q \in \mathcal{R}$, we learn a relation-specific multi-hop reasoning agent to search for reasoning paths and target entities over $\mathcal{G}$, which is based on the on-policy RL approach proposed by Lin et al. (2018).

4.1.1 Reinforcement Learning Formulation

The search process over $\mathcal{G}$ can be seen as a Markov Decision Process (MDP): We express $\mathcal{G}$ as a directed graph, with entities and relations as nodes and edges respectively. When given a query and its answer (e_s, r_q, e_o), we expect the agent for r_q can start from the source entity e_s and walk through several edges to reach the target entity e_o. More specifically, the MDP is defined as follows.

States The state of the t-th time step is defined as a tuple $s_t = (r_q, e_s, \hat{e}_t)$, where r_q is the

Algorithm 1 Meta-Learning for multi-hop reasoning over knowledge graphs

Require: $p(\mathcal{R})$: distribution over relations
Require: α, β: learning rate hyperparameters
1: Randomly initialize θ for meta policy network
2: **while** not stop training **do**
3:   Sample batch of relations $r \sim p(\mathcal{R})$
4:   **for all** relation r **do**
5:     Sample supporting set $\mathcal{D}_S$ and query set $\mathcal{D}_Q$ for task $\mathcal{T}_r$
6:     Evaluate $\nabla_\theta L_r^{\mathcal{D}_S}(\theta)$ in Eq. (3)
7:     Compute adapted parameters: $\theta'_r = \theta - \alpha \nabla_\theta L_r^{\mathcal{D}_S}(\theta)$
8:   **end for**
9:   Update $\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\mathcal{T}_r} L_r^{\mathcal{D}_Q}(\theta'_r)$
10: **end while**

query relation, e_s is the source entity and $\hat{e}_t$ is the current entity over $\mathcal{G}$.

Actions The action space $\mathcal{A}_t$ for a given state s_t includes all outgoing edges and next entities of $\hat{e}_t$. Formally, $\mathcal{A}_t = \{(r_{t+1}, \hat{e}_{t+1})| (\hat{e}_t, r_{t+1}, \hat{e}_{t+1}) \in \mathcal{G}\}$. We add a self-loop edge to every $\mathcal{A}_t$, which is similar to a "STOP" action.

Transition For the state s_t, if the agent selects an action $(r_{t+1}, \hat{e}_{t+1}) \in \mathcal{A}_t$, the state will be changed to $s_{t+1} = (r_q, e_s, \hat{e}_{t+1})$. The transition function is defined as $\delta(s_t, \mathcal{A}_t) = (r_q, e_s, \hat{e}_{t+1})$. In this paper, we unroll the search over $\mathcal{G}$ up to a fixed number of time steps T, and finally achieve the state $s_T = (r_q, e_s, \hat{e}_T)$.

Rewards The reward $R(s_T|r_q, e_s)$ will be 1 if the agent finally stops at the right entity, i.e., $\hat{e}_T = e_o$, otherwise it will get an embedding-based reward $f(e_s, r_q, \hat{e}_T)$, where f is a score function from knowledge graph embedding methods to measure the probability over $(e_s, r_q, \hat{e}_t)$.

4.1.2 Policy Network

To solve the above MDP problem, we need a model which has policy to choose actions at each state. Specifically, different from normal RL problems, we apply a policy network considering the search history over $\mathcal{G}$. Formally, after embedding all entities and relations in $\mathcal{G}$ as $\mathbf{e} \in \mathbb{R}^d$ and $\mathbf{r} \in \mathbb{R}^d$ respectively, each action $a_t = (r_{t+1}, \hat{e}_{t+1}) \in \mathcal{A}_t$ is represented as $\mathbf{a}_t = [\mathbf{r}_{t+1}; \hat{\mathbf{e}}_{t+1}]$. We use an LSTM to encode the search path,

$$\mathbf{h}_t = \text{LSTM}(\mathbf{h}_{t-1}, \mathbf{a}_{t-1}). \quad (1)$$

Then, we represent the action space by stacking all actions in $\mathcal{A}_t$ as $\mathbf{A}_t \in \mathbb{R}^{|\mathcal{A}_t| \times 2d}$. The parameterized policy network is defined as,

$$\pi_\theta(a_t|s_t) = \text{softmax}(\mathbf{A}_t(\mathbf{W}_2 \text{ReLU}(\mathbf{W}_1[\hat{\mathbf{e}}_t; \mathbf{h}_t; \mathbf{r}_q]))), \quad (2)$$

Model	FB15K-237			NELL-995		
	MRR	Hits@1	Hits@10	MRR	Hits@1	Hits@10
NeuralLP	10.2	7.0	14.8	17.9	4.8	**35.1**
NTP-λ	21.0	17.4	30.8	15.5	10.2	33.4
MINERVA	30.5	28.4	34.1	20.1	16.2	28.3
MultiHop(DistMult)	38.1	38.1	50.3	20.0	14.5	30.6
MultiHop(ConvE)	42.7	36.7	53.3	23.1	17.8	32.9
Meta-KGR(DistMult)	45.8	40.3	58.0	24.8	**19.7**	34.5
Meta-KGR(ConvE)	**46.9**	**41.2**	**58.8**	**25.3**	**19.7**	34.7

Table 1: Experimental results for link prediction. The MRR, Hits@1 and Hits@10 metrics are multiplied by 100.

where $\pi_\theta(a_t|s_t)$ is the probability distribution over all actions in $\mathcal{A}_t$.

4.1.3 Loss Function

Given a query relation r and a batch of triples set $\mathcal{D}$ with relation r, the overall loss for this relation-specific policy network is defined as:

$$\mathcal{L}_r^{\mathcal{D}}(\theta) = -\mathbb{E}_{(e_s,r,e_o)\in\mathcal{D}}\mathbb{E}_{a_1,...,a_{T-1}\in\pi_\theta}[R(s_T|e_s,r)]. \tag{3}$$

4.2 Meta-Learning

In meta-learning, we aim to learn well-initialized parameters θ^*, such that small changes in the parameters will produce significant improvements on the loss function of any task (Finn et al., 2017).

Formally, we consider a meta policy network with parameters θ. When adapting to a new task $\mathcal{T}_r$, the parameters of the model become θ'_r. Following MAML, the updated parameter θ'_r is computed using one or more gradient descent updates on task $\mathcal{T}_r$. For example, assuming a single gradient step is taken with the learning rate α

$$\theta'_r = \theta - \alpha\nabla_\theta L_r^{\mathcal{D}_S}(\theta), \tag{4}$$

where $\mathcal{D}_S$ is a supporting set randomly sampled from the triples belonging to $\mathcal{T}_r$. After the relation-specific parameters θ'_r is learned, we evaluate θ'_r on the query set $\mathcal{D}_Q$ belonging to $\mathcal{T}_r$, which is sampled like $\mathcal{D}_S$. The gradient computed from this evaluation can be used to update the meta policy network with parameters θ. Usually, we will go over many tasks in a batch and update θ as follows:

$$\theta = \theta - \beta\nabla_\theta \sum_{\mathcal{T}_r} L_r^{\mathcal{D}_Q}(\theta'_r), \tag{5}$$

where β is the meta-learning rate. We detail the meta-learning algorithm in Algorithm 1.

After previous meta-learning steps, Meta-KGR can fast adapt to a relation-specific policy network for every few-shot relation by using θ as well-initialized parameters θ^*.

Dataset	#Ent	#Rel	#Triples
FB15k-237 (normal)	14,448	200	268,039
FB15k-237 (few-shot)	3,078	37	4,076
NELL-995 (normal)	63,524	170	115,454
NELL-995 (few-shot)	2,951	30	2,680

Table 2: Statistics of datasets.

5 Experiments

5.1 Datasets

We use two typical datasets FB15K-237 (Toutanova et al., 2015) and NELL-995 (Xiong et al., 2017) for training and evaluation. Specifically, we set $K = 137$ and $K = 114$ to select few-shot relations from FB15K-237 and NELL-995 respectively. Besides, we rebuild NELL-995 to generate few-shot relations in valid and test set. Statistics are given separately for normal relations and few-shot relations in Table 2.

5.2 Baselines

We compare with four multi-hop reasoning models in experiments: (1) Neural Logical Programming (NerualLP) (Yang et al., 2017); (2) NTP-λ (Rocktäschel and Riedel, 2017); (3) MINERVA (Das et al., 2018) and (4) MultiHop (Lin et al., 2018). For MultiHop and our model, we use both DistMult (Yang et al., 2015) and ConvE (Dettmers et al., 2018) as the reward function to create two different model variations, which are labeled in parentheses in Table 1.

5.3 Link Prediction

Given a query $(e_s, r_q, ?)$, link prediction for QA aims to give a ranking list of candidate entities from the KG. Following previous work (Dettmers et al., 2018; Lin et al., 2018), we use two evaluation metrics in this task: (1) the mean reciprocal rank of all correct entities (MRR) and (2) the proportion of correct entities that rank no larger than N (Hits@N).

Threshold	MultiHop		Meta-KGR	
	MRR	Hits@1	MRR	Hits@1
$K = 1$	20.8	16.9	**22.3**	**19.3**
$K = 5$	25.7	20.8	**29.6**	**26.6**
$K = 10$	29.1	25.0	**31.3**	**27.2**
$K = \max$	42.7	36.7	**46.9**	**41.2**

Table 3: Experimental results for robustness analysis.

Evaluation results on two datasets are shown in Table 1. From the table, we can conclude that: (1) Our models outperform previous work in most cases, which means meta parameters learned from high-frequency relations can adapt to few-shot relations well. (2) ConvE is better than DistMult when used as the reward function in our models. This indicates that more effective knowledge graph embedding methods may provide fine-grained rewards for training multi-hop reasoning models. (3) Compared with NELL-995, FB15K-237 is denser. Our models perform well on both datasets, which demonstrates Meta-KGR can accommodate different types of KGs.

5.4 Robustness Analysis

We can use different frequency thresholds K to select few-shot relations. In this section, we will study the impact of K on the performance of our model. In our experiments, some triples will be removed until every few-shot relation has only K triples. We do link prediction experiments on FB15K-237 and use ConvE as our reward function. The final results are shown in Table 3. $K = \max$ means we use the whole datasets in Table 2 and do not remove any triples. From Table 3 we can see our model is robust to K and outperforms MultiHop in every case.

6 Conclusion

In this paper, we propose a meta-learning based model named Meta-KGR for multi-hop reasoning over few-shot relations of knowledge graphs. Meta-KGR uses training triples with high-frequency relations to find well-initialized parameters and fast adapt to few-shot relations. The meta information learned from high-frequency relations is helpful for few-shot relations. In experiments, our models achieve good performance on few-shot relations and outperform previous work in most cases. Some empirical analysis also demonstrates that our models are robust and generalized to different types of knowledge graphs.

References

Antoine Bordes, Nicolas Usunier, Alberto Garcia-Duran, Jason Weston, and Oksana Yakhnenko. 2013. Translating embeddings for modeling multi-relational data. In *NIPS*.

Wenhu Chen, Wenhan Xiong, Xifeng Yan, and William Yang Wang. 2018. Variational knowledge graph reasoning. In *NAACL*.

Rajarshi Das, Shehzaad Dhuliawala, Manzil Zaheer, Luke Vilnis, Ishan Durugkar, Akshay Krishna-murthy, Alex Smola, and Andrew McCallum. 2018. Go for a walk and arrive at the answer: Reasoning over paths in knowledge bases using reinforcement learning. In *ICLR*.

Tim Dettmers, Pasquale Minervini, Pontus Stenetorp, and Sebastian Riedel. 2018. Convolutional 2d knowledge graph embeddings. In *AAAI*.

Ming Ding, Chang Zhou, Qibin Chen, Hongxia Yang, and Jie Tang. 2019. Cognitive graph for multi-hop reading comprehension at scale. In *ACL*.

Chelsea Finn, Pieter Abbeel, and Sergey Levine. 2017. Model-agnostic meta-learning for fast adaptation of deep networks. In *ICML*.

Jiatao Gu, Yong Wang, Yun Chen, Victor OK Li, and Kyunghyun Cho. 2018. Meta-learning for low-resource neural machine translation. In *EMNLP*.

Xu Han, Hao Zhu, Pengfei Yu, Ziyun Wang, Yuan Yao, Zhiyuan Liu, and Maosong Sun. 2018. Fewrel: A large-scale supervised few-shot relation classification dataset with state-of-the-art evaluation. In *EMNLP*.

Brenden M Lake, Ruslan Salakhutdinov, and Joshua B Tenenbaum. 2015. Human-level concept learning through probabilistic program induction. *Science*, 350(6266):1332–1338.

Xi Victoria Lin, Richard Socher, and Caiming Xiong. 2018. Multi-hop knowledge graph reasoning with reward shaping. In *EMNLP*.

Tim Rocktäschel and Sebastian Riedel. 2017. End-to-end differentiable proving. In *NIPS*.

Yelong Shen, Jianshu Chen, Po-Sen Huang, Yuqing Guo, and Jianfeng Gao. 2018. Reinforcewalk: Learning to walk in graph with monte carlo tree search. In *ICLR*.

Baoxu Shi and Tim Weninger. 2018. Open-world knowledge graph completion. In *AAAI*.

Kristina Toutanova, Danqi Chen, Patrick Pantel, Hoifung Poon, Pallavi Choudhury, and Michael Gamon. 2015. Representing text for joint embedding of text and knowledge bases. In *EMNLP*.

Yunxuan Xiao, Yanru Qu, Lin Qiu, Hao Zhou, Lei Li, Weinan Zhang, and Yong Yu. 2019. Dynamically fused graph network for multi-hop reasoning. In *ACL*.

Ruobing Xie, Zhiyuan Liu, Jia Jia, Huanbo Luan, and Maosong Sun. 2016. Representation learning of knowledge graphs with entity descriptions. In *AAAI*.

Wenhan Xiong, Thien Hoang, and William Yang Wang. 2017. Deeppath: A reinforcement learning method for knowledge graph reasoning. In *EMNLP*.

Wenhan Xiong, Mo Yu, Shiyu Chang, Xiaoxiao Guo, and William Yang Wang. 2018. One-shot relational learning for knowledge graphs. In *EMNLP*.

Bishan Yang, Wen-tau Yih, Xiaodong He, Jianfeng Gao, and Li Deng. 2015. Embedding entities and relations for learning and inference in knowledge bases. In *ICLR*.

Fan Yang, Zhilin Yang, and William W Cohen. 2017. Differentiable learning of logical rules for knowledge base reasoning. In *NIPS*.

Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William Cohen, Ruslan Salakhutdinov, and Christopher D Manning. 2018. Hotpotqa: A dataset for diverse, explainable multi-hop question answering. In *EMNLP*.