Standing on the Shoulders of Predecessors: Meta-Knowledge Transfer for Knowledge Graphs

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Abstract

Knowledge graphs (KGs) have become widespread, and various knowledge graphs are constructed incessantly to support many in-KG and out-of-KG applications. During the construction of KGs, although new KGs may contain new entities with respect to constructed KGs, some entity-independent knowledge can be transferred from constructed KGs to new KGs. We call such knowledge meta-knowledge, and refer to the problem of transferring meta-knowledge from constructed (source) KGs to new (target) KGs to improve the performance of tasks on target KGs as meta-knowledge transfer for knowledge graphs. However, there is no available general framework that can tackle meta-knowledge transfer for both in-KG and out-of-KG tasks uniformly. Therefore, in this paper, we propose a framework, MorsE, which means conducting Meta-Learning for Meta-Knowledge Transfer via Knowledge Graph Embedding. MorsE represents the meta-knowledge via Knowledge Graph Embedding and learns the meta-knowledge by Meta-Learning. Specifically, MorsE uses an entity initializer and a Graph Neural Network (GNN) modulator to entity-independently obtain entity embeddings given a KG and is trained following the meta-learning setting to gain the ability of effectively obtaining embeddings. Experimental results on meta-knowledge transfer for both in-KG and out-of-KG tasks show that MorsE is able to learn and transfer meta-knowledge between KGs effectively, and outperforms existing state-of-the-art models.

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1 Introduction

Knowledge graphs (KGs) which consist of a large number of facts formed as triples, \((h, r, t)\) for short, have benefited a lot of downstream tasks. Nowadays many large-scale knowledge graphs, including Freebase \cite{BollackerEtAl2008}, NELL \cite{CarlsonEtAl2010}, Wikidata \cite{Vrande\v{c}i\c{c}EtAl2014} and so on, have been proposed and supported many in-KG applications, e.g., link prediction \cite{BordesEtAl2013} and triple classification \cite{WangEtAl2014}, as well as out-of-KG applications, e.g., question answering \cite{YasunagaEtAl2021} and recommender systems \cite{ZhangEtAl2016,ZhangEtAl2021}.

The construction of KGs is ongoing every day, in other words, new KGs are emerging at any given moment. For example, knowledge graph service providers (e.g., Palantir Technologies and Kensho Technologies) may help some enterprises or individuals to construct their KGs for conducting in-KG and out-of-KG applications. Naturally, for new KGs, standing on the shoulders of their predecessors, namely constructed KGs, via transferring shared knowledge between them, will help improve the performance of tasks related to new KGs. For example (Figure 1), there is a constructed KG about the social environment of Eric \(G_{Eric}\) and a new KG about Lisa \(G_{Lisa}\). To conduct prediction in \(G_{Lisa}\) about \((\text{Dave, works_for, Univ.B})\), the triangle pattern in \(G_{Eric}\) could help, which shows entities (i.e., Jim and Univ.A) linked by \textit{advisor_of} and \textit{student_of} can also be linked by \textit{works_for}. In this paper, we collectively call such transferable entity-independent knowledge \textit{meta-knowledge}, and we propose an open problem that how to transfer meta-knowledge from constructed KGs to new KGs for improving the ability (i.e., convergence rate and performance) of conducting in-KG and out-of-KG tasks for the new KGs. For the concision of concepts, we refer to constructed KGs as source KGs and new KGs as target KGs.
Some previous studies can handle meta-knowledge transfer by learning entity-independent logical rules via discrete search (Galarraga et al. 2013; Meilicke et al. 2018) or in an end-to-end differentiable manner (Yang, Yang, and Cohen 2017), or learning entity-independent relational semantics by reasoning over subgraph structures independent of any particular entities (Teru, Denis, and Hamilton 2020). Nevertheless, these methods have a major drawback that they are specifically designed for one task such as inductive relation prediction (Teru, Denis, and Hamilton 2020), and are not general frameworks for meta-knowledge transfer. Thus in this paper, we aim at proposing such a framework for meta-knowledge transfer to help improve the performance of both in-KG and out-of-KG tasks on target KGs generally.

In our opinion, there are two challenges for proposing this framework, how to represent meta-knowledge and how to learn such meta-knowledge. In this paper, we propose a framework solving the challenge for meta-knowledge representation via Knowledge Graph Embedding (KGE) and the challenge for meta-knowledge learning by Meta-Learning, and we name it **MorsE**, which means conducting Meta-Learning for Meta-Knowledge Transfer via Knowledge Graph Embedding.

To handle the challenge of meta-knowledge representation, we adapt KGE, which embeds entities and relations of a KG into continuous vector spaces (i.e., embeddings), to MorsE. The design of MorsE follows the opinion that entity embeddings should be dynamically constructed from entity-independent information, instead of learning entity embeddings for a fixed set of entities, as do most conventional KGE methods. Thus in MorsE, entity embeddings are obtained via an entity initializer and a Graph Neural Network (GNN) modulator. The entity initializer initializes entity embeddings via entity-independent embeddings, including relation-domain embeddings and relation-range embeddings. The GNN modulator helps dynamically enhance entity embeddings based on entities’ neighbor structure. Overall, MorsE embeds meta-knowledge such as implicit entity types, rules and triangle patterns into parameters of above two modules, which are totally entity-independent.

To handle the challenge of meta-knowledge learning, MorsE enforces the entity initializer and the GNN modulator to obtain effective entity embeddings for arbitrary given KGs, which is also referred to as learning to learn entity embeddings. Thus the training of MorsE follows the paradigm of meta-learning where each training point is a task sampled from source KGs. For each task which has a support (i.e., training) and a query (i.e., testing) set, entity embeddings are obtained by the entity initializer and the GNN modulator based on its support set, and the loss is calculated on its query set using relation embeddings and obtained entity embeddings. Such meta-learning process helps MorsE gain the ability of obtaining reasonable and effective embeddings for a given KG based on entity-independent information.

We evaluate MorsE by meta-knowledge transfer for in-KG task link prediction and meta-knowledge transfer for out-of-KG task question answering. The results show that our model outperforms other baselines and can do meta-knowledge transfer for knowledge graphs effectively. The main contributions are summarized as follows:

- We propose a new task meta-knowledge transfer for KGs which cannot be solved uniformly by existing works.
- We propose a general framework MorsE for meta-knowledge transfer for KGs, which adapts knowledge graph embedding for meta-knowledge representation and applies meta-learning for meta-knowledge learning.
- We do extensive experiments demonstrating the effectiveness of our framework and ablation studies showing the necessity of different parts.

## 2 Related Work

### 2.1 From the Task’s Point of View

We devote to solving meta-knowledge transfer for both in-KG and out-of-KG tasks.

*As for meta-knowledge transfer for in-KG tasks (e.g., link prediction, relation prediction), GraIL-based methods, including GraIL (Teru, Denis, and Hamilton 2020), ComPyLE (Mai et al. 2021) and TACT (Chen et al. 2021), learn the ability of relation prediction by subgraph extraction and GNNs unrelated to any specific entities and such ability can generalize to unseen entities in complete new KGs. Rule-learning-based methods include AMIE (Galarraga et al. 2013) and RuleN (Meilicke et al. 2018) which learn logical rules explicitly, and Neural LP (Yang, Yang, and Cohen 2017) and DRUM (Sadeghian et al. 2019) which extract rules in an end-to-end differentiable manner. Since rules are independent of specific entities, rule-learning-based methods can handle link prediction among emerging entities. Furthermore, inductive embedding methods, including LAN (Wang et al. 2019b) and GEN (Baek, Lee, and Hwang 2020), learn embeddings by aggregating neighbor structure information of emerging entities, which can only tackle emerging entities linking to known KGs but not meta-knowledge transfer between two KGs.*

*As for meta-knowledge transfer for out-of-KG tasks (e.g., question answering and recommender systems), since text information is inherently inductive, most methods incorporate external text descriptions for entities (Feng et al. [2020] Yasunaga et al. [2021]). That is, using pre-trained language models to transform textual entity descriptions into entity vector representations. However, such methods cannot leverage structure information to enhance the KGs related specific out-of-KG tasks.*
(Finn, Abbeel, and Levine 2017) [Yao et al. 2020]; (3) metric-based methods, aka non-parametric methods, learn matching metrics generalized among all tasks for classification [Koch, Zemel, and Salakhutdinov 2015; Snell, Swersky, and Zemel 2017] [Vinyals et al. 2016]. Some recent works consider tackling problems related to knowledge graphs with meta-learning. For few-shot link prediction in KGs, which requires predicting triples with only observing a few samples for a specific relation, GMMatching [Xiong et al. 2018] and subsequent metric-based methods [Zhang et al. 2020] [Sheng et al. 2020] learn matching metrics by graph-structures and learned embeddings; MetaR [Chen et al. 2019] and GANA [Niu et al. 2021] leverage optimization-based methods for fast adaption of relation embeddings. Furthermore, GEN (Baek, Lee, and Hwang 2020) tackles few-shot out-of-graph link prediction problem by a meta-learning framework which meta-learns embeddings for unseen entities. Above works mainly focus on applying meta-learning on few-shot scenarios, while recently L2P-GNN [Lu et al. 2021] is proposed for pre-training GNN, which has the similar idea to ours that using meta-learning to pre-training a GNN and adapting it to new graphs.

Knowledge graph embedding (KGE) methods learn embeddings for entities and relations while preserving the inherent semantics of KGs [Wang et al. 2017]. Such embeddings can alleviate the drawbacks of representing a KG as structured triples and can be easily deployed to many in-KG tasks, including link prediction [Bordes et al. 2013; Zhang et al. 2020] and triple classification, and out-of-KG tasks including question answering [Hao et al. 2017] and recommender systems [Zhang et al. 2016]. A majority of works on KGE focus on designing expressive score functions to model the triples in a KG, based on some specific assumption of relation patterns, e.g., translation-based assumption [Bordes et al. 2013; Wang et al. 2014; Lin et al. 2015; Sun et al. 2019; Zhang et al. 2019b] and linear map assumption [Nickel, Tresp, and Kriegel 2011] [Yang et al. 2015] [Trouillon et al. 2016].

GNN for knowledge graphs, such as R-GCN [Schlichtkrull et al. 2018], CompGCN [Vashishth et al. 2020], adapt GNNs from simple undirected graph to multi-relational knowledge graphs. GNNs can be viewed as encoder models for entities in the relational graph, and such encoder models are applied to many KG tasks which need to aggregate neighbor information [Xiong et al. 2018] [Wang et al. 2019b] [Teru, Denis, and Hamilton 2020].

3 Method

A knowledge graph is defined as \( \mathcal{G} = (\mathcal{E}, \mathcal{R}, \mathcal{P}) \), where \( \mathcal{E} \) and \( \mathcal{R} \) are the entity and relation set, and \( \mathcal{P} = \{(h, r, t)\} \subseteq \mathcal{E} \times \mathcal{R} \times \mathcal{E} \) is the set of triples. Given a set of source KGs \( \mathcal{G}_s = \{G^i_s\} = \{(\mathcal{E}^i_s, \mathcal{R}^i_s, \mathcal{P}^i_s)\}_{i=1}^{n_s} \) and a set of target KGs \( \mathcal{G}_t = \{G^i_t\} = \{(\mathcal{E}^i_t, \mathcal{R}^i_t, \mathcal{P}^i_t)\}_{i=1}^{n_t} \) with relation sets that \( \bigcup_{i=1}^{n_s} \mathcal{R}^i_s \subseteq \bigcup_{i=1}^{n_t} \mathcal{R}^i_t \), the goal of meta-knowledge transfer for knowledge graphs is utilizing the meta-knowledge implied in \( \mathcal{G}_s \) to improve the performance of downstream, including in-KG and out-of-KG, tasks related to \( \mathcal{G}_t \). For the simplicity of notations, we will consider the scenario of one source KG and one target KG for describing our proposed framework, which means \( n_s = n_t = 1 \), \( \mathcal{G}_s = (\mathcal{E}_s, \mathcal{R}_s, \mathcal{P}_s) \) and \( \mathcal{G}_t = (\mathcal{E}_t, \mathcal{R}_t, \mathcal{P}_t) \).

To solve the meta-knowledge transfer problem, our MorsE needs to solve the following three sub-problems:

**P1** How to represent the meta-knowledge in MorsE, namely how to model such entity-independent knowledge?

**P2** How to learn the meta-knowledge in the source KG \( \mathcal{G}_s \)?

**P3** How to adapt the meta-knowledge to the target KG \( \mathcal{G}_t \) to achieve meta-knowledge transfer?

3.1 Representation of Meta-Knowledge

In this part we solve the sub-problem, **P1**: how to represent the meta-knowledge in MorsE. As for the transfer from the source KG \( \mathcal{G}_s \) to the target KG \( \mathcal{G}_t \), it’s natural that the information about relations is the most straightforward knowledge that can be transferred, since relations in the target KG are seen in the source KG. Thus, we design an **Entity Initializer** to initialize the embedding of each entity using the information of relations connected to it. However, such initialized entity embeddings are naive, as they can only convey type-level information but not instance-level information. For example, if two entities are both the head of relation \( \text{student} \), we can only infer that they are two persons but not exactly who they are. To solve this problem, we introduce a **GNN Modulator** to modulate the initialized embedding for each entity based on its neighborhood structure, since different local structure for entities can indicate who they are. In the following, we describe the process of the entity initializer and the GNN modulator given a KG \( \mathcal{G} = (\mathcal{E}, \mathcal{R}, \mathcal{P}) \).

**Entity Initializer** This module is designed for capturing the type-level information of entities. Thus, besides conventional relation embeddings \( \mathbf{R} \in \mathbb{R}^{n_r \times d} \), we design relation-domain embeddings \( \mathbf{R}^{\text{dom}} \in \mathbb{R}^{n_r \times d} \) and relation-range embeddings \( \mathbf{R}^{\text{ran}} \in \mathbb{R}^{n_r \times d} \) to represent the implicit type features of head and tail entities for each relation, where \( n_r \) is the number of relations and \( d \) is the dimension for embeddings. Specifically, \( \mathbf{R} \) reserves the internal information of relations and is used for the training of MorsE in Section 3.2 while \( \mathbf{R}^{\text{dom}} \) and \( \mathbf{R}^{\text{ran}} \) are used for entity initialization. For a specific relation \( r \), its relation embedding, relation-domain embedding and relation-range embedding are represented as \( \mathbf{R}_r, \mathbf{R}^{\text{dom}}_r \) and \( \mathbf{R}^{\text{ran}}_r \) respectively, as shown in Figure 2(a).

For the KG \( \mathcal{G} = (\mathcal{E}, \mathcal{R}, \mathcal{P}) \), MorsE initializes the entity embeddings based on their connected relations. Specifically, for an entity \( e \in \mathcal{E} \), its initialized embedding \( \mathbf{H}_e \) is calculated by the average of the relation-domain and relation-range embeddings of its connected relations,

\[
\mathbf{H}_e = \sum_{r \in \mathcal{O}(e)} \mathbf{R}^{\text{dom}}_r + \sum_{r \in \mathcal{I}(e)} \mathbf{R}^{\text{ran}}_r, \tag{1}
\]

where \( \mathcal{O}(e) = \{r \mid \exists x, (x, r, e) \in \mathcal{P}\} \) denotes the ingoing relation set for entity \( e \), \( \mathcal{I}(e) = \{r \mid \exists x, (e, r, x) \in \mathcal{P}\} \) denotes the outgoing relation set for entity \( e \). A visual illustration of using \( \mathbf{R}^{\text{dom}}_r \) and \( \mathbf{R}^{\text{ran}}_r \) for entity initialization is shown in Figure 2(b).
GNN Modulator This module is designed for capturing the instance-level information of entities via structure information from their neighborhoods. So far, several previous works have shown that the graph neural network has the capability of capturing the local structure information of knowledge graphs (Schlichtkrull et al., 2018, Teru, Denis, and Hamilton, 2020). Thus, the modulation of initialized entity embeddings is archived by a GNN modulator. Following the multi-relational R-GCN (Schlichtkrull et al., 2018), our GNN modulator calculates the forward-pass update in the $l$-th layer for an entity $e$ as follows,

$$h_e^l = \alpha \left( \frac{1}{|\mathcal{N}(e)|} \sum_{(h, r, t) \in \mathcal{N}(e)} W^r_e h_{h}^{l-1} + W^0_e h_{e}^{l-1} \right),$$

where $\alpha$ is an activation function and we use ReLU here; $\mathcal{N}(e) = \{(h, r) \mid (h, r, e) \in P\}$ denotes the set of immediate ingoing neighbor relations and corresponding head entities of the entity $e$; $W^r_e$ is the relation-specific transformation matrix for relation $r$ in the $l$-th layer; $W^0_e$ is a self-loop transformation matrix for each entity in the $l$-th layer; $h_0^e$ denotes the hidden entity representation of entity $e$, and the input representation $h_0^e = H_e$.

To make full use of hidden entity representations of every layers, and let the model leverage the most appropriate neighborhood range flexibly for each entity, we also apply a jumping knowledge (JK) structure (Xu et al., 2018) based on the concatenation of hidden representations, as follows,

$$E_e = \bigoplus_{l=0}^{L} W^\text{JK} h_e^l,$$

where $E_e$ is the final entity embedding for the entity $e$; $\bigoplus$ denotes successive concatenation; $L$ is the number of GNN modulator layers; $W^\text{JK}$ is a matrix to transform concatenate hidden representations to output entity embeddings.

Summary Given a KG $\mathcal{G} = (\mathcal{E}, \mathcal{R}, \mathcal{P})$, the process of entity initializer is,

$$H = \text{INIT}_\theta(\mathcal{P}),$$

where $H$ is the initialized entity embeddings of $\mathcal{E}$, and $\theta$ is the parameter set including $R^\text{dom}$ and $R^\text{ran}$. Next, the process of the GNN modulator can be viewed as,

$$E = \text{MODULATE}_\phi(\mathcal{P}, H),$$

where $E$ is the entity embeddings of $\mathcal{E}$, and $\phi$ is the parameter set of the GNN modulator. The whole procedure can be viewed as,

$$E = \text{REP}_\theta,\phi(\mathcal{P}) = \text{MODULATE}_\phi(\mathcal{P}, \text{INIT}_\theta(\mathcal{P})), \quad (5)$$

### 3.2 Learning of Meta-Knowledge

In this part we solve the sub-problem, P2: how to learn the meta-knowledge in the source KG $\mathcal{G}_S$. Our framework handles the challenge of learning meta-knowledge based on meta-learning, namely “learning to learn”. In this part, we first illustrate the concept of meta-learning and the corresponding setting in MorsE. Then, we describe the training regime based on meta-learning.

Meta-Learning Setting Current meta-learning models are trained on a set of tasks which simulate the “training and evaluation” process to achieve learning to learn. In other words, meta-learning models treat entire tasks as training examples (Finn, Abbeel, and Levine, 2017). Following previous standard meta-learning settings, the training tasks in MorsE are constructed to do “obtaining and evaluating entity embeddings”. Specifically, to learn the meta-knowledge from $\mathcal{G}_S$, we sample sub-KGs $\{\mathcal{G}_{Si} = (\mathcal{E}_{Si}, \mathcal{R}_{Si}, \mathcal{P}_{Si})\}_{i=1}^{m}$ from $\mathcal{G}_S$ to form tasks $\{T_{Si}\}_{i=1}^{m}$, where each task consists of a support and a query set, i.e., $T_{Si} = (\mathcal{S}_i, \mathcal{Q}_i)$. For each task, the query set is formed by triples sampled from the sub-KG $\mathcal{G}_{Si}$, and the remaining triples constitute the support set, as follows,

$$T_{Si} = (\mathcal{S}_i = \{(h,r,t) \sim \mathcal{P}_{Si}\}, \mathcal{Q}_i = \{(s,p,o) \sim \mathcal{P}_{Si}\})$$

s.t. $\mathcal{S}_i \cap \mathcal{Q}_i = \emptyset$, $\{p\} \subseteq \{r\}$, $\{\{s\} \cup \{o\}\} \subseteq \{(h) \cup \{t\}\}$.

$$\mathcal{L}$$

Figure 2: The illustration of embeddings for a relation $r$, an entity initialization example, and the meta-training process.
where the support set and query set are mutually exclusive, as well as entities and relations in the query set are present in the support set. This setting is reasonable since we want to enforce our framework to gain the ability of obtaining effective entity embeddings for arbitrary KGs instead of learning embeddings for a fixed set of entities.

**Meta-Training Regime** Following the meta-learning setting, meta-knowledge are learned based on the tasks sampled from \( \mathcal{G}_S \), which is also referred to as the meta-training process. During meta-training, the entity embeddings are obtained based on the support set and evaluated by the query set. Formally, the overall meta-training objective is,

\[
\min_{\theta} \sum_{i=1}^{m} \mathcal{L}(Q_i, \text{REP}_{\theta,\phi}(S_i), \mathbf{R}),
\]

where \( \mathbf{R} \) is the relation embeddings, and \( \{\phi, \theta, \mathbf{R}\} \) are learnable parameters. The visual illustration of meta-training process is in Figure 2(c).

We describe the details of the loss function by a specific task \( \mathcal{T} = (S, Q) \), and use \( \mathcal{L} \) as the simplified notion of the loss function in Equation (8). We first describe the score function for scoring the plausibility of a triple \((h, r, t)\),

\[
s(h, r, t) = \gamma - \| \mathbf{E}_h + \mathbf{R}_r - \mathbf{E}_t \|,
\]

where \( \mathbf{E} = \text{REP}_{\theta,\phi}(S) \); \( \gamma \) is a fixed margin; \( \| \cdot \| \) denotes the L2 norm. This score function follows the simple and effective assumption of TransE (Bordes et al., 2013) that the head entity embedding \( \mathbf{E}_h \), relation embedding \( \mathbf{R}_r \) and tail entity embedding \( \mathbf{E}_t \) of a true triple \((h, r, t)\) satisfy \( \mathbf{E}_h + \mathbf{R}_r = \mathbf{E}_t \). This score function can be easily substituted by other KGE score functions.

Moreover, we use the loss function based on self-adversarial negative sampling (Sun et al., 2019),

\[
\mathcal{L} = - \sum_{(h, r, t) \in Q} \log \sigma(s(h, r, t))
\]

\[
- \sum_{i=1}^{k} \log \sigma(-s(h'_i, r, t'_i))
\]

where \( \sigma \) is the sigmoid function; \( k \) is the number of negative samples for each triple; \( (h'_i, r, t'_i) \) is the \( i \)-th negative triple by corrupting head or tail entity; \( p(h'_i, r, t'_i) \) is the self-adversarial weight calculated by,

\[
p(h'_i, r, t'_i) = \frac{\exp \beta s(h'_i, r, t'_i)}{\sum_{j=1}^{k} \exp \beta s(h'_i, r, t'_i)},
\]

where \( \beta \) is the temperature of sampling.

### 3.3 Adapting of Meta-Knowledge

In this part we tackle the sub-problem, P3: how to adapt the meta-knowledge to the target KG \( \mathcal{G}_T \). Adapting to a given target KG \( \mathcal{G}_T = (\mathcal{E}_T, \mathcal{R}_T, \mathcal{P}_T) \) is a reflection of meta-knowledge transfer, and this step is straightforward as the ability of outputting entity embeddings from \( \text{REP}_{\theta,\phi}(\mathcal{P}_T) \) allows MorsE to adapt to various in-KG and out-of-KG tasks flexibly. MorsE offers two adapting regimes as follows.

**Self Adapting** This adapting focuses on downstream tasks relying only on the \( \mathbf{E} \) output from \( \text{REP}_{\theta,\phi}(\mathcal{P}_T) \) and \( \mathbf{R} \), but not other entity and relation representations. Naturally, we can use \( \mathbf{E} \) and \( \mathbf{R} \) directly. We can also adapt meta-knowledge by fine-tuning the \( \mathbf{H} \) output from \( \text{INIT}_{\theta}(\mathcal{P}_T) \), as well as the \( \phi \) and \( \mathbf{R} \) with respect to the specific task. Furthermore, we can add a task-specific model (e.g., classifier) after \( \text{REP}_{\theta,\phi}(\mathcal{P}_T) \) and \( \mathbf{R} \) and fine-tune them together. This kind of adapting is appropriate for most in-KG tasks including link prediction and triple classification, and those having only one target KG.

**Fusion Adapting** This adapting focuses on downstream tasks relying not only on the \( \mathbf{E} \) output of \( \text{REP}_{\theta,\phi}(\mathcal{P}_T) \) and \( \mathbf{R} \), but also other original embeddings (e.g., \( \mathbf{E}^{ori} \)) in some existing models \( \mathcal{M}^{ori} \) and we need to fuse such embeddings with embeddings output from our MorsE. Such fusion can be easily conducted by,

\[
\mathbf{E}^{ori} := \mathbf{W}^{f} [\mathbf{E}; \mathbf{E}^{ori}],
\]

where \([\cdot; \cdot]\) denotes concatenation of entity embeddings and \( \mathbf{W}^{f} \) means the transformation matrix. During adapting, we can train \( \mathbf{W}^{f} \) with \( \mathcal{M}^{ori} \) together, and \( \{\phi, \theta, \mathbf{R}\} \) can be frozen or fine-tuned according to the actual situation. This kind of adapting is appropriate for most out-of-KG tasks where each training or testing example has one specific target KG, including question answering and recommender systems.

### 4 Experiments

In this section, we conduct extensive experiments to show the effectiveness of our method, and the key questions that we want to explore are as follows:

**Q1** How does the performance of MorsE compare to baselines in conducting meta-knowledge transfer for link prediction?

**Q2** How does the performance of MorsE compare to baselines in conducting meta-knowledge transfer for question answering?

**Q3** How necessary are the transfer as well as modules for representing meta-knowledge and the meta-learning setting for MorsE? What is the influence of relation overlap ratio and target KG sparsity on MorsE?

#### 4.1 Training Setup

In this part, we describe the overall training settings, including the strategy of sampling tasks from a source KG for meta-learning, and implementation details of training MorsE.

**Task Sampling** As described in Section 3.2 the tasks for meta-training are sampled from a source KG \( \mathcal{G}_s = (\mathcal{E}_s, \mathcal{R}_s, \mathcal{P}_s) \), thus we depict the procedure of sampling one task \( \mathcal{T} \) in the following.

1. **Random Walk Sampling.** First, we sample an entity \( e \in \mathcal{E}_s \), from which we conduct \( n_{rw} \) times random walk with length \( l_{rw} \), resulting in a set of entities \( \mathcal{E}_{rw} \). Second, we sample an entity \( e' \in \mathcal{E}_{rw} \), and repeat the first
We use datasets derived from original WN18RR (Dettmers et al. 2018), FB15k-237 (Toutanova et al. 2015) and NELL-995 (Xiong, Hoang, and Wang 2017) by Teru, Denis, and Hamilton (2020), which are created for fully-inductive relation prediction.
Baselines We compare our MorsE with two kinds of methods that can conduct meta-knowledge transfer for link prediction in KGs, rule-learning-based and GraIL-based methods. Rule-learning-based methods consist of RuleN (Melić et al. 2018), which explicitly extracts rules from KGs, and Neural-LP (Yang, Yang, and Cohen 2017) and DRUM (Sadeghian et al. 2019), which learn rules in an end-to-end differentiable manner. GraIL-based methods consist of GraIL (Teru, Denis, and Hamilton 2020), which learns a GNN to do relation prediction inductively and can handle unseen entities, and its improvement method, CoPILE (Mai et al. 2021).

Adaptation Details As described in Section 5.3, we adapt MorsE to the link prediction task by self-adapting, namely, after meta-training MorsE on the source KG, we fine-tune the initialized entity embeddings from the entity initializer, as well as relation embeddings and the GNN modulator on the corresponding target KG.

To be specific, meta-trained MorsE consists of an entity initializer \( \text{INIT}_{\theta}(\cdot) \) where \( \theta \) is the parameter set including \( \mathbf{R}^{\text{dom}} \) and \( \mathbf{R}^{\text{ran}} \), a GNN modulator \( \text{MODULATE}_{\phi}(\cdot) \) with the parameter \( \phi \), and a relation embedding matrix \( \mathbf{R} \).

When adapting MorsE to the training part (e.g., \( G_{\text{train}} \)) of a target KG, we first get the initialized entity embedding \( \mathbf{H} \) by,
\[
\mathbf{H} = \text{INIT}_{\theta}(G_{\text{train}}).
\]

Then we use the GNN modulator to obtain the entity embedding \( \mathbf{E} \),
\[
\mathbf{E} = \text{MODULATE}_{\phi}(G_{\text{train}}, \mathbf{H}).
\]

Finally, we use the entity embedding \( \mathbf{E} \) and the relation embedding \( \mathbf{R} \) to calculate the loss based on the same loss function as Equation (10) for fine-tuning. The hyper-parameters for fine-tuning are listed in Appendix B. We make the set of parameters \( \{ \mathbf{H}, \phi, \mathbf{R} \} \) as learnable parameters and fine-tune them. After fine-tuning, we test the performance of link prediction on the test triples of the target KG, using \( \mathbf{E} = \text{MODULATE}_{\phi}(G_{\text{train}}, \mathbf{H}) \) and \( \mathbf{R} \).

Result Analysis In Table 1, we show the results of adapting MorsE to the target KG immediately without fine-tuning (i.e., 0 epoch) and with fine-tuning in only few epochs (i.e., 1, 5, 10 epochs). Since MorsE is already meta-trained on the source KG and we are concerned with the ability of meta-knowledge transfer, we focus on the performance of fast adaptation (i.e., up to 10 fine-tuning epochs) rather than training to convergence on the target KG, which is more challenging while practical.

From these results, we have following observations. First, without fine-tuning, MorsE can get comparable performance with baselines and achieve 3.48% average relative improvement on all datasets. Second, after fine-tuning few epochs, MorsE achieves the best performance across most datasets, and obtains significant improvement compared to the baselines. In comparison with the best results of each dataset, the results of MorsE increase, on average, by 13.06%, 16.56% and 6.57% relatively for datasets derived from WN18RR, FB15k-237 and NELL-995 respectively. We show the time per fine-tuning epoch in the last line of Table 1 indicating that MorsE can obtain significant improvement in minimal time during meta-knowledge adapting. Finally, we also find that performance on FB15k-237 is better than that on WN18RR and NELL-995, and MorsE can get outstanding performance without fine-tuning on FB15k-237. This observation is reasonable, since there are more relations in FB15k-237 than others, and more meta-knowledge can be transferred. In summary, above observations answer Q1, and illustrate the effectiveness of MorsE on meta-knowledge transfer for link prediction.

4.3 Out-of-KG Task: Question Answering

For the task of meta-knowledge transfer for question answering, MorsE is meta-trained on a source KG, and adapted to the training QA tasks by training the SOTA QA model with MorsE, where each QA task includes a question, answer choices and a QA-related KG. Finally, the performance is evaluated on the testing QA tasks with trained (i.e., after being adapted) SOTA QA model with model.

Datasets and Evaluation Metrics We use the dataset CommonsenseQA (Talmor et al. 2019), having 12,102 5-way multiple choice QA pairs which require reasoning with commonsense knowledge to accomplish. For each QA pair, its corresponding commonsense is a KG retrieved from ConceptNet (Speer, Chin, and Havasi 2017), which is a general-domain knowledge graph, and we follow the pre-processing step in the previous work (Yasunaga et al. 2021). To evaluate the performance of meta-knowledge transfer on this task, we remove the entities appearing in KGs of QA pairs from ConceptNet, and then make the remaining part as the source KG and KGs of QA pairs as the target KGs. There are 17 relations, 650,763 entities and 1,148,711 triples in the source KG. Following previous works, we conduct the experiments on the in-house data split used in Lin et al. (2019), and report the accuracy (Acc.) of development set (IHdev) and test set (IHtest).

Baselines Since we transfer meta-knowledge for this task by fusing the output entity embeddings from MorsE into initial node embeddings of each QA-related KG, based on the model QA-GNN (Yasunaga et al. 2021). We compare our model to QA-GNN and its baseline models, including RoBERTa-large (Liu et al. 2019), and RoBERTa-large adding RN (Santoro et al. 2017), RGCN (Schlichtkrull et al. 2018), GeonAttn (Wang et al. 2019c), KagNet (Lin et al. 2019) and MHGRN (Feng et al. 2020).

Adaptation Details According to Section 5.3, we adapt MorsE to the question answering task by fusion adapting. We use meta-trained MorsE to obtain entity embeddings for the KG related to each QA pair, and fuse such entity embeddings to QA-GNN (Yasunaga et al. 2021), which is a SOTA model for reasoning with language models and knowledge graphs for question answering.

In general, given a QA pair \((q, a)\) and a KG \(G\) related to this QA pair, the goal of QA-GNN is to calculate the probability of \(p(a|q)\) based on the QA context and \(G\). In QA-GNN,
Table 3: Performance (%) of meta-knowledge transfer for question answering on CommonsenseQA. Results of baselines are taken from Yasunaga et al. [2021].

|               | IHdev-Acc. | IHtest-Acc. |
|---------------|------------|-------------|
| RoBERTa-large | 73.07 ± 0.45 | 68.69 ± 0.56 |
| + RGDN        | 72.69 ± 0.19 | 68.41 ± 0.66 |
| + GconAttn    | 72.61 ± 0.39 | 68.59 ± 0.96 |
| + KagNet      | 73.47 ± 0.22 | 69.01 ± 0.76 |
| + RN          | 74.57 ± 0.91 | 69.08 ± 0.21 |
| + MHGRN       | 74.45 ± 0.10 | 71.11 ± 0.81 |
| + QA-GNN      | 76.54 ± 0.21 | 73.41 ± 0.92 |
| + QA-GNN + MorsE | 77.67 ± 0.34 | 75.56 ± 0.21 |

4.4 Model Analysis

Ablation Study  First, we investigate the importance of meta-knowledge transfer, namely, the necessity of standing on the shoulders of predecessors. We compare the validation curves of adapting meta-trained MorsE with randomly initialized MorsE (i.e., MorsE w/o Transfer) on the target KG of WN18RR (v1) and FB15k-237 (v1), in Figure 3 (a) (b). We find that meta-trained MorsE can get outstanding performance even do no fine-tuning (i.e., epoch 0) during adapting, and can adapt to convergence quickly in 10 epochs, which shows the importance of meta-knowledge transfer from the source KG.

We also do ablation study on different components of MorsE. For removing the meta-learning setting, we train MorsE on the source KG directly while not on the tasks with support and query sets. For ablating the entity initializer, we initialize entity embeddings randomly for each task during meta-training and adapting. For ablating the GNN modulator, we skip the procedure of the GNN modulator and use the initialized embeddings from the entity initializer as entity embeddings. We show the ablation study results of fine-tuning meta-trained MorsE with 10 epochs in Table 4. The results show that different components are important and it’s beneficial to model them jointly. Specifically, the result decreases significantly when removing the GNN modulator on WN18RR (v1), so we check the performance with different fine-tuning epochs. We find that the performance decrease first and then increase as fine-tuning, and the Hits@10 is 49.28% before fine-tuning which is also lower than results without ablation.

Relation Overlap Analysis  In this part, we analyze how the relation overlap ratio would affect the results. We use $R_\ell = (R_o, R_n)$ to represent the relation set in the target KG, including relations (i.e., $R_o$) that are overlapped with relations in the source KG and relations (i.e., $R_n$) that are not. When adapting MorsE on the target KG and $R_n \neq \emptyset$, only entities that are connected to $R_o$ will be initialized by INIT ($\cdot$), and other entities will be randomly initialized. Furthermore, relations in $R_n$ are also be randomly initialized.

Since similar trends are observed for different datasets, we only report the results w.r.t. the FB15k-237 (v1). Figure 3 (c) shows the results of fine-tuning meta-trained MorsE with 10 epochs, under different relation overlap ratios. Specifically, we control the ratio of relations in the target KG that can be aligned to relations in the source KG to achieve different ratios. We find that the results become better steadily as the relation overlap ratio increases. Furthermore, the per-
formance improvement between 0% and 10% overlap is larger than that of other overlap increase, indicating that the improvement brought by meta-knowledge transfer is significant.

**Target KG Sparsity Analysis** To explore the influence of the target KG sparsity when adapting MorsE, we adapt MorsE on the target KG with different fractions of the original target training triples. In Figure 3(d), we show the results of fine-tuning 10 epochs on FB15k-237 (v4). Compared with MorsE w/o Transfer, MorsE is more robust to different fractions of the target KG triples. To be specific, the relative decrease is 2.39% and 56.25% for MorsE and MorsE w/o Transfer with the decrease of fraction from 100% to 50%. The results indicate that meta-knowledge transfer make MorsE relatively robust to the sparsity of the Target KG.

## 5 Conclusion

We propose a new task meta-knowledge transfer for KGs, and propose a framework, MorsE, to tackle the meta-knowledge transfer for both in-KG and out-of-KG tasks uniformly. In MorsE, we use an entity initializer and a GNN modulator, which are both entity-independent, to enable MorsE to obtain entity embeddings for any given KG but not a fix set of entities. Furthermore, MorsE uses meta-learning to train above two modules for gaining the ability of obtaining embeddings effectively. Experiments show that MorsE can accomplish meta-knowledge transfer better than baselines. In the future, we would like to adapt MorsE to more KG-related applications and datasets.

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### A Training Setup

The details of hyper-parameter settings during meta-training are listed in Table 5.

| Hyper-parameter               | LP | QA |
|------------------------------|----|----|
| Batch size                   | 64 | 16 |
| Learning rate                | 0.01 | 0.01 |
| Training epochs              | 10 | 5 |
| Gamma $\gamma$              | 10 | 10 |
| Number of negative samples $k$ | 32 | 32 |
| Temperature of sampling $\alpha$ | 1 | 1 |
| Number of training sub-KGs  | 10,000 | 10,000 |
| Number of validation sub-KGs | 200 | 200 |
| Random walk time $t_{rw}$    | 10 | 10 |
| Random walk length $l_{rw}$  | 5  | 5  |
| Random walk repeat $l_{rw}$  | 10 | 10 |
Furthermore, for each experiment related to link prediction task, we run 5 times and get the average, and for question answering task, we run 3 times.

B Adapting Details for Link Prediction

The details of hyper-parameter settings during adapting for link prediction task are list in Table 6.

Table 6: Hyper-parameter settings for adapting MorsE to the target KG for the link prediction task.

| Hyper-parameter                  | Value |
|---------------------------------|-------|
| Batch size                      | 512   |
| Learning rate                   | 0.001 |
| Adapting epochs                 | 1000  |
| Gamma $\gamma$                  | 10    |
| Number of negative samples $k$  | 64    |
| Temperature of sampling $\alpha$| 1     |