Learning Meta-Representations of One-shot Relations for Temporal Knowledge Graph Link Prediction

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Abstract—Few-shot relational learning for static knowledge graphs (KGs) has drawn greater interest in recent years, while few-shot learning for temporal knowledge graphs (TKGs) has hardly been studied. Compared to KGs, TKGs contain rich temporal information, thus requiring temporal reasoning techniques for modeling. This poses a greater challenge in learning few-shot relations in the temporal context. In this paper, we follow the previous work that focuses on few-shot relational learning on static KGs and extend two fundamental TKG reasoning tasks, i.e., interpolated and extrapolated link prediction, to the one-shot setting. We propose four new large-scale benchmark datasets and develop a TKG reasoning model for learning one-shot relations in TKGs. Experimental results show that our model can achieve superior performance on all datasets in both TKG link prediction tasks.

I. INTRODUCTION

Knowledge graphs (KGs) represent factual information in the form of triplets \((s, r, o)\), e.g., \((Joe Biden, is president of, USA)\), where \(s\) and \(o\) are the subject and the object of a fact, and \(r\) is the relation between \(s\) and \(o\). KGs have been extensively used to aid the downstream tasks in the field of artificial intelligence, e.g., recommender systems \([1]\) and question answering \([2]\), \([3]\). By incorporating time information into KGs, temporal knowledge graphs (TKGs) represent every fact with a quadruple \((s, r, o, t)\), where \(t\) denotes the timestamp specifying the time validity of the fact. With the introduction of temporal constraints, TKGs are able to describe the ever-changing knowledge of the world. For example, due to the evolution of world knowledge, the fact \((Angela Merkel, is chancellor of, Germany)\) is valid only before \((Olaf Scholz, is chancellor of, Germany)\). TKGs naturally capture the evolution of relational facts in a time-varying context.

Though KGs are constructed with large-scale data, they still suffer from the problem of incompleteness \([4]\). Hence, there has been extensive work aiming to propose KG reasoning models to infer the missing facts, i.e., the missing links, in KGs. Similar to KGs, TKGs are also known to be highly incomplete. This draws huge attention to developing TKG reasoning methods for link prediction (LP) on TKGs. While a lot of proposed methods focus on predicting the links in the interpolation setting \([5]–[9]\), where they predict missing facts at the observed timestamps, another line of work pays attention to forecasting the TKG facts at the unobserved future timestamps and achieving extrapolation \([10]–[13]\). Most of these methods require a huge amount of data associated with each relation to learn expressive relation representations, however, it has been found that a large portion of KG and TKG relations are sparse (i.e., these relations are long-tail and only occur for a handful of times) \([14]\), \([15]\). This leads to the degenerated link inference performance of the traditional KG and TKG reasoning methods when they are predicting the links concerning sparse relations. To tackle this problem, a number of few-shot learning (FSL) methods \([14]\), \([16]–[18]\) employ a meta-learning framework and learn to predict the unseen links concerning a sparse relation, given only very few observed KG facts associated to this relation. Based on these methods, \([15]\) develops a method aiming to alleviate this problem for TKGs. It formulates the one-shot TKG extrapolated LP task for learning the sparse relations in TKGs and proposes new datasets for it.

While \([15]\) manages to generalize the extrapolated LP task to the one-shot setting, it still has limitations: (1) \([15]\) fails to formulate the one-shot TKG interpolated LP task for the sparse relations. Since both interpolated and extrapolated LP serve as the fundamental tasks in TKG reasoning, it is also important to deal with the sparse relations in the interpolation setting; (2) For each to-be-predicted link \((s, r, o, t)\), traditional KG and TKG LP methods, e.g., \([5]\), \([19]\), consider predicting both the subject entity and the object entity, by deriving two LP queries \((s, r, ?, t)\) and \((?, r, o, t)\). However, the previously-proposed KG and TKG few-shot relational learning methods, e.g., \([14]\), \([15]\), only consider predicting the missing object entity, which makes the task settings unreasonable since both subject and object entity prediction are of great concern in KG and TKG LP; (3) The datasets proposed in \([15]\) for the one-shot TKG extrapolated LP task have certain flaws. The number of the associated quadruples for each sparse relation...
is extremely small, which leads to incomprehensive training and evaluation data. Training with incomprehensive training sets would cause instability during training, and evaluating on the tiny evaluation sets makes it hard to determine the model performance accurately. Inaccurate validation results would be misleading in parameter optimization, and the models cannot be fairly judged with inaccurate test results.

To this end, we extend both TKG interpolated and extrapolated LP to the one-shot setting, and propose a model learning meta-representations of one-shot relations for solving both tasks in TKGs (MOST). MOST learns the meta-representation of each sparse relation \( r \) based on its associated one-shot TKG fact. It further employs a metric function to compute the plausibility scores of the unobserved facts concerning \( r \). The main contribution of our work (with corresponding sections) is summarized as follows: (1) We propose the one-shot TKG interpolated LP task. To the best of our knowledge, this is the first work generalizing TKG interpolated LP to the one-shot setting for predicting the links concerning sparse relations (Section III); (2) We fix the unreasonable task setting employed by the previous TKG one-shot relational learning method, and redefine the one-shot TKG extrapolated LP task. We conduct both subject and object entity prediction on the quadruples regarding sparse relations (Section III); (3) We propose four new large-scale datasets for one-shot relational learning on TKGs. For every sparse relation, we have a substantial number of associated TKG facts, which promotes reliable model training and evaluation (Section IV-A); (4) We propose a model solving both interpolated and extrapolated LP for one-shot relations on TKGs (Section IV-B). We evaluate our model on all four newly-proposed datasets and compare it with recent baselines. Our model achieves state-of-the-art performance on all datasets in both tasks (Section V).

II. PRELIMINARIES AND RELATED WORK

A. Temporal Knowledge Graph Reasoning

Let \( E, R, T \) represent a finite set of entities, relations and timestamps, respectively. A temporal knowledge graph (TKG) \( G \) is a relational graph consisting of a finite set of facts denoted with quadruples in the form of \( (s, r, o, t) \), i.e., \( G = \{(s, r, o, t) | s, o \in E, r \in R, t \in T \} \subseteq E \times R \times E \times T \). A complete TKG \( G \) contains both the observed facts \( G_{obs} \) and the unobserved true facts \( G_{un} \), i.e., \( G = (G_{obs} \cup G_{un}) \), where \( G_{obs} \cap G_{un} = \emptyset \). Given \( G_{obs} \), TKG LP aims to predict the ground truth object (or subject) entities of LP queries \( (s, r, o_t, t_q) \) or \( (s, r_q, o_q, t_q) \), where \( (s, r, o, t) \in G_{obs} \). The prediction can be based on all the observed facts \( \{(s, r, o, t) | t \in T \} \subseteq G_{obs} \) from any timestamp in interpolated LP, while extrapolated LP regulates that the prediction can only be based on the observed facts \( \{(s, r, o, t_q) | t < t_q \} \subseteq G_{obs} \) appearing before the query timestamp \( t_q \). Both of two TKG LP tasks are fundamental in TKG reasoning. Recently, extensive studies have been done for both interpolated LP [5]–[9] and extrapolated LP [10]–[13]. In these researches, TKG interpolated LP is also termed as TKG completion and TKG extrapolated LP is also termed as TKG forecasting or TKG link forecasting.

B. Few-Shot Relational Learning for Knowledge Graphs

Few-shot learning (FSL) is a type of machine learning problems where models are asked to perform well on the unobserved data examples for each class, given only a few labeled class-specific observed data examples. When the number of the labeled examples equals 1, FSL problems become one-shot learning problems. Meta-learning approaches aim to quickly learn novel concepts (with only a few concept-related data examples) by generalizing from previously encountered learning tasks [20], which fits well to solving the problems in the few-shot setting. Episodic training [21] is a meta-learning framework, where a model is trained over episodes. Each episode can be considered as a mini-training process on a training task \( T \), where a number of "training examples" (support set \( S \)) and "test examples" (query set \( Q \)) are sampled and a loss function \( l_{\theta} \) is calculated over \( Q \) conditioned on \( S \), \( \theta \) denotes the model parameters. With episodic training, a model is trained over a large set of training tasks to explicitly learn to learn from a given support set to minimise a loss over a batch of examples in the query set. Assume we have a large set of training tasks \( T = \{T_i\}_{i=1}^N \), where \( T_i = \{S_i, Q_i\} \) and \( N \) is the total number of the training tasks, the training objective of a model is given as

\[
\theta = \arg \min_{\theta} \mathbb{E}_{T \sim \mathcal{T}} \left[ \frac{1}{|Q_t|} \sum_{q \in Q_t} [l_{\theta}(q|S_t)] \right].
\]

\( q \) denotes a data example in the query set \( Q_t \). Episodic training manages to simulate the few-shot situation when only a small number of data examples are sampled to form the support set of each training task \( T \), thus serving as a common meta-learning paradigm to solve FSL problems.

To better learn the sparse relations in KGs, [14] first introduces an FSL problem, i.e., few-shot KG LP, where models are asked to infer unobserved KG facts for each sparse relation \( r \) conditioned on only a few observed KG facts concerning \( r \). It further formulates few-shot KG LP into a meta-learning problem and trains its proposed method GMatching using episodic training. Several researches follow [14] and employ episodic training to train different FSL models for solving the few-shot KG LP task [16]–[18], [22]. [15] first introduces one-shot relational learning into TKGs and proposes one-shot TKG extrapolated LP. Following [14], it formulates the one-shot TKG extrapolated LP task into a meta-learning problem and employs episodic training for training its model OAT. Among these methods, GMatching [14], FSRL [17], FAAN [18] and OAT [15] are metric-based meta-learning approaches that use metric functions to do similarity matching of the few-shot examples and the to-be-predicted links. MetaR [16] and GANA [22] are optimization-based meta-learning approaches that employ Model-Agnostic Meta-Learning [23] for FSL. They learn a good initialization of model parameters and achieve fast adaption of them with very few relation-specific examples.

Recently, another line of work aims at learning newly-emerged few-shot entities in TKGs. [24] proposes an FSL problem, i.e., TKG few-shot out-of-graph (OOG) LP, that generalizes TKG interpolated LP to the few-shot setting.
A model called FILT is trained with episodic training to solve the problem. To improve performance on TKG few-shot OOG LP, [25] designs a meta-learning-based model using confidence-augmented reinforcement learning. [26] proposes another FSL problem, i.e., few-shot TKG reasoning, that extends the extrapolation LP setting to an FSL problem. Wang et al. develop MetaTKGR that addresses both few-shot and time shift challenges. These methods all focus on few-shot unseen entities, but cannot deal with sparse relations.

III. ONE-SHOT TEMPORAL KNOWLEDGE GRAPH LINK PREDICTION SETUP

We give the definition of our newly-proposed task one-shot TKG interpolated LP, and redefine one-shot TKG extrapolated LP to consider both subject and object entity prediction. For a TKG $G$, all its relations $R$ can be classified into two groups, i.e., frequent relations $R_{freq}$ and sparse relations $R_{sp}$, where $R_{freq} \cap R_{sp} = \emptyset$ and $R = (R_{freq} \cup R_{sp})$. A background graph $G' \subseteq \mathcal{E} \times R_{freq} \times \mathcal{E} \times T$ is constructed by including all the quadruples concerning frequent relations, where $G' \subseteq G$.

**Definition 1 (One-Shot TKG Interpolated Link Prediction).** Assume we observe only one quadruple $(s_0, r, o_0, t_0)$ corresponding to each sparse relation $r$, where $r \in R_{sp}$, $s_0, o_0 \in \mathcal{E}$ and $t_0 \in T$. Given $(s_0, r, o_0, t_0)$ and the whole background graph $G'$, one-shot TKG interpolated LP aims to predict the missing entity of each LP query, i.e., $(s_0, r, ?, t_0)$ or $(?, r, o_0, t_0)$ derived from the unobserved quadruples containing $r$, where $s_0, o_0 \in \mathcal{E}$ and $t_0 \in T$.

**Definition 2 (One-Shot TKG Extrapolated Link Prediction).** Assume we observe only one quadruple $(s_0, r, o_0, t_0)$ corresponding to each sparse relation $r$, where $r \in R_{sp}$, $s_0, o_0 \in \mathcal{E}$ and $t_0 \in T$. Given $(s_0, r, o_0, t_0)$, together with a set of observed TKG facts that appear prior to $t_0$ and belong to the background graph $G'$, one-shot TKG extrapolated LP aims to predict the missing entity of each LP query, i.e., $(s_0, r, ?, t_0)$ or $(?, r, o_0, t_0)$, derived from the unobserved quadruples containing $r$, where $s_0, o_0 \in \mathcal{E}$, $t_0 \in T$ and $t_0 > t_0$. In our definitions, we consider both subject and object prediction, which fixes the unreasonable setting of previous few-shot relational learning methods that neglect subject prediction. To achieve subject prediction, following previous TKG reasoning methods, e.g., [12], we add reciprocal relations for every quadruple, i.e., adding $(s, r, o, t)$ for every $(s, r, o, t)$. If $r \in R_{sp}$, we treat $r^{-1}$ as a separate sparse relation and transform every subject prediction query $(?, r, o, t)$ of $r$ to an object prediction query $(o, r^{-1}, ?, t)$ of $r^{-1}$. If $r$ and $r^{-1}$ are in the same split, e.g., if $r$ belongs to sparse training relations $R_{train}$, then $r^{-1} \in R_{train}$.

We further formulate the one-shot TKG LP tasks into meta-learning problems. Following [14], [15], we assume that we have access to a set of training tasks for episodic training. Each training task $T_r$ corresponds to a sparse relation $r \in R_{train}^{'meta-train}$ ($R_{train}^{'meta-train} \subset R_{sp}$). $T_r = \{S_r, Q_r\}$, where $S_r$ is the support set of $T_r$ containing only one support quadruple $(s_0, r, o_0, t_0)$, and $Q_r = \{(s,q, r, o_0, t_0)\}$ is the query set of $T_r$ containing a number of $r$-related quadruples other than $(s_0, r, o_0, t_0)$. The set of all training tasks is denoted as the meta-training set $T_{meta-train}$. A loss function $L_\theta((s_q, r, o_q, t_q)|S_r)$ is used to indicate how well the TKG reasoning model works on the query quadruple $(s_q, r, o_q, t_q)$, given the support set $S_r$. $\theta$ denotes the model parameters. The training objective of the model is given as $\theta = \arg\min_{\theta} \mathbb{E}_{T_r \sim T_{meta-train}} \left[ \frac{1}{|S_r|} \sum_{q \in Q_r} L_\theta(q|S_r) \right]$, where $q$ represents a query quadruple $(s_q, r, o_q, t_q)$. $T_r$ is sampled from the meta-training set $T_{meta-train}$, and $|Q_r|$ denotes the number of the query quadruples regarding the sparse relation $r$. After training, the TKG reasoning model will be evaluated on a meta-test set $T_{meta-test}$ corresponding to unseen sparse relations $R_{test}^{sp}$, where $R_{test}^{sp} \subset R_{sp}$ and $R_{train}^{'meta-train} \cap R_{test}^{sp} = \emptyset$. We also validate the model performance with a meta-validation set $T_{meta-valid} = (R_{valid}^{sp} \subset R_{sp}$, $R_{train}^{'meta-train} \cap R_{valid}^{sp} = \emptyset$, $R_{valid}^{sp} \cap R_{test}^{sp} = \emptyset)$. Similar to meta-training, for each sparse relation in meta-validation and meta-test, only one associated quadruple serves as its support set, and all the links in its query set are to be predicted. For each sparse relation $r$, in the interpolated LP, there is no constraint for the support timestamp $t_0$, while in the extrapolated LP, temporal constraint is imposed that $t_0 < \min\{t_q|(s_q, r, o_q, t_q) \in Q_r\}$. We present one example in Fig. 1a for each of the one-shot TKG LP task. Following [15], to prevent exposing the models to the future information, in the extrapolation task, we further keep the spans of the quadruples’ timestamps from different meta-learning sets ($T_{meta-train}$, $T_{meta-valid}$, $T_{meta-test}$) in a non-overlapped sequential order (Fig. 1b).

IV. NEW DATASETS AND OUR METHOD

A. Proposing New Datasets

By taking subsets of two benchmark TKG databases, i.e., ICEWS [27] and GDELT [28], Mirtaheri et al. [15] propose two one-shot extrapolated LP datasets, i.e., ICEWS17 and GDELT. They first set upper and lower thresholds, and then select the relations with frequency between them as sparse relations (frequency 50 to 500 for ICEWS17, 50 to 700 for GDELT). To prevent time overlaps among meta-learning sets (Fig. 1b), they further remove a significant number of quadruples regarding sparse relations. Assume a relation $r$ is selected as a sparse relation and $T_r \in T_{meta-train}$. The ending timestamp of the meta-training set is $t_1$. Then all the quadruples in $\{(s, r, o, t)|s, o \in \mathcal{E}, t > t_1\}$ are removed from the dataset. This leads to a considerably smaller query set $Q_r$ when a large number of $r$-related facts take place after $t_1$. If $r$’s frequency is close to the lower threshold before removal, it is very likely that after removal, the number of associated quadruples left in $\{(s, r, o, t)|s, o \in \mathcal{E}, t \leq t_1\}$ becomes extremely small, leading to a tiny $Q_r$ that causes instability during training. Similarly, if $T_r \in (T_{meta-valid} \cup T_{meta-test})$, evaluation over a tiny $Q_r$ makes it hard to accurately determine the model performance since the test data is incomprehensive. Fig. 2 shows that a large portion of sparse relations in ICEWS17 and GDELT have very few associated quadruples.
To be specific, in ICEWS17, 31 out of 85 sparse relations have less than 50 associated quadruples, and in GDELT, 24 out of 69 sparse relations have less than 50 associated quadruples. Moreover, 4 out of 14 test relations have even less than 10 associated quadruples in ICEWS17, and this also applies for 11 out of 14 test relations in GDELT. This indicates that the datasets proposed in [15] have certain flaws.

To overcome these problems, we construct two new large-scale extrapolation LP datasets, i.e., ICEWS-one_ext and GDELT-one_ext, also by taking subsets from ICEWS and GDELT. ICEWS-one_ext is constructed with the timestamped political facts happening from 2005 to 2015, while GDELT-one_ext is constructed with the global social facts from Jan. 1, 2018 to Jan. 31, 2018. For sparse relation selection, we set the upper and lower thresholds of frequency to 100 and 1000 for ICEWS-one_ext, 200 and 2000 for GDELT-one_ext, and then split these relations into train/valid/test groups. We take the relations with higher frequency as frequent relations \( R_{\text{freq}} \) and build background graphs \( G' \) with all the quadruples containing them. Following [15], we then remove a part of quadruples associated with sparse relations to prevent time overlaps among meta-learning sets. After removal, we further discard the relations with too few associated quadruples (less than 50 for ICEWS-one_ext, 100 for GDELT-one_ext). In this way, we prevent including meta-tasks \( T_r \) with extremely small query set \( Q_r \). From Fig. 2, we observe that ICEWS-one_ext and GDELT-one_ext have a substantial number of associated quadruples for each sparse relation, which promotes reliable model training and evaluation. We also construct two datasets, i.e., ICEWS-one_int and GDELT-one_int, for one-shot TKG interpolated LP. Since in interpolation, models are allowed to be exposed to the information from any timestamp, we do not have to remove quadruples to eliminate time overlaps among meta-learning sets. To this end, we set the upper and lower thresholds of sparse relations’ frequency to 50 and 500 for ICEWS-one_int, 100 and 1000 for GDELT-one_int, and then split these relations into train/valid/test groups. Statistics of our datasets are presented in Table I.

| Dataset          | \( |R_{\text{sp}}| \) | \( |\mathcal{G}| \) | \( |\mathcal{T}| \) | \( |\mathcal{T}_{\text{sp}}| \) | \( |\mathcal{G}_{\text{sp}}| \) | \( |\mathcal{T}_{\text{sp}}| \) |
|------------------|----------------|----------------|----------------|----------------|----------------|----------------|
| ICEWS-one_ext    | 7,934          | 109            | 4,017          | 544,960        | 408,413        | 36,550         |
| ICEWS-one_int    | 10,356         | 155            | 4,017          | 74,910         | 441,853        | 22,051         |
| GDELT-one_ext    | 6,647          | 155            | 2,751          | 55,711         | 2,205,316      | 2,237,534      |
| GDELT-one_int    | 7,677          | 181            | 2,751          | 64,8/8         | 2,237,534      | 2,237,534      |

**B. Our Method**

We propose a metric-based meta-learning model, i.e., MOST, to solve both one-shot TKG interpolated and extrapolated LP. Fig. 3 shows the overview of MOST. Given
Fig. 3. Overview of MOST. It extracts meta-information from support entities, learns the meta-representation of the sparse relation and uses it to predict related links. Better viewed with the equations and notations in Section IV-B.

a support quadruple $(s_0, r, o_0, t_0)$ of the sparse relation $r$, MOST extracts the meta-information from the time-aware representations of support entities $s_0$, $o_0$ with a meta-information extractor, and uses a meta-representation learner to learn $r$’s meta-representation based on it. A metric function is then employed to compute the plausibility scores of TKG quadruples concerning $r$.

1) Meta-Information Extractor: Given the support quadruple $(s_0, r, o_0, t_0)$ of a sparse relation $r$, MOST aims to extract the meta-information of $r$ from its support entities $s_0$, $o_0$. MOST first employs a time-aware relational graph encoder to learn the contextualized time-aware entity representations of support entities. For every support entity (or $o_0$), MOST finds its temporal neighborhood for $s_0$. It searches for the available background facts whose object entity corresponds to this support entity, and constructs a temporal neighborhood, e.g., $s_0$’s temporal neighborhood is denoted as $\mathcal{N}_{s_0} = \{(e', r', t') | r' \in R_{\text{freq}}, (e', r', s_0, t') \in G'\}$. It keeps a fixed number of temporal neighbors nearest to the support timestamp $t_0$ (MOST ensures the kept neighbors are prior to $t_0$ for one-shot TKG extrapolated LP). The number of sampled neighbors is a hyperparameter and can be tuned. We denote the filtered neighborhood as $\hat{\mathcal{N}}_{s_0}$ and $\hat{\mathcal{N}}_{o_0}$; MOST then computes the time-aware representations of the support entities by aggregating the information provided by their temporal neighbors. The time-aware entity representations $h_{(s_0, o_0)}$, $h_{(o_0, t_0)}$ of $s_0$, $o_0$ are derived as follows:

$$
\begin{align*}
\hat{h}_{(s_0, o_0)} &= h_{s_0} + \delta_1 \sigma \left( \frac{1}{|\hat{\mathcal{N}}_{s_0}|} \sum_{(e', r', t') \in \hat{\mathcal{N}}_{s_0}} W_g (f(h_{e'} \| \Phi(t')) \circ h_r), \\
\hat{h}_{(o_0, t_0)} &= h_{o_0} + \delta_1 \sigma \left( \frac{1}{|\hat{\mathcal{N}}_{o_0}|} \sum_{(e', r', t') \in \hat{\mathcal{N}}_{o_0}} W_g (f(h_{e'} \| \Phi(t')) \circ h_r)),
\end{align*}
$$

$h_{s_0}$, $h_{o_0} \in \mathbb{R}^d$ and $h_{s_0}$, $h_{o_0} \in \mathbb{R}^d$ denote the time-invariant entity representations of $s_0$ and $o_0$, respectively. $h_{e'} \in \mathbb{R}^d$ denotes the relation representation of the frequent relation $r'$. $d$ is the dimension of the representations. Moreover, $\circ$ represent Hadamard product and concatenation operation, respectively. $W_g \in \mathbb{R}^{d \times d}$ is a weight matrix that processes the information in the graph aggregation. $f : \mathbb{R}^{2d} \rightarrow \mathbb{R}^d$ is a layer of feed-forward neural network. $\delta_1$ is a trainable parameter deciding how much information from the temporal neighbors is included in updating entity representations. $\sigma$ is an activation function. $\Phi(t')$ denotes the time encoding function that encodes timestamp $t'$ as $\Phi(t') = \sqrt{2} [\cos(\omega_1 t' + \phi_1), \ldots, \cos(\omega_d t' + \phi_d)]$, where $\omega_1 \ldots \omega_d$ and $\phi_1 \ldots \phi_d$ are trainable parameters. We name our model with this timestamp encoder as MOST-TA. Besides, we develop another model variant MOST-TD by encoding time differences instead of timestamps. We input $t_0 - t'$ instead of $t'$ into the time encoder.

$$
\begin{align*}
h_{(s_0, o_0)} &= h_{s_0} + \delta_1 \sigma \left( \frac{1}{|\mathcal{N}_{s_0}|} \sum_{(e', r', t') \in \mathcal{N}_{s_0}} W_g (f(h_{e'} \| \Phi(t_0 - t')) \circ h_r), \\
h_{(o_0, t_0)} &= h_{o_0} + \delta_1 \sigma \left( \frac{1}{|\mathcal{N}_{o_0}|} \sum_{(e', r', t') \in \mathcal{N}_{o_0}} W_g (f(h_{e'} \| \Phi(t_0 - t')) \circ h_r).
\end{align*}
$$

We show in experiments (Section V-B) that both MOST-TA and MOST-TD can achieve state-of-the-art performance in one-shot TKG LP tasks. After obtaining $h_{(s_0, o_0)}$ and $h_{(o_0, t_0)}$, we compute the meta-information of $r$ as

$$
h_{(s_0, o_0, t_0)} = h_{(s_0, t_0)} | h_{(o_0, t_0)}. \quad (3)
$$

$h_{(s_0, o_0, t_0)} \in \mathbb{R}^{2d}$ represents the meta-information of $r$, given the support quadruple $(s_0, r, o_0, t_0)$.

2) Meta-Representation Learner: In the meta-representation learner, MOST derives the meta-representation of $r$ given the meta-information $h_{(s_0, r, o_0, t_0)}$ as follows:

$$
h_r = f_{\text{proj}} \left( h_{(s_0, r, o_0, t_0)} + f_{\text{r2}} \left( \sigma \left( f_{\text{r2}} \left( h_{(s_0, o_0, t_0)} \right) \right) \right) \right), \quad (4)
$$

where $f_{\text{r2}} : \mathbb{R}^{2d} \rightarrow \mathbb{R}^{4d}$, $f_{\text{r2}} : \mathbb{R}^{4d} \rightarrow \mathbb{R}^{2d}$, $f_{\text{proj}} : \mathbb{R}^{2d} \rightarrow \mathbb{R}^d$ are three single layer neural networks. The meta-representation $h_r \in \mathbb{R}^d$ will then be used in the metric function to compute the scores of the TKG quadruples.

3) Metric Function: To compute the plausibility score for the query quadruple $(s_q, r, o_q, t_q)$, our metric function requires the time-aware entity representations $h_{(s_q, o_q)}$, $h_{(o_q, t_q)}$ of the query entities $s_q$, $o_q$ at $t_q$, as well as the meta-representation of $r$. We derive $h_{(s_q, t_q)}$, $h_{(o_q, t_q)}$ as follows:

$$
\begin{align*}
h_{(s_q, t_q)} &= h_{s_q} + \delta_2 f(h_{s_q} \| \Phi(t_q)), \\
h_{(o_q, t_q)} &= h_{o_q} + \delta_2 f(h_{o_q} \| \Phi(t_q)).
\end{align*}
$$

$h_{s_q} \in \mathbb{R}^d$ and $h_{o_q} \in \mathbb{R}^d$ denote the time-invariant entity representations of $s_q$ and $o_q$, respectively. $\delta_2$ is a trainable parameter
controlling the amount of the injected temporal information. Different from Equation 1, we do not search temporal neighbors from the background graph for query entities and no aggregation is performed. Equation 5 states how we compute query entity representations in MOST-RA. Similarly, MOST-TD adapts Equation 5 to the following form to enable time difference learning, i.e., \( h_s(q_s, t_q) = h_s + \delta_2 f(h_s, \Phi(t_q - t_0)); \)
\( h_{o(q_s, t_q)} = h_q + \delta_2 f(h_q, \Phi(t_q - t_0)); \)

Inspired by the KG scoring function RotatE [29], we design a metric function that computes scores based on complex vectors, and treat the meta-representation of \( r \) as element-wise rotation in the complex plane. To achieve this, we first transform \( h_r \) into a complex vector \( h_r^C \) in \( \mathbb{C}^d \).

\[
h_r^C[j] = \frac{\pi}{\| h_r \|_\infty} h_r, \quad j = 1, \ldots, d
\]

\( h_r^C \) and \( h_r \) denote the \( j \)th element of the vectors \( h_r^C \) and \( h_r \), respectively, e.g., \( h_r^C = \[ h_r^C[1], \ldots, h_r^C[d] \] \). \( \| h_r \|_\infty \) denotes the infinity norm of the vector \( h_r \). We then map the query entity representations \( h_s(q_s, t_q) \) and \( h_{o(q_s, t_q)} \) to the complex space \( \mathbb{C}^d \) and get \( h_s^C(q_s, t_q) \) and \( h_{o(q_s, t_q)} \). The real part of each mapped vector is the first half of the original vector from \( \mathbb{R}^d \) and the imaginary part is the second half. For example, if \( h_s(q_s, t_q) = [2, 3] \) \( \in \mathbb{R}^2 \), we map it to \( h_s^C(q_s, t_q) = [2 + 3\sqrt{-1}] \) \( \in \mathbb{C}^2 \). Since unitary complex number can be regarded as a rotation in the complex plane (explained in [29]), \( h_s^C(q_s, t_q) \) \( \in \mathbb{C}^d \) can be interpreted as doing element-wise rotation from the query subject \( s_q \) in the complex plane. Based on it, the complete form of our metric function \( \psi \) is given as

\[
\psi(q|S_q) = \text{Sigmoid} \left( \text{Re} \left( h_s^C(q_s, t_q) \odot h_r^C \right)^\top h_{o(q_s, t_q)}^C \right),
\]

where \( q = (s_q, r, o_q, t_q) \) and \( \text{Sigmoid} \) denotes the sigmoid function. \( \text{Re} \) means taking the real part of the complex number and \( h_s^C(q_s, t_q) \odot h_r^C \) means the complex conjugate of \( h_s^C(q_s, t_q) \) \( \odot h_r^C \). \( \psi \) takes the real part of the dot product (Hermitian product) between \( h_s^C(q_s, t_q) \) \( \odot h_r^C \) and \( h_{o(q_s, t_q)} \) as the plausibility score of \( q \) given \( S_q \). Note that \( \psi \) can be viewed as doing similarity matching of support and query quadruples (the higher the score is, the more \( q \) resembles the support quadruple). Thus, MOST is taken as a metric-based meta-learning approach.

4) Parameter Learning: We train MOST with episodic training. In each episode, we sample one sparse relation \( r \) and \( r \)-related quadruple as its support quadruple \( S_r = (s_r, o_r, t_0) \). Sample \( q \)’s object entity \( o_q \) to every other entity \( e \in \mathcal{E} \setminus \{o_q\} \) in the TKG (\( \mathcal{E} \) denotes the set of all entities in this TKG) and construct \( |\mathcal{E}| - 1 \) polluted quadruples \( q^- \) for \( q \). Then, we use the binary cross entropy loss to optimize our model.

\[
L = \frac{1}{|\mathcal{E}|} \sum_q \frac{1}{|\mathcal{E}|} \left( l_q + \sum_{q^-} l_{q^-} \right),
\]

where \( l_q = -y_q \log (\psi(q|S_q)) - (1 - y_q) \log (1 - \psi(q|S_q)) \) and \( l_{q^-} = -y_{q^-} \log (\psi(q^-|S_q)) - (1 - y_{q^-}) \log (1 - \psi(q^-|S_q)) \) denote the binary cross entropy loss of \( q \) and \( q^- \), respectively. \( y_q = 1 \) and \( y_{q^-} = 0 \) because for \( q \in \mathcal{Q}_r \), we want its score \( \psi(q|S_q) \) to be maximized, while \( q^- \) is a polluted quadruple, and thus we want its score \( \psi(q^-|S_q) \) to be minimized. We describe our one-shot training procedure with Algorithm 1.

V. EXPERIMENTS

We evaluate MOST and several baselines on our newly-proposed datasets (Section V-B). We analyze model components with ablation studies in Section V-C. We also compare MOST with several strong baselines over the performance of different sparse relations and different support-query time difference \( |t_q - t_0| \) in Section V-D and V-E, respectively.

A. Experimental Setup

1) Evaluation Metrics: We employ two evaluation metrics, i.e., Hits@1/5/10 and mean reciprocal rank (MRR), to evaluate model performance. For each query quadruple \( (s_q, r, o_q, t_q) \in \mathcal{Q}_r, r \in \mathcal{R}_\text{test} \), we derive an object prediction query: \( (s_q, r, ?, t_q) \). We compute the rank of the ground truth missing entity \( o_q \) for every object prediction query based on the scores computed with score function \( \psi \). Let rank\(_{o_q} \) denote the rank of \( o_q \) in \( (s_q, r, ?, t_q) \). We compute MRR by averaging the reciprocal of ranks among all the query quadruples in the meta-test set:

\[
\frac{1}{\sum_{r\in\mathcal{R}_{\text{test}}} \sum_{q\in\mathcal{Q}_r \cup \{q^-\}}} \frac{1}{\sum_{q\in\mathcal{Q}_r \cup \{q^-\}}} \frac{1}{\text{rank}_{o_q}},
\]

where \( q \) denotes a query quadruple \( (s_q, r, o_q, t_q) \) in the meta-test set. Note that if \( r \in \mathcal{R}_{\text{test}} \), then its reciprocal relation \( r^-1 \in \mathcal{R}_{\text{test}} \). Performing object prediction over the query quadruples related to \( r^-1 \) equals performing subject prediction over the query quadruples related to \( r \). The restriction to only considering object prediction in MRR computation will not lead to a loss of generality. Hits@1/5/10 are the proportions of the predicted links where ground truth entities are ranked as top 1, top 5, top 10, respectively. We follow [19] and use filtered results for fairer evaluation.

Algorithm 1: One-Shot Episodic Training

\begin{algorithm}
\caption{One-Shot Episodic Training}
\begin{algorithmic}[1]
\Function{Training sparse relations $\mathcal{R}_{\text{test}}^p$} \text{for episode = 1: M do}
\State Shuffle relations in $\mathcal{R}_{\text{test}}^p$
\State Sample sparse relation $r$ from $\mathcal{R}_{\text{test}}^p$
\State Sample a $(s_0, r, o_0, t_0)$ to make the support set $S_r$
\EndFunction
\If{One-Shot Interpolated LP} \State Sample a batch of query quadruples $\mathcal{Q}_r = \{(s_q, r, o_q, t_q)\}$ \EndIf
\Else \text{One-Shot Extrapolated LP} \State Sample a batch of query quadruples $\mathcal{Q}_r = \{(s_q, r, o_q, t_q)|t_q < t_0\}$ \EndElse
\State Compute $h_{s(q), o(q), t(q)}$ with graph encoder
\State Compute meta-information $h_{s(q), o(q), t(q)}$
\State Learn meta-representation $h_s$ with meta-representation learner
\State Pollute each $q \in \mathcal{Q}_r$ and generate polluted quadruples \( q^- \)
\State Compute time-aware representations for entities in all $q$ and $q^-$
\EndFunction
\State Compute scores for all $q$ and $q^-$ with metric function $\psi$
\State Calculate the loss $\mathcal{L}$
\State Update model parameters using gradient of loss $\nabla \mathcal{L}$
\end{algorithmic}
\end{algorithm}
One-Shot TKG Interpolated Link Prediction

| Datasets  | ICEWS-one_int | GDELT-one_int |
|-----------|---------------|---------------|
| Model     | MRR | Hits@1 | Hits@5 | Hits@10 | MRR | Hits@1 | Hits@5 | Hits@10 | MRR | Hits@1 | Hits@5 | Hits@10 |
| TNGComplEx 23.34 | 14.57 | 11.95 | 6.76 | 15.58 | 21.78 |
| AITE 34.40 | 22.03 | 7.77 | 5.10 | 8.13 | 12.13 |
| TelML 35.38 | 24.42 | 59.12 | 10.41 | 5.97 | 13.28 | 18.87 |
| GANA 13.83 | 6.07 | 24.00 | 7.39 | 2.53 | 8.35 | 15.58 |
| MetaR 27.69 | 7.88 | 61.78 | 9.91 | 0.18 | 19.62 | 26.79 |
| GMMatching 30.59 | 15.46 | 58.62 | 12.53 | 6.55 | 17.14 | 24.15 |
| FSRL 33.98 | 18.94 | 52.61 | 14.11 | 7.61 | 19.56 | 27.54 |
| FAAN 35.48 | 23.27 | 49.45 | 17.74 | 7.67 | 21.35 | 27.11 |
| OAT 32.45 | 24.26 | 39.88 | 48.43 | 12.26 | 7.58 | 15.53 | 21.46 |
| MOST-TA 47.79 | 39.51 | 57.01 | 62.25 | 17.71 | 11.56 | 23.25 | 29.76 |
| MOST-TD 47.60 | 39.43 | 56.83 | 62.38 | 17.36 | 11.67 | 22.74 | 28.63 |

One-Shot TKG Extrapolated Link Prediction

| Datasets  | ICEWS-one_ext | GDELT-one_ext |
|-----------|---------------|---------------|
| Model     | MRR | Hits@1 | Hits@5 | Hits@10 | MRR | Hits@1 | Hits@5 | Hits@10 | MRR | Hits@1 | Hits@5 | Hits@10 |
| TANGO 10.23 | 3.94 | 15.88 | 25.78 | 13.88 | 9.61 | 16.93 | 22.29 |
| CyGNet 22.30 | 12.61 | 30.46 | 39.13 | 9.42 | 4.87 | 13.13 | 16.81 |
| xERTE 30.02 | 19.79 | 42.13 | 51.16 | 16.38 | 10.88 | 22.19 | 27.76 |
| GANA 13.83 | 6.07 | 24.00 | 7.39 | 2.53 | 8.35 | 15.58 |
| MetaR 27.69 | 7.88 | 61.78 | 9.91 | 0.18 | 19.62 | 26.79 |
| GMMatching 30.59 | 15.46 | 58.62 | 12.53 | 6.55 | 17.14 | 24.15 |
| FSRL 33.98 | 18.94 | 52.61 | 14.11 | 7.61 | 19.56 | 27.54 |
| FAAN 35.48 | 23.27 | 49.45 | 17.74 | 7.67 | 21.35 | 27.11 |
| OAT 32.45 | 24.26 | 39.88 | 48.43 | 12.26 | 7.58 | 15.53 | 21.46 |
| MOST-TA 32.94 | 26.35 | 39.97 | 47.19 | 15.69 | 10.14 | 20.54 | 26.38 |
| MOST-TD 38.46 | 31.51 | 46.02 | 52.32 | 17.36 | 11.64 | 22.46 | 28.15 |

TABLE II

Experimental results of both one-shot TKG interpolated and extrapolated LP on all four newly-proposed datasets. Evaluation metrics are filtered MRR and Hits@5/10. The best results are marked in bold.

2) Baseline Methods and Implementation Details: We consider five static KG FSL methods, i.e., GMatching [14], MetaR [16], FSRL [17], FAAN [18], GANA [22], and one TKG FSL method, i.e., OAT [15]. We provide static KG FSL methods with all the facts in the original datasets, and neglect time information, i.e., neglecting t in (s, r, o, t). Besides, three traditional TKG interpolation methods, i.e., TNGComplEx [6], ATiSE [30], TeLM [31], and three traditional TKG extrapolation methods, i.e., TANGO [12], CyGNet [11], xERTE [13] are considered. For each interpolation dataset, we build a training set by adding all the background quadruples r ∈ R∗ train sp , and the quadruples regarding every r ∈ R∗ train sp . We further add the support quadruple associated with each sparse relation r ∈ (R∗ valid sp ∪ R∗ test sp ) into the training set. For each extrapolation dataset, we build a training set by adding all the background quadruples during meta-training time and the quadruples concerning every r ∈ R∗ train sp . We do not include any quadruple regarding r ∈ (R∗ valid sp ∪ R∗ test sp ) into the training set due to the time constraint in the extrapolation setting, but we allow the models to use the support quadruples (Sp, r ∈ (R∗ valid sp ∪ R∗ test sp )) during inference. We test all methods over same test quadruples to ensure fair comparison. We implement all baselines with their official open-sourced implementations. We do all experiments (including baselines and MOST) with PyTorch [32] on a single NVIDIA Tesla T4. All experimental results are obtained with the mean of 5 runs with different random seeds.

B. Experimental Results

Table II reports the experimental results of one-shot TKG interpolated and extrapolated LP. MOST outperforms baseline methods on all datasets in both LP tasks. Traditional TKG reasoning methods are not FSL methods so it is hard for them to model sparse relations given only one associated quadruple. Static KG FSL methods do not consider temporal information so they are weaker than MOST. When computing support entity representations, the TKG FSL method OAT includes temporal information by employing a snapshot encoder that sequentially encodes a small number of historical graph snapshots right before the support timestamp t0. In interpolated LP, OAT loses information coming after t0, and in extrapolated LP, a short history length fails to include the abundant information outside the considered history. MOST searches for a fixed number of temporal neighbors of support entities in its graph encoder and impose no constraint on how temporally far away these neighbors are. This helps to incorporate temporally farther information. Besides, OAT employs cosine similarity for score computation, which is beaten by our metric function. Table II also shows that while MOST-TA beats MOST-TD in interpolated LP, MOST-TD outperforms MOST-TA in extrapolated LP. For MOST-TA, part of the TKG at every timestamp is observable during training, thus enabling the time encoder to learn from all timestamps. However, in the extrapolated LP, meta-training set does not span across the whole timeline, leading to MOST-TA’s degenerated performance during inference when we sample the temporal neighbors from the timestamps unseen in the meta-training set. For extrapolation, modeling time differences (MOST-TD) achieves better results since almost all time differences we encounter during inference are already seen and learned during meta-training.

C. Ablation Studies

Table III presents the results of ablation studies of MOST variants on ICEWS-based datasets. The best results are marked in bold.

TABLE III

Ablation studies of MOST variants on ICEWS-based datasets. The best results are marked in bold.

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in all model components (Equation 1, 2 and 5), creating a model without using any temporal information. Note that without \( \Phi \), MOST-TA equals MOST-TD. We observe that it is crucial to utilize temporal information in MOST for achieving strong results in one-shot TKG LP. (B) Changing graph aggregation function in meta-information extractor: In B1, we employ mean pooling over time-aware representations of temporal neighbors, e.g., Equation 1 becomes \( h(s_{0,t_0}) = \frac{1}{|N_{s_{0,t_0}}|} \sum_{(t' \in N_{s_{0,t_0}})} f(h_{t'}(\Phi(t'))) \) for \( s_0 \). In B2, we employ RGCN [33] coupled with \( \Phi \), e.g., Equation 1 becomes \( h(s_{0,t_0}) = \frac{1}{|N_{s_{0,t_0}}|} \sum_{(t' \in N_{s_{0,t_0}})} W_{t'}(f(h_{t'}(\Phi(t')))) \) for \( s_0 \). We observe that our graph aggregation function helps to effectively capture meta-information. (C) Changing metric function: In C1, we switch our metric function \( \psi \) to RotatE, i.e., Equation 7 becomes \( ||h_C^C_{s,t_0} \odot h_C^C_{c,t_0}||_1 \), where \( || \cdot ||_1 \) is the L1-norm. Note that we input time-aware entity representations into RotatE and thus C1 also achieves temporal reasoning. In C2, we switch \( \psi \) to the LSTM-based matcher proposed in [14]. We perform two steps of matching. Each step of matching is defined as \( h_{k+1}(c_{k+1}) = LSTM(h_{query_k, h_k, h_{support_k, c_k}})h_{k+1}(c_{k+1}) + h_{query_k, score_k} = h_{k+1}(c_{k+1})h_{support_k, LSTM(x, c, h)} \) is a standard LSTM cell [34] with input \( x \), hidden state \( h \) and cell state \( c \). \( h_{support_k} = h(s_{0,t_0})h(s_{0,t_0}) \) and \( h_{query_k} = h(s_{0,t_0})h(s_{0,t_0}) \) are time-aware for temporal reasoning. We find that our metric function works much better in our tasks.

D. Performance over Different Sparse Relations

We compare MOST with several strong baselines regarding the performance over different sparse relations. We choose to compare with the strongest traditional TKG interpolation and extrapolation baselines, i.e., TeLM and xERTE. We further choose to compare with the strongest KG FSL baseline, i.e., FAAN, since it outperforms almost all baselines in our main results in Table II. We aggregate the object prediction results of each original relation and its reciprocal relation to get the overall subject and object prediction results of the original relation. For example, for the original sparse relation \( r \), we aggregate the object prediction results of \( r \) and \( r^{-1} \) to get the overall subject and object prediction results of \( r \). We report the overall results in Table IV and Table V. From Table IV, we observe that MOST outperforms FAAN and TeLM in almost all relations, showing its strong robustness over different sparse relations in one-shot TKG interpolated LP. From Table V, we observe that MOST also shows strong robustness in one-shot TKG extrapolated LP by outperforming FAAN and xERTE in most sparse relations.

E. Performance over Different Support-Query Time Differences

We compare MOST with several strong baselines regarding the performance over different support-query time differences. We choose to compare with TeLM, xERTE and FAAN due to the reasons explained in Section V-D. For each sparse
relation $r$ in the meta-test set, we compute the time difference between the support timestamp $t_0$ and every query timestamp $t_q$. We want to study whether our model is robust to different $|t_q - t_0|$ by plotting the performance of MOST and the selected baseline methods according to the test quadruples with different values of $|t_q - t_0|$ (Fig. 4). Since the test quadruples are all associated to sparse relations, the number of test quadruples who share the same value of $|t_q - t_0|$ is prone to be small. Thus, following [15], we aggregate every 140 hours for ICEWS-one_int by combining each model’s performance over the test quadruples whose $|t_q - t_0|$ lie within each time interval (140 hours) to form a point in the plot representing each model’s overall test performance over them. For example, the first orange point from the left in Fig. 4a represents the overall performance of FAAN over the test quadruples whose $|t_q - t_0|$ lie within 0 and 140 hours. Similarly, we aggregate every 24 hours for ICEWS-one_ext. For GDELT-based datasets, we aggregate every 40 hours on GDELT-one_int and every 6 hours on GDELT-one_ext. We ensure that the original model performance is reported to plot Fig. 4 and every model’s performance is aggregated in the same way. From Fig. 4a to 4d, we observe that MOST constantly outperforms FAAN and TeLM on both one-shot TKG interpolated LP datasets. From Fig. 4e to 4h, we find that MOST outperforms FAAN and xERTE in most cases on both one-shot TKG extrapolated LP datasets. To this end, we show that MOST is robust to different support-query time differences $|t_q - t_0|$, indicating the effectiveness of its temporal reasoning components.

VI. CONCLUSION

We extend both TKG interpolated and extrapolated LP tasks to the one-shot scenario, fix the unreasonable task setting employed by previous work, and propose a model learning meta-representations of one-shot relations for solving both tasks (MOST). MOST learns sparse relations’ meta-representations based on the time-aware representations of the entities in the one-shot examples. It further employs a metric function for predicting missing entities from the unobserved TKG facts regarding sparse relations. To overcome the problem brought by previous datasets, we further propose four large-scale datasets for one-shot TKG LP. We compare MOST with recent baselines on our new datasets. Experimental results show that MOST achieves superior performance. MOST is designed only for one-shot learning and cannot be directly used in multi-shot cases, e.g., 3-shot. It is worthwhile to draw attention to the multi-shot scenario of TKG LP over sparse relations in the future.

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