A Simple But Powerful Graph Encoder for Temporal Knowledge Graph Completion

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Abstract

While knowledge graphs contain rich semantic knowledge of various entities and the relational information among them, temporal knowledge graphs (TKGs) further indicate the interactions of the entities over time. To study how to better model TKGs, automatic temporal knowledge graph completion (TKGC) has gained great interest. Recent TKGC methods aim to integrate advanced deep learning techniques, e.g., attention mechanism and Transformer, to boost model performance. However, we find that compared to adopting various kinds of complex modules, it is more beneficial to better utilize the whole amount of temporal information along the time axis. In this paper, we propose a simple but powerful graph encoder TARGCN for TKGC. TARGCN is parameter-efficient, and it extensively utilizes the information from the whole temporal context. We perform experiments on three benchmark datasets. Our model can achieve a more than 42\% relative improvement on GDELT dataset compared with the state-of-the-art model. Meanwhile it outperforms the strongest baseline on ICEWS05-15 dataset with around 18.5\% fewer parameters.

1 Introduction

A Knowledge Graph (KG) is a graph-structured Knowledge Base (KB) which stores relational facts. KGs have drawn increasing research interest since they serve as key drivers for a wide range of downstream tasks in artificial intelligence, e.g., question answering [Zhang et al., 2018], commonsense reasoning [Xing et al., 2021], and recommender systems [Wang et al., 2019]. A fact in a KG is described as a triplet $(s, r, o)$, e.g., (Joe Biden, is president of, USA), where $s$, $o$, $r$ denote the subject entity, the object entity, and the relation between $s$ and $o$, respectively. While KGs contain rich semantic knowledge of entities and the relational information among them, they do not consider the nature of ever-evolving relational facts over time. For example, consider a KG triplet (Donald Trump, is president of, USA). According to world knowledge, this triplet is valid only before Joe Biden took the place of Donald Trump as the president of the USA. This implies a shortcoming of KGs and calls for the introduction of Temporal Knowledge Graphs (TKGs). In TKGs, every fact is augmented with a specific timestamp $t$ such that it can be described with a quadruple $(s, r, o, t)$. In this way, every fact in TKGs has its own time validity and this enables TKGs to capture the factual information in a time-varying context.

Temporal Knowledge Graph Completion (TKGC) is a task aiming to infer the missing facts in TKGs. There exist two lines of TKGC methods. (1) A lot of prior methods attempt to incorporate temporal information into the existing KG reasoning scoring models and build novel time-aware score functions for TKGs [Leblay and Chekol, 2018; García-Durán et al., 2018; Lacroix et al., 2020; Messner et al., 2021]. (2) Another line of models take advantage of the recent progress of Graph Neural Networks (GNNs) [Niepert et al., 2016; Kipf and Welling, 2017] and develop time-aware relational graph encoders for TKGC [Wu et al., 2020; Jung et al., 2021]. Experimental results show that time-aware relational graph encoders help to achieve state-of-the-art performance on TKGC task. However, employing an additional graph encoder on top of the existing KG score functions normally leads to higher number of model parameters. The parameter consumption grows even more when these models are equipped with advanced deep learning structures, e.g. attention mechanism and Transformer [Vaswani et al., 2017].

In this paper, we follow the trend of the second line of methods and propose a time-aware relational graph encoder: Time-aware Relational Graph Convolutional Network (TARGCN). We find that our light-weighted time-aware relational graph encoder performs well on TKGC task, and it requires relatively few parameters. The contribution of our work can be summarized as follows:

- We propose a light-weighted, parameter-efficient TKG reasoning model for TKGC. Our model requires much fewer parameters compared with two recently proposed TKG reasoning models, TeMP [Wu et al., 2020] and T-GAP [Jung et al., 2021], who benefit from their powerful time-aware relational graph encoders. On ICEWS05-15 [García-Durán et al., 2018] dataset, our model beats T-GAP with a 4.78\% relative improvement in performance, but with only around 76\% as many as T-GAP’s parameters.

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2 Preliminaries and Related Work

2.1 Knowledge Graph Embedding Models

Knowledge graph embedding (KGE) models have shown great success in KG reasoning tasks. TransE [Bordes et al., 2013] is the first KGE model that introduces translational embeddings into KG representation learning. Many further works [Lin et al., 2015; Sun et al., 2019; Abboud et al., 2020] are inspired and extend the relational translations in different spaces to capture complex relational information. Another line of KGE methods are tensor factorization-based models [Nickel et al., 2011; Yang et al., 2015; Balazevic et al., 2019]. They encode entity and relation embeddings as vectors and then use bilinear functions to compute the plausibility scores for KG facts. Apart from these two mainstream types of KGE models, neural-based relational graph encoders have been rapidly developed and have shown great power in capturing structural information of KGs. R-GCN [Schlichtkrull et al., 2018] incorporates relation information into a Graph Convolutional Network (GCN) [Kipf and Welling, 2017] to enable relational reasoning on KGs. Recently, CompGCN [Vashishth et al., 2020] extends this idea and leverages a variety of composition operations between KG entities and relations. It shows great effectiveness on KG reasoning tasks.

2.2 Temporal Knowledge Graph Embedding Models

Temporal knowledge graph embedding (TKGE) models can be categorized into several classes according to the temporal information encoding techniques. A series of models treat every timestamp separately and assign a high-dimensional vector as its embedding [Tresp et al., 2017; Leblay and Chekol, 2018; Lacroix et al., 2020]. The assigned timestamp embeddings lie in the same space as entity and relation embeddings. Another series of models assume that every entity has a time-aware embedding which evolves over time [Xu et al., 2019b; Goel et al., 2020]. To achieve time-aware property, an entity together with a timestamp is input into a function (or neural network) to yield a time-aware entity representation at this timestamp. Besides, García-Durán et al. jointly encodes entity, relation and time information with Recurrent Neural Network (RNN) to learn time-aware graph representations [García-Durán et al., 2018]. Instead of modeling timestamp information, some recent models attempt to model time difference, i.e., time displacement, between the query event and known events [Wu et al., 2020; Jung et al., 2021]. It turns out that time displacement modeling can contribute to superior performance on TKG reasoning tasks.

Temporal Knowledge Graph Completion

Let \( E, R \) and \( T \) denote a finite set of entities, relations and timestamps, respectively. A temporal knowledge graph \( G \) is a graph which represents the evolution of interactions among entities over time. At any timestamp \( t \in T \), \( G(t) \) is called the TKG snapshot at \( t \), and it can be taken as a static KG containing the facts valid at \( t \). Any fact, i.e., event, can be described with a quadruple \((s, r, o, t)\), where \( s \in E \) represents the subject, \( o \in E \) represents the object, \( r \in R \) represents the relation between \( s \) and \( o \), and \( t \in T \) indicates the timestamp when this fact is valid. Therefore, at \( t \), the TKG snapshot can be summarized as a finite set of all the valid facts at this timestamp \( t \), i.e., \( G(t) = \{ (s, r, o, t) | s, o \in E, r \in R \} \). We denote a TKG as a sequence of TKG snapshots \( G = \{ G(1), \ldots, G(T) \} \), where \( T = |T| \) is the number of timestamps. Similarly, we can also denote a TKG as a finite set of all valid facts which happen at any timestamp \( t \in T \), i.e., \( G = \{ (s, r, o, t) | s, o \in E, r \in R, t \in T \} \).

We define the TKGC task as follows. For every snapshot \( G(t) \) in an observed TKG \( G = \{ G(1), \ldots, G(T) \} \), it contains all the observed facts at \( t \). Let \( \hat{G}(t) \) denote the set of all the true facts at \( t \) such that \( \hat{G}(t) \subseteq G(t) \). TKGC aims to predict the ground truth object (or subject) entities of queries \((s, r, ?, t)\) (or \((?, r, o, t)\)), where \((s, r, o, t) \in \hat{G}(t)\) but \((s, r, o, t) \notin G(t)\), given any \( t \in T \).

TKGC has recently gained increasing interest. Researchers have paid great attention to better model the temporal information brought by the nature of TKGs. As fancier techniques and advanced deep learning methods, e.g., attention mechanisms and Transformer [Vaswani et al., 2017], being extensively studied, recent TKG reasoning models [Wu et al., 2020; Jung et al., 2021] benefit from them and show great performance on TKGC.

3 Our Method

Figure 1: The encoding process in TARGCN for the query (Angela Merkel, Express intent to meet or negotiate, ?, 2014-10-15).

To solve TKGC task, our relational graph encoder TARGCN extensively collects information from the whole temporal context and update the time-aware representations of entities. For every link prediction query \((s_q, r_q, ?, t_q)\), TARGCN first creates a subgraph for the subject \( s_q \) according to its temporal neighborhood. Then it derives time-aware representations for the neighbors from the temporal neighborhood, and performs aggregation. After \( s_q \)’s time-aware representation is updated, a knowledge graph decoder (score function) is utilized to compute scores for every candidate object, which yields the plausibility of every candidate object being the ground truth object in the link prediction query.
\( (s_q, r_q, ?, t_q) \). Note that we only consider object prediction queries \( (s_q, r_q, ?, t_q) \) in our work since we add reciprocal relations for every quadruple, i.e., adding \( (o, r^{-1}, s, t) \) for every \( (s, r, o, t) \). The restriction to only predict object entities does not lead to a loss of generality. An example is presented in Figure 1 to show the encoding process of our model. For the query subject Angela Merkel appearing at 2014-10-15, TARGCN selects its temporal neighbors with a time difference dependent probability. Node aggregation is then performed to learn a contextualized representation \( h_{(s_q, t_q)} \), where \( s_q, t_q \) correspond to Angela Merkel and 2014-10-15, respectively. In our model, we do not apply any fancy techniques that might greatly increase parameters, e.g., Transformer-based temporal encoder. However, experimental results show that while the number of parameters remains quite low, our light-weighted encoder can still beat state-of-the-art models easily, thus showing a strong parameter-efficiency.

### 3.1 Subgraph Sampling in Temporal Neighborhood

Given a TKGC query \( (s_q, r_q, ?, t_q) \), TARGCN aims to learn a contextualized representation for the subject entity \( s_q \). Inspired by the inference graph proposed in [Han et al., 2020], we sample a Temporal Neighboring Graph (TNG) for \( (s_q, t_q) \) in TKGC context, where \( (s_q, t_q) \) is the node representing \( s_q \) at \( t_q \). We first find out all the temporal neighbors of \( (s_q, t_q) \), which can be described as a set \( N_{(s_q, t_q)} = \{ (e, t) | (e, r, s_q, t) \in G; e \in E, t \in T, r \in R \} \). The entity \( e \) of a temporal neighbor \( (e, t) \) forms a link with \( s_q \) at timestamp \( t \) and \( s_q \) bears an incoming edge derived from the temporal associated quadruple \( (e, r, s_q, t) \). Note that in TKGC, though we cannot observe all the true quadruples, we still can observe part of true quadruples at every timestamp. This enables TARGCN to search for the temporal neighbors of \( (s_q, t_q) \) along the whole time axis from \( t_1 \) to \( t_T \). Then we employ weighted sampling strategy according to the absolute time difference \( |t_q - t(e, t)| \) between \( (s_q, t_q) \) and the corresponding temporal neighbor \( (e, t) \). For every temporal neighbor \( (e, t) \), the probability of it being sampled into \( (s_q, t_q) \)'s TNG is computed by: \( \exp(-|t_q - t|)/\sum_{(e, t) \in N_{(s_q, t_q)}} \exp(-|t_q - t'|) \). In this way, higher probabilities are assigned to the temporal neighbors who are closer to \( (s_q, t_q) \) along the time axis. We adopt this sampling strategy since we assume that for the inference of a fact at \( t_q \), it is more likely to find clues from the factual information at nearer timestamps. Besides, we use a hyperparameter to limit the maximum number of the temporal neighbors included in \( (s_q, t_q) \)'s TNG to prevent over sampling less-concerned temporal neighbors. An example of \( (s_q, t_q) \)'s temporal neighborhood is presented in Figure 2. We can represent it as \( N_{(s_q, t_q)} = \{ (e_1, t_q - 1), (e_2, t_q + 1), (e_3, t_q - 3), (e_4, t_1), (e_5, t_T - 1) \} \). The probability of each temporal neighbor being sampled into \( (s_q, t_q) \)'s TNG is determined according to the time difference between \( t_q \) and the timestamp of this temporal neighbor (the darker the temporal neighbor shows, the higher the probability).

### 3.2 Time-aware Relational Aggregation

After sampling TNG for the subject entity \( s_q \), we then attempt to learn its contextualized representation. Since we have access to temporal neighbors from the whole timeline, we implicitly incorporate temporal information. For every temporal neighbor, we employ the functional time encoding method proposed in [Xu et al., 2020] to learn a time-aware node representation. In this way, we are able to distinguish the temporal neighbors, \( (e, t) \) and \( (e, t') \), who root from the same entity \( e \) but emerge at different timestamps \( t \) and \( t' \). The time-aware node representation is computed as:

\[
\text{h}_{(e, t)} = f(\text{h}_e \| K(t, t_q)),
\]

where \( \text{h}_e \in \mathbb{R}^{d_e} \) denote the time-invariant entity-specific representation of the entity \( e \). \( K(\cdot, \cdot) \) is a kernel mapping the time difference \( t - t_q \) to a finite dimensional functional space \( \mathbb{R}^{d_k} \). We concatenate the time-invariant entity embedding with its corresponding time difference embedding, and learn a combined representation of them with a layer of feed-forward neural network \( f \). Note that the sign of \( t - t_q \) will affect the output of the time difference encoding module.

We aggregate the information from \( (s_q, t_q) \)'s temporal neighbors with a relational graph aggregator:

\[
\text{h}_{(s_q, t_q)} = \frac{1}{|N_{(s_q, t_q)}|} \sum_{(e, t) \in N_{(s_q, t_q)}} W(\text{h}_{(e, t)} | \text{h}_e).
\]

\( N_{(s_q, t_q)} \) denotes a finite set of temporal neighbors sampled from \( (s_q, t_q) \)'s temporal neighborhood, i.e., all the neighbors in \( (s_q, t_q) \)'s TNG. \( r \) is the relation appearing in the temporal associated quadruple \( (e, r, s_q, t) \) where temporal neighbor \( e \) is sampled. We assume relation representations are time-invariant and we incorporate relational information into the graph encoder by concatenating time-aware node representation with them. Our graph encoder outputs the time-aware representation of \( s_q \) at query time \( t_q \), by combining not only the raw entity representation \( h_e \), but also the implicit time difference information from its temporal neighbors. Prior work T-GAP also pays attention to modeling time displacement, i.e., time difference, to better learn time-aware entity representations. However, T-GAP explicitly models time displacement with a discretized embedding, and it includes three different weight matrices in their graph encoder for the facts happening in the past, at present or in the future, thus increasing parameter consumption. We will discuss this later and compare its efficiency with our model.

### 3.3 Learning and Inference

Figure 3 illustrates how TARGCN, together with a KG score function, i.e., Distmult [Yang et al., 2015], predicts the ground truth missing object for the TKGC query \( (s_q, r_q, ?, t_q) \). Given \( s_q \), we use the sampling strategy and our time-aware relational graph encoder to compute a time dependent node representation for \( (s_q, t_q) \). Then we use a simple KG score function Distmult to compute the plausibility of every candidate entity. We choose Distmult because it does not introduce additional parameters, which encounters our flavor of building a parameter-efficient TKGC model. Note that for
the candidate entities, we do not sample TNG for them to avoid huge time consumption during inference. Instead, for every candidate entity $e$, we simply derive its time-aware representation by computing $h_{(e,t_q)} = f(h_e || \mathcal{K}(t_q,t_q))$. The time encoding kernel $\mathcal{K}$ will also return a time representation of all entities for score computation. The entity producing highest score is selected as the predicted answer.

We employ cross entropy-loss for parameter learning:

$$
\mathcal{L} = \sum_{(s,r,o,t) \in \mathcal{G}} -\log \left( \frac{\text{score}(\hat{h}_{(s,t)}, \hat{h}_r, h_{(o',t)})}{\sum_{o' \in \mathcal{G}} \text{score}(\hat{h}_{(s,t)}, \hat{h}_r, h_{(o',t)})} \right),
$$

(3)

where $o'$ denotes all candidate entities and we sum over all observed quadruples in $\mathcal{G}$. Note that our TARGCN encoder can be equipped with any KG score functions since our encoder returns time-aware representations for entities. In our work, $\text{score}(\hat{h}_{(s,t)}, \hat{h}_r, h_{(o',t)}) = \langle \hat{h}_{(s,t)}, \hat{h}_r, h_{(o',t)} \rangle$.

4 Experiments

We evaluate our model on three TKGC benchmark datasets. We compare our model’s performance with several existing TKGC methods. To further show the parameter efficiency of our model, we do an analysis on parameter usage of our model, compared with two recent proposed powerful TKGC models TeMP [Wu et al., 2020] and T-GAP [Jung et al., 2021].

4.1 Experimental Setup

Datasets

We perform evaluation on three TKGC benchmark datasets: (1) ICEWS14 [García-Durán et al., 2018] (2) ICEWS05-15 [García-Durán et al., 2018] (3) GDELT [Leetaru and Schrodt, 2013]. ICEWS14 and ICEWS05-15 are two subsets of Integrated Crisis Early Warning System (ICEWS) database. ICEWS14 contains timestamped political facts happening in 2014, while the timestamps of factual events in ICEWS05-15 span from 2005 to 2015. We follow [Wu et al., 2020] and use the GDELT subset proposed by [Trivedi et al., 2017]. It contains facts from April 1, 2015 to March 31, 2016. The detailed dataset statistics is presented in Table 1.

| Dataset          | $N_{\text{train}}$ | $N_{\text{valid}}$ | $N_{\text{test}}$ | $|V|$ | $|K|$ | $N_{\text{obs}}$ |
|------------------|-------------------|--------------------|-------------------|------|------|----------------|
| ICEWS14          | 72,826            | 8,941              | 8,963             | 90   | 730  | 230,365       |
| ICEWS05-15       | 386,962           | 46,275             | 46,092            | 10,488 | 4017  | 500,366       |
| GDELT            | 2,735,085         | 341,961            | 341,961           | 500  | 20   | 20,366        |

Table 1: Dataset statistics. $N_{\text{train}}$, $N_{\text{valid}}$, $N_{\text{test}}$ represent the number of quadruples in the training set, validation set, and test set, respectively. $N_{\text{obs}}$ denotes the number of observations, where we take a snapshot of the TKG at each observation.

Evaluation Metrics

We employ two evaluation metrics for all experiments, i.e., Hits@1/3/10 and Mean Reciprocal Rank (MRR). For every test fact $(s_q, r_q, o_q, t_q) \in \mathcal{G}$, we derive an associated TKGC query $(s_q, r_q, ?, t_q)$. We let models compute the rank of the ground truth entity $o_q$ among all the
candidates. Hits@1/3/10 are the proportions of the test facts where ground truth entities are ranked as top 1, top 3, top 10, respectively. MRR computes the mean of the reciprocal setting proposed by [Bordes et al., 2013] to achieve fairer evaluation.

Baseline Methods
We take fifteen methods as baseline models. The first four baselines are static KG reasoning methods, i.e., TransE [Bordes et al., 2013], Distmult [Yang et al., 2015], ComplEx [Trouillon et al., 2016] and SimplE [Kazemi and Poole, 2018]. The other methods are developed to solve TKGC, including TTransE [Leblay and Chekol, 2018], TA-Distmult [García-Durán et al., 2018], HyTE [Dasgupta et al., 2018], DE-SimplE [Goel et al., 2020], AtiSER [Xu et al., 2019a], TNTComplEx [Lacroix et al., 2020], ChronoR [Sadeghian et al., 2021], TelM [Xu et al., 2021], BoxTE [Messner et al., 2021], TeMP [Wu et al., 2020] and T-GAP [Jung et al., 2021]. Among all baselines, only TeMP and T-GAP employ GNNs as graph encoders, similar to our TARGCN setting. Therefore, we further compare the parameter efficiency among these three models.

4.2 Experiment Results
Table 2 reports the experiment results of all methods on three benchmark datasets. We can observe that TARGCN outperforms all baselines on all datasets. The margin is particularly huge on GDELT dataset. TARGCN achieves an over 42% relative improvement on MRR (0.150 absolute improvement) compared with state-of-the-art method BoxTE. TARGCN also leads in Hits metrics greatly. It improves Hits@1/3/10 by 0.141, 0.168 and 0.167, respectively. On ICEWS datasets, though TARGCN does not take a huge step forward, it still achieves best results on MRR. TARGCN also shows particularly strong performance on Hits@1, which can be taken as the main contribution to its superior results on MRR.

We argue that the performance gap varies because of the characteristics of different datasets. While ICEWS datasets are more sparse, GDELT is much denser. As shown in [Wu et al., 2020], the temporal variability in ICEWS is much larger than in GDELT. This implies that GDELT contains substantially more temporal patterns, while ICEWS datasets are more prone to be biased by a large number of isolated events, which are mainly dominated by sparse entities and relations. Hence, we argue that reasoning on GDELT requires much stronger techniques, and this can also be deduced by the performance of TKGC models. From Table 2, we can observe that for prior models, though several TKGC methods outperform static methods on GDELT, the improvements are not substantial (TTransE, TA-Distmult and HyTE perform even worse than ComplEx). However, on GDELT, TARGCN achieves a 136% relative improvement on MRR, compared with the strongest static KG baseline ComplEx. This shows the superior effectiveness of our time-aware relational graph encoder in capturing various temporal patterns. For ICEWS datasets, our model can also achieve state-of-the-art performance. This demonstrates its strong ability in capturing the temporal KG information brought by sparse entities and relations.

4.3 Parameter Efficiency Analysis
While TARGCN serves as a strong TKGC model, it also preserves a quite low parameter cost. In this Section, we compare the parameter efficiency of TARGCN with two recently proposed GNN-based TKGC models, i.e., TeMP and T-GAP. For our model, we adjust the embedding size of both entities and relations to keep the number of parameters lower than that in TeMP and T-GAP.

In Figure 4, we show that TARGCN performs better as we increase the embedding size of entities and relations (increase model parameters). More importantly, even with much fewer parameters, TARGCN still outperforms TeMP and T-GAP on ICEWS14.

For ICEWS05-15 and GDELT, we summarize the number of parameters as well as performance difference in Table 3. We compare across the models with parameter settings that leads to the experiment results shown in Table 2. On ICEWS05-15, T-GAP uses 30.89% more parameters than our model, but its performance drops by 4.56%. TeMP-GRU achieves almost same result as TARGCN on ICEWS05-15, however, it uses 18.45% more parameters than our model. Fewer parameters are used in TeMP-SA, but it also leads to worse performance. On GDELT, we observe that though TeMP-GRU employs 50.07% more parameters than TARGCN, its performance is 45.33% lower than our model. TeMP-SA shows worse performance (with a 53.88% performance drop), although it has even 5.19% fewer parameters than TARGCN. To this end, we argue that our model is extremely parameter-efficient.

We attribute such high parameter efficiency to our simple but powerful time-aware relational graph encoder. Note that in the TNG sampling process, we explicitly force our model to choose the temporal neighbors who are nearer to the source node on the time axis, by assigning higher sampling probabilities to them. This can also be interpreted as a "hard-coded attentional process". Models like TeMP and T-GAP explicitly employ self-attention modules to let models choose their attention themselves through parameter learning. We argue that even if such modules are powerful, it can be simplified in the context of TKGC. In our model, we force our TNG sampler to focus on the facts happening at time which is closer to the query timestamp, i.e., pay more “attention” to the nearest facts. Our TNG sampling process does not include any additional parameters, while self-attention modules normally increase parameters and bring heavier burdens for parameter optimization.

Another crucial point is that, compared with TeMP who encodes temporal information only from a fixed short time span of $2\tau$, our TNG sampling range spans across the whole timeline. This means that even if a temporal neighbor is derived from a sparse entity and it appears only at far-away timestamps from the query timestamp, our sampler still has the ability to include it into the TNG and enables information aggregation. Similar to TARGCN, T-GAP, with the help of its Preliminary GNN (PGNN), is able to find any temporal associated quadruples related to any entity appearing at any time. However, in its PGNN, it employs three weight matrices, i.e. $W_{past}$, $W_{present}$, $W_{future}$ together with time-displacement embeddings $h_{\Delta t}$ to fully express the supporting factual information coming from the past, the present and
the future. We find it redundant to utilize three matrices in a relational graph encoder. In TARGCN, we use a functional time encoding kernel such that whatever the time difference’s sign is (minus for neighbors happening after query timestamp, opposite for plus), we can directly output a unique time difference representation. And we do not have to use three separate weight matrices in our graph encoder, thus cutting parameter consumption.

5 Conclusion

We propose a simple but powerful time-aware relational graph encoder TARGCN for *Temporal Knowledge Graph Completion* (TKGC). TARGCN employs a *Temporal Neigh-boring Graph* (TNG) sampling strategy, which enables it to extensively utilize the information from the whole temporal context. Experiment results show that TARGCN achieves state-of-the-art performance on three benchmark TKGC datasets, including a more than 42% relative improvement on GDELT dataset compared with the strongest baseline. Besides, TARGCN enjoys an extremely high parameter efficiency. It beats two recently proposed strong GNN-based TKGC methods, i.e. TeMP and T-GAP, with much fewer parameters. We find that it is not always necessary to incorporate complex modules, e.g., Transformer, into TKG reasoning models. Instead, developing methods to capture more extensive temporal information may be more beneficial.

Table 2: Temporal knowledge graph completion results on three benchmark datasets. Evaluation metrics are filtered MRR and Hits@1/3/10. The best results are marked in bold. Results marked with [▼], [★], [♥] are taken from [Wu et al., 2020], [Jung et al., 2021], [Messner et al., 2021], respectively.

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