

TempoQR: Temporal Question Reasoning over Knowledge Graphs

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Abstract

Knowledge Graph Question Answering (KGQA) involves retrieving facts from a Knowledge Graph (KG) using natural language queries. A KG is a curated set of facts consisting of entities linked by relations. Certain facts include also temporal information forming a Temporal KG (TKG). Although many natural questions involve explicit or implicit time constraints, question answering (QA) over TKGs has been a relatively unexplored area. Existing solutions are mainly designed for simple temporal questions that can be answered directly by a single TKG fact. This paper puts forth a comprehensive embedding-based framework for answering complex questions over TKGs. Our method, called temporal question reasoning (TempoQR), exploits TKG embeddings to ground the question to the specific entities and time scope it refers to. It does so by augmenting the question embeddings with context, entity and time-aware information via three specialized modules. The first computes a textual representation of a given question, the second combines it with the entity embeddings for entities involved in the question, and the third generates question-specific time embeddings. Finally, a transformer-based encoder learns to fuse the generated temporal information with the question representation, which is used for answer predictions. Extensive experiments show that TempoQR improves accuracy by 25–45 percentage points on complex temporal questions over state-of-the-art approaches and it generalizes better to unseen question types.

Introduction

A knowledge graph (KG) is a set of facts that are known to be true in the world or in a specific domain. The facts are usually represented as tuples (subject, relation, object), where the subject and object correspond to KG entities. Certain KGs include additional attributes such as temporal information forming a temporal knowledge graph (TKG). In TKGs, each fact is associated with a timestamp or time interval, and is represented as (subject, relation, object, timestamp) or (subject, relation, object, [start.time, end.time]), respectively.

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Knowledge Graph Question Answering (KGQA) attempts to answer a natural question using the KG as a knowledge base (Lan et al. 2021). Natural questions often include temporal constraints, e.g., “Which movie won the Best Picture in 1973?” and to aid temporal question answering, TKGs are utilized. The first step is to identify and link the entities, relations and timestamps of the questions to the corresponding ones in the TKG, e.g., “Which movie won the Best Picture in 1973?” to (Best Picture, WonBy, ?, 1973). This problem is known as entity linking (Kolitsas, Ganea, and Hofmann 2018).

Recently, (Saxena, Chakrabarti, and Talukdar 2021) proposed CronKGQA that solves QA over TKGs by leveraging TKG embedding methods, e.g., TComplEx (Lacroix, Obozinski, and Usunier 2020). TKG embedding methods learn low-dimensional embeddings for the entities, relations and timestamps by minimizing a link prediction objective attuned at completing facts of the form (subject, relation, ?, timestamps) and (subject, relation, object, ?). CronKGQA answers the mapped question (Best Picture, WonBy, ?, 1973) as a link prediction task over the TKG. CronKGQA performs very well on simple questions that are answerable by a single TKG fact (Hits@1 of 0.988). However, on more complex questions, that involve additional temporal constraints and require information from multiple TKG facts (e.g., “Which movie won the Best Picture after The Godfather?”), CronKGQA performs poorly (Hits@1 of 0.392).

To effectively handle both simple and complex temporal questions, we design a new method called temporal question reasoning (TempoQR). TempoQR exploits TKG embeddings to ground the question to the specific entities and time scope the question refers to. To illustrate the key idea of our approach, consider the question “Which movie won the Best Picture after The Godfather?” which involves the TKG entities ‘Best Picture’ and ‘The Godfather’. The high-level approach of TempoQR is shown in Figure 1. The first reasoning step is to understand the context of the question (context-aware step). The context of the question here involves a movie (“Which movie...”). The next step is to ground the question to the entities it refers to (entity-aware step). The question refers to a movie that has won the Best Picture. Finally, the question needs to be grounded with cer-

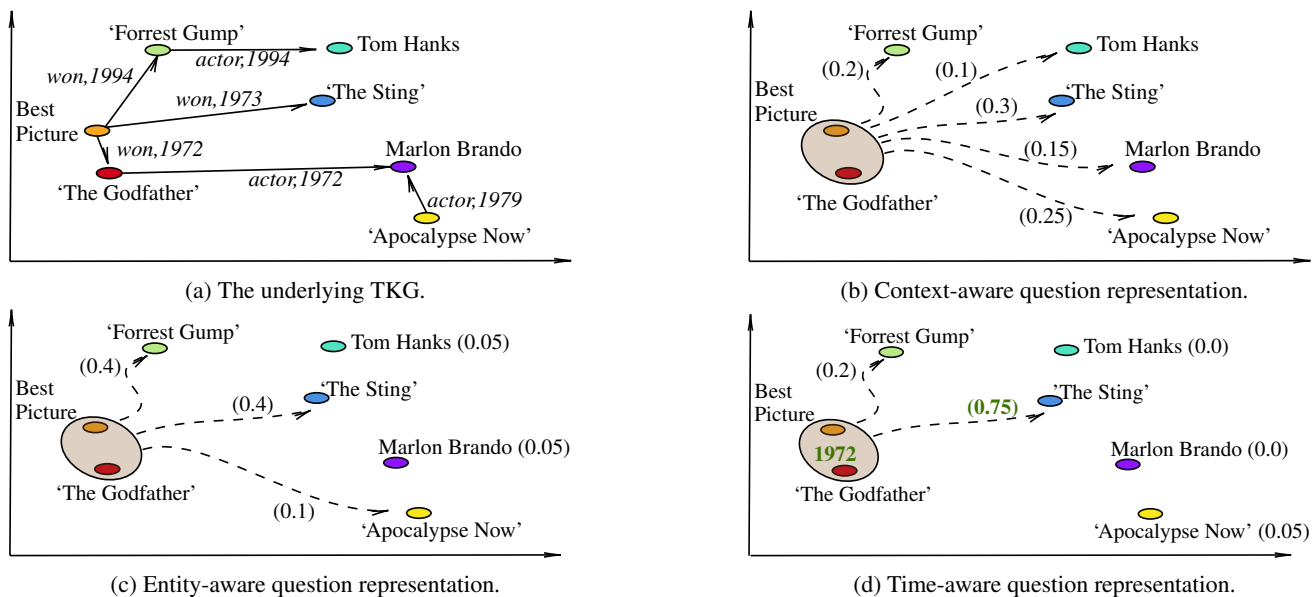


Figure 1: (a) The underlying TKG for the question “Which movie won the Best Picture after The Godfather?”; Answer: ‘The Sting’. (b) The context-aware question representation (dashed arrows) scores higher (numbers in parentheses) movie entities. (c) The representation is grounded to the entity ‘Best Picture’ and gives higher scores to movies that won the Best Picture. (d) The representation is grounded to the correct time scope (after year 1972) and gives higher scores to the movies that won the Best Picture after 1972, i.e., ‘The Sting’.

tain temporal constraints (time-aware step). The movie won the Best Picture after The Godfather, i.e., after 1972.

TempoQR performs the above reasoning steps using three specialized modules. First, it uses the question’s text to generate a representation of the question by employing a language model (LM). Next, it fuses the text-derived representations with KG entity representations to ground the question to the entities it refers to. Third, it extracts from the TKG question-specific temporal information to enhance the question’s representation with two complementary approaches. The first *retrieves* the relevant information from the underlying TKG based on the annotated entities of the question. The second *infers* temporal information by solving a link prediction problem obviating the need to access the TKG. A dedicated information fusion layer combines the context, entity and time-aware information together to a final question representation. We empirically show that TempoQR is able to model temporal constraints of the question and outperforms other time-unaware methods for complex questions (25–45 percentage points improvement at Hits@1). Our contributions are summarized below:

- We solve complex temporal question answering by learning context, entity and time-aware question representations.
- We develop two different approaches to recover question-specific temporal information.
- We achieve state-of-the-art performance on temporal complex questions and provide additional strong baselines.

Related Work

KGQA approaches typically leverage KG pre-trained embeddings (Bordes et al. 2013; Yang et al. 2014; Trouillon et al. 2017) to answer the questions (Saxena, Tripathi, and Talukdar 2020). Such approaches perform well for simple questions that can be easily mapped to incomplete facts in the KG but are challenged by complex questions.

Addressing the limitations of the aforementioned approaches, (Miller et al. 2016; Xu et al. 2019; Zhou, Huang, and Zhu 2018; Qiu et al. 2020; He et al. 2021) enhance the question representation to address complex questions. Such methods employ logical reasoning (Miller et al. 2016; Xu et al. 2019; Zhou, Huang, and Zhu 2018; Qiu et al. 2020; He et al. 2021) or leverage available side information in the form of text documents (Sun et al. 2018; Sun, Bedrax-Weiss, and Cohen 2019; Xiong et al. 2019; Han, Cheng, and Wang 2020). Nevertheless, these approaches are not suited for handling temporal constraints.

TempQuestions (Jia et al. 2018a) was introduced to benchmark the reasoning capabilities of existing with temporal constraints. Recently, additional benchmarks have been developed (Jin et al. 2021; Souza Costa, Gottschalk, and Demidova 2020; Chen, Wang, and Wang 2021; Neelam et al. 2021) that model temporal information in various domains (including both KG and text data). (Jia et al. 2018b) and (Jia et al. 2021) are methods that tackle the temporal QA problem over KGs. However, they mostly employ hand crafted rules to handle temporal information which is not flexible for incomplete KGs. By leveraging TKG embeddings, CronKGQA (Saxena, Chakrabarti, and Talukdar 2021) provides a learnable reasoning process for temporal

KGQA, which does not rely on hand-crafted rules. Although CronKGQA performs extremely well for answering simple questions, it is challenged by complex questions that require inference of certain temporal constraints. Our work is motivated by this limitation.

Background

A TKG $\mathcal{K} := (\mathcal{E}, \mathcal{R}, \mathcal{T}, \mathcal{F})$ contains a set of entities \mathcal{E} , a set of relations \mathcal{R} , a set of timestamps \mathcal{T} , and a set of facts \mathcal{F} . Each fact $(s, r, o, \tau) \in \mathcal{F}$ is a tuple where $s, o \in \mathcal{E}$ denote the subject and object entities, respectively, $r \in \mathcal{R}$ denotes the relation between them, and $\tau \in \mathcal{T}$ is the timestamp associated with that relation.

TKG Embeddings

Given a TKG $\mathcal{K} = (\mathcal{E}, \mathcal{R}, \mathcal{T}, \mathcal{F})$, TKG embedding methods typically learn D -dimensional vectors $\mathbf{e}_\epsilon, \mathbf{v}_r, \mathbf{t}_\tau \in \mathbb{R}^D$ for each $\epsilon \in \mathcal{E}$, $r \in \mathcal{R}$ and $\tau \in \mathcal{T}$. These embedding vectors are learned such that each valid fact $(s, r, o, \tau) \in \mathcal{F}$ is scored higher than an invalid fact $(s', r', o', \tau') \notin \mathcal{F}$ through a scoring function $\phi(\cdot)$, i.e., $\phi(\mathbf{e}_s, \mathbf{v}_r, \mathbf{e}_o, \mathbf{t}_\tau) > \phi(\mathbf{e}_{s'}, \mathbf{v}_{r'}, \mathbf{e}_{o'}, \mathbf{t}_{\tau'})$. Please see (Kazemi et al. 2020) for notable TKG embedding methods.

TComplEx (Lacroix, Obozinski, and Usunier 2020) is an extension of the ComplEx (Trouillon et al. 2017) KG embedding method designed for TKGs. TComplEx represents the embeddings as complex vectors in $\mathbb{C}^{D/2}$ and the scoring function $\phi(\cdot)$ is given by

$$\phi(\mathbf{e}_s, \mathbf{v}_r, \bar{\mathbf{e}}_o, \bar{\mathbf{t}}_\tau) = \text{Re}(\langle \mathbf{e}_s, \mathbf{v}_r \odot \mathbf{t}_\tau, \bar{\mathbf{e}}_o \rangle) \quad (1)$$

where $\text{Re}(\cdot)$ denotes the real part, $\bar{(\cdot)}$ is the complex conjugate of the embedding vector and \odot is the element-wise product.

TComplEx employs additional regularizers to improve the quality of the learned embeddings such as enforcing close timestamps to have similar embeddings (closeness of time). The embedding learning procedure makes TComplEx a suitable method for inferring missing facts such as $(s, r, ?, t)$ and $(s, r, o, ?)$ over an incomplete TKG. Throughout the manuscript, we generate TKG embeddings via TComplEx due to its aforementioned benefits.

Type	Example Questions
Simple Time	<i>When did $\{\text{Stoke}\}_s$ have $\{\text{Tom Holford}\}_o$ in their team</i>
Simple Entity	<i>Which movie won the $\{\text{Best Picture}\}_s$ in $\{1973\}_\tau$</i>
Before/After	<i>Which movie won the $\{\text{Best Picture}\}_s$ after $\{\text{The Godfather}\}_o$</i>
First/Last	<i>Name the award that $\{\text{Sydney Chapman}\}_s$ first received</i>
Time Join	<i>Name a teammate of $\{\text{Thierry Henry}\}_s$ in $\{\text{Arsenal}\}_o$</i>

Table 1: Different types of temporal questions. $\{\cdot\}_s$, $\{\cdot\}_o$, and $\{\cdot\}_\tau$ correspond to annotated entities/times.

QA Over TKGs

Given a TKG $\mathcal{K} = (\mathcal{E}, \mathcal{R}, \mathcal{T}, \mathcal{F})$ and a natural language question q , the task of QA over a TKG (TKGQA) (Saxena, Chakrabarti, and Talukdar 2021) is to extract an entity $e' \in \mathcal{E}$ or a timestamp $\tau' \in \mathcal{T}$ that correctly answers the question q . The entities $\epsilon \in \mathcal{E}$ and timestamps $\tau \in \mathcal{T}$ of the question are annotated, i.e., linked to the TKG. Please refer to Table 1 for examples of such questions.

Note that a question, e.g., “Which movie won the Best Picture in 1973”, could be answerable by a single TKG fact, i.e., (Best Picture, WonBy, The Sting, 1973). Thus, a common solution for TKGQA is to infer the relation ‘WonBy’ by the question’s context and solve the problem as link prediction, i.e., (Best Picture, q , ?, 1973).

CronKGQA (Saxena, Chakrabarti, and Talukdar 2021) is a typical method that solves TKGQA as a link prediction task. The idea is to use the question as a ‘virtual relation’ in the scoring function $\phi(\cdot)$.

Suppose s and τ are respectively the annotated subject and timestamp in a given question (e.g., ‘Best Picture’ and ‘1973’) and o^* is the correct answer (e.g., ‘The Sting’). CronKGQA learns a question representation \mathbf{q} such that $\phi(\mathbf{e}_s, \mathbf{q}, \mathbf{e}_{o^*}, \mathbf{t}_\tau) > \phi(\mathbf{e}_s, \mathbf{q}, \mathbf{e}_{o'}, \mathbf{t}_\tau)$ for all incorrect entities $o' \neq o^*$, where $\mathbf{e}_s, \mathbf{e}_{o^*}, \mathbf{e}_{o'}$, and \mathbf{t}_τ are pre-trained TKG embeddings, e.g., with TComplEx. Note that if either s or τ is not present in the question, a random one from the TKG (dummy) is used. The methodology is modified accordingly when the answer is a timestamp τ^* by giving the maximum score to $\phi(\mathbf{e}_s, \mathbf{q}, \mathbf{e}_o, \mathbf{t}_{\tau^*})$, where τ^* is the correct timestamp and s, o are the annotated subject and object.

CronKGQA is designed for simple temporal questions that can be transformed to link predictions over TKGs. This limits the applicability of CronKGQA to more complex questions that involve additional temporal constraints, e.g., ‘Before/After’, ‘First/Last’ and ‘Time Join’ questions of Table 1. This is confirmed by the experiments presented in (Saxena, Chakrabarti, and Talukdar 2021), where CronKGQA achieves a 65% performance improvement over non-TKG embedding methods for simple questions, but only a 15% improvement for complex questions as the ones here.

Method: TempoQR

TempoQR leverages pre-trained TKG embeddings of entities and timestamps that encode their temporal properties, i.e., TComplEx. Although TKG embeddings are designed for simple questions, our method overcomes this shortcoming by incorporating additional temporal information in the question representation \mathbf{q} to better handle constraints. We design TempoQR by following the human reasoning steps to answer temporal questions; see also Figure 1. In the following subsections, we describe in detail the architecture of TempoQR.

Context-aware Question Representation.

Given a question’s text, we use pre-trained LMs, e.g., BERT (Devlin et al. 2019), to encode the question’s context into an embedding vector. The [CLS] token is inserted into

the question, e.g., “[CLS] Which movie won the Best Picture after The Godfather?”, which is transformed to a tokenized vector \mathbf{q}_0 . Then, we compute a representation for each token as

$$\mathbf{Q}_B = \mathbf{W}_B \text{BERT}(\mathbf{q}_0), \quad (2)$$

where $\mathbf{Q}_B := [\mathbf{q}_{B_{\text{CLS}}}, \mathbf{q}_{B_1}, \dots, \mathbf{q}_{B_N}]$ is a $D \times N$ embedding matrix where N is the number of tokens and D are the dimensions of the TKG embeddings. \mathbf{W}_B is a $D \times D_B$ learnable projection matrix where D_B is the output the dimension of the LM ($D_B = 768$ for BERT(\cdot)).

Entity-aware Question Representation.

We utilize the TKG entity embeddings to ground the question to the specific entities it involves. Inspired by other approaches (Zhang et al. 2019; Févry et al. 2020) that compute entity-aware text representations, we replace the token embeddings of the entities and timestamps of \mathbf{Q}_B with their pre-trained TKG embeddings. Specifically, the i th column of the entity-aware token embedding matrix \mathbf{Q}_E is computed as

$$\mathbf{q}_{E_i} = \begin{cases} \mathbf{W}_E \mathbf{e}_\epsilon, & \text{if token } i \text{ is linked to an entity } \epsilon, \\ \mathbf{W}_E \mathbf{t}_\tau, & \text{if token } i \text{ is linked to a timestamp } \tau. \\ \mathbf{q}_{B_i}, & \text{otherwise,} \end{cases} \quad (3)$$

where \mathbf{W}_E is a $D \times D$ learnable projection. As a result, the token embedding matrix $\mathbf{Q}_E := [\mathbf{q}_{E_{\text{CLS}}}, \mathbf{q}_{E_1}, \dots, \mathbf{q}_{E_N}]$ incorporates additional entity information from the TKG. This enriches the question with entity information from the TKG.

Time-aware Question Representation.

A question may refer to a specific time scope which the answer needs to be associated, e.g., “after The Godfather” refers to “after 1972”. We develop two alternatives that recover such temporal information. The first approach *retrieves* the question-specific time scope from the TKG based on the annotated entities. We call this approach *hard-supervised*, since it accesses available facts in the TKG. The second approach *infers* question-specific temporal information based on the question’s representation. We term this approach *soft-supervised*, since it may recover missing temporal facts by operating in the embedding space.

Hard Supervision: We utilize the annotated entities of the question to retrieve the relative time scope from the underlying TKG. For the example question “Which movie won the Best Picture after The Godfather?”, the entities ‘Best Picture’ and ‘The Godfather’ appear together in a TKG fact with timestamp 1972. Hence, the time embedding of 1972 can be utilized to further enhance the question representation.

First, we identify all facts that involve the annotated entities of the question. These facts involve specific timestamps which we collect together (retrieved timestamps). In some cases, we may retrieve multiple timestamps, but we only keep the *start* and *end* timestamps after we sort them (since we aim at recovering a question-specific time scope). We recover two temporal embeddings \mathbf{t}_1 and \mathbf{t}_2 that correspond

to the TKG embedding for start and end timestamps, respectively. We term this method TempoQR-Hard.

Soft Supervision: Instead of retrieving timestamps from the TKG, we may directly obtain time embeddings by utilizing ϕ to infer missing temporal information. We generate a time-aware question embedding \mathbf{q}_{time} as

$$\mathbf{q}_{\text{time}} = \mathbf{W}_T \mathbf{q}_{B_{\text{CLS}}}, \quad (4)$$

where $\mathbf{q}_{B_{\text{CLS}}}$ corresponds to the [CLS] token embedding of \mathbf{Q}_B and \mathbf{W}_T is a $D \times D_B$ learnable projection matrix. The time-aware \mathbf{q}_{time} is used as a ‘virtual relation’ in the scoring function ϕ . TComplex assigns a score to a timestamp τ that potentially completes a fact $(s, r, o, ?)$ as

$$\langle \text{Re}(\mathbf{e}_s) \odot \text{Re}(\mathbf{u}_{ro}) - \text{Im}(\mathbf{e}_s) \odot \text{Im}(\mathbf{u}_{ro}), \text{Re}(\mathbf{t}_\tau) \rangle + \langle \text{Re}(\mathbf{e}_s) \odot \text{Im}(\mathbf{u}_{ro}) + \text{Im}(\mathbf{e}_s) \odot \text{Re}(\mathbf{u}_{ro}), \text{Im}(\mathbf{t}_\tau) \rangle, \quad (5)$$

where $\mathbf{u}_{ro} = \mathbf{v}_r \odot \bar{\mathbf{e}}_o$. Thus, the real $\text{Re}(\cdot)$ and imaginary $\text{Im}(\cdot)$ part of the time embedding \mathbf{t}_τ can be approximated by

$$\begin{aligned} \text{Re}(\mathbf{t}_\tau) &\approx \text{Re}(\mathbf{e}_s) \odot \text{Re}(\mathbf{u}_{ro}) - \text{Im}(\mathbf{e}_s) \odot \text{Im}(\mathbf{u}_{ro}), \\ \text{Im}(\mathbf{t}_\tau) &\approx \text{Re}(\mathbf{e}_s) \odot \text{Im}(\mathbf{u}_{ro}) + \text{Im}(\mathbf{e}_s) \odot \text{Re}(\mathbf{u}_{ro}). \end{aligned} \quad (6)$$

We follow the same computations to infer the real and imaginary part of the desired (soft-supervised) time embeddings. Here, we treat \mathbf{q}_{time} as a relation embedding \mathbf{v}_r and the annotated entities as subject s and object o interchangeably to generate \mathbf{t}_1 and \mathbf{t}_2 , respectively. If either s or o is not present, we use dummy ones. We term this method TempoQR-Soft.

Note here that the difference of hard and soft supervision relies on the available facts given during QA, i.e., access to the TKG. Moreover, soft-supervision may generalize better since it infers the temporal information in the embedding space. In Section (), we demonstrate the benefits and limitations of each approach.

Fusing Temporal Information: After obtaining time embeddings \mathbf{t}_1 and \mathbf{t}_2 , we leverage them to enhance the question representation with temporal information. Specifically, we compute the i th column of the time-aware token embedding matrix \mathbf{Q}_T as

$$\mathbf{q}_{T_i} = \begin{cases} \mathbf{q}_{E_i}, & \text{if token } i \text{ is not an entity,} \\ \mathbf{q}_{E_i} + \mathbf{t}_1 + \mathbf{t}_2, & \text{if token } i \text{ is an entity.} \end{cases} \quad (7)$$

with $\mathbf{Q}_T := [\mathbf{q}_{T_{\text{CLS}}}, \mathbf{q}_{T_1}, \dots, \mathbf{q}_{T_N}]$. Our intuition for summing the entity and time embeddings together follows the motivation of how transformer-based LMs, e.g., BERT use positional embedding for tokens (Vaswani et al. 2017). Here, time embeddings can be seen as entity positions in the time dimension. \mathbf{Q}_T contains text, entity and time-aware information. Next, we propose an information fusion layer to combine this information altogether into a single question representation \mathbf{q} .

Answer Prediction

Following (Févry et al. 2020), we use an information fusion layer that consists of a dedicated learnable encoder $f(\cdot)$ which consists of l Transformer encoding layers (Vaswani et al. 2017). This encoder allows the question’s tokens to

attend to each other, which fuses context, entity and time-aware information together. The final token embedding matrix \mathbf{Q} is calculated as

$$\mathbf{Q} = f(\mathbf{Q}_T), \quad (8)$$

where the columns of the embedding matrix correspond to the initial tokens $\mathbf{Q} := [\mathbf{q}_{\text{CLS}}, \mathbf{q}_1, \dots, \mathbf{q}_N]$. As a final question representation, we use the embedding of the [CLS] token $\mathbf{q} := \mathbf{q}_{\text{CLS}}$.

The final score of an entity $\epsilon \in \mathcal{E}$ being the answer is given by

$$\max \left(\phi(\mathbf{e}_s, \mathbf{P}_E \mathbf{q}, \mathbf{e}_\epsilon, \mathbf{t}_\tau), \phi(\mathbf{e}_o, \mathbf{P}_E \mathbf{q}, \mathbf{e}_\epsilon, \mathbf{t}_\tau) \right), \quad (9)$$

where s, o and τ are the annotated subject, object and timestamp, respectively, and \mathbf{P}_E is a $D \times D$ learnable matrix specific for entity predictions. Here, we treat the annotated subject and object interchangeably, and the $\max(\cdot)$ function ensures that we ignore the scores when s or o is a dummy entity.

In addition, the final score of an timestamp $\tau \in \mathcal{T}$ being the answer is given by

$$\phi(\mathbf{e}_s, \mathbf{P}_T \mathbf{q}, \mathbf{e}_o, \mathbf{t}_\tau), \quad (10)$$

where s, o are annotated entities in the question and \mathbf{P}_T is a $D \times D$ learnable matrix specific for time predictions. During training, the entity and time scores are concatenated and transformed to probabilities by a softmax function. The model’s parameters are updated to assign higher probabilities to the correct answers by minimizing a cross entropy loss.

Experimental Setting

CronQuestions (Saxena, Chakrabarti, and Talukdar 2021) is a temporal QA benchmark based on the Wikidata TKG proposed in (Lacroix, Obozinski, and Usunier 2020). The WikiData TKG consists of 125k entities, 203 relations, 1.7k timestamps (timestamps correspond to years), and 328k facts. In this TKG, facts are represented as (subject, relation, object, [start_time, end_time]). CronQuestions consists of 410k unique question-answer pairs, 350k of which are for training and 30k for validation and for testing. Moreover, the entities and times present in the questions are annotated. CronQuestions includes both simple and complex temporal questions (Table 1 for examples).

To illustrate how methods perform under incomplete TKGs, we provide a setting where the given WikiData TKG is corrupted at the time dimension. Specifically, for a fact (subject, relation, object, [start_time, end_time]) $\in \mathcal{F}$, we remove the associated timestamps with probability p . If the timestamps are removed, the fact becomes (subject, relation, object, no_time). Here, ‘no_time’ denotes that there is no timestamp associated with (subject, relation, object) and we treat it as a special timestamp.

We used the corrupted TKG to perform two experiments. In the first experiment, we substitute the original TKG with the corrupted one during the QA task. This affects only TempoQR-Hard since this is the only method that uses a

TKG during QA. The second configuration is to substitute the original TKG with the corrupted one throughout the process. This means that TCompLEx embeddings are generated on a corrupted TKG and, thus, may not encode important temporal information. All TKGQA embedding-based methods are affected by this configuration.

Although CronQuestions includes different question types, we manually create additional complex types. The idea is to evaluate how different methods perform on complex questions that were unseen during training but include the same keywords (and temporal constraints) with the training questions. We create (i) ‘before & after’ questions that include both ‘before’ and ‘after’ constraints and (ii) ‘before/after & first/last’ questions that include both ‘before/after’ and ‘first/last’ constraints. We describe the details of generating these QA pairs in the Appendix.

Model Configuration

We learn TKG embeddings with the TCompLEx method, where we set their dimensions $D = 512$. During, QA the pre-trained LM’s parameters and the TKG embeddings are not updated. We set the number of transformer layers of the encoder $f(\cdot)$ to $l = 6$ with 8 heads per layer. We also observed the same performance when setting $l = 3$ with 4 heads per layer. The model’s parameters are updated with Adam (Kingma and Ba 2014) with a learning rate of 0.0002. The model is trained for 20 maximum epochs and the final parameters are determined based on the best validation performance. The model is implemented with Pytorch (Paszke et al. 2019). For reproducibility, our code is available at: <https://github.com/cmavro/TempoQR>.

Baseline Methods

BERT (Devlin et al. 2019) and RoBERTa (Liu et al. 2019) are two well-established pre-trained LMs. To evaluate these models, we generate their LM-based question embedding and concatenate it with the annotated entity and time embeddings, followed by a learnable projection. The resulted embedding is scored against all entities and timestamps via dot-product.

Entity as Experts (EaE) (Févy et al. 2020) is an entity-aware method similar to TempoQR. The key differences are that EaE does not utilize a TKG embedding-based scoring function for answer prediction and that it does not fuse additional temporal information as in Section . As a baseline, we experiment with EaE combined with TCompLEx scoring function. Since this baseline is similar to TempoQR without the steps of Section (), we call it EntityQR.

CronKGQA is the TKGQA embedding based method described in Section . EmbedKGQA (Saxena, Tripathi, and Talukdar 2020) is similar to CronKGQA, but designed for regular KGs. EmbedKGQA is implemented for TKGQA as follows. Timestamps are ignored during pre-training and random time embeddings are used during the QA task. CronKGQA and EntityQR are extended to incorporate additional temporal information by the algorithmic steps in Section , which generate time embeddings \mathbf{t}_1 and \mathbf{t}_2 for TempoQR. Recall that TempoQR generates \mathbf{t}_1 and \mathbf{t}_2 by

Model	Hits@1					Hits@10				
	Overall	Question Type		Answer Type		Overall	Question Type		Answer Type	
		Complex	Simple	Entity	Time		Complex	Simple	Entity	Time
BERT	0.243	0.239	0.249	0.277	0.179	0.620	0.598	0.649	0.628	0.604
RoBERTa	0.225	0.217	0.237	0.251	0.177	0.585	0.542	0.644	0.583	0.591
EmbedKGQA	0.288	0.286	0.290	0.411	0.057	0.672	0.632	0.725	0.850	0.341
EaE	0.288	0.257	0.329	0.318	0.231	0.678	0.623	0.753	0.688	0.698
CronKGQA	0.647	0.392	0.987	0.699	0.549	0.884	0.802	0.992	0.898	0.857
EntityQR	0.745	0.562	0.990	0.831	0.585	0.944	0.906	0.993	0.962	0.910
TempoQR-Soft	0.799	0.655	0.990	0.876	0.653	0.957	0.930	0.993	0.972	0.929
TempoQR-Hard	0.918	0.864	0.990	0.926	0.903	0.978	0.967	0.993	0.980	0.974

Table 2: Comparison against other methods.

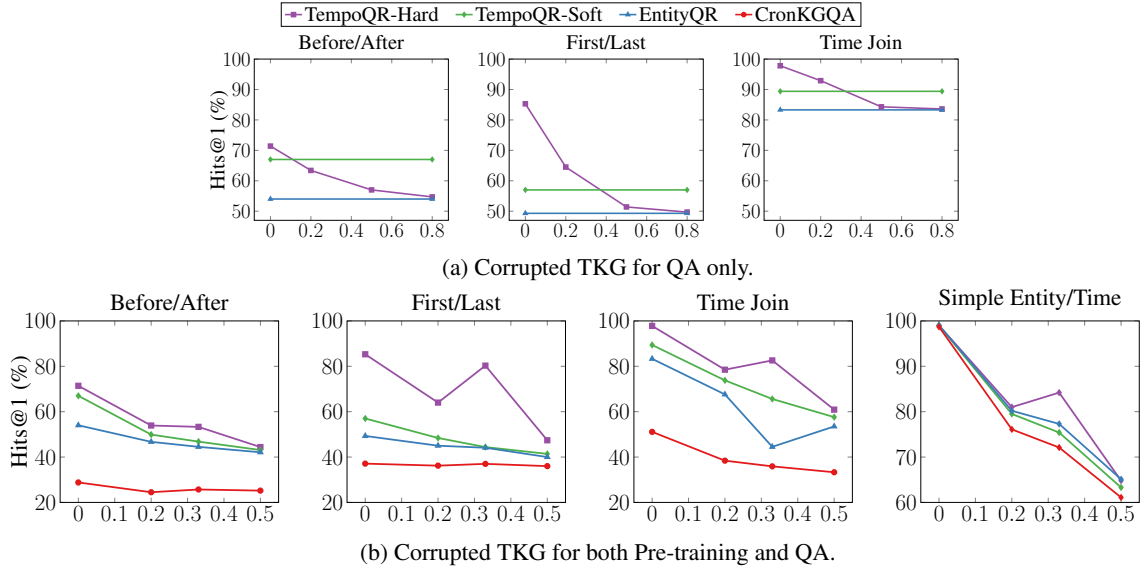


Figure 2: Performance with corrupted TKGs: x-axis corresponds to the corruption probability p of a fact.

either accessing the TKG or by inferring them in the embedding space. For CronKGQA and EntityQR, we generate \mathbf{t}_1 and \mathbf{t}_2 in the same way, but we employ them directly to the TComplex scoring function as follows. We modify (9), which scores an entity to be the answer, as

$$\max \left(\phi(\mathbf{e}_s, \mathbf{P}_{EQ}, \mathbf{e}_e, \mathbf{t}_1 + \mathbf{t}_2), \phi(\mathbf{e}_o, \mathbf{P}_{EQ}, \mathbf{e}_e, \mathbf{t}_1 + \mathbf{t}_2) \right), \quad (11)$$

to replace the embedding of a dummy timestamp \mathbf{t}_τ (if no time is annotated in the question) with $\mathbf{t}_1 + \mathbf{t}_2$. Based on how \mathbf{t}_1 and \mathbf{t}_2 are generated (hard or soft supervision), we term the methods CronKGQA-Hard and EntityQR-Hard or CronKGQA-Soft and EntityQR-Soft, respectively.

Results

In this section, we provide the experimental results under different configurations. As a performance metric, we report Hits@ k , which is the accuracy of the top- k predictions.

Main Results

Table 2 shows the results of our method compared to other baselines on CronQuestions. First, by comparing EntityQR to CronKGQA, we see that grounding the question to the entities it refers (entity-aware step) significantly helps for answering complex questions. In this case, the absolute improvement for complex questions is 17% and 10% at Hits@1 and Hits@10, respectively. Furthermore, comparing TempoQR to EntityQR, we see the benefit of adding temporal information to the question (time-aware step). The absolute improvement of TempoQR-Soft over EntityQR is 9% at Hits@1 for complex questions, while the respective improvement of TempoQR-Hard is more than 30%. Moreover, TempoQR-Hard outperforms TempoQR-Soft by 25% at Hits@1 when the answer is a time. This confirms that TempoQR-Hard provides accurate temporal information by retrieving it from the TKG, while TempoQR-Soft sometimes cannot infer as accurate information from the embedding space.

We also highlight that methods that score possible answers with the TComplex function (TempoQR, EntityQR

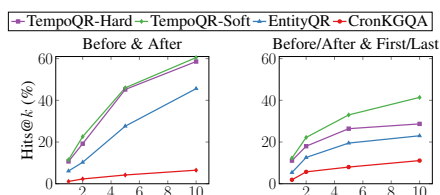


Figure 3: Evaluation for unseen complex types during inference. x-axis corresponds to k of Hits@ k .

and CronKGQA) answer 99% of the simple questions correctly. The other methods (BERT, RoBERTa, EmbedKGQA and EaE) cannot answer correctly more than 35% (Hits@1) and 76% (Hits@10). Similarly, BERT, RoBERTa, EmbedKGQA and EaE have 35%-65% and 11%-40% worse overall accuracy for Hits@1 and Hits@10, respectively, compared to TempoQR, EntityQR and CronKGQA.

	Complex Questions			All
	Before/After	First/Last	Time Join	
CronKGQA	0.256	0.371	0.511	0.647
EntityQR	0.540	0.493	0.833	0.745
CronKGQA-Soft	0.341	0.375	0.671	0.672
EntityQR-Soft	0.430	0.468	0.766	0.708
TempoQR-Soft	0.670	0.570	0.894	0.799
CronKGQA-Hard	0.379	0.445	0.942	0.728
EntityQR-Hard	0.442	0.470	0.955	0.748
TempoQR-Hard	0.714	0.853	0.978	0.918

Table 3: Hits@1 for different complex type questions.

Ablation Study

Table 3 shows how soft and hard supervision affect the performance of various methods for different question types. First, we see that both supervision approaches have a positive effect on CronKGQA, where the performance is improved by 2.5% and 6% over the original method (CronKGQA-Soft and CronKGQA-Hard, respectively, compared to CronKGQA). The same does not happen for EntityQR, where its performance drops (EntityQR-Soft and EntityQR-Hard compared to EntityQR). This is an effect of over-using TKG embeddings, since EntityQR-Soft and EntityQR-Hard use this information multiple times for answer prediction.

Moreover, TempoQR-Hard performs much better for ‘first/last’ questions compared to soft-supervision (27% absolute improvement). Since TempoQR-Hard always retrieves the start and end timestamps of the question entities, this provides more accurate temporal information to “*When was the first/last time...*” questions. On the other hand, this does not equally benefit ‘before/after’ questions; the improvement of hard-supervision over soft-supervision is only 3%. This indicates that both approaches handle such questions in a similar manner. Finally, TempoQR-Soft performs 8% worse in ‘time join’ questions compared to TempoQR-Hard. This indicates that there might be some room for improve-

ment for inferring more accurate time embeddings with soft-supervision.

Robustness Over Corrupted TKGs

Figure 2a shows the results when the given TKG is corrupted during the QA phase. TempoQR-Hard is the only method that depends on the quality of the TKG during QA and is greatly affected by a corrupted TKG. When a lot of facts are corrupted ($p = 0.8$) it performs similar to EntityQR, which does not use any additional temporal information. For ‘before/after’ questions, it performs worse than TempoQR-Soft even when the facts are corrupted by a probability $p = 0.2$. Finally, TempoQR-Hard is more robust for ‘first/last’ and ‘time join’ questions, where it better handles the non-corrupted timestamps of the facts.

Figure 2b shows the results when a corrupted TKG is given for both TKG embedding and QA. We can see that methods that rely on TKG embeddings (TempoQR-Hard, TempoQR-Soft) are greatly affected, since they perform similar to each other as well to EntityQR when the corruption probability p is large, e.g., $p = 0.5$. CronKGQA is the least affected by a corrupted TKG, but, still, its performance is much lower. The largest performance drop is observed for TempoQR-Hard for ‘first/last’ questions, which indicates that it cannot generalize well to such questions under a corrupted TKG. Finally, depending on the information that is corrupted, some methods benefit over others, i.e., compare TempoQR-Hard to EntityQR for $p = 0.33$ at ‘time join’ questions.

Unseen Question Types

Figure 3 shows the performance for unseen question types during training. As we can see, TempoQR-Soft performs the best for both generated question types. Since it learns to handle temporal constraints in the embedding space, it generalizes better than TempoQR-Hard which simply uses the TKG to answer such questions. In general, neither of these methods seems to be able to tackle unseen questions effectively, i.e., Hits@1 is below 20% for all the methods. This is also confirmed since the performance of the methods only increases when k is increased, i.e., the return more possible answers. This motivates the need for extending these methods in a way that ensures better performance for unseen questions.

Conclusion

This paper puts forth a comprehensive embedding framework specialized in answering complex questions over TKGs. The benefit of TempoQR comes by learning context, entity and time-aware question representations. The latter relies either on hard or soft supervision. Extensive experiments confirmed the benefits of each step performed in our method. TempoQR outperforms existing methods for complex questions by 25–45%. The limitations and advantages of hard and soft supervision are also showcased. Future research includes extending existing methods to generalize better to unseen question types.

References

- Bordes, A.; Usunier, N.; Garcia-Duran, A.; Weston, J.; and Yakhnenko, O. 2013. Translating embeddings for modeling multi-relational data. *Advances in neural information processing systems*, 26.
- Chen, W.; Wang, X.; and Wang, W. Y. 2021. A Dataset for Answering Time-Sensitive Questions. *arXiv preprint arXiv:2108.06314*.
- Devlin, J.; Chang, M.-W.; Lee, K.; and Toutanova, K. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *ACL*.
- Férvy, T.; Soares, L. B.; FitzGerald, N.; Choi, E.; and Kwiatkowski, T. 2020. Entities as Experts: Sparse Memory Access with Entity Supervision. In *EMNLP*.
- Han, J.; Cheng, B.; and Wang, X. 2020. Open Domain Question Answering based on Text Enhanced Knowledge Graph with Hyperedge Infusion. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, 1475–1481. Online: Association for Computational Linguistics.
- He, G.; Lan, Y.; Jiang, J.; Zhao, W. X.; and Wen, J.-R. 2021. Improving Multi-Hop Knowledge Base Question Answering by Learning Intermediate Supervision Signals. In *Proceedings of the 14th ACM International Conference on Web Search and Data Mining, WSDM '21*, 553–561. New York, NY, USA: Association for Computing Machinery. ISBN 9781450382977.
- Jia, Z.; Abujabal, A.; Saha Roy, R.; Strötgen, J.; and Weikum, G. 2018a. Tempquestions: A benchmark for temporal question answering. In *Companion Proceedings of the The Web Conference 2018*, 1057–1062.
- Jia, Z.; Abujabal, A.; Saha Roy, R.; Strötgen, J.; and Weikum, G. 2018b. Tequila: Temporal question answering over knowledge bases. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*, 1807–1810.
- Jia, Z.; Pramanik, S.; Saha Roy, R.; and Weikum, G. 2021. Complex Temporal Question Answering on Knowledge Graphs. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, 792–802.
- Jin, W.; Khanna, R.; Kim, S.; Lee, D.-H.; Morstatter, F.; Galstyan, A.; and Ren, X. 2021. ForecastQA: A Question Answering Challenge for Event Forecasting with Temporal Text Data. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, 4636–4650.
- Kazemi, S. M.; Goel, R.; Jain, K.; Kobayev, I.; Sethi, A.; Forsyth, P.; and Poupart, P. 2020. Representation Learning for Dynamic Graphs: A Survey. *arXiv:1905.11485*.
- Kingma, D. P.; and Ba, J. 2014. Adam: A Method for Stochastic Optimization. *arXiv:1412.6980*.
- Kolitsas, N.; Ganea, O.-E.; and Hofmann, T. 2018. End-to-End Neural Entity Linking. *arXiv:1808.07699*.
- Lacroix, T.; Obozinski, G.; and Usunier, N. 2020. Tensor Decompositions for Temporal Knowledge Base Completion. In *ICLR*.
- Lan, Y.; He, G.; Jiang, J.; Jiang, J.; Zhao, W. X.; and Wen, J.-R. 2021. Complex Knowledge Base Question Answering: A Survey. *arXiv preprint arXiv:2108.06688*.
- Liu, Y.; Ott, M.; Goyal, N.; Du, J.; Joshi, M.; Chen, D.; Levy, O.; Lewis, M.; Zettlemoyer, L.; and Stoyanov, V. 2019. RoBERTa: A Robustly Optimized BERT Pretraining Approach. *ArXiv*, abs/1907.11692.
- Miller, A.; Fisch, A.; Dodge, J.; Karimi, A.-H.; Bordes, A.; and Weston, J. 2016. Key-Value Memory Networks for Directly Reading Documents. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, 1400–1409. Austin, Texas: Association for Computational Linguistics.
- Neelam, S.; Sharma, U.; Karanam, H.; Iqbal, S.; Kapani-pathi, P.; Abdelaziz, I.; Mihindukulasooriya, N.; Lee, Y.-S.; Srivastava, S.; Pendus, C.; et al. 2021. SYGMA: System for Generalizable Modular Question Answering Over Knowledge Bases. *arXiv preprint arXiv:2109.13430*.
- Paszke, A.; Gross, S.; Massa, F.; Lerer, A.; Bradbury, J.; Chanan, G.; Killeen, T.; Lin, Z.; Gimelshein, N.; Antiga, L.; Desmaison, A.; Kopf, A.; Yang, E.; DeVito, Z.; Raison, M.; Tejani, A.; Chilamkurthy, S.; Steiner, B.; Fang, L.; Bai, J.; and Chintala, S. 2019. PyTorch: An Imperative Style, High-Performance Deep Learning Library. In Wallach, H.; Larochelle, H.; Beygelzimer, A.; d'Alché-Buc, F.; Fox, E.; and Garnett, R., eds., *Advances in Neural Information Processing Systems 32*, 8024–8035. Curran Associates, Inc.
- Qiu, Y.; Wang, Y.; Jin, X.; and Zhang, K. 2020. Stepwise Reasoning for Multi-Relation Question Answering over Knowledge Graph with Weak Supervision. In *Proceedings of the 13th ACM International Conference on Web Search and Data Mining, WSDM '20*. New York, NY, USA: Association for Computing Machinery. ISBN 9781450368223.
- Saxena, A.; Chakrabarti, S.; and Talukdar, P. 2021. Question Answering over Temporal Knowledge Graphs. In *ACL*.
- Saxena, A.; Tripathi, A.; and Talukdar, P. 2020. Improving Multi-hop Question Answering over Knowledge Graphs using Knowledge Base Embeddings. In *ACL*.
- Souza Costa, T.; Gottschalk, S.; and Demidova, E. 2020. Event-QA: A dataset for event-centric question answering over knowledge graphs. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*, 3157–3164.
- Sun, H.; Bedrax-Weiss, T.; and Cohen, W. W. 2019. PullNet: Open Domain Question Answering with Iterative Retrieval on Knowledge Bases and Text. *ArXiv*, abs/1904.09537.
- Sun, H.; Dhingra, B.; Zaheer, M.; Mazaitis, K.; Salakhutdinov, R.; and Cohen, W. 2018. Open Domain Question Answering Using Early Fusion of Knowledge Bases and Text. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, 4231–4242. Brussels, Belgium: Association for Computational Linguistics.
- Trouillon, T.; Dance, C. R.; Éric Gaussier; Welbl, J.; Riedel, S.; and Bouchard, G. 2017. Knowledge Graph Completion via Complex Tensor Factorization. *JMLR*.

- Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, L.; and Polosukhin, I. 2017. Attention is All You Need. In *NIPS*.
- Xiong, W.; Yu, M.; Chang, S.; Guo, X.; and Wang, W. Y. 2019. Improving Question Answering over Incomplete KBs with Knowledge-Aware Reader. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 4258–4264. Florence, Italy: Association for Computational Linguistics.
- Xu, K.; Lai, Y.; Feng, Y.; and Wang, Z. 2019. Enhancing Key-Value Memory Neural Networks for Knowledge Based Question Answering. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, 2937–2947. Minneapolis, Minnesota: Association for Computational Linguistics.
- Yang, B.; Yih, W.-t.; He, X.; Gao, J.; and Deng, L. 2014. Embedding entities and relations for learning and inference in knowledge bases. *arXiv preprint arXiv:1412.6575*.
- Zhang, Z.; Han, X.; Liu, Z.; Jiang, X.; Sun, M.; and Liu, Q. 2019. ERNIE: Enhanced Language Representation with Informative Entities. *arXiv:1905.07129*.
- Zhou, M.; Huang, M.; and Zhu, X. 2018. An Interpretable Reasoning Network for Multi-Relation Question Answering. In *COLING*.