Forecasting Question Answering over Temporal Knowledge Graphs

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Abstract

Question answering over temporal knowledge graphs (TKGQA) has recently found increasing interest. TKGQA requires temporal reasoning techniques to extract the relevant information from temporal knowledge bases. The only existing TKGQA dataset, i.e., CRONQUESTIONS, consists of temporal questions based on the facts from a fixed time period, where a temporal knowledge graph (TKG) spanning the same period can be fully used for answer inference, allowing the TKGQA models to use even the future knowledge to answer the questions based on the past facts. In real-world scenarios, however, it is also common that the given knowledge until now, we wish the TKGQA systems to answer the questions asking about the future. As humans constantly seek plans for the future, building TKGQA systems for answering such forecasting questions is important. Nevertheless, this has still been unexplored in previous research. In this paper, we propose a novel task: forecasting question answering over temporal knowledge graphs. We also propose a large-scale TKGQA benchmark dataset, i.e., FORECASTQUESTIONS, for this task. It includes three types of questions, i.e., entity prediction, yes-no, and fact reasoning questions. For every forecasting question in our dataset, QA models can only have access to the TKG information before the timestamp annotated in the given question for answer inference. We find that the state-of-the-art TKGQA methods perform poorly on forecasting questions, and they are unable to answer yes-no questions and fact reasoning questions. To this end, we propose FORECASTTKGQA, a TKGQA model that employs a TKG forecasting module for future inference, to answer all three types of questions. Experimental results show that FORECASTTKGQA outperforms recent TKGQA methods on the entity prediction questions, and it also shows great effectiveness in answering the other two types of questions.

Introduction

Knowledge graphs (KGs) model factual information by representing every fact with a triplet, i.e., \((s, r, o)\), where \(s\), \(o\), \(r\) are the subject entity, the object entity, and the relation between \(s\) and \(o\), respectively. World knowledge is ever-changing with time, however, KGs fail to capture these changes since they do not have temporal constraints. To adapt to the ever-evolving world, temporal knowledge graphs (TKGs) are introduced, where they additionally specify the time validity of every fact with a time constraint \(t\) (\(t\) is usually a timestamp), and represent each fact with a quadruple, i.e., \((s, r, o, t)\). For example, \((\text{Angela Merkel, is chancellor of Germany, 2018})\) is used to represent the fact that Angela Merkel is the chancellor of Germany in 2018. Recently, TKG reasoning has drawn greater attention. While a lot of methods (Leblay and Chekol 2018; Ma, Tresp, and Daxberger 2019; Lacroix, Obozinski, and Usunier 2020) focus on temporal knowledge graph completion (TKGC) where they predict missing facts at the observed timestamps, various recent methods (Jin et al. 2020; Han et al. 2021a, b; Li et al. 2021; Liu et al. 2022) pay more attention to forecasting the future facts on TKGs.

Knowledge graph question answering (KGQA) is a task aiming to answer the natural language questions using a KG as the knowledge base. Unlike traditional QA tasks that are solely based on natural language, KGQA requires QA models to extract answers from KGs, rather than extracting or summarizing answers from the given text contexts. In KGQA, the answer to a question is usually a KG entity. Saxena et al. first introduced question answering over temporal knowledge graphs (TKGQA) and proposed a TKGQA dataset CRONQUESTIONS, where answers can be either a KG entity or a time duration. The underlying knowledge base of CRONQUESTIONS is a TKG, and temporal reasoning techniques are required to answer the questions. Though CRONQUESTIONS manages to combine TKG reasoning with KGQA, it has limitations. Previous KGQA datasets, including CRONQUESTIONS, do not include yes-no questions and multiple choice questions, while these two question types have been extensively studied in reading comprehension QA, e.g., (Clark et al. 2019; Jin et al. 2021). Besides, the questions in CRONQUESTIONS are all based on the TKG facts that happen in a fixed time period, and an extensive TKG that is observable in the same time period can be used to infer the answers, which makes the answer inference less challenging. For example, the TKG facts from 2003, including \((\text{Stephen Robert Jordan, member of sports team, Manchester City, 2003})\), are all observable to answer the question \textit{Which team was Stephen Robert Jordan part of in 2003?}. CRONQUESTIONS manages to bridge the gap...
between TKGC and KGQA, however, there is still no existing work trying to combine TKG forecasting with KGQA, where only past TKG information can be used for answer inference.

In this work, we propose a novel task: forecasting question answering over temporal knowledge graphs (forecasting TKGQA), together with a forecasting TKGQA dataset, i.e., FORECASTTKGQUESTIONS. We generate forecasting questions based on the Integrated Crisis Early Warning System (ICEWS) dataverse (Boschee et al. 2015) from Jan. 1, 2021 to Aug. 31, 2021, and label every question with a timestamp. To answer a forecasting question, QA models are only allowed to access the TKG information prior to the question timestamp. The contribution of our work is three-fold:

- We propose forecasting TKGQA, a novel task aiming to test the forecasting ability of TKGQA models. To the best of our knowledge, this is the first work binding TKG forecasting with temporal KGQA.
- We propose a large-scale benchmark TKGQA dataset: FORECASTTKGQUESTIONS. It is twice as large as the only existing TKGQA dataset CRONQUESTIONS. It contains three types of questions, i.e., entity prediction, yes-no, and fact reasoning questions (in the form of multiple-choice questions), where the last two types of questions have never been considered in previous KGQA datasets.
- We propose a model, i.e., FORECASTTKGQA, aiming to solve forecasting TKGQA. It employs a TKG forecasting module and a pre-trained language model (LM) for answer inference. Experimental results show that it achieves superior performance on all three types of forecasting questions.

### Preliminaries and Related Work

#### Temporal Knowledge Graph Reasoning

Let $\mathcal{E}$, $\mathcal{R}$ and $\mathcal{T}$ denote a finite set of entities, relations, and timestamps, respectively. A temporal knowledge graph (TKG) $\mathcal{G}$ is defined as a finite set of TKG facts represented by quadruples, i.e., $\mathcal{G} = \{(s, r, o, t) | s, o \in \mathcal{E}, r \in \mathcal{R}, t \in \mathcal{T}\}$. We define the TKG forecasting task (also known as TKG extrapolation) as follows. Assume we have a query $(s_q, r_q, ?, t_q)$ (or $(?, r_q, o_q, t_q)$) derived from a target quadruple $(s_q, r_q, o_q, t_q)$, and we denote all the ground truth quadruples as $\mathcal{F}$. The TKG forecasting task aims to predict the missing entity in the query, given the observed past TKG facts $\mathcal{O} = \{(s_i, r_i, o_i, t_i) \in \mathcal{F} | t_i < t_q\}$. Such time constraint is not imposed in TKG completion (TKGC, also known as TKG interpolation), where the observed TKG facts can from any timestamp, including $t_q$, and the timestamps after $t_q$, can be used for prediction. In recent years, there has been extensive work done for both TKGC (Lacroix, Obozinski, and Usunier 2020; Jung, Jung, and Kang 2021; Ding et al. 2021b; Zhu et al. 2021; Han et al. 2021a) and TKG forecasting (Jin et al. 2020; Han et al. 2021b; Zhu et al. 2021; Han et al. 2021a).

#### Question Answering over Knowledge Graphs

Several datasets have been proposed for QA over non-temporal KGs, such as SimpleQuestions (Bordes et al. 2015), WebQuestionsSP (Yih et al. 2015), ComplexWebQuestions (Talmor and Berant 2018), MetaQA (Zhang et al. 2018), TempQuestions (Jia et al. 2018), and TimeQuestions (Jia et al. 2021). Their questions are created based on large-scale KGs, e.g., FreeBase (Bollacker et al. 2008). Among these datasets, only TempQuestions and TimeQuestions involve temporal questions that require temporal reasoning for answer inference, however, their associated KGs are non-temporal.

CRONQUESTIONS (Saxena, Chakrabarti, and Talukdar 2021) creates questions based on a time-evolving TKG, i.e., Wikidata (Vrandecic and Krötzsch 2014). Two types of questions, i.e., entity prediction questions and time prediction questions, are included. To answer CRONQUESTIONS, Saxena et al. propose CRONKGQA that uses TKGC methods, along with pre-trained LMs, which shows great effectiveness. Several work has been proposed on top of CRONKGQA, e.g., TempoQR (Mavromatis et al. 2022) and TSQA (Shang et al. 2022), where they achieve great improvement by better distinguishing the time scope of the questions. Since CRONQUESTIONS is proposed based on the idea of TKGC, it does not support TKG forecasting and contains no forecasting questions. One recent work, i.e., FORECASTQA (Jin et al. 2021), proposes a QA dataset that fully consists of forecasting questions. QA models are forced to make forecasting judgment for answer inference. However, FORECASTQA is not related to KGQA, where the answers to its questions are extracted from the text contexts. To this end, we propose FORECASTTKGQUESTIONS, aiming to bridge the gap between TKGC forecasting and KGQA. We compare FORECASTTKGQUESTIONS with recent KGQA datasets in Table 1.

| Datasets     | TKG | Temporal Portion | # Questions |
|--------------|-----|------------------|-------------|
| MetaQA       | ×   | 0%               | 400k        |
| TempQuestions| ×   | 100%             | 1271        |
| TimeQuestions| ×   | 100%             | 16k         |
| CRONQUESTIONS| ✓   | 100%             | 410k        |
| Our Dataset  | ✓   | 100%             | 847k        |

Table 1: KGQA dataset comparison. Statistics of all datasets are taken from (Saxena, Chakrabarti, and Talukdar 2021) and (Jia et al. 2021). Temporal Portion denotes the portion of temporal questions in a dataset.

#### Forecasting Question Answering over Temporal Knowledge Graphs

Forecasting question answering over temporal knowledge graphs aims to test the forecasting ability of TKGQA models. It requires QA models to predict future facts based on the past TKG information.

**Task Formulation** Given a TKG $\mathcal{G}$ and a natural language question $q$ generated based on a TKG fact whose valid timestamp is $t_q$, forecasting TKGQA aims to predict the answer to $q$. To ensure that QA models will not violate the forecasting setting, we label every question $q$ with the timestamp of its associated TKG fact $t_q$. QA models are only allowed
to use the TKG facts \(\{(s_i, r_i, o_i, t_i)|t_i < t_q\}\) before \(t_q\) for answer inference. In our work, we propose three types of forecasting TKGQA questions, i.e., entity prediction, yes-no, and fact reasoning questions. The answer to an entity prediction question is an entity \(e \in \mathcal{E}\). The answer to a yes-no question is either yes or no. We formulate fact reasoning questions as multiple choices and thus, the answer to a fact reasoning question corresponds to a choice \(c\).

**FORECASTTKGQUESTIONS**

**Temporal Knowledge Base**

We take a subset from the Integrated Crisis Early Warning System (ICEWS) database as the associated knowledge base for FORECASTTKGQUESTIONS. We collect all the events from Jan. 1, 2021 to Aug. 31, 2021, where we reformulate each event into the form of a quadruple \((s, r, o, t)\), e.g., \((Israel, Host a visit, Nikki Haley, 2021-06-18)\), and construct a TKG \(G\) called ICEWS21. We split ICEWS21 into three parts \(G^{\text{train}} = \{(s, r, o, t) \in G|t \in [t_0, t_1]\}\), \(G^{\text{val}} = \{(s, r, o, t) \in G|t \in [t_1, t_2]\}\), \(G^{\text{test}} = \{(s, r, o, t) \in G|t \in [t_2, t_3]\}\), where \(t_0, t_1, t_2, t_3\) correspond to 2021-01-01, 2021-07-01, 2021-08-01 and 2021-08-31, respectively. We generate training questions based on \(G^{\text{train}}\). Similarly, validation questions and test questions are generated based on \(G^{\text{val}}\) and \(G^{\text{test}}\), respectively. We ensure that there exists no temporal overlap between every two of them, i.e., \(G^{\text{train}} \cap G^{\text{val}} = \emptyset\), \(G^{\text{train}} \cap G^{\text{test}} = \emptyset\) and \(G^{\text{val}} \cap G^{\text{test}} = \emptyset\). In this way, we prevent QA models from observing any information from the evaluation sets during training.

**Question Categorization and Generation**

Questions in FORECASTTKGQUESTIONS are categorized into three categories, i.e., entity prediction questions, yes-no questions, and fact reasoning questions. We summarize the numbers of different types of questions in Table 2.

| Question Type                  | Train  | Valid | Test  |
|-------------------------------|--------|-------|-------|
| 1-Hop Entity Prediction       | 252,246| 42,991| 39,786|
| 2-Hop Entity Prediction       | 128,810| 18,138| 16,624|
| Yes-No Questions              | 251,537| 42,884| 39,695|
| Fact Reasoning                | 10,103 | 2694  | 1859  |
| **Total**                     | 642,696| 106,707| 97,964|

Table 2: FORECASTTKGQUESTIONS statistics.

**Entity Prediction Questions**

The answer to an entity prediction question corresponds to an entity. We generate two groups of entity prediction questions, i.e., 1-hop and 2-hop entity prediction questions. In ICEWS21, we have 253 relations. For each relation, we create a natural language template. For example, for the relation provide economic aid, we write its 1-hop template as Who will \{s\} provide economic aid for on \{t\}, where \(s\) and \(t\) denote the subject entity and the timestamp of a TKG fact, respectively. Same as previous KGQA datasets, e.g., ADVQA, entity linking is considered as a separate problem and is not covered in our work. We assume complete entity and timestamp linking, and annotate the entities and timestamps in our questions. This applies to all three types of questions in our dataset.

Each 1-hop question is generated from a single TKG fact, e.g., the natural language question Who will Sudan host on 2021-08-01? is based on (Sudan, host, Ramtane Lamamra, 2021-08-01). Relation templates are used during question generation. The underlined parts in the question denote the annotated entities and timestamps for KGQA. We consider all the facts in ICEWS21 and transform them into 1-hop entity prediction questions.

Each 2-hop question is generated from two associated TKG facts where they contain common entities. For example, the natural language question Who will a country, while United Kingdom engages in diplomatic cooperation with this country on 2021-08-03 is generated from the TKG facts (Juan Orlando Hernández, make a visit, United States, 2021-08-03) and (United Kingdom, engage in diplomatic cooperation, United States, 2021-08-03). The answer to a 2-hop question corresponds to a 2-hop neighbor of its annotated entity (United Kingdom in our example). We generate 2-hop questions by utilizing AnyBURL (Meilicke et al. 2020), a rule-based KG reasoning model. We first split ICEWS21 into KG snapshots, where each snapshot \(G_t = \{(s, r, o, t) \in G|t = t_t\}\) contains all the TKG facts happening at the same timestamp. Then we train AnyBURL on each TKG snapshot for rule extraction. We keep the 2-hop rules with a confidence higher than 0.5 returned by AnyBURL, and take them as the drafts of our 2-hop questions. After another round of manual rule checking, we fit the relation templates into the remaining drafts and search for the groundings in ICEWS21, where each grounding corresponds to a 2-hop question.

**Yes-No Questions**

Based on the idea of the triple classification task in KG reasoning\(^1\), we introduce the yes-no questions (popular in reading comprehension QA datasets, e.g., BoolQ (Clark et al. 2019), FORECASTQA (Jin et al. 2021)) into KGQA. We generalize triple classification to quadruple classification\(^2\) and then translate TKG facts into natural language questions. We take answering yes-no questions as solving the quadruple classification task. For every TKG fact in ICEWS21, we generate either a true question or a false question based on it. For example, for the fact (Sudan, host, Ramtane Lamamra, 2021-08-01), a true question is generated as Will Sudan host Ramtane Lamamra on 2021-08-01? and we label yes as its answer. A false question is generated by randomly perturbing one entity or the relation type in this fact, e.g., Will Germany host Ramtane Lamamra on 2021-08-01?, and we label no as its answer. We ensure that the perturbed version of the fact does not exist in the original TKG. We use 25% of total facts in ICEWS21 to generate true questions and the rest are used to generate false questions.

\(^1\)For a KG fact \((s, r, o)\), triple classification aims to predict whether this fact is valid or not.

\(^2\)To the best of our knowledge, quadruple classification has never been studied in previous work. We define it as predicting whether a TKG fact \((s, r, o, t)\) is valid or not.
Fact Reasoning Questions  The motivation for proposing fact reasoning questions is to study the difference between humans and machines in finding the supporting evidence for reasoning. We formulate fact reasoning questions in the form of multiple choices. We provide an example of fact reasoning questions in Figure 1. Each question is coupled with four choices. Given a TKG fact from a fact reasoning question, we ask the QA models to choose which fact in the choices is the most contributive (the most relevant cause of) the fact mentioned in the question.

We generate fact reasoning questions as follows. We first train a TKG forecasting model xERTE (Han et al. 2021a) on ICEWS21. Note that to predict a link prediction query \((s, r, ?, t)\), xERTE samples its related prior TKG facts and assigns contribution scores to them. It provides explainability by assigning higher scores to the more related prior facts. We perform link prediction and collect the link prediction queries where the ground-truth missing entities are ranked as top 1 by xERTE. For each collected query, we find its corresponding TKG fact (which is later used to generate a natural language question), and then we pick out four related prior facts found by xERTE. We take the prior facts with the highest contribution score, the lowest contribution score, and the median contribution score as Answer, Negative, and Median, respectively. Inspired by InferWiki (Cao et al. 2021), we include a Hard Negative fact with the second highest contribution score returned by xERTE. The intuition of introducing Hard Negative is to include a choice that is not trivial for QA models to make the right decision. We generate each fact reasoning question by turning the corresponding facts into a natural language question and four choices, and manage to use xERTE to generate a large number of questions. However, since the answers to these questions are solely determined by xERTE, there exist numerous erroneous examples. For example, the Hard Negative of lots of them are more suitable than their Answer to be the answers. We ask three graduate students to manually check all these questions and label them as reasonable or unreasonable according to their knowledge or through search engines. If two of them label a question as wrong, we filter out this question.

**FORECASTTKGQA**

FORECASTTKGQA employs a TKG forecasting model TANGO (Han et al. 2021b) and a pre-trained LM BERT (Devlin et al. 2019) for solving forecasting questions in FORECASTTKGQUESTIONS.

**Temporal Knowledge Graph Forecasting Model**

We train TANGO on ICEWS21 with the TKG forecasting task. We use ComplEx (Trouillon et al. 2016) as its scoring function. We learn the entity and relation representations in the complex space \(\mathbb{C}^d\), where \(d\) denotes the dimension of the complex vectors. The training set corresponds to all the TKG facts in \(\mathcal{G}^{\text{train}}\), and we evaluate the trained model on \(\mathcal{G}^{\text{valid}}\) and \(\mathcal{G}^{\text{test}}\). After training, we perform a one time inference on \(\mathcal{G}^{\text{valid}}\) and \(\mathcal{G}^{\text{test}}\). During inference, TANGO makes use of the prior TKG information to compute the representations of entities and relations at the current timestamp, e.g., TANGO uses all the facts from \(t - 4\) to \(t - 1\) to compute representations at \(t\). Note that it infers representations based on the prior facts, thus not violating our forecasting setting. We compute the entity and relation representations at every timestamp in ICEWS21 and keep them for aiding the QA systems.

To leverage the complex representations computed by TANGO with ComplEx, we map all the representations output by BERT to the same complex space \(\mathbb{C}^d\) as follows. For each natural language input, e.g., a natural language question, we treat the output representation of the [CLS] token computed by BERT as its BERT encoded representation. We project the BERT encoded representation to a 2d real space to form a 2d real valued vector, then we take the first half and the second half of it as the real part and the imaginary part of a \(d\)-dimensional complex vector, respectively. All the representations output by BERT have already been mapped to the complex space without further notice.

**Question Answering**

**Entity Prediction**  For every entity prediction question \(q\), we compute an entity score for every entity \(e \in \mathcal{E}\). The entity with the highest computed score is predicted as the answer to the question. To compute the score for \(e\), we first input \(q\) into BERT and map its output to a complex space \(\mathbb{C}^d\) to get the question representation \(h_q\). Inspired by ComplEx, we then define \(e\)'s entity score as

\[
es(e) = \text{Re} < h_{(s,t_q)}, h_q, h^*_q >.
\]

\(h_{(s,t_q)} = f_{ep}(h_{(s,t_q)})\) and \(h^*_q = f_{ep}(h_{(c,t_q)})\), where \(f_{ep}\) denotes a layer of neural network aligning TKG representations to the entity prediction questions. \(h_{(s,t_q)}\) and \(h_{(c,t_q)}\) denote the TANGO representations of the annotated entity \(s\) in \(q\) and the entity \(e\), respectively, where \(t_q\) is the annotated timestamp. Re means taking the real part of a complex vector and \(h^*_q\) means the complex conjugate of \(h_q\).
Yes-No Judgment For a yes-no question, we compute two scores, i.e., yes score $ys$ and no score $ns$. We first encode the natural language answers yes and no into representations $h_{ye}$ and $h_{no}$. Inspired by TComplEx (Lacroix, Obozinski, and Usunier 2020), we then compute the scores of yes and no as

$$\begin{align*}
ys &= \text{Re} < h_{(s,t,y)}, h_q, h_{(o,t,y)}, h_{yes} >, \\
ns &= \text{Re} < h_{(s,t,n)}, h_q, h_{(o,t,n)}, h_{no} >. 
\end{align*}$$

(2)

$h_{(s,t,y)} = f_{yn}(h_{(s,t)})$ and $h_{(o,t,y)} = f_{yn}(h_{(o,t)})$, where $f_{yn}$ denotes a layer of neural network aligning TKG representations to the yes-no questions. $h_{(s,t,y)}$ and $h_{(o,t,y)}$ denote the TANGO representation of $s$ and $o$ at the question timestamp $t_q$, respectively. $h_q$ is the question representation output by BERT. We take the candidate answer (either yes or no) with the higher score as the predicted answer.

Fact Reasoning We compute a choice score $cs$ for every choice in a fact reasoning question by using the following score function:

$$cs(c_i) = \text{Re} < h_{(s,t,i)}, h_q, h_{(o,t,i)}, h_q >,$n

(3)

where $c_i$ is the $i$th choice, and $h_q$ is the output of BERT mapped to the complex space $c^d$ given the concatenation of $q$ and $c_i$. $h_{(s,t,i)} = f_{fr}(h_{(s,t,i)})$, $h_{(o,t,i)} = f_{fr}(h_{(o,t,i)})$, where $f_{fr}$ is a projection network, and $h_{(s,t,i)}$ and $h_{(o,t,i)}$ denote the TANGO representations of the entities annotated in $c_i$, $h_q = f_{fr}(h_{(s,t,q)}) \parallel f_{fr}(h_{(o,t,q)})$, where $f$ serves as a projection and $\parallel$ denotes the concatenation operation. $h_{(s,t,q)}$ and $h_{(o,t,q)}$ denote the TANGO representations of the entities annotated in the question $q$. In this way, we manage to compute the contribution of a choice $c_i$ to the question $q$. We take the choice with the highest choice score as our predicted answer.

Parameter Learning

We employ the cross-entropy loss to train our model FORECASTTKGQA on all three types of questions separately. The loss function of the entity prediction questions is given by

$$\mathcal{L}_{\text{entity prediction}} = - \sum_{q \in Q^e} \log \left( \frac{es(c_{ans})}{\sum_{c_i \in E} es(c_i)} \right).$$

(4)

$Q^e$ denotes all the entity prediction questions and $c_{ans}$ is the answer to the question $q$. The loss function of the yes-no questions is defined as

$$\mathcal{L}_{\text{yes-no}} = - \sum_{q \in Q^n} \log \left( \delta_{\text{yes}} \cdot \frac{ys}{ys + ns} + \delta_{\text{no}} \cdot \frac{ns}{ys + ns} \right).$$

(5)

$\delta_{\text{yes}} = I[\text{answer} = \text{yes}]$ and $\delta_{\text{no}} = I[\text{answer} = \text{no}]$, where $I$ denotes the indicator function. $Q^n$ is the set of all yes-no questions in the dataset. The loss function of the fact reasoning questions is defined as

$$\mathcal{L}_{\text{fact reasoning}} = - \sum_{q \in Q^f} \log \left( \frac{cs(c_{ans})}{\sum_{c_i} cs(c_i)} \right).$$

(6)

c_{ans} is the Answer to a question, and $Q^f$ denotes all the fact reasoning questions.

Experiments

We compare FORECASTTKGQA with several baselines on all three types of questions in FORECASTTKGQUESTIONS. We show that FORECASTTKGQA can effectively utilize TKG representations for answering forecasting questions over TKGs. We also do further analysis to study our model and our dataset.

Evaluation Metrics

We use mean reciprocal rank (MRR) and Hits@k as the evaluation metrics of the entity prediction questions. For each entity prediction question, we compute the rank of the ground truth answer entity among all the TKG entities. Test MRR is then computed as $\frac{1}{|Q^e|} \sum_{q \in Q^e} \frac{1}{\psi_q}$, where $Q^e$ denotes all the entity prediction questions in the test set and $\psi_q$ is the rank of the ground truth answer entity. Hits@k is the proportion of the answered questions where the ground truth answer entity is ranked as top $k$. We employ the filtered setting proposed in (Bordes et al. 2013) for fairer evaluation. For yes-no questions and fact reasoning questions, we employ accuracy for evaluation. Accuracy is the proportion of the correctly answered questions out of all the questions.

Baseline Methods

Pre-trained Language Models We consider two pre-trained LMs, BERT (Devlin et al. 2019) and RoBERTa (Liu et al. 2019) as our baselines for all three types of questions. For entity prediction questions and yes-no questions, we add a prediction head on top of the question representations computed by BERT and RoBERTa, and use a softmax function to compute the answer probabilities. For fact reasoning question, we input into each pre-trained LM the concatenation of the question with each choice, add a prediction head on LM’s outputs, and then use a softmax function for answer prediction. Besides, we derive two model variants for each pre-trained LM by combining TKG representations with them. We first train TComplEx (Lacroix, Obozinski, and Usunier 2020) on ICEWS21. For every entity prediction question and yes-no question, we concatenate the question representation with the TComplEx representations of the entities and timestamps annotated in the question, and then perform prediction with softmax. For fact reasoning questions, we further include TComplEx representations into choices in the same way. We call this type of variants BERT_int and RoBERTa_int since TComplEx is a TKGC (TKG interpolation) method. Similarly, we also introduce TANGO representations into pre-trained LMs and derive BERT_ext and RoBERTa_ext, where TANGO serves as a TKG extrapolation backend.

Knowledge Graph Question Answering Models We consider one KGQA method EmbedKGQA (Saxena, Tripathi, and Talukdar 2020), and two TKGQA methods, i.e., CRonKGQA (Saxena, Chakrabarti, and Talukdar 2021) and TempoQR (Mavromatis et al. 2022) as baselines. We run
Table 3: Experimental results of entity prediction questions. Evaluation metrics are filtered MRR and Hits@1/10. The best results are marked in bold.

| Model          | MRR | Hits@1 | Hits@10 |
|----------------|-----|--------|---------|
|                | Overall | 1-Hop | 2-Hop | Overall | 1-Hop | 2-Hop | Overall | 1-Hop | 2-Hop |
| RoBERTa        | 0.158 | 0.166 | 0.141 | 0.094 | 0.101 | 0.076 | 0.285 | 0.292 | 0.267 |
| BERT           | 0.260 | 0.291 | 0.187 | 0.171 | 0.199 | 0.106 | 0.439 | 0.473 | 0.357 |
| EmbedKGQA      | 0.268 | 0.308 | 0.171 | 0.181 | 0.217 | 0.094 | 0.439 | 0.485 | 0.327 |
| RoBERTa_int    | 0.237 | 0.276 | 0.142 | 0.152 | 0.185 | 0.075 | 0.409 | 0.462 | 0.285 |
| BERT_int       | 0.262 | 0.301 | 0.171 | 0.174 | 0.207 | 0.095 | 0.438 | 0.482 | 0.333 |
| CRONKGQA       | 0.115 | 0.128 | 0.084 | 0.066 | 0.078 | 0.038 | 0.214 | 0.228 | 0.181 |
| TempoQR        | 0.130 | 0.143 | 0.100 | 0.081 | 0.092 | 0.055 | 0.228 | 0.242 | 0.195 |
| RoBERTa_ext    | 0.261 | 0.301 | 0.166 | 0.173 | 0.207 | 0.091 | 0.433 | 0.480 | 0.321 |
| BERT_ext       | 0.284 | 0.323 | 0.193 | 0.194 | 0.228 | 0.111 | 0.464 | 0.506 | 0.364 |
| FORECASTTKGQA  | **0.293** | **0.331** | **0.203** | **0.200** | **0.236** | **0.115** | **0.474** | **0.514** | **0.380** |

Table 4: Experimental results of yes-no and fact reasoning questions. The evaluation metric is accuracy. The best results achieved by QA models are marked in bold.

| Question Type                  | Accuracy |
|--------------------------------|----------|
|                                | Yes-No   | Fact Reasoning |
| RoBERTa                       | 0.750    | 0.514          |
| BERT                          | 0.823    | 0.567          |
| RoBERTa_int                   | 0.768    | 0.482          |
| BERT_int                      | 0.845    | 0.582          |
| RoBERTa_ext                   | 0.800    | 0.531          |
| BERT_ext                      | 0.850    | 0.606          |
| FORECASTTKGQA                 | **0.882**| **0.636**      |
| Human Performance             | -        | 0.688          |

EmbedKGQA on top of the KG representations trained with ComplEx on ICEWS21, and run TKGQA baselines on top of the TKG representations trained with TComplEx.

**Main Results**

We report the experimental results in Table 3 and Table 4. In Table 3, we show that our entity prediction model outperforms all baseline methods. We observe that EmbedKGQA achieves a better performance than BERT and RoBERTa, showing that employing KG representations helps TKGQA. Besides, pre-trained LM variants outperform their original LMs, indicating that TKG representations help pre-trained LMs perform better in TKGQA. Further, BERT_ext shows stronger performance than BERT_int (this also applies to RoBERTa_int and RoBERTa_ext), which proves that TKG forecasting models provide greater help than TKGC models in forecasting TKGQA. CRONKGQA and TempoQR employ TComplEx representations as supporting information, and they perform poorly on our dataset. This implies that in forecasting TKGQA, employing TKG representations provided by TKGC methods may include noisy information. We also observe that CRONKGQA and TempoQR underperform BERT_int and RoBERTa_int. The reason is that in pre-trained LM variants, we employ a prediction head (a layer of neural network) that includes a large number of additional trainable parameters, while in CRONKGQA and TempoQR, the prediction is made by a parameter-free scoring function. Thus, pre-trained LM variants are able to exclude the noise by using excessive parameters. FORECASTTKGQA injects TANGO representations into a scoring module, showing its great effectiveness on entity prediction questions. For the other two types of questions, FORECASTTKGQA also achieves the best performance. Similar to the results in Table 3, we also observe that it is helpful to include TKG representations for forecasting TKGQA. Our scoring functions (Equation 2 and 3) serve as effective ways to infuse TKG information.

**Further Analysis**

**Knowledge Graph Representations** To study the effect of TKG representations, we train ComplEx on ICEWS21 and provide our model with its representations. We observe in Table 5 that TANGO representations are more effective than static KG representations in our proposed model. Besides, we switch TANGO’s scoring function to TuckER (Balazevic, Allen, and Hospedales 2019) when we train TANGO on ICEWS21. Table 5 shows that TANGO + ComplEx aligns better to our QA module (Equation 1, 2, 3).

**Cross Hop Generalization** We want to study whether the trained model can be generalized between 1-hop and 2-hop entity prediction questions. We train FORECASTTKGQA with only the 1-hop questions and evaluate it on the test set of the 2-hop questions. Similarly, we retrain our model with only 2-hop questions and evaluate it on the 1-hop test set. To achieve fair comparison, we randomly sample 1-hop training questions and construct a new 1-hop training set whose size is as same as the complete 2-hop training set, i.e., containing 128,810 questions. In this way, we ensure that when testing on the same test set, our model is trained with the same number of training examples. We observe in Table 6 that our model can preserve about 56% performance when it
generalizes from 2-hop to 1-hop questions, and 67% from 1-hop to 2-hop (MRR), showing a strong generalization power.

Table 5: Comparison of different KG representations. EP, YN, FR represent entity prediction, yes-no and fact reasoning questions, respectively.

| KG Model             | EP MRR | EP Hits@1 | YN Acc | YN Hits@1 | FR MRR | FR Hits@1 |
|----------------------|--------|-----------|--------|-----------|--------|-----------|
| ComplEx              | 0.283  | 0.192     | 0.877  | 0.603     |
| TANGO + TuckER       | 0.288  | 0.197     | 0.880  | 0.633     |
| TANGO + ComplEx      | 0.293  | 0.200     | 0.882  | 0.636     |

Table 6: Cross hop generalization.

| Evaluation | 1-Hop | 2-Hop |
|------------|-------|-------|
|            | MRR | Hits@1 | MRR | Hits@1 |
| Train      |     |       |     |       |
| 1-Hop      | 0.328 | 0.233  | 0.133 | 0.067  |
| 2-Hop      | 0.186 | 0.106  | 0.197 | 0.115  |

Study of Data Efficiency

We want to know how the models will be affected with less/more training data. For each type of questions, we modify the size of its training set. We train FORECASTTKGQA on the modified training sets and evaluate our model on the original test sets. We randomly sample 10%, 25%, 50%, and 75% of the training examples to form new training sets. Figure 2 shows that for every type of questions, the performance of FORECASTTKGQA steadily improves as the size of the training sets increase. This proves that proposing a large-scale dataset for forecasting question answering over TKGs is meaningful.

Figure 2: Model performance with varying sizes of training sets. FR means fact reasoning, and YN means yes-no.

FORECASTTKGQUESTIONS vs. CRONQUESTIONS

We make a comparison between FORECASTTKGQUESTIONS and CRONQUESTIONS to show that our dataset is more challenging. First, we compare their background TKGs, i.e., Wikidata and ICEWS21. In ICEWS21, we contain questions associated with 253 different relation types, while Saxena et al. only generate the questions from the TKG facts concerning the 5 most frequent relation types in Wikidata. As a result, our dataset has a greater diversity in question contents, thus being more challenging for both TKG reasoning and QA models. Besides, a big difference between Wikidata and ICEWS21 is that, in ICEWS21, TKG facts tend not to remain valid for several consecutive timestamps, while in Wikidata, a large number of TKG facts are valid within a time duration. This is because ICEWS21 records political events that are rapidly evolving every day, while Wikidata pays attention to world knowledge, e.g., Lionel Messi plays for FC Barcellona from 2004 to 2021, which tends to be less dynamic. Due to the higher temporal variability, it is harder for TKG reasoning models to model ICEWS21, which poses a challenge to developing TKGQA methods.

Compared to CRONQUESTIONS, our dataset contains two more types of questions, i.e., yes-no questions and fact reasoning questions, thus introducing greater question type varieties into TKGQA. Moreover, the TKG fact leading to the ground-truth answer to a forecasting question is always unavailable for QA models. Every question in our dataset is only allowed to be answered with the help of the TKG facts prior to the question timestamp, while CRONQUESTIONS does not impose such a restriction. Experimental results in Table 3 show that the recent TKGQA models developed for solving CRONQUESTIONS do not achieve superior performance on our dataset, indicating the high difficulty of FORECASTTKGQUESTIONS.

Human Performance on Fact Reasoning Questions

To study the difference between humans and models in fact reasoning, we benchmark human performance on fact reasoning questions. We ask 5 graduate students to ask 100 questions that are randomly sampled from the test set. Humans are asked not to use any search engine for answer inference. Table 4 shows that humans achieve much stronger performance than all QA models, which calls for a great effort to build fact reasoning TKGQA models in the future. Note that pre-trained LMs are trained with extensive textual contents, and therefore, it is highly probable that they have already learned the background knowledge of the entities, e.g., the identity of a person, in ICEWS21. In our human benchmarking process, when humans meet an entity that is unknown to them, they are not allowed to use search engines to acquire any background knowledge. The actual margin between the performances of current QA models and humans is larger than it shows in Table 4.

Conclusion

In this work, we propose a novel task: forecasting question answering over temporal knowledge graphs. To the best of our knowledge, it is the first work combining TKG forecasting and TKGQA. We propose a large-scale dataset, i.e., FORECASTTKGQUESTIONS, that contains various types of questions including entity prediction, yes-no, and fact reasoning questions. To solve forecasting TKGQA, we propose a QA model, i.e., FORECASTTKGQA, that leverages a TKG forecasting model with a pre-trained LM. Though experi-
mental results show that our model outperforms recent baselines and achieves superior performance, there still exists a large room for improvement compared with humans. We hope our work can benefit future research and draw attention to studying the forecasting power of TKGQA methods.

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