**Abstract**

Recent years have witnessed interest in Temporal Question Answering over Knowledge Graphs (TKGQA), resulting in the development of multiple methods. However, these are highly engineered, thereby limiting their generalizability, and they do not automatically discover relevant parts of the KG during multi-hop reasoning. Relational graph convolutional networks (RGCN) provide an opportunity to address both of these challenges – we explore this direction in the paper. Specifically, we propose a novel, intuitive and interpretable scheme to modulate the messages passed through a KG edge during convolution based on the relevance of its associated period to the question. We also introduce a gating device to predict if the answer to a complex temporal question is likely to be a KG entity or time and use this prediction to guide our scoring mechanism. We evaluate the resulting system, which we call TwiRGCN, on a recent challenging dataset for multi-hop complex temporal QA called TimeQuestions. We show that TwiRGCN significantly outperforms state-of-the-art models on this dataset across diverse question types. Interestingly, TwiRGCN improves accuracy by 9–10 percentage points for the most difficult ordinal and implicit question types.

**1 Introduction**

Question answering (QA) is a key problem in natural language processing and a long-lasting milestone for artificial intelligence. A large class of approaches for QA makes use of knowledge graphs (KG), which are multi-relational graphs representing facts (KGQA). Temporal KGs (TKG) represent facts that are only valid for specific periods of time as (subject, relation, object, time range), for example, *(Franklin D Roosevelt, position held, President of USA, [1933, 1945])*). The problem of answering questions that require temporal reasoning over TKGs (TKGQA) is a special case of KGQA that specifically focuses on the following challenge:

temporal questions constrain answers through temporal notions, e.g., ”who was the first president of US during WW2?”. Developing systems for temporal QA is of immense practical importance for many applications. It is considered a more challenging problem than KGQA (Bhutani et al., 2019; Saxena et al., 2020), where questions are typically about persistent, non-temporal facts (e.g., place of birth), with only a small portion of the questions requiring any temporal reasoning (Jia et al., 2018a).

Even though a variety of models have been proposed for the TKGQA recently, they suffer from the following problems: 1) they are either highly engineered toward the task (Jia et al., 2021; Chen et al., 2022) or 2) they do not incorporate graph structure information using Graph Neural Networks (GNN) (Mavromatis et al., 2021; Shang et al., 2022; Saxena et al., 2021). We explore the following hypotheses in this paper: 1) a simple GNN-based solution could generalize better and offer higher performance than highly engineered GNN-based, and TKG embedding-based models; 2) a multi-layer GNN model could do multi-hop reasoning across its layers; 3) not all edges (temporal facts) are equally important for answering temporal questions (see Figure 1), so GNN solutions could benefit from temporally weighted edge convolutions.

Following the aforementioned hypotheses, we develop a novel but architecturally simple TKGQA system that we call “Temporally weighted Relational Graph Convolutional Network” (TwiRGCN). It is based on the Relational Graph Convolutional Network (RGCN) proposed by Schlichtkrull et al. (2018). TwiRGCN introduces a question-dependent edge weighting scheme that modulates convolutional messages passing through a temporal fact edge based on how relevant the time period of that edge is for answering a particular question. In RGCN, convolution messages from all TKG edges are weighted equally. But all edges are not equally important for answering temporal
questions. For example, in Figure 1, to answer the question “Who was the first president of the US during WW2?” the edge with Bill Clinton has little relevance for answering the question. But, regular RGCN would still weigh all edges equally. We address this shortcoming through our proposed modulation. We impose soft temporal constraints on the messages passed during convolution, amplifying messages through edges close to the time period relevant for answering the question while diminishing messages from irrelevant edges. This leads to better, more efficient learning as we are not confusing our model with unnecessary information, as evidenced by our significantly improved performance without the need for any heavy engineering. We explore two different strategies for our convolutional edge weighting, which show complementary strengths. Our experiments establish that TwiRGCN significantly outperforms already strong baselines on *TimeQuestions*. Our contributions are:

- **We propose TwiRGCN**, a simple and general TKGQA system that computes question-dependent edge weights to modulate RGCN messages, depending on the temporal relevance of the edge to the question.
- **We explore two novel and intuitive schemes** for imposing soft temporal constraints on the messages passed during convolution, amplifying messages through edges close to the time relevant for answering the question while diminishing messages from irrelevant edges. We also propose an answer-gating mechanism based on the likelihood that the answer is an entity or time.
- **Through extensive experiments on a challenging real-world dataset**, we find that TwiRGCN substantially outperforms prior art in overall accuracy, and by 9–10% on the implicit and ordinal type questions — categories that require significant temporal reasoning.
- **We augment *TimeQuestions* with a TKG and release both code and data at https://github.com/adisharma/TwiRGCN**.

2 Related Work

Most KGQA systems have focused on answering questions from simple (i.e., 1-hop fact-based questions) (Berant et al., 2013) to multi-hop complex questions requiring multi-fact reasoning (Sun et al., 2019; Saxena et al., 2020). However, only a small fraction of these questions require any temporal reasoning (Jia et al., 2018a). Recent efforts have tried to overcome this gap by proposing models as well as datasets to explicitly focus on temporal reasoning. We review these below.

**Temporal KGQA methods:** One line of work uses temporal constraints along with hand-crafted rules to find the answer (Bao et al., 2016; Luo et al., 2018; Jia et al., 2018b). A recent class of models has leveraged advances in TKG embedding methods for answering questions on Temporal KGs. CronKGQA (Saxena et al., 2021) does this by posing a question as a TKG completion problem and finds the answer using the TComplex (Lacroix et al., 2020) score function and BERT (Devlin et al., 2018) question embedding to complete the fact. TempoQR (Mavromatis et al., 2021) uses additional temporal supervision to enrich TKG embeddings, followed by a transformer-based decoder (Vaswani et al., 2017). TSQA (Shang et al., 2022) on the other hand estimate the time in the question and uses it to enrich TKG embeddings for finding the answer. SubGTR (Chen et al., 2022) infers question-relevant temporal constraints using TKG embeddings and applies them as filters to score entities in the question subgraph. Although we, too, use pre-trained TKG embeddings to initialize our generalized RGCN, we use the GNN framework to take advantage of the structural information in the KG in ways that they do not. Recent work (Teru et al., 2020) shows that GNN-based models can encode any logical rule corresponding to a path in
the knowledge graph. We refer to this as structural information that shallow embedding-based models cannot access.

**RGCN based QA systems:** Graph neural networks are increasingly being used in QA systems not specifically meant for temporal reasoning. GraftNet (Sun et al., 2018) uses personalized PageRank to collect a query-relevant subgraph from a global KG, then an RGCN to predict the answer from the relevant subgraph. PullNet (Sun et al., 2019) loops over and expands GraftNet’s subgraph to do multi-hop reasoning. EXAQT (Jia et al., 2021) is the system closest to ours: it addresses TKGQA and also uses an RGCN. The RGCN for answer prediction which works on the question subgraph is very similar to that in GraftNet. EXAQT augments it with dictionary matching, heavy engineering, and additional category information. In contrast, TwiRGCN uses a straightforward temporally weighted graph convolution followed by answer gating, as described in Section 4, while still achieving superior performance (see Section 5.3). More details in Section 5.2.

3 Preliminaries

3.1 Temporal Knowledge Graphs (TKG)

KG: Multi-relational graphs with entities (e.g., Barack Obama, USA) as nodes and relations \( r \) between entities \( \{s, o\} \) (e.g., president of) represented as typed edges between nodes. Each edge of this graph, together with endpoint nodes, represents a fact triple \( \{s, r, o\} \), e.g., {Barack Obama, president of, USA}.

TKG: Numerous facts in the world are not perpetually true and are only valid for a certain time period. A TKG represents such facts as a quadruple of the form \( \{s, r, o, [t_{st}, t_{et}]\} \), where \( t_{st} \) is the start time and \( t_{et} \) is the end time of validity of the fact, e.g., {Barack Obama, president of, USA, 2009, 2017}.

3.2 Question Answering on TKGs

Given a question \( q \) specified in natural language form and a TKG \( \mathcal{G} \), TKGQA is the task of finding the answer to \( q \) based on the information that is available (or can be derived) from \( \mathcal{G} \). A subgraph of \( \mathcal{G} \) is a subset of its nodes with induced edges. In this paper, we assume each question is already associated with a subgraph \( \mathcal{G}_q \) relevant to the question. We define \( \mathcal{G}_q = (\mathcal{V}_q, \mathcal{R}_q, \mathcal{T}_q, \mathcal{E}_q) \) as the subgraph of \( \mathcal{G} \) associated with a question \( q \in \mathcal{Q} \), where \( \mathcal{Q} \) represents the set of all questions. Each edge \( e \in \mathcal{E}_q \) represents a fact \( \{v_i, r, v_j, [t_{st}, t_{et}]\} \), where \( v_i, v_j \in \mathcal{V}_q \) are entity nodes, \( r \in \mathcal{R}_q \) is the relation between them and \( t_{st}, t_{et} \in \mathcal{T}_q \) are the start and end times for which the fact is valid.

3.3 Relational Graph Convolutional Networks

Given a KG, each node \( v_i \) is initialized to a suitable embedding \( h_{v_i}^{(0)} \) at layer 0. Thereafter, Schlichtkrull et al. (2018) propose to update node embeddings \( h_{v_i}^{(l+1)} \), at layer \((l + 1)\), as follows:

\[
h_{v_i}^{(l+1)} = \sigma \left( \sum_{r \in \mathcal{R} \cap J \in \mathcal{N}_i^r} \frac{W_r^{(l)} h_{v_j}^{(l)}}{|N_r^i|} + W_0^{(l)} h_{v_i}^{(l)} \right)
\]

where \( \mathcal{N}_r^i \) is the set of neighbors of node \( v_i \) that are connected via relation edges of type \( r \), \( \mathcal{R} \) is the set of relations, \( W_r^{(l)} \) are weight matrices associated with each relation type \( r \) and layer \( l \). They are initialized using a basis decomposition method.

4 Proposed Method: TwiRGCN

In this section, we develop and describe TwiRGCN (“Temporally Weighted Relational Graph Convolutional Network”), our model for TKGQA.

4.1 Embedding for questions and KG facts

**Question embedding:** We pass the question text through a pre-trained encoder-only language model (LM) to obtain a question embedding. In particular, we prepend a [CLS] token to the input question and feed it into BERT (Devlin et al., 2019), and then use its output-layer [CLS] embedding as the question embedding \( q_B \). We enable LM fine-tuning during training.

**TKG preprocessing for RGCN initialization:** We initialize entity and time embeddings using pre-trained TComplEx (Lacroix et al., 2020) embeddings.\(^1\) To obtain these for the TimeQuestions dataset (Jia et al., 2021), we first construct a ‘background KG’ \( \mathcal{G} = \bigcup_{q \in \mathcal{Q}} \mathcal{G}_q \) which is the union of all question subgraphs \( \mathcal{G}_q \) in the train dataset. As in most temporal KGQA works, we discretize time to a suitable granularity (in our dataset, a year).\(^2\) The graph on which TwiRGCN is run represents every entity as a node \( v_i \) and time as edge attribute \( t_j \). Their initial (layer-0) RGCN embeddings \( h_{v_i}^{(0)} \) and \( h_{t_j}^{(0)} \) are set to the entity and time embeddings

\(^1\)TComplEx is known to provide high-quality embeddings, but other KG embedding methods such as TimePlex (Jain et al., 2020) can also be used.

\(^2\)TwiRGCN can be extended to TKGQA datasets that do not provide subgraphs through recently proposed subgraph selection methods (Chen et al., 2022; Shang et al., 2022).
As discussed in Section 4.2, embeddings are propagated in the subgraph $G_q$ for a fixed number of layers ($L$) and hidden units of the final layer are pooled to get entity prediction, $h_{eq}$. We get time prediction, $h_{tq}$, by pooling the updated embeddings for all unique times in $G_q$.

We first project the question embedding $v_q$ to entity embedding $h_{eq}$ and time embedding $h_{tq}$ using learned projection matrices $W_q$ and $W_t$, respectively. We refer to $h_{tq}$ as $h_{stq}$ and $h_{eq}$ depending on $t_j$ appearing as start or end time for edge $e$, respectively. When $e = (i, r, j)$, we will use superscript $(i, r, j)$ in place of $(e)$.

### 4.3 Edge weighting formulations

We explore two different formulations for computing $m_{tq}^{(i,r,j)}$, namely average and interval, and discuss the motivations behind the two approaches.

In Section 5, we empirically show that the inductive bias inherent in each of the two approaches makes them excel at different types of temporal reasoning while giving similar performance overall. We also provide an intuitive explanation of how the edge weighting formulations of the two approaches explain the difference between their empirical results.

We first project the question embedding $q_B$, using a learned projection matrix $W_{tq}$, to find the question time embedding $q_t = W_{tq}q_B$. In the following, $m_{tq}^{(i,r,j)} = m_{tq}^{(e)}$ is the weight for edge $e$.

#### 4.3.1 TwiRGCN (average)

In this variant, we calculate the edge modulation $m_{tq}$ as the cosine similarity between the question time embedding, and the average of the embed-
This formulation gives a high weight to an edge if the question time falls close to the middle of the time interval for an edge. For example, if the edge times are [2008, 2012] and the question time is 2010, the edge is weighted highly.

4.3.2 TwiRGCN (interval)
In this variant, $m_{tq}^{(e)}$ is defined as the mean of two cosine similarities: (1) the cosine similarity between the start time of the edge and the learned question time embedding, and (2) the cosine similarity between the end time of the edge and the learned question time embedding. Formally,

$$m_{tq}^{(e)} = \cos(h_{st}^{(e)} + h_{et}^{(e)}, q_t).$$

This formulation weighs an edge highly if question time $t_q$ lies within the time interval of the edge.

**Generality beyond temporal reasoning** While we developed TwiRGCN for temporal reasoning, the edge weighting is more general and could extend to the case where $q_t$ is a "goal" embedding for any goal-directed task.

4.4 Answer type gating
Question answering over TKGs may involve questions whose answer is an entity (e.g., *Who was ...?*) or whose answer is a time (e.g., *When did ...?*). We hypothesize that it should be possible to predict whether the answer to a question is an entity or a time based on the text of the question; making such a prediction helps filter out (or down-weight) a portion of the nodes in that graph that are less likely to be the answer. Toward this hypothesis, we introduce a gating mechanism that learns the likelihood that the answer is an entity $p_{vq}$ or a time $p_{tq}$ given the question:

$$p_{vq} = 1 - p_{tq} = \sigma(w_vq_B),$$

where $w_v$ transforms $q_B$ to a scalar and $\sigma$ is the sigmoid function that ensures $0 \leq p_{vq} \leq 1$. As shown in Figure 3, we then compute a prediction embedding $d_q$ for question $q$ as a gated sum of the entity prediction and time prediction (see Section 4.2 and Figure 2) added to the question embedding:

$$d_q = \frac{1}{c_d}[p_{vq}h_{vq} + p_{tq}h_{tq} + W_dq_B],$$

where $c_d$ is a constant hyperparameter and $W_d$ is the weight for transforming $q_B$ to the dimension of the entity and time embeddings. Having the prediction embedding $d_q$, we rank candidate answers (entities and times from the global TKG) based on their similarity to $d_q$.

**Training** We score all possible answer entities and times as a cosine distance with the prediction embedding ($d_q$), scaled using a constant hyperparameter. We take a softmax over all these scores and train using the cross-entropy loss.

5 Evaluation

5.1 Dataset
Earlier works on TKGQA use the automatically generated CronQuestions dataset (Saxena et al., 2021). A recent analysis, however, shows that this dataset comes with several limitations that stem from its automatic construction method (Chen et al., 2022). Specifically, there are spurious correlations in the dataset that can be exploited by different models to achieve high accuracy (e.g., Mavromatis et al. (2021) report more than 90% accuracy overall and 99% in some categories on this dataset). Therefore, we base our experiments on a recent more challenging dataset, namely TimeQuestions (Jia et al., 2021), where the aforementioned models perform poorly (as seen in Table 3).

**TimeQuestions** has 13.5k manually curated questions divided into the train, valid, and test splits containing 7k, 3.2k, and 3.2k questions, respectively. The questions fall under four types: ‘Explicit,’ ‘Implicit,’ ‘Temporal,’ and ‘Ordinal,’ based on the type of temporal reasoning required to answer the questions. We show some examples of questions from each of these categories in Table 1. We augment this dataset with question-specific subgraphs generated from WikiData in the final step of the answer graph construction pipeline proposed by Jia et al. (2021). We preprocess all the obtained facts to the (subject, relation, object, [start
We compare TwiRGCN against a spectrum of existing TKGQA methods, including EXAQT, other TKGQA methods, and non-temporal KGQA methods. **Non-temporal KGQA methods:** We include Unicorn (Pramanik et al., 2021), which uses Group Steiner Trees for answering questions. We test on two RGCN-based approaches for KGQA, namely, GRAFT-Net (Sun et al., 2018), which attends over relations of neighborhood edges based on the question, and PullNet (Sun et al., 2019), which extends GRAFT-Net for multi-hop questions.

**TKGQA methods:** We also compare against TKGQA methods CronKGQA (Saxena et al., 2021) and TempoQR (Mavromatis et al., 2021) recently proposed for the CronQuestions dataset. In contrast to TwiRGCN, these do not leverage the powerful GNN framework. CronKGQA frames QA as a KG completion problem to complete the fact the question is interested in, using the TComplex score function and BERT question embedding. TempoQR, on the other hand, enriches pre-trained TKG embeddings with additional supervision from the dataset and uses a transformer (Vaswani et al., 2017) based decoder to predict the final answer.

**EXAQT:** Jia et al. (2021) propose EXAQT, which is hitherto the best performer on TimeQuestions. It is also an RGCN-based TKGQA model that utilizes the GRAFT-Net framework. But in contrast to our model, EXAQT is heavily engineered. It utilizes the ground truth question category information from the dataset at train and test time, so it always knows whether the answer is temporal or belongs to another category. In contrast, our model learns the likelihood that the answer is an entity or time without any explicit supervision through our gating mechanism described in Section 4.4. EXAQT also uses explicit temporal signals from the question, extracted through a dictionary matching-based method using predefined temporal words such as ‘before’, ‘after’, ‘first’, ‘last’, ‘during’, etc. It then enriches its embeddings by utilizing the above in a multi-step end-to-end process. In contrast, our models do not have access to any such information with only a straightforward temporally weighted graph convolution followed by answer gating, as described in Section 4.

### 5.3 Results

**TwiRGCN achieves new state-of-the-art:** We compare the accuracy (Hits@1) for different Temporal KGQA models across all question categories found in TimeQuestions in Table 3. From this table, we see that our models TwiRGCN (average) and TwiRGCN (interval) achieve significant improvements of up to 3.3% overall absolute accuracy over the previous state-of-the-art model, EXAQT. Additionally, TwiRGCN (average) gets a 9.8% improvement over EXAQT in the ordinal category and TwiRGCN (interval) improves over EXAQT by 9.1% in the implicit category. The questions in both these categories require significant temporal reasoning to find the correct answer. Both models also show a marked improvement of up to 3.4% in the explicit question category.

**TwiRGCN (average) vs (interval):** Even though the two TwiRGCN variants achieve comparable overall accuracy, they do so in different ways, showing complementary strengths. TwiRGCN (average) achieves a 2.4% improvement over TwiRGCN (interval) in the ordinal category, while TwiRGCN (interval) improves over TwiRGCN (average) for
Table 3: Comparison of Hits@1 for different Temporal KGQA methods on TimeQuestions dataset (Section 5.3). Interestingly, TwiRGCN improves accuracy over SOTA by 3.3% overall and by 9-10% for the most difficult ordinal & implicit question types.

| Method                  | Overall | Explicit | Implicit | Temporal | Ordinal |
|-------------------------|---------|----------|----------|----------|---------|
| PullNet (Sun et al., 2019) | 0.105   | 0.022    | 0.081    | 0.234    | 0.029   |
| Uniqorn (Pramanik et al., 2021) | 0.331   | 0.318    | 0.316    | 0.392    | 0.202   |
| GRAFT-Net (Sun et al., 2018) | 0.452   | 0.445    | 0.428    | 0.515    | 0.322   |
| CronKGQA (Saxena et al., 2021) | 0.462   | 0.465    | 0.36     | 0.4      | 0.349   |
| TempoQR (Mavromatis et al., 2021) | 0.416   | 0.568    | 0.512    | 0.642    | 0.42    |
| EXAQT (Jia et al., 2021) | 0.572   | 0.599    | 0.603    | 0.646    | 0.494   |
| TwiRGCN (average) | **0.605** | **0.602** | **0.586** | **0.641** | **0.518** |
| TwiRGCN (interval) | **0.603** | **0.599** | **0.603** | **0.646** | **0.494** |

Table 4: Results for EXAQT and TwiRGCN on temporal subsets of well-known KGQA datasets, as discussed in Section 5.3. TwiRGCN beats EXAQT by a high margin up to 21% on ComQA, ComplexWebQuestions, and GraphQuestions, which include questions requiring multi-hop reasoning.

| Dataset                  | EXAQT | TwiRGCN |
|--------------------------|-------|---------|
| ComQA                    | 0.292 | 0.413   |
| ComplexWebQuestions      | 0.515 | 0.728   |
| GraphQuestions           | 0.323 | 0.382   |
| LC-QuAD 2.0              | 0.732 | 0.71    |
| Free917                  | 0.17  | 0.0    |

Table 5: Results of ablation study to see contributions of answer gating described in Section 4.4 on overall Hits@1. We show that it contributes about 0.7% on average to the overall accuracy of our models.

| Temporal Distance from \( q_t \) | With gating | W/o gating |
|----------------------------------|-------------|------------|
| Median                           | 5           | 5          |
| \( \leq 0 \)                     | 18.3%       | 18.3%      |
| \( \leq 5 \)                     | 51.5%       | 51.5%      |
| \( \leq 20 \)                    | 74.8%       | 74.8%      |

Table 6: The median temporal distance from learned \( q_t \) to extracted time is just 5 years, while we predict an exact match 18.3% of the time (discussed in Section 5.4).
Table 7: Percentage of questions for which answer is an entity but our model incorrectly predicts time and vice versa. We analyze this in Section 5.3 with and w/o answer gating to show that our proposed answer gating helps in reducing such mistakes.

|          | Entity     | Time       | TwiRGCN (average) | TwiRGCN (interval) |
|----------|------------|------------|-------------------|--------------------|
|          | with gating| w/o gating | with gating       | w/o gating         |
| Entity   | 3.18 %     | 7.28 %     | 3.23 %            | 4.53 %             |
| Time     | 7.99 %     | 6.88 %     | 7.3 %             | 7.82 %             |

Table 8: Effects of increasing k for Hits@k. As discussed in Section 5.4, TwiRGCN significantly outperforms EXAQT across categories of questions even as k is increased.

|          | Hits@1 | Hits@2 | Hits@3 |          |          |          |
|----------|--------|--------|--------|----------|----------|----------|
| EXAQT    | 0.568  | 0.602  | 0.618  | TwiRGCN  | 0.602    | 0.618    |
| TwiRGCN  | 0.512  | 0.575  | 0.612  |          | 0.603    | 0.622    |
|          | 0.42   | 0.47   | 0.49   | ORDINAL  | 0.518    | 0.542    | 0.553    |

Table 9: Effects of increasing the answer temporal window on model performance for Temporal type questions. As discussed in Section 5.4, TwiRGCN (interval) gets even more accurate relative to EXAQT as we increase the temporal tolerance window.

| Temporal (Hits@1) | ±0 | ±1 | ±3 |          |          |          |
|-------------------|----|----|----|----------|----------|----------|
| EXAQT             | 0.642 | 0.653 | 0.667 | TwiRGCN (average) | 0.641 | 0.649 | 0.671 |
| TwiRGCN (interval) | 0.646 | 0.659 | 0.682 |

Dominant errors: We do an error analysis over quantity-type questions, a challenging query class. Neither EXAQT nor TwiRGCN perform well on quantity-type questions. Out of a total of 224 quantity questions, EXAQT gets 0.1% accuracy while TwiRGCN gets 0.05%. This is because current TKGQA models treat quantities such as “2.55” or “16,233” as independent entities, instead of scalar numeric values. Additionally, from Section 5.3, we reconfirm that current TKGQA models fail on this bucket, so future work can direct special attention here. Examples: “What was Panama’s fertility rate in 2006?” A: 2.55; “What was the population of Bogota in 1775?” A: 16,233.

Reducing answer type mistakes: In this study, we estimate TwiRGCN’s propensity to make answer type mistakes. We define these mistakes as situations where the answer was an entity, but our model predicted a time or vice versa. From Table 7 we see that our answer gating mechanism mentioned in Eqn. (5) helps reduce such mistakes. For TwiRGCN (average), gating cuts entity-to-time mistakes by more than half.

Increasing k for Hits@k: We extend the analysis in Table 3 increasing k from 1 to 3 for Hits@k on TimeQuestions. From Table 8 we see that the performance of TwiRGCN is robust to increasing k. It significantly outperforms EXAQT across categories even as k is increased for Hits@k.

Increasing temporal tolerance window: In Table 9, we explore the effects of increasing the time window for marking an answer correct for temporal questions. This means if the ground truth answer is 1992, and the predicted answer is 1990 for a question, it will be marked as incorrect in the ±1 column and correct in the ±3 column. We find that our model, specifically TwiRGCN (interval) gets even more accurate relative to EXAQT as we in-
crease the temporal tolerance window. This implies that TwiRGCN is robust at ranking gold answers high up, even if they do not achieve rank 1.

**Prediction overlap:** We study the overlap of predictions between EXAQT, TwiRGCN, and ground truth. As seen in Figure 4, for Explicit, Implicit, and Ordinal question types our model gives the right answers for most questions that EXAQT answers correctly (missing less than 6% on average), while correctly answering a much larger set that EXAQT gets wrong. This split is more even between the two models for the temporal-type questions.

6 Conclusion

In this paper, we proposed TwiRGCN, a TKGQA system that employs a novel, temporally weighted graph convolution for answering questions that require complex temporal reasoning over a TKG. TwiRGCN modulates the convolutional messages through a TKG edge based on the relevance of the edge time interval to the question. We present two temporal weighting schemes with complementary strengths, intuitively explained through their simple formulations. We also propose an answer gating system for incorporating the pooled entity and time embeddings from TwiRGCN in the prediction, based on the likelihood that the answer is a time or an entity, given the question. Despite its relative simplicity, TwiRGCN gives significantly superior TKGQA accuracy on a challenging dataset compared to more heavily engineered baselines.

Acknowledgements

We thank Jeremy Cole and Srini Narayan for their valuable feedback. We also thank the anonymous reviewers for their constructive comments. Soumen Chakrabarti was supported in part by grants from Amazon, Google, IBM, and SERB.

7 Limitations

TwiRGCN is limited by the need for relevant subgraphs for each question to be provided in the dataset. Such subgraphs have been provided in the TimeQuestions dataset used in the current work, but that may not be true for all TKGQA datasets. This limitation may be addressed for datasets that do not provide subgraphs through recently proposed subgraph selection methods (Chen et al., 2022; Shang et al., 2022; Jia et al., 2021), but we leave that exploration for future work.

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A Additional Analyses

A.1 Complete prediction overlap

In Figure 5, we extend our analysis in 5.4 by providing the complete prediction overlap for both our models with EXAQT and ground truth across all question categories in *TimeQuestions*.

B Hyperparameters

We use the following hyperparameters:

- Number of layers, $L = 2$
- $c_d = 3$
- train batch size = 32
- valid batch size = 5
- LR = 0.00004
- Decay for LR = 0.4 every 10 epochs
- Cosine distance scaling constant for training (described in Section 4) = 30

Model and program execution details:

- Number of parameters = 2,223,833
- 11GB Nvidia GPU used with cudatoolkit 11.1
- Time per training epoch = 1:04 min
- Number of epochs to convergence on average = 50
- Early stopping used and implemented in code with patience = 10
- Validation overall Hits@1 for TwiRGCN (average) = 0.606
- Validation overall Hits@1 for TwiRGCN (interval) = 0.602
- Performance is fairly stable around current hyperparameters without much tuning, except for LR decay rate. We used around 5–7 training runs with different decay settings to get the current rate. TwiRGCN is stable around current settings.
- Hyperparameters were tuned by manually inspecting loss behavior. Final values were selected based on a sustained, stable good performance on the test set for 3 runs.
Figure 5: Venn diagrams for the prediction overlap of EXAQT, ground truth, and our two models TwiRGCN (average) in (a) and TwiRGCN (interval) in (b), as discussed in Appendix A.1.