Faithful Temporal Question Answering over Heterogeneous Sources

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ABSTRACT

Temporal question answering (QA) involves time constraints, with phrases such as "... in 2019" or "... before COVID". In the former, time is an explicit condition, in the latter it is implicit. State-of-theart methods have limitations along three dimensions. First, with neural inference, time constraints are merely soft-matched, giving room to invalid or inexplicable answers. Second, questions with implicit time are poorly supported. Third, answers come from a single source: either a knowledge base (KB) or a text corpus. We propose a temporal QA system that addresses these shortcomings. First, it enforces temporal constraints for faithful answering with tangible evidence. Second, it properly handles implicit questions. Third, it operates over heterogeneous sources, covering KB, text and web tables in a unified manner. The method has three stages: (i) understanding the question and its temporal conditions, (ii) retrieving evidence from all sources, and (iii) faithfully answering the question. As implicit questions are sparse in prior benchmarks, we introduce a principled method for generating diverse questions. Experiments show superior performance over a suite of baselines.

CCS CONCEPTS

Information systems → Question answering.

KEYWORDS

Question Answering, Temporal Questions, Explainability

ACM Reference Format:

Zhen Jia, Philipp Christmann, and Gerhard Weikum. 2024. Faithful Temporal Question Answering over Heterogeneous Sources. In *Proceedings of the ACM Web Conference 2024 (WWW '24), May 13–17, 2024, Singapore, Singapore.* ACM, New York, NY, USA, 12 pages. https://doi.org/10.1145/nnnnnn. nnnnnnn

1 INTRODUCTION

Motivation. Question answering (QA) comprises a spectrum of settings for satisfying users' information needs, ideally giving crisp, entity-level answers to natural-language utterances [46]. Temporal QA specifically focuses on questions with temporal conditions (e.g., [24, 31, 48]), making up a substantial portion of user needs [65],



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WWW '24, May 13–17, 2024, Singapore, Singapore © 2024 Copyright held by the owner/author(s). ACM ISBN 978-x-xxxx-x/YY/MM. https://doi.org/10.1145/nnnnnnnnnnn but poses challenges that are not properly met by universal QA systems. Consider the following example:

q_1 : Record company of Queen in 1975?

The band Queen had different record companies over the years, so it is decisive to consider the *explicit temporal constraint* (*"in 1975"*). Other questions with explicit time are lookups of dates, such as:

 q_2 : When was Bohemian Rhapsody recorded?

Another – underexplored and most challenging – situation is when questions involve *implicit temporal constraints*. These can involve the need to compare different time points or intervals, even when the user input does not explicitly state it. Examples are:

q₃: Queen's record company when recording Bohemian Rhapsody? q₄: Queen's lead singer after Freddie Mercury?

For q_4 , the system has to find out when Mercury died or left the band, in order to compute the correct answer that Brian May (the band's guitarist) took over as lead singer.

The research literature on temporal QA is substantial, including [9, 10, 16, 23–25, 31, 48, 58]. Most methods address all kinds of temporal questions, but are typically less geared for implicit questions. Some methods operate over curated knowledge bases (KBs) (e.g., [16, 23, 24]), while others are designed for processing text corpora such as news collections or Wikipedia full-text (e.g., [9, 35]).

State-of-the-art limitations. We observe three major issues:

- (i) Many methods use "soft-matching" techniques, based on latent embeddings or language models. This may lead to invalid answers, where the non-temporal part of a question is matched, but the temporal constraint is violated. For example, a question about "Queen's record company in 1990?" may erroneously return EMI instead of the correct value Parlophone, because EMI is more prominent and was Queen's company on most albums. Even when the output is correct, this could be by the prominence of the answer alone. For example, "Who was Queen's lead singer in 1975?" could return the most popular Freddie Mercury without checking the time. When we vary the question into "... in 2000?", many systems would still yield Freddie Mercury, although he was dead then. This indicates that the system has incomplete inference and is unable to explain its answer derivation. We call this phenomenon unfaithful QA.
- ii) A weak spot of temporal QA systems is the handling of *implicit questions*. These are infrequent in established benchmarks. Some methods [16, 23, 34] aim to transform the implicit conditions into explicit temporal constraints, based on classifying phrases starting with "during", "before" etc. However, they heavily rely

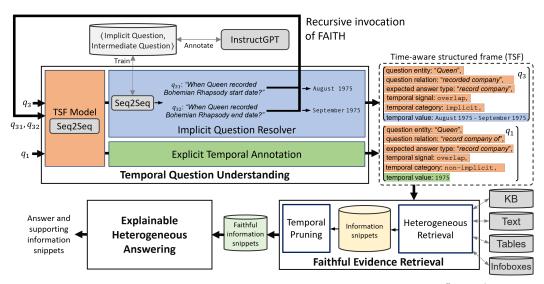


Figure 1: Overview of the FAITH pipeline. The figure illustrates the process for answering q_3 ("Queen's record company when recording Bohemian Rhapsody?") and q_1 ("Record company of Queen in 1975?"). For answering q_3 , two intermediate questions q_{31} and q_{32} are generated, and run recursively through the entire temporal QA system.

on hand-crafted rules which are rather limited in scope and cannot robustly handle unforeseen utterances.

(iii) Prior methods run on a *single information source*: either a KB or a text corpus. This limits QA coverage: KBs are incomplete and lack refined detail about events, whereas text collections are harder to extract answers from and often fail on complex questions [11, 16]. QA over heterogeneous sources, including also web tables, has been addressed by [13, 38], but these methods do not support temporal conditions.

Approach. To overcome these limitations, we propose FAITH (<u>FAI</u>thful <u>T</u>emporal question answering over <u>H</u>eterogeneous sources), a temporal QA system that operates over *heterogeneous* sources, seamlessly combining a KB, a text corpus and web tables. Inspired by the architecture of [13], FAITH consists of three main stages:

- (i) Temporal Question Understanding for representing the question intent into a structured frame, with specific consideration of the temporal aspects;
- (ii) Faithful Evidence Retrieval for identifying relevant pieces of evidence from KB, text and tables, with time-aware filtering to match the temporal conditions;
- (iii) Explainable Heterogeneous Answering to compute entitylevel answers and supporting evidence for explanation.

A key novelty in the question understanding is that implicit constraints are resolved into explicit temporal values by generating intermediate questions and recursively calling FAITH itself. For example, the implicit condition "when recording Bohemian Rhapsody" in q_3 is transformed into "when Queen recorded Bohemian Rhapsody?", and the recursive invocation of FAITH returns the explicit condition August 1975 - September 1975. This derived explicit condition is then used in a similar vein as the explicit condition 1975 in q_1 , making it easier to answer the information need. Note that this is not just question rewriting, but is driven by the full-fledged QA system itself over the full suite of heterogeneous sources. A second key novelty is that, in contrast to most prior works including large language models, FAITH provides *tangible provenance* for the answer derivation. By providing users with explanatory evidence for answers, FAITH is a truly faithful temporal QA system.

Existing benchmarks for temporal QA focus on a single information source at hand (either a KB or a text corpus), and include only few questions with implicit constraints (so the weak performance on these hardly affects the overall results). Therefore, we devise a new method for automatically creating temporal questions with *implicit constraints*, with systematic controllability of different aspects, including the relative importance of different source types (text, infoboxes, KB), coverage of topical domains (sports, politics etc.), fractions of prominent vs. long-tail entities, question complexity, and more. This way, we construct a new dataset named TIQ with 10,000 questions and answers accompanied by supporting evidence. Our code and data is available at **https://faith.mpi-inf.mpg.de**.

Contributions. The salient contributions of this work are:

- the first temporal QA system that taps into heterogeneous sources, and gives faithful answers with explanatory evidence;
- a mechanism that transforms implicit temporal constraints into explicit conditions, by recursively calling the QA system itself;
- a principled method for automatic construction of diverse and difficult temporal questions, releasing the TIQ benchmark.

2 CONCEPTS AND NOTATION

This section introduces salient concepts and notation for this work. **Temporal value**. A *temporal value* indicates a point in time or time interval. It can be a specific *date* (e.g., 24 November 1991), a *year* (e.g., 1975), or a time period (e.g., August 1975 – September 1975).

Temporal constraint. A *temporal constraint* specifies a condition about a time point or interval that has to be satisfied by the answer and its evidence. Temporal constraints consist of a temporal value,

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and a *temporal signal* (like *before*, *after*, *overlap*). An example of a (verbalized) temporal constraint is "in 1970".

Explicit question. An *explicit question* mentions a specific temporal constraint explicitly, as in *"Record company of Queen in 1975?"*. **Implicit question**. An *implicit question* also specifies a temporal constraint, but keeps this constraint *implicit* without mentioning the actual temporal value: *"Queen's record company when recording Bohemian Rhapsody?"*.

Answer. An *answer* to a question is either an entity (e.g., Brian May) or a literal such as a date (e.g., 24 August 1975), year (e.g., 1975) or number (e.g., 3).

Evidence. An *evidence* is given with an answer as explanatory support. The evidence consists of *information snippets* that are retrieved from a KB, a text corpus, a table, or a Wikipedia infobox. Following [12], we consider snippets on a sentence-level: text is split into sentences, and KB-facts, table rows and infobox entries are *verbalized* by concatenating the individual pieces.

Faithfulness. A system answers a question *faithfully* if its evidence, provided with the answer, contains: (i) the answer, (ii) all entities that appear in the question (with any surface name), (iii) all predicates that appear in the question (at least in paraphrased or implicit form), (iv) a temporal expression that satisfies the temporal constraint of the question. The first three aspects are valid in the context of any QA system; the fourth is specific to temporal QA.

3 FAITH METHOD

Fig. 1 provides an overview of the system architecture, illustrated with the processing of the running examples q_3 and q_1 . The following subsections present the three main components (understanding, retrieval, and answering), and will refer to these examples.

3.1 Temporal Question Understanding

The goal of this first stage is to capture the temporal information need in a frame-like structure. Notably, this stage identifies and categorizes temporal constraints in the user input, which is later used for pruning temporally-inconsistent answer candidates.

TSF. Inspired by [12] and [20] (both addressing other, non-temporal, kinds of QA), we propose to learn a *<u>T</u>ime-aware Structured Frame* (*TSF*) for an incoming temporal question. The TSF includes both general-QA-relevant slots:

- question entity,
- *question relation*,
- expected answer type,

and temporal-QA-relevant slots:

- *temporal signal*, indicating the kind of temporal relation,
- *temporal category*, indicating the type of temporal constraint,

• *temporal value*, the time point or interval of interest (if present). The *question entity* and *relation* are taken from the surface form of the question (i.e. *not* linked to KB) to allow for uniform treatment of heterogeneous sources. The *expected answer type* is learned from the training data, in which the KB-type of the gold answer is used. The *temporal signal* can be overlap (e.g., from cues like "*in*", "*during*"), before (e.g., from cues like "before", "prior to"), or after (e.g., from cues like "*after*", "follows"). We categorize the constraint into *implicit* (e.g., q₃ and q₄) and *non-implicit* (e.g., q₁ and q₂). The

temporal value can be a *year*, *date* or *time period*. Both the temporal signal and value are derived by identifying and normalizing key phrases in the input question. For example, the TSF for q_1 is:

< question entity: "Queen", question relation: "record company of", expected answer type: "record company", temporal signal: overlap, temporal category: non-implicit, temporal value: 1975 >

Note that in case the question does not specify temporal constraints (e.g., q_2), the respective fields are simply kept empty.

Resolving implicit questions. For the challenging case of implicit questions, such as q_3 or q_4 , the temporal value cannot be extracted from the question directly. To resolve this problem, we devise a novel mechanism, the *implicit question resolver*, based on recursively invoking the temporal QA system itself. To this end, the implicit temporal constraint in the question is identified and transformed into an *intermediate question*. For instance, the intermediate question for q_4 would be "when Freddie Mercury lead singer of Queen?". For q_3 , the temporal value should be a time interval (August 1975 - September 1975). Thus, two intermediate questions are required: (i) q_{31} : "When Queen recorded Bohemian Rhapsody start date?", and (ii) q_{32} : "When Queen recorded Bohemian Rhapsody end date?". Although these formulations are ungrammatical, the QA system can process them properly, being robust to such inputs.

The intermediate questions are fed into FAITH as a recursive call, to obtain the explicit temporal value for filling the TSF of the original question. The TSF for q_3 thus becomes:

< question entity: "Queen", question relation: "recorded company", expected answer type: "record company", temporal signal: overlap, temporal category: implicit, temporal value: August 1975 - September 1975 >

Note the similarity to the TSF of the explicit temporal question q₁. **Generating intermediate questions**. The intermediate questions are generated by a fine-tuned sequence-to-sequence (Seq2seq) model, specifically BART [27]. A major obstacle, though, is that no prior dataset has suitable annotations, and collecting such data at scale is prohibitive. Therefore, we generated training data using InstructGPT [39], leveraging its *in-context learning* [3] capabilities. We randomly select 8 implicit questions from our train set and label them manually. For each question, we give the intermediate question and the expected answer type as output. The exact prompts used are shown in Table 9 in the Appendix.

The expected answer type of an intermediate question can be date or time interval. When the expected answer type is a time interval (e.g., for q_3), two intermediate questions are created, appending "*start date*" and "*end date*" to the generated intermediate question, respectively (see q_{31} and q_{32} as example).

We use this technique to annotate all implicit questions in the train and dev sets, obtaining training data for fine-tuning the BART model. Note that GPT is used only for the generation of training data. It is not used at run-time to avoid its (computational, monetary, and environmental) costs and dependency on black-box models.

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Constructing the TSF. We also use a fine-tuned Seq2seq model, again BART, for generating the values for the question entity, question relation, expected answer type, temporal signal, and temporal category slots of the TSF representation. The training data this TSF construction model is obtained via (i) distant supervision (for question entity and question relation) [12], (ii) KB-type look-ups (for expected answer type), and (iii) annotations in the benchmark (for temporal signal and temporal category). Further detail in Sec. A.2.

The temporal values are obtained via the recursive mechanism discussed above for implicit questions, and via SUTime [6] and regular expression matching for explicit questions. Phrases like *"today"* or *"current"* are considered as well and properly normalized. We use the creation time of the question [5], as provided in the benchmarks, as reference time.

The TSF generated in this understanding stage is used for representing the temporal information need in the subsequent retrieval and answering stages, capturing its key temporal characteristics.

3.2 Faithful Evidence Retrieval

In this stage, we first retrieve evidence from heterogeneous sources, and then prune out information inconsistent with the temporal constraint expressed by the temporal signal and value in the TSF. **Heterogeneous retrieval**. This step largely follows the general-purpose QA method of [12], and makes use of entity linking. Entity mentions in the input are identified and linked via CLOCQ [11]. The input here is the concatenation of the *question entity*, the *question relation*, and the *expected answer type* of the TSF. For the resulting linked entities, we retrieve the Wikipedia pages for extracting text, tables, and infoboxes. Further, KB-facts with the linked entities are obtained from Wikidata.

All retrieved pieces of evidence are *verbalized* [38] into textual sentences, for uniform treatment. The KB-facts are verbalized by concatenating their individual parts; the text evidence is split into sentences; table rows are transformed by concatenating the individual (column headers, cell value) pairs; infoboxes are handled by linearizing all attribute-value pairs.

Temporal pruning. Explicit temporal expressions in the retrieved pieces of evidence are identified and normalized similarly as in the understanding stage. Evidence that does not match the temporal criteria is pruned out. We address two kinds of situations:

- (i) the question aims for a temporal value as answer and does not have any temporal constraints (e.g., "When ...?");
- (ii) the question has a temporal constraint which needs to be matched by the evidence.

In the first case, all evidence that does not contain any temporal values, and is thus unable to provide the answer, is dropped. In the second case, we remove pieces of evidence that do not match the temporal constraint, to ensure that answers are faithful to the temporal intent of the question.

The retrieval output is a smaller set of evidence pieces, faithfully reflecting the temporal constraints of the question. The final answer and its explanatory evidence are computed from this pool.

3.3 Explainable Heterogeneous Answering

In the final stage, the answer is derived from this set of evidence pieces that is already known to satisfy the temporal conditions.

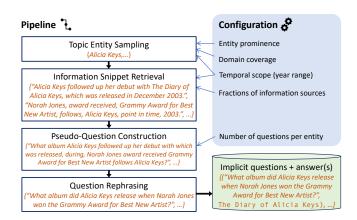


Figure 2: Steps to create implicit questions with our proposed methodology, highlighting the key configurable parts.

Since this part is not the main focus of this work, we employ a state-of-the-art answering model for general-purpose QA. We use the answering stage of EXPLAIGNN [13] that is based on graph neural networks (GNNs), and computes a subset of supporting evidence for the predicted answer. Thus, we ensure that the answer can be traced back through the entire system including the answering stage, for end user explainability. The input query to the GNNs is the concatenation of the question entity, question relation, and expected answer type.

4 TIQ BENCHMARK

Most existing benchmarks for temporal QA, like TEMPQUESTIONS [22], TIMEQUESTIONS [24] or TEMPQA-WD [34], have only few implicit questions (209, 1,476, and 154, respectively), falling short of evaluating one of the key challenges in temporal QA. CRONQUESTIONS [48] and TEMPREASON [53] have a larger fraction of implicit questions, but these are based on a small set of hand-crafted rules. Thus, the questions lack *syntactic diversity*. Further, questions in these benchmarks are always answerable using a single information source (either KB or text corpus).

Therefore, we construct a new benchmark with a primary focus on challenging and diverse implicit questions. The obvious idea of using crowdsourcing is expensive and error-prone. Also, crowdworkers increasingly use LLMs as a shortcut [54]. Thus, we pursue an automated process instead. To ensure that questions are not specific to a single input source, our process considers multiple sources: Wikipedia text and infoboxes, and the Wikidata KB.

4.1 Construction Methodology

Overview. An implicit question has two parts: the *main question* that specifies the information need disregarding time (e.g., "Queen's lead singer" for q_4), and the *implicit part* that provides the temporal constraint (e.g., "after Freddie Mercury" for q_4). The key idea is to build each of the two parts from independent pieces of evidence, denoted as *information snippets*. The two snippets can come from very different sources, but need to be thematically related. This construction process operates as follows:

- (i) sample a set of topic entities to start with;
- (ii) retrieve temporal information snippets for each such topic entity from Wikipedia text, Wikipedia infoboxes, and Wikidata;

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- (iii) concatenate information snippets using a suitable temporal signal and construct an interrogative sentence, a *pseudo-question*;
- (iv) rephrase the pseudo-question into a natural question using a generative model.

An overview of this process is provided in Fig. 2, including an example case of constructing an implicit question. Naturally, implicit constraints are global events (e.g., the COVID pandemic), or major events for a specific entity (e.g., a prestigious award).

Sampling topic entities. To obtain significant events, we start with Gregorian calendar year pages in Wikipedia (e.g., https://en. wikipedia.org/wiki/2023) that list notable events. From the pages for the years 1801 - 2025, we collect information snippets about such significant events. The entities in these snippets constitute the set of topic entities (href anchors are used for entity linking [17]).

In our example in Fig. 2 this set includes Alicia Keys.

Retrieving the grounding information snippets. We collect snippets about notable events in these year pages, and augment them with salient information about the topic entity from (i) the first five sentences (~ first passage) of the entity's Wikipedia page, (ii) the respective Wikipedia infobox, and (iii) the Wikidata facts.

As candidates for the main question part, we consider all information snippets that are retrieved for a topic entity from Wikipedia text, infoboxes and Wikidata, irrespective of their salience. To avoid questions that are trivially answerable without considering the temporal condition, multiple candidate snippets are retrieved for the main question, with different temporal scopes (e.g., a band's singers from different epochs). This is implemented by measuring semantic similarity among candidates using a SentenceTransformer¹ [45].

Creating a pseudo-question. Among the retrieved snippets for an entity, we identify pairs of candidate snippets that can be connected by a temporal conjunction/preposition (*"during"*, *"after"* and *"before"*). For such a pair, the temporal scopes have to be consistent with the temporal conjunction. A valid pair for the conjunction *"during"* would be: *"Alicia Keys followed up her debut with The Diary of Alicia Keys, which was released in December 2003."* (main question part from Wikipedia text) and *"Norah Jones, award received, Grammy Award for Best New Artist, follows, Alicia Keys, point in time, 2003."* (implicit part from KB). A *pseudo-question* is created by concatenating the main part with the conjunction and the implicit part. The answer is an entity (not the topic entity) from the main part (The Diary of Alicia Keys). The answer is substituted by the prefix *"what"* followed by the most frequent KB-type of the answer (album in this case).

The pseudo-question for the example is: "What album Alicia Keys followed up her debut with which was released, during, Norah Jones award received Grammy Award for Best New Artist follows Alicia Keys?", which is an ungrammatical and unnatural formulation. **Rephrasing to a natural question**. Therefore, in the last step, we rephrase the pseudo-question to a natural formulation. We use InstructGPT [39] with 8 demonstration examples (pseudo-questions and their natural re-phrasings), to generate the final question².

The pseudo-question of the example is rephrased into the following implicit question: "What album did Alicia Keys release when Norah Jones won the Grammy Award for Best New Artist?"

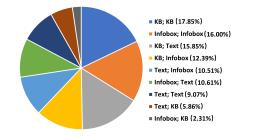


Figure 3: Distribution of questions over input source combinations (source for main part ; source for implicit part).

Table	1:	Basic	statistics	for	Тю
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Sources Questions	Wikipedia text, infoboxes, and Wikidata 10,000 (train: 6,000, dev: 2,000, test: 2,000)
Avg. question length	17.96 words
Avg. no. of question entities	2.45
Unique topic entities covered	10,000
Long-tail topic entities covered	2,542 (with < 20 KB-facts)
Prominent topic entities covered	2,613 (with > 500 KB-facts)

4.2 Benchmark Characteristics

Topic entities. For creating TIQ (<u>Temporal Implicit Questions</u>) we started with the years 1801-2025 and obtained an initial set of 229,318 entities. From this set, we uniformly sampled 10,000 topic entities based on their frequency, to capture a similar amount of long-tail and more prominent entities (see Table 1 for details). These fractions can be configured as required. Since some entity types were over-represented in the calendar year pages (e.g., politicians or countries), we also ensured that individual entity types are not taking up more than 10% of the topic entities. In general, the topic entity set allows to control the domain coverage within the generated implicit questions, by choosing entities of the desired types.

We did not specifically configure the proportions to which the individual information sources are used within the questions, since we observed a naturally diverse distribution. Fig. 3 shows the distribution among source combinations for initiating the main and implicit part. The questions are finally split into train (6,000), dev (2,000), and test sets (2,000). Table 1 shows the basic statistics, and Table 2 shows representative questions of the TIQ benchmark.

Meta-data. Tro provides implicit questions and gold answers, as strings as well as canonicalized to Wikipedia and Wikidata. The meta-data includes the information snippets grounding the question, the sources these were obtained from, the explicit temporal value expressed by the implicit constraint, the topic entity, the question entities detected in the snippets, and the temporal signal.

The TIQ dataset is available at https://faith.mpi-inf.mpg.de.

5 EXPERIMENTS

5.1 Experimental Setup

Benchmarks. We conduct experiments on our new Tiq benchmark and TIMEQUESTIONS [24], which has been actively used in recent work on temporal QA. For ordinal questions (e.g., "*what was the first album by Queen*?") in TIMEQUESTIONS, we apply the same method as outlined in Sec. 3, without applying any temporal filtering. **Metrics**. We use the standard QA metrics precision at 1 (P@1), mean reciprocal rank (MRR), and hit at 5 (Hit@5) [46].

¹https://huggingface.co/sentence-transformers/paraphrase-MiniLM-L6-v2 ²The prompt is given in Table 8 in the Appendix.

the [main question part;	implicit question part] (of the implicit question.		
1. Who bought the Gainesville	2. During Colin Harvey's senior	3. Which album released by Chris	4. What television series was	5. Who was Bristol Palin's part-
Sun after it was owned by Cowles	football career, which club was	Brown topped the Billboard 200	Hulk Hogan starring in when	ner before she participated in the
Media Company?	he a member of while he played	when he was performing in Sydney?	he signed with World Champi-	fall season of Dancing with the
	for the England national football		onship Wrestling?	Stars, and reached the finals, fin-
	team?			ishing in third place?
The New York Times Company	Everton F.C.	Fortune	Thunder in Paradise	Levi Johnston
[Text; KB]	[Infobox; KB]	[Text; Infobox]	[Text; Text]	[Infobox; Text]
6. During the onset of the COVID-	7. Who was the chief executive	8. After graduating from the Rostov-	9. Which national football team	10. What university did Robert
19 pandemic, who was the New	officer at Robert Bosch GmbH be-	on-Don College of Economics and	did Carlos Alberto Torres man-	Lee Moore work for after North-
York City head of government?	fore revenue reached €78.74 bil-	Finance, which political party did	age before joining Flamengo?	western University?
	lion?	Gyula Horn join?		
Bill de Blasio	Volkmar Denner	Hungarian Working People's Party	Oman national football team	University of Pennsylvania
[KB; Text]	[KB; Infobox]	[Infobox; Text]	[Infobox; Infobox]	[KB; KB]

Table 2: Representative questions from the TrQ benchmark. The sources below indicate the source that was used for populating the [main question part; implicit question part] of the implicit question.

Table 3: Main results comparing the performance of FAITH against baselines on the *test* sets of TIQ and TIMEQUESTIONS.

Benchmark \rightarrow		Τις		Tin	1EQUES:	TIONS
Method ↓	P@1	MRR	Hit@5	P@1	MRR	Hit@5
INSTRUCTGPT [39]	0.237	n/a	n/a	0.224	n/a	n/a
Gрт-4 [37]	0.236	n/a	n/a	0.306	n/a	n/a
UNIQORN [42]	0.236	0.255	0.277	0.331	0.409	0.538
Unik-Qa [38]	0.425	0.480	0.540	0.424	0.453	0.486
Explaignn [13]	0.446	0.584	0.765	0.525	0.587	0.673
ТемроQR [31]	0.011	0.018	0.022	0.438	0.465	0.488
CRONKGQA [48]	0.006	0.011	0.014	0.395	0.423	0.450
Exaqt [24]	0.232	0.378	0.587	0.565	0.599	0.664
FAITH (Proposed)	0.491	0.603	0.752	0.535	0.582	0.635
Un-Faith	0.459	0.604	0.799	0.571	0.640	0.724

Baselines. We compare FAITH with a suite of baselines, covering a diverse range of competitors:

- Generative LLMs. We compare with INSTRUCTGPT [39] ("textdavinci-003") and GPT-4 [37] ("gpt-4") using the OpenAI API³. We tried different prompts, and found the following to perform best: "Please answer the following question by providing the crisp answer entity, date, year, or number.". For computing P@1, we check whether the generated answer string matches with the label or any alias of the gold answer. If this is the case, P@1 is 1, else 0. Other (ranking) metrics are not applicable for LLMs.
- Heterogeneous QA methods. Further, we compare against a range of recent general-purpose methods for heterogeneous QA: UNIQORN [42], UNIK-QA [38], and the vanilla EXPLAIGNN [13].
- Temporal QA methods. We also compare with state-of-the-art methods for temporal QA: ТемроQR (TempoQR-Hard) [31], СколКGQA [48], and Exaqt [24].

Finally, we show results for a variant of our approach, which does *not prune out* evidence temporally-inconsistent with the temporal constraint, i.e. drops the temporal pruning component. We term this variant **Un-FAITH**.

Configuration. Wikidata [55] is used as the KB for FAITH and all baselines. We use Wikipedia text, tables and infoboxes as additional information sources for methods operating over heterogeneous sources. The BART models are initialized via Hugging Face⁴. We use AdamW as optimizer with a learning rate of 5×10^{-5} , batch

size of 10, weight decay of 0.01, 5 epochs, and 500 warm-up steps. EXPLAIGNN is run using the public code⁵, retaining the original settings and parameters for optimization.

For FAITH, we choose the candidate at rank 1 as the answer for intermediate questions in the implicit question resolver. In case too many evidences are obtained as input to the answering stage, we consider the top-100 evidences as computed by a BERT-based reranker [36]. Further detail is given in the Appendix A.4. We follow an epoch-wise evaluation strategy for each module and baseline, and take the version with the best performance on the respective dev set. All training processes and experiments are run on a single GPU (NVIDIA Quadro RTX 8000, 48 GB GDDR6).

5.2 Main Results

Answering performance of FAITH and baselines on TIMEQUESTIONS and on TIQ are in Table 3.

FAITH outperforms baselines on Tiq. The main insight from Table 3 is that FAITH surpasses all baselines on the Tiq dataset for P@1, which is the most relevant metric, demonstrating the benefits of our proposed method for answering implicit temporal questions. Temporal QA methods operating over KBs lack the required coverage on the Tiq dataset, and perform worse than general-purpose QA methods operating over heterogeneous sources. EXPLAIGNN comes close to the performance of FAITH, and even slightly improves on the Hit@5 metrics. Note, however, that EXPLAIGNN and all other baselines do not verify that temporal constraints are met during answering. Thus, the most prominent among answer candidates may simply be picked up, even if no temporal information is provided or matching. Such possibly "accidental" and *unfaithful* answers are, by design, not considered by FAITH.

Trade-off between faithfulness and answering performance. Results for Un-FAITH illustrate the effect of this phenomenon on our approach: especially the MRR and Hit@5 results are substantially improved. Consequently, Un-FAITH outperforms all competitors on TIMEQUESTIONS. However, its answers are not always faithfully grounded in evidence sources. These results emphasize the trade-off between faithfulness and answering performance.

FAITH shows robust performance on TIMEQUESTIONS. FAITH also shows strong performance on the TIMEQUESTIONS benchmark, on which it outperforms all baselines on P@1, except for EXAQT. This indicates the robustness of FAITH across different datasets.

⁵https://github.com/PhilippChr/EXPLAIGNN

³https://platform.openai.com

⁴https://huggingface.co

Table 4: Comparing the faithfulness of FAITH and Un-FAITH for correct answers, and how often temporal constraints are violated or ignored.

$Benchmark \rightarrow$	Τις		TIMEQUESTIONS		
Method ↓	Faithful	Temporally Unfaithful	Faithful	Temporally Unfaithful	
Faith Un-Faith	0.95 0.90	0.00 0.08	0.94 0.87	0.01 0.13	

Existing methods for temporal QA show major performance gaps between the two benchmarks: the P@1 of the strongest method on TIMEQUESTIONS, EXAQT, substantially drops from 0.565 at P@1 to 0.232 on the TIQ benchmark. Note that all methods are trained on the specific benchmark, if applicable.

LLMs fall short on temporal questions. Another key insight from Table 3 is that current LLMs are clearly not capable of answering temporal questions. INSTRUCTGPT and GPT-4 can merely answer $\approx 23-30\%$ of the questions correctly, and are constantly underperforming FAITH and baselines operating over heterogeneous sources. One explanation is that reasoning with continuous variables, such as time, is a well-known weakness of LLMs [15].

5.3 Faithfulness Evaluation

Our main results in Table 3 indicate that ignoring the temporal condition of the question can yield improvements on automatic metrics (compare performance of FAITH vs. Un-FAITH on TIMEQUESTIONS). However, we observe that this can lead to critical failure cases of QA systems and sometimes boils down to lucky guesses of the answer based on priors (e.g., prominence of an answer candidate).

FAITH refrains to answer in absence of consistent evidence. If there is no temporal information associated with the evidence of candidate answers, or the temporal information does not satisfy the temporal constraint, FAITH will refuse answering the question. For example, for the question *"Who did Lady Jane Grey marry on the 25th of May 1533?"*, there is no answer satisfying the temporal constraint because *Lady Jane Grey* did not marry anyone *on the 25th of May 1533*, since she was only born four years later in 1937. However, all of the baselines provide an answer to the question, without indicating that the temporal constraint is violated.

Since questions without a temporally-consistent answer are not available at large scale, we randomly sample 500 explicit questions from TIMEQUESTIONS, and replace the temporal value with a random date (e.g., *"12 October 6267"*). None of the resulting questions has a temporally-consistent answer. As expected, the competitors still provide answers⁶. In contrast, FAITH successfully refrained from answering for 467 of the 500 questions (93.4%). Upon investigating the failure cases, we noticed that the date recognition identifies four-digit numbers as years matching with the constraint (e.g., in the infobox entry *"Veysonnaz, SFOS number, 6267"*).

Fallback to Un-FAITH. Completely refraining from answering could also be sub-optimal: the user might have made a typo (e.g., *"May 1533"* instead of *"May 1553"*). We investigated to fall back to Un-FAITH in such scenarios, which could be indicated to end users with an appropriate warning. Performance on both datasets was slightly

Table 5: Ablation study using different source combinations as input for FAITH on *dev* sets. Note that FAITH is trained using *all sources* as input for all cases.

Benchmark \rightarrow		Τις		Тім	1EQUES'	TIONS
Method \downarrow	P@1	MRR	Hit@5	P@1	MRR	Hit@5
KB	0.293	0.368	0.468	0.425	0.464	0.513
Text	0.194	0.262	0.351	0.224	0.269	0.320
Infoboxes	0.169	0.223	0.296	0.093	0.117	0.149
Tables	0.032	0.057	0.083	0.078	0.094	0.114
KB+Text	0.429	0.527	0.649	0.520	0.567	0.626
KB+Tables	0.299	0.379	0.480	0.435	0.479	0.536
KB+Infoboxes	0.384	0.488	0.634	0.443	0.487	0.543
Text+Tables	0.196	0.267	0.362	0.252	0.298	0.350
Text+Infoboxes	0.283	0.372	0.490	0.251	0.299	0.355
Tables+Infoboxes	0.179	0.244	0.331	0.143	0.174	0.208
All sources	0.497	0.610	0.756	0.538	0.583	0.639

Table 6: Ab	olation stud	lies of FAIT	H on dev sets.
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$\begin{array}{l} \text{Benchmark} \rightarrow \\ \text{Method} \downarrow \end{array}$	Ті д Р@1	TimeQuestions P@1
Faith	0.497	0.538
w/o temporal pruning w/o implicit question resolver	0.443 0.467	0.573 0.559
w/o GNN-based answering	0.316	0.399

improved: the P@1 metric increased from 0.491 to 0.492 on TIQ and from 0.535 to 0.539 on TIMEQUESTIONS. We further investigated to fall back to Un-FAITH in case FAITH answered incorrectly. The P@1 metric was improved substantially on both datasets: from 0.491 to 0.622 on TIQ and from 0.535 to 0.653 on TIMEQUESTIONS.

Manual analysis. Finally, we investigated the faithfulness of *correct* answers provided by FAITH and Un-FAITH, to understand how often the question is answered correctly even though the evidence is not faithful to the question. To analyze this qualitatively, we randomly selected 100 questions (from each benchmark) for which both FAITH and Un-FAITH answered correctly, and then manually verified the faithfulness, based on the definition in Sec. 2. Results are in Table 4. FAITH provides faithful answers and evidence in 95%/94% of the time. By design, answers are faithful to the temporal constraints in the question (except for one question which specifies two different temporal constraints). In comparison, Un-FAITH violates or ignores the temporal condition in 8%/13% of the cases.

For example, to answer the question "What movies starring Taylor Lautner in 2011?" (answer: Abduction), the evidence for FAITH is "Taylor Lautner, Year is 2011, Title is Abduction, Role is Nathan Harper" (from table), while the evidence for Un-FAITH is "Abduction, cast member, Taylor Lautner" (from KB). Even though both pieces of evidence mention the correct answer Abduction, Un-FAITH fails to satisfy the temporal constraint ("in 2011") with its evidence.

5.4 In-depth Analysis

Integrating heterogeneous sources is decisive. We further investigated the effect of integrating heterogeneous sources into FAITH, and tested giving each individual source independently, and their pairwise combinations as input, in comparison to the default setting with "All sources". Results are in Table 5. Each information

⁶Except for the LLMs for which we are not able to investigate the behavior at scale, since they would often generate longer texts.

Table 7: Anecdotal examples that FAITH answered correctly in TIQ and TIMEQUESTIONS. Evidence shows the supporting information snippets along with their source provided in brackets. The part mentioning the predicted answer is in bold, and the detected temporal values are underlined. For the first example from the TIQ benchmark, we show the answering process of the intermediate question, which can be used by end users to verify the entire answer derivation of the system.

Benchmark	Τις
Question Answer TSF Evidence	After managing FC Nantes, which football club did Antoine Raab take on next? Stade Lavallois (question entity: "Antoine Raab, FC Nantes football", question relation: "After managing which club did take on next", expected answer type: "association football club", temp. signal: after, temp. category: implicit, temp. value: [1946, 1949]) Antoine Raab, Managerial career, 1949–1950, Stade Lavallois . (FROM INFOROX)
Intermediate questions Answers (to int. questions)	 (i) When Antoine Raab managed FC Nantes start date? (ii) When Antoine Raab managed FC Nantes end date? (i) 1946, (ii) 1949
TSFs (for int. questions)	 (i) (question entity: "FC Nantes, start, Antoine Raab", question relation: "When managed date", expected answer type: "year", temp. signal: _; temp. category: non-implicit; temp. value: _) (ii) (question entity: "FC Nantes, end, Antoine Raab", question relation: "When managed date", expected answer type: "year", temp. signal: _;
Evidence (for int. questions)	 (ii) (question endry. on -implicit; emp. value; _) (i, ii) Antoine Raab, Managerial career, 1946–1949, FC Nantes. (FROM INFOBOX) (iii) Antoine Raab, After the liberation of Nantes in 1944 Raab joined FC Nantes and played for the club until 1949. (FROM TEXT)
Benchmark	TIMEQUESTIONS
Question Answer TSF	What award did Thomas Keneally receive in the year 1982? Booker Prize (question entity: "Thomas Keneally", question relation: "What award did receive in the year 1982", expected answer type: "science award", temp. signal: overlap, temp. category: non-implicit, temp. value: 1982)
Evidence	Man Booker Prize , winner, Thomas Keneally, point in time, <u>1982</u> , for work, Schindler's Ark. (FROM KB) Thomas Keneally, Awards is Booker Prize , is Schindler's Ark, winner <u>1982</u> . (FROM TABLE) Thomas Keneally, He is best known for his non-fiction novel Schindler's Ark, the story of Oskar Schindler's rescue of Jews during the Holocaust, which won the Booker Prize in <u>1982</u> . (FROM TEXT)

source contributes to the performance of FAITH, and integrating more information sources consistently enhances all metrics.

Ablation studies. We tested variations of our pipeline on the dev sets. Table 6 shows results for Un-FAITH (w/o temporal pruning), results without the implicit time resolver, and results with a Seq2seq model for answering (we used BART) instead of the GNN-based approach. Using a GNN-based answering approach plays a crucial role, and enhances not only answering performance, but also explainability. The implicit question resolver is decisive on TIQ, but slightly decreases performance on TIMEQUESTIONS. Un-FAITH also shows strong performance on the dev sets. However, all modules contribute to the explainability and faithfulness of our approach. **Anecdotal examples**. Table 7 shows sample cases for which FAITH

provided the correct answer, and illustrates the answer derivation process providing traceable evidence for end users.

Error analysis. To better understand failure cases, we conducted an error analysis measuring the *answer presence* (i.e. whether the gold answer is among answer candidates) throughout the pipeline. We identified the following error cases and list their percentage among all failure cases for TIQ and TIMEQUESTIONS, respectively: (i) the answer was not found in the initial retrieval stage (3.14/29.89), (ii) the answer is lost during temporal pruning (22.00/25.81), (iii) the answer is lost during scoring/graph shrinking (8.45/10.33), (iv) the answer is not considered among top-5 answers (15.13/12.47), (v) the answer is among top candidates but not at rank 1 (51.28/21.51).

6 RELATED WORK

General-purpose QA. Question answering has extensive work using single sources like KBs (e.g., [2, 62, 64]) or text (e.g., [7, 21, 44]). Some works have shown that integrating different sources can substantially improve performance [8, 18, 47, 51, 52, 60, 61]. UNIK-QA [38] verbalizes snippets from a KB, text, tables and infoboxes, as

input to a Fusion-in-decoder (FiD) model [21] for answer generation. UDT-QA [29] improved the verbalization technique. EXPLAIGNN [13] constructs graphs among such verbalized snippets, and applies graph neural networks for computing answers and explanatory evidence. None of these methods is geared for temporal questions.

Another direction is to directly apply large language models (LLMs) for QA [3, 14, 41, 43]. However, LLMs cannot present traceable provenance for the generated outputs, falling short on faithfulness and explainability [1, 30, 33]. Also, LLMs struggle with reasoning on temporal conditions [15].

Temporal QA. Prior work that specifically targets temporal QA [9, 10, 16, 23–25, 28, 31, 34, 48–50, 57, 58, 63], can largely be divided into work using a KB (e.g., [24, 31, 34]), and work using text (e.g., [9, 35]). *Methods operating over KBs*, include template-based [16, 23, 34], KB-embedding-based [10, 31, 48, 58], and graph-based methods [24, 50, 63]. *Methods using textual inputs* typically involve an extractive or generative reader [9, 35].

The three methods [24, 31, 48] represent the state-of-the-art on temporal QA. However, temporal constraints are handled solely in the latent space, without explicitly (or *faithfully*) pruning out temporally inconsistent answer candidates. Other approaches are based on handcrafted rules, and hence bound to fail for unseen question patterns (e.g., [23]). None of the existing work on temporal QA has considered incorporating heterogeneous sources.

Temporal KBs. There is substantial work on temporal KBs [4, 19, 26, 32, 40, 56, 59], to assign temporal scopes to KB facts. Advances on the KB itself benefits QA, but is an orthogonal direction.

7 CONCLUSION

This work targets complex temporal QA, and proposes a new approach for *faithfully* answering temporal questions, with focus on

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the challenging case of implicit temporal constraints. Experiments show that our method FAITH outperforms the best unfaithful competitor on such implicit questions. On other temporal questions, our method performs almost on par, but adds the benefit of reliably matching the temporal conditions. Faithfulness is an important element in enhancing the trustworthiness of QA systems.

Acknowledgements. We thank Rishiraj Saha Roy and Magdalena Kaiser from the Max Planck Institute for Informatics for useful inputs at various stages of this work. Zhen Jia was supported by NSFC (Grant No.62276215 and No.62272398).

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Table 8: Prompt including demonstrations for rephrasing the pseudo-questions into natural questions.

Please rephrase the following input question into a more natural question

Input: What album Sting (musician) was released, during, Sting award received German Radio Award? Question: which album was released by Sting when he won the German Radio Award?

Input: What human President of Bolivia was the second and most recent female president, after, president of Bolivia officeholder Evo Morales Question: Which female president succeeded Evo Morales in Bolivia?

Input: What lake David Bowie He moved to Switzerland purchasing a chalet in the hills to the north of , during, David Bowie spouse Angela Bowie?

Question: Close to which lake did David Bowie buy a chalet while he was married to Angela Bowie? Input: What human Robert Motherwell spouse, during, Robert Motherwell He also edited Paalen 's collected

essays Form and Sense as the first issue of Problems of Contemporary Art? Question: Who was Robert Motherwell's wife when he edited Paalen's collected essays Form and Sense?

Input: What historical country Independent State of Croatia the NDH government signed an agreement with which demarcated their borders, during

Judependent State of Croatia? Question: At the time of the Independent State of Croatia, which country signed an agreement with the NDH government to demarcate their borders?

Input: What U-boat flotilla German submarine U-559 part of, before, German submarine U-559 She moved to Question: Which U-boat Flotilla did the German submarine U-559 belong to before being transferred to the 29th

U-boat Flotilla?

Input: What human UEFA chairperson, during, UEFA chairperson Sandor Barcs? Question: Who was the UEFA chairperson after Sandor Barcs?

Input: What human Netherlands head of government, during, Netherlands head of state Juliana of the Nether-lands? ${\it Question:} \ {\rm During \ Juliana \ of \ the \ Netherlands' \ time \ as \ queen, \ who \ was \ the \ prime \ minister \ in \ the \ Netherlands?}$

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FURTHER IMPLEMENTATION DETAILS Α

Training FAITH on TIQ A.1

FAITH requires train questions asking for temporal values to answer intermediate questions. Such questions exist in TIMEQUESTIONS,

but our new TIQ benchmark only has implicit questions (by design). We thus generate intermediate questions on the train and dev sets, using the implicit questions as input (similar as in Sec. 3.1). For these intermediate questions, the gold answer is the temporal value of the implicit part as annotated in the TIO benchmark, resulting in <question, temporal value> pairs. If the answer type of an intermediate question is a time interval, we create two questions asking for "start date" and "end date" respectively. We obtain 7,723 such pairs from the T₁Q train set and 2,542 questions from the dev set.

A.2 TSF Construction

Training. To obtain training data for the TSFs, we follow a similar distant supervision approach as in [13] for obtaining the target question entity and question relation. We run the heterogeneous retriever (see Sec. 3.2) on the full input question, which identifies entity mentions in the input, disambiguates these to KB-entities, and then retrieves information snippets for the KB-entities from heterogeneous sources. If the retrieved information snippets for a KB-entity contain the annotated gold answer, we annotate the corresponding entity mention as relevant question entity. The remaining parts of the question are annotated as question relation. The expected answer type is the most frequent (proxy for most prominent) KB-type of the gold answer. The temporal signal and the temporal category are looked up from the annotations in the benchmarks. These individual parts of the TSF are then combined and separated by pipes ("||"), to obtain the target TSFs that are used for training the TSF construction model (in Sec. 3.1). Details on the training configuration are provided in Sec. 5.1.

Inference. The input to the BART model for TSF construction is the question. The output is the concatenation of the individual slots, separated by two pipes ("||"): "{entities}||{relation}||{expected answer type}||{temporal signal}||{temporal categorization}". Example output for q_1 = "Record company of Queen in 1975?": "Queen||Record company of in 1975||record company||overlap||non-implicit".

A.3 Intermediate Question Generation

Training. To annotate intermediate questions (and its expected answer type) for implicit questions, we leverage in-context learning: we select and label 8 questions from the train set, and give these pairs as context to the LLM (InstructGPT). This way we annotate the remaining questions in the train and dev sets of TIQ/TIMEQUESTIONS resulting in 5,875/847 instances in the train set and 1,949/287 instances in the dev set. On this data we fine-tune the BART model to be independent of GPT at runtime. The prompts used for annotating the data can be found in Table 9. Training configuration is provided in Sec. 5.1.

Inference. For generating the intermediate questions at runtime, we provide the implicit question as input to the trained BART model. The output is the intermediate question that describes the implicit constraint, and the expected answer type for this question, separated by two pipes: "{intermediate question}||{expected answer type}". Example output for q_3 = "Queen's record company" when recording Bohemian Rhapsody?": "when Queen recording Bohemian Rhapsody||time interval".

Table 9: Prompts used to obtain the training data for generating intermediate questions, leveraging in-context learning.

TIMEQUESTIONS	Trq
Generate an explicit question and answer type for the implicit part of the temporal input question.	Generate an explicit question and answer type for the implicit part of the temporal input question.
<i>Input</i> : what position did djuanda kartawidjaja take after he was replaced by sukarano	Input: Who was the second director of the Isabella Stewart Gardner Museum when it was built
<i>Output</i> : when djuanda kartawidjaja replaced by sukarano∥date	Output: When Isabella Stewart Gardner Museum was built time interval
Input: american naval leader during the world war 2 Output: when world war 2 time interval	Input: When Wendy Doniger was president of the Association for Asian Studies, what publishing house was she based in New York Output: When Wendy Doniger was president of the Association for Asian Studies time interval
Input: who became president after harding died	Input: What administrative entity was Ezhou in before Huangzhou District became part of it
Output: when harding died date	Output: When Huangzhou District became part of Ezhou date
Input: who did luis suarez play for before liverpool	Input: After Bud Yorkin became the producer of NBC's The Tony Martin Show, who was his spouse?
Output: when luis suarez play for liverpool time interval	Output: When Bud Yorkin became the producer of NBC's The Tony Martin Show∥date
<i>Input</i> : which countries were located within the soviet union prior to its dissolution	Input: What book did Ira Levin write that was adapted into a film during the same time he wrote the play Deathtrap
<i>Output</i> : when soviet union dissolution date	Output: When Ira Levin wrote the play Deathtrap∥date
Input: who started the presidency earliest and served as president during wwii in the US	Input: What basketball team was Nathaniel Clifton playing for when his career history with the Rens began
Output: when wwii time interval	Output: When Nathaniel Clifton's career history with the Rens began∥time interval
Input: who replaced aldo moro as the minister of foreign affairs	Input: What team did Stevica Ristić play for before joining Shonan Bellmare?
Output: when aldo moro replaced as minister of foreign affairs date	Output: When Stevica Ristić joining Shonan Bellmare∥time interval
<i>Input</i> : what did harry s truman work before he was president	Input: Which album was released by the Smashing Pumpkins after Mike Byrne joined the band
<i>Output</i> : when harry s truman president∥time interval	Output: When Mike Byrne joined Smashing Pumpkins time interval

Table 10: Performance of FAITH (with all sources) on questions from different source combinations in TIQ (test set).

Question sources combination	P@1	MRR	Hit@5
[Text; Infobox] (157 questions)	0.573	0.644	0.752
[KB; Text] (378 questions)	0.519	0.634	0.770
[Infobox; KB] (43 questions)	0.395	0.534	0.721
[Infobox; Text] (225 questions)	0.476	0.595	0.760
[KB; Infobox] (251 questions)	0.478	0.598	0.753
[Text; KB] (142 questions)	0.359	0.509	0.725
[KB; KB] (127 questions)	0.582	0.676	0.807
[Text; Text] (306 questions)	0.598	0.679	0.787
[Infobox; Infobox] (376 questions)	0.407	0.529	0.689
All test questions (2,000 questions)	0.497	0.610	0.756

A.4 Evidence Scoring

As the set of candidate information snippets after temporal pruning can still be large, we use a re-ranker [36] to prune out irrelevant candidates, based on cross-encodings obtained via DistilRoBERTa⁷. **Training**. The training data are the <question, information snippet> pairs, annotated with either a positive label (in case the snippet contains a gold answer) or a negative label (otherwise). We randomly sample 1 positive <question, information snippet> pair from each knowledge source and 15 negative pairs, for each question. We use the concatenation of question entity, the question relation, and the expected answer type, as present in the TSF, to represent the question. For fine-tuning the classifier on this data, we use AdamW as optimizer with a learning rate of 2×10^{-5} , batch size of 16, weight decay of 0.01, 4 epochs, and a warm-up ratio of 0.1.

Inference. We score each candidate information snippet (known to be temporally faithful) and consider the top-100 information snippets as input for the final answering stage.

B FURTHER EXPERIMENTS

B.1 Intrinsic Evaluation

Temporal signal accuracy. We measure the accuracy of the generated temporal signals (*before, after* or *overlap*) in our TSF construction. On TIMEQUESTIONS the accuracy is 93.0%, and on TIQ it is 97.8%. The high accuracy scores indicate that our approach of generating the temporal signal is feasible.

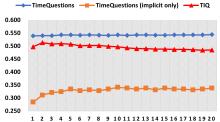


Figure 4: P@1 of FAITH when considering top-k answers for the generated intermediate question(s) of implicit questions.

Temporal category accuracy. We also measure the accuracy in predicting the temporal category, differentiating between implicit and non-implicit questions. The accuracy is 98.9% on TIMEQUES-TIONS and 100% on TIQ, which has only implicit questions.

Performance of implicit question resolver. The performance of the implicit question resolver is crucial for correctly answering implicit questions, as the resulting temporal values are directly used for pruning out evidence in the remainder of the pipeline. As there might be several temporal values per question (due to multiple intermediate questions), we measure macro-averaged precision, recall, and F1-score. We conduct experiments on the test set of TIQ, which has the ground-truth temporal values.

When using the top-1 answer candidate per intermediate question (default setting), precision is 0.537, recall is 0.562 and F1-score is 0.525. When increasing the number of candidates to 3, precision is 0.294, recall is 0.714 and F1-score is 0.401. With the top-5 candidates, precision is 0.196, recall is 0.773 and F1-score is 0.304.

Recall improves as we consider more answers, since the resulting explicit temporal constraint is relaxed. Hence, the evidence retained is noisier and may not satisfy the user-intended temporal constraints. This can negatively affect the system's faithfulness.

B.2 Additional Analysis

Relaxed temporal pruning. We also compute the effect of the number of answer candidates in the implicit question resolver on the end-to-end performance (*extrinsic* evaluation). Fig. 4 shows the results, varying the number of candidates k from 1 to 20. On

⁷ https://huggingface.co/distilroberta-base.

TIMEQUESTIONS, we observe that P@1 improves gradually as k increases until the set of candidate snippets converges resulting in a stable P@1. On TIQ, we only observe an improvement of the P@1 metric when increasing k to 2. As k increases further, more noisy candidate snippets are considered, resulting in a lower performance. **Answer presence analysis**. We measure the answer presence after the initial heterogeneous retrieval, and the effect of the subsequent pruning and scoring steps. Answer presence is measured as the fraction of questions for which the gold answer is present in the candidate set of information snippets [11]. These measurements are also used for the error analysis presented in Sec. 5.4.

We conduct the analysis on the test sets of TIQ/TIMEQUESTIONS. The answer presence after the heterogeneous retrieval is 0.984/0.861. After temporal pruning the answer presence drops to 0.872/0.741. Note that in this step, temporally inconsistent evidence is pruned out, enhancing the faithfulness of the approach. In the evidence scoring stage (based on a cross-encoder), the answer presence is mostly retained (0.867/0.726). Inside the EXPLAIGNN pipeline, the answer presence after evidence pruning is 0.829/0.693.

In general, as discussed in the error analysis, the key source of error is the fine-grained answer ranking step.

FAITH performance on heterogeneous questions. TIQ has questions originating from different source combinations (see Fig. 3). Table 10 shows how this affects the performance of FAITH (all sources are used as input for answering).

Results demonstrate that FAITH can deal with all of these questions, and there is no combination for which FAITH completely fails, indicating that FAITH successfully incorporates all heterogeneous sources during answering. FAITH shows the best performance on questions from text and infoboxes (P@1 of 0.573), and the worst performance on questions from text and KB (P@1 of 0.359).