SYGMA: System for Generalizable Modular Question Answering Over Knowledge Bases

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Abstract

Knowledge Base Question Answering (KBQA) tasks that involve complex reasoning are emerging as an important research direction. However, most KBQA systems struggle with generalizability, particularly on two dimensions: (a) across multiple reasoning types where both datasets and systems have primarily focused on multi-hop reasoning, and (b) across multiple knowledge bases, where KBQA approaches are specifically tuned to a single knowledge base. In this paper, we present SYGMA, a modular approach facilitating generalizability across multiple knowledge bases and multiple reasoning types. Specifically, SYGMA contains three high level modules: 1) KB-agnostic question understanding module that is common across KBs 2) Rules to support additional reasoning types and 3) KB-specific question mapping and answering module to address the KB-specific aspects of the answer extraction. We demonstrate effectiveness of our system by evaluating on datasets belonging to two distinct knowledge bases, DBpedia and Wikidata. In addition, to demonstrate extensibility to additional reasoning types we evaluate on multi-hop reasoning datasets and a new Temporal KBQA benchmark dataset on Wikidata, named TempQA-WD1 introduced in this paper. We show that our generalizable approach has better competitive performance on multiple datasets on DBpedia and Wikidata that requires both multi-hop and temporal reasoning.

1 Introduction

The goal of Knowledge Base Question Answering (KBQA) systems is to answer natural language questions by retrieving and reasoning over facts in a Knowledge Base (KB). KBQA has gained significant popularity both due to its practical real-world applications and challenging research problems associated with it (Fu et al. 2020). However, most existing datasets and research in this area are primarily focused on single/multi-hop reasoning on a single knowledge base (Trivedi et al. 2017 Usbeck et al. 2017 Yih et al. 2016). Consequently, this has encouraged research in methodologies that are tuned to a restricted set of reasoning types on a single knowledge base, in turn lacking generalizability (Kapanipathi et al. 2021 Zou et al. 2014a Sorokin and Gurevych 2018a). In this work, we propose a modular approach that is generalizable across knowledge bases and reasoning types.

Open Knowledge Bases such as DBpedia (Auer et al. 2007), Wikidata (Vrandečić and Krötzsch 2014), and Freebase (Bollacker et al. 2008) form the basis of many KBQA datasets. Each of these knowledge Bases, however, have different representations. For instance: information associated to the question “Who was roman emperor before Nero?” from DBpedia and Wikidata are shown in Figure 1. We can see that Wikidata represents properties of facts such as replaces, temporal and spatial with reification. On the other hand, DBpedia manages to represent it as a simple fact with the relationship to existing entity nodes. Handling such different representations is an unexplored challenge and requires to be addressed for a generalizable KBQA approach. The second aspect where KBQA approaches fail to generalize is in handling complex reasoning types such as temporal and spatial reasoning. Table 1 shows examples of questions that require different types of reasoning to answer them. Most research have focused on multi-hop reasoning questions (Bordes et al. 2015a Dubey et al. 2019 Berant et al. 2013), lacking both approaches and datasets that are adaptable to complex reasoning.

1https://github.com/IBM/tempqa-wd

Figure 1: A description of how information about Nero’s predecessor is represented in DBpedia vs. Wikidata
In this paper, we present a modular approach called SYGMA (System for Generalizable and Modular question Answering over knowledge bases), that is built on a framework adaptable to different KB representations and reasoning types. SYGMA introduces intermediate representations based on lambda calculus to adapt to new reasoning types and representations. SYGMA, following the recent advances in KBQA such as NSQA (Kapanipathi et al. 2021) and Re-Track (Chen et al. 2021), is a modular approach with independent Abstract Meaning Representation, Entity Linking, and Relation Linking modules. In contrast to NSQA which is tuned specifically to DBpedia-based KBQA datasets, SYGMA is generalizable to multiple knowledge bases and multiple reasoning types. In order to evaluate our generalizable approach, we consider datasets that have: (a) DBpedia and Wikidata as knowledge bases, and (b) multi-hop and temporal as the reasoning types.

In pursuit of this goal, we also address the lack of temporal reasoning datasets on knowledge bases that we are considering in this work, specifically Wikidata. We annotate and create TempQA–WD; a Wikidata-based dataset focused on temporal reasoning. TempQA–WD is a parallel dataset to TempQuestions dataset (Jia et al. 2018) which is a Freebase based temporal reasoning dataset derived from three other datasets Free917 (Cai and Yates 2013), WebQuestions (Bert, et al. 2013) and ComplexQuestions (Bao et al. 2016). While the Freebase dataset consists of question answer pairs along with temporal signal classifications, our dataset is annotated with intermediate SPARQL queries enabling evaluation of different modules in a KBQA pipeline.

| Category   | Example                                                                 |
|------------|-------------------------------------------------------------------------|
| Single-Hop | Who directed Titanic Movie? SPARQL: select distinct ?a where { w:d:Q44578 w:d:P57 ?a} |
| Multi-hop  | Which movie is directed by James Cameron starring Leonardo DiCaprio? SPARQL: select distinct ?a where { ?a w:d:P57 w:d:Q42574. ?a w:d:P161 w:d:Q38111. } |
| Temporal   | Who was the US President during cold war? SPARQL: in Figure 3            |

Table 1: Examples of Single-hop, Multi-hop and Temporal reasoning questions on Wikidata.

In summary, the main contributions of this paper are:

- A modular, generalizable approach, called SYGMA, for KBQA with lambda calculus based intermediate representations that enable adaptation to: (a) multiple knowledge bases, specifically DBpedia and Wikidata, and (b) multiple reasoning types such as multi-hop and temporal reasoning.

- A benchmark dataset, called TempQA–WD, for building temporal-aware KBQA systems on Wikidata with parallel annotations on Freebase.

- Experimental results show SYGMA achieves state-of-the-art numbers on LC-QuAD 1.0, WebQSP-WD, and comparable numbers on QALD-9 dataset. We also present baseline numbers for Simple WebQuestions and new dataset introduced in this paper; TempQA–WD.

2 Related Work

KBQA Systems: KBQA approaches can be primarily categorized into two groups: (a) Question-to-entities: where techniques output the answer entities from the knowledge graph ignoring the SPARQL query (Saxena, Tripathi, and Talukdar 2020; Sun et al. 2018; Vakulenko et al. 2019), and (b) semantic parsing based: where approaches output intermediate SPARQL queries (or logic forms) that can retrieve the answer from the knowledge base (Singh et al. 2018; Kapanipathi et al. 2021; Zou et al. 2014b). First, in question-to-entities category, (Vakulenko et al. 2019) leverages a message passing technique on a two hop graph from the entities mentioned in the question to retrieve answers from the knowledge graph. (Saxena, Tripathi, and Talukdar 2020) encodes both text and entities, text based on language models and entities based on knowledge graph embeddings (Trouillon et al. 2016) and shows that text can help KBQA in an incomplete setting. In contrast to question-to-entities approach, the semantic parsing based approaches improves interpretability and facilitates evaluation of different modules as shown by Frankenstein (Singh et al. 2018) and NSQA (Kapanipathi et al. 2021). Both, Frankenstein (Singh et al. 2018) and NSQA (Kapanipathi et al. 2021) follow a pipeline based approach with the differentiating factor being the use of Abstract Meaning Representation as a starting point by NSQA. We build on top of these representational efforts and introduce λ-expressions with the required additional functions for adapting to new knowledge graphs and new reasoning types.

KBQA Datasets: Over the years, many question answering datasets have been developed for KBQA, such as Free917 (Cai and Yates 2013), SimpleQuestions (Bordes et al. 2015b), WebQuestions (Bert, et al. 2013), QALD-9 (Usbeck et al. 2017), LC-QuAD 1.0 (Trivedi et al. 2017), and LC-QuAD 2.0 (Dubey et al. 2019). In Table 2, we compare each of these datasets across the following features: (a) underlying KB, including subsequent extensions, e.g. Wikidata (Diefenbach et al. 2017) and DBpedia (Azmy et al. 2018) based versions of SimpleQuestions, as well as the Wikidata subset of WebQSP (Sorokin and Gurevych 2018a); (b) reasoning types that are emphasized in the dataset; (c) availability of SPARQL queries, entities, and relationships for intermediate evaluation; and (d) the use of question templates, which can often generate noisy, unnatural questions. As Table 2 shows, our dataset is distinguished from prior work in its emphasis on temporal reasoning, its application to both Freebase and Wikidata, and its annotation of intermediate representations and SPARQL queries. The most relevant KBQA dataset to our work is TempQuestions (Jia et al. 2018), upon which we base TempQA–WD, as described in dataset section. CRONQUESTIONS (Saxena, Chakrabarti, and Talukdar 2021) is another temporal QA dataset proposed recently over a small subset of Wikidata. It has template based questions targeted at temporal KG embeddings and QA.
### Table 2: This table compares most of the KBQA datasets based on features relevant to the work presented in this paper.

| Datasets          | Knowledge Base                                    | Emphasis | SPARQL | Intermediate Evaluation | Natural questions |
|-------------------|---------------------------------------------------|----------|--------|-------------------------|-------------------|
| QALD-9            | DBpedia                                           |          |        |                         |                   |
| LC-QuAD 1.0       | DBpedia                                           |          |        |                         |                   |
| LC-QuAD 2         | DBpedia, Wikidata                                 |          |        |                         |                   |
| Simple Questions  | Freebase, DBpedia, Wikidata                       |          |        |                         |                   |
| Web Questions     | Freebase                                          |          |        |                         |                   |
| WebQSP            | Freebase, Wikidata                                 |          |        |                         |                   |
| Complex Web Questions | Freebase                  |          |        |                         |                   |
| TempQuestions     | Freebase                                          |          |        |                         |                   |
| TempQA-WD         | Freebase, Wikidata                                 |          |        |                         |                   |

### 3 SYGMA: System Description

Motivated by Kapanipathi et al. (2021), SYGMA is designed as a neuro-symbolic system, avoiding the need for end-to-end training. Figure 2 shows the overall KBQA pipeline with independent modules and their intermediate representations. The approach is designed with the goal of generalization across multiple KBs and reasoning types. Supporting generalization is accomplished in two stages as shown in Figure 2, driven by an example in Figure 3. The first is a KB-agnostic question understanding stage, which takes in a natural language question as input and outputs an intermediate representation that can be common across different KBs. The second is question mapping and reasoning stage where, first, the necessary heuristics to introduce templates for new reasoning types are applied. Next, the KB-agnostic representation is mapped to the vocabulary of the KG to output KB-specific representation that has a deterministic mapping to SPARQL. We use Wikidata and DBpedia to show generalization across KBs, and use multi-hop and temporal reasoning to evaluate across reasoning types. Before we get into the details of these modules and intermediate representations, we give a brief description of the Lambda calculus and the temporal functions used by SYGMA to generate its intermediate logic representation.

#### Lambda Calculus

\(\lambda\)-calculus, by definition, is considered the smallest universal programming language that expresses any computable function. In particular, we have adopted Typed \(\lambda\)-Calculus presented in Zettlemoyer and Collins (2012) which support addition of new higher order functions necessary for handling various reasoning types. We use constants and logical connectives like AND, OR, NEGATION and functions like argmin, argmax, count, etc., presented in this work. Apart from this, we also added new temporal functions to demonstrate the system’s adaptability to support new reasoning types. For example, consider the following question and its corresponding logical form:

**Question:** When was Barack Obama born?

**Logical Form:** \(\lambda t. \text{born}(b, "Barack Obama") \land \text{interval}(t, b)\)

Here, \(b\) is instance variable for event \(\text{born}(b, "Barack Obama")\) and \(\text{interval}(t, b)\) finds time for the event denoted by \(b\). Variable \(t\) is unknown which is marked as \(\lambda\) variable.

#### Temporal Functions

We introduce \(\text{interval}, \text{overlap}, \text{before}, \text{after}, \text{teenager}, \text{year}\); where \(\text{interval}\) gets time interval associated with event and \(\text{overlap}\), \(\text{before}, \text{after}\) are used to compare temporal events. \(\text{teenager}\) gets teenager age interval for a person, and \(\text{year}\) return year of a date.

### 3.1 KB-Agnostic Question Understanding

The modules in this stage aim at deriving logical expressions of the natural language question that is common for all the knowledge bases. In particular, we use the formalism of \(\lambda\)-calculus for logical representation, i.e., to map questions to their corresponding \(\lambda\)-expressions representing the semantics.

#### AMR

In order to have a generic parse (logical expression) that is common across KBs, SYGMA performs initial language understanding using Abstract Meaning Representation (AMR) (Banarescu et al. 2013), a semantic representation language based on PropBank. AMR encodes the meaning of a sentence into a rooted directed acyclic graph where nodes represent concepts and edges represent relations. We adopt an action pointer transformer architecture of Zhou et al. (2021) for transition-based AMR parsing and self-training technique of Lee et al. (2020) for domain adaptation to KBQA.

AMR provides generic representation that can be used for multi-hop reasoning (Kapanipathi et al. 2021). However for temporal expressions with \(\text{time}\) relation, we have to augment the AMR annotations with implicit predicates that cannot be captured by ellipsis and/or re-entrancies. An example of AMR annotation for the question *Who was US president during cold war?* is given in Figure 3. The representation encodes time edge with cold war event as sub-event of time. Also in case of before/after constraints it explicitly captures the constraint as part of the time edge. If there are no explicit constraints like before/after or ordinal in the time edge, we treat them as overlap constraints.

#### KB-Agnostic Lambda Expression

AMR is a fairly granular representation. However, for a KBQA system, specifically
Figure 2: Architecture of SYGMA that shows the pipeline with independent modules and intermediate representations. The intermediate representations are supported by appropriate heuristics to facilitate generalizability.

Figure 3: An illustration of the outputs at the intermediate stages of the pipeline in SYGMA

on KGs such as DBpedia, Wikidata, and Freebase, such granularity can add noise. Therefore to construct KB-agnostic λ-expressions of the questions from their corresponding AMRs and their identified entity and relation mentions, we use the transformational heuristics described in Table 3. The table shows the transformation from AMR frame (high level) to the corresponding Lambda expression. The rule type describes where the rule is in general applied to all reasoning (base) vs temporal. We handle these as conjunction of multiple triples in the KB with some projection variable and/or numerical operation to get the final answer. We use AMR unknown/imperative constructs to identify the projection variables and AMR polarity/interrogative frames for queries which fall into boolean answers or ASK questions in SPARQL.

3.2 Question Mapping and Reasoning

This is the second stage which comprises of modules that transform the KB-agnostic λ-expression of the questions into KB-specific λ-expression. These modules are entity linking and relationship linking that are specific to the underlying KB along with any KB specific rules to handle special forms of transformation or reasoning. The modules are interchangeable to different knowledge graphs. Currently, we demonstrate the adaptability of these modules to DBpedia and Wikidata.

KB-Specific Lambda Expression: Structurally, it is similar to λ-expression with all entities and relations mapped to KB entities and relations respectively.

Entity Linking: The goal of Entity Linking is to map entity mentions as captured in the λ-expression of the question to their corresponding KB-specific entities. We use a recently proposed zero-shot entity linking approach called BLINK (Wu et al. 2020). For a question where entity mentions are already identified, bi-encoder piece of the BLINK is used to predict top-K entities. For this prediction, we use an entity dictionary of 5.9M English Wikipedia entities, mapped to their corresponding Wikidata and DBpedia entities.

Relation Linking: SYGMA’s Relation linking component takes in the question text and an AMR graph as input and returns a ranked list of KG relationships. For instance, given a question such as “Who was the US President during cold war?” (see Fig 3) and the corresponding AMR, the goal of the relation linking component is to find the corresponding Wikidata KB relations position held (P39), start time (P580),...etc can be added. Table 3 shows an example template for spatial questions such as “which states are to the south of California?”.

The next set of rules present in Table 3 are few sample template rules used to capture temporal events and constraints to help in temporal reasoning. Figure 4 gives an example question that falls into the temporal overlap rule in the table and how the AMR constructs are used to split the events is highlighted with nodes being bold in the table. Complete set of rules used can be found in the supplementary material. Note that we covered temporal reasoning as an additional form of reasoning in the current system. However, more reasoning templates like spatial reasoning with additional operators like coordinates(), south() ...etc can be added. Table 3 shows an example template for spatial questions such as “which states are to the south of California?”.
end time (P582). For this task, we use state-of-the-art AMR-based relation linking approach with models built for both DBpedia and Wikidata [Naseem et al. 2021].

**Sparql Query:** This module maps KB-specific λ-expressions onto SPARQL queries through a deterministic approach. Each KB-specific λ-expression construct is mapped to an equivalent SPARQL construct, as rules given in Table 4. Each of lambda expressions contains one or more predicates connected via ∧ or ∨. Translation of different predicates is present in Table 4. Some of the KB-specific aspects like handling reification in Wikidata are shown in the Table. To get the time interval in case of reified events, Start time(wdt:P580), end time(wdt:P582), or point in time(wdt:P585) connected to intermediate statement node are used.

### 4 TempQA-WD Dataset

In order to evaluate our approach on temporal reasoning, specifically on DBpedia and Wikidata as KGs, we require a dataset to be based on one of these two KGs. TempQuestions (Jia et al. 2018) is the first KBQA dataset intended to focus specifically on temporal reasoning. However, TempQuestions is based on Freebase. We adapt TempQuestions to Wikidata to create a temporal QA dataset that has three desirable properties. First, we create a generalizable benchmark that has parallel answer annotations on two KBs. Second, we take advantage of Wikidata’s evolving, up-to-date knowledge. Lastly, we enhance TempQuestions with SPARQL queries which was missing in original dataset. We also add entity, relation, intermediate lambda expression annotations for a subset of the dataset that are used by the SYGMA.

There has been two previous attempts at transferring Freebase-QA questions to Wikidata; namely WebQSP-WD (Sorokin and Gurevych 2018a) and SimpleQuestions-WD (SWQ-WD) (Diefenbach, Singh, and Maret 2017). SWQ-WD contains only single triple questions whereas WebQSP-WD have only the final question answers that map directly to corresponding entities in Wikidata. However, as stated (Sorokin and Gurevych 2018a), one challenge is that not all Freebase answers can be directly mapped to entities in Wikidata. For example, the Freebase answer annotation for the question “When did Moscow burn?” is “1812 Fire of Moscow”, despite the year being entangled with the event itself. In contrast, Wikidata explicitly represents the year of this event, with an entity for “Fire in Moscow” and an associated year of “1812”. Thus, a direct mapping between the two answers is not possible, as it would amount to a false equivalence between “1812 Fire of Moscow” and “1812”.

In order to address such issues, we enlisted a team of annotators to manually create and verify SPARQL queries, ensuring not only that the SPARQL formulation was correct, but that the answers accurately reflected the required answer type (as in the “Fire in Moscow” example above) and the evolving knowledge in Wikidata. Having SPARQL queries also facilitates intermediate evaluation of the approaches that use semantic parsing to directly generate the query or the query graph, increasing interpretability and performance in some cases (Sorokin and Gurevych 2018a).

**Dataset Details** Table 5 gives details of our new benchmark dataset. We took all the questions from TempQuestions dataset (of size 1271) and chose a subset for which we could find Wikidata answers. This subset has 839 questions that constitute our new dataset, TempQA-WD. We annotated this set with their corresponding Wikidata SPARQL queries and Wikidata answers. We also retained the Freebase answers from the TempQuestions dataset effectively creating parallel answers from two KBs. Additionally, we added a question complexity label to each question, according to the reasoning complexity required to answer the question. Details of categorization are present in supplementary material. Within this dataset, we chose a subset of 175 questions for detailed annotations as described in Set-C in the table description leaving 664 question as test set.
Table 4: Translation of KB Specific Lambda Expression

| Expression/Predicate E | SPARQL S = \phi(E) |
|------------------------|---------------------|
| \lambda x.T            | SELECT DISTINCT ?x WHERE { \phi(T) } |
| count(\lambda x.T)     | SELECT (COUNT(?x) AS ?c) WHERE { \phi(T) } |
| argmax(\lambda x.T1, \lambda x.T2, O, L) | SELECT DISTINCT ?x WHERE { \phi(T1) \phi(T2) } ORDER BY DESC(?yStart) LIMIT L OFFSET O |
| IRI_p(s, IRIs, o|IRIo) | ?s|wd:QID1 p:PID ?e. \phi ps:PID ?o|wd:QID2. ?e|pq:P580 ?e1Start. \phi |pq:P582 ?e1End. |
| wdt:PID(e, s|wd:QID1, o|wd:QID2) \land interval(e', e) | FILTER(?e1Start<=?e2End & & ?e2Start<=?e1End) |
| overlap(e1, e2)        | FILTER(?e1End<=?e2End) |
| before(e1, e2)         | FILTER(?e1End<=?e2Start) |
| after(e1, e2)          | FILTER(?e1Start>=?e2End) |

Table 5: Benchmark dataset details. TempQuestions denote original dataset with Freebase answers [Jia et al. 2018]. Second row is the subset adapted to Wikidata and the third row is the devset taken out of it. Set-A denote TempQuestions with- {temporal signal, question type, data source}. Set-B -{Wikidata SPARQL , answer, category}. Set-C- {AMR, \lambda-expression, entities, relations, KB-specific \lambda-expression}

5 Evaluation

Implementation Details: We implemented our pipeline using a Flow Compiler [Chakravarti et al. 2019] stitching individual modules exposed as gRPC services. We defined the ANTLR grammar to define \lambda-expressions. KB-Specific \lambda-expression to SPARQL module is implemented in Java using Apache Jena SPARQL modules, to create SPARQL objects and generate the final SPARQL query that is run on target KB end point. The rest of the modules are implemented in Python and are exposed as gRPC services.

Datasets: We considered two different KBs namely DBpedia and Wikidata to evaluate our system. We did not consider Freebase as its no longer actively maintained and is not up-to-date. Along with the new benchmark dataset TempQA-WD introduced in this paper, we also evaluate our baseline system on two other benchmark datasets adopted from Wikidata, to evaluate its effectiveness beyond temporal questions. They are SWQ-WD [Diefenbach et al. 2017], which consists of 14894 train and 5622 test set questions, and WebQSP-WD [Sorokin and Gurevych 2018], which consists of 2880 train and 1033 test set questions. For DBpedia, we used QALD-9 [Usbeck et al. 2017], that has 408 training and 150 test questions, and LC-QuAD 1.0 [Trivedi et al. 2017] data set, that has 4k training set and 1k test set. Each of these datasets operate on their own version of the DBpedia and SPARQLs provided and we used the same instance of DBpedia for evaluation. The baseline system is tuned with dev sets of 175 from TempQA-WD and 200 from SWQ-WD train and 200 from LC-QuAD 1.0 and evaluated on all the five test sets.

Baselines We compare SYGMA with various KBQA baseline systems as given in Table 6. To our knowledge there is no other system that works across both DBpedia and Wikidata. We took the numbers reported from NSQA [Kapanipathi et al. 2021] work, which is current state-of-the-art on both LC-QuAD 1.0 and QALD-9 datasets. We also compare our work with GGNN [Sorokin and Gurevych 2018a] which is the only known benchmark for WebQSP-WD dataset. We also compare our work with WDAqua [Diefenbach, Singh, and Maret 2017], gAnswer [Zou et al. 2014b] and QAMP (Vakulenko et al. 2019) systems.

5.1 Results & Discussion Table 6 shows performance of SYGMA on two different KBs with five different datasets described in Section 5. We also show the type of reasoning required for each dataset along with the precision/recall and F1 measure. We use GER-BIL [Usbeck et al. 2019] to compute performance metrics from the pairs of gold answers and system generated answers from the pipeline. To our knowledge, ours is the first system reporting KBQA numbers across two different KBs and varying reasoning types. We get state of the art numbers beating NSQA [Kapanipathi et al. 2021] on LC-QuAD 1.0 and also achieve comparable numbers for QALD. For WebQSP-WD dataset we get state of the art numbers nearly 20% gain over GGNN [Sorokin and Gurevych 2018a]. The accuracy numbers for Wikidata datasets show that there is ample scope for improvement for different modules. This gets evident when we look at the module performances on a small set of development sets across datasets. For WebQSP-WD we did not have any ground truth for evaluating entity linking and relation linking.

AMR: Table 7 show the performance of the AMR parser on
Table 6: SYGMA’s Performance across knowledge bases and reasoning types. Baseline numbers are taken from Kapanipathi et al. (2021) and Sorokin and Gurevych (2018). P-Precision, R-Recall, F1-F1.

| Dataset → | KB | Smatch | Exact Match |
|-----------|----|--------|-------------|
| LC-QuAD 1.0 | DBpedia | 87.6 | 30.0 |
| QALD-9 | DBpedia | 89.3 | 41.8 |
| WebQSP-WD | Wikidata | 88.0 | 43.8 |
| SWQ-WD | Wikidata | 83.0 | 37.8 |
| TempQA-WD | Wikidata | 89.6 | 39.8 |

Table 7: AMR parser performances on the development sets.

| KB | Precision | Recall | F1 |
|-----|-----------|--------|----|
| LC-QuAD 1.0 | DBpedia | 0.52 | 0.50 | 0.50 |
| QALD-9 | DBpedia | 0.55 | 0.53 | 0.53 |
| TempQA-WD | Wikidata | 0.43 | 0.43 | 0.42 |
| SWQ | Wikidata | 0.67 | 0.68 | 0.67 |

Table 8: Entity linking performance on development sets when gold mentions are provided. The numbers inside parentheses denote the Hits@5 scores.

| KB | Accuracy (%) |
|----|--------------|
| LC-QuAD 1.0 | 86.81 (91.94) | 84.00 (90.50) |
| QALD-9 | 89.52 (94.28) | 89.79 (93.87) |
| TempQA-WD | 74.01 (82.47) | 57.14 (69.71) |
| SWQ | 72.27 (83.18) | 70.14 (81.59) |

Table 9: Relation linking performance on development sets.

| KB | Precision | Recall | F1 |
|----|-----------|--------|----|
| NO GT | 0.47 | 0.50 | 0.47 |
| GT-AMR | 0.50 | 0.51 | 0.50 |
| GT-λ | 0.52 | 0.53 | 0.52 |
| GT-EL | 0.60 | 0.62 | 0.59 |
| GT-RL | 0.92 | 0.93 | 0.92 |
| GT-KB-λ | 0.93 | 0.93 | 0.93 |
| GT-SPARQL | 1.0 | 1.0 | 1.0 |

Table 10: Ablation Study on TempQA-WD and LC-QuAD 1.0 dev sets. P-Precision, R-Recall, F1-F1.

6 Conclusion

In this paper, we present SYGMA system that is generalizable across knowledge bases and reasoning types. We introduce KB-agnostic question understanding component that is common across KBs with AMR based intermediate λ-Calculus representation. Question Mapping and reasoning module on the specific KB is customized per KB. we also presented rule modules that can aid in adding new reasoning type. We introduced a new benchmark dataset TempQA-WD for tem-
poral KBQA on Wikidata. Experimental results show that SYGMA indeed achieves its generalization goals with state of the art results on LC-QuAD 1.0 and WebQSP-WD.

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