

# Formal Query Generation for Question Answering over Knowledge Bases

Hamid Zafar \*, Giulio Napolitano \*\*, Jens Lehmann \*,\*\*

\* SDA group, University of Bonn, Germany

\*\* Fraunhofer IAIS, Germany

### Agenda

- Introduction
- SPARQL Query Generator (SQG)
  - Capture subgraph
  - Find valid walks
  - Rank queries
- Empirical results
- Summary



#### Introduction

Question answering over Knowledge graphs



#### Introduction

#### Transform question posed in natural language to a formal language

What are some artists on the show whose opening theme is Send It On?

SELECT DISTINCT ?uri WHERE {

?x <http://dbpedia.org/ontology/openingTheme> <http://dbpedia.org/resource/Send\_It\_On> .
?x <http://dbpedia.org/property/artist> ?uri .

?x <https://www.w3.org/1999/02/22-rdf-syntax-ns#type> <http://dbpedia.org/ontology/TelevisionShow>}

#### **Common Architectures**

#### **End-to-End**

- Single process
- + No error propagation
- Limited support for complex questions

#### Pipeline

- Consists of multiple components including
  - Named Entity Disambiguation
  - Relation Extraction
  - Query Generation (QG)
- + Reusable components
- + Limited focus
- Propagate the error along the pipeline

#### **Pipeline Architecture**

#### **Query Generation Component**

- The **Query Generation** is a common components in QA systems
- Error analysis from [4] showed the importance of the Query Generation and its effect on the overall performance of the QA pipeline

#### Requirements of Query Generation

- Cope with large-scale KGs
- Ability to manage noisy input to handle error propagation
- Question type identification
- Support for composite question
- Syntactic ambiguity of the input question

### **SPARQL Query Generation (SQG)**

- Hypothesis: The formal interpretation of the question is a walk in the KG which contains the target entities and relations of the input questions plus the answer node.
- **Inputs:** Question along with the linked entities and relations

#### Inputs





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#### Feature identification

- SVM model on tf-idf representation of input questions
  - Establish the type of the question (e.g. boolean, count or list)
    - Affects the query formation process
  - Hidden relation identification (e.g. what is the birthplace of X and Y)

#### **Query Generation- Capturing subgraph**

- Capture the connected subgraph which contains the linked entities/relation and arbitrary unbounded nodes.
- Limited to one and two hop distance



#### Valid walks



- Walk: A walk in a knowledge graph is a sequence of edges along the nodes they connect.
- Valid Walk: A walk is valid w.r.t a set of entities and relations, if and only if it contains all of them.

#### Extract valid walks from the subgraph



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#### Extract valid walks from the subgraph



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#### **Ranking Model**

- Goal: Rank the valid walks w.r.t. the semantic of the input question
- **Hypothesis:** the structure of the walks is a distinctive feature to distinguish the similarity between the candidate walks and the input question

#### LSTM





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#### **Tree-LSTM**



[1] Tai et al."Improved semantic representations from tree- structured long short-term memory networks"



### **Dependency Parsing Tree**



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#### **Tree-Rep. of Candidate Queries**





### **Tree-LSTM as Ranking model**



#### **Evaluation Setup**

• Dataset: LC-QuAD



- 5000 Q/A pairs with different complexity and types of questions
- Baseline QA systems:
  - **Sina** Shekarpour et al. "SINA:semantic interpretation of user queries for question answering on interlinked data. Web Semant"
  - NLIWOD https://github.com/dice-group/NLIWOD
- Baseline for the Ranking Model:
  - LSTM

#### **Evaluation- Scenarios**

- Top-1 correct: Questions annotated w. correct entities/relations
- Top-5 EARL+correct: Questions annotated w. list of candidate entities/relations (correct ones forcefully injected if not exists)
- Top-5 EARL: Questions annotated w. list of candidate entities/relations

- EARL: an entity/relation linking tool, Dubey et a.l. "EARL: joint entity and relation linking for question answering over knowledge graphs"

### **Evaluation- Ranking model**

Considering the tree-representation significantly improves the performance.

Scenario	LSTM F1-measure	Tree-LSTM F1-measure		
Top-1 correct	0.54	0.75	-	Better generalization
Top-1 EARL+correct	0.41	0.84		
Top-1 EARL	0.32	0.74		

- Micro F1-measure



#### **Evaluation- vs. Baselines**

Approach	Precision	Recall	F1-measure
Sina*	0.23	0.25	0.24
NLIWOD*	0.48	0.49	0.48
SQG	0.76	0.74	0.75

\* Sina and NLIWOD results are taken from Singh et al."Why reinvent the wheel-lets build question answering systems together"

- on a subset of LC-QuAD containing 3,200 questions

#### Summary

- Reusable and Scalable approach
- Managing noisy annotations
- Exploit structural similarity of input question and candidate queries

Thanks you for you attention.

## **Questions?**

Code is available at: <u>https://github.com/AskNowQA/</u> SQG

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