Simple Question Answering over *Wikidata*

Master's thesis

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A Knowledge Base contains many facts

Example

"The mother of Albert Einstein is Pauline Koch."

Facts are stored using RDF

Example

“The mother of Albert Einstein is Pauline Koch.”

In RDF

```
"Albert Einstein" "has mother" "Pauline Koch"
```

We can use *SPARQL* to extract information

Query

```
SELECT ?target WHERE {
  "Albert Einstein" "has mother" ?target .
}
```

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```

Result

?target
"Pauline Koch"

Names are ambiguous

Albert Einstein (famous scientist)

- `<http://www.wikidata.org/entity/Q937>`
- `wd:Q937`

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"has mother" relation

- `<http://www.wikidata.org/prop/direct/P25>`
- `wdt:P25`

The question and the associated query are very different

Query

```
SELECT ?target WHERE {
  wd:Q937 wdt:P25 ?target .
}
```

The question and the associated query are very different

Question

"Who is the mother of Albert Einstein?"

Query

```
SELECT ?target WHERE {
  wd:Q937 wdt:P25 ?target .
}
```

The variable can also be in the subject position

Question

"Which books did J. R. R. Tolkien write?"

Query

```
SELECT ?book WHERE {
  ?book wdt:P50 wd:Q892 .
}
```

The result can contain more than one item

Question

“Which books did J. R. R. Tolkien write?”

Query

```
SELECT ?book WHERE {
  ?book wdt:P50 wd:Q892 .
}
```

Result

?book
wd:Q1101425
wd:Q15228
wd:Q17029228
...

We use a shorter form for queries

This query ...

```
SELECT ?t WHERE {
  wd:Q937 wdt:P25 ?t .
}
```

... becomes

```
wd:Q937 wdt:P25 ?t
```

This query ...

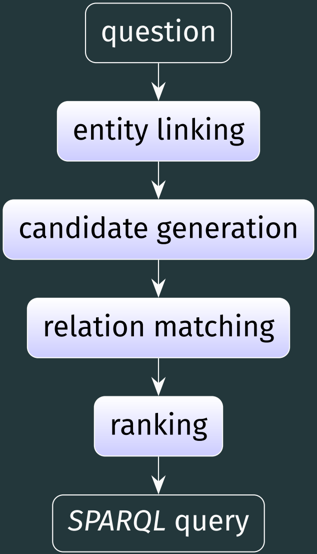
```
SELECT ?b WHERE {
  ?b wdt:P50 wd:Q892 .
}
```

... becomes

```
?b wdt:P50 wd:Q892
```

Questions?

The input question goes through multiple steps



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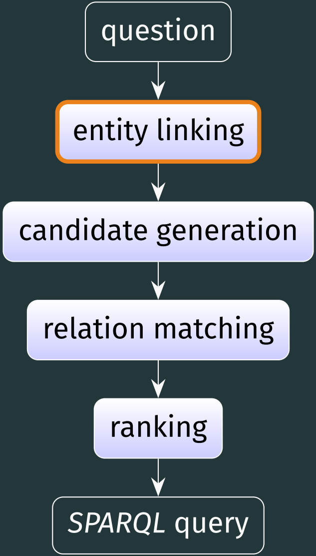


Entity linking matches entities to words

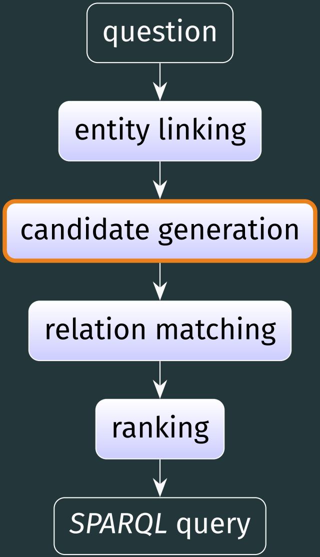
Question

"Who is the mother of Albert Einstein?"

Matches

"Albert Einstein"	wd:Q937 (famous scientist)
"Albert Einstein"	wd:Q13426745 (music album)
"Einstein"	wd:Q76346 (Mileva Marić)
"the mother"	wd:Q169632 (novel)
"the mother"	wd:Q464879 (spiritual guru)
	...

- Sort by number of matched words, then by entity popularity
- Keep the first N_e of these matches


question
entity linking
candidate generation
relation matching
ranking
SPARQL query

Every matched entity leads to several candidates

Candidates for wd:Q76346

```
wd:Q76346 wdt:P25 ?O
wd:Q76346 wdt:P26 ?O
wd:Q76346 wdt:P569 ?O
?O wdt:P25 wd:Q76346
...
```

Candidates for wd:Q937

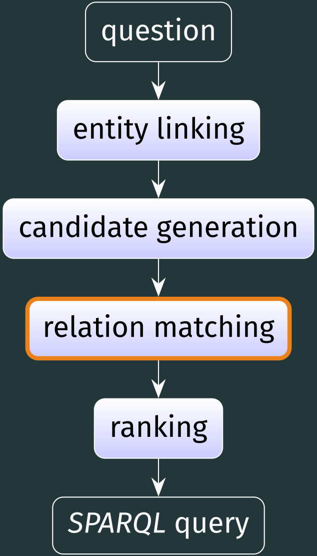
```
?O wdt:P1038 wd:Q937
wd:Q937 wdt:P103 ?O
wd:Q937 wdt:P1196 ?O
wd:Q937 wdt:P25 ?O
...
```

...

...

Relations

- wdt:P25 (mother)
- wdt:P26 (spouse)
- wdt:P103 (native language)
- wdt:P569 (date of birth)
- wdt:P1038 (relative)
- wdt:P1196 (manner of death)


question
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SPARQL query

We find relation matches for each candidate

Question

“Who is the mother of ~~Albert Einstein~~?”

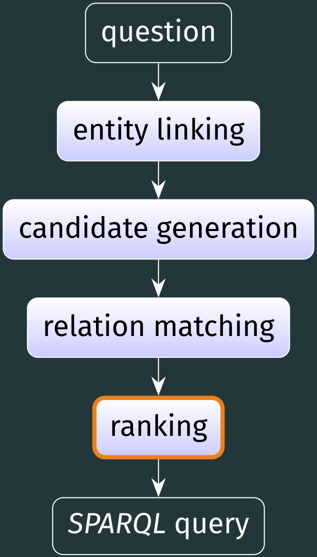
`wd:Q937 wdt:P103 ?0`

“mother” partially matches the alias “mother tongue” of `wdt:P103` (native language)

`wd:Q937 wdt:P1196 ?0`

No match for `wdt:P1196` (manner of death)

Keep only the candidates with some kind of relation match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We map each candidate to a ten-dimensional vector of features

- number of entity words
- number of relation words
- word coverage
- entity popularity score
- ...

Feature vector of `wd:Q937 wdt:P25 ?0`

$(1, 1.0, 283, 1, 2, 2, 1, 1, 1, 1)$

We rank the generated candidates

Rule-based ranker

Rank candidates with a hard-coded scoring function

Learned ranker

- Pairwise ranking as binary classification
- Random forest

Questions?

We use a subset of *SimpleQuestionsWikidata* as a benchmark

- Originally created from/for *Freebase*
- Subset classified as “answerable”
- 19481/5622 (train/test)
- Question together with gold *SPARQL* query

We use a subset of *SimpleQuestionsWikidata* as a benchmark

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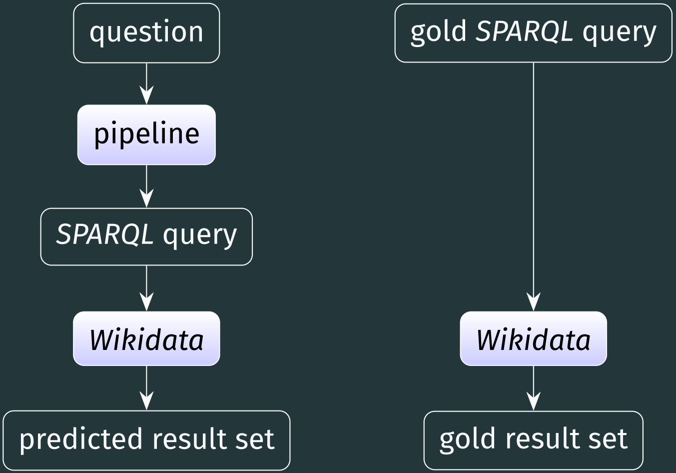
Example

```
Q2662597 P19 Q2868 where was paolo de la haza born?
```

Corresponding query

```
wd:Q2662597 wdt:P19 ?O
```

We compare the result sets of two *SPARQL* queries



QA system	Accuracy
Our system (rules, $N_e = 10$)	0.537
Our system (learned, $N_e = 10$)	0.564
Our system (rules, $N_e = 500$)	0.586
Oliya et al. (2021)	0.682

Questions?

Problem definition

QA over *Wikidata*

Given a natural language question q, find a *SPARQL* query c such that the intended answer for question q is the result of executing the *SPARQL* query c over *Wikidata*.

Simple QA over *Wikidata*

The query c is of the form

```
SELECT ?t WHERE {
  <body>
}
```

where `<body>` is one triple pattern with the variable `?t` being either in the subject or in the object position.

All features

- pattern complexity
- token coverage
- entity score
- entity label matches
- number of entity tokens
- number of entity tokens no stop
- number of exact relation matches
- number of no-stop relation matches
- number of contained relation matches
- number of relation tokens

Examples of feature vectors

`wd:Q937 wdt:P25 ?O`

$(1, 1.0, 283, 1, 2, 2, 1, 1, 1, 1)$

`wd:Q937 wdt:P103 ?O`

$(1, 1.0, 283, 1, 2, 2, 0, 0, 1, 1)$

`wd:Q76346 wdt:P25 ?O`

$(1, 0.67, 57, 0, 1, 1, 1, 1, 1, 1)$

Entities and relations

- wd:Q937 (Albert Einstein)
- wd:Q76346 (Mileva Marić)
- wdt:P25 (mother)
- wdt:P103 (native language)

Manual scoring function

$$
\begin{aligned}
s(c) := {} & 1000\hat{f}_{10}(c) \\
& + 100\left(\hat{f}_5(c) + \hat{f}_6(c) + \hat{f}_7(c)\right) \\
& + 10\hat{f}_2(c) \\
& + \hat{f}_1(c)
\end{aligned}
$$

$f_1(c)$	entity popularity score
$f_2(c)$	number of entity label matches
$f_5(c)$	number of exact relation matches
$f_6(c)$	number of contained relation matches
$f_7(c)$	number of no-stop relation matches
$f_{10}(c)$	word coverage

Training the ranker

- Run question through pipeline (except ranker)
- Find the correct candidates
- Build pairs of one correct and one incorrect candidate (c_k, c_m)
- Create two training samples from every such pair:
    - $((f(c_k) - f(c_m)), f(c_k), f(c_m)) \in \mathbb{R}^{30}$ with label 1
    - $((f(c_m) - f(c_k)), f(c_m), f(c_k)) \in \mathbb{R}^{30}$ with label 0

QA system	Accuracy (FB2M)	Accuracy (FB5M)	Accuracy (*Wikidata*)
Bordes et al. (2015)	0.627	0.639	-
Yin et al. (2016)	0.683	0.672	-
Dai et al. (2016)	-	0.626	-
He et al. (2016)	0.709	0.703	-
Lukovnikov et al. (2017)	0.712	-	-
Yu et al. (2017)	**0.787**	-	-
Mohammed et al. (2018)	0.749	-	-
Huang et al. (2019)	0.754	**0.749**	-
Oliya et al. (2021)	-	-	**0.682**
Our system (rules)	-	-	0.586
Our system (learned)	-	-	0.564

Evaluation for different numbers of used entities

Rule-based ranker

N_e	R@1	R@2	R@3	R@5	R@10	R@100	AD (s)
500	**0.59**	**0.67**	**0.71**	**0.74**	**0.77**	**0.82**	7.09
50	0.58	**0.67**	**0.71**	**0.74**	**0.77**	**0.82**	5.52
10	0.54	0.66	0.69	0.72	0.75	0.77	**1.46**