$\mathcal{I}(\mathtt{p})$. This characteristic is modeled by computing the *support* of the pattern.

2. A good NLE θ for `p` allows to retrieve text segments such that the placeholders `?D?` resp. `?R?` can be matched to labels of entities whose `rdf:type` correspond with `rdfs:domain` resp. `rdfs:range` of `p`. We call this characteristic *typicity.*

3. A good NLE θ is used exclusively to express `p`, i.e, it occurs in a small number of pattern mappings. We call this last characteristic *specificity.*

To be able to compute these characteristics of good patterns numerically, BOA collects the following supplementary information during the NLE extraction process:

- the number of sentences that led to θ and that contained $label(x)$ and $label(y)$ with $(x,y) \in \mathcal{I}(\mathtt{p})$, which we denote $l(x,y,\theta,\mathtt{p})$, and

- $\mathcal{I}(\mathtt{p},\theta)$, the subset of $\mathcal{I}(\mathtt{p})$ which contains only pairs (s,o) that led to θ.

4.2.1 Support

We calculate the support $sup(\theta,\mathtt{p})$ of the pattern θ for the predicate `p` as the product of the number of subject-object pairs the pattern has been learned from and the maximum value for a single subject-object pair:

$$sup(\theta,\mathtt{p}) = \log\left(\max_{(s,o)\in\mathcal{I}(\mathtt{p})} l(s,o,\theta,\mathtt{p})\right)\log(|\mathcal{I}(\mathtt{p},\theta)|). \quad (2)$$

Since both components of the support follow a long-tail distribution, we use the logarithm to reduce the boosting of very popular patterns.

4.2.2 Typicity

A pattern θ is considered to display a high typicity with respect to a predicate `p` if its placeholders ?D? and ?R? match only labels of entities whose `rdf:type` matches the range and domain restrictions of `p` in the reference corpus. Let d resp. r be functions that map each `p` to its `rdfs:domain` resp. `rdfs:range`. Furthermore, let $d(\theta,s)$ resp. $r(\theta,s)$ be functions which map the class of the named entity used to substitute ?D? resp. ?R in the pattern θ for the given sentence s. Finally, let the function $\delta(x,y)$ be Kronecker's delta function, which returns 1 if $x=y$ and 0 in all other cases. We define the typicity of θ as

$$typ(\theta,\mathtt{p}) = \sum_{s\in S}\left(\frac{\delta(d(\mathtt{p}),d(\theta,s))+\delta(r(\mathtt{p}),r(\theta,s))}{2|S|}\right)\log(|S|+1), \quad (3)$$

where `S` is the set of sentences used to evaluate the typicity of θ. Note that the first term of the typicity is simply the precision of the pattern. We multiply this factor with the logarithm of (|S|+1) to prevent overly promoting patterns which have a low recall, i.e., patterns that return only a small number of sentences.

4.2.3 Specificity

A NLE θ is considered to be specific if it is used to expressed a small number of predicates `p`. We adapted the idea of inverse document frequency (idf) as known from Information Retrieval to capture this characteristic. The specificity $spec(\theta)$ is thus given by the following expression:

$$spec(\theta) = \log\left(\frac{|P|}{|M(\theta)|}\right), \quad (4)$$

where $M(\theta)$ is the set of predicates of which θ is a NLE.

All three equations can now be combined to the global confidence score $c(\theta,\mathtt{p})$ used by BOA as shown in Equation 5:

$$c(\theta,\mathtt{p}) = sup(\theta,\mathtt{p})\cdot typ(\theta,\mathtt{p})\cdot spec(\theta). \quad (5)$$

5. QUERY RANKING AND SELECTION

After identifying entities that could fill the slots of a template, we arrive at a range of possible SPARQL queries. The task now is to rank these queries and to pick one, which is then used to retrieve the answer to the input question.

The goal of the query ranking step is to provide a function for deciding on the order of execution of queries that possibly match a question. Given a slot that is to be filled, we compute two scores for each possible entity e that can be used to fill a slot: a similarity score and a prominence score. The similarity score $\sigma(e)$ is the string similarity used during the entity detection phase. The prominence score $\varphi(e)$ is given by

$$\varphi(e) = \begin{cases}\log_2|\{(\mathtt{x},\mathtt{y}) : \mathtt{x\ e\ y}\}| & \text{if } \mathtt{e} \text{ is a property}\\ \log_2|\{(\mathtt{x},\mathtt{y}) : \mathtt{x\ y\ e}\}| & \text{else,}\end{cases} \quad (6)$$

where `x e y` holds when this triple can be found in the reference knowledge base K. The final score $score(e)$ of each entity is then definded as

$$score(e) = \alpha \max_{s'\in\mathcal{S}(s)} \sigma(s',label(e)) + (1-\alpha)\varphi(e), \quad (7)$$

where $\alpha \in [0,1]$ decides on the impact of similarity and prominence on the final score of each entity.

The score of a query is computed as the average of the scores of the entities used to fill its slots. In addition to this, we perform type checks on queries: We first extract all triple patterns of the form `?x rdf:type c` in the query, where `?x` stands for a variable and `c` for a class. We compute $\text{types}(?x,q) = \{c \mid (?x,\mathtt{rdf:type},c)\in TP(q)\}$ where TP stands for the set of triple patterns in the considered query q. For each such variable, we search for triple patterns `?x p e` and `e p ?x` in the query. In the former case, we check whether the domain of the property `p` is disjoint with an element of $\text{types}(?x,q)$. In the latter case, we perform the same check with the range of `p`. If any of these type checks fails, the query is rejected. We perform this to avoid queries, which do not follow the schema of the knowledge base, but could still return results because of modelling errors in the data.

Once a ranked list of SPARQL queries is available, we need to decide which of those queries should be returned as answer. If only the highest ranking query would be returned, the problem arises that most of those queries actually do not return a result. The reason for this is that the query ranking method can only take limited information into account for reasons of efficiency. It uses string similarity, prominence of entities and the schema of the knowledge base to score a query. However, this does not guarantee that the combination of triple patterns in a query is meaningful and leads to a non-empty result. Therefore it is necessary to execute and test queries before returning a result to the user. Our system returns the highest scored query with a non-empty result. A special case are COUNT queries: In most of those queries, a return value of 0 is also discarded in our method, since this usually means that the WHERE clause of the corresponding SPARQL query does not yield a match in the considered RDF graph.

6. EVALUATION AND DISCUSSION

The evaluation is based on the QALD[5] benchmark on DBpedia[6] [10]. It comprises two sets of 50 questions over DBpedia, annotated with SPARQL queries and answers. Each question is evaluated w.r.t. precision and recall defined as follows:

$$\text{Recall} = \frac{\text{number of correct resources returned by system}}{\text{number of resources in gold standard answer}}$$

$$\text{Precision} = \frac{\text{number of correct resources returned by system}}{\text{number of resources returned by system}}$$

Before we turn to the evaluation results, one important preliminary remark: The reported results are results based on natural language questions tagged with ideal part-of-speech information. The reason is that questions often lead to POS tagging errors. For example, in Which films did Leonardo di Caprio star in, the infinitive verb form star is tagged as a noun by the Stanford POS tagger as well as the Apache OpenNPL[7] POS tagger, which leads to a parse failure. The same holds for a range of infinitives such as play, border, die, cross and start. In order to separate such external errors from errors internal to our approach, we manually corrected erroneous POS tags in seven questions, that otherwise would not have been parsed. But this is only a temporal solution, of course; the next step is to train a POS tagger model on a corpus containing a sufficient amount of questions.

6.1 Evaluation results

Of the 50 training questions provided by the QALD benchmark, 11 questions rely on namespaces which we did not incorporate for predicate detection: FOAF[8] and YAGO[9]. Especially the latter poses a challenge, as YAGO categories tend to be very specific and complex (e.g., `FemaleHeadsOf-Government` and `HostCitiesOfTheSummerOlympicGames`). We did not consider these questions, thus only 39 questions are processed by our approach. Of these 39 questions, 5 questions cannot be parsed due to unknown syntactic constructions or uncovered domain-independent expressions. This mainly concerns the noun phrase conjunction as well as and ordinals (the 5th, the first). These constructions will be added in the future; the only reason they were not implemented yet is that they require significant additional effort when specifying their compositional semantics.

Of the remaining 34 questions, 19 are answered exactly as required by the benchmark (i.e. with precision and recall 1.0) and another two are answered almost correctly (with precision and recall > 0.8). Figure 3 at the very end of the paper lists the results of each of the 39 processed questions.

[5]`http://www.sc.cit-ec.uni-bielefeld.de/qald`
[6]`http://dbpedia.org`
[7]`http://incubator.apache.org/opennlp/`
[8]`http://www.foaf-project.org/`
[9]`http://www.mpi-inf.mpg.de/yago-naga/yago/`

The mean of all precision scores is therefore 0.61 and the mean of all recall scores is 0.63, leading to an F-measure[10] of 0.62. These results are comparable with those of systems such as FREyA and PowerAqua. The key advantage of our system is that the semantic structure of the natural language input is faithfully captured, thus complex questions containing quantifiers, comparatives and superlatives pose no problem, unlike in PowerAqua. Moreover, our system does not need any user feedback, as FREyA does.

6.2 Discussion

In the following, we identify the main sources of errors and discuss how they can be addressed in future work.

In the examples given in this section, we will use the following abbreviations for relevant DBpedia namespaces:

- `res` for `<http://dbpedia.org/resource/>`
- `onto` for `<http://dbpedia.org/ontology/>`
- `prop` for `<http://dbpedia.org/property/>`

Incorrect templates

It only very rarely happens that a parse is found but no sensible template is constructed. However, it does happen that none of the constructed templates captures the structure of the data. One example is question 36 (Is there a video game called Battle Chess?), where the generated template assumes a property slot *title* or *name* corresponding to the participle called; however, none such property exists in DBpedia. The appropriate property `rdfs:label`, on the other hand, is not part of the index and thus is not found by the predicate detection algorithm.

Incorrect templates are most eminent when the semantic structure of the natural language question does not coincide with the triple structure of the target query. For example, the phrase join the EU would lead to a template containing a property slot *join* related to the resource *EU*; the appropriate property in DBpedia, however, is `prop:accessioneudate`. The same structural mismatch would arise with complex YAGO caterogies. Cases like these suggest that the fixed structure of the templates is sometimes too rigid. We are currently working on two solutions to this problem, see Section 9 below.

Another reason for incorrect templates is the sporadic failure of named entity recognition. E.g., if a phrase like Battle of Gettysburg is not recognized as a named entity, no resource slot is built – instead the template would contain a slot for a class *battle* related to an entity *Gettysburg*, which does not lead to a meaningful result.

Entity identification

Errors due to entity identification occur when a resource, class or property cannot be found on the basis of the slot. These are the most frequent errors in our approach.

A particularly hard case for entity identification is when a property in the intended target query does not have a correspondent in the natural language question. This is the case in questions 11 (Give me all soccer clubs in the Premier League) and 29 (Give me all movies with Tom Cruise). The templates constructed for these questions contain a property slot that arises from the prepositions in and with; the correct properties `onto:league` (for 11) and `onto:starring`

[10]$(2 \times \text{precision} \times \text{recall})/(\text{precision} + \text{recall})$

(for 29), however, could be found only by inferences on the basis of Premier League and films. This type of inferences is not part of our approach at the moment.

Examples for entities which do have a correspondent in the natural language input but are nevertheless hard to match are the following:

- inhabitants, the correct property being `prop:population` or `prop:populationTotal` (question 9)
- owns, the property specified in the Gold query being `onto:keyPerson` (question 10)
- higher, the target property being `prop:elevationM` (question 33)

These cases would require the incorporation of additional semantic similarity measures, such as *Explicit Semantic Analysis* [8].

Query selection

Sometimes the correct entity is among the entity candidates, but still a query with the wrong entity instantiating the slot is picked. An example of this is question 32 (Who wrote The pillars of the Earth?). The expression wrote is matched with the property `onto:writer`, as this is higher ranked than the property `onto:author`. Using the former, the name The pillars of the Earth is incorrectly matched with `res:The_Pillars_of_the_Earth_(TV_Miniseries)` because it gives a non-empty result in combination with `onto:writer`.

Another case in which the wrong entity is picked is when the slot contains too little information in order to decide among candidates. E.g., there are three questions (24, 41, 44) containing the participle founded. There are several candidates of properties that founded could correspond to, e.g. `prop:foundation`, `prop:foundingYear`, `prop:foundingDate`, `onto:foundationPerson`, `onto:foundationPlace`. Without a hint about the intended range of the property, the decision for one of these properties has to be quite arbitrary. In order to capture these cases, slots would need to comprise more information, e.g. also specify the property's range, in order to distinguish constructions like founded in 1950, founded in California and founded by Goofy. A first step towards this goal is already implemented: In case the argument is a numeral or the question contains a wh-word like when or where, the slot contains the information that a date or place is intended (thus question 41 works fine and for question 24 a sensible template is built, although it fails due to query ranking and selection).

Other reasons

In some cases our approach is doing the right thing, however not, or only partially, matching the Gold query. One example is question 13 (What languages are spoken in Estonia?). The target query specified in the Gold standard contains a union of countries related to Estonia via the property `onto:language` and countries related to Estonia via the property `onto:spokenIn`. Our approach finds the former property and stops, thus misses the latter and thereby achieves 1.0 precision but a lower recall. The solution would be to perform an exhaustive search, i.e. not stopping after one successful query is found.

Another example is question 38, which asks for the country with the most official languages. Our approach choses the property `onto:officialLanguage`, while the Gold query uses the more general (and arguably less appropriate) property `onto:language`.

In general, question answering over DBpedia has to face the challenge of two schemas – a manually created ontology modelling mostly neat and consistent data in the `ontology` namespace, and an automatically created one modelling a large amount of quite noisy data in the `property` namespace. The namespaces partly overlap and chosing one over the other often leads to different results of different quality.

7. PROTOTYPE

A prototype for the described algorithm was implemented and deployed, see Figure 2. It is a freely accessible web application, which allows a user to enter natural language questions. The answers are shown in a tabular view if appropriate. The view allows the user to enrich the generated answers by displaying further appropriate property values for the returned resources. Interesting queries can be saved and reused by other users.

For the prototype, we used DBpedia as underlying knowledge base. To be able to use the mentioned techniques, some components were created offline: Separate Lucene indices were created for resources, properties and classes by querying for the labels of those elements in the used DBpedia triple store. Additionally, a BOA index was created for properties, since it vastly improves the mapping of properties in natural language queries compared to using a text index. The same approach can be applied to other knowledge bases and we plan to evaluate this in future work.

8. RELATED WORK

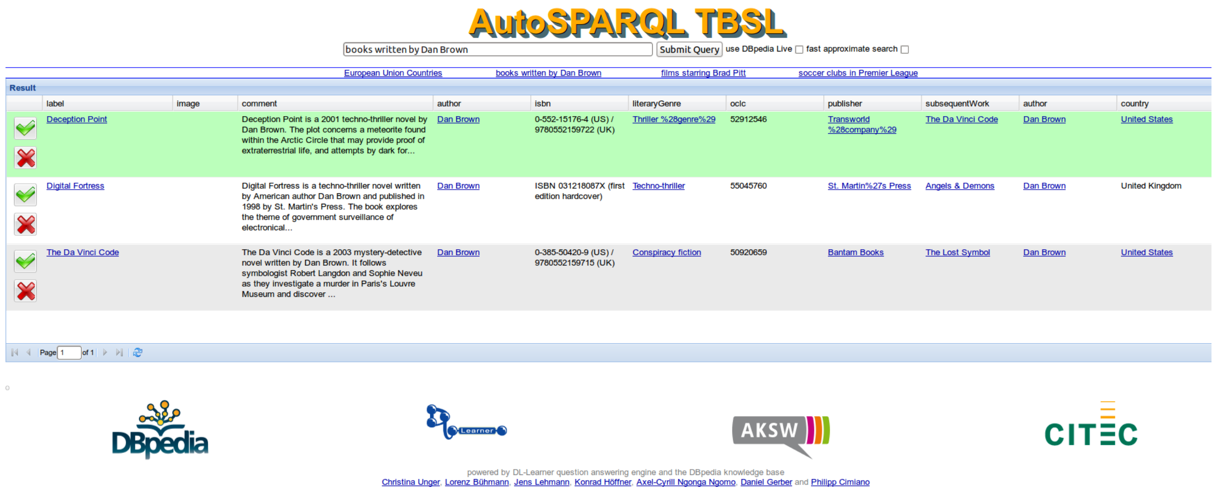
Several approaches have been developed for the purpose of question answering.

PowerAqua is a question answering system over Linked Data that is not tailored towards a particular ontology; especially it does not make any assumptions about the vocabulary or structure of datasets. The main focus of the system is to combine and merge data from different sources, focusing on scalability, and using iterative algorithms, filtering and ranking heuristics to limit the search space. PowerAqua is therefore very strong on large, heterogeneous datasets, although it does struggle on complex mappings such as the aforementioned YAGO categories. For a detailed explanation of the system's architecture and an evaluation see, e.g., [15, 13]. The major shortcoming of PowerAqua is its limited linguistic coverage. In particular, PowerAqua fails on questions containing the most (such as question 31), and more than (such as question 12), which pose no problem for a system with a deeper linguistic analysis of the input question.

Pythia [22] is such a system. It relies on a deep linguistic analysis (on which the approach based in this paper is based) and can therefore handle linguistically complex questions, in particular questions containing determiners such as the most and more than. Pythia's major drawback is that it requires a lexicon, which up to this moment has to be created manually. It therefore fails to scale to very large datasets.

The approach proposed in this paper tries to combine both a deep linguistic analysis with the flexibility of approaches focusing on matching natural language questions to RDF triples. The triple structure is derived from the semantic structure of the question.

Another possibility to determine the triple structure is



books written by Dan Brown

European Union Countries · books written by Dan Brown · films starring Brad Pitt · soccer clubs in Premier League

Result

	label	image	comment	author	isbn	literaryGenre	oclc	publisher	subsequentWork	author	country
✓ ✗	Deception Point		Deception Point is a 2001 techno-thriller novel by Dan Brown. The plot concerns a meteorite found within the Arctic Circle that may provide proof of extraterrestrial life, and attempts by dark for...	Dan Brown	0-552-15176-4 (US) / 9780552159722 (UK)	Thriller %28genre%29	52912546	Transworld %28company%29	The Da Vinci Code	Dan Brown	United States
✓ ✗	Digital Fortress		Digital Fortress is a techno-thriller novel written by American author Dan Brown and published in 1998 by St. Martin's Press. The book explores the theme of government surveillance of electronical...	Dan Brown	ISBN 031218087X (first edition hardcover)	Techno-thriller	55045760	St. Martin%27s Press	Angels & Demons	Dan Brown	United Kingdom
✓ ✗	The Da Vinci Code		The Da Vinci Code is a 2003 mystery-detective novel written by Dan Brown. It follows symbologist Robert Langdon and Sophie Neveu as they investigate a murder in Paris's Louvre Museum and discover ...	Dan Brown	0-385-50420-9 (US) / 9780552159715 (UK)	Conspiracy fiction	50920659	Bantam Books	The Lost Symbol	Dan Brown	United States

powered by DL-Learner question answering engine and the DBpedia knowledge base
Christina Unger, Lorenz Bühmann, Jens Lehmann, Konrad Höffner, Axel-Cyrill Ngonga Ngomo, Daniel Gerber and Philipp Cimiano

Figure 2: Screenshot of prototype available at `http://autosparql-tbsl.dl-learner.org`.

by exploration of the dataset, as in the question answering system *FREyA* [2, 3]. However, FREyA partly relies on the user's help in selecting the entity that is most appropriate as match for some natural language expression. The drawback of such an approach is that the naive end-user is often not informed about the modeling and vocabulary of the data and thus is not able to help.

Further approaches related to question answering over Linked Data include, e.g., *Treo* [7], which combines entity search, semantic relatedness and spreading activation for exploring RDF data, and *Ontolook* [12], which focuses on relation-based search. In addition to question answering, keyword-based approaches have been gaining momentum over the past years. This led to semantic search engines, such as Swoogle [5], Watson [4], Sigma [20] and Sindice [21], which aim to index RDF across the Web and make it available for entity search. The approaches described in [17] and [19] extend upon the paradigm of simple entity search and try to generate interpretations of keyword queries which exploit the semantics available on the Linked Data Web. Especially, [19] implements a graph exploration approach to detect subgraphs of the input knowledge base that can be used to compute an answer to the user's query. On the other hand, [17] uses schema knowledge to infer SPARQL queries that represent possible interpretations of the user-given keywords.

9. CONCLUSION AND FUTURE WORK

We presented a novel approach to question answering over Linked Data that relies on a deep linguistic analysis yielding a SPARQL template with slots that need to be filled with URIs. In order to fill those slots, possible entities were identified using string similarity as well as natural language patterns extracted from structured data and text documents. The remaining query candidates were then ranked and, on the basis of scores attached to the entities, one of them was selected as final result.

One of the strengths of this approach is that the generated SPARQL templates capture the semantic structure of the natural language input. Therefore questions containing quantifiers like the most and more than, comparatives like higher than and superlatives like the highest do not pose a problem – in contrast to most other question answering systems that map natural language input to purely triple-based representations.

However, in some cases the semantic structure of the question and the triple structure of the query do not coincide, thus faithfully capturing the semantic structure of the input question sometimes leads to too rigid templates. We are currently exploring two approaches to solve this problem. The first one concentrates on more flexible processing. On the one hand side, we are considering a preprocessing step that can detect complex (especially YAGO) categories before parsing the natural language question. On the other hand side, we are investigating the relaxation of templates, such that the triple structure is not completely fixed but is discovered through exploration of the RDF data.

The second approach concerns incorporating a more flexible fallback strategy in case no successful SPARQL query is found. In particular, we are working on combining our approach with active learning methods as described in [11]. Active learning allows the user to give feedback on the presented query results, i.e. the user can say whether particular query results are incorrect and/or whether further results should be returned. This will allow two enhancements over the presented question answering system: First, if the returned answers are incorrect or incomplete, then the user can indirectly modify the query via his feedback. And second, if our approach cannot generate a query at all, then the system can still recover by allowing the user to specify one or more query results. This procedure can be assisted with standard search and disambiguation methods.

Once these enhancements are in place, i.e. once the shortcomings mentioned in Section 6.2 are addressed, we will evaluate our approach on a larger scale, for example using the data provided by the second instalment of the QALD open challenge, which comprises 100 training and 100 test questions on DBpedia, and a similar amount of questions on MusicBrainz. In particular, we will test how well our approach carries over to different types of domains. Additionally, we plan to conduct a small usability study.

Ultimately, our goal is to provide robust question answering for large scale heterogeneous knowledge bases. Our vision is that this robustness can help to make the usage of question answering systems a standard task in everyday life in a similar but more powerful way as web search.

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id	question	precision	recall
2	Who has been the 5th president of the United States of America		
4	Who was Tom Hanks married to	1.0	1.0
5	Which people were born in Heraklion	0.91	1.0
7	Which companies work in the aerospace industry as well as on nuclear reactor technology		
8	Which people have as their given name Jimmy		
9	Who developed the video game World of Warcraft	1.0	1.0
10	Who was the wife of president Lincoln	1.0	1.0
12	Which caves have more than 3 entrances	1.0	1.0
13	Which cities have more than 2000000 inhabitants	0.04	0.26
14	Who owns Aldi		
16	Give me all soccer clubs in the Premier League	0.5	0.86
17	In which programming language is GIMP written	1.0	1.0
18	What languages are spoken in Estonia	1.0	0.14
20	Which country does the Airedale Terrier come from	1.0	1.0
21	What is the highest mountain	1.0	1.0
24	Which organizations were founded in 1950	0.0	0.0
25	Which genre does DBpedia belong to	1.0	1.0
26	When was DBpedia released	1.0	1.0
27	Who created English Wikipedia	1.0	1.0
28	Which companies are located in California USA	0.8	0.76
30	How many films did Leonardo DiCaprio star in	1.0	1.0
31	Who produced the most films	1.0	1.0
32	Is Christian Bale starring in Batman Begins	1.0	1.0
33	Which music albums contain the song Last Christmas		
34	Give me all films produced by Hal Roach	1.0	1.0
35	Give me all actors starring in Batman Begins	1.0	0.86
36	Give me all movies with Tom Cruise	0.08	0.75
37	List all episodes of the first season of the HBO television series The Sopranos		
38	Which books were written by Danielle Steel	1.0	1.0
39	Who wrote the book The pillars of the Earth	0.5	1.0
40	Which mountains are higher than the Nanga Parbat	0.0	0.0
41	When was Capcom founded	1.0	1.0
42	Which software has been published by Mean Hamster Software	1.0	1.0
43	Is there a video game called Battle Chess	0.0	0.0
44	Which software has been developed by organizations founded in California		
45	Which country has the most official languages	0.0	0.0
47	Is Natalie Portman an actress	1.0	1.0
48	Who produced films starring Natalie Portman	1.0	1.0
49	In which films did Julia Roberts as well as Richard Gere play		

Figure 3: This table shows precision and recall values for each processed question (i.e. all questions that do not require the YAGO or FOAF namespace). For questions with no precision and recall specified, no query was constructed. Questions printed in cells with red background were not parsed, questions in white cells succeeded and for questions in lightgray cells queries with quality equal or close to the Gold query were built, while questions in yellow cells fail due to a query selection problem and questions in orange cells fail due to some entity identification problem.