BIGCQ: A large-scale synthetic dataset of competency question patterns formalized into SPARQL-OWL query templates

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Abstract. Competency Questions (CQs) are used in many ontology engineering methodologies to collect requirements and track completeness and correctness of an ontology being constructed. Although they are frequently suggested by ontology engineering methodologies, the publicly available datasets of CQs and their formalizations in ontology query languages are very scarce. Since first efforts to automate processes utilizing CQs are being made, it is of high importance to provide large and diverse datasets to fuel these solutions. In this paper, we present BIGCQ, the biggest dataset of CQ templates with their formalizations into SPARQL-OWL query templates. BIGCQ is created automatically from a dataset of frequently used axiom shapes. These pairs of CQ templates and query templates can be then materialized as actual CQs and SPARQL-OWL queries if filled with resource labels and IRIs from a given ontology. We describe the dataset in details, provide a description of the process leading to creation of the dataset and analyze how well the dataset covers real-world examples. We also publish the dataset as well as scripts transforming axiom shapes into pairs of CQ patterns and SPARQL-OWL templates, to make engineers able to adapt the process to their particular needs.

Keywords: Competency Questions · Ontology Engineering · SPARQL-OWL · OWL · Verbalization · Natural language to query language translation

1 Introduction

Ontologies are formal representations of a given domain of interest used to model entities and relationships between them. They are often expressed using logic-based representations, out of which Web Ontology Language (OWL) is the most commonly used. The incorporation of logic-based formalization allows to define knowledge precisely and to infer new facts, even if they are not explicitly modelled. Unfortunately, engineers struggle to use such formalization, because it requires proficiency in formal logic. Especially, the logical consequences of modelled knowledge are hard to predict. Also, describing a large, vocabulary-rich domain of interests requires to control how much of vocabulary is already
modelled. To address these issues, multiple ontology engineering methodologies guiding engineers how to model knowledge are proposed. They differ in the usage context, but they all share the same goal of making ontology development easier.

Many ontology engineering methodologies adopted the idea of defining a set of natural language questions, called Competency Questions (CQs), that a finished ontology should be able to answer to correctly. These CQs can be e.g. used to define, as proposed in the NeOn [17] methodology, so-called Glossary-of-Terms defining what vocabulary should be modelled in an ontology and to track the maturity of the ontology by controlling how many CQs can be correctly answered at a given stage of ontology development. If an ontology can answer all CQs it may be regarded as correct and complete.

We have shown [22] [20] that an automation of tasks involving CQs, such as automatic Glossary-of-Terms extraction or automatic translation of CQs into an ontology query language targeting T-Box level of the ontology is achievable. SPARQL-OWL [11] used for querying T-Box level knowledge is a variant of SPARQL [7] with an OWL 2 DL entailment regime. Both problems can be addressed using machine learning based approaches, but these require a huge amount of data to fuel the models with. Although some datasets exists, they are still quite small. To fill this gap, we introduce BigCQ, a big dataset of CQ patterns mapped to SPARQL-OWL query templates generated automatically from frequently observed axiom shapes extracted from ontologies. These templates can be filled with vocabulary from an ontology to generate a huge number of examples of CQ to SPARQL-OWL query translations in an automatic manner. The CQs alone can be used to create Glossary-of-Terms extractors, while the pairs of CQs and SPARQL-OWL queries can be used to provide a method of automatic translation of CQs into queries.

The dataset that we introduce, as well as all scripts used to create BigCQ are published on GitHub [1] and can be cited using DOI [21].

The remainder of this paper is structured as follows: Section 2 describes related work, Section 3 describes datasets that were involved in the process of creation and evaluation of the quality of BigCQ. Section 4 provides details on how the dataset is created. Section 5 provides an analysis of the dataset: its size, features, coverage on existing datasets and discusses cases which are not covered by BigCQ. Section 6 discusses the impact of the dataset. Finally, Section 7 concludes the paper.

2 Related work

Ontology methodologies utilizing CQs The work of Gruninger and Fox [6] was the first methodology for design and evaluation of ontologies that incorporates CQs and use them to define informal questions extracted from ontology motivating scenarios. This idea was later adopted to other methodologies, each of which defining good practices fitting various ontology creation scenarios. Lopez

[1] https://github.com/dwisniewski/BigCQ
et al. proposed METHONTOLOGY [4], a methodology focusing on an evolving prototype scenario, which, in contrast to classic waterfall-like approaches, allows engineers to move back to previous ontology construction phases. METHONTOLOGY suggest to use CQs to specify requirements for the ontology being built. Suarez-Figueroa et al. presented NeON [17] methodology defining 9 scenarios of ontology creation process. These scenarios address use cases like: creating ontologies from scratch, reusing resources, restructuring or localizing ontological resources. In the context of NeON, CQs are also stated to collect requirements as part of ontology specification phase.

Ontology requirements and their analysis In recent years several attempts to collect and analyze ontology requirements, defined as natural language CQs and statements have been made. Ren et al. [15] provided an analysis of the structure of CQs and extracted 19 archetypes of CQs that are defined in terms of CQ templates to be filled with vocabulary (e.g. “Which [CE1] [OPE] [CE2]?”). Wisniewski et al. [23] provided an analysis of even bigger dataset of 234 CQs defined for 5 ontologies. Additionally, they provided formalizations of those CQs in terms of SPARQL-OWL queries and analyzed how CQ patterns relate to SPARQL-OWL query templates. The dataset of CQs and their translations was published online. Fernandez-Izquierdo et al. [3] published CORAL - a large ontological requirements corpus annotated with lexico-syntactic patterns. This collection of requirements covers both requirements expressed as CQs as well as declarative sentences.

Analysis of modelling styles among ontologies Lawrynowicz et al. [12] provide a way of extracting modeling patterns that recur in ontologies. These frequent formalizations of knowledge are then used to identify emerging ontology design patterns (ODPs), which are solutions to ontology modelling problems. Wang et al. [18] analyzed how often OWL language constructs occur in a set of ontologies. Mortensen et al. [14] analyzed how ODPs are used in ontologies collected from BioPortal. The authors encoded 68 ODPs using the Ontology PreProcessor Language (OPPL).

Automating processes involving CQs CQs are used in order to collect requirements and to measure the maturity of the ontology. To automate the process of vocabulary extraction from CQs, Wisniewski et al. [22] proposed a machine learning-based tagger, which automatically detects candidates for classes and properties to be modelled in an ontology. Wisniewski also proposed the idea of automatic translation of CQs into SPARQL-OWL queries [20], so that having an ontology under development, a set of CQs can be used to evaluate the quality of the ontology without the need of manual translation of CQs into query formalization.

Question generation Generating questions automatically from a given portion of text is an NLP task named question generation. The methods addressing this task often use rule-based systems and neural networks to generate questions.
Wang et al. [19] proposed QG-Net, a recurrent neural network-based approach generating quiz questions for educational purposes. Aldabe et al. [1] used NLP tools and specific linguistic information to generate questions. Liu et al. [13] proposed an automatic question generator for literature review writing support. This generator is based on a set of templates and the content elements.

Ontology verbalization Ontologies expressed using OWL are hard to be read by people. To understand the content of ontologies easier, there are several approaches to translate the OWL formalization into natural language proposed, so that axioms from the ontology can be expressed as natural language statements. The most popular approach, ACE verbalizer was proposed by [8]. Here, axioms are transformed into Attempto Controlled English [5], a controlled language reducing complexity of sentences and providing a simple vocabulary to build sentences. The ACE verbalizer, to work properly, assumes that ontology classes and instances have nouns as labels, and properties are named using verbs.

3 Existing datasets used to produce and evaluate BigCQ

3.1 Frequent axiom patterns

The dataset of frequent axiom patterns introduced by Lawrynowicz et al. [12] and published online [2] is the main inspiration of BigCQ. To fit our needs, we preprocessed each axiom pattern in the dataset, replacing all missing fragments and all vocabulary (apart of RDF, RDFS, OWL and XSD) with IRIs coming from http://example.ns namespace. These IRIs encode, as part of local names, the resource type and numerical identifier allowing to detect when the same IRI is referenced multiple times in one axiom. All kinds of artificial IRIs are defined in Table 1. As part of this process, we also serialized each axiom using Turtle language [3]. This procedure transformed frequent axiom patterns mined from BioPortal into domain-agnostic shapes, so that variables and domain-dependent IRIs are removed, leaving only the axiom shape providing information on how are resources frequently related. We expect that these shapes may be often reused when designing new ontologies.

As a result of this procedure, 239 axiom shapes were collected. An example of a frequently reused OWL axiom shape is:

```
<http://example.ns#OP1> a owl:ObjectProperty .
<http://example.ns#C1> a owl:Class .

<http://example.ns#C2> a owl:Class; rdfs:subClassOf [ a owl:Restriction; owl:onProperty <http://example.ns#OP1>; owl:hasValue <http://example.ns#C1>; ] .
```

[2] https://semantic.cs.put.poznan.pl/bioportal-patterns/
[3] https://www.w3.org/TR/turtle/#language-features
Table 1. The types of artificial IRIs used in frequent axiom shapes.

| artificial IRI | short name (label) | meaning         |
|----------------|-------------------|----------------|
| http://example.ns#C{NUM} | C{NUM}          | a class         |
| http://example.ns#I{NUM} | I{NUM}          | an individual   |
| http://example.ns#OP{NUM} | OP{NUM}         | an object property |
| http://example.ns#DP{NUM} | DP{NUM}         | a data property |
| http://example.ns#DT{NUM} | DT{NUM}         | a data type     |

3.2 Existing datasets of requirements and their formalizations

The dataset introduced by Wisniewski et al. [23] (further referenced as CQ2SPARQLOWL) and their analysis on how CQs are constructed and how they are related to provided SPARQL-OWL queries was our main guide on how to relate CQs to queries. Because in BigCQ SPARQL-OWL query templates are produced from axiom shapes by applying simple substitutions of IRIs with variables followed by preamble and postamble adding and because the ontologies used to generate axiom shapes are disjoint with ontologies in CQ2SPARQLOWL, we used all SPARQL-OWL queries from CQ2SPARQLOWL to measure the coverage of BigCQ query templates.

However, CQ2SPARQLOWL was used intensively to observe how existing queries relate to real CQs. Because of that, in order to evaluate the coverage of CQ templates we used another dataset of CQs to check how well our CQ templates cover unseen, real CQs. The CORAL dataset introduced by Fernandez-Izquierdo et al. [3] is the biggest compilation of requirements expressed as either CQs or declarative sentences. The dataset overlaps with CQ2SPARQLOWL, so we used only CQs that were not present in CQ2SPARQLOWL as an evaluation set to calculate the coverage of CQ templates from BigCQ.

Table 2. The size of requirement datasets involved in BigCQ construction and evaluation.

| Dataset                              | Number of CQs |
|--------------------------------------|---------------|
| CORAL (all CQs + sentences)          | 834           |
| CORAL (all CQs)                      | 469           |
| CORAL (all CQs that are not in CQ2SPARQLOWL) | 324           |
| CQ2SPARQLOWL (all CQs)               | 234           |
| CQ2SPARQLOWL (all CQs with SPARQL-OWL queries defined) | 131           |
4 **BIGCQ - a dataset of CQ templates matched with corresponding SPARQL-OWL formalization templates**

In this section we describe the process of transformation of each axiom shape into a pair of CQ template and SPARQL-OWL template. To achieve this goal, we first verbalize each axiom shape to obtain statements which can be easily transformed later into questions. Then each axiom shape is transformed into SPARQL-OWL query templates by adding appropriate preamble and postamble and replacing IRIs with variables.

4.1 **Verbalizing axiom shapes**

Using ACE verbalizer[^4], we verbalized each of the 239 axiom shapes into natural language statements. An example OWL axiom shape from the dataset:

```
<http://example.ns#OP1> a owl:ObjectProperty .
<http://example.ns#C1> a owl:Class .
<http://example.ns#C2> a owl:Class ; rdfs:subClassOf [ a owl:Restriction;
  owl:onProperty <http://example.ns#OP1>;
  owl:hasValue <http://example.ns#C1> ; ] .
```

is verbalized by ACE verbalizer into *Every C2 OP1 C1* statement.

4.2 **Analysis of axiom shapes and their formalizations**

Each axiom shape collected uses either `rdfs:subClassOf` or `owl:equivalentClass` to relate two class expressions, which can be simple named classes or complex class expressions. In general any axiom collected can be expressed as `CE1 rdfs:subClassOf CE2` or `CE1 owl:equivalentClass CE2`, where `CE{NUM}` represents a given class expression. Each verbalization of collected axiom shapes follow the `{LHS} {VERB} {RHS}` pattern, where `{VERB}` is a main verb (the root of the dependency tree constructed from the verbalization[^5]), and `{LHS}` (left-hand-side) and `{RHS}` (right-hand-side) are related to class expressions `CE1` and `CE2` from the axiom shape that was verbalized. If `CE2` begins with a property restriction (as can be observed in an example in Section 4.1), the `{VERB}` becomes the property label (which ACE assumes to be some `verb[^6]`), otherwise, the `{VERB}` becomes a word `is` representing subsumption relation between two class expressions. These two possible mappings are visualized in Figure 1.

The distinction between what `{VERB}` can be defines two classes of verbalizations:

[^4]: https://github.com/Kaljurand/owl-verbalizer
[^5]: In order to to build valid dependency trees from verbalizations, we temporality (only for the task of dependency tree building) substituted artificial property names (op1, dp1, ...) with verbs, so that correct part of speech tags can be assigned to tokens and correct dependency trees can be constructed.
[^6]: http://attempto.ifi.uzh.ch/site/docs/owl_to_ace.html
1. expressing subject-property-object (SPO) relation: All verbalizations linking left-hand-side (LHS) and right-hand-side (RHS) of the main verb (VERB) with a property label express some non-taxonomical relation (e.g. a verbalization of Every C1 OP1 C2, further materialized with ontology vocabulary into e.g. Every computer executes code states that computer has the ability to execute code).

2. expressing subclass-superclass (SS) relation: If LHS and RHS of the main verb are linked with is verb, the verbalization expresses a subsumption relation between two class descriptions (e.g. Every C1 is C2, further materialized into e.g. Every programmer is a person).

**Transformation from SPO to SS** It is worth to mention that the SPO case can be transformed into the SS by injecting is something that before the main verb (property label). Every C1 OP1 C2 (Every computer executes code) can be transformed into Every computer is something that executes code. Using this transformation is becomes the new main verb (the new dependency-tree root) and something that executes code as a whole becomes RHS of this verb.

**BiDGQ design choices** An in-depth analysis of axiom shapes and their verbalizations revealed the following characteristics of the data collected:

- There are 2 main groups of axiom shapes, 73 of them use owl:equivalentClass as the class axiom type, while others use rdfs:subClassOf. Stating CQs regarding the first group, we should include words and phrases like: identical, the same, equal, etc. On the other hand, stating CQs regarding the second group, we should include words and phrases like: a kind of, a type of, a specialization of, etc.
- The distinction between SPO and SS classes of verbalizations is required to state grammatically correct CQs. Forms of CQs that can be applied to cases following the SPO relation, may not work well for the SS. For instance, a sentence: Every animal eats grass (an instantiation of Every C1 OP1 C2) can be transformed into a question: Does every animal eat grass?. However, the same transformation cannot be applied to a sentence: Every...
animal is a living being (an instantiation of Every C1 is C2). We can rephrase the SPO to the SS by injecting is something that and then use procedure defining transformations of statements into questions that were defined for the SS case.

– Although we can construct questions and queries that target any combination of resource labels and resource IRIs, we decided to simplify the problem:

1. Among the CQ2SPARQL2OWL dataset, less than 2% of CQs ask for more than one resource at once. Thus, we decided that all CQ templates and query templates in BigCQ are stated with at most one resource as a query target.

2. In general we can ask for any resource stated in an axiom, but for axioms involving complex class expressions it becomes hard to produce a question regarding resources in these complex class expressions. Figure 2 presents 4 examples of verbalizations. First two of them use named classes in both LHS and RHS. In these cases it is trivial to state questions targeting resources C1 and C2. In example 1, we can state e.g. What are the kinds of C2? to taget resource C1 or state What is the name of the category that C1 falls into? to target resource C2. Similarly, we can state What things OP1 C2? to target resource C1 in example 2 and What things does C1 OP1? to target resource C2. But if a resource is a part of a complex class expression, like resource C1 in example 4 or resources C2, C3 or C4 in example 3, it becomes very hard to produce a question targeting these resources. Even if if is possible, such questions are likely to be very complicated. Considering above, we decided that we will create CQs and queries targeting the whole (i) LHS if it contains a single named class, (ii) RHS if it contains a single named class (iii) VERB if it is a property label (in that case, we can state questions like What relates C1 and C2?).

Fig. 2. 4 examples of verbalizations created from axiom shapes, split into {LHS}, {VERB} (the root node of the dependency tree) and {RHS} parts.
4.3 SPARQL-OWL query shapes generation

The SPARQL language standard\footnote{https://www.w3.org/TR/rdf-sparql-query/#QueryForms} defines 4 forms of SPARQL queries that can be stated:

- **ASK** - used to check if a given query pattern is matched in the ontology.
- **SELECT** - used to select the IRIs of variables bound in a query pattern match.
- **DESCRIBE** - used to obtain RDF graphs that describe the resources found.
- **CONSTRUCT** - used to obtain RDF graphs constructed by substituting variables in a set of triple templates.

CQ2SPARQL\footnote{CQ2SPARQL\footnote{https://www.w3.org/TR/rdf-sparql-query/#QueryForms}}, the biggest to date dataset of CQ to SPARQL-OWL translations utilizes only two forms of queries: **ASK** and **SELECT**. Both types return results that are easy to be interpreted by humans, since **ASK** queries return a boolean answer and matches binary (yes/no) questions, while **SELECT** queries return resource identifiers and matches Wh- questions. In contrast, **DESCRIBE** and **CONSTRUCT** return RDF-graphs that show how the knowledge is modelled rather than what is modelled and we consider them out of scope for the CQs usage. In this section, we describe how axiom shapes are transformed into **ASK** and **SELECT** SPARQL-OWL query shapes.

Before transforming each axiom shape into SPARQL-OWL query, from each axiom shape we removed declarations associating types to IRIs and replaced IRIs with short placeholders encoding resource local name enclosed with <>. These placeholders contain identifiers required to link them with CQ templates.

There are 7 types of queries that can be stated if we follow the simplification mentioned at the end of Section 4.2. All types, as well as examples of SPARQL-OWL query shapes are listed in Table 3. As can be seen, **ASK** query is produced simply by wrapping the axiom shape with **ASK WHERE { ... }**; **SELECT** queries by wrapping the axiom shape with **SELECT ?x WHERE { ... }** and transforming resources (if they are single named classes) related to {LHS}, {RHS} and {VERB} into a variable named ?x and **SELECT COUNT** queries are produced out of **SELECT** queries by further substituting **SELECT ?x** with **SELECT COUNT (?x)**.

Each axiom shape can be transformed to at most 7 queries. This is possible if both {LHS} and {RHS} of the verbalization describe single named classes and if {VERB} is a property label. If {LHS} and {RHS} are both complex expressions, and the main verb is represented by is, then, only **ASK** query is produced.

4.4 Statements to CQ templates transformation

For each query type defined, we handcrafted a set of transformations that can be used to transform a given verbalization (statement) into CQ templates depending on a given question type. In Table 3 we provide a single example for each category for verbalizations following the SPO type, if a corresponding axiom shape does not use **owl:equivalentClass**.
Table 3. All supported forms of questions generated from \( <C_1> \text{rdfs:subClassOf} [\text{a owl:Restriction; owl:onProperty} <\text{OP1}>; \text{owl:someValuesFrom} <\text{C2}>] \) axiom shape.

| Question Type | Query shape example |
|---------------|---------------------|
| ASK           | \text{ASK WHERE} {<C_1> \text{rdfs:subClassOf} [\text{a owl:Restriction; owl:onProperty} <\text{OP1}>; \text{owl:someValuesFrom} <\text{C2}>]} |
| SELECT LHS    | \text{SELECT} ?x \text{WHERE} {?x \text{rdfs:subClassOf} [\text{a owl:Restriction; owl:onProperty} <\text{OP1}>; \text{owl:someValuesFrom} <\text{C2}>]} |
| SELECT RHS    | \text{SELECT} ?x \text{WHERE} {<C_1> \text{rdfs:subClassOf} [\text{a owl:Restriction; owl:onProperty} <\text{OP1}>; \text{owl:someValuesFrom} ?x]} |
| SELECT VERB   | \text{SELECT} ?x \text{WHERE} {<C_1> \text{rdfs:subClassOf} [\text{a owl:Restriction; owl:onProperty} <\text{OP1}>; \text{owl:someValuesFrom} <\text{C2}>]} |
| SELECT COUNT LHS | \text{SELECT COUNT}(?x) \text{WHERE} {?x \text{rdfs:subClassOf} [\text{a owl:Restriction; owl:onProperty} <\text{OP1}>; \text{owl:someValuesFrom} <\text{C2}>]} |
| SELECT COUNT RHS | \text{SELECT COUNT}(?x) \text{WHERE} {<C_1> \text{rdfs:subClassOf} [\text{a owl:Restriction; owl:onProperty} <\text{OP1}>; \text{owl:someValuesFrom} ?x]} |
| SELECT COUNT VERB | \text{SELECT COUNT}(?x) \text{WHERE} {<C_1> \text{rdfs:subClassOf} [\text{a owl:Restriction; owl:onProperty} ?x; \text{owl:someValuesFrom} <\text{C2}>]} |

Table 4. Examples of transformations applicable for verbalizations, among which \{VERB\} is a property label

| Question type                  | Example of CQ template                           |
|--------------------------------|--------------------------------------------------|
| ASK                            | \text{Does (LHS) \{VERB\} (RHS)?}               |
| QUESTION TARGET LHS            | \text{What \{VERB\} (RHS)?}                     |
| QUESTION TARGET RHS            | \text{What does \{LHS\} \{VERB\}?}              |
| QUESTION TARGET VERB           | \text{What relates \{LHS\} and \{RHS\}?}        |
| QUESTION TARGET COUNT LHS      | \text{How many things \{VERB\} \{RHS\}?}       |
| QUESTION TARGET COUNT RHS      | \text{How many things does \{LHS\} \{VERB\}?}  |
| QUESTION TARGET COUNT VERB     | \text{How many relations are there between \{LHS\} and \{RHS\}?} |
The {LHS}, {VERB}, {RHS} markers introduced among these examples are replaced with fragments of verbalizations that were marked as {LHS}, {VERB}, {RHS}. Using such a replacement, we can, even if a single transformation type provided, generate multiple CQ templates if verbalizations provide various {LHS}, {VERB}, {RHS} forms.

We defined separate transformations for verbalizations expressing equivalence (where questions should ask for equality between classes) and for those expressing subsumption. We also defined separate transformations for verbalizations following the SPO and the SS classes.

Similarly to the process defined in Section 4.3, if both {LHS} and {RHS} represent single named classes and the main verb is a property label, we construct lists of CQs for each of 7 possible question types. However, if {LHS} or {RHS} defines a complex class expression or if the main verb is simply is, only a subset of the 7 question types will be addressed. In the worst case scenario (both {LHS} and {RHS} represent complex class expression and the main verb is is), we state only ASK questions.

4.5 Synonyms substitution in CQ templates

In English, there are words or phrases that can be used interchangeably. For example a type, a kind, a specialization all share the same meaning. We use the interchangeability of words to introduce synonym sets into our CQ templates. Transformations used to produce CQ templates can introduce special markers, which if found, are replaced with all possible synonyms in the synonym set.

For example, a CQ template: [What] C1 are [types] of C2? contains two synonym set markers [What] and [types]. These tokens are mapped to predefined synonyms lists, e.g: [What] = What or which, [types] = types or kinds. If synonyms substitution is applied, these markers are replaced with all possible forms to generate multiple CQ templates: (i) What C1 are types of C2? (ii) Which C1 are types of C2? (iii) What C1 are kinds of C1? (iv) Which C1 are kinds of C2? The more synonym set markers occur and the more synonyms they list, the more paraphrases of questions we can generate.

4.6 Relating CQ templates to SPARQL-OWL query templates

Every verbalized axiom shape is transformed using predefined transformations into CQ templates and then paraphrases are generated during synonym substitution phase. These CQ templates are linked during transformation phase to 7 categories introduced in Table 4. Similarly, SPARQL-OWL query templates from axiom shapes are also linked to 7 related categories introduced in Table 3. We pair all CQ templates with query templates sharing the same category.

5 Dataset analysis

The BigCQ dataset is summarized in Table 5. As can be seen, BigCQ provides over 77575 distinct CQ templates. This is over 93x more than the size
of the biggest to date requirements dataset name CORAL. However, CQ templates should be filled with vocabulary from actual ontologies to create CQs, so regarding all possible ways of filling templates based on vocabulary from an ontology, we can generate a dataset of CQs being thousands or millions times bigger than CORAL. Also, regarding the number of SPARQL-OWL query templates, 549 query templates provided in BigCQ is much more than the number of SPARQL-OWL queries defined in the biggest dataset of SPARQL-OWL queries CQ2SPARQL (CQ2SPARQLOWL defines 131 queries, out of which many share the same SPARQL-OWL query template). Also here, there are multiple ways of filling templates with resource IRIs, so that a huge number of queries can be generated easily. There are many-to-one relations between CQ templates and SPARQL-OWL templates, since natural language allows us to define multiple synonymous forms of the same question. There are also many-to-one relations between multiple query templates and a single CQ template, coming from cases in which there are multiple interpretations of the question i.e. What is C1? can be interpreted as a question about listing subclasses (providing definition by listing examples) or about listing superclasses (providing definition by putting the class in a broader context).

The dataset consists mainly, as presented in Figure 3 of ASK type CQs, since these we found the easiest to paraphrase in natural language. We found questions about numbers the hardest to paraphrase, so their representation is quite small (the category with the least number of questions, COUNT QUERY TARGET RHS contains 234 unique CQ templates). In Table 5 we aggregated details on the OWL vocabulary used in SPARQL-OWL query templates in our dataset. We listed constructs that occurred in more than 5% of examples.

We also analyzed how well BigCQ covers existing datasets. In order to do that, we checked if CQ templates from BigCQ match CQs from CORAL, that were not a part of CQ2SPARQLOWL. The results are presented in Table 5. As we can see, there is a decent coverage of CQ forms. As one may suppose, the richness of expression possibilities of natural language makes it impossible to cover all forms of CQs. Moreover, some CQs stated in CORAL used words like: who, where, when, how often as question starters. These are not supported by our transformations, since the decision on which form should be used requires information on what is the type of the resource that fills the CQ template (e.g. if the type of a resource being a question target represents a person, the CQ should start with ‘who’ word).

The analysis of the coverage of SPARQL-OWL templates revealed that there is a high variety between the coverage depending on which from the 5 available ontologies in CQ2SPARQLOWL are checked. The highest coverage was obtained on queries from African Wildlife Ontology [10] (71%), the lowest, on Stuff Ontology [9] (9%). The analysis of errors showed that 19.38% of all SPARQL-OWL queries from CQ2SPARQLOWL used the following query template:

```sparql
select ?x where { [] rdfs:subClassOf <C1>, [owl:onProperty ?x; owl:someValuesFrom [] ].}
```
which is not covered by our SPARQL-OWL templates. This kind of query however, was used only in the context of Dem@Care [10] ontology.

The next 11.63% of the CQ2SPARQLOWL expected a query template that is also not covered by BigCQ:

```
SELECT ?x WHERE {<C1> rdfs:subClassOf [a owl:Restriction ;
    owl:onProperty <OP1> ;
    owl:someValuesFrom ?x ] .
?x rdfs:subClassOf <C2> }
```

This kind of query was shared among multiple ontologies. The problem in that case comes from the fact that in BigCQ right-hand side of the property can be a variable, but there is no type restriction on that variable introduced. This functionality however, can be easily added in the next version of BigCQ. In the future, addressing only the described two cases can increase the coverage to over 75%. The remaining 25% of unsupported queries come from various situations, among which, we can distinguish:

1. Using auxiliary variables that are not expected to be returned by the query.
2. Using `union` instead of `owl:unionOf`.
3. Using `owl:disjointWith` which is not observed among the most frequent axiom shapes.
4. Asking about resources being a part of a complex class description (most often these are classes at the end of long property chains).
5. Querying for more than one resource.

| Measured dimension                      | measured value |
|-----------------------------------------|----------------|
| Number of distinct CQ templates         | 77575          |
| Number of distinct SPARQL-OWL query templates | 549            |
| Average number of CQ templates per SPARQL-OWL template | 171.68        |
| Average number of SPARQL-OWL templates per a CQ     | 1.22           |

## 6 The impact of BigCQ

As we presented in Section 5, BigCQ provides the biggest available dataset of CQ templates mapped to SPARQL-OWL templates.

We focused on making the scripts generating BigCQ as easy to read and edit as possible. We hope that such approach will make it effortless to extend the number of axiom shapes, the number of transformations producing CQ templates from verbalizations and the database of synonyms that are all provided as
simple textual representations. Thus, we hope that it will be interesting and easy for other researchers to improve the dataset, making it bigger and of better quality.

This dataset may be helpful for a broad range of research, like: providing training data for automatic CQ to SPARQL-OWL translators and Glossary of Terms extractors, improving controlled natural languages for CQ generation, automating ontology design methodologies and finally to understand the relation between CQs and ontologies better.

7 Conclusions

CQs are frequently used to gather requirements and to validate the quality of the ontology being constructed. The lack of large scale corpora of CQs with their formalizations in query languages make it hard for engineers to automate processes involving the use of CQs. Our dataset, BigCQ attempts to fill this gap by providing a large set of synthetically generated CQ templates matched with their SPARQL-OWL template forms. These templates may be used to be filled with resource labels and IRIs of actual resources from a given ontology to generate even bigger dataset, the size of which should be sufficient to fuel novel deep learning based approaches to information extraction or automatic translation from CQs into SPARQL-OWL. In this work, we decided to create our own solution to the problem of question generation from verbalizations. There are two reasons for this: (i) we wanted to obtain question templates that are constructed similarly to already collected sets of CQs. (ii) Existing question generation solutions focus on generating a limited number of questions. In our dataset, we wanted to obtain as big as possible dataset of CQ forms. (iii) Using the process described in the paper, it was easy to link CQ templates to SPARQL-
Table 6. The number of the most occurring (present in more than 5% of the dataset) constructs among the list of all unique SPARQL-OWL query templates

| construct                  | times observed |
|----------------------------|----------------|
| owl:Restriction            | 504/549        |
| owl:onProperty             | 504/549        |
| owl:intersectionOf         | 319/549        |
| rdfs:subClassOf            | 268/549        |
| owl:equivalentClass        | 281/549        |
| owl:someValuesFrom         | 273/549        |
| owl:qualifiedCardinality   | 87/549         |
| owl:hasValue               | 71/549         |
| owl:unionOf                | 69/549         |
| owl:allValuesFrom          | 56/549         |
| owl:maxQualifiedCardinality| 38/549         |
| owl:complementOf           | 37/549         |
| owl:minCardinality         | 30/549         |

Table 7. The coverage of templates on real-world cases

| Dataset                  | Coverage   |
|--------------------------|------------|
| SPARQL-OWL queries from CQ2SPARQLLOWL | 45.74%     |
| CQs from CORAL           | 63.89%     |

OWL queries. We published the dataset itself, the source code generating CQ to SPARQL-OWL template pairs from frequent axiom shapes as well as we provide a proof-of-concept code generating materialized CQ to SPARQL-OWL query pairs filled with labels and IRIs from a given ontology. We also generated the persistent URI to the dataset using Zenodo.

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