Assessing and Enhancing Bottom-up CNL Design for Competency Questions for Ontologies

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Abstract

Competency questions (CQs) are used in ontology development to demarcate the scope, provide insights into their content, and verification. Their use has been impeded by problems with authoring good CQs. This may be assisted by a controlled natural language (CNL), but its development is time-consuming when carried out manually. A recent study on data-driven CNL design to learn templates from a set of CQs, resulting in CLaRO, had somewhat better coverage and some noise due to grammar errors in the source CQs. In this paper, we aim to investigate such a bottom-up approach to CNL development for CQs regarding the effects of 1) improving the quality of the source data 2) whether more CQs from other domains induce more templates and 3) if the structure of knowledge in subject domains has a role to play in the matching of patterns to templates; therewith might indicate that possibly a structure of knowledge in a subject domain may continue to affect bottom-up CNL creation. The CQ cleaning increased the number of templates from 93 to 120 main templates and an additional 12 variants. The new CQ dataset of 95 CQs generated 27 new templates and 7 more variants. Thus, increasing domain coverage had most effect on the CNL. The CLaRO v2 with all generated templates has 147 templates and 59 variants thereof and showed 94.1% coverage.

1 Introduction

Competency questions (CQs) are natural language expressions which are used among others in the design, development and verification of ontologies (Suárez-Figueroa et al., 2012). CQs have attracted research interest in ontology engineering since the mid 1990s and are noted as a key requirement for ontology development by methodologies such as the NeON methodology (Suárez-Figueroa et al., 2012). They have been shown to serve different purposes in the engineering of ontologies, including demarcating their scope, providing insights into their contents, and ensuring their answerability (Ren et al., 2014). However, there is limited acceptance and use of CQs. Several reasons have been proposed for that. There is limited support for authoring CQs (Keet et al., 2019; Ren et al., 2014) and their translatability into queries over the ontology or candidate axioms. Also, CQs developed for one ontology or subject domain often cannot be reused for another related ontology or domain, which impedes the re-usability of CQs (Fernández-López et al., 2019). This spurred the inquiry into controlled natural language (CNL)-assisted CQ authoring as a holistic solution to these issues, including archetypes (Ren et al., 2014), patterns (Bezerra et al., 2014), and the template-based Competency question Language for specifying Requirements for an Ontology, model, or specification (CLaRO) (Keet et al., 2019) that has been shown to have broader coverage than the former two.

CLaRO was developed in a bottom-up method using a dataset of 234 CQs for five ontologies as-is together with NLP-based sentences analyses (Potoniec et al., 2020; Wiśniewski et al., 2019). However, as is well-known for other data-driven tasks, the quality of the output is dependent on the coverage and quality of the data and the quality of the algorithms. In this case, manual inspection of the CQs indicated grammar issues, the CQs were for only five ontologies, and the sentence chunking was not closely investigated. Since methods for data-driven template creation from 'small data' for specialised tasks still can be useful to be able to do, we aim to investigate this in more detail. To this end, this paper seeks to answer the following research questions:

1. What is the effect of 'cleaning' (correcting) CQs to the set of templates in CLaRO?
2. What are the effects of increasing the number and diversity of CQs to the template development?
3. What role does the structure of knowledge in subject domains play in the matching of patterns to templates, if any; and if so, how?

Correcting CQs has been carried out manually, whereas for the second question, we collected 70 new CQs related to ontologies in different domains and added 22 newly formed CQs inspired by some CQs in the initial CQs set. They all went through the template design process. Unlike the manual evaluation for CLaRO, our evaluations have been automated with the same chunking algorithm, intended as a step toward increased automation of CQ authoring and use and automation of CNL evaluation.

CQ correction applied to 9% of the original dataset and 17.8% of the new CQ set (the 70 CQs for different ontologies), of which the effects on the number of templates are 10 and 8 templates, respectively. The new CQs for the *Cleaned CLaRO* had a coverage of 40% and upon adding those 52 new templates and 19 variants generated from them, reaching 147 templates and 59 variants in total, its coverage reached 94%, compared to 88% for just ClaRO. Increasing domain coverage further thus had a bigger impact on CNL design than better source data.

The remaining sections of the paper are structured as follows: related work is described in Section 2; the methodology in Section 3; results and discussion in Sections 4; and conclusions in Section 5.

2 Related Work

The importance of CQs in ontology engineering has been documented with a focus on their use as part of the requirement specification in ontology development (Bezerra and Freitas, 2017; Keet and Lawrynowicz, 2016; Suárez-Figueroa et al., 2012), as noted in Section 1. There is limited evidence of uptake of CQs, however, and a substantial number of CQs have a range of issues (Potoniec et al., 2020), such as being unanswerable by an ontology and grammar. Since CQs are typically developed for specific ontologies and no guidelines exist for authoring, this continues to affect the quality of CQs and hamper the uptake by ontology engineers.

To address the lack of authoring support, a set of 12 core and 7 variant archetypes from 150 CQs for the Pizza and SWO ontologies has been proposed (Ren et al., 2014). The variables in their "archetypes" (templates) are ontology elements (OWL class and object property), rather nouns and verbs, therewith narrowing the use to OWL and having a 1:1 mapping to the ontology that dictates axiomatisation. Bezera et al. identified 14 patterns and 3 CQs types, also for use in only OWL ontologies ontology elements for variables. Their set omits the 'Who, Where' question types in their identification, even though these question types exist within their source data CQs used (also for the Pizza ontology), further limiting the coverage (Bezerra et al., 2014).

Other studies include (Malheiros et al., 2013), who use of grammatical tags with a set of rules for the CQs, which is limited to three predefined types (is-a, yes/no, and existence question) and also contain a 1:1 mappings to the ontology. Wisniewski et al. created 106 patterns through a process where the linguistic structures of 234 CQs from 5 different ontologies (Dem@care, Stuff, AWO, OntoDT and SWO) were chunked using NLP methods, replacing the nouns and verbs with the terms entity chunks and predicate chunks (Wiśniewski et al., 2019; Potoniec et al., 2020). These 106 patterns were used to develop the initial CLaRO CNL templates (Keet et al., 2019). The patterns from (Wiśniewski et al., 2019; Potoniec et al., 2020) and CLaRO and templates do not have 1:1 mappings or CQs type restriction and are thus not only for OWL ontologies. With more CQs, it showed to have better coverage (Keet et al., 2019), suggesting that an even larger set of CQs may increase coverage further.

3 Methodology

To begin this section, we provide an overview of how the initial CLaRO was created which also forms part of the method in this study. Note that the CQs used in CLaRO and for this study were only in the English Language.

3.1 Preliminaries: CLaRO development

The CLaRO templates of (Keet et al., 2019) were developed using patterns obtained from 234 CQs drawn from 5 different ontologies through a semi-automated process in a previous study conducted by (Wiśniewski et al., 2019; Potoniec et al., 2020). The authors of the patterns employed a linguistic approach in understanding the structure of CQs in order to create an abstract identification of each CQs since most of them were different from one another in their natural language form. Two main text chunks were used to represent the linguistic structures. They were called entity chunk (for a noun or noun phrase), and predicate chunk (which represents a verb phrase). By doing so, CQs with identical structures were grouped together and considered as patterns. The patterns used were identified and implemented in the following manner:

1. CQs were manually checked to ensure that they were T-BOX questions.
2. CQs were divided into two types: materialised (were the entities are embedded in the CQs) and dematerialised (were the entities are replaced by a placeholder such as $task\ X$, it, $datatype\ Y$, $gene\ X$.
3. After CQs are chunked into patterns, if the same structures occurs in more than one CQs, be it within or across the ontologies, they are selected as patterns. Individual CQs chunks are referred to as "candidate patterns".
4. Text chunks from dematerialised CQs (i.e., CQs with placeholders) are considered as patterns even if they are observed only once.
5. Text chunks from materialised CQs (i.e., CQs without placeholders) can only be considered as patterns if they are observed more than once in the entire CQs.

This resulted in 106 patterns (Wiśniewski et al., 2019), which were used in the development of the templates of CLaRO. The design for that CLaRO also included tackling issues such as redundant words and pronouns in templates, generating additional templates to cater for negation, handling of plural/singular forms as well as synonym usage (Keet et al., 2019). There were 93 templates and 40 variants in CLaRO before this study was conducted.

3.2 Current Design and Evaluation Process

Following the same semi-automated, data-driven bottom-up approach on which the initial CLaRO (referred to as *CLaRO v1* from now on) was designed (Keet et al., 2019), a series of activities were designed to assess grammar quality of base CQs dataset for *CLaRO v1* and the effect of this, possible increase in the number of templates created as a result of increases number and diversity of CQs. These activities are presented as three steps carried out in the design. Fig. 1 gives a pictorial representation of the processes described below.

3.2.1 Step1: Cleaning and Verification

We begin by assessing the CQs dataset used in pattern development stage for the CLaRO v1 templates (Potoniec et al., 2020; Keet et al., 2019). The first task thus was centered around cleaning the CQs set. The original CQs dataset was sent to a linguist for analysis, who reviewed them and provided suggestions for cor-

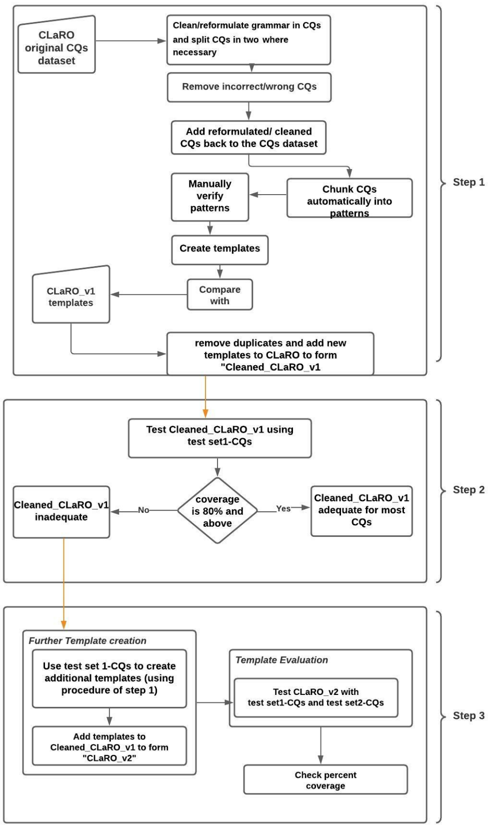

Figure 1: Cleaned CLaRO and CLaRO v2 development procedure

rections. This grammar analysis step of the cleaning process was carried out manually. The incorrect questions were removed from the dataset while the corrected form of the CQs and any new CQs which arose from question splits were added to the dataset (e.g., due to splitting up a long sentence). Subsequently, this new CQs dataset were then automatically chunked and verified automatically with the algorithm used. Afterwards, a manual verification was done by checking the candidate patterns generated against the CQs from which they were generated. For 5 patterns, manual corrections were made; for example: *What PC1 EC1 PC2 EC1 PC2?* had the original chunking failing to pick up 'algorithms' as an *EC* (*What PC1 algorithms PC2 EC1 PC2?*). Another example is: *How well [PC1] is [EC1] for [EC2]?* where the original chunk failed to pick up *documented* as a *PC* (*How well documented is [EC1] for [EC2]?*). With cleaning and verification of patterns completed, new templates were developed and then compared with the existing *CLaRO v1* templates. Similar occurrences were also observed with the newly sourced Evaluation CQs discussed in step2. Templates found in the new set that were also found in *CLaRO v1* were removed, the remaining were added to the *CLaRO v1* templates to make up what called the *Cleaned CLaRO v1* templates.

3.2.2 Step2: Template Evaluation

The next step was to test the *Cleaned CLaRO v1* using a new set of CQs. To select CQs, we searched widely to find ontologies with accompanying research papers that listed their CQs. Some of them were found within the papers while others pointed to Github repositories where the CQs could be found. It is unknown if the CQs were carefully reviewed. They did have some grammar-related corrections and most of them were CQs that could be answered by an ontology were publicly available. These CQs were collected as our set of new CQs. All of the new CQs were not part of any previous CQs used in *CLaRO v1*. The larger portion of the CQs were set aside for the first test and labeled as *test-set1*. These CQs come from 4 ontologies which include xAPI ontology (CQs=6) (Vidal et al., 2018), MEMON ontology (CQs=2) (Masmoudi et al., 2018), EM-KPI ontology (CQs=10) (Li et al., 2019) and INHD ontology (CQs=52) (Stucky et al., 2019). Another set of 22 new CQs inspired by a part of the initial CQs dataset in the *CLaRO v1* CQs processing phase were authored in line with recommendations form the linguist. These 22 additional CQs were added because they were semantically similar to the original CQs in the dataset and they serve to address CQs authoring preferences i.e., bring flexibility to authoring styles of asking questions which produce the same answers in the ontology. They were added to the *test-set1* CQs bringing the total to 92 CQs. These CQs were chunked to obtain patterns (note: such chunked sentences are called 'candidate patterns' in (Wiśniewski et al., 2019)), which were manually verified, and then automatically checked against the set of templates to see if they matched any of the *Cleaned CLaRO* templates. For this test purpose, we set an adequacy benchmark of 80%. If it is lower, then the *test-set1* CQs should be used as a dataset to create additional templates.

3.2.3 Step3: Final Curation

This step has two processes: further template creation and template evaluation. If the evaluation carried out in step2 shows the coverage to be adequate (i.e., up to or more than the benchmark set), then the step3 template evaluation process is carried out immediately after. However, if the it shows the coverage to be less than the desired benchmark, the additional template creation process will take place before the template evaluation process in done. On carrying out the step2 evaluation (see results below), the coverage was less than required and thus, further template enhancement was needed. We repeat the procedure in step1. However, this time we make use of the *test-set1* CQs as our dataset. The templates comparison was done between the newly created templates and *Cleaned CLaRO v1* templates. The combination of any new templates found in this process and the *Cleaned CLaRO v1* templates form what we shall call *CLaRO v2* templates. Finally, the step3 template evaluation process is carried out and then we ascertain the coverage in relation to our benchmark. It is worth nothing that the domain knowledge areas of the ontologies used for creation of *CLaRO v2* ranges from software, stuff, to dementia as part of the initial set of CQs in *CLaRO v1* to knowledge domains of the ontologies for the *test-set1* CQs that included energy management, environmental analytics, insects natural history, object oriented code, depression care and biomedical. To evaluate *CLaRO v2*, a second test was carried out using a combination of *test-set1* CQs and *test-set2* CQs (which consist of the remaining part of the newly sourced CQs) obtained from (Jung et al., 2017; Azzi et al., 2019; de Aguiar et al., 2019) ontologies. Using the same benchmark and partially automated test process as in step 2, we check for the percentage coverage of our results.

The data, code, and results are available from `https://github.com/mkeet/CLaRO`.

4 Results and Discussion

To start with step 1 of the method section, 22 out of the 234 CQs were identified with either grammar related issues or could not be answered in an ontology in its current state and so were reformulated from the 234 CQs set used in creating the patterns in the *CLaRO v1* study; see samples in Table 1. Another example of a problematic question (an open-ended question) encountered was: *To what extent does [the software] support appropriate open standards?* which is reformulated as: *Does [the software] support open standards?*. These CQs as stated in the method section, were reformulated or split were necessary and added to the dataset; their original formats were removed from the dataset.

The number of patterns identified were 145 (which gives an additional 39 patterns to the previous 106 patterns in the previous study). As with the original study, after some manual cleaning of the patterns were necessary, all the patterns found that met the design decisions were included as templates, no new negation templates were added. Having obtained the patterns and proceeded to create new templates, on comparing the new templates with *CLaRO v1*, we found that most of the resulting templates were present. When the templates are put together, an added 27 templates and 12 variant to bring the total to 120 templates and 52 variants, now referred to as *Cleaned CLaRO v1* templates.

In Step2, a new set of CQs were used to carry out a first test on the *Cleaned CLaRO v1* templates. After chunking and cleaning, their patterns were compared with the templates in a bid to find a match. Of the 92 CQs in *test-set1*, 38 patterns were found not to present in *Cleaned CLaRO v1*. Given our benchmark percentage set at the beginning of the study, a 40% coverage was inadequate to declare that

Cleaned CLaRO v1 was sufficient for most unseen CQs. Thus, the *test-set1* CQs were used as a dataset for the creation of another set of templates. Following the procedure outlines in the preliminary section above and applied in step 1 of the method section, 35 patterns were found to have fulfilled the design decisions and were included as templates. When the new templates were compared with *Cleaned CLaRO v1*, four were found to be present.The rest 34 templates when split into actual templates and variants, are 27 templates and 7 variants. We then combined them to *Cleaned CLaRO v1*, making the total number of 147 templates and 59 variants. This new total of templates were now called *CLaRO v2*.

For the evaluation of *CLaRO v2*, *test-set2* CQs (n = 26) from (Jung et al., 2017; Azzi et al., 2019; de Aguiar et al., 2019) ontologies as well as *test-set1* CQs were used. CQs that were removed include *How are classes logically organized in an OO source code?*, since no ontology will be able to answer this due to its descriptive nature. One duplicate question was removed: *What are the signs and symptoms of adolescent depression?* and *What are the physical symptoms of adolescent depression?*. The overall results show that 111 of the 118 CQs had their patterns present in the *CLaRO v2* templates on first try, i.e., 94.1%, with a few of the matching templates coming from *CLaRO v1* and the rest templates found in the greater *CLaRO v2*. With this result surpassing our 80 percent benchmark set in step 2 of the method section, we accept *CLaRO v2* as being adequate for most unseen CQs. Table 2 shows the results from the first test on *Cleaned CLaRO v1* as well as the results of the second test on *CLaRO v2*.

Table 1: Sampling of reformulated CQs.

Grammaticality
1. What are the values of a rain properties (unit, location, date, etc.)? **Comment:** *Incorrect English, illustration* **Reformulated CQ and pattern:** Where are the property values of a rainfall? *What are EC1 of EC2?* (new template: Yes)
2. Is [it] open source or not? **Comment:** *Informal writing* **Reformulated CQ:** Is [it] open source? *Is EC1 EC2?* (new template: No)
Answerability
1. How do I get help with [it]? **Comment:** *A descriptive question* **Reformulated CQs and pattern:** What are the sources of support for [it]? *What are EC1 of EC2 for EC3?* (new template: No)
2. How can I get problems with [it] fixed? **Comment:** *A descriptive question* **Reformulated CQ and pattern:** Who can fix problems with [it]? *Who PC1 EC1 with EC2?* (new template: No)
Two-in-one question
1. Do I know anyone who has used [this software] or processed [this type of data]? **Comment:** *A personalized question (also two questions in one)* **Reformulated CQs and pattern:** a. Who has used [this software] in the past successfully? *Who PC1 PC1 EC1?* (new template: Yes) b. Who has processed [this type of data]? *Who PC1 PC1 EC1 in EC2 EC3?* (new template: Yes)

4.1 Discussion

We attempt to answer the first research question which addresses the role of cleaning in the identification of templates, we saw from the results that having reformulated and splitting problematic CQs, some of their patterns resulted into templates in *Cleaned CLaRO v1*. The second research question which aims at assessing if there are identifiable linguistic patterns to knowledge structures in different subject domains and if these patterns influenced the matching of CQs patterns to CLaRO v2 templates. We looked at our results in terms of their distribution according to the domains of the ontologies in the *CLaRO v2*, this is to determine how much of the test CQs patterns were matched within the templates that made up *Cleaned CLaRO v1*. The results showed that most of the patterns where matched in *CLaRO v2*, leaving only a few in *Cleaned CLaRO v1* alone. For the third research question which aims at assessing how the increased number and diversity of CQs from more ontologies impacts the template creation. A total of ad-

Table 2: Evaluation results of Cleaned CLaRO v1 versus CLaRO v2 using generated patterns from test CQs

Cleaned CLaRO v1	Count	Coverage%
Absent	57	60%
Present	38	40%
CLaRO v2	Count	Coverage%
Absent	7	5.9%
Present	111	94.1%

ditional of 54 templates and 19 variants were created and added to the *CLaRO v1*'s 93 templates and 40 variants to form the 147 templates and. Consequently, a wider coverage was achieved for CQs from many different ontologies as seen in the test results.

Also worth reporting in our findings is the distribution of templates in terms of knowledge domains; we analysed *CLaRO v2* results using the test-set2 CQs which only came into use as part of the second test in our study, we found that majority of the templates matched in this group were found to be specifically in *Cleaned CLaRO v1* templates. On further observation, we also found the templates matched patterns from the SWO and Dem@care CQs. This observation may be linked to the fact that the Knowledge domains of the test-set 2 CQs were from adolescent depression, object oriented code and biomedical (which had very few CQs compared to the other two), and these domains are some-what related in knowledge to the knowledge found software and Dementia. For instance *What are [EC1] for [EC2]?* from SWO number 19, *What [PC1] [EC1]?* from Dem@care number 146 and *What [EC1] [PC1] [EC2]?* from SWO number 12 patterns can be observed in the test-set2 patterns. With the test-set2 CQs alone, *CLaRO v2* templates all patterns from the depression care CQs were present; object oriented code CQs and the biomedical knowledge domains also most of their CQs patterns present. The results can be seen in Table 3.

There were some situations where the limitation of the algorithm produced some strange pattern outputs like *Who else [PC1] [PC1] [EC1] [PC1]?* for *Who else has used [tool x] today?* which would clearly give a different pattern when it is generated manually. Another example is the presence of past tense in CQs which not handled properly, as seen with *Has [species X] been collected at lights?* which produces *[PC1] [EC1] been [PC1] [EC2]?*. With the breakdown of the final results in this study showing over 90% coverage for *CLaRO v2* and the diversity of the domains which the CQs/ontologies were drawn from, we assume that although the knowledge structure in domains may play a role in the matching of templates to CQs patterns, that role is minimal in our study.

Ontologies are known to represent real world complexities using the knowledge structures they contain (Litovkin et al., 2018; Hnatkowska et al., 2020). The use of CQs as a functional requirement for ontology development makes it possible for ontologies to capture holistically, the knowledge in the given domain or sub domain. With the very general nature of the *CLaRO v2* templates, it is expected that they serve as a guide for ontology developers as they author their own CQs developed across different domains. Given the coverage obtained in this study, there may be an increase of the willingness to make use of CQs, and also a reduction in the frustrations that have characterised developers' experiences in authoring good quality CQs. Also, these templates potentially move us closer to achieving re-usability of CQs.

The results of this study will also enable ontology developers construct CQs that can provide users adequate information on the content of the ontology and at the same time provide the ontology with a quality verification tool. This study also shows the feasibility of bottom-up approaches to CNL design with better insight derived from these methods. *CLaRO v2* will enable subject experts and ontology developers develop CQs that are suitable for ontologies to answer and possibly give ideas of what other forms of CQs could still be derived

Table 3: Results of Cleaned CLaRO v1 compared with CLaRO v2 on matched test-set2's chunked CQs representation, separated by domain.

CLaRO	Depression	Biomedical	OO code
Cleaned CLaRO v1	7 of 9 (78%)	2 of 7 (28.6%)	4 of 6 (66.7%)
CLaRO v2	9 of 9 (100%)	5 of 7 (71.4%)	5 of 6 (83.3%)
Absent	0	2 of 7 (28.6%)	1 of 6 (16.7%)

for the ontology that may not have been considered. Although not the focus of this study, domain knowledge structures have become important to the advancement of CNL for CQs. With *CLaRO v2* now containing several new templates which has base CQs drawn from a range ontologies from different knowledge domains, we can expect that CQs patterns from more knowledge domains will be sufficiently catered for with the templates in *CLaRO v2* increasing the possibility of that it indeed has the potential of representing templates across many different domains.

5 Conclusion

In cleaning the source data and extending the *CLaRO v1* templates, we have been able to show that there is sufficient reason to assume that CQ templates can be reused across ontologies. Increasing domain coverage of the source CQs has a larger effect on the quality and number of templates than correcting erroneous CQs. The extended *CLaRO v2* templates created on the basis of the CQs patterns derived from a total of 329 CQs for SWO AWO, Stuff, Dem@care, OntoDT, xAPI, EM-KPI, inhd and memon ontologies, and has recorded a 94.1% accuracy.

The templates can assist CQ authors in writing good CQ that should be answerable by an ontology. Future work includes investigating further the role that domain knowledge structures play in the matching of CQs patterns and the possibility of identifying more templates. To achieve this would mean being intentional on seeking to identify the representation of CQs from a wide range of knowledge domains that are clearly unrelated to the those present in *CLaRO v2*. We also plan to update the CLaRO CQ editor tool with the new templates.

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