Web Semantics: Science, Services and Agents on the World Wide Web 34 (2015) 40–54

Contents lists available at ScienceDirect

Web Semantics: Science, Services and Agents on the World Wide Web

journal homepage: www.elsevier.com/locate/websem

A novel approach to generate MCQs from domain ontology: Considering DL semantics and open-world assumption

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ARTICLE INFO

Article history:
Received 5 May 2014
Received in revised form
15 May 2015
Accepted 19 May 2015
Available online 11 June 2015

Keywords:
OWL ontologies
Semantic web
Multiple choice questions
Automatic question generation

ABSTRACT

Ontologies are structures, used for knowledge representation, which model domain knowledge in the form of concepts, roles, instances and their relationships. This knowledge can be exploited by an assessment system in the form of multiple choice questions (MCQs). The existing approaches, which use ontologies expressed in the Web Ontology Language (OWL) for MCQ generation, are limited to simple concept related questions — "*What is C?*" or "*Which of the following is an example of C?*" (where *C* is a concept symbol) — or analogy type questions involving roles. There are no efforts in the literature which make use of the terminological axioms in the ontology such as existential, universal and cardinality restrictions on concepts and roles for MCQ generation. Also, there are no systematic methods for generating incorrect answers (distractors) from ontologies. Distractor generation process has to be given much importance, since the generated distractors determine the quality and hardness of an MCQ. We propose two new MCQ generation approaches, which generate MCQs that are very useful and realistic in conducting assessment tests, and the corresponding distractor generating techniques. Our distractor generation techniques, unlike other methods, consider the open-world assumption, so that the generated MCQs will always be valid (falsity of distractors is ensured). Furthermore, we present a measure to determine the difficulty level (a value between 0 and 1) of the generated MCQs. The proposed system is implemented, and experiments on specific ontologies have shown the effectiveness of the approaches. We also did an empirical study by generating question items from a real-world ontology and validated our results with the help of domain experts.

1. Introduction

Automated assessment systems serve as a method to measure the level of learning as well as to provide a faster solution for large scale assessments. Many tests like TOEFL, IELTS, GRE and GMAT are dependent on online assessment systems to make the assessment task easier. Such systems mainly use multiple choice questions rather than subjective questions for conducting the test.

Using Multiple Choice Questions (MCQs) for assessments has both merits and demerits. They are preferred for assessing broad range of knowledge. This is mainly because they require less administrative overhead and provide instant feedback to test takers. However, studies by Barbara Gross [1] and Sidick et al. [2] show that, developing effective objective type questions is time consuming and requires domain expertise to generate good quality MCQs. So, there is a need for an automated method for MCQ generation from a given knowledge source.

Recently, a handful of studies [3–9] explored the use of structured domain knowledge in the form of description logic based ontologies to automatically generate MCQs. This would enable online assessment systems to utilize existing knowledge bases for the assessment of learner's knowledge and skills. But, there are challenges involved in generating MCQs from these ontologies. Some of the challenges that the existing approaches tried to address are: (i) How to frame interesting and good quality questions from ontologies? (ii) How to generate proper incorrect answers (distractors) for the framed question? (iii) How to control the difficulty level of the generated questions? Although the previous efforts were not in vain, there are substantial shortcomings in fully exploiting the formalized knowledge in an ontology for MCQ generation. In this paper, we show that, with a better understanding of the semantics of a given ontology (expressed in Web Ontology Language), the three challenges can be addressed more elegantly.

Challenge 1. Framing interesting and good quality questions. In the literature, the approaches that use ontologies have the limitation

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http://dx.doi.org/10.1016/j.websem.2015.05.005
1570-8268/

that they generate simple concept related questions – "*What is C?*" or "*Which of the following is an example of C?*" (where C is a concept symbol) – or analogy type questions involving roles. These questions are very basic [10] and do not contain any domain related specifics. In other words, the approaches which generate such questions, do not appropriately make use of the axiomatized knowledge in an ontology. Furthermore, restrictions (existential, universal and cardinality) on concepts and roles in ontologies are not utilized properly for question generation in any of the current approaches.

Consider a movie ontology with statements,
`Movie(braveHeart)`
`MovieDA ≡ Movie ⊓ ∃isDirectedBy.Actor`
`MovieDA(braveHeart)`
With respect to this, we can frame a question about the instance `braveHeart`: "*Choose a movie directed by an actor?*" Our approach in this paper is an effort in this direction.

Challenge 2. Proper distractor generation. Under the closed-world assumption (CWA), we can choose any instance which is different from the instance `braveHeart` as a distractor for the question in the example above. But, Web Ontology Language (OWL) adheres to the open-world assumption (OWA): statements which are not logical consequences of a given knowledge base are not necessarily considered false. Therefore, not all distractors which are generated under CWA can be guaranteed as true distractors.

We observed that most of the existing MCQ generation techniques [7] randomly select instances which do not belong to the class of the correct answer as distractors. The incorrectness of the distractors cannot be ensured by this random selection method, which in turn made it necessary to manually check the correctness of the question items before making use of them. We address this issue by proposing a systematic method to generate only those question items which are valid under OWA.

Challenge 3. Control the difficulty level of the generated MCQ. MCQs of varying difficulty level are necessary to assess the depth of knowledge of a learner (student). We introduce a measure to find out the difficulty level of the generated MCQs based on the similarity-based theory suggested by Alsubait et al. [11].

In this paper, we propose two approaches (i) node-label-set based approach (ii) edge-label-set based approach to generate (two) interesting types of MCQs. We adopt description logic specifications of the ontology to generate the so called *label-sets* (node-label-sets and edge-label-sets). A measure to estimate the difficulty level of generated MCQs is also proposed by means of these label-sets. We study the feasibility of our approaches by implementing them and generating MCQs from some sample ontologies. In Appendix A, we list some of the MCQs, which are generated from Geographical Entity ontology. To validate our new approaches and difficulty measure, we generated question items from a real-world ontology and got them evaluated by domain experts. Statistics of our empirical evaluation validate our arguments and are detailed in Section 6. The new notations and abbreviations that we introduced in this paper are listed in Appendix B along with their meaning.

2. Related work

Papasalouros et al. [5] suggested 11 strategies based on classes, properties and terminologies of ontologies for framing MCQs and the corresponding distracting answers. Their MCQ generation methods lack proper theoretical support for when to use which strategy, and the stem of all the generated questions remains the same ("*Choose the correct sentence*").

Cubric and Tosic [4] and M. Cubric [6] generated MCQs of knowledge level ("*Which of the following definition describes the concept C?*"), comprehension level ("*Which one of the following response pairs relates in the same way as a and b in the relation R?*"), application level ("*Which one of the following examples demonstrates the concept C?*") and analysis level ("*Analyze the text x and decide which one of the following words is a correct replacement for the blank space in x.*"). Their work is an extension of the approach by Holohan et al. [12], by introducing stems that use annotation information in the ontology. Strategies similar to Papasalouros's strategies are adopted to find the distractors for the generated question statements.

Another MCQ generation method is by Alsubait et al. [3]. They presented an approach called similarity-based approach for generating analogy type questions. In their question generation algorithm, a set of parameters are introduced to control the difficulty level of the generated questions. They argue that the difficulty level of a question item can be increased by finding the distractors which are similar to the correct answer(s). The approach which the authors illustrate is limited to analogy type questions.

Other than the above MCQ generation approaches, there are works like Abacha et al. [13], Ben Abacha and Zweigenbaum [14] and Åitko et al. [9], which make use of simple ontology statements: concept inclusions, role hierarchy and (concept and role) assertions, to generate basic domain related questions.

In addition to the above MCQ generation approaches, a few researchers worked on rule-based methods for question answer generation. The work by Zoumpatianos et al. [8] uses Semantic Web Rule Language (SWRL), a combination of OWL with RuleML,[1] to generate MCQs.

3. Preliminaries

In this section, we describe: MCQ, the Description Logic (DL) $\mathcal{SHIQ}$ based ontologies ($\mathcal{SHIQ}$ ontologies) and an example ontology (Harry-Potter-Book ontology).

3.1. Multiple choice questions

A multiple choice question (MCQ) is a type of question in which students are asked to choose correct answers from a set of alternatives, in response to a question-statement. MCQ tests are mainly used to evaluate whether (or not) a student has attained a certain learning objective.

Definition 1. MCQ is a 3-tuple $\langle S, K, D\rangle$, where, S is a statement that introduces the problem, K is a non-empty set of correct solutions to S, and D is a non-empty set of incorrect solutions to S. Here, S, K and D are called Stem, Keys and Distractors, respectively.

In this work, we only consider MCQs with 1 key and 3 distractors (total 4 choices), which is a common format used in MCQ tests.

3.2. $\mathcal{SHIQ}$ DL and $\mathcal{SHIQ}$ ontologies

The Description logic $\mathcal{SHIQ}$ is based on an extension of the well-known logic $\mathcal{ALC}$ [15], with added support for role hierarchies, inverse roles, transitive roles, and qualifying number restrictions [16].

We assume N_C and N_R as countably infinite disjoint sets of *atomic concepts* and *atomic roles* respectively. A $\mathcal{SHIQ}$ *role* is either $R \in N_R$ or an *inverse role* R^- with $R \in N_R$. To avoid considering roles such as $(R^-)^-$, we define a function $Inv(.)$ which returns the inverse of a role: $Inv(R) = R^-$ and $Inv(R^-) = R$.

[1] http://wiki.ruleml.org/index.php/RuleML_Home (last accessed 11th Dec. 2014).