A Fuzzy Knowledge Representation Model for Student Performance Assessment

Farshad Badie, Tommaso Soru, Jens Lehmann
AKSW, Department of Computer Science
University of Leipzig
04109 Leipzig, Germany
e-mail: {badie,tsoru,lehmann}@informatik.uni-leipzig.de

***Abstract*—Knowledge representation models based on Fuzzy Description Logics (DLs) can provide a foundation for reasoning in intelligent learning environments. While basic DLs are suitable for expressing crisp concepts and binary relationships, Fuzzy DLs are capable of processing degrees of truth/completeness about vague or imprecise information. This paper tackles the issue of representing fuzzy classes using *OWL2* in a dataset describing Performance Assessment Results of Students (*PARS*).**

***Keywords*-Knowledge Representation; Fuzzy Description Logic; OWL2 Ontologies; Semantic Web; Intelligent Educational System; E-Learning**

I. Introduction

The state of the art of representing knowledge in intelligent educational systems has recently improved significantly. We also have had a modernization of Semantic Web technologies in the area of e-learning systems which can support learning environments. They allow for the support of more accurate representations of learners, learners' needs, learning components, learning goals and assessments, e.g. [1]. An ontology is a specification of a conceptualization on a domain of interest. Since ontologies based on the *OWL2 W3C* standard[1] form the backbone of a number of Semantic Web applications, the underlying Description Logics (*DLs*) are now one of the most widely used knowledge representation (*KR*) formalisms in the Semantic Web. Typical Description Logics are limited to dealing with well-defined crisp concepts. However, DLs with a possibilistic approach allow both certainty (necessity measure) and possibility measure to be handled in the same formalism [2]–[4].

Educational applications based on the Semantic Web standards use URIs to represent resources, usually in triple-based structures (based on subjects, properties and objects) that can be held in educational databases[2]. In this article, we propose a fuzzy KR model for the educational domain by enriching an appropriate educational dataset. Our main goal is to represent incompleteness and vagueness of classes and reason over them. We thus need to model various descriptive features (e.g., qualities, attributes or modifiers). In OWL2[3] such descriptive features are modelled as classes whose range specifies the constraints on the values that the class can take on. The core contributions of this article are: (i) Modelling of educational data containing fuzzy classes. (ii) Extending the educational environment by creating different fuzzy sets regarding educational needs and demands. In the following, we present preliminaries, a use case description for our model and future work.

II. Preliminaries

Description Logic: DLs represent knowledge in terms of individuals, concepts, and roles (see [5] for details). Individuals correspond to constants, concepts to unary predicates, roles to binary predicates in first-order predicate logic.

Fuzzy Logic: In [6], [7], fuzzy logic is proposed to manage imprecise, vague and incomplete knowledge. In fuzzy set theory elements can belong to a set to some degree. Changing the usual true/false convention leads to a new type of propositions, called *fuzzy propositions*. Each fuzzy proposition may have a degree of truth/completeness in $[0, 1]$, denoting the compatibility of the fuzzy proposition with a given state of facts is a matter of degree, usually called the degree of truth/completeness of the statement.

Fuzzy DL $\mathcal{SROIQ}(\mathcal{D})$: This logic is a subset of Description Logics with fuzzy capabilities. Regarding [8], concepts denote fuzzy sets of individuals and roles denote fuzzy binary relations. Axioms are also extended to the fuzzy case and some of them hold to a degree. In fact, the *fuzzification* acceptance of OWL2 largely depends on Fuzzy DL $\mathcal{SROIQ}(\mathcal{D})$.

III. Modelling Educational Data

In this paper, we chose a real dataset concerning students' knowledge status[4]. We enriched this model with some primary characteristics related to students and named it *Performance Assessment Results of Students* (*PARS*). Based on [9]–[11], we use the fuzzy extension of $\mathcal{SROIQ}(D)$

[1] http://www.w3.org/standards/techs/owl#w3c_all
[2] http://infomesh.net/2001/swintro/
[3] http://www.w3.org/TR/swbp-specified-values
[4] http://archive.ics.uci.edu/ml/datasets/User+Knowledge+Modeling

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for modelling the corresponding DL of the ontology description language. Let us illustrate the vocabulary using an example: John is a student (denoted by class `S`) written as `S(John)`. He has a level of knowledge (denoted by property `LK`) based on assessment, therefore `LK(John,.9)`. A simple example to illustrate the concept of a fuzzy class is the following: John is a successful student. This fuzzy proposition has a degree of truth in the $[0, 1]$ range. `SuccessfulStudent` has a direct relationship with `LK` and has no exact definition, thus it can be modelled only using a fuzzy class. `VerySuccessfulStudent` and `UnsuccessfulStudent` could be other fuzzy terms regarding success also depending on `LK`. Note that *success* differs in the case of different properties, the measurements, the values and even the expectations we have in different conditions. We may have various measures for evaluating students regarding different qualifications. So we could increase the number of properties related to John in order to obtain a more comprehensive and accurate picture for his success (e.g., his exam performances, repetition in studying).

A. Use Case Description

Students are the main classes in our educational system. We also have some properties related to students, which are the attributes within the data model. The descriptive features presented above are used in the ontology representation of PARS. The different measures between 0 and 1 can be considered as the degree of completeness in classes. Students can thus be classified as `SuccessfulStudent` or `UnsuccessfulStudent` with different truth/completeness values.

In general, a successful student is a student who has a high level of knowledge. Formally, we declare: $\texttt{SuccessfulStudent} \equiv \texttt{Student} \sqcap \exists\ \texttt{LK}.\{\texttt{High}\}$ where `High` is a fuzzy modifier which corresponds to a degree of truth belonging to the interval $(.7, 1]$. Likewise, we have $\langle \texttt{Medium}, (.4, .7]\rangle$, $\langle \texttt{Low}, (.2, .4]\rangle$ and $\langle \texttt{VeryLow}, [0, .2]\rangle$. Now, let us introduce the property `StudyTime` to improve the precision of our concept. A student's success is thus directly dependent on both his/her level of knowledge and his/her study time, which might not be necessarily correlated. For example, students John and Bob have a high level of knowledge but Bob has been studying much longer. Within this model, John and Bob are successful students with different truth values.

IV. Work-Related and Future Work

We will utilize our KR model as background for learning class expressions in *DL-Learner* with fuzzy capabilities. DL-Learner[5] is a machine-learning framework for learning concepts in DL and OWL. It widens the scope of Inductive Logic Programming to DLs and the Semantic Web. [12]. In fact, we use argumentation theory based on OWL class expressions for engineering ontologies as a step towards intelligent learning approaches. We also use *fuzzyDL*[6] – a Description Logic reasoner which supports fuzzy logic and fuzzy rough set reasoning. It has a significant applicability in the area of Logic-based Fuzzy Control Systems.

Moreover, future work will be focused on the evaluation of our model by studying fuzzy class expressions based in an inductive learning setting. Such an approach will provide assessments and support for decision making in an intelligent educational system.

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