Crowd-sourcing and Automatic Generation of Semantic Information in Blended-Learning Environments

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ABSTRACT

Personalized learning environments rely on repositories of digital learning materials, and on meta-data that provides semantic information about the digital content. The semantic information is typically generated by domain experts, but this process is very time consuming, and fails to address the dynamic nature of the content and the contexts in which it is used. In addition, experts may fail to capture semantic properties that are not within their area of expertise. Overall, expert-based semantic generation processes do not scale, and produce limited information. Thus, the goal of my research is to study means to scale and improve the process of collecting and updating semantic information, using two different approaches: crowdsourcing from teachers and learners and automatic tagging that is based on machine-learning algorithms. As a proof-of-concept, two pilot experiments were conducted: the first was with two groups of physics teachers who are using an Open Educational Repository. The main goal was assessing the quality of the semantic information that the teacher-sourcing produces, and factors affecting it. The second experiment aimed at automatic tagging, and focused on comparing several ML approaches to automatically tag learning resources in a K-12 Math online learning environment. In this paper I will present the preliminary findings from these experiments, discuss future directions for my research, and seek advice concerning several issues involved with my research.

Keywords

Personalized Learning, Semantic Information, crowdsourcing

1. INTRODUCTION

Personalized learning environments rely on repositories of digital learning materials (e.g., interactive questions, online labs, videos), and on meta-data that provides rich semantic information about the digital content. The term 'semantic information' refers to information describing the content and different attributes of the online learning resources, such as the topic, the level of difficulty, its intended use - whether as a test, class practice or homework, which grade it is appropriate for, the estimated amount of time required to complete the activity, the technological aids required for it (e.g., a computer, projector, mobile devices), and more.

The semantic information is fundamental to the ability of AI agents to make 'intelligent' decisions such as recommending content to learners, to assist teachers in search & discovery of learning resources, and for re-using and sharing materials between contexts [1, 2, 3]. However, while high-quality digital content is in many cases readily available on the web, it is the semantic information that is usually missing, inadequate, or partial. Thus, having scalable processes for generating high-quality semantic information can contribute significantly to the development of personalized learning environments.

Semantic information is typically generated by domain experts, but this process is very time consuming, and the experts may fail to capture semantic properties that are not within their area of expertise [5]. In addition, the content repository and the context in which it is used are dynamic, requiring frequent revisions and updates. Overall, expert-based semantic generation processes do not scale, and produce limited information. My research aims to address these issues, by studying means to produce semantic information at scale, as detailed in the next section.

2. RESEARCH DIRECTIONS

The high-level goal of my research is to study two main approaches for collecting and updating semantic information: The first is crowdsourcing (more accurately: teacher- and learner-sourcing, which are the terms that are used hereafter), and the second is automatic tagging using machine learning algorithms. More specifically, this goal is further divided into the following issues:

Semantic Information Required. The first issue that I want to examine is what types of semantic information assist teachers in search & discovery of educational resources in open repositories. With the transfer of a growing number of

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teachers to blended learning, teachers often rely on learning resources found online. These resources are commonly organized in Open Educational Repositories (OER) that offer teachers a large pool of instructional materials. For teachers, selecting appropriate and effective instructional materials from an OER is a challenging and time-consuming process. Thus, I wish to explore what semantic information is required for supporting teachers in this process.

Sources for Obtaining Semantic Information. As aforementioned, I will focus on two approaches for obtaining semantic information about the learning resources: crowdsourcing from teachers and learners, and automatic tagging that is based on ML algorithms. I will compare two aspects of the information obtained from these approaches: the accuracy of the information, and coverage – how much information can be obtained from each of these sources.

Factors That Affect the Quality of Teacher and Learner-Sourced Information. The goal of this research direction is to study the different factors that affect the quality of teachers and learner-sourced semantic information. I will address both the issue of teachers' and learners' *ability* to accurately tag learning resources with semantic information, and their *motivation* to do so. In terms of ability, I will study issues and task definitions that support accurate tagging. For instance, can teachers and students tag resources without having full knowledge of the taxonomy from which the tags are taken? to which resolution do teachers and learners need to go in analyzing the questions in order to provide accurate tags? The second issue is teachers and learners motivation to contribute time and effort to tagging, as this is a time-consuming and cognitively demanding process, with no perceived reward. Providing incentives for crowdsourcing is a known issue [4], and it is reasonable to assume that engaging teachers and learners in crowdsourcing would require appropriate incentive design.

Effect of Tagging Process on Teachers and Learners. The last aspect of crowdsourcing that I wish to examine is the effect (if there is any) of the tagging process on teachers' professional development, and on students' learning. With respect to teachers, I will focus on the effect of participation on their ability to provide personalized learning and adapt tasks to individual needs of different students. With respect to learners, I intend to focus on whether the reflective nature of the tagging process contributes to student understanding, as reflective processes has been repeatedly shown to improve learning.

3. PRELIMINARY RESULTS

To date, two pilot experiments were conducted, each addressing a different approach for obtaining semantic information. The first experiment was held with two groups of Physics teachers. The teachers were requested to tag questions taken from a blended-learning environment named *PeTeL* (described below), and their tagging was compared to that of domain experts. In the second experiment, a supervised machine-learning approach was applied to ~ 400 activities taken from a Math learning environment named *STEP* (see below), which are tagged according to different dimensions, such as their topic (Geometry, Algebra, Verbal Problems, Infinitesimal Calculus etc.)

3.1 First Experiment - Teacher Sourcing

The first experiment was designed as a proof-of-concept for teachers' ability to accurately tag learning resources with semantic information. The participating teachers were requested to tag questions taken from a learning unit on Magnetism according to a detailed taxonomy prepared by a group of expert teachers and researchers.

Learning Environment - PeTeL. The experimental setup is based on a learning environment named PeTeL, which is both an OER, and an LMS that also includes social network features and learning analytics tools. It is developed within the Department of Science Teaching at Weizmann Institute of Science, with the goal of providing STEM teachers with a blended learning environment for personalized instruction. PeTeL is divided into separate modules for each subject matter: Biology, Chemistry and Physics. The Physics module is currently being used by approximately 200 teachers and 7000 high school students. All the teachers who participated in the experiment use PeTeL in their classes.

Procedure and Results. Two groups of Physics teachers participated in this experiment. The first group consisted of eight teachers who were presented each with three questions from PeTeL. Each question contains a picture or diagram of a certain Physics situation (e.g. a particle moving through a magnetic field, or an electric circuit), and a question regarding that diagram (See example in Figure 1). For each question i, the teachers were presented with four tags. Then, for each tag, the teachers were requested to decide whether it applies to i. Overall, we received 95 responses. In 74 out of 95 responses, the teachers agreed with the domain expert as to whether the content knowledge described in the tag is required for solving the question (78% agreement, Cohen's kappa: 0.56).

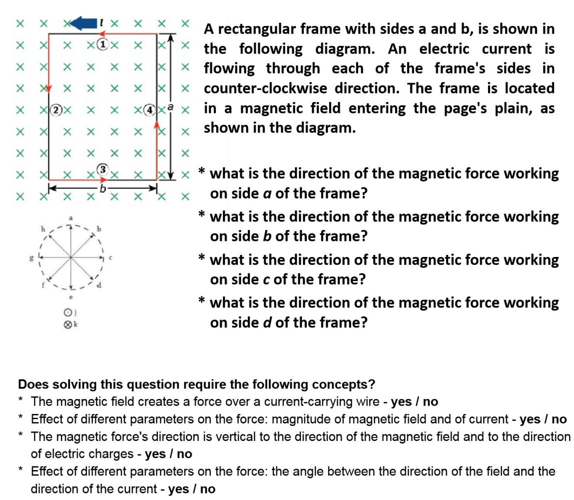

Figure 1: Tagging Task Example

The second part of the experiment took place about a month after the first one, with a different group of seven Physics teachers, and followed a similar protocol. A total of 56 responses were collected. In 43 out of 56 responses, the teachers agreed with the domain expert as to whether the content knowledge described in the tag was required for solving the questions (77% agreement, Cohen's kappa: 0.54).

3.2 Second Experiment - Automatic Tagging

The second experiment was conducted in the context of STEP, an OER for junior-high and high-school Math, which was developed by the Department of Math Education in the University of Haifa.

Procedure. 407 learning activities were taken from STEP. Fifty keywords were selected as features (e.g., 'angle', 'function', 'speed', 'derivative', 'linear', 'sinus', etc.). Each activity was encoded as a one-hot vector according to the presence of these keywords, and labeled with its Math topic (Geometry, Algebra, Verbal Problems, etc.). Then, three ML algorithms (Naive Bayes, Random Forest, and Logistic Regression) were applied to the data in an attempt to evaluate the feasibility of classifying activities into topics based on these features.

Results. Measured with k-fold cross-validation, the accuracy of the classification produced by the ML algorithms was 95% (achieved by the Naive Bayes and the Random Forest algorithms).

3.3 Conclusions

The results of these two small-scale experiments suggest that regarding teacher-sourcing, when the tagging task is formulated in a certain way (e.g., "yes/no" questions), teachers can tag items relatively accurately (Cohen's kappa: 0.56) without being trained on the taxonomy from which the tags are taken. Regarding automatic tagging by ML algorithms, these preliminary results are encouraging as to the ability to produce quality semantic information without the need for human intervention.

On the next step, we intend to run these experiment on a larger scale, using a technological tool to teacher-source semantic information from a much larger pool of teachers, to expand our work to learner-sourcing as well, and to apply learning algorithms to a multitude of learning resources in an attempt to reach much more fine-grained semantic information.

4. PROPOSED CONTRIBUTION

I hope that my work will have both a practical contribution to the learning environments that I study, and through this, to teaching and learning, and will contribute to EDM research by providing a better understanding of effective means to enrich learning environments with semantic information.

5. DISCUSSION AND ADVICE SOUGHT

I seek advice regarding four major issues in my research: the first is *what are the most effective means to enhance teachers' and learners' motivation to invest time and effort in the tagging process?* In this regard, since we saw indications that teachers' motivation affects the quality of their tagging, I feel that positive incentives, rather than negative ones (e.g., requiring participation for receiving access to materials) are more likely to produce quality results.

The second issue is *how to optimize the relationship between coverage (i.e. how many tags are requested from each teacher or learner) and motivation.* On one hand, presenting the teacher/learner with numerous requests for tagging could easily deter him/her and would result in low rates of participation. On the other hand, minimizing the interaction with the user would result in low coverage.

The third aspect is how to evaluate the quality of the semantic information received from teachers and learners? After receiving tags produced by either teachers or learners, there is the question of how reliable those tags are. Possible solutions are random evaluation by an expert, or wisdom-of-the-crowd based ranking solutions.

And last, regarding the process of automatic tagging – a main challenge is abstracting different types of information representation (text, figures, symbols) into a common layer of semantic meaning, probably relying on NLP, object recognition, etc. I would appreciate receiving information regarding relevant research that I can build upon.

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