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Automatic detection of expert models: The exploration of expert modeling methods applicable to technology-based assessment and instruction

Min Kyu Kim [a, *], Amal Zouaq [b], So Mi Kim [c]

[a] The Research Laboratory for Digital Learning, The Ohio State University, 310K Ramseyer Hall, 29 West Woodruff Avenue, Columbus, OH 43210, USA

[b] School of Electrical Engineering and Computer Science, University of Ottawa, Bureau: STE 5062, 75Laurier Ave E, Ottawa, ON K1N 6N5, Canada

[c] The School of Information Sciences and Learning Technologies, University of Missouri, 104London Hall, Columbia, MO 65211, USA

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ABSTRACT

This mixed methods study explores automatic methods for expert model construction using multiple textual explanations of a problem situation. In particular, this study focuses on the key concepts of an expert model. While an expert understanding of a complex problem situation provides critical reference points for evidence-based formative assessment and feedback, the extraction of those reference points has proven challenging. Building upon semantic analysis, this study utilizes deep natural language processing techniques to facilitate the automatic extraction of key concepts from textual explanations written by experts. The study addresses the following question: (a) whether experts in a domain represent a common understanding of a problem situation through shared key concepts, (b) which metrics extract key concepts from textual data most accurately, and (c) whether automatic methods enable expert model construction from a corpus of textual explanations instead of a pre-defined, ideal explanation created using the Delphi method. The OntoCmap tool was used to extract concepts from multiple textual explanations and to generate diverse metrics assigned to each concept. The findings indicate that (a) experts have varying ways of understanding a problem situation, (b) graph-based filtering metrics (i.e., betweenness and reachability) performed better in building a set of key concepts, and (c) a single, pre-defined explanation led to a more accurate set of key concepts than a corpus of explanations from various experts.

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1. Introduction

Expert studies have sought to explain what constitutes expertise in a particular task and how expertise develops across short-term and long-term changes (Alexander, 2004; Chi, 2006; Ericsson, Charness, Feltovich, & Hoffman, 2006; Flavell, 1992). Experts exhibit knowledge and skills in problem solving that are clearly distinguishable from novices (Glaser, Chi, & Farr, 1988; Spector & Koszalka, 2004). Expert models have been used not only to shape curriculum (Nkambou, 2010) and

* Corresponding author.
E-mail addresses: kim.5988@osu.edu (M.K. Kim), azouaq@uottawa.ca (A. Zouaq), kimsomi@missouri.edu (S.M. Kim).

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instructional materials (Gobet & Wood, 1999; Seel, 2003) but also to scaffold learning progressions (Feyzi-Behnagh & Azevedo, 2012; Molloy & Boud, 2014). For example, the key concepts provided by expert models are vital to evidence-based assessment, precise and targeted feedback, and learning guidance (Kim, 2015; Shute et al., 2010). Among the many aspects of an expert model, the current study focuses on expert-identified key concepts that explain a particular problem situation.

Key concepts identified by experts are often used in educational learning systems. For example, Intelligent Tutoring Systems (ITSs) such as AutoTutor use pre-defined key concepts to detect student understanding of a problem through dialogue with a system agent and to provide higher-level feedback such as prompts, hints, and examples (Lintean, Rus, & Azevedo, 2012; Rus, D'Mello, Hu, & Graesser, 2013). Suppose that students in an earth science class are asked to write responses to a system-generated question: “describe which factors have influenced the frequency of wildfires in California in 2015?” An agent could identify concepts from student responses and compare them to the concepts in an expert model. Another popular application is automated essay scoring to evaluate written work. For instance, the c-rater scoring engine developed by ETS is designed to recognize specific content (e.g., concepts) in a student response (Burstein, Tetreault, & Madnani, 2013; Gopal et al., 2010; Shermis, 2010; Shermis, Burstein, & Leacock, 2006). Automated natural language processing techniques determine whether a student response contains information that shows a topic has been learned (Shermis, 2010; Shermis et al., 2006).

In spite of all these benefits, modeling expert knowledge is demanding, expensive, and time consuming. For instance, building a consentient expert model of a complex problem situation often involves diverse and inter-related concepts, principles, propositions, and various unknown features (Jonnassen & Philip, 1996; Kim, 2012a, 2013; Spector, 2010). In order to tackle these issues, current technologies have promoted methods for automatically representing expert knowledge that potentially contains the key concepts of a problem situation (Clariana, Wolfe, & Kim, 2014; Kim, 2013).

One of the most popular methods involves natural language processing (NLP), which can be used to analyze textual explanations in order to construct knowledge models (Allen, Snow, & McNamara, 2015). For example, many ITSs use NLP tools to analyze the linguistic properties of conversations between an agent and learner, a process that results in student models (McNamara, Crossley, & Roscoe, 2013; Nye, Graesser, & Hu, 2014; Rus et al., 2013). The same techniques can be used to build expert models, against which student models are compared in order to identify knowledge gaps. Yet whether these technological methods can generate expert concepts as reliably and efficiently as human can remains debatable (Allen et al., 2015). In an attempt to respond to these issues, the current study explores automatic methods for extracting key concepts from multiple expert explanations of a complex problem situation.

2. Theoretical and methodological underpinnings

2.1. Expert modeling for a complex problem situation

Expert models are essential to an accurate evaluation of student input in technology-enhanced learning systems. Nevertheless, whether building an expert model is always plausible or reasonable remains an open question. In fact, one might experience difficulty in establishing reference models for a complex problem situation. Complex problems (e.g., an ecology problem in 9^{th}-grade science class—identifying the complex nature of global warming and its connection to frequent wild fires in California) involve interrelated and multilayered concepts, factors, and unknown variables, which often render a common understanding of the problem situation impossible (Jonassen, 2014; Pretz, Naples, & Sternberg, 2003).

Despite this skepticism, we still need expert models to identify, monitor, and promote levels of expertise in problem-solving situations. Anderson (1980) defined problem solving as a goal-directed cognitive effort. In the course of problem solving, problem solvers typically conceptualize the problem space in which all of the possible conditions of a problem exist (Newell & Simon, 1972; Pretz et al., 2003). Although experts in the same discipline might exhibit a similar and clearly recognizable understanding of a problem situation, their solutions could be multiple and diverse (Spector, 2008). Therefore, the current study analyzed expert conceptualizations—problem spaces— of a problem situation and investigated how similar or dissimilar these problem spaces were. To this end, natural language (e.g., written responses) is often used to elicit expert understanding for two primary reasons: it enables descriptive verbal knowledge representations (Axelrod, 2015; Pirnay-Dummer & Ifenthaler, 2010) and saves time and effort (Brown, 1997). Cognitive and learning scientists have used verbalized explanations to model expert knowledge (Allen et al., 2015; Chi, De Leeuw, Chiu, & Lavancher, 1994; Dascalu, Trausan-Matu, Dessus, & McNamara, 2015; Johnson-Laird, 2013). Externalized articulation reflects internal mental structures. Accordingly, one can infer internal mental models by extracting meaningful concepts and their relations (i.e., propositions) from language representations (e.g., expert accounts of a problem) (R. B. Clariana & Wallace, 2009; Jonassen, Beissner, & Yacci, 1993).

2.2. Source of expertise modeling

The general approach to constructing an expert model (i.e., key concepts of a problem situation) is to draw on human expert-generated data. Lintean et al. (2012) proposed three sources used by intelligent learning systems to obtain human expert data related to a problem situation: (a) a set of key concepts related to the problem task directly defined by human

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