Core Aspects of Affective Metacognitive User Models

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Abstract. As User Modelling moves away from a tightly integrated adjunct of adaptive systems and into User Modelling Services provision, it is important to consider what facets or characteristics of a user might need to be contained within a user model in order to support particular functions. Here we examine previous mechanisms for creating a metacognitive user model. We then take first steps to describe the necessary characteristics of a user model we envisage being utilised by an affective metacognitive modelling service and make some suggestion for the source, form and content of such characteristics.

Keywords: Affect, metacognition, user model

1 Introduction

The successful learner has a rich cognitive repertoire of strategies and traits, which allows them to gain new knowledge, insights and understanding in a way most suited to them. Learning is not the simple transmission of information, but rather a complex process of interaction between the learner, their environment, their goals, and their informational milieu.

Technology enhanced education (eLearning) that reflects this rich learning process is an ever-evolving field. The earliest educational software of the 60's and 70's took a very simplistic approach, almost akin to an electronic book. With the development of hypertext systems in the 80's-90's Intelligent Tutoring Systems wherein a model of the learner became important, allowing them to be tailored to a greater or lesser extent to a particular type of learner or the individual. Modern systems now encompass a wide range of system architectures from mixed initiative through dialogic; serious games, inquiry-based Information Retrieval, providing animated pedagogical agents, various Virtual Learning Environments (both Open Source and Commercial) and computer supported collaborative learning.

The User Model has allowed eLearning systems to adapt to learners' behaviour and provide adaptive feedback. The most recently developed educational software assemble interactions that infer the link between measurable outcomes (e.g. rule based inference) and resources, as well as how the user interacts with these resources. Commonly three types of knowledge are modelled to aid learning: the area being studied – the domain model, the person studying the area – the student model, and how the learning is being undertaken – the pedagogical (or androgogical) model [1].

The User Model has evolved from a component of a monolithic learning environment to become one facet of a distributed learning framework. Rather than persist the user model entirely in one application or system, they can now be delivered as a service. This means that data can be harvested from multiple sources in order to learn about the user's collective state. In this new, distributed framework, the learning service and user model may be owned and managed independently.

As eLearning frameworks have evolved, so have their models of the learner from simple group competency-based models (e.g. stereotypes) to complex domain/skill matrices. However, many still continue to focus on the modelling of the progression of competency within a knowledge domain. The monitoring of the progression of the skills of a learner *in learning* is also vital, as well as the personal context of the learner. These personal traits of the learner – their affective and metacognitive states – fundamentally affect the learning process.

How do we reflect metacognitive or affective aspects of the learner in our learning systems? Metacognition involves the monitoring and subsequent regulation of cognitive processes in order to learn and solve problems [2, 3]. Metacognitive skills develop through observation of others, and subsequent internal self-monitoring [4]. Conati argues the higher the level of the user states to be captured, the more difficult they are to assess unobtrusively from simple interaction events. More fully: How do we track the individual metacognitive differences of a learner over time and discover relevant patterns of measures that can be used to predict metacognitive/affective outcomes? The next section outlines some previous systems that have attempted to do just that.

2 Metacognitive/Affective Systems

Perhaps one of the most well known early systems to model some of the above-mentioned aspects is the Cognitive Tutor – PAT (Pump Algebra Tutor) [5]. This applies the ACT-R (Adaptive Control of Thought—Rational) theory of learning and performance [6, 7]. This type of cognitive model includes procedural knowledge and declarative knowledge as well as tracing the learners' knowledge growth over time. By developing mathematical modelling skills, learners can construct a deeper understanding of problem situations such that multiple, unanticipated questions can be addressed and answered. This has similarities with understanding of metacognitive awareness including knowledge about cognition and the regulation of cognition.

Sherlock [8], and its successor, Sherlock 2, arose out of task analysis research. These Intelligent Tutoring Systems leveraged contingent teaching that uses knowledge tracing to choose the next problem that is approximately challenging. They model the process of learning and monitor the skills not only in performing a task, but also deciding how a task should be performed. Aleven's Help Tutor [9] supports the learner at becoming better at seeking help in geometry. The tutor keeps track of students' knowledge growth over time using Bayesian algorithm to estimate their mastery of target skills. Although the help-seeking tutor achieved positive effects because students followed advice, they did not internalize the help-seeking principles [10].

Tutoring systems aim to emulate student-teacher interactions, however, agent based systems, such as Betty's Brain Teachable Agent [11] emulate peer interactions. This uses AI reasoning techniques in order to externalize the thought process. Students track the agent's metacognitive reasoning, and remediate the result if necessary. The idea comes from the fact that children can monitor errors in another person counting easier than monitoring their own errors. In the Triple-A Challenge Gameshow [12] multiple Teachable Agents, each taught by a student, compete in a game show. Students wager on whether their agents will get answer correctly. The teachable agents reason using rules taught by the students. Students showed greater motivation in learning when teaching their agents.

Narrative interaction is an important part of metacognitive skill development, whether between a student and a coach or with internal dialogues, such as learner reflection. The ACE system (Adaptive Coach for Exploration) [13] supports student exploration of mathematical functions via interactive simulations. It assesses whether a learner self-explains (metacognitive skill) their exploratory actions by using evidence for their interactions with the system and eye-tracking gaze time. Crystal Island [14] uses pedagogical agent feedback in a narrative-centred environment in order to try and keep students in an affective state that is conducive to learning. The character serves both narrative and pedagogical roles by providing task-based feedback and affective feedback. They show there was an increased performance of models including affect over those monitoring situational data alone, demonstrating the importance of empathetic support/feedback. AutoTutor [15] is a dialog-based problem-solving environment. The multimodal affect detector combines conversational cues, body language and facial features in order to infer the learner's emotions. The face was the most indicative of the emotion, but accuracy improved using multiple indicators. Goby [16] is delivered as a separate service that is loosely coupled with the APeLS adaptive eLearning system. The metacognitive state of the learner is modeled via dialog-based interactions. The structure of Goby's cognitive user model is analogous to that of psychometric inventories, and specifically models the MAI (Metacognitive Awareness Inventory) [17].

All of the above systems have attempted to leverage aspects of a learner's awareness of their learning processes (metacognition) and/or their emotional (affective) state. Next is outlined an overview of mechanisms for recording and measuring these aspects.

3 Exemplar Metacognitive / Affective Models

In order to model metacognitive aspects of the learner, it seems key to represent the process or context that the metacognition arises from. Such a model is ETTHOS (Emulating Traits and Tasks in Higher Order Schema) [16], where each learner possesses Traits – these traits influence a learner's approach to tasks. Traits are high-level metacognitive aspects such as Metacognitive Knowledge, subdivided into Factors (lower level, such as Planning). A factor can be described as a linear sum of variables. The combination of a number of related observable items describe each factor. (I pace myself while learning, I ask myself questions). The tasks are modelled as a set of activities, each activity may be broken down into Sub Activities: for example the Activity *Overviewing the Learning Object* (part of the "Before Starting" task), may be broken down into sub activities such as Noting important parts, Gathering information relevant to the goal, Determining what to do in detail.

Modelling the affective state of a learner is inherently problematic as it can be difficult to create an effective metric of affective states. Ortony's Affective Lexicon [18] provides an often-used source of affect words grouped into affective categories. These are expansions of Ekman's [19] basic emotions - happy, sad, anger, fear, disgust, and surprise. However, handcrafted models are difficult to generalize e.g. Dyer's DAYDREAMER [20] – which, whilst effective in place, would be unsuitable to employ as a component of a user modelling framework. As such, the work of Liu *et al* [21] provides an important reference point to existing models and affective techniques. D'Mello & Graesser [15] have mapped key emotions during learning – boredom, confusion, delight, flow, frustration, and surprise.

4 Core Aspects of the Model

Given all of the above, what then, are the core aspects of an affective metacognitive user model? They can be divided into the content, form and source of the user model, as discussed below:

The *Content* of the User Models to date that have considered either metacognitive or affective traits of the learner incorporate metrics from either structured inventories (e.g. Macarthur [16]) or bespoke solutions (e.g. Ekman [19]). The use of bespoke solutions may benefit the particular learning objectives of a course, however, if we are moving towards delivering the user model as a service, then cognitive inventories should also be considered. Over one hundred psychometric inventories are currently available for clinical, educational, and organizational evaluations. The benefit of incorporating these into the user model is that they have already been ratified and tested e.g. 16-PF [22], Myers-Briggs Type Indicator [23].

The *content* of the user model would therefore include, firstly, an overarching strategy for Pedagogy /Androgogy– the learning process that is being undertaken, represented by a set of formative and summative learning objectives. In particular, self-regulated learning (SRL) [24, 25] is key to learning objectives that incorporate metacognitive functions. SRL can provide a rich source of information for the user model, because the learner will engage in reflection during the SRL process. The model will also contain a narrative – that monitors and subsequently regulates communication with the learner by recording the users' interaction with the learning environment, or through richer capture of a dialogic structure. The model should also contain aspects of cognition – the process of thought that is modelled within a metacognitive user model. Finally a learner's emotional state must be captured, for example, by incorporating multi-dimensional axes of Ekman's basic sextet [19].

What *Form* should such a User Model take? Competency-based user models have a clear metric – the comprehension of the domain in question. However, the processes discussed here are more complex. While some elements of metacognitive skills may be understood as competency based, temporal progression and, context are also important. We therefore propose a multi-dimensional matrix that records temporal, metacognitive competency and affective indices. These could be represented as both a set of metrics such as those in personality inventories as well as a number of formative learning objectives like those assessed in self-reflective journals.

The *Source* of the User Model can be entirely self-contained, with explicit and implicit information gathered straight from the learning environment within which it is being used. However, it could also embrace aspects of the open social web. This means that the user model content may come from a variety of sources, both purpose-built for the eLearning framework and out in *the wild*, such as Twitter feeds. Twitter feeds can, for example, contain affective statements, such as "I so happy I am finding my coursework very straightforward" and metacognitive information, such as, "I have spent all today planning for my tomorrow's classes". Information could also be taken from analysis of online forum contributions, and other social networking ephemera, such as locational and contextual cues from check-in services (e.g. Foursquare). Equally as important, from a social constructivist [4] point of view are peer interactions through declarative living within a learner's social graph. A rich user model comes from an in-depth inspection of the cognitive processes and affective cues collected from the user across their learning life, not just during direct encounters with learning technology. It also allows the representation of subtle affective and metacognitive characteristics, rather than simplistic steps on a chart.

4 Conclusions

As the model of learning and the learner becomes ever more complex so the need for a firm basis for the creation of a metacognitive and affective model for the learner becomes ever more necessary. We have outlined some basic characteristics we feel are key to any attempt to create such a model, based on previous work, divided into the content, form and source of the model. We suggest that such a model should be based upon externally validated inventories, with a representation of the progression of a learner through metacognitive competencies and affective states that is both temporal and stateful, respecting context. There is still much work to be done in reliably creating, updating and applying these models.

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References

1. Conati, C.: How to evaluate models of user affect? Affective Dialogue Systems 3068/2004, 288-300 (2004)
2. Flavell, J.H.: Metacognitive aspects of problem solving. In: L.B. Resnick (eds.) The nature of intelligence. pp. 231-236. Erlbaum, Hillsdale, NJ (1976)
3. Brown, A.L.: Metacognitive development and reading. In: R.J. Spiro, B. Bruce, W. Brewer (eds.) Theoretical issues in reading comprehension. pp. 453-482. Hillsdale, N.J. (1980)
4. Vygotskiĭ, L.S., Cole, M.: Mind in society: the development of higher psychological processes. Harvard University Press, Cambridge, MA (1978)
5. Koedinger, K.R.: Cognitive Tutors as Modeling Tool and Instructional Model. In: K.D. Forbus, P.J. Feltovich (eds.) Smart Machines in Education: The Coming Revolution in Educational Technology. pp. 145-168. AAAI/MIT Press, Menlo Park, CA (2001)
6. Anderson, J.R.: ACT: A simple theory of complex cognition. American Psychologist 51, 355-365 (1996)

7. Anderson, J.R.: Rules of the Mind. Lawrence Erlbaum Associates, Inc., Hillsdale, N.J. (1993)
8. Lesgold, A.M.: The nature and methods of learning by doing. American Psychologist 56, 964-973 (2001)
9. Aleven, V., McLaren, B.M., Roll, I., Koedinger, K.R.: Toward meta-cognitive tutoring: A model of help seeking with a Cognitive Tutor. International Journal of Artificial Intelligence in Education 16, 101-130 (2006)
10. Roll, I., Aleven, V., McLaren, B.M., Koedinger, K.R.: Can Help Seeking Be Tutored? Searching for the Secret Sauce of Metacognitive Tutoring. In: Proceedings of the 13th International Conference on Artificial Intelligence in Education (AIED 2007), pp. 203-210. IOS Press Amsterdam, The Netherlands, Los Angeles, CA (Jun. 2007)
11. Biswas, G., Leelawong, K., Schwartz, D.L., Vye, N.: Learning by Teaching: A New Agent Paradigm for Educational Software. Applied Artificial Intelligence 19, 363-392 (2005)
12. Chase, C.C., Chin, D.B., Oppezzo, M.A., Schwartz, D.L.: Teachable agents and the protege effect: Increasing effort towards learning. Journal of Science Education and Technology 18, 334-352 (2009)
13. Conati, C.: Intelligent Tutoring Systems: New Challenges and Directions. In: Proceedings of the 14th International Conference on Artificial Intelligence in Education (AIED), pp. 2-7. Brighton, England (2009)
14. Robison, J.L., McQuiggan, S.W., Lester, J.C.: Modeling Task-Based vs. Affect-Based Feedback Behavior in Pedagogical Agents: An Inductive Approach. In: Proceedings of the Fourteenth International Conference on Artificial Intelligence in Education, pp. 25-32. (2009)
15. D'Mello, S.K., Graesser, A.: Multimodal semi-automated affect detection from conversational cues, gross body language, and facial features. User Modeling and UserAdapted Interaction 20, 147-187 (2010)
16. Macarthur, V., Conlan, O.: Modeling Higher-order Cognitive Skills in Technology Enhanced Distance Learning. In: 4th International Conference on Distance Learning and Education (ICDLE), pp. 15-19. (2010)
17. Schraw, G., Sperling Dennison, R.: Assessing metacognitive awareness. Contemporary Educational Psychology 19, 460–475 (1994)
18. Ortony, A., Clore, G.L., Collins, A.: The Cognitive Structure of Emotions. Cambridge University Press, (1990)
19. Ekman, P.: Facial expression and emotion. American Psychologist 48, 384-392 (1993)
20. Dyer, M.: Emotions and their computations: Three computer models. Cognition & Emotion 1, 323-347 (1987)
21. Liu, H., Lieberman, H., Selker, T.: A model of textual affect sensing using real-world knowledge. Proceedings of the 8th international conference on Intelligent user interfaces IUI 03 125-132 (2003)
22. Cattell, R.B.: Description and measurement of personality. Harcourt, Brace & World, (1946)
23. Myers, I.B., McCaulley, M.H., Quenk, N.L., Hammer, A.L.: The MBTI manual. Consulting Psychologists Press, (1998)
24. Azevedo, R., Robinson, D., Schraw, G.: The Role of Self-Regulated Learning about Science with Hypermedia. Recent innovations in educational technology that facilitate student learning. pp. 127-156. Information Age Publishing, (2008)
25. Zimmerman, B.J.: Investigating Self-Regulation and Motivation: Historical Background, Methodological Developments, and Future Prospects. American Educational Research Journal 45, 166-183 (2008)