Motivationally Intelligent Systems: diagnosis and feedback

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Abstract: Motivationally intelligent systems deploy resources and tactics dynamically to *maintain or increase* the student's *desire to learn* and her *willingness to expend effort* in so doing. Three categories of diagnostic inputs and feedback reactions are outlined each with its associated meta-level. The meta-level includes the account which learners tell themselves, the system and others about what they know, how they feel, and the conditions under which they learn best.

Keywords: motivation, affect, evaluation of meta-cognitive and affective issues

Introduction

Motivational pedagogy that can be applied in an AIED context comprises two distinct kinds of theory: (i) how systems should act or react in order to change the motivational state of the student, and (ii) how a student's motivational state affects her learning.

1. Motivational diagnosis and feedback

In terms of the first kind of theory, [1,2,3] provide qualitative guidance. In terms of process models, at one end of the continuum there are complex models of general emotional processing that model how emotions emerge, develop and change. OCC is a well known instance [4]. At the other end of the continuum are "thermostat" models of motivation, based on interactions between a small number of motivational variables (e.g. [5]). Finally there are models somewhere in between that cover only those emotions that are relevant in educational situations, motivation included (e.g. [6]).

As far as how motivation affects learning, there are various accounts of the complex relations between motivation and other issues, such as goal-orientation, metacognition, values and beliefs, and (indeed) emotion (e.g. [7, 8]). Given the complexity of operationalising educational theory in systems, new useful approaches are being adopted to mine the large amounts of user interaction data now available. These methods are used to find relationships within that data and to measurable variables such as post-test performance (e.g. via hidden Markov models, [9]).

We define three broad categories within which motivationally intelligent systems operate together with their associated diagnostic inputs and feedback reactions, see Table 1. By "diagnostic input" we mean the kind of event or measurement that provides input data to the system, such as the student asking for help, dominating a discussion, or their posture. By "feedback reactions" we mean actions or outputs by the system, such as changing the facial expression of an online agent, setting a harder problem, putting two students in touch with each other and so on. Note that each of the categories has a "meta-level". This corresponds to the degree that the student (and the system) is able to reflect on and articulate the impact of that level on her learning.

Table 1: Categories of diagnostic input and feedback reaction.

CATEGORY		DIAGNOSTIC INPUTS	FEEDBACK REACTIONS
DOMAIN	Knowledge and skills of the student.	Performance, latencies, effort, focus of attention [10]	Activity choice, pace or order of work, provision of help [5]
META-COGNIT-IVE	What the student knows, can articulate and regulate about her knowledge and skills	Difficulty of work chosen, use of available help (including gaming), goal orientation [11]	Conversation about performance, degree of challenge, use of help, narrative framework [12]
AFFECT-IVE	How the student feels about the learning activity	Demeanour of student e.g. happy, engaged [13]	Praise, encouragement, criticism, politeness, teacher's demeanour [14]
META-AFFECT-IVE	What the student knows, can articulate and regulate about her actual and expected feelings	Comments from student about expectations of feelings, motivation [15]	Conversations about expectations of feelings, state of motivation, engagement [16]
PHYSIO-LOGICAL	Bodily aspects such as heart and breathing rate, skin conductance, facial expression, body language and posture.	Sensors: skin, body movements, Cameras: facial expression, posture [3]	Breathing exercises, mantras, pauses [17]
META-PHYSIO-LOGICAL	What the student knows, can articulate and regulate about her physiological responses.	Comments from student about her body	Conversations about physiological response
CONTEXT	The spatial, social and temporal milieu within which the student is learning.	Location e.g. classroom, home, library, why learning [18]	Use of available peers and others, change of location, lighting [19]
META-CONTEXT	What the student knows, can articulate and regulate about the learning context.	Comments from the student about the context	Conversations about the nature of the context

2. Conclusions

Three categories of system input and output have been identified, each with an associated meta-level. Just as a reflectively self aware student will be able to reason about how each category bears on her learning, so a challenge for the design of motivationally intelligent systems is to reason in a similar fashion and also converse with the student at that level. Few systems have attempted to interact with the learner at the meta-levels: for example, in the case of the meta-affective, discussing with the learner the kinds of feelings that they are likely to experience in future learning interactions or inviting self-reflection from learners about how past learning experiences felt. Similar arguments can be made for meta-physiological and meta-context discussions: “why can’t I concentrate?”, “why do I need music on to work?”.

References

[1] Lepper, M. R., Aspinwall, L. G., Mumme, D. L., and R.W. Chabay (1990). Self-perception and social-perception processes in tutoring: Subtle social control strategies of expert tutors. In J. M. Olson & M. P. Zanna (Eds.), *Self-Inference Processes: The Ontario Symposium*, Vol. 6 (pp. 217-237). Hillsdale, NJ: Lawrence Erlbaum Associates.

[2] Keller, J. M. (1983). Motivational Design of Instruction. In *Instructional-Design theories and models: An overview of their current status*. C. M. Reigeluth (Ed.). Hillsdale, Erlbaum. pp 383-434.

[3] Prendinger, H., Mori, J. and M. Ishizuka (2005) Recognizing, modelling, and responding to users’ affective states in Liliana Ardissimo, Paul Brna, and Antonija Mitrovic, editors, *Proceedings of 10th International Conference, User Modelling 2005, Edinburgh*, number 3538 in Lecture Notes in Artificial Intelligence, pp 60-69. Springer-Verlag.

[4] Orthony, A., Clore, G. L., & Collins, A. (1988). *The cognitive structure of emotions*. Cambridge University Press, Cambridge, New York, New Rochelle, Melbourne, Sydney.

[5] del Soldato, T. and B. du Boulay (1995). Implementation of motivational tactics in tutoring systems. *International Journal of Artificial Intelligence in Education* **6**: 337-378.

[6] Conati C and Mclaren H. (2005). Data-driven Refinement of a Probabilistic Model of User Affect. *Proceedings of UM2005 User Modeling: Proceedings of the Tenth International Conference,* Lecture Notes in Computer Science, Volume 3538/2005, Springer Berlin / Heidelberg

[7] Pintrich, P. R. and E. V. d. Groot (1990). "Motivation and self - regulated learning components of classroom academic performance" *Journal of Educational Psychology* **82**(1): pp 33-40.

[8] Pintrich, P. R. (2000). "An achievement goal perspective on issues in motivation terminology, theory, and research" *Contemporary Educational Psychology* **25**(1): 92-104.

[9] Soller, A. and A. Lesgold (2003) A computational approach to analyzing online knowledge sharing interaction. In U. Hoppe, F. Verdejo and J. Kay (Eds) Artificial *Intelligence in Education: Shaping the future of learning through intelligent technologies*. pp 253-268, IOS press.

[10] Qu, L. and W. L. Johnson (2005). Detecting the Learner's Motivational States in An Interactive Learning Environment. In *Artificial Intelligence in Education: Supporting Learning through Intelligent and Socially Informed Technology*, pp 547-554, IOS Press.

[11] Heiner, C. , Beck, J. and J. Mostow (2005) When do students interrupt help? Effects of individual differences. Workshop on Motivation and Affect in Educational Software, in *AIED2005, 12th International Conference on Artificial Intelligence in Education*, Amsterdam, pp 47-49, IOS Press.

[12] Luckin, R. and L. Hammerton (2002). Getting to know me: helping learners understand their own learning needs through Metacognitive scaffolding. *Proceedings of the sixth Conference on Intelligent Tutoring Systems*. Biarritz, France, Berlin : Springer.

[13] Arroyo, I. and B. Woolf (2005) Inferring learning and attitudes from a Bayesian Network of log file data. In *Artificial Intelligence in Education: Supporting Learning through Intelligent and Socially Informed Technology*, in Frontiers in Artificial Intelligence and Applications, pages 33-40. IOS Press.

[14] Blanchard, E, & C. Frasson (2004) An autonomy-oriented system design for enhancement of learner’s motivation in e-learning. In J. C. Lester, R. M.Vicari, F. Paraguacu *Intelligent Tutoring Systems: 7th International Conference, ITS 2004*, Maceio, Alagoas, Brazil, Springer Lecture Notes in Computer Science 3220, pp 34-44, Springer.

[15] Beal, C.R. and H. Lee (2005) Creating a pedagogical model that uses student self reports of motivation and mood to adapt ITS instruction. Workshop on Motivation and Affect in Educational Software, at AIED2005, 12th International Conference on Artificial Intelligence in Education, Amsterdam, pp 39-46.

[16] Eccles, J. S. and A. Wigfield (2002). "Motivational beliefs, values, and goals" *Annual Review Psychology* **53**: 109-132.

[17] Yusoff, M.Z. and B. du Boulay (2005) Integrating domian-independent strategies into an emotionally sound affective framework for an intelligent tutoring system. In *Proceedings of the Symposium on Agents that Want and Like: Motivational and Emotional Roots of Cognition and Action, at AISB'05:*, University of Hertfordshire, pages 114-117.

[18] Wolters, C.A. and P.R. Pintrich (1998) Contextual differences in student motivation and self-regulated learning in mathematics, English, and social studies classrooms. *Instructional Science*, **26**, 27-47.

[19] Johnson, W. L., J. Rickel, et al. (2000). "Animated Pedagogical Agents: Face-to-Face Interaction in Interactive Learning Environments" *International Journal of Artificial Intelligence in Education* **11**: pp 47-78.