Motivational Diagnosis in ITSs: Collaborative, Reflective Self-Report

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Abstract. A central challenge in the design of motivationally intelligent tutoring systems lies in defining and diagnosing a learner's motivational state: in particular, in distinguishing between the learner's motivational and affective states. We discuss existing AIED approaches and outline an alternative approach that incorporates reflective peer collaboration. The paper raises questions about the basis for the design of motivationally intelligent tutoring systems.

Introduction

Motivation can be broadly defined as the force behind action that explains why a person acts in a particular way. It is a multi-faceted construct that is determined by many factors [1]. However, there is no overarching theory on how the different elements of motivation interact. Motivation research is also still at early stages in terms of our understanding of how motivation impacts the learning *process* and how tutors and school environments can foster a constructive motivational state.

A motivationally intelligent tutoring system must be able to diagnose and model a learner's motivational state accurately, and react to it in a constructive way. A first step in the design of such a system requires a basis on which the diagnosis of the learner's motivational state can be made. We focus on this aspect of system design. First we discuss the distinction between motivation and affect, as the two have not always been clearly distinguished in existing AIED systems. Then we examine how motivation has been defined in AIED systems and what information is used to diagnose the learners' motivational state. An alternative approach incorporating peer collaboration is outlined.

1. Motivation and Affect

Motivation and affect are closely intertwined in a bidirectional relationship. For example, if I perform well on an exam, I am likely to feel positive, which in turn is likely to increase my motivation to study for the next exam, which is likely to lead to a high outcome. However, it is important to distinguish between the two, as a positive affective state is neither necessary nor sufficient for high motivation and learning. The learning process may involve and even require negative affective states (for example, the frustration associated with problem-solving). It is the learner's motivation (e.g. via task value) that will determine how they react to those states (e.g. whether and how hard they persevere). Moreover, a positive affective state does not necessarily imply that a learner will be motivated to engage in increasing their competence; they may be content with avoiding comparison to others.

A system that can detect and react to a learner's affective state is not necessarily motivationally intelligent. For example, a learner who is anxious may be helped by the system reacting to the affective state, e.g. through reassurance, but if the anxiety is due to low self-efficacy then the impact of the reassurance may be temporary. That is not to say that a positive affective state is not beneficial. A motivationally intelligent tutoring system must also be affectively intelligent. But it must go beyond that. It must be able to diagnose the nature of the learner's engagement, e.g. their value of the task.

2. Motivational Diagnosis in AIED Systems

A fundamental issue in the design of motivationally intelligent tutoring systems is how motivation is conceptualised. Some specify the components of motivation on which diagnosis is based, which they derive from theory [2, 3]. For example, Pintrich [1] identifies three motivational components that are present across motivational theories (though the conceptualisation of each varies): beliefs about one's ability to perform a task (*expectancy* component), beliefs about the value of the task (*value* component), and affective reactions to the task (*affective* component). However, much research is based on a looser definition of motivation in terms of engagement and terms such as learner goals and attitudes are not defined in detail. For example, AutoTutor [4] focuses on the learner's affective state, but there appears to be an implicit definition of motivation in terms of engagement (without a clear separation of affect and motivation): "the other essential component is to build mechanisms that empower AutoTutor to intelligently respond to these emotions, as well as to their state of cognition, motivation, social sensitivity, and so on. In essence, how can an affect-sensitive AutoTutor respond to the learner in a fashion that optimizes learning and engagement?" ([4] p.37). Arroyo and Woolf [5] state that their approach "merges motivation, learning, and misuse of tutoring systems in one single Bayesian model" (p.33). However, they do not provide a definition of motivation, and the questionnaire instrument they used to diagnose learners' motivation and attitudes includes generic questions that reflect many components to learners' motivation. For example, "I just wanted to get the session over with, so I went as fast as possible without paying much attention". A learner might have agreed because she lacked confidence in her abilities and wanted to avoid performing poorly, but also because she found it boring.

There is also an implicit assumption about the connection between affect and motivation. For example, in AutoTutor [4] it is assumed that once the learner is in a negative affective state, such as frustration, she is unmotivated. The system appears to seek to react to negative affective states by trying to change them to positive ones through increasing engagement or challenge. There is no reference to the motivational state of the learner, which will determine how they react to those negative states and to what extent they will be engaged in learning.

A similar criticism also applies to the implicit consideration of motivation in OCC theory [6], which has formed the basis of much ITS research. The learner is assumed to be motivated to achieve a set of goals. However, it does not take into account variables relating to the nature of these goals which are important in the learning process. In some contexts (e.g. [7]) a learner may well have well-defined goals, such as to win a game. But in a more general context of learning with tutoring systems, a learner's motivation to engage with the system requires a more complex definition. A second issue is what information is used in order to make a diagnosis about the learner's motivational state. The above approaches have included interactional data and physiological and behavioural indicators of the learner's affective state. The approach by Arroyo and Woolf [5] raises questions about the reliability of the diagnosis of the learner's attitudes based on self-report at a single point in time. Many of the components of motivation may not be stable within a session [8].

3. Collaborative Reflection on Motivational State

The proposed system will be designed to support learning statistics in social science domains. It will take input from two computers and be used by pairs of learners. The motivational diagnosis of the system will be based on self-report, but the reported value of a particular motivational component for each learner will reflect both learners' assessment. Therefore, learners will need to agree on their report, as appropriate reflections of their motivational states. A question that arises from this approach is the extent to which it will be possible for learners to reach consensus. Note that we are not implying that both learners will be required to report a single, shared state of motivation, but they will need to agree on how each of their states is reported. This framework also allows for a different approach in the system's reaction to its motivational diagnosis. Many researchers conceptualise this in terms of what the system should "do" in order to improve the motivational state of the learner. Perhaps a more productive approach lies in assisting the learner to understand their own motivational state better and some of the factors that affect that state.

References

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