

# Visualization of Student Activity Patterns within Intelligent Tutoring Systems

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**Abstract.** Novel and simplified methods for determining low-level states of student behavior and predicting affective states enable tutors to better respond to students. The Many Eyes Word Tree graphics is used to understand and analyze sequential patterns of student states, categorizing raw quantitative indicators into a limited number of discrete sates. Used in combination with sensor predictors, we demonstrate that a combination of features, automatic pattern discovery and feature selection algorithms can predict and trace higher-level states (emotion) and inform more effective real-time tutor interventions.

**Keywords:** user modeling; pattern discovery; student emotion; engagement; regression; data analysis.

## Introduction

Tutoring systems have demonstrated effective learning over large amounts of students in classrooms in public schools [1][2][3], and some studies have shown evidence that the adaptive nature of tutoring systems is responsible for higher learning rates [4]. However, even the most effective tutoring system will fail if the student's behavior is not receptive to the material being presented. For example, disengagement has been shown empirically to correlate with a decrease in learning rate [4]. In addition, students often use tutors ineffectively, e.g., deliberately entering incorrect answers to elicit hints and, eventually, the correct answer from the tutor [4]. Although individualized learning provided by tutoring systems has shown to be beneficial overall, its effectiveness might be increased if maladaptive student behaviors could be identified and modeled, as well as higher level states such as student affect and engagement.

In the real situation of students using software in a public school, where the use of the software may not be even optional to them, very noisy data (about students' knowledge and emotion) might be collected. Trying to discern student behaviors that are likely to be unproductive in the long term and the reasons for those behaviors has significant potential for tutor intervention. Recent research has utilized dynamic assessment of students' performance to enhance the effectiveness of their tutor sessions [4]. Previous methods for examining behavioral trends have focused on behaviors correlated to specific outcomes assuming that students have completed their

activities, e.g., correlating engagement (e.g. fluctuations in attention, etc.) with successful and unsuccessful problem solving [3].

Many research groups use physiological sensors for posture detection to increase the “bandwidth” with the student (e.g. [D’Mello] [Cooper]) and being able to predict and trace their emotions better. While the use of sensors has been successful at improving the prediction of affective states, they are hard to deploy in real-life situations in schools, particularly for a full set of sensors. Using tutor data (e.g., *incorrect attempts*, etc.) in combination with self-reports of student emotions has the potential advantage of eliminating the need for labeling.

Also, if a low lever engagement state has a definable intervention, there is a possibility of intervening at a low level (engagement level) as well as at a high level (student emotion level). In addition, defining new interaction features can help in the prediction of students’ emotional state better, and reduce the need for sensors. Additionally, combining low and high level states provides rich information on potential interventions. For instance, a *gaming state* correlated to *high frustration* as this may indicate the need for a different intervention than *gaming with boredom*.

The goal of this research is to evaluate a practical and efficient methodology to find engagement states and pattern-based state features to help understand low-level engagement and how it relates to student higher level affective states.

This current work refines previous work in inferring and predicting student behavioral state based on tutor data. The process is a variation and an extension of time-based motif discovery [7] in student behaviors, now used for the prediction of emotional states.

We analyze tutor metrics in a manner that provides a minimal number of low-level states of engagement with a tutor activity. By choosing a limited set of well-defined states of engagement, we support implementation of interventions based on the occurrence of these low-level states, as well as on the occurrence of higher level states that may tap on the causes for the lower level engagement states to occur.



**Figure 1.** Sensors used in classrooms to detect student emotion; (clockwise) mental state camera, skin conductance bracelet, pressure sensitive mouse, and posture sensitive chair.

## Relevant Literature

Prior research has used data mining to discover patterns in the problem states that defined student behavior [8][9]. One of those studies began the process of categorizing raw problem metrics regarding time on task, accuracy and help received into more meaningful categories, or states [1][10]. Motif discovery was used to find

engagement patterns in windows of 10 student-problem interactions. These patterns could then be used to define new student behavior states. Limitations of this work were the difficulty of defining meaning to the patterns; redundancies among the states and the lack of clear meaning of some of the binning categories. Attempts to view the data visually were also difficult due to the large number of states.

**Modeling Emotions.** Prior research has also examined the relationship(s) between student emotion (e.g., *frustration, confusion, boredom, interest, confidence*) and students' relation to learning in mathematics, i.e., to identify whether a dependency exists between students' reported emotions and their learning of, motivation for, and attitudes toward mathematics [4]. These predictions of student emotion are informed directly from sensors, see Figure 1 and from emotion models [2, 3, 4]. For example, sensors were deployed in public schools, as students used tutoring systems. Data were gathered, summarized and synchronized to the software use, and helped in the prediction of student self reports of emotional states. In data analysis time, these sensorial input was summarized as average trends over the short lapses of time of a student-problem interaction, and used in combination with raw tutor metrics as features to feed a linear regression procedure that generated a linear model that would predict a student's subsequent self-report of emotions.

**Characterization of Emotion.** Past research has shown that students' self-report of emotion depends on events that occurred in the previous problem as well as on their incoming beliefs [5]. That research showed how fluctuating student emotions are related to what has just happened in the tutor, i.e. to the "context." In turn, fluctuating student reports on emotion were related to longer-term affective variables (e.g., value mathematics and self-concept) and these latter variables, in turn, are known to predict long-term success in mathematics [19].

**Characterization of Engagement.** Several models have been proposed to model engagement or disengagement. A latent response model [2] learned to classify student gaming the system and included gaming with no impact on pretest-posttest gain and gaming with a negative impact on pretest-posttest gain. The model features consisted of a student's actions in the tutor, and probabilistic information of student's latent skills. Beck [4] proposed a function relating response time to the probability of a correct response to model student disengagement in a reading tutor. The learned model showed that disengagement negatively correlated with performance gain. These models embody different assumptions about the variables required to estimate student motivation.

Guided by the findings reported from the literature, discussed above, our method examines student interaction with the tutor during problem solving. However, rather than looking at short-term behaviors over the lapse of one problem and relating it with higher level latent states or outcomes (e.g. emotions, mastery), we examine frequent behavioral patterns over several problems, and their predictive power of higher level affective states. The next sections describes this methodology.

## The Tutor and the Student Data

**The Tutor.** The data comes from students working with a Mathematics Tutor, an adaptive tutoring system that helps students learn to solve standardized-test questions, in particular state-based exams taken at the end of high school in the USA. This multimedia tutoring system teaches students how to solve geometry, statistics and algebra problems. Students are provided immediate feedback when they click on an answer (a check for correct or a cross for incorrect). Students may click on a help button for hints, and teachers/researchers encourage them to do so as many times as necessary, as hints are displayed in a progression from general suggestions to bottom-out solution. To answer problems in the Mathematics Tutor interface, students choose a solution from a list of multiple-choice options.

**The Data.** An empirical evaluation was conducted involving 295 high school students from a variety of classes in public high schools during Spring 2009. Students came to the computer lab to use the Mathematics Tutor for about a week, one-hour periods approximately, instead of their regular math class. Students went through various topics such as expressions with variables, perimeter, triangles, equations, etc. Every 5 minutes, and at the end of a math problem (no interruption), students were asked how they were feeling, which they reported in a continuous scale (1 to 5).

## Methodology

While previous research used this same method of discrete categorization, the advantages of eliminating all but the most important seven states became apparent in our current attempts to visually analyze time-based patterns of student states, see Figure 2. This visualization clarified the analysis to the point where the results were informative. The use of descriptive graphics described in this section, enabled us to quickly gain an understanding of high-level student states patterns, before using more traditional qualitative methods to describe student behavior state

During the **Data Pre-processing Phase**, the raw tutor data (on a per problem basis) is binned according to an exhaustive classification of “student-activity” interactions, or “student-problem” interactions, see Table 1. A variety of typical behavioral “states” are determined (e.g., student is *not reading the problem* --NOTR, or *solving a problem after hints are seen* --SHINT). These states are mutually exclusive, so that each student-problem interaction is classified as a single state. For example, an original problem metric, `timeToFirstAttempt` was used as a continuous predictor. But it produced a highly skewed distribution with a large number of values less than five seconds; a length of time insufficient to even read the problem [12]. While we don’t have a clear understanding the implications of `time_to_first_attempt` in a normal range, i.e., the significance of a student taking 20 seconds versus 45 seconds, we can clearly attempt interventions knowing the student attempted to answer before reading the problem. We categorize this as not reading (NOTR) problem state without regard for the other problem metrics.

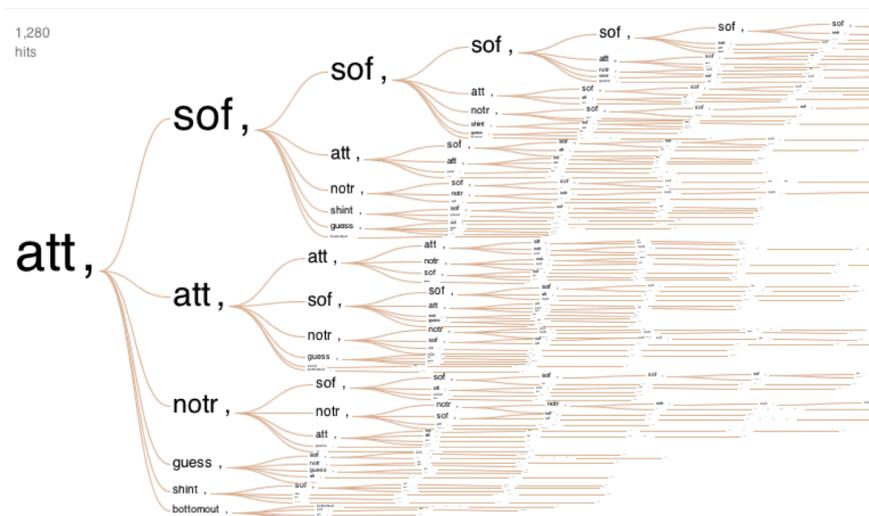
SOF categorizes all problems that are solved on first attempt without invoking help; this indicates content level is too low. BOTT implies gaming and the intervention could prevent this by not providing bottom out solution. GIVEUP indicates user and problem difficulty would be decreased. ATT indicates a student working on-task at an appropriate level; support provided to ensure continued success. SHINT similar to ATT but no support needed. GUESS indicates the student needs either help or lower problem difficulty. These states are mutually exclusive checked in this order. All of the students' problem states were sorted by student and time, resulting in a **35,000 problem state string** sequence representing the tutor interactions of 295 students across multiple sessions and schools.

State	Description	Possible intervention
NOTR	Not enough time to read the problem, before an action is taken.	Decrease problem difficulty, read problem aloud, invoke help/hints.
SOF	Solved on first attempt without help.	Increase problem difficulty.
BOTT	Getting answer from hints or help. Possibly seeing problem as example.	Show a very similar problem to the previous one, to facilitate transfer.
GIVEUP	Moved on before answering.	Decrease problem difficulty.
ATT	Answered after 1-2 incorrect attempts and self-corrected, without help.	Show student the full solution to the problem, after correct answer is entered.
SHINT	Answered with help, without guessing possible solved on first attempt	On task behavior, no intervention necessary.
GUESS	Guess answer after several attempts	Short-answer mode in next question.

**Table 1.** Student states that will be analyzed, with possible tutor interventions

During the **Pattern-Analysis stage**, a descriptive graphics tool is used to quickly gain an understanding of patterns. Discrete states were initially viewed using the IBM's Many Eyes Word Tree algorithm,<sup>1</sup> Figure 2. A word tree is typically used as a method for graphically summarizing text, for example gaining insight into a famous speech by viewing the word sequences and their frequency. We used the algorithm in a different way, with the student's states in sequential order. The algorithm allowed us to quickly discover the most frequent patterns of behavior and to quickly understand the frequency of proceeding and subsequent patterns of interactions (what state is most likely after another state, and which one after that, etc.). Figure 2 shows the total 1280 ATT (*attempted and solved with help*) events. Most frequently ATT was followed by a SOF event (see top tree). The second level of the tree shows that the sequence ATT ATT the highest frequent event changes to the ATT event, i.e. the shift in behavior occurs after two ATT states (see second tree and top branch). This indicates the ATT state is more often a solitary event, where the ATT ATT pattern will continue in the ATT state. Thus, from the analysis the most frequent 3 problem state patterns (e.g. NOTR-NOTR-NOTR) are determined (see third tree and second branch).

<sup>1</sup> Many Eyes Word Tree algorithm is freely available from [www-958.ibm.com/](http://www-958.ibm.com/).



**Figure 2.** Many Eyes shows student multi-state experiences within the tutoring system.

The last stage is the **Feature Selection and Model Building Stage**, in which we identify the benefit of these state-classifications and patterns over the prediction of a higher level emotional state (e.g. *frustrated?*) particularly in comparison to raw descriptors we were using before, such as *attempts* and *time on task*, and also in comparison to the sensorial data input. Can patterns compete with the predictive power that sensors bring to the prediction of emotions? To answer these questions, we produced: 1) 7 binary features or variables for each interaction, to potentially be used for the prediction of a future state, called **LastState**, or simply ‘**S**’ (e.g. ATT=true, NOTR=false, etc.); and 2) 14 binary variables corresponding to the most frequent state patterns (2 starting with each state), and we call this set of features **3-StatePatterns**, or simply ‘**3S**’ (e.g. ATT\_ATT\_SOF = true, meaning that the student solved the last problem on the first attempt, and made a mistake but corrected himself in the previous two). Thus, at this point, each student-problem interaction row has associated with it: a) variables for raw descriptors of the interaction with that problem (e.g. hints seen = 2, time spent = 2 minutes, incorrect attempts = 0); b) a state-based classification of the interaction (S); c) fourteen (14) binary variables for the presence or absence of the most common patterns (3S) during the last 3 problems seen.

We analyzed whether these new variables/features help in the prediction of higher level emotional states; in particular, we evaluated the contribution of adding or removing these S states triplet-motifs (3S) in the prediction of a higher level state at time  $t$ , where the motifs describe tutor activities at time  $t-1$ ,  $t-2$  and  $t-3$ .

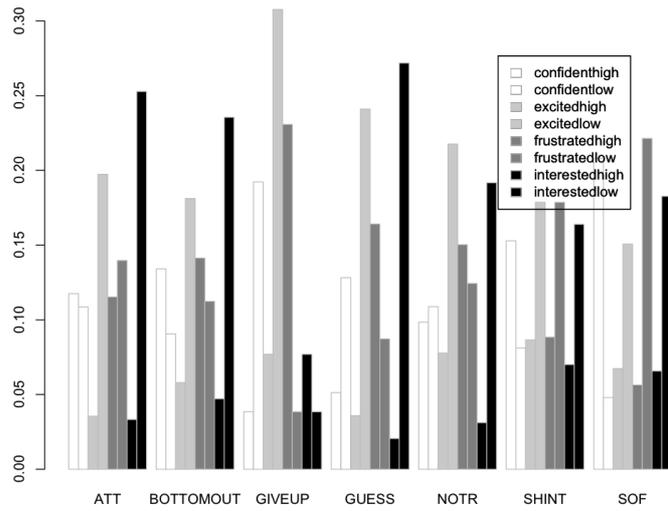


Figure 3. Relationship between States and Emotions

	Last Problem Raw Features	Last State	Last Problem RAW Features + Last State	Last State + 3-state Patterns	Last Problem RAW Features + Last State + 3-state Patterns	N
<b>No Sensors</b>	IncAttempts, HintsSeen, LC	SOF, GUESS, LC, SHINT, GIVEUP	IncAttempts, SOF, LC, HintsSeen, GIVEUP	SOF, GUESS, LC, SHINT, SHINT_SOF_SOF, SOF_SOF_ATT, ATT_ATT_ATT	IncAttempts, SOF, LC, HintsSeen, GIVEUP, ATT_ATT_ATT, NOTR	908
<b>Camera</b>	IncAttempts, HintsSeen, thinkingMean, concentratingStDev	SOF, concentratingMin, thinkingMean, GUESS	IncAttempts, HintsSeen, thinkingMean, concentratingStDev	SOF, concentratingMin, thinkingMean, GUESS	IncAttempts, HintsSeen, thinkingMean, concentratingStDev	307
<b>Seat</b>	IncAttempts, HintsSeen, sitForwardMin	SOF, sitForwardMin, GUESS	IncAttempts, SOF, sitForwardMin	SOF, sitForwardMin, SHINT_SOF_SOF, GUESS, ATT_ATT_ATT	IncAttempts, SOF, sitForwardMin, ATT_ATT_ATT, HintsSeen	463
<b>Mouse</b>	IncAttempts, EMPATHIC, probElapsed, mouseMin, LC, mouseMax	SOF, EMPATHIC, mouseMax, mouseMin	IncAttempts, EMPATHIC, SOF, mouseMax, mouseMin, LC, probElapsed	SOF, SHINT_SOF_SOF, EMPATHIC, mouseMax, mouseMin	IncAttempts, EMPATHIC, SOF, mouseMax, NOTR_NOTR_NOTR, mouseMin, SHINT_SOF_SOF	296
<b>Wrist</b>	IncAttempts, HintsSeen, wristConductanceMin	SOF	IncAttempts, Hint wristConductanceMin	SOF	IncAttempts, Hintsen, wristConductanceMin	124

Table 2. Predicting CONFIDENCE: Features Selected by Stepwise Regression

## Results

Stepwise regression was used to select relevant features and construct a linear model of a students' reported emotion. Stepwise Regression builds a model, reports its fit in an R value, and selects the features that are most useful, discarding others. For each of the two emotional variables (CONFIDENCE and FRUSTRATION) several results are provided. Tables 2 - 3 summarize the features that significantly help in the prediction of each emotion, with and without sensors. Table 4 shows the fit of each model and how the progression of adding more variables (e.g., raw + state variables) allows for a better fit.

The baseline is the kind of model constructed in our earlier work [13], where only raw variables that summarize behavior on the most recent problem are used (first column of Tables 2-3). In the case of confidence, results suggest that adding states and patterns of states contribute to a better prediction of the emotion. For instance, when sensors are not present (first column), the best raw predictors of confidence are incorrect attempts, hints seen in the last problem, and the presence of a learning companion. When adding the higher level states over the last problem, *solved on first attempt* (SOF) helps to predict some more variance, suggesting that when no sensors are present, states and 3-state-patterns are important predictors. Similar results were found for the subset of student data that had physiological sensors available. For instance, the fit of models (R values) improve for students who had seat and mouse data available. Similar results for frustration (Table 3) suggest that, when sensors are not present, adding states and state-patterns contributes to a better prediction of frustration. While incorrect attempts over the last problem keeps being important, as well as hints seen and the presence of the female character, a variety of other states over the last problem (SOF, GIVEUP, SHINT) are important predictors, and SOF\_SOF\_ATT in particular. A cross-validation revealed small gains in accuracy for the more sophisticated state-based models, ranging from 1%-5% improvement in

	Last Problem Raw Features	Last Problem State	Last Problem Raw Features + State Features	Last State & Last 3 States	Last Problem Features + Last 3 problem States	N
No Sensors	IncorrectAttempts, HintsSeen, JANE, JAKE	SOF, GUESS, GIVEUP, SHINT, LC	IncorrectAttempts, SOF, HintsSeen, GIVEUP, JANE, SHINT	SOF, GUESS, GIVEUP, JANE, ATT_ATT_ATT, ATT_SOF_SOF, SHINT, SOF_SOF_ATT	IncorrectAttempts, SOF, HintsSeen, GIVEUP, JANE, SHINT, SOF_SOF_ATT	1024
Camera	IncorrectAttempts, HintsSeen, JANE, interestedMin	SOF, SHINT, JANE, GUESS	IncorrectAttempts, HintsSeen, NOTR, JANE, interestedMin	SOF, SHINT, JANE, GUESS	IncorrectAttempts, HintsSeen, NOTR, JANE, interestedMin	351
Seat	IncorrectAttempts, HintsSeen, netbackchangeMax, LC	SOF, netbackchangeMax, SHINT, GUESS, LC	IncorrectAttempts, HintsSeen, netbackchangeMax, NOTR, LC, GIVEUP	SOF, netbackchangeMax, SHINT, GUESS, SOF_SOF_ATT, JANE, NOTR_SOF_SOF	IncorrectAttempts, HintsSeen, netbackchangeMax, NOTR, LC, GIVEUP, GUESS_NOTR_NOTR	527
Mouse	IncorrectAttempts, mouseMax, HintsSeen	SOF, mouseMax, GUESS	IncorrectAttempts, mouseMax, HintsSeen	SOF, mouseMax, GUESS	IncorrectAttempts, mouseMax, HintsSeen	326
Wrist	HintsSeen, IncorrectAttempts	SOF, BOTT	HintsSeen, IncorrectAttempts, NOTR	SOF, SOF_SOF_ATT, SHINT	HintsSeen, IncorrectAttempts, NOTR, SOF_SOF_ATT	144

Table 3: Predicting FRUSTRATION: Features Selected by Stepwise Regression

overall accuracy, and 3-10% better prediction of the remaining unpredicted cases, compared to the baseline models in column 2, *last problem raw features*. While this is not a large improvement in accuracy, making the models more interpretable is an extra advantage.

**Relationship between States and Emotions.** Using descriptive statistics and correlations we analyzed the relationships of the problem states and emotions, see Figure 3. Reading the result for SOF (right), this state correlates to low confidence, low excitement, low frustration, and low interest and reaffirms our definition as indicating a student working on problems below their level. *Guessing* (center) significantly correlates and helps to predict low confidence, low excitement, high frustration and very low interest; such emotional states in expected in a student in a unengaged state. The Pearson Chi-Square test for independence shows statistical significance with the CramerV 0.116.

	RW	S	RW+S	S+3S	RW+S+3S
No Sensors	0.39/ 0.39	0.32/ 0.34	0.41/ 0.42	0.34/ 0.37	0.42/ 0.43
+ Camera Data	0.40/ 0.46	0.37/ 0.41	0.40/ 0.48	0.37/ 0.41	0.40/ 0.48
+ Seat Data	0.39/ 0.47	0.31/ 0.43	0.39/ 0.50	0.34/ 0.45	0.41/ 0.51
+ Mouse Data	0.41/ 0.41	0.35/ 0.33	0.42/ 0.41	0.38/ 0.33	0.44/ 0.41
+ Wrist Data	0.55/ 0.42	0.41/ 0.37	0.55/ 0.46	0.41/ 0.43	0.55/ 0.48

Table 4. R Values for the prediction of CONFIDENCE/ or FRUSTRATION

R Values are for CONFIDENCE and then FRUSTRATION; all numbers are over the last problem except for the last two columns, which are over the last three problems. RW = raw variables only; S = state variables only; RW + S = Raw + state variables; S + 3S = state variables only and patterns over last 3 problems; RW + S + 3S = Raw + state variables over the last problem and triplet-problem pattern variables.

## Discussion and Future Work

We described a data-driven approach toward automatic prediction of students' emotional states without sensors and while students are still actively engaged in their learning. We created models from students' ongoing behavior, e.g., we showed in the case of both student confidence and frustration that adding behavioral states and patterns of states contribute to a better prediction of the emotion. A cross-validation revealed small gains in accuracy for the more sophisticated state-based models and better predictions of the remaining unpredicted cases, compared to the baseline models. An important opportunity exists for tutoring systems to optimize not only learning, but also long-term attitudes related to students' emotions while using software. By modifying the "context" of the tutoring system including students' perceived emotion around mathematics, a tutor can now optimize and improve their mathematics attitudes.

A variety of changes can be made that might improve the predictive power of models. For instance, we chose the two most frequent triplet patterns starting with a specific state. It is possible that rare patterns work better at predicting some emotions, particularly rare ones (for instance, we did not present results for boredom or excitement because students have sort of a floor effect on those emotions, thinking that math is always boring and unexciting, even at pretest time). Also, it is unclear that the order matters (e.g. ATT\_SOF\_SOF might really be equivalent to SOF\_ATT\_SOF). While we were considering permutations of states in each of these

triplets, it would be interesting to try combinations instead, regardless of order (eg. 2SOF+ATT) for the alternative feature states. Last, it is unclear if we need to look at the last 3 emotions, or the first 2 (for  $s_{t-3}$  and  $s_{t-2}$ ), as the last problem state ( $s_{t-1}$ ) is considered separately.

After highly accurate states have been found, future work consists of refining emotion models to predict desirable and undesirable learning states and attitudes. The outcome of the current study will be used to respond with interventions, and respond based on different levels of assessment of engagement and emotions combined.

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