

Transitions of Affective States in an Intelligent Tutoring System

Thea Faye G. Guia¹
theafayeguia@yahoo.com

Ma. Mercedes T. Rodrigo¹
mrodrigo@ateneo.edu

Michelle Marie C. Dagami¹
rhyzz_craig_08@yahoo.com

Jessica O. Sugay¹
jsugay@ateneo.edu

Francis Jan P. Macam¹
f_macam@yahoo.com

Antonija Mitrovic²
tanja.mitrovic@canterbury.ac.nz

ABSTRACT

This paper aims to determine the natural transitions that take place among students' affective states while using SQL-Tutor, a constraint-based intelligent tutor that teaches Structured Query Language (SQL). Intelligent tutoring systems, such as SQL-Tutor, have been used by various institutions to overcome the difficulties of students in learning difficult subject matter. In this paper, the researchers intend to determine how an affective state at a given time influences the affective state at a later time. Likely transitions of affective states were mined from the observation files gathered from students during interaction with the tutor. The researchers were able to identify several affective transitions that were unlikely to occur. Identifying these natural transitions is a stepping stone towards designing interventions that might help sustain desirable affective states, encourage productive affective transitions and mitigate states and transitions that may be deemed detrimental to learning.

Keywords

SQL-Tutor, constraint-based tutors, observation files, affective states, affective transitions.

1. INTRODUCTION

An Intelligent Tutoring System (ITS) is a subtype of computer-based learning systems that supplements teaching effectiveness through application of artificial intelligence [2]. In corroboration with its goal of engaging students in cognitive tasks and adapting to students' behavior [1], ITSs improve teaching by equipping students with guided learning support during problem solving activities.

For many years, researches explored different ITSs' support for cognition. Recently, these studies have extended into detecting and modeling learner behaviors [2-4] and affective states [5, 6]. The present paper will specifically explore the relationship between affect and learning within a constraint-based tutor.

Previous researches have shown significant results that suggest affect is associated with cognition and learning. These studies found learning gains to have a positive correlation with confusion and flow, and a negative correlation with boredom [5, 6].

In recent years, studies have moved beyond examining these affective states in isolation, investigating instead student affective dynamics or the natural shifts or transitions among these states. In D'Mello et al.'s [7] exploration on students' affective trajectories during learning with AutoTutor, recorded videos of faces of

students and their interaction histories was used, and then played back for the participants to judge their own affective states. The researchers developed a metric L , to measure the relative likelihood of transitions from an initial affective state at a previous time to a subsequent affective state at a later time. Their finding is that there are transitions from the state of boredom into confusion, flow into frustration, and confusion into boredom.

Baker et al. in [8] analyzed the affective states and usage choices of students as an antecedent to affect within The Incredible Machine: Even More Contraptions, a non-affective simulation problem-solving environment. They conducted the analysis using D'Mello's transition likelihood metric, L [7]. They found that a student being in flow, boredom, confusion, frustration and delight, at a given time is likely to be in the same affective state a moment later. A state of surprise at a given time is not associated with being surprised after some time. These findings correspond with D'Mello et al.'s study [7].

In Rodrigo et al. [9], researchers analyzed whether motivational agents might have an effect on the affective states of students. The platforms used for these experiments were Ecolab and M-Ecolab, where the latter was a version of Ecolab with an agent. The results suggest that the motivationally-aware version of the ITS seems to maintain the delighted state of students over time. Boredom still persisted, which also agrees with Baker et al.'s findings in [10]. Likewise, a student who is frustrated is likely to remain frustrated. However, both versions of the software were also able to sustain flow. There were a number of factors to which the researchers attributed these patterns. The persistence of flow and the low incidence of boredom and frustration in the game environments suggested that the game elements would be highly engaging. Confronting the students with challenging problem solving situations could explain the persistence of confusion. The game-like elements in The Incredible Machine could also have prompted a greater emotional investment from the students, causing both positive and negative affective states to persist to a greater degree [10].

It is the purpose of the study to identify which affective states students exhibit during interaction with an ITS called the SQL-Tutor [11]. Of particular interest to us is to determine whether the pattern of persistence of states continues to exist in the dataset.

2. METHODS

The data used in this study were from the human coded observation files. Observation files were gathered through

classroom observation of undergraduate students during interaction with the learning environment, SQL-Tutor.

2.1 Population

Participants in this study are composed of sixty third-year BS Management Information Systems students from Ateneo de Manila University, Philippines. These participants are enrolled in the Introduction to Applications Development class, which requires knowledge in database programming, and thus the use of SQL. The students are randomly selected across three classes. The participants are asked to use SQL-Tutor for 60 minutes. None of the students had previously used SQL-Tutor.

2.2 SQL-Tutor

Constraint-based Tutors are based on a student modeling approach called Constraint-based Modeling that focuses on student errors [11] and aims to represent the domain knowledge by constraints on correct solution in that domain [12]. What distinguishes it from the typical ITS is that the constraint-based tutor aspires to overcome the complexity of the formal knowledge representation that ITSs researchers have inherited from the field of artificial intelligence. The knowledge representation of a typical ITS requires an overly detailed, accurate and specific student model since there are dozens or hundreds of individual knowledge elements. On the other hand, a constraint-based tutor uses an approach that simplifies and limits the specificity of this modeling process by making use of constraints [12]. Constraints are used to represent the tutor's domain knowledge, expert model and student model.

Previous studies have explored constraint-based tutors and successfully obtained extremely good experiences in various aspects such as student cognition and behavior. However, only preliminary research has been done on constraint-based tutors related to affect. The present paper would attempt to further explore student affect and its role in learning within constraint-based tutors.

Computer Science and Information Technology majors have Database Management Systems as one of their core courses. Since SQL is currently the dominant database language for querying relational databases and is an essential topic in introductory database courses in higher education [13], learning it should receive a significant amount of attention. Several studies have identified common problems that students encounter while learning SQL. These struggles are: burden of memorizing the database schema, misunderstanding of the basic elements of SQL, first order logic and the relational data model in general, the difficulty of the declarative nature of SQL for learners to grasp, and the possibility of incorrect perception of a query problem as being easy [13].

The students utilized SQL-Tutor, which was developed at the University of Canterbury in Christchurch, New Zealand, in 1996. This educational software is a knowledge-based teaching system which supports students learning SQL by intelligently and adaptively guiding students as they practice their database querying skills.

At the moment, the system covers only SELECT statement of SQL, but the same approach could be used with other statements. Students can obtain the descriptions of databases, tables or

attributes by selecting appropriate options from the Help menu, or by directly selecting table/attribute names (see Figure 1). The Help menu also provides descriptions of various clauses and elements of SQL such as function, expressions, predicates and operators.

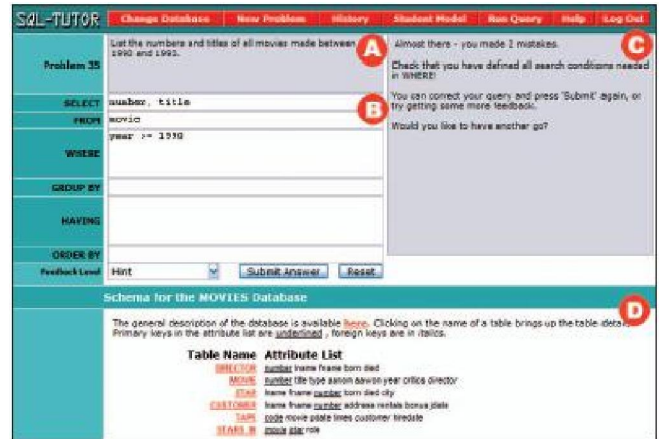


Fig. 1. A screenshot of SQL-Tutor with its parts: (A) problem text, (B) workspace for composing SQL queries, (C) feedback panel, and (D) database schema.

SQL-Tutor evaluates students' solutions by matching them with constraints. This software contains almost 700 constraints describing the fundamental principles that all solutions must satisfy.

2.3 Observation

Data regarding student affective states were collected through quantitative field observations similar to method used in [5, 14]. The observations were carried out by a team of four observers who worked in pairs. The observers are composed of two Master students and one Undergraduate student in Computer Science, and one assistant instructor, all of whom were co-authors of this paper. The assistant instructor was highly experienced in field observations, having participated in several such studies in the past. The two masters students and undergraduate student were members of the Ateneo Laboratory for the Learning Sciences who were in training for this type of fieldwork as it was related to their theses. A pre-observation discussion on the meaning of the affective categories was conducted to train the observers. Observations were conducted according to a guide that gave examples of actions, utterances, facial expressions, or body language that would imply an affective state, and practiced the coding categories during an unrelated observation prior to this study.

The affective categories coded are boredom, confusion, delight, surprise, frustration, flow and neutral. The definitions of these affective states are as follows [8, 10, 15]:

1. Boredom (BOR) – slouching, resting the chin on palm and yawning.
2. Confusion (CON) – asking the professor or classmate questions, frowning and wrinkling of the eyebrows, or scratching the head.

3. Delight (DEL) – smiling, laughing or any display of pleasure.
4. Surprise (SUR) – gasping or sudden raising of eyebrows, widening of eyes and opening of mouth.
5. Frustration (FRU) – banging the keyboard, swearing under breath and holding the head.
6. Flow (FLO) – intent reading and talking to self regarding the current activity, and typing SQL statements.
7. Neutral (N) – a student is away from keyboard, staring blankly at the screen and doing unrelated activities, or when the student displays an affect that could not be certainly determined by the observer.

The observers looked at facial expressions, gestures and utterances of students that imply these emotions. However, the ones enumerated are not precise and are considered to approximately indicate the present affective states of participants.

Each coder observed 10 students, working individually. Every student was observed for twenty seconds. A timer was placed at the far rear side of the classroom within the range of vision of observers to synchronize their coding. The observation was conducted using peripheral vision, which means the observers were standing diagonally behind or in front of the student being observed. Also, the observers occasionally took surreptitious glances at the students or their screens.

If two distinct affective states are seen during an observation, only the first was coded, and any behavior by a student other than the student currently being observed were not be coded. Each student was observed once per 200 seconds.

Some of the affective categories may not be mutually exclusive, though others clearly are. For tractability, however, the observers only coded one affective state per observation. Eighteen pairs of observations were collected per student. Interrater reliability computed using Cohen’s Kappa, a statistical measure that controls for the possibility that the two raters agreed by chance. A Kappa of 0 means that there was no agreement between raters. A Kappa of 1 means there was perfect agreement between raters. Cohen’s $\kappa=0.79$ for affect observations, which is considered to be a high level of agreement.

3. RESULTS

In computing the likelihood of an affective transition, it is important to take into account the base rates of each affective category. Frequencies of each affective state of students are outlined in Table 1. The base rates were computed by counting the number of times a student was observed exhibiting an affective state and dividing that number by the total number of observations. Each observation was considered independently. If two raters differed in an observation, each observation was essentially given half a credit.

Table 1. Base rates of each affective state in SQL-Tutor.

Affective State	Base Rates
Boredom	10.91%

Confusion	11.90%
Delight	2.88%
Flow	68.75%
Frustration	0.40%
Neutral	5.16%
Surprise	0.00%

Flow is the most common affective state displayed by students while using SQL-Tutor (68.75%). This finding is similar to previous experiments with other learning environments such as The Incredible Machine (61%) [15], Ecolab (61.5%) and M-Ecolab (67.4%) [9], and across three different ITSs (60%) studied in [10]. The second most frequent affective state was Confusion (11.9%), which is followed by Boredom (10.91%). Meanwhile, frustration was coded very rarely (0.4%). The state of surprise was never coded during the classroom observation.

More than how common each affective state is, it is important for the metric to consider the temporal relationship between states. For this study, the researchers adopted D’Mello’s transition likelihood metric L , as used in [7-10]. L is statistically equivalent to Cohen’s κ . It gives the probability that a transition between two affective states will occur, given the base frequency of the destination state. It is computed as:

$$L = \frac{\Pr(\text{NEXT} | \text{PREV}) - \Pr(\text{NEXT})}{1 - \Pr(\text{NEXT})}$$

The value of L is scaled between 1 and $-\infty$. A value of 1 signifies that the transition will always occur. Meanwhile, a value of 0 signifies that the likelihood of the transition is equivalent to what it would be given only the base frequency of the destination state.

The researchers found nine statistically significant and one marginally significant less likely affective states transitions. A full table of affective transitions within SQL-Tutor is given in Table 2. Frustration transitioning to any affective state is omitted from the table because it was too rare to produce a statistically detectible result.

Results showed that students who are experiencing boredom have a significantly less likely than chance to transition to frustration ($t(20)=-1.03$; $p<0.001$) and neutral state ($t(20)=-3.51$; $p<0.001$). Students who are initially confused also have a significant less likely than chance to be frustrated ($t(17)=-9.47$; $p<0.001$) and neutral ($t(17)=-1.62$; $p<0.001$), and a marginally significant less likely than chance to be in flow ($t(17)=-1.76$; $p=0.09$) later. Meanwhile, students who are experiencing delight are unlikely to transition into confusion ($t(9)=-1.46$; $p<0.001$) and neutral state ($t(9)=-2.35$; $p<0.001$). Experience of flow by students is also unlikely to transition to neutral ($t(28)=-2.33$; $p=0.02$). Lastly, students who are in neutral state have a significantly less likely than chance to transition to affective states of delight ($t(8)=-2.41$; $p<0.001$) and frustration ($t(8)=-6.50$; $p<0.001$).

Table 2. Affective Transitions within SQL-Tutor. First row titles are antecedent affective states while first column titles are subsequent affective states. The first number in each cell represents mean of D’Mello’s *L* while the number in parentheses represents standard deviation. Statistically significant relationships are shaded in dark gray and marginally significant relationships are in light gray.

	BOR	CON	DEL	FLO	FRU	N
BOR	0.105 (0.29)	-0.060 (0.19)	0.012 (0.10)	0.011 (1.07)	-0.004 (0.00)	-0.054 (0.00)
CON	0.173 (0.43)	0.060 (0.29)	0.021 (0.14)	-0.548 (1.28)	-0.004 (0.00)	-0.054 (0.00)
DEL	0.231 (0.45)	-0.135 (0.00)	0.054 (0.16)	-0.268 (1.28)	-0.004 (0.00)	-0.054 (0.00)
FLO	-0.027 (0.11)	0.023 (0.24)	-0.006 (0.06)	0.138 (0.75)	-0.00 (0.02)	-0.034 (0.08)
N	-0.036 (0.30)	-0.026 (0.31)	-0.030 (0.00)	-0.292 (1.28)	-0.004 (0.00)	0.189 (0.32)

Previous studies reported the persistence of affective states over time. One of which is Baker et al.’s study [10]. Specifically, they studied the incidence, persistence and impact of students’ affective states while using three different learning environments: Aplusix, AutoTutor and The Incredible Machine: Even More Contraptions. They computed for the persistence of states using D’Mello’s *L*. The results in their study indicate different overall degrees of persistence of different affective states. Boredom was identified as the most persistent affective state within the three ITSs: AutoTutor (mean $L=0.13$, $t(27)=4.17$, $p<0.001$), The Incredible Machine (mean $L=0.26$, $t(7)=2.27$, $p=0.06$) and Aplusix (mean $L=0.21$, $t(38)=3.69$, $p<0.01$). Given boredom’s persistence in all contexts previously studied [10], boredom came closest to being a non-transitory “mood”—an affective state that tends to persist over long periods. Moreover, Baker et al. were able to find four other affective states that showed persistence within at least two ITSs: confusion and engaged concentration within AutoTutor and The Incredible Machine, frustration within Aplusix and AutoTutor, and delight within The Incredible Machine and Aplusix.

Contrary to the findings by previous study, the results of this experiment did not show any persistence of affective states. This might be explained in part by individual differences among the participants in the studies. Differences in age might be a factor. The students using the SQL-Tutor are in third year college. The Aplusix and Incredible Machine participants were in first year high school. Emotions displayed and the actions performed by students can be affected by age. Changes in emotion are age-related. The degree of emotional expressivity is generally higher in younger people than older people [16].

Cultural differences might also have had an impact on the participants’ expressivity. In Filipino culture, there is a premium placed on avoiding outward signs of conflict. People are expected to behave in a socially acceptable fashion and maintain smooth interpersonal relationships [17]. In the United States, where the AutoTutor test was conducted, independence is valued above obedience [18]. Hence, Filipinos have a greater tendency to maintain at least a façade of civility and conformity.

4. CONCLUSION

Flow was the most common affective state displayed by students during interaction with SQL-Tutor. From the analysis, the researchers found nine statistically significant less likely affective transitions: boredom to frustration and neutral, confusion to frustration and neutral, delight to confusion and neutral, flow to neutral, and neutral to delight and frustration. These findings suggest that students frequently shift from one affective state to another while interacting with SQL-Tutor. The results are showing that many of the students’ antecedent affect are unlikely to lead to states of frustration and neutral over time.

Based on the results, we have seen that the pattern of persisting affective states does not appear in our data. We consider age differences as well as cultural differences among the factors that might account for the variations between our findings and those of previous similar work.

Identifying the affective transitions might help the developers of ITSs, constraint-based tutors in particular, in further improving the system architecture. Probably by altering the tutor’s pedagogical strategies, the ITS might lead students to more positive affective states and hence enhance performance. Furthermore, such constraint-based tutors might apply affect-based interventions to students that can help them in transitioning into a more desirable affective state. The differences between our findings and those from previous similar studies, however, suggest that the affective states students experience might be more heavily influenced by individual differences than we had originally thought (Ryan Baker, personal communications).

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6. REFERENCES

- [1] Corbett, A. T., Koedinger, K. R. and Anderson, J. R. 1997. Intelligent Tutoring Systems. *Handbook of Human-Computer Interaction*, Second, Completely Revised Edition in M. Helander, T. K. Landauer, P. Prabhu (Eds), Elsevier Science B. V., 1997, Chapter 37, p. 849-874.
- [2] Bate, A. E. C. and Rodrigo, M. M. T. 2003. Automatic Detection of Student Off-Task Behavior while using an Intelligent Tutoring System for Algebra. *Philippine Computing Journal*.
- [3] Baker, R. S. J. d., Mitrovic, A. and Mathews, M. 2010. Detecting Gaming the System in Constraint-Based Tutors. *User Modeling, Adaptation, and Personalization*, vol. 6075, p. 267-278.
- [4] Baker, R. S. J. d., Corbett, A. T., Koedinger, K. R. and Wagner, A. Z. 2004. Off-Task Behavior in the Cognitive Tutor Classroom: When Students ‘Game the System’.

Proceedings of ACM CHI 2004: Computer-Human Interaction, p. 383-390.

- [5] Lagud, M. C. V. and Rodrigo, M. M. T. 2010. The Affective and Learning Profiles of Students While Using an Intelligent Tutoring System for Algebra. *2010 Intelligent Tutoring Systems Conference*, p. 255-263.
- [6] Craig, S. D., Graesser, A. C., Sullins, J. and Gholson, B. 2004. Affect and Learning: An Exploratory Look into the Role of Affect in Learning with AutoTutor. *Journal of Educational Media*, vol. 29, no. 3, p. 241-250.
- [7] D'Mello, S., Taylor, R. S. and Graesser, A. 2007. Monitoring Affective Trajectories during Complex Learning. *Proceedings of the 29th Annual Meeting of the Cognitive Science Society*.
- [8] Baker, R. S. J. d., Rodrigo, M. M. T. and Xolocotzin, U. E. 2007. The Dynamics of Affective Transitions in Simulation Problem-Solving Environments. *Proceedings of the 2nd International Conference on Affective Computing and Intelligent Interaction*.
- [9] Rodrigo, M. M. T., Rebolledo-Mendez, G., Baker, R. S. J. d., du Boulay, B., Sugay, J. O., Lim, S. A. L., Espejo-Lahoz, M. B. and Luckin, R. 2008. The Effects of Motivational Modeling on Affect in an Intelligent Tutoring System. *International Conference on Computers in Education*, p. 49-56.
- [10] Baker, R. S., D'Mello, S. K., Rodrigo, M. M. T., and Graesser, A. C. 2010. Better to Be Frustrated than Bored: The Incidence, Persistence and Impact of Learners' Cognitive-Affective States during Interactions with Three Different Computer-Based Learning Environments. *International Journal of Human-Computer Studies*, vol. 68, no. 4, p. 223-241.
- [11] Mitrovic, A. 1998. Learning SQL with a Computerized Tutor. *Proceedings of the 29th SIGCSE Technical Symposium on Computer Science Education*, p. 307-311.
- [12] Mitrovic, A. and Ohlsson, S. 1999. Evaluation of a Constraint-Based Tutor for a Database Language. *International Journal of Artificial Intelligence in Education*, vol. 10, p. 238-256.
- [13] Dekeyser, S., Raadt, M. d. and Lee, T. Y. 2007. Computer Assisted Assessment of SQL Query Skills. *Proceedings of the 18th Conference on Australasian Database*, vol. 63, p. 53-62.
- [14] Rodrigo, M. M. T., Baker, R. S. J. d. and Nabos, J. Q. 2010. The Relationships between Sequences of Affective States and Learner Achievement. *Proceedings of the 18th International Conference in Education*.
- [15] Rodrigo, M. M. T., Baker, R. S. J. d., Lagud, M. C. V., Lim, S. A. L., Macapanpan, A. F., Pascua, S. A. M. S., Santillano, J. Q., Sevilla, L. R. S., Sugay, J. O., Tep, S. and Viehland, N. J. B. 2007. Affect and Usage Choices in Simulation Problem-Solving Environments. In R. Luckin, K. R. Koedinger, J. Greer (Eds.), *Artificial Intelligence in Education: Building Technology Rich Learning Contexts that Work*, p. 145-152, Amsterdam, The Netherlands: IOS Press.
- [16] Gross, J. J., Carstensen, L. L., Tsai, J., Skorpen, C. G. and Hsu, A. Y. C. 1997. Emotion and Aging: Experience, Expression, and Control. *Psychology and Aging*, vol. 12, no. 4, p. 590-599.
- [17] Lynch, F. 1984. Social Acceptance Reconsidered. In A. A. Yengoyan and P. Q. Makil (Eds) *Philippine Society and the Individual: Selected Essays of Frank Lynch (1949-1976)*, USA: Center for South and Southeast Asian Studies, University of Michigan.
- [18] Inglehart, R. Inglehart-Welzel Cultural Map of the World. Retrieved February 17, 2009, from: http://margaux.grandvinum.se/SebTest/wvs/articles/folder_published/article_base_54.

7. AUTHORS' INSTITUTIONAL AFFILIATION

¹Ateneo Laboratory for the Learning Sciences, Department of Information Systems and Computer Science, Ateneo de Manila University, Loyola Heights, Quezon City, Philippines, +63 (2) 426-6071

²Department of Computer Science and Software Engineering, University of Canterbury, Private Bag 4800, Christchurch, New Zealand