Characterizing an Adaptive Tutoring Learning Effect Chain for Individual and Team Tutoring

Robert A. Sottilare, Ph.D., Benjamin Goldberg, Ph.D.
U.S. Army Research Laboratory-Human Research and Engineering Directorate
Orlando, Florida
{robert.sottilare, benjamin.goldberg}@us.army.mil

Charles Ragusa, Michael Hoffman
Dignitas Technologies, LLC
Orlando, Florida
{cragusa, mhoffman}@dignitastechnologies.com

ABSTRACT

Military organizations worldwide are aiming to mature artificially-intelligent agents (e.g., computer-based intelligent tutoring systems (ITS) and virtual humans) to lead, support, and tailor training to the needs of individuals and small units. Goals for ITS are: to match or exceed the learning effect of expert human tutors; reduce the cost of authoring, delivering, and managing training; lower entry skills needed to author ITS; and develop quality standards, accessibility, and flexibility for the learner. This paper focuses on improving learning effect and explores how learning gains (e.g., knowledge and skill acquisition, and enhanced performance) might be realized in ITS for tutoring both individual and small unit tactical tasks. To this end, an adaptive tutoring learning effect chain (ATLEC) for both individual and team learning is put forth. Originally developed by Sottilare (2012), ATLEC for individual tutoring models the relationships of concepts for learner data (behavioral, physiological, historical, and trait), learner states (cognitive and affective), instructional strategy selection, and learning gains. This model is a key methodology incorporated within the Generalized Intelligent Framework for Tutoring (GIFT). This paper expands the ATLEC model to include small unit tutoring and an expanded array of learning gains (e.g., accelerated learning and enhanced retention). A key to learning gains in human tutoring is the ability of the tutor to detect and interpret behavioral cues from the learner to aid them in assessing the learner's cognitive (e.g., engagement) and affective (anxiety, frustration, boredom and confusion) states in order to optimally select their next instructional strategy. ITS must use other means (e.g., behavioral and physiological sensors) to detect and interpret learner states which is an advantage over human tutors. The product of this paper will be a model of learning effect that can be used to drive standards and the development of ITS for training and education.

ABOUT THE AUTHORS

Robert A. Sottilare serves as the Chief Technology Officer (CTO) of the Simulation & Training Technology Center (STTC) within the Army Research Laboratory's Human Research and Engineering Directorate (ARL-HRED). He also leads adaptive tutoring research within ARL's Learning in Intelligent Tutoring Environments (LITE) Laboratory where the focus of his research is in automated authoring, instructional management, and analysis tools and methods for intelligent tutoring systems. His work is widely published and includes recent articles in the *Cognitive Technology* and the *Educational Technology* Journals. Dr. Sottilare is a co-creator of the Generalized Intelligent Framework for Tutoring (GIFT). He received his doctorate in Modeling & Simulation from the University of Central Florida with a focus in intelligent systems. In January 2012, he was honored as the inaugural recipient of the U.S. Army Research Development & Engineering Command's Modeling & Simulation Lifetime Achievement Award.

Charles Ragusa is a senior software engineer at Dignitas Technologies with over thirteen years of software development experience. After graduating from the University of Central Florida with a B.S. in computer science, Mr. Ragusa spent several years at SAIC working on a variety of R&D projects in roles ranging from software engineer and technical/integration lead to project manager. Noteworthy projects include the 2006 DARPA Grand Challenge as an embedded engineer with the Carnegie Mellon Red Team, program manager of the SAIC CDT/MRAP IR&D project, and lead engineer for Psychosocial Performance Factors in Space Dwelling Groups. Since joining Dignitas Technologies in 2009, he has held technical leadership roles on multiple projects, including his current role as the principal investigator for the GIFT project.

Michael Hoffman is a software engineer at Dignitas Technologies with over seven years of experience in software development. Upon graduating from the University of Central Florida with a B.S. in Computer Science, he spent a majority of his time on various OneSAF development activities for SAIC. He worked on the DARPA Urban Challenge, where he provided a training environment for the robot by simulating AI traffic and the various sensors located on Georgia Tech's Porsche Cayenne in a OneSAF environment. Soon after earning a Master of Science degree from the University of Central Florida, Michael found himself working at Dignitas. Both at Dignitas and on his own time, Michael has created several iPhone applications. One application, called the Tactical Terrain Analysis app, provides mobile situation awareness and can be used as a training tool for various real world scenarios. More recently he has worked to determine if unobtrusive sensors can be used to detect an individual's mood during a series of computer interactions. Michael excels in integrating both software and hardware systems such as third party simulations and sensors. Michael has been the lead software engineer on GIFT since its inception over two years ago.

Benjamin Goldberg is a member of the Learning in Intelligent Tutoring Environments (LITE) Lab at the U.S. Army Research Laboratory's (ARL) Simulation and Training Technology Center (STTC) in Orlando, FL. He has been conducting research in the Modeling and Simulation community for the past 4 years with a focus on adaptive learning and how to leverage Artificial Intelligence tools and methods for adaptive computer-based instruction. Currently, he is the LITE Lab's lead scientist on instructional strategy research within adaptive training environments. Dr. Goldberg holds doctorate and master's degrees in Modeling & Simulation from the University of Central Florida. Prior to employment with ARL, he held a Graduate Research Assistant position for two years in the Applied Cognition and Training in Immersive Virtual Environments (ACTIVE) Lab at the Institute for Simulation and Training.

Characterizing an Adaptive Tutoring Learning Effect Chain for Individual and Team Tutoring

Robert A. Sottilare, Ph.D., Benjamin Goldberg, Ph.D.
U.S. Army Research Laboratory-Human Research and Engineering Directorate
Orlando, Florida
{robert.sottilare, benjamin.goldberg}@us.army.mil

Charles Ragusa, Michael Hoffman
Dignitas Technologies, LLC
Orlando, Florida
{cragusa, mhoffman}@dignitastechnologies.com

INTRODUCTION

Research is ongoing in the United States military, Pacific Rim and NATO countries to enhance the adaptive capabilities of computer-based intelligent tutoring systems (ITS) to support more tailored and effective learning experiences. The U.S. Army Research Laboratory (ARL) is conducting adaptive tutoring research to enhance instructional strategy selection to support the Army Learning Model (ALM) goal of self-regulated, tailored instruction. Other services are exploring the development of cognitive models to support tutoring and the U.S. Office of the Secretary of Defense Advanced Distributed Learning Initiative is conducting research leading to a Personalized Assistant for Learning (PAL). Australia and New Zealand along with the U.S., Canada and United Kingdom are participating in a Joint and Coalition research agreement under the Technical Cooperation Program that includes goals to explore individual and small unit tutoring technologies. Finally, NATO has established a Research Task Group to assess Intelligent Tutoring System (ITS) technologies and opportunities to support agent-regulated learning. So it appears that interest worldwide in enhancing the capabilities of ITS is high and in particular learner-centric approaches are preferred.

Today's ITS have an average learning effect equivalent to improvements of one letter grade (VanLehn, 2011), an increase of median scores from the 50^{th} percentile to the 79^{th} percentile or a learning effect of 0.8 sigma over traditional classroom training. VanLehn's meta-analysis examined tutoring methods that provided static tutoring (e.g., seated at a desk with a laptop computer) in well-defined domains (e.g., mathematics, physics). If we can improve their adaptiveness, ITS have potential for higher learning gains in more kinetic and ill-defined military training contexts as well as static/well-defined domains currently observed in ITS today.

Background

A key to improving learning effect over traditional classroom training lies in modeling selected behaviors of expert human tutors. To realize accelerated knowledge and skill acquisition, and enhanced performance and retention facilitated by ITS, Sottilare (2012) explored learning moderators (e.g., engagement, confusion, frustration, boredom), expert human tutoring processes (e.g., INSPIRE - Lepper, Drake, and O'Donnell-Johnson, 1997), conditions of learning (Gagne, 1985), and existing ITS information flow to develop the adaptive tutoring learning effect chain (ATLEC). The initial version of ATLEC modeled the relationships between concepts for *learner data* (behavioral, physiological, historical, and trait), *learner states* (cognitive and affective), *instructional strategy selection*, and *learning gains*. The enhanced ATLEC model described in this paper includes new concepts for *instructional context* and *instructional tactic selection* for both individual and team modeling and expanded descriptions of ATLEC elements and implementation not previously described. ATLEC is a guiding methodology implemented within the Generalized Intelligent Framework for Tutoring (GIFT), an open-source tutoring architecture to support authoring, instructional management, and experimental analysis of effect.

Since they are often confused, it is worth mentioning the differences between adaptive and adaptable systems. In short, adaptable systems can be modified by users whereas adaptive systems automatically make changes in response to changing conditions. Effective adaptive tutors automatically respond to changes within the learner's states and the instructional environment (context) to support optimal learning.

During human-regulated tutoring, the ability of the tutor to detect and interpret behavioral cues from the learner aids the tutor in assessing the learner's cognitive (e.g., engagement) and affective (anxiety, frustration, boredom and confusion) states which informs the tutor's selection of the next instructional strategy (e.g., prompt the learner for additional information). ITS must use other means (e.g., behavioral and physiological sensors) to detect and interpret learner states which may offer an advantage over human tutors who may not be aware of learner's physiological states. ATLEC, as originally developed, focused on individual learners. The goal of this paper is to highlight an expanded ATLEC model which includes small unit tutoring and learning effect on an expanded array of learning gains (e.g., accelerated learning and enhanced retention). This paper describes a comprehensive model of individual learning effect and introduces a model of team tutoring that can be used to drive standards and the development of ITS for training and educational applications.

ADAPTIVE TUTORING LEARNING EFFECT CHAIN FOR INDIVIDUAL LEARNERS

This section examines the elements, theory, influences, and effect of an enhanced ATLEC model for individual learners. Since its debut in 2012, the adaptive tutoring learning effect chain (ATLEC) for individual learners has been enhanced (Figure 1) to include tactical actions (e.g., specific questions, prompts, feedback) which account for domain-dependent instructional context during tutoring sessions. The premise of ATLEC is that improving any link in the chain improves subsequent links and thereby learning gains. New additions to the ATLEC model for individual learners presented in this paper are shown in red and detailed descriptions of learner data, learner states, instructional strategies and tactics, and learning gains are provided below.

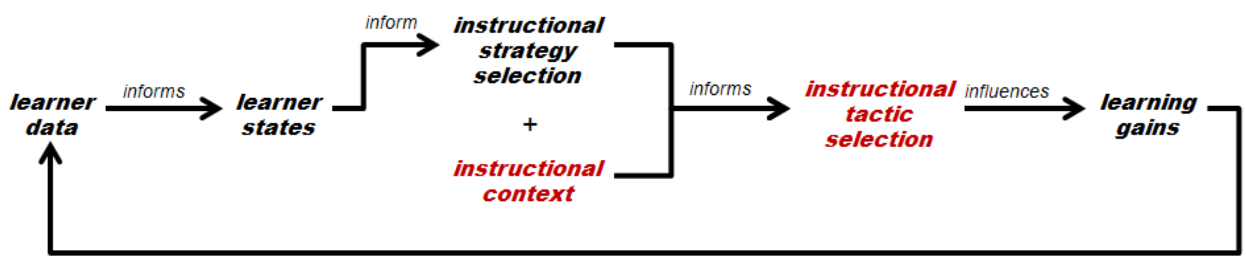

Figure 1. Enhanced ATLEC for Individual Learners

Learning gains are a function of instruction strategy selection accuracy. Instructional strategy selection accuracy is a function of learner state classification accuracy, and learner state classification accuracy is a function of the availability of relevant learner data.

Learner Data

A description of key learner data concepts are discussed in this section. Learner data is any information about the learner's traits, measures, and historical data (e.g., previous training history, experience) that may be used to infer current or future learner states (e.g., competence, cognitive, affective, and performance). Since data collection is often an obtrusive, expensive, and messy process, it is preferable to collect only the data that is relevant to desired learning outcomes (e.g., learning gains) and necessary for accurate state classification and instructional decisions. Methods that are passive (unobtrusive) are also preferred to keep from interfering with the learning process. Less is more if classification of learner states can remain accurate while reducing the amount of data, types of sensors and other collection methods, and the number of interventions with the learner.

Based on the literature, the following categories of learner data have been determined to indicate critical positive learner states such as motivation and engagement, and negative learner states such as long term confusion, frustration, and boredom. With the exception of behaviors and physiological measures, most learner data categories are not directly observable and must be derived from other data or through learner queries. Once captured, values, preferences, interests, and goals have significant persistence and should be considered for inclusion in long-term, persistent learner models as trait data.

Values - Value is a measure of worth and personal values include principles and standards developed through family, religion, culture, media and other sources that drive learner decision-making, beliefs, motivation, preferences, interests, and affect (personality, mood, and emotions) and thereby influence learning (knowledge and skill acquisition and retention). Standard methods to quantify values for use in instructional decisions have not yet been established.

Preferences - Derived from values, preferences are a measure of the degree to which a learner values one choice over another. Examples of preferences include personality preferences (e.g., extraversion vs. introversion), learning style (e.g., active or reflective), or goal-orientation, the disposition toward developing/demonstrating ability when during achievement opportunities (VandeWalle, 1997). Affect (e.g., emotions) may be used to predict preferences (North, Todorov, and Osherson, 2010) and we can therefore expect that preferences may be used to infer the affective state of the learner where positive affect is generally associated with experiences that align with learner preferences and negative affect may result from experiences that oppose learner preferences.

Interests - Interests include activities of significant value to the learner. Understanding the learner's interests may aid in capturing and maintaining the learner's motivation and engagement during challenging (e.g., complex or tedious) learning experiences.

Goals - Defining the learner's purposes and desired achievements, goals moderate motivation and thereby influence learning. Goal orientations are significant in understanding and supporting learner goals. Master goal orientation is focused on developing competency while performance approach goal orientation is focused on demonstrating competency (Midgley, et al, 2000). A learner with a performance avoidance goal orientation is striving to avoid the demonstration of incompetence (Midgley, et al, 2000).

Behaviors - Behaviors are directly observable and include the physical actions of the learner (conscious and unconscious) which consist of facial dynamics (e.g., frowns and smiles), gestures, posture, head position, and speech which may be used to infer cognitive or affective states (e.g., workload, engagement, frustration, confusion). In general, behaviors have low persistence and are only useful at indicating recent states, but may also include actions (e.g., responses to questions) that indicate performance.

Physiological Measures - Physiological measures are quantifiable learner data (e.g., heart rate, breathing rate, electrical impulses) captured by sensors (e.g., thermal cameras, electro-encephalographs) which may be used to infer cognitive (e.g., workload or engagement) or affective states (e.g., frustration or confusion) (Calvo & D'Mello, 2010). In general, physiological measures have low persistence and are only useful at indicating recent states.

Within the GIFT sensor module, sensor data is acquired, processed, and/or filtered. The resulting filtered data is transmitted to the learner module using standard messages (sensor data and sensor filter data messages) to join other available learner data (e.g., values, preferences, interests, goals) to inform the learner state classification process. Sensor module configuration may be altered to support the inclusion of customized filters and writers. Filters convert data to a form suitable for communication to other GIFT modules. Writers permit time stamped sensor data to be written to disk as CSV files for post-processing by researchers for the purpose of model development and refinement. Currently sensor processing thresholds are static. For optimal performance, future implementations will target dynamic calibration and perhaps individualized baselines using historical learner data.

The sensor module uses a configurable plug-in architecture which supports a wide range of both hardware and software sensors. Hardware sensors can include any behavioral/physiological sensor capable of capturing a signal and reporting the signal to the computer (via serial port, USB, or blue tooth). Hardware sensors integrated to date include electro-encephalographs (EEGs), an electro-dermal activity sensor, a temperature and humidity sensor (via instrumented mouse), various bio-sensors for breathing and heart rate detection, the Inertial Labs Weapon Orientation Module (WOM; for adaptive marksmanship), and Microsoft Kinect for gesture, posture, head pose, and facial marker recognition. Software sensors can also be employed and are typically used as surrogates for actual hardware sensors, which is useful for testing and validation, or for direct input of self- assessment by the learner. A plug-in for the Institute for Creative Technologies Multi-Sense toolkit to interpret states from sensor data is also included in the most recent version of GIFT.

Learner States

For individual learners, ATLEC includes six state categories which are important to guiding strategy and tactic selection by the tutor:

Potential State - Also known as competence or expected success, potential is a long term measure which is derived from the learner's previous successful experiences, training, and education in fields related to the current training task. Success is commonly testable and measures the learner's knowledge and skill acquisition, and retention.

Performance State - Contrasted with potential state or expected success, performance state measures actual learner progress toward goals. Performance is derived from learner behaviors including responses to tests/quizzes, decisions, and actions measured by speed and accuracy against potential, goals and standards to determine whether the learner is above, at, or below expectations for a given lesson, task or concept.

Cognitive State - A measure of learner thinking capacity, problem-solving capability, and focus, the determination of cognitive states uses learner behaviors to indicate increases in complex and abstract mental capabilities (Anderson & Krathwohl, 2001). Of significance in cognitive learning are attention, engagement and working memory. A revision of Bloom's taxonomy (Anderson & Krathwohl, 2001) tracks a series of behaviors from low cognitive state to high as follows: remembering, understanding, applying, analyzing, evaluation, and creating.

Affective State - A measure of feeling with varying duration and relationship to identifiable sources (Gebhard, 2005), affective states include personality (long duration, multiple sources), mood (moderate duration, vague sources), and emotions (short duration, specific sources). Learner behaviors indicate affective growth and the manner in which the learner handles emotions during learning experiences and in particular when presented with significant challenges. Reported feelings, values, appreciation, enthusiasms, motivations, and attitudes indicate affective states including from low to high: receiving, responding, valuing, organizing, and characterizing (Krathwohl, Bloom and Masia, 1964).

Motivational State - Broken out separately due to its importance in expert tutoring models (e.g., INSPIRE - Lepper, Drake & O'Donnell-Johnson, 1997), motivation is influenced by goals, preferences, and interests.

Psychomotor State - Associated with physical tasks (e.g., marksmanship) which include physical movement, coordination, and the use of the motor-skills. Development of motor-skills requires practice and is measured in terms of speed, precision, distance, procedures, or techniques during execution (Simpson, 1972). Simpson's hierarchy of psychomotor states ranges from low to high: perception - the ability to use sensory cues to guide motor activity; set or readiness to act; response - early stages of learning a complex skill through imitation and trial and error; mechanism - habitual learned responses; complex overt response - skillful performance of complex movements; adaptation - well-developed skills that are modified to support special requirements; and origination - the development of new movement patterns to fit unique situations.

States are determined by the learner module using inputs from sensors, surveys, historical profiles, etc. (learner data) and the domain module (learner progress against expectations). GIFT defines an enumerated list of learner state attributes, each of which has an enumerated list of possible values. For example, the learner attribute of "potential" can take on the values of "unknown", "novice", "journeyman", or "expert". At any point in time, learner state is represented by a set of learner state attributes and a short term, a long term, and a predicted value for each.

To determine learner's states, classification models rely on input from sensors, a persistent learner model (e.g., historical data from surveys, instruments and profiles), and the domain model (e.g., performance data). To date, GIFT computes learner state from sensor data and scored surveys using classifiers to determine current states and predict future states. Translators allow for a preprocessing step that can be used for unit conversion or normalization and the like. Translated data are passed on to one or more learner state classifiers. Classifiers are preconfigured for the input channel (e.g., specific sensor channel). Each classifier processes assigned data to compute a single short term value (nominal or numerical). Classified states tracked over time are used to identify general trends to predict future values. The current approach in GIFT allows for the computation of divergent learner state attributes which must be deconflicted. The implementation of a probabilistic schema for addressing learner states and strategy selection is desirable given the accuracy of many classification models today range from 60-80%.

The importance of the availability of learner data and the accuracy of learner state classification models cannot be understated. Unreliable or unavailable learner data lowers state classification accuracy. Lower state classification accuracy drastically affects the overall probability of selecting the most appropriate strategies to meet the needs of the learner. For example, if the strategy selection classifier is individually 80% accurate given 100% accurate learner states and the tactics selection classifier is individually 80% accurate given 100% accurate strategy recommendations, then the best tactics classification that can be expected for the learning effect chain (serial learner state-strategy-tactics set of classifiers) is 51% if the learner state classifier is only 80% accurate. This is a virtual coin flip and is unacceptable. An ITS must classify learner state very accurately (> 90%) for the learning effect chain to realize significant learning gains. Classifier accuracy is determined by the area under a receiver operating characteristic (ROC) curve (Figure 2) where the true positive rate (TPR) or sensitivity (see equation 1) for three classifiers are plotted against the false positive rate (FPR) or 1 minus the specificity (see equation 2). Higher sensitivity is accompanied by a decrease in specificity.

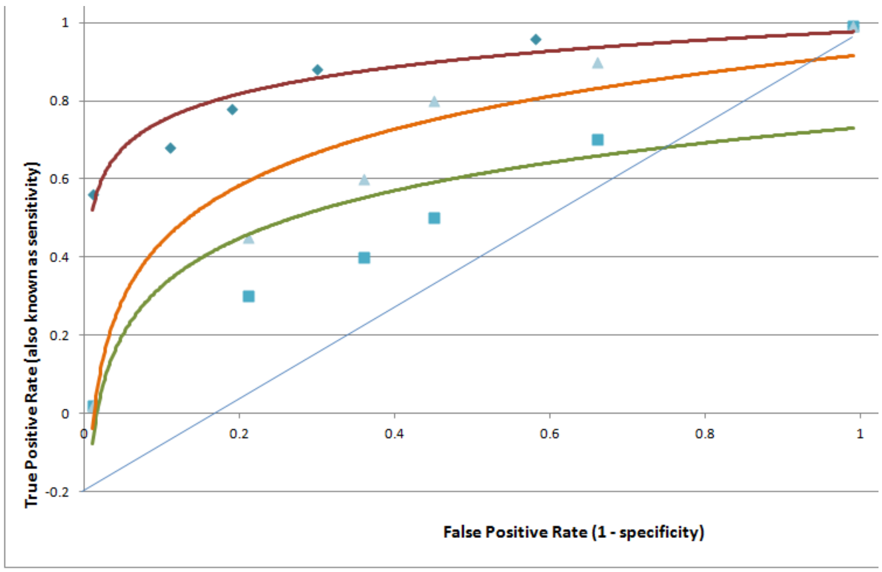

Figure 2: Example Receiver Operating Characteristic (ROC) curves for state classifiers

$$TPR = sensitivity = TP/(\mathrm{TP}+\mathrm{FN}) \qquad (1)$$

where TP = # true positive predictions of learner state
and FN = # false negative predictions of learner state

$$FPR = \mathrm{FP}/(\mathrm{FP}+\mathrm{TN}) \qquad (2)$$

where FP = # false positive predictions of learner state
and TN = # true negative predictions of learner state

Instructional Strategies and Tactics for Individual Learners

This section describes how strategies, instructional context, and tactics interact as part of the learning effect chain. Within ATLEC, there are two categories of strategies: *macro-adaptive* and *micro-adaptive*. Macro-adaptive instructional strategies are informed by the learner's traits (values, preferences, interests, and goals) and the learner's potential state. Macro-adaptive strategies are generally implemented prior to the tutoring session to initialize the scenario. Macro-adaptive strategies influence the selection of tutoring scenarios based on their level of complexity relative to the learner's potential. For example, a macro-adaptive strategy for a learner with low prior knowledge might be to limit the learner's control of navigation in the learning environment. Macro-adaptive strategies do not rely on instructional context (e.g., current performance) and are domain-independent.

Micro-adaptive instructional strategies are a real-time adaptation of the initial or planned scenario and are informed by a more comprehensive model of learner states and traits. In particular, the learner's performance state is critical in selecting micro-adaptive strategies. For example, a micro-adaptive strategy during tutoring might be to assess the level of performance and provide additional navigational control as the learner demonstrates higher levels of performance. Micro-adaptive strategies are also domain-independent. This is important since pedagogical engines using domain-independent strategies may be reused across multiple training domains/tasks.

Tactics selection is informed by strategy recommendations (macro or micro) and instructional context (Goldberg et al., 2012). Tactics are domain-dependent. An example of a tactic selection is to allow access to additional navigational controls within a specific course based on a micro-adaptive strategy recommendation to allow the learner additional control. In the context of ATLEC, we assert that well timed and executed instructional tactics will in turn affect subsequent learner data used for inferring a state determination. If an adaptive tactic is successful, the result can be seen in the data that ultimately triggered the learning effect cycle. The goal is to use pedagogical strategies to improve learning gains (e.g., skill acquisition or performance) with increases being linked to changes in the learner's raw physiological or behavioral data.

The collection of performance metrics directly following the execution of a tactic is important because this information can be used to evaluate the effectiveness of a pedagogical decision for a particular learner. In essence, GIFT can use data following implementation of a pedagogical intervention to further refine the strategy selections based on associated outcomes. From this approach, methods can be applied to close the loop of the ATLEC model to evaluate the effectiveness of applied strategies and tactics on state determinations for a specific type of learner. This assessment can run in real-time, modifying strategy selection candidates by evaluating how specific strategies influence performance within that specific learning session. If a strategy is found to have a neutral or negative effect on subsequent performance, GIFT can modify strategy selection conditions so that that particular strategy is not executed when the same learner model data is present. From a different perspective, the evaluation can be applied in an offline capacity through data mining techniques that take into account all of a learner's data from previous sessions to identify the optimal strategies that have been found to positively affect outcomes for a specific individual. Analysis in an offline mode can also take into consideration between-subject methods to examine how particular strategies work across similar learner profiles. As GIFT and other tutoring systems develop around the theorized benefits of personalized instruction, evaluating how individuals with common characteristics react to strategy selections and how those tactics influence subsequent outcomes will be important in quantifying the adaptiveness of ITSs. Through the application of educational data mining practices, analytical methods can be used to explore the unique types of data present in learning systems (training or education) to better understand how learners progress in different settings (www.educationaldatamining.org).

Adaptive Tutoring Techniques

The Institute of Education Sciences (2007) identified seven instructional strategies which are supported by science and can be reliably applied to both human and computer-based teaching/tutoring: space learning over time; interleave worked example solutions with problem solving exercises; combine graphics with verbal descriptions; connect and integrate abstract and concrete representations of concepts; use quizzing to promote learning; help students allocate study time effectively; and ask deep explanatory questions.

Durlach and Ray (2011) identified several promising adaptive techniques that generally align with the Institute of Education Sciences strategies to support effective learning. These include: error-sensitive feedback, mastery learning, adaptive spacing and repetition for drill-and-practice items, metacognitive prompting, and fading worked examples. Each is described below in relationship to how each fits within ATLEC.

- *Error Sensitive Feedback* - an intervention triggered when the learner commits errors that are either individually or cumulatively significantly divergent from the ideal as defined in the expert model of the ITS
- *Mastery Learning* - a strategy where the ITS ensures the learner masters (can recall and apply) prerequisite lessons or concepts before allowing the learner to move on to the next lesson/concept
- *Adaptive Spacing and Repetition* - a strategy where the learner more easily recalls knowledge items/objects when the knowledge is exposed to the learner repeatedly over a long time span rather than repeatedly studied during a short span of time (Dempster, 1988)
- *Metacognitive Prompting* - a strategy where the ITS encourages the learner to self-reflect and evaluate, self-explain, and self-correct rather than provide the answer directly

- *Fading Worked Examples* - "a step-by-step demonstration of how to perform a task or how to solve a problem." (Clark, Nguyen, and Sweller, 2006, p. 190) from which parts have been deliberately removed or faded (Atkinson, Renkl, and Merrill, 2003)

Implementation of Domain-Independent Macro-Adaptive Strategies within GIFT

This section describes how the pedagogical module processes learner traits (value, preferences, interests and goals) which are used to support selection of macro-adaptive strategies (pre-training strategies) and provides a description of Merrill's Component Display Theory (rules, examples, recall, and practice) as implemented in GIFT.

Learner state messages sent by the learner module are used by the GIFT pedagogical module to determine macro-adaptive strategies (e.g., the challenge level of the course object) in a domain-independent fashion. The *Engine for Macro-Adaptive Pedagogy,* also known as eMAP, dynamically manages flow through the course material based on the Component Display Theory (CDT - Merrill, Reiser, Ranney, and Trafton, 1992). Thus, GIFT course authors now have the option of inserting one or more CDT branching points as a top-level element in a GIFT course. All course elements in GIFT are classified as one of the CDT quadrants. In the rule quadrant, the tutor tells the learner what they need to know (facts, rules and principles). In the example quadrant, the tutor shows the learner how to do necessary tasks. In the recall quadrant, the tutor asks the learner to recall information previously presented. Finally, in the practice quadrant, the tutor prompts the learner to apply their knowledge.

Each CDT branching point assumes the existence of independently authored meta-data tagged content for use in eMAP. While a linear course flow has pre-scripted steps, CDT guides strategy selection by using the current CDT quadrant (rule, example, recall or practice) along with the current learner performance, motivation, and other learner states. To determine the next step, the Pedagogical module provides the learner states and performance (e.g., at expectation, below expectation, or above expectation) to eMap. The eMap then uses this data for its CDT query and returns a set of metadata attributes describing the most desirable content package for the next iteration of content presentation. Metadata attributes are communicated to the Domain Module in the form of a branch request. Upon receipt of the branch request, the domain module consults the metadata files for the currently executing course and compares metadata of the available content packages (lessons) with the data in the branch request. Finally, the lesson material with the best matching metadata attributes is selected for presentation to the learner.

Implementation of Domain-Independent Micro-Adaptive Strategies within GIFT

This section describes how the pedagogical module processes learner state attributes (engagement, motivation) to support the selection of micro-adaptive strategies (real-time, in-situ training strategies). Rules for applying micro-adaptive strategies are defined in a lesson specific Domain Knowledge File (DKF) which is authored in advance by an instructional designer, and read at run time by the Domain Module which then shares the necessary micro-adaptive strategy configuration information with the Pedagogical module. The rules are mappings from transitions in learner state attribute values (e.g. "engagement=LOW" to "engagement=HIGH") to one or more domain independent micro adaptive instructional strategies. Multiple attribute-values can also be combined using the logical AND operator to form complex transition definitions. Logical OR and logical NOT operators are not currently supported, but will be supported in future versions of GIFT.

The Pedagogical Module detects the learner state attribute transitions by comparing incoming learner state with previously received learner state. When state changes (transitions) are detected, the micro-adaptive strategy rule base is checked for a match. If a match is found, one of the matching micro-adaptive strategies is selected and sent to the domain module in the form of a pedagogical request. Currently, in cases where multiple strategies have been defined for a transition, only the first one listed is used. However, by allowing for multiple strategies to be listed, we leave open the possibility for a more sophisticated selection methodology to be employed in future versions of GIFT. If a match is not found the transition is ignored.

Implementation of Domain-Dependent Tactics within GIFT

This section describes how domain-dependent tactics are selected based on domain-independent macro and micro-adaptive strategy recommendations and instructional context (who, what, when, where, how) within training courses. Methods of tactics selection (rule-based, decision trees, machine learning algorithms, and Markov Decision Processes) are also discussed.

The Domain module receives domain independent macro and micro adaptive strategy requests from the Pedagogical module while the user is in a course. Those requests are carried out by the Domain module using domain-dependent implementations. Currently, micro-adaptive strategy implementations are authored in a DKF which is used during a lesson (e.g. training application scenario). Upon receipt of a request, the Domain module locates the appropriate strategy handler, either based on the authored DKF or using the default logic, and then provides that request to the handler. Sometimes, a request will contain more than one strategy type at which point the current logic is to select the first one in the list. In the future, more robust tactics for strategy selection will be used such as machine learning algorithms and Markov Decision processes. GIFT developers can choose to either create new strategy handlers or use one of the strategy handlers already included. Strategy handlers range from very simple to very complex depending on the type of domain dependent strategy being implemented. Thus a single handler may have multiple courses of action available to it. Which course of action is taken can vary depending on the context. For example repeated requests for feedback on a concept can result in variations in the feedback presented to the user (e.g., first iteration of feedback may be a gentle admonition, whereas the third feedback could be a stern warning). The current approach for this type of strategy escalation is a rule based system. Future implementations of handlers also have the opportunity of being improved with the use of more complex decision algorithms. Furthermore, the system lacks request conflict resolution, where as if one or more strategy requests are received in a short amount of time, the applied domain dependent implementations could be incoherent or misconstrued. For example, during the handling of presenting feedback for one request, another request arrives that is contradictory. Of course this is just one simple example among many request permutations that could happen when such an adaptive system is used.

Learning Gains

This section describes desired learning gains and how each might be influenced by earlier processes in the learning effect chain. Effect size is a measure for quantifying the difference between multiple (two or more) datasets (e.g., groups, methods, individuals measured over time). Learning effect measures the difference in instructional methods (strategies or tactics) on learning gains (knowledge or skill acceleration, performance, or retention). Learning gains include:

Accelerated learning - Learning is the acquisition of knowledge and the development of skills. Accelerated learning results from adaptive instructional methods and is a decrease in the amount of time needed to acquire a unit of knowledge or develop a skill compared to traditional (currently implemented) instructional methods. Any method that enhances the tutor's capability to optimally select instructional strategies and tactics, and keeps the learner focused on germane tasks will likely result in accelerated learning.

Enhanced performance - Whereas learning is the acquisition of knowledge and skills, performance is the application of knowledge and skills. If competence is a measure of potential skill, performance is a test of skill. Rote performance of a task is not a true measure of skill, but allowing the learner to be tested in a variety of applications of acquired knowledge and skill can demonstrate true ability to perform. Providing a variety of performance tests that sufficiently covers knowledge of the domain is costly unless much of the process of authoring ITS can be automated.

Enhanced retention - Retention is the ability to maintain a level of knowledge and skill to remain proficient in a particular task. The idea that desirable difficulties (Bereiter & Scardamalia,1985; Bjork, 1988) can gel learning and support longer term retention is a principle adopted within GIFT's pedagogical structure in the form of "indirectness" as defined in the INSPIRE model of tutoring (Lepper, Drake, and O'Donnell-Johnson, 1997)

ADAPTIVE TUTORING LEARNING EFFECT CHAIN FOR TEAMS

Sottilare (2010) proposed a distributed team training model that incorporated architectural concepts for communications between distributed team models for trust and performance based on locally derived individual learner states (e.g., affect and competence). Sottilare, Holden, Brawner and Goldberg (2011) expanded this concept to include team models for performance, competency, cognitive state, affective state, trust, and communications. Fletcher & Sottilare (2013) built upon these conceptual team models and Sottilare's (2012) original ATLEC model to examine how a learning effect chain might be implemented for teams. This section introduces an enhanced ATLEC model for teams (Figure 3) that includes new concepts shown in red.

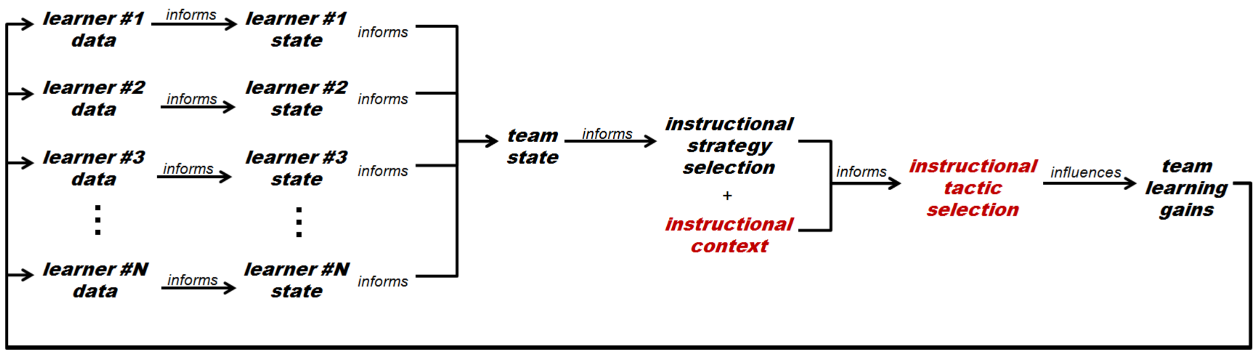

Figure 3. Enhanced ATLEC Model for Teams

As in individual learner models, learner states are informed by learner data. Learner states are then used to inform team states. Research is ongoing to identify the relationship of individual behaviors, knowledge, skills, roles and responsibilities, and interactions to support team level state models of potential (competency), performance, shared cognition, shared affect, trust, and communication (Sottilare, Holden, Brawner & Goldberg, 2011). A comprehensive literature review is forming the basis for the structure and initial development of these state models which will be evaluated using GIFT as a testbed. Team states are used to inform the selection of team strategies that could include individual or group feedback recommendations, scaffolding (support strategies), or changes to the training scenario challenge level.

Team strategy recommendations along with contextual data (e.g., who, what, where, and when) from the training environment (e.g., simulation or game) are used to inform instructional tactic selection. For each defined strategy, a complementary tactic is authored for the purpose of being implemented when that pedagogical manipulation is called for by GIFT. For example, if the strategy recommendation is to increase the challenge level of the scenario, the tactic selection for a building clearing scenario might be to increase the number of opposing forces in real-time. The focus of strategy and tactics selection in team training models is to develop and maintain a level of flow where the learners are neither bored nor overwhelmed, but sufficiently challenged by the task.

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

ATLEC offers a structured methodology for understanding interactions between individual learners and tutoring systems. The ATLEC model considers essential links between the learner and the ITS (as noted in the literature) leading to potential learning gains. ATLEC is largely domain-independent and offers instructional designer cues to drive the development of standard processes to drive learning gains within ITS. The ATLEC model may also be used as a testbed methodology to support learning effect evaluations and ITS technology comparison studies. GIFT, an open-source architecture for tutoring, has adopted ATLEC as its guiding development model for adaptive tutoring, but there remains much work to do. The following recommendations are provided for consideration as future adaptive tutoring research areas:

Unobtrusive methods to acquire learner data - Develop standoff sensing methods that do not interfere or detract from the learning process, but support sufficient granularity of learner data for state classification. Commercial hardware-based sensors (e.g., Microsoft Kinect) and software-based sensors (e.g., learner voice classifiers) are candidates for evaluation.

Methods to improve the classification accuracy of learner states - Create and evaluate methods to enhance the classification accuracy of real-time models based on learner data. Examine the efficacy of offline models for individuals and teams and evaluate their potential for generalization.

Methods to improve the selection of appropriate and effective instructional strategies and tactics - Enhance the current deterministic, decision-tree implementations (e.g., Merrill's Component Display Theory in GIFT) with probabilistic models using rewards as a basis for selection (e.g., Markov Decision Processes).

Create and evaluate team state models - While ATLEC for teams has begun to define essential interactions between groups of learners and tutoring systems, additional research is needed to develop structure for initial team state models and empirically evaluate/validate these models.

Representation and computation of learner state, and methods to optimize the selection of instructional strategies and tactics are areas of ongoing research by the GIFT development team and others. In addition to learner modeling and instructional strategies, GIFT design is informed by empirical research, the literature, and a series of advisory boards on subjects that include authoring and expert modeling, domain modeling, learning effect, and team tutoring.

REFERENCES

Anderson, L. W., and Krathwohl, D. R. (Eds.). (2001). A taxonomy for learning, teaching and assessing: A revision of Bloom's Taxonomy of Educational Objectives: Complete edition, New York: Longman.

Atkinson, R. K., Renkl, A. and Merrill, M.M. (2003). "Transitioning From Studying Examples to Solving Problems: Effects of Self-Explanation Prompts and Fading Worked-Out Steps." Journal of Educational Psychology 95(4)

Bereiter, C., & Scardamalia, M. (1985). Cognitive coping strategies and the problem of "inert knowledge". In S. F. Chipman, J. W. Segal, & R. Glaser (Eds.), *Thinking and learning skills: Vol. 2. Current research and open questions* (pp. 65-80). Hillsdale, NJ: Erlbaum.

Bjork, R. A. (1988). Retrieval practice and maintenance of knowledge. In M. M. Gruneberg, P. E. Morris, & R. N. Sykes (Eds.). Practical aspects of memory: *Current research and issues. (Vol 1),* pp. 396-401. NY: Wiley.

Calvo, R. A., & D'Mello, S. (2010). Affect Detection: An Interdisciplinary Review of Models, Methods, and Their Applications. IEEE Transactions on Affective Computing, 1(1), 18-37.

Clark, R.C., Nguyen, F., and Sweller, J. (2006). Efficiency in learning: evidence-based guidelines to manage cognitive load. Wiley & Sons. ISBN 0-7879-7728-4.

Dempster, F.N. (1988). The spacing effect. American Psychologist, 43, 627-634.

Durlach, P. J. & Ray, J. M. (2011). Designing Adaptive Instructional Environments: Insights from Empirical Evidence. U. S. Army Research Institute Technical Report.

Fletcher, J.D. and Sottilare, R. (2013). Shared Mental Models and Intelligent Tutoring for Teams. In R. Sottilare, A. Graesser, X. Hu, and H. Holden (Eds.) *Design Recommendations for Intelligent Tutoring Systems: Volume I - Learner Modeling.* Army Research Laboratory.

Gagne, R. (1985). *The Conditions of Learning* (4th.). New York: Holt, Rinehart & Winston.

Gebhard, P., (2005). ALMA - A Layered Model of Affect. In Proceedings of the Fourth International Joint Conference on Autonomous Agents & Multi Agent Systems (AAMAS), Utrecht, Netherlands, July 2005.

Goldberg, B., Brawner, K. W., Sottilare, R., Tarr, R., Billings, D. R., & Malone, N. (2012). *Use of Evidence-based Strategies to Enhance the Extensibility of Adaptive Tutoring Technologies.* Paper presented at the Interservice/Industry Training, Simulation, and Education Conference (I/ITSEC) 2012, Orlando, FL.

Institute of Education Sciences of the United States Department of Education. (2007). Organizing Instruction and Study to Improve Student Learning.

Krathwohl, D.R., Bloom, B.S., and Masia, B.B. (1964). Taxonomy of Educational Objectives: Handbook II: Affective Domain. New York: David McKay Co.

Lepper, M. R., Drake, M., & O'Donnell-Johnson, T. M. (1997). Scaffolding techniques of expert human tutors. In K. Hogan & M. Pressley (Eds), *Scaffolding student learning: Instructional approaches and issues* (pp. 108-144). New York: Brookline Books.

Merrill, D. , Reiser, B, Ranney, M., and Trafton, J. (1992). Effective Tutoring Techniques: A Comparison of Human Tutors and Intelligent Tutoring Systems. The Journal of the Learning Sciences, 2(3), 277-305.

Midgley, C., Maehr, M. L., Hruda, L. Z., Anderman, E., Anderman, L., Freeman, K. E., ... & Urdan, T. (2000). Manual for the patterns of adaptive learning scales. Ann Arbor, 1001, 48109-1259.

North, M. S., Todorov, A., and Osherson, D. N. (2010). Inferring the preferences of others from spontaneous, low-emotional facial expressions. Journal of Experimental Social Psychology, 46(1109{1113).

Simpson, E. (1972). *The classification of educational objectives in the psychomotor domain:* The psychomotor domain. Vol. 3. Washington, DC: Gryphon House.

Sottilare, R. (2010). Toward the Development of an Intelligent Tutoring System for Distributed Team Training through Passive Sensing. In V. Aleven, J. Kay, & J. Mostow (Eds.), Proceedings of the 10th International Conference on Intelligent Tutoring Systems (ITS ’10), Pittsburgh, Pennsylvania, June 2010, LNCS (Vol. 6095, pp. 411-413). Berlin: Springer.

Sottilare, R., Holden, H., Brawner, K., & Goldberg, B. (2011). Challenges and Emerging Concepts in the Development of Adaptive, Computer-based Tutoring Systems for Team Training. In Proceedings of the Interservice/Industry Training, Simulation, and Education Conference, Orlando, Florida, December 2011.

Sottilare, R. A. (2012). Considerations in the development of an ontology for a generalized intelligent framework for tutoring. In Proceedings of the International Defense and Homeland Security Simulation Workshop 2012.

VanLehn, K. (2011). "The Relative Effectiveness of Human Tutoring, Intelligent Tutoring Systems, and Other Tutoring Systems." Educational Psychologist 46(4): 197-221.

VandeWalle , D. (1997), Development and validation of a work domain goal orientation instrument, Educational and Psychological Measurement, 8, 995-1015.