Designing Representations and Support for Metacognition in the Generalized Intelligent Framework for Tutoring

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Abstract. An important component of metacognition relates to the understanding and use of strategies. Thus, measuring and supporting students' strategy understanding in complex open-ended learning environments is an important challenge. However, measuring students' strategy use and understanding is a difficult undertaking. In this paper, we present our design for representing and supporting students in their understanding of strategies while working in complex, open-ended learning environments using the Generalized Intelligent Framework for Tutoring (GIFT). Our approach utilizes a wealth of previous research and relies on three primary instructional interventions: contextualized conversational assessments and feedback; reviewing knowledge and strategies; and teaching through analogies. We believe that incorporating these approaches into GIFT will allow for powerful instruction of complex tasks and topics.

Keywords: Metacognition · Strategy instruction · Feedback · Open-ended learning environment

1 Introduction

The Generalized Intelligent Framework for Tutoring (GIFT) is a software platform for designing, developing, and implementing online and in-class educational programs [1, 2]. The goals of GIFT are many, including reducing the high development costs and low reusability of educational applications while also creating engaging and adaptive learning spaces that students can access as needed. A critical aspect of GIFT that makes it different from a number of conventional tutoring systems is its emphasis on accumulating and tracking long-term information about each student. This helps the system

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evaluate an individual student's learning progress and behaviors over an extended period of time and then use this information to provide support, recommendations, and tutoring sessions that are specific to the student's experiences and previously-demonstrated understanding of targeted concepts.

In general, collecting and studying long-term data about students' use of learning technologies is not new; learning management systems have been used to study multi-year trends in students' progressions through their degree programs [3, 4]. However, GIFT is designed to collect finer-grained data about students' interactions with a variety of educational technologies. For example, GIFT can collect and evaluate data on students' understanding of doctrinal and tactical concepts of battlefield operations across a variety of pedagogical media that vary from PowerPoint presentations and videos to simulations of offensive and defensive battlefield tactics in the Virtual Battlespace simulator [5]. Integrating information about a student's learning and performance across such disparate formats and contexts over extended periods of time is challenging, but there is promise that this information is the key to providing more effective and individualized adaptive support to learners.

In this paper, we present our design for supporting students in learning to employ metacognition while working in complex, open-ended learning environments [6, 7] through GIFT. We present an overview of metacognition, challenges in assessing students' use of metacognitive processes, and a framework for interactively assessing metacognition and providing students with adaptive support based on their needs.

2 Background

Metacognition [8] describes the ability to reason about and explicitly manage one's own cognitive processes. It is often broken down into two sub-components: knowledge and regulation [9, 10]. Metacognitive knowledge refers to an individual's understanding of their own cognition and strategies for managing that cognition. Metacognitive regulation refers to how metacognitive knowledge is used in order to create plans, monitor and manage the effectiveness of those plans, and then reflect on the outcome of plan execution in order to refine metacognitive knowledge [11].

When applied to learning, metacognition is considered a subset of self-regulated learning (SRL). SRL is an active theory of learning that describes how learners are able to set goals, create plans for achieving those goals, continually monitor their progress, and revise their plans when necessary [12]. In terms of SRL, metacognition deals directly with cognition without explicitly considering its interactions with emotional or motivational constructs [13]. Despite this, models of self-regulation are valuable in depicting key metacognitive processes. For example, [14] describes SRL as containing "multiple and recursive stages incorporating cognitive and metacognitive strategies" (p. 286). This description of SRL involves phases of orientation and planning, enactment and learning, and reflection and self-assessment.

Students may start by orienting themselves to the task and formulating task understanding (*i.e.*, an understanding of what the task is). A student's task understanding is necessarily influenced by her metacognitive knowledge about her own abilities and available strategies for completing the task [15]. Together, these two sources of information, task understanding and metacognitive knowledge, provide a foundation that, in conjunction with other student attributes such as self-efficacy, governs students' subsequent goal-setting and planning processes. Once a plan has been formulated, students begin executing it. As they carry out the activities specified in their plans, students may exercise metacognitive monitoring as they consciously evaluate the effectiveness of their plans and the success of the activities they are engaging in. The result of these monitoring processes may lead students to exercise metacognitive control by evaluating and then modifying or even abandoning their plan as they execute it. Once a plan has been completed or abandoned, students may engage in reflection as they analyze the overall effectiveness of their approach and their planning processes. Such reflection may lead students to add to or revise their metacognitive knowledge and task understanding.

In this paper, our focus on metacognition is centered on students' understanding of and use of *strategies*, which have been defined as consciously-controllable processes for completing tasks [16]. Strategies comprise a large portion of metacognitive knowledge; they consist of declarative, procedural, and conditional knowledge that describe the strategy, its purpose, and how and when to employ it [9]. The research community has identified several types of strategies based on the tasks for which they are designed. For example, strategies may be cognitive (*e.g.*, a strategy for applying a particular procedure, or completing an addition problem), metacognitive (*e.g.*, strategies for choosing and monitoring one's own cognitive operations), involve management (*e.g.*, for managing one's environment to promote focused attention), be directed toward learning (*e.g.*, a strategy for memorizing new information), or involve a combination of these [17, 18]. For example, a metacognitive learning strategy might involve *activating prior knowledge* before learning about a topic by consciously bringing to mind information one already knows about the topic [19]. When faced with a complex task, students must either identify a known strategy for completing it or invent one using their metacognitive knowledge.

An important characteristic of a strategy is its *level of generality*. That is, some strategies apply to very specific situations (*e.g.*, an approach to adding two-digit numbers) while other strategies apply to a broader set of situations (*e.g.*, summarizing recently learned information to improve retention). An understanding of more general strategies, as well as their specific implementations for concrete tasks, is important for developing one's ability to adapt existing strategies to new situations or even invent new strategies. Thus, our goal in GIFT is to explicitly teach students general strategies and help students understand how to apply them to complex tasks. In the longer run, as students encounter different situations in which a strategy applies, we hope to make students aware of how strategies, such as those for maintaining situational awareness, monitoring the execution of one's plan, and evaluating the benefits and drawbacks of a previously-executed task, may generalize across tasks and domains [20]. A pre-requisite to achieving this goal in the GIFT framework is to develop the ability to conceptualize and build domain-independent structures for representing metacognitive strategies and processes.

2.1 Measuring Strategy Understanding

Measuring students' understanding of strategies by observing their behavior in real time is a difficult task; it requires determining whether their behaviors are consistent with a strategy. For small tasks the interpretation is straightforward. For example, to assess a student's understanding of an algebraic problem-solving strategy, a learning environment can present multiple problems and observe the steps that a student takes to solve these problems. If the student carries out a sequence of steps that matches the steps prescribed by the strategy, the learning environment can assume that the student understands the strategy. This approach is employed in many step-based intelligent tutoring systems such as Cognitive Tutors [18, 21, 22].

However, for complex tasks, interpretation is more difficult. For example, open-ended learning environments (OELEs; [6, 7]) present students with a learning context and a set of tools for exploring and building solutions to problems. Students are expected to use the environment's resources to learn needed information, construct and test solutions, and manage their own learning and problem solving processes. Succeeding in these tasks involves breaking up the overall task into sub-tasks, setting goals, and applying strategies for completing each sub-task. Thus, learning environments need methods for inferring: (1) the student's chosen task decomposition; (2) the sub-task the student is currently working on; (3) the strategy they are using to complete that sub-task; and (4) whether or not they are executing the strategy correctly. The open-ended nature of OELEs further exacerbates the measurement problem; a student may constantly change her chosen task decomposition, the task she is working on, or the strategies she is utilizing, and the analysis technique must be able to detect these changes. Moreover, incomplete or incorrect metacognitive knowledge may lead the student to employ suboptimal strategies, and detecting and properly interpreting these sub-optimal strategies presents additional analysis challenges.

Researchers have approached this problem from multiple angles. For example, *MetaTutor* [19] adopts a very direct approach with some similarities to self-report; it provides interface features through which students explicitly state the tasks they are working on (called sub-goals) and the strategies they are using to complete those tasks. For example, students can use the interface to indicate that they would like to create a sub-goal or employ a specific learning strategy. This allows the system to directly capture students' strategy use without having to make inferences based solely on their activities in the system. However, this relies on students' accurately communicating their intent to the system.

Another approach avoids measuring specific task decompositions, goals, and strategies entirely and instead defines a *model of desired performance* [23] describing desirable and productive qualities of students' problem-solving behaviors. If students' behaviors conform to this model, then they are assumed to understand effective strategies for solving the problem. For example, previous research with *Betty's Brain* [24] used an approach called *coherence analysis* (CA) [7] to estimate students' strategy understanding. In *Betty's Brain*, students learn about a science topic by reading about it and constructing a causal model that represents the topic as a set of entities connected by directed links.

Instead of measuring students' uses of specific strategies, CA identifies logical relationships in students' behaviors as they view sources of information (typically hypertext pages) and apply the information acquired to constructing and refining their causal models. The model of desired performance underlying CA is as follows: (1) when students encounter information that could help them add to or refine their causal models, they should act on that information by making the indicated changes to their model; and (2) students should not rely on guessing to change their causal model, so changes should usually be motivated by information encountered in the environment (*i.e.*, their model edits should be *supported* by previously-viewed information). Behavior that adheres to these two properties is said to be *coherent*, and the assumption is that as long as students' behaviors are coherent, they understand effective strategies for accomplishing the task.

The CA approach is attractive because it simplifies the analysis and interpretation tasks. The proposed hypothesis is that as long as students' actions are coherent, they are demonstrating an understanding of the task and a set of effective strategies for completing it. It also allows flexibility in interpretation: students can develop behaviors (presumably linked to strategies) that work best for them as long as these behaviors lead to coherent behavior. However, the challenge of applying CA is that observing non-coherent behavior provides little information regarding the *reasons* behind the non-coherence. Students exhibiting non-coherent behavior may be struggling with task decomposition, sub-task selection (*i.e.*, choosing the next sub-task to work on), strategy selection (*i.e.*, choosing a strategy for completing a task), or strategy execution. Alternatively, they may lack domain knowledge understanding that is critical for systematically solving the problem. Thus, the learning environment must rely on (or gather) additional information in order to support students who are struggling.

2.2 Supporting Strategy Understanding

If a learning environment determines that a student does not understand a specific strategy, then it may take steps to support the student in learning about that strategy. This can involve teaching students declarative, procedural, and conditional knowledge about the strategy [9]. Several effective approaches for *strategy instruction* (*i.e.*, directly instructing students on particular strategies) have been developed and tested by researchers (*e.g.*, [25]). These include: (1) providing students with worked examples of the strategy applied to a concrete task (*e.g.*, [26]); (2) engaging students in guided strategy practice with feedback (*e.g.*, [27]); and (3) holding conversations with the student that explain the strategy, its purpose, when it should be used, and its value in helping the student (*e.g.* [28]). These conversations are often contextualized by the student's current learning task and their recent activities in the learning environment.

In developing metacognitive tutoring for GIFT, we seek to leverage this wealth of previous research and incorporate it into GIFT. Our design, presented in the next section, takes advantage of coherence analysis, contextualized conversational feedback, and strategy instruction through guided practice. When students perform sequences of non-coherent or otherwise suboptimal behaviors, our approach employs contextualized conversational assessment to probe the student's metacognitive knowledge further.

When appropriate, these conversations also include feedback of the types (1)-(3) discussed above. The goals are to: (1) more accurately identify the source of students' errors so that we can (2) provide tailored instruction on the strategies (either cognitive or metacognitive) that they are struggling with. Toward this end, we are developing a strategy monitoring approach that will allow GIFT to analyze students' learning behaviors according to an understanding of how strategies are executed. The next section describes our design approach in detail.

3 Designing Metacognitive Tutoring in GIFT

3.1 Representations and Learner Modeling

To represent metacognition in GIFT, we will extend its current learner modeling capabilities. In GIFT, a learner model consists of a set of named *concepts* that are assessed continually while students are interacting with designated course materials. At any time, each concept may be assessed as being below, at, or above expectation, and higher level concepts may be related hierarchically to lower level concepts. Thus, a *basic mathematics* concept may be based on assessments of its component concepts: *addition*, *subtraction*, *multiplication*, and *division*. The data representation is similar to the sampling of a stream: GIFT monitors each student's task performance over time, updating the concept assessments based on his or her most recent performance. Thus, a student may perform above expectation on one addition problem and below expectation on the next. A history of these assessments is maintained for feedback purposes, both during and after learning.

Building from this, we will employ a three-level framework for analyzing and representing students' skill and strategy proficiency, shown in Fig. 1. Analyses will involve making a set of inferences based on students' observed behaviors while using the learning environment. In this framework, direct observations of students' behaviors will serve as assessments of their ability to correctly execute strategies. To accomplish this, we will design tools that allow learning environment designers to specify how actions can be combined to enact a strategy. The resulting strategy model can be used online to interpret students' action sequences in terms of these strategies. The strategy that best matches students' behaviors will be assumed to be the strategy they are applying, and further assessments will examine whether or not they execute the strategy correctly. For example, a student may be using a monitoring strategy in which they check their recently-completed work to make sure it is correct. However, they may erroneously conclude that their work was completed correctly, indicating an ineffective execution of the strategy.

These assessments and interactions, along with continued monitoring of student behavior, will serve as the basis for assessing students' understanding of domain-specific strategies. When GIFT observes a correctly-executed strategy, it will increase its confidence in the student's understanding of the associated procedural knowledge. Similarly, when GIFT observes a strategy executed at an appropriate time, it will increase its confidence in the student's understanding of the associated conditional

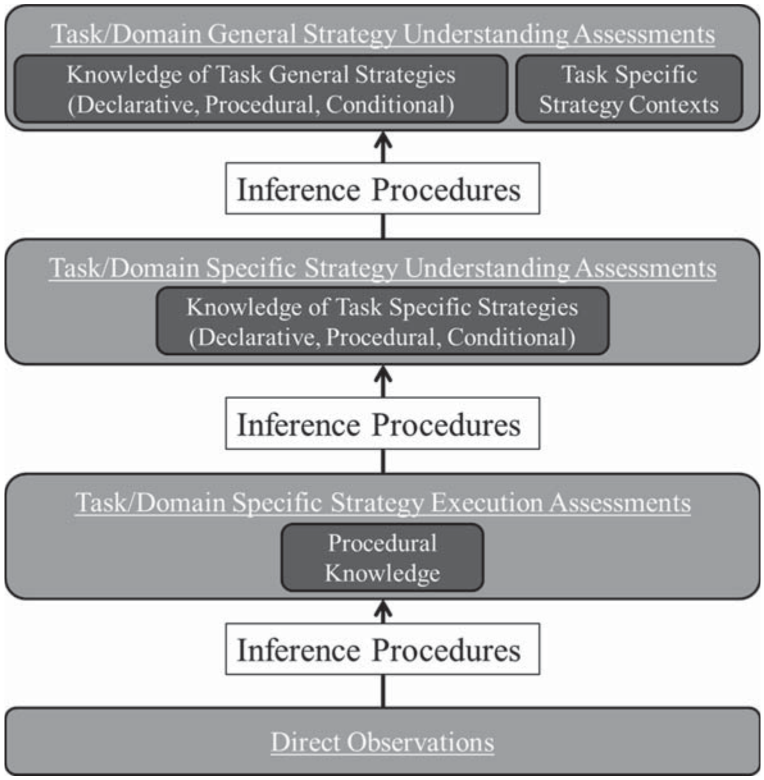

Fig. 1. Metacognitive learner modeling approach

knowledge. To test students' declarative knowledge, GIFT will interact with them directly and ask them questions testing their understanding.

The final level of our framework involves linking students' understanding of task-specific strategies to task-general representations of those strategies. An important aspect of metacognition is that the declarative form of a number of strategies can be expressed in a domain-general form. In other words, many strategies can be applied to multiple tasks, situations, and contexts. Our approach leverages this property by developing new GIFT capabilities for tracking and supporting task-general strategies in multiple contexts. When a student correctly employs a task-specific strategy, GIFT will link this use of the strategy to its task-general representation and the context in which the strategy was applied. This information will be stored in GIFT's long-term learner model and can be referenced during future learning sessions with GIFT. The goal is to integrate information about a student's use of strategies across multiple formats and contexts. This will allow GIFT to provide instruction and guidance that draws connections between a learner's current learning tasks and their previous experiences. For example, GIFT may guide the student through an analogy: "*This task is just like when you had to do [X] in [ENV] back in [MONTH]. The main difference is [Y]*".

3.2 Developing Instructional Strategies for GIFT

Even with the learner modeling and assessment approach described above, it is difficult to form a complete and accurate model of students' understanding of strategies while using an open-ended learning environment. For example, if a student never uses a strategy, then we have no data to assess whether or not they can properly execute it. Similarly, observing a student correctly executing a strategy does not help us assess their declarative knowledge of the strategy. Such a situation occurs when a student can "*do* but not *explain*" [29]. Thus, accurately modeling students in OELEs may require directly interacting with them in order to obtain additional information not directly revealed through their actions.

However, this interaction represents a trade-off. While it provides the learning environment with a more elaborate learner model, repeated querying may become a distractor that disrupts the student's attention and reduces time available for working on their task. To balance this trade-off, our approach takes advantage of the model of desired performance discussed in Sect. 2.1. For example, we may employ coherence analysis as was done in *Betty's Brain*. As long as a student's behavior conforms to our model, we allow her to proceed and desist from intervening until such time that her behavior becomes clearly suboptimal or non-coherent. At such times, our approach employs contextualized conversational assessments to interact with the student in order to collect additional evidence necessary to better interpret the source of her difficulties.

Once a difficulty is understood and characterized, GIFT can select the appropriate instruction to help the student. Currently, we are designing three primary forms of instructional interventions: contextualized conversational assessments and feedback; reviewing knowledge and strategies; and teaching through analogies (as discussed earlier). In this paper, we will focus on the first two intervention types.

Strategy 1: Collect Evidence through Contextualized Conversational Assessments
When GIFT observes that the student has performed sub-optimal or non-coherent behaviors, it may use its current learner model to generate multiple potential reasons linked to lack of domain and/or strategy knowledge for explaining the student's performance. For example, the student may not have been aware of important details in the environment (perhaps indicating the use of a poor strategy for analyzing the task). Alternatively, she may have been unsure of how to apply the important details she encountered (indicating poor strategy knowledge). Still another possibility is that she understands that the information is important, knows what strategy to use, but makes mistakes when executing the strategy.

To properly assess this student's strategy understanding, GIFT needs to interact with her using conversational assessments. For example, GIFT may decide to ask her about important details in the environment, awareness of which is needed to succeed in her current task(s). GIFT may also choose to probe her understanding of how identified information may be used to perform a chosen task. The student's answers to these questions can provide a better understanding of what she knows and which tasks, strategies, and environmental conditions are causing her trouble.

In holding these conversations with students, GIFT can embed contextualized instructional guidance for the student. For example, the following is a short excerpt of a conversation we envision taking place between GIFT and a student learning about counter-insurgency using UrbanSim, a counter-insurgency command simulation:

GIFT: Uh oh. Take a look at this report. It looks like insurgents took out a gas station in the southwestern section of the city in our area of operation. What is your assessment?

STUDENT: This is bad. We should rebuild it ASAP and then commit forces to protecting it!

GIFT: Why do you think it is such a high priority? What effect will the loss of this gas station have on our operations?

STUDENT: Without this gas station, the local population will struggle to travel throughout the area, prepare their food, and control the temperature of their homes.

GIFT: Agreed. Where will you pull resources from to accomplish this?

STUDENT: I'll recommit the engineering squad from bridge building to repairing the gas station, and I will pull some troops from the central square to provide the protective cover. The central square is pretty secure right now so I do not think that the loss of protection will involve much risk.

GIFT: I have another idea. Did you know there was another gas station in the area?

STUDENT: No, I didn't! Where is it?

GIFT: It is in the north-east. It is actually well supplied and in a less hostile area. If we commit forces to protecting that gas station, we will not have to commit funds to rebuilding the other station and we can continue building the bridge, which will open up a key supply route. This will allow us to meet gasoline demands for the area with the other gas station while continuing to make progress toward improving living conditions for the locals. If we rebuild the gas station, the same insurgents that destroyed it the first time might destroy it a second time; this may bolster their confidence.

STUDENT: That makes a lot of sense! I will follow that, and thanks for the help.

In this conversation, GIFT combines assessment with explanation and instruction. In the first three exchanges, GIFT collects information in order to better understand the student's awareness of critical information and ability to make trade-offs in the counter-insurgency scenario. Once it has collected this information, it presents and justifies an alternative approach to the student based on specific strategies (*e.g.*, gain control of an area before rebuilding its infrastructure and commit resources where there is greatest added benefit). Through these conversations, students will hopefully come to understand the cognitive and metacognitive processes important for success in their learning task. For some students, instruction through conversational assessment and feedback should be sufficient to aid their learning and consequently improve their problem solving behaviors. However, other students may continue to participate in conversational assessments, receive contextualized feedback, but show little improvement on their task performance. For these students, additional, more targeted instruction may be required.

Strategy 2: Review Knowledge and Strategies

As GIFT collects evidence about students' understanding of various strategies, it may determine that a student has continued to struggle with understanding tasks and strategies for completing those tasks despite conversational assessment and feedback. When this happens, GIFT will transition the learner from their current task into a more targeted training environment. For example, if the student seems to have forgotten key background or pre-requisite information, GIFT may decide that she needs to review a PowerPoint presentation and correctly answer questions about the material she has reviewed before she can come back to work on her primary tasks in the problem scenario. If she seems unaware of an important strategy, GIFT can place the student into a guided-practice environment to instruct her on the use of the strategy [14, 28]. This can help develop and confirm the student's declarative, procedural, and conditional knowledge by practicing the strategy and correctly answering questions about the strategy. The idea here is that a complex open-ended task requires a basic understanding of several different concepts and strategies. If a student does not have this understanding, she may not profit much from attempting to complete the complex tasks. Therefore, it is prudent to help her overcome her lack of understanding in-the-moment, because this can improve both current and future performance.

Another important aspect of this approach is that a student's difficulties in her primary task can serve as motivation to learn needed information. It is possible that the student would not be engaged in relevant PowerPoint slides until she realized the importance of the information for being able to succeed in the primary task. Thus, we would like GIFT to draw explicit connections between the student's experiences in an environment like UrbanSim and the remediation she is about to experience. For example, GIFT might say "*I would like you to take a break from UrbanSim and focus on learning strategies for maintaining situational awareness. This will help you better understand how to manage the large amount of information that is available in this learning environment, and it will help you have more success in defeating the insurgents"*.

4 Discussion and Conclusions

In this paper, we have presented the design of our approach to incorporating metacognitive instruction in the Generalized Intelligent Framework for Tutoring (GIFT). Our approach focuses on modeling students according to their understanding and use of strategies for completing tasks. Such strategy understanding is a critical aspect of students' metacognitive knowledge, and students who utilize good strategies have been shown to perform better in learning and problem solving tasks ([18]).

In addition to modeling students' understanding of strategies, our approach also helps students develop their understanding of strategies for completing their learning tasks in open-ended learning environments. We plan to utilize contextualized conversations for assessment and feedback and strategy instruction through guided practice with feedback. Further, we plan to extend these approaches by incorporating students' prior experiences in the GIFT platform into conversations. The goal is to use these prior experiences to help provide instruction in the current task through analogies, as described briefly in Sect. 2.2. We believe that incorporating these approaches into GIFT will allow for powerful instruction of complex tasks and topics.

As we implement this design into GIFT, we will develop a suite of authoring tools that allow future GIFT users to design metacognitive strategy instruction for their learning tasks and environments. We will also study the effectiveness of this approach with students from US Army training programs in order to test its usefulness and effect on students. We expect to learn many lessons from these studies, and this will help us refine our design and implementation of the GIFT Meta-tutoring environment.

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