Bootstrapping learner's self-regulated learning

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Abstract

Self-regulating learners can be characterized as learners who actively research what they do to learn and how well their goals are achieved by variations in their approaches to learning. Extensive research on how and how well learners understand and apply the scientific method demonstrates that they encounter significant challenges in designing and validly interpreting experiments. I juxtapose these two views to make a case that learners need significant support to carry out a progressive program of research to make self-regulated learning productive. One key to this endeavor is gathering data that can accurately and systematically reflect how learning unfolds. I describe a software system called nStudy that is designed to do this, and I speculate on how software systems like nStudy can play powerful roles in improving learning and simultaneously advancing learning science.

Key words: learning technologies, metacognition, process feedback, self-regulated learning

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My 2-year old niece's language is blossoming. Every waking hour is densely populated with talk about her toys, her family's and our dogs and their behavior, food, her doll, and scores of other topics. She is engaging in extensive – some days it seems excessive – deliberate practice (Ericsson, Krampe, & Tesch-Römer, 1993). Her practice is not merely repeating routines but a directed exploration of forms for language, contexts that shape its use, as well as psychomotor and kinesthetic information that helps her communicate with prosody and clear articulation.

In a very natural and culturally supported way, my niece is intensely engaged in a program of personal experimentation with language. Often it is trial and error and at other times, given her developmental stage, it is an approximately hypothetico-deductive activity. Her parents, my wife and I, and others with relatively more advanced language skills, in varying ways and with varying immediacy of effects, provide frequent, timely and encouraging formative and summative feedback. We play roles as human instruments – we assess data she generates in operationalizing her hypotheses about complex elements and relationships that govern language. We display not merely our readings of these data but interact in ways that help her extend her perceptions about the correctness, appropriateness and communication "value" of her utterances. In a few more years, except for common errors (e.g., some instances of subject-verb agreement, grammatically correct use of I and me), my niece likely will have achieved expertise. She is fortunate to live in a world that actively and nearly constantly supports her personal research program.

Various researchers, including me (e.g., Winne, 2010; Zimmerman, 2008), maintain that skills for learning, like skills in language, can be instructed with positive effects. Hundreds of research studies demonstrate that learners who are taught simple tactics and strategic methods for carrying out academic tasks outperform peers from whom such instruction is withheld. One clear and powerful example is the self-regulated strategy development model for writing (e.g., Harris & Graham, 1999). A recent meta-analysis found that students taught this strategy produced writing that was better than peers' writing by a weighted mean effect size of 1.14 (Graham & Perin, 2007). Such studies also demonstrate that students participating in these experiments' control groups (or "business as usual" comparison groups) have regrettably underdeveloped learning skills.

Why is this difference the case? In my view, as is the case in other professional fields, teaching practices in schools typically lag behind the leading edge of research. Moreover, students in schools too infrequently receive direct and effective instruction in learning skills. On the presumption that teaching can make a difference, this is a logical deduction given findings like those just cited. If teaching practices kept apace with research, comparison groups in research would not fare as poorly as they do because learners would have compensatory skills to apply to their tasks.

In the context I attribute to schools, students likely engage in personal programs of research about how to learn more effectively. For example, after being taught a few first-letter mnemonics – for example, Chief SOH CAH TOA for the trigonometric relations of sine, cosine and tangent defined by the ratio of a triangle's opposite, adjacent and hypotenuse sides; or ROY G BIV for colors of the spectrum in order from longer to shorter wavelength – it seems likely that students experiment with similar mnemonics given the

reasonably quick and reliable success such tactics offer. But the positive results of experimental educational psychology demonstrate that these personally framed research programs, to the extent they are operative, are not sufficiently progressive.

I posit two causes for this result. First, while the school environment provides many occasions for students to experiment with learning skills, students probably struggle to do this. The numerous, heterogeneous and rapidly sequenced objectives that are addressed in a day's instruction focus on mastery of curriculum, not inquiry about and deliberate practice of learning skills. Second, teachers are insufficiently educated about learning skills that they could teach learners (which is not a fault of teachers but of those who design and certify teacher education and professional development programs). The volume and pace of prescribed curricula pushes instruction and guided practice of learning skills out of the practical bounds of lessons and of teachers' capacities to provide extensive, timely and tailored feedback about students' uses of learning skills. Students themselves have underdeveloped skills for monitoring what they do (e.g., Winne & Jamieson-Noel, 2002) and what they do is not well matched to what research would prescribe (Winne & Jamieson-Noel, 2003).

Despite this less than optimal environment, students carry out personalized enquiries about how to learn better than they do at present. In an investigation of what teachers and students perceived about cognitive and metacognitive features of lessons, Marx and I observed that fifth grade students often referred to nascent learning skills they claimed to use or were "working on" (Winne & Marx, 1982). But it is not only students' learning environments that hinder successful deliberate practice of learning skills. Students and most people are not naturally skilled experimenters (Zimmerman, 2007).

In the following sections, I first overview challenges people face in developing and learning from experiments in general. Then, I relate how these factors are predicted to hamper students in programs of research they carry out on becoming more effective learners, that is, bumps on a path to becoming productive, self-regulating learners. Given this context, second, I describe software we have developed that, with some extension, may help students overcome some of these challenges and improve their capabilities to deliberately practice learning skills on a path to become an expert learner. Finally, I offer suggestions for realizing these predicted gains in everyday schooling.

Learning skills of scientific inquiry

In her comprehensive synthesis of research on the development of scientific thinking skills across the developmental spectrum from mid-elementary grades to adulthood, Zimmerman (2007) defined scientific thinking as

> the application of the methods or principles of scientific inquiry to reasoning or problem-solving situations, and involves the skills implicated in generating, testing and revising theories, and in the case of fully developed skills, to reflect on the process of knowledge acquisition and change …. Participants engage in some or all of the components of scientific inquiry, such as designing experiments, evaluating evidence and

making inferences in the service of forming and/or revising theories about the phenomenon under investigation. (p. 173)

In a preview of her synthesis, she observed:

> Sufficient research has been compiled to corroborate the claim that investigation skills and relevant domain knowledge "bootstrap" one another, such that there is an interdependent relationship that underlies the development of scientific thinking. However, as is the case for intellectual skills in general, the development of the component skills of scientific thinking "cannot be counted on to routinely develop" (Kuhn & Franklin, 2006, p. 974). (p. 173)

Bumps on a road to becoming a skilled researcher

Klahr's (2005) model of scientific discovery as dual search describes three overarching processes in conducting a scientific inquiry: searching for hypotheses, searching for experimental designs to generate data for testing hypotheses, and evaluating evidence afforded by data. In pursuing these activities, children and adult experimenters often suffer shortcomings and fail to surmount them. I draw and synthesize findings from Zimmerman's (2007) review; citations to primary research relating to these can be found there.

In the general population, and particularly among less developmentally advanced or younger experimenters, people sometimes struggle or fail to:

1. Frame discriminating hypotheses.

2. Explore all relevant combinations of variables they hypothesize or are told have bearing on outcomes.

3. Design experiments involving multiple variables to test a specific (targeted) hypothesis. Rather, variables and their combinations are chosen on the basis of availability (in the environment or the mind), representativeness, salience, or other inconsistent and weak heuristics.

4. Vary a causal factor that produces a positive outcome, thus reproducing positive results that yield confounded interpretations about true causes.

5. Design experiments to investigate the same causal system when a hypothesis is framed as a positive versus a negative relation.

6. Design experiments to test rival hypotheses or hypotheses that are capable of disconfirming a held theory.

7. Seek or attend to evidence that could disconfirm hypotheses. Alternatively, evidence is conceptually integrated with the hypothesis such that disconfirming evidence is judged not relevant.

8. Avoid overgeneralizing mere covariation as sufficient grounds for inferring causation.

9. Avoid tendencies to discount, ignore or even misrepresent evidence that challenges background knowledge or preference.

10. Avoid mistakes of reasoning when data are outliers and, more generally, make use of statistical tools and concepts when considering patterns in data.

11. Take account of and compensate for their beliefs about the epistemological status of claims that influence non-scientific forms of reasoning.

12. Keep records of their enquiries and consult them. Memory for important features of experimental enquiries is fragile and biased.

13. Develop skills involved in valid and efficient scientific reasoning on their own, i.e., without prompts and guidance.

14. Apply skills of scientific reasoning in social domains as well as they do in physical science domains.

15. Cope with inconsistent ways they use valid rules of scientific reasoning over multiple experiments.

16. Treat experimentation as a subject of study beyond the topic(s) directly explored in experiments; that is, engage with experimentation metacognitively.

The good news is that student experimenters likely can overcome these challenges if they experience well-designed instruction that provides deliberate practice, that is, extensive, spaced trials with accurate and timely knowledge-of-results feedback. When the focus of students' experiments is becoming a better learner, they also need formative feedback (Hattie & Temperly, 2007; Shute, 2008) and, particularly, they need process feedback that describes variables they manipulated to change how they learn (Butler & Winne, 1995). The next section examines this process of personal experimentation to improve learning, called self-regulated learning.

Self-regulated learning

In brief (see Zimmerman & Schunk, 2010, for elaboration), self-regulated learning (SRL) is a dynamic blend of two metacognitive operations, metacognitive monitoring and meta-cognitive control. Together, these metacognitive operations change *how* activities, like learning, are carried out so that goals can be met and met in a more satisfying way. In exercising SRL, learners attempt to discover "what works" in striving to develop knowledge and skills, as well as "what works better." A model of SRL Hadwin and I developed (Winne & Hadwin, 1998; see also Greene & Azevedo, 1997) is tightly coupled to the proposition that learners are agents. Agents gather data about factors in their environment – the internal environment of cognition and motivation, and the external environment – then set goals and devise plans to reach those goals. As work on a task unfolds, monitoring may identify discrepancies between goals and achievements, and metacognitive monitoring may identify differences between plans for achieving goals and processes enacted. Learners then may exercise metacognitive control in at least three ways: revising goals, adapting plans or changing operations.

More specifically, the Winne and Hadwin (1998) model segments SRL into four weakly sequenced and recursive phases. In phase one, learners construct an idiosyncratic profile of features in the environment surrounding a learning task. This profile blends cognitive, motivational and affective data. In phase two, learners set goals and design a plan to achieve them in the context of the environment they perceive. In phase 3, learners call on tactics and strategies to move toward goals. Modest adaptations may be made on the fly. In phase four, which is optional, learners consider whether and how to change their elements in the preceding three phases.

Over time, the self-regulating learner's aim is to improve learning by (a) adapting the environment and (b) acquiring and improving methods for learning. In this sense, self-regulating learners experiment with how they learn so that learning becomes successively more effective and more satisfying (Winne, 1997, 2006). However, as noted earlier, there are significant challenges to doing such research. And, empirical findings document that learners are not expert at learning. This chicken-and-egg dilemma may account for why forging a productive personal program of SRL research is a *very* difficult task for students in schools (see also Winne & Hadwin, in press).

Can learners be supported to break this cycle? In this article, I first summarize features of software we have designed to research and support online learning. In the course of this summary, I describe how the software gathers data that can be used to assemble a picture of how a learner learns. Then, I describe features we plan to add to this software that make it into a tool learners can use to carry out a personal program of research to improve learning. In this latter section, I describe how these plans are intended to help learners become better at researching their learning, that is, how the software can scaffold improvements in self-regulated learning.

nStudy

Software has potential to be a powerful tool to help learners research learning and a boon to "professional" researchers investigating learning and SRL (Nesbit & Winne, 2008; Winne, 2006; Winne & Nesbit, 2009). So far, however, few software technologies have been designed to help learners pull up learning by their bootstraps. This is one of the goals of the nStudy project.

nStudy (Winne, Hadwin & Beaudoin, 2010; see also http://learningkit.sfu.ca/lucb/celc-2009-nStudy.pdf) is a web application, that is, software that runs on an internet server and displays its products in a web browser's window. We designed nStudy to serve three purposes. First, it is a tool learners can use to study information online. The information can be of any kind that is formatted using the hypertext markup language (HTML). As learners study, nStudy records extensive, fine-grained, time-stamped data about operations they apply to selections of information. As is described in the next sections, nStudy's second purpose is to gather these data so that researchers can characterize *how* learners learn without suffering shortfalls of self-reports that arise due to imperfections of human memory (see Winne, Zhou & Egan, 2010). Third, these same data are raw materials learners need to carry out a progressive, personal program of research on SRL.

An extension to nStudy is being designed that will allow learners to access and analyze these data to support individualized "N = me" research on learning.

Interventions and traces

HTML content that is viewed in nStudy can be material that an instructor or researcher designs, or it can be information available anywhere in the Internet. In the former case, researchers can present particular information, for example, headings or "self-check" questions that operationalize a treatment condition that is the topic of an experiment. Or, information can be formatted in ways that operationalize variables of interest; for example, a causal system can be described as text or as a graphical display of factors. In this way, nStudy can mimic many kinds of treatments studied in conventional experiments.

nStudy is also an instrument that gathers traces of learners' cognition and metacognition. What are traces? They are records of behavior, a form of performance assessment, that provide grounds for inferring a learner's cognitive and metacognitive activities (see Winne et al., 2010).

To generate a trace datum, a learner carries out an observable activity on or with information. For example, suppose a window provides a list of files and the learner double clicks a particular item to open it. Setting aside the possibility that this is random behavior, it is plausible to infer the learner (a) is searching for some target information in particular, (b) forecasts the target information is available in this particular file based on the file's title and/or the name of the directory in which it is located, and (c) opens the file because the target information is judged to be not fully or accurately stored in memory, or handily available. The specifics of (c) can have several explanations, for example, the learner judges the target information is: (a) not in memory; or (b) stored in memory but can't be retrieved according to a feeling of knowing; or (c) may be stored in memory but it is easier to open the file to "retrieve" it. Double-clicking a particular file traces these features of cognition.

In nStudy, when a learner opens a file-like item, for example, a bookmark to a web page, nStudy logs extensive, fine-grained, time-stamped information that, in the aggregate, traces the cognitive event. Some of the information logged includes: the title of the window containing the item that was double-clicked, the time that container window was opened or made active, the title of the item that was opened, the time the double-click was effected, and the window that opened. Time data can provide grounds for interpreting the cognitive load involved in, for example, locating the target item. The title of the item double-clicked provides semantic information for estimating kinds of information the learner seeks. The log of these data is constructed nearly simultaneously with the cognitive event. The learner need not describe what was done but merely acts, thus avoiding vagueness or misspoken descriptions. The context for this action, while not necessarily a full representation of the state of the learner's working memory, is well specified.

nStudy's browser window and bookmarks

Learners access information on a web page by entering a universal resource locator (URL) into an address field, for example, http://mypage.domainname. Once the web page is displayed, nStudy provides a variety of tools learners can use to operate on its information. One tool guides the learner to bookmark a web page. To create a bookmark, the learner generates a title for the bookmark and, optionally, can enter a description of the web page.

The simple act of titling a bookmark generates trace data that support inferences about at least three cognitive events. First, choosing to create a bookmark signals that the learner forecasts information on this web page that may have value in the future. A bookmark preserves a way to re-access it and, thus, second, it traces planning. Third, assigning a title to a bookmark to replace nStudy's default title of "untitled – year.month.day.hour.minute" signals that the learner classifies the information in this web page as belonging to a category (e.g., "Darwin's theory") or fits a task in which this information might play a role (e.g., "arguments: evolution"). Fourth, the semantic content of the title makes observable at least some of the standards the learner used in meta-cognitively monitoring the web page's information.

Tags

nStudy allows learners to tag information in a web page by selecting text, then mod-clicking[2] to pop up a contextual menu from which a tag can be chosen (see Figure 1). This links the selected text to the tag. A generic tag titled *Highlight* is always available at the top of the popup menu. Below that is a further option, *Tags…* that opens another window (not shown) where the learner can review all tags that have been constructed so far, and assign one of those or create a new tag for the target information. The next five items in the popup menu are the five most recently used tags; in Figure 1, these are: Can do, Can't do, Fallacy, funny and is this a learning objective. Once information is tagged, a background corresponding to the tag's color is created (the color can be set by the learner as a preference), and the tagged information, which we call a quote, is copied to the panel at left in Figure 1. For example, "Describe the major scientific ideas …" is the first quote tagged with "Can do." Double clicking on a quote in that panel scrolls the text to show the quote in its surrounding context.

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[2] A mod-click is a right-click when running Firefox and nStudy under the Windows operating systems and a control-click under the Macintosh operating system.
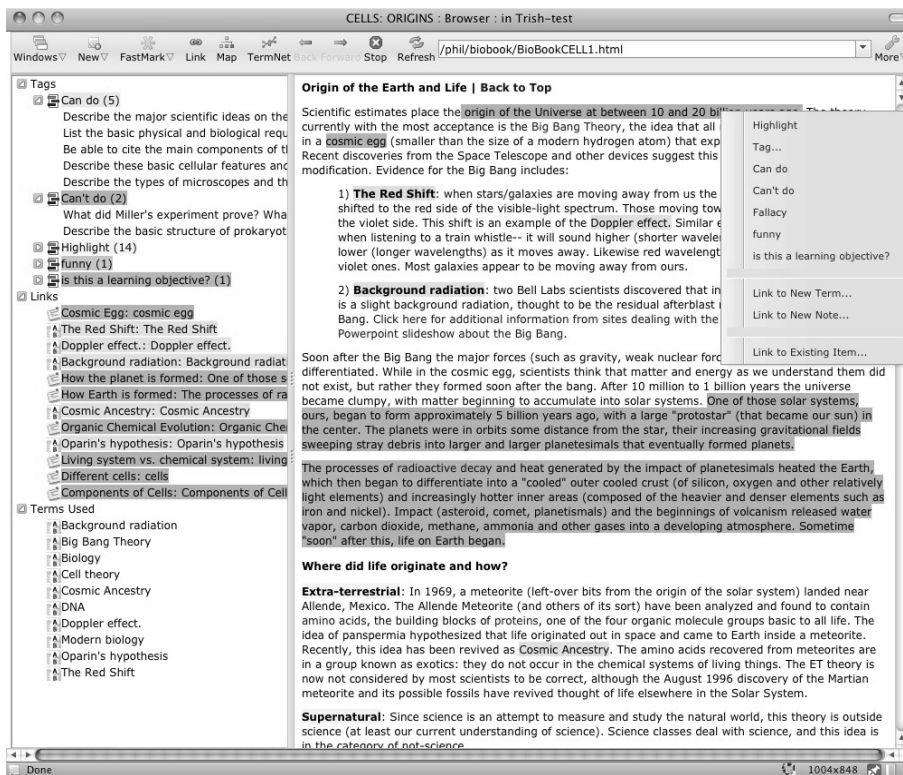
Figure 1:
The nStudy browser window running inside a Firefox window showing its table of quotes and linking tools

Selecting text for tagging traces that the learner is metacognitively monitoring it. The tag chosen or created identifies what standards the learner used to metacognitively monitor. The five most recent tags might be inferred to identify a current set of discriminations the learner is considering about the information being read in the web page.

Notes

Figure 2 shows a basic note. Learners can link notes to quotes in a web page and to bookmarks representing entire web pages. Each note is automatically assigned a default title of *untitled* that the learner can change. The text selected for annotation is automatically quoted in the linked note's *Quote* field along with a link to the web page in which that quote appears.
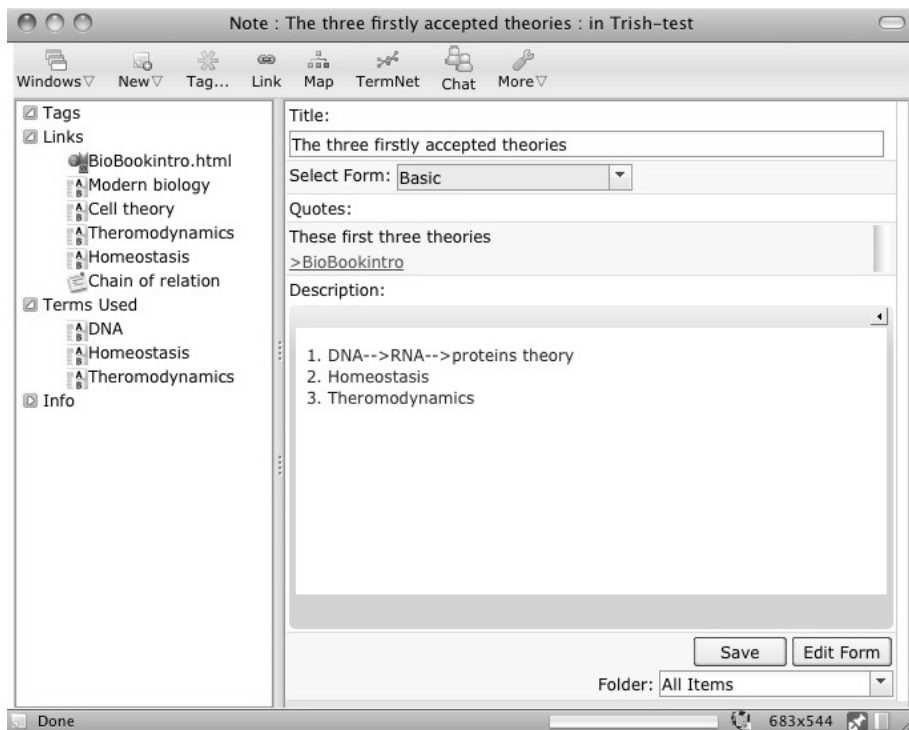
Figure 2
A basic note in nStudy

Notes are web forms that operationalize schemas for annotation. Learners choose a schema from the dropdown list, *Select Form*. An option in this dropdown list is to create a new form. Figure 3 shows the editor that learners (and researchers) can use to tailor an existing note form or to create an entirely new schema for annotating information. Modified or new note forms can be a one off design or they can be saved for future use. Various kinds of fields are provided for adapting forms. They can be added to a note by a drag-and-drop operation. Properties of a field, such as its label(s) or end points for a slider are set in the *Set Properties* tab at the far right of the editor's tabs bar.

As with nStudy's other tools, making a note traces several key cognitive and metacognitive events. For reasons of limited space, just a few are elaborated. As with tags, the act of creating a note reflects metacognitive monitoring of information in relation to a goal. The quote selected in a browser is elaborated by information the learner enters into fields in the note. Customizing a note form or creating a new form traces a major metacognitive event: an available schema is judged inappropriate and a new schema is constructed.
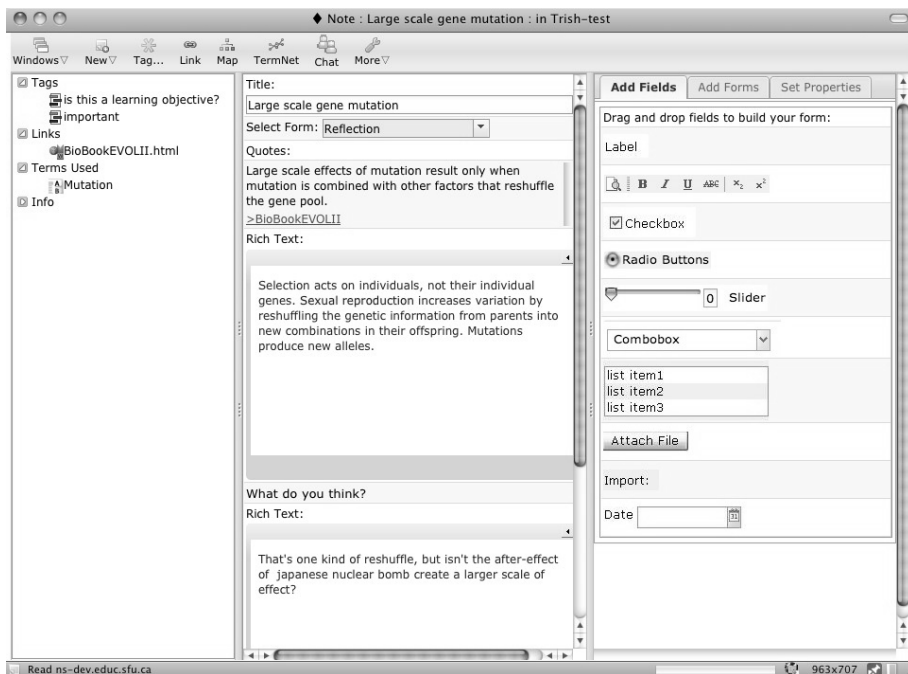
Figure 3:
An nStudy note showing a form and the editor for modifying and creating new forms that
operationalize new schemas for notes

Terms

A learner can create terms (see Figure 4) for concepts that are central to the topic being studied. All terms use one form. Making a term traces metacognitive monitoring of information that the learner judges to be a term, and assembles that new term and its linked quote with information input to the *Description* field.

In any nStudy browser window, note window, and term window, nStudy scans the text for terms. Terms it identifies are posted in that window under *Terms Used* in the left panel (e.g., see Figures 1 and 2). Double-clicking a term opens the term in a new window like Figure 4. This traces metacognitive monitoring about the retrievability of a term's description.
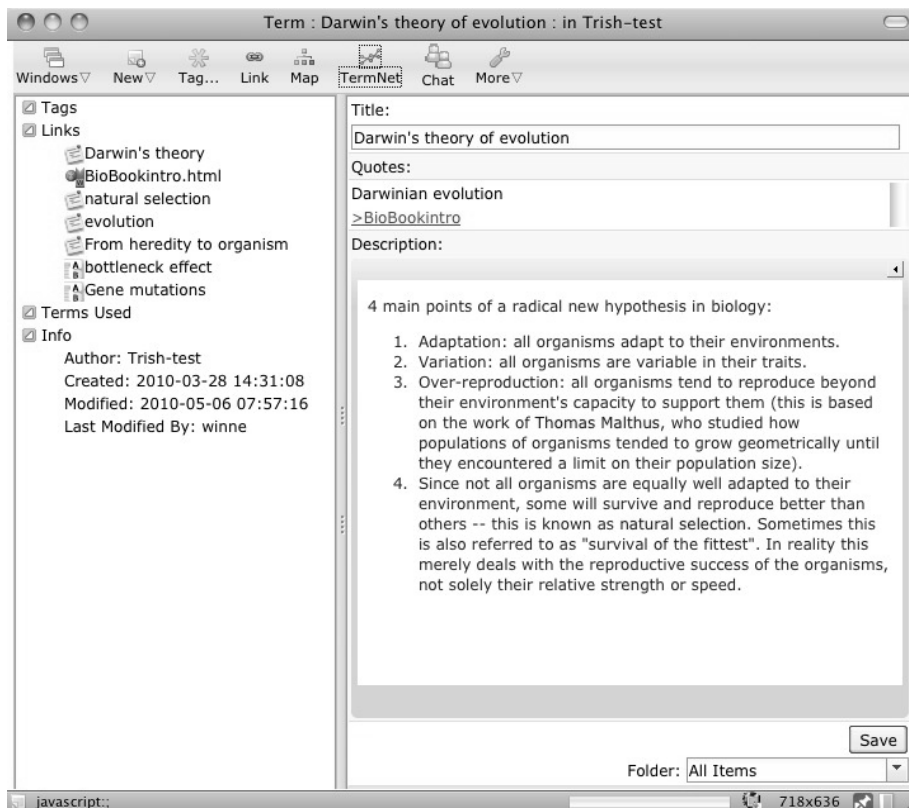
Figure 4:
An nStudy term

The Termnet

nStudy also traces when a learner examines how terms relate to one another in a display called the Termnet (see Figure 5). Links between two terms, A and B, are created if A's description uses B or vice versa. The link represents a literal "in terms of …" relation. The Termnet shows terms and in-terms-of links for every window the learner has open and can be viewed by clicking an icon in the toolbar of any one of those windows. The click traces a metacognitive judgment about a goal to examine how terms in the window in which the click is made relate to other terms in the set of windows that are open. In the Termnet window, any particular term can be reviewed by double clicking it. This traces a metacognitive judgment of utility in reviewing a term, presumably because its description cannot be retrieved from memory. A term of interest can be found in a complex graphical display by entering it in the search field of the Termnet's toolbar. As with the double-click of a term, this traces a term on which the learner is currently focusing attention.
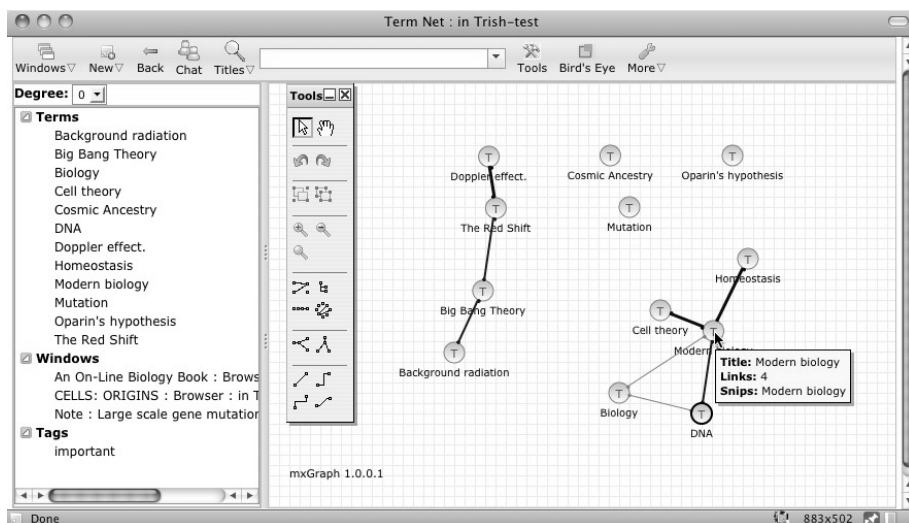
Figure 5:
An nStudy Termnet showing terms used in all windows currently open

Library

A display of all the information items a learner has created can be viewed in nStudy's Library table (see Figure 6). Items in the table can be filtered by: (a) type of information item by selecting options in the dropdown menu *Show*, (b) folders into which items are organized by selecting a folder in the left panel, and (c) tags applied by selecting a tag in the left panel. By clicking on a column in the table, items can be sorted according to several kinds of metadata including those shown in Figure 6 as well as creator, last editor (in a shared workspace) and more. When learners filter and sort items, standards being used to search for information are traced. The learner also can search for a particular item by its content, title or both by entering text in the *Search* field. The learner can operate on one or a set of several items by selecting them, mod-clicking to expose a contextual menu and choosing a desired operator. As in other windows, double clicking an item opens its window. This traces a metacognitive expectation that the learner holds about information recorded in the item being opened.
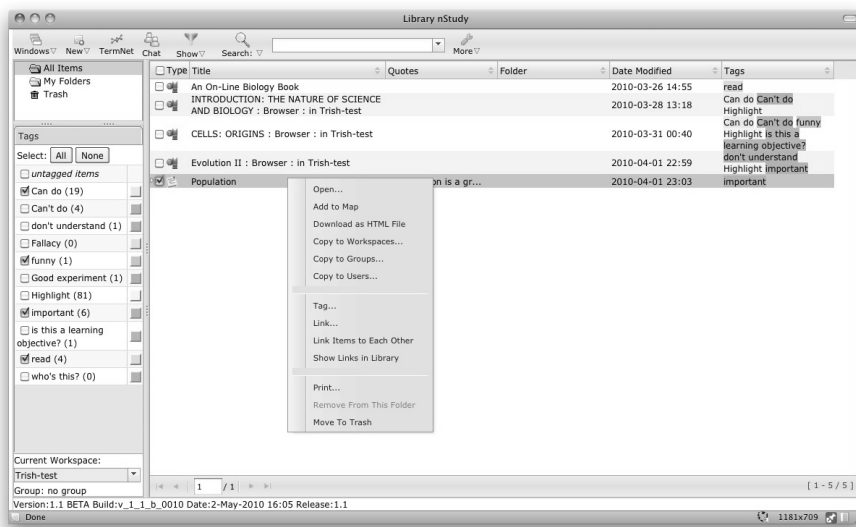
Figure 6:
nStudy's Library and Operators

Analyzing nStudy logs of studying events

Trace data that nStudy gathers unobtrusively and on the fly as learners engage with their tasks are readily examined using conventional methods such as counts and averages. These are data and statistics that researchers can use to examine SRL and, pending a planned extension to nStudy, that learners will be able to examine as process feedback. Beyond this conventional information, additional descriptions about how studying is carried out can be gleaned by: (a) taking into account temporal features of trace data and (b) examining patterns among traces that can yield quantitative indexes and pictorial views of how learners study (see Winne, Zhou & Egan, 2010).

Extending counts: Conditional IF-THEN pairs and patterns of studying events

Suppose a form for an nStudy note, a "goal" form, provides fields for learners to describe goals for learning – *Goal, Evidence of success, Need to work on …* – plus a slider to rate the degree to which each goal is achieved. A count of notes a learner makes using this form indexes the number of goals set. While number of goals set is a common measure of goal setting, nStudy's log of studying events allows more penetrating examinations of the role of goals in learning. By scanning backward along a timeline of logged events, it is possible to identify at least two important IF-THEN relationships: contexts that precede when a learner (a) sets a goal and (b) revisits previously set goals to adjust estimates of

success. For contexts deemed similar (using an index of structural equivalence described in Winne, Jamieson-Noel & Muis, 2002), these relationships can be expressed as a conditional probability: given a particular context, IF X & Y & …, THEN what is the probability the learner sets or revisits a goal, which nStudy logs as creating or revisiting any note that uses the goal form.

The binary IF-THEN architecture of studying events can be extended in ways that allow the measurement of more complex patterns – learning strategies if you will. This kind of analysis begins by building a transition matrix that can be translated into a graph of transitions (see Figure 7). Briefly, in a transition matrix, each tally in a cell corresponds to a transition from an event designated in a row (IF) to the event that follows it (THEN) in a column. For example, in Figure 7, A is followed by B so a tally is recorded in cell A,B. Event B is now the context for a subsequent event, D. And so on.

Sequence of traces: A B D B C E D B C E D A C E D A B C F …

Transition Matrix

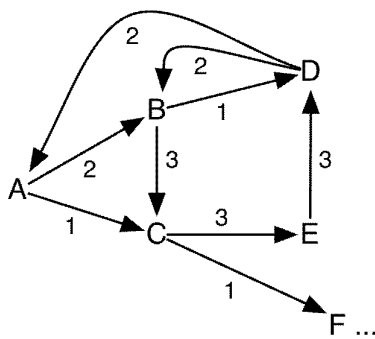|	A	B	C	D	E	F
A		//	/			
B			///	/		
C					///	/
D	//	//				
E				///		
F						

Figure 7:
A trace sequence, its transition matrix and a graph of the pattern of traces

The transition matrix can be transformed to picture the pattern of transitions as illustrated. Properties of this graph can be quantified in terms of, for example, the degree of regularity in the pattern, the degree to which one pattern is "geometrically" congruent to another, and whether specific nodes or small neighborhoods of the graph play the same structural role relative to the graph as a whole (see Winne, Jamieson-Noel & Muis, 2002). Hadwin, Nesbit, Jamieson-Noel, Code and Winne (2007) illustrate using this kind of analysis to describe levels and forms of learners' cognitive and metacognitive activities.

Software supports for SRL as a program of personal research on learning

Assume for sake of argument that: (a) goal setting boosts achievement (it does; see Morgan, 1985) and (b) contexts can be operationally defined in a form that software can recognize by a researcher's analysis or, with very large samples, by software data mining methods (they can; see Zhou, Xu, Nesbit & Winne, 2010). In this situation, nStudy might be extended to intervene in several ways designed to promote self-regulated learning as a personal program of research. For example, if the learner does not consistently (a) set goals when goal-setting contexts arise or (b) revisit goals in a context where this is appropriate, alerting the learner to this situation may help overcome a production deficiency, that is, a context (IF) where a useful studying tactic (THEN) was not engaged.

Equipped with these kinds of information and extensions to nStudy (which are not yet developed but planned), learners may be helped to smooth several of the bumps previously described that people encounter when they research causal systems, such as how they learn. Here are some conjectures that speak directly to issues 1, 2, 3, 7 and 12 previously listed as bumps on the road to becoming a skilled researcher. In the following scenarios, I use the label nStudy+ to refer to a future version of nStudy that is being designed but has not yet been implemented.

First, with information about contexts that are and are not very likely to lead to an increase in estimates of goal success, the learner might be prompted to frame more discriminating hypotheses about kinds of contexts that are more or less a boon to improving knowledge (bump #1). A method for describing these contexts in terms of learning events logged by nStudy+ could be a neighborhood of study events displayed in a graph like Figure 7. A shortcoming of this display is that it characterizes context in terms of operations the learner applies to study information but omits characteristics of the information studied.

Second, for contexts in which the conditional probability of an upward revision of goal success is small, nStudy+ might invite the learner to investigate the termnet for each context. This invitation involves the consideration of which key concepts and what it is about their conceptual configuration that might be impeding progress. This further discriminates grounds for hypotheses about effects and extends exploration of variables beyond operations applied to affect studying to include the semantic content of what was studied (bump #2).

Third, reminding the learner that particular operations were applied to particular information provides a fuller account than just counting the frequency of studying activities or showing only the content on which operations, like tagging, were applied. nStudy+ sets the stage for the learner to design an experiment – with some guidance by nStudy+ – about multiple variables that affect the growth of and confidence in knowledge (bump #3). Because nStudy+ has available all instances of contexts and associated termnets, the learner benefits from a complete sample rather than what is available to forgetful, biased and erroneously reconstructive memory. This, for example, helps the learner seek evi-

dence that can disconfirm as well as support hypotheses (bump #7) based on a complete record of data rather than a sample (bump #12).

Research targets for the near and moderate range future

The proposition I advance is that, to be successful, learners need to learn more than subjects they study in school. They need to develop skills that allow them to carry out a personalized, progressive program of research on how to learn. Such development is researched today under the banner of self-regulated learning. Becoming a productive self-regulated learner is challenging. First, learners lack sufficient and valid data about how they learn. Their memories of learning experiences can be invalid because factors of human memory lead to biased, incomplete and erroneously reconstructed representations of data and relations among data. Second, learners (and people in general) face a number of challenges – bumps on the road – to doing penetrating and valid research.

Instruments like nStudy can gather, sort, analyze and display information of the kind, and in ways, that learners need to form and test hypotheses about learning, that is, to self-regulate learning. This can supplement the typical school environment (Winne, 2006) in areas where schools are not (yet) well equipped.

It would be naïve to believe that simply installing powerhouse software could be sufficient to achieve the challenging goals described in this paper. Beyond having tools, learners must be motivated to use them and have a context that invites using them. The hope that natural consequences associated with improved learning skills will be enough may collapse if systemic features of education foster performance goal orientations, value grades more than deep understanding, and foreground an entity view of learning where ability is inelastic (see Wigfield & Cambria, 2010). Moreover, I conjecture that succeeding as a self-regulated learner entails adopting an epistemological stance that *learning* is a topic of inquiry *because* it is a skill that can be honed with deliberate practice. Under this view, research in educational psychology widens from inquiries into "the way things are" in an experimental condition or new school curriculum to studies of "the way learners make things" (Winne & Nesbit, 2010). With multifaceted support, such as conjectured for nStudy+, learners themselves can be tapped as a powerful resource for improving their education. The data they generate simultaneously can leverage significant advances in learning science by providing much more complete, authentic and longitudinal records of how learners go about building knowledge and skills (Winne, 2006).

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