

nStudy: Software for Learning Analytics about Learning Processes and Self-Regulated Learning

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Abstract

Data used in learning analytics rarely provide strong and clear signals about how learners process content. As a result, learning as a process is not clearly described for learners or for learning scientists. Gašević, Dawson, and Siemens (2015) urged data be sought that more straightforwardly describe processes in terms of events within learning episodes. They recommended building on Winne's (1982) characterization of traces — ambient data gathered as learners study that more clearly represent which operations learners apply to which information — and his COPES model of a learning event — conditions, operations, products, evaluations, standards (Winne, 1997). We designed and describe an open source, open access, scalable software system called nStudy that responds to their challenge. nStudy gathers data that trace cognition, metacognition, and motivation as processes that are operationally captured as learners operate on information using nStudy's tools. nStudy can be configured to support learners' evolving self-regulated learning, a process akin to personally focused, self-directed learning science.

Keywords

Cognition, metacognition, self-regulated learning, trace data.

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1. Introduction

Data gathered to advance learning science and used in generating learning analytics are diverse. Like Gašević, Dawson, and Siemens (2015), we recommend that work on learning analytics pay more attention to learning events. Questions about how learning events affect achievement are common. Is information learned when a learner highlights it? What can be inferred about a learner's command of key concepts if, when key concepts are used to build more advanced descriptions, the learner often reviews definitions of the key concepts? When a text describes a complex causal system, is transfer improved if the learner generates an annotation that explains how the system is organized? To gather data about learning events to construct mirroring learning analytics and to operationalize constructs about how learning unfolds, we designed a software system called nStudy. Before describing nStudy and some of its potential uses, we introduce a concept of volatile data. Then, we explore how volatile data relate to models that describe learning as a process, particularly models that characterize learners as motivated agents who self-regulate learning.

2. Volatile Data and Traces

One property of data about learning events is the time scale over which values vary. This property, which we call volatility, has implications for developing interpretations about learning.

Some data and the phenomena they operationalize are inert. Values for these data endure from the instant they are generated. Such data need be gathered just once. Examples include language first spoken, socioeconomic status of an undergraduate's high school at the time of the student's admission, the timestamp marking when a learning object was downloaded, whether a prerequisite course was completed, and the grade the learner earned in it.

Other data are gathered across several, sometimes distantly separated points in time. These data have low volatility. They are designed to reflect phenomena that vary over comparatively longer time intervals. Examples include age scaled in years, socioeconomic status of the postal code of a learner's residence, the learner's income bracket, grade point average, academic major, and a measure of intelligence.

A third class of data are gathered across very brief time intervals. These data are highly volatile. They represent factors theorized to vary over correspondingly brief intervals. Examples include heart rate, galvanic skin potential (or electrodermal activation), configurations of facial muscles, pupil dilation, and the duration of gaze points and tracks across a display of information.

To account for or predict learner achievements, data of mixed volatility are common in studies investigating interventions and gathered for learning analytics. For example, an intelligent tutoring system might predict the likelihood a learner will correctly respond to a task using a blend of inert data, such as grade in a prior course, low volatile data that vary slowly over time, such as final scores in prior modules, and highly volatile data, such as facial expressions. In work on learning analytics, an early alert system might forecast low probability of success in a course using data varying in volatility, such as: academic major, grades on major assignments, dates when a learner accessed project files, and number of posts to a discussion board the day before an exam.

Recent work in learning science and learning analytics is exploring operational definitions for gathering highly volatile data. A logic supporting this shift can be grounded on viewing learning as a process. From a process perspective, a specific learning event can be conceptualized as a cognitive operation applied to particular information in a particular context. Each learning event updates information available to the learner for the next round of cognitive engagement. A series of volatile learning events — a learning episode — can lead to changes in knowledge, skill, affect, and motivation. Cognitive operations and information processed by each operation vary rapidly over time within a learning episode. In everyday terms, learning proceeds at the speed of thought.

A second property of data about learning, including relatively volatile data, is the conceptual distance between a datum and inferences about a learning event. This is the methodologist's concern for "construct validity." How clearly and reliably do data support an inference? For example, measures of knowledge gathered before a learning episode are reasonably interpreted to signal whether the learner's memory contains and can retrieve general information about a domain. It is typically reasoned that such knowledge might benefit learning new information in that domain. But the validity of such inferences can be questioned because data in hand support only a correlational relationship. Moreover, to corroborate this correlation, research would need to gather data documenting two conditions, as Winne (1987) argued in a cognate case of process-product research in teaching: 1) a learner recalled and processed particular domain information in a learning event; and 2) the learner developed new knowledge. Furthermore, it would need to be documented that the learner could not develop that new knowledge in the absence of recalling and processing particular domain information. We are not aware of research satisfying both conditions. In other words, prior knowledge possibly has not been experimentally tested as a causal factor affecting learning of conceptually related information.

In this light, almost all data about learning should be considered as proxy moderator variables. Such variables correlate with but are not causal factors affecting learning. Proxy moderator variables — e.g., first spoken language, grade in a prior course or level of affective arousal signalled by change in skin potential — do not describe operations on information that cause learning or particular information a learner processes in a learning event or learning episode. Instead, these variables may predict whether a learner chooses unknown particular information to be operated on in unknown particular ways. When such correlations are dependable, the proxy moderator is sufficient to predict whether learning will occur. However, most proxy moderator variables are distal and usually poor accounts for the operations that learners apply to learn or information they process using those operations. In part, this is because many proxy moderators are not sufficiently volatile.

Trace data are intended to supply stronger and more direct evidence about learning than proxy moderator variables can. An ideal trace datum provides an objective (i.e., readily agreed to) account about how a learner operates on particular information at a point in time and in a relatively well-identified context. Ideally, a trace datum is strongly bound to a theory about which volatile cognitive or metacognitive operation(s) have which kinds of effects. Preferred instrumentation would gather trace data in an ambient way, intruding minimally on what a learner normally does in the natural course of studying (Winne, 2019).

We conjecture that adding trace data to the mix of data can significantly increase the potency of learning analytics. In this article, we describe a software system, called nStudy, designed to gather relatively ambient trace data as learners go about learning (see Winne, Nesbit, & Popowich, 2017). Our long-term goal is to develop analytics involving trace data that can accelerate learning science and contribute to learning analytics that help learners and their instructors reach goals for education.

3. Models for Data

We view learning as a process that can be identified by three main factors. The first factor is information that learners represent in working memory where it is processed. This representation combines a learner-biased sample of information available in the environment with knowledge of various kinds (declarative, procedural, episodic) the learner retrieves from long-term memory. Fuller treatments of this factor are provided by Baddeley (2012), Winne (2018), and Winne and Marzouk (2019).

The second factor is operations learners apply to information represented in working memory. Operations are the topics of many and somewhat variable theories about how the mind “works.” Challenging questions about this factor: How does a learner choose (attend to) information in the environment to be represented in working memory, and is that representation veridical? How does a learner sample knowledge stored in long-term memory? What does the learner do to this bundle of information to develop and monitor whether it is comprehensible? What does the learner do to build comprehension? How is an emended bundle of information in working memory stored in a form that later affords recalling it later and applying it under slightly to substantially different circumstances?

The third factor acknowledges that learners choose particular operations to apply to selected information. This is the construct of learner agency. As agents, learners make decisions about information on which they operate and tactics they use for learning. For example, they decide what text to mark, whether and when to review an annotation, whether to generate their own example of category or principle, whether to explain a process, how thoroughly to search memory when posed a question or self-generating an explanation, and so forth. In everyday terms, learners have goals and they are in the driver’s seat — they set goals and decide how to pursue them. From an agentic perspective, instructional designs can be considered guidance offered to learners about how they might learn. Learners may take up that guidance, pursue different options, or even withdraw.

A model summarizing features agentic learners consider about a learning event is Winne’s (1997; 2017a; Winne & Marzouk, 2019) COPES model. C represents conditions a learner perceives to have bearing on learning and the subset of those the learner will take into account in a learning event. O is a slot for operations a learner applies to information. These are tactics and strategies comprising the “how” of learning. Rehearsing a definition or assembling a first-letter mnemonic like COPES are examples. P is the product generated in a learning event when operations are applied to information. Some products are “inside” a learning task, e.g., a definition of a concept or a set of steps that accomplish a task. Other products are “meta” because they describe properties of work learners do. For example, learners may perceive a particular operation is rather difficult to carry out or is not reliably predictive of a particular outcome. Because learners are agents with goals, E marks that a learner evaluates properties of learning events. For example, how much effort does an operation require? Is a product correct? To make evaluations, learners use standards, the S in COPES. A profile of standards defines the goal against which the learner evaluates features of a learning event.

Choices learners make about how they learn are contextualized by their goals in relation to their perceptions of various costs and benefits (Winne & Hadwin, 2008). Goals are reflected in the COPES model as the configuration of standards. Motivations are evaluations predicted or experienced in a particular learning event. Learners can forecast (E), likely imperfectly, what meta-qualities of a learning event will be the case if particular operations (O) are applied to create a product (P). This generates an outcome expectation, one important condition bearing on learners’ choices about whether and how to engage a learning event. Another forecast learners can make is whether they have skill needed to carry out those operations in a current context. This is an efficacy expectation. Before or after operating on information in a learning episode, learners can generate reasons they call on to account for success or failure. These are attributions. Finally, learners may inquire whether engaging in the learning event or episode will help them gain benefits or solve a puzzle (incentive/interest). Together, these judgments — outcome expectations, efficacy expectations, attributions, and incentives — are compiled using an unknown calculus to estimate the utility of each choice compared to others. Each component is a factor in the AEIOU (attributions, efficacy expectation, incentive, outcome expectation, utility) model of motivation (see Winne & Marzouk, 2019).

We conceptualize learning as a process directed by an agentic learner with motivations. Thus, we recommend instruments be designed to gather ambient data for generating learning analytics that help learners answer this motivation-laden question: “What should I do to learn better?” Such data have three properties.

First, data should be sampled approximately on the same timescale as operations are applied to information. Ideally, each operation should be identified. We acknowledge this is inherently challenging because operational definitions for data are not identical to constructs the data are intended to describe. In short, trace data should track volatile learning processes as best as it can be managed.

Second, data should identify the particular information to which the learner applies a particular (set of) operation(s). When a measure of achievement assesses that particular information, and data are available to document which operation the learner used to process that information, it becomes possible to identify whether that operation was responsible for what a learner learns (Winne, 1987).

Third, data should be contextualized. This means representing, as best can be discerned, what learners attend to that triggers their exercise of agency in choosing particular tactics or strategies to operate on particular information. Mapping context is

one key to discovering what learning systems and teachers might do to guide learners toward learning more effectively, i.e., what to include in instructional designs. We conjecture learning analytics grounded in data with these three properties can improve learners' (and researchers') opportunities to know what was done to learn and to consider motivation to repeat or adapt that routine when a similar learning task arises in the future.

Few data presently available to learning science and learning analytics have all these properties. Modern learning management systems were engineered to log data of much coarser grain with volatility poorly matched to learning episodes. The data gathered by LMSs mostly reflect constructs with low volatility. Such data are poor grounds for generating valid interpretations about how learners carry out learning moment to moment because those data are not well operationalized to describe learning as a process. Therefore, because learning processes are poorly reflected by those data, it is quite challenging to mine from them advice about how to learn better. Data about proxy moderators do not make clear what learners do as they learn. We designed nStudy to gather ambient trace data that more closely describe how learners learn when they study in laboratory settings, classroom activities and online contexts anywhere.

4. nStudy

4.1. Artifacts and Trace Data

nStudy's learner-facing features are implemented as an extension to the Chrome web browser. The extension is designed to offer a multifaceted interface where learners engage with information, with peers, and with a chatbot as they carry out common operations on information to learn. Two key concepts are woven throughout the extension: artifacts and trace data.

4.1.1. Artifact

Artifacts are tangible or observable constructions created when people operate on materials. In the context of learning in nStudy, a simple example is text a learner highlights. To execute a highlight operation in nStudy, the learner clicks, holds the click and drags the cursor across a string of text, e.g., "detection of organic molecules" (see Figure 1). On releasing the click, a popup menu automatically appears offering the learner options for operating on the just-selected text. One option is `Create Highlight`. Positioning the cursor on `Create Highlight` and clicking that option applies a persisting coloured fill to white space surrounding letters in the selected text — it is highlighted. As the learner carries out this operation, the nStudy software logs several things:

- The text selected (± 20 characters beyond the head and tail of the selection to represent local context)
- The source (identified by the URL, the uniform resource locator, where the text is found)
- The menu option the learner selected from the popup menu (`Create Highlight`)
- A timestamp $\pm .001$ s

Combined, these data constitute a highlight artifact. Other artifacts generated as learners use nStudy's features to study are described in later sections.

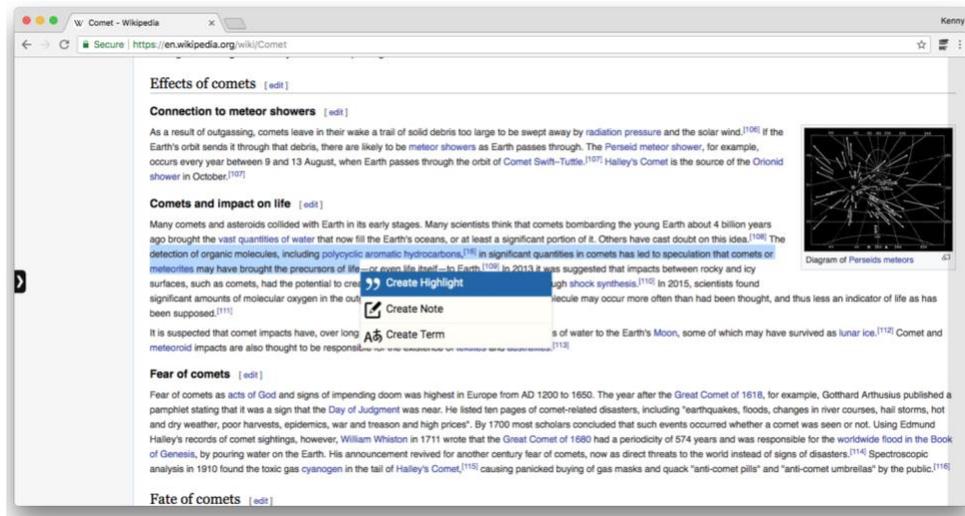


Figure 1. Highlighting text in the study view of nStudy

4.1.2. Trace Data

As previously described, a trace datum represents a learning event in a way that supports strong inferences about motivated cognitive operations that a learner applies to specific information in a particular context. Consider the highlight artifact just described. To select particular words for highlighting, theory describes the learner as monitoring information in the webpage for particular qualities. For example, perhaps the learner predicts the text selected for highlighting represents information likely to be tested in an upcoming exam. Monitoring qualities of information — the likelihood that information will be tested — is based on information *about* the selected information; for example, that organic molecules detected in comets suggests how life began. This is metacognitive monitoring. The highlight artifact logged by nStudy is a trace of an operation — metacognitive monitoring — applied to specific information — the text selected for highlighting — in the context of information presented in this webpage and a history of previously gathered trace data.

A further inference is plausible because the learner knows that the highlight persists. If all the learner intended was to monitor information metacognitively, there would be no utility in spending energy to create a persisting highlight artifact. Metacognitive monitoring can proceed without using the software feature to select and highlight text. Because the learner chose to create a persistent highlight artifact, it is reasonable to infer the learner also is planning to review or use that highlighted information in the future. Highlighted text is easier to locate visually and significantly reduces the text that would need to be scanned if the highlight was not present. If this reasoning is plausible, the trace supports two additional inferences beyond the inference about metacognitive monitoring: 1) the learner believes that review (to restudy or reuse the highlighted information) is an operation that can be done efficiently (efficacy) and has value (incentive); and 2) the learner is presently motivated to review this highlighted information later.

This set of inferences about a simple highlighting action has a shortcoming. It does not make clear what standard(s) the learner was using to select information for highlighting. nStudy offers a feature to fill this gap. When the learner chooses `Create Highlight` from the popup menu after selecting text, nStudy can automatically open a second popup window. In it, beneath a copy of the text selected for highlighting, is a text field where the learner can catalog the selected information — i.e., tag it. For example, the learner may choose to tag this text `test` instead of tagging it `interesting` or `doubtful`. By tagging the highlight artifact, the learner exposes the standard used to monitor that information metacognitively: “This is information I predict might valuable to review because it will be on a test.” The artifact also represents exercise of metacognitive control because the learner actually operated on information. Spending energy to perform that action instantiates motivation. Tagging the selected text surpassed a threshold of utility and had greater utility than other options, e.g., not selecting any text or more extensively processing information, e.g., by making a note about the text.

nStudy is designed to generate trace data like these in a relatively ambient way. That is, learners generate trace data by doing very little more than is required just to use the software’s tools to perform everyday studying activities, like highlighting. In a later section, we propose that very fine-grained trace data are keys to developing learning analytics that can guide learners toward productive self-regulated learning (SRL).

4.2. Types of Artifacts in nStudy

Learners using nStudy can undertake a variety of everyday learning projects such as researching a term paper, studying assigned readings, drafting and revising reports and essays, and reviewing for exams. Because the learner’s tasks differ moderately across these activities, nStudy offers different views tuned to particular forms of engagement. In each view, learners create one or more classes of artifacts comprised of data representing information on which the learner operates along with metadata, such as a timestamp or source, associated with the artifacts a learner generates.

4.2.1. Bookmark

Paralleling modern web browsers, learners can create a bookmark artifact to return easily to a source of information on the Internet by clicking the bookmark. Metadata describing each bookmark include its date of creation, date last visited, tags the learner may assign, and comments the learner generates about the bookmark. Beyond bookmarks a learner creates, nStudy logs every URL a learner visits.

4.2.2. Highlight

In views where learners study a text or video, they can select a text string or, in a video, mark a time point or interval. This creates a highlight artifact. The text learners select for highlighting or a description learners create to label a video highlight are available for browsing or searching in a sidebar on the left. Metadata elaborate each highlight artifact by describing the URL in which the selection resides, optional tags the learner applies to the selected information and a timestamp identifying when the highlight artifact was created. Tags are configurable. A researcher can supply a fixed set of tags (e.g., `important`, `vague`, `FollowUp`) for learners to use, learners can be given freedom to generate idiosyncratic tags, or both.

4.2.3. Note

In several of nStudy's views, learners can create notes. Each note is a set of fields a researcher or instructor designs to represent a template or schema. For example, a note template for bookmarks might include editable text fields labelled `Title`, `Tags`, and `Comment` plus a non-editable field identifying the date `Last Visited`. A `Debate` note template designed to represent an arguable point might include text fields labelled `Topic`, `Claim`, `Evidence`, `Warrant`, and a slider field labelled `My Position` with endpoints labelled `Against` and `For`.

Notes that learners create are referenced in a sidebar using text the learner enters into a first field to create a title or topic label for the note. Notes can include non-editable (static) text to provide instructions or label editable fields, as well as graphics (e.g., icon, stylized symbol). Note templates also can include several kinds of learner-editable fields: text, slider, a list of radio buttons allowing a single selection in the list, a list of checkbox buttons allowing multiple selections, date, graphic, and link. Note templates introduce learners to schemas for content (e.g., the scientific method) and conceptual templates (e.g., arguments, explanations, etc.).

4.2.4. Term

A term is a note with special properties. A default version of the `Term` template includes editable fields labelled `Term`, `Tags`, `Description`, and `Links`. If the string representing a term appears in any of nStudy's views, nStudy classifies the term as present in that view and can display it in the retractable sidebar. Rules can be designed to trigger actions when terms are present or absent. For example, a learner could receive a notification inviting review of terms appearing in a never-before-accessed webpage if a term had not been viewed within a particular time interval (e.g., within 3 days). Other rules might be designed to notify the learner that a term previously tagged `vague` appears in the just-opened webpage.

4.2.5. Essay

An essay is a container for student-generated information. Content in essays can be formatted using styled text (italics, bold, underline, colour, fonts) and paragraph formatting (e.g., heading level, flush or hanging indent, bullet and number lists). Content can also appear in several formats (e.g., date, link, graphic, or table). Essay artifacts can represent various products (e.g., a term paper, a reflective journal, a lab report, poetry, or notes for an oral presentation).

4.2.6. Folder

Folders are containers for artifacts, including other folders. Learners can file artifacts in folders and label folders. Example folders might be labeled `Stat 100`, `Labs`, or `To Do`. A note template elaborating a folder's contents or purpose can be associated with the folder.

4.2.7. Post

Contributions learners make to nStudy's view for carrying on discussions, the hub (described shortly), are posts. A post is a reserved type of note template that can be designed to guide discussion. Default fields of a post include `author`, `date`, `tags`, `reply-to`, and `reply`. A post template designed to scaffold discussion might provide a dropdown menu from which the learner selects a role that then reveals "starters" appropriate to that role. For example, a learner adopting the role of critic in replying to a peer's post might be presented with starters such as these: `What is your evidence for ...?` and `How do you reconcile that with different information I found at [URL]?`

4.2.8. Query

Learners can search for artifacts using a tool to build a search query expressed in terms of facets and values for facets. Facets include data (e.g., text in a note), title of an artifact, type of artifact (e.g., highlight, note), tags applied to an artifact, date values (e.g., yesterday, before 2019 Feb 01), author, revision status (created, reviewed, modified), and so forth. A useful query can be saved for repeated use.

4.3. Views

Each view in nStudy offers a set of tools within an interface designed to support a particular kind of work.

4.3.1. Faceted Search View

Learners can access the faceted search view by clicking a button in any other view. To frame a search, learners first select a facet, e.g., type of artifact or date, by choosing an option from a dropdown menu. For example, a learner might choose `Artifact` from the dropdown menu. nStudy responds by offering a second dropdown menu listing each type of artifact. The learner chooses one, say, `Highlights`. Clicking a button labelled `More...` adds a new row beneath the previous row where the learner can select other parameters and supply values to narrow the scope of the search. For example, the learner might

limit this search for highlights to those in a particular folder that also contain the text “comet.” A Save button in the view pops up a note template where the learner can title the search query that will be saved for future use, tag it if desired, and add text in a field to describe the saved query’s purpose. A saved query may serve as a learning analytic; for example, by detecting whether particular artifacts have been reviewed within a specified time period.

4.3.2. Study View

The study view is where learners read and annotate assigned webpages, PDF documents, and videos or sources they find by searching the Internet. Figure 2 is a screenshot.

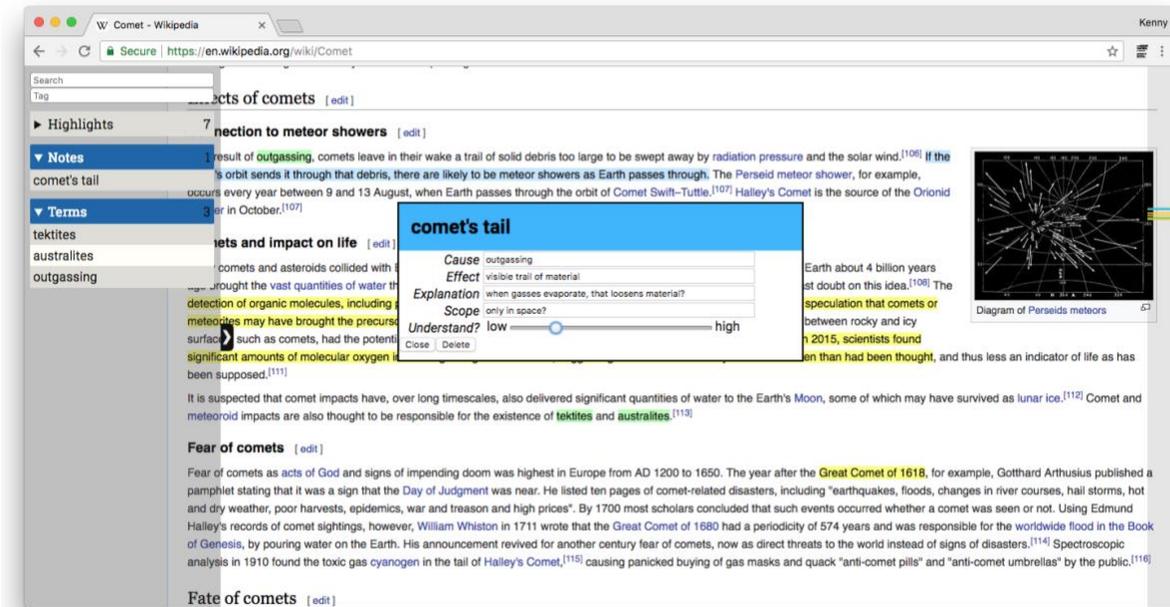


Figure 2. Study view in nStudy.

A sidebar on the left can be exposed or retracted using a handle on its right edge. At the top is a search button. Clicking it presents the faceted search view. In this sidebar, there are three headers: Highlights, Notes, and Terms. Headers can be configured. On the right of each header is an indication of the number of that type of artifact associated with the currently viewed webpage. In Figure 2, the learner has created seven highlights and one note about comets’ tails. The Terms header shows this webpage contains three term artifacts the learner (or a researcher) has previously created: “tektites,” “australites,” and “outgassing.” Clicking a header unfolds it to display a scrollable list of titles of that type of artifact. Clicking a header whose list is unfurled folds up the header to reclaim space.

Along the right edge of the browser window are small coloured bars, called nubs. For videos, nubs are arrayed along the horizontal scrub bar of the video player. Nubs mark the relative positions of artifacts throughout the file. Clicking a nub scrolls to the location or time mark of the selection it represents.

When a learner selects text or clicks during play of a video, nStudy automatically pops up a menu identifying related artifacts the learner can create to refer to the selection.

4.3.3. Essay View

The essay view is a basic html editor. A toolbar across the top provides buttons to apply various styling options to content. The same retractable sidebar as in the study view is available to display highlights, notes, and terms in the essay view. These artifacts may be created in the essay or previously created artifacts, e.g., bookmarks, posts, or even other essays, the learner dragged-and-dropped (or copied and pasted) into the essay for re-use or editing. When appropriate metadata are available — for example, about the URL associated with a re-used highlight — nStudy automatically builds a formatted reference to compile a bibliography for the learner.

4.3.4. Hub View

The hub view (under development) supports exchanging posts and other artifacts (bookmarks, highlights, notes, and terms) among learners, and between a learner and an instructor/researcher and nStudy’s chatbot. Its sidebar adds two headers to the study view sidebar: Indexes and Peers. Posts and artifacts committed to a topic are formatted in html. This allows a

learner to add personal annotations (highlights, notes, and terms) to amplify the accumulated discussion.

4.3.5. Library View

In the Library, learners can organize and filter artifacts by content and metadata, including folders. Timestamped data are generated for every engagement a learner has with information, e.g., text selected, text generated, tag applied, content searched, saved search query reapplied, library folder opened, and post contributed to the hub.

4.3.6. Server Side Systems

Each learner's data are stored server-side in two databases. The time stream of event data is recorded in an Apache Cassandra database. This allows recording the temporal history of learner behaviour. Relationally structured artifacts (e.g., a note titled *comets* and *religion* tagged *FollowUp* related to text selected at a particular URL) are organized within the ArangoDB database. These "composite" artifacts identify how behaviours and information cohere into "whole" studying events such as reviewing a note that includes several kinds of information per the note's template.

A query editor is being developed to allow researchers to identify and extract data from the databases and format that output for input to systems for analyzing data. This tool will be modelled after the learner's faceted search. For example, a researcher might be interested to examine terms the learner highlighted as a subset of all terms appearing in sources the learner reviewed last week.

A library of R shell scripts is being developed. Scripts will take as input one or more data tables generated by data queries made of the databases. Output will be learning analytics and other information (e.g., counts of artifacts, latent semantic analyses of notes compared to sources from which they originate). For each learner, data are their own, and the system strictly enforces private access. In classrooms and research projects, learners will be invited to contribute data per local policies and typical forms of consent. The system, again, strictly enforces authorization. Data can be de-identified for researchers to analyze in the aggregate and to be shared among research teams.

The researcher's query just described might be analyzed to generate output in the form of a heatmap-coded horizontal bar chart in which each horizontal bar corresponds to one term. The length of a term's bar is proportional to the time interval in hours between when the learner first operated on a term (created it, first highlighted it) and when the term was first reviewed. Heatmap shading signals the number of times each term appearing in sources was highlighted; dark blue represents fewer highlights and bright red represents more highlights. Bar length depicts opportunity to realize the spacing effect and retrieval practice. Heat map coding conveys information about the extent to which a term was operated on, an indicator of opportunities to build comprehension about it (e.g., see Miyatsu, Nguyen, & McDaniel, 2018).

5. Sample Learning Analytics about Self-Regulated Learning

Self-regulating learners carry out a loosely sequenced and recursive set of activities (Winne, 2018). They generally cover the following four phases: 1) catalog features of an assigned task and resources in the task environment; 2) set goals and design plans to approach them; 3) engage in the task, monitoring successively updated results and making small adjustment to improve progress toward the goal; and 4) survey work on the task to design major adjustments for forward-reaching transfer (Salomon & Perkins, 1989). Volatile ambient trace data collected by nStudy, along with other data gathered from other systems, could be processed to develop learning analytics that mirror these activities and build recommendations about how learners might productively self-regulate learning. We describe two examples that could be realized using trace data gathered by nStudy.

Consider the study tactic of self-explaining, "a constructive cognitive activity learners can enact at will or in response to a prompt ... [to] generate inferences about causal connections or conceptual relationships. The content of self-explanations ranges widely; for example, explanations can describe how a system functions, the effects of serial steps in a procedure, the motives of characters in a story, or concepts presented in expository text" (Bisra, Liu, Nesbit, Salimi, & Winne, 2018, p. 703). Bisra et al.'s meta-analysis reported the overall weighted mean effect size of self-explaining was $g = .55$. This suggests learning analytics might be developed to track and guide learners' self-explaining.

nStudy can be configured to offer an *Explain* note template designed to guide learners to construct explanations. The template contains five labelled text fields to receive learner input, each labelled and elaborated with replacement text (i.e., information in gray font that disappears as the learner begins to enter text in the text field). Labels for the text fields and replacement texts are as follows: *Topic* (what needs explaining), *Effect* (what happened), *Cause* (what made it happen), *Explanation* (how does it work?), and *Scope* (how general is this?). The template also includes a slider labelled *My Understanding* marked by increments of 1 from 0 to 3 with labels: *Not at all*, *Some*, *Good*, and *Totally*.

Learners can select information as they are reading an assignment, select the *Explain* note template from the popup that automatically appears, then, in the note window nStudy displays, fill in fields and adjust the slider in the template. On the

server, an algorithm could develop assessment items about each explanation using text the learner selected in the source and entered in the text boxes. When the learner leaves the URL after studying source information, nStudy could report the number of self-explanations generated as a mirroring analytic. It could also prompt retrieval practice by forming simple questions such as “What causes [text entered into effect field]? How do you explain that?”

If a classifier can be designed and trained to select segments in source texts about which a learner might generate an explanation, questions can be posed just in time or post-study session about those segments: “Can this be explained: [paste segment of source]? Why or why not?” This invites the learner to self-explain about a metacognitive phenomenon (i.e., standards for metacognitively monitoring information to judge whether it is a target for an explanation). As well as providing supervised training data for the classifier, this analytic — that a segment of information in a source has a high probability it can be explained — recommends the learner pay more careful attention about engaging in self-explanation. As the learner gains skill to identify where explanations can be generated and, with nStudy’s help, keeps track of the effects of using this study tactic across successive studying sessions, these learning analytics set a stage for more productive SRL.

A second example of learning analytics designed to guide SRL might be engineered using trace data that record how a learner rehearses and elaborates new terms when studying. In texts introducing broad fields of study, the so-called “101” courses, authors frequently introduce a concept and elaborate it in a first chapter, then contrast that concept to others in a subsequent chapter. In a Psychology 101 textbook, for instance, a preceding chapter might introduce key features of a theory of motivation. In the next chapter, which covers a different theory, the author might write, “As discussed in the preceding chapter, drives were considered the major motivators of behaviour. In the theory we examine in this chapter, expectations of success (or failure), termed efficacy expectations, and value associated with predicted outcomes of behaviour fill the role of motivators of behaviour.”

Over multiple study episodes, nStudy can track how a learner interacts with terms relevant to theories of motivation such as drive, efficacy expectation, and value. Suppose while studying a first chapter, the learner created multiple highlights and notes about drives. While studying a following chapter a week later, the term drive is included in the text. nStudy will list it in the sidebar of the study view. The learner chooses not to review the term (i.e., the artifact is not opened). This trace — not opening the artifact to review the description of the concept of drive — indicates the learner, while studying the second chapter, judged knowledge of that concept was adequate. In contrast, while studying the first chapter, suppose no trace data were generated about the concept of cognitive dissonance — the learner never highlighted text including that term and did not make notes in which text entered in fields included cognitive dissonance. While studying the following chapter, the learner reviewed the cognitive dissonance artifact when that concept was first mentioned in the text. If this pattern repeated for multiple terms across several studying episodes, an agent working on the server could compute an analytic and post this message to the hub:

```
How's it going, Phil? I've noticed a pattern in your study tactics.
Maybe you'll find it interesting. When a new term is introduced
in a study session, and you highlight it a few times and use that
term in 2-3 notes during that same study session, you don't have
to review that term when it comes up in the next study session.
But, when you don't highlight a new term and don't make a few
notes using that term in a first study session, you decide you
need review it when it comes up in following study sessions.
Maybe making a few highlights and notes about new terms when you first
encounter them helps you learn terms better?
```

nStudy can automatically track the learner’s uptake of this suggestion. Suppose the learner follows the recommendation, highlighting new terms and using them in notes during the study session in which terms are first presented. When those terms appear in later study sessions, if the learner’s judgment of learning is strong enough, review is not necessary. If the learner judges that their knowledge is weak, review is likely — the learner opens the term’s description. nStudy’s analytics engine can support the learner’s personal experiment about this study tactic by examining accumulating trace data. If the learner forgoes review after applying the recommended study tactic, the hypothesis is corroborated. If the learner continues to review terms in study sessions following ones where the tactic was applied, the hypothesis is discounted. Sharing nStudy’s analysis of trace data with the learner provides empirical guidance about how the learner can self-regulate learning more productively.

The agent might ease the learner’s work on this longitudinal program of research into learning by adding this suggestion to the preceding post:

```
Would you like me to save a Query that identifies how you work
with new terms? I'll file it in your folder "My Analytics." If
you create a Study Goal note to run the query, maybe every Friday,
I'll post a profile to the hub describing new terms presented
```

that week and how you worked with them. Click the OK button if you want me to open a new Study Goal note for you.

6. Advantages Gained with nStudy

nStudy was designed to supply learners with a suite of easy-to-use tools while engaging with a wide range of learning tasks — studying online texts, researching term papers, drafting and polishing essays and lab reports, discussing projects, and sharing work products. As much as possible, features were designed to generate trace data that have relatively strong links to constructs articulated in contemporary models and theories in learning science. Our example of highlighting interpreted using a lens of metacognitive monitoring and metacognitive control illustrates this kind of link.

A significant benefit of nStudy's design is the opportunity to multiply the volume, variety, and velocity of gathering data about each learner's studying activities inside the bookends of logging into a learning management system to access or download online materials and logging out. Consider the following scenario. Orlando, Caverly, Swetnam, and Flippo (1989) estimated an average university student is assigned approximately 2400 pages to read each semester. Assume that, when first studying those assignments, each learner averages three highlights and one note per page. This generates 9600 learning events per learner per semester. Presume half of this set of learning events is tagged with one of just two tags, say, *important* or *unclear*. As well, imagine half of the 9600 selections contain one term. Suppose further that each student reviews half of the artifacts they create when they study for a single final examination, generating another 4800 learning events. In addition, they survey and use 100 artifacts to develop a short essay. Each student's learning activities are described by 14,500 learning events. In a first- or second-year survey course enrolling 200 students, nStudy's databases would record 2,900,000 time-stamped learning events. Each learning event is a multivariate assembly of data and metadata: kind of operation, context triggering the operation, semantic content, a timestamp, and configurations of data such as whether text a learner enters in a note includes one or several terms previously highlighted but not yet reviewed. In a university like ours, where eight Faculties might offer an average of five such courses every semester, 116 million learning events are amassed. Opportunities abound to mine that volume of big data within and across individuals and tailor learning analytics to learners, courses, types of content, and assignments; to identify clusters of students for whom instructional policies can be adapted; and to advance learning science (Winne, 2017b; Winne & Baker, 2013).

nStudy's design serves a second purpose. Names for its artifacts (e.g., bookmark, highlight) and the operations learners apply to information (e.g., tag, search, review) were engineered to form an easy-to-understand lexicon describing study tactics, learning strategies, and SRL. Consider highlighting, perhaps the most popular of all study tactics (Gier, Kreiner, & Natz-Gonzalez, 2009; see also Dunlosky, Rawson, Marsh, Nathan & Willingham, 2013). Without delving further into theory about metacognition or findings of learning science about effects of spacing review sessions, learning analytics prompting adaptive variation of studying tactics can be relayed to learners in language they readily understand:

```
I notice you don't usually review information you highlight. At least, I don't observe you click in the sidebar to review what you highlight or search for highlighted material. Research in learning science recommends reviewing information a few days after you study it. Even better, I can create some practice test items using your highlights and show those practice items automatically on a schedule a few days after you study. Would you like to try this over the next few weeks?
```

This analytic can be created simply when learners use nStudy's highlighting feature. By labelling learning activities in terms of names for interface features and how a learner used them, engagements with learning take form as engagements with software features. Options for learning differently can be presented in terms that describe using the interface differently.

nStudy's moderately and highly volatile data about learning events can be combined with less volatile data generated through student engagement with learning management systems (LMS). This mixed-source data can build a broader platform for learning analytics and support student thinking about learning. Consider this example: LMS features such as module titles allow instructors to identify major course topics and how topics are temporally distributed along the course timeline. Students using nStudy to study the texts and videos categorized by topic can be provided with analytics that depict how major concepts — terms in nStudy's system — flow across topics. A visualization in the form of a bipartite graph of terms \times topics can display how terms and topics map to one another. Such a display can invite learners to consider whether review of particular concepts is needed and how terms can bridge separate topics. As learners study, nStudy can gather data about how they behave in the context of this display. Do they review terms introduced earlier? Do they annotate current topics using note templates that guide synthesizing concepts introduced earlier? Adding achievement data to this mixture, gathered using an LMS quiz feature,

sets the stage for computing conditional probabilities describing whether particular learning events are productive for each learner.

More generally, we view SRL as a learner's personal program of research in learning science. Agentic learners striving to improve how they learn construct hypotheses, gather data, analyze those data and interpret results to decide whether and how to adapt study tactics and learning strategies. Unfortunately, learners are disadvantaged as learning scientists (Winne, 2010, 2017a, 2017b). They are not trained in the scientific method nor how to apply it to their learning activities. They are rarely encouraged to experiment with how they learn. Latitude is not often given to sacrifice achievements while working to hone new skills for learning. They have meager and biased samples of data about their learning activities. They lack even rudimentary tools for analyzing data about learning. In this context, systems like nStudy can offer meaningful benefits in the short term and scaffold learners at the same time they extend learning science (Winne, 2017b, 2019). While no software system can lower demands for covering a curriculum in a fixed (often too short) time, ambient trace data, back-end analyses of big data juxtaposed with personally focused data, and a productive mix of just-in-time and just-in-case learning analytics can lend support to every learner's SRL.

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