Chapter 11
Roles for Information in Trace Data Used to Model Self-Regulated Learning

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Abstract When researchers use software and other technologies to gather data about learning, an operational definition details what to record about timestamped learning events as a learner engages with information, e.g., selecting text in a webpage or tagging selections to index them. Theory assigns meaning to such operational definitions: (a) selecting text signals metacognitive monitoring; (b) tagging reveals properties the learner monitors as descriptive of selections, e.g., interesting, to investigate; (c) the learner ascribes utility to effort spent to select and tag. Prevailing approaches to analyzing trace data examine events in terms of presence/absence, frequency, contingency, and pattern. For example, does the learner metacognitively monitor? How many times? If the learner tags information "interesting," does the learner contingently search for supplementary information? Properties of the information on which learners operate are underappreciated in analyses of trace data. What features of information lead a learner to: rehearse it vs. not; … tag it important vs. interesting vs. to investigate? … annotate it vs. search for supplemental material? … bin it, e.g., very difficult or not worth effort to learn? This chapter explores roles for information as information that can enrich trace data describing learning events. For example, can information a learner tags imply prior knowledge? Do tags signal mastery vs. performance goal orientation? Attending to information as information expands views about trace data and their uses in learning analytics and researching self-regulated learning.

Keywords Trace data · Learning events · Self-regulated learning · Learning analytics

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1 Introduction

Research literatures about online learning, self-regulated learning (SRL), learning science, and learning analytics often refer to and analyze processes involving cognition, metacognition, and motivation. Processes label operations learners are theorized to apply to information (Winne, 2018, in press). For example, rehearsing is one cognitive operation. It reproduces specific information in working memory, theoretically with near perfect accuracy. Monitoring is another cognitive operation. It produces a list recording matches or a profile comparing properties of a "target" chunk of information, an object, to properties of a "standard" chunk of information. Monitoring can be a cognitive or a metacognitive operation depending on whether information monitored *is* the topic of a task – What are steps in graphing a linear equation? – or information *about* the topic of a task – Do I feel more confident graphing a linear equation using method A or method B? A motivational operation is choosing among options. For example, studying art history to develop knowledge for its own sake is a choice among reasons for studying. This choice represents mastery goal orientation. Or, the choice of reasons for studying art history may be to prepare to demonstrate expertise to others. Choosing this reason to justify behavior represents performance goal orientation.

Operationally defining operations in learning is challenging. For example, a learner surveying a webpage to identify source material to use in a term paper may judge (monitor) the content is uninteresting. Or, the learner may judge this source is helpful because text descriptions of complex systems or principles are translated as diagrams. How can judgments like these be observed? A learning scientist may ask the learner to talk aloud while working, hoping the learner reports each learning event precisely, fully, and reliably. Some researchers have used facial recognition technologies coupled with systems tracking eye gaze to assemble a signal they interpret as the learner reaching a judgment like this.

A third approach is to operationally define trace data. Trace data are typically recorded in software logs when learners use software features on-the-fly. Instances or patterns of trace data are theorized to correspond to fundamental operations and patterns of operations that manipulate information (Winne, 2020a). For example, learners may select (monitor) and tag (assemble) text *interesting*. Text not tagged is inferred to have been monitored as uninteresting per se or not sufficiently interesting or otherwise of value to be selected and tagged. Or learners may annotate a diagram using a schema operationalized as a structured note form in which distinct labels for each of several fields prompt the learner to describe key features of a system, their functions, contingencies, and other properties recognized in the diagram.

Researchers are actively exploring how to operationally define operations learners engage during work on assigned and self-chosen tasks. The vast majority of this work addresses a basic question: What did the learner do? Answers often take form as an account of singular events or patterns relating learning events. Learning events can be ordered across a timeline of their occurrences. Both relatively simple and rather sophisticated methodologies – graph theory (Winne et al., 1994) and process mining (Saint et al., 2021), respectively – are available to characterize contingencies and patterns of learning events. In this chapter, I develop a case that approaches like these give too little attention to the information operated on in a learning event. In effect, those methods describe "empty" learning events. Theorizing how learning events relate to knowledge a learner develops (or doesn't), motivation guiding a learner's choices, and affect a learner experiences requires incorporating information in accounts of learning events because self-regulating learners select operations they apply according to content and properties of information. To approach clarity needed to observe and measure that information, a first step is describing how a learning event can be modeled.

2 Learning Events

The literatures mentioned earlier describe learning events as operations or processes. Operations manipulate information. I posit a set of basic operations referenced by the first-letter mnemonic SMART: searching, monitoring, assembling, rehearsing, and translating (e.g., Winne, 2018, in press). Table 11.1 provides definitions and examples. As entries in Table 11.1 describe, operations like the SMART set inherently require inputs and generate products. Inputs may be elemental propositions describing any topic, including feelings and reasons for engaging in behavior, i.e., motivations. (See Renninger & Hidi, 2019 for a compendium of motivation theories positing reasons for behavior.) Inputs also can be complex structures of information, such as a graph contrasting changes in energy levels across the lifespan of a catalytically assisted chemical reaction as contrasted to that reaction without the catalyst. Without information inputs, there would be no "content" on which to operate.

Notably, operations always are carried out in the context of surrounding conditions which may bear on how a learner regulates operations. Conditions can be external to the learner, such as whether peers are nearby to observe, or that time allowed for executing a task is nearly expired. Conditions also can be internal to the learner, such as enduring motivations, prior knowledge encoded in long-term memory and expectations the learner forecasts about standards by which a product will be evaluated. An important class of internal conditions not addressed further in this chapter but not to be forgotten are individual differences such as working memory span.

When operations are executed on information and a product is generated, the learner's state is updated. The updating of states marks a learning event. Having generated a product, the learner is now in position to monitor its properties in relation to standards for work that generated that product(s), to assemble an attribution describing that result and assemble a feeling with that information complex. Monitoring those inputs and assembling those accounts defines another learning event. For example, did work to translate the symbolic expression $y = 2x + 3$ into graphic form proceed straightforwardly, step-by-step, or were retreats necessary to

Table 11.1 The SMART operations

Operation	Input	Product	Example
Searching	Information active in working memory. This includes perceptions about features in the external environment and neighborhoods in the network of long-term memory	Information elsewhere in long-term memory becomes activated in working memory because network paths connect that information to inputs	Sodium has the chemical symbol …?
Monitoring	A list or configuration (e.g., schema, step-by-step procedure) of standards for judging an information input or a product of thought or behavior	Classification (yes/no; multicategory) or rating of a target according to whether or how well its properties correspond to standards	A zebra displays each defining characteristic of a mammal
Assembling	Two or more units of information (e.g., propositions, chunks, instantiated schemas) active in working memory	A relational property describing the union or intersection of the units of information	If the temperature of water at standard pressure exceeds 100 °C, then its state changes from liquid to gas
Rehearsing	One unit of information active in working memory	A (near perfect) reproduction of active information in working memory	Mentally repeating an assembly relating the term *deciduous* to its definition
Translating	A unit of information active in working memory	A re-presentation of the input in a changed form that preserves core meaning, and possibly introduces new information	A paraphrase A graph of $y = 2x + 3$

correct errors? Is a correct graph attributed to dedicated effort or "dumb luck"? Does that attribution engender a feeling of efficacy or anxiety about similar future tasks? Each of these products arises in a context of previously updated information – internal and external conditions – as the task unfolds. Those conditions are examined by the self-regulating learner to make next choices about possible operations, operations actually applied, products each set of operations can generate, and evaluations of those products in reference to standards. A first letter mnemonic COPES – conditions, operations, products, evaluations, and standards – assembles these information topics as a unit.

Elsewhere, I model a bundle of internal conditions contributing to a learner's decision-making policy about whether and how to engage tasks. Making choices about tasks enacts motivation. One facet of motivation is attributions, reasons a learner constructs to explain evaluations of products (Weiner, 2010). Efficacy expectations are the learner's predictions about the degree to which current knowledge and skills are available to succeed at a task. Efficacy expectations are informed by standards that characterize a high-quality product. Outcome expectations are the learner's perceptions about what product will result if particular operations are executed, and what are the properties of that product. Efficacy and outcome expectations are pillars in Bandura's model of social learning (Bandura, 1997). Incentives are values the learner associates with COPES aspects of tasks as well as emotions arising from attributions (Weiner, 2010). Based on these perceptions about conditions, the learner constructs a utility judgment for each task: What is the balance of costs relative to benefits if a task is engaged by applying particular operations under present conditions when particular standards apply? AEIOU – attribution, efficacy expectation, incentive, outcome expectation, and utility – is a convenient first-letter mnemonic assembling these internal products of cognition into one unit (Winne, 2022).

These three schemas jointly characterize features of learning events. The set of SMART operations distinguishes operations for processing and creating information by inputs and products. COPES identifies facets of information describing a task in which operations, SMARTs, are executed. Information the learner produces in the form of AEIOU assembles motivation and affect with COPES.

States are point-in-time snapshots. A state is stable for a brief instant when it materializes, then it is replaced by the next state as subsequent operations generate new products. That transition marks a learning event. Learning events arising across the timeline of a task represent learning as a dynamically connected series of autoregressive states.

2.1 Modeling One Learning Event: If-Then-Else

I borrowed from other disciplines, especially computer science, to model learning as a sequence of If-Then-Else productions (e.g., Winne, 2018, in press). If collects conditions, the amalgam of external factors under which a learner may engage a task plus internal conditions integrated by the AEOIU model. Depending on the profile or constitution of Ifs, the learner Then executes one operation or a strategic pattern of operations. Should conditions be configured otherwise, then Else some other operation(s) are selected. For example, a learner encountering a technical term formatted in italics (If) regularly selects and tags it for review (Then) excepting (Else) terms which the learner already knows well.

The If-Then-Else model spans time by bridging the transition from a preceding state, If generated by monitoring information, to a subsequent state, an information product generated by Then or Else. How a learner chooses to learn – to self-regulate learning – is conditional on Ifs. Modeling learning events requires examining sequences of If-Then-Else events that modulate in response to varying Ifs. Modeling and analyzing SRL event data is dynamic because each event updates conditions characterizing the next moment in time.

It merits pointing out this model emphasizes the learner is in full control. The learner perceives states and chooses how to behave. This includes how to think, which operations are applied to what information. While observers and even learners may interpret choice is removed when learning is habitual (automatically engaged with apparently no deliberation or apparent draw on resources of working memory), that is a false proposition. SRL is ubiquitous but its forms vary based on information the learner processes, potentially moderated by external conditions (Winne, 1995). Automated routines encapsulate SRL in ways that bury inside automated productions a learner's choices about learning. Observers and even learners can be unaware of complex cognition (Vatansever et al., 2017). Choice was front-and-center, however, when such routines were first created and along the way leading to automated status.

3 Information Is the Subject of Operations

Every facet in each of the COPES, SMART, and AEIOU models is centered on information a learner attends to and uses in the course of SRL. In the case of SMART operations and strategic assemblies of them, more commonly called learning strategies, the information referred to is steps in a procedure, a script. What is the role of information in SRL, specifically, in motivation, cognition, and metacognition? The next three sections illustrate answers to this question, laying groundwork for this proposition: When accounts of SRL are limited to occurrences, frequencies, or patterns of operations (processes), those accounts cannot represent enough of the story of SRL.

3.1 Motivation

A learner's motivation has an explicit topic. Learners are curious about certain subjects, appreciate feedback with particular properties, or are anxious about a specific social event. Motivation is also situationally anchored. For example, a learner participating in a think-aloud protocol might remark, "I think I can solve *this* problem but I need to be careful" (emphasis added). This utterance is referenced to specific external conditions the learner perceives in this moment. This information lies alongside memories the learner samples from their experiential history. Sampling is influenced by the learner's perceptions about current external conditions, such as whether an answer key is available which would afford the option to select a strategy of working backward. Jointly, these conditions figure into the learner's choice about how to proceed. Every self-report questionnaire I have examined reflects the situationality of motivation. Instructions to respondents set boundaries on the situation they are asked to keep in mind as they respond to questionnaire items. For example, a questionnaire's instructions may advise the learner to consider "this course" or the discipline of "science" when rating motivation about the incentive to score higher on achievement measures than classmates (performance goal orientation) or as a measure of subject matter mastery (mastery goal orientation).

Self-report data are problematic (Winne, 2020b), in part because humans have fallible and biased memories of past experience, and because they may unintentionally bias perceptions about current states and events. Modern technologies such as software logging, and facial recognition and eye tracking systems may improve data about motivation. For example, clickstream logging can identify whether a learner visited an assigned webpage, and eye tracking data can confirm whether a learner's gaze oscillated several times between text describing a complex relation, such as activation energy in a catalytic reaction, and a figure translating textual information about that relation (e.g., see Fig. 12.19 at https://openstax.org/books/chemistry-2e/pages/12-7-catalysis; Flowers et al., 2019). These online data can lend support to inferences about a learner's rating of motivation described by a questionnaire item about utility of a learning tactic: "Do you analyze diagrams and graphs to build understanding when you study?" But validity is still in some jeopardy. Data gathered online then coupled with the self-report datum do not reveal whether the learner analyzed information. Motivation is present, but motivation about what topic and motivation to engage in what particular cognition? To confirm the learner analyzed information, data about information input to and produced by analytic thinking is needed.

I offer this axiom regarding motivation: Behavior is motivated. Put another way, excepting for autonomic and automated responses to information states – e.g., reducing blinking rate under cognitive load (e.g., Dubovi, 2022), modulating reading pace according to punctuation (Chung & Bidelman, 2022) – learners (and people, in general) behave as they do because they deliberately reason to reach judgments about which behavior is preferred. People are rational but their rationality is rooted in *idiosyncratic* reasons and *personal* logic. Consequently, a learner's reasons and logic for motivated behavior may not correspond to norms or an instructor's goals. Learners may appear irrational from others' points of view.

The axiom that behavior is motivated stimulates extending the analysis of thinking as a behavior. The network of information that is long-term memory propagates activation across nodes of information in a non-deliberative way. Propagation is not under the learner's direct control as information is activated. Activation spreads because information has the structure it has in long-term memory. In contrast, learners can decide, based on utility they calculate according to a schema like AEIOU, whether to apply particular operations – learning tactics and strategies – to information currently active in working memory. Working memory is where the learner can exercise choice. Perceptual systems, built up over extensive experience, filter information from the external environment. That system and information in long-term memory are not systems available to controlled activation. For example, a learner may notice an instructional designer's cues such as italicized font, propositions in text having a particular format (e.g., "We define …"), and an option offered on a menu in a software application. Learners also may be ignorant of or overlook (not attend to) phrases and other instructive conventions an author intends to cue particular operations applied to particular information.

In this context, the learner exercises choice about operations, standards, the schedule of evaluations, and AEIOU accounts of learning activities that unfold in working memory. Examples related to the preceding external conditions the learner re-presents in working memory might be: a judgment that italics strongly predicts utility for highlighting the italicized text, choosing to postpone looking up confusing terms because an efficacy expectation forecasts later text can be analyzed to fill gaps of understanding, a reminder offered by the menu option *Tag…* signals it is possible to catalog (assemble) selected information in a way that eases locating it under future conditions, e.g., cramming for next week's exam.

Identifying the information underlying motivated operations can be a challenge for observers, especially when compactly unified patterns of behavior, cognition, metacognition, and motivation are bound together in automated, multi-event packages triggered and executed practically without the learner's awareness. An everyday example in my experience is making careful (rational, by my standards) word choices while enthusiastically promoting a controversial point to a friend while I'm in the midst of planning a turn at a traffic intersection crowded with cars, buses, and pedestrians.

In cases of motivated behavior we observers characterize as SRL, whether deliberative or automated, the IF-THEN-ELSE model begs for specifying what information constitutes IFS. As noted just above, motivation questionnaires do this in at least two ways: (a) describing a situational context within which to consider one's response to a generic experience or topic – this course, science; and (b) a particular state or experience – knowing one's own and others' scores on a measure of achievement. The question needing address in research carried out in dynamic online contexts is how to identify IFS learners identify in everyday learning activities that are gateways to THENS or ELSES.

3.2 Cognition

Instructional designs explicitly and implicitly guide learners about operations they might apply when working on tasks. Explicit directions may be provided by learning (instructional) objectives presented at the beginning of chapters and self-test questions appearing at the end of chapters. Implicit cues about selecting content on which to operate and tactics for learning can be observed, e.g., as headings for sections of chapters and "leading" questions embedded in text.

Such directions and cues have a 2-part grammar: task + topic. In this illustrative instructional objective, differently styled underlining marks task and topic: Develop an argument, pro or con, for reducing on-street parking to allow widening bike lanes. Arguments can be described by a schema with facets or slots such as: claim, evidence supporting the claim, and warrants validating evidence as appropriate to the claim. This basic argument schema can be expanded to include more than one instance of and multiple kinds of evidence. More complete arguments (a) add counterarguments shaped by this same schema but presenting the case opposite to the pro argument, then (b) end with a summary resolution balancing the pro and con presentations. The argument schema provides informational cues about kinds of information to search, how to assemble those information products when weighing costs and benefits of widening bike lanes that reduce on-street parking, and standards for evaluating a draft argument.

In many cases where an argument is assigned as an essay or in-class presentation, the learner engages three further tasks. A first is searching curated sources or the wide-open internet for information relevant to the proposition to be argued. A second is determining the credibility of evidence that will be selected and cited, a multi-operation process called sourcing (Braasch & Bråten, 2017). Sourcing involves evaluating properties of information in a source such as the author's credentials, characteristics of the medium of publication (e.g., blind reviewed publication vs. unmoderated posts in social media), and the presence and nature of boundary conditions the author provides for claims (e.g., Everyone knows … vs. In the case of one-way side streets …). The third major task is crafting the essay or talking points to form the argument per se.

Operationally defining data to record some operations when a learner engages in these tasks is straightforward. A learner's search for sources and information within them is easily logged when a learner enters words into a search engine or, after a source is loaded, a search box. Monitoring content for evidence can be traced if software provides tools for the learner to highlight text and tag those selections as *evidence*. Recording that a learner monitors properties of information regarding credibility can be tracked if tags are available to mark it as *trustworthy* vs. *doubtful*. Or, a structured note can cue monitoring these features by presenting a form with a text box labeled *evidence* followed by a checkbox list to monitor properties (standards) applied in evaluating the credibility of that evidence. Software features like these might be considered prompts or scaffolds designed to stimulate operations like monitoring and assembling. When learners use tools like these, individual or a package of operations can be traced because the learner operates on particular information.

3.3 Metacognition

When self-regulating learners track and adapt their engagements in learning, metacognition is applied in two ways. First, learners monitor information in working memory. That information is selectively imported from external sources and registered alongside information retrieved from long-term memory. This bundle of information can be monitored to classify its properties and rate its features. For example, a learner may judge a diagram is complicated, or a science lab experiment described on an assignment sheet is interesting. Products of these operations can activate additional information in long-term memory and supply standards for searching external sources for particular information.

Metacognitive monitoring is a relational concept involving two bins of information which Nelson and Narens (1990) labeled the object level and the meta level. In the preceding example of monitoring a diagram, the object level concerns information the diagram represents, e.g., the water cycle (e.g., see https://www.noaa.gov/education/resource-collections/freshwater/water-cycle; National Oceanic and Atmospheric Administration). The meta level refers to the learner's evaluation(s) of properties of that information. Is it complex vs. simple or unimportant? Is it clear or too complicated? Reaching a metacognitive judgment – e.g., the diagram is complex – is the product of monitoring not what the water cycle is – e.g., water changes states due to evaporation and condensation – or the meaning of terms like evaporation. Information monitored at the meta level concerns properties of object level information, e.g., the water cycle diagram has a degree of complexity, or certainty about the meaning of condensation is low. Tracking the learner's operations on information at the meta level might be inferred if an eye tracking system records relatively long focus on a particular area of interest in the diagram, suggesting effort; or if the learner enters condensation in a search tool. The information in focus or entered in the search box is the key to observing this metacognitive operation.

Operational definitions for metacognitive control include two sequential steps. First, monitoring information at the meta level generates a product in working memory. Second, a particular operation the learner controls is selected for execution because the product of that monitoring operation has particular properties. Metacognitive control thus has the form of an If-Then-Else event. The learner who monitors properties of the water cycle diagram and reaches a meta-level characterization that it is complex may next apply an assembling operation that analyzes the cycle as a step-by-step chain of sequentially paired states: rain falls on land, water runoff accumulates in a lake, lake water evaporates … etc. Software annotations where the learner can select from a numbered list to label each successive pair can trace this operation.

4 Integrating Information with Trace Data

Models proposed to describe cognitive, metacognitive, and motivational operations involve slots filled by information, the subject of an operation. Without information, there is nothing on which to operate. As learners self-regulate learning, they can monitor information describing properties and products of operations to decide how they will tailor next-chosen operations to satisfy motivation. Products can be results of operations on subject matter as well as results describing perceptions about operations, e.g., an operation's pace, effort required, and so forth. This leads to the proposition introduced earlier: Information is a necessary component when developing accounts of learning events modeled by If-Then-Else. How does this perspective apply to identifying and analyzing SRL?

4.1 Examining Effects of One Operation

Table 11.2 presents fabricated data for three learners' scores on four measures of achievement about chemical bonds. For each subject matter topic identified in a row of Table 11.2, software logged whether students applied or did not apply operation X to that topic. Columns on the right side of Table 11.2 record for each student their scores on some items gauging motivation, a test of knowledge or some metacognitive event relating to the topic. For example, data trace all three students applied operation X to subject matter information about the electron shell. Alex and Tracy indicated they were motivated to learn that topic (e.g., tagging it *interesting* or it merits effort to *review*), or learned it (e.g., correctly answered a practice quiz item) or metacognitively judged high confidence about it (e.g., typed the topic label into a note titled *Learned Concepts*). Kris' scores show the opposite.

Table 11.2 records identical total scores for each student. These were computed by summing item scores. Also shown is the conditional probability operation X generated an effect. This is computed by counting events where operation X is applied and the learner's score is 1, then dividing the sum of those "successful" events by the number of observed events. For Alex, on each occasion when operation X was applied, the score on a measure of whether the operation generated a "positive" product (positive motivation, achievement, positive metacognitive judgment) was 1. For learning events when Alex did not apply operation X, the product was not positive. In other words, operation X worked perfectly for Alex and any operation other than X was not productive (as gauged by a single measure of the product).

In Tracy's case, there is no discernable pattern relating using operation X and positive products.

Kris scored 1 on a product only if some operation other than X was applied. For Kris, operation X was consistently unproductive while some other operation was consistently productive.

All three students appear identically motivated, or equally cognitively or metacognitively engaged when their use of operation X is considered as an aggregate (total). But operations clearly had differential effects. Using aggregate scores, neither a learning scientist nor a learner receiving learning analytics to guide SRL could be clear about "what works," how operations relate to effects. Moreover,

Table 11.2 Data and conditional probability statistics measuring effects of operation X

		Score pattern		
Information	Operation X applied?	Alex	Tracy	Kris
Electron shell	Yes	1	1	0
Ionic bond	No	0	1	1
Covalent bond	Yes	1	0	0
Metallic bond	No	0	0	1
Total (sum)		2	2	2
Pr[effect | operation]		1.00	0.00	0.50

neither person can be alerted to opportunities to identify operations other than X that are consistently productive for learners like Kris. Nor would they be alerted to exploring IFs, conditions or evaluations, differentiating when operation X was productive for Tracy.

When data have patterns like those in Table 11.2, and when products of learning events are aggregated without identifying which operation was applied to which information, pinpointing the effects of an operation is indeterminate. Without fine-grained data about information operated on, decisions about updating an instructional design or a learner's decision policy guiding SRL can have erratic results.

4.2 How Information Enriches Trace Data About Operations

When learning events enacted by self-regulating learners are modeled in terms of IF-THEN-ELSE, operations implementing a learning tactic or strategy, THEN or ELSE, are initiated based on the results of a learner monitoring a bundle of conditions, the IFs. Fundamental IFs include:

- Internal information describing the learner's motivation cataloged by the AEIOU model.
- Knowledge the learner retrieves from long-term memory about the topic of the learning task.
- Features the learner perceives about the external learning context, e.g., access to supplementary content, help, tools available.
- Standards activated in working memory the learner will use to monitor properties of the learning event (e.g., pace, effort, confidence) and its product(s).
- Standards presented in the instructional design.
- Cues presented in the instructional design intended as guides for SRL.
- Information in sources, the subject to be learned.
- Information in learner-created artifacts – highlighted text, notes, etc. – representing products of the learner's operations on object-level (subject matter) information and on meta-level (properties of AEIOU, operations) information.

The last four entries in this list share an important and useful property. Each can be observed directly and with no or negligible intrusion on the learner's everyday approach to learning.

4.2.1 Operations Mark Conditions Learners Monitor

Content in sources learners study online can be delivered in a range of formats: words, symbolic expressions (e.g., mathematical relations, chemical reactions, graphic symbols), diagrams, graphs, photographs, animations, and more. Whatever the medium, self-regulating learners choose standards to monitor information at the object level – What does the information communicate about the subject matter being studied? – and at the meta level – What properties of mental state (e.g., motivation, frustration), operations (e.g., pace, effort), and object-level information (familiarity, complexity, clarity) characterize the current learning task? IF characteristics of information forming that bundle of conditions match the profile of standards currently in effect, THEN the learner exercises metacognitive control by applying a preferred operation. If not – ELSE – the learner self-regulates differently.

Operations learners enact can signal conditions have been monitored. This has a significant implication: Information in sources learners study and artifacts learners create as they study can be mined to identify standards self-regulating learners use to monitor IFs in learning events. For example, does a learner almost always select sentences defining constructs for highlighting? When a text refers to a diagram, does the learner scroll to display that diagram again or open a companion window to view the diagram alongside text describing it? When standards conveyed as information – italicized text, phrasing such as "As Fig. 5 shows …" – can be identified, a fuller picture of SRL can be painted by pairing those IFs with trace data reflecting operations, THENS. This coupling of conditions-as-information in sources with trace data sets a stage to develop conditional probability statements as illustrated in Table 11.2.

4.2.2 Standards Can Be Supplied Explicitly in Sources

Sources often plainly recommend standards learners might choose to monitor learning in the form of learning objectives. These cues explicitly name topics in a discipline, e.g., Newton's laws of motion or major products of a country; and kinds of information, e.g., principles and examples. Trace data describing SMART (or other) operations learners use is enriched by appending the topic(s) and kind(s) of information learners are cued to process.

Objectives also identify standards for tasks, e.g., define, apply, or analyze. Named tasks label schemas with slots for declarative information or steps in a structured procedure (script). For example, a *define* task might label a schema with slots: concept label, critical property 1, critical property 2 …, family membership, example. A procedural schema for graphing a straight line given a symbolic expression like $y = 3x + 5$ might proceed in steps: identify the intercept in the expression, plot the intercept point, identify the slope coefficient, starting at the plotted intercept move 1 x-unit to the right then upward if the coefficient is positive or downward if the coefficient is negative a number of units equal to the coefficient, plot the point, connect the two plotted points. Trace data reflecting operations learners apply as they create artifacts to accomplish a learning objective can be augmented by the subject matter information and task schema in the objective.

4.2.3 Information in Sources

When information in sources is formatted as text or can be automatically translated to text from other formats, such as videos or images, that information can be analyzed to identify concepts on which it would be predicted learners should operate as they learn. Several approaches are available.

Content creators often using conventions to format content as prompts for learners to operate on particular information. Examples include italicized and bolded words to prompt monitoring understanding, blue font in webpages to prompt a direct search for information to be assembled with information in a current source, arrow symbols in diagrams suggesting rehearsing a sequence or self-explaining why A → B, and numbered lists suggesting the learner activate an order-preserving mnemonic to store items. Learners' operations on formatted information can be traced. For example, consider a numbered list of sequenced steps describing a process. A 2-column note form – step/reason – can be designed to trace whether learners assemble an explanation describing how that process progresses from step to step. Re-listing steps in the note traces rehearsing of a step. If learners paraphrase the source, natural language processing (NLP) methods can gauge the semantic correspondence of each description to the source, indexing the operation of translating. A final text box in the note form labeled *Make a 1st-letter mnemonic* traces assembling information represented in steps as a unitized multi-step procedure.

Some sources learners study include a glossary. Its entries are subject matter concepts learners should engage as they study that source. Key concepts and related concepts can sometimes be automatically identified by cataloging HTML <a href>*link text*<a> tags. Phrasing conventions can be searched to identify key disciplinary concepts, e.g., "We define …" or "X is the [key, dominant, main …] factor in …." Keyword extraction algorithms also might be used to extract key concepts.

Terms in a source's text, in a provided glossary and terms learners create often are defined using other terms in the glossary. Based on this in-terms-of relation, software systems like nStudy (Winne et al., 2019) can relate terms via edges in a node-link graph, a termnet. Learners' artifacts – e.g., notes, selected and tagged text, described in the next section – can be analyzed using the termnet to identify whether they include terms and how learners assemble knowledge using those terms. A learner using terms in artifacts that the termnet relates directly signals rehearsing a meaningful assembly. When a learner's artifact includes terms, say A and D, related by traversing interventing nodes in the termnet, say A–B–C–D, this traces the learner assembling conceptual structures beyond those explicitly provided in the source's definitions. Walks across intervening nodes in a termnet graph suggest more about what a learner knows than just the text a learner enters in an artifact. As well, examining terms learners search relative to those included in their notes can traces gaps, represented as intervening terms in a termnet, the learner is searching because those gaps need filling to assemble a multi-node information structure.

4.2.4 Selections, Notes, and Tags

Learners commonly select text to highlight and as anchors for notes about subject matter (Miyatsu et al., 2018; Peverly & Wolf, 2019). Selections signal monitoring, and the text selected contains clues about why monitoring was executed. What standards does the learner use as governors for searching and monitoring which text to select?

Providing tags learners may choose to index content is expected to stimulate their search for content by standards the tags describe. Consider a learner studying a text about research methods in psychology. Providing tags such as *independent variable* and *confound* likely encourages the learner to activate standards for searching information about those types of variables. When selections are assembled with one of those tags, this is evidence of monitoring for particular kinds of variables. What the learner selects reveals information judged to be one or the other kind of variable.

In some software systems, like nStudy, notes can be designed by researchers or instructors to present schemas prompting learners' annotations. Slots in those schemas guide learners to assemble structured accounts of subject matter. Each schema can be labeled, e.g., ARGUMENT or EXPLAIN. Its slots, fields in which learners enter information, also can be labeled. When learners select (a) information to anchor a note and (b) a labeled note schema for the note they will make, this traces monitoring by the learner: the selected information has a role in the chosen schema. As the learner enters information in slots of the schema, the note artifact records which information the learner assembles according to that schema.

Beyond supplying more detailed data for analyzing conditional probabilities, illustrated by Table 11.2, notes could be leveraged by an algorithm to automatically generate self-test questions or self-explanations. For example, if the learner is annotating a step-by-step process with explanations, questions can be algorithmically constructed: "What process begins with [paste step 1]?" This question affords opportunity for the learner to monitor assembling the name of a process with its initiating step. Another question might be: "Why is it important that [paste step 2] precede [paste step 3]?" This prompts self-explanation, a learning event with proven value (Bisra et al., 2018). As well, such questions directly associate operations on information which the learner performed while studying with items measuring whether products of those operations match targets for achievement. As in Table 11.2, these data are more direct tests of effects operations have. As well, information for the learner to restudy can be recommended alongside learning analytics about which learning tactic was not successful in promoting achievement.

Selection artifacts, such as text or regions of a graph the learner highlights, can be counted as instances of metacognitive monitoring to gauge the learner's overall engagement. By examining what information learners select relative to structures like a termnet, models can be developed to describe the learner's attention to specific content. Coupled with the aforementioned automatically generated (self)test items, predictive models might be developed to gauge not just how much a learner is learning while they study, but also topics and kinds of content they can be prompted to process.

Information selections also provide meta-level information about rhetorical roles for the selected information, e.g., definitions, principles, examples, and so forth. Learners can be offered tags to classify selections by role, enriching traces of metacognitive monitoring by revealing the learner's attention to and use of metacognitive standards.

Tagging is already practiced by many learners. Perhaps the most widely used and most basic tag is the yellow (or blue or pink or …) highlight. It marks information selected by monitoring; selected information matches an unspecified standard that has utility for the learner. Tagging systems can operationally define those standards, making them observable. Some learners tag using symbols for selections. Examples are:? identifies information the learner metacognitively judges is vague or confusing.! marks especially important information. Modern software systems can offer multiple semantic and symbolized tags. Learners may be encouraged to use tags because tags can be applied to filter and retrieve selections, notes, and bookmarks tagged for particular purposes (e.g., nStudy; Winne et al., 2019). For example, a tag like *Huh?* could be used to filter all content about which a learner wants to seek help from a teaching assistant or peer. Follow-up data in the form of an online chat with peers or an email to the TA validates the learner's plan and subsequent execution.

Basic classes of tags might span four categories. Discipline-specific role tags mark information as an instance of a disciplinary class. In earth science, tags might classify information related to igneous, metamorphic, and sedimentary rocks. Rhetorical structure tags index content by roles information plays in a conceptual structure. These might include principle, example, and critical detail. Tags labeling tasks signal a learning event where selected information will be the subject of particular operations at some future time. Examples include: review, research, quotation (in an essay to be drafted). Affect tags can reflect a learner's monitoring of an emotional reaction to information. Instances might include: *wow!* (surprise), *duh* (boredom), and *cool* (interest). The information tags convey coupled with information tagged provides more precise tracing of SRL than simply counting instances of a monitoring event.

5 Analyzing Information-Enriched Trace Data

Almost all analyses of learning processes begin with data structured as a timeline of sequential events, often with timestamps marking onset or offset of the event. Some forms of analysis examine this data structure directly to identify patterns; e.g., an ABC pattern in x, m, k … ABC … x, y, z … ABC …. In some analyses, patterns allow for "skipping" intervening events bounded by a regular sequence of events initiating a pattern and another regular sequence terminating the pattern, e.g., an ABCDE pattern in x, m, k … ABCgDE … ABChDE … ABCjDE …. Others analyses transform the sequential timeline of events into a n × n matrix. This format records tallies for every possible pairwise sequence of events representing transitions from an initial event in a row to a follow-on event in a column. Every type of event (A, B, C …) in a transition can play the role of the initial event, condition in the COPES model, and a follow-on event, P in the COPES model.

Such "information-free" analyses of occurrence, frequency, timing, and patterning of operations ignore information learners operate on in learning events. Information is the condition that triggers any operation. And, information is the product of every operation. Omitting information from analyses of learning events classifies conditions and products as irrelevant to operations. As previously described, operations are "empty" in these analyses.

It is likely sophisticated extensions to conventional analyses of process data can be developed to incorporate information to which operations are applied. But relatively simple and straightforward analyses may suffice. Here is one example.

Suppose a learner is studying a unit about conic sections: circles, ellipses, hyperbolas, and parabolas. Sources the learner studies present terms (e.g., center, focus, major axis, eccentricity), equations describing each conic section and graphical examples of each. Among a variety of operations traced, consider two: translating and assembling. Classes of information rehearsed are terms (definitions) and examples. Examples can have two formats: text and graphs. In the source material the learner studies, there are:

- 8 terms (A, B, C, D, W, X, Y, Z), each with its definition
- 1 abstract equation for each conic section in which coefficients are variables (e.g., *a, b*)
- 1 example equation corresponding to each abstract equation in which coefficients are integers, and
- 1 graph of each conic section labeled with the integers appearing in each example equation.

The learner generates notes when studying this source:

- 4 notes: The definition of each term A, B, C, and D is copied (rehearsing) from the source and pasted in a note.
- 4 notes: The learner paraphrases (translating) the definition of each term W, X, Y, and Z.
- A note compares graphs of the parabola and hyperbola. The learner induces a principle (assembling), "As the coefficient of the vertex gets larger, the graphs extend farther from the origin."

If these 8 definitions are the only definitions in this source, the learner can be judged to have useful standards for monitoring information presented as a definition and is motivated to learn definitions. If the source contained, say, 20 definitions, there are several possibilities meriting analysis given the data in this example. This learner may have prior knowledge of the 12 (=20 – 8) definitions for which trace data were not generated. Or, the learner may lack clear standards for monitoring cues that mark a definition. This hypothesis could be tested in the next learning session by posting an instructional objective inviting the learner to tag definitions or, to leverage benefits of generative learning, create term notes. Roelle and Nückles' (2019) study suggests the latter guide for SRL will have differential effects depending on the source text's cohesiveness and density of elaborations, and whether the learner engages in retrieval practice. Cohesion can be gauged automatically using tools like Coh-metrix (McNamara et al., 2014). Retrieval practice can be promoted by an automatic question generation tool (e.g., see Das et al., 2021).

Suppose the learner recalls definitions A and D but not B and C. Rehearsing definitions appears not predictive of learning; odds are 1:1 applying the operation of rehearsing promotes learning. But an order effect – primacy, recency – may be operative if timestamps are considered.

Suppose the learner can recall definitions W, X, and Z but not Y. Translating (paraphrasing) definitions appears effective with odds 3:1, and translating definitions was more productive than rehearsing them. The order effect is moot when the learner translates definitions. A learning analytic based on these results could recommend the learner try to paraphrase definitions more often. As data accumulate across future learning sessions where subject matter changes, the potency and generalizability of translating definitions can be tested for $N = \text{me}$. Future analytics can be refined as additional data accumulate.

Suppose data show, after the learner assembles a principle based on information in the source, graphing parabolas and hyperbolas given algebraic expressions is accurate. While slim, data support a conjecture: The learner understands how coefficients in algebraic expressions locate vertices for these conic sections. Odds cannot be proposed yet because there is only one instance of this conditional relation.

With big data sets describing each learner and homogenously formed clusters of learners displaying approximately equivalent learning signatures formed using information-rich trace data, this approach to analyzing data offers promise for guiding SRL at the same time helps advance learning science (Winne, 2022). The learner's SRL is depicted in ways that generate serviceable learning analytics. Moreover, variance in the learner's selections of operations invites investigating motivation and conditions that discriminate whether this learner uses particular operations to learn. The AEIOU model and theories on which it stands can guide that investigation, strengthening links between learning science and learning analytics.

6 Conclusion

Learners are ubiquitously self-regulating agents (Winne, 1995, 2018). In the context of an instructional design or the architecture of a website, learners select information targets they aim to learn and operations they will apply to learn. Information available in the environment and recalled to or generated in working memory is what learners think with and think about. Topics range widely: declarative and procedural knowledge comprising a discipline; metaknowledge about genres and presentation formats (text, tables, and graphics); fixed and emergent properties of tasks;

forecasts and feelings about learning tactics as steps to execute as well as perceptions about that execution across the lifespan of task engagement; and more.

This account leads to an important proposition: Processes – O in the COPES model and the SMART model elaborating operations learners apply in learning tasks – are insufficient to advance theory, research, and productive applications of learning science and learning analytics. To successfully model SRL as a process requires accounting for information in three ways implied by the IF-THEN-ELSE model of a learning event.

First, information, the IF, sets a stage for the learner to select subjects on which to operate and operations to apply. Conditions (C) in the COPES model of a learning task is a placeholder for the wide-ranging information a learner considers in relation to an about-to-be-executed operation, a THEN. Without data representing that information, the onset of learning processes is a mystery.

Second, as learners execute an operation, unless it is automated to the extent it proceeds without monitoring, properties describing that operation are generated. Some examples are pace, fluidity, and effort. These emergent properties are products learners can monitor relative to personal and externally recommended standards.

Third, beyond just noted products of an operation arising because a self-aware person executes the operation, operations also generate products transforming their subject, the curriculum. Monitoring these products relative to standards creates evaluations in two domains. One is the subject-matter per se, e.g., a summary of an article, a solution to a problem. The other is the bundle of motivations and emotions represented via incentives and attributions in the AEIOU model.

A great deal of data representing these kinds of information can be unobtrusively and almost immediately gathered when learners study online. Information can be analyzed when presented via text, figure and table captions, and images and speech automatically transcribed to text. Formatting via markup tags that deliver content provides data to detect properties of information. Labeled software and architectural features – e.g., labeled hyperlinks, labeled buttons (e.g., NEXT, BACK), search boxes where learners' queries can be recorded – unobtrusively deliver important data about information.

Other information internal to learners' thinking can be revealed by perceptively engineering traces. Ideal traces generate data across multiple elements of the COPES, AEIOU, and SMART models. For example, a learner making a note in the nStudy system selects text, chooses a particular schema for assembling information about that selection, and enters text and selections among options in labeled lists formatted as checkboxes, radio buttons, or a slider. Making notes is an everyday studying activity, a relatively unobtrusive technique to gather information about C, O, P, S, and potentially E depending on slots presented in the note's schema.

All this information should enrich accounts of learning events beyond records logging time-sequenced logs of "information-empty" processes. Because self-regulating learners regulate learning based on and generating information, merging this data gathered unobtrusively is a major step toward generating new and more useful theory for learning science. At the same time, by developing sharper accounts of the information learners can consider in SRL, learning analytics will be more strongly positioned to help self-regulating learners as learning scientists conducting their personal programs of research for N = me (Winne, 2022).

6.1 Next Steps

Incorporating information presented to learners and generated by them in studies of learning events can take some direction from basic characteristics of current instructional designs and build from sophisticated methods now coming into use.

First, subject matter disciplines are founded on and distinguished by, in part, key concepts of which they are constituted. Glossaries identify those concepts and afford a representation of the discipline's conceptual structure as a termnet constructed using the in-terms-of relation previously described. The field should improve on this representation to track and, when self-regulating learners request information or interventions introduce information for learners to consider, supply concepts for learners to consider based on conceptual structures fundamental to a discipline. A termnet offers one mechanism to do this.

Second, there is widespread acceptance and use of terminology describing tasks, perhaps most publicized in the form of the revised "taxonomy" cataloged by Bloom and colleagues (Anderson & Krathwohl, 2001; Bloom et al., 1956). These terms and their synonyms can be readily mined using NLP technologies applied to content learners study, including direct mention of tasks in learning objectives, and text they create as notes and essays. Blending termnets (or more sophisticated representations) with standards for judging these tasks provides resources for designing note schemas learners might use to assemble content, automatically generating (self) test items and monitoring content learners select for tagging and annotations. An especially intriguing possibility is to investigate the possibility of accurately predicting what a learner learns by analyzing trace data instead of having to administer a posttest following the study.

Third, process maps now generated to investigate how learners' operations are patterned (e.g., Saint et al., 2021) need extension. Information learners study instantiates a pattern that triggers operations learners apply based on their metacognitive knowledge about how to learn modeled by If-Then-Else. Analytical tools now used to examine patterns of process data empty of information need extension to incorporate the information units (e.g., schemas, rules) on which those processes operate.

This is an ambitious and exciting agenda. It merges state-of-the-art work in learning science, learning analytics, knowledge representation, NLP, and modeling of dynamic events. Big data about information learners study and tools they use to study are needed as raw material to fuel this research. Fortunately, that resource is becoming increasingly accessible as education and training migrates to online platforms supported by systems learners can use every day to study and complete assignments (see Winne, 2017).

References

Anderson, L. W., & Krathwohl, D. R. (2001). *A taxonomy for learning, teaching, and assessing: A revision of Bloom's taxonomy of educational objectives*. Longman.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. W. H. Freeman. https://doi.org/10.1891/0889-8391.13.2.158

Bisra, K., Liu, Q., Nesbit, J. C., Salimi, F., & Winne, P. H. (2018). Inducing self-explanation: A meta-analysis. *Educational Psychology Review, 30*, 703–725. https://doi.org/10.1007/s10648-018-9434-x

Bloom, B. S., Engelhart, M. D., Furst, E. J., Hili, W. H., & Krathwohl, D. R. (1956). *Taxonomy of educational objectives: Handbook I: cognitive domain*. David McKay.

Braasch, J. L. G., & Bråten, I. (2017). The discrepancy-induced source comprehension (D-ISC) model: Basic assumptions and preliminary evidence. *Educational Psychologist, 52*, 167–181. https://doi.org/10.1080/00461520.2017.1323219

Chung, W. L., & Bidelman, G. M. (2022). Acoustic features of oral reading prosody and the relation with reading fluency and reading comprehension in Taiwanese children. *Journal of Speech, Language, and Hearing Research, 65*(1), 334–343. https://doi.org/10.1044/2021_JSLHR-21-00252

Das, B., Majumder, M., Phadikar, S., & Sekh, A. A. (2021). Automatic question generation and answer assessment: A survey. *Research and Practice in Technology Enhanced Learning, 16*(1), 1–15. https://doi.org/10.1186/s41039-021-00151-1

Dubovi, I. (2022). Cognitive and emotional engagement while learning with VR: The perspective of multimodal methodology. *Computers & Education, 183*, 104495. https://doi.org/10.1016/j.compedu.2022.104495

Flowers, P., Theopold, K., Langley, R., & Robinson, W. R. (2019). *Chemistry 2e*. OpenStax. https://openstax.org/details/books/chemistry-2e

Kuhn, T. S. (2012). *The structure of scientific revolutions*. University of Chicago Press. https://doi.org/10.1177/1745691617710510

McNamara, D. S., Graesser, A. C., McCarthy, P. M., & Cai, Z. (2014). *Automated evaluation of text and discourse with Coh-Metrix*. Cambridge University Press. https://doi.org/10.1017/CBO9780511894664

Miyatsu, T., Nguyen, K., & McDaniel, M. A. (2018). Five popular study strategies: Their pitfalls and optimal implementations. *Perspectives on Psychological Science, 13*(3), 390–407. https://doi.org/10.1177/1745691617710510

National Oceanic and Atmospheric Administration. (2019, February 01). *Water cycle*. https://www.noaa.gov/education/resource-collections/freshwater/water-cycle

Nelson, T. O., & Narens, L. (1990). Metamemory: A theoretical framework and new findings. In G. H. Bower (Ed.), *The psychology of learning and motivation* (Vol. 26, pp. 125–141). https://doi.org/10.1016/s0079-7421(08)60053-5

Peverly, S. T., & Wolf, A. D. (2019). Note-taking. In J. Dunlosky & K. A. Rawson (Eds.), *The Cambridge handbook of cognition and education* (pp. 320–355). Cambridge University Press. https://doi.org/10.1017/9781108235631.014

Renninger, K. A., & Hidi, S. E. (2019). *The Cambridge handbook of motivation and learning*. Cambridge University Press. https://doi.org/10.1017/9781316823279

Roelle, J., & Nückles, M. (2019). Generative learning versus retrieval practice in learning from text: The cohesion and elaboration of the text matters. *Journal of Educational Psychology, 111*(8), 1341–1361. https://doi.org/10.1037/edu0000345

Saint, J., Fan, Y., Singh, S., Gasevic, D., & Pardo, A. (2021, April). Using process mining to analyse self-regulated learning: A systematic analysis of four algorithms. In *LAK21: 11th international learning analytics and knowledge conference* (pp. 333–343). https://doi.org/10.1145/3448139.3448171

Vatansever, D., Menon, D. K., & Stamatakis, E. A. (2017). Default mode contributions to automated information processing. *Proceedings of the National Academy of Sciences, 114*(48), 12821–12826. https://doi.org/10.1073/pnas.1710521114

Weiner, B. (2010). The development of an attribution-based theory of motivation: A history of ideas. *Educational Psychologist, 45*, 28–36. https://doi.org/10.1080/00461520903433596

Winne, P. H. (1995). Self regulation is ubiquitous but its forms vary with knowledge. *Educational Psychologist, 30*, 223–228. https://doi.org/10.1207/s15326985ep3004_9

Winne, P. H. (2017). Leveraging big data to help each learner upgrade learning and accelerate learning science. *Teachers College Record, 119*(3), 1–24. https://doi.org/10.1177/016146811711900300

Winne, P. H. (2018). Cognition and metacognition within self-regulated learning. In D. Schunk & J. Greene (Eds.), *Handbook of self-regulation of learning and performance* (2nd ed., pp. 36–48). Routledge. https://doi.org/10.4324/9781315697048-3

Winne, P. H. (2020a). Construct and consequential validity for learning analytics based on trace data. *Computers in Human Behavior, 112*. https://doi.org/10.1016/j.chb.2020.106457

Winne, P. H. (2020b). A proposed remedy for grievances about self-report methodologies. *Frontline Learning Research, 8*, 165–174. https://doi.org/10.14786/flr.v8i3.625

Winne, P. H. (2022). Modeling self-regulated learning as learners doing learning science: How trace data and learning analytics help develop skills for self-regulated learning. *Metacognition and Learning, 17*, 773. https://doi.org/10.1007/s11409-022-09305-y

Winne, P. H. (in press). Assessing learning processes. In R. Tierney, F. Fizvi, K. Ercikan, & T. N. Hopfenbeck (Eds.), *International encyclopedia of education assessment and accountability* (4th ed.). Elsevier.

Winne, P. H., Gupta, L., & Nesbit, J. C. (1994). Exploring individual differences in studying strategies using graph theoretic statistics. *Alberta Journal of Educational Research, 40*, 177–193.

Winne, P. H., Teng, K., Chang, D., Lin, M. P.-C., Marzouk, Z., Nesbit, J. C., Patzak, A., Raković, M., Samadi, D., & Vytasek, J. (2019). nStudy: Software for learning analytics about processes for self-regulated learning. *Journal of Learning Analytics, 6*, 95–106. https://doi.org/10.18608/jla.2019.62.7