Chapter 11
Designs for Learning Analytics to Support Information Problem Solving

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In recent years, learning science researchers have turned with growing interest toward investigating information problem solving (IPS). Problems are situations in which people identify a goal, although not always fully and precisely, and are uncertain how to achieve it. Information problems are a class of problems in which people are challenged to identify, find, examine, use, and communicate information to learn about a new topic, create a product, or solve an overarching problem. IPS can be carried out alone or in collaboration.

In the post-secondary setting, a nearly universal assignment that calls for IPS is the term project. It has several common forms: a major paper (10 pages or more) assigned in a course, a business plan, or a proposal for scholarly research or a thesis. Students almost universally engage in information problem solving when they tackle term projects throughout their academic career. Professors and mentors intend these exercises in information problem solving to substantially extend students' knowledge and deepen understanding about the topic of the project, e.g., how polling affects modern political elections or whether a carbon tax effectively controls pollution. To denote this purpose explicitly, we label these large, complex assignments as learning projects.

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By synthesizing Brand-Gruwel, Wopereis, and Walraven's IPS-1 model (Brand-Gruwel, Wopereis, & Walraven, 2009) and Winne and Hadwin's model of self-regulated learning (Winne, 2017a; Winne & Hadwin, 1998), we describe round-trip IPS in a learning project as including a variety of specialized problem solving activities (cf. Eisenberg, 2008):

- Setting an overall goal that identifies key attributes of the product to be generated by engaging successfully in a learning project,
- Defining and setting parameter values for kinds of information that contribute to the learning project,
- Searching for and filtering information sources (websites, documents, videos) that are judged to contribute high-quality information needed to meet goals,
- Analyzing and extracting information from filtered sources and organizing that content,
- Designing and drafting a product (e.g., the term paper or research proposal), and
- Evaluating and revising the draft(s) of that product to produce a polished final version.

Beyond learning about a topic, we believe mentors intend learning projects to provide their students opportunities to develop generalizable knowledge and skills for solving information problems. Many label these as lifelong learning skills. Alongside "cold" knowledge and skills used to work directly on solving information problems and managing workflow, "hot" features are infused in IPS (e.g, Schwarz, 2002; Wyatt et al., 1993). These include strategies students use to motivate themselves and cope with the demands of IPS tasks, and strategies for managing emotions, particularly obstacles or setbacks arise. We are quick to add an assumption: Students and their mentors sometimes, perhaps often, do not explicitly or deliberately attend to warmer features of learning projects.

At the start of the first author's academic career, nothing like today's array of tools was available to support practically instant search for sources of topical information or search for particular information within sources. It was tedious rather than simple to edit drafts. The upshot of a round of editing rarely preserved changes that could be easily undone. After editing, the manuscript was left in a state that hardly allowed studying it to discern how changes affected its architecture, clarity, and cogency. Sharing drafts with peers to gather their constructive critiques required meeting them, then meeting again to retrieve their commented copies. Coordinating their commentaries and editorial suggestions across multiple paper copies was unduly time consuming and, with more than two peers providing reviews, a trial of organizational skills. This environment was poorly structured to promote learning. "Getting to work" demanded effort and robbed time that might have been allocated to learning.

Today, students' opportunities to engage in all the multiple facets comprising round-trip IPS are dramatically different. The advent of modern computing technologies, the Internet, and search engines significantly facilitate locating sources, workflow, information sharing and organization, and revisions of draft products.

These are steps toward an effective design for learning. At the same time, however, these affordances generate new information problems. Examples are a surfeit of available information that can appear relevant, tools that allow for tailored and potentially excessive cataloging and tagging of a very large volume of snippets of information, and systems that gather but don't help organize peers' reviews of draft reports. In this newer world of digital "info-wealth," learners need to develop and apply skills to cope in new ways. Successful learners are productive self-regulated learners. Can technologies provide assistive adaptivity to help?

A Framework for Learning Analytics about Information Problem Solving

Alongside the upsurge in research on IPS and its constituents, recent years have seen skyrocketing interest in and research on search for meaningful patterns in data—analytics—and the specialization of analytics about learning—learning analytics. As is common in emerging fields, there is in the field of learning analytics abundant variety in kinds of data gathered, techniques applied to analyze data, and proposals for assembling and formatting reports to learners about patterns in data that describe learning and work constituting IPS.

What distinguishes learning analytics from conventional feedback intended to guide learning? We propose three major but not exclusive characteristics (see also Winne, 2017b). First, compared to an achievement test score or the average of responses to items on a self-report survey gauging motivation, learning analytics are commonly constructed using data about learning activities in conjunction with conventional data. Second, while by no means universal, learning analytics commonly are generated across a timeline of activities rather than data gathered at just one point in time. Third, these two features lend emphasis to the purpose of learning analytics as being formative. That is, learning analytics are intended to guide change(s) in a process to bring about a desired change in a product, such as a learning project. In these three ways, learning analytics are well positioned to help learners become better at solving information problems.

In this chapter, we frame learning analytics within the context of a modern approach to solving information problems, namely, when the student uses a state-of-the-art software system that can capture very fine-grained, time-stamped information about the learner's work on a learning project within an environment of practically limitless information. We leverage affordances of this technology as a tool for supporting learning-controlled assistive adaptivity by gathering, analyzing, and delivering reports about students' work as they engage with common information problems (e.g., see Marzouk et al., 2016). We adopt a perspective of learners as self-interested, self-regulated learners who seek better and minimally taxing ways to solve information problems (Winne, 2017b; Roll & Winne, 2015).

The learning analytics we sketch in this chapter are designed to serve two purposes. The first is to identify particular features of students' work in a learning project that, if the learner adapted them, would enhance learning about the topic the learner researches. The second is providing process feedback that guides self-regulated learning about skills for successfully addressing information problems. In this vein, we extend common frameworks for a learning analytic by adding a requirement that data gathered and interpretations of analytics generated with that data align to one or several empirically-supported principles in learning science. We believe mining empirical research in learning science will increase the likelihood learning analytics can help learners build topic knowledge and improve skills for addressing information problems.

Context: Researching a Term Paper Using nStudy

Suppose a learner has been assigned a learning project: Research and develop a 10-page paper arguing for or against this contentious proposition: "A national consumption (e.g., sales) tax is a better option for funding a nation's priorities than a tax on its citizen's wages (e.g., an income tax)." Our learner—we name her Mia—works on this learning project using state-of-the-art software called nStudy. nStudy is an extension to the Chrome web browser. It records data about every bit of information Mia operates on when she uses nStudy's features, how Mia operates on that information and the time at which each operation occurs accurate to approximately 1/100th s. Metaphorically, these data form a script that, if "played back," completely and exactly reveals what a person hovering over Mia's shoulder could observe about how Mia works on the learning project except for Mia's self-talk that she elects not to enter in nStudy as a "note to self." As Mia works, these data are transmitted in approximately real time to a remote server where they are stored in a database. Modules on the server combine a database query that extracts particular data that are then processed by scripts that analyze those data using tools within the statistical/analytic framework R. Output generated by those modules is then formatted using other R packages to create analytics as a web page. URLs pointing to those web pages are delivered to Mia when she asks for them or by the system when attributes describing the state of Mia's work match conditions in rules of a production system. In the latter case, the production system plays the role of a dynamic help system that monitors in nearly real time conditions that signal Mia might benefit from learning analytics reports about how she is working and what information is processed by her work activities.

nStudy

When learners use nStudy's tools, they create artifacts that nStudy stores for them and trace data that describe how information in an artifact was processed. Traces are

operational definitions of cognition, metacognition, and motivation. Typing a URL into the browser's address field or clicking an existing bookmark in nStudy's library of artifacts logs the URL of the sought information in nStudy's database. This trace datum identifies Mia is seeking information, she predicts information she seeks is available in a particular artifact, and is motivated to inspect the web page (or pdf file) that will be displayed in her web browser. Metacognitively, the trace indicates Mia judges information she cannot recall well enough or judges she does not know exists in the particular web page that will be displayed in the web browser.

Dragging the cursor across a string of text in a web page selects it and automatically pops up a menu where Mia can create a quote, a note, or a term. The text Mia selects is automatically copied by nStudy into a sidebar for future access; hence, we label it a quote. If Mia chooses, she can tag any instance of quoted text by typing a tag (or several tags) into a text box. As she types, a dropdown list of existing tags is displayed, reminding Mia of tags already created. The dropdown list of tags is successively filtered as Mia types additional letters into the text box.

A note elaborates a quote. Each note has a text field where Mia identifies the topic of the note, a second text box where she can tag the note independently of the quote she may have applied to the quote associated with a note, and at least one labeled field for the note itself. Notes can have more complex designs called a note template. A note template can be basic, e.g., just a single text field labeled "Comment." Or a note template can represent a larger schema, e.g., four text fields providing a note that represents a causal relation: "Cause," "Effect," "Context," and "Reason." A variety of types of fields can be configured to design multifaceted note templates that include text fields, lists of checkbox items (select one or many), lists of radio button items (select only one), sliders, date, image, and a link field where Mia can create a hyperlink joining the note she is currently making to another artifact, e.g., a bookmark representing a different web page. A note template has a name, e.g., "quality of expression" or "reasoning." nStudy automatically tags each note Mia creates with the name of the note template she chose for annotating text she quoted.

A term note is a special note template for creating entries in a glossary of key concepts. The topic field of a term note contains the concept being described. A "Description" text box holds the concept's description or definition. A link field lists other concepts associated with this term based on a relationship. One kind of relationship is the in-terms-of relation. It is automatically created by nStudy when one term's description includes another term. Key concepts and terms in sources relate in ways beyond definitions. Under the assumption that authors of sources construct conceptually coherent and valid sentences, a second relation is created when terms co-occur in a sentence.

A display of key concepts and their relationships to one another can be pictured in a node-link graph called a termnet. Terms are vertices in this graph and links (edges) are defined by either or both the in-terms-of relation and sentence co-occurrence relations. As a mathematical graph, the termnet allows indexes to be calculated that describe, e.g., the "importance" of a concept or the complexity of a neighborhood of concepts.

Quotes, notes, and terms are copied into a sidebar associated with the web page in which these artifacts were created. Artifacts in the sidebar can be filtered by typing in a text field; e.g., typing the tag "vague" filters out all artifacts not tagged "vague." Each artifact is also represented by a colored nub adjacent to the scroll bar at the right edge of the window. Clicking an artifact in the sidebar or a nub scrolls the web page to the location of the quote associated with that artifact and opens a window over the web page showing the artifact's contents in context.

nStudy also provides an HTML editor Mia can use to draft her essay. The essay tool provides a toolbar with common formatting features (e.g., italic, bold, levels of headings, bullet list, sequential list) to format the essay. As well as typing directly to draft her essay, Mia can copy an artifact, e.g., a quote or note, and paste its information into the essay. Because the essay is actually a web page, Mia (and peers, see below) can annotate it by identifying text (quoting it), and tagging and annotating it.

Each time Mia selects text, types text, or clicks a "live" feature associated with an artifact, nStudy records a 3-tuple: text, operation, time. For example, if Mia filters the sidebar by typing the tag "vague," the data recorded are a complete representation of Mia's engagement.

nStudy's collaborative tool, called the Hub, is a channel for Mia to communicate with peers, share learning artifacts and give and receive feedback on her learning project in the form of peers' reviews and learning analytics. Discussions are supported by a dropdown list that suggests roles she and peers can adopt, e.g., critic, analyst, or manager. To guide Mia's participation in discussions, nStudy offers prompts keyed to each role. For example, in the critic role, sample prompts might be: "Is the evidence for ___ reliable?" or "Is the view that ___ corroborated?" Clicking a prompt inserts it into the text box where Mia can fill in blanks and add additional information before sending her contribution to the discussion. Mia can also drag and drop artifacts, such as a tagged bookmark, a note, or her draft essay into the message box to share with peers.

Empirically-Grounded Learning Analytics About Learning Projects

Students like Mia face many challenges as they work on a learning project, such as the example we introduce here of researching and developing an argument about a relatively new topic. Here, we elaborate just three: planning and learning how to plan more accurately, monitoring whether a draft essay has appropriate coverage of a topic, and developing new knowledge about a topic. For each challenge, we describe: the challenge itself, data nStudy gathers as the learner works, aims served by a learning analytic developed with that data, a learning analytic report for presentation to the learner, and a rationale from learning science that provides grounds for predicting the learner can benefit by maintaining or adapting features of work on the learning project as described by the learning analytic.

Challenge 1: Planning and Learning How to Plan More Accurately

In researching material for a learning project, students need to search for relevant information, study sources they locate, extract and synthesize content, and develop an understanding of a topic to form a conceptual foundation for generating a product. In the context of these IPS tasks, students engage in various metacognitive tasks, e.g., estimating time required for subtasks, planning a path through the space of the information problem, monitoring progress toward goals, and adjusting time and foci for planned efforts as work on the learning project proceeds. These are known challenges for many learners (Buehler, Griffin, & Ross, 1994; Kruger & Dunning, 1999; Winne, 2001; Zimmerman, Bonner, & Kovach, 1996). We describe an nStudy feature in development, the PlanNet, to help learners address these challenges.

nStudy Data

As Mia searches the Internet for raw materials she will mine for her essay, nStudy traces her search queries. Among sources she finds, she bookmarks selections in her nStudy library. Mia can tag a bookmarked source, and content in a source can be annotated by quotes, tagged or not, and notes, tagged or not. In addition, Mia can create terms. As described earlier, throughout all her work on the learning project, nStudy logs data about Mia's exposure to terms in sources she views and her use of terms in the text of artifacts she creates: searches, quotes, notes, terms, and her essay.

The PlanNet (see Fig. 11.1.) doubles as a tool for developing plans and an interactive analytic. As Mia uses its features to customize a PlanNet display, nStudy logs data identifying bookmarked sources she cites in the essay she is developing, values that mark time points in time within plans and for reviewing plans, and metadata about terms displayed in a termnet or that are targeted for planned action. The metadata about terms identify whether Mia selects a term (a node) and how Mia chooses to operate on it (e.g., to review it, to search for it). As the state of the PlanNet changes, metadata about terms are updated to identify whether, at each state of Mia's work, a term is a member of the subset of terms defined by Mia's configuration of PlanNet features. For example, if Mia selects a single bookmark as the scope for the PlanNet display, nStudy logs data that identifies whether each term in that selected source appears in the draft of Mia's essay as of a date (version) she specifies for the essay's state.

Conceptual Description of Learning Analytics

The PlanNet window shown in Fig. 11.1. has several features. In the upper left is a list of artifacts. The first is a dropdown list identifying versions of Mia's essay.
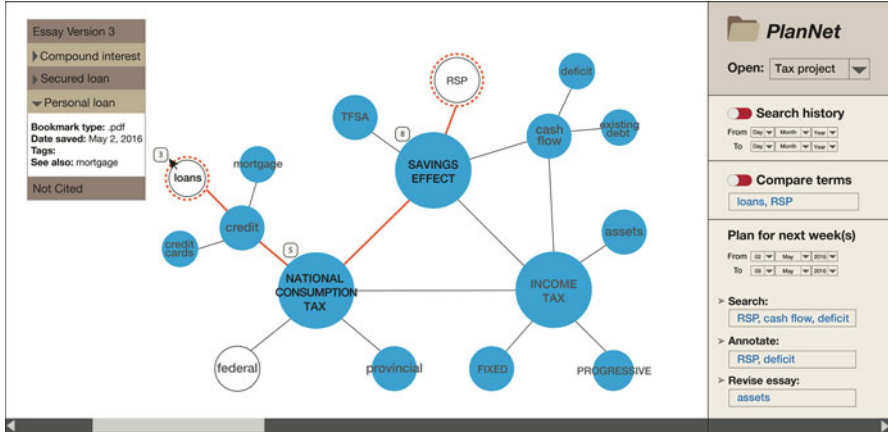
Fig. 11.1 PlanNet for Mia's Project

Mia can select a particular version to examine in the PlanNet. Next listed is the subset of sources Mia bookmarked while researching her topic, which she has cited in the selected version of her essay. The final entry in the list, "Not Cited," is a folder. Clicking it lists sources Mia bookmarked while researching her topic but are not cited in the selected version of her essay. Selecting an artifact in this list (or multiselecting several sources) marks terms in the termnet shown in the main area of the window by changing color codes identifying how a term is used, as discussed next.

In the center of the PlanNet window is a termnet. It is a union of the "seed" termnet Mia's instructor provided to help students begin their learning project with the complete set of terms Mia created while researching her topic. Several features are found in the termnet:

- Node diameter is proportional to a term's importance relative to all sources Mia bookmarked, i.e., the greatest scope of information Mia judged relevant in her research about the topic. Importance of a term is measured by an index of that term's centrality relative to all other terms across Mia's bookmarked sources (Dehmer & Emmert-Streib, 2009).
- Distances separating nodes (the lengths of nondirectional edges in the graph) are inversely proportional to linked terms' co-occurrences within sources and across them (Manning, Raghavan & Schütze, 2008a, 2008b). While simple, representing text this way highlights useful properties of information (Hopkins & King, 2010). To generate a readable termnet within a confined space, the ForceAtlas2 algorithm (Jacomy, Venturini, Heymann, & Bastian, 2014) is applied. This pushes highly connected nodes (hubs) away from each other and arrays nodes associated with a hub in clusters around hubs. If Mia selects any

two terms, nStudy applies coloring to links that form the shortest path between them.

- Terms "seeded" by Mia's instructor appear in all uppercase font.
- Font is black for terms appearing in bookmarked sources Mia cites in the current version of her essay. Font color is gray for other terms unique to sources Mia is not citing in the current version of her essay.
- When Mia selects her Essay in the list of artifacts, nodes representing terms included in the current version of her essay are filled with light blue.
- When a source other than the Essay is selected, the weight of the perimeter stroke for nodes representing terms in the source increases $+2$.

Nodes in the termnet are decorated according to metadata. Numbered bubbles adjacent to nodes mark the number of bookmarked sources Mia used in her essay in which the term appears. Clicking a bubble lists the titles Mia assigned when she created those bookmarks. Decorations in the termnet help Mia quickly identify important qualities of information in her essay relative to one or several sources cited in it. Selecting different sources redecorates the termnet to highlight differences in concepts the source(s) describe.

Mia can quickly review information about a term by double-clicking a node. This opens a term window showing the term, the definition/description of that key concept, and a list of bookmarks in which the term appears. Clicking a bookmark opens it for quick review to support a scan for specific information related to that concept or extended restudy.

To support Mia's exploration of "what if" scenarios, i.e., plans, Mia can use PlanNet tools in the right-hand sidebar to adjust the termnet display. As she does, the termnet is redecorated to reflect her plan cast as a configuration of key concepts. First, Mia identifies an interval when she will work to implement a plan selecting start and due dates. She then might drag-and-drop a node from the termnet into the Search box. This changes the fill color of that node and its radiating neighbors to a shade of blue using heatmap shading. Intensity of the fill color fades as terms become more distant from the focal term. This invites Mia to (re)consider information that might be added to or elaborated through her search and subsequently in her essay. Mia can operationalize a plan to expand her understanding of a term by dragging it into the Annotate box, thus marking a term for further study. If the redecorated termnet is sufficient to influence Mia to revise her essay in relation to a term, she can drag it into the Revise Essay box. When "done" with work relating to a term, Mia can place it in the Completed box.

Mia's interactions with the PlanNet are fully traced. Data record how she explores conceptual configurations represented by redecorated termnets, plans she devises for revising essays and how this work unfolds in relation to the time marks she sets for work on a plan.

Mia also needs to check she understands the instructor's seed terms, and plan how to integrate those concepts in her essay as she searches and reviews sources. When uppercase font terms are filled in blue, this goal is met. For these terms, and others she decides are important to her essay, a plan can be developed using

the PlanNet's features. nStudy can remind her which terms in her plan have not yet received attention as she planned, and whether she is on schedule according to the plan interval she set. Displays contrasting a simple timeline of work planned to work accomplished, e.g., expanding annotations about a term, inform Mia about whether she might increase or reduce workload in a plan interval. By toggling the drop-down time range to "on" and adjusting dates in the Search history section of the PlanNet sidebar, Mia can compare progress on her project as reflected by work planned and work accomplished. As an analytic, data collected in the PlanNet and elsewhere in nStudy explicitly represent conceptual development as a function of goals, type of work, and time. Mia can review how earlier plans were defined, track what she accomplished relative to plans, and compare the state of her project now to its forecasted forms.

Learning Analytics Reports and Learning Science Principles

Based on Mia's interaction with the PlanNet, nStudy generates five learning analytics reports that are embedded within the PlanNet. This design builds on a rich history of two-dimensional graphic organizers as visual representations that support students' use of knowledge (Alvermann, 1981; Ives & Hoy, 2003; Winn, 1991). A meta-analysis by Nesbit and Adesope (2006) compared concept maps to other learning activities (e.g., reading texts, attending lectures, and class discussion participation). They reported concepts maps were more beneficial for promoting retention and transfer of information across various learning settings, topics, and learners' educational level. They conjectured these benefits resulted from greater opportunities for engaging with information in a concept map compared to other media and learning activities.

Analytic Report 1: Use of Terms. Decorations in the PlanNet are analytics that afford Mia opportunities to metacognitively monitor features of key concepts (terms) related to the learning project. Numbers in bubbles adjacent to terms reflect the scope of sources Mia has bookmarked about key concepts. Low numbers or the absence of bubbles signal limited or no search, a nudge to plan additional research into these concepts. Terms in black font (included in Mia's essay) relative to terms in gray font (not included) indicate how well Mia's essay spans the complete set of concepts, including those her instructor marked as critical (uppercase).

These analytics are grounded on the coherence effect (25 learning principles, 2015): learning benefits from a connected and articulated representation of main ideas in material (Mayer, 2001). The termnet is such a representation. Also, vocabulary knowledge influences strategies learners choose to study, inferences they form from source materials and, ultimately, achievement (Cromley, Snyder-Hogan, & Luciw-Dubas, 2010). For students pursuing learning projects where content and language learning are integrated (CLIL), word choice and phrasing affect the register and quality of writing in the product of a learning project (Whittaker, Llinares, & McCabe, 2011).

As Mia extends her knowledge of key concepts, support provided by this interactive analytic may increase. Gurlitt and Renkl (2008) reported university students benefited more from low map coherence where they had to create and label links. In the termnet, as Mia adds concepts to those her instructor provided, she creates and can subsequently edit descriptions of how they relate conceptually. As her prior knowledge grows over the timeline of her learning project and as she actively engages with the termnet of concepts, she successively records elaborations of her knowledge via the termnet.

Analytic Report 2: Mapping Term Relationships. The PlanNet's interactive analytics mark relationships among terms Mia has not used yet in her essay. To explore how she might introduce new content given what Mia has included in her essay, she can select two or more terms in the termnet and PlanNet will map the shortest path between (among) them. This analytic is based on Mayer's (2001) notion of actively engaging with information to form a coherent mental representation or mental model. Here, terms are key, conceptually structured items that Mia is modeling in her essay.

If Mia elects to preserve a particular set of conceptually related terms, she can save the artifact in the sidebar under "Compare Terms." Clicking it at a later time shows Mia how terms in the set relate by decorating the paths that link them. Like other artifacts, Mia can annotate a conceptual relationship, e.g., creating a "superordinate" term or a note that elaborates the conceptual structure. According to Bransford and Schwartz (1999), comparing conceptual structures, represented via the PlanNet as different conceptual structures, can help novices notice deep features that otherwise may be unnoticed. Here, Mia may observe new relationships involving a particular term or neighborhoods of terms.

Mia controls how she uses the termnet, how many sets of terms she explores, and the span of each conceptual structure. This aligns to the Goldilocks principle (25 learning principles, 2015): learning improves when the scope of information is tailored to current abilities.

The termnet also implements the Organization Effect, which emphasizes the importance of integrating and synthesizing information (25 learning principles, 2015). As Mia adds terms and annotates them, and when she traces coverage of her searches and her draft essay, she is actively and constructively (Chi, 2009) engaged with content.

Analytics Report 3: Comparing a Draft Term Paper and PlanNet. Mia can select the current or a past version of her essay in the dropdown list at the upper left corner of the PlanNet. This draws a termnet representing the content in that version of the essay over a backdrop formed by the termnet of all terms across all of Mia's instructor's terms, terms Mia added, and her bookmarked sources. This may help Mia monitor deeper features of information in the drafts of her essay relative to neighborhoods in the domain and the entire domain of her topic (Bransford & Schwartz, 1999).

Several studies reported mapping and graphical planning strategies are an effective pre-writing activity to promote students' understanding of text organization (Cronin, Sinatra & Barkley, 1992; Pieronek, 1994; Saddler, Moran, Graham &

Harris, 2004; Schultz, 1991; Washington, 1988). These activities correlate with beliefs of control over concepts and the writing task (Bascones & Novak, 1985; Novak, 1991, 1998). Reynolds and Hart (1990) reported concept maps were stronger supports for planning writing than traditional outlining or brainstorming.

As well, planning by mapping is also reported to help learners manage memory (Novak, 1990; Novak & Wandersee, 1991), increase vocabulary (Harley, Howard, & Roberge, 1996; Johnson & Steele, 1996), and promote reading comprehension (Baumann & Bergeron, 1993; Lipson, 1995) and comprehension in the subject area (Patterson, 2001; Roth, 1994). All of these effects contribute to meaningful learning (Ojima, 2006).

Analytics Report 4: Feedback About Planning. Productively self-regulated learners forge plans about how they will learn (Winne, 2017b; Winne & Hadwin, 1998). They monitor progress and adjust the strategy or the goal as needed, and set a new subgoal when the current one is attained (Schunk, 2001). When a work session is complete, they analyze them to generate forward-reaching transfer that will improve plans they will make in the future (Winne, 2017a).

Learners find it difficult to determine progress toward a distant goal (Schunk, 1995); proximal, short-term goals are achieved more quickly, with greater motivation and better self-regulation compared to long-term goals (Bandura, 1997; Boekaerts et al., 2000; Locke & Latham, 1990). Thus, the PlanNet is designed to invite students to divide large learning projects—the full termnet—into subgoals expressed as self-set, short- to moderate-term, concept-explicit goals about searching for key concepts, developing understanding about them through annotations, and displaying what has been understood by using terms in the product of their learning project.

In the Plans sector of the PlanNet sidebar, Mia can enter or drag-and-drop terms from the termnet to identify a focus for new searches, new annotations, and revisions to her essay. She also can define a time interval within which this work should occur. Each configuration of these features operationally defines a subgoal relating to Mia's learning project.

Using data nStudy gathers in the PlanNet and as Mia uses its other features, analytics can be generated that describe characteristics of Mia's plans as well as how well she matches actual work to her plans. For example, students often underestimate time to complete a project (e.g., the planning fallacy; Buehler et al., 1994; Kahneman & Tversky, 1979). nStudy can track and report about whether Mia searches for and annotates terms identified in the plans sector of PlanNet. In the essay tool, nStudy can track whether Mia edits or adds sentences or paragraphs that contain terms she targeted for revision. Comparing plans to actual work provides Mia with raw data she needs to consider in how to set goals and plan in the future (Anderman & Wolters, 2006).

Regulating work along a timeline is also an important component of effective planning. When Mia sets a time interval for a plan regarding specific concepts and particular actions applied to them (e.g., developing annotations about the concept of deficit), nStudy can post alerts when deadlines approach or are missed. A timeline contrasting deadlines to when work of particular kinds on particular concepts was

begun can invite Mia to consider whether and why she procrastinates (Patzak & Winne, 2016).

Analytics Report 5: Planning History. If Mia sets dates in the Plan sector of PlanNet's sidebar to values in the past, earlier plans are retrieved and attributes of terms in the termnet that relate to that plan are set to their retrospective values. By "paging through" a timeline of plans, Mia can inspect their temporal and conceptual scope to develop an evidence-based perception about how well she plans. This sets a stage for more accurate planning and time management (Kruger & Dunning, 1999) that characterize self-regulating learners (Winne, 2017a; Winne & Hadwin, 1998).

Challenge 2: Learning about the Topic

When learners research a topic about which they have limited or only basic knowledge, we predict they are challenged to accurately characterize what they have learned about the topic and how well the product they generate—Mia's essay—represents the topic.

With respect to a learner's judgment of what has been learned about a topic, much research suggests learners overestimate how much they know and how well they know (can recall) it, and, moreover, may not benefit from repeated feedback about their overconfidence (e.g., Foster, Was, Dunlosky, & Isaacson, 2016).

Regarding how aptly a product represents the topic, we suggest three "views." First, how thoroughly does the product—Mia's essay—sample information available in sources she identified as relevant to her learning project? Second, is information sampled in her essay configured like information in the sources? Third, how well does the profile of emphasis in Mia's essay align to that in sources she studied? If learners can more accurately judge these matters, results of studies such as Cerdán and Vidal-Abarca's (2008) indicate they develop a more extensive and deeper understanding of the topic.

nStudy Data

As Mia studies source documents, she selects text representing key concepts and terms that play critical roles in her topic and creates term notes. Terms Mia creates are added to those seeded by her instructor's termnet.

Conceptual Description of Learning Analytics

Termnets can be displayed for a single bookmarked source, across the corpus of sources Mia studied, and in Mia's essay. Indexes can be computed to describe quantitative properties of terms and collections of terms in a termnet. For example, the number of terms associated with a focal term (the centrality index) can suggest

the conceptual importance of a term in a different manner than counting the frequency of a term's appearance as an indicator of emphasis given that concept in a source or in Mia's essay. A betweenness centrality index gauges the degree to which a term plays the role of a key mediator between clusters (neighborhoods) of other concepts.

With the termnet as a backdrop, basic questions can be framed about particular nodes and neighborhoods of nodes. These can guide Mia to more accurately estimate whether and what she has learned about the topic she researched, setting a stage for restudying material she hasn't learned well. Creating a termnet of terms appearing in the sources Mia cites in her essay and contrasting it to another termnet of terms Mia has used in her essay sets a stage for learning analytics describing content selection and topical coverage in the essay relative to that in the sources.

Learning Analytics Report and Learning Science Principles

After studying several source documents and creating a glossary of terms appearing in them, Mia drafts her essay. She then asks nStudy for an analysis of her essay that compares it to sources she cited in the essay. Although Mia did not directly request it, nStudy will first engage her in an "interactive" analytic that helps Mia determine how well she has learned about the topic writ large.

nStudy shows Mia a termnet developed from sources cited in her essay. Nodes are labeled by terms they represent. Terms with high centrality and betweenness centrality are highlighted. Alongside this display is this instruction: "To test your understanding, please click a highlighted term in the termnet." When Mia does so, nStudy computes whether the term's betweenness centrality exceeds a threshold.

If the betweenness centrality threshold is not exceeded, a window pops up with a four-part web form (an nStudy note template). In the first part, labeled "Term," nStudy displays the term. Part two is a slider labeled "How well I know this" with a scale labeled from 0 to 100. Part three is a text box labeled "Description." Inside the text box is gray replacement text that will disappear as Mia begins typing her reply; the replacement text is "Enter what you remember about this term." Last, a label "Click if you need to review" is printed next to a button "Review." Clicking that button opens the source in which Mia first defined the term, scrolls to the text she selected when the term was created, and opens the term's note to display what Mia entered at the earlier time when she was studying that source.

If the betweenness centrality threshold is exceeded, a window pops up with the same four parts as just described plus an additional text box located between the Description and Review parts of the preceding template. The new text box is labeled "Explain." Replacement text in the box is: "What important role does this term play in the termnet?"

This interactive analytic has two purposes. First, by attempting to recall the descriptions/definitions of concepts/terms she used in her essay, Mia is engaging in retrieval practice. This form of cognition promotes learning by engaging the testing

effect (Roediger & Butler, 2011). Second, because Mia estimates her knowledge by positioning the slider, she engages in a judgment of learning. As Mia engages with each key term in the termnet, nStudy computes probabilities she reviews a term's source material as a function of her judgment of learning. After Mia has completed several of these exercises for important terms, nStudy provides a further analytic describing, as would be predicted based on the research literature, her overconfidence. More accurate judgments of learning are associated with better choices about how to study in the first place and what needs to be restudied after first engagement (Soderstrom, Yue, & Bjork, 2016). In addition, explaining the conceptual role of these terms with high betweenness centrality engages the self-explanation effect (Bisra, Liu, Salimi, Nesbit, & Winne, 2017).

The display of the termnet also includes a button: "Compare to sources." When Mia clicks it, another termnet is displayed alongside the termnet reflecting terms in her essay. This new termnet reflects the conceptual structure of terms in sources Mia cited. Terms appearing in sources that are not used in Mia's essay are color coded (e.g., blue). Terms appearing in both the termnet developed from Mia's essay and the termnet of sources she cited are heat-map shaded in proportion to the centrality index of terms in cited sources. Mia can visually compare these two termnets to examine not only the extent to which her termnet "covers" information in sources, but also how emphasis in her essay compares to that in the corpus of sources she cited in her essay. We hypothesize these comparisons can serve Mia well in considering whether and how to revise her essay. Also, various indexes can be computed to quantify how well Mia's essay structurally "correlates" with sources.

Challenge 3: Benefiting from and Contributing to Peer Review

Beyond researching her topic, Mia has two roles in relation to her learning project—she is an author and, because her instructor structured the course to involve students as peer reviewers, Mia and her peers are reviewers of several students' essays. Engaging students as peer reviewers implements findings that an author's writing can benefit from peers' feedback (Crossman & Kite, 2012; see also Cho & Cho, 2011). However, coordinating, organizing, and extracting meaningful information from multiple peers' reviews can be difficult (Cerdán & Vidal-Abarca, 2008).

nStudy Data

Drawing on source materials uploaded by her instructor, Mia will research and then draft her essay using nStudy's essay tool. In nStudy, each essay is formatted in html and assigned a unique URL; i.e., it is a web page. To participate in the peer review process, authors distribute that URL to reviewers through nStudy's hub. In Mia's

course, her instructor defined teams, so Mia's essay is automatically distributed to specific reviewers her instructor selected for her team.

In nStudy's hub, reviewers access their peers' essays by clicking the URLs distributed to them. Once an essay's web page has been opened, they make comments by selecting text to create a quote. Then, they use nStudy tags the instructor provided to operationalize features of a rubric that are relevant to the general theme of the course plus other tags empirical research in writing has demonstrated commonly need attention (Ferris, 2002, p. 70–71; Hacker, Keener, & Kircher, 2009; Haswell, 2000). Examples of the latter set of tags might include: vague expression, poor word choice, and needs transition.

Reviewers can associate a tag and a note to selections of text they quote in Mia's draft. To complete a note, the reviewer selects among note templates the instructor developed. Each note template available to reviewers was designed by the instructor to provide labeled text fields, checkboxes items, and radio buttons items that relate to schemas relevant to the course topic or writing skills (e.g., genre features). Specific feedback like this has proven beneficial to improve writing (e.g., Bangert-Drowns, Kulik, Kulik, & Morgan, 1991; Hattie & Timperley, 2007; Kluger & DiNisi, 1996). In addition, students perceive specific feedback is more helpful and they are more responsive to specific feedback than to peers' global comments like "good" or "needs work" (Lipnevich & Smith, 2009; Ng, Tay, & Cho, 2015).

While peers are reviewing Mia's essay and before Mia begins her reviews of essays drafted by her team members, she is re-examining her own draft that she distributed to them. In this task, Mia has access to the same nStudy tags and note templates she will use as a peer reviewer. Her task is to tag and annotate her draft to generate predictions about what her peers will identify as "needing work."

When a peer has completed a review, Mia is notified via nStudy's hub. Each reviewer's annotations of Mia's draft is accessible as a new web page with a new URL. The sidebar for a page contains all the quotes and notes reviewers created to guide Mia's attention when she revises her draft.

As Mia edits her draft, nStudy records changes she makes. Because nStudy logged text the reviewers selected to quote spots they recommended Mia attend to, the software can identify which parts in the draft Mia has and has not revised that a peer marked.

Conceptual Description of Learning Analytics

In a sidebar on the left of Mia's reviewed essay are headers labeled: tags, quotes, notes. "Inside" each header are the artifacts peer reviewers created when they reviewed Mia's draft. At the right edge of each header is a small box reporting the number of artifacts within the header. Nubs in the gutter area adjacent to the scrollbar on the right show the relative positions in the essay of all the reviewers' artifacts.

Mia can filter items in the sidebar by entering text in the search box at the top of the sidebar. Numbers of artifacts in each header change corresponding to the focus

of a filter. Mia can filter artifacts to focus on those created by a specific reviewer, with a particular tag (e.g., add transition), created using a particular note template (e.g., debate issue), or with specific text a reviewer quoted in Mia's draft or entered in a text box in a note template. nStudy hides the other artifacts not within Mia's focus.

To view the text a peer reviewer quoted in context, Mia clicks an artifact. nStudy scrolls to the quote associated with that artifact and opens a popup window to display the tag or note a reviewer used to comment about that selected text.

Learning Analytics Reports and Learning Science Principles

Analytic Report 1: Sharpening Metacognitive Monitoring. After Mia opens the web page containing her peers' reviews and a second window that displays her predictions about what might need revising, Mia can assess the accuracy of her predictions. Comparing her tags and notes predicting what reviewers would identify to reviewers' actual annotations generates feedback about standards for metacognitively monitoring one's writing (25 learning principles, 2015; Butler & Winne, 1995). Mia uses a note template to explain to herself why: (a) she picked targets her reviewers did not, (b) she missed issues her reviewers identified, and (c) her predicted targets for revision match reviewers'. Self-explaining by posing and answering such "Why?" questions has demonstrated positive benefits for learning in other areas (Bisra et al., 2017; Dunlosky, Rawson, Marsh, Nathan, & Willingham, 2013) even when feedback is not given for self-explanations (Schworm & Renkl, 2006). With repetition focusing on her drafts as well as reviewing peers' drafts (Cho & Cho, 2011), we predict this process of self-explaining reviewers' annotations relative to her forecasts will help Mia sharpen standards for accurately metacognitively monitoring her drafts and when serving as a reviewer of peers' draft essays. As well, this activity may counter overconfidence about qualities of one's own writing (Goldfinch & Hughes, 2007).

Analytic Report 2: Managing Cognitive Load and Focusing Attention. A problem novice writers face when revising an essay is high cognitive load (Kozma, 1991; Piolat, Roussey, Olive, & Amada, 2004). This challenge is exacerbated when multiple peer reviewers provide diverse recommendations for revisions dispersed throughout a draft. Several features can help Mia focus on particular issues and manage cognitive load.

First, Mia can filter reviewers' artifacts that mark particular issues to consider for revision, say, filtering tags to focus only on parts of her draft her reviewers tagged as "vague." Removing whatever other issues were identified and recommendations provided by reviewers reduces cognitive load. Also, rather than having to switch among a variety of issues that might unsystematically confront Mia if she worked through the draft from word one to the end, she can focus on one issue at a time. By refreshing the count indicator for quotes within the Tags header to report only quotes the reviewers tagged as "vague," Mia can survey which issues are most pressing (show the greatest count), and focus on those that most need attention.

Second, when Mia filters the sidebar, nStudy also filters nubs in the gutter area. Only nubs marking quotes that match the filter Mia used—in this instance, the tag "vague"—are shown. The spacing of nubs reveals whether issues are dispersed across the essay or clustered in a particular area. Again, Mia can choose an approach to revision that manages cognitive load.

Third, clicking through each instance of a single problem—vague expression— affords opportunity to monitor whether there is a common fault underlying vague expression—e.g., writing "there are several ..." versus "there are four ..." for items in an enumerable list—or whether local coherence is the issue when quotes tagged "vague" are viewed in context. Multiple examples of one concept help learners identify key attributes of that concept without overly taxing cognition (see Lee & Anderson, 2013).

Analytic Report 3: Re-evaluating Sentence Phrasing and Paragraph Construction. As described previously, nStudy provides means for learners to create terms, artifacts that describe conceptually significant concepts in the domain of a learning project. Once a term has been created, nStudy tracks its occurrences in sources learners view and review, and in drafts they produce. Because writing requires greater considerations about presentation beyond domain-specific concepts, and writing and revising elevate cognitive load. Mia likely struggles when considering how best to convey meaning.

For conceptually complex but discipline general concepts, such as "model" or "conjecture," an analytic modeled on WordVis (http://wordvis.com/; see Fig. 11.2.) and merged with nStudy's termnet will support Mia's re-evaluation of meaning and phrasing beyond a domain's technical terminology. The result will visually represent the conceptual elements of an individual sentence or a paragraph and offer comparisons—synonyms from the WordVis component and associated terms from the termnet component—to invite Mia to monitor whether her text represents her ideas as clearly and thoroughly as intended (cf. Trumpower & Sarwar, 2010).

Analytic Report 4: Judging Content Representation and Thesis Presentation. Modules on the server are available to apply natural language-processing techniques that create a synopsis of text. These routines can be applied to three individual corpora: sources Mia cited in her essay, quotes and notes Mia created while mining cited sources for information, and Mia's draft essay. The synopsis is a set of sentences extracted from a corpus that best represents the meaning conveyed within it. The "size" of a synopsis can be manipulated by setting values of a sampling parameter expressed as an absolute threshold (number of extractions) or a relative threshold (percent of extractions relative to the number of units in the corpus). Comparing these synopses may help students working on learning projects that arise because the process of developing expertise in the learning project's topic can overload cognitive resources, thus interfering with writing strategies (Beauvais, Olive, & Passerault, 2011).

Comparing the synopsis of sources cited in her draft to notes plus quotes invites Mia to consider how well her methods for extracting information capture the information available in sources. Mia might metacognitively consider whether her strategy for mining information is effective.
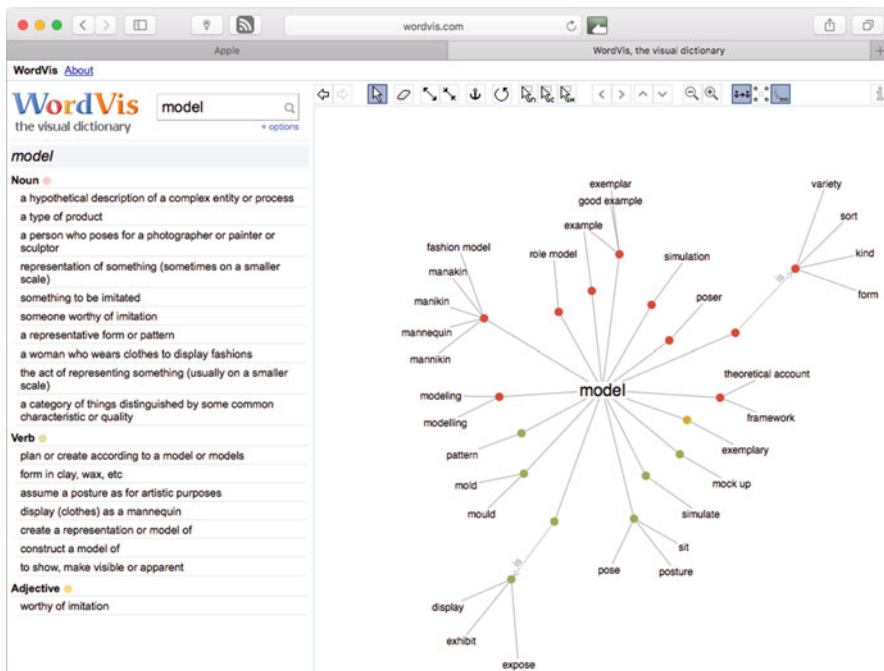
Fig. 11.2   WordVis analytic from http://wordvis.com/describing the concept "model"

Comparing the synopsis of the draft essay to the synopses of sources cited and her notes plus quotes to her draft essay affords Mia opportunity to address two metacognitive issues: First, how well does the essay reflect, or does it deliberately deviate from, information available in cited sources? In other words, is the essay biased and, if so, is the bias as intended? Second, by comparing the synopsis of her notes and quotes to that of her draft essay, Mia can metacognitively review whether criteria she uses for selecting annotations for use in her information are productive vis à vis her goals for the essay.

Conclusion

Modern computing technologies offer significant supports for learners to work on and learn from learning projects. While the Internet grants access to a hugely expanded and more diverse scope of sources for human informavores, access does not assure learners learn about the topics the research in learning projects. Nor can access to sources by itself support learners to develop knowledge and skills for solving information problems.

The information ecology we sketch includes state-of-the-art software like nStudy in a key role. nStudy mediates learners' interactions with information, recording fine-grained trace data that fuse information learners process and with an account of how information is processed and with time marks identifying when these proto-learning events occur. Trace data with this 3-tuple form supply raw material for learning analytics that can assist self-regulated learners in their quests for better marks on learning projects. Moreover, because trace data encapsulate information about skills used to address information problems, these data afford learning analytics that can be designed to advance generalizable skills for engaging metacognitively with information problems (Winne, 2013). In this newer digital learning environment, learners come to play a central role in designing effective learning environments forged as skills for solving IPS. They are supported in this task by learning analytics grounded in trace data.

We illustrated sectors of a common learning project where trace data and learning analytics developed with trace data offer strong potential to help learners cultivate both topical knowledge and skills for information problem solving. While we cited empirical support for elements within our sketches, it is important to note that direct empirical testing of our sketches is forthcoming. As the ecology of learning mediated by state-of-the-art software evolves, we predict significant benefits will arise by leveraging big data that is quite easily gathered when learners use systems like nStudy (Winne, 2017). As more and more data are amassed, and more frequent and completely authentic studies of those data are carried out, we are confident learning analytics can be designed to achieve the dual goals of boosting what learners learn in concert with advancing their skills for learning.

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