Representational Bias as Guidance for Learning Interactions: A Research Agenda

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Abstract. The author hypothesizes that variation in features of representational tools can have a significant effect on collaborative learning discourse, and hence on learning outcomes. Representational tools mediate collaborative learning discourse by providing learners with the means to express their emerging knowledge in a persistent medium, where the knowledge then becomes part of the shared context. The representational bias of these tools constrains the knowledge that can be expressed, and makes some of that knowledge more salient and hence a likely topic of discussion. This paper sketches a theoretical analysis of the roles of constraint and salience in the effect of representational bias on collaborative learning discourse, and suggests a research agenda for systematic investigation of these claims.

1 Introduction

The AI&ED community is witnessing an increased interest in software that provides learners with the means to construct and manipulate knowledge artifacts at their own initiative while interacting with other learners. This trend reflects decades of research into cognitive and social aspects of learning [6], which has developed a clear picture of the importance of learners' active involvement in the expression, examination, and manipulation of their own knowledge, as well as the equal importance of guidance provided by social processes and mentorship. There is a need for an empirically grounded theory of design for discourse – one that tells us how representational tools and collaborative learning processes can be designed together for more effective learning [24]. The present paper takes a step in this direction. Based on experience with "Belvedere," a software environment that supports collaborative learning of inquiry skills with a shared workspace for constructing "evidence maps," the author postulates that the representational bias of tools such as Belvedere can influence collaborative learning discourse in educationally significant ways. This paper sketches a theoretical account of the expected effects, outlines a research agenda, and comments on implications for AI&ED.

2 Representations in Critical Inquiry Software

To provide examples and motivation for discussion, several alternate representational approaches taken in computer supported collaborative learning (CSCL) systems for critical inquiry are characterized below.

Hypertext/hypermedia systems include CLARE [31], CSILE [25], the Collaboratory Notebook [17], Web-Camile and Web-SMILE [8]. (Seminal systems include gIBIS and NoteCards, which were not developed for educational applications.) These systems all have in common a linking of different comments relevant to an issue, usually with categorization of the hyperlinks or their targets with labels such as "answer, argument, problem, solution,

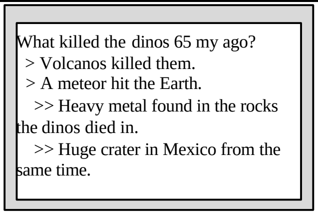


Figure 1. Threaded Discussion

comment," etc. There is wide variation in this category: some take the form of a threaded discussion or other tree structure that may be viewed in summary form (see Figure 1 for a characterization), while others support construction of graphs of "nodes" or "cards" through which one navigates, viewing one card at a time. Mature systems such as CSILE or its successor, Knowledge Forum, use several of the representational approaches discussed herein.

Several argument mapping environments, including Belvedere [28, 29], ConvinceMe [21], and Euclid [26], utilize node-link graphs representing rhetorical, logical, or evidential relationships between assertions (usually categorized as "hypothesis" versus "data" or "evidence"). Belvedere is characterized in Figure 2 (rounded shapes represent hypotheses and rectangles represent empirical observations). The entire graph is viewed and manipulated at once, distinguishing these systems from hypermedia environments in which one normally views and manipulates one node of the graph at a time.

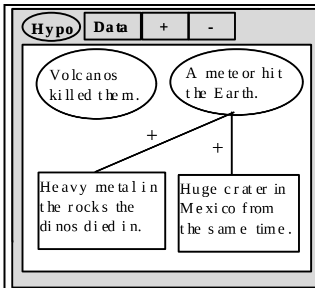


Figure 2. Graph

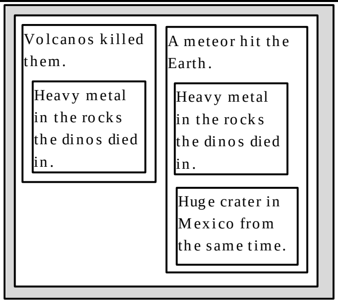


Figure 3. Containment

SenseMaker [1] exemplifies an intermediate approach between graphs and hierarchies. Statements are organized in a 2-dimensional space and viewed all at once, as in argument graphs (see Figure 3). However, SenseMaker uses containment rather than links to represent the relationship of evidential support: an empirical statement is placed inside the box of the theory it supports. SenseMaker also uses containment to represent decomposition of a theory into hypotheses, a feature that was tried in early versions of Belvedere.

Finally, another representation is an evidence or criteria matrix. Several forms are possible. One organizes hypotheses (or solutions) along one axis, and empirical evidence (or criteria) along another, with matches between the two being expressed symbolically in the cells of the matrix (e.g., Figure 4). Puntambekar *et al.* [20] experimented with a matrix representation in a paper-based collaboration tool.

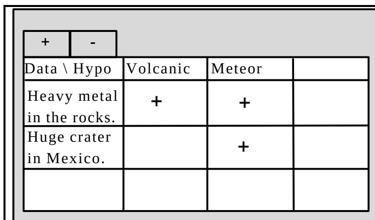


Figure 4. Matrix

Examining the figures above, the differences in representational notations provided by existing software for critical inquiry is striking. Yet more striking is the fact that there appear to be no systematic studies comparing the effects of external representations on collaborative learning discourse, although a number of valuable studies have been conducted on software utilizing single representational notations. Exceptions include [7, 33]. Given that these representations define the fundamental character of software intended to guide learning, a systematic comparison is overdue. The next section sketches a theoretical perspective to guide this research agenda.

3 A Theoretical Account

We begin with definitions. *Representational tools* are artifacts (such as software) with which users construct, examine, and manipulate external representations of their knowledge. The present analysis is concerned with symbolic as opposed to analogical representations. A notation/artifact distinction is critical to the present work: A representational tool is an implementation of a *representational notation* that provides a set of primitive elements out of which representations can be constructed. (For example, in Figure 2 the representational notation is the collection of primitives for making hypothesis and data statements and "+" and "-" links, along with rules for their use.) Developers choose a representational notation and instantiate it as a representational tool, while the user of the tool constructs particular *representational artifacts* in the tool. (For example, in Figure 2 the representational artifact is the particular diagram of evidence for competing explanations of mass extinctions.) *Learning interactions* includes interactions between learners and the representations, between learners and other learners, and between learners and mentors such as teachers or pedagogical software. The present analysis focuses on interactions between learners and other learners, specifically verbal and gestural interactions termed *collaborative learning discourse*.

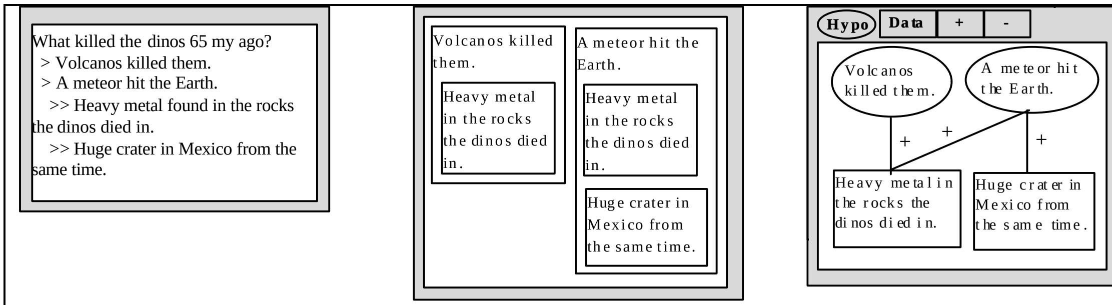
3.1 Representational Bias

Each given representational notation manifests a particular *representational bias,* expressing certain aspects of one's knowledge better than others [30]. The phrase *knowledge unit* is used to refer generically to components of knowledge one might wish to represent, such as hypotheses, statements of fact, concepts, relationships, rules, etc. Representational bias manifests in two major ways: *Constraints:* limits on logical expressiveness, and in the sequence in which knowledge units can be expressed [22, 27]; and *Salience:* how the representation facilitates processing of certain knowledge units, possibly at the expense of others [12]. Representational tools mediate collaborative learning discourse by providing learners with the means to articulate emerging knowledge in a persistent medium, inspectable by all participants, where the knowledge then becomes part of the shared context. Representational bias constrains the knowledge that can be expressed in the shared context, and makes some of that knowledge more salient and hence a likely topic of discussion. Sources of constraint and salience are discussed below.

Zhang [34] distinguishes *cognitive* and *perceptual* operators in reasoning with representations. Cognitive operations operate on internal representations; while perceptual operations operate on external representations. Perceptual operations take place without making an internal copy of the representation, although internal representations may change as a result of these operations. Expressed in terms of Zhang's framework, the present analysis is concerned primarily with perceptual operations on external representations. This is because the analysis is concerned with how representations that reside in learners' perceptually shared context mediate collaborative learning interactions. While it is the case that cognitive operations on internal representations will influence interactions in the social realm, CSCL system builders do not design internal representations – they design tools for constructing external representations.

Stenning and Oberlander [27] distinguish constraints inherent in the logical properties of a representational notation from constraints arising from the architecture of the agent using the representational notation. This corresponds roughly to the present author's distinction between "constraints" and "salience." Constraints arise from logical limits on the information that can be expressed in the representational notation, while salience arises from how easily the agent recovers the information (via perception) from the representational artifacts. Information that is recoverable from a representation is salient to the extent to which it is recoverable by automatic perceptual processing rather than through a controlled sequence of perceptual operators [13, 34].

The discussion now turns to predictions based on differences between representational notations.



Threaded Discussion: *limited representation of relation.* ***Containment:*** *Implicit representation of relations.* ***Graph:*** *Relationship as object of perception.*

Figure 5. Example of Elaboration Hypothesis

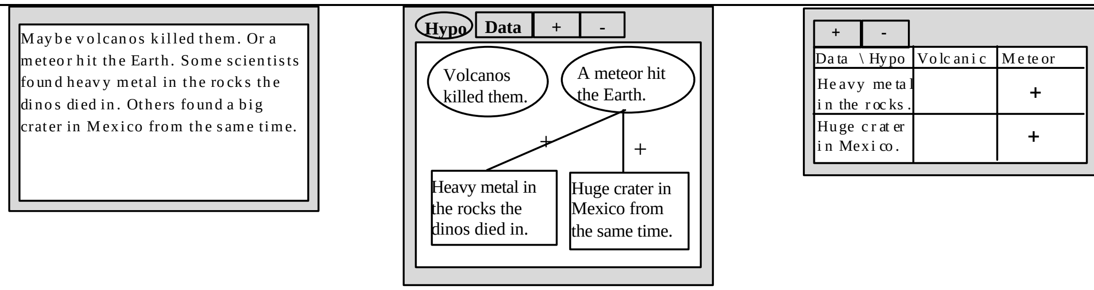
3.2 Representational Notations have Ontological Bias

The first major hypothesis claims that important guidance for learning interactions comes from ways in which a representational notation *limits* what can be represented [22, 27]. A representational notation provides a set of primitive elements out of which representational artifacts are constructed. These primitive elements constitute an "ontology" of categories and structures for organizing the task domain. Learners will see their task in part as one of making acceptable representational artifacts out of these primitives. Thus, they will search for possible new instances of the primitive elements, and hence (according to this hypothesis) will be biased to think about the task domain in terms of the underlying ontology.

3.3 Salient Knowledge Units Receive More Elaboration

This hypothesis states that learners will be more likely to attend to, and hence elaborate on, the knowledge units that are perceptually salient in their shared representational workspace than those that are either not salient or for which a representational proxy has not been created. The visual presence of the knowledge unit in the shared representational context serves as a reminder of its existence and any work that may need to be done with it. Also, it is easier to refer to a knowledge unit that has a visual manifestation, so learners will find it easier to express their subsequent thoughts about this unit than about those that require complex verbal descriptions [3]. These claims apply to any visually shared representations. However, to the extent that two representational notations differ in kinds of knowledge units they make salient, these functions of *reminding* and *ease of reference* will encourage elaboration on different kinds of knowledge units. The ability to manipulate learners' elaborations is important because substantial psychological research shows that elaboration leads to positive learning outcomes (e.g., [2, 5]).

For example, consider the three representations of a relationship between four statements shown in Figure 5. The relationship is one of evidential support. The middle notation uses an implicit device, containment, to represent evidential support, while the right-hand notation uses an explicit device, an arc. It becomes easier to perceive and refer to the *relationship* as an object in its own right as one moves from left to right in the figure. Hence the present hypothesis claims that relationships will receive more elaboration in the rightmost representational notation. The opposite prediction could be made in situations where learners see their task as one of putting knowledge units "in their place" in the representational environment. Once a unit is put in its place, learners may feel it can be safely ignored as they move on to other units not yet placed. This suggests the importance of making missing knowledge salient.



Text: *No relation is saliently missing.* ***Graph:*** *Partial salience of missing relations.* ***Matrix:*** *Salience of all missing relations.*

Figure 6. Example of Salient Absence Hypothesis

3.4 Salience of Missing Knowledge Units Guides Search

Some representational notations provide structures for organizing knowledge units, in addition to primitives for construction of individual knowledge units. Unfilled "fields" in these organizing structures, if perceptually salient, can make missing knowledge units as salient as those that are present. If the representational notation provides structures with predetermined fields that need to be filled with knowledge units, the present hypothesis predicts that learners will try to fill these fields.

For example, Figure 6 shows artifacts from three representational notations that differ in salience of missing evidential relationships. In the textual representation, no particular relationships are salient as missing: no particular prediction about search for new knowledge units can be made. In the graph representation, the lack of connectivity of the volcanic hypothesis to the rest of the graph is salient. However, once some connection is made to one data item, the hypothesis will appear connected, so one might predict that only one relationship involving each object will be sought. In the matrix representation, all undetermined relationships are salient as empty cells. The present hypothesis predicts that learners will be more likely to discuss all possible relationships between objects when using matrices.

4 A Research Agenda

Substantial research has been conducted concerning the role of external representations in individual problem solving, generally showing that the kind of external representation used to depict a problem may determine the ease with which the problem is solved [11, 12, 14, 34]. One might ask whether this research is sufficient to predict the effects of representations in collaborative learning. A related but distinct line of work undertaken in collaborative learning contexts is needed for several reasons. The interaction of the cognitive processes of several agents is different than the reasoning of a single agent [16, 19], so may be affected by external representations in different ways. In particular, shared external representations can be used to coordinate distributed work, and will serve this function different ways according to their representational biases. Also, the mere presence of representations in a shared context with collaborating agents may change each individual's cognitive processes. One person can ignore discrepancies between thought and external representations, but an individual working in a group must constantly refer back to the shared external representation while coordinating activities with others. Thus it is conceivable that external representations have a greater effect on individual cognition in a social context than they do when working alone (Micki Chi, personal communication). Finally, much prior work on the role of external representations in individual problem solving has used well-defined problems. Further study is needed on ill structured, open-ended problems such as those typical of scientific inquiry.

The author has begun studies that test the effects of representational notations on collaborative discourse and learning. At this writing, pilot studies have been run and are under analysis, and a proposal for in-depth study has been funded. Four representational notations are being compared in a proximal collaborative learning configuration, to test the predictions of the previous section. The four notations, characterizations of systems being deployed today, are *threaded discussions* (Figure 1), *graphs* (Figure 2), *containment* (Figure 3), and *matrices* (Figure 4). The question is not “what system is better?” but rather “what kinds of interactions, and therefore learning, does each representational notation encourage?” It may well be the case that all of the above representations are useful, albeit for different learning and problem solving phases or task domains.

The empirical study intentionally uses representations that differ on more than one feature (see Table 1). The research strategy is to maximize the opportunity to observe predicted effects on learners’ discourse and on learning outcomes, in order to explore the large space of experimental comparisons within the time scale on which collaborative technology is being adapted. These results will then inform well-motivated selection of studies that vary one feature at a time as needed to disambiguate alternate representational explanations for the results. The author hopes that this paper will serve as a call for others to join the effort.

Table 1. Features of Selected Representational Notations

	Threaded	***Containers***	***Graphs***	***Matrices***
Organization of Inquiry Activity	Discussion topics are posted, followed by chronologically organized replies.	Hypotheses are first recorded as boxes in the workspace. Empirical observations are sorted by placing them in boxes.	Hypotheses and empirical observations are recorded at any time as shapes placed in the workspace. Evidential relations are recorded by linking shapes together.	Hypotheses and empirical observations are recorded at any time by creating new columns & rows. Evidential relations are recorded by placing symbols in empty cells.
Ontology	Implicit: ♦ statements ♦ reply chronology	Implicit: ♦ hypothesis ♦ empirical observation ♦ consistency	Explicit: ♦ hypothesis ♦ empirical observation ♦ consistency ♦ inconsistency	Explicit: ♦ hypothesis ♦ empirical observation ♦ consistency ♦ inconsistency
Salience of Known Relations	Implicit in Context: ♦ reply chronology	Implicit in Context: ♦ consistency	Explicit Object: ♦ consistency ♦ inconsistency	Explicit Object: ♦ consistency ♦ inconsistency
Salience of Missing Relations	No salience.	Lack of *some* consistency relation for a hypothesis.	Lack of *some* consistency or inconsistency relation for a statement.	Relations for *all combinations* of hypothesis and empirical observation.

5 Where’s the Artificial Intelligence?

The phrase “Artificial Intelligence and Education” most immediately brings to mind the endeavor to build smart machines that teach. Ideally, such machines would “know” a great deal about a particular subject matter, being able to both articulate concepts and principles and engage in expert level problem solving. They would also know about pedagogy, being able to track the progress of individual students and choose the best feedback strategies and trajectory through a curriculum for a particular student [32]. This vision of AI&ED might be termed "strong AI&ED." Although work on "traditional" intelligent tutoring systems continues with a recent emphasis on agent-based systems, other work that does not fall within mainstream AI approaches is increasingly appearing in the AI&ED and ITS conferences.

Some of this work (e.g., [15, 18]) can be characterized as "minimalist AI&ED." Instead of attempting to simulate a teacher and/or model the minds of students, these efforts provide machines with minimal abilities to respond (in a manner believed to be educationally relevant) to the semantics of student activities and constructions. This research tests the educational value of these minimal abilities, and adds functionality as needed to address deficiencies in the utility of the system. As a research strategy, this incremental approach ensures that we understand the capabilities and limitations of each representational and inferential device unencumbered by the simultaneous complexities of an attempted complete pedagogical agent.

The present article exemplifies a newly emerging third category of AI&ED work, one that does not attempt to build reasoning machines, even of the minimalist sort, yet which constitutes a contribution of AI to education, and potentially even a source and test-bed of AI ideas. This kind of application can be seen most clearly in the design of representational notations. An artificial intelligence sensitivity to the properties of formal representations for automated reasoning can be applied to the analysis and design of external representations for human reasoning as well as machine reasoning. One revisits the notions of epistemological and heuristic adequacy, but now the interpreter is human and "representational bias" includes a perceptual component [12, 34]. The AI "in" software systems built under this approach is residual, influencing the design but being a run-time factor only for human rather than artificial agents. Examples of work in this category include [4, 9, 10, 23, 27], and the present work.

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