Representations for model construction in collaborative inquiry environments

Simone Löhner and Wouter van Joolingen, Graduate School of Teaching and Learning, University of Amsterdam, {simone, wouter}@ilo.uva.nl

Abstract

The creation and manipulation of models by learners is increasingly recognized as a potentially powerful technique within constructive learning environments. In this paper we review several existing modeling tools and examine their characteristics, such as textual or graphical representation, the primary entities they use and use of scaffolding. We find that there are differences between the representations that are used; in the way they support the collaboration process and the way in which they can elicit discussion between learners. As several researchers have shown, representational salience and representational determinism can have an important effect on thinking about a problem and also on collaboration. We argue that choosing a representation means making choices for the collaborative modeling process. To fully understand the modeling process and the collaboration process between learners, representational features of the model must be taken into account.

Keywords: modeling, collaboration, representations

1 Introduction

The creation and manipulation of models by learners is increasingly recognized as a potentially powerful technique within constructive learning environments (Mandinach, 1988). In modeling environments, learners create executable models of phenomena in, for instance, physics or biology. Modeling requires coordination and integration of facts with scientific theory rather than a mere passive collection of facts and formulas (Hestenes, 1987). Because a model is a conceptual representation of a real system that behaves in accordance with physical laws creating models will help learners to focus on conceptual reconstruction of reality and thus help constructing a unified and coherent view of science (Hestenes, 1987; Doerr, 1995).

Model building has been associated with constructing accurate and appropriate mental models. Through model building a learner is able to 'run' his own mental model of a phenomenon (Jackson, Stratford, Krajcik, & Soloway, 1996) and it provides a way of asking whether he can understand his own way of thinking about a problem (Doerr, 1995).

We are interested in environments in which learners collaboratively construct models of physical phenomena. In such environments learners create models by constructing an external representation of these phenomena, which can be fed into a simulation engine to compute the behavior of the model. In the current paper we investigate the possible interaction between the *representation* learners use to build their models and the *collaboration processes* between learners.

Model representations are a means to construct models, but representations also serve as a vehicle for thought. External representations are not simply inputs and stimuli to the internal mind; rather they are so intrinsic to many cognitive tasks that they guide, constrain and even determine cognitive behavior and the way the mind functions (Zhang, 1997). Zhang calls this phenomenon 'representational determinism'. Zhang did his research on the influence of representation in problem solving activities, but we believe his conclusions will also hold for modeling tasks.

As representations play a role in supporting, guiding and constraining the cognitive processes in model building, we can also assume that they will have a strong influence on the way learners will communicate and collaborate when constructing models together. Suthers (1999) states:„…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…" (p.612). Tools in which learners can organize their knowledge, mediate collaborative learning discourse by providing the means to articulate emerging knowledge in a persistent medium, inspectable by all participants, where the knowledge then becomes part of the shared context.

In the current paper we review several model representations used in existing modeling tools from the perspective of the effects they can have on the collaboration between learners, based on the biases and determinism that is implicit in the representations used. First we will describe the representations that we review, followed by an analysis of the modeling characteristics of the representations. We conclude with a discussion of the collaborative and inductive aspects of the representations discussed.

2 Representations for modeling

In recent years, a number of tools for the modeling of scientific phenomena by learners have been developed by several groups of researchers. In the current section we describe the representations for models that have been used in these tools. For the purpose of comparing these representations we present a simple model of radioactive decay, as represented in each of these representations. Figure 1 presents these small models. In these models *x* is the number of atoms currently present, *F* is the decay rate and *k* is the decay constant.

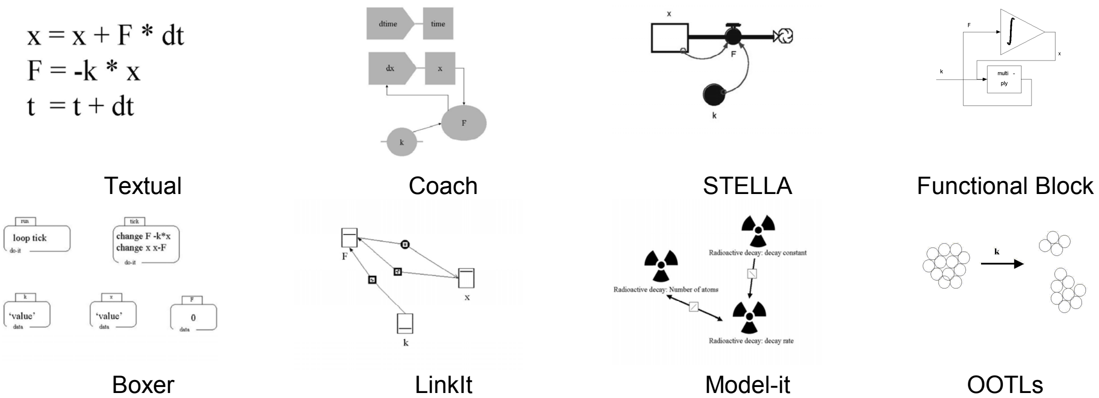

Figure 1 The eight representational formalisms presented in the current paper. Each of the examples above represents the same model of simple radioactive decay**.**

Textual representations

A number of tools use a textual representation of models. Models are represented as algebraic differential (or difference) equations. Textual representations can be found in DMS (see: Robson & Wong, 1985), Modellus (Teodoro, 1997) and a number of other modeling tools. In the case of DMS, the text is interpreted as lines in a computer program.

Coach

Coach is a data collection and analysis tool developed at the AMSTEL institute of the University of Amsterdam. It includes a modeling tool is based on DMS. In addition to the textual representation it also offers a graphical one offering different building blocks for models –step variables (*dtime* and *dx*), ordinary variables (*F*) and constants (*k*). Relationships between variables are denoted as arrows between building blocks. Once the relationship arrows have been drawn the quantitative relationships are filled in after clicking on the variables. The model will only run if all the relationships are given in the form of an equation. The graphical representation has a one-on-one relationship with the textual one: each relation corresponds to one equation.

Stella

Stella (Steed, 1992) is based on System Dynamics. Variables are denoted as levels (*x*) rates (*F*) and ordinary variables (*k*). After the graphical representation of the model is drawn, relationships must be filled in quantitatively after clicking on an object. The program generates a set of basic fill-in equations and is also able to suggest which variables might belong in the equation on the basis of the connections made in the graphical representation. It is also possible to define a relationship by filling in the values in table form.

Functional block representations

Functional block representations use the metaphor of electronic signal processing. Variables are presented as signals (lines) and operations (blocks). It is used in professional modeling tools like 20-SIM (Broenink, 1999). A standard library of processing blocks usually is available. We have found no evidence of its use in schools. This is probably due to the fact that to be able to use this representation, the user must be familiar with the different processing blocks.

Boxer

Boxer (DiSessa, Abelson, & Ploger, 1991) is a programming environment based on LOGO. It was developed by the Boxer group at the University of California, Berkeley, School of Education, with Andrea di Sessa as principal investigator. Program elements are represented as boxes, which can be nested and 'looped'. Exact equations have to be filled in as text and also the program structure must be correct.

LinkIt

LinkIt, as well as its predecessor IQON, was developed by the London Mental Models Group during their Tools For Exploratory Learning Program (Mellar, Bliss, Boohan, Ogborn, & Tompsett, 1994). In LinkIt variables are linked together with relationship-arrows. Variables as well as relationships can be opened and edited. The user either fills in a table of values or uses a 'semi-quantitative' relationship that he can choose from a menu. The options vary from direct relationships, which can be linear with different slopes or exponential, to rate of change relationships. Different relationship-arrows leading to one variable can be combined by adding, subtracting, multiplication, division and averaging. In calculating quantities LinkIt follows the direction of the links. A horizontal line, moving up and down while the simulation runs, indicates the value of a variable. Because of the default values of the relationships any model in LinkIt will run as soon as the variables are connected.

Model-It

Model-It (Jackson et al., 1996) was developed by the Highly Interactive Computing in Education (hi-ce) group at the University of Michigan. Although its final representation of a model is similar to that in LinkIt, there is a difference. Model-It, just like LinkIt consists of variables connected by links, which can be edited separately. The relationships also are qualitative verbal representations of the actual mathematical relationships. But in Model-It additionally there is a different representation consisting of the 'real world' objects (such as cars, the atmosphere or a factory). These objects have 'factors', which are the modeling variables (for example the level of ozone in the atmosphere, denoted as 'atmosphere: level of ozone'). The values of the factors can be changed or viewed during the running of the model through meters and graphs.

Object-based representations

Object-based representations, such as OOTLs, are based on an object interaction metaphor. Objects are represented as graphical icons, which interact with one another. Interactions are denoted by arrows. The developers of OOTLs feel that (Neumann, Feurzeig, Garik, & Collins, 1997) students typically find it very difficult to express problems in the standard formal mathematical representations and the symbolic language of differential equations, for example, is very far removed from students' mental models of the objects and object interactions involved in problem situations. The program can be applied to 'well-stirred' systems composed of large numbers of dynamically interacting objects.

3 Representations and the modeling process

In the current section we will describe a number of characteristics of the representations that have been studied. This results in a number of dimensions to which modeling representations can be compared. The characteristics we discuss emerge from the structure of the representations and address possibilities and limitations on the modeling process.

Text or graphics oriented

An obvious characteristic of a representation is whether it is based on text or on graphical diagrams. Textual representations (DMS, Boxer) require the learner to explicitly write down a sort of equation, whereas the graphical representations either additionally or exclusively use a graphical representation, such as a flow chart or icons to represent objects or variables in the model.
Many researchers feel that there is an advantage to a graphical representation. According to Larkin & Simon (1987) diagrams can be better representations, not because they contain more information, but because the indexing of this information can support computational processes by the user. Graphical representations provide a visual overview of the model, whereas textual representations concentrate on the details of the underlying relations.

Quantitative or qualitative reasoning

The second main characteristic of model representation is the type of relationships that can be modeled: qualitative models vs. quantitative models. Quantitative models require the learner to fill in relations in their precise mathematical form. This is the case in representations as DMS, Stella and Boxer. Models only run when a consistent and correct mathematical description is entered. Qualitative representations will also run when relations have been specified in the form: 'If A goes up, B goes up'. This is the case in representations such as LinkIt and Model-It. Qualitative models are simulated by substituting default quantitative relations where qualitative relations have been specified. According to Jackson et al. (1996) representing a relationship qualitatively is much closer to the way students seem to naturally think and express themselves. Of course this will depend on the context and prior knowledge of the learners.

Primary model entities

Some of the modeling techniques see the variables as the central entities to reason about, others focus more on the relations. In a variable oriented representation, relations are specified as properties of the variable. This is the case in for example Stella, where clicking on one of the variables opens an editor in which the equation for that variable can be entered. Also textual representations are variable oriented ($F=k*x$). In a representation with more emphasis on the relation, the relations are edited independently from the variable. An example is LinkIt, where clicking on the variable opens the variable editor, in which properties such as the range of the variable can be entered. Clicking on the relationship on the other hand, opens the relationship editor. Here properties of the relationship such as the type, the direction and the strength of the effect can be entered.

Complex relations

Complex relations are relations in whom more than one variable takes part, for instance when two variables both influence a third. In textual representations such relations are no problem, both variables are simply entered in one equation. For graphical representations, and especially those with variables as central objects, constructing such relations is not trivial. The learner can draw influences from two variables to a third, but there is no obvious choice for the resulting relation. Influences can be added, multiplied, or averaged, with or without weight factors. When more than two variables are involved the number of options explodes. Most ‘qualitative’ tools, (LinkIt, Model-it) make a default choice and offer the learner a choice for others. In an object-based representation representing complex relationships is virtually impossible.

Visibility of the simulation engine

In modeling tools models are simulated in order to show their behavior. Some tools explicitly involve the learner in this simulation and require some programming. For example in DMS, Coach and Boxer the user has to explicitly give the program an instruction for incrementing the time step using an equation like “$T := T + dT$”. In many others the simulation engine is hidden from the user. The advantage of this is that the learner need not bother with details of the simulation formalism. This opens the way to more accurate but also more complex formalisms for simulation, like Runge-Kutta integration. A drawback can be that it may not be obvious why certain effects, resulting from peculiarities of the simulation occur, especially where the underlying formalism is not accurate. For instance in modeling oscillating systems, due toe computational error, energy will not be conserved when using simple Euler integration.

Internal or external representation

In an internal representation most rules and connections must be established in and retrieved from memory, whereas in an external representation they are immediately clear from the representation itself. Zhang (1997; Zhang & Norman, 1994) showed that problem solving became much easier when more information was presented externally, because the cognitive load decreases. We believe that this will also hold for modeling representations. When the representation is mostly external such as in LinkIt or OOTLs, it is immediately obvious to the user how the different variables are interconnected. In an internal representation such as DMS on the other hand, the modeler has to distil the 'big picture' of the model from the equations himself. In several of the other representations the interconnectedness of the variables is directly visible, but the relationship they have to each other cannot be seen from the representation. We call these internal/external representations.

Scaffolding

The goal of scaffolding is to enable students to carry out a reasoning process or achieve a goal that would be impossible without help, and to facilitate learning to achieve the goal without support (Narayannan et al., 1995). Modeling environments can scaffold the modeling process by offering suitable defaults during model building. For instance, LinkIt and Model-It offer an environment where any model entered will work, because the system assumes simple defaults. In this way the learner can incrementally build a model and continuously test it. Also offering various kinds of choices, standard relations etc. such as is done in Stella and functional block representations scaffolds the modeling process.

Discussion

In Table 1 we present an overview of the characteristics of modeling representations that were found in the review of modeling tools. In summary, the characteristics we identify determine the nature of the modeling process by learners: what are the primary entities to focus on, what is the modeling target, and to what extent is there intrinsic support by the representation. Not all combinations of representational properties will be possible or sensible. For instance, it would not make sense to use a textual, qualitative representation with a visible simulation engine.

Choosing a representation means making choices for the modeling process. Representations will to a large extent determine the reasoning steps that learners can express in the modeling tool. A reasonable expectation is that reasoning steps that cannot be expressed in a representation also will not be taken. In such a way the representation acts as a major *constraint* on the modeling process.

	Text/graphics	Qualitative/ quantitative	Primary entities	Complex relations	Simulation engine	Internal or external representation	Scaffolding
DMS	Text	Quantitative	Variables	User-defined	Visible	Internal	No
Coach	Both	Both*	Variables	User-defined	Visible	Internal/ External	No
Stella	Both	Both*	Variables	User-defined	Hidden	Internal/ External	Yes
Functional Blocks	Graphics	Quantitative	Relations	User-defined	Hidden	External	Yes
Boxer	Text	Quantitative	Variables/ Relations	User-defined	Visible	Internal	No
LinkIt	Graphics	Qualitative	Relations	Solved by tool	Hidden	External	Yes
Model-It	Graphics	Qualitative	Relations	Solved by tool	Hidden	External	Yes
Object oriented	Graphics	Both*	Objects	Impossible	Hidden	External	No

Table 1 Overview of representational characteristics, and the properties of the reviewed modeling tools according to these characteristics. * A tool that is scored both qualitative and quantitative offers a graphical qualitative representation but also the possibility of specifying quantitative relations.

4 Representations, collaboration and induction

The discussion of constraints imposed by representations can be augmented by representational *biases* that are induced by them. In the current section we discuss the biases of model representations for collaborative inquiry learning, meaning those situations in which learners collaboratively construct models, but also are able to compare these models to empirical data they can collect within the learning environment. Apart from collaborative processes such as discussion and grounding (Baker, 1999) also processes of induction, like generating hypotheses, performing experiments and relating experimental outcome to hypotheses (Njoo & De Jong, 1993) are important. Inductive reasoning is one of the most important ways in which new knowledge is created (Holland, Holyoak, Nisbett, & Thagard, 1986). In a problem of induction, some material is presented and the problem solver tries to find a general principle or structure that is consistent with the material (Greeno & Simon, 1984). We will discuss the relation of representation with both collaboration and induction, using the modeling characteristics defined in the previous section as a starting point.

Factors promoting collaboration between learners

A very important factor in collaborative learning is discussion. It is the main vehicle for learners to construct a common knowledge base (Linden, Erkens, Schmidt, & Renshaw, in press). According to Van Joolingen (2000) communication in collaboration can serve as a cognitive tool or instructional measure in discovery learning environments. Suthers (1999) has shown that collaborative talk is elicited by the most salient elements in a representation. Also, it is easier to refer to a knowledge unit that has a visual manifestation, so learners will find in easier to express their subsequent thoughts about these units than about those that require complex verbal descriptions.

Between textual and graphical representations there is a clear difference in representational salience, and hence the discussion they will elicit. We expect that in most graphical representations talk will focus on the structure of the model, whereas in a textual representation talk will concentrate on the exact form of the relation (e.g. multiply or add, what factor).

We also expect influence of the ease with which intermediate simulations can be run, as immediate running seems to elicit discussion (Ogborn 1998; Jackson et al., 1996). The visibility of the simulation engine and the handling of complex relations determine the ease of running intermediate simulations, because the less the user has to program, the less errors can be made, which will prevent the model from running. This will lead to immediate feedback and more discussion about whether or not the results agree with expectations. An important drawback of immediate running is that incomplete models can generate nonsensical behavior.

Therefore another important factor for collaborative modeling is making sure that the representation is not error-prone, i.e. that it is relatively easy to prevent or remedy syntactical and semantical mistakes. That will cause the discussion to focus on meaningful behavior of the model instead of strange behavior, caused by modeling mistakes. This is of course supported by an external representation but also by the tool handling complex relations. In that case each relation can be edited separately so to repair a faulty relationship, only that relationship will have to be changed, without influencing other relationships. Scaffolding can be used to limit the possibilities for constructing relations and thus prevent users from making mistakes.

Discussion can also be aided by making it easy for learners to check each others reasoning about the model in the representation. A graphical representation emphasizes structure of the model and makes it easy to follow links. An external representation reduces the cognitive load of choosing the links to follow in a mental simulation, and which reasoning steps to take. In a graphical representation with high externality, discussion statements become possible of the type: “If this goes up, that goes down rapidly making that go up again”, with the possibility for all collaborators to actually check the reasoning in the graphical representation.

This qualitative reasoning about the behavior of the model, also called running mental simulations, (Jackson et al., 1996) can be facilitated by using representations that have a qualitative component. Williams, Hollan, & Stevens (1983) have shown that mental models consist of qualitative inference relationships, which makes computer modeling representations based on qualitative reasoning closer related to the existing mental models. Graphical and external representations can also aid in ensuring that learners know they are discussing the same thing, because they are working on a common representation that clearly shows it's meaning and has a clear common interpretation.

Factors promoting inductive reasoning

In environments for collaborative inquiry, modeling tools can be seen as sophisticated tools for expressing hypotheses and generating qualitative or quantitative predictions from them. For generating these hypotheses, and for testing them, an intimate relation with generated data should be established. There is a number of ways to connect data to models. The obvious way is to allow learners to map model output to experimental data in order to test the predictions generated by the model. Another interesting method is to use empirical data inside the model, i.e. represent a model relation by inserting empirical data for defining the relation. The target for the learners would then be to redefine such relations in an abstract form, for instance an equation.

In order to define a relation in terms of empirical data, the representation must accommodate a relation concept that allows such a definition. This is the case for the variable centered graphical representations, such as Stella and Model-It. Functional blocks would also support data as a relation, but inductive reasoning steps may be more difficult because they would be represented by replacing the ‘empirical data’ functional block by others.

In constructing models it is easiest for a learner to start with a small and/or simple model and then extend and elaborate it (Williams et al., 1983). Models can be extended, meaning that more variables and relations are taken into account, and models can be elaborated meaning that the existing relations are specified more precisely.

Extension is supported by representations that provide a good structural overview of the model, so that it is easily visible where relationships could be added. Also, when the modeling tool handles complex relationships adding new relationships is easy, because there is no need to change existing relationships. Elaboration is supported by representations that combine several mechanisms of specifying the model, for instance those who combine textual/mathematical specification with qualitative representations. In these representations it is possible to elaborate, one by one, the existing relations and keep the model structure intact. Including scaffolding options to help building the relationships and guide the user in the transition from qualitative to quantitative reasoning could further encourage this. For induction it is also important that mistakes can be either prevented or easily corrected. As discussed in the previous section this can be accomplished by using an external representation where the tool handles complex relations, with the use of scaffolding.

5 Discussion

In the current paper we presented a review of representations for model construction by learners and discussed the relevant properties of these representations for use in environments for collaborative inquiry. We first focused on the relation between the representation and the modeling process itself, and continued with a discussion on the relation between the modeling characteristics and processes of collaboration and induction. With respect to the modeling process, we extracted a number of modeling characteristics from the representations reviewed, varying from the way relations are specified (text or graphical) to the amount of scaffolding that is implicit in the representation, or in the tool supporting it. From the description of the characteristics it will be clear that representations can determine the modeling process to a rather large extent: representations determine the nature of the model that is constructed, e.g. qualitative or quantitative, and the process leading to it, e.g. by suggesting relations or offering sensible defaults.

Also it is clear that there is a trade-off between the various characteristics of the representations. For instance, it is impossible to let learners focus on both the structure of the model and the details of the relations constructed in one representation. Choosing a graphical overview means emphasizing the qualitative model characteristics, choosing text implies a focus on the quantitative details of the relations. If the goal is to let the learner to do both, the representation must offer different views of the model, like a zoom function on relations and/or variables. One way this can be done is by using multiple external representations (MER's) (Ainsworth, 1999). Ainsworth shows that different representations used simultaneously can constrain interpretation, construct deeper understanding or complement each other. In modeling for example the interpretation of a qualitative graphical model can be constrained by a quantitative textual model. The problem with MER's however is that, as Ainsworth shows, learners find it difficult to translate between the different representations.

There is also a trade-off between the ease of use of a representation and the expression power. The LinkIt representation for example is easy to use and will always yield a running model but the level of expression cannot go deeper than semi-quantitative relations. A deeper specification would break down the internal simulation mechanism. This makes it impossible to specify relations between more than two variables at a reasonably precise level.

With respect to collaborative and inductive properties of representation, it is clear that issues like representational determinism and representational salience will be of paramount interest for understanding the collaborative modeling process. It will be impossible to understand the modeling process and the collaboration process between learners without taking the representational features of the model into account. The representations that were reviewed in this study differ widely in the way they can support the collaboration process and the way in which they can elicit discussion between learners. The central objects in the representation and the way the representation supports mental simulation of the model seem to be especially important. Of course, all findings presented here need to be supported by empirical work.

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