

Differentiating Qualitative Representations into Learning Spaces *

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Abstract

The DynaLearn interactive learning environment allows learners to construct their conceptual ideas and investigate the logical consequences of those ideas. By building and simulating causal models, students develop an understanding of how systems work. The DynaLearn interactive learning environment introduces six modes of interaction, called learning spaces. By working in a particular learning space, teachers can emphasise particular aspects of modelling a system (e.g. causality, conditional knowledge). The DynaLearn software is based on the Garp3 qualitative modelling and simulation workbench, but integrates the interface into a single screen and adds learning spaces.

Introduction

Qualitative Reasoning (QR) provides means to express conceptual knowledge such as system structure, causality, conditions for processes to start and finish, assumptions and conditions under which facts are true, qualitatively distinct behaviours, etc. Qualitative models provide formal means to externalise thought on such conceptual notions.

This paper describes the DynaLearn Interactive Learning Environment (ILE) (Bredeweg (ed.) et al. 2009). DynaLearn is specifically created for students to develop their conceptual knowledge of systems. The DynaLearn ILE offers diagrammatic presentations for learners to construct their ideas, and test these by running simulations.

The DynaLearn ILE is based on the qualitative modelling and simulation workbench Garp3 (Bredeweg et al. 2009; Bredeweg and Salles 2009a). However, the DynaLearn ILE was developed to accommodate different requirements. Firstly, the software should be usable by different groups of students, ranging from end of high school to bachelor

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and master students. Secondly, DynaLearn should allow the modelling process to focus on a particular type of knowledge depending on what is appropriate in the domain of discourse. As such, the DynaLearn ILE has six different modes of interaction, which can be considered complete applications tailored to a particular type of knowledge. These *learning spaces* can be chosen based on the student's level of expertise, and the kind of phenomenon dealt with.

Educational Dimensions

Conceptual models contain different types of knowledge, such as ontological or causal knowledge. From a teaching perspective, these knowledge types can be considered educational dimensions. Depending on the learning goal that has to be achieved by the learner, a focus on a particular educational dimension will be appropriate, and thus a particular modelling paradigm should be used.

Ontological Knowledge

Ontological knowledge pertains to the vocabulary that is used within a particular domain of discourse. An important distinction in the types of ontological knowledge is the difference between what is conceptual and instance knowledge. Conceptual knowledge tends to refer to concepts. We use the terms *generic* and *specific* knowledge instead of these terms, as these words apply more naturally to situations (which are modelled in QR models).

Generic situations refer knowledge to that applies to more than one situation, for example, all the situations in which heat exchange happens. Specific situations refer to a single particular situation. For example, the river Mesta is a particular river. Similarly, the state of the river Mesta during last winter is an example of a specific situation.

Structural and Behavioural Knowledge

Structural knowledge represents arrangements of the things that constitute the system, i.e. the (usually static) objects and their relationships. Structural knowledge can be contrasted with behavioural knowledge, which encompass the dynamic aspects of the system. Behavioural knowledge describes the possible states of the system.

Causal Knowledge

Causality links two events (the cause and the effect) in such a way that the second event is the result of the first event. Causal knowledge represents which quantities in a system affect each other and how. Of particular importance is the direction of causality, and whether the quantities inversely affect each other or not.

Propagation Propagation causality is when changes in one quantity causes changes in another quantity.

Processes Processes are the conceptualization of a sequence of observable changes of a system, and consistently affect quantities while they are active. As such they are properties of dynamic systems. Processes consist of a set of related quantities, of which some serve as input and some as output. Examples of processes are: photosynthesis, oxidation, and birth. Processes have different features that are important to communicate (Bredeweg et al. 2008):

- What should the structure of the system look like, for the process to be applicable?
- Which quantities are involved? Which quantities are affected by the process? How do the changes caused by the process propagate through the system.
- Under what conditions does the process become active? E.g. the boiling process becomes active when the temperature reaches the boiling point. Under what conditions does the process stop being active?

Assumptions and Scope

Every model and scientific theory includes assumptions. For example, the *ceteris paribus* assumption ('all other things being equal') is central to predictions. The choice of the scope of the system (what to model and what not to model) is an assumption that (for the purposes of that model) other processes have no effect. When teaching a scientific theory or a particular model, the assumptions made are essential to convey. Two typical categories of assumptions that are distinguished are simplifying assumptions and operating assumptions (Forbus and Falkenhainer 1991).

Learning Spaces

The DynaLearn ILE provides six Learning Spaces (LSs) of increasing complexity (in terms of the model ingredients that can be used to construct knowledge). Each LS is a self-contained interactive workspace meant to learn specific details about system behaviour. In LS1-4 learners work in a single representation called an *expression*. The LSs and the model ingredients introduced in each LS are shown in Table 1. The interfaces that can be used to inspect the simulation results on each LS can be seen in Table 2. Progression between LSs happens by augmenting the current level with the smallest subset of possible modelling ingredients, again ensuring that the next level is self-contained (Table 1).

Learning Space 1: Concept map

The first learning space in DynaLearn is meant to allow the definition of the key concepts and relationships in a domain

Nr	Learning space	Introduced ingredients
1	Concept map	Entities Configurations
2	Causal model	Attributes Quantities Value assignments Derivatives Causal relationships (+ and -)
3	Causal model with state graph	Quantity spaces Correspondences
4	Causal differentiation	Causal relationships: Influences Proportionalities Inequalities Operators: (+ and -) Agents Assumptions
5	Conditional knowledge	Conditional expressions
6	Generic and reusable	Scenarios Model fragments Entity, agent, and assumption definitions

Table 1: Overview of modelling ingredients per learning space in the DynaLearn software. Each LS augments the representation with a new set of model ingredients.

of discourse. As such, the focus of this learning space is mostly ontological. Learners using this learning space are encouraged to structure their thoughts.

A concept map (sometimes referred to as an entity-relation graph) is a graphical representation that consists of two primitives: nodes and arcs. Nodes reflect important concepts, while arcs show the relationships between those concepts (Novak and Gowin 1984). An example of a concept map is shown in Figure 1a. The educational dimensions relevant in the LS are:

Ontological knowledge The concepts and relationships a learner introduced should reflect the terminology that is used in the domain of discourse.

Scope The chosen system scope determines the result.

Concept maps do not capture dynamic behaviour, and do not allow for computer-based reasoning (simulation). However, having this learning space is useful from an educational point of view, as it is the basis from which more complex knowledge representations emerge. The DynaLearn ILE does not attempt to replicate the advanced features of other concept map tools (that for instance allow nested nodes, colouring and adding media) (Cañas et al. 2004).

Learning Space 2: Causal model

The second learning space allows learners to create a causal model (Figure 1b). As the name suggest, the main focus of this level is the representation of *causal knowledge*. There

Nr	Learning space	Introduced simulation views
1	Concept map	
2	Causal model	Simulation in expression
3	Causal model with state graph	State graph Quantity values Value history Transition history
4	Causal differentiation	Equation history
5	Conditional knowledge	Entities, Configuration, and Attributes Dependencies view Model fragments view
6	Generic and reusable	

Table 2: Overview of simulation views per learning space in the DynaLearn software.

is a causal relationship that is directed and can be either positive or negative. These relationships can be placed between quantities. For example: $Amount \xrightarrow{\pm} Height$ represents that height of a contained liquid is positively affected by amount of liquid.

An important ontological distinction that is introduced in this level is that between *structural and behavioural knowledge*. The structural aspects of the system are modelled using entities, configurations and attributes. For example: $Container \xrightarrow{\text{Contains}} Liquid$. The behavioural aspects of the system consist of quantities that are connected to entities ($Liquid : [Amount, Height, Pressure]$), their derivatives ($\delta Amount \in \{\blacktriangle, \emptyset, \blacktriangledown\}$), derivative value assignments ($\delta Amount_v = \blacktriangle$), and the causal relationships mentioned above. The learner only defines the names of the quantities, while the possible derivative values are predefined.

The causal model LS is the first learning space that introduces semantics to the representation. Whereas a concept map only gives a syntactic specification of the structure of a system, LS2 adds meaning to the model representation, resulting in a simulation of the modelled system’s future behaviour. In this LS, a single state simulation is performed that is visualised in the model representation that the learner is manipulating (Table 2). The assigned values in Figure 1b become grey, while derivative value assignments that are inferred by the simulator are added in blue. The reasoning engine computes the derivatives of the quantities based on the derivative value assignments and the causal relationships between the quantities. This can result in the derivative being (1) unknown, (2) uniquely derivable, (3) ambiguous (multiple value assignments), or (4) inconsistent (question mark is visualised on top of the model).

The relevant educational dimensions in this LS are:

Structural and behavioural knowledge Learners have to be able to distinguish between the structural description of the system and the behavioural aspects that capture its behaviour.

Causal knowledge The focus in this LS is particularly on the causal relationships between quantities.

The representational approach taken for LS2 relates to Betty’s brain (Leelawong and Biswas 2008). One difference is that Betty’s brain allows causal relationships with different strengths. In DynaLearn this kind of knowledge can be represented using inequality statements, but these are available at LS4 and beyond (Causal differentiation, see below). Another difference is the explicit inclusion of structural knowledge in DynaLearn at LS2.

Learning Space 3: Causal Model with State Graph

Where LS2 focussed on causality and direction of change, the causal model with state graph learning space focusses on the prediction of changes in time. The representation of the causal model level is augmented with the notion of values of a quantity. Quantities can be assigned a quantity space that indicates which values a quantity can have (e.g. $Pressure_v \in \{zero, low, average, high, max\}$). Furthermore, value assignments can be put on these values ($Pressure_v = low$).

The introduction of current values for quantities has the consequence that the simulation results cannot be represented inside the expression (which is a visualisation of a single state of behaviour). The reason is that it cannot adequately show how the values of quantities change in time. As such, the simulation results are represented as a state graph (Figure 1c), in which each state identifies a qualitatively unique situation and each transition a possible change from one situation to another (Table 2). A sequence of states from the begin state to the end state is called a behaviour path, and the visualisation of a sequence of values that for a quantity in these states is called a value history (Figure 1c).

Another notion that is introduced in this learning space is co-occurrence. Consider that *Height* and *Pressure* should have the same values at the same time, and both have the quantity space $\{zero, low, average, high, max\}$. To represent this notion, correspondences are introduced. There are quantity correspondences (e.g. $Height \overset{Q}{\leftrightarrow} Pressure$), and value correspondences (e.g. $Height(zero) \overset{V}{\leftrightarrow} Pressure(zero)$), which can both be either directed or undirected. The value correspondence indicates that if $Height_v = zero$ then $Pressure_v = zero$. If the value correspondence is bidirectional, the reverse inference is also possible. Quantity correspondences can be considered a set of value correspondences between each consecutive pair of the values of both quantities. There are also inverse quantity space correspondences ($Q_1 \overset{Q}{\leftrightarrow} Q_2$) that indicate that the first value in Q_1 corresponds to the last value in Q_2 , the second to the one before last, and so on.

In this LS the following steps are made in the education dimensions:

Behavioural Knowledge With the introduction of quantity spaces, the notion of qualitative distinct states, transitions become important. The notion of a prediction and changes in time are key here.

Assumptions Since the causal relationships on this LS do not cause change themselves, the assigned derivative values are assumed to persist through the entire simulation.

For the stable derivative option, this is similar to the steady-state assumption.

Learning Space 4: Causal Differentiation

The causal differentiation learning space (Figure 1d) focusses particularly on the notion of *processes*. To accommodate this, the causal relationships (+ and -) are refined into influences and proportionalities (Forbus 1984). The other representational elements LS3 remain the same. Quantities that represent processes have influence relationships to other quantities in the system (e.g. $Birth\ rate_v \stackrel{I\pm}{\rightarrow} Size$). The structure of the system exemplifies a particular situation in which the process is applicable.

In order to be able to control simulation results, inequalities ($Birth\ rate_v > Death\ rate_v$) and operators (+ and -) are introduced. The operators are useful when there are multiple conflicting causal relationships (e.g. $Birth\ rate_v + Immigration_v > Death\ rate_v + Emigration_v$, which results in $\delta Size = \blacktriangle$). How inequalities change in time is visualised in the equation history (Table 2). Since inequality statements remove particular behaviour from the simulation, assumptions becomes important. Assumption labels can be used to indicate that particular statements are true for purposes of the simulation, but are not true in general.

When modelling, learners are encouraged to focus on a constrained set of phenomena. For purposes of modelling this choice constitutes the system, while all other effects on the modelled phenomena are considered to be outside the system. For this purpose, this LS introduces the notion of an agent, which models an influence from outside the system.

The cause of the effects of agents tend not be modelled explicitly. For example, in a model about the eutrophication of lakes due to agriculture runoff, the processes that result in the runoff are less relevant to the message that the model tries to convey. Since these processes are also not affected by the eutrophication, they do not have to be modelled explicitly. Instead, they can be considered constant influences from outside the system. This can be modelled by introducing an agent agriculture and a quantity runoff. Typically, the behaviour of the runoff is provided via an *exogenous quantity behaviour* (Bredeweg, Salles, and Nuttle 2007; Bredeweg et al. 2009), such as increasing, decreasing, stable, sinusoidal, generate all values. Such exogeneous behaviour makes the quantity of the agent exhibit specific behaviour, without the need to explicitly model this behaviour.

LS4 affects the following educational dimensions:

Process knowledge Having influences allows the correct modelling of processes. Important aspects consider are the structure required for the process to be applicable, the quantities affected by the process, and how the changes propagate through the system.

Causal knowledge The notion of causality is refined.

Assumptions The introduction of assumptions and inequalities (and operators) makes it possible to explicitly model operating assumptions, operating modes and steady state assumptions.

Scope Agents can be used to model external influences.

The representation in LS4 relates to VMODEL (Forbus et al. 2005). One difference is that VMODEL works with single state simulations, while the DynaLearn LS4 has multiple state simulations. Therefore, Dynalearn LS4 also facilitates multiple views to inspect the simulation results.

Learning Space 5: Conditional Knowledge

The conditional knowledge learning space focusses particularly on the activation conditions of processes. Consequently, choosing good landmark values in quantity spaces is an important task to solve. For example, the quantity space for the height of a bathtub should have a maximum value, as at this point the overflow process becomes active.

Learners can create an expression using the same vocabulary as in LS4. The knowledge in the expression (except the value assignments) always applies. However, in this level multiple conditional expressions can be defined. Conditional expressions consist of the expression and a set of conditional and consequential model ingredients (Figure 1e). If the conditions are true, the consequences also apply. For example, in a model of a pan with water on a stove, the cooking process only becomes active if the temperature of the water is greater or equal than the cooking point. In the conditional expression of the boiling process (Figure 1e), the inequality $Temperature \geq Cooking\ point$ is the condition that makes $Boiling\ rate_v = Positive$ (the consequence).

The conditional expression introduced in LS5, make modelling assumption more natural. Where in LS4 all assumptions and related model ingredients are inside a single expression, in LS5 each assumption (modelled as a condition) can be combined with a set of consequential model ingredients in a conditional expression. Assumptions can be added to the expression to run simulations.

Given that the structure and behavioural relationships can dynamically change on LS5, the *Entities, configurations and attributes* and the *dependencies* views are introduced (Table 2). The former shows the structure of the model, while the latter shows the behavioural relationships in a particular state. The *Model fragment* view shows which of the conditional expressions have become active.

The introduction of conditional expressions affects the following educational dimensions:

Process knowledge Conditional expressions allow the modelling when processes become active.

Assumptions Being able to have different conditional assumptions in different conditional expressions allows learners to more easily vary with different assumptions.

Learning Space 6: Generic and Reusable

The main focus of the generic and reusable learning space is on generic knowledge and first principles. This LS reflects an improved version of Garp3. In contrast with the earlier LSs, where it is more natural to talk about specific instances of situations where certain processes are active, in LS6 the knowledge is represented in a generic way in model fragments. These can be considered formalisations of the knowledge that applies in certain general situations. Model

fragments can be considered rules indicating that if certain model ingredients are present (conditions), certain other model ingredients must also apply (consequences). They can be represented as: *conditions* \Rightarrow *consequences*.

Three types of model fragments are distinguished: (1) process fragments are used to model processes, (2) agent fragments are used to represent the effects of agents, and (3) static fragments are used for the static structure of the system. Model fragments are organised in a is-a hierarchy, which causes model ingredients to be inherited to child model fragments. Furthermore, this LS allows model fragments to be reused in other model fragments.

Next to model fragments, different *scenarios* can be modelled. These represent specific cases of systems (with specific initial values). As such, behavioural relationships cannot be modelled in scenarios (only in model fragments), as these belong to the general knowledge. DynaLearn can run simulations of models based on a particular scenario. As in the previous LSs, the result of a simulation is a state graph.

At this level the notion of model ingredient definitions becomes important. Entity definitions are organised in an is-a hierarchy (e.g. a Lion is an animal). By specifying such ontological knowledge, it becomes possible to develop generally applicable model fragments, but particular cases in scenarios. Simulations then show how the generic knowledge applies to that particular case.

In terms of educational dimensions, substituting expressions for model fragments and scenarios and adding model ingredient definitions has the following consequences:

Ontological knowledge While in the earlier LSs it is more natural to model specific cases, in LS6 the focus is on general knowledge. The model fragments should represent the situations in which certain processes apply in a generic way. Scenarios can be used to model specific cases to which this general knowledge applies. Another difference is that model ingredient definitions (general knowledge) have to be created before they can be used in model fragments and scenarios. For example, hierarchies of entity definitions are made to bridge the gap between specific cases and the general knowledge.

Examples of models in LS6 can be found in a special issue of Ecological Informatics (Bredeweg and Salles 2009b).

Conclusion

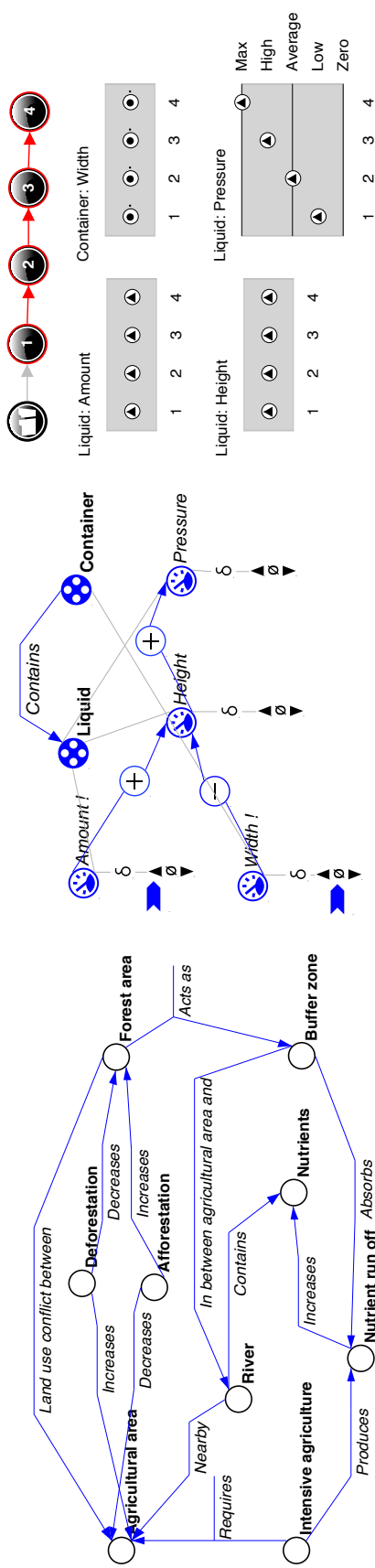
The first iteration of the DynaLearn Interactive Learning Environment (ILE) for constructing conceptual knowledge has been successfully completed. The main contribution in this version is the development of learning spaces (LSs). The LSs allow teachers and learners to work on different levels of complexity, making the software accessible for our target audience of end of high school students and students starting university. Furthermore the LSs focus on particular representational features in order to highlight and investigate specific qualitative aspects of systems behaviour. Each of the consecutive LSs introduces or refines a set of model ingredients that emphasize a particular education dimension. The educational dimensions that are relevant on the lower LSs are also relevant on the higher LSs.

In addition to the learning spaces, DynaLearn has also integrated the interactive windows into a single workspace (single screen). Furthermore, adding model ingredients in expressions on LSs up until LS6 only require a single interaction. We anticipate that these changes will make the DynaLearn usable for our target audience. The software is available via the DynaLearn website¹.

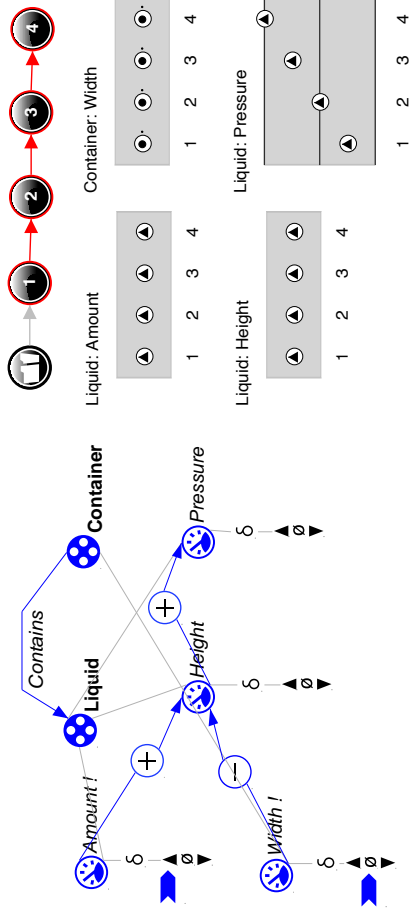
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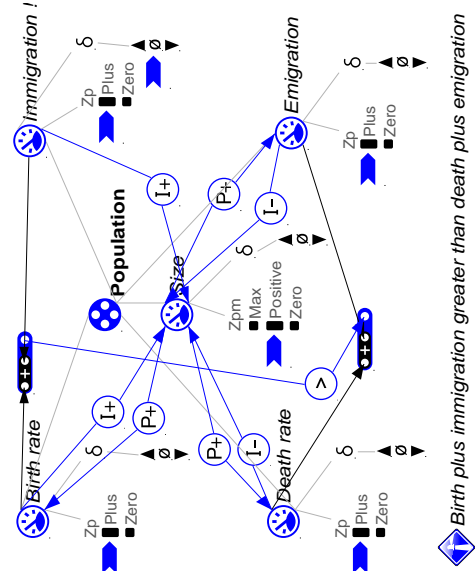
¹<http://www.DynaLearn.eu>



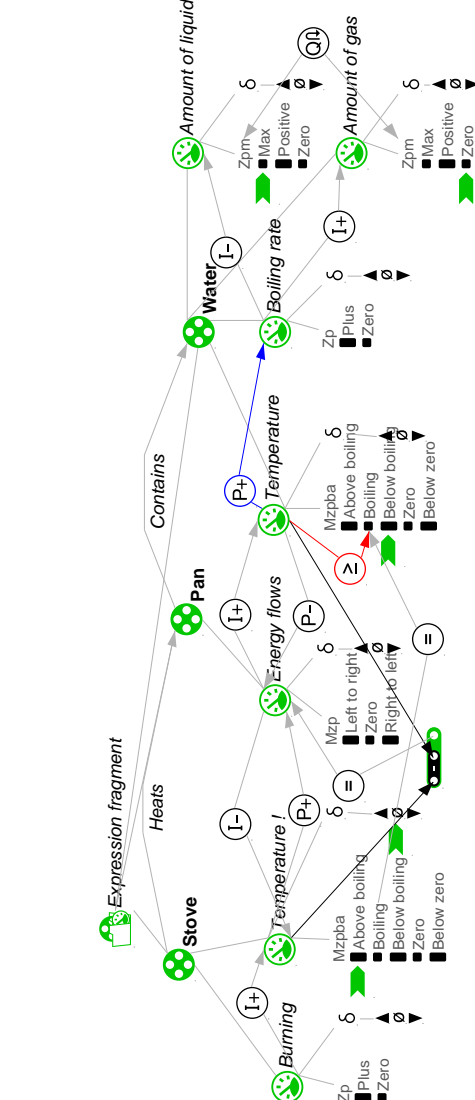
(a) Learning Space 1: Land use conflict concept map



(b) Learning Space 2: Expression of contained liquid (c) Learning Space 3: State graph and value history model



(d) Learning space 4: Expression of population model



(e) Learning space 5: Conditional expression of boiling process. The conditional expression introduces $Temperature_{P+} \geq Boiling\ rate$, if $Temperature_v \geq Boiling$. The other content is inherited from the expression.

Figure 1: Overview of some of the representations on learning spaces 1 through 5.