Context-Sensitive Control of Adaptation: Self-Modeling Networks for Human Mental Processes Using Mental Models

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Abstract. Within their mental and social processes, humans often learn, adapt and apply specific mental models of processes in the world or other persons, as a kind of blueprints. In this paper, it is discussed how analysis of this provides useful inspiration for the development of new computational approaches from a Machine Learning and Network-Oriented Modeling perspective. Three main elements are: applying the mental model by internal simulation, developing and revising a mental model by some form of adaptation, and exerting control over this adaptation in a context-sensitive manner. This concept of controlled adaptation relates to the Plasticity Versus Stability Conundrum from neuroscience. The presented analysis has led to a three-level computational architecture for controlled adaptation. It is discussed and illustrated by examples of applications how this three-level computational architecture can be specified based on a self-modeling network and used to model controlled learning and adaptation processes based on mental models in a context-sensitive manner.

Keywords. Mental model, Adaptive network, Control of adaptation, Self-modeling network

1. Introduction

Historically, analysis of human neural, mental and social processes often has provided inspiration for interesting new methods and techniques in AI and Machine Learning. In this paper, the focus is on how in their mental and social processes, humans often learn, adapt and apply specific mental models as a kind of blueprints, schemas or maps. Although a vast majority of the large amounts of publications on mental models in multiple disciplines is informal and not computational, it is shown how analysis of them still can be used as inspiration for the development of new computational approaches from an AI and Machine Learning perspective. Three elements came out of this analysis: (1) applying a mental model by internal (mental) simulation, (2) to develop and maintain a mental model, adaptation of it takes place (which usually involves learning, extinction or forgetting, and revision), and (3) in a context-sensitive manner, control is exerted over this adaptation. Here in particular (3) is an interesting topic. In a wider neuroscientific context, for example, in [1], this topic is discussed in relation to what is called the Plasticity Versus Stability Conundrum and to the notion of metaplasticity; e.g., [2]. It has

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been found that in the brain plasticity is not constant and various neural mechanisms have been discovered by which the extent of plasticity varies by being controlled in a context-sensitive manner; [1, 2, 3, 4]. Also, within an AI-context, in machine learning examples of this conundrum and controlled adaptation to address it are known, such as the (decreasing) temperature parameter in simulated annealing and the sensitive balancing between exploration and exploitation in reinforcement learning, also called the explore-exploit dilemma [5, 6, 7]. This is explained in [7] as follows.

> 'When you go to your favourite restaurant, do you always order the same thing, or do you try something new? Sticking with an old favourite ensures a good meal, but if you are willing to explore you might discover something better. This simple conundrum, deciding between something you know and something you do not, is commonly referred to as the exploration– exploitation dilemma.'

This quote also illustrates that on the one hand decision making based on known mental models can be very efficient (like navigating based on a well-known map), but on the other hand this may prevent someone from learning even better decisions (like exploring still unknown territory). The analysis of how humans use mental models in their mental processes has led to a three-level computational architecture for context-sensitive controlled adaptation where at the base level internal simulation based on a mental model takes place, at the next level adaptation of this mental model and at the second-next level context-sensitive control over this adaptation. In this paper, it is pointed out and illustrated by examples how this three-level computational architecture can be modeled as a self-modeling network: a network in which parts of the network's own structure characteristics are represented by nodes within the same network.

2. How Humans Use Mental Models

In their mental processes, humans use mental models in three different ways: for internal simulation, for learning, and for (self-)control; these uses are explained as follows.

Simulation: Mental Models Simulate. Mental models are often used for internal simulation. This can take place in different forms, for example, visualisation or flashbacks (in sport or in PTSD). In his often cited book [8], Kenneth Craik describes a mental model as a *small-scale model* that is carried by an organism within its head:

> 'If the organism carries a "small-scale model" of external reality and of its own
> possible actions within its head, it is able to try out various alternatives, conclude
> which is the best of them, react to future situations ….' ([8], p. 61)
> '…it is a physical working model which works in the same way as the process it
> parallels…' ([8], p. 51).

Internal simulation is assumed to be based on causal relations for world processes; e.g., [9, 10, 11, 12]. For example, in [13], the functioning of a car in interaction with its driver is simulated based on a person's mental model, and in [14] a flashback experience of a course of events is addressed as internal simulation based on a mental model of this course of events.

Adaptation: Mental Models Adapt. Mental models are adapted often (e.g., learning, revising, forgetting); for example:

> 'Model-based learning is a dynamic, recursive process of learning by building mental
> models. It incorporates the formation, testing, and subsequent reinforcement, revision, or
> rejection of mental models of some phenomenon.' [15]

Observational learning concerns observation of others or of oneself while 'learning by doing' or 'learning by discovery'. Learners may see someone perform a behavior and

then start to imitate it; e.g., [16, 17]. Mirror neurons are a basis for learning by observation; e.g., [18, 19, 20]. On the other hand, *instructional learning* is a useful addition as only learning based on observation may be not very efficient; e.g., [21].

Control: Mental Models Respond to Control. For learning mental models, *control* is exerted; see also [22, 23, 24]. Such control is also referred to as metacognition; e.g., [25, 26, 27, 28]. Also, the term self-regulation is used [28].

Overall architecture. Based on the processes for mental models summarized above, a cognitive architecture for handling mental models has been designed covering the three types of processes in an integrated manner as depicted in Figure 1.
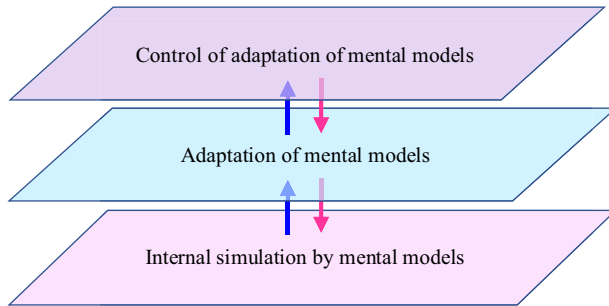
Figure 1. A cognitive architecture for mental model handling.

Here, mental models are addressed through multiple representations: they can be viewed from three levels of representation according to the three planes depicted in Figure 1. At the base level depicted by the lower (pink) plane, a mental model, which essentially is considered to be a relational structure, is represented by its nodes and the relations between the nodes. For internal simulation, the nodes have activation levels that vary over time: based on the relations these activation levels affect each other over time. Next, at the adaptation level depicted in Figure 1 by the middle (blue) plane, it is represented how the mental model relations change over time by some adaptation specification. Finally, at the top level depicted by the upper (purple) plane in Figure 1 it is indicated how the adaptation at the middle level is controlled. For more details of this architecture and its application, see [29].

3. Modeling by Self-Modeling Networks

The Network-Oriented Modelling approach based on adaptive temporal-causal networks as self-modeling networks from [30, 31] is a suitable modeling approach to represent in an adaptive and controlled manner the causal relations and the way they can be processed to generate mental processes. Using this approach, adaptive networks of multiple orders can be modelled relatively easily. Network nodes X have state values indicated by real numbers $X(t)$ that vary over time t; nodes are also called states. The characteristics defining a network are:

- **Connectivity characteristics**: *connections* from states X to Y, having *connection weights* $\omega_{X,Y}$ specifying their strengths
- **Aggregation characteristics**: each state Y has a *combination function* $\mathbf{c}_Y$ that specifies how impact from all incoming connections on Y is aggregated. Based on

a list of basic combination functions $\mathbf{bcf}_i$ (each with some parameters) provided by an available library, such a combination function can be specified by weights γ_i and parameters $\pi_{i,j}$ for these basic combination functions $\mathbf{bcf}_i$

- **Timing characteristics**: each state Y has a *speed factor* η_Y specifying how fast Y changes

The numerical representation created by the available dedicated software environment is based on the following equations based on the above network characteristics (where $X_1, \ldots, X_k$ are the states from which state Y gets incoming connections):

$$\mathbf{impact}_{X,Y}(t) = \omega_{X,Y}\, X(t) \tag{1}$$

$$\mathbf{aggimpact}_Y(t) = \mathbf{c}_Y(\mathbf{impact}_{X_1,Y}(t),\ldots, \mathbf{impact}_{X_k,Y}(t)) = \mathbf{c}_Y(\omega_{X_1,Y}X_1(t),\ \ldots,\ \omega_{X_k,Y}X_k(t)) \tag{2}$$

$$Y(t+\Delta t) = Y(t) + \eta_Y\,[\mathbf{aggimpact}_Y(t) - Y(t)]\,\Delta t$$
$$= Y(t) + \eta_Y\,[\mathbf{c}_Y(\omega_{X_1,Y}X_1(t),\ \ldots,\ \omega_{X_k,Y}X_k(t)) - Y(t)]\,\Delta t \tag{3}$$

A computational network engine developed within this software environment based on the generic equations (3) takes care for the processing of all network states thereby using their connections and other network characteristics.

Self-modeling networks to model adaptivity and control. To design network models that are adaptive, the concept *self-modeling network* (also called reified network) introduced in [30, 31] has turned out to be very useful. A self-modeling network is obtained if for some of the network characteristics $\omega, \gamma, \pi, \eta$ as introduced above, network states are added to the network that represent their value. For example, for a connection weight $\omega_{X,Y}$ an additional state $\mathbf{W}_{X,Y}$ (called a *first-order self-model state*) is added to the network that represents the value of this weight $\omega_{X,Y}$ and is indeed used as value for that weight in the processing. For such an additional network $\mathbf{W}$-state, also additional network characteristics are added to get an adequate embedding in the obtained self-modeling network. For example, for Hebbian learning [32] a specific combination function $\mathbf{hebb}_\mu(V_1, V_1, W)$ from the library can be used involving a persistence parameter μ:

$$\mathbf{hebb}_\mu(V_1, V_2, W) = V_1 V_2\,(1-W) + \mu\,W \tag{4}$$

Here, V_1, V_2 are activation levels of the connected states and W is the activation level of the self-model state $\mathbf{W}_{X,Y}$ for the connection weight. As a simpler alternative, sometimes the function

$$\mathbf{smin}_\lambda(V_1, V_2) = \mathbf{min}(V_1, V_2)/\lambda \tag{5}$$

is used for Hebbian learning, where λ is a scaling factor; e.g., see [33].

As an example at a next (*second-order self-model*) level, for the combination function $\mathbf{hebb}_\mu(V_1, V_1, W)$ of a self-model state $\mathbf{W}_{X,Y}$, the persistence parameter μ can be represented by another self-model state $\mathbf{Mw}_{X,Y}$. The latter network state is a *second-order self-model state* as it represents a network characteristic related to (first-order) self-model state $\mathbf{W}_{X,Y}$. Another example of a second-order self-model state is a state $\mathbf{Hw}_{X,Y}$ that represents the speed factor (learning rate) η of (first-order) self-model state $\mathbf{W}_{X,Y}$. These

two types of self-model states can be used in an adaptive network model to control the learning of mental models: if the activation level of $\mathbf{Mw}_{X,Y}$ gets lower, more extinction takes place which occurs when mental models are forgotten. Moreover, decreasing activation values of $\mathbf{Hw}_{X,Y}$ model make the learning slow down, and a value 0 causes a complete freezing of the learning (no plasticity).

These first- and second-order self-model states directly relate to the three levels in the architecture depicted in Figure 1. Within the lowest (pink) plane the base network states are depicted, within the middle (blue) plane the first-order self-model states (such as states $\mathbf{W}_{X,Y}$), and within the upper (purple) plane the second-order self-model states (such as states $\mathbf{Mw}_{X,Y}$ and $\mathbf{Hw}_{X,Y}$).

4. Examples of Self-Modeling Network Models for Mental Models

In this section, as illustrations two examples of self-modeling network models for mental models are briefly discussed. They are both instantiations of the generic three-level architecture discussed in Section 2.

Using metaphors as mental models. This example (described in more detail in [34]) addresses the use of metaphors as mental models to support joint decision making; see Figure 2 for a part of this network model. At the base levels two different metaphor options are modeled: cooperative metaphor state met_{coo} and competitive metaphor state met_{com}; see the lower (pink) plane in Figure 2. The incoming and outgoing connections for these metaphor states are adaptive, modeled by the first-order self-model $\mathbf{W}$-states; see the middle (blue) plane. The control of the adaptation of all these $\mathbf{W}$-states is modeled by the second-order self-model $\mathbf{Hw}$-state; see the upper (purple) plane.
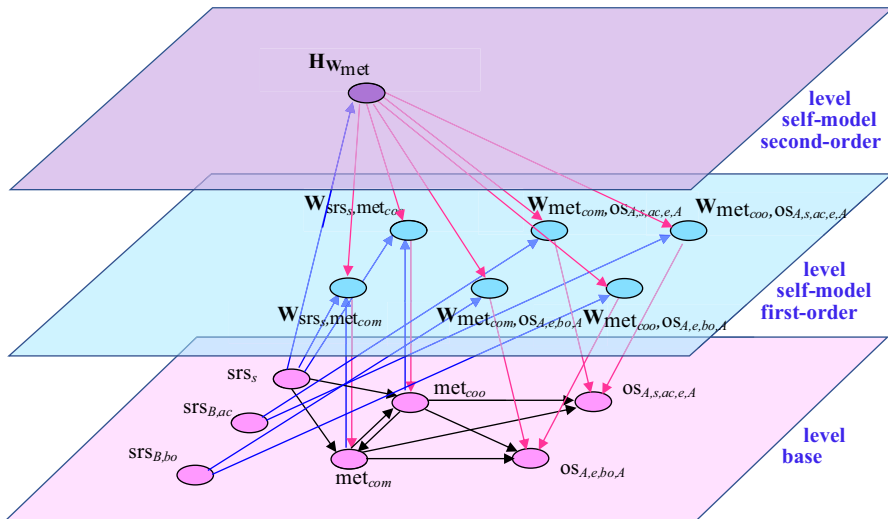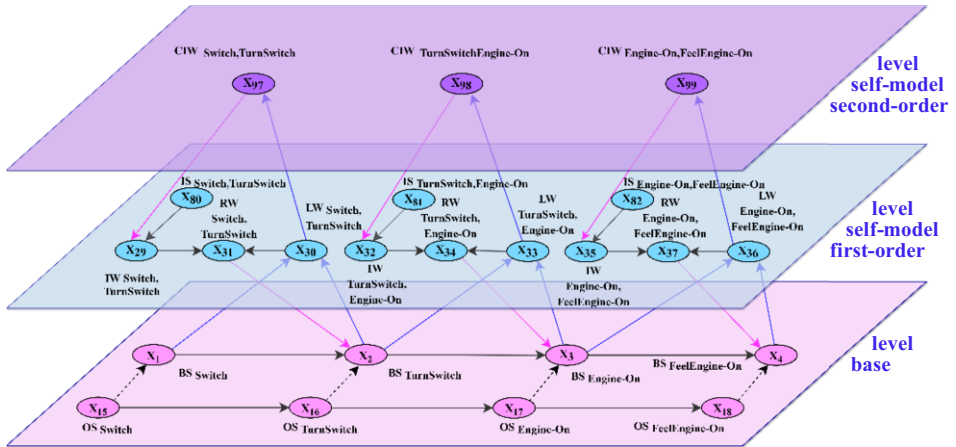

Figure 2 Connectivity of a part of an adaptive network model for mental models for metaphors with their activation and effect connections at the base level, their learning at the first-order self-model level and the control of the learning at the second-order self-model level.

The two $\mathbf{W}$-states for the incoming connections for the metaphor states determine when the metaphor should be activated. These connections are learnt by Hebbian

learning, which has as effect that the more often they are used in a certain context (represented by stimulus representation srs_s), the stronger their activations become when that context occurs. The four **W**-states for the outgoing connections from the metaphor states determine the effect of the metaphor states on the self-owner states; they are adapted based on whether the other person tends to go for action *ac*, and whether the other person has a good feeling *bo* about it (states $srs_{B,ac}$ and $srs_{B,bo}$). For each of these six **W**-states, its adaptation is controlled through the second-order self-model **Hw**-state which represents the learning rate of the related **W**-state. This form of second-order adaptation is based on the second-order adaptation principle 'adaptation accelerates with increasing stimulus exposure' [4].

Learner-controlled learning. The second example (described in more detail in [35]) addresses how a learner controls at what times instruction by a teacher takes place; see Figure 3 for a representative part of this model. Here the three **RW**-states in the middle (blue) plane represent the weights of the connections in the mental model (that is learned) depicted at the (pink) base level plane. For example, state $RW_{Switch,TurnSwitch}$ within the first-order self-model plane, also indicated by X_{31}, represents the weight of the connection in the base plane from state BS_{Switch} to state $BS_{TurnSwitch}$ (the arrow from X_1 to X_2).

Figure 3. Connectivity of a part of an adaptive network model for mental models for learner control of a teacher's instruction.

These **RW**-states are based on input from observational learning (modeled by the corresponding **LW**-states) and instructional learning (modeled by the corresponding **IW**-states). For example, state $RW_{Switch,TurnSwitch}$ has incoming connections from $LW_{Switch,TurnSwitch}$ and $IW_{Switch,TurnSwitch}$. The **LW**-states are adaptive based on Hebbian learning; to this end they use combination function (4) from Section 3. For this scenario, they are not (explicitly) controlled. In contrast, for the **IW**-states, their incoming connections from the **IS**-states (representing the communication channel from the information source **IS**-state, which is the teacher) are controlled. This control is modeled by the second-order self-model **CTW**-states at the upper (purple) level; these are also denoted as **Ww**-states. For example, state $CIW_{Switch,TurnSwitch}$ in the (purple) second-order self-model plane controls the connection from $IS_{Switch,TurnSwitch}$ to $IW_{Switch,TurnSwitch}$, which

models the communication from instructor to learner about the connection from BS_{Switch} to state $BS_{TurnSwitch}$. Such a control state $CIW_{Switch, TurnSwitch}$ is activated once the corresponding **LW**-state $LW_{Switch, TurnSwitch}$ has a sufficient action level: the learner has (partially) learnt it based on observation and asks the teacher for confirmation. So, these **CIW**-states determine when the communication channels have to be opened for the instructional learning.

Learning by counterfactual thinking. A third case to illustrate the approach is adopted from [36]; it addresses learning by counterfactual thinking; see Figure 4. Here after a negatively evaluated experience modelled by the red box in the base plane, the person considers internal simulation of mental models for alternative action options and their expected results (see the orange box in the base plane). The counterfactual status of this is modelled by the process modelled in the middle blue plane and that process is controlled by the upper level **CS**-states in the purple plane. See [36] for more details.
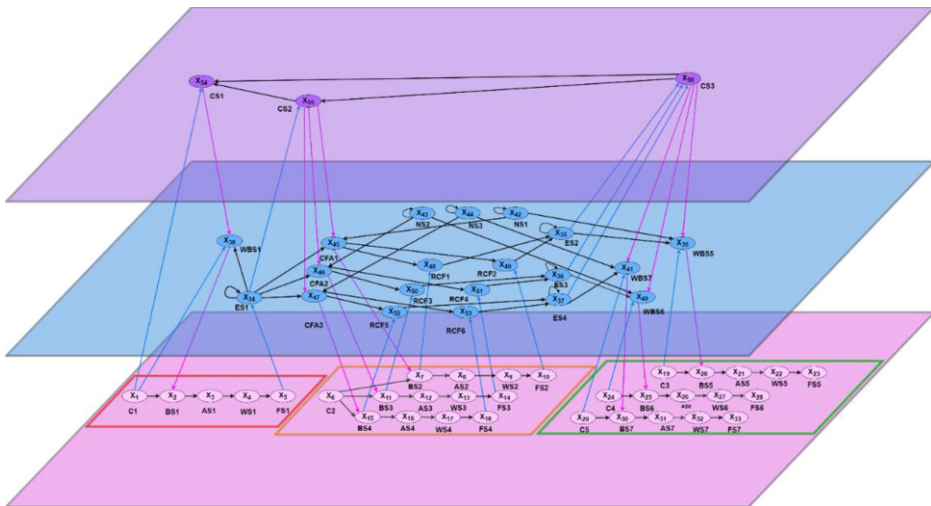

Figure 4. Connectivity of the controlled adaptive network model for counterfactual thinking.

5. Options for Control of Adaptation using Self-Modelling Networks

In Section 4, some examples of adaptation control for mental models were discussed, for two cases within the context of self-modelling networks used as a vehicle. In this section, a more systematic overview is discussed of different ways in which control over mental models and their adaptation can be exerted, thereby again making use of the network structure provided by self-modelling networks. In a controlled adaptive network model for mental models based on a self-modelling network, adaptation is modelled by a first-order self-model. There are a number of network characteristics involved in the first-order self-model states used for the adaptation. In particular, by systematically going through all possible network characteristics, the following examples of network characteristics for adaptation to be controlled can be distinguished and are illustrated by various examples:

- **Control by adaptive connectivity characteristics of first-order self-model states**
  - o Adaptive connections of the causal pathways to the self-model states and their weights $\boldsymbol{\omega}$; for example:
    - ▪ Choosing a mental model to be applied. For example, a decision to use a specific metaphor-based mental model as in the model in Section 4 taken from [34] or a decision to use a geometric mental model to support learning of an arithmetic mental model, as described in [37]
    - ▪ Opening a communication channel from an information source to enable instructional learning of a mental model (decision to ask), as in the model in Section 4 taken from [35] and in the model described in [38]
    - ▪ Opening an observation channel to enable observational learning of a mental model (decision to observe), as in the model described in [38]
  - o Adaptive connections of the causal pathways from the self-model states to other states and their weights $\boldsymbol{\omega}$; for example:
    - ▪ Modelling the effects of a chosen metaphor as in the model in Section 4 taken from [34]
- **Control by adaptive aggregation characteristics of first-order self-model states**
  - o Adaptive choice of combination function; for example:
    - ▪ For Hebbian learning of mental model connections a weighted average of $\mathbf{hebb}_{\boldsymbol{\mu}}(V_1, V_2, W)$ and $\mathbf{smin}_{\boldsymbol{\lambda}}(V_1, V_2)$, with adaptive weights $\boldsymbol{\gamma}_1$ and $\boldsymbol{\gamma}_2$.
  - o Adaptive parameters of chosen combination functions; for example:
    - ▪ Adaptive values for the persistence factor $\boldsymbol{\mu}$ of $\mathbf{hebb}_{\boldsymbol{\mu}}(..)$ as in the self-modelling network model for shared mental models described in [38] or for the scaling factor $\boldsymbol{\lambda}$ of $\mathbf{smin}_{\boldsymbol{\lambda}}(V_1, V_2)$.
- **Control by adaptive timing characteristics of first-order self-model states**
  - o Adaptive adaptation speed (learning rate) $\boldsymbol{\eta}$; for example:
    - ▪ Addressing the Plasticity Versus Stability conundrum [1] based on some context factors indicating when plasticity is needed fully and when plasticity should be limited or frozen.
    - ▪ Accelerating adaptation speed upon increased stimulus exposure [4], for example as applied in the example model in Section 3 taken from [34]

In Table 1 an overview is given of a large number of applications of such self-models to model human processes based on mental models as brought together in book [29].

Recall from Section 3 how at some level self-model states can be introduced to represent network characteristics from a lower level. The naming is as follows: self-model state $\mathbf{W}_{X,Y}$ represents connection weight $\boldsymbol{\omega}_{X,Y}$ from the lower level, $\mathbf{H}_Y$ represents speed factor $\boldsymbol{\eta}_Y$ from the lower level, and so on. Such self-model states can be generally called $\mathbf{W}$-states or $\mathbf{H}$-states, for example. By iterating this, for example, second-order self-model state $\mathbf{H}\mathbf{w}_{X,Y}$ represents the adaptation speed of first-order self-model state $\mathbf{W}_{X,Y}$ and second-order self-model state $\mathbf{M}\mathbf{w}_{X,Y}$ represents the persistence parameter $\boldsymbol{\mu}\mathbf{w}_{X,Y}$ of first-order self-model state $\mathbf{W}_{X,Y}$. Similarly, second-order self-model state $\mathbf{W}_{Z,\mathbf{w}_{X,Y}}$ represents the weight $\boldsymbol{\omega}_{Z,\mathbf{w}_{X,Y}}$ of the connection from some state Z to state $\mathbf{W}_{X,Y}$. Such second-order self-model states can be generally called $\mathbf{H}\mathbf{w}$-states, $\mathbf{M}\mathbf{w}$-states, or $\mathbf{W}\mathbf{w}$-states. Note that in most cells in Table 1 further references are included, but for those cells where no references are included, in general this means that these options are yet to be addressed in detail.

Table 1 Overview of different types of controlled adaptation for example mental models as collected in [29]

Learning by	Control of adaptation via connectivity	Control of adaptation via aggregation	Control of adaptation via timing
Observation and monitoring	Controlled learning by observation for a mental model **W**-state for bonding via a W_W-state ([29], Ch 13; formation of a mental model of another person; see also [33])	Hebbian mental model learning **W**-state persistence control via an M_W-state ([29], Ch 14; controlled forgetting of a mental model relation; see also [39])	Hebbian mental model learning **W**-state speed control via an H_W-state: adaptation accelerates with increasing exposure ([29], Ch 5, Ch 7, Ch 10, Ch 11, Ch 12; e.g., learning mental models for flashback experiences [14], analysis and support tasks [40], metaphors [34], God-models [41], self- and other-models [33])
Excitability adaptation	Incoming connection for an adaptive mental model excitability **T**-state control via a W_T-state ([29], Ch 7; learning excitability [42, 43] of a mental model's states; see also [40])	Excitability mental model learning **T**-state aggregation control, for example through adaptive (steepness σ and threshold τ) parameters of a logistic combination function used for the **T**-state represented by S_T- and T_T-states	Excitability mental model learning **T**-state speed control via an H_T-state ([29], Ch 7; learning excitability [42, 43] of a mental model's states; see also [40])
Communication	Learner-controlled instructional learning of a mental model **W**-state via a W_W-state ([29], Ch 9; opening a communication channel with the instructor by asking; see also [35]) Controlled learning by communication for a mental model **W**-state for bonding via a W_W-state ([29], Ch 13 opening a communication channel with the other person by asking; see also [38])	Learner-controlled instructional learning of a mental model **W**-state via a T_W-state for excitability [42, 43] of the **W**-state (opening a communication channel with the instructor by more sensitive listening)	Learner-controlled instructional learning of a mental model **W**-state via an H_W-state (controlling the timing of a communication channel with the instructor)
Other mental models	Controlled connection **W**-state for counterfactual activation of a mental model via a W_W-state ([29], Ch 6; see also [36])	Controlled connection **W**-state for counterfactual activation of a mental model via a T_W-state addressing excitability [42, 43] of the **W**-state	Controlled inter mental model exchange connection **W**-state via H_W-state ([29], Ch 4; exchange from arithmetic mental model to geometric mental model; see also [37])
Contextual factors	Controlled connection **W**-state for activation of mental model via a W_W-state ([29], Ch 6; activation of a mental model for possible future action; see also [36])	Controlled connection **W**-state for activation of mental model via a T_W-state addressing excitability of the **W**-state based on contextual factors	Controlled adaptive mental model effect connection **W**-state via an H_W-state ([29], Ch 10; adapting the own choices based on the context given by the other person; see also [34])

6. Discussion

This paper addressed how in mental and social processes, humans often apply specific mental models and learn and adapt them in a controlled manner. It was explored how analysis of such processes may provide useful inspiration for the development of computational approaches from an AI, computational intelligence and machine learning

perspective. It was discussed how controlled adaptation relates to the Plasticity Versus Stability Conundrum in neuroscience [1]. From the analysis a three-level computational architecture for controlled adaptation was obtained. It was discussed how this three-level computational architecture can be modeled as a self-modeling network [30, 31], illustrated by a number of examples.

The work discussed here can be considered as part of the area of human-like machine learning. Also, within machine learning in general there are a few approaches that do (explicitly) address control of adaptation. A simple example is Simulated Annealing, where the temperature parameter can be considered an adaptive adaptation control parameter. Another example is the Explore-Exploit Dilemma in reinforcement learning, where the challenge is to find criteria on the context that can be used to decide in a context-sensitive manner between explore or exploit; e.g., [5, 6, 7]. Two limitations of the current state of the presented work that may be identified are:

- The approach has only been explored yet for deterministic models. In principle, probabilistic models are possible when combination functions are added to the library with some probabilistic or random effects, but this still has to be explored in more detail
- Analysis of the wider domain of human-like approaches to control of adaptation, in particular for mental model adaptation as discussed here, may provide inspiration for further development of machine learning methods. This is also an area that has not yet been explored in more detail.

It may be noted from this paper that for human-like controlled adaptation much input and inspiration was obtained from the area of neuroscience; for example, in [1, 2, 3, 4] and many other papers on metaplasticity several second-order adaptation principles for context-sensitive control of adaptation can be found. This is in strong contrast with the area of social science. Literature on adaptive social relations or adaptive social networks is available including computational models for it, such as [44, 45], but although adaptation control is certainly also in this area a very relevant factor, approaches addressing the control of adaptation seems to be lacking in such literature, where only just a few more or less incidental exceptions can be found such as [6, 30, 34, 38, 39, 46, 47] and [31], Ch 6. Much progress would become possible for social science by explicitly addressing this issue more systematically and on a much larger scale like it was already done within neuroscience.

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