A Computational Analysis of Emotions and Social Influence in Learning

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Abstract In this paper, it is analysed how emotions and social environment affect people’s active and reflective learning processes. First, a conceptual analysis is made using recent insights from Cognitive, Affective and Social Neuroscience on the roles of emotions and social interactions in learning. A computational analysis is made using a computational model of learning processes following these insights. In this analysis, neural mechanisms for the impact of both a person’s own emotions and the emotions of others are taken into account. In particular, it is considered how these impacts influence different learning types, such as active or reflective learners. The analysis shows how emotions and social interaction strengthen the learning process. It is discussed how from these insights indicators can be obtained that can be used to design technology-enhanced learning environments able to exploit these impacts.

6.1 Introduction

Recently it has been advocated that new insights for learning and teaching can be gained from findings in Cognitive, Affective and Social Neuroscience (Immordino-Yang and Fischer, 2011). In particular, this has been put forward for the role of emotions and social interaction in learning (Immordino-Yang and Faeth, 2010; Immordino-Yang and Fischer, 2007). In the current paper this line is explored by contributing neurologically based conceptual and computational analyses on how emotions and the social environment influence learning, in particular in relation to different learning styles such as reflective and active learners (Felder and Brent, 2005; Felder and Silverman, 1988).

Using relevant findings from a number of neurological theories on the role of emotions, reflection and social contagion in behavior and learning (Damasio, 1999; Hebb, 1949; Iacoboni, 1
6.2.1 Agent-based support for behavior change

2008; Immordino-Yang and Fischer, 2007; Moore and Haggard, 2008), a qualitative causal model was designed and used for a conceptual analysis. Furthermore, through refinement and formalization a dynamical computational model was obtained and implemented to conduct a number of simulation experiments. In these experiments, the role of emotions, reflection and social interactions on active and reflective learning styles was explored in more detail. It was shown how affective states contribute to effectiveness of a learning process, thereby creating a personal and emotionally grounded awareness experience for the learner.

To increase learning effects, a learner has to feel involved and attached to the elements in a learning process by experiencing ownership and responsibility for own choices and behavior (Kolb and Kolb, 2005). Therefore, experiencing affective states relating to behaviors and becoming aware of them in a reflective manner form an important part of a learning process. In particular, this may concern affective states related to valuing specific options for how to address an issue (or problem) before choosing one. Moreover, it may concern feeling satisfaction (or lack thereof) about choosing a particular approach after it was executed. These feelings may provide emotionally grounded prior and retrospective awareness of these options, and thus may strengthen learning by reinforcing choices with positive evaluation. In a social context co-learners do not only interact in a cognitive sense but also by transferring affective states. Both facilitating the experience and exchange of emotions, and stimulating awareness of these emotions is an important basis for emotionally grounded forms of reflection, and can make an essential contribution to the learning process.

The work reported above has identified several useful elements from the neurological domain concerning the learning process, such as Hebbian learning, internal simulation, interaction of emotion and cognition, emotion-related valuing of decision options, awareness states and reflection, mirroring and social contagion of emotion. In this paper, these elements were used as the basis of a conceptual and computational dynamical model that was developed to provide insight into the role of emotions and social interactions in learning processes. It is shown how the model was useful in conducting a variety of agent-based simulation experiments displaying how emotions and social interaction can strengthen different types of learning processes. Based on these findings, guidelines and support are offered for the development of technology-enhanced learning environments facilitating the role of emotions, reflection and social interaction in learning.

In this paper, first, in Section 6.2 relevant neurological literature is addressed. Using findings from this literature, in Section 6.3, a conceptual model is discussed. In Section 6.4, the conceptual model is formalized to a computational model and used for computational analysis based on simulation experiments. Section 6.5 describes several guidelines following from initial simulation experiments that demonstrate the behavior of the model. Section 6.6 demonstrates how the model can be applied to account for different types of learners as identified by the literature, and Section 6.7 describes several simulation experiments for agents with such different learning styles. Finally, Section 6.8 is a discussion.

6.2 Neurological insights concerning affective and social learning

Recent developments in Cognitive Neuroscience have revealed mechanisms behind the generation and contagion of affective states, and the roles they play in mental processes involved in generating behavior. In this section they will be briefly reviewed.
6.2.1 Prior and retrospective awareness of behavior

It is often emphasized that for learning processes based on experiences of actions or behaviors, awareness of ownership and valuing of such experiences is of crucial importance. One example comes from Kolb and Kolb (Kolb and Kolb, 2005, p. 207) and reads: “To learn experientially learners must first of all own and value their experience”. In recent neurological literature mechanisms responsible for developing awareness of an action are reported (Moore and Haggard, 2008; Voss, Moore, Hauser, Gallinat, Heinz, and Haggard, 2010). A distinction is made between awareness prior to execution and retrospective awareness. Prior awareness is, among others, based on prediction of effects of a prepared action. It plays an important role in valuing action options and choosing or initiating the actual execution of an action. In retrospective awareness in addition the monitored execution of the action and the sensed actual effects play an important role (Moore and Haggard, 2008; Treur, 2011). Retrospective awareness plays an important role in reflecting on one’s own functioning in order to learn from the consequences of a choice made, and adapt the valuation of that option for the future.

To obtain prior awareness of an action, internal simulation is used as a means to predict the (expected) effects of a prepared action (Haggard, 2008; Wolpert, 1997). The idea behind internal simulation is that in certain contexts (which may entail sensed aspects of the external world, but also internal aspects such as goals and attitudes) preparation states for actions are activated, which in turn through prediction links activate sensory representation states for (predicted) consequences of the action. Such an internal simulation process can go on in arbitrary depth. The notion of internal simulation has a longer tradition, for example in the context of predicting effects of prepared motor actions (Becker and Fuchs, 1985), imagination (Hesslow, 2002), processes related to emotional responding (as-if body loops; Damasio (1994, 1999), and reading another person’s mind (Goldman, 2006). Usually the predicted effects of a prepared action are valued. If this valuation is satisfactory, this may entail a ‘go’ decision for the actual execution of the action option, thus exerting control over action execution. In contrast, predicted effects valued as less satisfactory may lead to a ‘no go’ decision.

Over the years the idea has developed that retrospective action awareness is based on some form of co-occurrence of predicted effects and sensed actual effects. Traditionally, this co-occurrence was described by a ‘comparator model’ (Feinberg, 1978; Wolpert, 1997). More recently it has been analysed that the predicted effect and the sensed actual effect are in fact not compared but added to each other in some integration process (Moore and Haggard, 2008; Treur, 2011; Voss et al., 2010).

6.2.2 The role of emotions in awareness and valuing of behavior

Awareness of behavior has a strong emotional component, which shows itself both in the valuing of behavior options before deciding, and in retrospect after a behavior has been executed. In recent neurological literature this has been studied in relation to a notion of value as represented in the amygdala (Bechara, Damasio, and Damasio, 2003; Bechara, Damasio, Damasio, and Lee, 1999; Morrison and Salzman, 2010; Rangel, Camerer, and Montague, 2008). In opting for a particular behavior, experiences with the environment (from the past) play an important role. In a retrospective process, by taking into account experiences, the valuations (and their related emotions) of behavior options are adapted through learning processes. This is a form of adaptation. Parts of the prefrontal cortex (PFC) and other areas in the human brain such as the hippocampus, basal ganglia, and hypothalamus have extensive, often bidirectional connections with the amygdala (Ghashghaei, Hilgetag, and Barbas, 2007; Morrison and Salzman, 2010; Salzman and
Fusi, 2010). A role of amygdala activation has been found in various processes involving emotional aspects (Murray, 2007). Usually emotional responses are triggered by stimuli for which a predictive association is made of a rewarding or aversive consequence, given the context including the person's goals. Feeling these emotions is a way of experiencing the value of such a prediction, and to which extent it is positive or negative. In this sense the felt emotions strongly relate to prior valuation of an option. Similarly, feelings of satisfaction are an important element of retrospective valuation of what is experienced after behavior has been chosen. These affective aspects of the concept of value form a point of departure of recent work on the neural basis of decision making processes and economic choice in neuroeconomics (Bechara et al., 2003, 1999; Morrison and Salzman, 2010; Rangel et al., 2008; Sugrue, Corrado, and Newsome, 2005).

6.2.3 Emotion contagion impact on behavior

In Section 6.2.2 it has been discussed how emotions relate to awareness of behavior. In this subsection it is discussed how, in a social context, a learner's processes can be strengthened by the affective states of others. Affective states play an important role as their occurrence in one person (a co-learner or tutor) can easily affect the same affective state in another (a learner). In a social context, the idea of emotion-related valuing can be combined with recent neurological findings on the mirroring function of certain neurons (Iacoboni, 2008; Rizzolatti and Sinigaglia, 2008). Mirror neurons are neurons that, in the context of the neural circuits in which they are embedded, show both a function to prepare for certain actions and a function to represent states of other persons. They are active not only when a person intends to perform a specific action (or body state), but also when the person observes somebody else intending or performing this action or body change. Indeed, if states of others are affecting some of the person's own states, which at the same time are connected via neural circuits to states that are crucial for his/her own feelings and actions, then this provides an effective mechanism for persons to fundamentally affect each other's actions and feelings. As mirror neurons cause that specific sensory inputs (such as an observed person) directly links to the relevant own preparation states, mirroring is a process that fully integrates mirror neuron activation states in the on-going internal simulation processes. This includes expressing emotions in body states, such as facial expressions. This mechanism of mirror neurons and internal simulation thus provides a neural basis for emotion contagion.

6.2.4 On the role of reflection in behavior

It is widely accepted that reflection plays an important role in most learning processes (Moon, 2004). Reflection can take place with respect to multiple aspects of a learning process, for example, on the learned knowledge or behavior itself, on emotions, to goals and motivation, or to the planning over longer time periods. Reflection on these aspects contributes to an awareness of a personal and emotionally grounded experience for the learner. This avoids a type of learning process in which a learner acts in a detached manner involving hardly conscious reactive patterns in response to environmental cues that happen to be offered over time, as sometimes suggested in a behaviorist perspective on learning (Skinner, 1986). Here an opposite perspective is adopted, according to which a learner is aware of his or her own choices and actions and experiences ownership and responsibility for them. Reflection covers (mental) activities during a learning process that contribute to this. The learner's environment can stimulate such mental activities, for example, in the form of a tutor or coach asking specific questions that may provoke reflection, or of a co-learner asking for explanation or displaying a specific behavior and emotion.
In the conceptual and computational model used in this paper, reflection regarding learned behavior is addressed. More specifically, it concerns reflection of the behavioral choices made to respond to encountered situations. This reflection is expressed by awareness of different options and their valuations prior to choosing one of them, and (in retrospect) awareness of the valuation of the chosen option after a choice was made and executed. On the one hand this perspective is in line with Damasio's notion of core consciousness (Damasio, 1999), which is based on the feeling of emotions and how these emotions are associated to a situation or object. This approach fully integrates emotions and reflection. On the other hand this perspective adopts the idea of multiple unconscious states and processes which occur in parallel and compete to become part of consciousness; see, for example, Dennett's multiple draft model (Dennett, 1991), and Baars' Global Workspace Theory (Baars, 1997). The Global Workspace Theory was developed to describe how a single flow of conscious experience is able to result from a large multiplicity of parallel (unconscious) processes. The general idea is that a winner-takes-it-all competition takes place to determine which of these processes will get dominance and will be included in the single flow of consciousness.

6.2.5 The Hebbian perspective on learning

Up until now, learning or adaptation of behavior over time was not yet discussed. In Hebb (1949), a principle was put forward describing how the strength of a connection between two states is adapted over time based on simultaneous activation of the two states ('neurons that fire together, wire together'). The principle recently gained enhanced interest and this has resulted in more extensive empirical support (Bi and Poo, 2001) and more advanced mathematical formulations (Gerstner and Kistler, 2002). This quite simple principle turns out to be very useful in practice to explain or computationally model learning processes, and it will be used in the conceptual and computational model proposed here. The principle can be applied to the connections from sensory representations of stimuli to preparation states, and to the connections from preparation states to the associated (predicted) feeling states. Given the mechanisms of internal simulation and valuing described earlier, by adapting such connections the activations of specific behavior options can change over time.

6.3 Conceptual model for the influence of emotions and social context in learning

The analyses made in this paper assume a learning process where the learner encounters multiple items or situations over time for which decisions for an appropriate approach or response have to be learned. Such learning processes are quite general; they occur in diverse contexts, varying, for example, from learning to address mathematics or physics problems by choosing effective approaches, to learning to undertake appropriate actions in the context of developing a healthy lifestyle. The contributed analyses address how emotions and social interactions affect this type of learning process. More specifically, learning processes are considered in which, for a specific context, a learner learns to choose between certain options (for actions or behaviors). In accordance with what was discussed in Section 6.2, affective states play an important role in processes such as:

- valuing different options before choosing one of them;
- experiencing a level of satisfaction when a chosen option leads to a state in accordance with the learner's goals;
6.3.3  Agent-based support for behavior change

- experiencing a level of prior and retrospective awareness of behavioral choices made (reflection);
- feeling adequate levels of self-confidence and motivation.

6.3.1  A conceptual model

In this section the conceptual model is used as a basis for conceptual analysis of the role of emotion and social influence in learning; see Figure 6.1 for an overview.

6.3.2  Sensory representations and preparation states

For the model a sensed item is indicated by a number of stimuli $s_i$. Note that these $s_i$ may refer to multiple aspects and elements in reality, such as the elements of a mathematical problem description, or the different aspects of a context of a person trying to adopt a healthy lifestyle. As a first step in the process, via the sensor states for $s_i$ the learner generates internal sensory representations for the stimuli $s_i$. Such internal representations have associations (of different strengths) to preparation states for a number of alternative options $b_k$ to address the item, on which a decision has to be learned. In this decision making process two further elements play an important role: the feeling state associated to the option $b_k$, and the (reflective) awareness state for the option $b_k$.

6.3.3  Associated feeling states

Before performing an action, feeling states for the options $b_k$ are affected by predictive as-if body loops (cf. Damasio 1994, 1999)) via the sensory representation states for $b_k$. This corresponds to the notion of internal simulation that results in a degree of prior awareness regarding a prepared

Figure 6.1: A conceptual model for emotions and social influence in learning
action and its expected outcome. The as-if body loop predicts this evaluation value prior to
evolution of an action and by this valuing provides an important impact on the decision to be
made. The valuation depends on the strength of the feeling associated to the option, which is
represented by the strength of the connection from the preparation state for the option \( b_k \) to the
sensory representation for \( b_k \). After performing an action for \( b_k \), the feeling state associated to
\( b_k \) is affected both through an external execution loop, as (indirectly) through the effector state
for \( b_k \). This effector state represents the execution of option \( b_k \), and influences the sensor state
for \( b_k \) and the sensory representation state for \( b_k \). Through these sensory states the action result
is observed, which plays the evaluative role of retrospective awareness. The evaluation value is
determined by the activation level of the sensor state for \( b_k \) which depends on the connection
strength from the effector state for \( b_k \) to the sensor state for \( b_k \). High connection strength
represents success of the chosen option and low strength represents failure (in satisfying the
learner). In short, the feeling state combines the prior awareness of the predicted effect and the
retrospective awareness of the sensed actual effect, thus complying with the findings in Moore
and Haggard (2008); Voss et al. (2010), as addressed in Section 6.2.

6.3.4 Hebbian learning

In the model the connection strengths of two types of connections are adapted using Hebbian
learning: from sensory representation state for \( s_i \) to preparation state for \( b_k \) (adapting direct
associations), and from preparation state for \( b_k \) to sensory representation state for \( b_k \) (adapting
the associations to feelings). As Hebbian learning depends on the activation levels of the con-
nected states, a positive evaluation of a performed action has a positive effect on the learning,
as in this case it results in a higher activation level of the sensory representation state for \( b_k \).
When the connection strength from the preparation state for \( b_k \) to the sensory representation
state for \( b_k \) increases by the Hebbian learning mechanism, this implies that for a next occasion
when the item is encountered the valuing of that particular option (before a decision is made)
will be higher. In addition, through the sensory representation state for \( b_k \), and the feeling state
for \( b_k \), the preparation state for \( b_k \) obtains a higher activation value as well, which, again via
Hebbian learning, increases the connection strength from the sensory representation state for \( s_i \)
to the preparation state for \( b_k \). This way, both the direct association between the represented
stimulus and preparation, and the association between preparation and feeling used for valuing
are adapted during the learning process.

6.3.5 Reflection

The activation of an awareness state for a behavior option \( b_k \) results in a degree of awareness for
this option (prior or retrospective for the behavior), as a way of modeling reflection. Activation
of an awareness state not only depends on the sensory representations for the \( s_i \) but also on the
feeling state associated to the option \( b_k \) and the active goals \( g \) the person has. The connection
between the feeling and awareness states models the reflective influence of the feeling state for
\( b_k \). This way the resulting awareness is grounded in feeling an emotion, in line with Dama-
sio (1999). Moreover, the awareness states for different options are in competition with each
other due to mutual inhibiting connections, following the perspectives of Baars (1997); Dennett
(1991). Purely reactive and other non-conscious responses to stimuli bypass the awareness states
and are modeled by the direct links from goals and sensory representations to preparations. The
awareness state thus serves a similar function as the global workspace in Global Workspace Theory, where sensory representations can be passed on to the global workspace and a competition determines which content then becomes conscious; cf. Baars and Franklin (2009).

### 6.3.6 Impact of social interaction

The effects of social interaction come into play when the learner senses the expression of options by others: some of the stimuli $s_i$ sensed by the learner are actually stimuli $s_{B,b_k}$ that represent the effector states for option $b_k$ of another agent $B$; see Figure 6.2. This specific type of stimulus indicates the extent to which option $b_k$ and their associated emotions are expressed by agent $B$. For agents $B$ in contact with the considered learner, these emotions are assumed to be sensed and represented by the learner using sensor states and representation states for $s_{B,b_k}$.

As a form of mirroring a representation state for agent $B$’s expressed option $b_k$ has impact on the agent’s own preparation state for the same option $b_k$ through the connection between the representation state and preparation state; see also Section 6.2. Via this connection the preparation state for $b_k$ gets the functionality of a mirror neuron: it is not only activated when the learner him- or herself prepares for the action, but also when another agent performing the action is observed. As a second effect, in the model the sensory representation state for agent $B$’s expression of the option $b_k$ also affects the awareness state of the option $b_k$. This models a direct way in which interaction with another agent about an option stimulates to become (more) aware of the option. Thus the effect of social interaction on reflection is modeled in two ways: through the latter direct association, and through the mirroring process via the as-if body loop using the preparation, sensory representation and feeling states for $b_k$. 

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Figure 6.2: Interaction between two learners
6.4 The Computational Model

Modeling causal relations discussed in neurological literature in the manner as presented in previous sections and Figure 6.1 does not take large numbers of specific neurons into consideration but uses more abstract mental states. By this abstraction neurological knowledge is lifted to a mental (cognitive/affective) modeling level. The type of learner model that results shows some technical elements also used in the neural modeling area. More specifically, it takes states as having a certain activation level in the interval \([0, 1]\), which, for example, makes reciprocal cognitive/affective loops possible. The modeling approach exploits techniques used in continuous-time recurrent neural networks, in line with what is proposed in Beer (1995). In particular, for a state causally affected by multiple other states, to obtain their combined impact, first the activation levels \(V_i\) for these incoming states are weighted by the respective connection strengths \(\omega_i\) thus obtaining \(X_i = \omega_i V_i\). Then these values \(X_i\) are combined using a combination function \(f(X_1, \ldots, X_n)\). Note that such combination functions also play a role in the area of modeling imperfect reasoning, for example, based on fuzzy information. In this case, a combination function based on a logistic threshold function has been chosen:

\[
f (X_1, \ldots, X_n) = \text{th}(\sigma, \tau, X_1 + \cdots + X_n)
\]  

(6.1)

with

\[
\text{th}(\sigma, \tau, X) = \frac{1}{1 + e^{-\sigma(\tau - X)}} - \frac{1}{1 + e^{\sigma \tau}}(1 + e^{-\sigma \tau})
\]  

(6.2)

For larger values of \(\sigma \tau\) (e.g., \(> 20\)) this is approximated by \(\text{th}(\sigma, \tau, X) = \frac{1}{1 + e^{-\sigma (\tau - X)}}\). Table 6.1 shows which impacts contribute to the value of the different states at any time point \(t\) (as can also be observed from Figure 9.1).

6.4.1 Dynamics of activation levels of states

Using the above combination function, dynamics of the activation levels of states are described by:

\[
V(t + \Delta t) = V(t) + \gamma [\text{th}(\sigma, \tau, <\text{combined_impact_value}>)] - V(t)) \cdot \Delta t
\]  

(6.3)

Here \(<\text{combined_impact_value}>\) is the combined impact as specified in the last column of Table 6.1. Note that \(\omega(X, X) = 0\) is assumed as a convenient notation. Parameter \(\gamma\) is an update speed parameter.

6.4.2 Dynamics of connections based on Hebbian learning

The connection strengths from \(\text{srs}(s_i)\) to \(\text{prep}(b_k)\) and from \(\text{prep}(b_k)\) to \(\text{srs}(b_k)\) are adapted using the following Hebbian learning rule, taking into account a maximal connection strength 1, a learning rate \(\eta\), and an extinction rate \(\zeta\) (usually taken small):

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Table 6.1: Overview of the impacts on states

<table>
<thead>
<tr>
<th>state notation</th>
<th>state notation</th>
<th>impacts on state</th>
<th>combined impact value ($\Sigma$ value - connection)</th>
</tr>
</thead>
<tbody>
<tr>
<td>stimulus s</td>
<td>$stim(s_i)$</td>
<td>-</td>
<td>$stim(s_i) \cdot \omega(stim(s_i), ss(s_i))$</td>
</tr>
<tr>
<td>sensor state for s</td>
<td>$ss(s_i)$</td>
<td>$stim(s_i)$</td>
<td>$stim(s_i) \cdot \omega(stim(s_i), ss(s_i))$</td>
</tr>
<tr>
<td>sensory representation for s</td>
<td>$srs(s_i)$</td>
<td>$ss(s_i), goal(g_k), srs(s_i)$</td>
<td>$ss(s_i) \cdot \omega(ss(s_i), srs(s_i)) + \Sigma_i \cdot \omega(goal(g_k), srs(s_i))$ + $\Sigma_j \cdot \omega(srs(s_i), srs(s_i))$</td>
</tr>
<tr>
<td>workspace state for b</td>
<td>$ws(b_h)$</td>
<td>$srs(s_i), goal(g_j), feel(b_h), ws(b_m)$</td>
<td>$\Sigma_i \cdot \omega(srs(s_i), ws(b_h)) + \Sigma_j \cdot \omega(goal(g_j), ws(b_h)) + feel(b_h) \cdot \omega(feel(b_h), ws(b_h))$ + $\Sigma_m \cdot \omega(ws(b_m), ws(b_h))$</td>
</tr>
<tr>
<td>goal for g</td>
<td>$goal(g_k)$</td>
<td>$ss(s_i), ws(b_h), feel(b_h), goal(g_j)$</td>
<td>$ss(s_i) \cdot \omega(ss(s_i), goal(g_k)) + ws(b_h) \cdot \omega(ws(b_h), goal(g_j)) + feel(b_h) \cdot \omega(feel(b_h), goal(g_j)) + \Sigma_i \cdot \omega(goal(g_j), goal(g_j))$</td>
</tr>
<tr>
<td>sensor state for b</td>
<td>$ss(b_k)$</td>
<td>$es(b_k)$</td>
<td>$es(b_k) \cdot \omega(es(b_k), ss(b_k))$</td>
</tr>
<tr>
<td>sensory representation for b</td>
<td>$srs(b_k)$</td>
<td>$ss(b_k), prep(b_k)$</td>
<td>$ss(b_k) \cdot \omega(ss(b_k), srs(b_k)) + \Sigma_i \cdot \omega(prep(b_k), srs(b_k))$</td>
</tr>
<tr>
<td>feeling for b</td>
<td>$feel(b_k)$</td>
<td>$srs(b_k)$</td>
<td>$srs(b_k) \cdot \omega(srs(b_k), srs(b_k))$</td>
</tr>
<tr>
<td>preparation state for b</td>
<td>$prep(b_k)$</td>
<td>$srs(b_k), goal(g_j), feel(b_h), prep(b_m)$</td>
<td>$\Sigma_i \cdot \omega(srs(b_k), prep(b_k)) + ws(b_h) \cdot \omega(ws(b_h), prep(b_k)) + \Sigma_j \cdot \omega(goal(g_j), prep(b_k)) + feel(b_h) \cdot \omega(feel(b_h), prep(b_k)) + \Sigma_m \cdot \omega(prep(b_m), prep(b_k))$</td>
</tr>
<tr>
<td>effector state for b</td>
<td>$es(b_k)$</td>
<td>$ws(b_k), prep(b_k)$</td>
<td>$ws(b_k) \cdot \omega(ws(b_k), es(b_k)) + prep(b_k) \cdot \omega(prep(b_k), es(b_k))$</td>
</tr>
</tbody>
</table>
A simulation with two learners

The computational model was implemented as an agent-based model and variety of simulation experiments have been performed. Some observations on the dynamics of these simulations will be offered in this section. One scenario is selected and described in detail as an example of the workings of the model. This scenario involves two different agents in an environment in which they are presented with a repeated stimulus to which they have to learn the appropriate response. To what extent the response behavior is appropriate or not is determined by feedback from the environment (e.g., a tutor). An agent will evaluate its action with this feedback, which is modeled by the weights that are given to the evaluative connection \( \omega(es(b_k), ss(b_k)) \). In the simulation the model incorporates one environmental stimulus, a ‘cue’, where s1 has activation level either 1 or 0. Stimulus \( s_1 \) has a direct link to sensor state \( ss(s_1) \). This \( ss(s_1) \) activates the relevant sensory representation \( srs(b_1) \) and affects one or multiple goals. The goals, in turn, influence one or multiple states \( srs(s_i), prep(b_k) \). For reasons of clarity and simplicity, it is assumed that there exist two goals, \( goal(g_1) \) and \( goal(g_2) \), which correspond with two possible options the learner can execute in reaction to the stimulus. All other states (with the exception of \( srs(s_i) \) that corresponds to \( s_1 \)) have instances that correspond to these two options, for example, there are two feeling states: \( feel(b_1) \) that corresponds with a (positive) feeling for option 1, and \( feel(b_2) \) that corresponds with a (positive) feeling for option 2.

The discussed model focuses on the effects of collaborative learning in relation to the feelings associated with the options for responses. Several explorative simulation experiments were conducted to establish that the model is able to capture the dynamics between two learners with different reactions to a stimulus (e.g., with different goals or feelings associated with the stimulus). In these simulations, initially learner A is strongly inclined to respond to the stimulus with behavior option 1, while learner B is somewhat inclined to respond with option 2. Option 1 is the highest externally valued option (the ‘good’ option).

\[
\omega(\text{prep}(b_k), \text{srs}(b_k))(t + \Delta t) = \omega(\text{prep}(b_k), \text{srs}(b_k))(t) + [\eta \text{ prep}(b_k) \cdot \text{srs}(b_k)(t) - (1 - \omega(\text{prep}(b_k), \text{srs}(b_k))(t)) - \zeta \omega(\text{prep}(b_k), \text{srs}(b_k))(t)] \Delta t \tag{6.4}
\]

\[
\omega(\text{srs}(s_i), \text{prep}(b_k))(t + \Delta t) = \omega(\text{srs}(s_i), \text{prep}(b_k))(t) + [\eta \text{ srs}(s_i) \cdot \text{prep}(b_k)(t) - (1 - \omega(\text{srs}(s_i), \text{prep}(b_k))(t)) - \zeta \omega(\text{srs}(s_i), \text{prep}(b_k))(t)] \Delta t \tag{6.5}
\]

A similar Hebbian learning rule can be found in Gerstner and Kistler (2002, p. 406). By the factor \( 1 - \omega(\text{prep}(b_k), \text{srs}(b_k))(t) \) (resp. \( 1 - \omega(\text{srs}(s_i), \text{prep}(b_k))(t) \)) the learning rule keeps the connection strengths bounded by 1 (which could be replaced by any other positive number); Hebbian learning without such a bound usually provides instability. When the extinction rate is relatively low, the upward changes during learning are proportional to the activation levels of both connected states and maximal learning takes place when both are 1. Whenever one of these activation levels is 0 (or close to 0) extinction takes over, and the connection strength slowly decreases (unlearning).
When the agents are learning together, they are able to observe each other’s expressed effector states $es(b_k)$. These observations affect a corresponding $srs(s_i)$ with $s_i = S_{B,b_k}$ for learner B observed by learner A, similar to other stimuli. In turn these representation states reinforce or inhibit the preparations triggered by the stimulus. The main dynamics that can be derived from these explorative simulation experiments are:

1. When learning separately, agents A and B continue to respond with their preferred option. Learner A’s $feel(b_1)$ increases caused by feedback from the environment, which leads to higher values for $es(b_1)$. Learner B however, will receive negative feedback on his/her preferred option 2, which causes his/her $es(b_1)$ levels to remain lower than those of A.

2. When learning together, due to the interaction with A, learner B will start to associate positive feelings with option 1. Learner B thus starts to perform suitable behavior $es(b_1)$, stimulated by the activations levels of $es(b_1)$ of A. The stimulus continues to trigger $prep(b_2)$ in learner B, though they are inhibited by his activations levels for $prep(b_1)$.

3. When learning together, even a learner who already tends to perform the right behavior can benefit from social interactions. Learner A can improve because observing $es(b_1)$ of learner B can contribute to his/her $prep(b_1)$ and $feel(b_2)$.

These results show how learning with a partner can be beneficial to someone who is not able to learn the appropriate response on his or her own. A more specific scenario will investigate these dynamics in detail. The scenario is composed of three phases: phase 1 (time point 1 to 150, first two stimuli) in which two persons learn separately, phase 2 (time point 150 to 300, stimuli 3-5) in which they learn together, and phase 3 (time point 300 to 500, last two stimuli) in which they are separated again. One could imagine this kind of learning being the case when a tutor would observe that B is not learning the appropriate response on his own, and accordingly decides that B could benefit from interaction with learner A by putting them together for a while.

Tables 6.2 and 6.3 show the connection weights and parameter settings used in this simulation. As is shown by the table, in this scenario a similar setting is used as described above, in which A has a strong predisposition towards option 1, and B a moderate predisposition towards option 2 (see e.g. the settings for $\omega(ss(s_i), goal(g_{gg}))$, and for $\omega(srs(s_i), prep(b_k))$. Again, option 1 is the highest externally valued option. It is also assumed that learner B is fast to learn feelings that are associated with options, as displayed by the learning rate $\zeta$ in Table 6.3. As this simulation serves to demonstrate the dynamics of the learning process without unlearning, the extinction rate is kept at 0.

Figure 6.3 shows the results of this simulation. During phase 1 (the green vertical lines delimit the phases), the occurrence of the stimulus affects $ss(s_1)$, which leads to a high activation level of $goal(g_1)$ for learner A, and somewhat increased activation for both $goal(g_1)$ and $goal(g_2)$ for learner B. It can be seen that although learner B’s $goal(g_1)$, $ws(b_1)$, and $prep(b_1)$ states are somewhat activated, this will not result in any action execution ($es(b_1)$ stays low). The activation levels are too low and do not receive any stimulation from a positive feeling associated with the option. Agent A on the other hand does react to the stimulus by performing behavior 1. Notice how $feel(b_1)$ steadily increases.

In phase 2 the two learners are joined and thus the $es(b_1)$ become observable and serve as additional input for the learners $ss(s_i)$. Because of this, the $goal(g_1)$, $ws(b_1)$ and $prep(b_1)$ states for agent B become more strongly activated. This in turn strengthens $\omega(srs(s_1), prep(b_1))$, as can be seen in the lower left of the figure. During this phase, both learners develop higher levels for $feel(b_1)$, which is reinforced by the increasing value of $\omega(prep(b_1), srs(b_1))$ for prior awareness by internal simulation. The feelings have significant reflective effects on the goals, workspace states, and preparations of the learners and push these activation values to higher levels. At the
Figure 6.3: Simulation results for learning in three phases (time at the x-axis, activation value at the y-axis)
### Table 6.2

| Weight connection values used in the simulation scenario (double entries are used to indicate personalized settings and are of the form A,B) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| from | to | stim | s(s) | srs(s) | goal | ws | prep | ss(b) | srs(b) | feel | es |
| 1 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 |
| 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |

### Table 6.3

| Parameter settings used in the simulation scenario (personalized settings are of the form A,B) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| learning rate | ⌧ | 0.5 |
| extinction rate | ⌡ | 0.4 |
| update speed | ⌘ | 0.6 |
| ⌘ | ⌝ | 0.8 |
| ⌝ | ⌠ | 1.0 |

---

*Agent-based support for behavior change*
end of phase 2, both learner A and B have high connection values for $\omega(srs(s_1), prep(b_1))$ and $\omega(prep(b_1), srs(s_1))$.\(^1\)

In phase 3, when the learners are separated again, these learned connections ensure that when the stimulus occurs, $prep(b_1)$ is activated and is associated with strongly positive feelings. The activation value of $es(b_1)$ for learner A is higher than it was in phase 1. Moreover, learner B now immediately responds with a high activation of $es(b_1)$, which shows that the agent has learned to respond correctly and is able to apply this on its own.

Although this section mainly focuses on one particular scenario, the model allows for the implementation of a very broad range of scenarios that include, for example, large groups of learners, different stimuli, or connection and parameter settings that reflect the different personalities and characteristics of heterogeneous learners.

### 6.6 More specific characteristics of learners and learning processes

In this section, a conceptual analysis of the model is given by examining how the model is able to account for different learning phenomena and learner types as identified by literature. Some guidelines will be provided on how the model can be used to describe and simulate these learning processes.

#### 6.6.1 Different types of learners

In their 1988 paper, Silverman and Felder identified a variety of learning styles based on the notion that learning is a two-step process involving (i) the reception and (ii) the processing of information (Felder and Silverman, 1988). One of the dimensions of learning styles addressed in their work concerns active and reflective learning styles; see also the Felder Index of Learning Styles (Felder and Silverman, 1988; Felder and Spurlin, 2005). This dimension originates from a learning style model developed by Kolb (Kolb, 1984). Recently, the Kolb model has seen some major revisions (Kolb and Kolb, 2005). It includes a new 9 learning style typology, sharing the same underlying assumption addressed in (Felder and Silverman, 1988) that learning involves (i) a grasping experience (i.e., reception of information), and (ii) a transforming experience (i.e., processing of information). A further distinction is made: grasping type experiences are defined by the dimension of experiencing (feeling) and conceptualizing (thinking), while transforming experiences are defined by action and reflection.

These different individual abilities for how to grasp and transform information can be combined to result in a learning space with different learning types. Individuals’ learning style positions them in this space according to the two dimensions. Each dimension is determined by a combination of individual characteristics and environmental factors. Note that individuals can have abilities to a certain degree, or have abilities that lie on both ends of one dimension (for example, being able to balance feeling and thinking). These dimensions can also be regarded as different parts of a learning cycle, showing a learner’s preference for one part of the cycle. A simplified overview of this combined learning space can be seen in Figure 6.4.

Although these learning style dimensions are continuous and should not be regarded as either/or categories, the extremes are very effective to describe behavioral patterns. The poles of the dimensions describe persons with a strong preference or ability for that type of grasping or processing. In Subsection 6.6.2, these poles will be used to show how the corresponding learning

\(^1\)Notice that because of the simultaneous activation of $srs(s_1)$ and $prep(b_2)$, learner B also strengthens $\omega(srs(s_1), prep(b_2))$. However, this never leads to an activation of $es(b_2)$ because of the lack of positive valuation through retrospective awareness for this option.
6.6.2 Learning dimensions in the model

First, learners who have feeling as dominant grasping learning ability rank high on the experiencing dimension and act on gut feelings rather than on logical analysis. Intuitive experience is often more important to them than processing the concrete representations. In the model, this relates to strong connections to and from the feeling states (see Figure 6.5, left-hand side). Information that is received will have a strong influence on (associated) feelings, which is represented by strong connections from the sensory representation (of body states b) states to the feeling states. Feelers are also more easily aware of intuitive emotions, represented by strong connections between the feeling states and the awareness states. Their emotions have a grounded influence on which goals and behavior options get high activation levels, shown in strong connections between the feeling states and the goal and preparation states.

Second, learners with strong thinking abilities prefer to solve problems and make decisions based on finding solutions to questions. They grasp information by focusing on the symbolic complexity of a problem and prefer abstract conceptualizations. In the model this corresponds to enhanced awareness represented by the awareness states where conscious content is shaped (see Figure 6.5, right-hand side). That is, the sensory representation (of s) states, where internal representations of the stimuli and context are developed, have a strong connection to the awareness states, which in turn strongly influence the preparation states. Furthermore, the direct connections from the awareness states to the effector states are strong, enabling the thinker to let his or her actions be informed mostly by conceptual and symbolic representations, with a smaller part to play for the associated feelings.

Third, learners with dominant reflective processing abilities have good capacities to internally reflect on the received information. They often need time to think things through in order to process the perceptual complexity of stimuli into abstract concepts. Reflectors are good in generating ideas and come up with different approaches, but they are careful to translate them into actions. In the model, these learning abilities can be represented by initially having an stronger internal loop (which by learning is strengthened even further) from preparation to sensory representation (of b) states through which the person is able to perform mental simulations and predictions of
action consequences (see Figure 6.6, left-hand side). This reflector’s chain of thought based on internal simulation strongly influences the action options that become active.

Last, learners with a preference for acting in order to process information are more comfortable with, or better at, active experimentations. Testing and trying provides them with insights and they are able to learn from hands-on experience. For active learners, the connections from the preparation states to effector states, from the effector states to the sensor states (of b), and from these sensor states to the corresponding sensory representation states are strong (see Figure 6.6, right-hand side). Through their evaluations the actions inform further information processing. Furthermore, since actors often feel less comfortable with reflection and prefer to start exploring the behavioral aspects of a problem, in the model the connections between the sensory representations and the preparations states are strong, bypassing the awareness states.

The model thus provides a framework for analysis of the factors that determine a learner’s experience and learning type. It can also be used as a tool to reason about the consequences of learning a different learning style (for example: a reflector who is being exposed to an educational setting in which active experimentation is required), or about the consequences of interactions between learners with different learning styles. For example, it appears that active learners prefer to work in groups, while reflective learners prefer to work alone or with a single familiar partner (Felder and Spurlin, 2005). Furthermore, teams with members with diverse learning styles among the members perform significantly better than teams with all members with the same learning style (Wolfe, 1977), and teams made up of members whose learning styles were balanced among the four learning modes performed better on a critical thinking task than teams whose members had specialized learning styles (Kayes, 2002). The model introduced in this paper can be used to create and analyze these and other scenarios of groups of learners with different capabilities. This will be discussed in Section 6.7 based on agent-based simulations.
6.6.3 Guidelines for enabling conditions

The conceptual model described in Section 6.3 has as its purpose to provide a basis for analysis of social interactions in learning and can also be used to design technology-enhanced learning environments in which emotions and their contagion are an important driving force. In such environments, enabling this contagion and monitoring it are key elements. In order to monitor and analyse whether certain emotions occur and to what extent they are transferred between different persons in a learning process, a number of technical devices can be used. In the area of affective computing usually the focus is on individual emotions and methods to measure or estimate them, for example, by sensing and interpreting face expressions, voice expressions, heart rate, or skin conductivity. Such methods can be used as far as they are relatively unobtrusive. However, the focus of the presented approach also covers the role of social interaction and the way in which emotions are transferred from one learner to another learner, or between a tutor or (virtual) coach and a learner. Therefore, more specifically, emotion transfer is to be enabled by the environment, and monitoring of this transfer should be incorporated in it. This means that different forms of interactions need to be analysed with respect to their emotional content, for example, by recognition of figurative language and linguistic analysis, or, in case of direct visual interactions or the use of video connections, by analysis of face expressions.

Not all exchanged emotions are relevant, but particularly those associated to specific types of mental states. Relevant examples of such mental states are:

- emotions related to prior awareness and valuation of behavior options;
- emotions related to retrospective awareness and valuation of chosen behavior (satisfaction);
- emotions related to goals;
- emotions related to attitude aspects;

These aspects of emotions have an amplifying effect on learning. Table 6.4 provides an overview of examples of such impacts. One important impact is that due to emotion contagion the related mental states are strengthened, and because of that the associations between feeling and option are strengthened. Moreover, other relevant types of impact are experiencing and showing empathic understanding for such a state, and (through interaction) making aware the experiencing of the emotion felt, which is a contribution to reflection. To be able to make use of the impacts of emotions in technology-enhanced learning, conditions can be identified that enable these effects, and can monitor the transfer of the emotions. Table 6.5 shows an overview of examples of such aspects. Note that part of this is the organisation of the social network of learners, i.e. how they are connected.

6.7 Simulation experiments to demonstrate learning styles

This section describes simulation experiments that were performed in order to demonstrate how the computational model can be used to analyse the dynamics of the modeled learning processes in a more detailed manner. For the experiments, again a scenario is considered with two agents: Alice and Bob. Alice and Bob both try to learn an appropriate response to a stimulus (for example, a proper approach to a mathematical problem). For the sake of simplicity, here it is assumed that there is one appropriate response to the stimulus, namely behavior $b_1$ (with expression denoted as $es(b_1)$), that Alice and Bob are learning. The activation level of this expressed behavior $b_1$ is considered an indication of how well this behavior has been learnt, seen from an externally observable perspective. From an internal perspective, the strengths of the connections from
### Table 6.4: Emotion impact: Strengthening a mental state M, reflection on M, and empathy for M

<table>
<thead>
<tr>
<th>for mental state M</th>
<th>type of interaction</th>
<th>strengthening mental state M</th>
<th>empathic understanding for mental state M</th>
<th>strengthening reflection on M</th>
</tr>
</thead>
<tbody>
<tr>
<td>- prior valuation of behavior options (intentions) -retrospective valuation of chosen behavior (satisfaction) -goals (long term, short term) -attitude aspects (e.g., beliefs)</td>
<td>emotion impact from learning to learner</td>
<td>display of emotion for M: - nonverbal (face expressions, emoticons) - verbal (emotion-loaded language in speech and written form)</td>
<td>nonverbal and verbal display of the other person’s emotion and verbal acknowledgement of recognition of the other person’s emotion in relation to M (face expressions, emotionloaded language, emoticons)</td>
<td>verbal interaction to make the learner aware of M via the experienced feeling (talking, writing on M)</td>
</tr>
<tr>
<td>emotion impact from virtual coach to learner</td>
<td>virtual display of emotion in relation to M: -nonverbal (virtual face expressions, emoticons) -verbal (virtual emotion-loaded speech and text messages)</td>
<td>virtual nonverbal and verbal display of the learner’s emotion and virtual verbal acknowledgement of recognition of the learner’s emotion in relation to M (virtual face expressions, emoticons, virtual speech and virtual text messages about the learner’s emotion in relation M)</td>
<td>virtual verbal interaction on M (virtual speech and virtual text messages about M)</td>
<td></td>
</tr>
</tbody>
</table>

### Table 6.5: Enabling and monitoring different types of emotion impact

<table>
<thead>
<tr>
<th>emotion impact</th>
<th>verbal emotion impact examples</th>
<th>verbal emotion impact enabling monitoring</th>
<th>nonverbal emotion impact examples</th>
<th>nonverbal emotion impact enabling monitoring</th>
<th>for mental state M</th>
</tr>
</thead>
<tbody>
<tr>
<td>from learner to learner</td>
<td>emotion in audio connection</td>
<td>acoustic and linguistic speech analysis</td>
<td>face expressions</td>
<td>video connection</td>
<td>recognition of faces</td>
</tr>
<tr>
<td></td>
<td>emotion in textual connection</td>
<td>linguistic text analysis</td>
<td>graphical indications: mood scores, emoticons</td>
<td>connection</td>
<td>interpretation of graphical objects</td>
</tr>
<tr>
<td>from virtual coach to learner</td>
<td>emotion in virtual speech</td>
<td>synthesizing from generation of speech with emotions</td>
<td>virtual face expressions</td>
<td>connection</td>
<td>of generation of graphical objects</td>
</tr>
<tr>
<td></td>
<td>emotion in virtual text</td>
<td>automated generation of text with emotions</td>
<td>graphical indications: mood scores, emoticons</td>
<td>connection</td>
<td>from generation of graphical objects</td>
</tr>
</tbody>
</table>

Simulation experiments to demonstrate learning styles.
stimuli representation for $s_1$ to preparation states for $b_1$ and from preparation to feeling states for $b_1$ are considered indications of how well the behavior has been learnt. In relation to these indications, the learning speed relates to the steepness of the graphs of the activation levels of these states and connection strengths over time. The simulations provide a closer look at the dynamics of learners with different feeling and thinking capabilities. The threshold and steepness settings used for these simulations can be found in Table 6.6; the parameter settings of $\eta$, $\zeta$, and $\gamma$ are the same as described in Table 6.3 ($\eta = 0.2$, $\zeta = 0$, $\gamma = 0.5$). Note that the extinction rate is chosen 0 in order to clearly demonstrate the learning process without unlearning or forgetting.

### Figure 6.7: Non-social learning of Alice (low feeling capabilities) and Bob (high feeling capabilities)

#### 6.7.1 Effects of feeling capabilities on learning

First the case is considered in which Alice and Bob have different learning styles with respect to feeling. For Bob feeling is a dominant learning style; in the model his feeling states are strongly connected to his sensory representation states and his awareness, goals and preparations states ($\omega = 0.9$, see also Section 6.3.2, Figure 6.5). In contrast, Alice does not include her feelings much in the learning process, which is modeled by very weak connections to and from her feeling states ($\omega = 0.1$). An overview of the connection values can be found in Table 6.7. Note that the inhibitory and excitatory relations of competing states are 0, as for these scenarios only one proper behavior option is considered with no competing goals or awareness states.

As literature indicates that a good performing learner has capabilities across all dimensions (e.g., Kayes (2002)), it is expected that Bob would learn faster and better than Alice. In Figure 6.7 all state activations can be seen for Alice and Bob. This simulation shows how Alice and Bob
Table 6.6: Threshold and steepness values used in the simulation scenarios

<table>
<thead>
<tr>
<th></th>
<th>ss(s)</th>
<th>srs(s)</th>
<th>goal</th>
<th>ws</th>
<th>prep</th>
<th>ss(b)</th>
<th>srs(b)</th>
<th>feel</th>
<th>es</th>
</tr>
</thead>
<tbody>
<tr>
<td>threshold τ</td>
<td>0.5</td>
<td>0.4</td>
<td>0.6</td>
<td>0.6</td>
<td>1</td>
<td>0.5</td>
<td>0.4</td>
<td>0.4</td>
<td>0.4</td>
</tr>
<tr>
<td>steepness σ</td>
<td>6</td>
<td>4</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>4</td>
<td>2</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 6.7: Connection weight values used for a learner with feeling capabilities. Double entries are used to indicate personalized settings and are of the form $<A, B>$

<table>
<thead>
<tr>
<th>from</th>
<th>to</th>
<th>stim</th>
<th>ss(s)</th>
<th>srs(s)</th>
<th>goal</th>
<th>ws</th>
<th>prep</th>
<th>ss(b)</th>
<th>srs(b)</th>
<th>feel</th>
<th>es</th>
</tr>
</thead>
<tbody>
<tr>
<td>stim</td>
<td>1</td>
<td>-</td>
<td>1 (stim)</td>
<td>1 (stim)</td>
<td>2 (es other)</td>
<td>1</td>
<td>0</td>
<td>0.8</td>
<td>0.2</td>
<td>0.5</td>
<td>0</td>
</tr>
<tr>
<td>ss(s)</td>
<td>I</td>
<td>1 (stim)</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0.6</td>
<td>0.6</td>
<td>0.5</td>
<td>0</td>
<td>0.1</td>
</tr>
<tr>
<td>srs(s)</td>
<td>I</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.1</td>
</tr>
<tr>
<td>goal</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.1</td>
</tr>
<tr>
<td>ss(b)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>srs(b)</td>
<td></td>
<td></td>
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<tr>
<td>feel</td>
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<tr>
<td>es</td>
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</tr>
</tbody>
</table>

- $<A, B>$: Indicates personalized settings.
perform when learning separately, which explains why there is no activation in the sensor input and representation states of another learner (ss(es₁1) and srs(s₁2)); see also Section 6.3.6. The fact that Bob has a dominant feeling strategy can clearly be deduced from the activity in the feeling state (feel(b₁)), which shows regular activity for Bob, but hardly any for Alice. Consequently, the goal, awareness and preparation activations are all significantly higher for Bob than they are for Alice. The same holds for the resulting effector state (es(b₁)) that represents the action and for its valuation states (ss(b₁) en srs(b₁)). Figure 6.7 also shows that the association between preparation and sensory representation states used for valuing (ω(prepa₁₁), srs(b₁)) reaches its optimal value of 1 quicker for Bob than for Alice. In sum, Bob will reach higher activation levels for the appropriate response and will learn the corresponding valuations quicker than Alice.

It is now examined how Alice and Bob influence each other’s learning process when learning together. Inspired by Wolfe’s work in which it was observed that teams with diverse learning styles among the members perform better than teams with all members with the same learning style (Wolfe, 1977), it was hypothesized that learning together will strengthen Alice’s learning as she is able to benefit from the feeling capabilities of Bob. Figure 6.8 shows the simulation results. The sensor and sensory representation state for another learner (ss(es₁₁), srs(s₁₂)) now show different activation levels for Alice and Bob: Alice receives a high activation level from the observed effector state from Bob, whereas Bob receives somewhat lower activation levels resulting from the lower effector state of Alice. Overall, even though Alice still has little to no feelings that are associated with the stimulus, she now has higher activation levels for her goal, awareness and preparation states, resulting from the incoming activation that is the result of observing.
Bob. Consequently, her effector states show higher activation levels when learning together than when learning separately: $es(b_1)$ has activation levels of 0.48 versus 0.59, respectively. Also, the learning association $\omega(prep(b_k), srs(b_k))$ is optimized faster than when learning alone. Bob maintains his high activation and learning levels.

### 6.7.2 Effects of thinking capabilities on learning

Another pair of simulations was performed to analyse the effects of different thinking capabilities. In this scenario, Bob’s dominant learning style is thinking, which is indicated by strong incoming and outgoing connections of the awareness state ($\omega = 0.9$). Alice on the other hand has trouble to grasp the symbolic or abstract conceptualizations of a problem. She has weak connections to and from her awareness state ($\omega = 0.1$).

Figure 6.9 shows the activation levels of Alice’s and Bob’s states when learning separately. The difference between Alice and Bob is striking: Bob reaches high activation levels for his states, while the low awareness state for $b1(as(b_1))$ of Alice do not contribute to any activation, resulting in very low activation for her effector state for $b1(es(b_1))$. When looking at the results from Hebbian learning (the three graphs at the bottom of Figure 6.9), it can be seen that the learning process for both the adaption to direct associations between sensory representations of stimuli $s_i$ and preparations for $b_k(\omega(srs(s_i), prep(b_k)))$ and the adaption of the connection from preparation to feeling $b_k(\omega(prep(b_k), srs(b_k)))$ has much slower progress for Alice than for Bob. It is clear from this simulation that the awareness state plays a crucial role in the learning process.
6.7.3 Agent-based support for behavior change

Figure 6.10: Social learning of Alice (low thinking capabilities) together with Bob (high thinking capabilities)

When learning together, a similar pattern to the feeling simulations can be observed. From Figure 6.10 it is clear that although Alice's awareness state still has low activations, her other states are far more active, resulting in a much higher effector state ($es(b_1)$), increased from 0.29 to 0.44. The Hebbian learning of the connections is faster. In short, learning together involving observing Bob's behavior, helps Alice to be a better learner.

6.7.3 Effects of learning together on individual learning

In more detailed simulation experiments it has been investigated how beneficial it is for a reasonably good thinking style learner to interact with another thinking style learner. The social interaction effect differs for different strengths of thinking style learner A (let's call her Alice again) upon learner B (Bob) with a thinking style component of 0.7. In Figure 6.11 it is shown that when the learning process is long enough, the final effect on the behavior of Bob is limited. The base line for Bob for learning his behavior without social interaction is 0.66, and by social interaction this can be increased to 0.76, depending of the strength of Alice as a thinking style learner. So in this respect the social interaction provides a modest benefit for Bob, even when Alice performs worse than he does.

It has also been analysed how fast the learning proceeds with different strengths of a co-learner. The results are shown in Figure 6.12. The figure shows the time duration that is elapsed before reaching connection strength 0.8 for the two connections that are adapted by Hebbian learning. The graph in Figure 6.12a shows the connection from preparation to sensory representation of bodily state $b$. A substantial reduction the learning time of Bob occurs when the
6.8 Discussion

In this paper the role of affective states and social interactions in learning processes was addressed, based on recent insights from Cognitive, Affective and Social Neuroscience. A computational analysis was made of learning processes, mechanisms for these processes, both from a learner him/herself and from others. The perspective followed in this paper is in the spirit of what is advocated in Immordino-Yang and Faeth (2010); Immordino-Yang and Fischer (2007). An important difference is that the latter work is informal and rather general whereas in the current paper the ideas are more concrete since the ideas are formalized and analyzed both in a conceptual and computational manner for specific types of learners. The conceptual and computational models are based on recent neurological insights concerning a number of relevant processes: internal simulation (Damasio, 1994), interaction of emotion and cognition, emotion-related valuing (Bechara et al., 2003), awareness states and reflection (Baars, 1997), mirroring

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**Figure 6.11:** The effect of different strengths of a thinking style of learner A (horizontal axis) on the behavior strength for A and B (vertical axis)

(a) The connection from preparation to sensory representation of $b$

(b) The connection from sensory representation of stimulus $s$ to preparation of $b$

**Figure 6.12:** The effect of different strengths of a thinking style of learner A (horizontal axis) on the learning time for A and B: number of time units to reach connection strength 0.8 (vertical axis)

The strength of the thinking style of Alice is above 0.7, which is the strength of Bob’s thinking style. Note that for the non-social case this duration is 178 time units. These results seem to indicate for these specific circumstances that without social interaction almost the same behavior can be learned, but the time to learn the same level of behavior may be substantially longer without social interaction. However, the graph displayed in Figure 6.12b for the connection from sensory representation of the stimulus $s$ to preparation of $b$ shows no reduction of the learning time of Bob. Here for the nonsocial case the duration to reach a learning rate of 0.8 is 59 time units, which is the same for both Alice and Bob in the social scenario when they have a thinking style component larger than 0.7. One explanation could be that learners with a strong thinking component do not rely heavily on direct processing of information from the sensory representations to the preparation nodes and optimization takes place elsewhere.
and social contagion of emotion (Iacoboni, 2008; Rizzolatti and Sinigaglia, 2008) and Hebbian learning (Hebb, 1949). For example, the models used are in accordance with recent neurological insights that processing and interpreting sensory information (grasping), and preparing for actions, are often not isolated processes but are in principle strongly intertwined (Pulvermüller and Fadiga, 2010).

The basic learning model includes elements of stimulus-response association learning (for the connections between stimuli representations and preparation states) as known from the behaviorist tradition (Skinner, 1986), but extends this substantially by providing possibilities to integrate emotional elements in the learning process (for the connections between preparations and feelings), and of how these are affected by social contagion of emotions. Furthermore, the model incorporates a notion of awareness of actions as a basis for the roles of thinking and reflection in learning. Learning together as addressed here means that both learners learn and can observe each other’s learning process and behavior. Note that cases in which one learner, in a kind of tutor role, explicitly provides help to another learner were not addressed in the model. Although the reported experiments have been designed to illustrate the principles of the approach for two interacting learners, they can easily be extended to larger groups of learners. An issue for further research may be to investigate more extensively by computational analysis how exactly learning results depend on different combinations of learning styles present in groups with more members.

The approach and the computational model provide means to analyze learning processes with different types of learners, more specifically the integrating effect of emotions and social interaction on these processes. In particular they provide a basis for the design and testing (in silico, by simulation) of technology-enhanced learning environments that enable and support emotions in individual and social contexts. Simulations as performed can inspire new hypotheses and specifications of learning theories. For example, to achieve these learning experiences in a (technology-enhanced) learning environment, enabling conditions are important. Consider a situation where the learners are not in the same room, in this case suitable interaction media should be available that enable emotion exchange between peers, e.g., exchange of figurative language elements such as emoticons, a video connection enabling face expressions, or an audio connection to transfer emotion in someone’s voice. Similarly, facilities are needed to enable the transfer of affective states and empathic understanding between tutor and learner; for a virtual agent coach, these facilities can exist for example of emotion recognition techniques and face expressions in a human-like and believable manner.

The model provides two types of indications for how well behavior has been learnt: from an externally observable perspective and from an internal perspective. From the external perspective the activation levels of expressed behaviors (upon offering the stimuli) are considered an indication. From the internal perspective, the strengths of the connections from stimuli representation to preparation states for the behavior, and from preparation to feeling states for the behavior are considered indications of successfulness of the learning process. Moreover, indications for the learning speed are found in the steepness of the graphs of the activation levels of these states and connection strengths over time. Note that the internal and external perspective need not provide the same indications. Based on the given models, it might well be the case that learners based on modest internal connections show good results in externally observable behavior, or conversely, that learners with strong internal connections perform weaker with respect to observable behaviors. This may be an issue for further research.
References


Prentice-Hall.