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A Computational Model of Habit Learning to Enable Ambient Support for Lifestyle Change

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Abstract Agent-based applications have the potential to assist humans in their lifestyle change, for instance eliminating addictive behaviors or adopting new healthy behaviors. In order to provide adequate support, agents should take into consideration the main mechanisms underlying behavior formation and change. Within this process habits play a crucial role: automatic behaviors that are developed unconsciously and may persist without the presence of any goals. Inspired by elements from neurological literature, a computational model of habit formation and change was developed as a basis for support agents able to assist humans in lifestyle and behavior change. Simulations are presented showing that the model exhibits realistic human-like behavior.

3.1 Ambient Support for Lifestyle Change

In Western societies health policy is directed at the reduction of medical costs by switching more and more from the treatment of diseases resulting from unhealthy lifestyle to promotion of healthy lifestyle habits (Miller and Cohen, 2001). Lifestyle change may comprise eliminating bad habits, for example addictive behaviors (e.g., smoking, alcohol or drugs use), and may simultaneously be directed at adopting new healthy habits, such as dieting and increasing physical activity (e.g., Gollwitzer and Sheeran (2006); Neal and Wood (2009); Quinn, Pascoe, Wood, and Neal (2010); Webb and Sheeran (2008); Wood and Neal (2007)). Considering the fact that lifestyle change requires intensive support, monitoring and supervision (e.g, Skinner (1938)), the potential of smart ambient applications that assist humans in their daily life is substantial, as they allow for constant monitoring and instant feedback. In order to provide adequate support

[1] The authors are mentioned in alphabetical order and have made a comparable contribution to the article.

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for humans, these support applications should be able to reason about the main determinants of human behavior and the mechanisms underlying behavior change.

Apart from conscious goals and decisions, human behavior is often based on *habits* – automatic behaviors that can be developed and maintained unconsciously. Habits may persist without the presence of any clear and definite goals and are very difficult to overcome. The model for habit learning and change presented In this paper can be used as basis for ambient intelligence applications to support lifestyle change. Using the model, an ambient application can predict – given a certain context or cue – the behavior of a person with already formed habits. In addition, the system can exploit the model to reason about required changes in the context or goals that need more attention in order to form new habits or get rid of old ones.

The proposed computational model of habit learning was inspired by elements from the neurological literature on habit learning (e.g., Ashby, Turner, and Horvitz (2010); Everitt, Belin, Economidou, Pelloux, Dalley, and Robbins (2008); de Wit, Corlett, Aitken, Dickinson, and Fletcher (2009); Yin and Knowlton (2006)), and neural plasticity, such as Hebbian learning (e.g., Bi and Poo (2001); Gerstner and Kistler (2002)), and adopts such adaptive mechanisms. The model has been formally specified in an executable manner, in order to conduct experiments and to allow the model to be embedded in an intelligent software agent that can support humans in their lifestyle and behavior change.

This paper is organized as follows. Section 3.2 addresses some background information on habit learning and change and the neural mechanisms underlying these processes. In Section 3.3 the description of the model is presented, Section 3.4 demonstrates some simulation and verification results. Finally, Section 3.5 contains a discussion on the topic.

3.2 Background on Habit Learning

Habits are learned dispositions to repeat past responses (cf. (Yin and Knowlton, 2006, p. 843)), which by themselves were goal-driven. Once habits have been acquired, they are triggered by the cues in a certain context that co-occurred frequently with past performance, and which activate habitual responses directly, without the mediation of goals. These cues can be locations, objects, sequence of actions or presence of particular persons during or preceding the action performance. Habits formation corresponds thus to a context- response learning that is acquired slowly with experience (Yin and Knowlton, 2006, p. 844).

Behaviorists described habits as behavior as creation of connections between stimulus and a particular response (e.g., Tang, Pawlak, Prokopenko, and West (2007); Watson (1913)). The cognitivist perspective on human behavior suggests the existence of a central executive controller of behavior (e.g., Oulette and Wood (1998)). Nowadays, neurological literature describes the mechanisms underlying habit formation, which explain the behaviorists' stimulus-response-based learning phenomenon, and introduces the concept of neural plasticity. Learning occurs due to the change of the connections strengths, for example, based on a principle known as Hebbian learning (e.g., Bi and Poo (2001); Gerstner and Kistler (2002); Lymberis and Rossi (2004)). It states that if two or more neurons are co- activated, the connections between these neurons strengthen. For example, repeated action in a certain context results to the gradual strengthening of the connection between the context representation and this particular response.

These associations are difficult to override, though it is possible to influence habits (indirectly) via the activation of new goals. Strong goals that aim to direct one's behavior are associated with activation in the prefrontal cortex. This activation can inhibit the activation of subcortical structures (e.g., basal ganglia and cerebellum), associated with habitual behavior (e.g., Ashby et al. (2010); Mowrer (1960); Watson (1913); Webb, Sheeran, and Luszczynska (2009); de Wit et al. (2009). Thus, when habits and goals are both present to guide action, they interact such that under some circumstances humans respond habitually and under other they exert regulatory control to inhibit the cued response.

Although a habit is no longer goal-mediated, it can be regulated by post-hoc goal inference or cue control, for example, by 1) inhibiting the performance of responses, 2) drawing one's attention to the undesired behavior, 3) associating the learned context with multiple responses or 4) altering exposure to the cues in the context (Yin and Knowlton, 2006). Summarising, from neurological literature such as Ashby et al. (2010); Everitt et al. (2008); Haigh, Kiff, Myers, Guralnik, Geib, Phelps, and Wagner (2004); Mowrer (1960); Port and van Gelder (1995); Watson (1913); de Wit et al. (2009), the following characteristics of habit learning have been identified:

- Under repeated occurrence of cues and under influence of goal-directed behavior leading to satisfaction, habits are developed.
- When a habit has developed, the behavior will also occur without the presence of a goal, when the cue is present.
- A developed habit will persist when the relevant goal is present, also in absence of the cue.
- A developed habit will persist when the relevant goal is present, also in absence of the cue.

These patterns have served as requirements for the design of the adaptive computational model described in Section 3.3. The patterns themselves will be formalized in Section 3.4 and checked for simulation traces of the computational model.

3.3 The Computational Model for Habit Learning

The structure of the computational model presented in this section is based on the literature described in the previous section. The model is at a cognitive level, which still reflects the underlying neurological concepts, but without taking into account too many neurological details. It uses temporal relationships to describe the mechanisms at work. An overview of the model is depicted in Figure 3.1. It enables two alternative ways (paths) in which behavior can be generated. The first is by the activation of a long term goal (e.g., loose weight), a short term goal corresponding to this long term goal (reduce consumption of high calorie food), generation of an intention (able to achieve the goals), and finally execution of this intended action. The second path goes directly via cue activation in a certain context to the activation of a particular intention that leads to the action execution. This path corresponds to the habit, which is learned over time: the connection between cue and intention changes dynamically after their simultaneous activation according to the Hebbian learning principle.

In the model also the influence of feeling on the chosen action has been incorporated: frequent execution of a particular action provides a reinforcement by the feeling of satisfaction after the performed action, and this feeling leads in turn to the higher activation of the intention related to this action. For example, a positive feeling of satisfaction resulting from the consumption of delicious cookies will lead to higher activation of the intention of eating these cookies. The model allows for multiple goals and intentions that result in behavior. In principle each long term goal has connections with different strengths to short term goals, and the same holds for cues.

The dynamical relationships below describe the model in semi-formal form and in a formal temporal relation notation in LEADSTO (cf. Bosse, Jonker, van der Meij, and Treur (2007)). Within LEADSTO a dynamic property or temporal relation a $\rightarrow$ b denotes that when a state property a (or conjunction thereof) occurs, then after a certain time delay, state property b will occur. Below, this delay will be taken as a uniform time step Δt. The first dynamic relationship

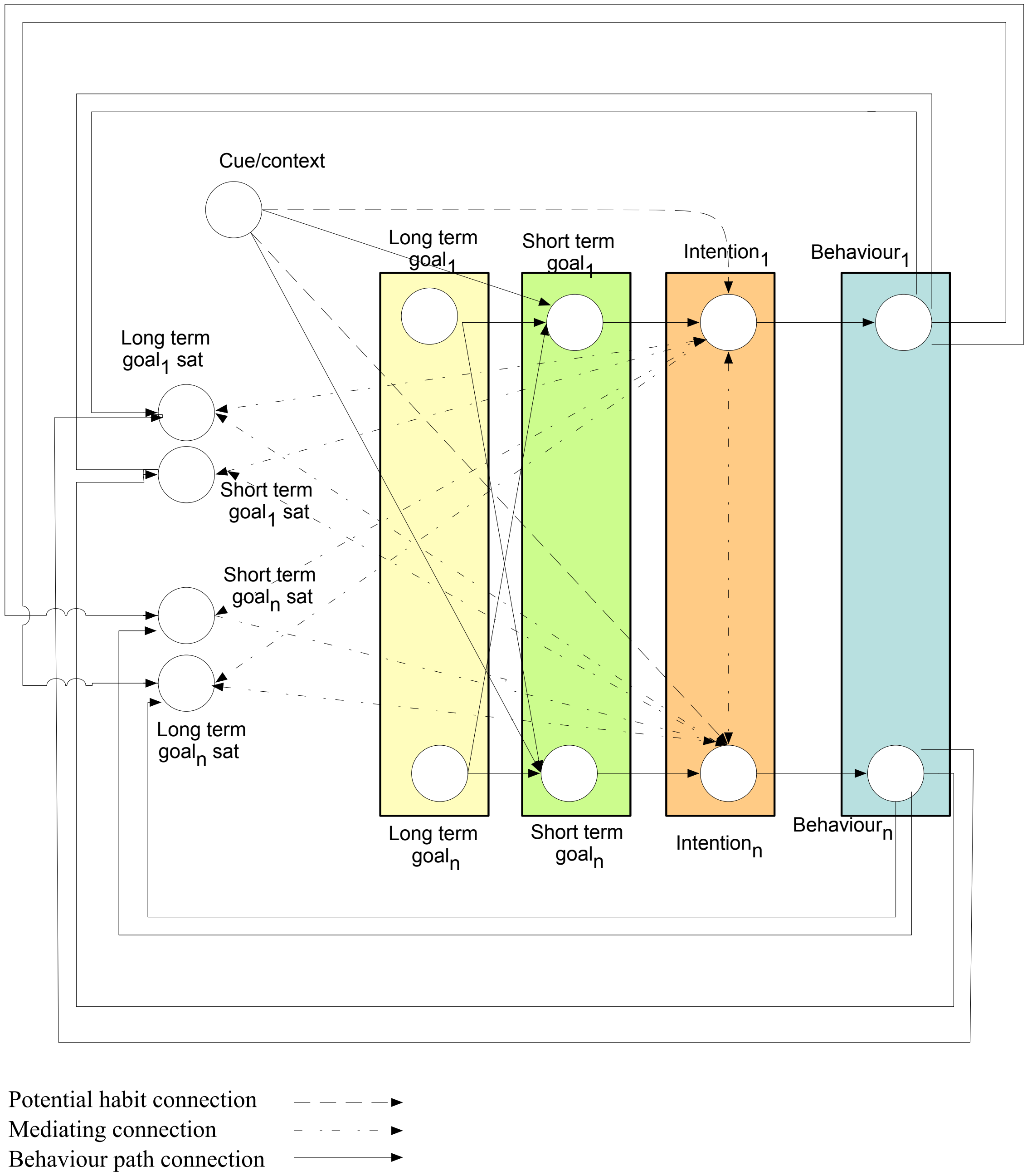


Figure 3.1: A conceptual model for emotions and social influence in learning

addresses the Hebbian learning principle applied for the connections between cues en intentions, as also described in (Gerstner and Kistler, 2002, p. 406).

LP1 Cue-intention connection adaptation

If	relevant cue C with level V_1 occurs and intention I has value V_2
and	learning rate from cue C to intention I is η and extinction rate from cue C to intention I is ζ
and	the connection strength between cue C and intention I is w_1
then	after Δt the connection from cue C to intention I will have strength: $w_1 + (\eta \cdot V_1 \cdot V_2(1 - w_1) - \zeta \cdot w_1) \cdot \Delta t$

$cue(C, V_1)$ & intention(I, V_2) & learning_rate(C, I, η) & extinction_rate(C, I, ζ) & connection_strength$(C, I, w_1) \rightarrow$ connection_strength$(C, I, w_1 + (\eta \cdot V_1 \cdot V_2(1 - w_1) - \zeta \cdot w_1) \cdot \Delta t)$

The following relationship specifies how activations of short term goals are deter- mined based on long term goals and cues.

LP2 Short term goal from cue and long term goals

If	relevant cue C with level V_0 occurs,
and	long term goal LG_1 has value V_1 ... and long term goal LG_n has value V_n
and	the connection strength between cue C and short term goal SG is w_0
and	the connection strength between long term goal LG_1 and short term goal SG is w_1
and	the connection strength between long term goal LG_2 and short term goal SG is w_2
	...
and	the connection strength between long term goal LG_n and short term goal SG is w_n
and	short term goal SG_1 has value V_3
then	short term goal SG_1 after Δt will have level: $levelV_3 + \alpha(g(\sigma_1, \tau_1, V_0, V_1, V_2, \ldots, V_n, w_0, w_1, w_2, \ldots, w_n) - V_3)\Delta t$

cue(C, V_0)& ltgoal(LG_1, V_1) & ...ltgoal(LG_n, V_n) & connection_strength(C, SG, w_0) & connection_strength(LG_1, SG, w_1) & ...connection_strength(LG_n, SG, w_n) & stgoal$(SG_1, V_3) \rightarrow$ stgoal$(SG_1, V_3 + \alpha(g(\sigma_1, \tau_1, V_0, V_1, V_2, V_n, w_0, w_1, w_2, w_n) - V_3)\Delta t)$

Here α is a speed parameter that defines the impact of long term goals and context cues upon the new activation value of the short term goal. Moreover, g is a combination function for which various choices are possible; a logistic threshold function has been chosen: $g(\sigma, \tau, V_0, \ldots, V_n, w_0, \ldots, w_n) = th(\sigma, \tau, w_0V_0 + \cdots + w_nV_n)$ with $th(\sigma, \tau, V) = 1/1 + e^{-4\sigma(V-\tau)}$.

Parameters σ and τ define steepness and threshold values of the function. The thresh- old function ensures that the value of the goal is most often either close to zero or close to one. Only when the input for the threshold function is close to the threshold value itself, the values of the goal are somewhere between 0 and 1. In all subsequent formulae the combination function g is always based on a threshold function of this form.

The third relationship of the model describes how intentions are determined. Intentions depend on short term goals and cues, and the feelings of satisfaction for both short and long term goals. Moreover, different intentions also affect each other by a form of mutual inhibition. Note that for the sake of simplicity in LP3 only two long term and short term goals are considered.

LP3 Intention dynamics

If short term goal satisfaction $SGSAT_1$ has value V_1
and long term goal satisfaction $LGSAT_1$ has value V_2
and short term goal satisfaction $SGSAT_2$ has value V_3
and long term goal satisfaction $LGSAT_2$ has value V_4
and relevant short term goal SG_1 has value V_5
and relevant cue C has value V_6
and intention I_1 that corresponds to these goals has value V_7
and intention I_n has value V_8
and the connection strength between short term goal SG_1 and intention I_1 is w_3
and the connection strength between cue C and intention I_1 is w_4
and the connection strength between short term goal satisfaction $SGSAT_1$ and intention I_1 is w_5
and the connection strength between long term goal satisfaction $LGSAT_1$ and intention I_1 is w_6
and the connection strength between short term goal satisfaction $SGSAT_2$ and intention I_1 is w_7
and the connection strength between long term goal satisfaction $LGSAT_2$ and intention I_1 is w_8
then intention $I1$ that corresponds to these goals after Δt will have value
$V_7 + \beta(g((\sigma_2, \tau_2, V_8, V_9, V_1, V_2, V_3, V_4, V_5, V_6, w_3, w_4, w_5, w_6, w_7, w_8, w_1) - V_7) \cdot \Delta t$

stg_satisfaction($SGSAT_1, V_1$) & ltg_satisfaction($LGSAT_1, V_2$) & stg_satisfaction($SGSAT_2, V_3$) & ltg_-satisfaction($LGSAT_2, V_4$) & stgoal(SG_1, V_5) & cue(C, V_6)& intention(I_1, V_7) & intention(I_n, V_8) & connection_strength(I_1, I_n, w_1) & connection_strength(SG_1, I_1, w_3) & connection_strength(C, I_1, w_4) & connection_strength($SGSAT_1, I_1, w_5$) & connection_strength($LGSAT_1, I_1, w_6$) & connection_-strength($SGSAT_2, I_1, w_7$) & connection_strength($LGSAT_2, I_1, w_8$)
$\rightarrow$
intention($I_1, V_7 + \beta(g((\sigma_2, \tau_2, V_8, V_9, V_1, V_2, V_3, V_4, V_5, V_6, w_3, w_4, w_5, w_6, w_7, w_8, w_1) - V_7) \cdot \Delta t$)

Here β feeling of satisfaction from the performed actions upon the intention to perform new actions. Weight w_1 is negative here as it defines inhibition from the alternative competing intention(s). It is assumed that different intentions are conflicting, in other words one cannot perform two behavior simultaneously to satisfy different goals; for this reason the weights between the intentions are always negative, or inhibitory. The step from intention to behavior has been kept simple:

LP4 From intention to behavior

If intention I with level V occurs, and $V > threshold$
then behavior with level V will occur

intention(I, V) & $V > threshold \rightarrow$ behavior(B, V)

The feeling of satisfaction for a long term goal was modeled as follows:

LP5 Long term goal satisfaction

If behavior B_1 with level V_1 occurs and intention I_1 has value V_2
and long term goal LG corresponding to this behavior has value V_3
and long term goal satisfaction $LTSAT$ has value V_4
and connection strength from behavior B_1 to the long term goal satisfaction $LTSAT$ is w_1
and connection strength from intention I_1 to long term goal satisfaction $LTSAT$ is w_2

then long term goal satisfaction $LTSAT$ after Δt will be $V_4 + \theta(f((\sigma_3, \tau_3, V_3, V_1, V_2, w_1, w_2) - V_4) \cdot \Delta t$

behavior(B_1, V_1) & intention(I_1, V_2) & ltgoal(LG, V_3) & ltg_satisfaction($LTSAT, V_4$) & connection_strength($B_1, LTSAT, w_1$) & connection_strength($I_1, LTSAT, w_2$) → ltg_satisfaction($LTSAT, V_4 + \theta(f(\sigma_3, \tau_3, V_3, V_1, V_2, w_1, w_2) - V_4) \cdot \Delta t$)

Here parameter τ defines the impact of a long term goal, behaviors and intentions upon the long term goal satisfaction. The feeling of satisfaction for a short term goal was modeled in a similar manner:

LP6 Short term goal satisfaction

If behavior B_1 with level V_1 occurs and intention I_1 has value V_2
and short term goal SG corresponding to this behavior has value V_3
and short term goal satisfaction $STSAT$ has value V_4
and connection strength from behavior B_1 to the short term goal satisfaction $STSAT$ is w_1
and connection strength from intention I_1 to short term goal satisfaction $STSAT$ is w_2
then short term goal satisfaction $STSAT$ after Δt will be $V_4 + \tau(f((\sigma_4, \tau_4, V_3, V_1, V_2, w_1, w_2) - V_4)\Delta t$

behavior(B_1, V_1) & intention(I_1, V_2) & stgoal(SG, V_3) & stg_satisfaction($STSAT, V_4$) & connection_strength($B_1, STSAT, w_1$) & connection_strength($I1, STSAT, w2$) → stg_satisfaction($STSAT, V4 + \tau(f(\sigma_4, \tau_4, V_3, V_1, V_2, w_1, w_2) - Vv4) \cdot \Delta t$)

3.4 Simulation and Verification

The cognitive computational model described in the previous section was implemented in the Matlab environment. A number of simulations of 50 and 200 time steps have been performed. For the sake of simplicity only two initial long term goals and the corresponding behaviors were assumed. In this section four example simulation runs of 50 time steps are presented. These simulations illustrate the ability of the computational model to exhibit important patterns of habit learning and change. In Table 4.1 the values are shown used for learning and extinction rate, steepness and threshold values, speed factors, and connection weights (note that weight values for interaction between two options are symmetric). In order to investigate whether the computational model indeed learns and behaves according to what is expected, some logical properties (requirements) have been identified, formalized, and verified against the simulation traces of the model (see also the characteristics informally described at the end of Section 3.2). In this section, first the language used to express such properties is briefly introduced, followed by the specification of the actual properties, presentation of an example trace illustrating the pattern, and the result of their verification.

Formal specification of desired properties of the computational model enables automatic verification of them against simulation traces. This was performed using the hybrid language TTL and its software environment (Bosse, Jonker, van der Meij, Sharpanskykh, and Treur, 2009). TTL is built on atoms referring to *states* of the world, *time points* and *traces*, i.e. trajectories of states over time. *Dynamic properties* are temporal statements formulated with respect to traces in the following manner. Given a trace γ, the state in γ at time point t is denoted by $state(\gamma, t)$. These

Table 3.1: Parameter and connection weight values used

η	ζ	α	σ_1	τ_1	β	σ_2	τ_2	thresh	θ	σ_3	τ_3	σ_4	tau_4
0.5	0.01	0.8	15	0.9	0.8	20	0.5	0.5	0.8	15	0.2	15	0.6

connection	*weight*	*connection*	*weight*	*connection*	*weight*
$cue - int_1$ init.	0.1	$stsat_1 - int_1$	0.2	$int_1 - stsat_1$	0.9
$cue - int_2$ init.	0.1	$int_1 - beh_1$	1	$beh_1 - stsat_1$	0.9
$cue - stgoal_1$	0.1	$int_2 - beh_2$	1	$int_2 - ltsat_1$	0.2
$cue - stgoal_2$	0.1	$int_1 - int_2$	-0.9	$beh_2 - ltsat_1$	0.1
$ltgoal_1 - stgoal_1$	0.9	$int_2 - int_1$	-0.9	$int_2 - stsat_1$	0.2
$ltgoal_1 - stgoal_2$	0.2	$int_1 - ltsat_1$	0.9	$beh_2 - stsat_1$	0.1
$ltgoal_2 - stgoal_1$	0.2	$beh_1 - ltsat_1$	0.9	$beh_1 - ltsat_2$	0.1
$ltgoal_2 - stgoal_2$	0.9	$int_2 - ltsat_1$	0.1	$beh_1 - stsat_2$	0.1
$ltsat_1 - int_1$	0.9	$int_2 - stsat_1$	0.1	$beh_2 - ltsat_2$	0.9
$ltsat_1 - int_2$	0.2	$int_1 - ltsat_2$	0.1	$beh_2 - stsat_2$	0.9
$stsat_1 - int_1$	0.9	$int_1 - stsat_2$	0.1		

states are related to state properties via the infix predicate $\models$, where $state(\gamma, t) \models p$ denotes that state property p holds in trace γ at time t. Based on these statements, dynamic properties are formulated in a sorted first-order predicate logic, using quantifiers over time and traces and the usual first-order logical connectives such as $\neg, \wedge, \vee, \Rightarrow, \forall, \exists$. For more details on TTL, see Bosse et al. (2009).

Each of the three subsections addresses one scenario. In the figures that demonstrate the simulation results, time is depicted on the horizontal axis and the activation values of the variables of interest are depicted on the vertical axis.[1]

3.4.1 Habit Formation

In this simulation a specific behavior is generated by a strong long term goal related to this behavior in the presence of a strong cue. As a result even after a decrease of the value of the goal corresponding to this behavior after time point 24, the behavior persists up to end of the simulation; see Figure 3.2a. The value of the second long term goal is kept low during the whole simulation; therefore the second type of behavior that corresponds to this goal does not come to expression. To verify this pattern formally, it first has to be checked whether a specific behavior results from the presence of a high-level goal and a cue:

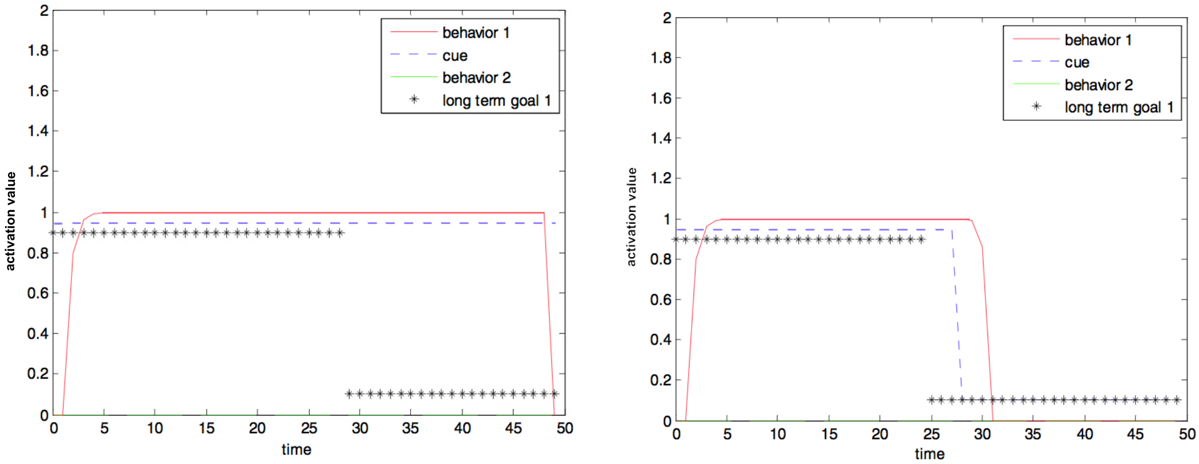
P0: Long-term goal and cue leads to behavior

If a cue and a high-level goal are present for a certain time duration min_duration, then at some later time the corresponding behavior will be present.

$\forall \gamma : TRACE, t : TIME \Big[\; habit\_learning\_phase(\gamma : TRACE, t : TIME, MIN\_DURATION, ACT\_VALUE_2) \Rightarrow \exists t_2 : TIME > t, R_3 : REAL \;\; state(\gamma, t_2) \models has\_value(beh_1, R_3) \wedge R_3 > ACT\_VALUE_2 \Big]$

Here (and in the other properties below) the following abbreviation is used:

[1]Note that gradual values for intentions, cues and goals are assumed, which represent the strength of the presence of these variables as perceived by the subject.



(a) Habit formation and persistence

(b) Habit formation and cue removal

Figure 3.2: Activation values of behaviors, goals and cues over time.

$habit\_learning\_phase(\gamma : TRACE, t : TIME, MIN\_DURATION : INTEGER, ACT\_VALUE : REAL) \equiv \forall t_2 : TIME > t \wedge t_2 < t + MIN\_DURATION \Big[\exists R_1 : REAL \;\; state(\gamma, t_2) \models has\_value(ltg_1, R_1) \wedge R_1 > ACT\_VALUE_2 \wedge \exists\, R_2 : REAL \;\; state(\gamma, t_2) \models has\_value(cue_1, R_2) \wedge R_2 < ACT\_VALUE_2 \Big]$

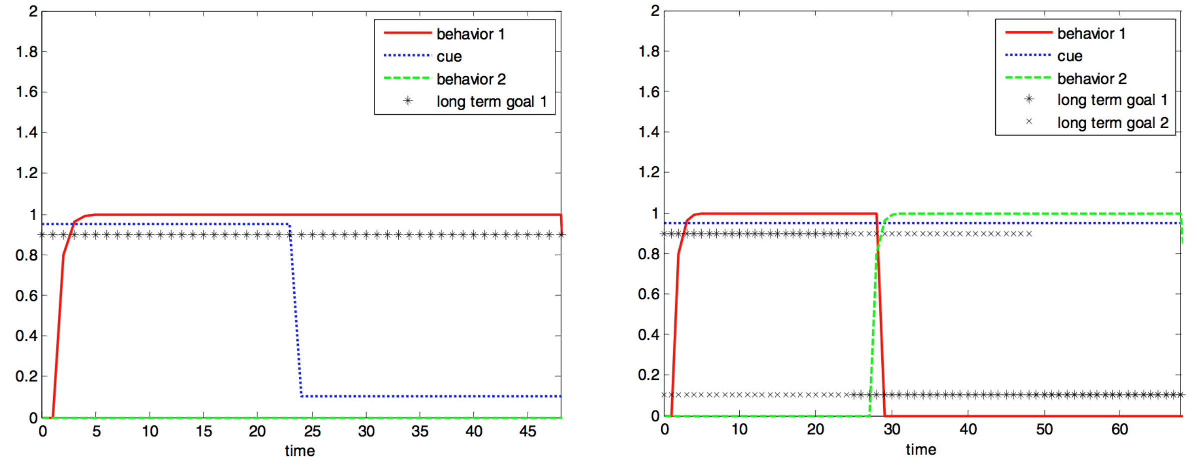
Property P0 corresponds to characteristic pattern 1 of habits as defined at the end of Section 3.2, and has been automatically checked and proven to be true for the following values of the constants: $MIN\_DUR = 2, MAX\_LEVEL\_P1 = 0.5, ACT\_VALUE_1 = 0.5, ACT\_VALUE_2 = 0.7$. All properties described in the remainder of this section have been automatically verified and found satisfied for these values. The pattern of habit formation itself (characteristic pattern 2) was specified as follows:

P1: Habit persistence

If a cue and a high-level goal have been present for some time period MIN_DURATION, the behavior will exist in the presence of a cue even if the goal is no longer present.

$\forall \gamma : TRACE, t : TIME \Big[habit\_learning\_phase(\gamma : TRACE, t : TIME, MIN\_DURATION, ACT\_VALUE_2) \wedge \forall t_2 : TIME > t + MIN\_DURATION, R_3 : REAL[state(\gamma, t_2) \models has\_value(ltg_1, R_3) \Rightarrow R_3 < ACT\_VALUE_1]$
$\Rightarrow \forall t_3 : TIME > t_2, R_4 : REAL \;[state(\gamma, t_3) \models has\_value(cue_1, R_4) \wedge R_4 > ACT\_VALUE_2 \Rightarrow \exists t_4 : TIME > t_3, R_5 : REAL \;\; state(\gamma, t_4) \models has\_value(beh_1, R_5) \wedge R_5 > ACT\_VALUE_2] \Big]$

When in the scenario in Figure 3.2b, after time point 26 the value of the cue is substantially decreased, habitual behavior is not performed anymore from time point 31. As expected, and shown in Figure 3.2b, the second behavior (‘behavior 2’) does not occur. Formally, the illustrated characteristic is specified as follows:



(a) Influence of the goal on behavior in the absence of the original cue

(b) Behaviors resulting from the goal change

Figure 3.3: Activation values of behaviors, goals and cues over time.

> **P2: Habit and cue removal**
>
> IF A HABIT IS FORMED AND THE CUE AND THE GOAL ARE NO LONGER PRESENT, THE BEHAVIOR WILL AFTER SOME TIME CEASE TO EXIST.
>
> $\forall \gamma : TRACE, t : TIME \Big[habit\_learning\_phase(\gamma, t, MIN\_DURATION, ACT\_VALUE_2) \wedge \forall t_2 : TIME > t + MIN\_DURATION, R_1, R_2 : REAL \ [state(\gamma, t_2) \models has\_value(cue_1, R_1) \Rightarrow R_1 < ACT\_VALUE_1 \wedge state(\gamma, t_2) \models has\_value(ltg_1, R_2) \Rightarrow R_2 < ACT\_VALUE_1]$
> $\Rightarrow \exists t_3 : TIME > t_2, R_3 : REAL \ state(\gamma, t_3) \models has\_value(beh_1, R_3) \wedge R_3 < ACT\_VALUE_1 \Big]$

3.4.2 Influence of Long Term Goal on Behavior

This scenario demonstrates how behavior is influenced by goals in the absence of the learned cue; see Figure 3.3a. In the beginning habitual behavior is formed: a strong cue is present and a behavior pattern that coincides with the first long term goal. The value of the goal remains the same during the whole run, but the cue almost disappears after time point 24. The low value of the cue does not prevent the behavior to occur due to the strong influence of the long term goal. This corresponds to characteristic habit pattern 3 from Section 3.2. This was specified as follows:

> **P3: Habit and cue removal in presence of strong goal**
>
> IF A HABIT IS FORMED, THE BEHAVIOR WILL STILL EXIST IF THE CUE IS NOT PRESENT ANY MORE AND THE HIGH-LEVEL GOAL IS PRESENT.
>
> $\forall \gamma : TRACE, t : TIME, \Big[habit\_learning\_phase(\gamma, t, MIN\_DURATION, ACT\_VALUE_2) \wedge \forall t_2 : TIME > t + MIN\_DURATION, R_3 : REAL [state(\gamma, t_2) \models has\_value(cue_1, R_3) \Rightarrow R_3 < ACT\_VALUE_1]$
> $\Rightarrow [\forall t_3 : TIME > t_2, R_4 : REAL \ state(\gamma, t_3) \models has\_value(ltg_1, R_4) \wedge R_4 > ACT\_VALUE_2 \Rightarrow \exists t_4 : TIME > t_3, R_5 : REAL \ state(\gamma, t_4) \models has\_value(beh_1, R_5) \wedge R_5 > ACT\_VALUE_2] \Big]$

3.4.3 The Effect of Goal Change

In this simulation the result of the switch from one goal to another is demonstrated in the presence of a strong cue. As shown in Figure 3.3b, the habitual behavior ('behavior 1' in the picture) does not disappear immediately after adopting a new goal, conflicting with the previous one. It takes a little time to perform new behavior pattern after the new goal has been adopted. This simulation demonstrates how the old undesired habitual behavior can be substituted with the new positive behavior. The formal specification of this pattern is:

P4: New goal results in new habit
IF A HABIT IS FORMED FOR LONG TERM GOAL ltg_1, WHICH DISAPPEARS, A NEW BEHAVIOR WILL BE DEVELOPED IF ANOTHER LONG TERM GOAL ltg_2 IS PRESENT
$\forall \gamma : TRACE, t : TIME\_DURATION \Big[[habit\_learning\_phase(\gamma, t, MIN\_DURATION, ACT\_VALUE_2) \wedge \forall t_2 > t + MIN\_DURATION, R_1, R_2, REAL \quad [state(\gamma, t_2) \models has\_value(ltg_1, R_1) \Rightarrow R_1 < ACT\_VALUE_1] \wedge [state(\gamma, t_2) \models has\_value(ltg_2, R_2) \Rightarrow R_2 > ACT\_VALUE_2]] \Rightarrow \exists t_3 : TIME > t_2, R_3, R_4, REAL \quad [state(\gamma, t_3) \models has\_value(beh_1, R_3) \wedge R_3 < ACT\_VALUE_1] \wedge [state(\gamma, t_3) \models has\_value(beh_2, R_4) \wedge R_4 > ACT\_VALUE_2] \Big]$

Figure 3.3b also shows the effects of P1, which demonstrate that the new behavior results in a habit after some amount of time: the behavior persists even after the corresponding long term goal is no longer present. Combined, P1 and P4 account for characteristic habit pattern 4.

3.5 Discussion and Conclusions

The cognitive computational model presented above can form the basis of an intelligent ambient support application. To this end, an agent based approach for creating ambient intelligence applications can be used (Bosse, Hoogedoorn, Klein, and Treur, 2008). Within such a framework, the ambient system consists of components, i.e., agents, that have context awareness about human behaviors and states, and (re)acts on these accordingly. For this purpose, the behavior of the subject of the system (a person taken care of) relevant to the support provided should be explicitly described, e.g., via a computational model. If this is the case, an ambient agent can (re)act by undertaking actions in a knowledgeable manner that improve the human's wellbeing and performance.

Reasoning using an explicit model of the behavior of a process is called model-based reasoning (Pearl and Verma, 1991). Basically, there are two ways in which model-based reasoning of habits can be used within an intelligent support application. First, predictions can be made of what will happen given certain cues/contexts, long term goals and short term goals. For example, if the system has identified a specific behavior – such as the eating of cookies at work – several times in the past, and it has knowledge about the short-term and long-term goals, it can predict whether a person in the work- context will again eat a cookie. These predictions capabilities allow a support application to take action before an undesired habit actually took place. Second, the model can be used to perform analysis of the causes of the undesired behavior and the effect of interventions on the behavior of a person (Duell, Hoogendoorn, Klein, and Treur, 2008). Causes of behavior can be determined by backward abductive reasoning. For example, if an undesired behavior is taking place, the presented computational model can be used to find hypothetical causes for this behavior, for example a short term goal that leads to the intentions for the undesired behaviors. Symmetrically, forward deductive model-based reasoning derives the effect of interventions on the behavior. For example, determining the effect of a different or more important long term goal after some time. This can be used by the ambient intelligence application to explicitly change the situation, e.g. removing cues, generating additional intention for long term goals leading to different behavior, or suggesting actions to create new (more desired) habits.

Existing models of habit learning take either the perspective of behaviorism that does not follow the internal mechanisms underlying habit development (e.g., Cohen and Frank (2009); Machado (1997)) or propose the description of habit learning in a very detailed manner at the lowest neurological level (e.g., Baldasarre (2002); Cohen and Frank (2009); Gurney, Prescott, Wickens, and Redgrave (2004)). The proposed computational model is at a cognitive level, between the neurological and behavioral level. The proposed way of modeling is a manner to exploit within the computational modeling area principles from the neurological literature, by lifting neurological knowledge to a mental (cognitive/affective) level. In order to successfully model more complex and human-like behavior, for example incorporating mutual cognitive/affective interactions, and adaptive behavior, the modeler has to consider such numerical modeling techniques; see also Port and van Gelder (1995).

In future work, the model will be deployed on actual data and used to improve habit performance. Also, the model could be improved by taking into account the environment in which a person is embedded, which is currently limited to perceiving cues, but preferably also incorporates socio-environmental factors shown to play a role in habit formation development (e.g., Giles-Corti and Donovan (2002)).

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