Neural Network Modeling of Learning of Contextual Constraints on Adaptive Anticipations

Frédéric Lavigne and Sylvain Denis
Laboratoire de Psychologie Expérimentale et Quantitative
Université de Nice – Sophia Antipolis
24 Avenue des Diables bleus 06357 Nice Cedex 4, France
e-mail: lavigne@unice.fr ; web: http://www.unice.fr/LPEQ

Abstract
Anticipatory processes take into account of the contextual events occurring in the environment to anticipate probable upcoming events, and to select the best behavioral responses. The necessary knowledge for prediction of events adapted to context can be learned by classical associative conditioning, which allows associations between events occurring close in a sequence. Context can then correspond to events perceived in the environment as well as to the reinforcing valence of the event eliciting emotional states in the system, both orienting anticipations in memory. Knowledge for anticipation of adapted behaviors to context can be learned by operant reinforced conditioning, which allows associations between behaviors and reinforcing events in the environment, as a function of the reinforcing valence of the event (positive or negative). In this case the processing of a contextual event can select behavioral responses orienting the system to positive reinforcers rather than to negative reinforcers. An attractor neural network model is proposed to account for the different types of anticipatory processes presented as well as for the learning principles of conditioning allowing adapted anticipations.
Keywords - semantic anticipation - conditioning - context - emotions - neural networks

1 Adaptive Anticipations of Events and Behaviors

Why anticipatory processes are based on context?

Anticipations for prediction of events are cognitive abilities allowing living systems to adapt their behavior to their environment. Dynamic anticipations in memory of possible future events likely to occur in the environment are based on associative learning of sequences of events. It leads to faster and more accurate perceptive processes of events when previously anticipated; as well as to rapid and accurate preprogrammed motor responses. Behavioral adaptation then depends on anticipatory processes linking motor responses to perceived events (Berthoz, 1996; Glenberg, 1997; Lavigne & Lavigne, 2000; Sun & Giles, 2001; Varela, Thompson & Rosh, 1999; Wang, 2001).

Improved perception and action performances are based on anticipatory processes which can be activatory or inhibitory, as a function of physical properties of the contextual events perceived in the environment, and of representational properties of the events anticipated in dynamic memory. Through perceptual constraints and

International Journal of Computing Anticipatory Systems, Volume 12, 2002
Edited by D. M. Dubois, CHAOS, Liège, Belgium, ISSN 1373-5411 ISBN 2-9600262-6-8

learning, properties of the contextual events determine semantic and attentional anticipations allowing better adaptation to complex sequences of events (Laberge, 1995; Lecas, 1992; Jones, 1976; Jones & Boltz, 1989; Jones & Yee, 1993; Neely, 1991; Posner & Snyder, 1975; see Lavigne & Denis, 2001).

1.1 Adaptive Anticipations to Contextual Constraints

To achieve good adaptation of living systems to the environment, anticipatory processes must take into account of the contextual events occurring in the environment to select the best behavioral responses. These two types of knowledge are intricately associated in memory to allow anticipations of various possible behavioral responses as a function of perceived sequences of events, as well as of the consequences of each possible behavior. Adaptive anticipations allow speeded and more accurate perception of predicted events as well as speeded and adapted behavioral responses when preselected by anticipation (see Lavigne & Lavigne, 2000). Memory can then be seen not as a static internal representation of the structure of the environment, but as dynamic processes of anticipations of behaviors adapted to possible events as a function of perceived contextual events. This defines adaptation as based on cognitive anticipatory processes of perceptive and behavioral interactions between a living system and its environment.

1.2 Neural Network Modeling

Given the mathematical description of anticipations as involving states in a system as depending on both its current state (t) and anticipated states (t+1) (see Rosen, Dubois), many neural networks models can account for anticipatory processes as processes of automatic spreading of activation from a neuronal representation to associated ones, which can be interpreted as anticipatory processes (Anderson, 1983; Collins & Loftus, 1975; Collins & Quillian, 1969; Gillund & Shiffrin, 1984; Grossberg & Stone, 1986; Hinton & Shallice, 1991; Kintsh, 1988; Masson, 1991, 1995, 1999; Ratcliff & McKoon, 1988, 1994; Sharkey & Sharkey, 1992; Wang, 1996, 2000; see Lavigne & Lavigne, 2000). However, these models do not account for associative and reinforced learning such as defined in artificial life models (Macintosh, 1983).

A way to achieve good modeling of both classical and reinforced learning, as well as of non trivial cognitive anticipatory processes (see Lavigne & Lavigne, 2000; Lavigne & Denis, 2001) is to use attractor neural networks (Amit, 1989; Hopfield, 1982; Hopfield & Tank, 1986), some being able to attribute different attractors to different perceived events by autonomous perceptive learning (Hopfield & Brody, 2000, 2001). Furthermore, particular types of biologically plausible recurrent networks have the ability to associate events presented in temporal sequences (Amit, Brunel & Tsodyks, 1994; Brunel, 1996 for a mathematical description; Lavigne & Lavigne, 2000; Lavigne & Denis, 2001 for computer implementation and simulations of semantic anticipatory processes).

The proposed neural network model is an elaboration of Lavigne & Denis model (2001; see Lavigne & Lavigne, 2000; Brunel, 1996), in which transduction (transfer) function parameters and learning parameters can be varied to fit the process to modelize (see Lavigne & Denis, 2001 for prevous simulations):

The network is a fully connected network of excitatory $_{(E)}$ and inhibitory $_{(I)}$ neurons, with equal probability of having a synapse on any other neuron (connectivity parameter c = 0.3). The network has then S_{EE} excitatory to excitatory synapses, S_{EI} and S_{IE} excitatory to inhibitory and inhibitory to excitatory synapses, and S_{II} inhibitory to inhibitory synapses. Excitatory neurons code for events perceived by the network and inhibitory neurons prevent runaway propagation of activation throughout all the excitatory neurons and maintain stable states in the network.

Neurons are connected through four types of pre-synaptic (j) to post-synaptic (i) synapses. Synaptic efficacies correspond to post-synaptic potentials (mV) provoked by a spike, and are initially randomly defined as Jij_{EE} (excitatory to excitatory), Jij_{EI} mV (excitatory to inhibitory), and Jij_{IE}=Jij_{II} (respectively inhibitory to excitatory and inhibitory to inhibitory), with a synaptic variability taken to be Δ=J.

All neurons in the network are leaky integrate-and-fire neurons converting input currents I (mV) in firing rates νi (spikes.s-1), according to the transduction (transfer) function

$$v_i = \Phi(I) = O \,\|_{[0,I1[} + [(I - \alpha)(\beta I + \chi)] \,\|_{[I1,I2[} + [\delta I - \varepsilon] \,\|_{[I2,+\infty[} \qquad (1)$$

approximating Brunel's (1996) values for Ricciardi's (1977) transduction function, with $\|_{[Ix,Iy[} = 1$ for the corresponding intervals of I, O if not.

A neuron receives a total input intensity

$$Ii_{(tot)} = Ii_{(ext)} + \tau_E \Sigma\, v_{j(E)} J_{ij(E)} - \tau_I \Sigma\, v_{j(I)} J_{ij(I)} + \tau_{(t)} Ii_{(\mu)} + \tau_{SP} \Sigma\, v_{j(SP)} J_{ij(SP)} + \tau_{SN} \Sigma\, v_{j(SN)} J_{ij(SN)} \qquad (2)$$

$Ii_{(ext)}$ is the external input current received by 50% of the neurons from the other cortical areas outside the network. $\tau_E \Sigma v_{j(E)} J_{ij(E)}$ is the internal input current received by the neurons from excitatory neurons; and $\tau_I \Sigma v_{j(I)} J_{ij(I)}$ is the internal input current received by the neurons from inhibitory neurons; with τ_E and τ_I the time constants for excitatory and inhibitory neurons respectively, v_j the spike rates of neuron i and s and J_{ij} the synaptic efficacies from neuron j to neuron i. $\tau_{(t)} Ii_{(\mu)}$ is the external input current when an event μ is perceived, applied to excitatory neurons coding for the corresponding event μ. $\tau_{(t)}$ is the time variable slowly increasing with perception duration (t) of the event, which guarantees slow spike rate dynamics during event perception.

Two types of sensory neurons (positive or negative excitatory neurons on attractor neurons, $_{SP}$ and $_{SN}$ respectively) code for the affective valence of perceived events (see § 2. and 3.), transmitting $\tau_{SP} \Sigma\, v_{j(SP)} J_{ij(SP)}$ or $\tau_{SN} \Sigma\, v_{j(SN)} J_{ij(SN)}$ (internal input currents from excitatory sensory neurons coding positive or negative events, respectively).

Synapses connecting excitatory neurons (J_{EE}) coding for perceived events are plastic and sensitive to hebbian learning. Synaptic dynamics incorporates both associative long term potentiation (LTP) and depression (LTD) defining modifications of the synaptic efficacies J_{ij} between neurons j and i (Amit & Brunel, 1995; see Lavigne & Denis, 2001 for an implementation):

$$\tau_c dJ_{ij}/dt = -J_{ij} + C_{ij} + J_{0\,1} \tag{3.1}$$

calculated in the network as in Lavigne & Denis (2001)

$$J_{ij(t+1)} = (\tau_c - 1)J_{ij(t)}\ \ \tau_c + C_{ij(t)}\ \tau_c + J_{0\,1}\ \tau_c \tag{3.2}$$

J_{ij} vary according to the time constant τ_c. $J_{0\,1}$ takes the minimum or maximum values when J_{ij} crosses (getting respectively lower or upper) a threshold w_{ij}, which stochastically vary between $J_0 + \theta$ and $J_1 - \theta$, with steps of ξ.

Potentiation or depression of the synapse is given by the values of $C_{ij(t}$ defined by the Hebb learning rule according to Brunel (1996):

$$C_{ij(t)} = \lambda_+ v_{i(t)}\ v_{j(t)} - \lambda_- [\, v_{i(t)} + v_{j(t)}] \tag{4}$$

$v_{i(t)}$ and $v_{j(t)}$ are the spike rates of neurons i and j respectively, and λ_+ and λ_- are the potentiation and depression parameters respectively.

Each cycle in the network consists in a random updating of the spike rates of the neurons as a function of the intensities they receive. In order to simulate slow variations of attentional activation of the attractors in the network, slow network dynamics are guaranteed by a variable increase of input intensity $Ii_{(\mu)}$.

Before learning, the network has no structured attractor corresponding to events stored in memory. After learning of sequences of events, learned attractors coding for each event correspond to neurons activated by the event, which are strongly associated. When perceiving the corresponding event, neurons in a same attractor transmit activation within the attractor, the activation being sustained and progressively decreasing through time after removal of the perceived event.

This recurrent model codes in memory internal representations of dynamic sequences of events. The model can then perform a spatial associative coding in memory of temporal sequences in the environment. In this anticipatory attractor neural networks, event's meanings are coded as patterns of activation across a subset of excitatory neurons of the entire network, inhibitory neurons preventing from runaway excitation in the network.

2 Anticipations Based on Learning by Classical Associative Conditioning

How classical conditioned learning allows prediction of events adapted to context?

To allow anticipatory processes in dynamic memory, associative learning of temporal sequences is a key property to associate anticipated events to perceived contextual events. Associations between representations of events in memory code the temporal co-occurrence between the events perceived in the environment (Sun & Giles, 2001; Wang, 2001; Hopfield & Brody, 2000, 2001; citations Wang;). The more frequently two events are encountered as co-occurrent in the environment, the more their representations are associated in memory (Conrad, 1972; Freedman & Loftus, 1971; Landauer, Foltz, & Laham, 1998; Perlmutter, Sorce, & Myers, 1976; Spence and Kimberly, 1990 for studies on word meaning associations; see Lavigne & Lavigne, 2000 for a review). This is closely related to classical conditioning, in which two events frequently co-occurrent in the environment of a living system are associated in memory (see Macintosh; 1983). Indeed, Since Hebb's first proposal, numerous researches in neurosciences have demonstrated that co-activated neurons increase their associative strength (Long Term Potentiation), whilst neurons associated but not co-activated decrease their associative strength (Long Term Depression; Brunel, 1996). The basic principles of Hebbian like rules of neuronal learning can account for associative conditioning as well as forgetting, and are extensively used in neural network modeling

Within the recurrent network presented (Lavigne & Lavigne, 2000; Lavigne & Denis, 2001), classical conditioning can be accounted for by associative learning of co-occurrent events: Given an Unconditioned Stimulus (US = 'a rattle sound in the bush') and an Unconditioned Response to this US (UR = 'to walk back away from the snake'), learning by classical conditioning consists in presenting a Conditioned Stimulus (CS = 'a shout') preceding the US in a sequence. The CS is then learned as warning signal of the US, until the association between CS and US in memory is strong enough to allow the CS alone to trigger the UR (which then become a CR). Then Learning by classical conditioning allow every learned event (CS) to become a contextual cue to run anticipations of probable upcoming events (US) to trigger adapted behaviors.

2.1 Anticipations from Polysemic Events

To accomplish behaviors adapted to complex contexts in the environment, a cognitive system must be able to adapt its anticipations to several contextual events.

In absence of strongly predictive context, models of context-independent processing propose that an event's associated meanings are all activated in memory (see Onifer & swinney, 1981; Swinney, 1979). Indeed, most events are polysemic and can activate several different anticipations in cases when classical (pavlovian) conditioned learning previously led to associate the event (e. g., 'a brushing sound in the bush') with several and different co-occurrent events (e. g., 'snake' and 'lizard' respectively). The advantage of activating all meanings associated to the perceived event would be to represent its whole meaning (e. g., both a 'snake' and a 'lizard' can make 'brushing sounds'), and prepare behavior to every possibility. However, anticipated behavioral responses, adapted to the different meanings of the event, can be incompatible with each other if impossible to be made at the same time (e. g., 'to walk back away from the snake', or 'to take a photo shot of the lizard'). Given that the polysemy of a single contextual event can lead to ambiguous anticipations of incompatible behavioral responses, the most adapted response must be selected on the basis of further contextual cues (e. g., 'a rattle sound' specific of a rattlesnake).

Given that several contextual events (e. g., 'a rattle sound' and 'a brushing sound') can be associated to a same one (e. g., 'a snake') by classical conditioning, a context dependent view of semantic anticipations would posit that several contextual events can be strongly predictive and allow the cognitive system to anticipate only the behavioral response appropriate to the set of events (e. g., 'to walk back away from the snake'; see Lavigne & Dubois, 1999; Lavigne, Vitu & d'Ydewalle, 2000; Tabossi, 1988a,b; Tabossi & Zardon, 1993). Cases of strongly predicting context would allow the system to anticipate only the part of the event's meaning adequate to the multiple contextual events in order to run anticipations, without the need to select the appropriate one among the whole set of anticipated responses (see Lavigne & Lavigne, 2000 for a review).

To account for context effects on anticipations from ambiguous events, the model a neuron receives a total input intensity

$$Ii_{(tot)} = Ii_{(ext)} + \tau_E \Sigma v_{j(E)} J_{ij(E)} - \tau_I \Sigma v_{j(I)} J_{ij(I)} + \tau_{(t)} Ii_{(\mu)} + \tau_{SP} \Sigma v_{j(SP)} J_{ij(SP)} + \tau_{SN} \Sigma v_{j(SN)} J_{ij(SN)} \qquad (2)$$

with $\tau_{SP} = \tau_{SN} = 0$, which means that excitatory neurons cording for events do not receive any activation from sensory neurons.

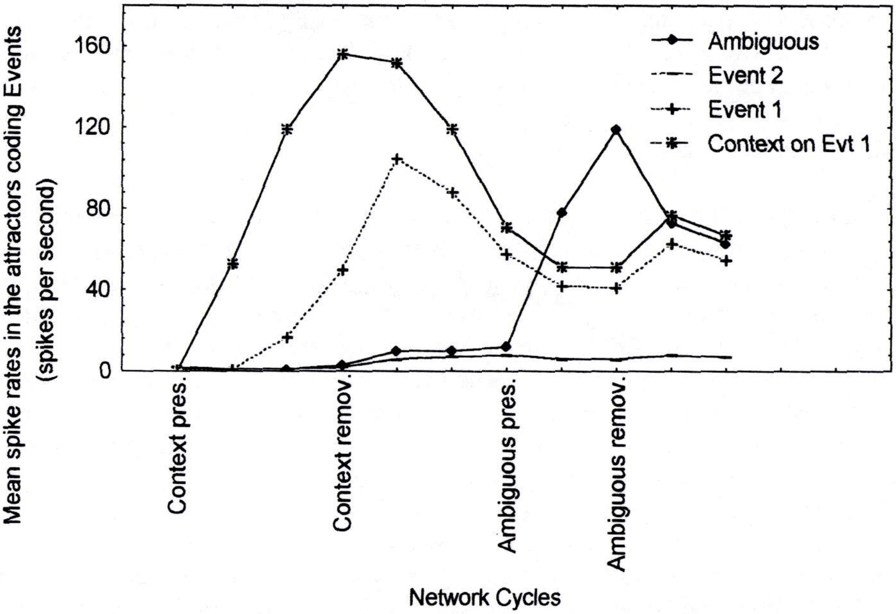

Figure 1: Activatory anticipation of event 1 associated to both the perceived ambiguous event and the context; at the expense of event 2 associated only to the ambiguous event.

2.2 Anticipations from Positive and Negative Event

Some events perceived in the environment are unlearned reinforcers (e. g., 'food' or 'pain') which lead to affective states genetically programmed to trigger automatic taxes. The event's affective valence trigger behavioral responses orienting the system toward positive-appetitive events (approaching behavior) and away of negative-aversive events (avoiding behavior; see Rolls, 1999). The positive or negative valence of unlearned reinforcers (e. g., 'food' or 'pain') can be associated to learned secondary reinforcers (e. g., 'places where there is food' or 'dangers which cause pain') by classical conditioning when the two events are frequently temporally correlated.

With regard to their affective valence, some events (e. g., 'going to the mountain') are ambivalent and can lead to qualitatively different anticipations of positive or negative associated events (e. g., respectively, 'enjoying a picnic with friends' or 'risking a fall from a cliff'). Semantic anticipations (i. e., priming, that is the facilitatory effect of a prime 'mountain' on the processing of an associated target 'summit'; see Neely, 1991; Lavigne & Lavigne, 2000) are stronger when prime and target events share the same affective valence (Bargh, Chaiken, Govender & Pratto, 1992; De Houwer, Hermans & Spruyt, 2001; Fazio, Sanbonmatsu, Powel & Kardes, 1986; Hermans, De Houwer & Eelen, 1994; see Fazio, 2001 for a review). Then the affective valence of a contextual event (e. g., 'enthusiastic and hungry friends' or 'a vertigo at looking over a cliff') can automatically, involuntarily and rapidly elicit different emotions in an anticipatory way (Bargh et al., 1992; Draine & Greenwald, 1998; Hermans et al., 1994; Fazio et al., 1986; Klauer, Rossnagel & Mush, 1997). Such induced positive or negative mood qualitatively modulate the type of anticipations toward the corresponding event (respectively 'enjoying a picnic with friends' or 'risking a fall from a cliff'). These semantic and emotional anticipations would allow the system to get ready for either positive or negative events (see Fazio, 1995, 2000, 2001; and Rolls, 1999, for reviews).

Furthermore, with regard to a given event (e. g., 'going to the mountain'), the affective valence of a context (e. g., 'enthusiastic and hungry friends' or 'a vertigo at looking over a cliff') elicit different affects influencing the quantitative amount of anticipations, which are stronger in positive than in negative emotions. Indeed, semantic priming is observed in positive context but not always in negative context (Hänze & Hesse, 1993; Hänze & Meyer, 1998; see Fazio, 2001). This would lead the system to anticipate more in positive emotional states, allowing automatic intuitive and creative processes (Fiedler, 1988) in safe and unproblematic situations which doesn't need changes in cognitive anticipations (Clore, Schwarz & Conway, 1994; Schwarz, 1990). However negative emotional states would lead to more controlled and effortful attentional processes allowing detail-oriented representations of perceived events without anticipations in dangerous situations (Frijda, 1988; Schwarz & Bless, 1991; Schwarz, 1990; see Hänze & Meyer, 1998).

To account for stronger anticipations from positive than negative events, a neuron receives a total input intensity

$$Ii_{(tot)} = Ii_{(ext)} + \tau_E \Sigma v_{j(E)} J_{ij(E)} - \tau_I \Sigma v_{j(I)} J_{ij(I)} + \tau_{(t)} Ii_{(\mu)} + \tau_{SP} \Sigma v_{j(SP)} J_{ij(SP)} + \tau_{SN} \Sigma v_{j(SN)} J_{ij(SN)} \qquad (2)$$

with $\tau_{SP} > \tau_{SN} \approx 0$, which guarantee that positive events are more activated than negative events and lead to strong associative learning and anticipations, since negative events lead only to weaker associative learning and anticipations.

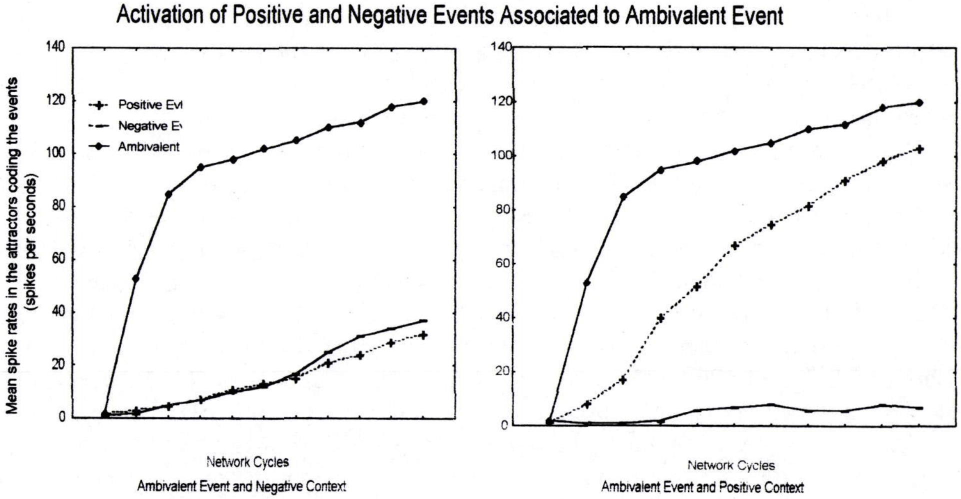

Figure 2: Activatory anticipations of positive and negative events from perception of an ambivalent event as a function of a positive or negative context.

3 Anticipations Based on Learning by Operant Instrumental Reinforced Conditioning

How operant reinforced conditioned learning allows adapted anticipations of behaviors?

Classical conditioned learning allows to anticipate events as a function of the emotional state induced by the perception of an event (see Rolls, 1999). This allow the system to get ready for either positive or negative events (e. g., 'enjoying a picnic with friends' or 'risking a fall from a cliff'; see Fazio, 2001). However this does not automatically orient behavior toward positive events or away of negative ones (e. g., 'how to enjoy a picnic with friends' or 'how to avoid a fall from a cliff'). To trigger adapted behaviors from both positive and negative events, the cognitive system must be able to associate adapted actions with perceived events. This can be accomplished by natural selection of neural networks as well as by instrumental reinforced learning (see Rolls, 1999) allowing emotional decisions (Barnes & Thagard, 1996; see Damasio, 1998).

3.1 Anticipations of Actions Adapted to Positive and Negative Events

A first case of learning consists in natural selection behaviors adapted to the system's environment (Darwin, 1859). This would be achieved by selection of genetically coded neural networks (see Rolls, 1999). These elementary networks allow living systems to anticipate (approaching or avoiding) behaviors adapted to primary reinforcers (e. g., respectively 'food' or 'pain'). This can be accomplished by genetically coded associations between sensory representations of primary events and simple reflex-like behavioral responses. Sensory representations (e. g., 'smell of food' or 'pain') induced by the perception of events (e. g., respectively 'food' or 'a bite') activate representations of approaching or avoiding behaviors (e. g., respectively 'tasting the food' or 'moving in the opposite direction of the bite').

To account for automatic behaviors to perceived events, neurons triggering approaching ($_{AP}$) or avoiding ($_{AV}$) behaviors are directly and automatically activated by (respectively positive and negative) sensory neurons by strong and non-plastic synapses $J_{ij(SP)}$ and $J_{ij(SN)}$, according to

$$Ii_{(totAP)} = \tau_{SP}\Sigma\, v_{j(SP)}J_{ij(SP)} - \tau_{SN}\Sigma\, v_{j(SN)}J_{ij(SN)} \quad (5.1)$$
$$Ii_{(totAV)} = -\,\tau_{SP}\Sigma\, v_{j(SP)}J_{ij(SP)} + \tau_{SN}\Sigma\, v_{j(SN)}J_{ij(SN)} \quad (5.2)$$

This allow the model to automatically trigger behaviors to primary reinforcers that does not need to be learned.

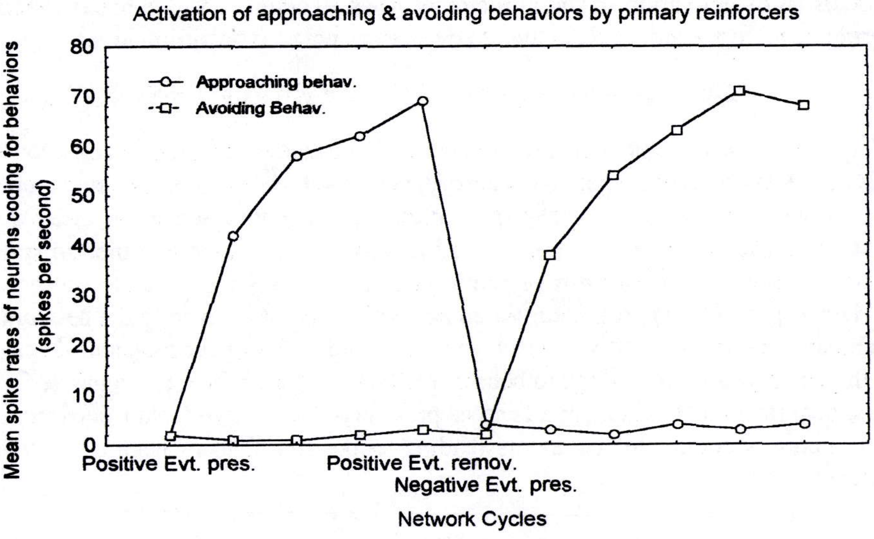

Figure 3: Automatic anticipatory activation of (approaching or avoiding) behavioral responses to (positive or negative) perceived events.

3.2. Anticipations for Adapted Behavioral Responses to Positive or Negative Events

Instrumental reinforced learning allow the system to associate not only events together (classical learning), but behaviors of the system and events perceived as responses in the environment (secondary reinforcers). For a given event (e. g., 'going to the mountain'), semantic anticipations (respectively 'enjoying a picnic with friends' or 'risking a fall from a cliff') can lead the system to anticipate approaching or avoiding (the edge of the cliff) behaviors. They are not automatic and must be learned as a function of secondary reinforcers. Behaviors modify the environment in which new events are perceived as positive or negative secondary reinforcers, according to their affective value (e. g., avoiding the cliff and 'enjoy the pic-nic' or approaching the cliff and 'experiencing vertigo'). Positive reinforcers, or "rewards", as well as negative reinforcers or "punishers", can elicit emotional states influencing learning and behavior (Millenson, 1967; Weiskrantz, 1968; Gray, 1975, 1987; Rolls, 1986, 1990, 1999). Neuronal learning allows the system to vary the frequency of a behavior in order to obtain a "reward" and avoid a "punisher". To this aim associations between a given behavior and a reinforcing event are strengthened in positive emotional states and stable or weakened in negative emotional states; by the way of increased neuronal activations in positive emotional states compared to negative ones (see Rolls, 1999 about the neural basis of learning in positive and negative states).

To account for behavioral responses of the network that are not automatic reflex-like responses to primary reinforcers, but are learned behavioral responses to secondary reinforcers (i. e., activation of the attractor neurons $_{BE}$ coding for a behavior), neurons triggering behaviors are directly activated by sensory neurons according to

$$Ii_{(totBE)} = Ii_{(ext)} + \tau_E \Sigma v_{j(E)} J_{ij(E)} - \tau_I \Sigma v_{j(I)} J_{ij(I)} + \tau_{(t)} Ii_{(\mu)} + \tau_{SP} \Sigma v_{j(SP)} J_{ij(SP)} + \tau_{SN} \Sigma v_{j(SN)} J_{ij(SN)} \qquad (2)$$

with $\tau_{SP} > \tau_{SN} \approx 0$, which guarantee that positive events are more activated than negative events, and with positive sensory neurons presenting a sustained activity ($v_{j(SP)} > 0$ positive even if no event is presented) since negative sensory neurons do not ($v_{j(SN)} = 0$ if no event is perceived). This lead to stronger activation and then to stronger associative learning when a positive reinforcer ('reward') is presented to the network than when a 'punisher' is presented. When no reinforcement is given to the network, the spontaneous activity of positive sensory neurons leads to stronger associative learning when the perceived event leading to behavior is positive than when it is negative.

This guarantee that when an event is presented, the network can activate more strongly neurons coding for behaviors leading to positive than to negative secondary reinforcers.

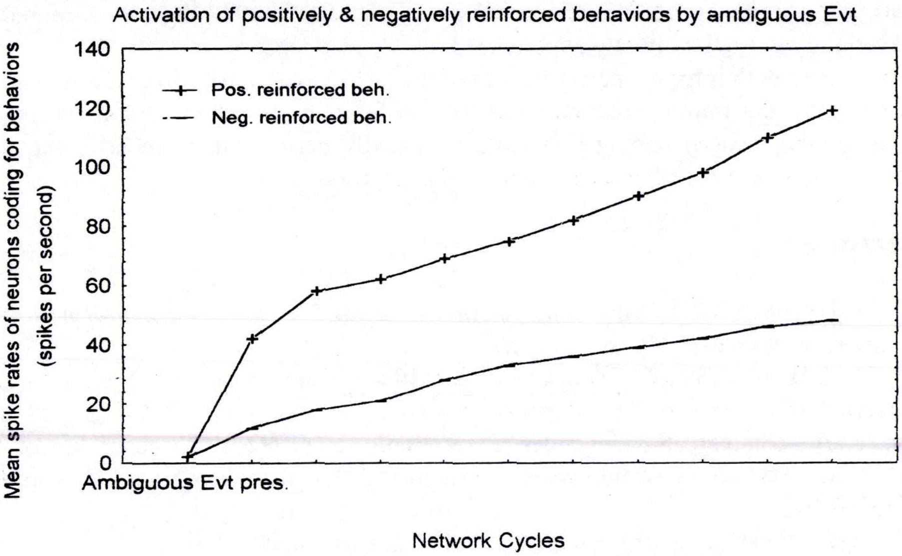

Figure 4: Activatory anticipations of (either avoiding or approaching) behaviors from the perception of an ambiguous event, as a function of the learned reinforcement of the behaviors by positive or secondary reinforcers.

4 Anticipations Learned by Mimetic Learning

Emotional states, elicited by the affective value of perceived events, can influence the strength of associative learning as well as the type of dynamic anticipatory processes. Associative learning and anticipations are qualitatively modulated by both the type of contextual events and the type of emotional states elicited by the affective value of contextual events. They are also quantitatively modulated, being stronger in positive emotional states than in negative ones. In addition, reinforced learning allow the system to anticipate adapted behaviors, approaching positive events and avoiding negative ones, as a function of the emotional states elicited by the perceived events.

Furthermore, mimetic learning (Billard, 2001; Billard & Hayes, 1999) can involve both types of associative and reinforcement learning. This would consists in considering as events in sequences for a given system (i) events perceived by another system, (ii) behavioral responses of the other system, and (iii) the reinforcing events to this other system. These sequences can be learned by associating in memory events and behaviors that are not directly behaved by the system, which lead to reproduce the same behaviors as the ones of the observed system when the same context is perceived, without the need for the system to experiment by itself the behaviors in response to the perceived event. Even if mimetic learning allows learning without the need of direct experiment, it does not guarantee adapted behaviors in cases when the reinforcing events cannot be observed but have to be directly experienced.

In order to both improve performances of the model and to modelize a larger variety of learning such as mimetic learning, further modifications of the network are necessary such as adding neuron coding behaviors to actually perform that are different from neurons coding for possible and incompatible behaviors.

References

Amit, D. J. (1989). *Modeling Brain Function: The world of attractor neural networks.* Cambridge University Press.

Amit, D. J., Brunel, N., & Tsodyks, M. V. (1994). Correlations of hebbian cortical reverberations: Experiment vs. theory. *Journal of Neurosciences, 14,* 6635.

Bargh, J. A., Chaiken, S., Govender, R. & Pratto, F. (1992). The generality of the automatic attitude activation effect. *Journal of Personality and Social Psychology, 62,* 893-912.

Berthoz, A. (1996). *Les sens du mouvement.* Paris, Odile Jacob.

Billard, A. (2001). Learning motor skills by imitation: a biologically inspired robotic model, *Cybernetics & Systems* , 32, 1-2. pp. 155-193.

Billard, A. & Hayes G. (1999). DRAMA, a connectionist architecture for control and learning in autonomous robots, *Adaptive Behavior Journal,* Vol. 7:1. pp.35-64.

Brunel, N. (1996). Hebbian learning of context in recurrent neural networks. *Neural Computation, 8,* 1677-1710.

Brunel, N. (1994). Dynamics of an attractor neural network converting temporal into spatial correlations. *Network, 5,* 449.

Clore, G. L., Schwarz, N. & Conway, M. (1994). Affective causes and consequences of social information processing. In R. S. Wyer & T. K. Srull (Eds.), Handbook of Social Cognition, 1: Basic Processes (2nd ed., 323-417). Hillsdale, NJ: Erlbaum.

Conrad, C. 1972. Cognitive economy in semantic memory. *Journal of Experimental Psychology, 92,* 149-154.

Damasio, A. R. (1994). Descartes' Error. Putnam.

Darwin, C. 1859. On the Origin of Species by Means of Natural Selection, or the Preservation of Favoured Races in the Struggle for Life. First Ed. http://www.literature.org/authors/darwin-charles/the-origin-of-species/index.html

De Houwer, J., Hermans, D. & Spruyt, A. (2001). Affective priming of pronunciation responses: Effects of target degradation. *Journal of Experimental Social Psychology, 37,* 85-91.

Draine, S. C. & Greenwald, A. G. (1998). Replicable unconscious semantic priming. *Journal of Experimental Psychology: General, 127,* 286-303.

Dubois, D. M. (1998a). Introduction to Computing Anticipatory Systems. *International Journal of Computing Anticipatory Systems, 2,* 3-14. D. Dubois (Ed.), CHAOS (Publisher).

Dubois, D. M. (1998b). Computing Anticipatory Systems with Incursion and Hyperincursion. Computing Anticipatory Systems: CASYS – first international conference, D. Dubois (Ed.), American Institute of Physics (Publisher), *AIP conference proceedings 437*, 3-29.

Fazio, R. H. (1995). Attitudes as object-evaluation associations: Determinants, consequences, and correlates of attitude accessibility. I, R. E. Petty & J. A. Krosnick (Eds.), *Attitude strength: Antecedents and consequences*, 247-282. Hillsdale, NJ: Erlbaum.

Fazio, R. H. (2000). Acessible attitudes as tools for object appraisal: Their costs and benefits. In G. Maio & J. Olson (Eds.), *Why we evaluate: Functions of attitudes* (1-36). Mahwah, NJ: Erlbaum.

Fazio, R. H. (2001). On the automatic activation of associated evaluations: An overview. *Cognition and emotion, 15*, (2), 115-141.

Fazio, R. H., Sanbonmatsu, D. M., Powel, M. C. & Kardes, F. R. (1986). On the automatic activation of attitudes. *Journal of Personality and Social Psychology, 50*, 229-238.

Fiedler, K. (1988). Emotional mood, cognitive style, and behavior regulation. In K. Fiedler & J. P. Forgas (Eds.), *Affect, cognition, and social behavior* (100-119). Toronto: Hogrefe.

Freedman, J. L. & Loftus, E. F. (1971). Retrieval of words from long term memory. *Journal of Verbal Learning and Verbal Behavior, 10*, 107-115.

Frijda, N. H. (1988). The laws of emotion. *American Psychologist, 43*, 349-358.

Gillund, G. & Shiffrin, R. M. (1984). A retrieval model for both recognition and recall. *Psychological Review, 91*, 1-67.

Glenberg, A. M. (1997). What memory is for, *Behavioral and Brain Sciences, 20* (1), 1-55.

Gray, J. A. 1975. Elements of a Two-Process Theory of Learning. Academic Press.

Gray, J. A. 1987. The Psychology of Fear and Stress. 2nd ed. Cambridge Univ. Press.

Grossberg, S., Levine, D. S. & Schmajuk, N. (1992). Associative learning and selective forgetting in a neural network regulated by reinforcement and attentive feedback. In Levine, D. S. & Leven, S. J. (Eds), *Motivation, emotion and goal direction in neural networks* (pp 37-62), Lawrence Erlbaum Associates, Hillsdale, N.J.

Grossberg, S. & Stone, G. (1986). Neural dynamics of word recognition and recall: Attentional priming, learning, and resonance. *Psychological Review*, 93, 1, 46-74.

Hänze, M. & Meyer, H. A. (1998). Mood influences on automatic and controlled semantic priming. *American Journal of Psychology, 111*(2), 265-278.

Hänze, M. & Hesse, F. W. (1993). Emotional influences on semantic priming. *Cognition & Emotion*, 7(2), 195-205.

Hermans, D., De Houwer, J. & Eelen, P. (1994). The affective priming effect: Automatic activation of evaluative information in memory. *Cognition and Emotion, 8*, 515-533.

Hinton, G. E. & Shallice, T. (1991). Lesioning an Attractor Network: Investigations of Acquired Dyslexia. *Psychological review*, 98, 1.

Hopfield, J. J. (1982). Neural networks and physical systems with emergent collective computational abilities. *Proceedings of National Academy of Science, 79*, 2554-2558.

Hopfield, J. J. and Brody C. D. (2000). What is a moment? 'Cortical' sensory integration over a brief interval (I). Proc. Natl. Acad. Sci. USA 97, 13919-13924.

Hopfield, J. J. and Brody C. D. (2001). What is a moment? Transient synchrony as a collective mechanism for spatiotemporal integration (II). http://www.neuron.princeton.edu/

Hopfield, J. J. & Tank, D. W. (1986). Computing with neural circuits: A model. *Science, 233*, 625-633.

Kintsch, W. (1988). The role of knowledge in discourse comprehension: a construction-integration model. *Psychological Review, 95*, 163-182.

Klauer, K. C., Rossnagel, C. & Mush, J. (1997). List-context effects in evaluative priming. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 23*, 246-255.

Jones, M. R. (1976). Time, our lost dimension: toxard a new theory of perception, attention and memory, *Psychological Review, 83*, 323-355.

Jones, M. R. & Boltz, M. (1989). Dynamic attending and response time, *Psychological Review, 3*, 459-491.

Jones, M. R. & Yee, W. (1993). Attending to auditory events: the role of temporal organization, in S. McAdams & E. Bignand (Eds.), *Thinking in sound*, Oxford, Clarendon Press.

Laberge, D. (1995). *Attentional Processing*, Cambridge, Mass., Harvard University Press.

Lecas, J. C. (1992). *L'attention Visuelle*, Bruxelles, Mardaga.

Landauer, T. K., Foltz, P. W. & Laham, D. (1998). An introduction to latent semantic analysis. *Discourse Processes, 25*, 259-284.

Lavigne, F. & Dubois, D. (1999). Context effects and associative anaphora in reading, *Journal of Pragmatics, 31*, 399-415.

Lavigne, F. & Vitu, F. (1997). Time course of facilitatory and inhibitory semantic priming effects in visual word recognition. *International Journal of Psycholinguistics, 13*, 311-349.

Lavigne, F., Vitu, F & d'Ydewalle. (in press). Context effects and parafoveal preview in sentence reading, *Acta Psychologica, 104*, 191-214.

Macintosh, N. J. (1983). Conditioning and Associative Learning. Oxford University Press.

Masson, M. E. J. (1991). A distributed memory model of context effects in word identification, In D. Besner and G. Humphreys (Eds.), *Basic processes in reading: Visual word recognition* (pp. 233-263) Hillsdale, Hove, London, Lawrence Erlbaum.

Masson, M. E. J. (1995). A distributed memory model of semantic priming. *Journal of Experimental Psychology: Learning, Memory & Cognition, 21*, 3-23.

Millenson, J. R. (1967). Principles of Behavioral Analysis. Mac Millan.

Neely, J.H. (1991). Semantic priming effects in visual word recognition: A selective review of currents findings and theories. In D. Besner & G. Humphreys (Eds.), *Basic processes in reading: Visual word recognition* (pp. 264-336). Hillsdale, Hove, London: Lawrence Erlbaum.

Onifer, W. & Swinney, D. A. (1981). Accessing lexical ambiguities during sentence comprehension: Effects of frequency of meaning and contextual bias. *Memory and Cognition,* 9, 225-236.

Perlmutter, J., Sorce, P. & Myers, J. L. (1976). Retrieval processes in recall. *Cognitive Psychology, 8,* 32-63.

Posner, M. J. & Snyder, C. R. R. (1975a). Facilitation and Inhibition in the processing of signals. In P. M. A. Rabitt & S. Dornic (Eds.), *Attention and performance V* (pp. 669-698). New York: Academic Press.

Posner, M. J. and Snyder, C. R. R. (1975b). Attention and cognitive control. In R. L. Solso (Ed.), *Information processing and cognition: The Loyola Symposium* (pp. 55-85), Hillsdale, NJ: Erlbaum.

Ratcliff, R. & Mc Koon, G. (1988). A retrieval theory of priming in memory, *Psychological Review, 95,* 385-408.

Ratcliff, R. & McKoon, G. (1994). Retrieving information from memory: Spreading activation theories versus compound-cue theories. *Psychological Review, 101,* 177-184.

Rolls, E. T. (1986) A theory of emotion, and its application to understanding the neural basis of emotion. In: *Emotions. Neural and Chemical Control* , pp. 325-344, ed. Y. Oomura. Karger.

Rolls, E. T. (1990) A theory of emotion, and its application to understanding the neural basis of emotion. *Cognition and Emotion* 4: 161-190.

Rolls, E. T. (1999) *The Brain and Emotion* . Oxford University Press.

Rosen, R. (1985). Anticipatory Systems – Philosophical, Mathematical and Methodological Foundations. Pergamon Press.

Sharkey, A. J. C. & Sharkey, N. E. 1992. Weak contextual constraints in text and word priming. *Journal of Memory and Language, 31*, 543-572.

Schwarz, N. (1990). Feelings as information: Informational and motivational functions of affective states. In E. T. Higgins & R. M. Sorrentino (Eds.), *Handbook of motivation and cognition. Foundation of Social behavior*, vol. 2, pp. 527-561). New York: Guilford.

Schwarz, N. & Bless,H. (1991). Happy and mindless, but sad and smart? The impact of affective states on analytic reasoning. In J. P. Forgas (Ed.), *Emotion and social judgements*, pp. 55-72. Oxford: Pergamon.

Spence, D. P. & Kimberly, C. O. (1990). Lexical co-occurrence and association strength, *Journal of Psycholinguistic Research, 19*, 317-330.

Swinney, D. (1979) Lexical access during sentence comprehension: (Re)consideration of context effects. *Journal of verbal Learning and verbal Behavior*, 18(6), 645-659.

Tabossi, P. (1988a). Effects of context on the immediate interpretation of unambiguous Nouns. *Journal of Experimental Psychology: Learning, Memory and Cognition*, 14, 153-162.

Tabossi, P. (1988b). Accessing lexical ambiguity in different types of sentential contexts. *Journal of Memory and Language*, 27, 324-340.

Tabossi, P. & Zardon, F. (1993). Processing ambiguous words in context. *Journal of Memory and Language*, 32, 359-372.

Barnes, A. & Thagard, P. (1996). Emotional decisions. Proceedings of the 18th Annual Conference of the Cognitive Science Society, pp. 426-429, NJ: LEA.

Varela, F., Thompson, E. & Rosh, E. (1999). The embodied mind: Cognitive science and human experience, MIT Press: Boulder, Co.

Wang, D. L. (1996). Incremental learning of complex temporal patterns. *IEEE Transactions on Neural Networks*, 7, 6, 1465-1481.

Wang, D. L. (2000). Anticipation models for sequential learning of complex sequences. In R. Sun & C. L. Giles (Eds.): *Sequence Learning*, LNAI 1828, pp. 53-79, Springer-Verlag, Berlin Heidelberg.

Weiskrantz, L. (1968) Emotion. In: *Analysis of Behavioural Change* , pp. 50-90, ed. L. Weiskrantz. Harper and Row.