The University of Tokyo

DoctorThesis

博士論文

Exploring New Neural Architectures for Adaptation to Complex Worlds

(新しい構造に基づいて複雑性に対処するニューラルネットワークの研究)

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Prologue

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Doctor

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by Sinapayen Lana

Action, Prediction, Classification.

The world is a dynamical system producing countless complex data streams: noisy, stochastic, aperiodic data. To manipulate the environment to its advantage, an organism needs to filter these data streams and produce appropriate actions. The efficiency of actions is improved by predicting consequences, and the efficiency of predictions is improved by classifying inputs. Yet the amount of energy available to living organisms is limited, and these three functions cannot afford being both slow and computationally expensive. In this thesis, we present two algorithms to help machines learn from complex input and produce appropriate outputs while optimizing the computational cost.

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Abbreviations

LSA	Learning by Stimulation Avoidance
MSE	Mean Squared Error
SRP	Stimulus Regulation Principle
STDP	Spike-Timing Dependent Plasticity
STP	Short Term Plasticity
STM	Short Term Memory
PrW	Prediction Weight
PaW	Pattern Weight

Chapter 1

Introduction

The real world, compared to simulated models, contains massive amounts of information. The amount of information itself is not complexity, but the way this information comes together is referred as environmental complexity.

There are many definitions of complexity; two of these definitions seem particularly relevant to this work. In 1947, Weaver gave a definition that identified two subtypes of complexity [1] : disorganized complexity and organized complexity. Disorganized complexity refers to data that is produced by many components of system loosely interacting together. This type of data looks complex if each point is observed in isolation, but can be described in a simple way using probability distributions: Brownian motion is an example of disorganized complexity. Organized complexity involves components strongly coupled together, producing organized data that cannot be described using only statistics: Darwinian evolution is an example of organized complexity. In 1989, Crutchfied [2] gave a different definition of complexity as being a mix between two types of simple systems: random systems, which look complex but are statistically simple, and periodic systems, which are simple to predict. Systems in-between these two extremes qualify as complex. Weaver's disorganized complexity seems to align with Crutchfield's random systems, while Weaver's organized complexity is the same as Crutchfield's true complexity.

So what is complex behavior for an agent? Behavior consists in selecting the right actions from processing input data. Even in complex environments, agents do not have access to all of the world's information; they only have access to a small part of it, as data streaming through their sensors. The combined sensory information forms their Umwelt [3], and is entirely dependent on darwinian evolution. The kind of actions that an agent can perform is also totally dependent on evolution, and the amount of

information going from the controller to the actuators of an agent depends on the agent's body plan.

But even a minimally simplistic agent with one binary sensor (e.g. a touch sensor) and one binary actuator (e.g. a button-pushing appendage) could, in theory, exhibit complex behavior if its action decision process itself is complex, neither random nor periodic: for example, pushing the button only after receiving an extremely long binary string as input, partially depending on hidden random internal states.

Behavior is the most basic need of an agent, and action is the evolutionary function that emerged to fulfill this need. By acting, the agent goes from being a simple self-reproducing machine to being an agent. The need for behavior created a need for two other functions: prediction and classification. By predicting, the agent goes from simply reacting to stimuli, to being proactive in anticipation for future stimuli. By classifying, it goes from only predicting consequences of previously encountered stimuli, to predicting consequences of all new stimuli belonging to known classes. Here classes are taken to be units for prediction, as in Crutchfield's Epsilon Machine: if two seemingly separate units have the same consequences (eg a sweet taste), they represent the same cause (sugar on your tongue) and belong to the same class (fruits). The more units in the Epsilon Machine, the more complex the original input stream.

Action, Prediction, Classification: by order of importance, these are the functions an organism needs to use a complex environment to its advantage. Accordingly, not all 3 are needed by all organisms and the functions emerge from the bottom up: prediction emerges from action and classification emerges from prediction. Fig. 1.1 shows how these 3 functions are linked, and the environmental needs that have resulted into these functions evolving. We can sketch out the following rules regarding the complexity of the agent's cognitive processes:

- The complexity of a perfect action selection process has the number of possible actions as a lower bound
- The complexity of a perfect predictive process has the number of known classes as a lower bound
- The complexity of a perfect classification process has the number of classes (causes explaining a data stream) existing in the real world as a lower bound.

The hierarchy of evolution goes from the most basic need to the more complex: action, prediction, classification. In theory, there is no higher bound to the complexity of the cognitive process, as an infinitely complex prediction machine can always be constructed

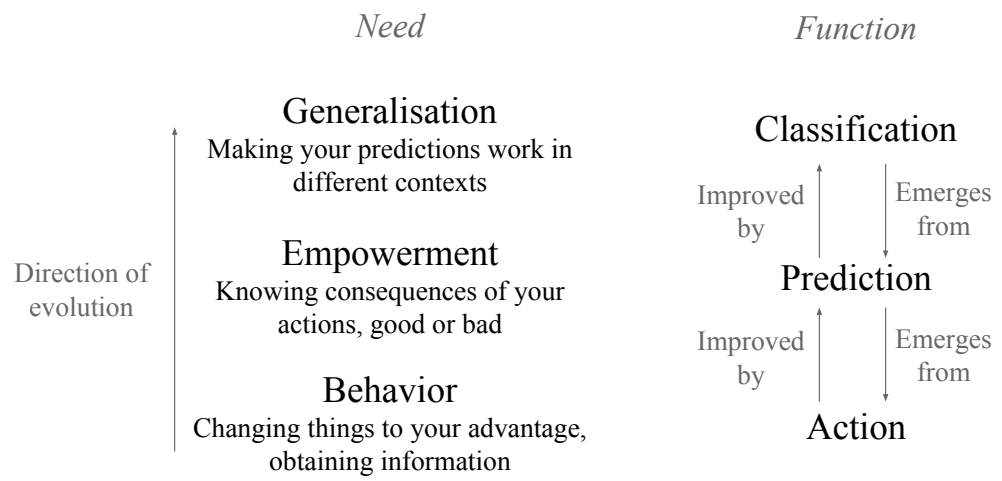


FIGURE 1.1: **Evolutionary needs and their corresponding solutions.** An organism needs behavior; this need is met by the evolution of actuators to modify the world. It also needs to be empowered, which depends on prediction to anticipate appropriate actions. Finally, it needs to generalize these predictions, which is the role of classification. Prediction emerges from the need for better actions, and classification emerges from the need for better predictions.

even to explain the simplest data stream. In reality, cognitive processes have a cost of energy, and evolution will always match the cost of cognition to the benefits of the actions: for two levels of cognitive complexity that produce the same results in terms of actions, evolution will favor the least complex one. The cognitive process must not be too costly, and it does not even have to be perfect: it just has to be sufficient for the agent's needs, as brilliantly demonstrated by Hoffman [4]. Cognitive complexity is therefore bounded by the level of complexity of what the agent can perceive of the real world through its sensory inputs (and optionally by the attentional mechanisms that sort through this input).

How can we obtain similar results artificially, and program a machine to adjust its cognitive complexity to the environment so that prediction emerges from action and classification emerges from prediction? In this thesis, I present two models of networks.

The first network, presented in Chapter 2, is inspired from biology and proposes a learning rule for networks of spiking neurons as a way for the brain to close the input-output loop via action. Action must have been the first function to evolve in simple organisms, and in this sense the model proposed here solves the oldest issue that might have been faced by nervous systems: how to associate desirable/undesirable inputs with the actions that cause these inputs? No learning rule has so far been accepted as a general solution for networks of real neurons and biologically-inspired networks. We argue for the existence of a principle allowing to steer the dynamics of biological and biologically-inspired neural networks: "Learning by Stimulation Avoidance" (LSA). Using carefully

timed external stimulation, the network can be driven towards a desired dynamical state. LSA sifts through high levels of noise in the input, finding the signal to which the network must react. In this sense it gives us a creature of habit, a purely reactive agent. As presented by Charles Duhigg in his book The Power of Habit [5], the process of creating habits can be costly, but once the habit is formed it yields fast and effortless behavior, to the point that breaking the habit becomes the costly behavior.

In addition to separating signal from noise, LSA has the advantage of explaining so-far-unexplained existing biological data. I demonstrate through simulation that the minimal sufficient conditions leading to LSA in artificial networks are also sufficient to reproduce learning results similar to those obtained in biological neurons by Shahaf and Marom [6, 7], and to explain synaptic pruning. I examine the underlying mechanism by simulating minimal networks with up to 3 neurons, then scale it to one hundred neurons. I show that LSA has a higher explanatory power than existing hypotheses about the response of biological neural networks to external simulation, and can be used as a learning rule for an embodied application: learning of wall avoidance by a simulated robot.

In other works, reinforcement learning with spiking networks is obtained through global reward signals akin to simulating the dopamine system: this is the first research demonstrating sensory-motor learning with random spiking networks through Hebbian learning without a separate reward system.

One disadvantage is that LSA looks at very low-level phenomena, down to the individual spiking dynamics of neurons. For this reason, after solving the issue of action learning in biological and biologically-inspired networks, we turn to a higher level view of the brain and in Chapter 3 I present a second model, the ϵ-network. This model looks at neurons as binary units and disregards all low level dynamics, taking inspiration from both research in the field of dynamical systems and from research in cognitive science, using concepts like Short Term Memory or pattern recognition to tackle higher-level cognitive issues. It proposes a way to simultaneously solve the issues of Prediction and Classification, emerging predictions and classifications from a data stream while insuring that the network's complexity matches the complexity of the input data. In the Epsilon Network (ϵ-network) the number of neurons is variable, a unique aspect of this second model: it automatically adjusts its size to the complexity of a stream of data, while performing online learning. It optimizes its topology during training, simultaneously adding and removing neurons and weights to its structure: it adds neurons where they can raise performance, and removes redundant neurons while preserving performance. The model can be seen as a neural realization of the ϵ-machine devised by Crutchfield et al [2].

I train the network to predict the future scenes in video frames, evaluate it on simple,

complex, and noisy videos and show that the final number of neurons is a good indicator of the complexity and predictability of the data stream. A downside of the ϵ-network is that it does not perform any actions, and it attempts to predict the whole input data, frame after frame, without regard to whether all data really is worth spending predictive power on. These two issues are coincidentally the two strong points of the LSA model: ignoring irrelevant data to perform the right action. This makes LSA and the ϵ-network not simply opposite but complementary: this thesis solves the entirety of the Action, Prediction and Classification issues in two separate, complementary models. LSA and the ϵ-network work at different levels of abstraction, but they both use variants of Hebbian learning rules and do not have a global reward function or a reward center. This makes an unifying framework possible, either by modeling the ϵ-network down to micro-phenomena like LSA does and finding biologically plausible ways to implement it, or by putting aside low-level biological concerns modeling LSA as a more abstract module between the input data and the prediction engine as a submodule of the ϵ-network, which is the approach that we have chosen as a work in progress and is discussed in Chapter 4.

This thesis is divided in 4 chapters: this introduction; Chapter 2 presents LSA as a method to close the environment-action loop while sifting through irrelevant noise; Chapter 3 presents the ϵ-network as a way to close the prediction-classification loop. Chapter 4 summarizes the impact of this thesis for our understanding of adaptive complexity and where to go from there.

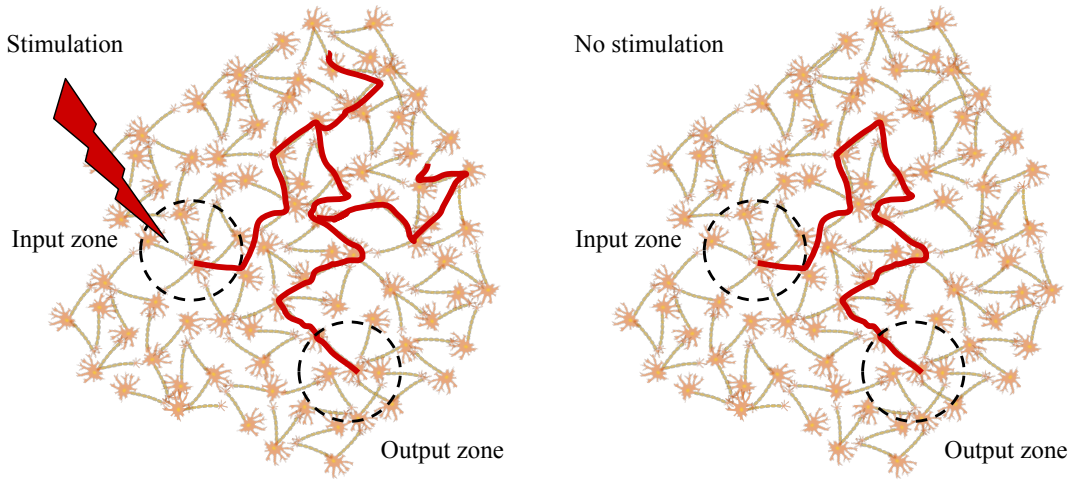
Chapter 2

Learning by Stimulation Avoidance

2.1 Background

In two papers published in 2001 and 2002, Shahaf and Marom conduct experiments with a training method that drives rats' cortical neurons cultivated in vitro to learn given tasks [6, 7]. They show that stimulating the network with a focal current and removing that stimulation when a desired behaviour is executed is sufficient to strengthen said behaviour. By the end of the training, the behaviour is obtained reliably and quickly in response to the stimulation. More specifically, networks learn to increase the firing rate of a group of neurons (output neurons) inside a time window of 50 ms, in response to an external electric stimulation applied to another part of the network (input neurons). This result is powerful, first due to its generality: the network is initially random, the input and output zones' size and position are chosen by the experimenter, as well as the output's time window and the desired output pattern. A second attractive feature of the experiment is the simplicity of the training method. To obtain learning in the network, Shahaf and Marom repeat the following two steps: (1) Apply a focal electrical stimulation to the network. (2) When the desired behavior appears, remove the stimulation.

At first the desired output seldom appears in the required time window, but after several training cycles (repeating steps (1) and (2)), the output is reliably obtained. Marom explains these results by invoking the Stimulus Regulation Principle (SRP, from [8, 9]). The mechanism of the SRP is summarized in fig. 2.1. At the level of neural network, the SRP postulates that stimulation drives the network to "try out" different topologies by modifying neuronal connections ("modifiability"), and that removing the



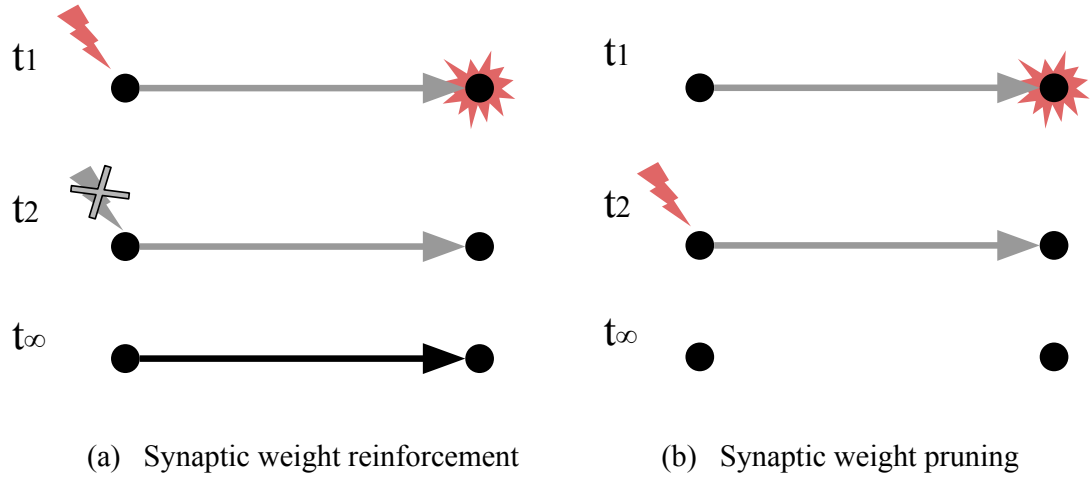
(a) Modifiability (b) Stability

FIGURE 2.1: **The Stimulus Regulation Principle (SRP).** (a) The SRP postulates that the structure of the network randomly changes when focal electric stimulation is applied, creating new paths (modifiability). (b) When the stimulation is stopped, the structure of the network stops changing (stability). This idea does not explain how newly formed paths would avoid being destroyed when stimulation is applied to the network again like in Shahaf's training method.

stimulus simply freezes the network in its last configuration ("stability"). The SRP explicitly postulates that no strengthening of neural connections occurs as a result of stimulus removal.

The simplicity and generality of the results obtained by Shahaf and Marom suggest that this form of learning must be a very basic property of biological neural networks. Yet the SRP does not entirely explain the experimental results. Applying several cycles of stimulation to the network is in direct contradiction with both ideas of modifiability and stability. "Modifiability" conflicts with the idea of learning: we cannot prevent the "good" topology to be modified by the stimulation at each new training cycle. Why are several training cycles necessary if "stability" guarantees that the configuration of the network is preserved after stopping the stimulation? The SRP might be at work in different frameworks, but is not suitable to explain the experimental results.

Another interesting feature in Shahaf's experiment is that there is no global reward signal sent to the network. In our work we also do not have global reward signals or reward modules. This is a difference in the object of study between existing papers about learning in spiking networks coupled with a dopamine-like system [10, 11, 12] and the present thesis. Accepting Shahaf and Marom' s macro-phenomenological description of the behavior, we provide a possible mechanism at the micro scale: the principle of Learning By Stimulation Avoidance (LSA, [13, 14]). LSA is an emergent property of



(a) Synaptic weight reinforcement (b) Synaptic weight pruning

FIGURE 2.2: **Strengthening or pruning of synapses according to LSA.** The timing of the stimulation to a pre-synaptic neuron relative to the firing of the post-synaptic neuron the causes the strengthening or pruning of the synapse. If the stimulation stops just after the post-synaptic spike, the synapse is strengthened; if the stimulation starts just after the post-synaptic spike, the synapse is pruned.

spiking networks coupled to Hebbian rules [15] and external stimulation. LSA states that the network learns to avoid external stimulus by learning available behaviors e.g. moving away from or destroying the stimulation sources only as a result of local neural plasticity.

In opposition to the SRP, LSA does not postulate that stimulus intensity is the major drive for changes in the network, but rather that the timing of the stimulation relative to network activity is crucial. LSA relies entirely on time dependent strengthening and weakening of neural connections (fig. 2.2). In addition, LSA proposes an explanatory mechanism for synaptic pruning, which is not covered by the SRP.

LSA emerges from Spike-Timing Dependent Plasticity (STDP), which has been found in both in vivo and in vitro networks. We take STDP as a one basic mechanism governing the neural plasticity [16] and a Hebbian learning rule as a classical realization of STDP in our model. STDP relies on processes so fundamental that it has been consistently found in the brains of a wide range of species, from insects to humans [17, 18, 19]. STDP causes changes in the synaptic weight between two firing neurons depending on the timing of their activity: if the presynaptic neuron fires within 20 ms before the postsynaptic neuron, the synaptic weight increases; if the presynaptic neuron fires within 20 ms after the postsynaptic neuron, the synaptic weight decreases.

Shahaf postulates that the SRP might not be at work in "real brains". Indeed, SRP has not yet been found to take place in the brain, unlike STDP. Although STDP occurs at neuronal level, it has very direct consequences on the sensory-motor coupling

of animals with the environment. In vitro and in vivo experiments based on STDP can reliably enhance sensory coupling [20], decrease it [21], and these bidirectional changes can even be combined to create receptive fields in sensory neurons [22, 23].

Therefore, although STDP is a rule that operates at the scale of one neuron, LSA can be expected to emerge at network level in real brains as well as it emerges in artificial networks. LSA at a network level requires an additional condition that is burst suppression. In this paper, we have tested two mechanisms. One is that we add white noise to all neurons and we reduce the number of connections in the network; the other is that we use a Short Term Plasticity rule (STP [24]) that prevents global bursting (see Section 2.5).

The structure of the paper is as follows: we show that the conditions necessary to obtain LSA are sufficient to reproduce biological results, study the dynamics of LSA in a minimal network of 3 neurons and present burst suppression methods in Section 2.3. We show that LSA works in a scaled up network of 100 neurons with burst suppression by additive noise in Section 2.4. We show that LSA also works with burst suppression by STP with 100 neurons in Section 2.5, even when there are no direct connections between input and output neurons. Finally we implement a simple embodied application using LSA and STP for burst suppression in a simulated robot in Section 2.6.

2.2 Model

We use the model of spiking neuron devised by Izhikevich [25] to simulate excitatory neurons (regular spiking neurons) and inhibitory neurons (fast spiking neurons) with a simulation time step of 1 ms. This model of neuron is presented by Izhikevich as being the fastest computationally and the closest to the known spiking dynamics of live neurons. This model can reproduce the spiking dynamics of several types of neurons. The equations of the neural model and the resulting dynamics are shown in Fig 2.3. These equations are integrated until the membrane voltage v reaches a threshold, then v is reset to its initial value.

We simulate a fully connected network of 100 neurons (self-connections are forbidden) with 80 excitatory and 20 inhibitory neurons. This ratio of 20% of inhibitory neurons is standard in simulations [25, 26] and close to real biological values (15%, [27]). The initial weights are random (uniform distribution: $0 < w < 5$ for excitatory neurons, $-5 < w < 0$ for inhibitory neurons). LSA may have different features with different network topologies and time delays; however, we believe that the conditions simulated here are the simplest setup for having LSA. The neurons receive three kinds of input: (1) Zero-mean Gaussian noise m with a standard deviation $\sigma = 3$ mV is injected in

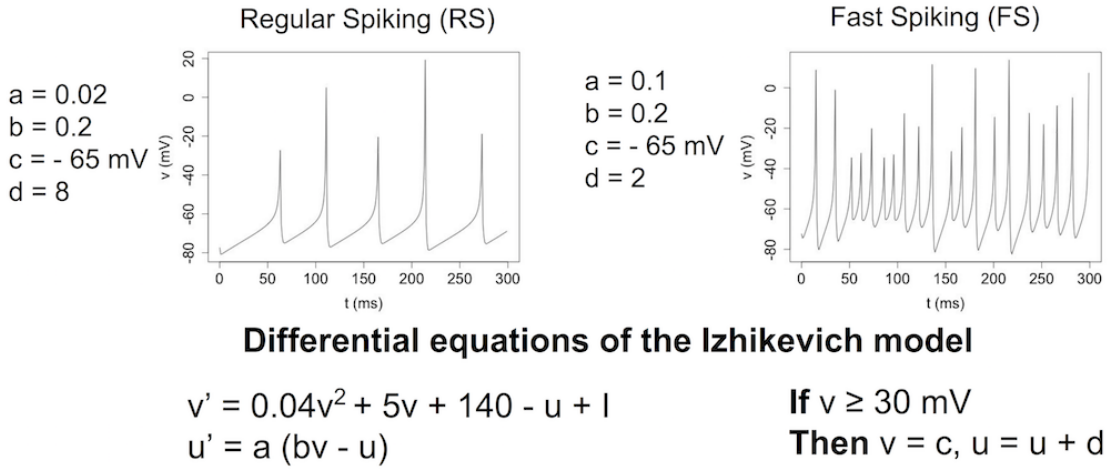


FIGURE 2.3: **Equations and dynamics of regular spiking and fast spiking neurons simulated with the Izhikevich model.** Equations and dynamics of regular spiking and fast spiking neurons simulated with the Izhikevich model.

each neuron at each time step; (2) External stimulation e with a value of 1 mV and a frequency of 1000 Hz. The external stimulation is stopped when the network exhibits the desired output. (3) Stimulation from other neurons: when a neuron a spikes, the value of the weight $w_{a,b}$ is added as an input for neuron b without delay. All these inputs are added for each neuron n_i at each iteration as:

$$I_i = I_i^* + e_i + m_i \ . \tag{2.1}$$

$$\begin{aligned} I_i^* &= \sum_{j=0}^{n} w_{j,i} \times f_j \ , \\ f_j &= \begin{cases} 1, & \text{if neuron j is firing} \\ 0, & \text{otherwise.} \end{cases} \end{aligned} \tag{2.2}$$

We add synaptic plasticity in the form of STDP as proposed in [24]. STDP is applied only between excitatory neurons; other connections keep their initial weight during all the simulation. We use additive STDP: Fig 2.4 shows the variation of weight Δw for a synapse between connected neurons. As shown on the figure, Δw is negative if the post-synaptic neuron fires first, and positive the pre-synaptic neuron fires first. The total weight w varies as:

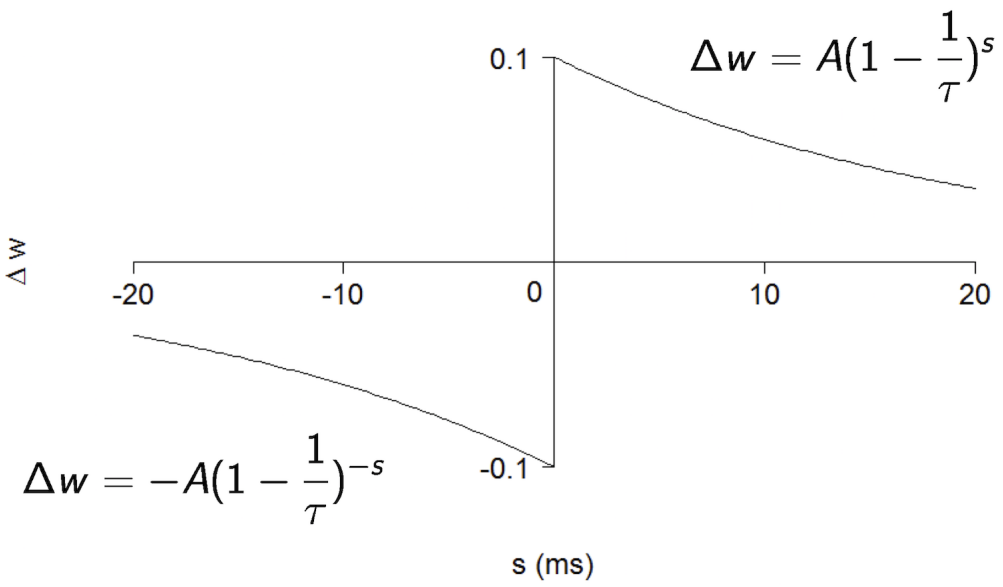


FIGURE 2.4: **The Spike-Timing Dependent Plasticity (STDP) function** governing the weight variation Δw of the synapse from neuron a to neuron b depending on the relative spike timing $s = t_b - t_a$. $A = 0.1$; $\tau = 20$ ms.

$$w_t = w_{t-1} + \Delta w \ . \tag{2.3}$$

The maximum possible value of weight is fixed to $w_{max} = 10$. if $w > w_{max}$, w is reset to w_{max}. In the experiments with 100-neurons networks, we also apply a decay function to all the weights in the network. The decay function is applied at each iteration t as:

$$\forall w_t, \ w_{t+1} = (1 - \mu) w_t \tag{2.4}$$

We fix the decay parameter as $\mu = 5 \times 10^{-7}$.

When mentioned, we use STP as way to prevent bursting behavior. STP is a reversible plasticity rule that decreases the intensity of neuronal spikes if they are too close in time, preventing the network to enter a state of global synchronized activity. As in the original paper, we apply STP to the output weights from excitatory neurons to both excitatory and inhibitory neurons.

$$w^*_{i,j} = uxw_{i,j} \tag{2.5}$$

$$\frac{dx}{dt} = \frac{1-x}{\tau_d} - uxf_i \tag{2.6}$$

$$\frac{du}{dt} = \frac{U-u}{\tau_f} + U(1-u)f_i \tag{2.7}$$

where the initial release probability parameter U=0.2, and $\tau_d = 200$ ms and τ_f=600 ms are respectively the depression and facilitation time constants. Briefly speaking, x is a fast depression variable reducing the amplitude of the spikes of neurons that fire too often, while u is a slow facilitation variable that enhances the spikes of these same neurons. As a result of the interplay of x and u, neurons constantly firing at high frequency are inhibited, while neurons irregularly firing at high or low frequency are unaffected (the maximum value of ux is 1). STP acts as a short term reversible factor on the original synaptic weight, with the side effect of preventing global bursting of the network. Eq. 2.2 becomes

$$\begin{aligned} I_i^* &= \sum_{j=0}^{n} w_{j,i}^* \times f_j \ , \\ f_j &= \begin{cases} 1, & \text{if neuron j is firing} \\ 0, & \text{otherwise.} \end{cases} \end{aligned} \tag{2.8}$$

2.3 LSA is Sufficient to Explain Biological Results

In Subsection 2.3.1 we show that a simulated random spiking network built from [26, 28] combined to STDP can be driven to learn desired output patterns using a training method similar to that of Shahaf et al. Shahaf shows that his training protocol can reduce the response time of a network. The response time is the delay between the application of the stimulation and the observation of a desired output from the network. In Shahaf's first series of experiments ("simple learning" experiments), the desired output is defined by the fulfillment of one condition:

- **Condition 1:** the electrical activity must increase in a chosen Output Zone A.

We show that the same methods are sufficient in artificial networks to obtain results similar to the second series of experiments performed by Shahaf ("selective learning"

experiments), in which the desired output is the simultaneous fulfillment of Condition 1 as defined before and a second condition:

- **Condition 2:** a different output zone (Output Zone B) must not exhibit enhanced electrical activity. When both conditions are fulfilled, the result is called selective learning because only Output Zone A must learn to increase its activity inside the time window, while Output Zone B must not increase its activity. We reproduce the experiment as follows.

2.3.1 Superficial selective learning experiment

In this section we reproduce in simulation the biological results obtained by Shahaf. A group of 10 excitatory neurons are stimulated (Input Zone). Two different groups of 10 neurons are monitored (Output Zone A and Output Zone B). We define the desired output pattern as: $n >= 4$ neurons spike in Output Zone A (Condition 1), and $n < 4$ neurons spike in Output Zone B (Condition 2). Both conditions must be fulfilled simultaneously, i.e. at the same millisecond. We stop the external stimulation as soon as the desired output is observed. If the desired output is not observed after 10,000 ms of stimulation, the stimulation is also stopped. After a random delay of 1,000 to 2,000 ms, the stimulation starts again. We reformulate this setting in terms of embodiment and behavior by using it in a simple game (fig. 2.5).

There are important differences with the biological experiment: the stimulation frequency (Shahaf uses lower frequencies), its intensity (this parameter is unknown in Shahaf's experiment) and the time window for the output (in Shahaf's results the activity of Output Zone A is arguably higher even outside of the selected output window). We also use a fully connected network, while the biological network grown in vitro is likely to be sparsely connected [29].

Despite these differences, we obtain results comparable to those of Shahaf: the reaction time, initially random, becomes shorter with training. Fig. 2.6 and 2.7 show typical learning curves of the network, with a decrease in the time delay between the beginning of the stimulation and the apparition of the desired firing pattern. The network goes through different phases; a learning curve is clearly visible. By the end of the experiment, the network exhibits the desired firing pattern consistently and rapidly after the beginning of the stimulation. Fig. 2.8 shows the evolution of the network' s firing patterns. The global activity of the network shows a particularly clear distinction between the dynamics of the input neurons and the other groups (input neurons fire less often than other neurons, due to reduced input weights from the rest of the network).

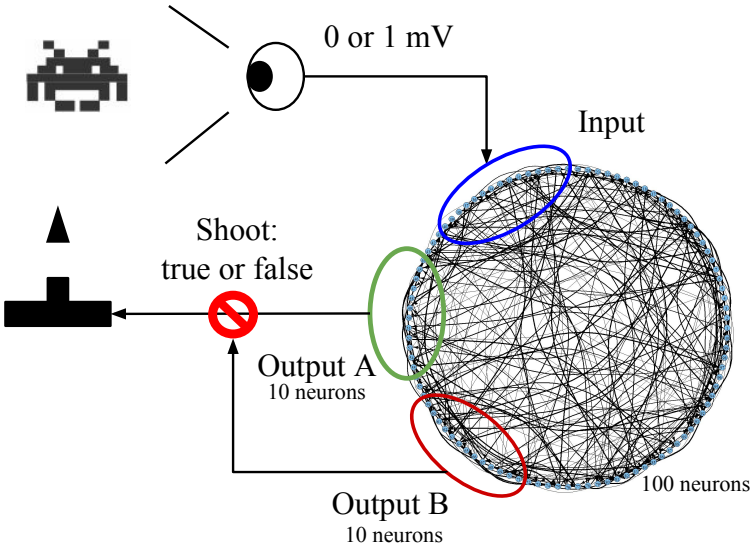


FIGURE 2.5: **The Shahaf experiment reformulated as a game.** The network controls a spaceship. There is one possible action: shooting, and one binary input: presence or absence of an alien. Shooting destroys the alien. When an alien appears, the network's "eye neurons" are stimulated (Input Zone). If Output Zone A fires, the spaceship shoots. If Output Zone B fires at the same time as Output Zone B, the command is cancelled and the spaceship does not shoot.

The insets show the gradual partial desynchronization of the different groups. The initialization phase (a) is dominated by long, sparse, highly synchronized bursts involving all neurons. At the learning phase (b), these completely synchronized bursts have been replaced by more temporally distributed firing. After the desired behavior is learned in (c), the raster plot shows high global activity of the network, with short, strongly structured bursts.

Fig. 2.9 shows the final weight matrix, compared to the initial random matrix. The synaptic weights never follow a trivial distribution, where the input neurons directly cause the firing of the output neurons ($w_{input,A} = w_max$). This makes the weight distribution difficult to analyze, but the fact that the initial weight matrix is random is certainly the biggest factor explaining the complex distribution of the final weights.

We perform different versions of this experiment, and find several interesting properties. First, the synaptic weights never follow a trivial distribution, where the input neurons directly cause the firing of the output neurons. Second, removing inhibitory neurons and setting all 100 neurons as excitatory prevents the network from learning (Fig. 2.10); all synaptic weights increase until saturation of the network. It is possible that inhibitory neurons prevent the network from forming too many recurrent excitation loops. Finally, we performed the experiment with no stimulation (e = 0 mV) as a null hypothesis. Fig. 2.11 shows that this condition does not lead to learning of the firing

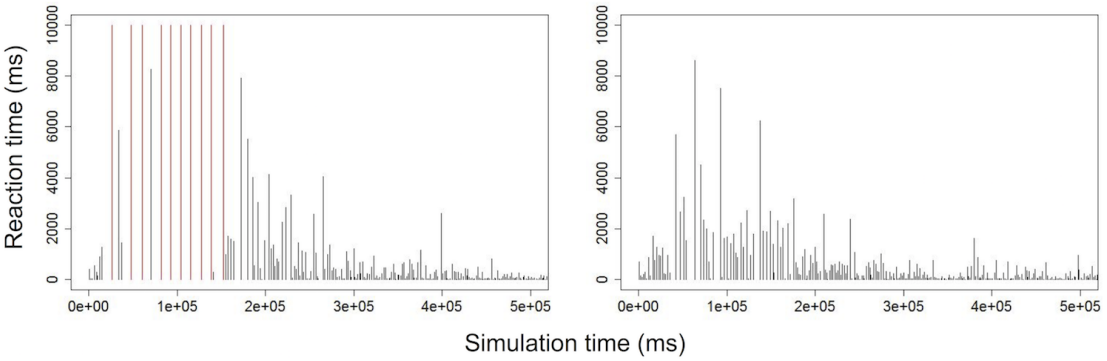


FIGURE 2.6: **Evolution of the reaction times of 2 successful neural networks at the selective learning task.** 20 networks were simulated, 18 of which successfully learned the task (Table 2.1). Red lines represent when there was no response from the network. A learning curve is clearly visible.

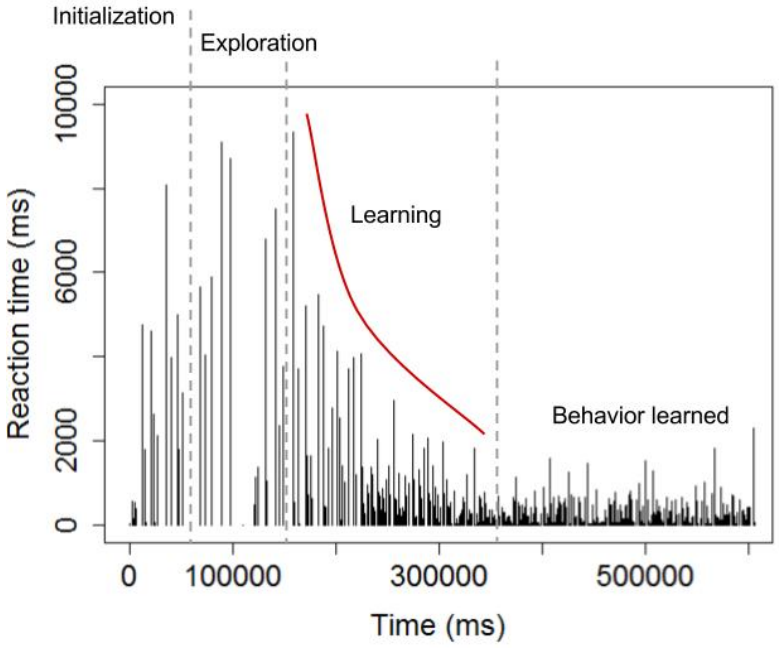


FIGURE 2.7: **A typical learning curve.** During the initialization phase, the network activity is high, causing randomly short reaction times. In the exploration phase, the activity has stabilized and the reaction times are long; sometimes the expected output never fires. During the learning phase, the reaction time steadily decreases. Finally the behavior is learned and the reaction time stabilizes at short values.

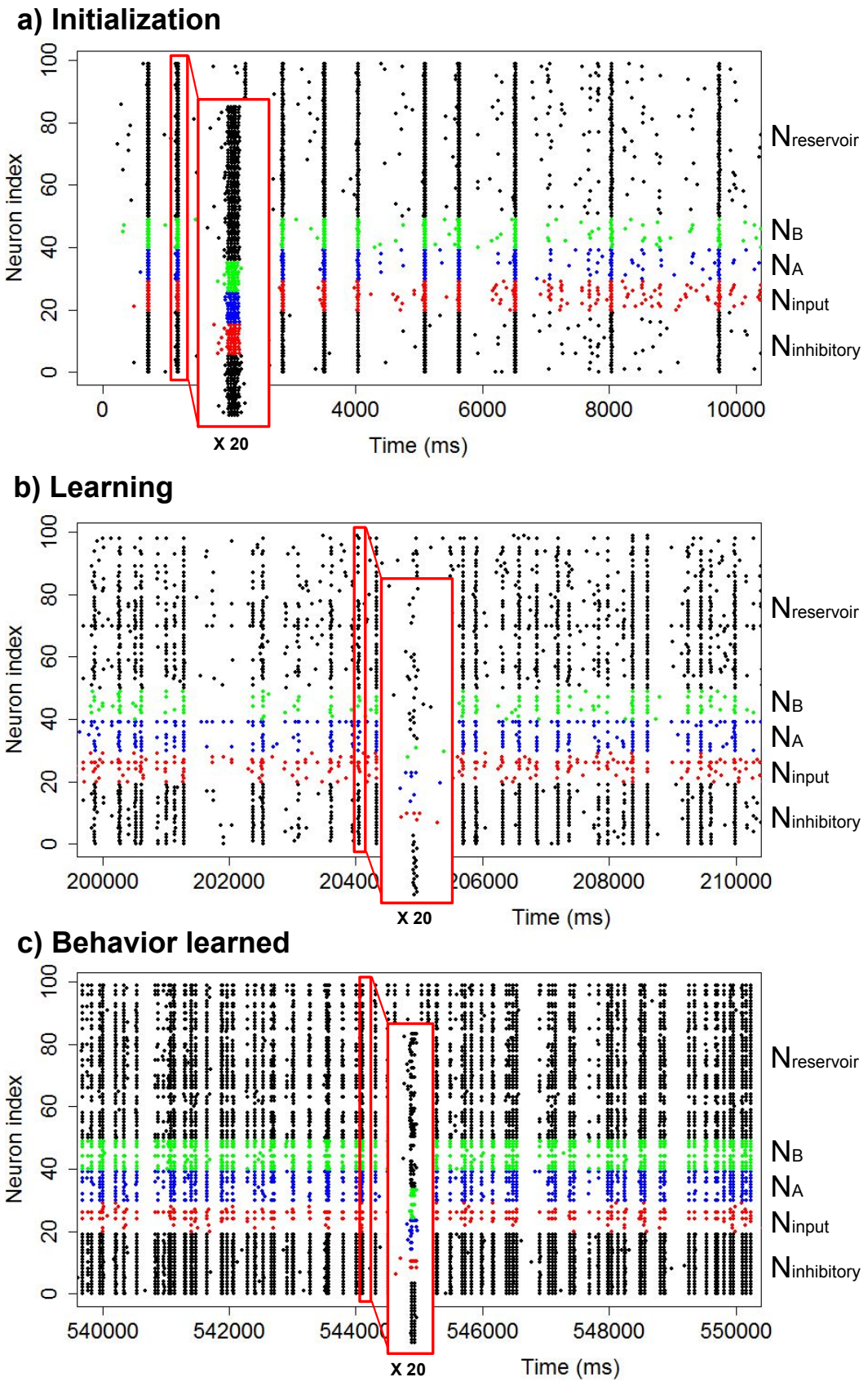


FIGURE 2.8: **Raster plot of the temporal firing of the network at different phases of the experiment.** During initialization, the network's activity is strong and highly synchronized (global bursts). During learning, the bursts are more common but shorter and less synchronized. After learning, the network has very high activity with numerous bursts.

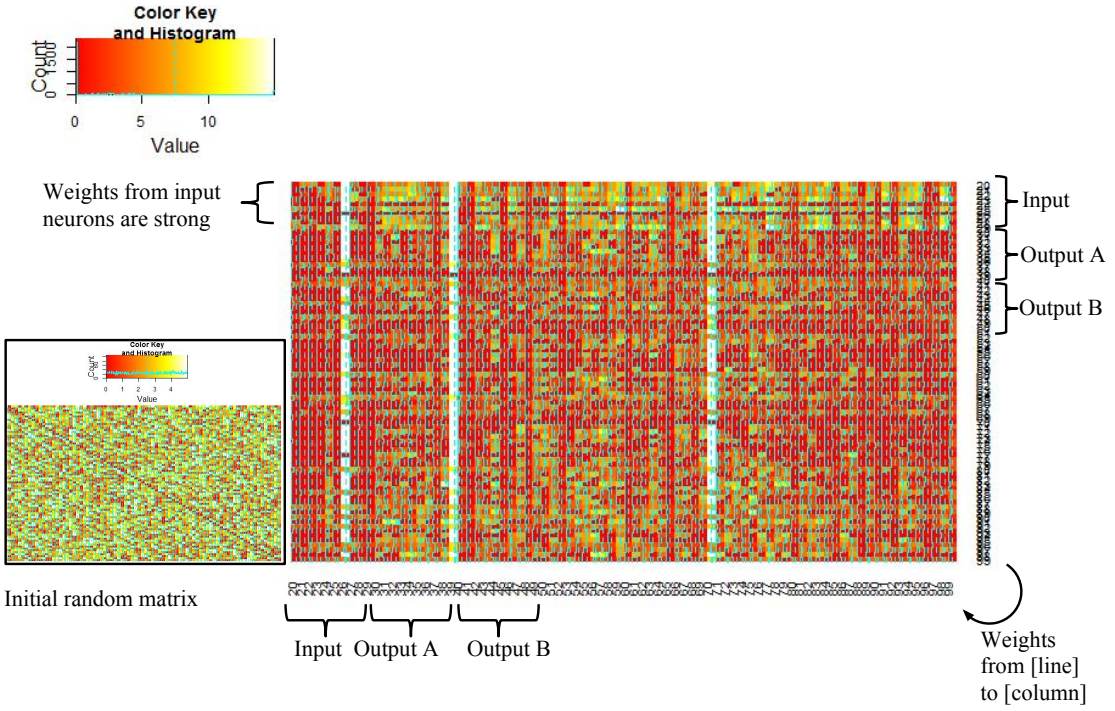


FIGURE 2.9: **Weight matrix after learning.** Initially the matrix is random, but after learning a structure is somewhat visible. Weights from the input neurons to all other neurons are high, including weights to Output Zone B.

TABLE 2.1: **Statistical performance of the network**

Condition	Success rate	Learning time	Attained reaction time
Selective learning	90%	187 ± 16 s	389 ± 54 ms
No external stim.	0%	–	–

Learning time: the task is learned when the reaction time of the network reaches a value inferior to 4,000 ms and keeps under this limit. The success rate is the percentage of networks that successfully learned the task in 400,000 ms or less (N = 20 networks per condition). The attained reaction time is calculated for successful networks after learning. Standard error is indicated.

pattern, as expected. We find a success rate of 0%; the statistics of the selective learning experiment are summarized in Table 2.1.

As shown by these results, the network exhibits selective learning as defined by Shahaf. But we also find that despite a success rate of 90% at exhibiting the desired firing pattern, both the firing rates of Output Zone A and Output Zone B increase in equivalent proportions: the two output zones fire at the same rate but in a desynchronized way (see also Fig 2.19-b). The task was to activate Output Zone A and suppress the activity in Output Zone B. But the opposite result also occurs at the same time, in an opposite phase. Although data about firing rates is not specifically discussed in Shahaf's

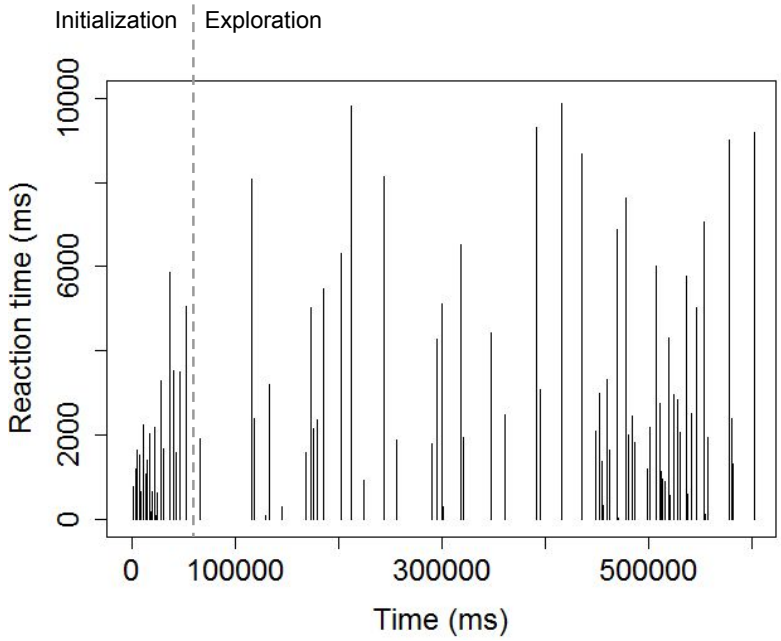


FIGURE 2.10: **Simple Learning experiment with no inhibitory neurons in the network.** The initialization phase is as long as in the original conditions, but the network is stuck in the exploration phase and never reaches the learning phase.

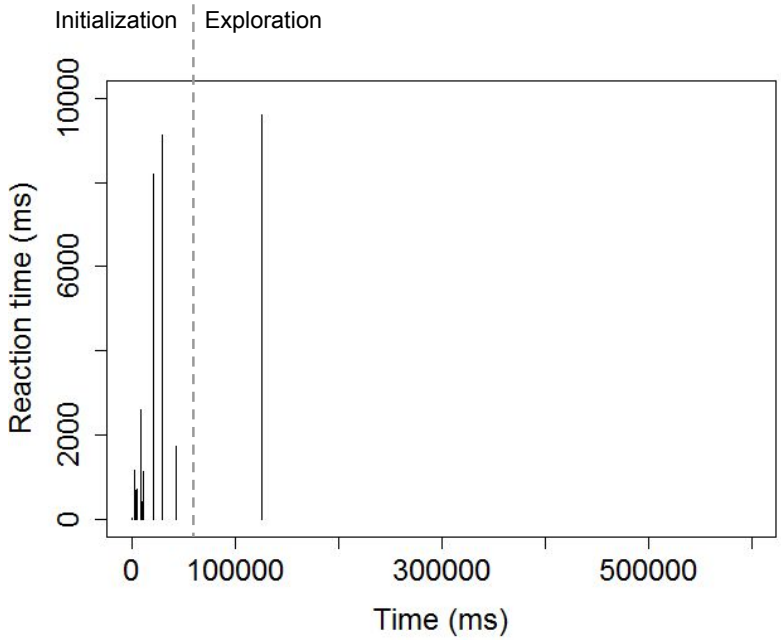


FIGURE 2.11: **Simple Learning experiment with no external stimulation.** The initialization phase is as long as in the original conditions, but with no way to differentiate the correct firing pattern from other firing patterns, the network has no proper exploration phase and does not reach the learning phase. The desired firing pattern stops being exhibited.

paper, it is possible that the same phenomenon did happen. Shahaf himself reports in his experiment that only half of the in-vitro networks succeeded at selective learning, while all succeeded at the "simple learning" task. Our hypothesis is that bursts are detrimental to learning [30] and explain the difficulty of obtaining selective learning. If this hypothesis is true, burst suppression is essential to obtain learning. We explain why burst suppression is necessary by first explaining how learning works in a small network. Then we study 100-neurons networks with global bursting suppression.

2.3.2 Dynamics of LSA in 2-Neuron Paths

We focus on STDP between excitatory neurons exclusively. We demonstrate three hypotheses concerning LSA:

- 1. STDP alone is sufficient to realize LSA at the level of an individual synapse.
- 2. STDP-enabled neurons are able to react selectively to simultaneous simulations in several synapses.

Hypotheses 1 and 2 explain why STDP-based LSA scales up to the level of an entire network.

2.3.2.1 Dynamics in a single synapse

We design the first experiment to study the weight variation in one synapse between two neurons (Fig. 2.12). We control the external stimulation e_0 in the presynaptic neuron N_0 under 3 conditions summarized in Fig. 2.13: (a) Stop the stimulation if the postsynaptic neuron N_1 fires; (b) Start the stimulation if N_1 fires; (c) Stimulate N_0 whatever the behavior of N_1. The delay between two training cycles is 30 ms (except in (c) where the stimulation goes uninterrupted). We set the stimulation as $e_0 = 2$ mV and the noise standard deviation as $\sigma = 10$. These parameters are chosen rather arbitrarily as there is no network effect to take into consideration. The initial weight is $w_{0,1} = 5$.

At the beginning of the experiment, the synaptic weight is comparatively low and N_1 fires in reaction to both the firing of N_0 and the high random noise m_1. STDP is applied to the minimal network, causing the weight $w_{0,1}$ to vary according to the results in Fig. 2.14.

During a training cycle in (a), firing of N_1 causes the stimulation in N_0 to stop, therefore N_0 stops firing. N_0 lastly fired just before N_1 did, so as a result of STDP, $w_{0,1}$

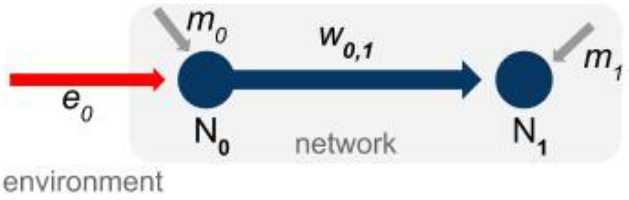


FIGURE 2.12: **Experimental setup.** The minimal network counts 2 neurons and 1 synapse. Random noise m is added as input to both neurons. An external stimulation e_0 is applied to N_0. The dynamics of e_0 depend on the experimental conditions.

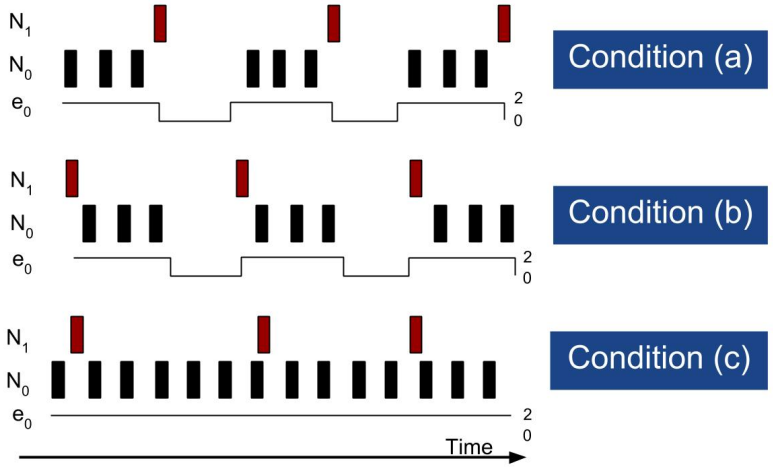


FIGURE 2.13: **The three conditions used in Experiment 1 summarized as a raster plot.** The rectangles represent neuronal spikes. The external stimulation e_0 causes N_0 to fire rhythmically; firing of N_0 causes stimulation in N_1. In real conditions, the noise and synaptic weight variations cause less regular spiking.

is strengthened. This stronger weight in the synapse eventually leads to N_1 firing directly in reaction to the firing of N_0; the delay between the application of the stimulation to N_0 and the firing of N_1 decreases with time. In other words, the minimal network learns to immediately produce the behavior leading to stimulation removal: the external causal loop works. The learning consists in associating a given stimulus (external stimulation of N_0) with a behavior (firing of N_1).

In (b), random firing of N_1 causes the stimulation in N_0 to start (therefore N_0 starts firing). N_1 fired just before N_0 starts firing, so $w_{0,1}$ is decreased by STDP: the pre-synaptic neuron N_0 will have less and less influence on the post-synaptic neuron N_1. The synaptic weight finally reaches 0. The network learns to avoid the behavior that causes stimulation (firing of N_1). The same behavior that was learned in (a) is now avoided.

In (c), N_0 is continuously stimulated. The synaptic weight increases slowly but continuously: as long as the firing of N_1 is not clearly the cause of the external stimulation of N_0, the connexion will be slowly strengthened. The slow increase of the weight, as

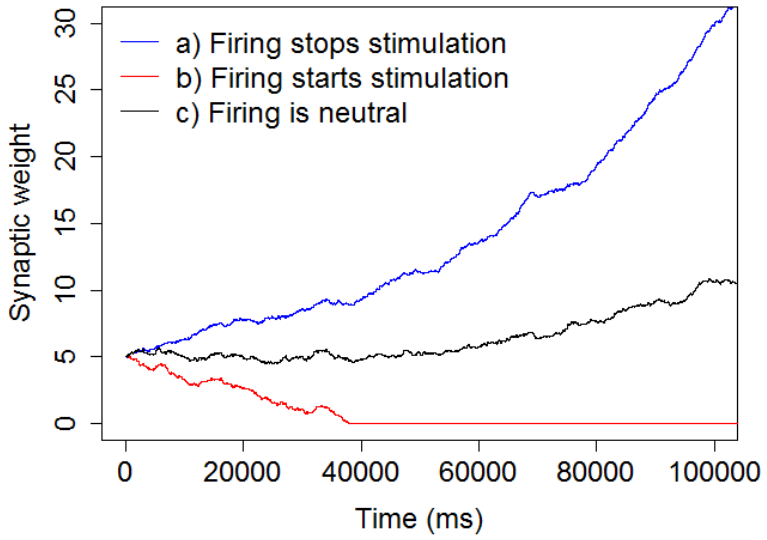


FIGURE 2.14: **Weight variation in one synapse depending on the effect of post-synaptic neuron firing.** The principle of LSA is verified: behaviors conducting to stimulation avoidance are reinforced via synaptic strengthening or synaptic pruning. The default dynamics of STDP lead to weight strengthening in neutral conditions, behavior which can be partly avoided by applying a decay function.

opposed to stable variations around the initial value of 5, is explained by two factors. First, N_0 contributes to the stimulation in N_1. Therefore, N_1 if more likely to fire after N_0 fired: spikes of N_1 will on average be closer to the last spike N_0 than to its next spike. This leads to $w_{0,1}$ being reinforced; in return, this stronger weight causes smaller time delays between the spikes of the two neurons. This can potentially be exploited as an exploratory behavior, but in practice, in large networks it leads to a state of weight saturation where all neurons are constantly firing. One way to deal with the issue is to apply a decay function on the weights. In our network, noise is mainly responsible for the exploration process, so we apply the decay function to avoid weight saturation.

This simple experiment with a minimal network validates Hypothesis 1: STDP alone is sufficient to realize LSA at the level of an individual synapse. In a minimal network with a single synapse, the synapse is strengthened to reinforce post-synaptic firing if it leads to removal of pre-synaptic stimulation; the same synapse is pruned if post-synaptic firing causes pre-synaptic stimulation. Therefore STDP is sufficient to realize Learning by Stimulation Avoidance at the level of a single synapse. Additionally, by running experiments with different values of external stimulation e_0 and noise m, we find that the learning speed tends to decrease when the noise level or the stimulation level are decreased. For example, reducing the noise standard deviation to $\sigma = 5$ and the stimulation to $e_0 = 1$ leads to a weight of only 10 in the reinforced synapse after

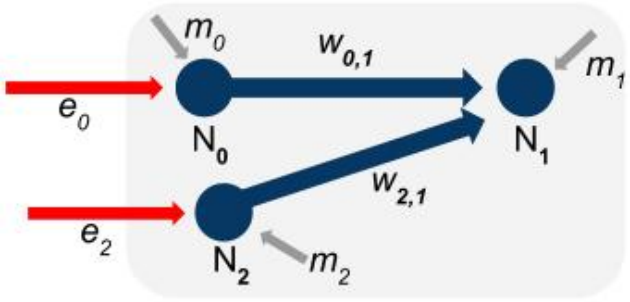


FIGURE 2.15: **Augmented experimental setup:** 3 neurons and 2 synapses. Random noise m is added as input to all neurons. The dynamics of the external stimulations e_0 and e_2 are different and depend on the experimental conditions.

100 000 ms, compared to a weight of 30 in Experiment 1. Both high noise and high stimulation values tends to increase the firing rate of N_1, which increases the learning speed. This leads to the paradoxical observation that noise increases the performance of the minimal network. Furthermore, the results still hold for extremely low signal to noise ratio (high noise, low stimulation). In the next experiment, we validate Hypothesis 2 and show that the minimal network is capable of selective learning.

2.3.2.2 Effect-based differentiation of stimuli

In Experiment 2, we add one neuron to the minimal network (Fig. 2.15). The noise standard deviation is reduced to $\sigma = 5$ to account for the increased stimulation in the network (due to both $w_{2,1}$ and e_2). The external stimulations e_0 and e_2 vary independently between 0 mV and 2 mV. N_0 is stimulated until N_1 fires, then e_0 is stopped for 30 ms. N_2 is stimulated by e_2 during those 30 ms. So the firing of N_1 causes external stimulation in N_2, but stops external stimulation in N_0. The network must tell apart these influences despite the noise: we expect $w_{0,1}$ to increase as a realization of LSA, since firing of N_1 is beneficial to N_0 (it stops the external stimulation). Meanwhile, the firing of N_1 is detrimental to N_2, as it causes external stimulation: if LSA is realized, $w_{2,1}$ should decrease. These are indeed the results of the experiment, as shown in Fig. 2.16: $w_{0,1}$ (in blue) increases and $w_{2,1}$ (in red) decreases at the same time. This result is explained by the fact that despite the noise, there are overall more spikes of N_0 just before spikes of N_1 than just after, leading through STDP to an increase in weight. Similarly, there are overall more spikes of N_2 just after spikes of N_1 than just before, leading to an decreasing weight.

We also perform a variant of this experiment where the stimulation in N_0 stops 5 ms after the firing of N_1 (instead of stopping instantly). Therefore not only the causality between the spikes of N_1 and the end of the stimulation is delayed, but additionally the stimulations in the two pre-synaptic neurons N_0 and N_2 overlap for 5 ms. Despite

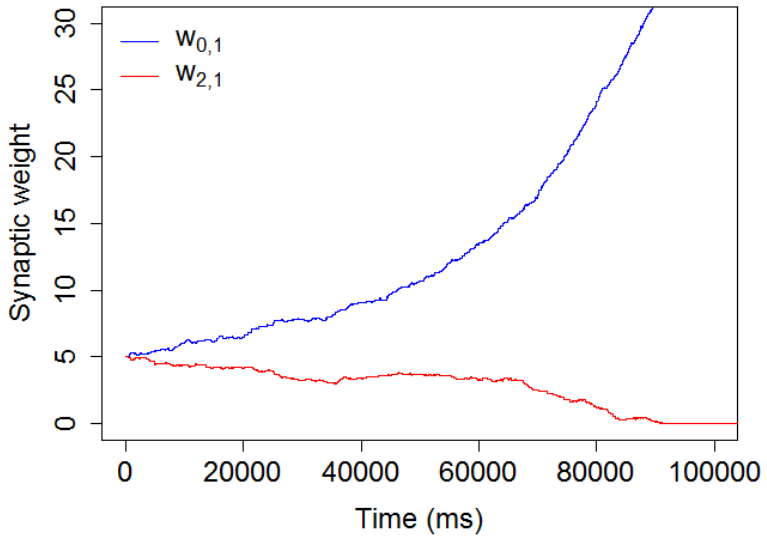


FIGURE 2.16: **Parallel processing of two input synapses in one neuron.** One synapse is pruned while the other is strengthened: the post-synaptic neuron can process inputs from both pre-synaptic neurons simultaneously.

these additional difficulties, the results stay qualitatively the same as in the original experiment, with an increased learning speed ($w_{2,1}$ reaches 0 at $t \approx 40\ 000$ ms). The increase in speed is due to the increased firing rate of N_0 as a consequence of stimulation building up during the additional 5 ms.

These results validate Hypothesis 2: one neuron can receive simultaneous signals from two synapses and proceed to prune one while strengthening the other. Therefore the neuron will react differently to two stimulations with conflicting effects. In the next subsection, we show that LSA also works in a chain of 3 neurons, were a "hidden" neuron is placed between the input and output neurons.

2.3.3 Dynamics of LSA in 3-Neuron Paths

In this experiment we examine the weights dynamics in a chain of 3 excitatory neurons all connected to each other: one neuron is used as input, one as output, and they are separated by a "hidden neuron".

Neurons are labeled 0 (input neuron), 1 (hidden neuron) and 2 (output neuron). Fig 2.17 shows the results of experiments with different learning conditions and different initial states. The results can be summarized as follows: (1) In the reinforcement condition, direct connections between input and output are privileged over indirect connections. All connections are updated with the same time step (1 ms), therefore the

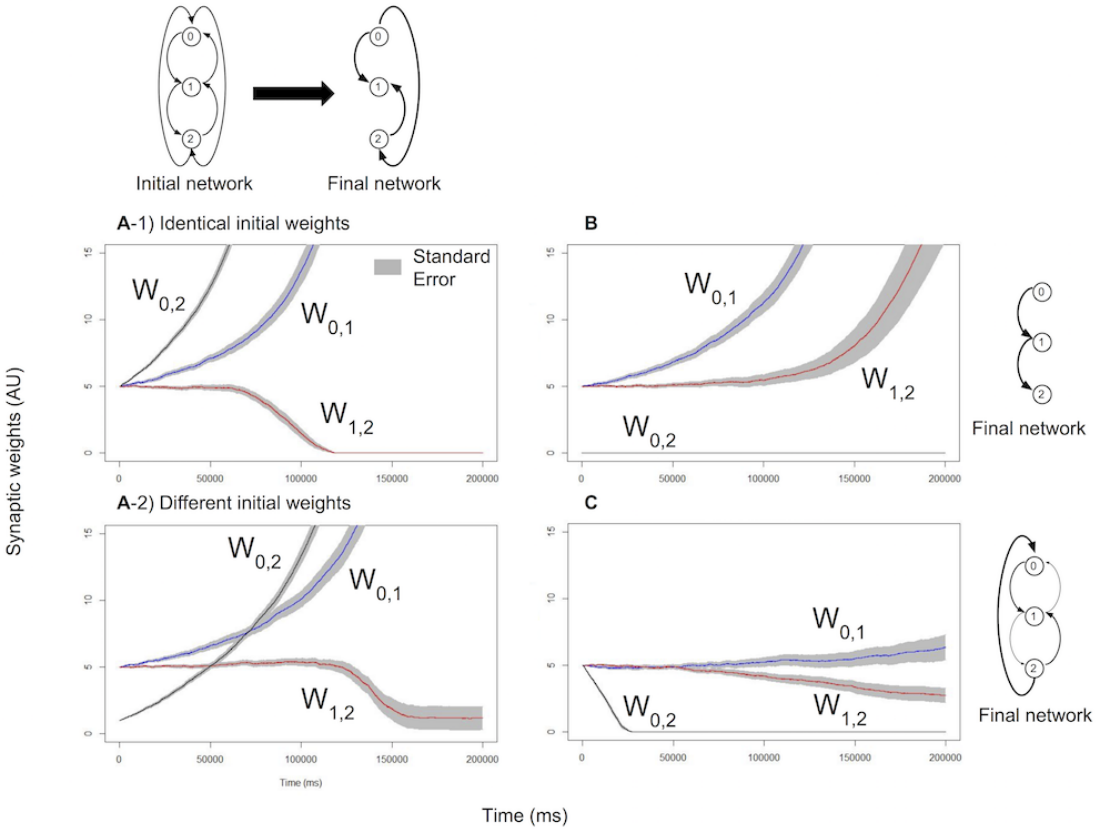


FIGURE 2.17: **Dynamics of weight changes induced by LSA in small networks of 3 neurons.** A) Reinforcement: spiking of neuron 2 stops the stimulation in neuron 0. The direct weight $w_{0,2}$ grows faster than other weights, even when starting at a lower value. B) Artificially fixing the direct weight $w_{0,2}$ to 0, a longer pathway of 2 connections $0 \rightarrow 1 \rightarrow 2$ is established. C) Pruning: spiking of neuron 2 starts external stimulation to neuron 0. As a result, $w_{0,2}$ is pruned.

fastest path (direct connection) will always cause neuron 2 to fire before the longer path (made of several connections) can be completely activated. When no direct connection exists, weights on longer paths are correctly increased. (2) LSA explains a behaviour that is not discussed in the SRP: synapse pruning. LSA predicts that networks evolve as much as possible towards dynamical states that cause the less external stimulation. Here LSA only prunes weights of direct connections between the input and output, as this is sufficient to stop all stimulation to the output neuron. (3) For neurons that are strongly stimulated (here, neuron 0) the default behaviour of the output weights is to increase, except if submitted to the pruning influence of LSA. Neurons that fire constantly bias other neurons to fire after them, automatically increasing their output weights.

This raises concerns about the stability of larger, fully connected networks; all weights could simply increase to the maximum value. But introducing inhibitory neurons in the network can improve network stability [31]. In our experiments with 100-neuron networks, 20 are inhibitory neurons with fixed input weights and output weights. In addition, we make the hypothesis that global bursts in the network can impair LSA, as

all neurons fire together make it impossible to tease apart individual neuron's contributions to the postsynaptic neuron's excitation. Global bursts are also considered to be a pathological behaviour for in vitro networks, and do not occur with healthy in vivo networks [30].

In the next section, we use two different methods to obtain burst suppression. The first method is to add strong noise to the neurons and to reduce the initial number of connections in the network. This produces a desynchronization of the network activity. In Section 2.4, we show that this method allows LSA to work in networks of 100 neurons. The second method is to apply Short Term Plasticity to all the connections in the network. In Section 2.5 and Section 2.6 we show that this method of burst suppression allows proper selective learning even in the absence of direct connections between input and output; we also show an application to a robot experiment.

2.4 Burst Suppression by Adding Noise

2.4.1 Selective Learning with burst suppression

In this experiment, burst suppression is obtained in the 100-neuron network by reducing the number of connections: each neuron has 20 random connections to other neurons (uniform distribution, $0 < w < 10$), a high maximum weight of 50, high external input $e = 10$ mV and high noise $\sigma = 5$ mV[1]. These networks are less prone to global bursts and exhibit strong desynchronized activity, as shown in Fig 2.18.

We monitor two output zones and fix two independent stimulation conditions:
(Stop Condition) Input Zone A is stimulated. After $n >= 1$ neurons in Output Zone A spike, the external stimulation to Input Zone A is stopped. If the desired output is not observed after 10,000 ms of stimulation, the stimulation is also stopped. After a random delay of 1,000 to 2,000 ms, the stimulation starts again.
(Stimulus Condition) After $n >= 1$ neurons spike in Output Zone B, the whole network (excluding inhibitory neurons and Output Zone B itself) is stimulated for 10 ms. The goal is to obtain true selective learning, by increasing the weights to Output Zone A and prune those to Output Zone B, therefore obtaining different firing rates. This Stimulus Condition is opposite to the Stop Condition. It requires stimulus when a neuron in the output region fires. Here we use the minimal threshold (=1) for the Stop Condition, but for later experiments we use a threshold of 4 neurons.

[1] Variations in the number of connections and the weight variance are examined later in this paper

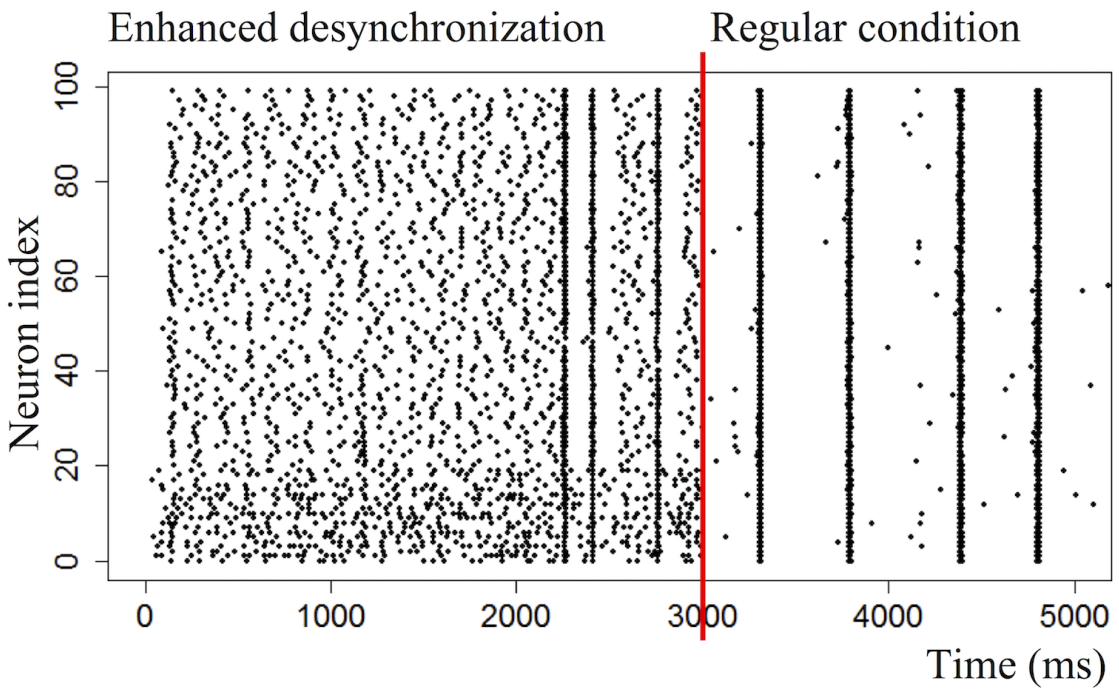


FIGURE 2.18: **Raster plots of a regular network (activity concentrated in bursts) and a network of which parameters have been tuned to reduce bursting and enhance desynchronized spiking.** The desynchronizing effect of sparsely connecting the network and increasing the noise are clearly visible.

Only a few (comparatively to the network size) spiking presynaptic neurons are necessary to make a postsynaptic neuron fire if the connection weights are high. In consequence, the Stimulus Condition must be able to prune as many input synapses to Output Zone B as possible. It is therefore important to suppress global bursts: they cause Output Zone B to fire at the same time as the whole network, making it impossible to update only relevant weights without also updating unrelated weights.

As a result of LSA, the network must move from a state where both output zones fire at the same rate, to a state where Output Zone B fires at lower rates and Output Zone A fires at higher rates. This prediction is realized, as we can see in Fig 2.19-a: the trajectory of firing rates goes to the space of low external stimulation. In Fig 2.19-b, we show for comparison the trajectory for networks with only the Stop Condition applied: on average the firing rates of both output zones are equivalent, with individual networks trajectories ending up indiscriminately at the top left or bottom right of the space.

These results could potentially be reproduced in a network in vitro: the Izhikevich model of spiking network that we use has been found to exhibit the same dynamics as real neurons, and our experiments with STDP can reproduce some results of biological experiments; therefore there is a probability that this results predicted by LSA still holds

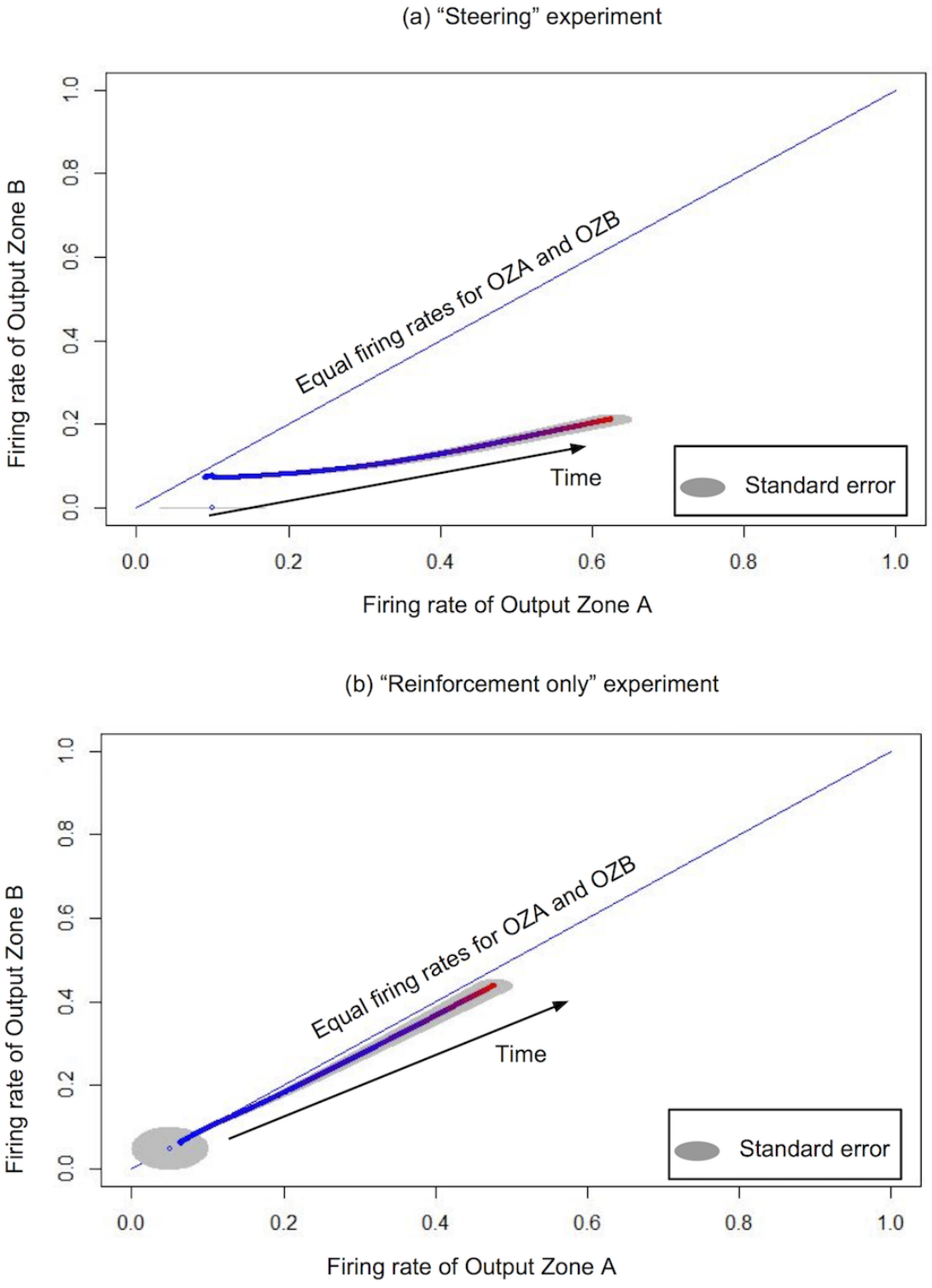


FIGURE 2.19: **Trajectory of the network in the two-dimensional space of the firing rates of Output Zone A and Output Zone B.** Using LSA, we can steer the network in this space; by contrast, the “reinforcement only” experiment maintains the network balanced relatively to the two firing rates. (a) leads to the low external stimulation region but (b) does not. Statistical results for N = 20 networks.

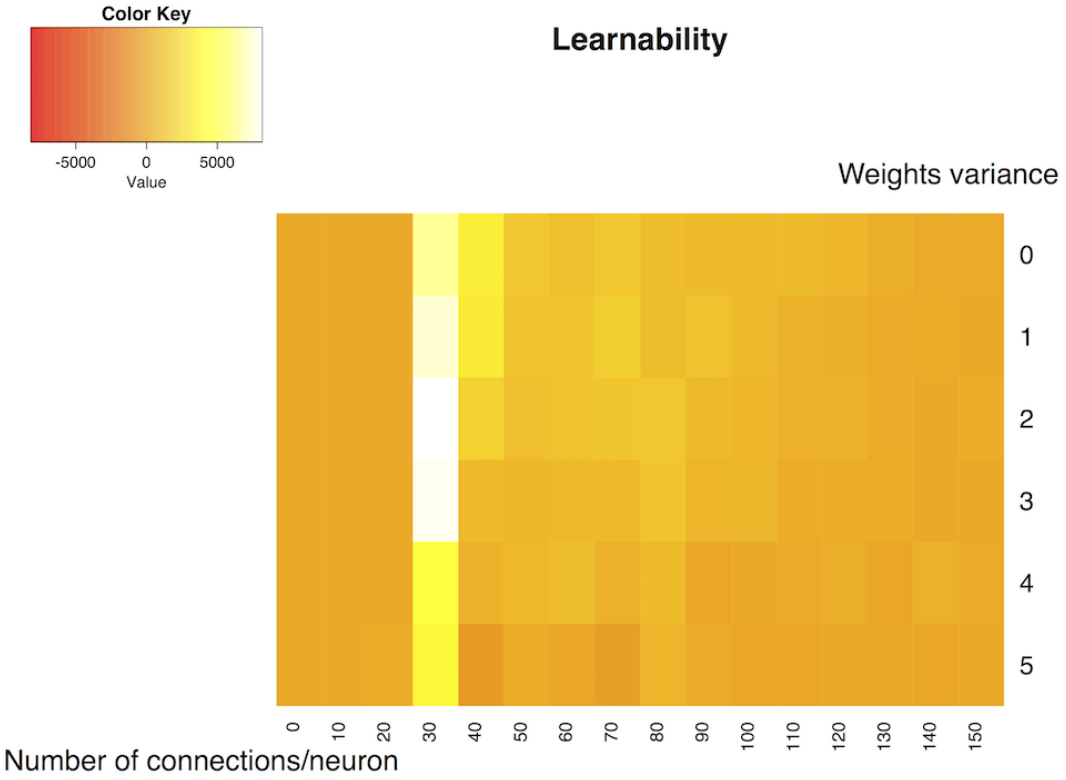


FIGURE 2.20: **Performance of learning depending of network connectivity and initial weights variance.** Learnability is defined as the average difference between the firing rate of the Output Zone during the first 100 seconds and the last 100 seconds. The ideal region of the parameter space to obtain good learning results is between 20 and 30 connections per neuron. By comparison, the variance has less influence. Statistical results for N= 20 networks for each parameter set.

in biological networks with suppressed bursts, especially since we have shown that LSA gives promising results on biological networks embodied in simple robots [14].

2.4.2 Parameter Exploration

We perform a parameter search to explore the working conditions of the "simple learning" task. In this section, we vary the number of connections in the network and the variance v of the weights. For each neuron an output connection is chosen at random and the weight is initialised at $w = 5 + \omega$ ($w = -5 + \omega$), with ω following a uniform distribution between $-v$ and v. This process is repeated M times for each neuron, $0 < M < 150$. The same connection can be chosen twice at random, so the actual number of connections can be inferior to M.

For each set (ω, M) we perform N = 20 experiments (with Stop Condition but no Stimulus Condition) of length T = 500 seconds. Learnability is defined as the average difference between the firing rate of the Output Zone during the first 100 seconds and

the last 100 seconds and is reported on the heat map Fig 2.20. This figure shows that the variance in the initial weights has low influence on the final learning results, but the ideal region to obtain good learning results is between 20 and 30 connections per neuron. Above these values, the increased connectivity of the network might cause too many bursts, affecting the learning results. Below these values, we there may not be a path connecting the input neurons to the output neurons, making the learning task impossible. This does not mean that direct connections between input and output are necessary to obtain learning: in the next section we show that LSA works even without direct connections between input and output.

2.5 Burst Suppression by Short Term Plasticity

In this section we set all weights from input neurons to output neurons to 0. The initial weights are random (uniform distribution: $0 < w < 5$ for excitatory neurons, $-5 < w < 0$ for inhibitory neurons). Zero-mean Gaussian noise m with a standard deviation $\sigma = 3$ mV is injected in each neuron at each time step. The maximum possible value of weight is fixed to $w_{max} = 20$. The external stimulation value is $e = 10$ mV. Burst suppression is obtained by adding a phenomenological model of Short Term Plasticity (STP, [32]) to the network, as a way to suppress bursts despite the network being fully connected. STP is a reversible plasticity rule that decreases the intensity of neuronal spikes if they are too close in time, preventing the network to enter a state of global synchronized activity.

As in Section 2.3.1 the goal is for Output Zone A to increase its firing rate and Output Zone B to decrease it. The conditions are as follows:
(Stop Condition) Input Zone A is stimulated. After $n >= 4$ neurons spike in Output Zone A and if only $n < 4$ neurons spiked in Output Zone B, the external stimulation to Input Zone A is stopped. After a random delay of 1,000 to 2,000 ms, the stimulation starts again.
(Stimulus Condition) After $n >= 1$ neurons in Output Zone B spike, the whole network (excluding inhibitory neurons and Output Zone B itself) is stimulated for 10ms.

The conditions are therefore stricter than in Section 2.3.1. Fig 2.21 shows the distribution of firing rates before and after learning the task. Before learning, only the input neurons have a high firing rate due to the external simulation. After learning, 50 % of the Output Zone A is contained in the highest firing rate zone (region II of Fig 2.21), and 50 % of the Output Zone B in the lowest firing rate zone (region I). Even if the stimulus condition is controlled by a single neuron in the region B, the average firing rate in output regions A and B is sufficiently distinguished as is shown in Fig 2.21.

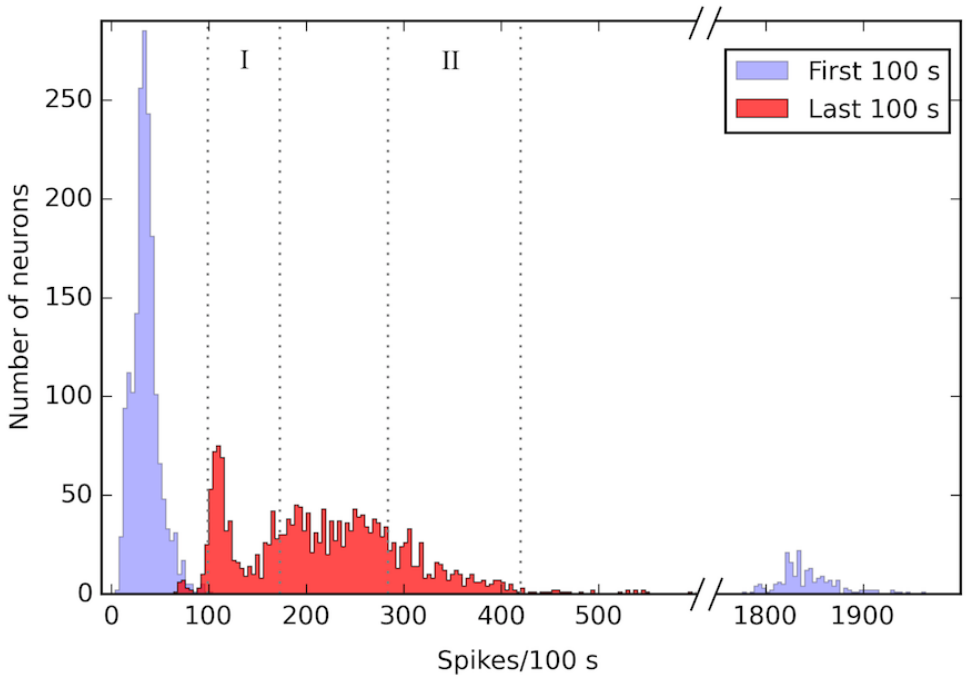


FIGURE 2.21: **Firing rate distribution.** This figure shows the cumulative number of neurons in each firing rate bin for 20 networks. Before learning (first 100 s, blue), most neurons have a very low firing rate (leftmost peak) except for the input neurons (rightmost peak). After learning (last 100 s, red), the neurons are distributed in 2 groups: low firing rate (2nd peak from the left) and medium firing rate. 50 % of the Output Zone B neurons are contained in the zone marked I; 50 % of the Output Zone A neurons are contained in the zone marked II.

This experiment shows that LSA works with a different burst suppression method, even when direct input-output connections are cut. In the next section, we propose a simple application of LSA in a simulated robot.

2.6 Embodied Application: Wall Avoidance with a Robot

We show that LSA can be used in a practical embodied application: wall avoidance learning. The principle of this experiment is that a robot has distance sensors that stimulate the network when the robot is close to walls: the more the robot learns to avoid walls, the less stimulation it receives. Burst suppression is achieved through STP.

We simulate a simple robot moving inside a closed arena. The robot has two distance sensors on the front (right and left), allowing it to detect walls (Fig 2.22). A 100-neuron network takes the two sensors' values as respective input for two input zones (10 excitatory neurons each). Activity in two output zones of the network (10 excitatory neurons

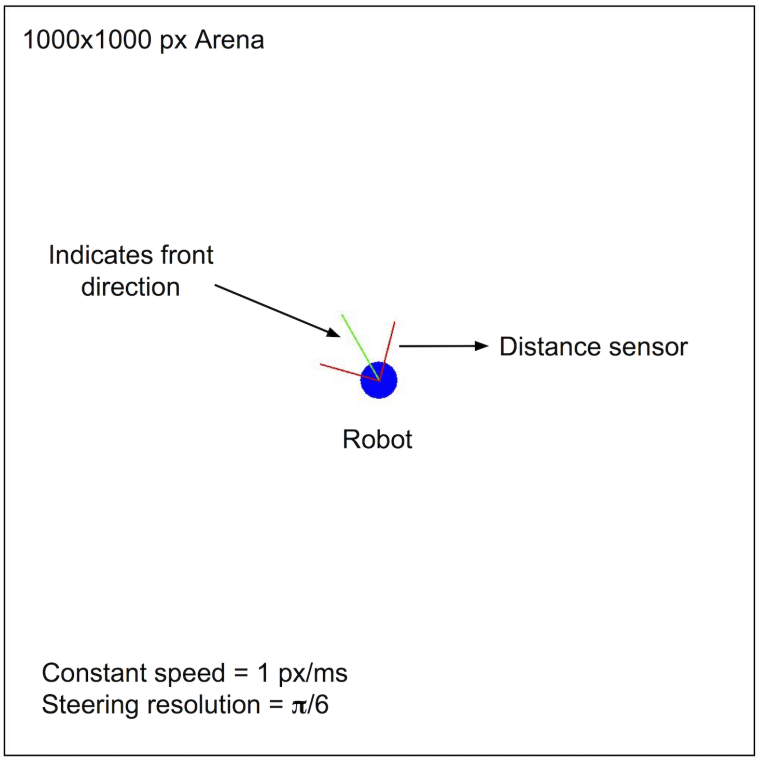


FIGURE 2.22: **Robot simulation.** The robot has distance sensors and must learn to stay away from the arena's walls.

each) allows the robot to turn right or left. In these conditions, steering when encountering a wall can stop the stimulation received by the input zones from the distance sensors, if the new direction of the robot points away from the walls. The behaviour enhanced by LSA should therefore be wall avoidance. We call this experiment a "closed loop" experiment, because steering away from the walls automatically stops the external stimulation at the right timing.

The arena is a square of size 1000 px (pixels). The robot is a 25 px radius circle, constantly moving at 1 px/ms except in case of collision with a wall. The robot has two distance sensors oriented respectively at $\pi/4$ and $-\pi/4$ from the front direction of the robot. The sensors have a range of 80 px; they are activated when the robot is at less than 80 px from a wall, on the direction supported by each sensor's orientation. Two input zones in the network (10 neurons each) receive input in mV at a frequency of 1000 Hz from the sensors as $input = sensitivity/distance$.

The *sensitivity* of the sensors is fixed at a constant value for the duration of each experiment. For simplicity, the robot's steering is non-differential. It is controlled by the spikes of two output zones in the network (10 neurons each). For each spike in the left output zone, the robots steers $\pi/6$ radian (to the left); for each spike in the right output zone, the robots steers $-\pi/6$ radian (to the right).

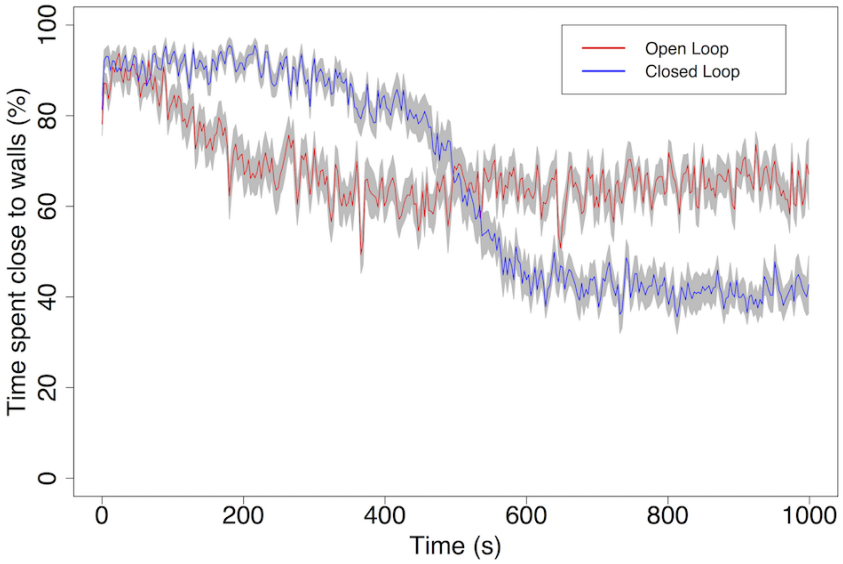


FIGURE 2.23: **Learning curves of the wall avoidance task.** The robot is considered to be "close" to a wall if it is less than 80 pixels from the wall, which corresponds to the range of its distance sensors. The results show that random steering due to high random activity in the network leads to spending 64% of the time close to walls, while learning due to LSA leads to only 43% time spent close to walls. Statistical results for N= 20 networks, standard error is indicated.

We compare the results of this experiment (closed loop experiment, sensor *sensitivity* = 8 mV) with a control experiment where a constant stimulation (8 mV) is applied to the network's input zones, independently of the distance or orientation of the robot relative to the walls (open loop experiment). Both conditions are tested 20 times and averaged. Fig 2.23 shows two important effects: (1) Constant stimulation leads to higher activity in the network, provoking random steering of the robot which leads to some level of wall avoidance, but (2) Closed loop feedback is necessary to obtain actual wall avoidance learning. Indeed, by the end of the closed loop experiment the robot spends only 43% of its time at less than 80 pixels from any wall (the range of the distance sensors), against 64% in the open loop experiment. The importance of feedback over simply having high stimulation is further demonstrated by the fact that the open loop robot is receiving overall a greater amount of stimulation than the closed loop robot. At 400 s, when the learning curve of the closed loop robot starts sloping down, the robot has received on average 1.54 mV of stimulation per millisecond. The open loop robot, which by that time has reached its best performance, has received 16 mV/ms. In a different experiment, we give to open loop robots the same amount of average stimulation that is received by closed loop robots; by the end of the experiment (1000 s) the open loop robots still spend more than 80% of the time close to arena walls.

We also compare our model with a standard wall avoidance robot. In the standard

model, the robot goes straight; if its left sensor is stimulated, it turns right; if its right sensor is stimulated, it turns left. The closer to the wall, the sharper the steering angle (increases by steps of $\pi/6$ as for the LSA robot). For the comparison to be fair, we add as much noise to this robot as to the LSA robot: gaussian noise with mean = 3, added to each sensor value once per millisecond. We do not add noise to the output of the robot. The model is fixed, there is no learning.

Unsurprisingly, the standard robot spends most of its time spinning on itself without moving much in the arena. There is so much noise that behavior of the robot becomes unrelated to the sensory input . On 20 robots, we find an average of 22% of time spent close to a wall, with a large variance. Some spend as little as 7% of the time close to the wall, some 40% . In reality, the "good performing" robots spend so much time spinning on themselves that they never even get a chance of getting close a to a wall. An example of track for the 7% robot is shown on Fig. 2.24. Adding more noise gives the same mean of 22%, indicating that this is simply the performance of a robot spinning on itself, independently of its actual surroundings. In comparison, the networks with LSA start by always moving straight and being stuck against the walls 90% of the time, then learn to avoid it. The final average of 43% is obtained not because the robot randomly spins at a point far from a wall, but because the robot goes through the entire arena until it finds a wall, then turns away from it, as shown on video at `https://youtu.be/T2bVgxToKCY`.

The standard model is blinded by the amount of noise that a network with LSA withstands easily. The standard model is very sensitive to noise and cannot be used in these conditions. A spiking neural network with random stimulation is able also do not perform as well as the network with LSA.

We further study the effect of stimulation strength and feedback on learning performance by varying the sensitivity of the distance sensors. The average state in the last 300 seconds of each task (total duration: 1000 s) is reported on Fig 2.25. The open loop result of the previous experiment is included for reference. Fig 2.25 indicates that the learnability of the task is improved by having more sensitive sensors, up to a limit of about 40%. Having sensors with a sensitivity of more than 7 mV does not improve the performance of the robot. This result is in direct contradiction with the SRP's leading hypothesis, which postulates that the intensity of stimulation is the driving force behind network modification. If that was the case, more sensitive sensors should always lead to better learnability. By contrast, LSA emphasizes timing, not strength of the simulation. The 40% limit could be due in part to unreliable feedback, as steering away from a wall can put the robot directly in contact with another wall if it is stuck in a corner: the same action can lead to start or removal of stimulation depending on the context.

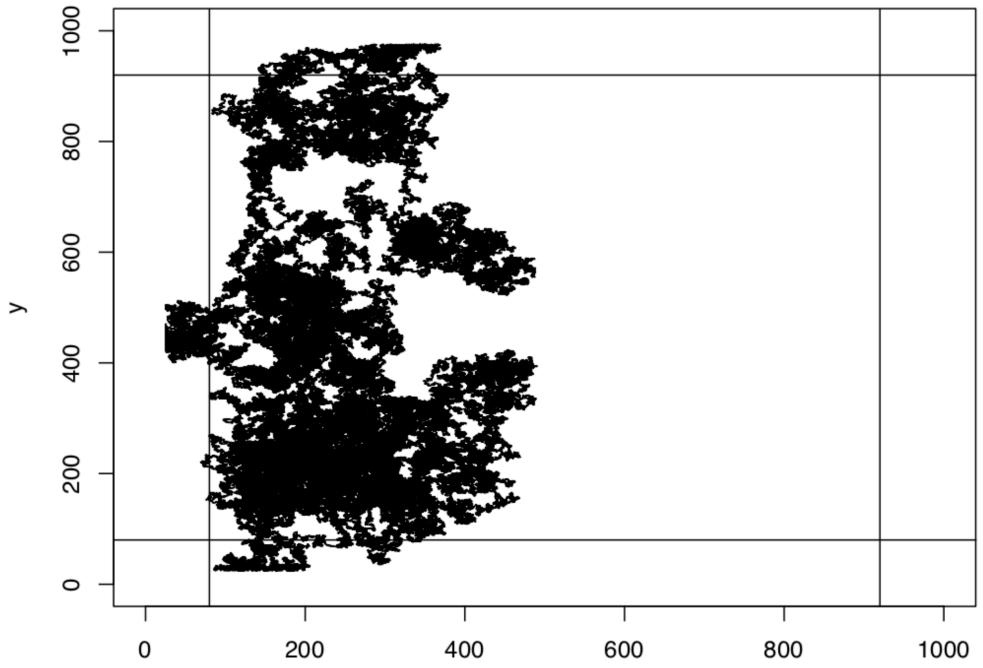


FIGURE 2.24: **The track of a "good performing" robot with the standard model.** The crossing lines are the limits beyond which the robot is considered to be close to a wall. Because the robot spends most of its time spinning on itself as an effect of the noise, it barely gets a chance to get close to the wall. Its "only 7% of the time close to a wall" performance is not really a measure of its actual usefulness.

2.7 Discussion

I have introduced LSA, a principle explaining the dynamics of spiking neural networks under the influence of external stimulation. I use the same training method as Shahaf and Marom [6, 7]. However, because I use a simulation, the mechanisms necessary to obtain learning can be stripped down to find the minimum working conditions. As a result, I could show that the conditions to obtain learning with this method are: (1) Causal coupling between neural network behavior and environmental stimulation; (2) Burst suppression.

Shahaf and Marom proposed that the Stimulus Regulation Principle (SRP [8, 9]) could explain their results, but this hypothesis was never tested. LSA is opposed to the explanation proposed by the SRP and is demonstrated experimentally:

- The SRP says that weights in the network change randomly as a result of external stimulation. I show that the weights modification is not random, but depends on the timing of the stimulation.
- The SRP says that after being modified randomly, the weights on the "correct" path from input to output are stabilized by the absence of stimulation. This is a

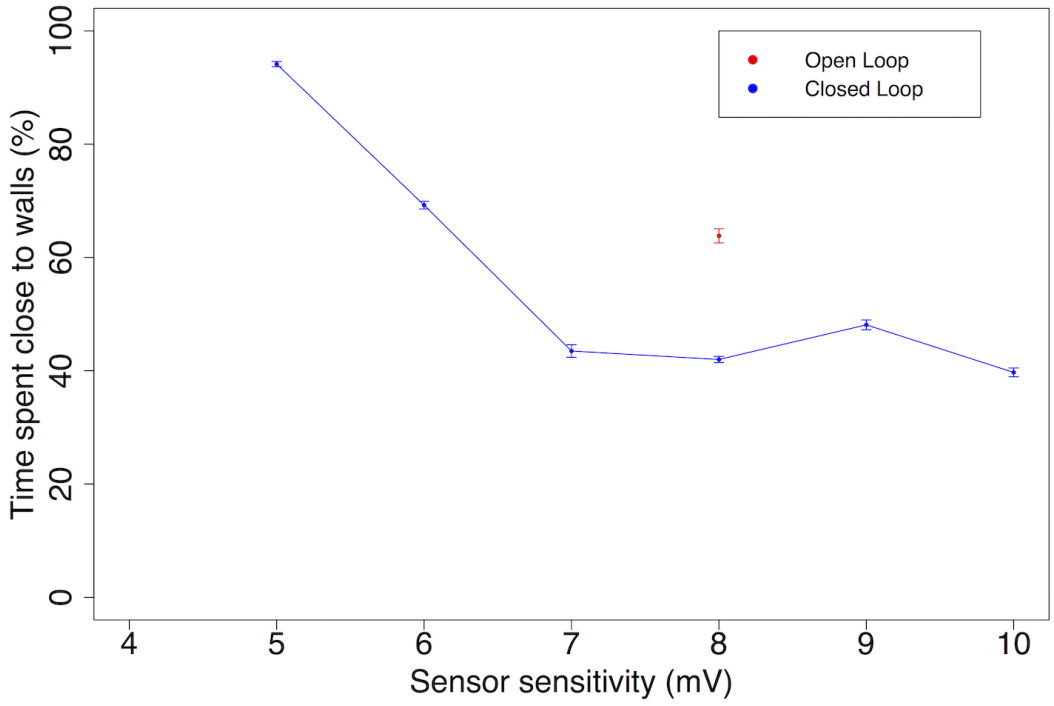


FIGURE 2.25: **Learnability of wall avoidance based on sensor sensitivity.** High numbers on the x axis indicate high sensitivity. Under 5 mV, the task cannot be learned; learnability improves until 7 mV, leading to the maximum performance of the robot. The open loop and closed loop results for the same sensitivity of 8 mV are reported from Fig 2.23. We have omitted the open loop cases as they are insensitive to the walls, but shown for the case at the sensor sensitivity = 8 mV. Statistical results for N= 20 networks with standard error.

paradox: if the expected path is stabilized, then destroyed randomly by the next stimulation, why are several rounds of training necessary for the network to learn? LSA shows that several of training gradually reinforce the weights, which explains why several rounds of training are necessary.

As in Shahaf's paper, the network is trained by stopping external stimulation at the right timing. However, this chapter also shows that the network can be trained by starting the external stimulation at the right timing, not only stopping it. I use a biologically inspired model of neuron and STDP, but unlike real biological neurons, all detailed dynamics can be analyzed. As a consequence, I could show that the training method works for 2 or 3 neurons as it works for 100 neurons.

In [33], Masumori performed LSA-based experiments on even larger simulated networks. Using STP for burst suppression, he showed that STP can robustly suppress bursts in networks of 100 to 3000 neurons. The paper also showed that as a consequence of burst suppression, STP also increased the learning ability of networks up to at least

3000 neurons. These larger networks could learn using LSA, although all other parameters being equal, bigger networks learn slower than smaller networks. This finding suggests that there is an ideal network size for learning using LSA, and it is possible that modularization could help maintain learning speed in bigger networks.

LSA does not support the theory of the Stimulus Regulation Principle, but is closer to the Principle of Free Energy Minimisation introduced by Friston [34]. The Free Energy Principle states that networks strive to avoid surprising inputs by learning to predict external stimulation. An expected behaviour of networks obeying the Free Energy Principle, or obeying LSA is that they can fall into the dark room paradox, avoiding incoming input by cutting all sources of external simulation. A key difference between LSA and the Free Energy Principle is that our network does not predict incoming input. Most importantly, LSA happens as an outcome of the external causal loop, which let stimuli from environment terminate at the right timing so that the network can self-organize using environmental information.

This research is close to the work on spiking networks presented in [10, 11, 12], as they also train spiking networks to perform a predetermined task. The difference is with this work is that they couple the network with a bio-inspired dopamine-like system, while the model presented here do not have global reward signals or reward modules. This means that LSA is at work at a more basic level in neural networks, even simply between 2 neurons connected by one synapse.

There are different forms of STDP, presented for example in [35]. In this thesis I only treated the most classical type of STDP, a symmetrical function happening between pairs of excitatory neurons. The other forms of STDP, especially from inhibitory to excitatory neurons could lead to more complex behavior. Even so, LSA is the best explanation that we have so far to understand the results obtained by Shahaf. Therefore LSA is not just an another theoretical neural learning rule, but provides a new interpretation to the learning behavior of neural cells in vitro.

I simulated LSA on pairs of neurons, showing that the weights change to allow the minimal network to avoid stimulation. We evaluated it by measuring the value of the weights in conditions where spiking of the output neuron causes the stimulation to start or to stop in the input neuron. The results shows that stimulation timing drives the increase and decrease of weight values, leading to stimulation avoidance. This is entirely a consequence of the STDP function.

I showed that these results still held for chains of 3 neurons and for output neurons that have opposite effects on input neurons. These results support the idea that LSA scales up, and I showed that a 100-neuron network could reproduce the results of the

experiments of Shahaf, by gradually reducing the response time of a network between the start of external stimulation and the expected firing pattern.

After showing that LSA is supported by robust experimental results, I demonstrate that LSA can be used beyond reproduction of existing experiments by extending Shahaf's Selective Learning experiments. The results show that to obtain true Selective Learning, burst suppression is necessary, because the synchronous activity that happens during bursting prevents STDP from picking apart the contributions of different neurons. This offer an explanation as to why only half of Shahaf's networks could learn the task: bursts that happen both in in vitro and simulated networks (but not in healthy in vivo networks) can prevent selective learning. In the experiments, I obtain burst suppression by increasing the input noise in the model or by using STP. In healthy biological neurons, the neuronal noise could be introduced by spontaneous neuronal activity, or simply by the richness of the external environment. By suppressing bursts and using weight pruning, I show that LSA can obtain true selective learning.

In the last experiment, I show that LSA can be used beyond reproducing and extending existing results and can have applications: LSA allows a robot to learn wall avoidance in the embodied experiment. The robot can gradually learn to avoid the walls. This requires that the sensory-motor coupling should be chosen carefully, so that learning the task ultimately lead to the removal of external stimulation. When this condition is not met, the robot does not learn.

The model presented is very simplified compared to biological neurons, as it uses only two types of neurons, one type of STDP, no homeostatic mechanism, etc. Nevertheless, the model is able to reproduce key features of experiments conducted with biological neurons by Shahaf et al. and explain results obtained in vitro with neurons submitted to external stimulation. It also has practical applications: by engineering causal relationships between neural dynamics and external stimulation, we can induce learning and change the dynamics of the neurons from the outside.

Future work should examine the consequences of the different types of STDP to discover if they lead to different learning rules or rather enhance LSA. It should also introduce time delays on the neuron's axons, which could enable learning longer temporal correlations, and even provide a link with the function of prediction, which was not studied in this chapter.

Code and Data

The source code for these experiments can be found at https://github.com/LanaSina/JavaLSA; the data is stored at the Open Science Framework https://osf.io/n8c82/.

Chapter 3

The Epsilon Network

3.1 Background

In this chapter we propose a new neural network that fits the number of its neurons to the complexity of visual input data. The network uses the concepts of surprise, short term memory and attention to optimize its topology. As a result, conceptual classes emerge and are represented as individual neurons in the network. We answer this question: How can a network's experience influence neural generation and neural pruning, to reach optimal size in a given environment? We think of the ϵ-network as a step towards an implementation of decision making in embodied robotic agents. This is why the focus on online learning is important in this work.

A review paper in [36] identified families of network topology optimization methods (growing, pruning, regularization) that we can also divide according to the timing of optimization:

- Topology is usually optimized before training, especially in Deep Learning. The architecture of the network is decided before training, using parameter values known in the field for giving good results, generally obtained by trial and error.
- Topology can be optimized post-training: post-training optimization uses pruning techniques aiming to reduce the network size while preserving the performance level.
- Finally, Genetic Algorithms are used to find optimal topology during training but are unsuited to online learning.

By contrast, our network optimizes its topology during training, using a measure of surprise to simultaneously add and remove neurons and weights: it adds neurons

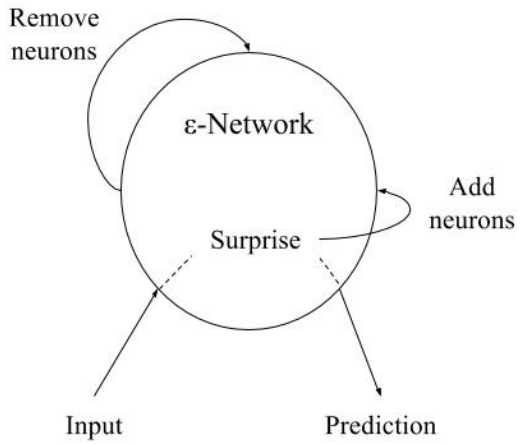


FIGURE 3.1: **Conceptual view of online optimization in the ϵ-network.** The network produces predictions from the input. Errors in this prediction cause surprise, which is used to add neurons and weights at appropriate locations in the network, improving future predictions. Periodically, neurons producing similar predictions are fused together, reducing the number of neurons and weights in the network.

where they can raise performance, and removes redundant neurons while preserving performance (Fig. 3.1).

Predictive coding, the idea that intelligence and learning come from attempts to predict the world, has recently been gathering interest in the field of Artificial Intelligence, partly because of the influence of the theoretical framework laid by Friston ([37, 38, 39]). Friston builds a framework aiming to explain how prediction and inference can explain not only learning in the brain, but also an agent's actions. The core idea is that agents strive to minimize "surprise" (unpredicted events). It is a theoretically appealing framework, but its extreme computational cost and the complexity of the core concepts makes it difficult to grasp, let alone implement in a computer, despite its having been used in a very simplified version as inspiration for implementing a deep learning predictive network ([40, 41]).

Around the same time as Friston published his first papers on predictive coding, Hawkins published his own ideas on prediction: the Memory-Prediction Framework [42]. That theory aims to explain how the neocortex works; it does not have the advantage of a sound mathematical framework as Friston's work does, but Hawkins' work resulted in a fair number of applications and publications: for example [43] shows a model capable of image recognition; [44] are also able to do image recognition, in a moving robot; [45] coupled the framework to reinforcement learning to produce behavior. That model has a fixed topology; its implementation is not related to our work but the underlying ideas about prediction and prediction are close.

The concept of surprise is core in approaches where prediction reflects the performance of the network. [46] define the concept of Bayesian surprise as the distance between the prior probability distribution and the posterior distribution, a definition closer to the human experience than the Shannon surprise (the occurrence of rare events). In our work, surprise itself is used to decide how to update the prior, therefore we use a different definition than both the Shannon and Bayesian definition of surprise. Here surprise is defined as the unpredicted activation of a neuron.

Our network implements a concept that is deemed biologically plausible by [42]: hierarchically ordered "name cells", which are cells that act as pattern detectors. Yet we do not aim to directly emulate biology, but to tackle issues that biological organisms face while also being backed up from a statistical point of view by the work of [2]. In that paper, Crutchfield proposes ϵ-machines as a measure of complexity for phenomena that fall on the spectrum between periodic and random behavior. Complexity is, in his words, "the information contained in the minimum number of equivalence classes obtained by reducing a data set modulo a symmetry." This symmetry is "time translation invariance, the symmetry appropriate to forecasting": complexity is predictability. ϵ-machines model phenomena through automata built from a stream of data. First, we build a hierarchical tree where nodes represent the data and edges represent the probability of transition between nodes. The nodes of the tree are then pruned to eliminate redundancy: two nodes with the same probabilities on successive edges are considered equivalent. The graph complexity of an ϵ-machine, in Crutchfield's words, "measures the computational resources required to reproduce a data stream". Our ϵ-network, like the ϵ-machine, results in a graph that can reproduce a data steam and adapt the computational resources to the complexity of the input data steam. The neurons are equivalent to nodes, the weights are equivalent to edges, and the pruning mechanism is functionally equivalent to Crutchfield's pruning methods. The main significant differences are that our ϵ-network has a growing mechanism based on the notion of surprise, several nodes can be active simultaneously as we deal with multivariate data streams, and we do not yet deal with the concept of indeterminacy of transitions.

As we calculate probabilities on events, it is easier to treat events as binary values "happened" or "did not happen". Therefore the activation of neurons is a binary value. The network itself is not completely binary, as the weights have real values. Binary Neural networks are typically less costly to train and run than real valued or spiking networks, but they also have worse performance. The main specificities of our approach compared to existing networks is that we propose online topology optimization, and in our network the count of neurons reflects the complexity of the data. A disadvantage is that learning is not trivial (we do not use Genetic Algorithms or backpropagation), and it is not easy to compare our results with existing methods.

We present the results of the network on a clean versus a noisy dataset, and a simple vs a complex dataset.

3.2 Model

Deep Learning papers often use the word "prediction" to describe the output of their networks as a synonym for "class". We believe this is the symptom of a misconception about the relationship between classification and prediction. Here are 3 ways in which these concepts are related but different:

- Classification is necessary for adaptive predictions, and prediction is necessary for adaptive actions.
- Classes can be built from predictions. Predictions can be made about classes' dynamics.
- Static inputs can be classified. Predictions are by definition made through time between successive inputs.

A class is not a prediction, it is a mean to a prediction. In models that mix the two indistinctly, like predictive auto-encoders or the PredNet architecture [41] , both functions cannot be optimized according to their specific characteristics. We believe that this is a current issue with most predictive coding research. This model makes an attempt at solving it. Classes are learned by regrouping all patterns that lead to similar predictions. Predictions can then be made about entire classes instead of being made pixel-by-pixel, leading to a form of generalization. Classifying and predicting are therefore strongly interdependent yet distinct enough that their optimization rely on different parameters. Classification can be optimized by adapting the definition of "similarity" when looking for similar predictions; prediction can be optimized by adapting the threshold for surprising events.

The ϵ-network learns transition probabilities between two successive inputs. There are 2 conceptual flows of information in our network, each corresponding to one type of weight and one function:(Fig. 3.2): classification and prediction. The classification flow corresponds to pattern weights and to the neuron removal function. Pattern weights link several subclasses to the superclass they belong to. Two neurons are fused ("snapped") together when they represent the same class (having the same values for successive probability weights). The prediction flow corresponds to prediction weights and to the neuron adding function. Prediction weights represent probabilistic time transitions

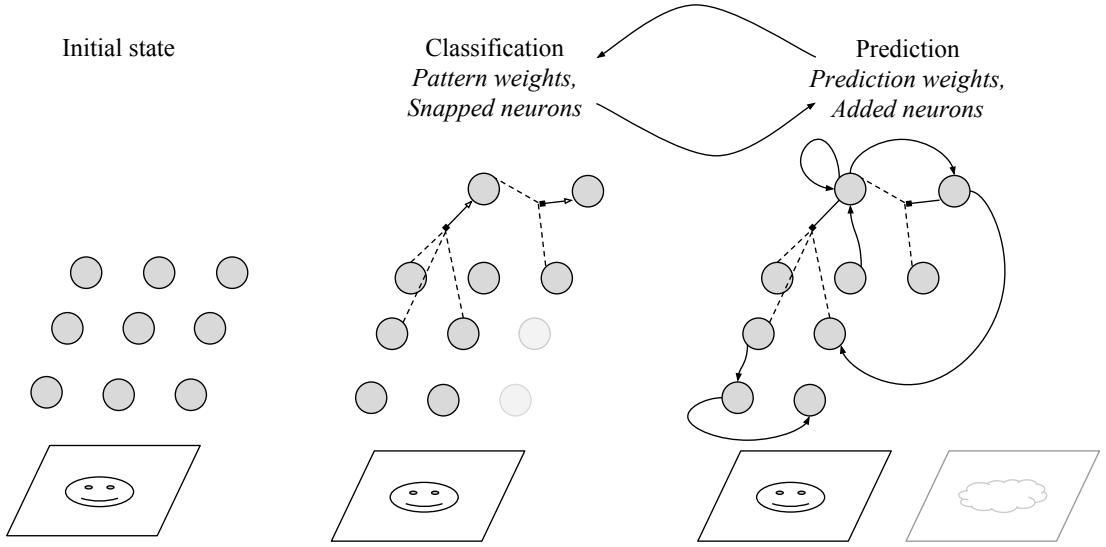


FIGURE 3.2: **Classification and Prediction as interdependent functions.** Initially, there are no weights in the network and each neurons is simply activated from stimulation in its receptive field. During learning, new neurons and weights can be added; neurons can also be fused together ("snapped"). Snapped neurons represent classes. Pattern weights link several subclasses to the superclass they belong to. Prediction weights represent probabilistic time transitions between two neurons. Prediction weights determine which neurons can be snapped, and pattern weights carry predictions down to their subclasses, closing the classification-prediction loop.

between two neurons. Neurons and weights are added to reduce the number of surprised neurons after a transition.

The difference between the prediction computed by the network and the actual input at $t + 1$ is used to update the weight values. The number of neurons is increased to minimize the value of the surprise; simultaneously, redundancy is calculated by finding equivalent output probabilities on neurons, and redundant neurons are pruned. We detail the procedure in this section.

3.2.1 Network architecture

The ϵ-network's architecture and update rules are fundamentally different from what can be found in existing approaches. The network itself is composed of one type of neuron and 3 types of weights (prediction weights (PrW) ,pattern weights (PaW) and inhibitory weights). The PrW are equivalent to a boolean circuit with OR gates and the PaW are equivalent to AND gates. The inhibitory weights annulate some predictions. The XOR function, that would grant to this network a complete set of boolean operators, cannot be formally computed but in practice there are some equivalences. During training, there is no null input to the network: not a (respectively not b) is exactly equivalent to another set of symbols X (respectively Y) being all TRUE. Using a XOR $b = (a$ OR $b)$

AND (X OR Y), the network does forms a complete set of boolean operators {AND, XOR}. The PrW, together with Short Term Memory and the attention mechanism, are an extra layer of information that allows to optimize the network. We define the network's components as:

- Neurons have a discrete activation value of 0 (not activated) or 1 (activated). A neuron is activated when at least one input PaW are activated.
- PaW have a discrete activation of 0 or 1. PaW are composed of strands coming from their input neurons. A PaW is activated when a precise number of their input strands are activated (see 3.2.3.2 for the activation rule). As a result PaW are activated when their input pattern is present in the network, with no time delay. Strands have one input neuron, one output neuron and a discrete activation of 0 or 1. A strand is activated or inactivated simultaneously with its input neuron, with no time delay.
- PrW have one input neuron and one output neuron. They have a discrete activation of 0 or 1, a continuous prediction probability value between 0 and 1, and a discrete maturity value of 0 or 1. A PrW becomes activated when its input neuron is activated, but is inactivated with a delay of one timestep after the input neuron. They carry information on the probability that the output neuron will become activated at the next time step. This information is used only for optimization: PrW do not influence the activation of the output neuron. The maturity value determines whether this weight can still be updated or not. Neurons with immature weights cannot be fused together.
- Inhibitory weights have one input neuron and one output neuron. They have a discrete activation of 0 or 1, a continuous probability value between 0 and 1, and a discrete maturity value of 0 or 1. An inhibitory weight becomes activated when its input neuron is activated, and inactivated when its input neuron is inactivated. These weights are used to inhibit some predictions. The maturity value determines whether this weight can still be updated or not.

The network takes an array of external sensors as input (here, visual sensors). There are between 6 to 15 groups of sensors, each sensitive to one shade of grey (Fig. 3.3). At the initial state, each neuron has a receptive field corresponding to one sensor as shown on Fig. 3.4. We call these initial neurons sensory neurons.

Initially, there are no weights in the network. During one timestep:

- the predicted activation is calculated;

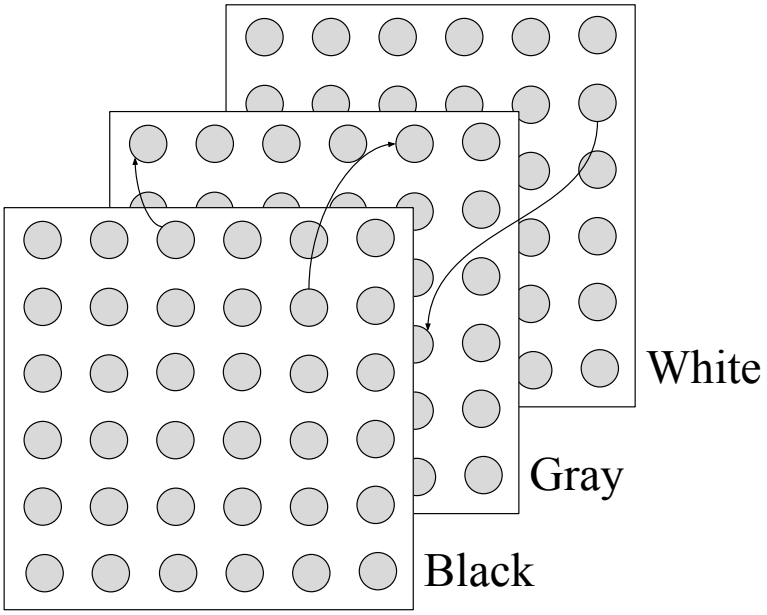


FIGURE 3.3: **Neurons sensitive to different shades of gray.** Because we use visual images as input, we can think of these neurons as being on different layers; in reality, there is no concept of layer in the network and all neurons in a module can communicate together.

- activation is propagated through the network via the PaW,
- activation is compared to the predicted activation to update PrW values.

This loop is repeated at the next timestep (Alg. 1).

3.2.2 Creating and updating prediction weights

3.2.2.1 Creating PrW

At the initial state, there are no PrW in the network. To detect whether a new PrW is necessary, we introduce the notion of surprise, close to the idea of Friston and to Shannon surprise. Surprise is defined as a prediction error: the number of neurons which have an activation value of 1 while their predicted activation was 0. This is only one of several choices as a visual indicative of performance, all not optimal; but it is a good proxy for what is happening in the network as surprise is used to update the structure of the network.

We create PrW when a neuron was surprised, by adding one from each neuron that was activated at $t-1$ to the surprised neuron activated at t (Fig. 3.5). For the implementation of this concept we introduce the concept of Short Term Memory (STM). The STM simply stores the ID of all the neurons that were activated a $t-1$. At t, PrW are

Algorithm 1: Activation and weights update

```
for each neuron do
    Neuron.activation = 1;
    Neuron.OutputStrands.Activation = 1;
end
for each PaW do
    if PaW.activation == 1 then
        PaW.outputNeuron.activation = 1;
        //recursively propagate activation from neurons to PaW and from PaW to
        output neurons.
    end
end
for each PrW do
    if PrW.activation == 1 then
        update PrW.p;
        PrW.activation=0;
        //update the probability value of the predictions based on the prediction error,
        then reset activation
    end
end
for each neuron do
    if neuron.activation==1 then
        for each neuron.PrW do
            PrW.activation=1;
            //calculate the next prediction by activating the weights
        end
    end
end
for each element in neuron, PaW do
    element.activation=0;
    //reset activations before reading the next input
end
```

Algorithm 2: Prediction probability update

```
/* Initialized when PrW is created:                                    */
value=1;
age=1;
/* Each timestep                                                       */
while running do
    if PrW.activation == 1 && PrW.outputNeuron.activation == 1 then
        value=value+1;
    end
    if PrW.inputNeuron.activation==1 then
        age=age+1;
    end
    /* prediction value                                                */
    p = value/age;
end
```

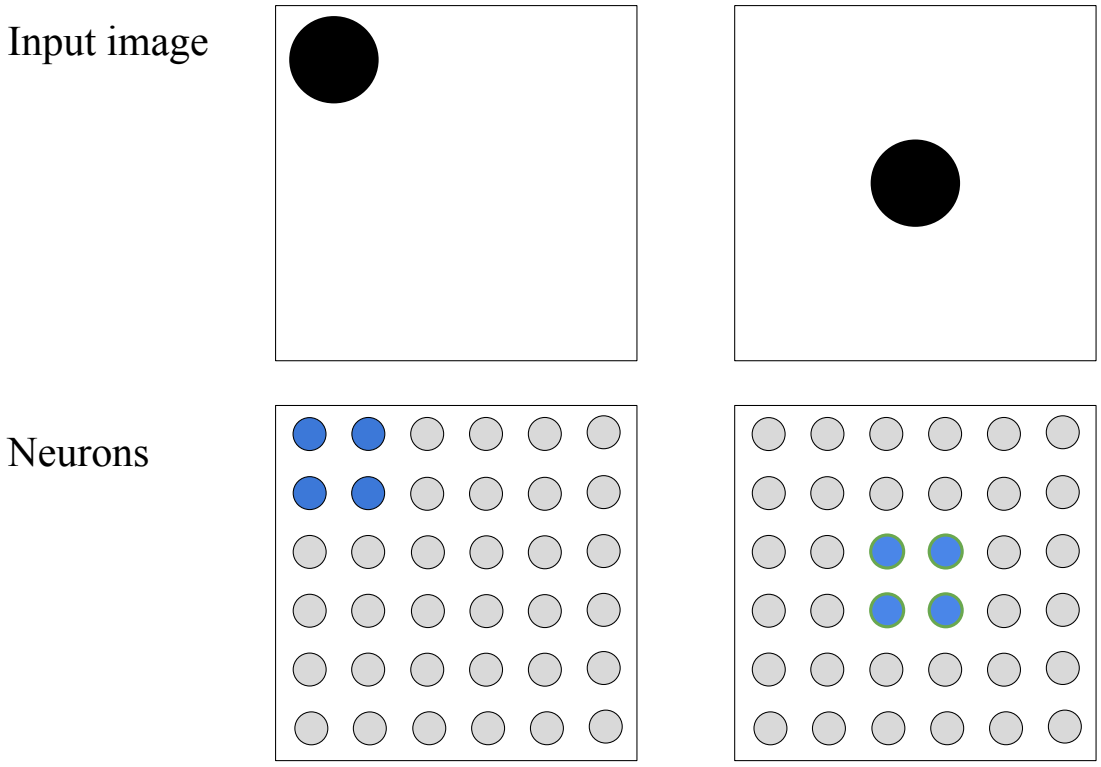


FIGURE 3.4: **Network before adding weights and neurons**. The greyscale input is discretized so that the area has 6 sensors respectively activated by one of 6 shades of grey. Here we show the receptive field of neurons sensitive to black.

created from all neurons in the STM to all currently surprised neurons. PrW are not created if a PrW already exists between an input neuron and an output neuron. The value of the the weight represents the exact probability that the post-synaptic neuron is activated one timestep after the pre-synaptic neuron and is updated as long as the weight can learn (Fig. 3.6).

The *age* variable of PrW counts the number of times that the input neuron was activated, while the *value* variable counts the times when the output neuron was activated 1 timestep after the input neuron (Eq. 3.1). p is therefore the exact probability for a neuron to be activated $t+1$ after another neuron. We can interpret this in terms of ϵ-machine: it is the probability of going from one state to another state, each state here being a neuron. p is therefore a prediction value calculated from the past experience of 2 neurons; it is reminiscent of Hebbian rules, except that we get exact probabilities. The network takes multiple inputs and therefore, several neurons can be activated at a given timestep.

$$p = value/age \ , \tag{3.1}$$

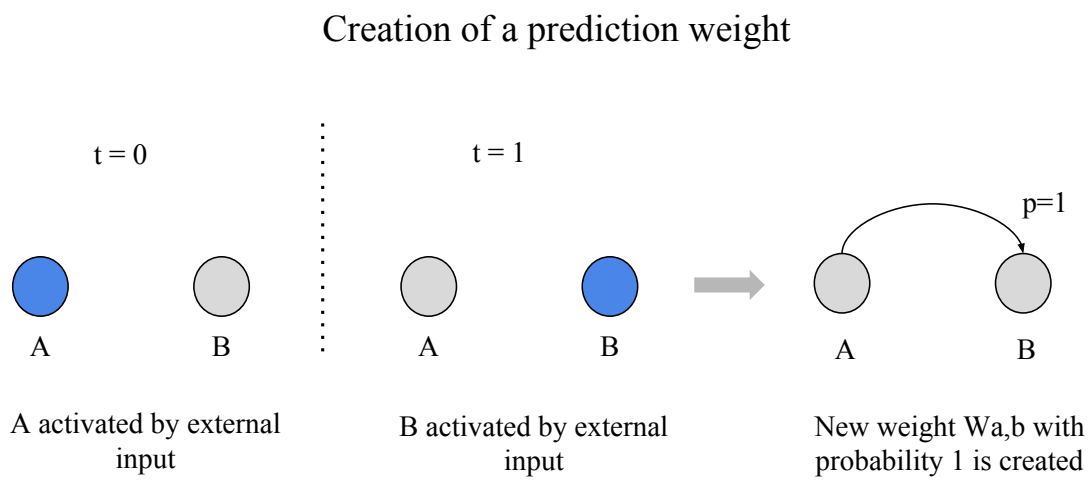


FIGURE 3.5: **Rule of creation of a prediction weight**. The weight is created if a neuron is surprised (the neuron is activated unexpectedly). The prediction value p is used to predict whether the output neuron will be activated at the next timestep, and updated during learning.

with age = number of pre-synaptic activations and $value$ =number of times that a post-synaptic activation happened at t+1 after a pre-synaptic activation. The ensemble of all the neurons having an input PrW satisfying $p > x$, $x = 0.8$ defines the predicted activation at $t+1$. The predicted input is $a = 1$ for the neurons with high probability of activation and $a = 0$ for all other neurons. The maturity value is defined as 0 if $age < M$, 1 otherwise. $M = 20$ is a constant defining how many times the probability value of a PrW can be updated. It avoids pruning neurons that are still actively in a learning phase.

3.2.3 Creating and updating pattern weights

3.2.3.1 Creating a PaW

Initially predictions are made neuronwise (from one neuron to one other neuron), but some events require to know the state of several neurons to be correctly predicted (AND boolean operation). These events can be predicted by PaW. When a neuron is surprised by an unpredicted activation event, if no new PrW can be created, then a new PaW is created with input strands from all neurons in the STM. Additionally, one neuron is created with the new PaW as input weight and one PrW to the surprised neuron (Fig. 3.7). This is repeated for all currently surprised neurons.

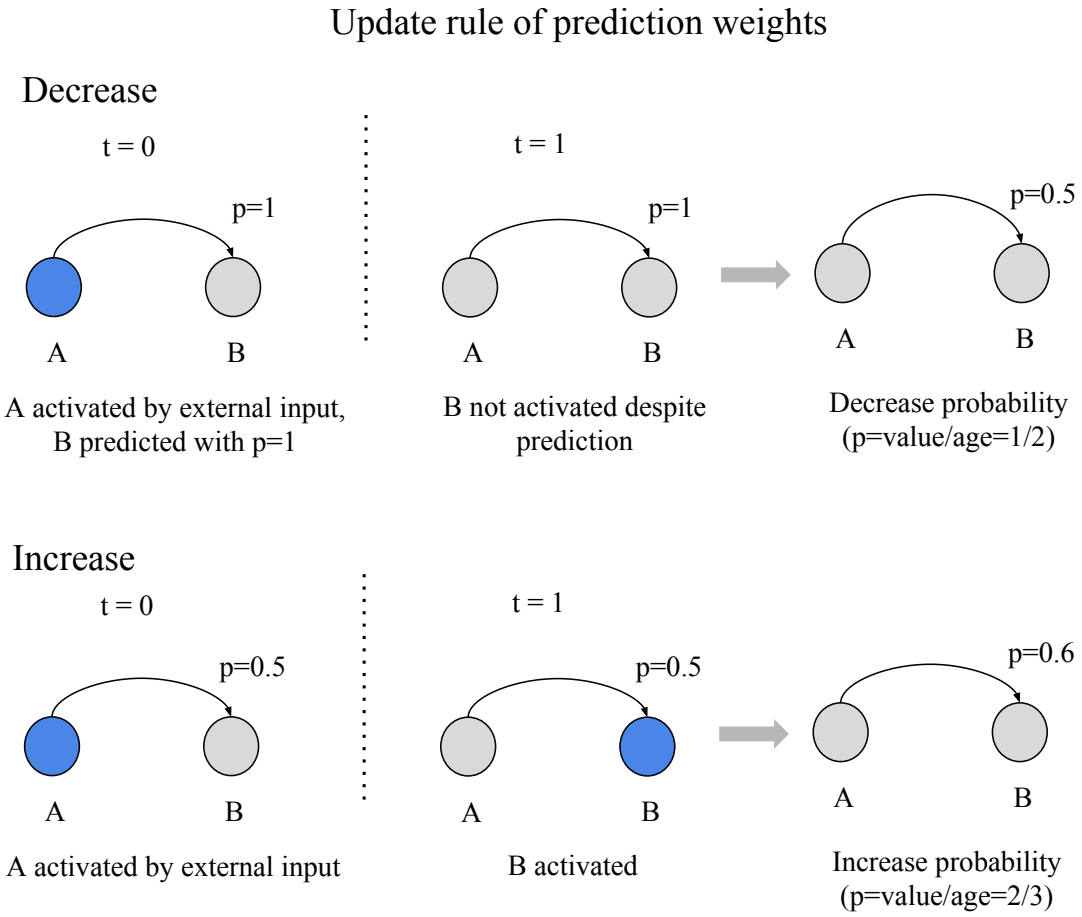


FIGURE 3.6: Rule of update of a prediction weight. The prediction value p is updated by counting how many times B is activated after A, yielding the exact probability of activation.

3.2.3.2 Updating a PaW

So far PaW are treated as being AND boolean operators, and it is sufficient to have good results in simple experiments. But to keep with the probabilistic framework and improve resistance to noise, we define an update rule and an activation for PaW (Fig. 3.8). The goal is to have a probabilistic AND allowing PaW to be activated by partial and noisy patterns, not only by complete patterns.

If 20% of a pattern is constantly obscured by random noise, how can we still detect it? The update rule works by decreasing the value of the weights on strands that are not necessary to the prediction of the target neuron (the neuron predicted by the output of the PaW). When updating a PaW, we follow algorithm 3 which is similar to the algorithm for updating PW probabilities.

The activation rule for a neuron j is Eq. 3.2:

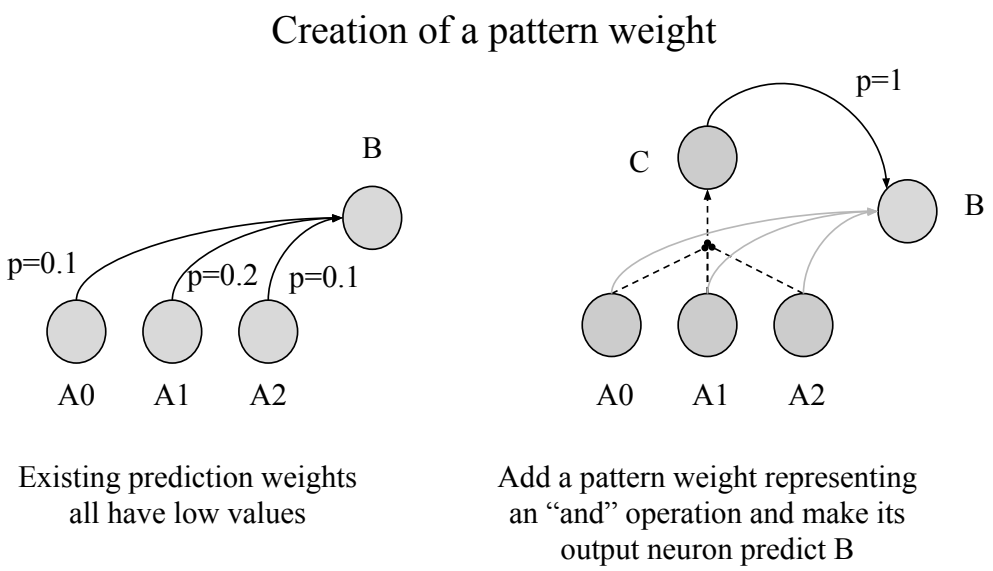


FIGURE 3.7: **Creation of a pattern weight.** When prediction weights from $A_{0..2}$ to B already exist but none can accurately predict B because the probability on each weight is too small, B will continue being surprised. When this happens we create a pattern weight with $A_{0..2}$ as input and a new neuron C as output. We also add a prediction weight ($p = 1$) from C to B. Next time that all 3 of $A_{0..2}$ are activated, C will also be activated, and B will be correctly predicted.

Algorithm 3: Pattern recogintion probability update

```
/* probability p = value/age                                          */
for each neuron N in the PaW do
    /* potentially decreases p                                        */
    N.age = N.age+1;
    if STM contains N then
        /* if N was activated at t-1, this line means that p does not
           change                                                     */
        N.value = N.Value+1;
    end
end
```

$$activation = \begin{cases} true, & \text{if } \forall w = ||w_{i,j}|| \text{ between 0 and 1, } \frac{|A_w|}{|S_w|} > w, \\ false, & \text{otherwise.} \end{cases} \tag{3.2}$$

w is defined between 0 and 1 with an increment of 0.1 (0, 0.1, 0.2 etc) ; $|S_w|$ is the size of the set of all neurons with a weight equal to w , and $|A_w|$ is the size of the set of activated neurons with the weight value equal to w. This activation rule is a probabilistic version of a boolean AND operator: for the PaW to be activated: all of the input neurons with $p = 1$ have to be activated, AND more than 90% of the neurons with $p = 0.9$ have to be activated, AND more than 80% of the neurons with $p = 0.8$ have to be activated etc. If a pattern is constantly obscured by 20% of random noise,

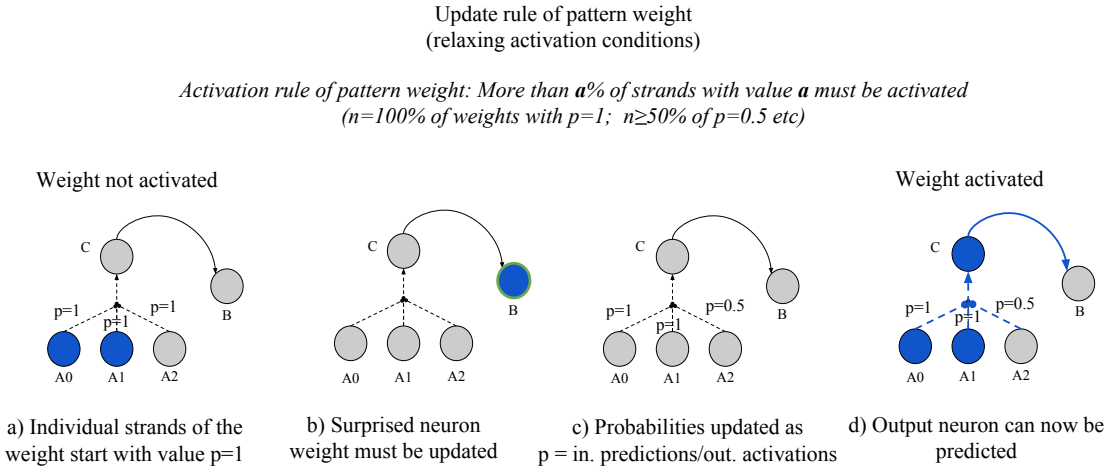


FIGURE 3.8: **Update rule of the pattern weight.** In a), the PaW is made only of strands with p=1. According to the activation rule 100% of the strands with $p = 1$ should be activated for the PaW to be activated, so with only A0 and A1 activated for the PaW is not activated. Therefore the condition of activation of the PaW must be relaxed by decreasing the value of A2. b) The PaW was not activated, so C was not activated and B could not be predicted, leading to surprise. The surprise means that the PaW must be updated. c) The weight of each strand is updated depending on whether the input neuron was activated at $t - 1$. A0 and A1 were activated at $t - 1$ so their weights are still $p = 1$; A2 was not activated so its weight is decreased to $p = 0.5$. d) Next time that A0 and A1 are activated, this is sufficient to activate C and predict B. (50% of neurons with $p = 0.5$ are also required to be activated; there is only one such neuron so it can be ignored.)

the strands of the PaW detecting this pattern will all have a value of $p = 0.8$, and this pattern will still be detected as long as at least 80% of the neurons are activated. Therefore, in opposition to the usual understanding of weight values, here the higher the weight the higher the number of presynaptic neurons are necessary to activate the postsynaptic neuron.

In our implementation, we do not add all types of weights each time that a neuron is surprised. Instead each time that a neuron is surprised, we first try to add PrWs as these weights are suitable for simple one-to-one prediction; if there is no PrW to add, we try to add PaW, which are suitable for pattern-based prediction; if that is not possible, we update the weights of all PaW for neurons that have strong PrW (>= 0.9) leading to the currently surprised neuron. This allows us to relax the conditions of activation of PaW that could have been used to predict the surprised neuron. An example showing the ability of the network to recognize noisy input is shown at https://youtu.be/RdQhr5-xBJo (to be compared with the same dataset without inhibitory weights as explained in the following subsections, at https://youtu.be/20LnwTpOHl0).

3.2.3.3 Decreasing the number of neurons and weights

Decreasing the number of neurons is referred as the "snapping" procedure; this procedure is conducted periodically after a predefined number of timesteps (every 50 timesteps in this paper). If 2 neurons or more are "similar", these neurons are considered redundant and they are fused together (Fig. 3.9). The concept of similarity here is defined as: PrW are similar if they have the same output neuron and the same prediction value. Neurons are similar if all their output PrW are similar and none is immature. It is the implementation of the idea that if two events lead to the exact same consequences, these two events must be equivalent. Concretely in our paper, it means that a visual pattern or object that was represented by many neurons will now be represented by only one neuron; if two objects have the same motion dynamics they will be identified as the same object. It also means that if some patterns have the same abstract consequences (e.g., all cats meow) they will be considered as belonging to the same "cat" class and end up activating a bottom up cascade of neurons and PaW leading to the same unique neuron. It also fits nicely with the concept of "name cell" in the work of Hawkins, where the same pattern (a visual object, a song...) ultimately always activates the same dedicated name cell. When 2 neurons are fused into one, all PaW and input PrW are redirected to one neuron; the redundant weights are deleted, so the global number of weights is less or equal than before snapping. This falls outside the focus of this thesis, but different choices could be made to report the input weights, leading to different consequences in terms of generalization of inferences. For example, when the 2 neurons have 2 PaW sharing some of their input neurons, should we treat them as 2 different PaW fo the fused neuron as well? Or should we gather the common input neurons in a single PaW, and discard the neurons that were not present in both fused neurons? In this work, we adopt the following approach:

- When neurons A and B are snapped together into a new neuron C, input PrW are reported to C.
- When A had input PrW from a presynaptic neuron and B did not have any input from the same neuron (no conflict), the input weight is reported to C without change
- When A and B had input PrW from the same neuron (conflict), we calculate the value of the resulting fused PrW as a weighted average where the weights depend on the coactivation rate of A and B.
- All input PaW are reported to C without any change, even if they are redundant or conflicting

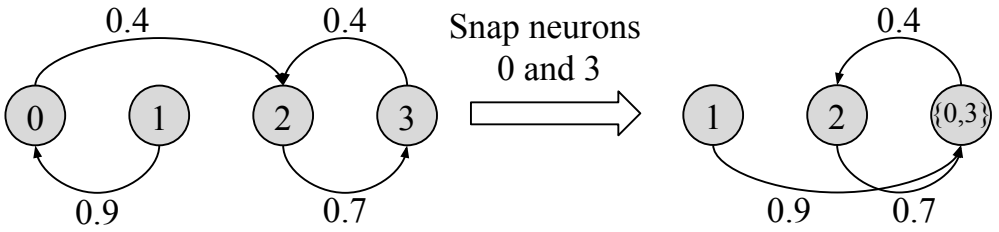


FIGURE 3.9: Example of snapping procedure: two neurons are fused together if they have the same output values; their input weights are reported to the fused neuron.

3.2.4 Short Term Memory and Attention Mechanism

We only consider predictions 1 timestep in the future, so the STM only stores neurons that were activated at the previous timestep. In addition, not all activated neurons can enter the STM. If a PaW is activated, its output neuron can enter the STM but the input neurons that caused its activation do not enter the STM. It makes sense as a pattern-activated neuron "stands for" all the neurons that constitute this pattern. We can create weights from this one neurons rather than from each one of the neurons that constitute this pattern. This is quite similar to attentional mechanisms in humans that allow us to perceive a face as a whole rather than as a group of separate parts.

3.2.5 Hierarchical structures

In the introduction to this chapter, we mentioned the fact that knowledge gained about classes can be used to make class-to-class prediction and not only pixel-to-pixel prediction. This is made possible when a PrW is created between neurons that have take input from PaW. Fig. 3.10 illustrates this principle: A predicts B, but when B is predicted, all the patterns that belong to the class represented by B are also predicted. If I predict that I will see a dog, it make sense to predict that I will also see the different parts that a dog is made of: ears, eyes, body...

This allows the network to reuse the knowledge learned about classes to make better predictions and not be surprised by trivial facts, and also reduces the number of weights in the network as we do not need to add one PrW from A to each of B sub-classes. But it also means that many more neurons than necessary will be predicted. The different body parts of a dog can be at any position in an image, yet simply predicting that all of the pixels of the image will be activated cannot be considered as a good prediction: that prediction contains no information. Fig. 3.11 illustrates this issue with example where the network is made to learn 2 sequences. A bomb is always followed by a fire, and a fire is always followed by a game over screen. After snapping, the network has a class for "bomb" and a class for "fire", both independent from the position of the bomb

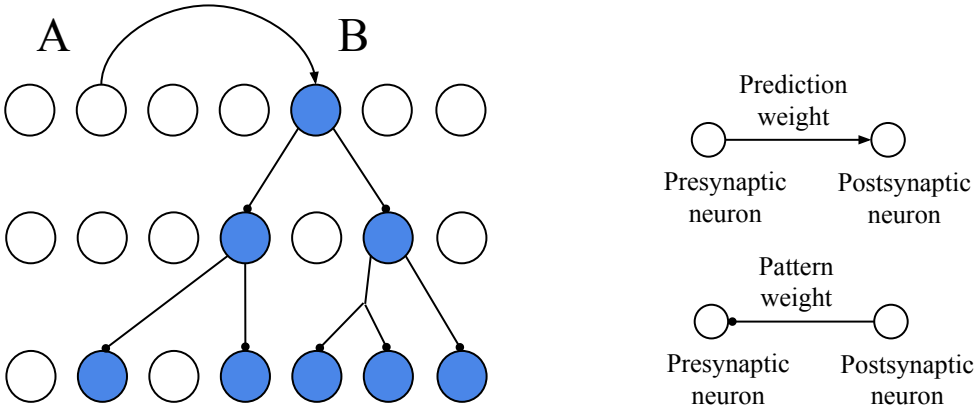


FIGURE 3.10: **Hierarchical prediction.** Pattern weights introduce the possibility for hierarchical prediction from neuron (class) A to neuron (class) B and all of the neurons that are part of a pattern that can activate B, instead of having prediction weights from A to each of B's sub-classes.

or the position of the fire. These are great as abstract representations, but how do we retrieve the spatial information when making a prediction? In its compressed state, the network will always predict an illusion of fire at a position where there is no fire at all.

The network needs to use previous information (the position of the bomb) and it also needs to know that some predictions never happen simultaneously. One solution is to take the strength of prediction into consideration and to introduce inhibitory weights. Inhibitory weights will help choosing between two possible predictions locally at each level: the prediction made stronger by local neurons can inhibit other predictions as needed. Even after adding these local inhibitory weights, we still need less connections in total in the network than if we had no hierarchical predictions, which would require a fully connected network; we also must have better predictions as we can take advantage of the generalization enabled by hierarchy and avoid making over-reaching predictions like "all pixels will be simultaneously activated at the next step". An example of this over-prediction can be found at https://youtu.be/YGpaHVyUYkU ; compare with https://youtu.be/yWNsiVHh_D8 . The value of the weight of an inhibitory connection is, as for PrW, a counter of how many times the weight lead to a correct prediction.

3.2.6 Modularity

In the worse case, we can have a fully connected network of PrW, and $n!$ PaW. The computation cost is high. To make the network more efficient, we can divide it in small modules as in Fig. 3.13. Each module is sensitive to several shades of gray, but only receives input from a small part of the image. Each module having its own short term memory, a neuron can only make new weights towards neurons in the same module. This prevents communication between modules; to solve this issue, neurons from high

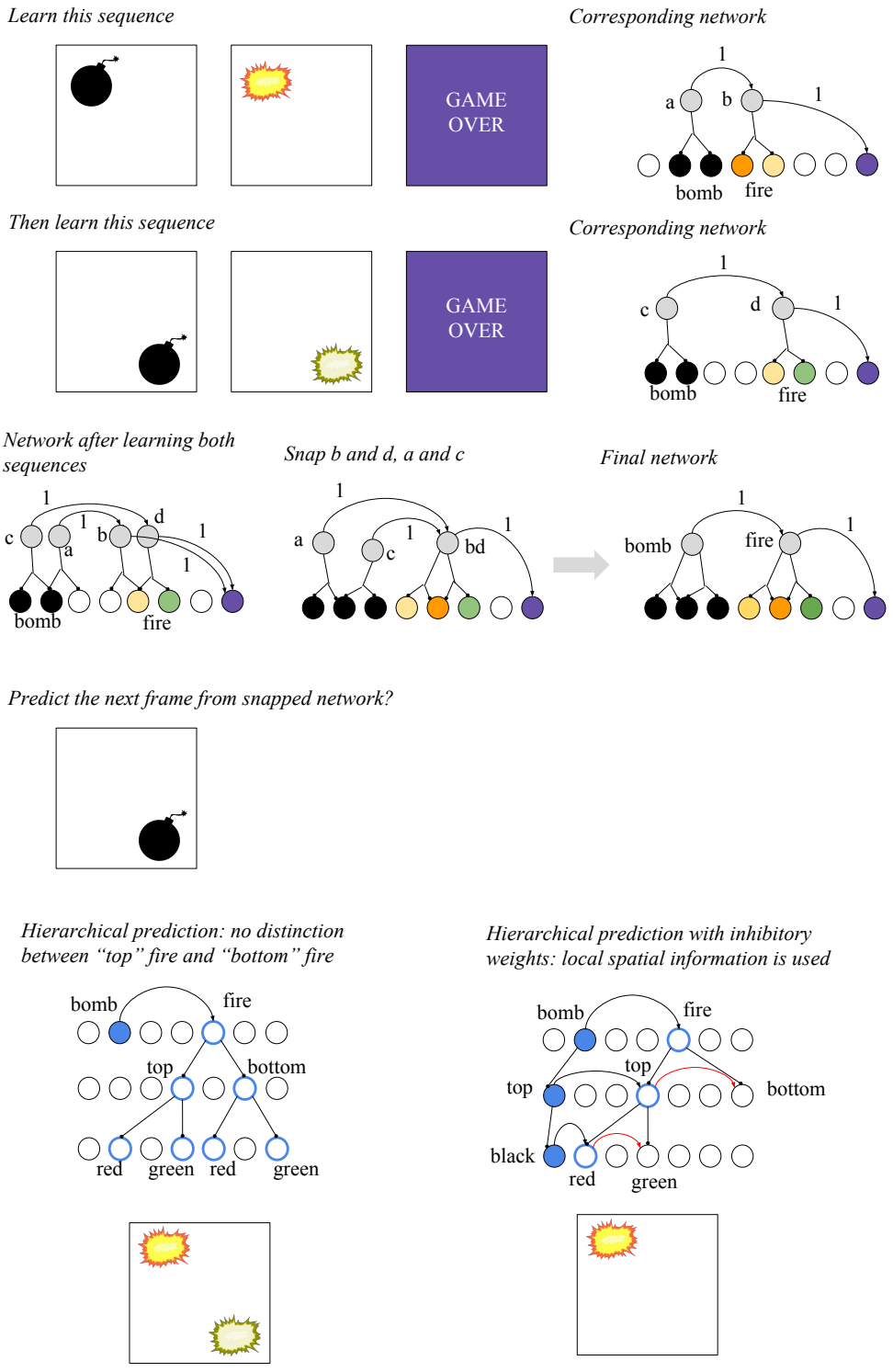


FIGURE 3.11: **Generalizing using hierarchical predictions while avoiding over-prediction with inhibitory weights**. The network is trained on simple time series and learns the patterns for bombs and fires. Snapping causes the neurons for "fire" to be fused, generalizing the concept of fire by losing spatial information. When "fire" is predicted, the network does not know at which position. Inhibitory weights allow the prediction to use local spatial information from the lower levels of the network.

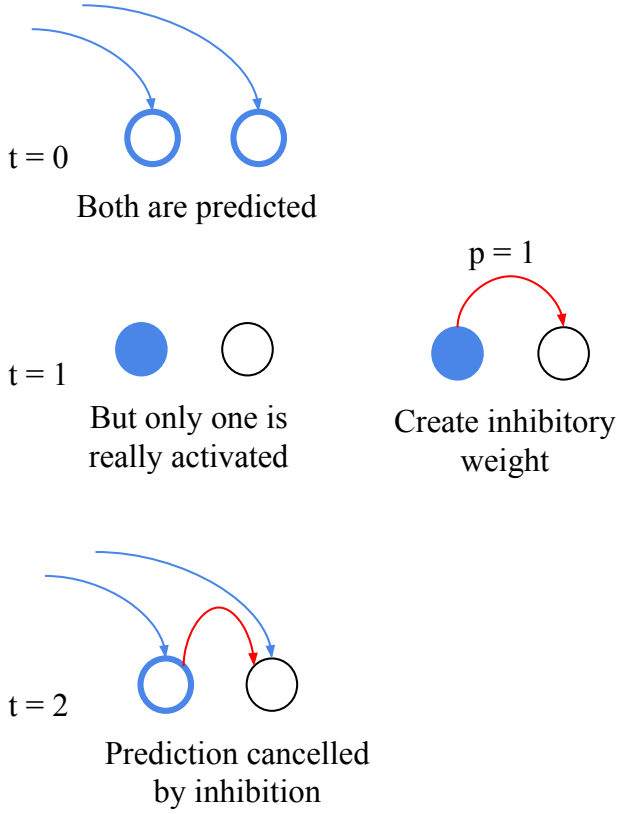


FIGURE 3.12: **Creation of an inhibitory weight**. Inhibitory weights are created from neurons that were correctly predicted to false positive neurons that were predicted but not activated. The update rule of the weight value is similar to the rule for prediction weights: p is the number of times that the post-synaptic neuron's prediction was correctly inhibited (inhibited and not activated at t+1) divided by the total number of activations of the pre-synaptic neuron.

hierarchies (having more several levels of neurons below them) are periodically picked up from all modules and added as input to a common, unifying module. This happens just after each snapping procedure. This way, neurons representing the most abstract classes can communicate with each other through PrW and PaW, even in the neurons below cannot communicate outside the module. When using the modular structure, we typically use 10x10 pixels as the size of all initial modules.

In conclusion, the ϵ-network does much of the optimization by itself, changing its structure and parameters. There are still parameters that must be selected for the implementation and could possibly be optimized:

- The length of the Short Term Memory: how many previous steps can the network remember when building new weights? Here we only remember 1 timestep.

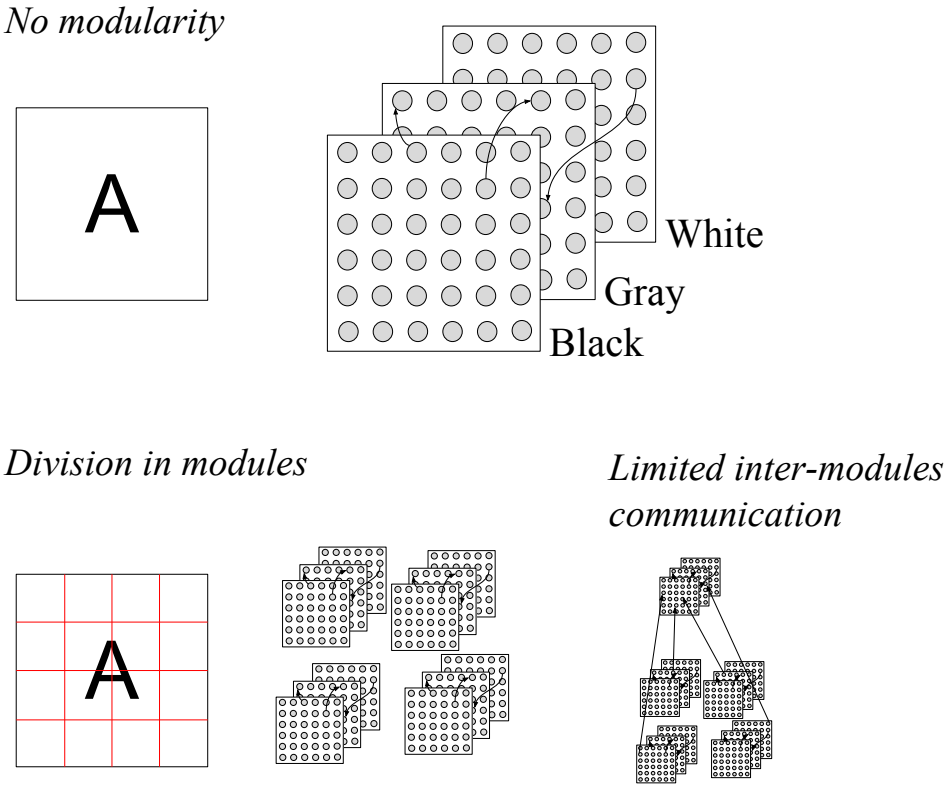


FIGURE 3.13: **Division of the network into modules**. Each module takes input from a small part of the image. Periodically during learning, higher level neurons from existing modules are added as input to the neurons of the hierarchically higher modules, creating a possibility for inter-module communication. One neuron or one pixel cannot belong to several modules at once, so this is not similar to a convolutional network.

- The threshold at which weights stop learning: this could be unbounded, but to speed up computation we choose 20 as the maximum number of times that a weight can be updated (bound of the weights *age* variable).
- The threshold at which a probability is strong enough to be considered as a reliable prediction. We choose 0.9: if the weight value p exceeds this threshold, the post-synaptic neuron is counted as predicted.
- The initial sensory configuration: how many greyscales can we use (15 here), and what is the density of receptive neurons (here 1 neuron per 2x2 pixels or 5x5 pixel depending on the experiment)
- The size of the modules (here 10*10 pixels)
- Which neurons to select for inter-module communication (here, neurons from levels > 4)

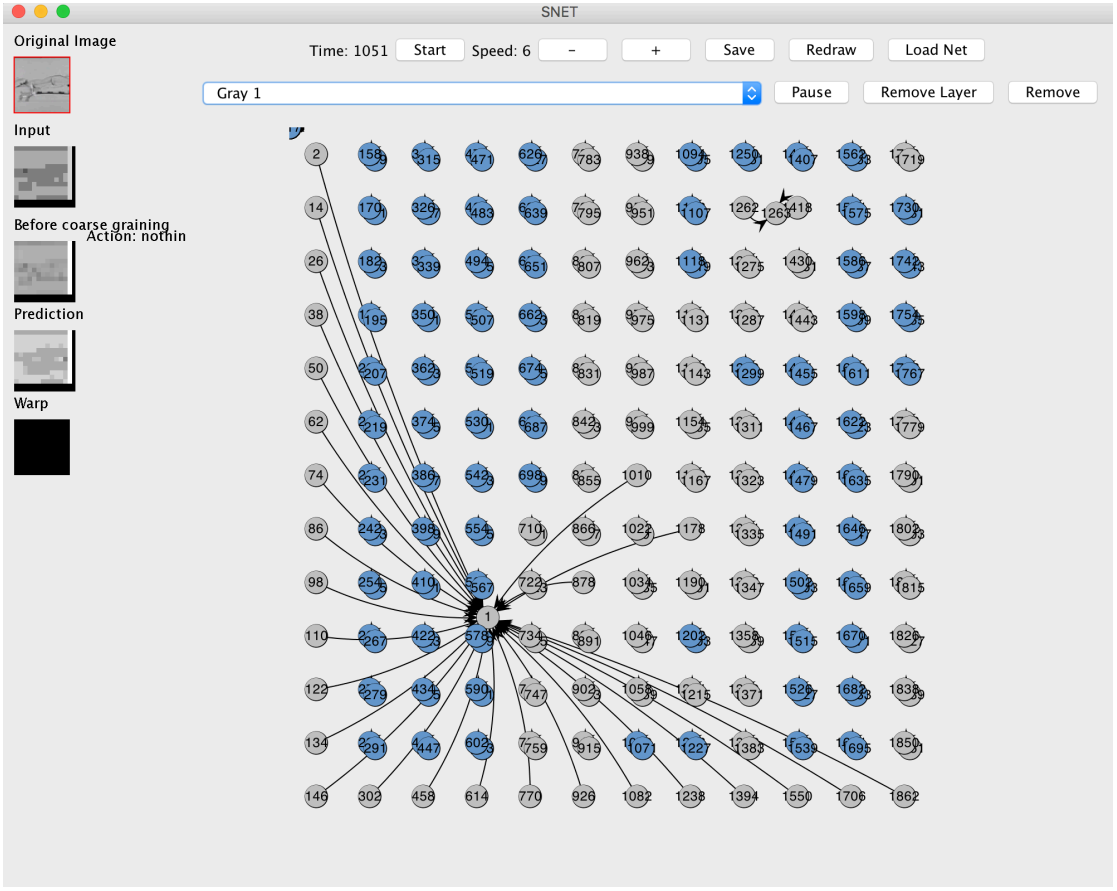


FIGURE 3.14: **User Interface of the program.** On the left from top to bottom it displays the source image, its coarse grained version, as well as the network prediction for the next image. On the right we can see the complete network or parts of it, in this case the neurons for the first gray scale value. On top we can control the speed, change the network display, save and load existing networks.

All of these parameters except from the last one also have to be decided by hand in classical deep learning networks, but many of the parameters necessary to do deep learning are not necessary to the ϵ-network: the type of layers, the number of layers, the size of the successive layers. Although in terms of performance we cannot yet catch up to deep learning methods, in terms of optimization this network requires less guesswork.

3.2.6.1 User Interface

We developed a UI for the experiments, allowing live control of the network and its display (Fig. 3.14 and Fig 3.15). The speed of the experiment can be controlled, as well as which group of greyscale-sensitive neuron is displayed. The prediction of the network is also displayed, as well as the modular division when it exists, and the current timestep.

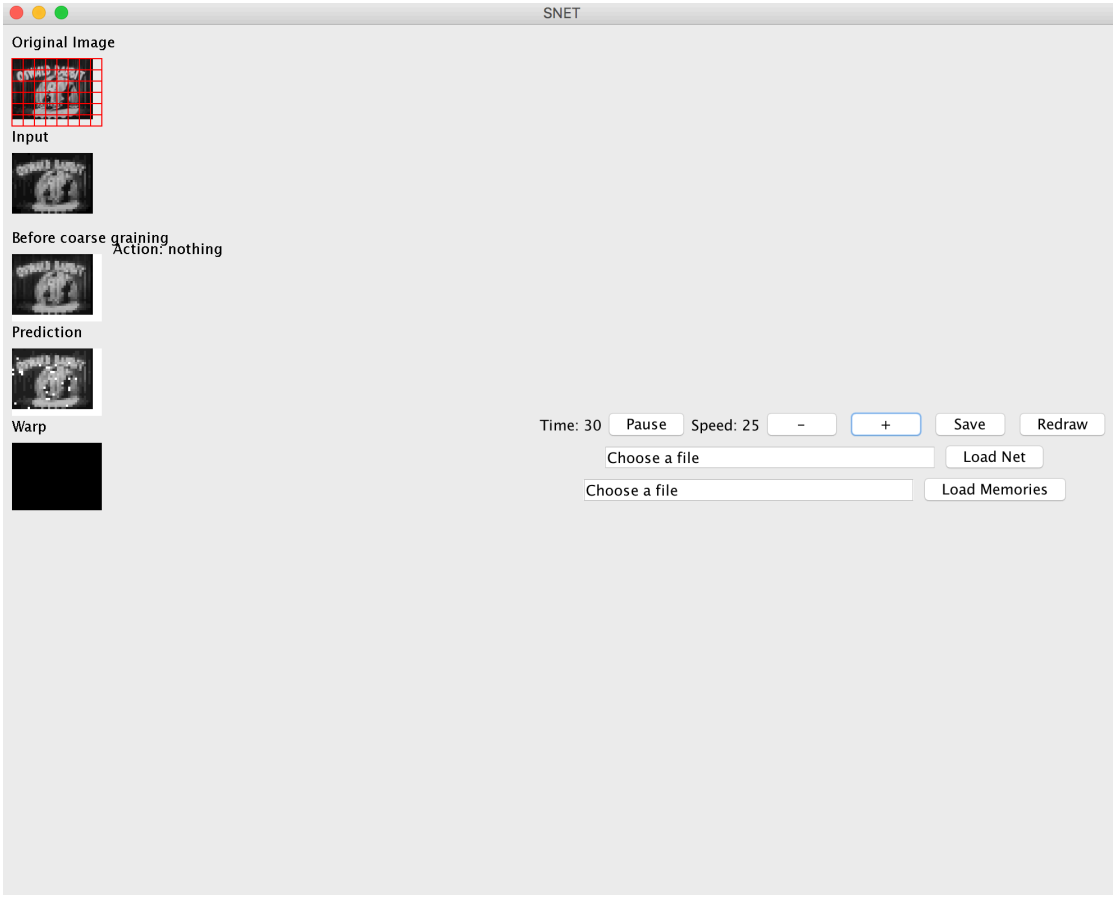


FIGURE 3.15: **User Interface of the program.** This experiment used a modular structure: image division is shown by red lines. The network structure is not displayed. In this experiment we used higher resolution images and by step 30 the prediction is excellent. White spots indicate the places where the network does not have a predicted value.

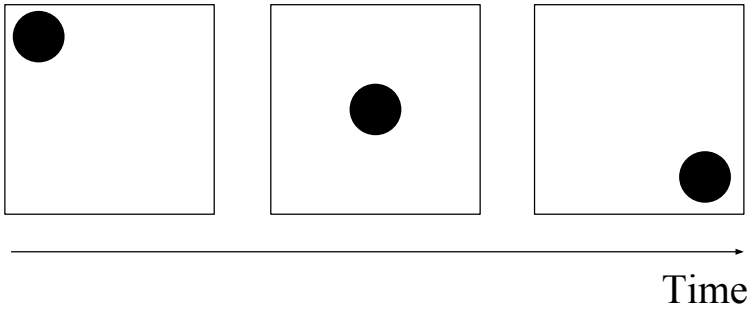


FIGURE 3.16: **Simple sequence of 3 images of a ball falling.**

3.3 Results

3.3.1 Minimal automaton

To show that the network does work as expected, we perform a simple modeling task where the data can be analyzed with the naked eye. The time series consists of 3 frames

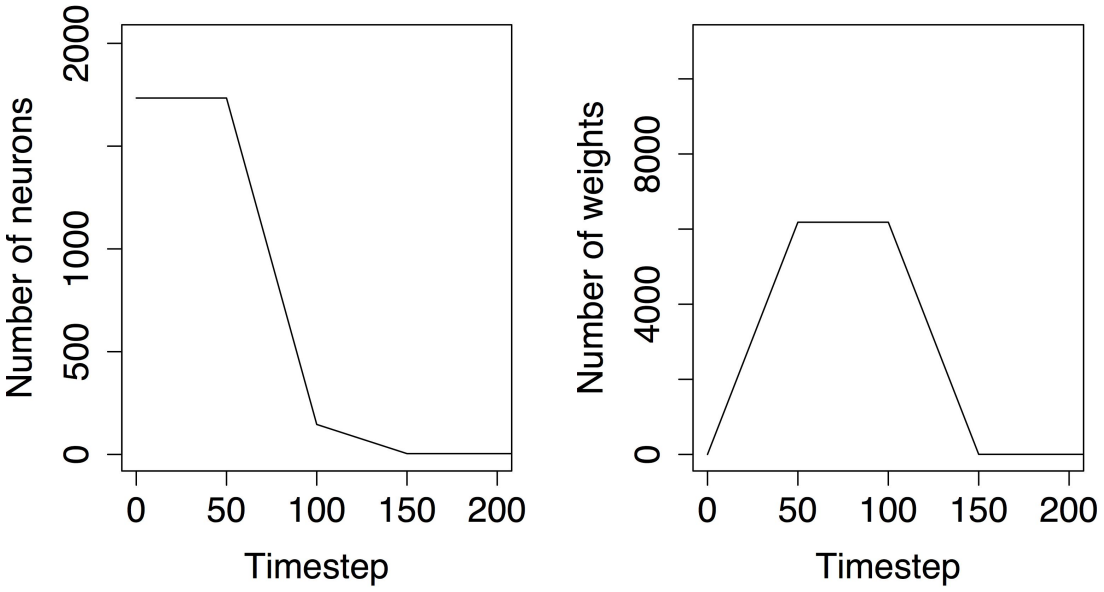


FIGURE 3.17: **Evolution of the number of neurons (left) and of probability weights (right)**. After a few snapping procedures, the number of neurons falls to 4 (one neuron for each position of the ball and a 4th neuron gathering all unused inputs like the grayscale values absent from the dataset); after the initial increase, the final number of PrW is 3.

(50x50 pixels) of a ball falling (Fig. 3.16). To keep things simple, the network has only one module and we do not use inhibitory weights. The network is trained by looping on these images.

The results are summarized Fig. 3.17. Videos are also available at `https://youtu.be/jvT_jmgehJ4` and `https://youtu.be/GE7AHtg3Lhw`. First, we can see that the number of neurons decreases until there are only 4 neurons left. The number of weights increases at first, then decreases proportionally with the number of neurons. At the end of the task, the network (Fig. 3.18 and more detailed explanation in 3.20) perfectly represents the automaton describing the time series: 1 neuron for each state of the automaton (equivalent to the position of the ball, see Fig. 3.19), with weight transitions of value 1 between the 3 states. The 4th neuron is the result of all unused neurons having been snapped together. In this dataset, for example there are no grey pixels: all neurons for those have no output weights and are detected as redundant. They are snapped into one single neuron. In this case each position of the ball is identified as a different object, but ideally we want the network to recognize it as the same object simply with different coordinates. As the network identifies similarity of inputs if they lead to the same predictions, this ball would be identified as a single entity if an identical prediction was attached to each position of the ball. For example, cross modal inputs (touch and vision) would be a solution to this issue, as a ball held in your hand gives the same input through touch independently of its position in your visual field. Identify

using prediction is one way to identify physical objects as well as abstract concepts.

FIGURE 3.18: **Evolution of the network's topology:** $t = 50$ **and** $t = 200$. The final topology perfectly represents the automaton of the time series, with each neurons corresponding to a state and each weight to a transition with probability 1. The 4th neuron, with no output weights, is omitted.

Next we try a time series that requires the creation of PaW. We use a similar setting as before, with a variation for half of the trials (Fig. 3.21): one time out of two, a cue appears at the 2nd image and the 3rd image shows the ball in the upper right corner of the image. The results are shown on Fig. 3.22. This time 5 neurons are left, and 11 weights. The 5 neurons are the 3 same as the previous experiment, plus 2 pattern neurons for the two ambiguous situations ($t = 2$ and $t = 4$).

These are simple cases; in the next experiments, we perform modelling of more complex videos.

3.3.2 Clean or noisy environments

For this experiment, we use videos from the KITTI dataset ([47], Fig. 3.23), which are videos taken from a moving car's perspective. Again, the network has only one module and no inhibitory weights. We resize the set 2011_09_26/*image*_00 (83 frames) to the size of 79x51 pixels. In the first experiment we use the images without further modifications; in the second experiment, we add random noise to the image at each timestep: 10% of the pixels are selected at random and to the greyscale value ($0 <= g <= 255$) we add noise from the uniform distribution on the interval $[-50, 50]$). Fig. 3.24 presents the results of both experiments: the final number of weights and neurons is smaller without noise, and bigger with noise. The higher number of weights for the noisy data should be mainly weights with low predictive power, as they are created to try to predict unpredictable noise. When counting only the strong weights with a value $p > 0.9$ (Fig 3.25), which we call effective weights, we indeed find that the network with noise

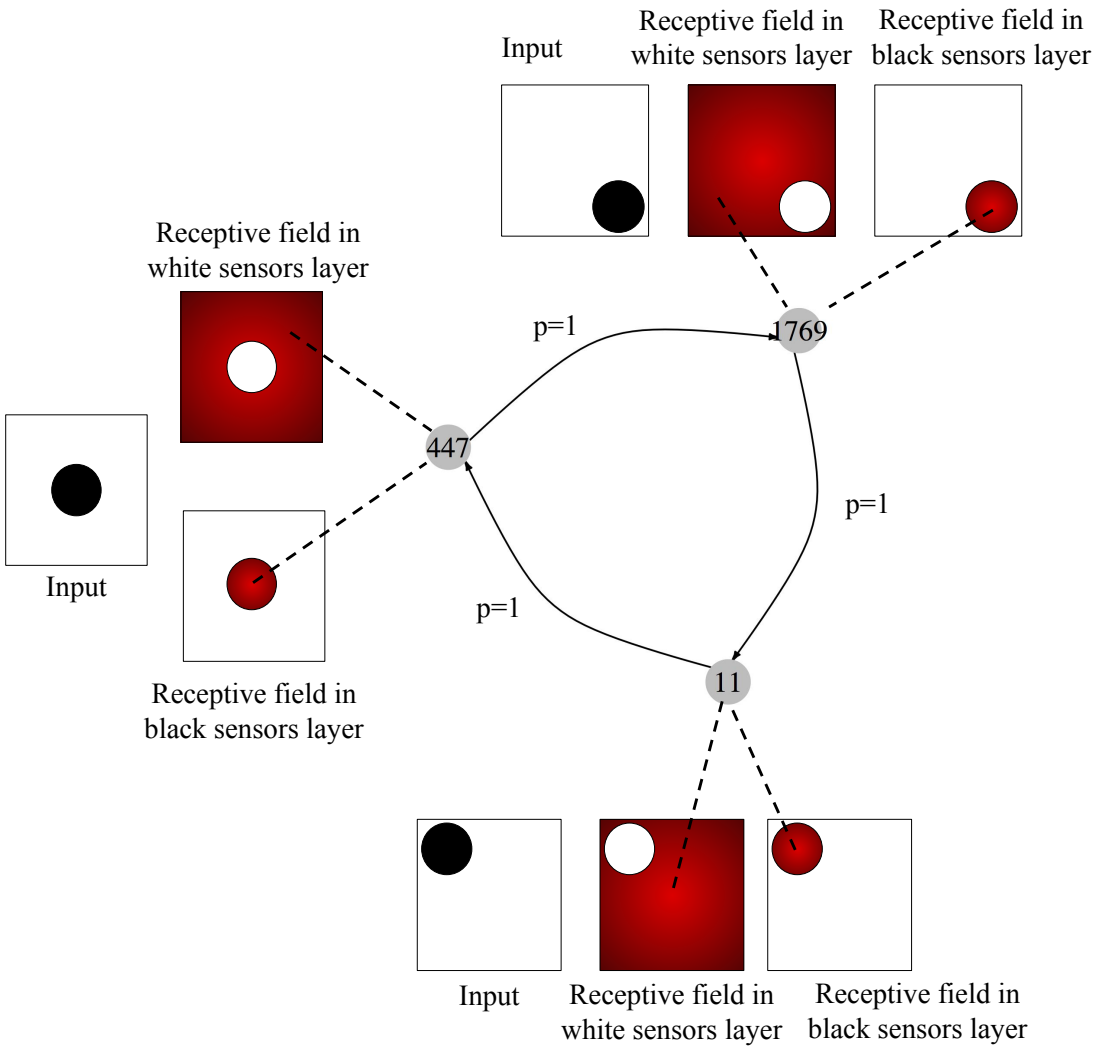


FIGURE 3.19: **Detail of the final receptive field of each neuron.** As the result of the snapping procedure, each neuron can now be activated by any of the sensors in large receptive fields, as activation of any of these sensors is sufficient to predict the next frame accurately. The receptive fields span the width and height of the image but also several greyscale values. From the neurons activation, we can still deduce which image the network is seeing.

and without noise have similar values. The network discriminates the noisy dataset from true complexity in the sense of Crutchfield, where noise is not complex as its statistical properties can be easily reproduced.

Finally, Fig. 3.26 shows the evolution of the surprise value for the first 100 timesteps. Both networks end up with the same performance, despite the noisy experiment requiring more neurons and weights. Initially the network is "naive" and the surprise is very big until the 5th frame. The value slowly decreases as the networks learn the data. At t=82 (black line), the video sequence starts a new loop which is a sudden and highly surprising event for the network. This peak of surprise comes at the end of each loop

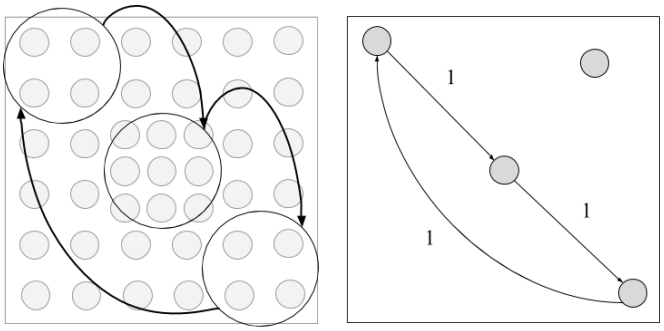


FIGURE 3.20: **Emergence of classes in the simple experiment.** The neurons in each group in (a) have similar output weights, therefore are snapped together, resulting in (b). The unused neurons (from the background and from greyscales never stimulated in this experiment) also have the same output weights and are snapped together into one neuron with no weights.

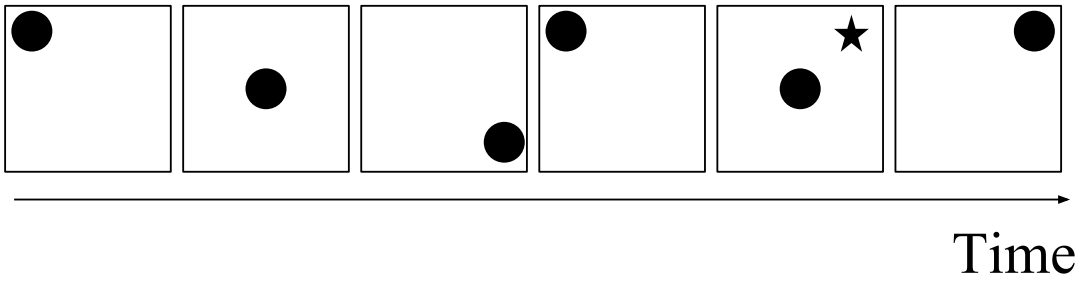


FIGURE 3.21: **Sequence with a cue**: we introduce a variation in the ball position on the 3rd and 6th frames.

during the whole experiment.

3.3.3 Complex data stream and simple data stream

For this experiment, we use sequences from the public domain 1932 cartoon "Oswald the Lucky Rabbit: Mechanical Man" ([48]). The network has only one module and no inhibitory weights. We sample the video at 5 frames/s and resize it to 50x50 pixels. We use two sequences of 40 frames. In the first experiment, we use a sequence where the background almost does not change, and in the foreground two characters do an almost periodic motion. In the second experiment, we use an action packed sequence where the background changes, the action in the foreground has no repetitive elements, and there is one change of scene in the middle of the sequence (Fig. 3.27). In these experiments, there is a higher concentration of sensors in the middle of the image (1 sensor for an area of 2x2 pixels) than in the periphery (1 sensor for 5x5 pixels) to reduce computational time. A video of the learned predictions and live updating can be found at https://youtu.be/E4p0H3Yfbos .

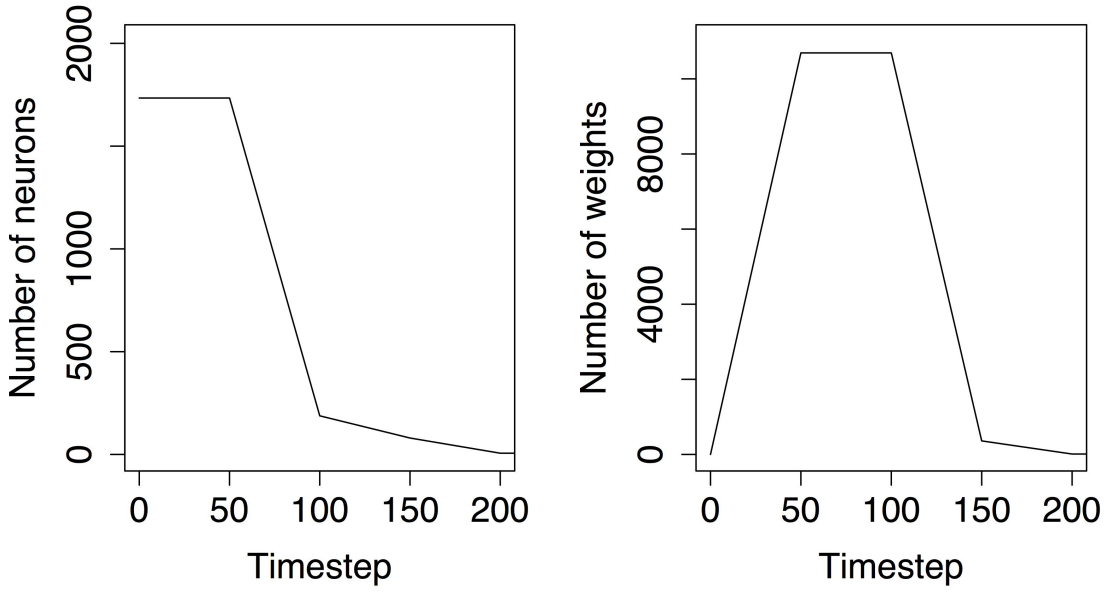


FIGURE 3.22: **Evolution of the number of neurons (left) and of probability weights (right) for the modified sequence**. The final number of neurons is 6; the number of probability weights rises more sharply than for the simple sequence, but then decreases from more than 9,000 to only 11 PrW.

FIGURE 3.23: Examples of frames from the KITTI dataset

The results are summarized in Fig. 3.28: although both networks start with the same number of neurons, for the simple sequence the final number of neurons is almost half that of the complex sequence. The number of connections is also much lower for the simple video, even only considering only effective weights ($p > 0.9$, Fig. 3.29). Another interesting result is that it takes less than a 1 complete loop (40 frames, black line) for the surprise to decrease in either network (Fig. 3.30, 3.31), which shows that the network is not simply memorizing the whole video sequence. Instead, early experience is generalized to later frames. In addition, the prediction performance (surprise) is the same for both tasks, which means that it has reached optimal value despite the differences in the two tasks. This optimal value is not 0, as prediction cannot be perfect if we use only very short term dependency (our network only has a 1 timestep memory). This performance stays stable even as the size of the networks decrease drastically.

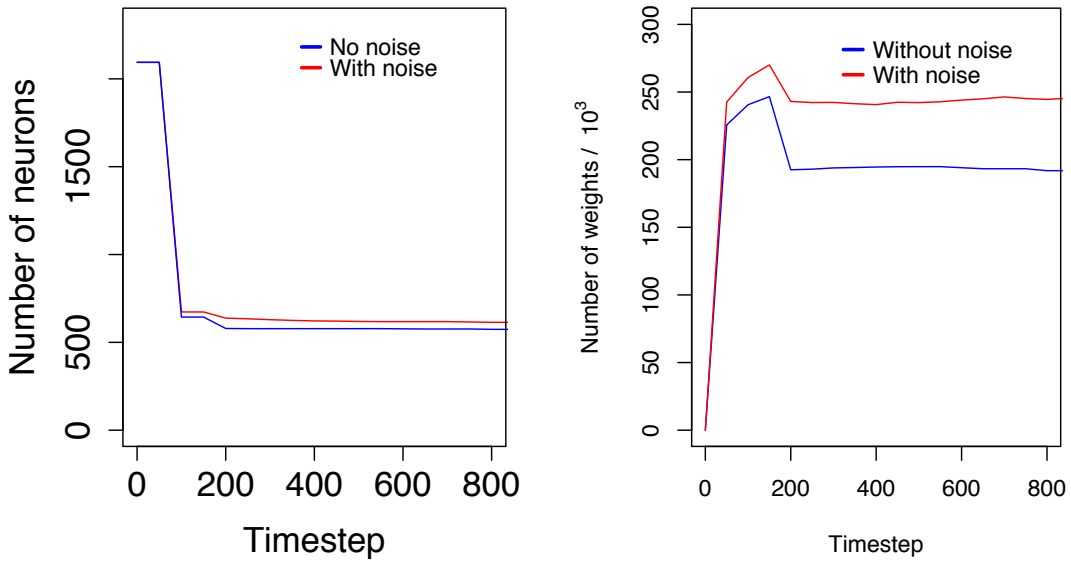


FIGURE 3.24: **Evolution of the number of neurons (left) and of prediction weights (right)** on a clean video (blue lines) and a noisy version of the same video (red lines). The final results capture nicely the complexity induced by trying to predict a noisy dataset.

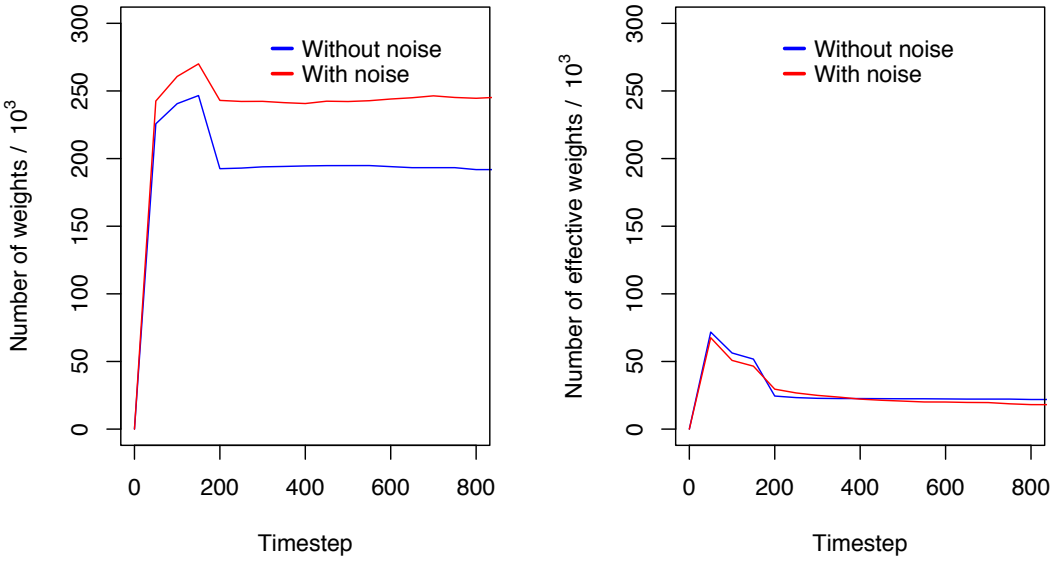


FIGURE 3.25: **Evolution of the total number of prediction weights (left) and of the number of effective prediction weights ($p > 0.9$, right)** on a clean video (blue lines) and a noisy version of the same video (red lines). There are more weights in the network for the noisy video, but these additional weights have low predictive power and the number of strong prediction weights is the same for the noisy and non noisy video.

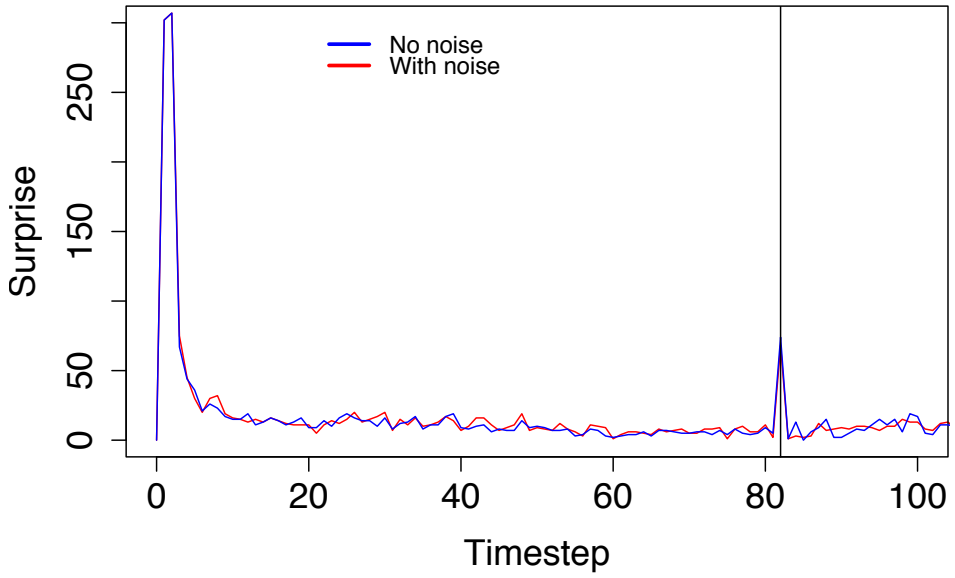


FIGURE 3.26: **Evolution of the surprise in the network with and without noise**. The value slowly decreases as the networks evolves. At $t = 82$ (black line), the video sequence starts a new loop which is a sudden and highly surprising event for the network.

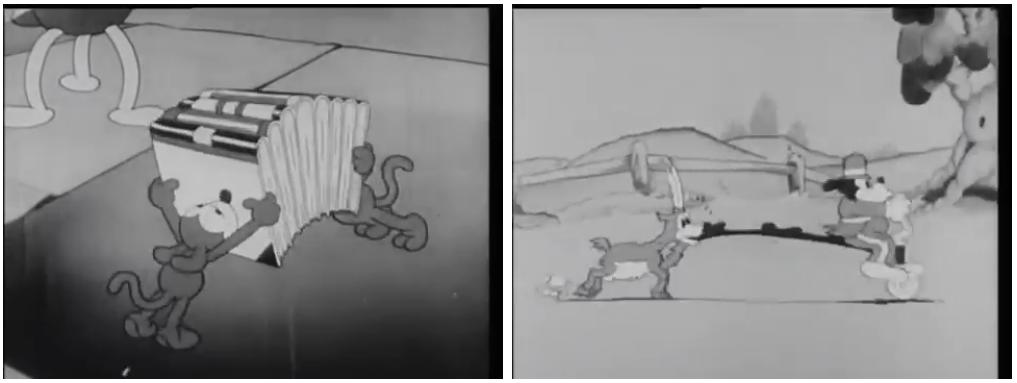


FIGURE 3.27: **Frames from a simple sequence (2 characters play the accordion in almost periodic motion, static background) and a complex sequence (a character rides a bicycle, the background changes)**

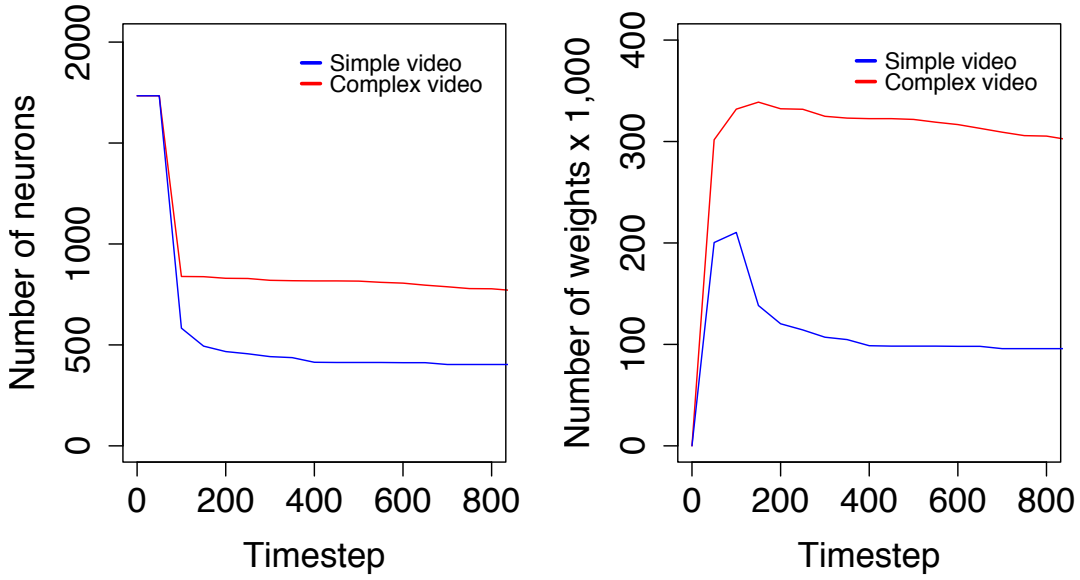


FIGURE 3.28: **Evolution of the number of neurons (left) and of weights (right) for the two experiments.** Although both videos have the same number of frames, the number of neurons and connections is much higher for the complex video sequence.

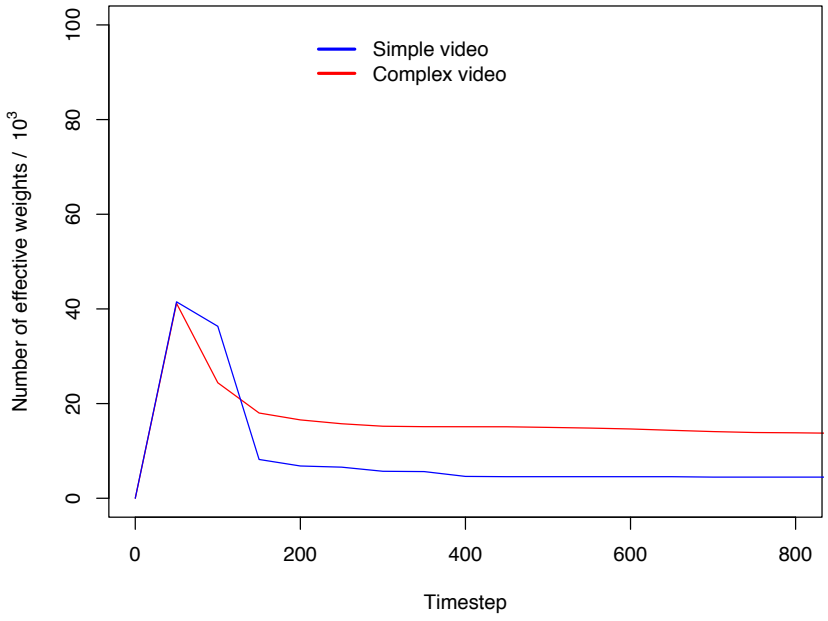


FIGURE 3.29: **Evolution of the number of effective weights ($p > 0.9$) for the simple and complex videos.** Unlike the results with or without noise, even when discounting the weak weights the complex video requires more weights than the simple one. This is true complexity in the sense of Crutchfield.

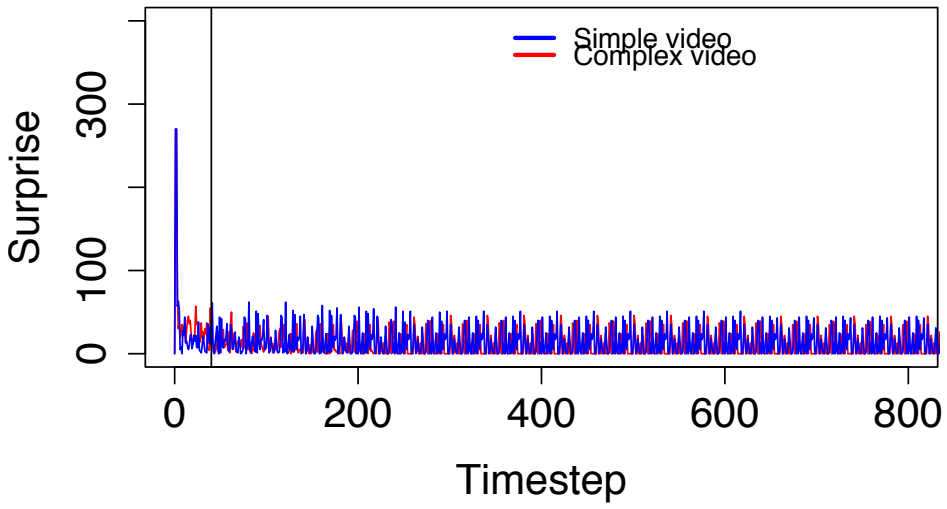


FIGURE 3.30: **Evolution of the surprise in the simple and complex task.** The surprise decreases sharply at the beginning of either task, then stays stable at the network optimizes its size.

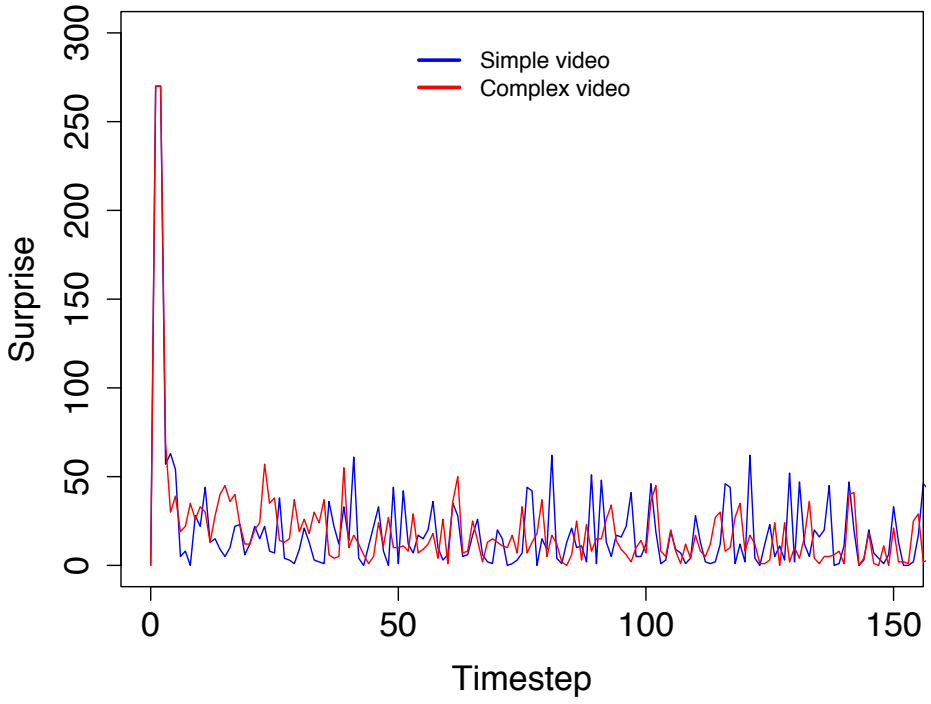


FIGURE 3.31: **Evolution of the surprise in the simple and complex task.** Zoom on the first 150 steps shows small differences between the two time series, especially at the first loop of the videos, the surprise is higher for the complex video.

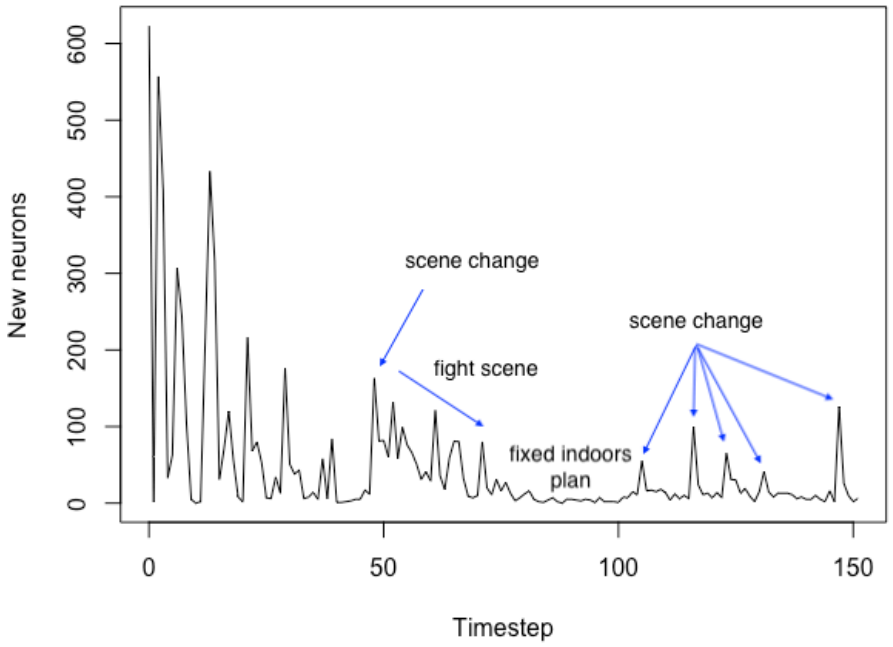


FIGURE 3.32: **Peak of new neurons indicating surprising events in the first 150 frames**. The first few timesteps the network has no knowledge, so everything is surprising. After this naive period, all peaks correspond to significant events.

3.3.4 Surprising events

Due to its update rules, the network should be able to detect unexpected events and react by creating new weights and new neurons. As a qualitative experiment, we let the network (same parameters as the previous section) run on the Oswald cartoon and examine the number of neurons, looking for peaks. As Fig. 3.32 and 3.32 show, each scene change provokes a peak, and all other notable peaks correspond to reasonably surprising events, like sudden apparition of monsters or a fight scene. This simple analysis shows that the network can be used to detect events of interest in a video.

3.3.5 Full model and long videos

We train the network on the entire Oswald video at a higher framerate (20 fps, 6644 frames), with bigger images (72*54 pixels) and higher resolution (1 neuron per 2*2 pixels). The network can create inhibitory weights. Every 50 timesteps, after the snapping procedure, new modules are created as follows: all neurons from layer 4 or above are collected from all existing modules and serve as sensory input to a single common module. A video of the first learning timesteps can be found at `https://youtu.be/yWNsiVHh_D8`.

We compare the results for different snapping intervals: in Fig 3.34, 3.35 snapping is performed every 50 steps, 100 steps, or never. The results show that not snapping gives

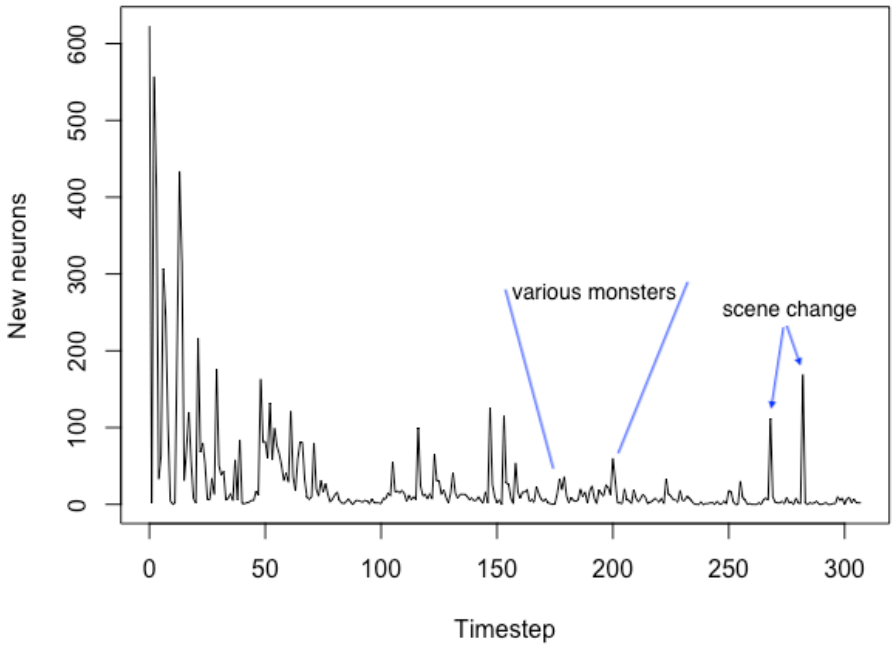


FIGURE 3.33: **Peak of new neurons indicating surprising events in the first 300 frames**. The biggest peaks can be seen for scene changes, which are very much unpredictable.

the best predictions, but requires a higher number of weights. This highlights one issue of this network: it is possible that 2 neurons have the exact same output prediction weights at early training time, but that these neurons would end up having different output prediction weights after more training. If the neurons are compared too early, they will be fused together and there is no possibility to un-fuse them. For example, here the video begins with black frames for several timesteps. When the network snaps, the neurons sensitive to white pixels have no output weights or only few output weights and they are all fused together: the network becomes forever unable to perceive or predict separately entire groups of white pixels. These bad predictions cause a higher number of surprised neurons; when trying to reduce this surprise the network paradoxically end up creating more neurons than a networks that does not perform the snapping procedure. A brute force solution would be to find the ideal snapping frequency for a given dataset; a more elegant solution would be to detect when a neuron is the result of a too-early fusion (for example, the neuron becomes unable to make any correct prediction) and divide it into as many neurons as needed when necessary.

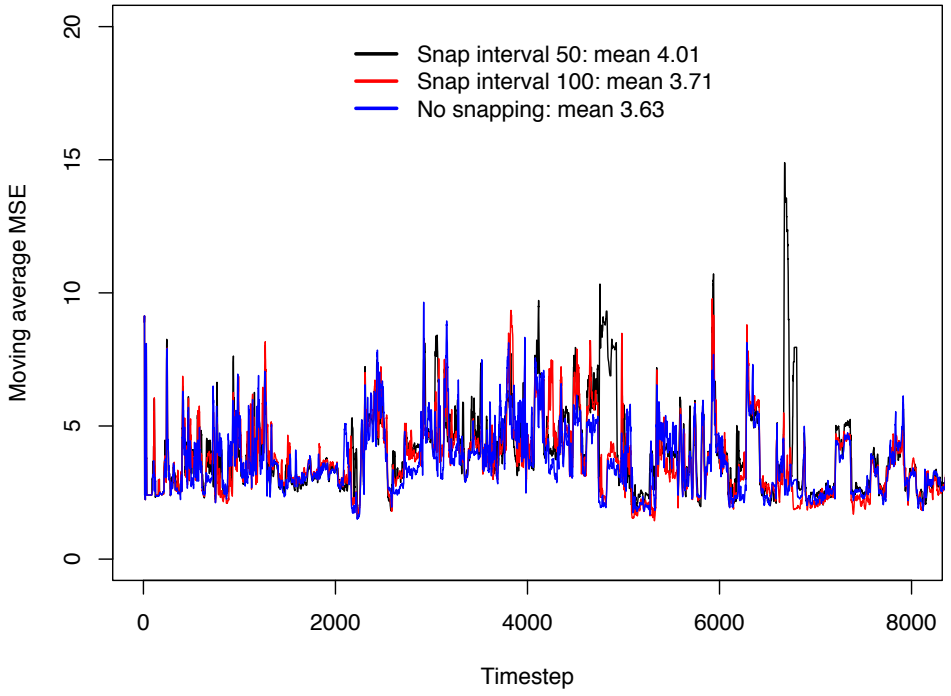


FIGURE 3.34: **Mean Squared Error of the predictions for snapping every 50 steps, 100 steps, or not snapping at all**. We can see that the error gets smaller if we snap the network less often. This means that when fusing neurons together, a small amount of information is lost that cannot be recovered.

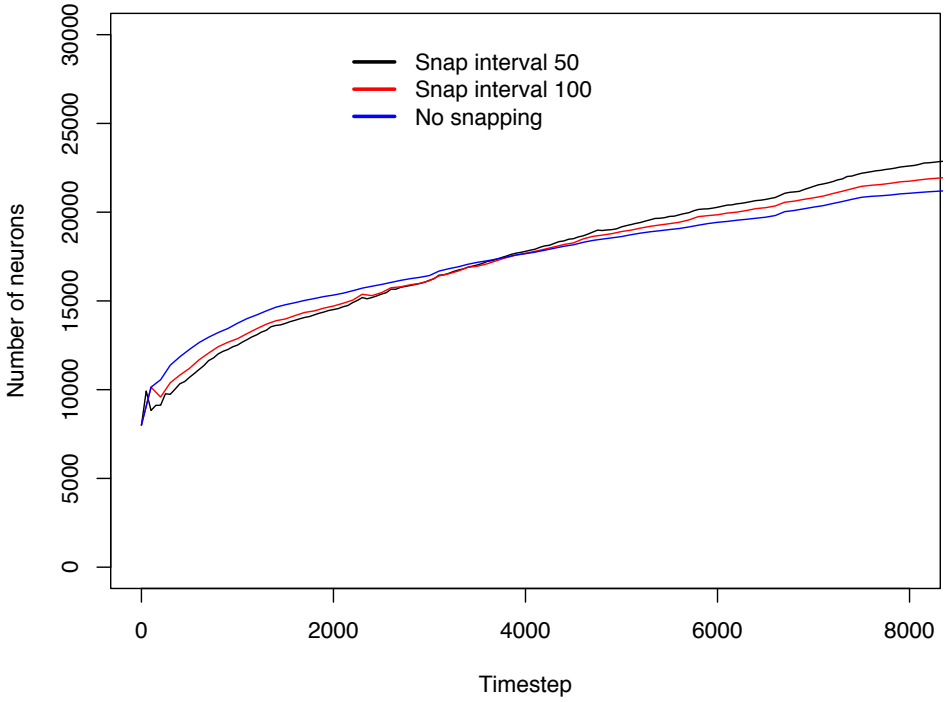


FIGURE 3.35: **Mean Number of neurons for snapping every 50 steps, 100 steps, or not snapping at all**. Snapping initially works as a method to reduce the number of neurons, but some information is lost by fusing neurons too early. Overtime this results in some bad predictions and number of neurons greater than without snapping.

TABLE 3.1: **Quantitative differences between the models**

Model	Neurons	MSE	Training time/set/epoch
PredNet	$5.4x10^{10}$	0.82	0.5 minute on 2 GPUS
ϵ-network	$2.6x10^{3}$	7.9	0.2 minute on 1 CPU

The ϵ-network has 10^7 times less neurons than PredNet but its final performance is 10 times worse. It is also 2 times faster even if it is trained on a much less powerful architecture. On the other hand, the ϵ-network does not require an extensive and time consuming parameter search as does PredNet, as the same architecture can be used for any dataset.

3.3.6 Comparison with the state of the art: PredNet

The ϵ-network has different ambitions from the current Deep Learning (DL) boom, but how does it compare? As our model is in its infancy, we cannot expect to obtain extreme performance in terms of prediction, especially since we are more preoccupied with complexity modeling and online learning than with prediction performance and repetition training. It is also not totally fair to compare the number of neurons used by a DL network with the number of neurons of the ϵ-network, as DL networks run on architectures specifically conceived to support large amounts of neurons. Several dozens of hours of training on GPU machines and hundred of repetitions per dataset are accepted as a trade off in exchange for extremely high performance.

Comparing parameters might be instructive if just to see how many orders of magnitude are between the two models. In this experiment, we compare the ϵ-network with a state of the art DL network, PredNet [41]. We train the ϵ-network on the first 4 video sets in the KITTI dataset and compare the results on 2 other sets with the results of Prednet. In terms of qualitative differences, it should be noted that in the paper PredNet was trained on the full 57 sets of KITTI, by batches of 10 frames of size 128x160 pixels, for at least 150 epochs or more on GPUs. The ϵ-network is not meant to be trained by rote repetition, but to perform online learning. We train it on 108 frames of per video set, for 2 epochs; then we evaluate it on test data. The MSE cannot be directly compared with PredNet because the image format and pre-processing are different, but we use the naive MSE (MSE of the current frame and the previous frame) of both models as a conversion factor and find the results in Table 3.1

Although the comparison is unfair due to differences in maturity of the models, goals, training protocol and amount of data, here is what we learn from this: the number of neurons used by the ϵ-network is 7 orders of magnitude lower than the number of

neurons of PredNet (even extrapolating to 150 epochs and 57 video sets with the worse possible growth conditions, our network should only reach $8x10^6$ neurons, likely less). The performance of PredNet is almost 2 orders of magnitudes greater than our model. This seems to hold true even in the first few epochs of PredNet training. Training time is the same order of magnitude, but PredNet is highly optimized and runs on a powerful architecture, while the ϵ-network runs on a laptop PC (12 hours for PredNet for 57 sets/50 epochs, 2 minutes for 4 sets/2 epochs for the ϵ-network). In addition, the parameters of PredNet (number of layers, number of channels, learning rate) have to be optimized using heuristics, which multiplies the actual training time by as many times as a new parameter has to be tested.

The conclusion of this experiment is that if someone was hesitating about which model to use for which applications, we could give the following advice: if the application depends on highly reliable predictions, the type of data is known in advance and there is no limit on available computing power or training time, PredNet is the right choice. If the application tolerates moderately noisy predictions, requires to learn new inputs on the fly in real time and with limited resources, the ϵ-network is the right choice.

3.4 Discussion

In this chapter, I presented the ϵ-network, a network that automatically adjusts its size to the complexity of a dataset while learning to predict its inputs. The network is inspired from Crutchfield's work on the Epsilon Machine [2] and both models aim to measure complexity by predicting time series. One major difference is that the ϵ-network performs online learning, when the Epsilon Machine requires to know the entire dataset in advance. This makes the ϵ-network more suitable for tasks where real time processing is required and the data cannot be obtained beforehand.

Another major difference is that the Epsilon Machine operates on univariate time series and only has one node active at any given time, while the ϵ-network operates on multivariate time series and can have several neurons activated at the same time. This makes the ϵ-network more fit for tasks like video prediction or tasks with several simultaneous sources of data.

The last main difference with the Epsilon Machine is that the ϵ-network can adapt to noise automatically, without requiring to perform a parameter search to find the structure adapted to a specific level of noise as the Epsilon Machine does. This means with my model, the same architecture can be used without any change to process a clean dataset or a dataset with an arbitrary level of noise. This is especially useful when we do not know the data in advance.

There are other ways to adjust the size of a network during training [36]. Genetic Algorithms are used to optimize the size of a neural network for a dataset, but unlike the ϵ-network, they are not well suited for online learning. Genetic Algorithms require to train several networks simultaneously for several generations in order to find the most appropriate for the dataset. In contrast, the ϵ-network optimizes its size on the fly, it is not necessary to train several networks simultaneously. It can adapt to the dataset in real time.

Among the models of networks with self-adjusting size, the Growing Neural Gas [49] and Growing When Required [50] networks are models where the number of nodes is adjusted to match a spatial topology. There are two main differences with the ϵ-network. First, these models focus matching spatial structured – the networks literally grows to match the shape of a 2D or 3D object. The ϵ-network does not address the issue of the physical position of the neurons, but the temporal relationships between changing inputs. Indeed, except for the sensory neurons that are distributed over the 2D image frame, the neurons in my model do not have spatial coordinates at all. Furthermore, the ϵ-network grows to match its output to a dynamical input that changed at every step, while the Growing Neural Gas and Growing When Required networks are primarily concerned with inputs that stay static for many steps. In a sense, all models try to fit statistical distributions, but the ϵ-network with its strong focus on prediction is more suited to dynamical time series.

The main paradigm in neural network research is currently Deep Learning, and I provided a comparison of the ϵ-network with a Deep Learning network, PredNet [41]. Both models perform predictive coding on video datasets, but in Deep Learning, the size and structure of the networks do no change dynamically, and usually informs us not about some property of the dataset but about how much computing power the research team had access to. Deep Learning networks are notoriously difficult to analyze and the meaning of high performing topologies is an open issue. On the other hand, the ϵ-network's main interest resides in the fact that its structure informs us about the nature of the data it was trained on. Not only how difficult the dataset is to predict, which represents its complexity, but how much of this complexity is due to random noise and how much of this complexity is intrinsic to the dataset.

In [37, 38, 39]), Friston presents Free Energy Minimization as a way to explain how prediction and inference can explain not only learning in the brain, but also an agent's actions. As in this chapter, the focus is on prediction. In Friston's work, agents learn and act to minimizing the value of surprise, which is related to the value of Free Energy. Similarly, in our work, surprise is also minimized by making the network learn. Our value of surprise, as Friston's, is not defined by the Shannon information where rare events are

surprising, but by the difference between prediction and input. This value of surprise is used to increase the number of neurons, while comparing predictions allows us to decrease the number of neurons. This last points is relatively important for computers, but even more important for living organisms. Although we do not suggest that such drastic changes in brain density happen in animals, this network has a similarity with famous cases of hydrocephaly (water in the brain) where humans retain complete abilities while only a thin outer layer of brain cells remains alive.

For simple datasets, I showed that the ϵ-network can actually find the minimal automaton representing this dataset, just as its inspiration the ϵ-machine[2] does. For more complex datasets, it is not obvious if the network will always find the minimal structure necessary to reproduce the data stream. Yet as shown in the clean vs noisy dataset experiment, the network has similar numbers of strong weights for datasets where the only difference is the level of random noise. This suggests that the ϵ-network does in fact capture the minimal structure representing a dataset. In addition, it adapts to noise automatically, while the epsilon machine of Crutchfield requires a parameter search to determine which structure is more adapted to the level of noise in the data. This is another advantage of our model.

I also show how the ϵ-network can be used to compare the complexity of two different datasets. The number of weights and neurons, even if we only consider the strongest values of weights, reflects the complexity of the datasets. As Crutchfield has said, periodic behaviors are predictable and therefore have lower complexity than aperiodic behaviors, and the the ϵ-network capture this difference.

Despite not competing in terms of performance, when compared to PredNet, our approach shows interesting ratios: our network uses 10^7 times fewer neurons than PredNet, but only performs 10 times worse and also trains faster. In addition, it can perform online learning, which PredNet cannot; and it does not require hand tuning hundreds of parameters (number of layers, number of neurons).

To improve the ϵ-network, we could increase the capacity of the short term memory. Although computationally costly at the beginning of tasks, this might lead to even smaller networks at the final stage of the learning task, as deeper temporal relationships are captured. For example, the modified falling ball task could theoretically be solved with only 3 neurons instead of 6 with a bigger short term memory. We could easily adapt pattern weights to detect temporal patterns. We are also in the process of implementing actions and proprioception in the network; early results suggest that this reduces the final size of the network for complex datasets, by allowing the network to recognize an object even if it appears at different positions of the visual field.

Chapter 4

General Discussion

This thesis has presented two types of neural networks focusing on implementing action, prediction and classification in complex environments. The models address complexity as defined by Crutchfield (data produced by a mix of noise and periodicity) but also complexity as defined by Weaver (data where several highly correlated part interact together). LSA faces noisy inputs as well as unreliability of the output's effects, but still manages to map the inputs to the correct outputs. The ϵ-network faces purely periodic data as well as data that is a mix of noise of periodicity, and data that is not purely periodic but results from highly correlated systems.

LSA allows a network to perform simple actions, mapping inputs and outputs in simple networks as we have seen in Section 2.3.2. LSA scales up to bigger networks of 100 neurons despite high noise, as Section 2.4 demonstrates. These results were extended to networks of 3000 neurons in [33]. It therefore offers a convincing explanation to the existing results of biological experiments of Shahaf, and our explanation is backed up by experimental results. I also demonstrated the necessity of burst suppression, which was not addressed by Shahaf, in Section 2.4.1. LSA is also robust to unreliability of the output's effects, as the embodied application in Section 2.6 shows. LSA is based on biological data, and Chapter 2 as a whole updates our understanding of low level questions about the biological implementation of prediction, explains so far unexplained biological results and offers a way to develop more applications for biological or simulated spiking networks. What LSA identifies as noise is entirely dependent on whether the network's actions can manipulate the value of its sensory inputs: internal noise cannot be manipulated and is ignored.

In Section 3.17 I showed how the ϵ-network can extract the minimal probabilistic automaton of a multivariate time series. The experiment demonstrated how the ϵ-network can replicate the functionality of the epsilon machine of Crutchfield, despite having a

different implementation. Because our implementation is so different and we perform online learning on multivariate time series, there could be a concern that the network does not do as well as an epsilon machine, but this experiment on a toy dataset demonstrates the validity of our model. The ϵ-network is able to adapt its topology to maintain performance despite random noise, and to separate signal from noise; it can also adapt to true complexity as shown in Section 3.3.2. It is based on more speculative, high-level hypotheses than LSA, but offers many advantages over the existing ϵ-Machines: optimized online learning instead of offline building of the machine, processing of multivariate streams instead of univariate streams, and automatic adaptation to noise instead of parameter search. As a whole, Chapter 3 proposes answers to high level questions about intelligence, such as how does classification emerges from prediction, the relationship between the the unconscious and memory, and the relationship between surprise and prediction:

- Objects belong to the same class if they allow similar predictions
- Higher level classes block the access of their subclasses to short term memory
- Surprise is used as a measure of error to improve prediction performance.

With LSA, learning consists in adapting the complexity of the agent's behavior to its empowerment, defined by Polani as "how much influence and control an agent has over the world it can perceive" [51]. In Polani's research, agents act as to always maximize empowerment, but empowerment is known in advance. However, with LSA, it is empowerment itself that is learned by the network. Everything that cannot be manipulated, including random external input, is irrelevant to the network's goal and considered as noise.

With the ϵ-network, learning consists in predicting of an input stream. The Epsilon Machine of Crutchfield has the same goal. However, unlike the Epsilon Machine, the ϵ-network does not require to know the data in advance. This makes the the ϵ-network especially suited to online learning.

In this way, my research can be linked to existing work about predictive coding, especially the work of Friston and al. on Free Energy Minimisation [37, 38, 39]. Friston also speculates about how learning can happen in agents in the real world and how prediction can guide action. Nevertheless, because of its extreme complexity, there have been few complete implementations of Friston's ideas. Especially, implementation is focused on agent that already have a perfect model of the world. My model focuses on learning and building this model of the world, so that the agent does not have to know anything at the start of the experiment.

Deep Learning networks can also be used for predictive coding and can have excellent performance. However, their structure is fixed and they cannot perform online learning either. The ϵ-network not only performs prediction of an input stream, but it adjust its internal structure to the complexity of the input data. This allows us to draw conclusions about the data just by looking at the structure of this network.

Although drastic volume changes in the mammal brain are not commonplace, the ϵ-network also offers cues into how can humans lose neurons during development while at the same time becoming more and more performant; why in some pathological cases someone can lose 90% of the volume of their brain and still behave appropriately in daily life [52]; and how some bird and mammal species can drastically reduce and grow back their number of neurons depending on the season while still being able to exhibit normal behavior [53, 54, 55].

The ϵ-network can also be viewed as an implementation of the Interface Theory of Perception [4]. In his paper, Hoffman says that an organism does not have to perceive the world as it is or as accurately as possible, but instead perceive the world as accurately as is necessary and not more accurately than necessary. The ϵ-network starts with as much accuracy as its sensors allow, but as it learns, inputs are classified according to the similarity of the prediction they offer. Once snapped together, inputs become indistinguishable. This is the definition of "perceiving the world as accurately as is necessary and not more" as Hoffman presented it.

The two networks that I presented change their topology to minimize different quantities: LSA seeks behaviors that can reduce external stimulation, while the ϵ-network reduces the amount of surprise caused by external inputs. It is possible to integrate both approaches in one single framework: if only unpredicted inputs cause stimulation, LSA becomes a low level implementation of the ϵ-network, but the notion of action is lost. We can go further and define stimulation as "unmanipulable inputs": can the agent have an effect on some of the input values, and if yes, can this effect be predicted? If the effect of the agent's actions on the input stream cannot be predicted, this unpredictability becomes stimulation. In this case, we get the best of both LSA and the ϵ-network: the agent is motivated to act when it cannot predict the results of its own actions, until its predictions become accurate. Such an agent would display a form of intrinsic motivation that depends not simply on an assigned task or on a reward signal, but on its own knowledge of the environment and understanding of its own abilities. "Can I predict what happens if I push this button? If not, I have to push it and learn what can happen." Such an agent would learn not only a model of its environment, but a model of its empowerment in that environment; and that model would have just the right amount of complexity to map the agent's abilities to the world it lives in.

A topic that will be of particular interest is the relationship between episodic memories and predictive coding. The consensus about episodic memory is that it is not"stored" somewhere like we would store a video tape (see [56]), but each memory is reconstructed each time that we want to access it. Memories are modified each time that they are reconstructed, according to what we think "probably happened" at that time. In other words, predictions play a role when we remember past episodes of our life. Since our predictions also change depending on what we learn from day to day, this could be the real source for erroneous and false memories. Indeed, early work with the ϵ-network suggests that when episodic memories are reconstructed by generating video frames from partial input enhanced by strong prediction weights, false memories can be implanted in the network using the same techniques of suggestion that are used on humans: creating associations between past objects and new stimuli, mentally rehearsing the false memory.

Prediction is also theorized to be the engine of the "System 1" identified by the behavioral economist Daniel Kahneman in his book [57]: System One directs human beings' automatic actions and reactions, intuitions, and every decision that relies on speed rather than accuracy. System 2 is in charge of deliberate decision making, decisions that take time and require precision. Switching from System 1 to System 2 during a decision process happens when the expectations of System 1 about the world are so wrong that inputs cannot be processed automatically anymore. In terms of ϵ-network, System 1 would be an automatic process treating strong prediction weights as if they were real inputs, running in quasi-closed loop without needing to use the Short Term Memory. System 1 would make processing faster by omitting the whole bottom-up classification and top-down trickle of predictions to lower modules. System 2 would be a process waiting for actual environmental inputs to reach the STM and classifying these inputs before making the next predictions, and using these predictions to take decisions. This aligns nicely with Kahneman's observation that the processes of System 1 do not stay in memory, and when taking decisions in this form of autopilot, humans cannot explain why they took these decisions. In the ϵ-network, the STM is only used to update weights, and is not necessary to generate predictions from existing weights. System 1 does not need to use the memory, and so its decision process remains unconscious and inexplicable by the conscious agent itself.

Beyond the speculative and explanatory aspects of my research, existing applications exist as future work. Both LSA-based networks and the ϵ-network put emphasis on low computational cost: in combination, they could improve the chances of developing applications that depend on prediction in everyday devices: object tracking, self localization... For higher level applications, the ϵ-network's ability to classify time series can be used for identifying entities in swarms and other highly dynamic systems. On the

contrary, its inability to predict the dynamics of a single entity could be used to detect agency: if an object's trajectory cannot be predicted only from its environment's history, maybe that trajectory is controlled from internal parameters akin to agency.

Many functions of the brain seem to happen independently of external rewards, and for now the model learns without reward signal. However, goal directed behavior is an important part of the life of biological organisms. We are in the process of implementing reinforcement learning for reward-based behaviors. Because the network makes predictions, it can also predict the activation of reward neurons, and therefore choose the actions that lead to higher activation of these reward neurons. The reward neurons activation can be decided by implementing simple policies, as in standard reinforcement learning frameworks. The ϵ-network can have many interesting applications, and I plan to work more on the integration of action and embodiment.

Acknowledgements

All my gratitude goes to the members and honorary members of the Ikegami Lab for the hours of discussion that ultimately lead to this thesis: Norihiro Maruyama, Atsushi Masumori, Martin Biehl, Olaf Witowski, Nathaniel Virgo, Hiroki Kojima, Itsuki Doi, Julien Hubert. I am thankful to Ikegami Takashi for his support during my research, and to Nicholas Guttenberg for joining our discussions despite the distance.

Special thanks to the dedicated readers who volunteered to comment on my thesis: Paul Harland, Rafaela Libano, Rodolfo Cruz-Silva, Eric Sinapayen, Marie-Noelle Sinapayen, Sean Aubin, Julien Hubert.

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