

Effects of Fast Presynaptic Noise in Attractor Neural Networks

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We study both analytically and numerically the effect of presynaptic noise on the transmission of information in attractor neural networks. The noise occurs on a very short timescale compared to that for the neuron dynamics and it produces short-time synaptic depression. This is inspired in recent neurobiological findings that show that synaptic strength may either increase or decrease on a short timescale depending on presynaptic activity. We thus describe a mechanism by which fast presynaptic noise enhances the neural network sensitivity to an external stimulus. The reason is that, in general, presynaptic noise induces nonequilibrium behavior and, consequently, the space of fixed points is qualitatively modified in such a way that the system can easily escape from the attractor. As a result, the model shows, in addition to pattern recognition, class identification and categorization, which may be relevant to the understanding of some of the brain complex tasks.

1 Introduction

There is multiple converging evidence (Abbott & Regehr, 2004) that synapses determine the complex processing of information in the brain. An aspect of this statement is illustrated by attractor neural networks. These show that synapses can efficiently store patterns that are retrieved later with only partial information on them. In addition to this time effect,

artificial neural networks should contain some synaptic noise. That is, actual synapses exhibit short-time fluctuations, which seem to compete with other mechanisms during the transmission of information—not to cause unreliability but ultimately to determine a variety of computations (Allen & Stevens, 1994; Zador, 1998). In spite of some recent efforts, a full understanding of how brain complex processes depend on such fast synaptic variations is lacking (see Abbott & Regehr, 2004, for instance). A specific matter under discussion concerns the influence of short-time noise on the fixed points and other details of the retrieval processes in attractor neural networks (Bibitchkov, Herrmann, & Geisel, 2002).

The observation that actual synapses endure short-time depression or facilitation is likely to be relevant in this context. That is, one may understand some observations by assuming that periods of elevated presynaptic activity may cause either a decrease or an increase in neurotransmitter release and, consequently, the postsynaptic response will be either depressed or facilitated depending on presynaptic neural activity (Tsodyks, Pawelzik, & Markram, 1998; Thomson, Bannister, Mercer, & Morris, 2002; Abbott & Regehr, 2004). Motivated by neurobiological findings, we report in this article on the effects of presynaptic depressing noise on the functionality of a neural circuit. We study in detail a network in which the neural activity evolves at random in time regulated by a “temperature” parameter. In addition, the values assigned to the synaptic intensities by a learning (e.g., Hebb’s) rule are constantly perturbed with microscopic fast noise. A new parameter is involved by this perturbation that allows a continuum transition from depression to normal operation.

As a main result, this letter illustrates that in general, the addition of fast synaptic noise induces a nonequilibrium condition. That is, our systems cannot asymptotically reach equilibrium but tend to nonequilibrium steady states whose features depend, even qualitatively, on dynamics (Marro & Dickman, 1999). This is interesting because in practice, thermodynamic equilibrium is rare in nature. Instead, the simplest conditions one observes are characterized by a steady flux of energy or information, for instance. This makes the model mathematically involved, for example, there is no general framework such as the powerful (equilibrium) Gibbs theory, which applies only to systems with a single Kelvin temperature and a unique Hamiltonian. However, our system still admits analytical treatment for some choices of its parameters, and in other cases, we discovered the more intricate model behavior by a series of computer simulations. We thus show that fast presynaptic depressing noise during external stimulation may induce the system to scape from the attractor: the stability of fixed-point solutions is dramatically modified. More specifically, we show that for certain versions of the system, the solution destabilizes in such a way that computational tasks such as class identification and categorization are favored. It is likely this is the first time such behavior is reported in an artificial neural network as a consequence of biologically motivated stochastic behavior of synapses.

Similar instabilities have been reported to occur in monkeys (Abeles et al., 1995) and other animals (Miller & Schreiner, 2000), and they are believed to be a main feature in odor encoding (Laurent et al., 2001), for instance.

2 Definition of Model

Our interest is in a neural network in which a local stochastic dynamics is constantly influenced by (pre)synaptic noise. Consider a set of N binary neurons with configurations $\mathbf{S} \equiv \{s_i = \pm 1; i = 1, \dots, N\}$.¹ Any two neurons are connected by synapses of intensity:²

$$w_{ij} = \bar{w}_{ij} x_j \quad \forall i, j. \quad (2.1)$$

Here, \bar{w}_{ij} is fixed, namely, determined in a previous learning process, and x_j is a stochastic variable. This generalizes the hypothesis in previous studies of attractor neural networks with noisy synapses (see, e.g., Sompolinsky, 1986; Garrido & Marro, 1991; Marro, Torres, & Garrido, 1999). Once $\mathbf{W} \equiv \{\bar{w}_{ij}\}$ is given, the state of the system at time t is defined by setting \mathbf{S} and $\mathbf{X} \equiv \{x_i\}$. These evolve with time—after the learning process that fixes \mathbf{W} —via the familiar master equation:

$$\begin{aligned} \frac{\partial P_t(\mathbf{S}, \mathbf{X})}{\partial t} = & -P_t(\mathbf{S}, \mathbf{X}) \int_{\mathbf{X}'} \sum_{\mathbf{S}'} c[(\mathbf{S}, \mathbf{X}) \rightarrow (\mathbf{S}', \mathbf{X}')] \\ & + \int_{\mathbf{X}'} \sum_{\mathbf{S}'} c[(\mathbf{S}', \mathbf{X}') \rightarrow (\mathbf{S}, \mathbf{X})] P_t(\mathbf{S}', \mathbf{X}'). \end{aligned} \quad (2.2)$$

We further assume that the transition rate or probability per unit time of evolving from (\mathbf{S}, \mathbf{X}) to $(\mathbf{S}', \mathbf{X}')$ is

$$c[(\mathbf{S}, \mathbf{X}) \rightarrow (\mathbf{S}', \mathbf{X}')] = p c^{\mathbf{X}}[\mathbf{S} \rightarrow \mathbf{S}'] \delta(\mathbf{X} - \mathbf{X}') + (1 - p) c^{\mathbf{S}}[\mathbf{X} \rightarrow \mathbf{X}'] \delta_{\mathbf{S}, \mathbf{S}'}. \quad (2.3)$$

This choice (Garrido & Marro, 1994; Torres, Garrido, & Marro, 1997) amounts to considering competing mechanisms. That is, neurons (\mathbf{S}) evolve stochastically in time under a noisy dynamics of synapses (\mathbf{X}), the latter

¹ Note that such binary neurons, although a crude simplification of nature, are known to capture the essentials of cooperative phenomena, which is the focus here. See, for instance, Abbott and Kepler (1990) and Pantic, Torres, Kappen, and Gielen (2002).

² For simplicity, we are neglecting here postsynaptic dependence of the stochastic perturbation. There is some claim that plasticity might operate on rapid timescales on postsynaptic activity (see Pitler & Alger, 1992). However, including x_{ij} in equation 2.1 instead of x_j would impede some of the algebra in sections 3 and 4.

evolving $(1 - p)/p$ times faster than the former. Depending on the value of p , three main classes may be defined (Marro & Dickman, 1999):

1. For $p \in (0, 1)$, both the synaptic fluctuation and the neuron activity occur on the same temporal scale. This case has already been preliminarily explored (Pantic et al., 2002; Cortes, Garrido, Marro, & Torres, 2004).
2. The limiting case $p \rightarrow 1$. This corresponds to neurons evolving in the presence of a quenched synaptic configuration, that is, x_i is constant and independent of i . The Hopfield model (Amari, 1972; Hopfield, 1982) belongs to this class in the simple case that $x_i = 1, \forall i$.
3. The limiting case $p \rightarrow 0$. The rest of this article is devoted to this class of systems.

Our interest for the latter case is a consequence of the following facts. First, there is adiabatic elimination of fast variables for $p \rightarrow 0$, which decouples the two dynamics (Garrido & Marro, 1994; Gardiner, 2004). Therefore, an exact analytical treatment—though not the complete solution—is then feasible. To be more specific, for $p \rightarrow 0$, the neurons evolve as in the presence of a steady distribution for \mathbf{X} . If we write $P(\mathbf{S}, \mathbf{X}) = P(\mathbf{X}|\mathbf{S})P(\mathbf{S})$, where $P(\mathbf{X}|\mathbf{S})$ stands for the conditional probability of \mathbf{X} given \mathbf{S} , one obtains from equations 2.2 and 2.3, after rescaling time $tp \rightarrow t$ (technical details are worked out in Marro & Dickman, 1999, for instance) that

$$\frac{\partial P_t(\mathbf{S})}{\partial t} = -P_t(\mathbf{S}) \sum_{\mathbf{S}'} \bar{c}[\mathbf{S} \rightarrow \mathbf{S}'] + \sum_{\mathbf{S}'} \bar{c}[\mathbf{S}' \rightarrow \mathbf{S}] P_t(\mathbf{S}'). \quad (2.4)$$

Here,

$$\bar{c}[\mathbf{S} \rightarrow \mathbf{S}'] \equiv \int d\mathbf{X} P^{\text{st}}(\mathbf{X}|\mathbf{S}) c^{\mathbf{X}}[\mathbf{S} \rightarrow \mathbf{S}'], \quad (2.5)$$

and $P^{\text{st}}(\mathbf{X}|\mathbf{S})$ is the stationary solution that satisfies

$$P^{\text{st}}(\mathbf{X}|\mathbf{S}) = \frac{\int d\mathbf{X}' c^{\mathbf{S}}[\mathbf{X}' \rightarrow \mathbf{X}] P^{\text{st}}(\mathbf{X}'|\mathbf{S})}{\int d\mathbf{X}' c^{\mathbf{S}}[\mathbf{X} \rightarrow \mathbf{X}']}. \quad (2.6)$$

This formalism allows modeling fast synaptic noise, which, within the appropriate context, will induce a sort of synaptic depression, as explained in detail in section 4.

The superposition, equation 2.5, reflects the fact that activity is the result of competition among different elementary mechanisms. That is, different underlying dynamics, each associated with a different realization of the stochasticity \mathbf{X} , compete and, in the limit $p \rightarrow 0$, an effective rate results

from combining $c^X[\mathbf{S} \rightarrow \mathbf{S}']$ with probability $P^{\text{st}}(\mathbf{X}|\mathbf{S})$ for varying \mathbf{X} . Each of the elementary dynamics tends to drive the system to a well-defined equilibrium state. The competition will, however, impede equilibrium, and in general, the system will asymptotically go toward a nonequilibrium steady state (Marro & Dickman, 1999). The question is whether such a competition between synaptic noise and neural activity, which induces nonequilibrium, is at the origin of some of the computational strategies in neurobiological systems. Our study seems to indicate that this is a sensible issue. In matter of fact, we shall argue below that $p \rightarrow 0$ may be realistic a priori for appropriate choices of $P^{\text{st}}(\mathbf{X}|\mathbf{S})$.

For simplicity, we shall be concerned in this article with sequential updating by means of single neuron, or "spin-flip," dynamics. That is, the elementary dynamic step will simply consist of local inversions $s_i \rightarrow -s_i$ induced by a bath at temperature T . The elementary rate $c^X[\mathbf{S} \rightarrow \mathbf{S}']$ then reduces to a single site rate that one may write as $\Psi[u^X(\mathbf{S}, i)]$. Here, $u^X(\mathbf{S}, i) \equiv 2T^{-1}s_i h_i^X(\mathbf{S})$, where $h_i^X(\mathbf{S}) = \sum_{j \neq i} \bar{w}_{ij} x_j s_j$ is the net (pre)synaptic current arriving at (or local field acting on) the (postsynaptic) neuron i . The function $\Psi(u)$ is arbitrary except that for simplicity, we shall assume $\Psi(u) = \exp(-u)\Psi(-u)$, $\Psi(0) = 1$ and $\Psi(\infty) = 0$ (Marro & Dickman, 1999). We report on the consequences of more complex dynamics in Cortes, et al. (2005).

3 Effective Local Fields

Let us define a function $H^{\text{eff}}(\mathbf{S})$ through the condition of detailed balance, namely,

$$\frac{\bar{c}[\mathbf{S} \rightarrow \mathbf{S}^i]}{\bar{c}[\mathbf{S}^i \rightarrow \mathbf{S}]} = \exp \left\{ - \left[H^{\text{eff}}(\mathbf{S}^i) - H^{\text{eff}}(\mathbf{S}) \right] T^{-1} \right\}. \quad (3.1)$$

Here, \mathbf{S}^i stands for \mathbf{S} after flipping at i , $s_i \rightarrow -s_i$. We further define the effective local fields $h_i^{\text{eff}}(\mathbf{S})$ by means of

$$H^{\text{eff}}(\mathbf{S}) = -\frac{1}{2} \sum_i h_i^{\text{eff}}(\mathbf{S}) s_i. \quad (3.2)$$

Nothing guarantees that $H^{\text{eff}}(\mathbf{S})$ and $h_i^{\text{eff}}(\mathbf{S})$ have a simple expression and are therefore analytically useful. This is because the superposition 2.5, unlike its elements $\Psi(u^X)$, does not satisfy detailed balance in general. In other words, our system has an essential nonequilibrium character that prevents one from using Gibbs's statistical mechanics, which requires a unique Hamiltonian. Instead, here there is one energy associated with each realization of $\mathbf{X} = \{x_i\}$. This is in addition to the fact that the synaptic weights w_{ij} in equation 2.1 may not be symmetric.

For some choices of both the rate Ψ and the noise distribution $P^{\text{st}}(\mathbf{X}|\mathbf{S})$, the function $H^{\text{eff}}(\mathbf{S})$ may be considered a true effective Hamiltonian (Garrido & Marro, 1989; Marro & Dickman, 1999). This means that $H^{\text{eff}}(\mathbf{S})$ then generates the same nonequilibrium steady state as the stochastic time evolution equation, which defines the system (see equation 2.4), and that its coefficients have the proper symmetry of interactions. To be more explicit, assume that $P^{\text{st}}(\mathbf{X}|\mathbf{S})$ factorizes according to

$$\mathbf{P}^{\text{st}}(\mathbf{X}|\mathbf{S}) = \prod_j P(x_j|s_j) \quad (3.3)$$

and that one also has the factorization

$$\bar{c}[\mathbf{S} \rightarrow \mathbf{S}^i] = \prod_{j \neq i} \int dx_j P(x_j|s_j) \Psi(2T^{-1}s_i \bar{w}_{ij} x_j s_j). \quad (3.4)$$

The former amounts to neglecting some global dependence of the factors on $\mathbf{S} = \{s_i\}$ (see below), and the latter restricts the possible choices for the rate function. Some familiar choices for this function that satisfy detailed balance are the one corresponding to the Metropolis algorithm, that is, $\Psi(u) = \min[1, \exp(-u)]$; the Glauber case $\Psi(u) = [1 + \exp(u)]^{-1}$; and $\Psi(u) = \exp(-u/2)$ (Marro & Dickman, 1999). The last fulfills $\Psi(u+v) = \Psi(u)\Psi(v)$, which is required by equation 3.4.³ It then ensues after some algebra that

$$h_i^{\text{eff}} = -T \sum_{j \neq i} \left[\alpha_{ij}^+ s_j + \alpha_{ij}^- \right], \quad (3.5)$$

with

$$\alpha_{ij}^{\pm} \equiv \frac{1}{4} \ln \frac{\bar{c}(\beta_{ij}; +) \bar{c}(\pm \beta_{ij}; -)}{\bar{c}(-\beta_{ij}; \mp) \bar{c}(\mp \beta_{ij}; \pm)}, \quad (3.6)$$

where $\beta_{ij} \equiv 2T^{-1} \bar{w}_{ij}$, and

$$\bar{c}(\beta_{ij}; s_j) = \int dx_j P(x_j|s_j) \Psi(\beta_{ij} x_j). \quad (3.7)$$

³ In any case, the rate needs to be properly normalized. In computer simulations, it is customary to divide $\Psi(u)$ by its maximum value. Therefore, the normalization happens to depend on temperature and the number of stored patterns. It follows that this normalization is irrelevant for the properties of the steady state; it just rescales the timescale.

This generalizes a case in the literature for random \mathbf{S} -independent fluctuations (Garrido & Munoz, 1993; Lacomba & Marro, 1994; Marro & Dickman, 1999). In this case, one has $\bar{c}(\pm\kappa; +) = \bar{c}(\pm\kappa; -)$ and, consequently, $\alpha_{ij}^- = 0 \forall i, j$. However, we are concerned here with the case of \mathbf{S} -dependent disorder, which results in a nonzero threshold, $\theta_i \equiv \sum_{j \neq i} \alpha_{ij}^- \neq 0$.

In order to obtain a true effective Hamiltonian, the coefficients α_{ij}^\pm in equation 3.5 need to be symmetric. Once $\Psi(u)$ is fixed, this depends on the choice for $P(x_j|s_j)$, that is, on the fast noise details. This is studied in the next section. Meanwhile, we remark that the effective local fields h_i^{eff} defined above are very useful in practice. That is, they may be computed, at least numerically, for any rate and noise distribution. As far as $\Psi(u + v) = \Psi(u)\Psi(v)$ and $\mathbf{P}^{\text{st}}(\mathbf{X}|\mathbf{S})$ factorizes,⁴ it follows an effective transition rate as

$$\bar{c}[\mathbf{S} \rightarrow \mathbf{S}^i] = \exp(-s_i h_i^{\text{eff}}/T). \quad (3.8)$$

This effective rate may then be used in computer simulation, and it may also serve to be substituted in the relevant equations. Consider, for instance, the overlaps defined as the product of the current state with one of the stored patterns:

$$m^v(\mathbf{S}) \equiv \frac{1}{N} \sum_i s_i \xi_i^v. \quad (3.9)$$

Here, $\xi^v = \{\xi_i^v = \pm 1, i = 1, \dots, N\}$ are M random patterns previously stored in the system, $v = 1, \dots, M$. After using standard techniques (Hertz, Krogh, & Palmer, 1991; Marro & Dickman, 1999; see also Amit, Gutfreund, & Sompolinsky, 1987), it follows from equation 2.4 that

$$\partial_t m^v = 2N^{-1} \sum_i \xi_i^v \sinh(h_i^{\text{eff}}/T) - s_i \cosh(h_i^{\text{eff}}/T), \quad (3.10)$$

which is to be averaged over both thermal noise and pattern realizations. Alternatively, one might perhaps obtain dynamic equations of type 3.10 by using Fokker-Planck-like formalisms as, for instance, in Brunel and Hakim (1999).

4 Types of Synaptic Noise

The above discussion and, in particular, equations 3.5 and 3.6, suggest that the system emergent properties will importantly depend on the details

⁴ The factorization here does not need to be in products $P(x_j|s_j)$ as in equation 3.3. The same result (see equation 3.8) holds for the choice that we introduce in the next section, for instance.

of the synaptic noise \mathbf{X} . We now work out the equations in section 3 for different hypotheses concerning the stationary distribution, equation 2.6.

Consider first equation 3.3 with the following specific choice:

$$P(x_j|s_j) = \frac{1 + s_j F_j}{2} \delta(x_j + \Phi) + \frac{1 - s_j F_j}{2} \delta(x_j - 1). \quad (4.1)$$

This corresponds to a simplification of the stochastic variable x_j . That is, for $F_j = 1 \forall j$, the noise modifies \bar{w}_{ij} by a factor $-\Phi$ when the presynaptic neuron is firing, $s_j = 1$, while the learned synaptic intensity remains unchanged when the neuron is silent. In general, $w_{ij} = -\bar{w}_{ij}\Phi$ with probability $\frac{1}{2}(1 + s_j F_j)$. Here, F_j stands for some information concerning the presynaptic site j such as, for instance, a local threshold or $F_j = M^{-1} \sum_v \xi_j^v$.

Our interest for case 4.1 is twofold: it corresponds to an exceptionally simple situation and reduces our model to two known cases. This becomes evident by looking at the resulting local fields:

$$h_i^{\text{eff}} = \frac{1}{2} \sum_{j \neq i} [(1 - \Phi)s_j - (1 + \Phi)F_j] \bar{w}_{ij}. \quad (4.2)$$

That is, exceptionally, symmetries here are such that the system is described by a true effective Hamiltonian. Furthermore, this corresponds to the Hopfield model, except for a rescaling of temperature and the emergence of a threshold $\theta_i \equiv \sum_j \bar{w}_{ij} F_j$ (Hertz et al., 1991). It also follows that, concerning stationary properties, the resulting effective Hamiltonian, equation 3.2, reproduces the model as in Bibitchkov et al. (2002). In fact, this would correspond in our notation to $h_i^{\text{eff}} = \frac{1}{2} \sum_{j \neq i} \bar{w}_{ij} s_j x_j^\infty$, where x_j^∞ stands for the stationary solution of certain dynamic equation for x_j . The conclusion is that (except perhaps concerning dynamics, which is something worth investigating) the fast noise according to equation 3.3 with equation 4.1 does not imply any surprising behavior. In any case, this choice of noise illustrates the utility of the effective field concept as defined above.

Our interest here is in modeling the noise consistent with the observation of short-time synaptic depression (Tsodyks et al., 1998; Pantic et al., 2002). In fact, equation 4.1 in some way mimics that increasing the mean firing rate results in decreasing the synaptic weight. With the same motivation, a more intriguing behavior ensues by assuming, instead of equation 3.3, the factorization

$$P^{\text{st}}(\mathbf{X}|\mathbf{S}) = \prod_j P(x_j|\mathbf{S}) \quad (4.3)$$

with

$$P(x_j|\mathbf{S}) = \zeta(\vec{\mathbf{m}}) \delta(x_j + \Phi) + [1 - \zeta(\vec{\mathbf{m}})] \delta(x_j - 1). \quad (4.4)$$

Here, $\vec{\mathbf{m}} = \vec{\mathbf{m}}(\mathbf{S}) \equiv (m^1(\mathbf{S}), \dots, m^M(\mathbf{S}))$ is the M -dimensional overlap vector, and $\zeta(\vec{\mathbf{m}})$ stands for a function of $\vec{\mathbf{m}}$ to be determined. The depression effect here depends on the overlap vector, which measures the net current arriving to postsynaptic neurons. The nonlocal choice, equations 4.3 and 4.4, thus introduces nontrivial correlations between synaptic noise and neural activity, which is not considered in equation 4.1. Note that therefore we are not modeling here the synaptic depression dynamics in an explicit way as, for instance, in Tsodyks et al. (1998). Instead, equation 4.4 amounts to considering fast synaptic noise, which naturally depresses the strength of the synapses after repeated activity, namely, for a high value of $\zeta(\vec{\mathbf{m}})$.

Several further comments on the significance of equations 4.3 and 4.4, which is here a main hypothesis together with $p \rightarrow 0$, are in order. We first mention that the system time relaxation is typically orders of magnitude larger than the timescale for the various synaptic fluctuations reported to account for the observed high variability in the postsynaptic response of central neurons (Zador, 1998). On the other hand, these fluctuations seem to have different sources, such as, for instance, the stochasticity of the opening and closing of the vesicles (S. Hilfiker, private communication, April 2005), the stochasticity of the postsynaptic receptor, which has its own causes, variations of the glutamate concentration in the synaptic cleft, and differences in the potency released from different locations on the active zone of the synapses (Franks, Stevens, & Sejnowski, 2003). This is the complex situation that we try to capture by introducing the stochastic variable x in equation 2.1 and subsequent equations. It may be further noticed that the nature of this variable, which is microscopic here, differs from the one in the case of familiar phenomenological models. These often involve a mesoscopic variable, such as the mean fraction of neurotransmitter, which results in a deterministic situation, as in Tsodyks et al. (1998). The depression in our model rather naturally follows from the coupling between the synaptic noise and the neurons' dynamics via the overlap functions. The final result is also deterministic for $p \rightarrow 0$ but only, as one should perhaps expect, on the timescale for the neurons. Finally, concerning also the reality of the model, it should be clear that we are restricting ourselves here to fully connected networks for simplicity. However, we have studied similar systems with more realistic topologies such as scale-free, small-world, and diluted networks (Torres, Munoz, Marro, & Garrido, 2004), which suggests one can generalize the present study in this sense.

Our case (see equations 4.3 and 4.4) also reduces to the Hopfield model but only in the limit $\Phi \rightarrow -1$ for any $\zeta(\vec{\mathbf{m}})$. Otherwise, the competition results in rather complex behavior. In particular, the noise distribution

$P^{\text{st}}(\mathbf{X}|\mathbf{S})$ lacks with equation 4.4 the factorization property, which is required to have an effective Hamiltonian with proper symmetry. Nevertheless, we may still write

$$\frac{\bar{c}[\mathbf{S} \rightarrow \mathbf{S}^i]}{\bar{c}[\mathbf{S}^i \rightarrow \mathbf{S}]} = \prod_{j \neq i} \frac{\int dx_j P(x_j|\mathbf{S}) \Psi(s_i x_j s_j \beta_{ij})}{\int dx_j P(x_j|\mathbf{S}^i) \Psi(-s_i x_j s_j \beta_{ij})}. \quad (4.5)$$

Then, using equation 4.4, we linearize around $\bar{w}_{ij} = 0$, that is, $\beta_{ij} = 0$ for $T > 0$. This is a good approximation for the Hebbian learning rule (Hebb, 1949), $\bar{w}_{ij} = N^{-1} \sum_v \xi_i^v \xi_j^v$, which is the one we use hereafter, as far as this rule stores only completely uncorrelated, random patterns. In fact, fluctuations in this case are of order \sqrt{M}/N for finite M —of order $1/\sqrt{N}$ for finite α —which tends to vanish for a sufficiently large system, for example, in the macroscopic (thermodynamic) limit $N \rightarrow \infty$. It then follows the effective weights,

$$w_{ij}^{\text{eff}} = \left\{ 1 - \frac{1 + \Phi}{2} [\zeta(\vec{\mathbf{m}}) + \zeta(\vec{\mathbf{m}}^i)] \right\} \bar{w}_{ij}, \quad (4.6)$$

where $\vec{\mathbf{m}} = \vec{\mathbf{m}}(\mathbf{S})$, $\vec{\mathbf{m}}^i \equiv \vec{\mathbf{m}}(\mathbf{S}^i) = \vec{\mathbf{m}} - 2s_i \vec{\xi}_i/N$, and $\vec{\xi}_i = (\xi_i^1, \xi_i^2, \dots, \xi_i^M)$ is the binary M -dimensional stored pattern. This shows how the noise modifies synaptic intensities. The associated effective local fields are

$$h_i^{\text{eff}} = \sum_{j \neq i} w_{ij}^{\text{eff}} s_j. \quad (4.7)$$

The condition to obtain a true effective Hamiltonian, that is, proper symmetry of equation 4.6 from this, is that $\vec{\mathbf{m}}^i = \vec{\mathbf{m}} - 2s_i \vec{\xi}_i/N \simeq \vec{\mathbf{m}}$. This is a good approximation in the thermodynamic limit, $N \rightarrow \infty$.

Otherwise, one may proceed with the dynamic equation 3.10 after substituting equation 4.7, even though this is not then a true effective Hamiltonian. One may follow the same procedure for the Hopfield case with asymmetric synapses (Hertz et al., 1991), for instance. Further interest in the concept of local effective fields as defined in section 3 follows from the fact that one may use quantities such as equation 4.7 to importantly simplify a computer simulation, as we do below.

To proceed further, we need to determine the probability ζ in equation 4.4. In order to model activity-dependent mechanisms acting on the synapses, ζ should be an increasing function of the net presynaptic current

or field. In fact, $\zeta(\vec{m})$ simply needs to depend on the overlaps, besides preserving the ± 1 symmetry. A simple choice with these requirements is

$$\zeta(\vec{m}) = \frac{1}{1 + \alpha} \sum_v [m^v(\mathbf{S})]^2, \quad (4.8)$$

where $\alpha = M/N$. We describe next the behavior that ensues from equations 4.6 to 4.8 as implied by the noise distribution, equation 4.4.

5 Noise-Induced Phase Transitions

Let us first study the retrieval process in a system with a single stored pattern, $M = 1$, when the neurons are acted on by the local fields, equation 4.7. One obtains from equations 3.8 to 3.10, after using the simplifying (mean field) assumption $\langle s_i \rangle \approx s_i$, that the steady solution corresponds to the overlap,

$$m = \tanh\{T^{-1}m[1 - (m)^2(1 + \Phi)]\}, \quad (5.1)$$

$m \equiv m^{v=1}$, which preserves the symmetry ± 1 . Local stability of the solutions of this equation requires that

$$|m| > m_c(T) = \frac{1}{\sqrt{3}} \left(\frac{T_c - T}{\Phi - \Phi_c} \right)^{\frac{1}{2}}. \quad (5.2)$$

The behavior of equation 5.1 is illustrated in Figure 1 for several values of Φ . This indicates a transition from a ferromagnetic-like phase (i.e., solutions $m \neq 0$ with associative memory) to a paramagnetic-like phase, $m = 0$. The transition is continuous or second order only for $\Phi > \Phi_c = -4/3$, and it then follows a critical temperature $T_c = 1$. Figure 2 shows the tricritical point at (T_c, Φ_c) and the general dependence of the transition temperature with Φ .

A discontinuous phase transition allows much better performance of the retrieval process than a continuous one. This is because the behavior is sharp just below the transition temperature in the former case. Consequently, the above indicates that our model performs better for large negative Φ , $\Phi < -4/3$.

We also performed Monte Carlo simulations. These concern a network of $N = 1600$ neurons acted on by the local fields, equation 4.7, and evolving by sequential updating via the effective rate, equation 3.8. Except for some finite-size effects, Figure 1 shows good agreement between our simulations and the equations here; in fact, the computer simulations also correspond to a mean field description given that the fields 4.7 assume fully connected neurons.

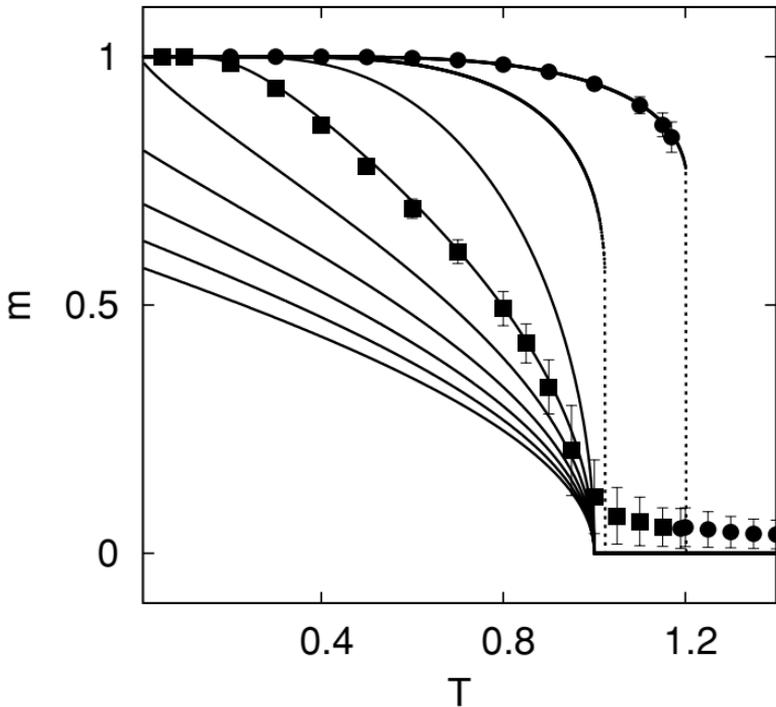


Figure 1: The steady overlap $m(T)$, as predicted by equation 5.1, for different values of the noise parameter, namely, $\Phi = -2.0, -1.5, -1.0, -0.5, 0, 0.5, 1.0, 1.5, 2.0$, from top to bottom, respectively. ($\Phi = -1$ corresponds to the Hopfield case, as explained in the text.) The graphs depict second-order phase transitions (solid curves) and, for the most negative values of Φ , first-order phase transitions (the discontinuities in these cases are indicated by dashed lines). The symbols stand for Monte Carlo data corresponding to a network with $N = 1600$ neurons for $\Phi = -0.5$ (filled squares) and -2.0 (filled circles).

6 Sensitivity to the Stimulus

As shown above, a noise distribution such as equation 4.4 may model activity-dependent processes reminiscent of short-time synaptic depression. In this section, we study the consequences of this type of fast noise on the retrieval dynamics under external stimulation. More specifically, our aim is to check the resulting sensitivity of the network to external inputs. A high degree of sensibility will facilitate the response to changing stimuli. This is an important feature of neurobiological systems, which continuously adapt and quickly respond to varying stimuli from the environment.

Consider first the case of one stored pattern, $M = 1$. A simple external input may be simulated by adding to each local field a driving term $-\delta\xi_i$, $\forall i$, with $0 < \delta \ll 1$ (Bibitchkov et al., 2002). A negative drive in this case of

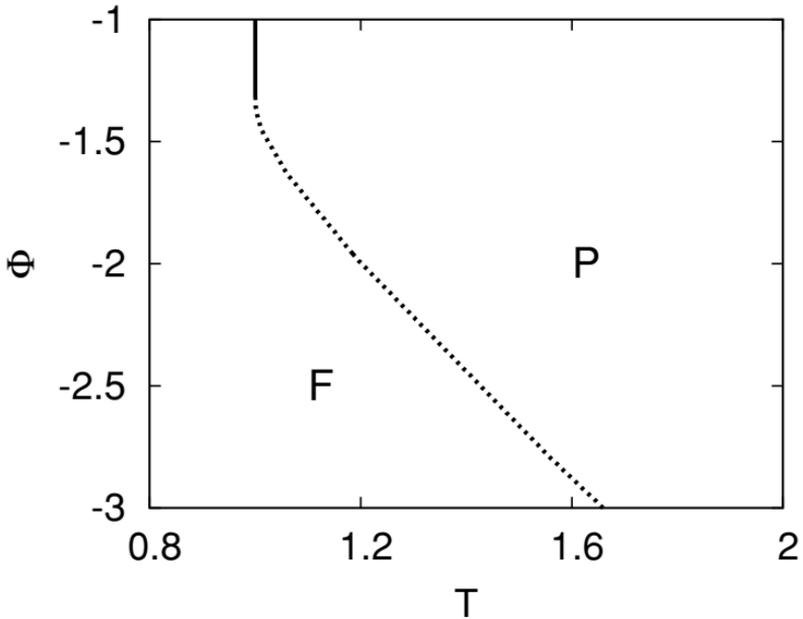


Figure 2: Phase diagram depicting the transition temperature T_c as a function of T and Φ . The solid (dashed) curve corresponds to a second- (first-) order phase transition. The tricritical point is at $(T_c, \Phi_c) = (1, -4/3)$. F and P stand for the ferromagnetic-like and paramagnetic-like phases, respectively. The best retrieval properties of our model system occur close to the lower-left quarter of the graph.

a single pattern ensures that the network activity may go from the attractor, ξ , to the “antipattern,” $-\xi$. It then follows the stationary overlap,

$$m = \tanh[T^{-1}F(m, \Phi, \delta)], \quad (6.1)$$

with

$$F(m, \Phi, \delta) \equiv m[1 - (m)^2(1 + \Phi) - \delta]. \quad (6.2)$$

Figure 3 shows this function for $\delta = 0$ and varying Φ . This illustrates two types of behavior: (local) stability ($F > 0$) and instability ($F < 0$) of the attractor, which corresponds to $m = 1$. That is, the noise induces instability, resulting in this case in switching between the pattern and the antipattern. This is confirmed in Figure 4 by Monte Carlo simulations.

The simulations correspond to a network of $N = 3600$ neurons with one stored pattern, $M = 1$. This evolves from different initial states, corresponding to different distances to the attractor, under an external stimulus $-\delta\xi^1$

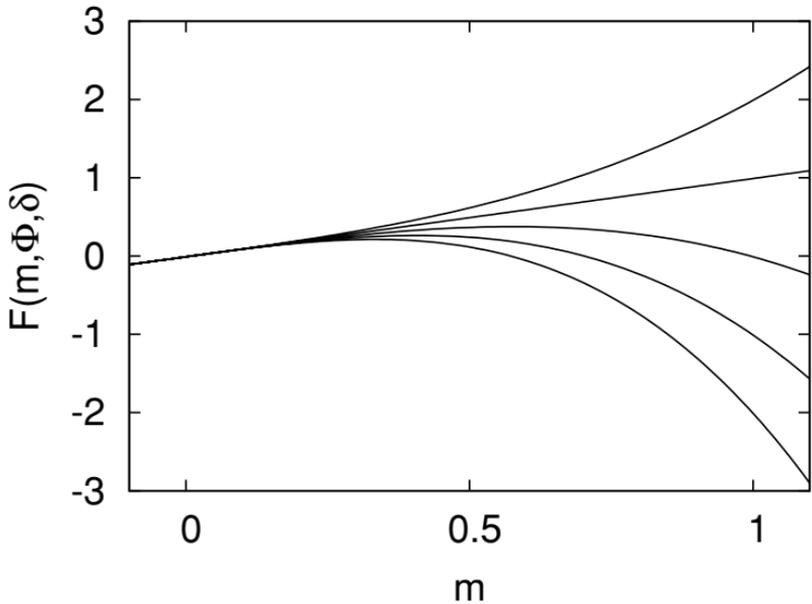


Figure 3: The function F as defined in equation 6.2 for $\delta = 0$ and, from top to bottom, $\Phi = -2, -1, 0, 1,$ and 2 . The solution of equation 6.1 becomes unstable so that the activity will escape the attractor ($m = 1$) for $F < 0$, which occurs for $\Phi > 0$ in this case.

for different values of δ . The two left graphs in Figure 4 show several independent time evolutions for the model with fast noise, namely, for $\Phi = 1$; the two graphs to the right are for the Hopfield case lacking the noise ($\Phi = -1$). These, and similar graphs one may obtain for other parameter values, clearly demonstrate how the network sensitivity to a simple external stimulus is qualitatively enhanced by adding presynaptic noise to the system.

Figures 5 and 6 illustrate similar behavior in Monte Carlo simulations with several stored patterns. Figure 5 is for $M = 3$ correlated patterns with mutual overlaps $|m^{v,\mu}| \equiv |1/N \sum_i \xi_i^v \xi_i^\mu| = 1/3$ and $|\langle \xi_i^v \rangle| = 1/3$. More specifically, each pattern consists of three equal initially white (silent neurons) horizontal stripes, with one of them colored black (firing neurons) located in a different position for each pattern. The system in this case begins with the first pattern as initial condition, and, to avoid dependence on this choice, it is let to relax for 3×10^4 Monte Carlo steps (MCS). It is then perturbed by a drive $-\delta \xi^v$, where the stimulus v changes ($v = 1, 2, 3, 1, \dots$) every 6×10^3 MCS. The top graph shows the network response in the Hopfield case. There is no visible structure of this signal in the absence of fast noise as far as $\delta \ll 1$. In fact, the depth of the basins of attraction is large enough in the Hopfield model to prevent any move for small δ , except

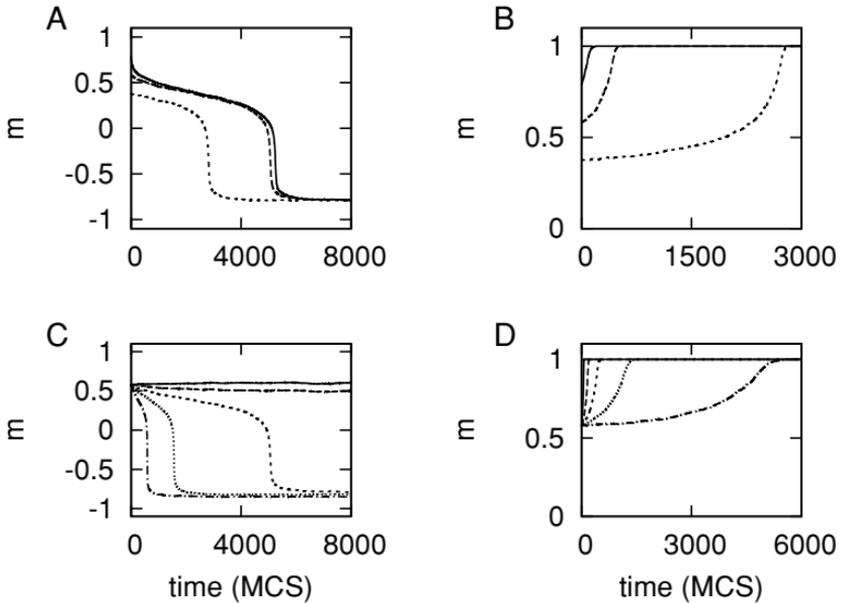


Figure 4: Time evolution of the overlap, as defined in equation 3.9, between the current state and the stored pattern in Monte Carlo simulations with 3600 neurons at $T = 0.1$. Each graph, for a given set of values for (δ, Φ) , shows different curves corresponding to evolutions starting with different initial states. The two top graphs are for $\delta = 0.3$ and $\Phi = 1$ (graphs A and C) and $\Phi = -1$ (graphs B and D), the latter corresponding to the Hopfield case lacking the fast noise. This shows the important effect noise has on the network sensitivity to external stimuli. The two bottom graphs illustrate the same for a fixed initial distance from the attractor as one varies the external stimulation, namely, for $\delta = 0.1, 0.2, 0.3, 0.4$, and 0.5 from top to bottom.

when approaching a critical point ($T_c = 1$), where fluctuations diverge. The bottom graph depicts a qualitatively different situation for $\Phi = 1$. That is, adding fast noise in general destabilizes the fixed point for the interesting case of small δ far from criticality.

Figure 6 confirms the above for uncorrelated patterns, for example, $m^{v,\mu} \approx \delta^{v,\mu}$ and $\langle \xi_i^v \rangle \approx 0$. This shows the response of the network in a similar simulation with 400 neurons at $T = 0.1$ for $M = 3$ random, orthogonal patterns. The initial condition is again $v = 1$, and the stimulus is here $+\delta \xi^v$ with v changing every 1.5×10^5 MCS. Thus, we conclude that the switching phenomenon is robust with respect to the type of pattern stored.

7 Conclusion

The set of equations 2.4 to 2.6 provides a general framework to model activity-dependent processes. Motivated by the behavior of neurobiological

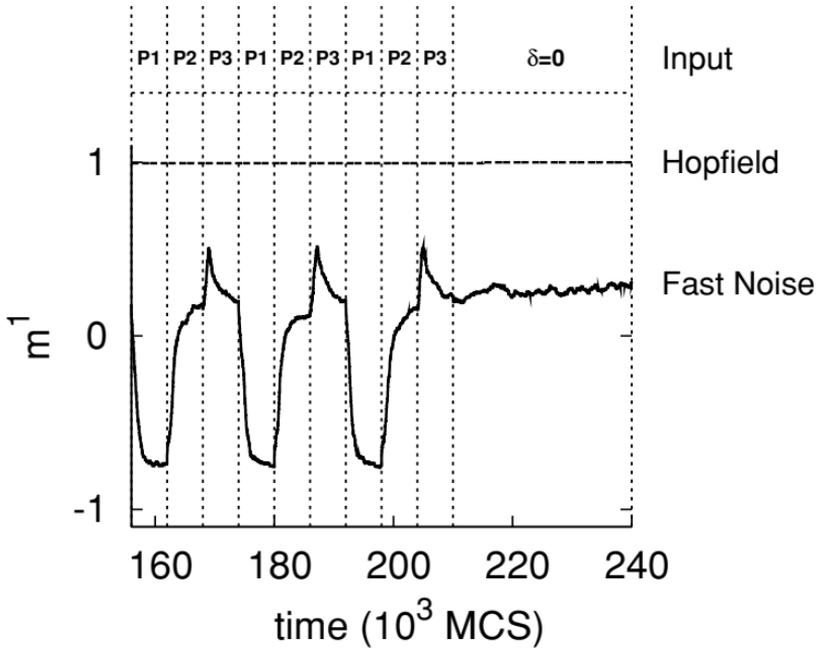


Figure 5: Time evolution during a Monte Carlo simulation with $N = 400$ neurons, $M = 3$ correlated patterns (as defined in the text), and $T = 0.1$. The system in this case was let to relax to the steady state and then perturbed by the stimulus $-\delta\xi^\nu$, $\delta = 0.3$, with $\nu = 1$ for a short time interval and then with $\nu = 2$, and so on. After suppressing the stimulus, the system is again allowed to relax. The graphs show as a function of time, from top to bottom, the number of the pattern used as the stimulus at each time interval; the resulting response of the network, measured as the overlap of the current state with pattern $\nu = 1$, in the absence of noise, that is, the Hopfield case $\Phi = -1$; and the same for the relevant noisy case $\Phi = 1$.

systems, we adapted this to study the consequences of fast noise acting on the synapses of an attractor neural network with a finite number of stored patterns. We presented in this letter two different scenarios corresponding to noise distributions fulfilling equations 3.3 and 4.3, respectively. In particular, assuming a local dependence on activity as in equation 4.1, one obtains the local fields, equation 4.2, while a global dependence as in equation 4.4 leads to equation 4.7. Under certain assumptions, the system in the first of these cases is described by the effective Hamiltonian, equation 3.2. This reduces to a Hopfield system—the familiar attractor neural network without any synaptic noise—with rescaled temperature and a threshold. This was already studied for a gaussian distribution of thresholds (Hertz et al., 1991; Horn & Usher, 1989; Litinskii, 2002). Concerning stationary properties, this case is also similar to the one in Bibitchkov et al. (2002). A more intriguing

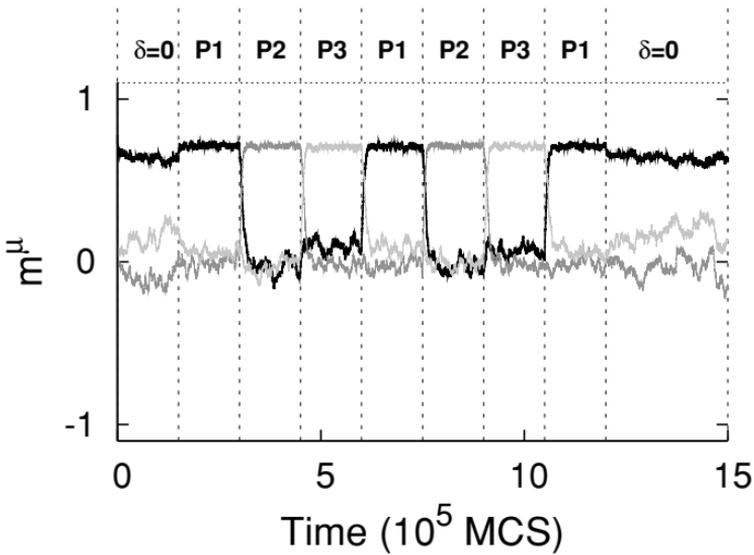


Figure 6: The same as in Figure 5 but for three stored patterns that are orthogonal (instead of correlated). The stimulus is $+\delta\xi^\nu$, $\delta = 0.1$, with $\nu = \nu(t)$, as indicated at the top. The time evolution of the overlap m^ν is drawn with a different color (black, dark gray, and light gray, respectively) for each value of ν to illustrate that the system keeps jumping between the patterns in this case.

behavior ensues when the noise depends on the total presynaptic current arriving at the postsynaptic neuron. We studied this case both analytically, by using a mean field hypothesis, and numerically, by a series of Monte Carlo simulations using single-neuron dynamics. The two approaches are fully consistent with and complement each other.

Our model involves two main parameters. One is the temperature T , which controls the stochastic evolution of the network activity. The other parameter, Φ , controls the depressing noise intensity. Varying this, the system describes the route from normal operation to depression phenomena. A main result is that the presynaptic noise induces the occurrence of a tricritical point for certain values of these parameters, $(T_c, \Phi_c) = (1, -4/3)$. This separates (in the limit $\alpha \rightarrow 0$) first from second-order phase transitions between a retrieval phase and a nonretrieval phase.

The principal conclusion in this letter is that fast presynaptic noise may induce a nonequilibrium condition that results in an important intensification of the network sensitivity to external stimulation. We explicitly show that the noise may turn the attractor or fixed-point solution of the retrieval process unstable, and the system then seeks another attractor. In particular, one observes switching from the stored pattern to the corresponding antipattern for $M = 1$ and switching between patterns for a larger number of

stored patterns, M . This behavior is most interesting because it improves the network ability to detect changing stimuli from the environment. We observe the switching to be very sensitive to the forcing stimulus, but rather independent of the network initial state or the thermal noise. It seems sensible to argue that besides recognition, the processes of class identification and categorization in nature might follow a similar strategy. That is, different attractors may correspond to different objects, and a dynamics conveniently perturbed by fast noise may keep visiting the attractors belonging to a class that is characterized by a certain degree of correlation among its elements (Cortes et al., 2005). In fact, a similar mechanism seems to be at the basis of early olfactory processing of insects (Laurent et al., 2001), and instabilities of the same sort have been described in the cortical activity of monkeys (Abeles et al., 1995) and other cases (Miller & Schreiner, 2000).

Finally, we mention that the above complex behavior seems confirmed by preliminary Monte Carlo simulations for a macroscopic number of stored patterns, that is, a finite loading parameter $\alpha = M/N \neq 0$. On the other hand, a mean field approximation (see below) shows that the storage capacity of the network is $\alpha_c = 0.138$, as in the Hopfield case (Amit et al., 1987), for any $\Phi < 0$, while it is always smaller for $\Phi > 0$. This is in agreement with previous results concerning the effect of synaptic depression in Hopfield-like systems (Torres, Pantic, & Kappen, 2002; Bibitchkov et al., 2002). The fact that a positive value of Φ tends to shallow the basin, thus destabilizing the attractor, may be understood by a simple (mean field) argument, which is confirmed by Monte Carlo simulations (Cortes et al., 2005). Assume that the stationary activity shows just one overlap of order unity. This corresponds to the condensed pattern; the overlaps with the rest, $M - 1$ stored patterns, is of order of $1/\sqrt{N}$ (non-condensed patterns) (Hertz et al., 1991). The resulting probability of change of the synaptic intensity, namely, $1/(1 + \alpha) \sum_{v=1}^M (m^v)^2$, is of order unity, and the local fields, equation 4.7, follow as $h_i^{\text{eff}} \sim -\Phi h_i^{\text{Hopfield}}$. Therefore, the storage capacity, which is computed at $T = 0$, is the same as in the Hopfield case for any $\Phi < 0$, and always lower otherwise.

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