

A mean-field controlled gain regulation in echo-state networks

Fabian Schubert and Claudius Gros

Institute for Theoretical Physics, Goethe University, Frankfurt a.M., Germany.

Keywords: variance optimization, echo state network, spectral radius, biological plausibility, self-organization, universality

1 Model Description

1.1 Elements of the Model

The following elements constitute the model:

$\epsilon_{\mu y}, \epsilon_{\sigma y}, \epsilon_{\mu x}, \epsilon_{\sigma x}, \epsilon_a, \epsilon_b \in \mathbb{R}$	Adaptation Rates
$u \in \mathbb{R}^T, e \in \mathbb{R}^{N \times T}$	Input Sequence, External Neural Inputs
$w_{\text{in}} \in \mathbb{R}^N, W \in \mathbb{R}^{N \times N}$	External Input Weights, Recurrent Weights
$x, y \in \mathbb{R}^{N \times T}$	Membrane Potentials, Neural Activities
$\mu_y, \sigma_y^2, \mu_x, \sigma_x^2 \in \mathbb{R}^{N \times T}$	Trailing Averages
$\sigma_{\text{ymf}}^2 \in \mathbb{R}^{N \times T}$	Mean Field of Activity Variances
$a, b \in \mathbb{R}^{N \times T}$	Gains, Biases
$\mu_{\text{yt}} \in \mathbb{R}^N$	Target Activities

1.2 Dynamics

Subscript indices $(\cdot)_i$ or $(\cdot)_{ij}$ refer to the dimensions spanned by N in the respective objects, while $(\cdot)(t)$ refers to the index of the dimension spanned by T .

Network Dynamics

$$e_i(t) = u(t)w_{\text{in},i} \quad (1)$$

$$x_i(t) = \sum_j W_{ij}y_j(t-1) \quad (2)$$

$$y_i(t) = \tanh \{a_i(t-1)x_i(t) + e_i(t) - b_i(t-1)\} \quad (3)$$

Running Averages

$$\mu_{y,i}(t) = (1 - \epsilon_{\mu y})\mu_{y,i}(t-1) + \epsilon_{\mu y}y_i(t) \quad (4)$$

$$\sigma_{y,i}^2(t) = (1 - \epsilon_{\sigma y})\sigma_{y,i}^2(t-1) + \epsilon_{\sigma y} (y_i(t) - \mu_{y,i}(t))^2 \quad (5)$$

$$\mu_{x,i}(t) = (1 - \epsilon_{\mu x})\mu_{x,i}(t-1) + \epsilon_{\mu x}x_i(t) \quad (6)$$

$$\sigma_{x,i}^2(t) = (1 - \epsilon_{\sigma x})\sigma_{x,i}^2(t-1) + \epsilon_{\sigma x} (x_i(t) - \mu_{x,i}(t))^2 \quad (7)$$

$$\sigma_{\text{ymf},i}^2(t) = (1 - \alpha)\sigma_{y,i}^2(t) + \alpha \langle \sigma_{y,j}^2(t) \rangle_j \quad (8)$$

Gain and Bias Update

$$a_i(t) = (1 - \epsilon_a) a_i(t-1) + \epsilon_a R \sqrt{\sigma_{\text{ymf},i}^2(t) / \sigma_{x,i}^2(t)} \quad (9)$$

$$b_i(t) = b_i(t-1) + \epsilon_b (y_i(t) - \mu_{\text{yt},i}) \quad (10)$$

1.3 Distributions

$$p(W_{ij}) = \begin{cases} \delta(W_{ij}) & : i = j \\ (1 - p_W)\delta(W_{ij}) + p_W \mathcal{N}(W_{ij}, \mu = 0, \sigma = \sigma_W / \sqrt{p_W N}) & : i \neq j \end{cases} \quad (11)$$

$$p(w_{\text{in},i}) = (1 - p_{\text{win}})\delta(w_{\text{in},i}) + p_{\text{win}} \mathcal{N}(w_{\text{in},i}, \mu = 0, \sigma = 1) \quad (12)$$

$$p(\mu_{\text{yt},i}) = \mathcal{N}(\mu_{\text{yt},i}, \mu = 0, \sigma = \sigma_{\mu \text{yt}}) \quad (13)$$

1.4 Parameters

Table 1: Model Parameters

N	T	p_W	p_{win}	$\epsilon_{\mu y}$	$\epsilon_{\sigma y}$	$\epsilon_{\mu x}$	$\epsilon_{\sigma x}$	ϵ_a	ϵ_b	$\sigma_{\mu \text{yt}}$	α	R
10^3	$15 \cdot 10^3$	0.1	1.0	10^{-3}	$5 \cdot 10^{-3}$	10^{-3}	$5 \cdot 10^{-3}$	10^{-3}	10^{-3}	10^{-2}	1.0	1.0

The values/properties of u, R and σ_W were left open to experimentation. Generally, the goal of the mechanism was to adapt a in such a way that too large/too small variances in W are compensated, leading to a spectral radius of $\rho(a_i W_{ij})$ of R . We tested with u taken from a Gaussian distribution with 1/4 standard deviation, $R = 1$ and $\sigma_W = 5$. The latter initially caused the spectral radius to be 5.

Gains were initially set to 1, biases to 0.

2 Results

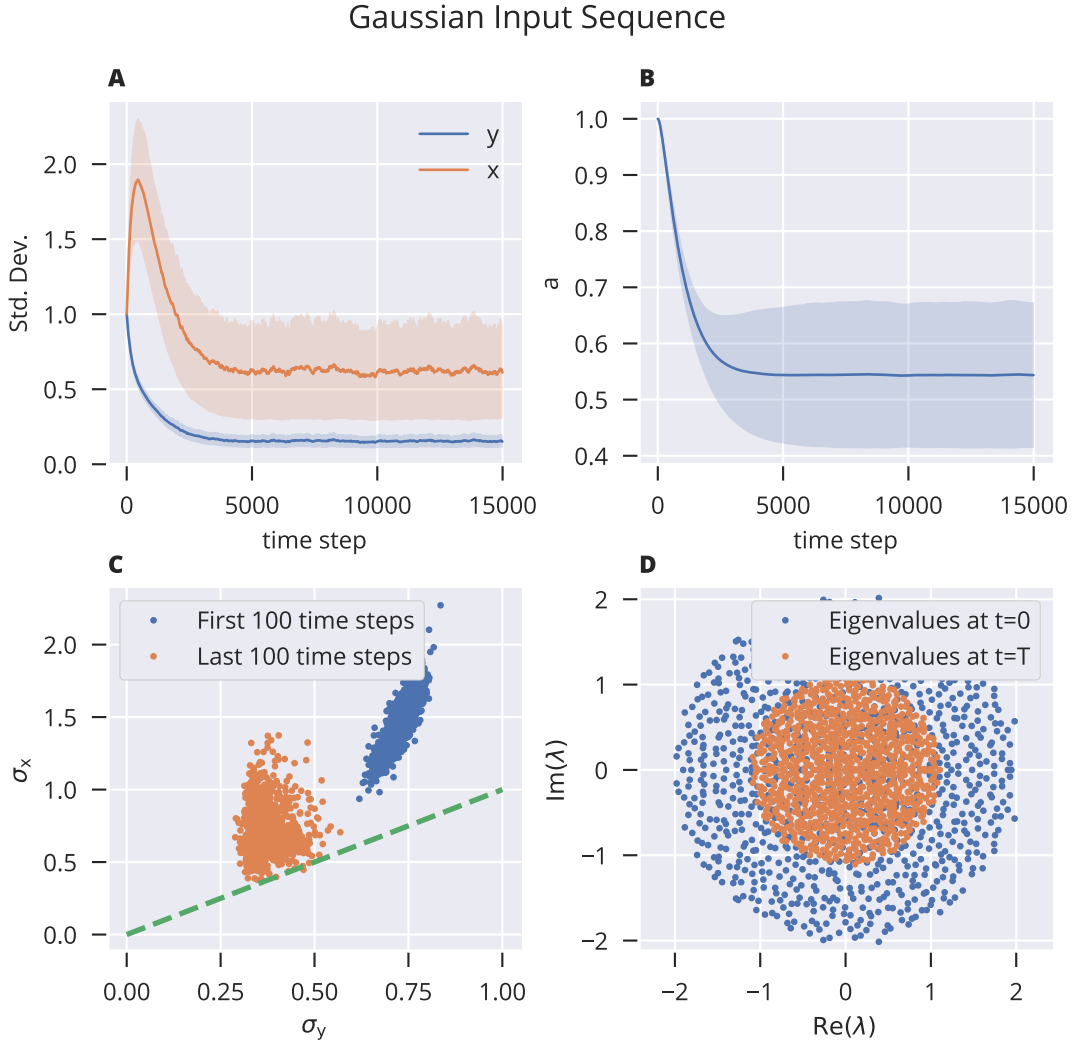


Figure 1: Results for u drawn from a Gaussian distribution with zero mean, $1/4$ standard deviation, $R = 1$ and $\sigma_W = 2$. Other parameters as in Table 1. **A**: Standard deviations (trailing average over time) of neural activities and membrane potentials. Shaded region denotes standard deviation over the neural population. **B**: Gain mean and standard deviation over the neural population. **C**: Standard deviations of membrane potentials versus standard deviations of activities. Each point represents a neuron. **D**: Eigenvalues of $a_i W_{ij}$.

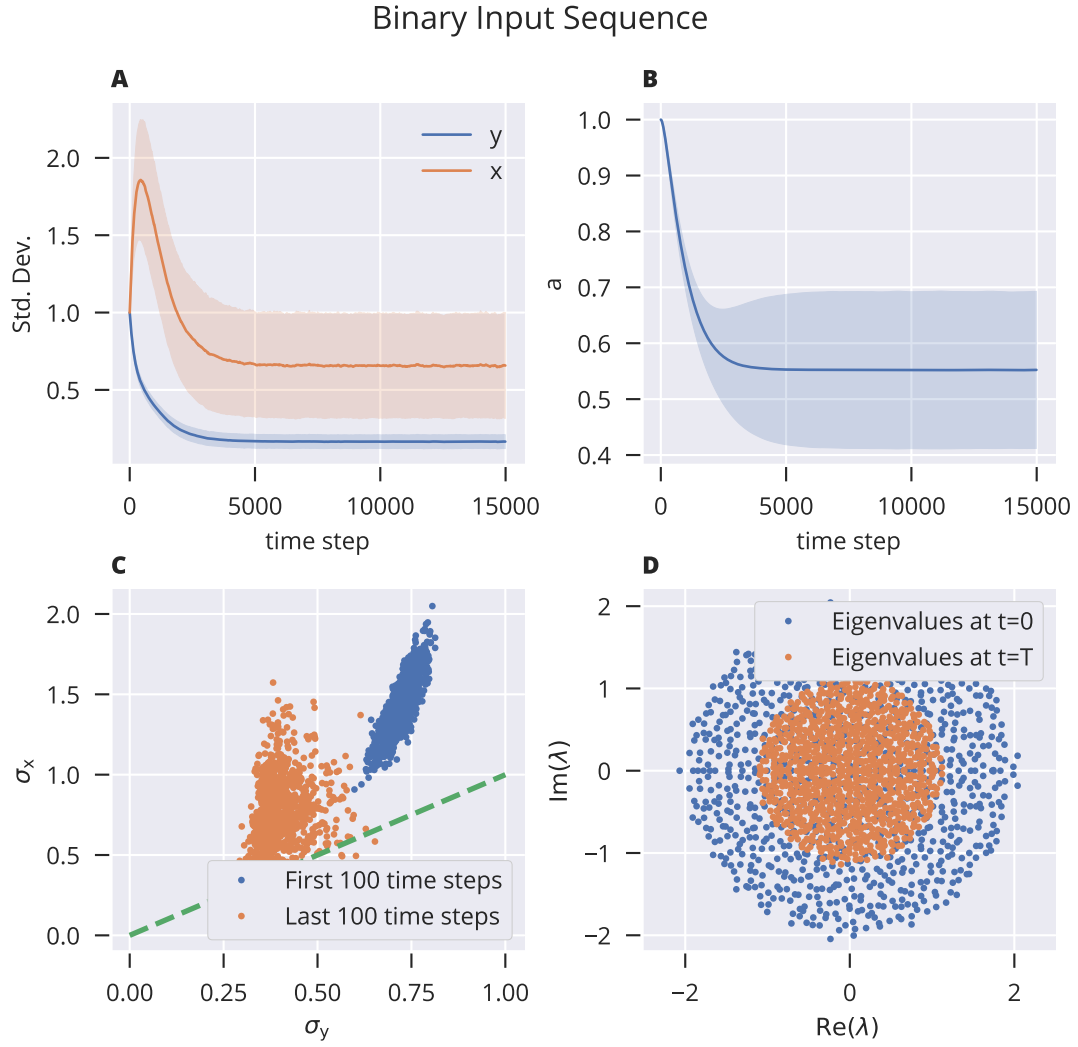


Figure 2: Results as presented in Fig. 1, for u drawn from a symmetric binary distribution, $u(t) \in (-1/4, 1/4)$.

Gaussian Input Sequence, Binary Recurrent Weights

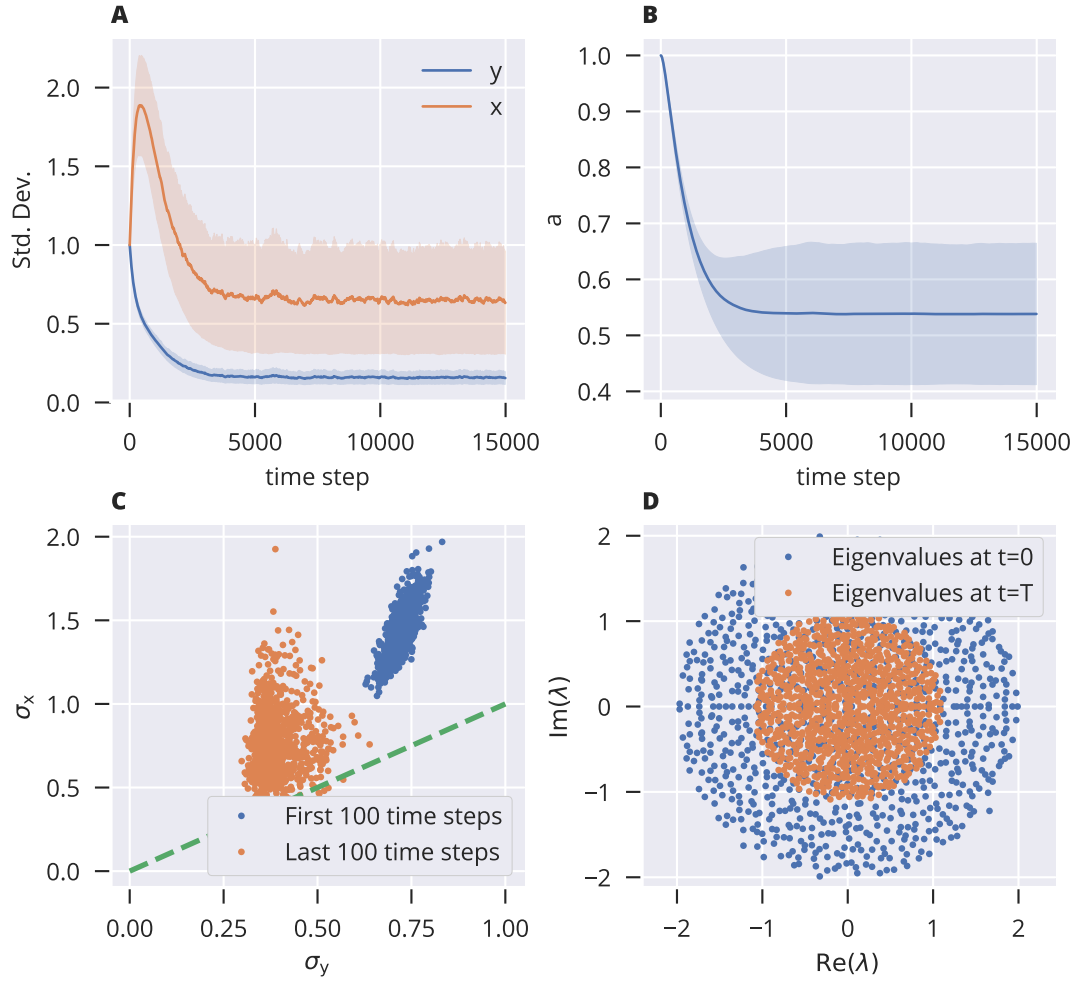


Figure 3: Results as presented in Fig. 1, for W_{ij} drawn from a binary distribution.

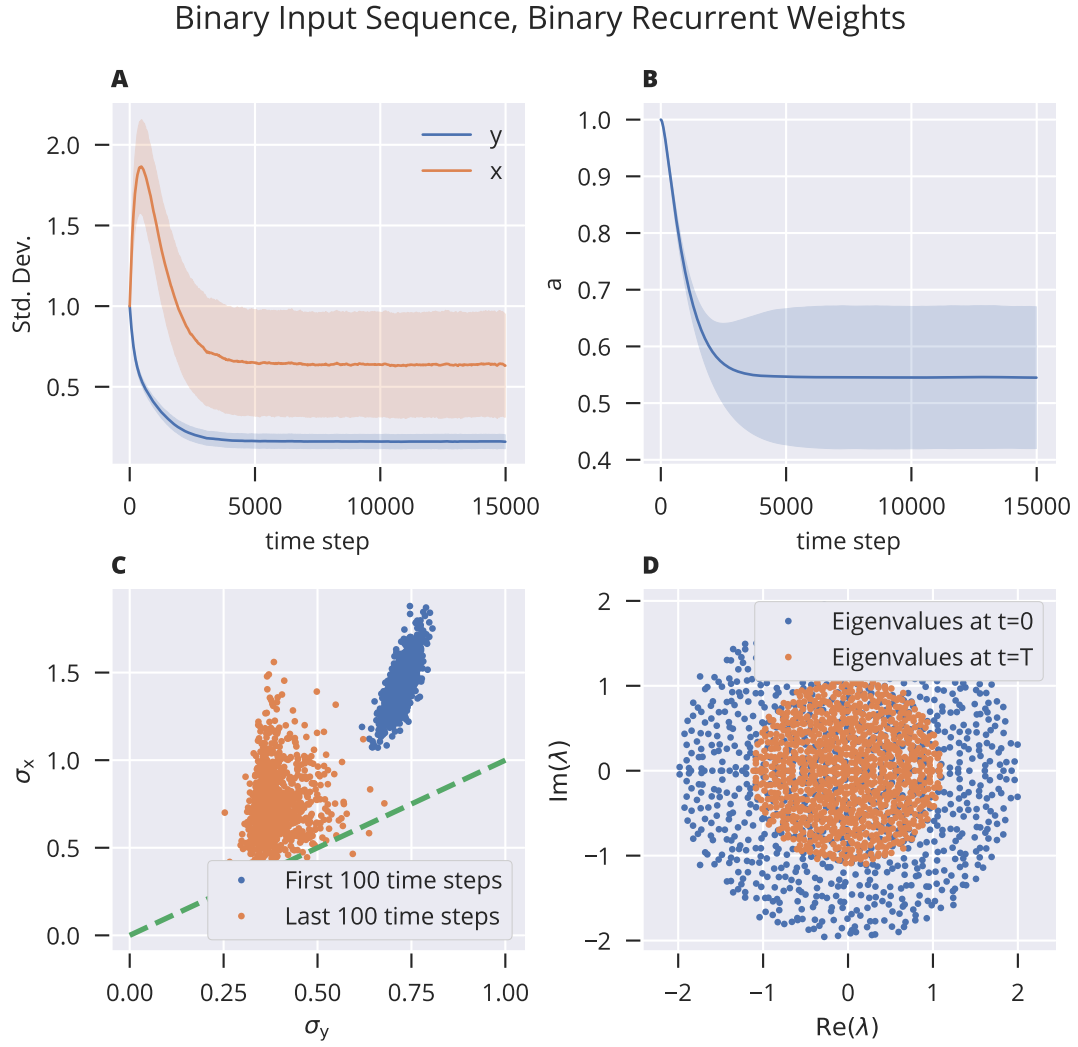


Figure 4: Results as presented in Fig. 1, for W_{ij} drawn from a binary distribution and u drawn from a binary distribution, $u(t) \in (-1/4, 1/4)$.