

# Coding with transient trajectories in recurrent neural networks

Giulio Bondanelli <sup>\*1</sup>, Srdjan Ostojic <sup>1</sup>,

<sup>1</sup> Laboratoire de Neurosciences Cognitives et Computationnelles, Département d'Études Cognitives, École Normale Supérieure, INSERM U960, PSL University, Paris, France

\*giulio.bondanelli@ens.fr

## Supporting information

### S6 Text

An interesting application of the results that we found for the unit-rank connectivity is the system composed of one excitatory and one inhibitory populations. The interactions between the two populations are described by the connectivity matrix

$$\mathbf{J} = \begin{pmatrix} w & -kw \\ w & -kw \end{pmatrix}, \quad (116)$$

where  $w$  is the excitatory weight and  $k$  represents the relative strength of inhibition with respect to the strength of excitation. We consider the regime in which inhibition is stronger than excitation, i.e.  $k > 1$ . Since  $\mathbf{J}$  has unit rank, we can express it in the form given by Eq. (41), where

$$\begin{cases} \Delta = w\sqrt{2(1+k^2)} \\ \mathbf{u} = \frac{(1,1)^T}{\sqrt{2}} \\ \mathbf{v} = \frac{(1,-k)^T}{\sqrt{1+k^2}}. \end{cases} \quad (117)$$

Therefore,  $\mathbf{J}$  has only one eigenvalue equal to

$$\lambda = w(1-k) \quad (118)$$

and one zero eigenvalue, while the correlation between the structure vectors  $\mathbf{u}$  and  $\mathbf{v}$  is given by

$$\rho = \frac{1-k}{\sqrt{2(1+k^2)}}. \quad (119)$$

Note that the correlation  $\rho$  depends only on  $k$ . For simplicity, we assume that  $k$  is fixed and slightly larger than unity:

$$k = 1 + \epsilon_k. \quad (120)$$

Thus, for  $\epsilon_k \ll 1$ , the parameters of the network are given by

$$\begin{cases} \Delta = 2w\left(1 + \frac{\epsilon_k}{2}\right) \\ \mathbf{u} = \frac{(1,1)^T}{\sqrt{2}} \\ \mathbf{v} = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ -1 \end{pmatrix} - \frac{\epsilon_k}{2} \mathbf{u} \\ \rho = -\frac{\epsilon_k}{2}. \end{cases} \quad (121)$$

Computing the symmetric part of the connectivity  $\mathbf{J}$  yields

$$\mathbf{J}_S = \begin{pmatrix} w & w(1-k)/2 \\ w(1-k)/2 & -kw \end{pmatrix}, \quad (122)$$

which has eigenvalues

$$\lambda_S^\pm = \frac{w}{2}(1-k) \pm \frac{w}{2}\sqrt{2(1+k^2)}. \quad (123)$$

The condition  $\lambda_S^+(w, k) > 1$  determines the region of the parameters  $w$  and  $k$  where transient amplification occurs. In the inhibition-dominated regime the system exhibits amplification if the excitatory strength  $w$  is approximately larger than one, when  $k$  is larger than but close to unity. In fact, if  $k$  is given by Eq. (120), we can write

$$\lambda_S^+ \simeq w \left( 1 + \frac{\epsilon_k^2}{4} \right) \quad (124)$$

so that the transient regime is defined by the condition

$$w \gtrsim 1 - \frac{\epsilon_k^2}{4} \quad (125)$$

We note that the inhibition-dominated regime  $k > 1$  is not necessary to achieve transient amplification, since a stable system can be amplified for  $k > 1$  or  $0 < k < 1$ . However, for fixed  $0 < k < 1$  the stability constraint  $k > 1 - 1/w$  limits the parameter region where stable amplification occurs (Fig. 2). For strongly amplified systems ( $w \gg 1$ ) this region is defined by the stability boundary  $k > 1 - 1/w \simeq 1$ , which approximately corresponds to the inhibition-dominated unit-rank EI networks.

In the regime of strong amplification (Eq. 55), we can compute the optimal initial condition  $\mathbf{R}_1^*$  and the corresponding readout vector  $\mathbf{L}_1^*$ . If Eq. (120) holds, the strong amplification condition is simply given by  $w \gg 1$ . Using Eq. (69) we find

$$\begin{cases} \mathbf{R}_1^* = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ -1 \end{pmatrix} + \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 2w - \epsilon_k \end{pmatrix} \begin{pmatrix} 1 \\ 1 \end{pmatrix} \\ \mathbf{L}_1^* = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \end{pmatrix} + \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 2w + \epsilon_k \end{pmatrix} \begin{pmatrix} 1 \\ -1 \end{pmatrix}. \end{cases} \quad (126)$$

We find that the optimal initial condition and the optimal readout are aligned respectively with the modes  $(1, -1)$  and  $(1, 1)$ . These modes correspond to the patterns of differential and equal firing of the excitatory and inhibitory units, respectively called the difference and sum modes in [1]. The analysis of balanced amplification in [1] explicitly focuses on the dynamics of the sum and difference modes. Here, by studying the amplification of the norm  $\|\mathbf{r}(t)\|$ , we show that these modes emerge as the optimal initial condition and the optimal readout, in the limit of strong amplification ( $w \gg 1$ ) and in the inhibition-dominated regime (with  $k = 1 + \epsilon_k$ ). Consistent with [1], our theory shows that under these assumptions a difference in the firing of the E and I units drives strong changes in the pattern of common activation of E and I neurons.

## References

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