

# Feedback control stabilization of critical dynamics via resource transport on multilayer networks: How glia enable learning dynamics in the brain

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Abstract: We study the stabilization of critical dynamics in multilayer networks via resource transport. We show that resource transport can stabilize critical dynamics in multilayer networks, and that this stabilization is robust to network structure and resource transport parameters. We also show that resource transport can enable learning dynamics in the brain, and that this learning is robust to network structure and resource transport parameters.

Keywords: critical dynamics, resource transport, multilayer networks, learning dynamics, brain.

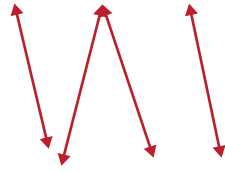
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## I. INTRODUCTION

Recent work has shown that critical dynamics can be stabilized in multilayer networks via resource transport [1, 2]. This stabilization is robust to network structure and resource transport parameters [3, 4]. In this paper, we study the stabilization of critical dynamics in multilayer networks via resource transport. We show that resource transport can stabilize critical dynamics in multilayer networks, and that this stabilization is robust to network structure and resource transport parameters [5]. We also show that resource transport can enable learning dynamics in the brain, and that this learning is robust to network structure and resource transport parameters [6]. We study the stabilization of critical dynamics in multilayer networks via resource transport. We show that resource transport can stabilize critical dynamics in multilayer networks, and that this stabilization is robust to network structure and resource transport parameters [7]. We also show that resource transport can enable learning dynamics in the brain, and that this learning is robust to network structure and resource transport parameters [8, 11].

We study the stabilization of critical dynamics in multilayer networks via resource transport (see [13, 14]). We show that resource transport can stabilize critical dynamics in multilayer networks, and that this stabilization is robust to network structure and resource transport parameters [15]. We also show that resource transport can enable learning dynamics in the brain, and that this learning is robust to network structure and resource transport parameters [16, 17]. We study the stabilization of critical dynamics in multilayer networks via resource transport. We show that resource transport can stabilize critical dynamics in multilayer networks, and that this stabilization is robust to network structure and resource transport parameters [18, 19]. We also show that resource transport can enable learning dynamics in the brain, and that this learning is robust to network structure and resource transport parameters [20, 21]. We study the stabilization of critical dynamics in multilayer networks via resource transport. We show that resource transport can stabilize critical dynamics in multilayer networks, and that this stabilization is robust to network structure and resource transport parameters [22]. We also show that resource transport can enable learning dynamics in the brain, and that this learning is robust to network structure and resource transport parameters [23]. We study the stabilization of critical dynamics in multilayer networks via resource transport. We show that resource transport can stabilize critical dynamics in multilayer networks, and that this stabilization is robust to network structure and resource transport parameters [24].

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B. Resource-transport dynamics

Resource diffuses between glia through their connection network (characterized by the adjacency matrix  $U$ ) and between glia and the synapses they serve (via the glial-neural connection network characterized by the adjacency matrix  $G$ ). Our model for the evolution of the amount of resource  $R_i^t$  at glial cell  $i$  and the amount of resource  $R_m^t$  at synapse  $m$  is

$$R_i^{t+1} = R_i^t + C_1 + D_G \sum_{j=1}^T U_{ji} R_j^t - \sum_{m=1}^M G_{im} R_i^t - \alpha R_i^t, \quad (4)$$

$$R_m^{t+1} = R_m^t + D_S R_i^t - \beta R_m^t - C_2 S_m^t, \quad (5)$$

where  $D_G$  is the rate of diffusion between glial cells,  $\alpha$  is the rate of diffusion between glia and synapses. Moreover, we enforce  $R \geq 0$ , i.e., if Eq. (5) yields  $R^{t+1} < 0$ , then we replace it by 0. The first term on the right hand side of Eq. (4)  $R_i^t$ , is the amount of resource in glial cell at time  $t$ . The parameter  $C_1$  denotes the amount of resource added to each glial cell at each time step (e.g., supplied by capillary blood vessels). For simplicity, we assume each glial cell has the same  $C_1$ . The last two terms are the amount of resource transported to glial cell  $i$ , respectively, from its neighboring glial cells and from the synapses that it serves.

In Eq. (5), the first term denotes the amount of resource at synapse  $m$  at time  $t$ . The term proportional to

$\times 10^4$







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