



类脑认知计算与脑机融合智能
Brain-inspired Cognitive Computation and
Brain-computer Integrative Intelligence



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Functional Building Blocks of Neural Networks: From Network Motifs to Collective Dynamics

Jian Zhang[†], Yue Sun[†], Wangzi Yao[†], Tielin Zhang^{*}



Connectivity and motifs in neural network



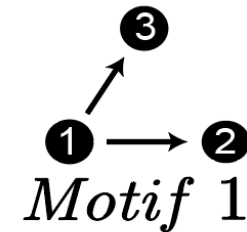
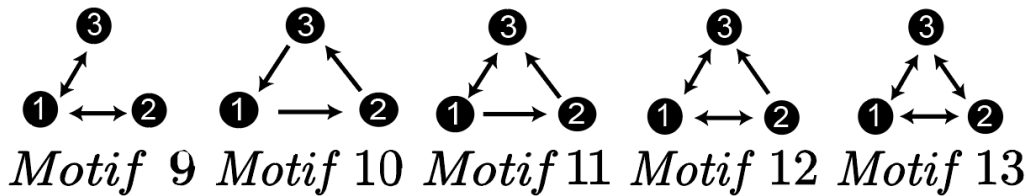
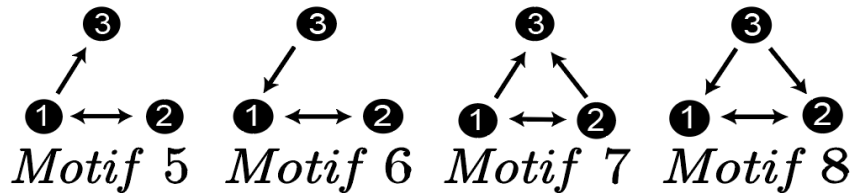
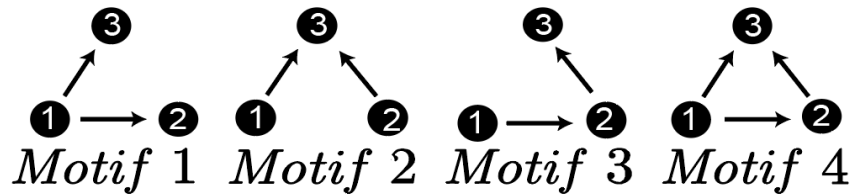
- **Connectivity** is fundamental to neural computation, shaping **rich collective dynamics** for deep learning progress
- **High-dimensional global connectivity** lacks interpretability, motivating the study of **low-dimensional network motifs**.



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- **High-dimensional global connectivity** lacks interpretability, motivating the study of **low-dimensional network motifs**.

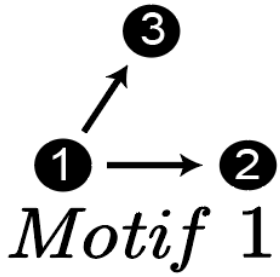


$$\begin{bmatrix} W_{11} & 0 & 0 \\ W_{21} & W_{22} & 0 \\ W_{31} & 0 & W_{33} \end{bmatrix}$$

- This study **bridges local motifs** and **whole-network computation** to selectively enhance robustness or flexibility.



Network motif training



$$\begin{bmatrix} W_{11} & 0 & 0 \\ W_{21} & W_{22} & 0 \\ W_{31} & 0 & W_{33} \end{bmatrix}$$

$$\begin{aligned} c_1(W) &= \frac{1}{2} \sum_{i,j,k} \bar{W}_{ji} \ddot{W}_{ij} \ddot{W}_{ik} \bar{W}_{ki} \ddot{W}_{kj} \ddot{W}_{jk} \\ &= \frac{1}{2} \sum_{j,k} \left\{ \sum_i [\bar{W} \otimes \ddot{W}^T]_{ji} [\ddot{W} \otimes \bar{W}^T]_{ik} \right\} [\ddot{W}^T \otimes \ddot{W}]_{jk} \\ &= \frac{1}{2} \sum_{j,k} [(\bar{W} \otimes \ddot{W}^T)(\ddot{W} \otimes \bar{W}^T)]_{jk} [\ddot{W}^T \otimes \ddot{W}]_{jk} \\ &= \frac{1}{2} L^T [(\bar{W} \otimes \ddot{W}^T)(\ddot{W} \otimes \bar{W}^T) \otimes \ddot{W}^T \otimes \ddot{W}] L, \end{aligned}$$



Local dynamics of three-node motifs



- By the Hartman–Grobman theorem, the local behavior near attractors of nonlinear dynamics is governed by the linearized dynamics.

Linear dynamical system

$$\frac{dX}{dt} = \begin{bmatrix} W_{11} & W_{12} & W_{13} \\ W_{21} & W_{22} & W_{23} \\ W_{31} & W_{32} & W_{33} \end{bmatrix} X.$$

Nonlinear dynamical system

$$\frac{dh_i}{dt} = -\frac{h_i}{\tau} + \sum_{j=1}^3 W_{ij}^{(m)} \phi(h_j) + I_i(t) + \eta_i(t),$$

The local behavior of the nonlinear system by linearizing it around an equilibrium \mathbf{h}^* :
using Jacobian matrix $J_{ij}(\mathbf{h}^*) = \partial \dot{h}_i / \partial h_j |_{\mathbf{h}=\mathbf{h}^*}$

$$\begin{bmatrix} -\frac{1}{\tau} + W_{11}[1 - \tanh^2(h_1^*)] & W_{12}[1 - \tanh^2(h_2^*)] & W_{13}[1 - \tanh^2(h_3^*)] \\ W_{21}[1 - \tanh^2(h_1^*)] & -\frac{1}{\tau} + W_{22}[1 - \tanh^2(h_2^*)] & W_{23}[1 - \tanh^2(h_3^*)] \\ W_{31}[1 - \tanh^2(h_1^*)] & W_{32}[1 - \tanh^2(h_2^*)] & -\frac{1}{\tau} + W_{33}[1 - \tanh^2(h_3^*)] \end{bmatrix},$$



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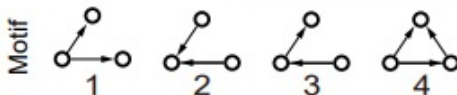
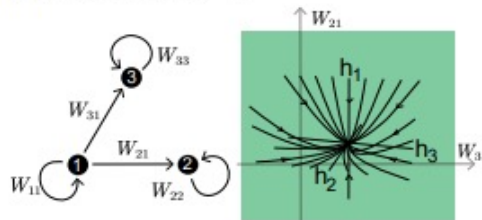
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- This allows the 13 directed three-node motifs to be grouped into three levels according to their stability conditions.

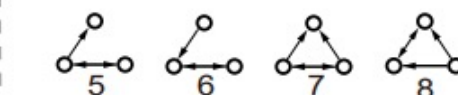
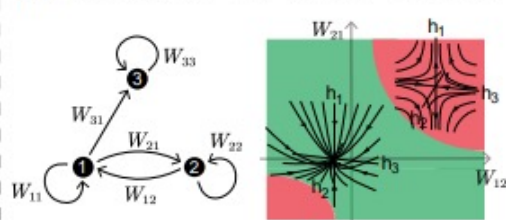
Level 1: Single stability condition:

(1) $W_{11}, W_{22}, W_{33} < 0$



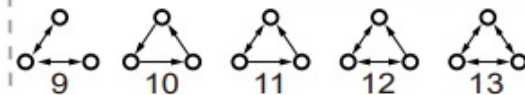
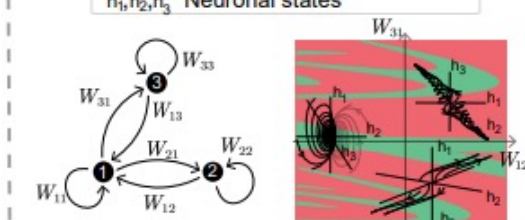
Level 2: Double stability conditions:

(1) $W_{11}, W_{22}, W_{33} < 0$ (2) $W_{11}W_{22} - W_{12}W_{21} > 0$



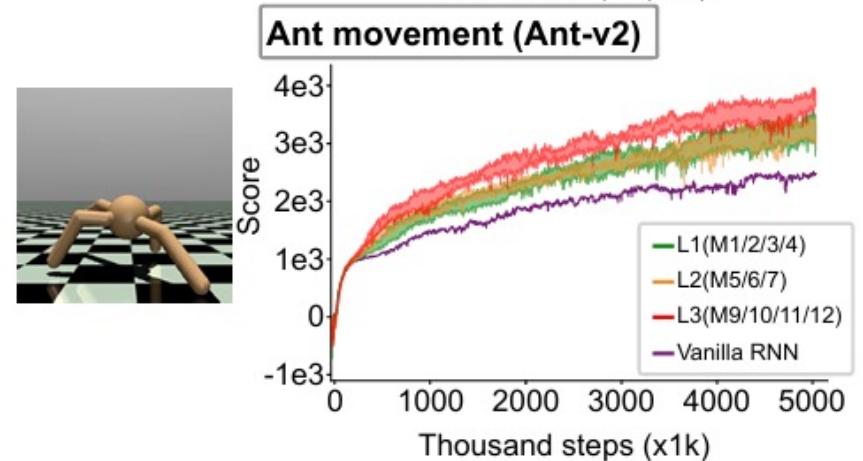
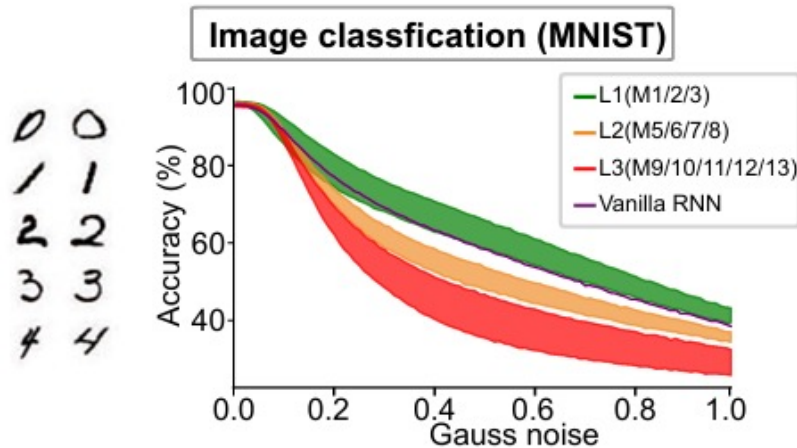
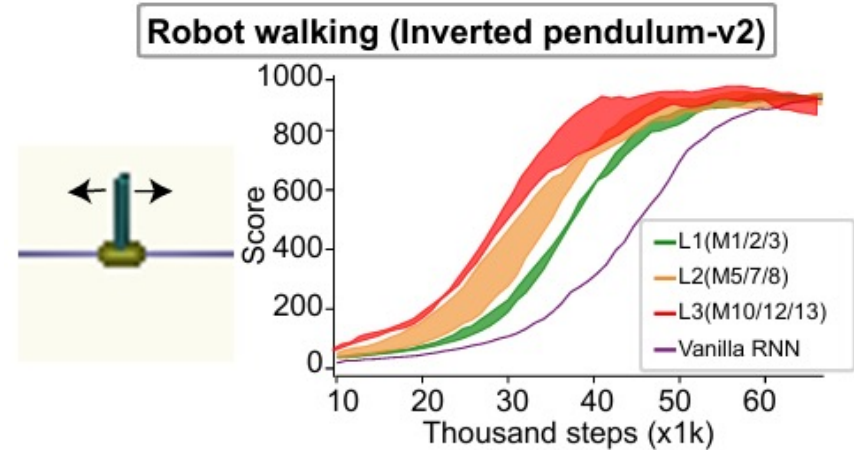
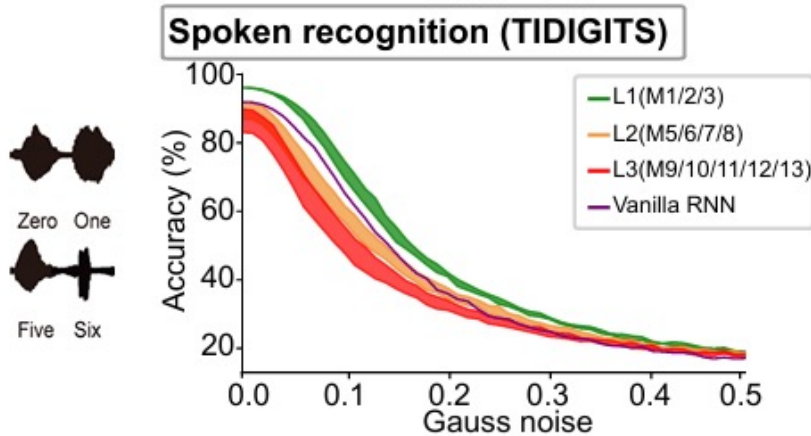
Level 3: Multiple stricter stability conditions

Stable Unstable
 h_1, h_2, h_3 Neuronal states





Computational Capabilities of Motif-Endowed Networks



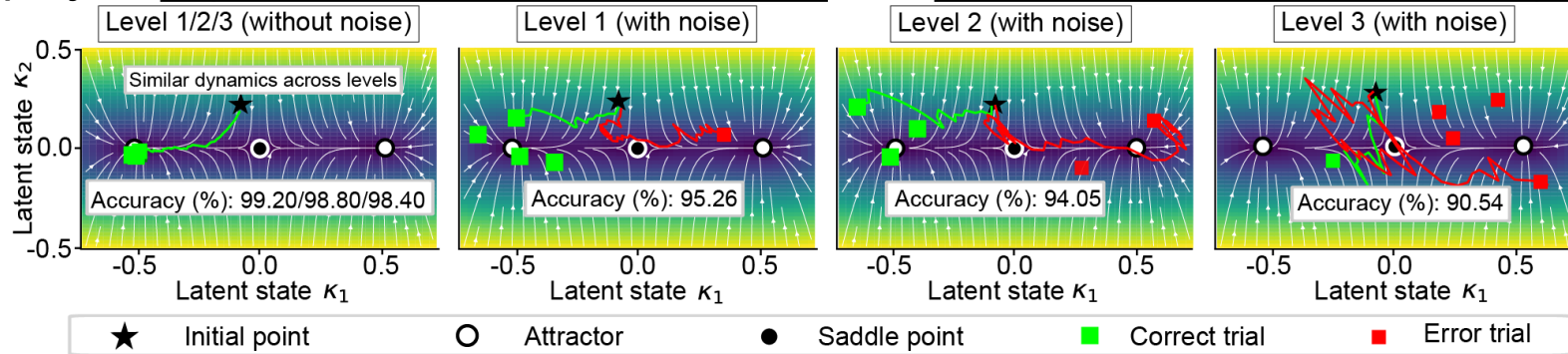
Networks enriched with **Level-1 motifs** enhance **accuracy under noise**, while networks with **Level-3 motifs** **accelerate reinforcement learning**.



Collective dynamics of Motif-Endowed Networks



We project *high-dimensional population* onto *a low-dimensional latent dynamics*:



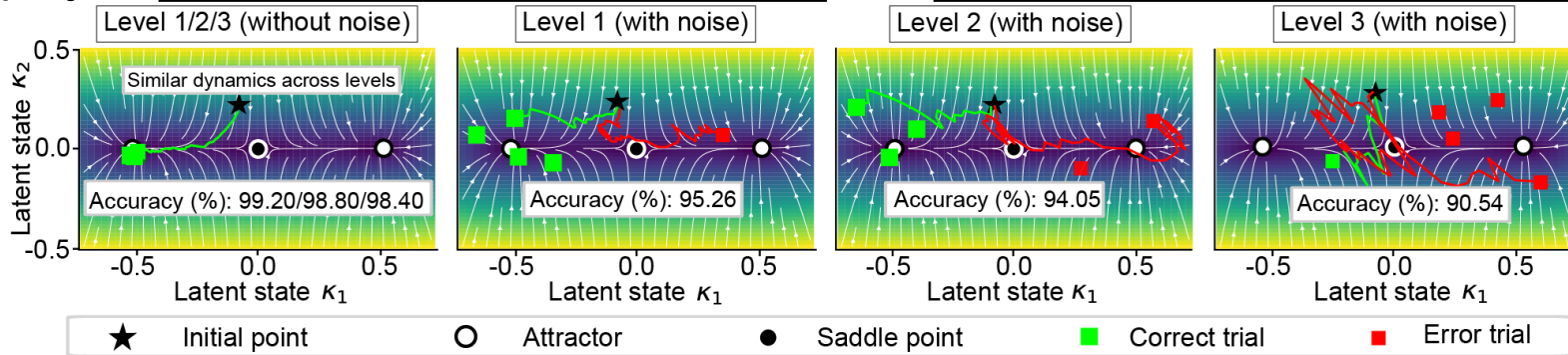
Networks enriched *with Level-1 motifs* form *latent trajectories* that *are more resistant to noise perturbations*



Collective dynamics of Motif-Endowed Networks

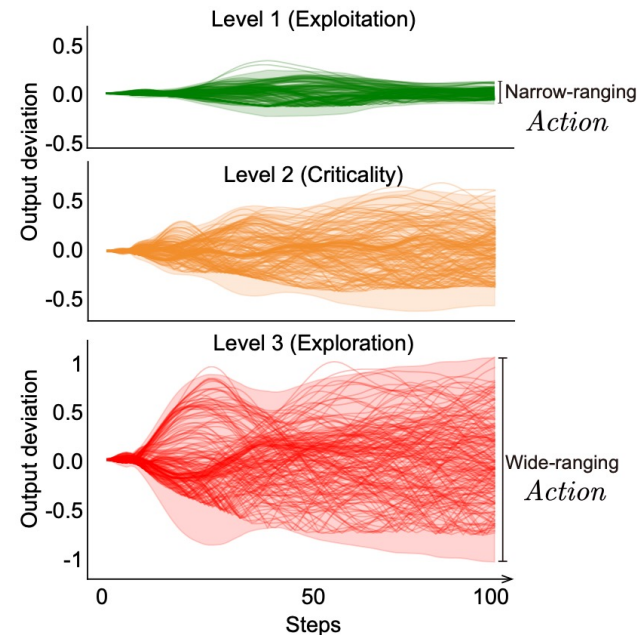


We project *high-dimensional population* onto *a low-dimensional latent dynamics*:



Networks enriched *with Level-1 motifs* form *latent trajectories* that *are more resistant to noise perturbations*

- We track the step-by-step output deviation observations over 100 steps
- Networks enriched with *Level-3 motifs* sustain *wide-ranging output deviations* that *facilitate exploration*.





Conclusion and future direction



- We developed scalable, differentiable framework for proactive network motifs of ANNs
- The 13 motifs are mathematically stratified into a three-tiered stability hierarchy.
- Altering motif composition shapes global dynamics to balance robustness and flexibility.
- Bridges local circuits to network capabilities, scaling to larger subgraphs, MLPs, and Transformers.

Paper

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