Biologically-Inspired Representations for Adaptive Control with Spatial Semantic Pointers

13/03/25

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Introduction and Motivation

- Adaptive control
  - Control system must adapt online
  - Application of system identification
  - Defined as a continuous learning problem
  - Learn weights over a set of basis functions
  - Adaptive control + PD control (Slotine & Li, 1987)

- Continuous learning
  - Prone to catastrophic forgetting
  - Need to generalize over input space
  - Requires sparsity

Background

- Spiking neural adaptive control (DeWolf et al., 2016)
  - Adapts to unknown dynamics
  - Uses spiking neurons as basis functions

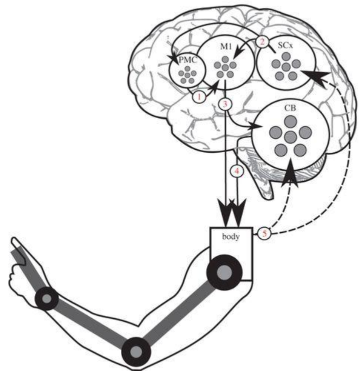

Figure 1: An overview of the REACH model (DeWolf et al., 2016)

- Improved (DeWolf et al., 2020)
  - Approach the problem of basis function selection
  - Project input to D+1 dimensional hypersphere

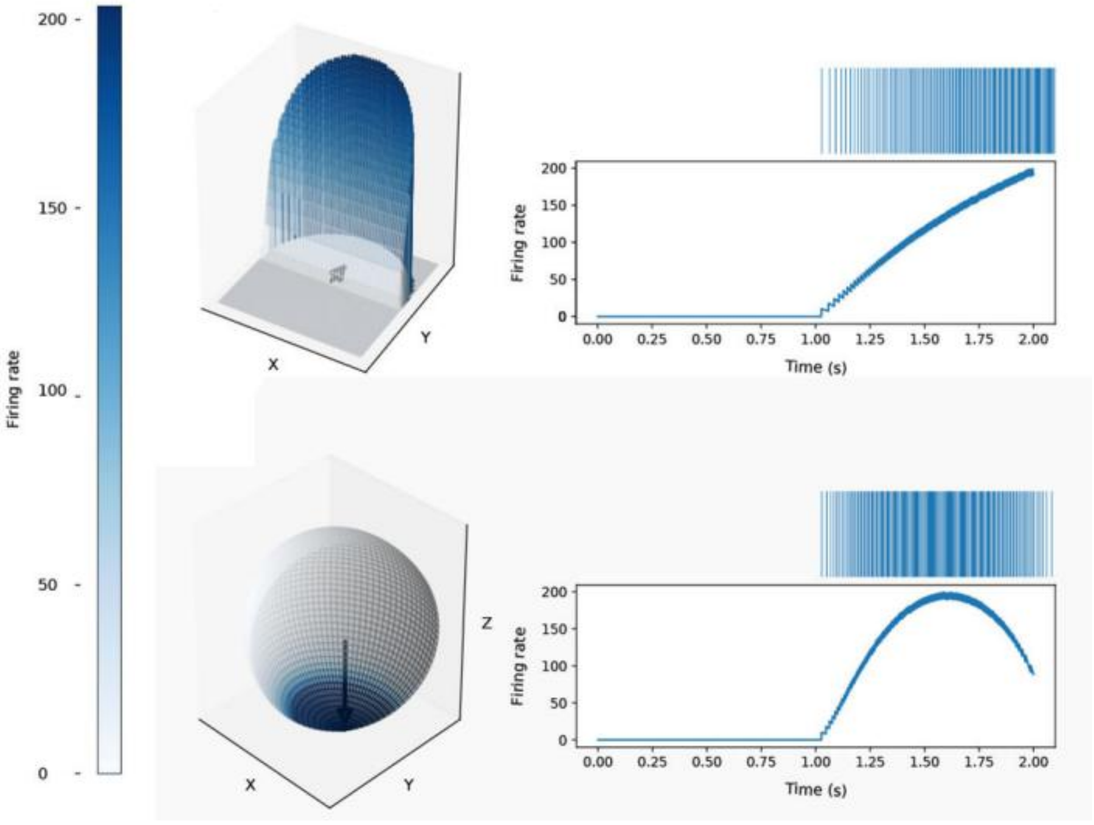

Figure 2: An example of how increasing encoder dimensionality can create neurons that are more selectively responsive (DeWolf et al., 2020)

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Background – Cont.

- Spatial semantic pointer (SSP) architecture
  - High-dimensional vector representation of lower-dimensional continuous spaces (Komer et al., 2019)

$$\phi_X(\lambda^{-1}X) = \mathcal{F}^{-1}\{e^{i\theta\lambda^{-1}X}\}$$

  - Developed within Semantic Pointer Architecture framework (Eliasmith, 2013)

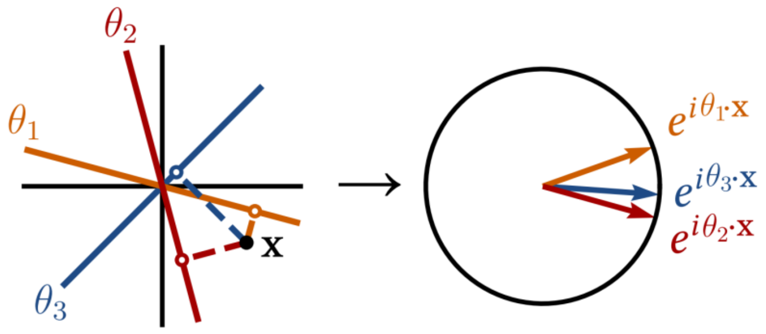

Figure 3: The Spatial Semantic Pointer (SSP) projection from a low dimensional space ($x \in \mathbb{R}^2$) to higher dimensional space (Dumont, 2025)

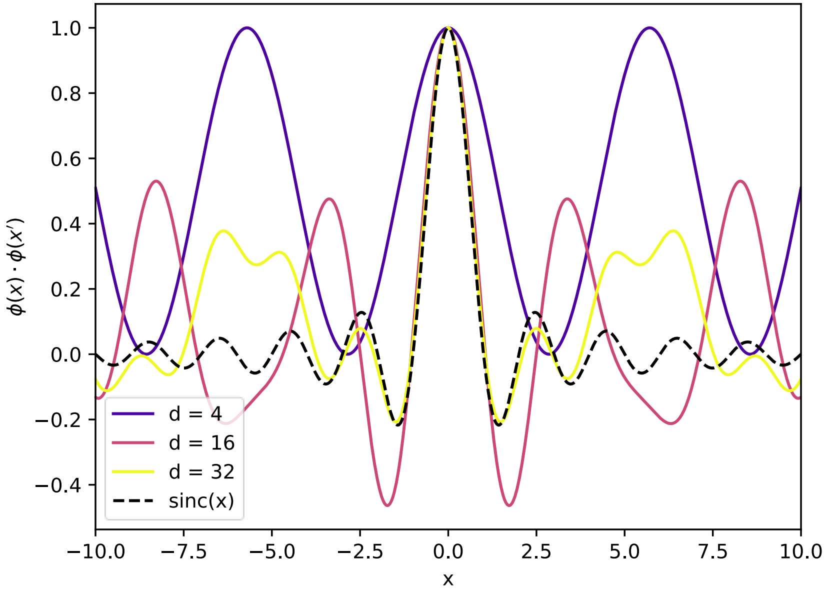

Figure 4: As dimensionality of the representation increases, the inner product between SSPs better approximates a sinc kernel, enabling a highly-localized basis

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Problem Statement and Contribution

- Using spiking neural population in continuous learning control
  - Selection of basis functions using SSP representation
  - Sparsity and catastrophic forgetting

- Contributions
  - Propose use of SSP representation as basis functions
  - Generate basis representations on spiking neurons using the Neural Engineering Framework (NEF) (Eliasmith & Anderson, 2003)
  - Provide stability guarantees with sliding mode control
  - Show 1.23 – 1.25x performance improvement on a simulated 3-link arm over past baselines

Methodology

- Sliding mode control is applied in parallel with adaptive control
  - Closed loop control algorithm
  - Constrains states to sliding manifold leading to convergence

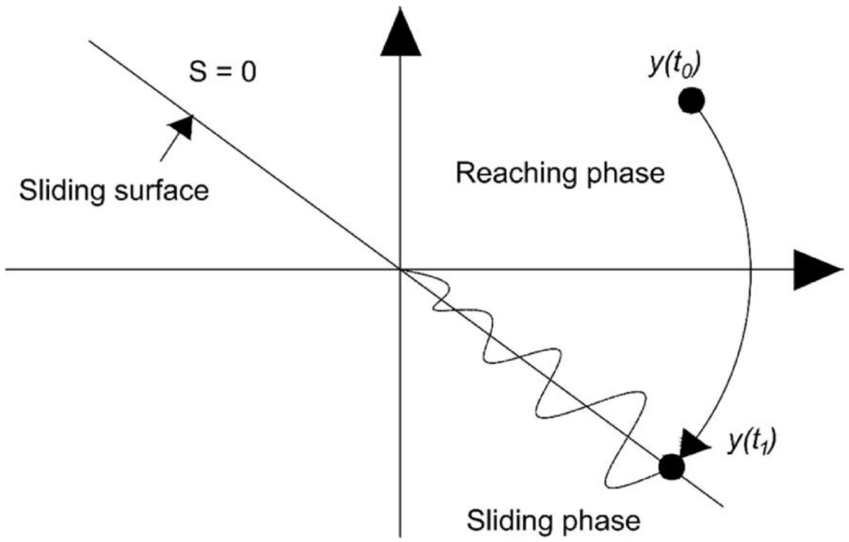

Figure 5: Sliding manifold in state space (Wani et al., 2022)

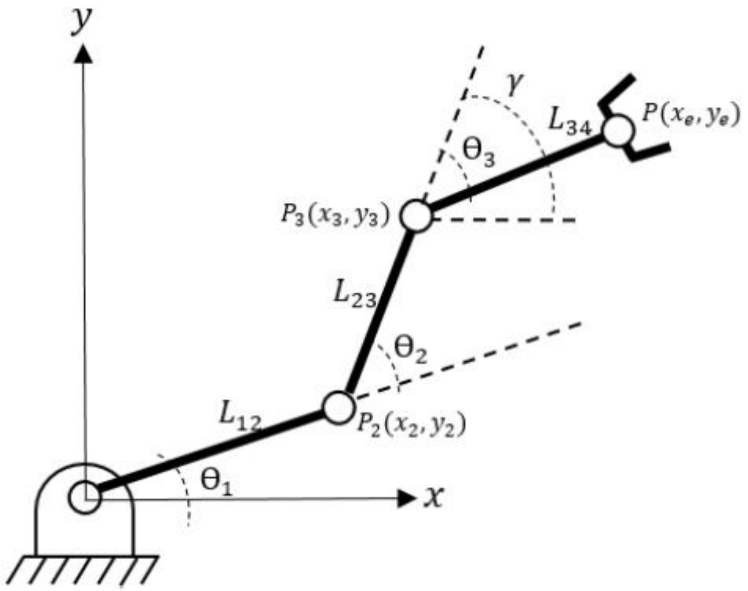

Figure 6: 2-D 3-link arm kinematics (Juecoree, 2021)

Methodology - Cont.

- Adaptive control
    - Define dynamics as linear combination of basis functions (ϕ) and weights (ω)

$$\hat{f}(x, \dot{x}) = \omega^T \phi(x, \dot{x})$$

    - By Lyapunov stability, gradient descent on the weights guarantees convergence of approximation
        - : learning rate
        - : error signal

$$\dot{\omega} = -\gamma s \phi(x, \dot{x})$$

- Neuromorphic structure
    - Learn decoders over a set of neurons

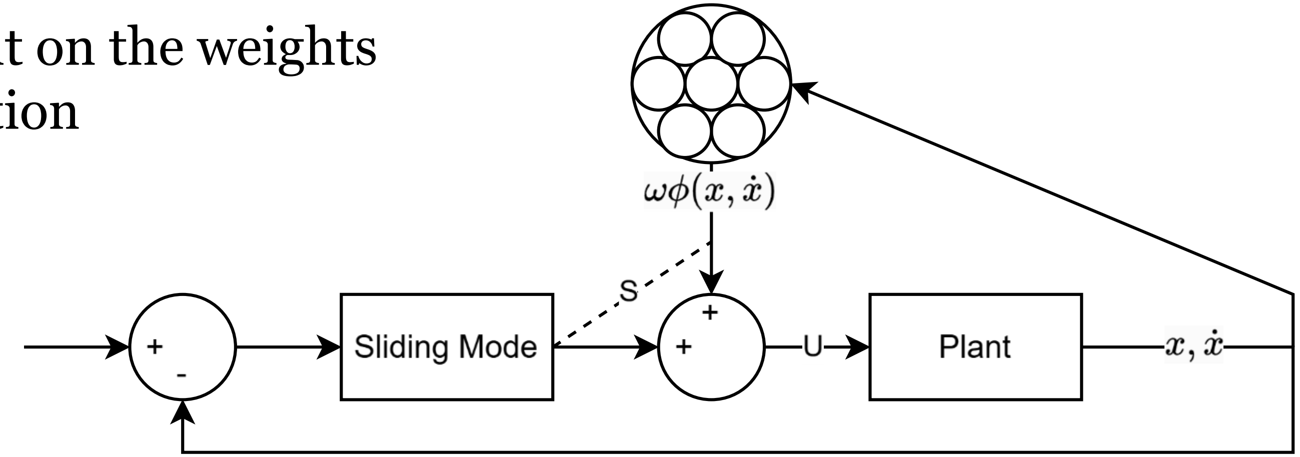

Figure 7: Control architecture block diagram with sliding mode control in parallel with the adaptive control network

Methodology - Cont.

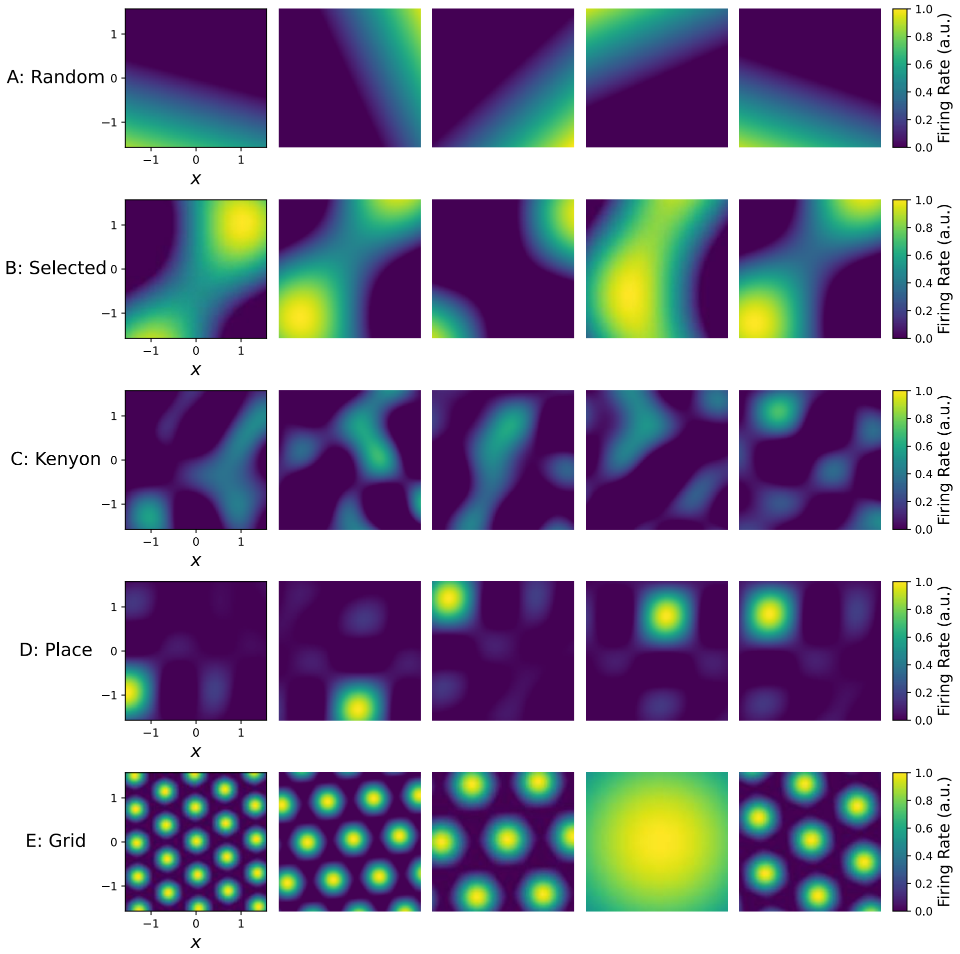

Figure 8: Examples of receptive fields of neurons in the hidden layer serving as the basis functions for the adaptive component

- 5 different representations of state space
- Previous baselines
  - Random
  - Selected
- Our proposed representations
  - Kenyon
  - Place
  - Grid

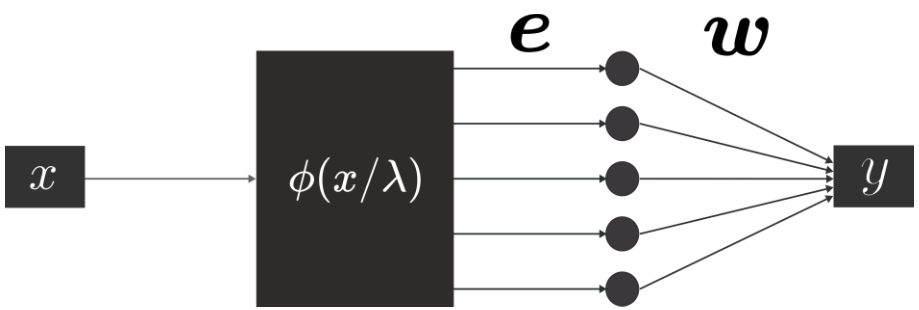

Figure 9: Architecture of the neural network providing the adaptive component of the controller, depicting the input x, SSP projection ϕ(x/λ), encoders e and weights ω

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Results and Discussion

- After hyperparameter tuning
- 2 tasks
- Place Cells had best performance in RMSE

	RMSE	
	Additional Mass Forcing	Cosine Forcing Function
Non-Adaptive	$2.568 * 10^{-2} \pm 0$	$5.679 * 10^{-2} \pm 0$
Random	$2.084 * 10^{-2} \pm 4.09 * 10^{-4}$	$4.290 * 10^{-2} \pm 1.28 * 10^{-3}$
Selected	$1.896 * 10^{-2} \pm 1.92 * 10^{-4}$	$3.684 * 10^{-2} \pm 0.26 * 10^{-3}$
Place	$\mathbf{1.539 * 10^{-2} \pm 7.26 * 10^{-4}}$	$\mathbf{2.939 * 10^{-2} \pm 0.87 * 10^{-3}}$
Grid	$1.932 * 10^{-2} \pm 1.02 * 10^{-4}$	$3.745 * 10^{-2} \pm 0.36 * 10^{-3}$
Kenyon	$2.358 * 10^{-2} \pm 2.24 * 10^{-4}$	$4.818 * 10^{-2} \pm 0.85 * 10^{-3}$

Table 1: Simulation results of different basis representations over two state-based disturbance tracking tasks

Results and Discussion – Cont.

- Circle reference
- Additional mass forcing
  - Turned on at 5s

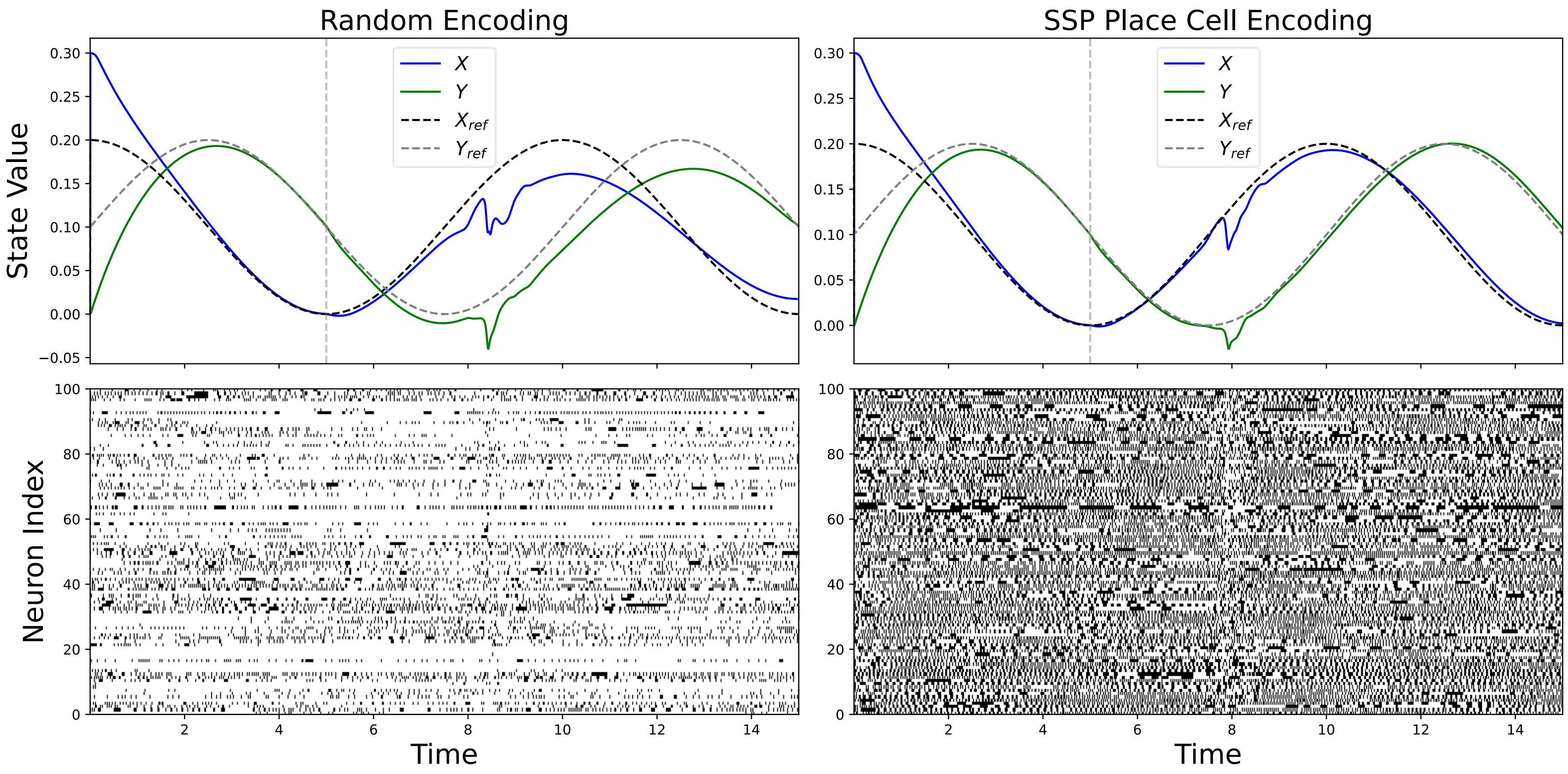

Figure 10: Sample trials of random and SSP place cell encoding of state space for circular tracking problem including mass disturbance. Both state values (Top) and neuron firing patterns (Bottom) are shown over time.

Conclusions

- Performance improvements
  - 1.23 – 1.25x over previous baseline
  - 1.67 – 1.93x over the non-adaptive

- Stability guarantees with given architecture
  - In parallel to sliding mode controller
  - Developed using spiking neurons with the NEF

- Place cell achieved highest performance
  - Through systematic comparison of biologically inspired basis functions

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