Symbolic computation in Spiking Neural Networks:

Spike-frequency adaptation enables cognitive computations

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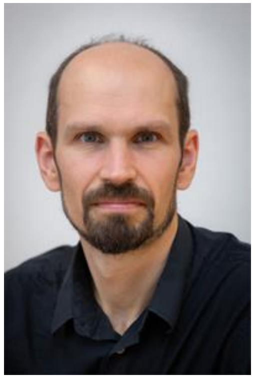



Darjan Salaj Anand Subramoney Guillaume Bellec Robert Legenstein Wolfgang Maass

D. Salaj, A. Subramoney, C. Kraišnikovic, G. Bellec, R. Legenstein, and W. Maass. [Spike-frequency adaptation provides a long short-term memory to networks of spiking neurons.] *bioRxiv*, 2020.

On symbolic computation

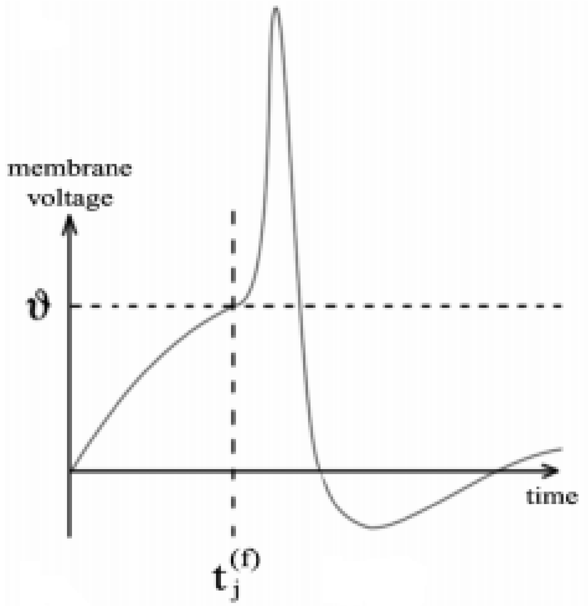
- “Symbolic computation” uses symbolic expressions.
  - Examples: x + y, instruction/rule, algorithm

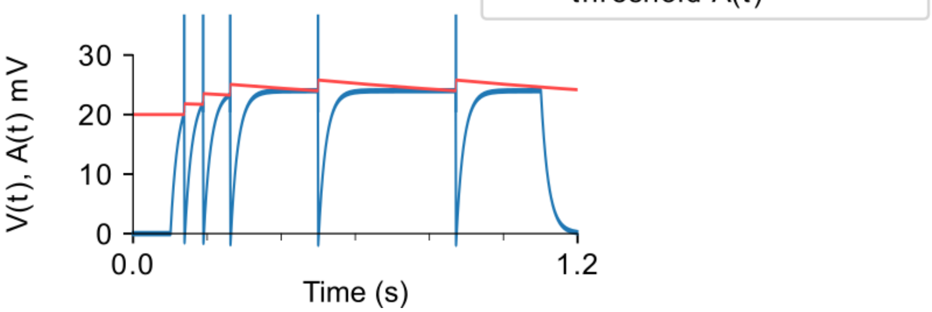
- Challenges for artificial neural networks:
  - Flexible cognitive control

    RED, GREEN, BLUE, PURPLE
  - Free generalization

    e.g., wug - wugged

Leaky Integrate-and-Fire neuron





LIF neurons are augmented with an adaptive threshold (**ALIF**).

Wulfram Gerstner and Werner Kistler. *Spiking Neuron Models: An Introduction*. Cambridge University Press, New York, NY, USA, 2002.

Allen Institute. Allen Cell Types Database Technical white paper: GLIF models. http://help.brainmap.org/download/attachments/8323525/glifmodels.pdf. Technical report, October 2017. v4.

12AX task

- First introduced in (O'Reilly and Frank, 2006)
- Input symbols: {1, 2, A, X, B, Y, C, Z}
- Output symbols: {L, R}

- Input: 1 … A [CZ] X … B ... Y
  Target: L … L … R … L … L

- Input: 2 … A … X … B [CZ] Y
  Target: L … L … L … L … R

- Performance: 97.79% fully correct episodes.

R. C. O'Reilly and M. J. Frank. Making working memory work: a computational model of learning in the prefrontal cortex and basal ganglia. Neural computation, 18(2):283-328, 2006.

Brain-like operations on sequences

- Input and output symbols: English alphabet
- Commands: DUPLICATE and REVERSE string

- An example input/output pair for DUPLICATE operation:

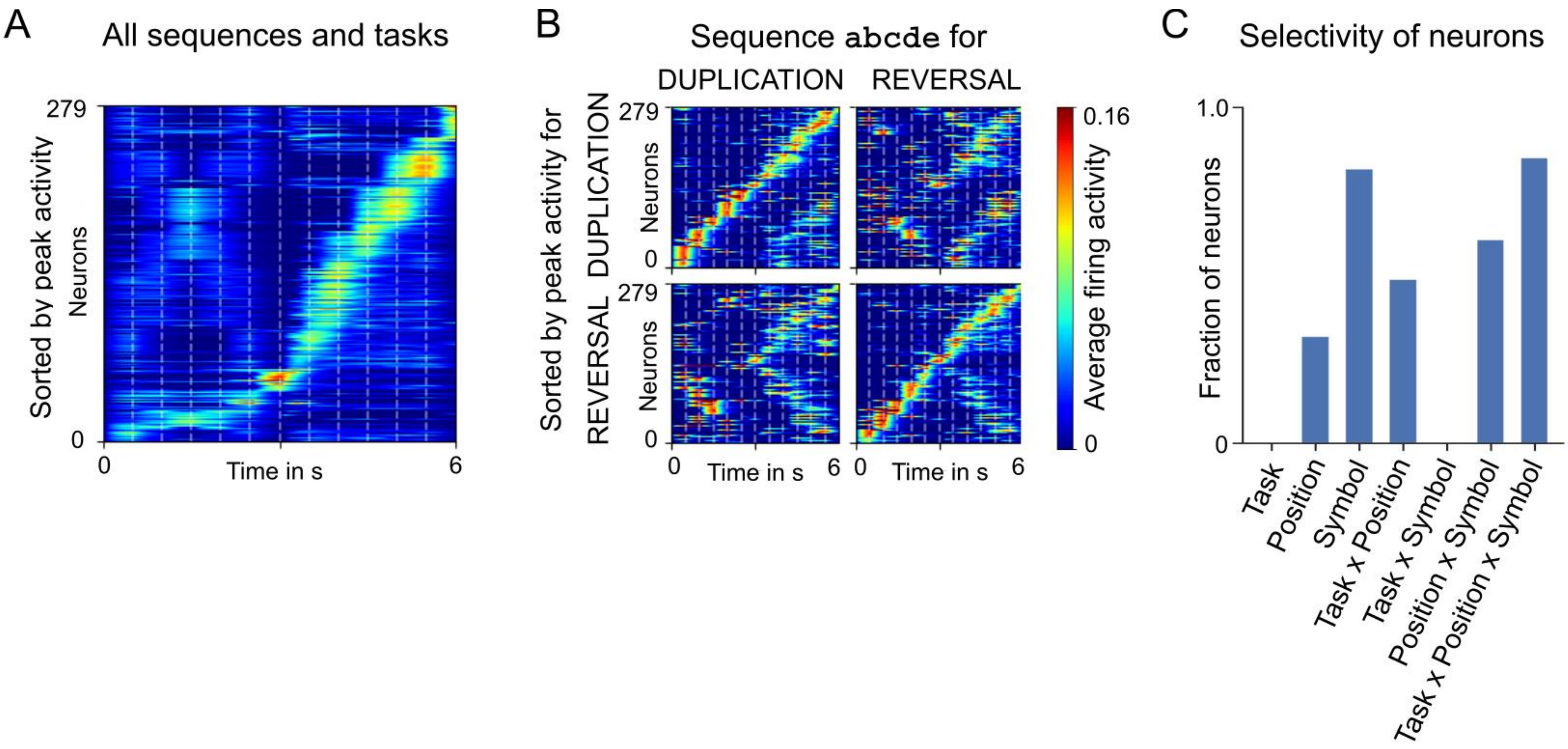
Input	a	b	c	x	y	*	?	?	?	?	?	?
Output							a	b	c	x	y	*

- An example input/output pair for REVERSE operation:

Input	a	b	c	x	y	*	?	?	?	?	?	?
Output							y	x	c	b	a	*

- Performance: 95.88% fully correct output strings, tested on previously unseen strings.

Emergence of neural codes



Thank you for your attention!
Questions?

Neuron Model

LIF

$$\tau_m \frac{du}{dt} = -u(t) + RI(t)$$

$$I_i(t) = \sum_j w_{ij} \sum_f \alpha(t - t_j^{(f)})$$

$$\alpha(s) = A\, exp\left(-\frac{s}{\tau_s}\right)\Theta(s)$$

τ_m- membrane time constant,
$u(t)$ - membrane voltage,
$I(t)$ - current, w_{ij} - efficacy,
$t_j^{(f)}$- firing time of neuron j,
τ_s-time decay constant,
$\Theta(s)$ - Heaviside step function

Adaptive LIF

$$\tau_m \frac{du_j}{dt} = -u_j(t) + R_m I_j(t)$$

$$\tau_{a,j} \frac{db_j}{dt} = b_j^0 - b_j(t)$$

τ_m – membrane time constant
$\tau_{a,j}$ – adaptation time constant

In discrete time:

$$u_j(t+dt) = \alpha u_j(t) + (1-\alpha) R_m I_j(t) - b_j(t) z_j(t)$$

$$b_j(t+dt) = \rho_j b_j(t) + \left(1-\rho_j\right) z_j(t)$$

$$\alpha = exp\left(-\frac{dt}{\tau_m}\right)$$

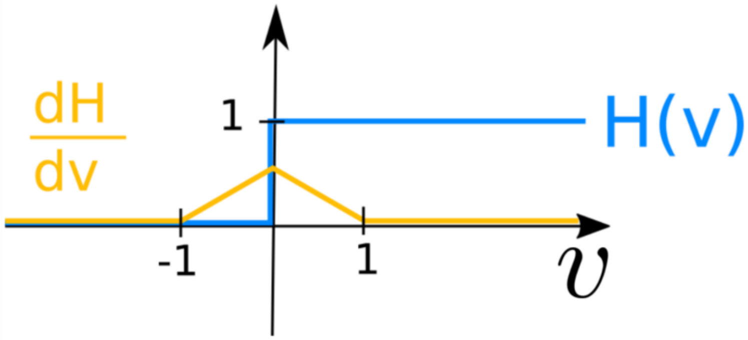
$$\rho_j = \exp\left(-\frac{dt}{\tau_{a,j}}\right)$$

Backpropagation Through Time (BPTT)

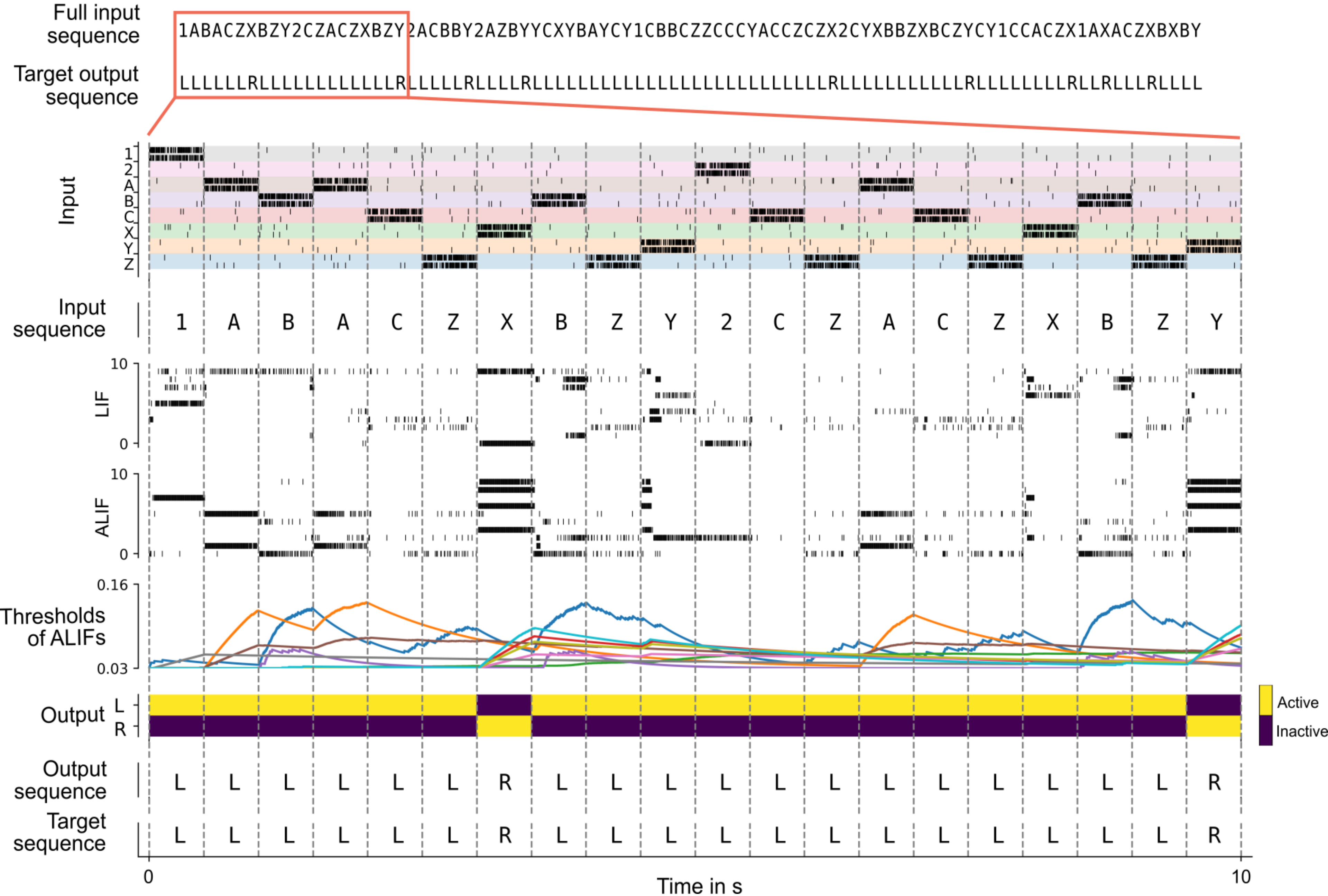
- BPTT is used to train RNNs.
  - Gradients are propagated through many steps.
- Outputs of spiking neurons are non-differentiable.
  - Dampened pseudo-derivative can be used instead.

$$\frac{dH}{dv} = \gamma \max\{0, 1 - |v|\},$$

v – normalized membrane potential, γ – dampening factor.



[G. Bellec, D. Salaj, A. Subramoney, R. Legenstein, and W. Maass. Long short-term memory and learning-to-learn in networks of spiking neurons. *32nd Conference on Neural Information Processing Systems (NIPS 2018), Montreal, Canada*, 2018.]



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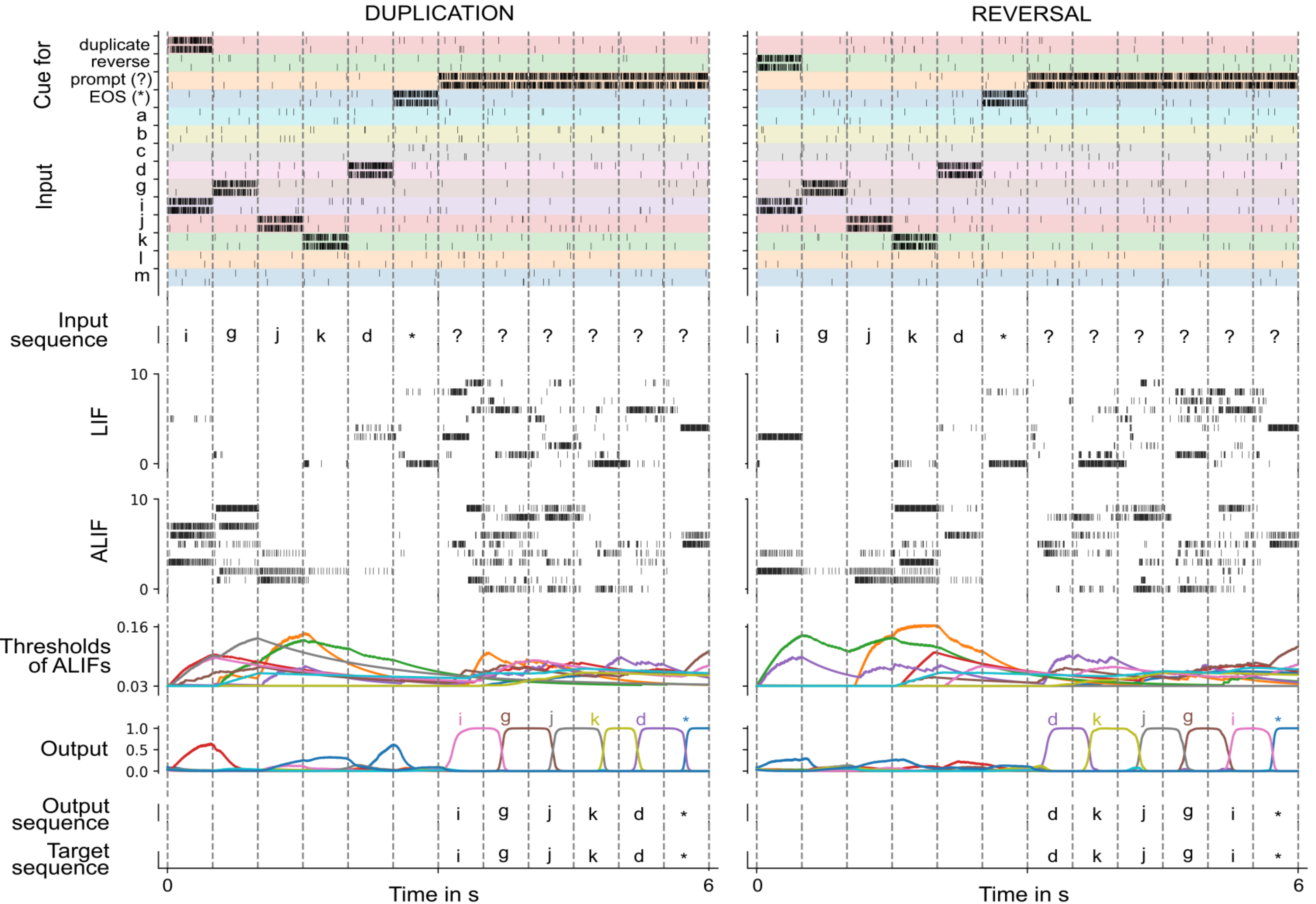

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