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Learning an inverse model for vocal production: toward a bio-inspired model

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Learning an inverse model for vocal production: toward a bio-inspired model

6th European Birdsong Meeting, April 12-13, 2018, Odense, Denmark

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(with Xavier Hinaut and Arthur Leblois)

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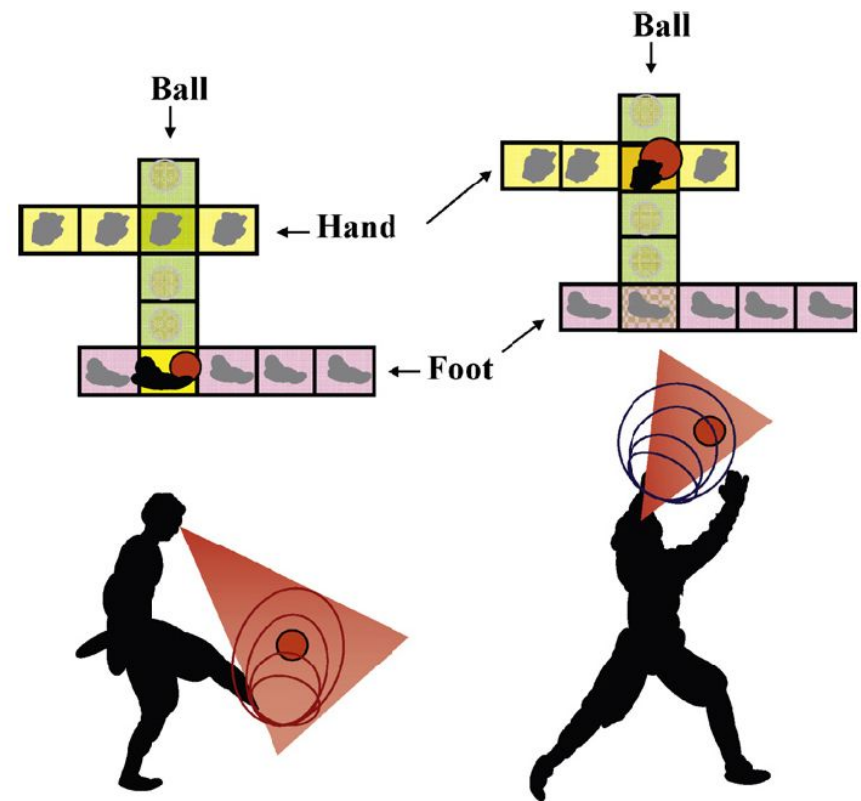


WHAT IS SENSORIMOTOR LEARNING?

Control problem which maps a sensory input into a motor output

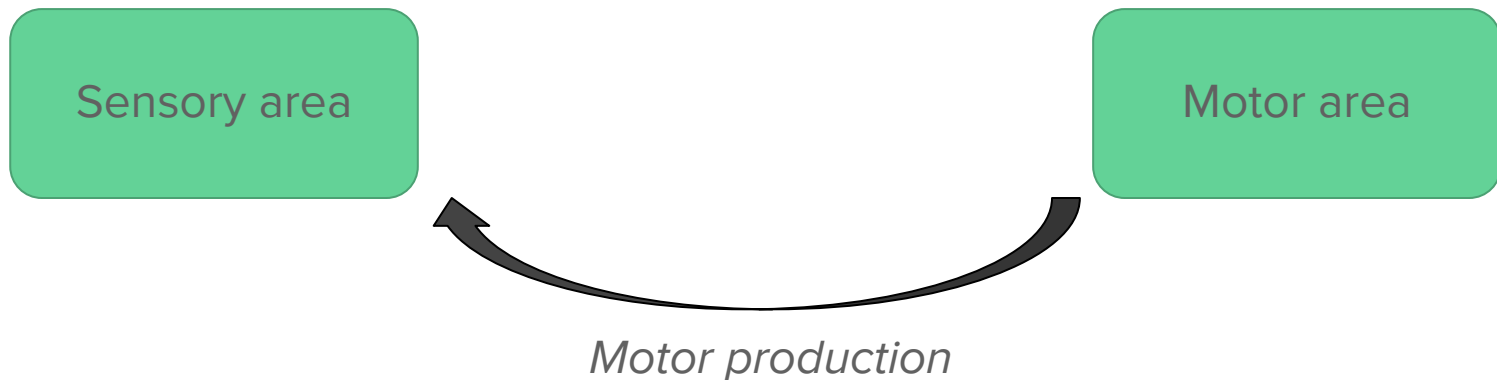
Basic components:

- Input: sensory stimulus
- Output: reproduction of the stimulus



LEARNING BY IMITATION AND INVERSE MODEL

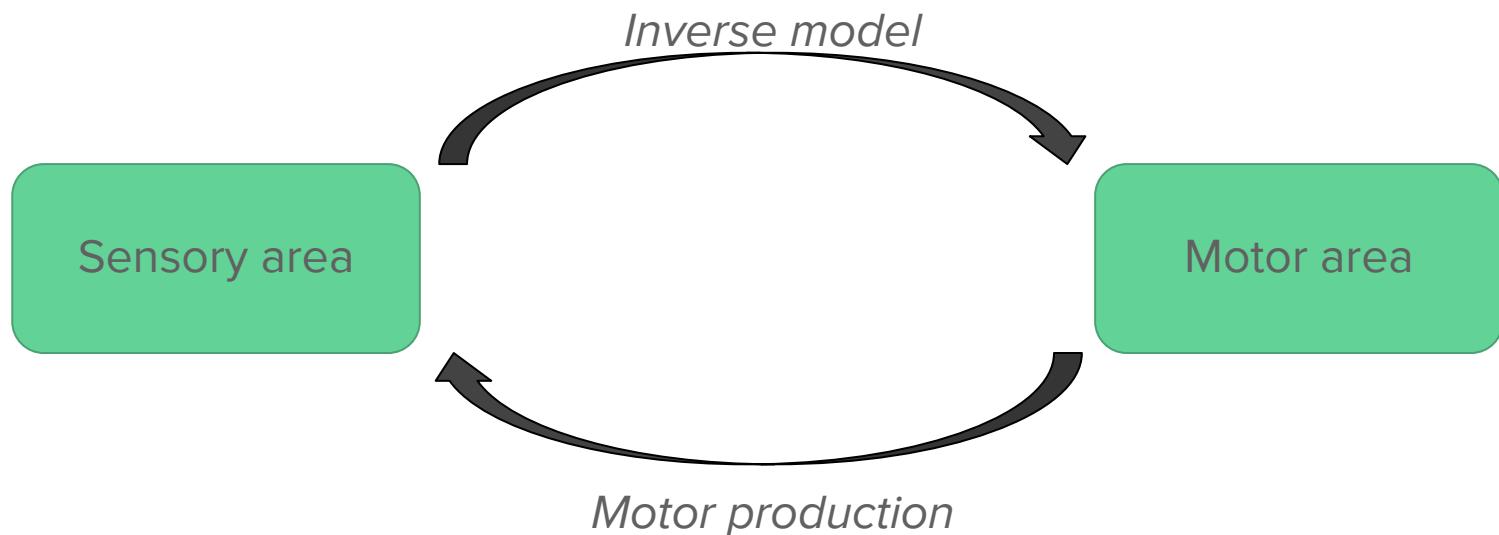
Imitation: learning from a tutor using a feedback guided error



LEARNING BY IMITATION AND INVERSE MODEL

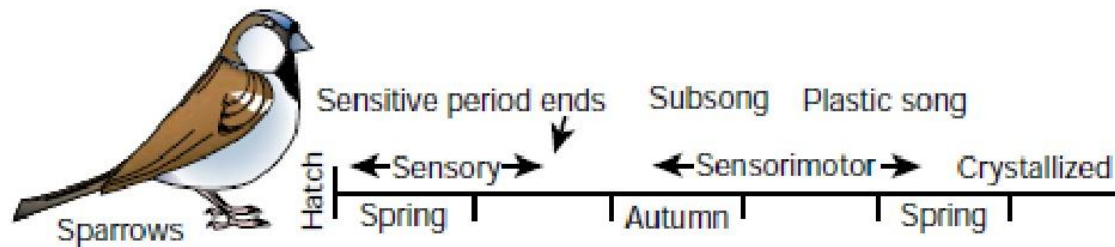
Imitation: learning from a tutor using a feedback guided error

Inverse model: the aim is to transform a sensory stimulus into the corresponding motor command



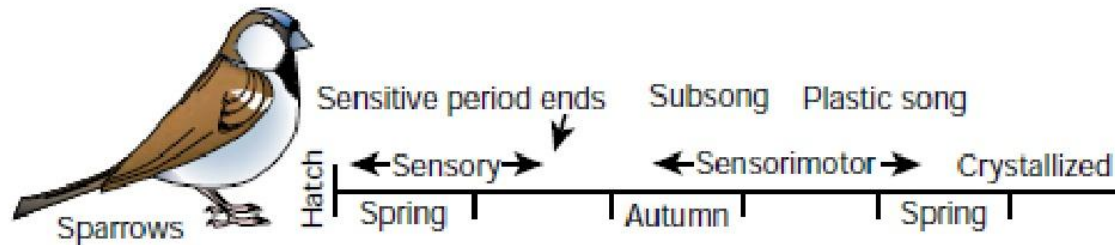
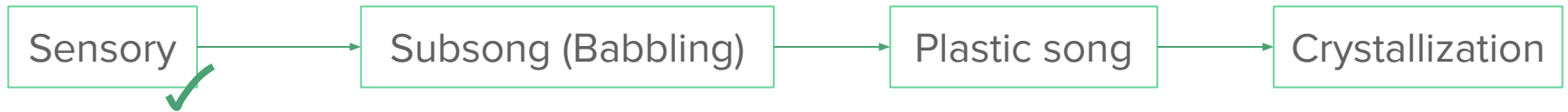
A BIOLOGICAL EXAMPLE: SONG LEARNING IN BIRDS

- Comparable learning mechanisms and behavior



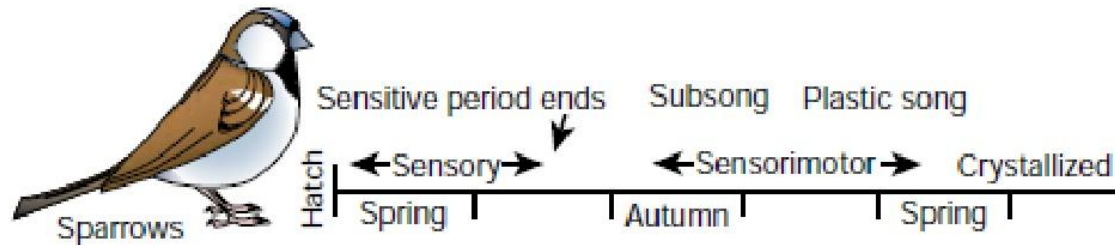
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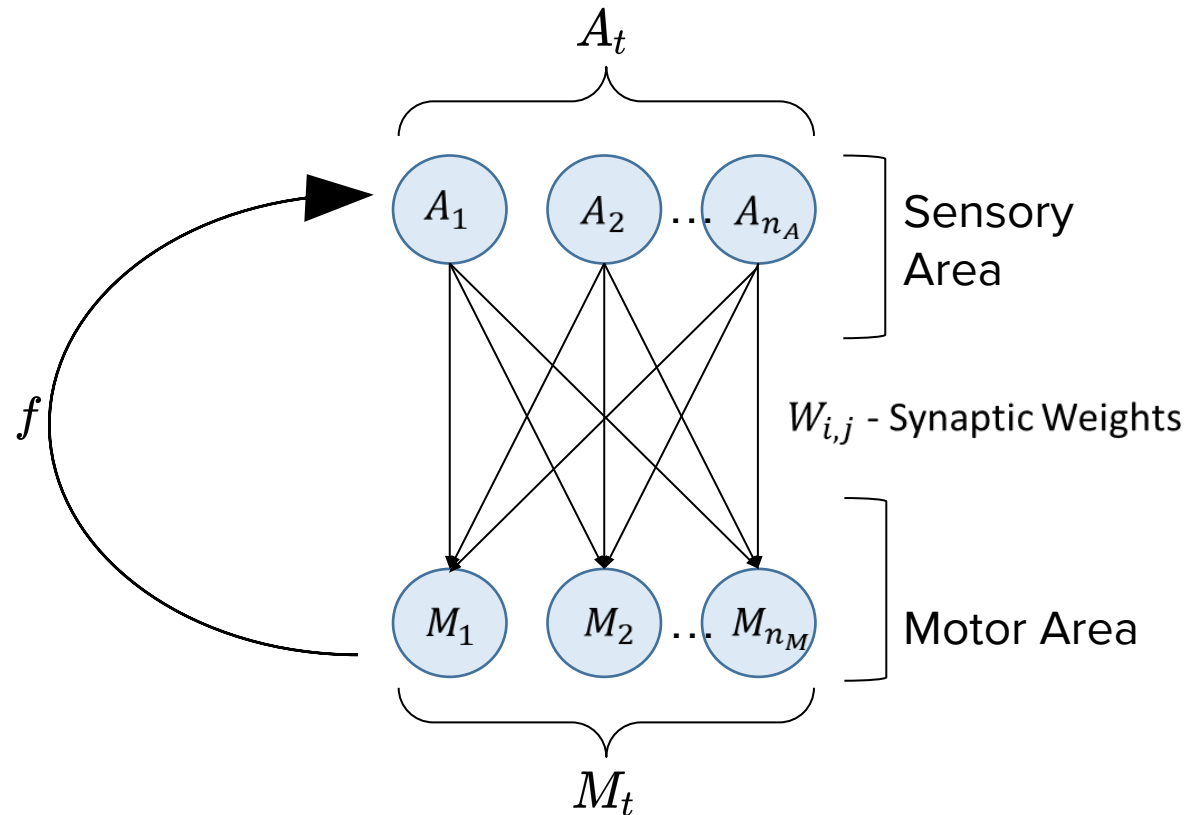
A BIOLOGICAL EXAMPLE: SONG LEARNING IN BIRDS

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LEARNING AN INVERSE MODEL

Synaptic weights $W_{t=t_0}$ initially weak

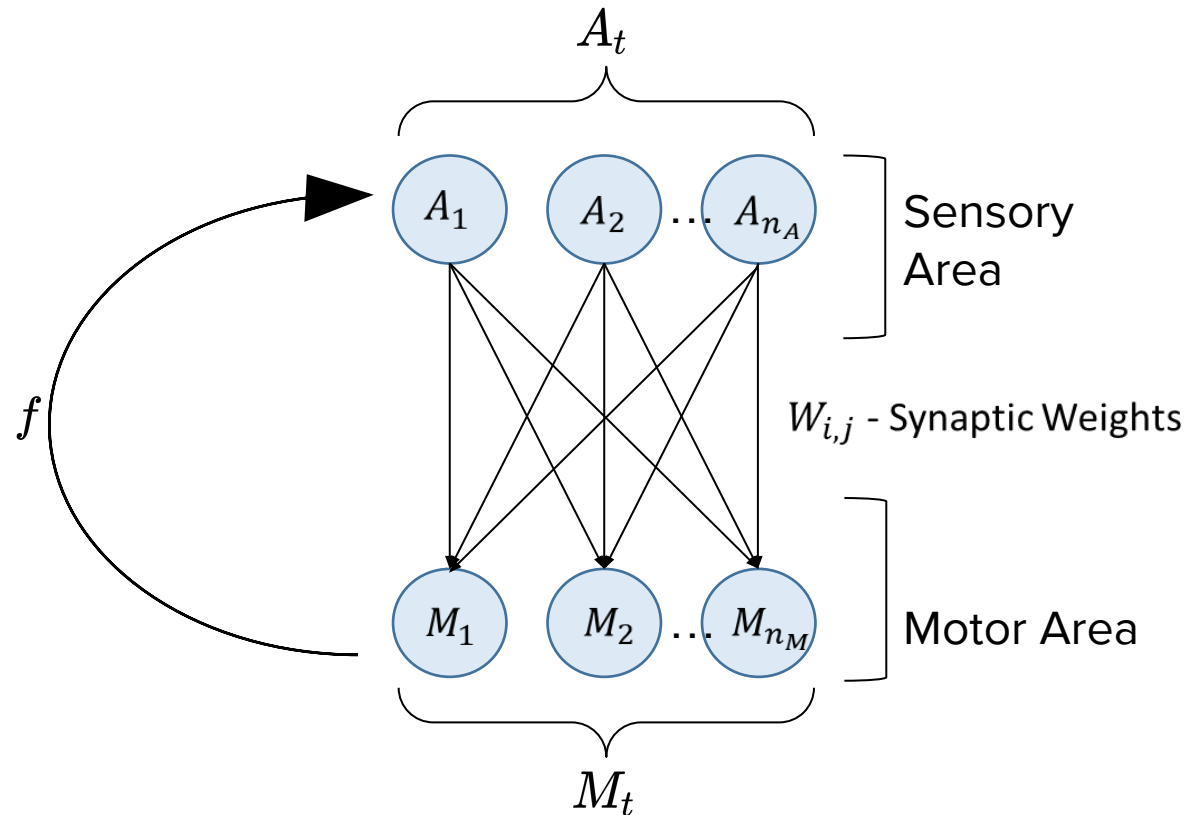


LEARNING AN INVERSE MODEL

Synaptic weights $W_{t=t_0}$ initially weak

At each time t :

- $A_t = f(M_t)$



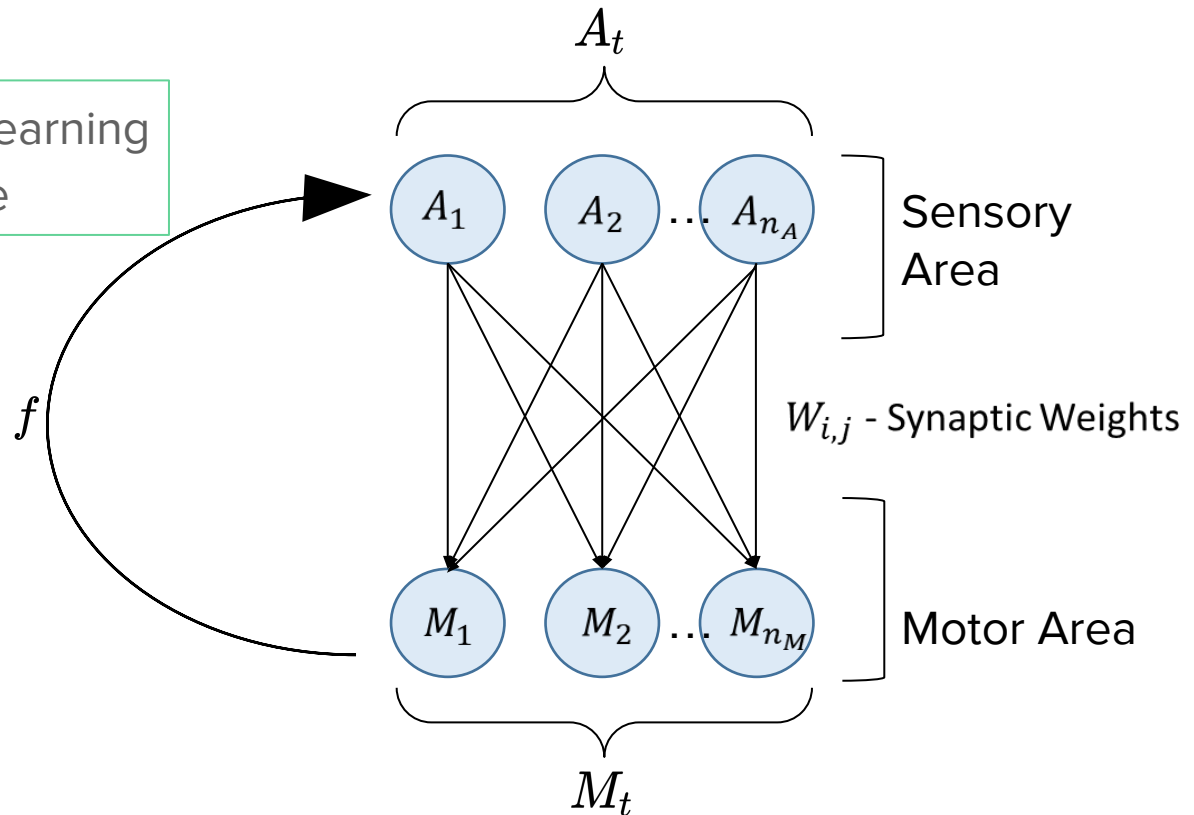
LEARNING AN INVERSE MODEL

Synaptic weights $W_{t=t_0}$ initially weak

At each time t :

- $A_t = f(M_t)$
- $\Delta W_t \propto \eta M_t A_t$

Hebbian learning rule



η : learning rate

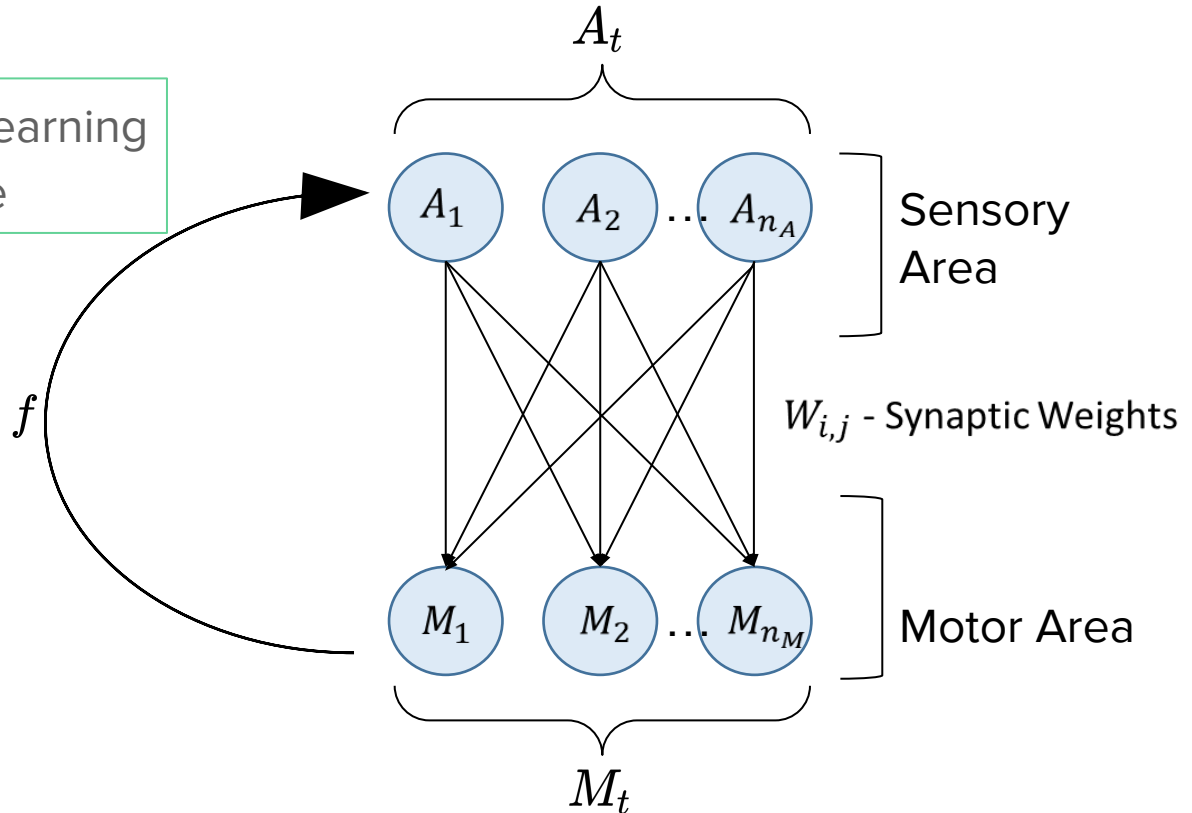
LEARNING AN INVERSE MODEL

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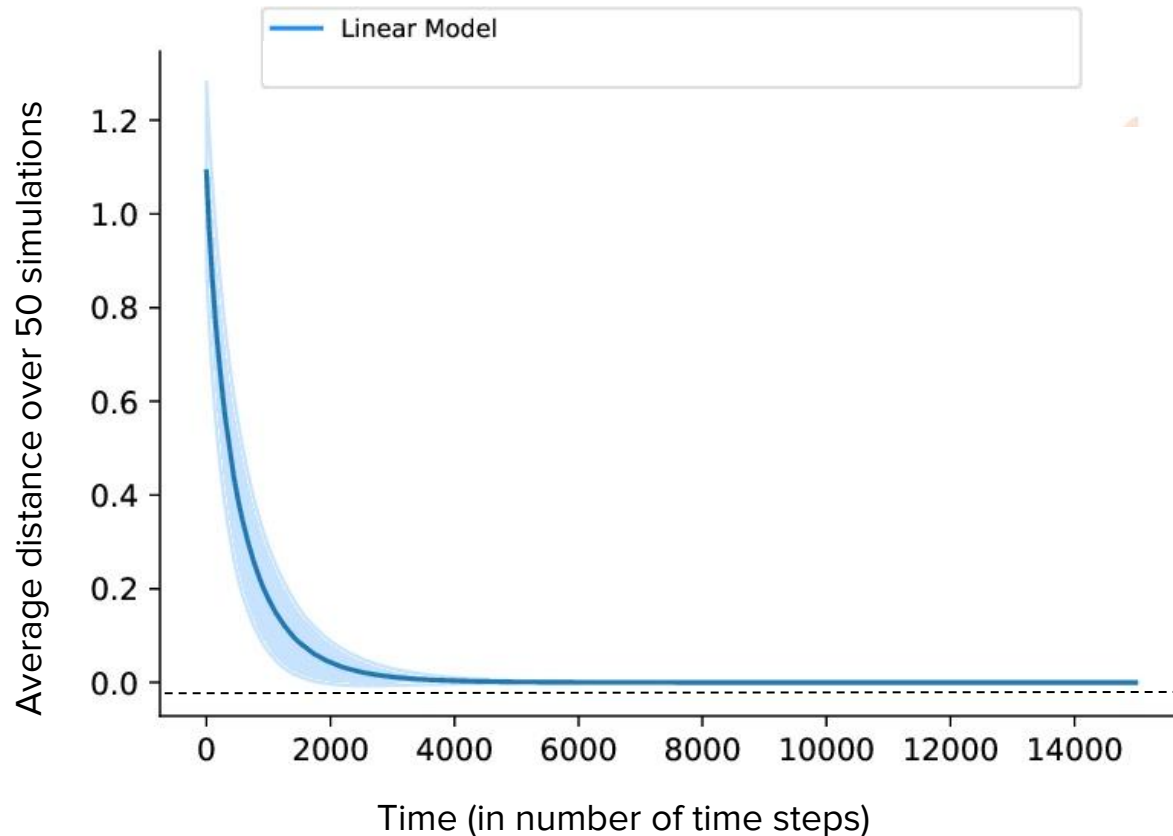
- $A_t = f(M_t)$
- $\Delta W_t \propto \eta M_t A_t$
- $W_t = W_{t-1} + \Delta W_t$

Hebbian learning rule



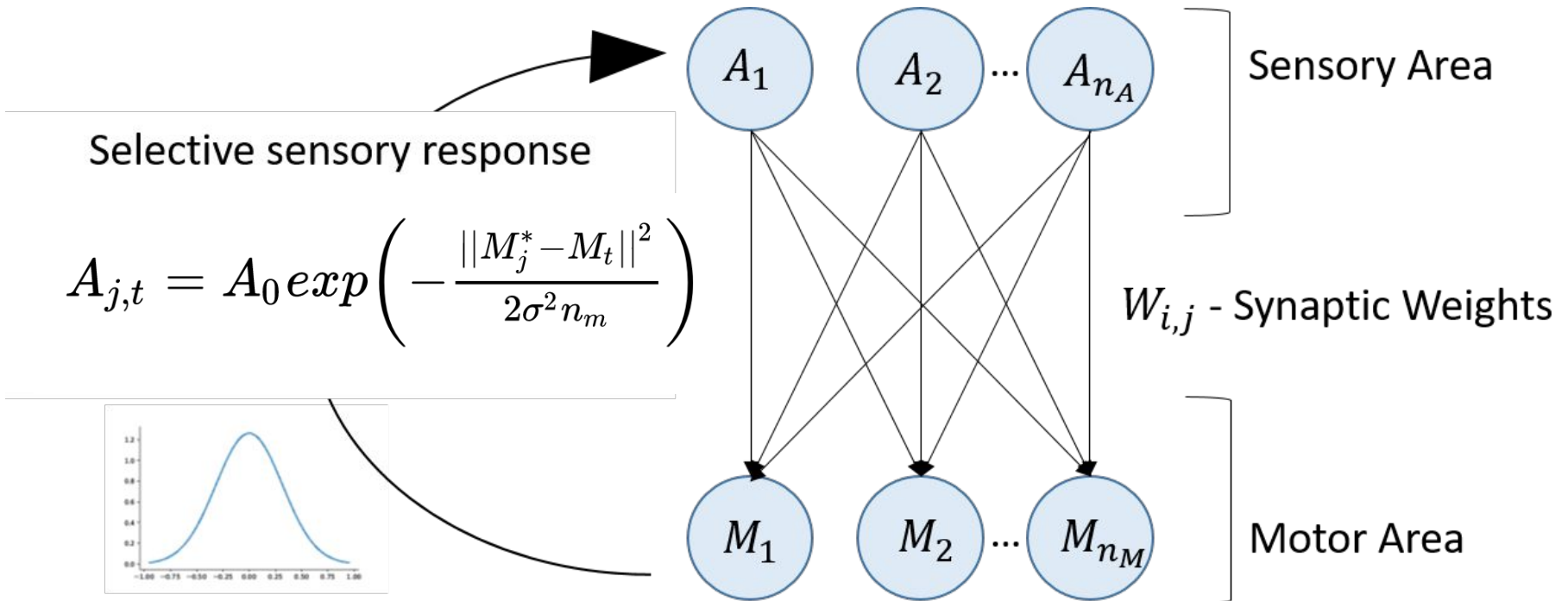
η : learning rate

HAHNLOSER-GANGULI THEORETICAL MODEL



$$\Delta W_t = \eta(M_t - W_{t-1} A_t) A_t^T$$

NONLINEAR MODEL INTRODUCTION

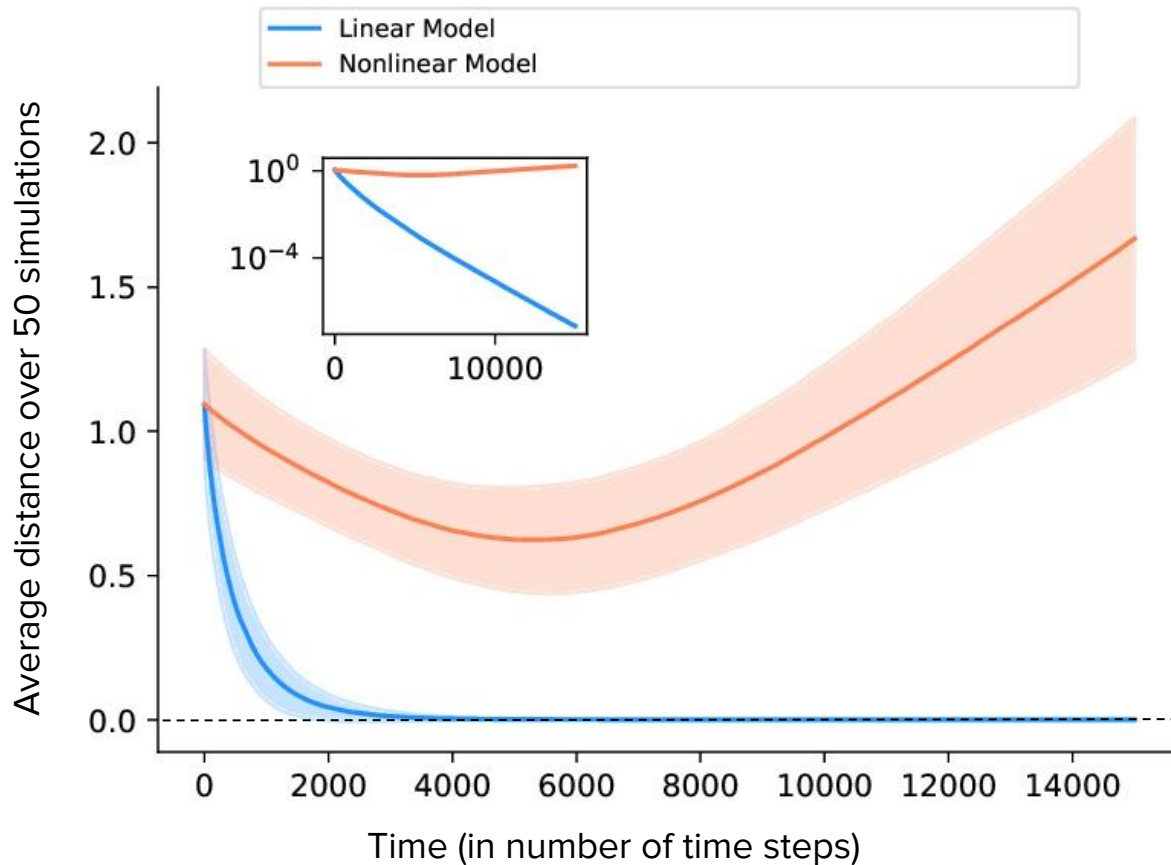


M^* : target motor pattern

σ : tuning selectivity width

$\|M_j^* - M_t\|^2$ represents the distance between the target and the random exploration

GANGULI-HAHNLOSER MODEL



$$\Delta W_t = \eta(M_t - W_{t-1}A_t)A_t^T$$

NORMALIZATION

Synaptic weights have a maximal value, related to the number of synaptic receptors one neuron is able to produce.

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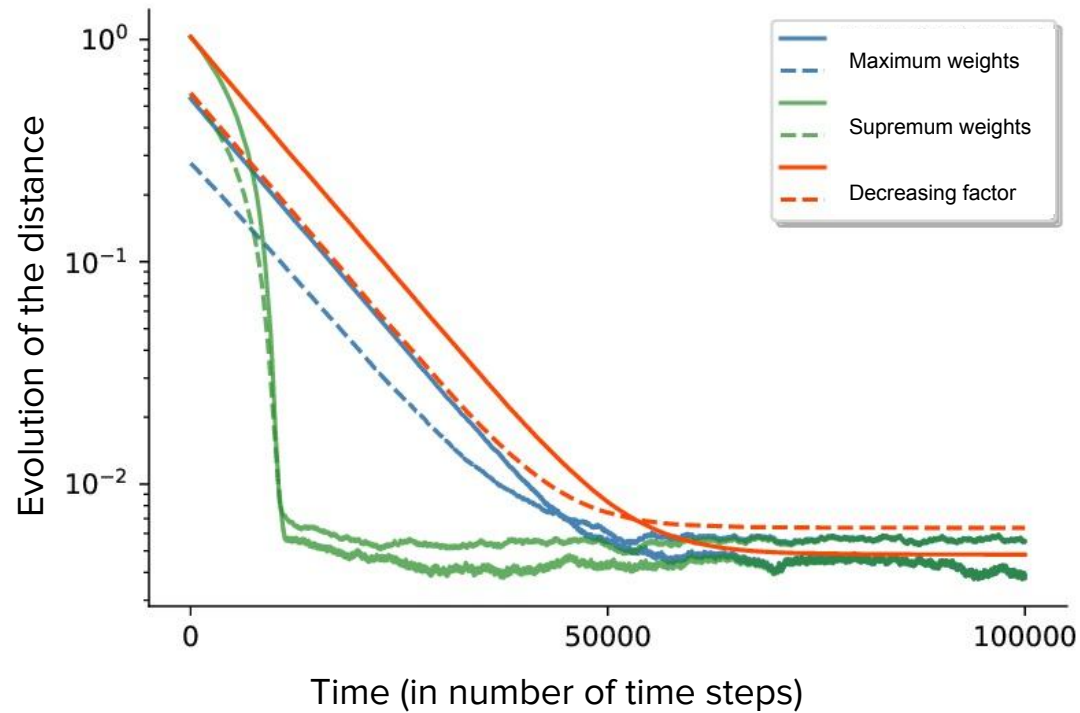
- Maximal weights normalization $W_{i,j} = \frac{W_{i,j}}{\langle W \rangle_{col}}$
- Supremum weights normalization $W_{i,j} = \begin{cases} W_{i,j} & \text{if } \langle W \rangle_{col} < 1 \\ \frac{W_{i,j}}{\langle W \rangle_{col}} & \text{otherwise} \end{cases}$

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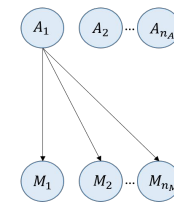
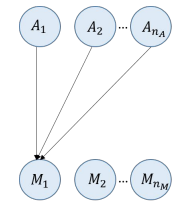
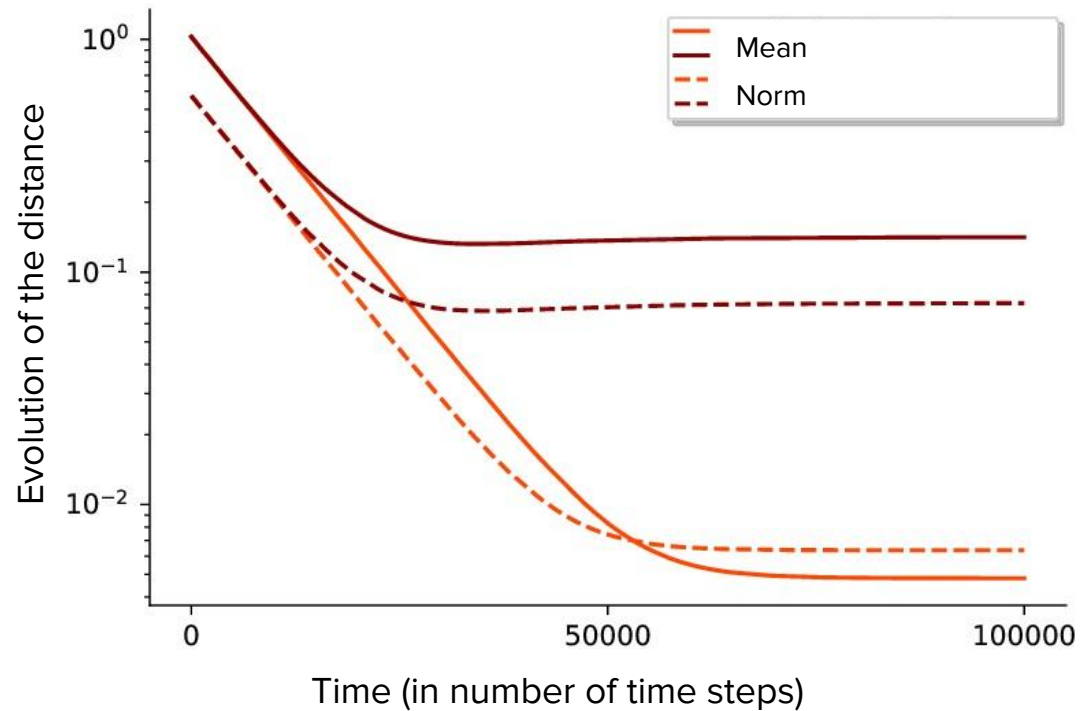
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- Decreasing factor normalization $\Delta W_{i,j} = \eta M_t A_t \left(1 - \langle W \rangle_{col} \right)$

NORMALIZED INVERSE MODEL



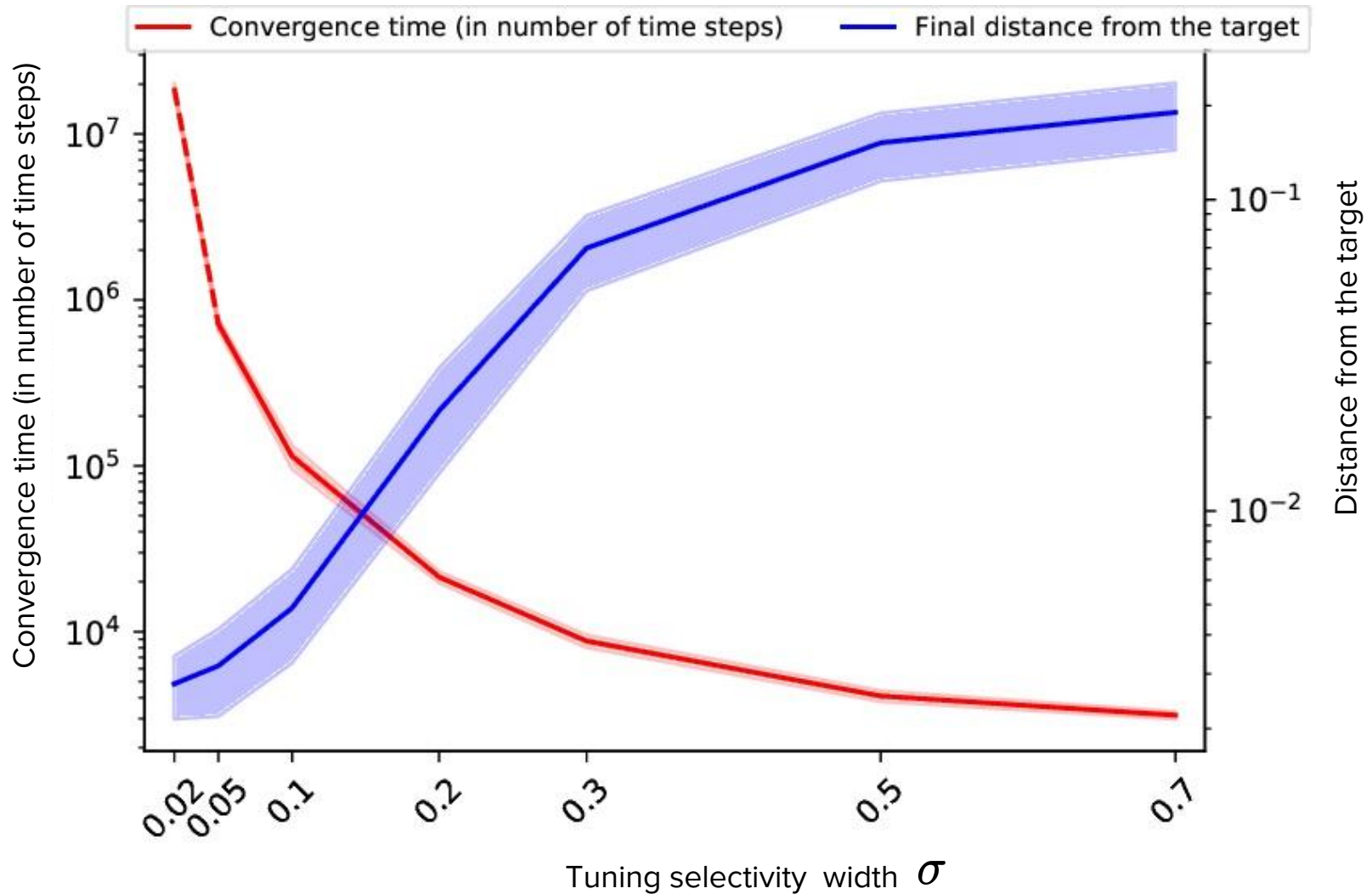
Normalization applied over the auditory neurons

NORMALIZED INVERSE MODEL

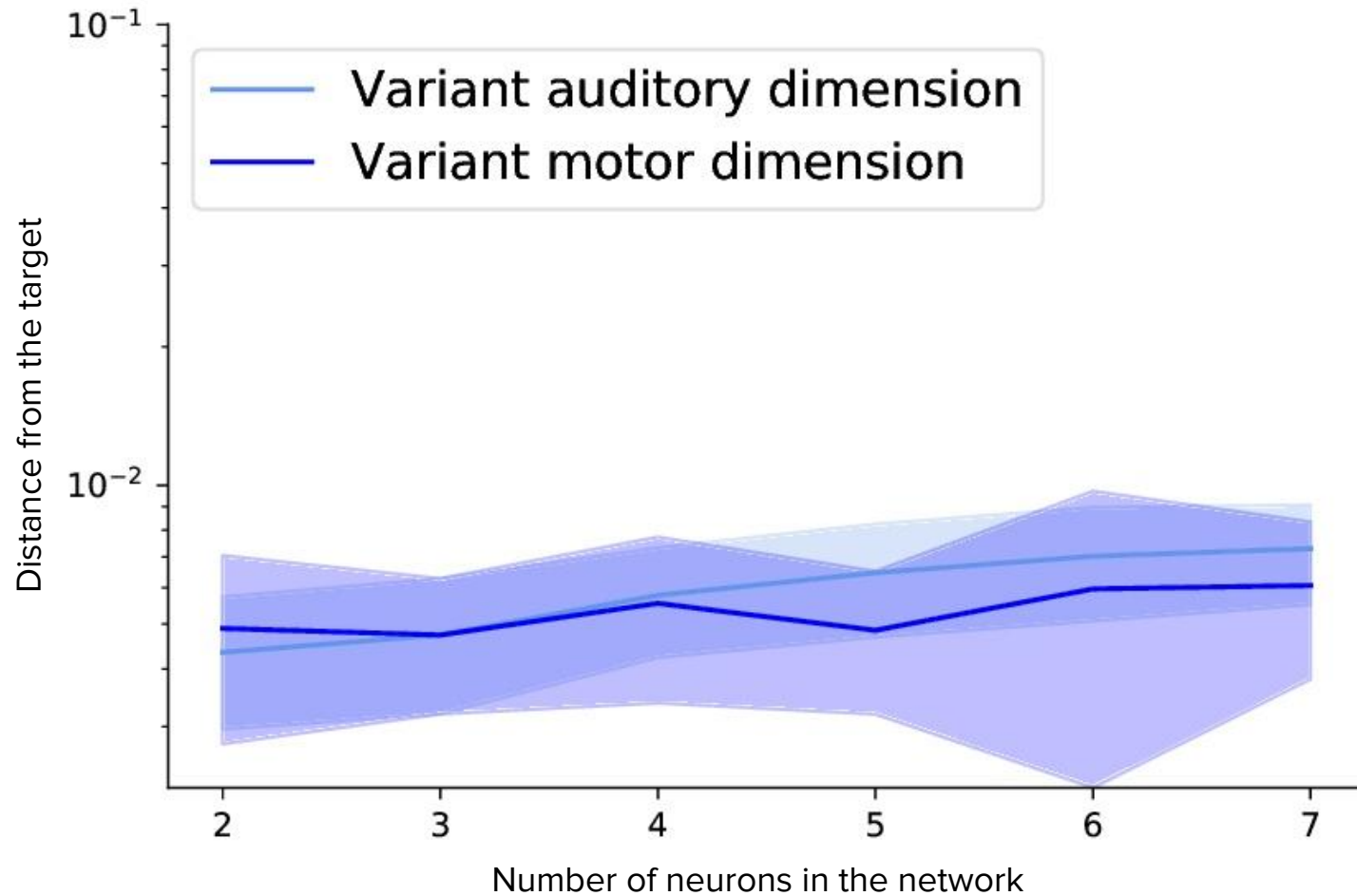


$$\Delta W_{i,j} = \eta M_t A_t \left(1 - \langle W \rangle_{col} \right)$$

AUDITORY SELECTIVITY EFFECT

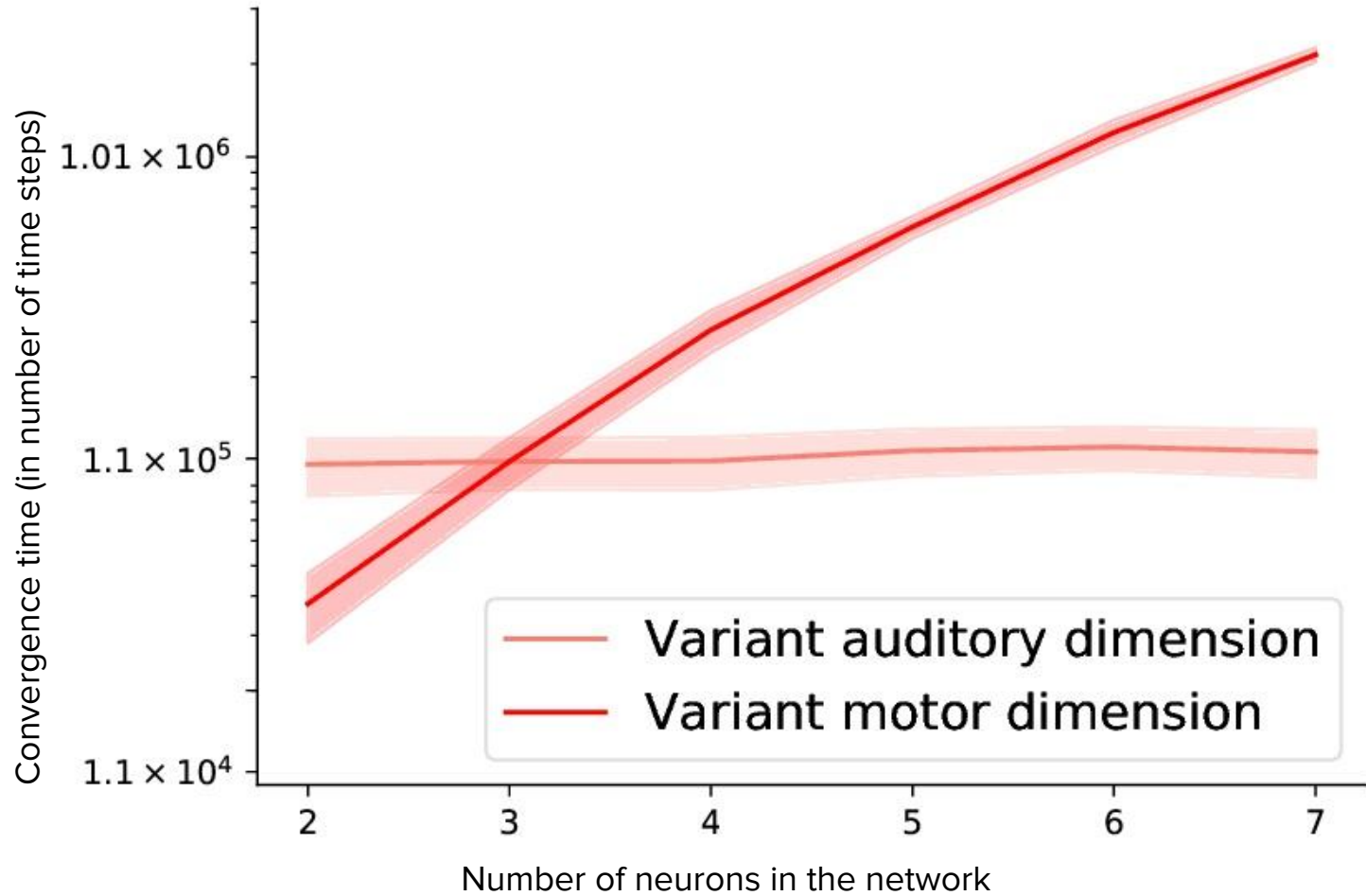


VARYING INPUT/OUTPUT DIMENSION



Distance from the motor target at convergence

VARYING INPUT/OUTPUT DIMENSION



Convergence time

SUMMARY

- Simple normalization schema are successful in the nonlinear model
- Decreasing tuning selectivity width:
 - convergence time explosion
 - accuracy of learning increases
- Auditory VS motor dimension

WHAT'S NEXT?

- Duration of syllable and feedback delay

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- Duration of syllable and feedback delay
- Production of sound

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- Production of sound

Enjoy the poster from
Xavier Hinaut



WHAT'S NEXT?

- Duration of syllable and feedback delay
- Production of sound
- Make prediction on experimental data

Enjoy the poster from
Xavier Hinaut



Thanks for the attention.

$$d_t = \frac{\|M^* - W_t A^*\|}{n_m}$$