Constraints on sequence processing speed in biological neuronal networks

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Introduction

Sequence processing (learning & prediction)

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- generation of a mismatch signal if prediction doesn’t match input

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  - artificial, adhoc connectivity constraints

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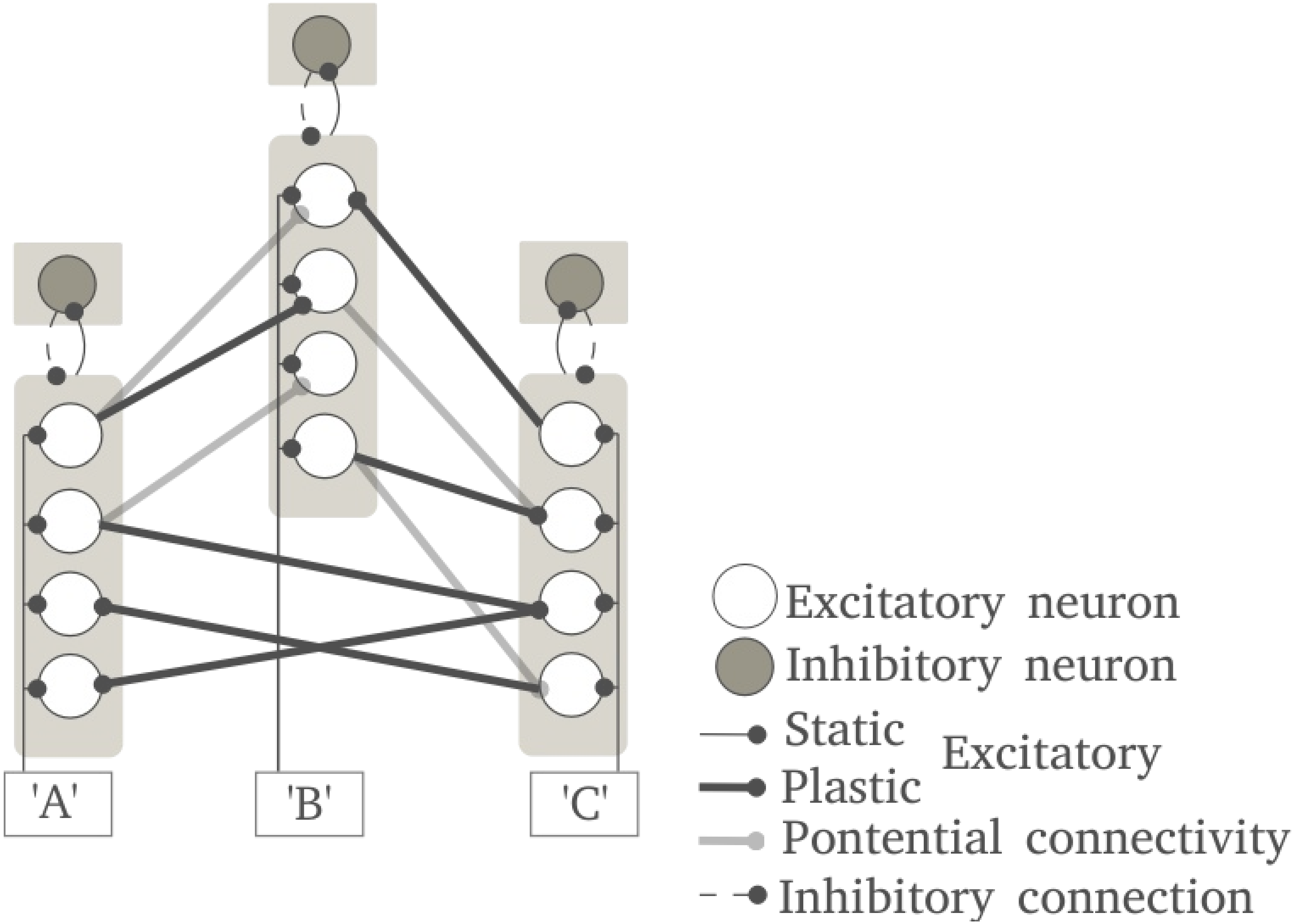
  - continuous time dynamics with spike based interaction between network elements, and
  - neuronal, synaptic and plasticity dynamics with realistic time constants [Avermann et al. 2012]

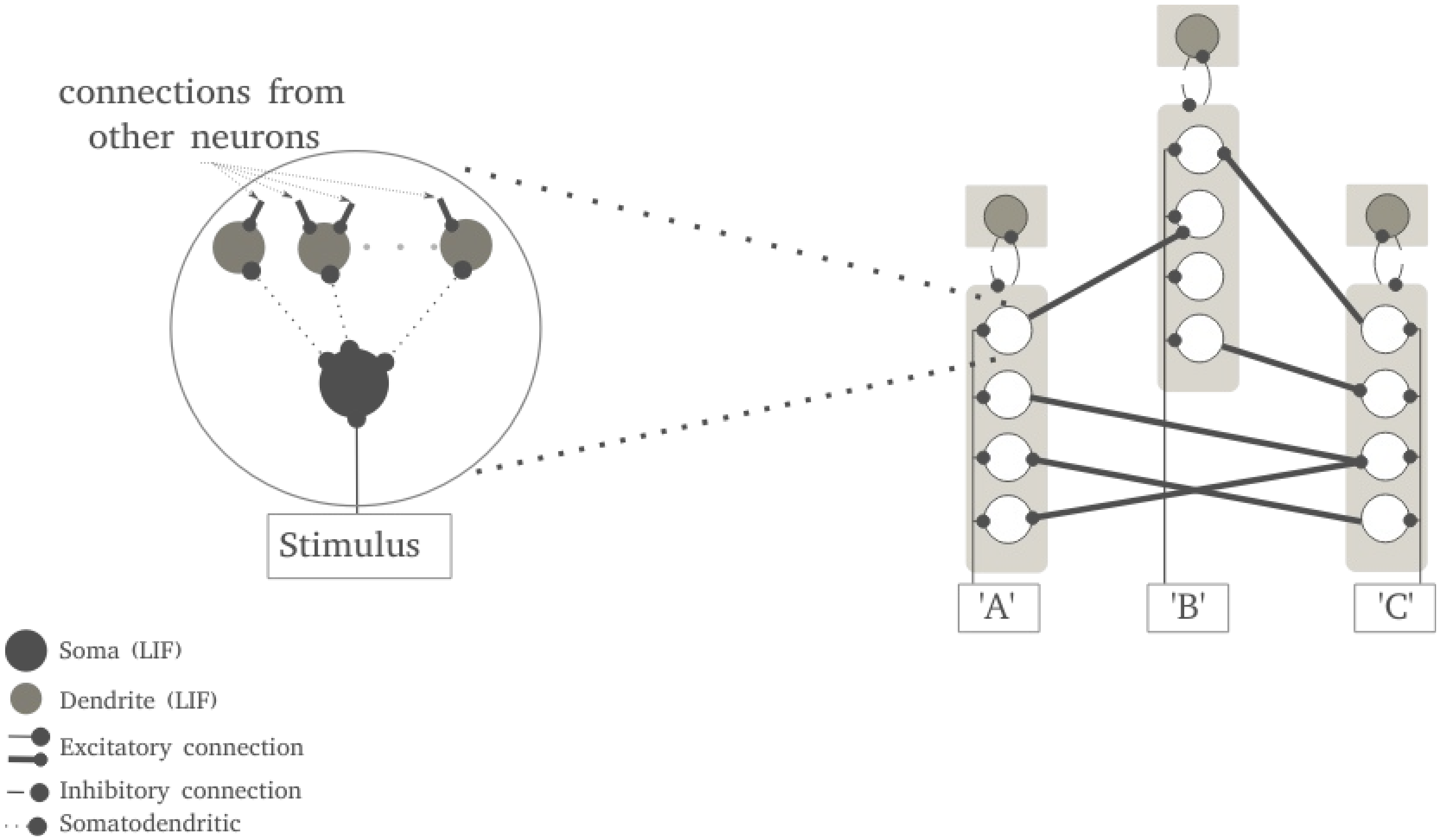
Model

Network



'A'
'B'
'C'
Excitatory neuron
Inhibitory neuron
Static
Plastic
Excitatory
Pontential connectivity
Inhibitory connection

Neurons


connections from other neurons
Stimulus
'A'
'B'
'C'
Soma (LIF)
Dendrite (LIF)
Excitatory connection
Inhibitory connection
Somatodendritic

Plasticity

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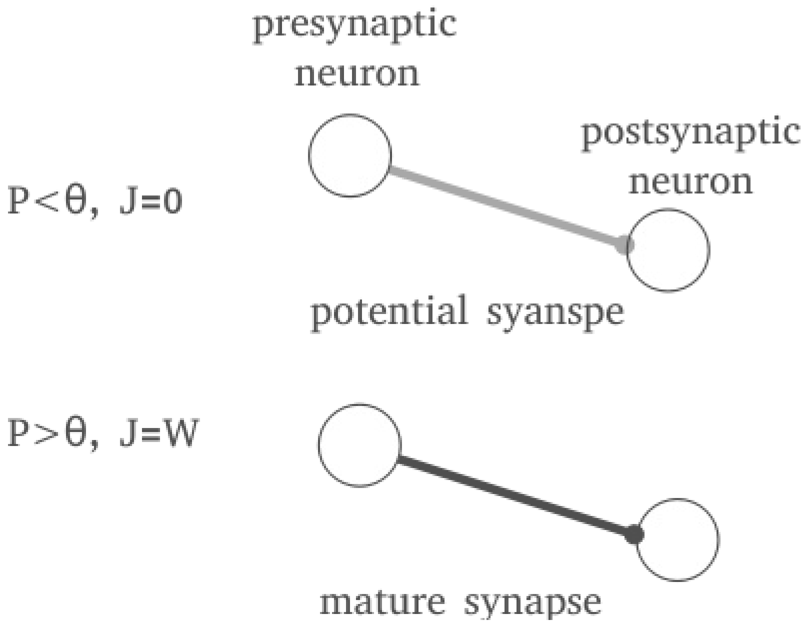

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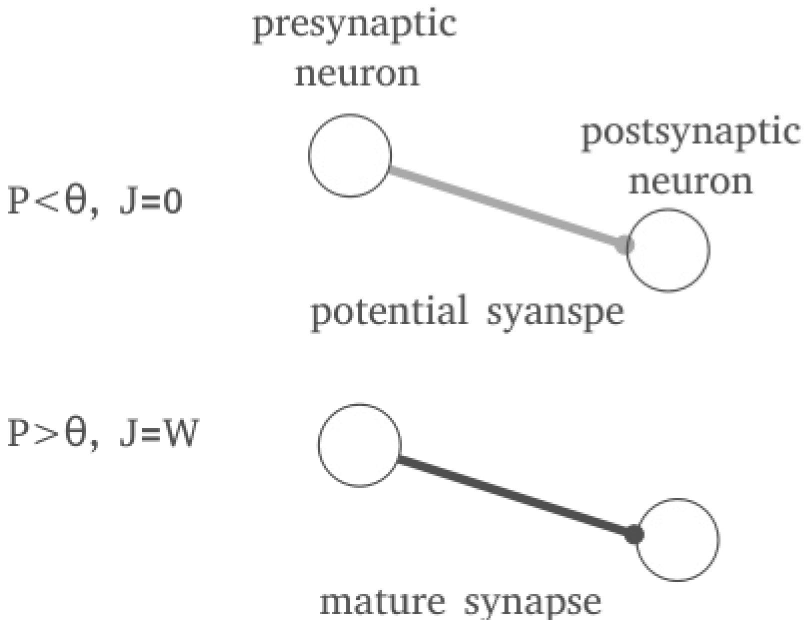
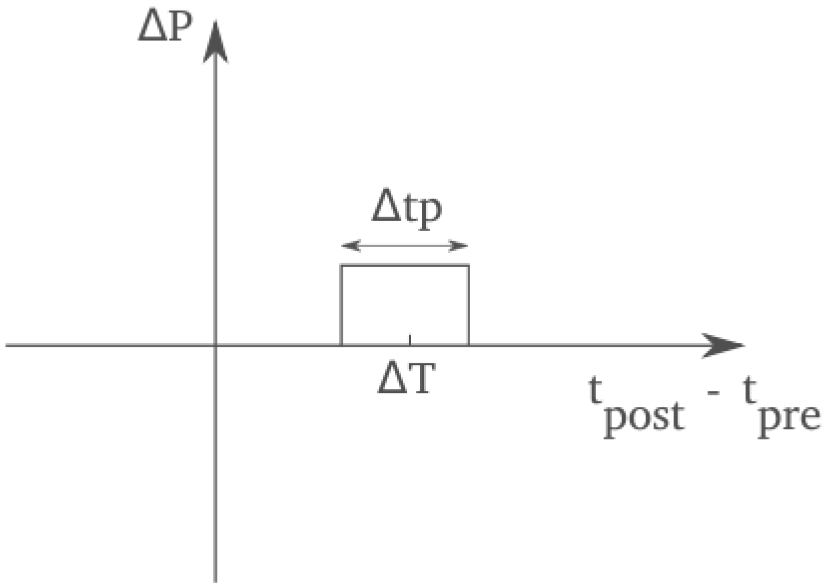
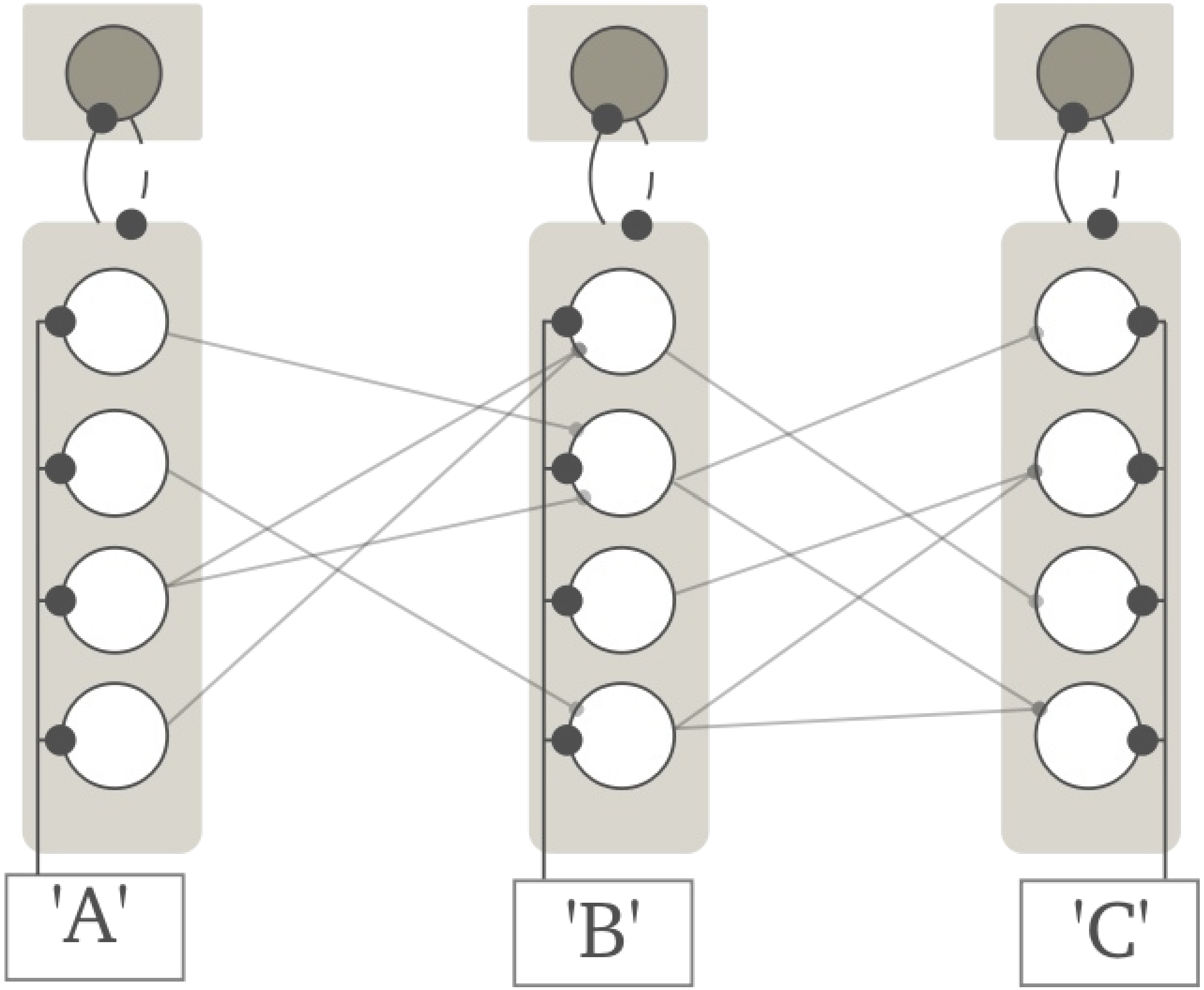




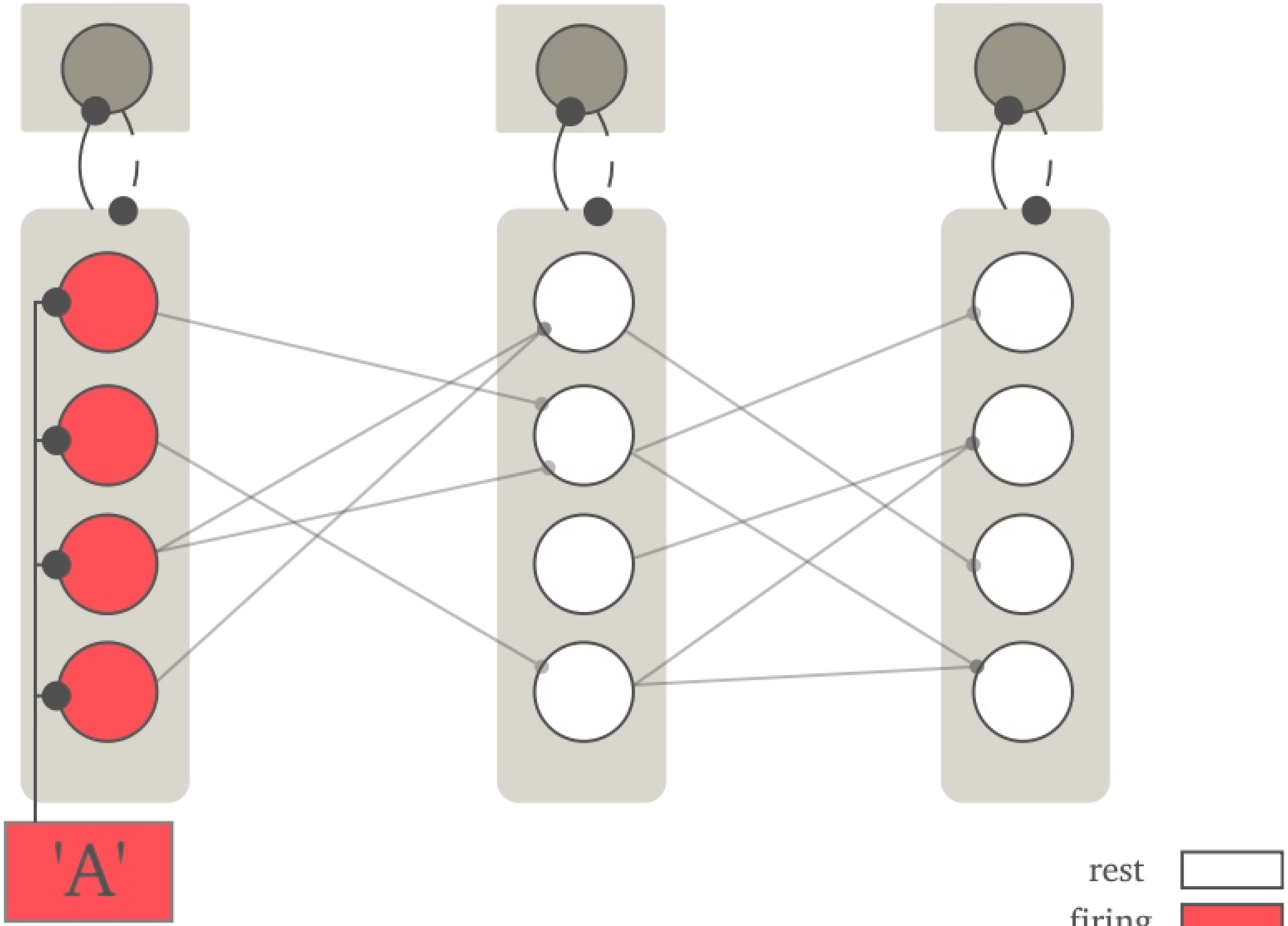
How the model learns sequence prediction?

Initialization

- sparse random connectivity between minicolumns
- random initial values of permanences



Before learning



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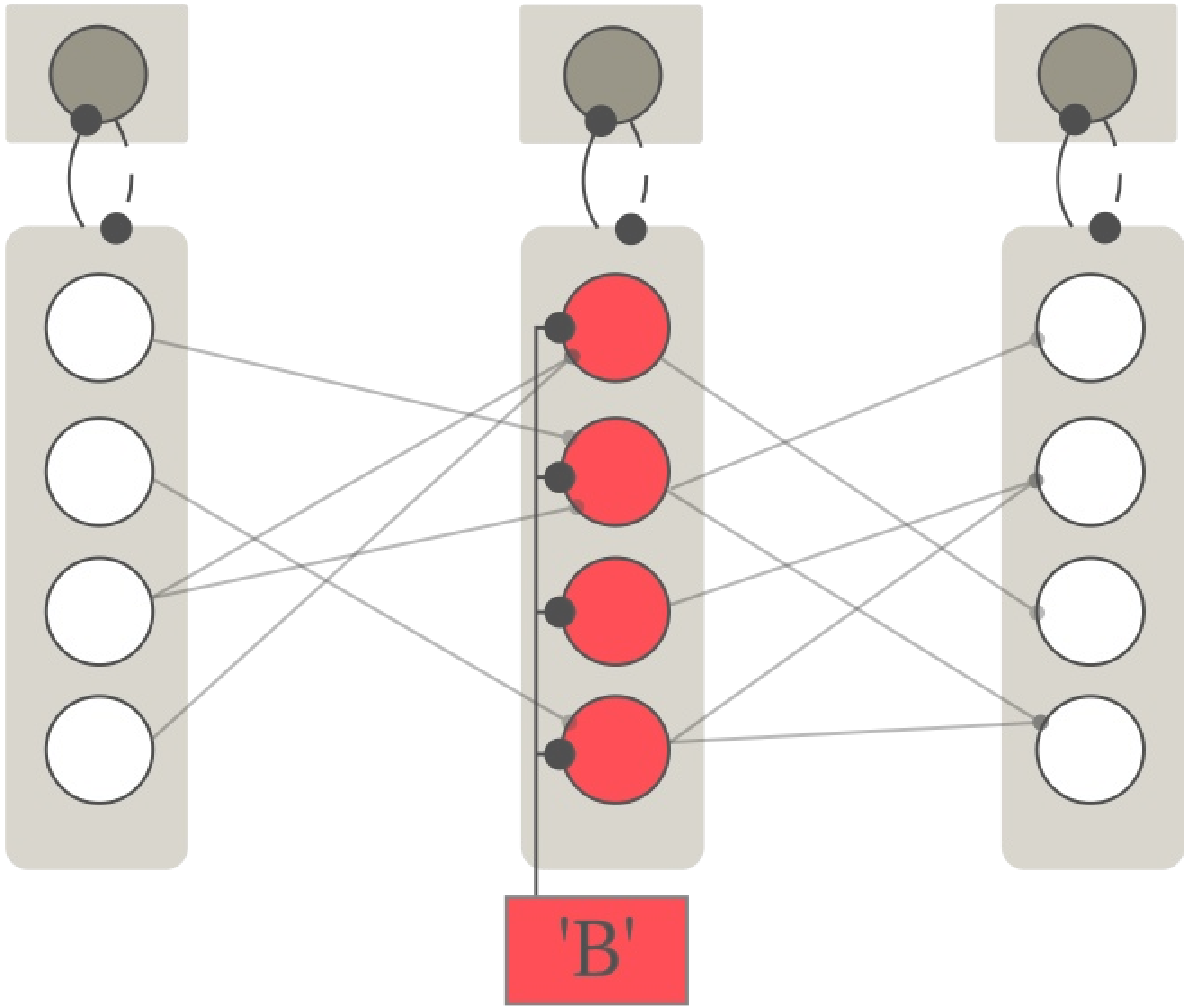

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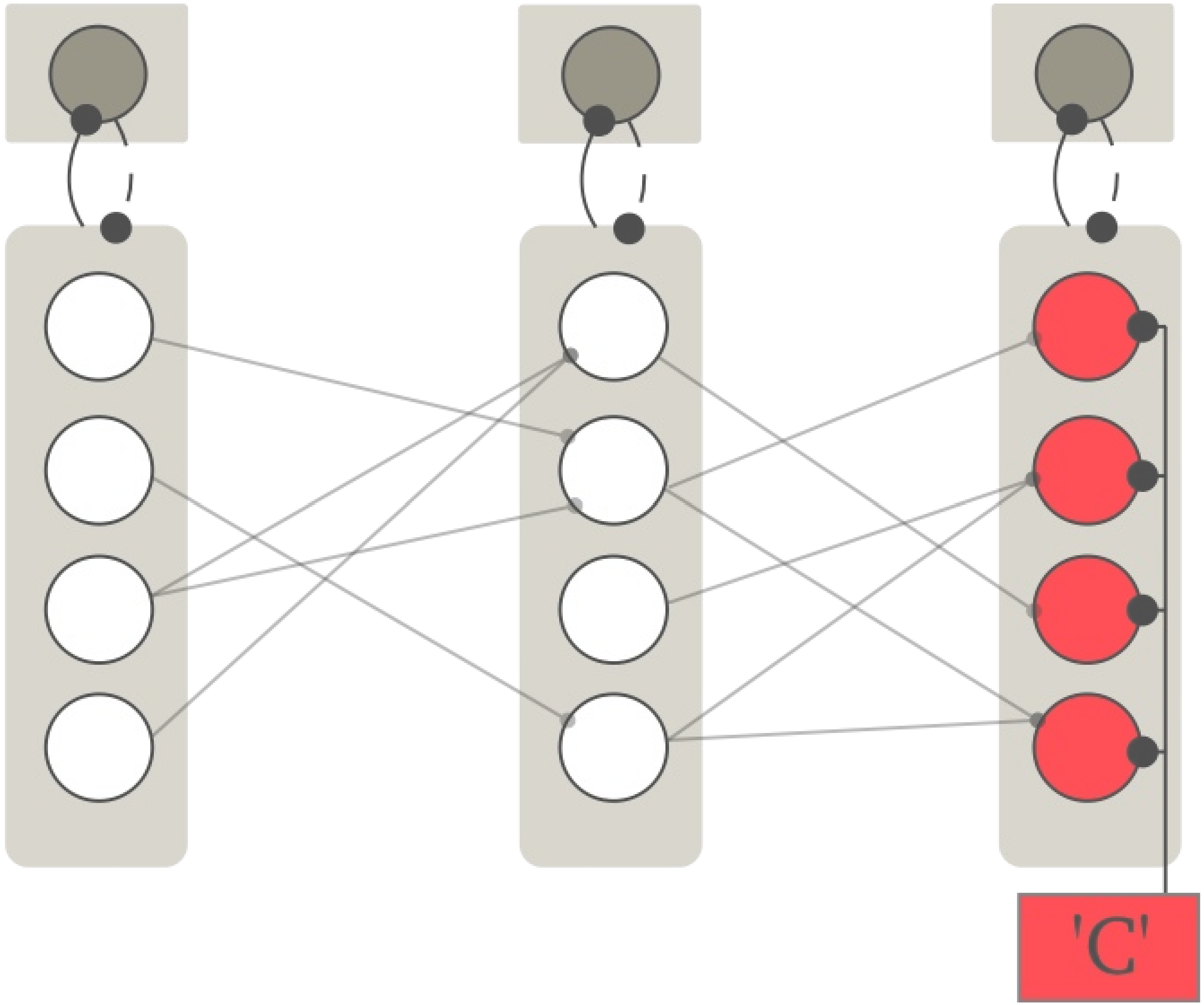
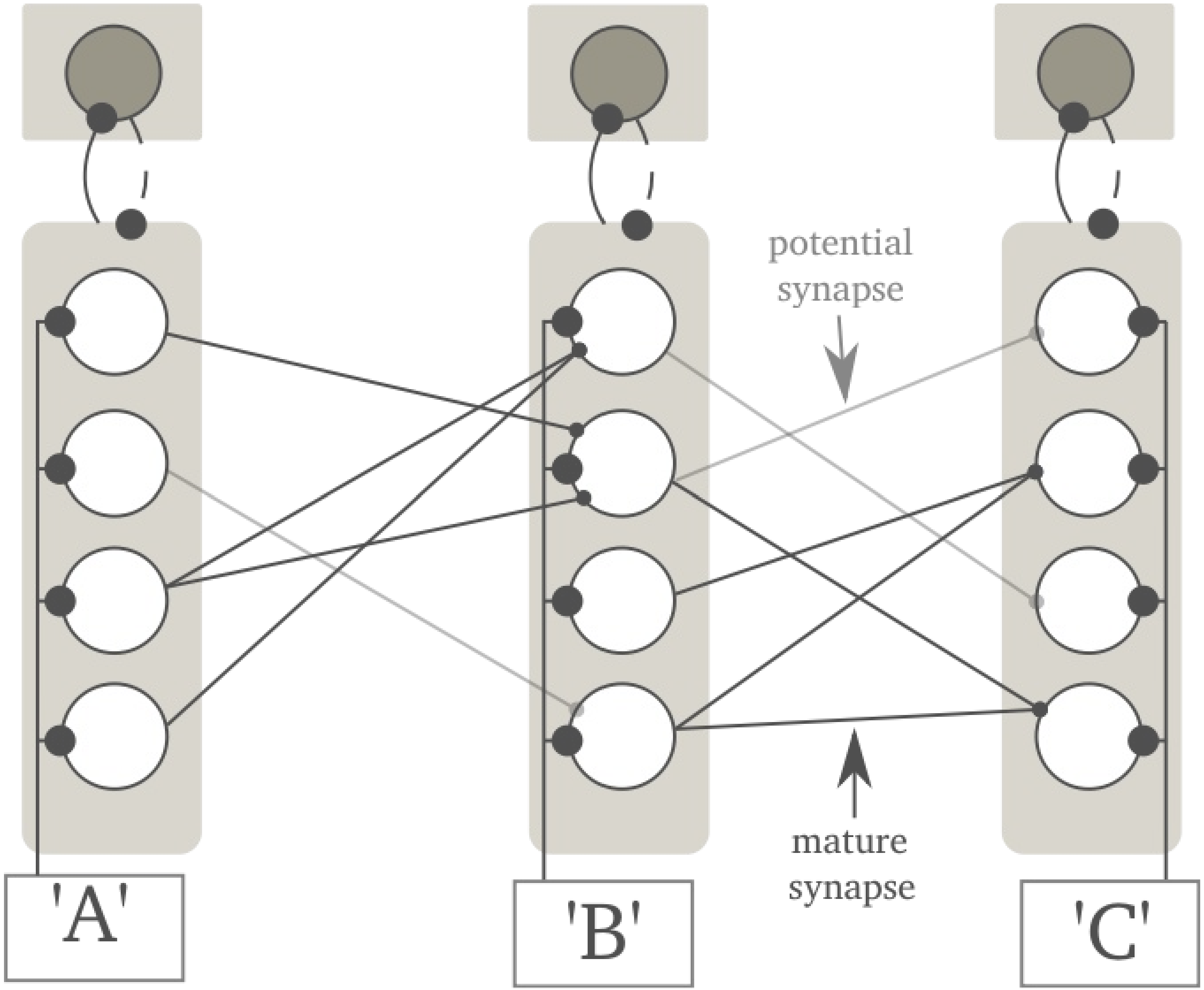


After learning



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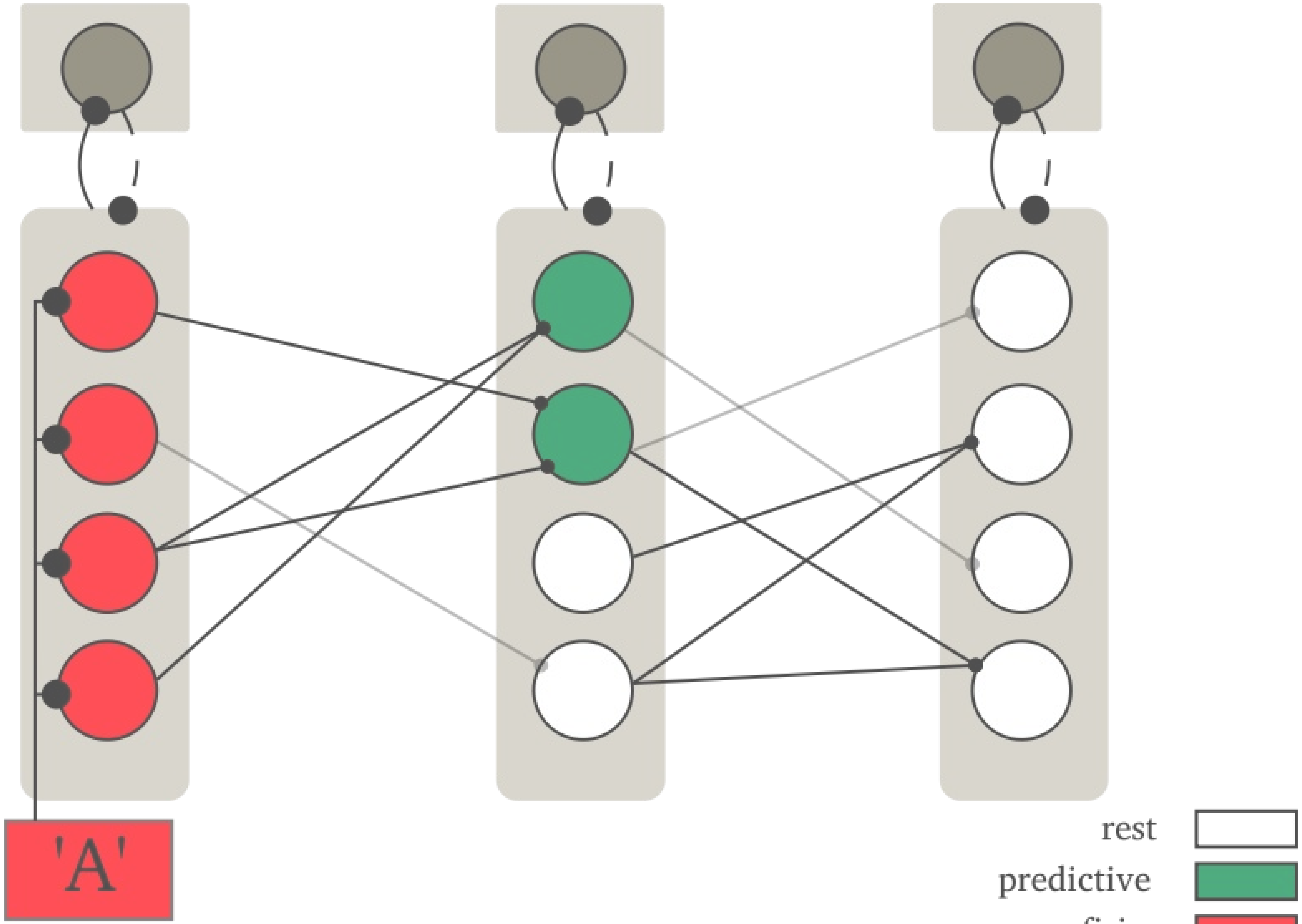

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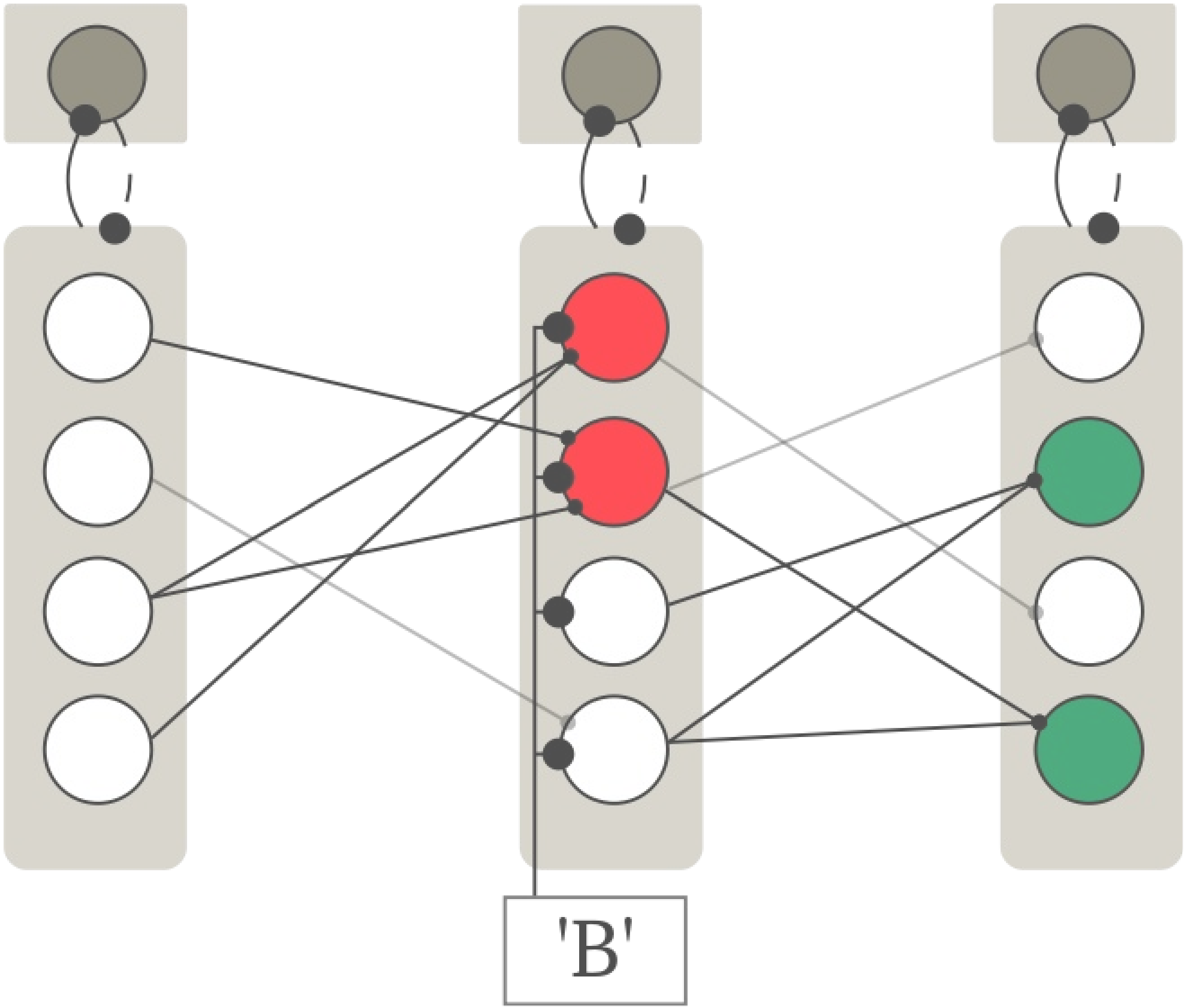

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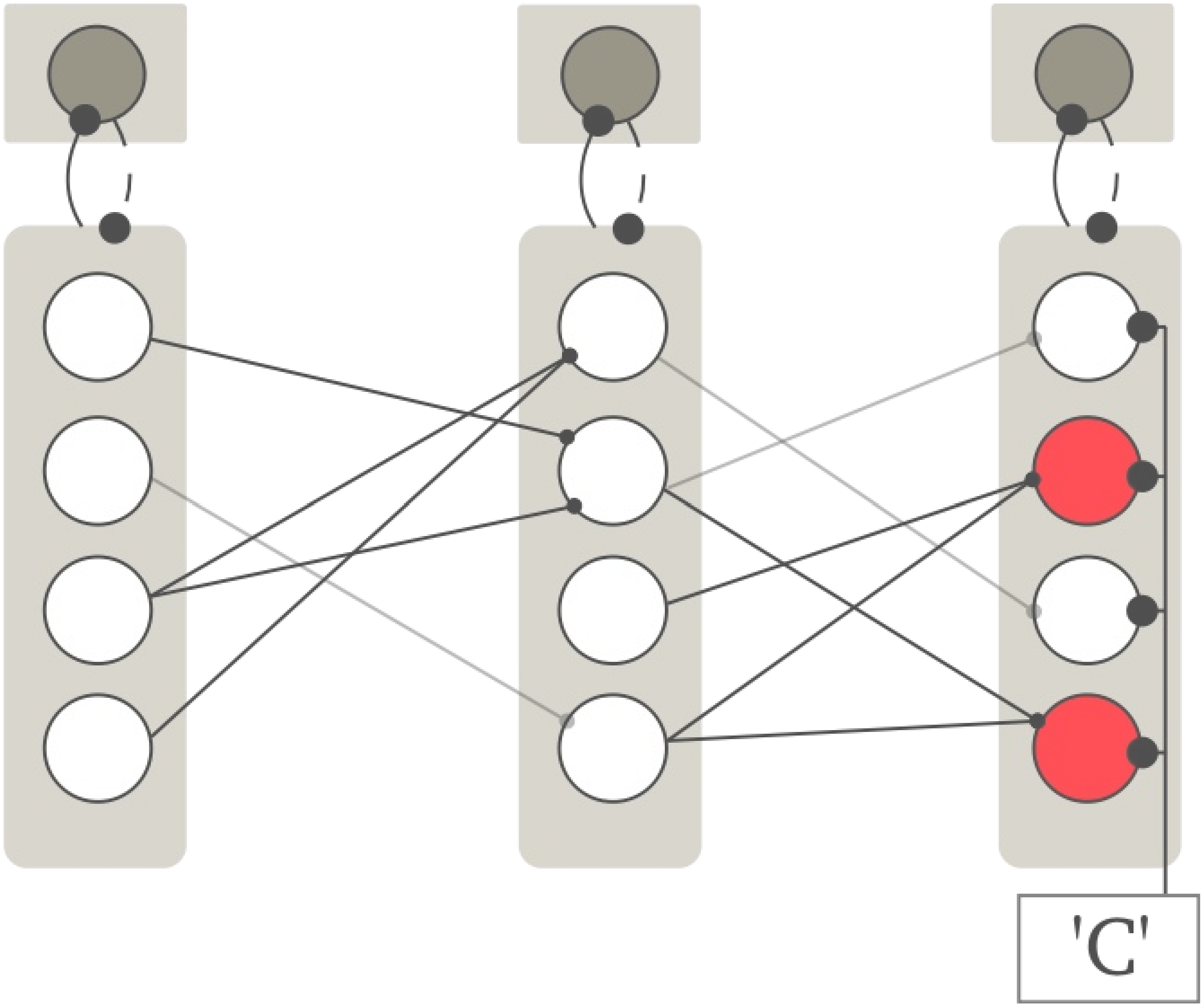


Results

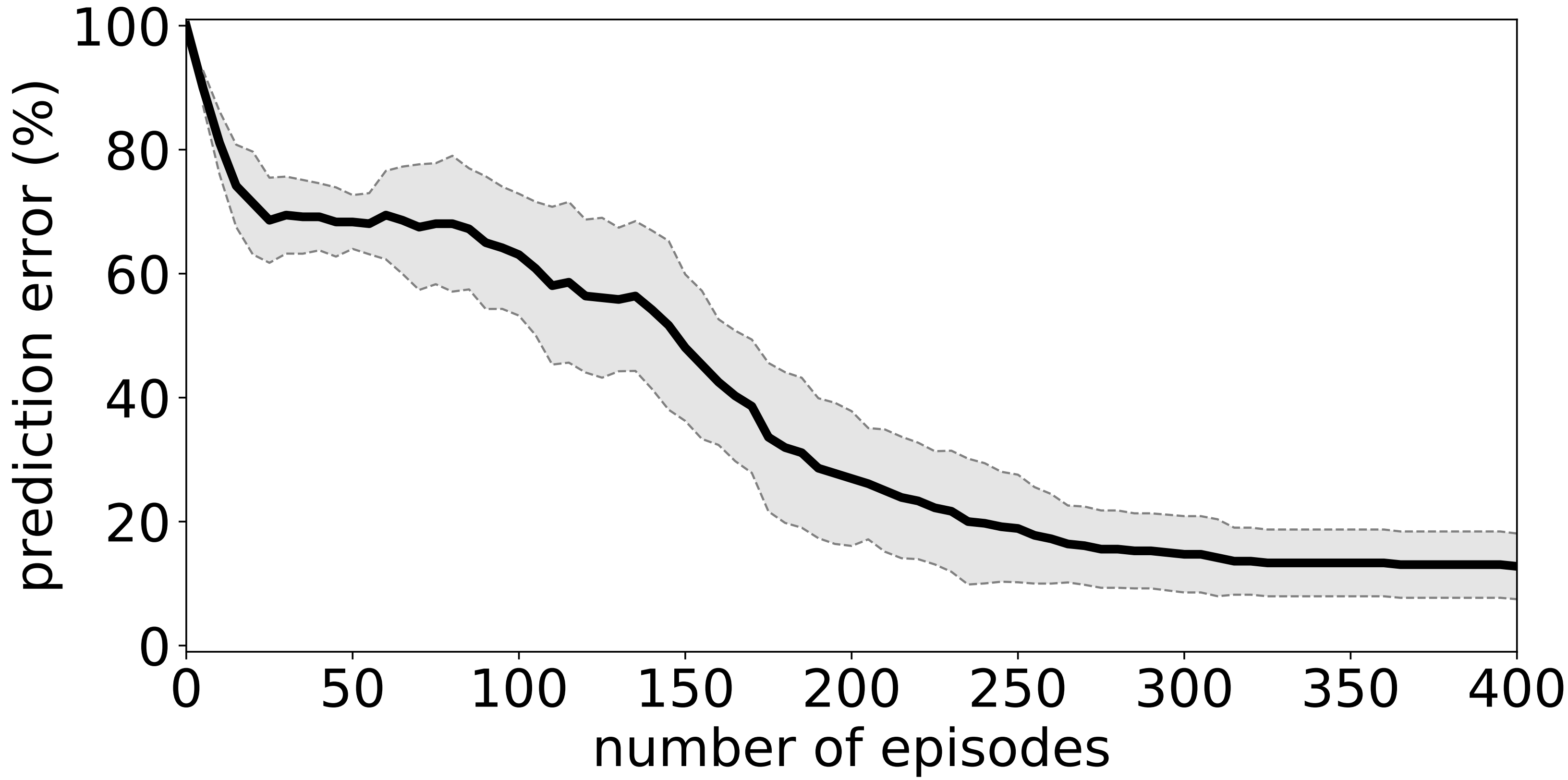
Task

- prediction of characters in a set of sequences of length L
  - sequence 1: A, B, C, D, E, F …
  - sequence 2: C, E, F, A, B, D …
  - …
  - sequence n: E, F, C, B, D, A …

- batch of data = [sequence 1, sequence 2, …, sequence n]

Prediction performance

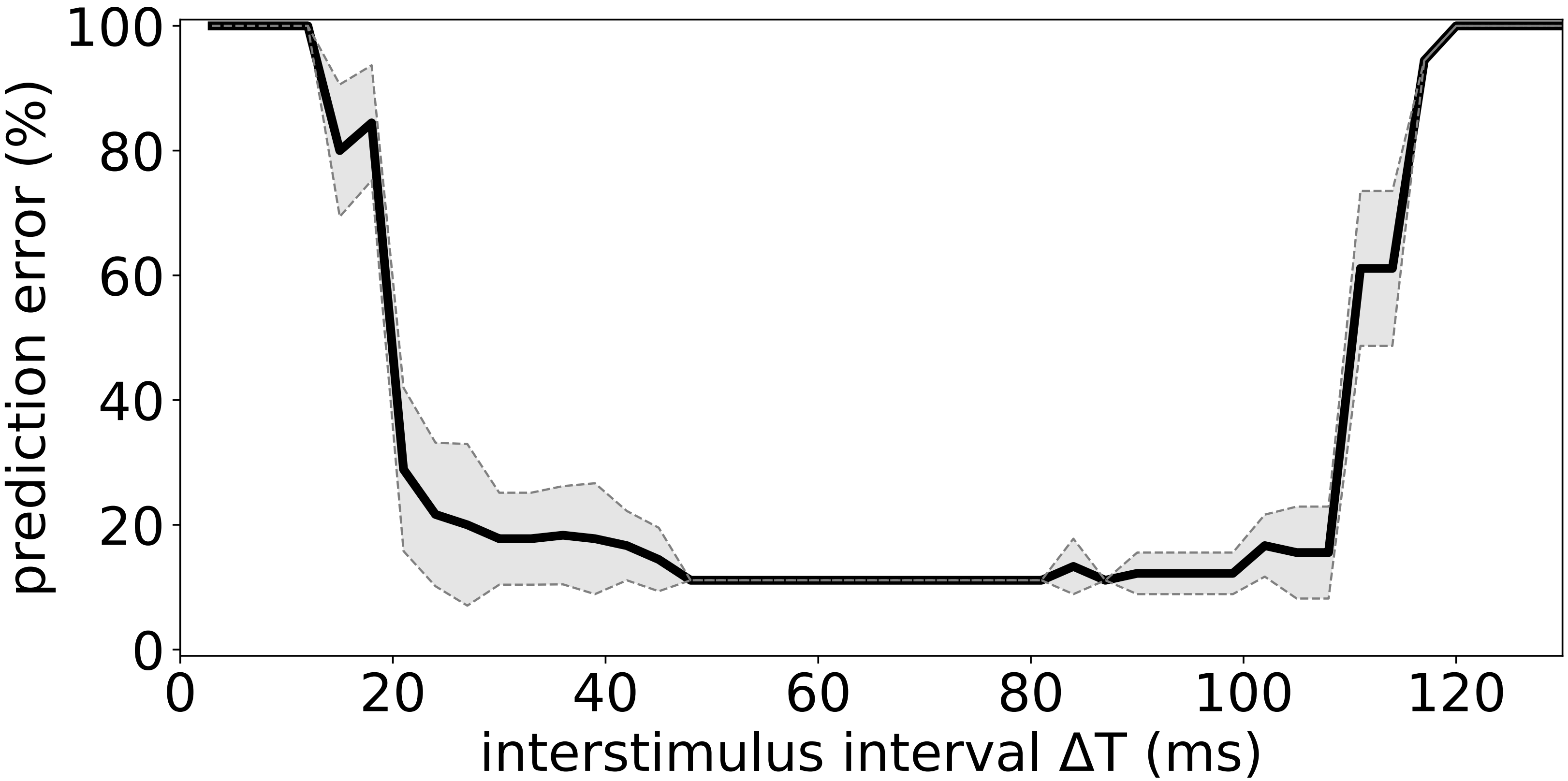
- monotonous decrease of prediction error with number of training episodes
- saturation of prediction error due to residual task ambiguity



number_of_minicolumns=10, number_of_E-neuron_per_mini-column=30, C=10, n=2

Processing speed

- model predicts optimal range of interstimulus intervals
- this range is determined by neural parameters



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- prediction of optimal range of processing speeds (inter-stimulus intervals) with lower and upper bounds constrained by neuronal and synaptic parameters (e.g. time constants, coupling strengths)

- Outlook:
  - upscaling of task complexity
  - comparison to results of psychophysical experiments

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Acknowledgments

- Helmholtz Association
- Juelich Research center
- Human Brain Project

References

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