Computational Neuroscience Course

An Introduction to Computational Neuroscience

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University of Science and Technology of China

Sep 16 2020

Course website

https://github.com/Wenlab/Computation-Neuro-Course/tree/Fall2020

Computational-Neuroscience-Course

This repository serves as an ongoing effort to create a systems and computational neuroscience course. I hope to develop a two-semester course for USTC biophysics students. The first semester will cover some basic materials, and the second semester will introduce more advanced topics for undergraduate and graduate students.

When: Wednesday 9:45 am - 11:25 am, Fall 2020
Where: 东区第二教学楼2504
Teacher: 温泉 qwen@ustc.edu.cn
Teaching Fellow: 吴宇翔 elephantameler@gmail.com 沈忱 ryougi.chen@gmail.com 杜熠辉 duyh@mail.ustc.edu.cn

Recommended Textbooks:

- Theoretical Neuroscience: Computational and Mathematical Modeling the Neural System
- Principles of Neural Design

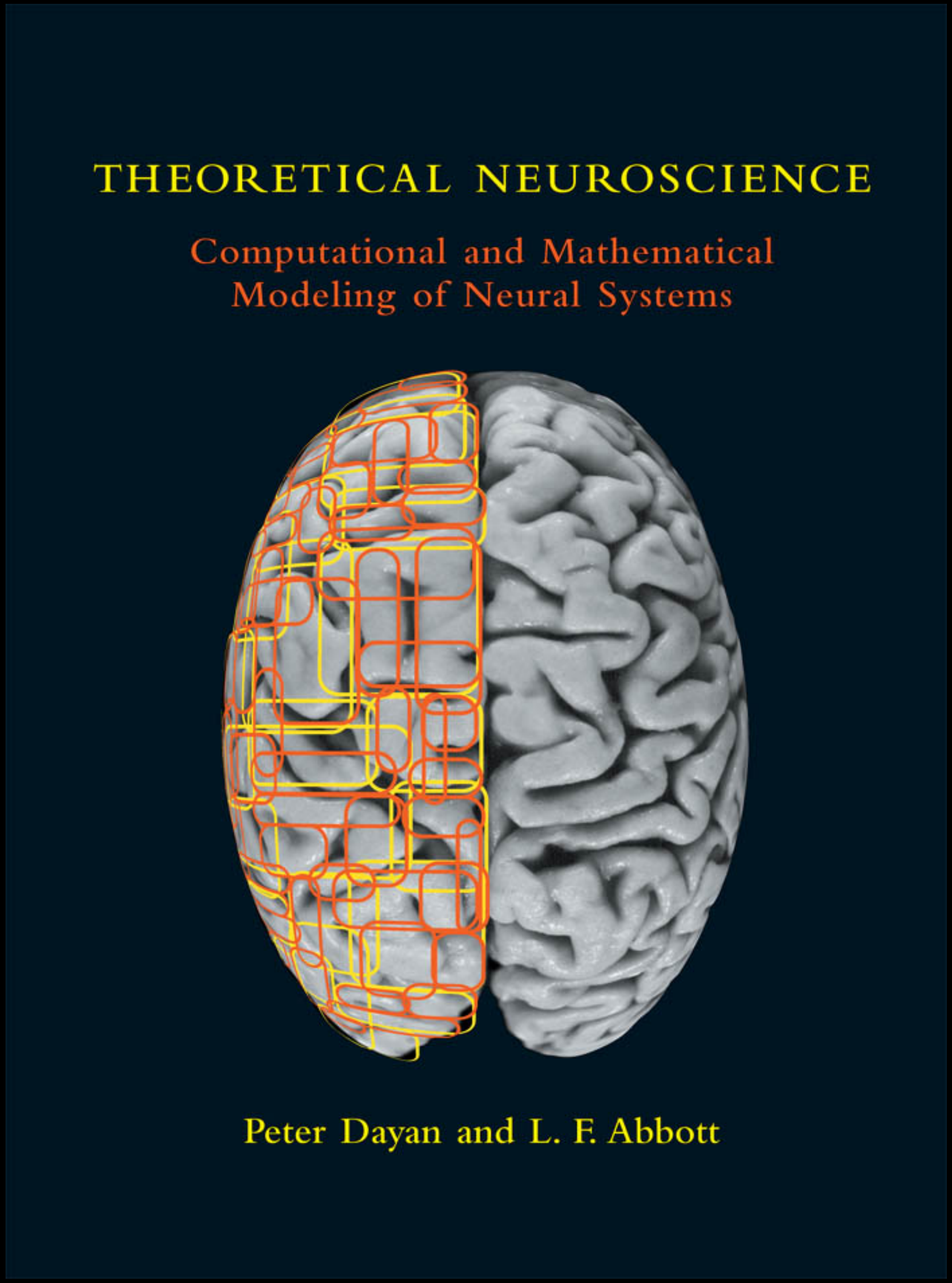
Course Performance Evaluation:

- Homework: 70%
- Final: 30%

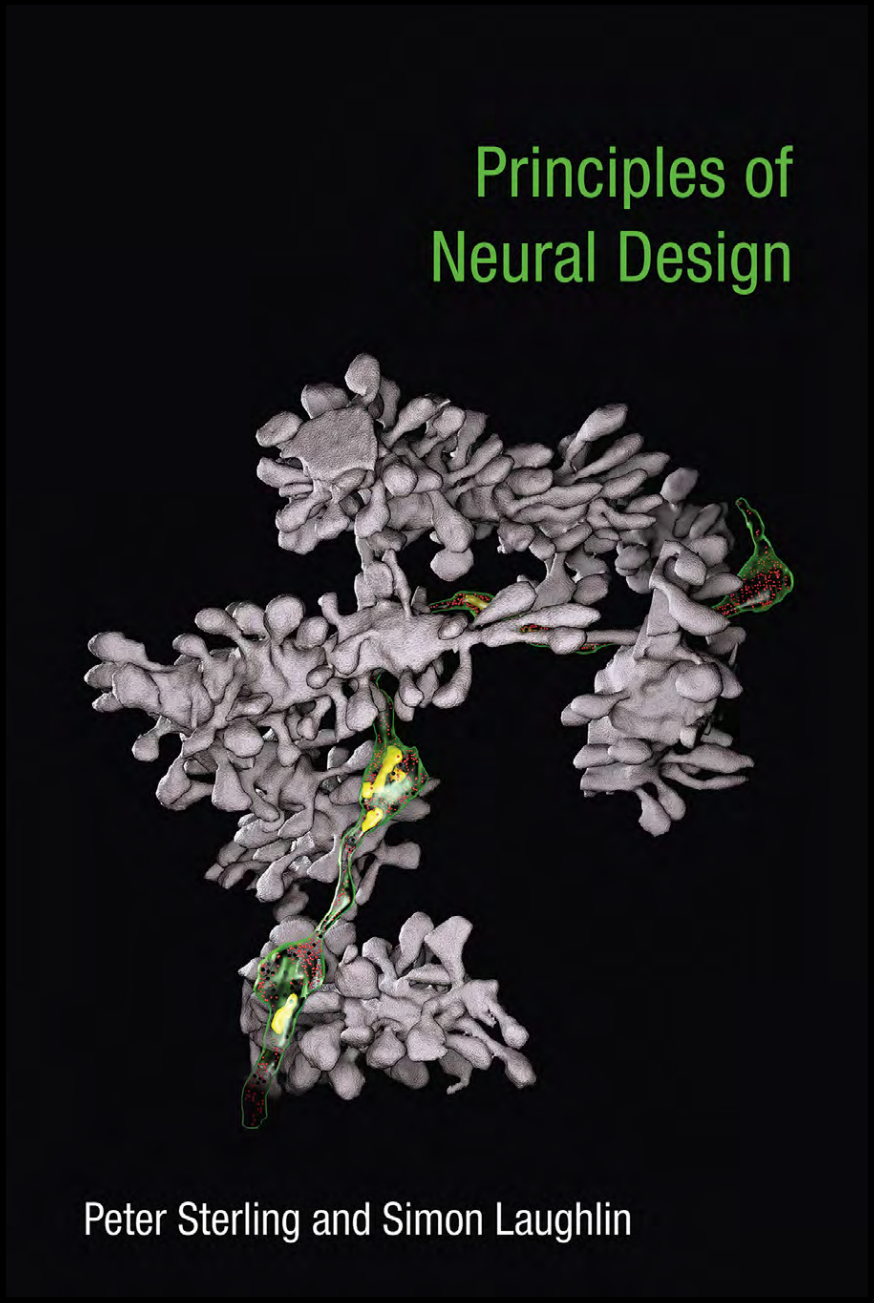
Summary

How intelligence and behavior emerge from complex and intricate interactions within the brain remain important and unsolved mysteries in modern science. This is an exciting time. In the last decade, we have seen rapid progress in experimental tools that now make it possible to monitor and manipulate brain circuits in unprecedented detail. This is also a confusing time. Neuroscientists are lost in the jungles of brain structures and dynamics. Mathematical theory is now pivotal to bring new insights, guide experiments, and identify unifying concepts and principles of brain function.

Recommended textbooks



How questions



Why questions

A brief pre-history

Theoretical Neurophysiology

1907 Lapique:
integrate-and-fire model

1952 Hodgkin-Huxley:
theory of action potential

1960's Rall:
cable theory of dendrites

1970's Wilson-Cowan:
firing-rate population models

1980's: Biophysics of neurons &
synapses, network dynamics

Psychology & Computer Science

1949 Hebb:
learning rules

1960's Rosenblatt, Minsky:
perceptrons

1960's Rosenblatt, Minsky:
perceptrons

1970's signal detection theory

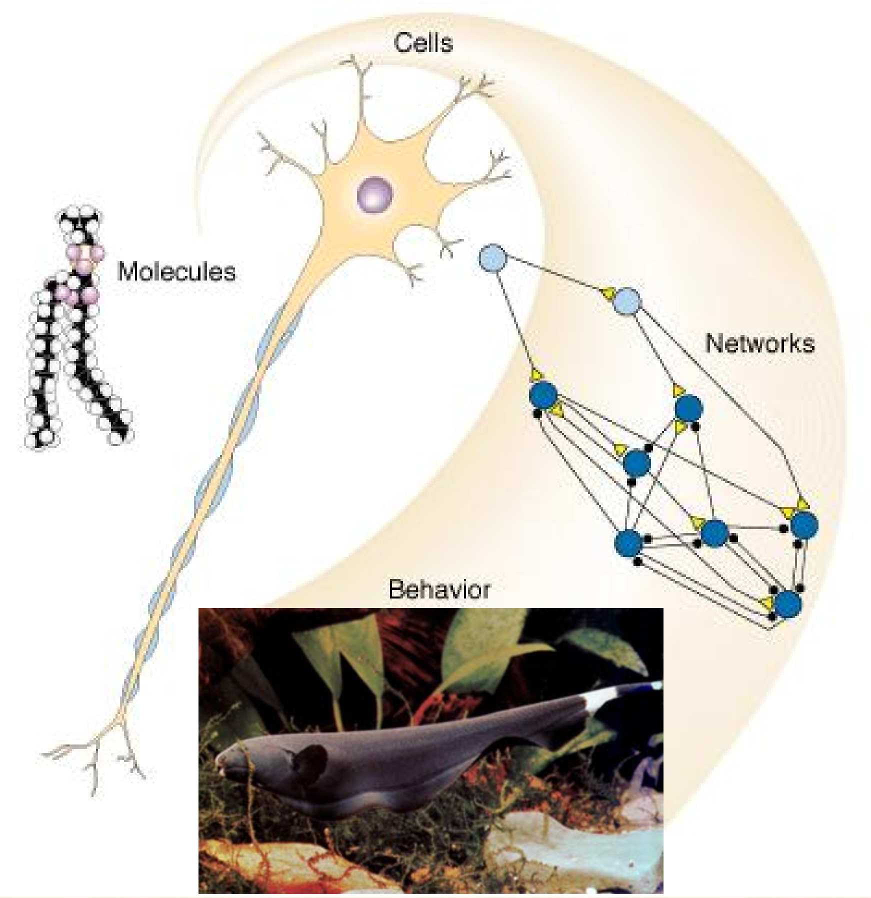
1980's Hopfield:
associative memory model

Sejnowski, Koch, Churchland, Computational neuroscience. Science *1988* 241: 1299-1306
Methods in Computational Neuroscience Summer School, Marine Biological Laboratory

adapted from Xiaojing Wang's slide

Principles of Neuroscience ?

Multiscale Organization of the Nervous System



Delcomyn 1998

Organism	**1 m**
System	**10 cm**
Map	**1 cm**
Column	**1 mm**
Neuron	**10 μm**
Synapse	**1 μm**
Molecule	**10 Å**

“To pile speculation on speculation, I would say that the next stage could be hierarchy or specialization of function, or both…. with increasing complication at each stage, we go on up the hierarchy of sciences. We expect to encounter fascinating and, I believe, very fundamental questions at each stage in fitting together less complicated pieces into the more complicated system and understanding the basically new types of behavior which can result.”

P. W. Anderson, 1972
Nobel Laureate
condensed matter physicist

More is different

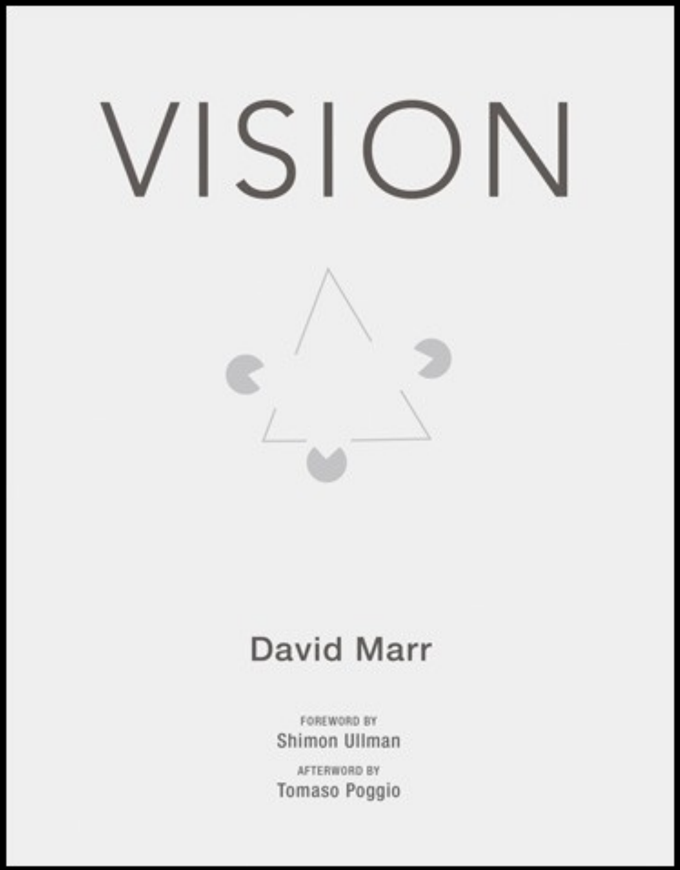
Fitzgerald: The rich are **different** from us.

Hemingway: Yes, they have **more** money.

a conversation somewhere in Paris in 1920s

David Marr
1945-1980

Henry Markram
1962 -



blue brain project

David Marr’s three level theory

- **Computational level**: Identify the computational problem and task that the brain solves.
- **Algorithmic level**: Find the mathematical procedures that solve the problem.
- **Implementation level**: How the algorithms are realized by the nervous system.

top-down

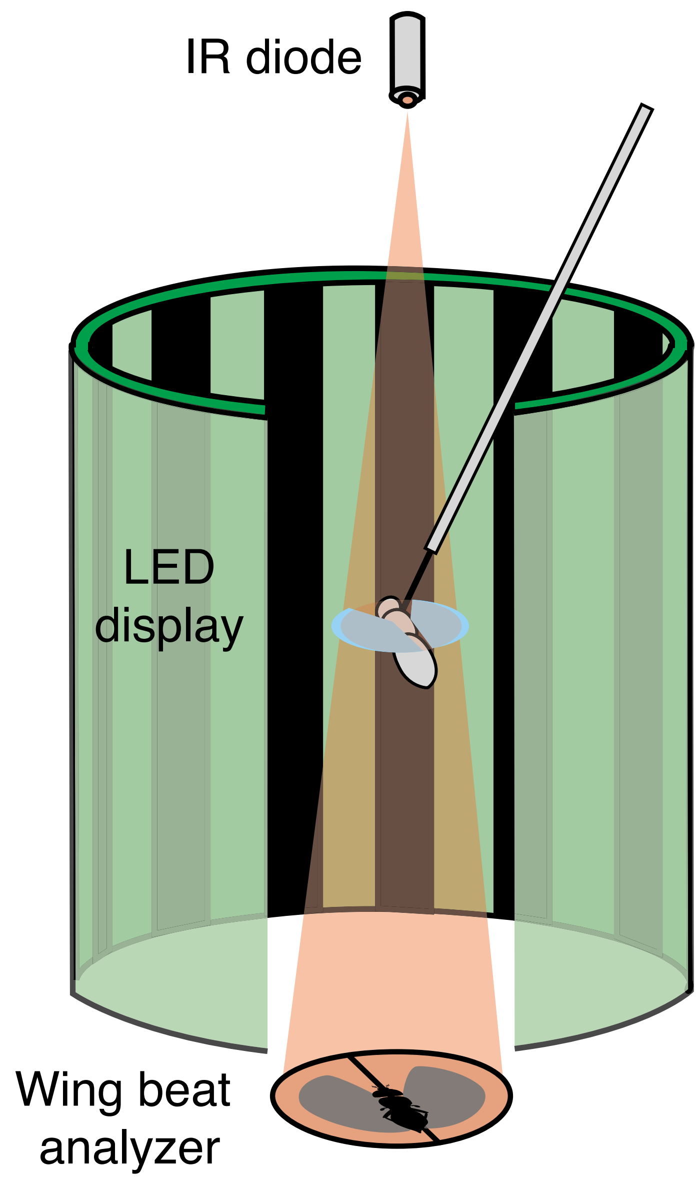
Henry Markram's three level theory

- **Systems level**: describe how population neural dynamics and behaviors emerge from ensembles of neurons.
- **Cellular level**: develop biophysically accurate models to describe input-output relationships of different cell types.
- **Structure level**: identify how neurons are statistically connected to each other in a circuit.

bottom-up

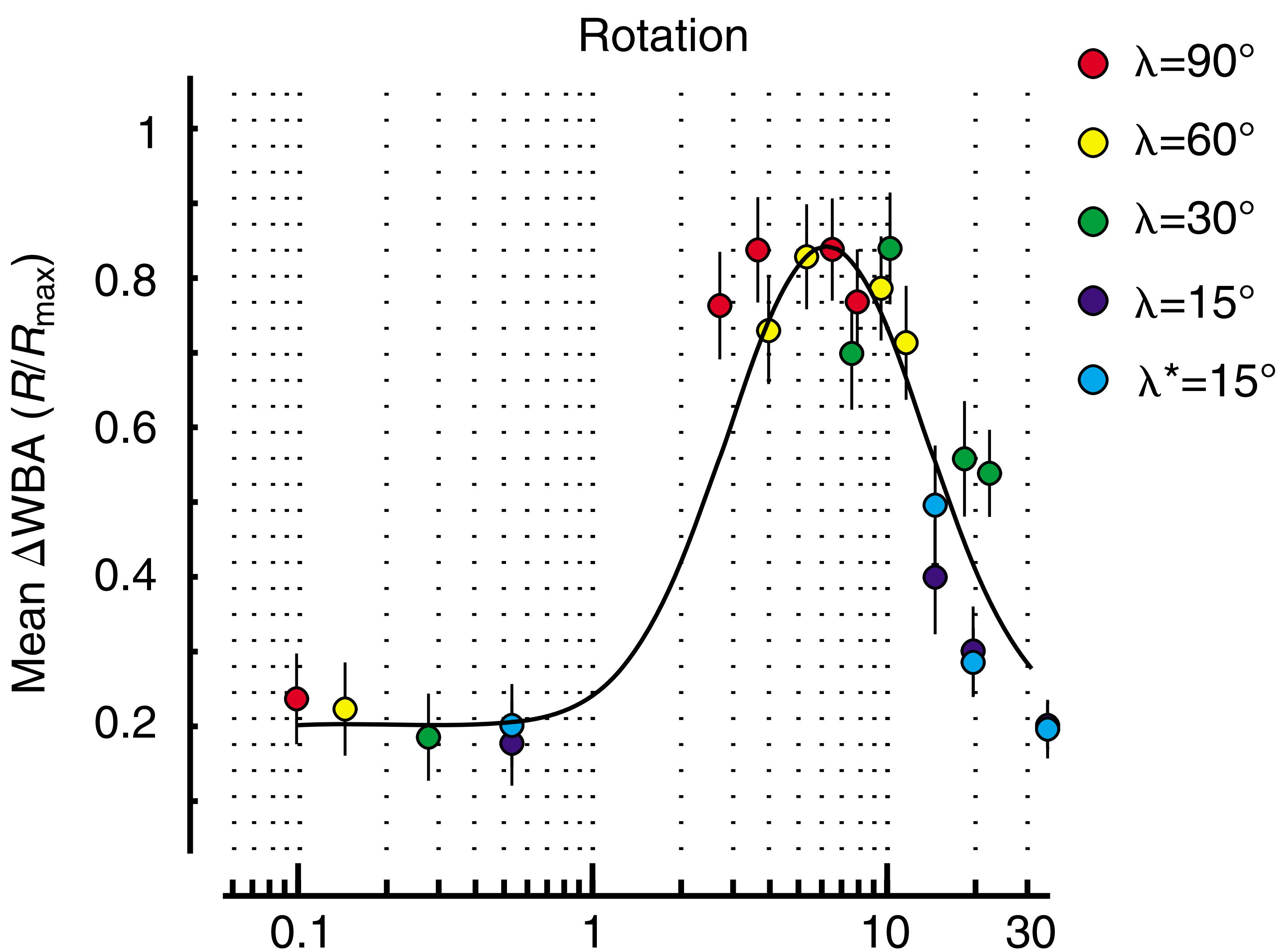
Motion detection, an example

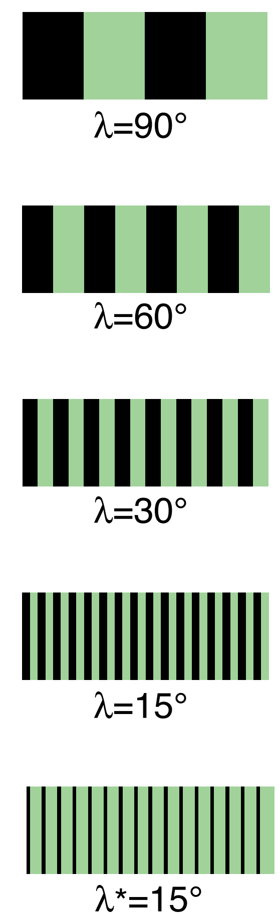
Optomotor response in fly



Duistermars B et. al., Journal of Experimental Biology 2007

Optomotor response in fly



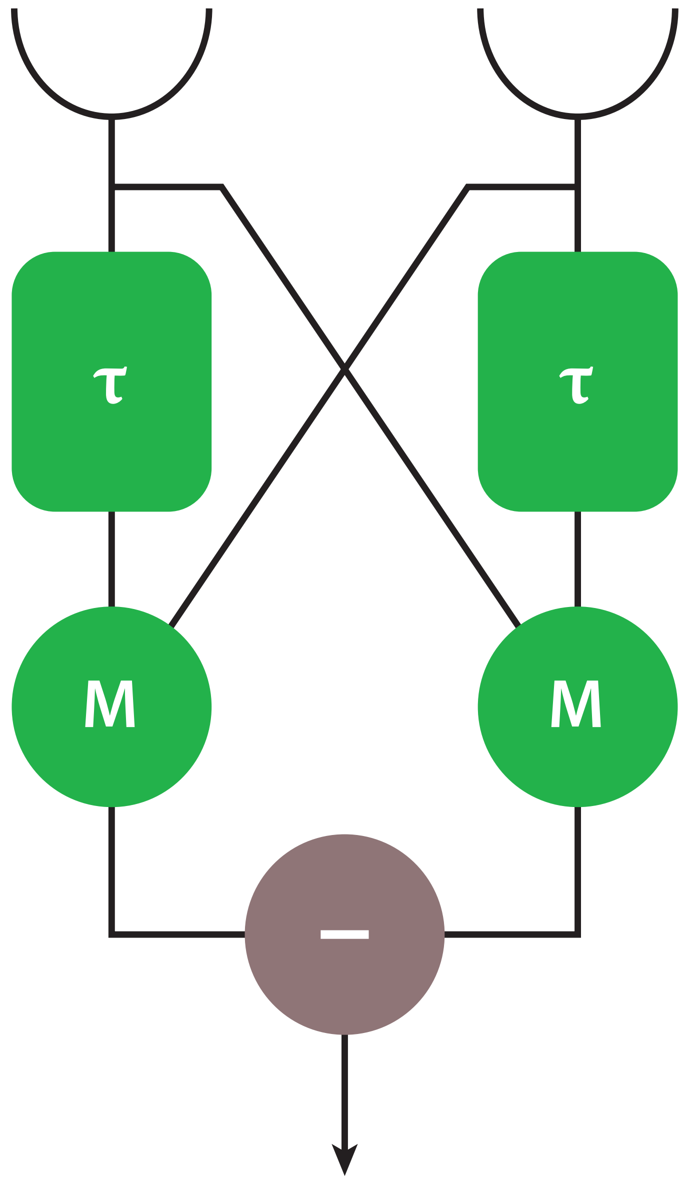


ω

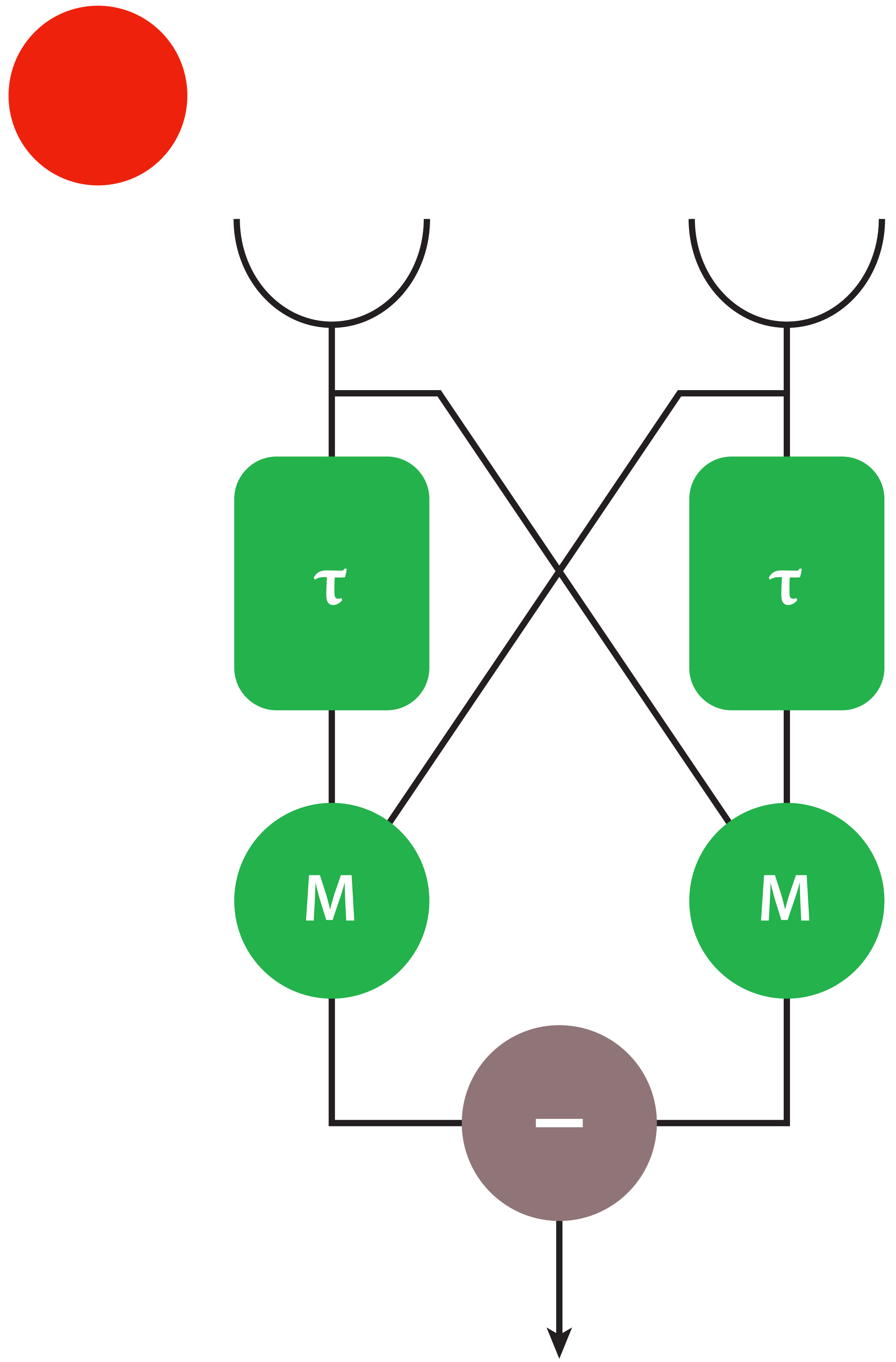
$$\omega = v/\lambda$$

Duistermars B et. al., Journal of Experimental Biology 2007

Hassenstein-Reichardt Detector Model



Werner Reichardt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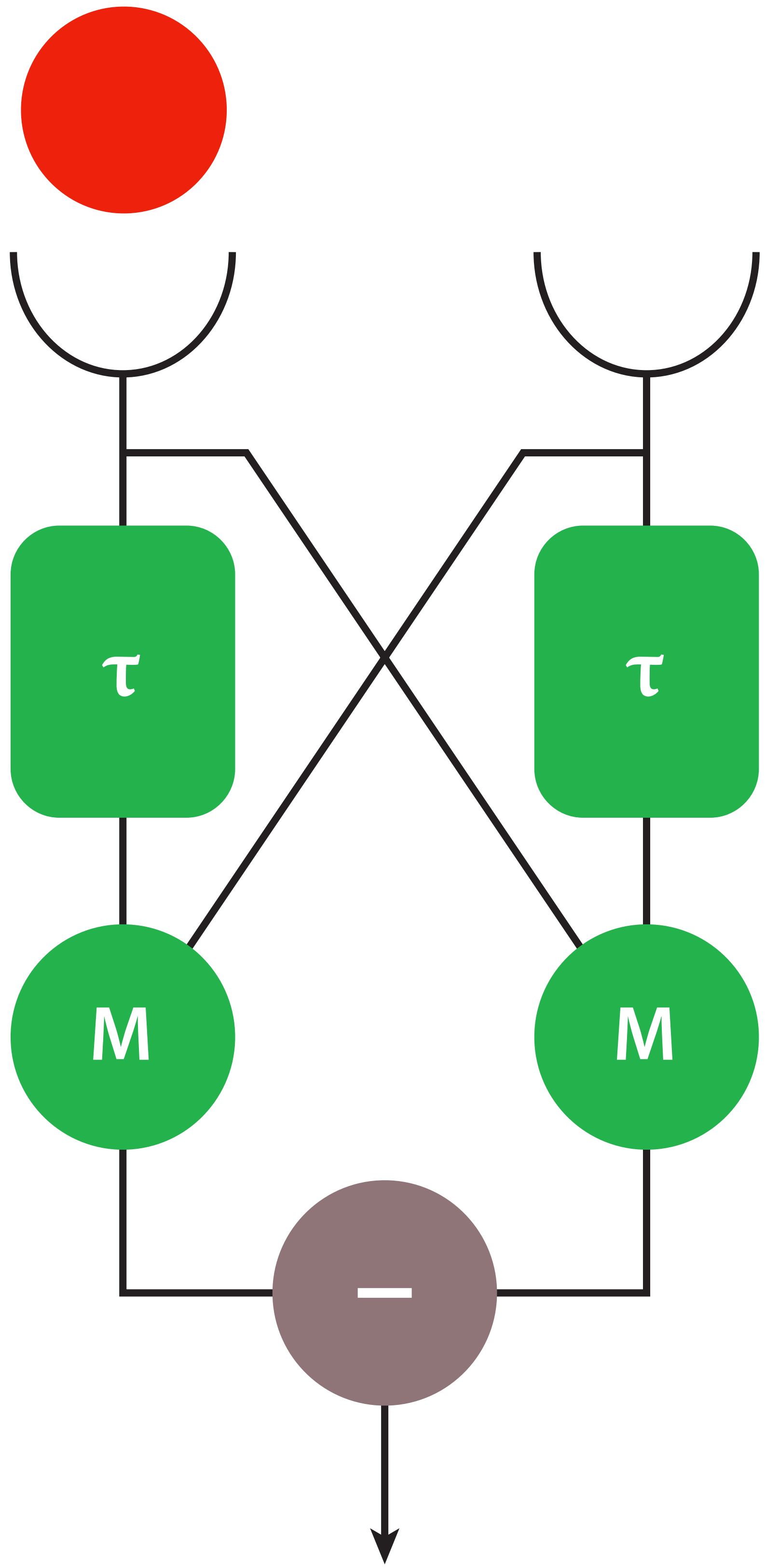
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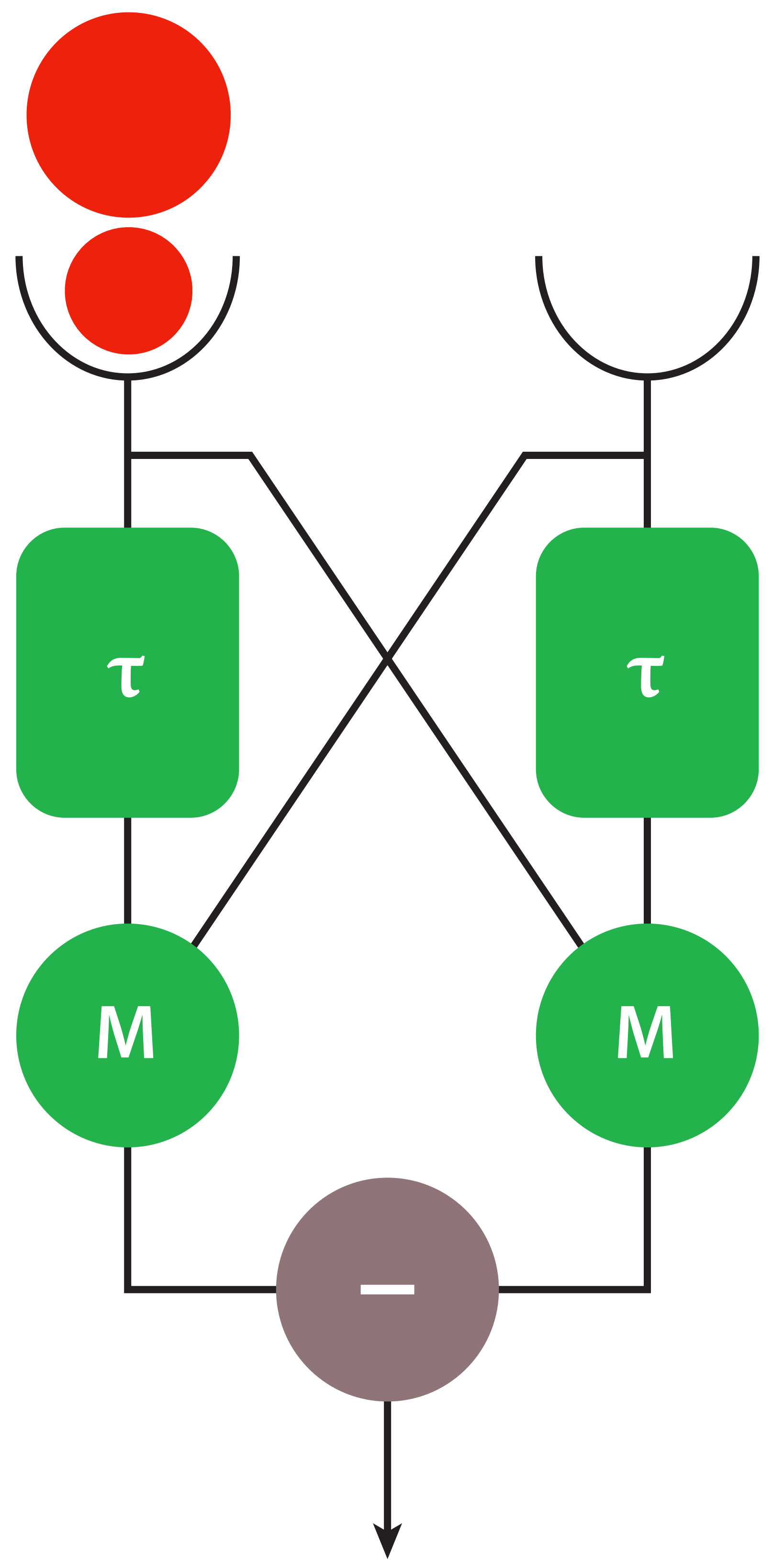

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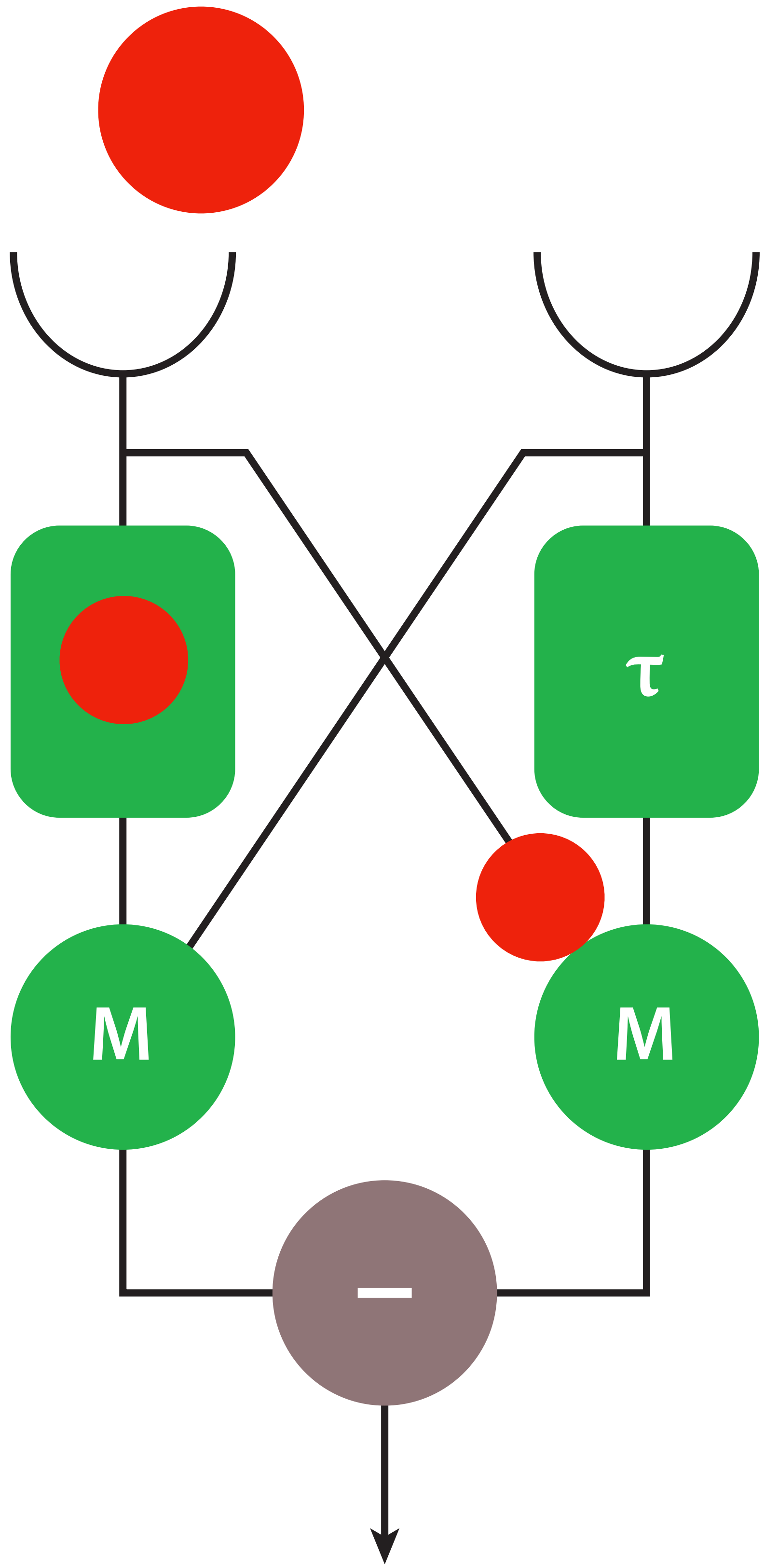
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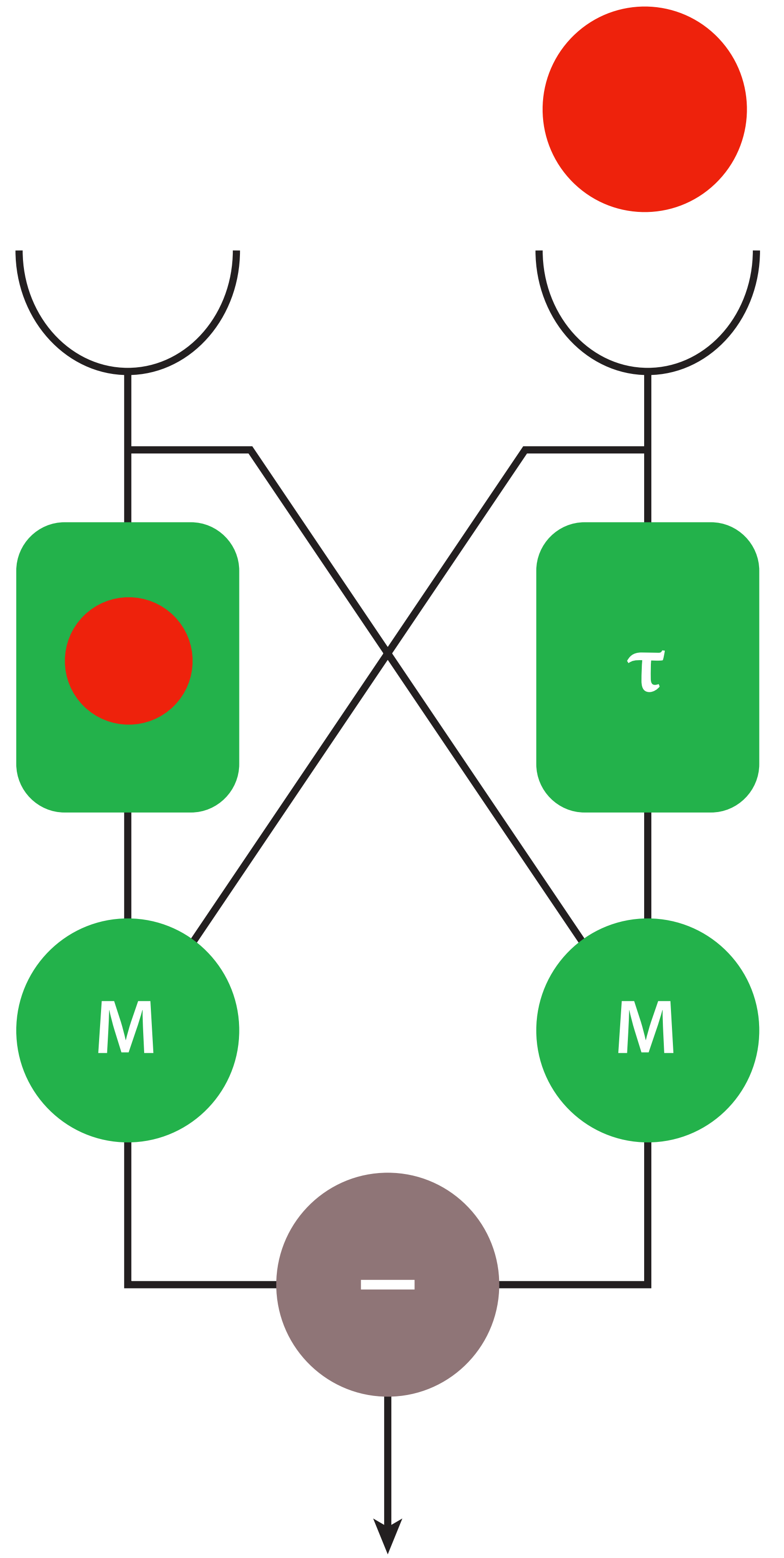
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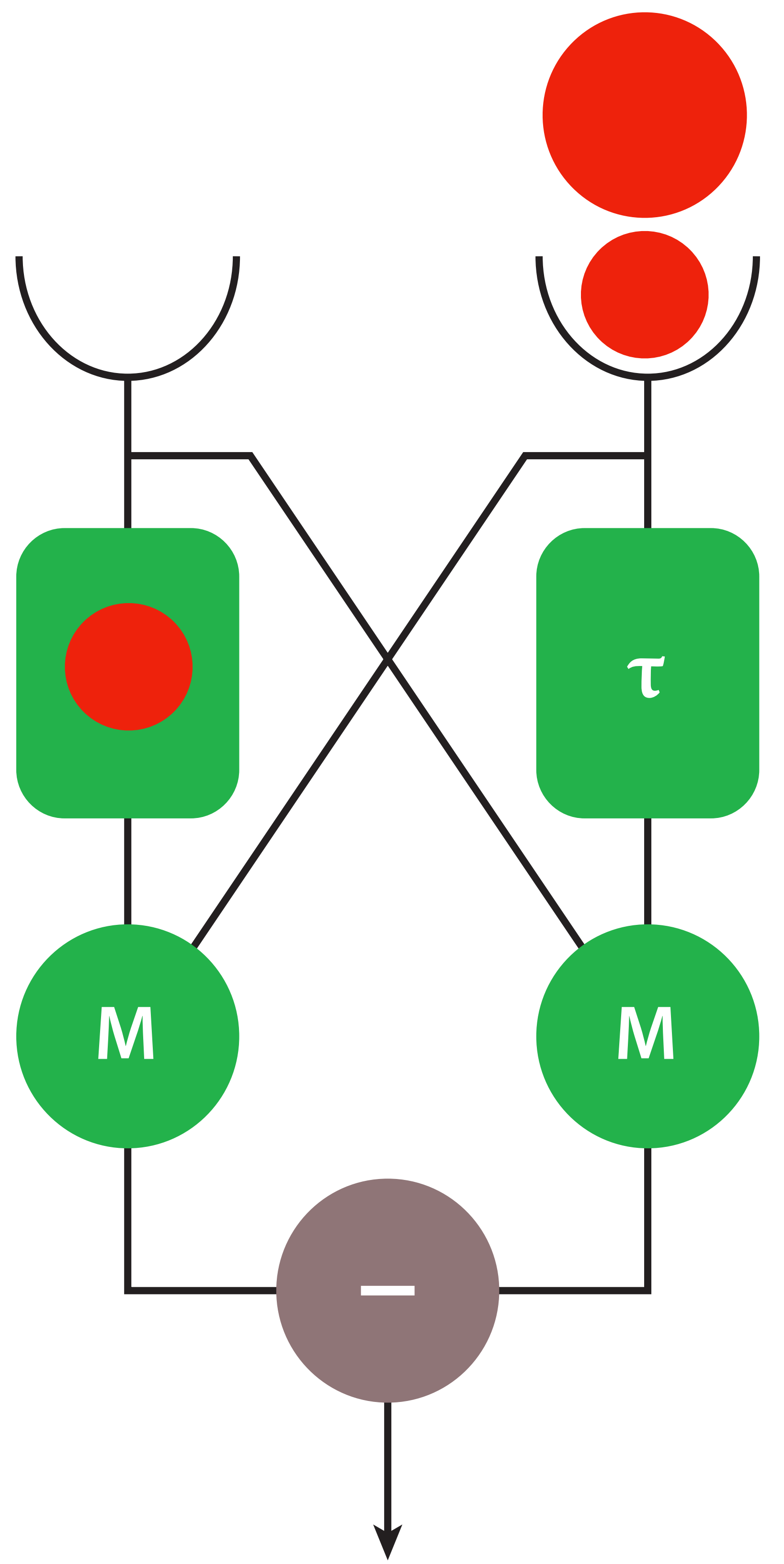

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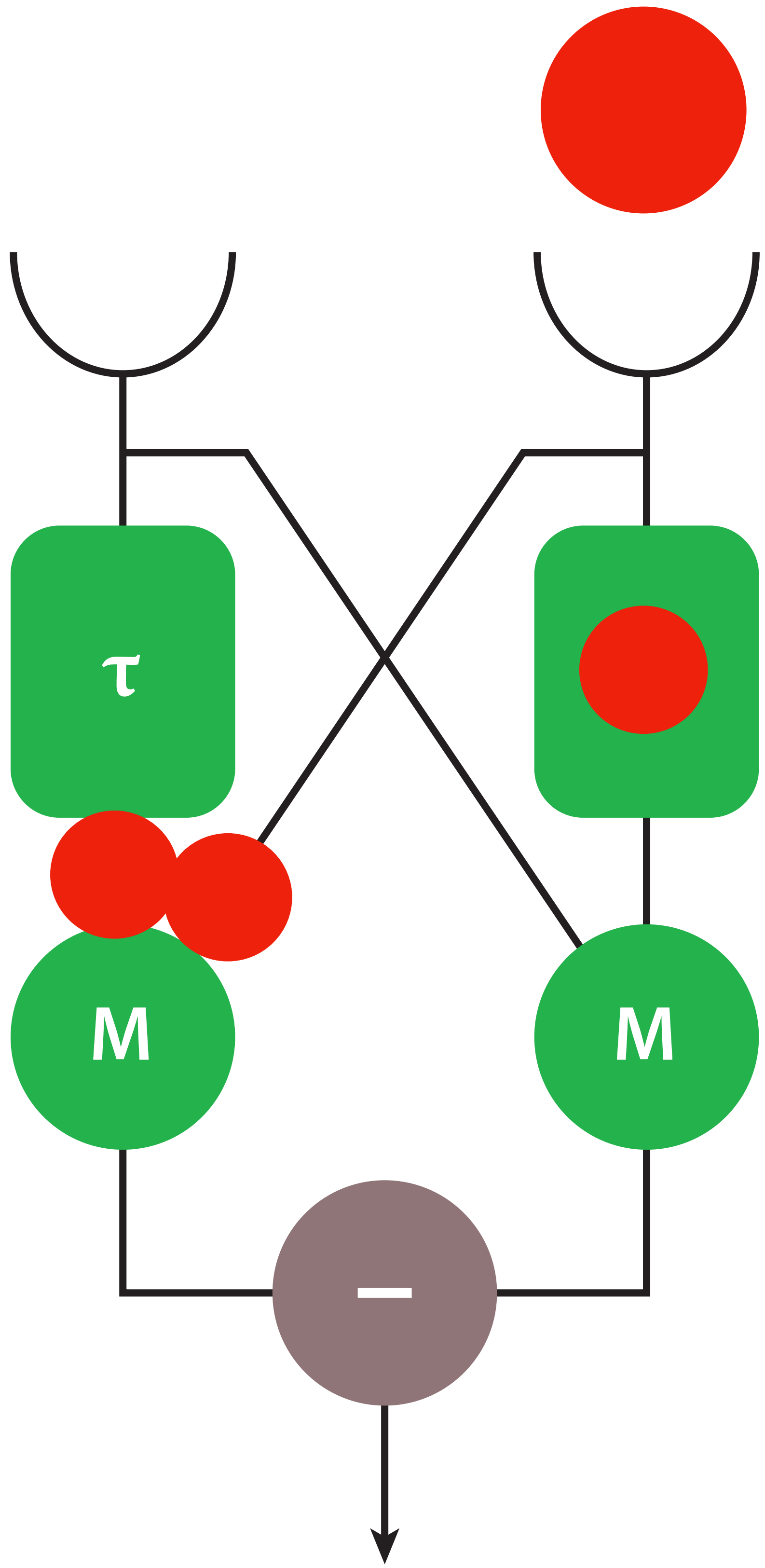
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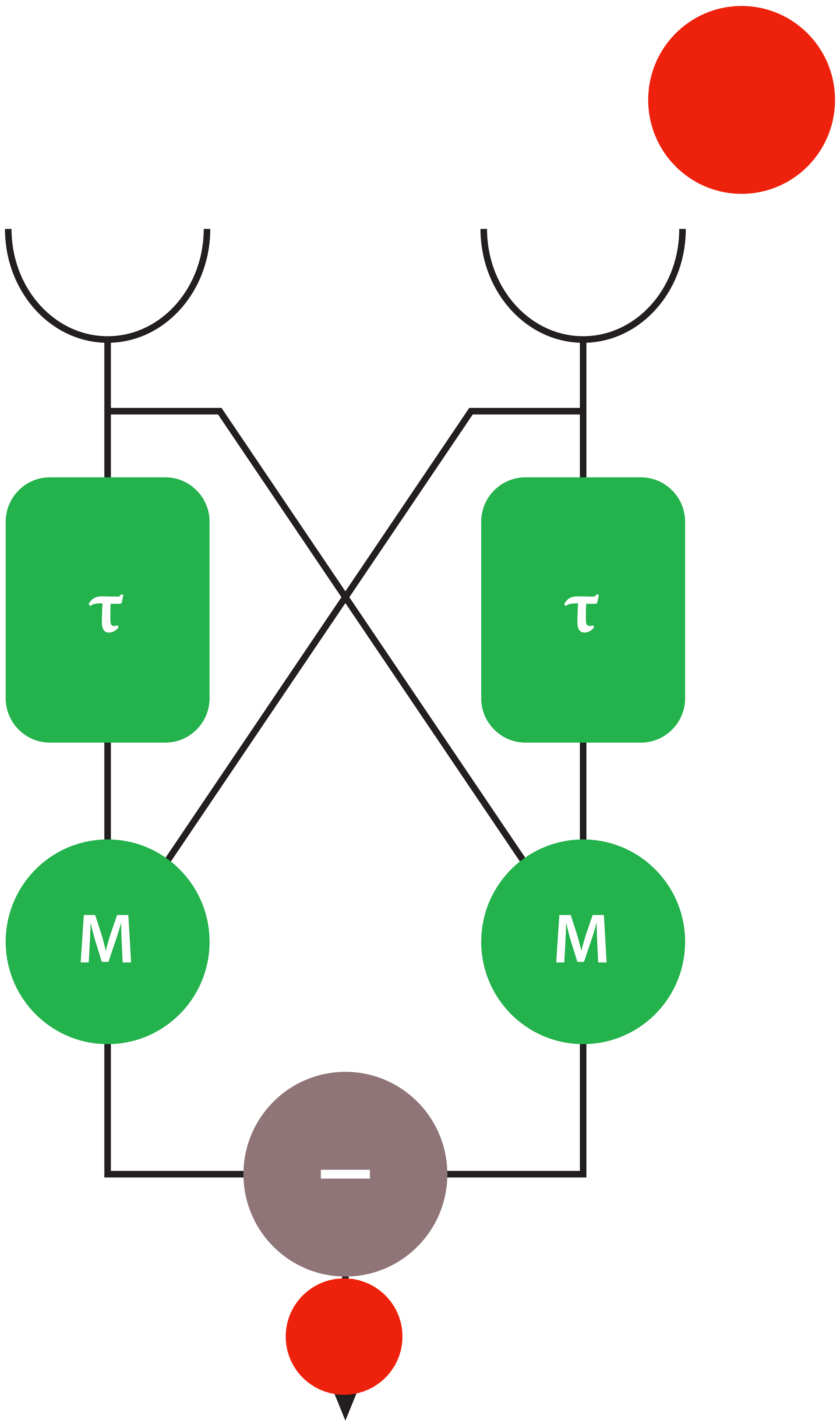

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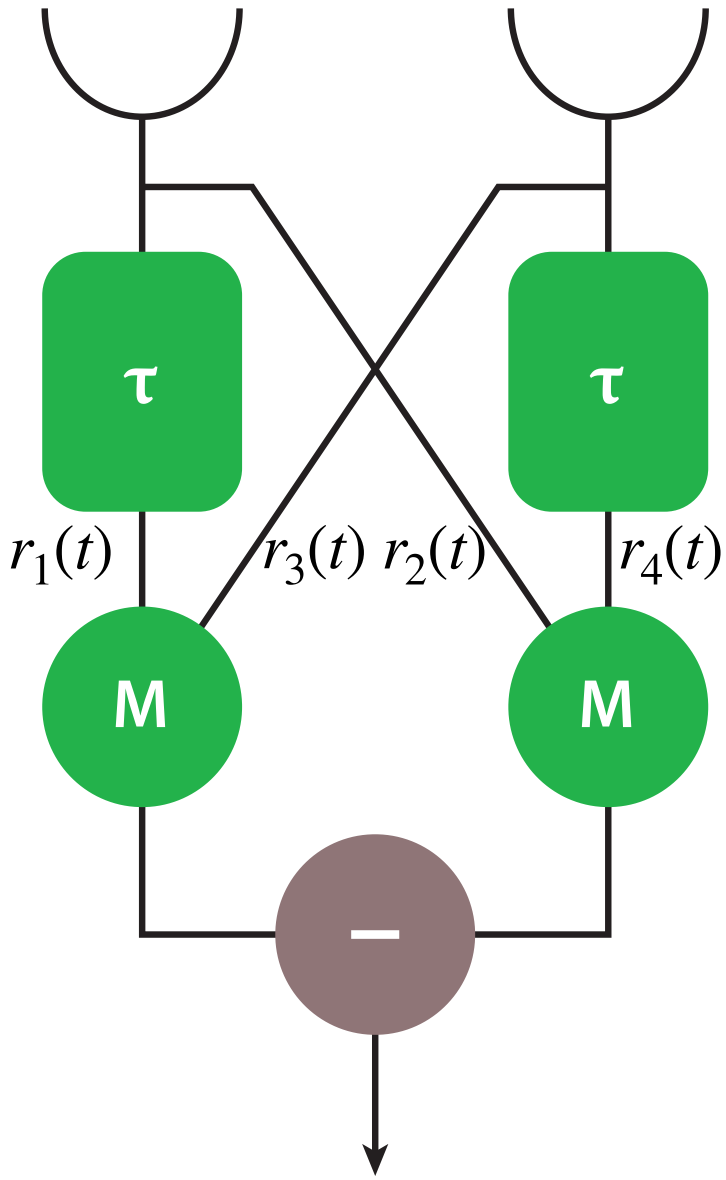
Hassenstein-Reichardt Detector Model



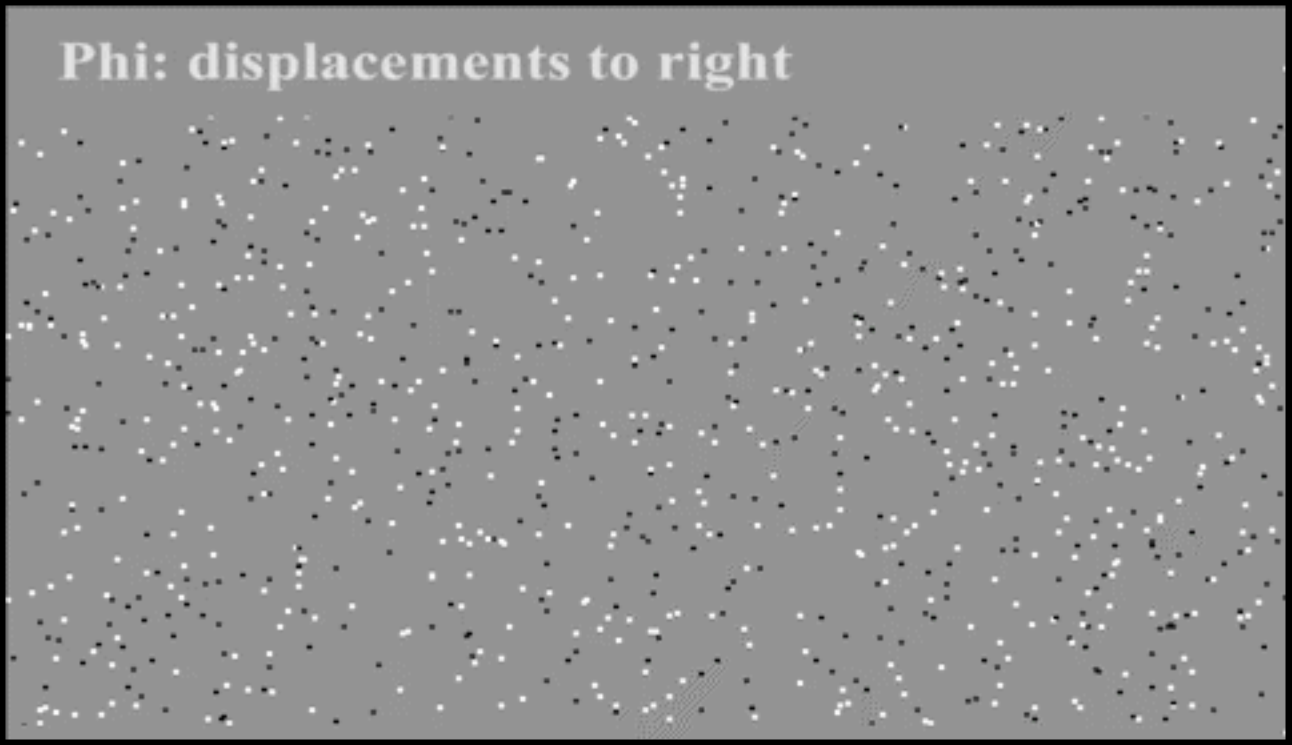
$$r_1(t) = \int_0^\infty s_1(t-\tau)D(\tau)d\tau;\ \ r_2(t) = \int_0^\infty s_1(t-\tau)\delta(\tau)d\tau$$

$$r_3(t) = \int_0^\infty s_2(t-\tau)\delta(\tau)d\tau;\ \ r_4(t) = \int_0^\infty s_2(t-\tau)D(\tau)d\tau;$$

$$R(t) = r_1(t)r_3(t) - r_2(t)r_4(t)$$

$$D(\tau) = \frac{1}{\tau_0}\exp(-\tau/\tau_0)$$

$$\langle R \rangle = \frac{\omega\tau_0}{\omega^2\tau_0^2 + 1}$$



adapted from Damon Clark’s slide

- **Computational level**: Identify the computational problem and task that the brain solves.

- **Algorithmic level**: Find the mathematical procedures that solve the problem.

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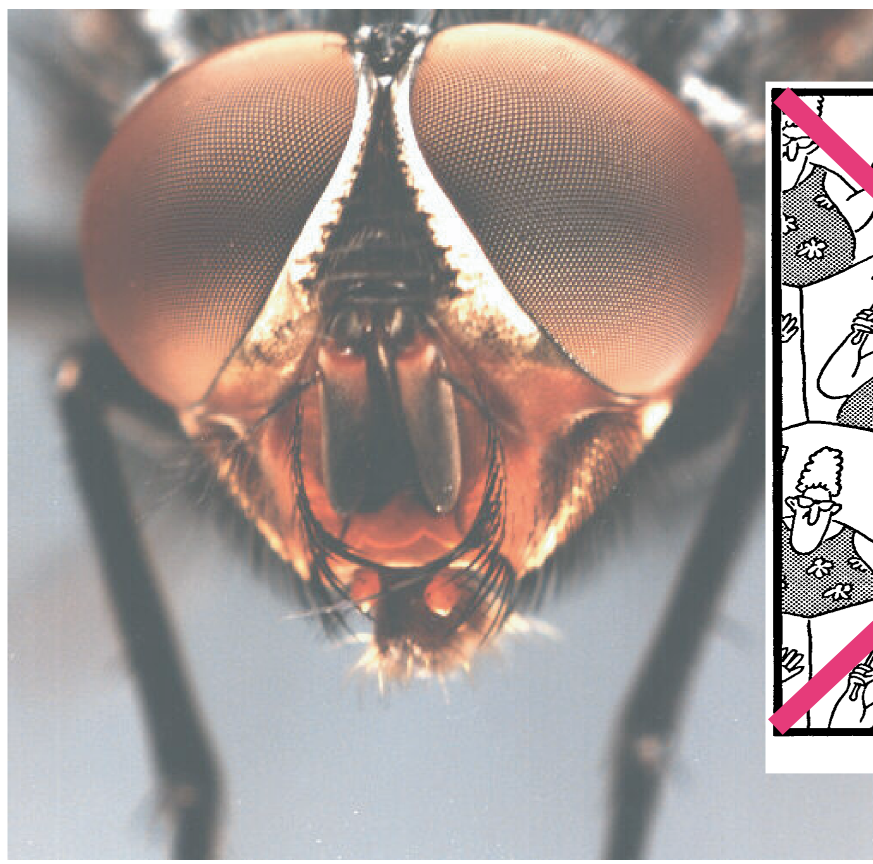
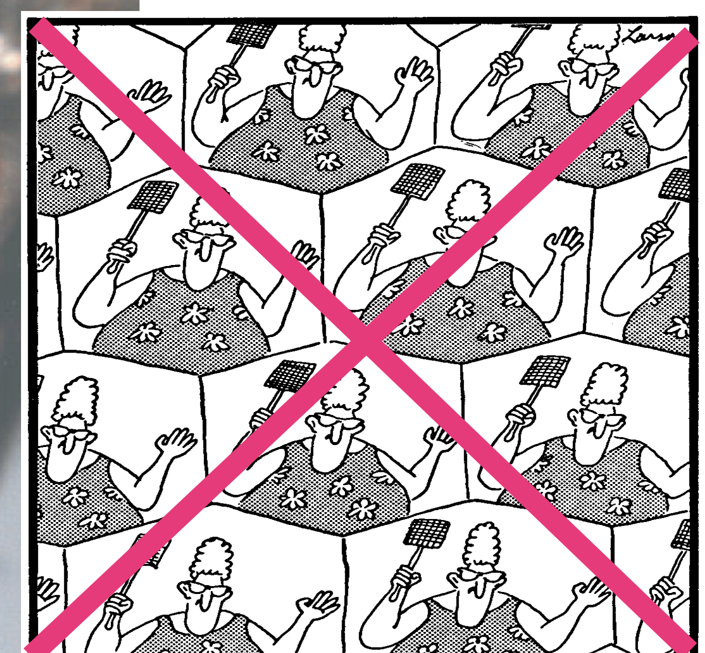
top-down

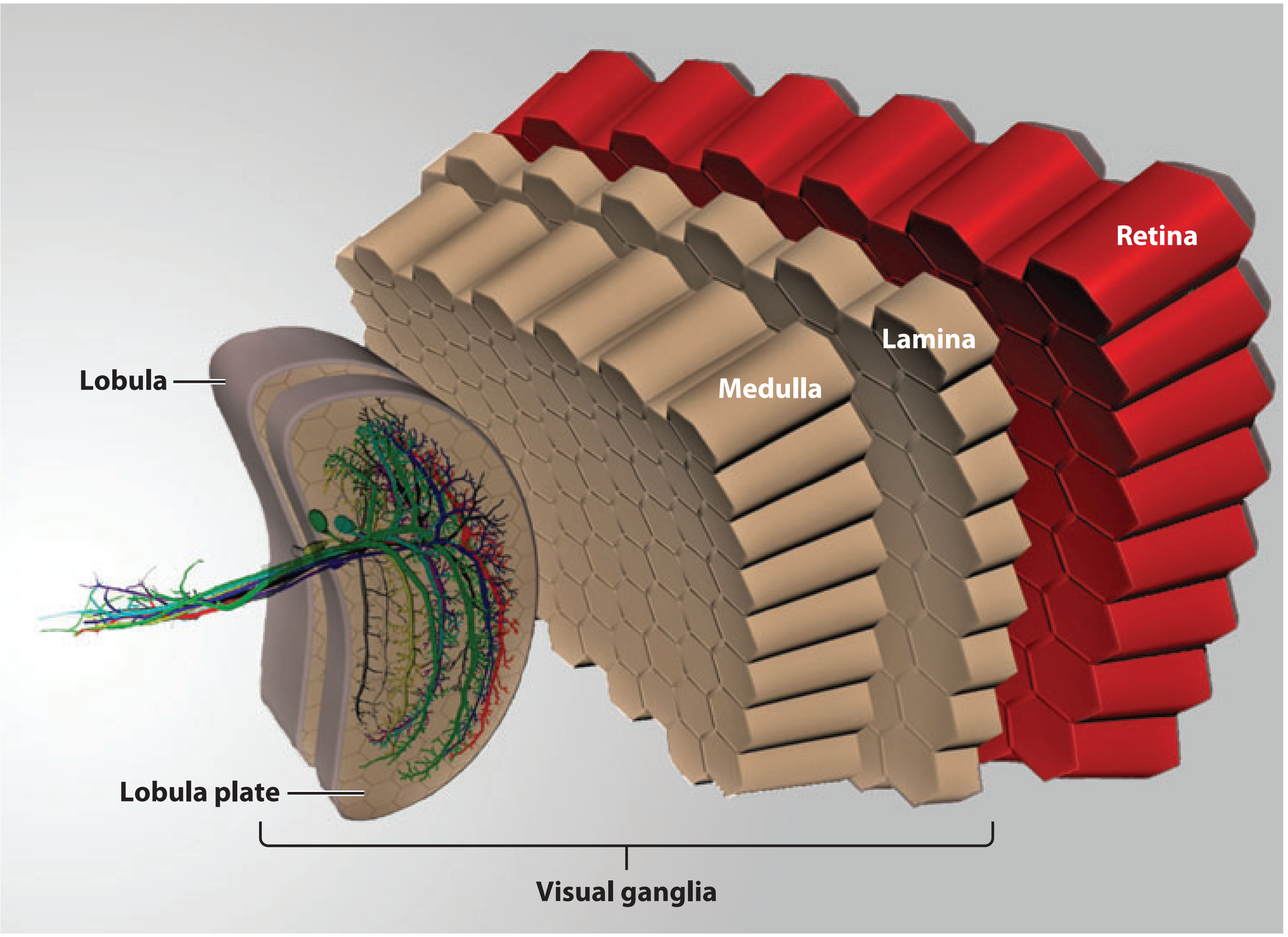
The Fly Visual System



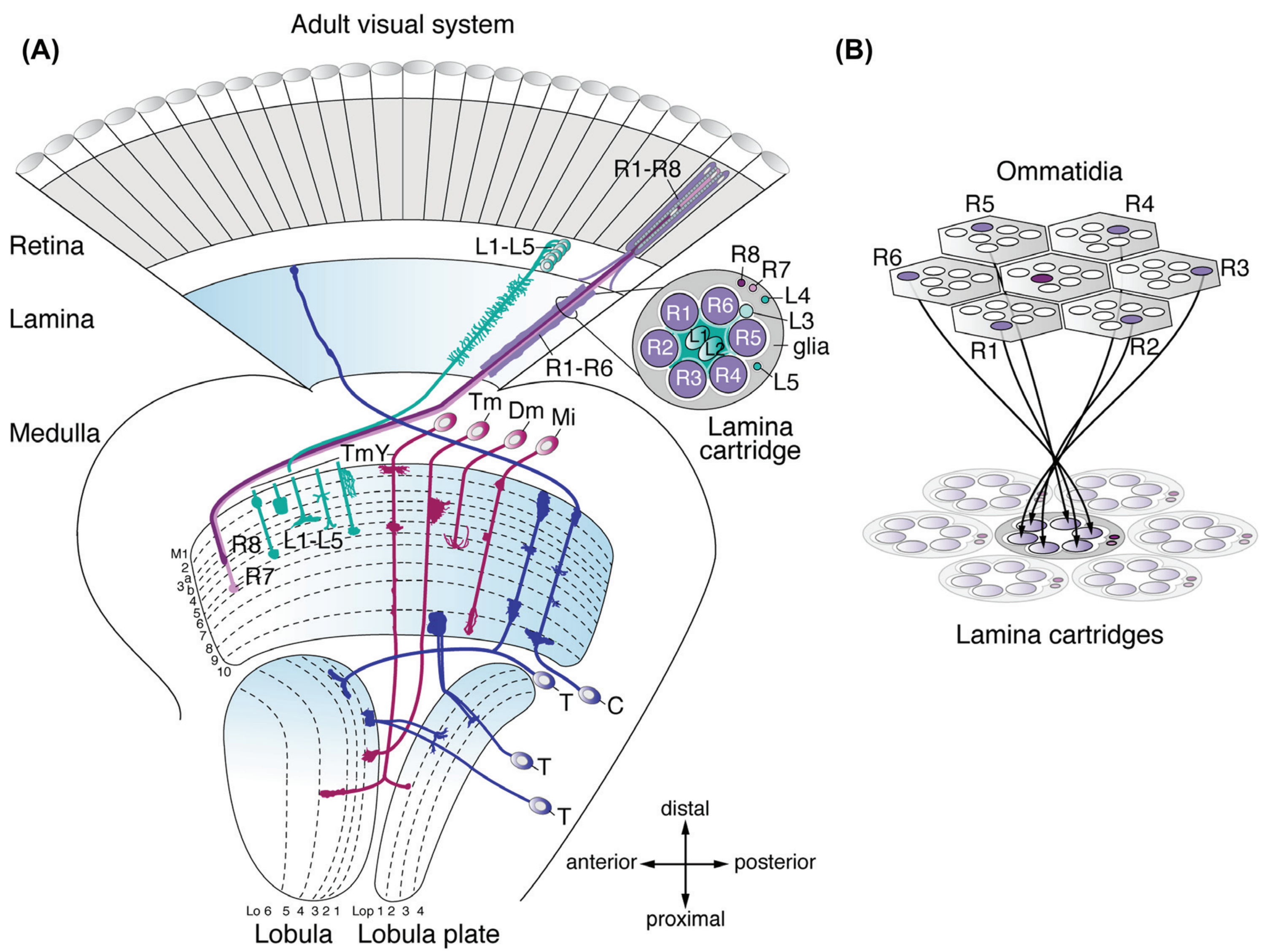


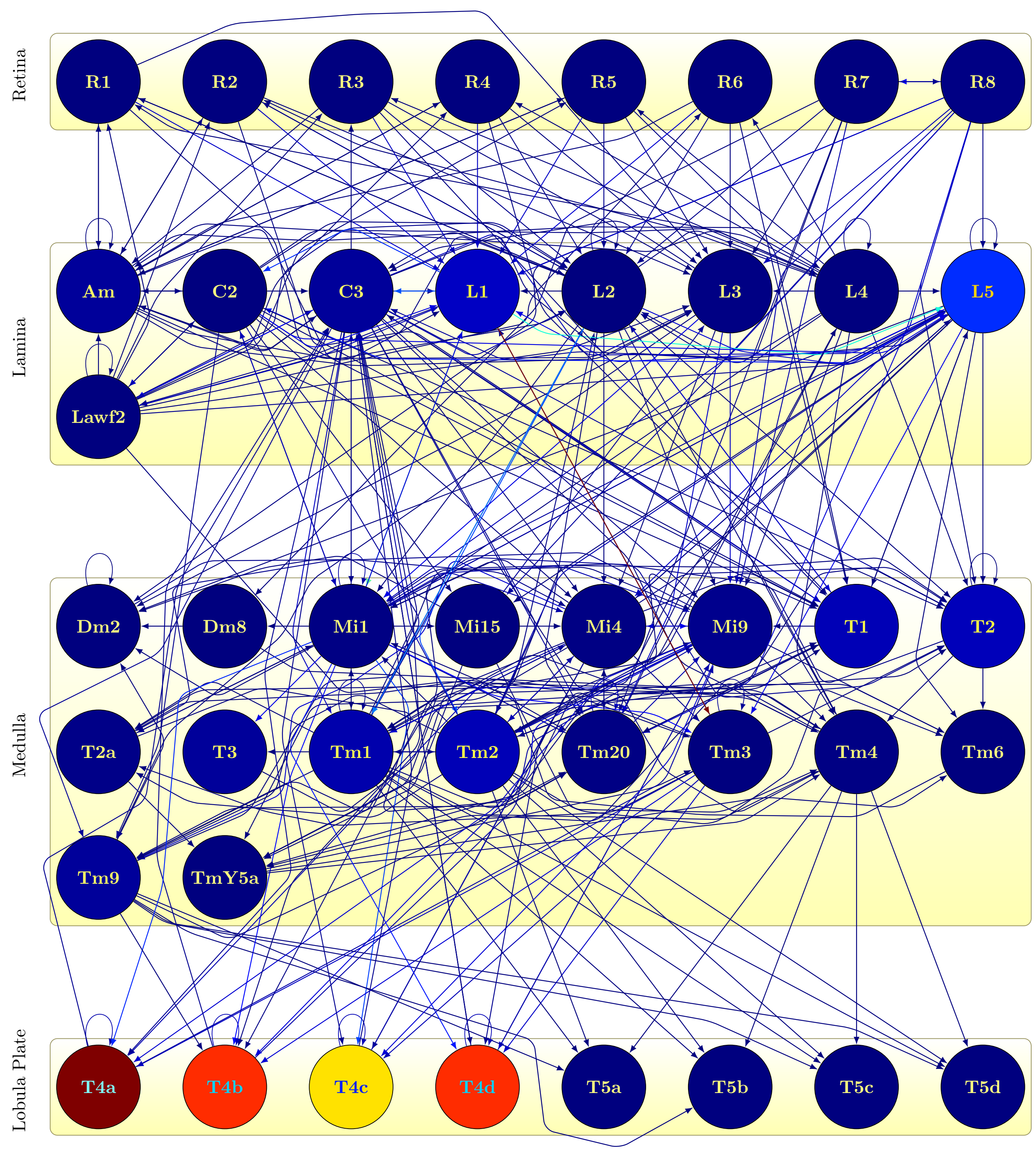
The last thing a fly ever sees

The Fly Visual System

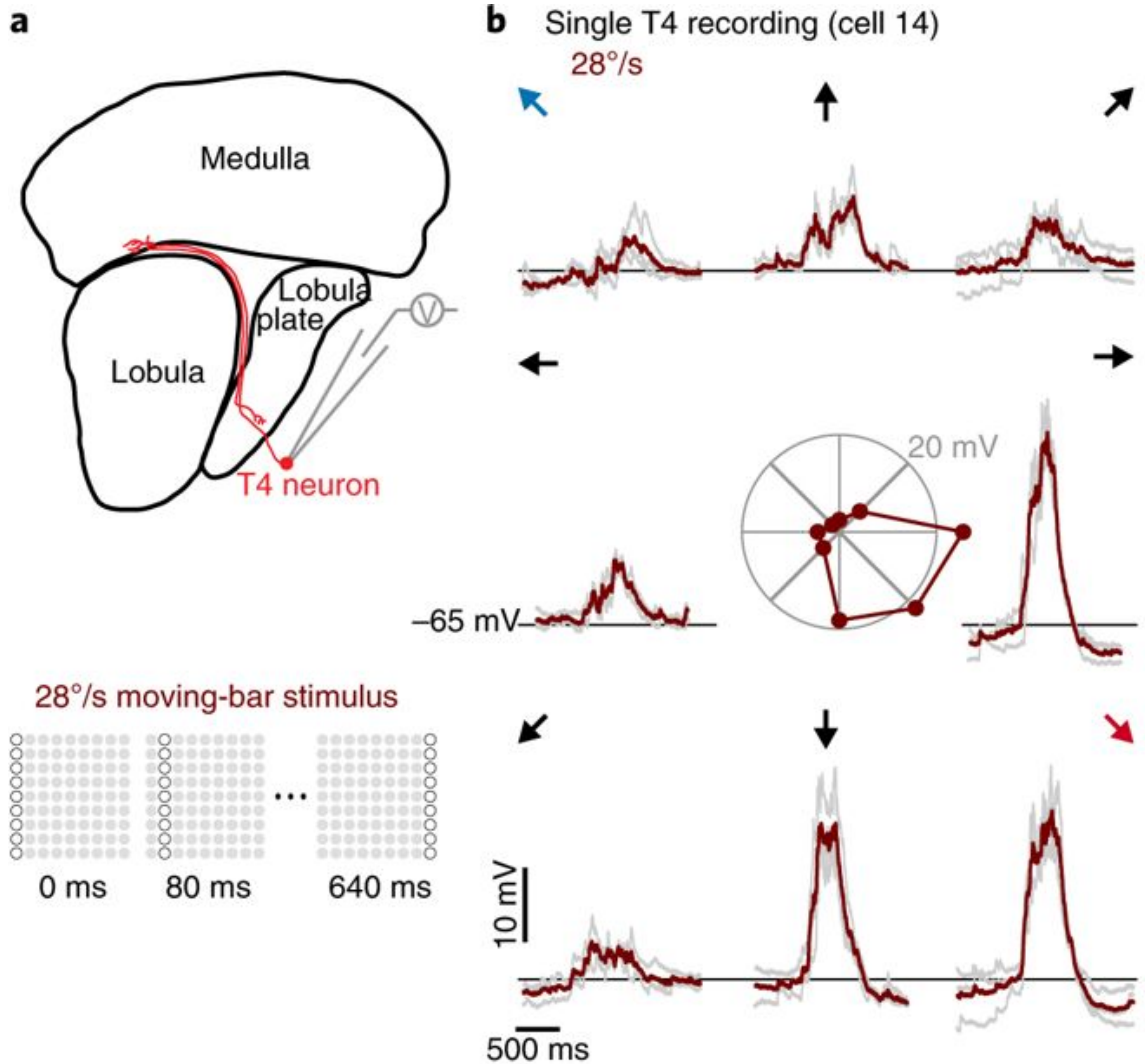


The Fly Visual System

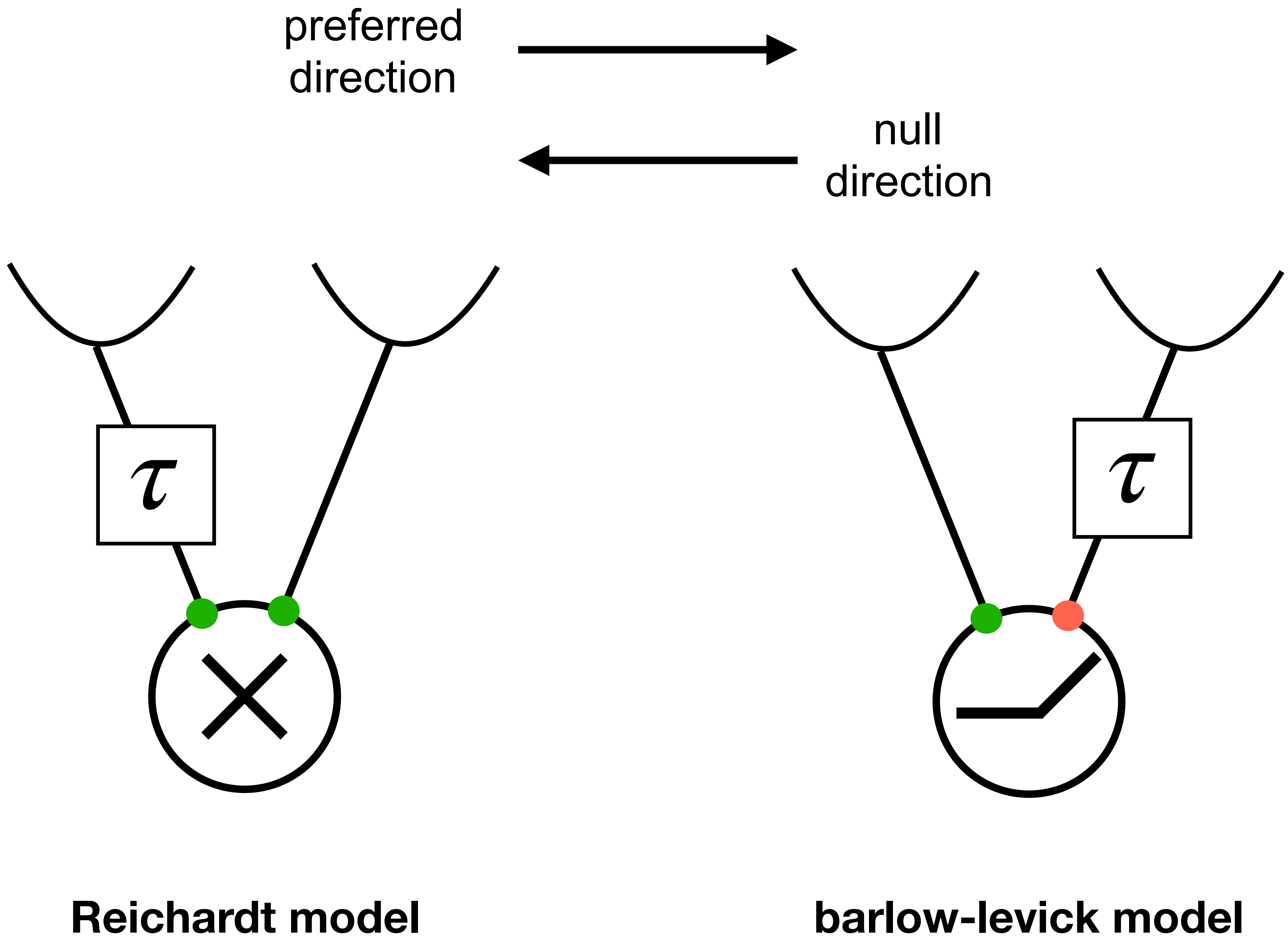




Takemura et. al., elife 2017



Gruntman, Romani and Reiser et. al., Nature Neuroscience 2018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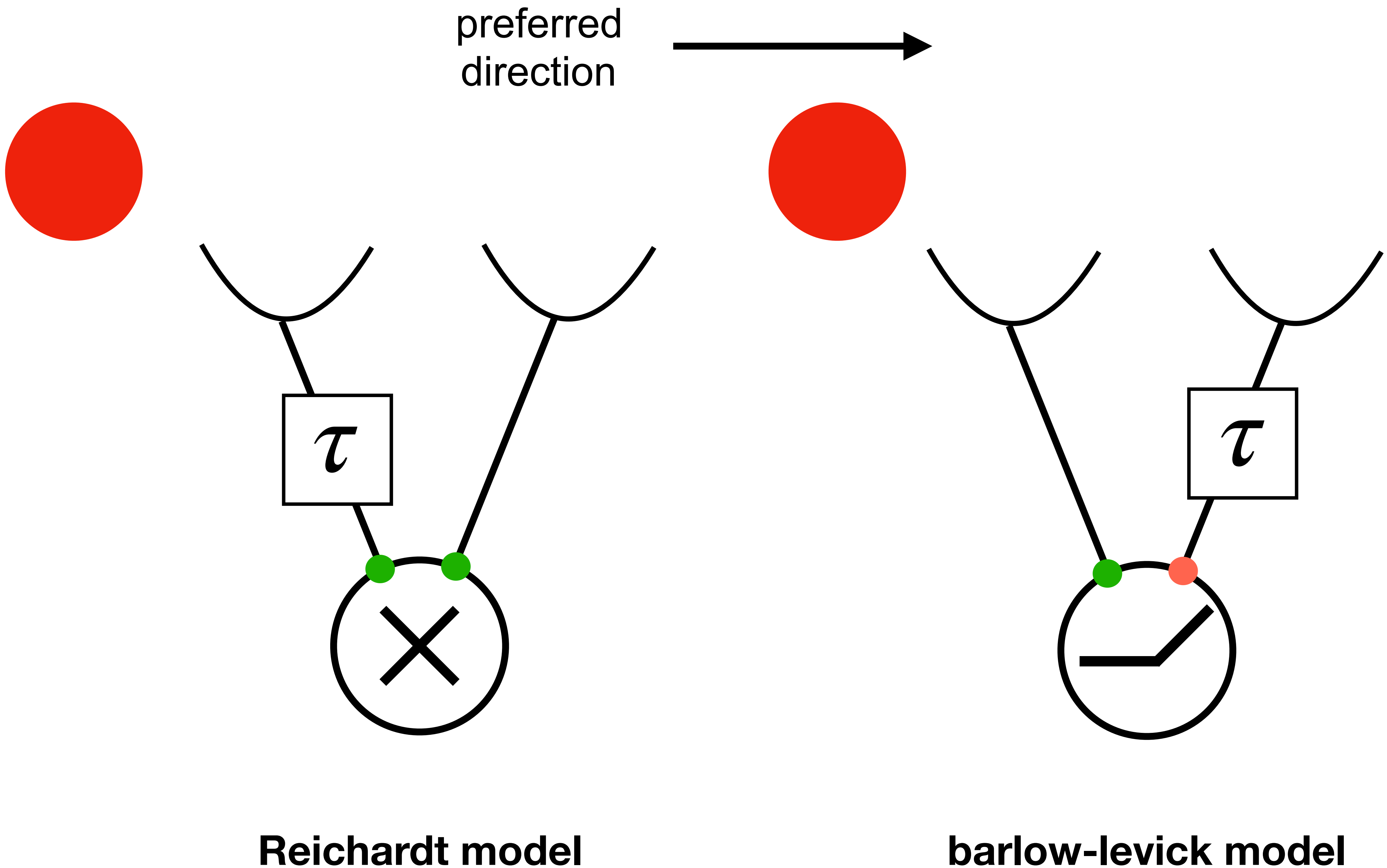
Reichardt model
barlow-levick model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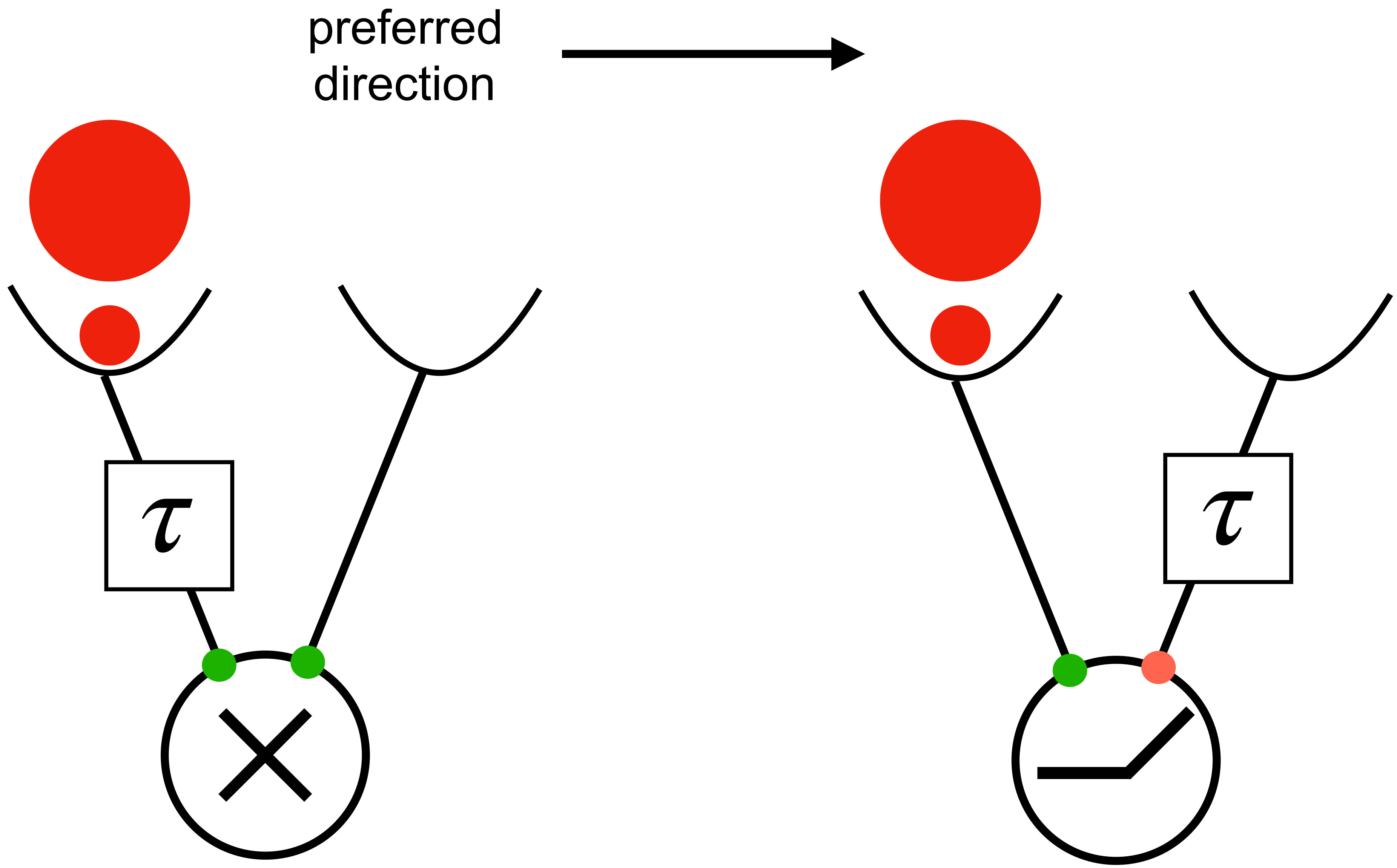
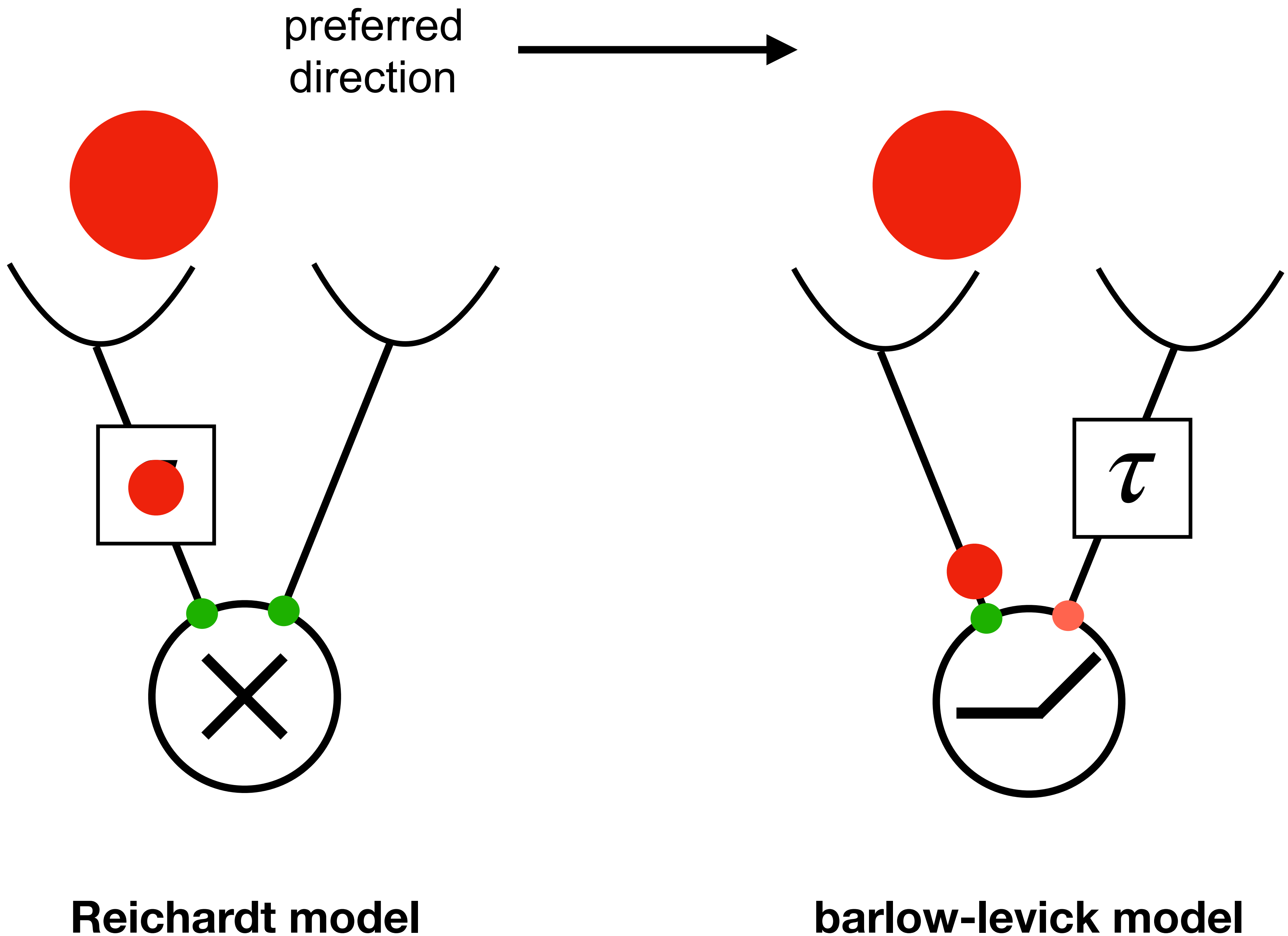


Reichardt model **barlow-levick model**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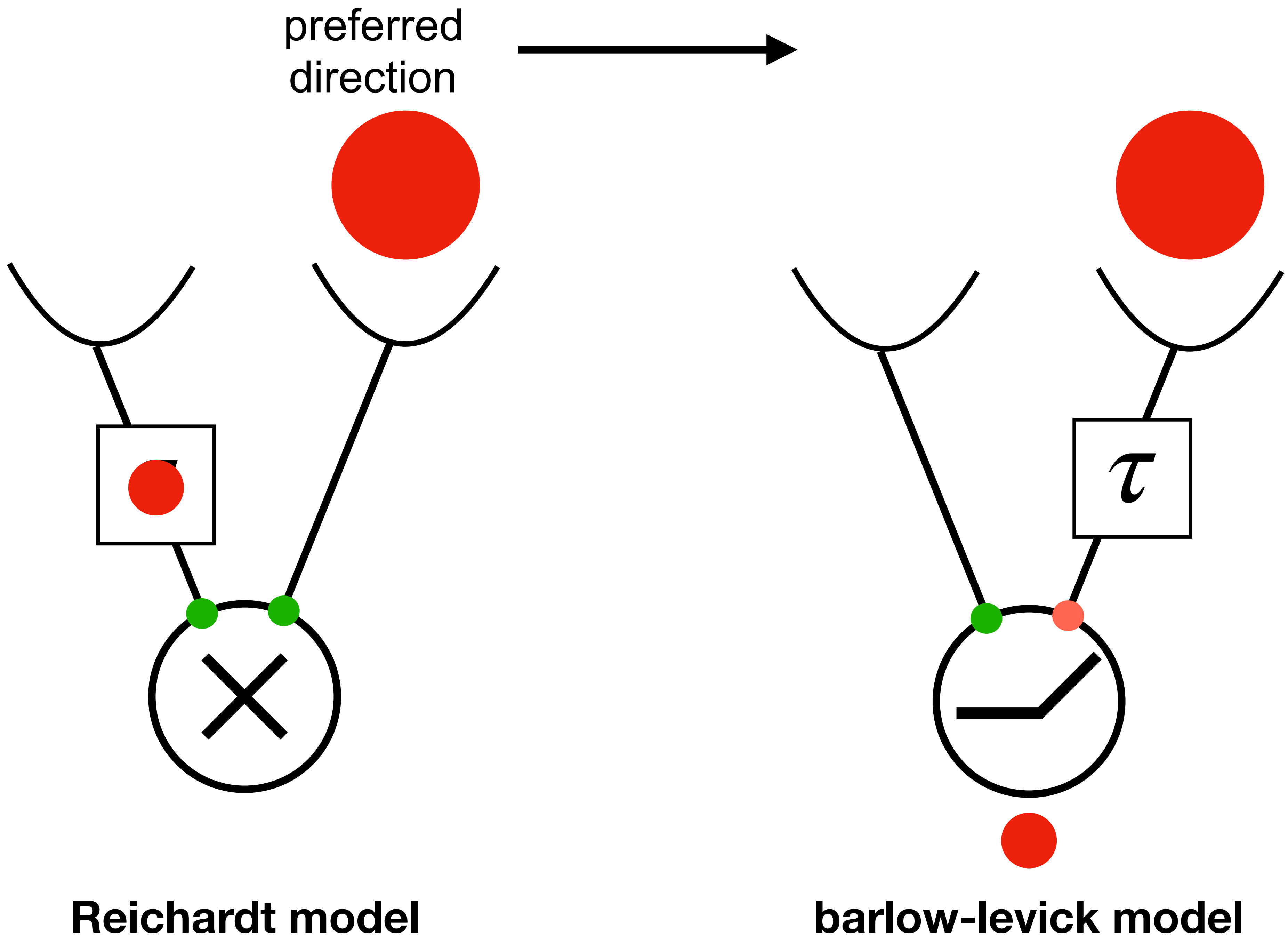
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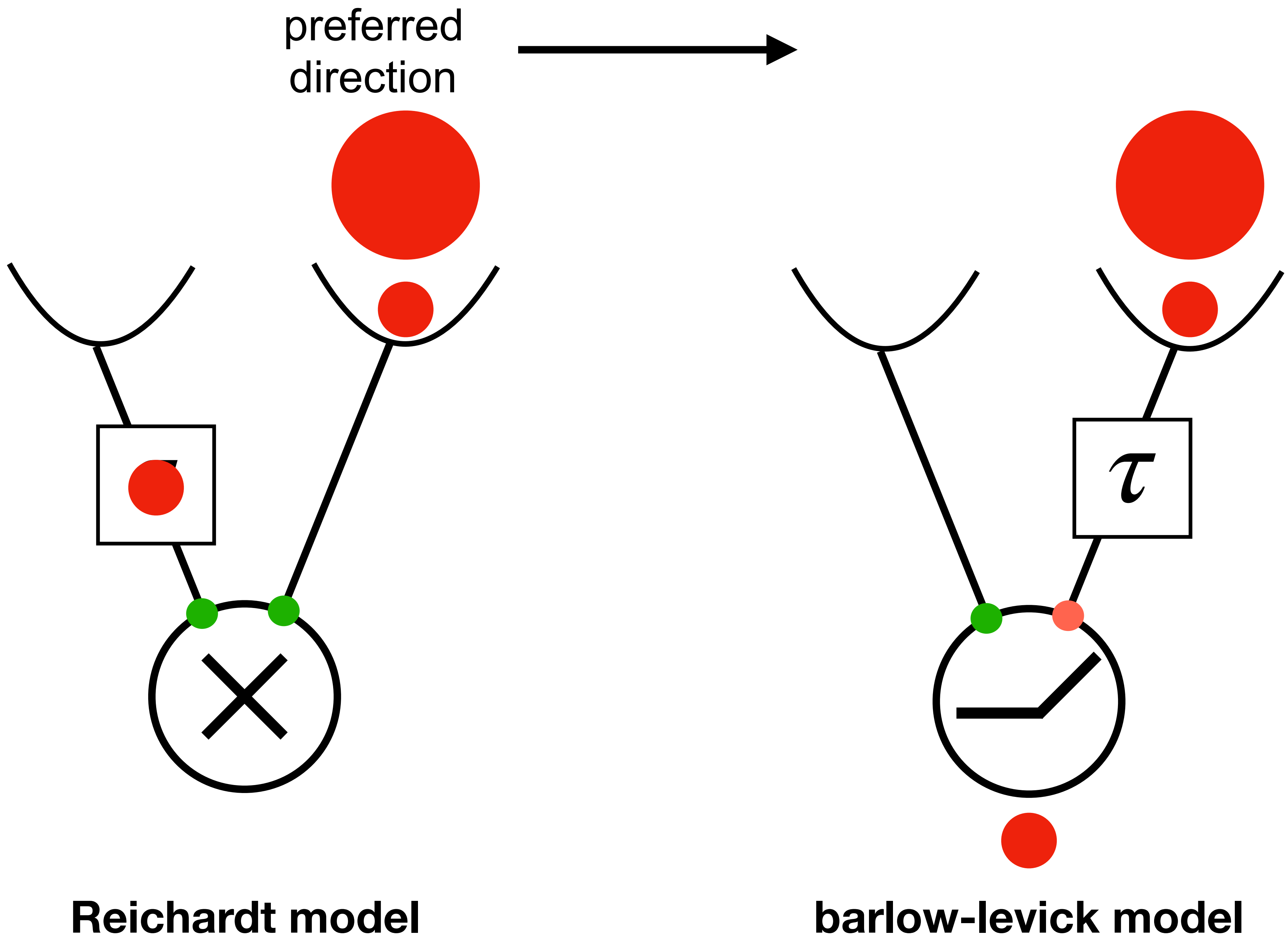

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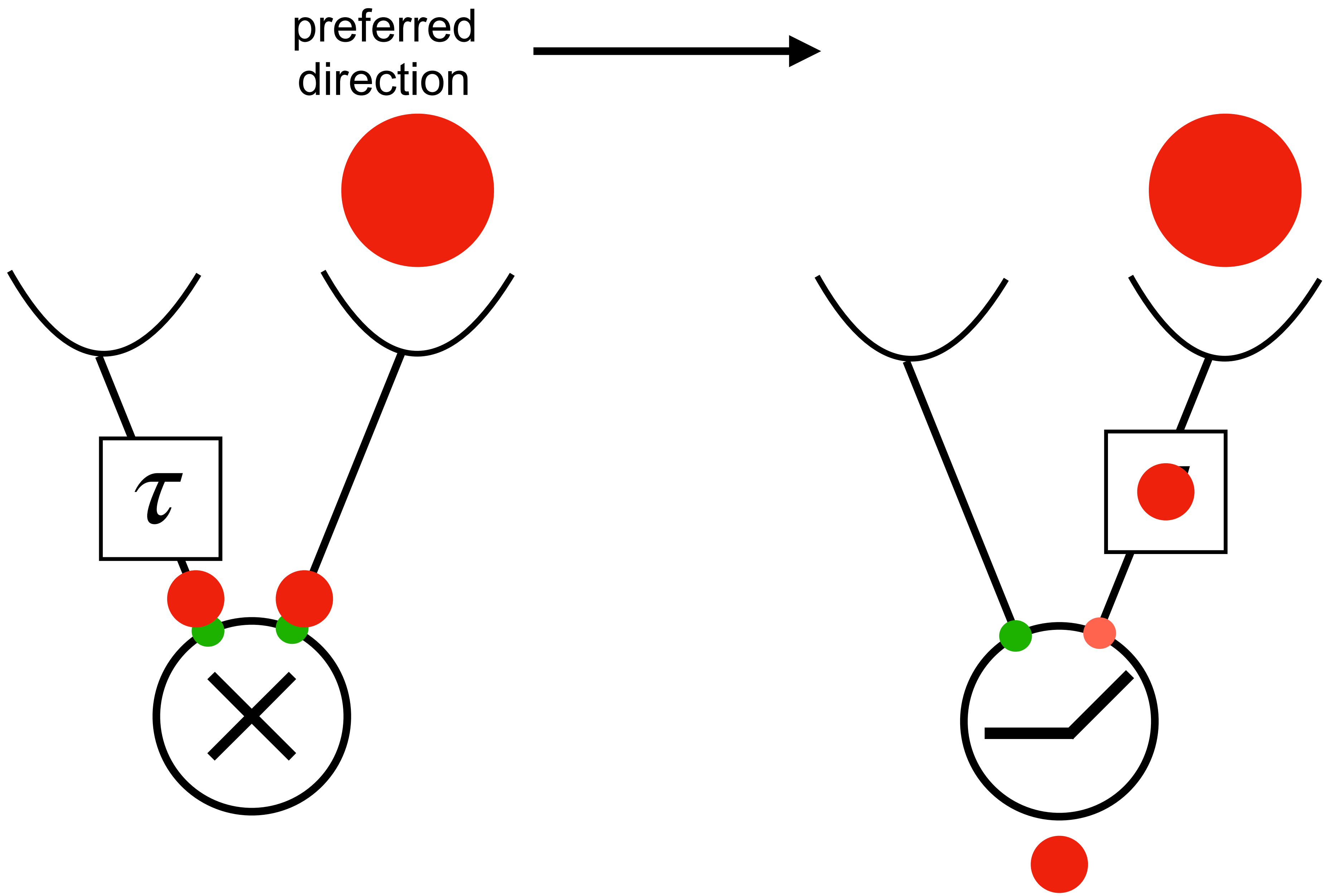
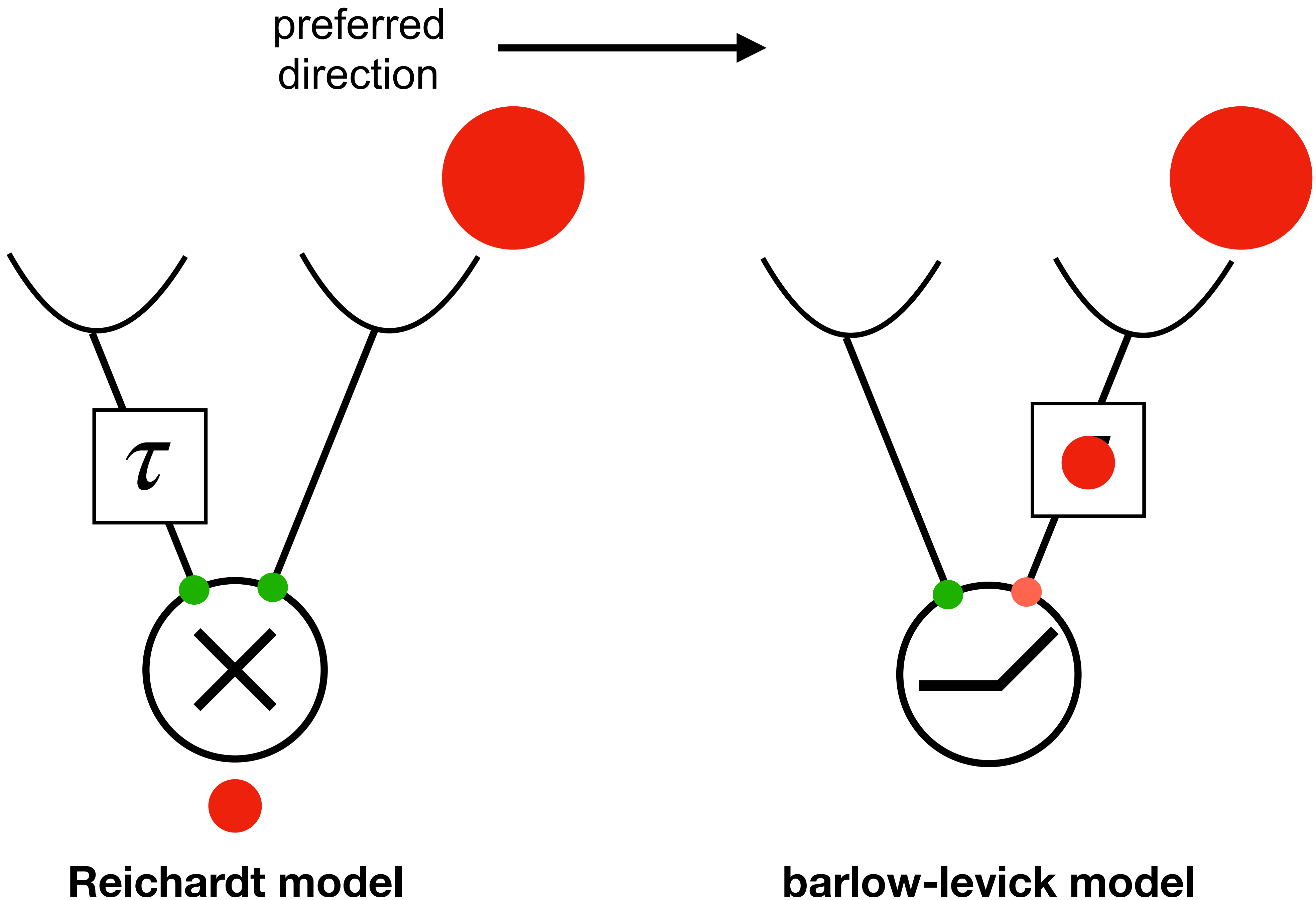


Reichardt model **barlow-levick model**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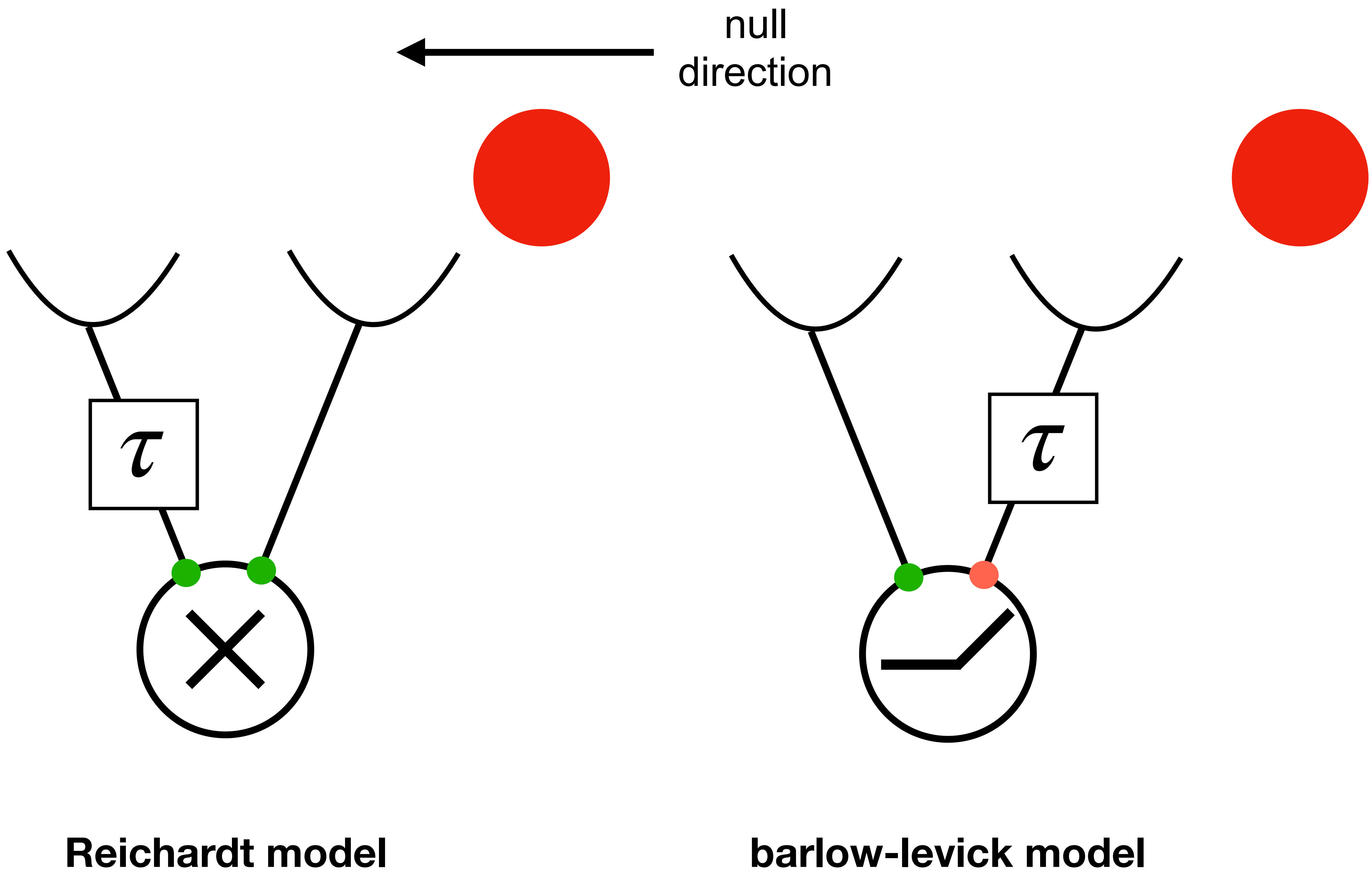
Reichardt model
barlow-levick model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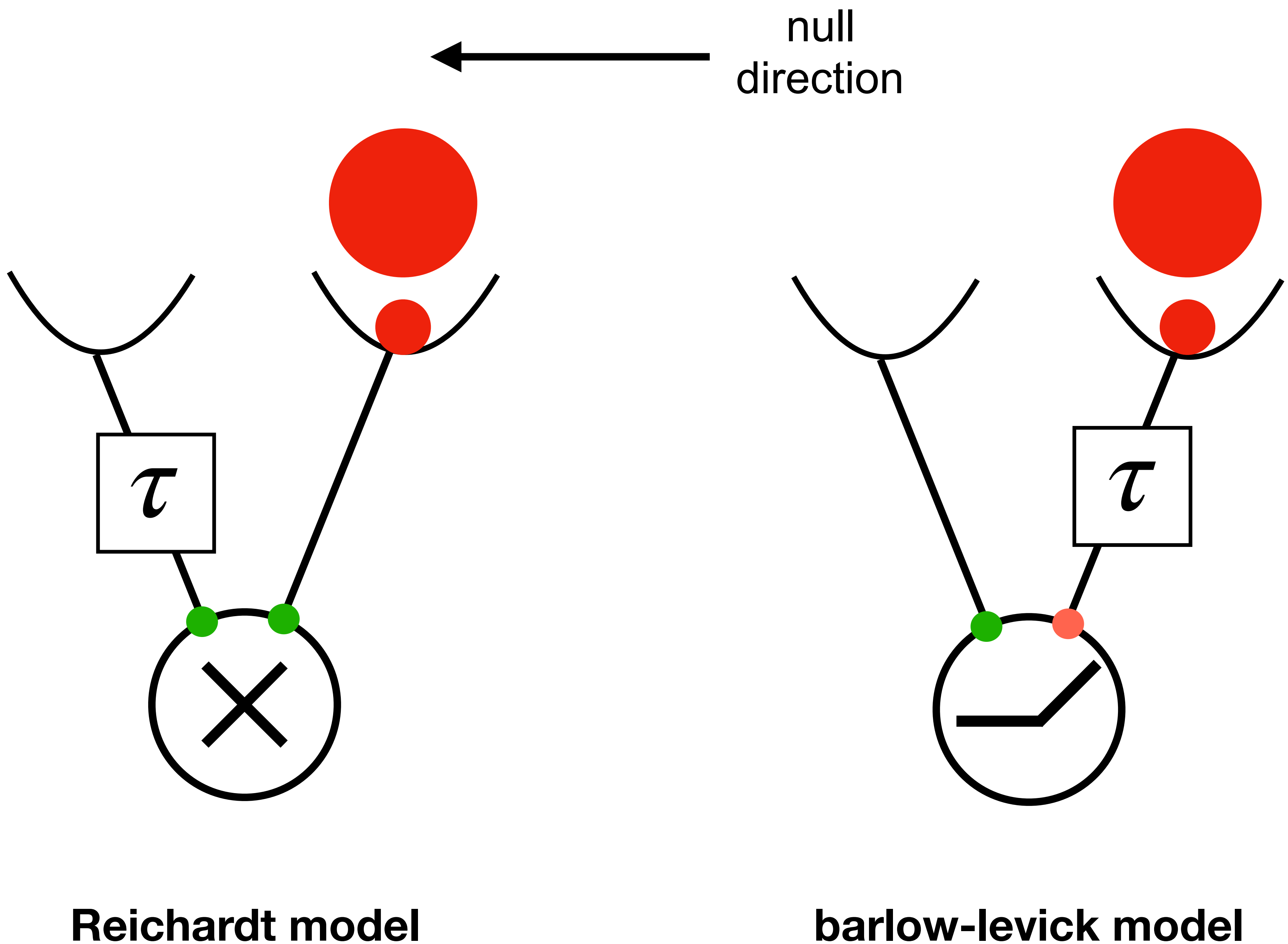

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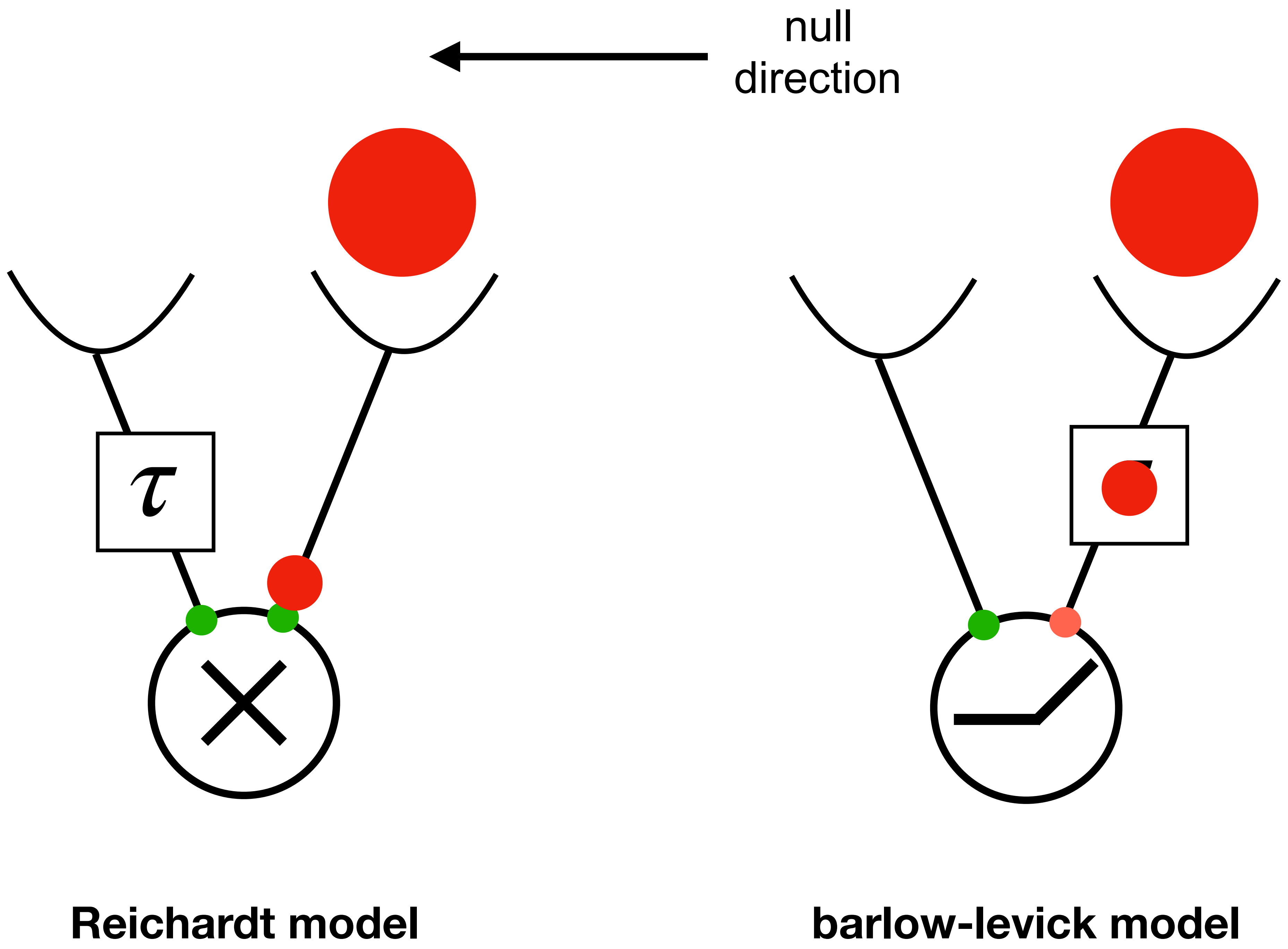

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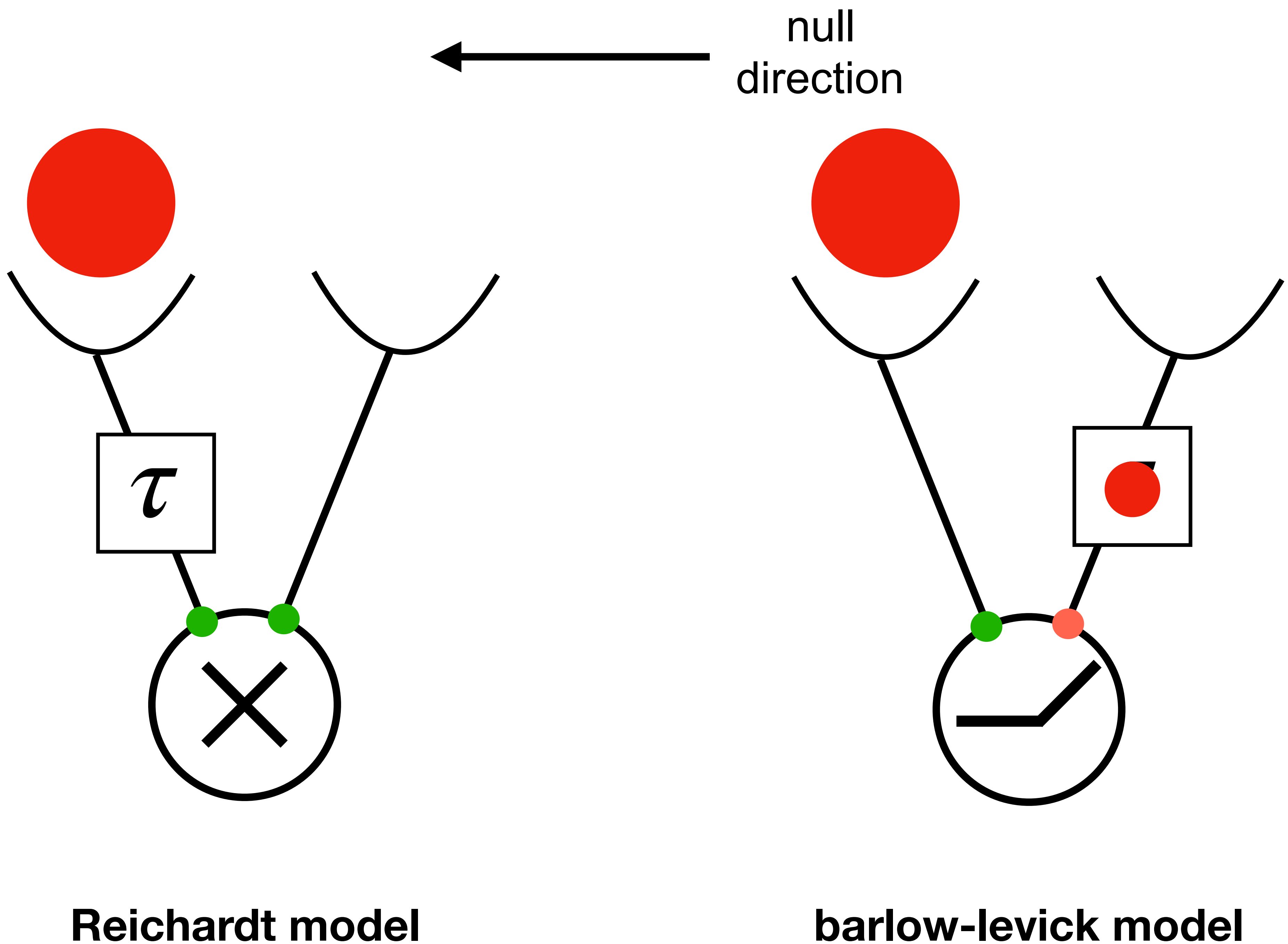
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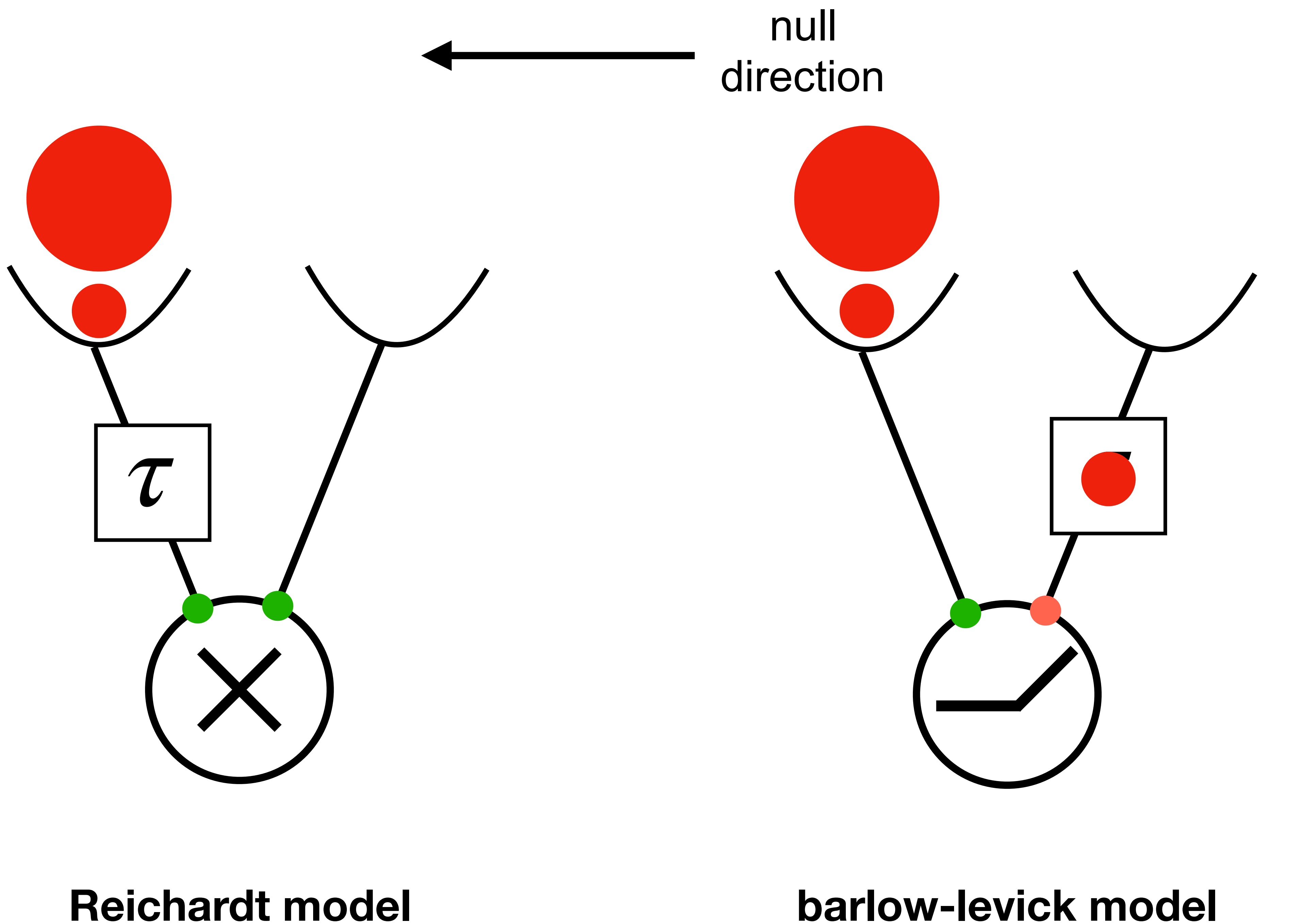
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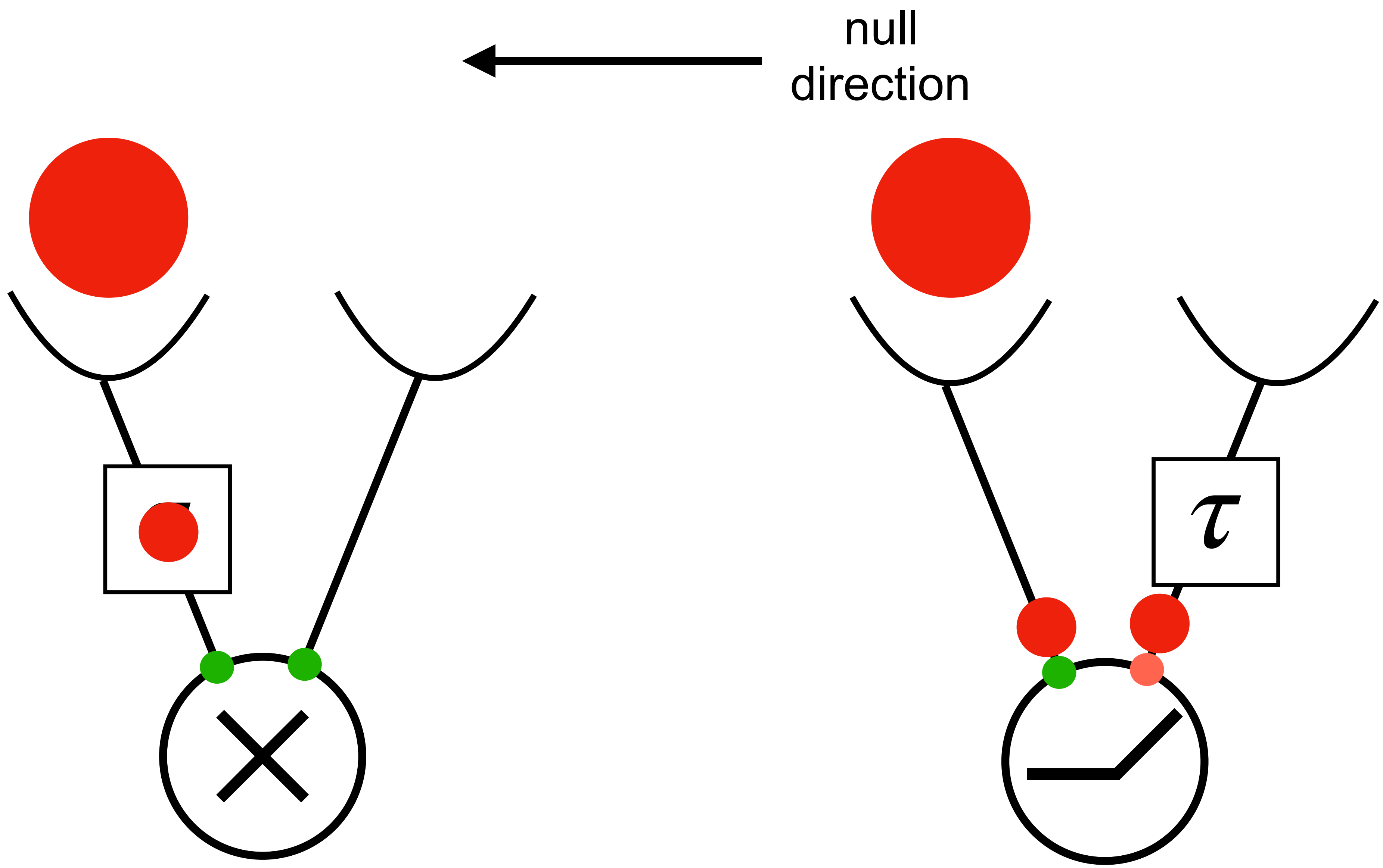
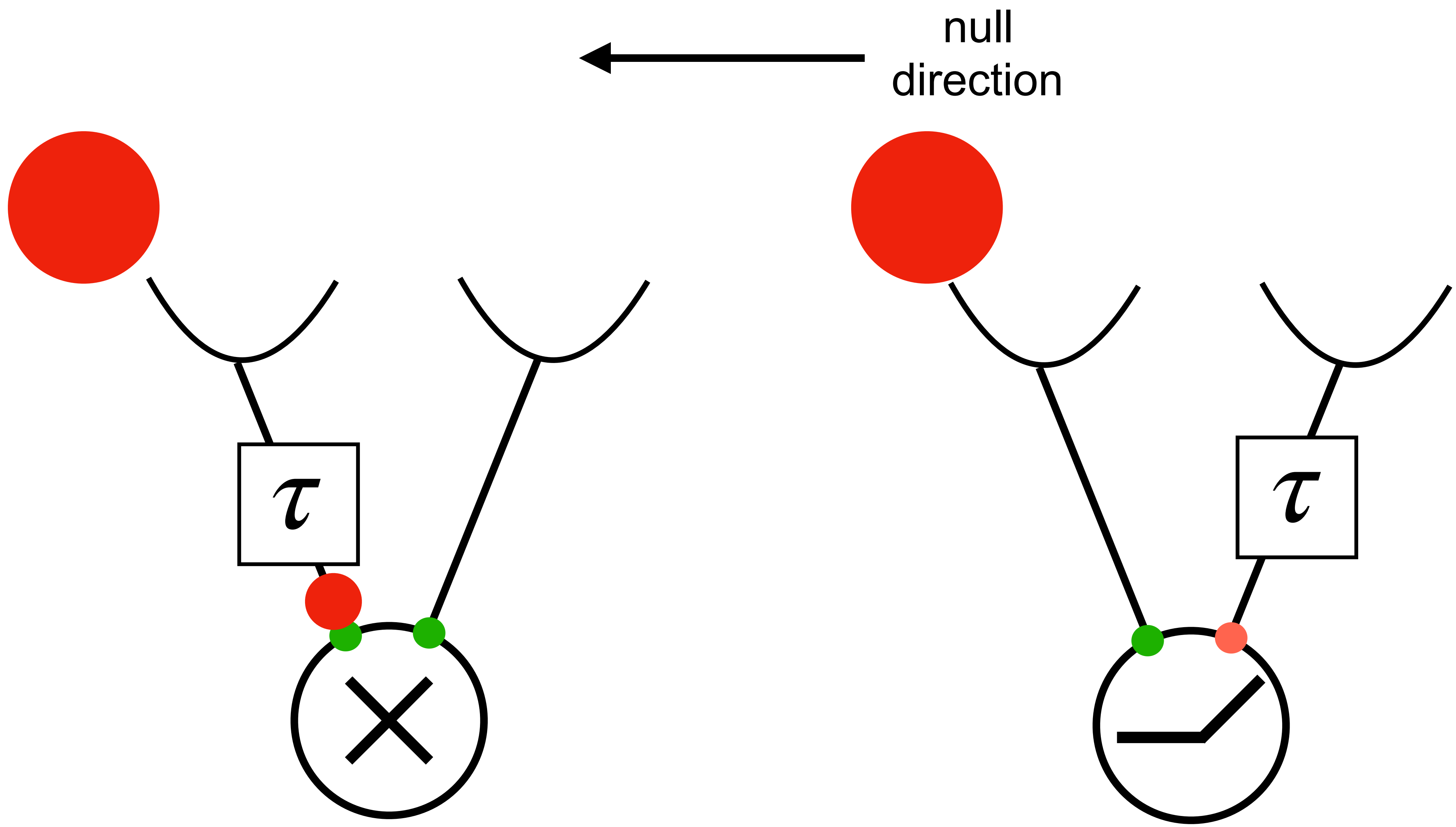
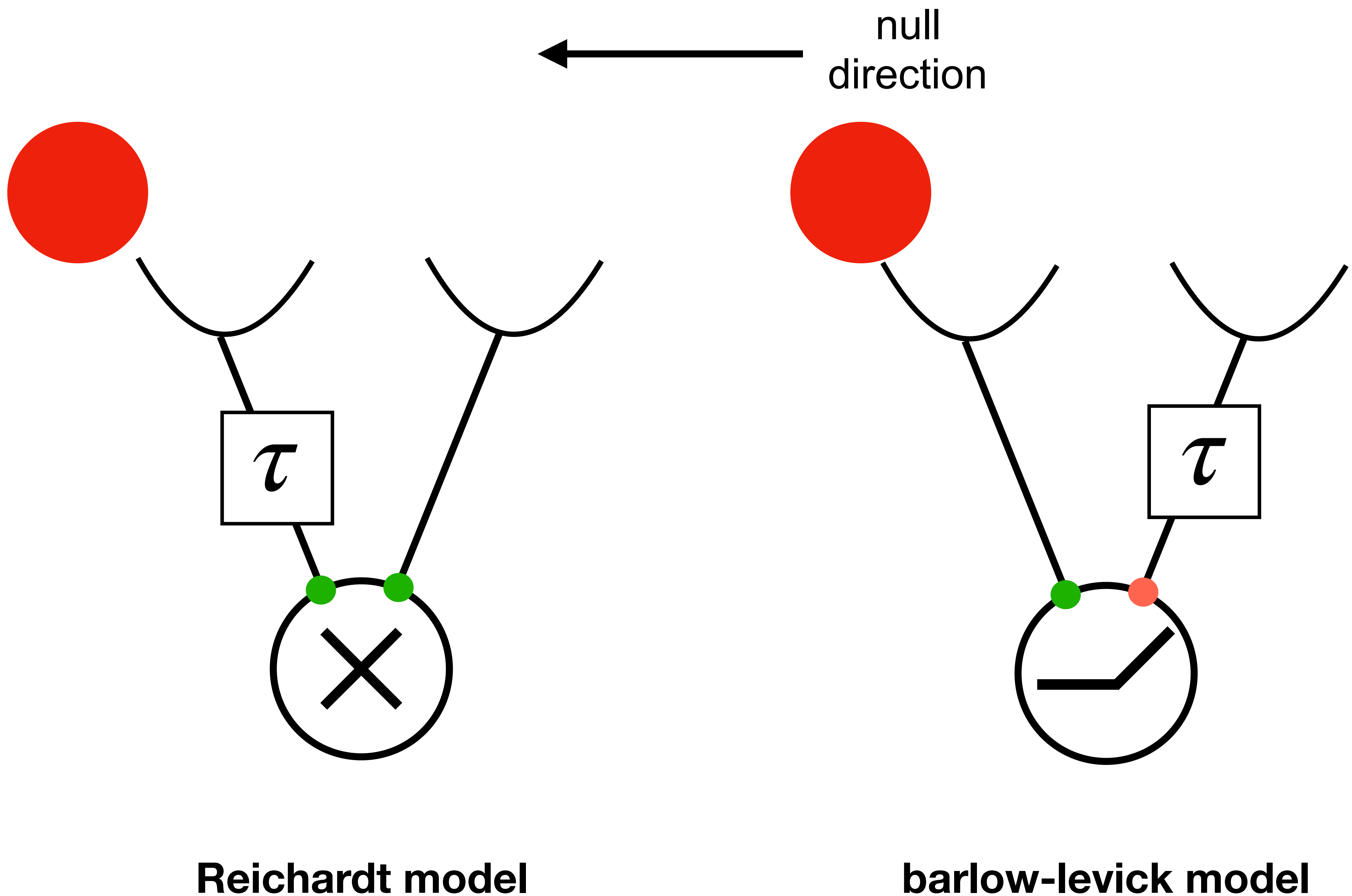


Reichardt model

barlow-levick model



Reichardt model **barlow-levick model**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Reichardt model
barlow-levick model

- Systems **level**: describe how population neural dynamics and behaviors emerge from ensembles of neurons.

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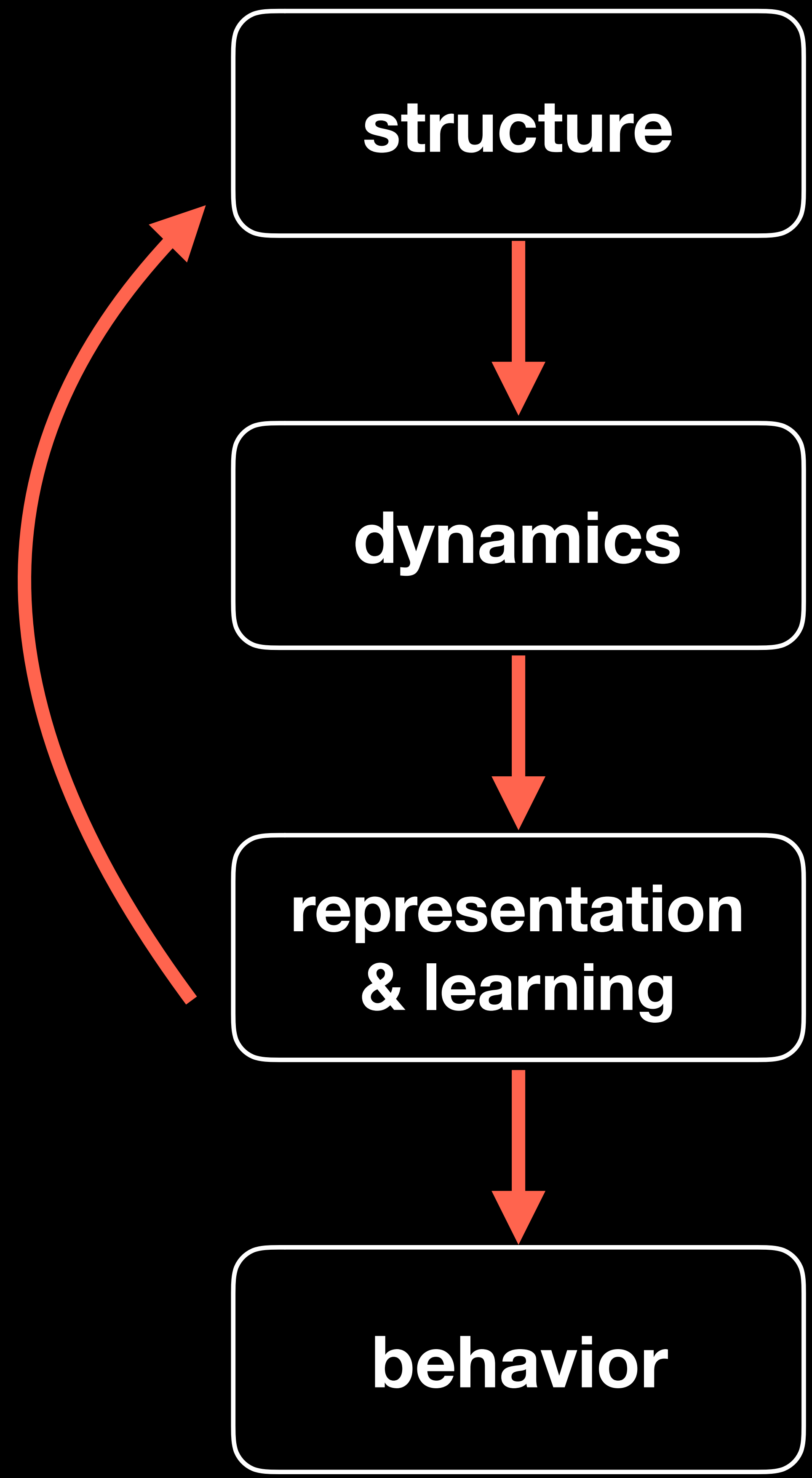
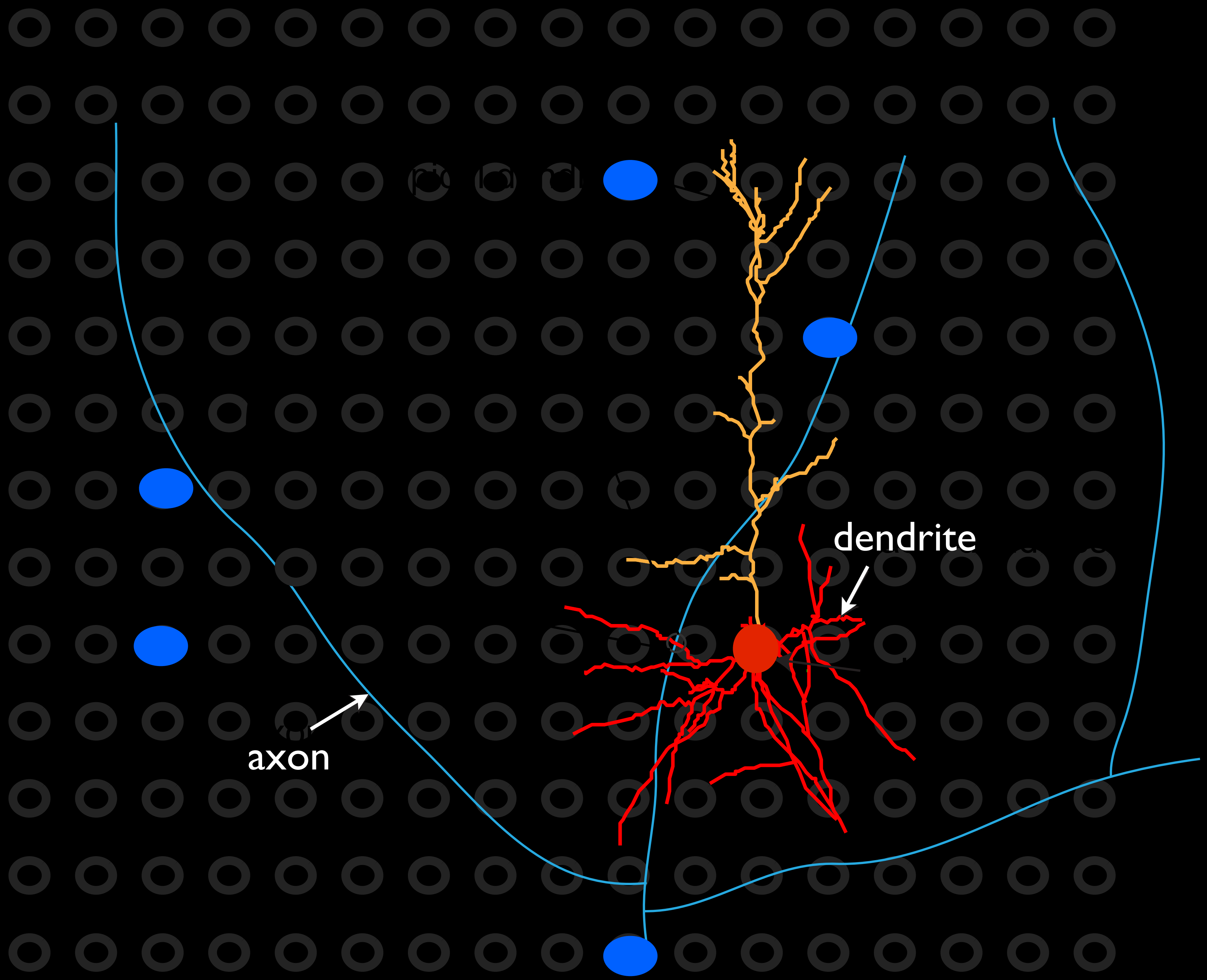
- **Structure level**: identify how neurons are statistically connected to each other in a circuit.

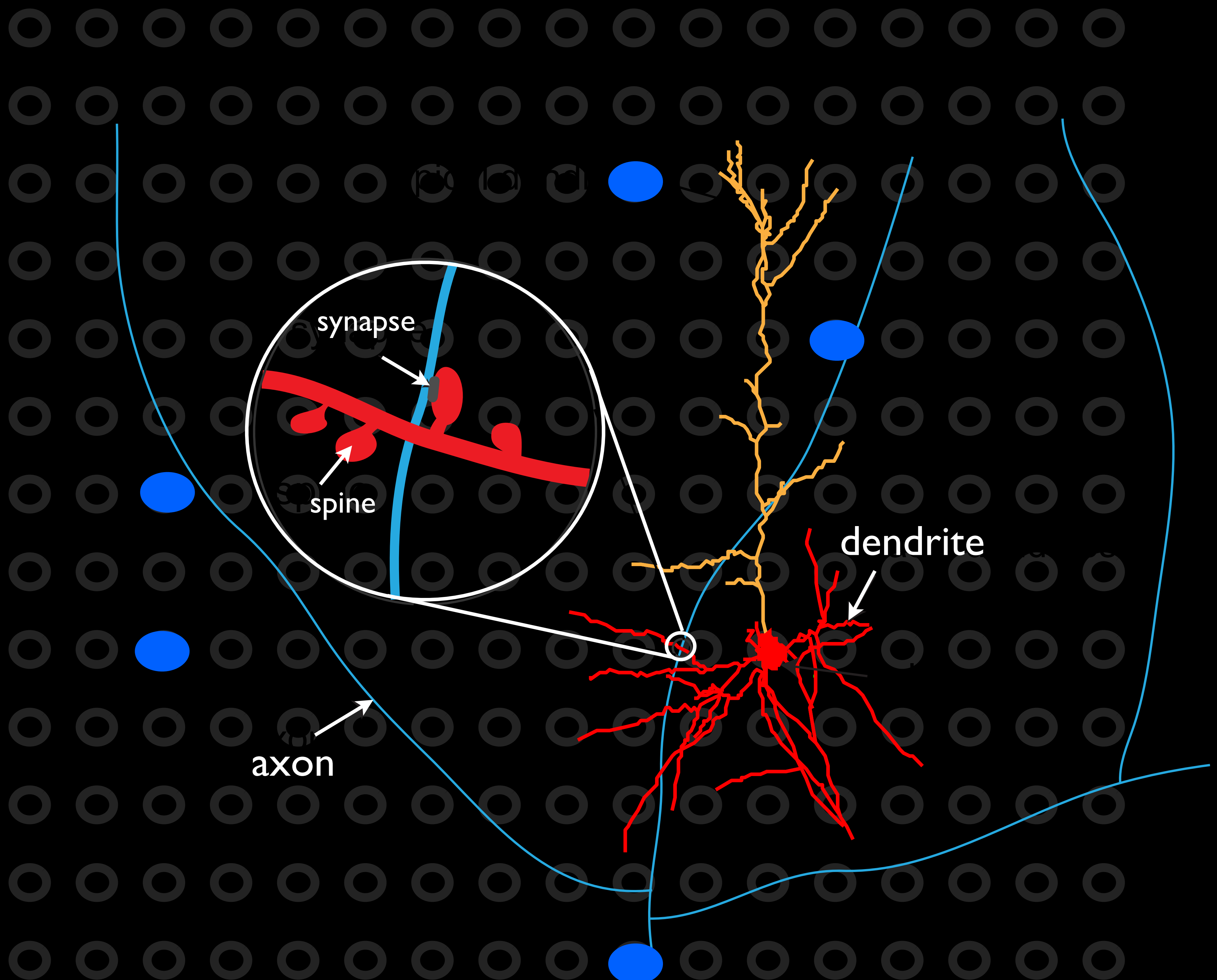
bottom-up

2020 *Fall Course Program*


structure
dynamics
representation & learning
behavior

The Neuron Doctrine


dendrite
axon

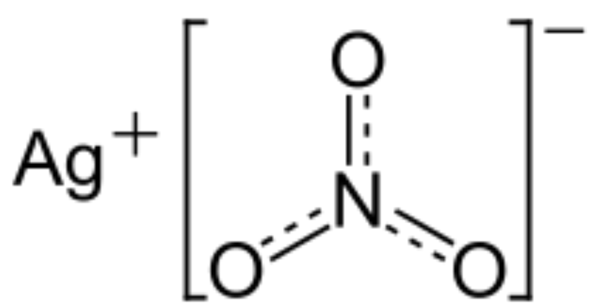

synapse
spine
dendrite
axon

The Debate between Cajal and Golgi

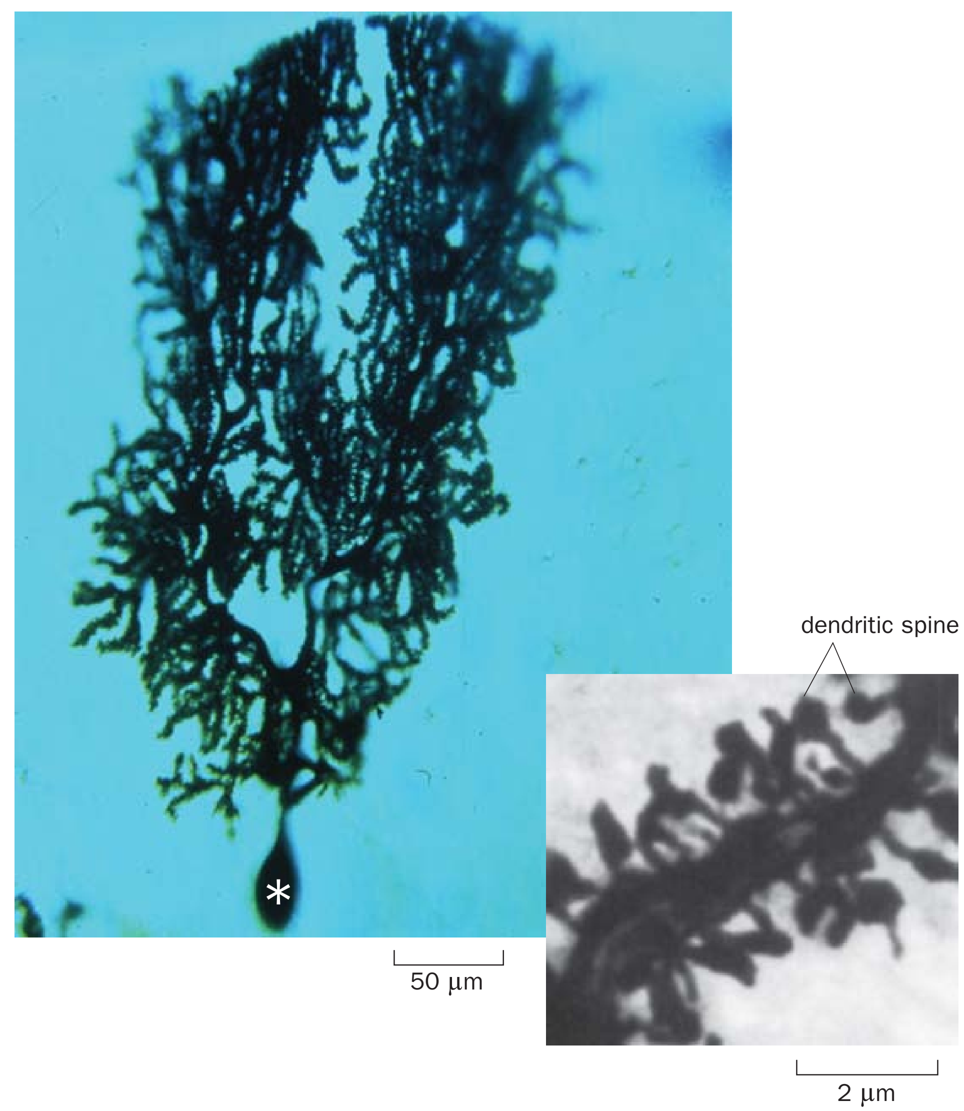
Ramon y Cajal

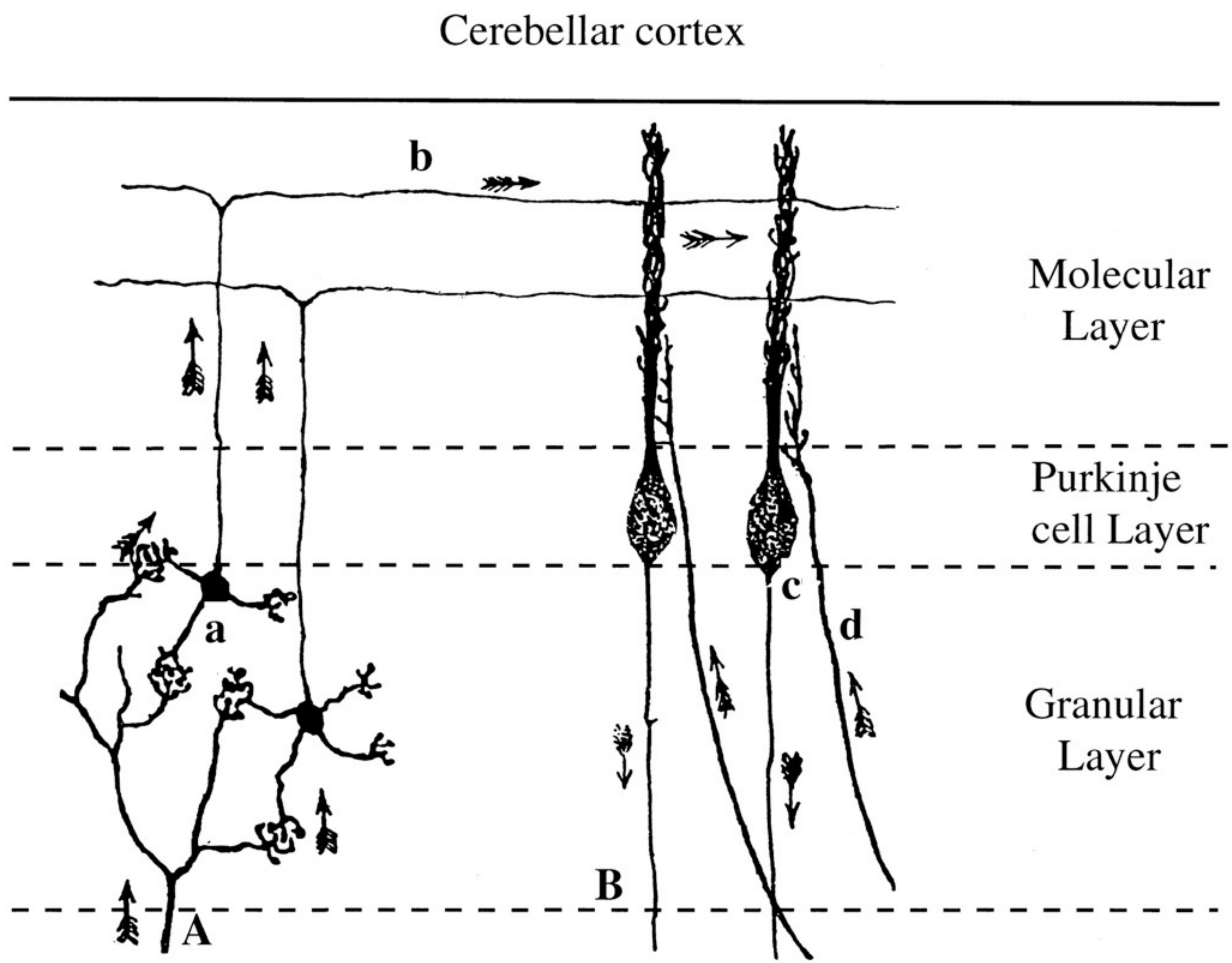
Camillo Golgi

Golgi Staining method



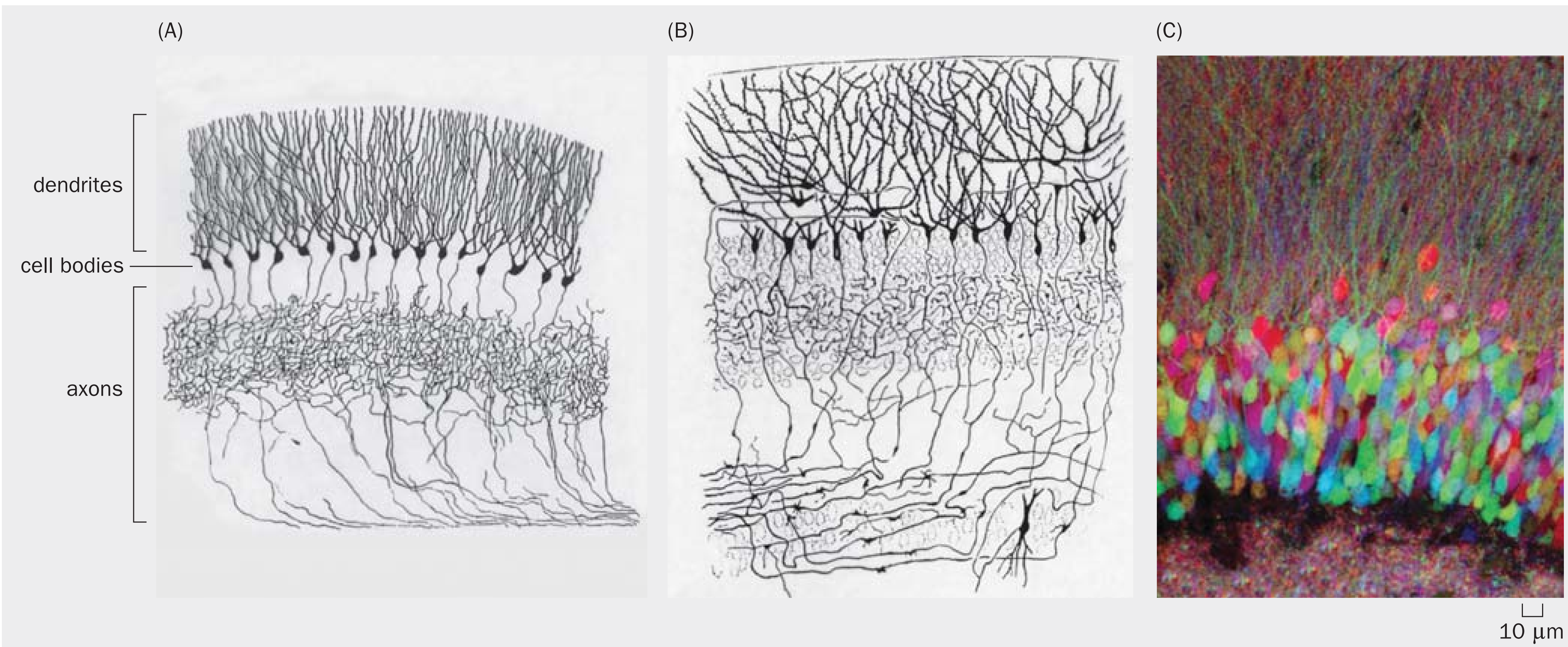
Silver nitrate





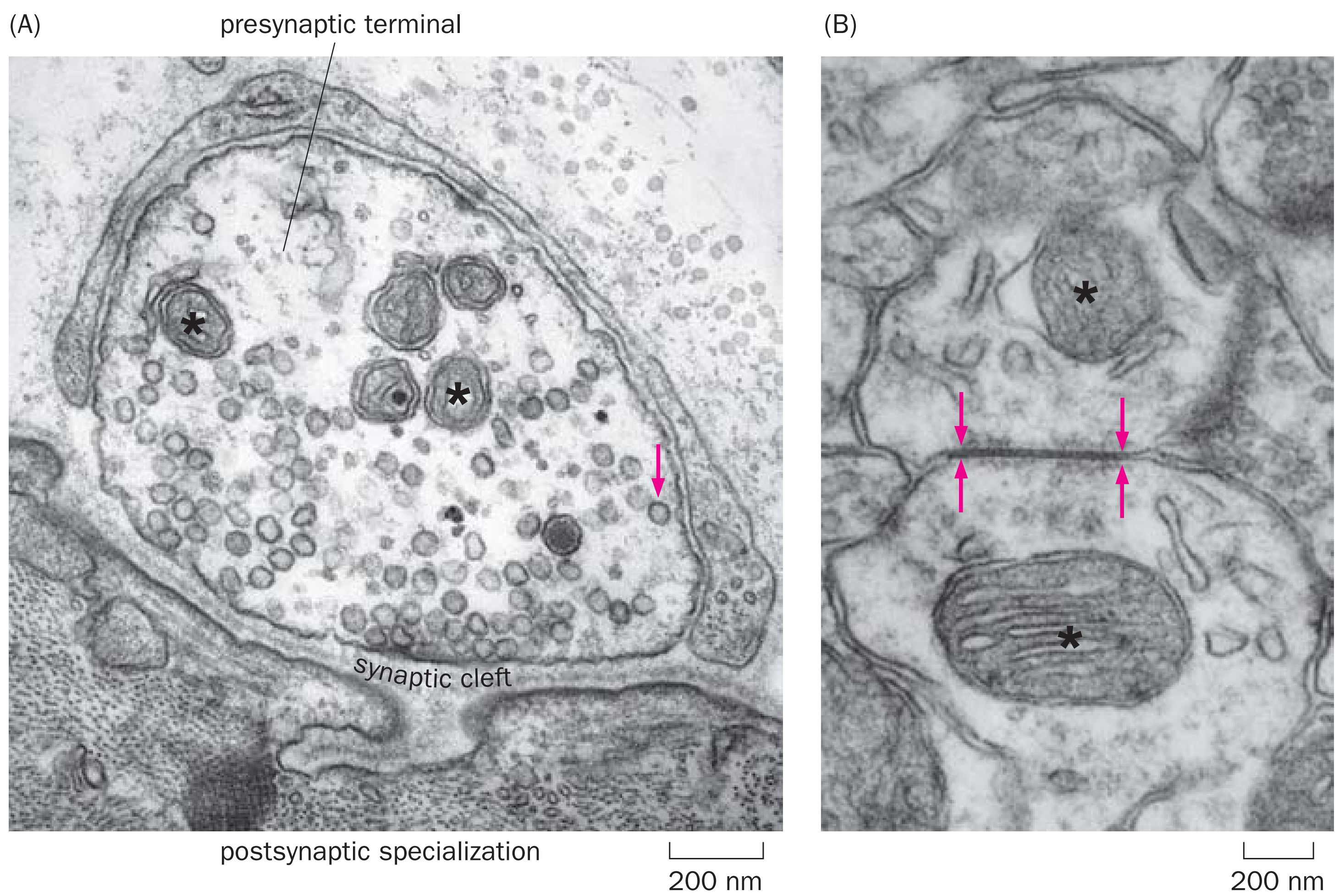
Cajal's drawing of the cerebellar cortex

Reticular Theory vs Neuron Doctrine



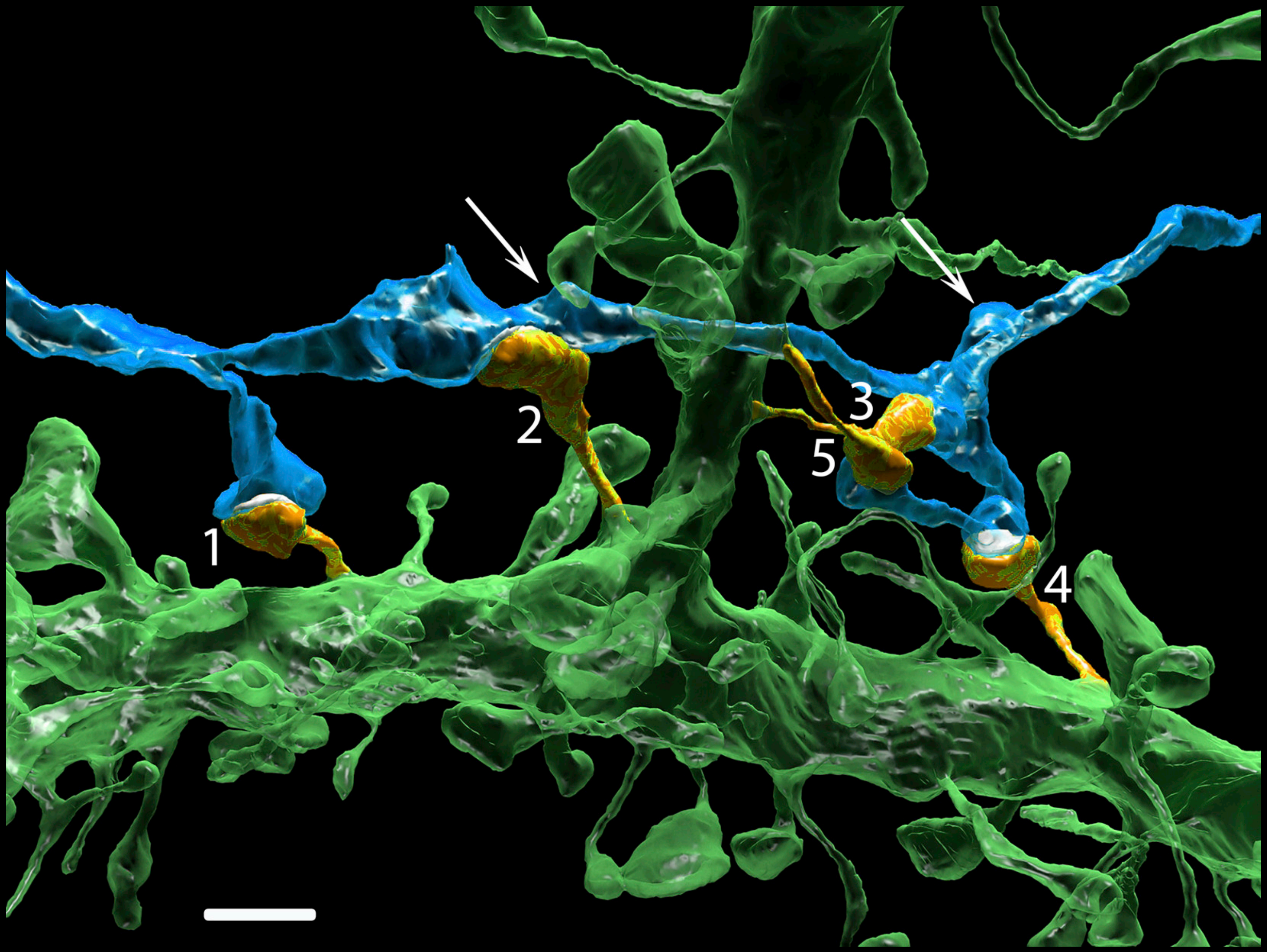
Synapse

How neurons communicate with each other?

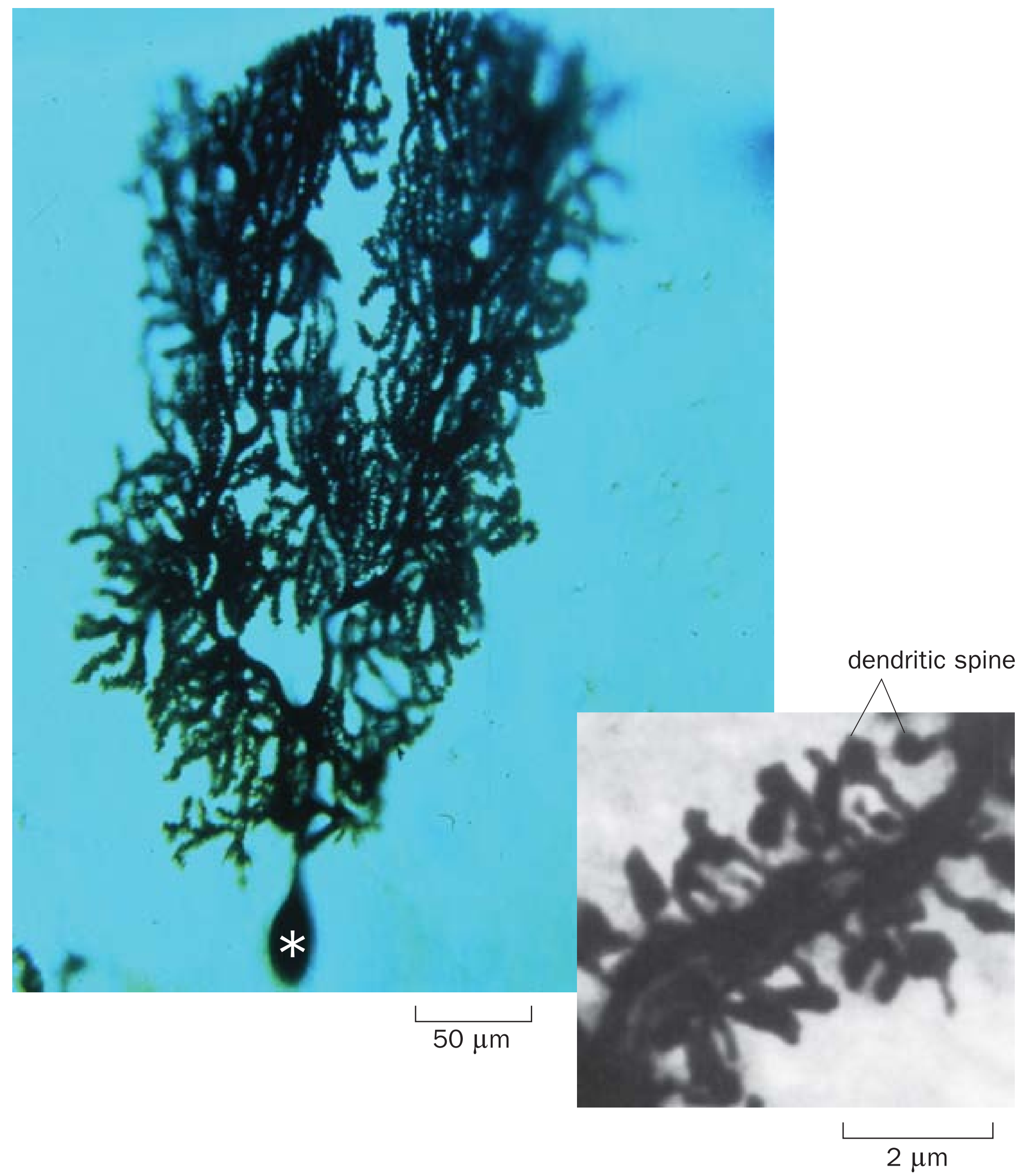


Chemical and electrical synapses

Synaptic Connectivity

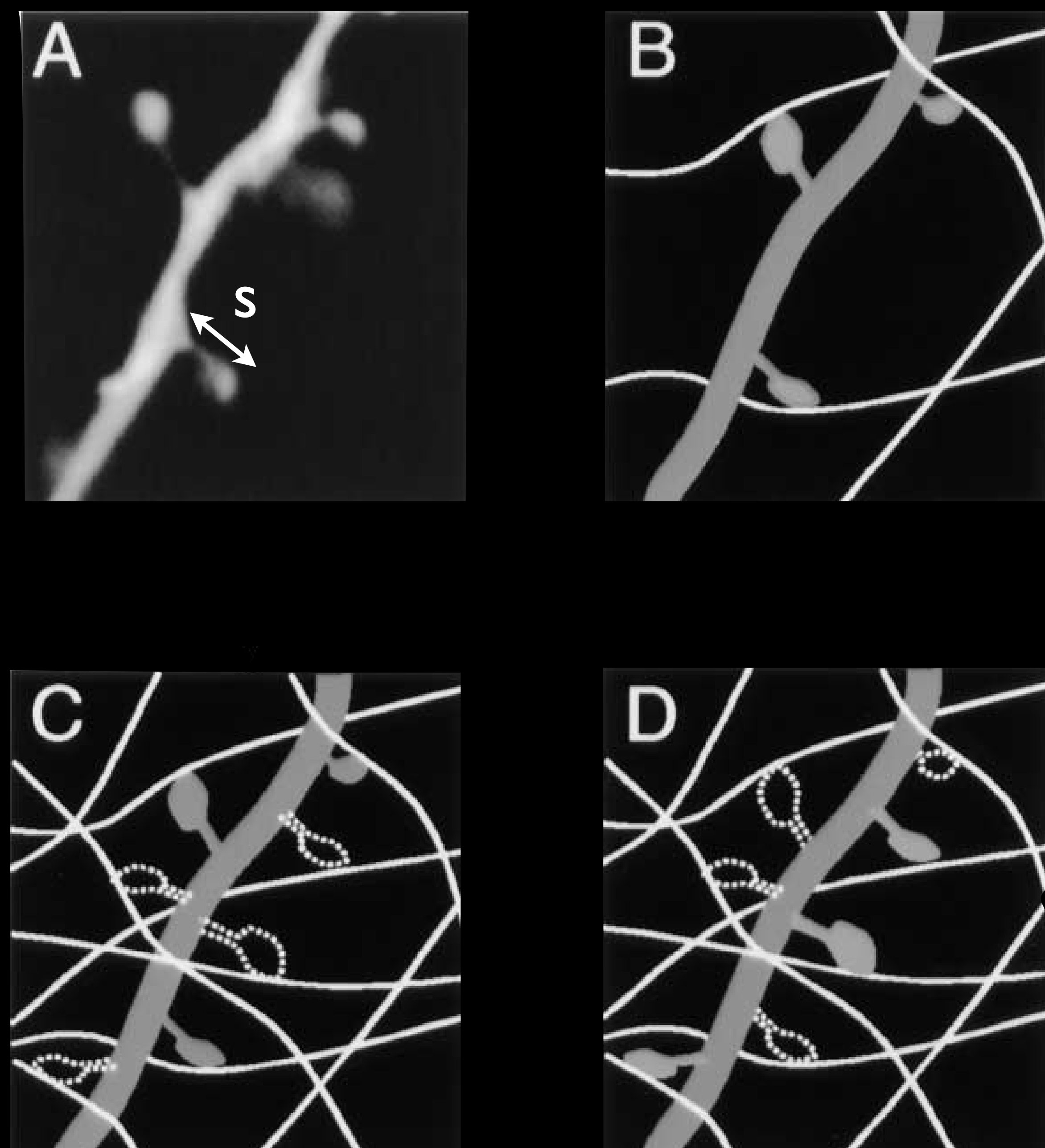


Kasthuri et. al, Cell 2015



Purkinjie cell in the cerebellum has the highest spine density in the brain

Structural Plasticity of Synaptic Connectivity



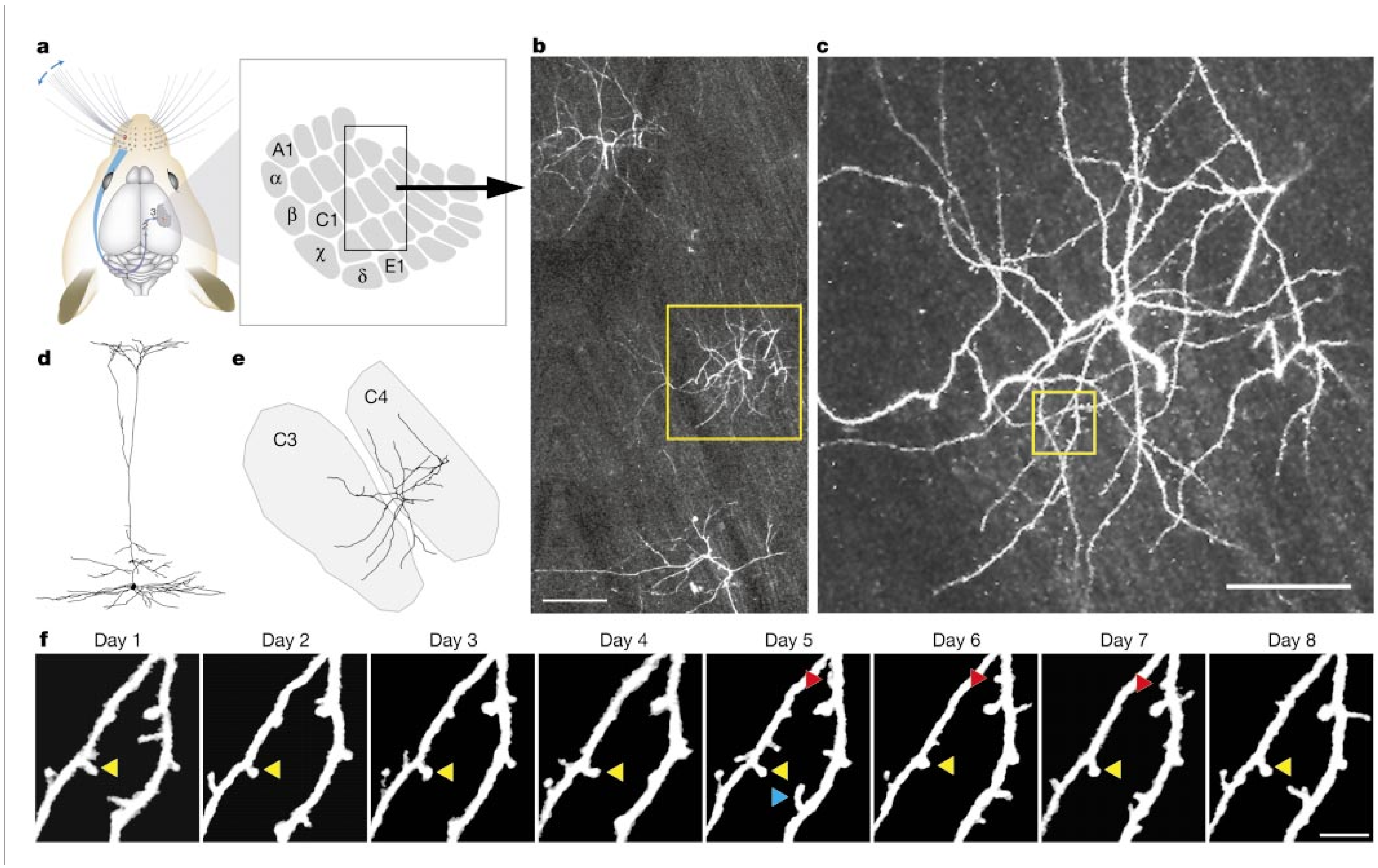
filling fraction = 3/7

$$f = \frac{2}{\pi s L_d b n}$$

s: spine length
L_d: total dendritic length per neuron
b: inter-bouton distance
n: neuronal density

Stepanyants et. al., *Neuron* 2001

Structural Plasticity of Synaptic Connectivity



Trachtenberg et., al. *Nature* 2002

Why do we need axons and dendrites?

Single Cortical Neurons as Deep Artificial Neural Networks

[1]David Beniaguev, [1,2]Idan Segev and [1,2]Michael London

[1]The Edmond and Lily Safra Center for Brain Sciences and [2]Department of Neurobiology, The Hebrew University of Jerusalem, Jerusalem, Israel.

Communication: David Beniaguev - david.beniaguev@gmail.com

Can Single Neurons Solve MNIST? The Computational Power of Biological Dendritic Trees

Ilenna Simone Jones[1] and Konrad Kording[2]

[1]Department of Neuroscience, University of Pennsylvania
[2]Departments of Neuroscience and Bioengineering, University of Pennsylvania

September 4, 2020

Occam’s Razor

entities should not be multiplied without necessity.

奥卡姆剃刀定律

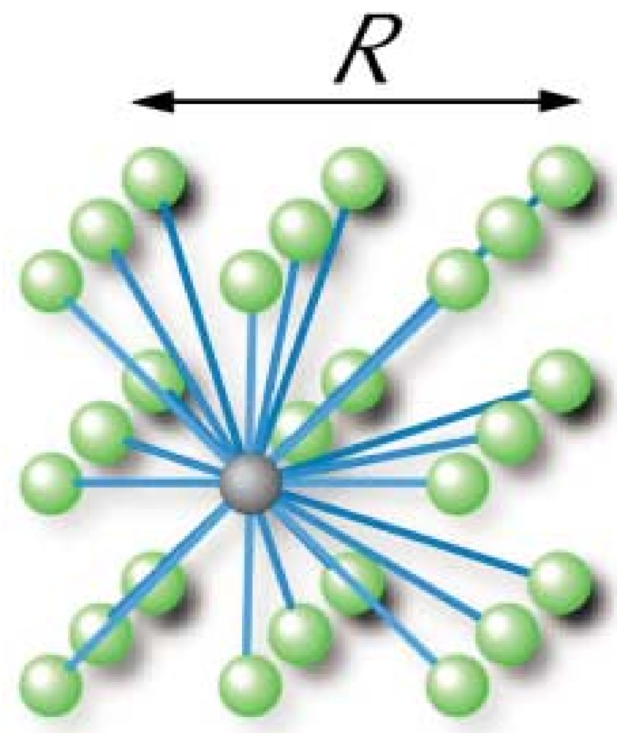
如无必要，勿增实体。简单有效原理。《箴言书注》：切勿浪费较多东西去做，用较少的东西，同样可以做好的事情。

Wiring Optimization of Neural Circuit

"After the many shapes assumed by neurons, we are now in a position to ask whether this diversity ... has been left to chance and is insignificant, or whether it is tightly regulated and provides an advantage to the organism. ... we realized that all of the various conformations of the neuron and its various components are simply morphological adaptations governed by laws of conservation for time, space, and material."

Ramon y Cajal

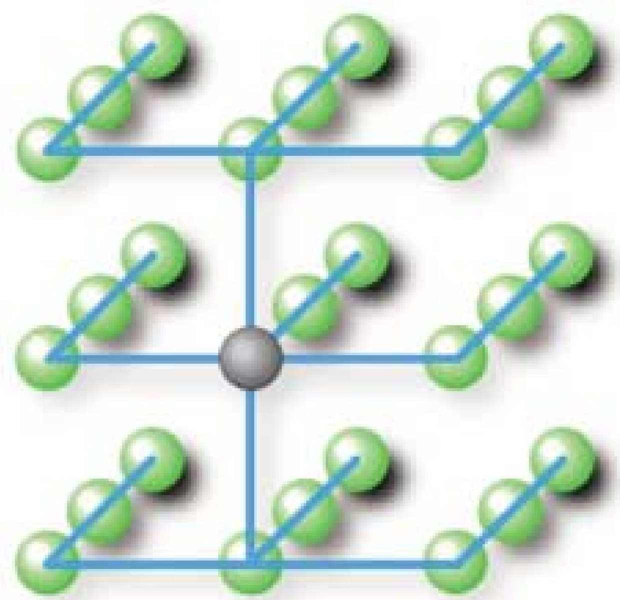
Why do we need axons and dendrites?



N: number of neurons
d: process diameter
R: network linear size

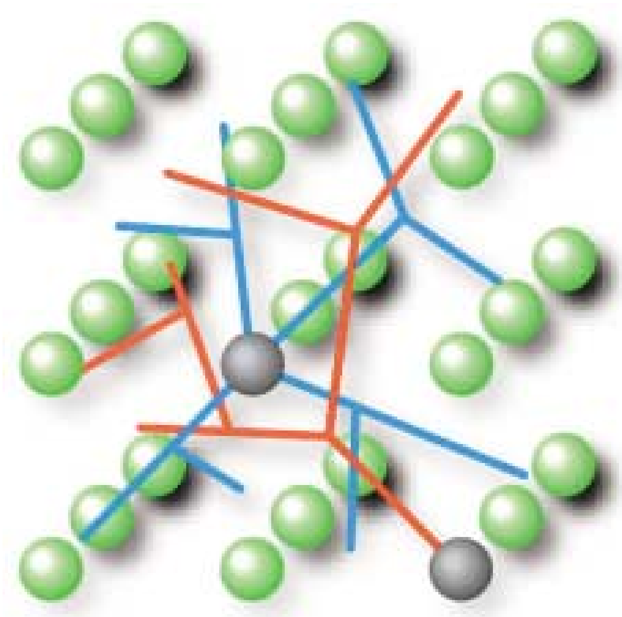
Design I

Why do we need axons and dendrites?



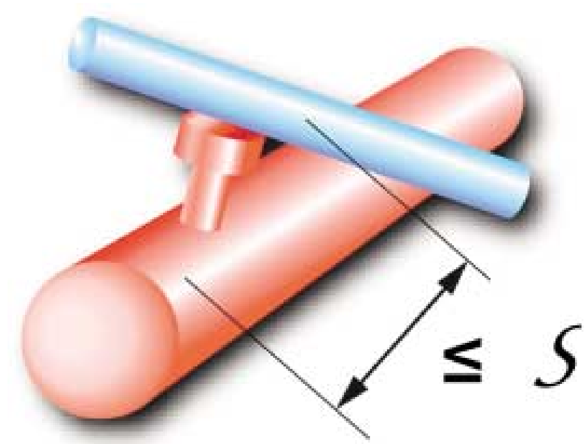
Design II

Why do we need axons and dendrites?



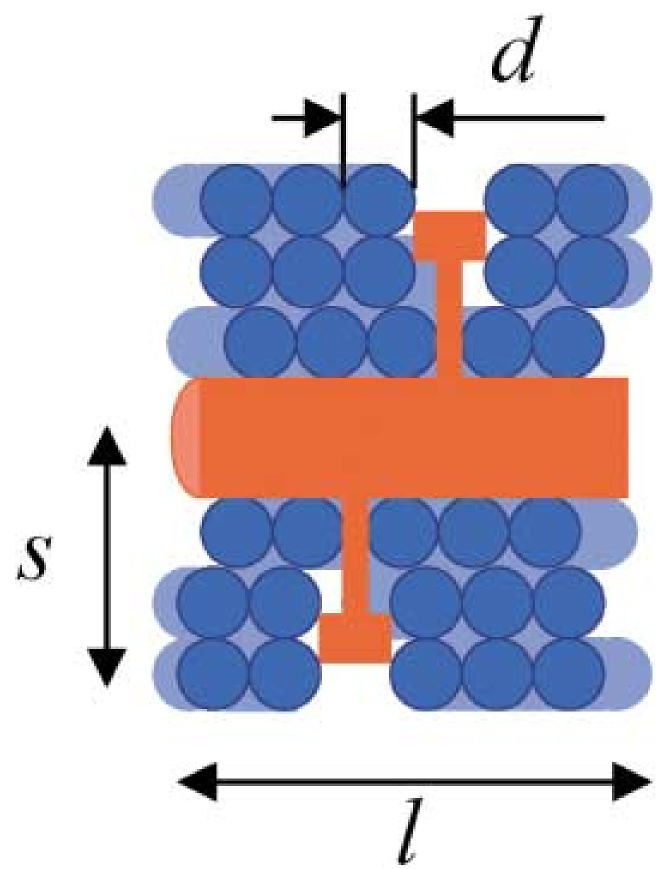
Design III

Why do we need axons and dendrites?



Design IV

Why do we need axons and dendrites?



The Optimality of the design

Chklovskii *Neuron* 2004

The cerebellar cortex