

# An Introduction to Computational Neuroscience

WEN quan (温泉)

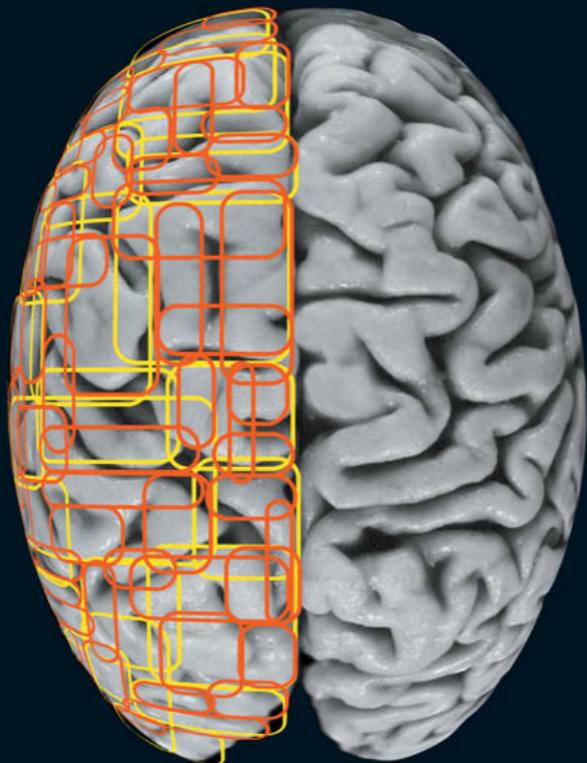
*University of Science and Technology of China*

September 2 2024

# Recommended textbooks

THEORETICAL NEUROSCIENCE

Computational and Mathematical  
Modeling of Neural Systems



Peter Dayan and L. F. Abbott

*How questions*

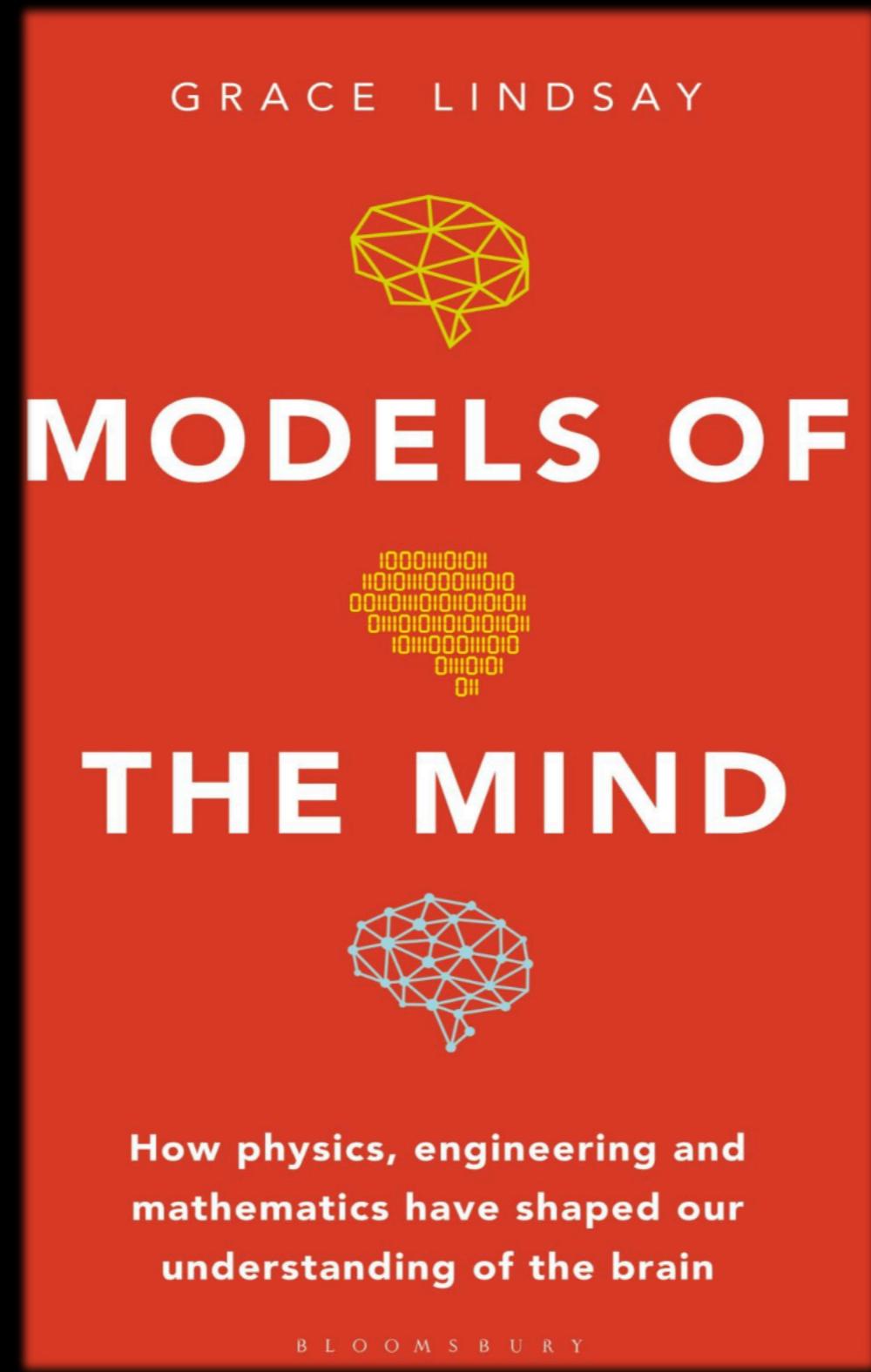
Principles of  
Neural Design



Peter Sterling and Simon Laughlin

*Why questions*

Recommended book for a general audience



# PRINCIPLES OF NEUROBIOLOGY

SECOND EDITION

— LIQUN LUO —



CRC Press  
Taylor & Francis Group

A GARLAND SCIENCE BOOK

**666 pages**

# SEARCHING FOR PRINCIPLES OF NEUROBIOLOGY

SECOND EDITION

— LIQUN LUO —



CRC Press

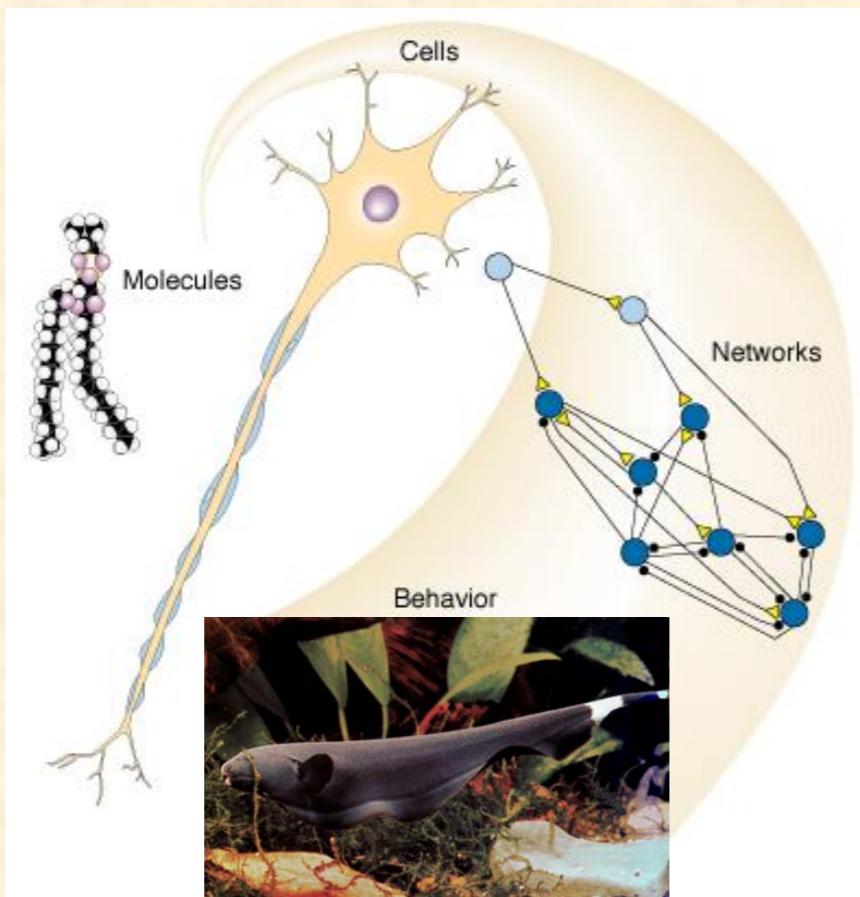
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A GARLAND SCIENCE BOOK

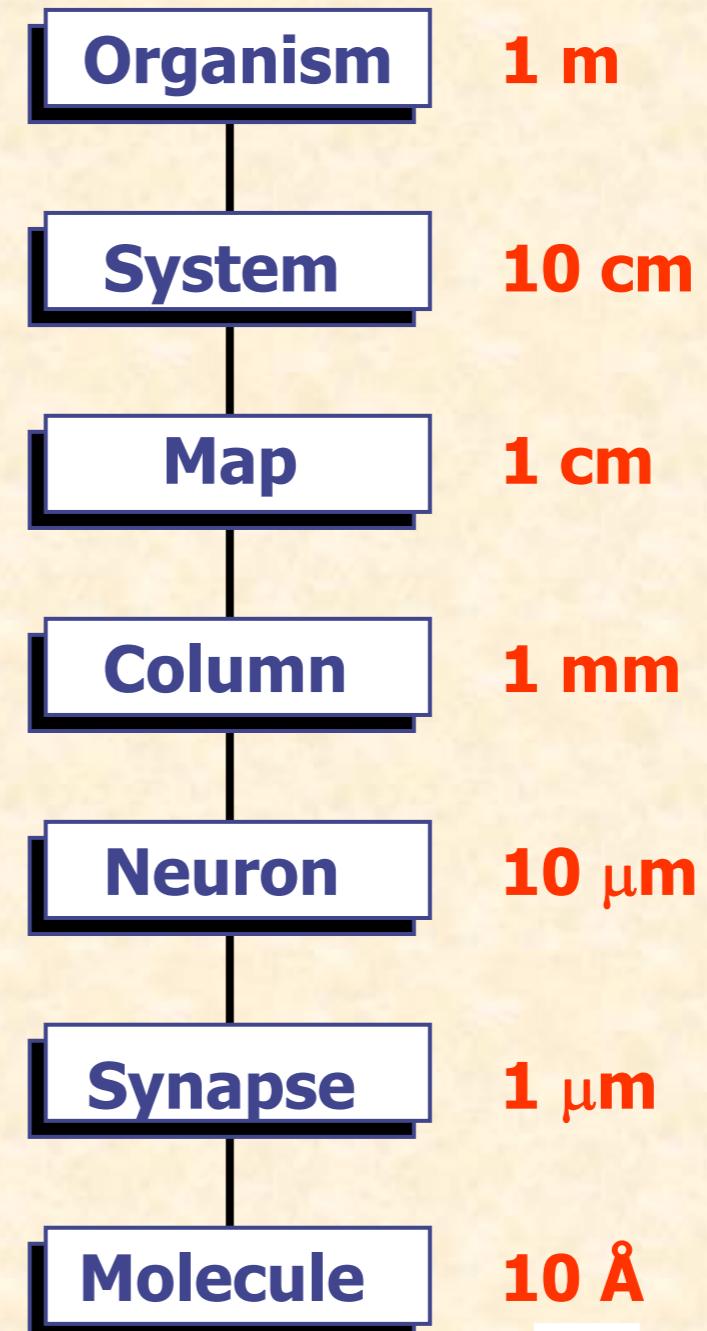
# A general impression of the brain

- The brain is squishy and messy. It may be impossible to understand the brain from a small number of principles just like in physics.
- There are too many (interesting) facts! And almost every rule has an exception.

# Multiscale Organization of the Nervous System



Delcomyn 1998



“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, Science 1972  
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

**“I never had to use an equation after high school”**

**David Hubel**

# What has theoretical component bought to neuroscience?

- The brain is squishy and messy. It may be impossible to understand the brain from a small number of (say 3?) principles just like in physics.
- There are too many facts! And almost every rule has an exception.
- However, most interesting facts are not singular. Instead, they must and can be connected to achieve a deeper understanding. And to build such a connection requires an integral approach, and mathematics are crucial during this process.

*“...Equations force a model to be precise, complete, and self-consistent, and they allow its full implications to be worked out. It is not difficult to find word models in the conclusions sections of older neuroscience papers that sound reasonable but, when expressed as mathematical models, turn out to be inconsistent and unworkable. Mathematical formulation of a model forces it to be self-consistent and, although self-consistency is not necessarily truth, self-inconsistency is certainly falsehood.”*

Larry Abbott  
Theoretical Neuroscience is rising  
Neuron 2008



**David Marr**  
**1945-1980**



**Henry Markram**  
**1962 -**

# VISION

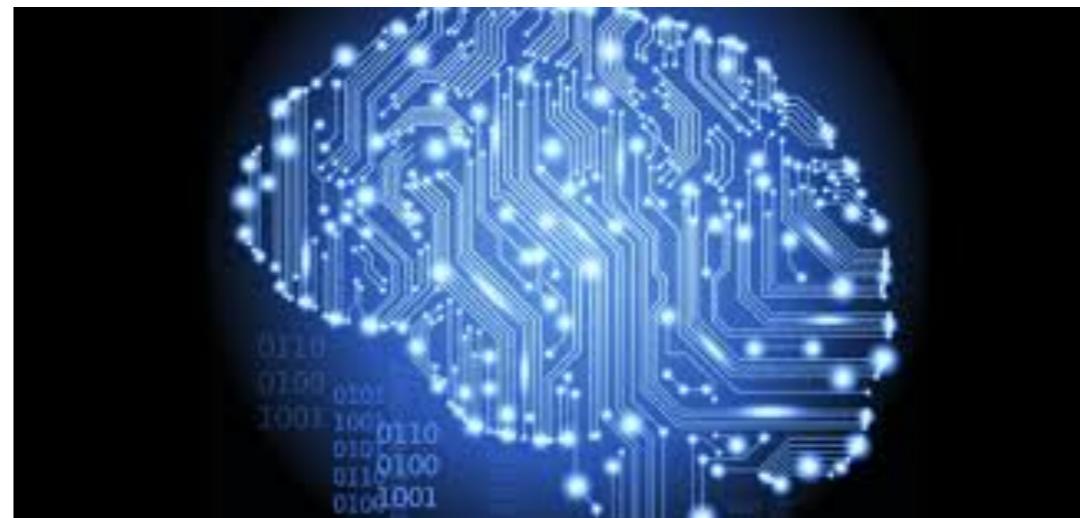


David Marr

FOREWORD BY  
Shimon Ullman

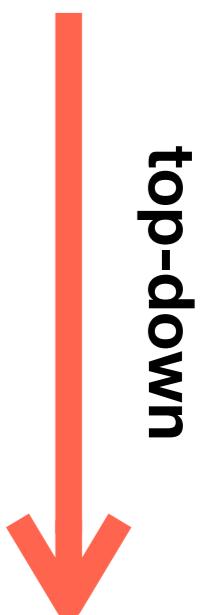
AFTERWORD BY  
Tomaso Poggio

## blue brain project



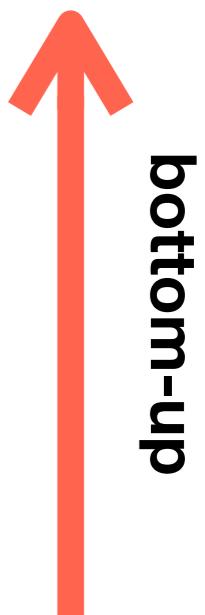
# David Marr's three level theory

- **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.



# 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.



The structure of an information processing machine does not tell you what computation it performs

*Anthony Movshon*

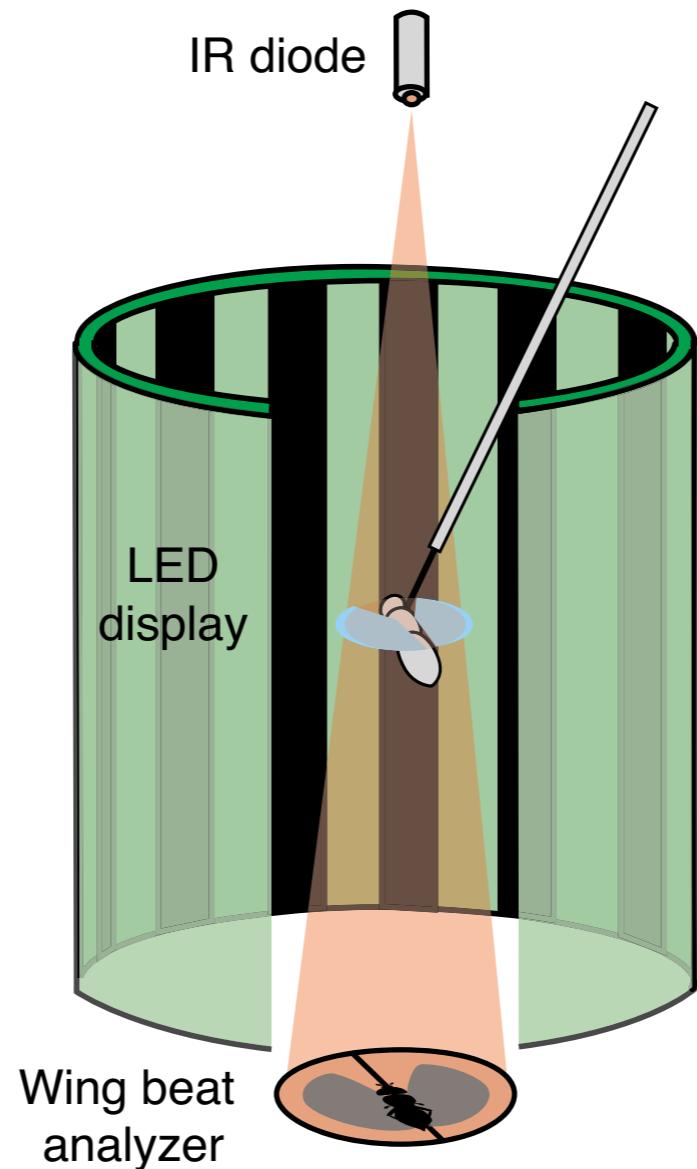
Circuit diagrams or connectomes are *absolutely* necessary but *completely* insufficient for understanding nervous system function.

*Eve Marder*

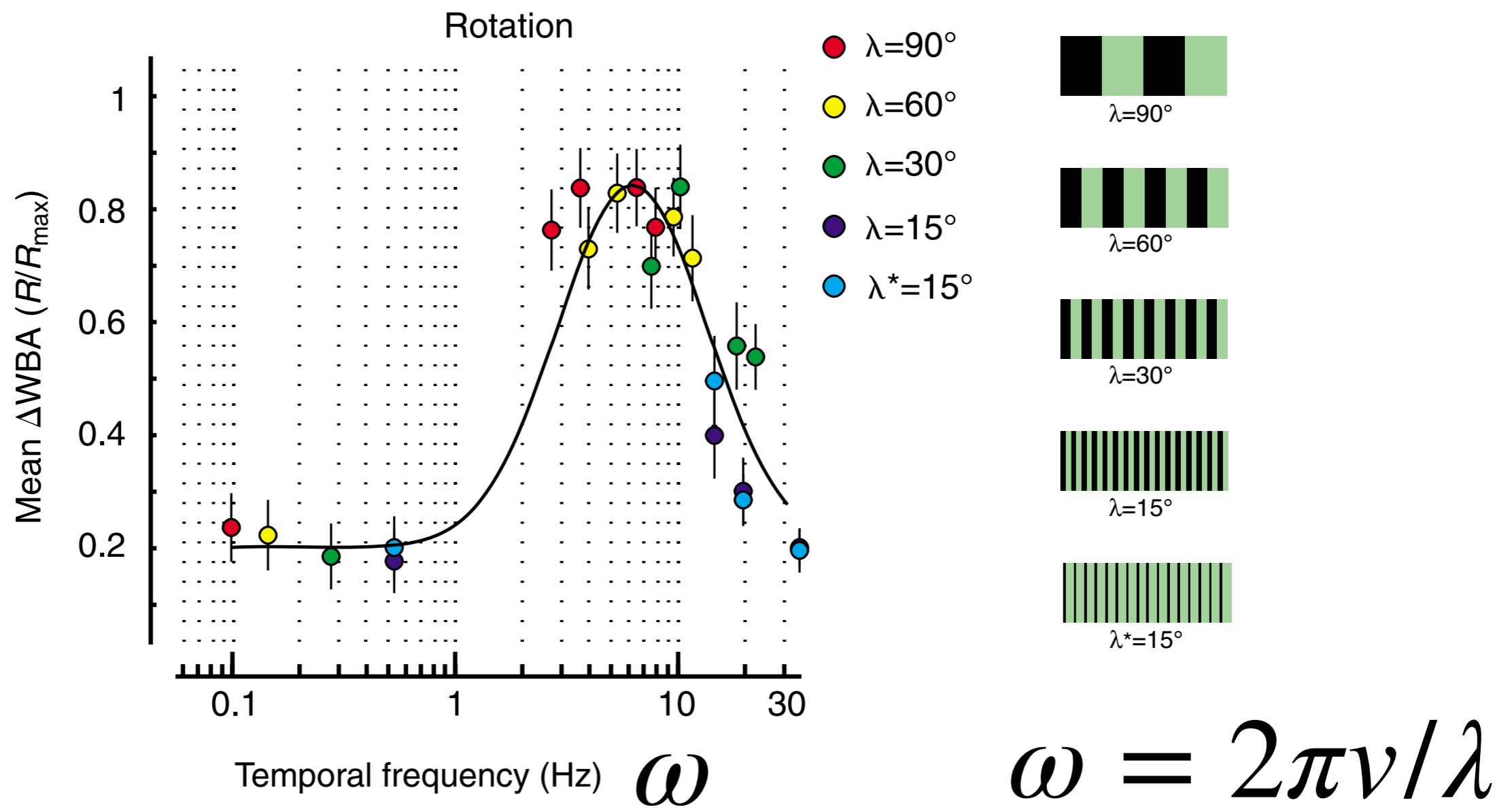
# **Motion detection, an example**



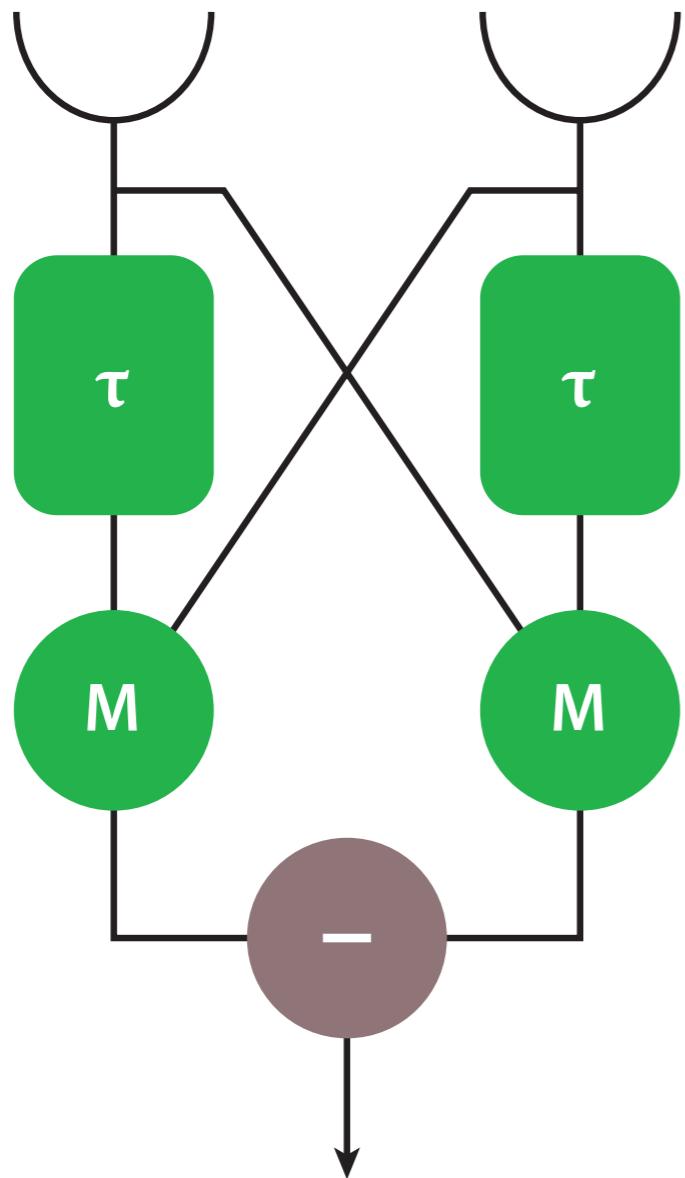
# Optomotor response in fly



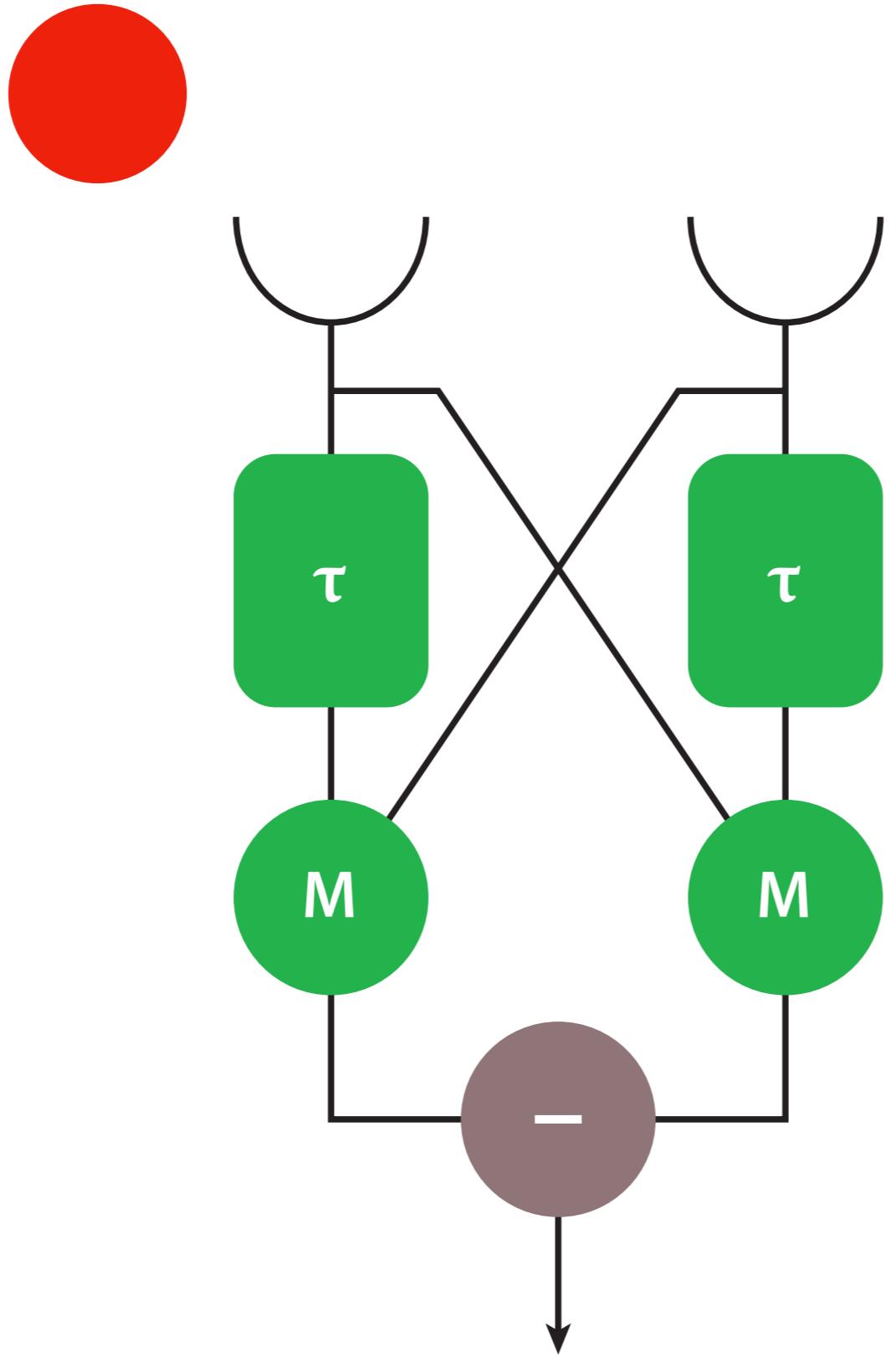
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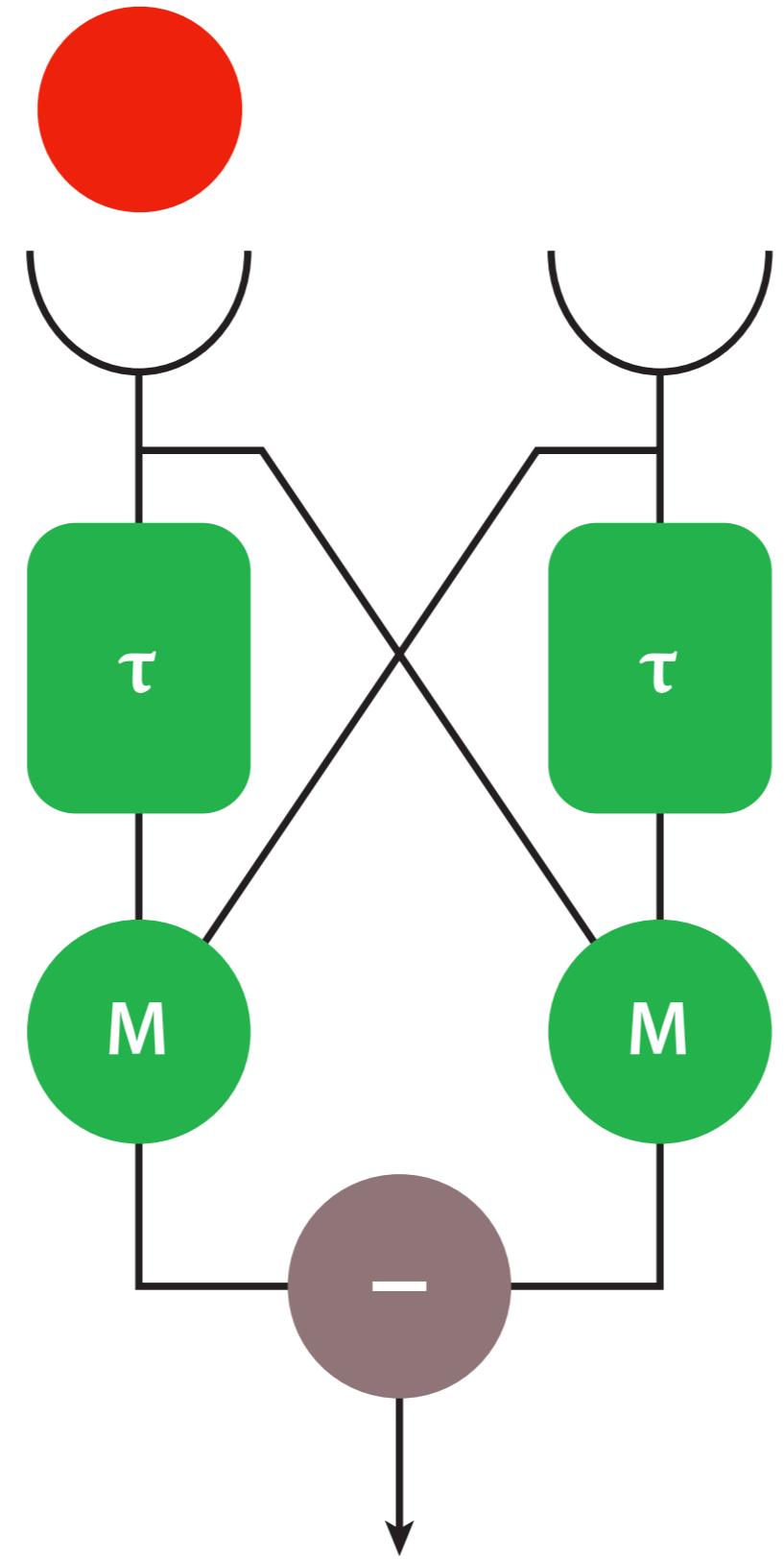


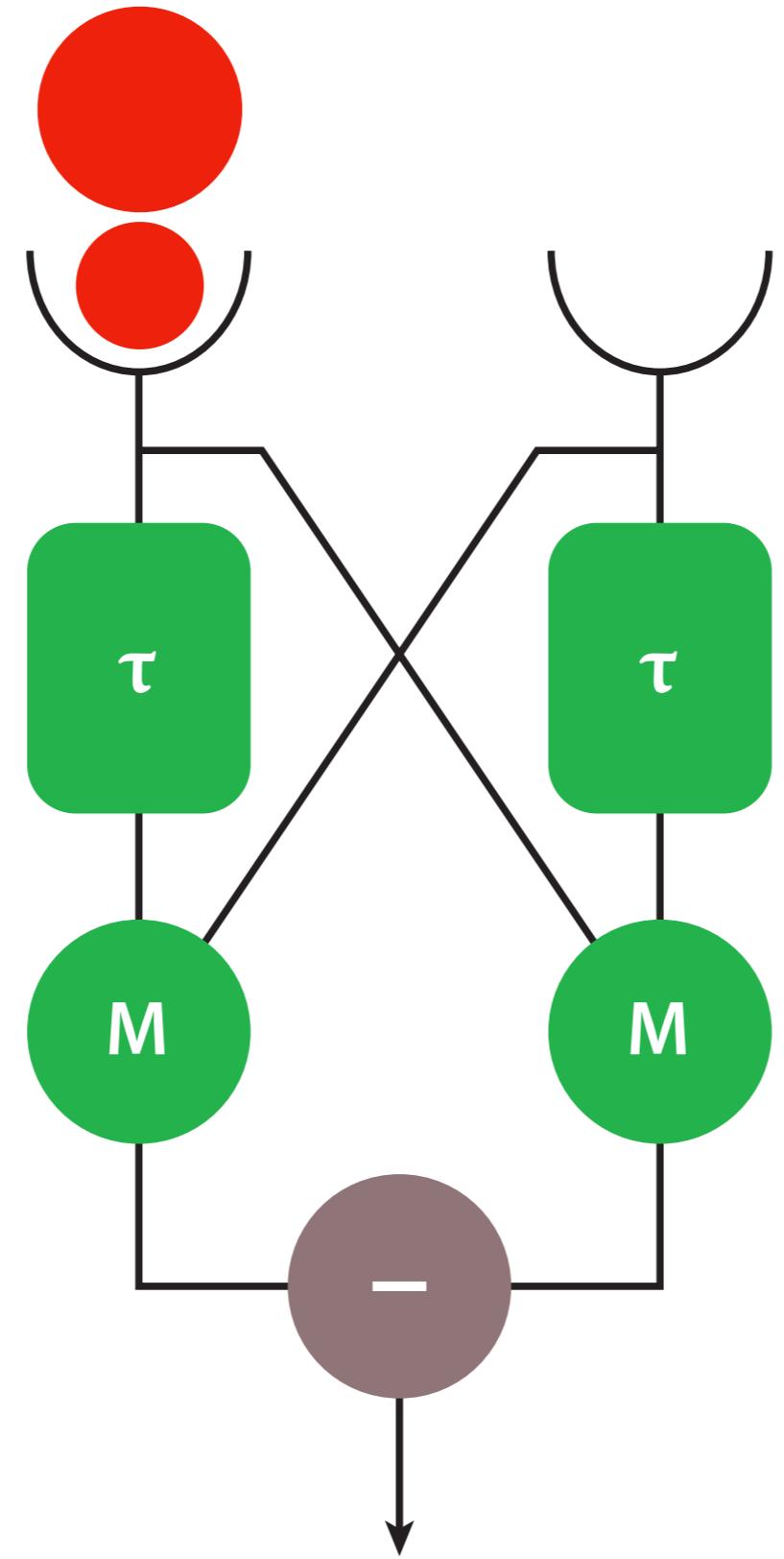
# Hassenstein-Reichardt Detector Model

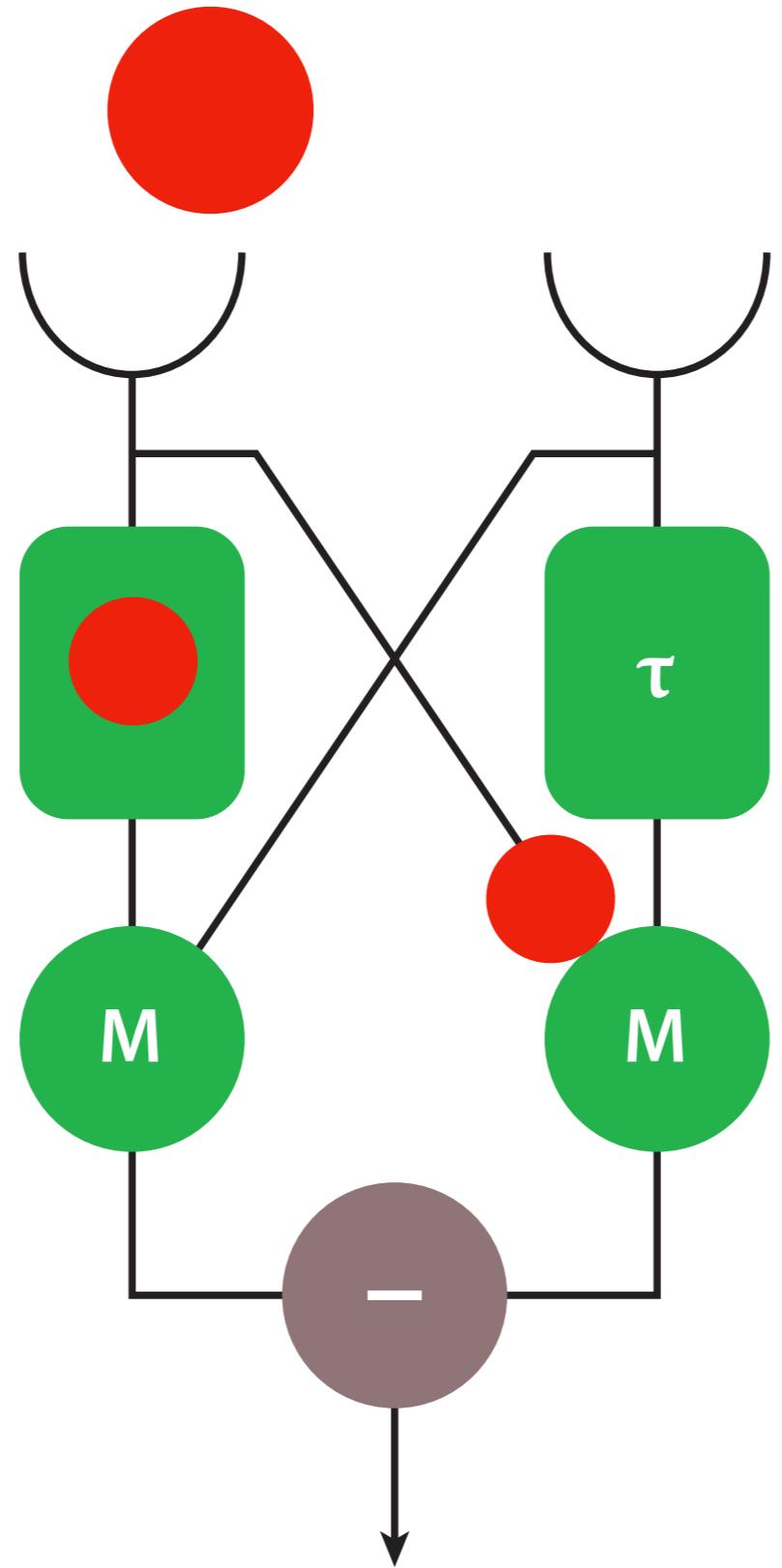


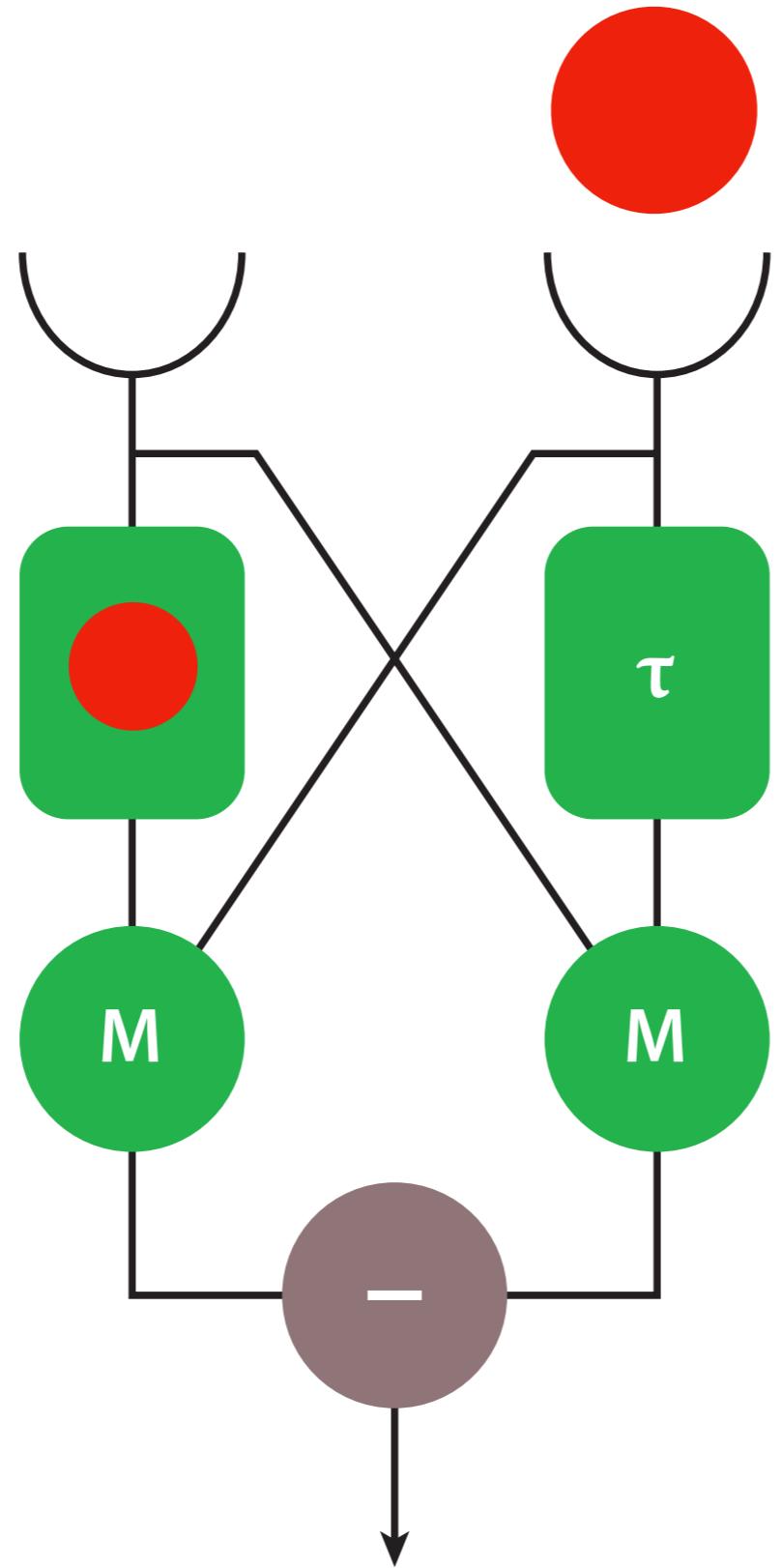
Werner Reichardt

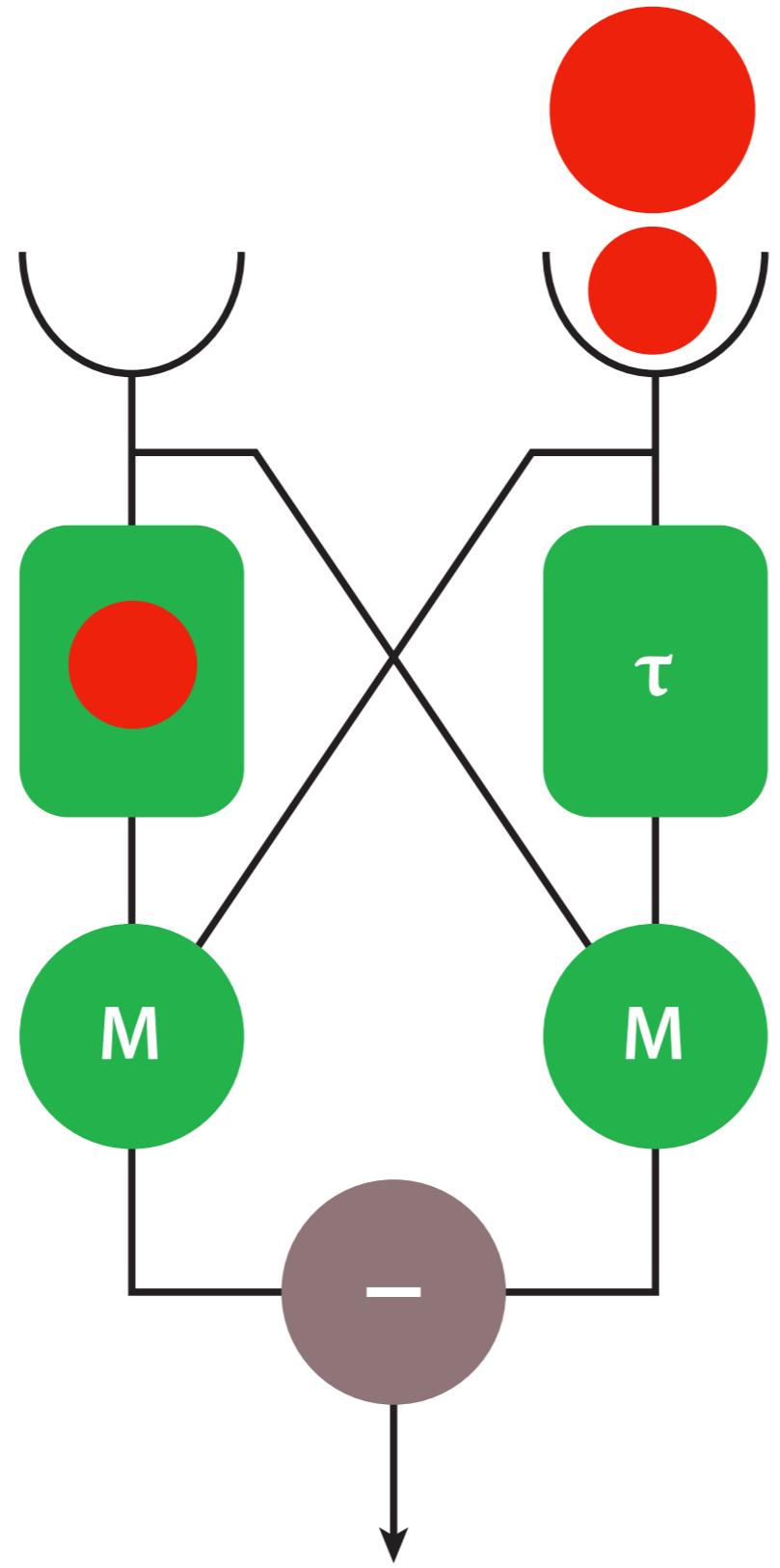


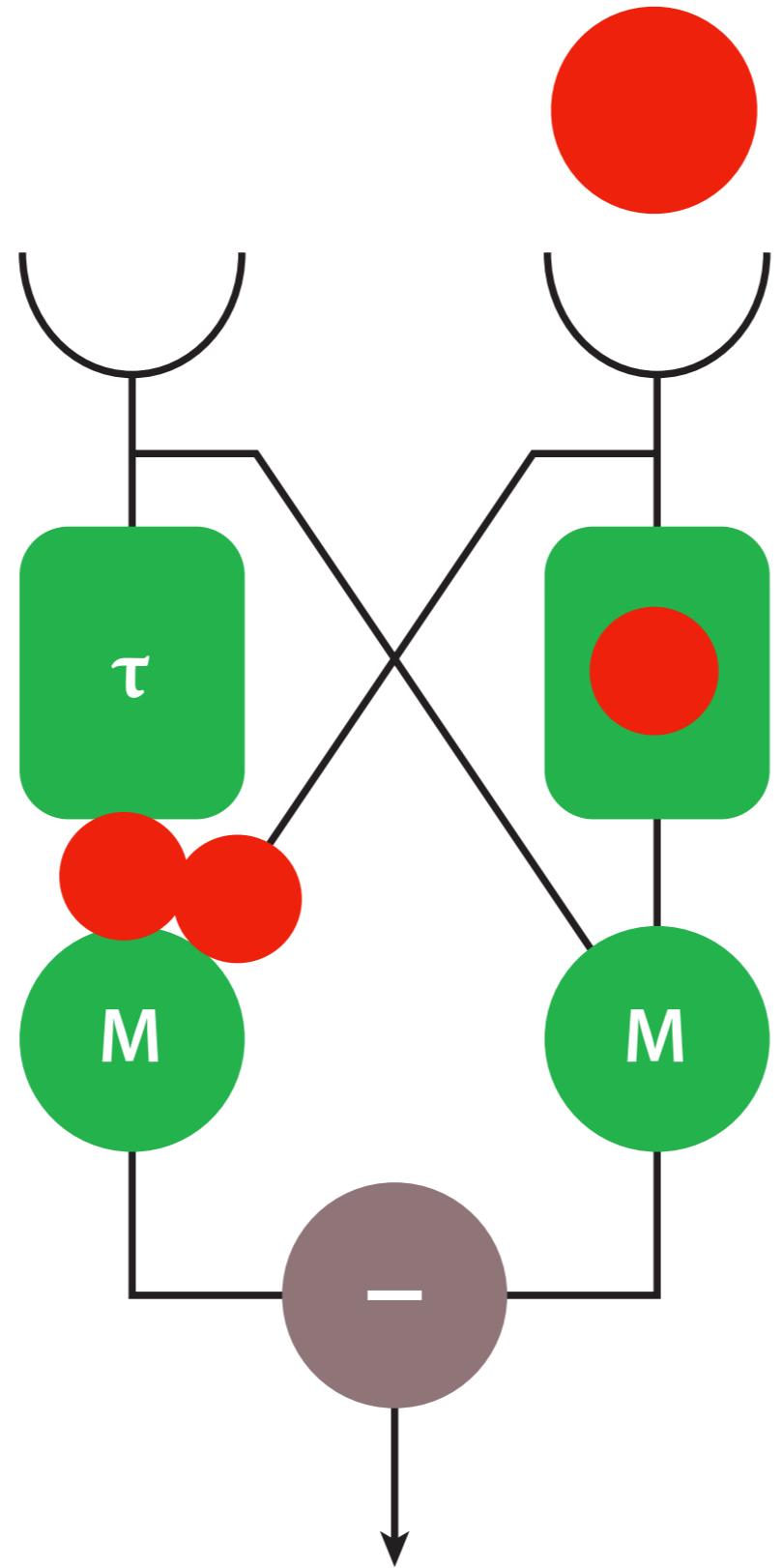


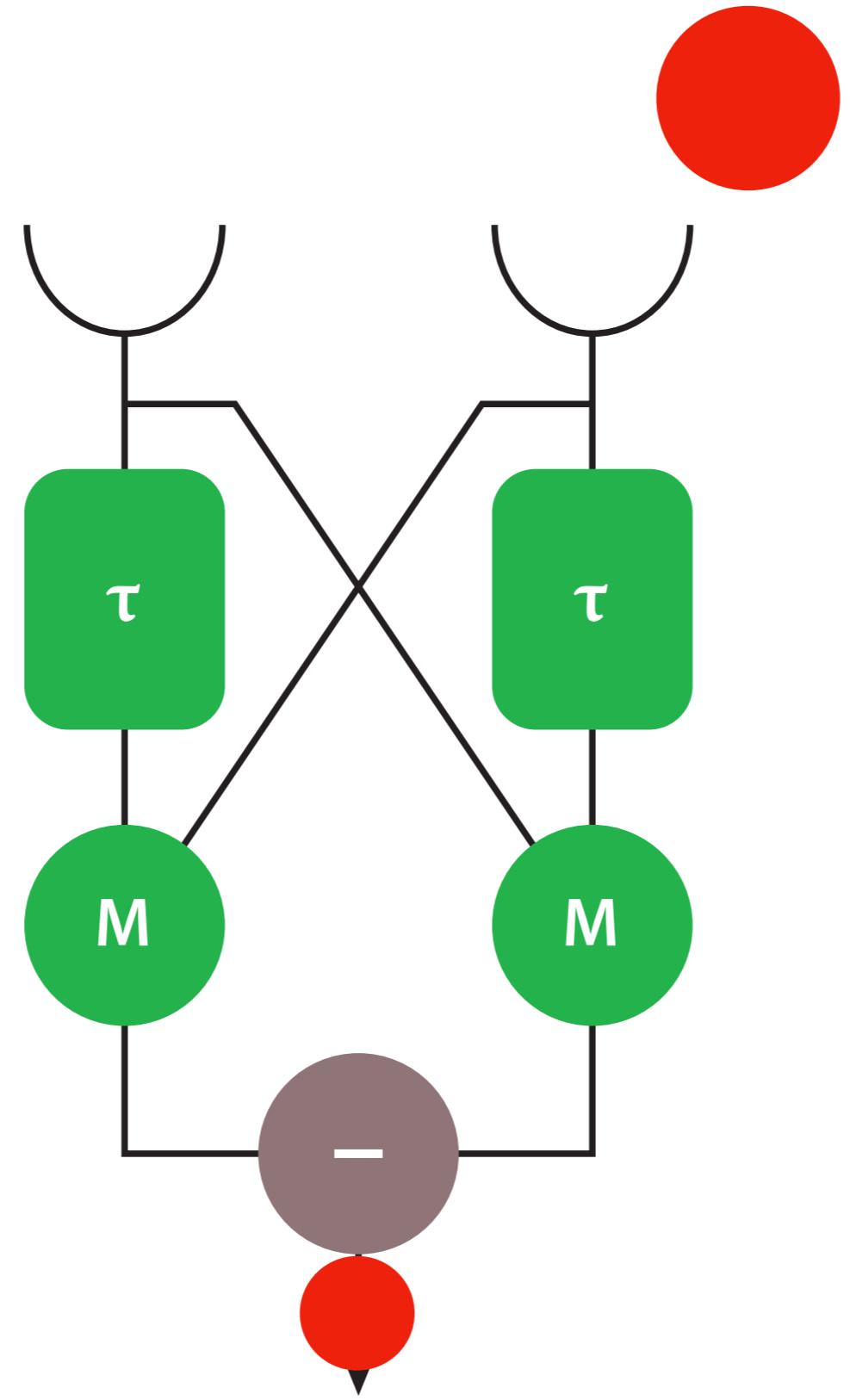




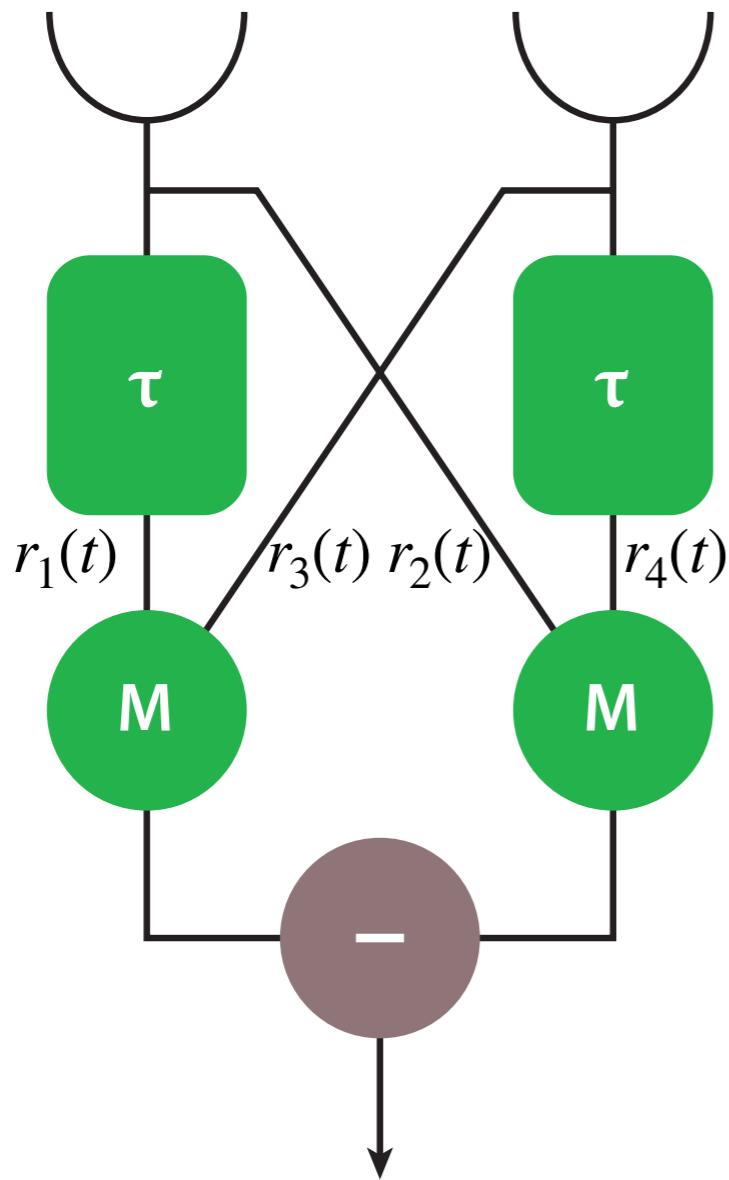








# Hassenstein-Reichardt Detector Model

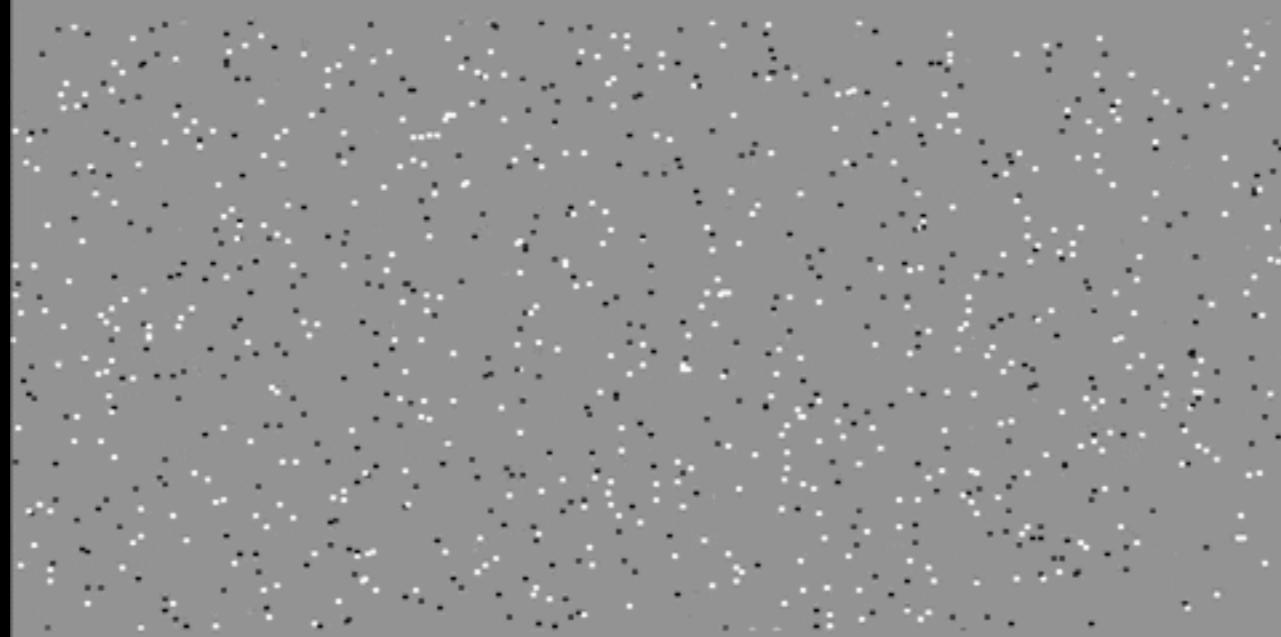


$$r_1(t) = \int_0^{\infty} s_1(t - \tau) D(\tau) d\tau; \quad r_2(t) = \int_0^{\infty} s_1(t - \tau) \delta(\tau) d\tau$$
$$r_3(t) = \int_0^{\infty} s_2(t - \tau) \delta(\tau) d\tau; \quad r_4(t) = \int_0^{\infty} s_2(t - \tau) D(\tau) d\tau;$$
$$R(t) = r_1(t)r_3(t) - r_2(t)r_4(t)$$

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

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

**Phi: displacements to right**

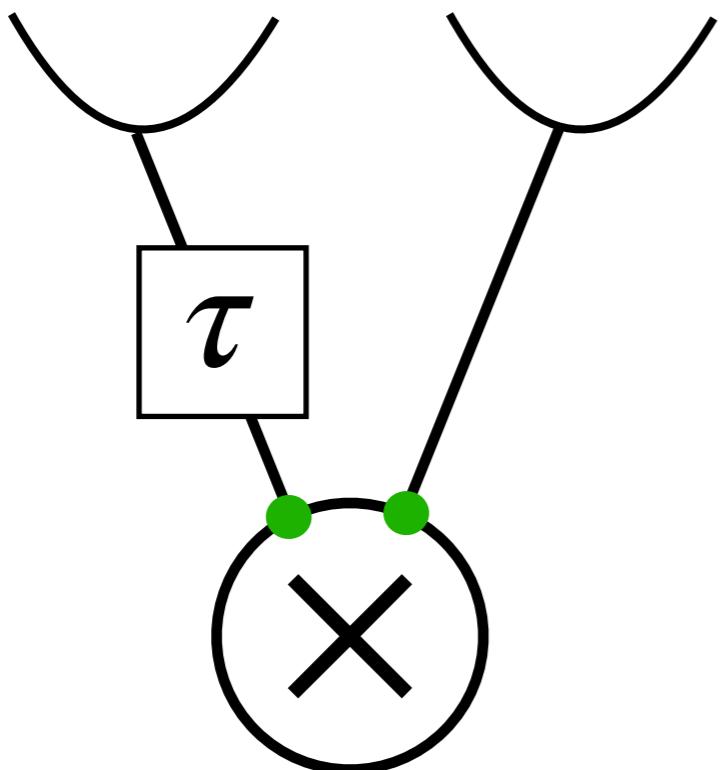


*adapted from Damon Clark's slide*

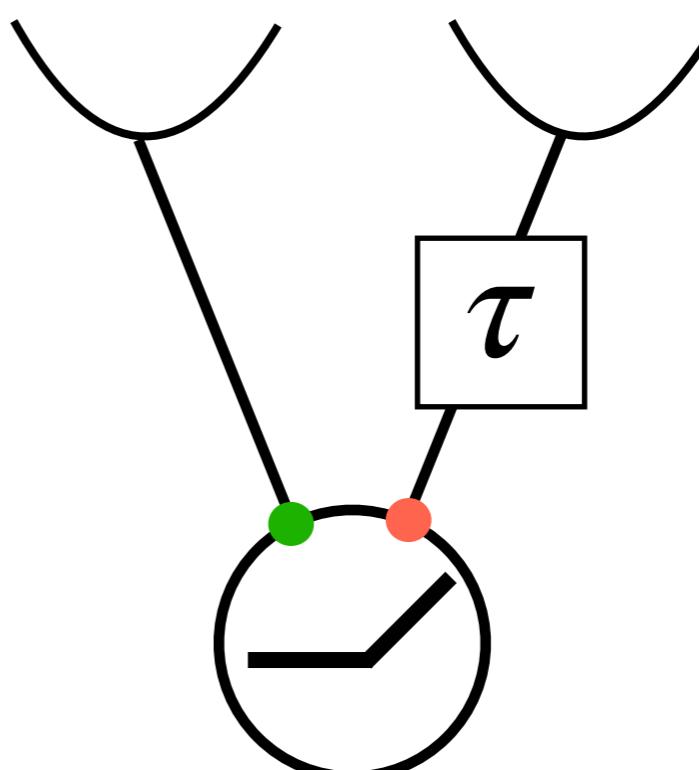
preferred  
direction



null  
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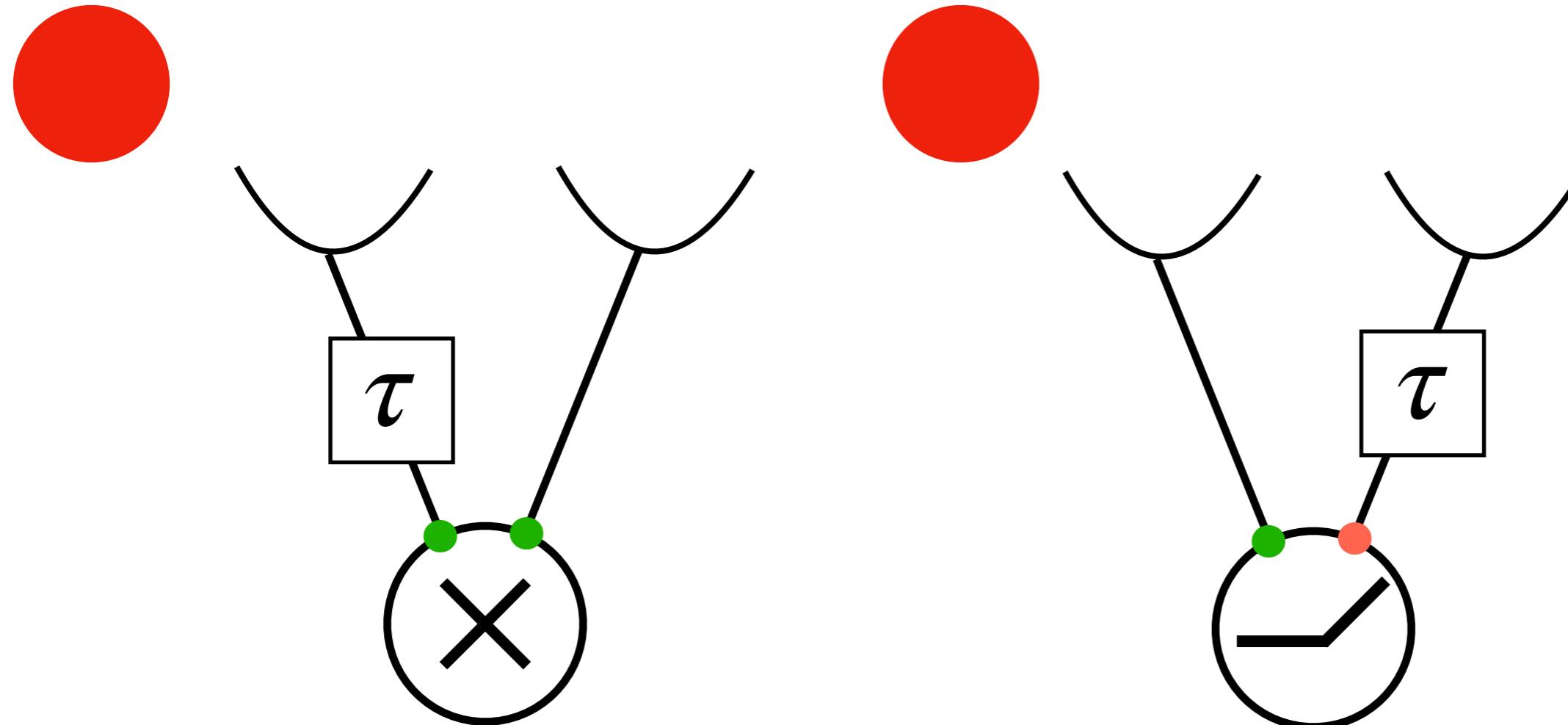


Reichardt model



barlow-levick model

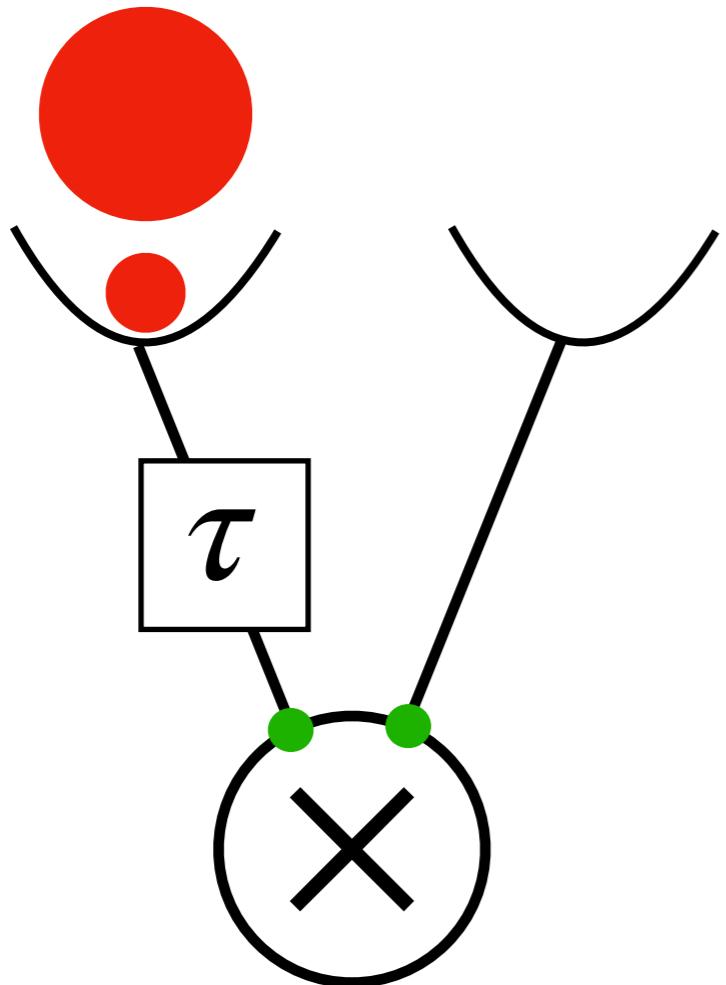
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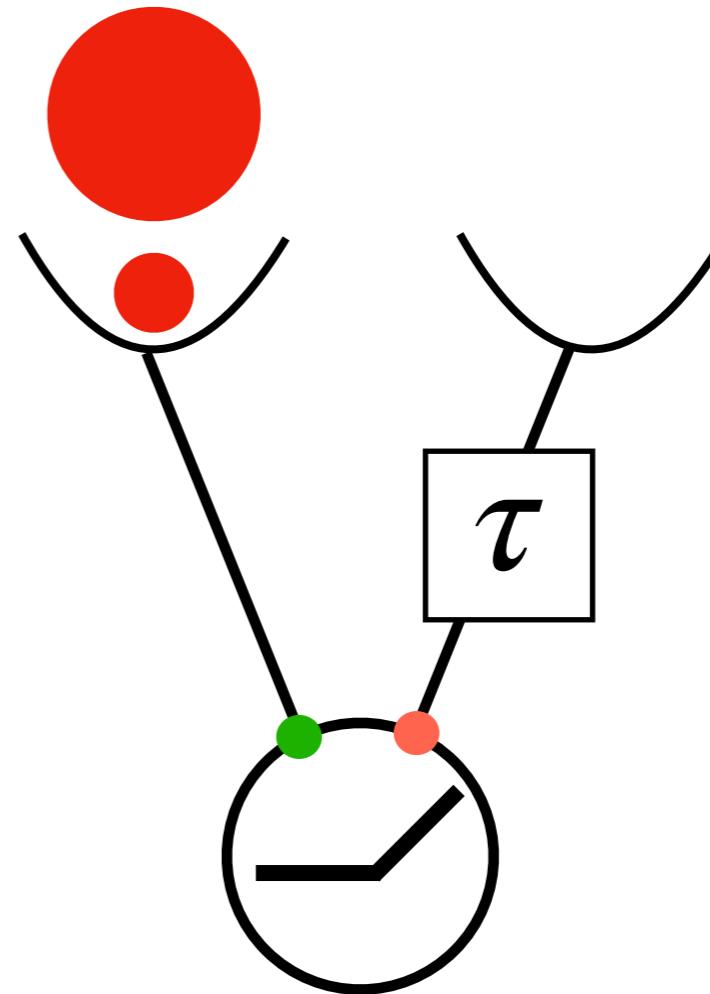
**Reichardt model**

**barlow-levick model**

preferred  
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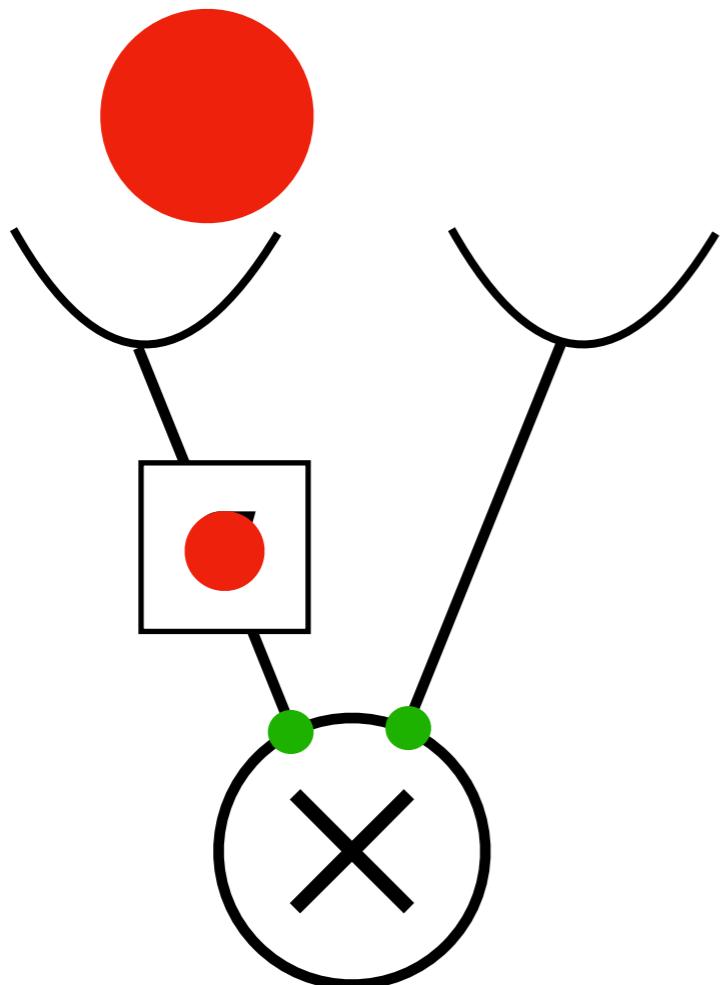


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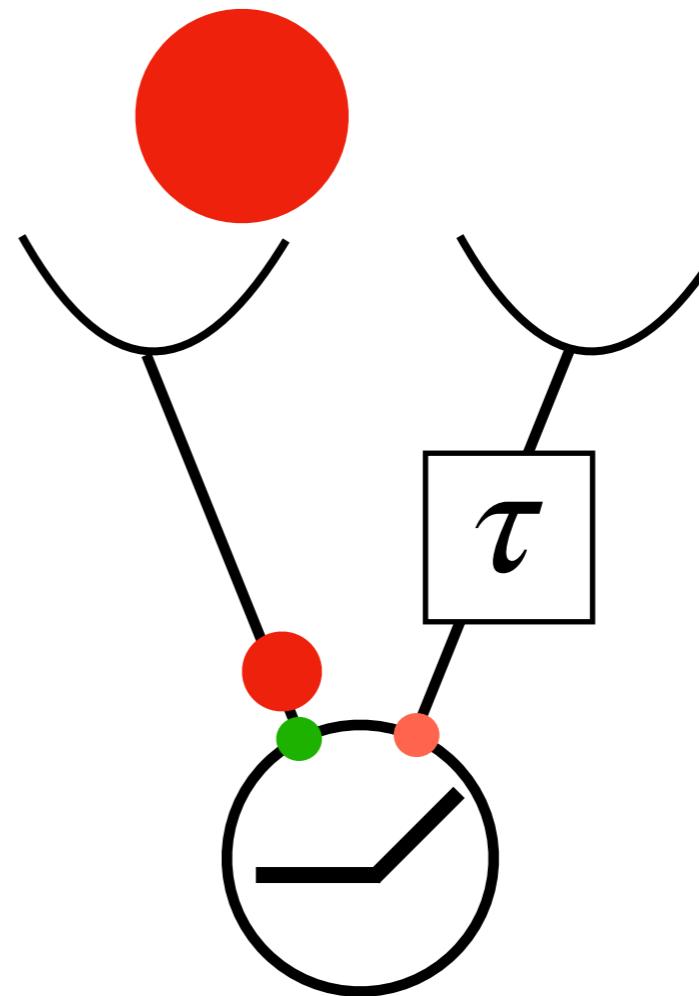


barlow-levick model

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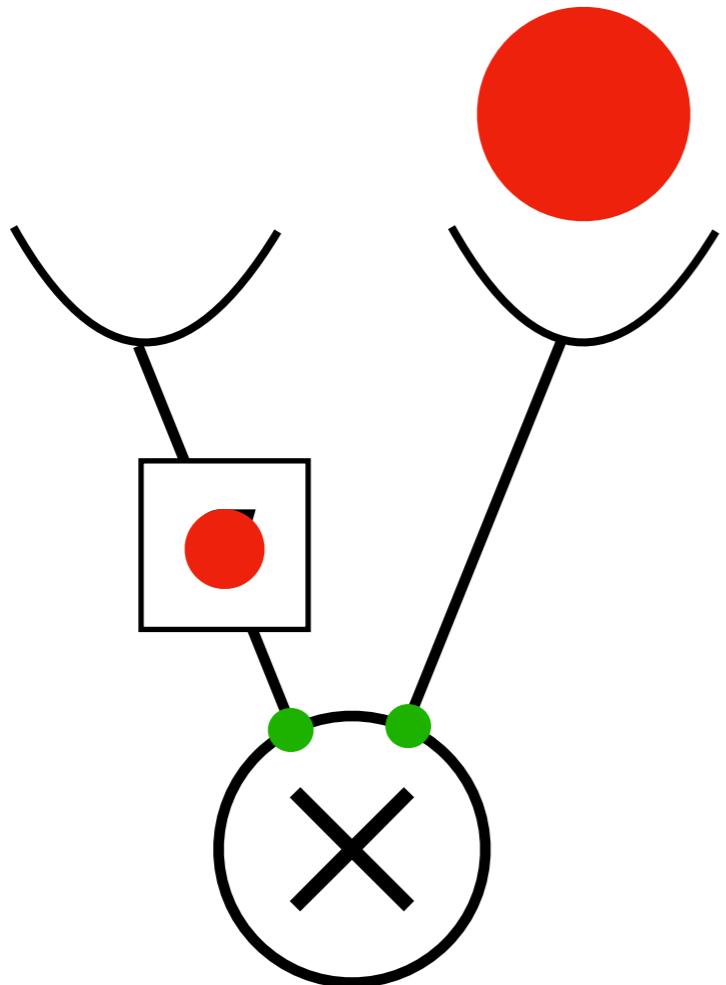


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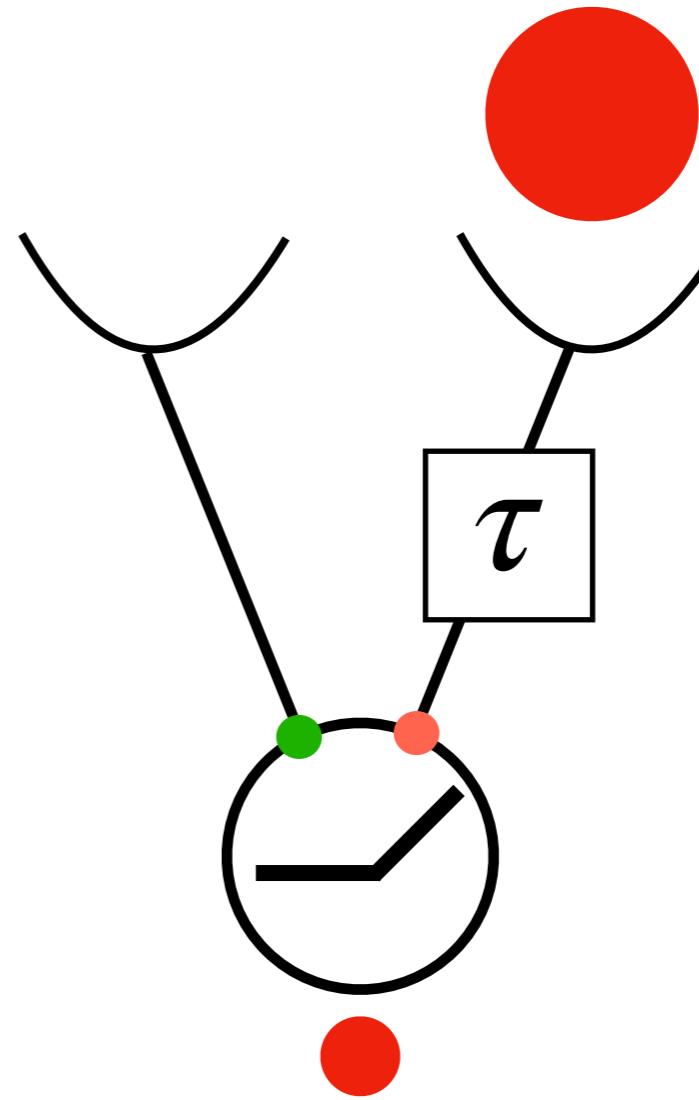


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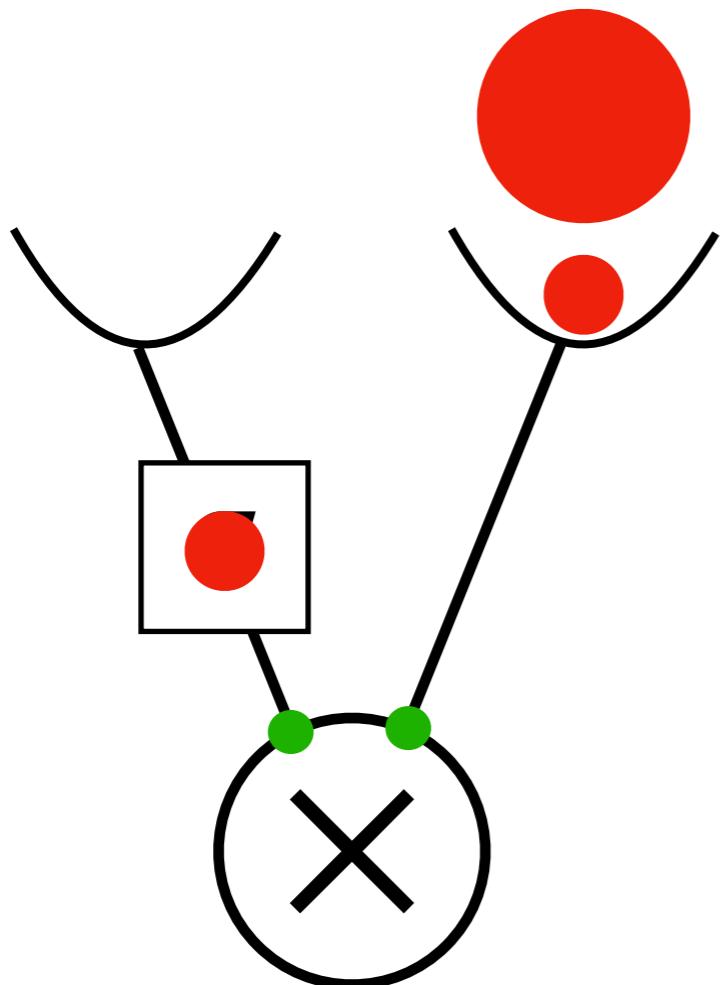


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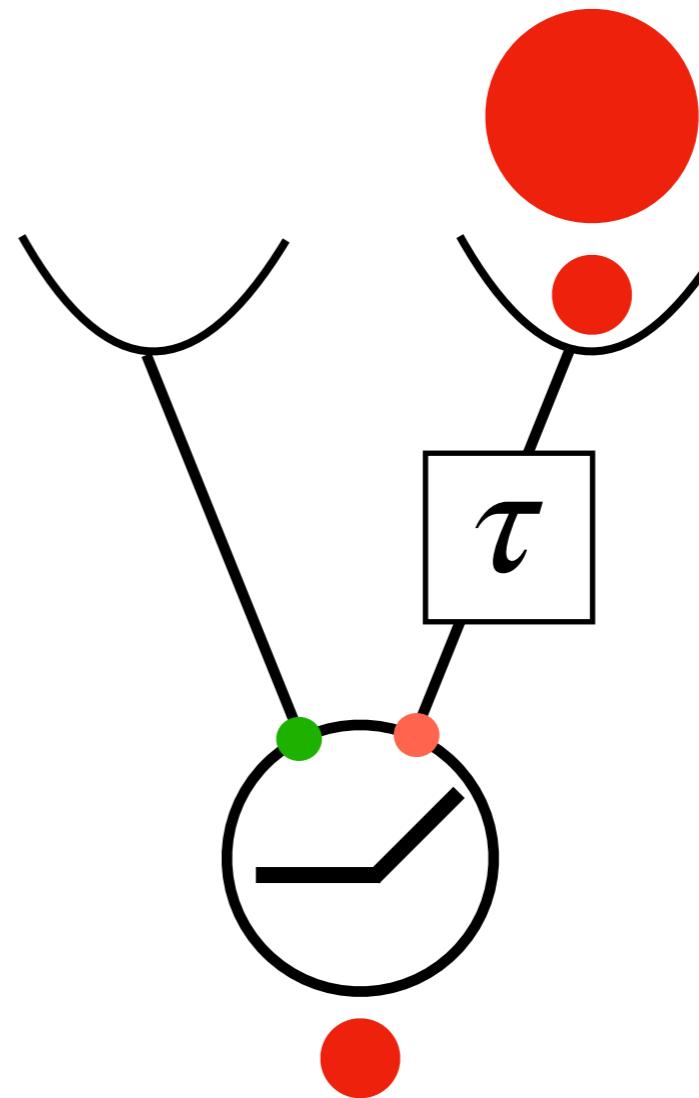


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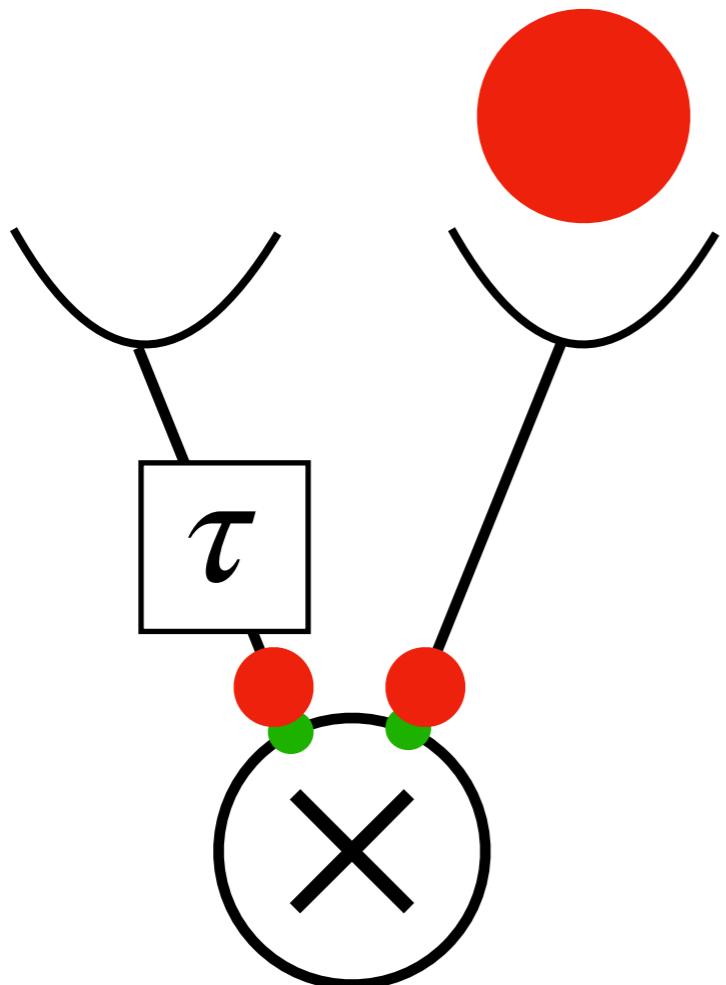


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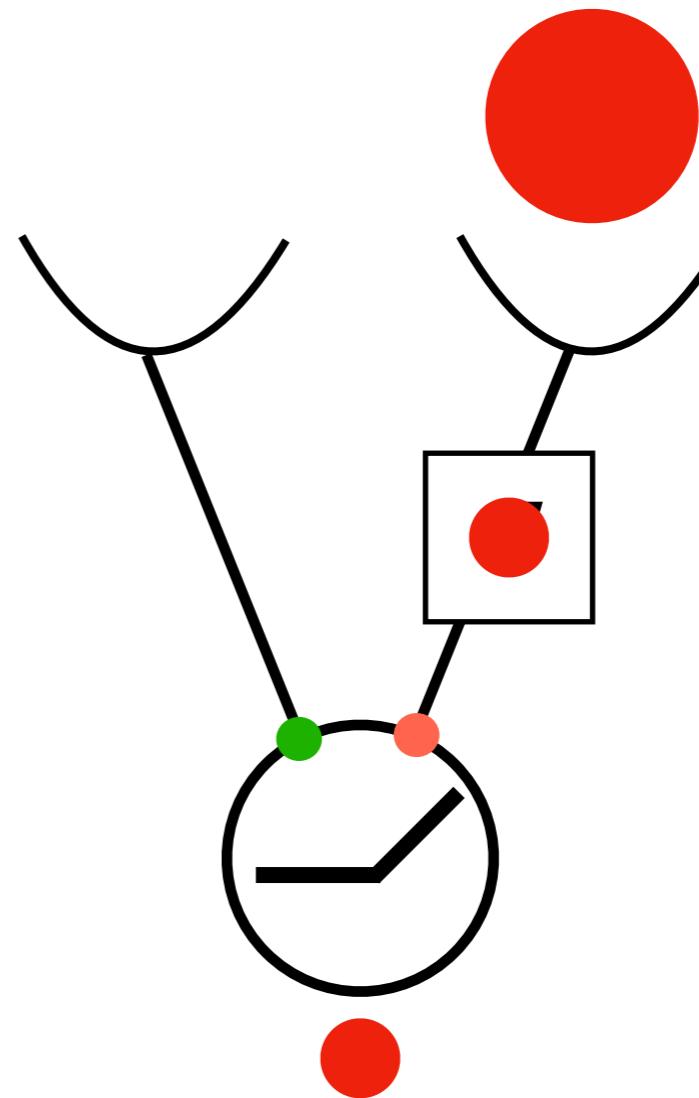


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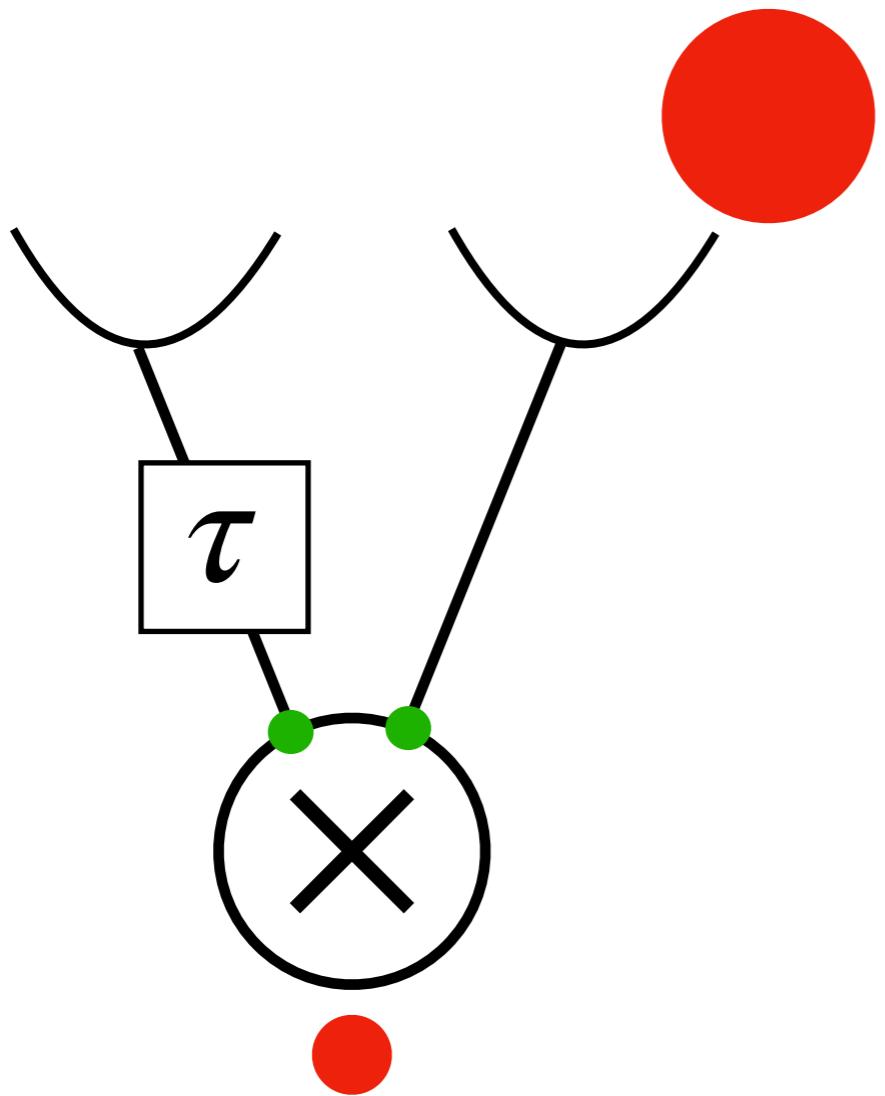


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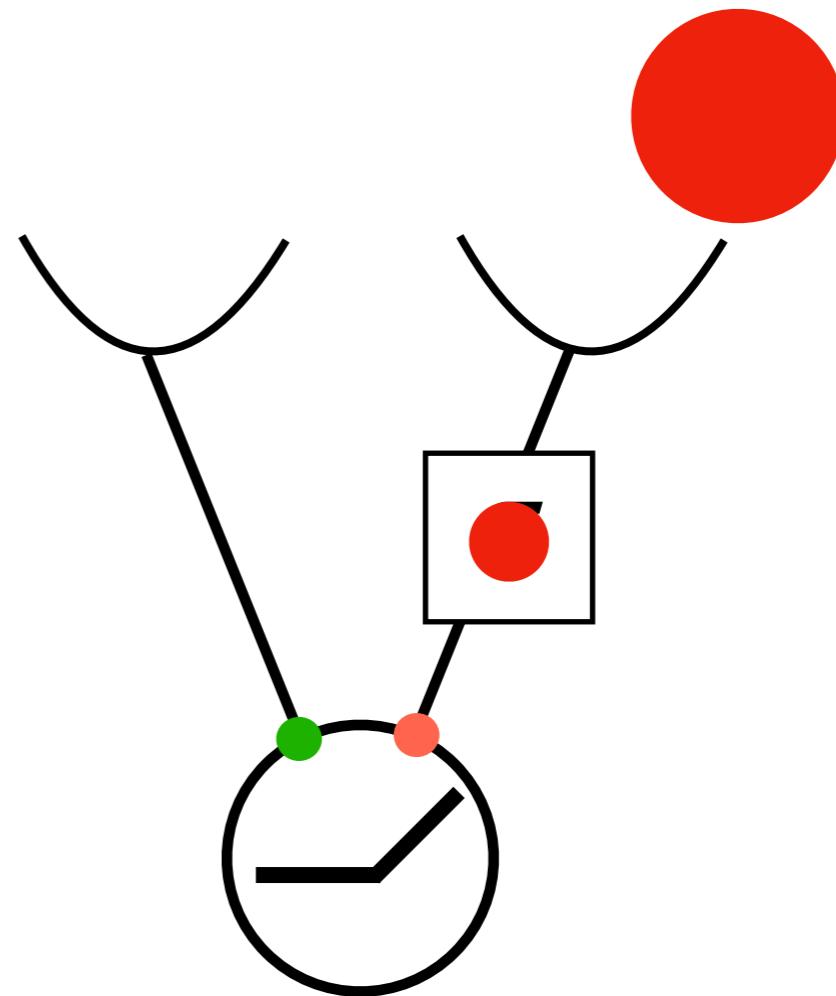


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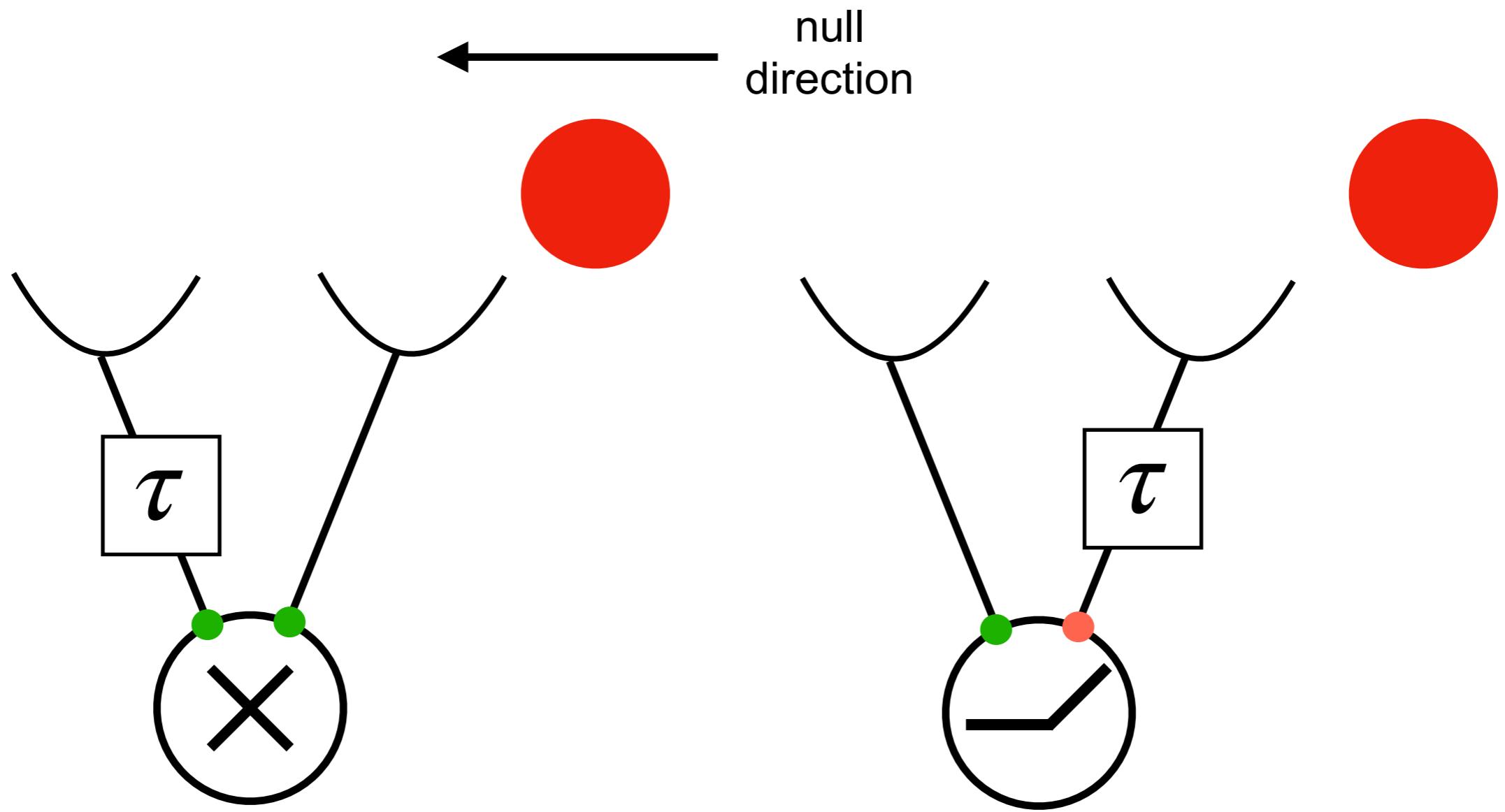
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Reichardt model



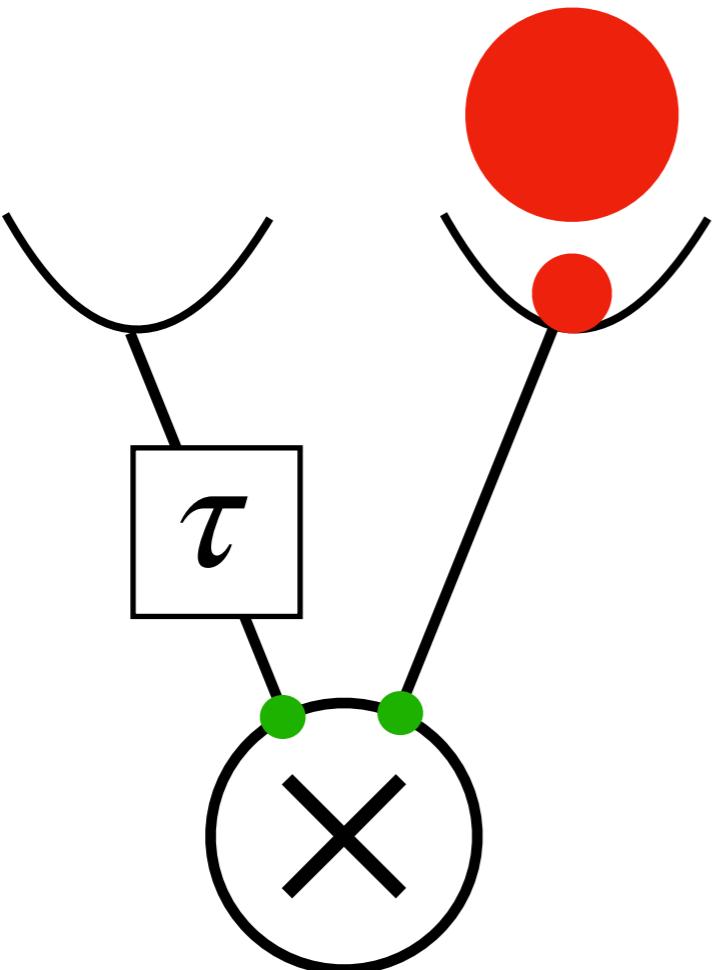
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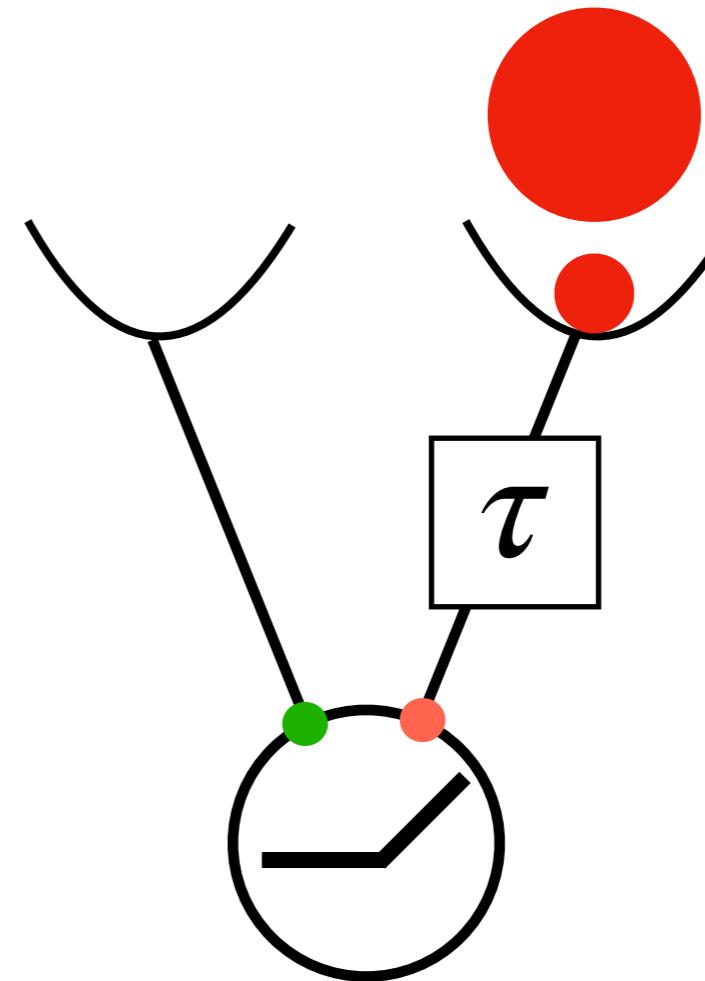
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barlow-levick model

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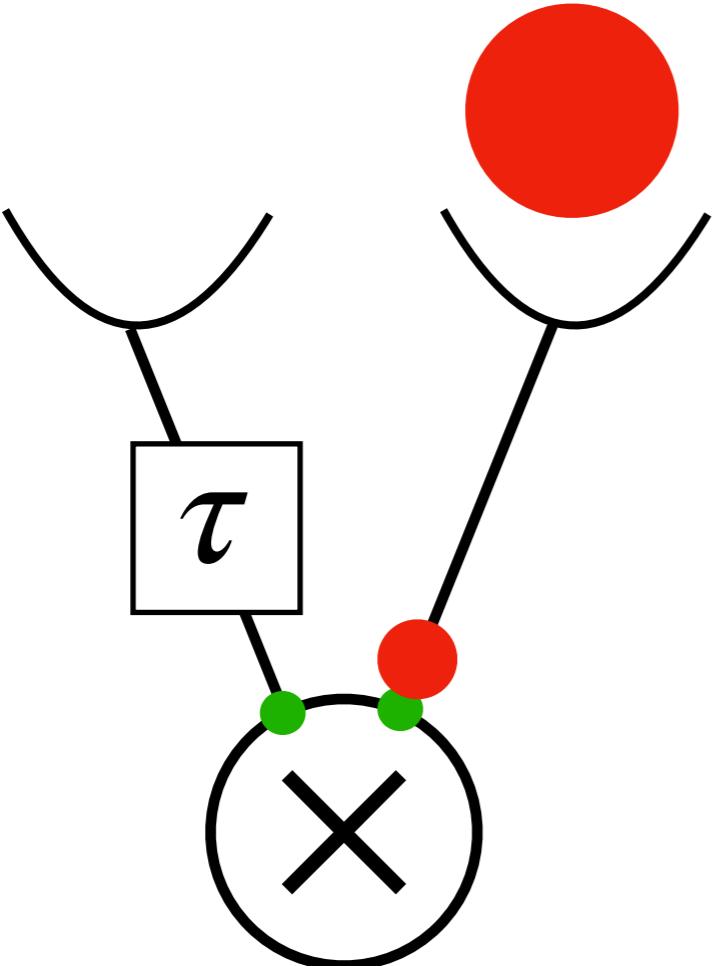


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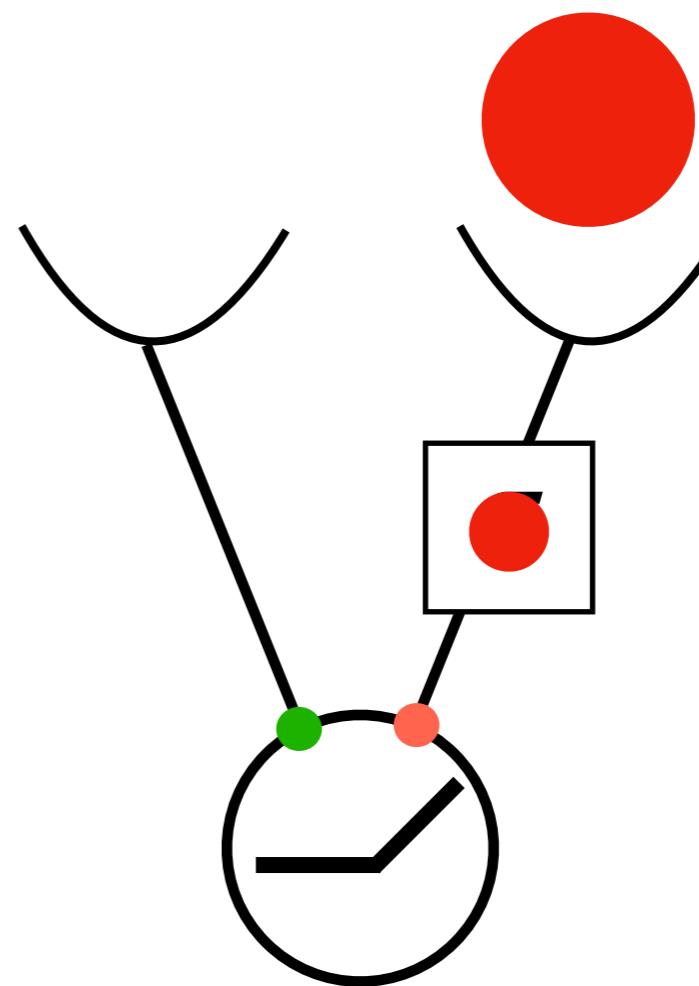


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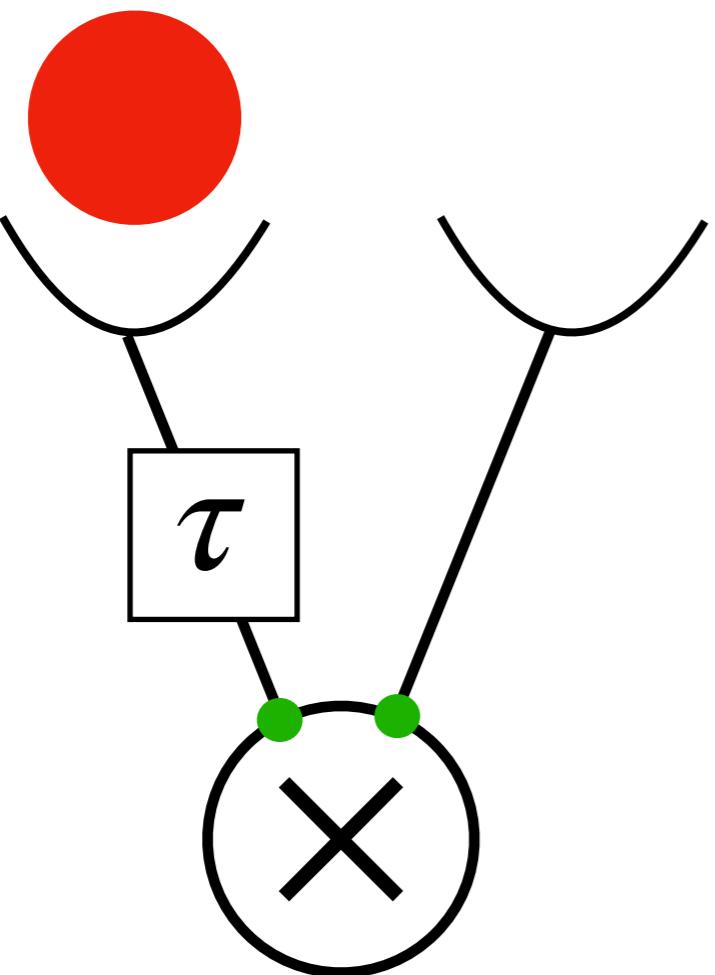


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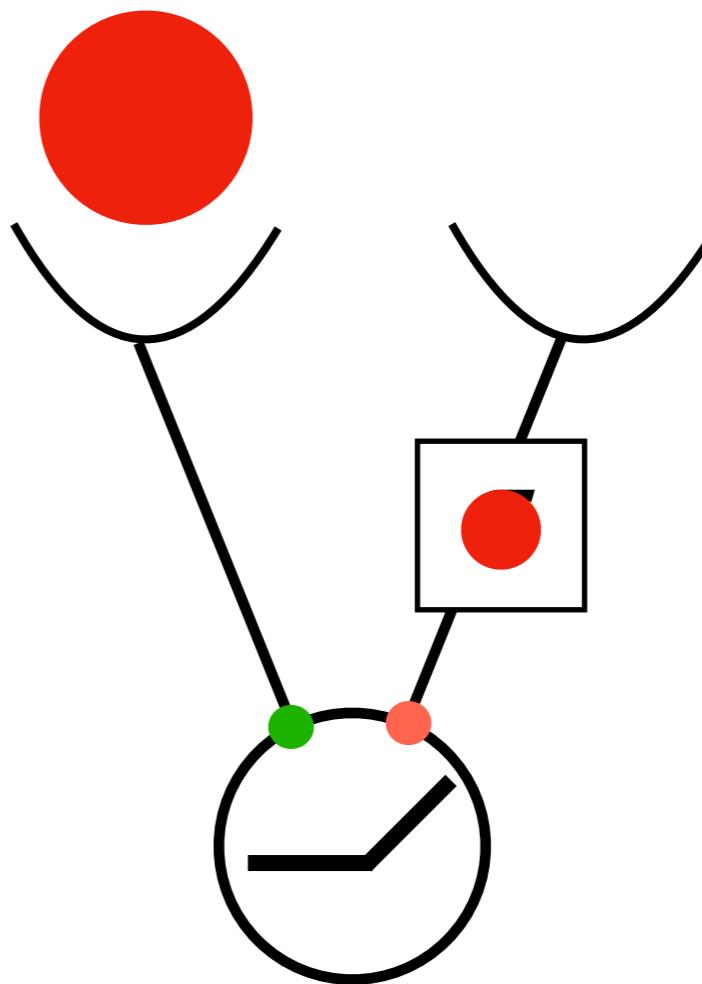


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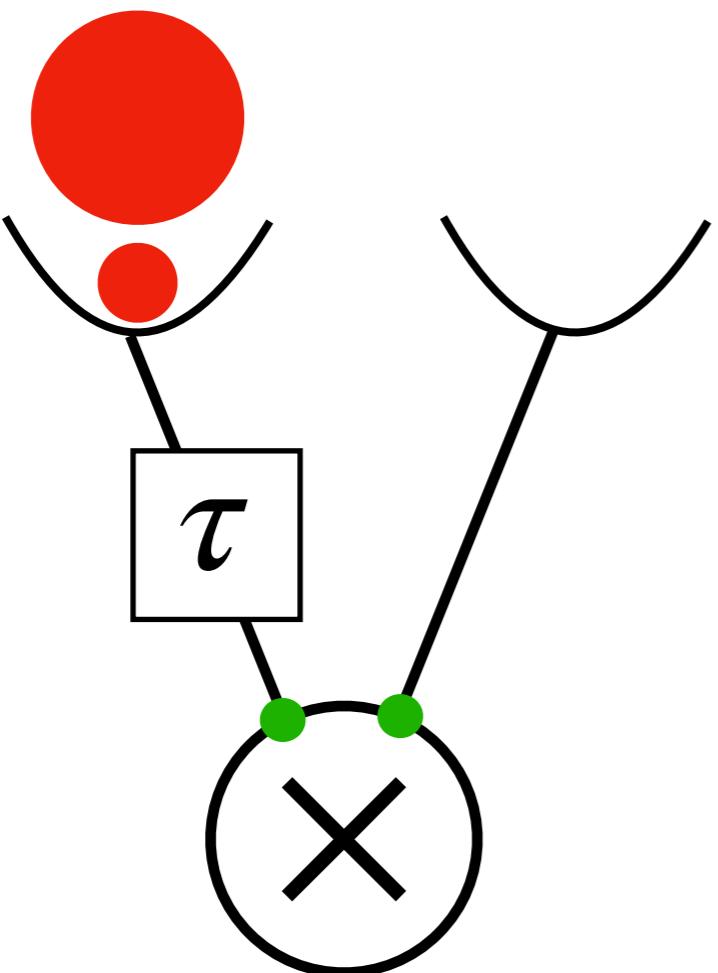


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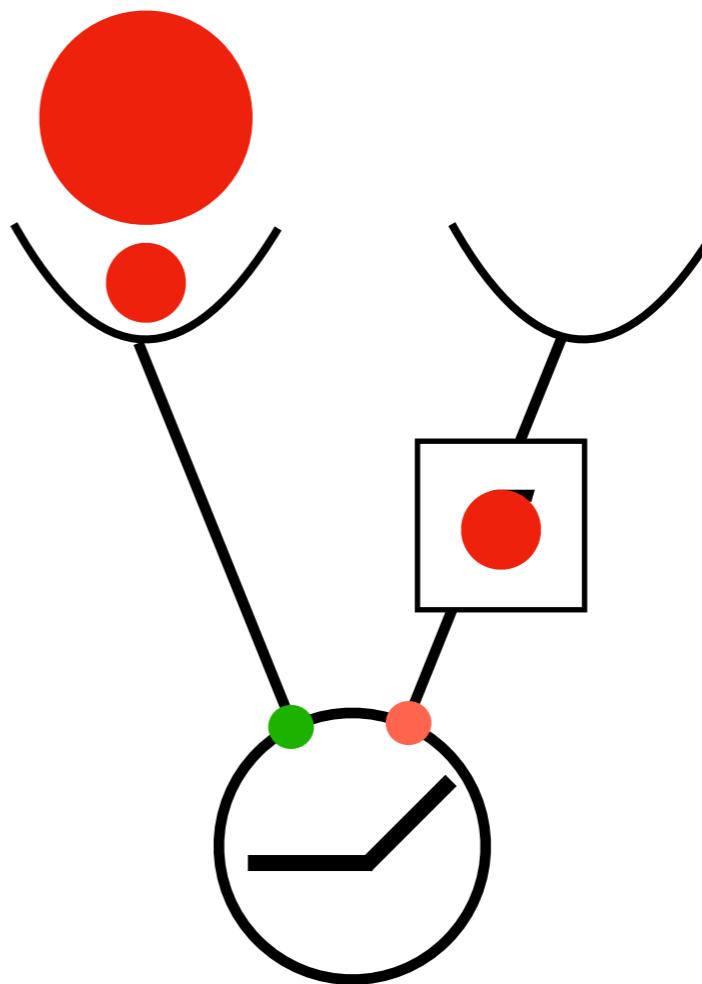


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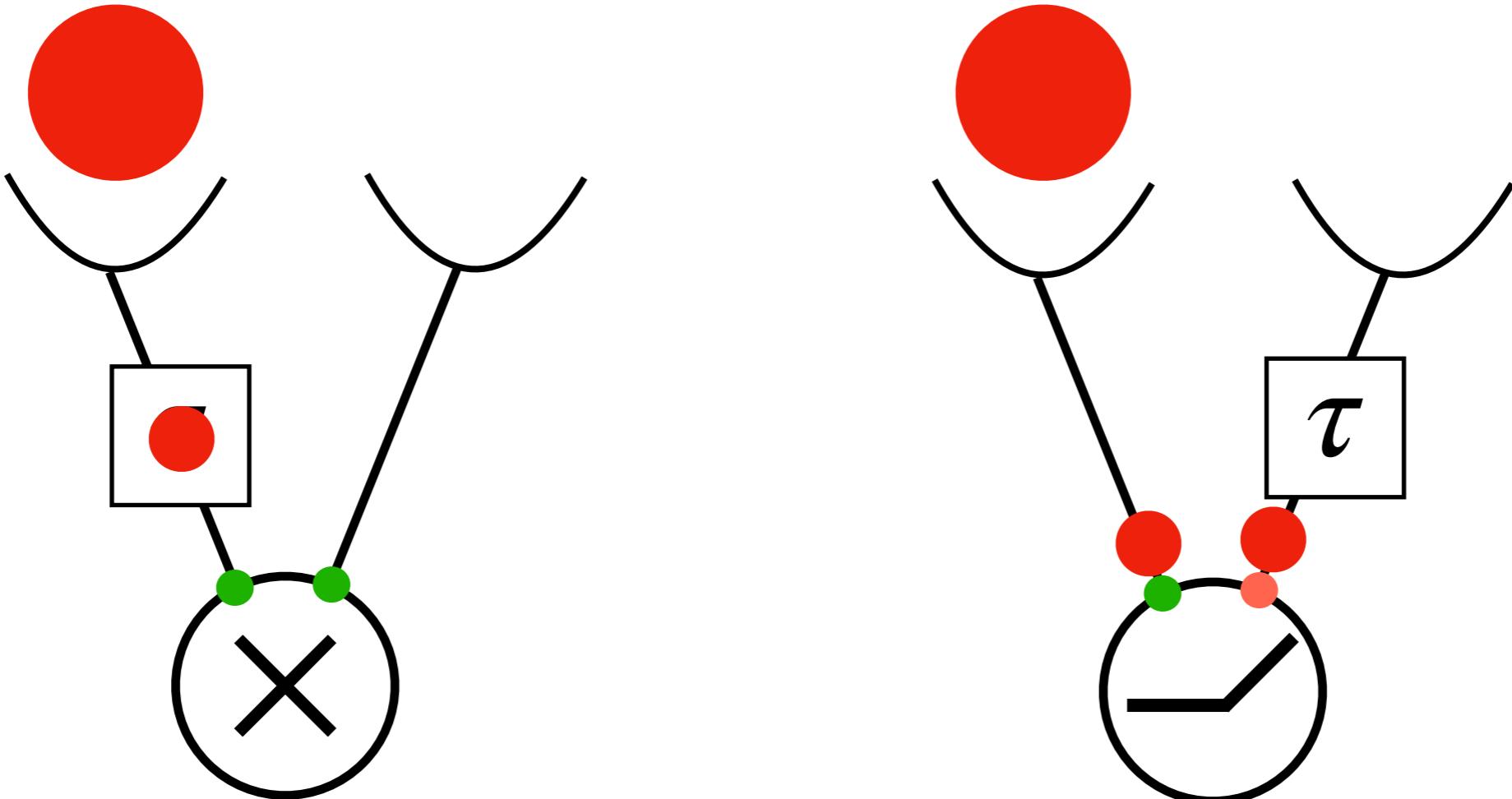
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Reichardt model

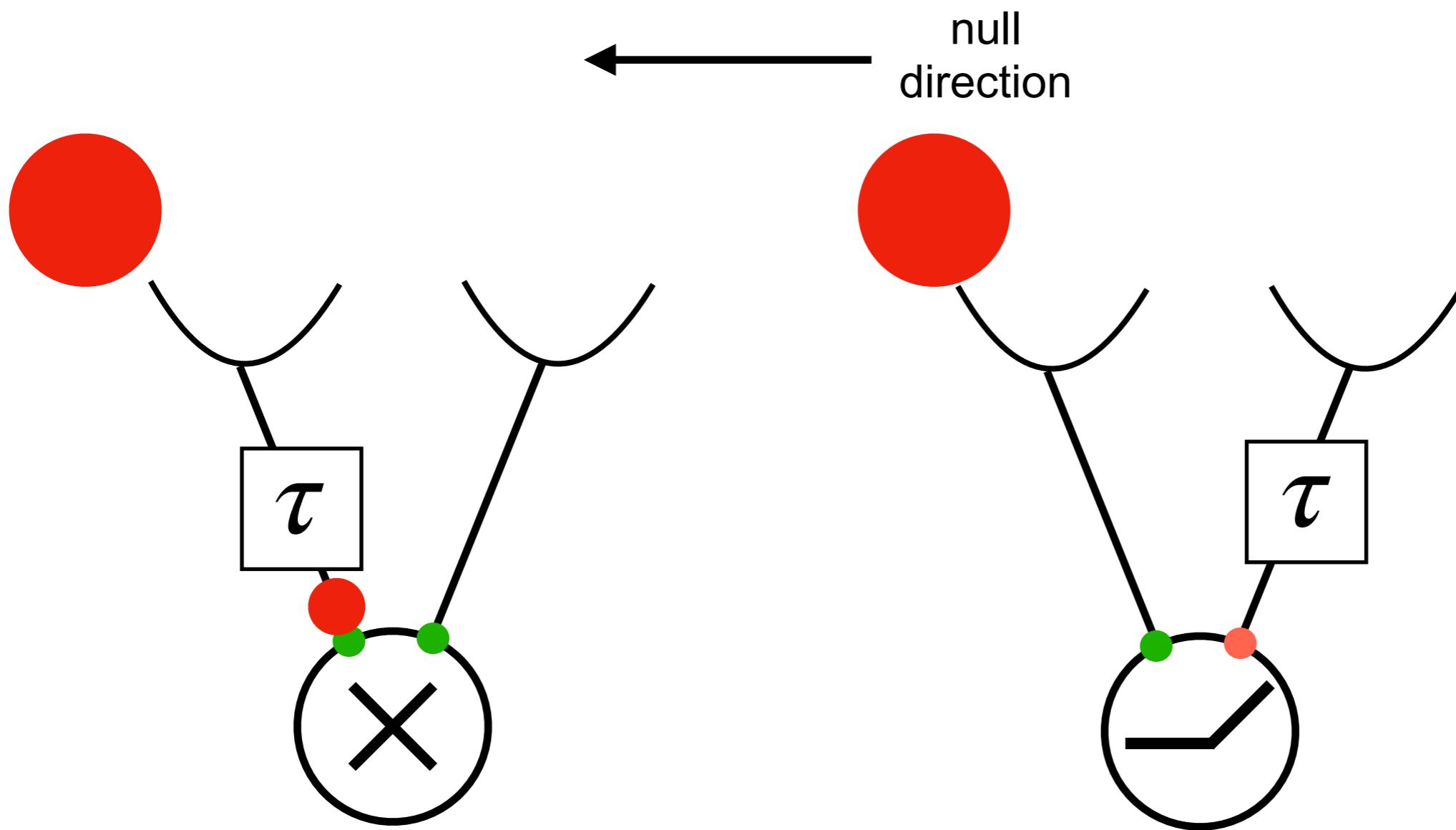


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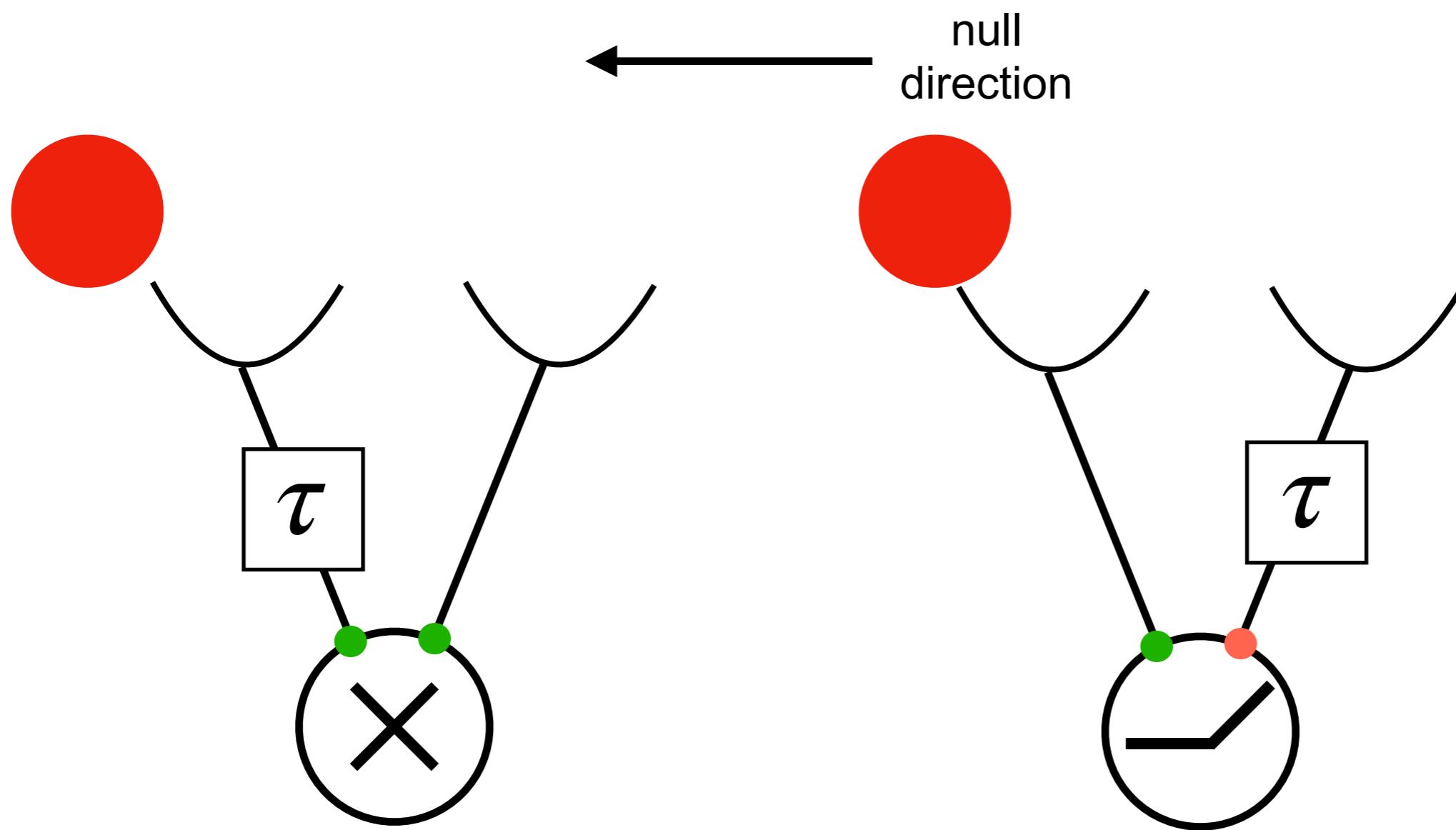
**Reichardt model**

**barlow-levick model**



Reichardt model

barlow-levick model



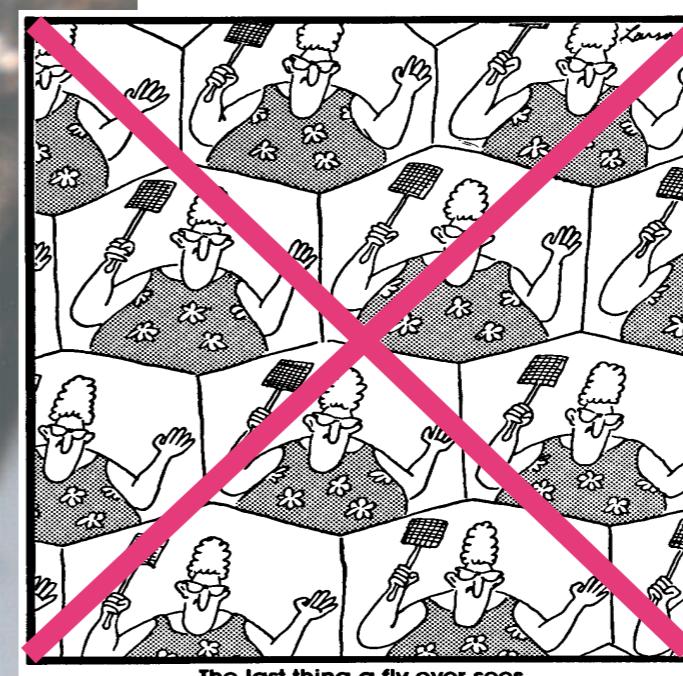
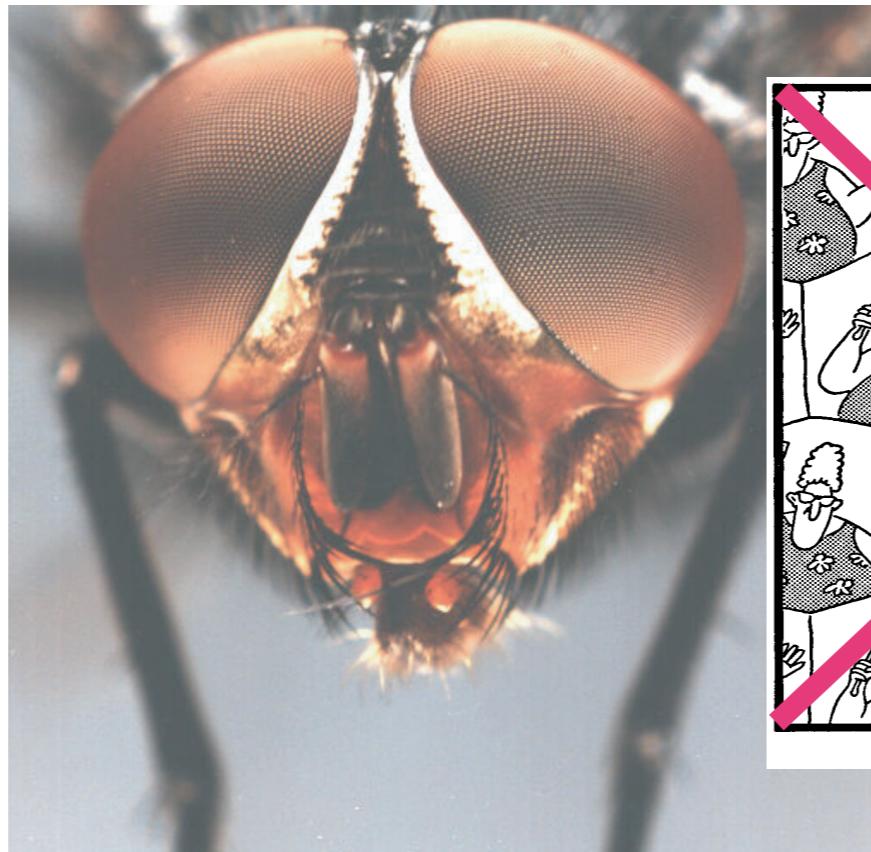
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barlow-levick model

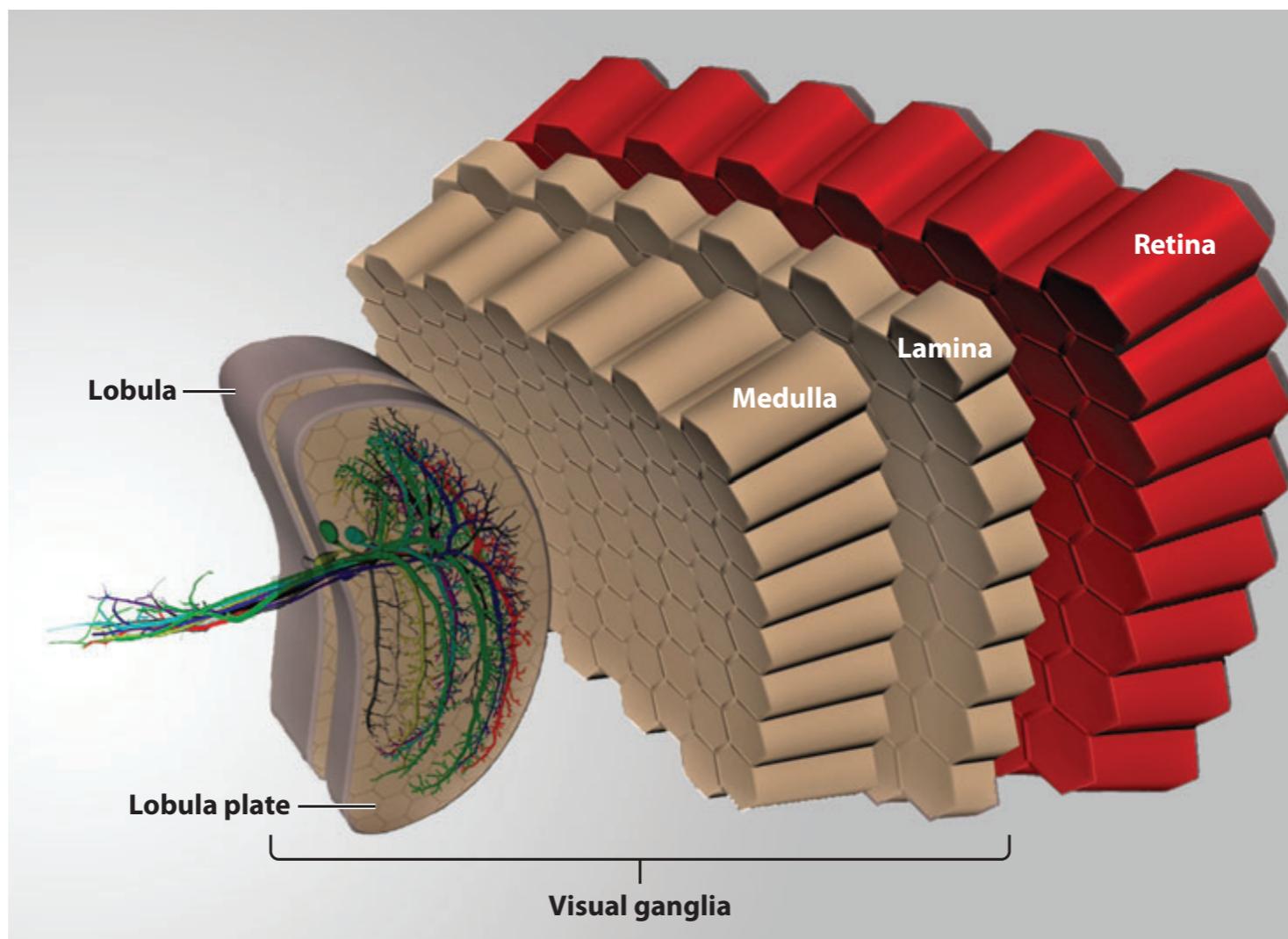
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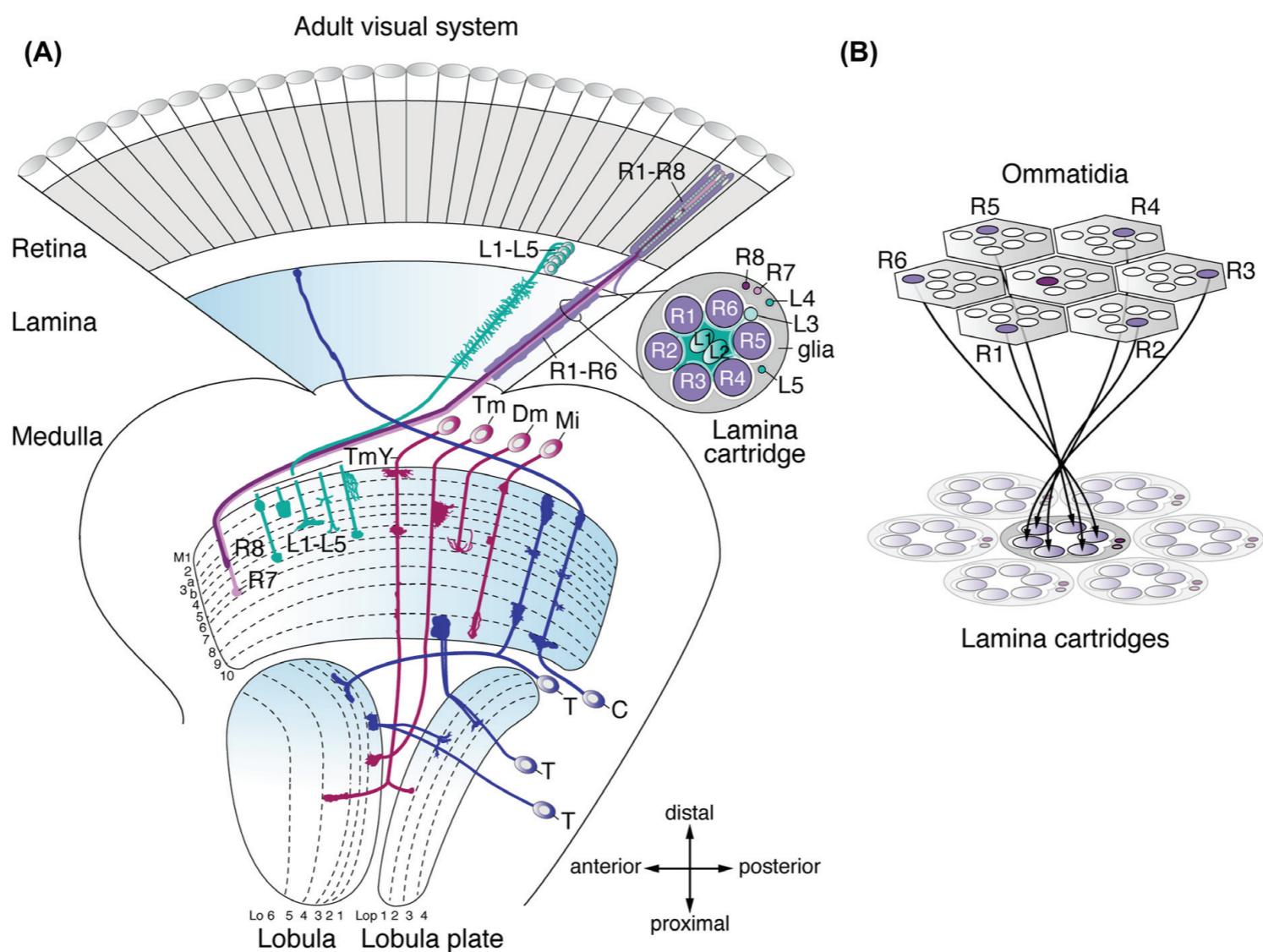
# The Fly Visual System

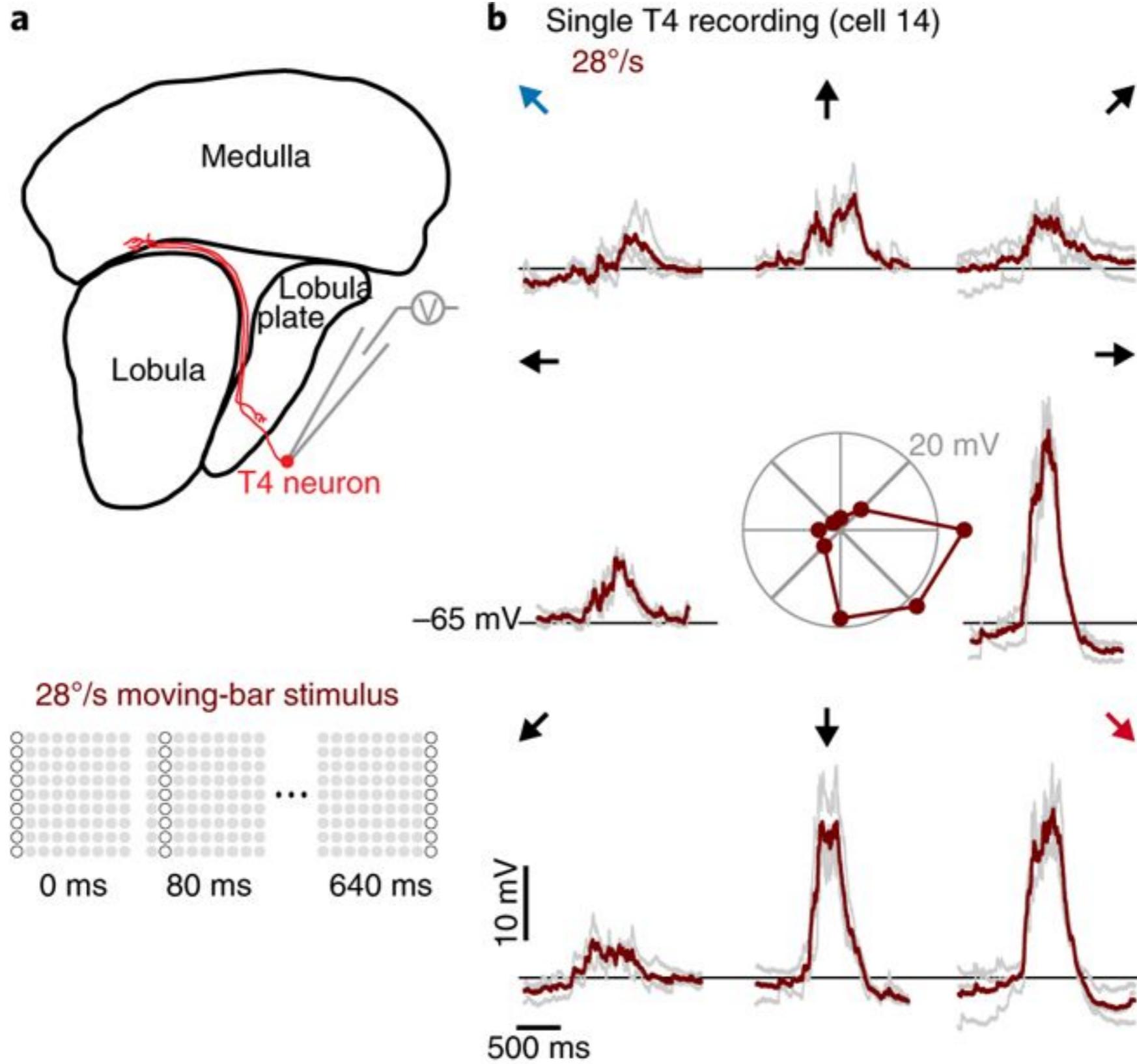


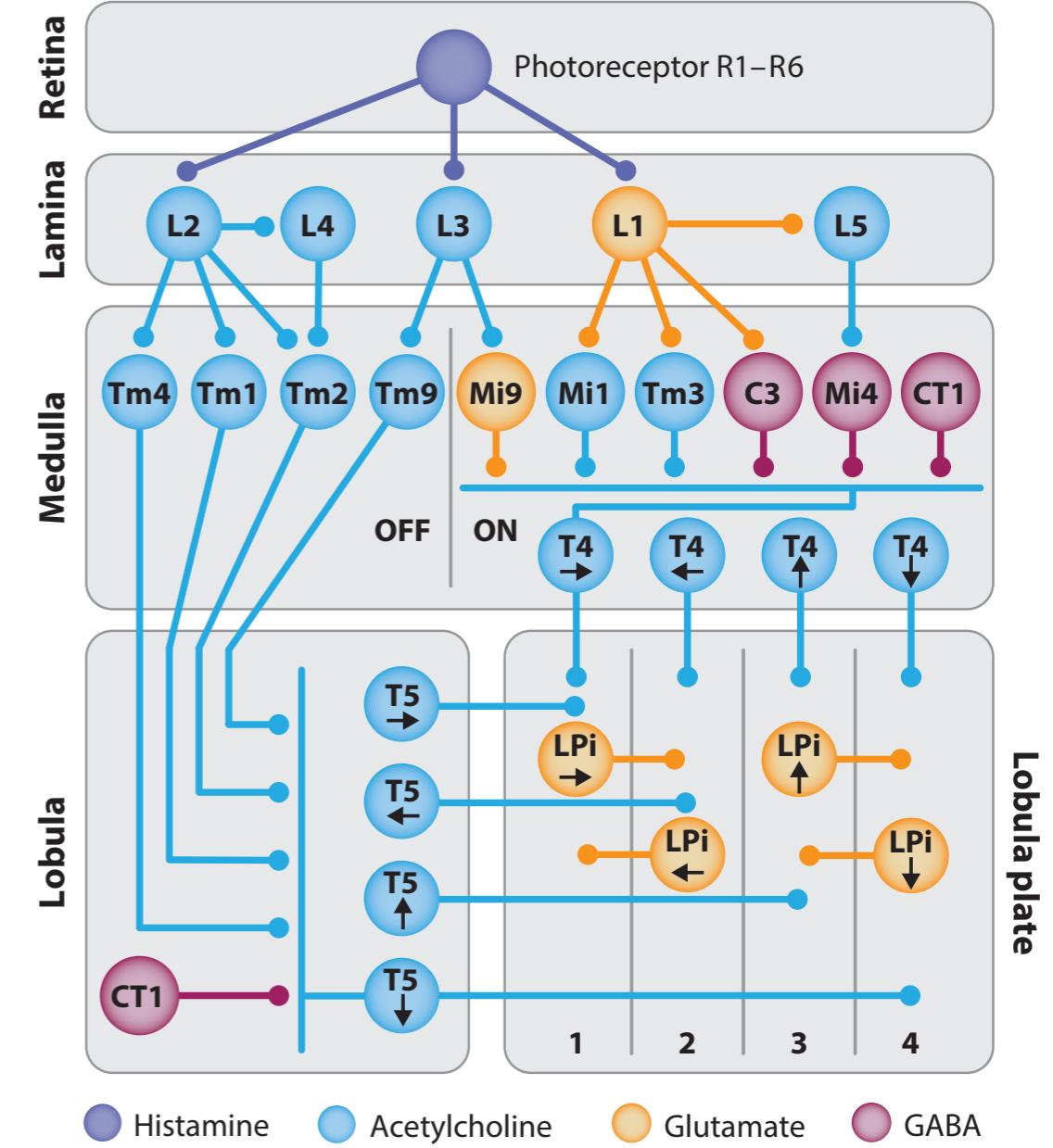
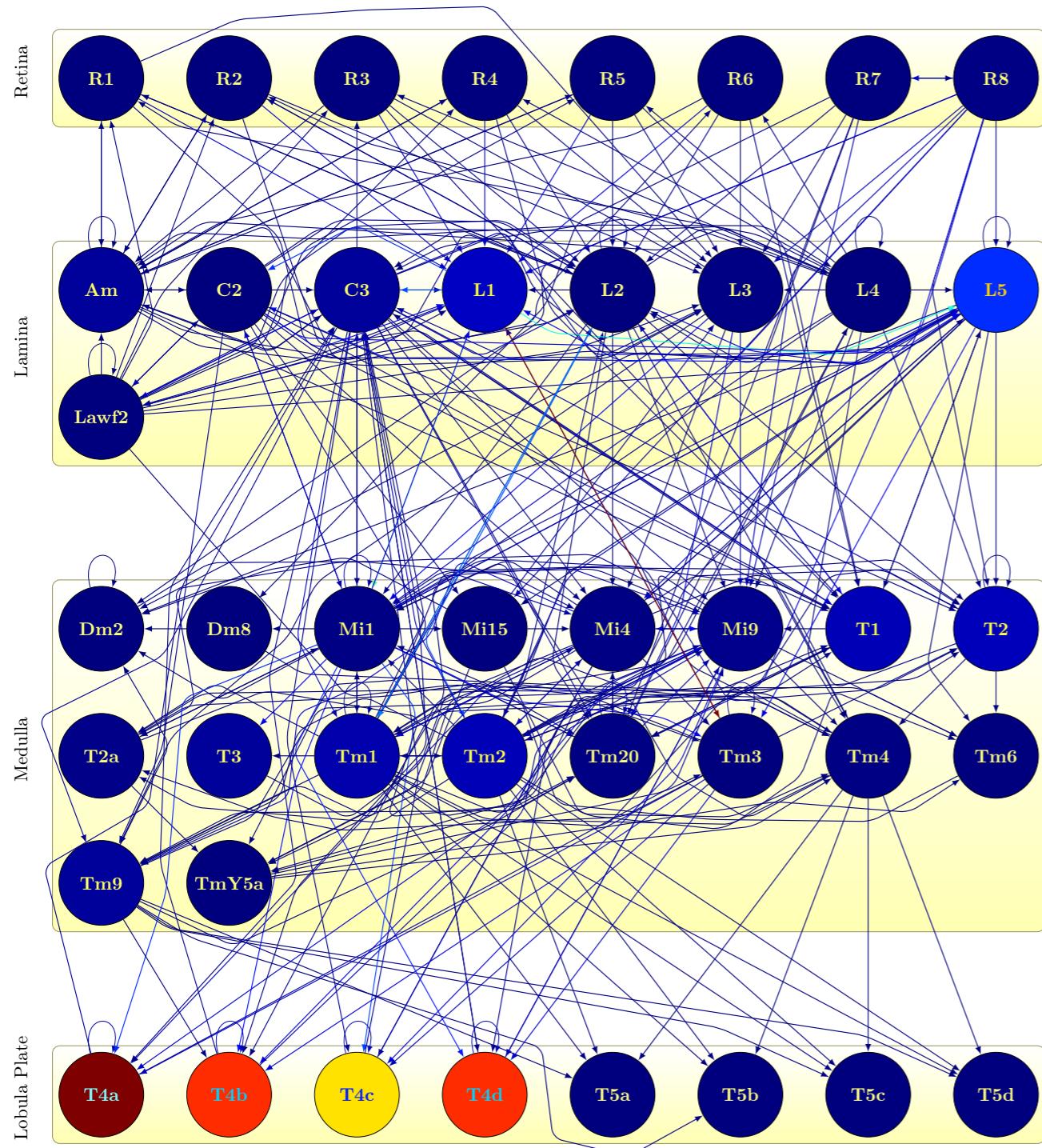
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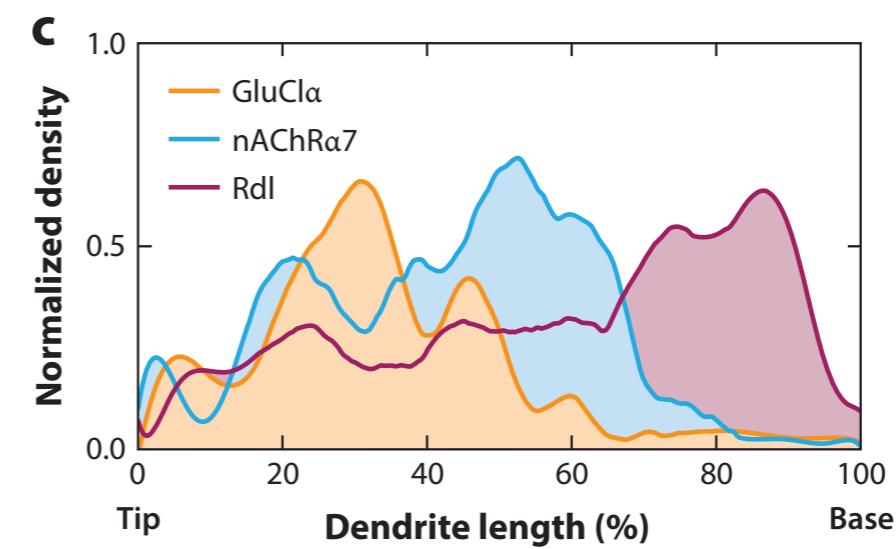
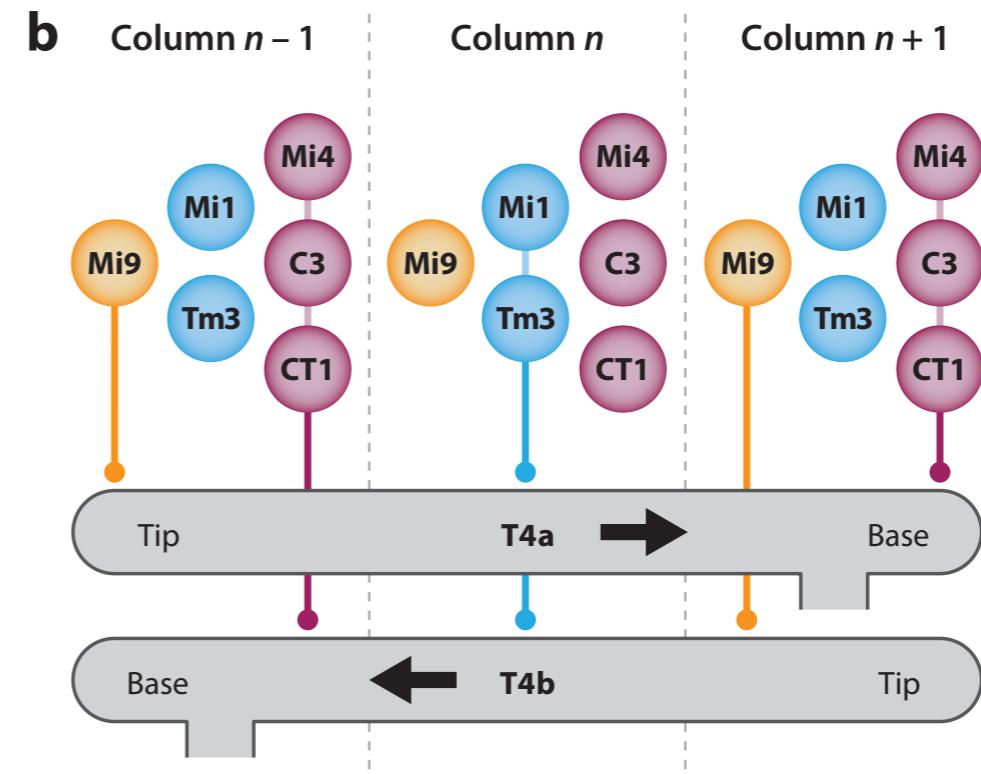
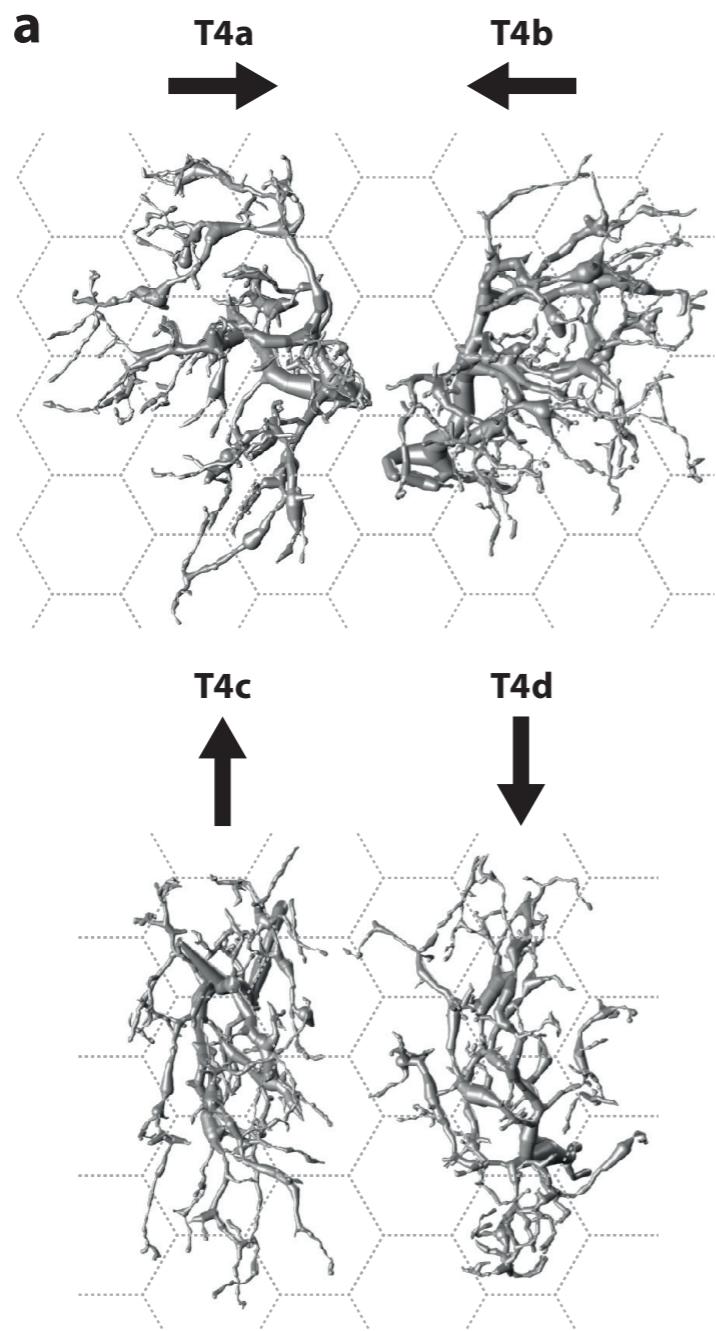


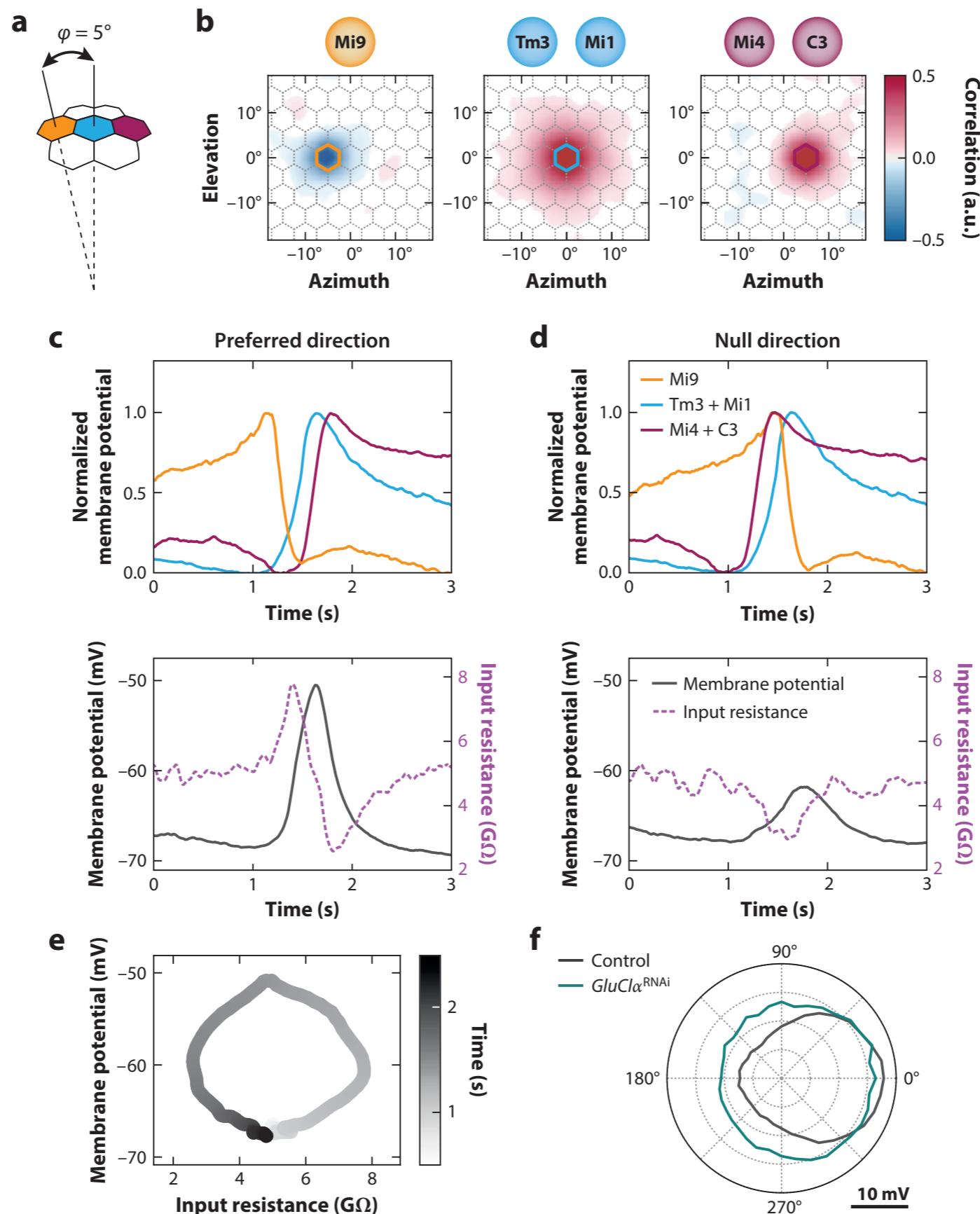
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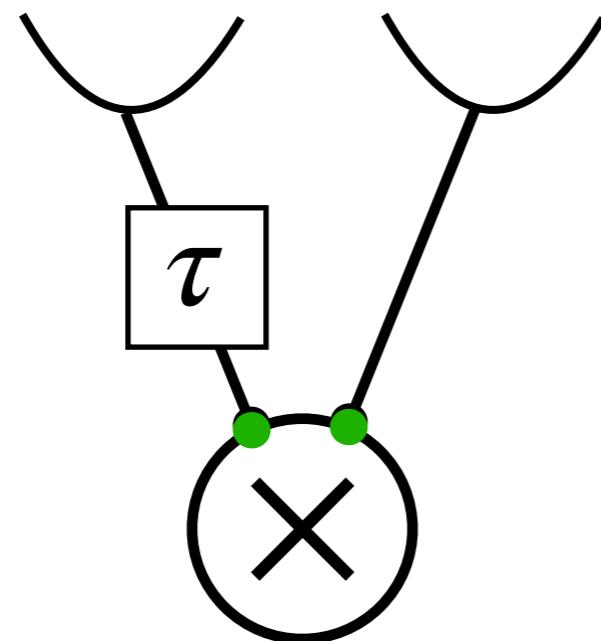




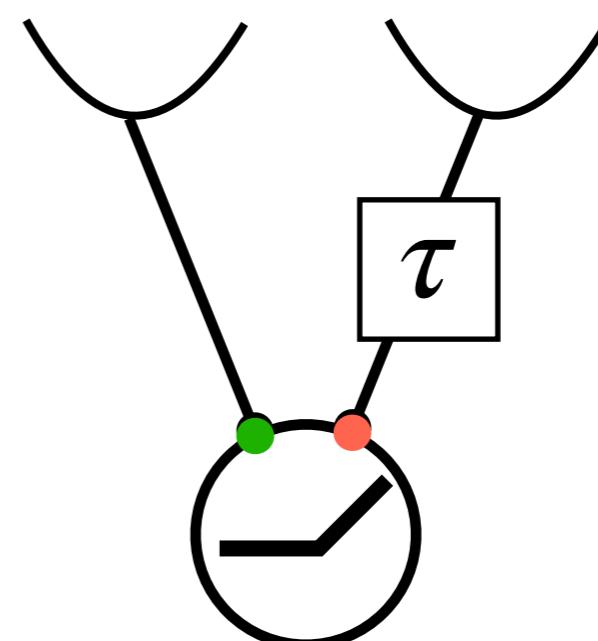




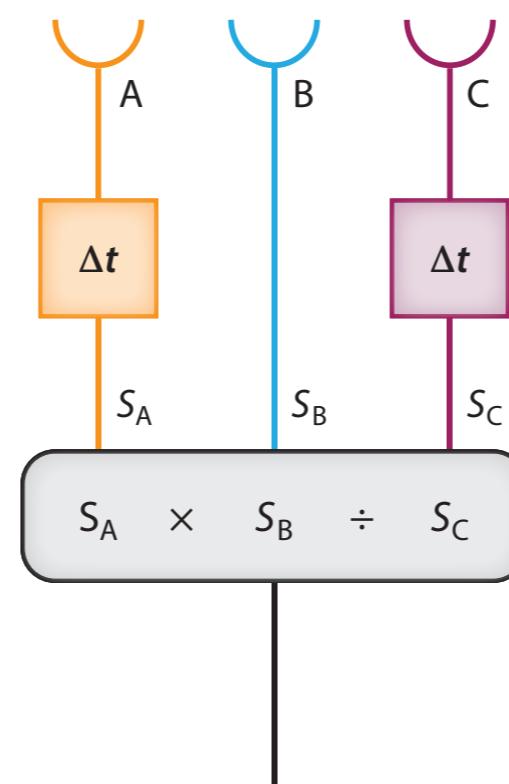


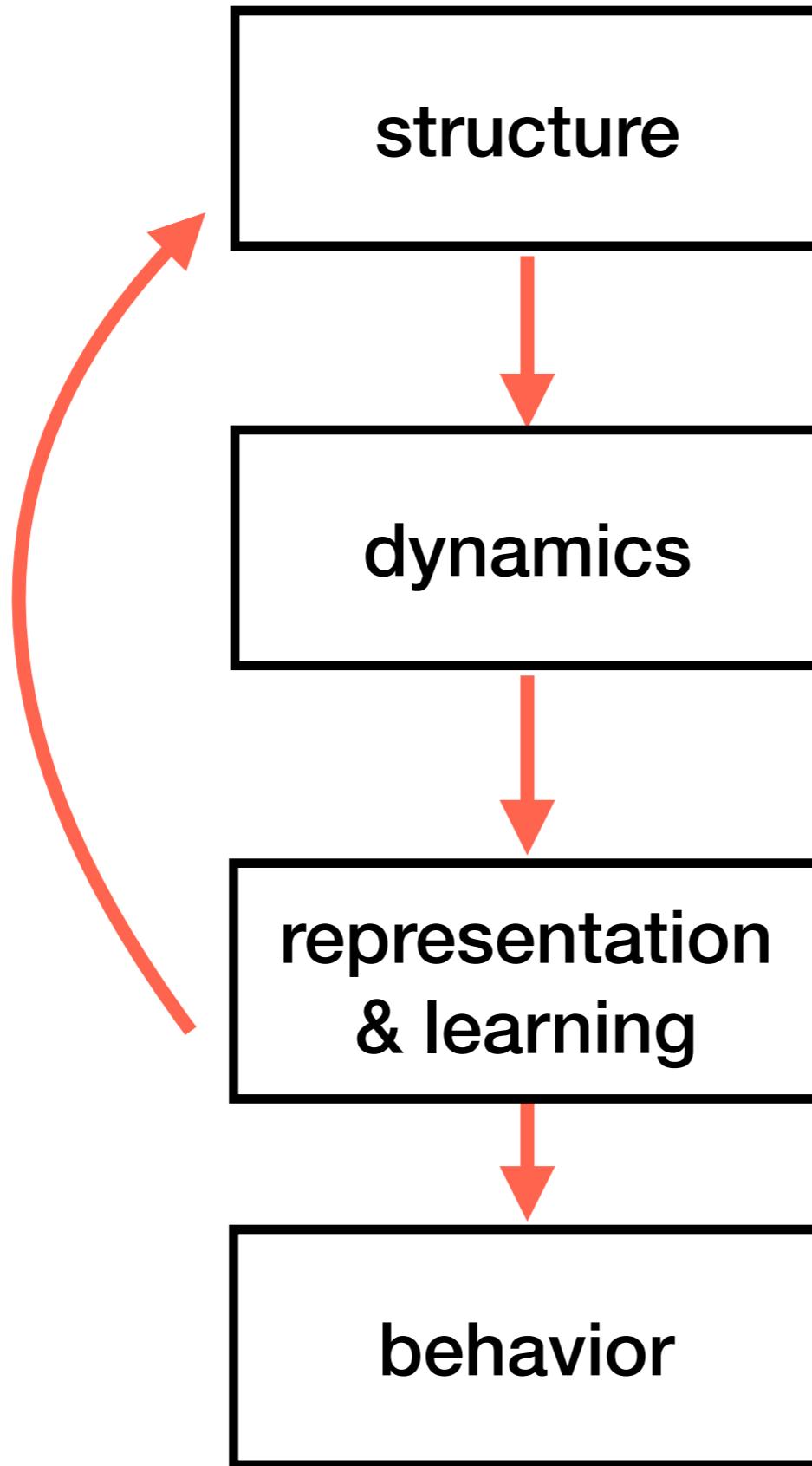


**Reichardt**



**barlow-levick**





# Course Curriculum

- **Introduction to Computational Neuroscience**
- **Single Neuron Computation**
- **Connect Neurons to Perform Computation**
- **Recurrent network and Attractor Dynamics**
- **E/I balance and Chaotic Dynamics**
- **Efficient coding principle**
- **Stimulus discrimination, Fisher information and Information-limited correlation**
- **Normative approach to neural computation and the emergence of sensory representation**
- **Dimensionality reduction and motor representation**
- **How does an animal move, an integrated approach, and insights from *C. elegans***
- **Reward and Reinforcement Learning**