

An Introduction to Computational Neuroscience

WEN quan (温泉)

University of Science and Technology of China

September 1 2026

Course website

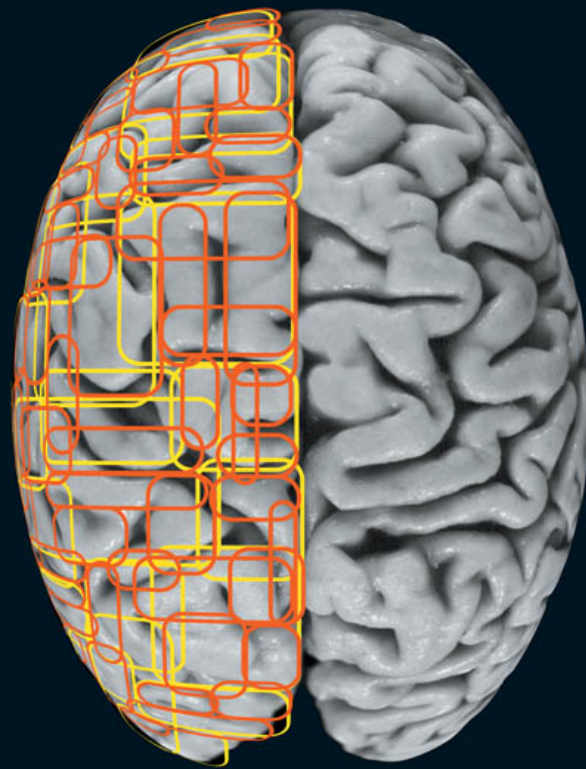
<https://wenlab.github.io/Computation-Neuro-Course/>



Recommended textbooks

THEORETICAL NEUROSCIENCE

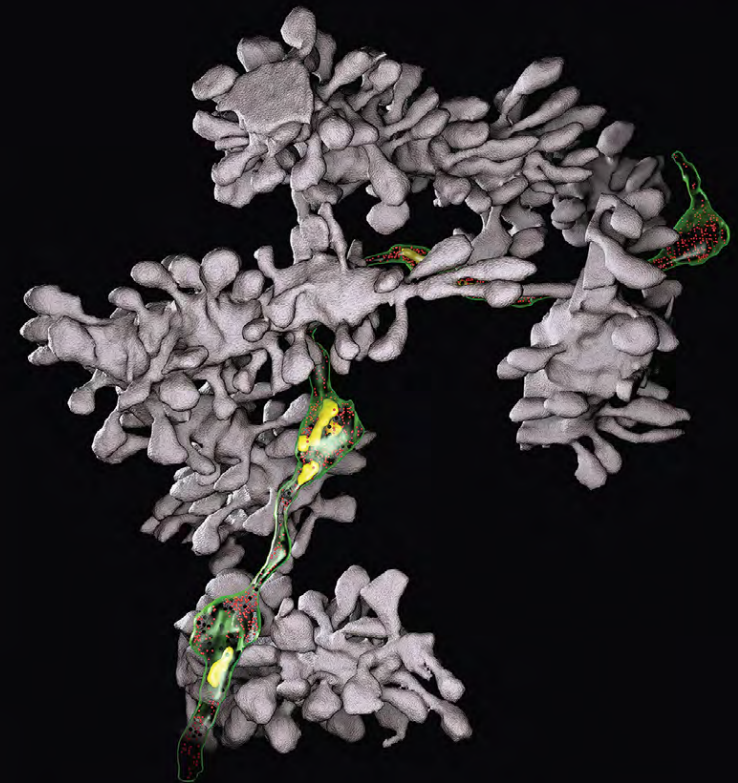
Computational and Mathematical
Modeling of Neural Systems



Peter Dayan and L. F. Abbott

How questions

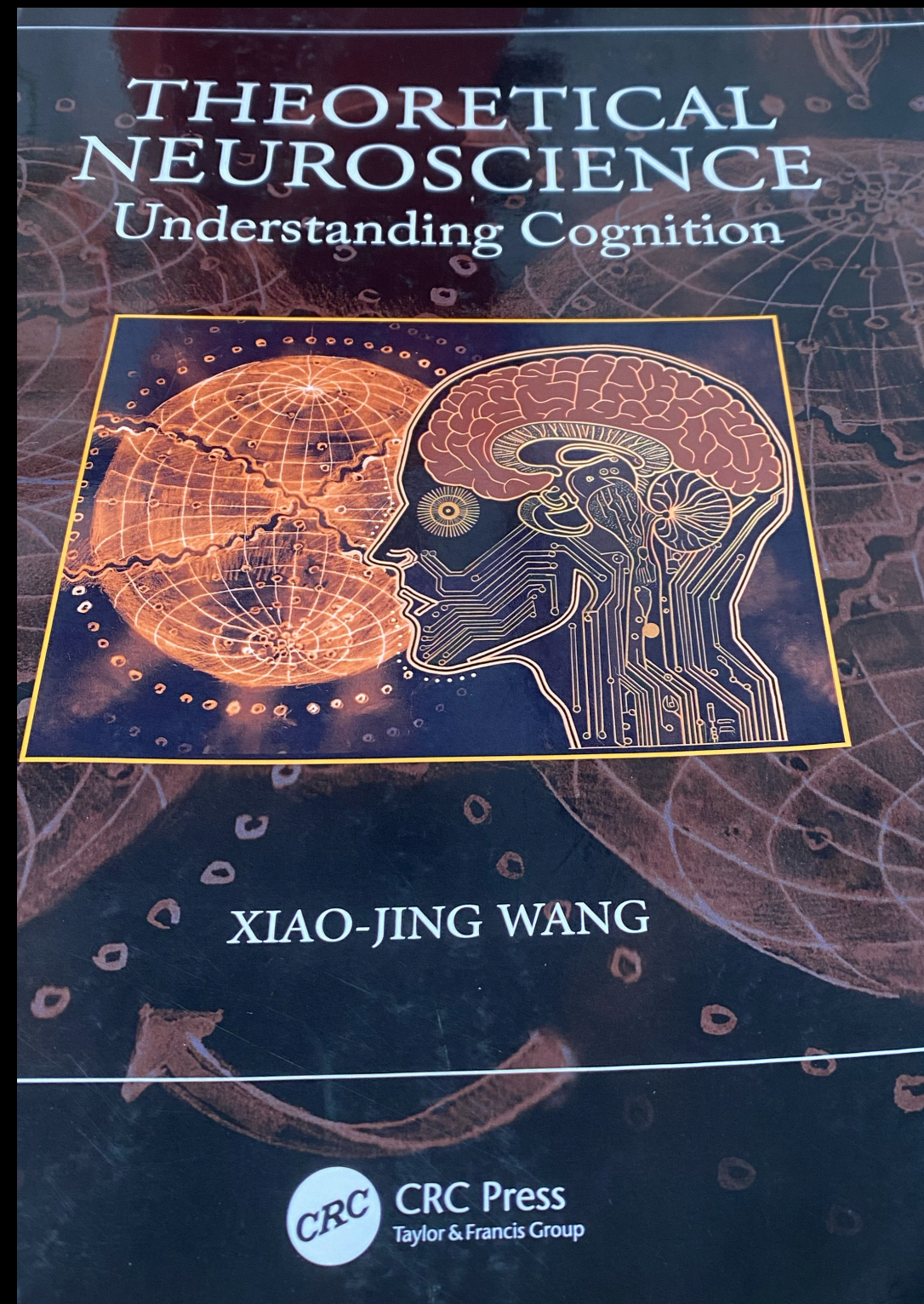
Principles of Neural Design



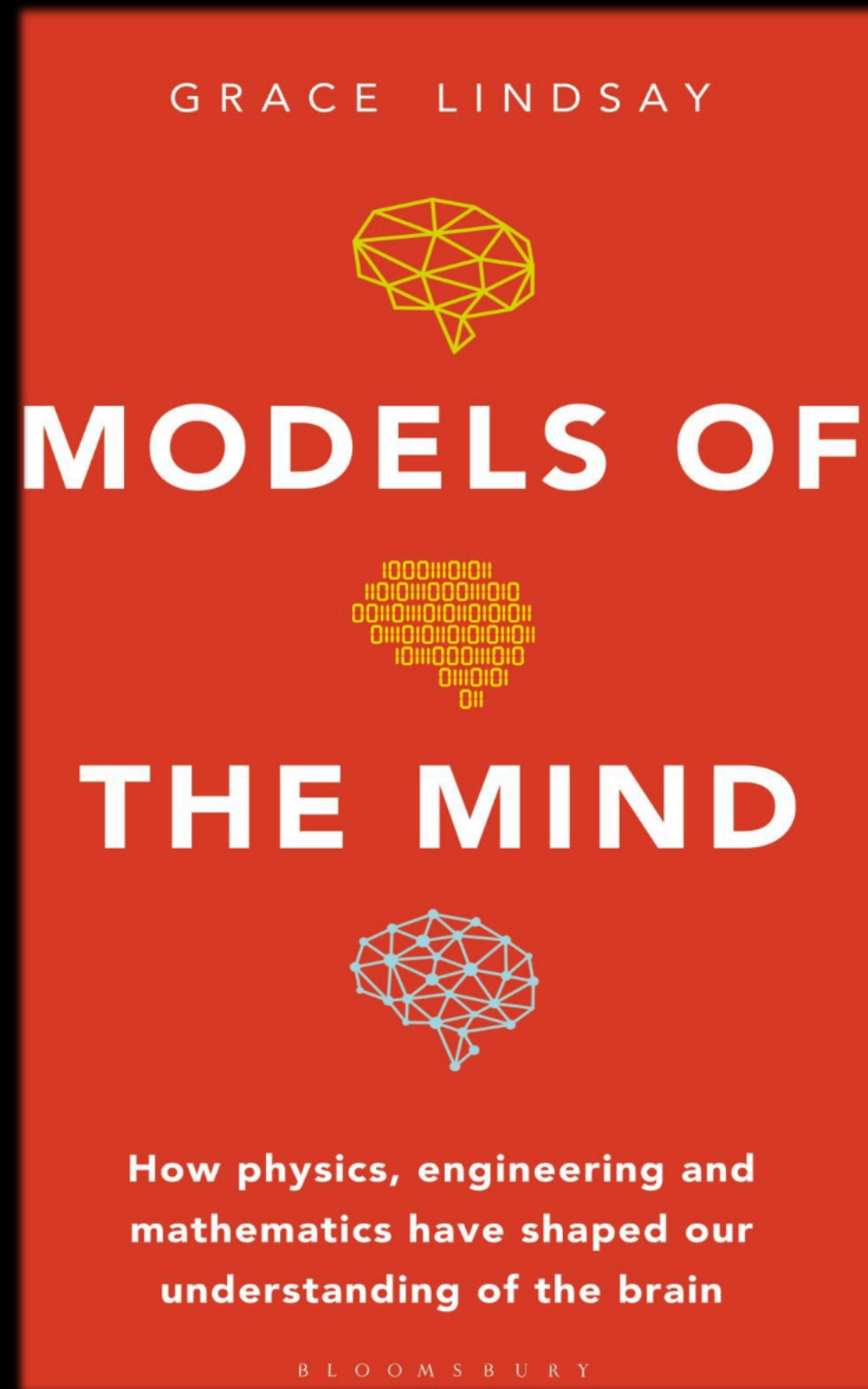
Peter Sterling and Simon Laughlin

Why questions

Recommended textbooks



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
Taylor & Francis Group

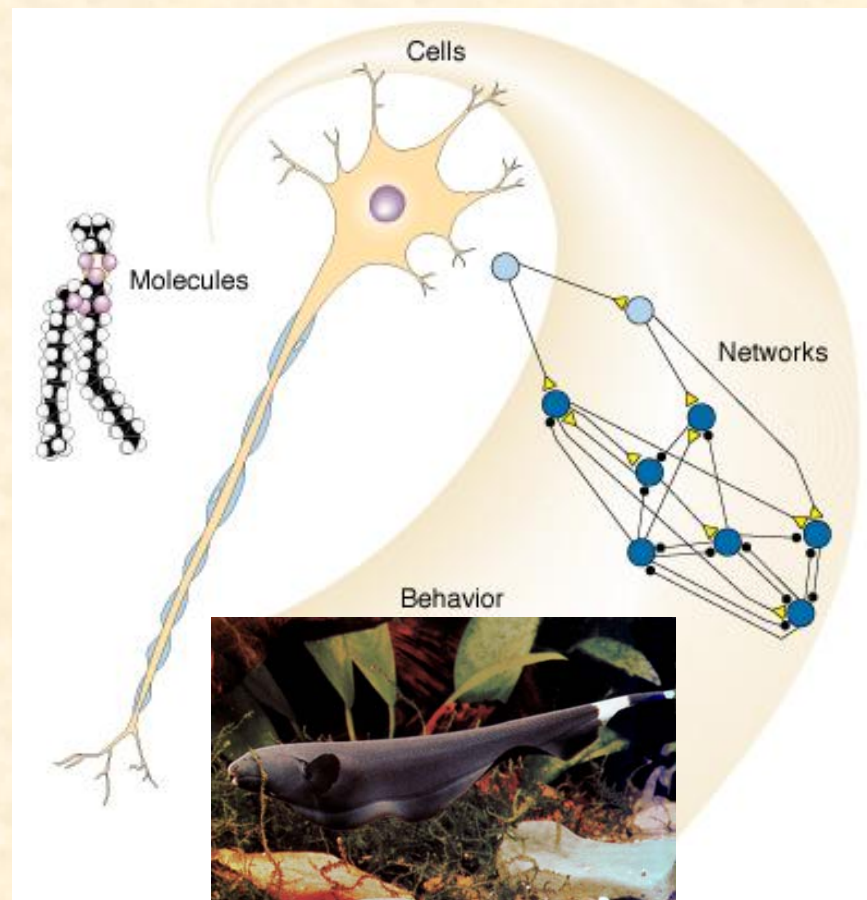
A GARLAND SCIENCE BOOK



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

Organism

1 m

System

10 cm

Map

1 cm

Column

1 mm

Neuron

10 μm

Synapse

1 μm

Molecule

10 $\text{\AA}$

“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 brought 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.”

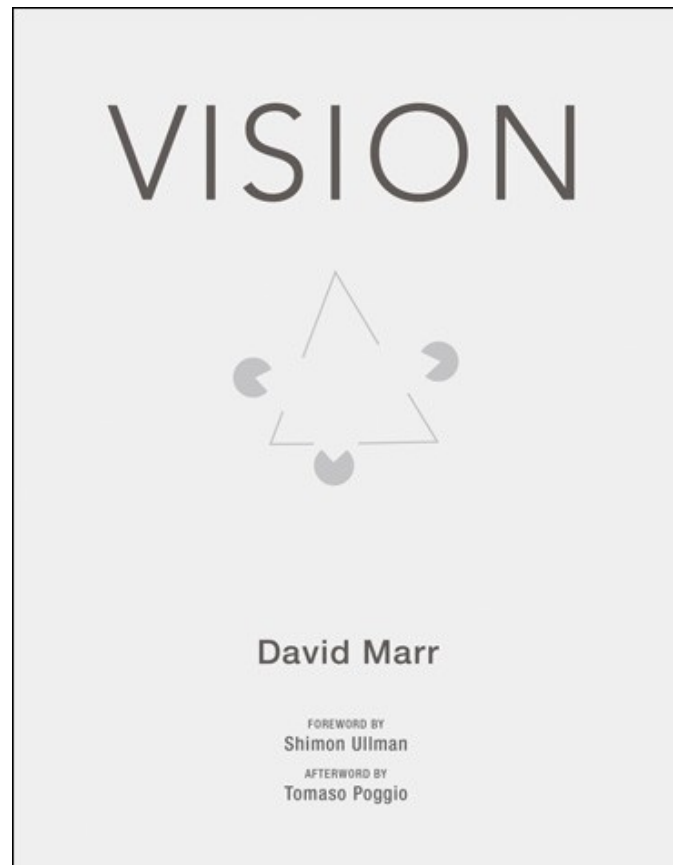
Larry Abbott
Theoretical Neuroscience is rising
Neuron 2008



David Marr
1945-1980



Henry Markram
1962 -

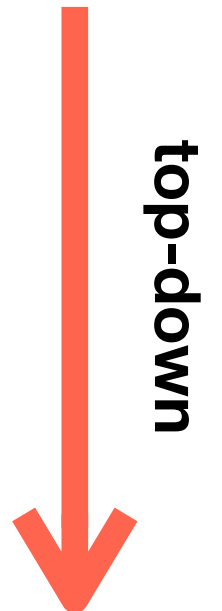


blue brain project



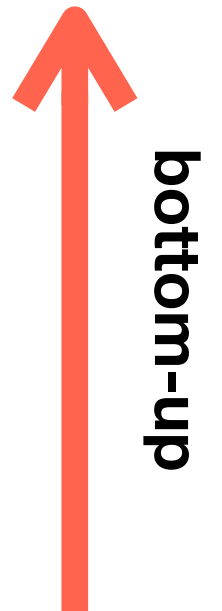
David Marr's three level theory

- **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

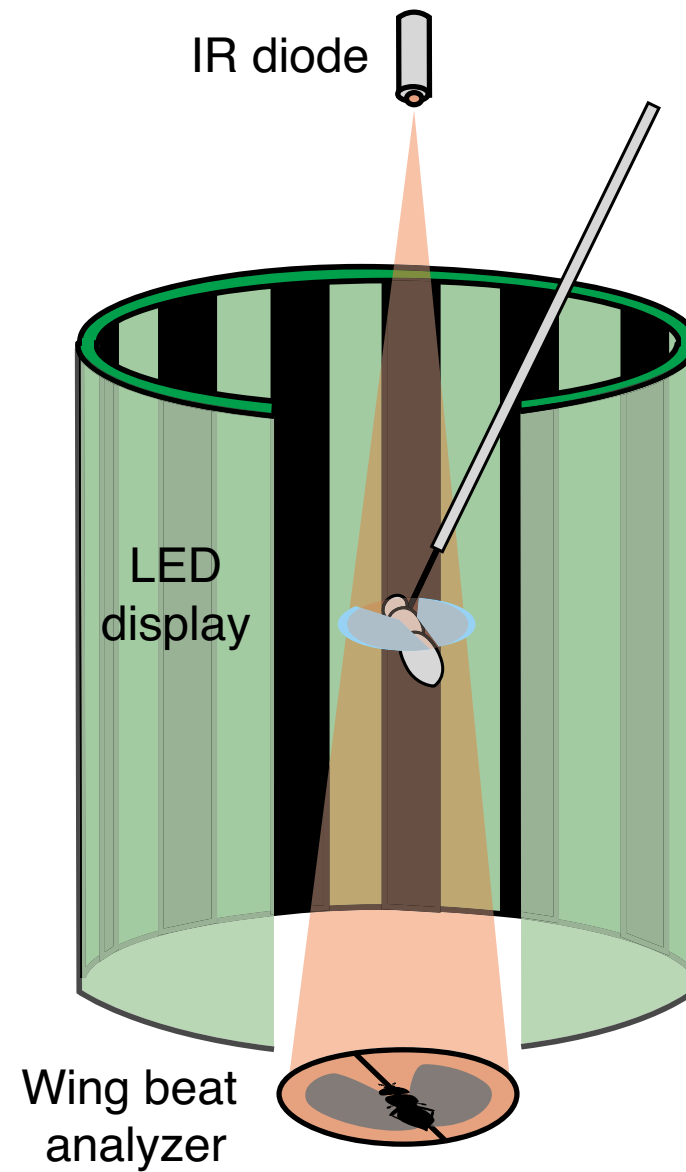
Circuit diagrams or connectomes are *absolutely* necessary but *completely* insufficient for understanding nervous system function.

Eve Marder

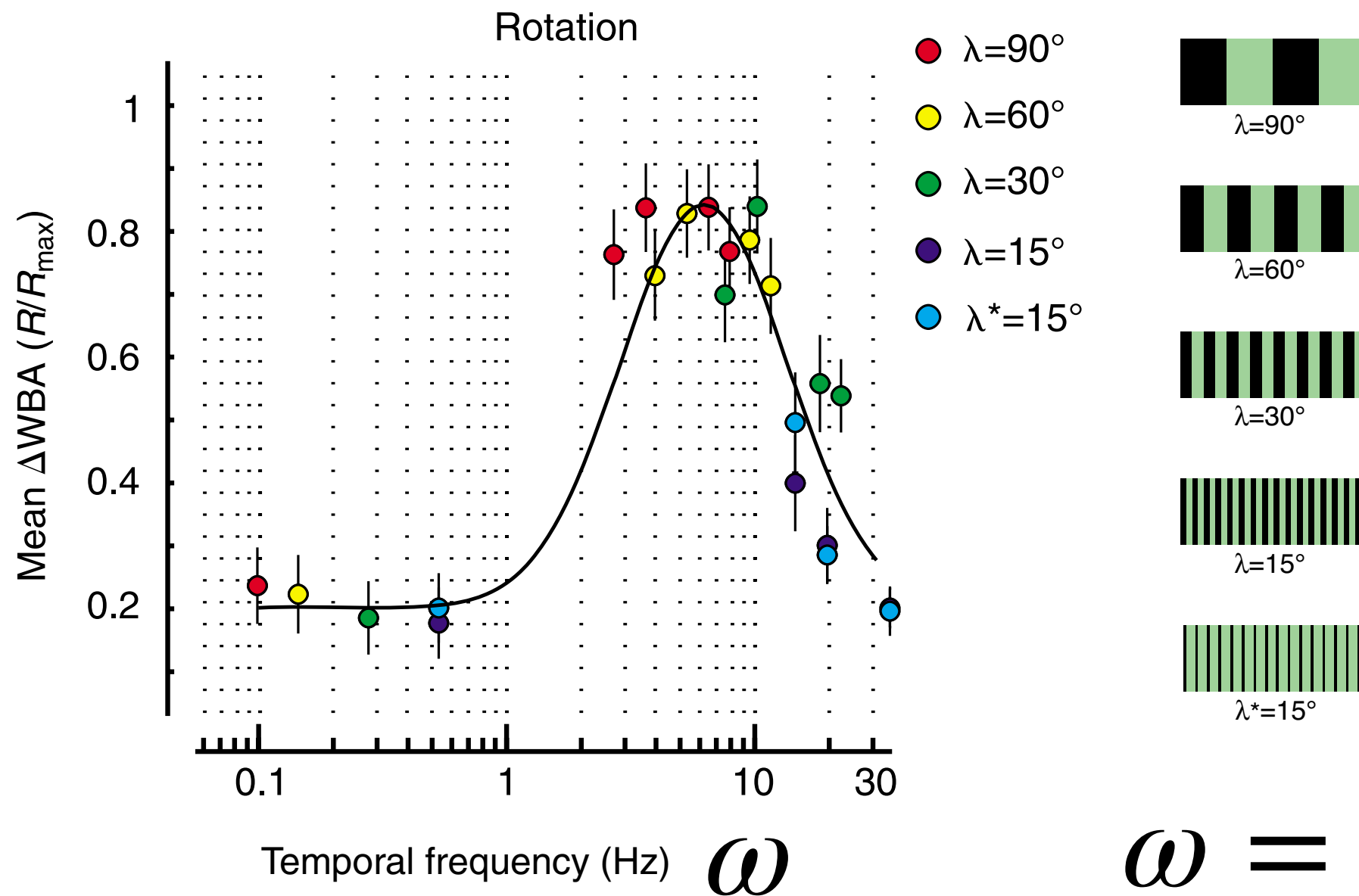
Motion detection, an example



Optomotor response in fly

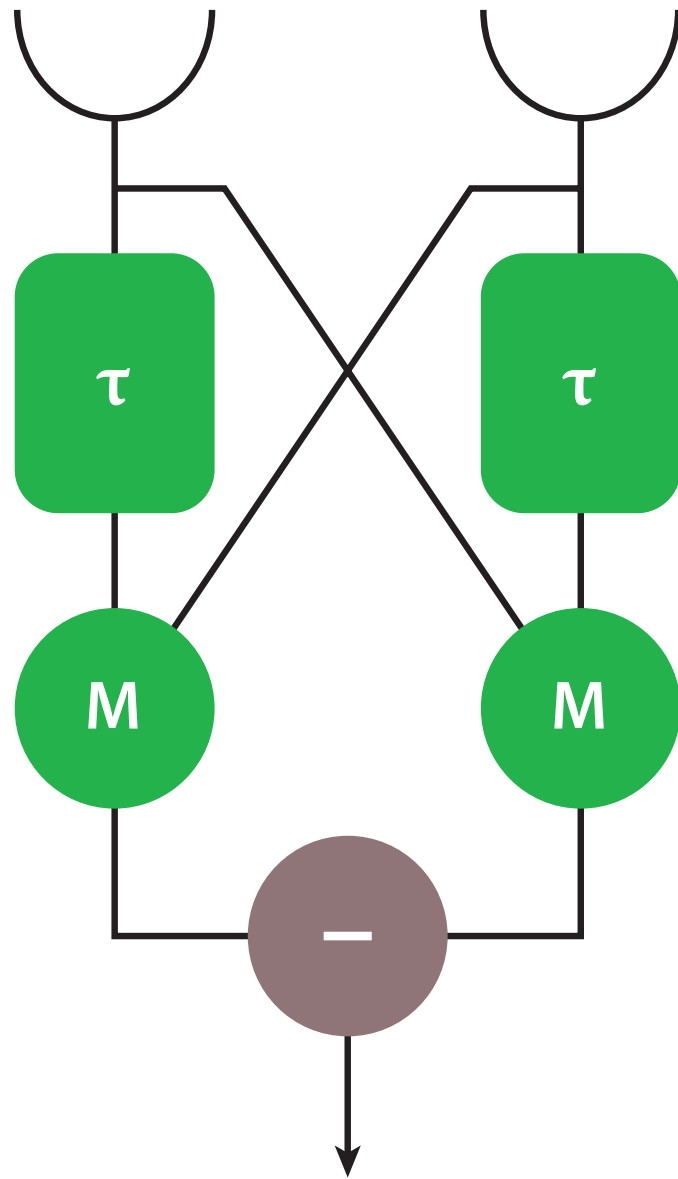


Optomotor response in fly

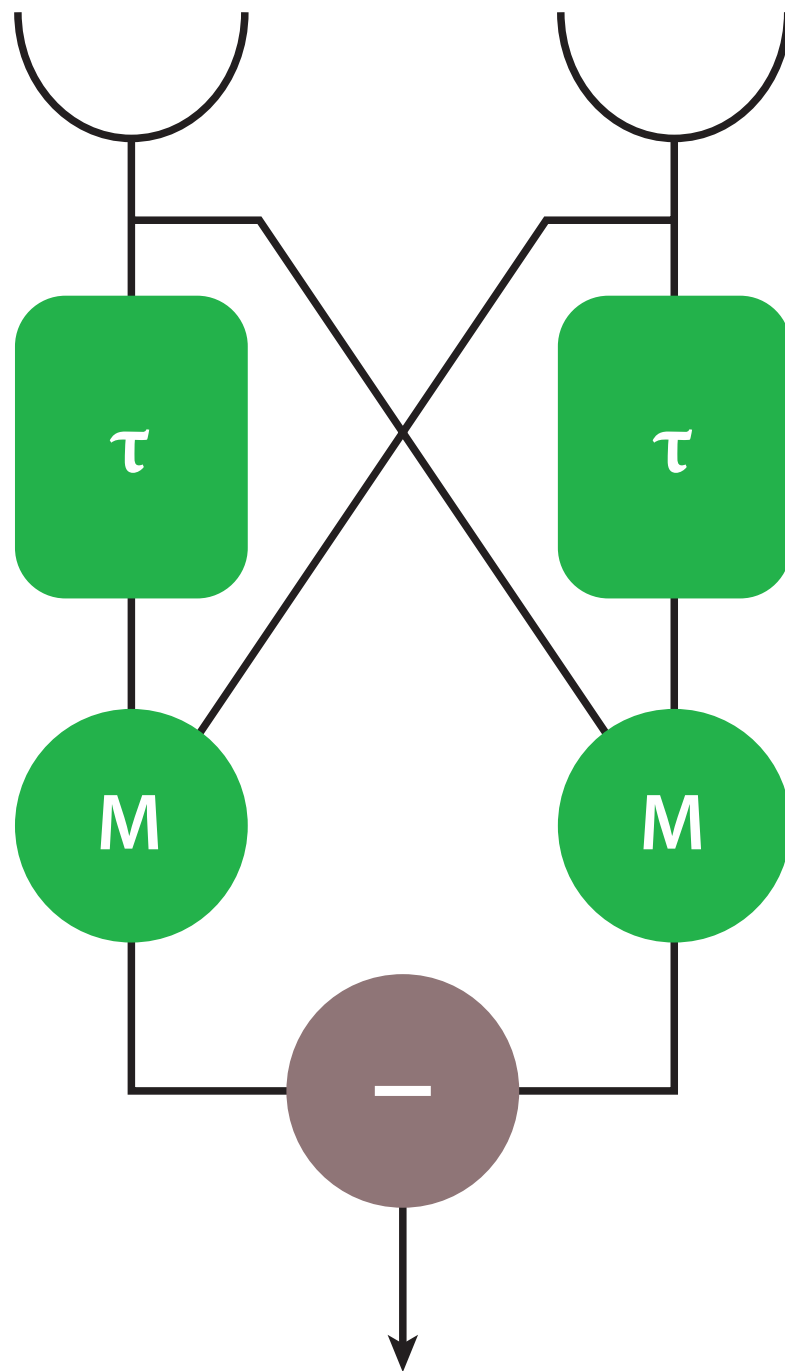
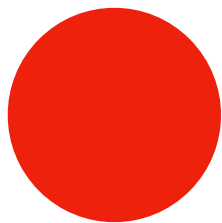


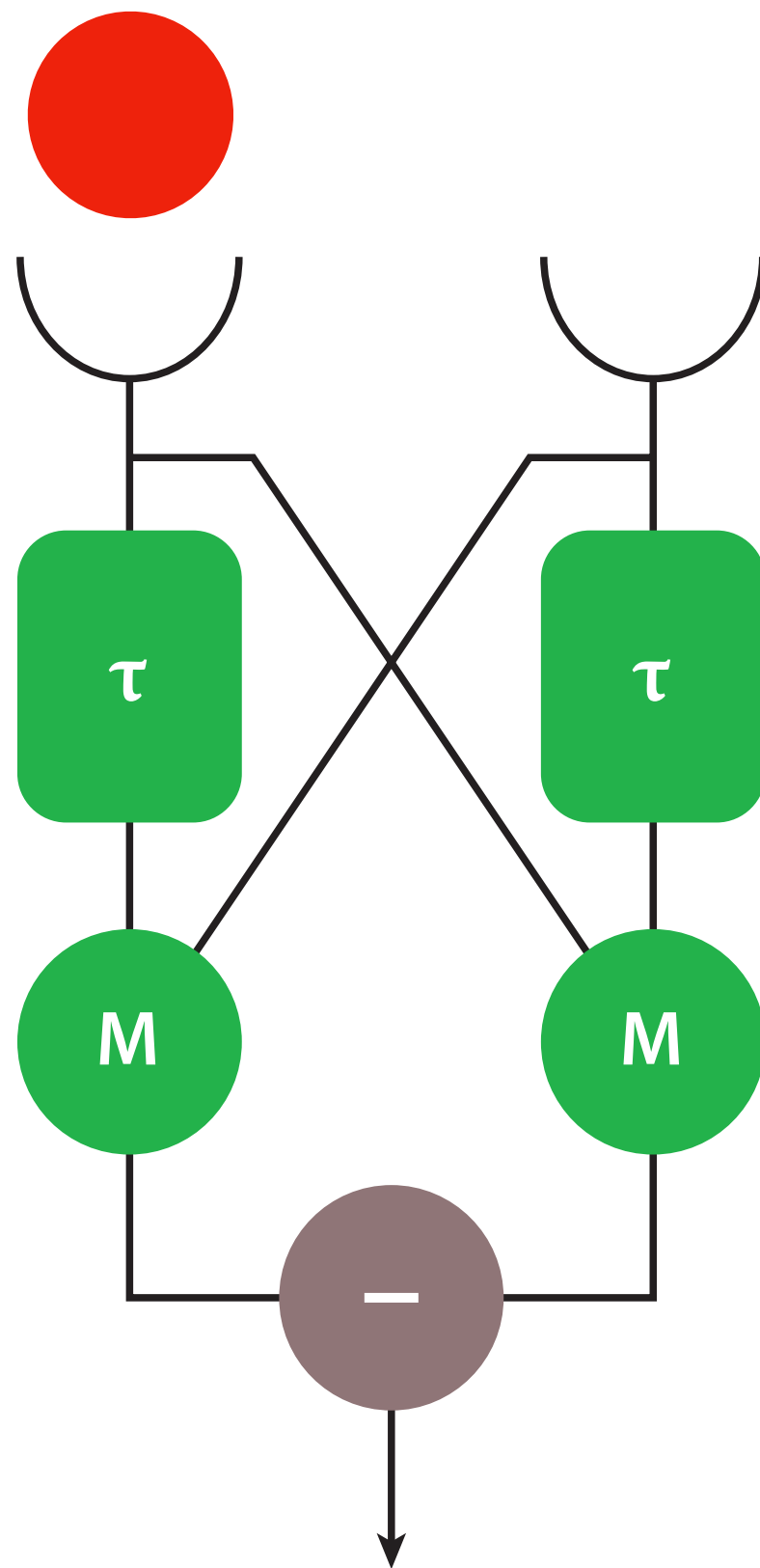
$$\omega = 2\pi\nu/\lambda$$

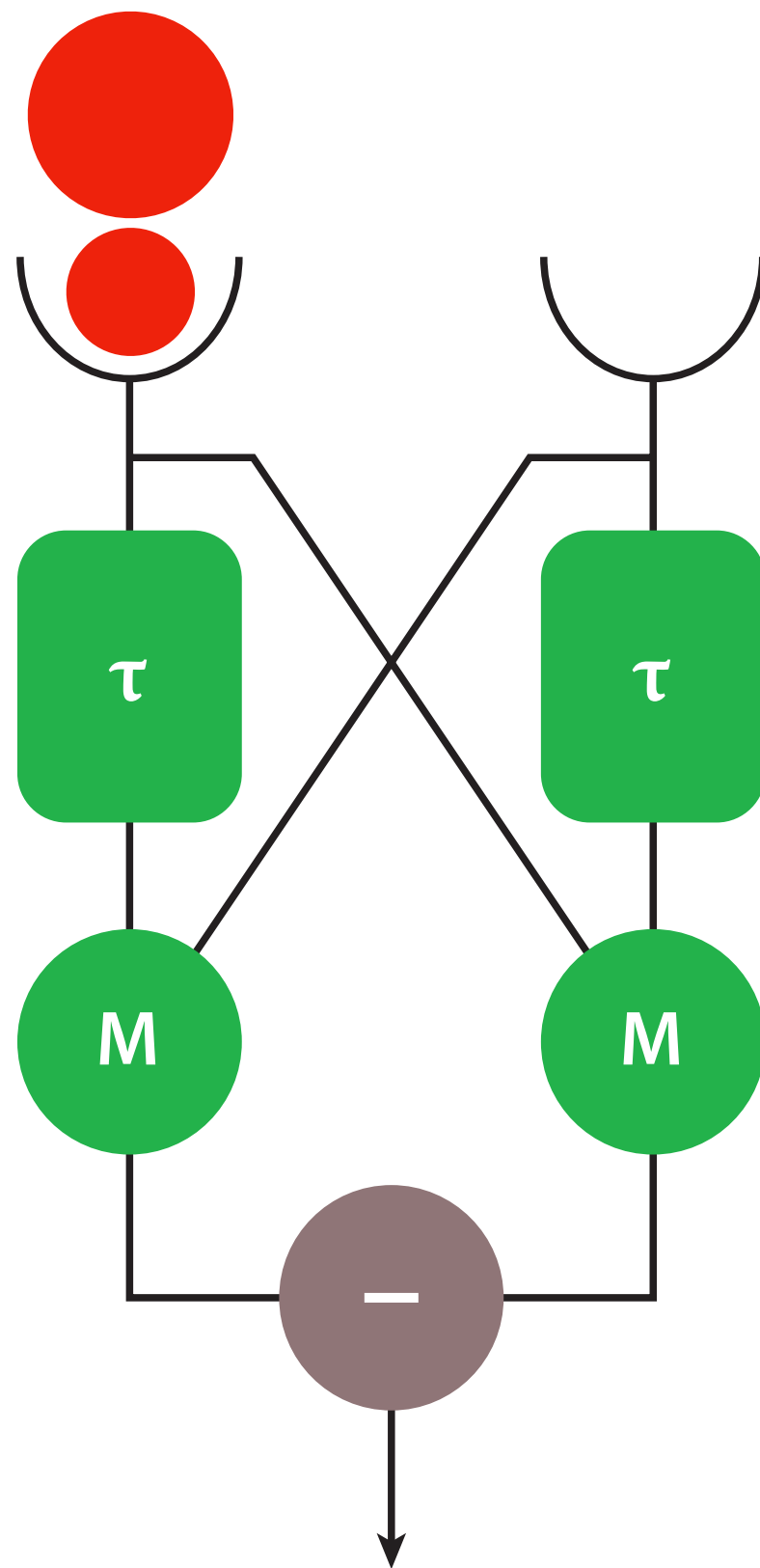
Hassenstein-Reichardt Detector Model

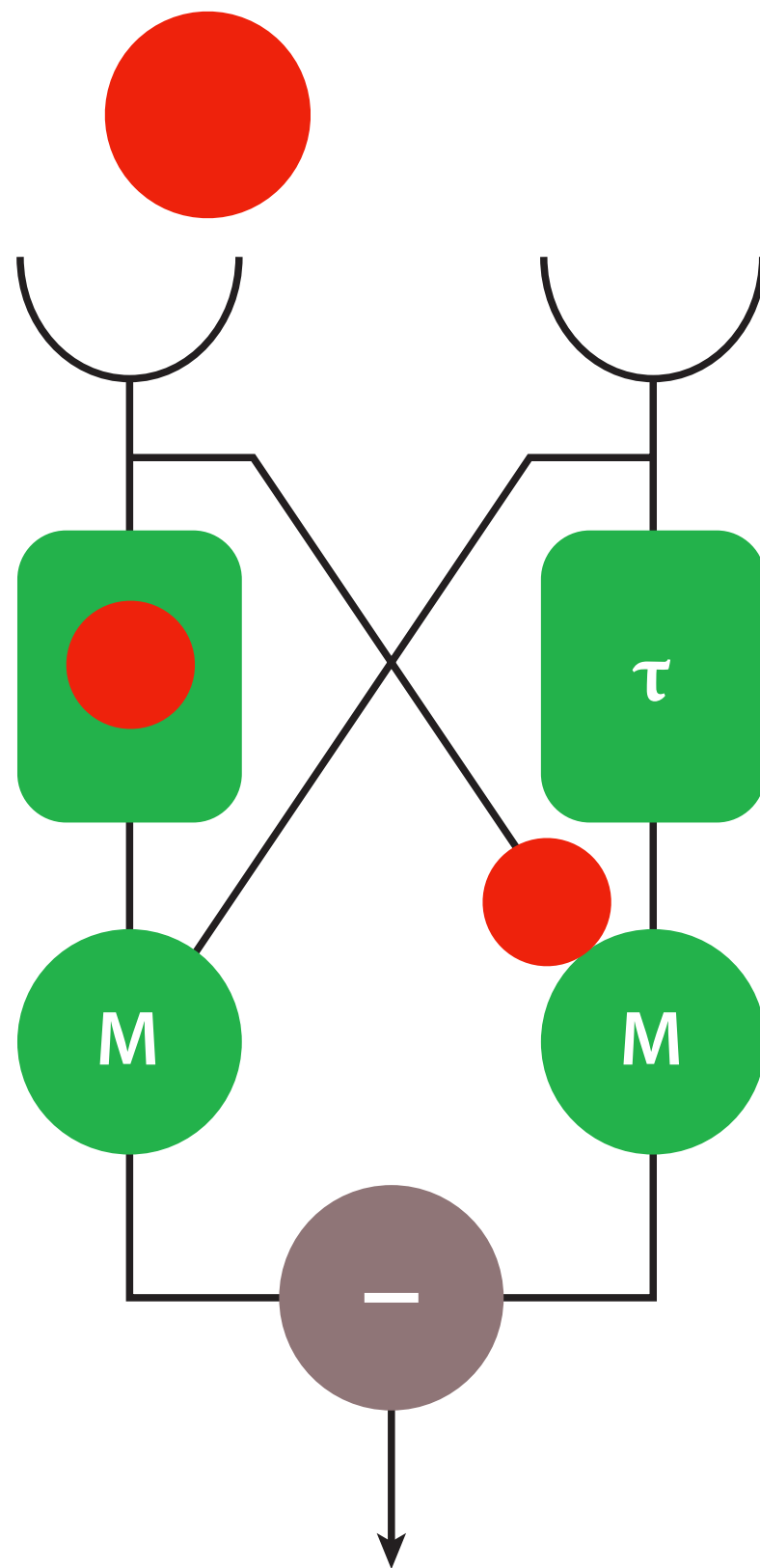


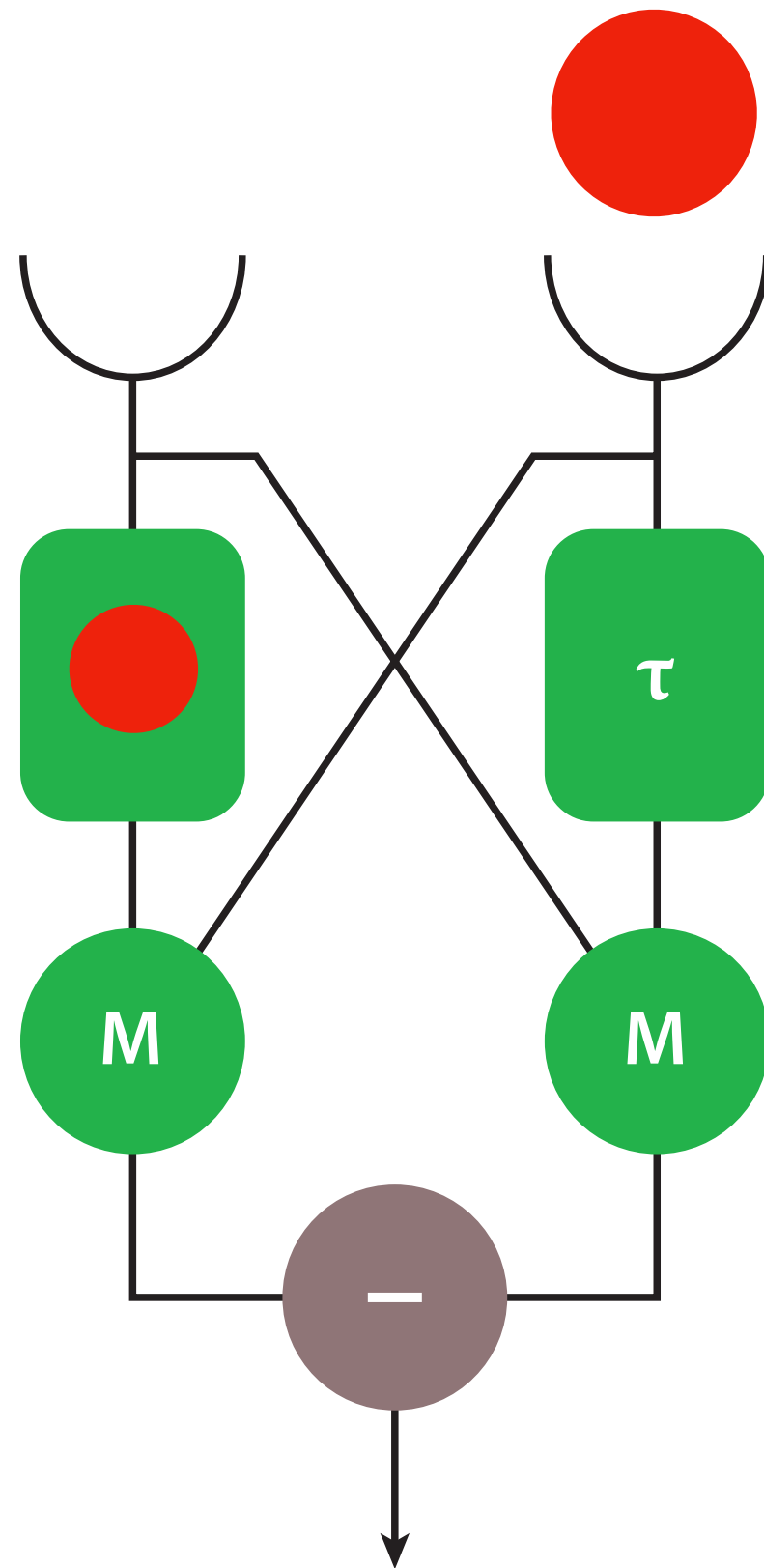
Werner Reichardt

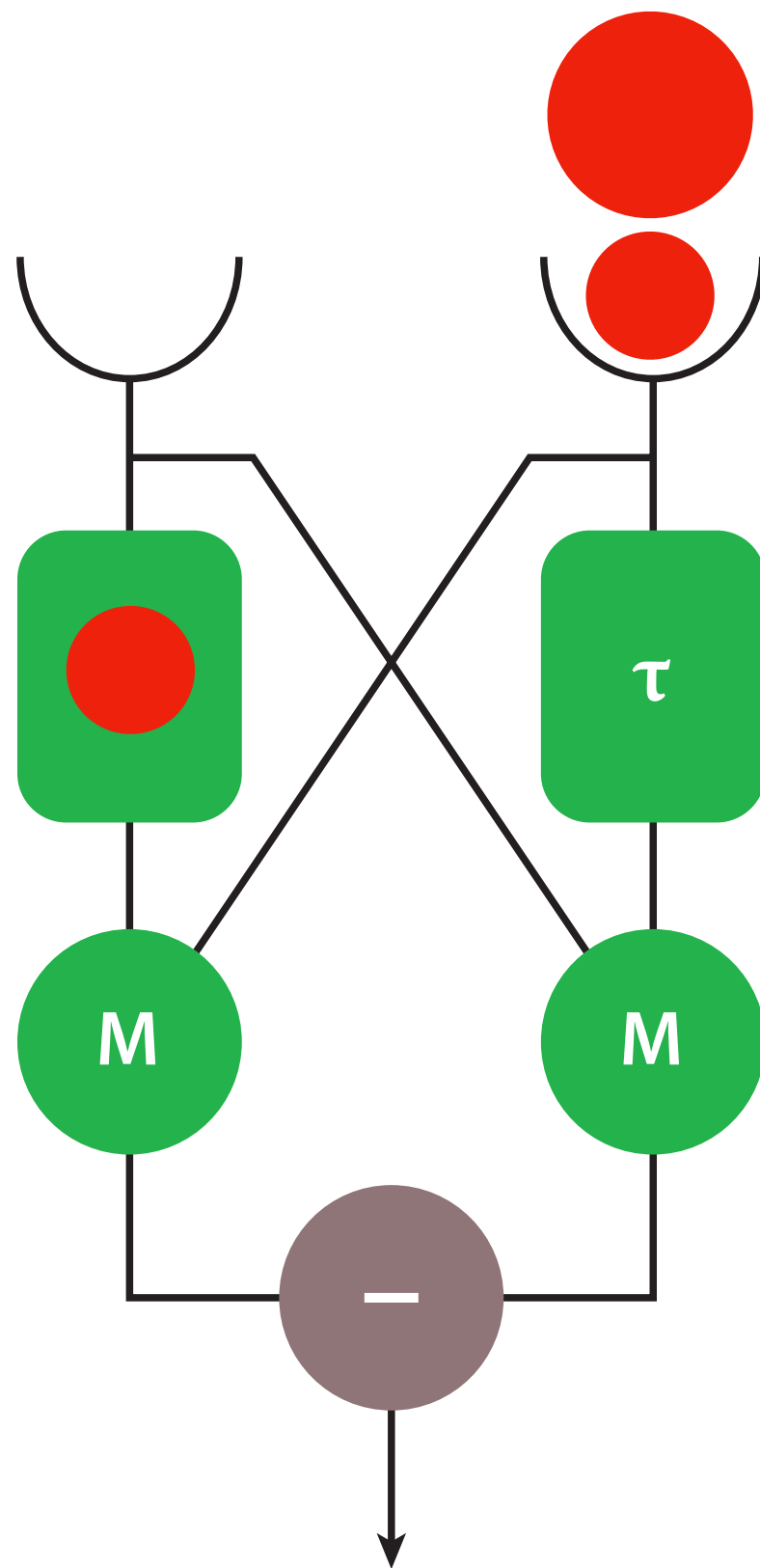


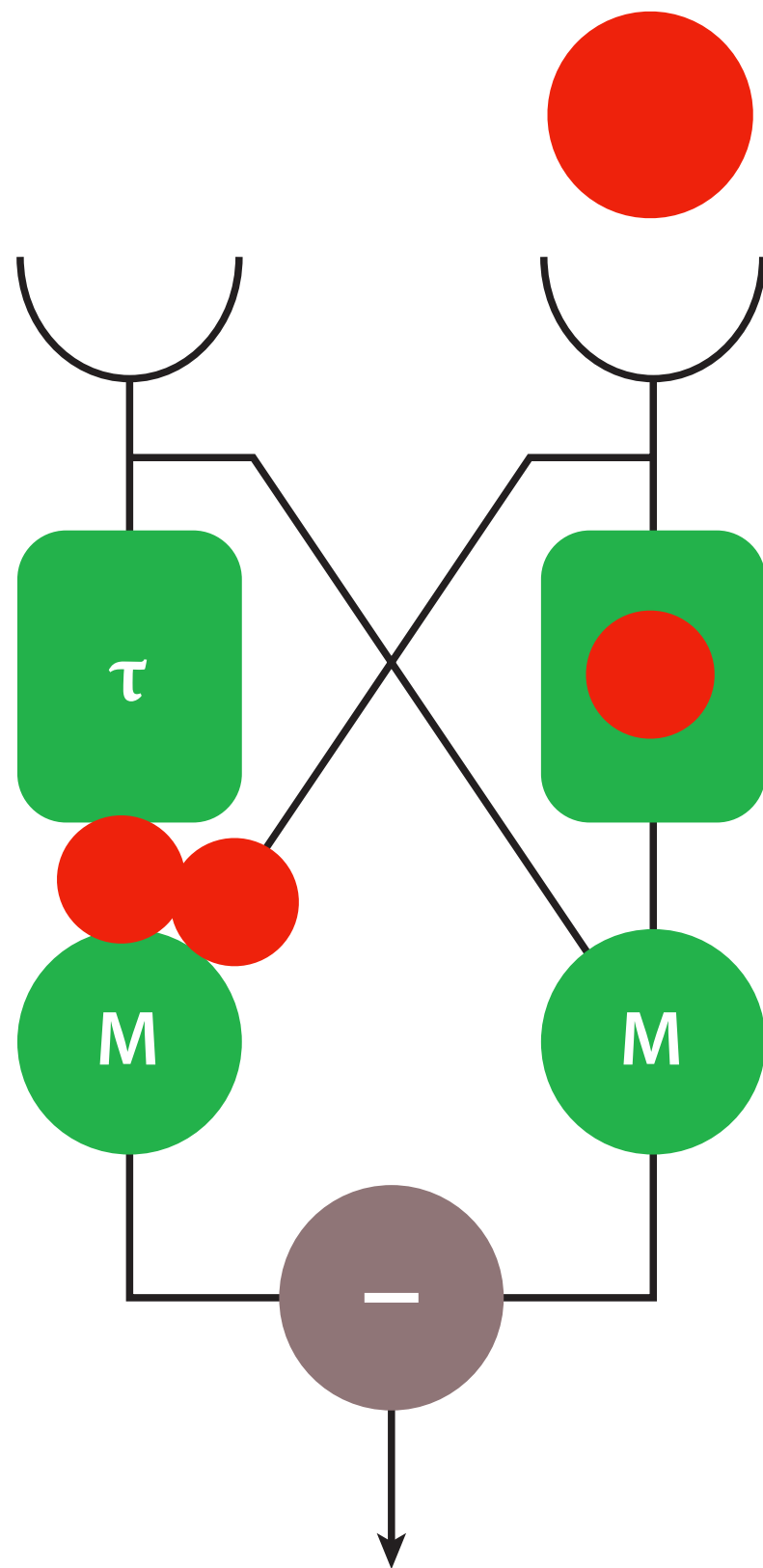


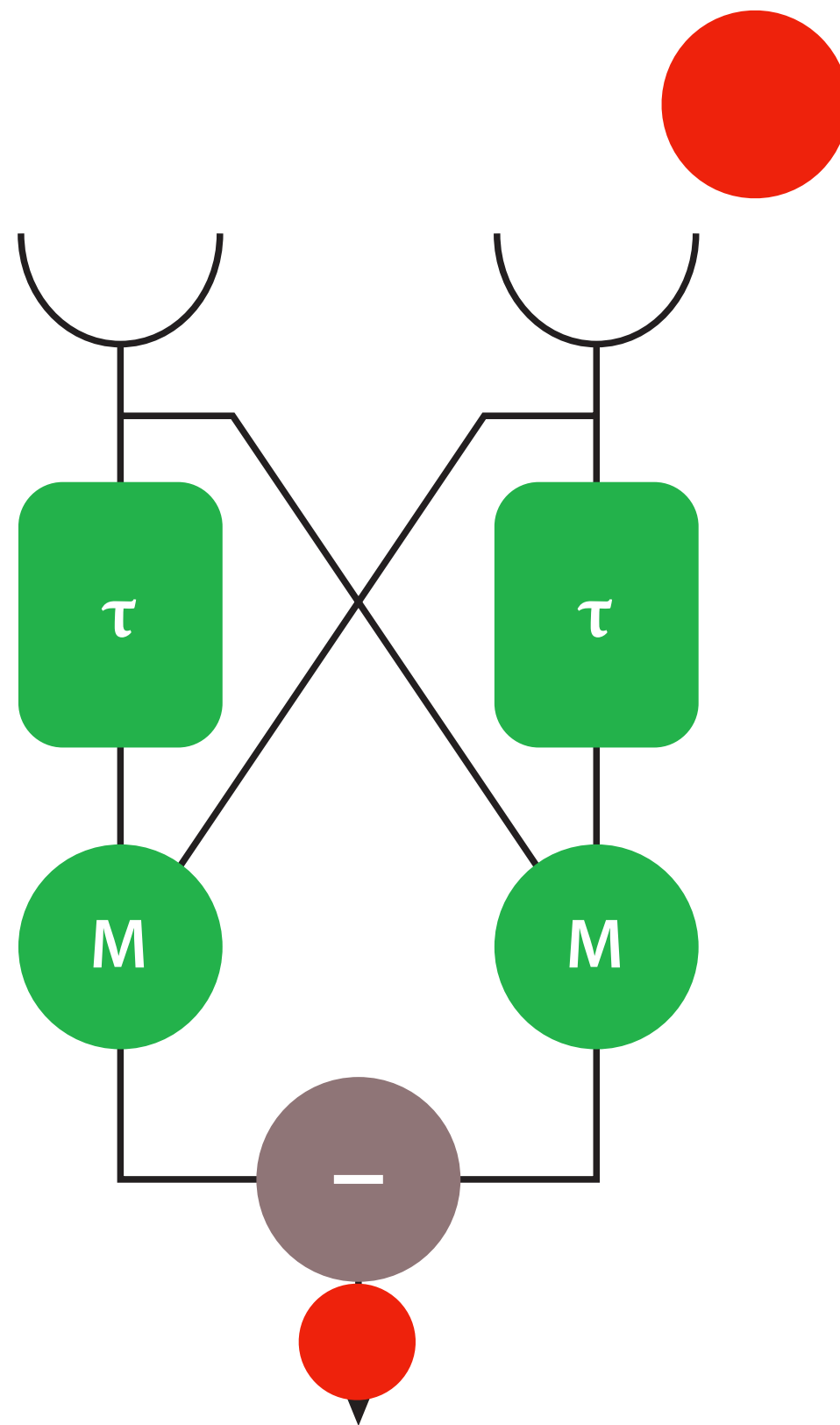




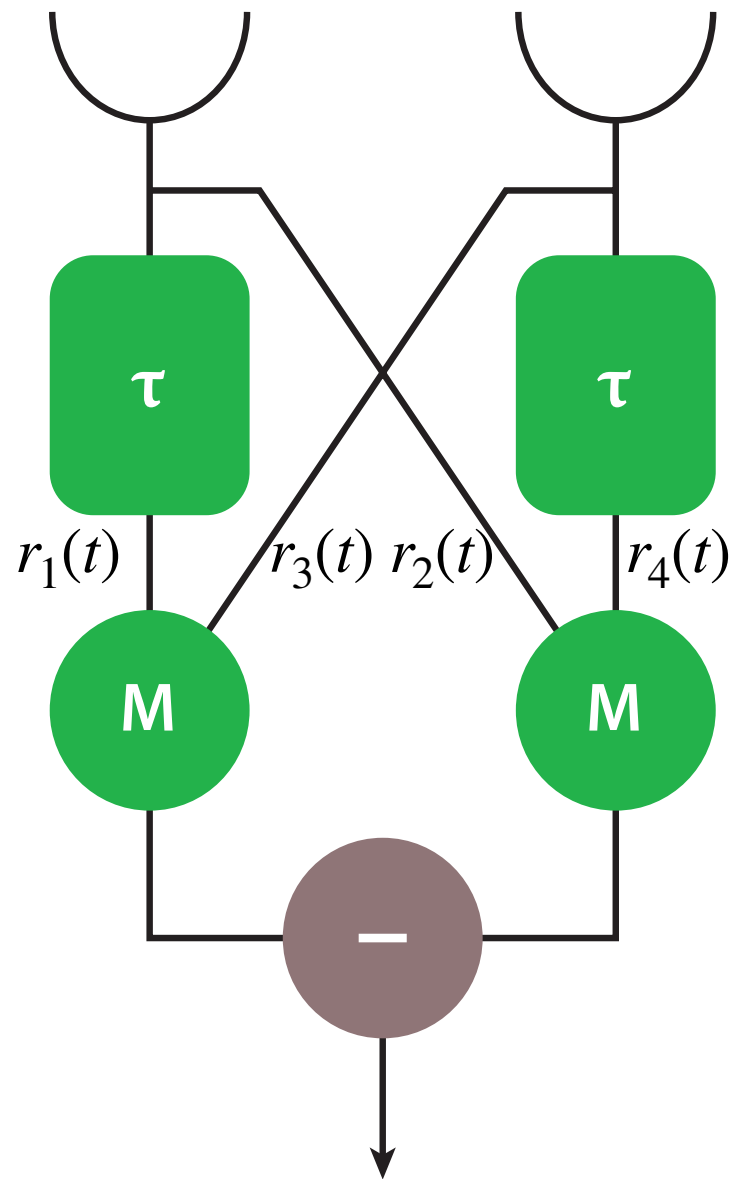








Hassenstein-Reichardt Detector Model



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

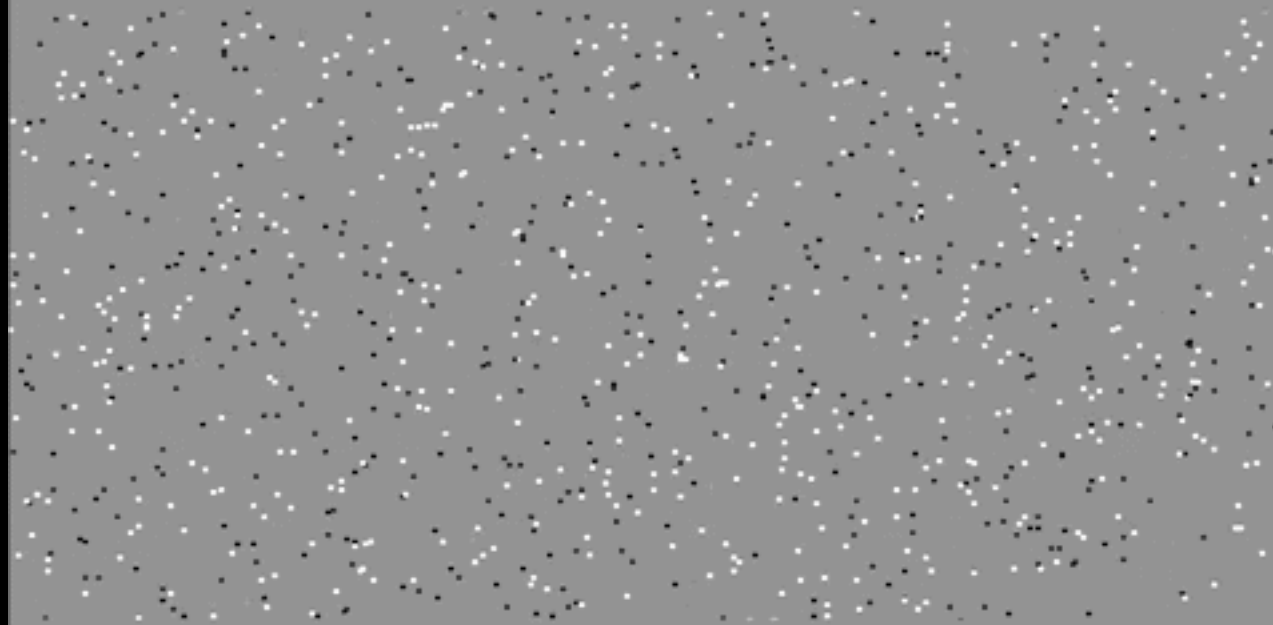
$$r_3(t) = \int_0^\infty s_2(t - \tau) \delta(\tau) d\tau; \quad r_4(t) = \int_0^\infty s_2(t - \tau) D(\tau) d\tau;$$

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

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

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

Phi: displacements to right

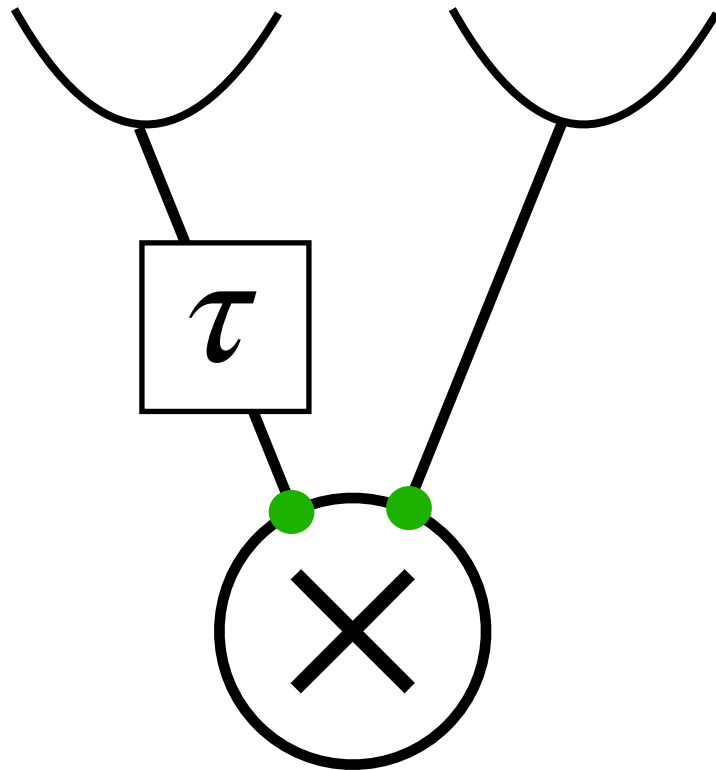


adapted from Damon Clark's slide

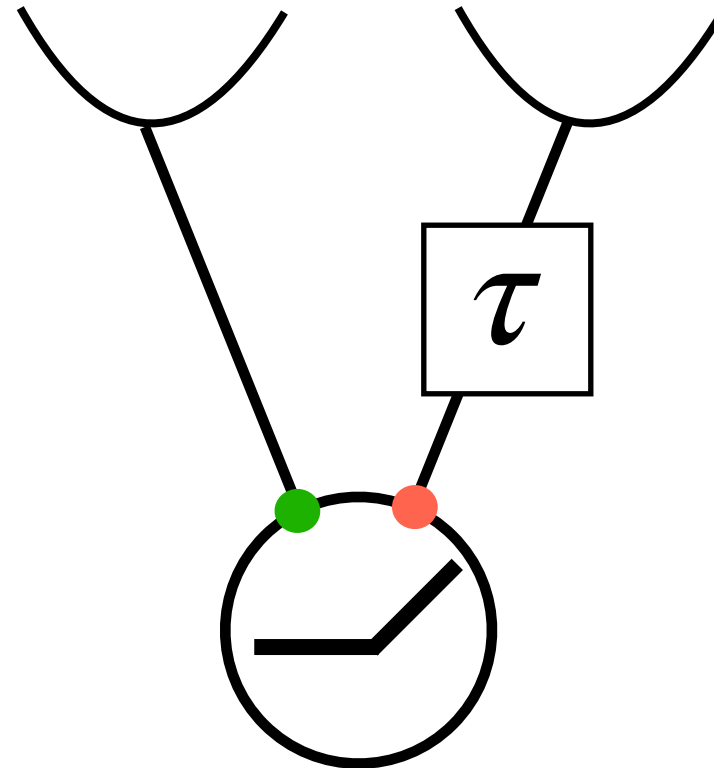
preferred
direction



null
direction

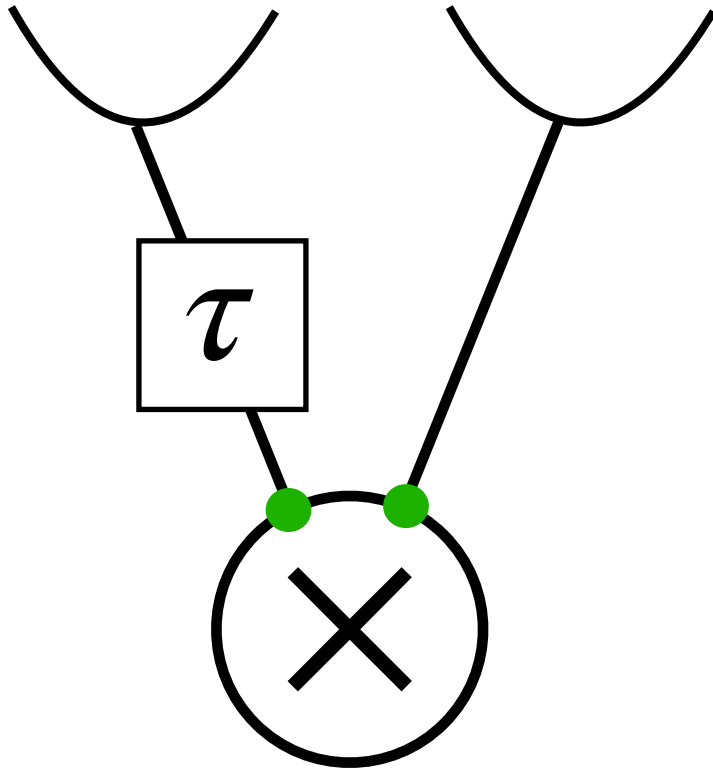
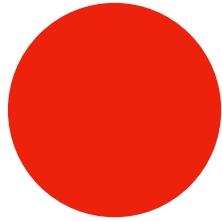


Reichardt model

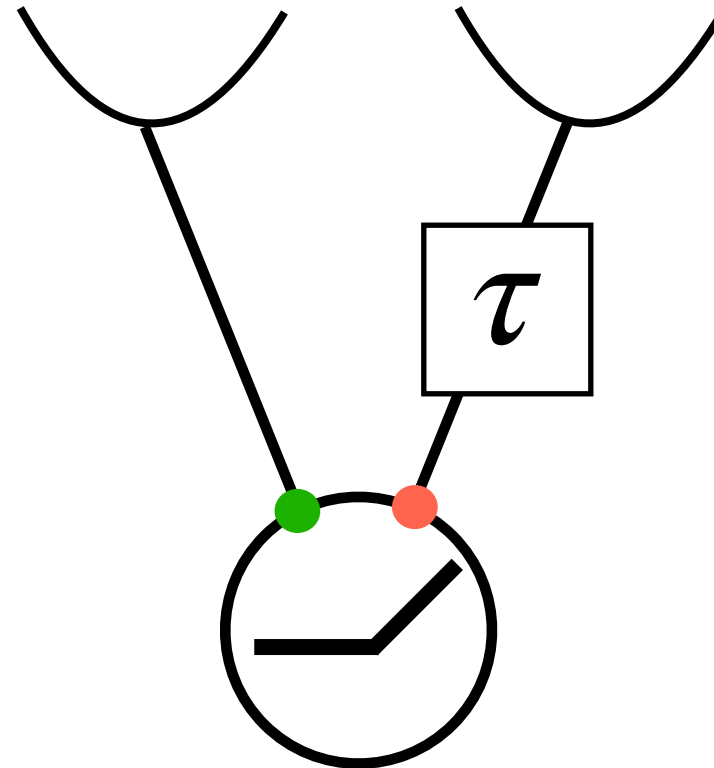
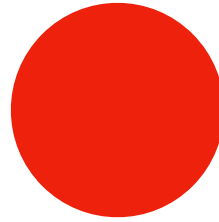


barlow-levick model

preferred
direction

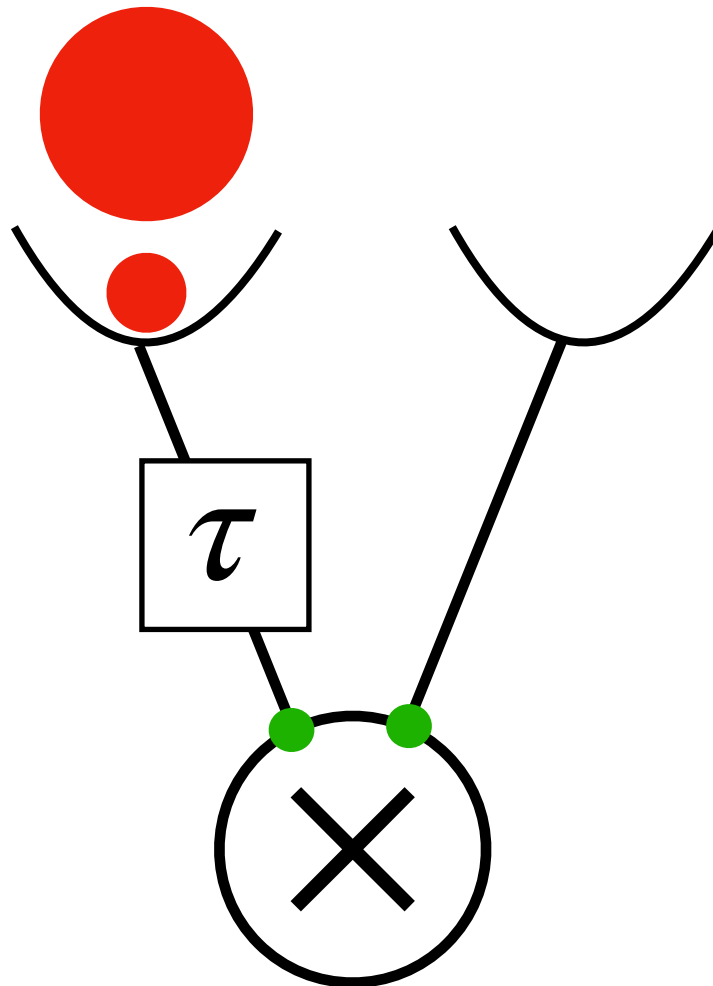


Reichardt model

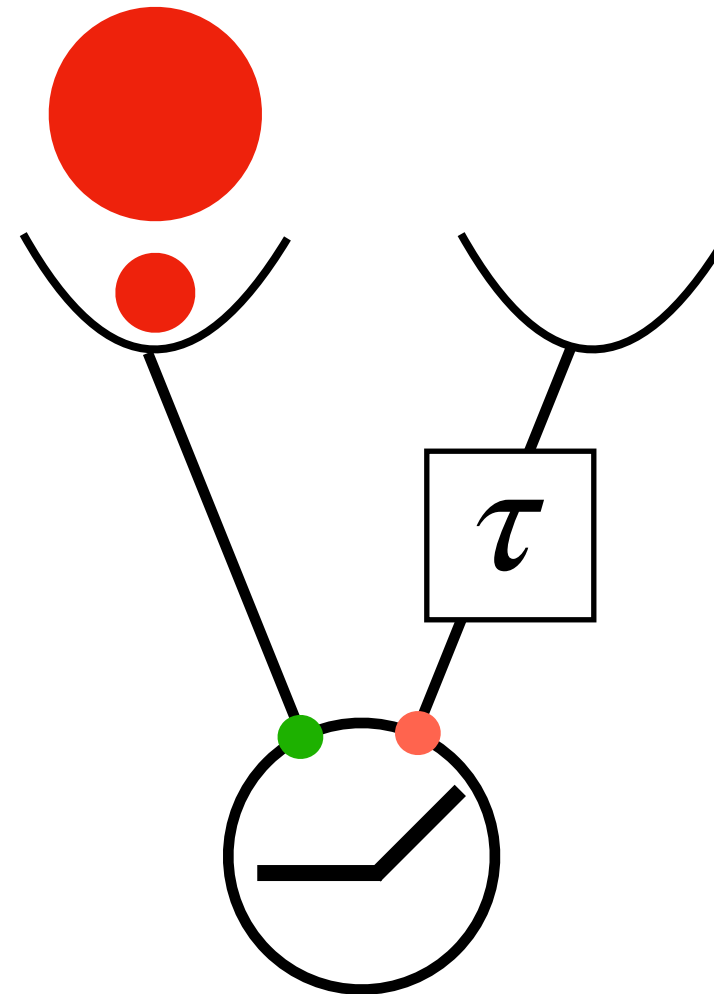


barlow-levick model

preferred
direction

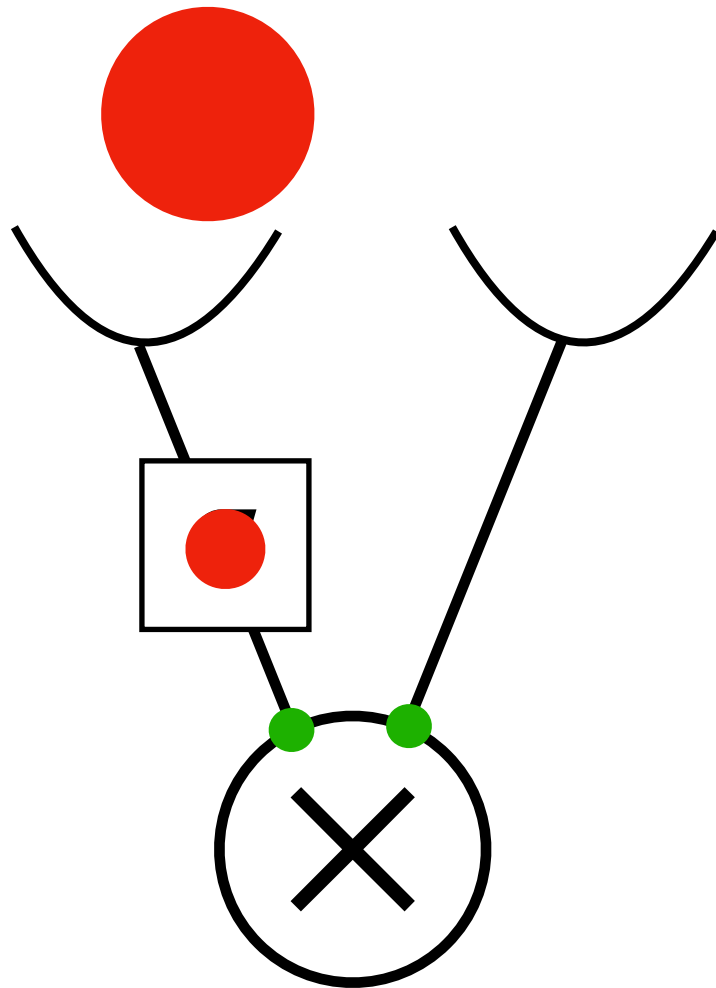


Reichardt model

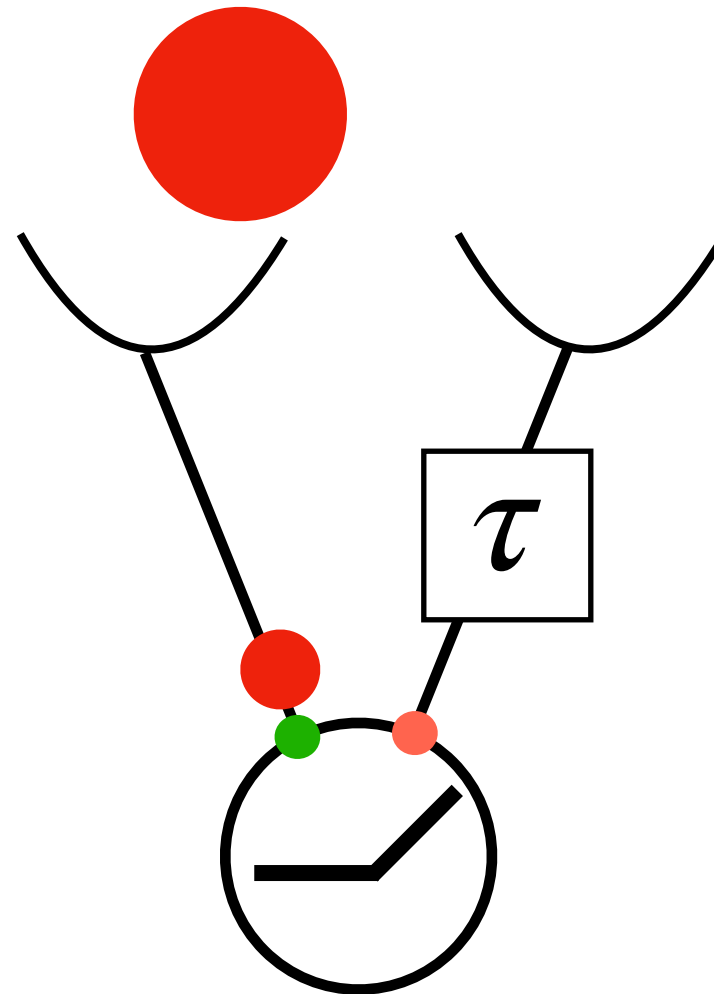


barlow-levick model

preferred
direction

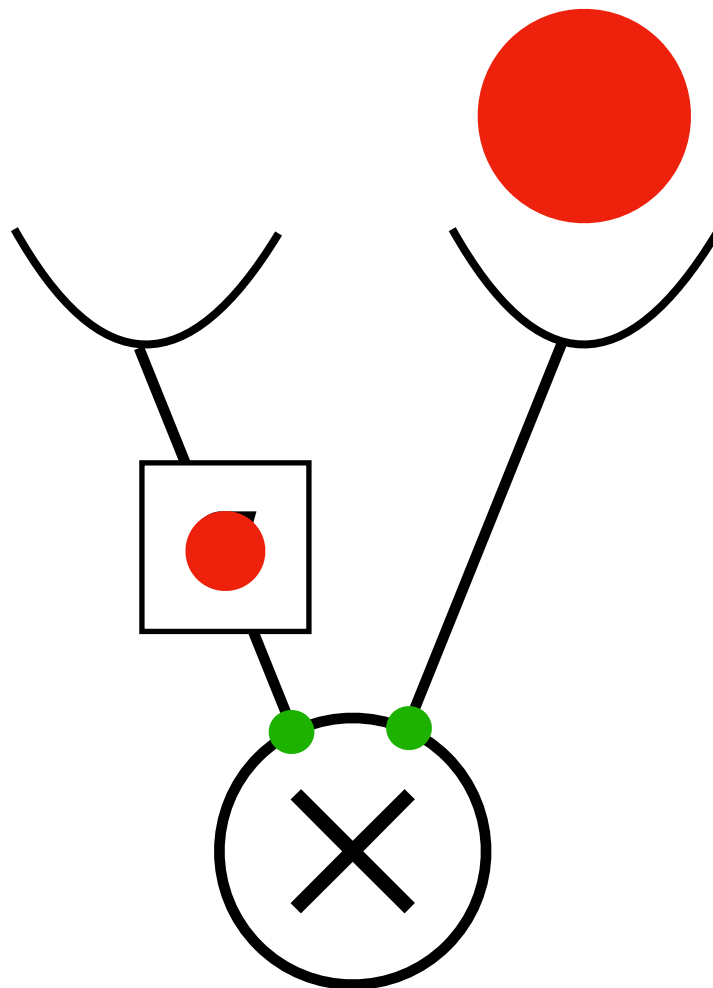


Reichardt model

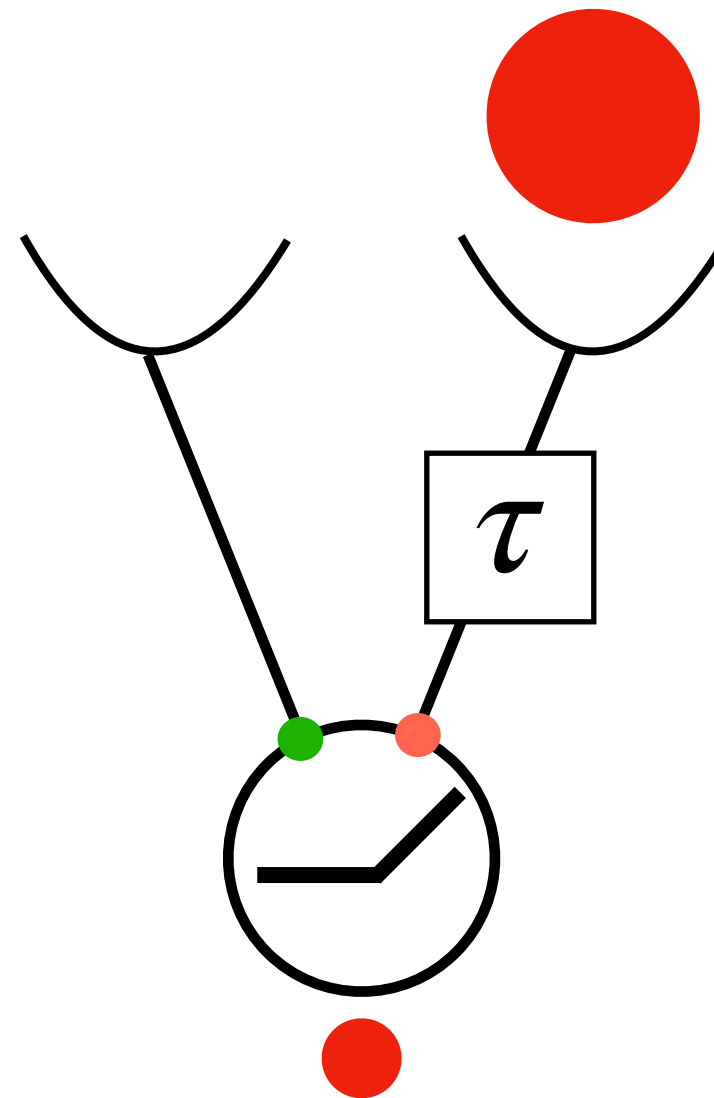


barlow-levick model

preferred
direction

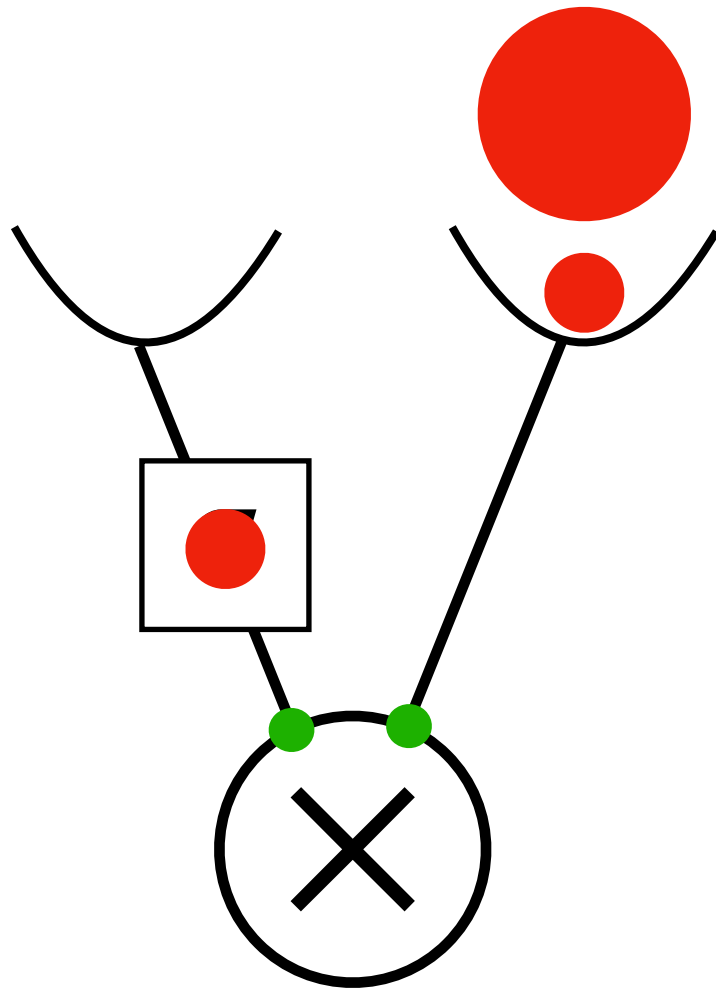


Reichardt model

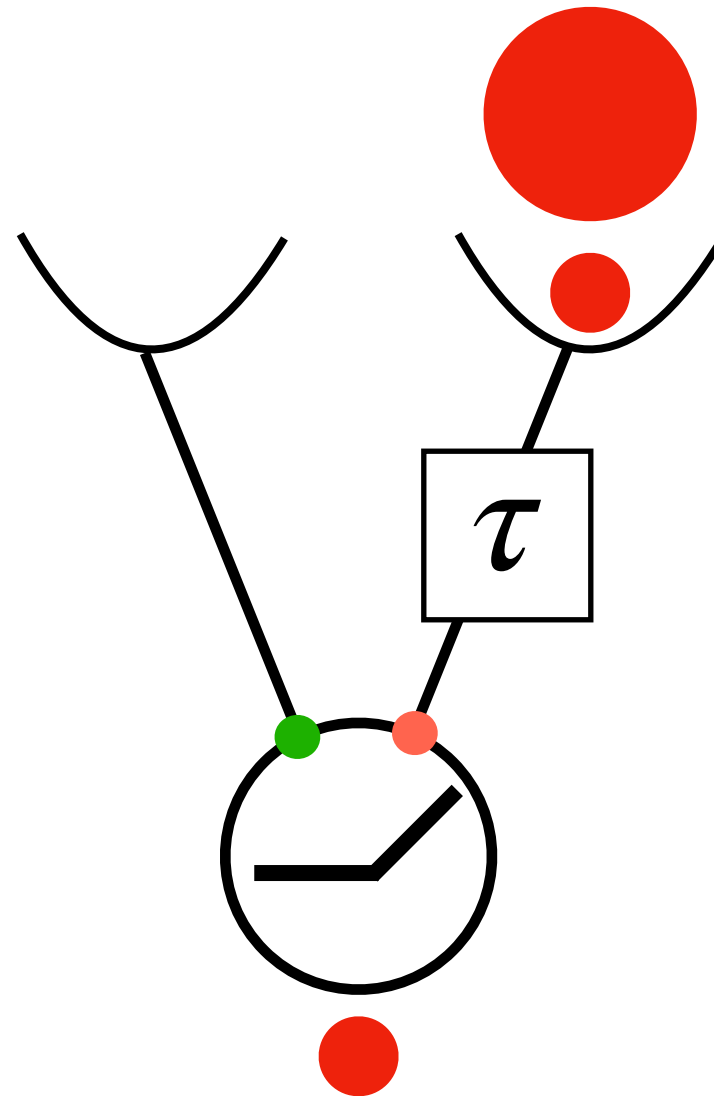


barlow-levick model

preferred
direction

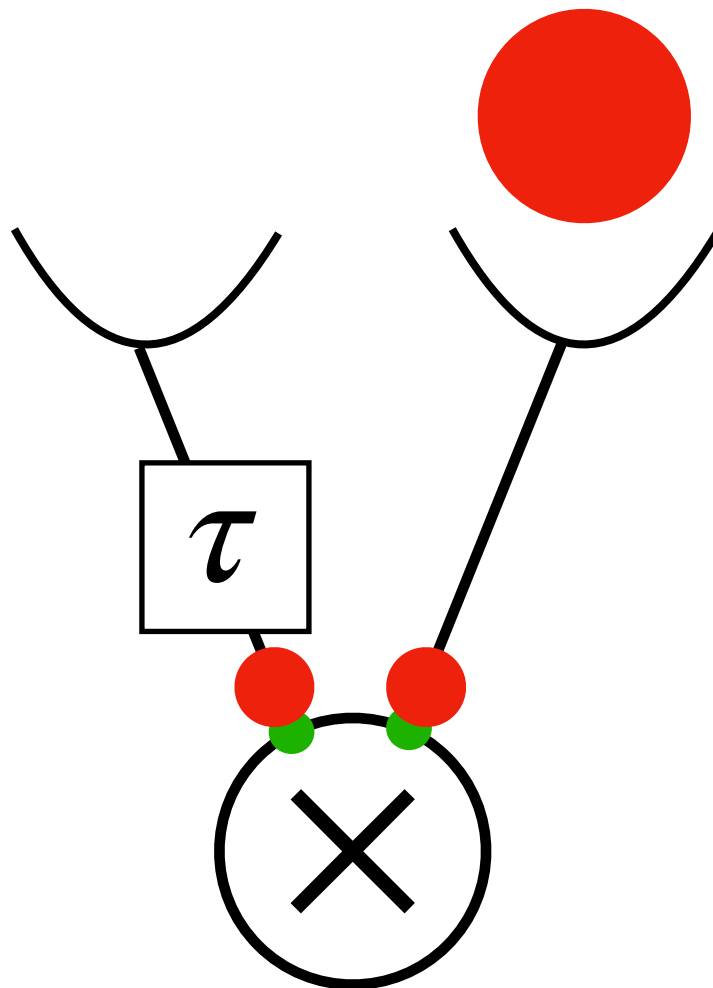


Reichardt model

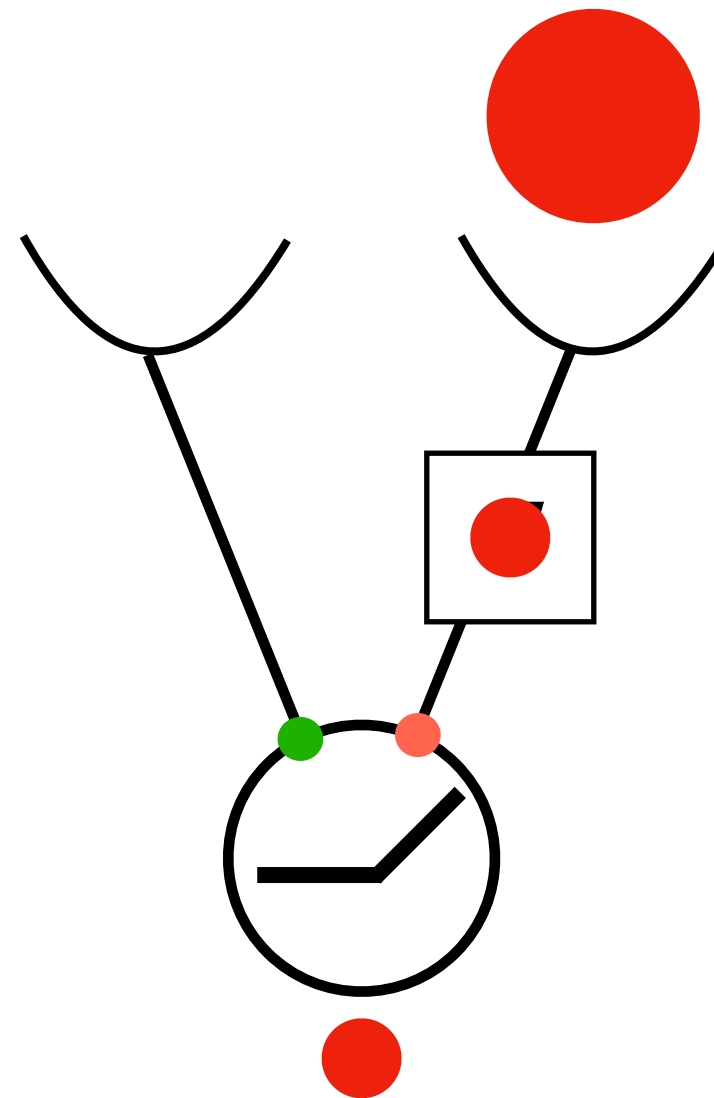


barlow-levick model

preferred
direction

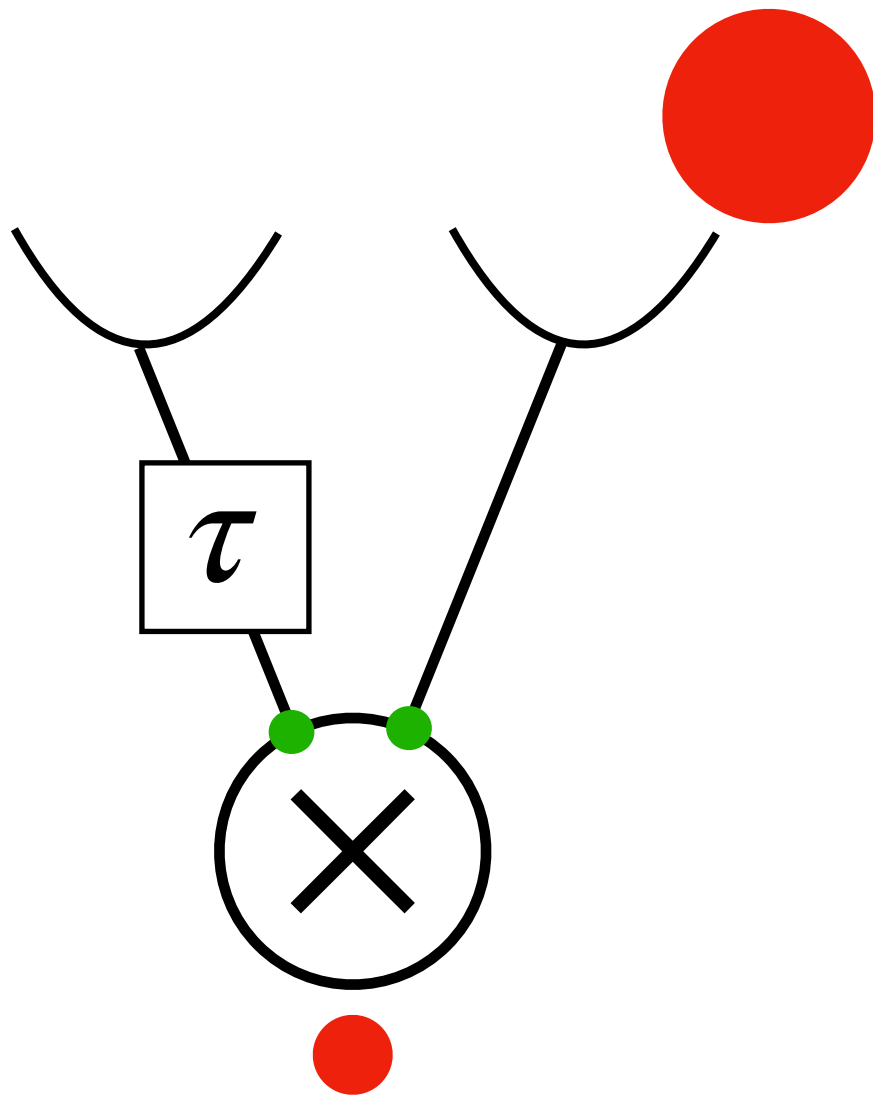


Reichardt model

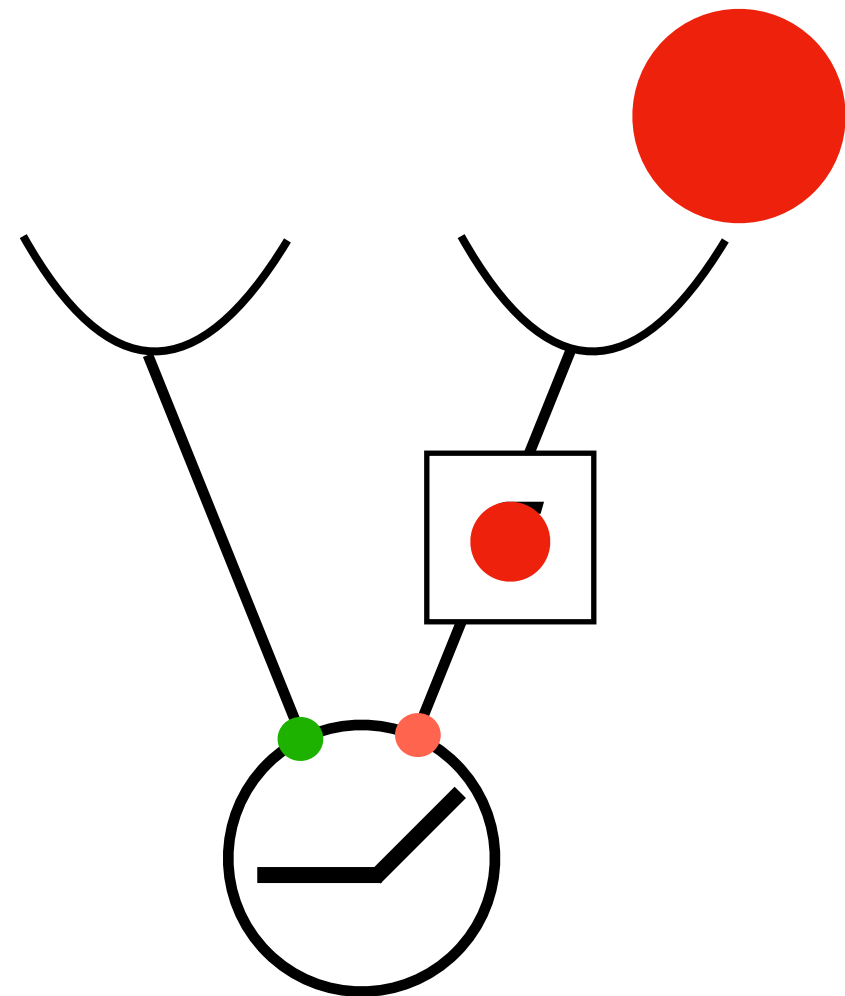


barlow-levick model

preferred
direction

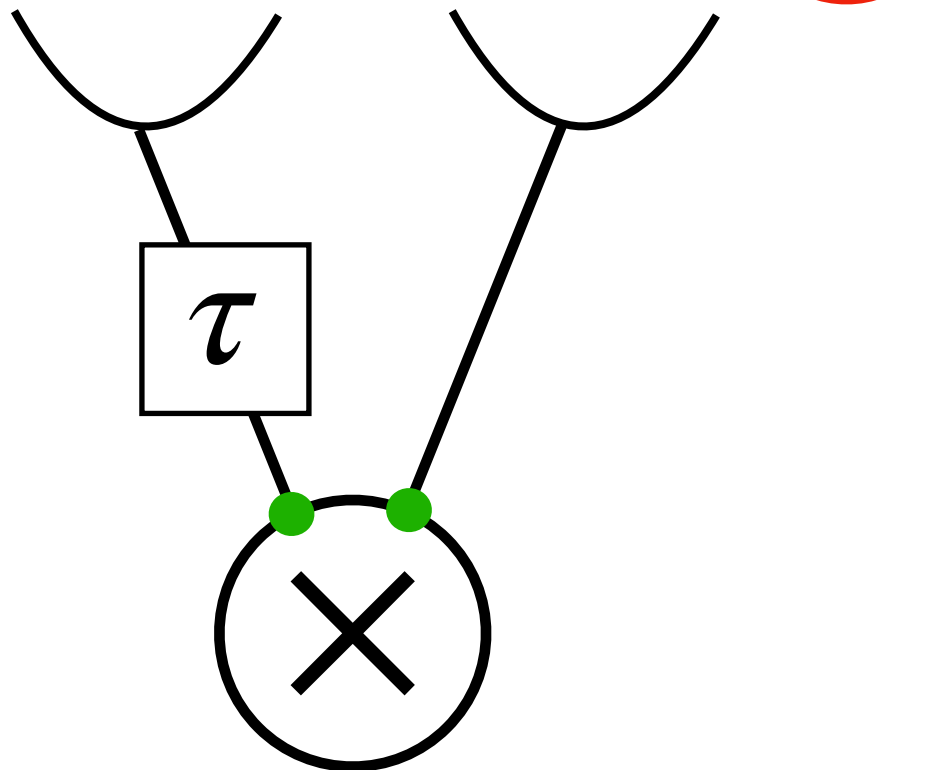


Reichardt model

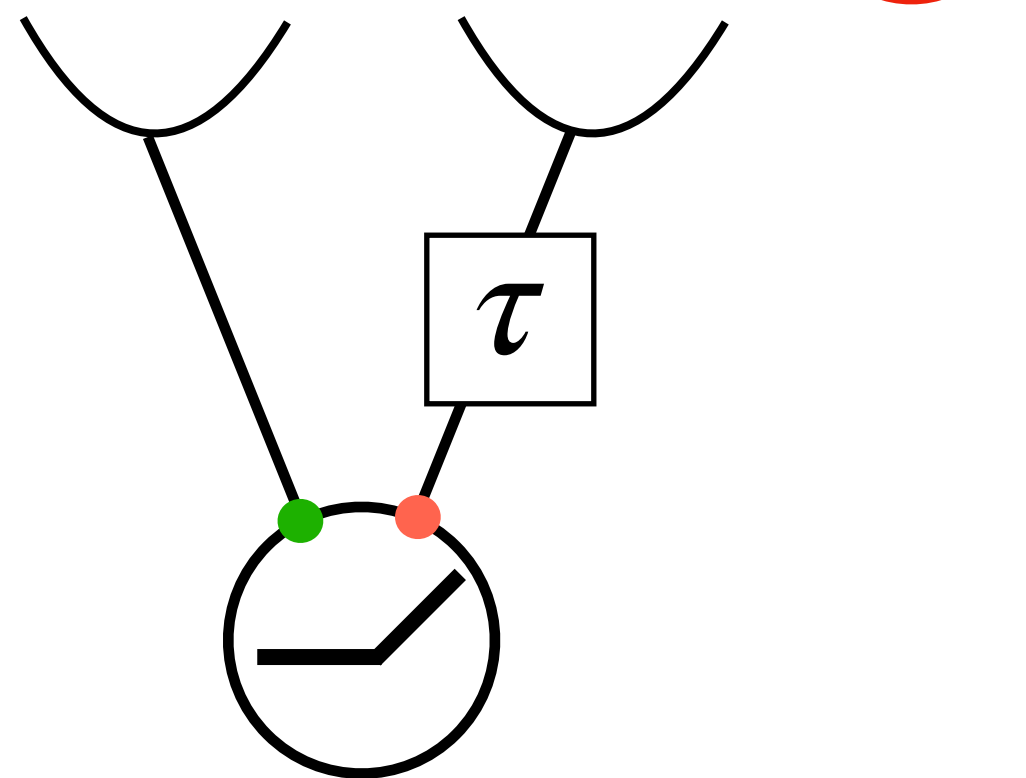


barlow-levick model

null
direction

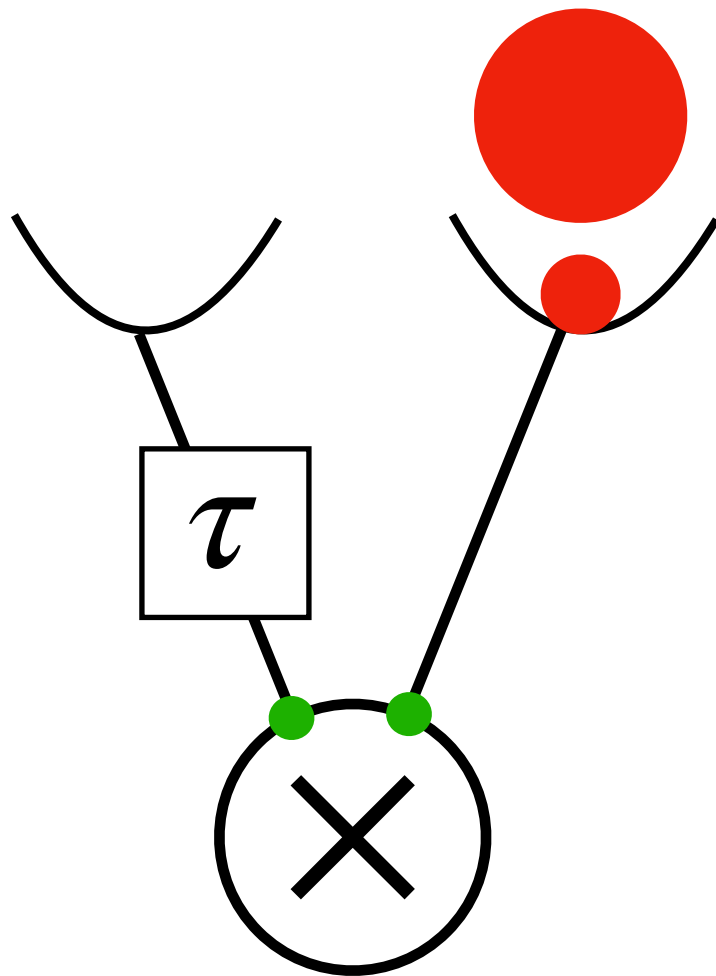


Reichardt model

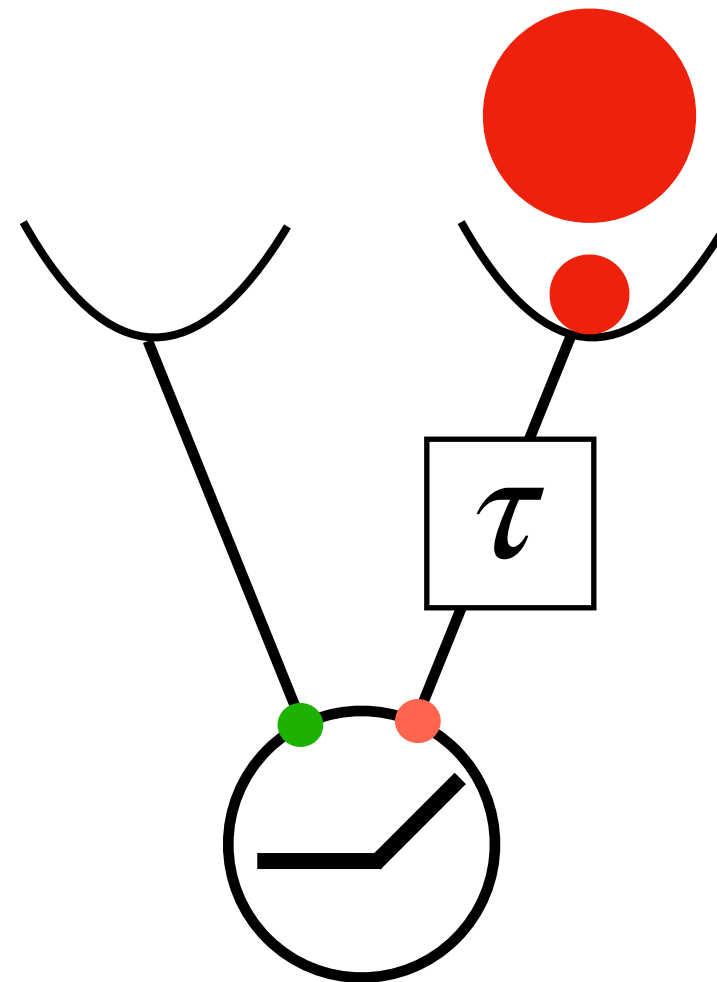


barlow-levick model

← null
direction

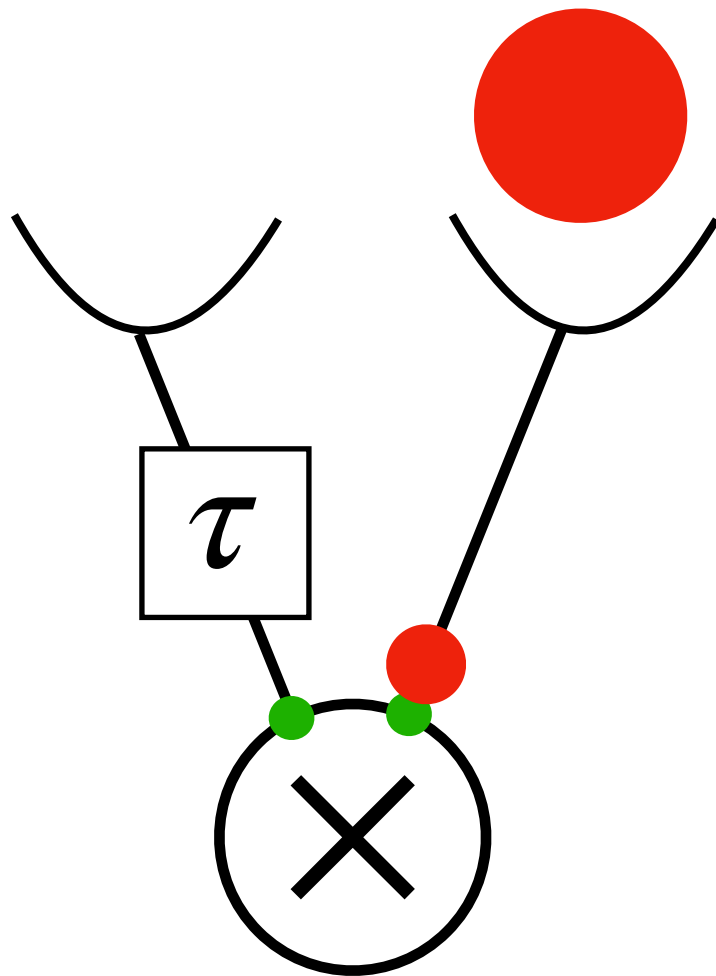


Reichardt model

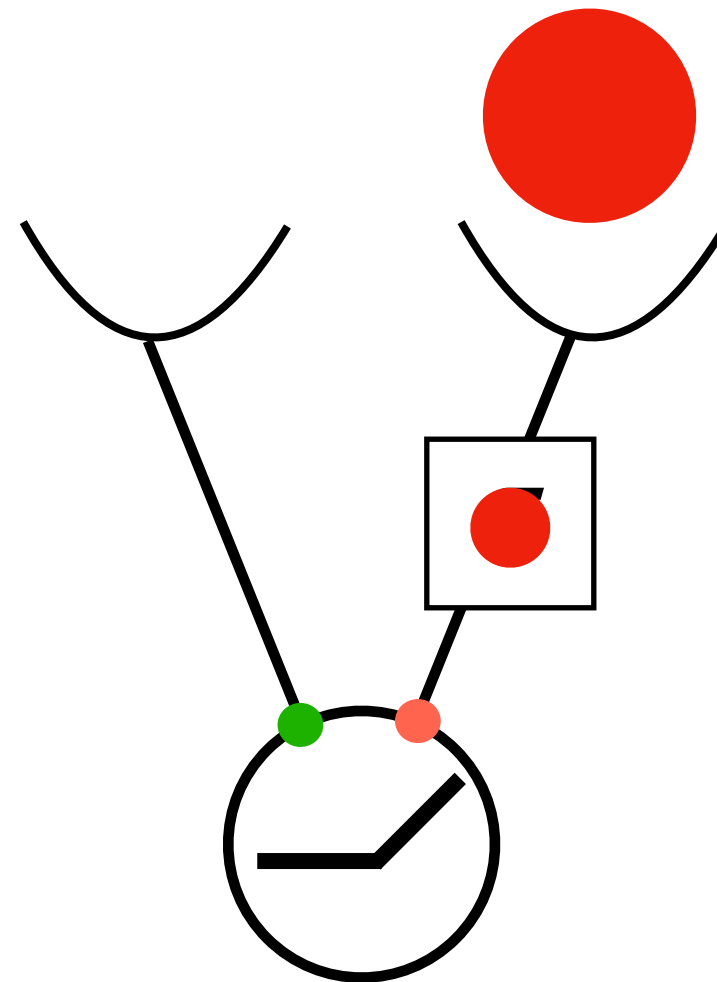


barlow-levick model

← null
direction

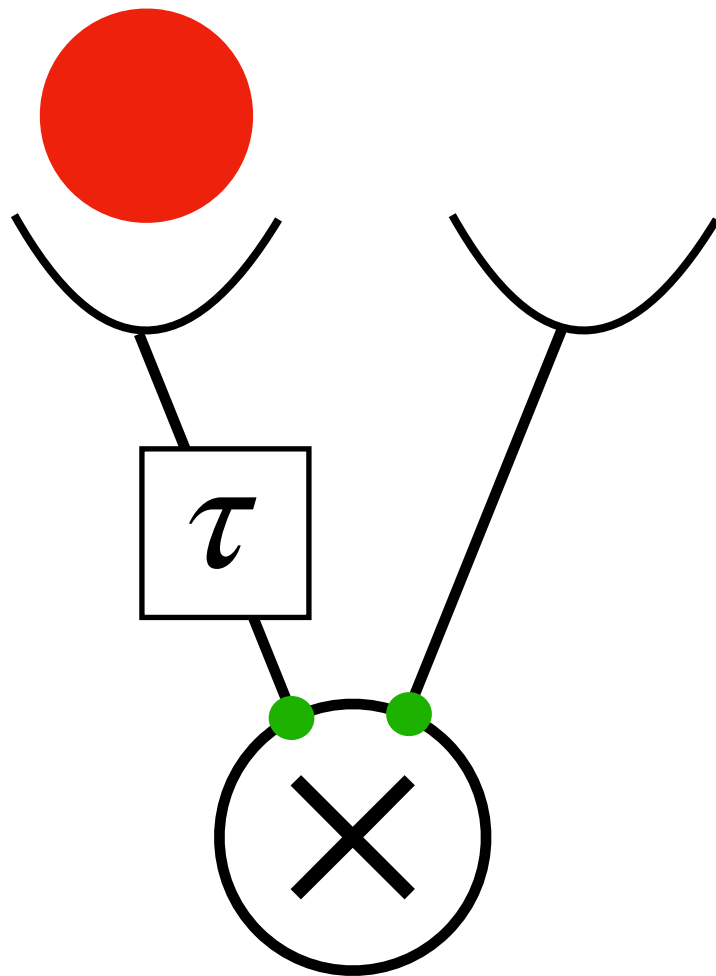


Reichardt model

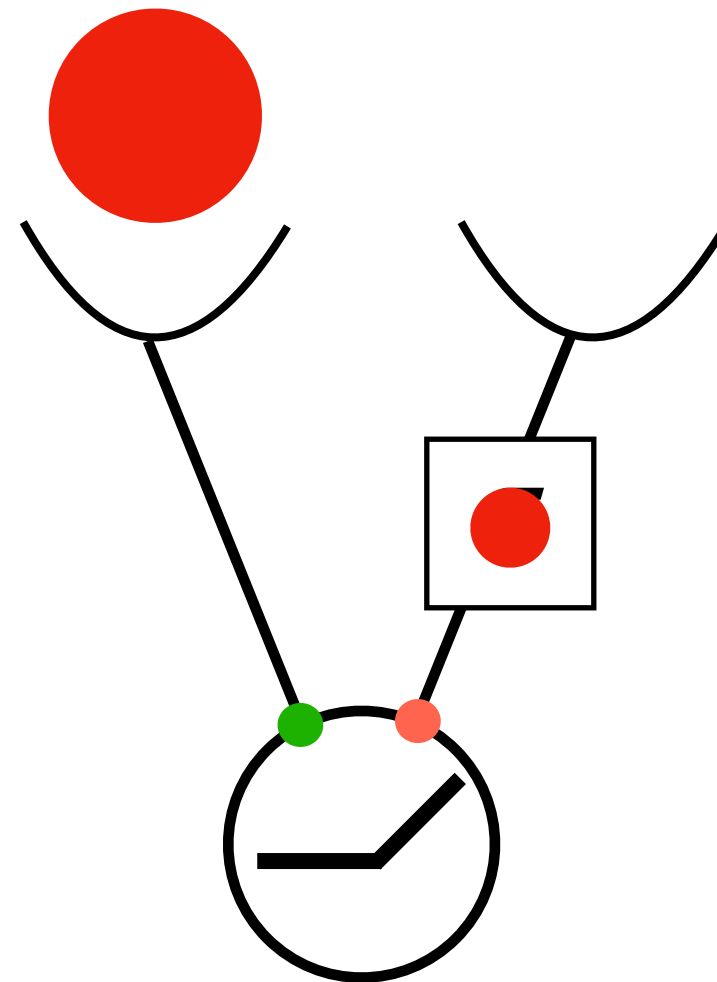


barlow-levick model

← null
direction

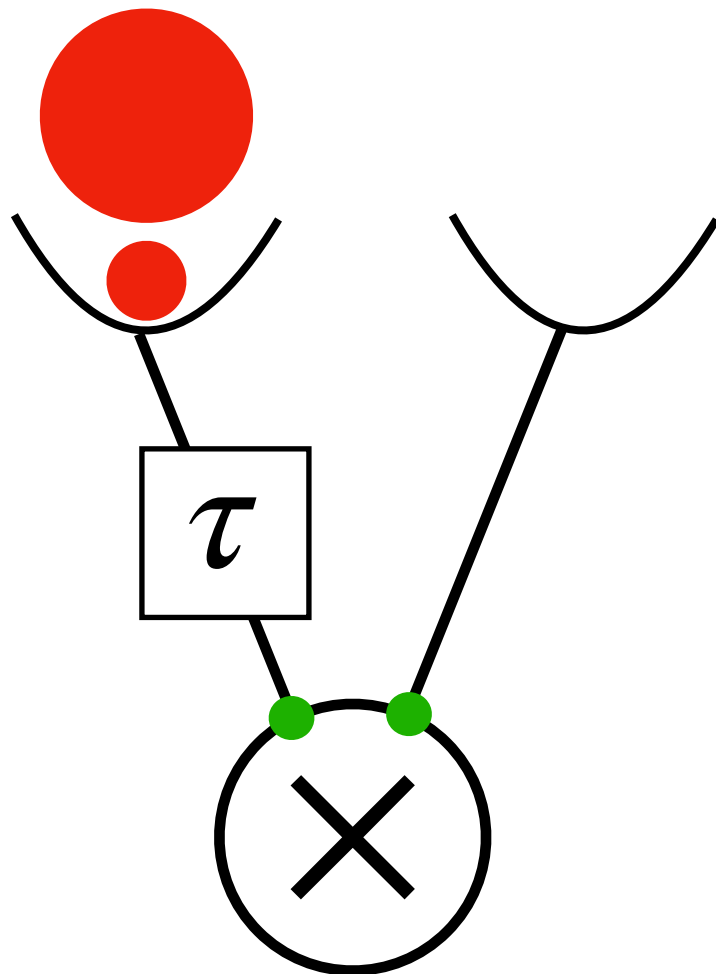


Reichardt model

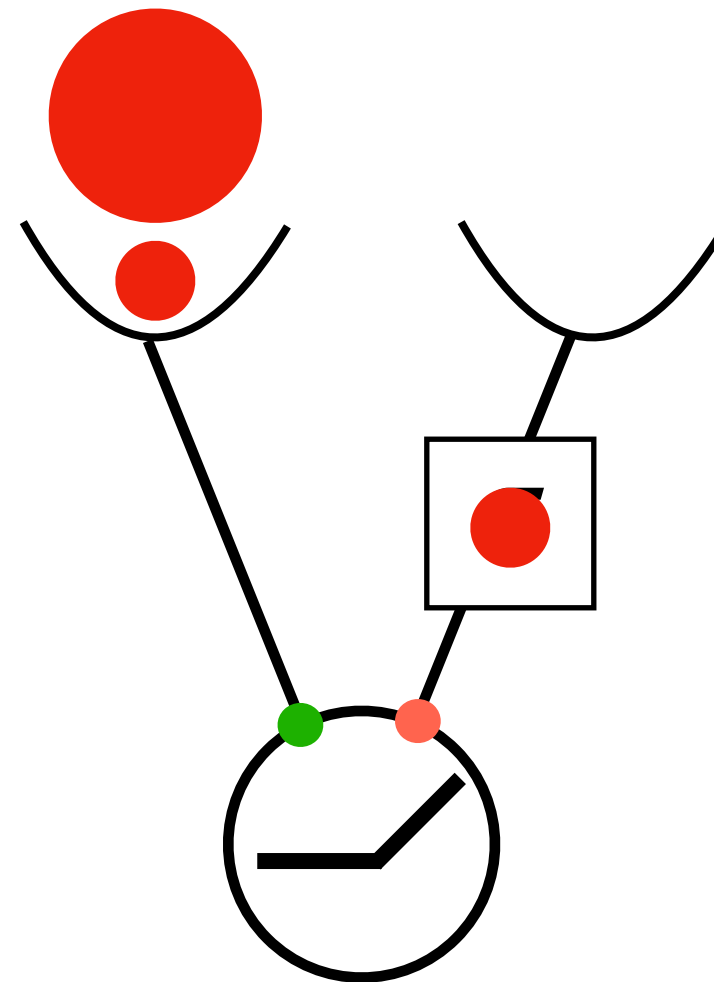


barlow-levick model

← null
direction

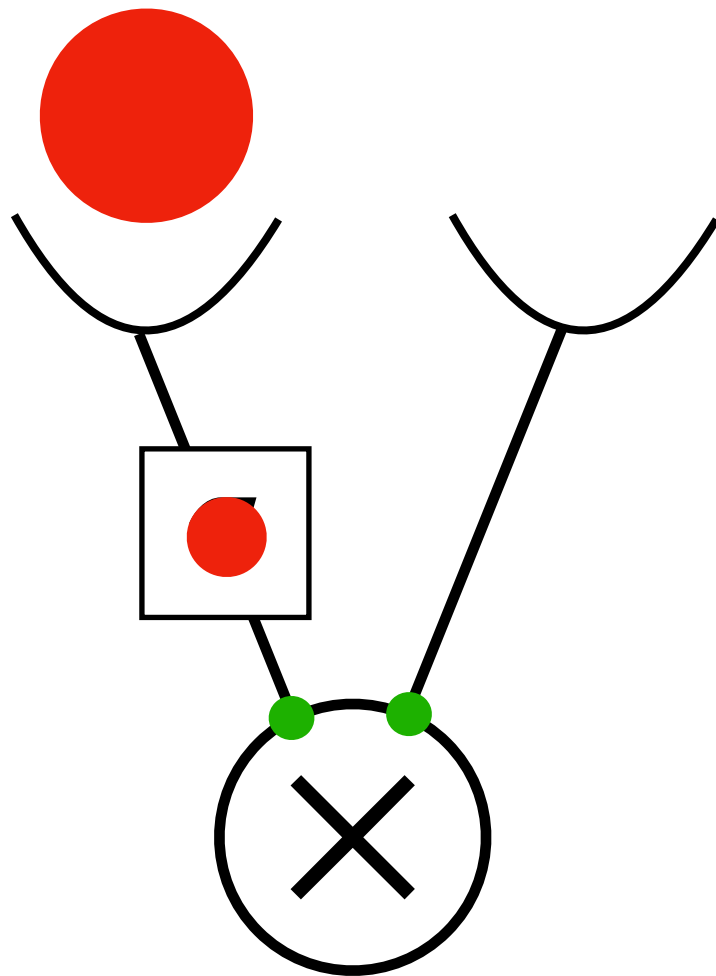


Reichardt model

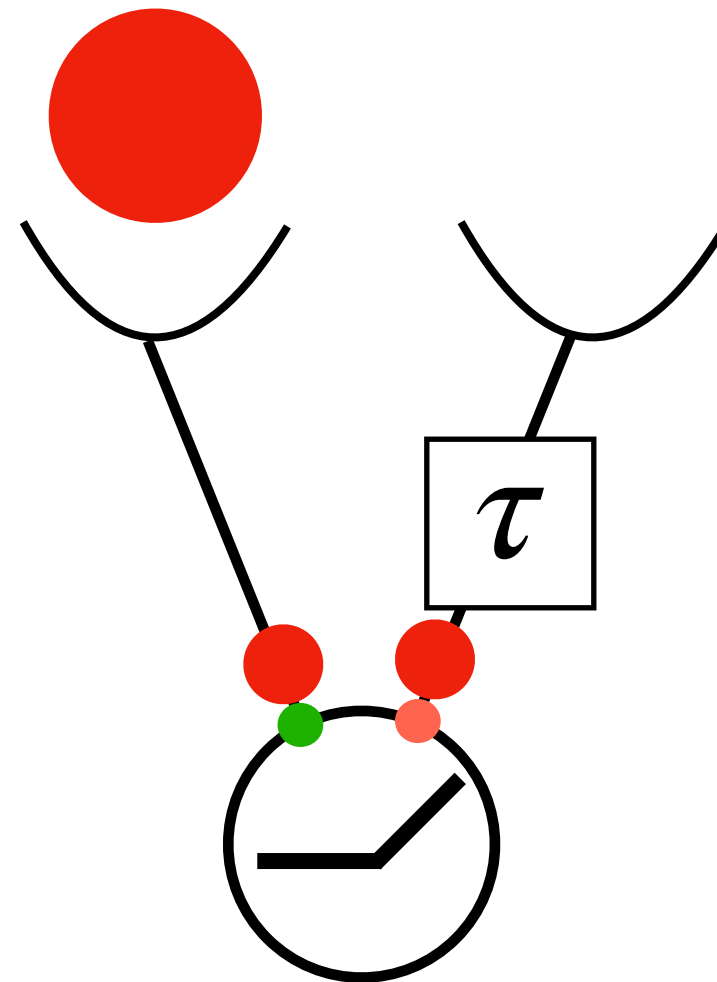


barlow-levick model

← null
direction

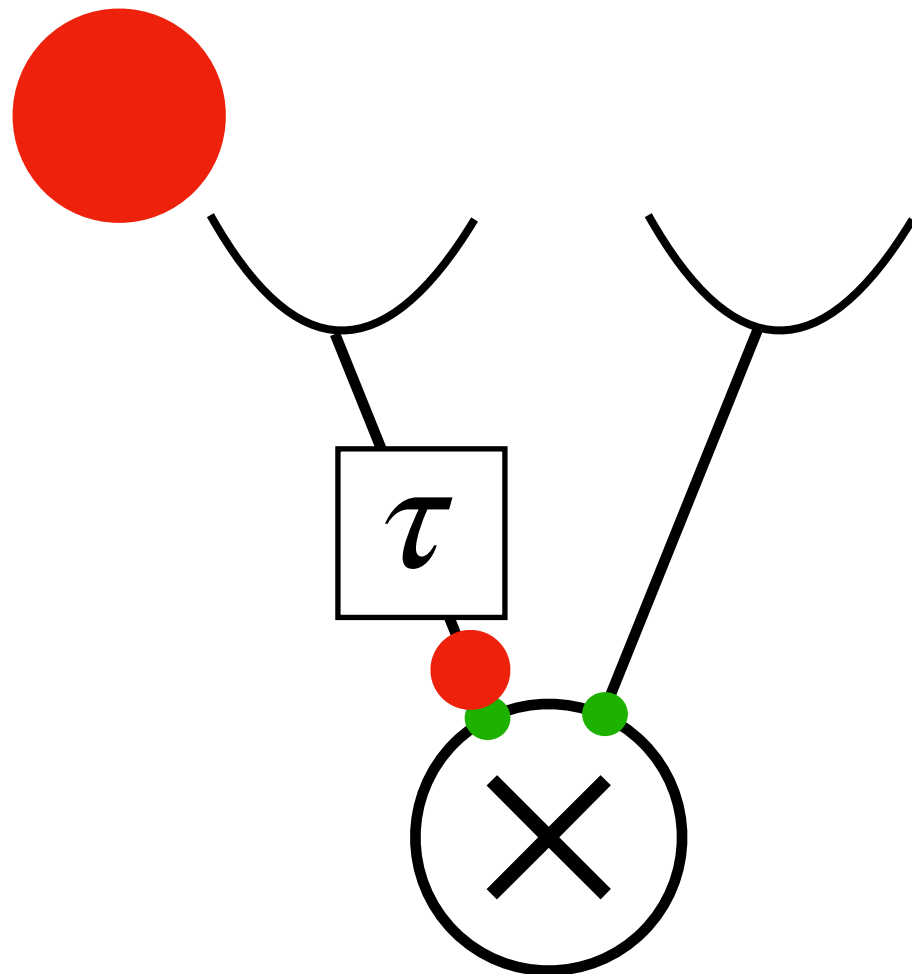


Reichardt model

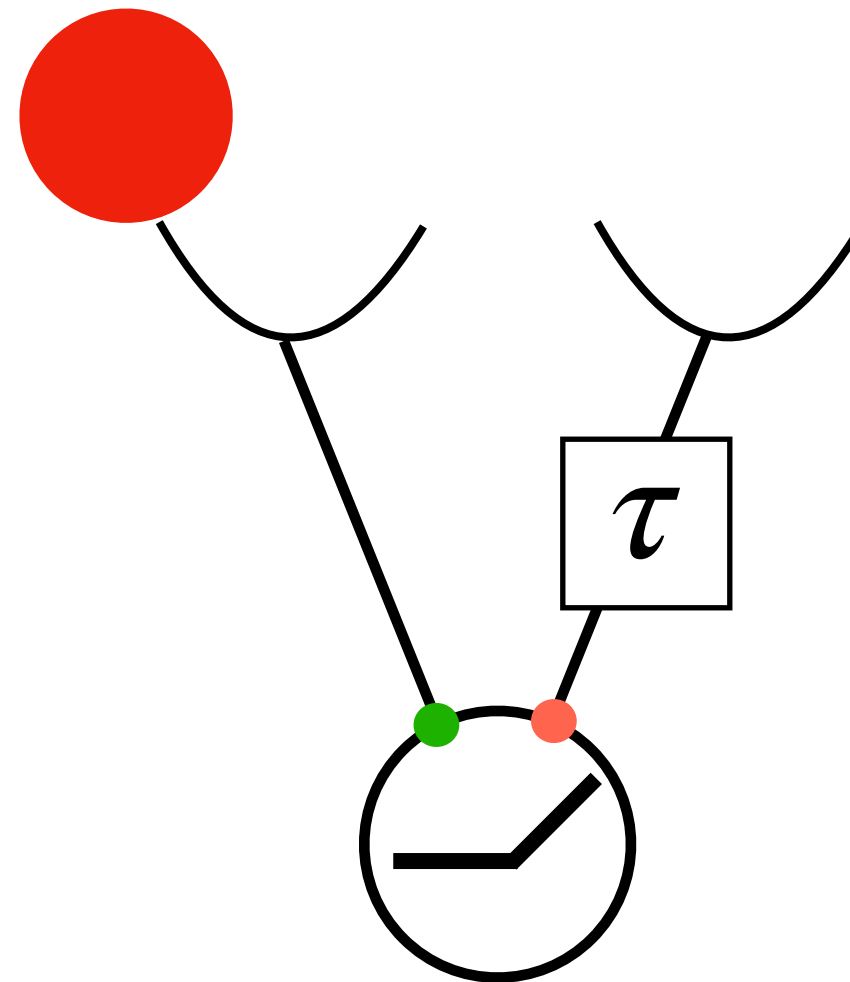


barlow-levick model

← null
direction

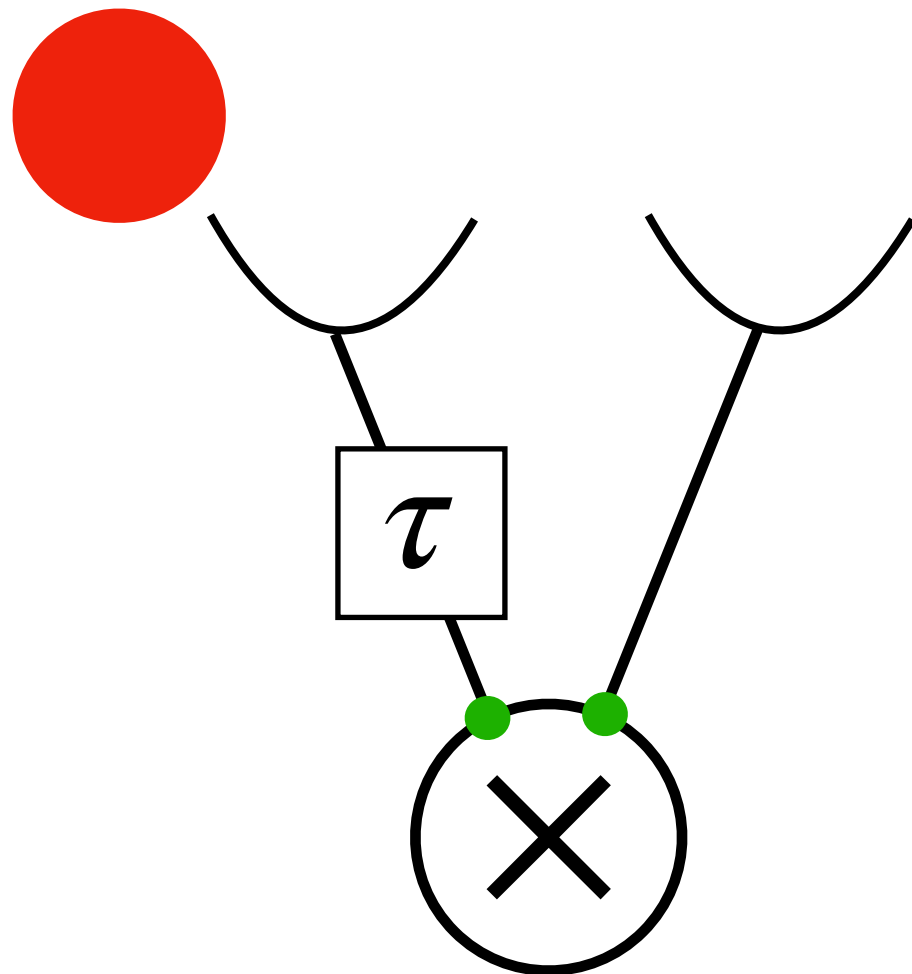


Reichardt model

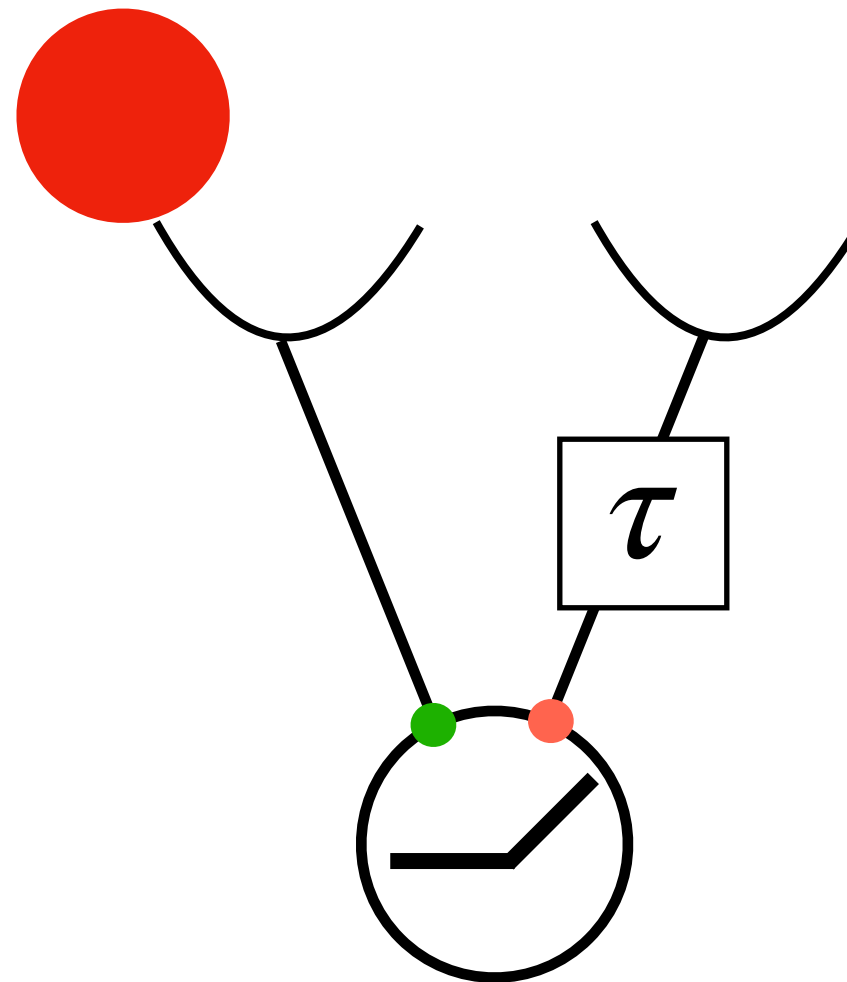


barlow-levick model

← null
direction



Reichardt model

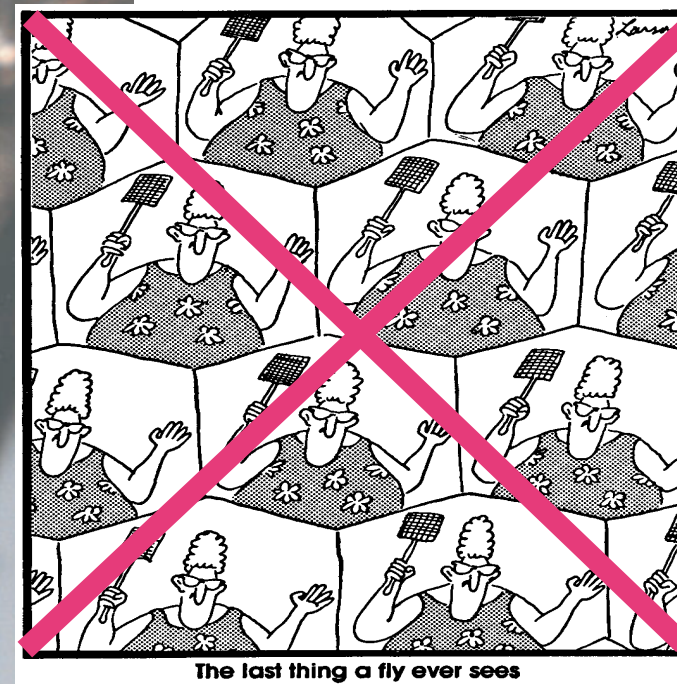
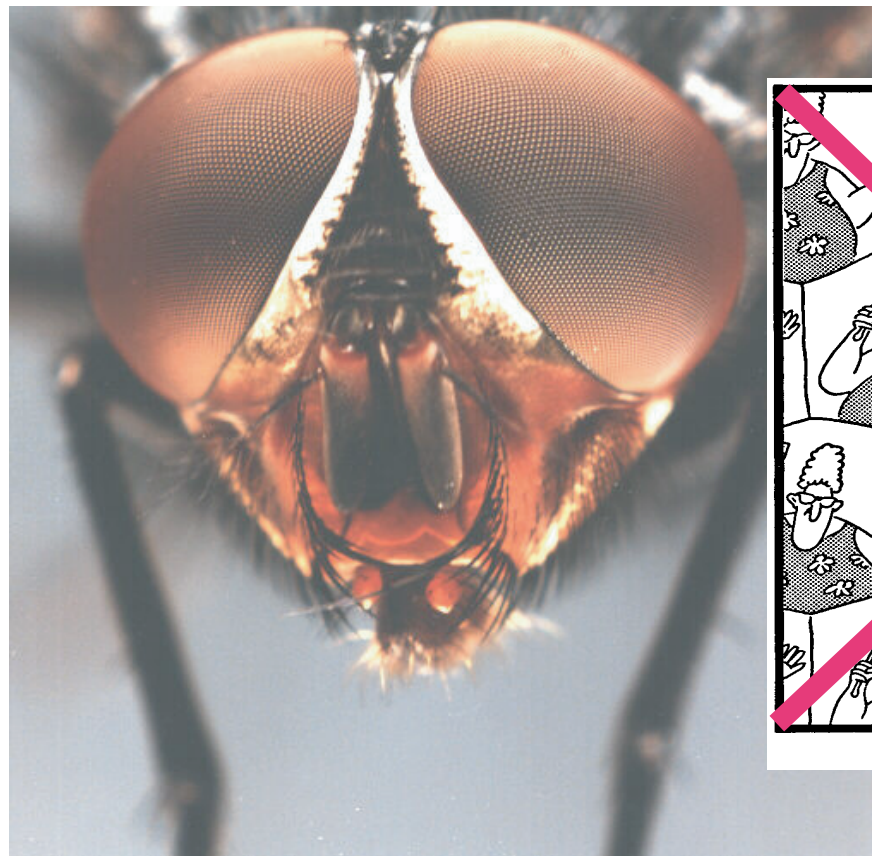


barlow-levick model

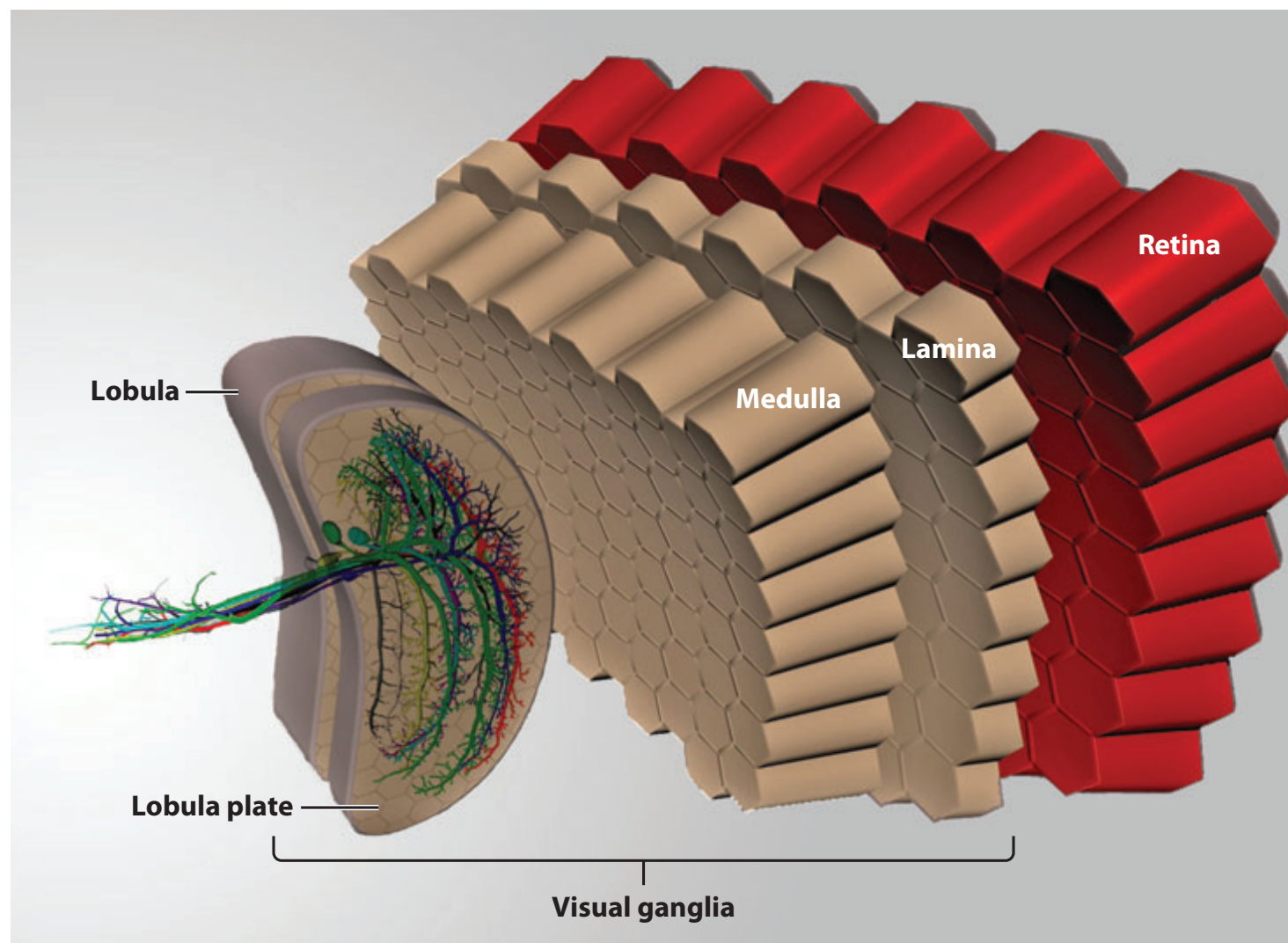
- **Computational level:** Identify the computational problem and task that the brain solves.
- **Algorithmic level:** Find the mathematical procedures that solve the problem.
- **Implementation level:** How the algorithms are realized by the nervous system.



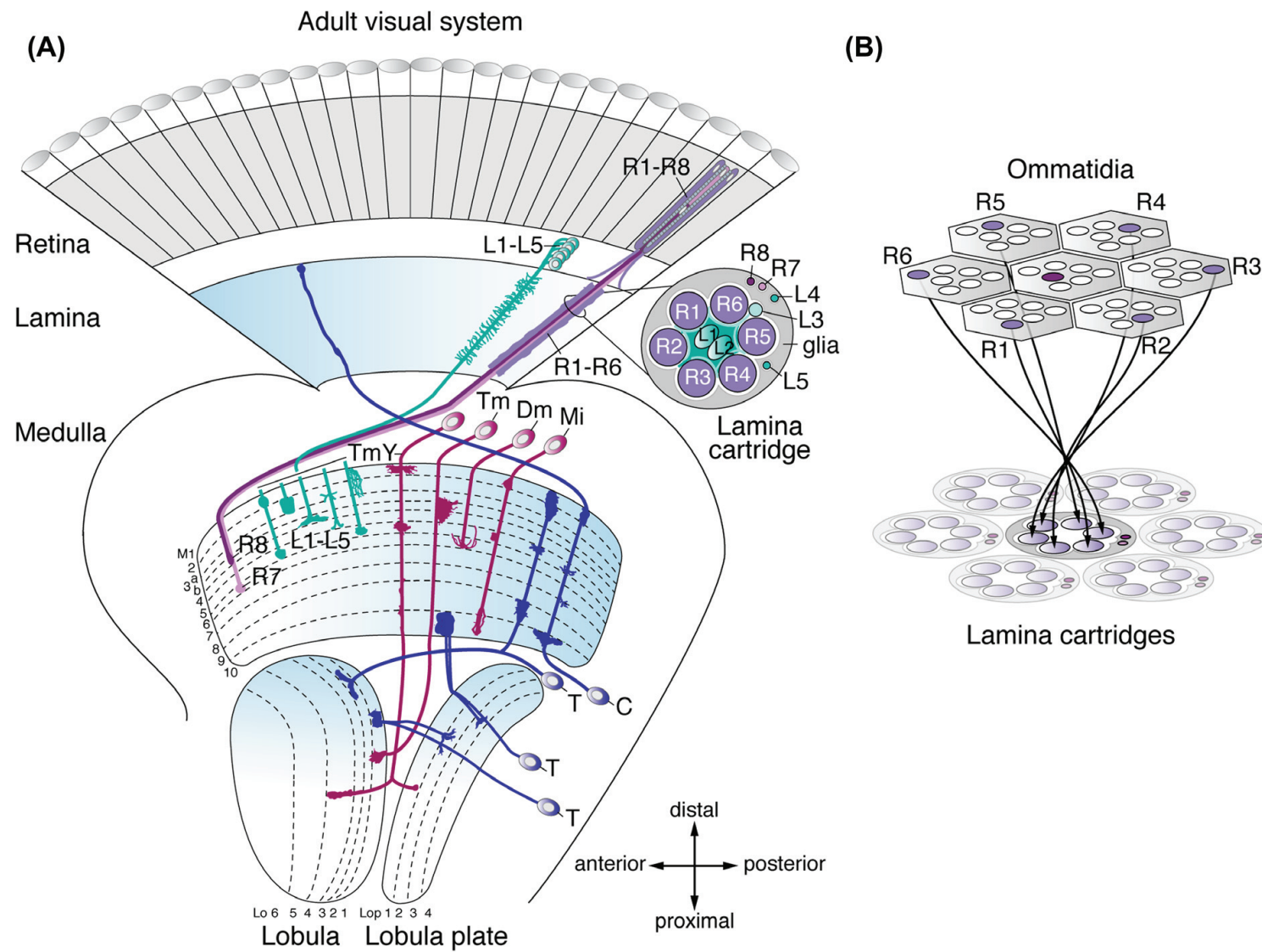
The Fly Visual System

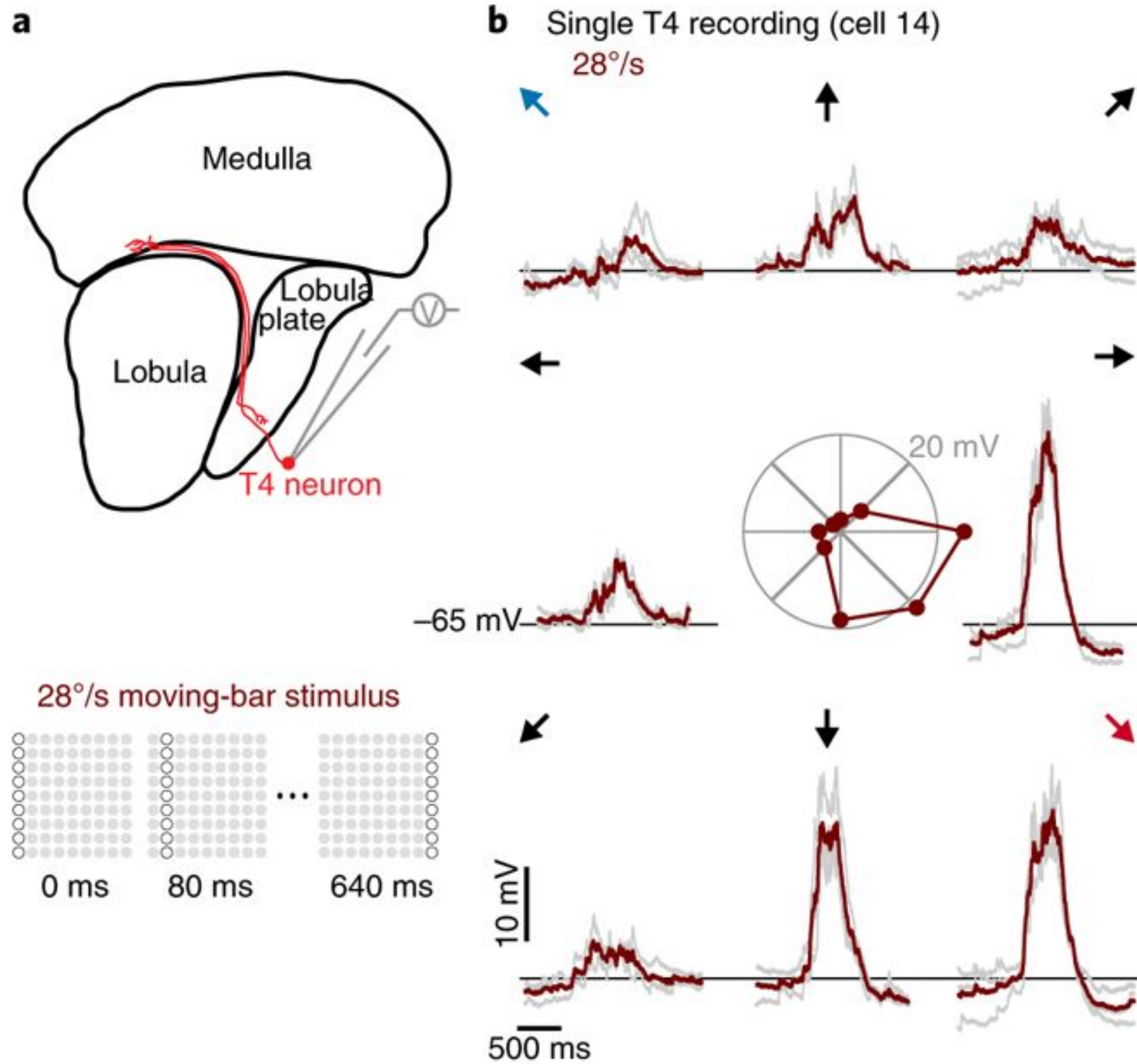


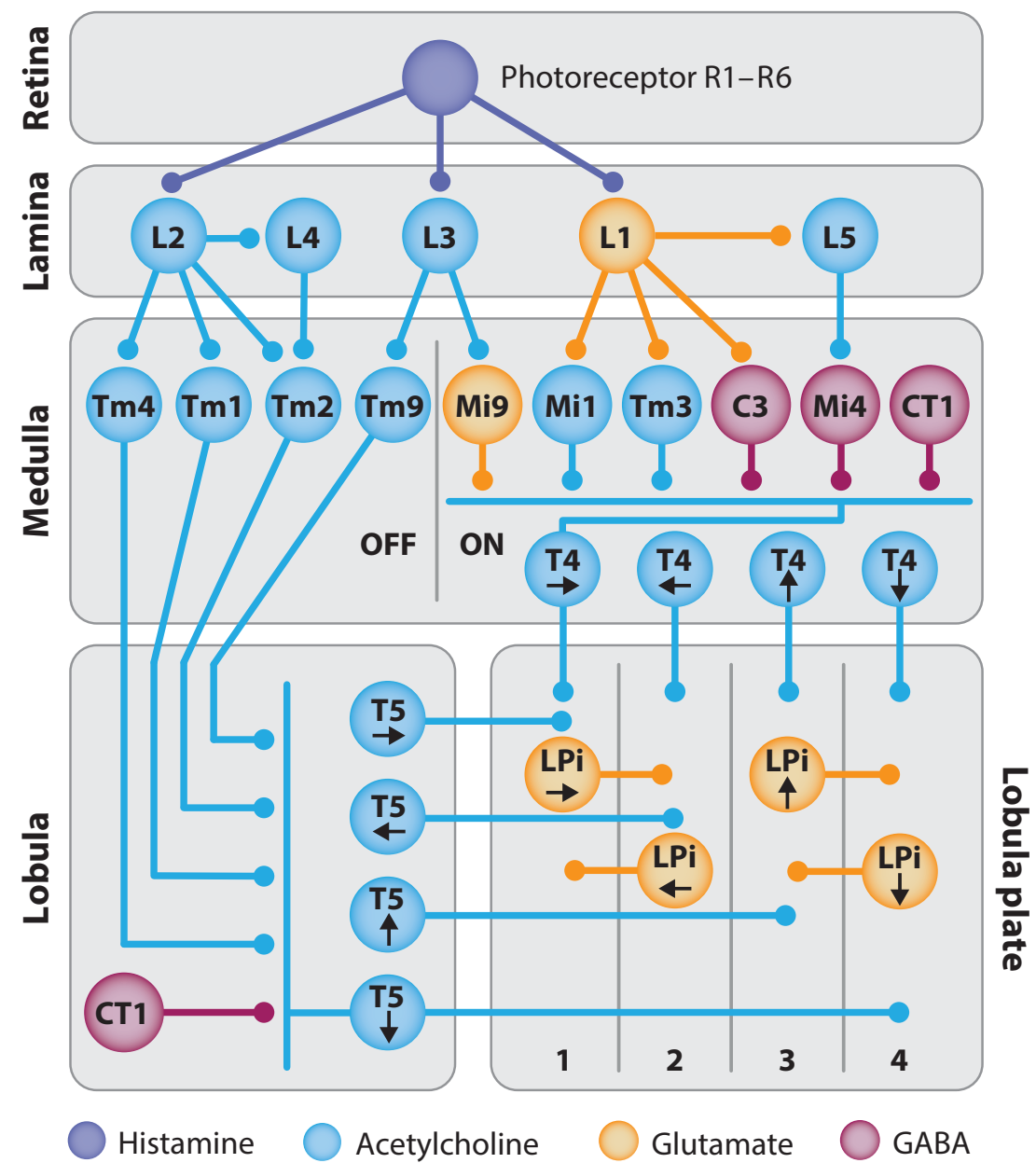
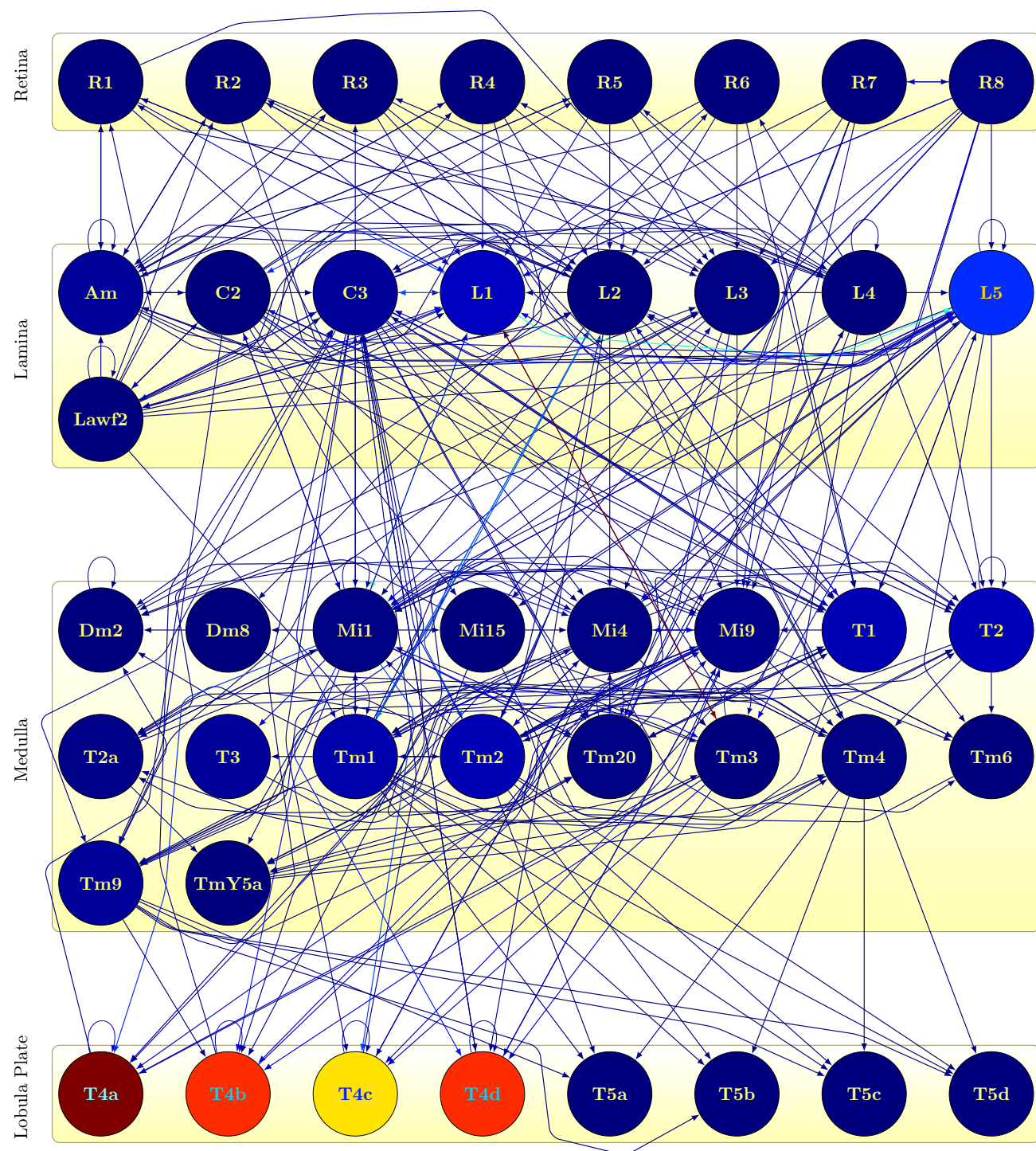
The Fly Visual System

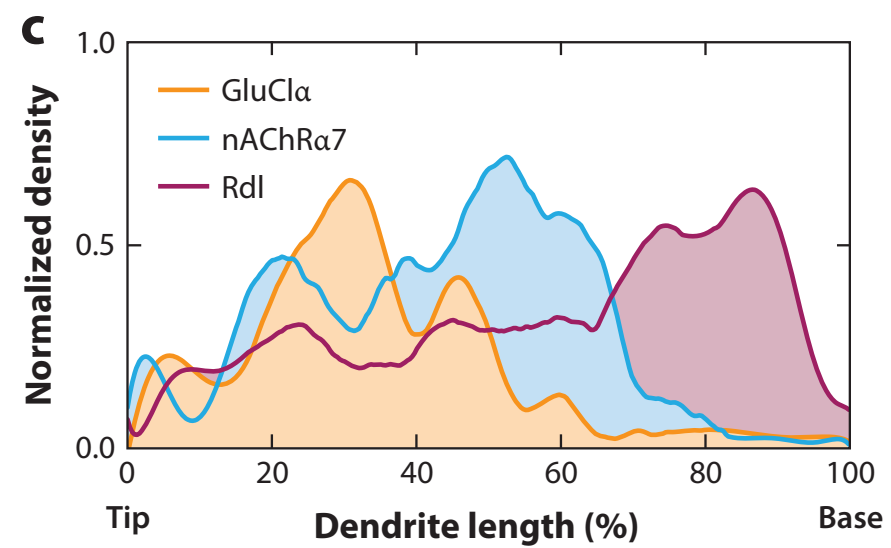
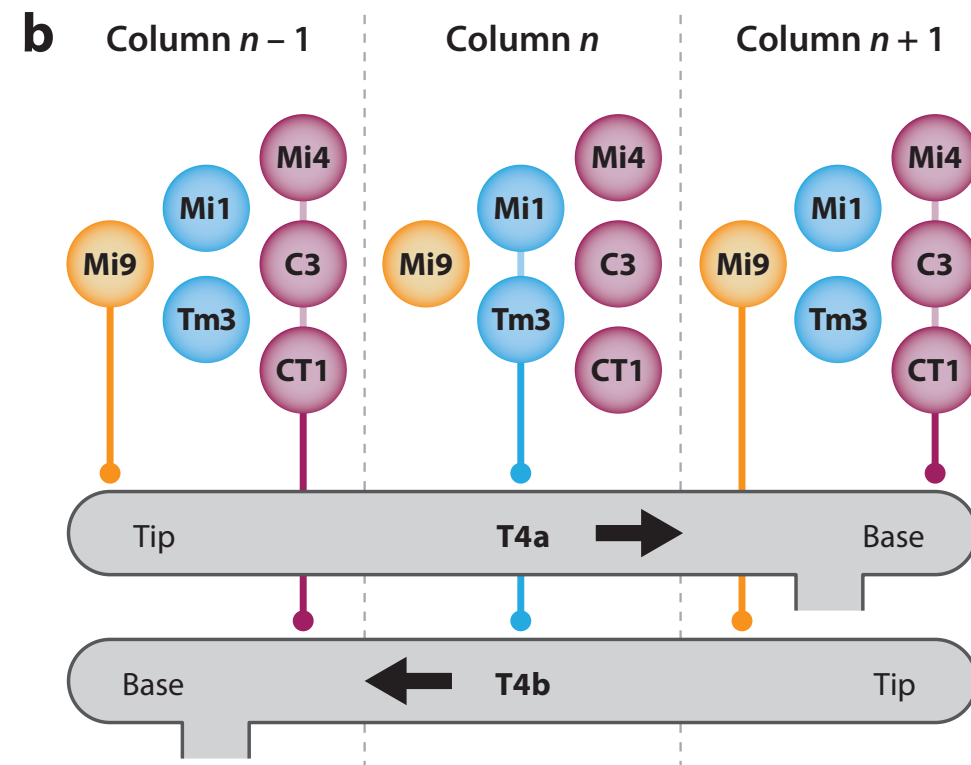
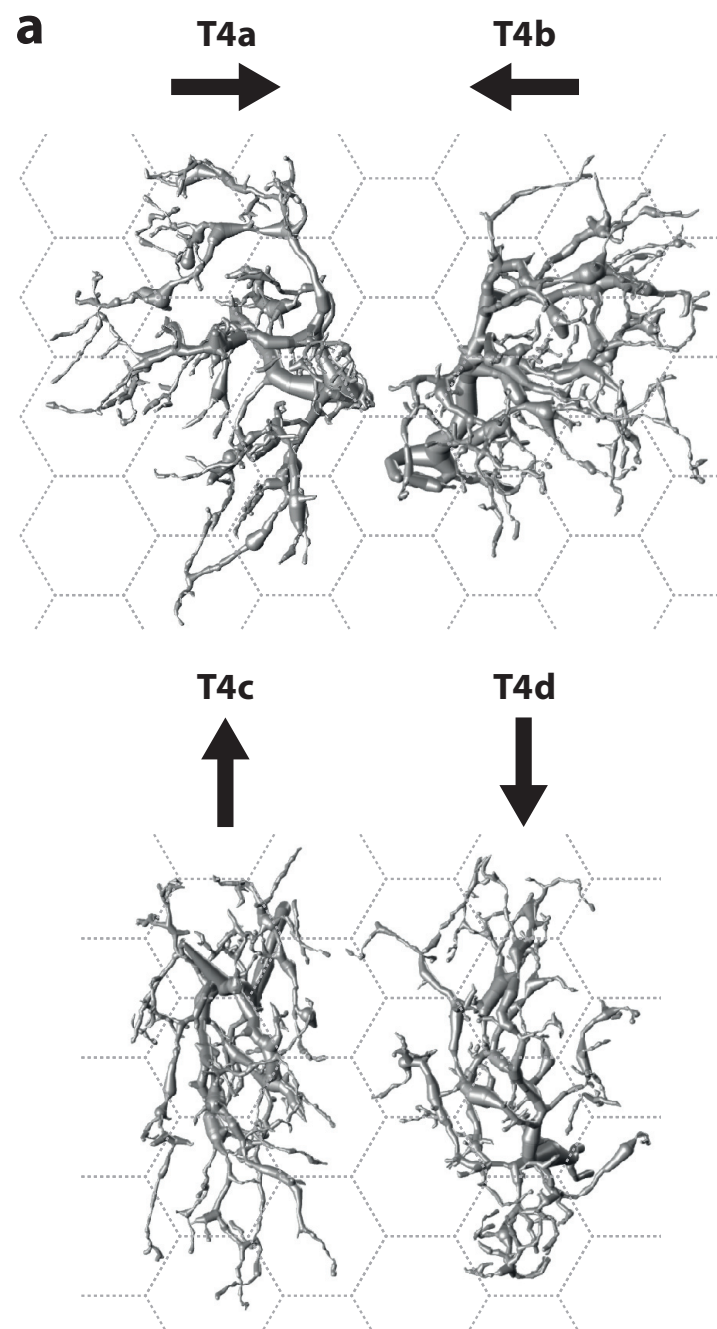


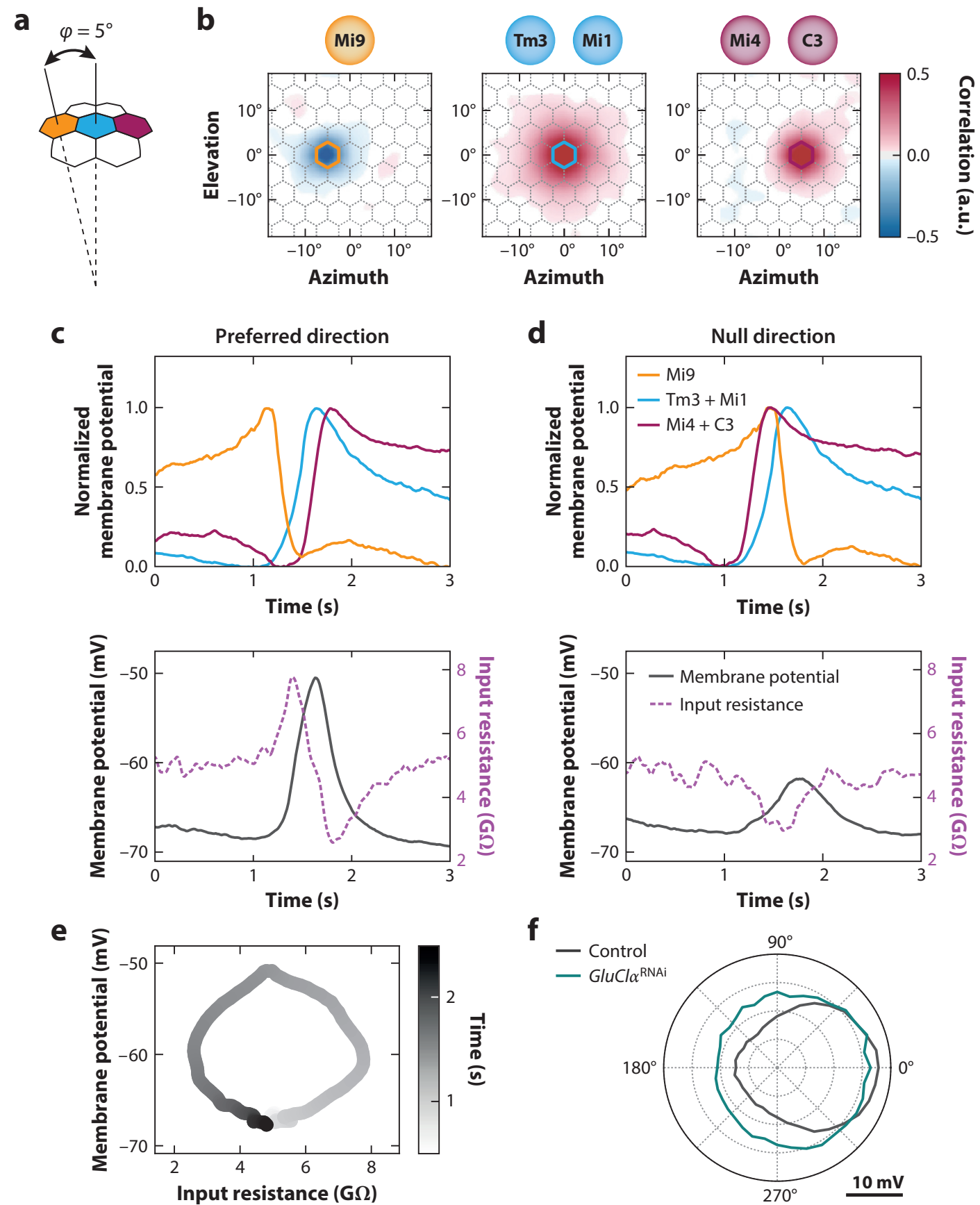
The Fly Visual System

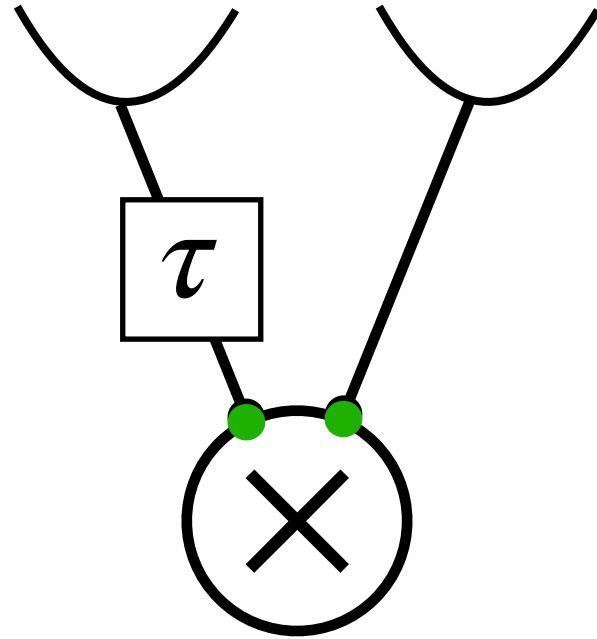




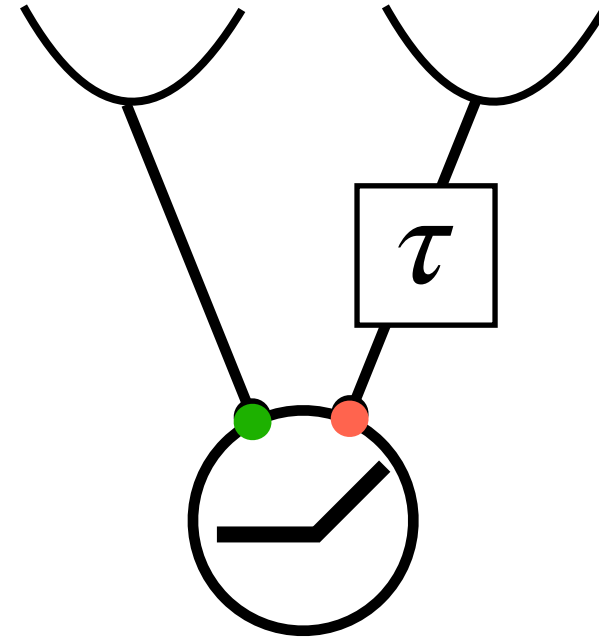




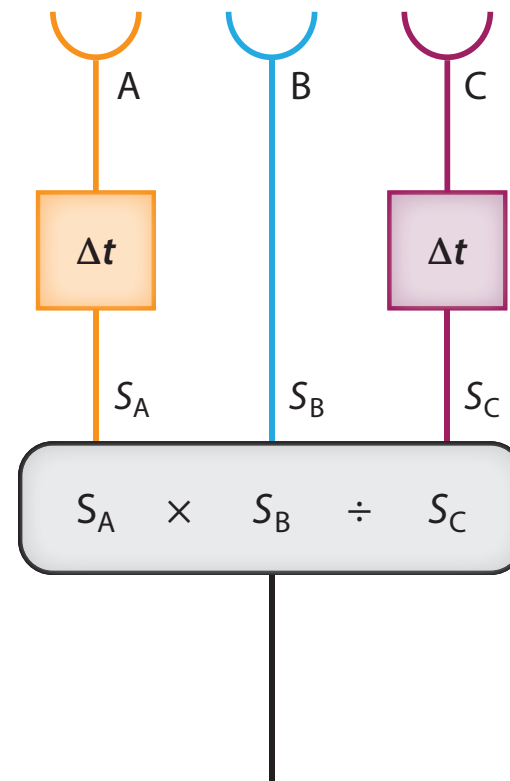




Reichardt



barlow-levick



中国计算神经科学的早期研究工作 ——对 1965 年“汪-顾模型”的再发现

司光伟¹，陈昭¹，栾贵波¹

¹ 中国科学院生物物理研究所，北京 100101

上世纪 80 年代后期，计算神经科学作为一个新学科领域开始兴起¹。它强调采用定量的方法，如数学建模、理论分析和数值模拟等来研究和解决神经科学中的重要科学问题。自此后的三十余年里，作为连接神经科学、认知科学与信息科学的前沿交叉学科，计算神经科学获得快速发展，为理解大脑运作的基本原理，攻克脑疾病以及推动人工智能技术的发展做出了关键贡献^{2,3}。

然而鲜为人知的是，早在上世纪 60 年代，中国科学家就曾在这领域做出过精彩的工作。1965 年，中国科学院生物物理研究所（以下简称生物物理所）汪云九^a、顾凡及^b通过分析动物视网膜神经电生理实验现象，提出了运动方向、速度检测的神经计算模型（简称为“汪-顾模型”），与同期西方学者提出的经典模型有异曲同工之妙。

65-3

第 页共 页

检查方向-速度的视网膜感受野

的数学模型

(中国科学院 生物物理所 北京)

付生组

一. 生理背景

近年来陆续发现某些动物的视觉系统中有一些神经节细胞, 对外界运动图像有特别敏感的反应。Hubel^[1,2]最先在猫的大脑视觉皮层找到一些细胞, 对沿特定方向运动的光条有最大的反应, 反方向运动则几乎没有反应。Lettvin等^[3]也在蛙的视网膜中发现有一类神经节细胞对移动边有特异反应。Grusser-Cornehl等^[4]又在蛙的顶盖(Tectum)上发现: 当刺激图形随时间而变化时, 这类细胞给出不同反应。Barlow等^[5]和Maturana等^[6]分别在兔子和鸽子的视网膜上发现一些对运动方向敏感的神经节细胞。

因为本文是对视网膜上的方向速度感受野进行模拟, 所以我们对Barlow等和Maturana等的实验结果作比较详细的介绍, 另一方面也可

20×20=400

北京市电车公司印刷厂印制

此文
1965年
初完成

$$K = \begin{pmatrix} 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \dots (5)$$

把K矩阵作如上推广后, 输入也相应地改变, 原先五个元素的向量变成十个元素的向量 $A(a_1, a_1', a_2, a_2', \dots, a_5, a_5')$, 若在 R_j 上给予刺激 a_j , 那么经过 τ 时刻后 a_j' 也取同样的值, 以便去开动有时延的那些联系。

假如有一光条从左向右运动, 每通过一个感受细胞需时 τ (图6a), 于是光条通过整个感受野这一过程可用下列一系列向量表示。

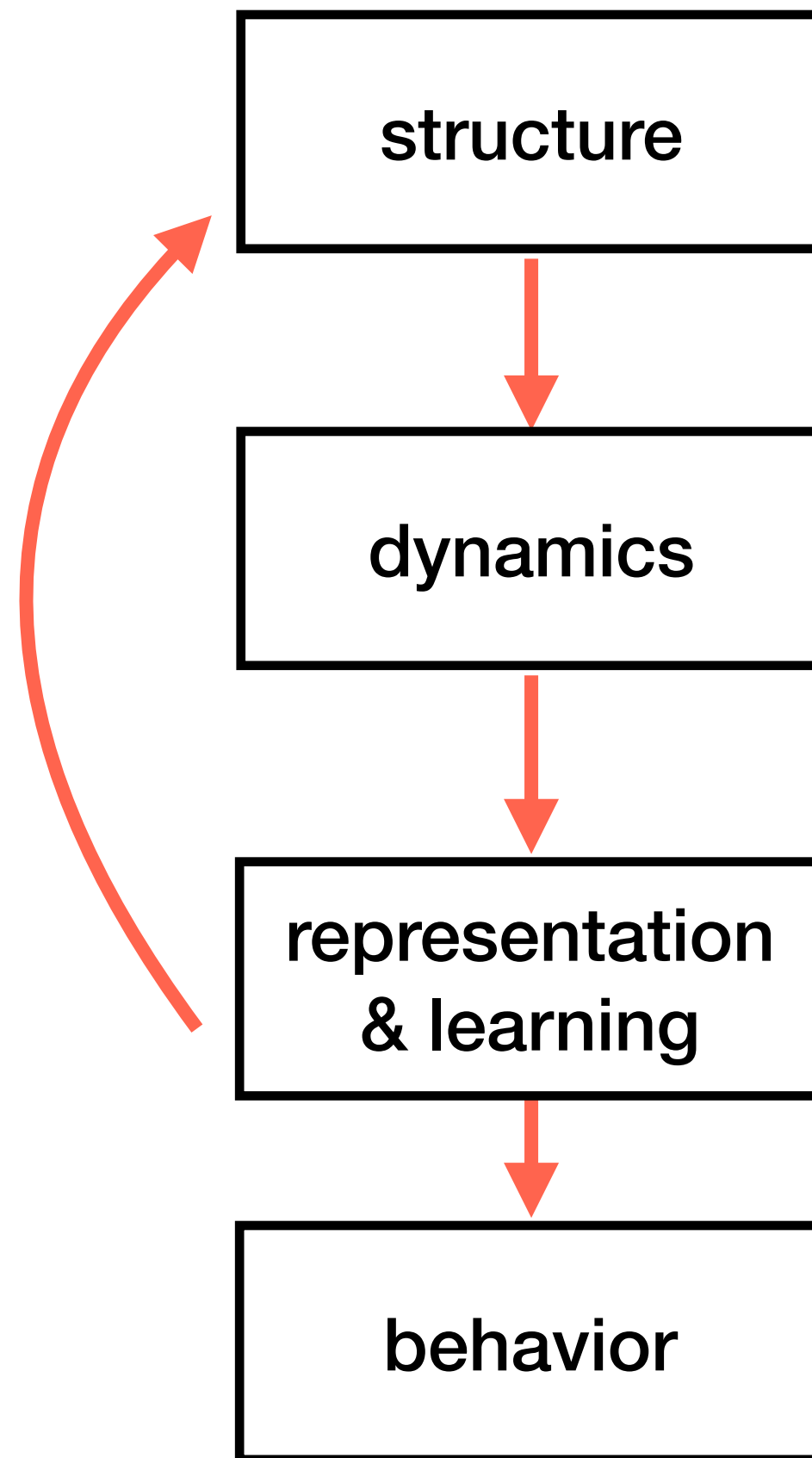
$$\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 0 \end{pmatrix}$$

$A_1, A_2, A_3, A_4, A_5, A_6$

如果 $W = (1, 1, 1, 1, 1)$, 阈值 $a=b=0$, 则根据公式(3)得到下式:

20×20=400

北京市电车公司印刷厂印制



Course Curriculum

- Introduction to Computational Neuroscience
- Connect Neurons to Perform Computation
- Recurrent network and Attractor Dynamics
- E/I balance and Chaotic Dynamics
- Geometry and dimensionality of population neural activity
- Efficient coding principle
- Stimulus discrimination, Fisher information and Information-limited correlation
- Normative approach to neural computation and the emergence of sensory representation
- Reward and Reinforcement Learning
- How does an animal move, an integrated approach