2- Questions and Discussion

Data Science and AI for Neuroscience Summer School 2022, Chen Institute at Caltech

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SYSTEMS NEURAL ENGINEERING LABORATORY
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EMORY UNIVERSITY

Georgia Tech

What you'll hear about in this lecture

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Neural network basics

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Deep autoencoders

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Intro to neural population dynamics

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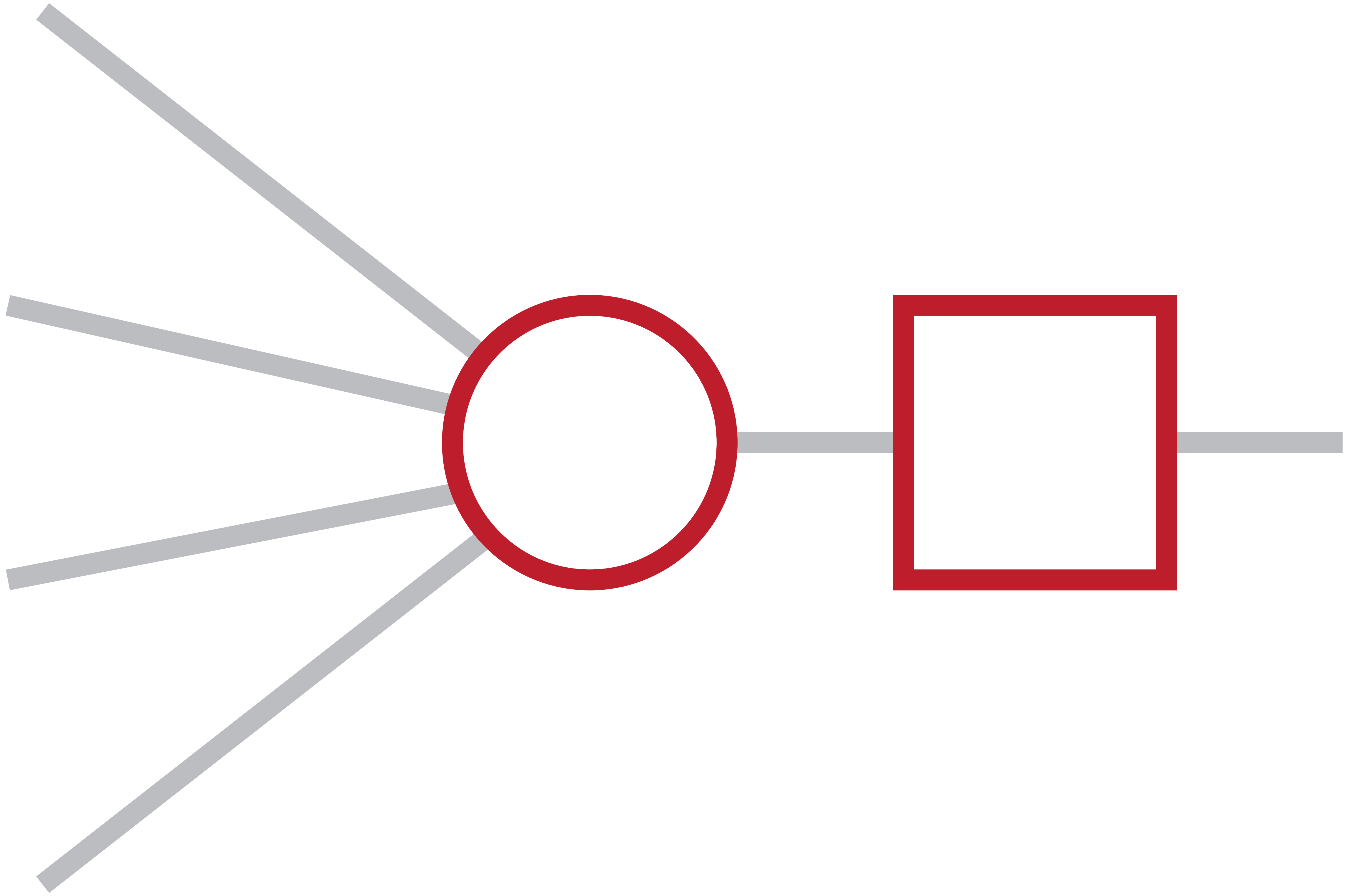
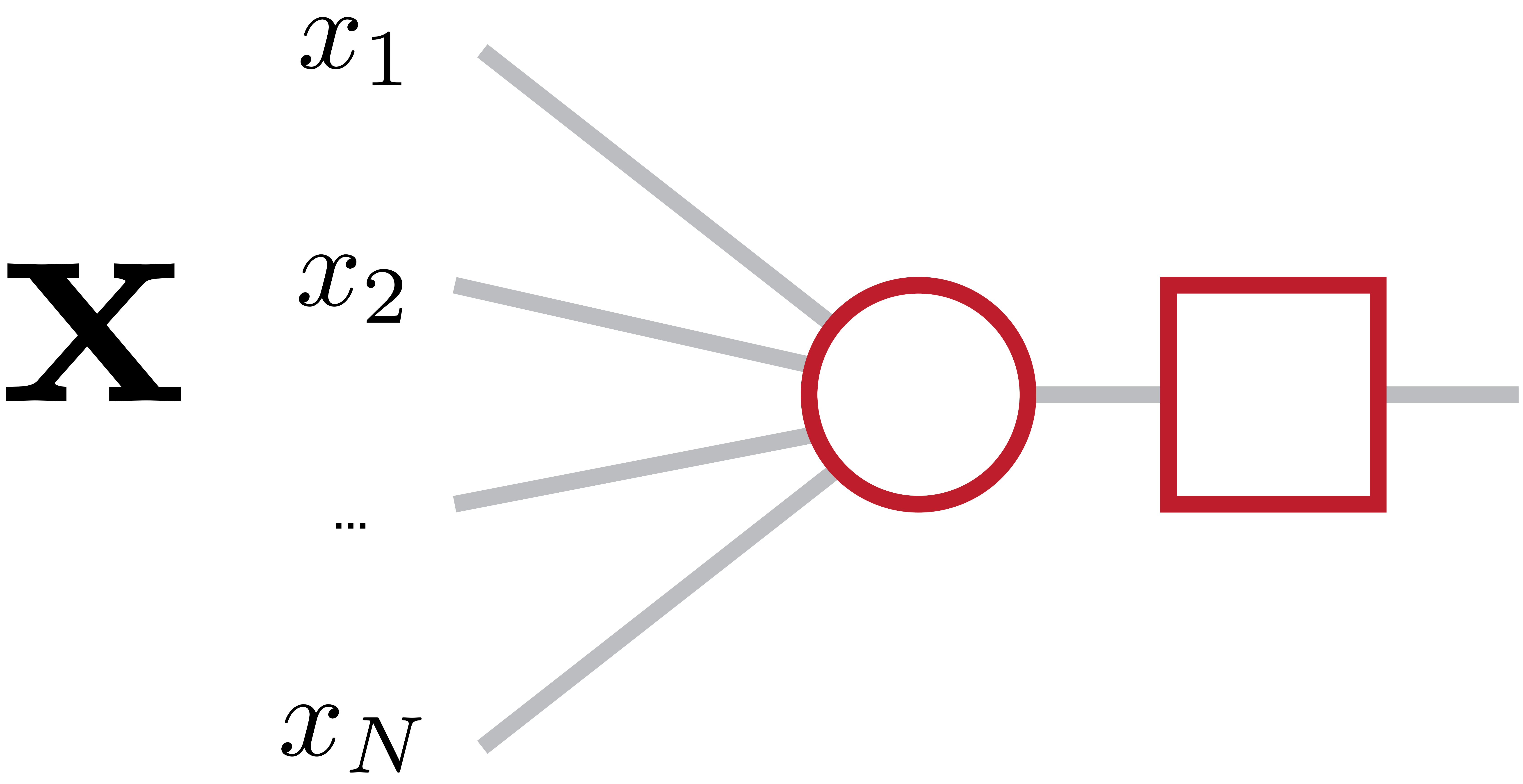
Artificial neurons

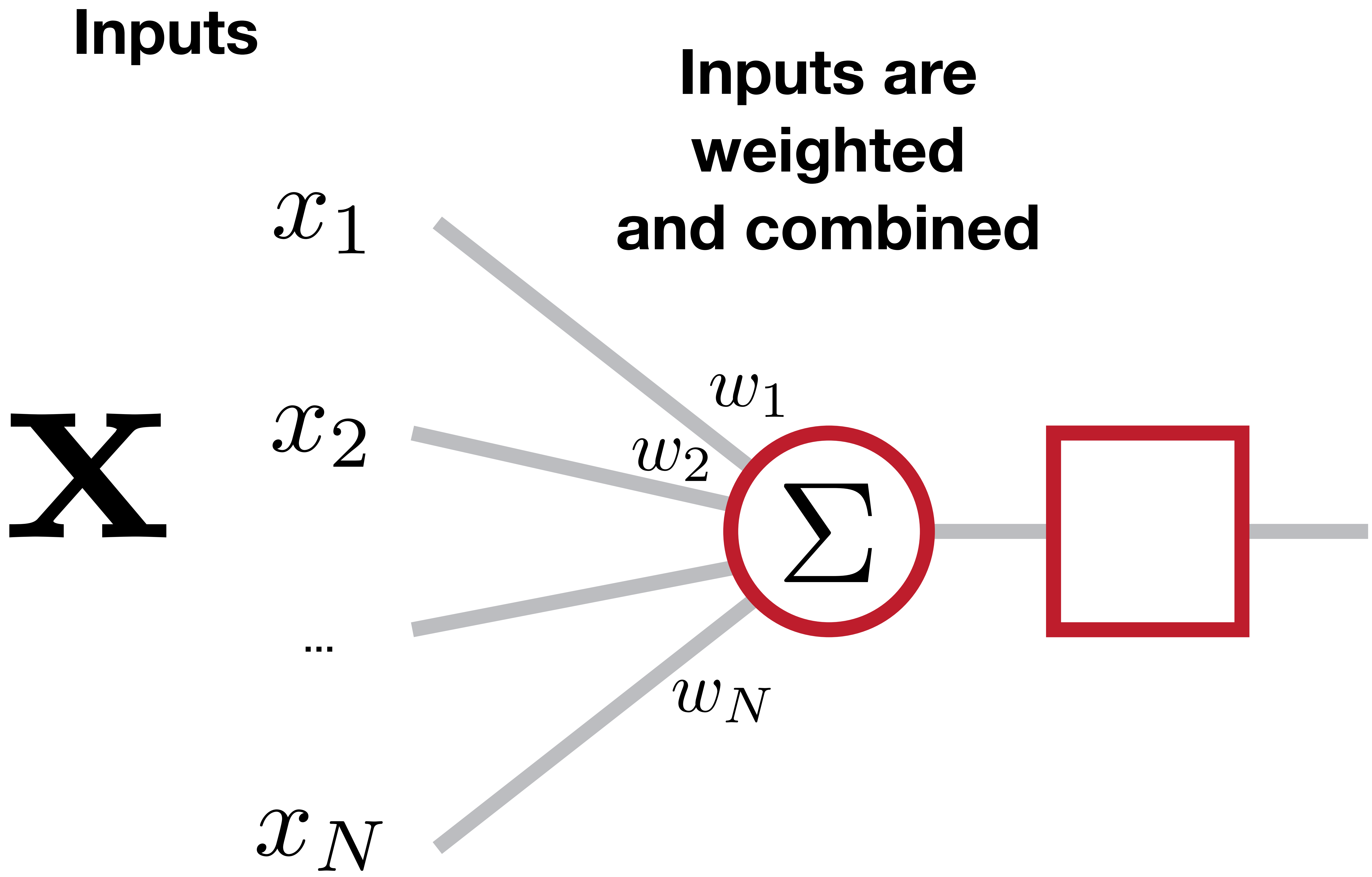


Artificial neurons

Inputs



Artificial neurons



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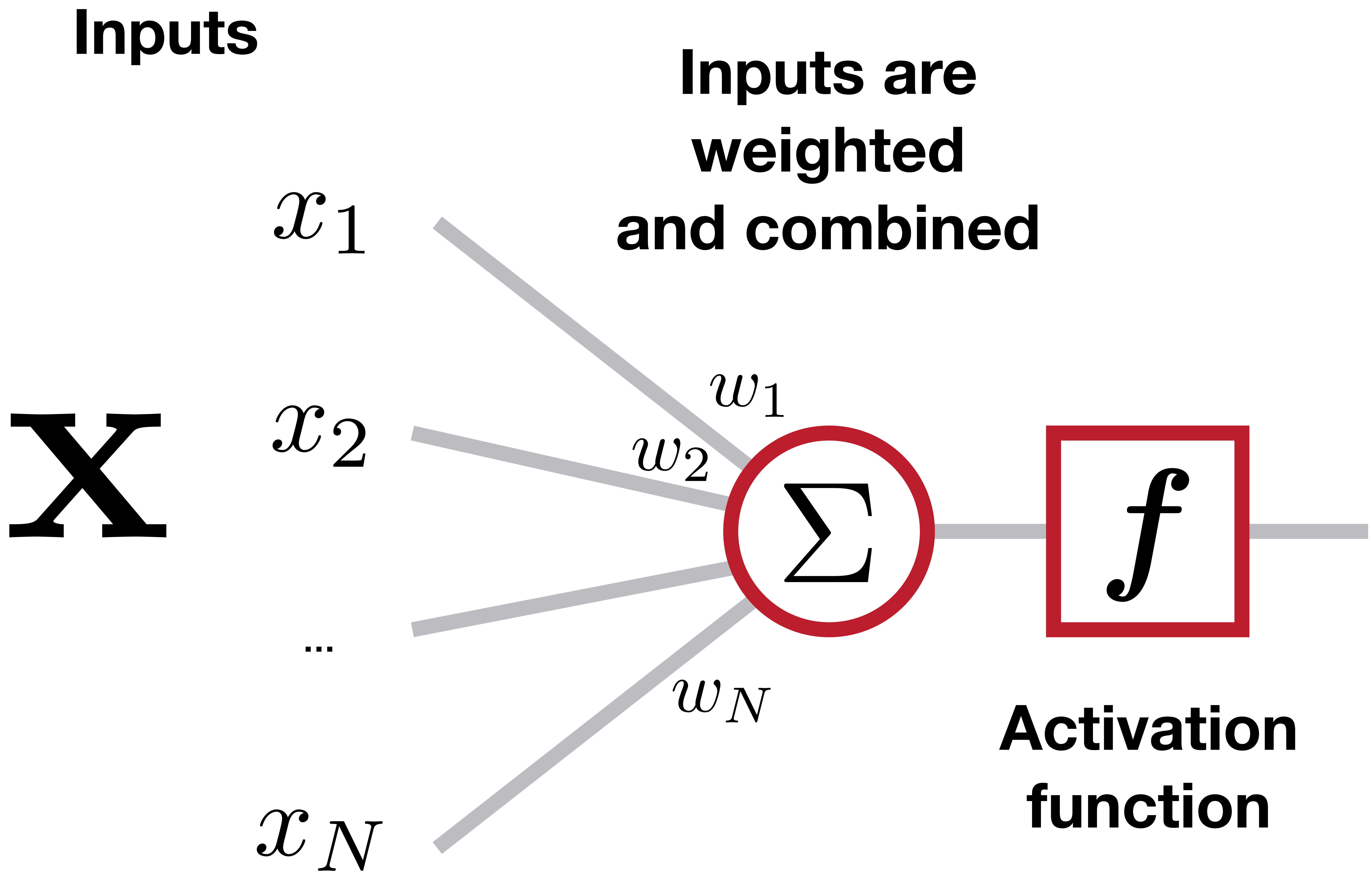

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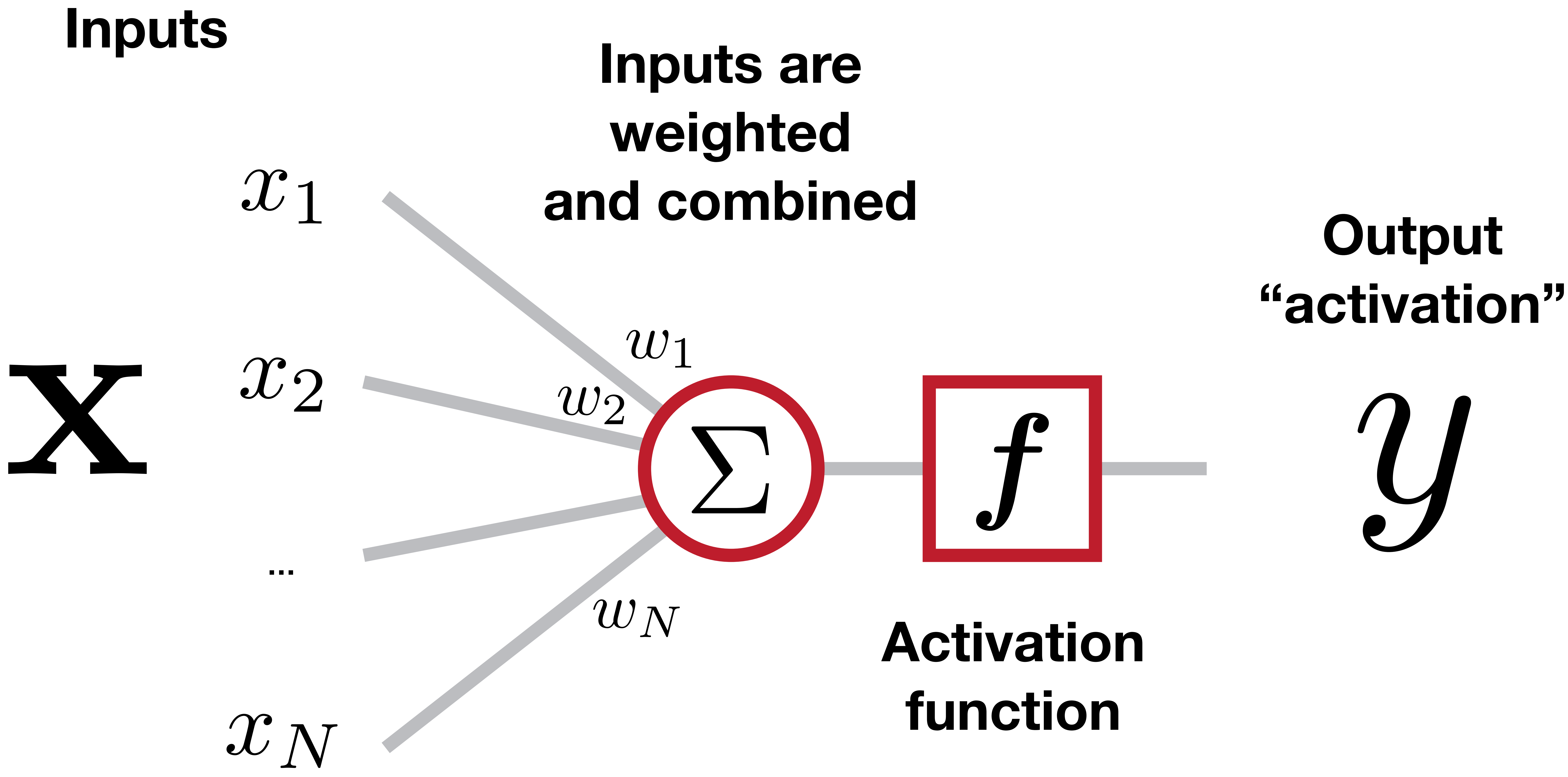

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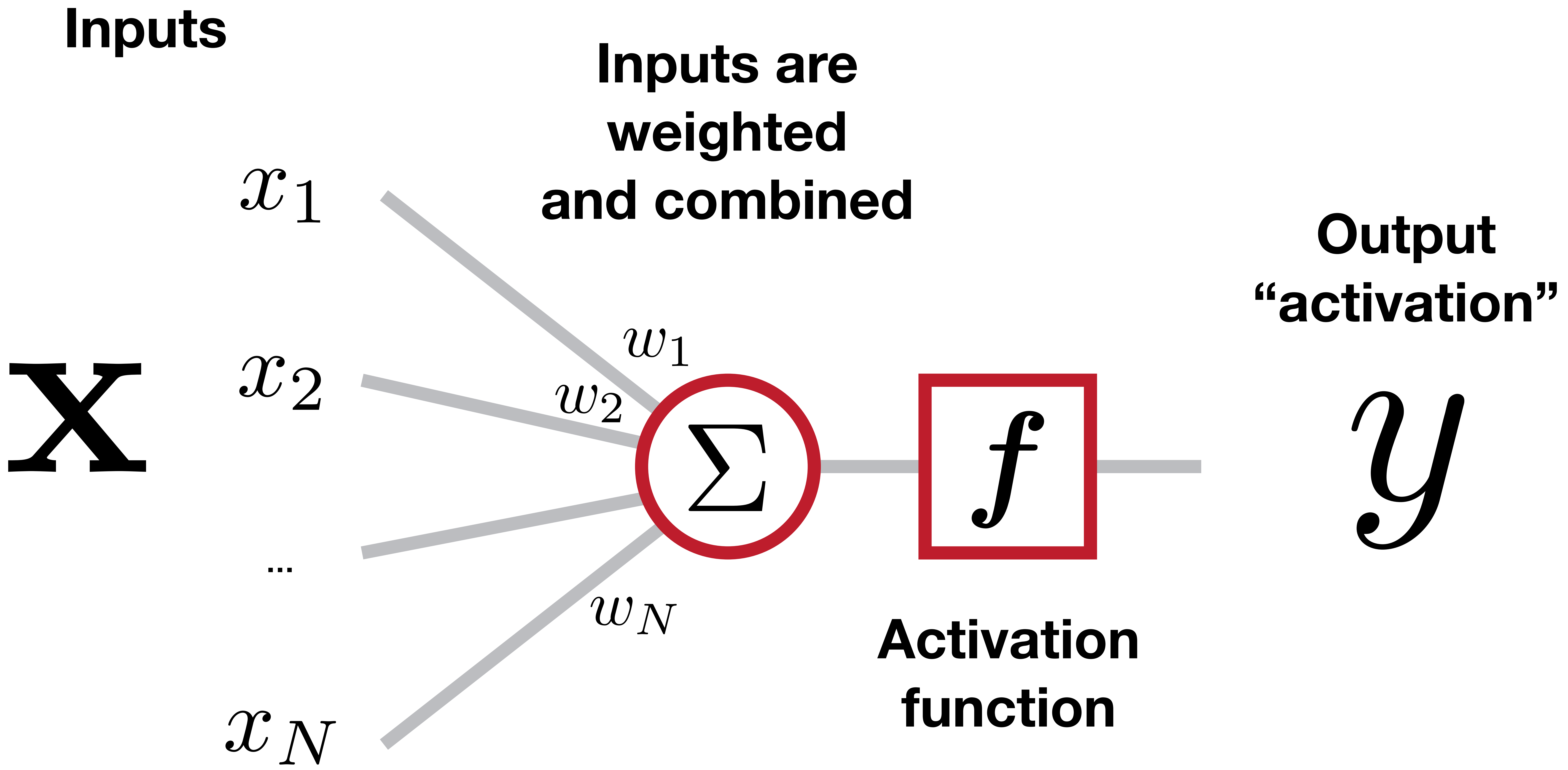
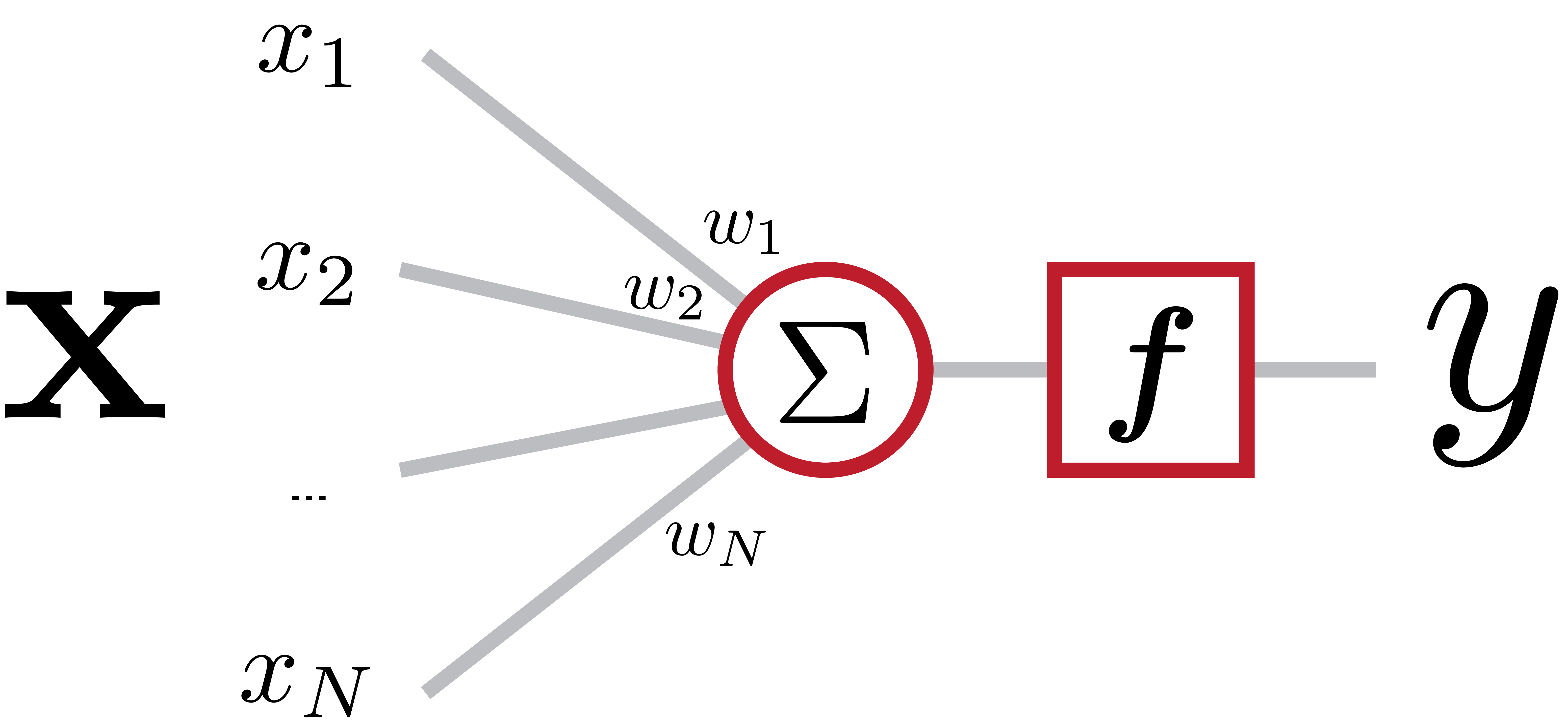


Warren S. McCulloch and Walter Pitts (1943)
"A logical calculus of the ideas immanent in nervous activity.”
Bulletin of Mathematical Biophysics 5:115-133

Artificial neurons

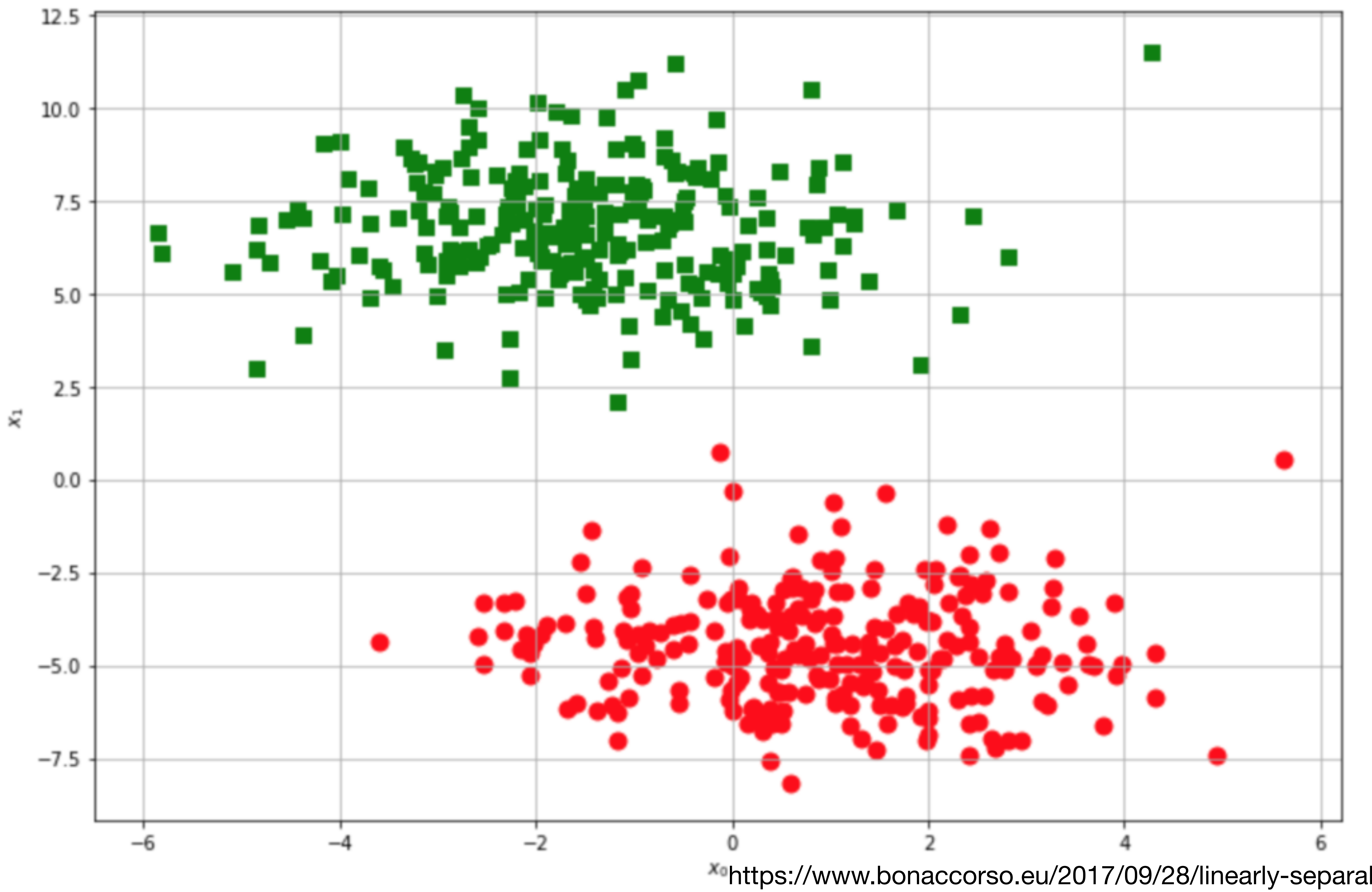


$$y = f(w_1 * x_1 + w_2 * x_2 + \ldots + b)$$

Simple problem - 2 dimensional classification

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

Green: class 0
Red: class 1



https://www.bonaccorso.eu/2017/09/28/linearly-separable-no-for-me-it-is-a-brief-introduction-to-kernel-methods/

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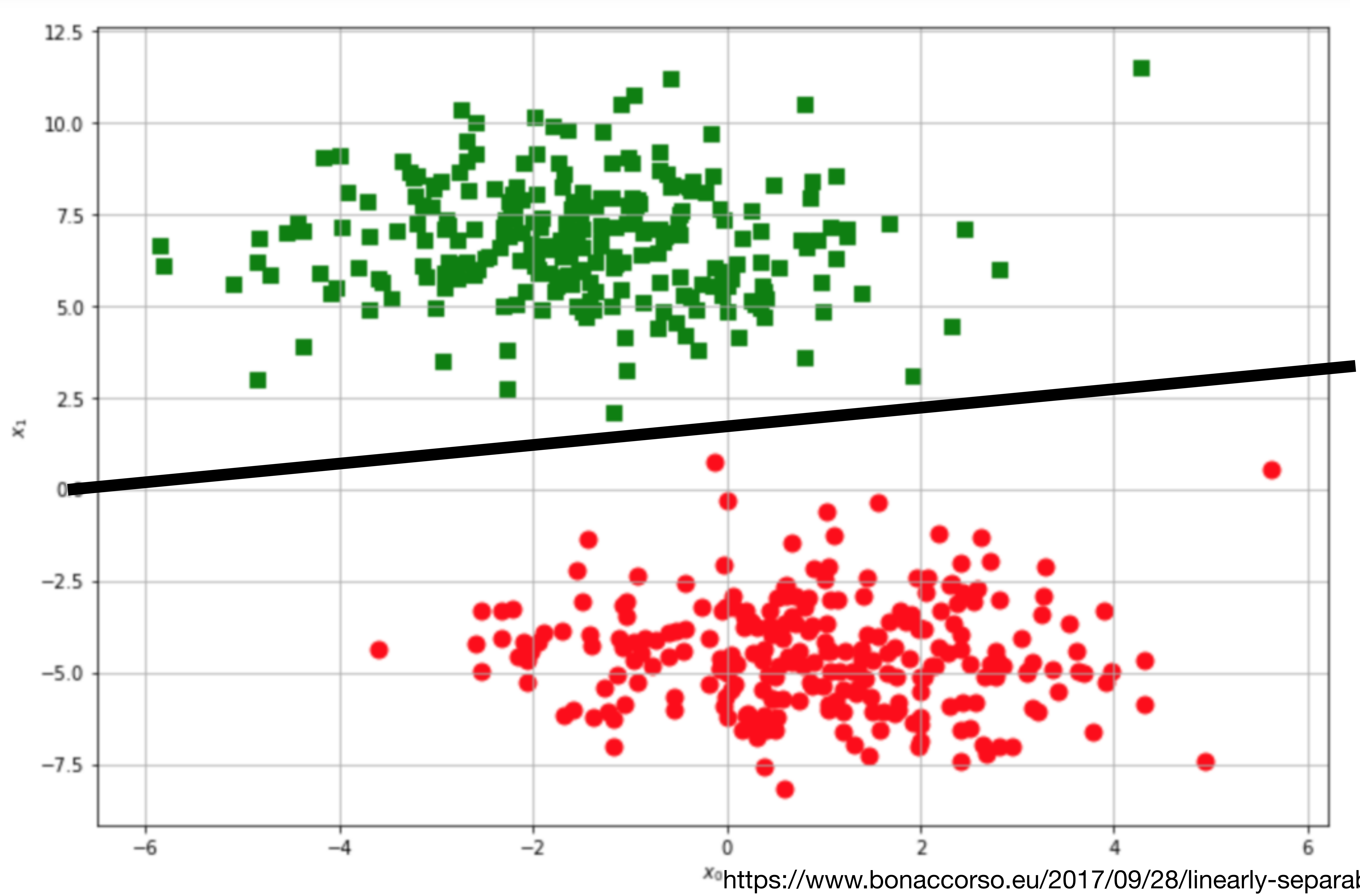

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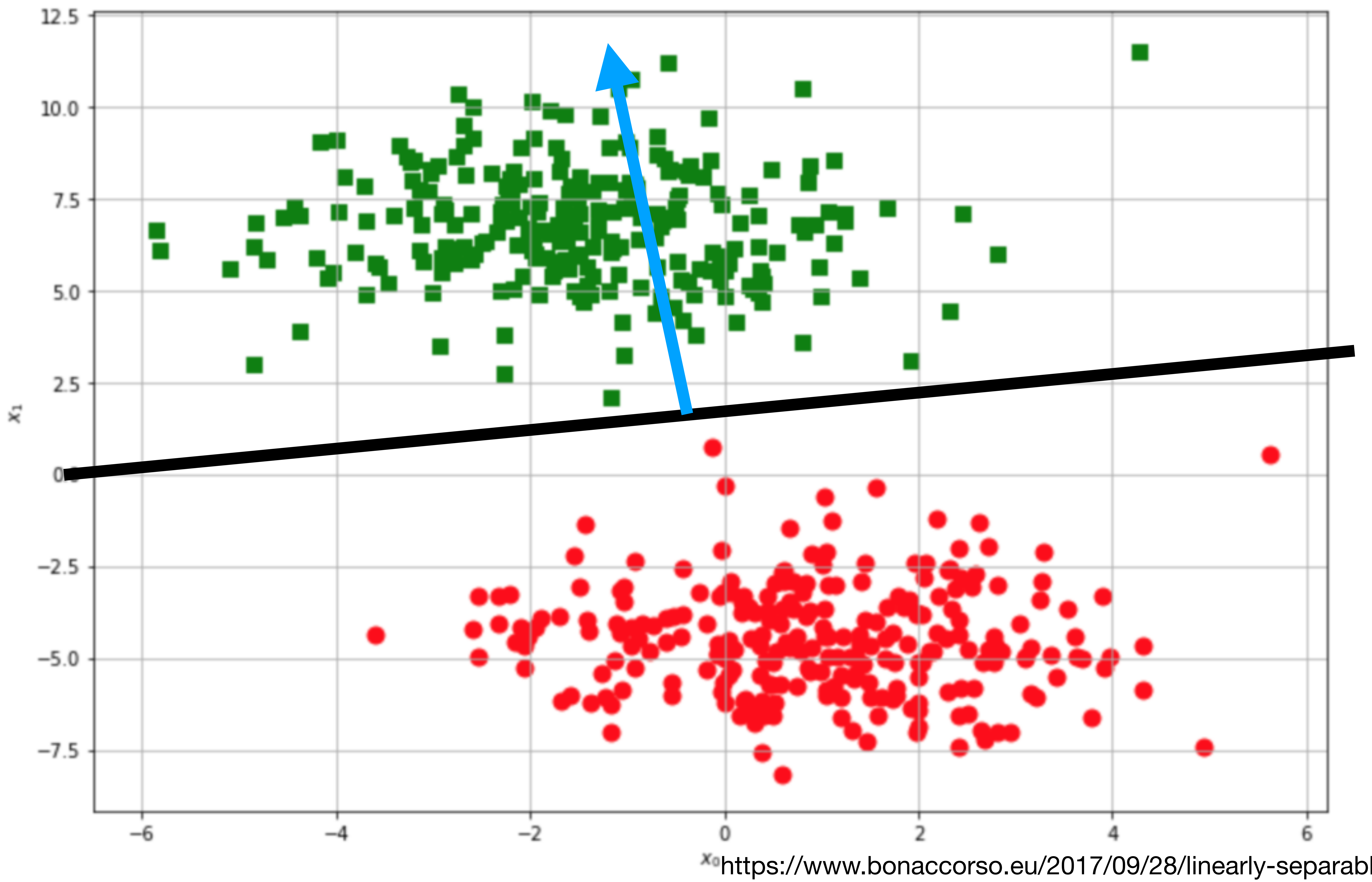

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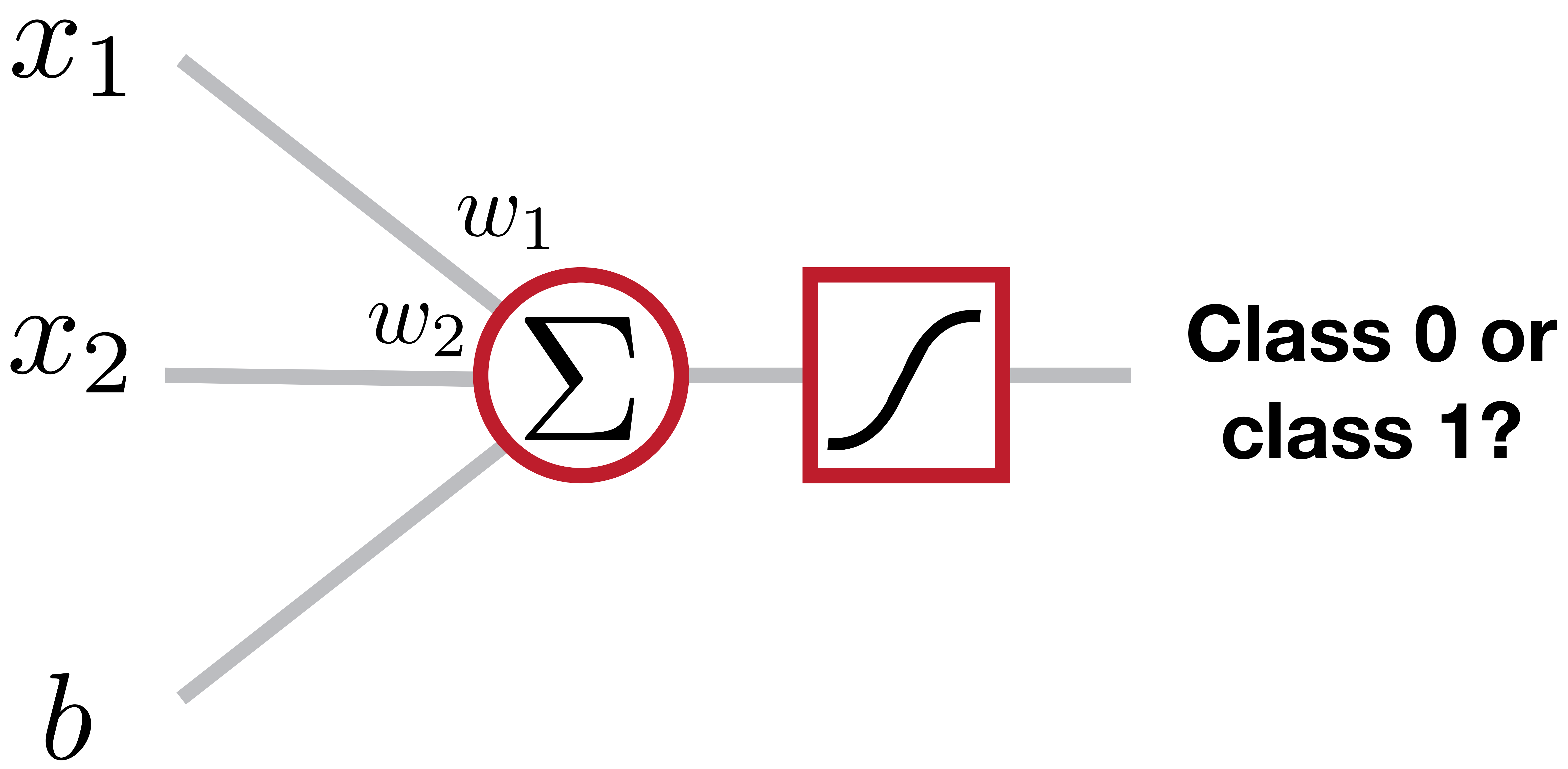
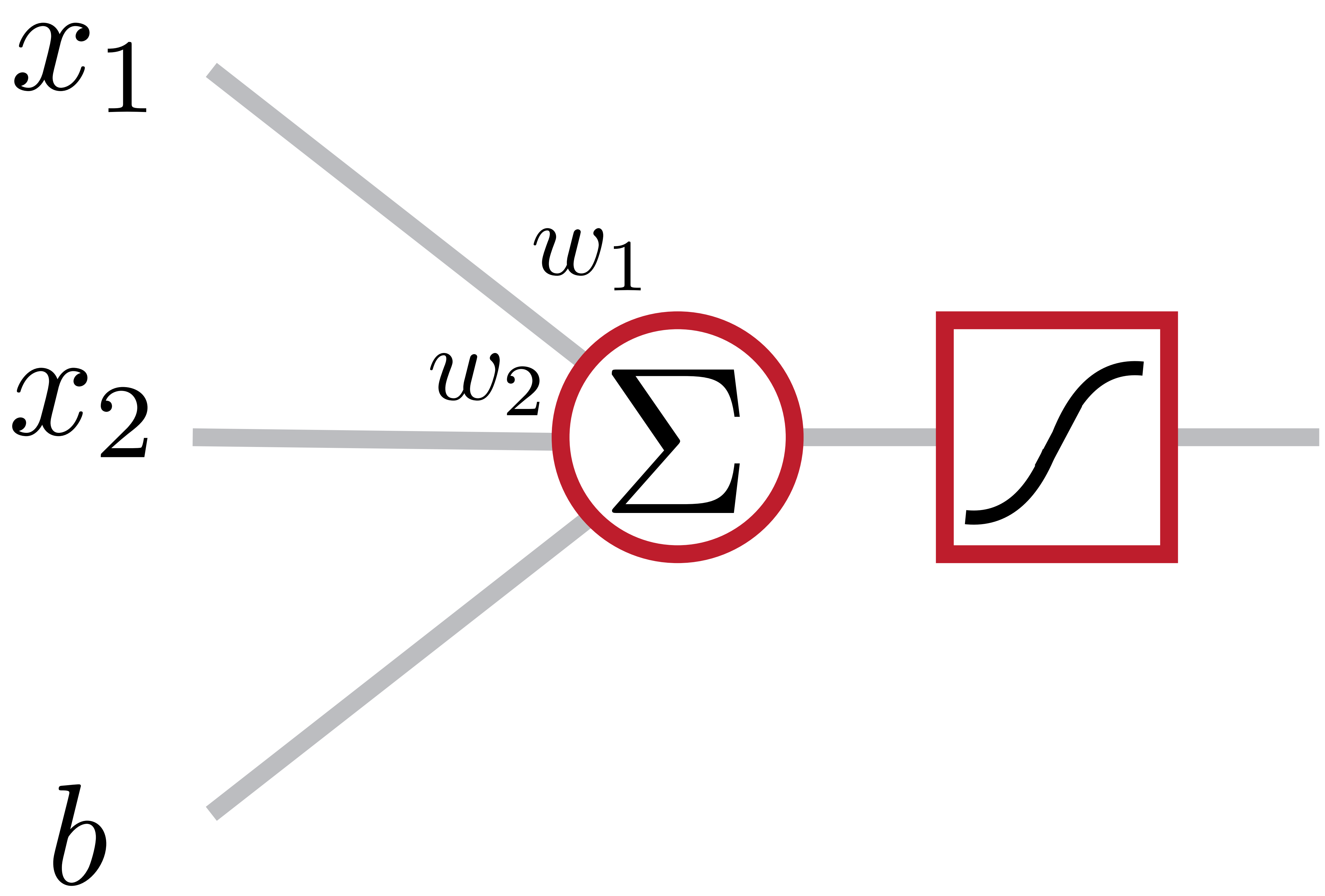
Simple classifier - Perceptron



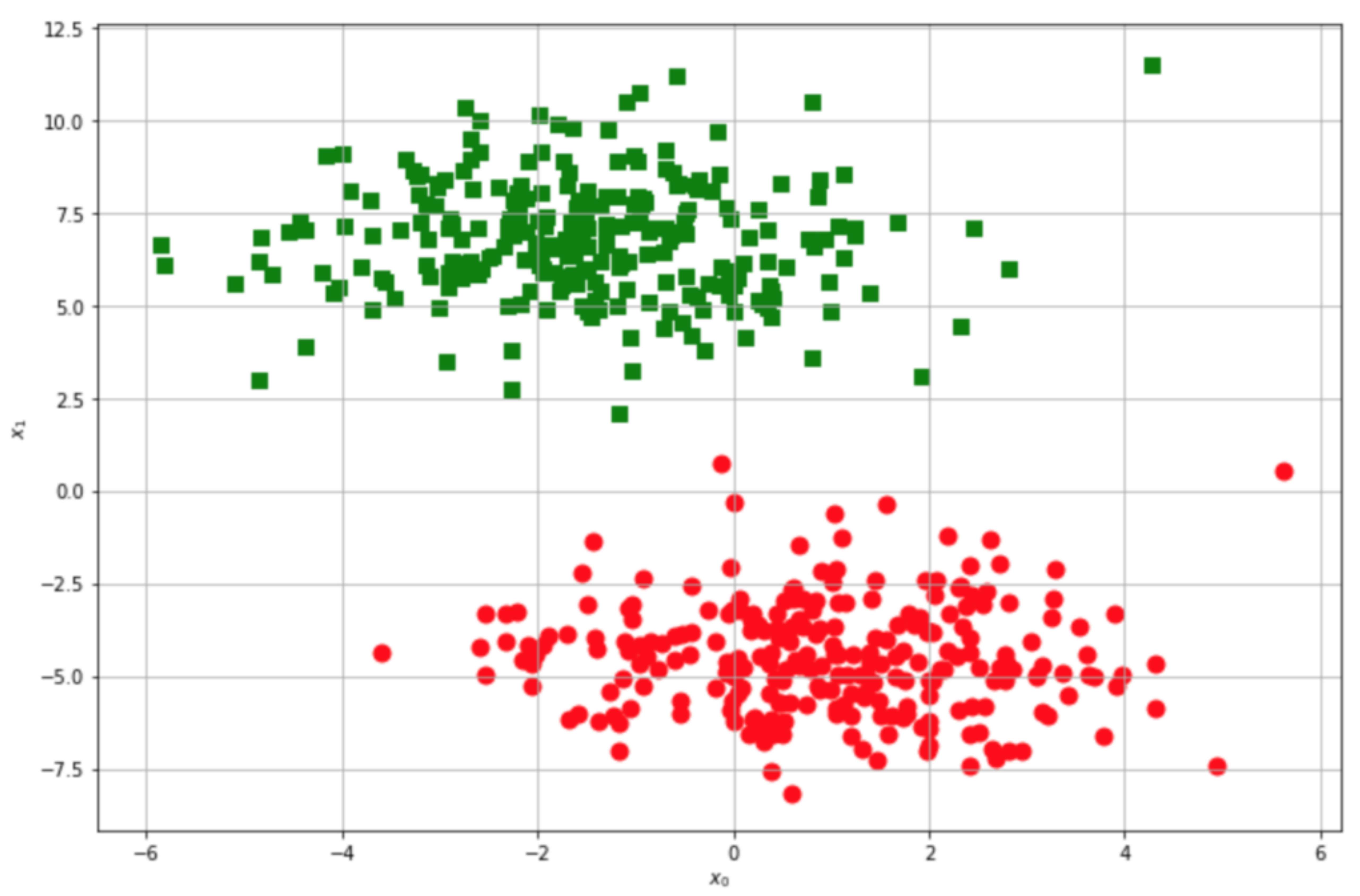
Simple classifier - Perceptron

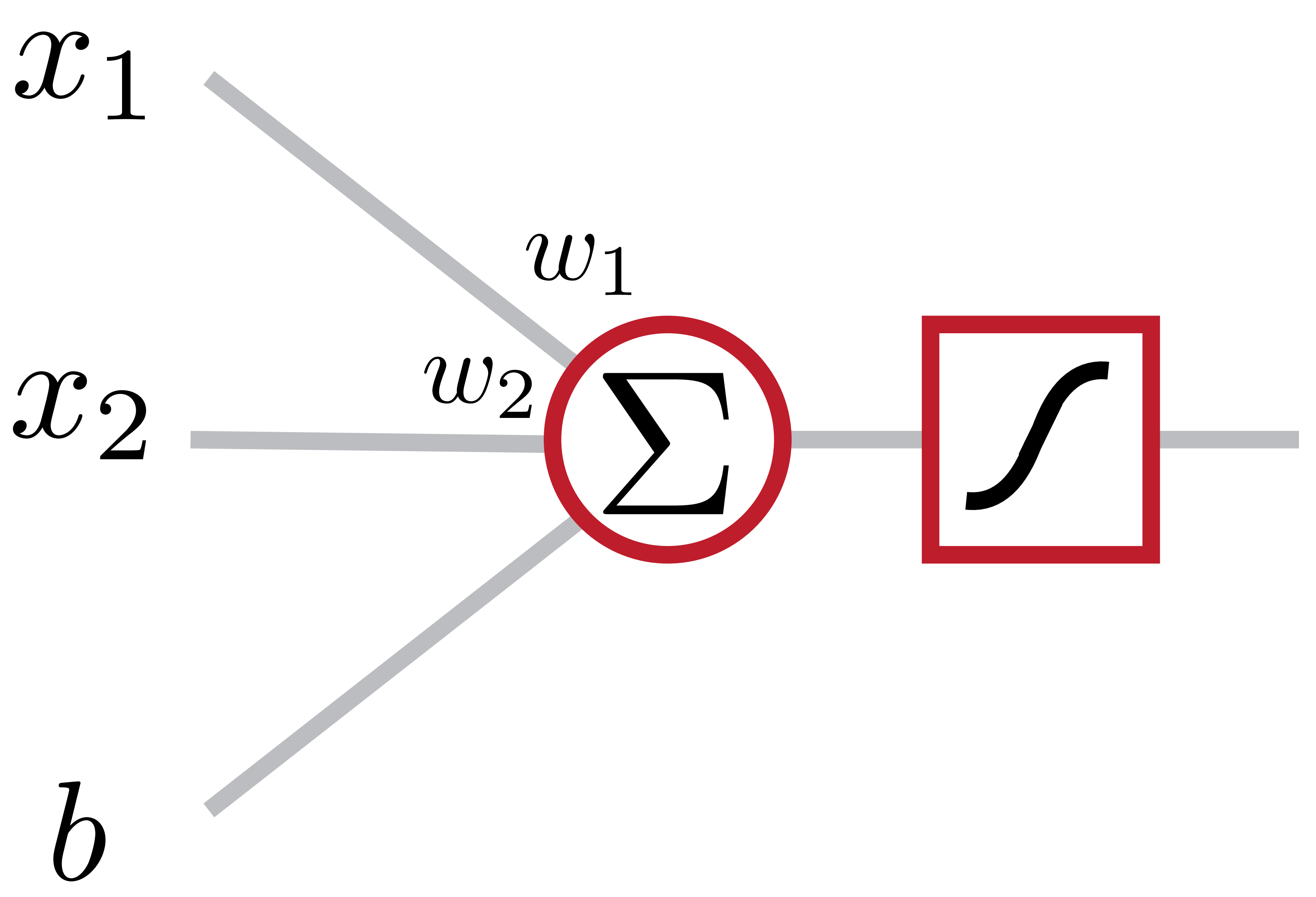


Class 0 or class 1?

Frank Rosenblatt (1957)
"The Perceptron — a perceiving and recognizing automaton."
Report 85–460–1, Cornell Aeronautical Laboratory.

Classification with the perceptron





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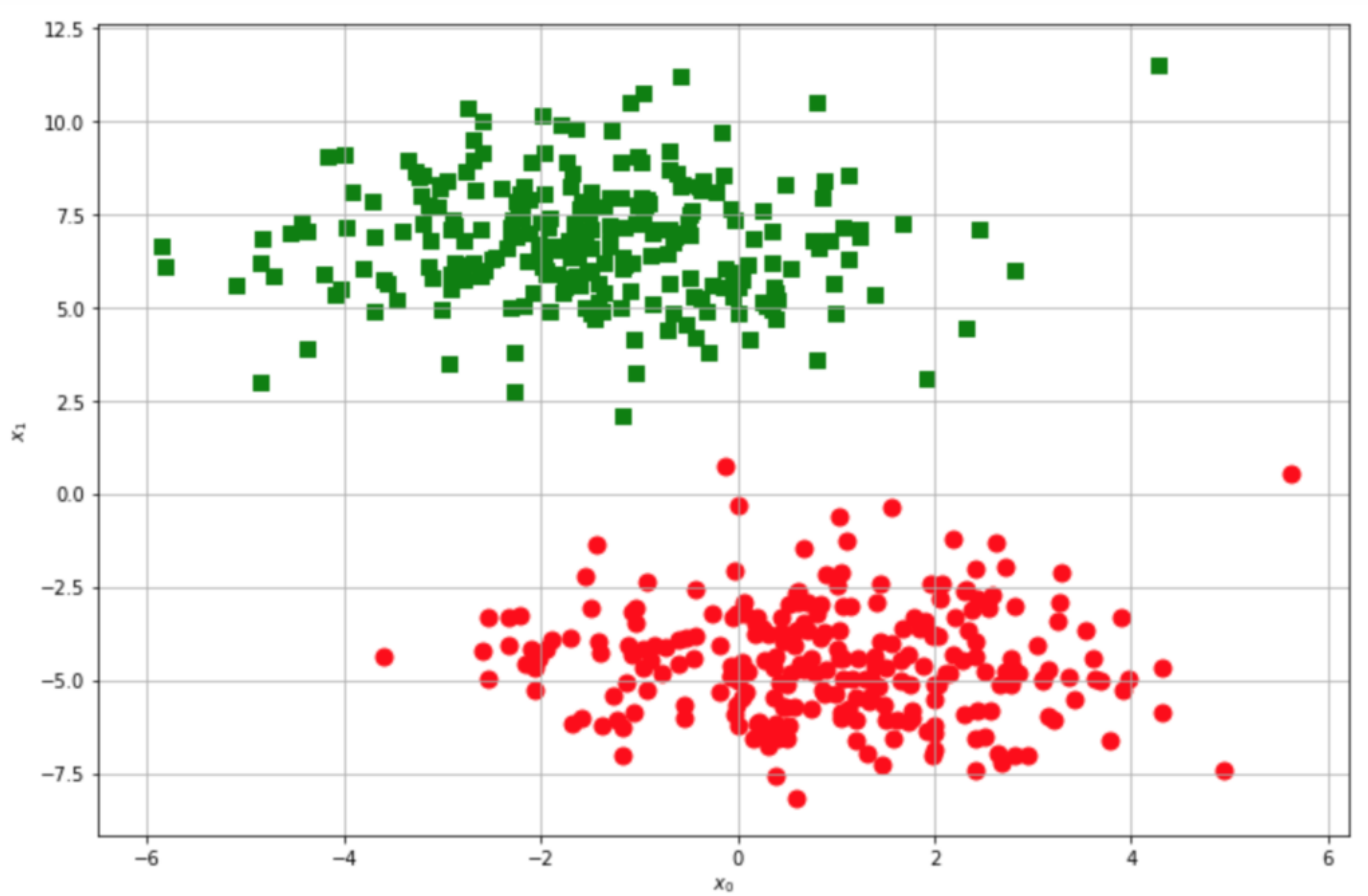
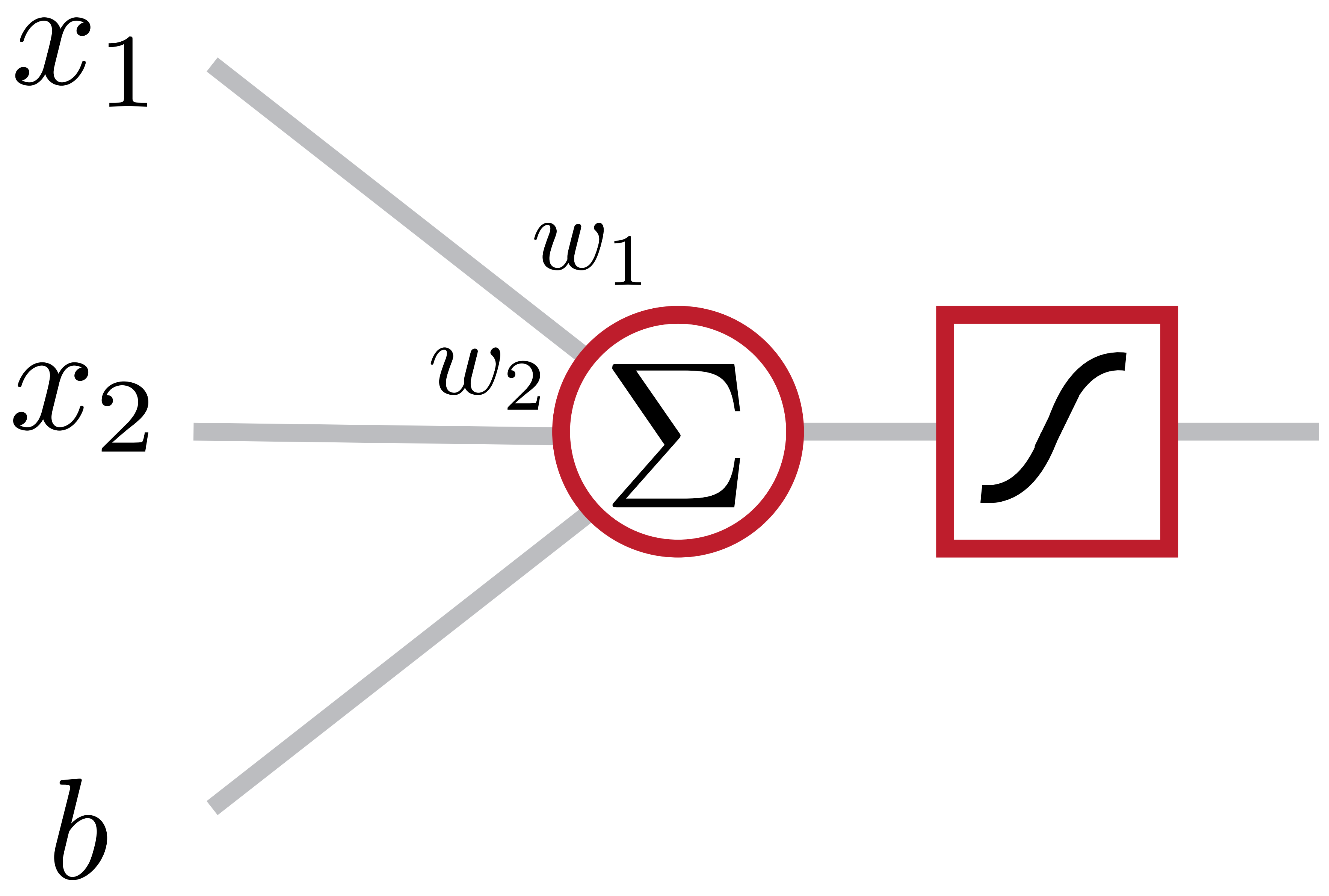
Classification with the perceptron





class 0
or
class 1?

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \bullet \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} + b$$

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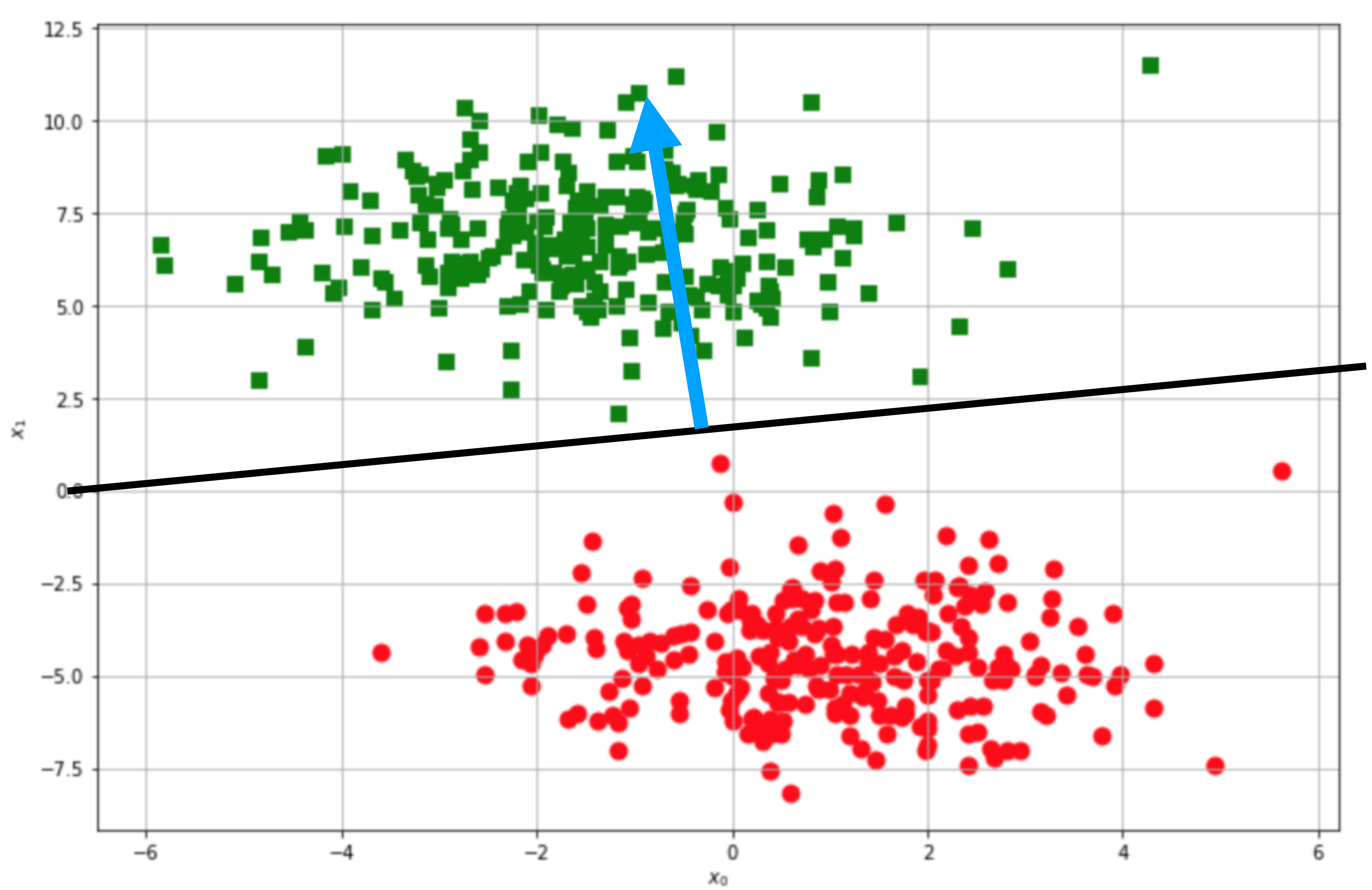
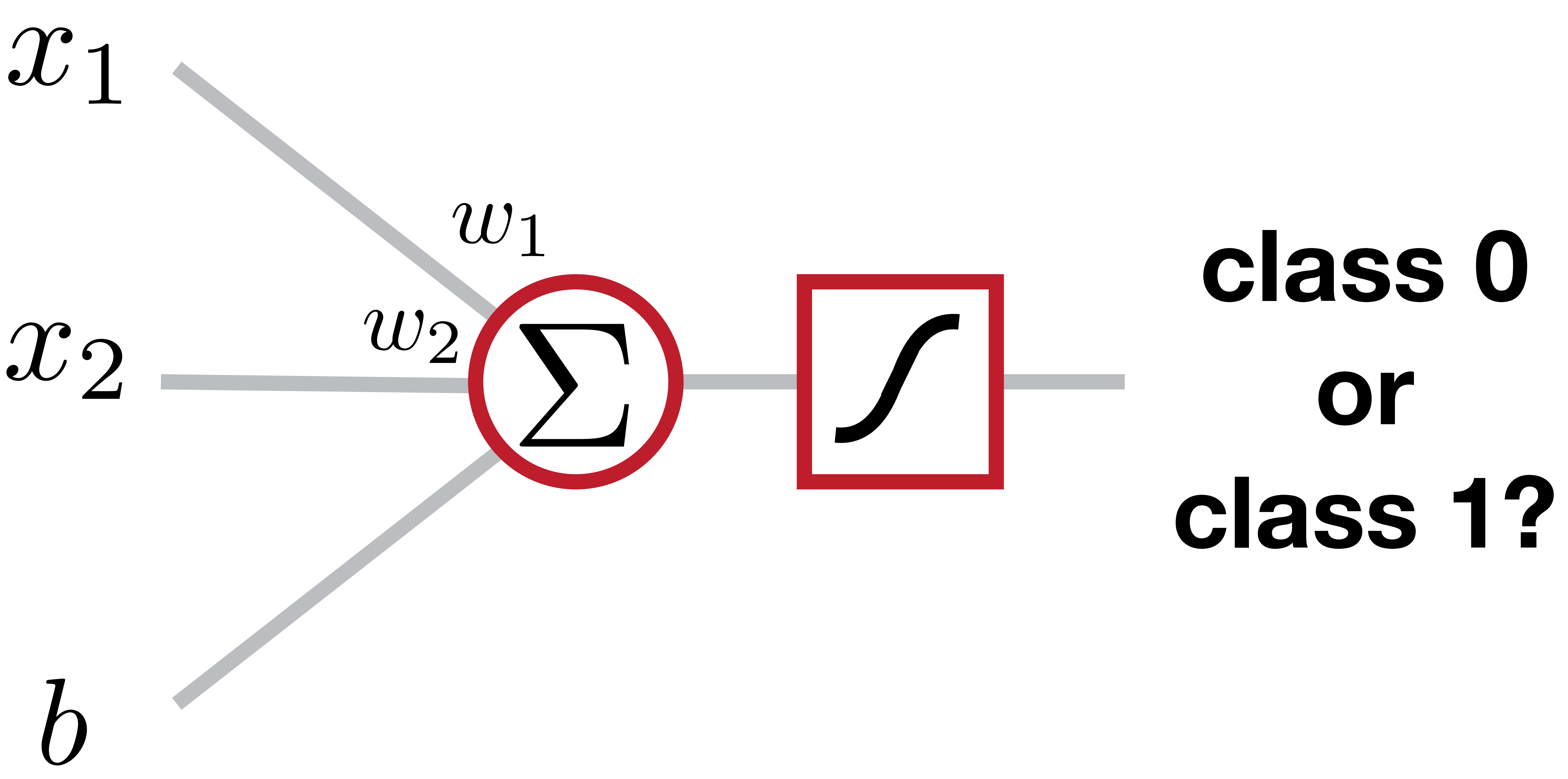
Classification with the perceptron





$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \bullet \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} + b$$

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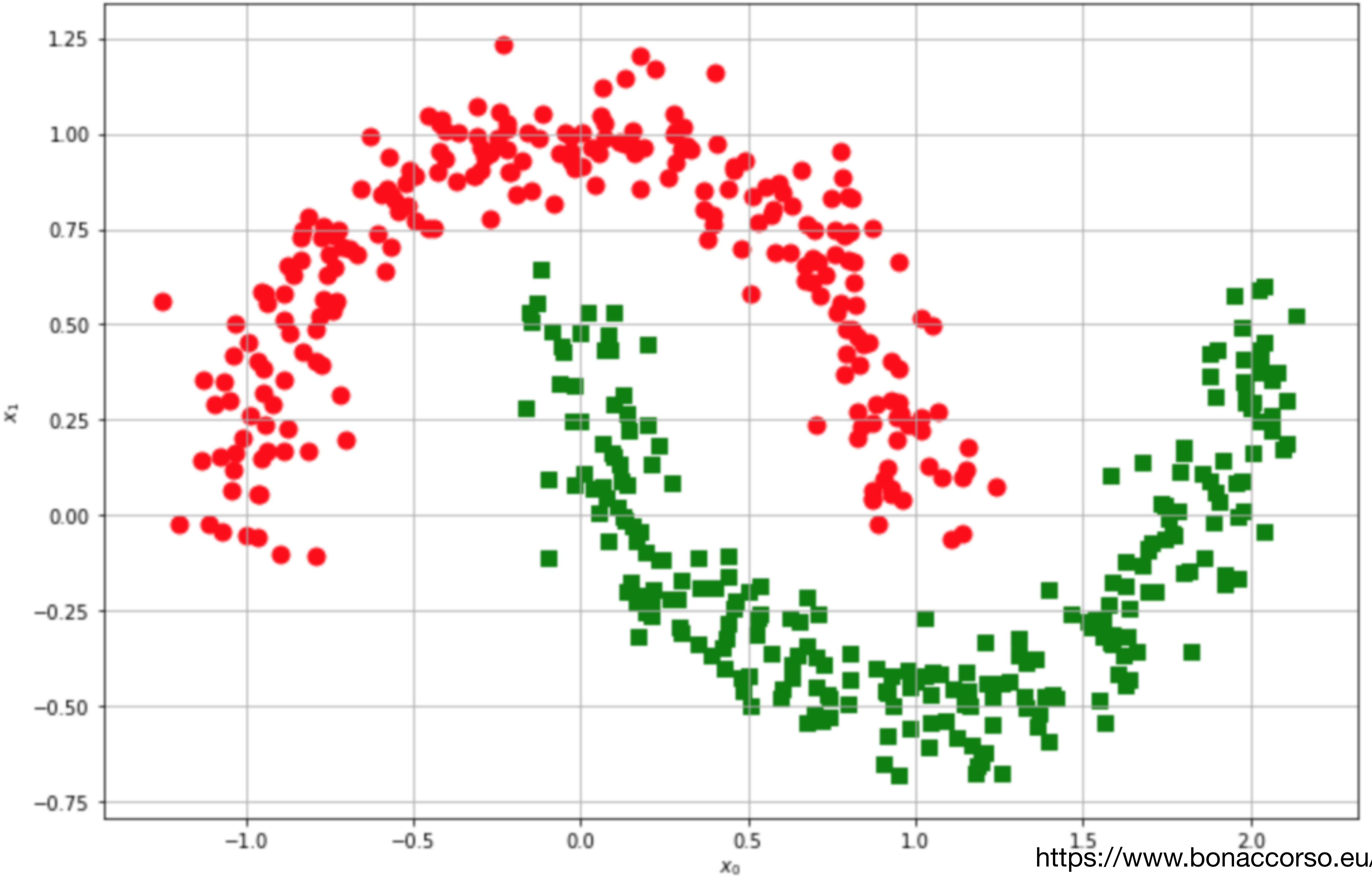
Harder problem



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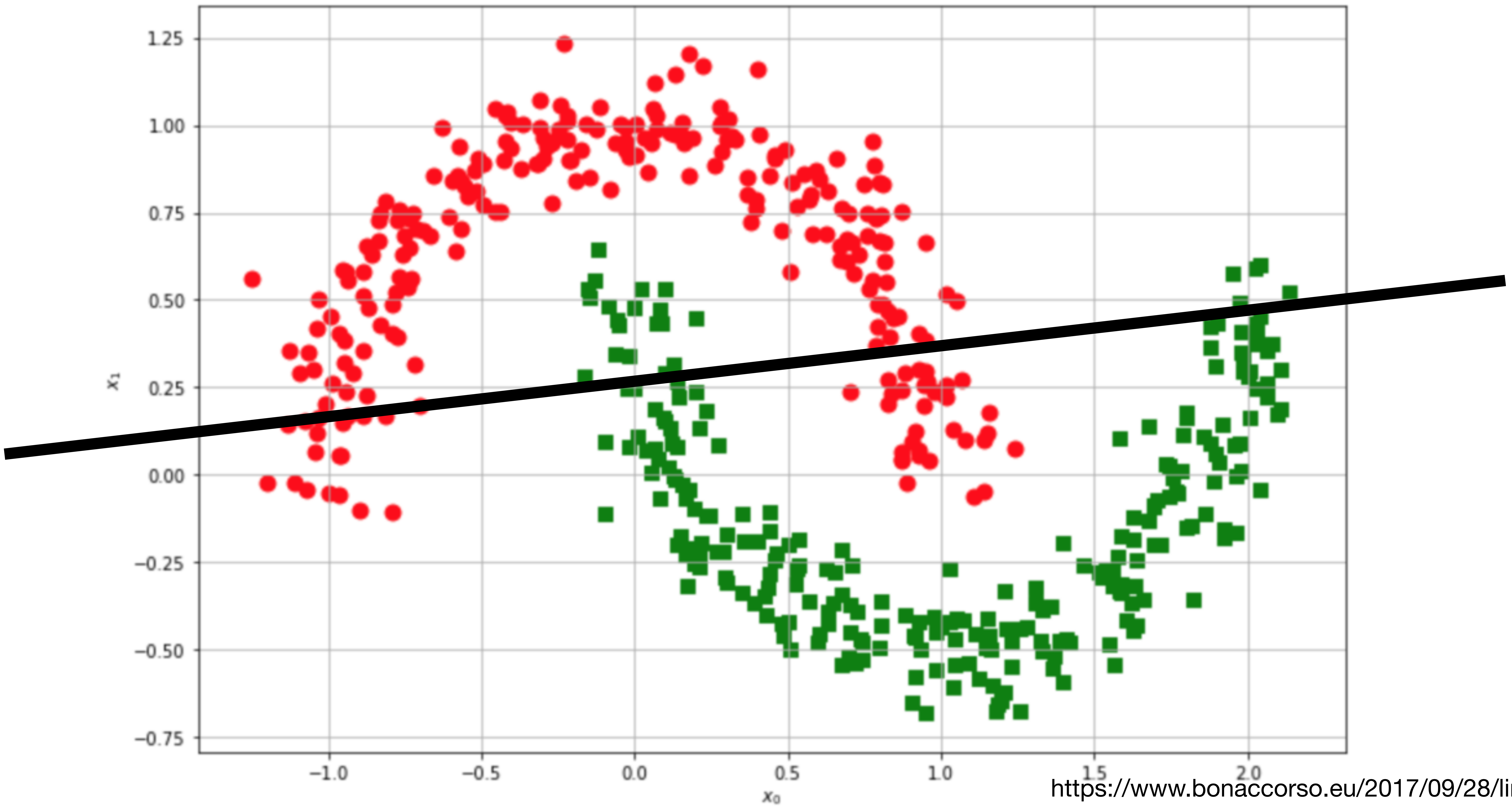

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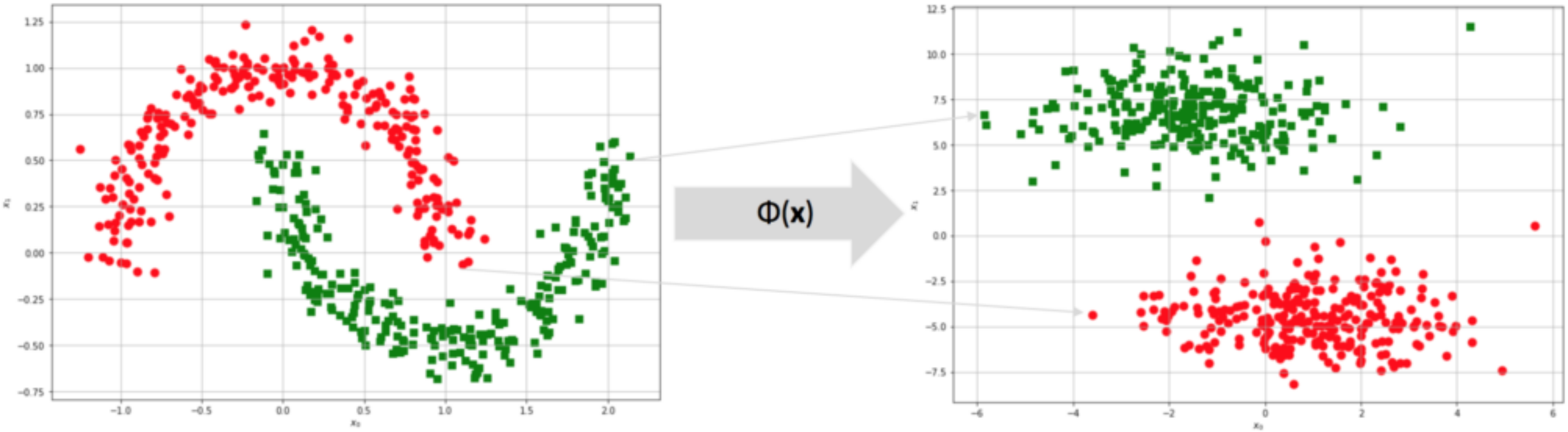
Strategy - multiple transformations



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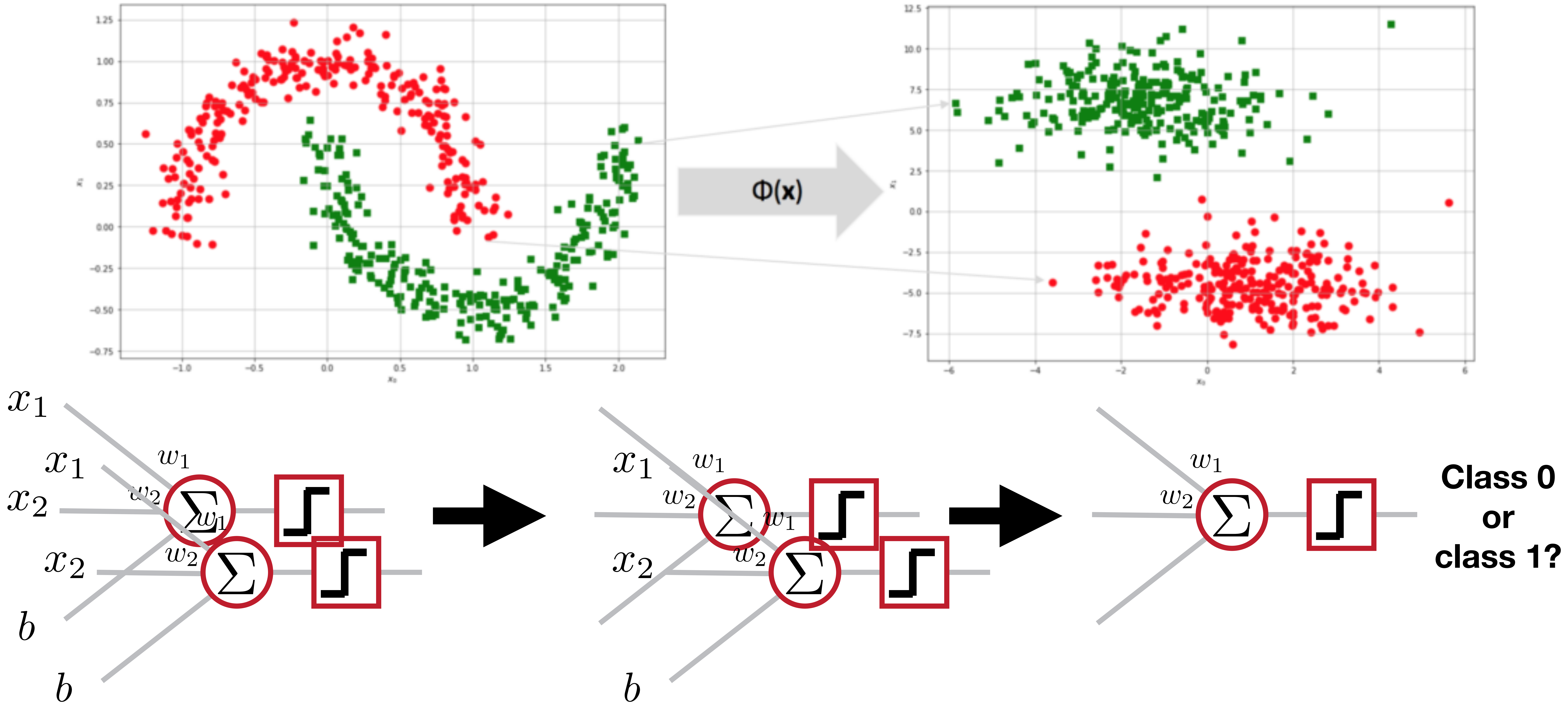
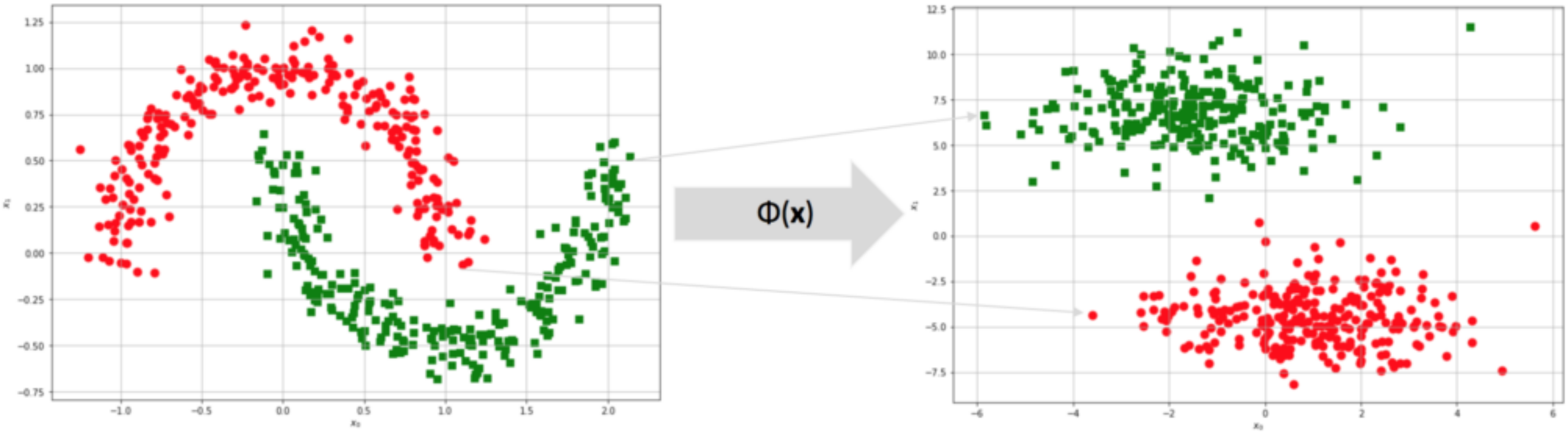
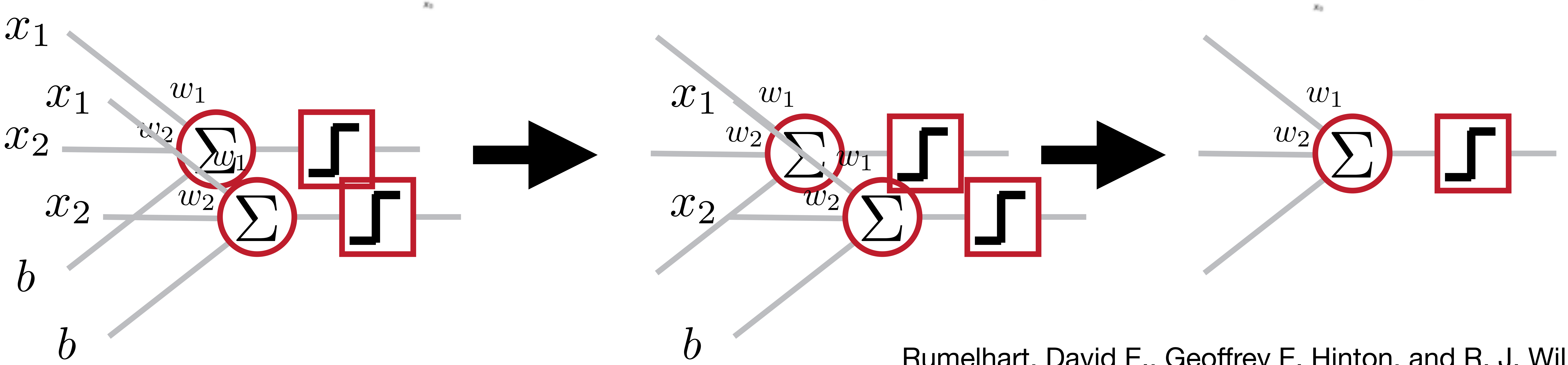
Multi-layer Perceptron (MLP)

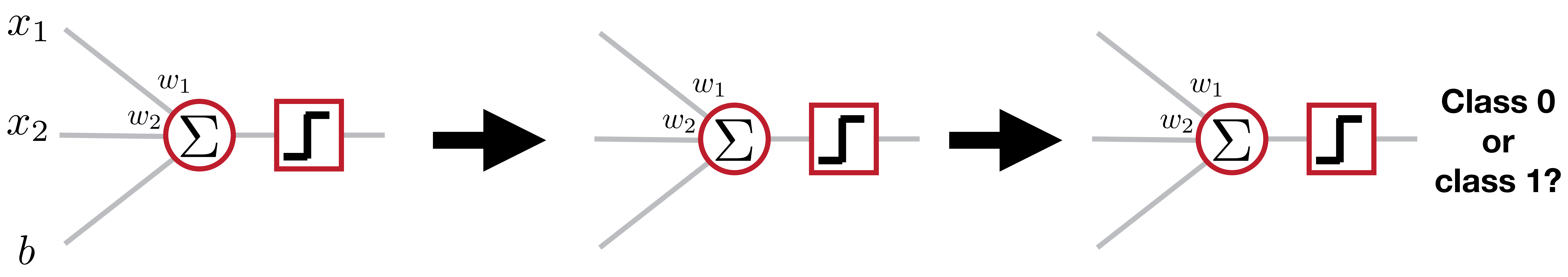


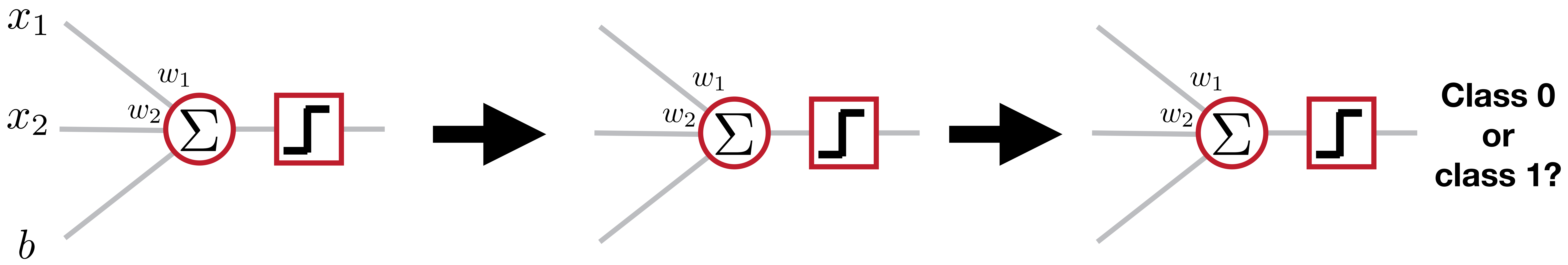
Multi-layer Perceptron (MLP)



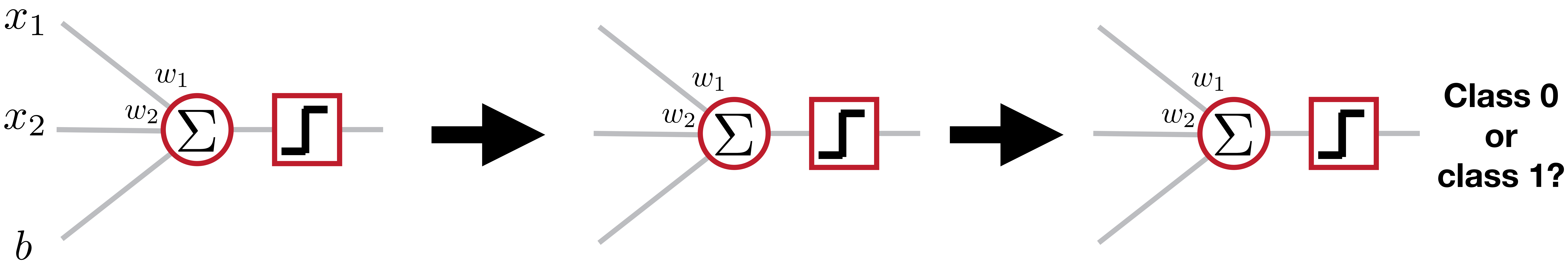


Rumelhart, David E., Geoffrey E. Hinton, and R. J. Williams. (1986) "Learning Internal Representations by Error Propagation". *Parallel distributed processing*


x_1
x_2
b
w_1
w_2
Σ
Class 0
or
class 1?

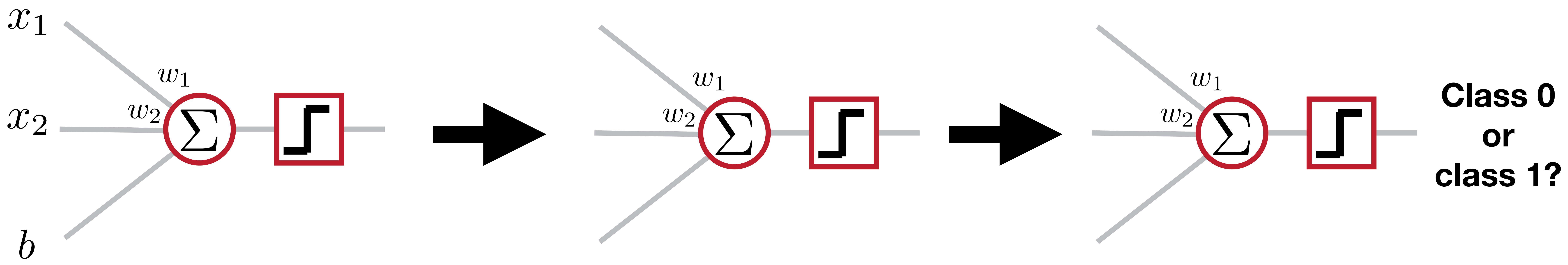


What are the parameters?



What are the parameters?

What is the objective (loss)?



What are the parameters?

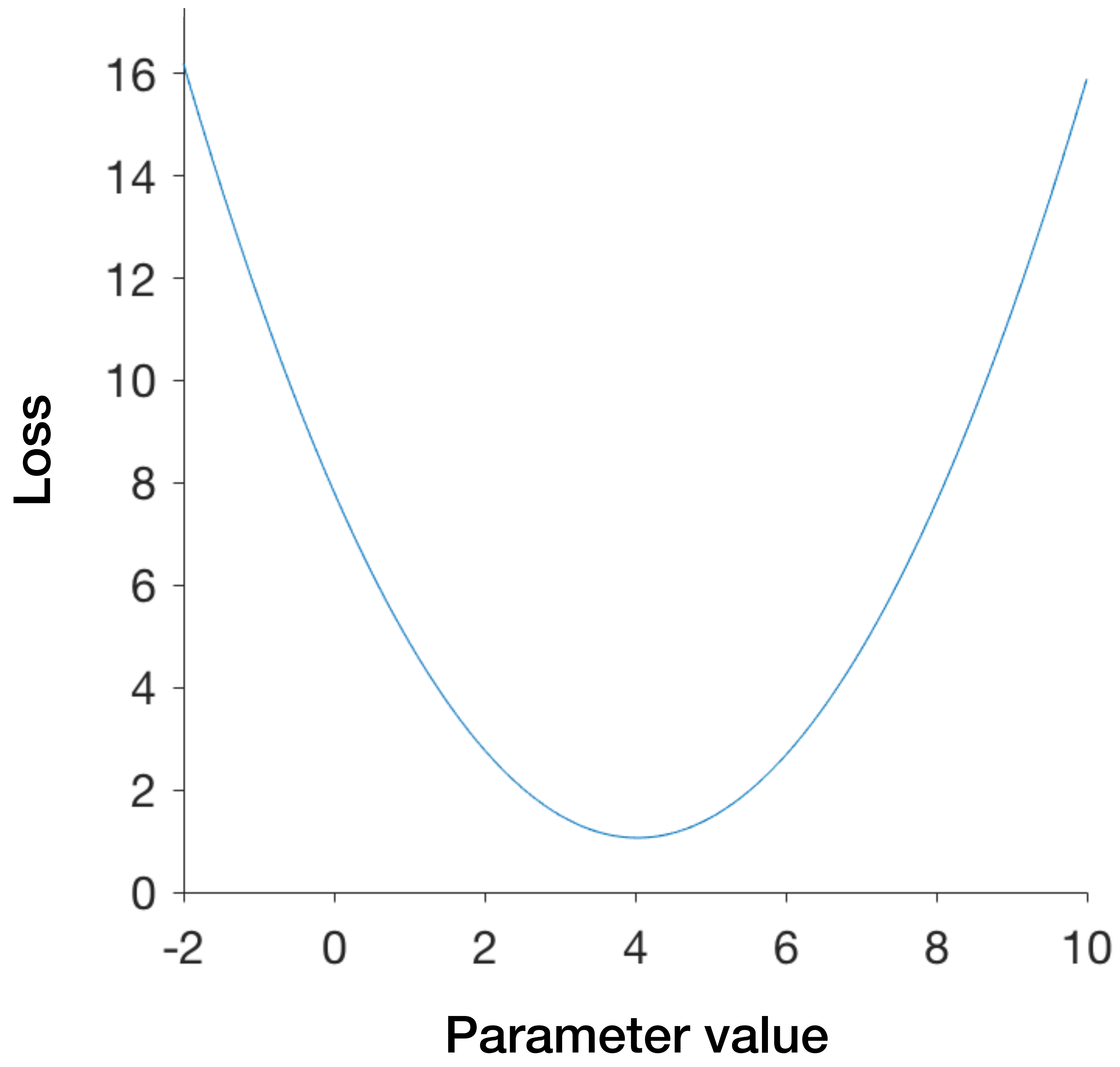
What is the objective (loss)?

How do we find the parameters?

Gradient descent for one parameter

(a.k.a., “try something, then keep trying to make it better”)

Loss landscape = loss for different parameter values



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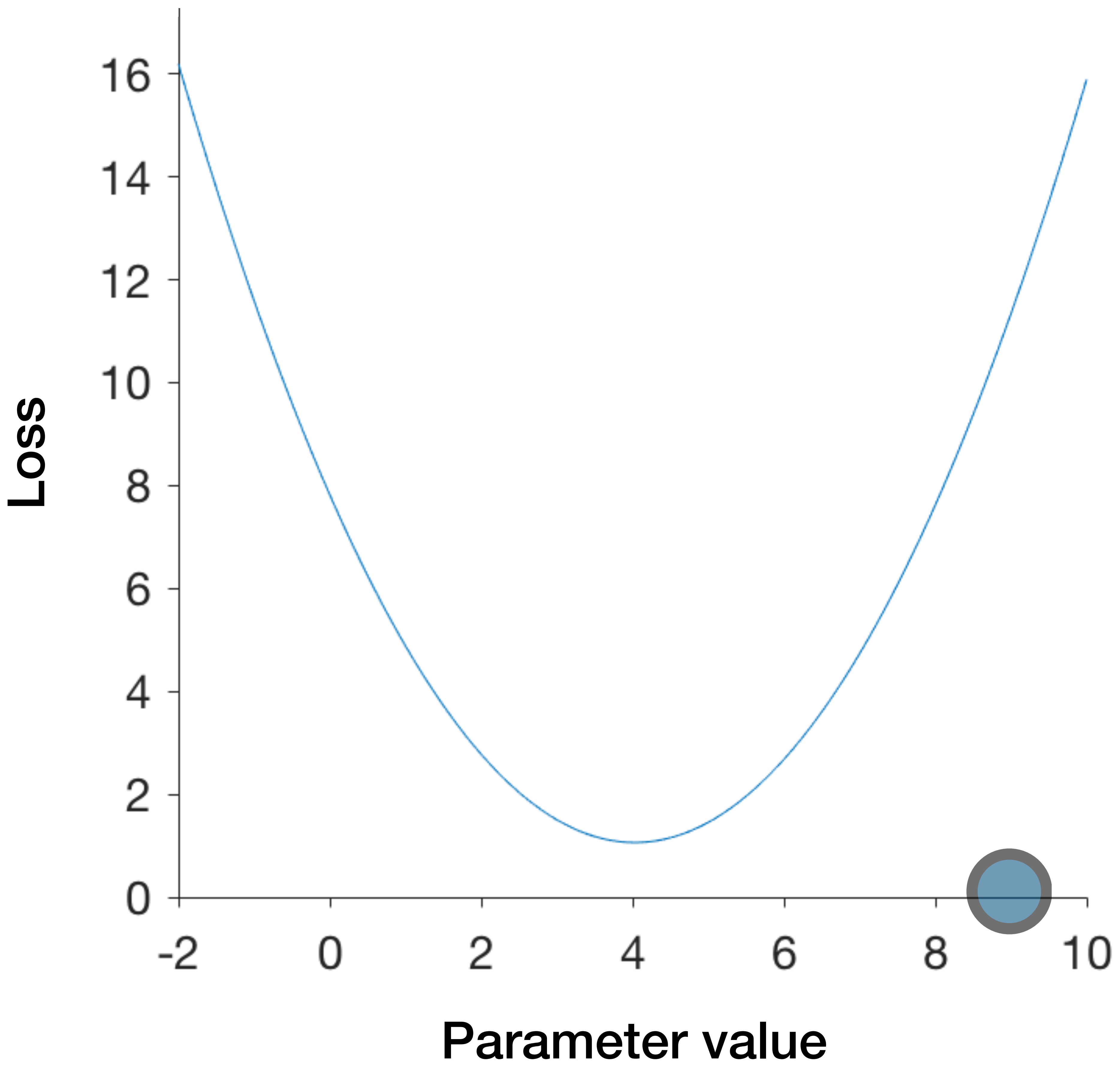

1. Guess a parameter value

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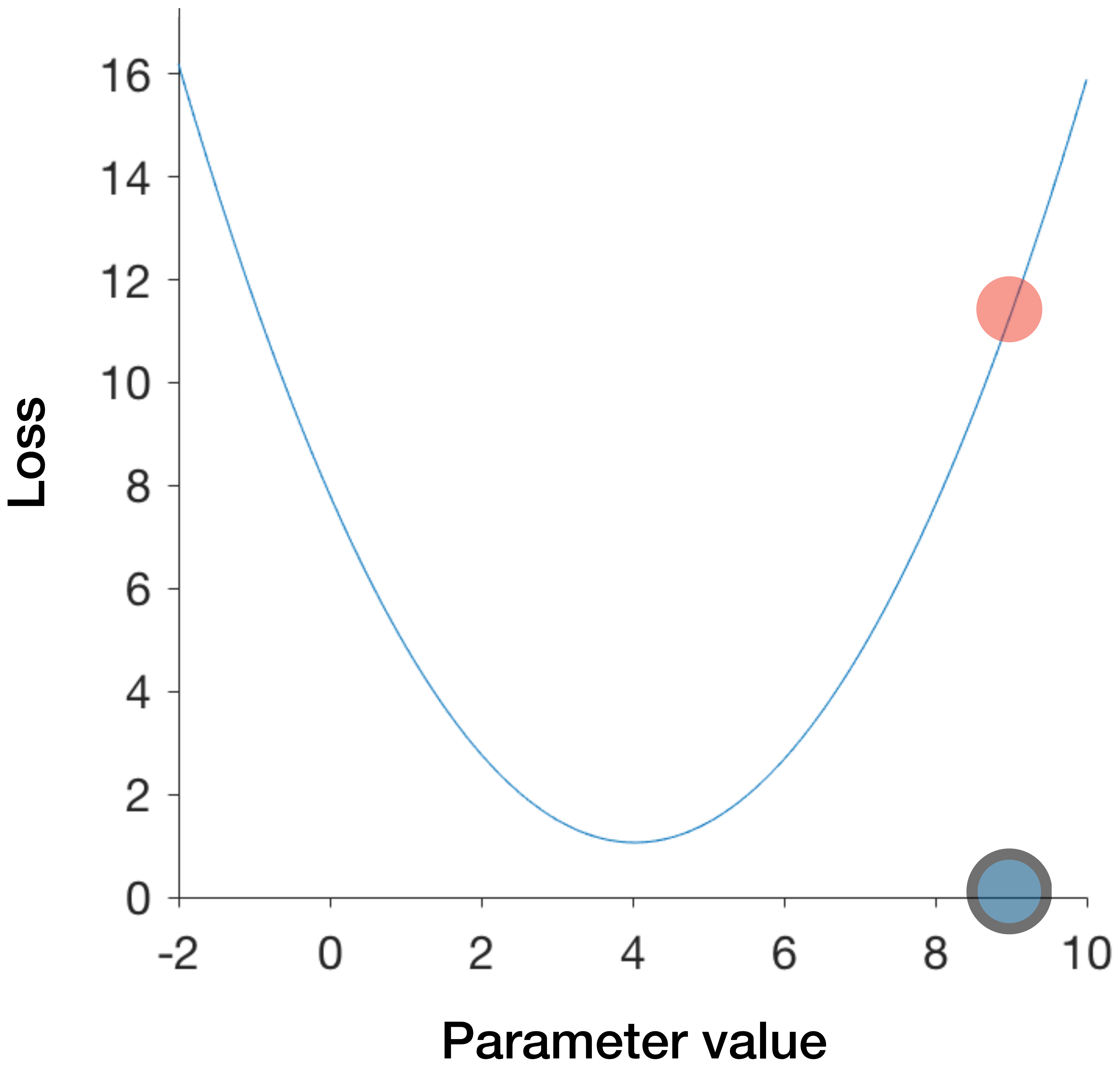

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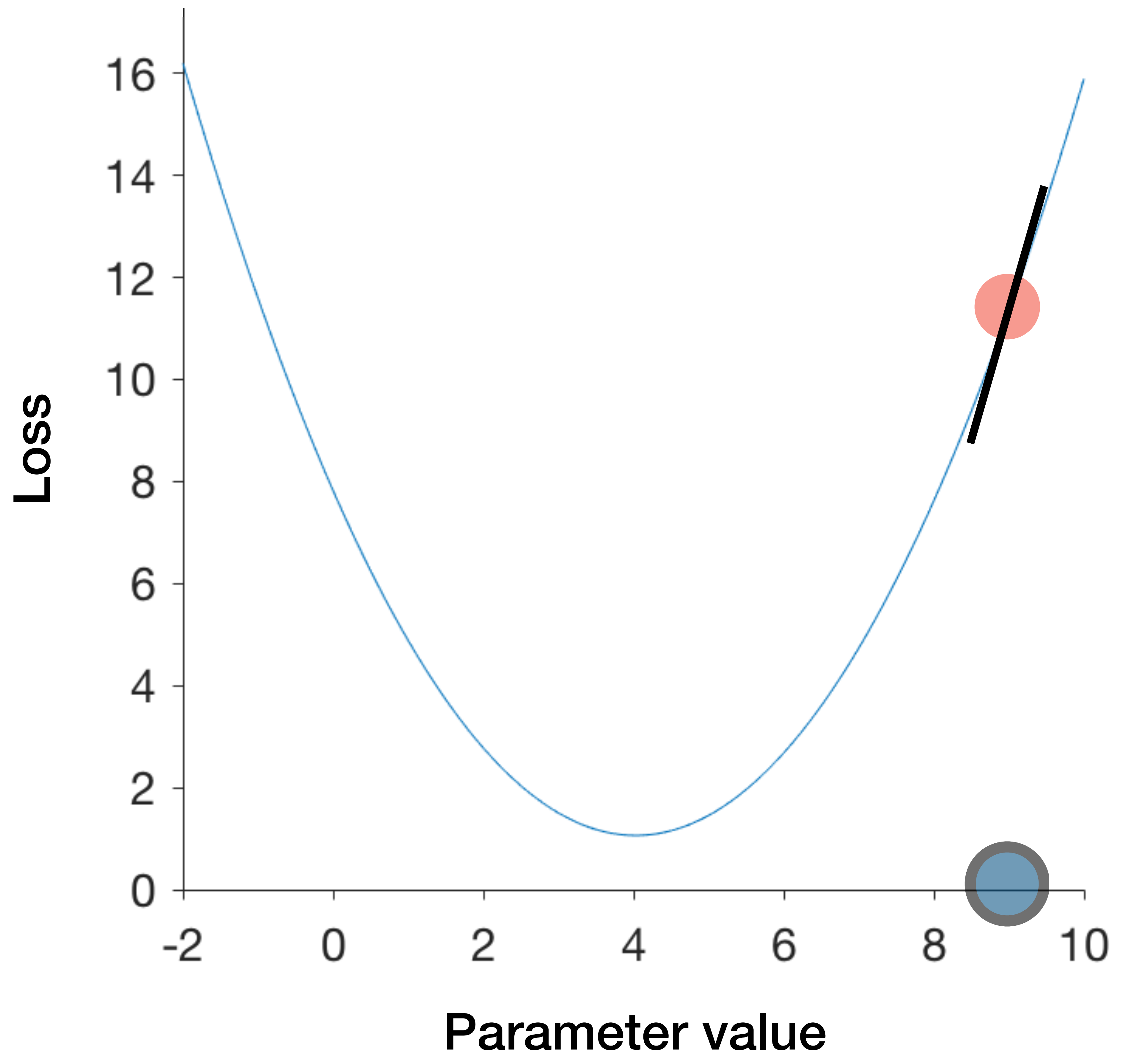

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3. Calculate loss derivative w.r.t. parameter (gradient)

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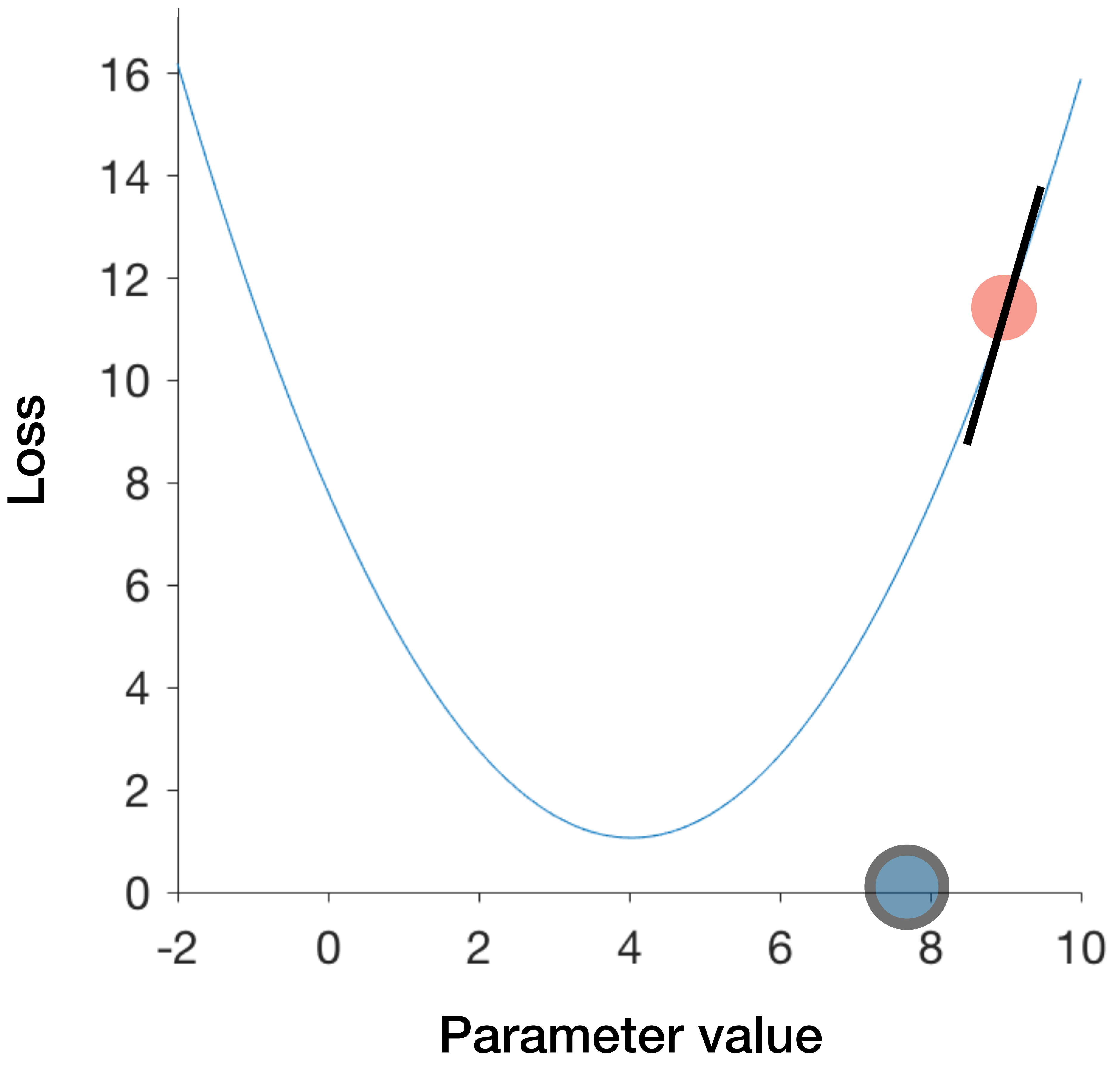

1. Guess a parameter value
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4. Step down the gradient

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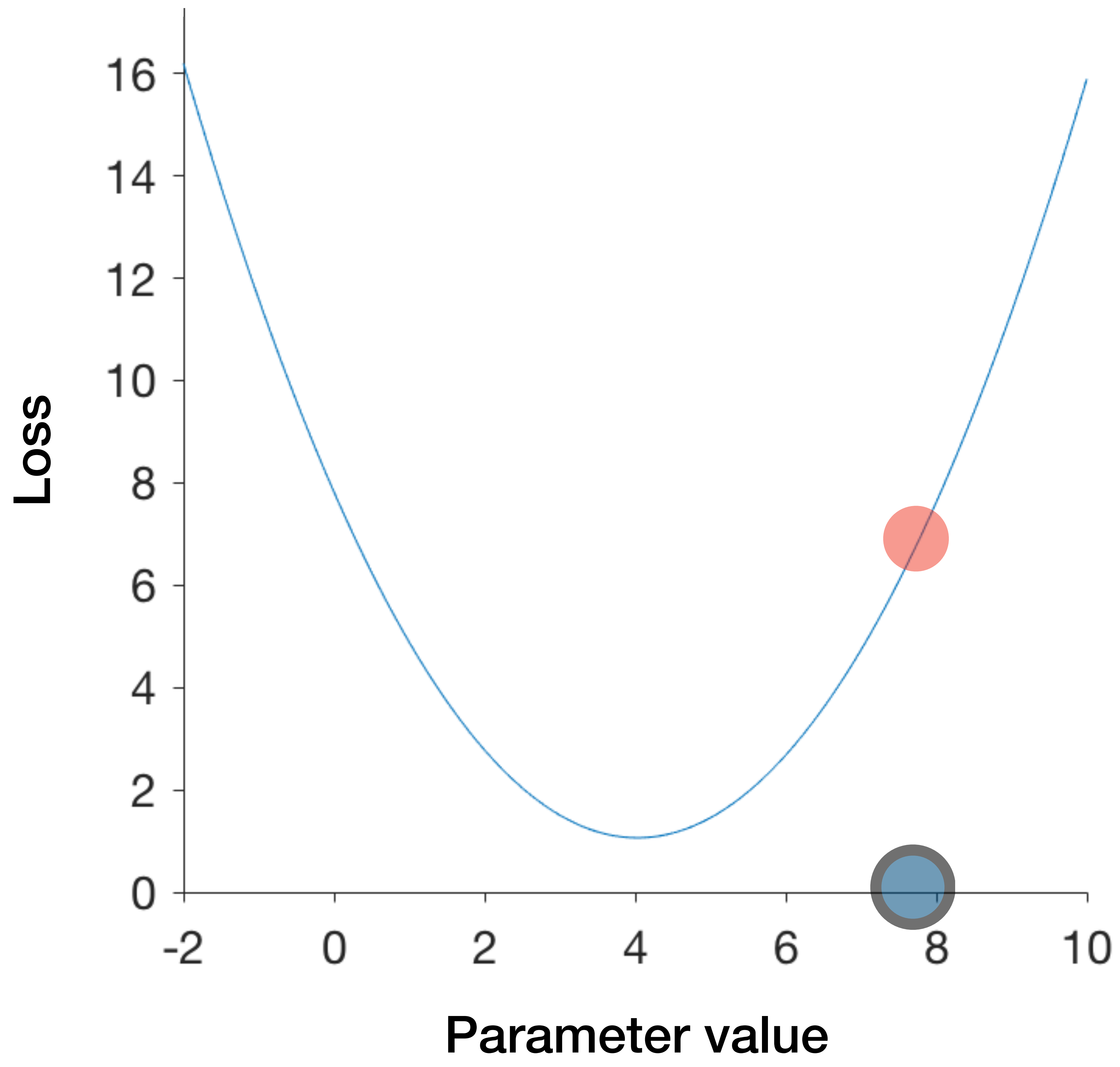

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3. Calculate loss derivative w.r.t. parameter (gradient)

4. Step down the gradient

5. Repeat!

Gradient descent for one parameter

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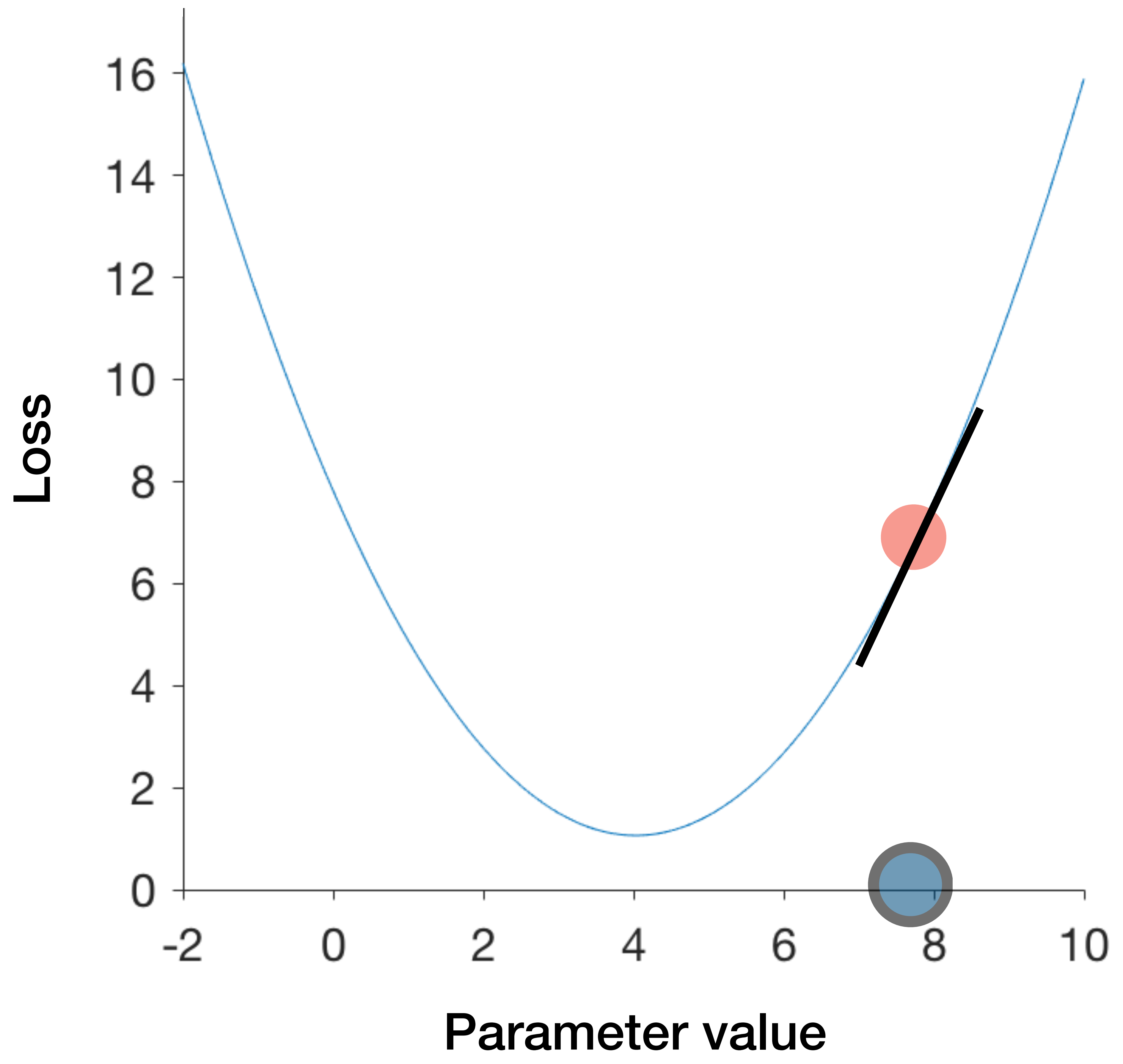

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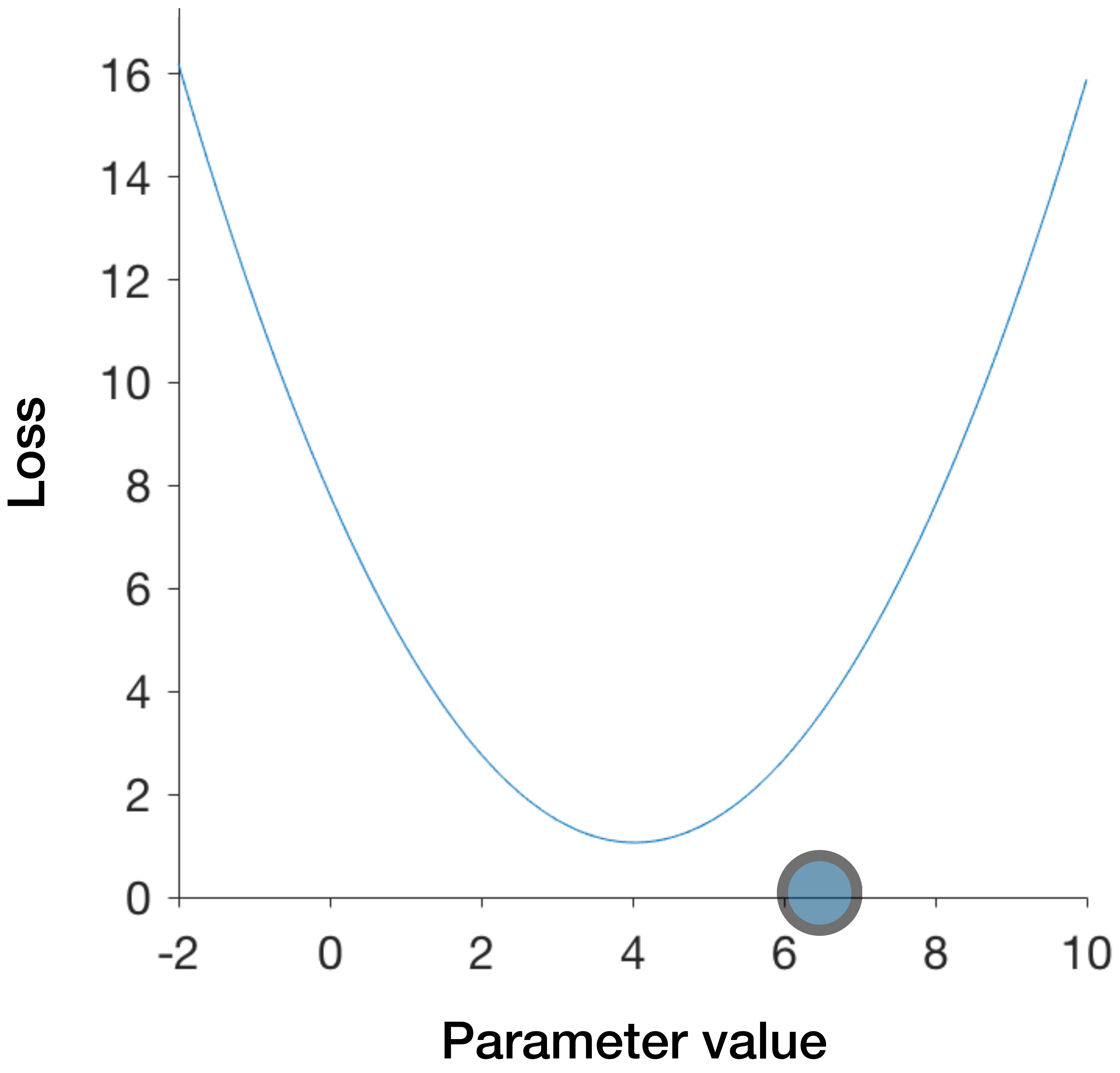

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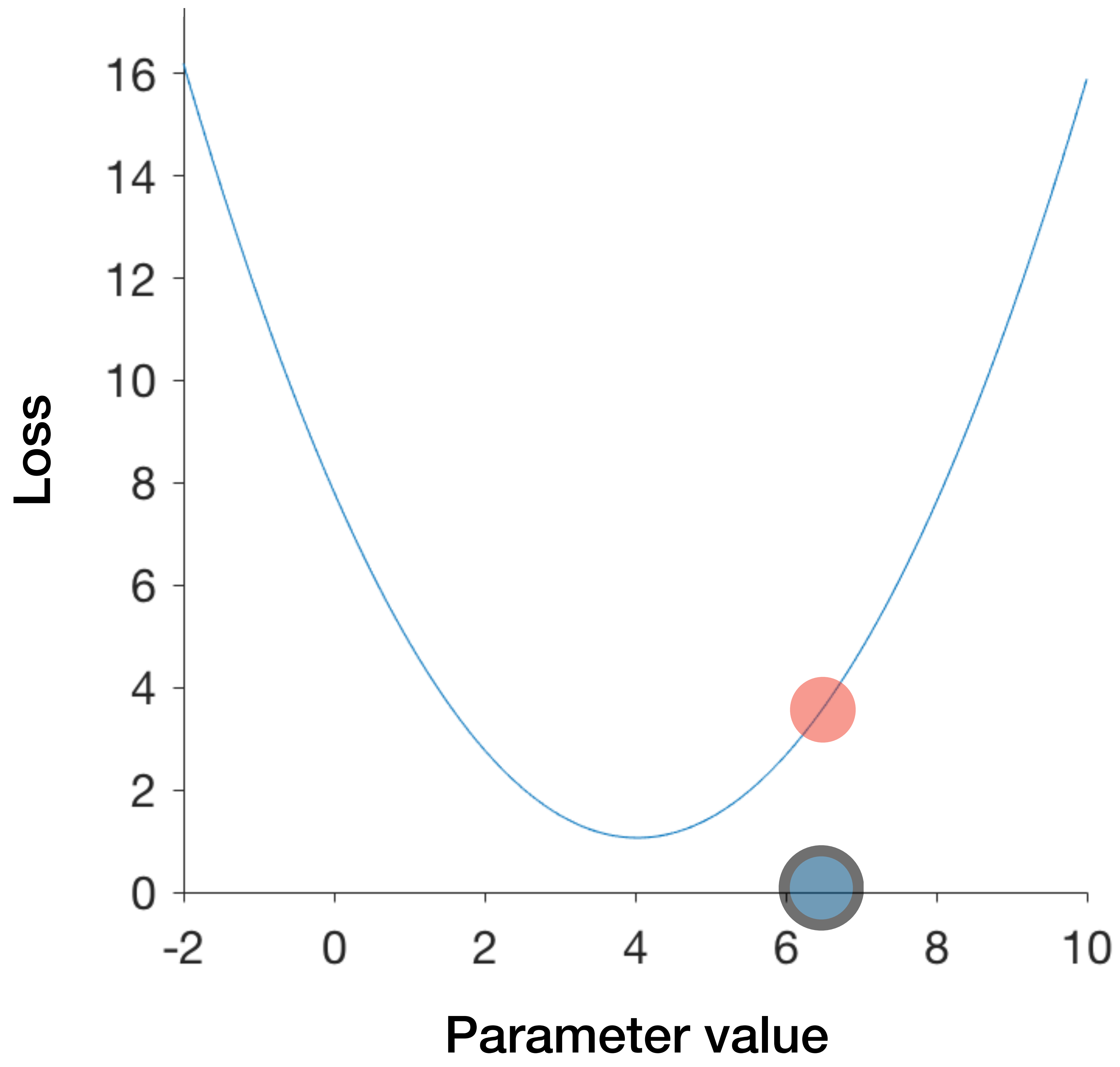

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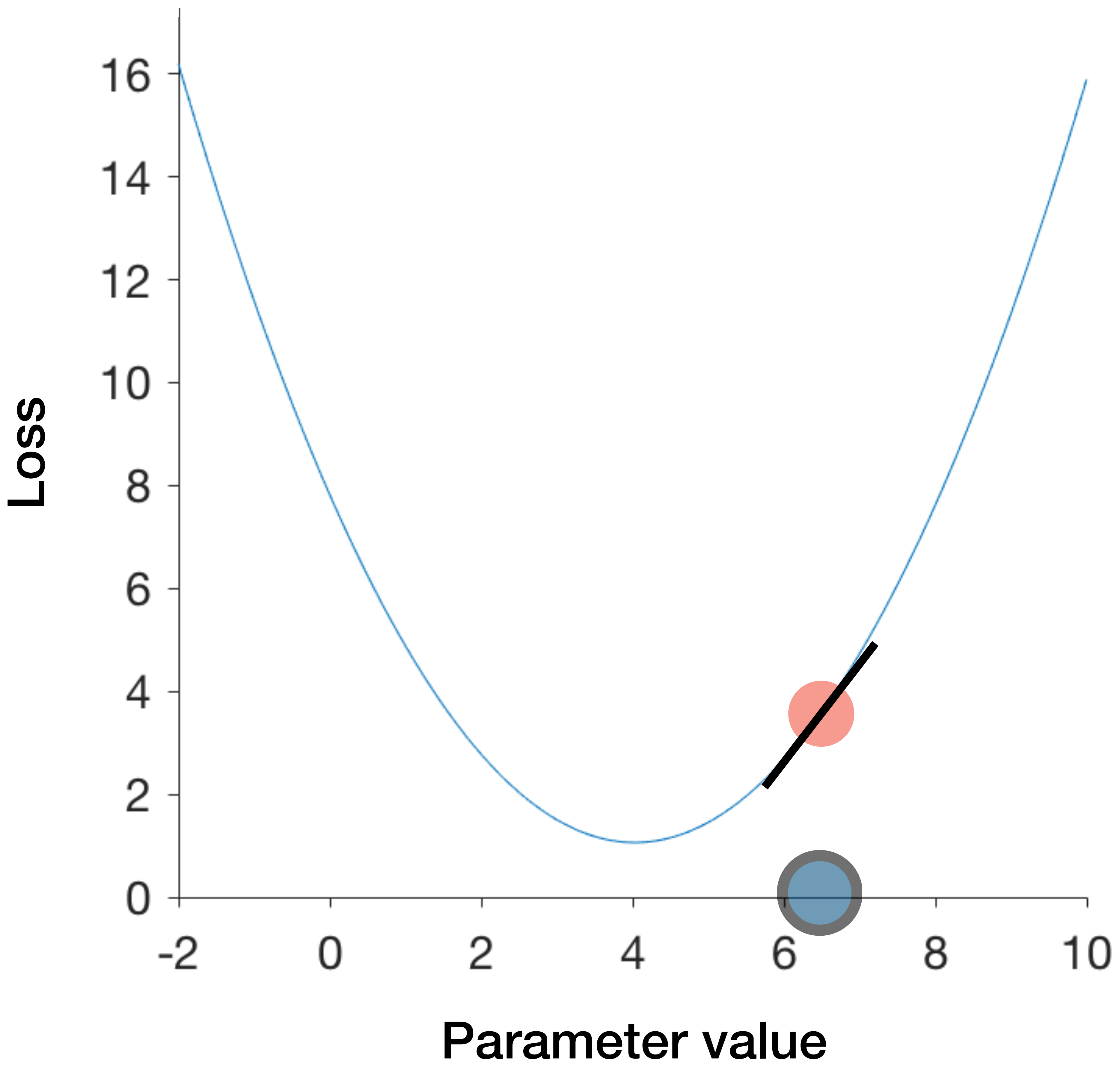

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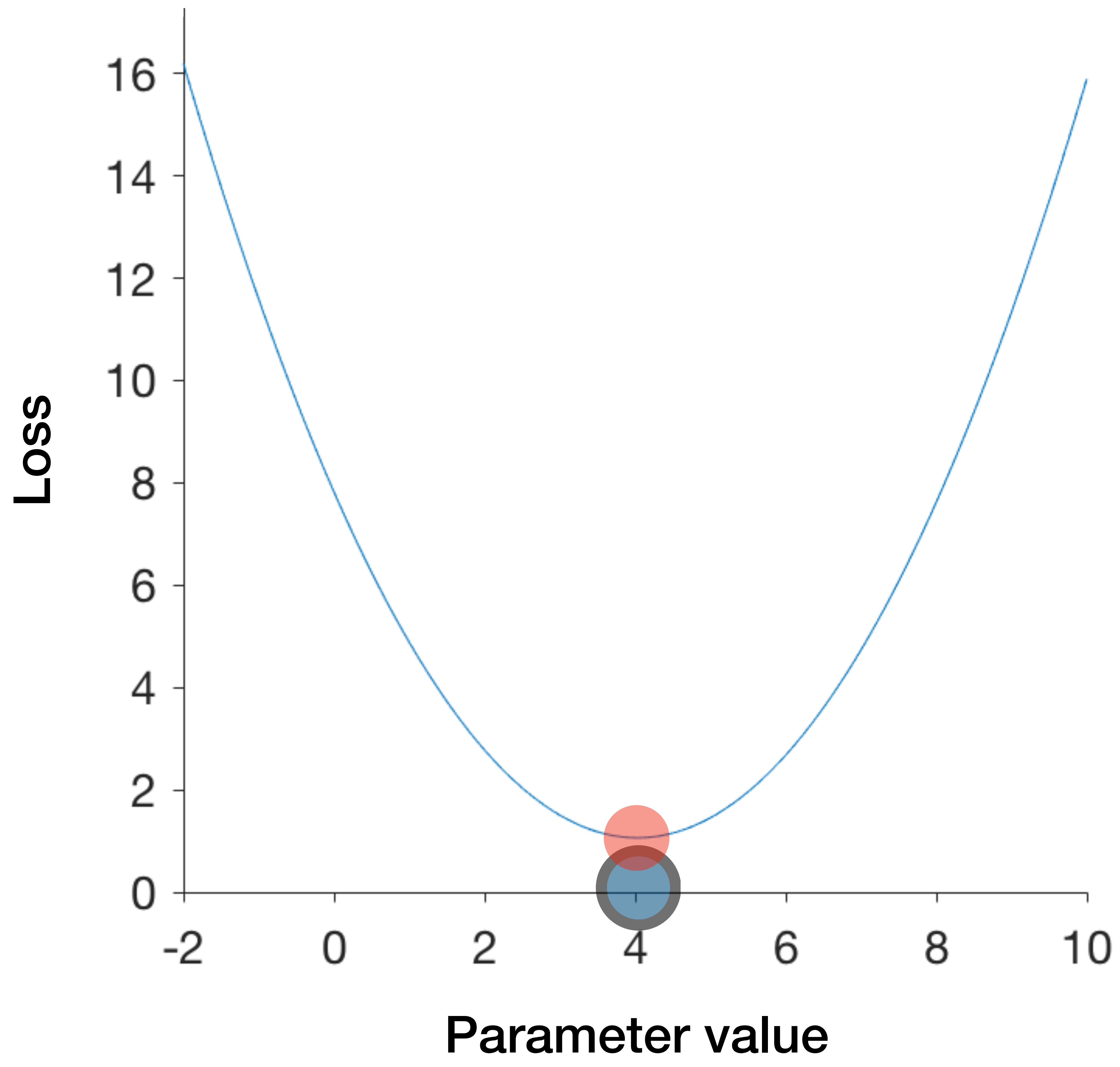

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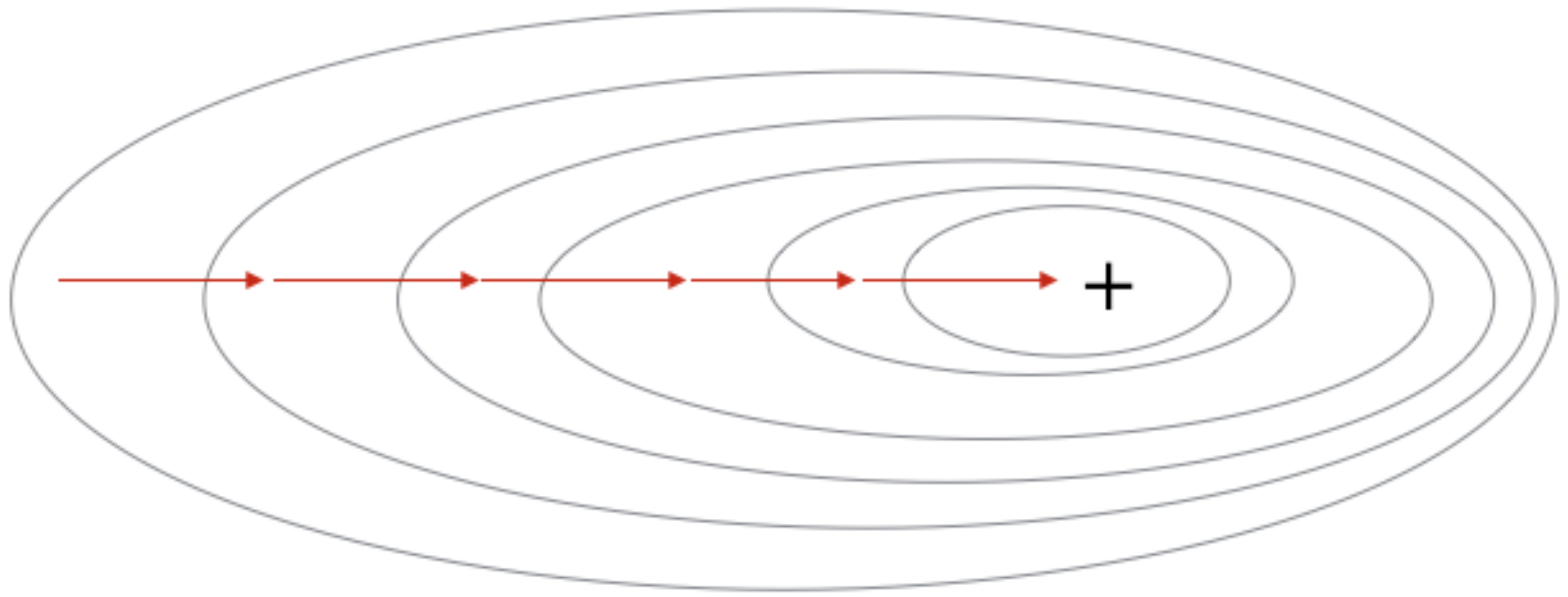
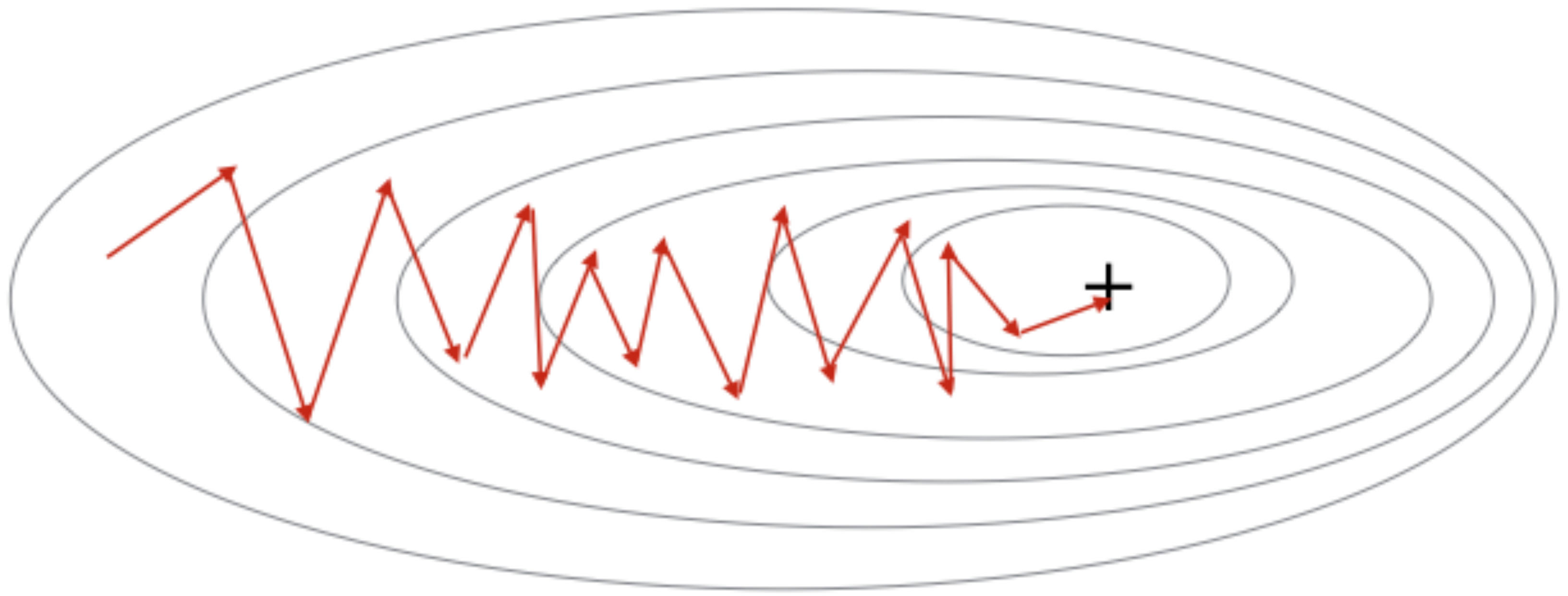
Gradient Descent and Stochastic Gradient Descent

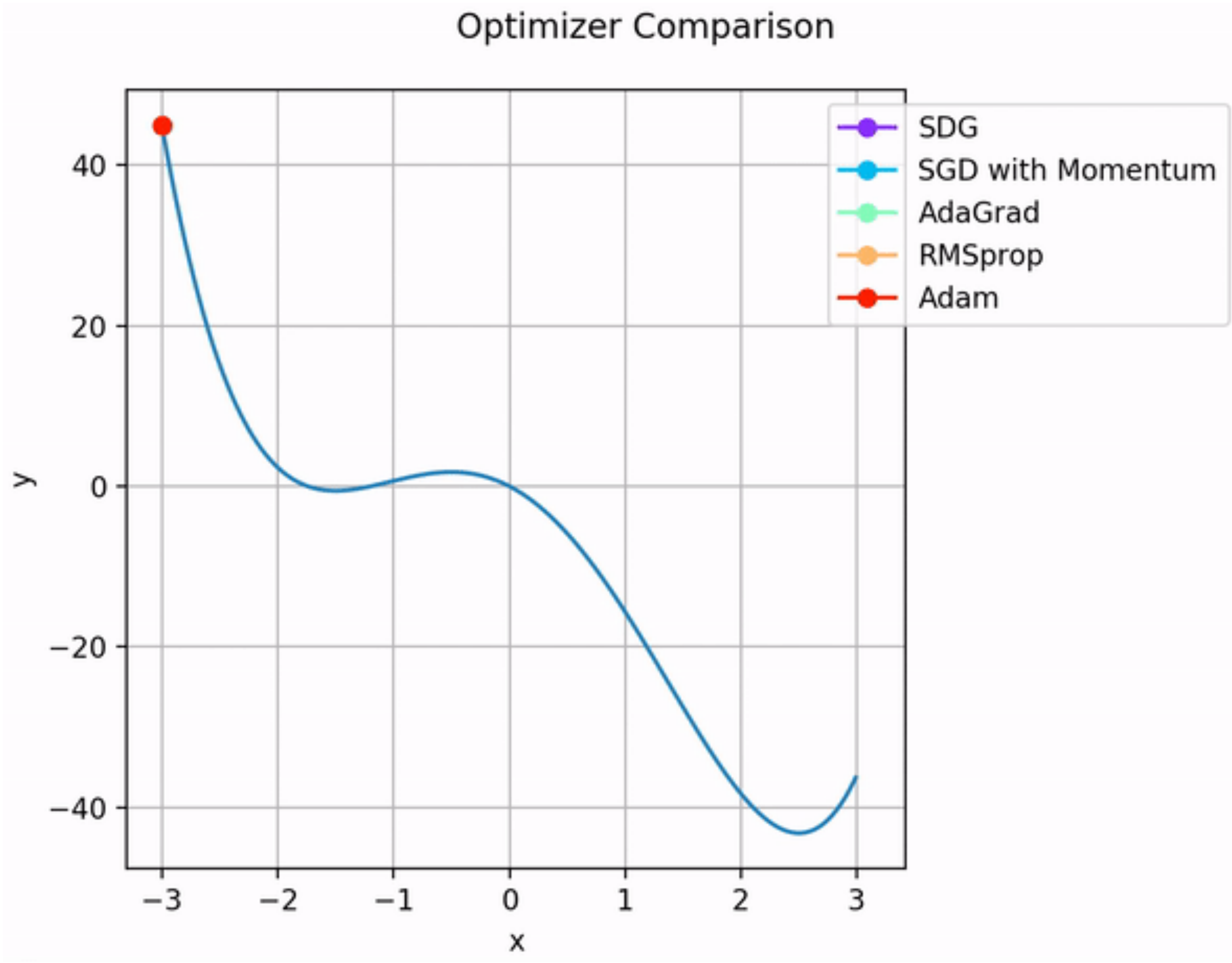
Gradient Descent



Stochastic Gradient Descent



https://towardsdatascience.com/complete-guide-to-adam-optimization-1e5f29532c3d



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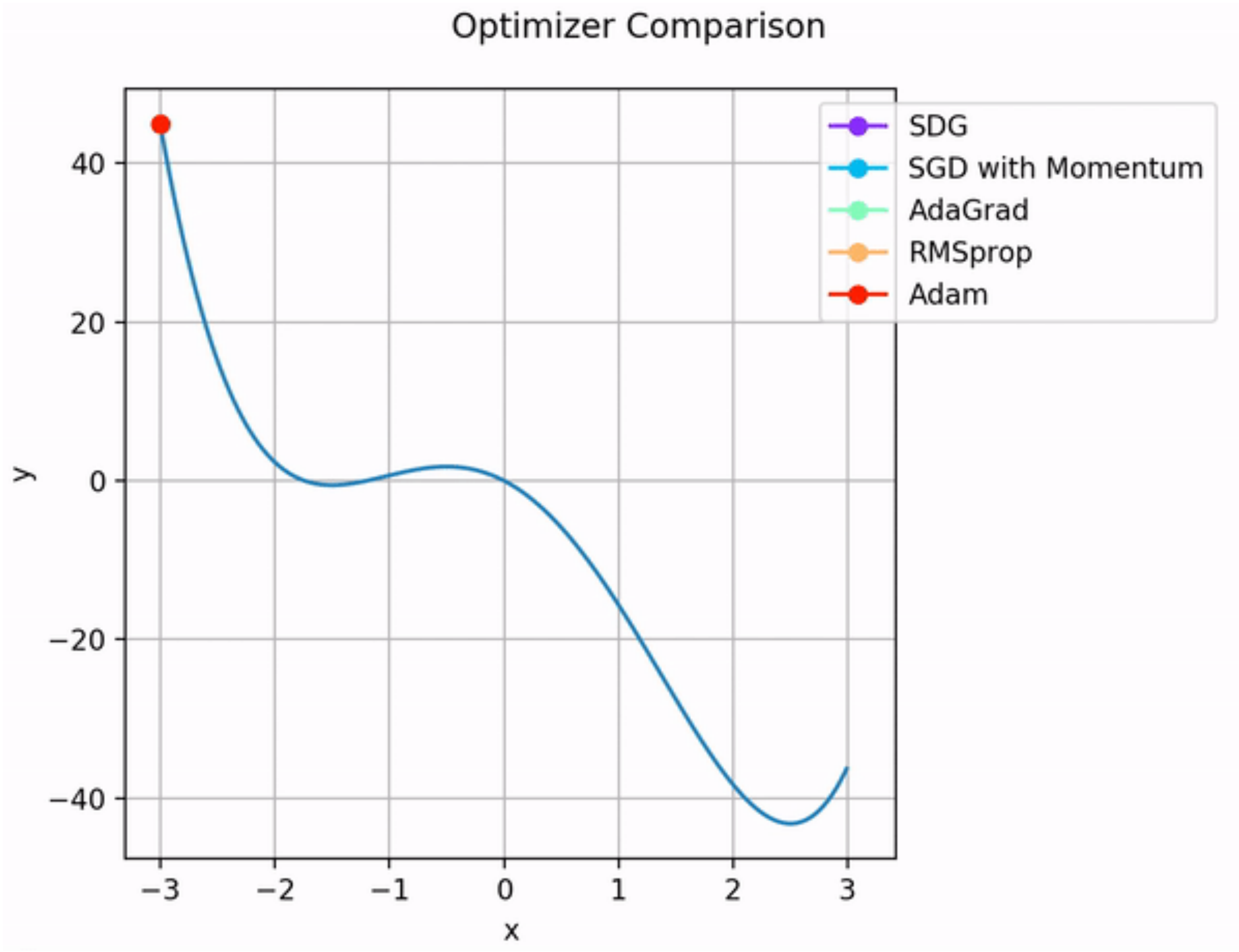

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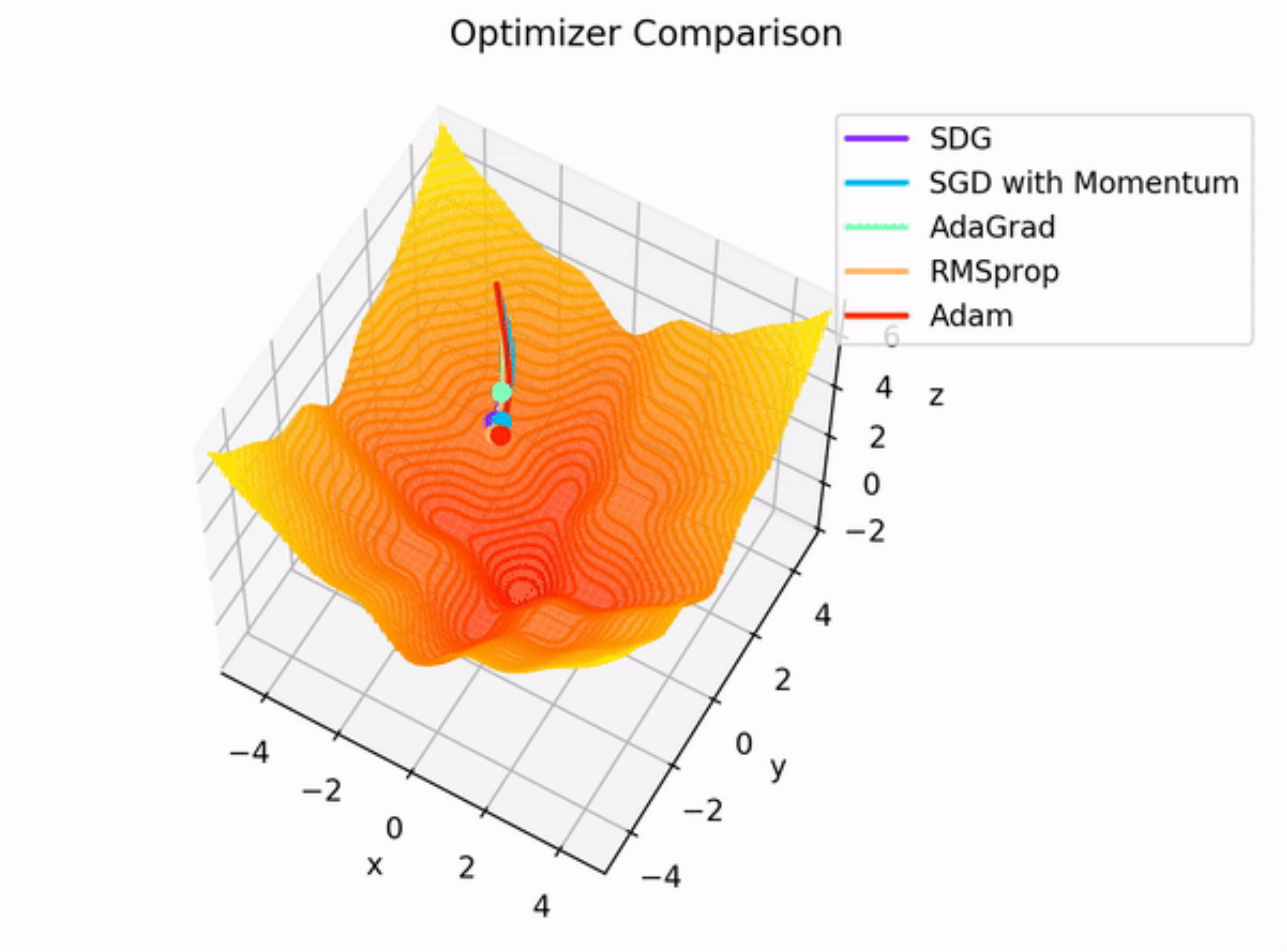

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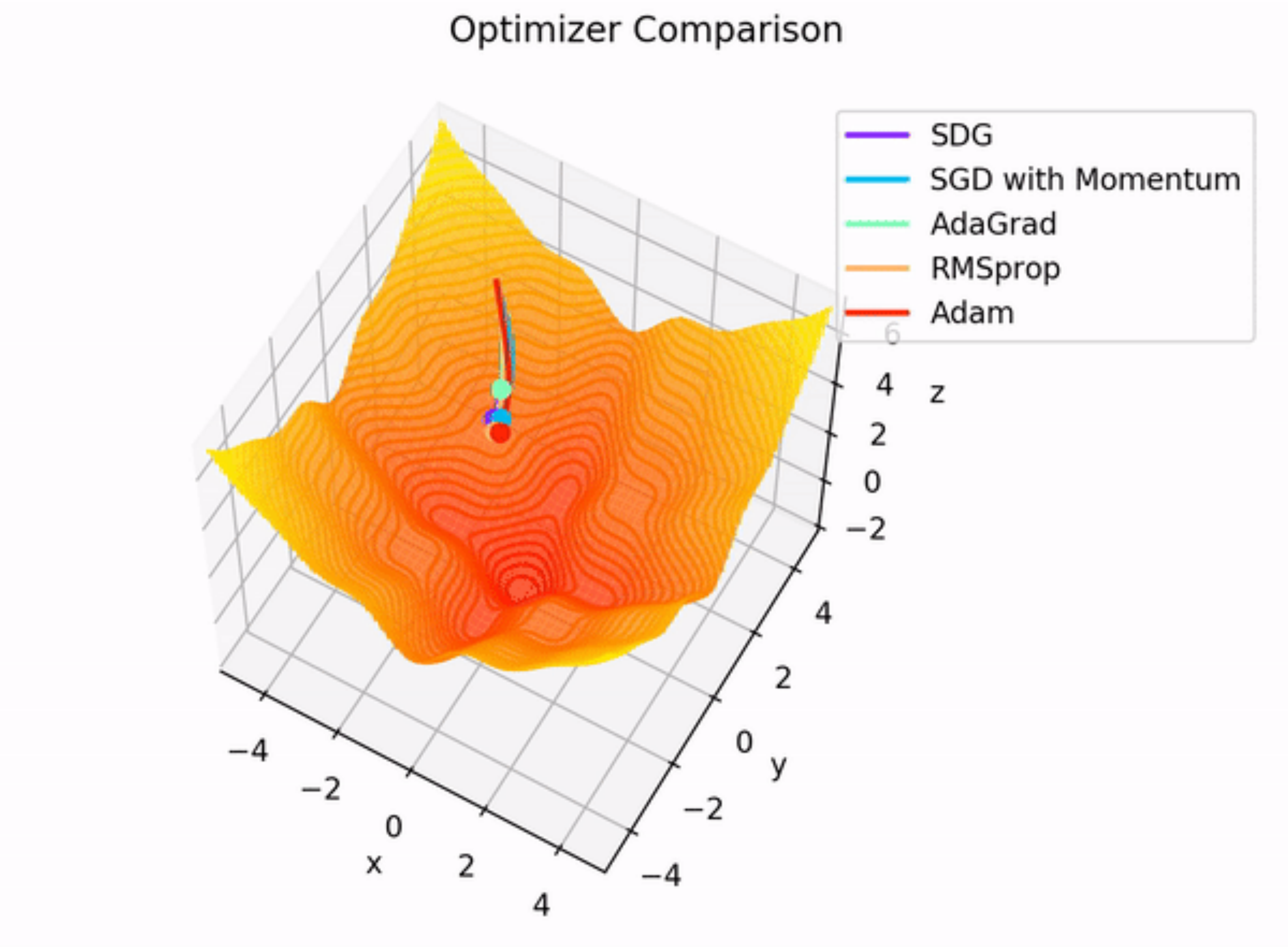

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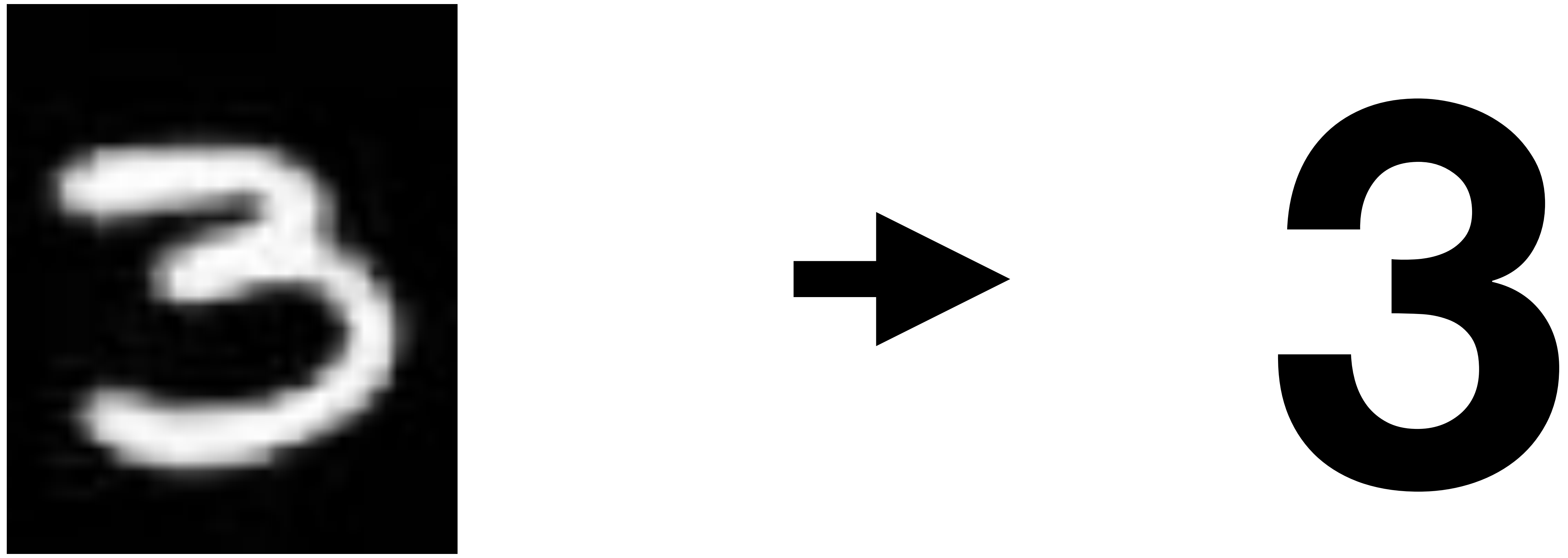
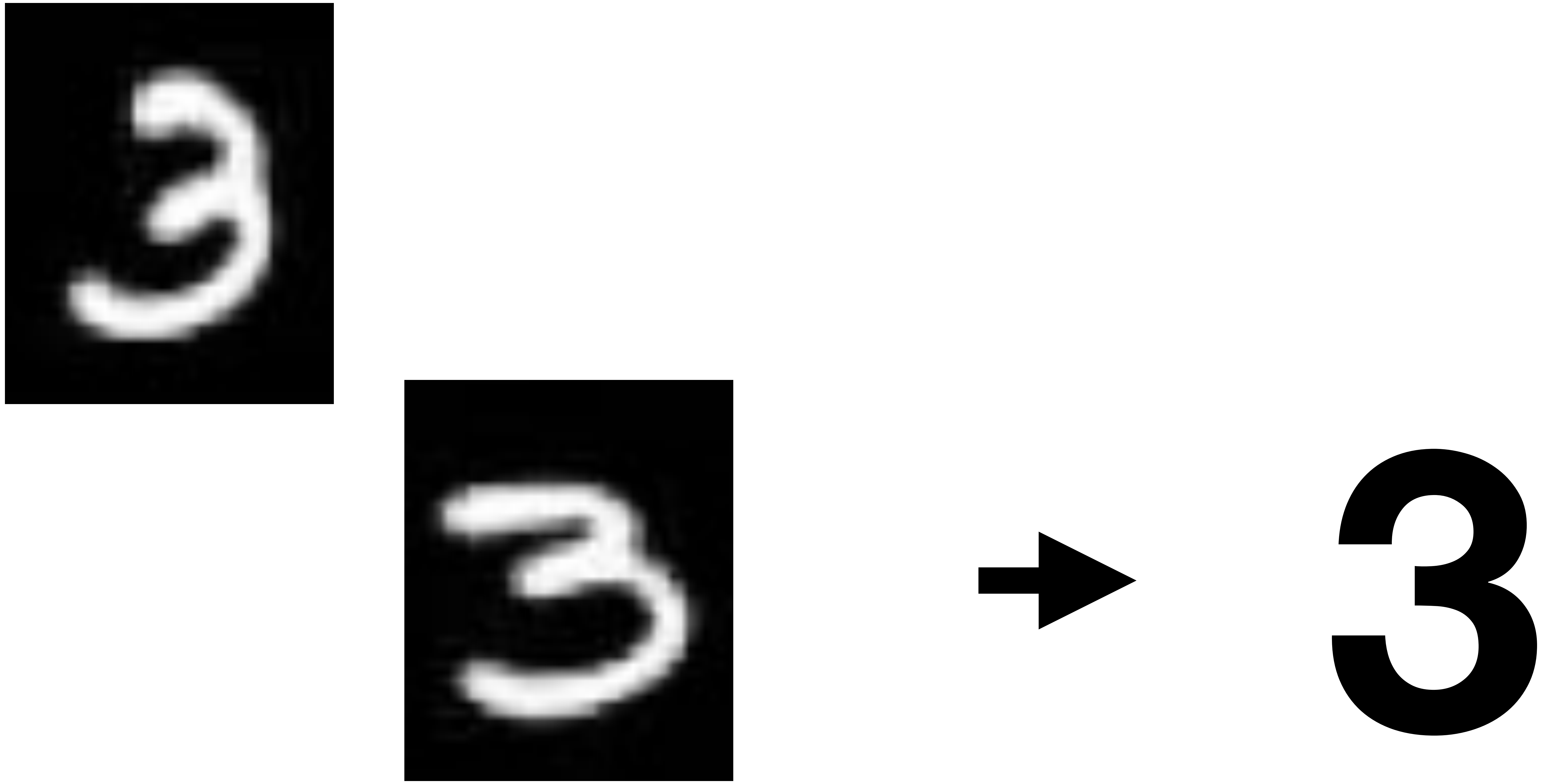
High-D problems



MNIST digits-
http://yann.lecun.com/exdb/mnist/

High-D problems



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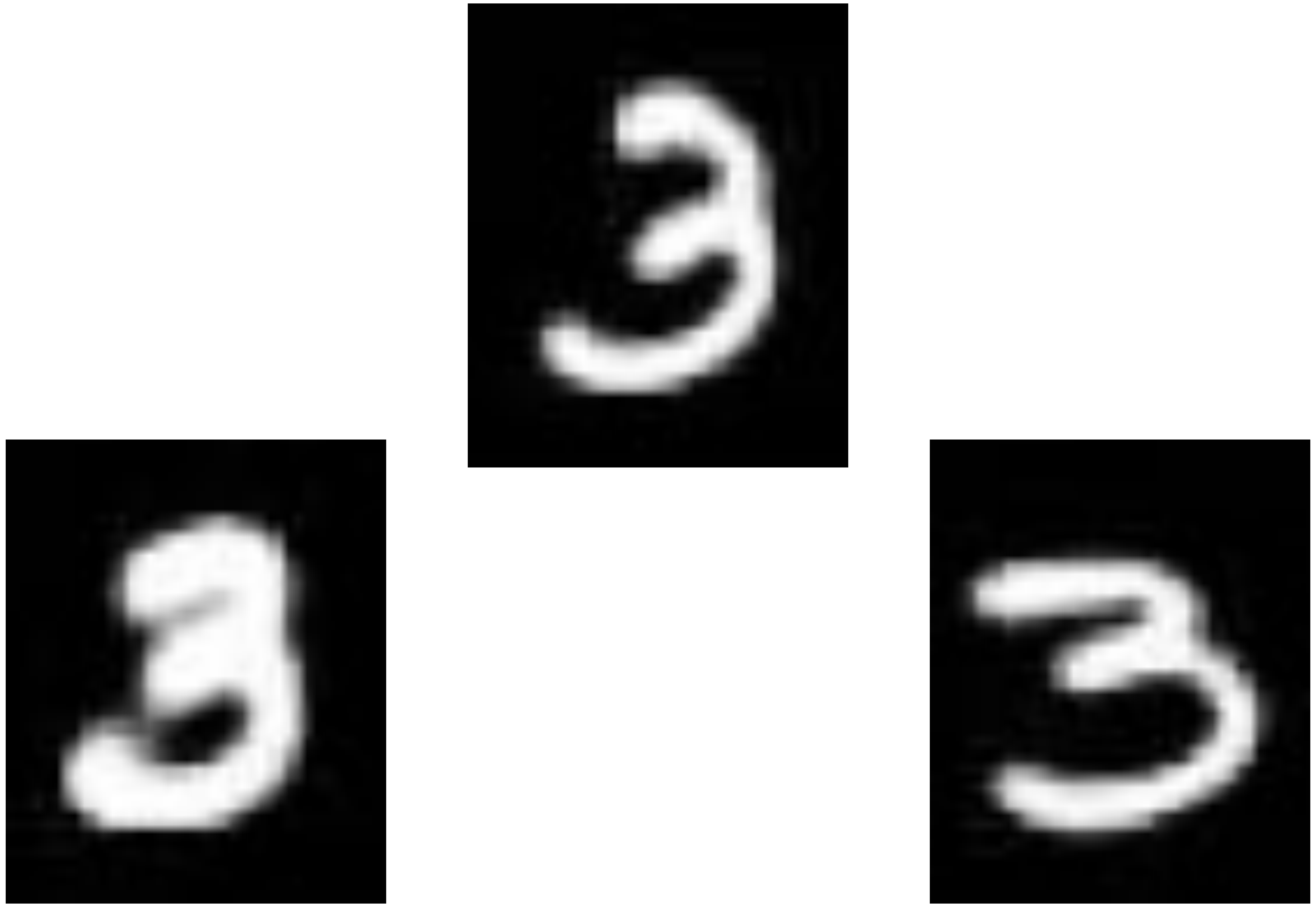
High-D problems



3

MNIST digits-
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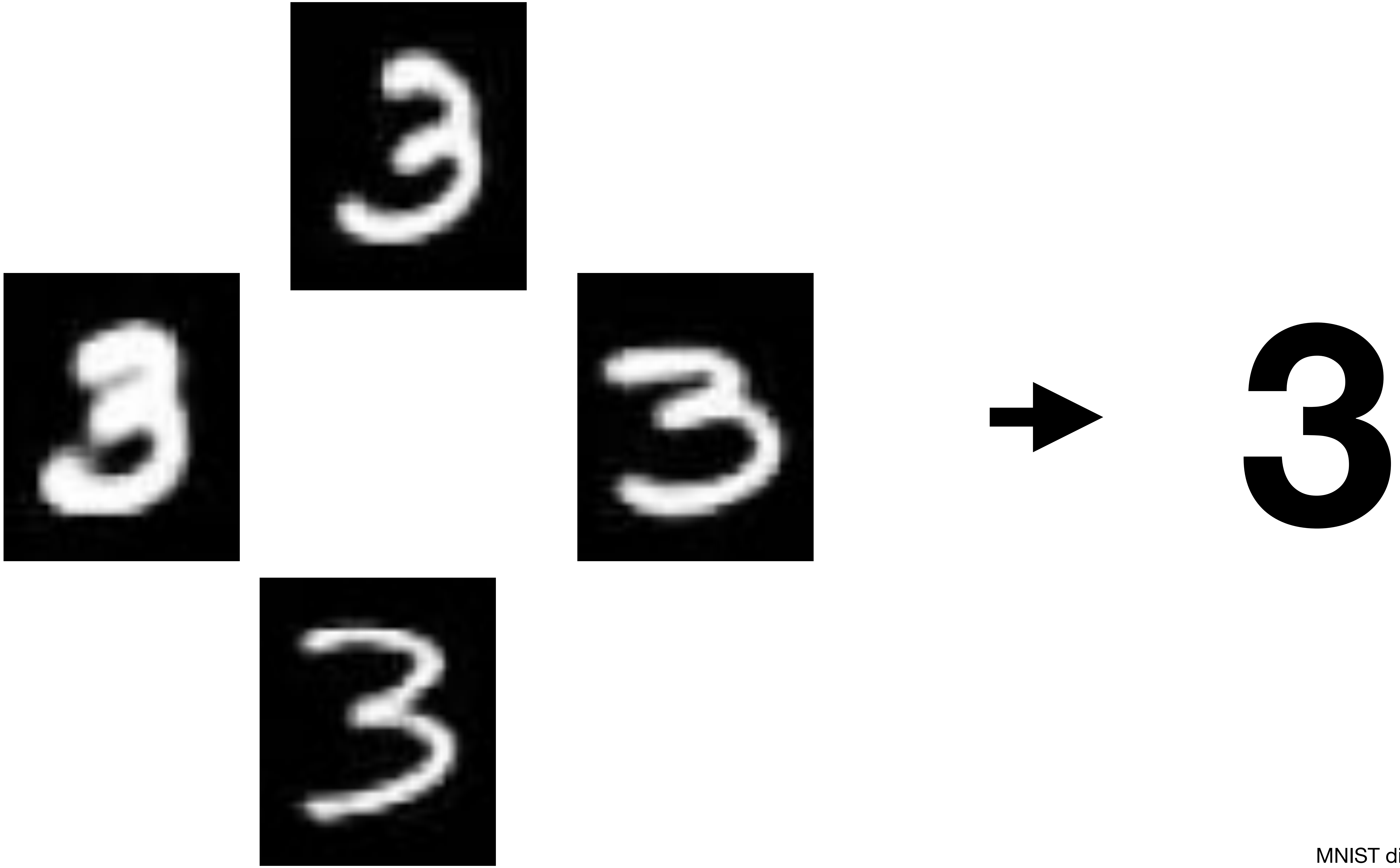
High-D problems



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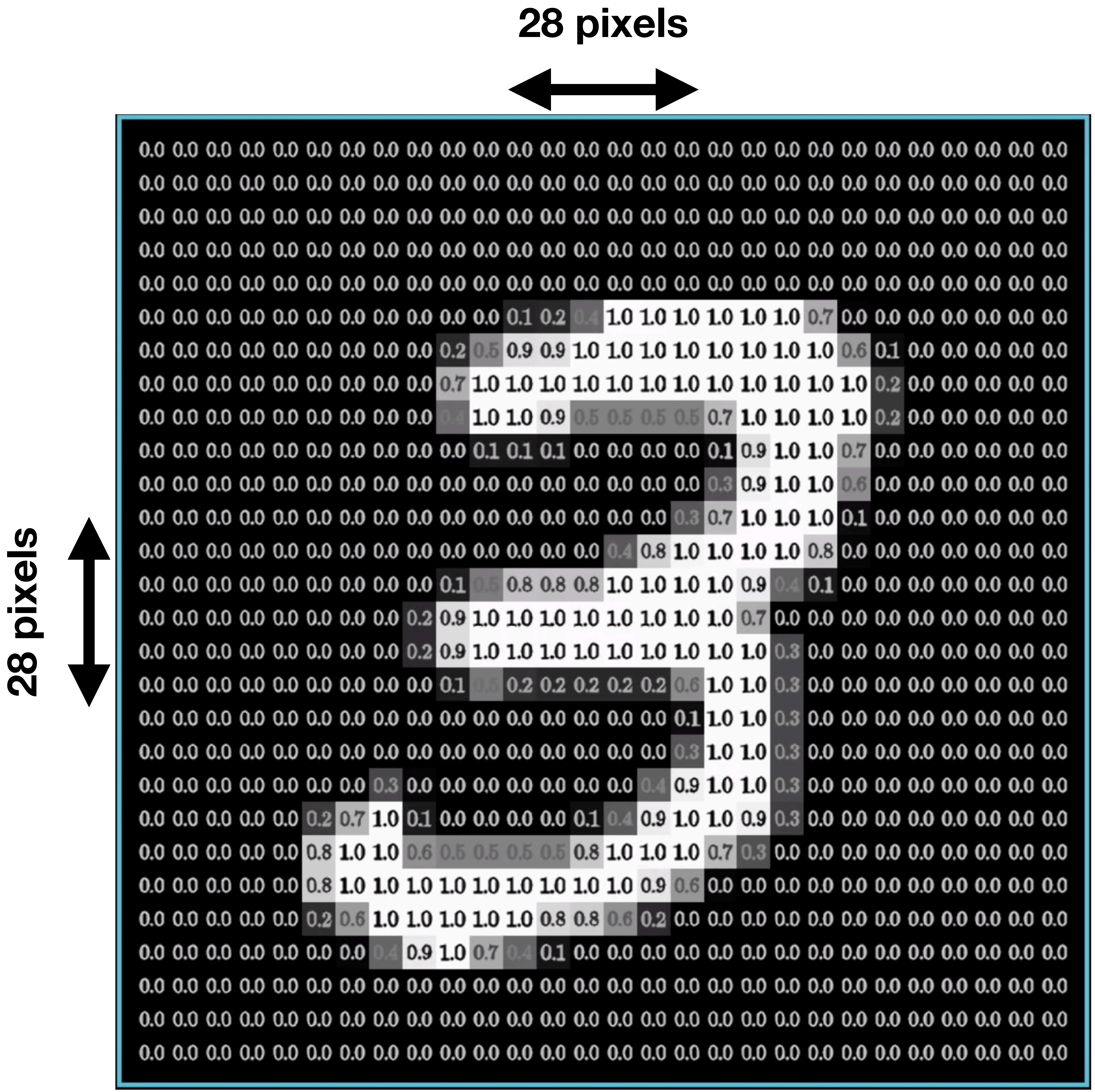
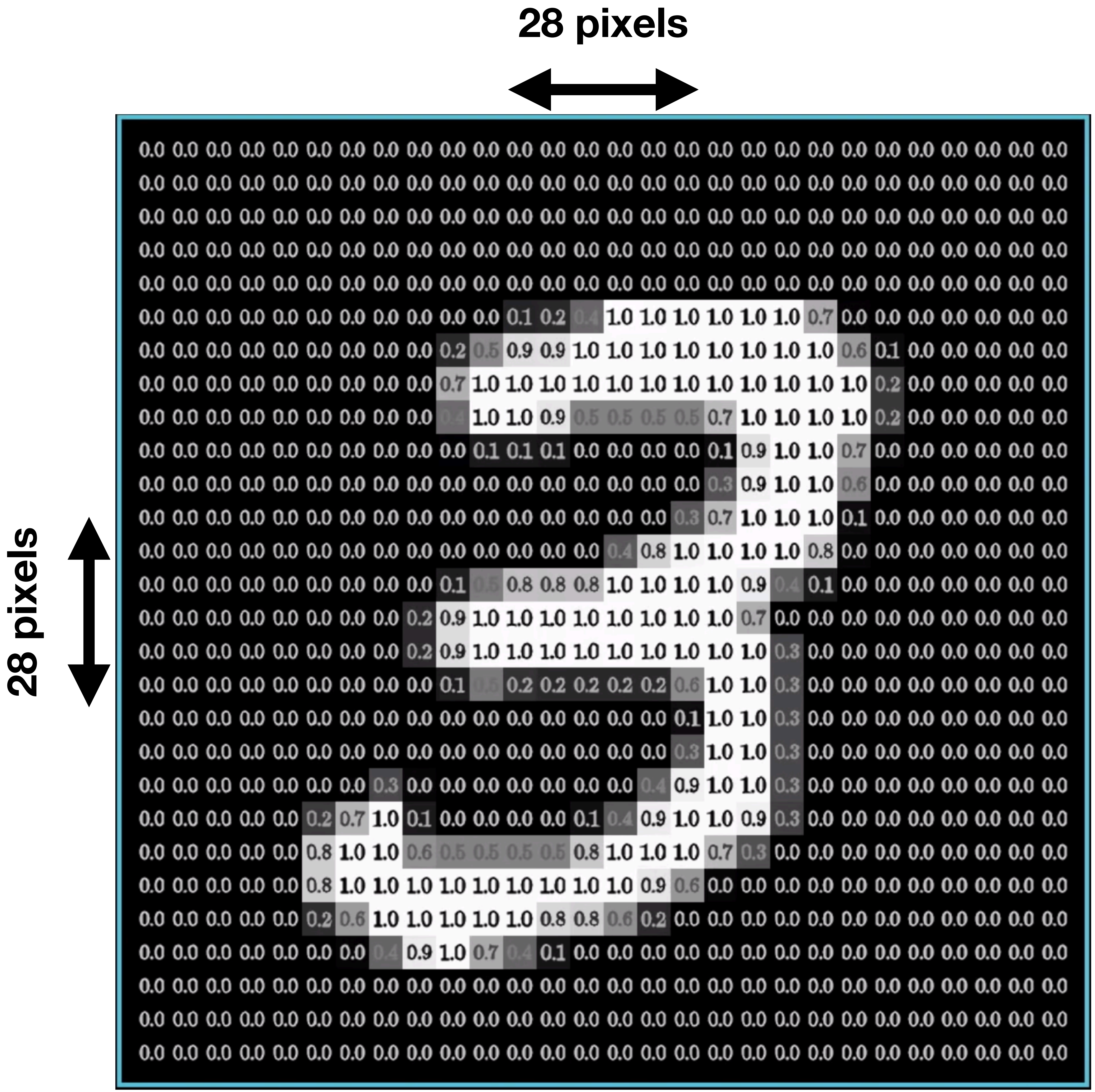


MNIST - 784 total pixels
each ranges from 0 to 1

3Blue1Brown (YouTube)
But what is a Neural Network? | Deep learning, chapter 1



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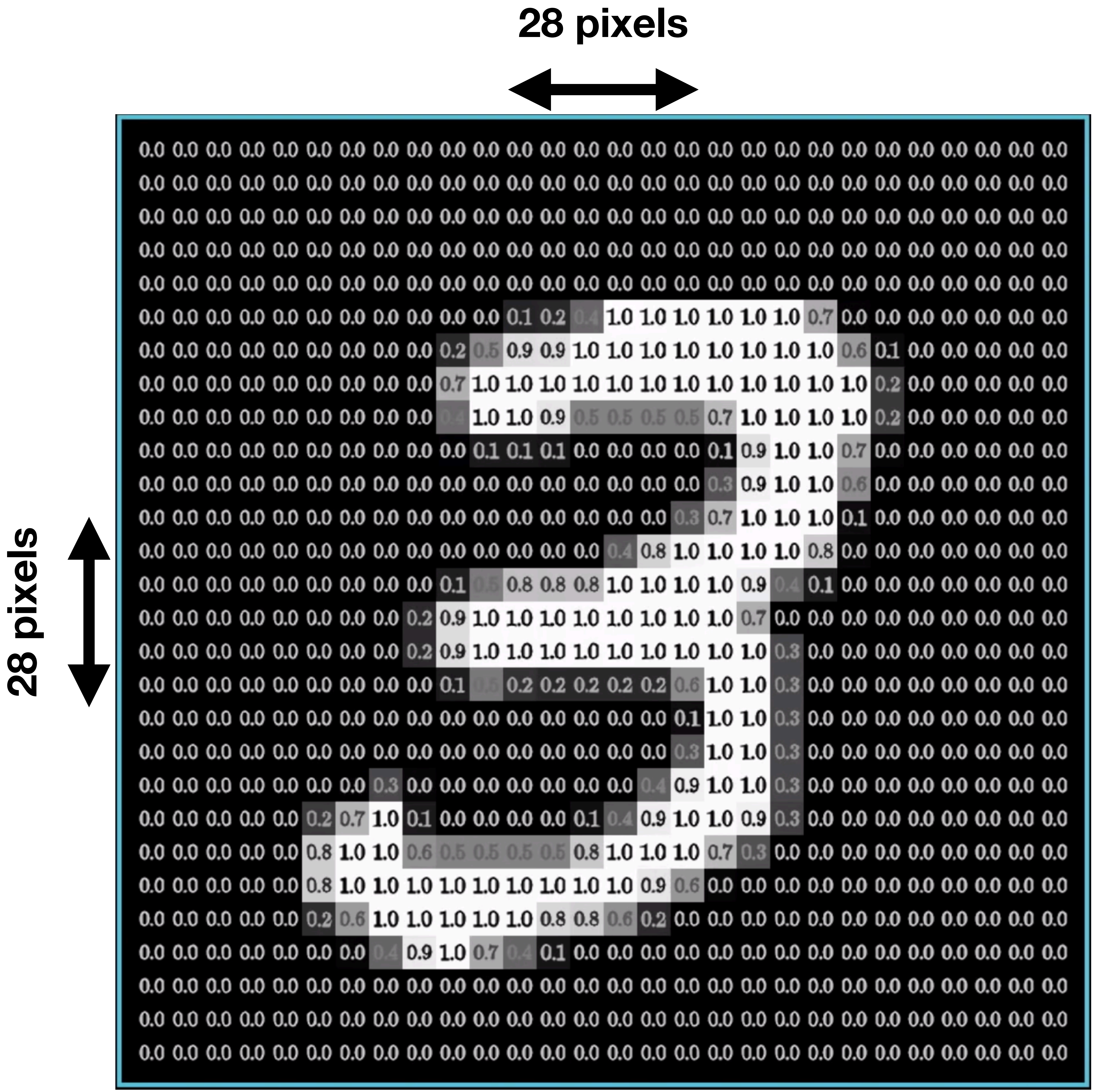

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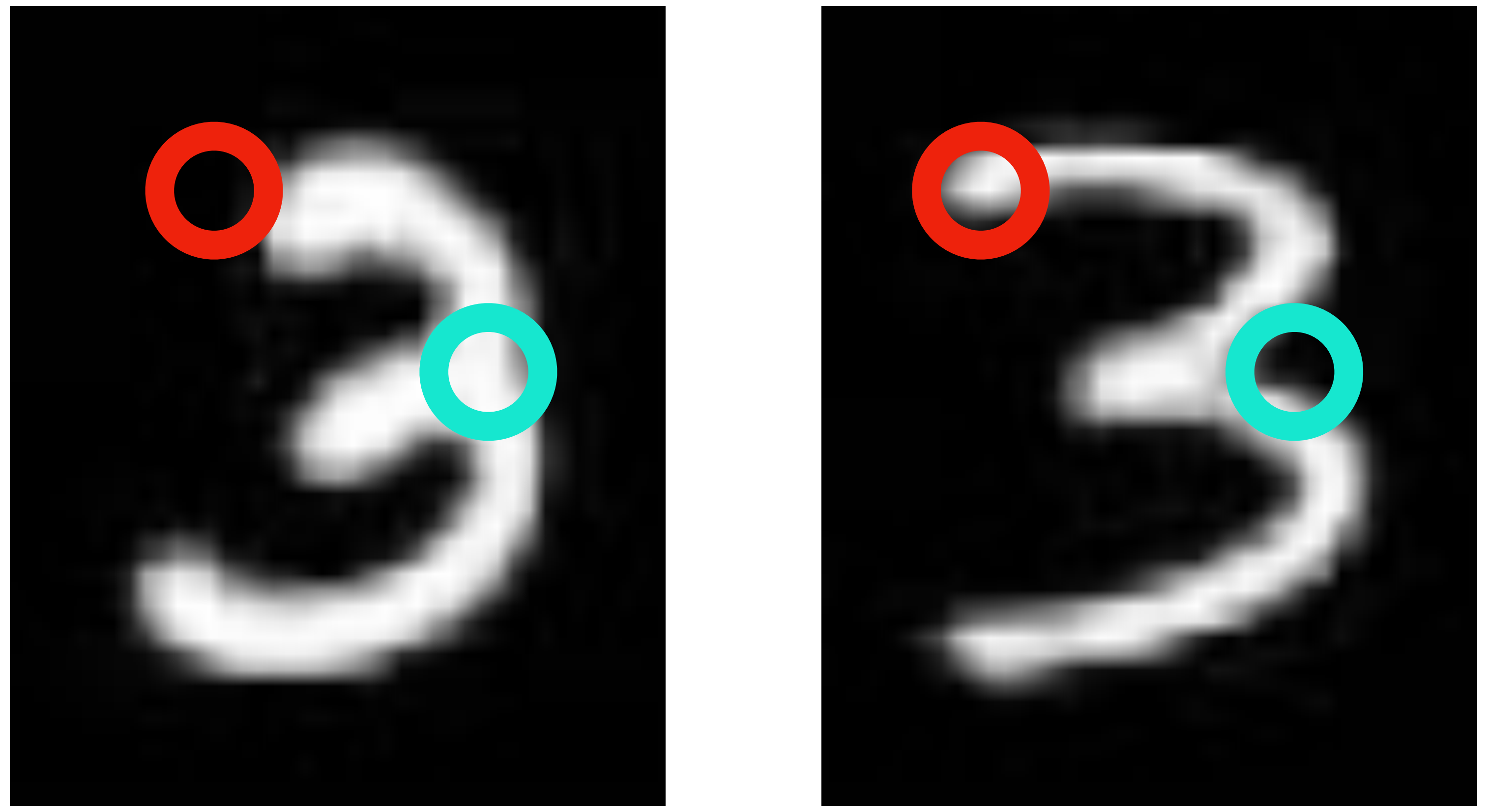

Specific pixel values are very different between images

3Blue1Brown (YouTube)
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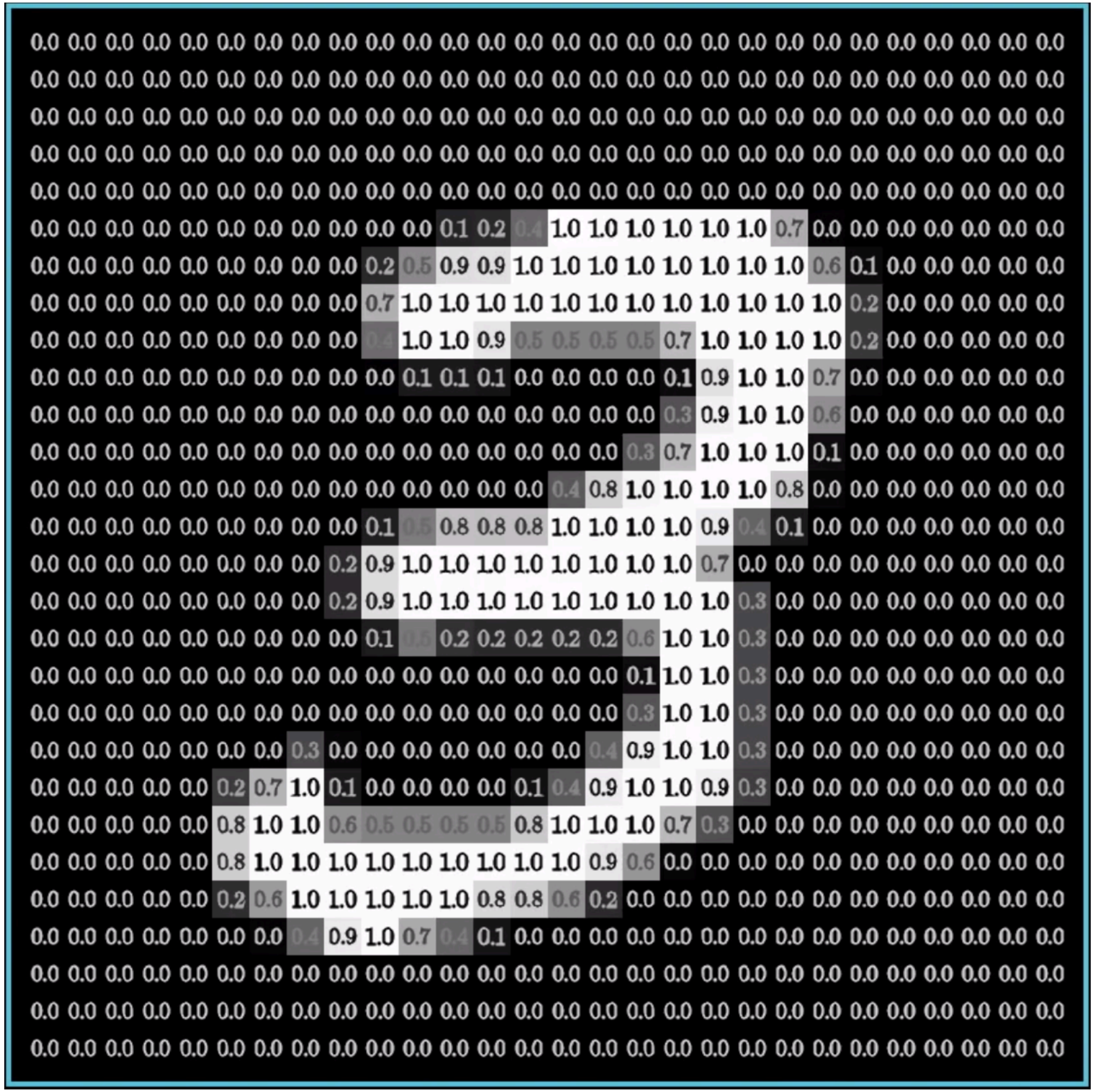
28 pixels

28 pixels

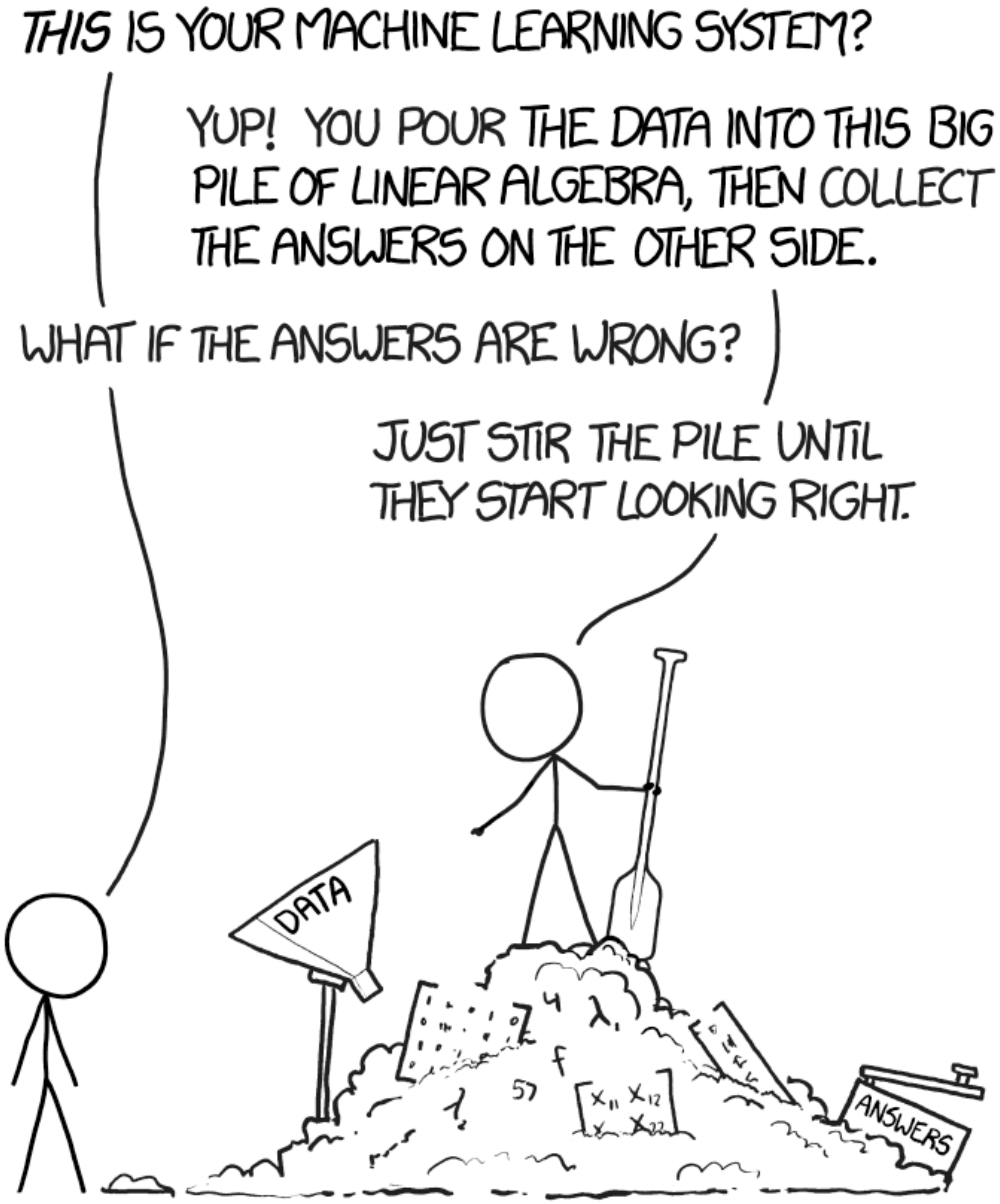


MNIST - 784 total pixels each ranges from 0 to 1

Specific pixel values are very different between images

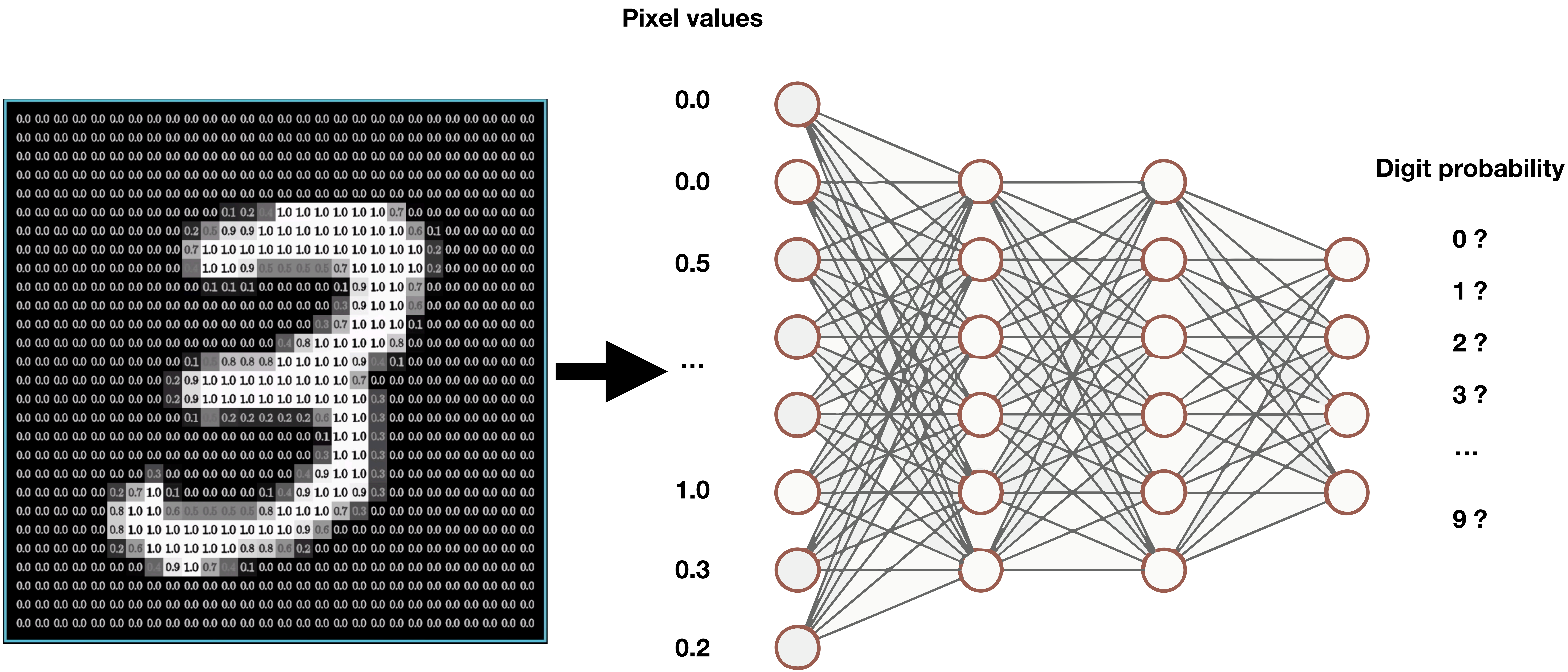
3Blue1Brown (YouTube)

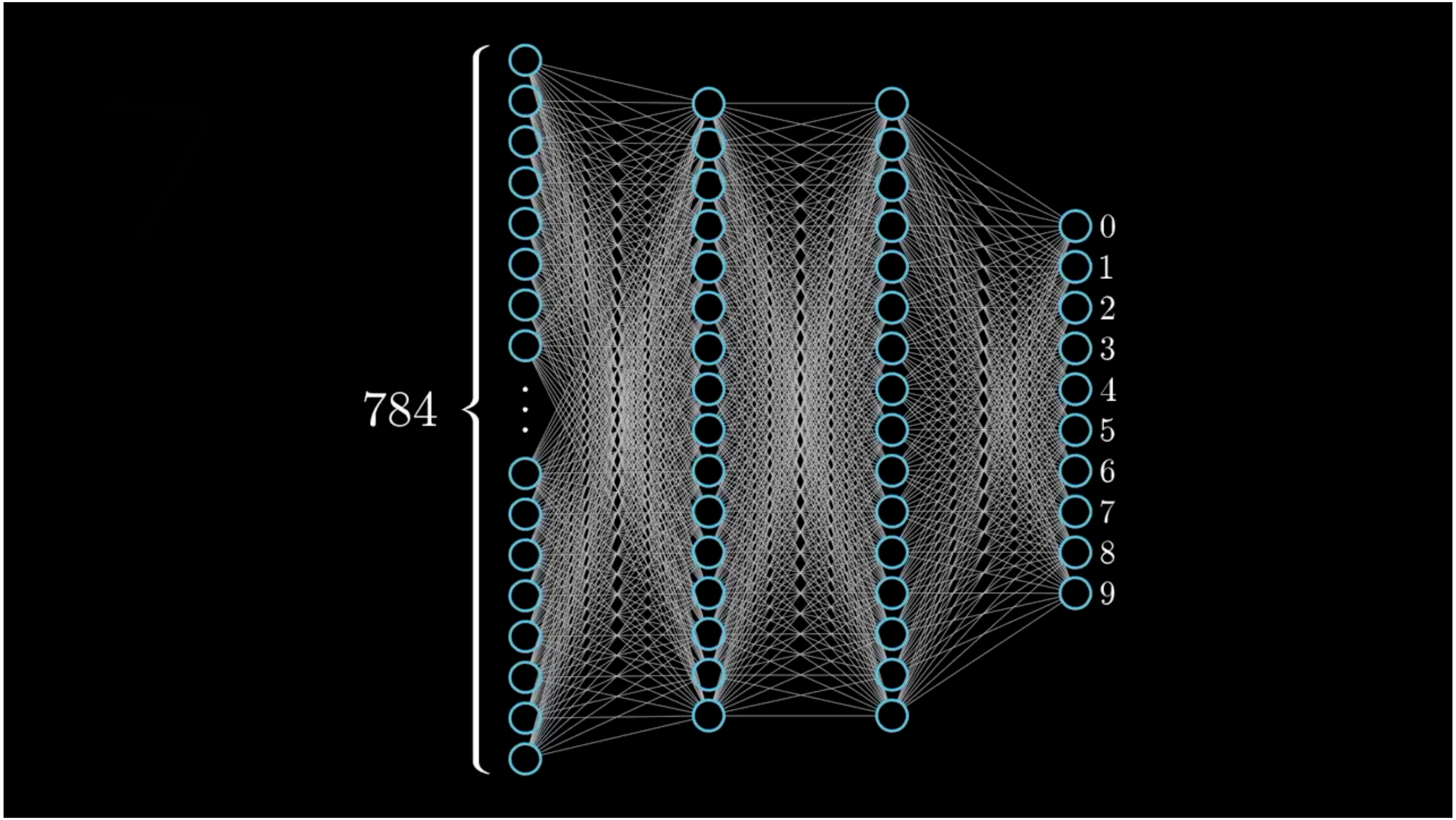
But what is a Neural Network? | Deep learning, chapter 1



https://xkcd.com/1838/

MLP for digit classification





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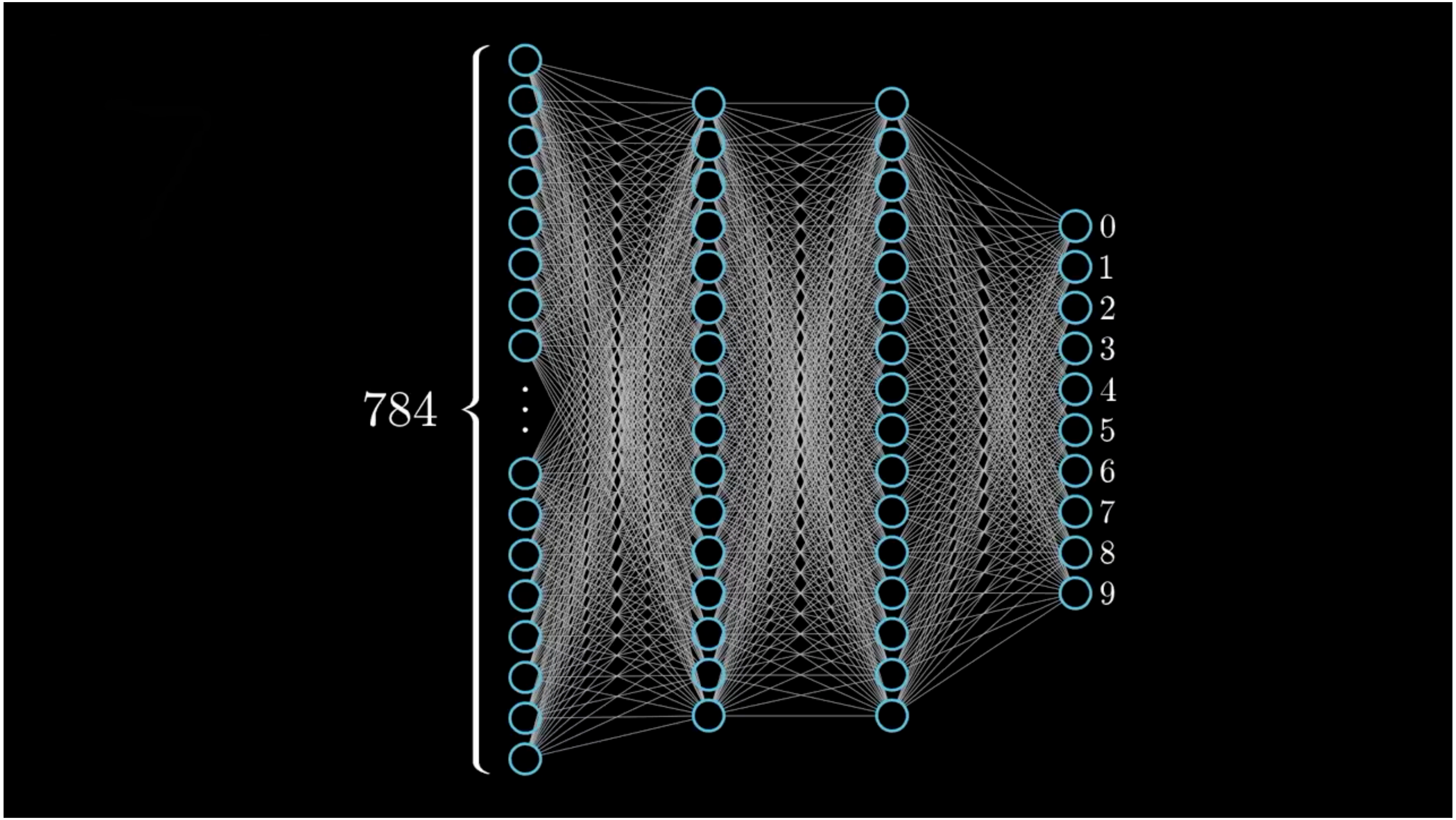

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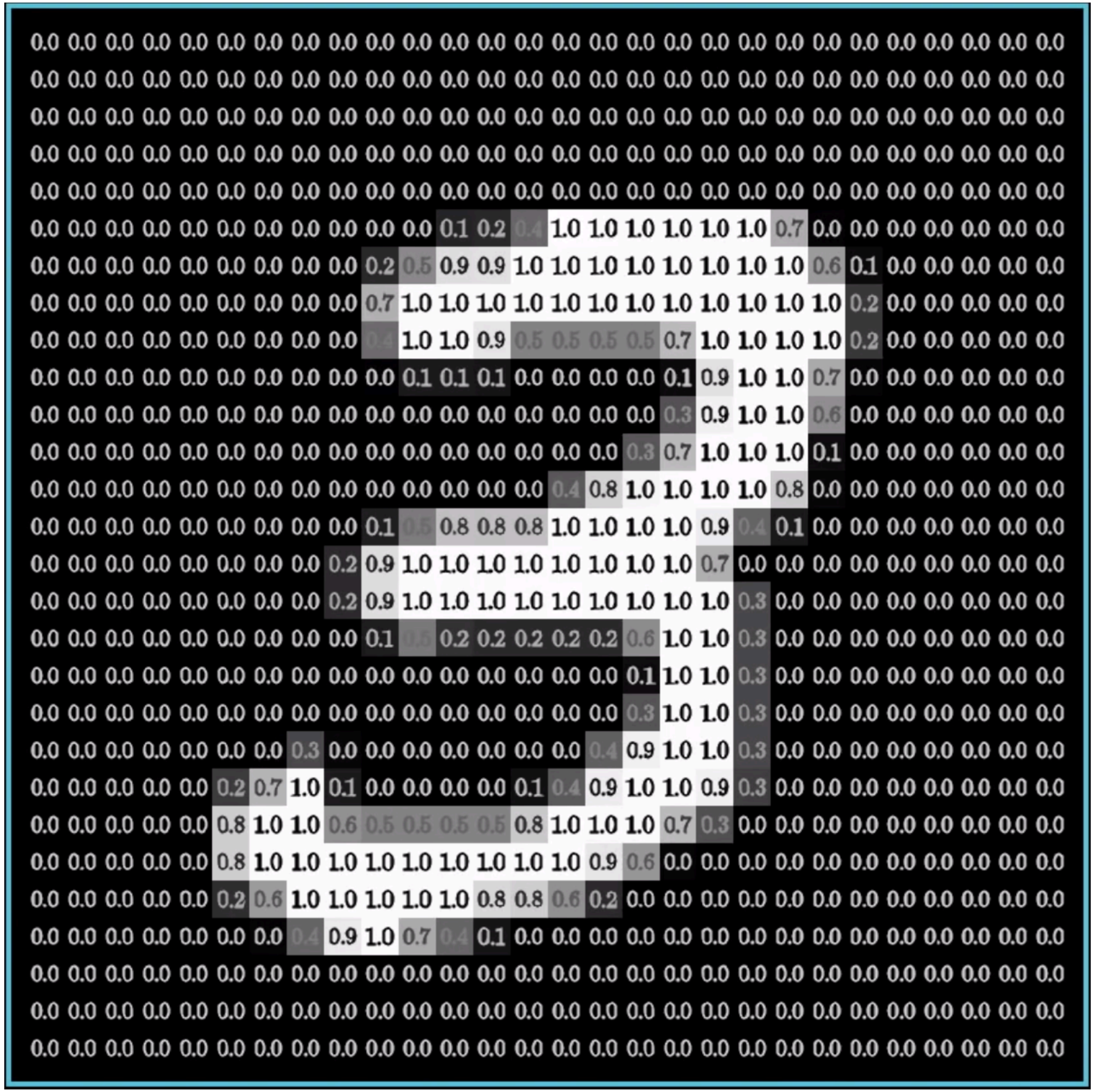
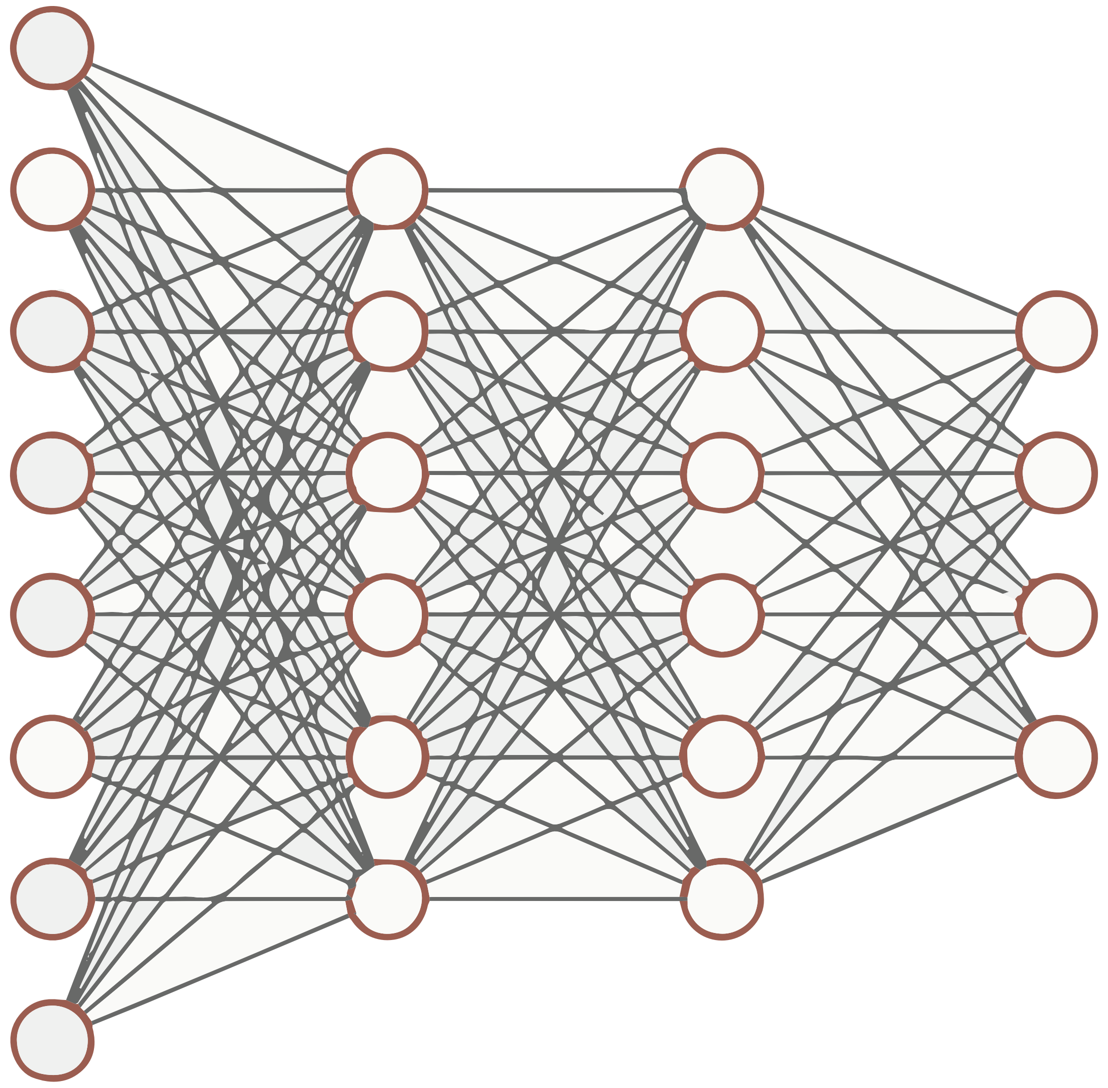
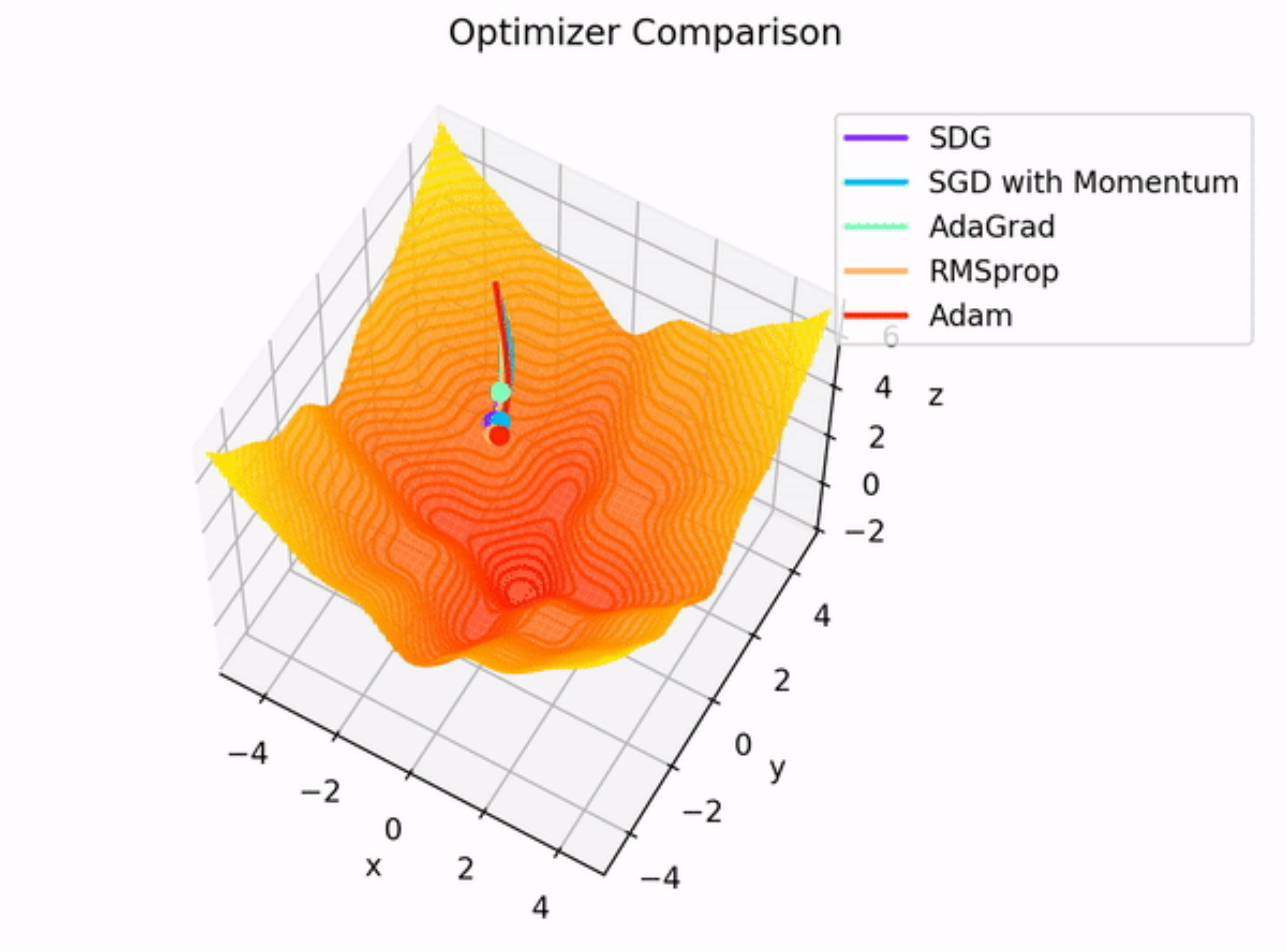
28 pixels

28 pixels



784-dimensional input





te-guide-to-adam-
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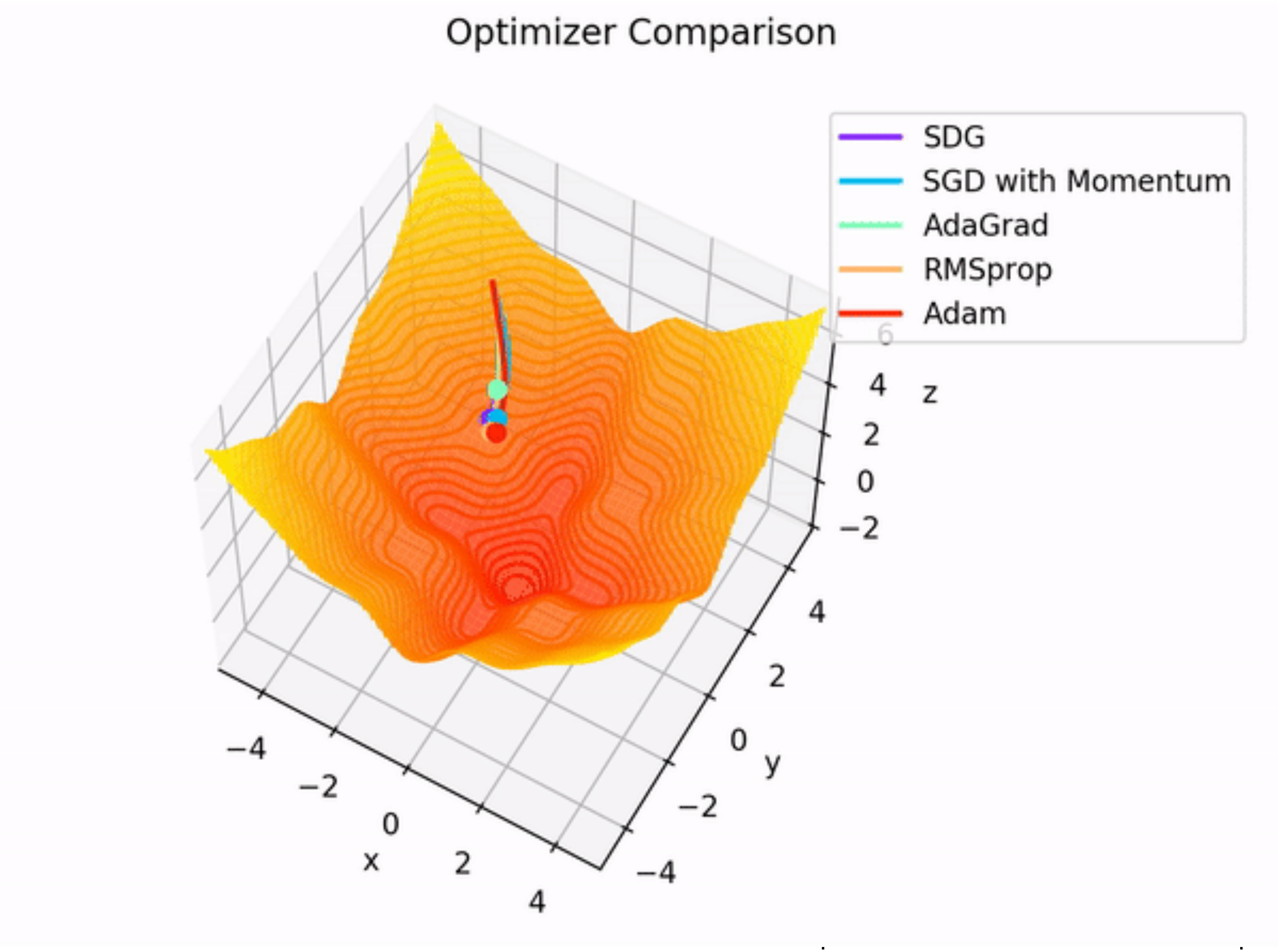

te-guide-to-adam-
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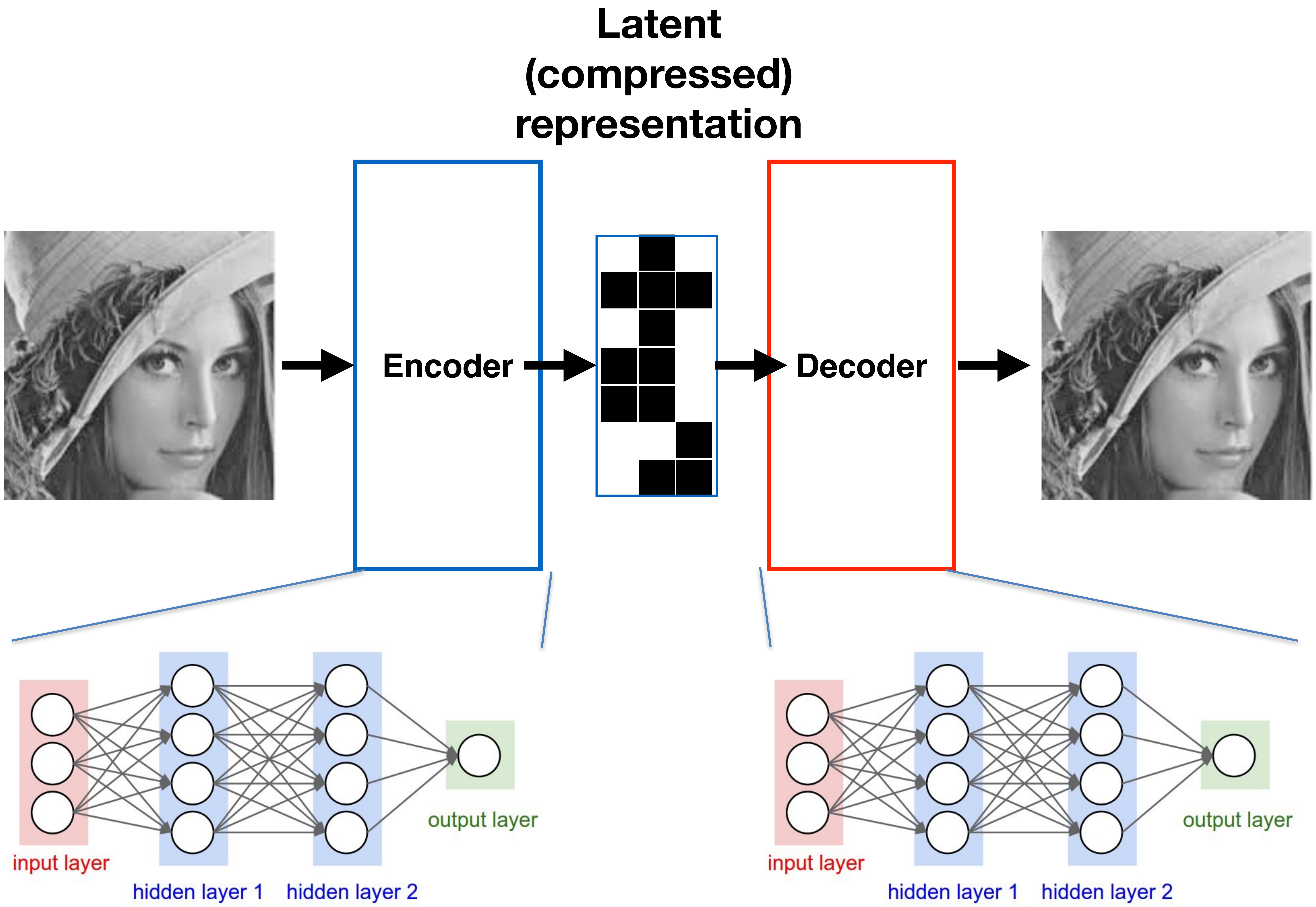
What you'll hear about in this lecture

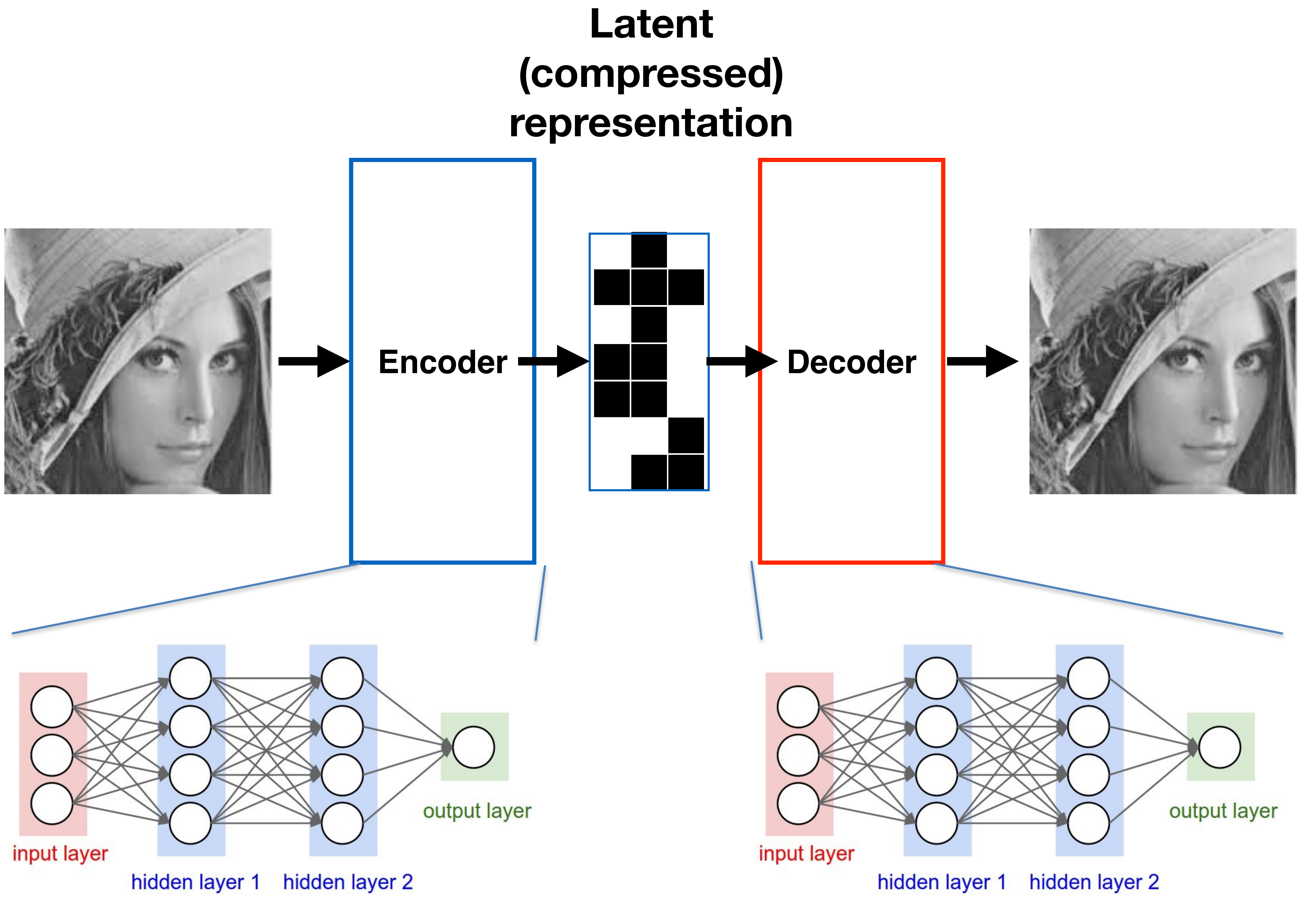
Neural network basics

Deep autoencoders

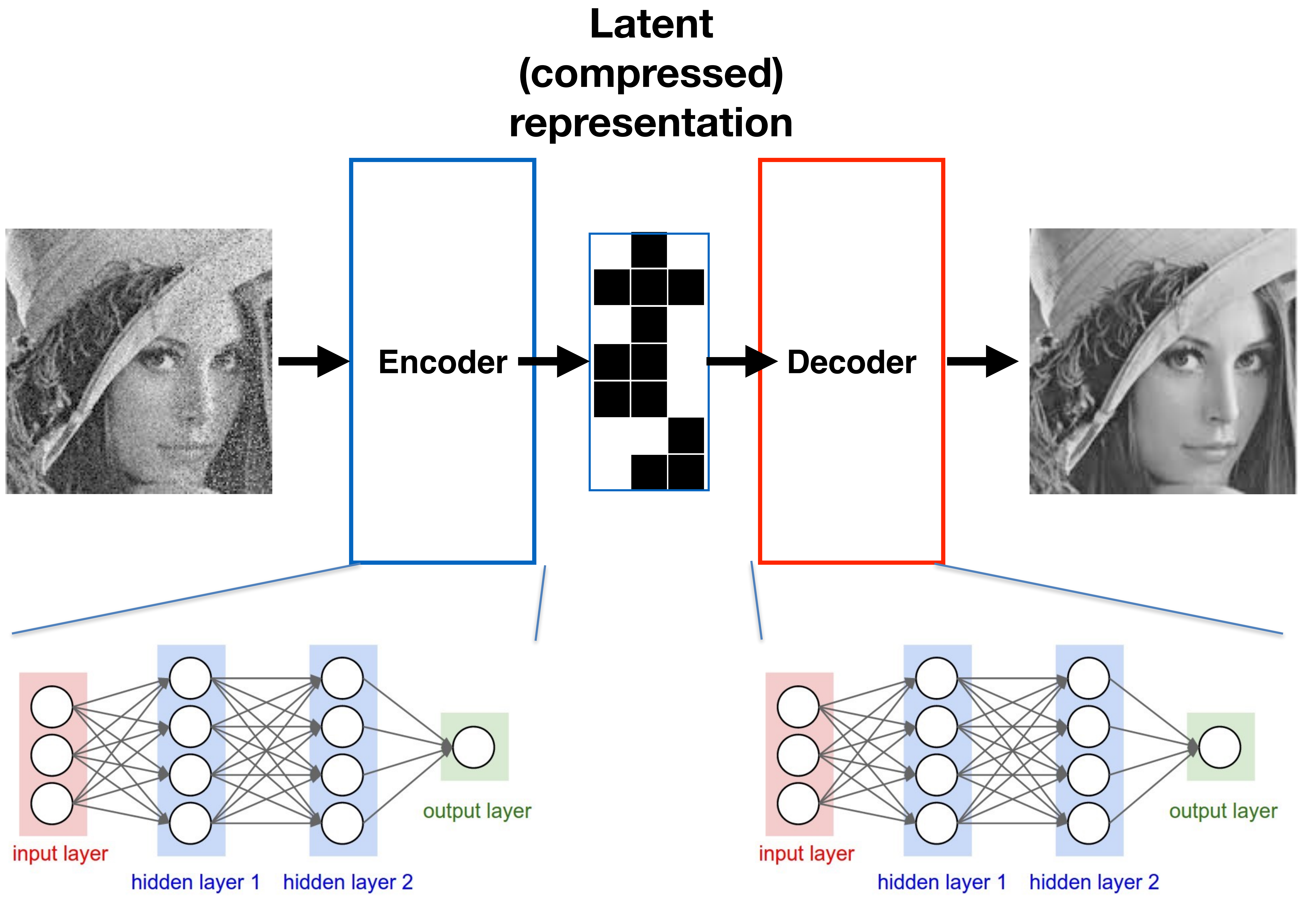
Intro to neural population dynamics



- Autoencoders consist of a pair of networks: an “encoder” and a “decoder”
- The encoder compresses the input down to a low-D representation. The decoder attempts to reconstruct the same input based on the low-D representation



- The compressed representation is a bottleneck - the encoder is forced to throw out irrelevant information and extract the “true” structure underlying the data
- Completely unsupervised - there are no data labels

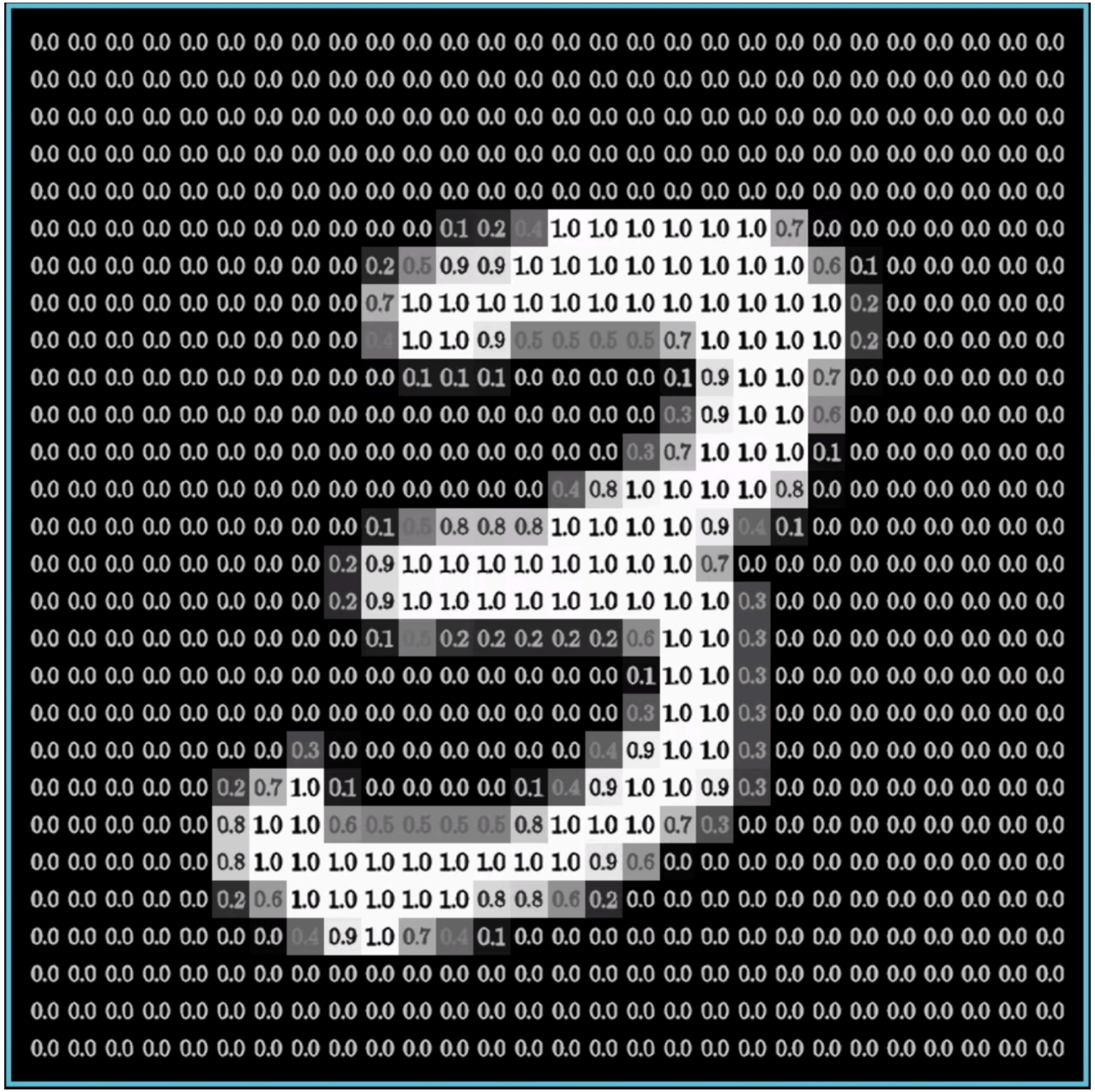


Applications

- An autoencoder can reject noise, that is, it filters out signals that don't correspond to the structure underlying the data

- The decoder must also learn to generate the data, i.e., it is a a generative model

28 pixels



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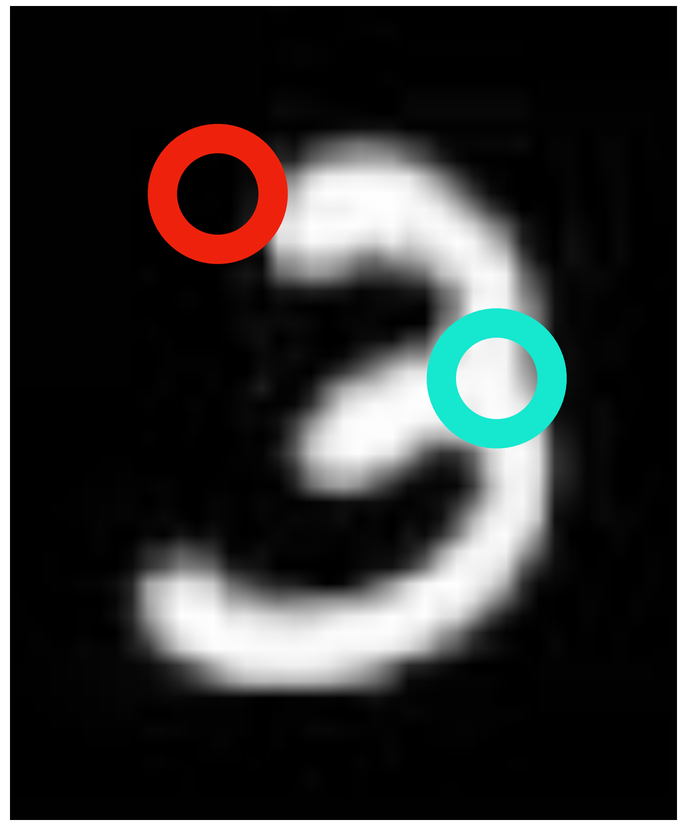

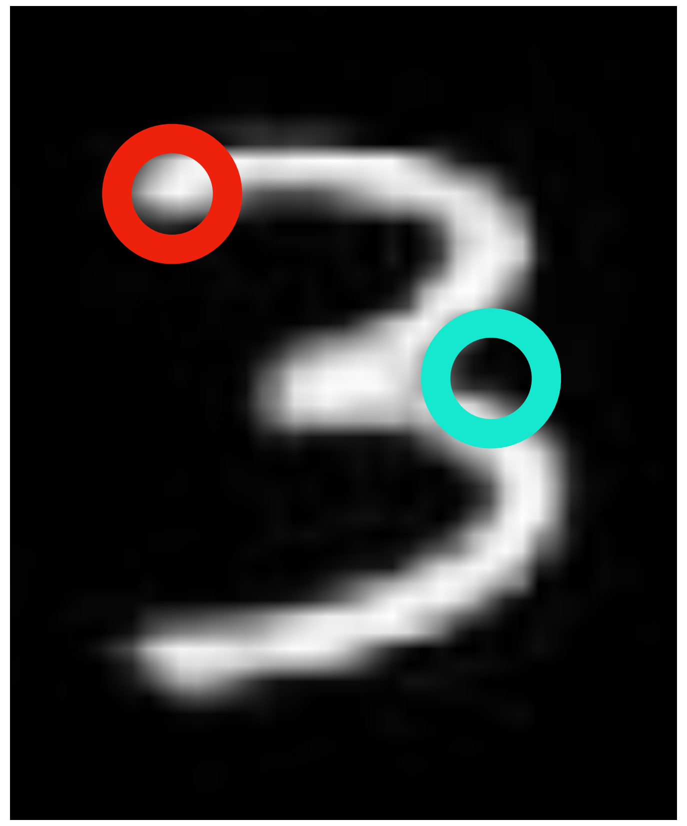

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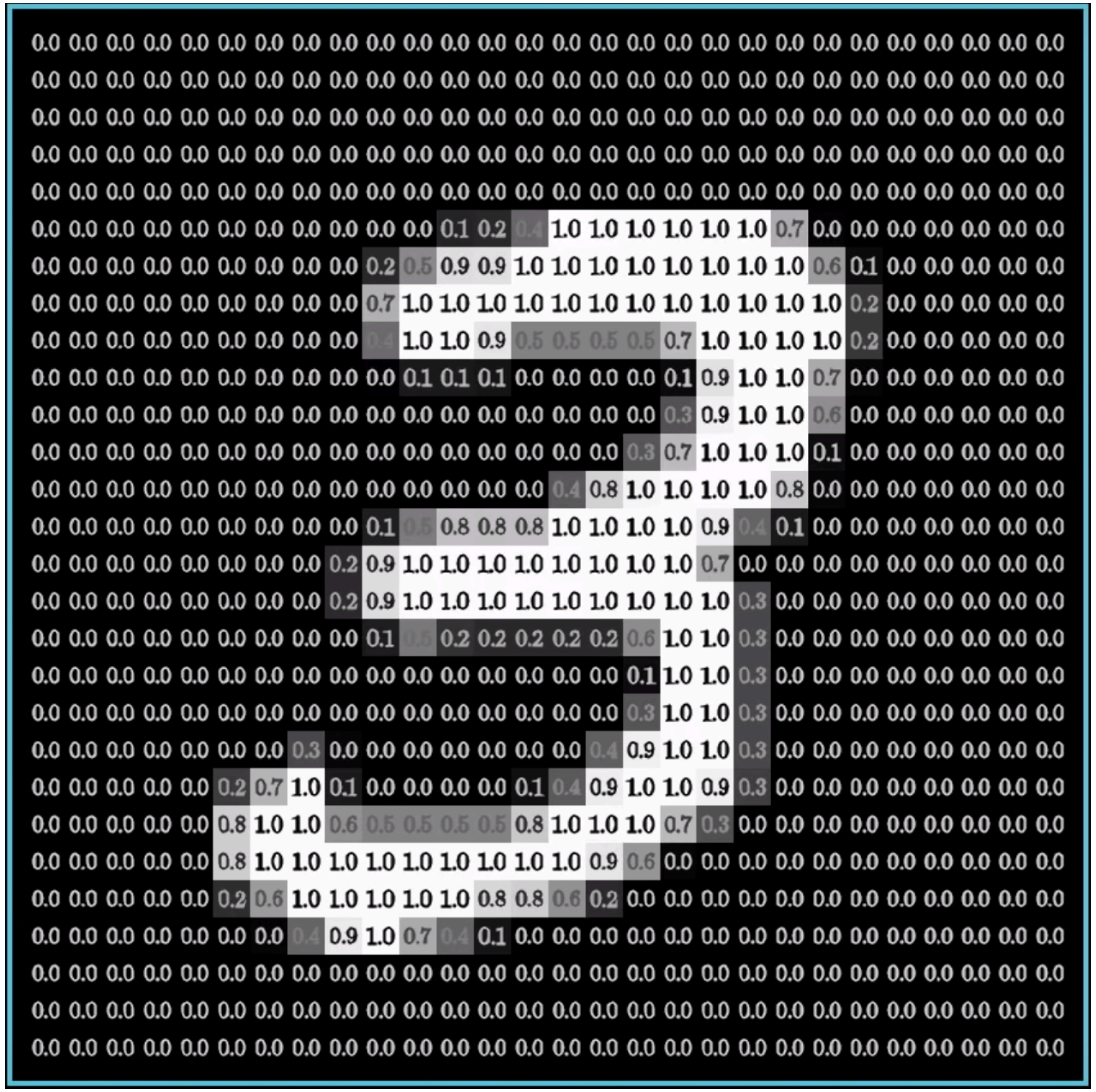
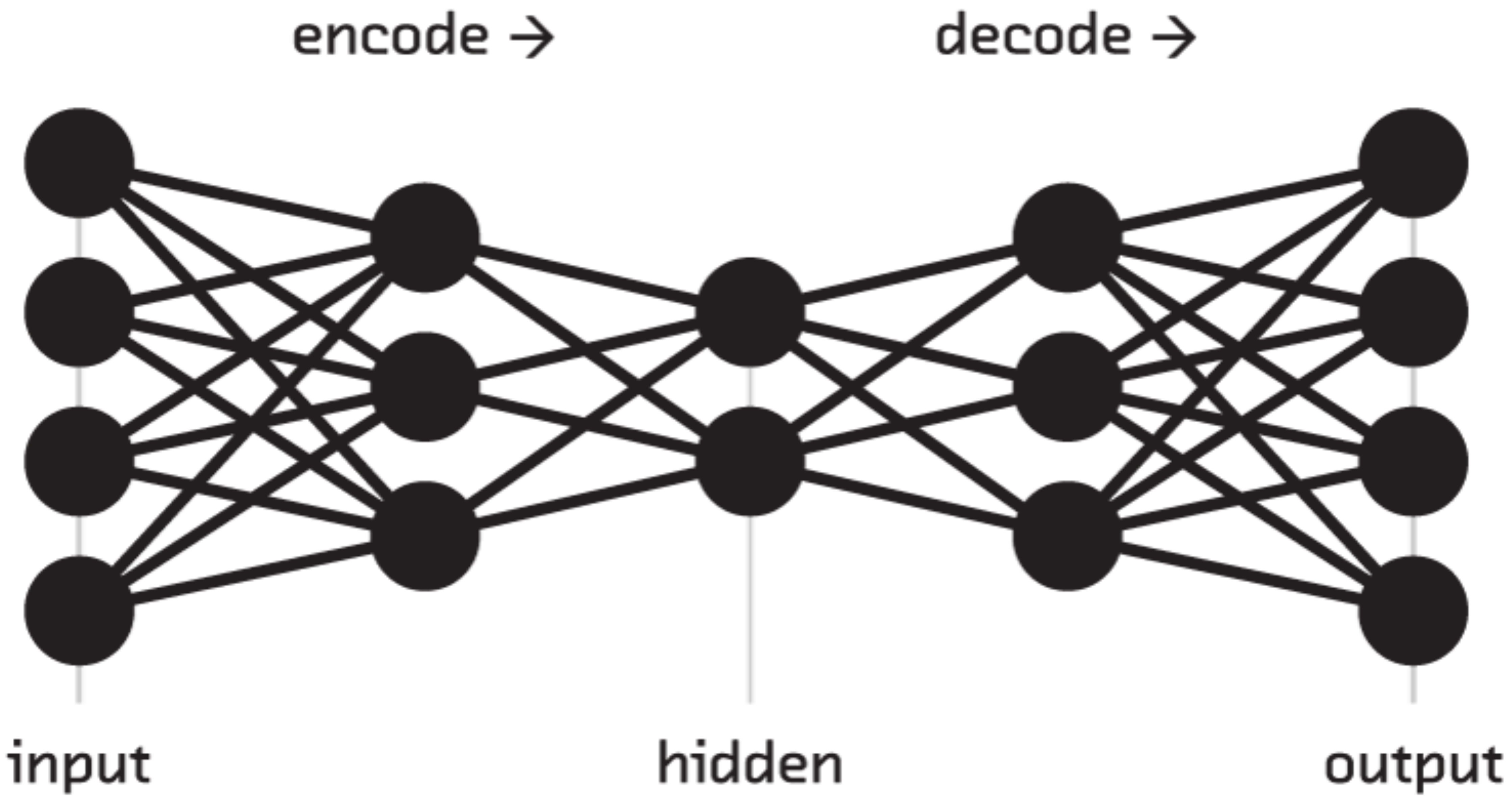
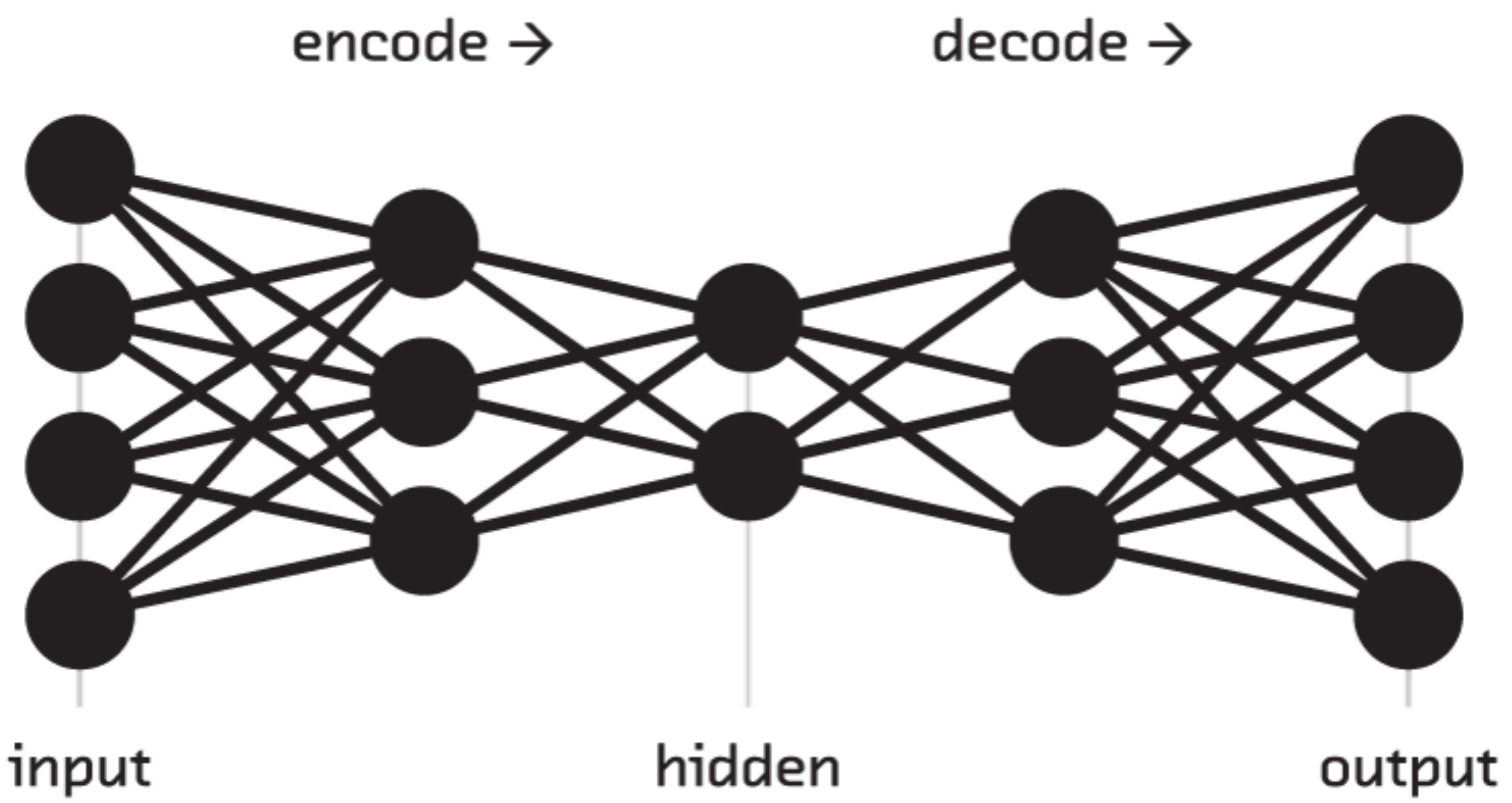




- Network weights are typically initialized completely randomly

- Through the course of training, the latent representation begins to exhibit structure that matches the structure in the data

https://blog.fastforwardlabs.com/2016/08/12/introducing-variational-autoencoders-in-prose-and.html



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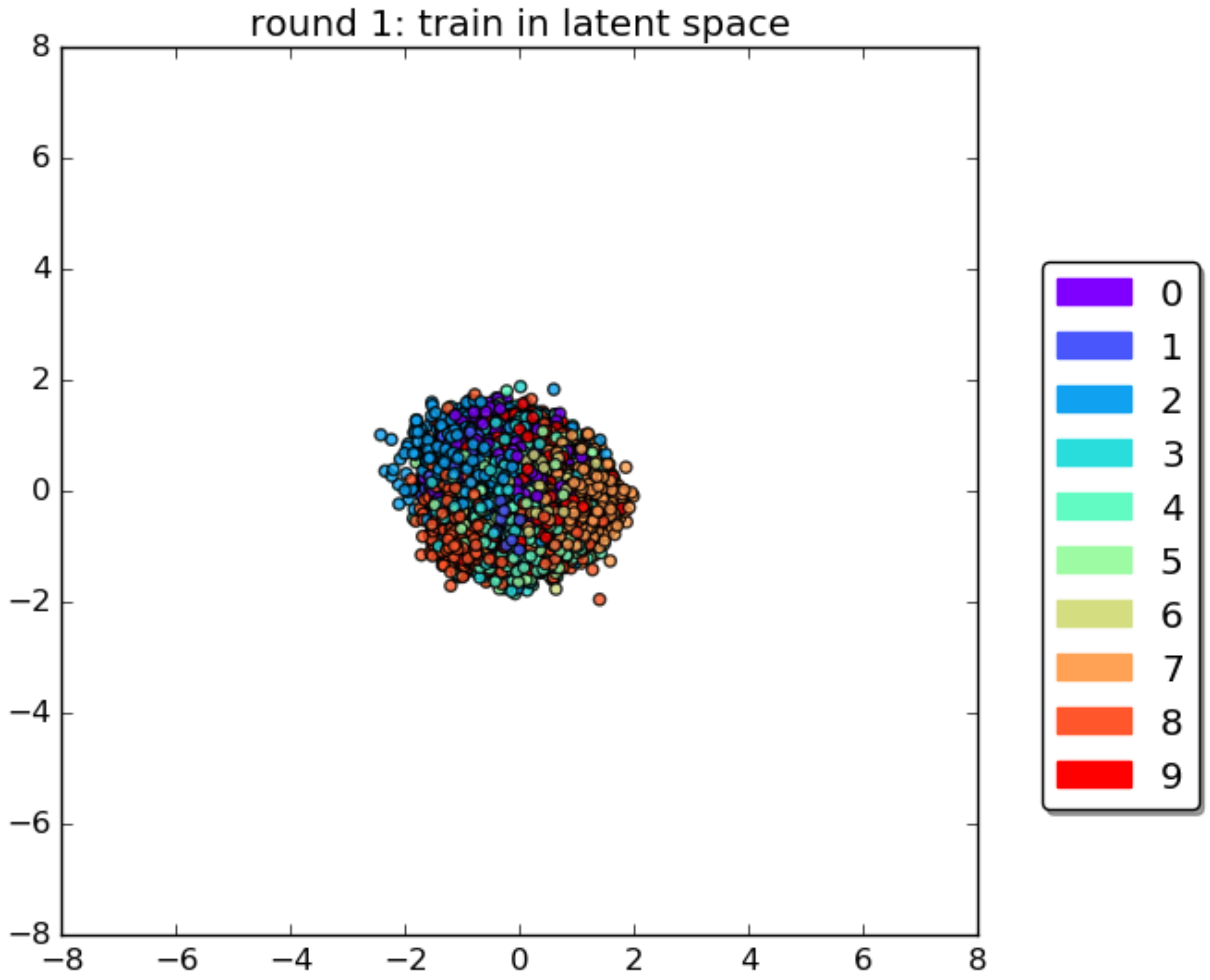

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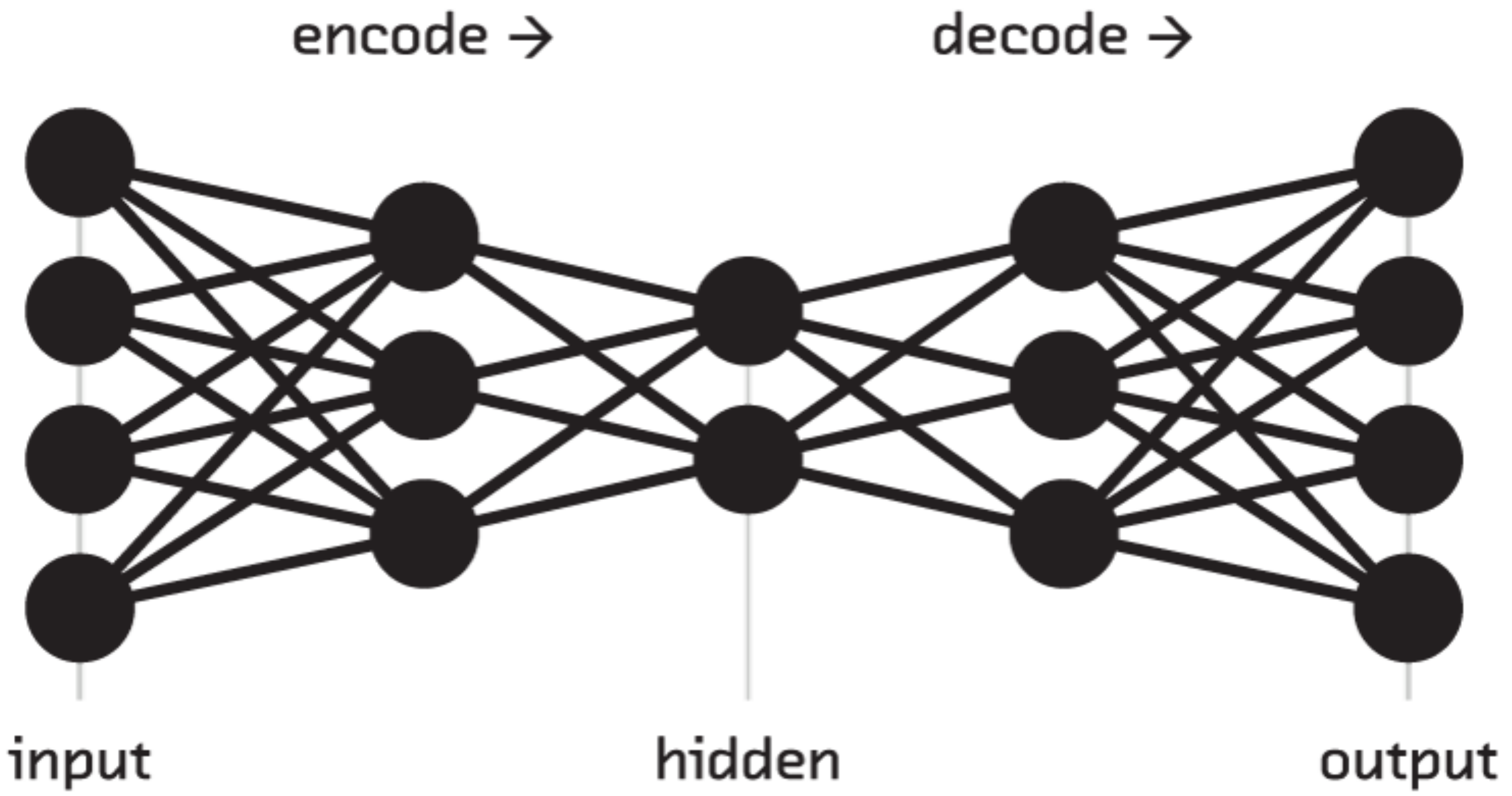

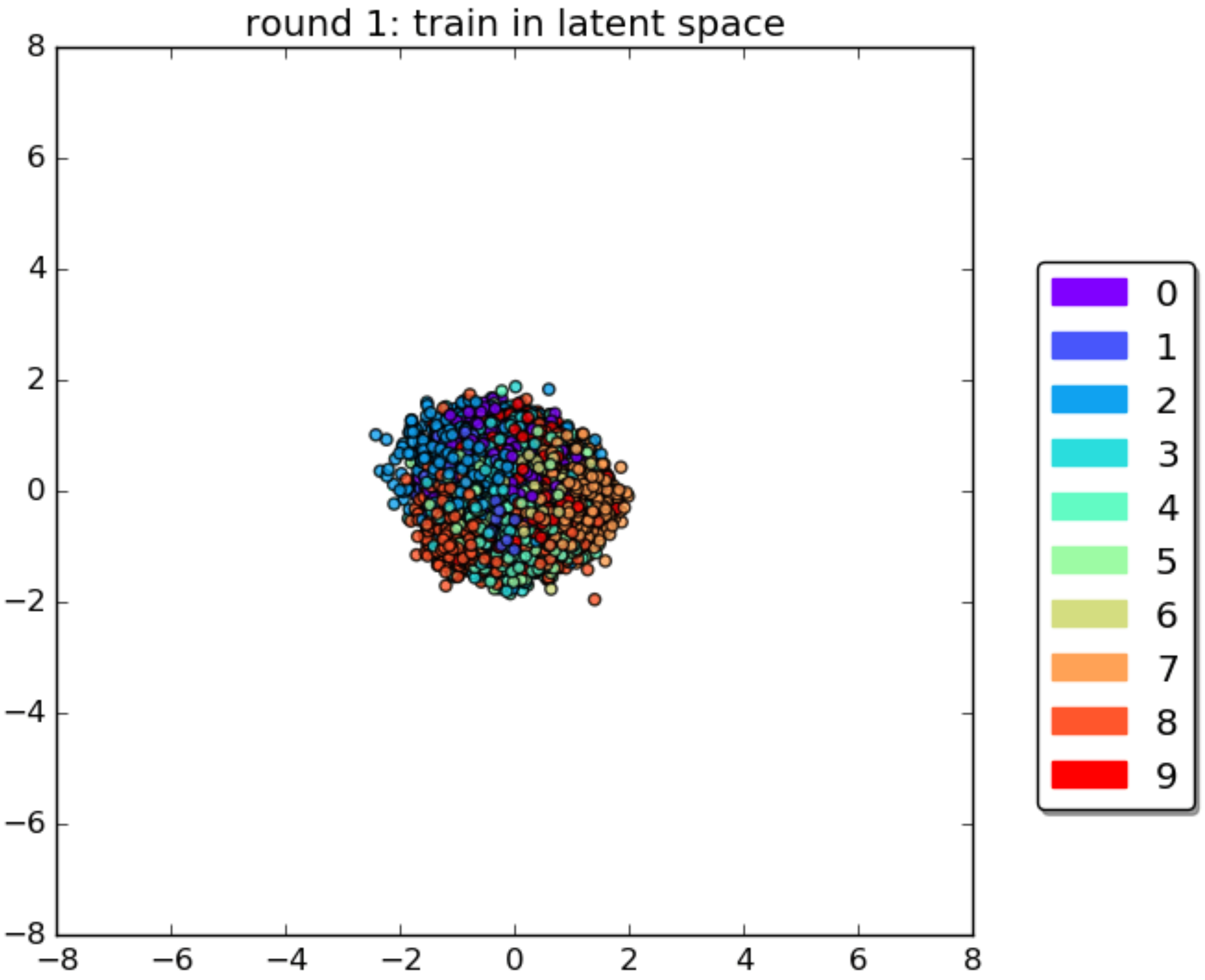

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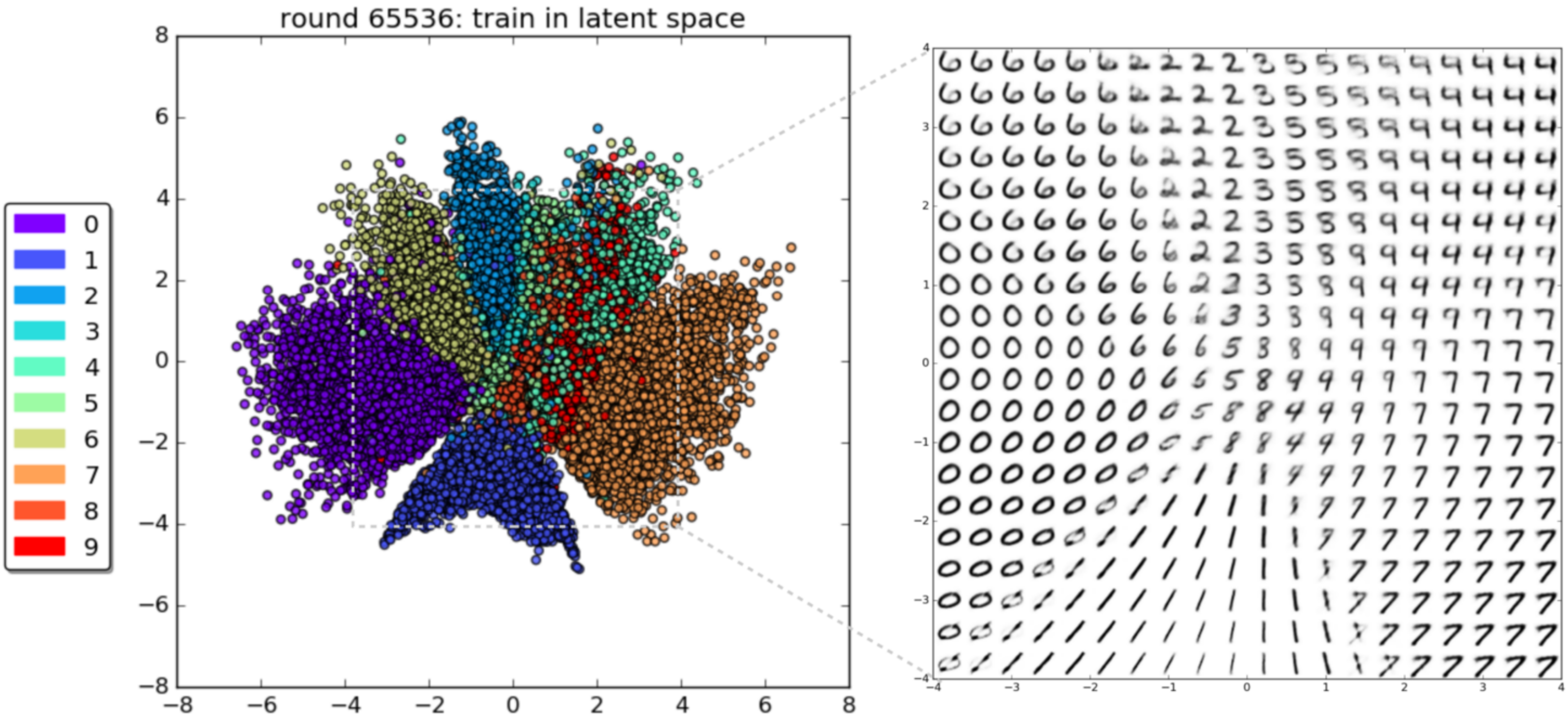

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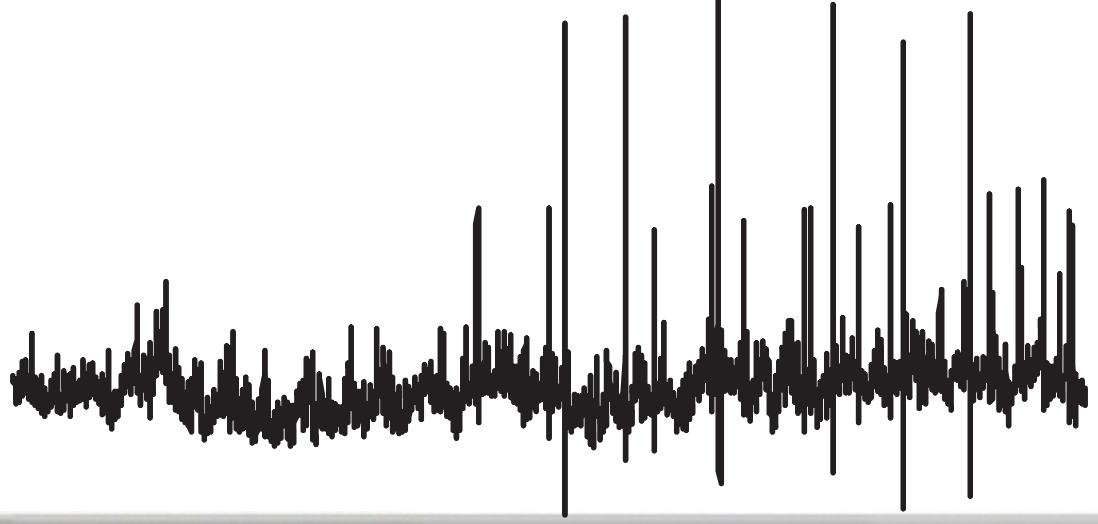
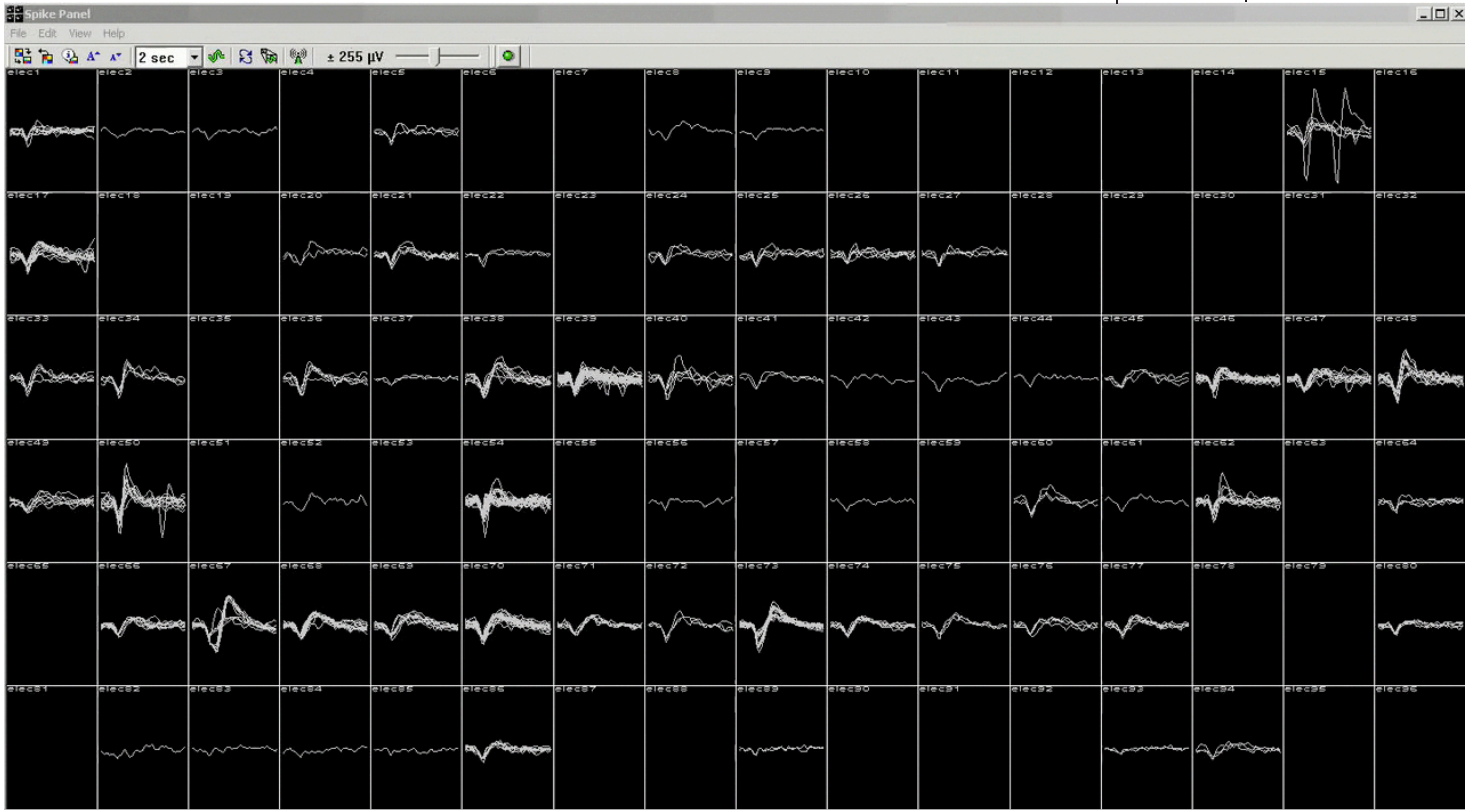
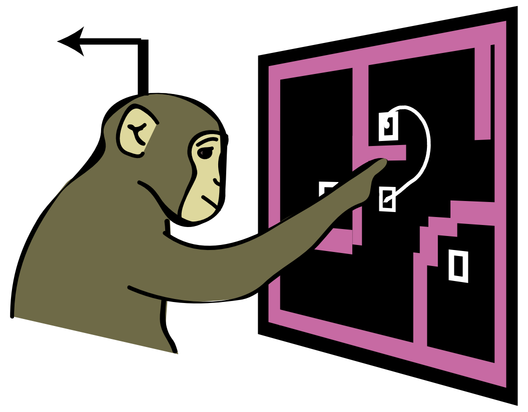
Intro to neural population dynamics

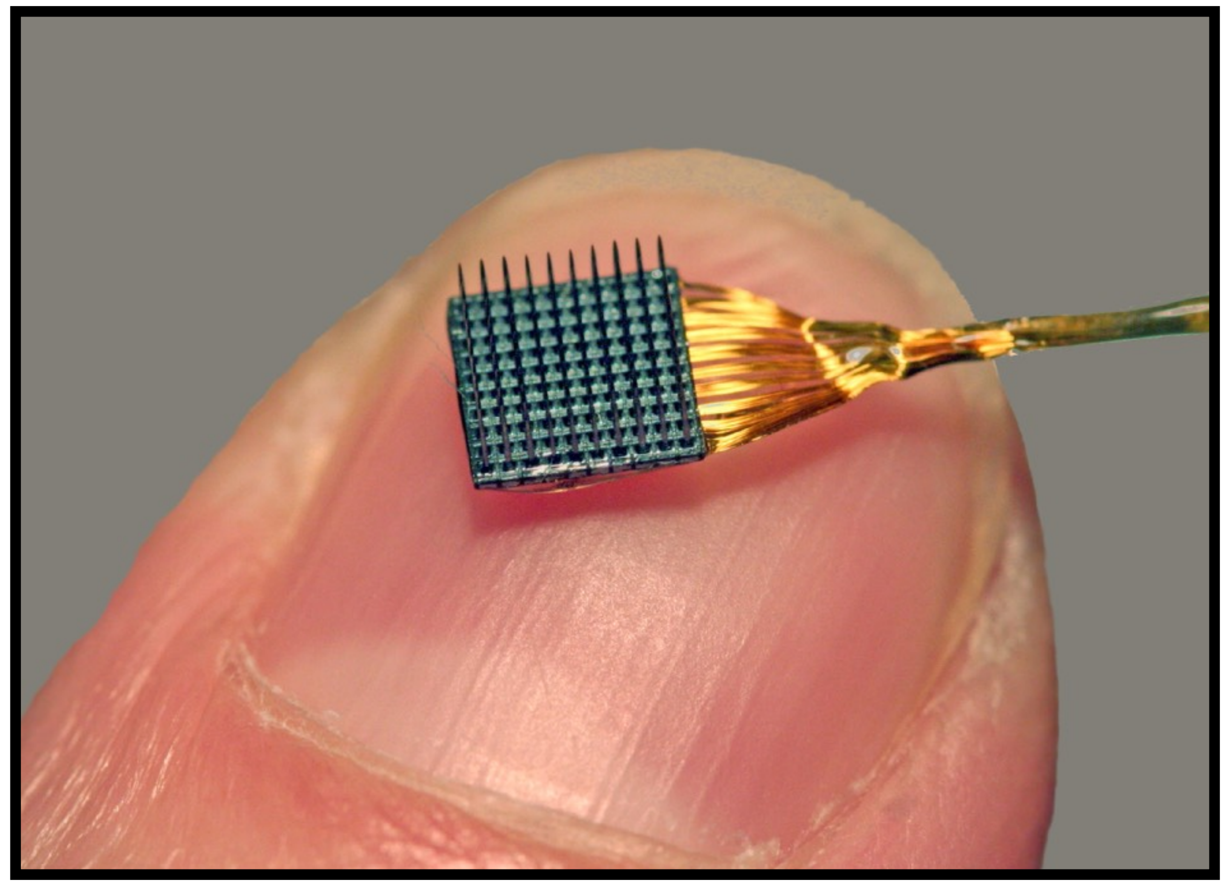
Intracortical electrophysiological recordings



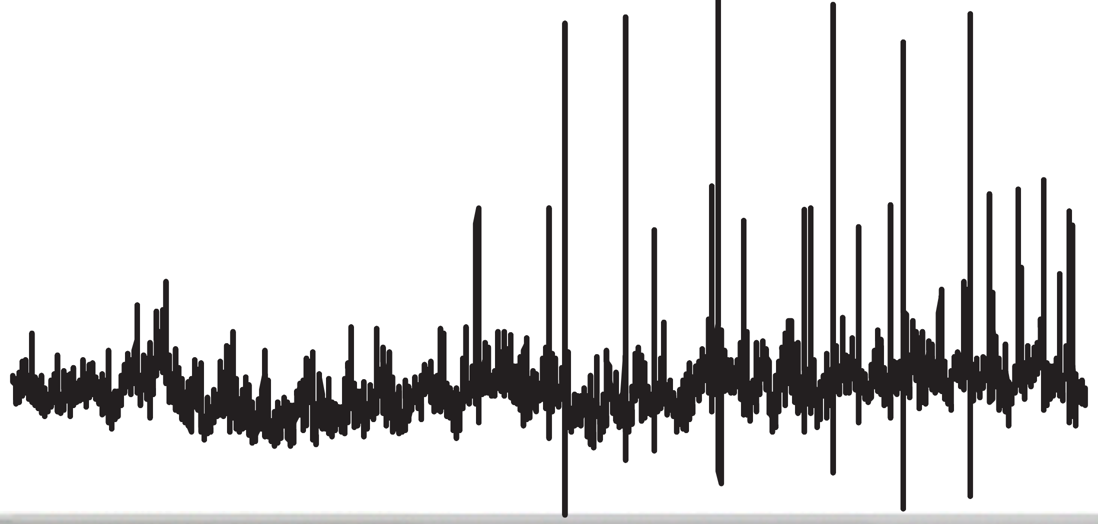


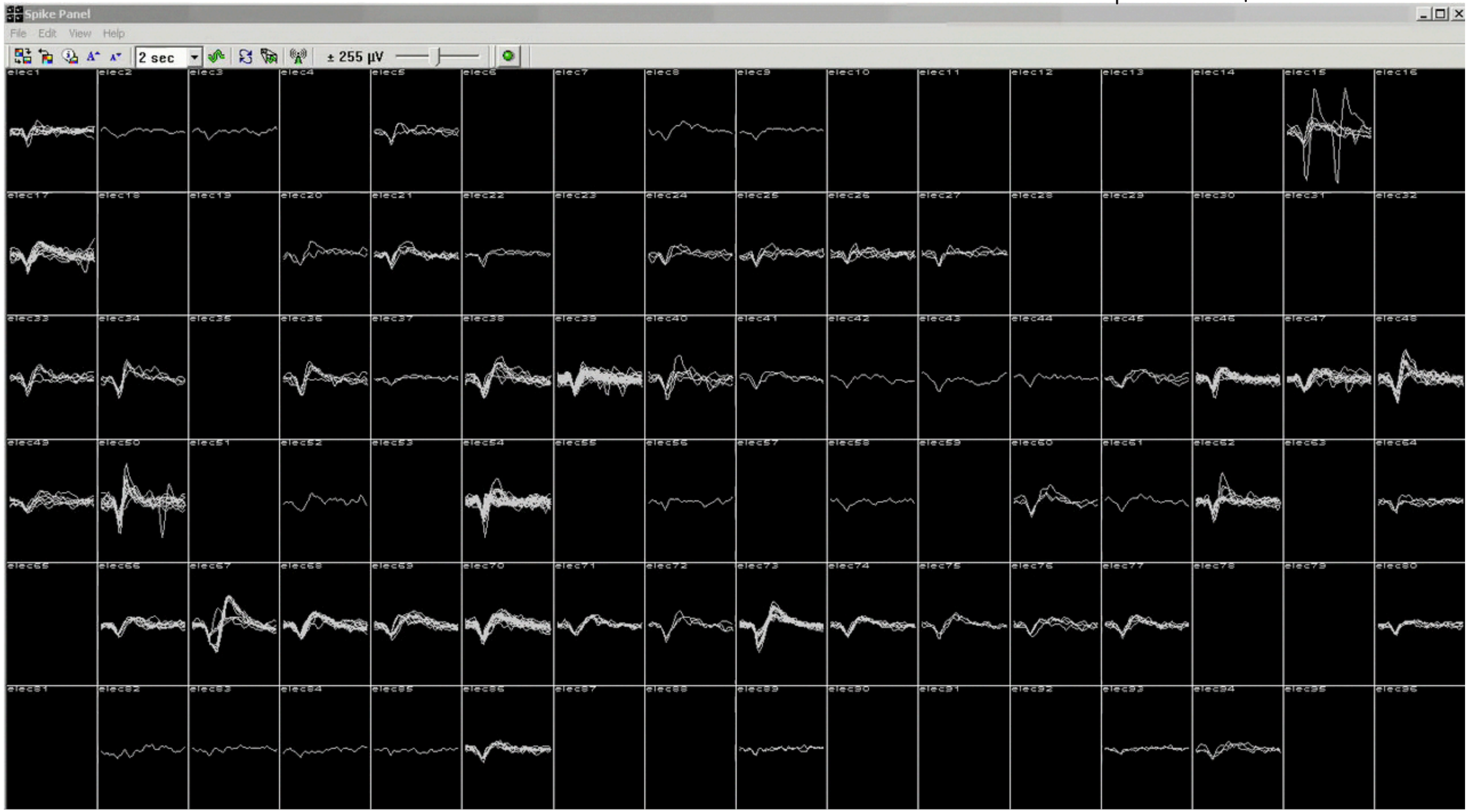
M1/
PMd





Intracortical electrophysiological recordings





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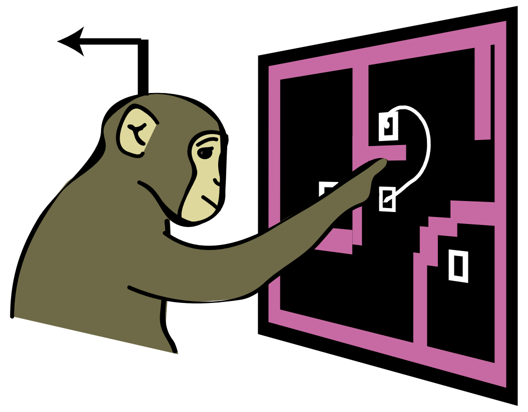
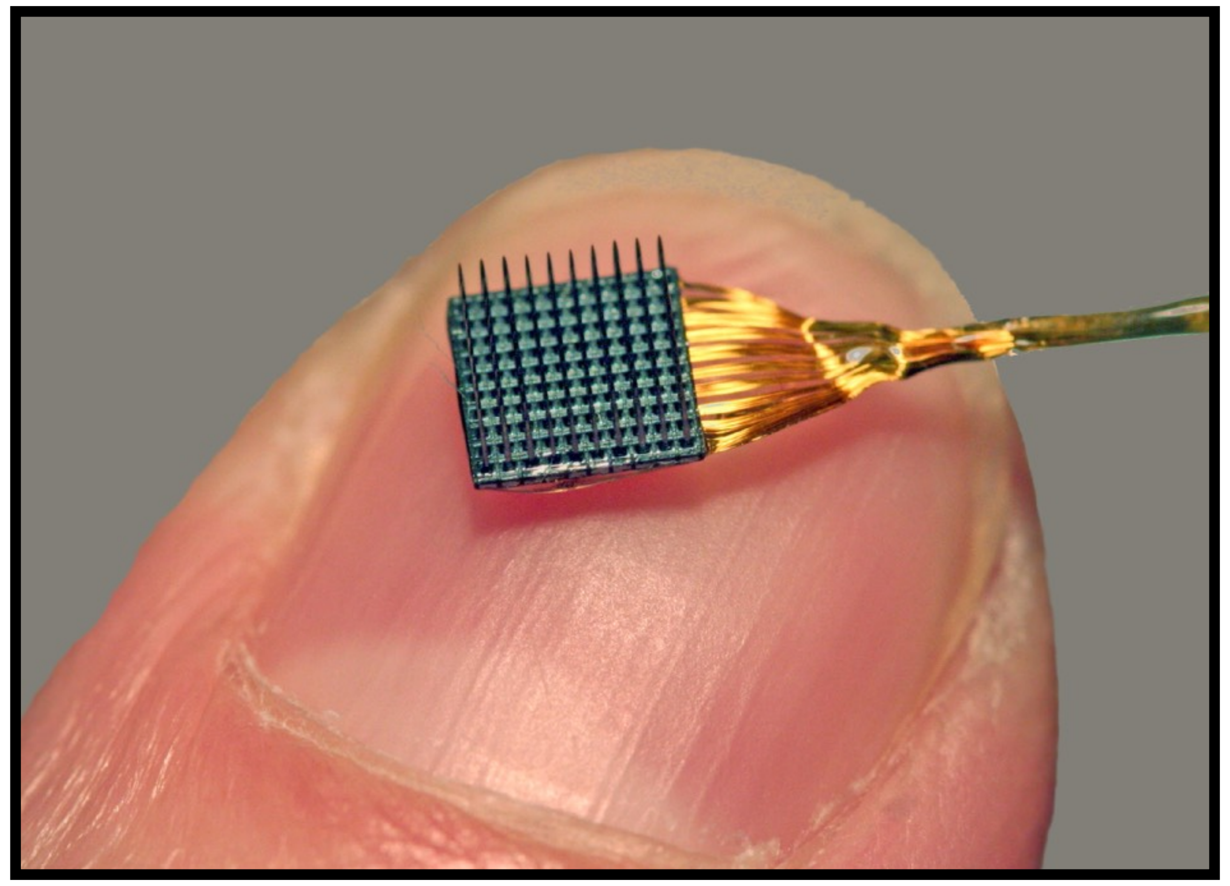
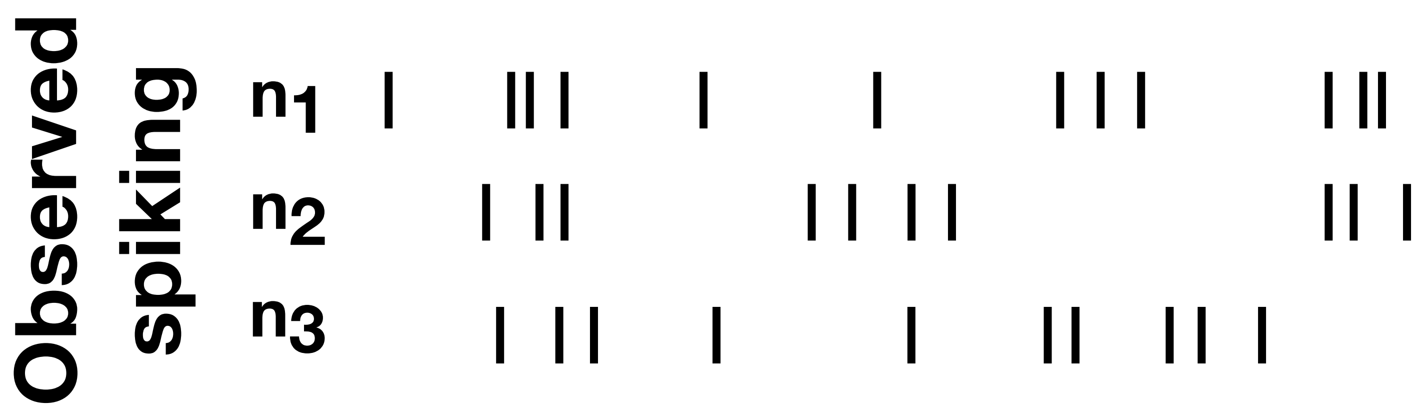




Neural population state spaces



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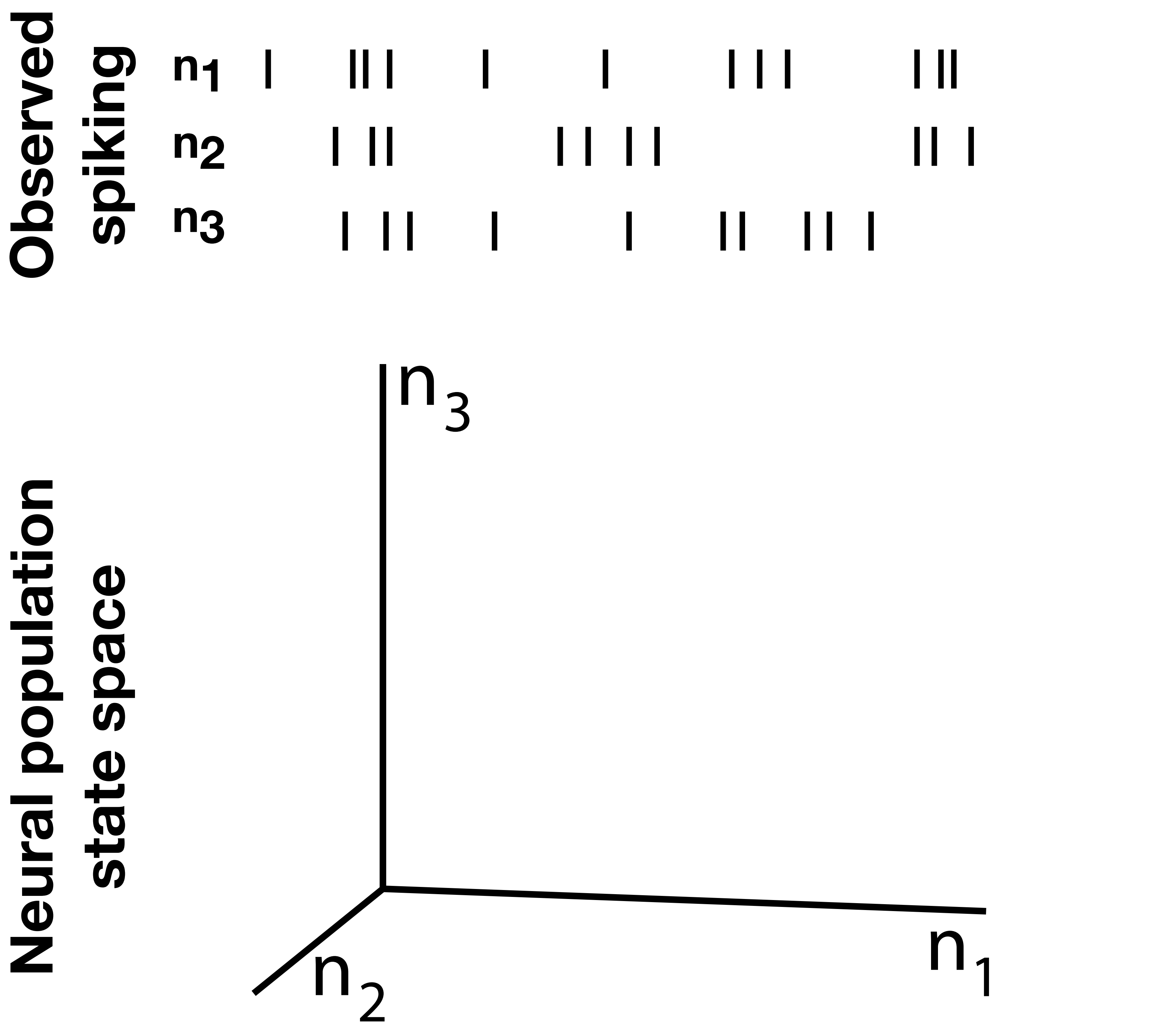
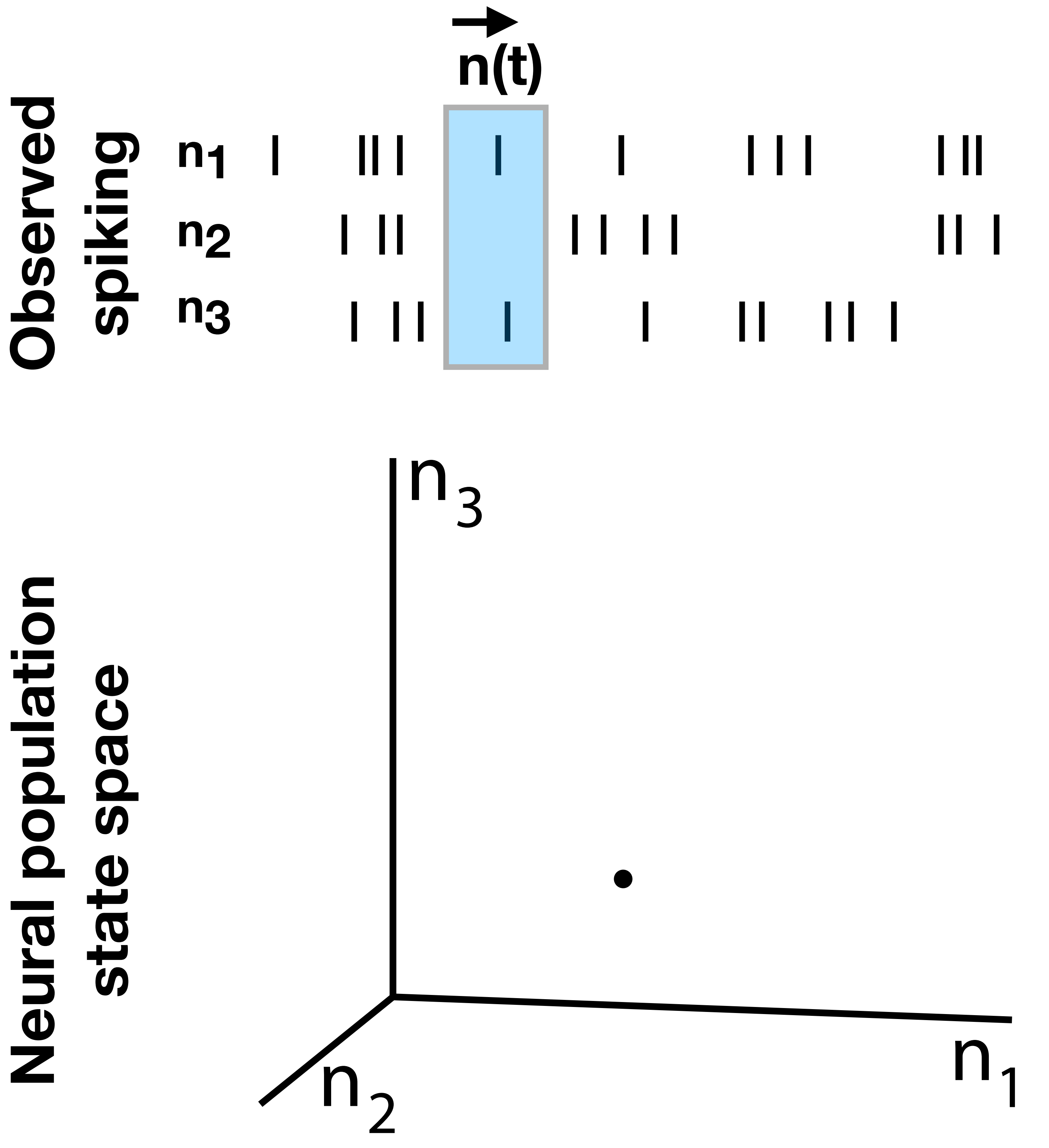


Adapted from Cunningham & Yu, *Nat Neuro* 2014
Dimensionality reduction for large-scale neural recordings

Neural population state spaces



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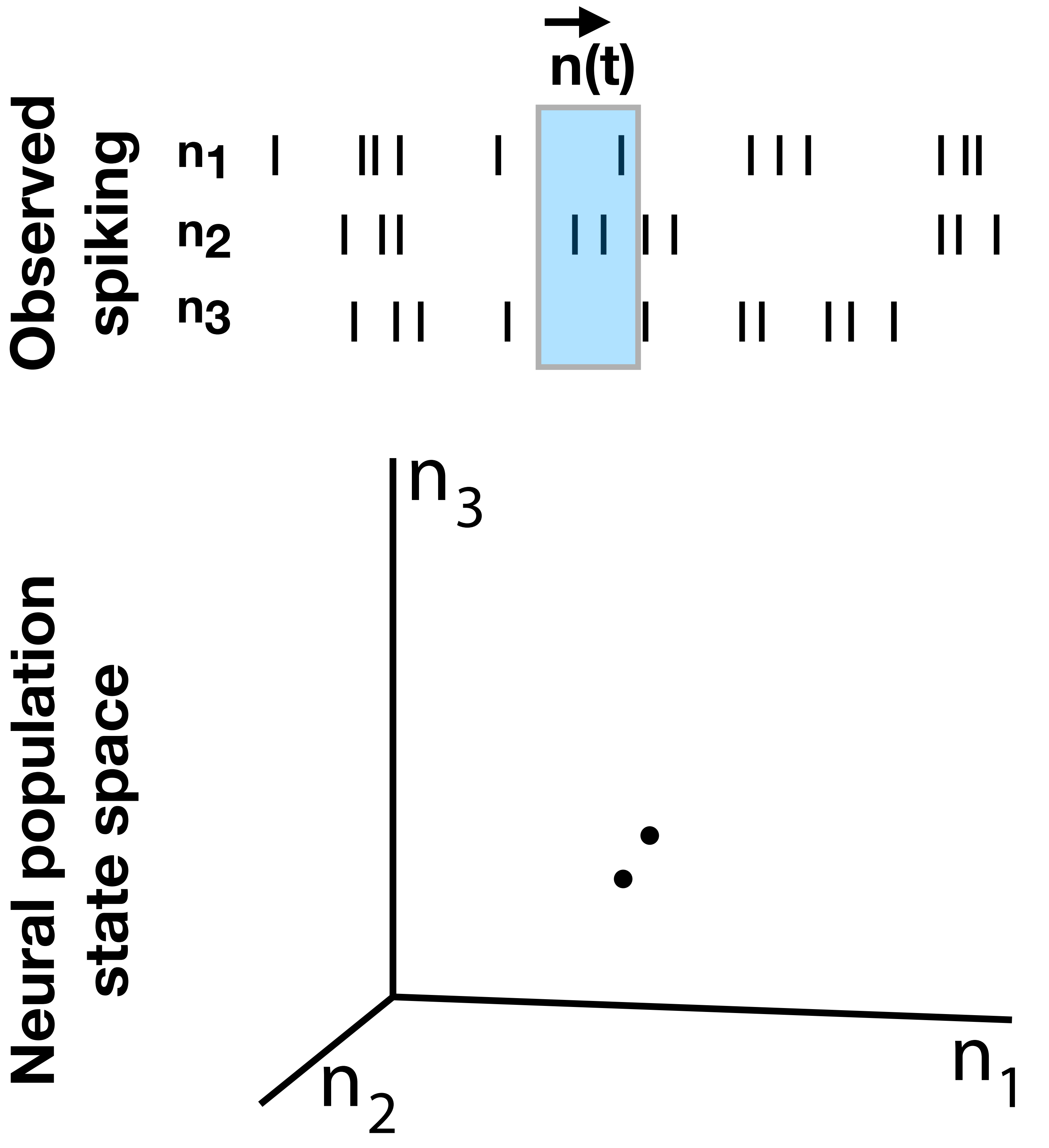
Dimensionality reduction for large-scale neural recordings

- The current state of the system is captured by the firing rates of all of its neurons

Neural population state spaces



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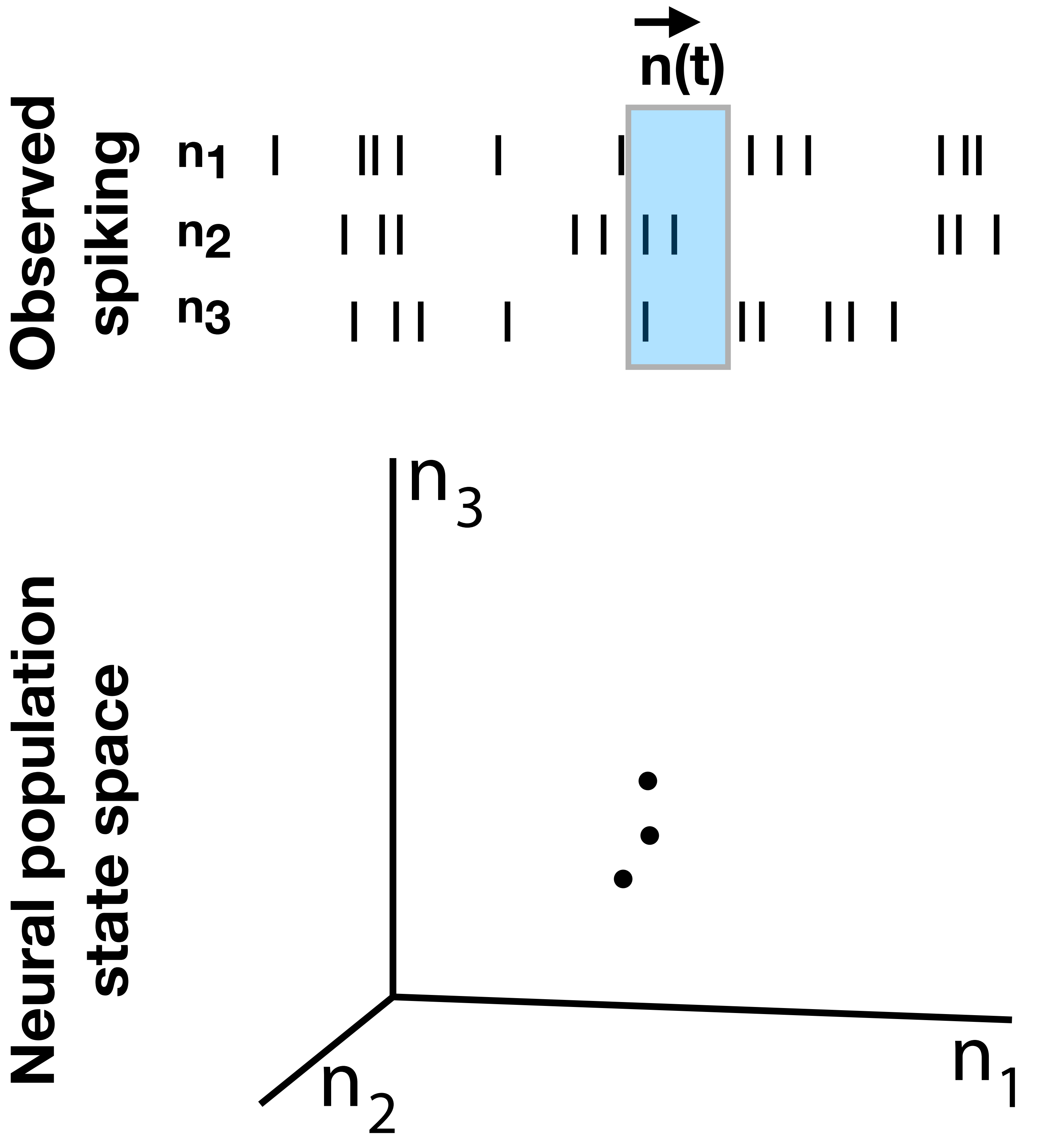

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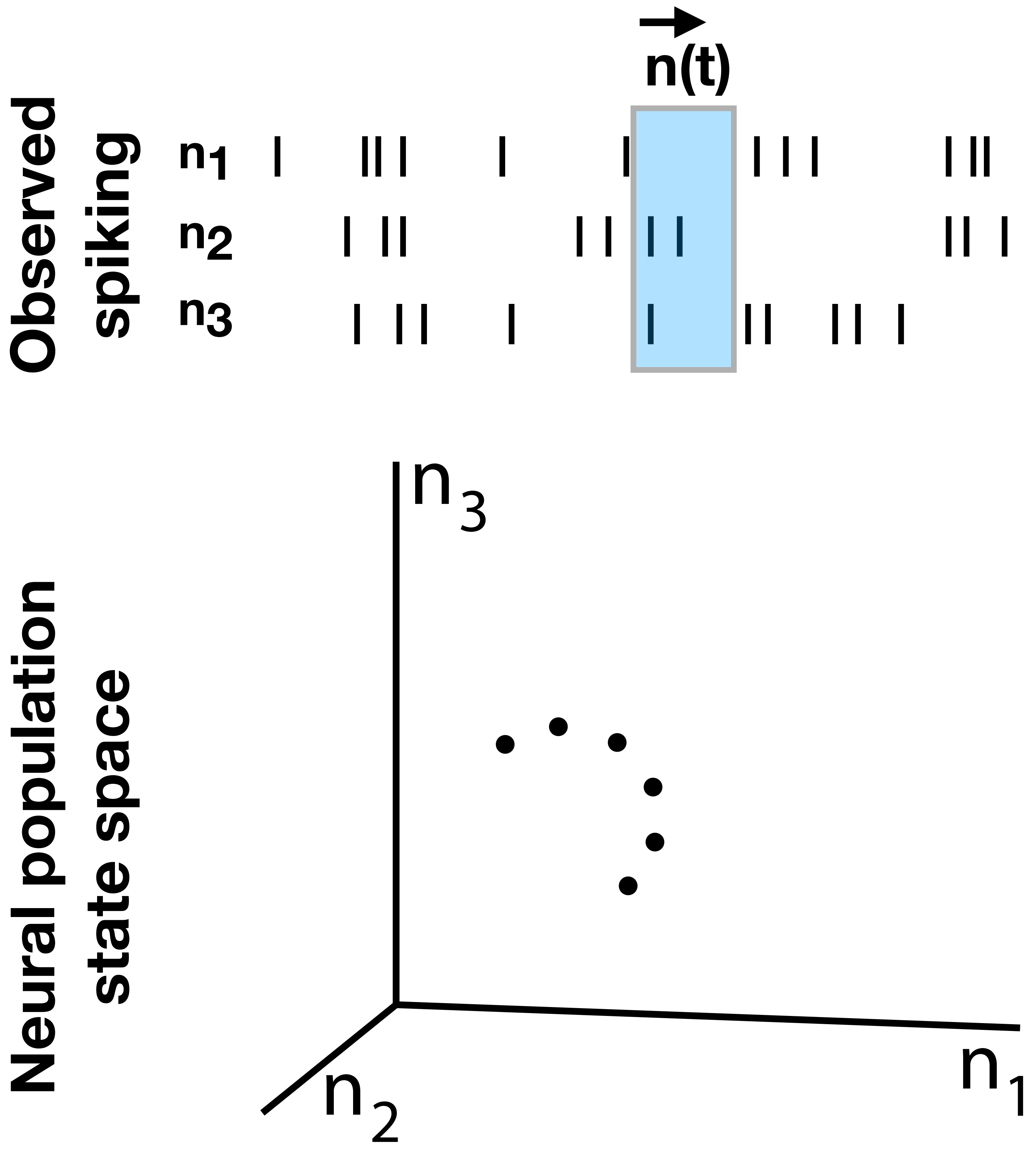

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- Activity does not uniformly fill the space - i.e., not all patterns of neural firing rates are equally likely

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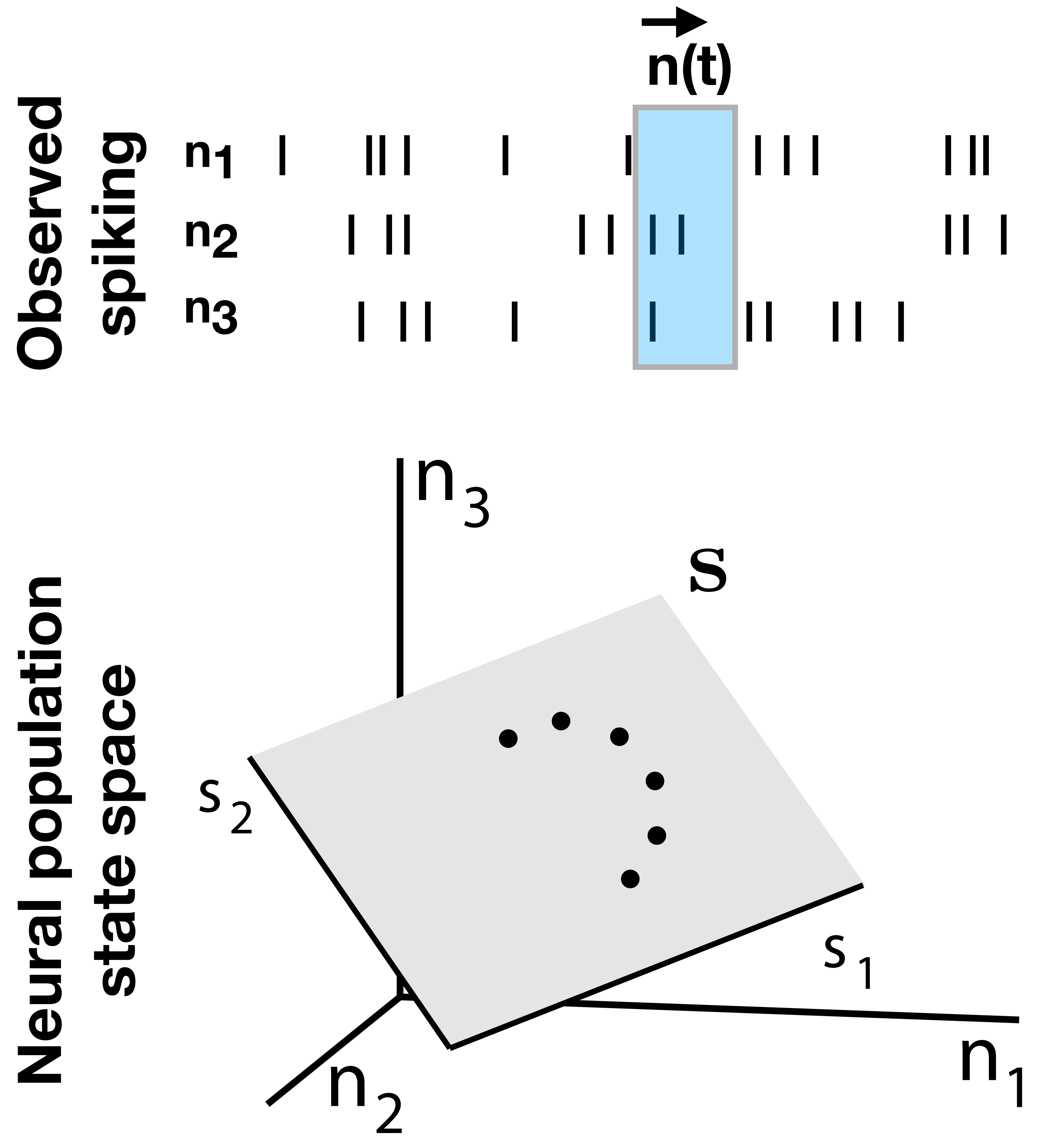

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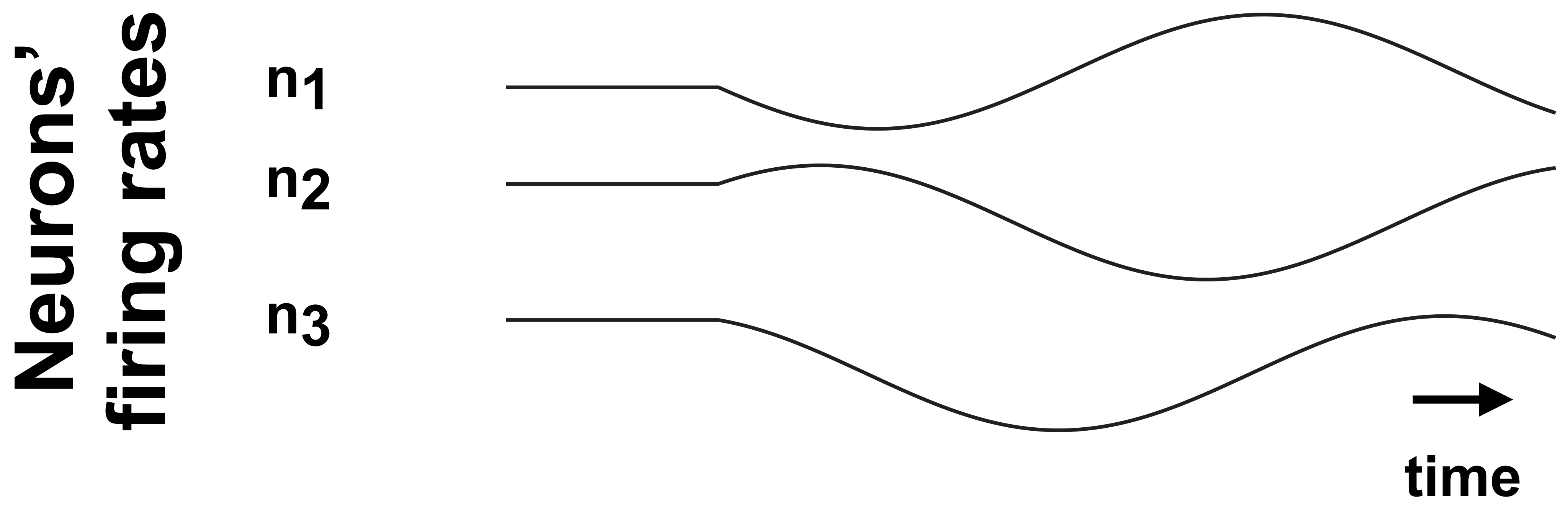
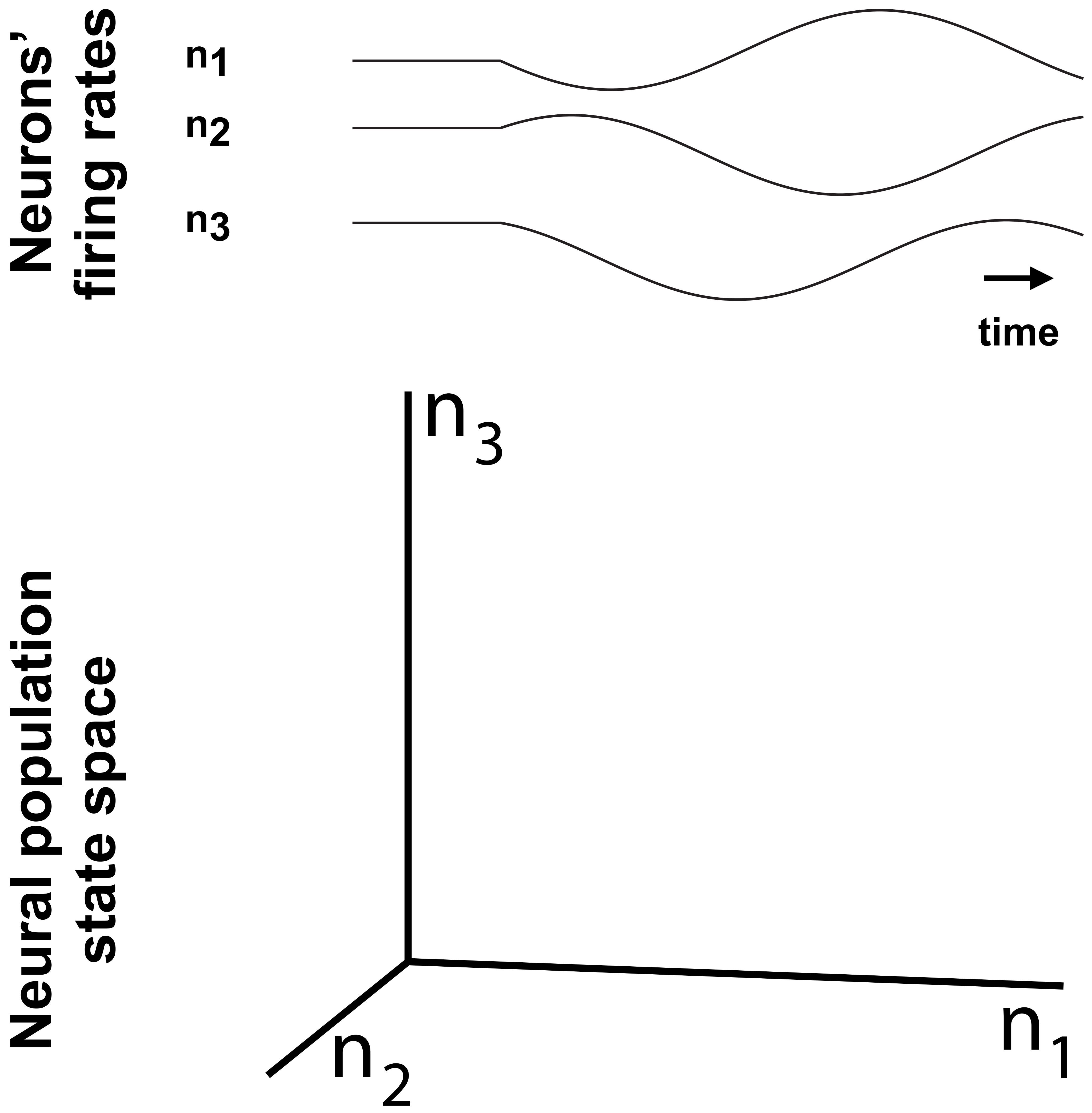
- The current state of the system is captured by the firing rates of all of its neurons
- Activity does not uniformly fill the space - i.e., not all patterns of neural firing rates are equally likely
- We can usually identify shared structure underlying the firing rates of the recorded neurons

Changes in neurons’ firing rates are coordinated

Changes in neurons' firing rates are coordinated



Changes in neurons’ firing rates are coordinated



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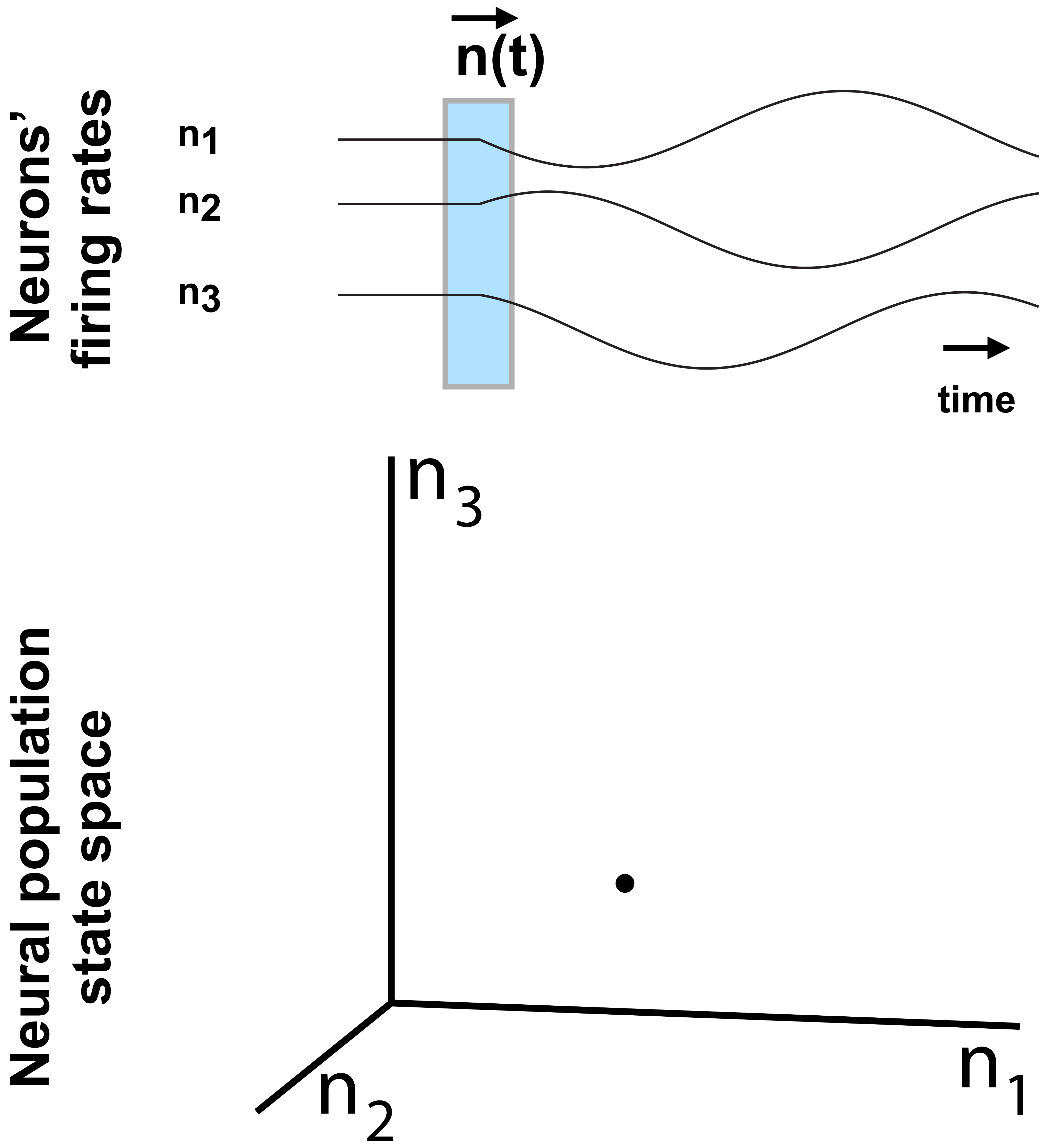

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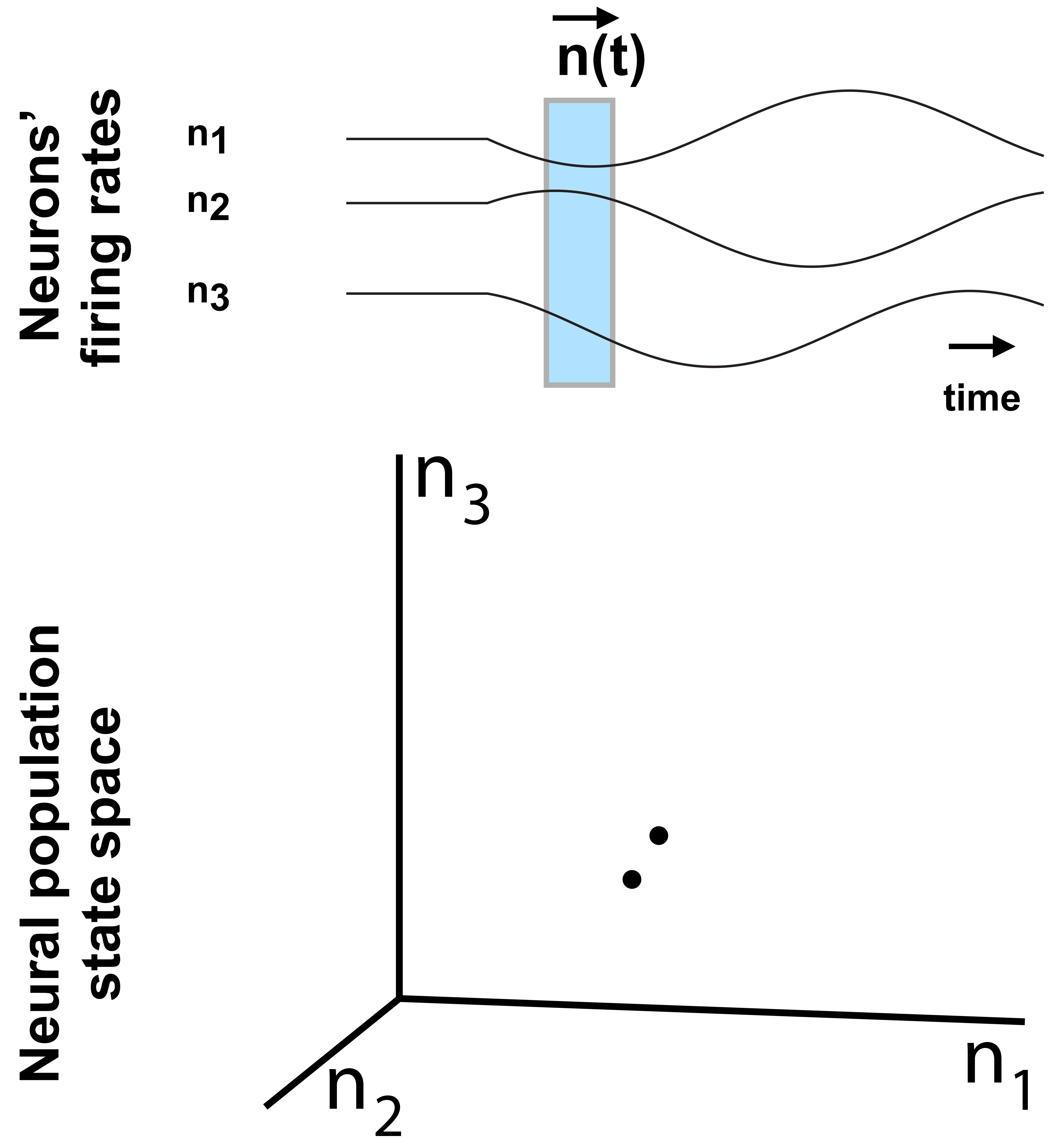

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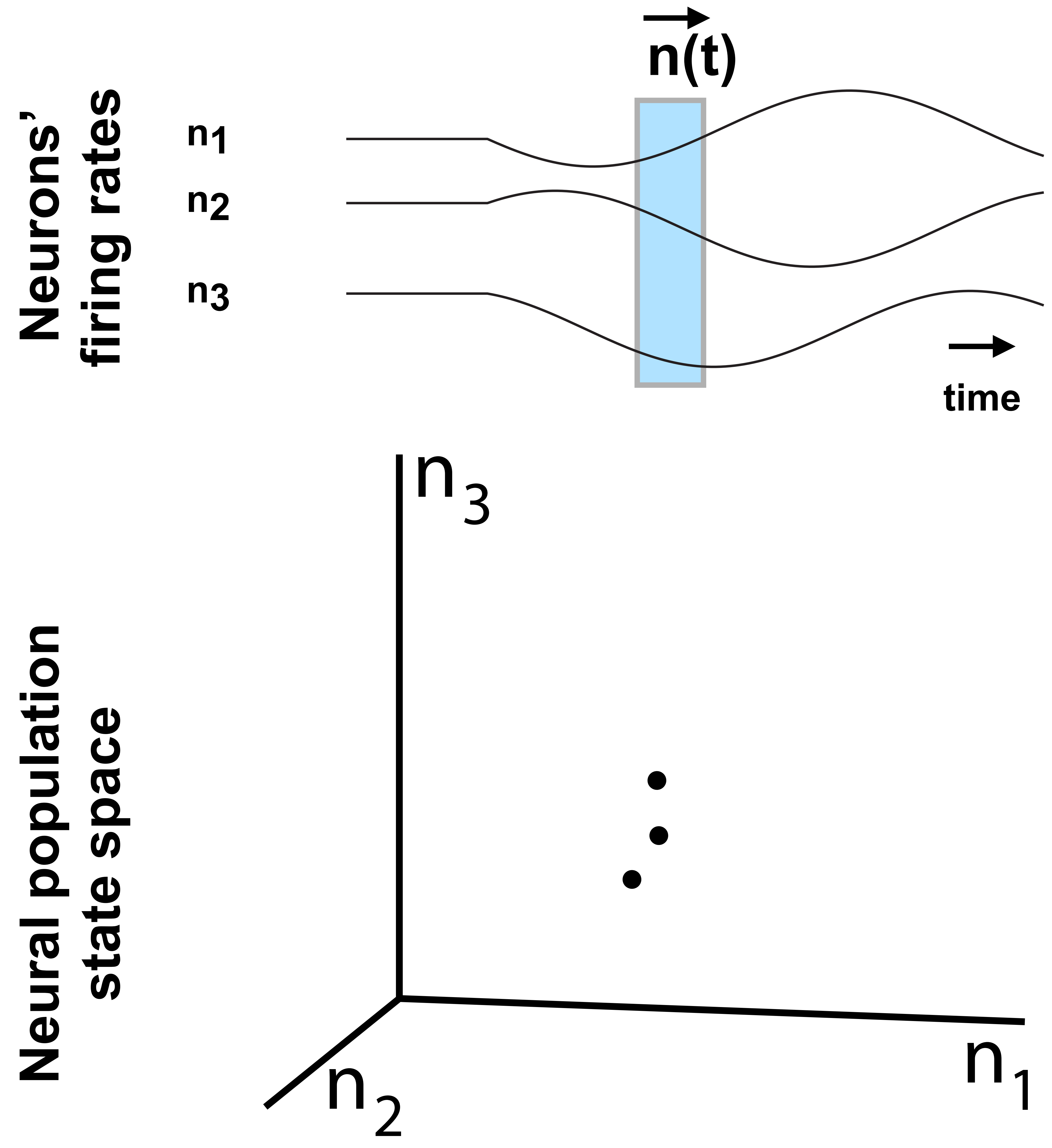

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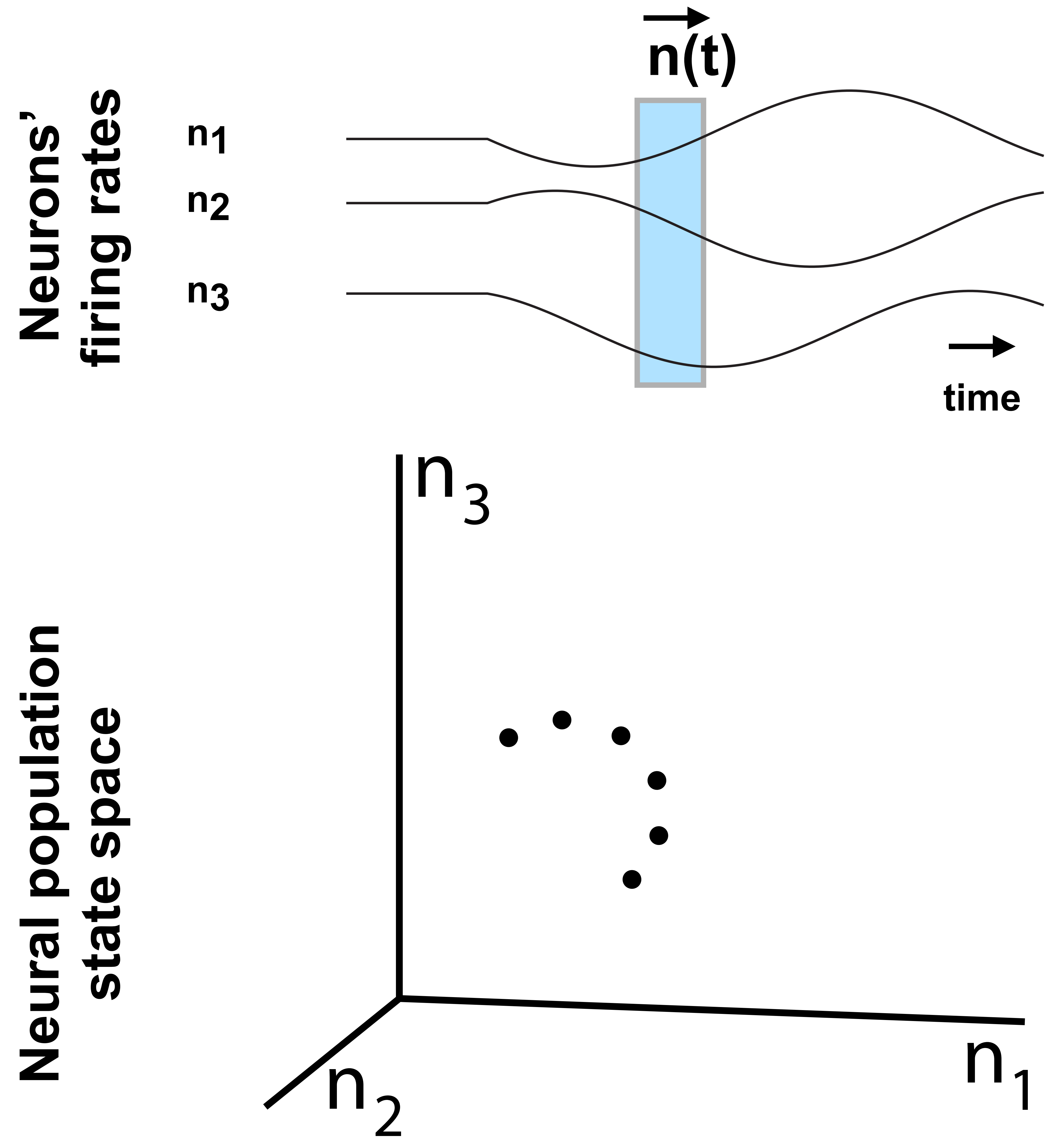

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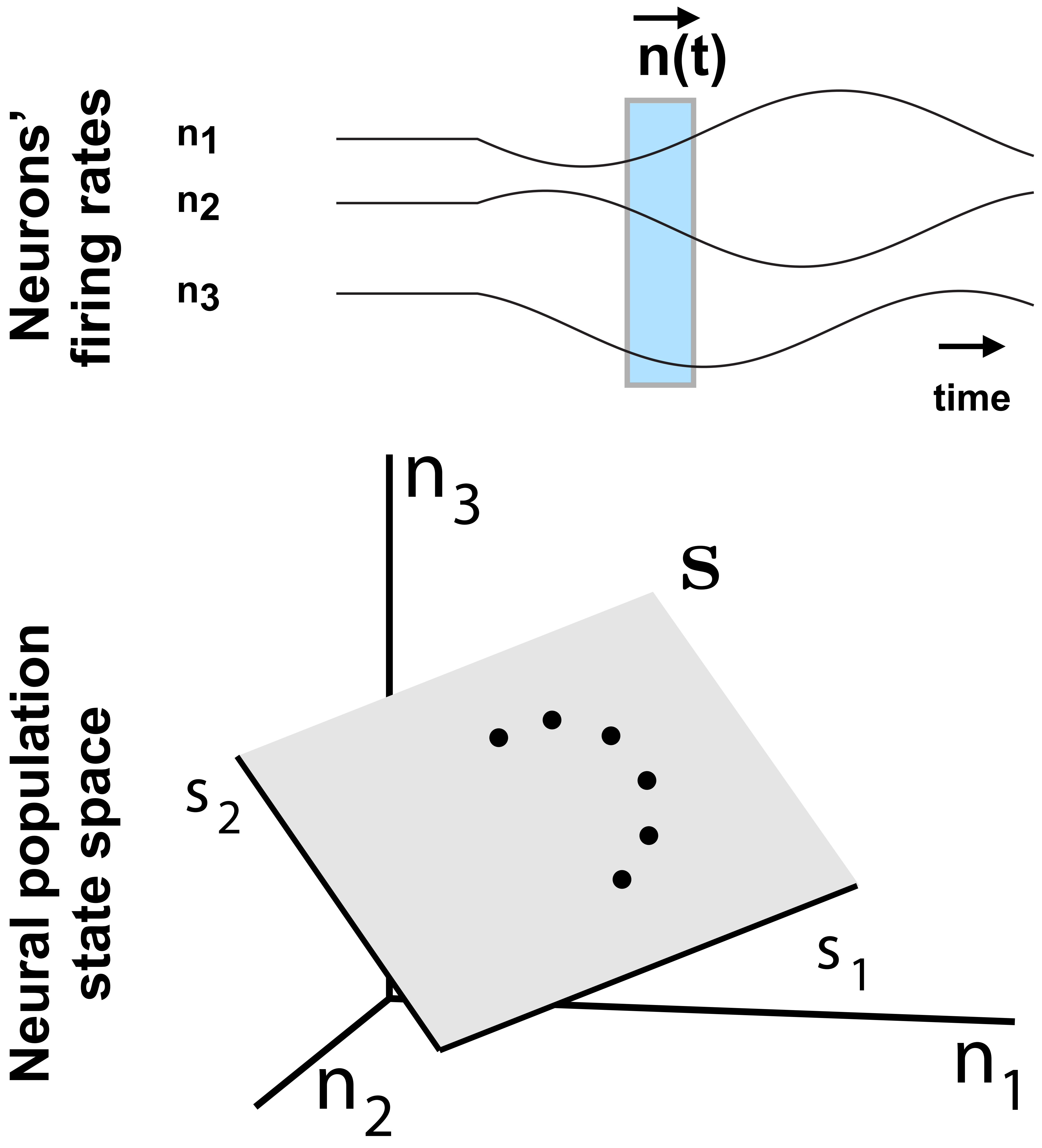

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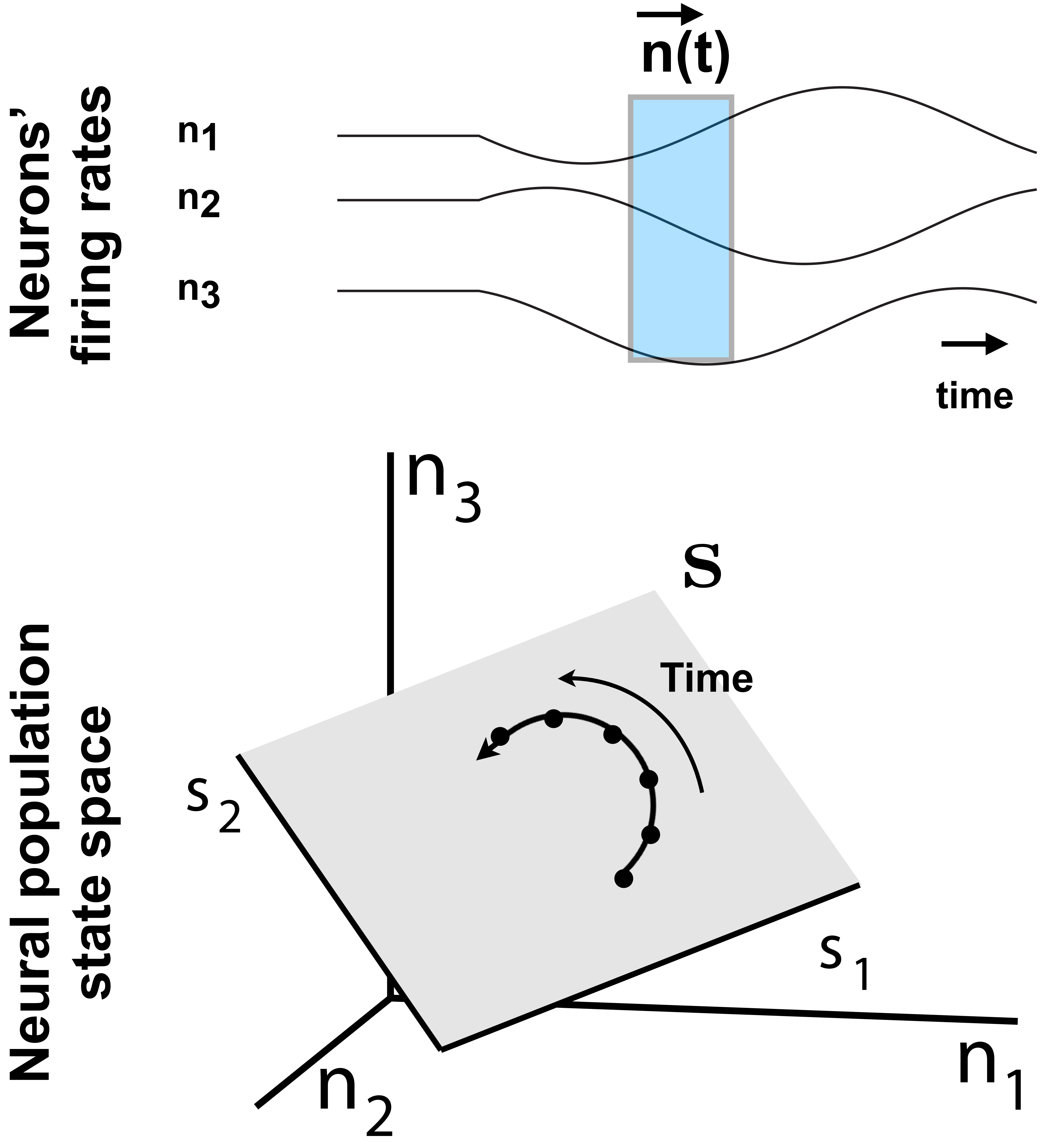
Neural population dynamics



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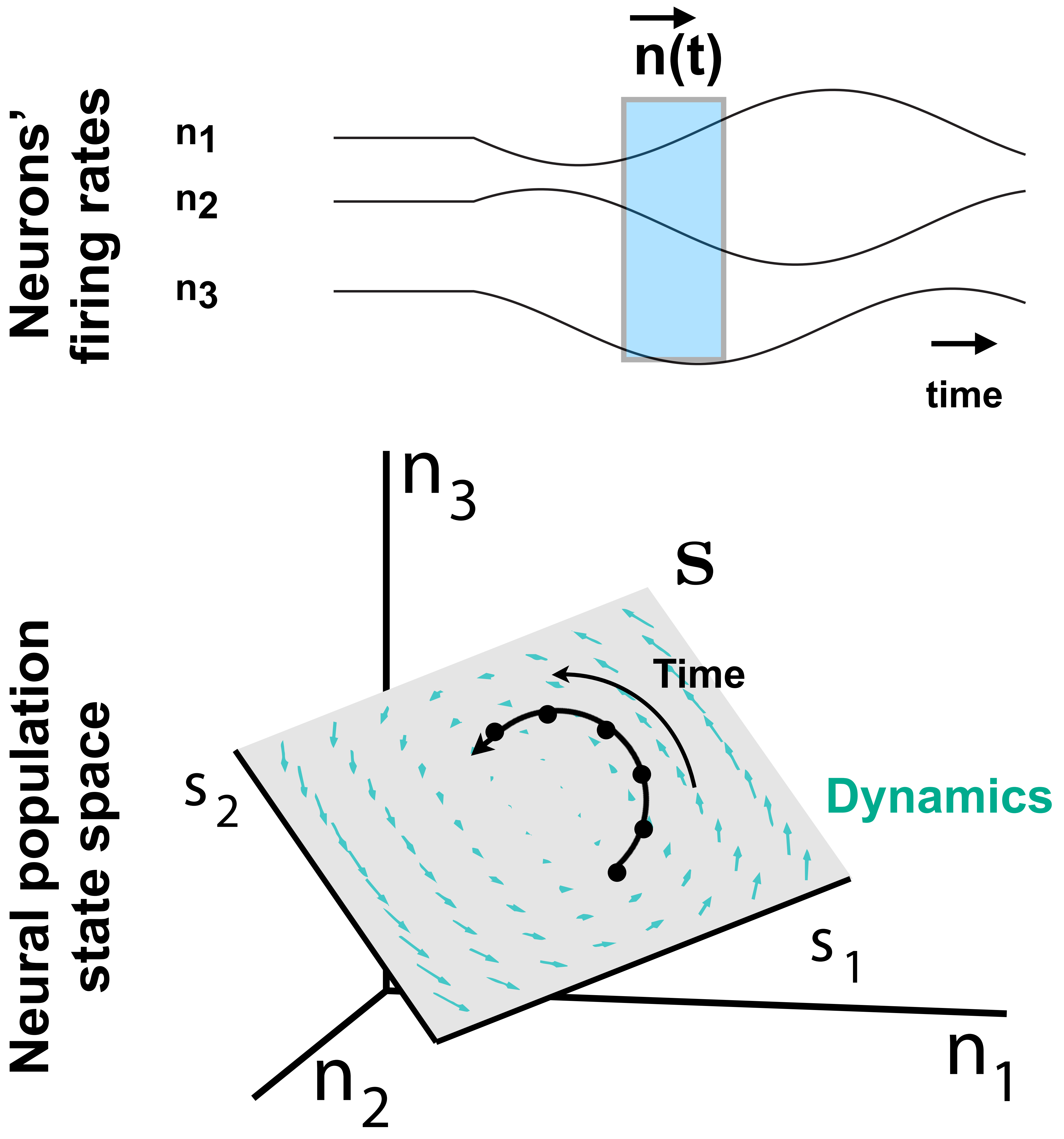

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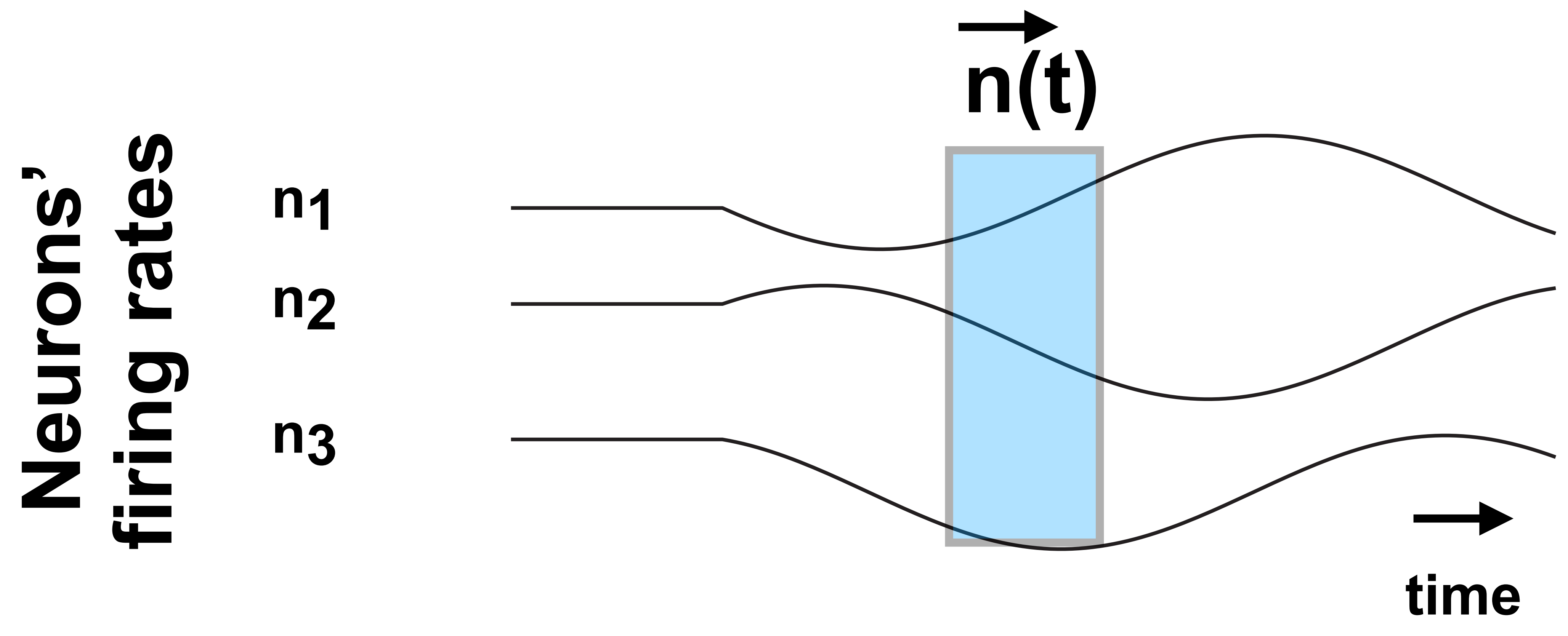
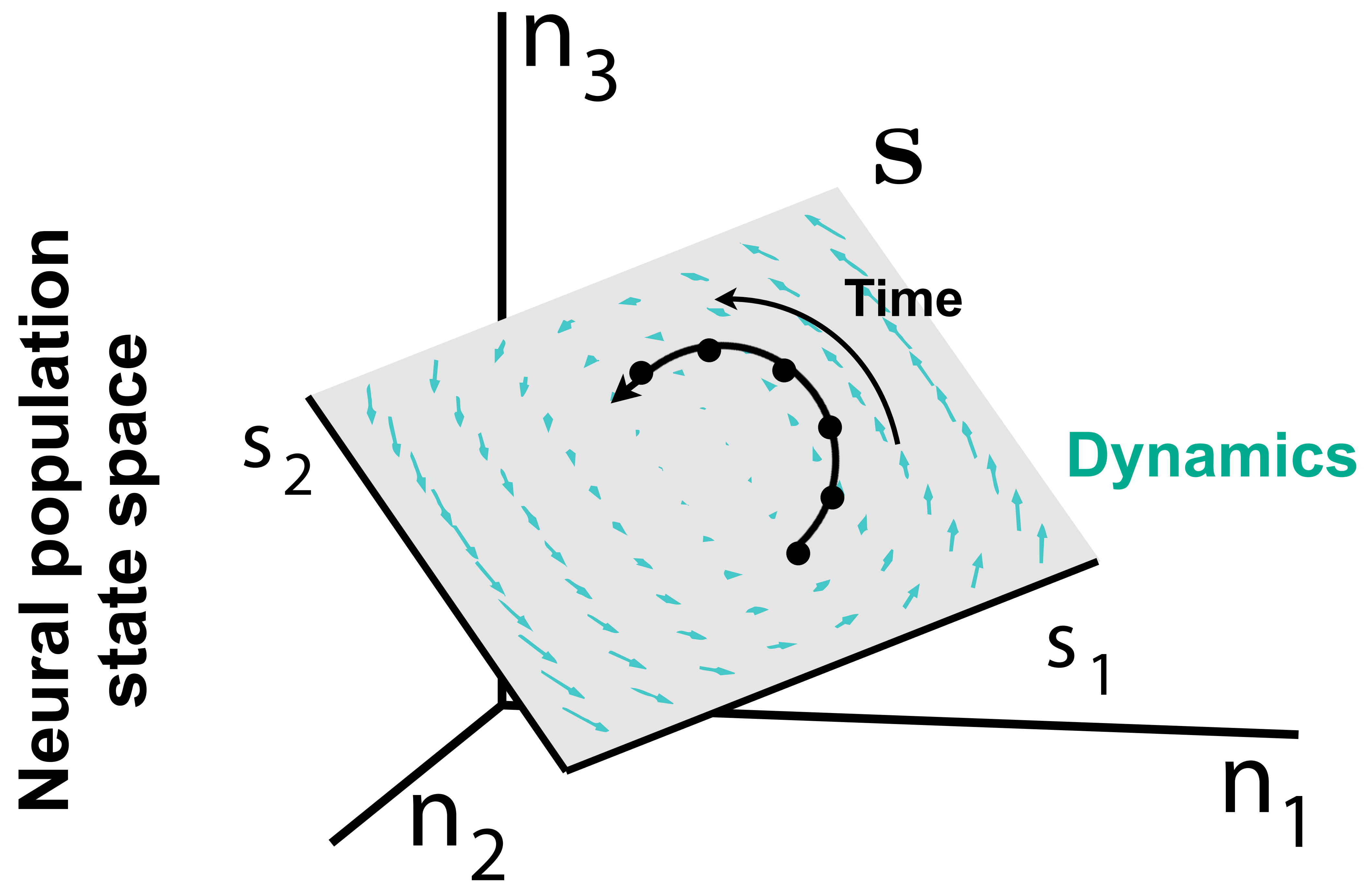
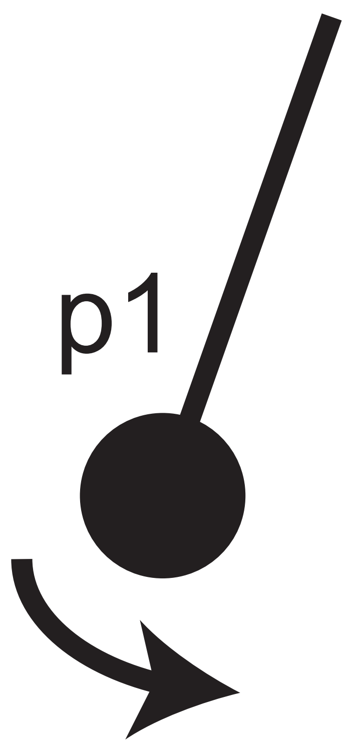
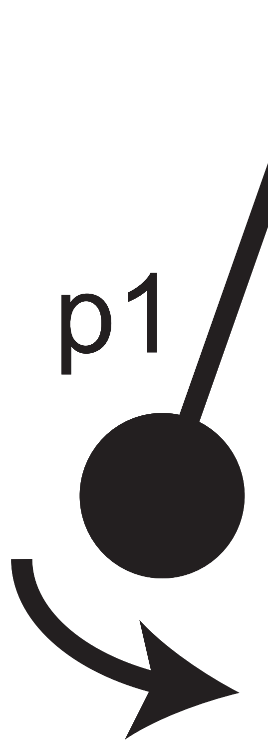


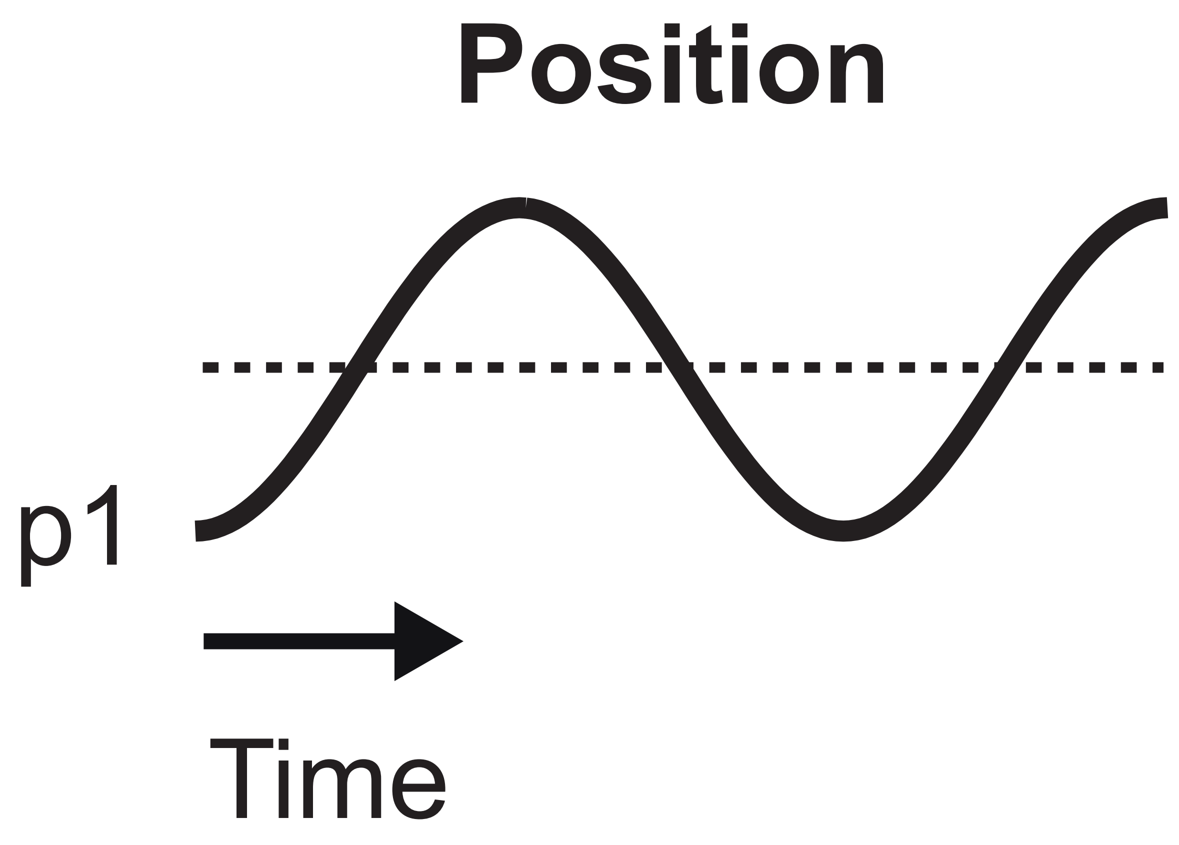
Predictable activity -
modeled by
autonomous
dynamics

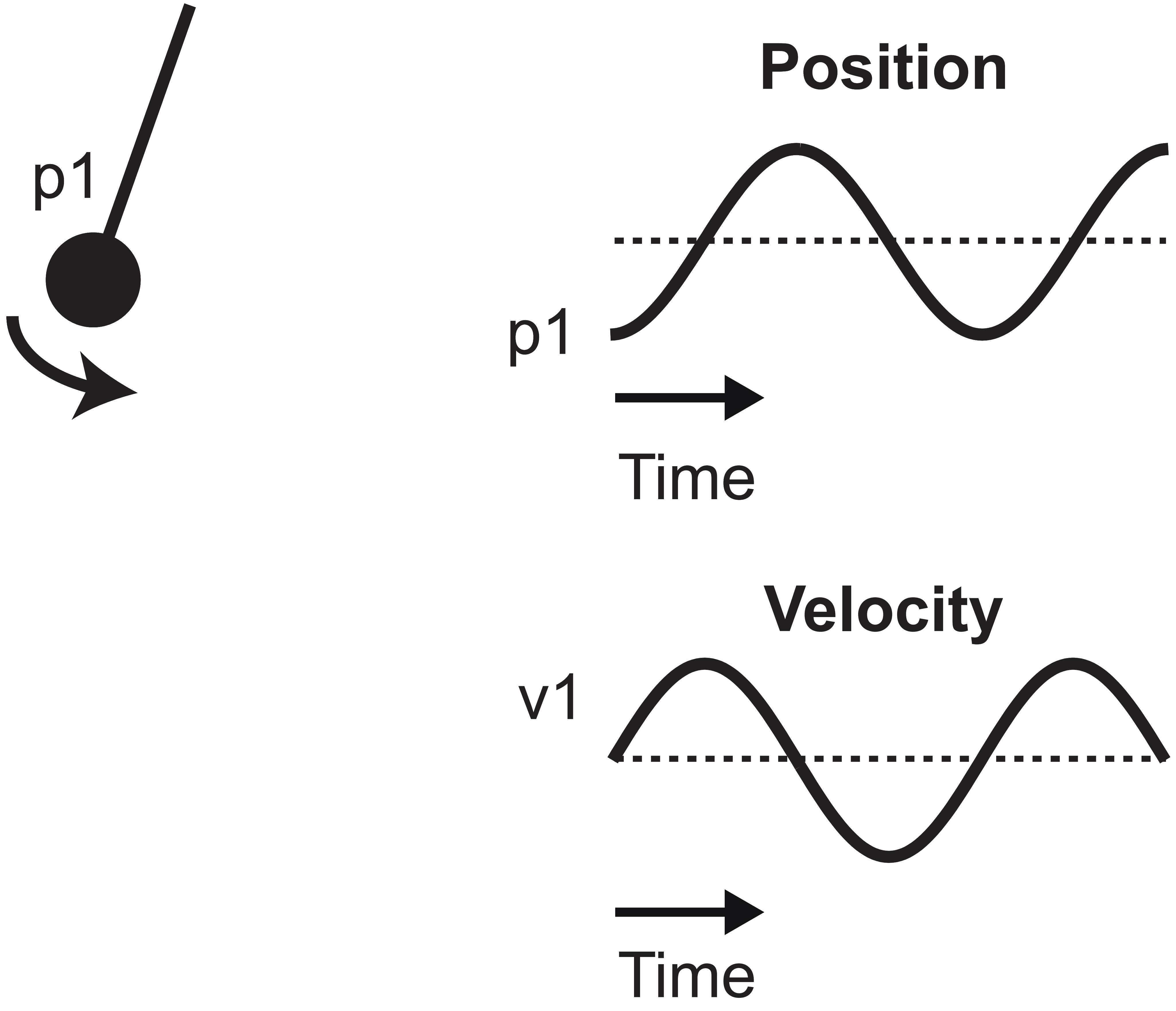
$$\frac{d\mathrm{s}}{dt} = f(\mathrm{s})$$

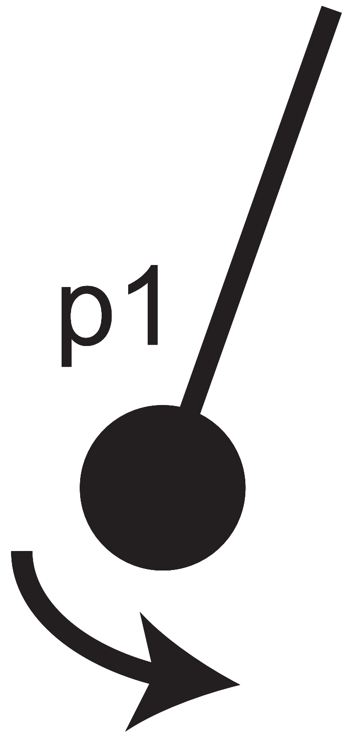


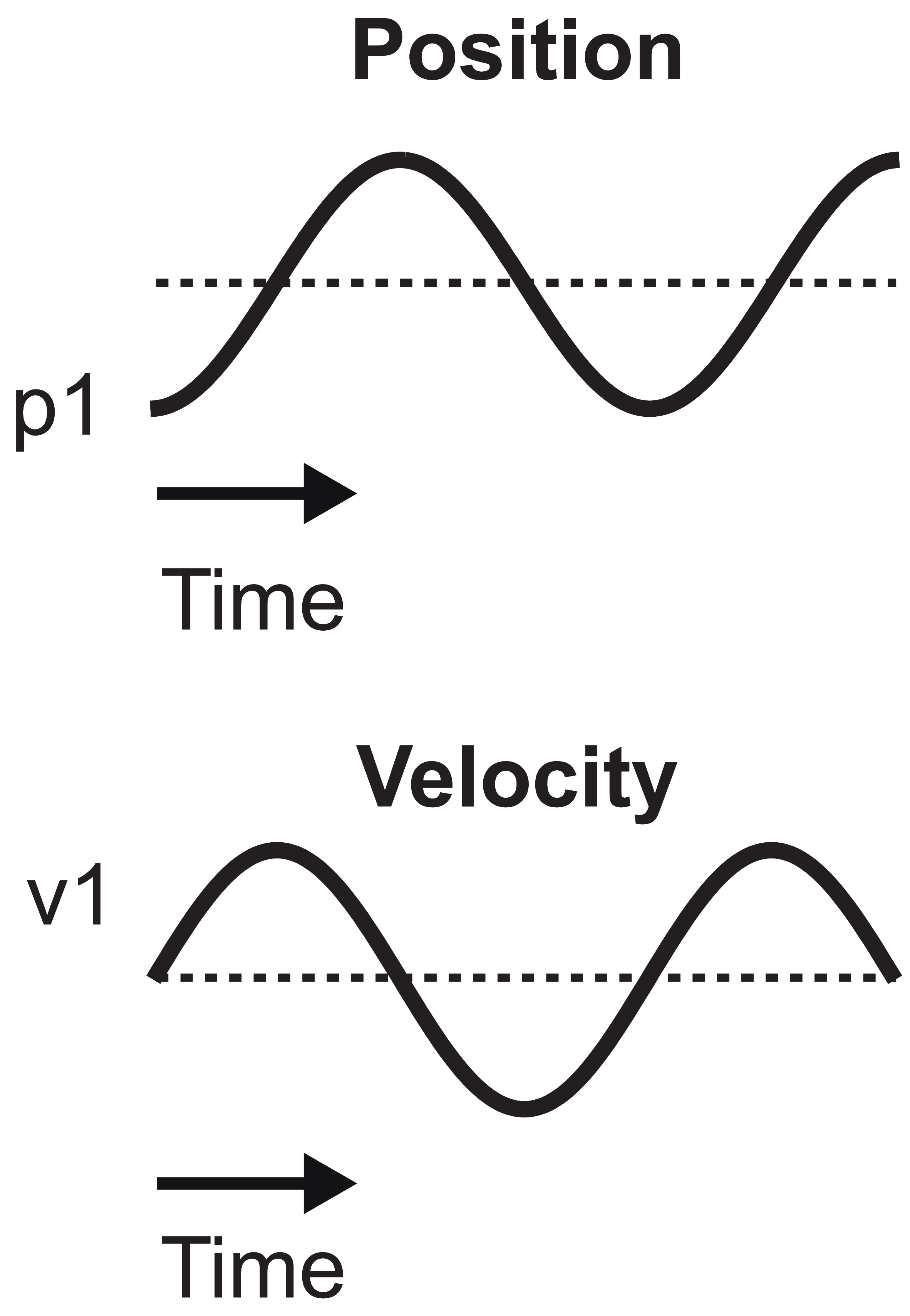

p1


p1

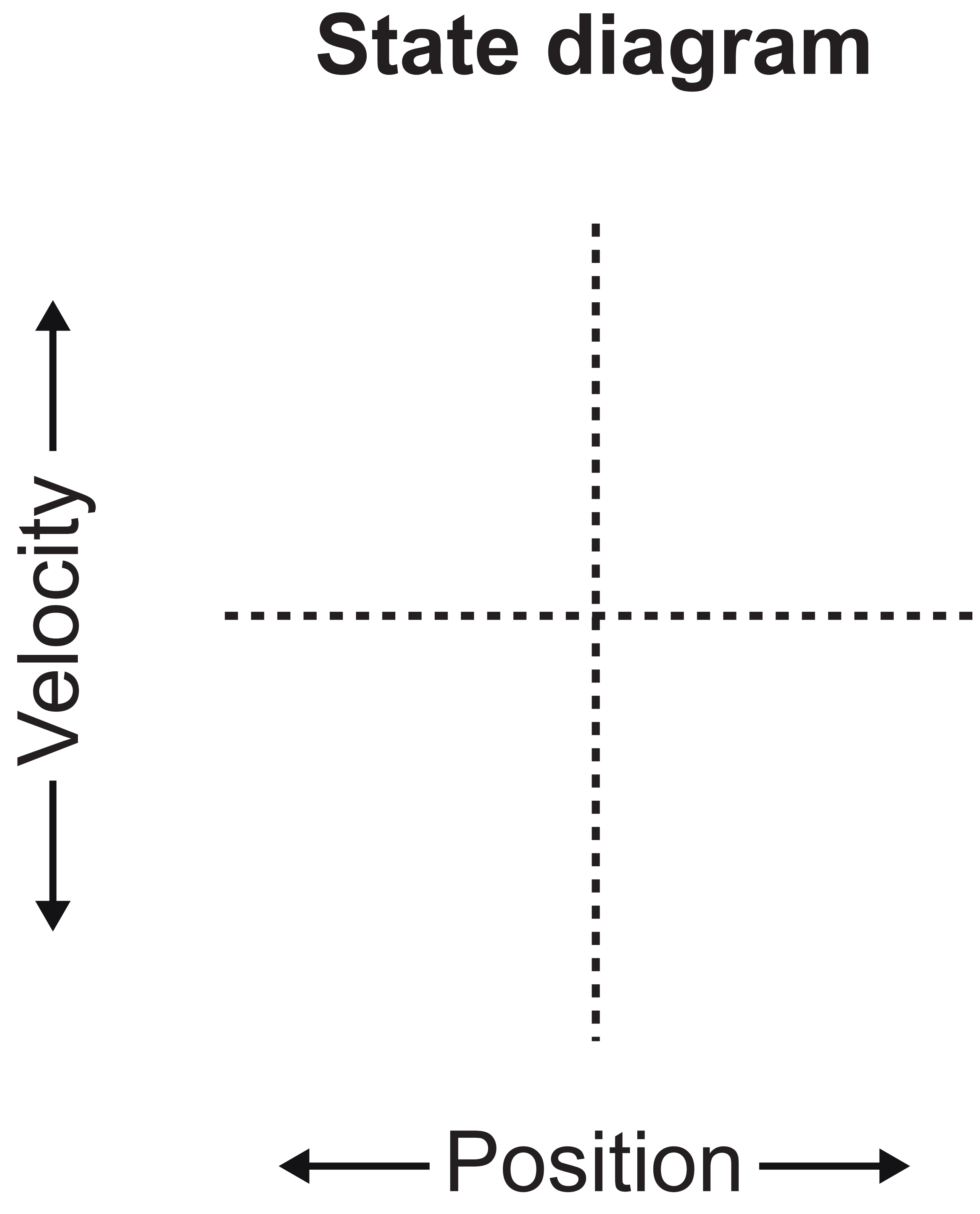

Position
p1
Time

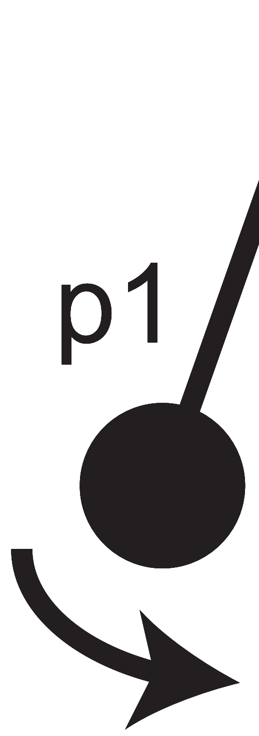

p1
Position
p1
Time
Velocity
v1
Time

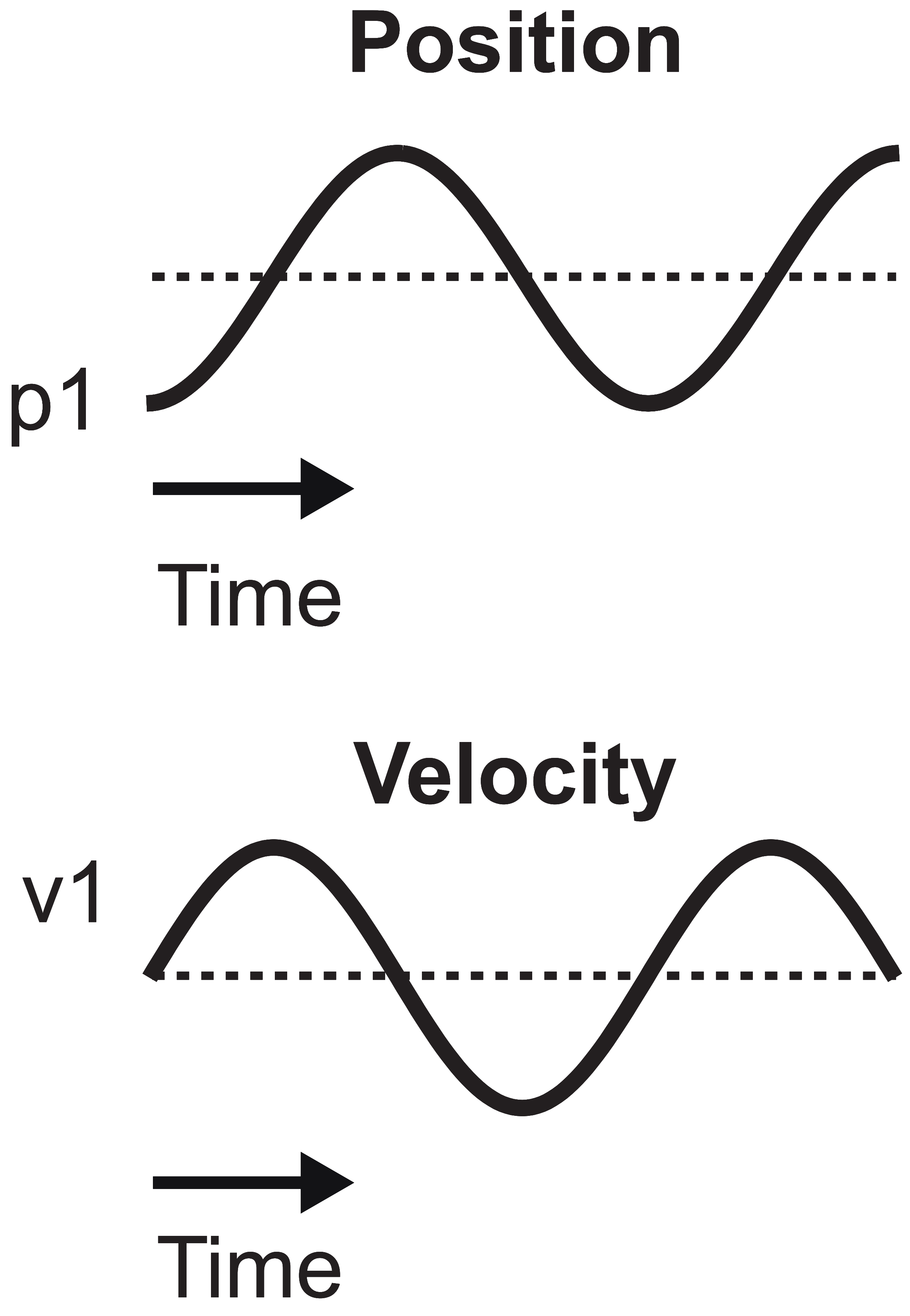




$$\mathbf{x} = \begin{bmatrix} p \\ v \end{bmatrix}$$







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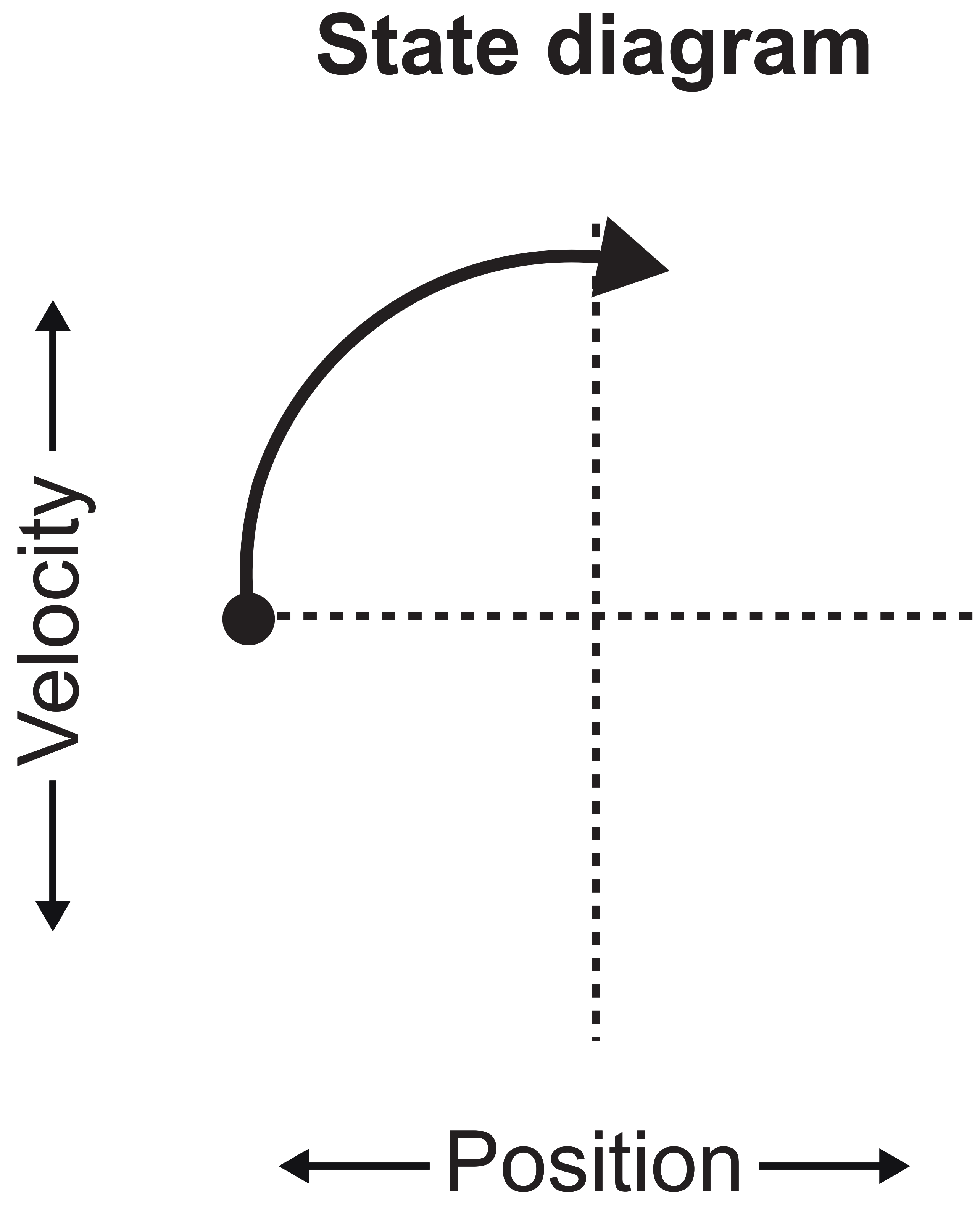

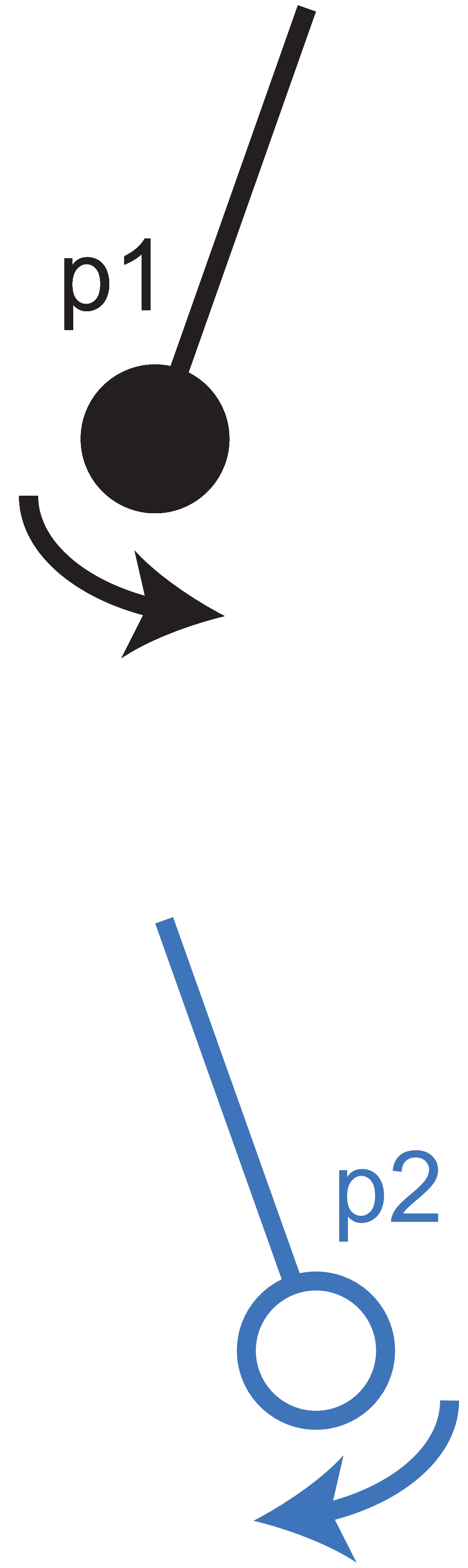

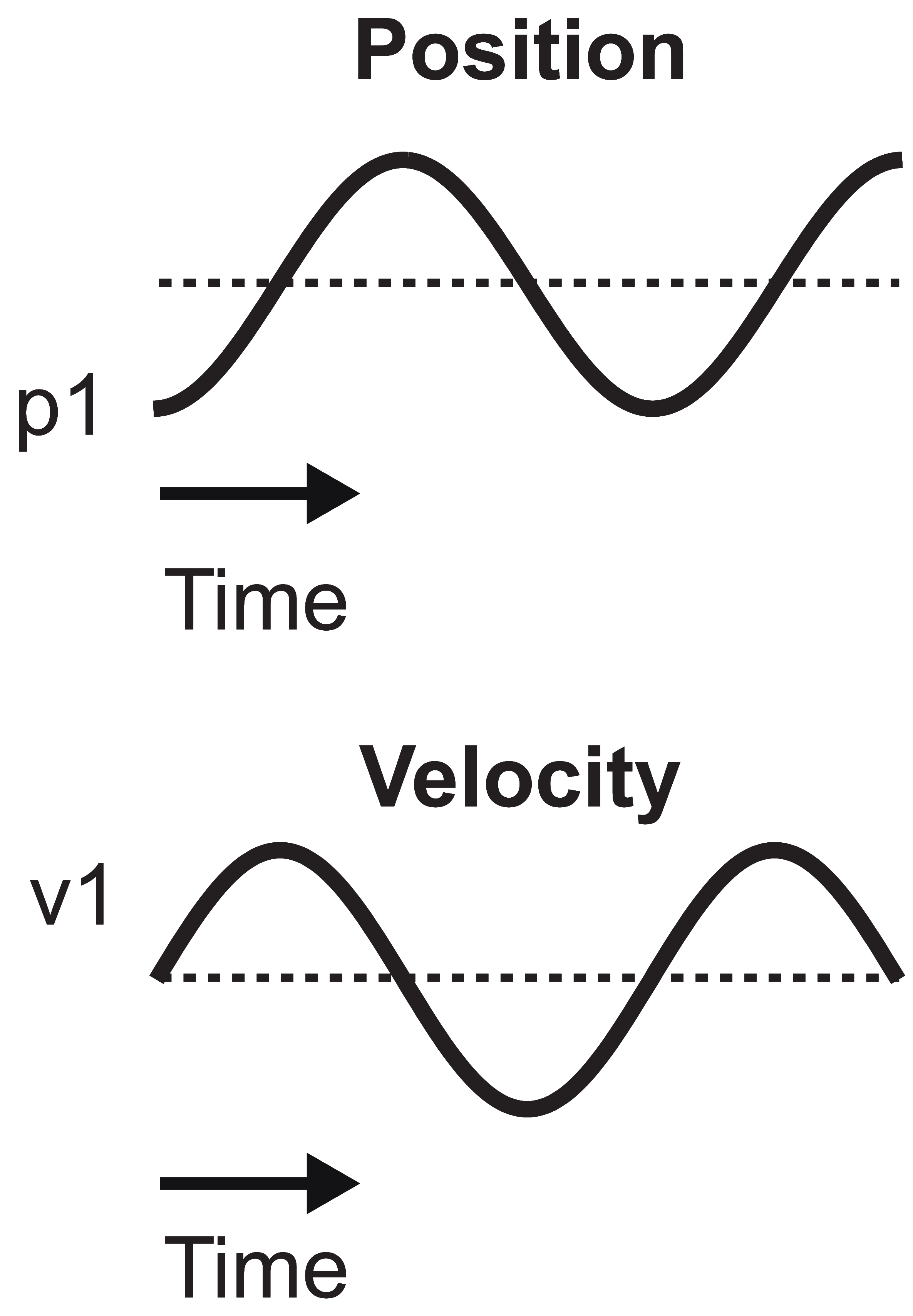

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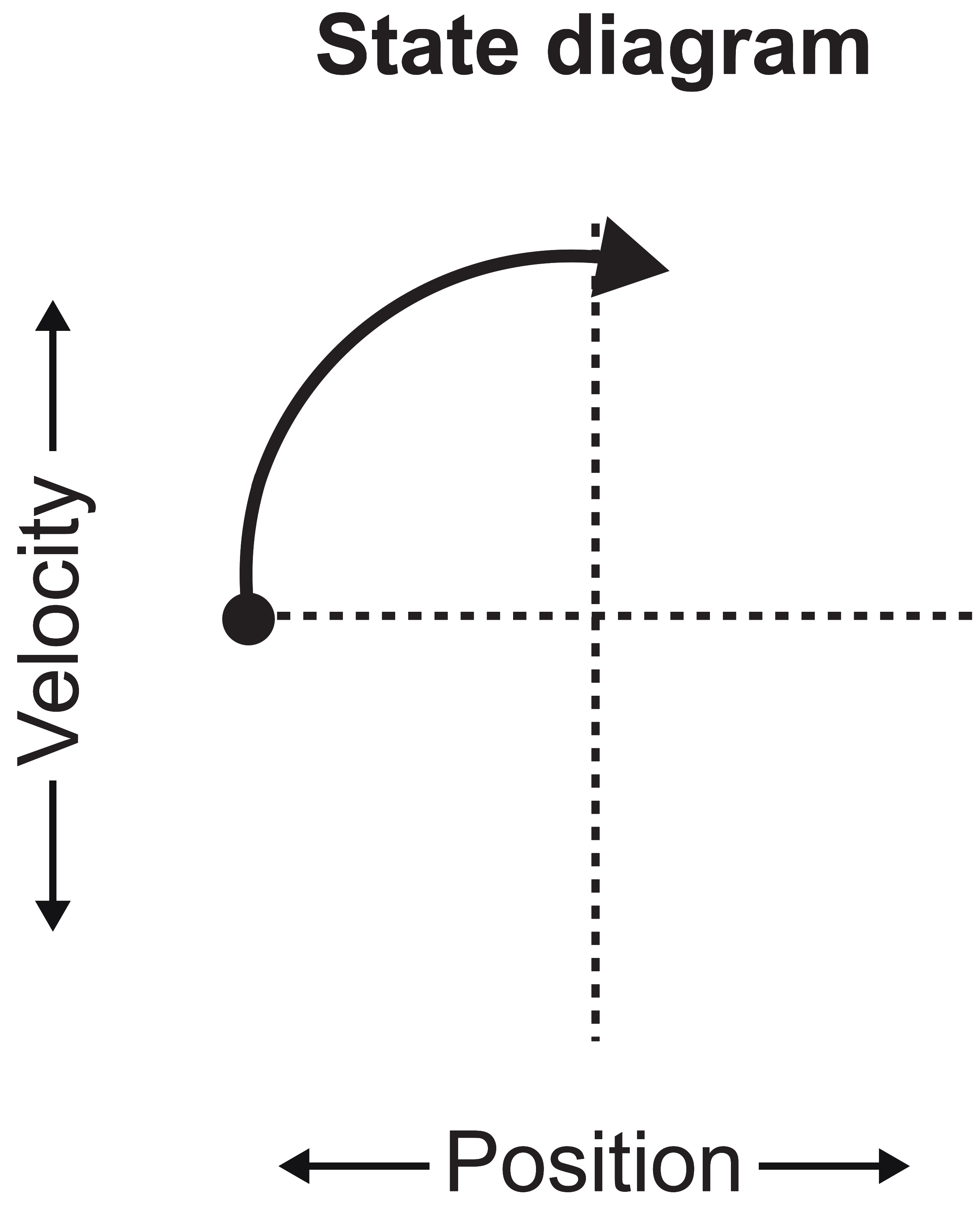

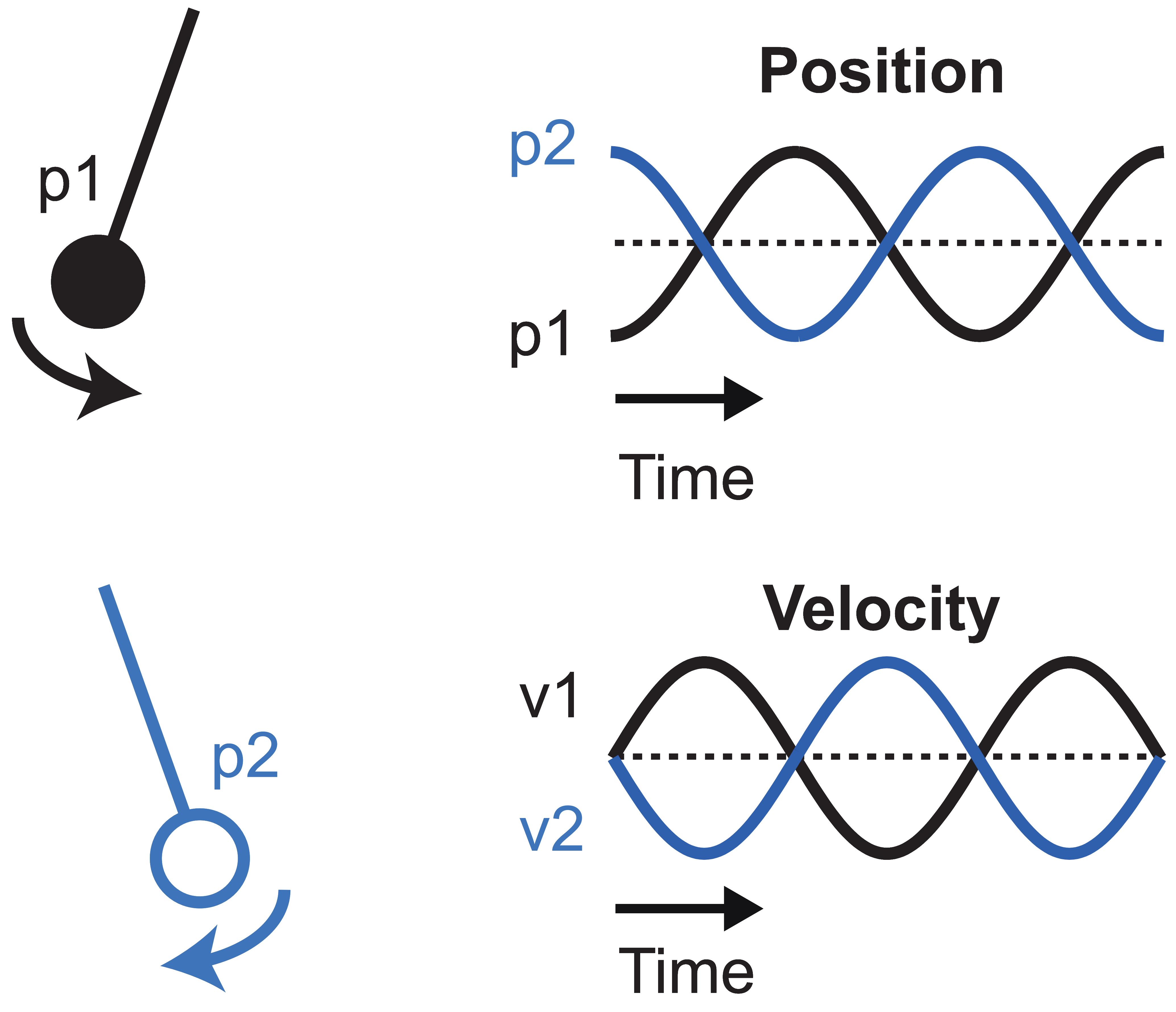

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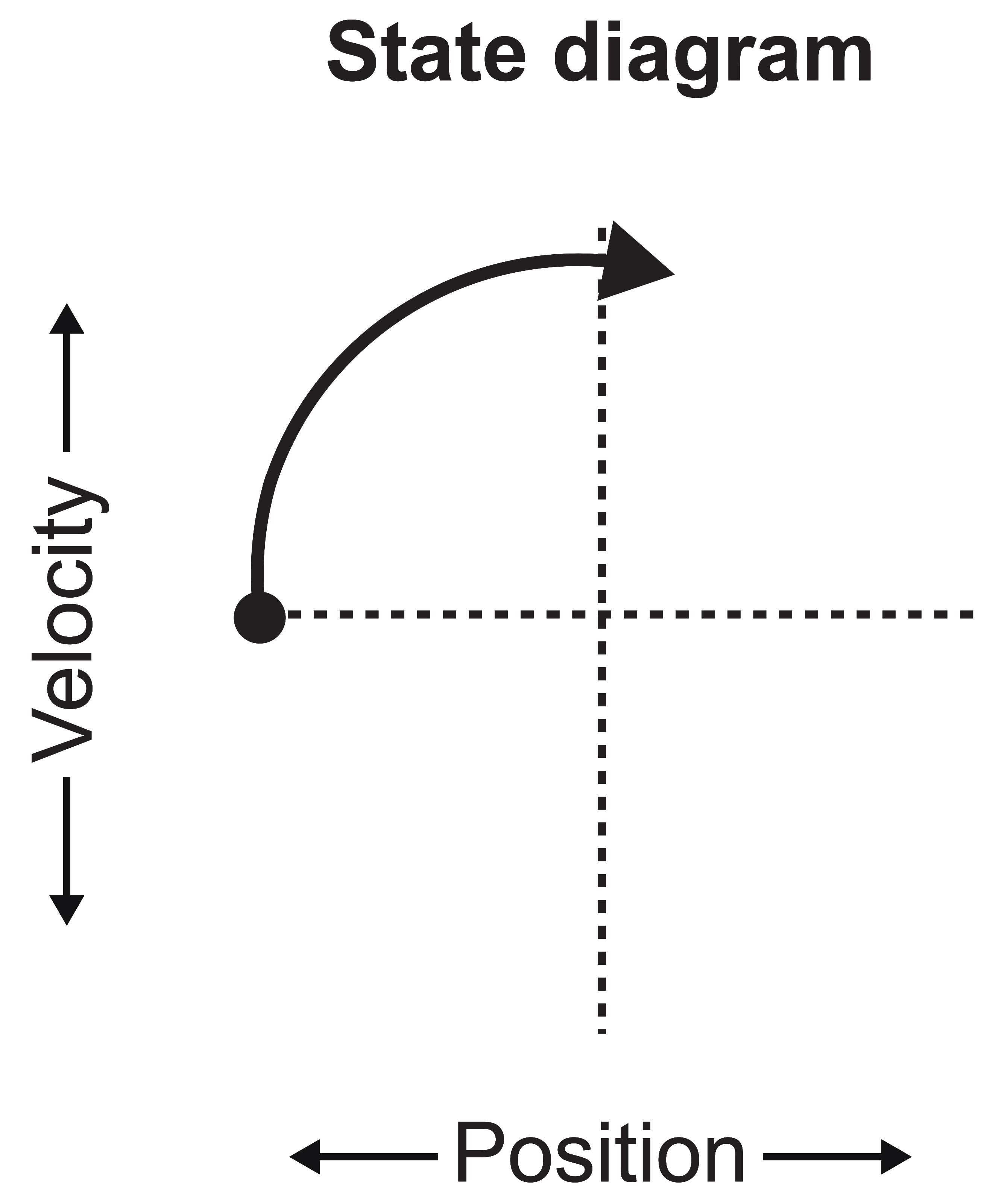

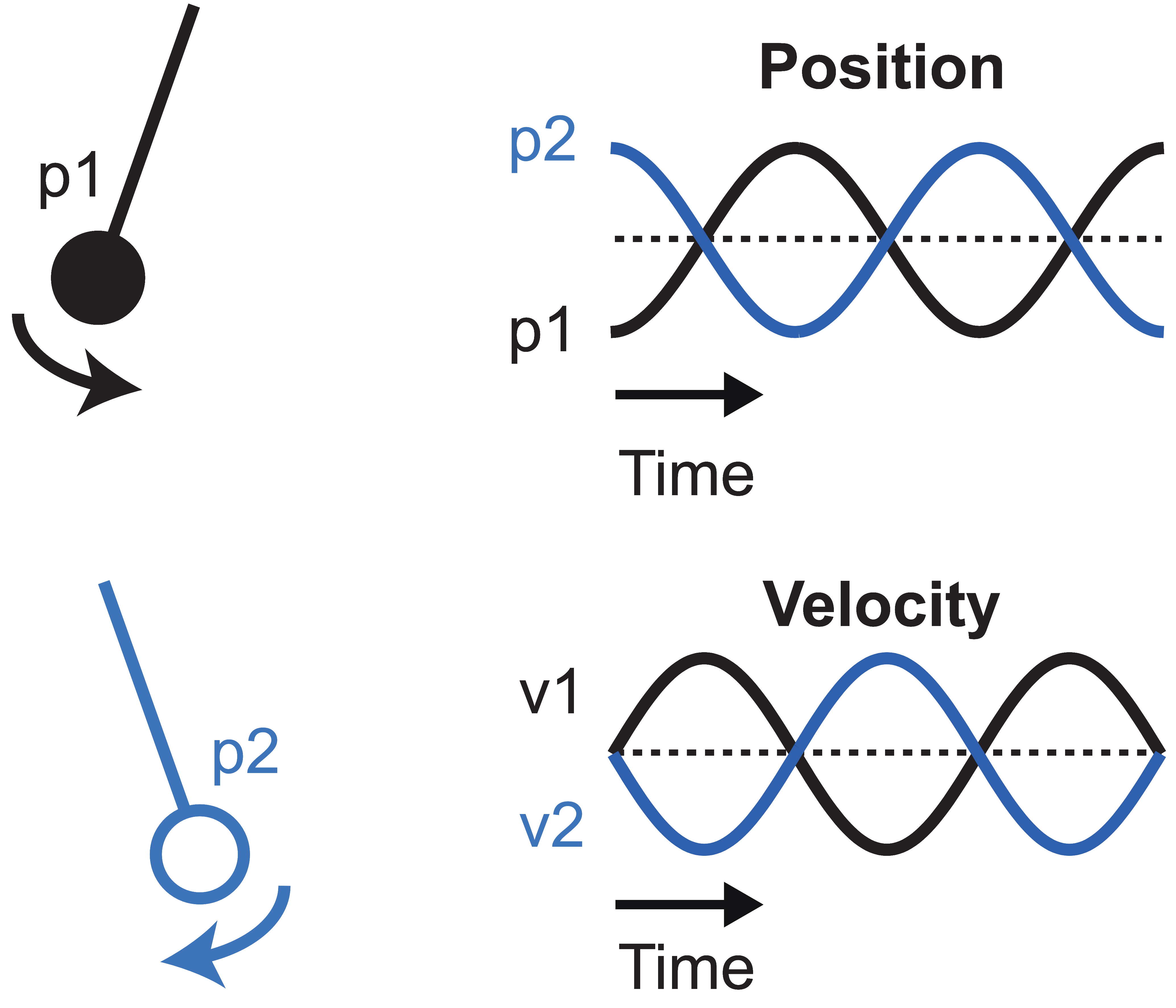

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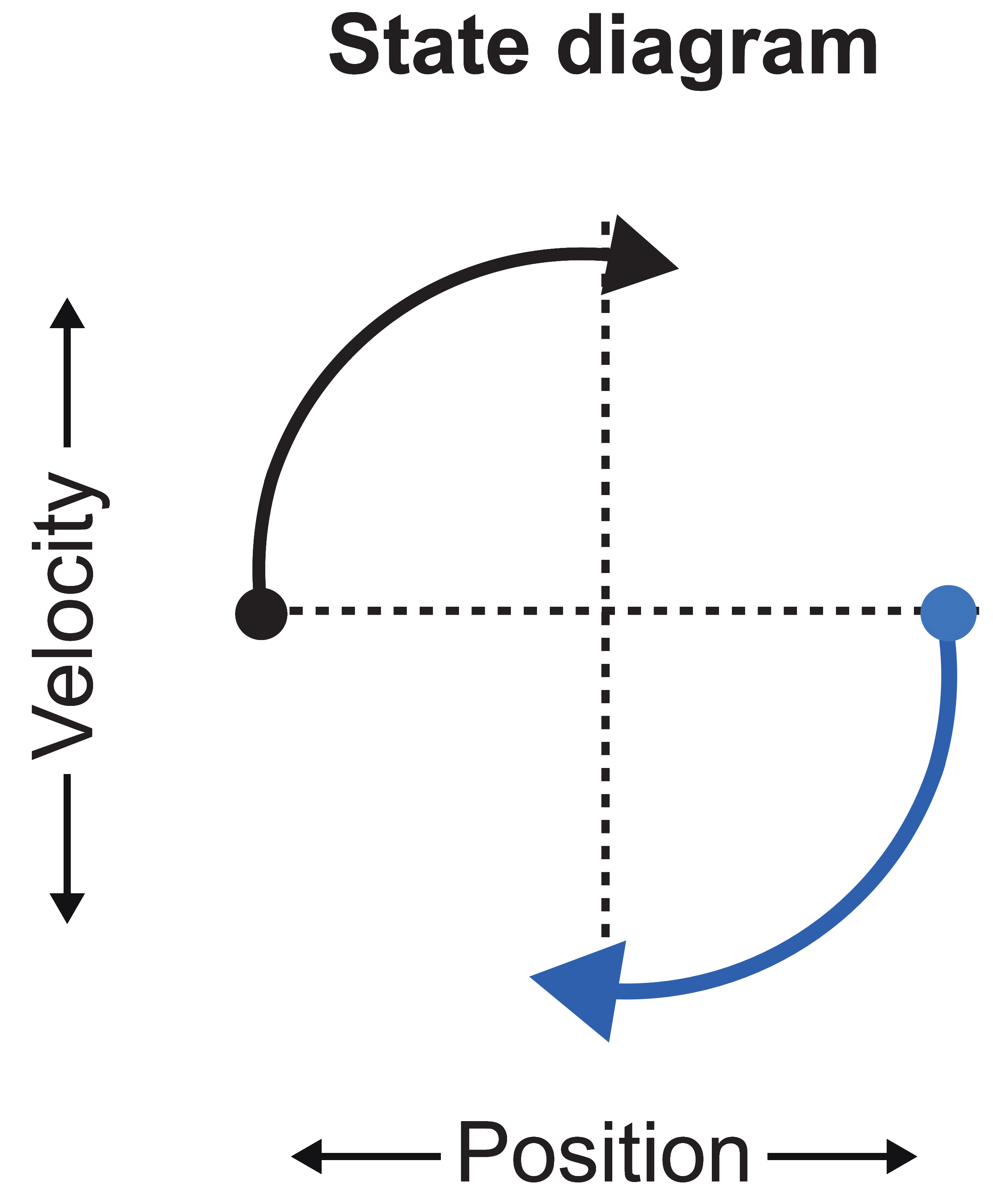
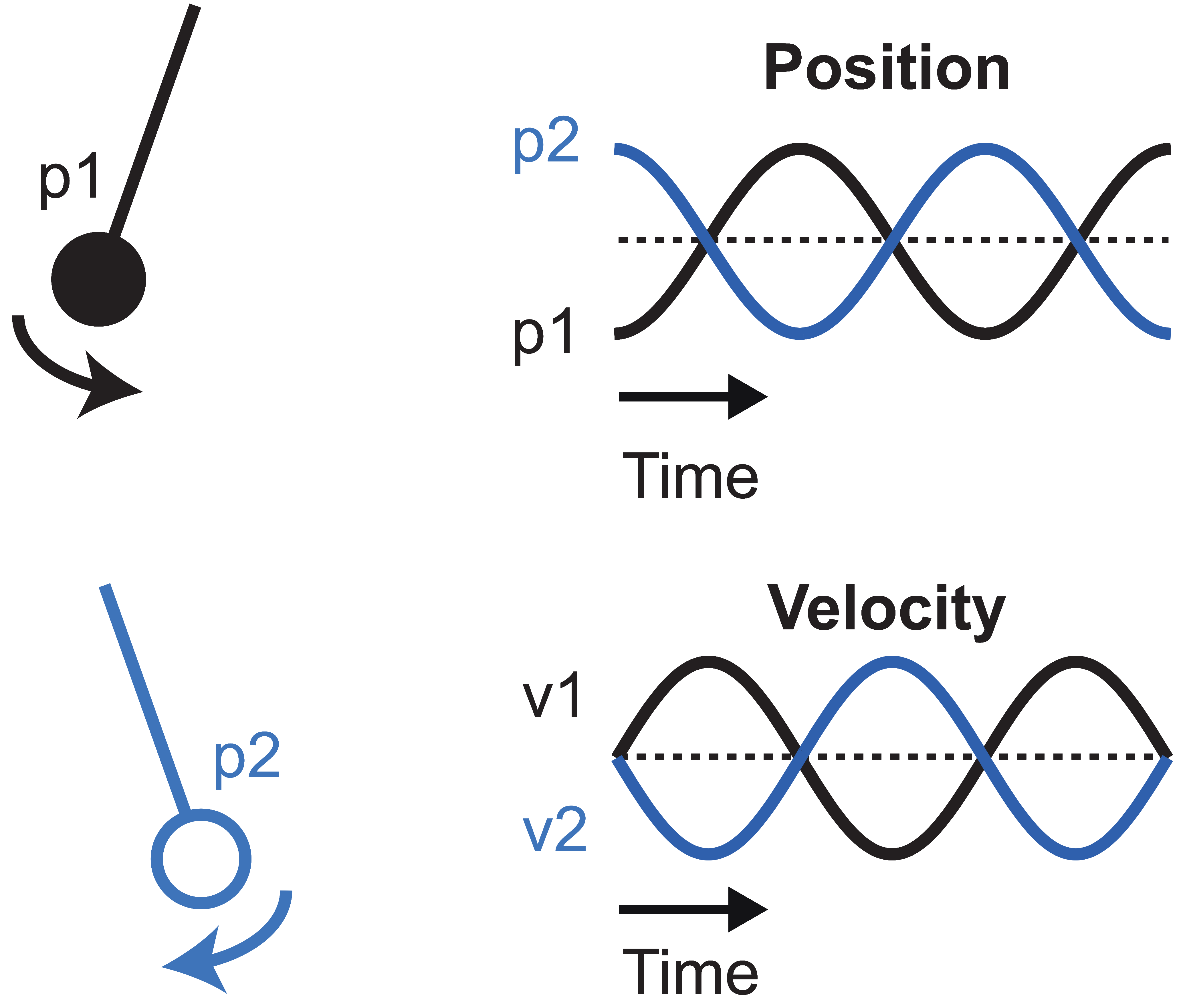
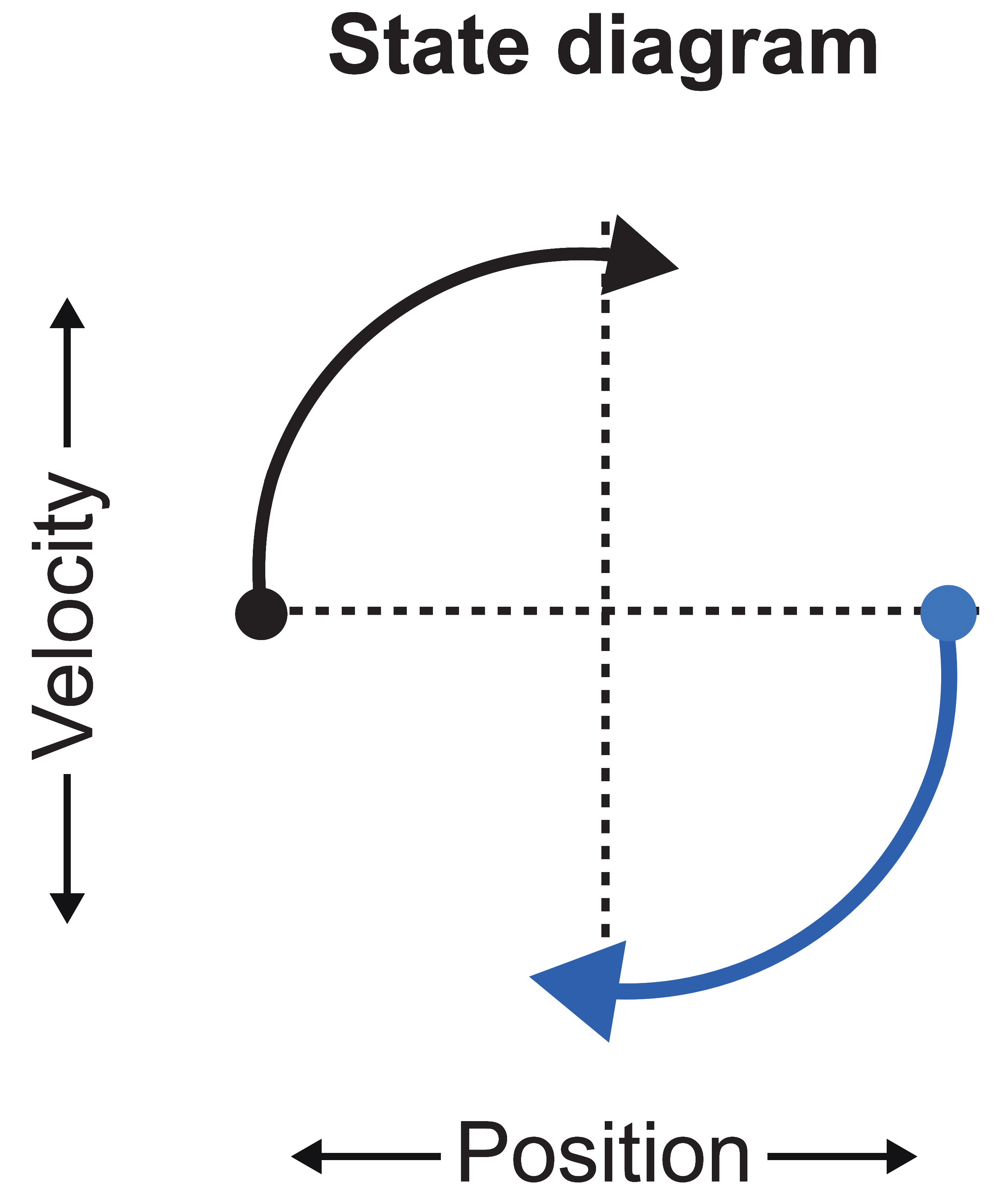
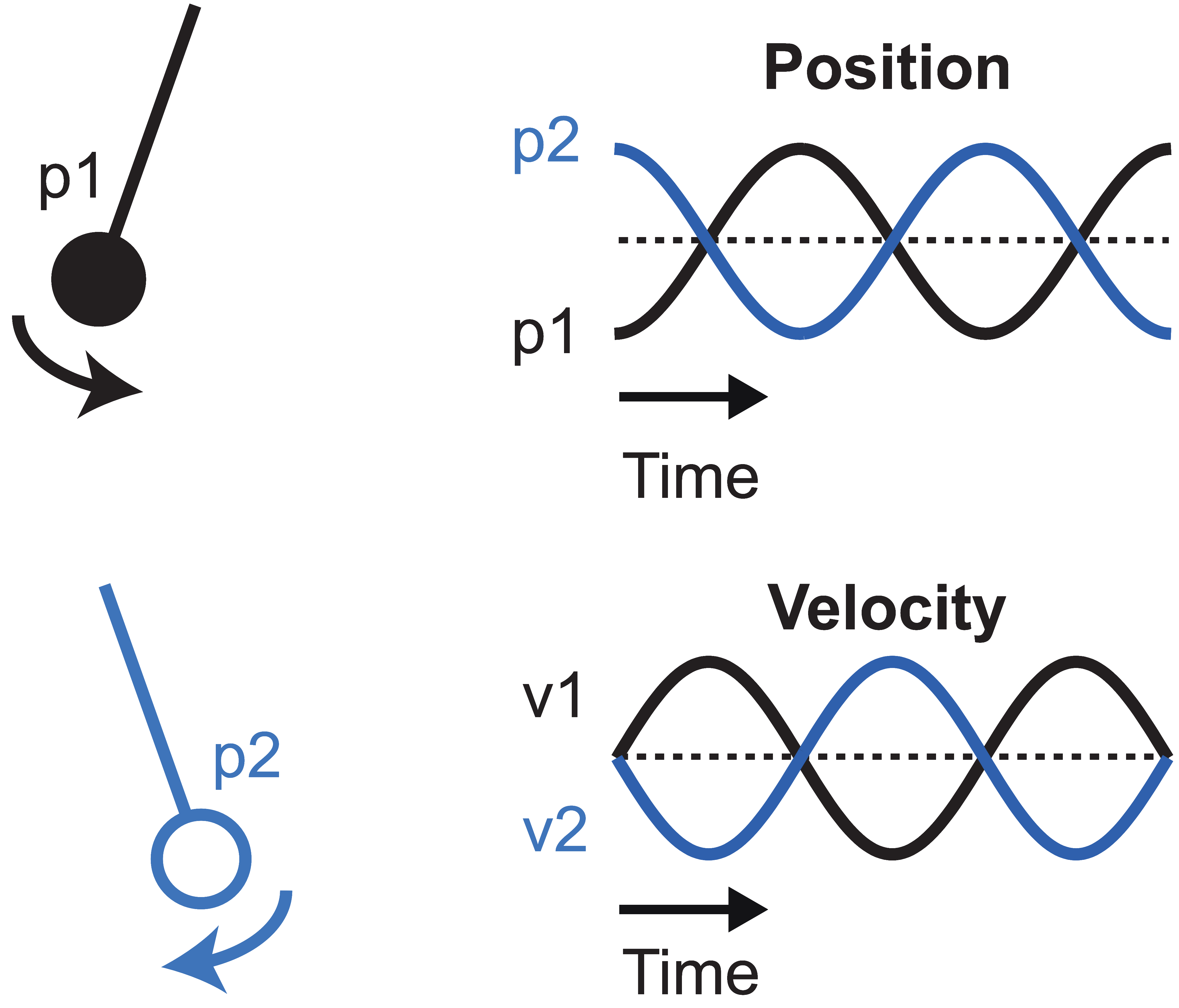




$$\mathbf{x} = \begin{bmatrix} p \\ v \end{bmatrix}$$

$$\dot{\mathbf{x}} = f(\mathbf{x})$$





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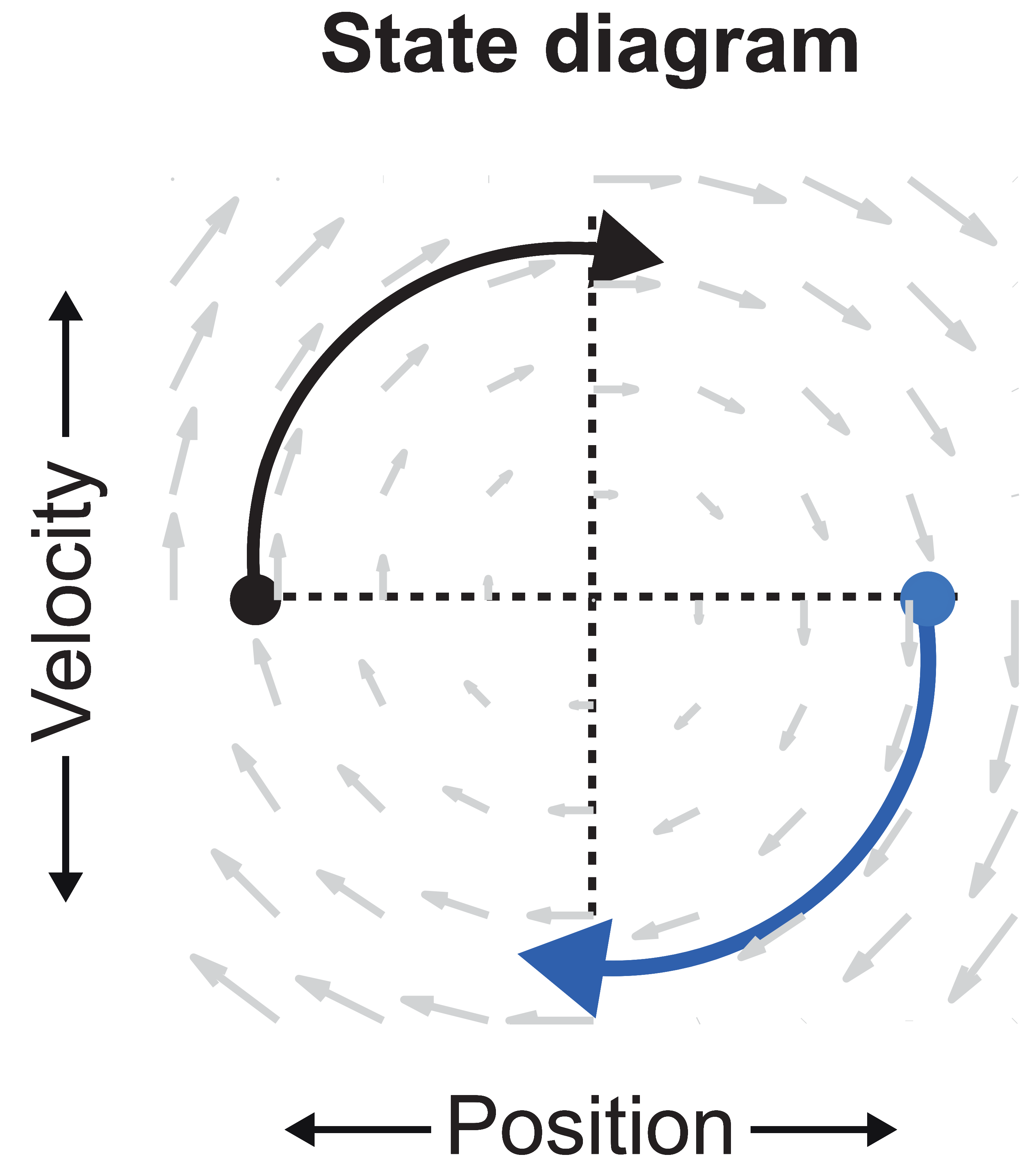
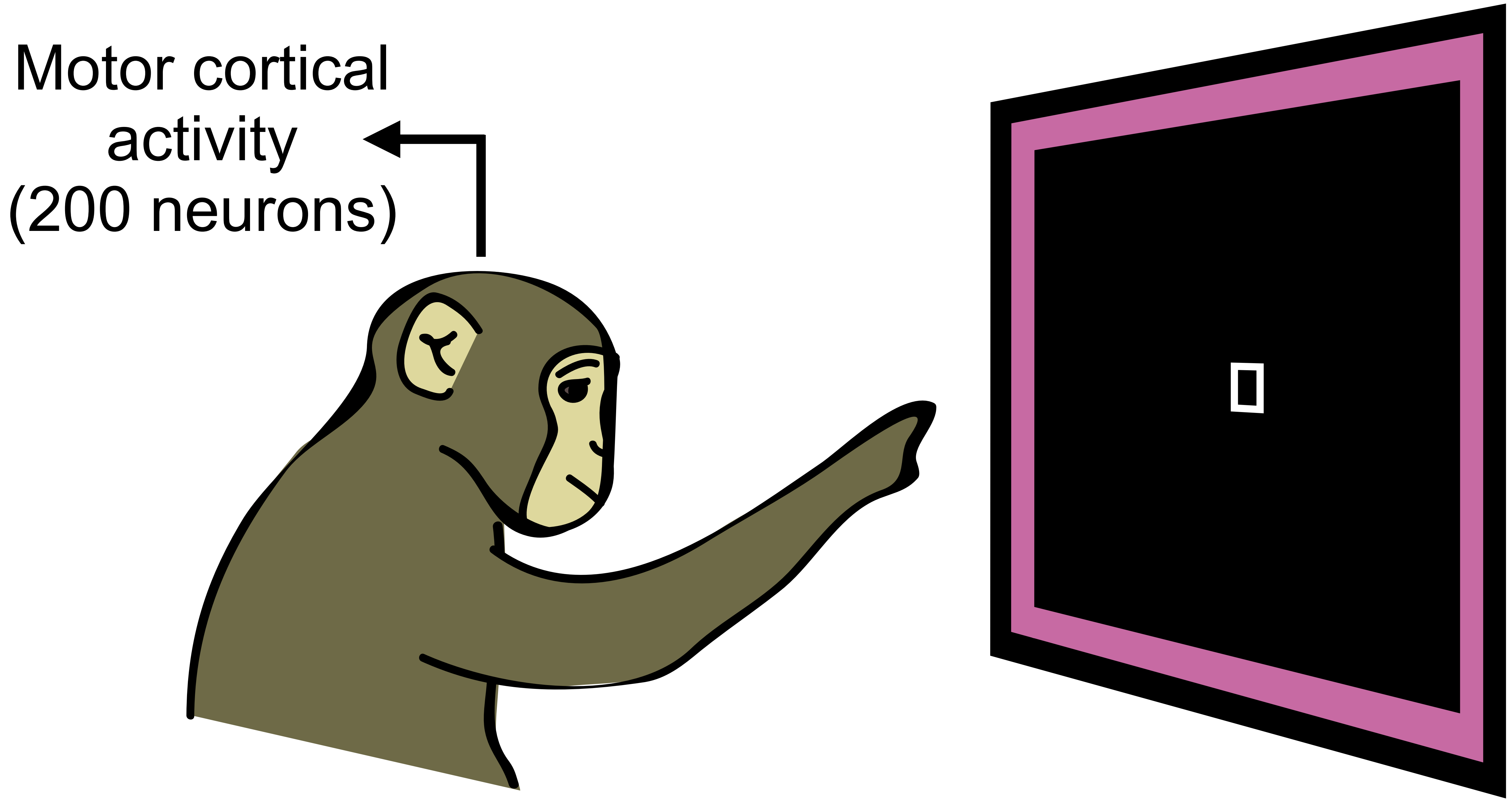


Predictable activity: delayed-reaching

“Maze” task

108 total conditions

- Motor cortex is set to an initial state during the preparatory phase
- Activity during movement execution is highly predictable based on initial state



Churchland*, Cunningham* … Shenoy, *Nature* 2012

Shenoy, Sahani, Churchland, *Ann Rev Neuro* 2013

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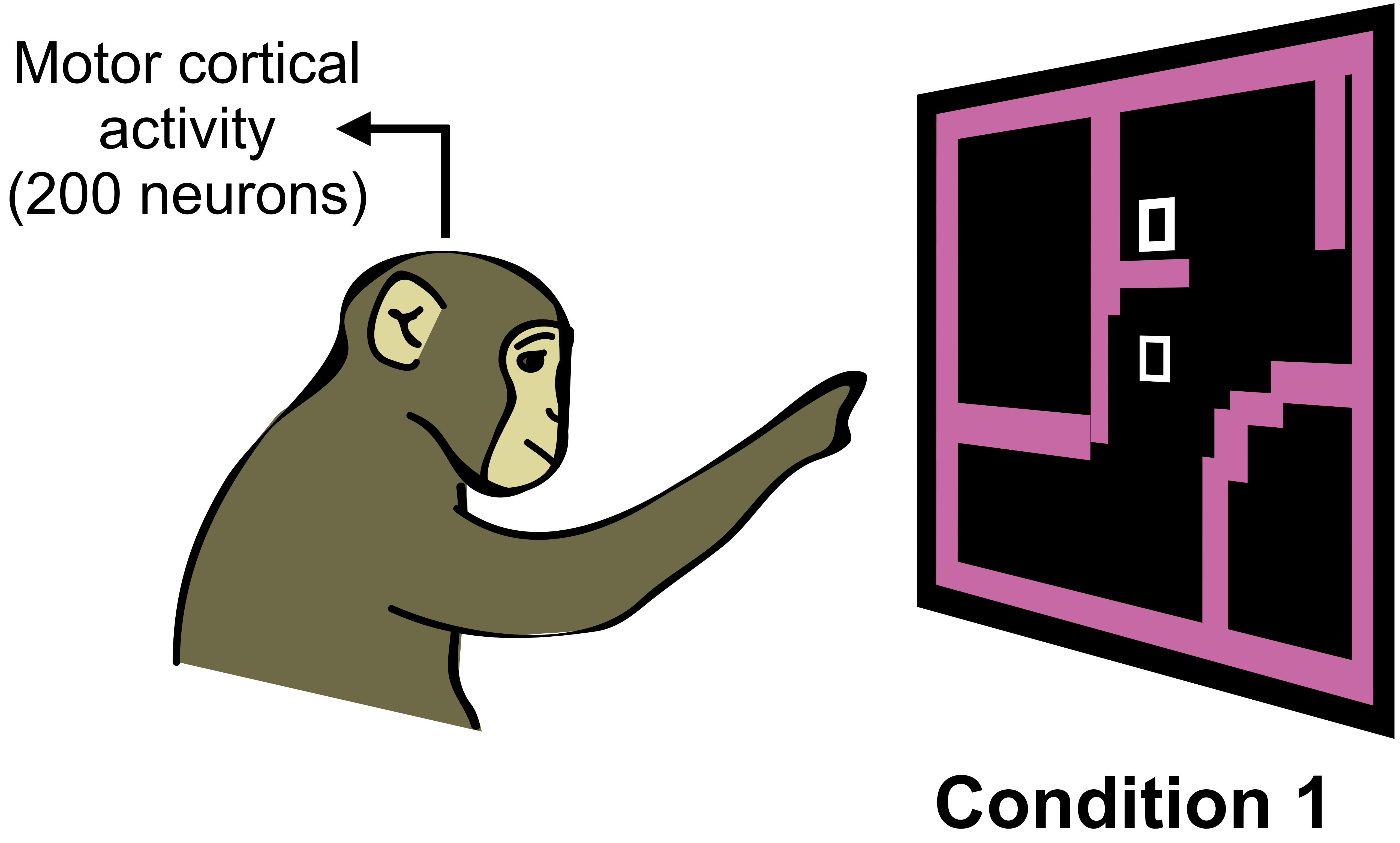

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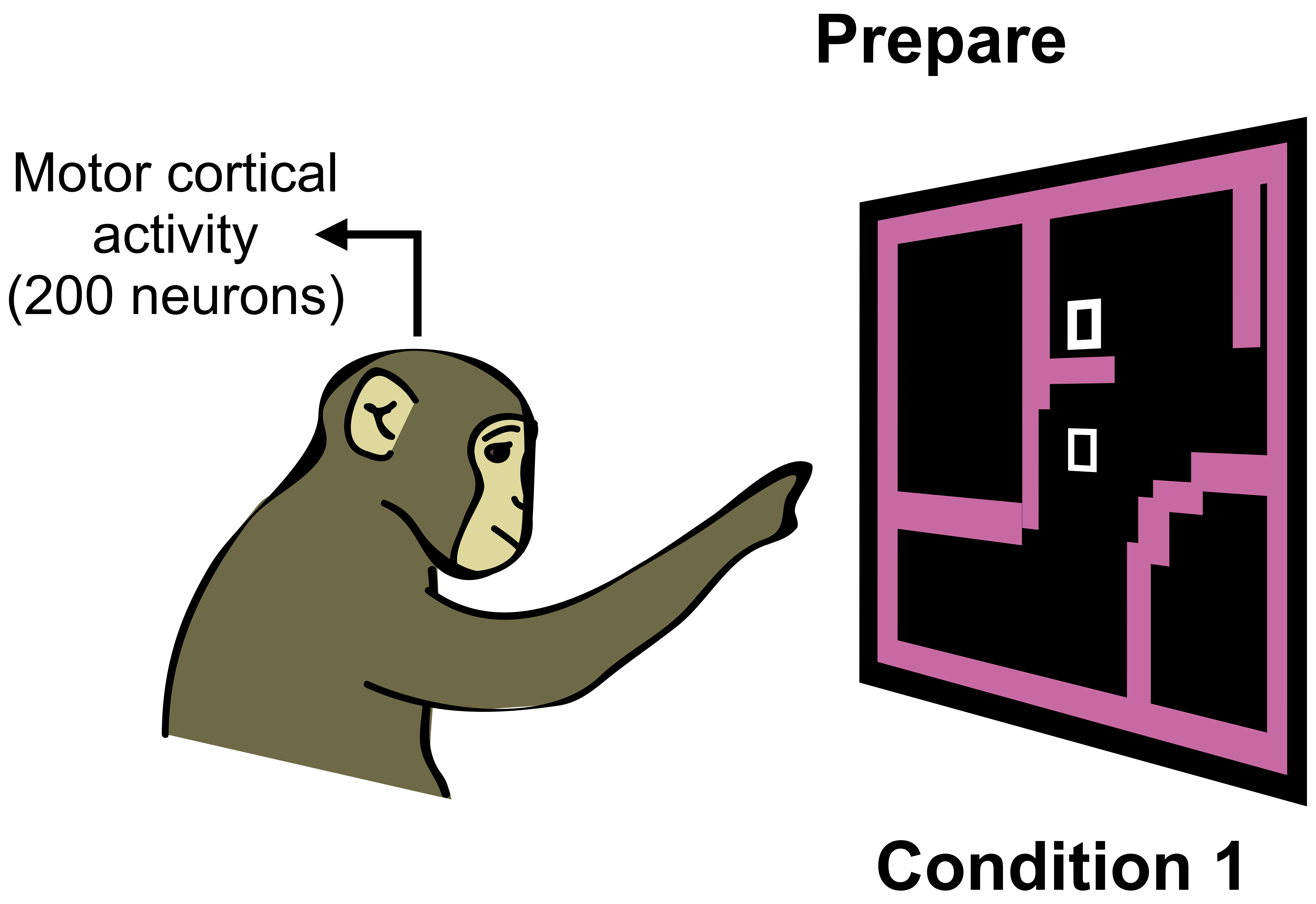

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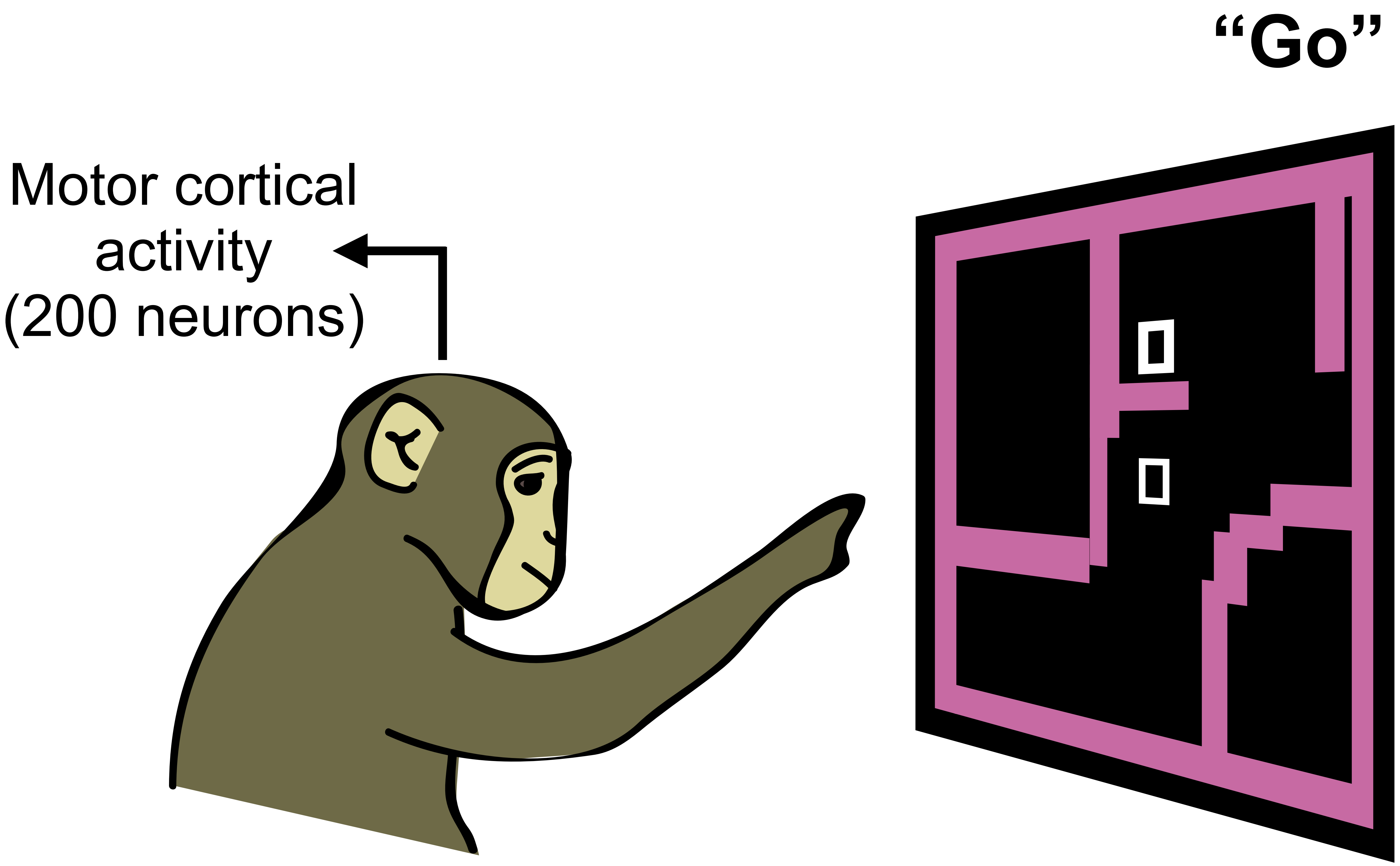

Condition 1

Churchland*, Cunningham* … Shenoy, *Nature* 2012

Shenoy, Sahani, Churchland, *Ann Rev Neuro* 2013

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“Maze” task

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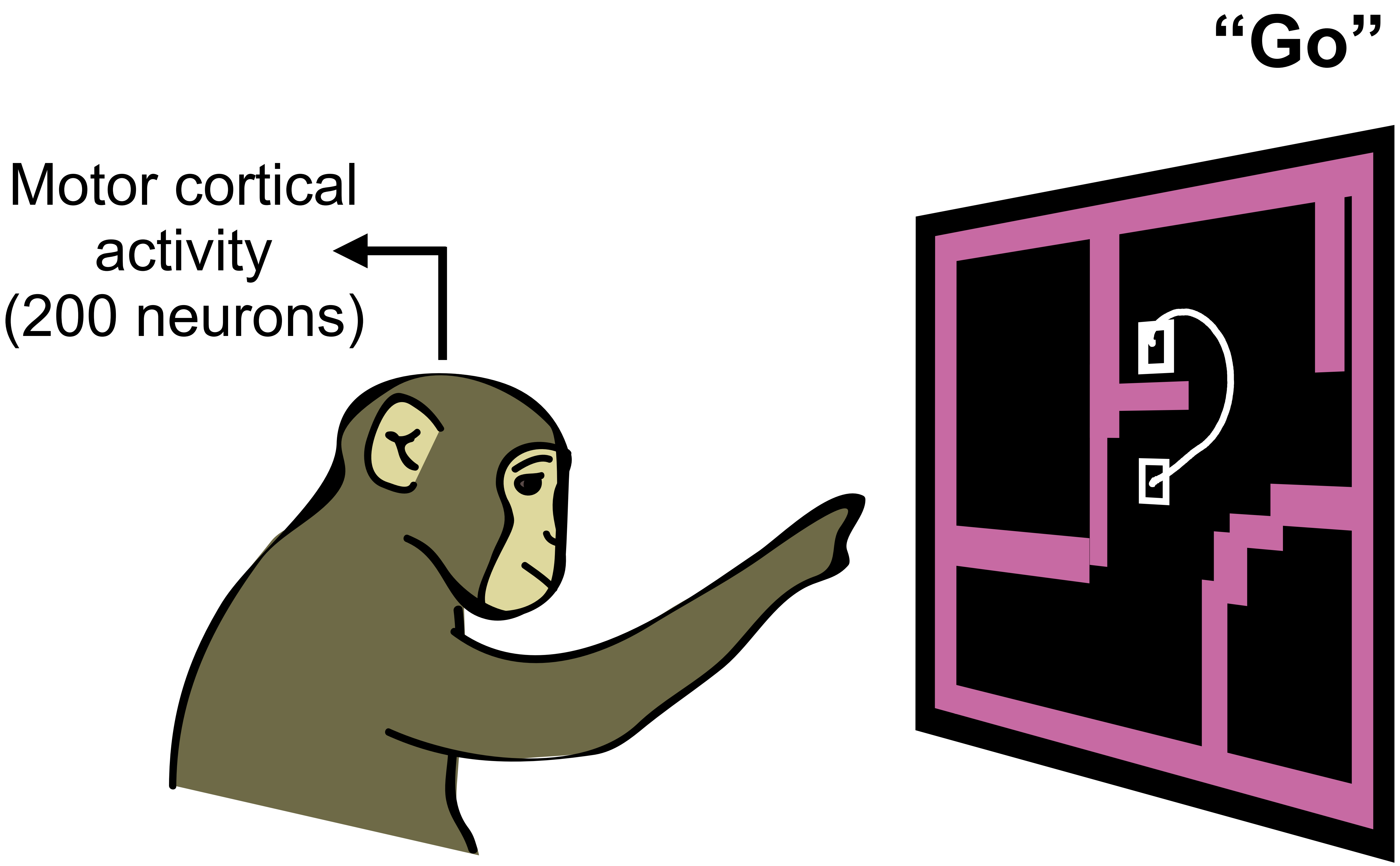
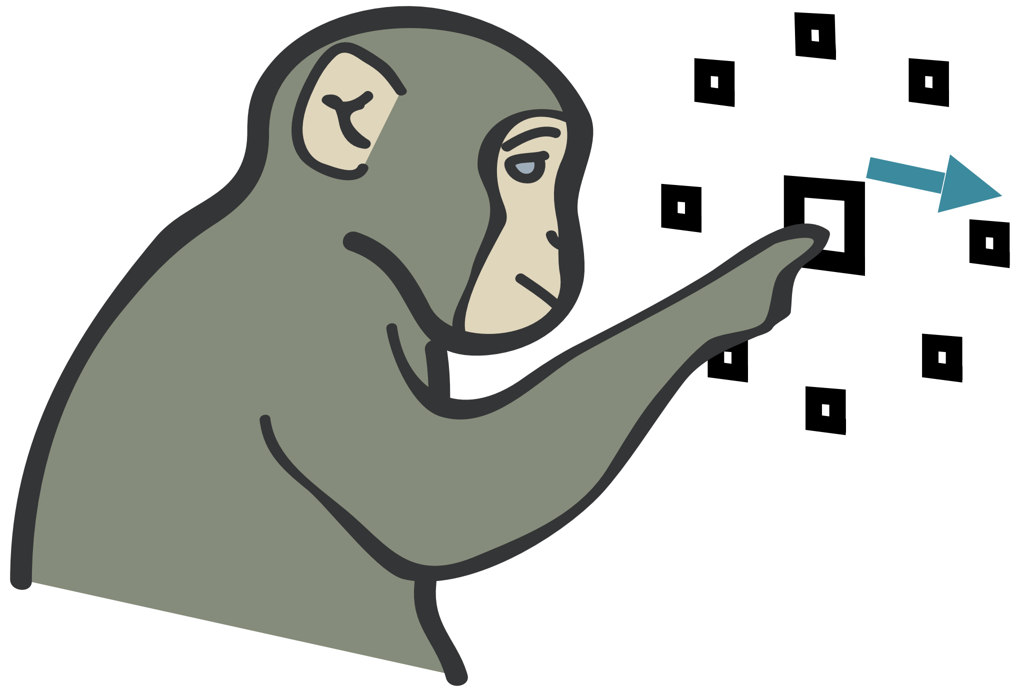


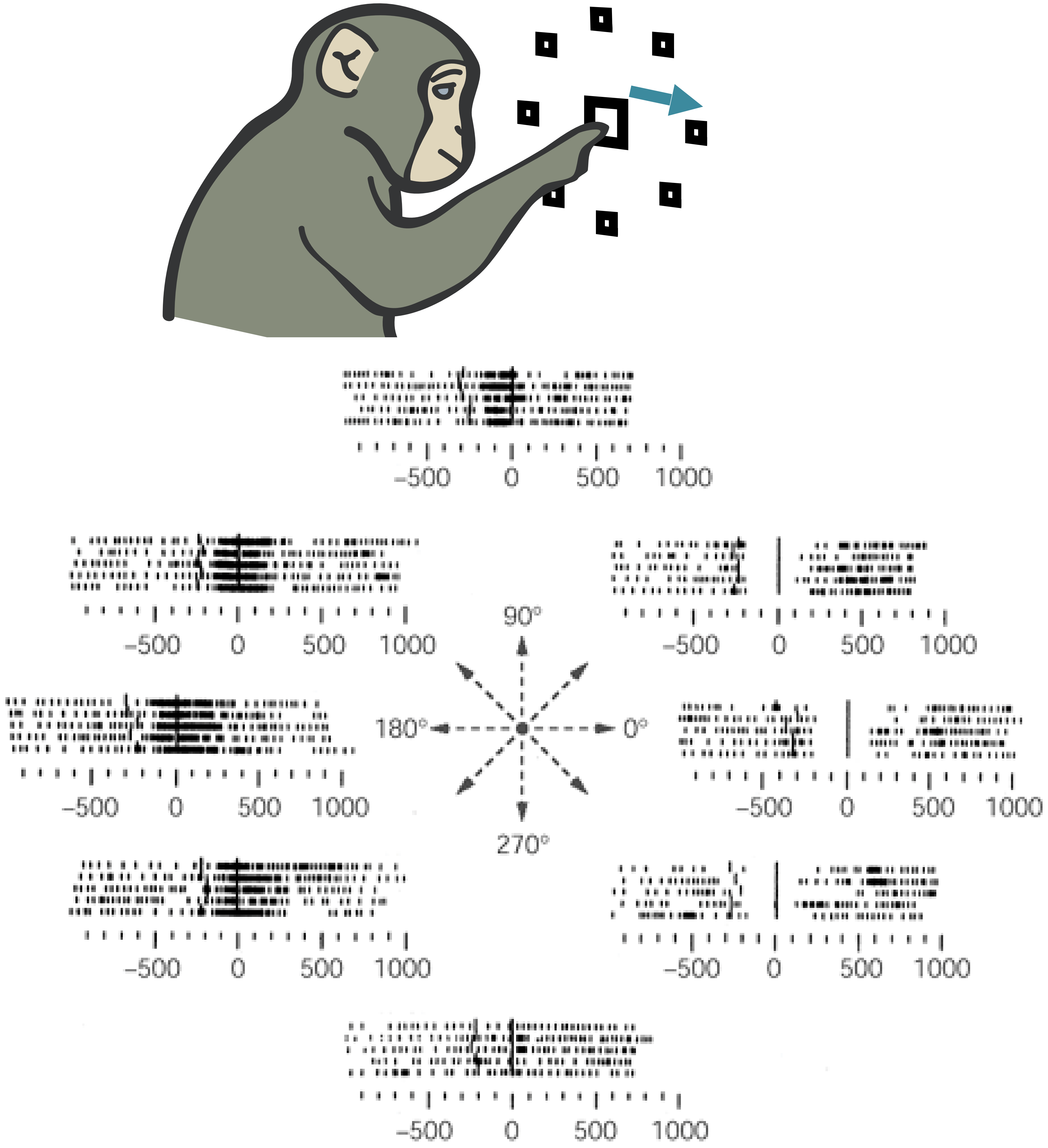
Condition 1

Churchland*, Cunningham* … Shenoy, *Nature* 2012

Shenoy, Sahani, Churchland, *Ann Rev Neuro* 2013



Georgopoulous et al. (1982)
Schwartz et al. (1988)



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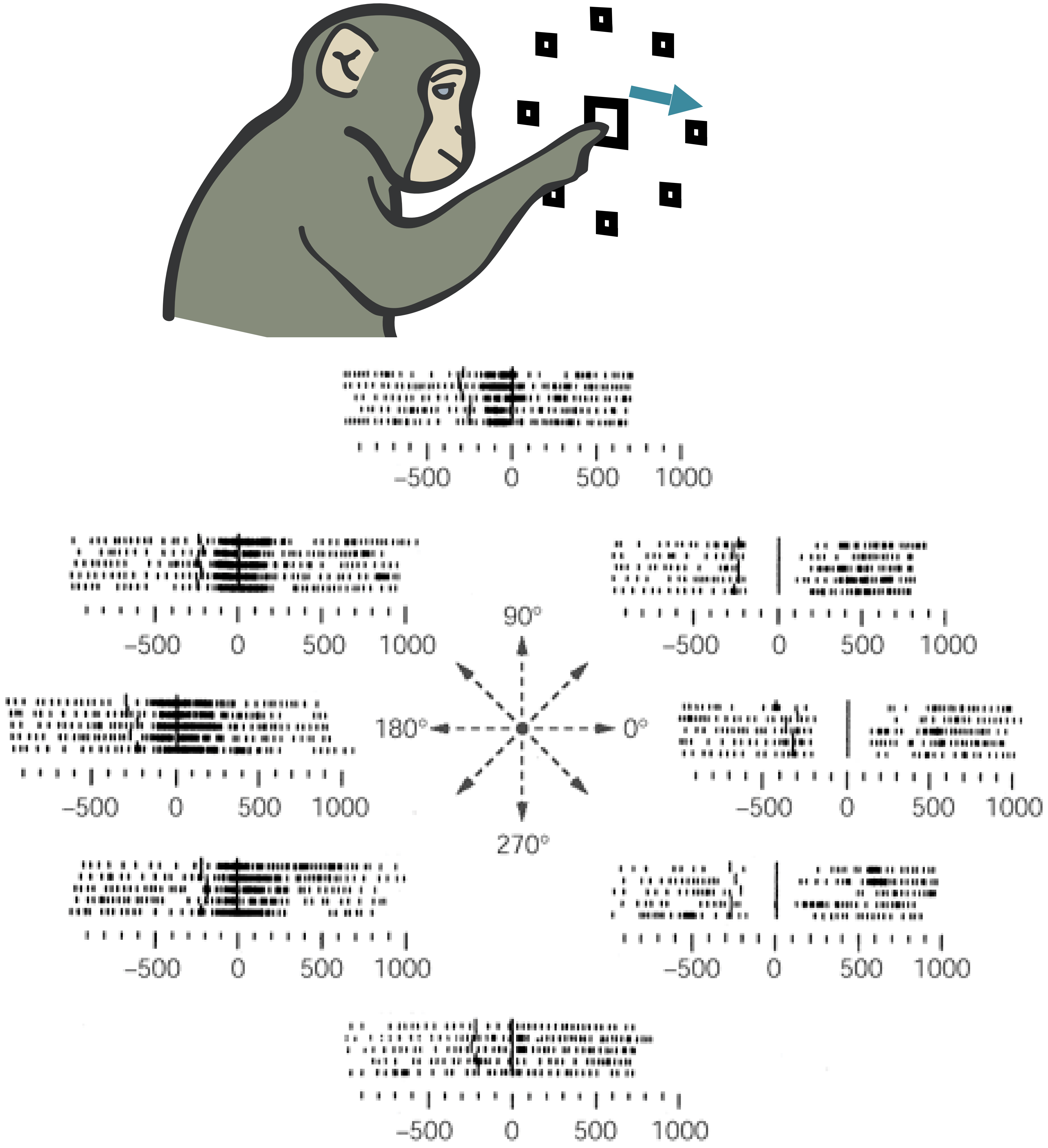

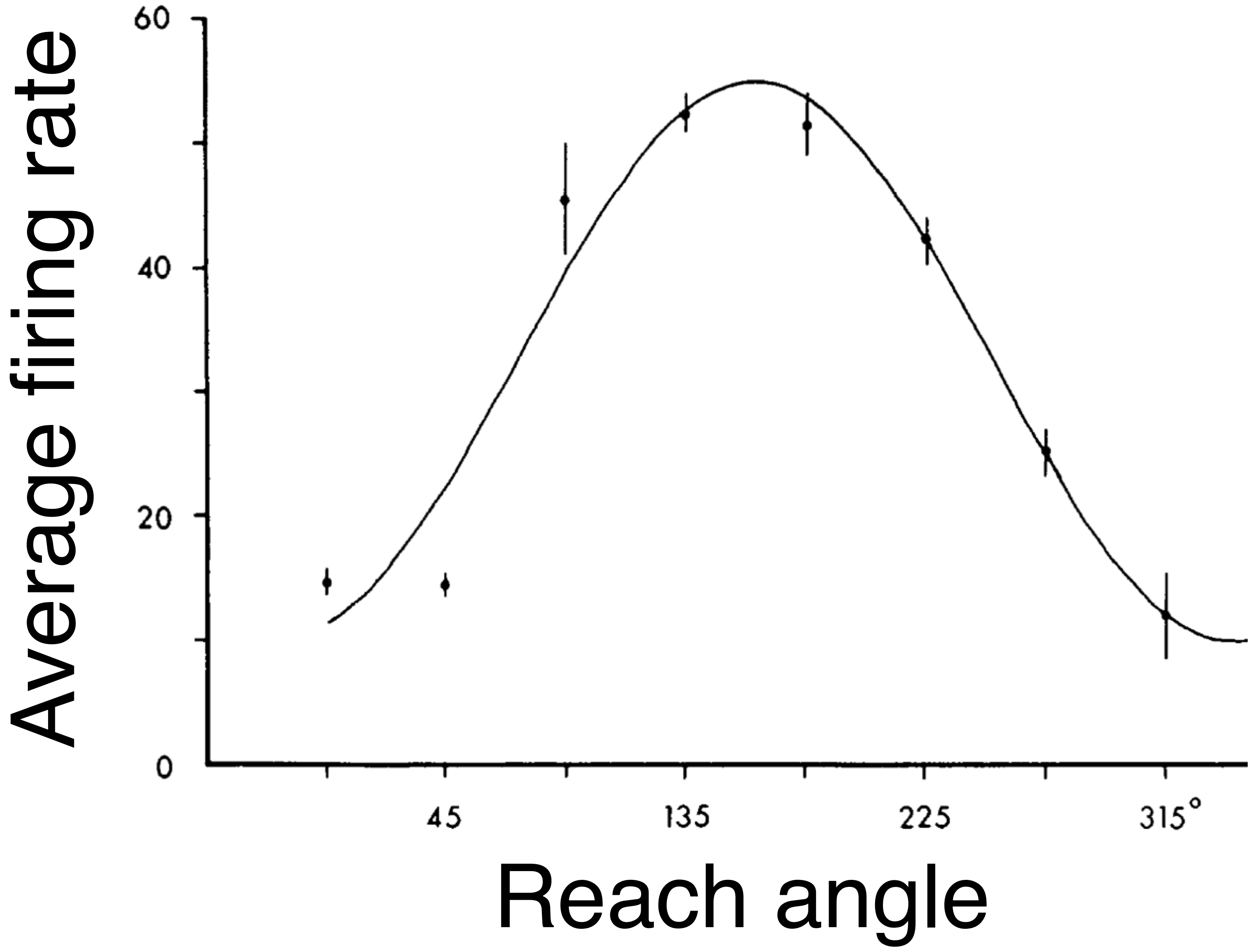

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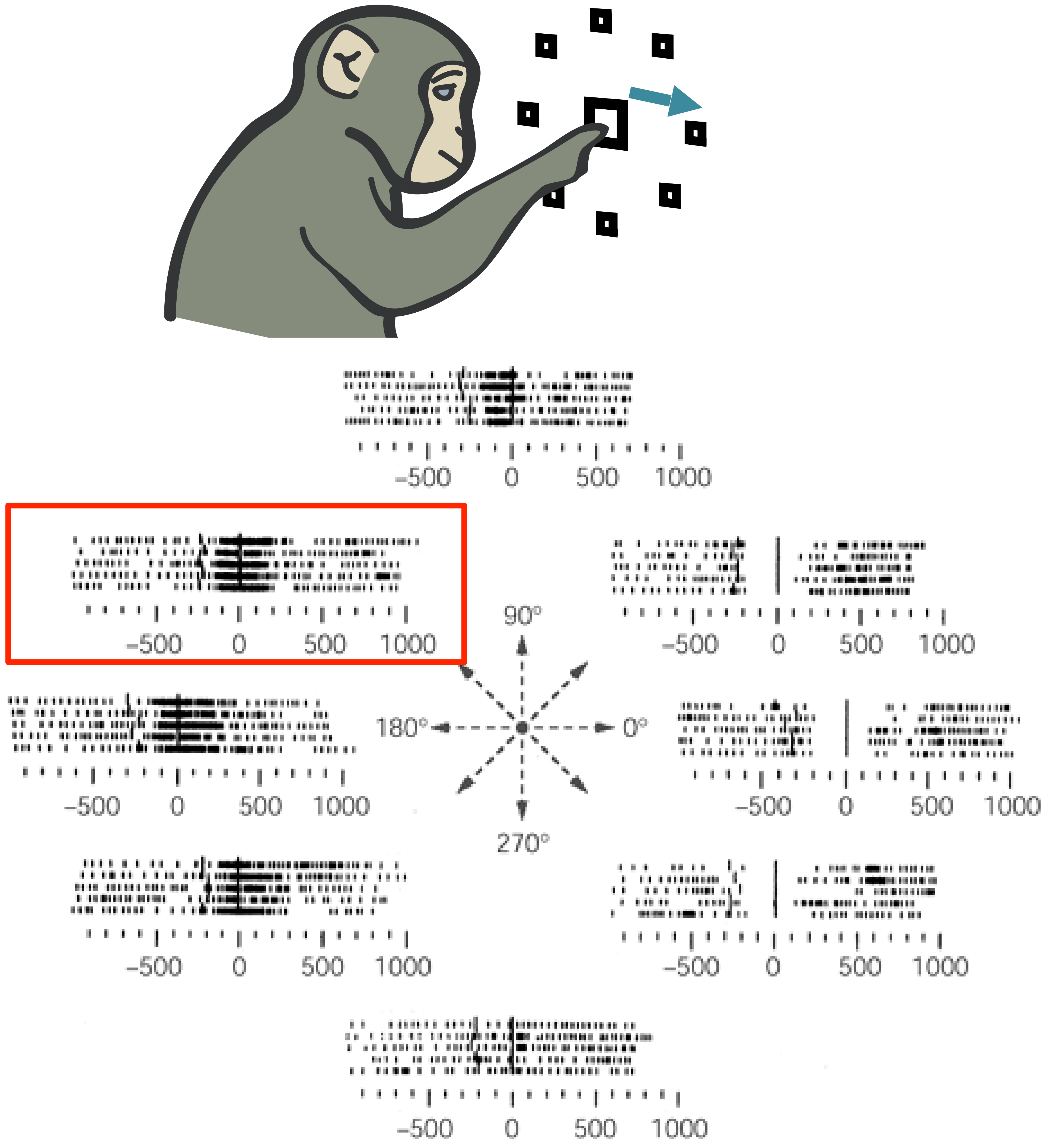

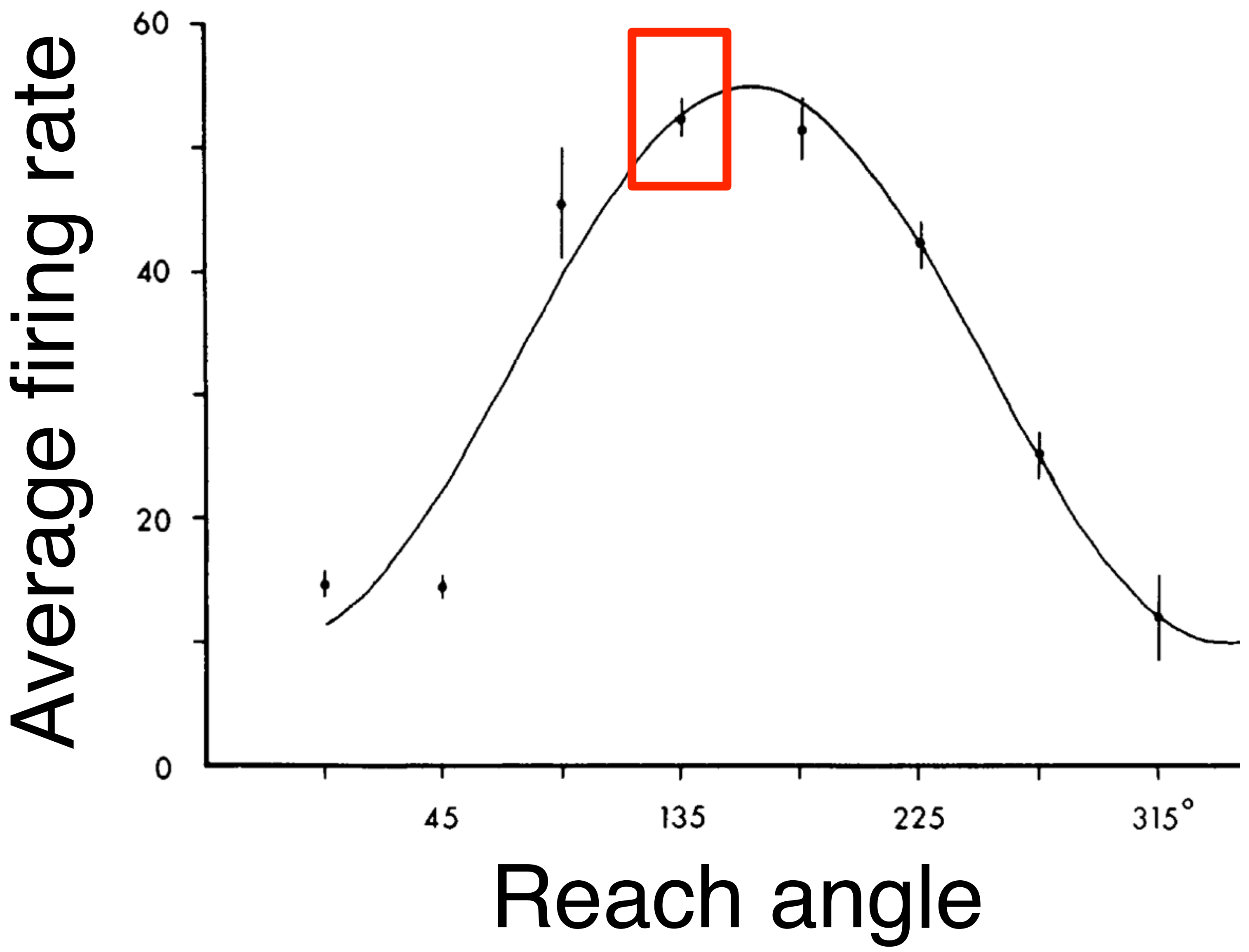

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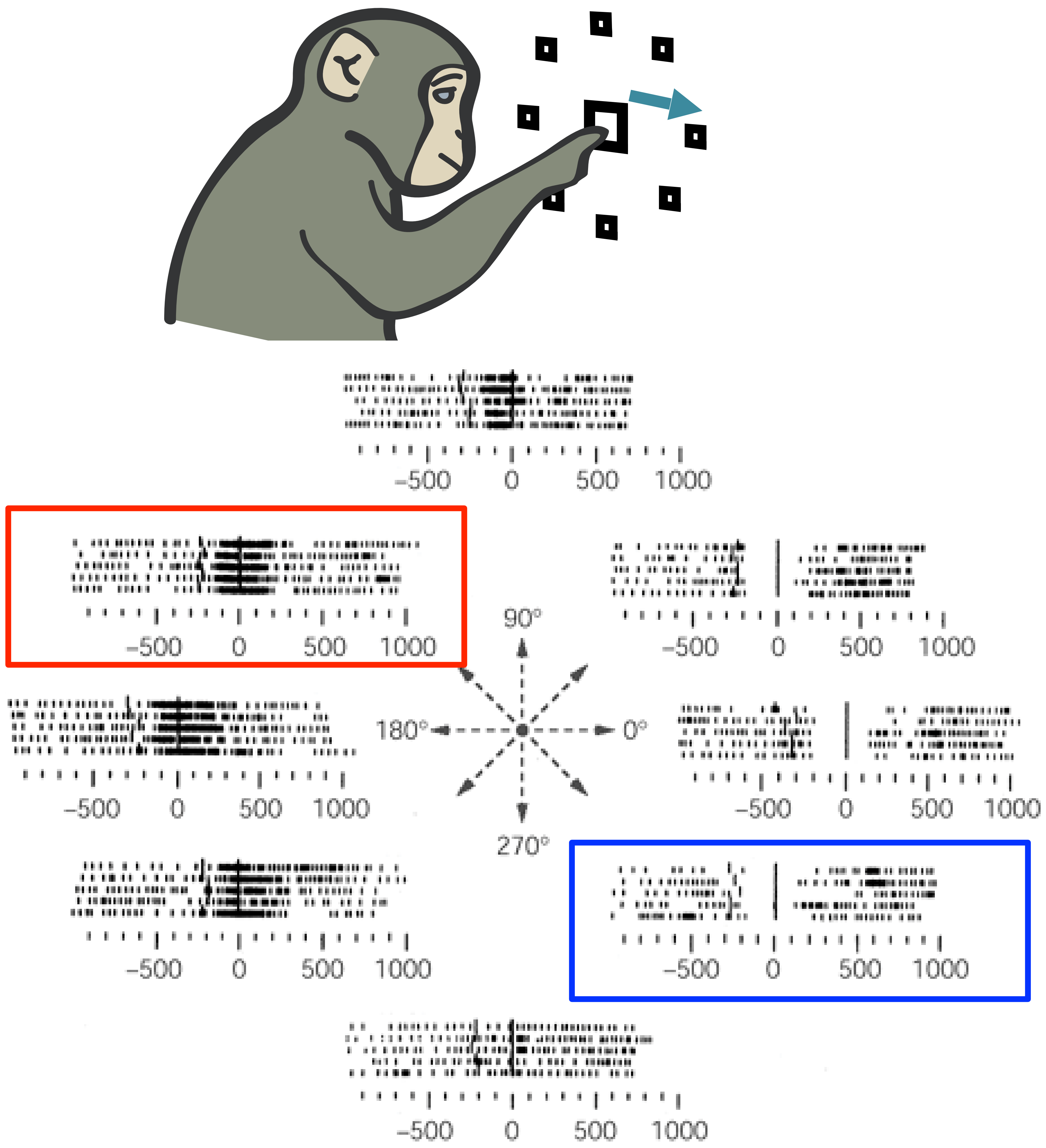

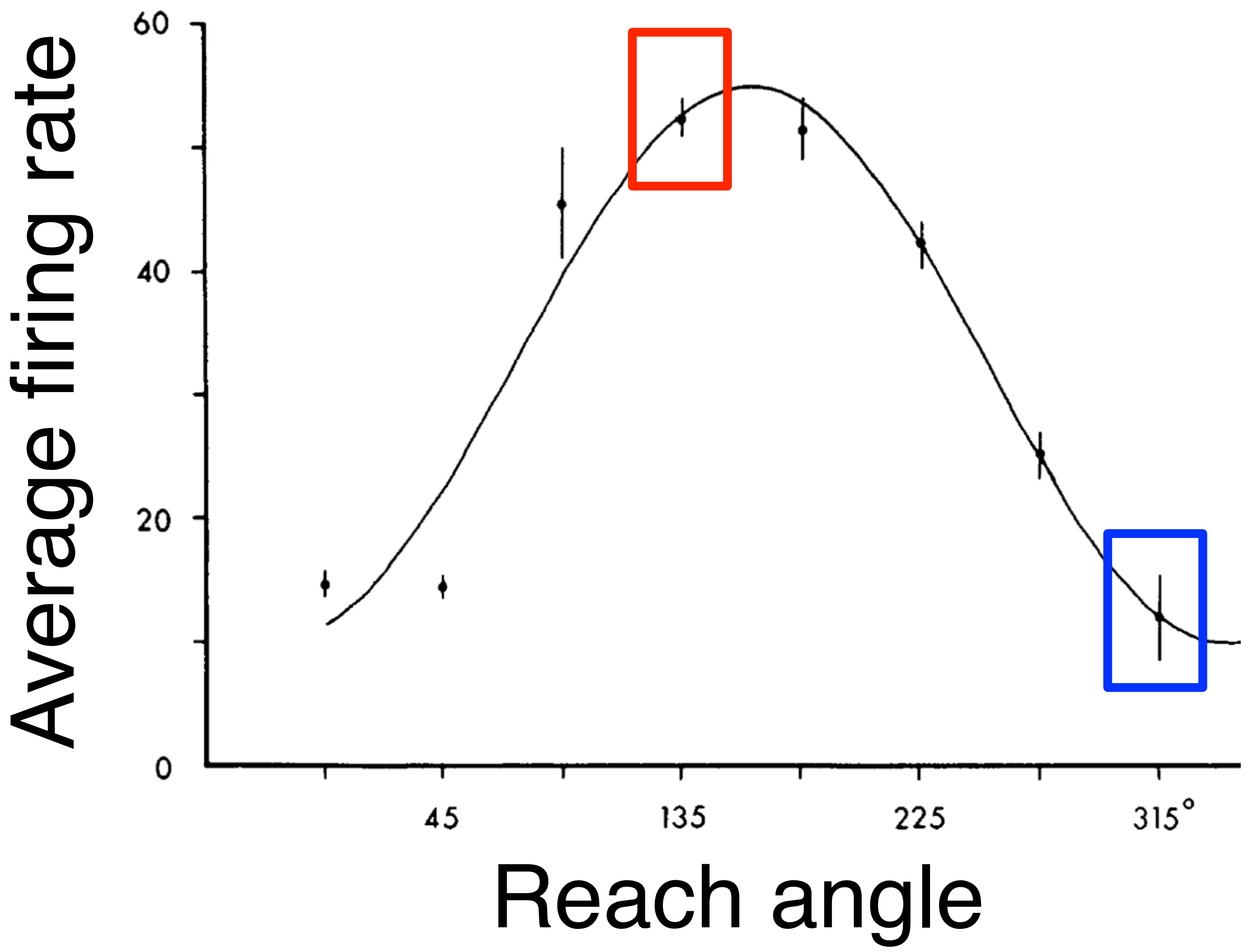

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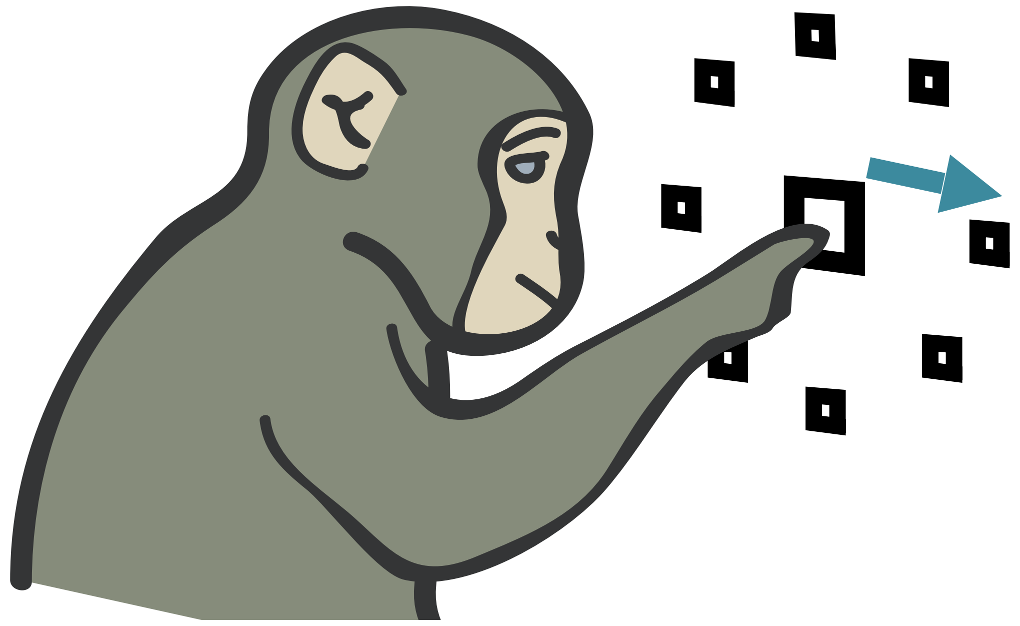
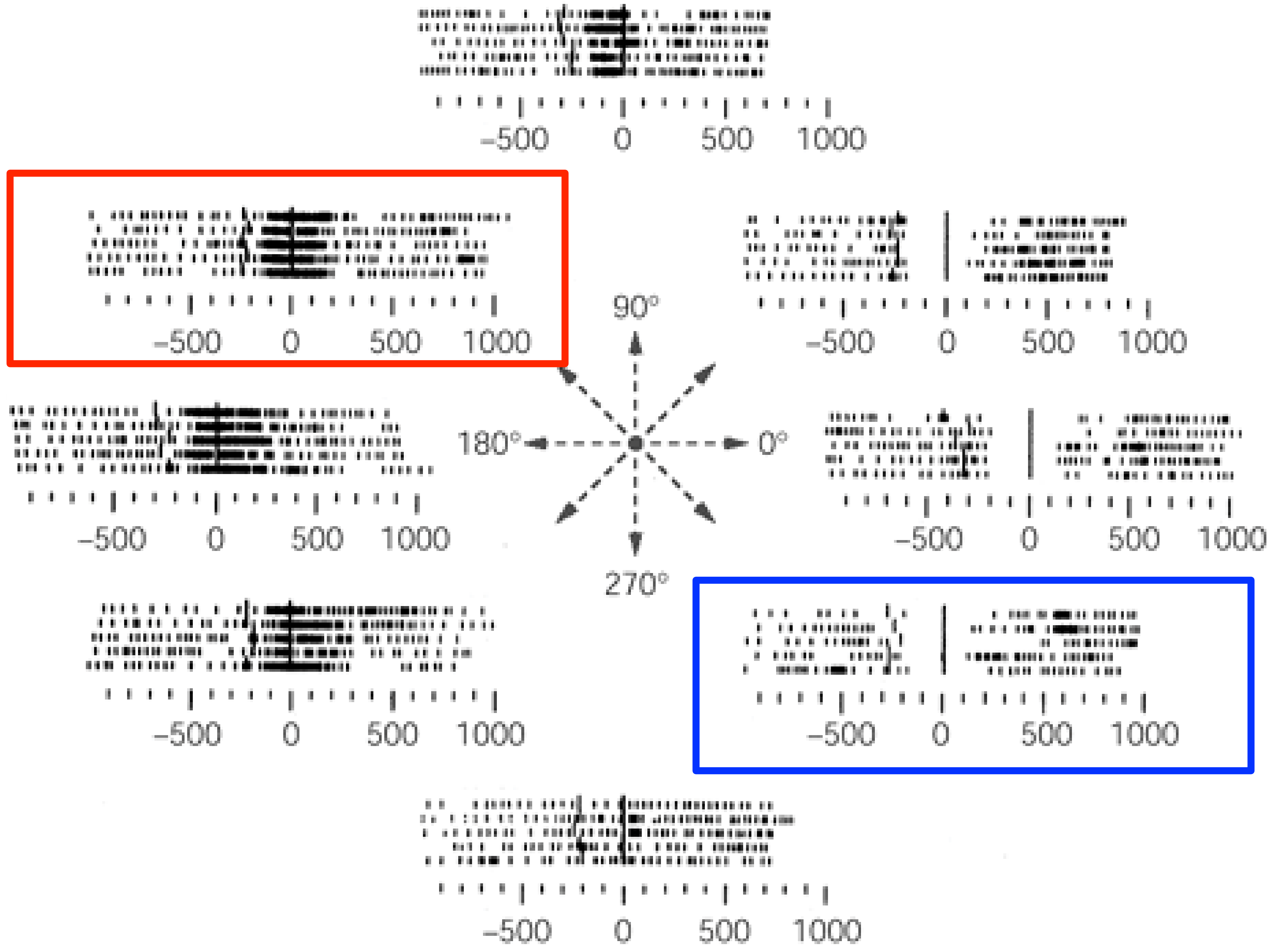
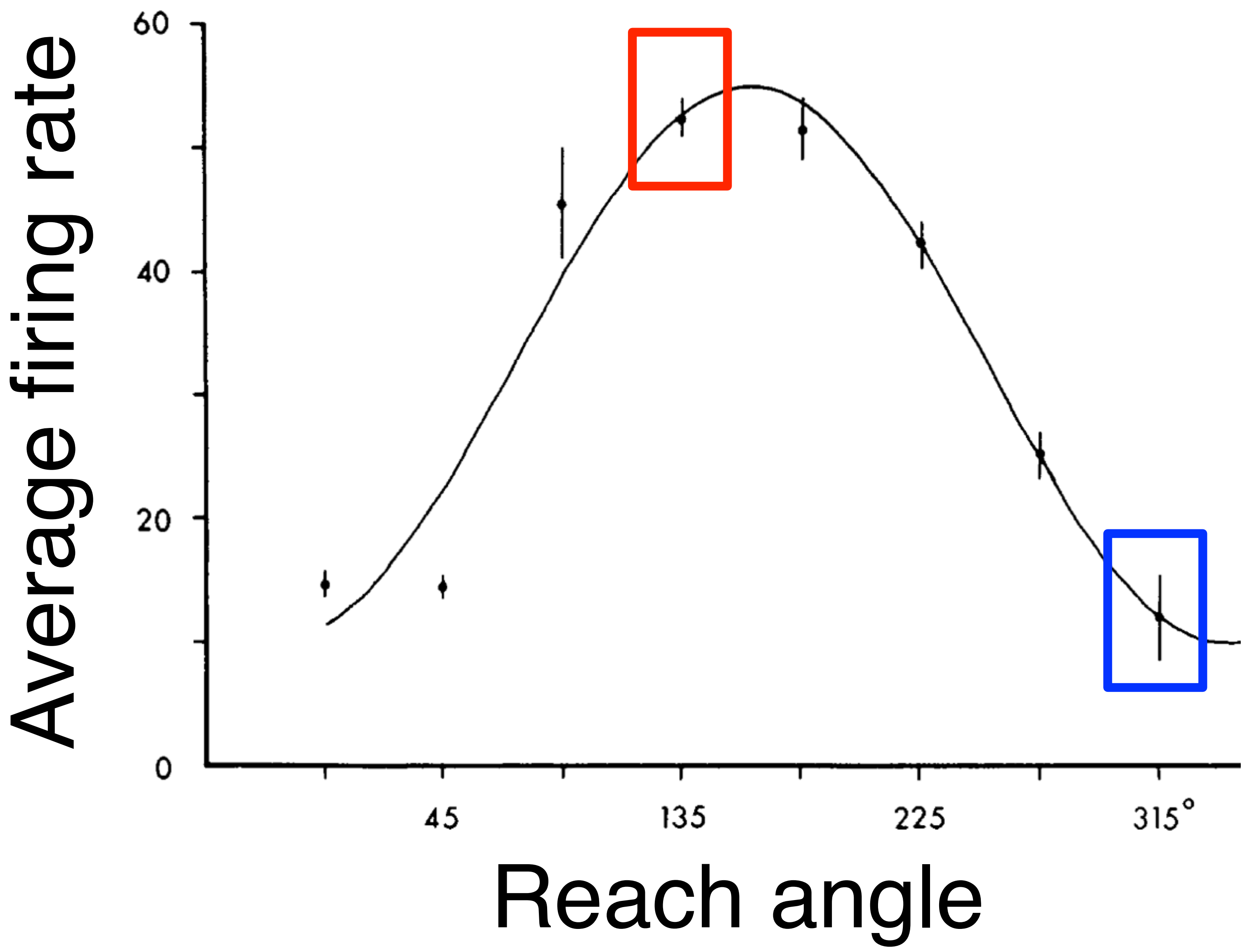






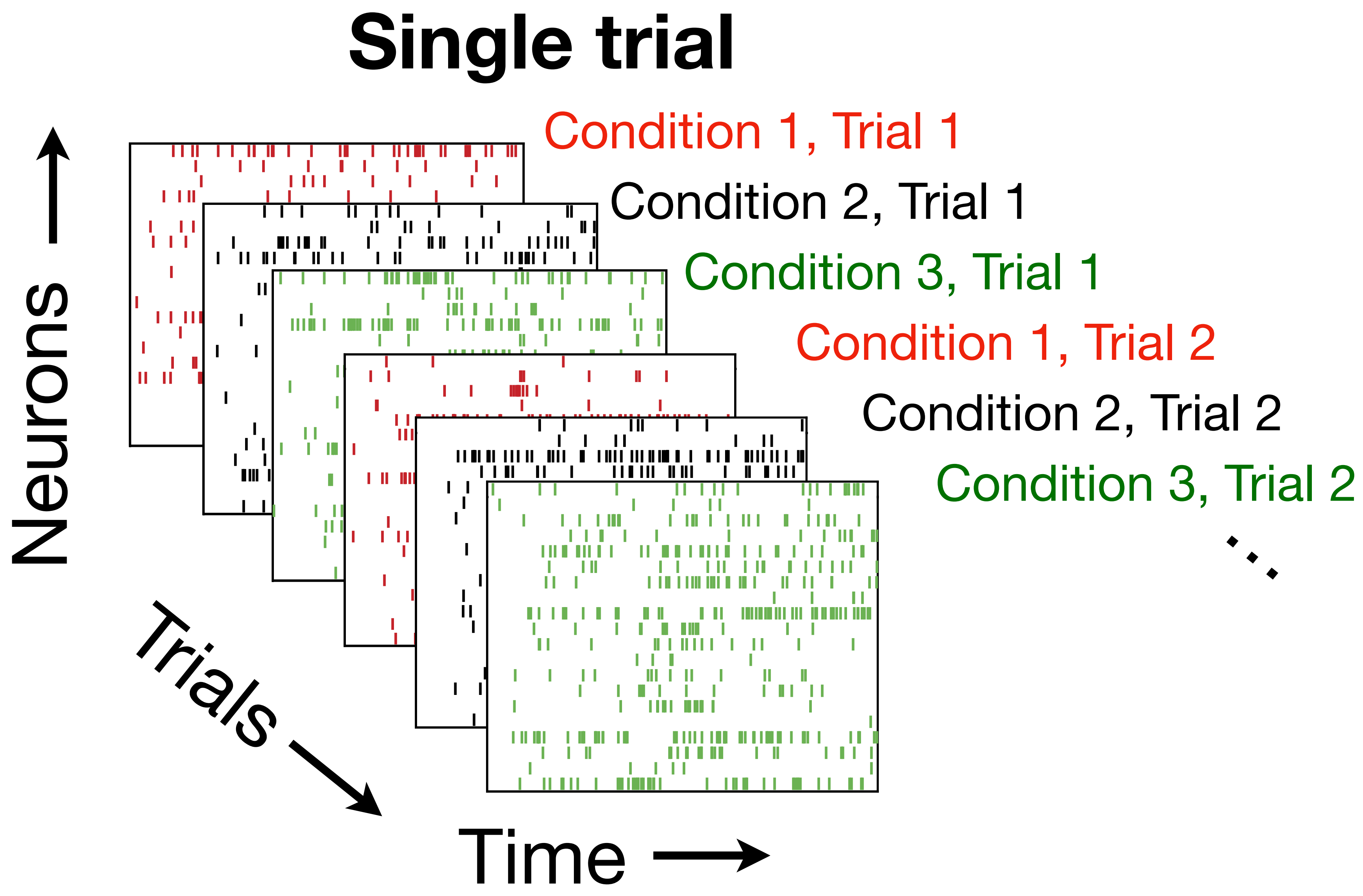
$$\mathbf{z} = f(\mathbf{k})$$

Neurons' firing rate

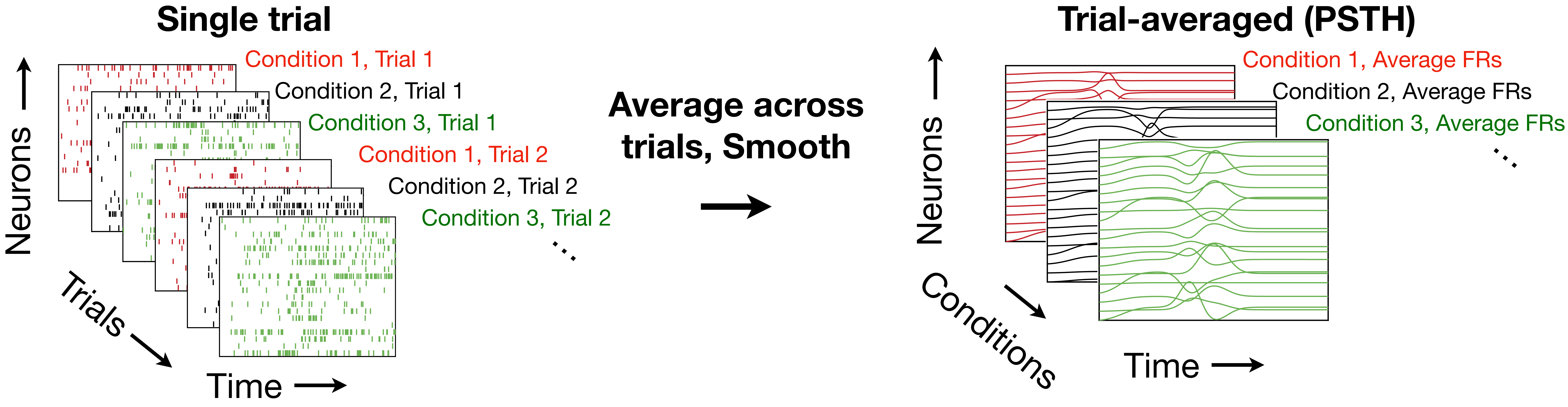
Kinematics
or kinetics

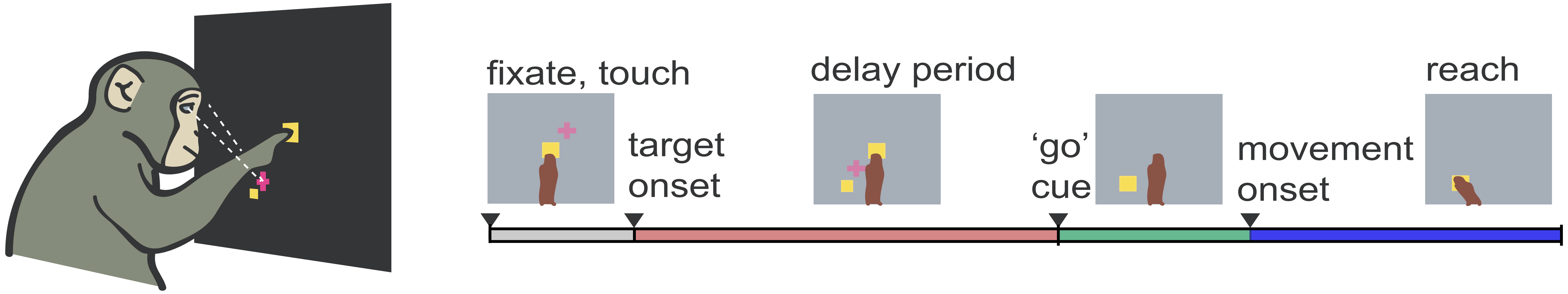
Georgopoulous et al. (1982)
Schwartz et al. (1988)

Visualizing the data

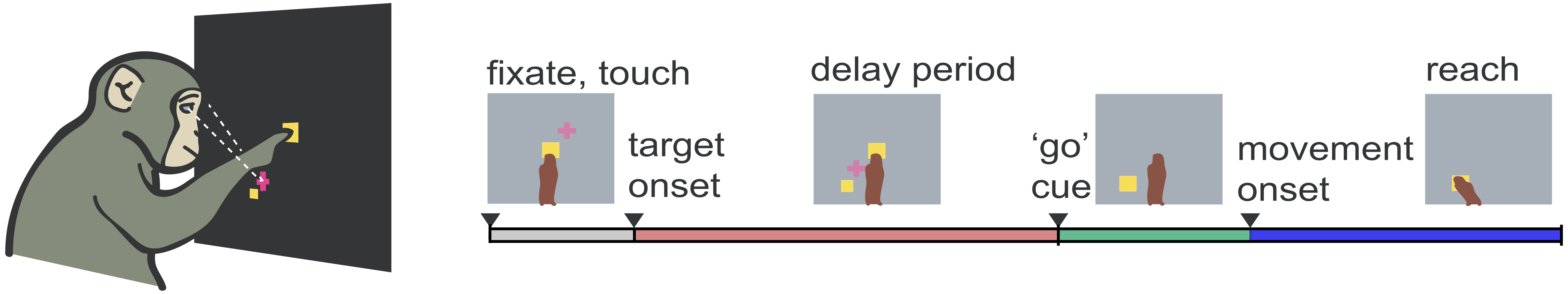


Visualizing the data

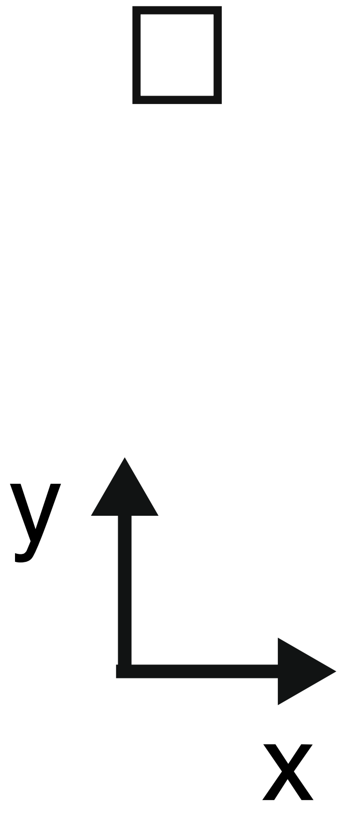




Churchland*, Cunningham* … Shenoy, *Nature* (2012)

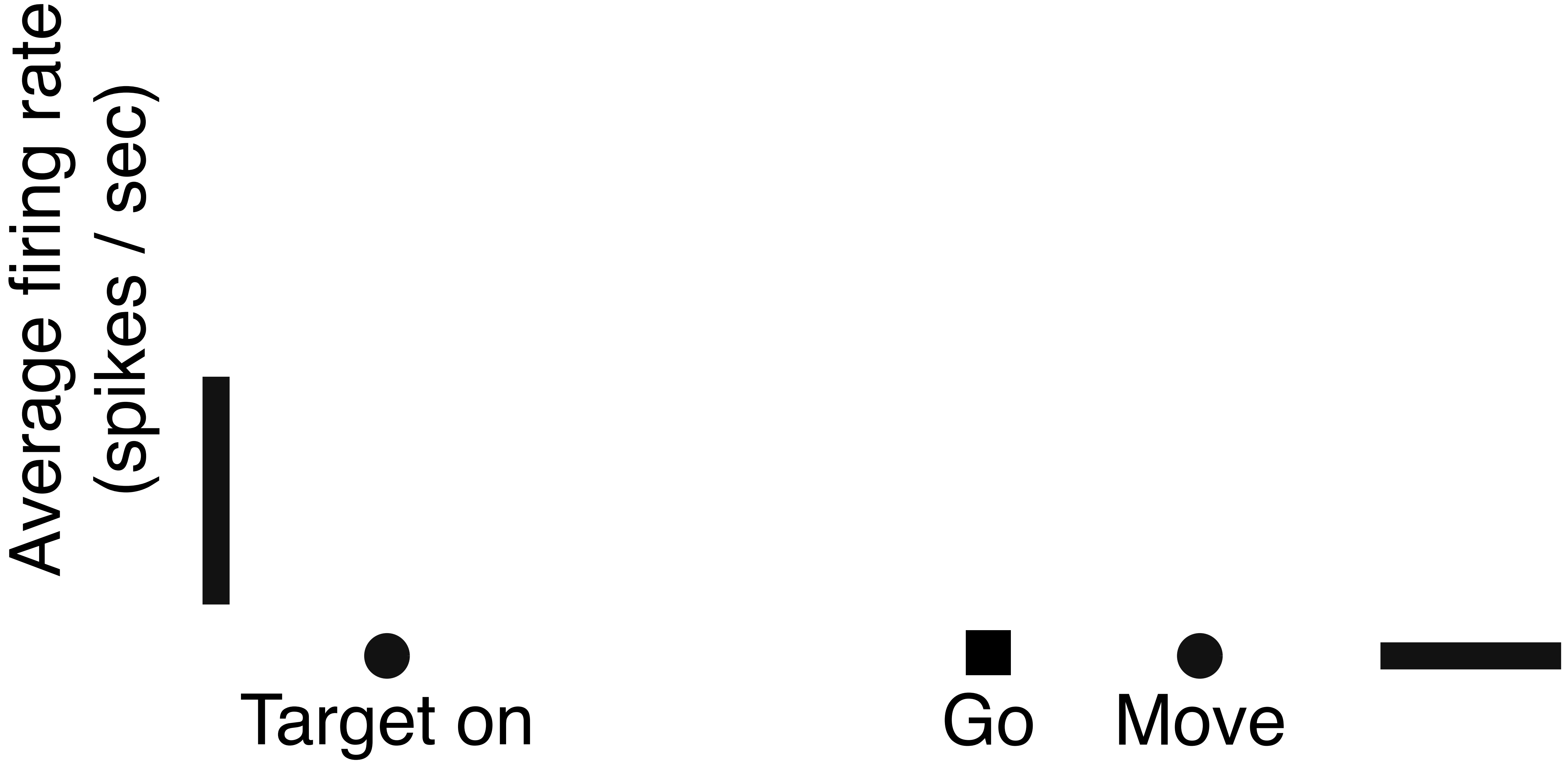


Reach trajectories



Single neuron firing rate (PSTH)

Cell 12
Monkey B



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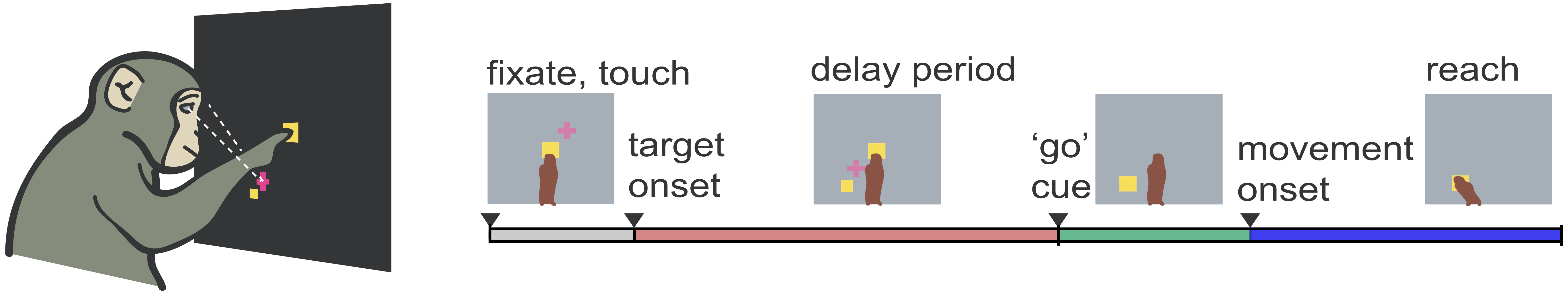

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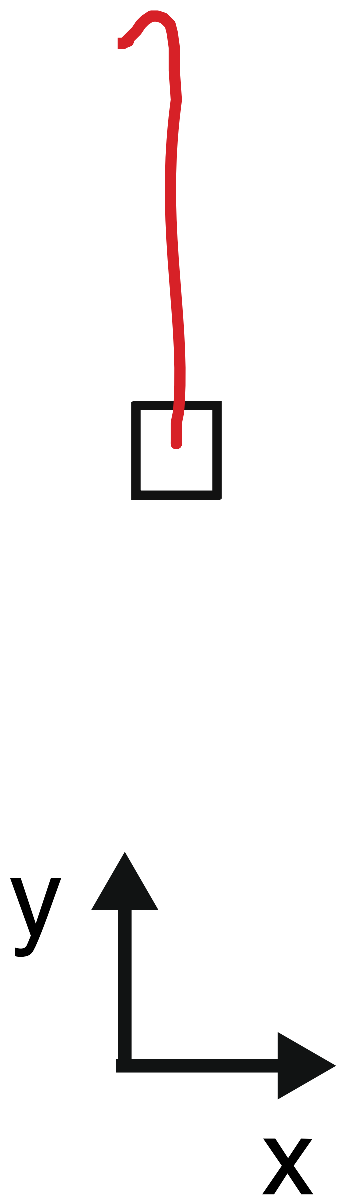

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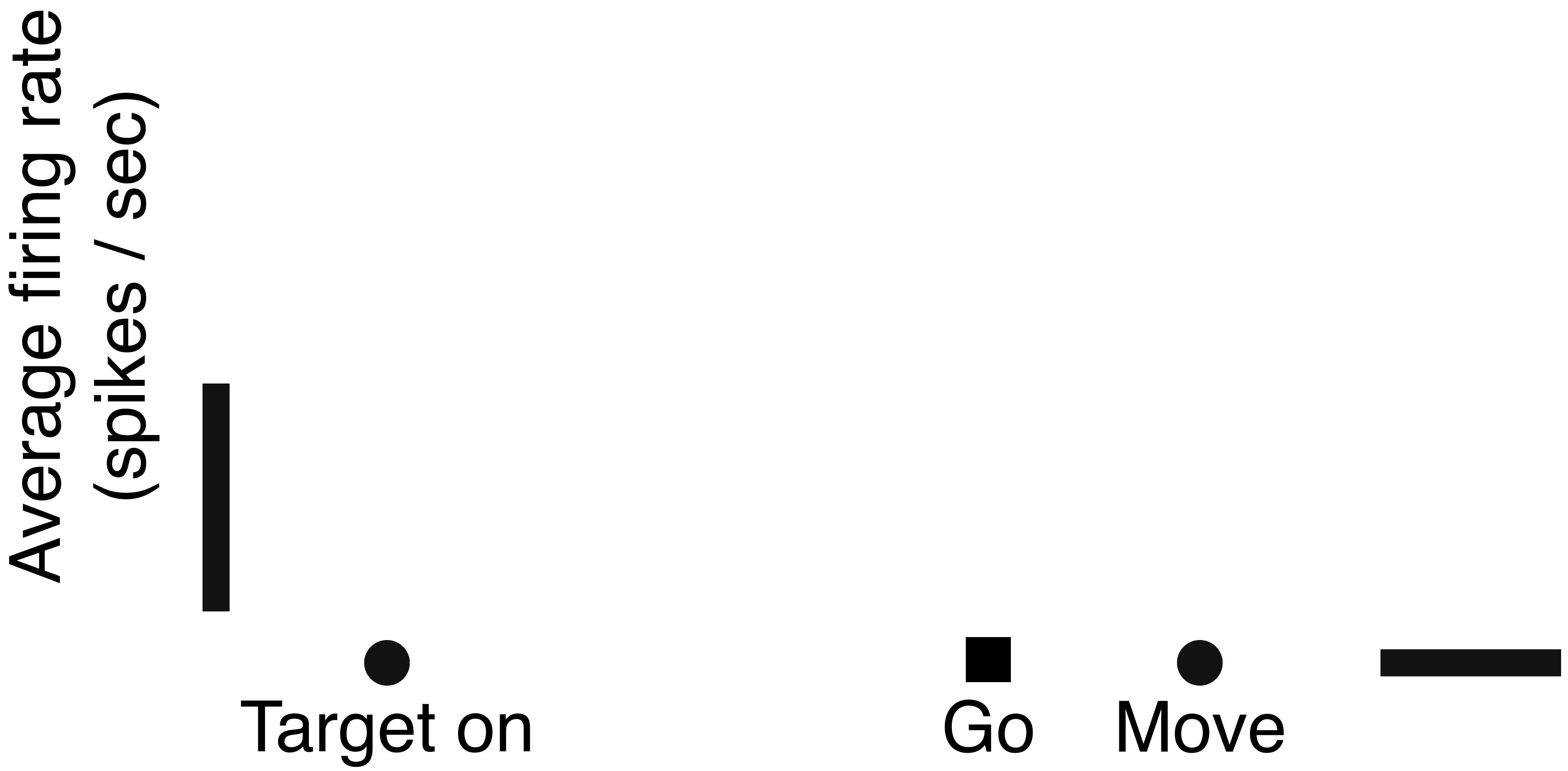

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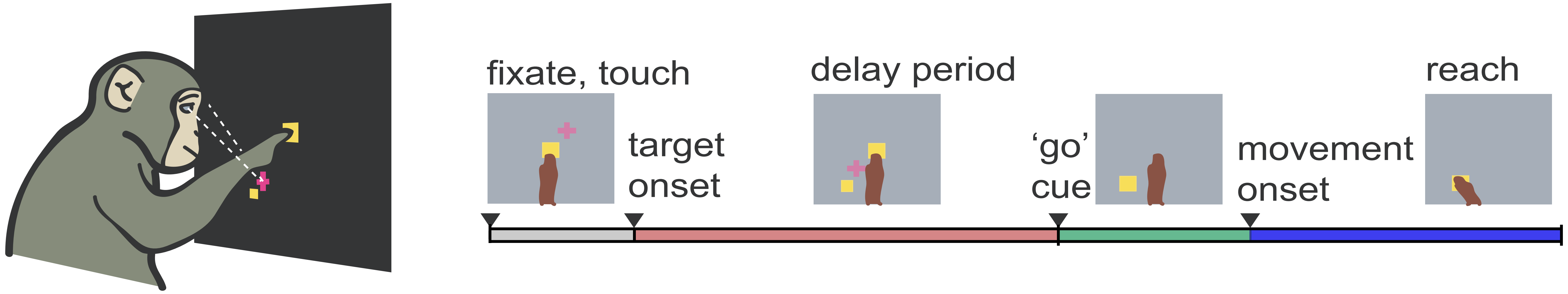

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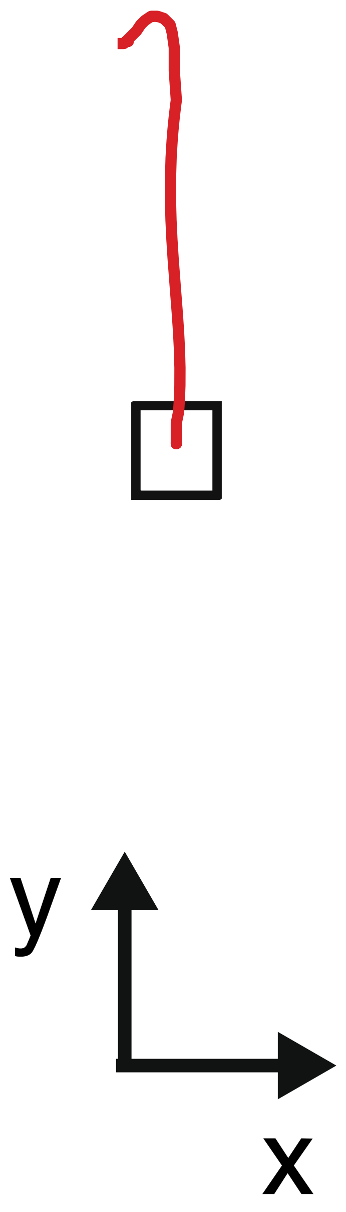

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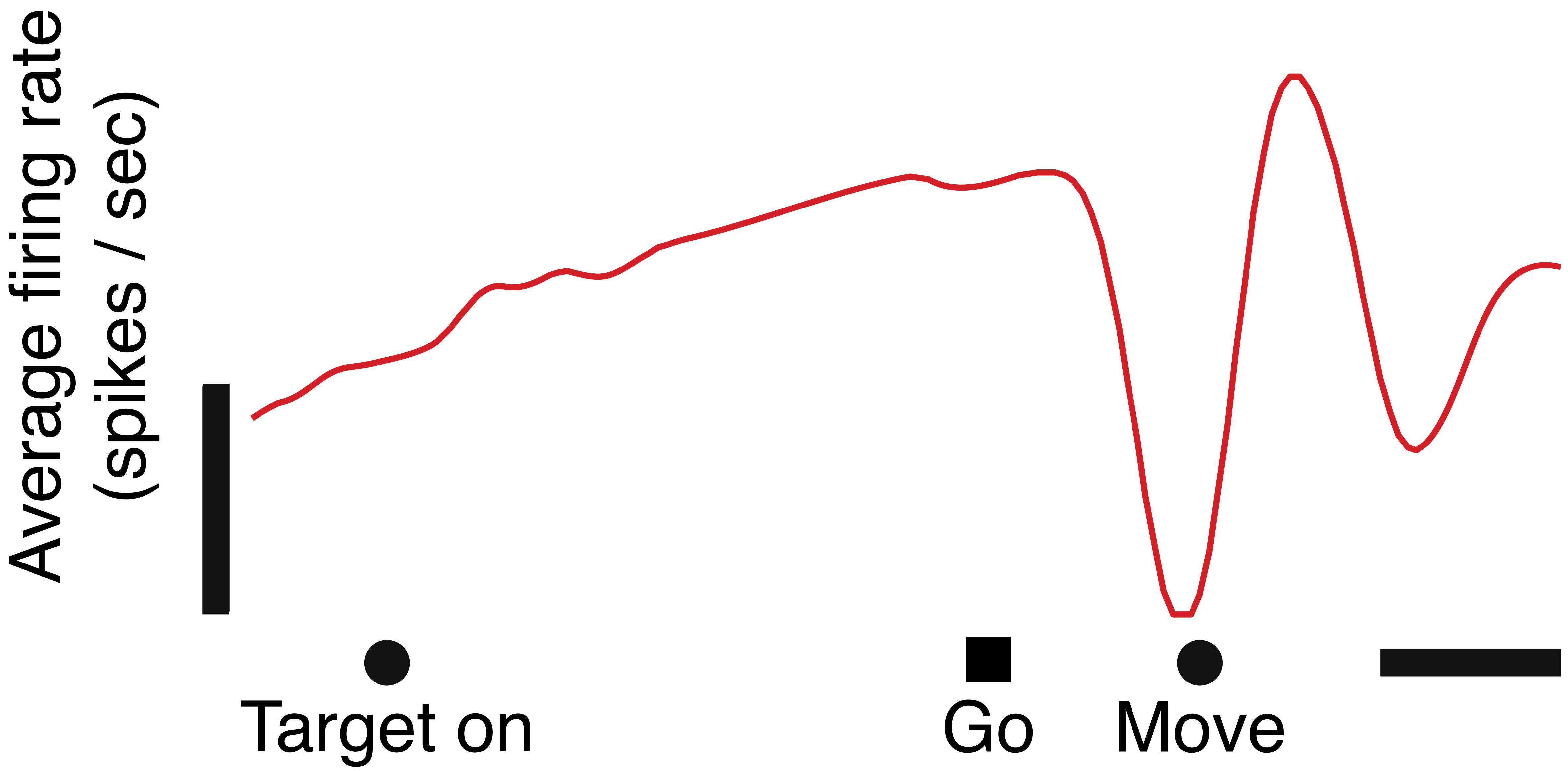

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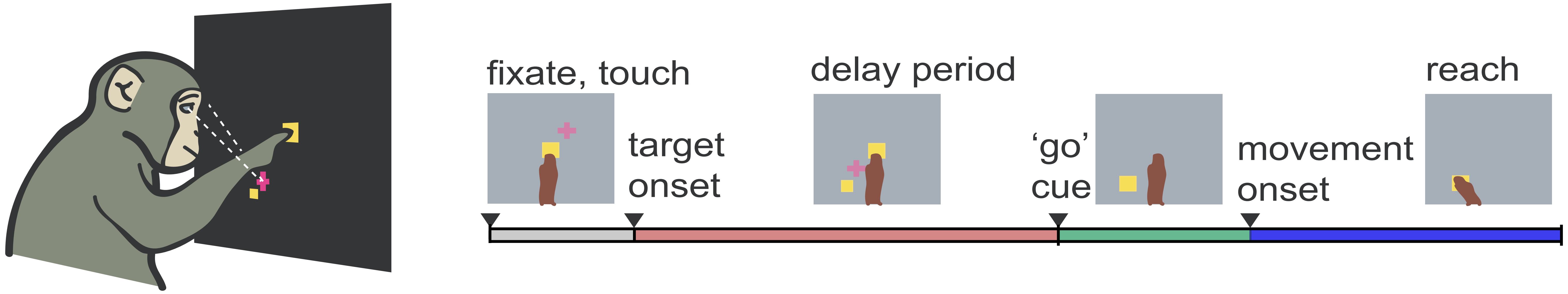

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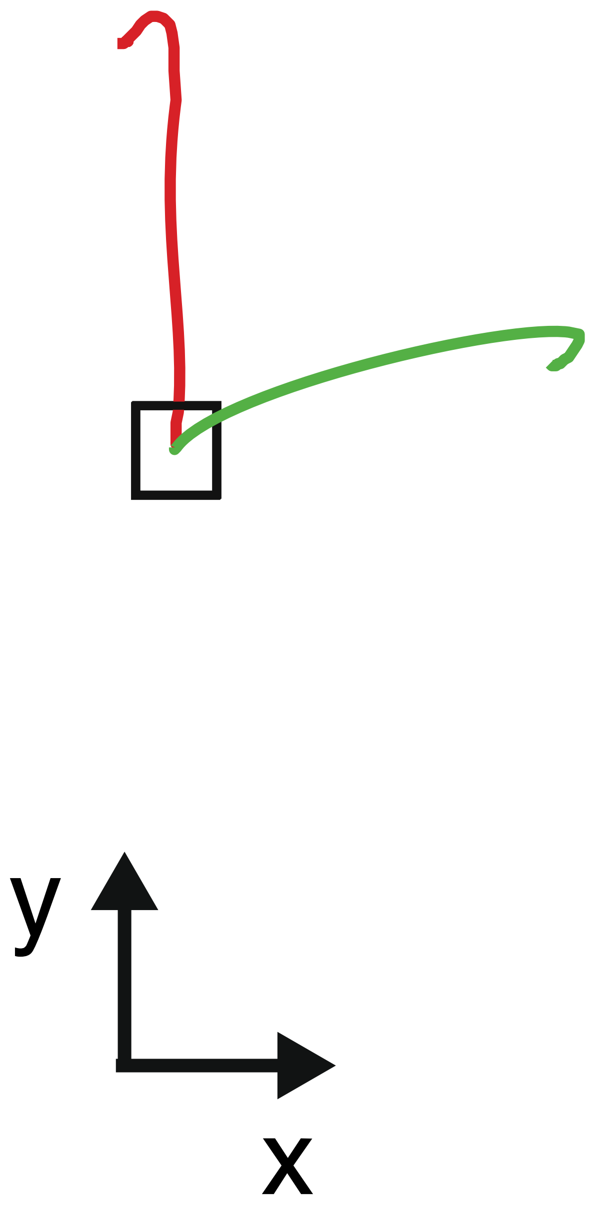

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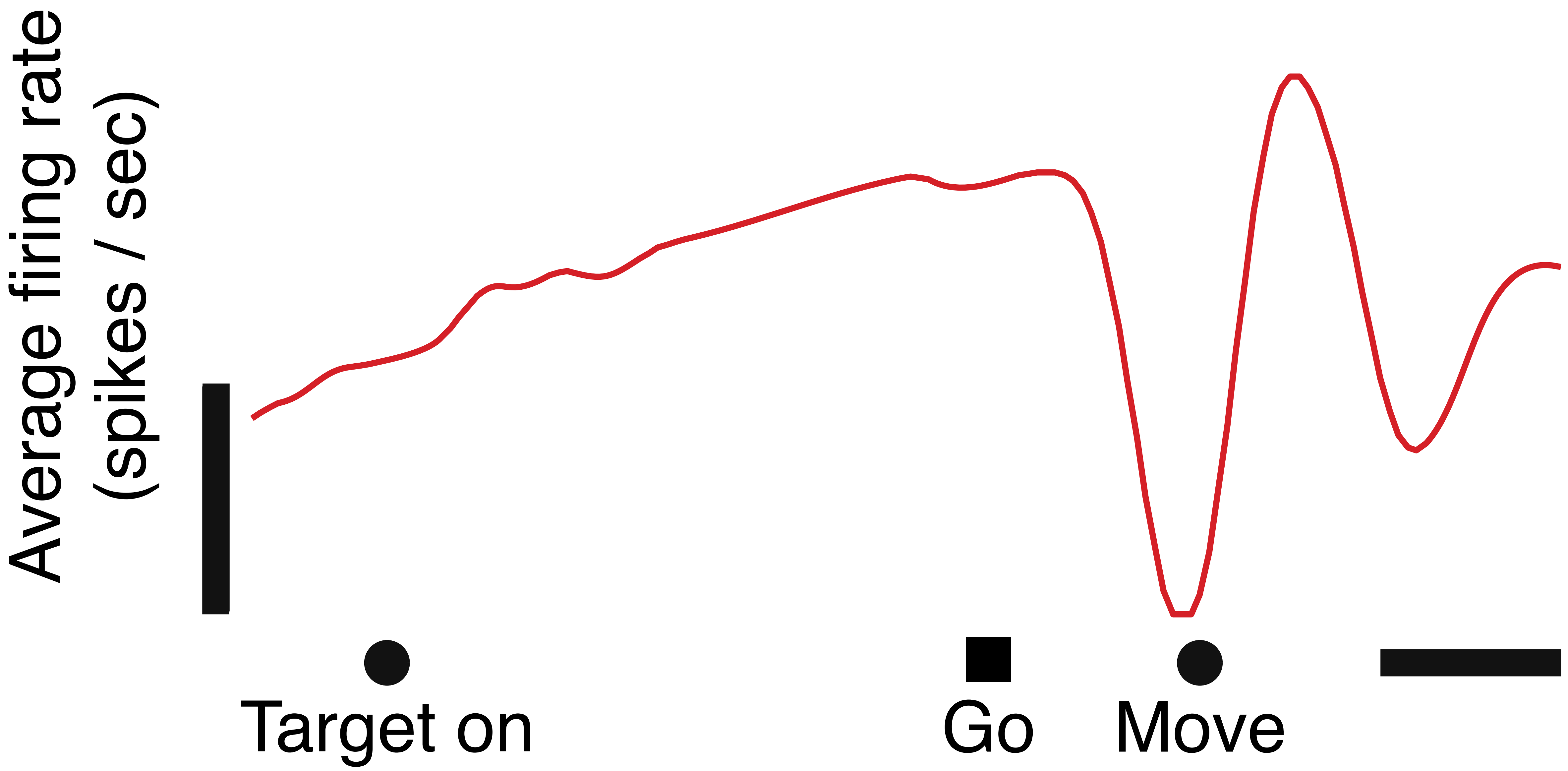

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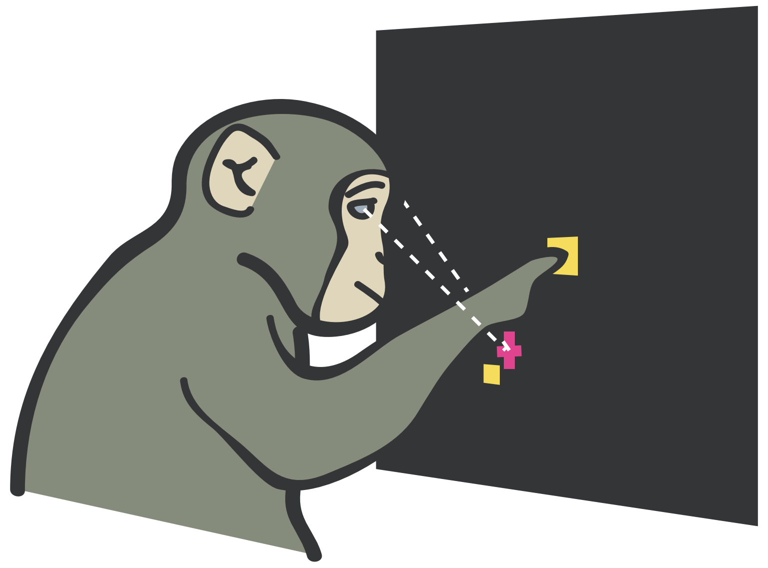

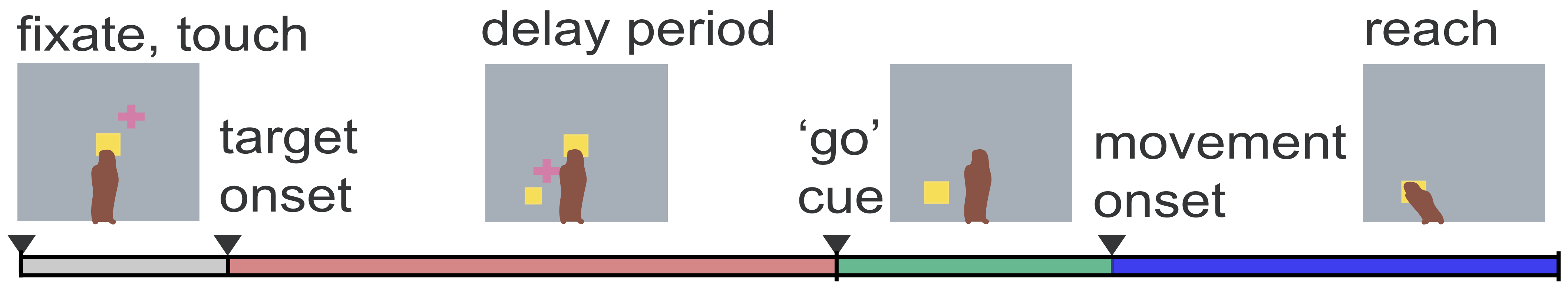

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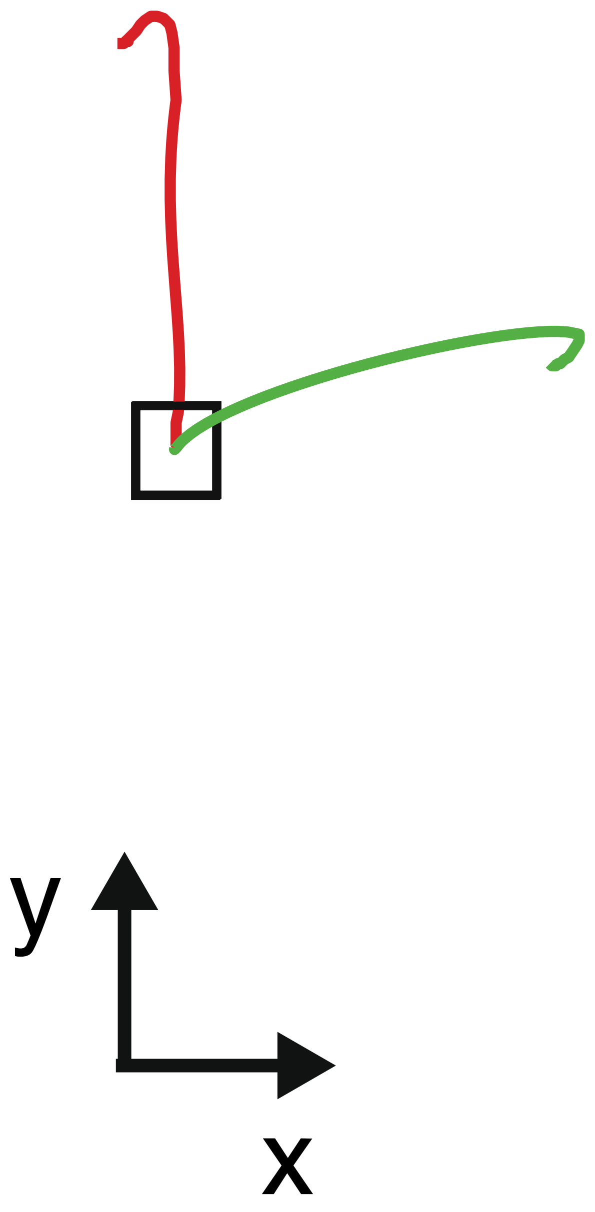

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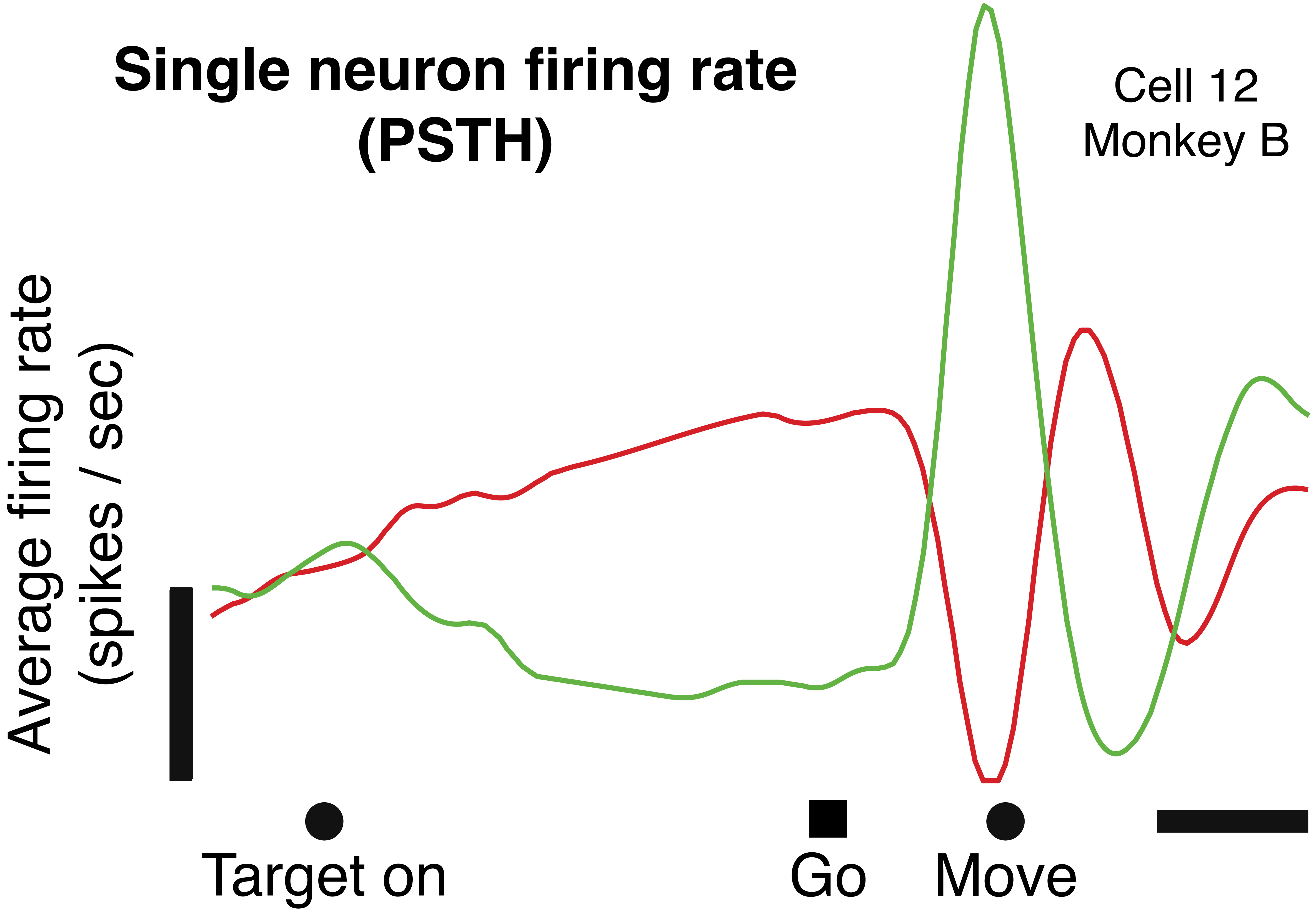

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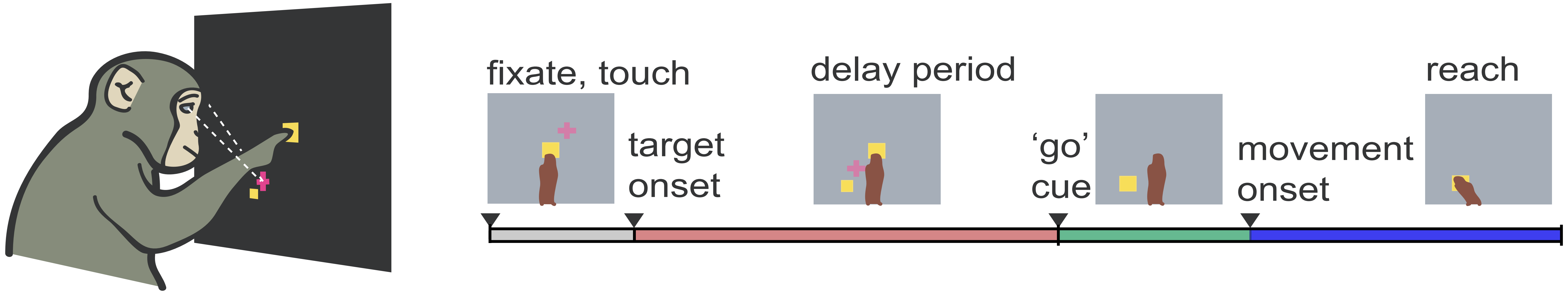

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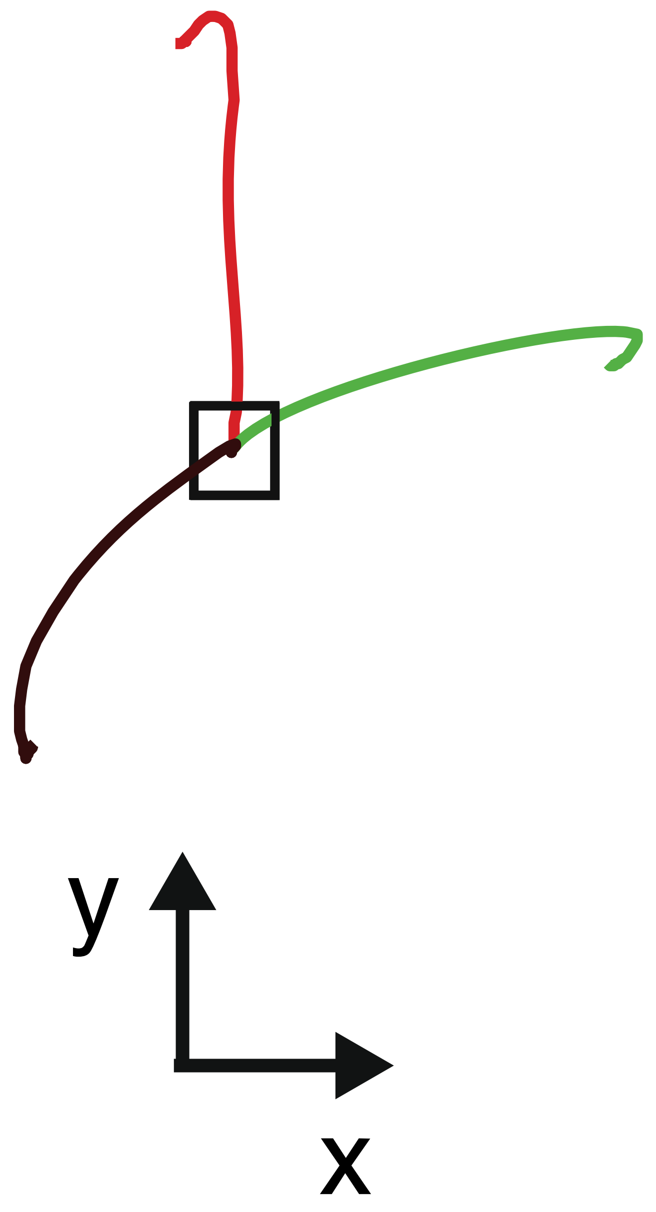

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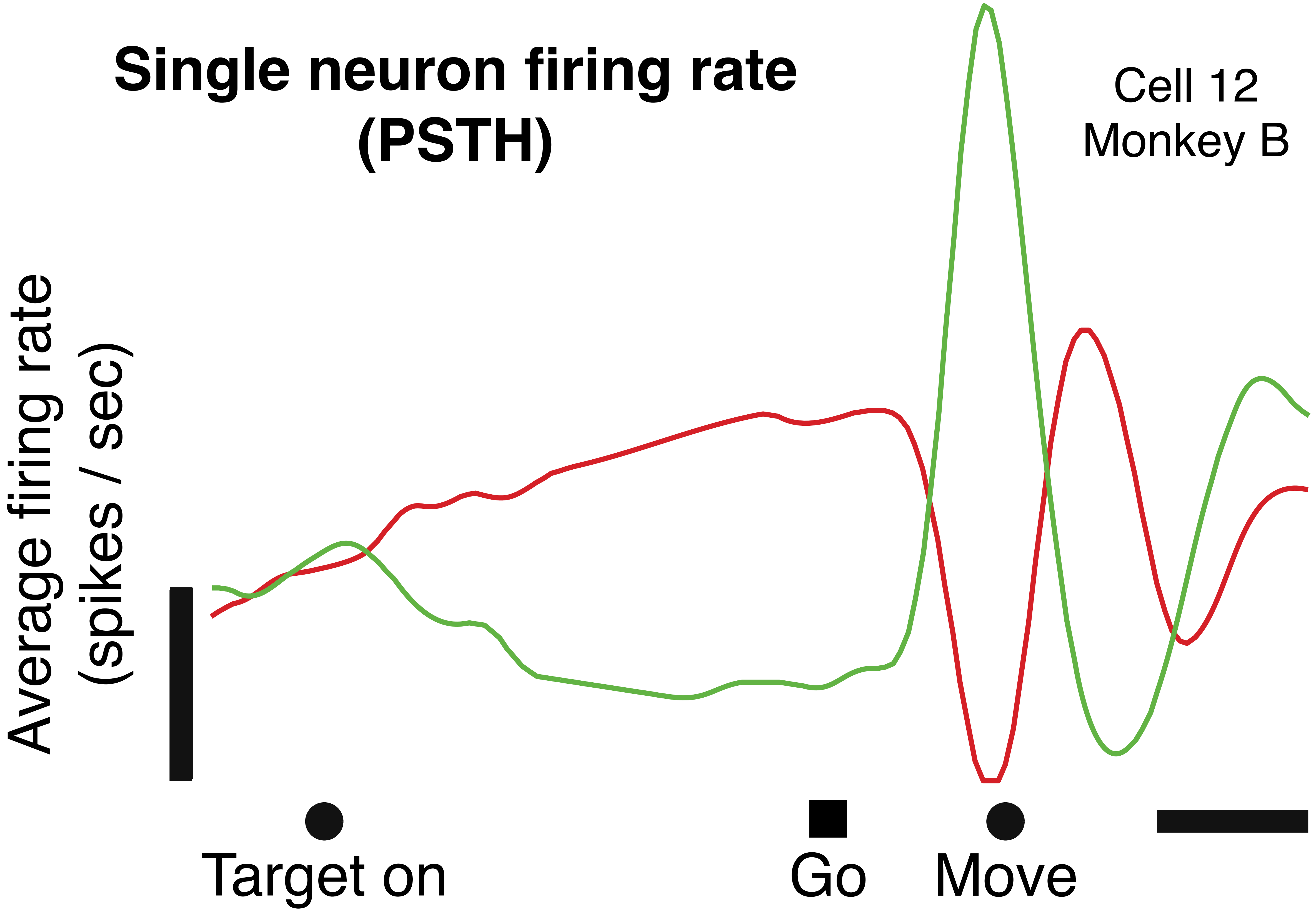

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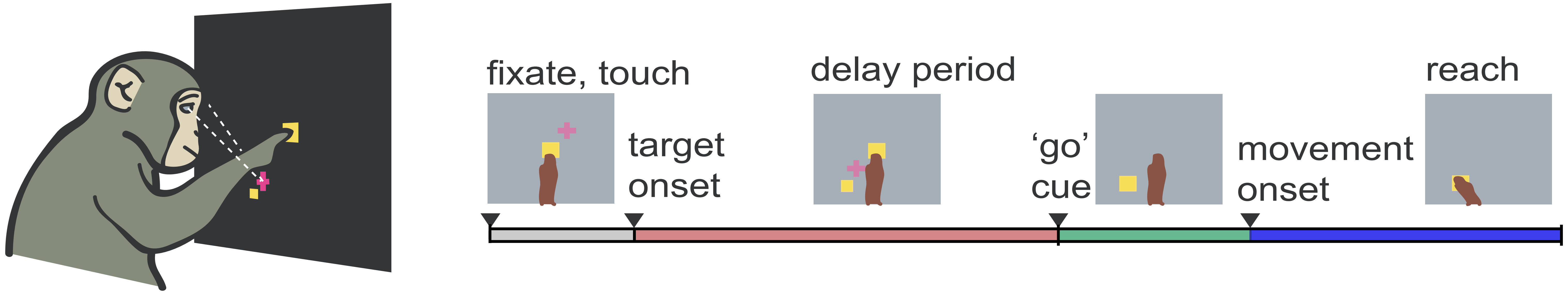

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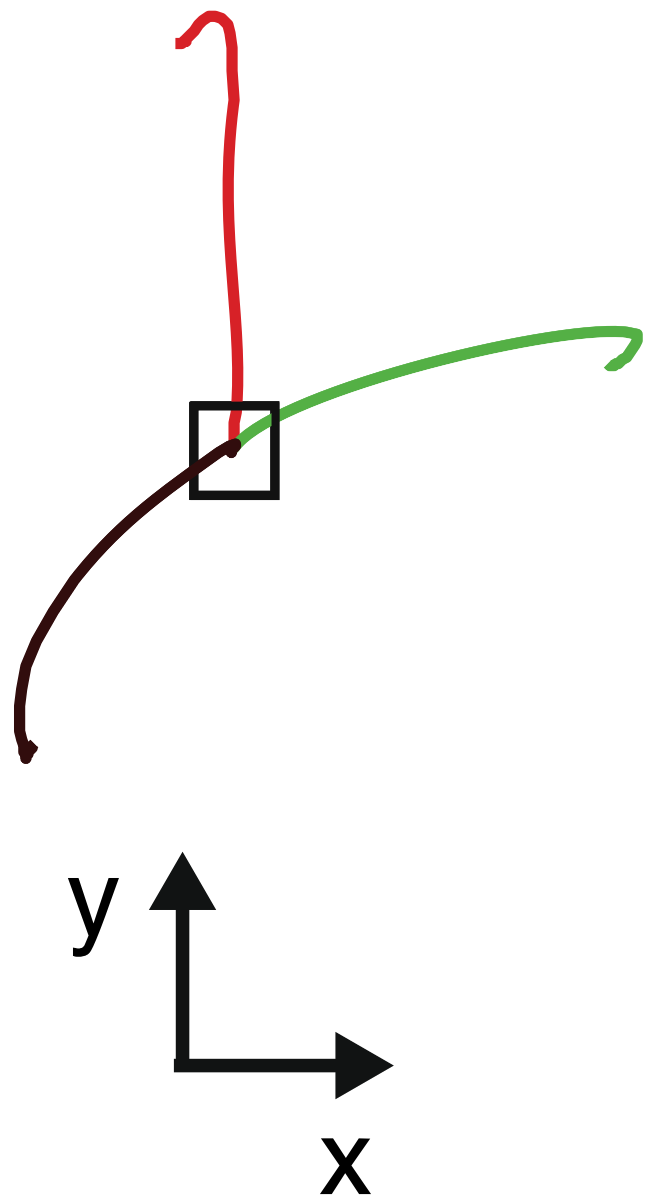

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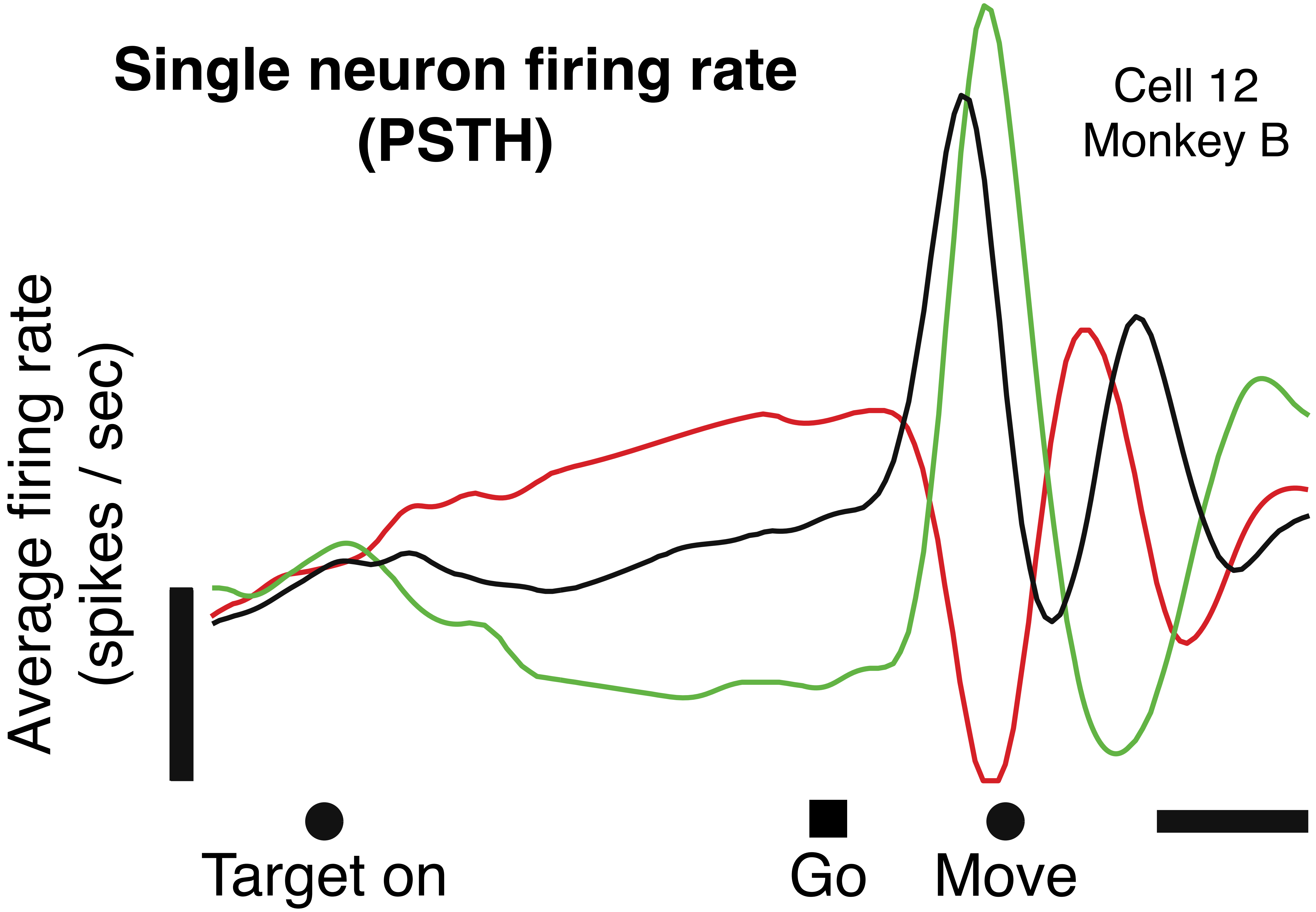

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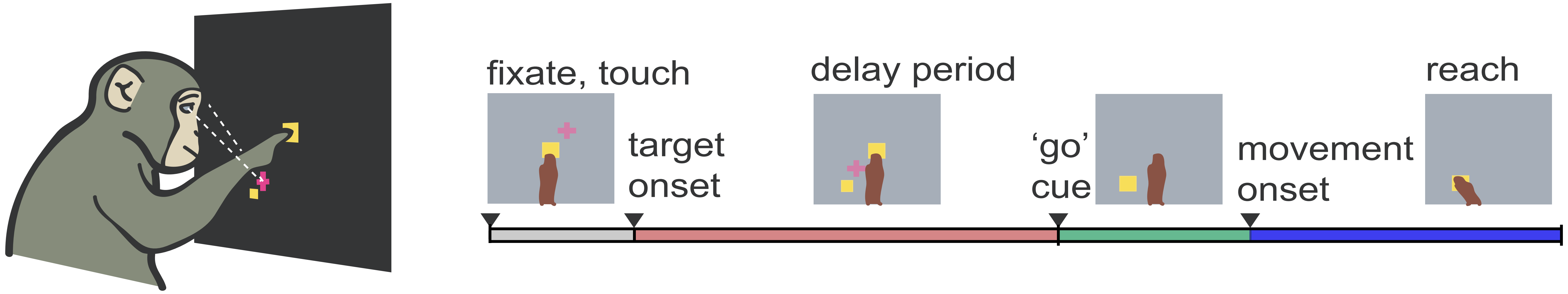

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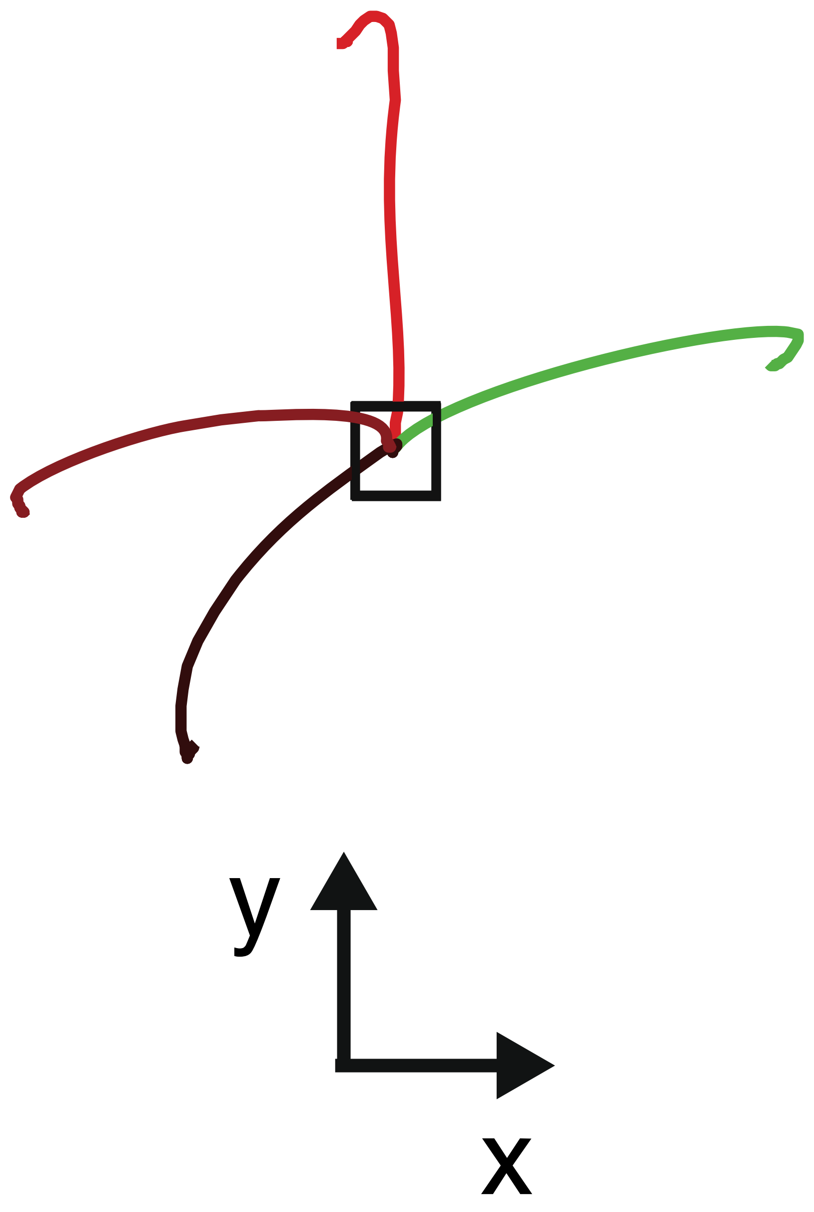

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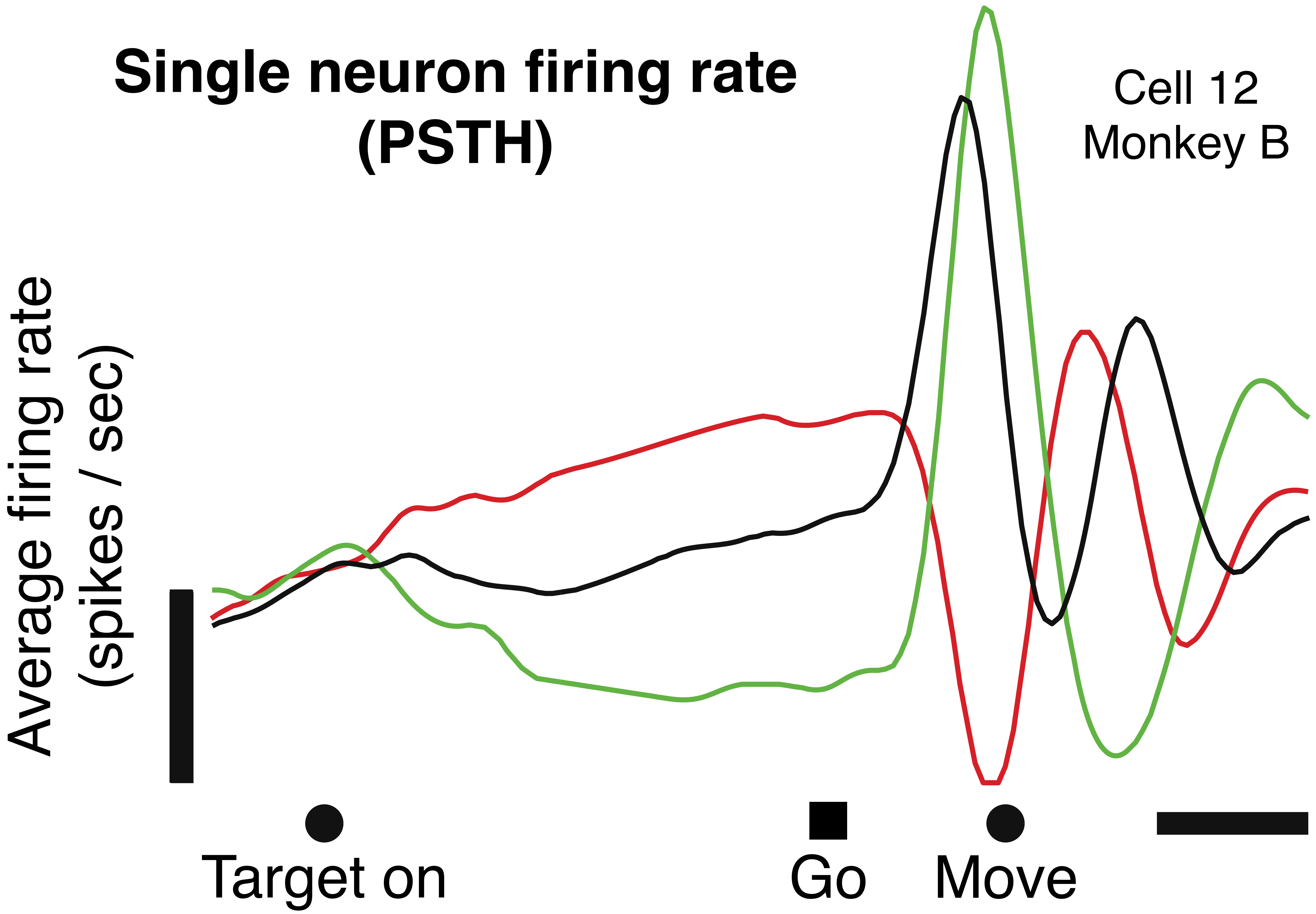

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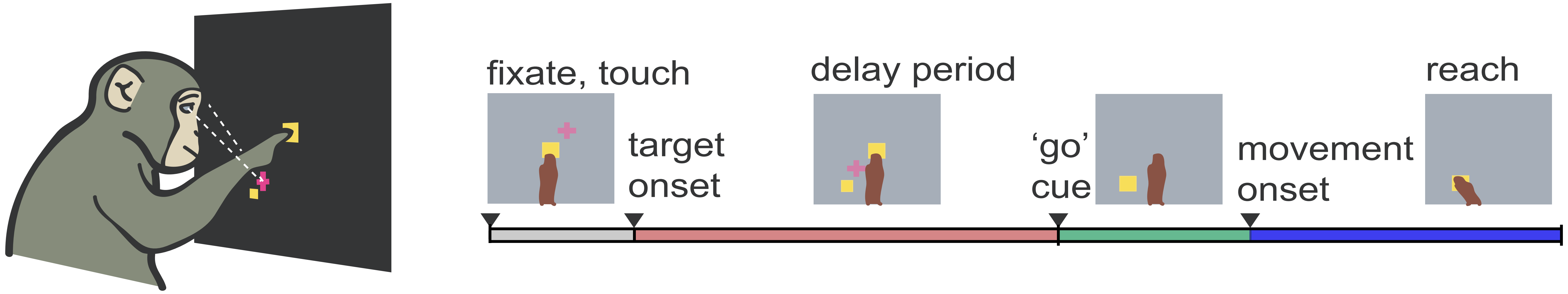

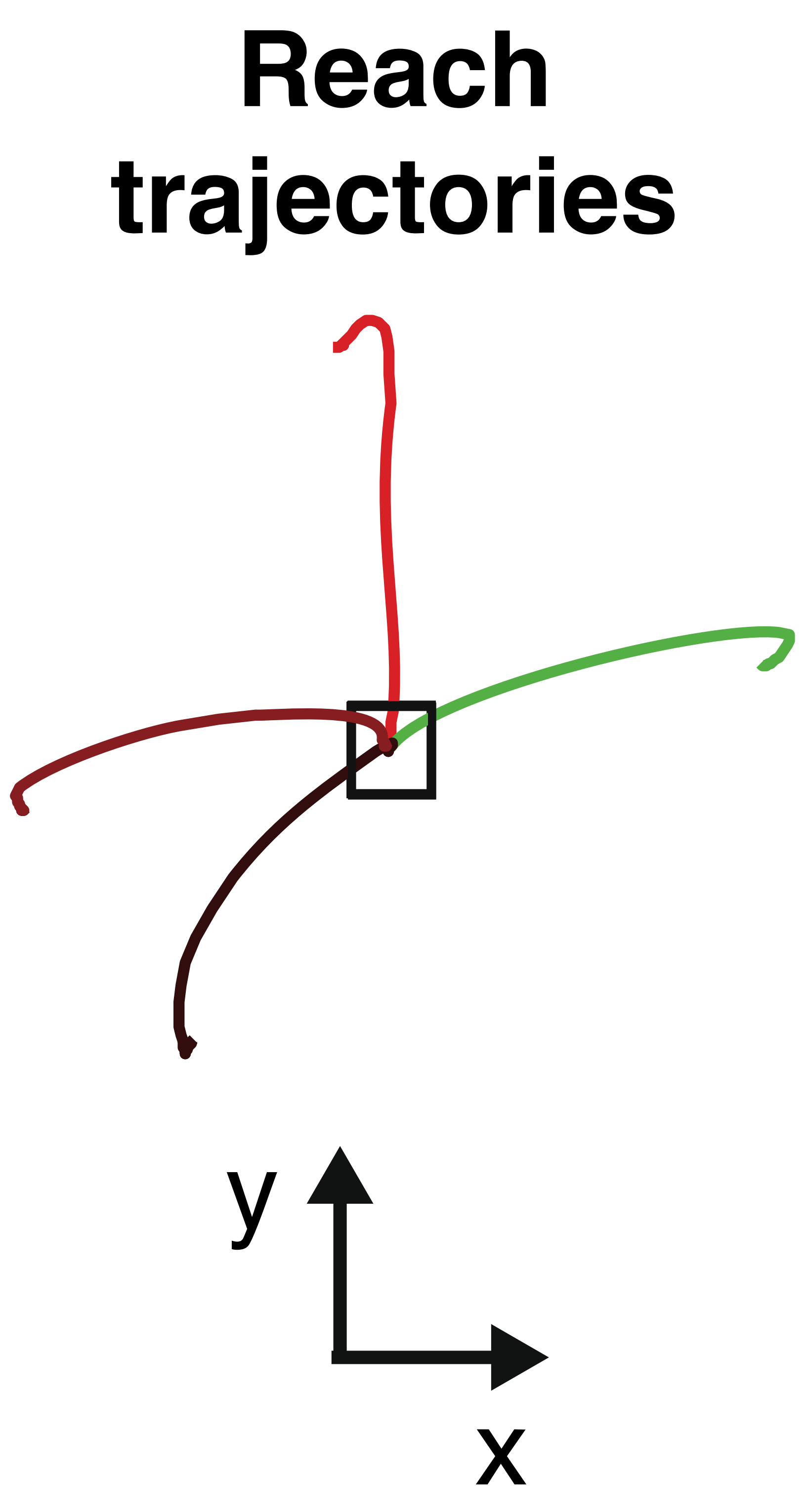

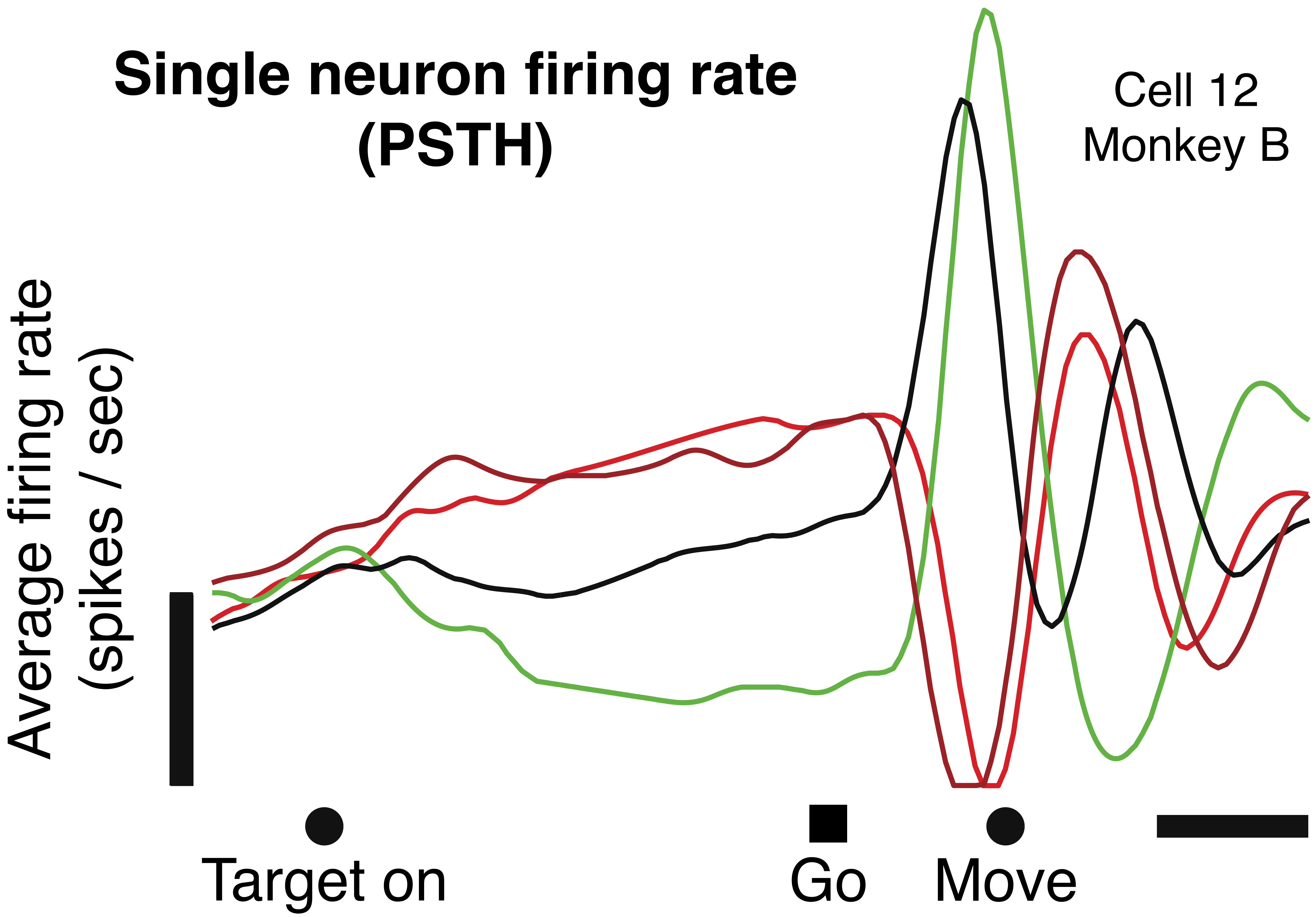

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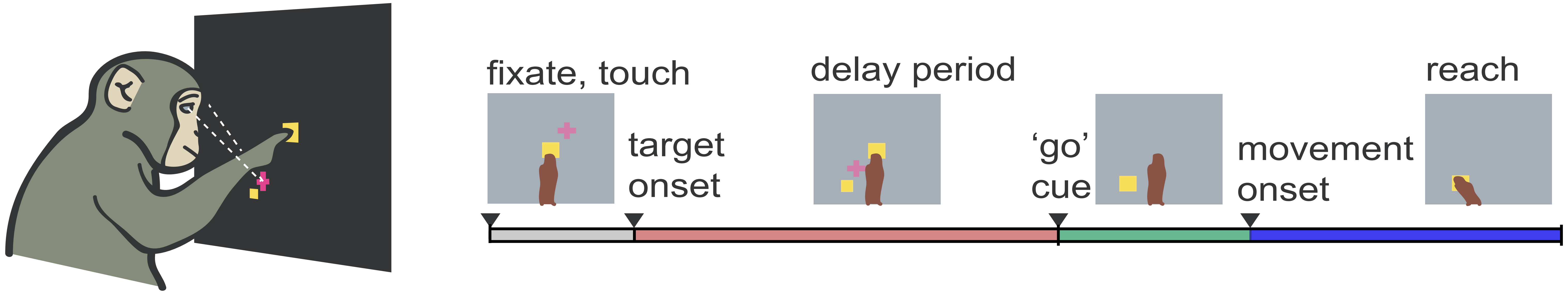

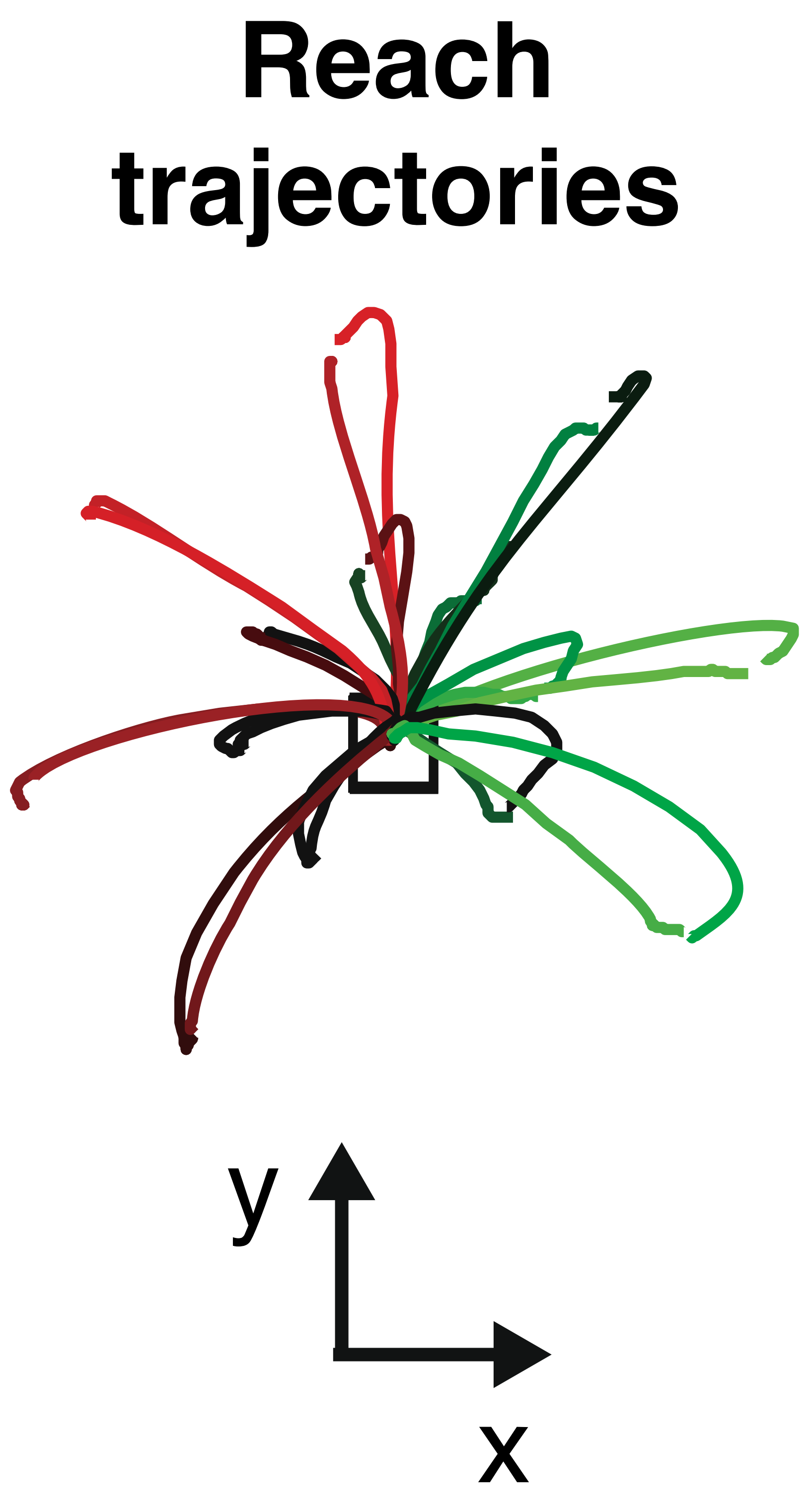

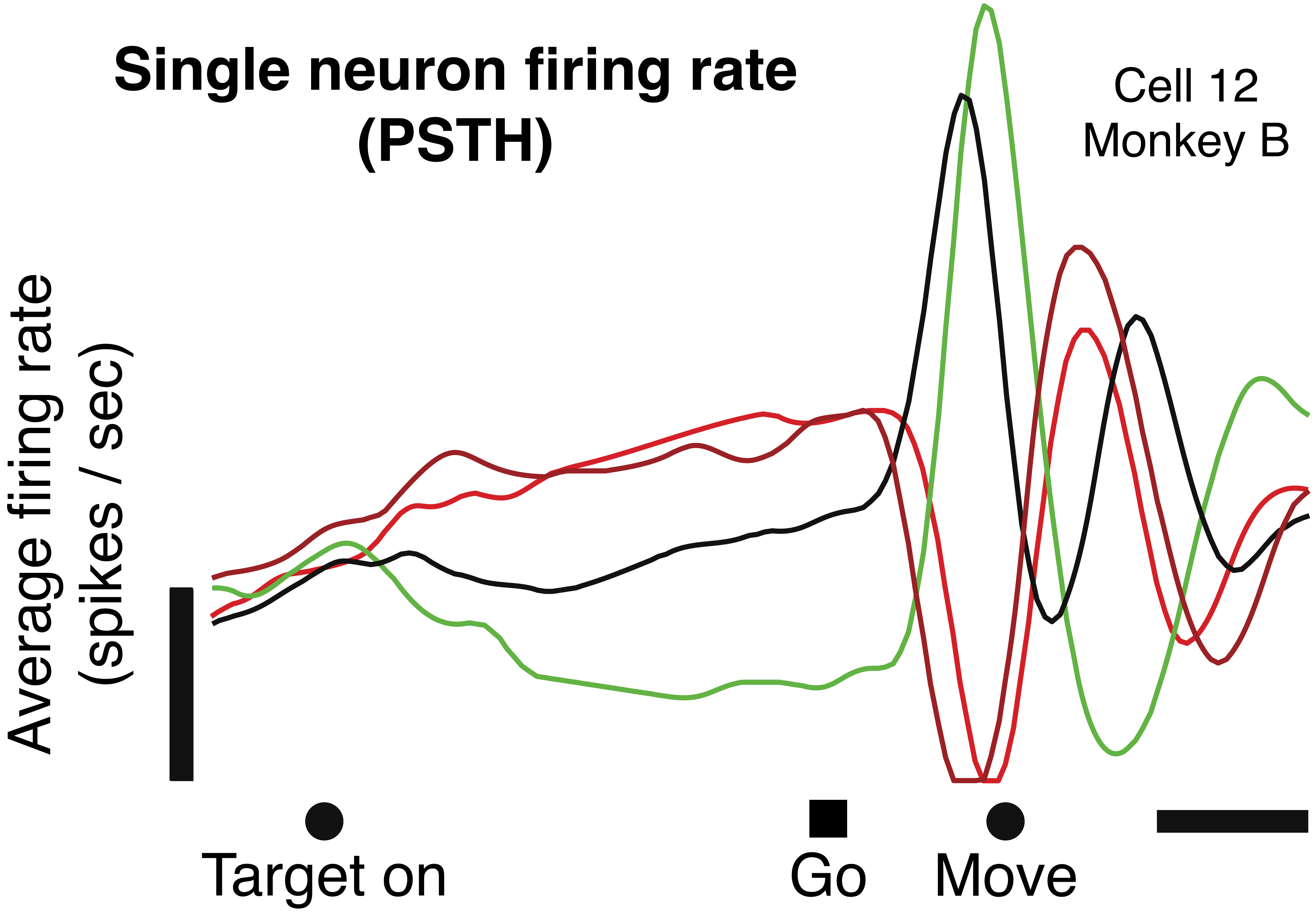

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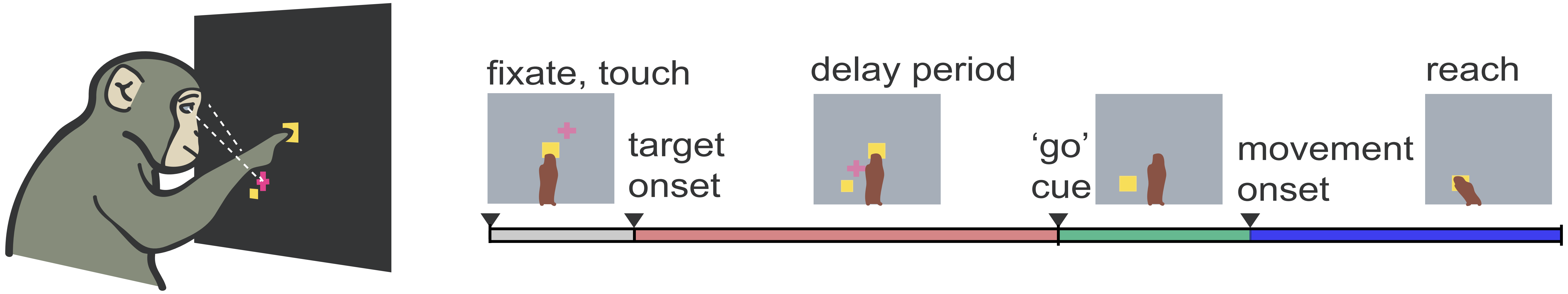
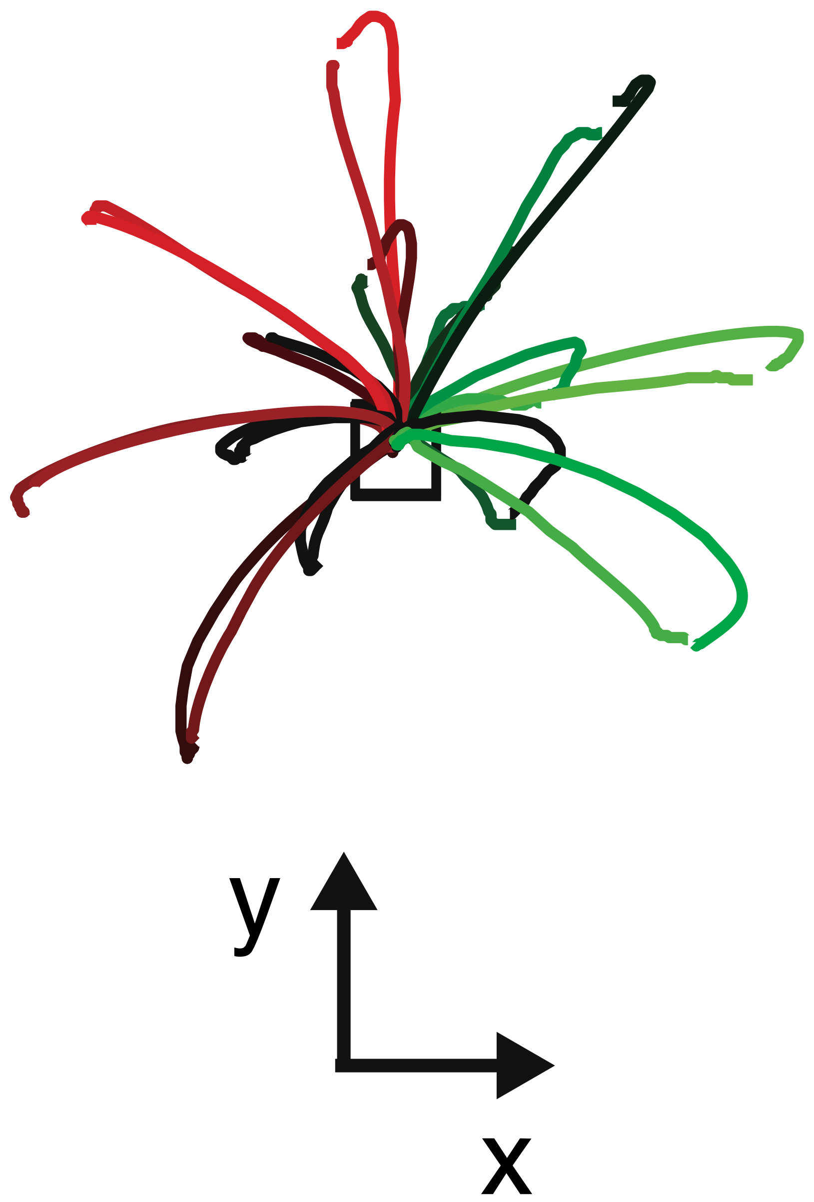
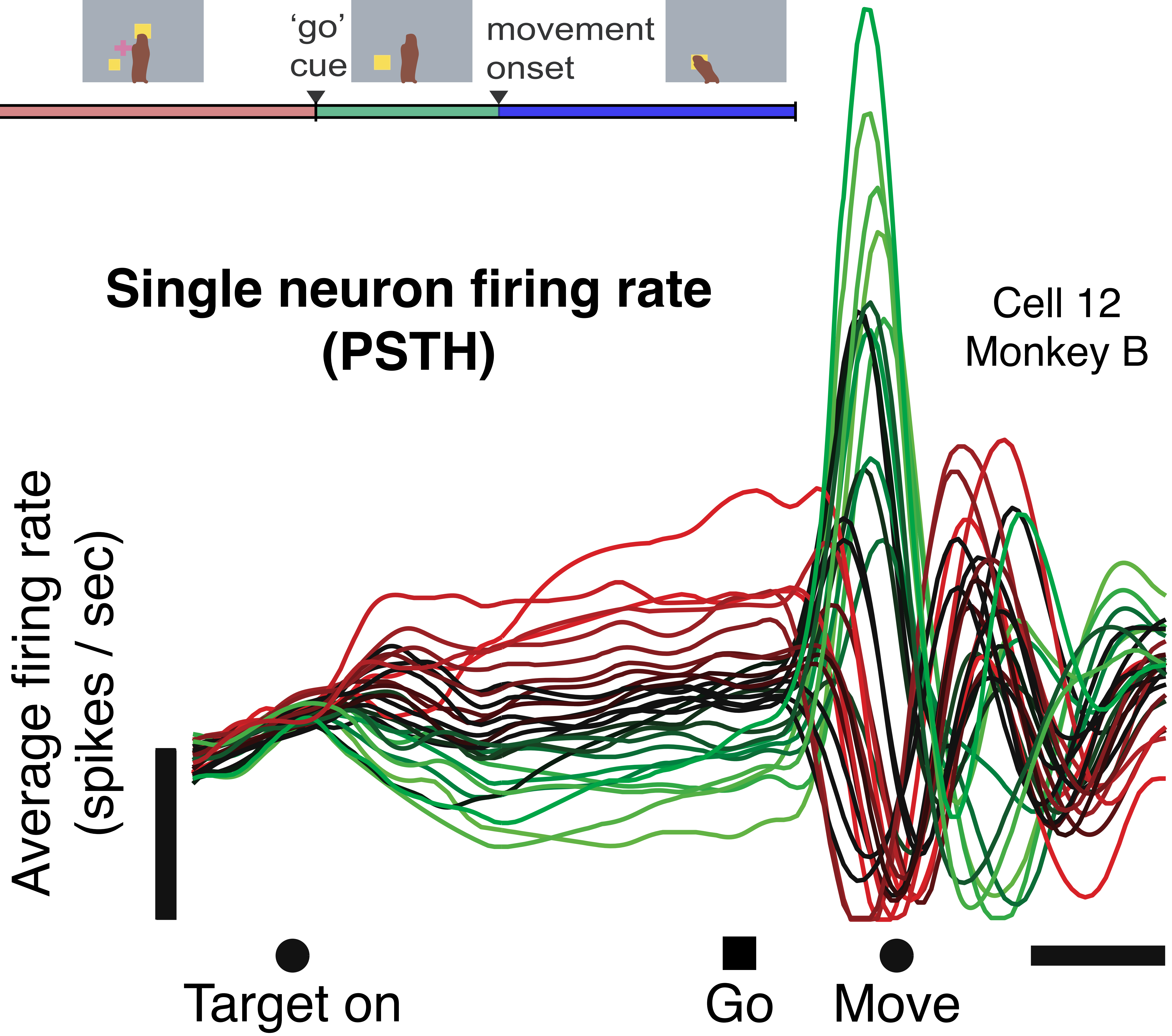


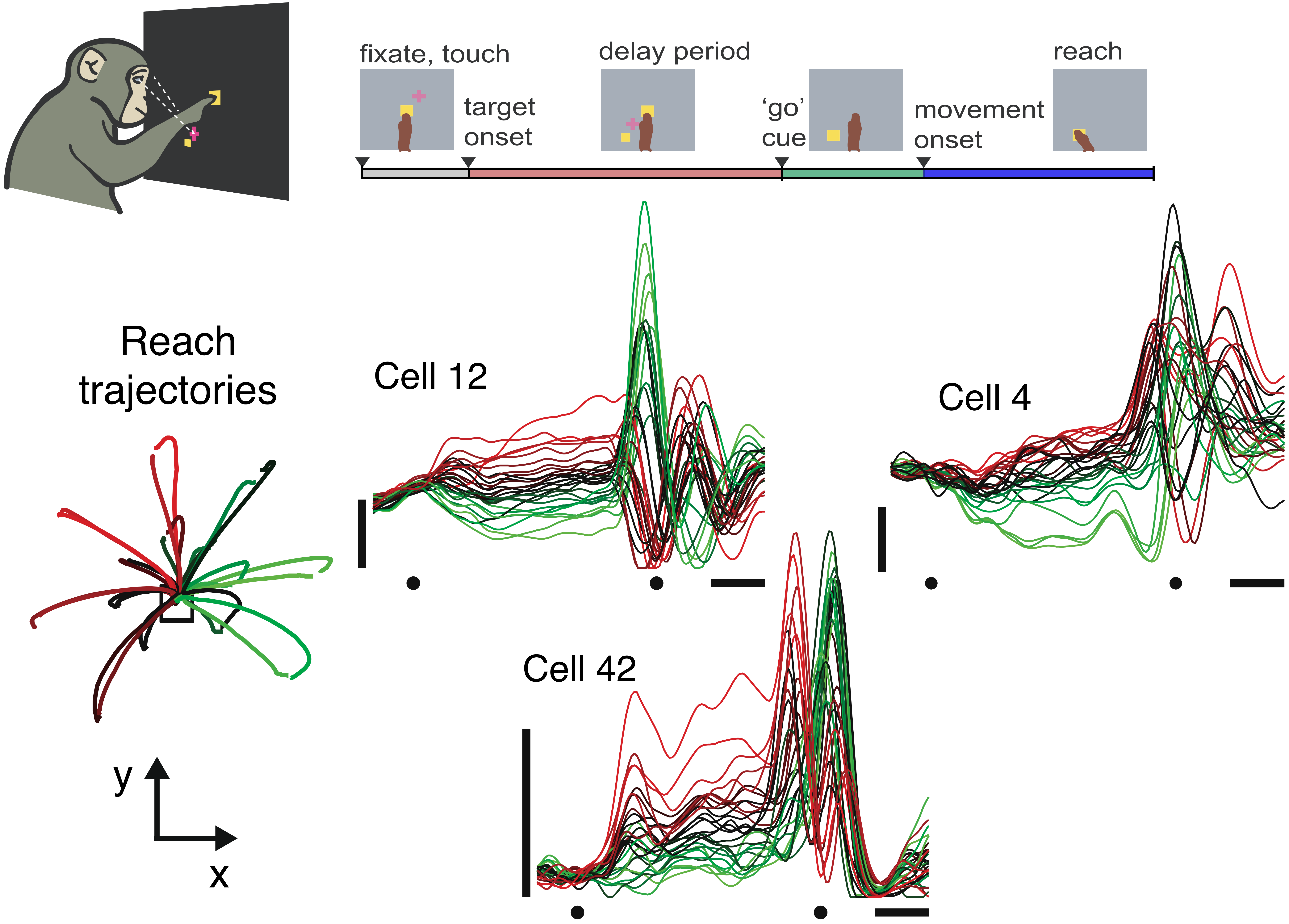
Reach trajectories



Single neuron firing rate (PSTH)

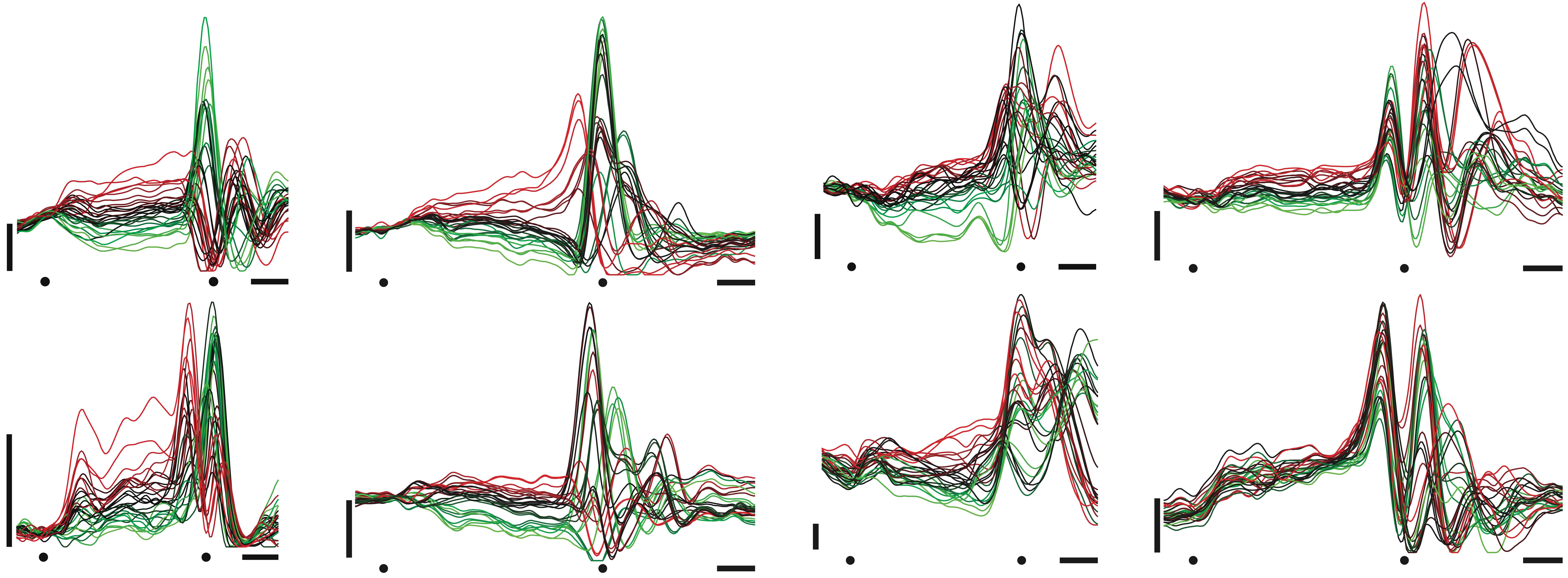


Churchland*, Cunningham* … Shenoy, *Nature* (2012)



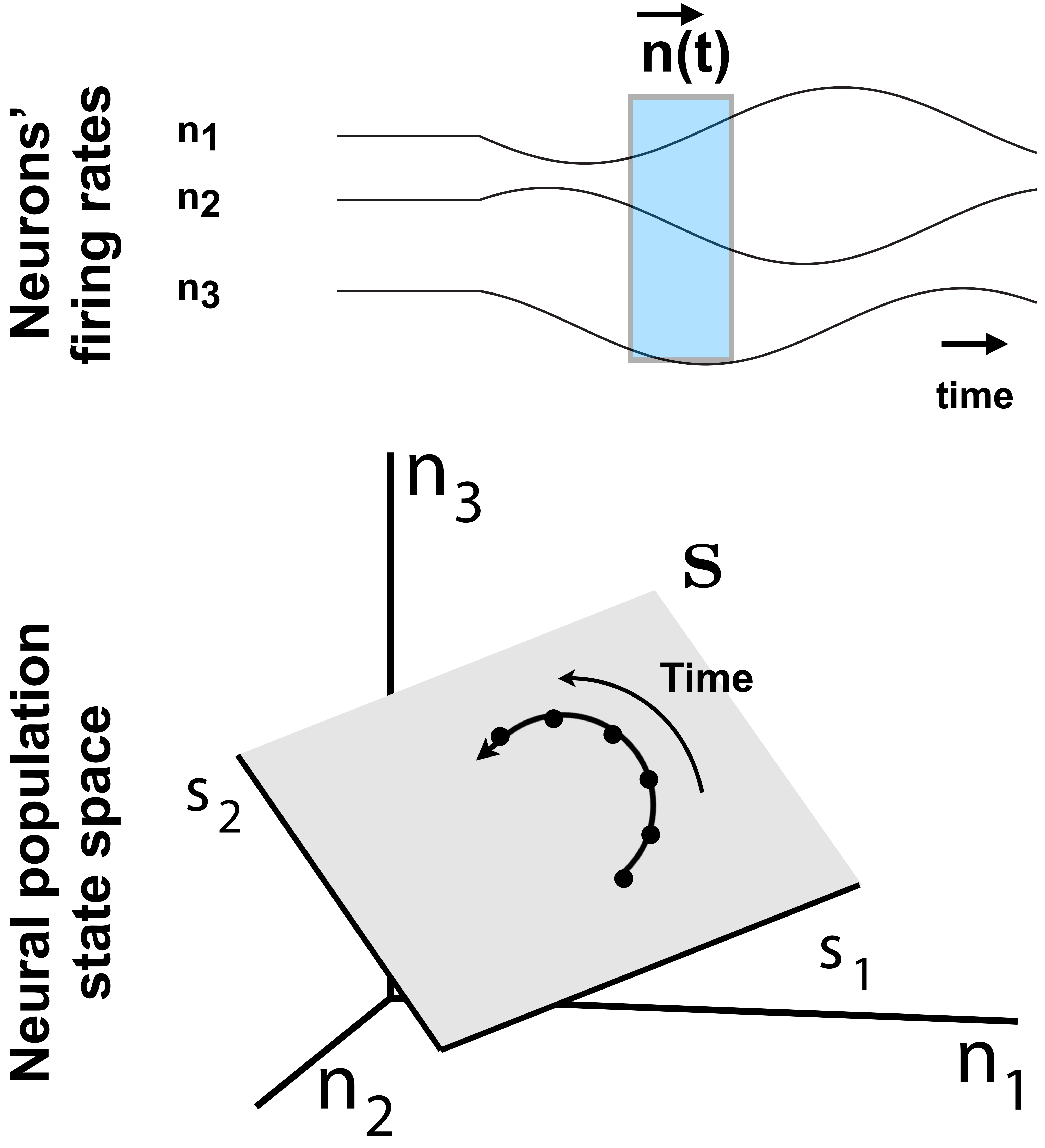
Churchland*, Cunningham* … Shenoy, *Nature* (2012)

Single-neuron data is confusing



Churchland*, Cunningham* … Shenoy, *Nature* (2012)

Uncovering neural population dynamics



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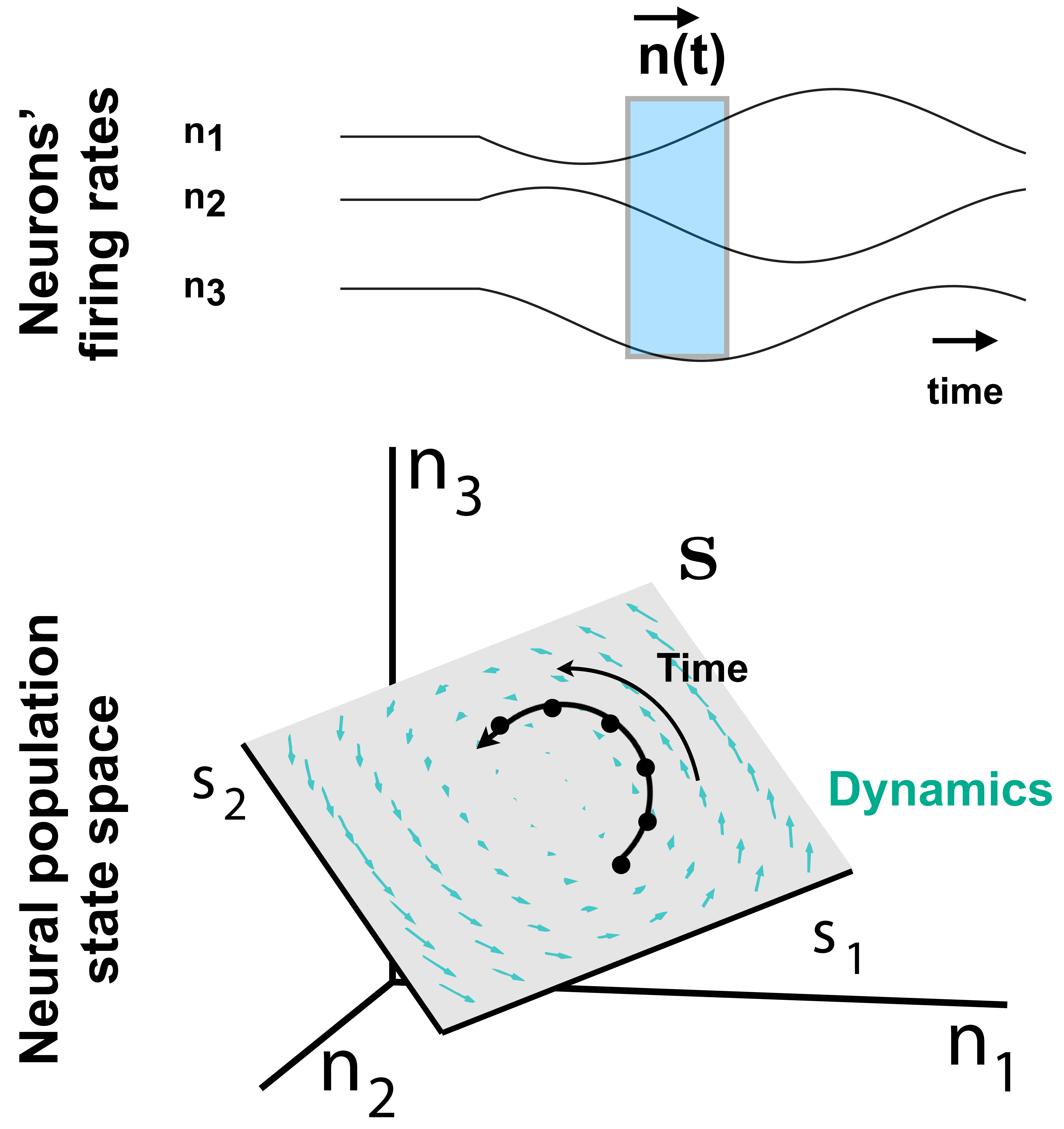

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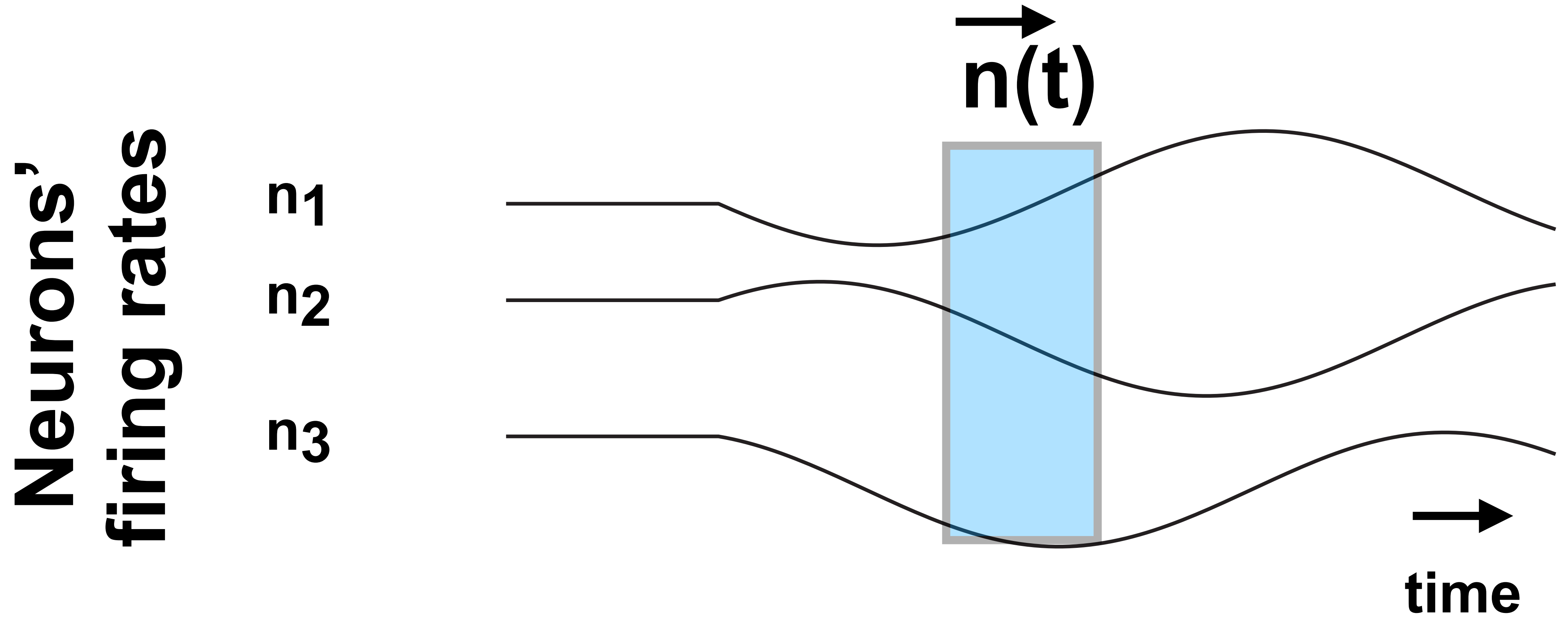
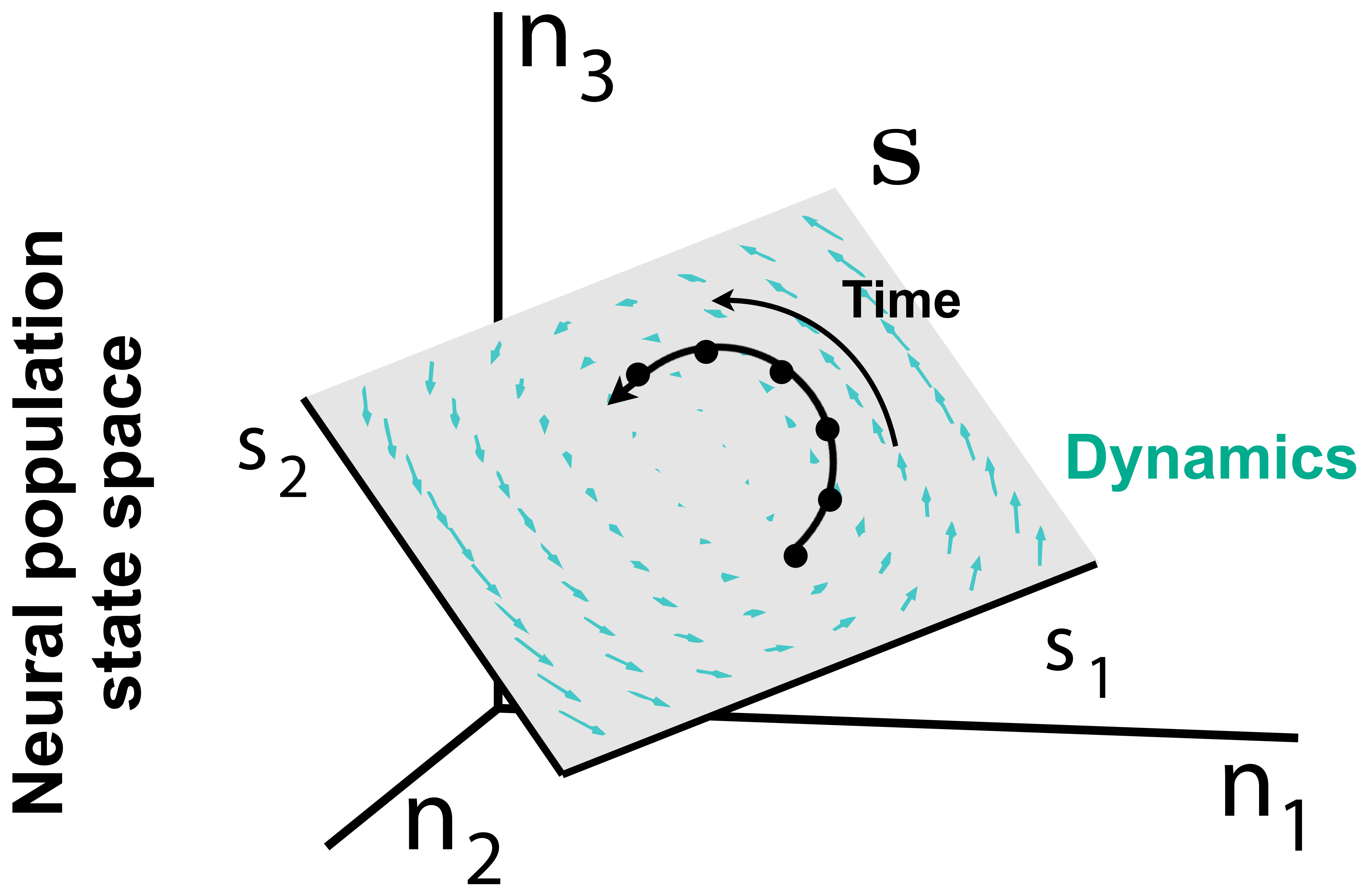


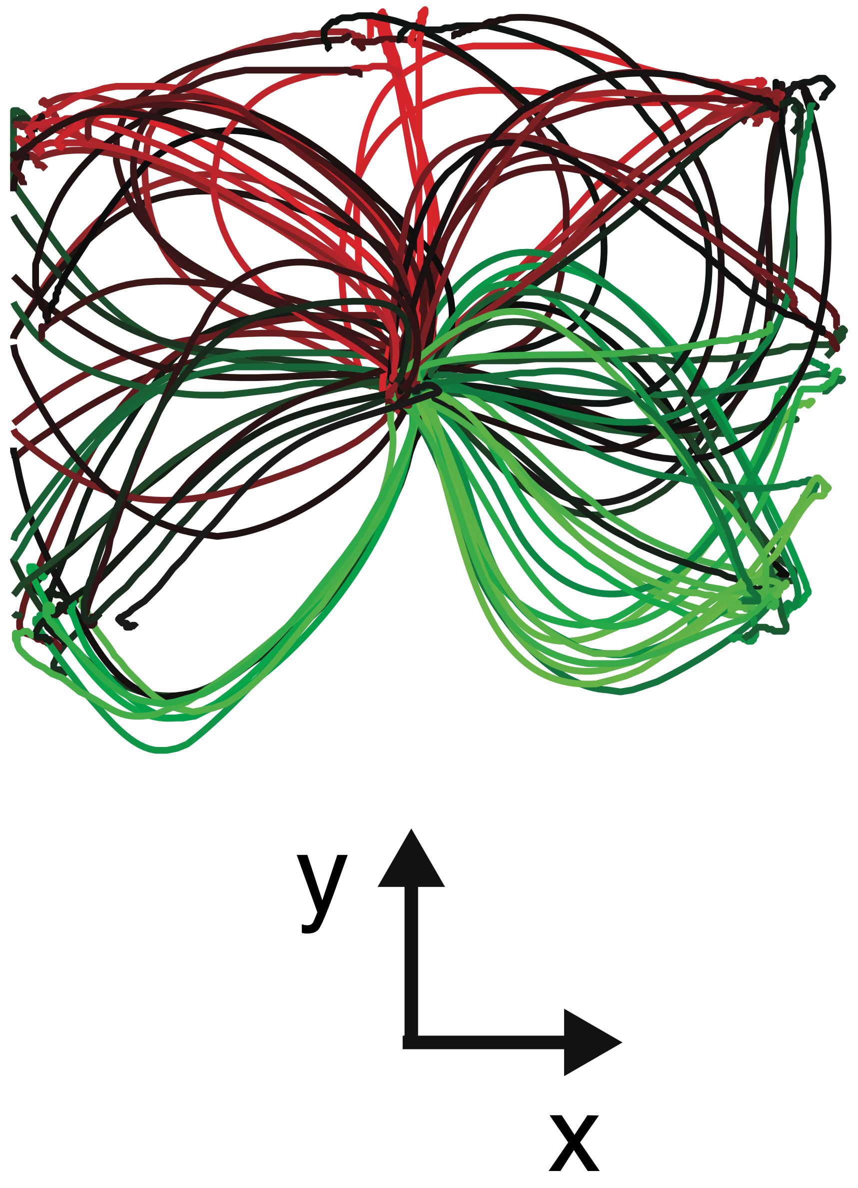
Predictable activity - modeled by *autonomous* dynamics

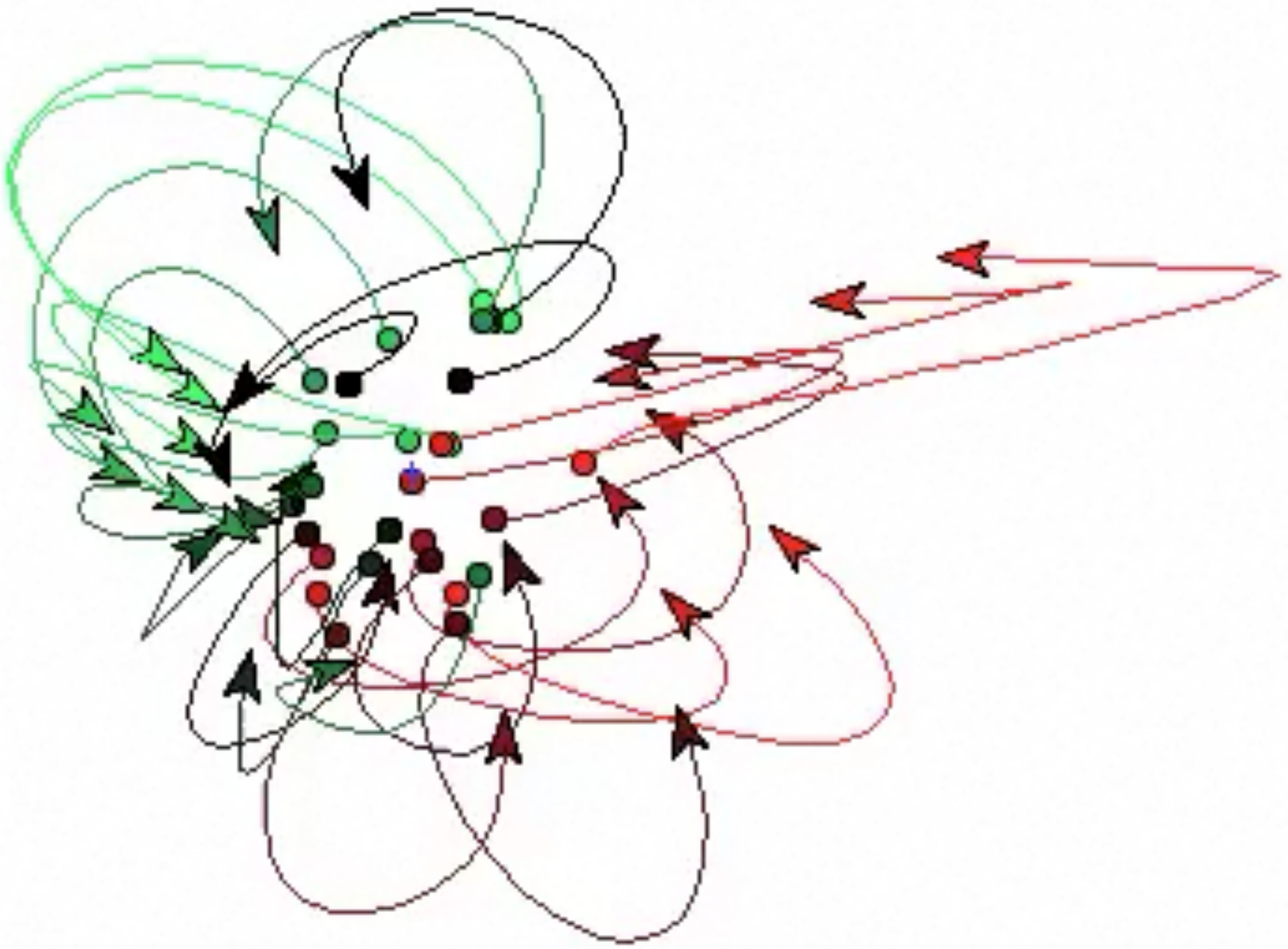
$$\frac{d\mathrm{s}}{dt} = f(\mathrm{s})$$



PCA / jPCA reveals underlying structure

Reach trajectories





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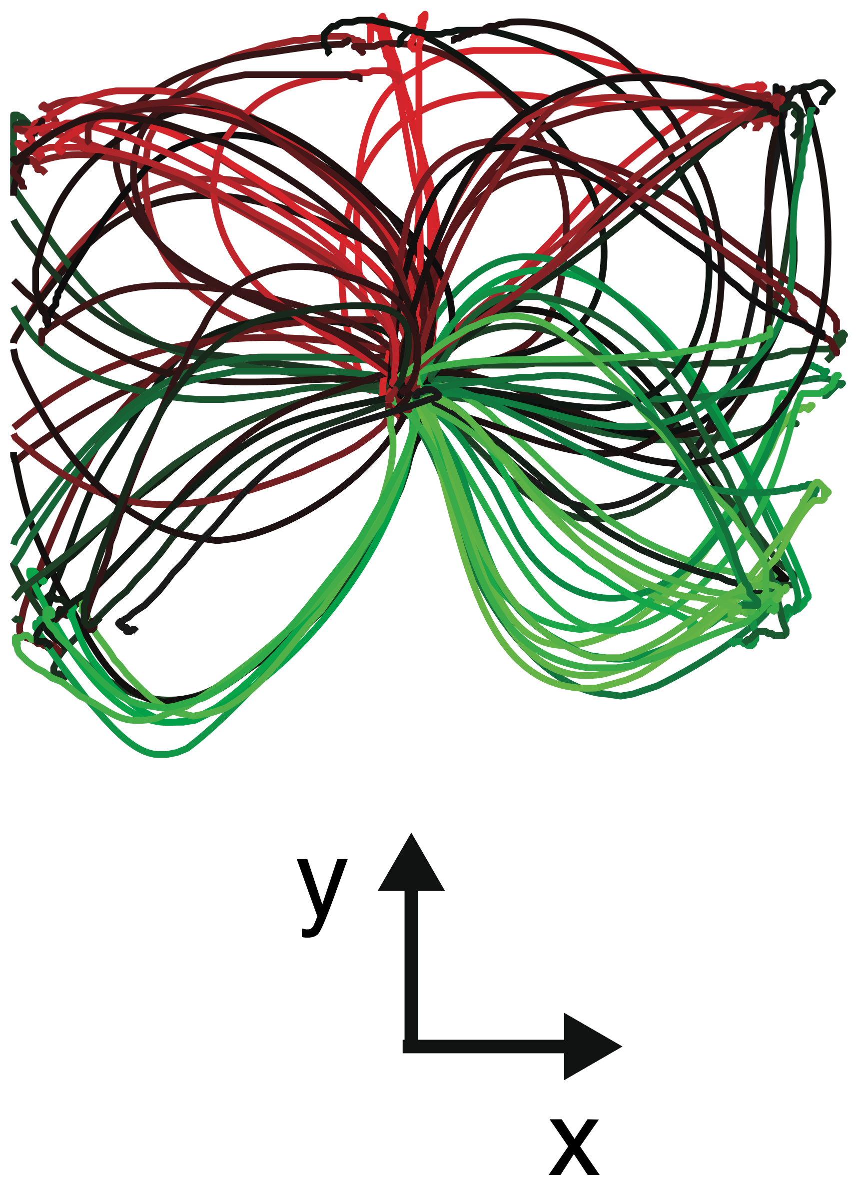
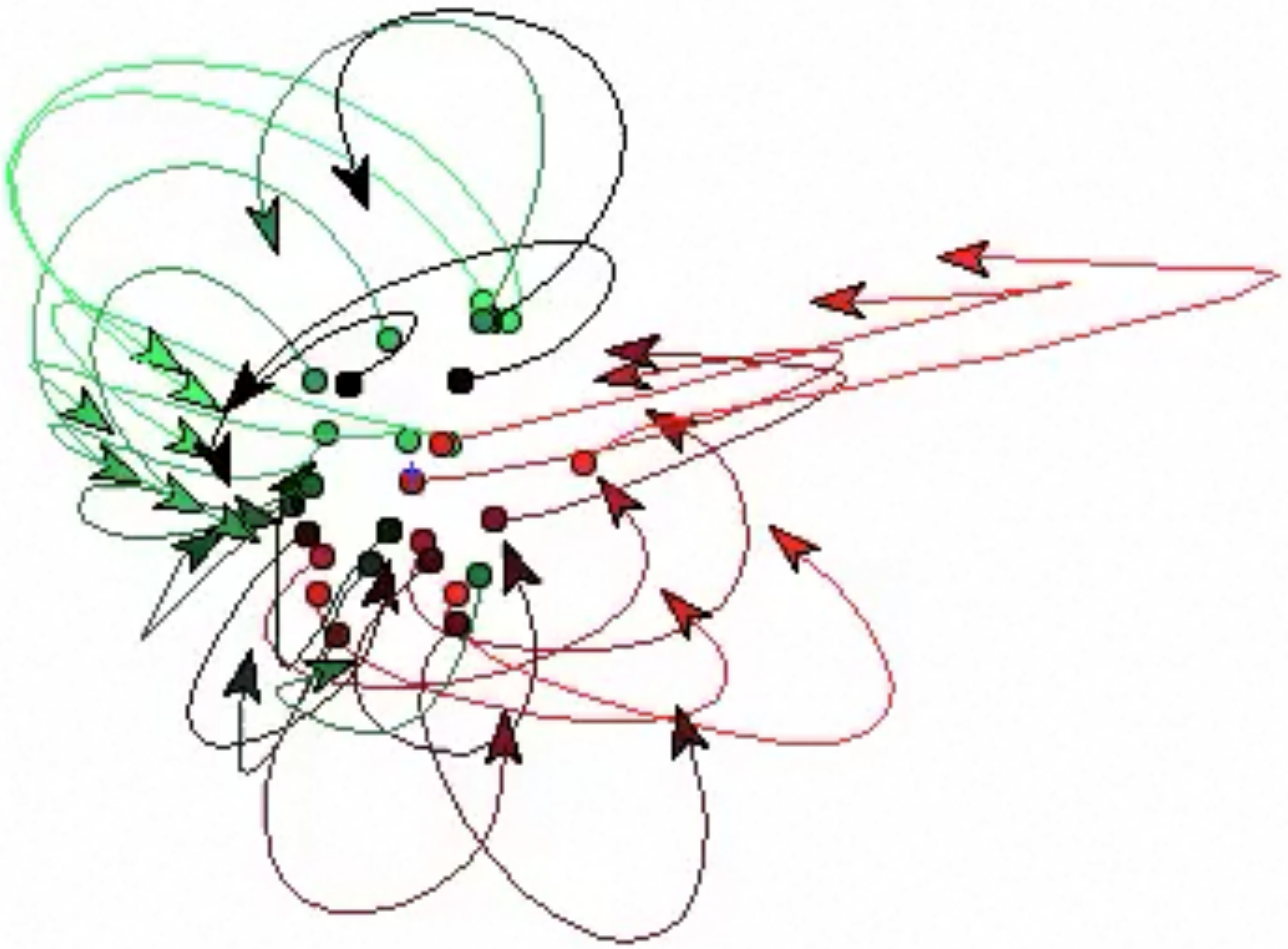
PCA / jPCA reveals underlying structure

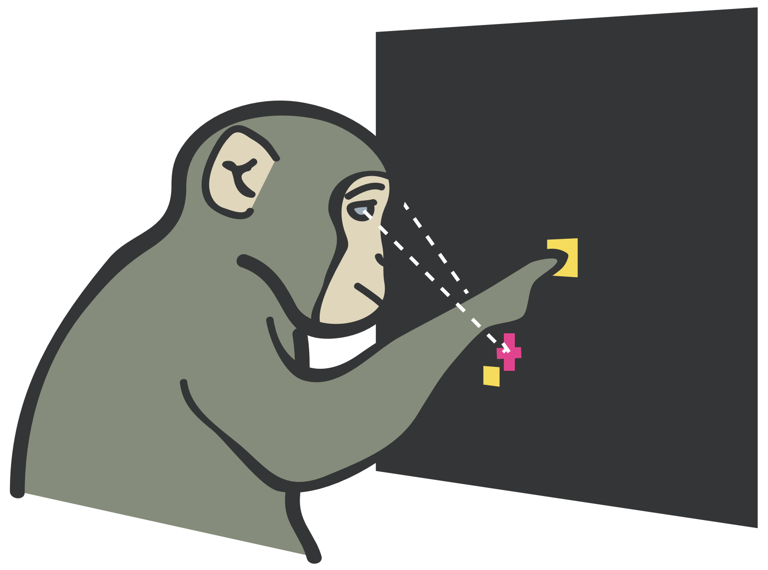
Reach
trajectories



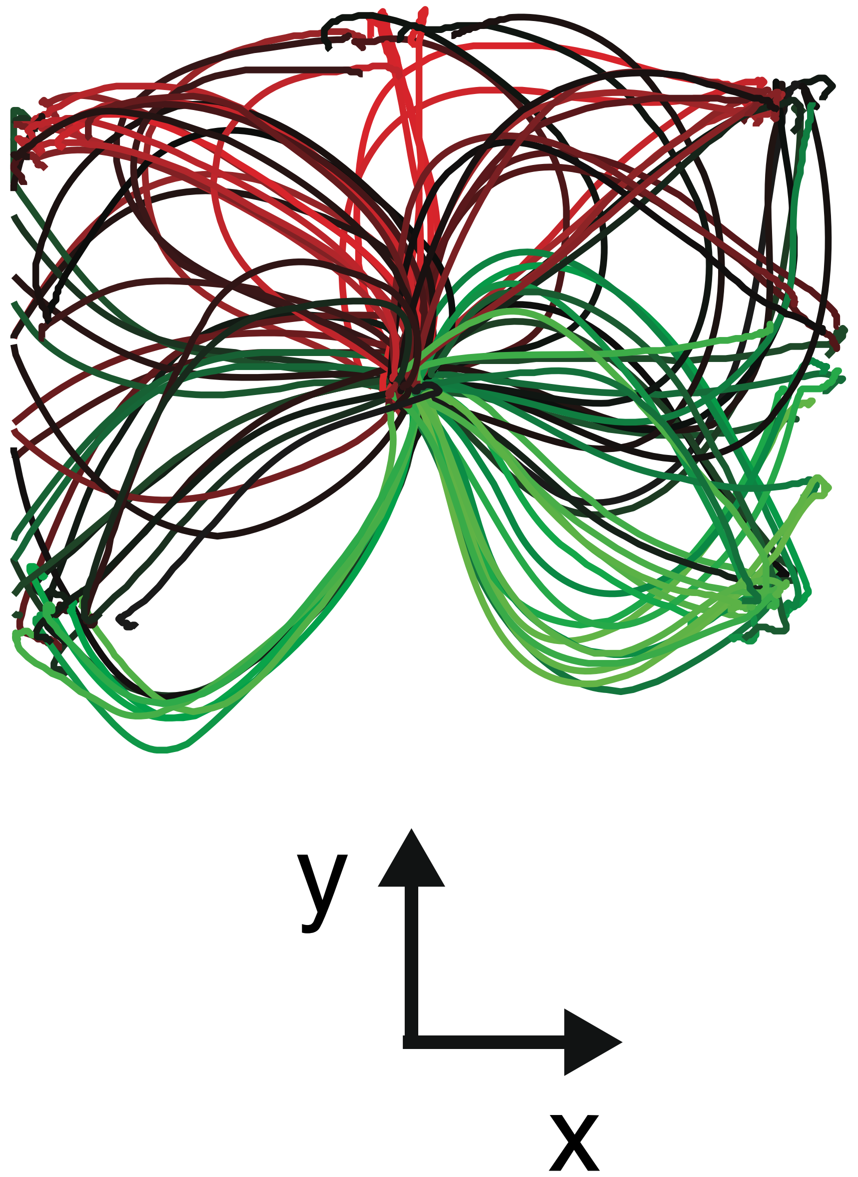


Churchland*, Cunningham* … Shenoy, *Nature* (2012)

Consistent rotational dynamics



Reach
trajectories



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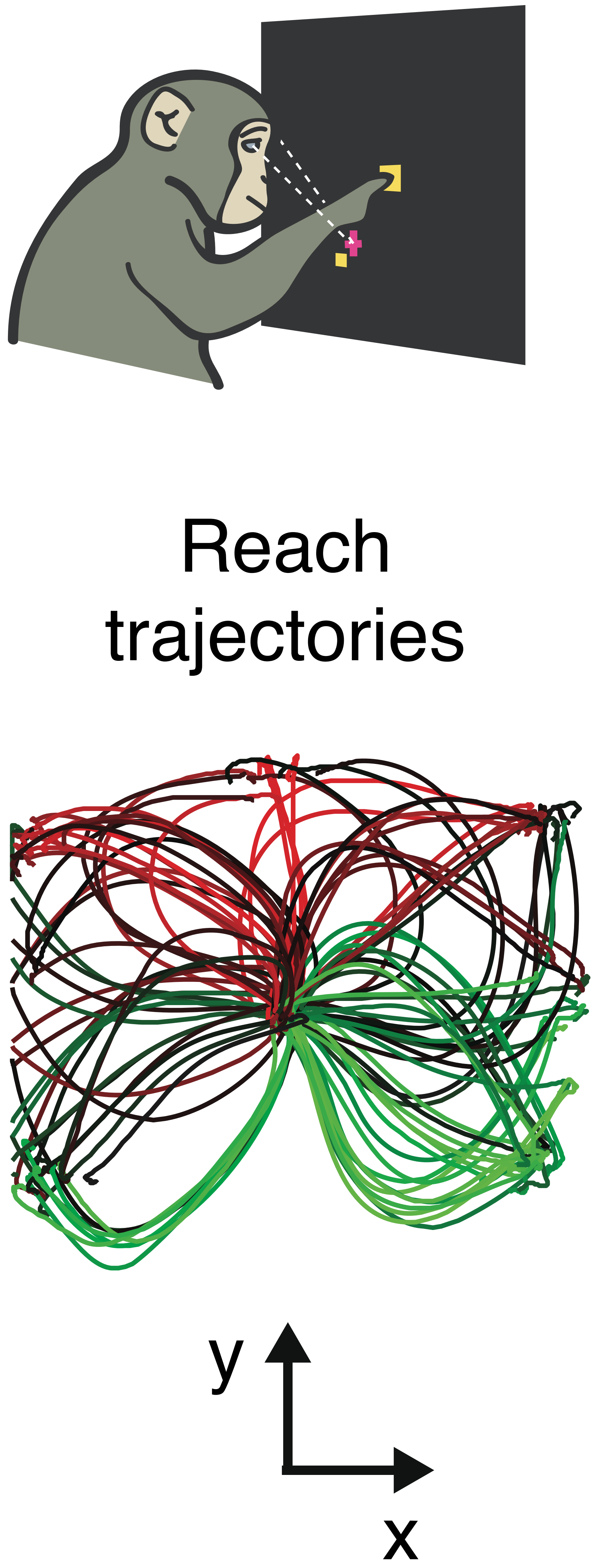

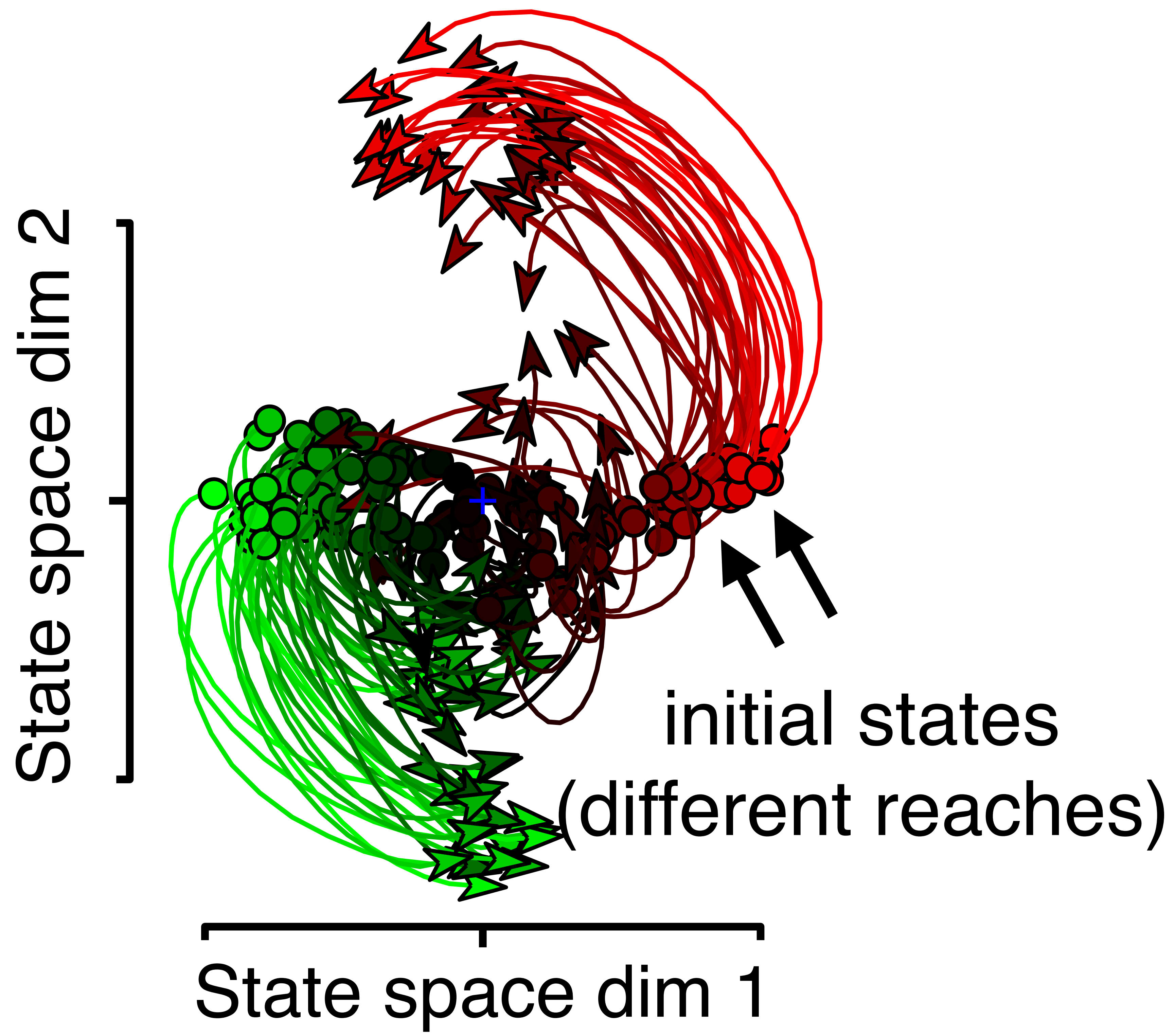

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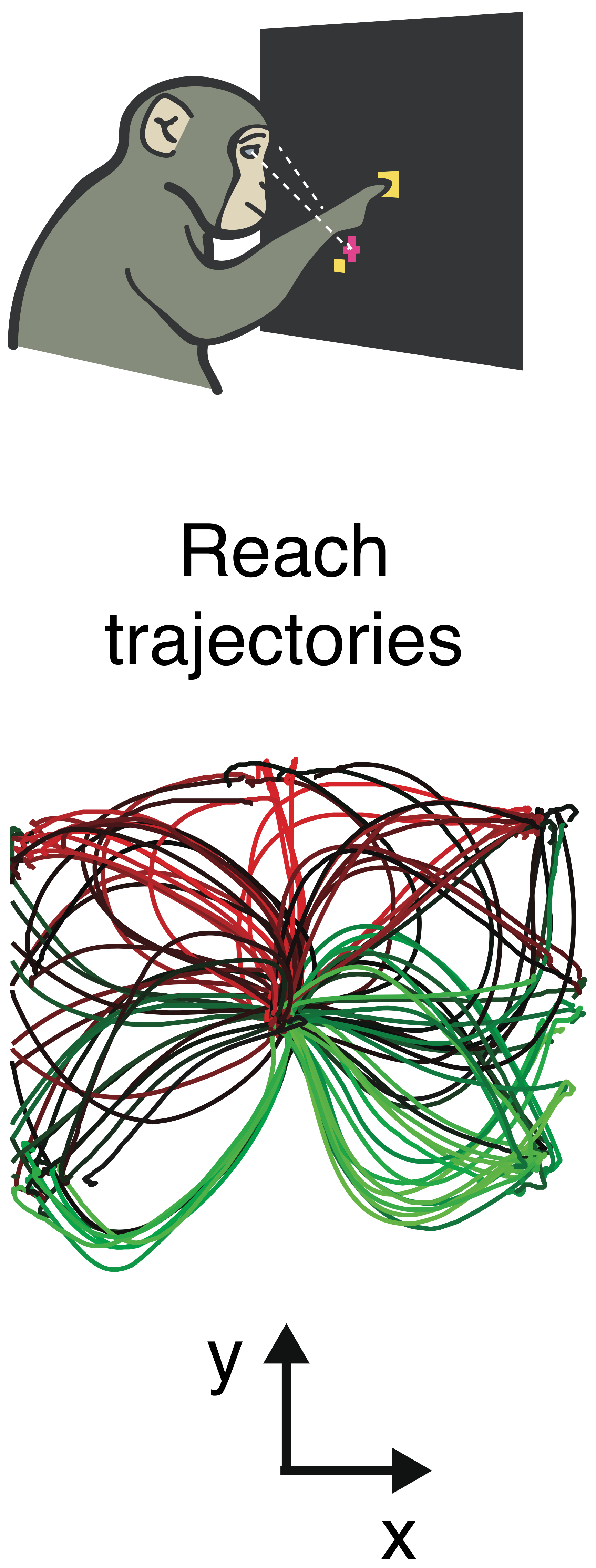

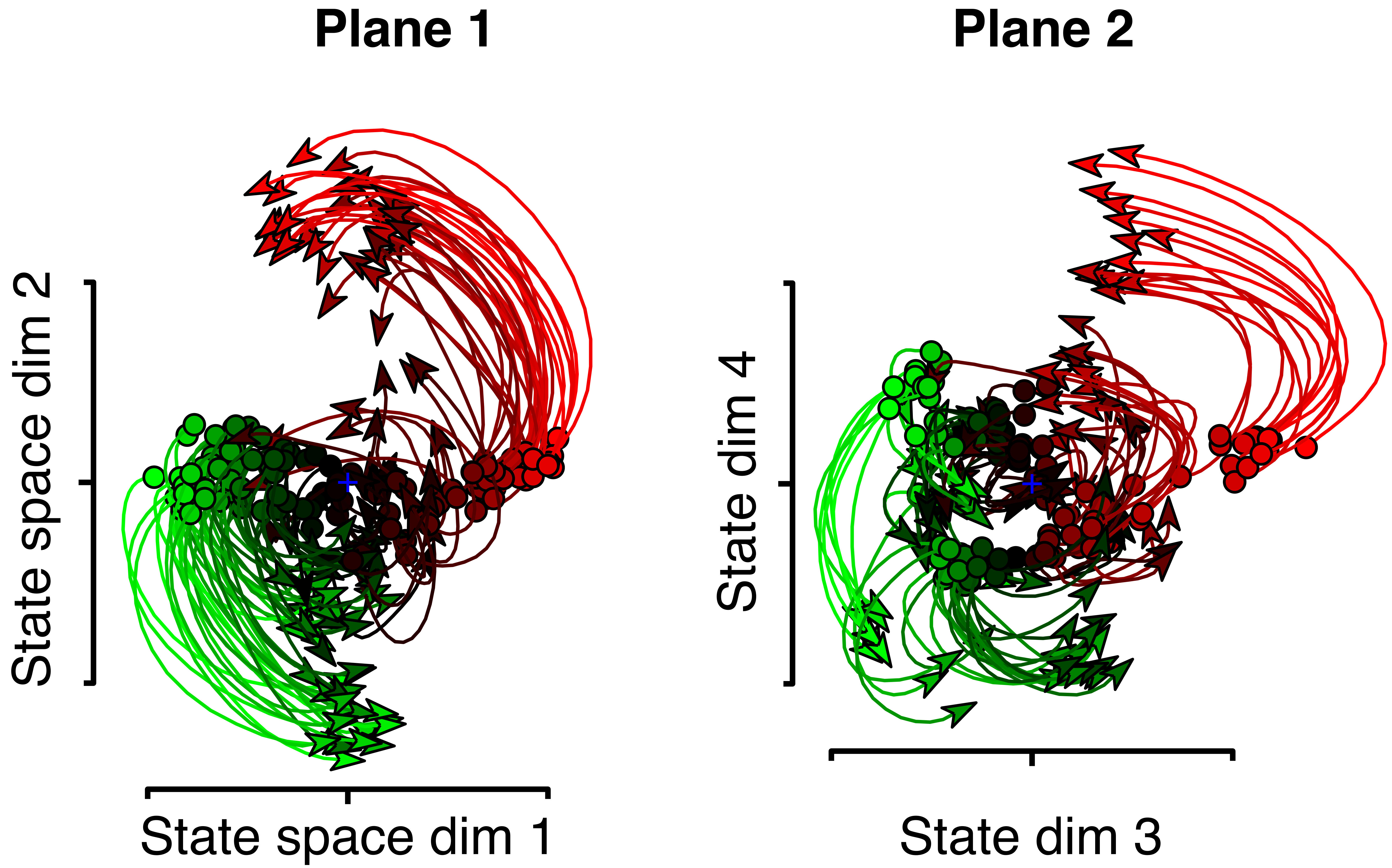

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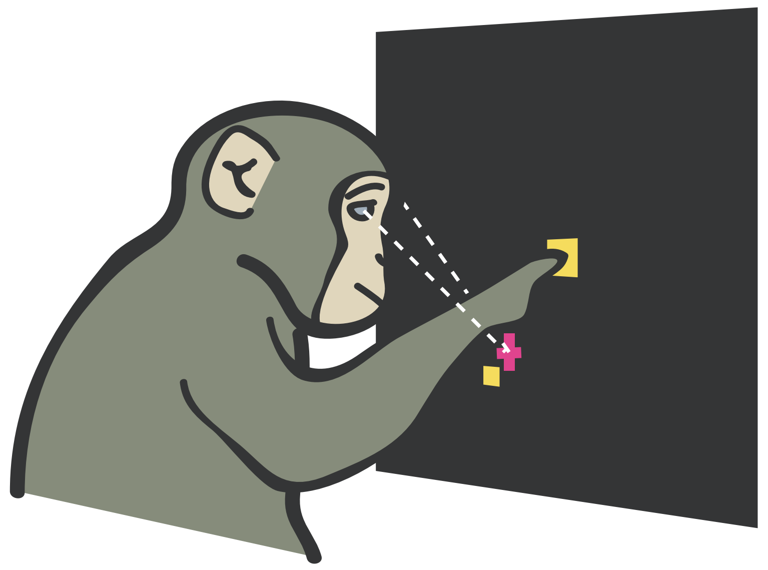
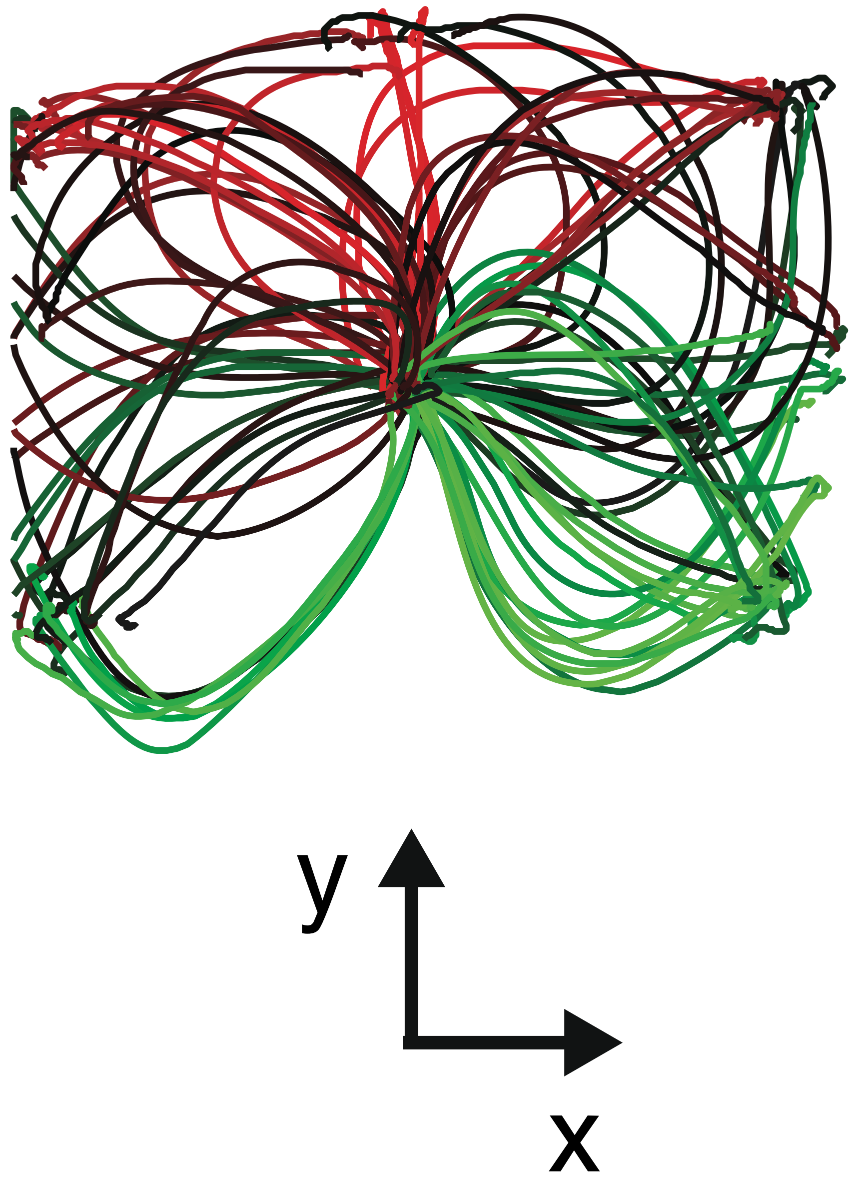
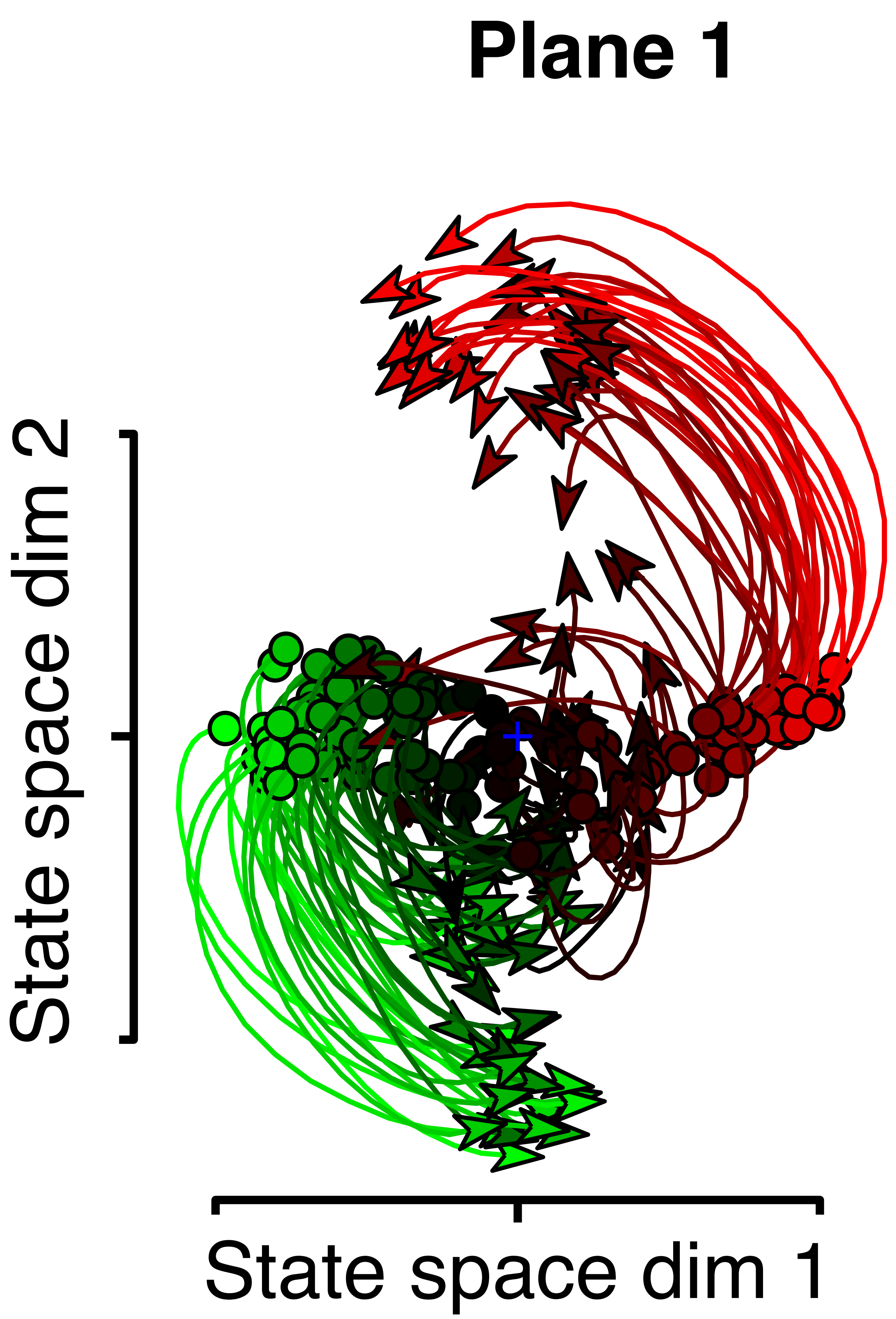
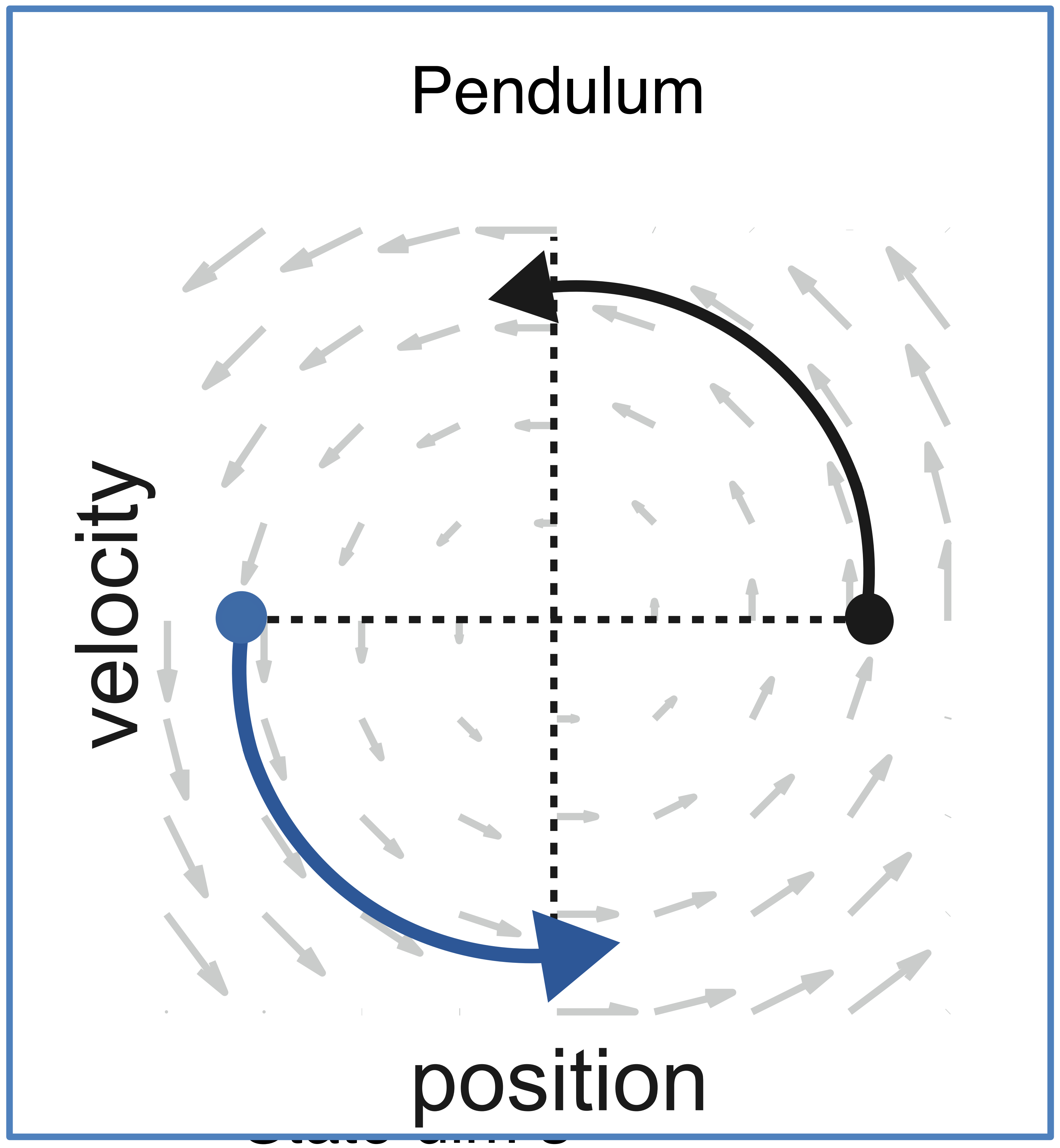


Reach trajectories







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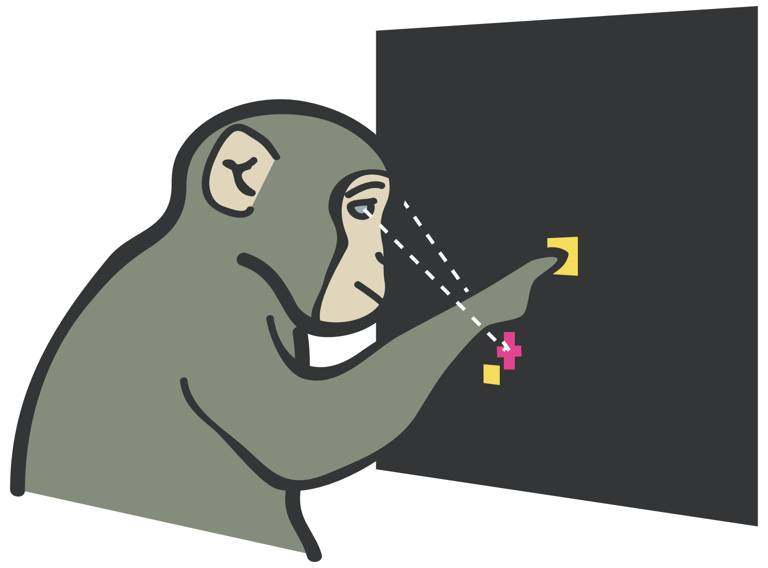

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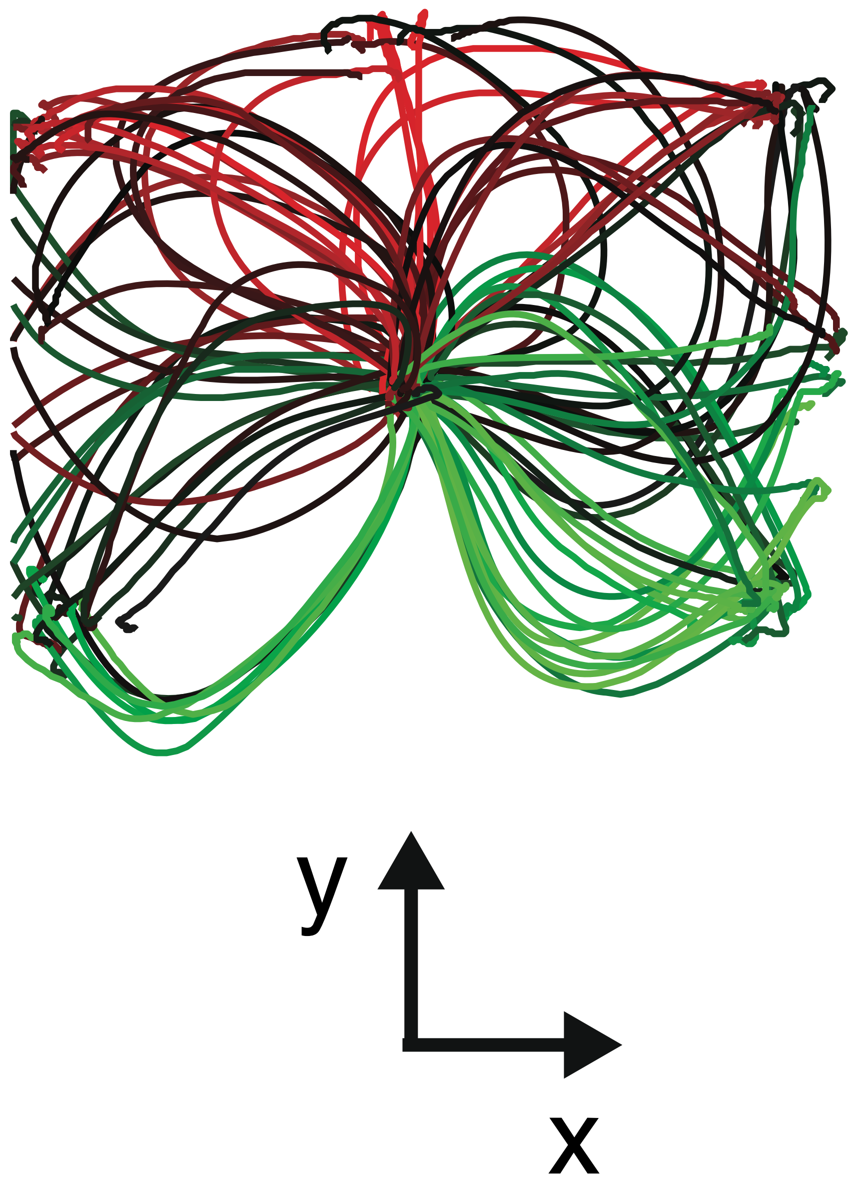

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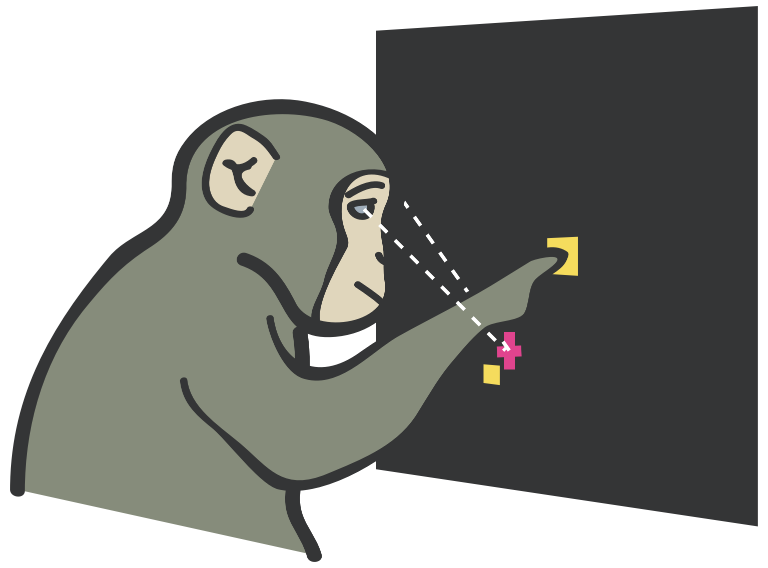

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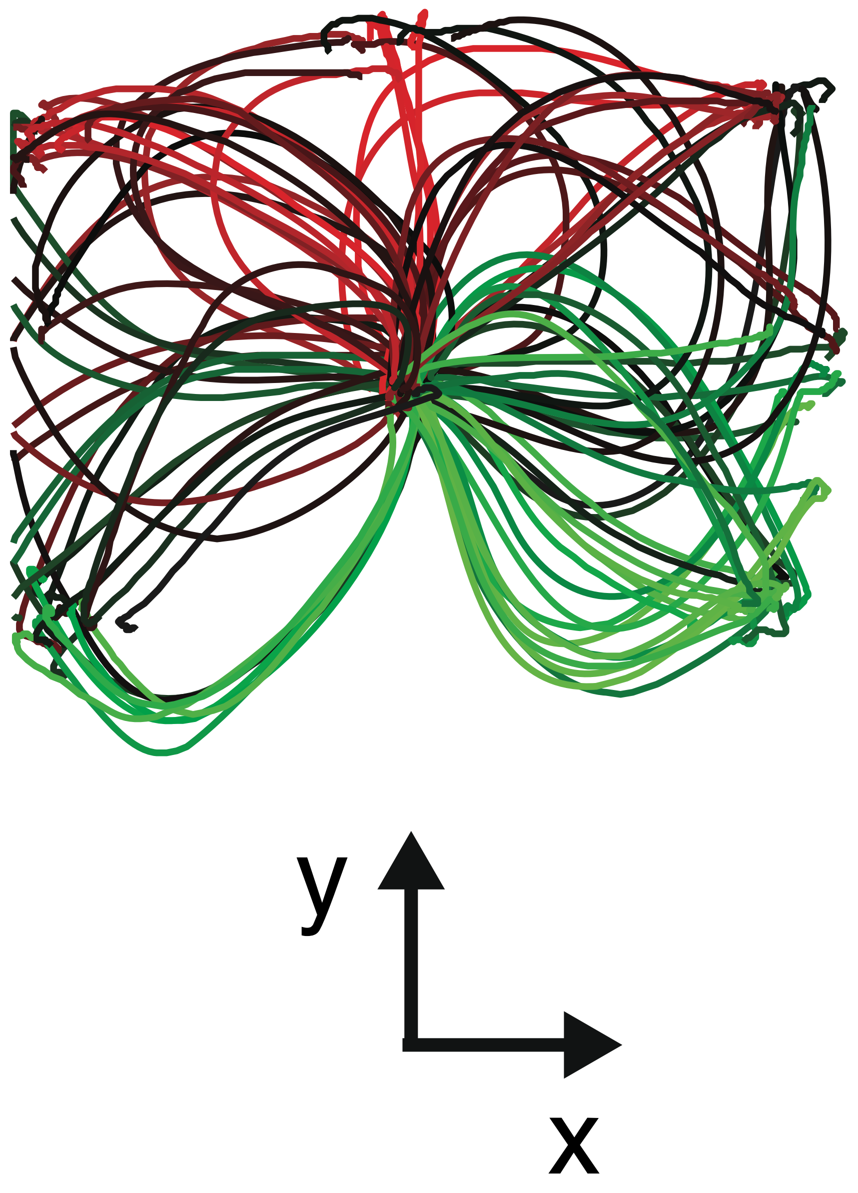

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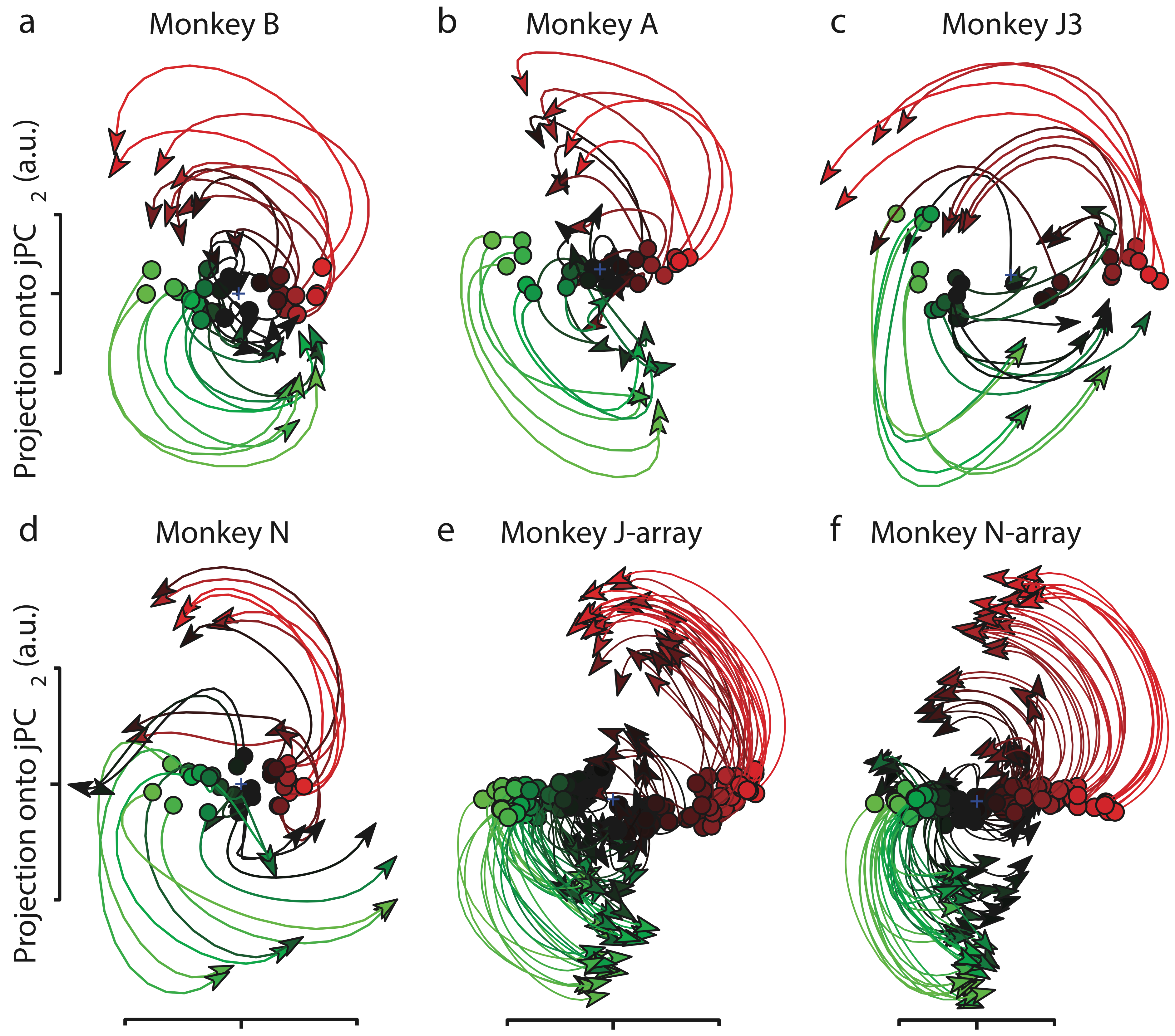
Rotational dynamics in monkeys & humans

Monkey



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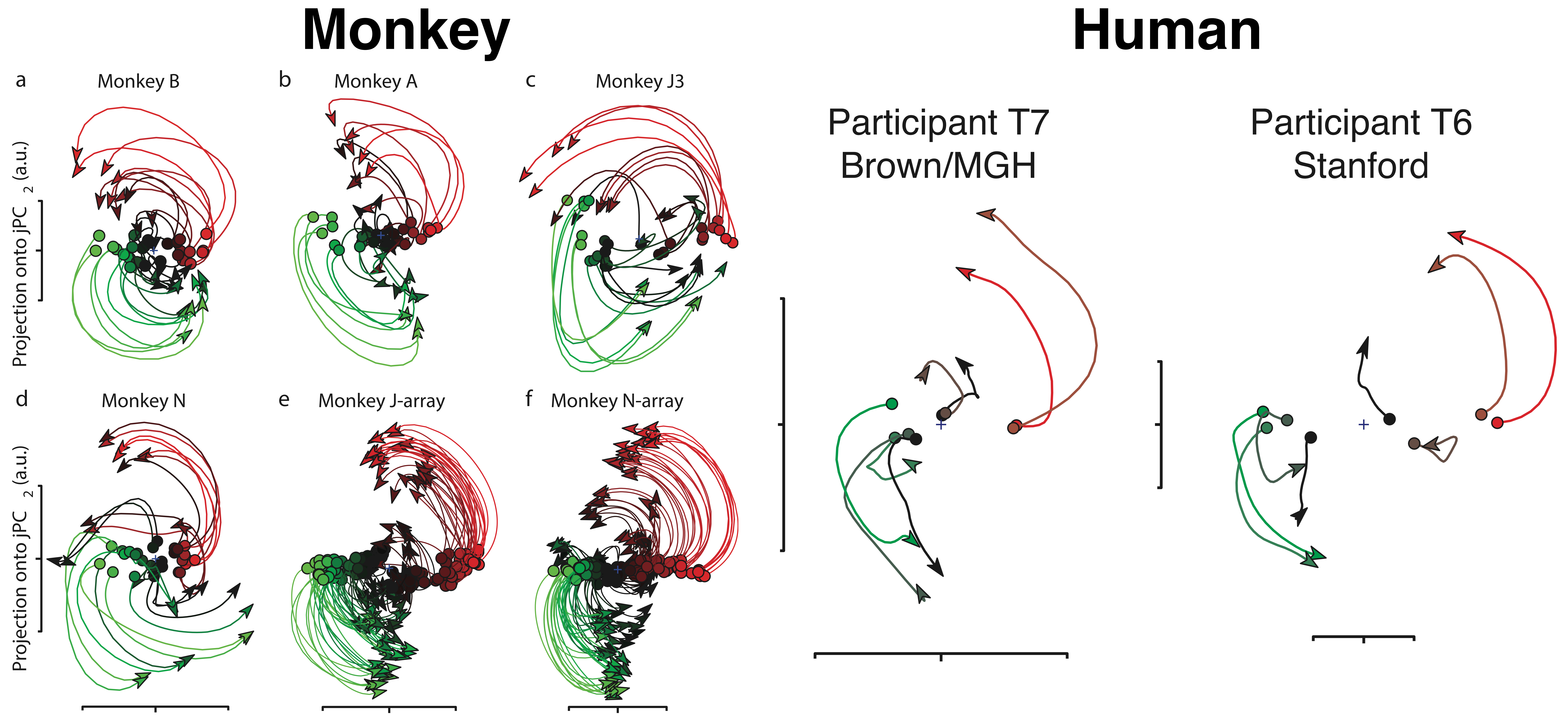

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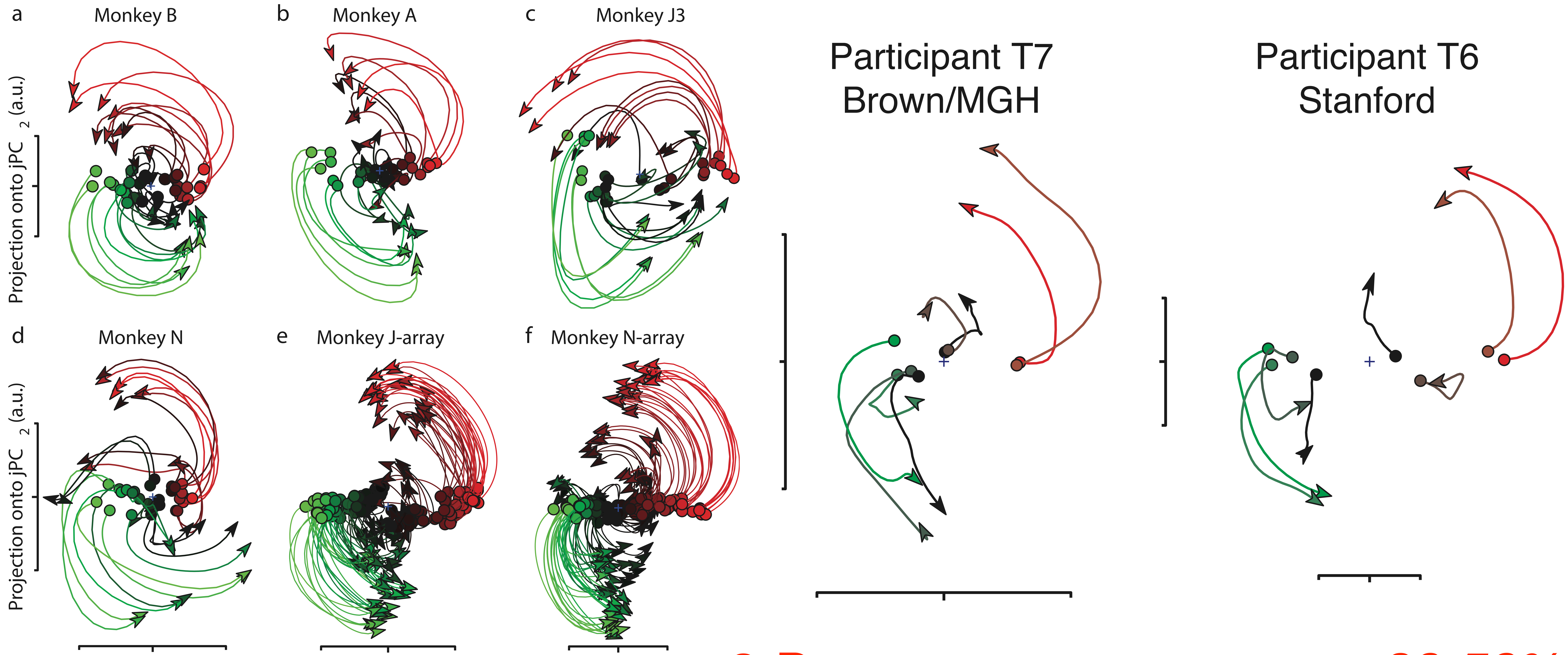

2-D state-space represents ***30-50%*** of data variance

Churchland*, Cunningham* … Shenoy, *Nature* (2012)

Pandarinath, … Hochberg, Henderson*, Shenoy*, *eLife* (2015)

What you'll hear about in this lecture

Neural network basics

Deep autoencoders

Intro to neural population dynamics

Population analyses shed light on network-level computation

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Session 1:
Record neuron
set A

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Session 2: Record neuron set B

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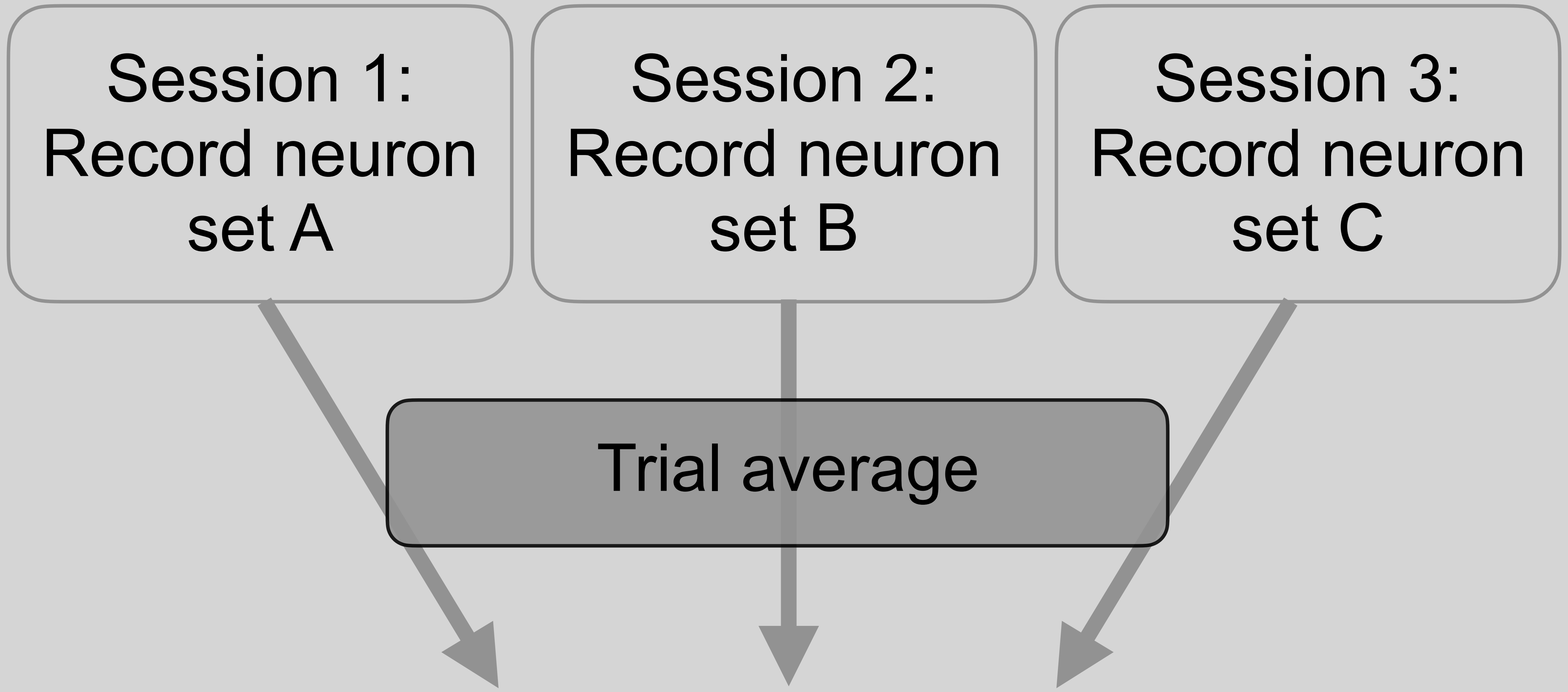

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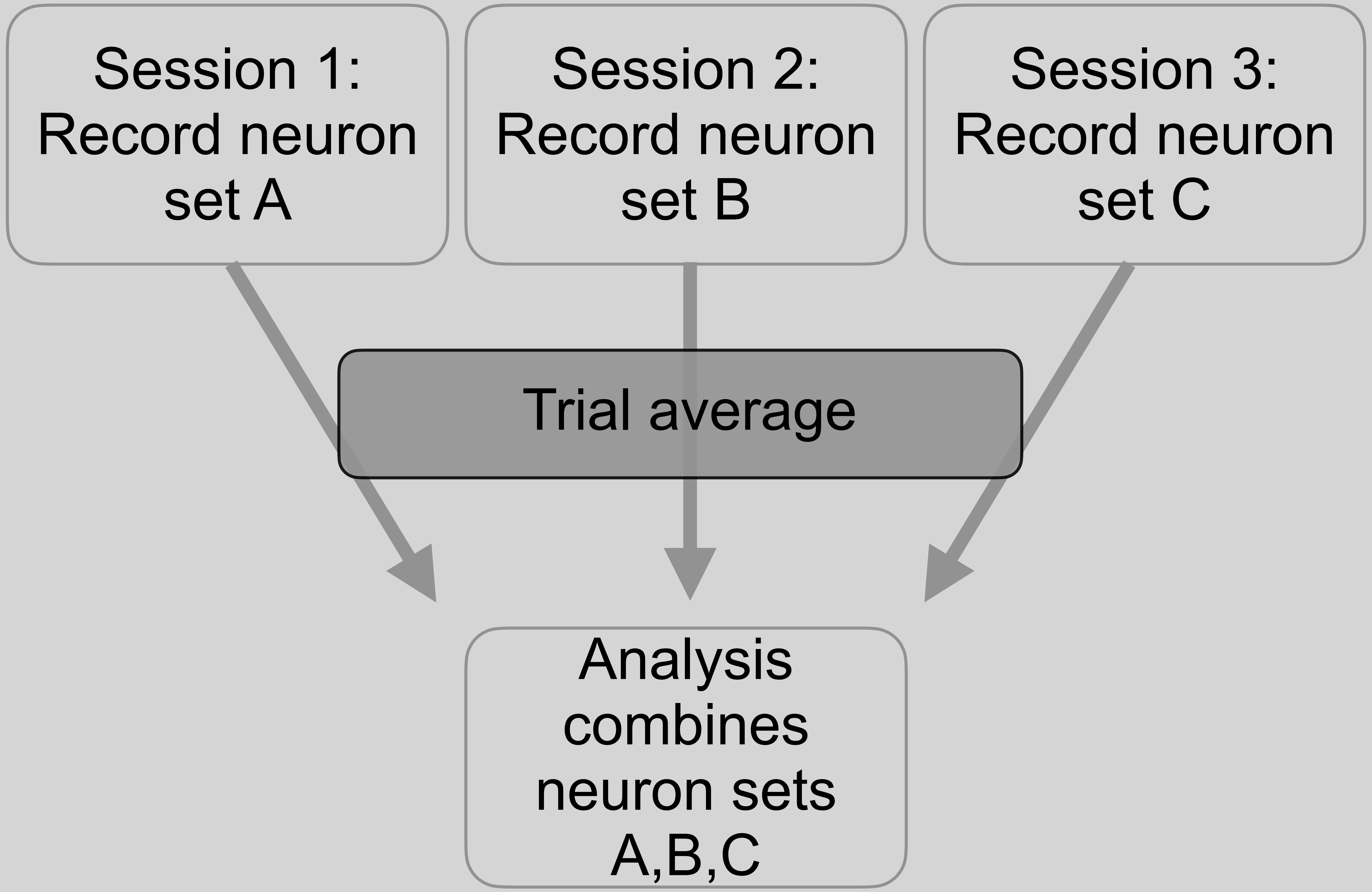

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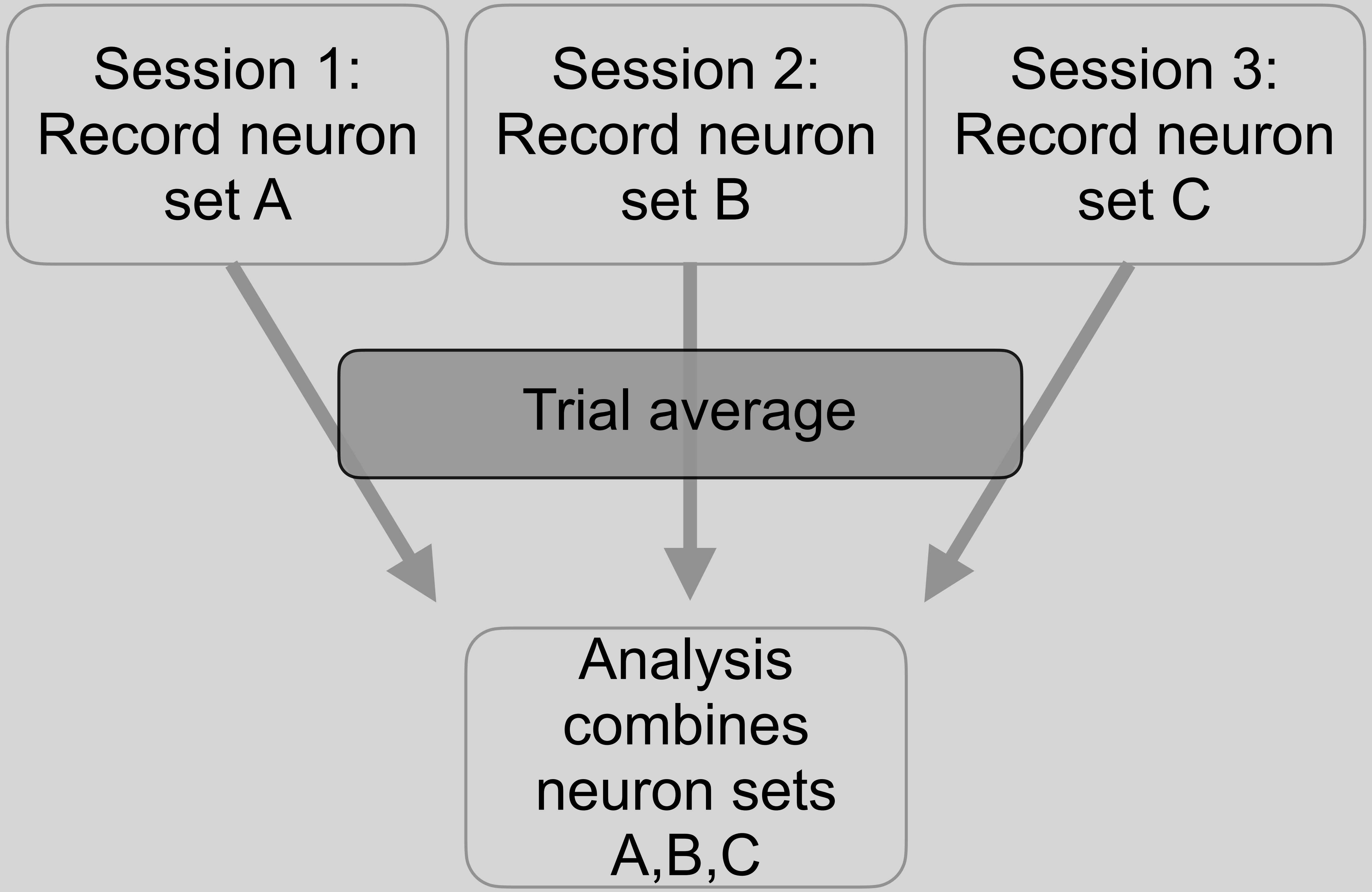
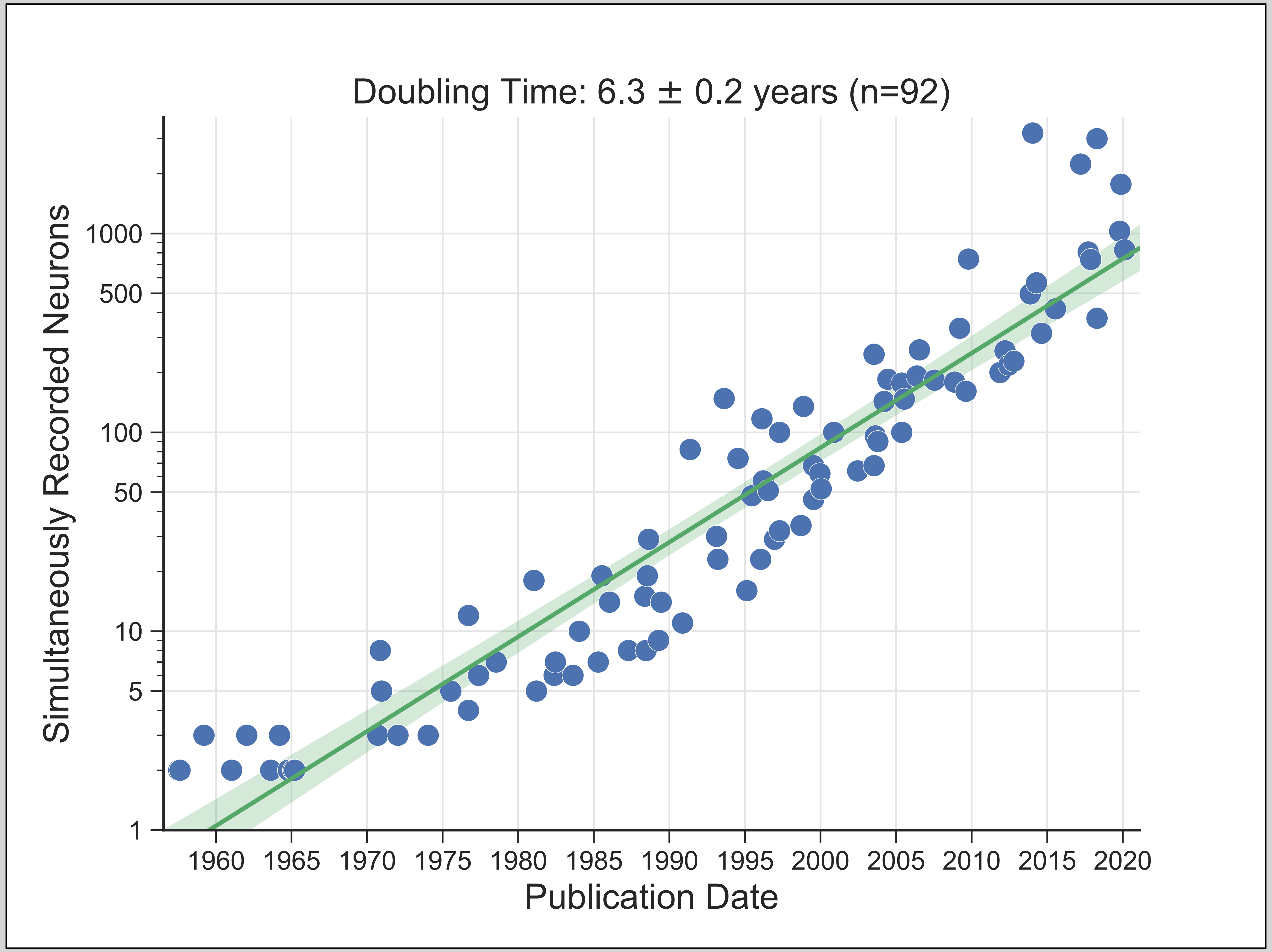
- Getting enough neurons used to require **highly-stereotyped behaviors**.
- But this is changing…



Recording capacity is increasing dramatically

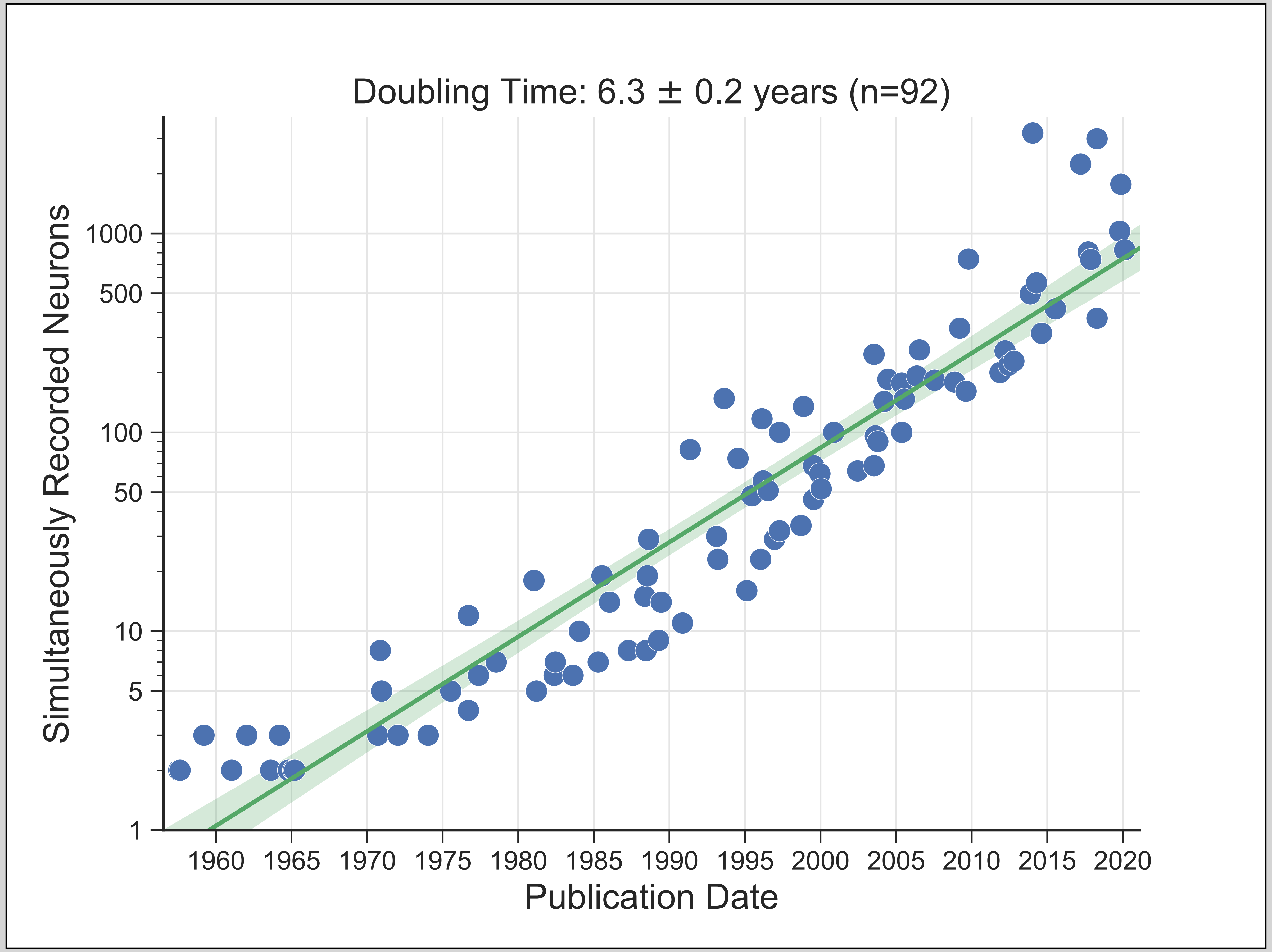


Stevenson & Kording, *Nat Neuro* 2011

updates: stevenson.lab.uconn.edu

Recording capacity is increasing dramatically

- Capacity doubling every ~6 years



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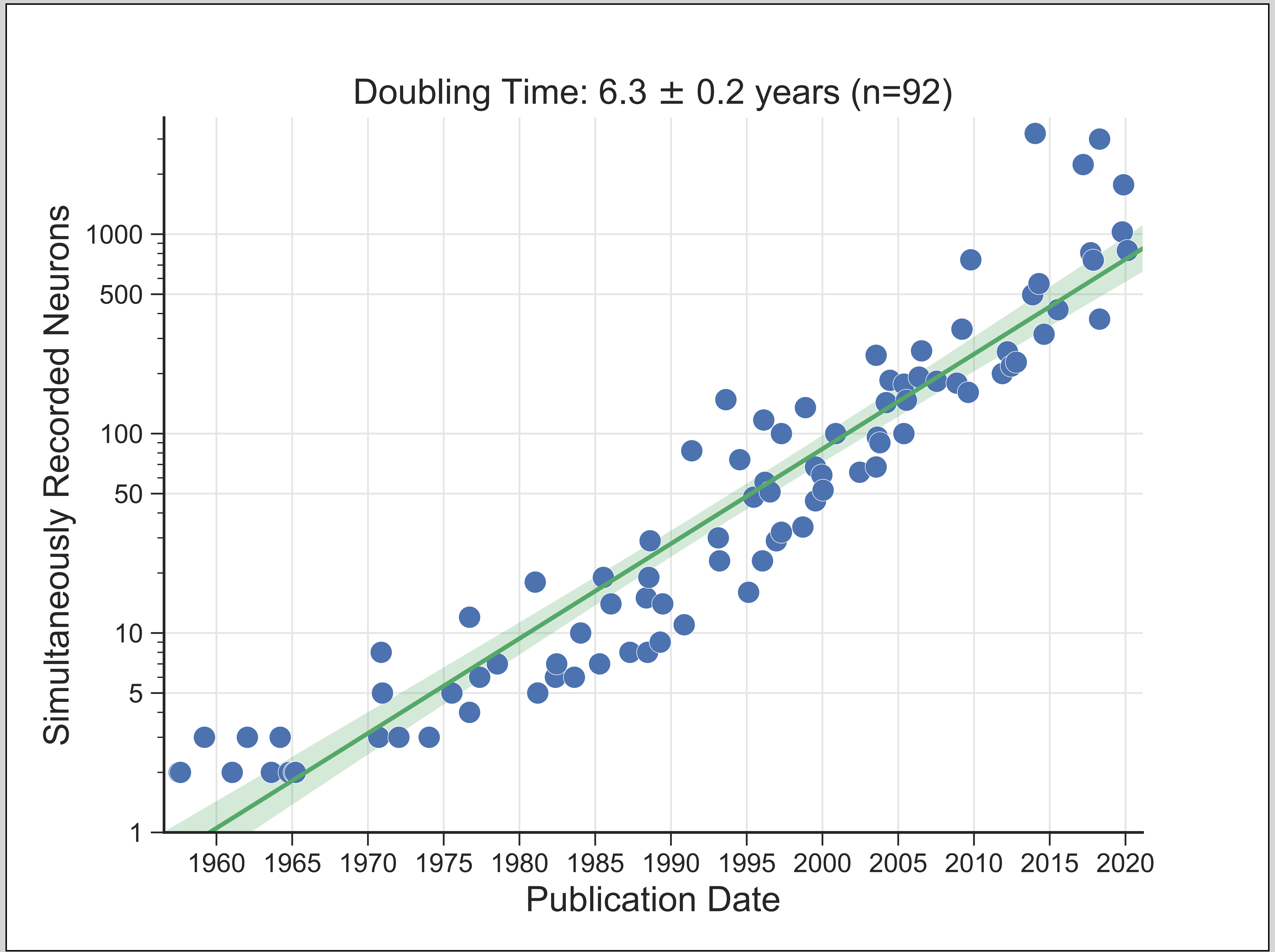

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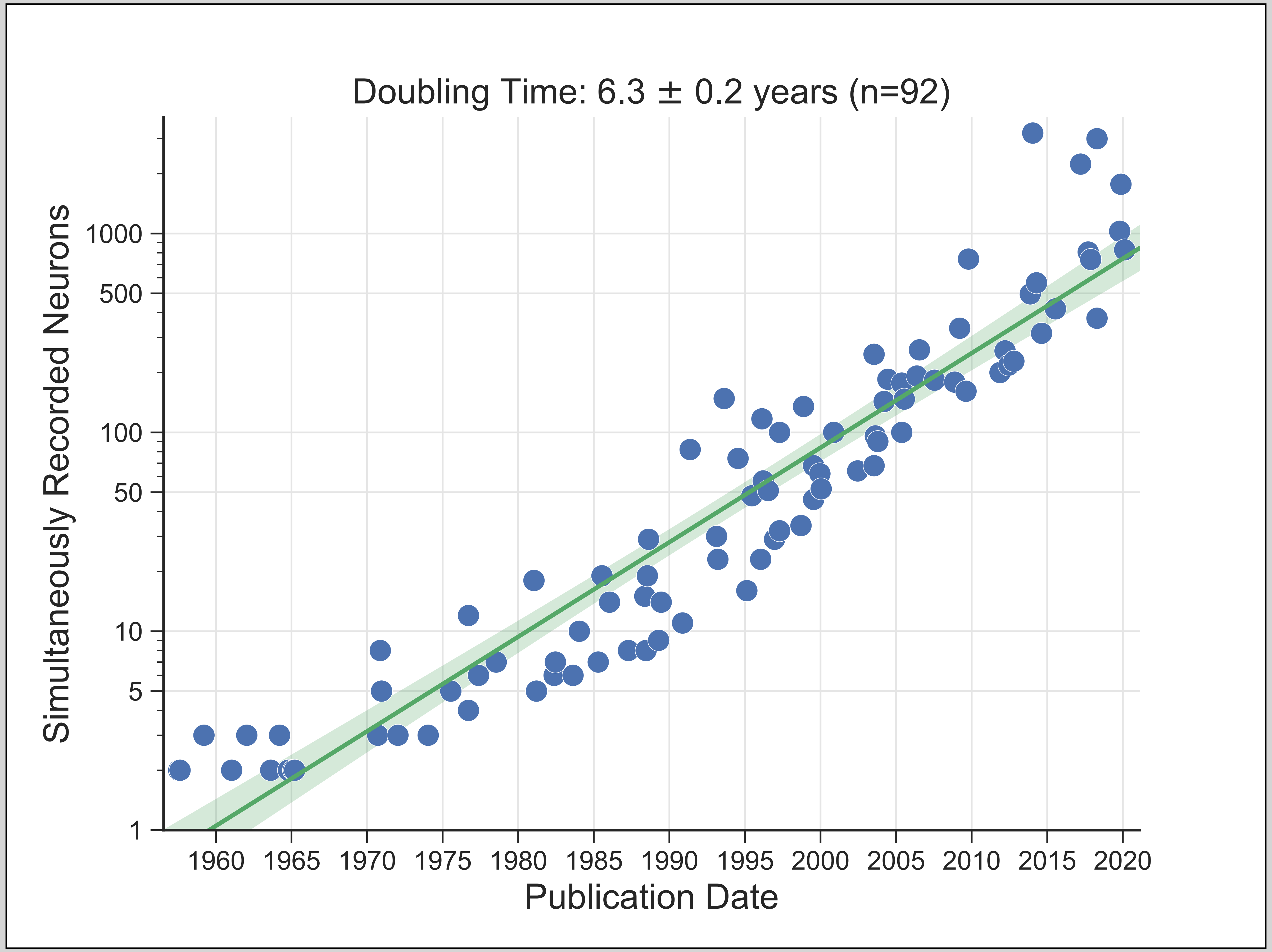

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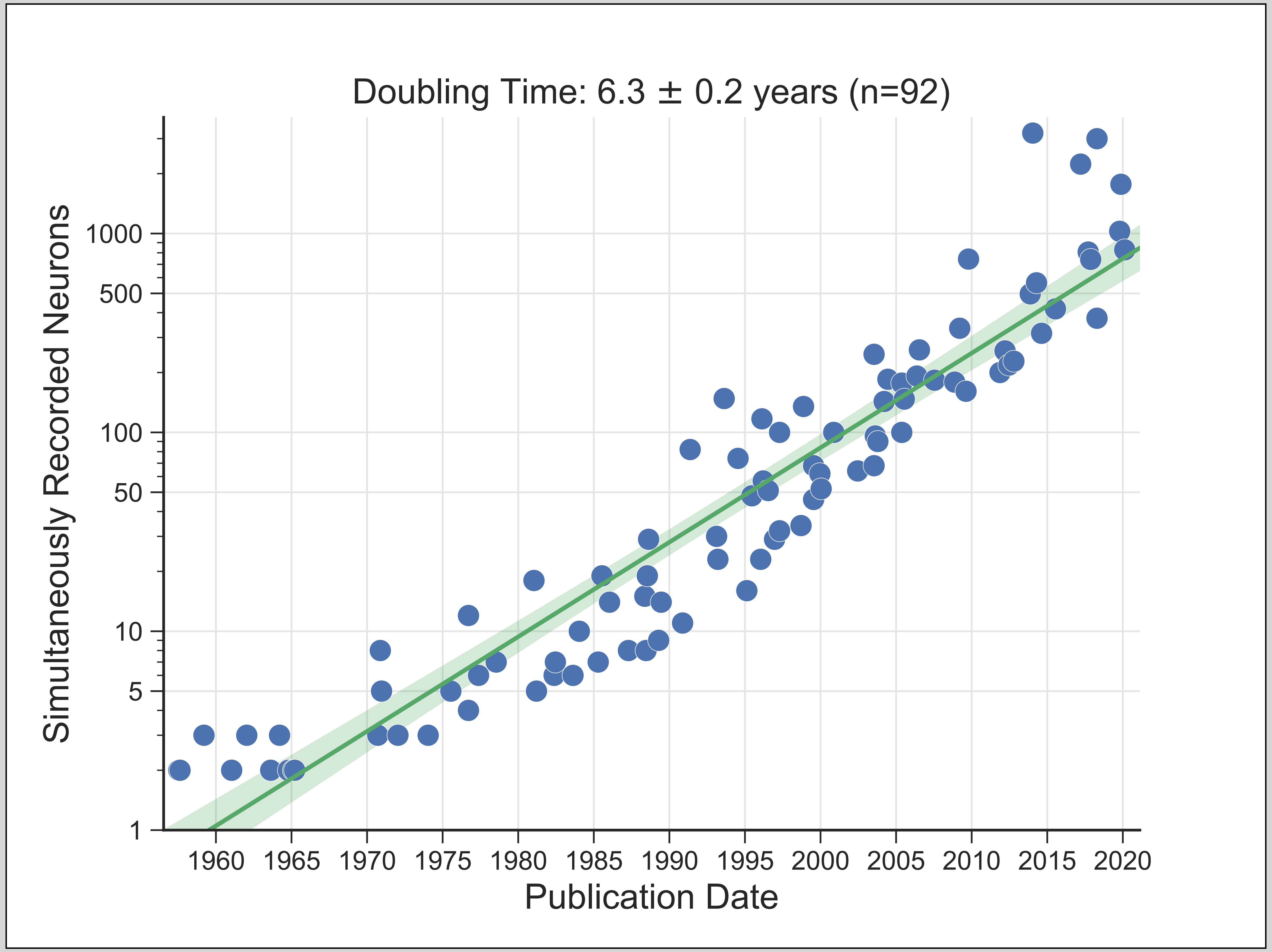

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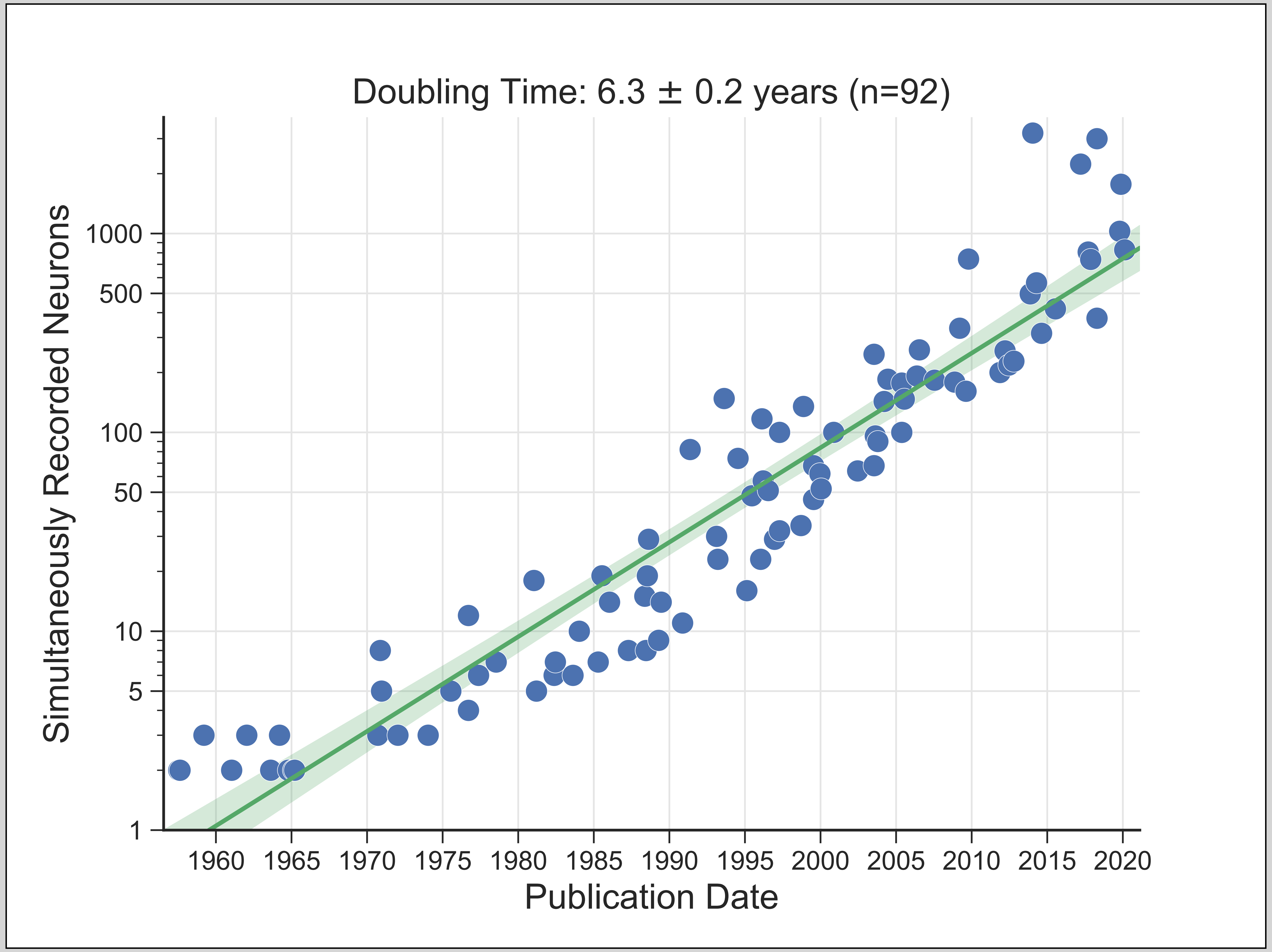

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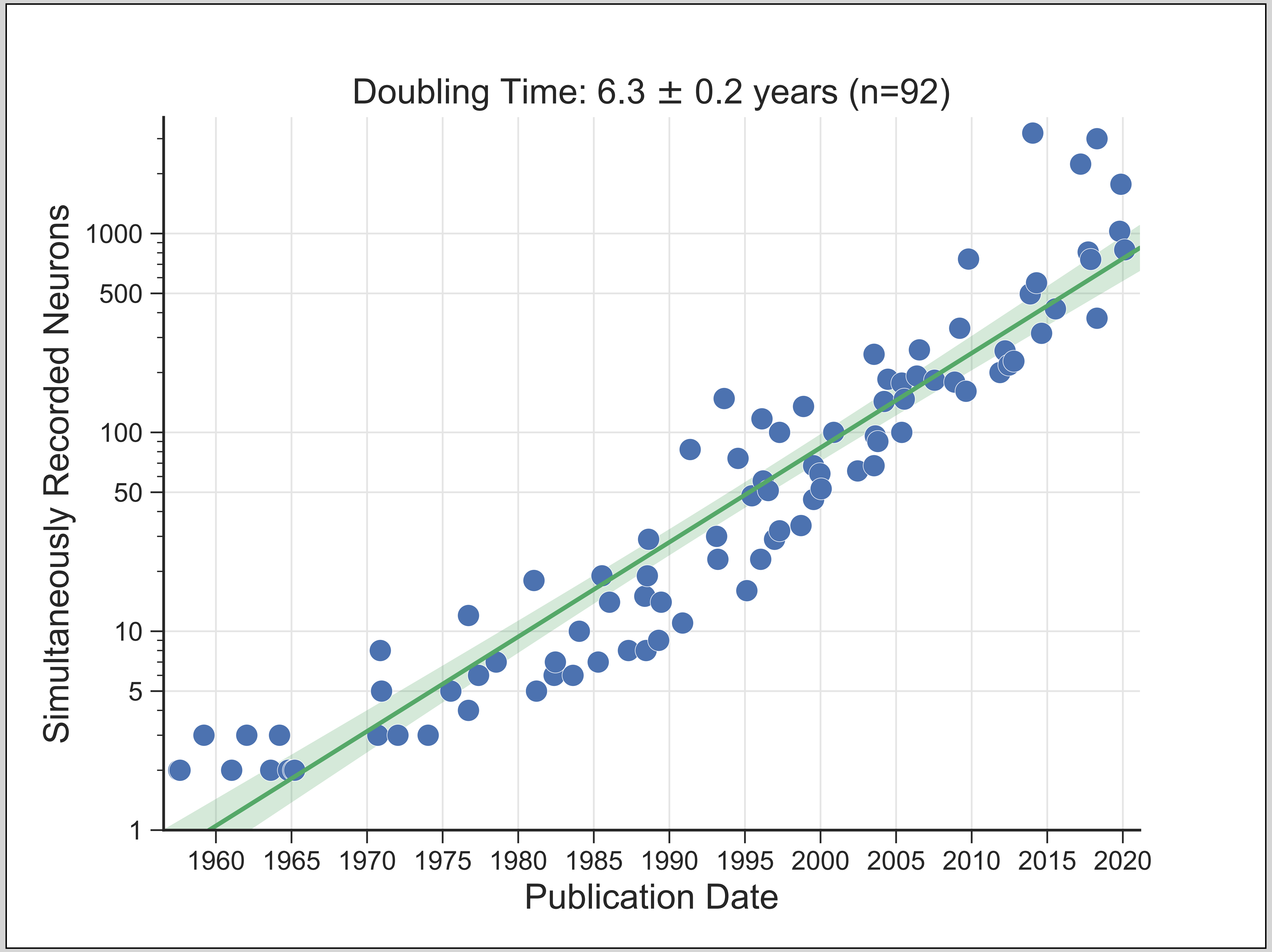
  - Brain-machine interfaces



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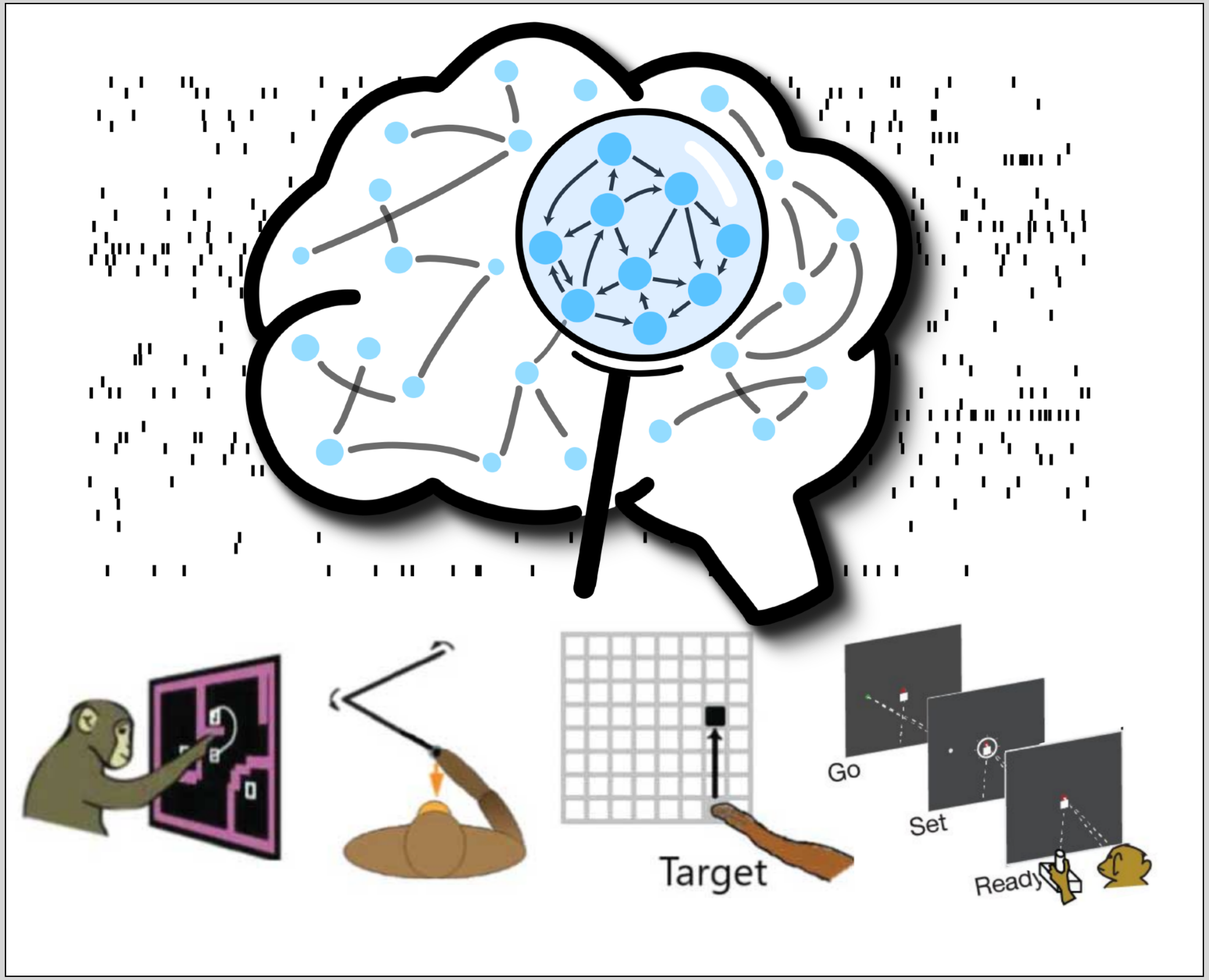
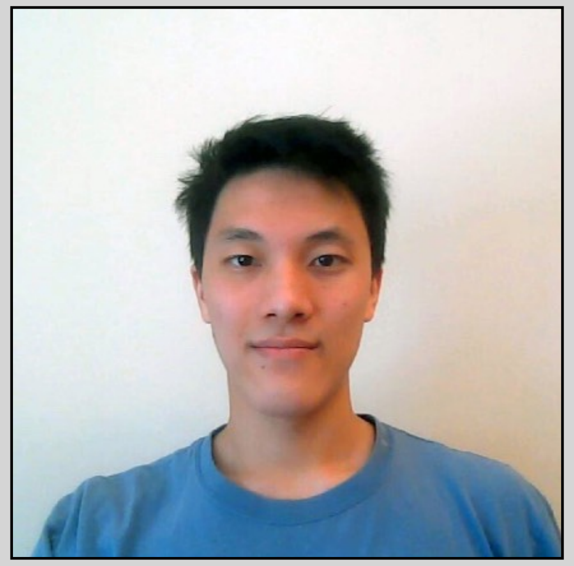


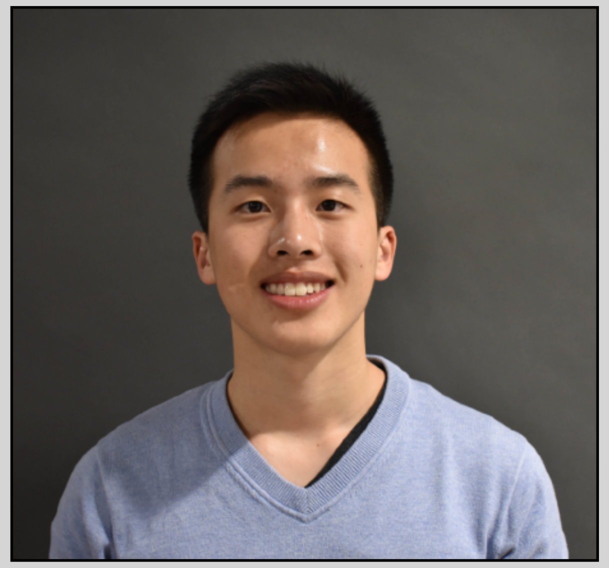
Neural Latents Benchmark ’21

A benchmark for latent variable models of neural data

Pe*, Ye*…Pandarinath, *NeurIPS 2021*
http://neurallatents.github.io



Felix Pe



Joel Ye

Pain points around model development

Pain points around model development

Users

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- Unclear which approaches perform well

Pain points around model development

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Developers

- Determine relevant datasets and evaluation criteria *de novo*

Pain points around model development

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Developers

- Determine relevant datasets and evaluation criteria *de novo*
- Responsible for determining best points of comparison

Pain points around model development

Users

- Unclear which approaches perform well
- Unsure whether an approach is relevant to their data
- Must adapt to different APIs

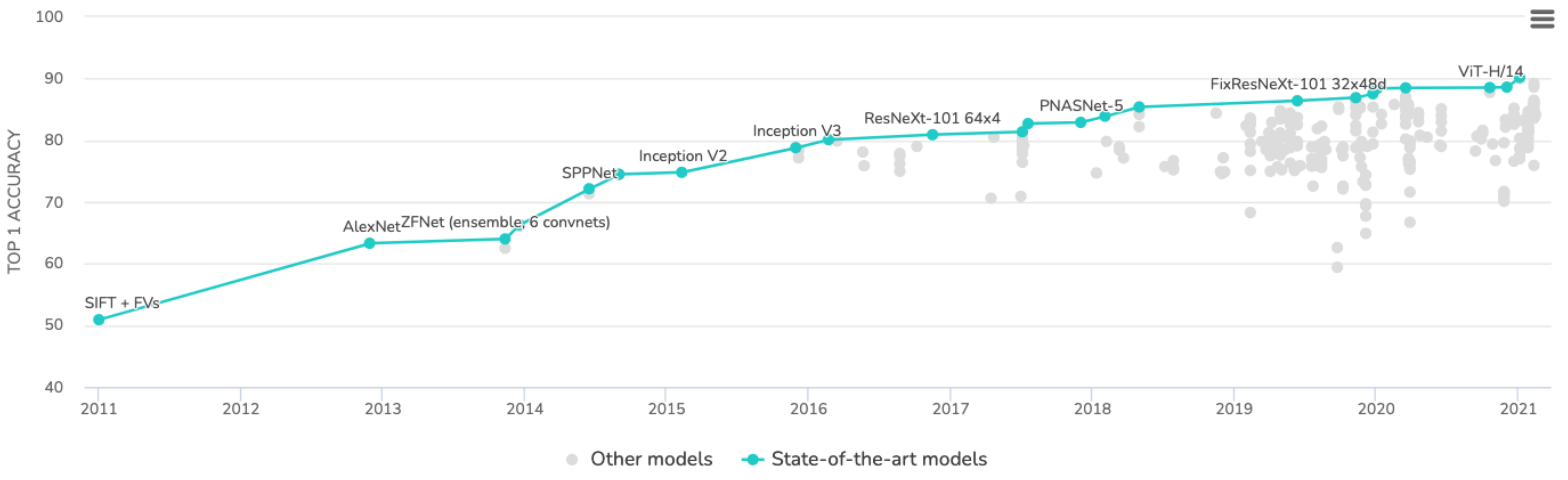
Developers

- Determine relevant datasets and evaluation criteria *de novo*
- Responsible for determining best points of comparison
- Forced to get other peoples' models to work!

Benchmarks facilitate progress

Image Classification on ImageNet

Leaderboard | Dataset



View: Top 1 Accuracy | All models | Edit

RANK	MODEL	TOP 1 ACCURACY	TOP 5 ACCURACY	NUMBER OF PARAMS	EXTRA TRAINING DATA	PAPER	CODE	RESULT	YEAR
1	**Meta Pseudo Labels** (EfficientNet-L2)	90.2%	98.8%	480M	✓	Meta Pseudo Labels			2021
2	**Meta Pseudo Labels** (EfficientNet-B6-Wide)	90%	98.7%	390M	✓	Meta Pseudo Labels			2021

- Hosted model evaluation on private, held-out data

EvalAI

- Hosted model evaluation on private, held-out data

- Example notebooks

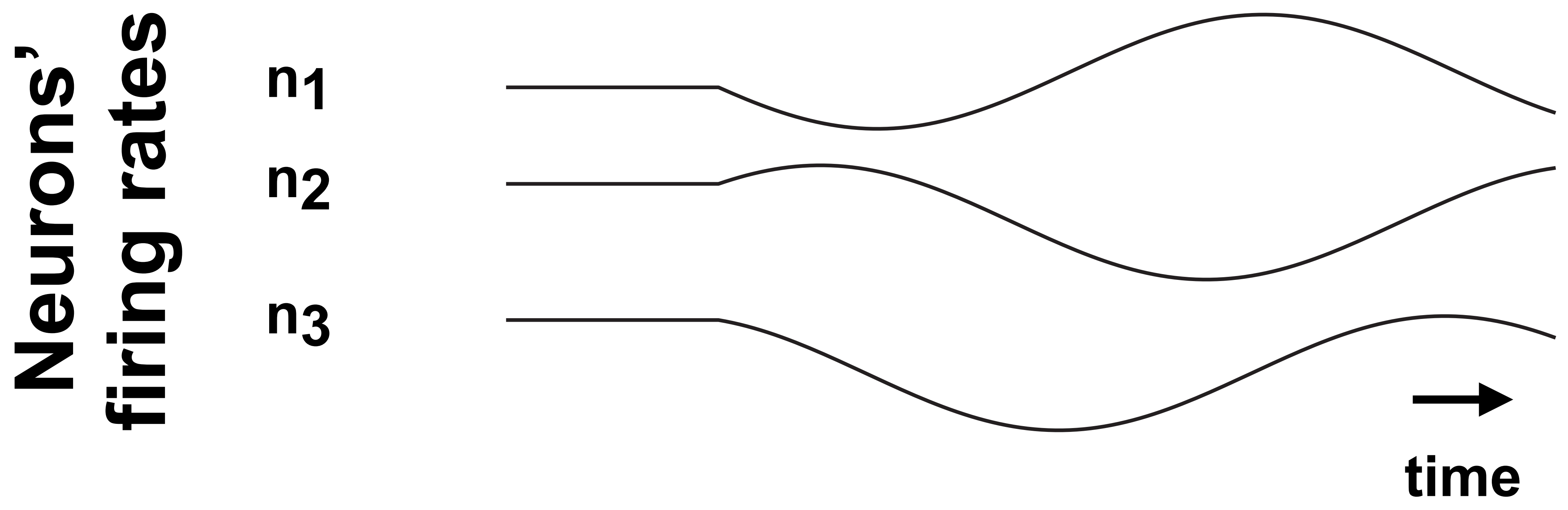
- Hosted model evaluation on private, held-out data
- Example notebooks
- Standardized dataset formatting / APIs

- Hosted model evaluation on private, held-out data
- Example notebooks
- Standardized dataset formatting / APIs
- Competition prizes!!


MC_Maze
MC_RTT
Area2_Bump
DMFC_RSG
Neuron count
Firing rate (spk/s)
Target onset
Go cue
Target acquisition
Bump
Ready
Set
Go
137 Channels
98 Channels
49 Channels
45 Channels
100 ms

Changes in neurons’ firing rates are coordinated

Changes in neurons' firing rates are coordinated



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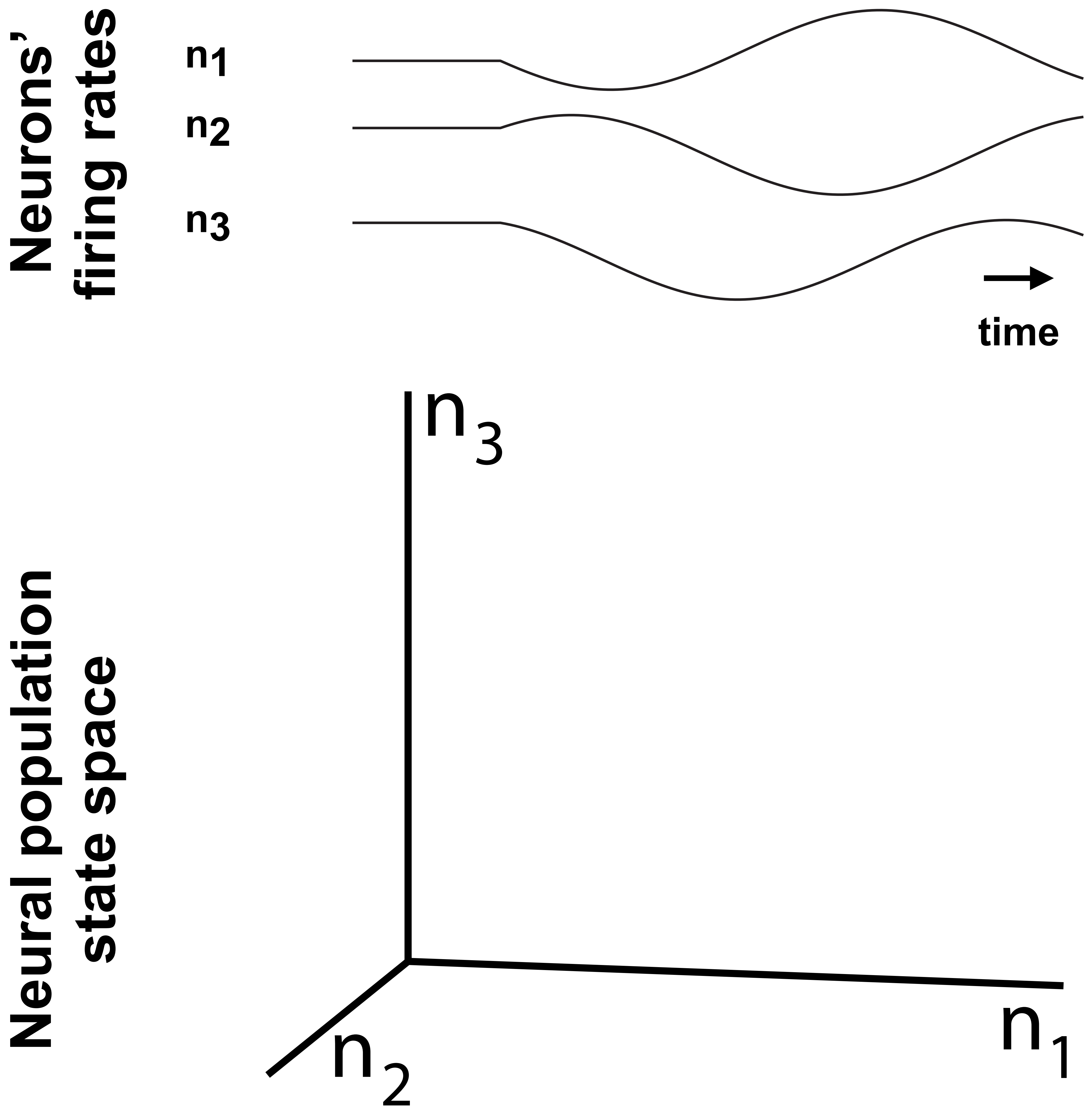

Adapted from Cunningham & Yu, *Nat Neuro* 2014

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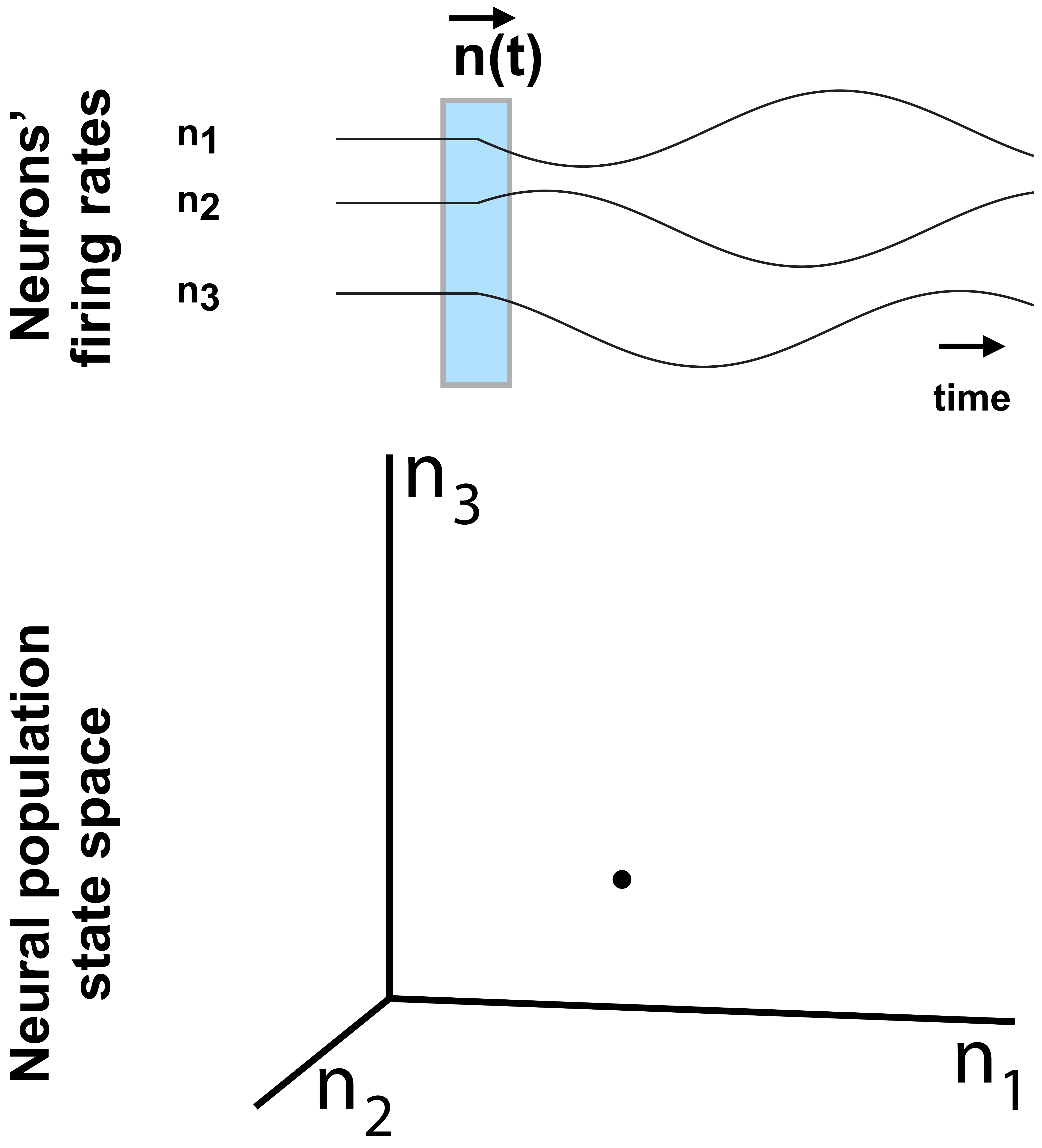

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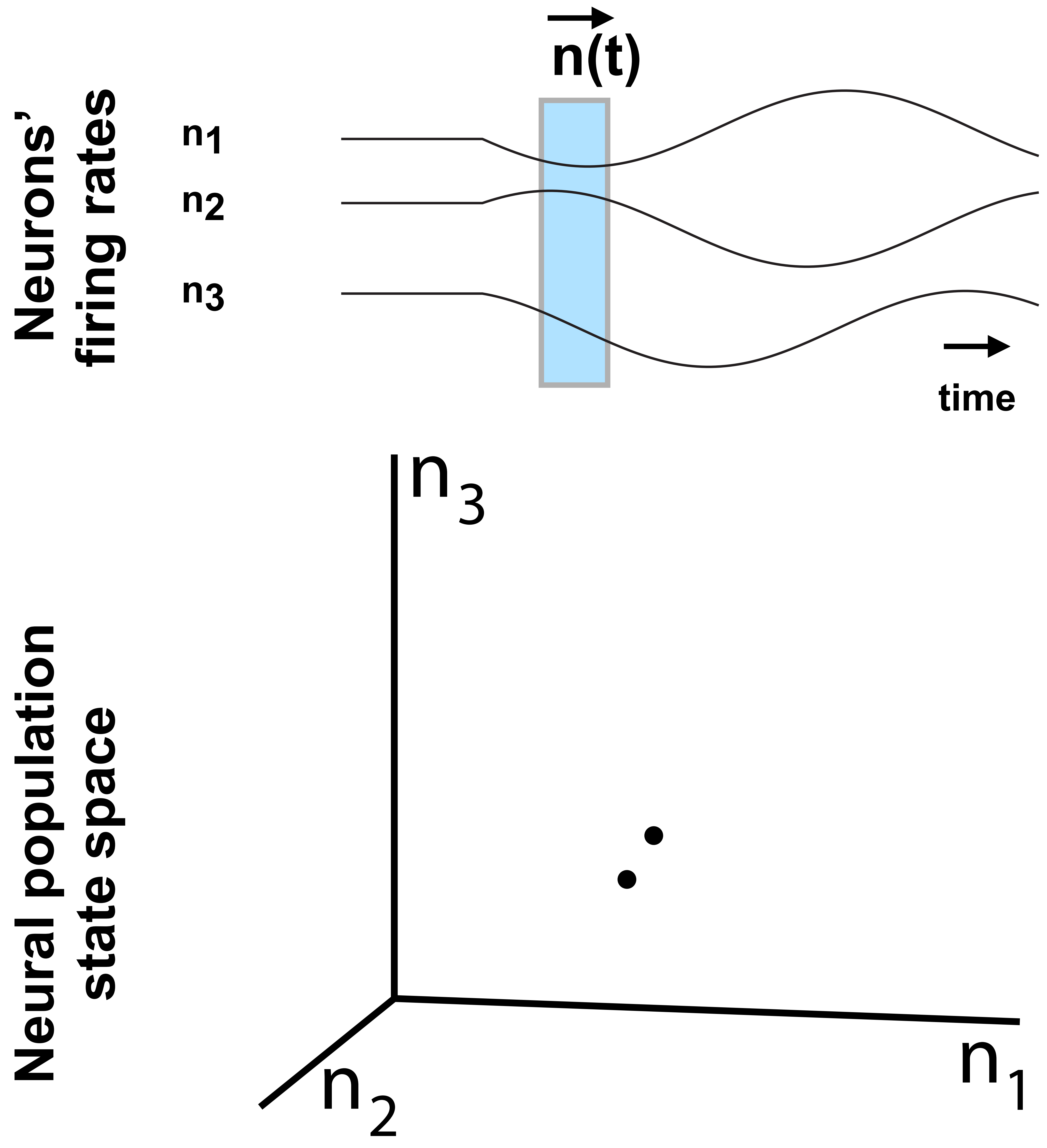

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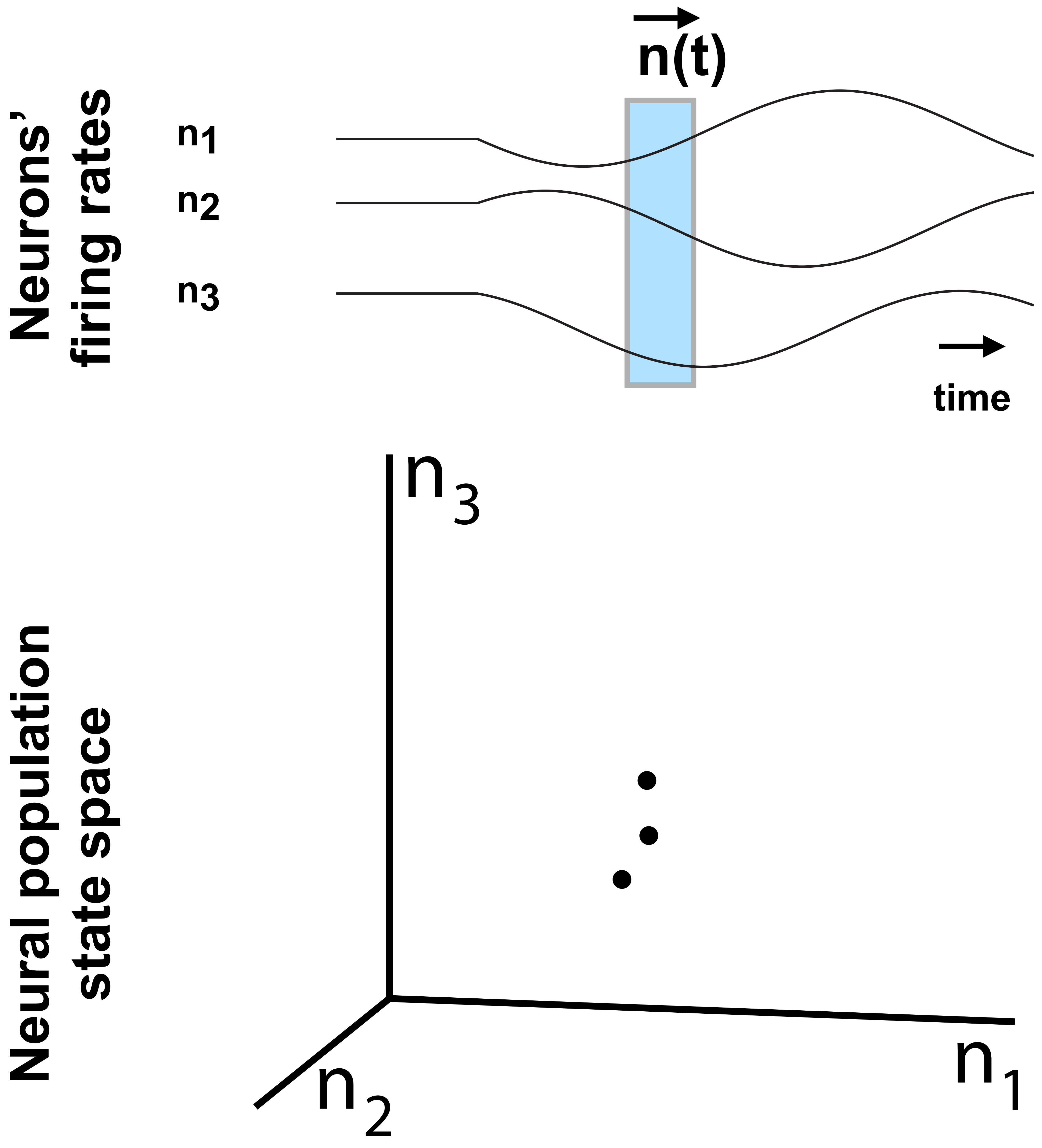

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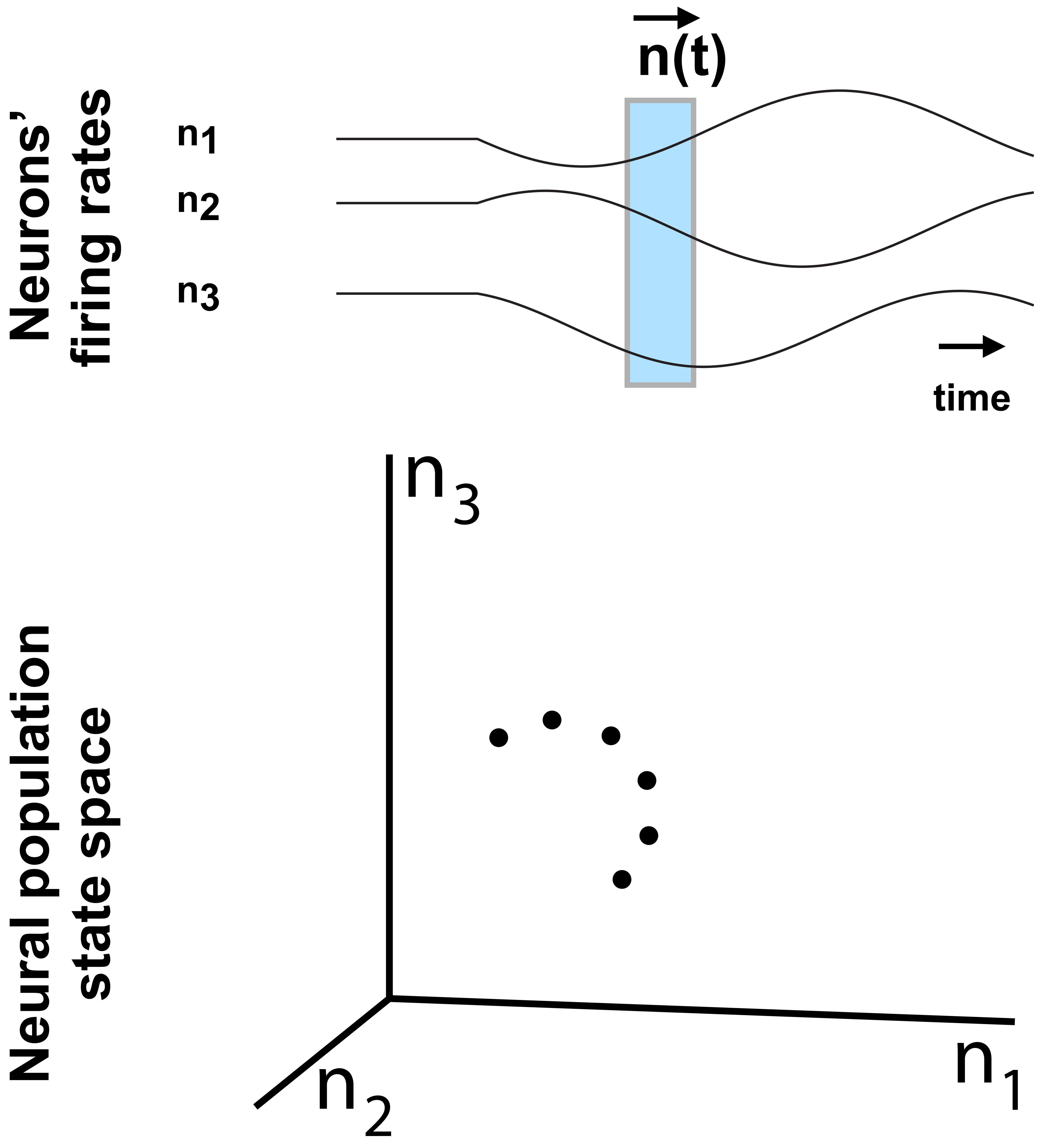

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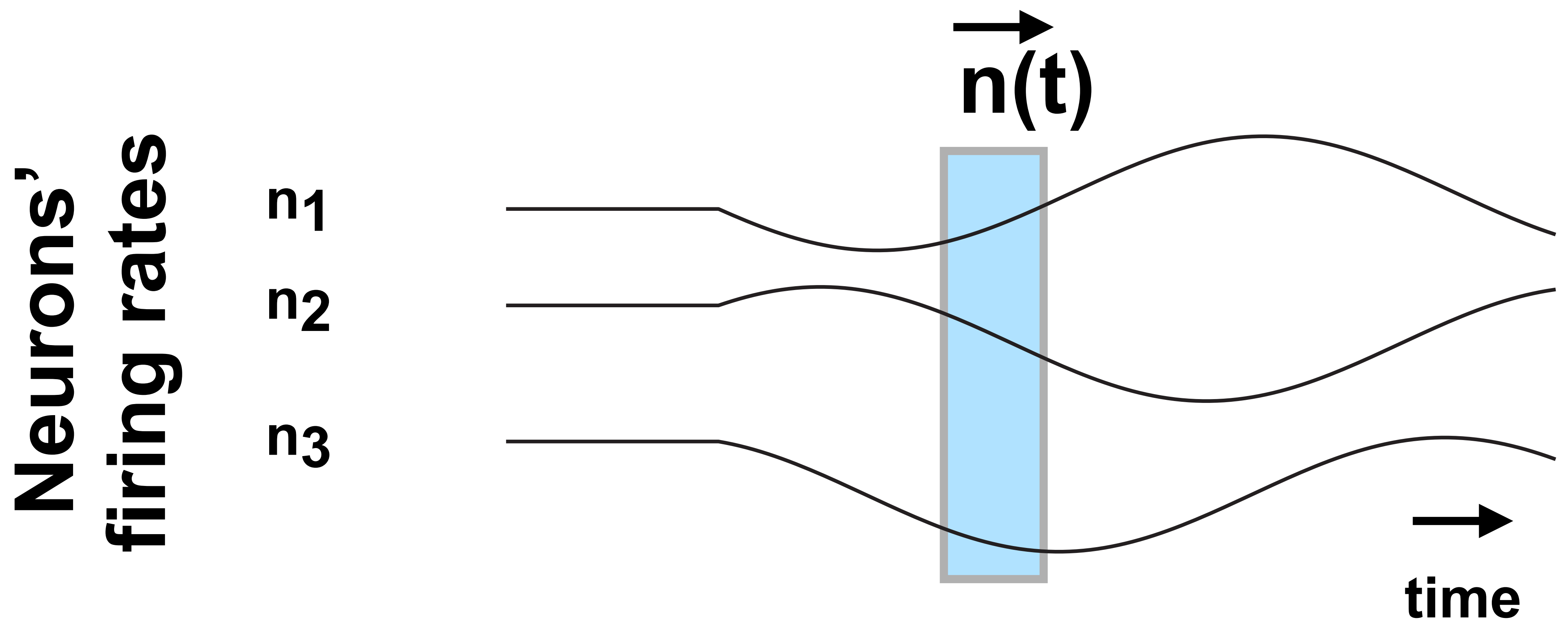

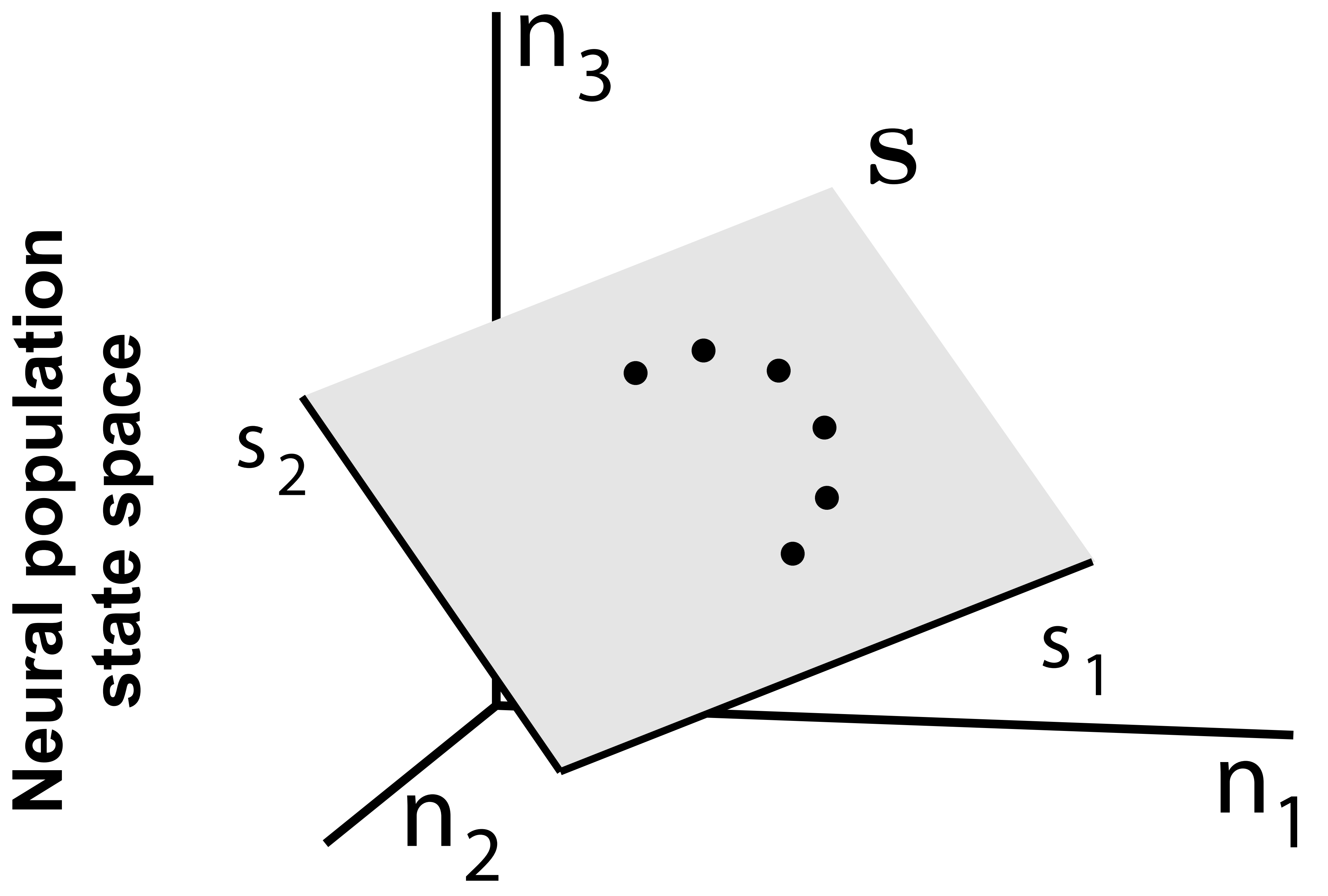

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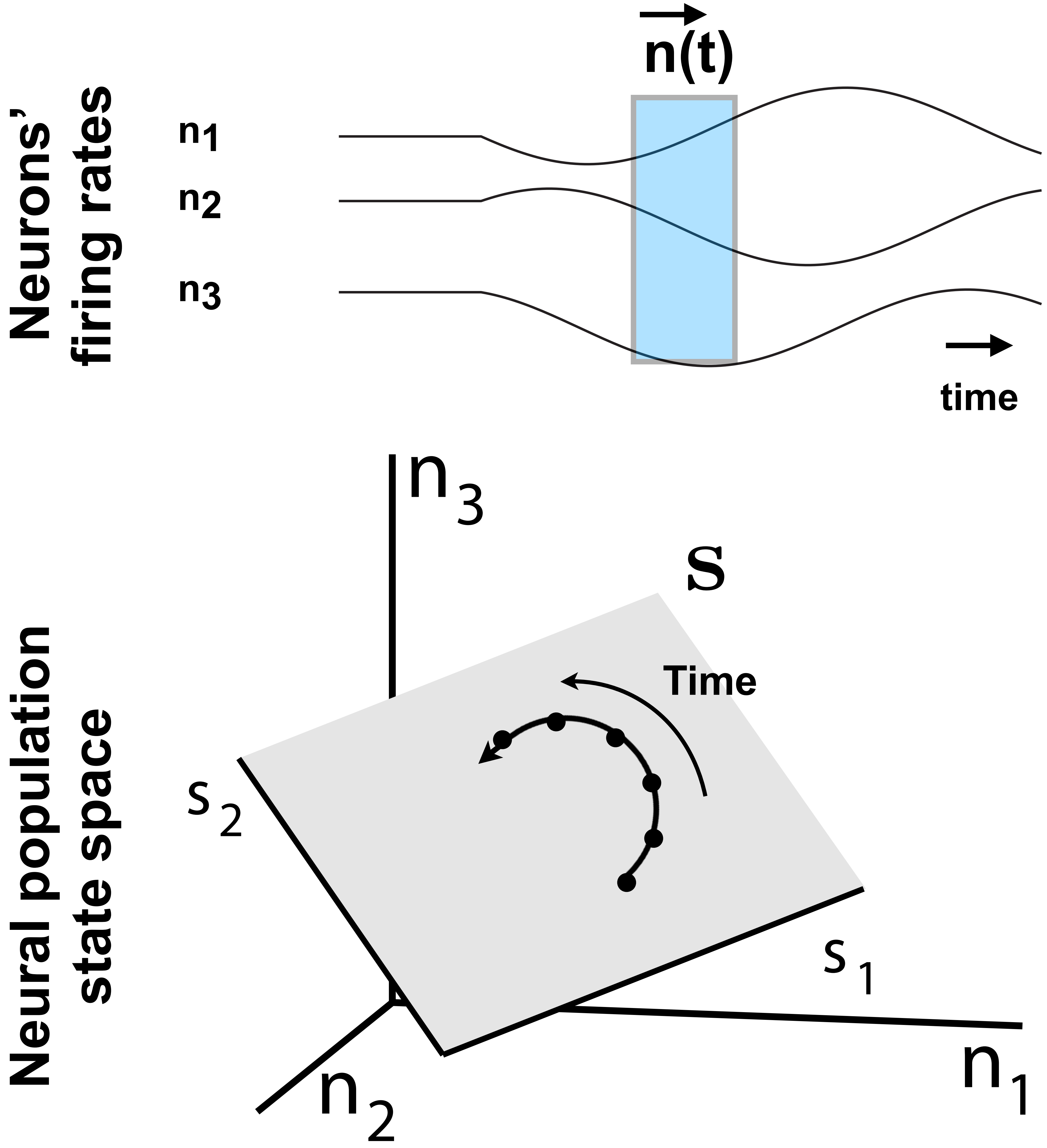
Neural population dynamics



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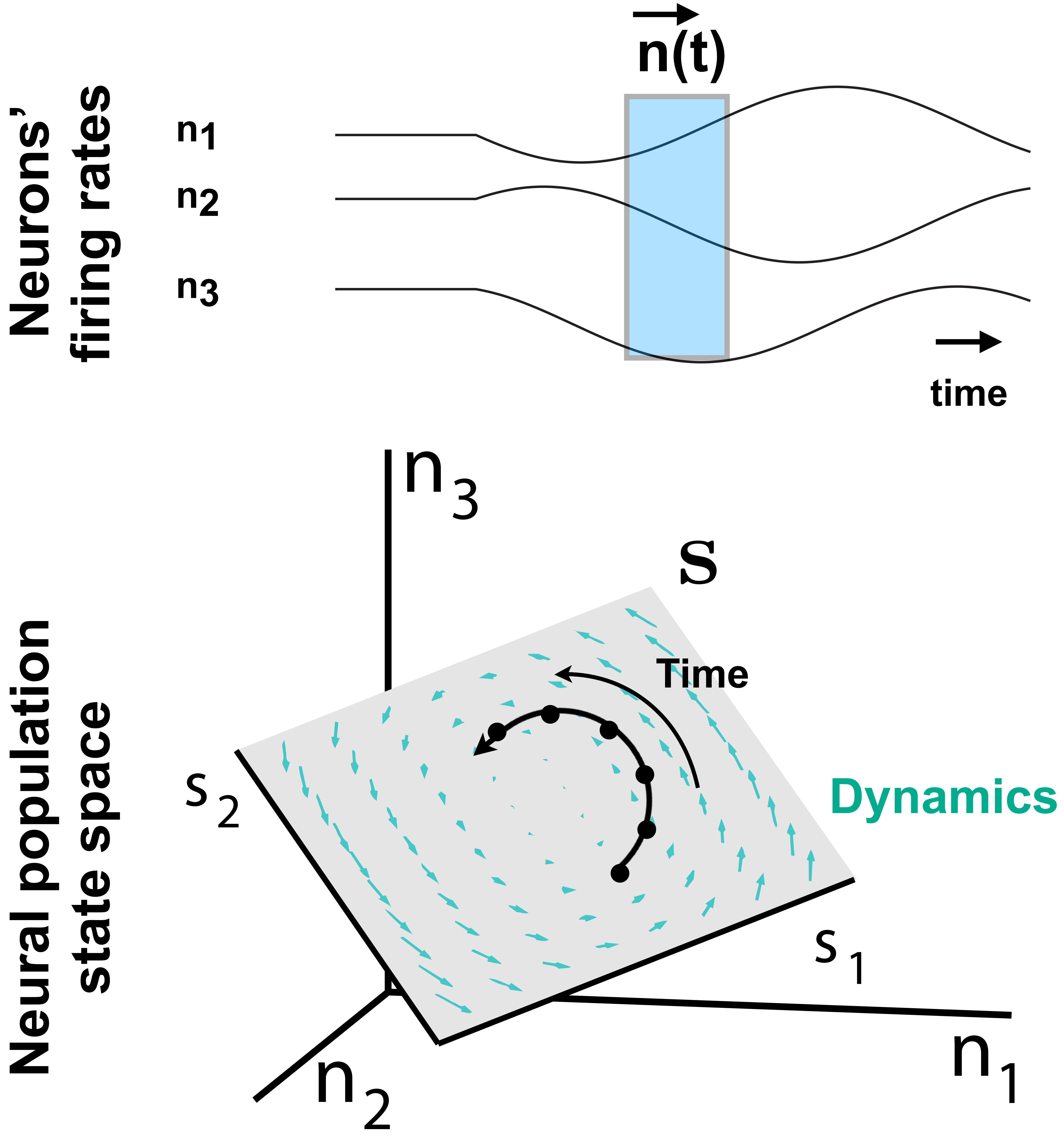

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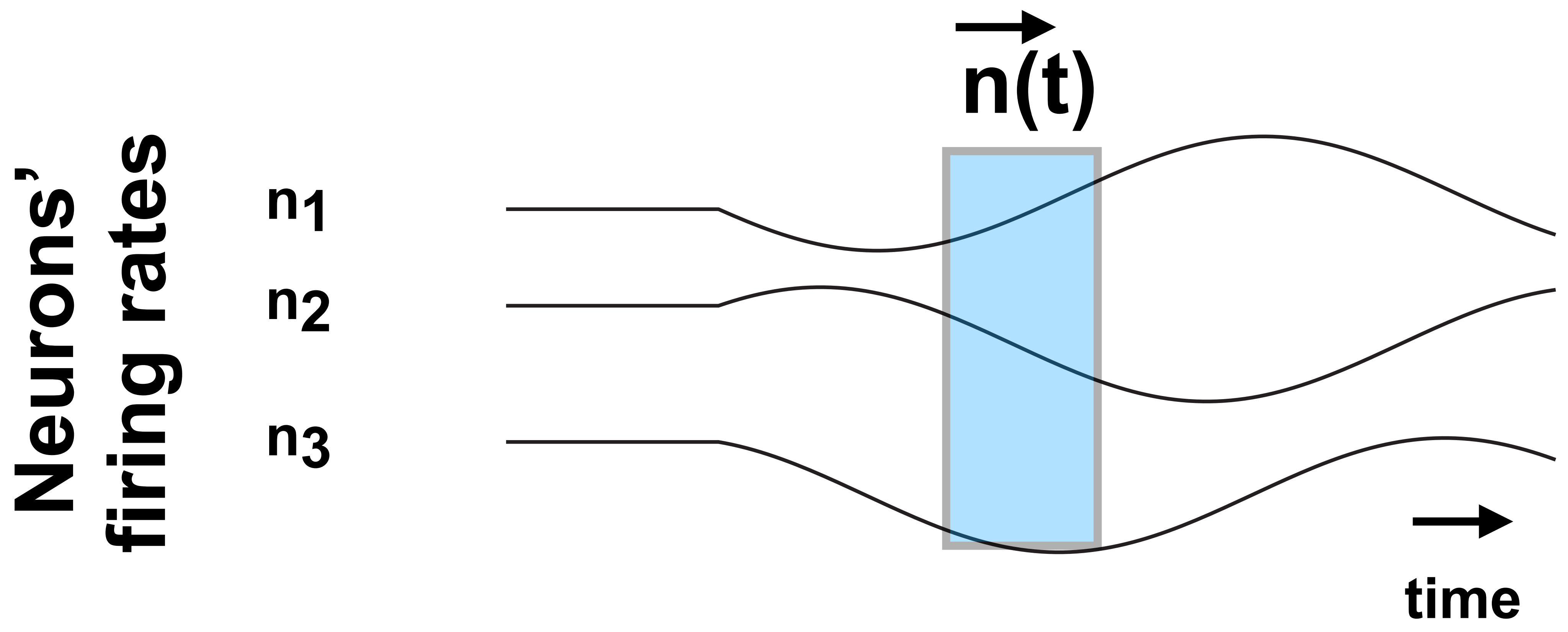
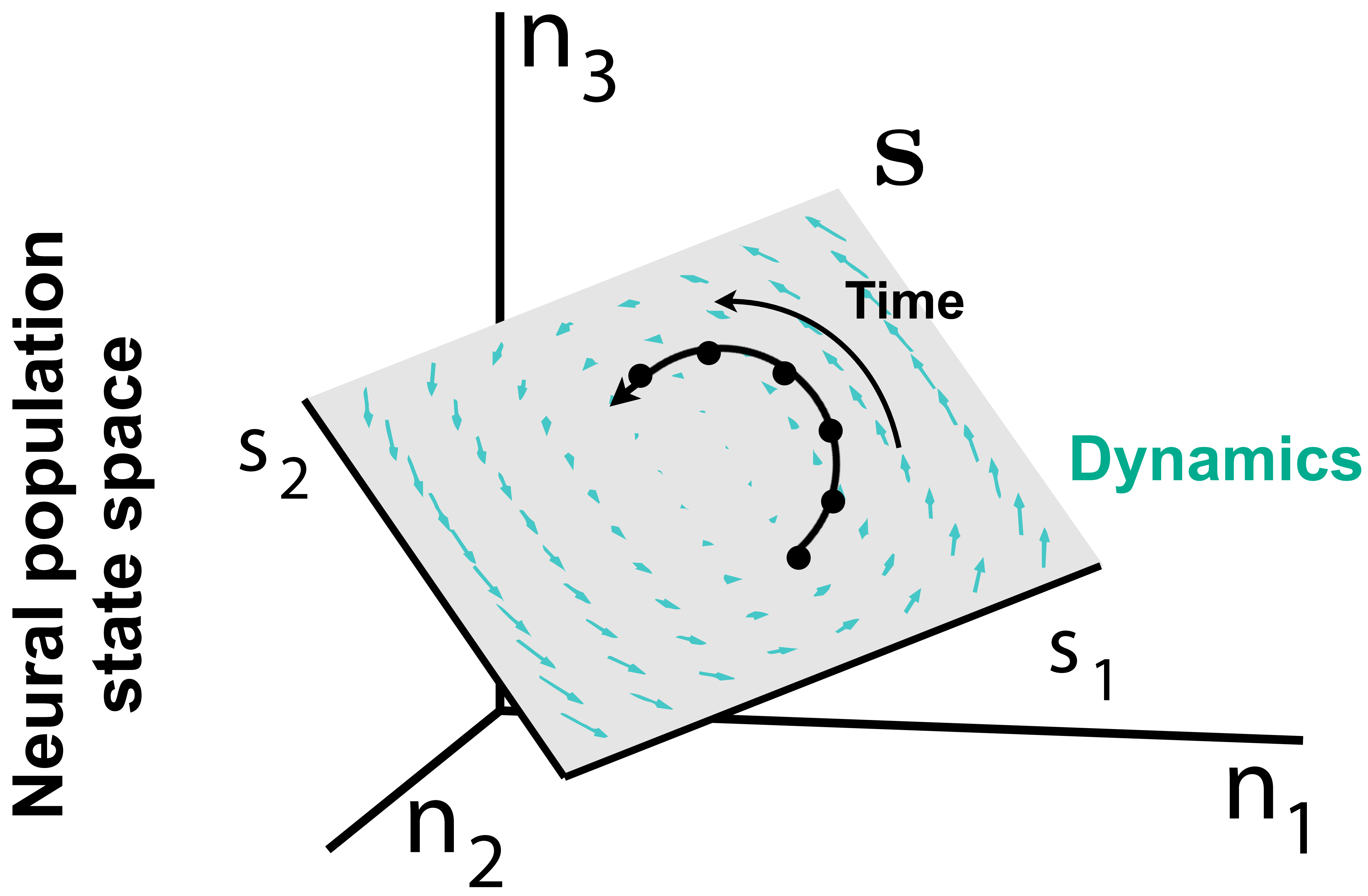
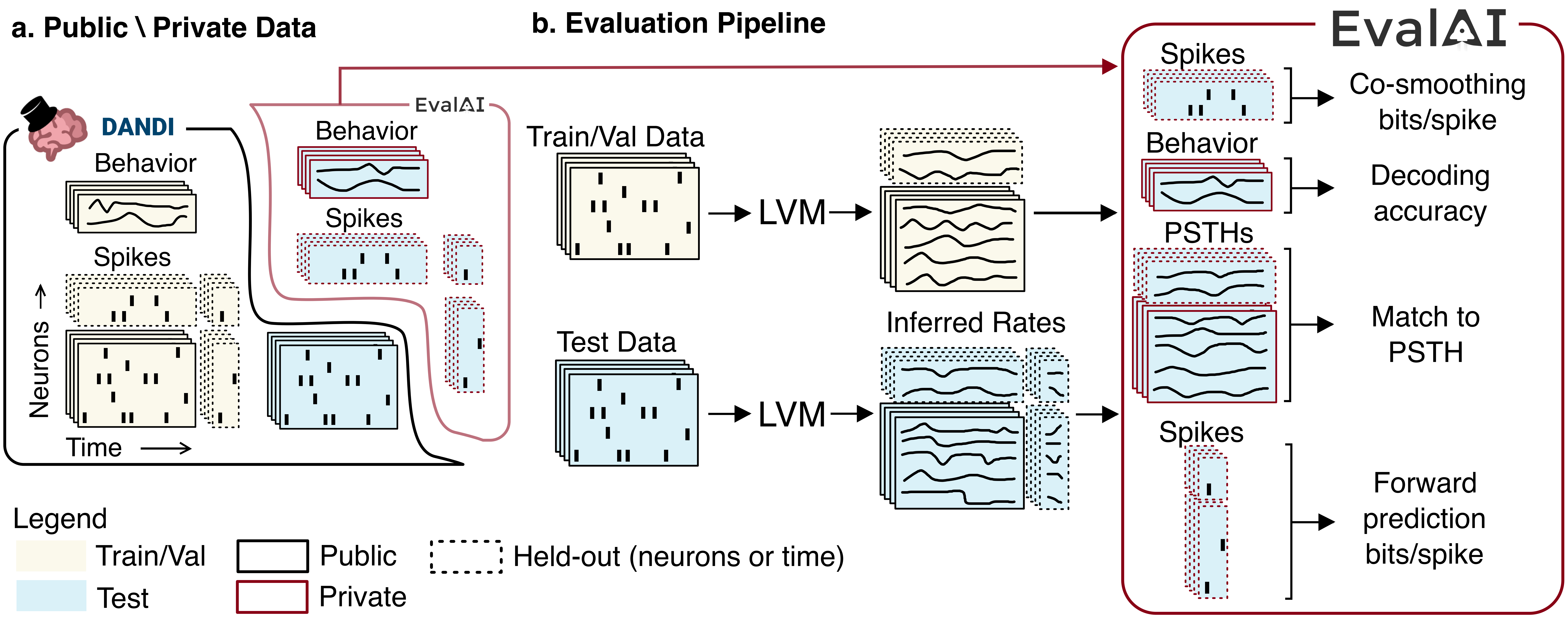


Predictable activity - modeled by *autonomous* dynamics

$$\frac{d\mathrm{s}}{dt} = f(\mathrm{s})$$




a. Public \ Private Data
b. Evaluation Pipeline
EvalAI
DANDI
Behavior
Spikes
Neurons →
Time →
EvalAI
Behavior
Spikes
Train/Val Data
LVM
Test Data
LVM
Inferred Rates
Spikes
Co-smoothing bits/spike
Behavior
Decoding accuracy
PSTHs
Match to PSTH
Spikes
Forward prediction bits/spike
Legend
Train/Val
Test
Public
Private
Held-out (neurons or time)

Leaderboards - Phase I

Maze

B - Baseline   * - Private   V - Verified

Rank	Participant team	co-bps (↑)	vel R2 (↑)	psth R2 (↑)	fp-bps (↑)	Last submission at
1	AE Studio. (AESMTE3)	0.3676	0.9114	0.6683	0.2589	5 days ago
2	AE Studio (AESMTE1)	0.3599	0.9105	0.6641	0.2470	1 month ago
3	Hennequin Lab (iLQR-VAE)	0.3559	0.8840	0.6062	0.1480	7 days ago
4	Neural Latents (AutoLFADS) B	0.3364	0.9097	0.6360	0.2349	3 months ago
5	Churchland Lab (MINT) B	0.3304	0.9121	0.7496	0.2076	2 months ago
6	Neural Latents (NDT) B	0.3229	0.8862	0.5308	0.2206	3 months ago
7	NCLab	0.3039	0.7581	-1.0294	-0.0061	11 days ago
8	Neural Latents (SLDS) B	0.2249	0.7947	0.5330	-1.1579	3 months ago
9	Neural Latents (Spike smoothing) B	0.2109	0.6238	0.1853	E	4 months ago
10	Neural Latents (GPFA) B	0.1872	0.6399	0.5150	E	3 months ago

Random Target

Rank	Participant team	co-bps (↑)	vel R2 (↑)	fp-bps (↑)
1	AE Studio. (AESMTE3)	0.2053	0.6334	0.1344
2	AE Studio (AESMTE1)	0.1927	0.6627	0.1229
3	Neural Latents (AutoLFADS) B	0.1868	0.6167	0.1213
4	Neural Latents (NDT) B	0.1749	0.5656	0.0970
5	Churchland Lab (MINT) B	0.1676	0.5953	0.1012
6	Neural Latents (SLDS) B	0.1649	0.5206	0.0620
7	Neural Latents (GPFA) B	0.1548	0.5339	E
8	Neural Latents (Spike smoothing) B	0.1468	0.4142	E
9	NCLab (S2S)	0.1021	0.3117	E

Area 2

Rank	Participant team	co-bps (↑)	vel R2 (↑)	psth R2 (↑)	fp-bps (↑)
1	AE Studio. (AESMTE3)	0.2860	0.8999	0.7109	0.1603
2	AE Studio (AESMTE1)	0.2801	0.8675	0.6367	0.1523
3	Churchland Lab (MINT) B	0.2735	0.8877	0.9135	0.1483
4	Neural Latents (NDT) B	0.2623	0.8672	0.6619	0.1184
5	Neural Latents (AutoLFADS) B	0.2569	0.8492	0.6318	0.1505
6	NCLab	0.2388	0.7174	-0.1357	E
7	Neural Latents (SLDS) B	0.1960	0.7385	0.5740	0.0242
8	Neural Latents (GPFA) B	0.1680	0.5975	0.5289	E
9	Neural Latents (Spike smoothing) B	0.1544	0.5736	0.2084	E

DMFC

Rank	Participant team	co-bps (↑)	tp corr (↓)	psth R2 (↑)	fp-bps (↑)
1	AE Studio. (AESMTE3)	0.1886	-0.7601	0.6064	0.1828
2	Neural Latents (AutoLFADS) B	0.1829	-0.8248	0.6359	0.1844
3	Churchland Lab (MINT) B	0.1821	-0.6929	0.7013	0.1650
4	AE Studio (AESMTE1)	0.1733	-0.6189	0.5267	0.1511
5	Neural Latents (NDT) B	0.1720	-0.5624	0.4377	0.1404
6	Neural Latents (SLDS) B	0.1243	-0.5412	0.3372	-0.0418
7	Neural Latents (Spike smoothing) B	0.1202	-0.5139	0.2993	E
8	Neural Latents (GPFA) B	0.1176	-0.3763	0.2142	E
9	NE (SRNN)	-0.0078	-0.0319	-0.6191	E
10	NCLab (SMLseq)	-10.7694	0.6388	-403.9015	-10.4915

Leaderboards - Phase I

Maze

B - Baseline   * - Private   V - Verified

Rank	Participant team	co-bps (↑)	vel R2 (↑)	psth R2 (↑)	fp-bps (↑)	Last submission at
1	AE Studio. (AESMTE3)	0.3676	0.9114	0.6683	0.2589	5 days ago
2	AE Studio (AESMTE1)	0.3599	0.9105	0.6641	0.2470	1 month ago
3	Hennequin Lab (iLQR-VAE)	0.3559	0.8840	0.6062	0.1480	7 days ago
4	Neural Latents (AutoLFADS) B	0.3364	0.9097	0.6360	0.2349	3 months ago
5	Churchland Lab (MINT) B	0.3304	0.9121	0.7496	0.2076	2 months ago
6	Neural Latents (NDT) B	0.3229	0.8862	0.5308	0.2206	3 months ago
7	NCLab	0.3039	0.7581	-1.0294	-0.0061	11 days ago
8	Neural Latents (SLDS) B	0.2249	0.7947	0.5330	-1.1579	3 months ago
9	Neural Latents (Spike smoothing) B	0.2109	0.6238	0.1853	E	4 months ago
10	Neural Latents (GPFA) B	0.1872	0.6399	0.5150	E	3 months ago

Random Target

Rank	Participant team	co-bps (↑)	vel R2 (↑)	fp-bps (↑)
1	AE Studio. (AESMTE3)	0.2053	0.6334	0.1344
2	AE Studio (AESMTE1)	0.1927	0.6627	0.1229
3	Neural Latents (AutoLFADS) B	0.1868	0.6167	0.1213
4	Neural Latents (NDT) B	0.1749	0.5656	0.0970
5	Churchland Lab (MINT) B	0.1676	0.5953	0.1012
6	Neural Latents (SLDS) B	0.1649	0.5206	0.0620
7	Neural Latents (GPFA) B	0.1548	0.5339	E
8	Neural Latents (Spike smoothing) B	0.1468	0.4142	E
9	NCLab (S2S)	0.1021	0.3117	E

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EvalAI