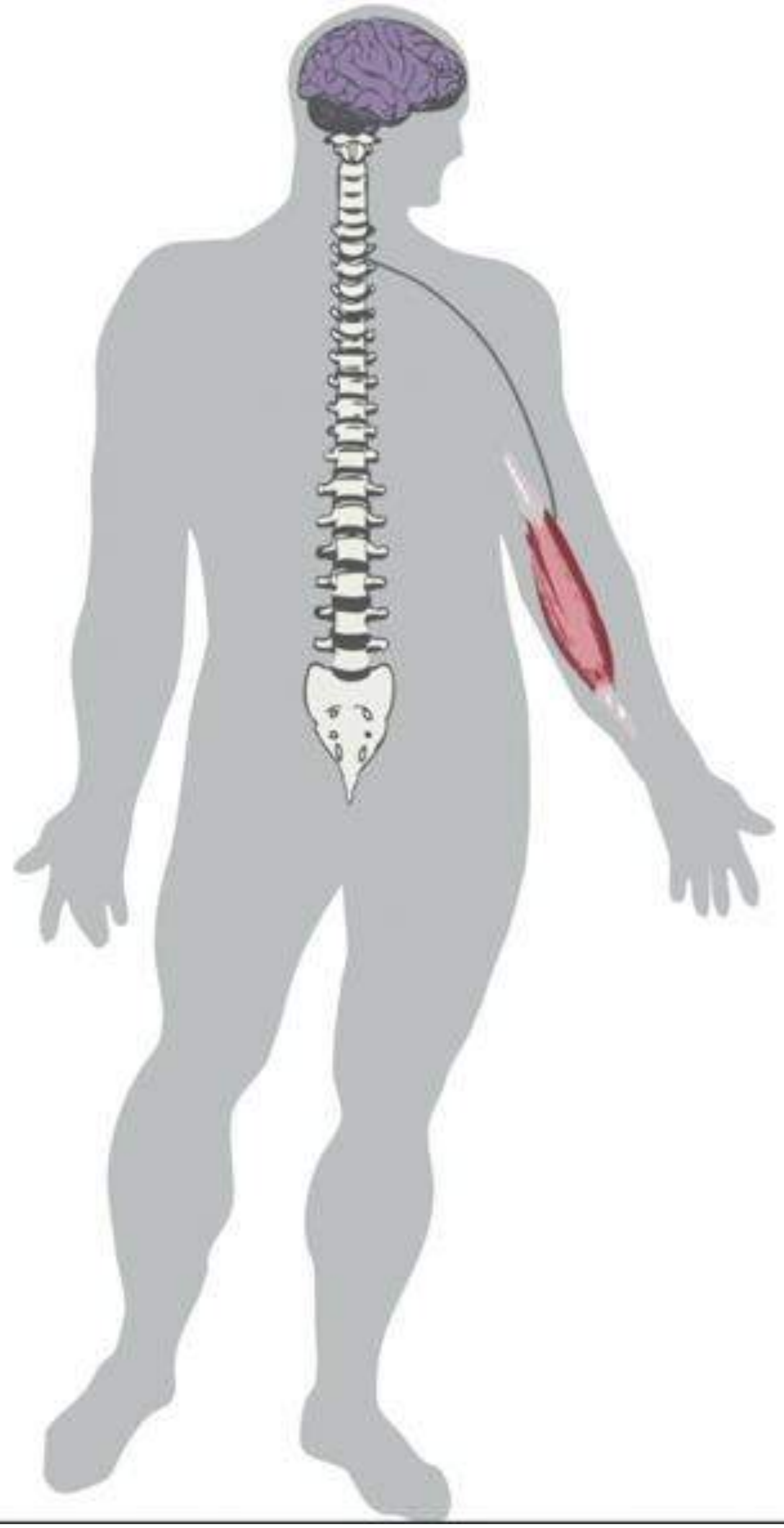
# Re-engineering brain-machine interfaces to optimize control and learning

**Amy L. Orsborn**

Microsoft Research
April 11, 2019

# Brain-machine interfaces can **restore** abilities



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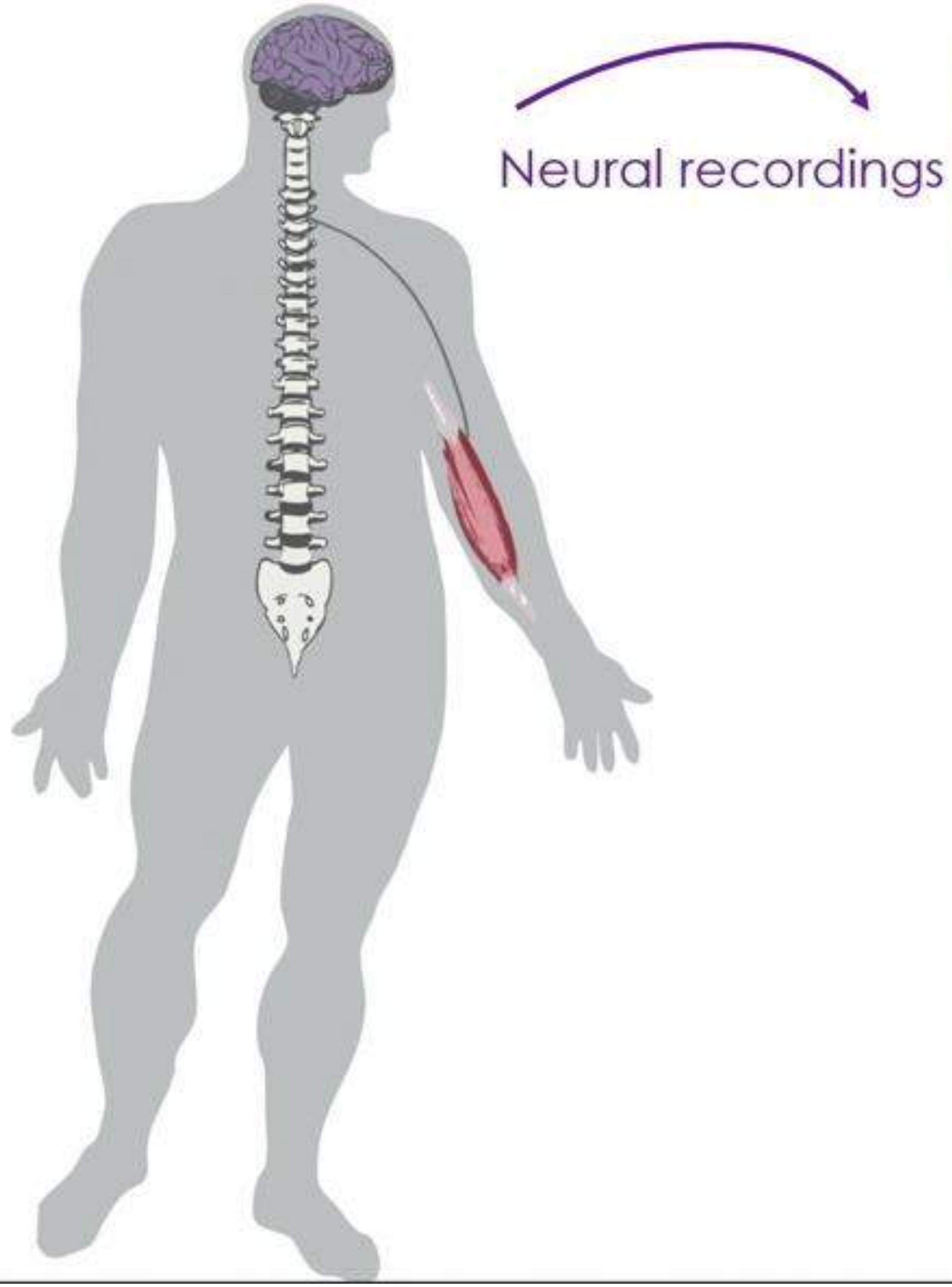


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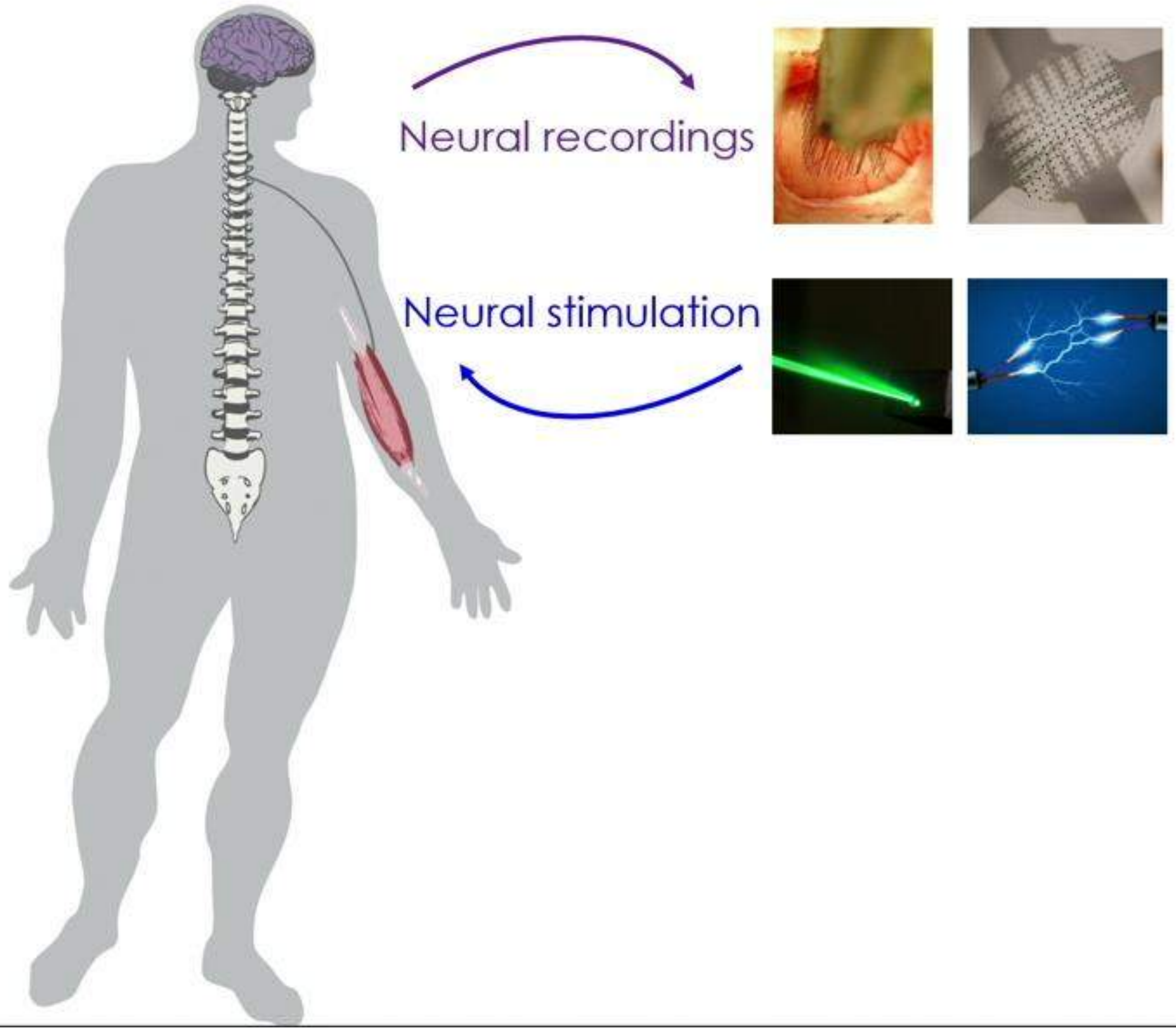

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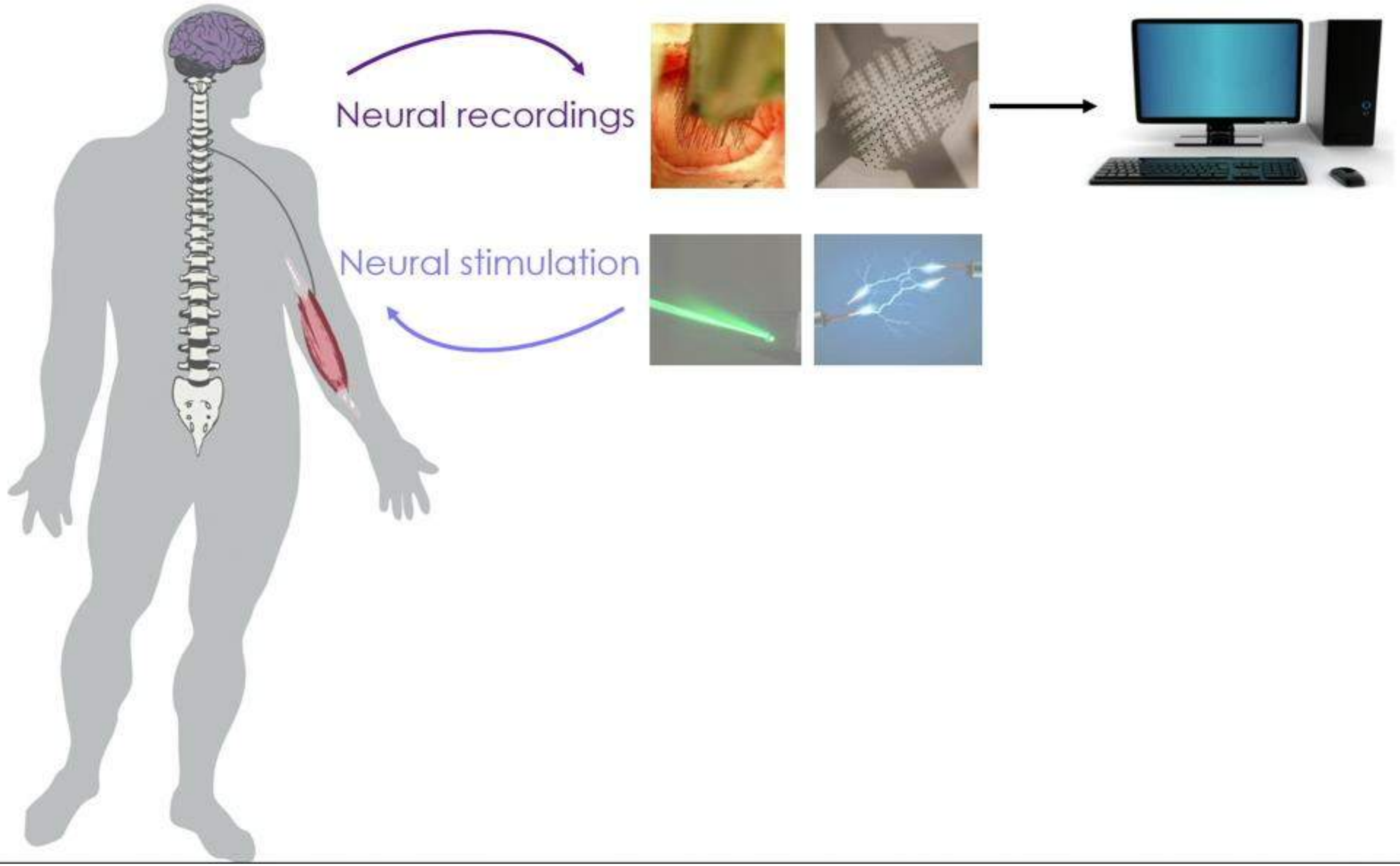

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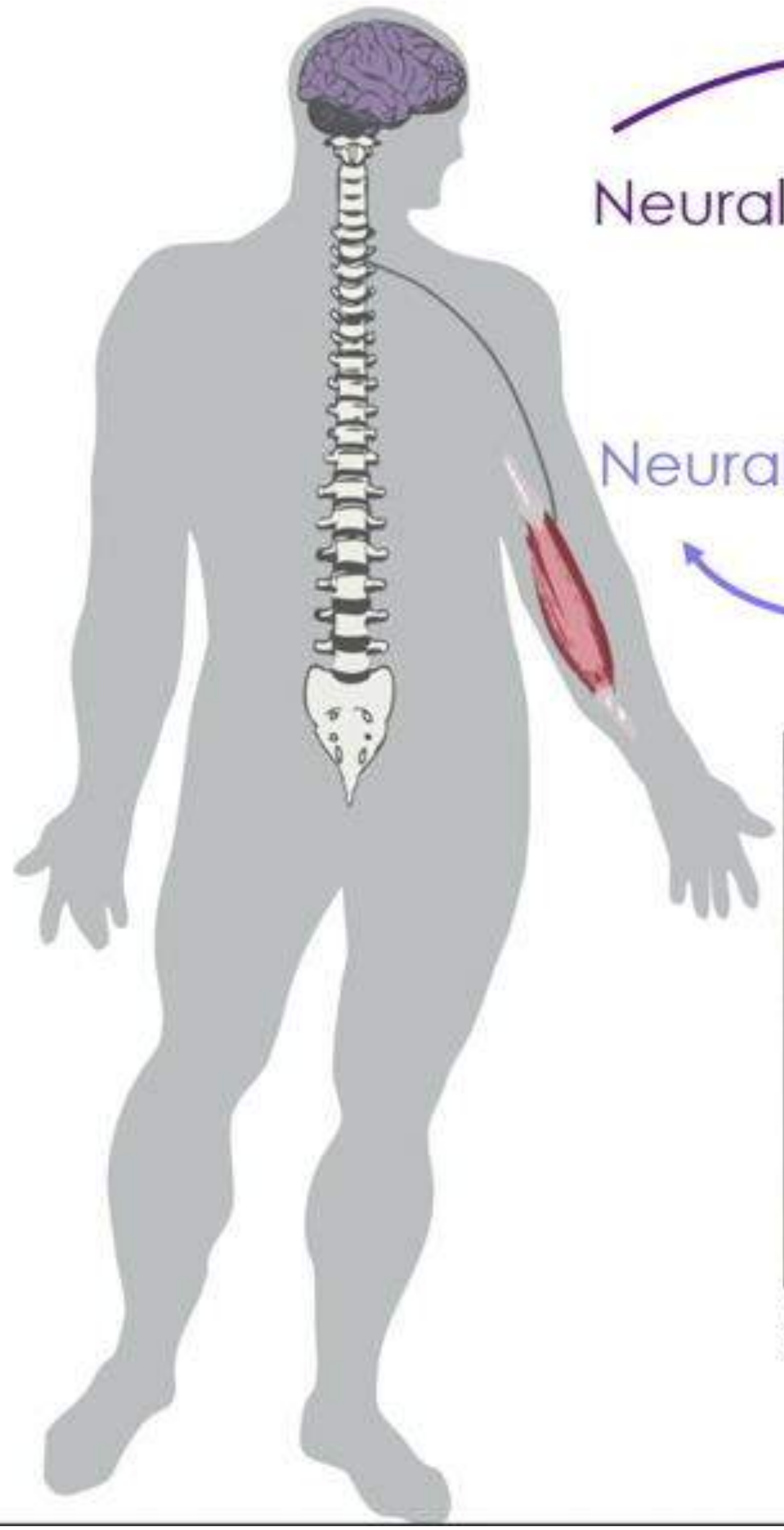

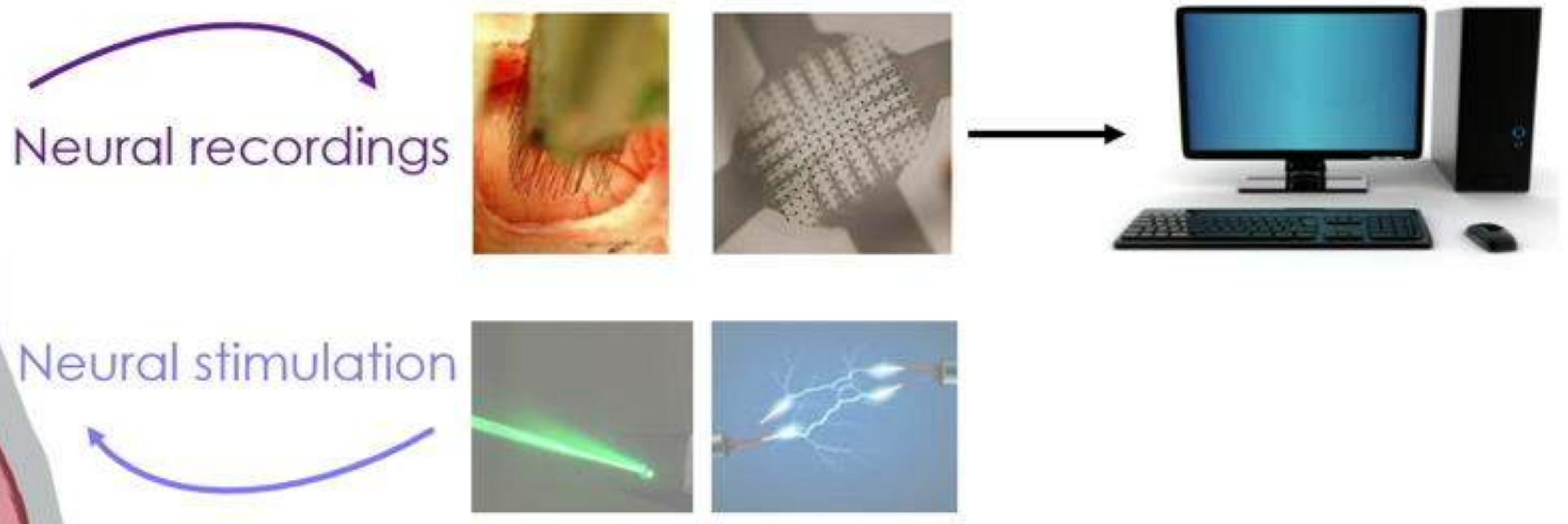


Hochberg et al., *Nature* 2012

Collinger et al., *Lancet* 2012

# **BMI challenges**: robust, real-world performance

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- Performance far from natural motor control
  - Lower dimensionality
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  - "BMI Illiteracy"

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  - "BMI Illiteracy"

- **Little principled, mechanistic understanding → no 'design principles'**

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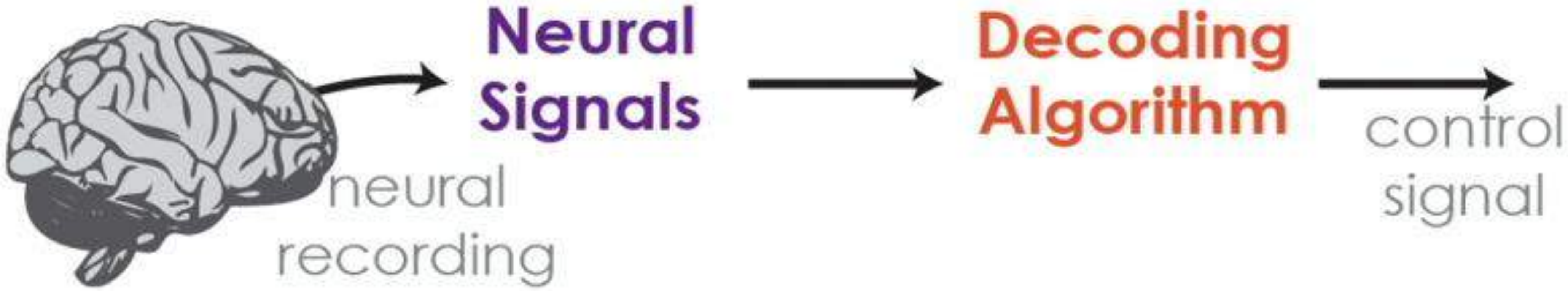

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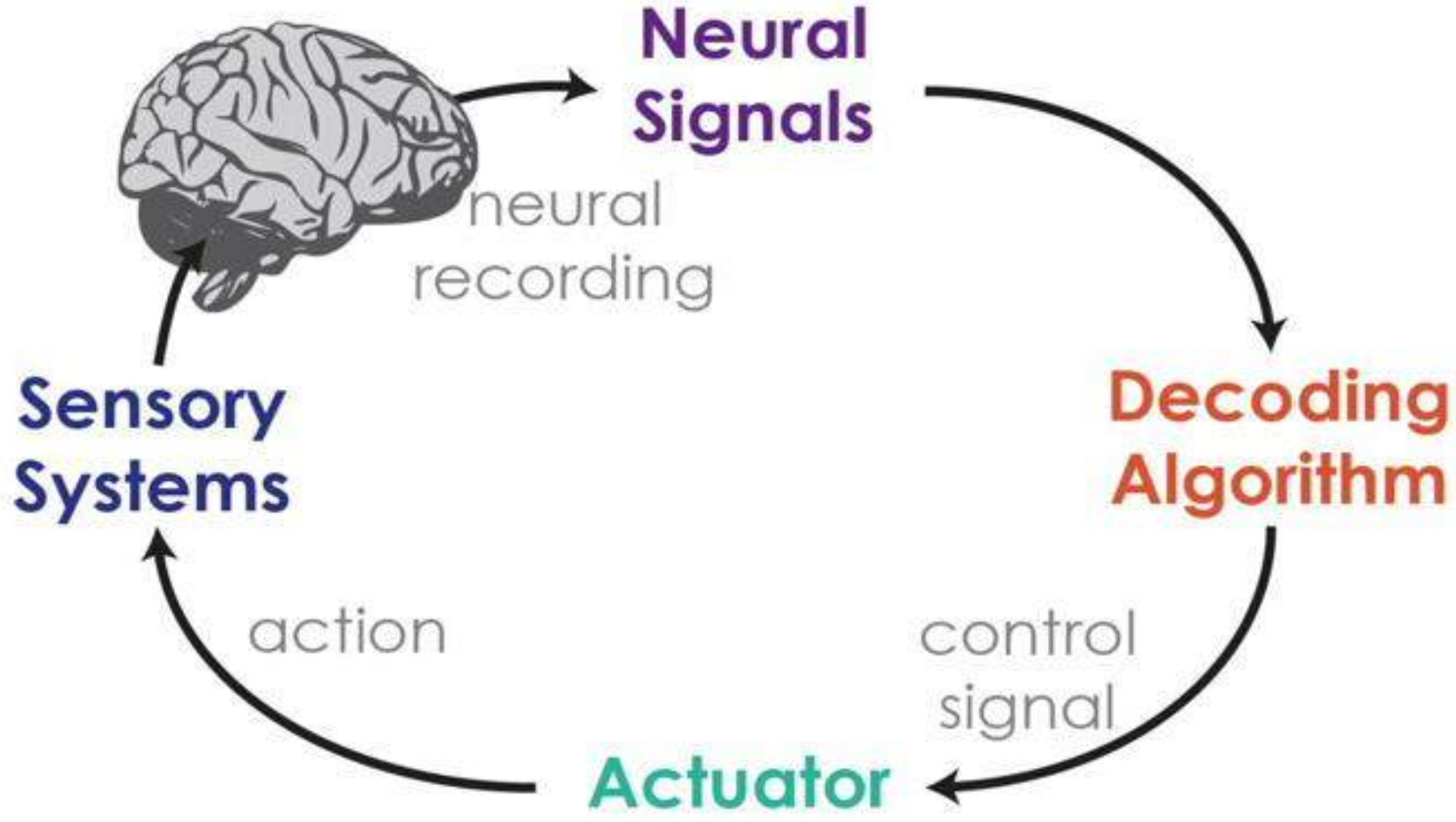
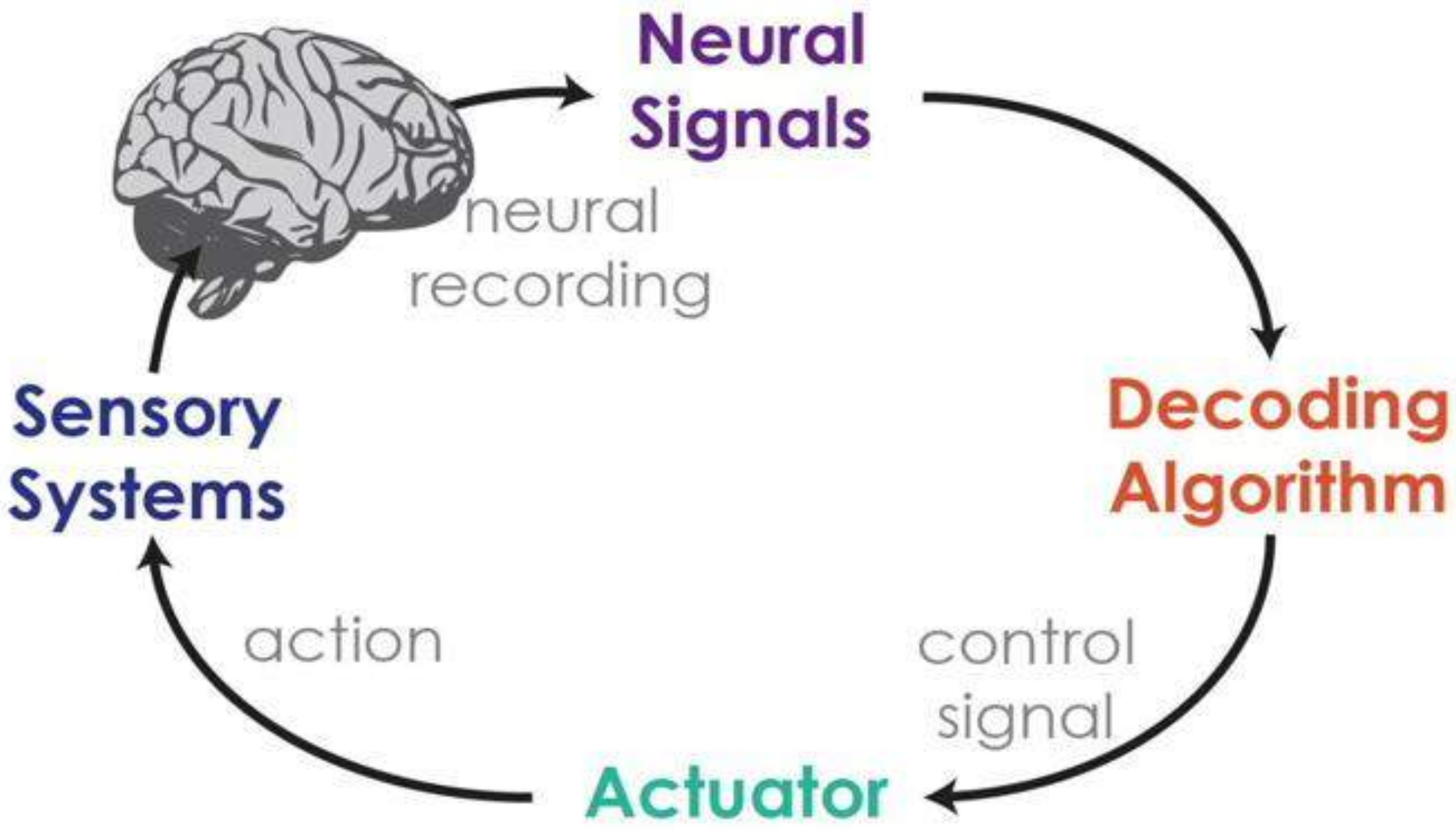


# BMIs **adaptively** repurpose neural activity

1. Neural "encoding" changes between BMI and arm movements




Fetz & Finocchio, *Science* 1971; Taylor et al., 2002; Carmena *et al.*, *PLoS Biol* 2003; Jarosiewicz *et al.*, *PNAS* 2008; Moritz et al., *Nature* 2008; Ganguly & Carmena, *PLoS Biol* 2009; Koyama *et al.*, *J Comp Neuro* 2010; Wander et al., *PNAS* 2013

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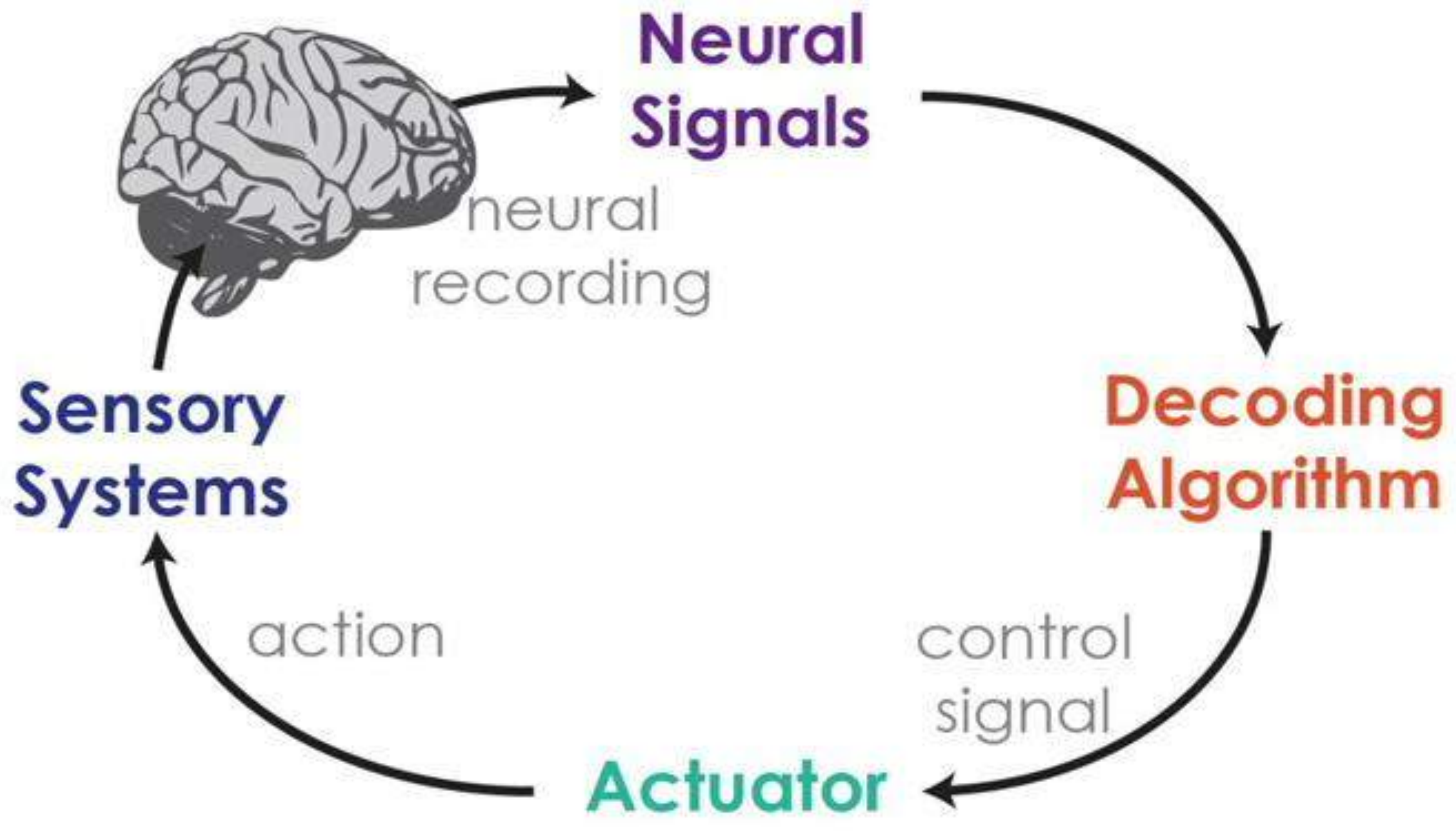



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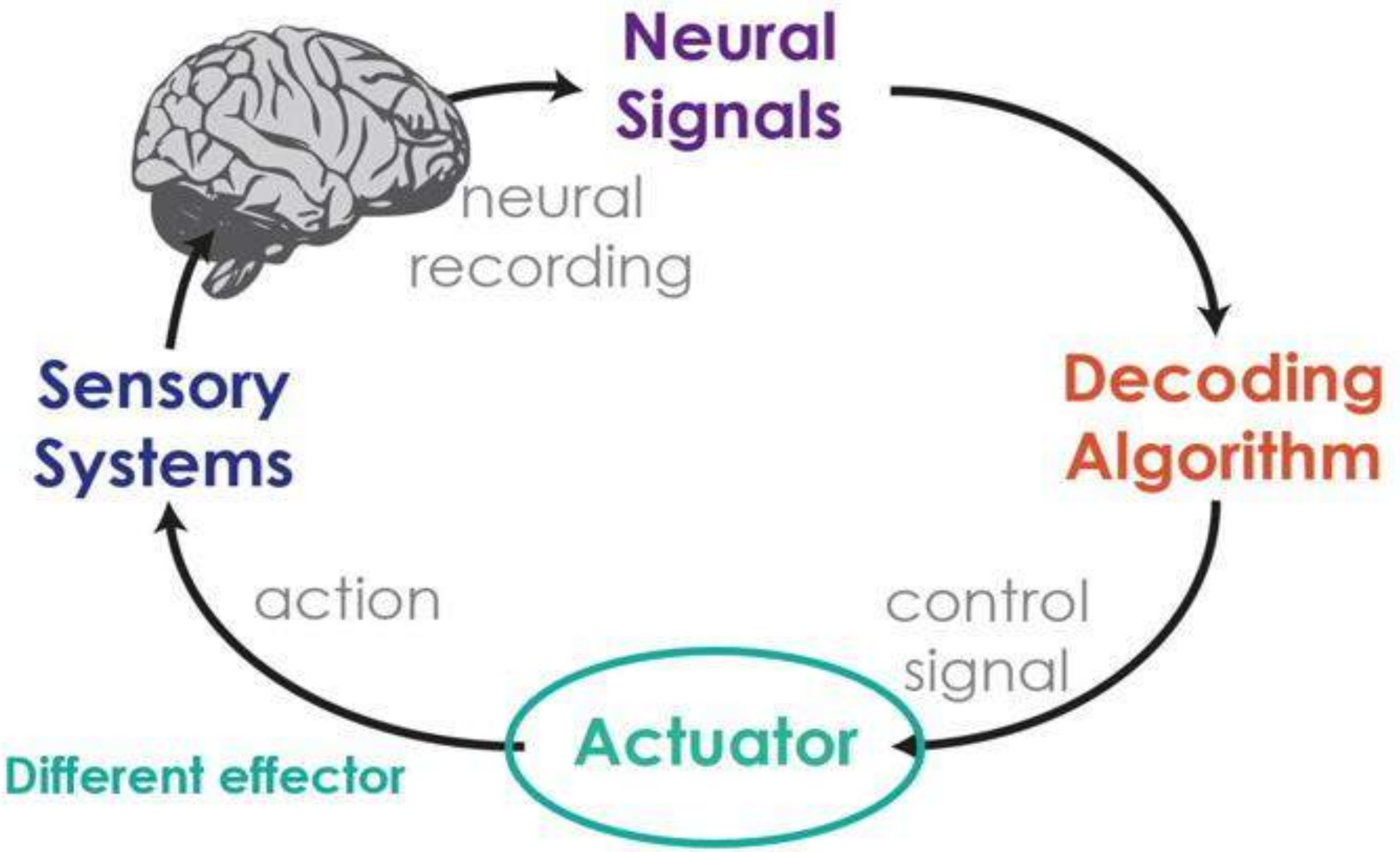


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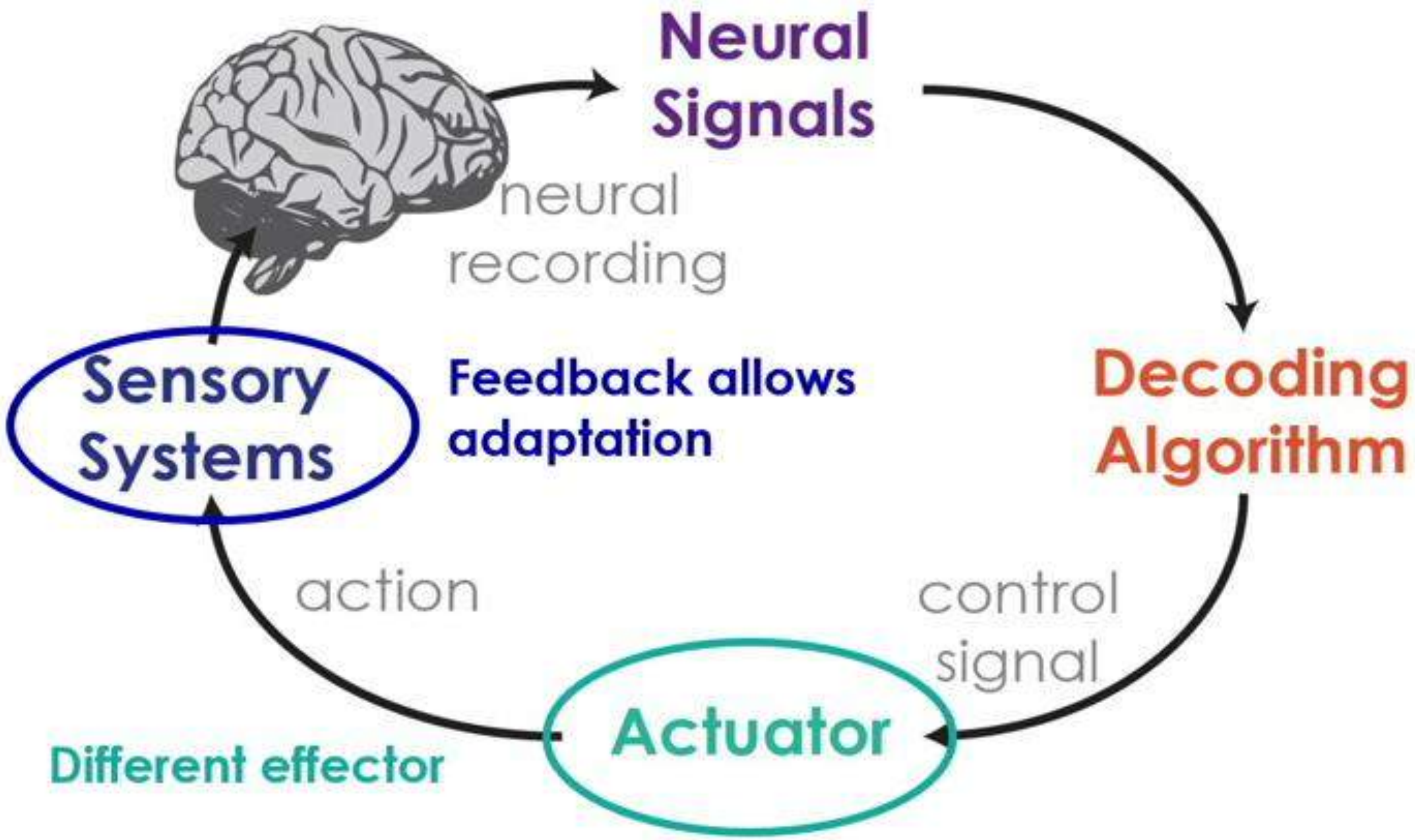


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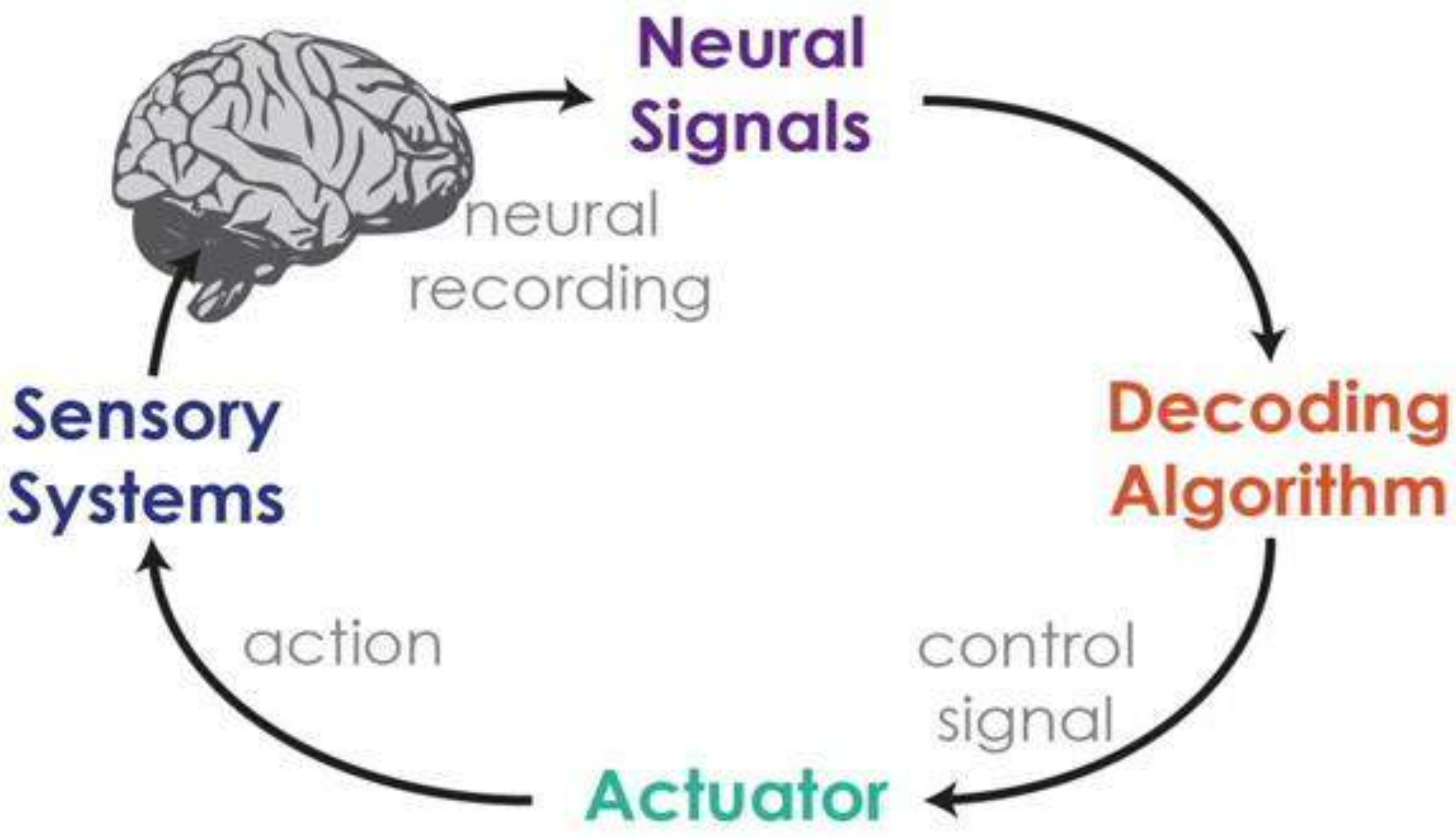
# Closed-loop engineering of learning & control




- Re-engineer BMIs:
  - Optimize learning and control

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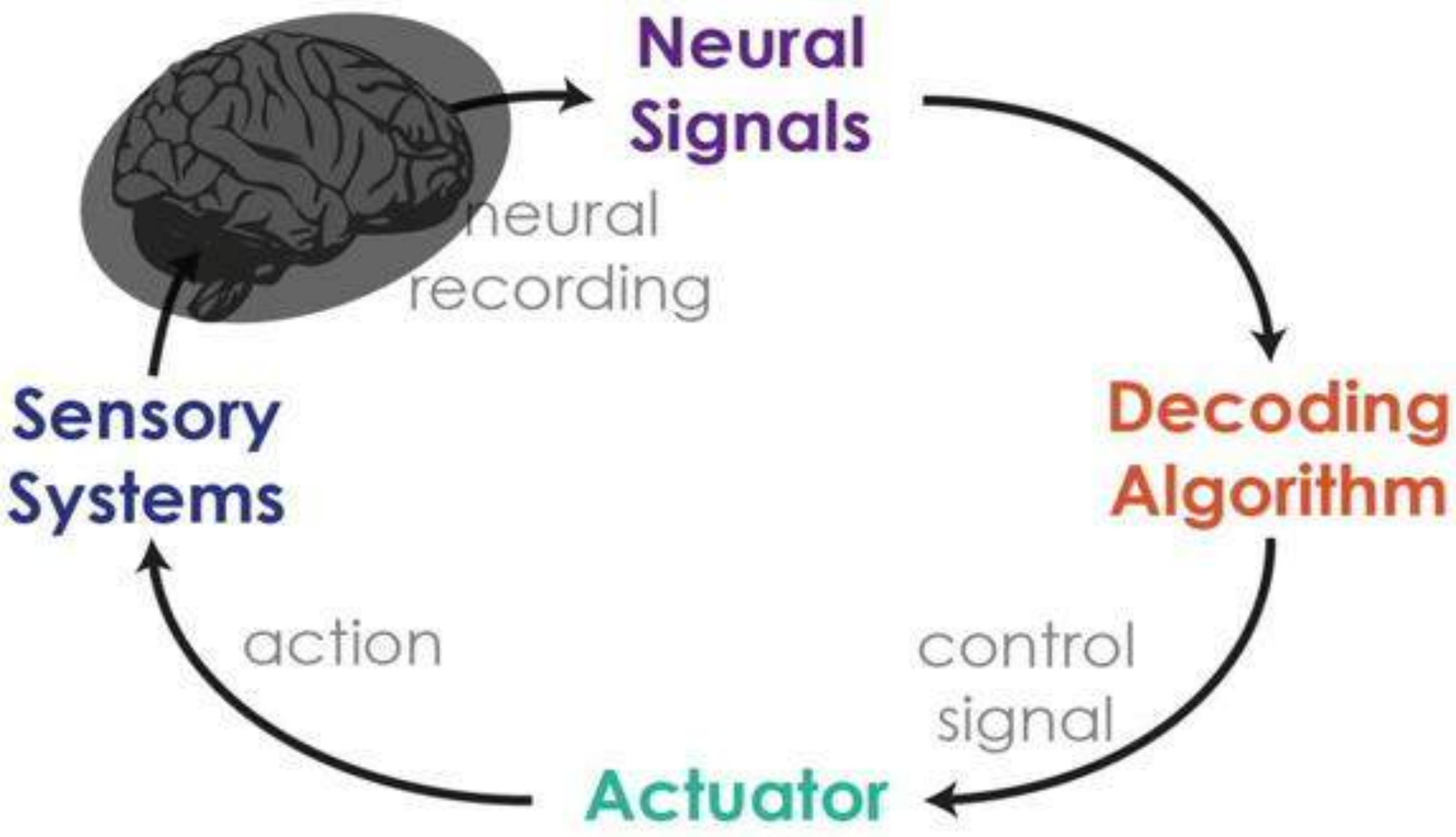


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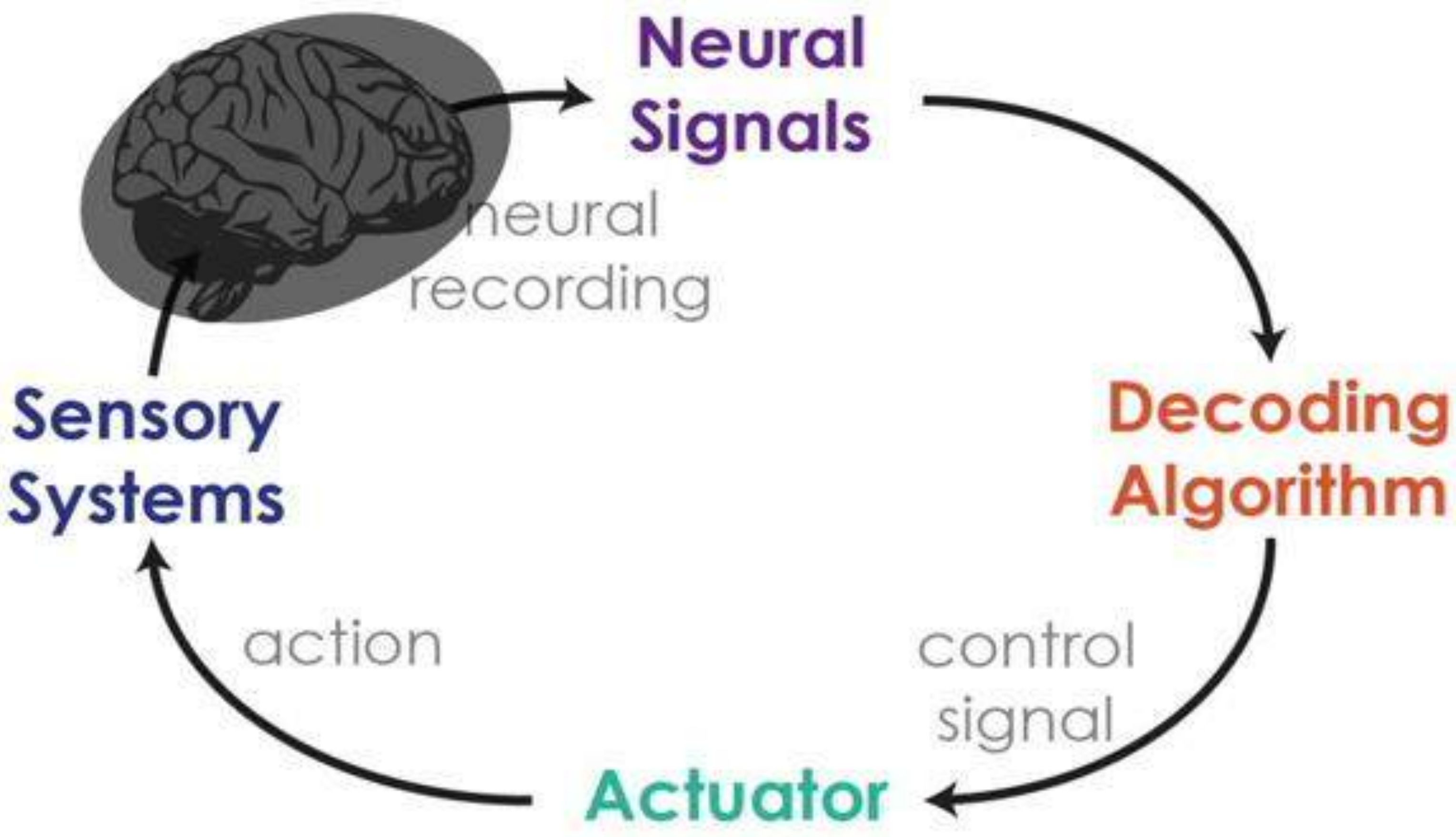


- Re-engineer BMIs:
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- Study learning in BMIs:
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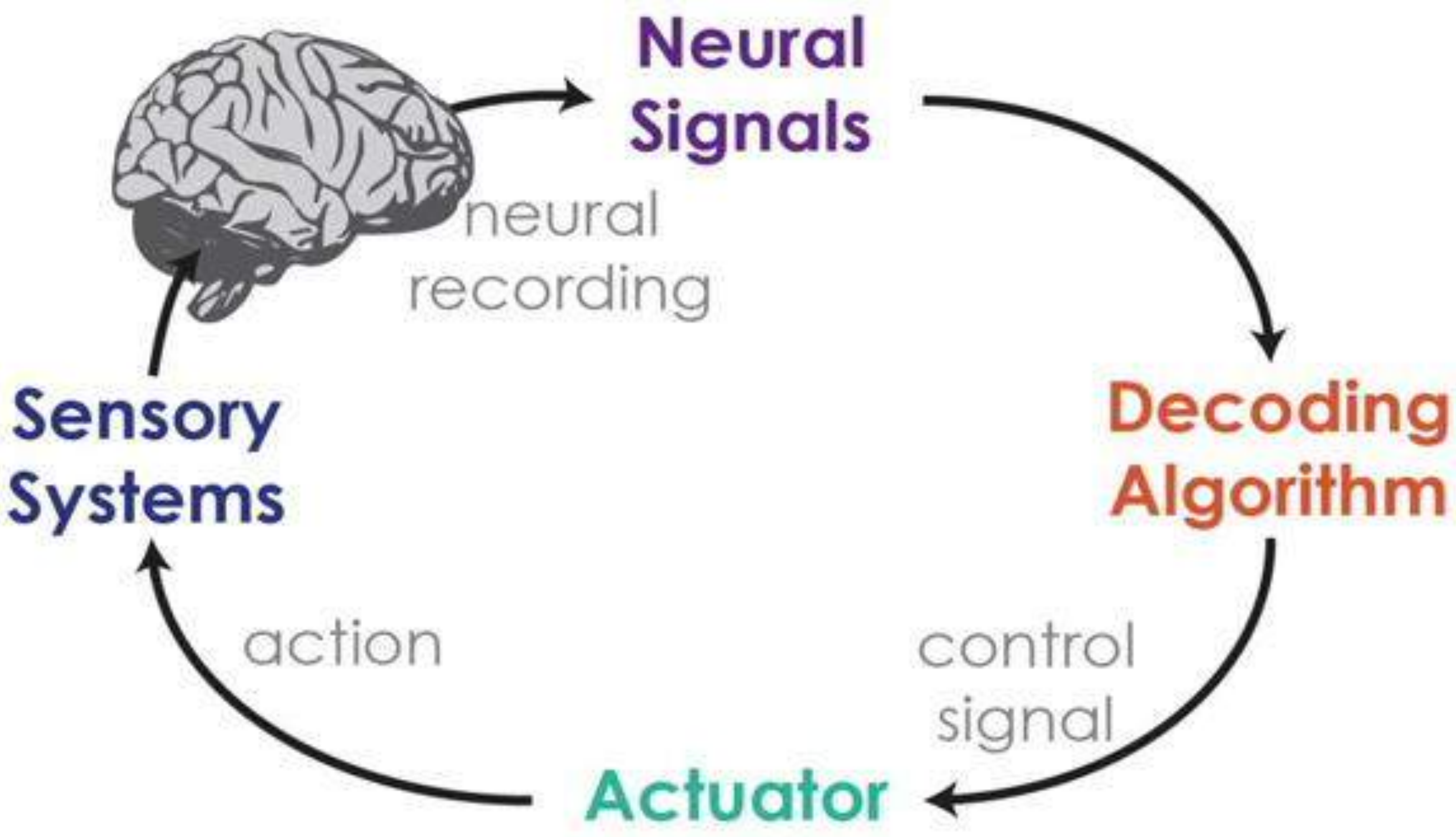


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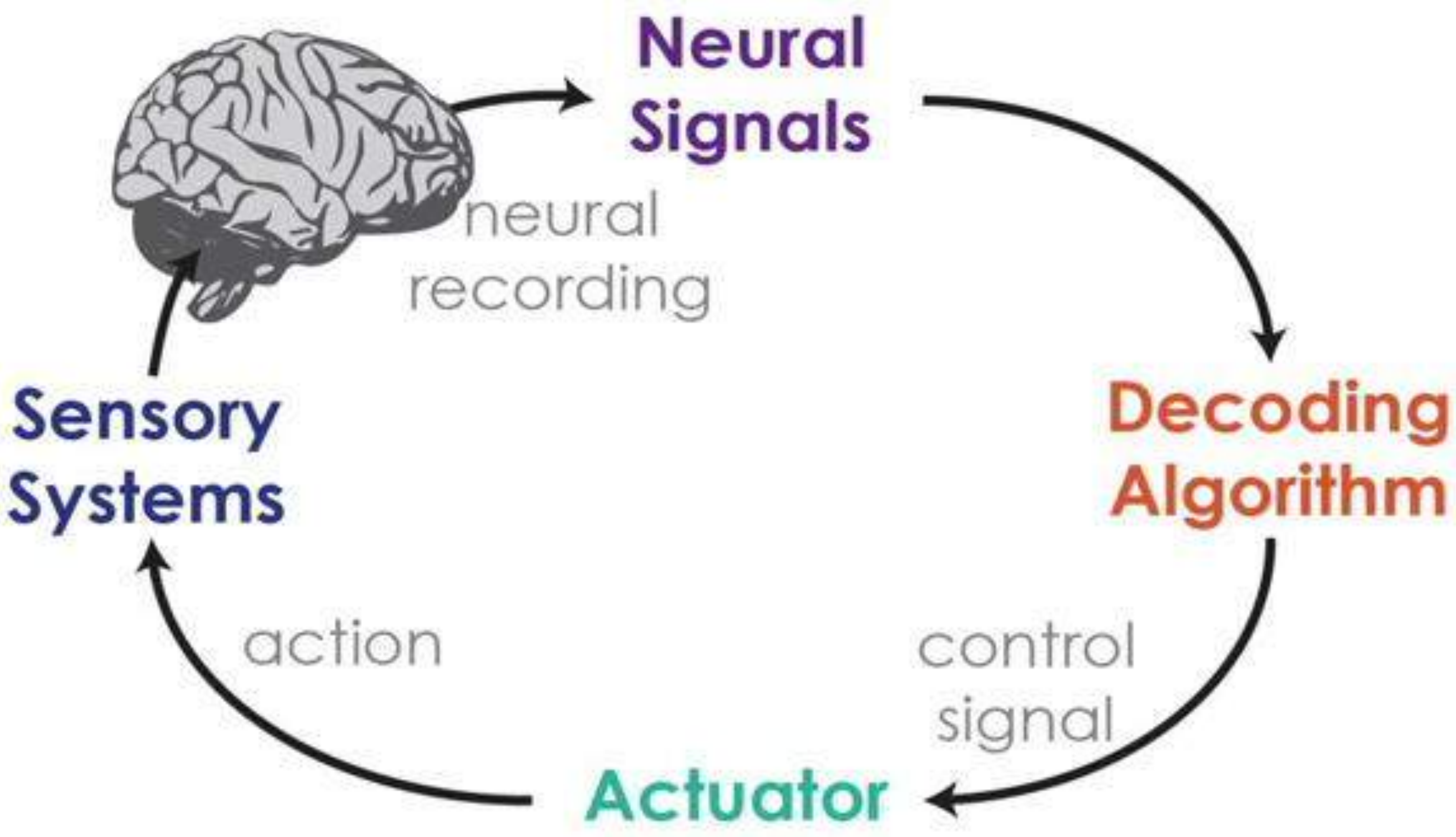


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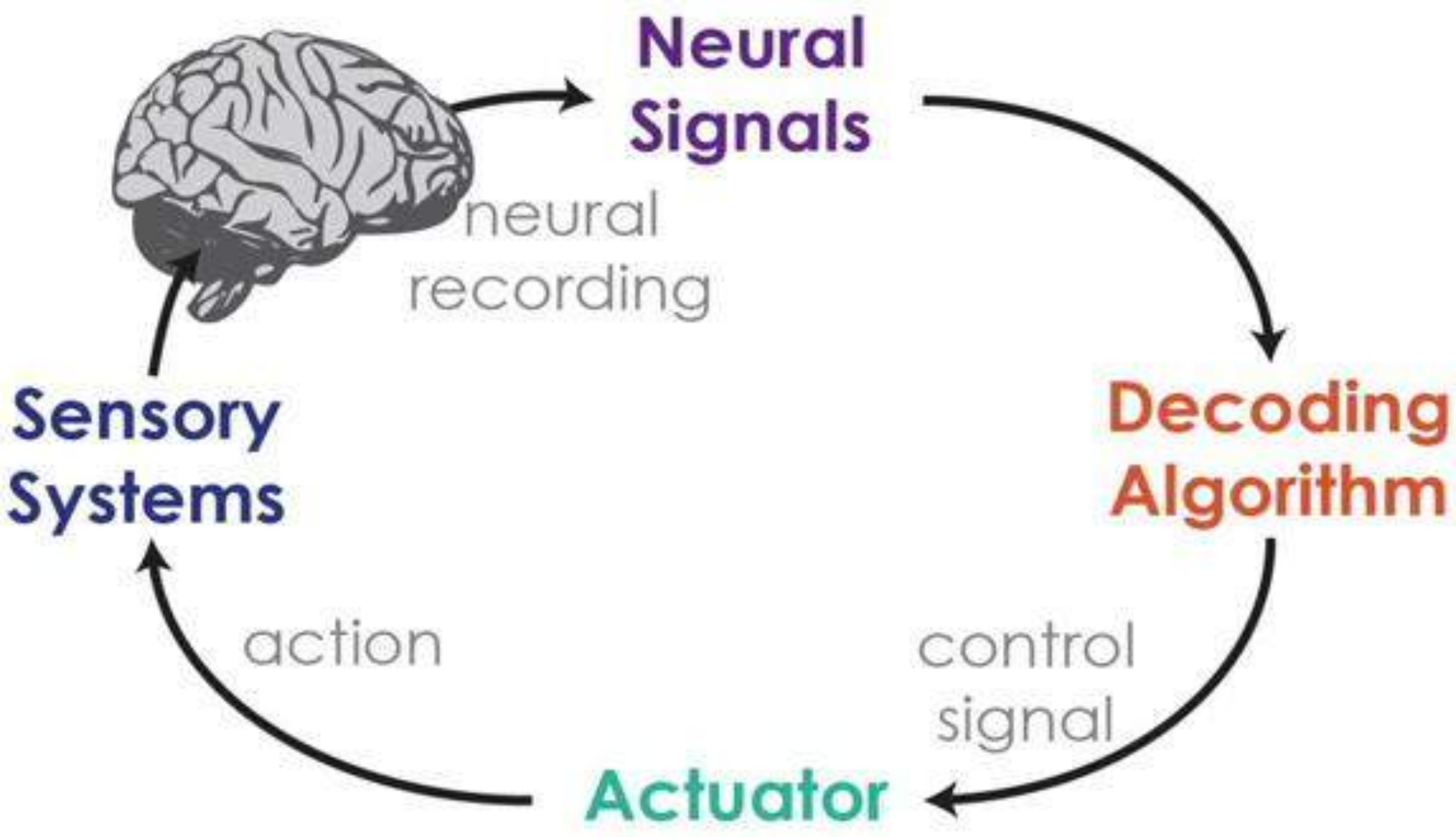


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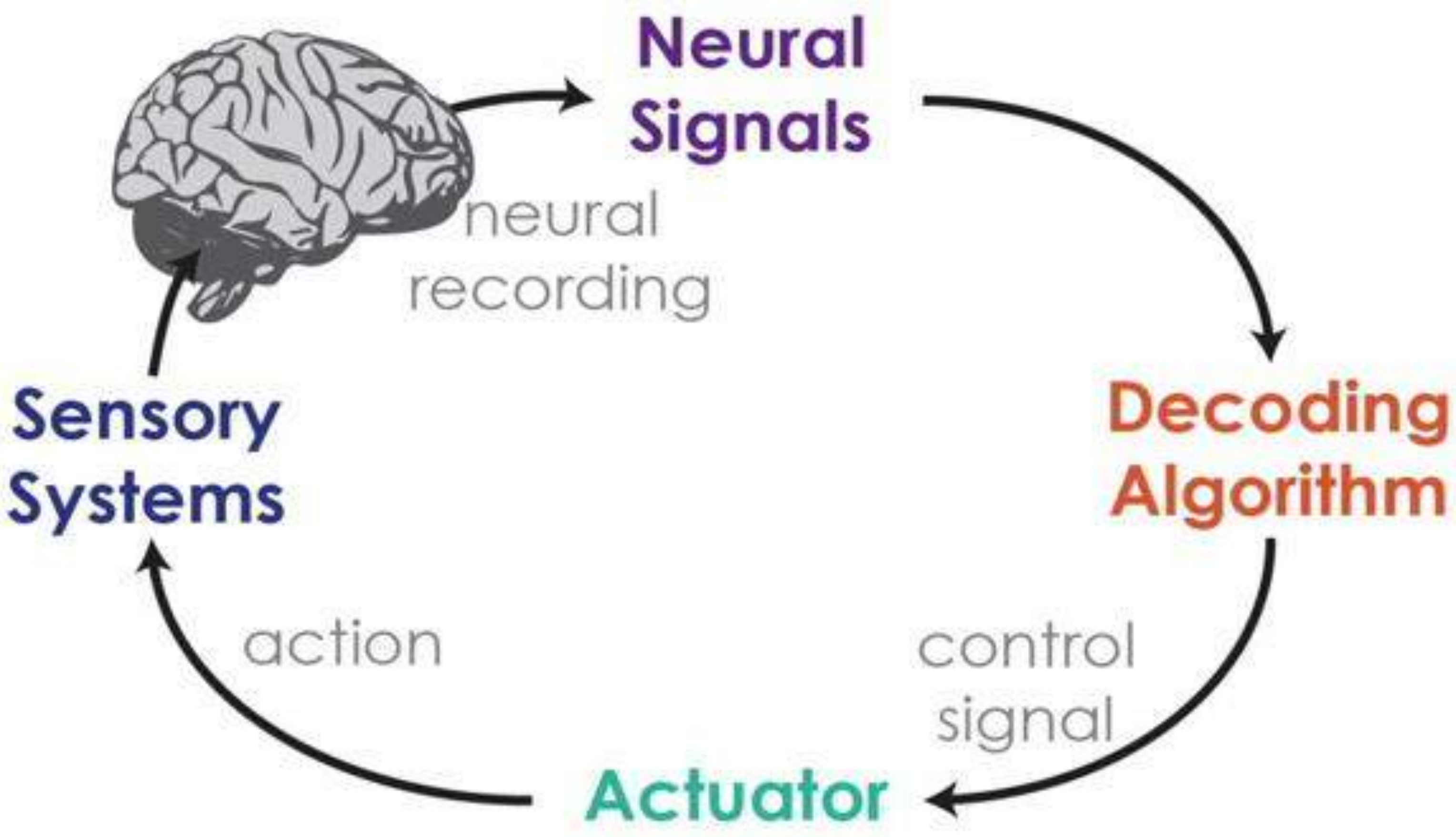


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- Study learning in BMIs:
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- Technology development for interfacing with brain networks

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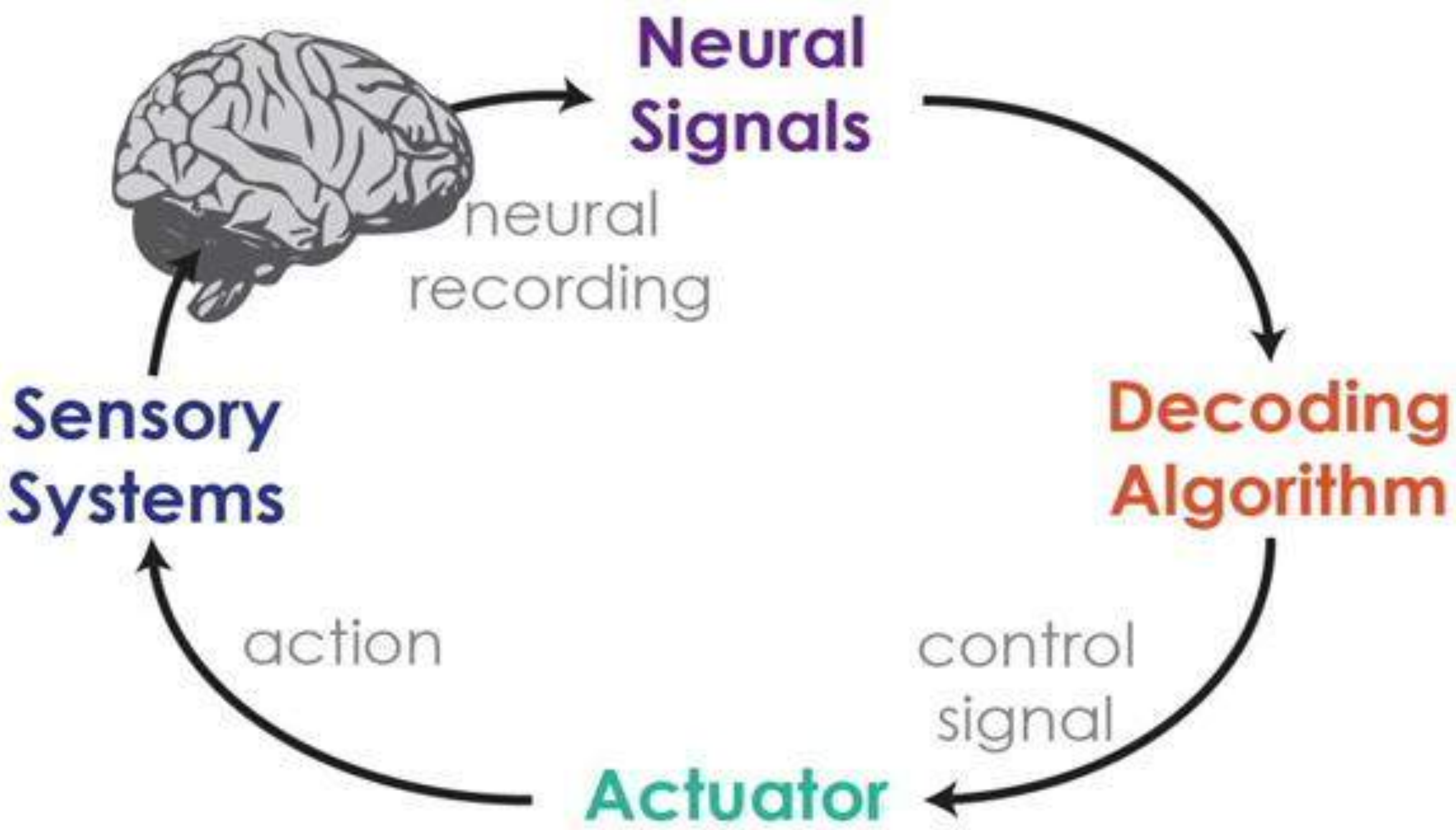


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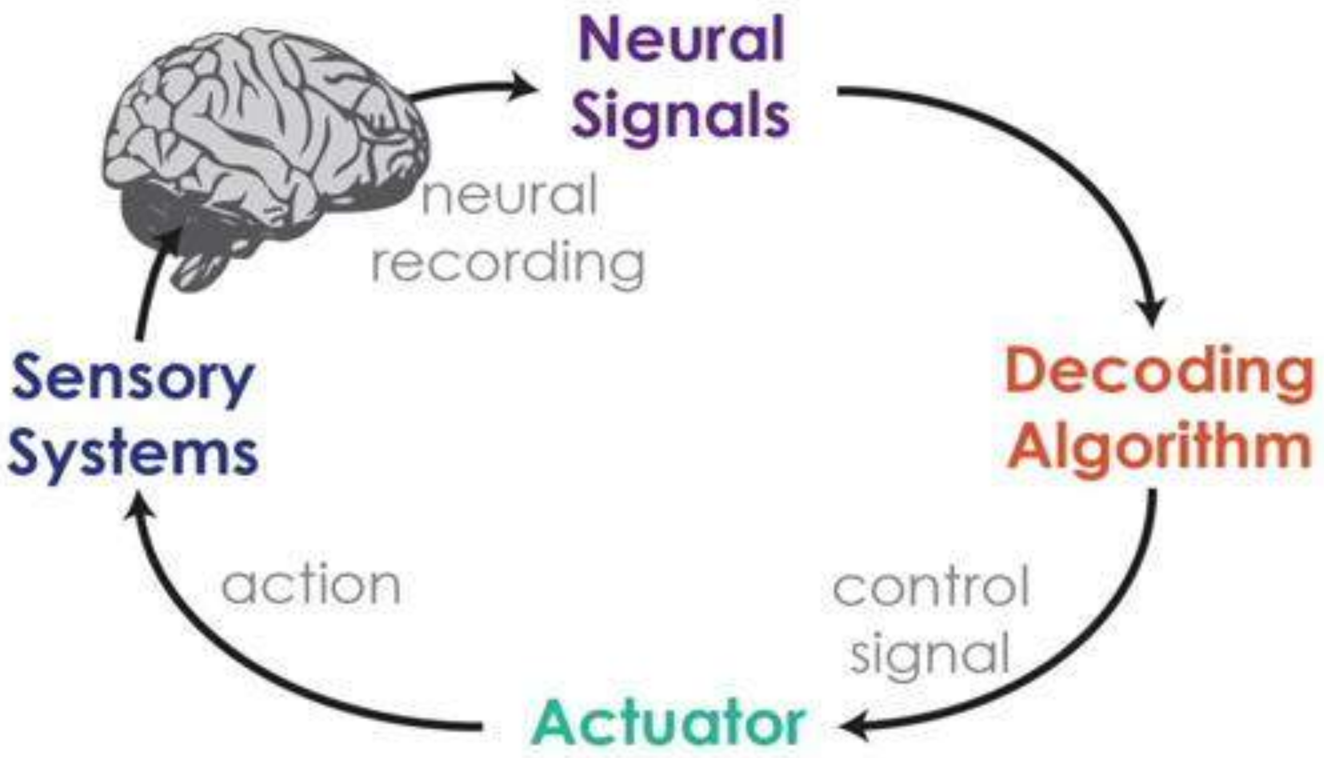
# Pre-clinical research motor BMI paradigm



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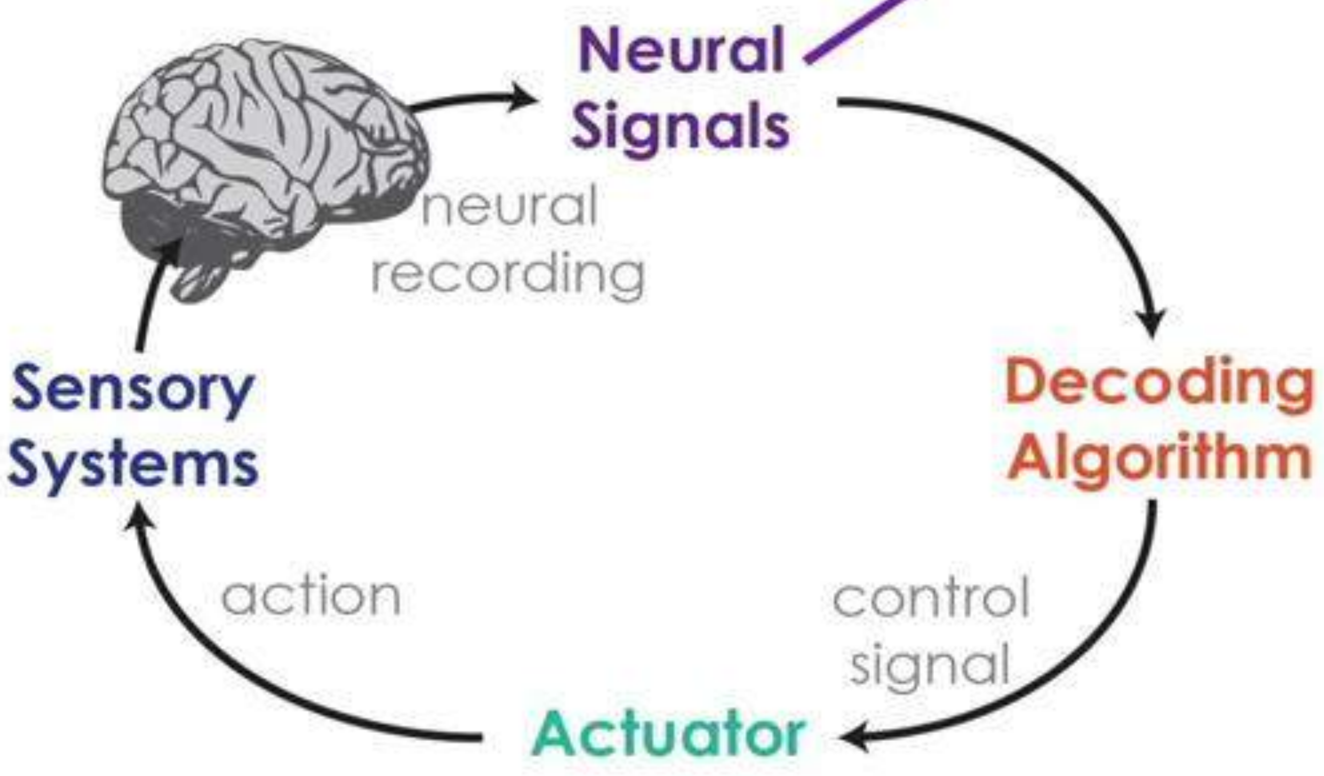


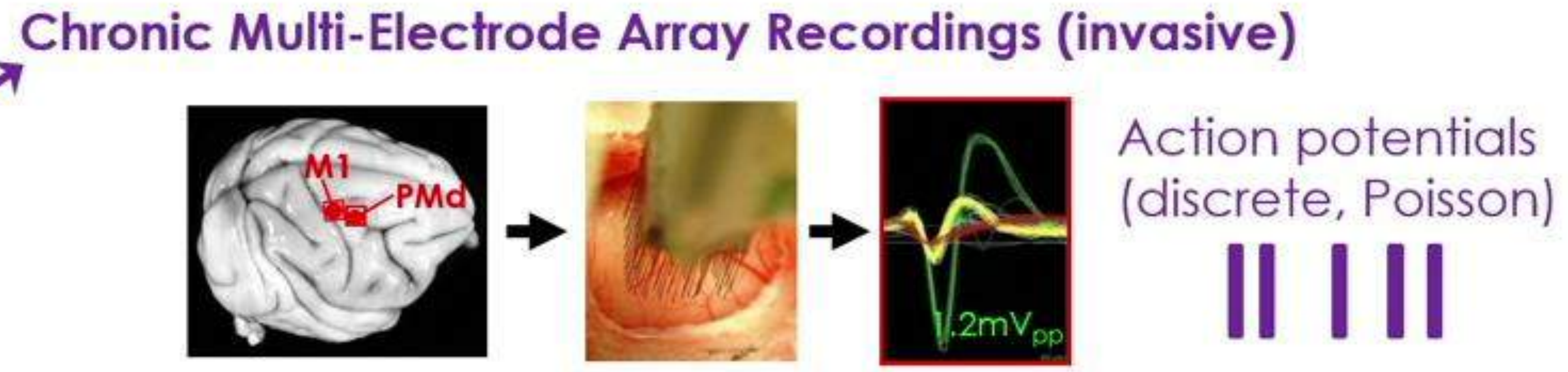

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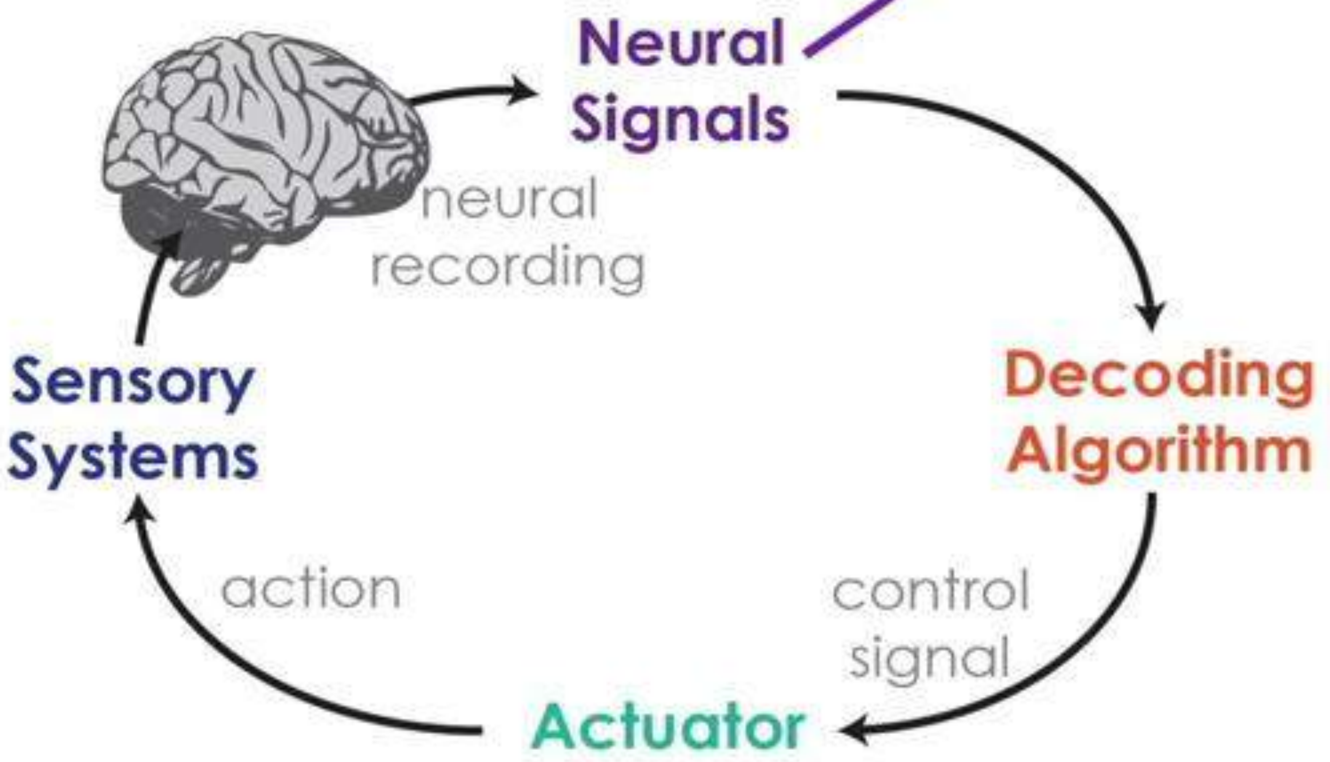
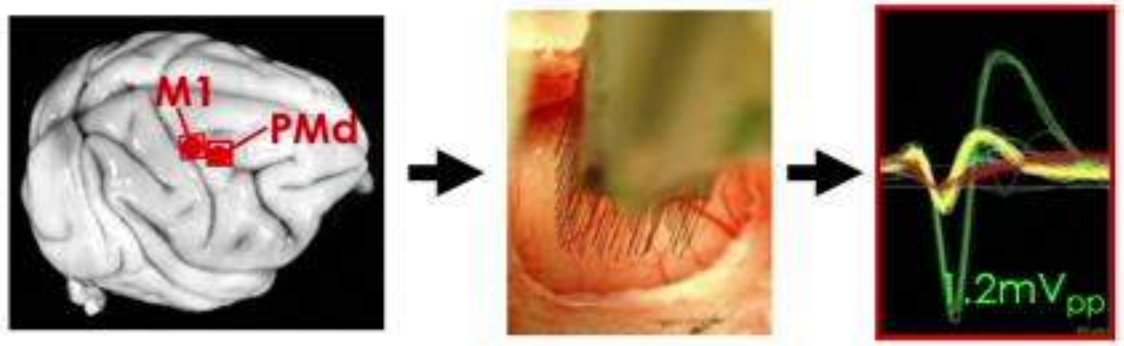



**Chronic Multi-Electrode Array Recordings (invasive)**




Action potentials
(discrete, Poisson)

**Linear filters (e.g. Kalman Filter)**

- **firing rates → kinematics**
- **20-30 neurons**

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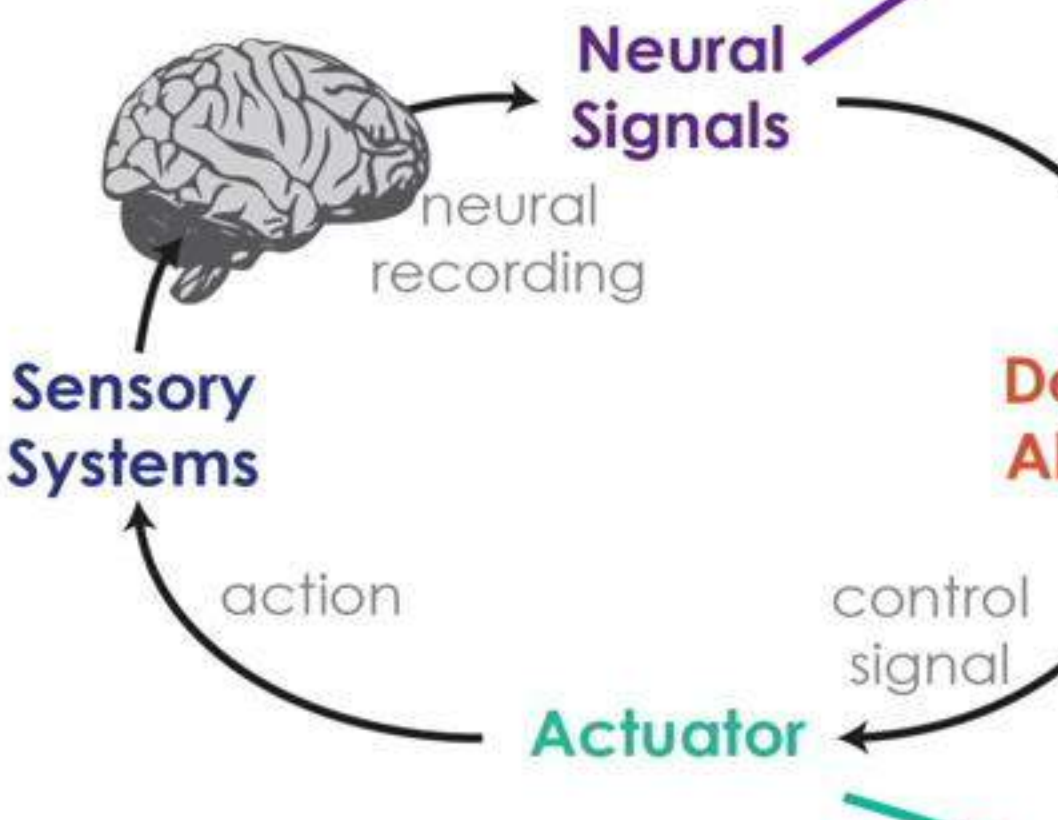


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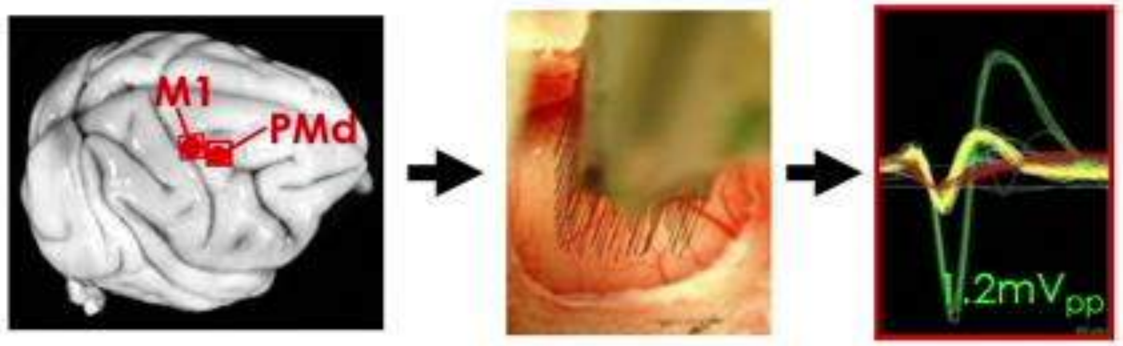


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- **firing rates → kinematics**
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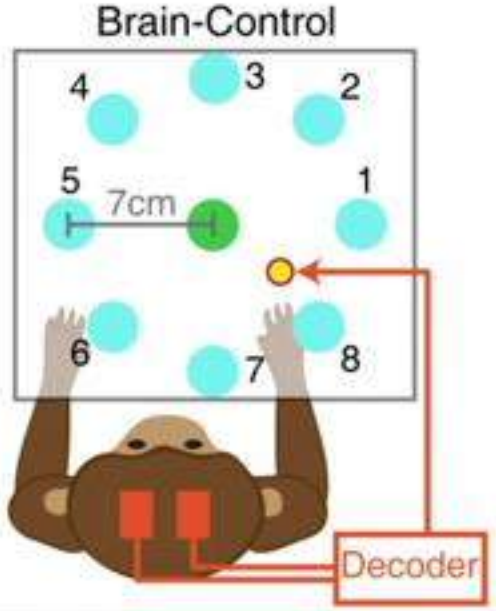
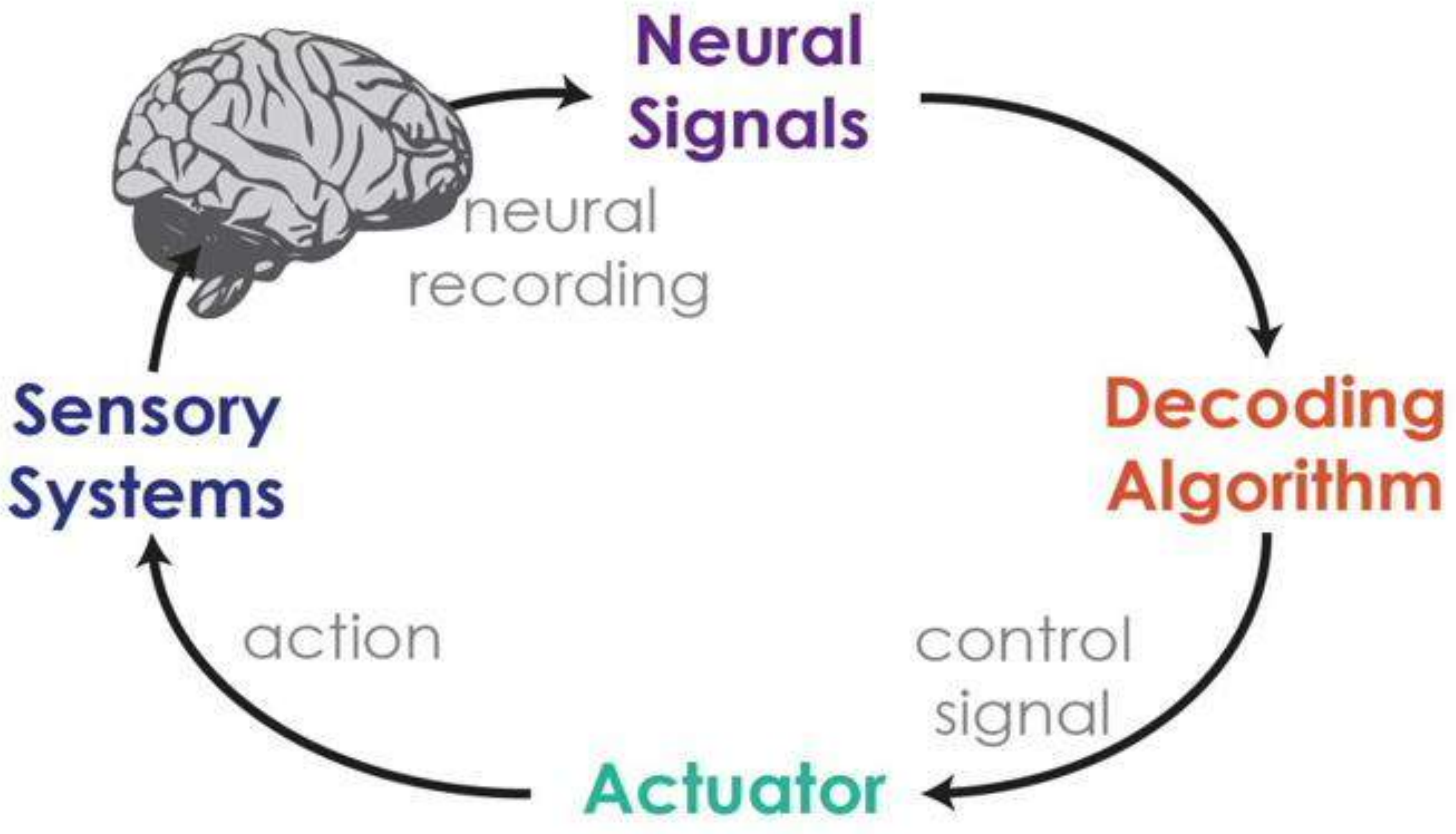
**2D Cursor control without overt movements,**

**Visual feedback**



# "Loop design" to optimize control



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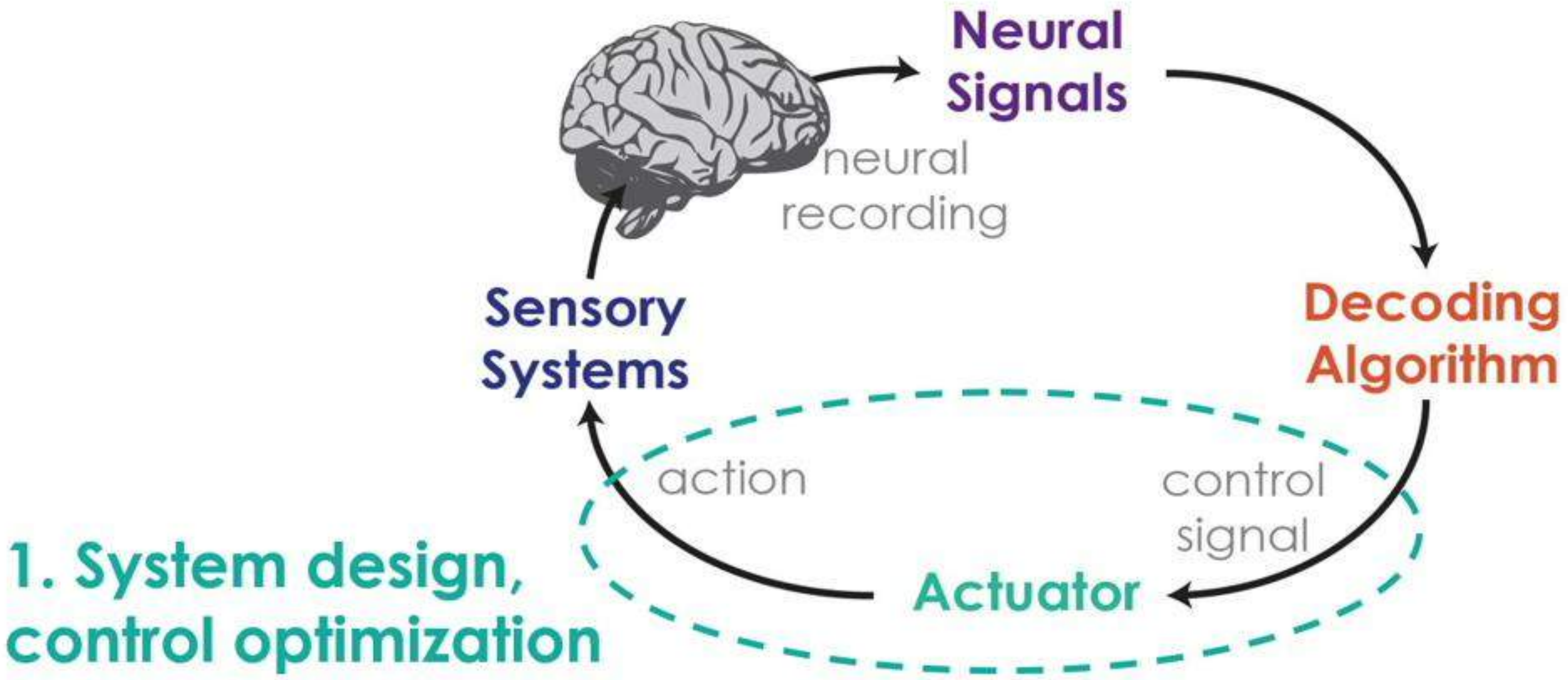

# Do control loop rates influence performance?

Shanechi*, Orsborn*, Moorman*, Gowda* et al., *Nature Comms 2017*

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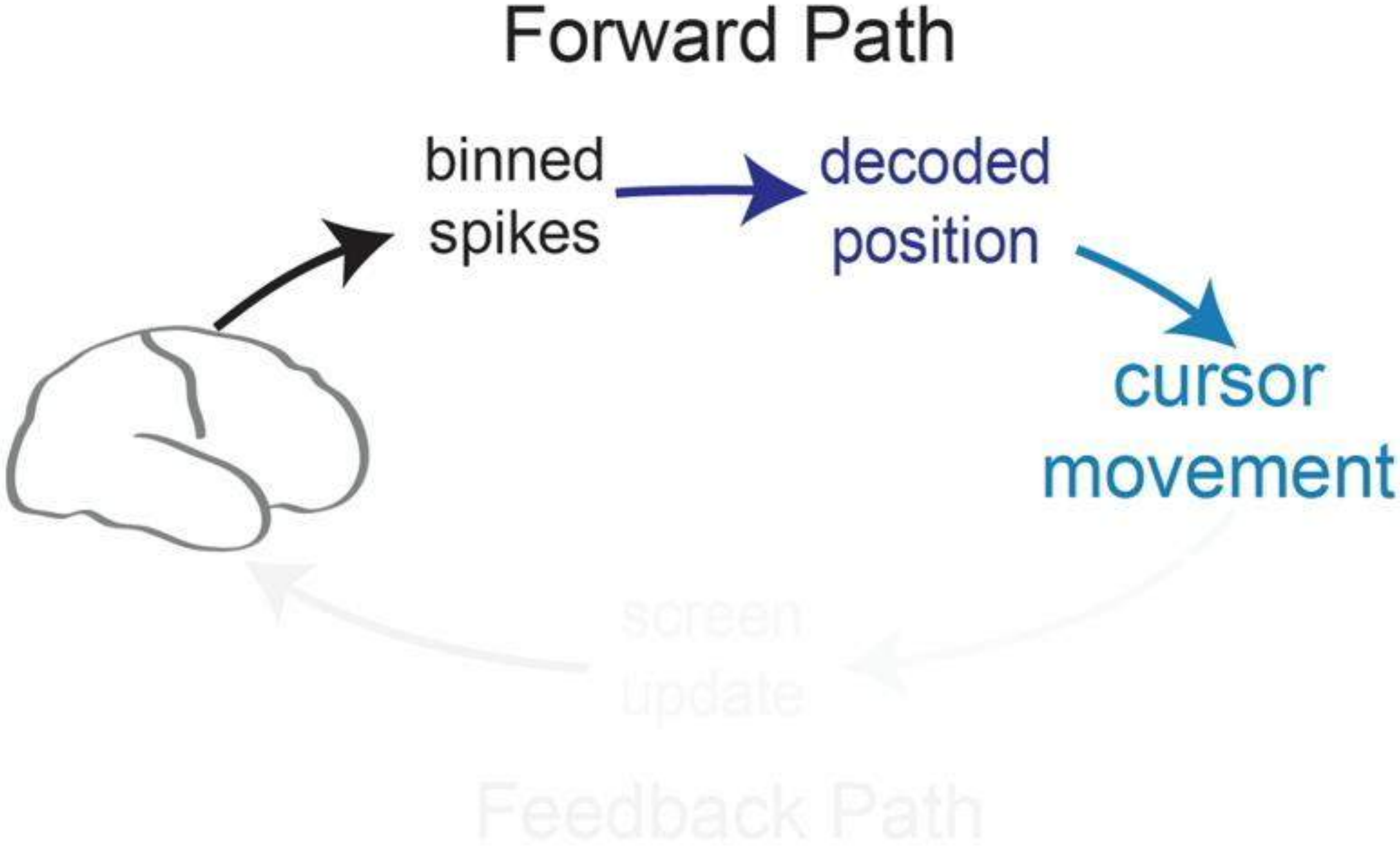


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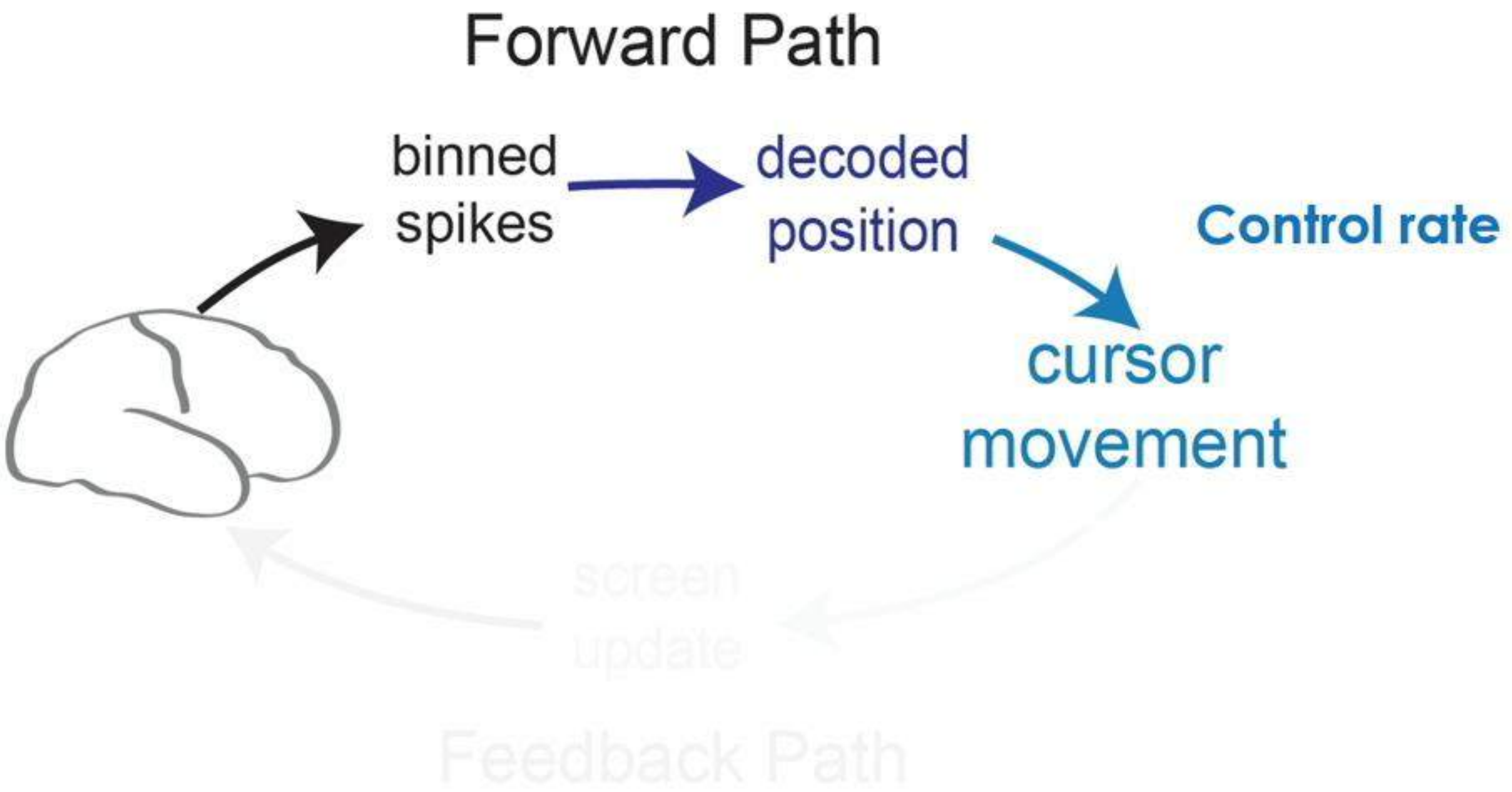


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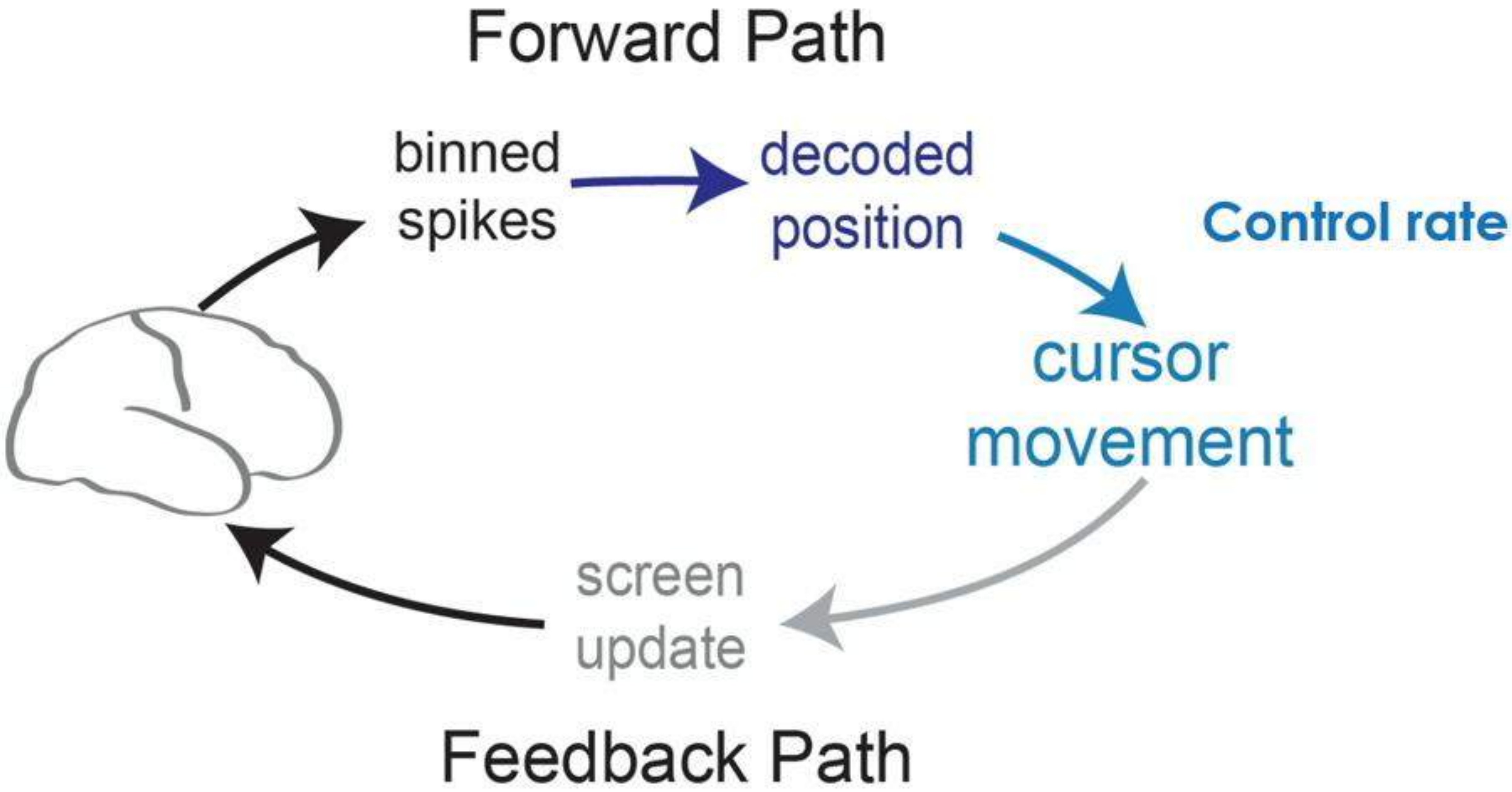


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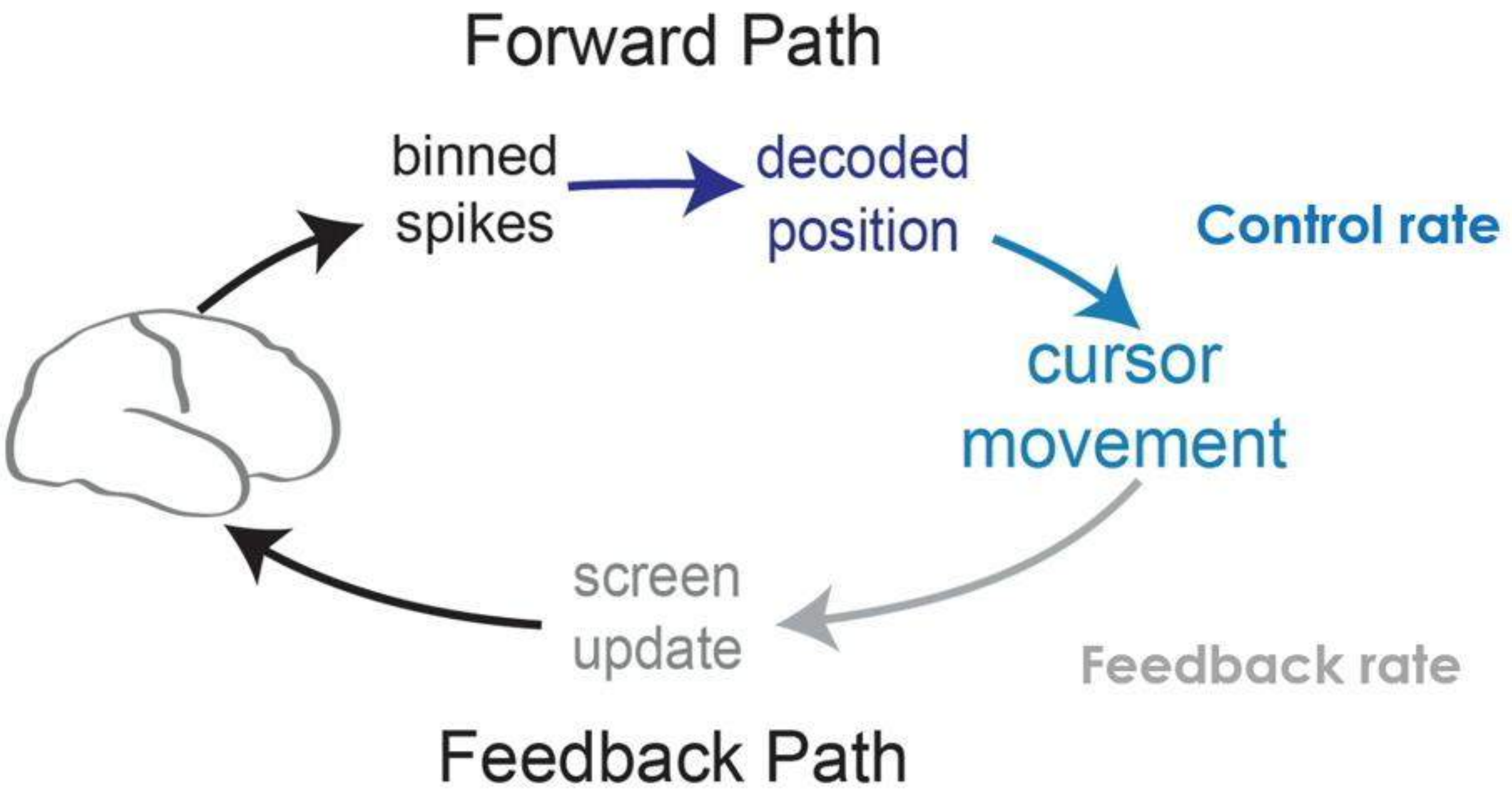


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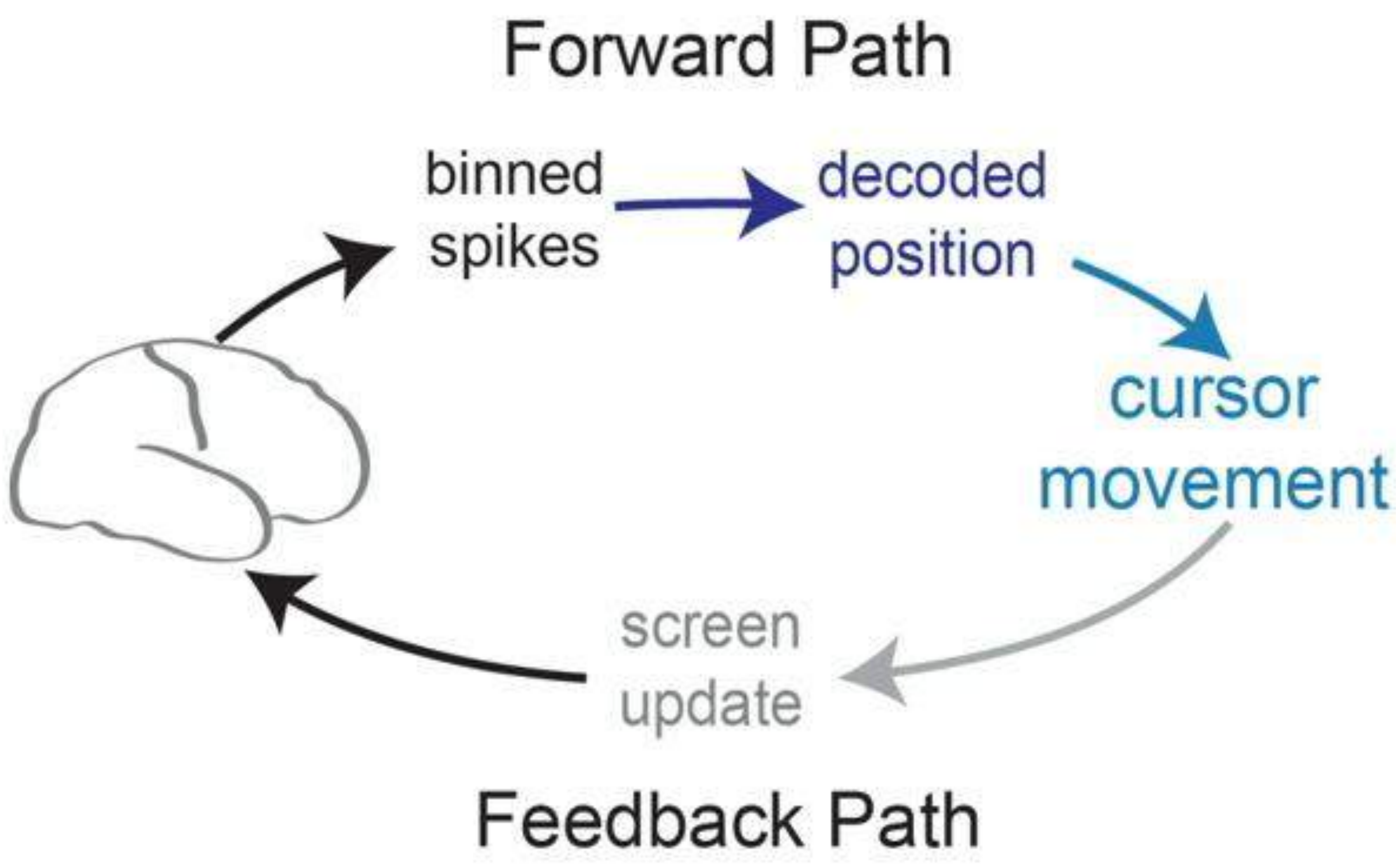


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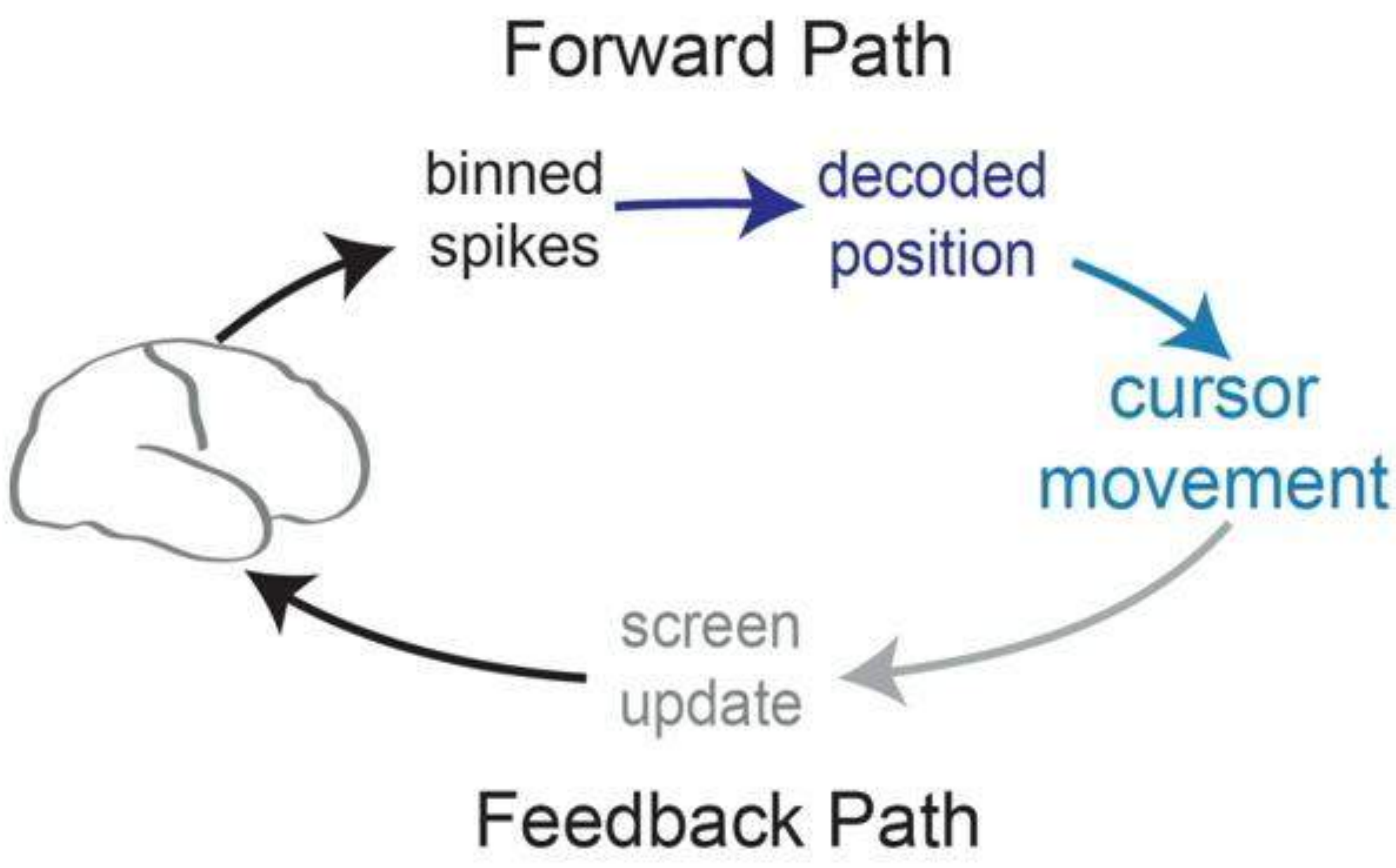
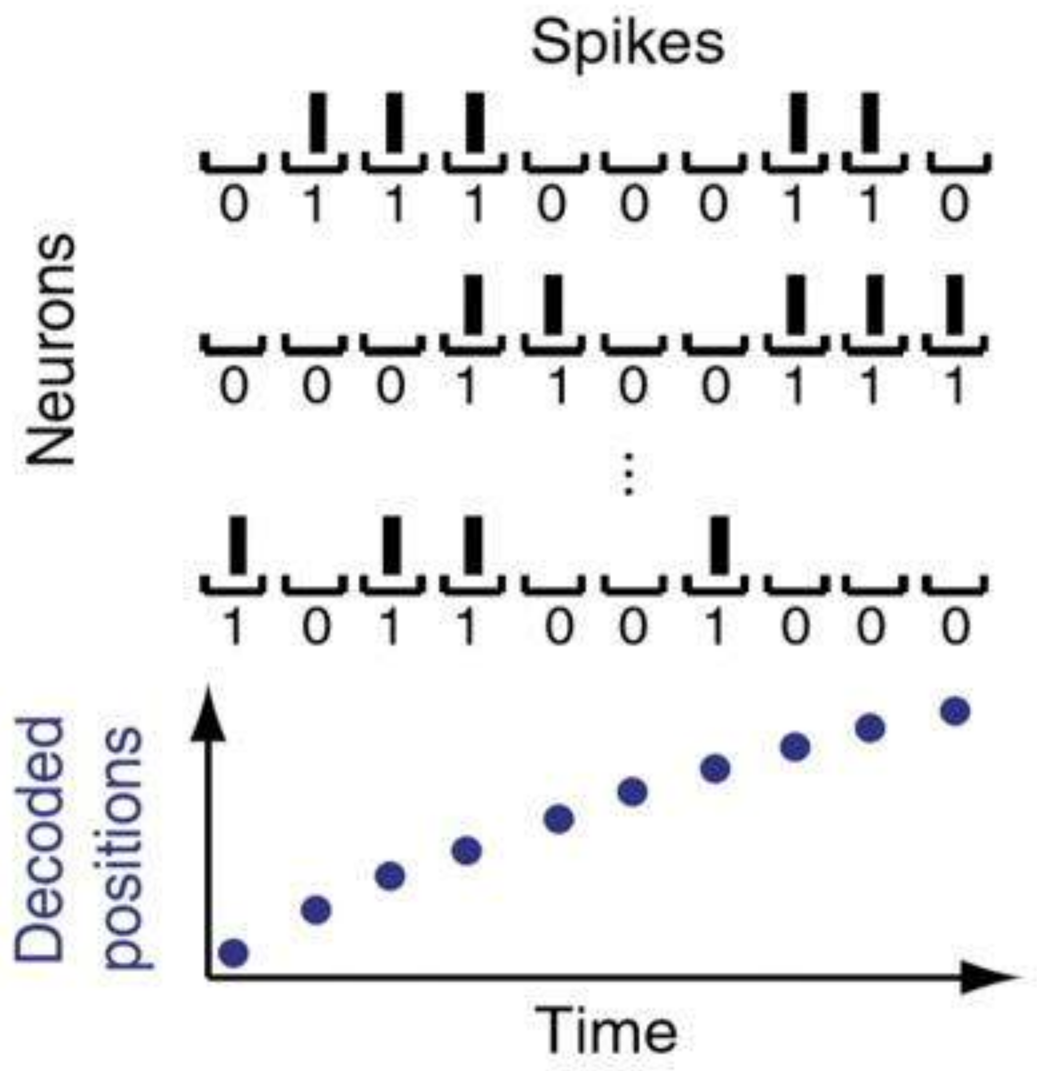



Rate-independent point-process filter (PPF)

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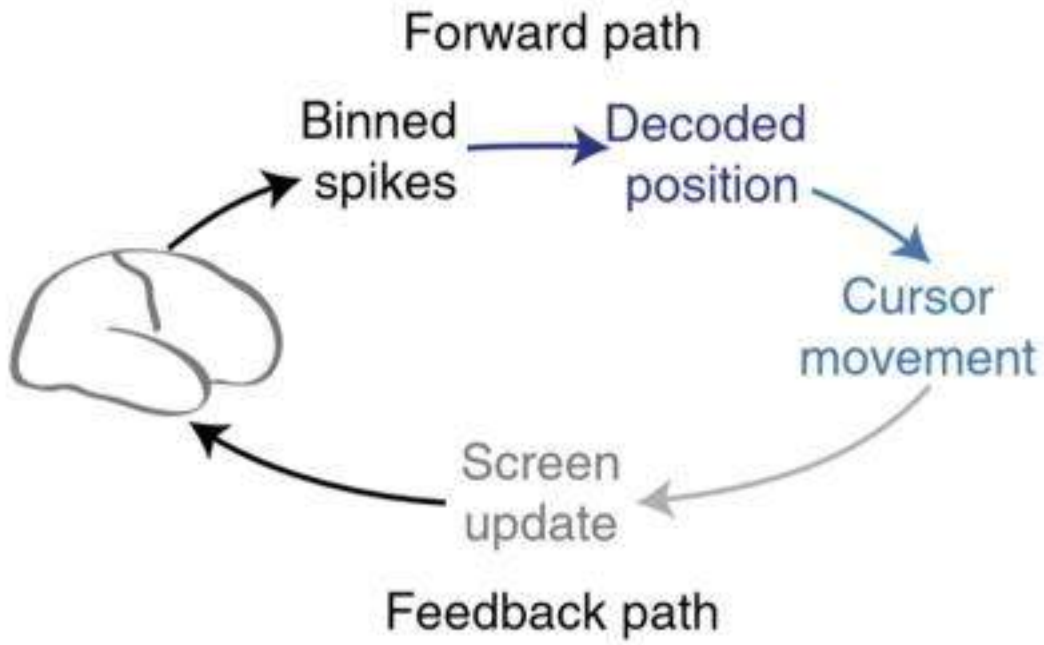
# Loop rate manipulations



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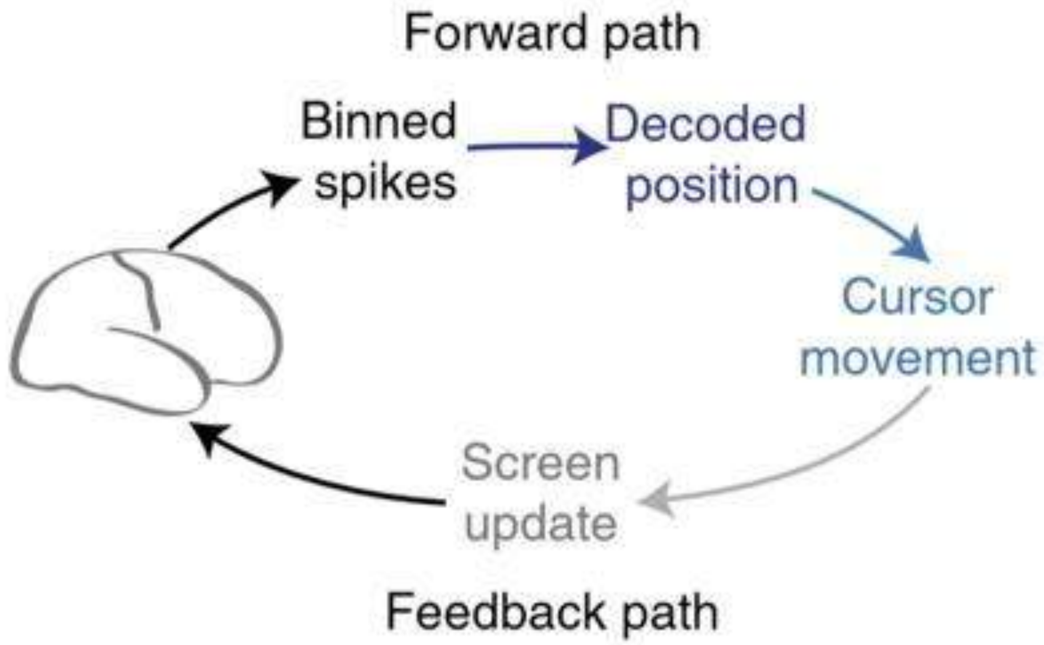


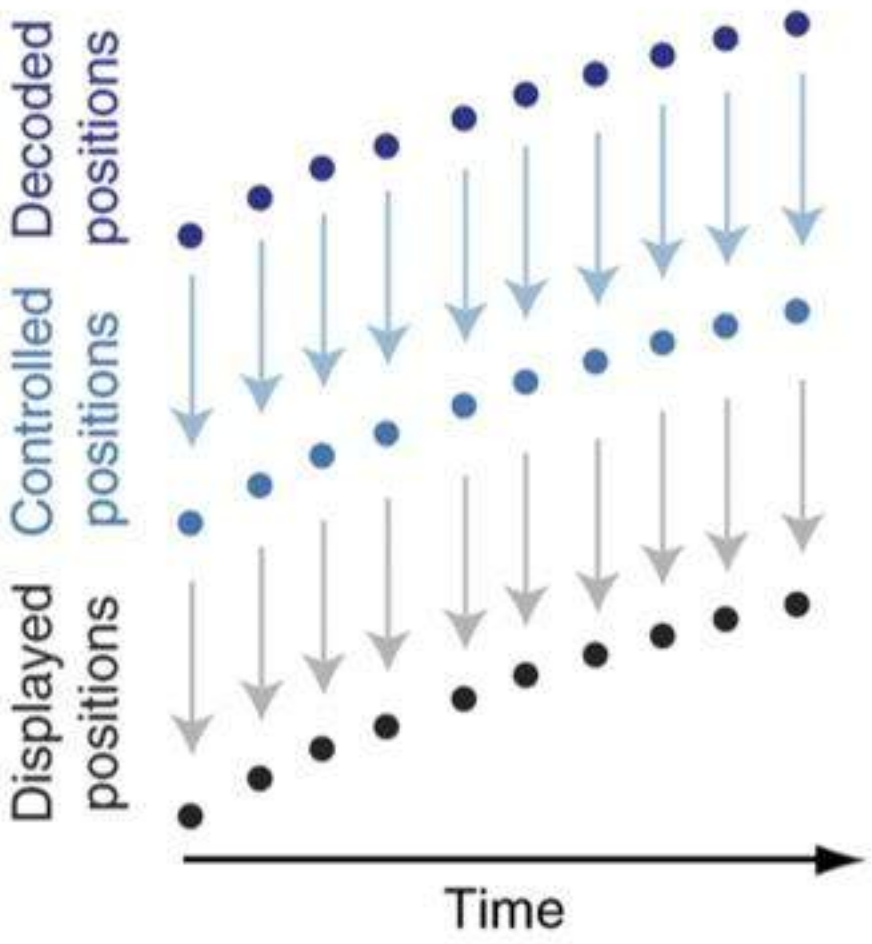

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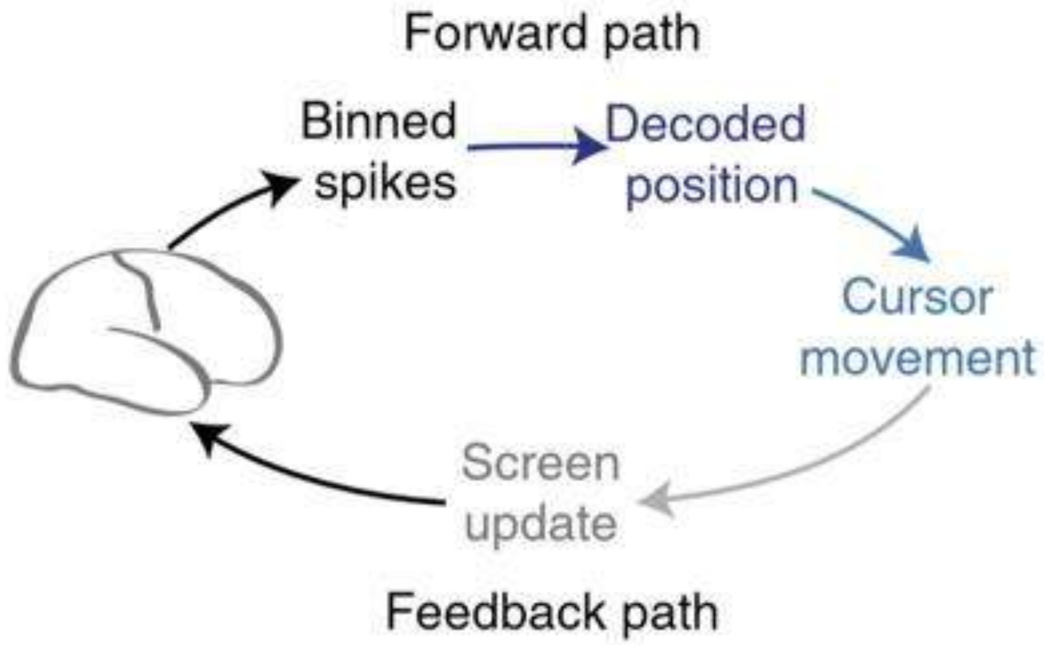
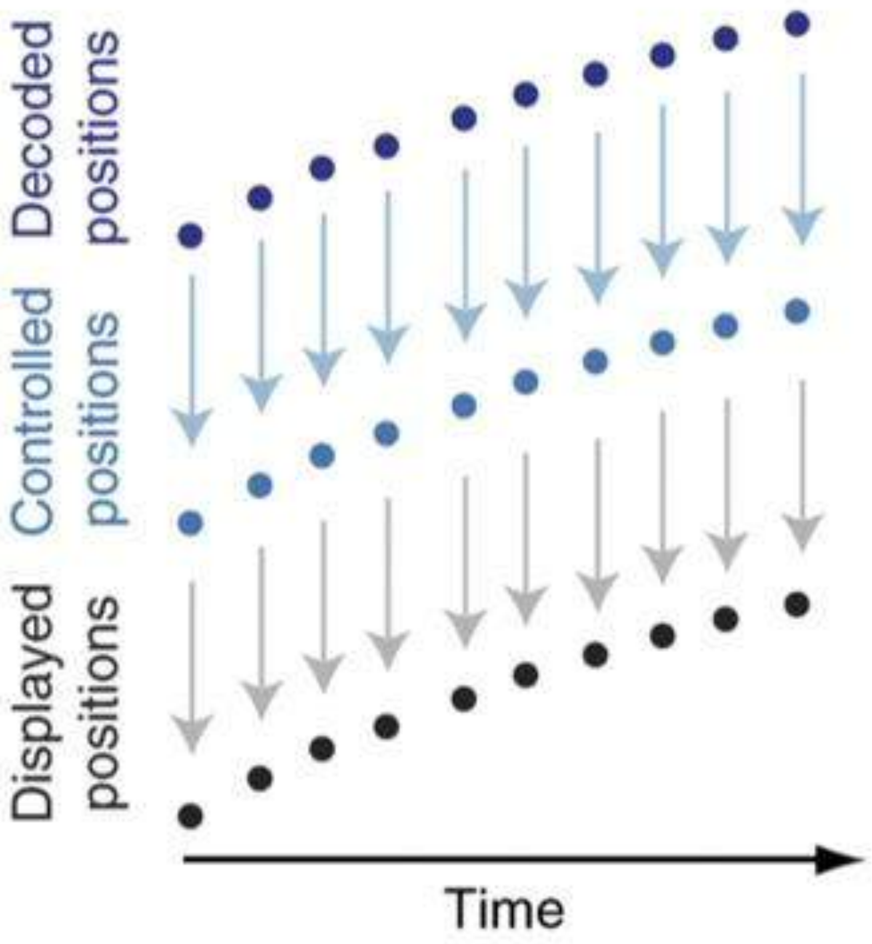



Fast control, Fast feedback



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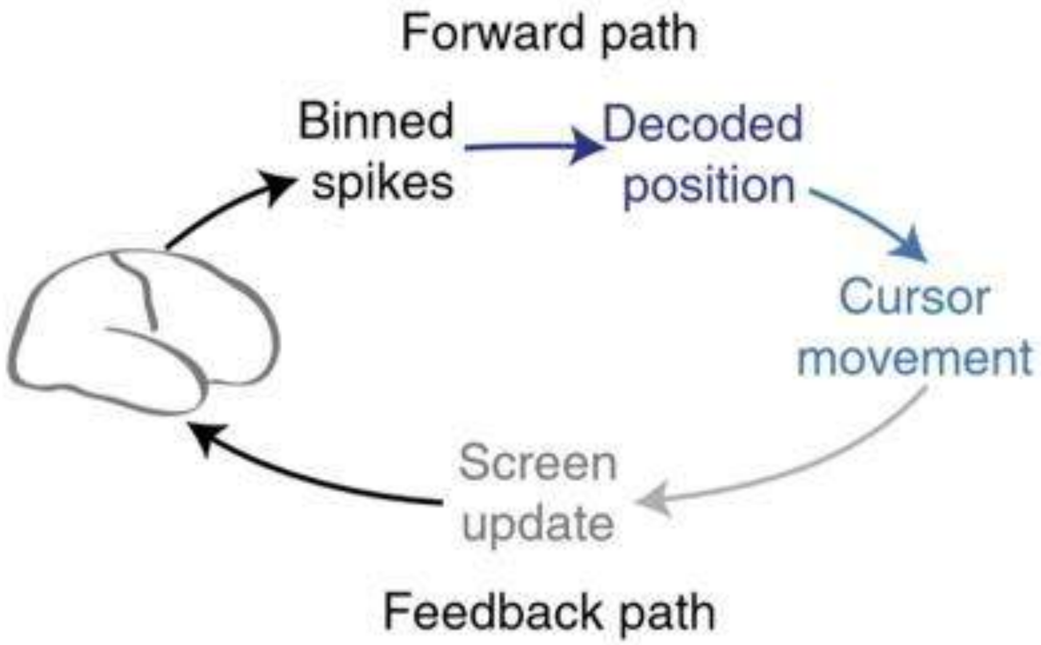


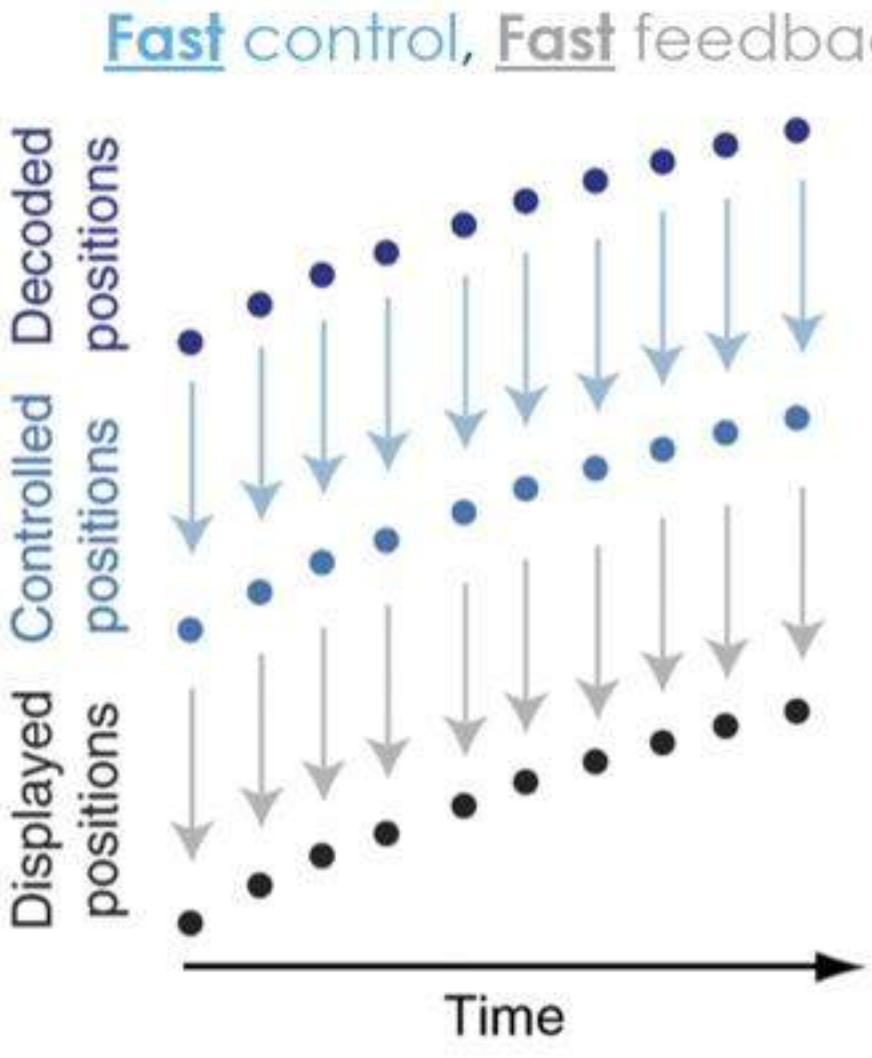


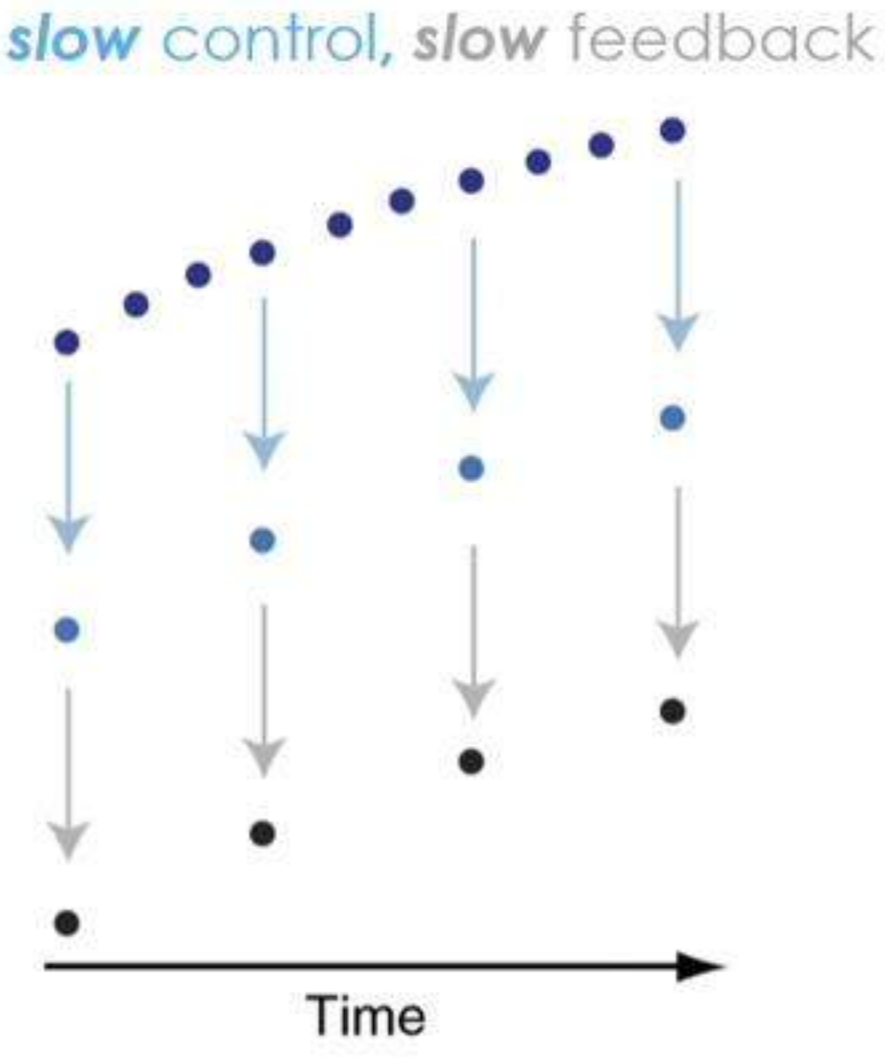

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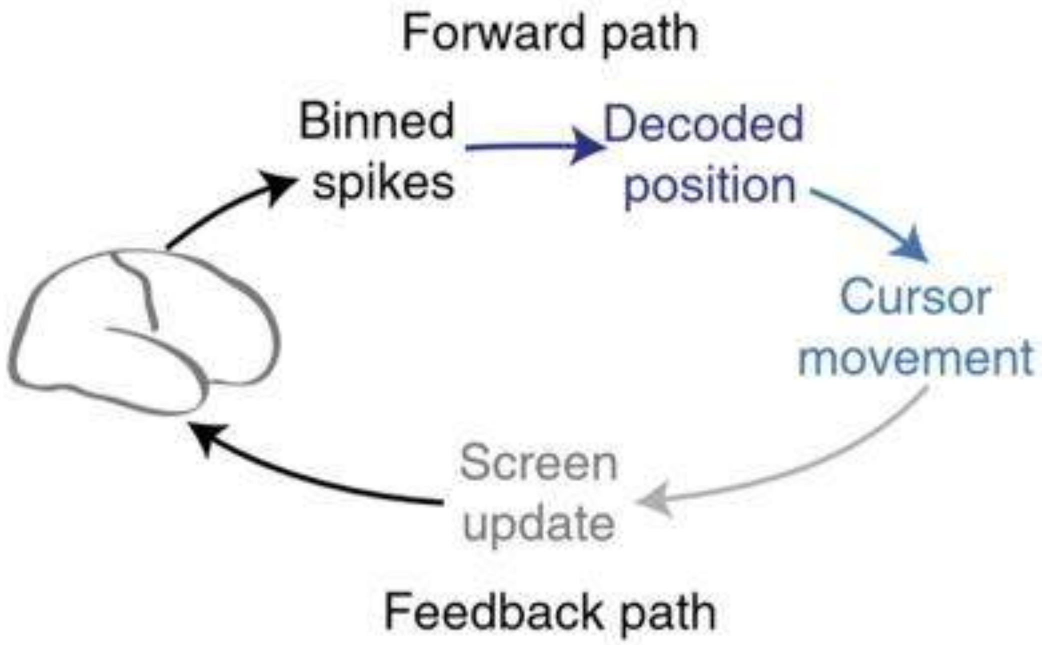


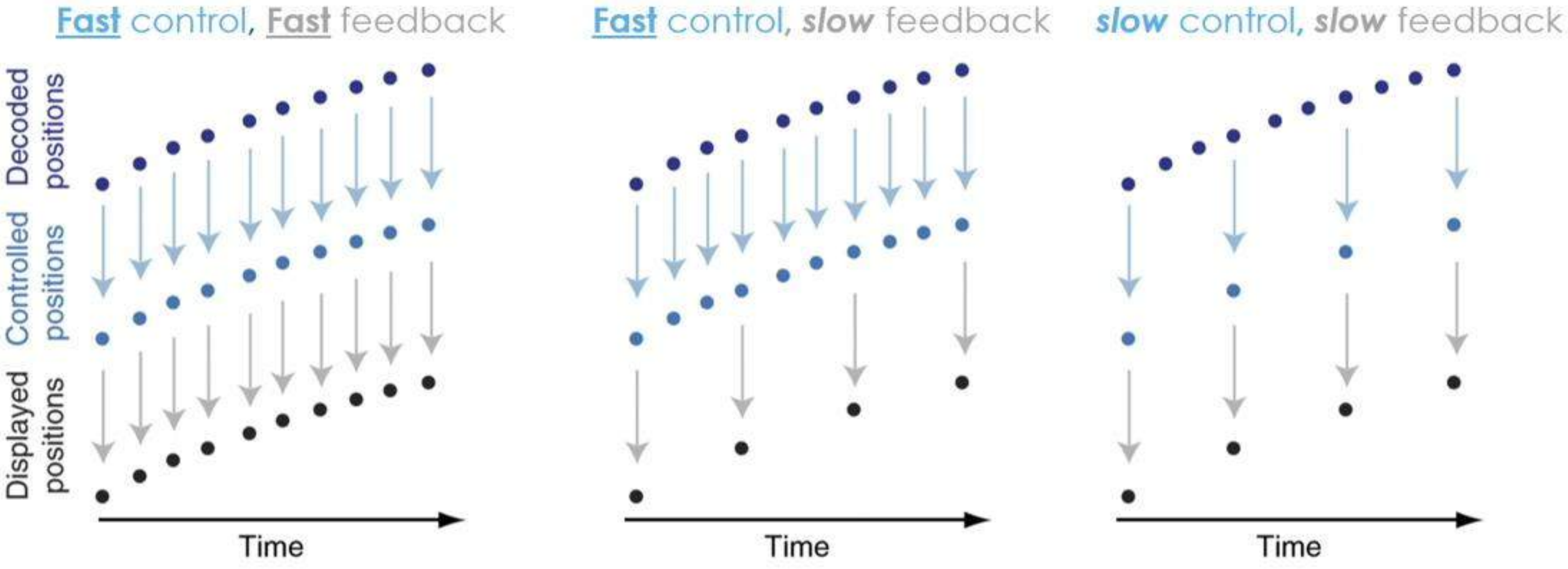

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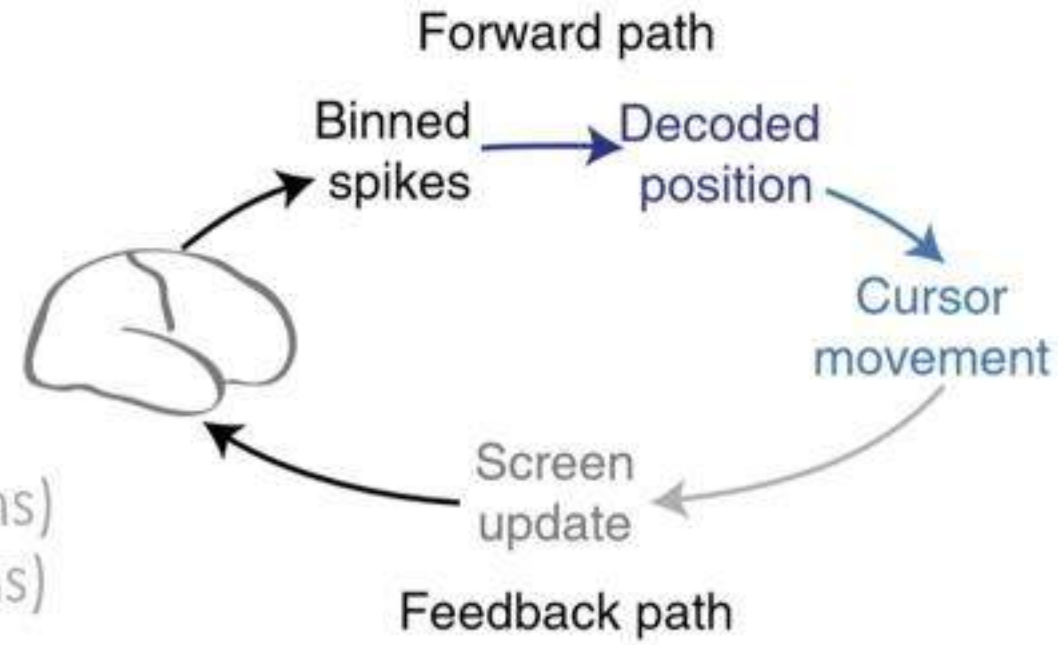
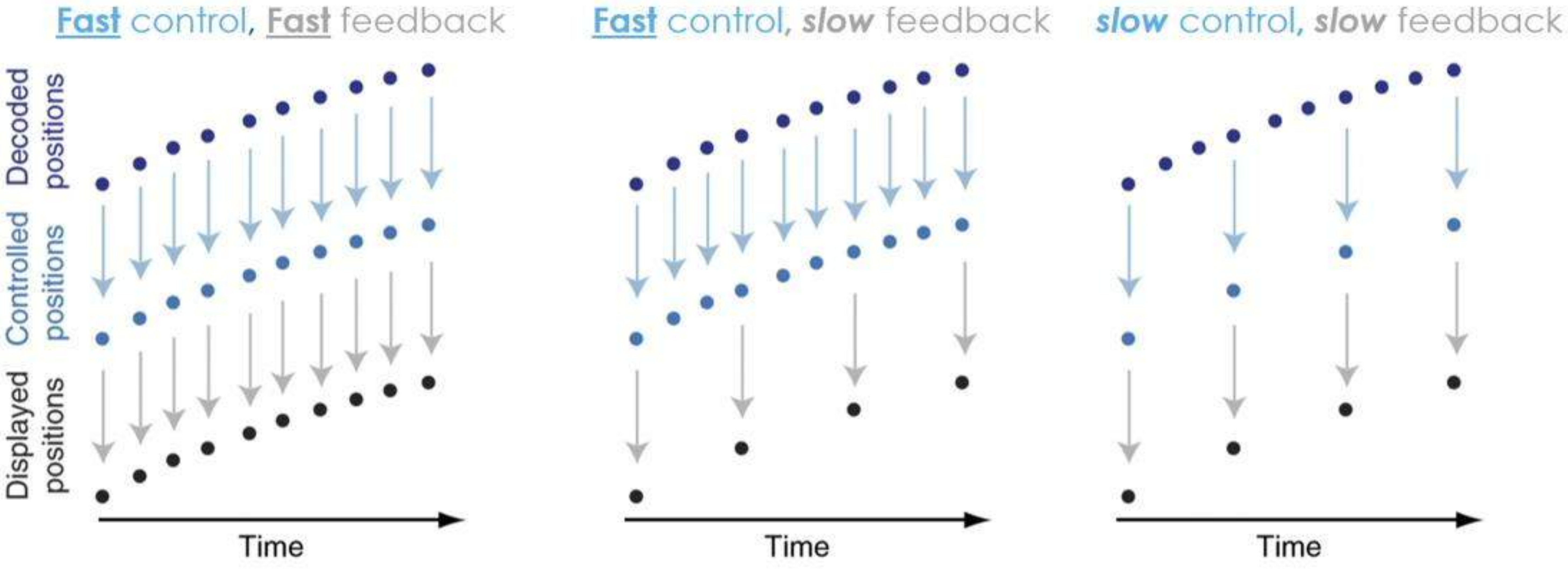
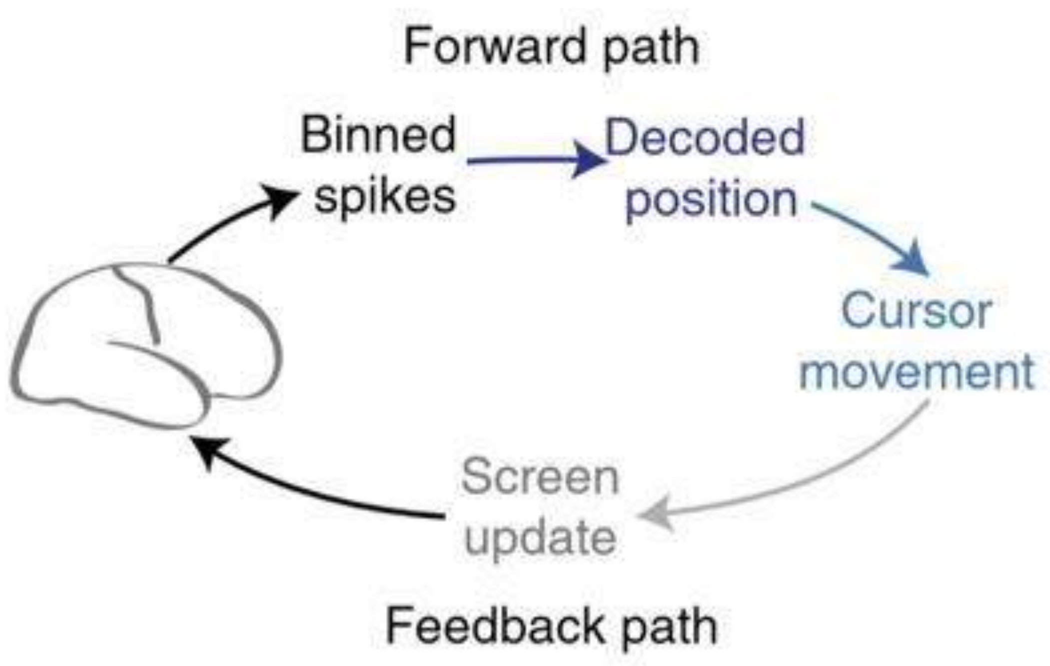


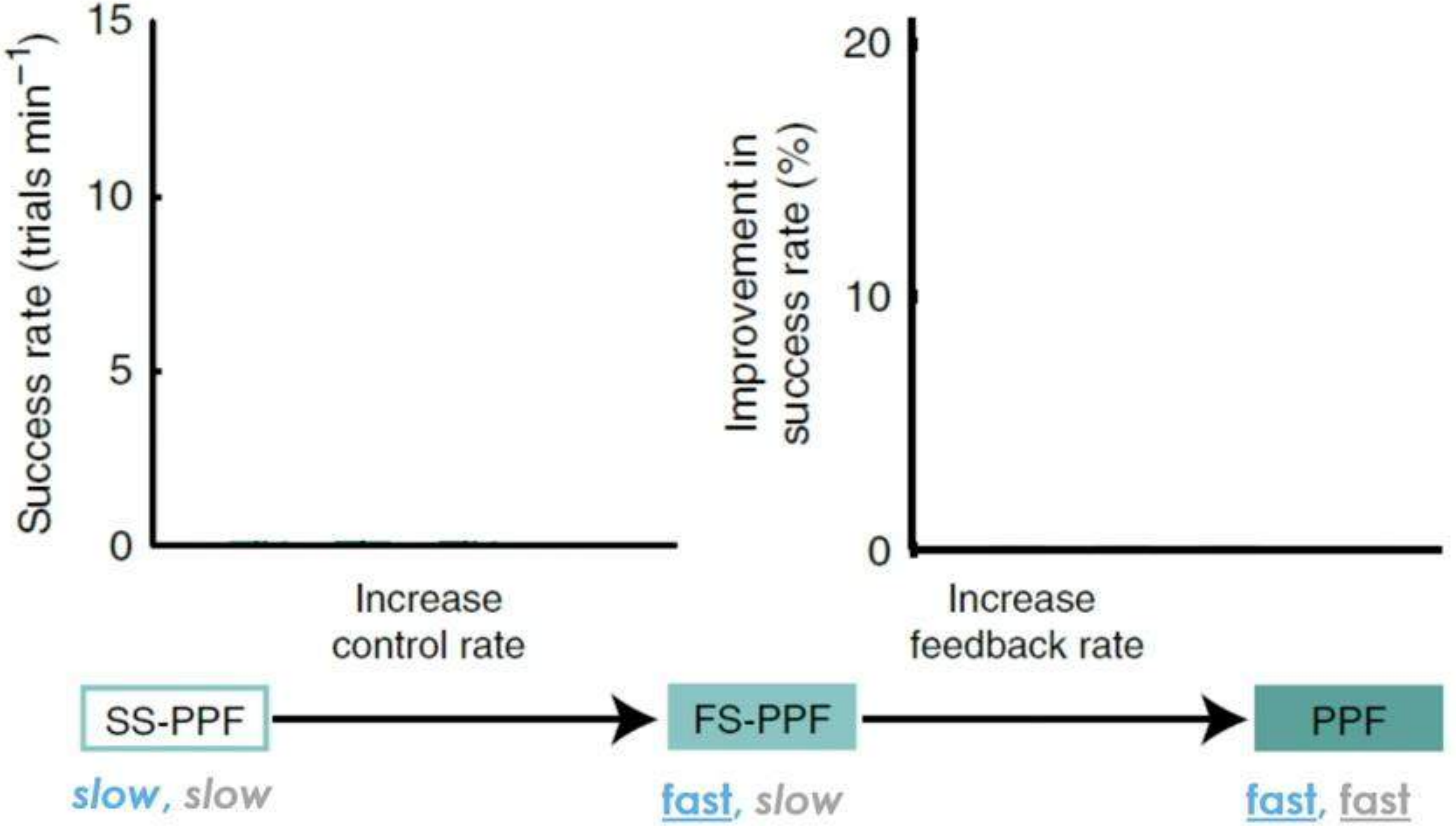

**fast** control = 200 Hz (5ms bins)
***slow*** control = 10 Hz (100ms bins)

**fast** feedback = 60 Hz (16.6 ms bins)
***slow*** feedback = 10 Hz (100ms bins)



# Both feedback and control rates impact performance



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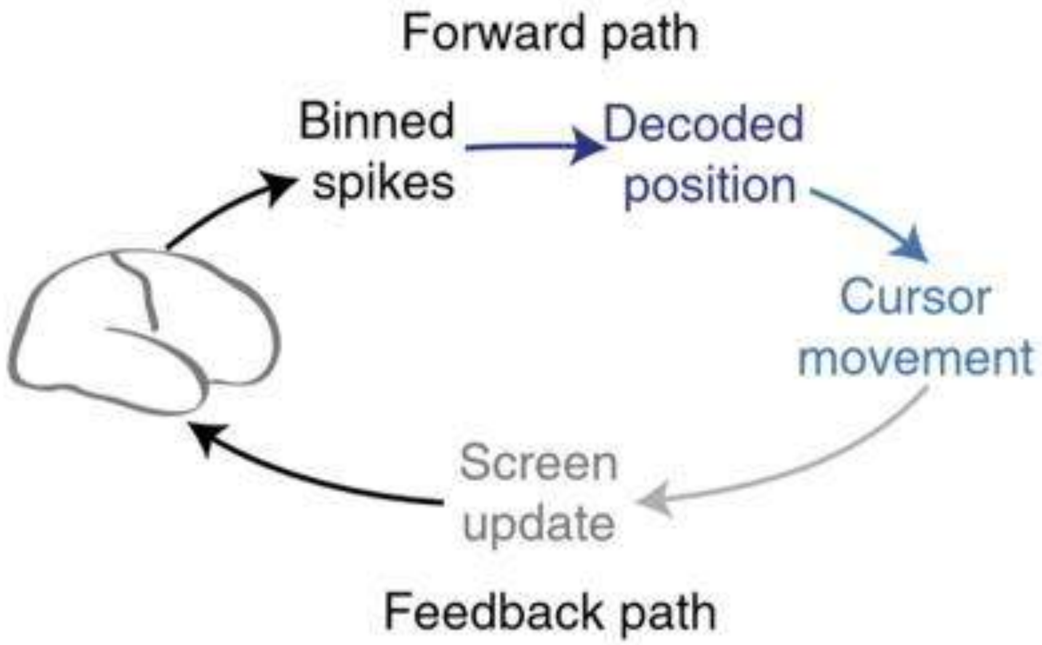


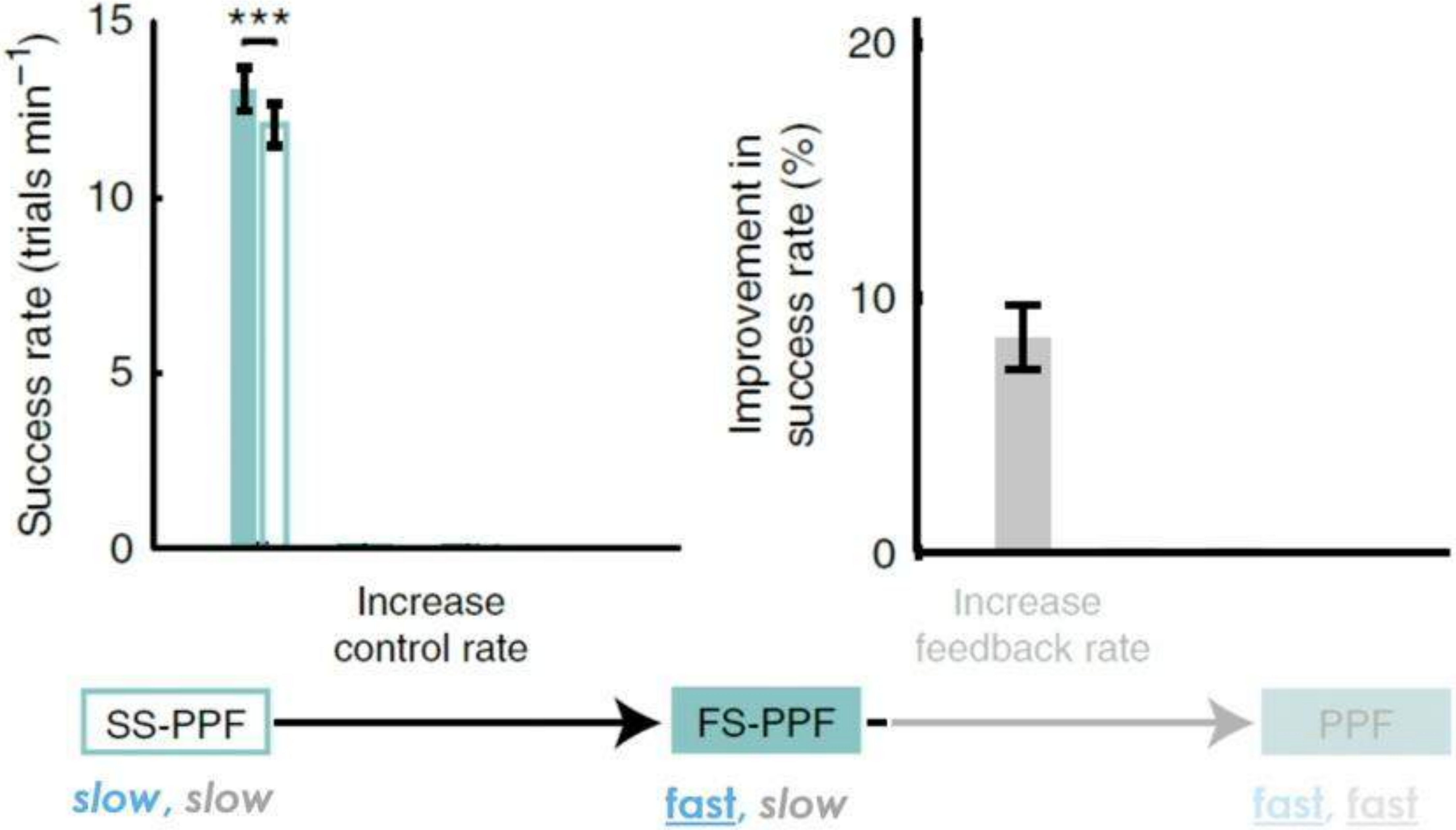


- Faster control improves performance w/o fast feedback
  - Feed-forward control

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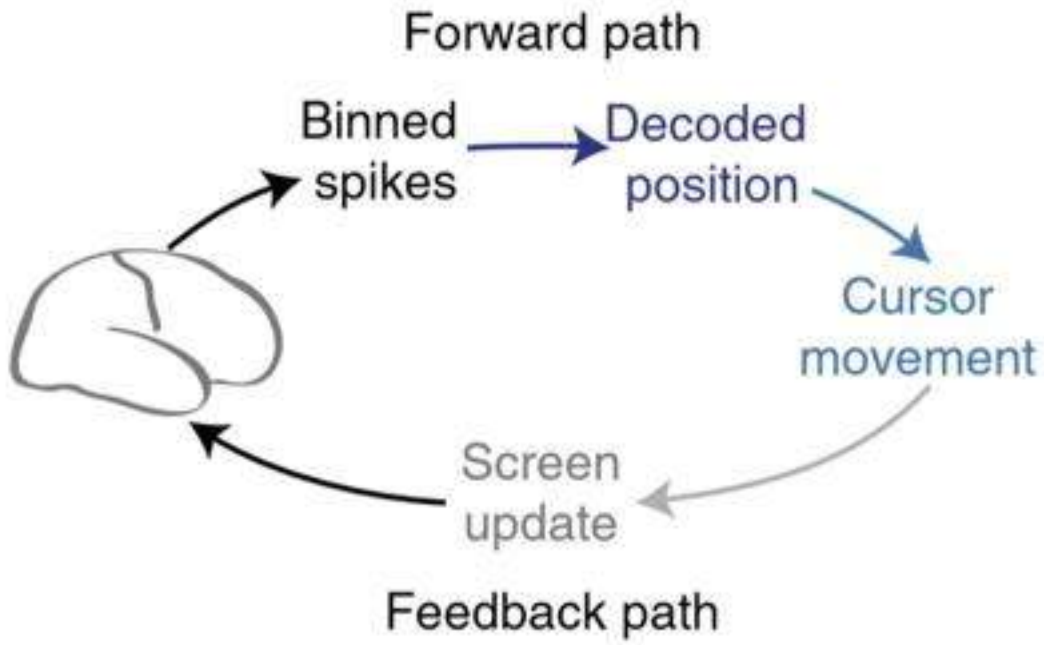


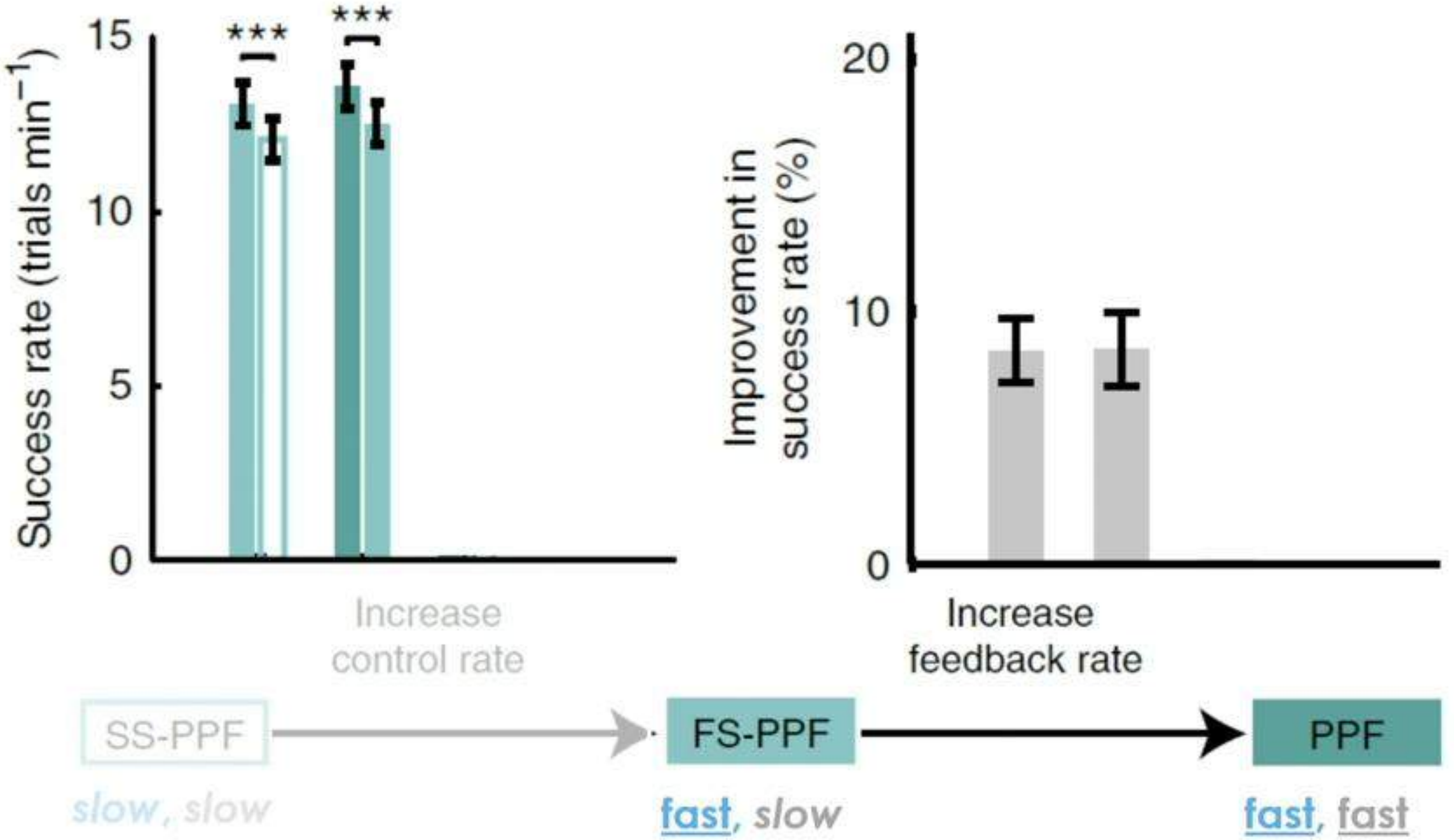


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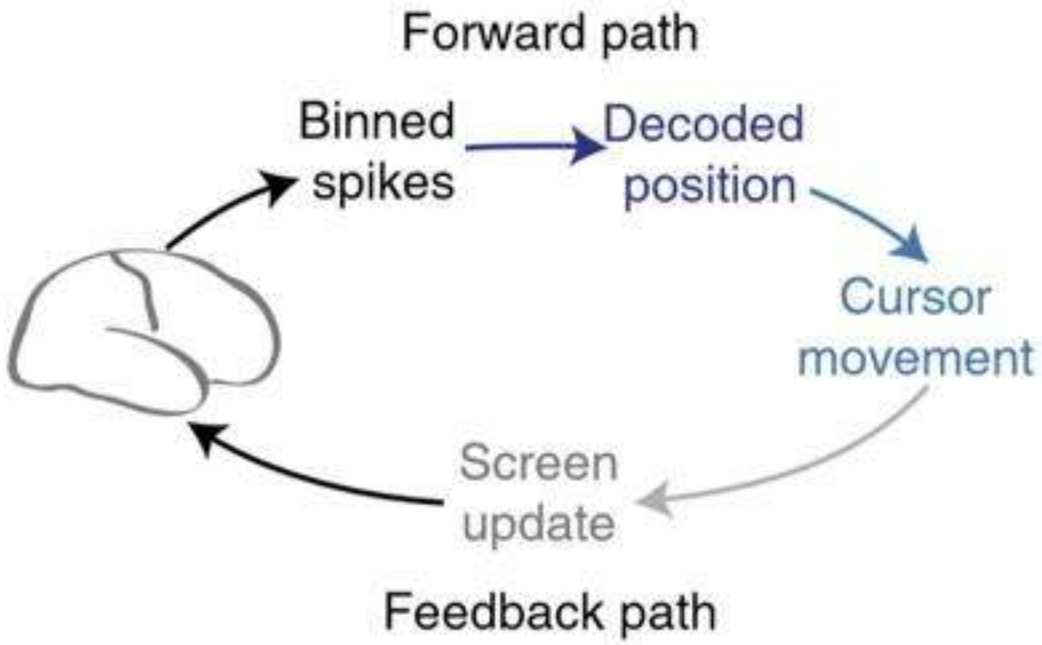


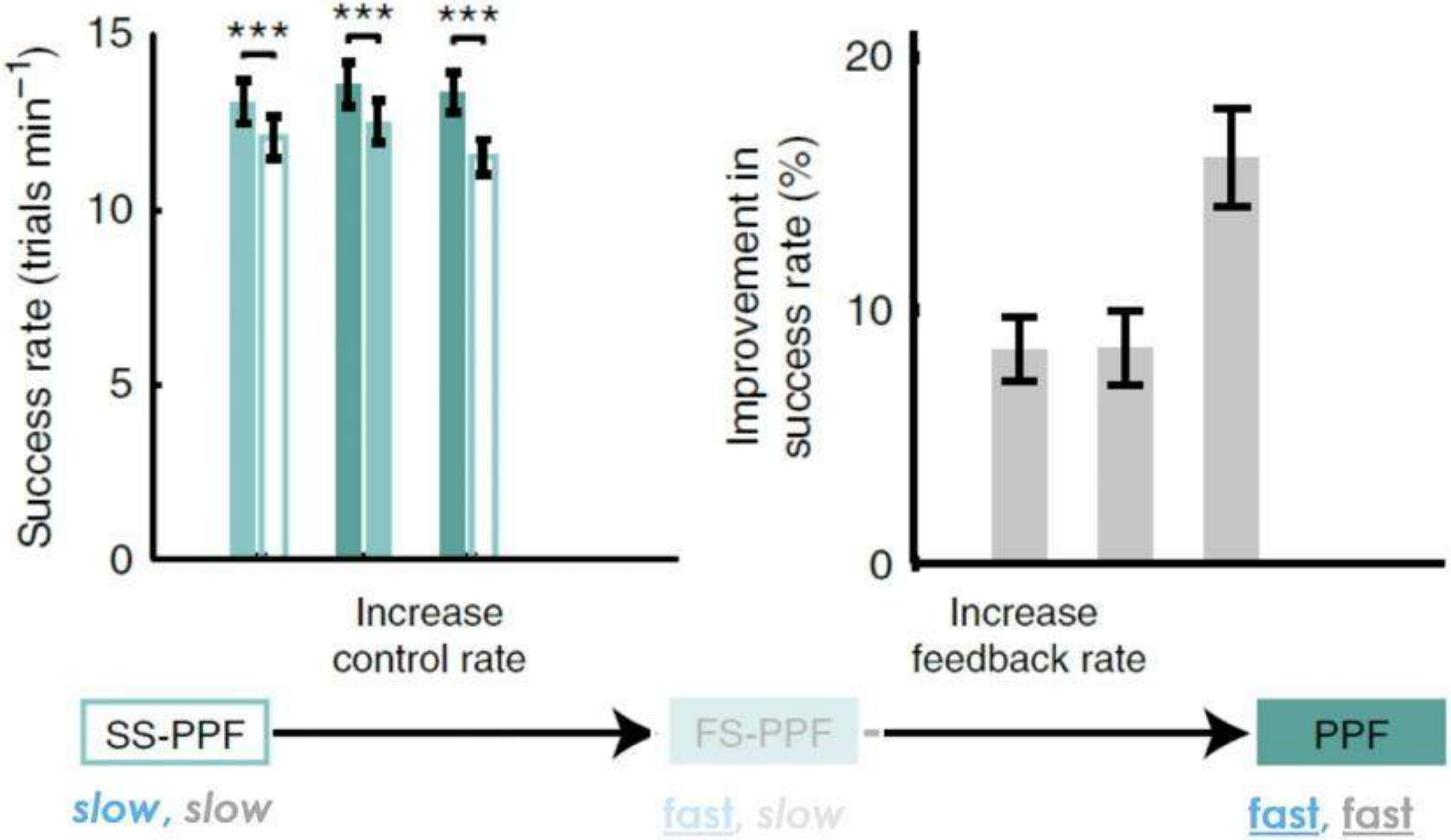


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- Feedback + control effects combine (~separate)

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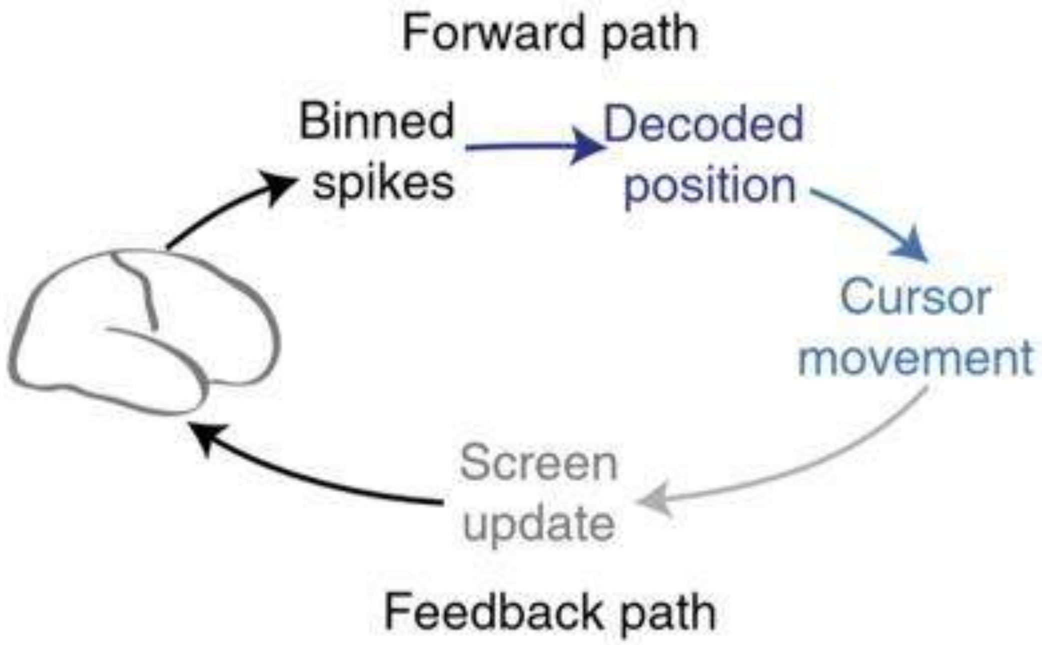
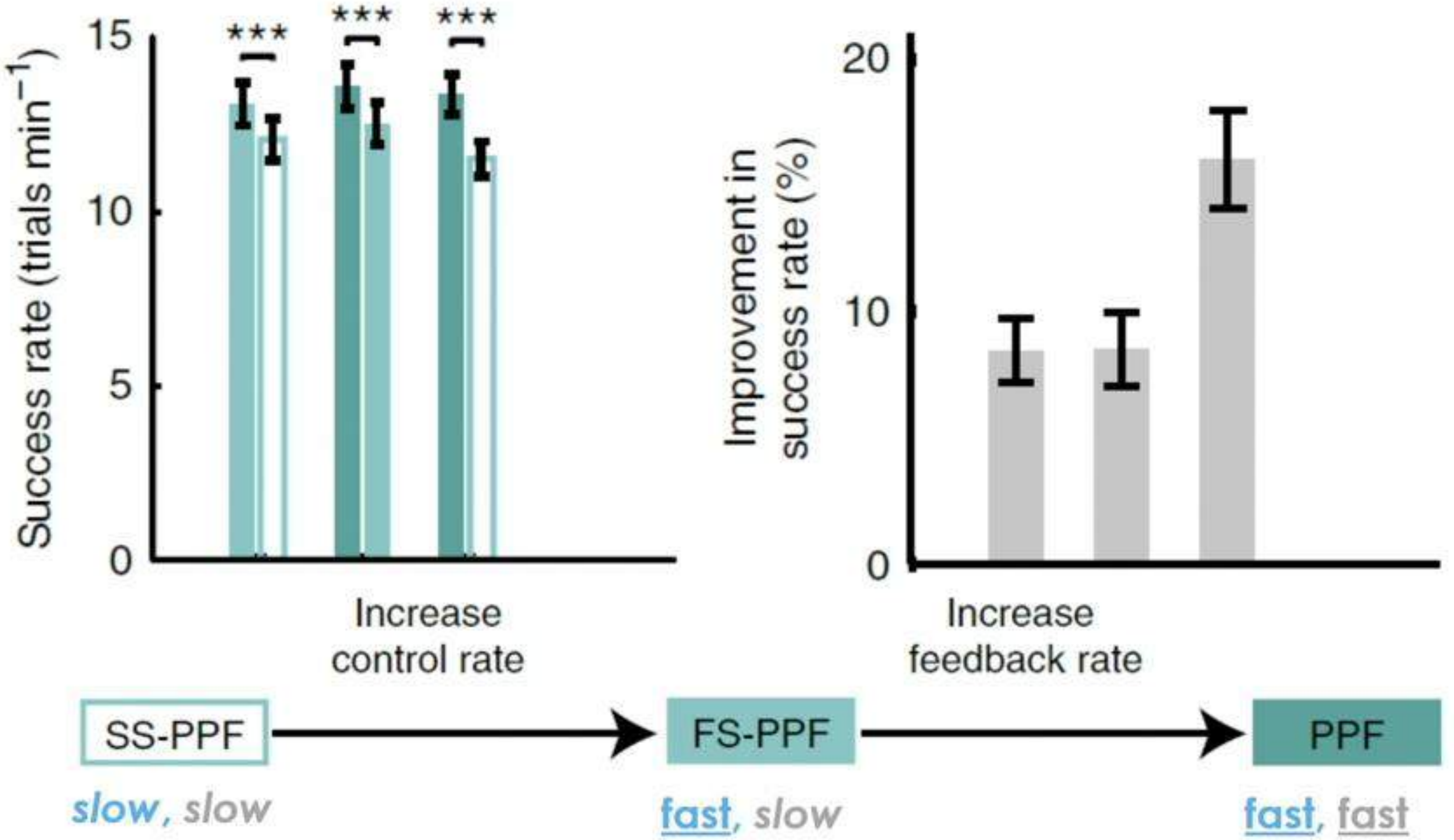
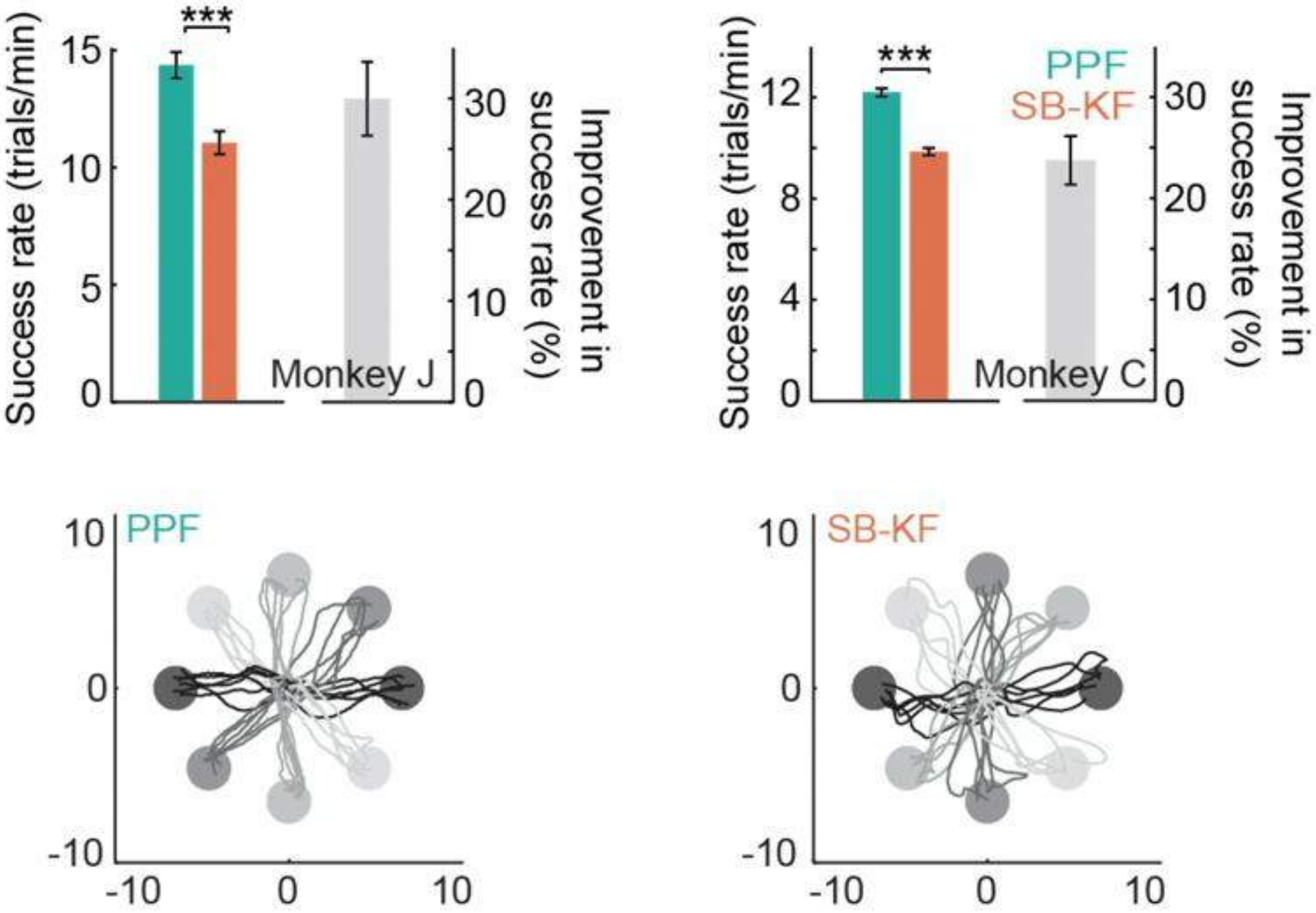


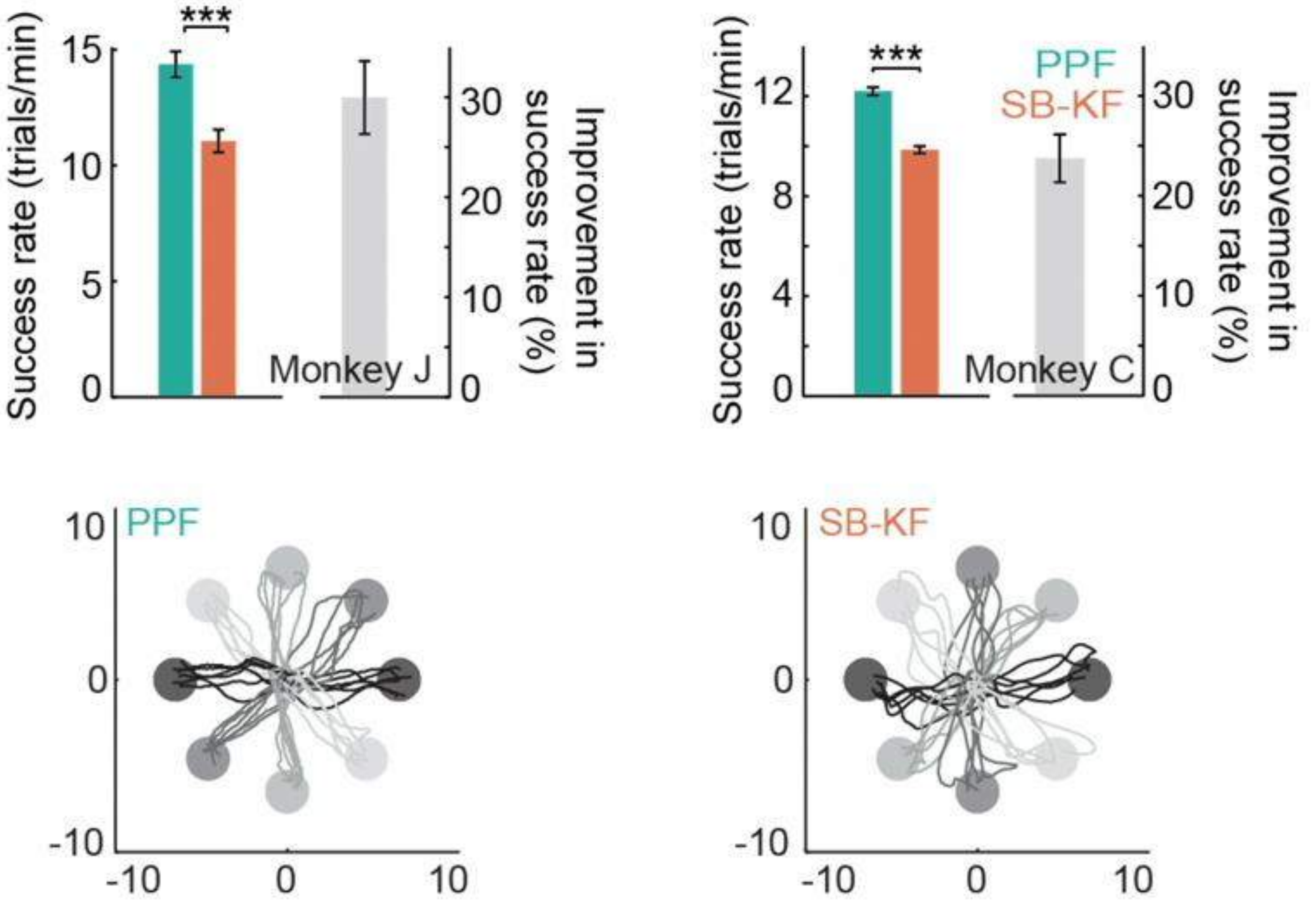

- Faster control improves performance w/o fast feedback
  - Feed-forward control
- Faster feedback improves performance
  - Feedback control
- Feedback + control effects combine (~separate)

# Control insights yield principled performance improvements




- PPF = fast, fast point-process BMI
- SB-KF = Kalman Filter
  - previous “state of the art”

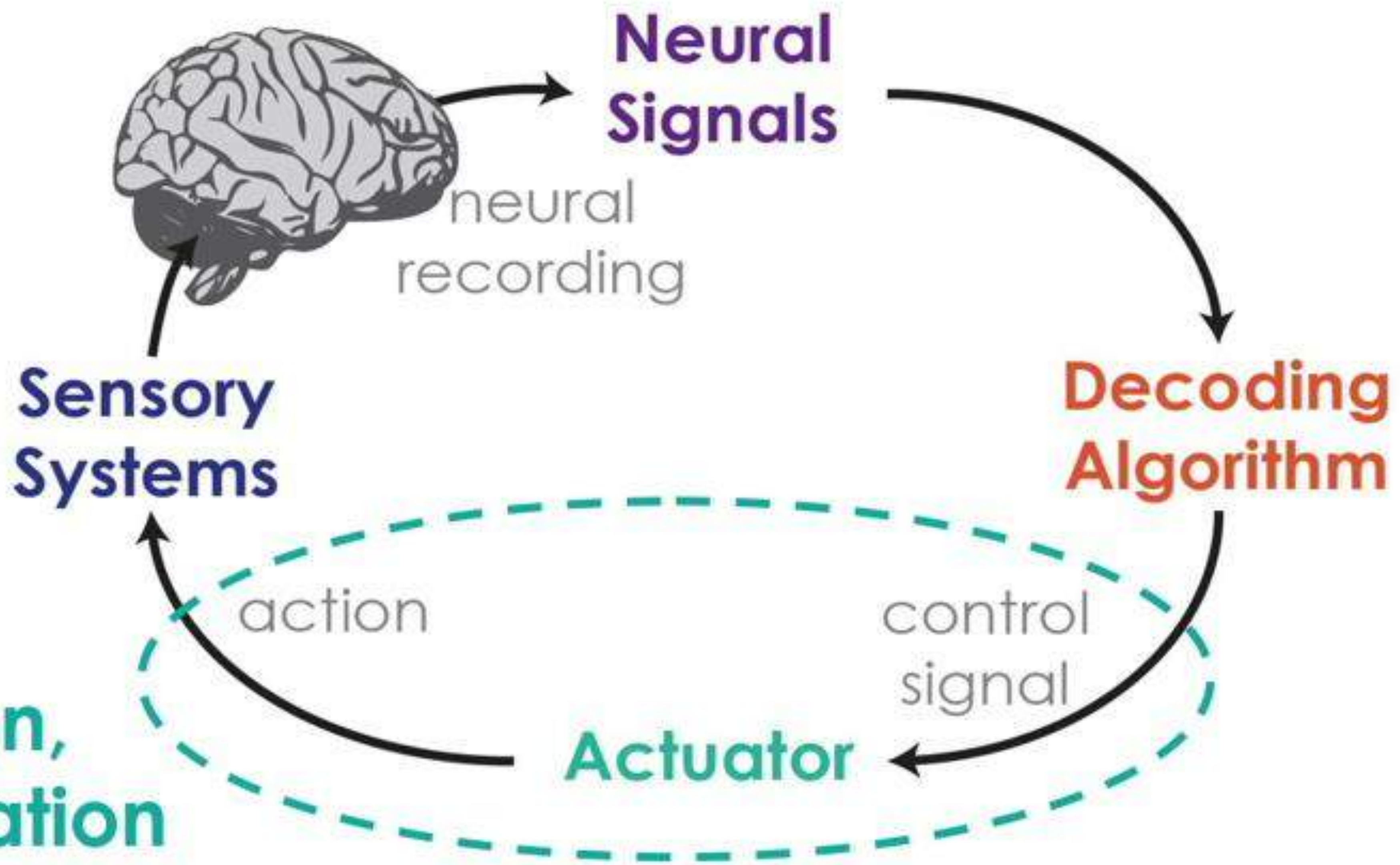
# Control insights yield principled performance improvements




- PPF = fast, fast point-process BMI
- SB-KF = Kalman Filter
  - previous "state of the art"

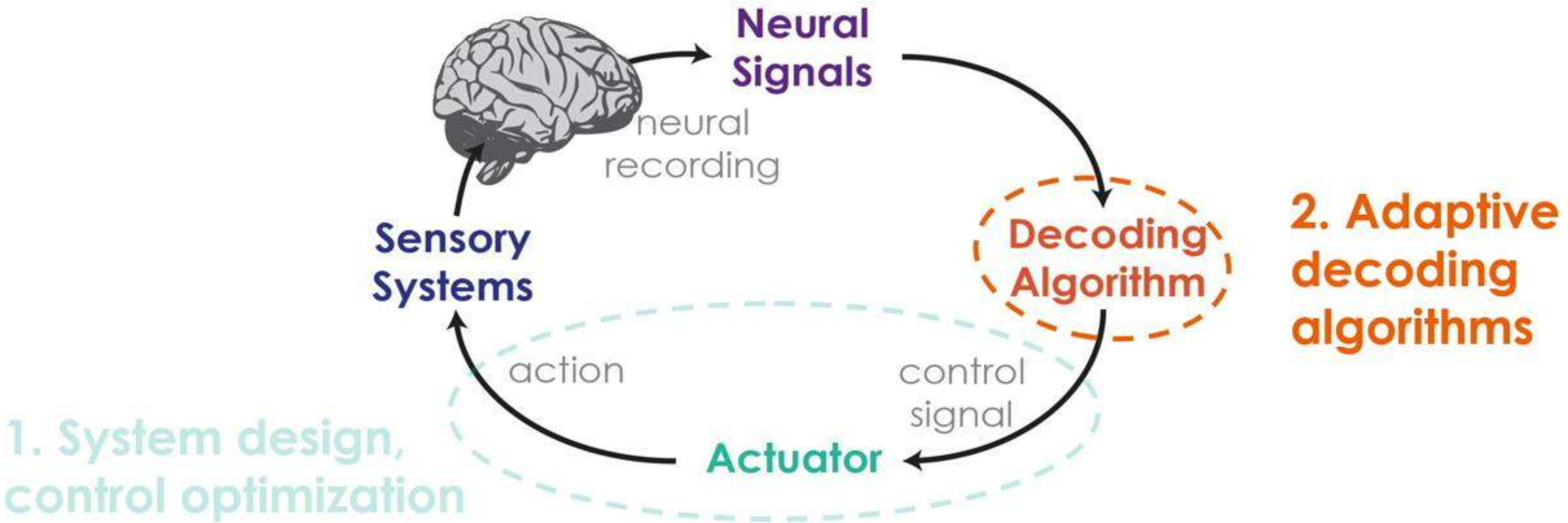
- 25-30% performance improvement
  - Faster feedback rate
  - Faster control rate
  - PPF model vs. KF Gaussian-assumption model

# How to design a decoder for an unknown system?

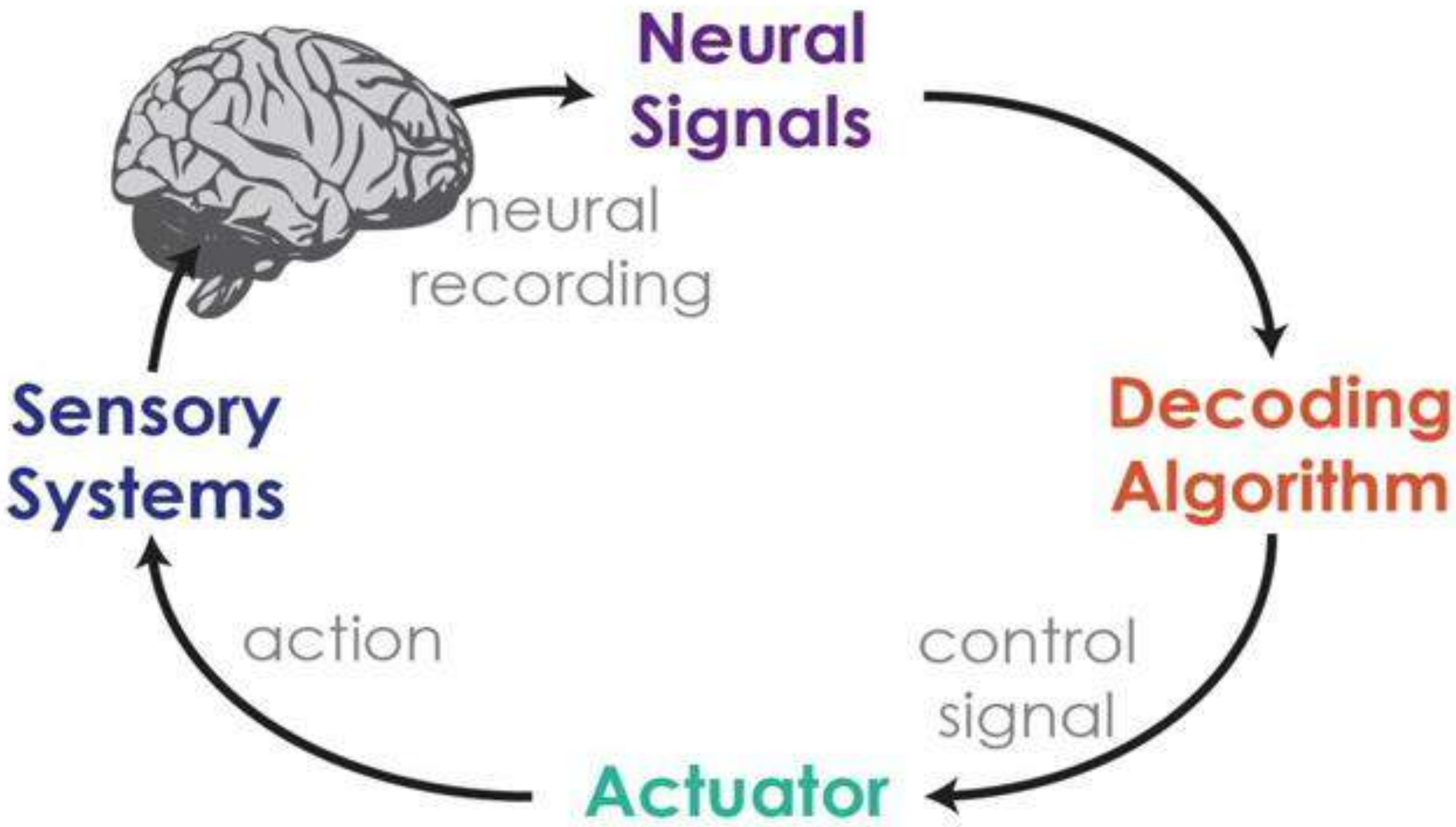



1. System design, control optimization

# How to design a decoder for an unknown system?



# Closed-Loop Decoder Adaptation (CLDA)



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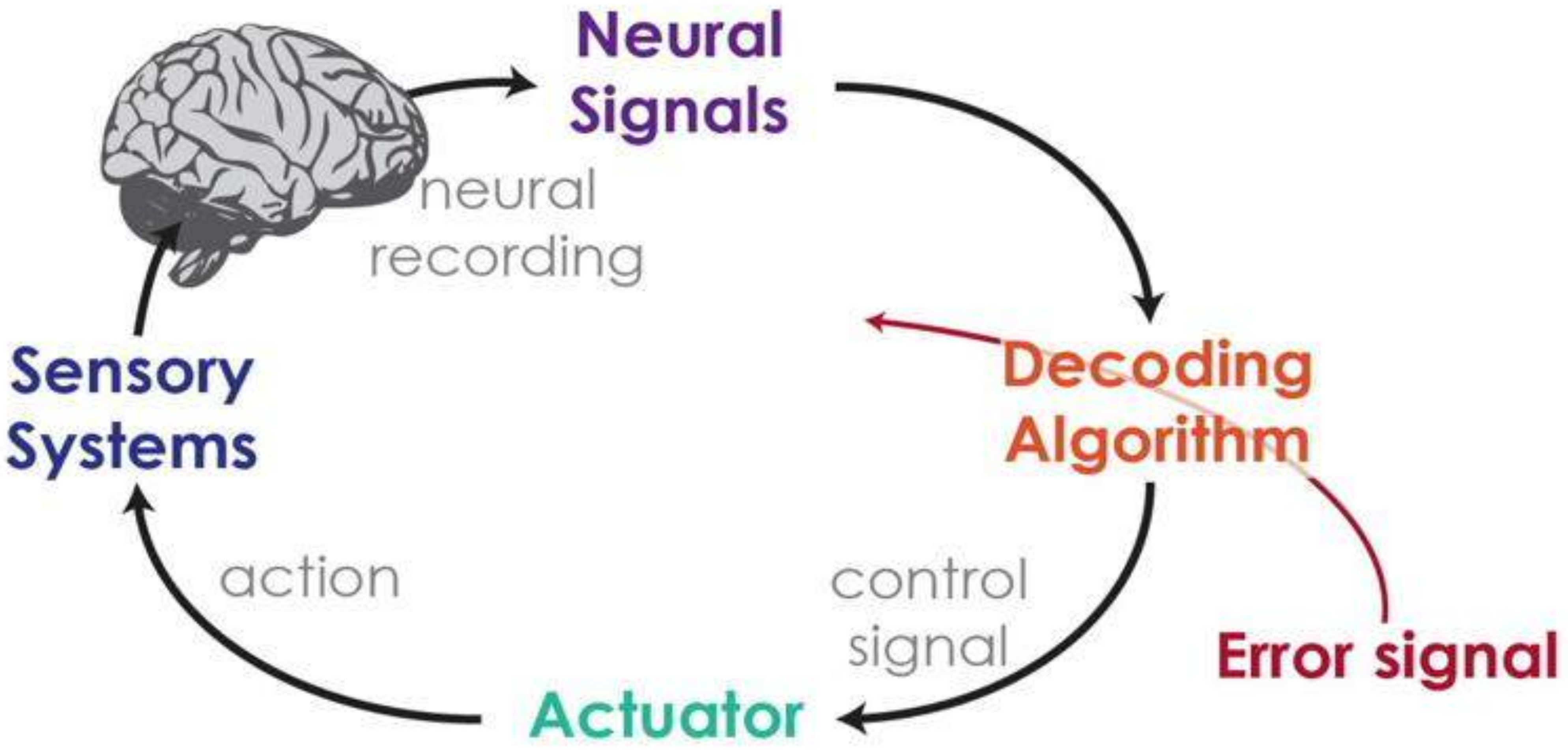

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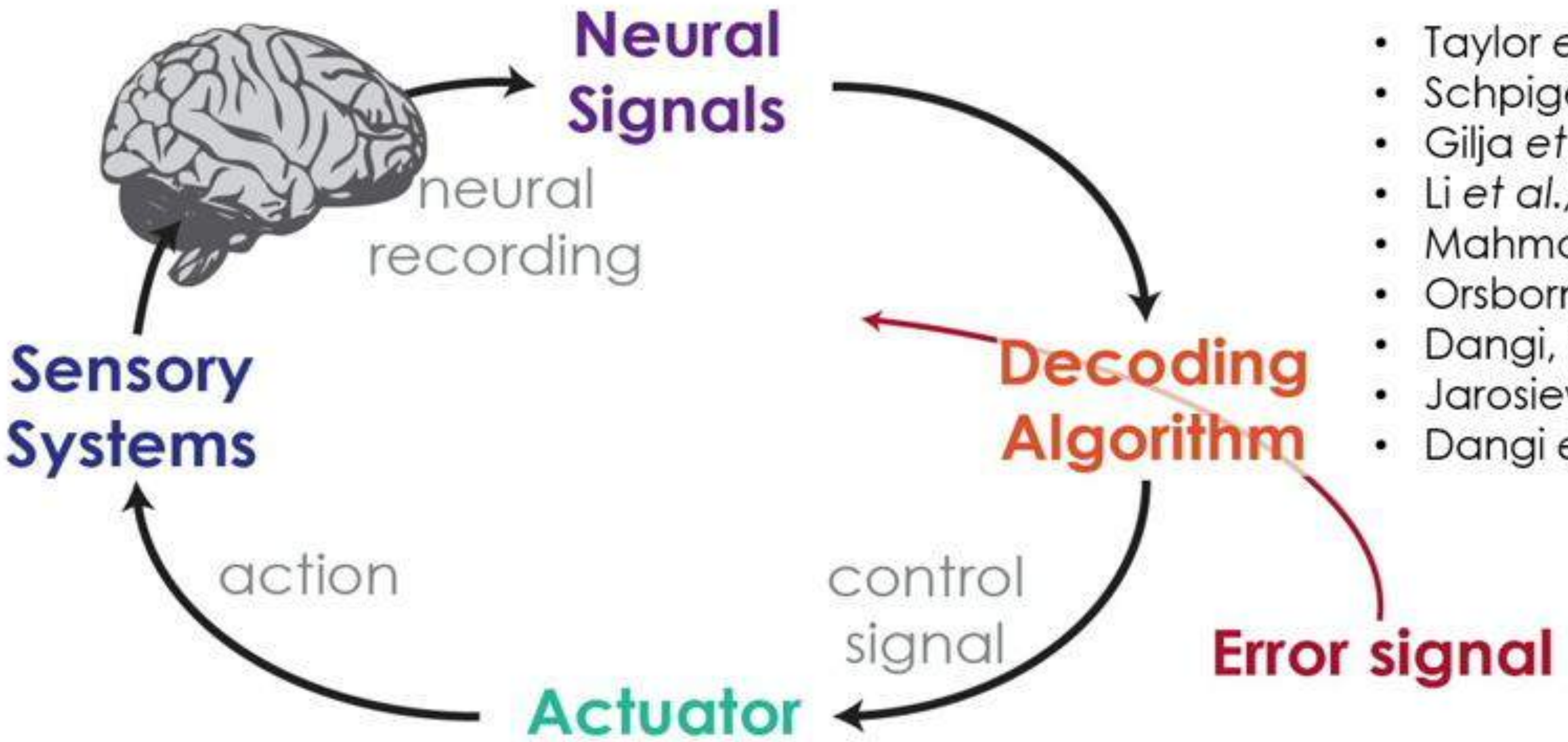


- Taylor *et al.*, 2002
- Schpigelman, 2008
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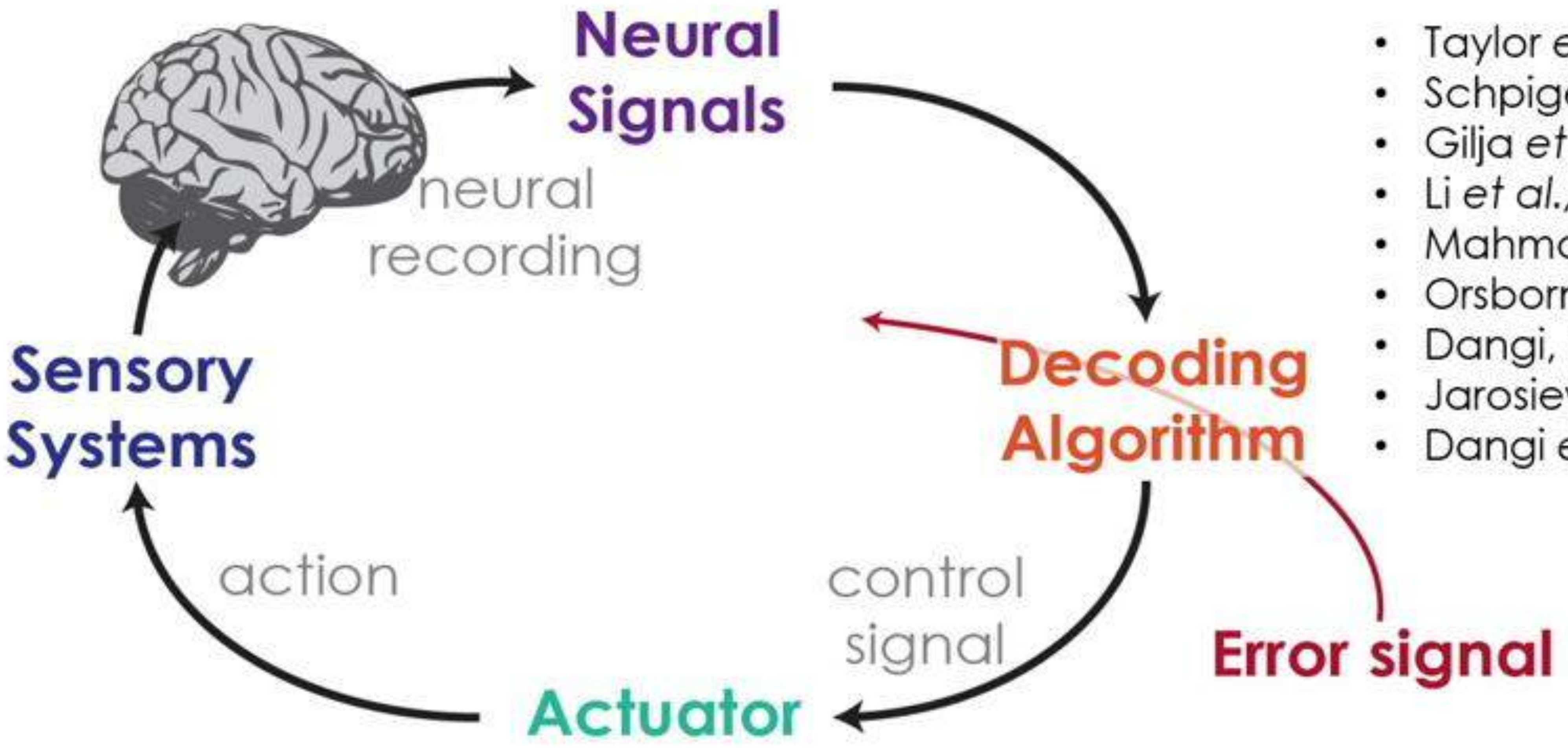


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Goal: Robustly, reliably learn a subject's strategy **regardless of the initial decoder**

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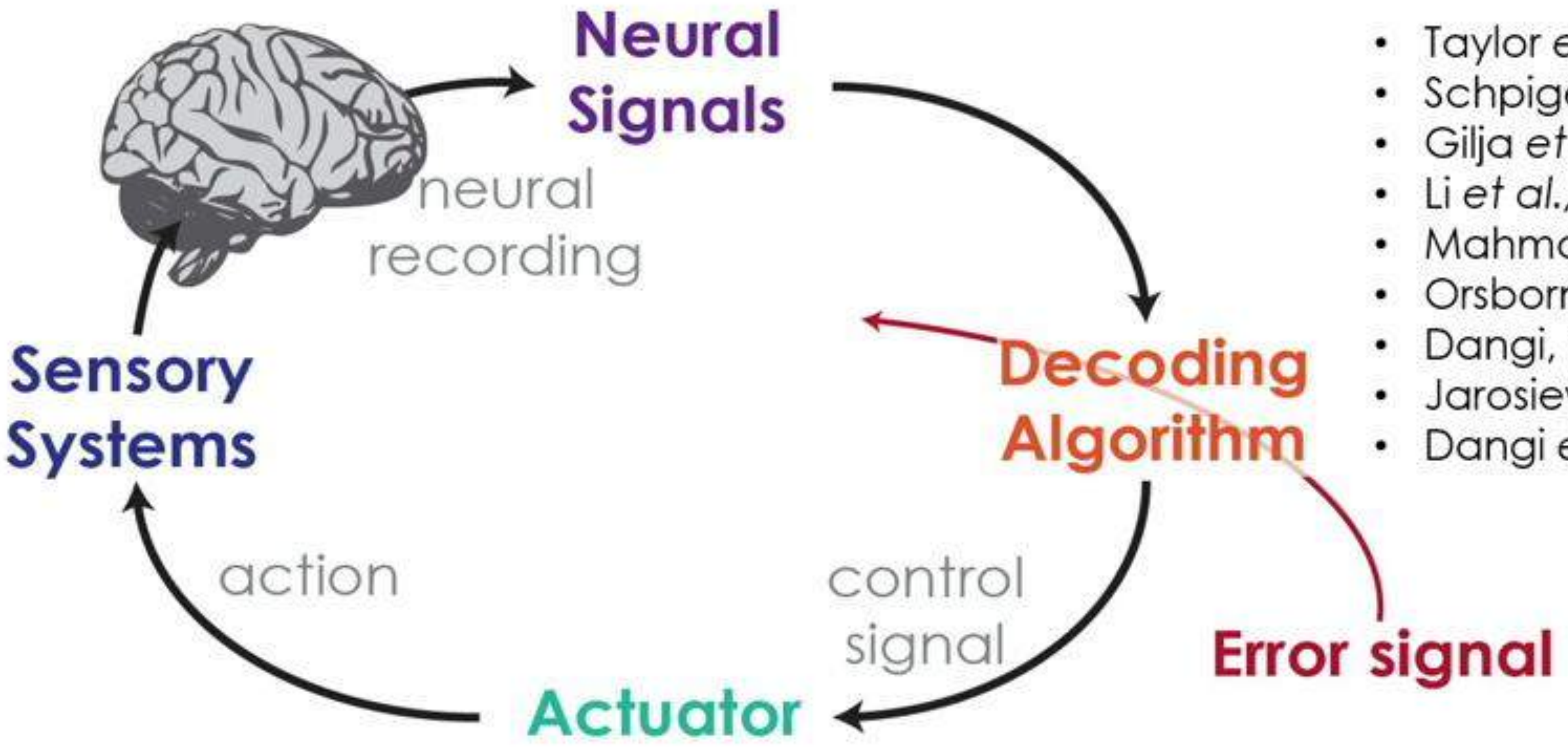


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Goal: Robustly, reliably learn a subject's strategy **regardless of the initial decoder**

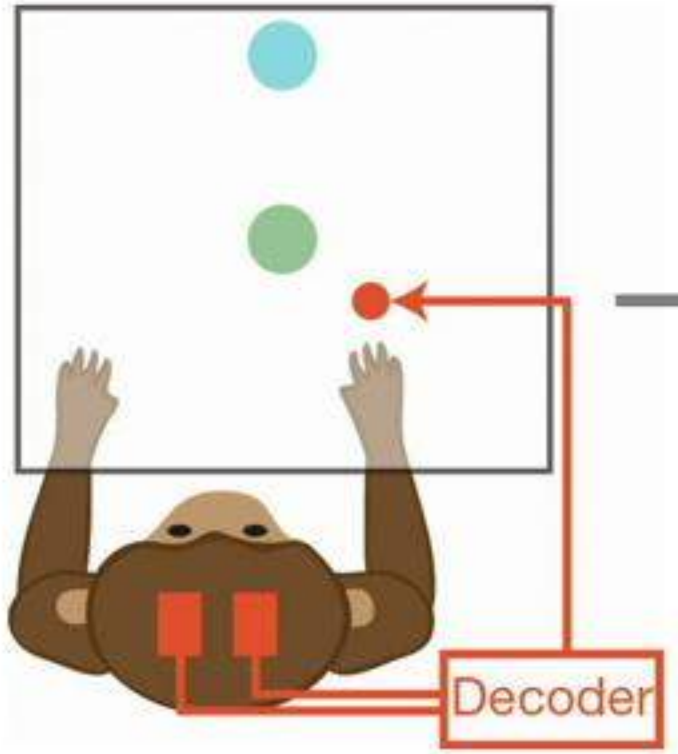
Subject may be trying to learn—cannot assume stationarity

# SmoothBatch Algorithm: Decoder learning faster than the subject

*Orsborn et al, IEEE TNSRE 2012*

# SmoothBatch Algorithm:
# Decoder learning faster than the subject

**Closed-loop BMI Operation**




**Collect Observation**
**(1-2min batches)**

**Spikes**

**Inferred kinematics**

**Update Decoder**

**Maximum-likelihood estimates of decoder parameters from batch**

**Sliding-window average of decoder parameters**

**Repeat as needed (until adequate performance)**

*Orsborn et al, IEEE TNSRE 2012*

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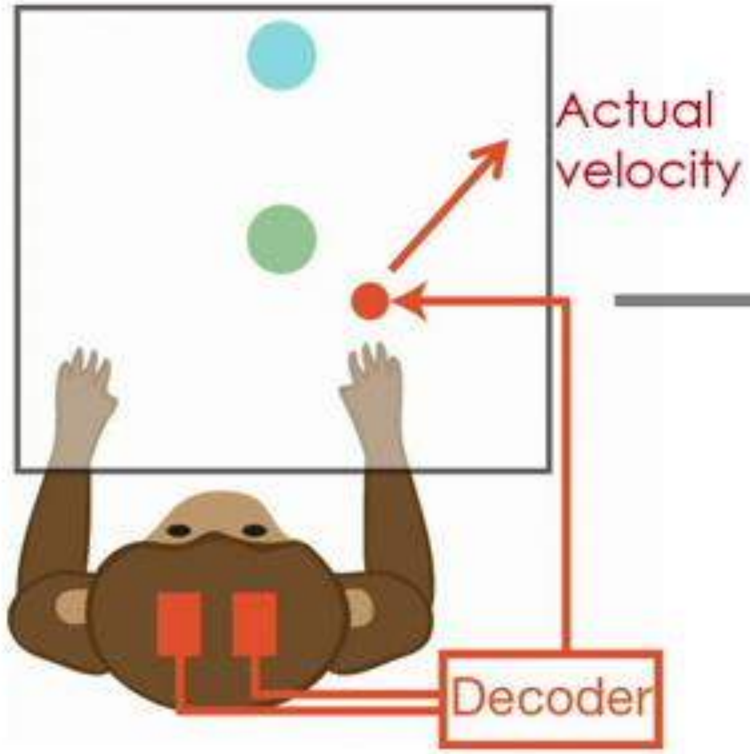


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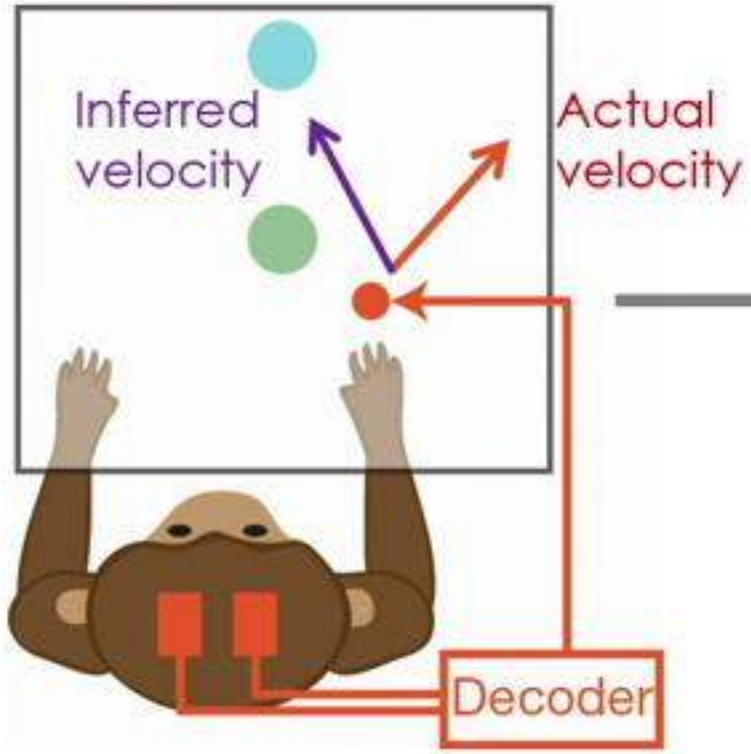


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# SmoothBatch rapidly, robustly improves performance


Orsborn *et al*, *IEEE TNSRE* 2012

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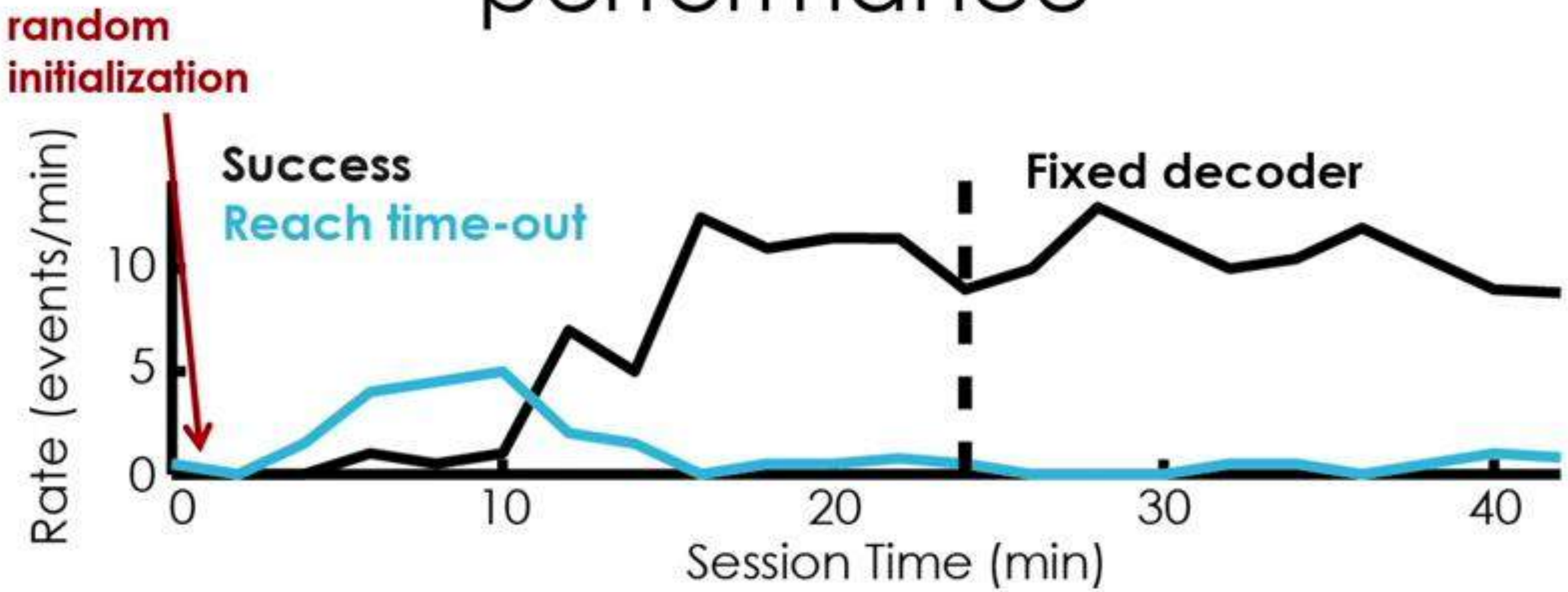


Orsborn *et al*, *IEEE TNSRE* 2012

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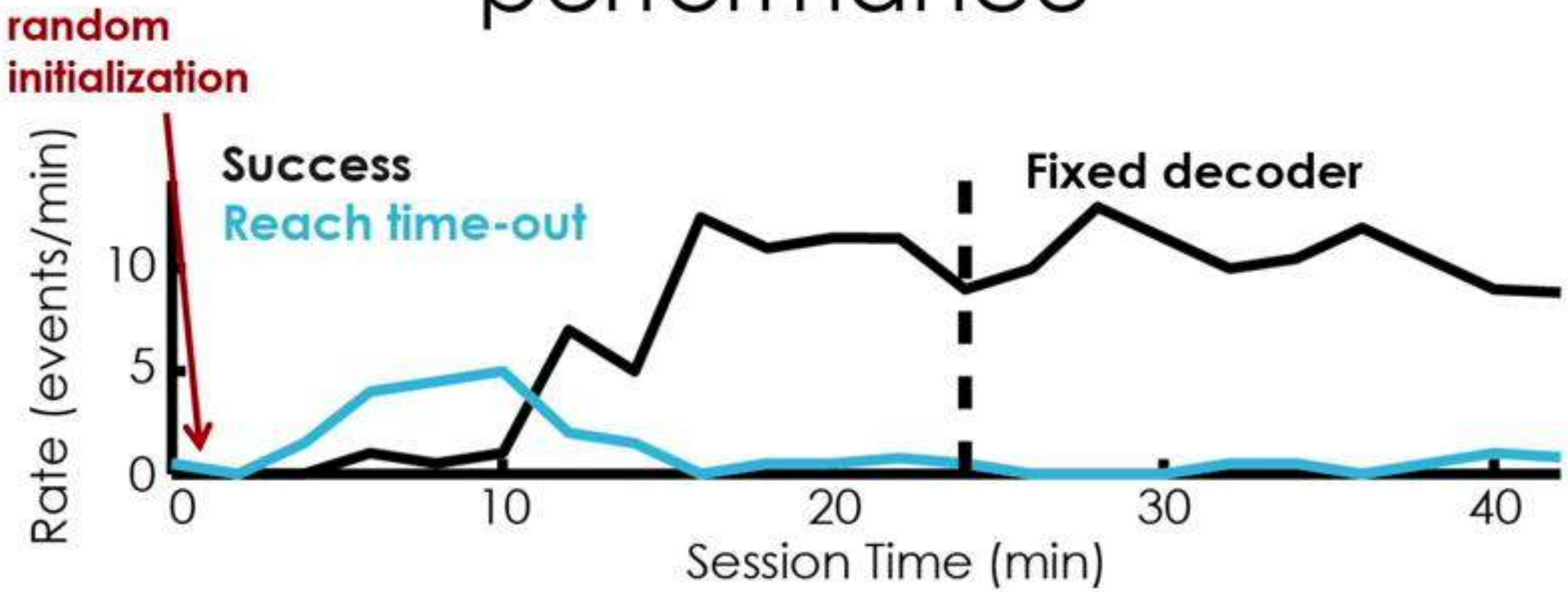


**Is it robust?**

Orsborn *et al*, *IEEE TNSRE* 2012

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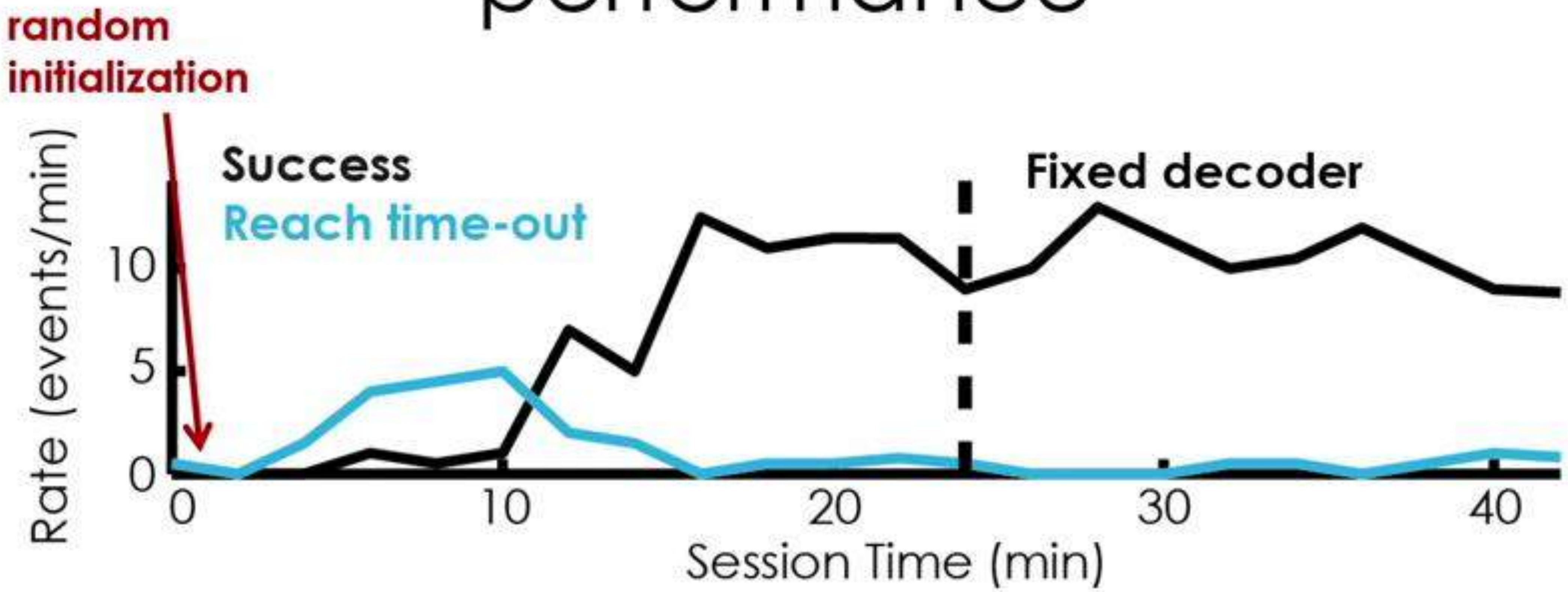


**Is it robust?**

- 56 sessions
- 4 different initialization methods

Orsborn *et al*, *IEEE TNSRE* 2012

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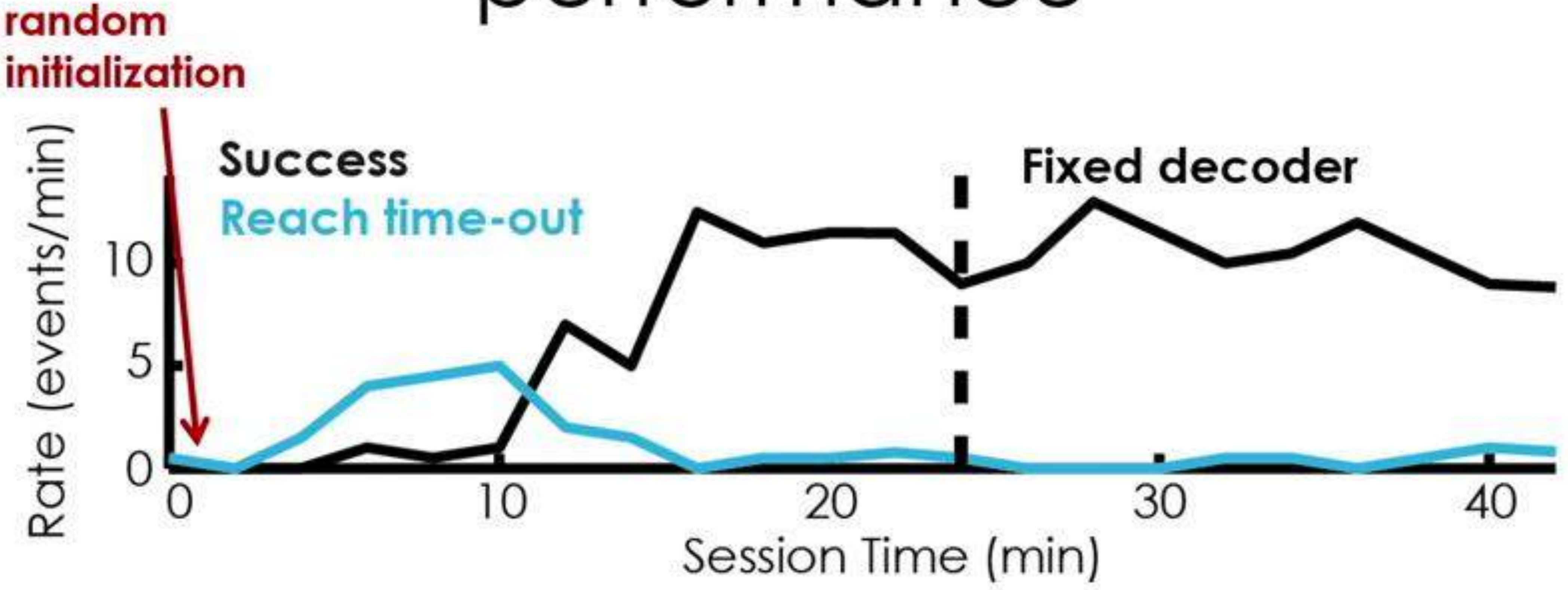


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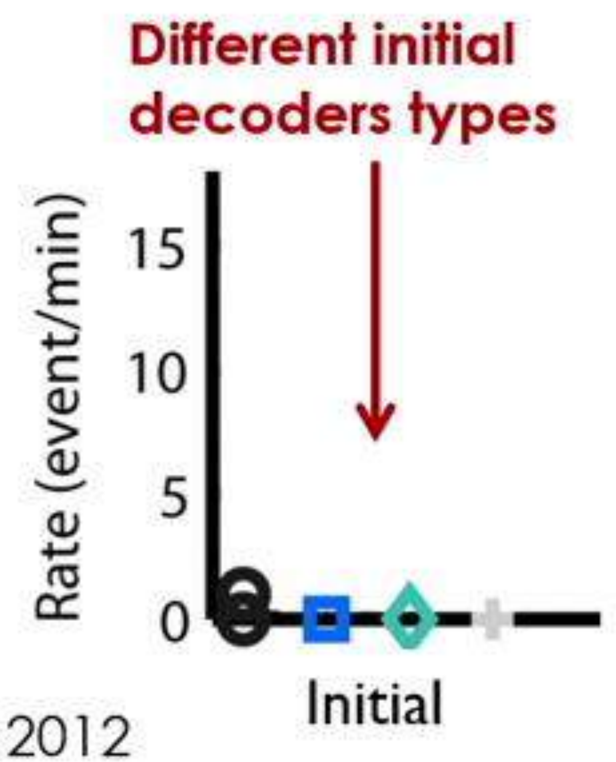


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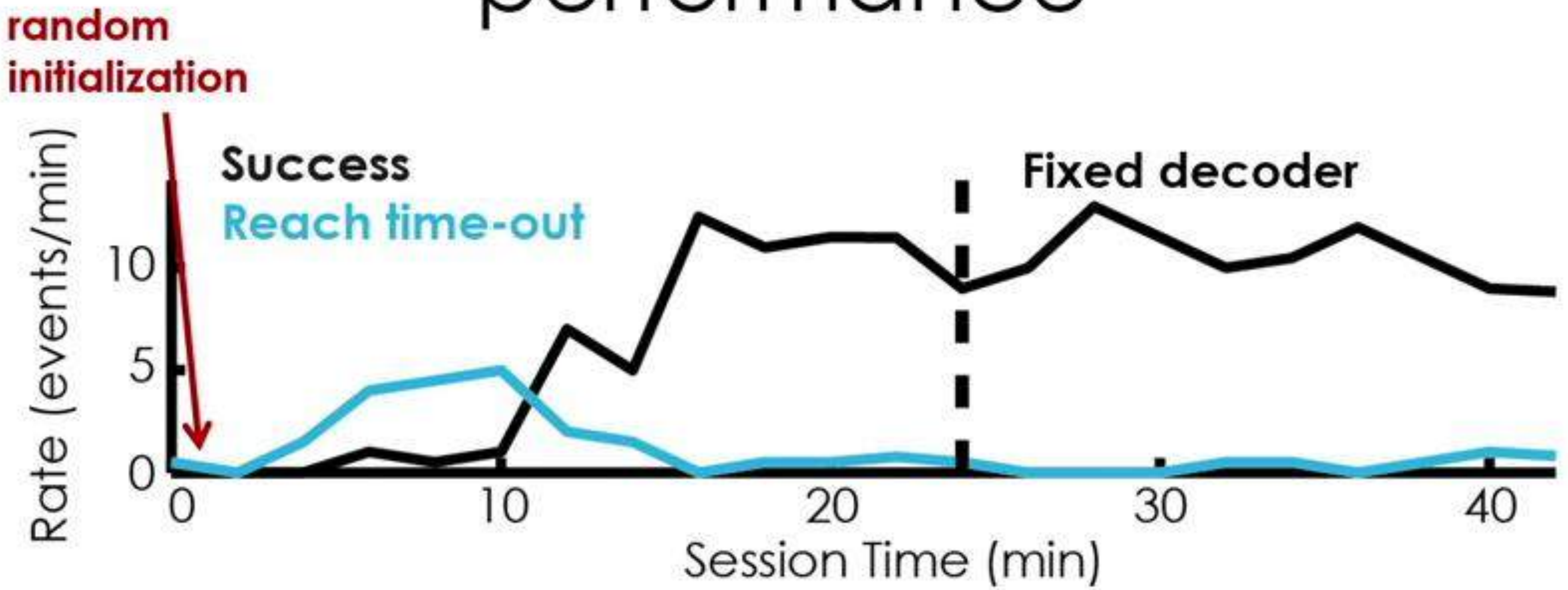


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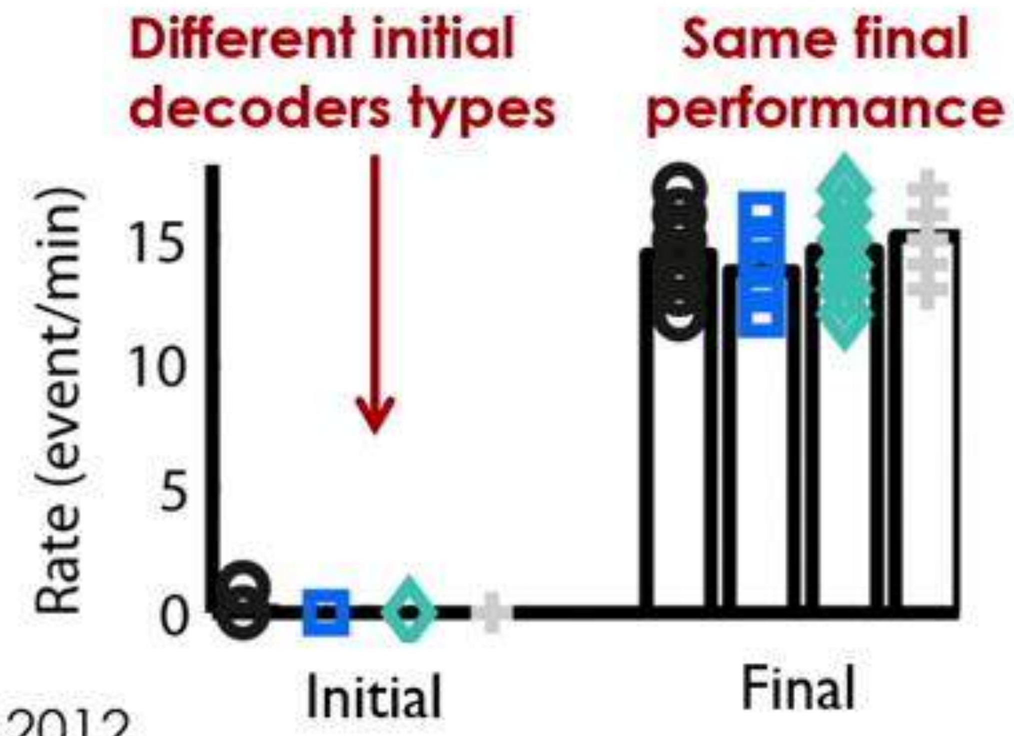


Orsborn *et al*, *IEEE TNSRE* 2012

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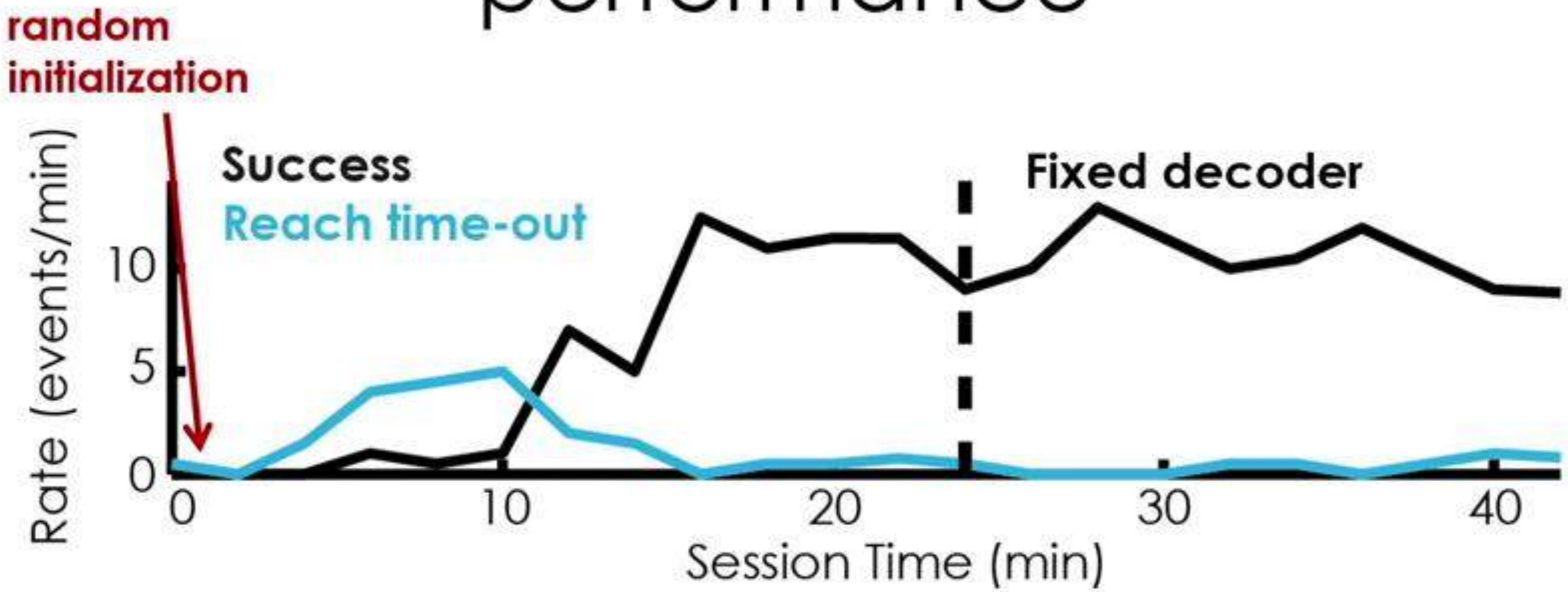


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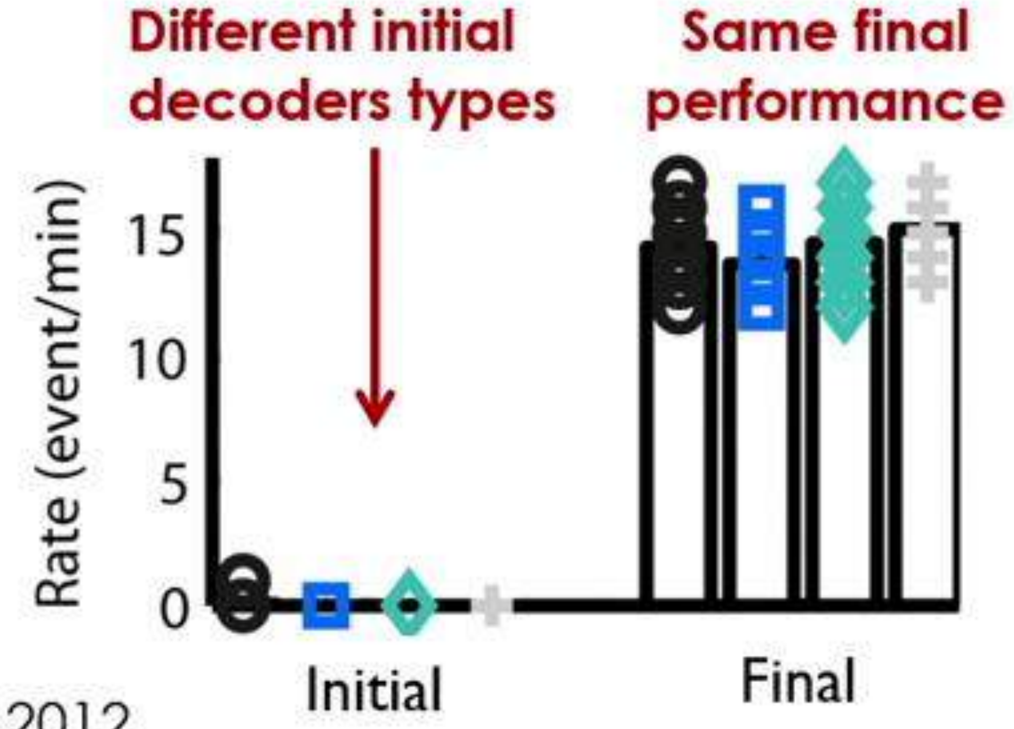


**Is it fast?**

Able to hit all targets:
13.1 ± 5.5 min

Max. performance:
20.75 ± 5.9 min

Orsborn *et al*, *IEEE TNSRE* 2012

# CLDA optimization further improves performance

Shanechi*, Orsborn* and Carmena, *PLoS Comp Bio* 2016

# CLDA optimization further improves performance

- **Adapt parameters each decoder iteration (ms scale)**

Shanechi*, Orsborn* and Carmena, *PLoS Comp Bio* 2016

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**Faster, more robust convergence**

| | |
|---|---|
| SmoothBatch | 18.7 ± 3.2 min |
| bin-by-bin adaptation | 6.5 ± 0.7 min |

Shanechi*, Orsborn* and Carmena, *PLoS Comp Bio* 2016

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- Optimal feedback control model
  - **Principled estimation of intention**

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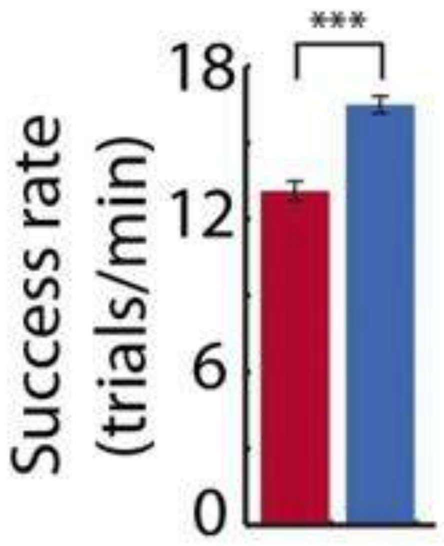


Re-aiming

Optimal Feedback Control

Shanechi*, Orsborn* and Carmena, *PLoS Comp Bio* 2016

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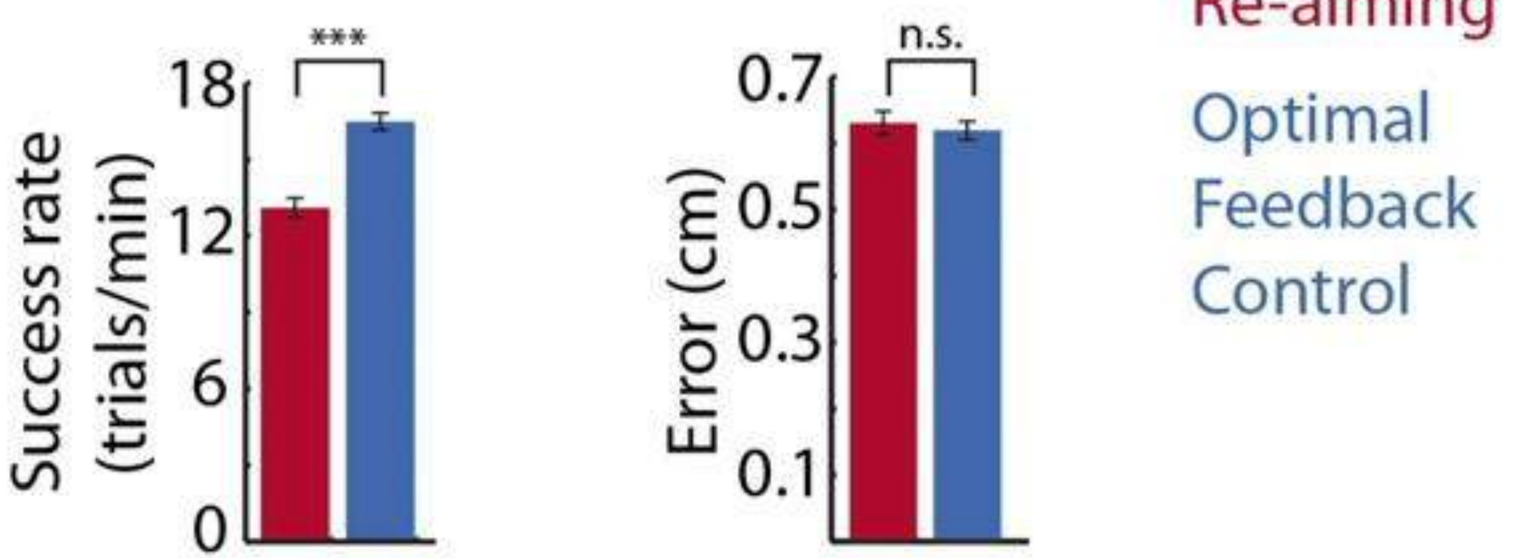
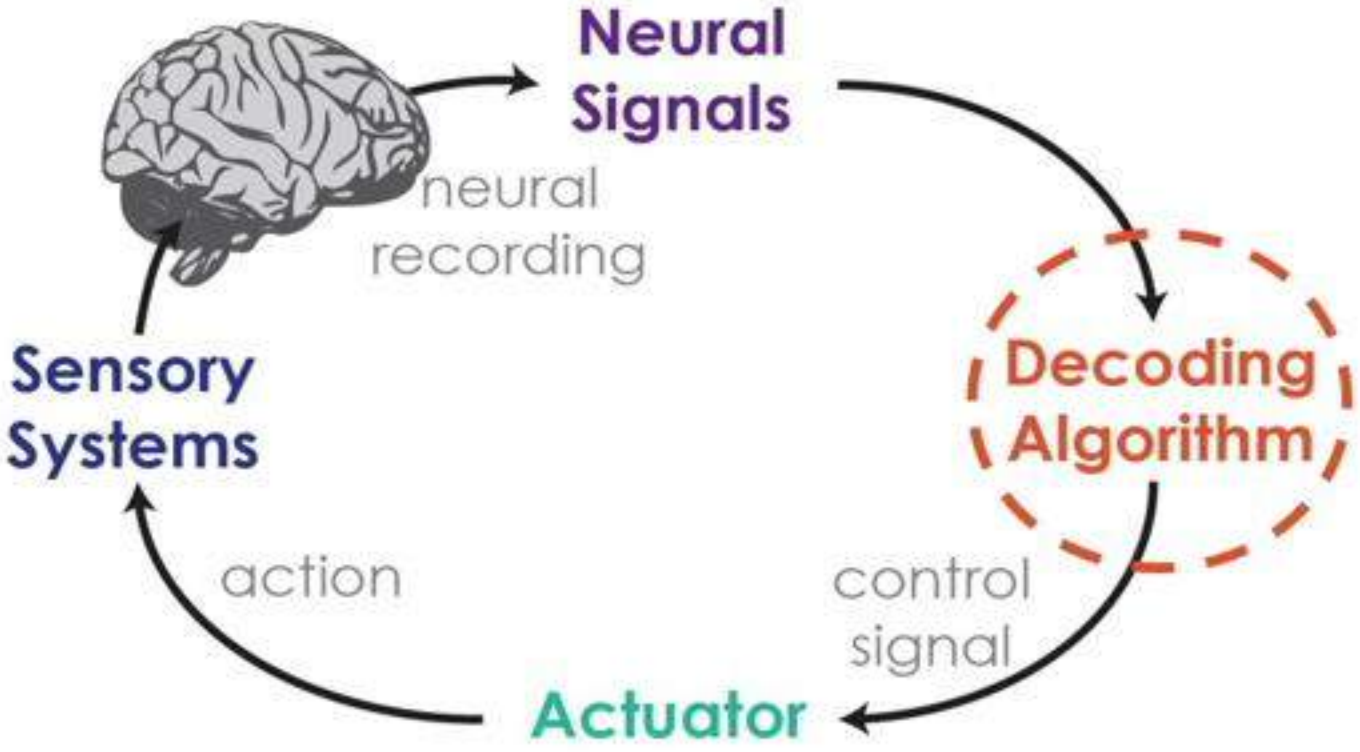
**Better intention estimation improves speed/accuracy tradeoff**




Shanechi*, Orsborn* and Carmena, *PLoS Comp Bio* 2016

# CLDA Summary



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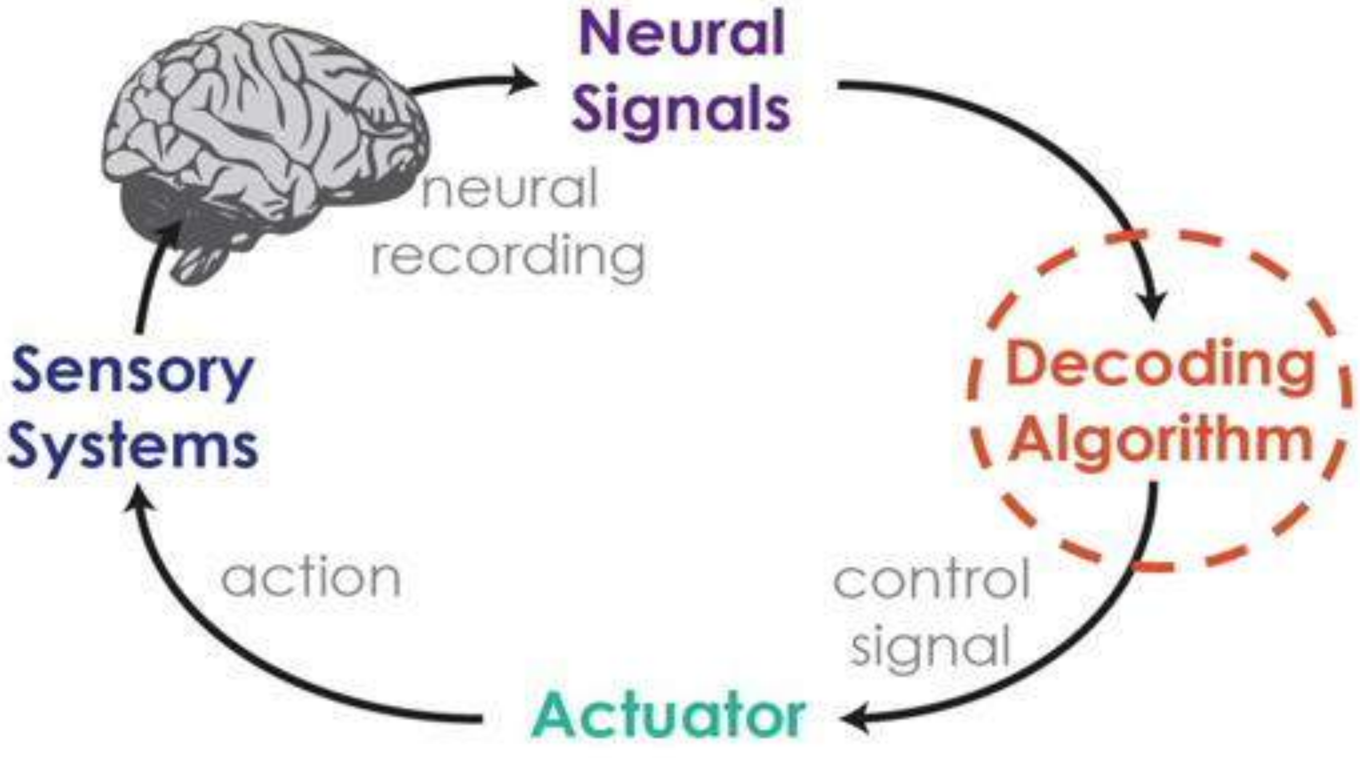
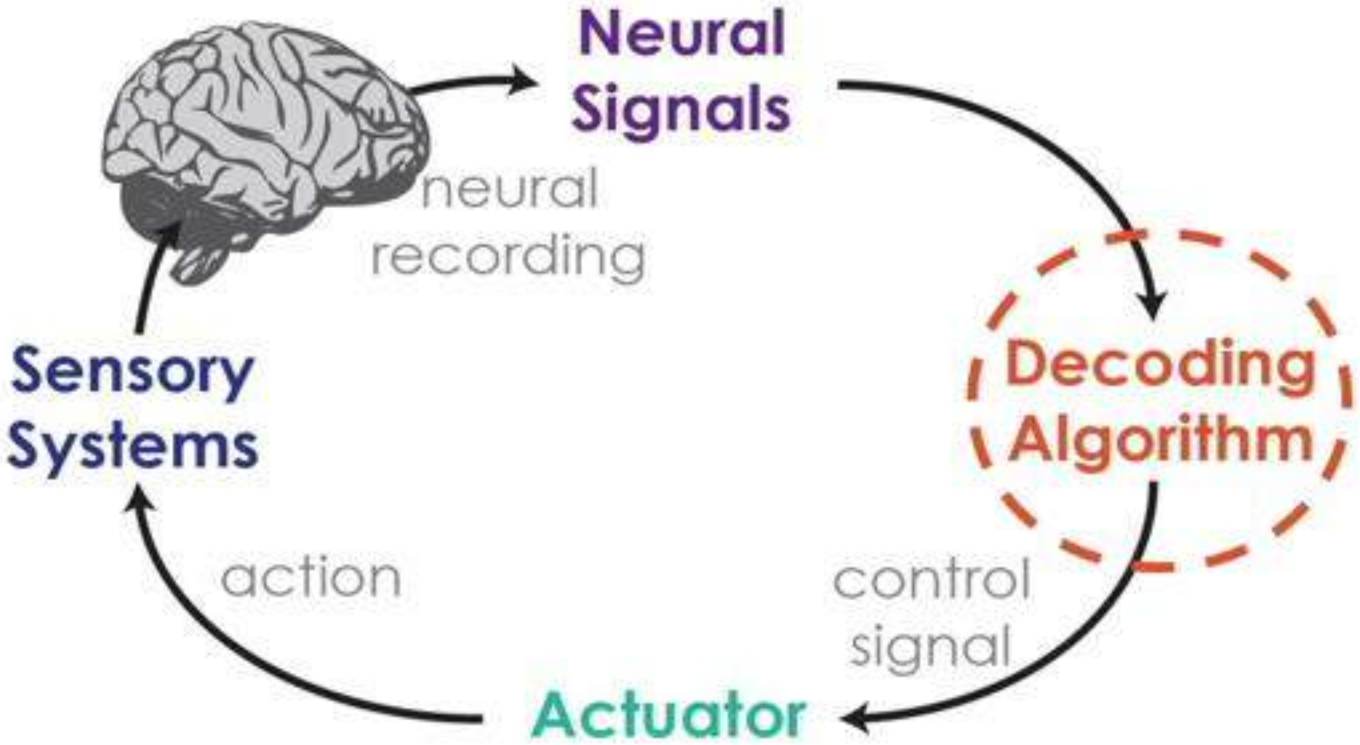



✓ Fast decoder adaptation can learn a subject's strategy
  - **Decoder learns faster than the subject**

# CLDA Summary




- ✓ Fast decoder adaptation can learn a subject's strategy
  - **Decoder learns faster than the subject**
- ✓ CLDA can rapidly improve performance

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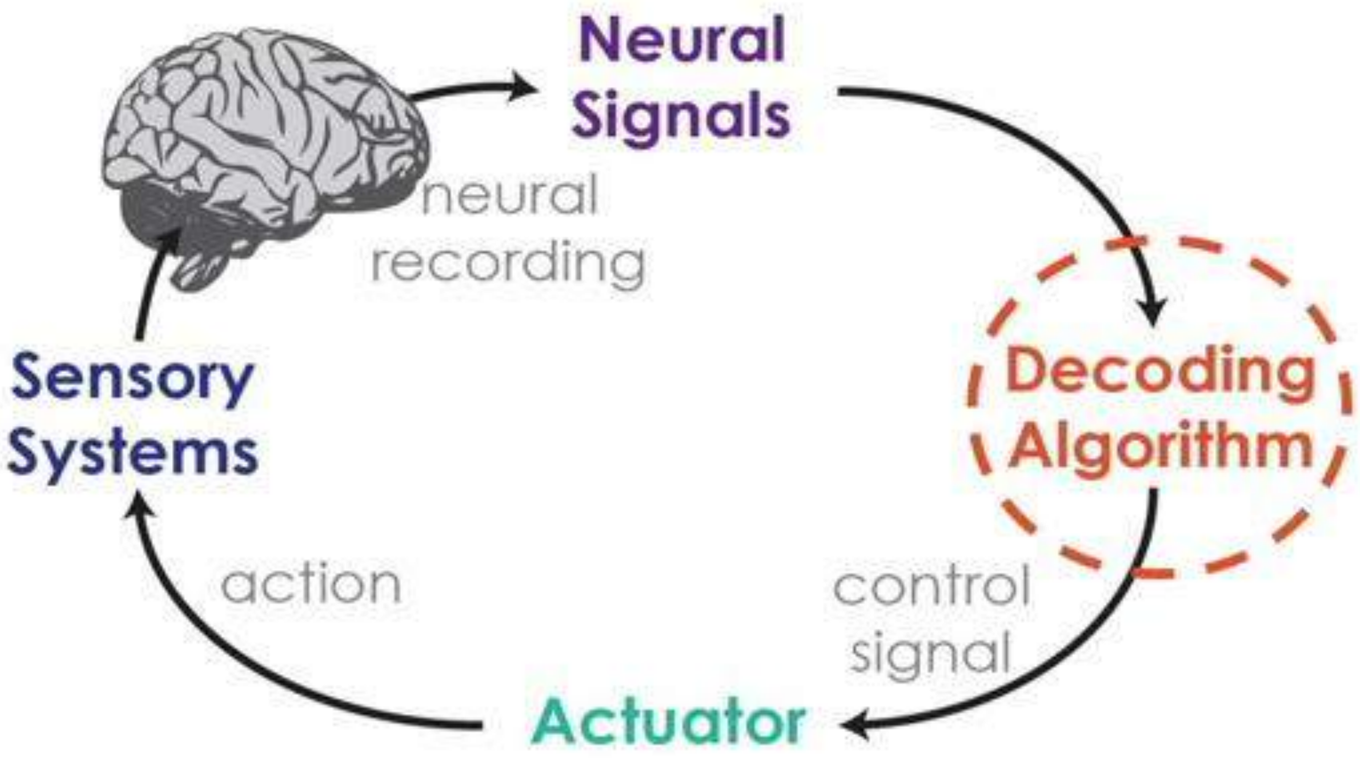
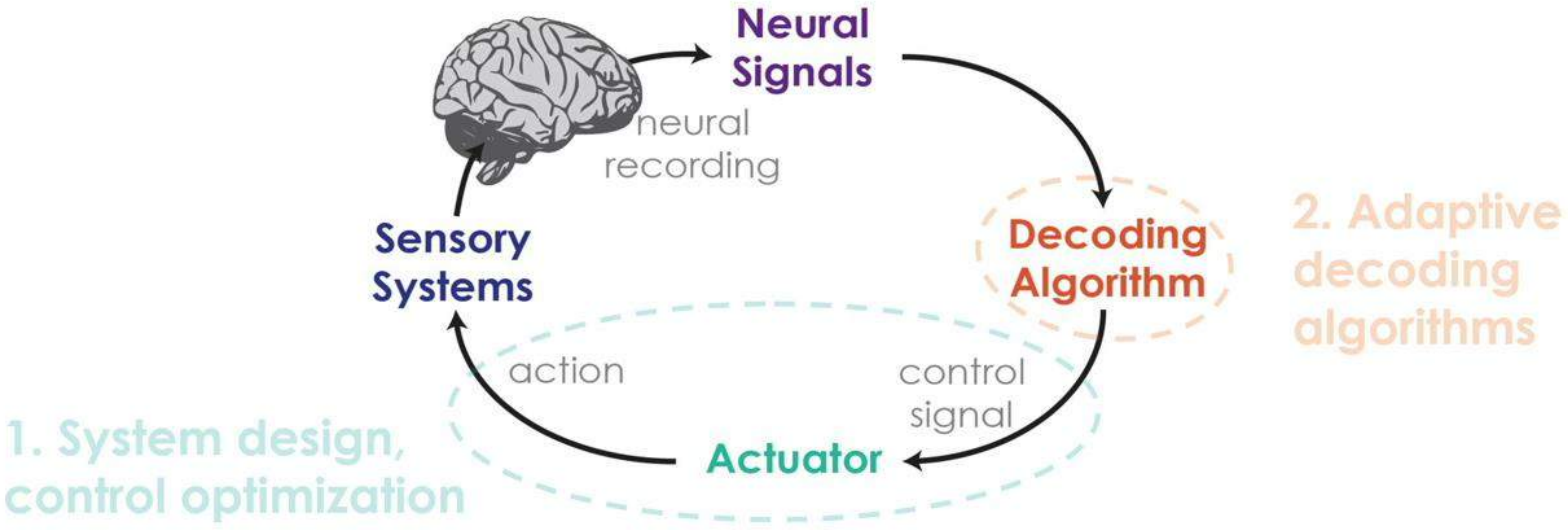



- ✓ Fast decoder adaptation can learn a subject's strategy
  - **Decoder learns faster than the subject**
- ✓ CLDA can rapidly improve performance
- ✓ Achieves high performance quickly regardless of the initial decoder
  - **Robust**

# How do we maintain performance?



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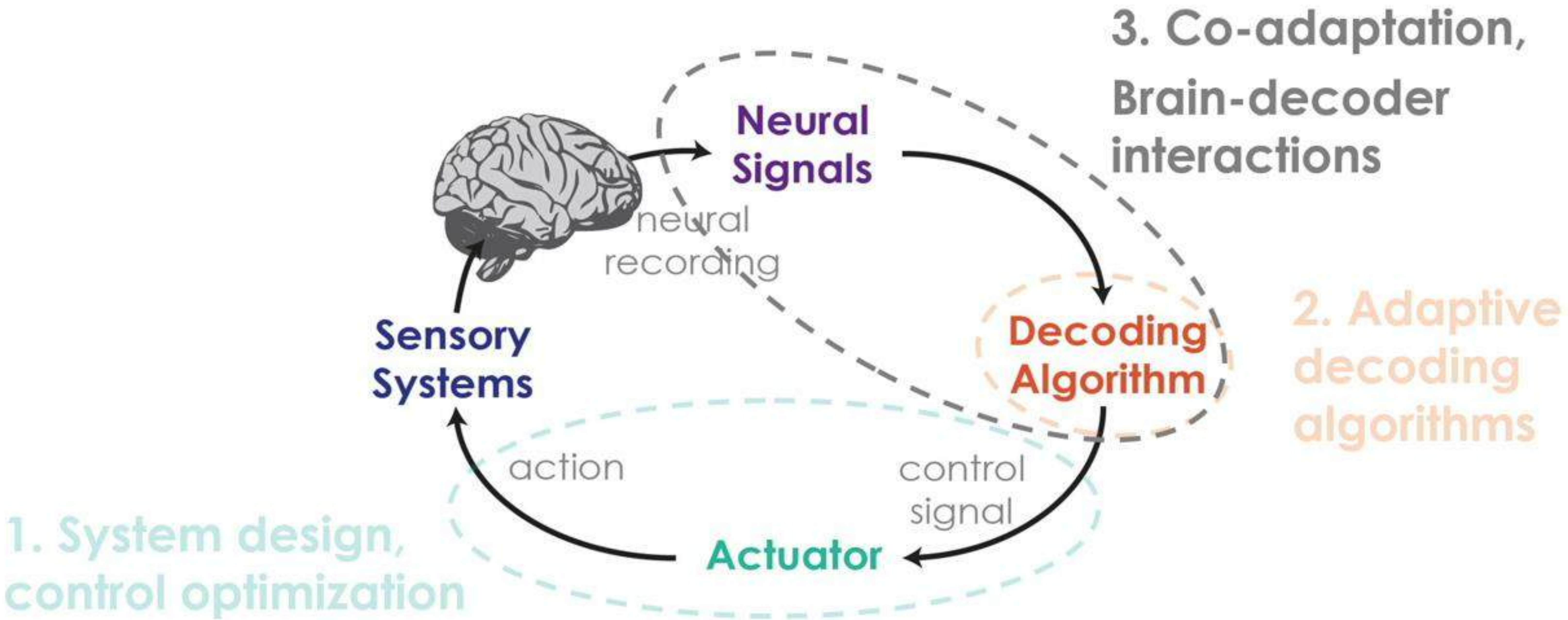

# **Challenge:** Consistent performance with measurement variability



Orsborn et al., *Neuron* 2014

# **Challenge:** Consistent performance with measurement variability

- Neural recordings can change day-to-day

Orsborn et al., *Neuron* 2014

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- Neural recordings can change day-to-day
- Can re-train CLDA each day
  - Avoid performance declines

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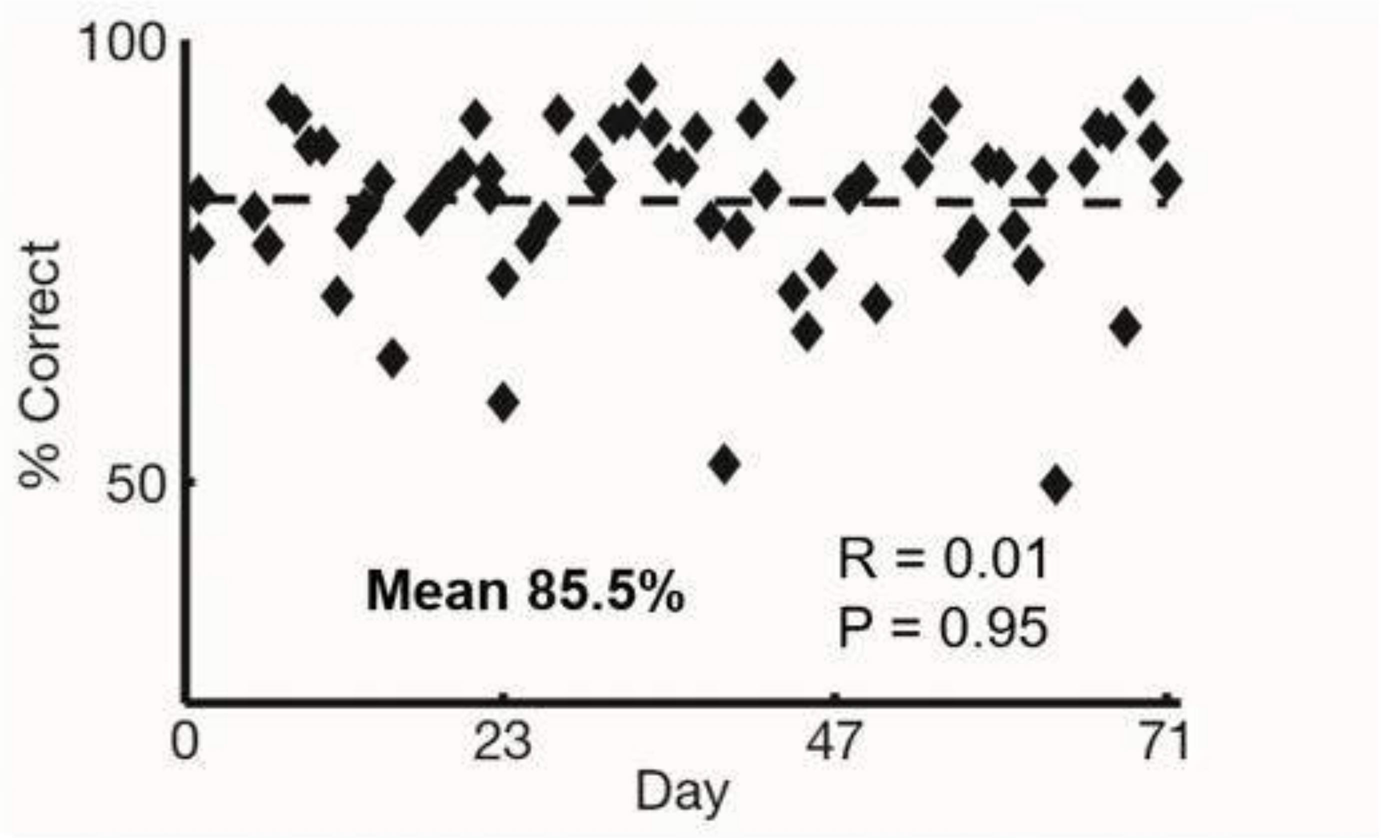


Can achieve high performance each day

Orsborn et al., *Neuron* 2014

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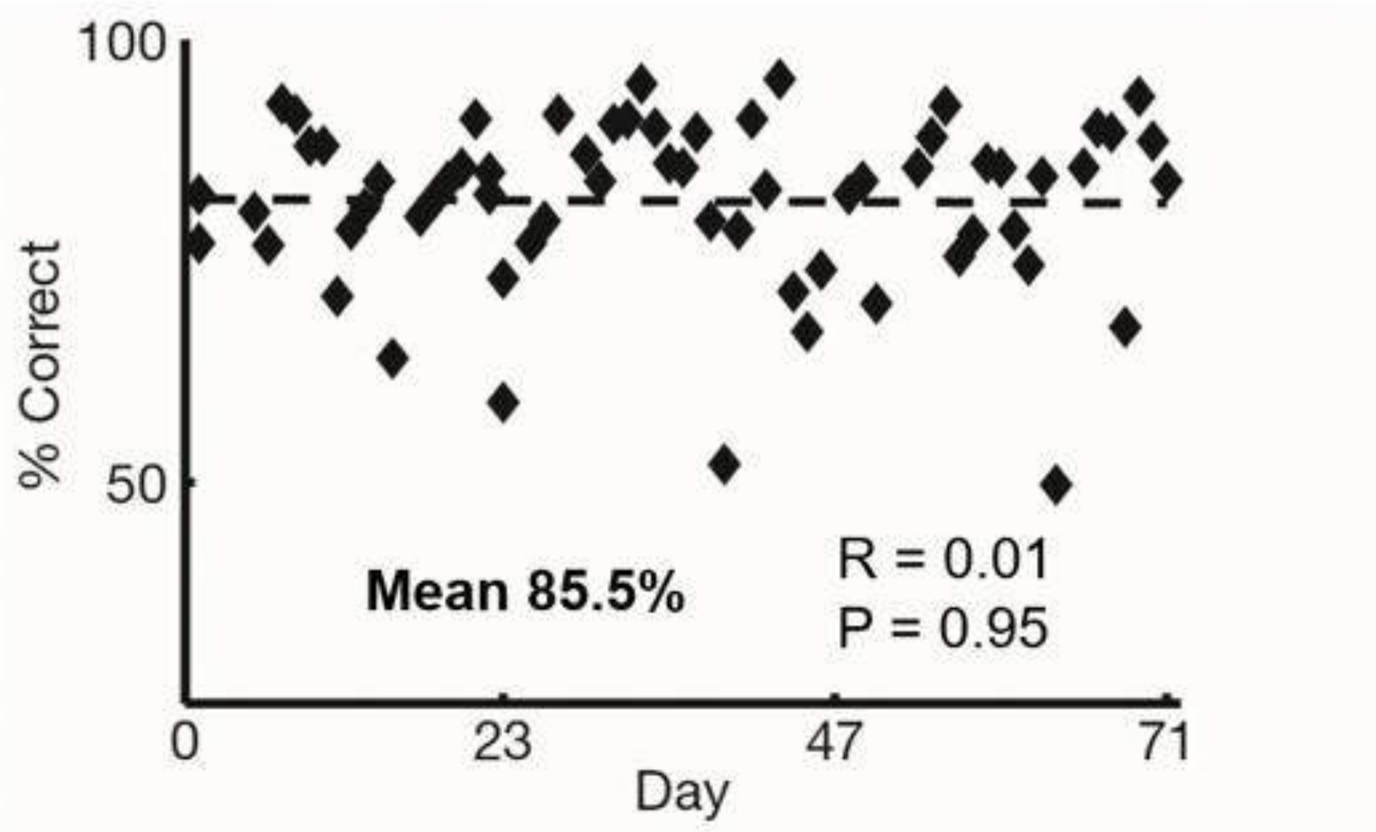
- Regular re-training doesn't eliminate variability
  - disrupts long-term learning ("skill")




Can achieve high performance each day

**But!**

-variable day-to-day.

-No improvement



Orsborn et al., *Neuron* 2014

# **Challenge:** Consistent performance with measurement variability

- Neural recordings can change day-to-day
- Can re-train CLDA each day
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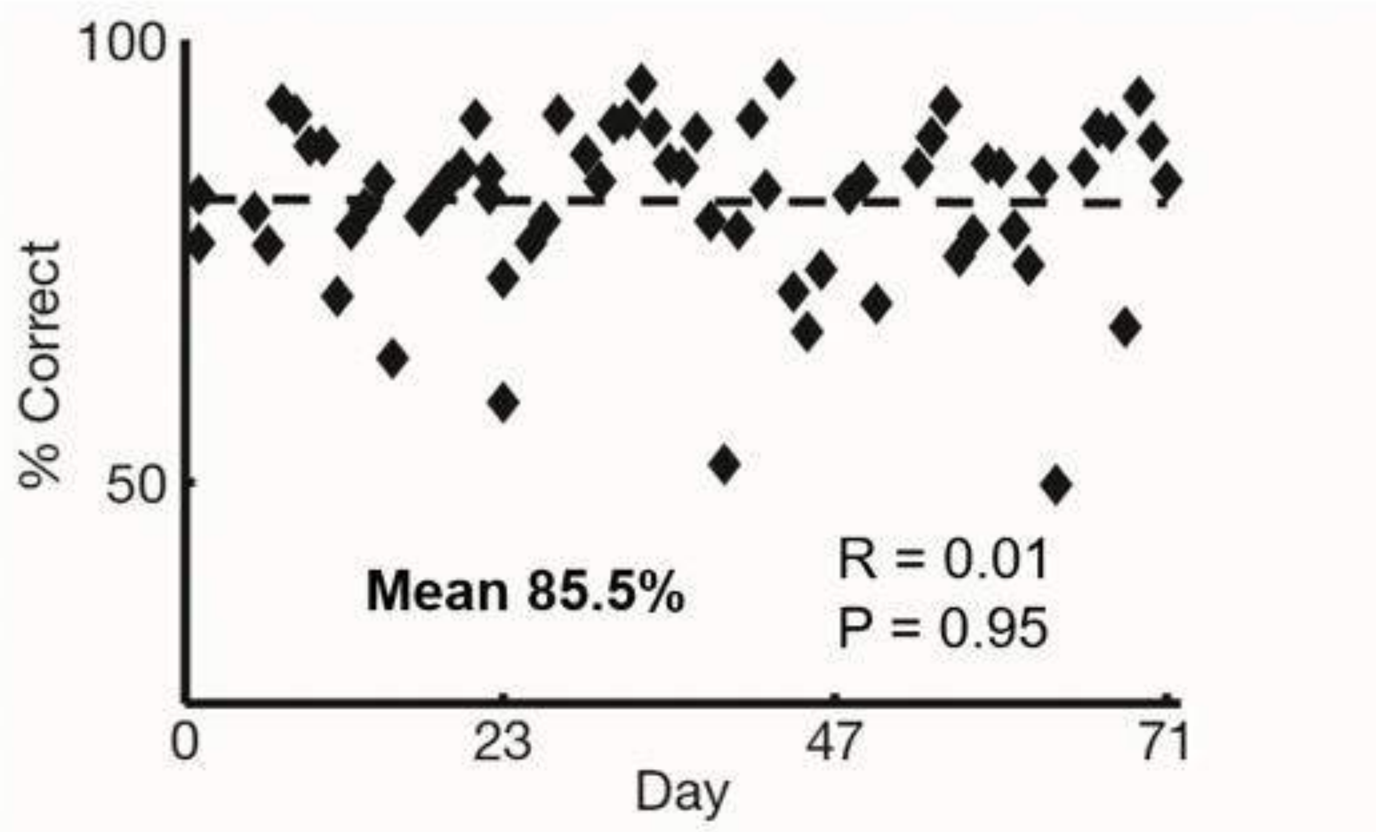
- Regular re-training doesn't eliminate variability
  - disrupts long-term learning ("skill")

- **Need decoding strategies compatible with long-term learning**

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Orsborn et al., *Neuron* 2014

# Co-adaptation paradigm

1. **decoder initialization**

Orsborn et al., *Neuron* 2014

# Co-adaptation paradigm

**1. decoder initialization** → **2. decoder adaptation (CLDA)**

Orsborn et al., *Neuron* 2014

# Co-adaptation paradigm

**1. decoder initialization** → **2. decoder adaptation (CLDA)** → **3. fixed ensemble + decoder**

Orsborn et al., *Neuron* 2014

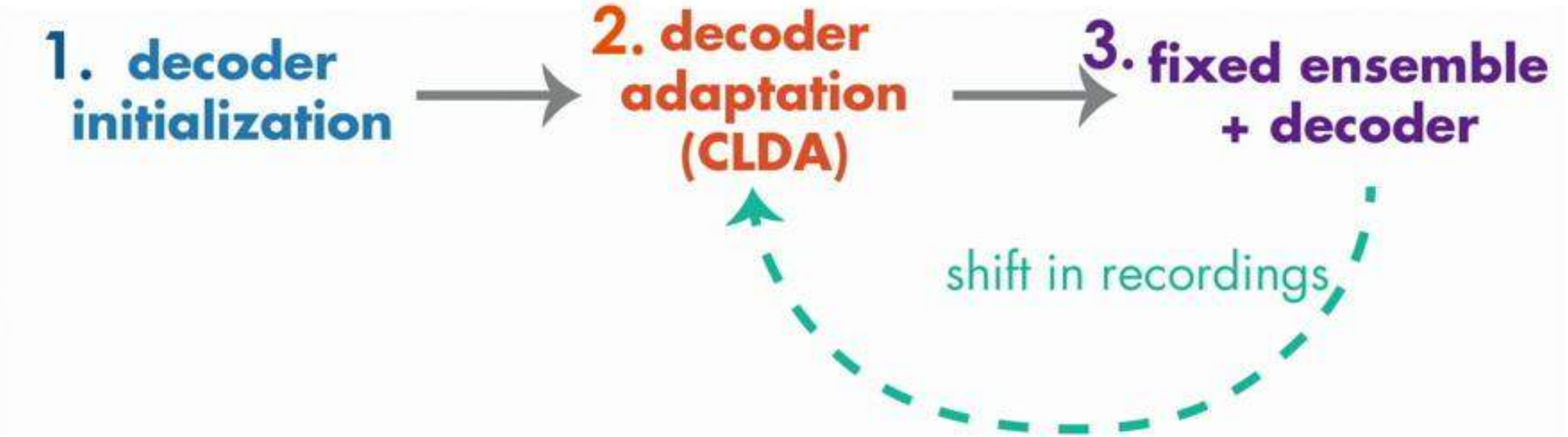
# Co-adaptation paradigm

1. **decoder initialization** → 2. **decoder adaptation (CLDA)** → 3. **fixed ensemble + decoder**

- **Allow plasticity**

Orsborn et al., *Neuron* 2014

# Co-adaptation paradigm

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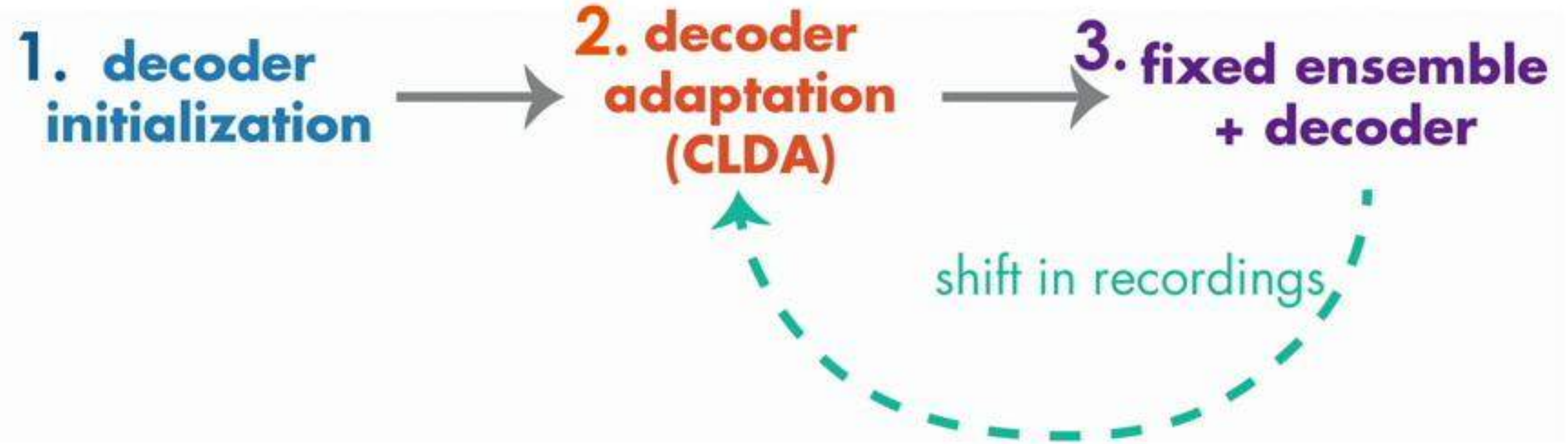
Orsborn et al., *Neuron* 2014

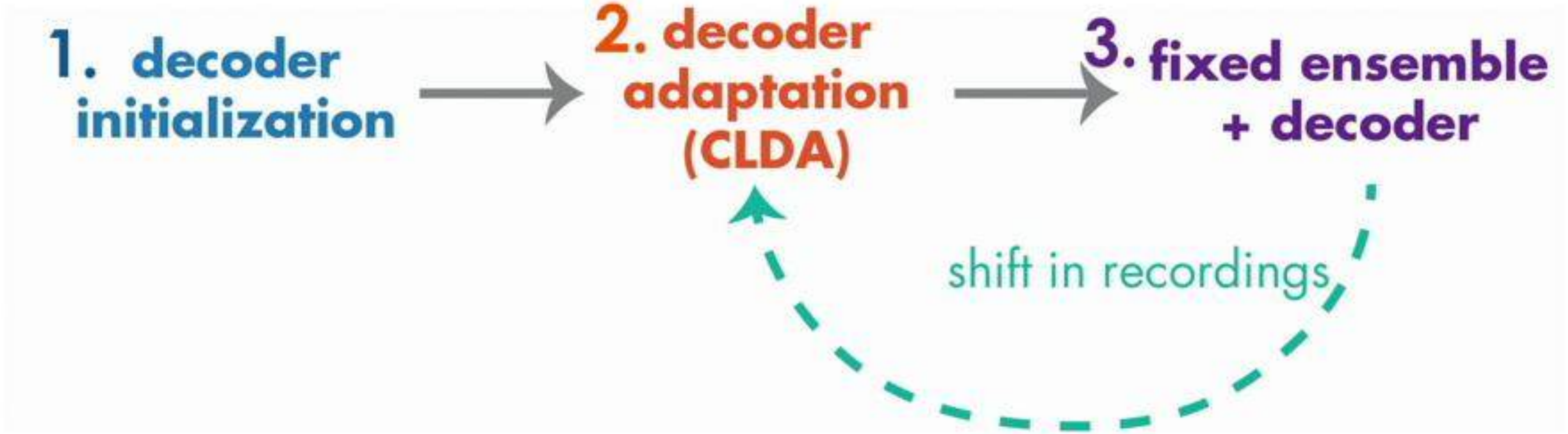
# Co-adaptation paradigm




- Allow plasticity
- Retain performance

Orsborn et al., *Neuron* 2014

# Co-adaptation paradigm




- Allow plasticity

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- Gradual shifts in ensemble

Orsborn et al., *Neuron* 2014

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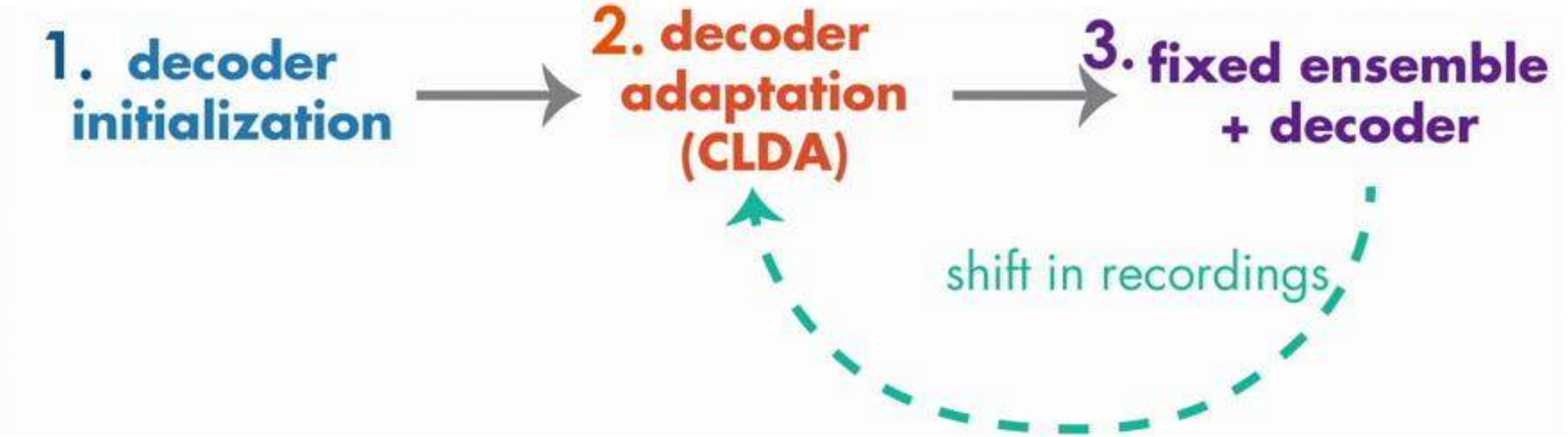


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Orsborn et al., *Neuron* 2014

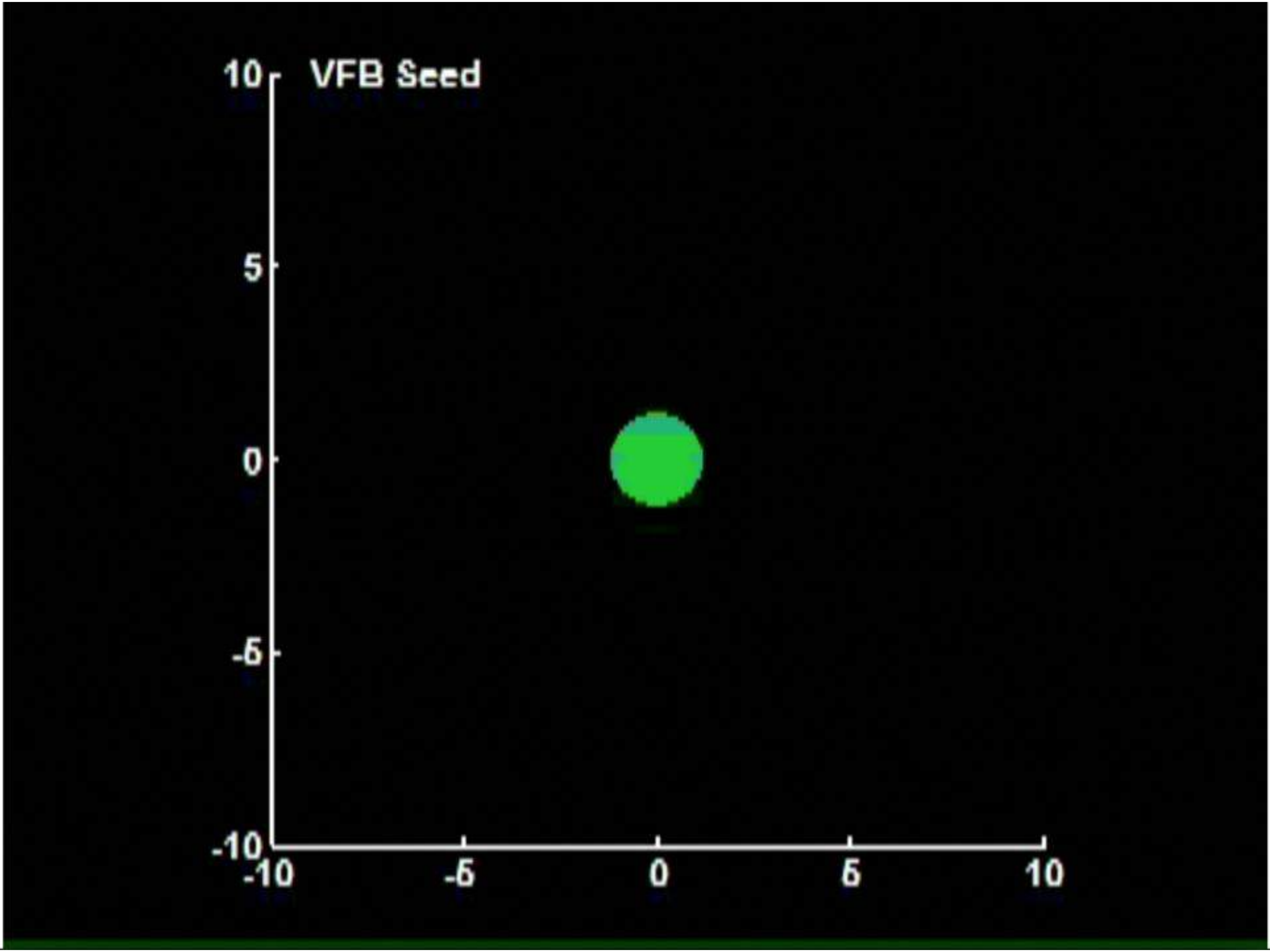
# Co-Adaptation in Brain-Machine Interfaces:

## Combining Smoothbatch decoder adaptation & neural plasticity

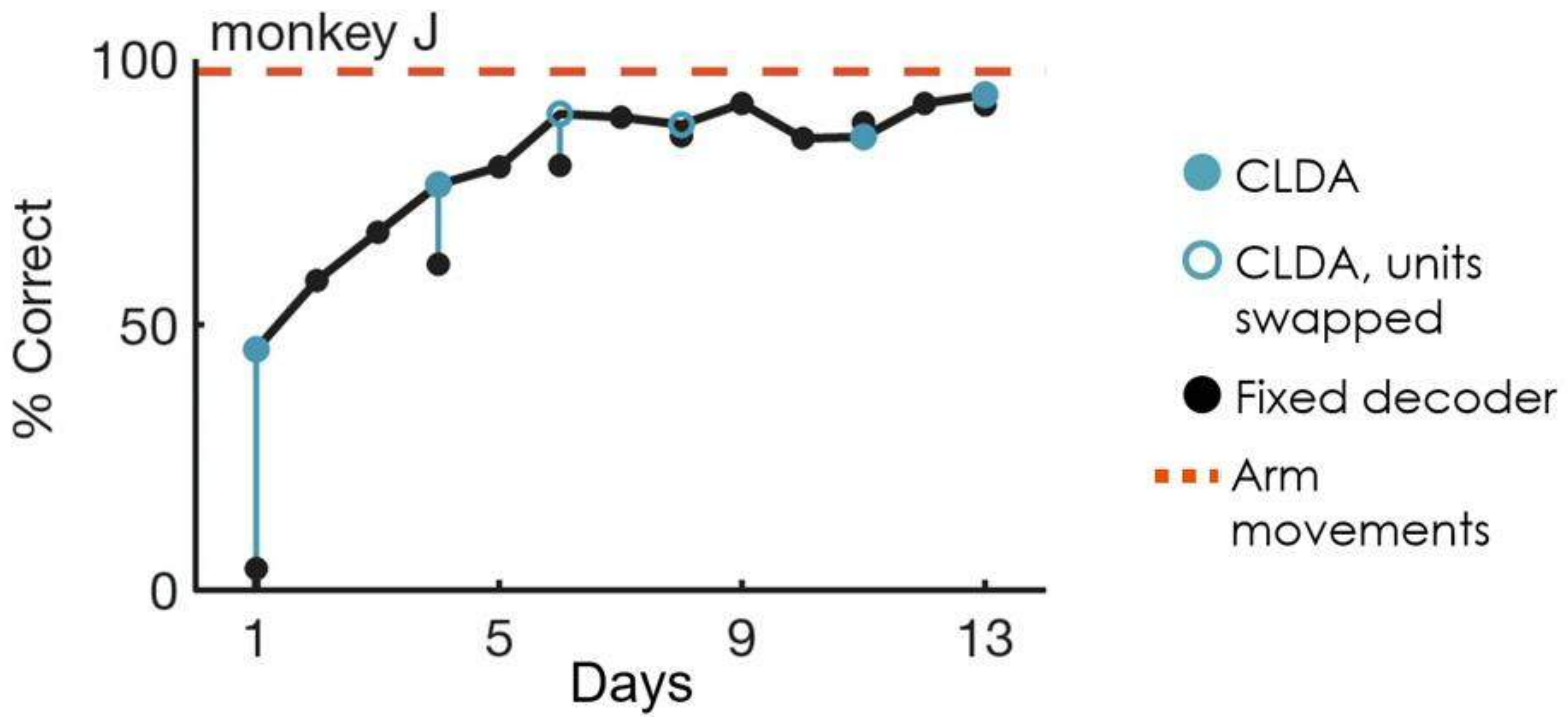
A.L. Orsborn
J.M. Carmena

Carmena Lab
UC Berkeley

jeev072312c-080412g


VFB Seed
10
5
0
-5
-10
-10
-5
0
5
10

# Coadaptation provides multi-day performance retention, improvements




- Performance improvements build across days
- Improvements continue after decoder adaptation

Orsborn et al., *Neuron* 2014

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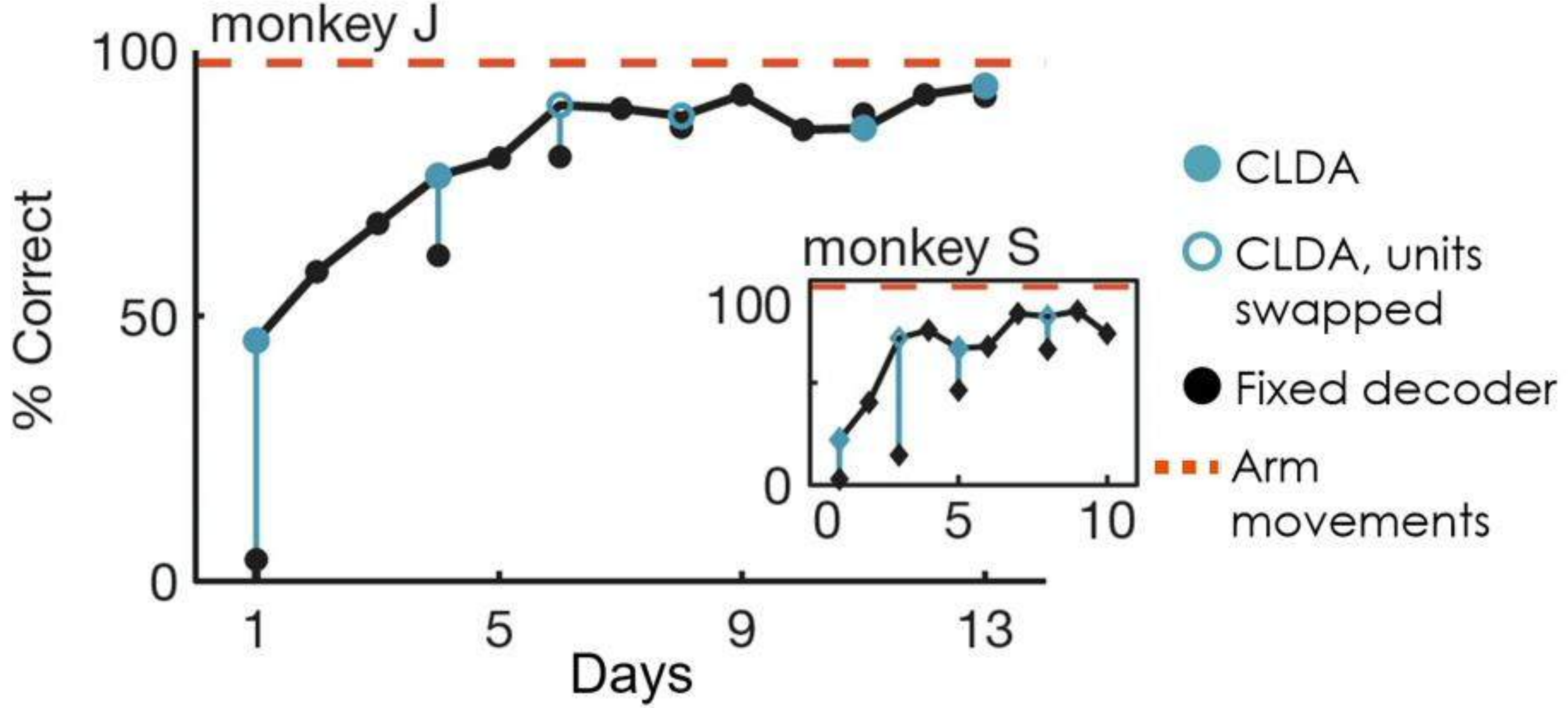


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# Neural adaptation can improve performance beyond CLDA

Orsborn et al., *Neuron* 2014

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- Maximize performance with CLDA

Orsborn et al., *Neuron* 2014

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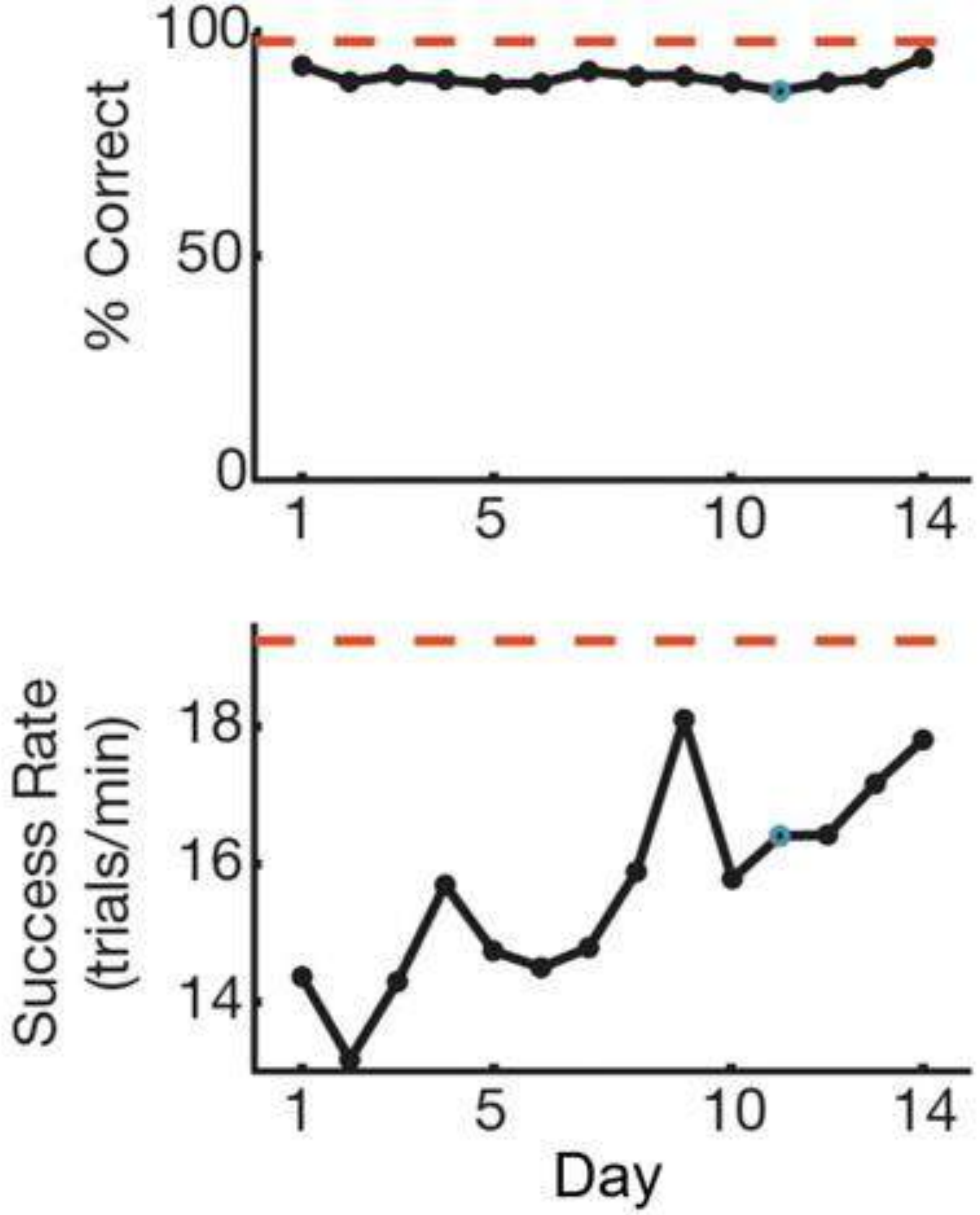


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Orsborn et al., *Neuron* 2014

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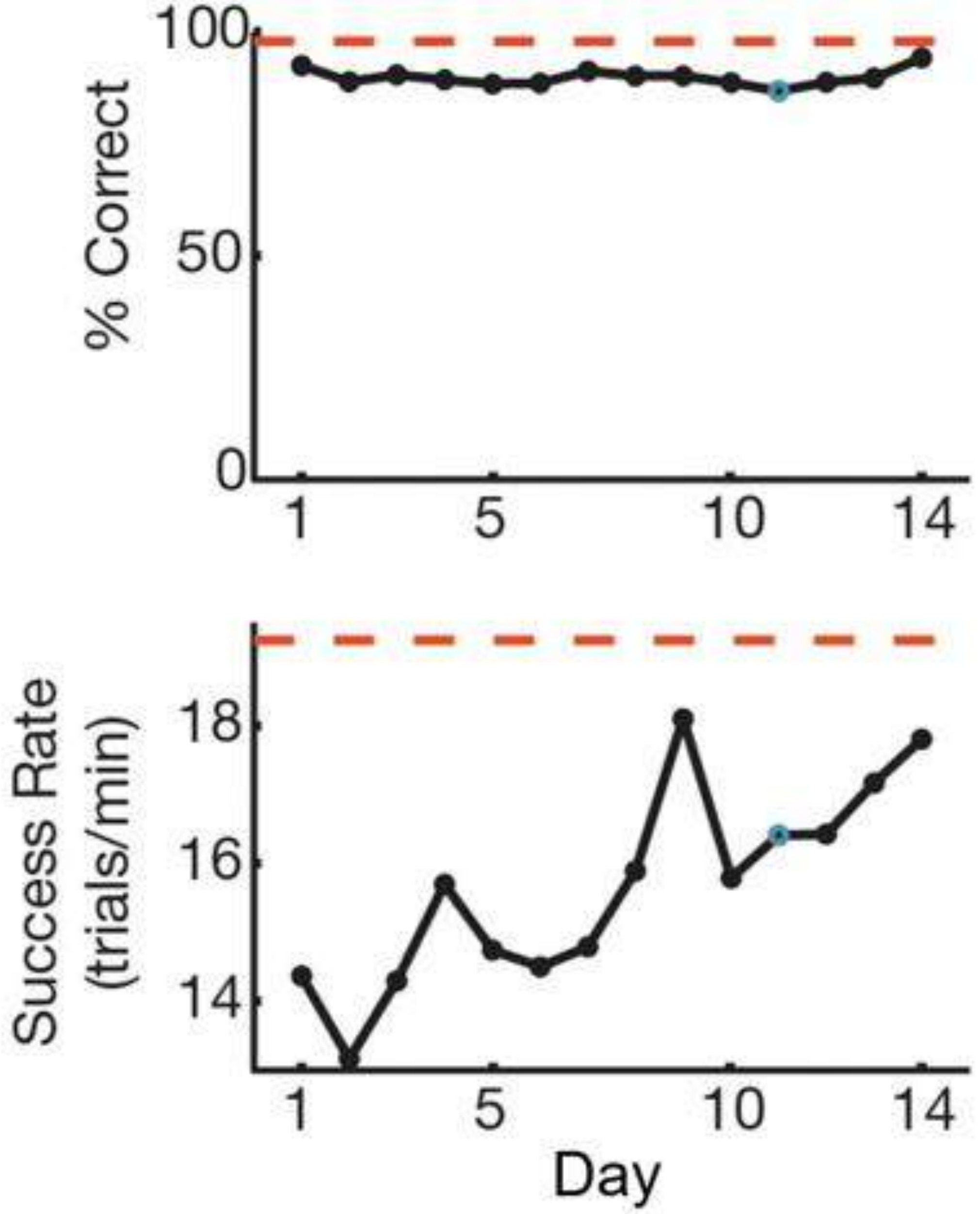



- Maximize performance with CLDA

**Brain might provide performance improvements beyond CLDA**

Orsborn et al., *Neuron* 2014

# Performance improves because subject learns to reliably modulate neurons controlling the BMI

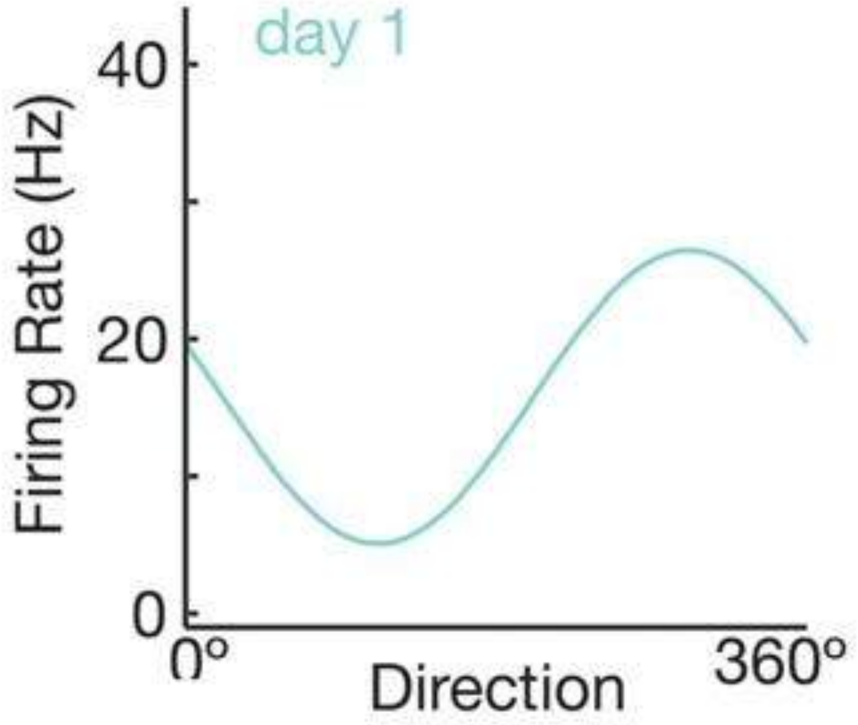
Orsborn et al., *Neuron* 2014

# Performance improves because subject learns to reliably modulate neurons controlling the BMI

- **Refinement**

Orsborn et al., *Neuron* 2014

# Performance improves because subject learns to reliably modulate neurons controlling the BMI

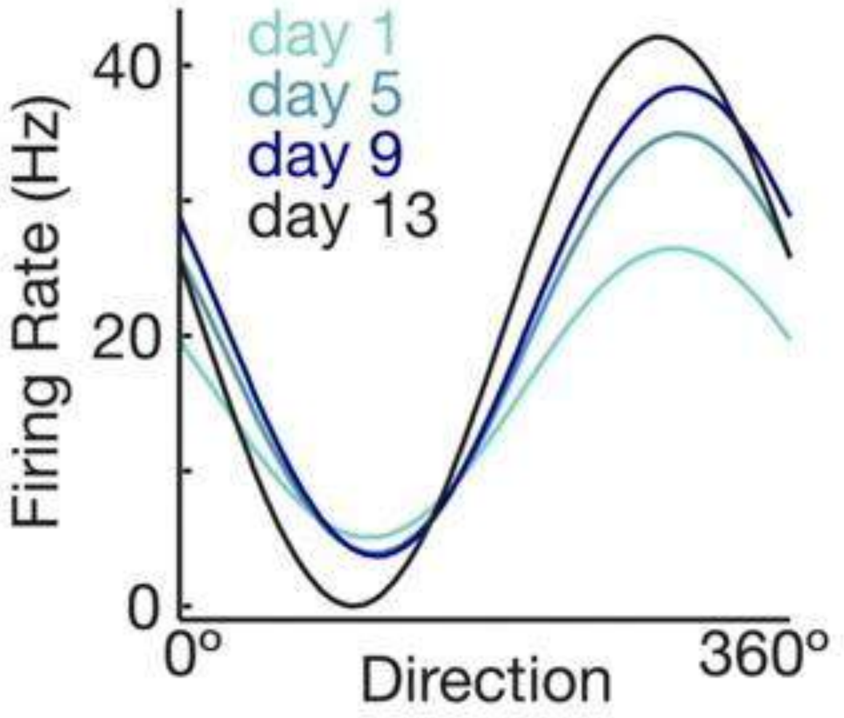



- **Refinement**

Orsborn et al., *Neuron* 2014

# Performance improves because subject learns to reliably modulate neurons controlling the BMI

**Increased direction tuning**

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  - Increased modulation of BMI neurons

Orsborn et al., *Neuron* 2014

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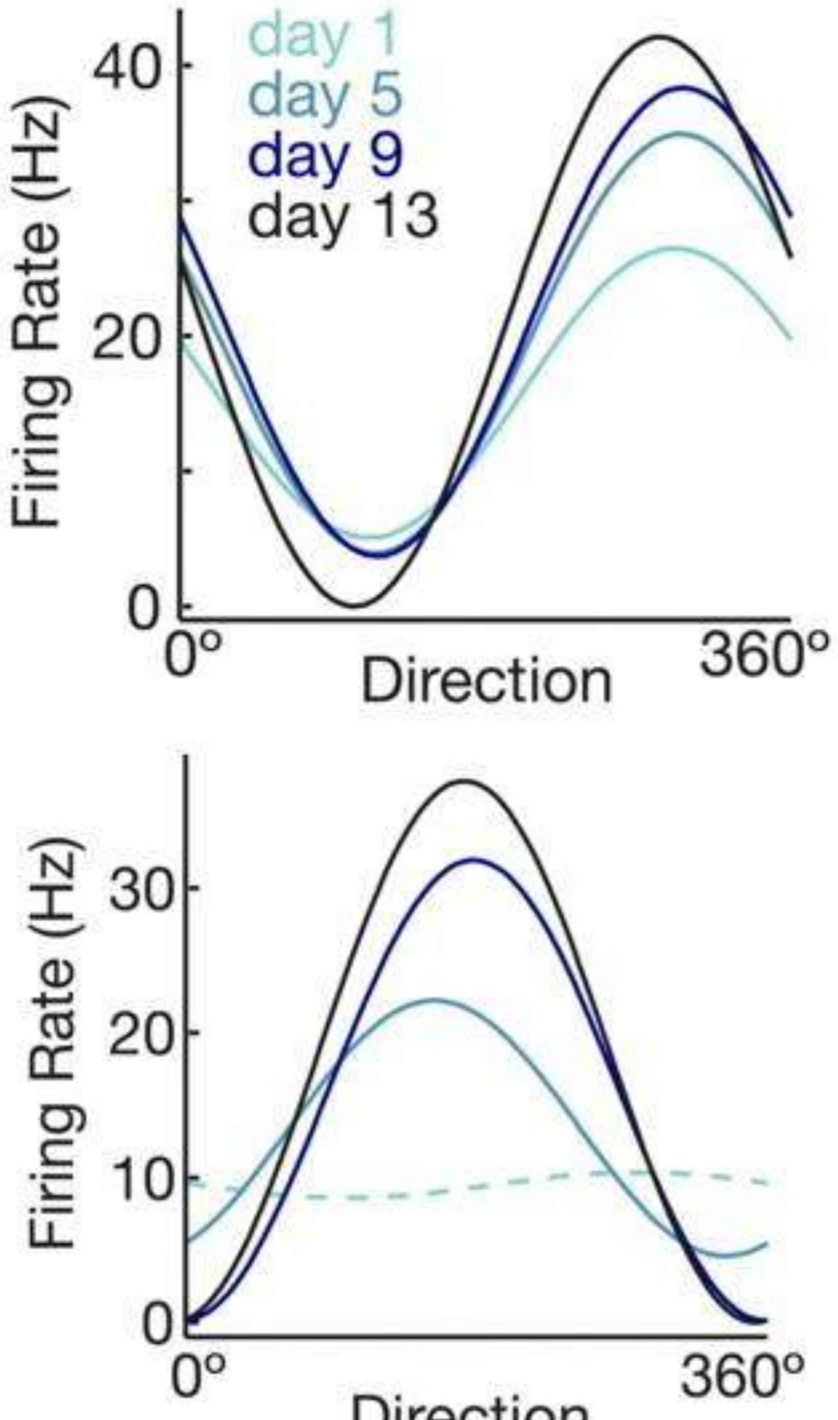


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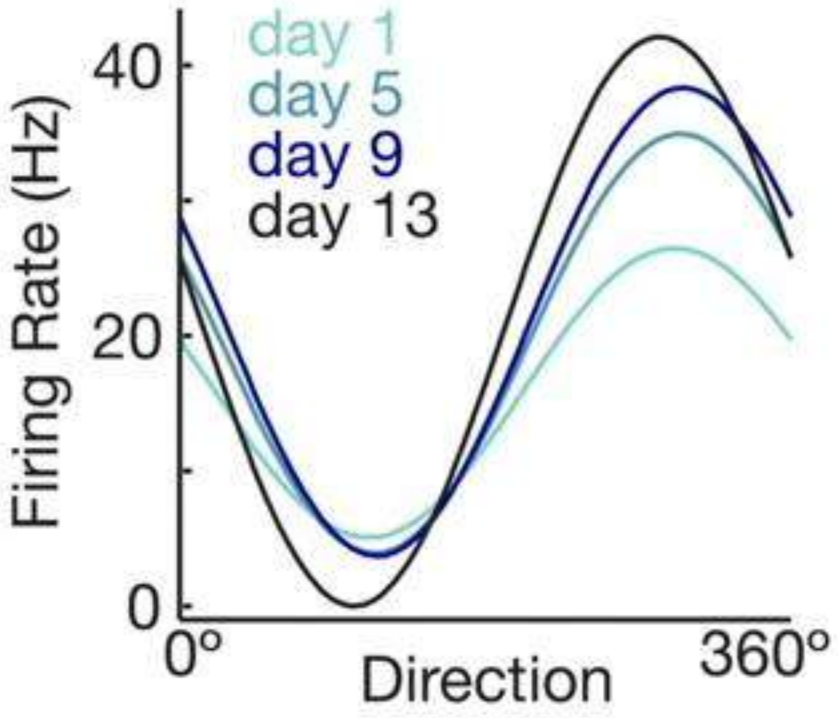


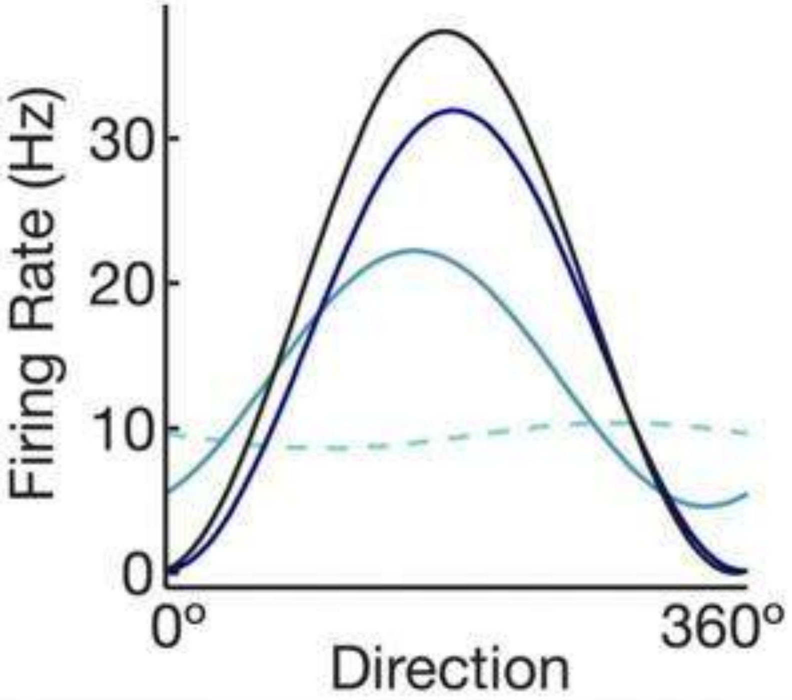


- **Refinement**
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  - Faster temporal recruitment

Orsborn et al., *Neuron* 2014

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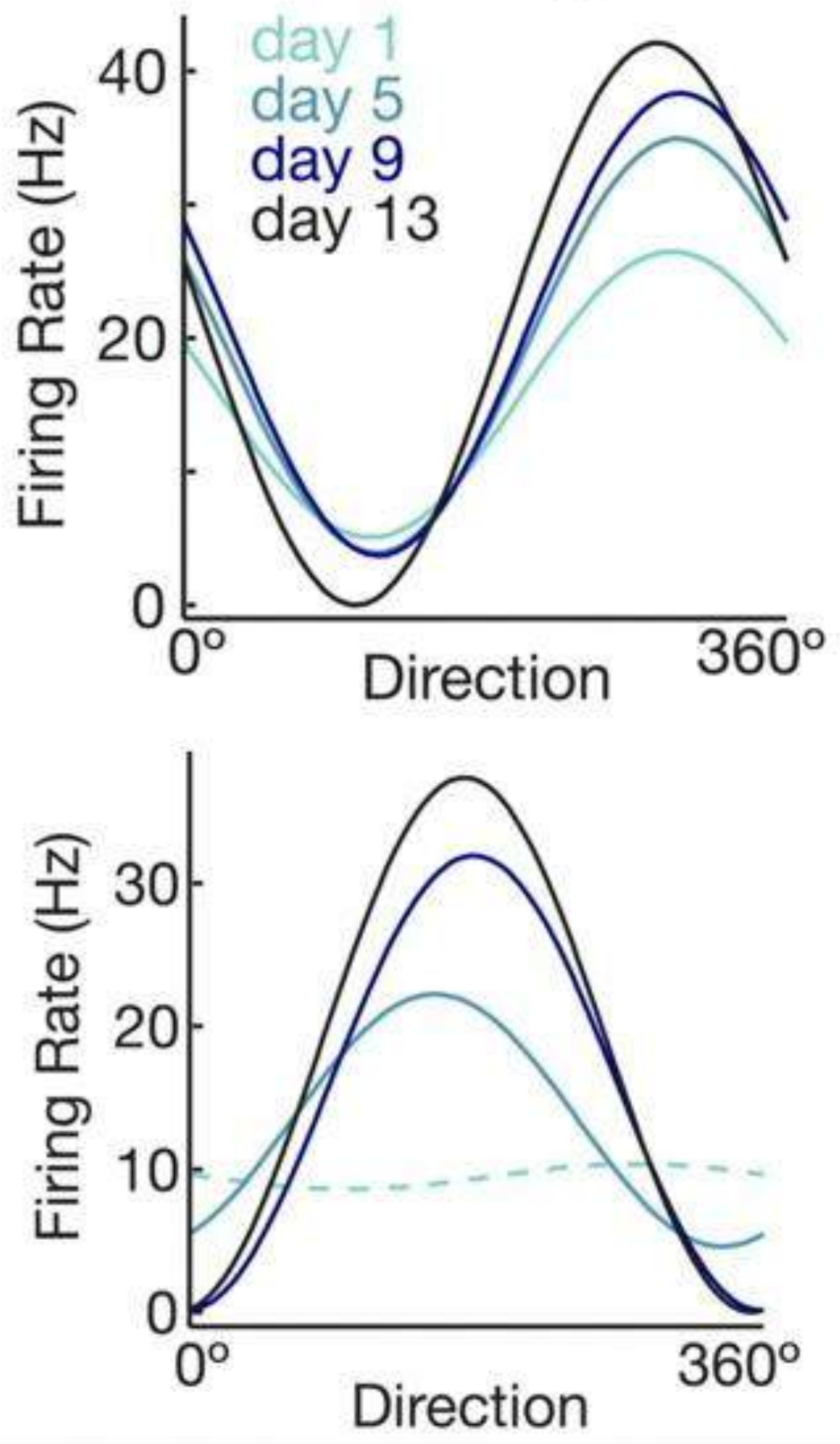


- **Refinement**
  - Increased modulation of BMI neurons
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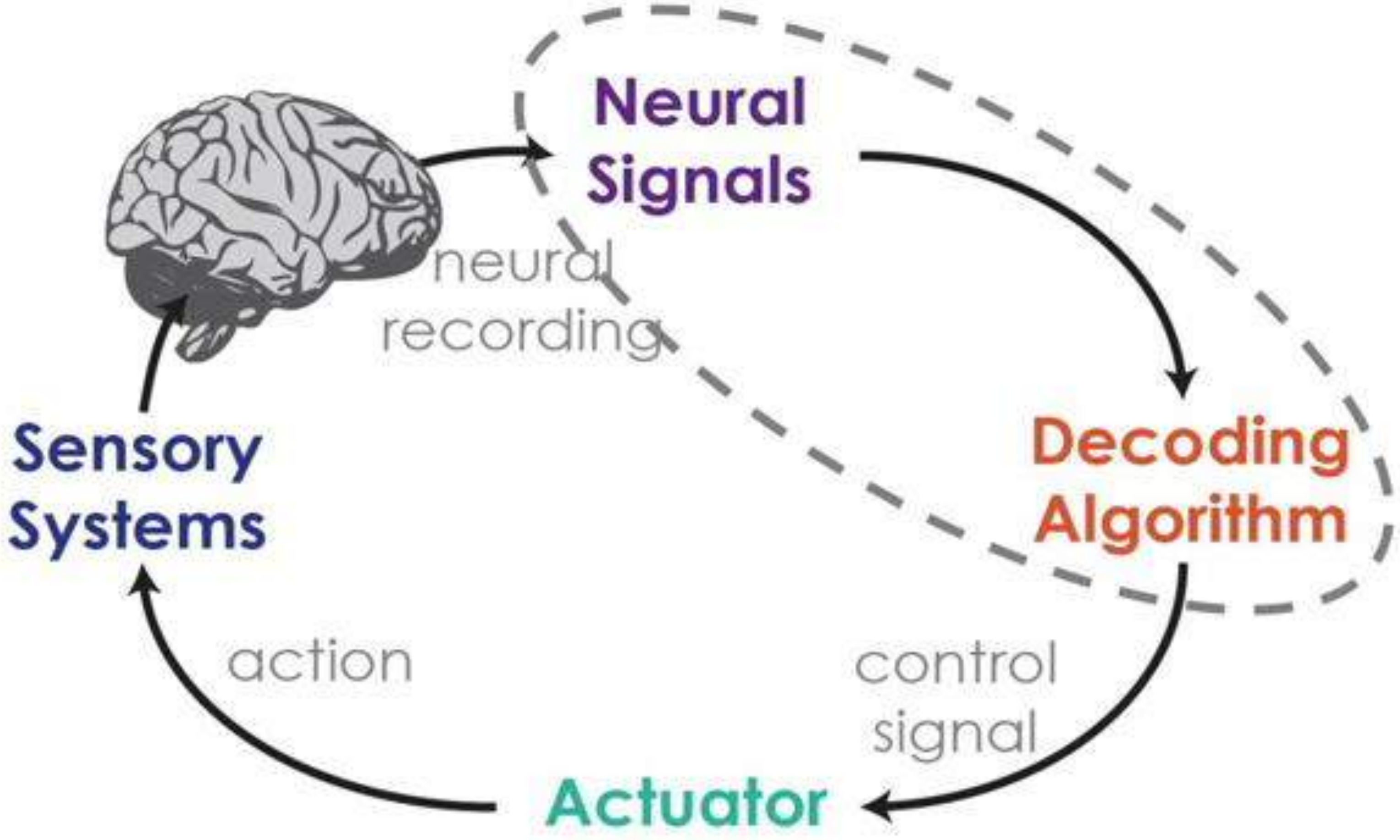
- **Neural patterns stabilize over time**
  - Show hallmarks of 'skill learning' (e.g. Ganguly and Carmena, *PLoS Biol* 2009)

Orsborn et al., *Neuron* 2014

# Co-adaptation adaptation summary



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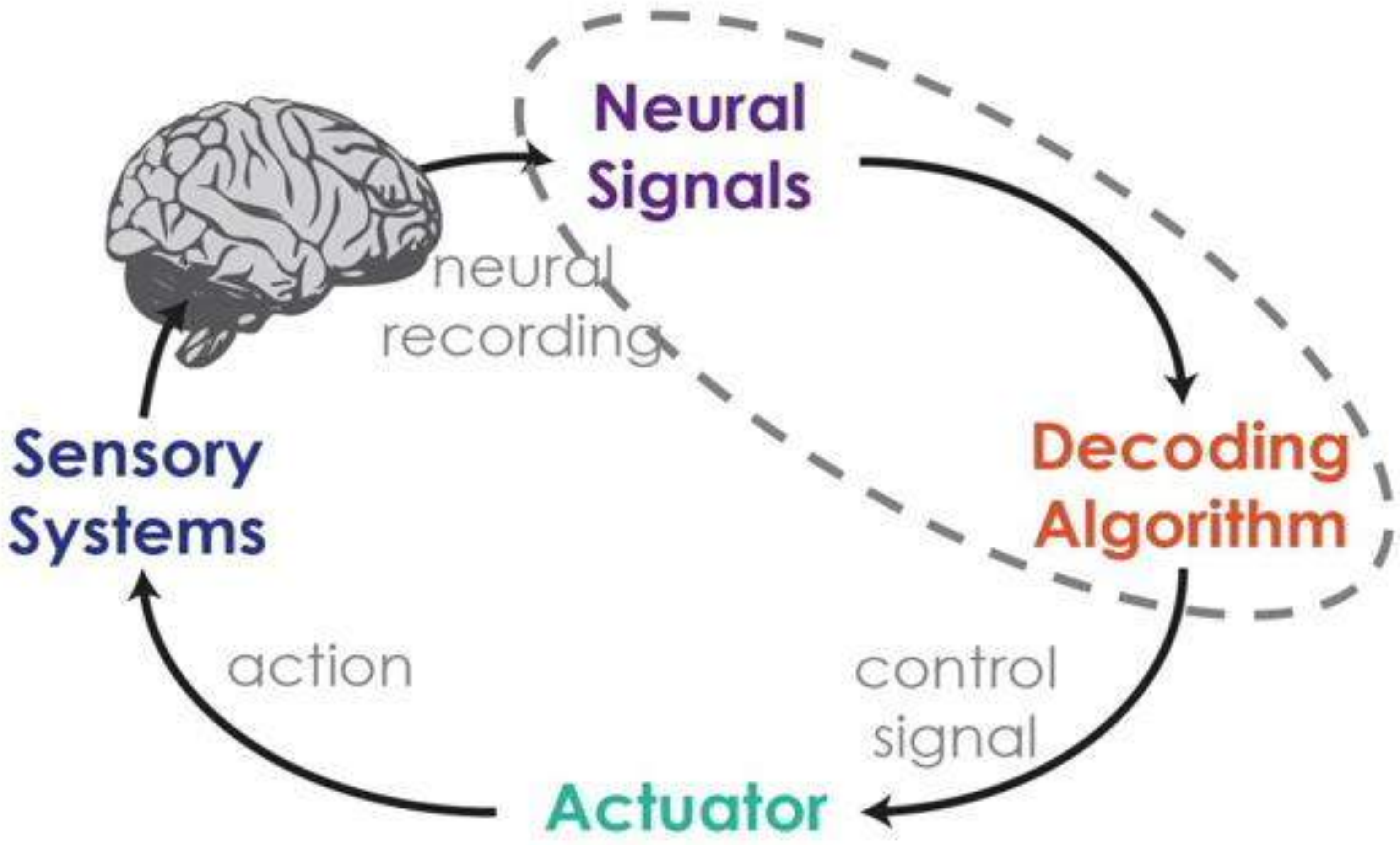


- Neural and decoder adaptation can interact synergistically

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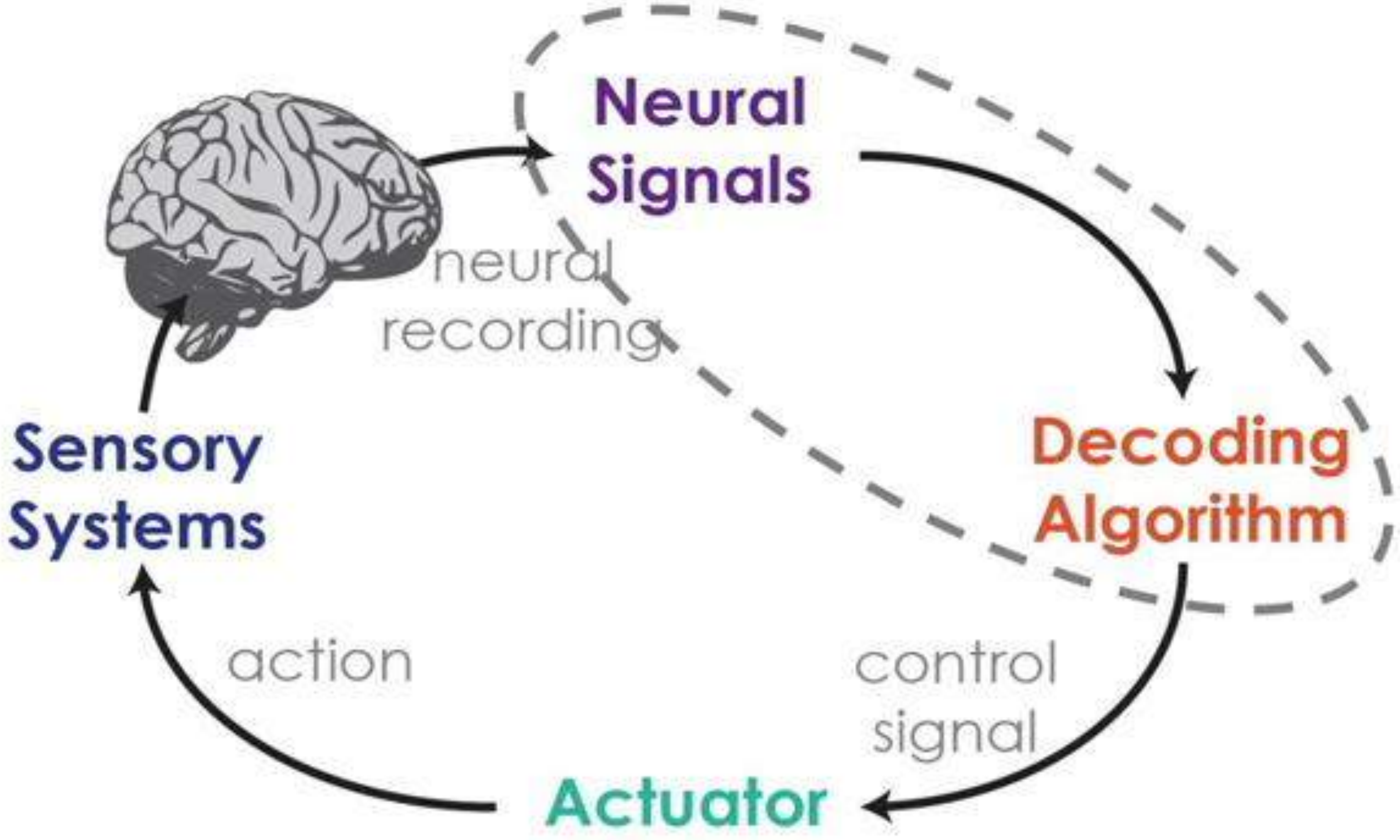


- Neural and decoder adaptation can interact synergistically
- Brain learning may be important for
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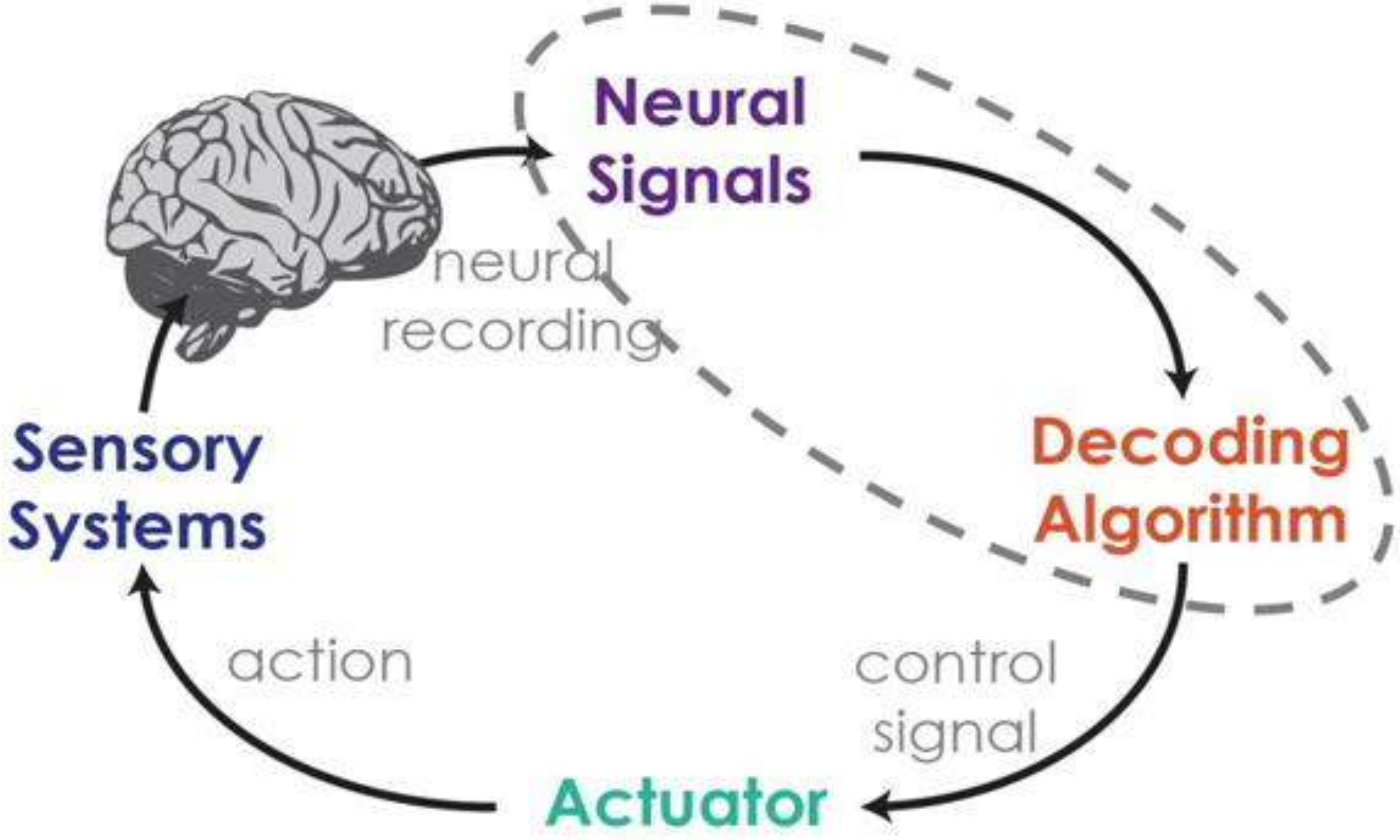


**A Next step:** scaling to higher dimensions?

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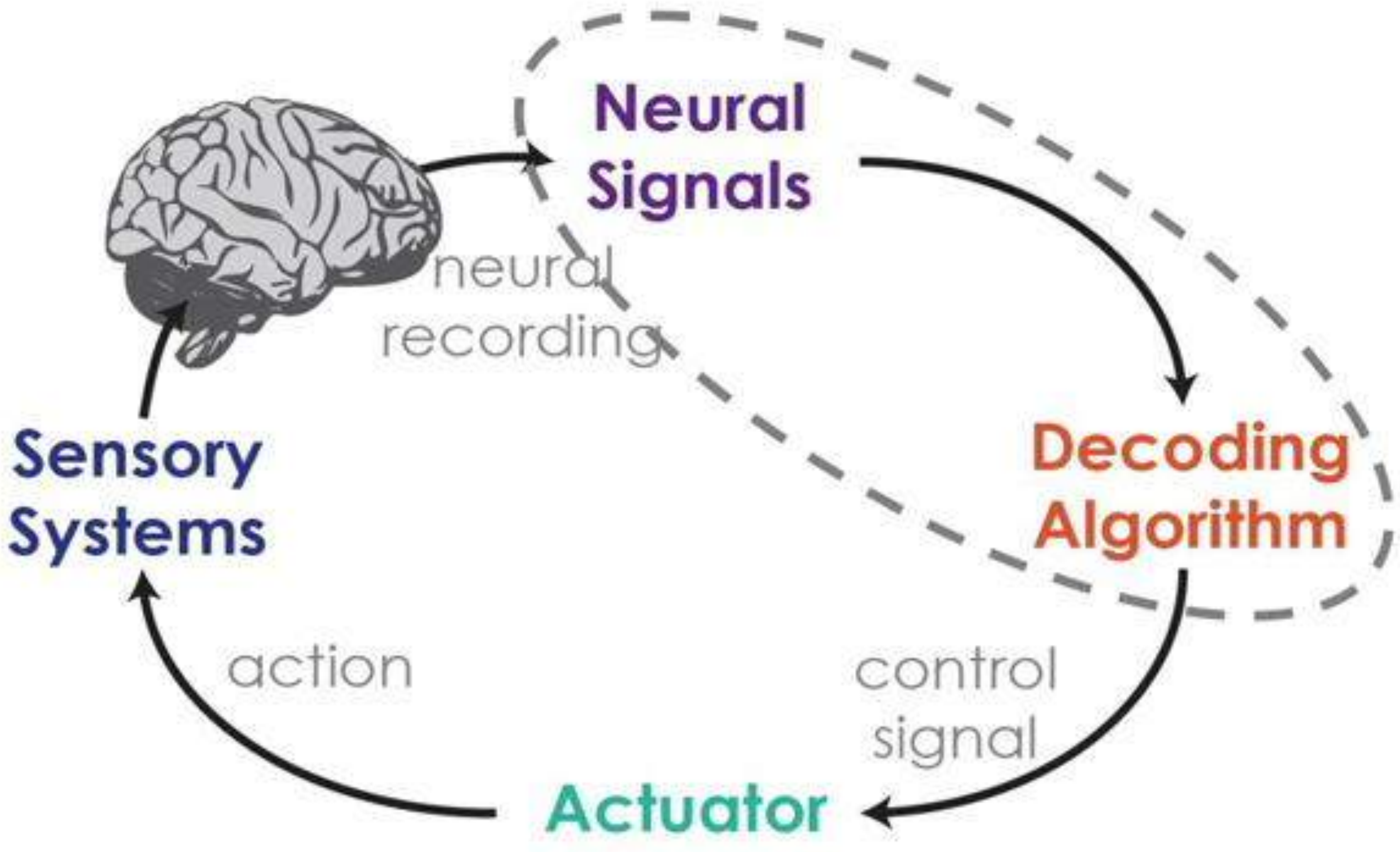


**A Next step:** scaling to higher dimensions?
→ **Technology** to study high DoF movements

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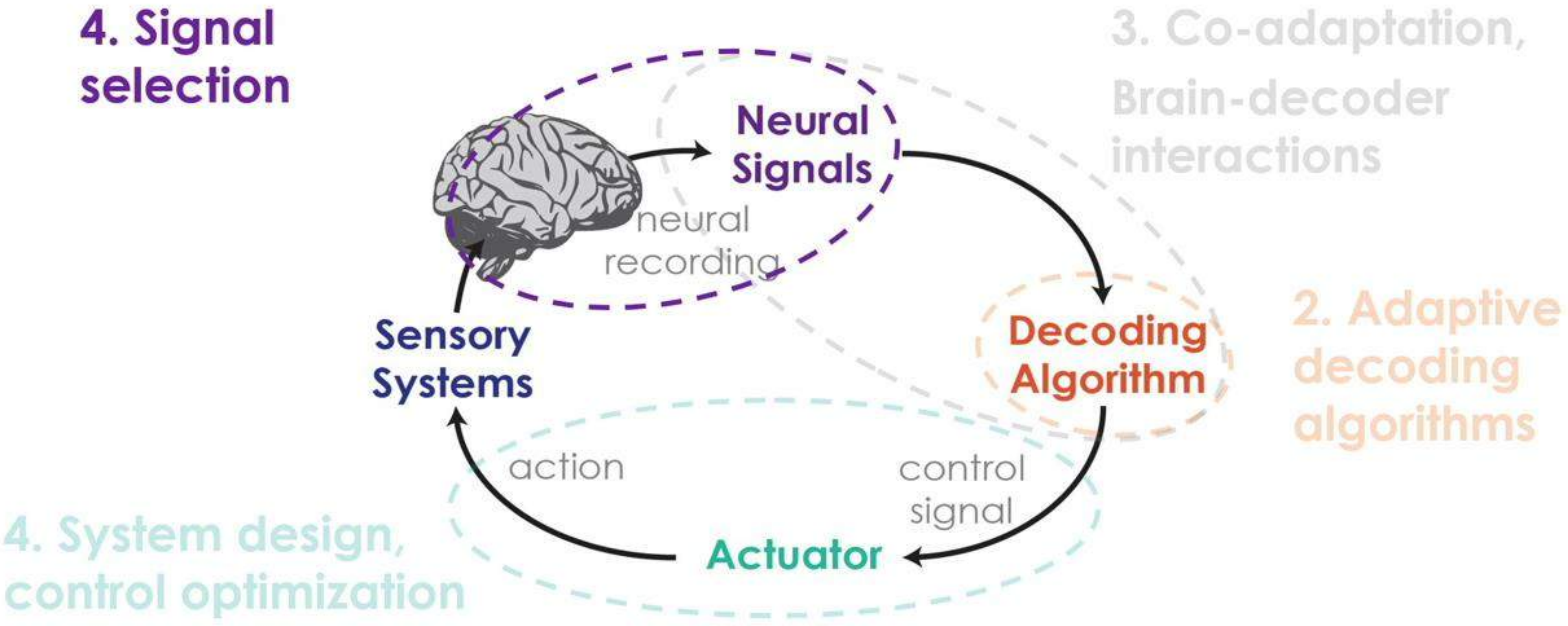
# Can neural signal selection optimize learning?



# Subject learning is the performance bottleneck

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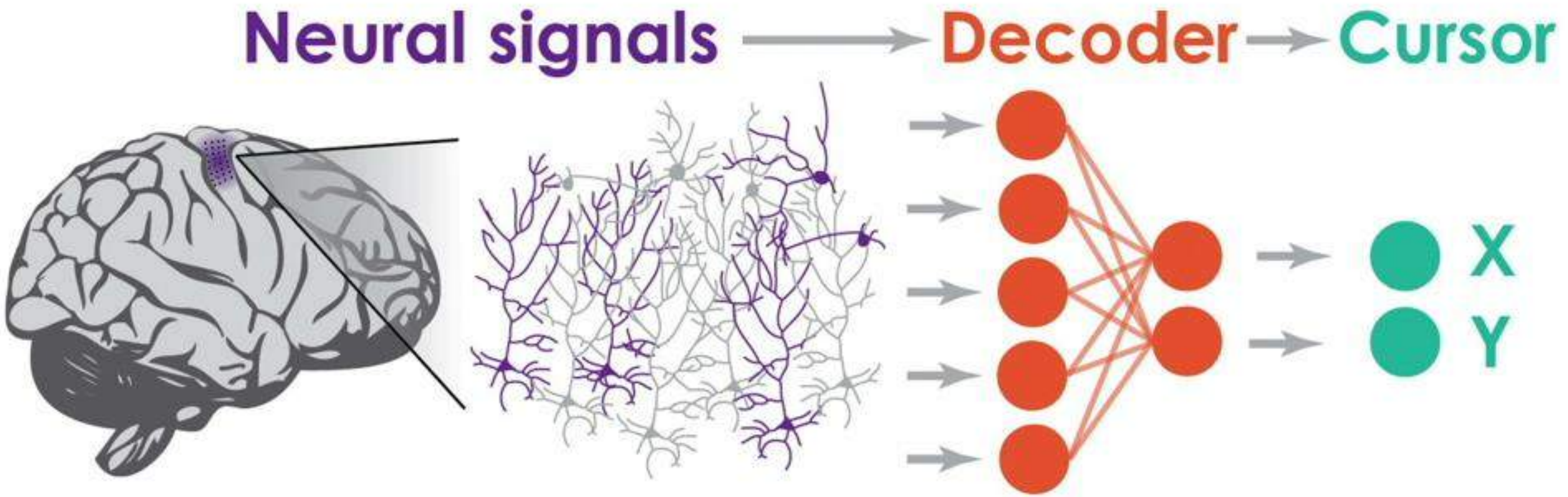

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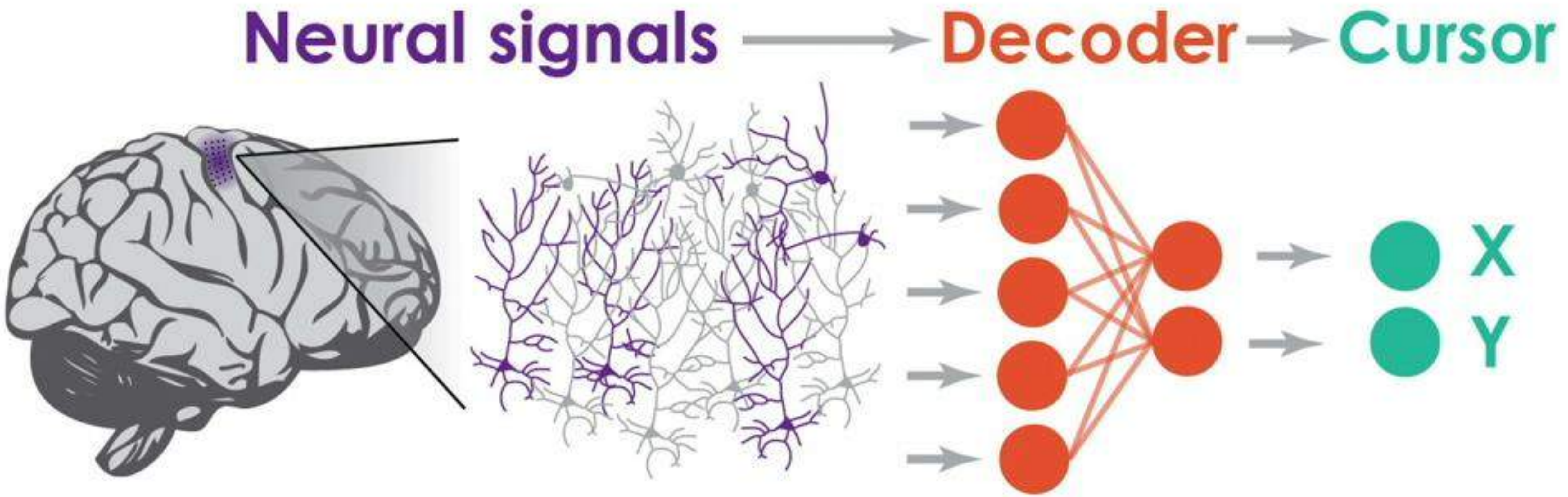


Two types of learning happening:

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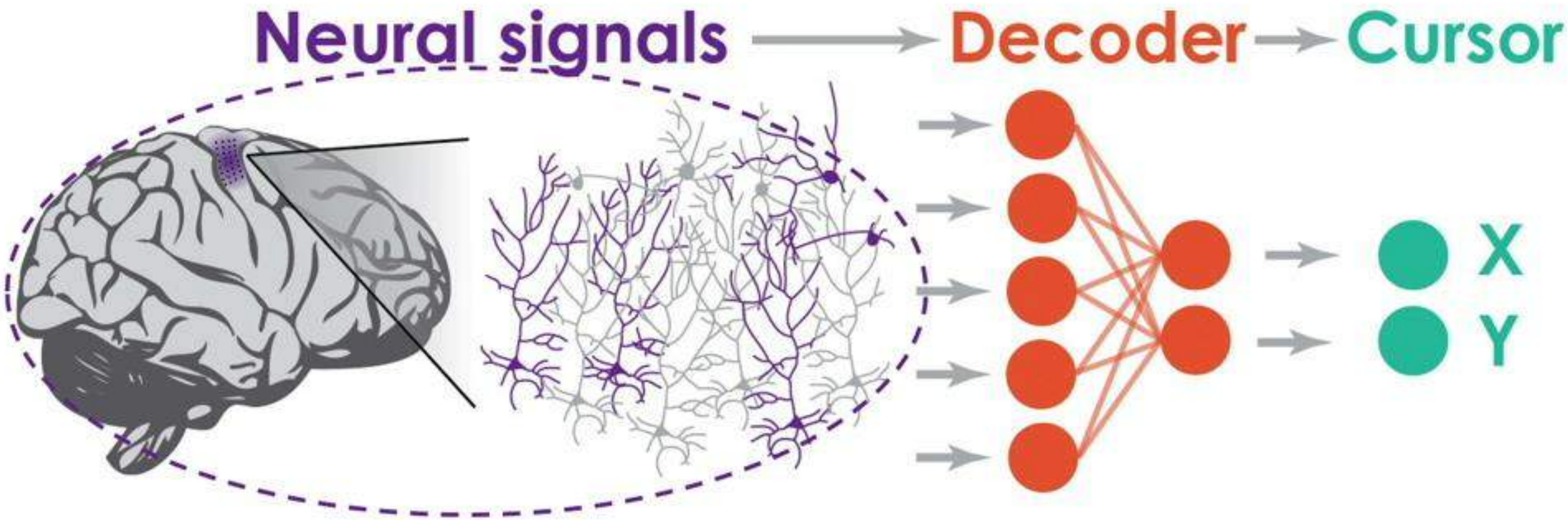


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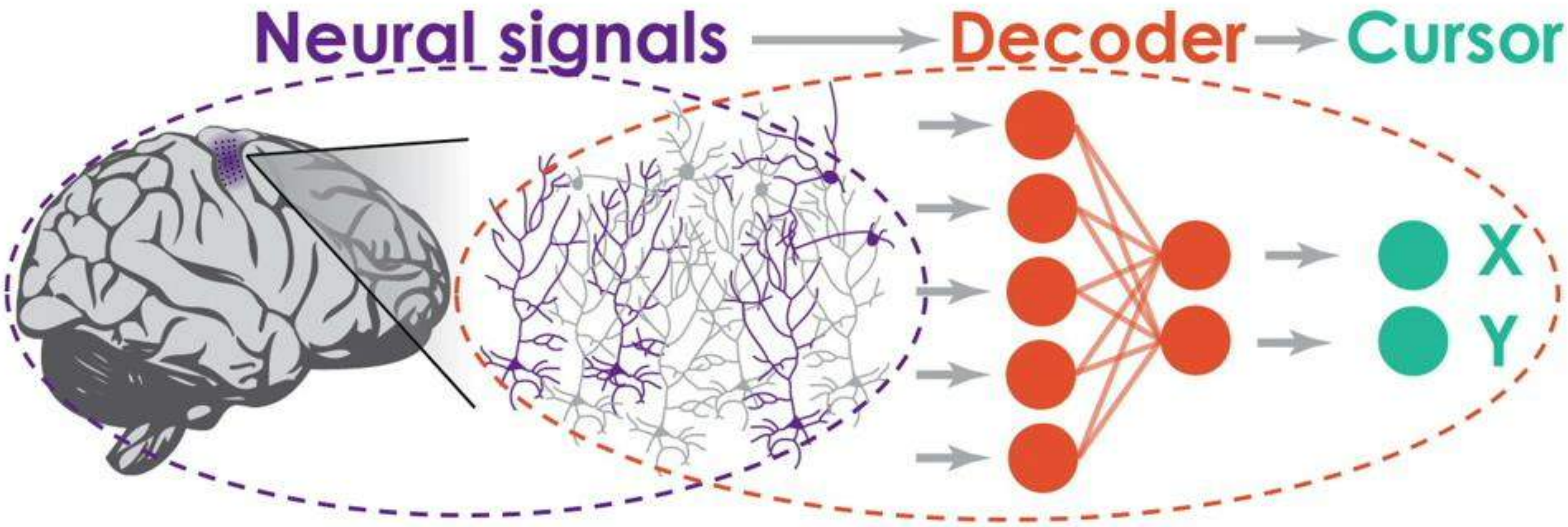


Two types of learning happening:

1. **Modulation:** Generate reliable patterns of neural activity
2. **Mapping:** Relating patterns of neural activity to cursor movements

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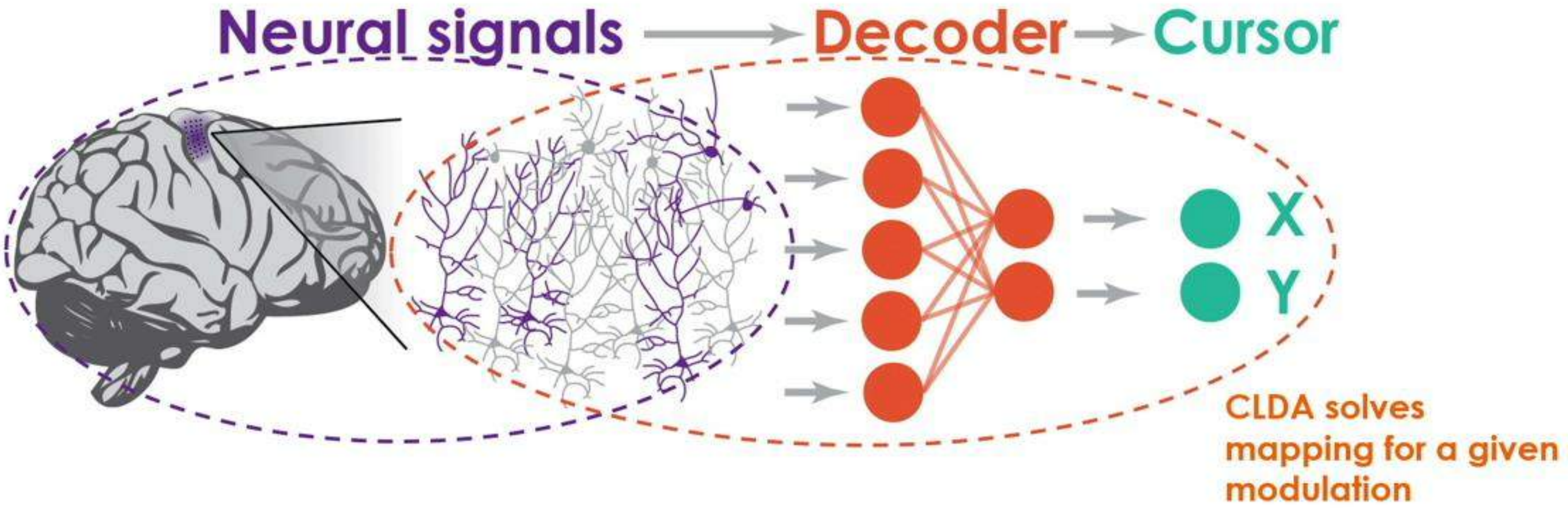


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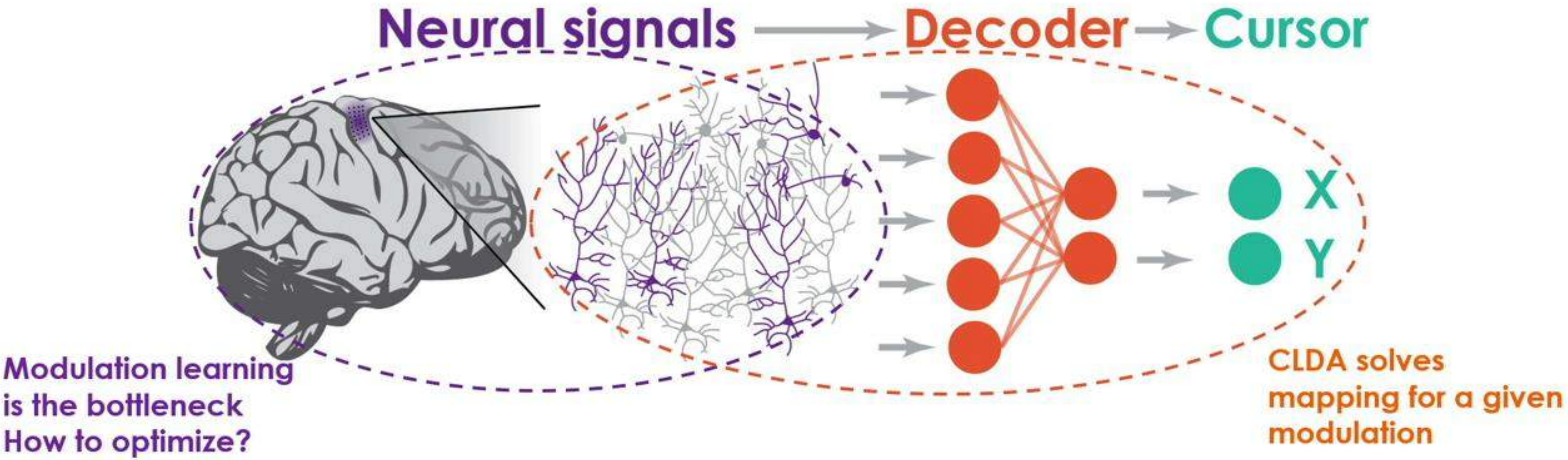


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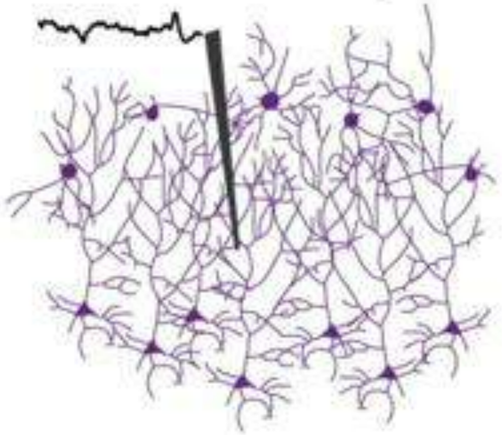

Local field potentials
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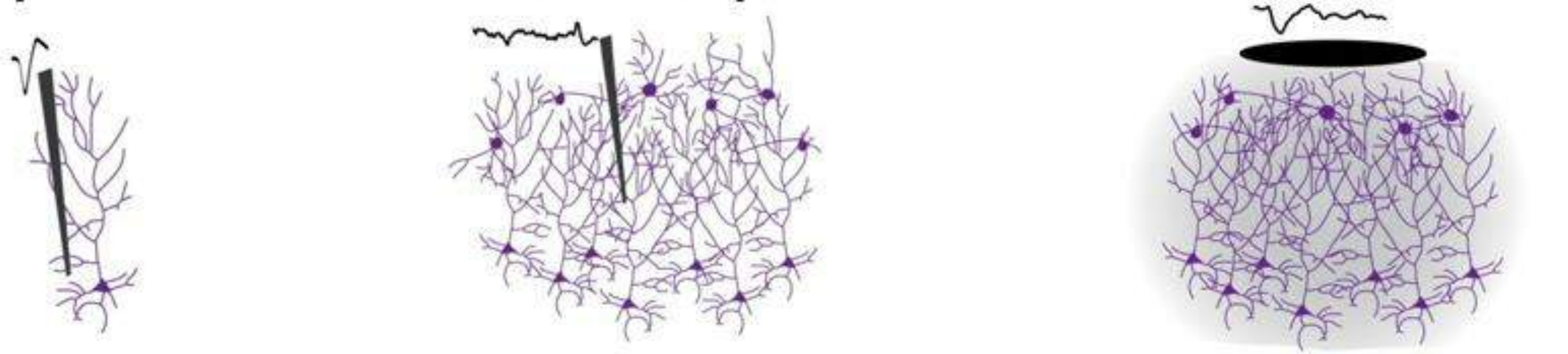

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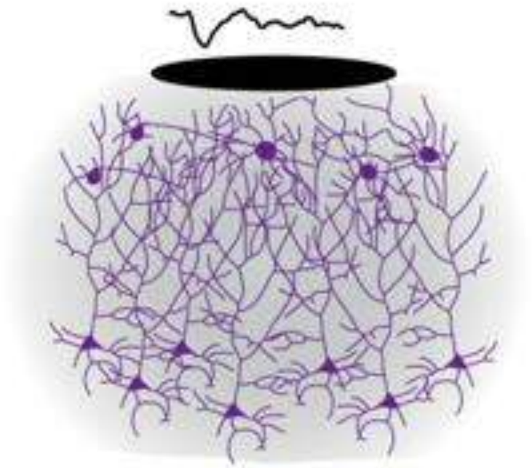

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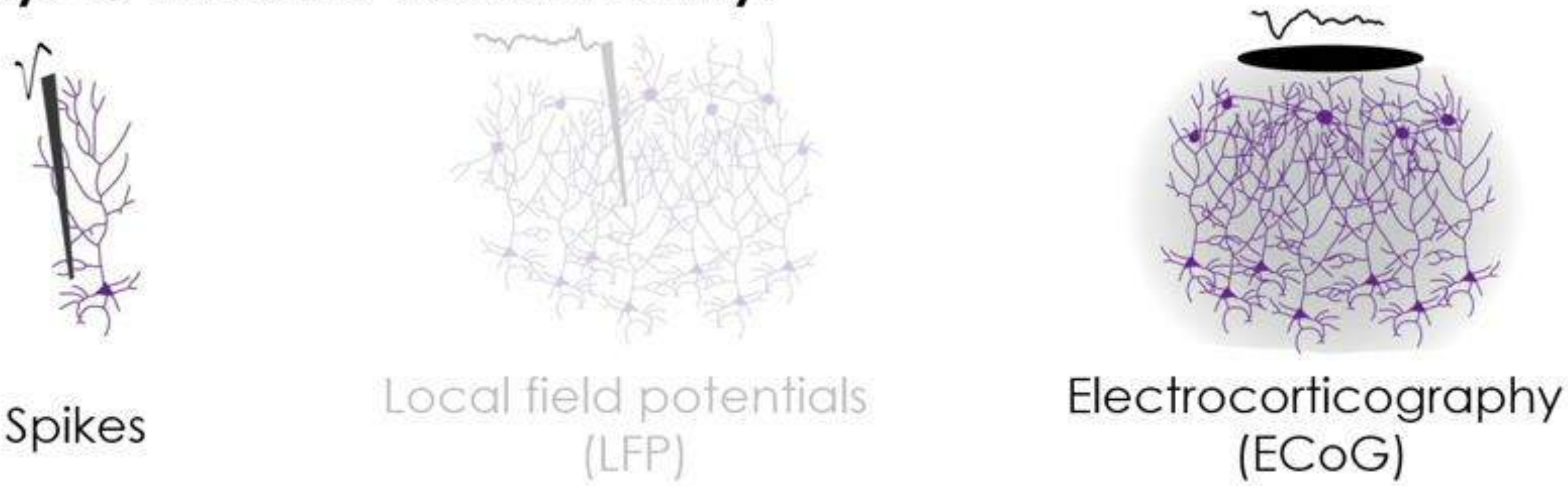


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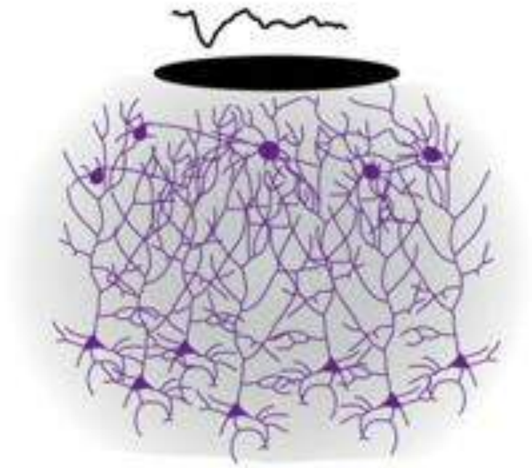

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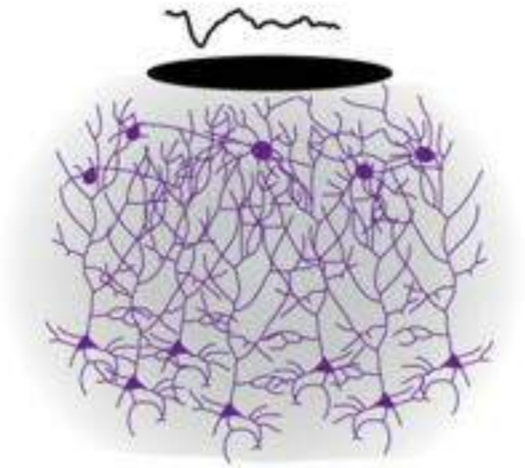

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## Modular, flexible brain interfaces

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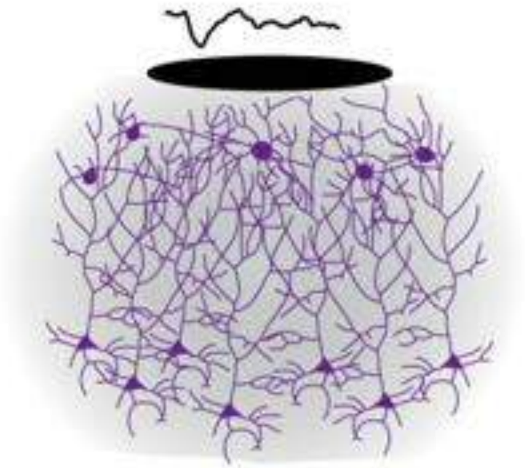

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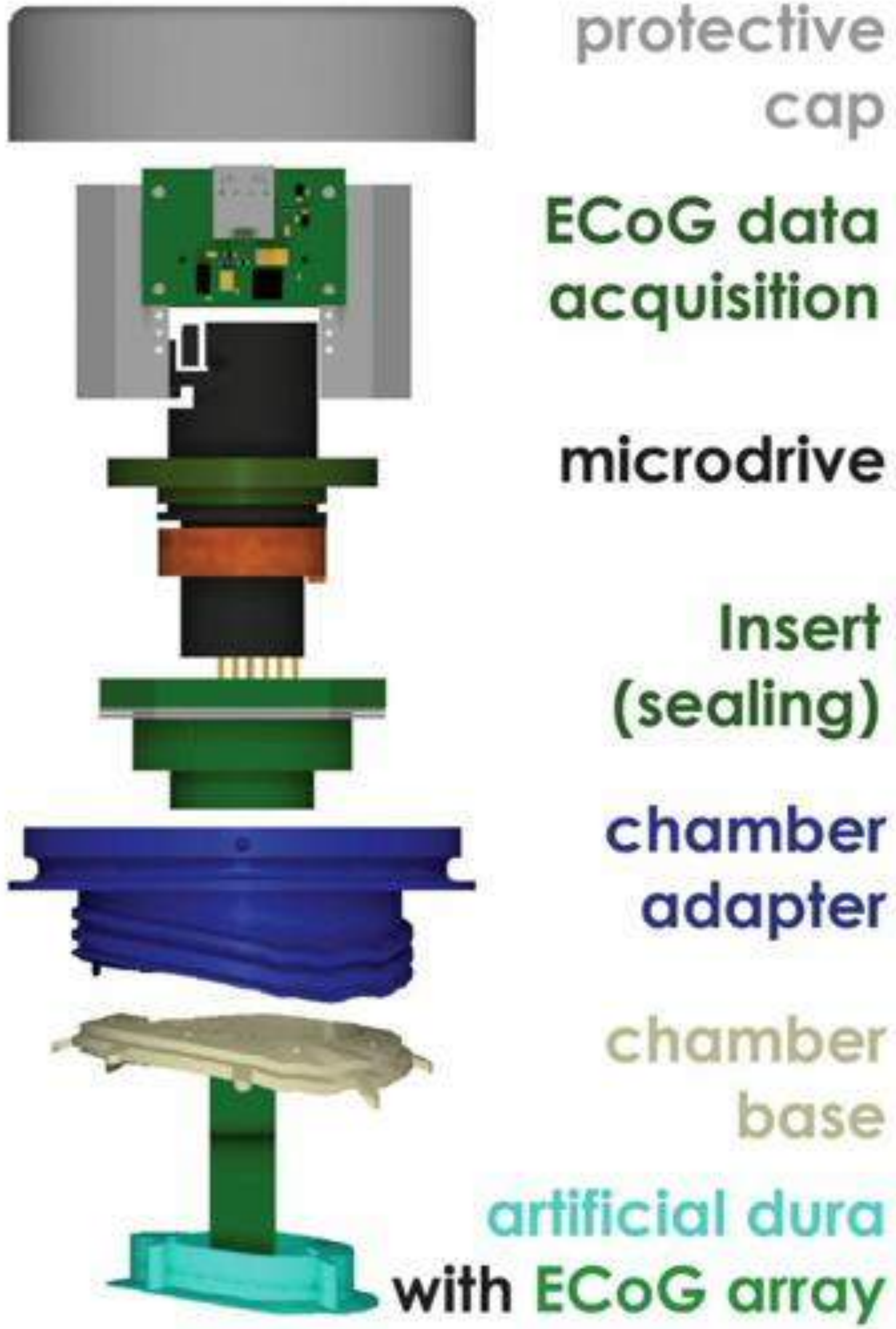
Enables:
- **Flexible recordings**
  - Electrical
  - Optical
- Causal manipulations
  - Stimulation
  - Silencing

# **Capability:** Simultaneous multi-scale ephys

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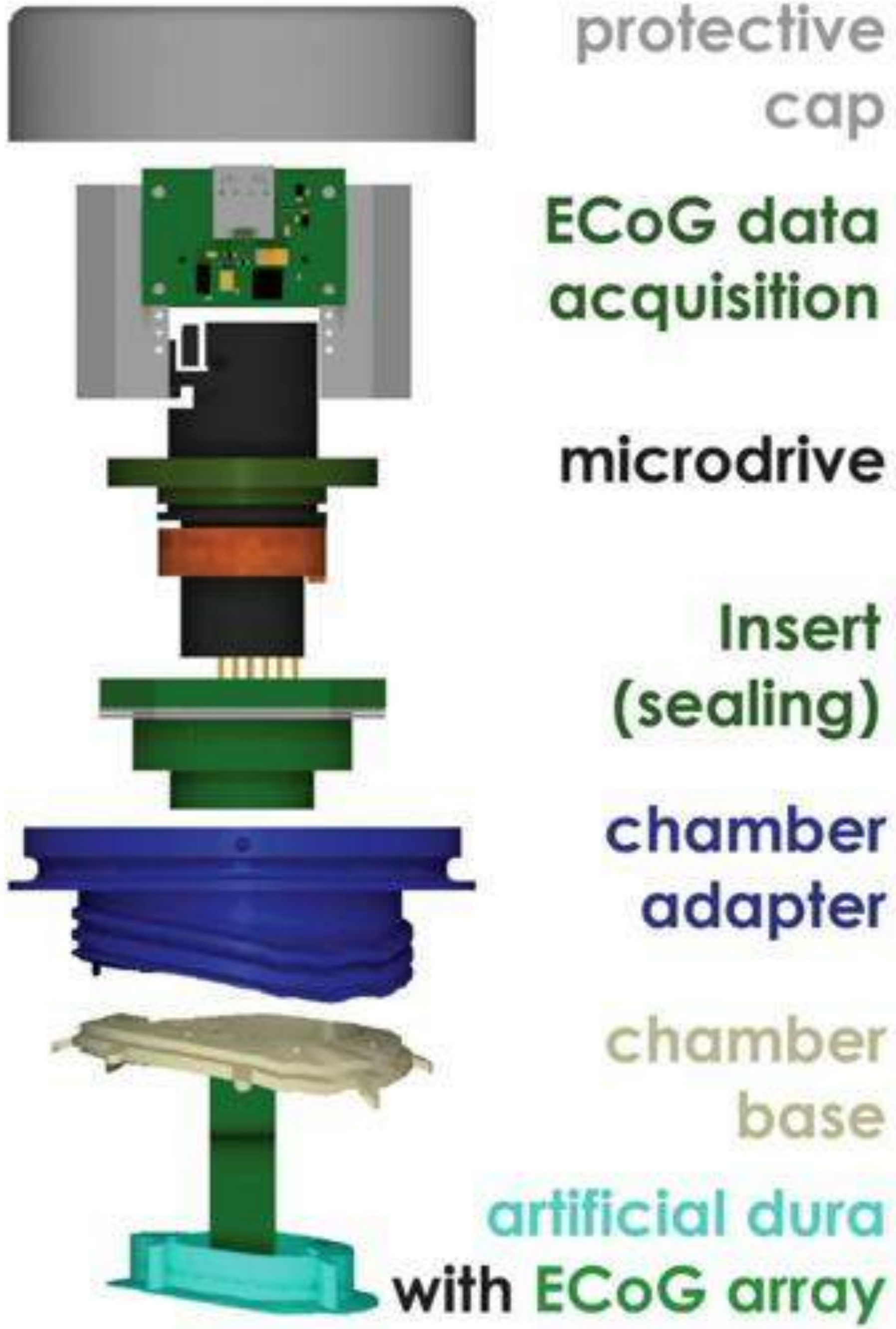


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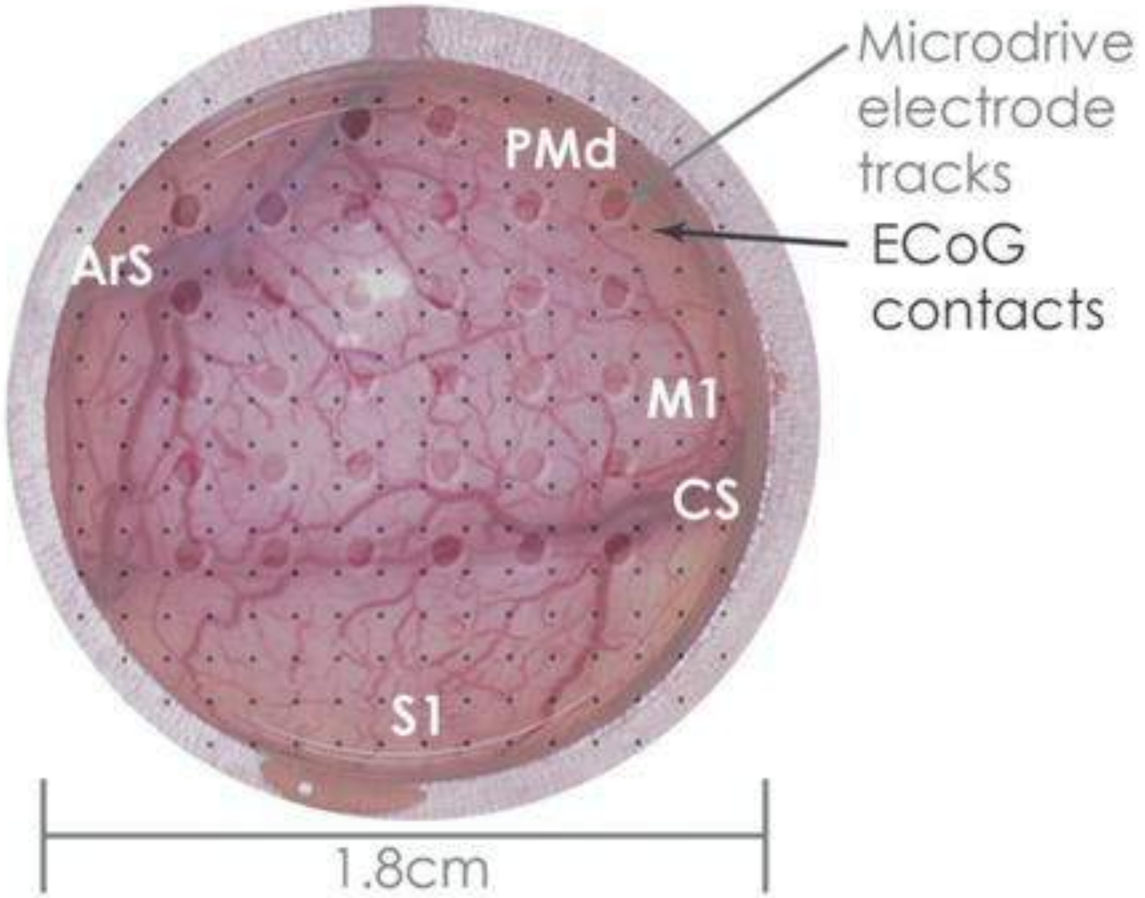

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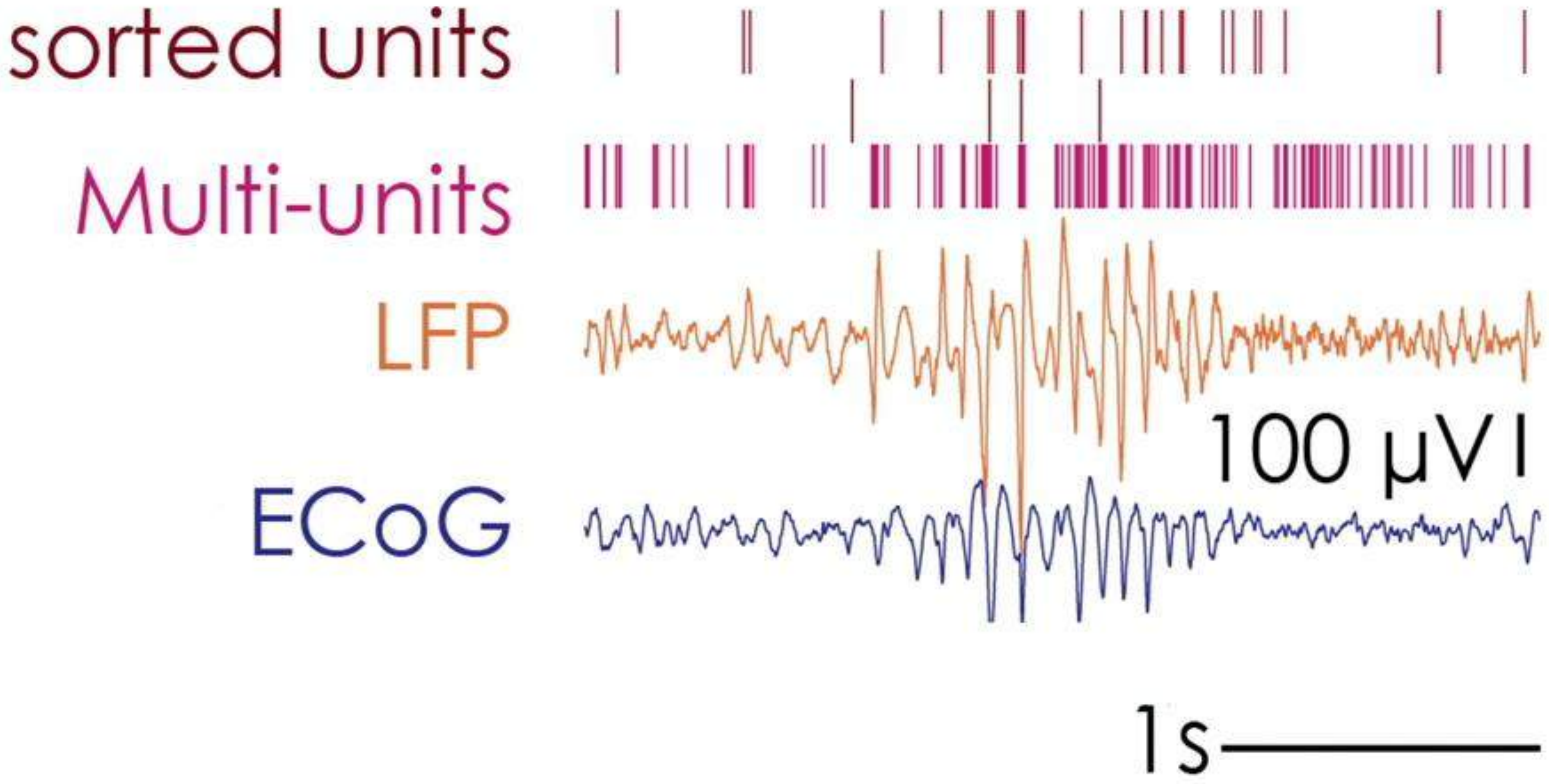

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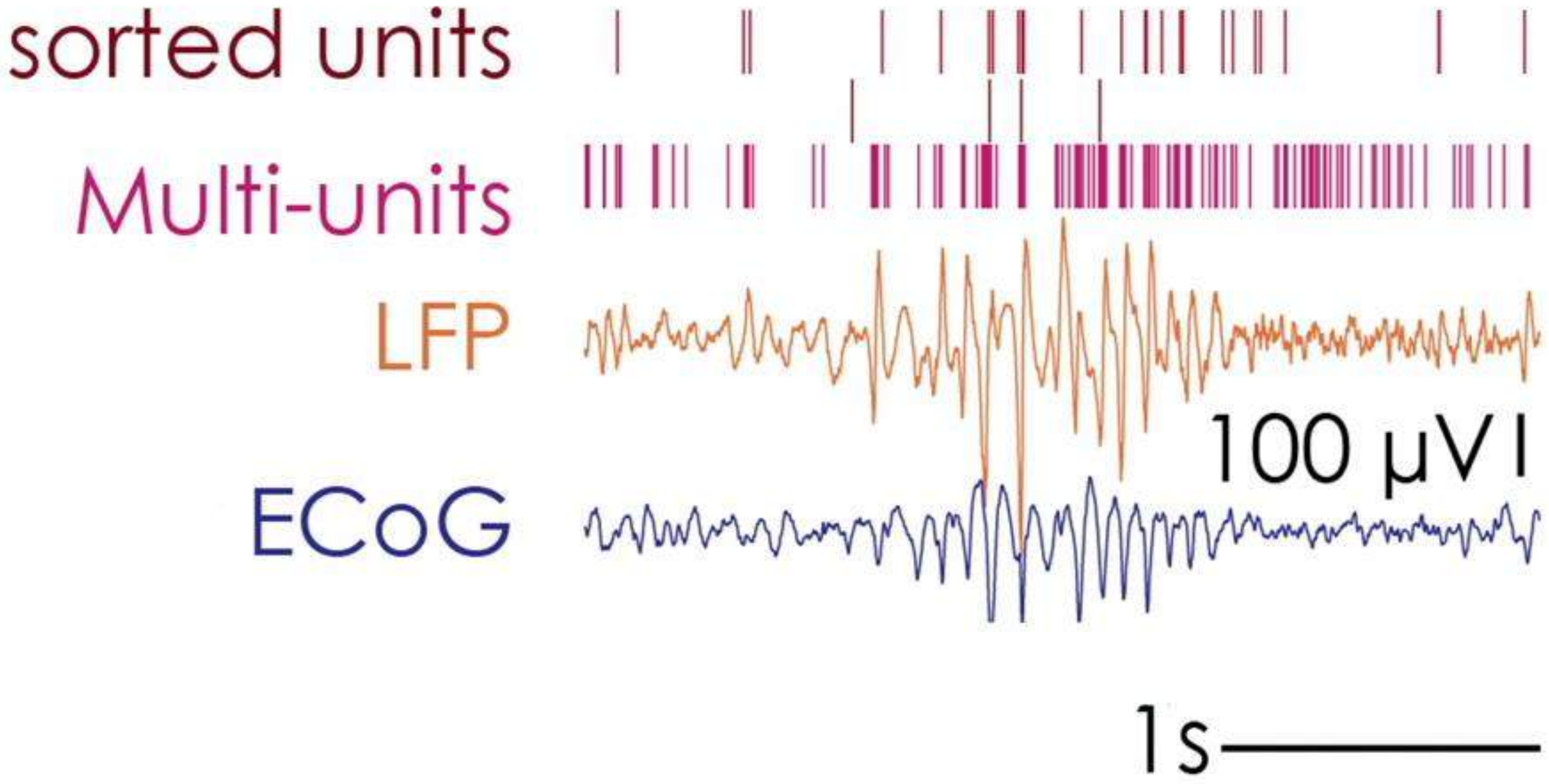
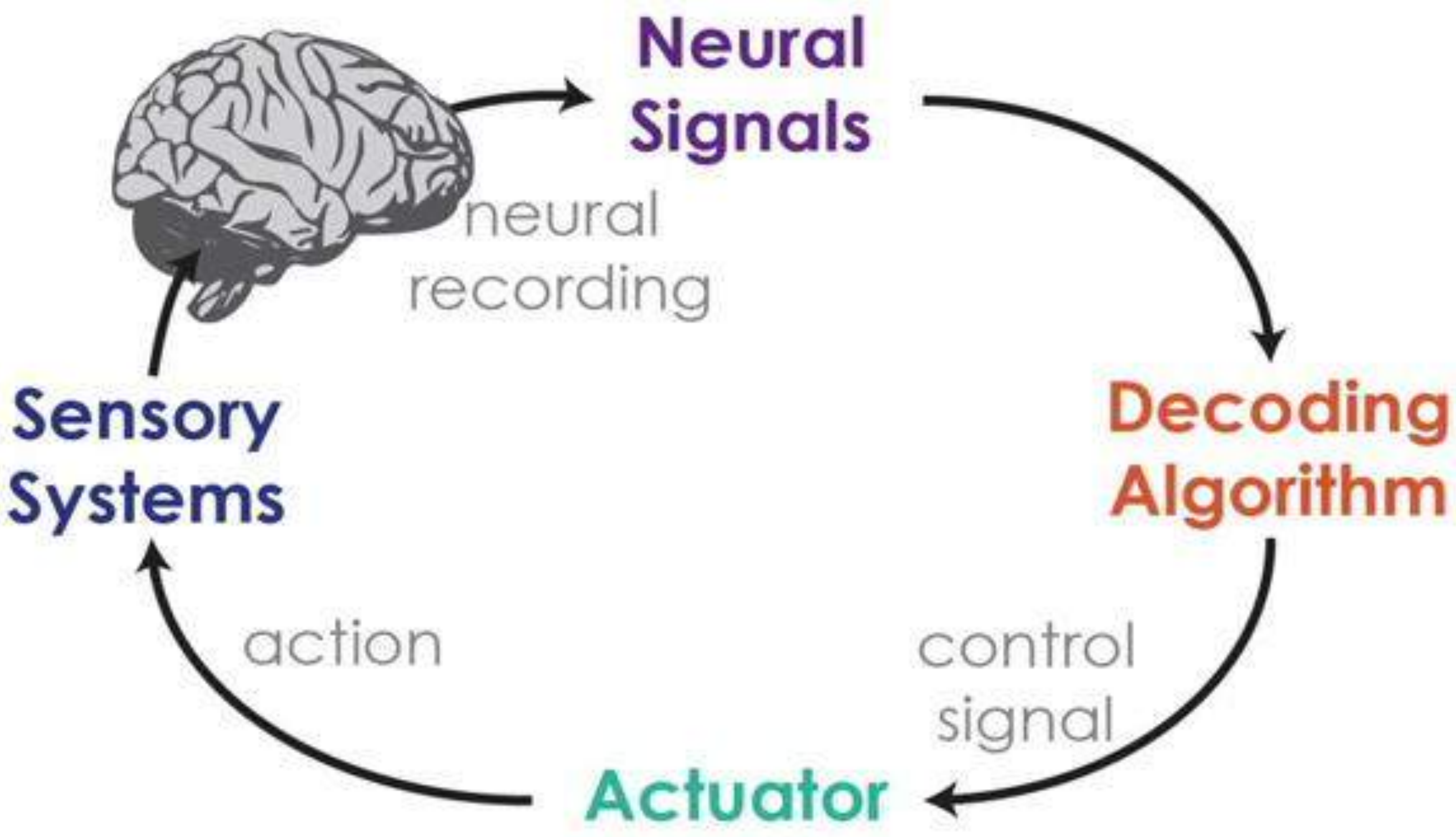



**Next steps: experiments to test how neural signals influence BMI learning**

# **Summary:** Closed-loop BMI design




- Revisiting system design to accommodate, facilitate learning and control
  - Adaptive decoding
  - Co-adaptation
  - 'Loop design'
  - Signal selection
- Critical for **robust** interfaces
  - Long-term stability
  - Cross-subject generalization
- Insights into control and learning strategies in BMI → neural interface **'design principles'**

# Thank you

**Berkeley work (loop manipulations, CLDA, co-adaptation)**
- Jose M. Carmena and lab
- Helene Moorman
- Maryam Shanechi
- Siddharth Dangi
- Suraj Gowda

**NYU work (multi-scale neural implants)**
- Bijan Pesaran and lab
- Charles Wang, Jessica Kleinbart
- Nia Channel Boles
- Ryan Shewcraft
- Jonathan Viventi (Duke)
- Michel Maharbiz (Berkeley)

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- DARPA (Carmena; Pesaran)
- NYU Challenge grant
- L'Oreal USA

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