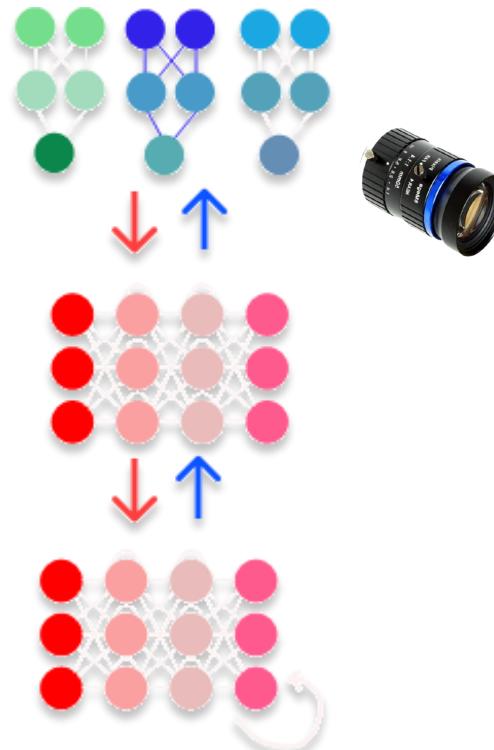
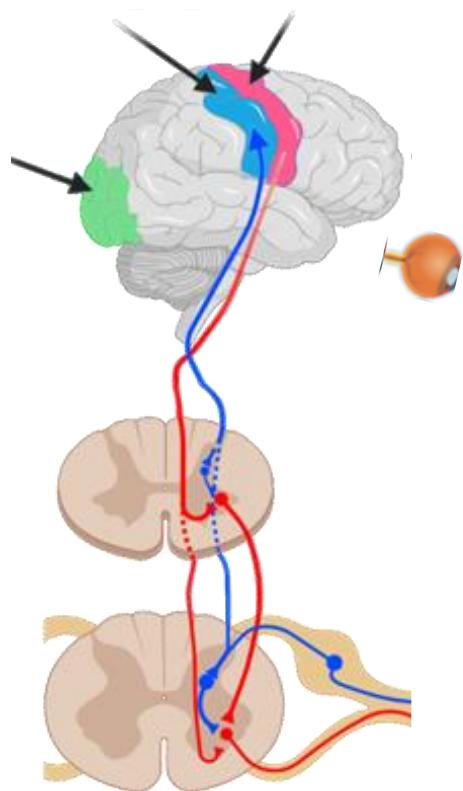


NX-414: Brain-like computation and intelligence

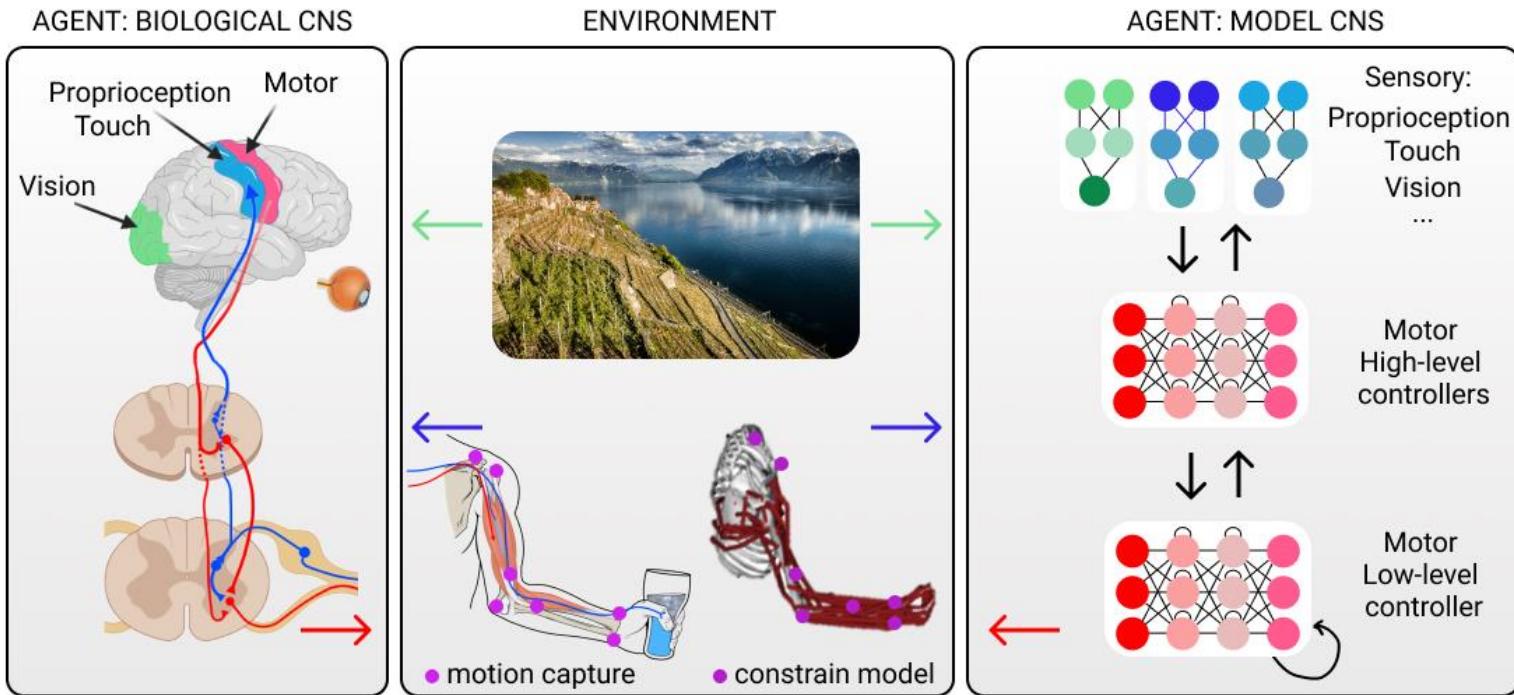
Alexander Mathis

alexander.mathis@epfl.ch

Lecture 7, April 2nd 2025

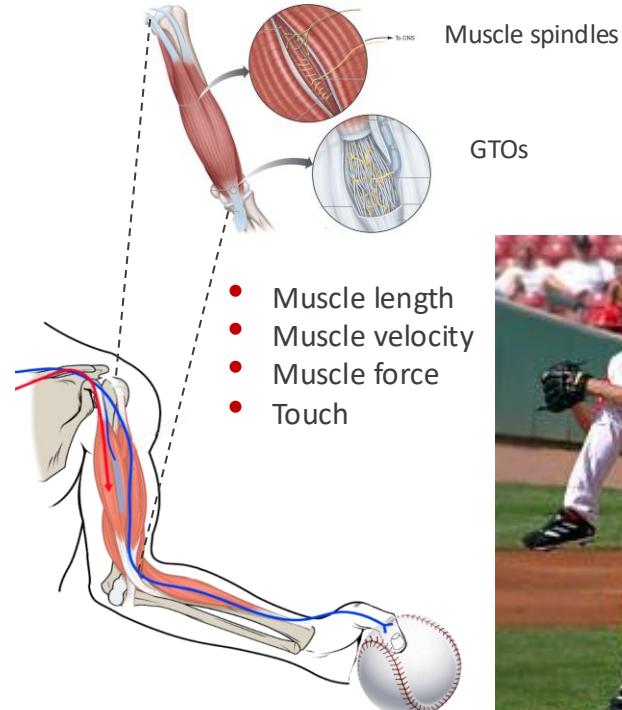
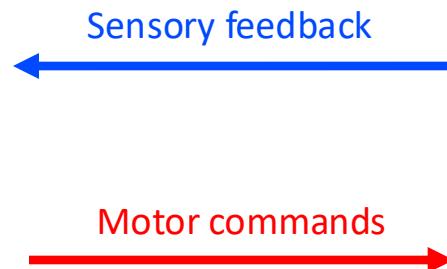
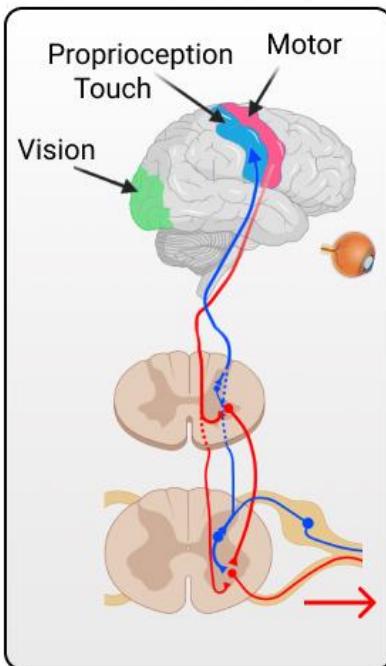


Reverse engineering neural circuits



Motor skills need sensory feedback

AGENT: BIOLOGICAL CNS

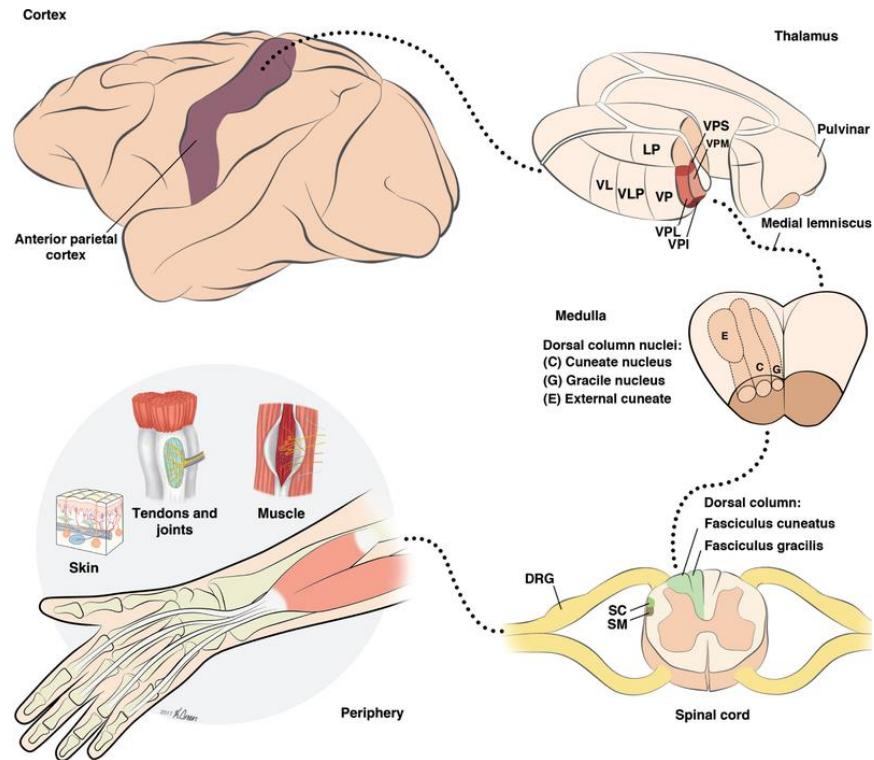


Simple skills require feedback



- Video taken from Roland Johansson Lab - Department of Integrative Medical Biology. Umea University, Sweden

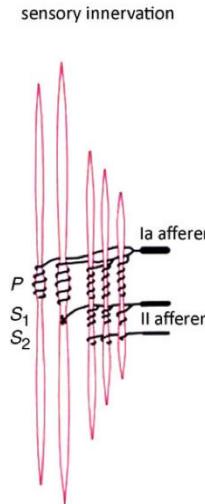
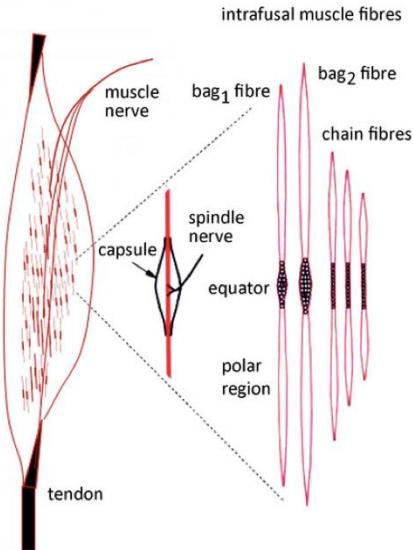
Proprioception (the sense of posture)



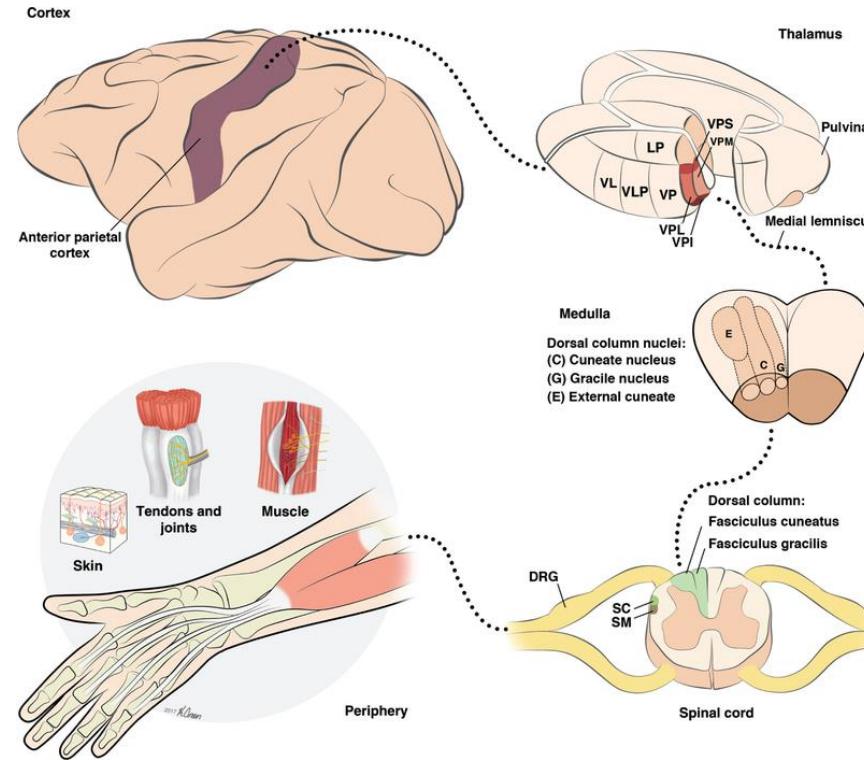
Delhaye et al., 2018

Proprioception (the sense of posture)

Muscle spindle

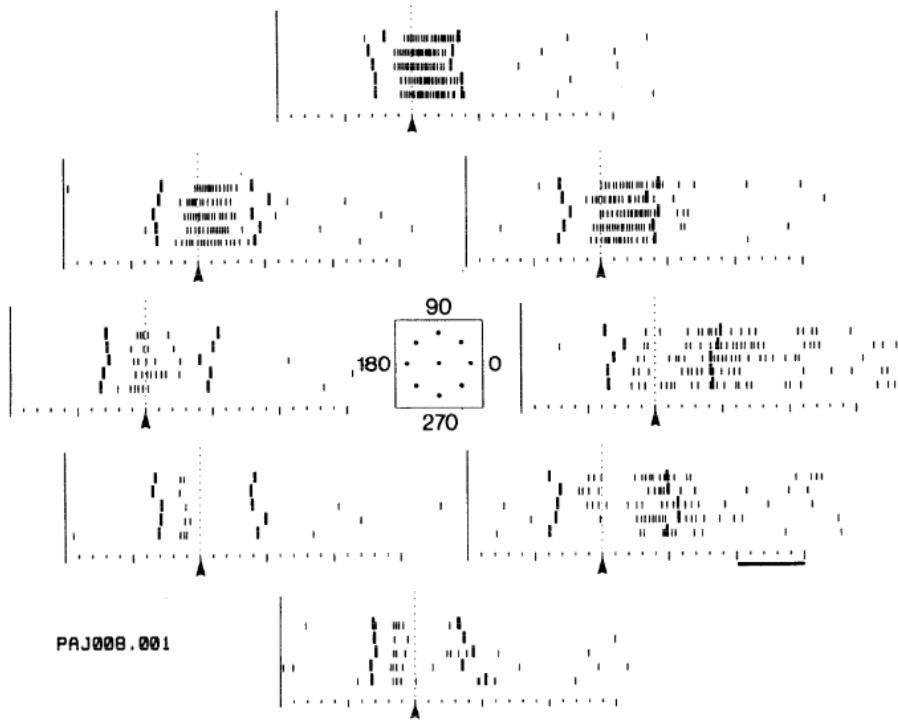


Banks 2020



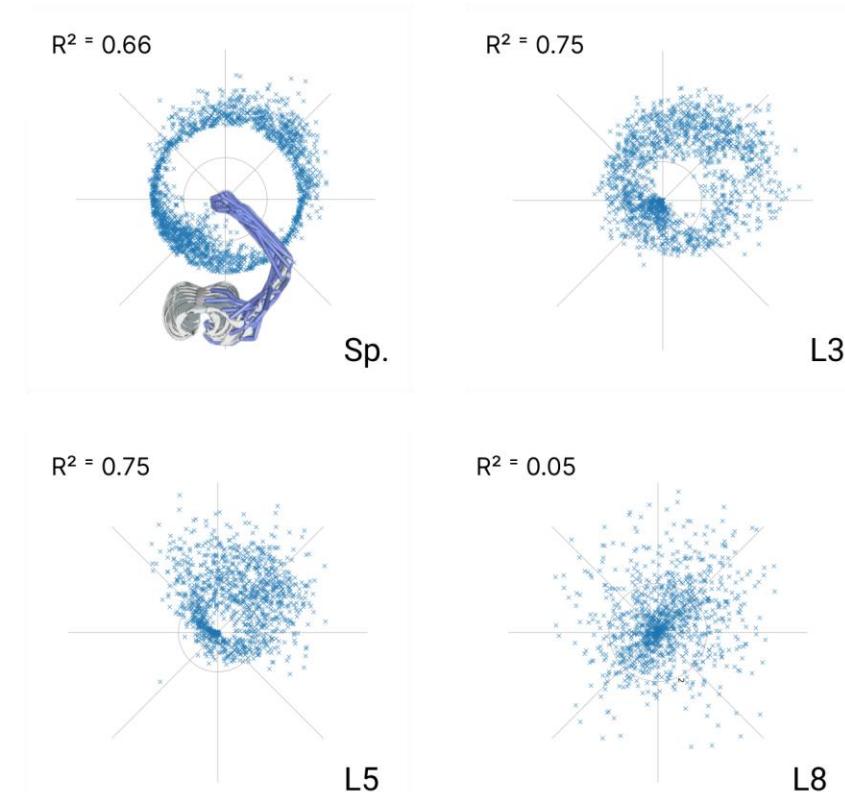
Delhaye et al., 2018

EPFL Tuning curves in somatosensory cortex



Prud'homme and Kalaska 1994

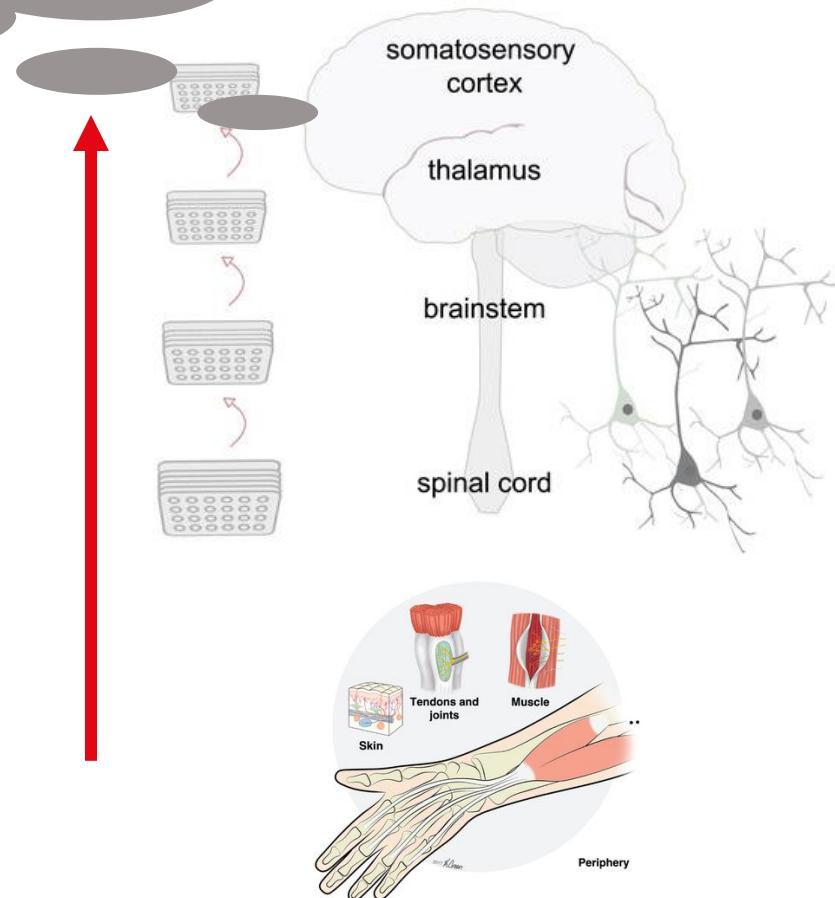
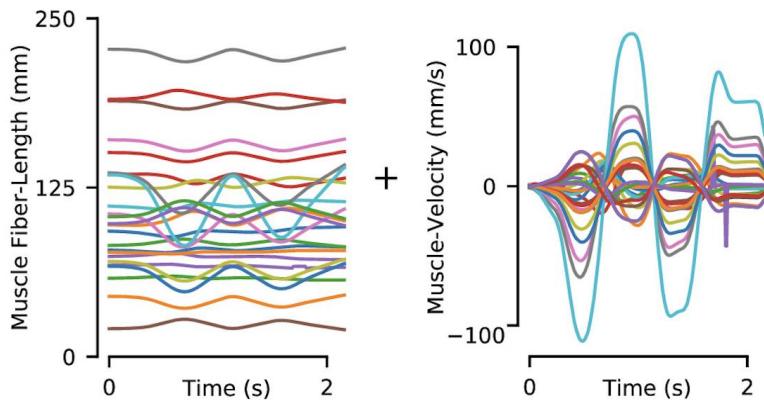
- Known: Direction, velocity, acceleration tuning...

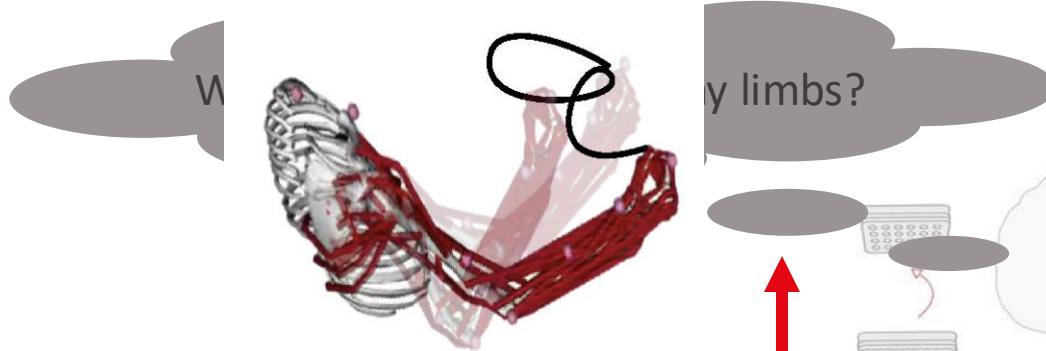


Sandbrink*, Mamidanna*, et al. eLife 2023

What's the trajectory of my limbs?

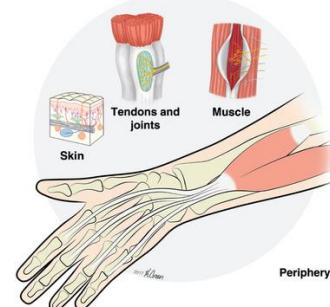
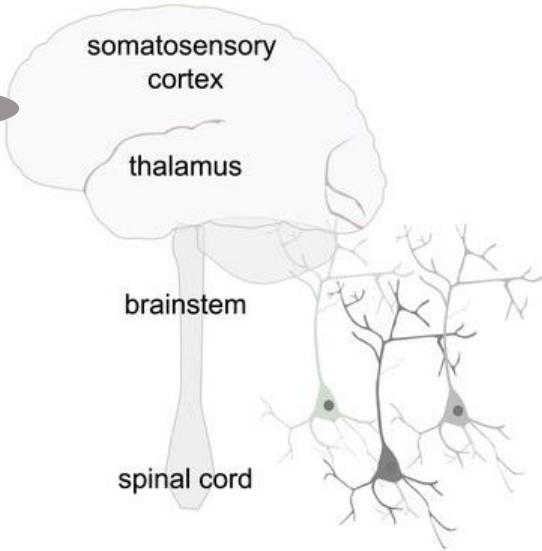
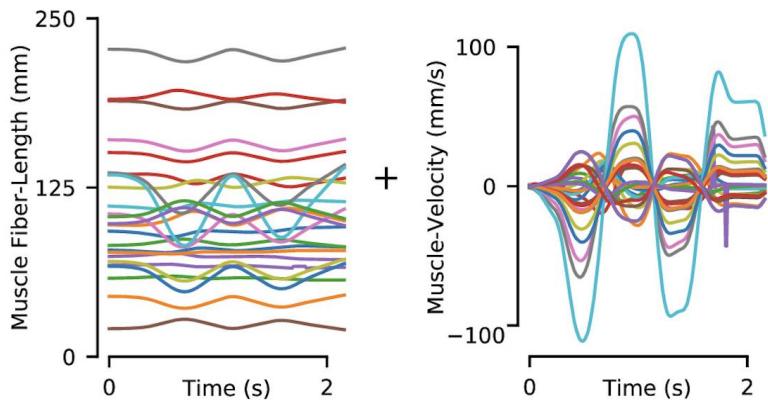
What is the integrative logic of proprioception?





Why limbs?

What is the integrative logic of proprioception?



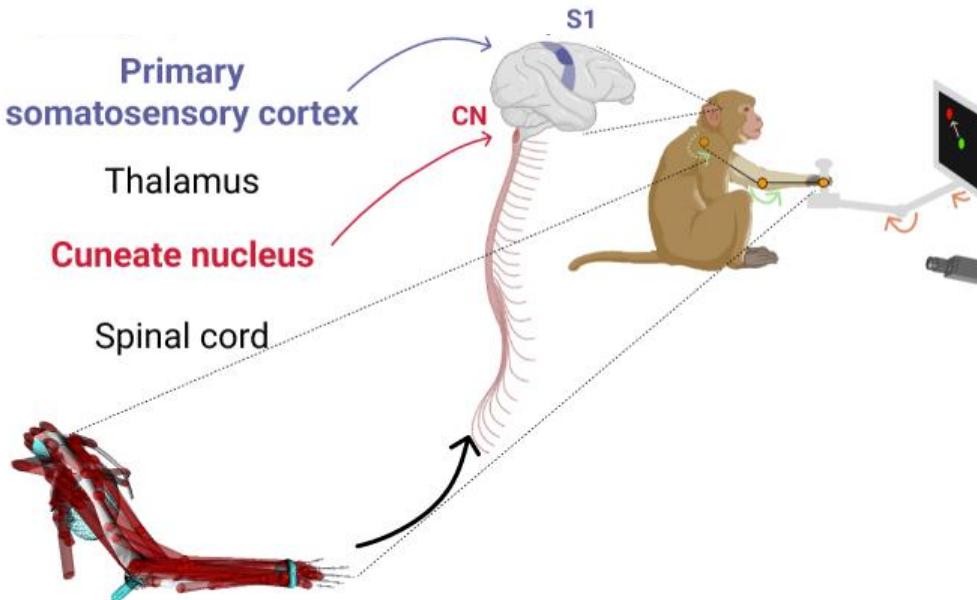
Reverse-engineering proprioception

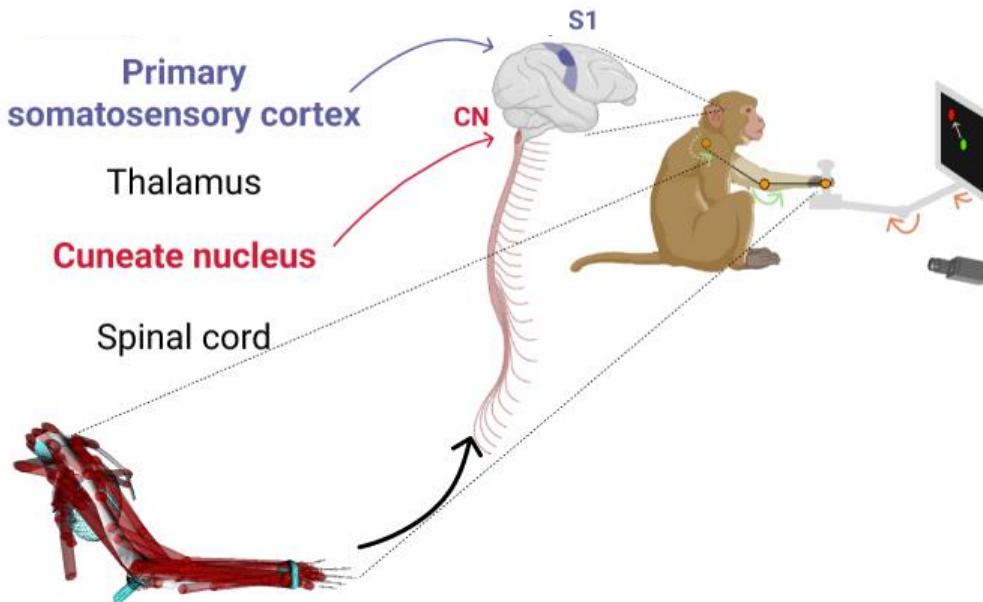


Alessandro Marin
Vargas



Axel Bisi
(MA student, now PhD
student with Carl Petersen)



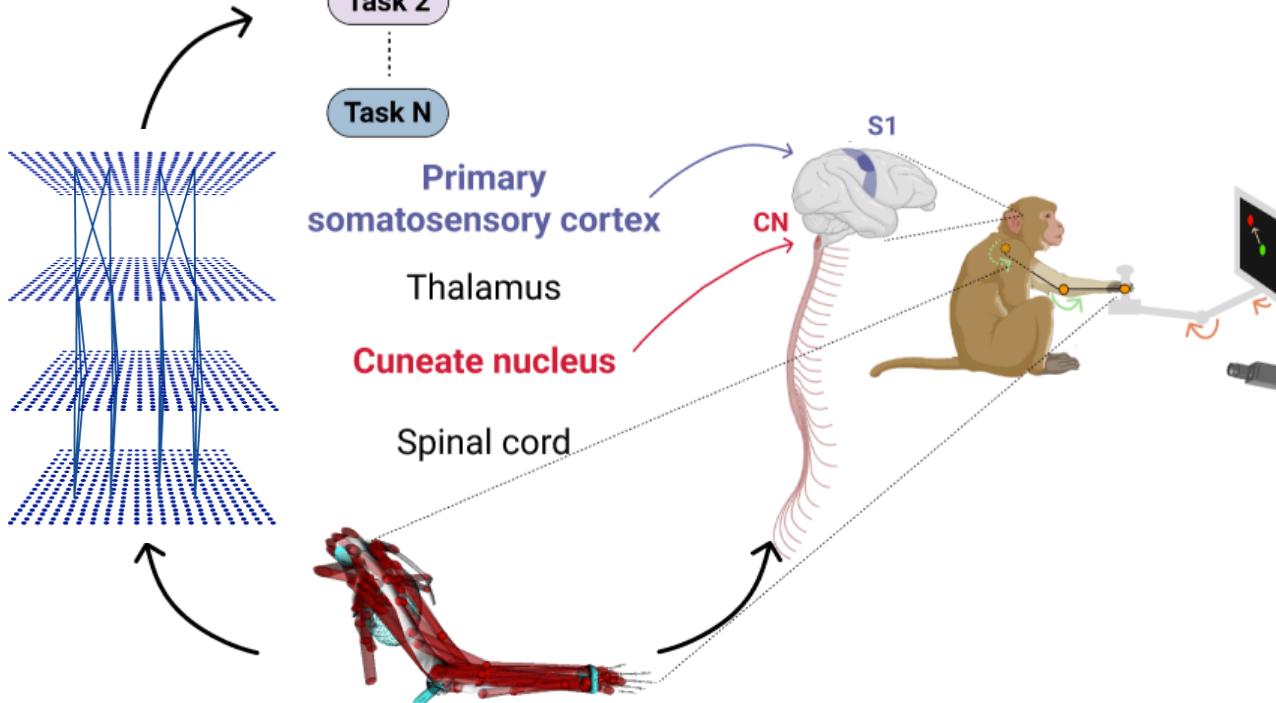


Creating task-driven models of proprioception

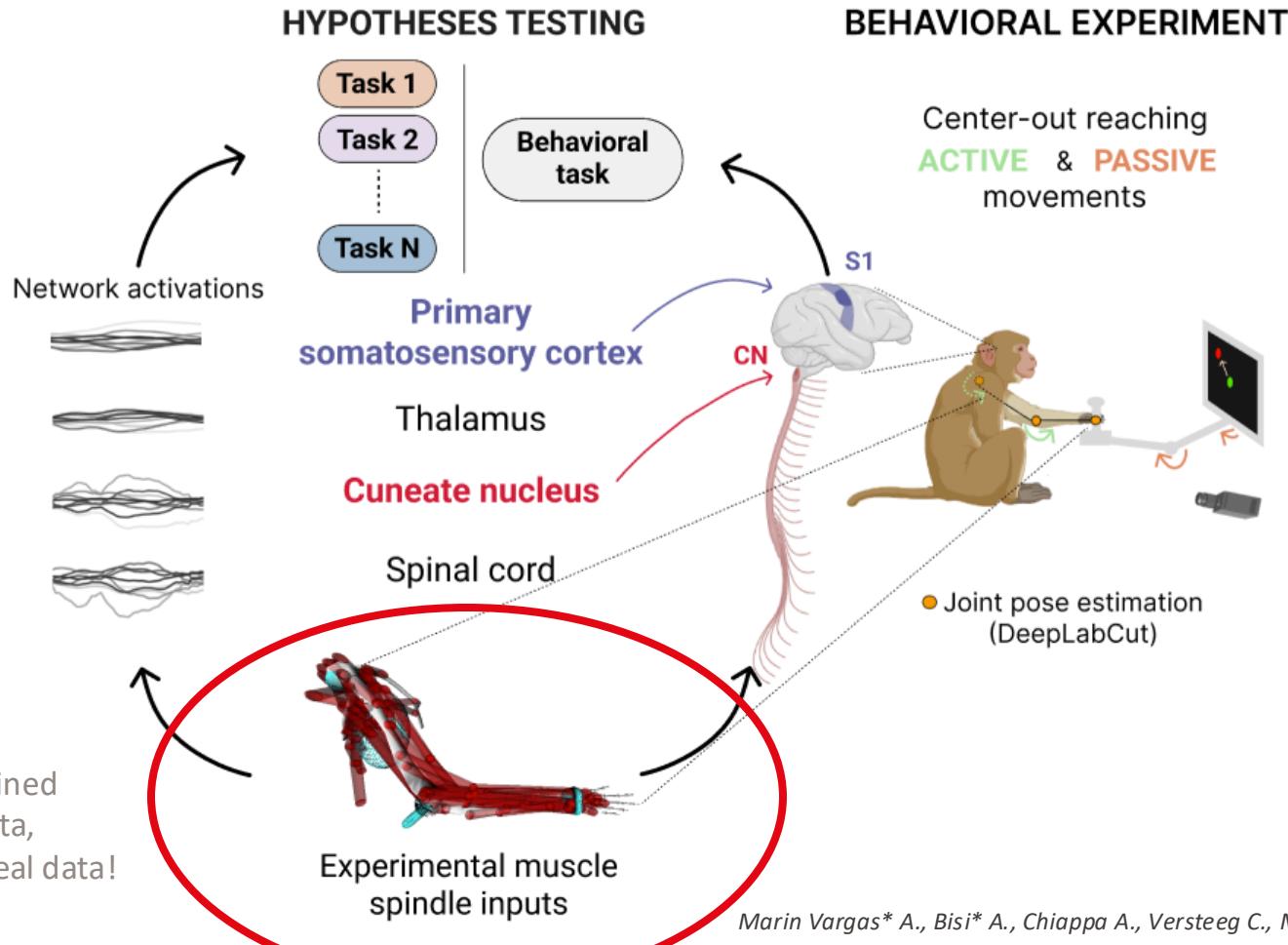
HYPOTHESES TESTING

Ingredient 3:

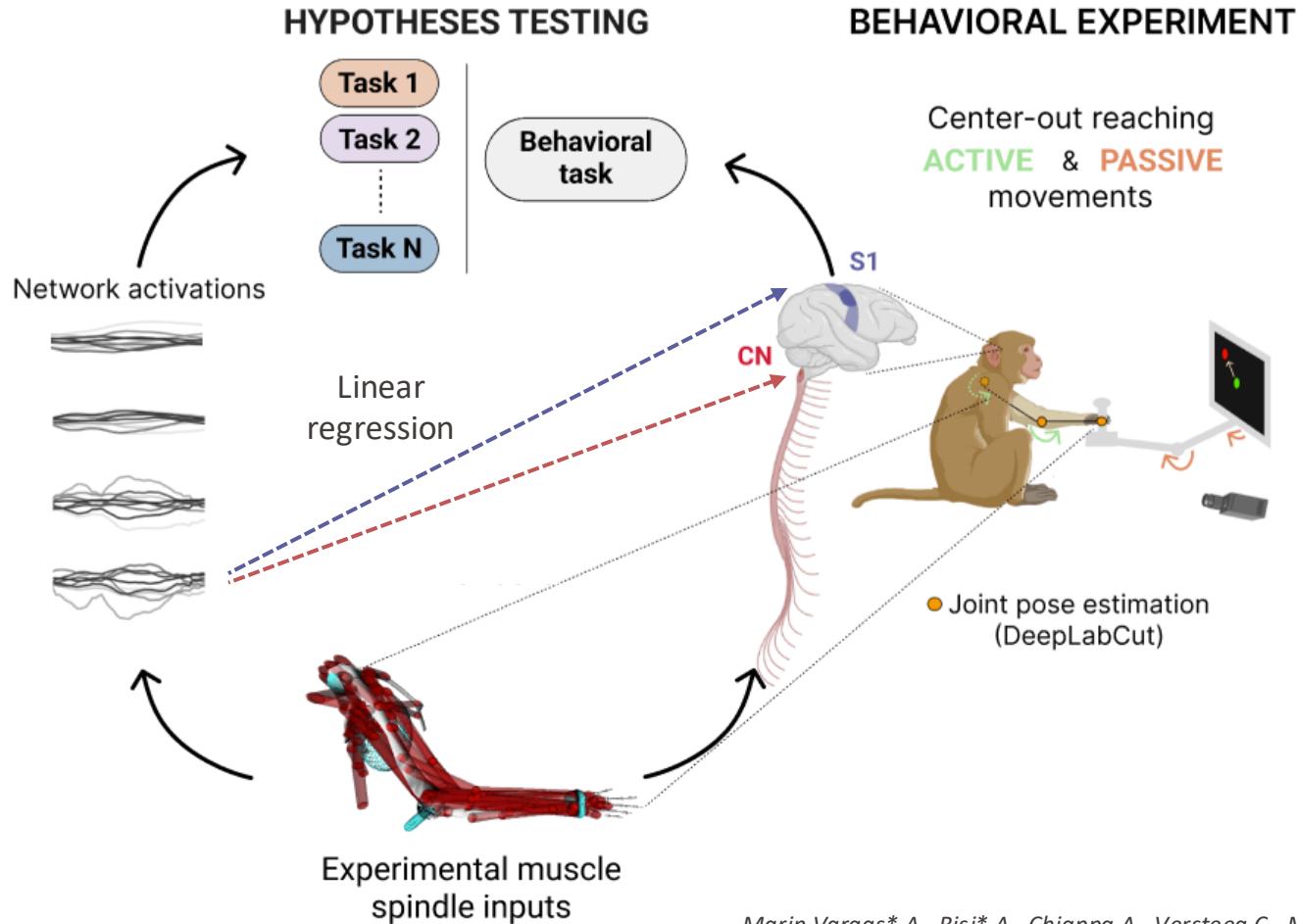
Putative goals (of proprioception)



Assessing task-driven models of proprioception

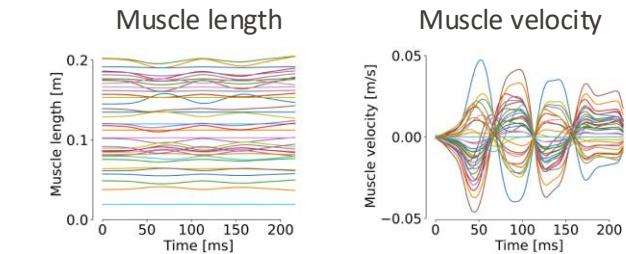
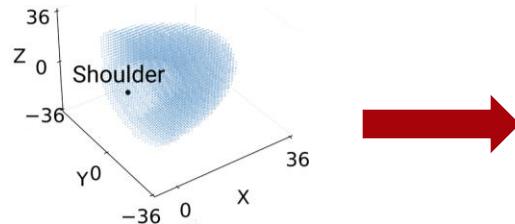


Reverse-engineering proprioception



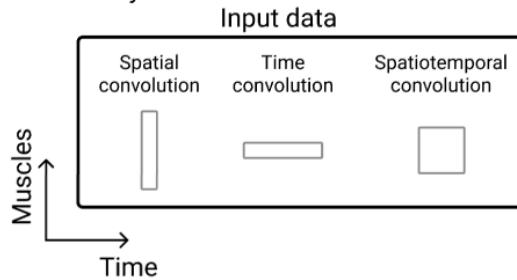
Creating synthetic data & candidate models

- Use biomechanics simulators to estimate spinal cord input at scale (muscle spindles)

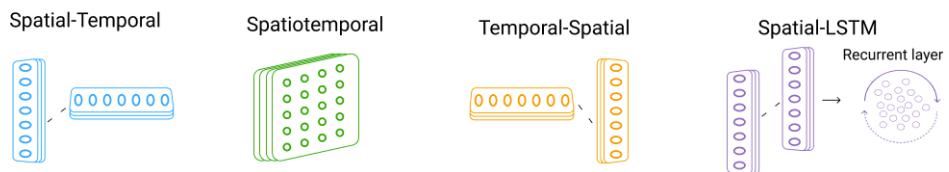


- Develop neural networks models that process information across muscles & time

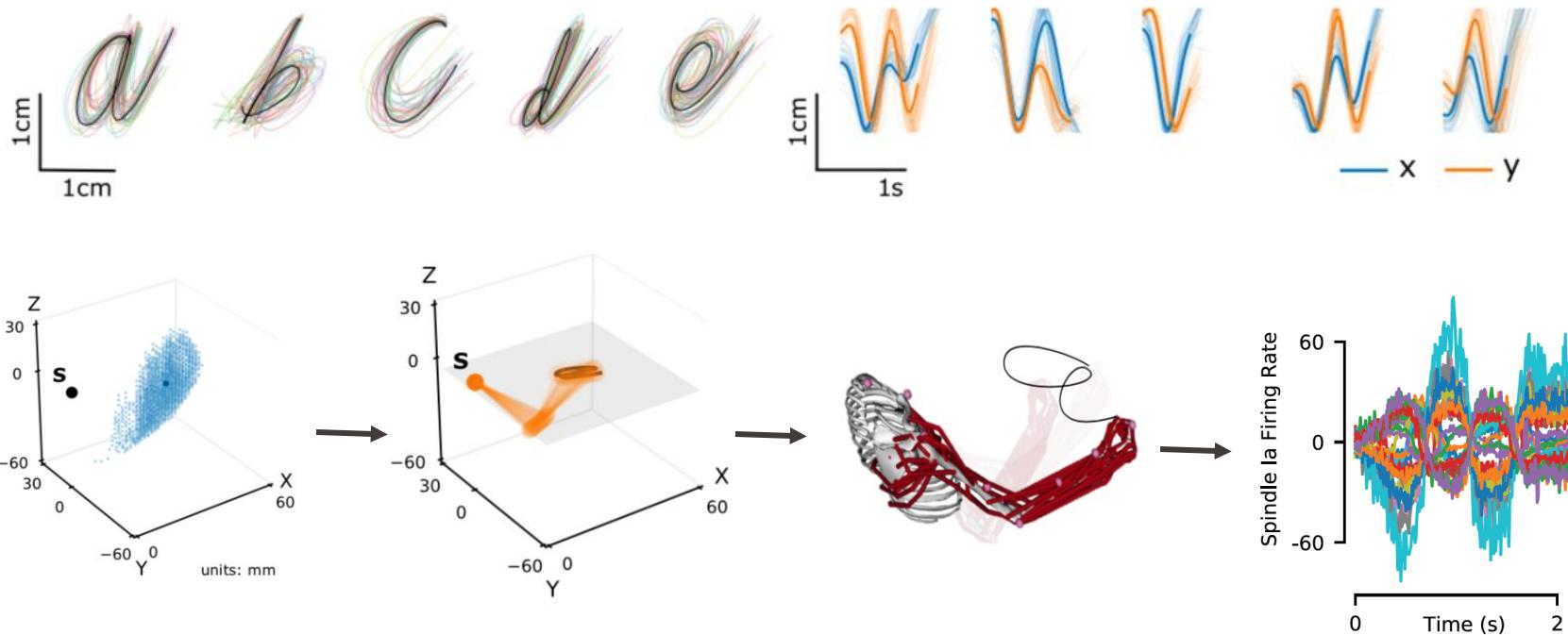
Convolutional layers:



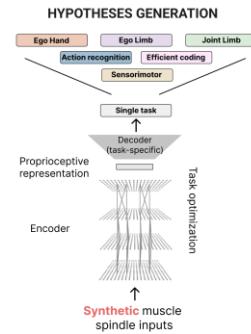
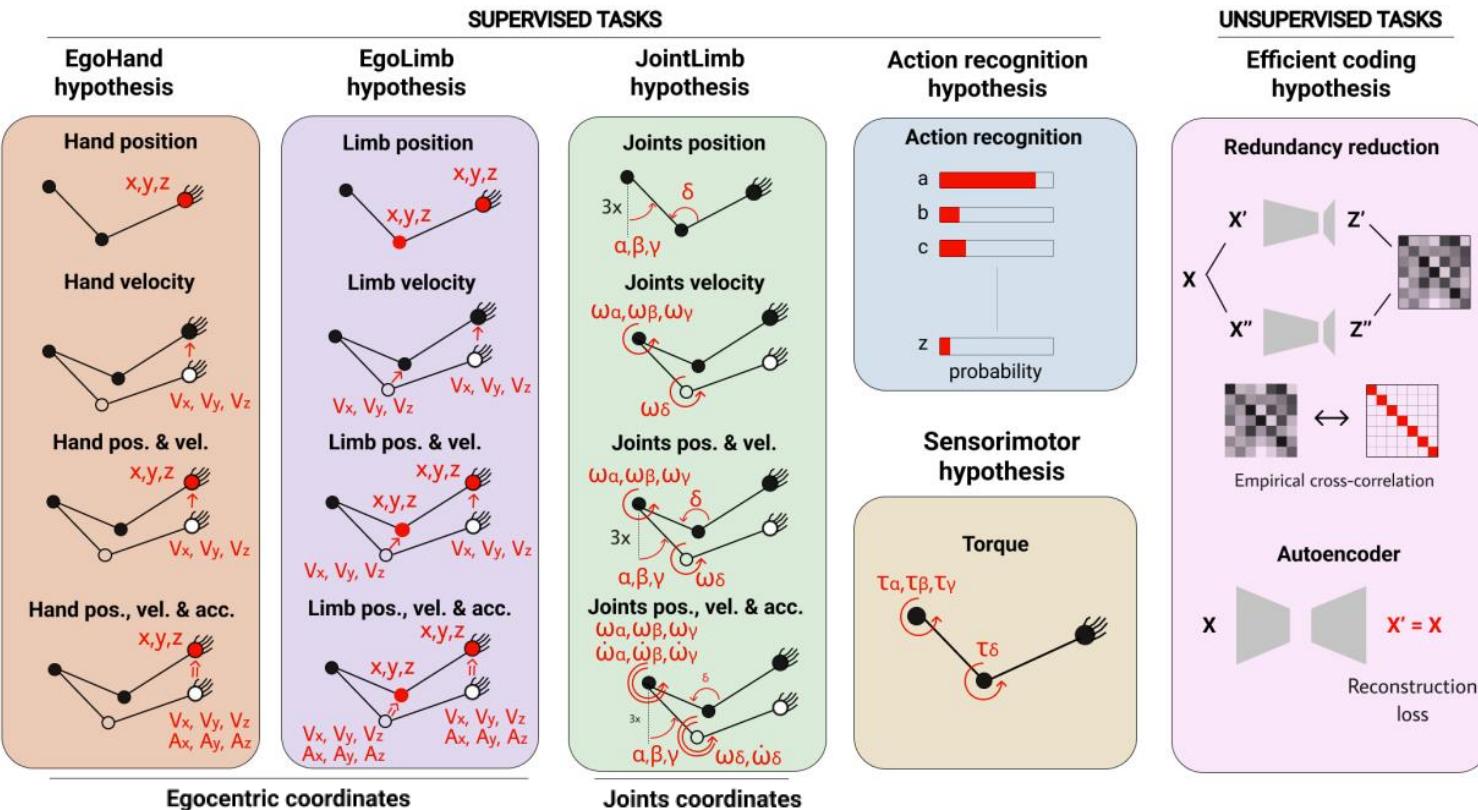
Architecture type:



Dataset: Creating input statistics

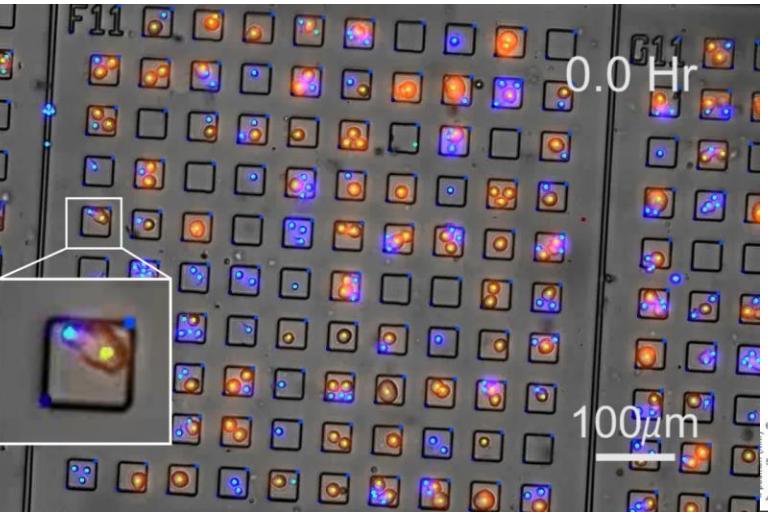


EPFL 16 computational tasks to create candidate models





Cells



Cachot et al. 2021
Science Advances

- www.deeplabcut.org
- Active user community (i.e., help!)
- > 110 code contributors on GitHub
- > 800,000 downloads
- > 4,300 citations for Nat Neuro '18
- Used in over 1,000 labs and institutes around the world

Tissues



Organisms



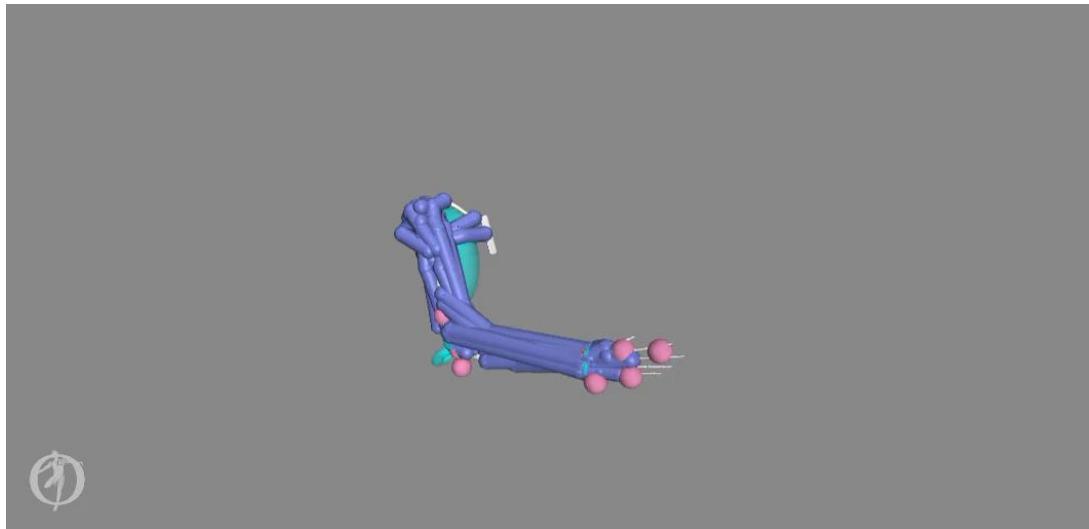
Joska et al.
2021
ICRA



Chan
Zuckerberg
Initiative

Nature Neuro 2018, Nature
Protocols 2019, Neuron 2020,
WACV 2021, ICRA 2021, CVPR-W
2021, Nature Methods 2022,
ICCV 2023, Nat Comms 2024

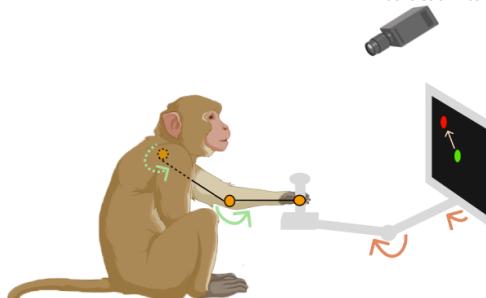
EXPERIMENTS TO TEST GENERALIZATION of the learned features



Data from Lee Miller's
Laboratory of Limb
Motor Control, Northwestern
University, Chicago.

BEHAVIORAL EXPERIMENT

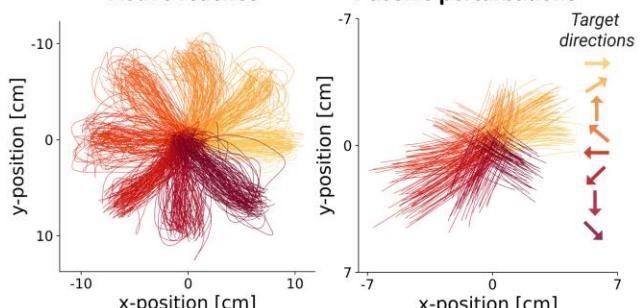
DeepLabCut
Mathis et al. Nat Neuro 2018



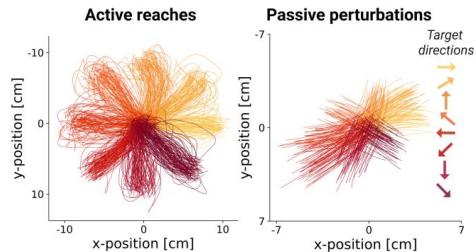
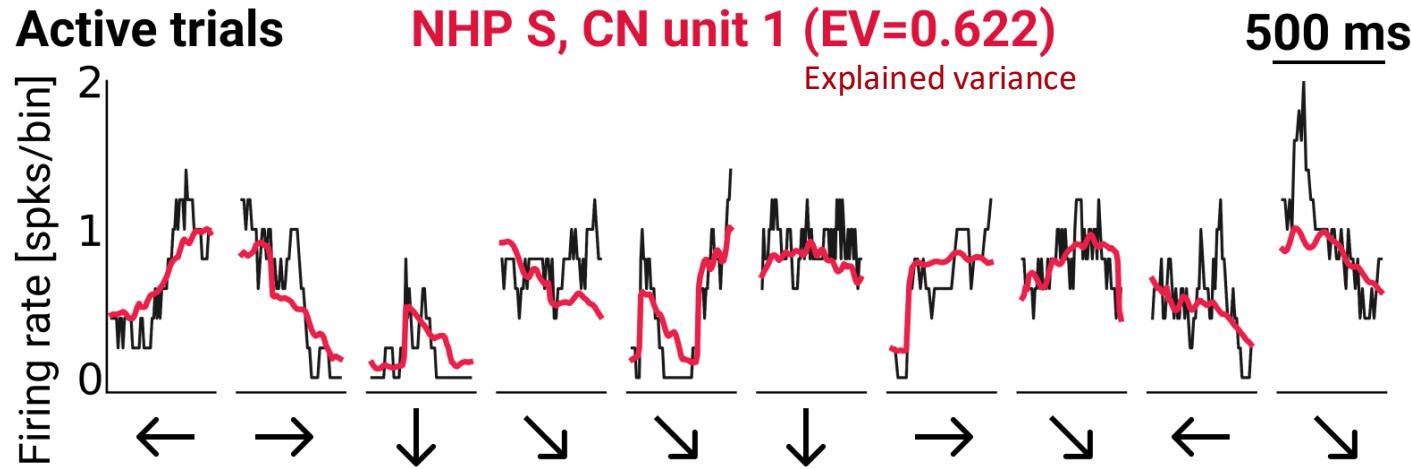
Joint pose
estimation

PASSIVE
ACTIVE

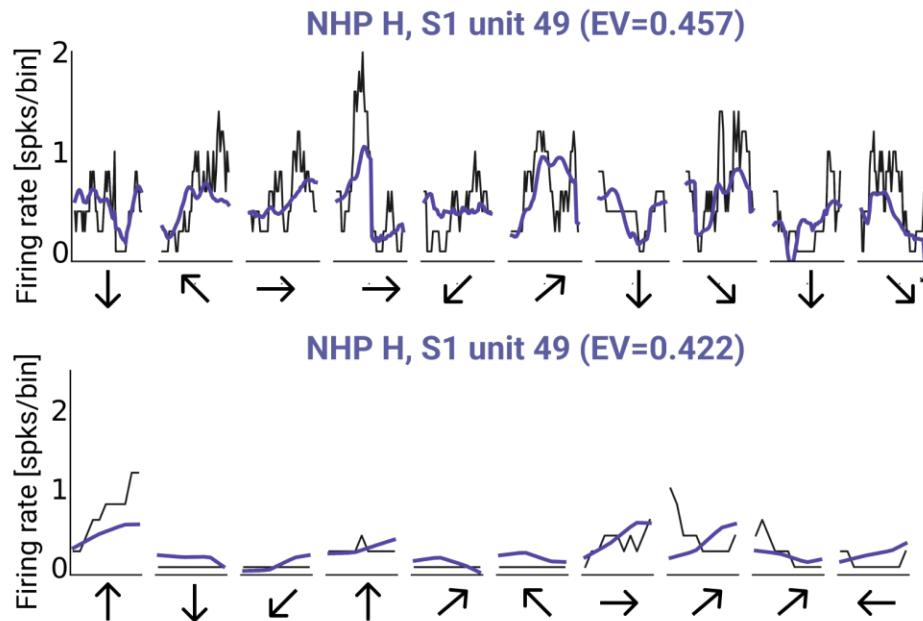
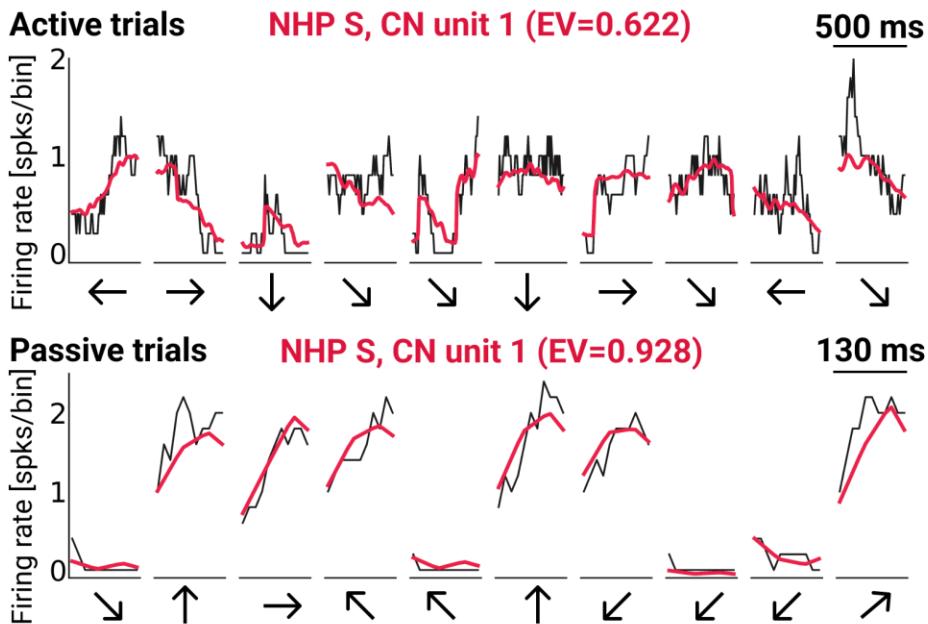
Active reaches



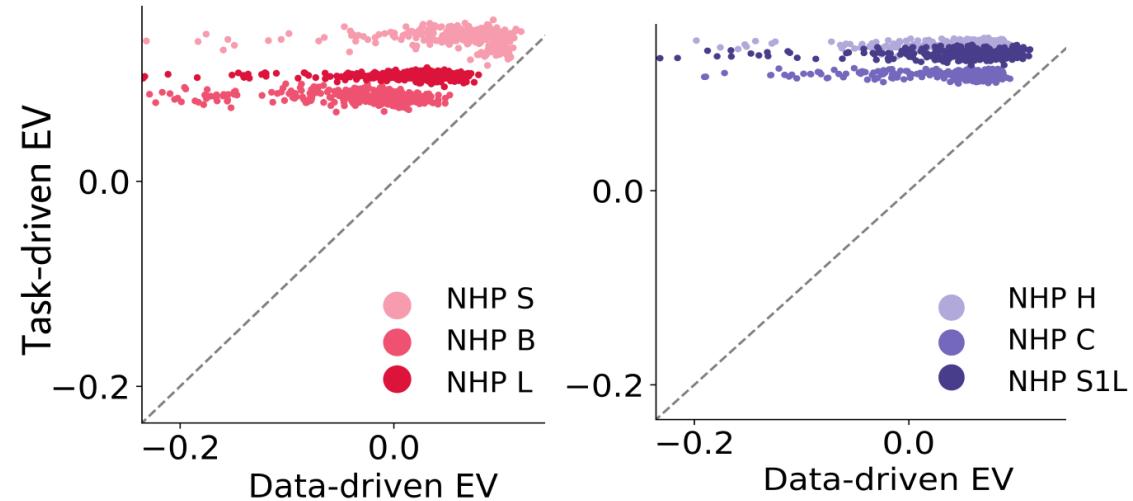
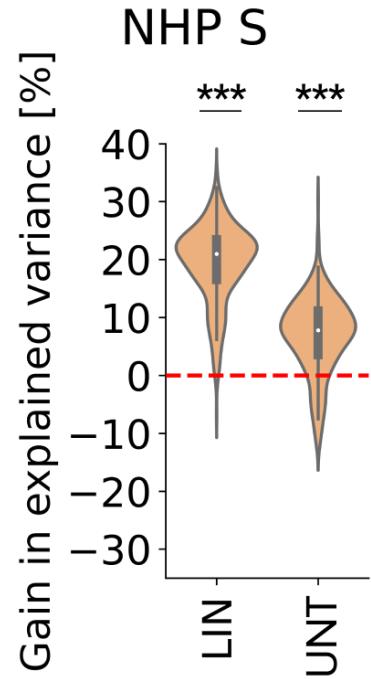
Task-trained models predict single neuron dynamics



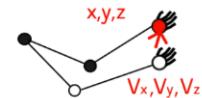
EXAMPLE SINGLE-NEURON SINGLE-TRIAL NEURAL PREDICTIONS



Task-trained models outperform linear, randomly initialized and data-driven models



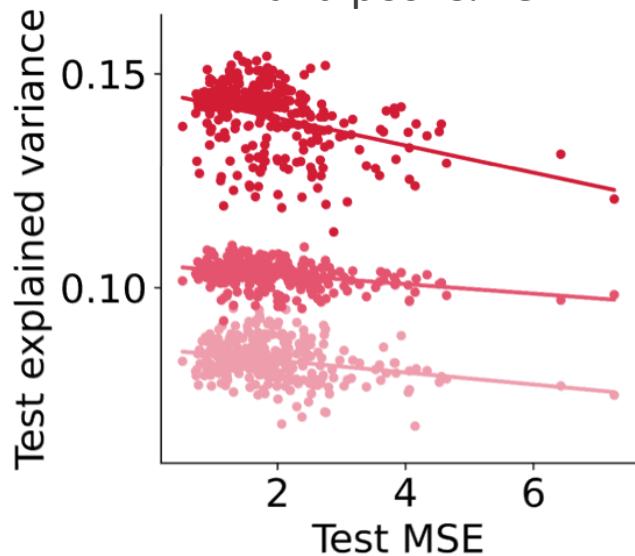
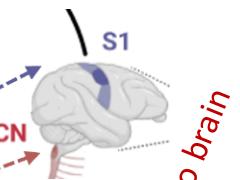
Task-performance and neural predictability are correlated



Hand position and velocity task (HP & HV)

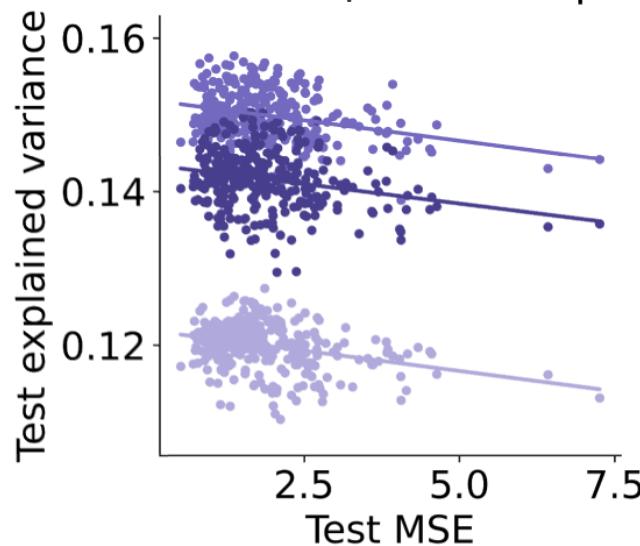
- $m=B$, $r=-0.268$, $p=2.55e-06$
- $m=L$, $r=-0.337$, $p=2.22e-09$
- $m=S$, $r=-0.374$, $p=2.18e-11$

Hand pos. & Vel



- $m=C$, $r=-0.313$, $p=3.10e-08$
- $m=H$, $r=-0.278$, $p=1.00e-06$
- $m=S1L$, $r=-0.241$, $p=2.48e-05$

Hand pos. & Vel



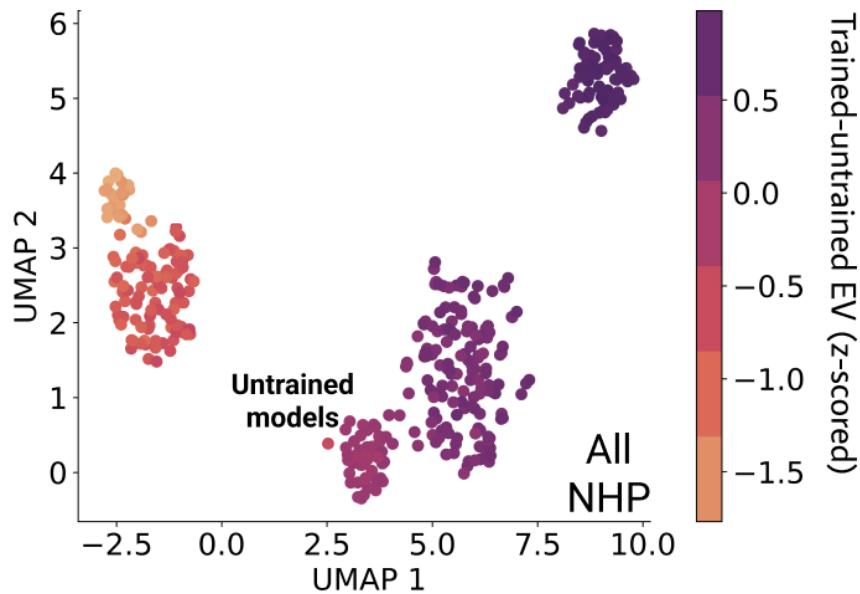
Optimized on biomechanics (body)

Different model architectures



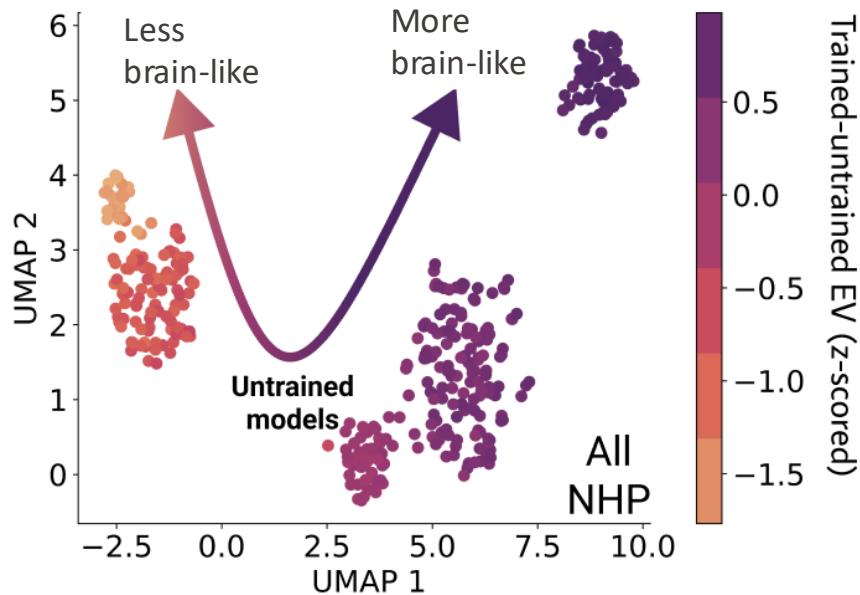
Unsupervised hypothesis comparison

ACTIVE



Unsupervised hypothesis comparison

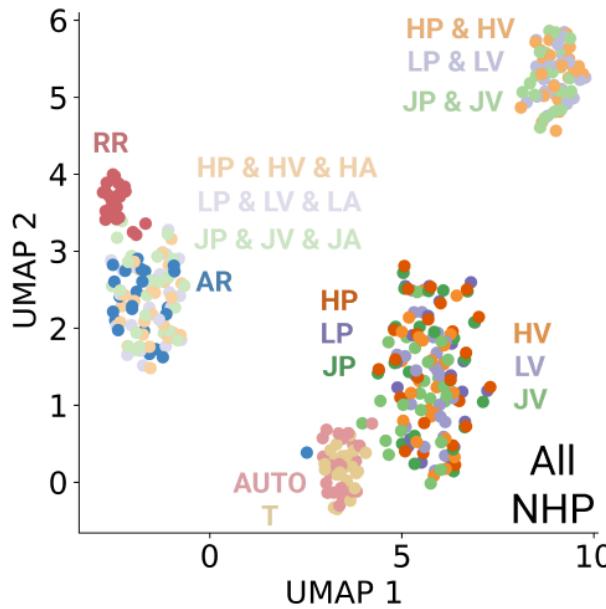
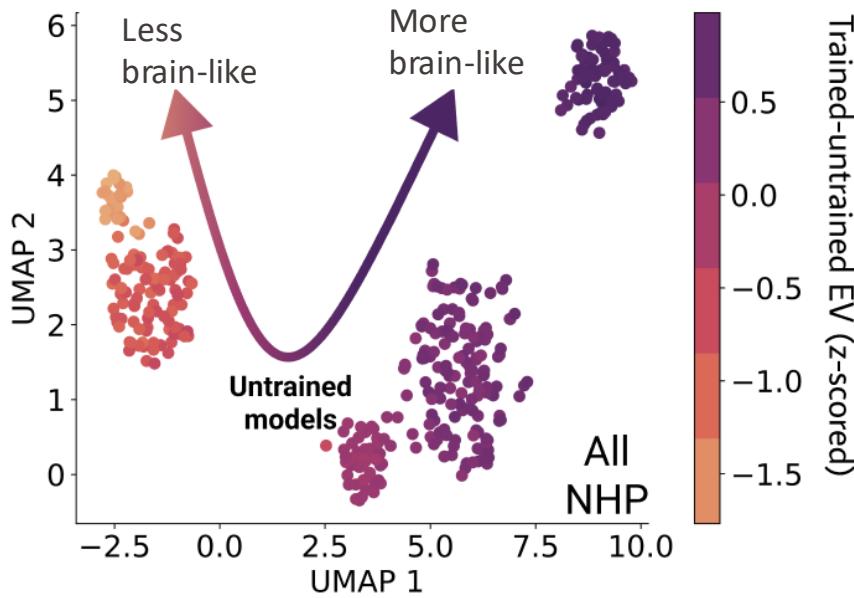
ACTIVE



Unsupervised hypothesis comparison

ACTIVE

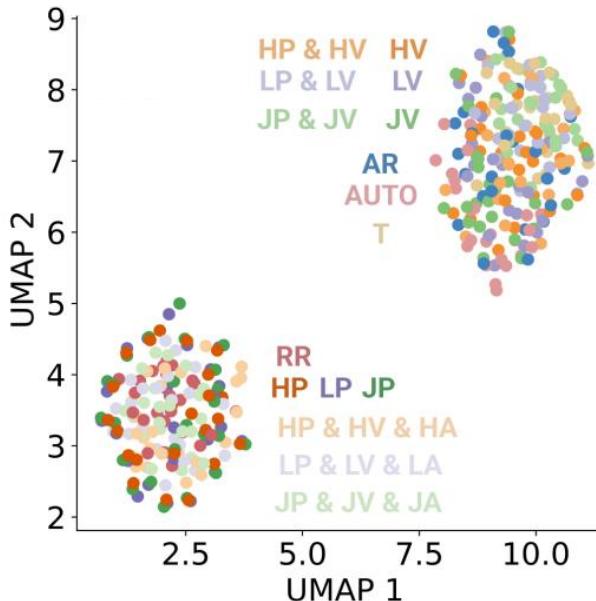
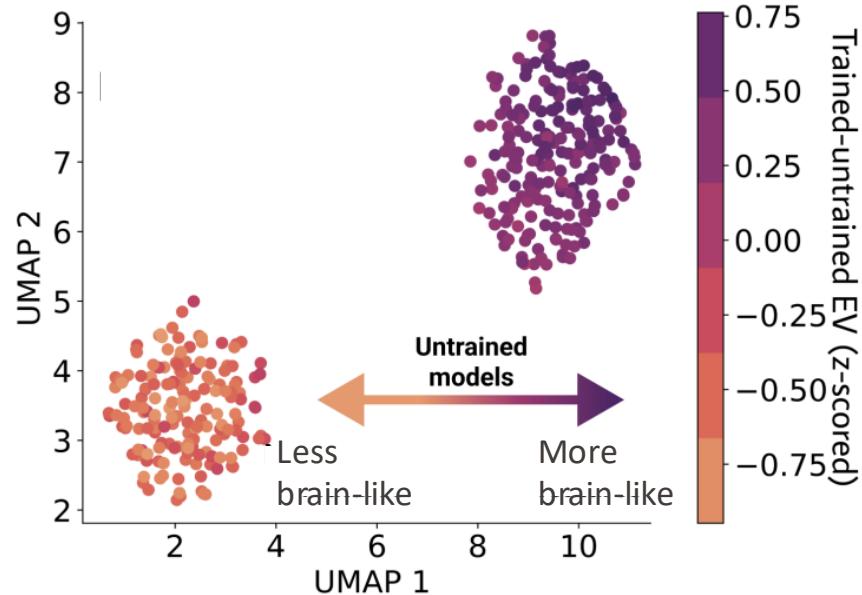
HP = Hand position **LP** = Limb position **JP** = Joint position
HV = Hand velocity **LV** = Limb velocity **JM** = Joint velocity
HA = Hand acceleration **LA** = Limb acceleration **JA** = Joint acceleration
RR = Redundancy Reduction **AUTO** = Autoencoder **AR** = Action Recognition
T = Torque



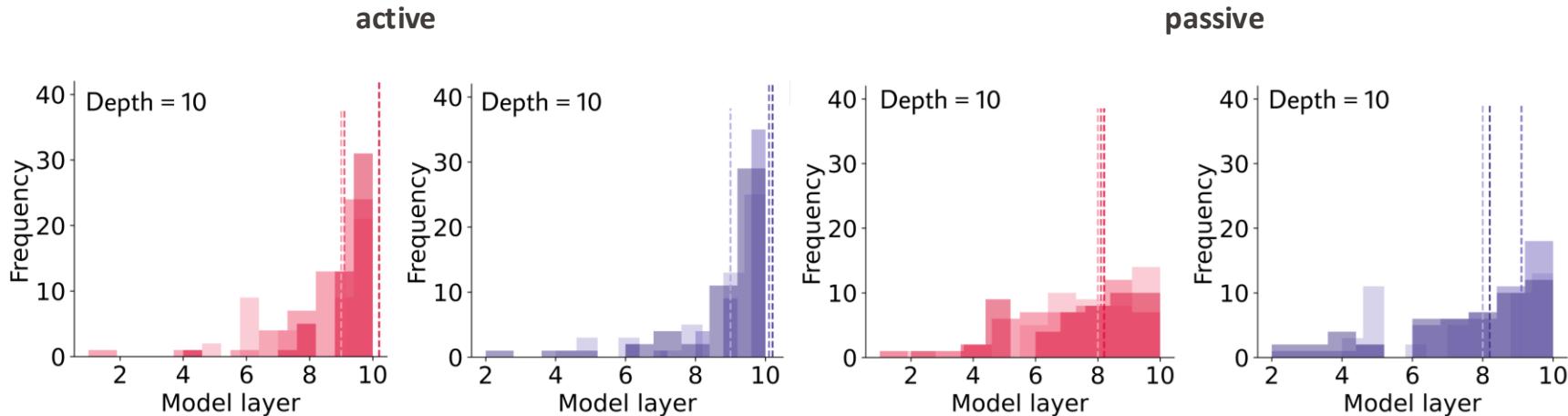
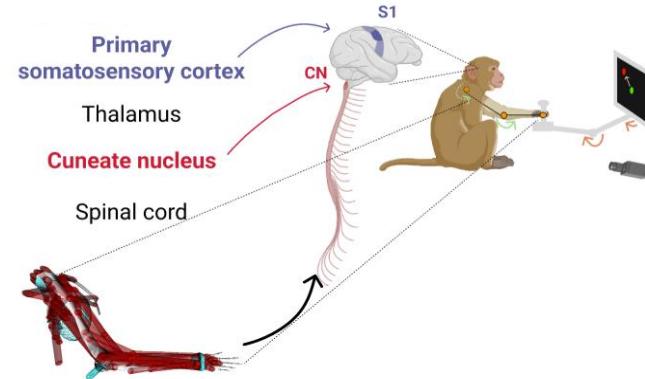
Unsupervised hypothesis comparison

PASSIVE

HP = Hand position **LP** = Limb position **JP** = Joint position **RR** = Redundancy Reduction
HV = Hand velocity **LV** = Limb velocity **JM** = Joint velocity **AUTO** = Autoencoder
HA = Hand acceleration **LA** = Limb acceleration **JA** = Joint acceleration **AR** = Action Recognition
T = Torque

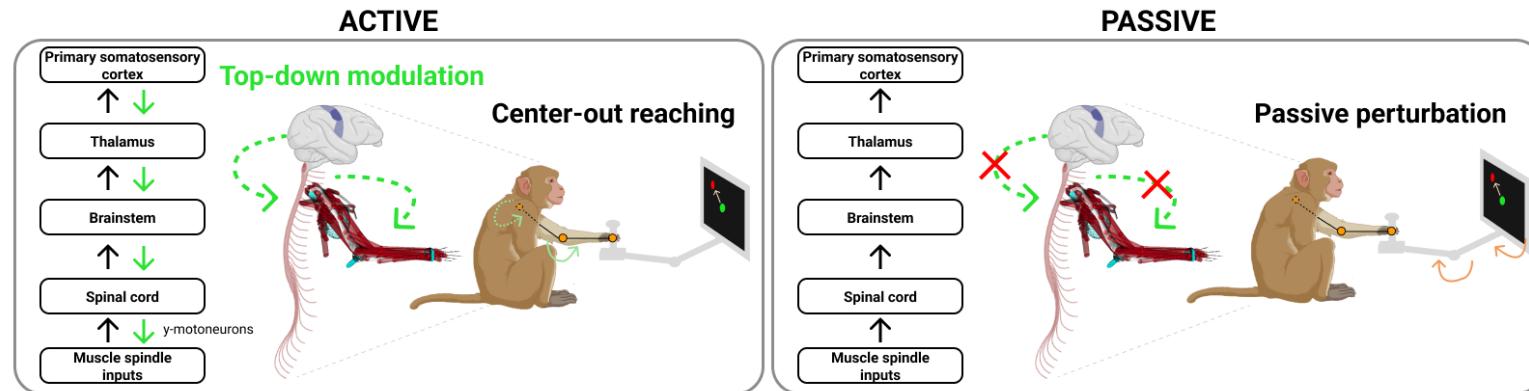


Lack of hierarchical representation



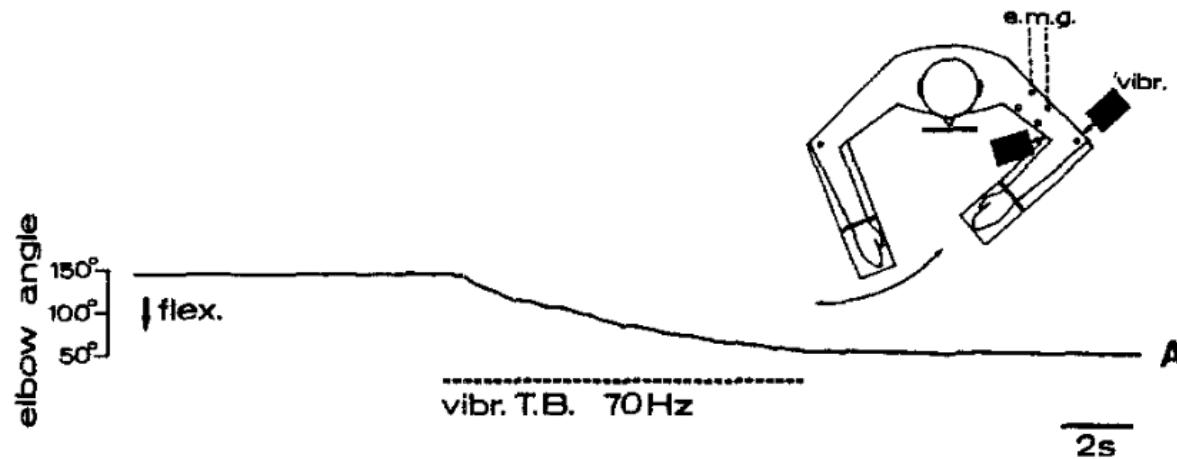
Discussion

- For all 16 hypotheses, if a *computation* is better learned on synthetic, passive spindle data, then the model also generalizes better to neural data
- Neural data (*in the active case*) is best explained by the **hypothesis that proprioception is optimized to encode the location and velocity of the body** (irrespective of coordinate framework)
- Lack of evidence for hierarchical processing; this suggests that proprioception even in the brain stem is dominated by efference copies



Proprioceptive illusions

Illusions of movement with muscle-tendon vibrations



Roll and Vedel *Exp Brain Research.* 1982

Effect on afferent firing rate

J. P. Roll and J. P. Vedel: Muscle Spindle Contribution to Kinaesthesia

183

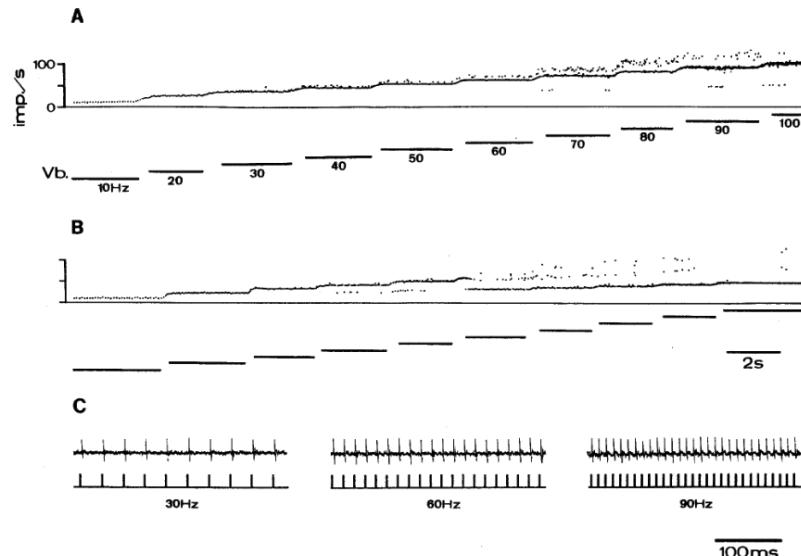


Fig. 4A–C. Driven activity (instantaneous frequency) of a spindle primary ending by mechanical vibration applied to the tendon of the receptor-bearing muscle (TA). A Optimal primary ending activation by tendon vibration from 10 to 100 Hz. B The same primary ending can eventually respond by a sub-harmonic discharge frequency to a particular vibration frequency (60 Hz in the example). C One-to-one primary ending responses to 30, 60, and 90 Hz tendon vibration

Roll & Vedel. *Exp Brain Research*. 1982

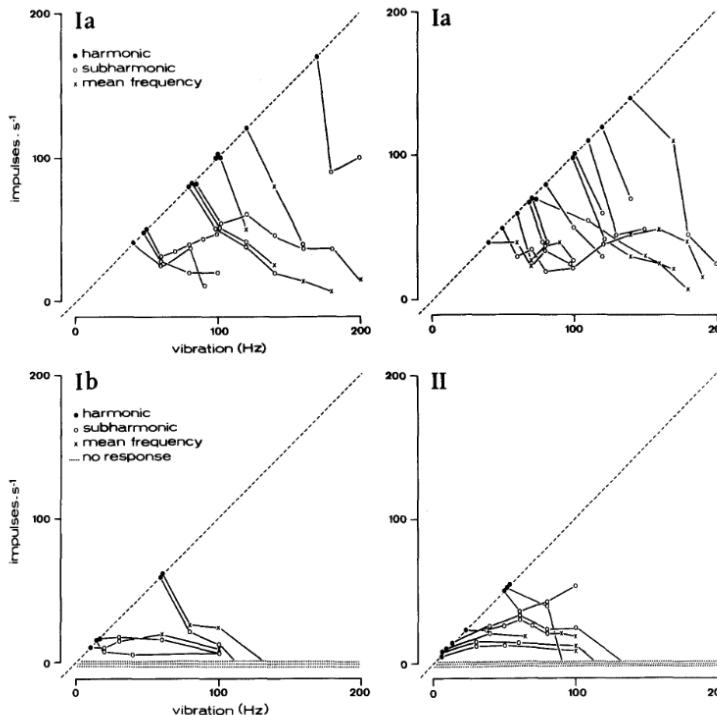
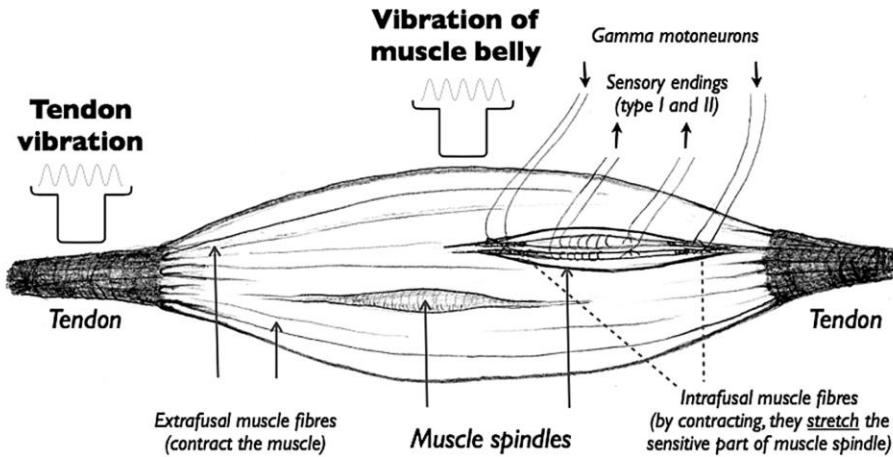


Fig. 1. Driving modalities of muscle spindle primary (Ia) and secondary (II) endings and tendon organ (Ib) activities induced by mechanical

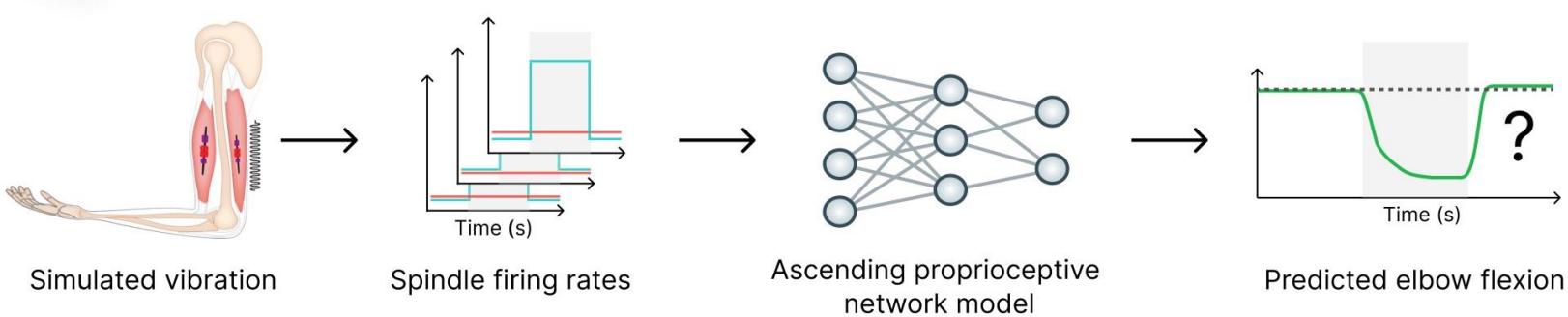
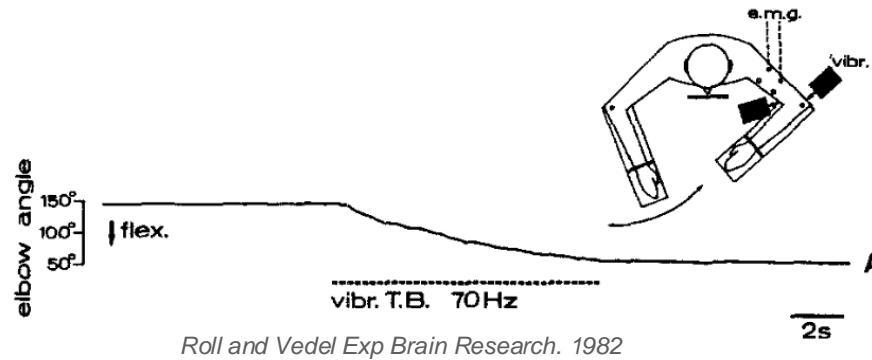
Roll, Vedel, and Ribot. *Exp Brain Research*. 1989

Details of vibration-induced illusions

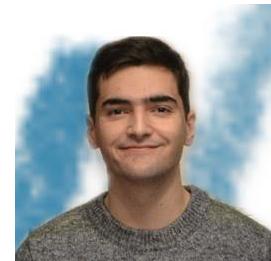


- Vibration over the tendon or muscle belly at ~100Hz
- Vibrations mainly affect Ia afferent output
- Limb muscle vibration creates an illusory limb movement in the direction corresponding to lengthening of the vibrated muscle.

Studying the effect of tendon vibrations

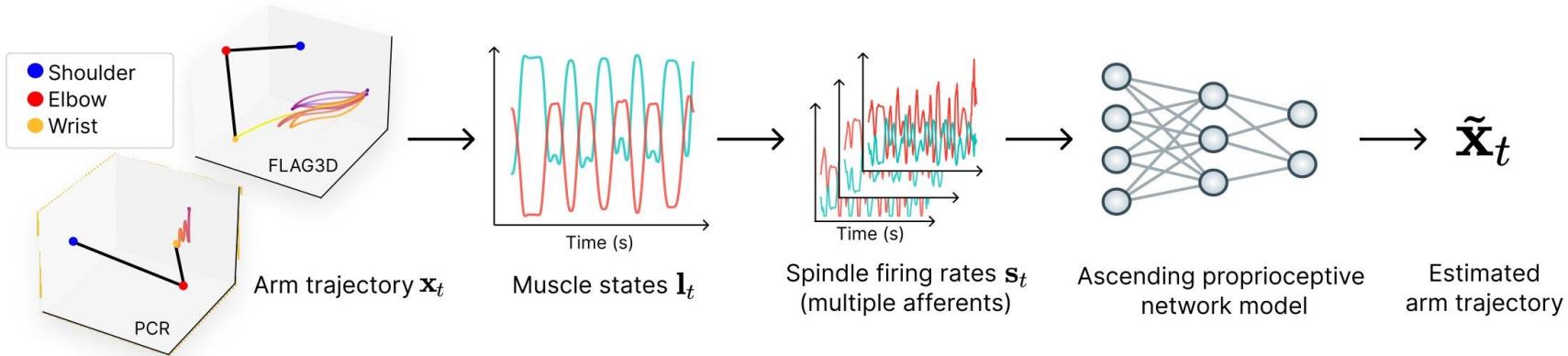


Modeling proprioceptive perception

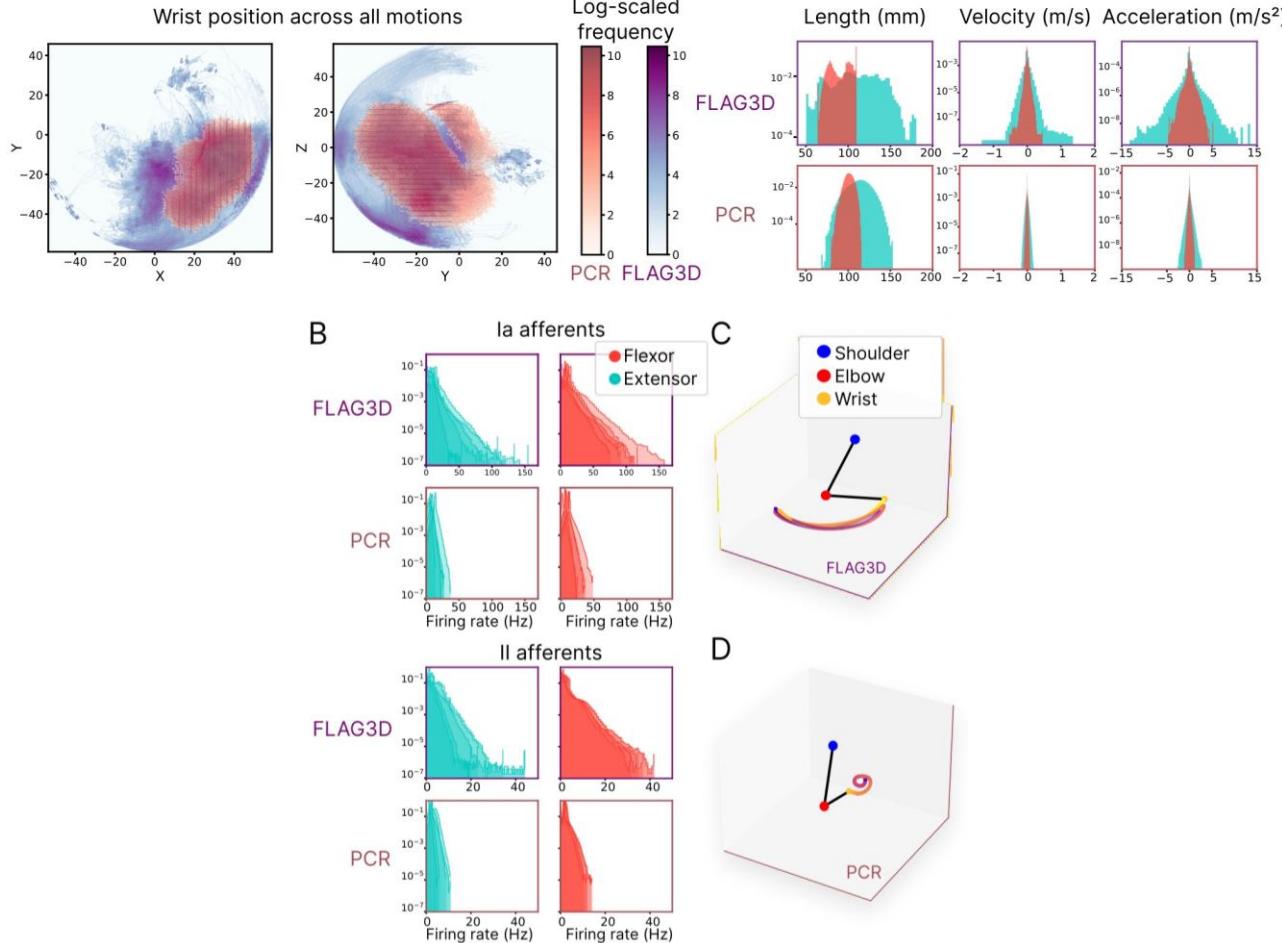


Adriana
Perez Rotondo

Merkourios Simos

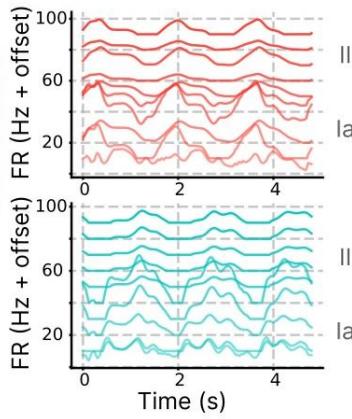


Dataset statistics

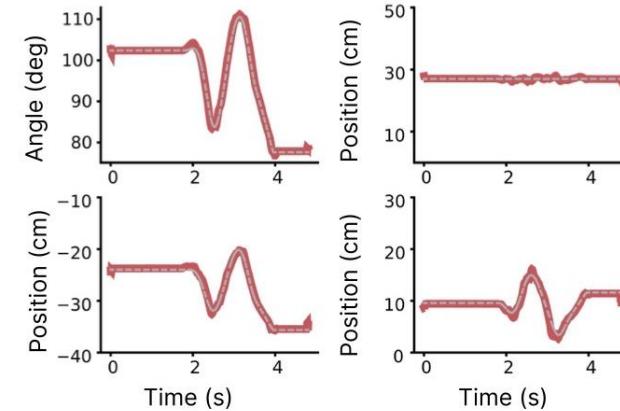
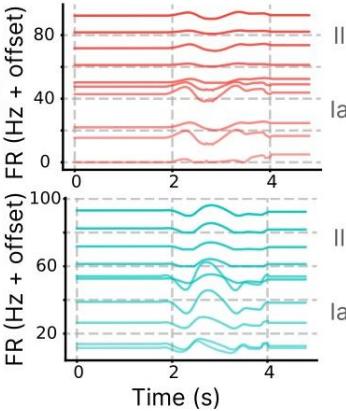
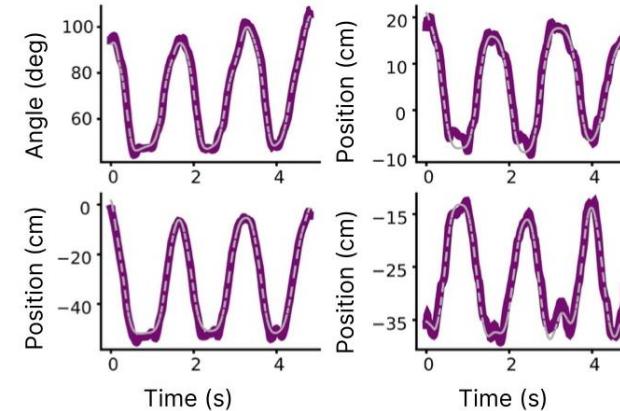


Model predictions

Spindle firing rates



Model predictions



Modelling tendon vibrations

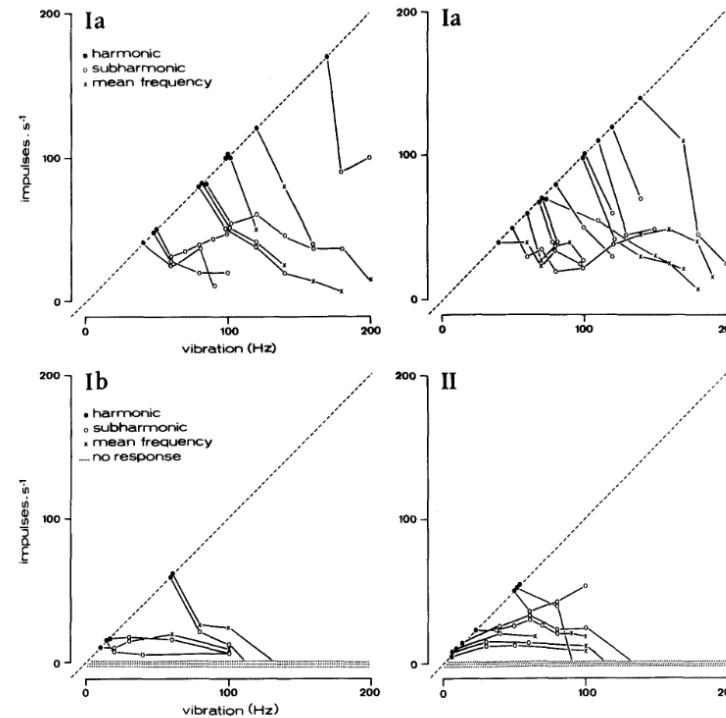
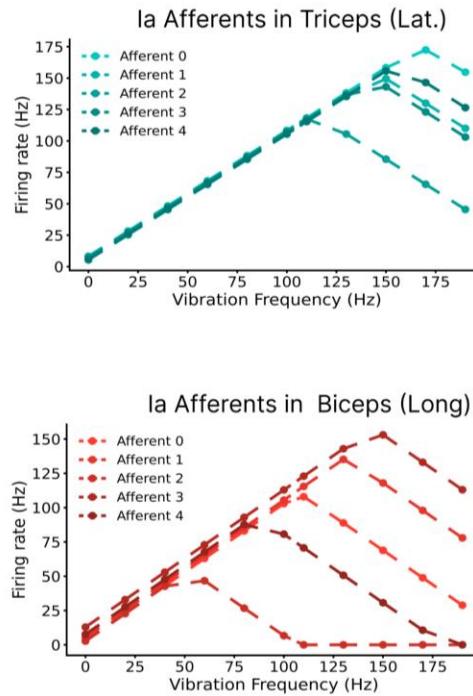
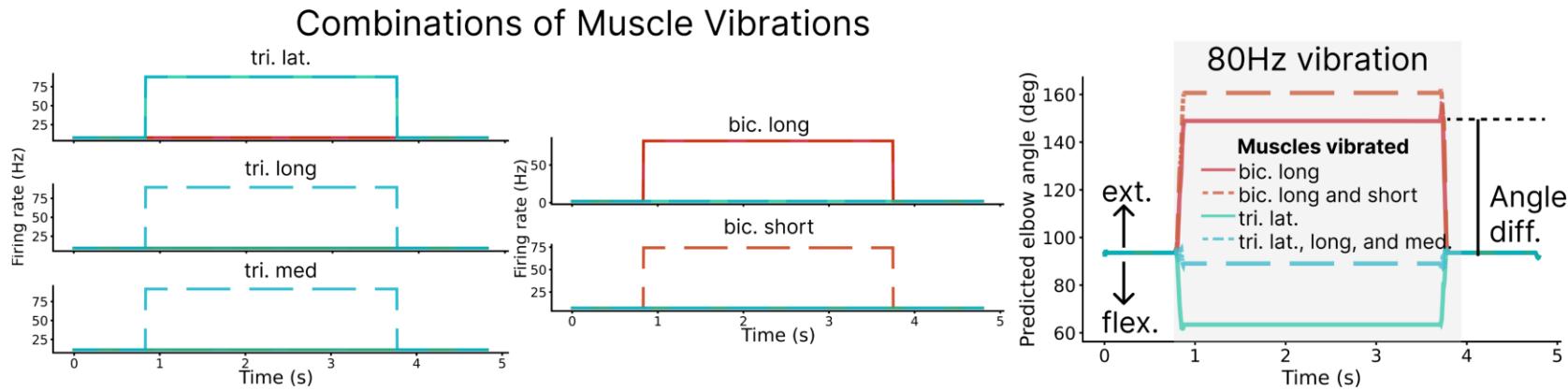
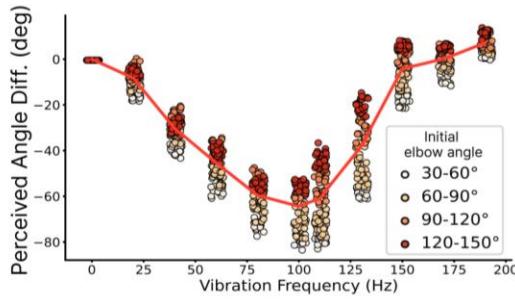
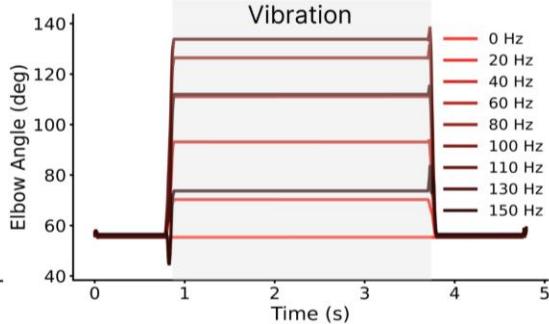
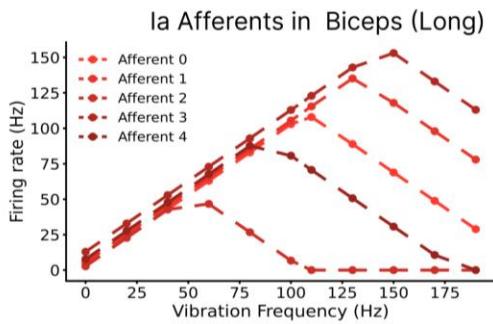
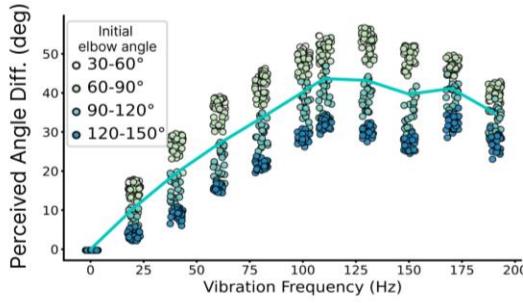
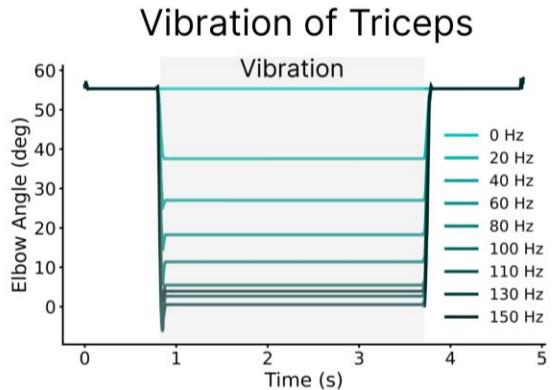
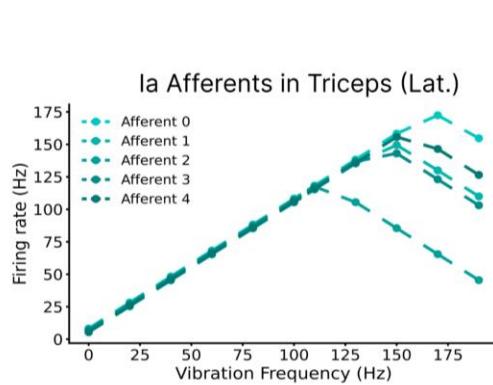


Fig. 1. Driving modalities of muscle spindle primary (Ia) and secondary (II) endings and tendon organ (Ib) activities induced by mechanical

Effect of (simulated) vibrations

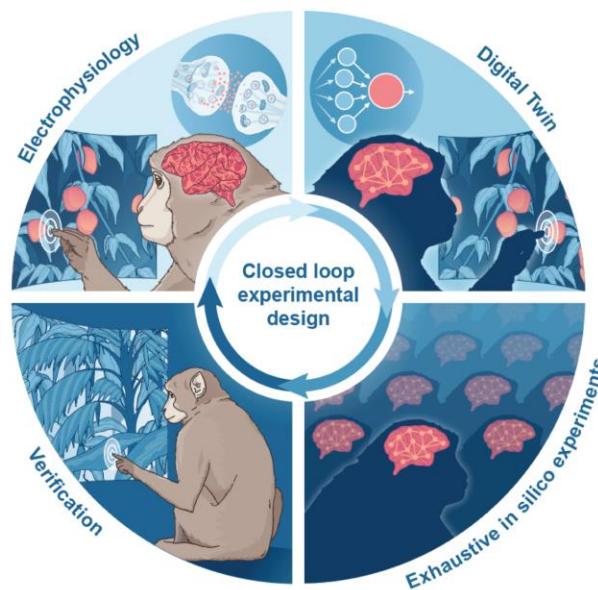


Effect of simulated vibrations



Statistical models

- We can build powerful models (data-driven or task-driven)
- We can compare hypotheses and scaling of models (*why* questions)
- Enables novel experiments (behavioral, physiology ...)



Take-home messages

- To study proprioception: we combined biomechanics, representation learning & neural data analysis.
- Networks trained on synthetic (muscle) data generalize to predict single-trial neural activity in the brain stem and cortex of primates performing limb center-out movements
- Architectures that are better at solving the tasks are also better at predicting the neural data.
- Models trained to predict the limb position and velocity were the best to predict neural activity. Note this could be supervised by vision.
- Thus, task-driven modeling allowed us to test multiple hypotheses
- Task-trained models are also susceptible to proprioceptive illusions
- NOTE: We simplified the system by *purposefully* isolating the sensory part of proprioception