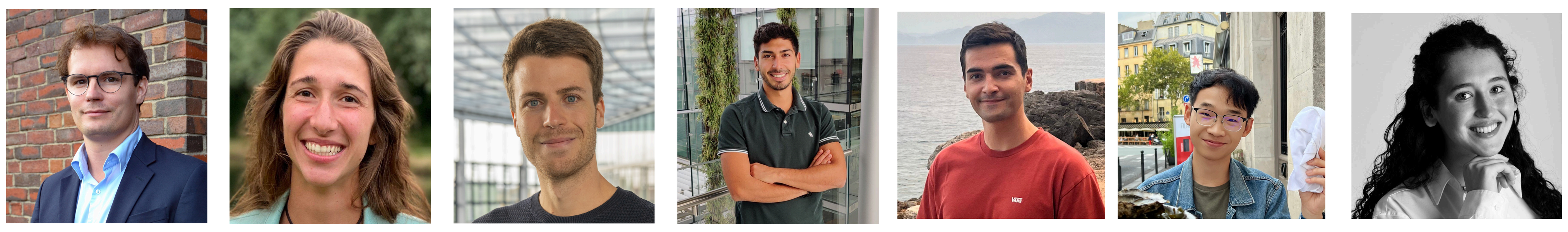
# Skill learning and modeling sensorimotor circuits

Mathis Group for Computational Neuroscience and AI

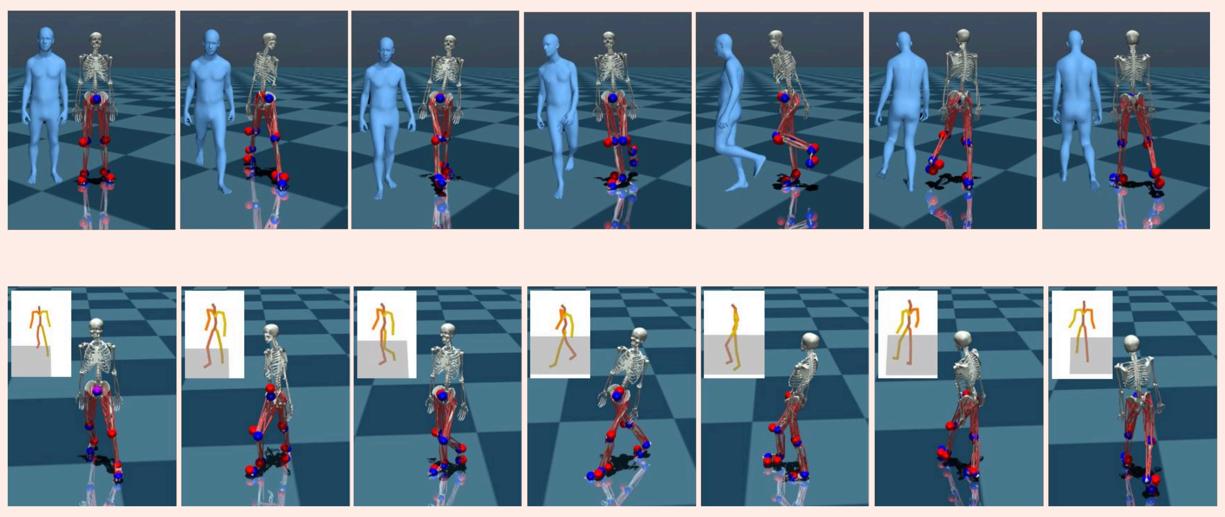
We develop **normative theories** of **neural systems** that are trained to perform **sensorimotor behaviors** as well as **task-driven models.**

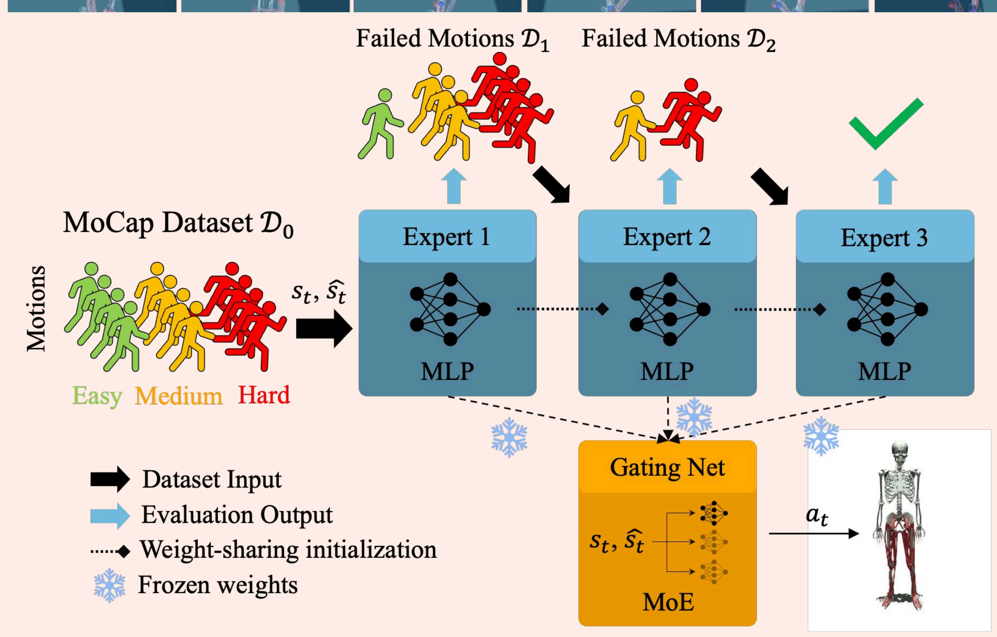


Join **us and Mackenzie Mathis' lab** in Geneva!

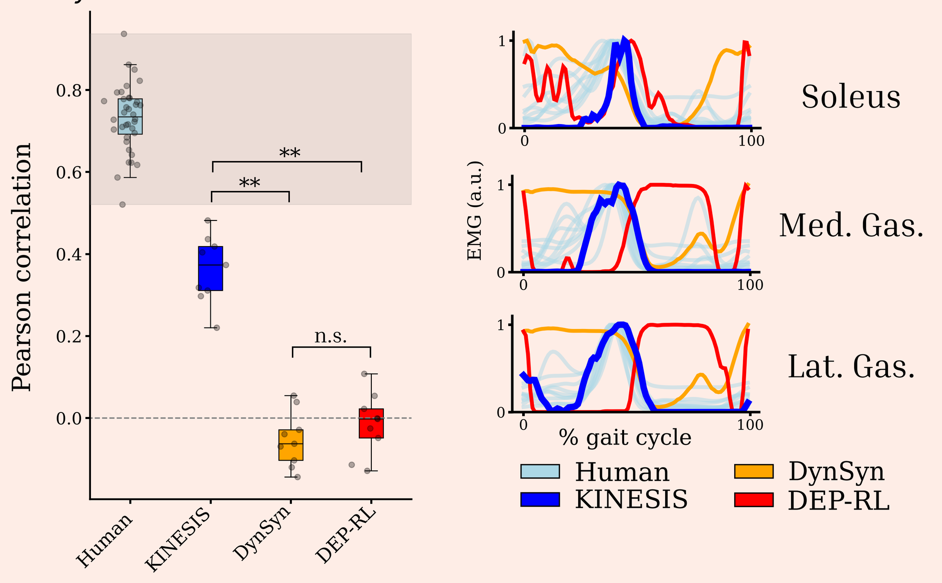
## KINESIS: Motion imitation learning for physiologically plausible motor control

*KINESIS is a model-free motion imitation framework to advance the understanding of muscle-based motor control. Using a musculoskeletal model of the lower body with 80 muscle actuators, we demonstrate that KINESIS achieves strong imitation performance, is controllable by natural language, and can be fine-tuned to carry out high-level tasks. KINESIS generates muscle activity patterns that correlate well with human EMG activity.*






*KINESIS generates muscle activity patterns that correlate well with human EMG activity.*



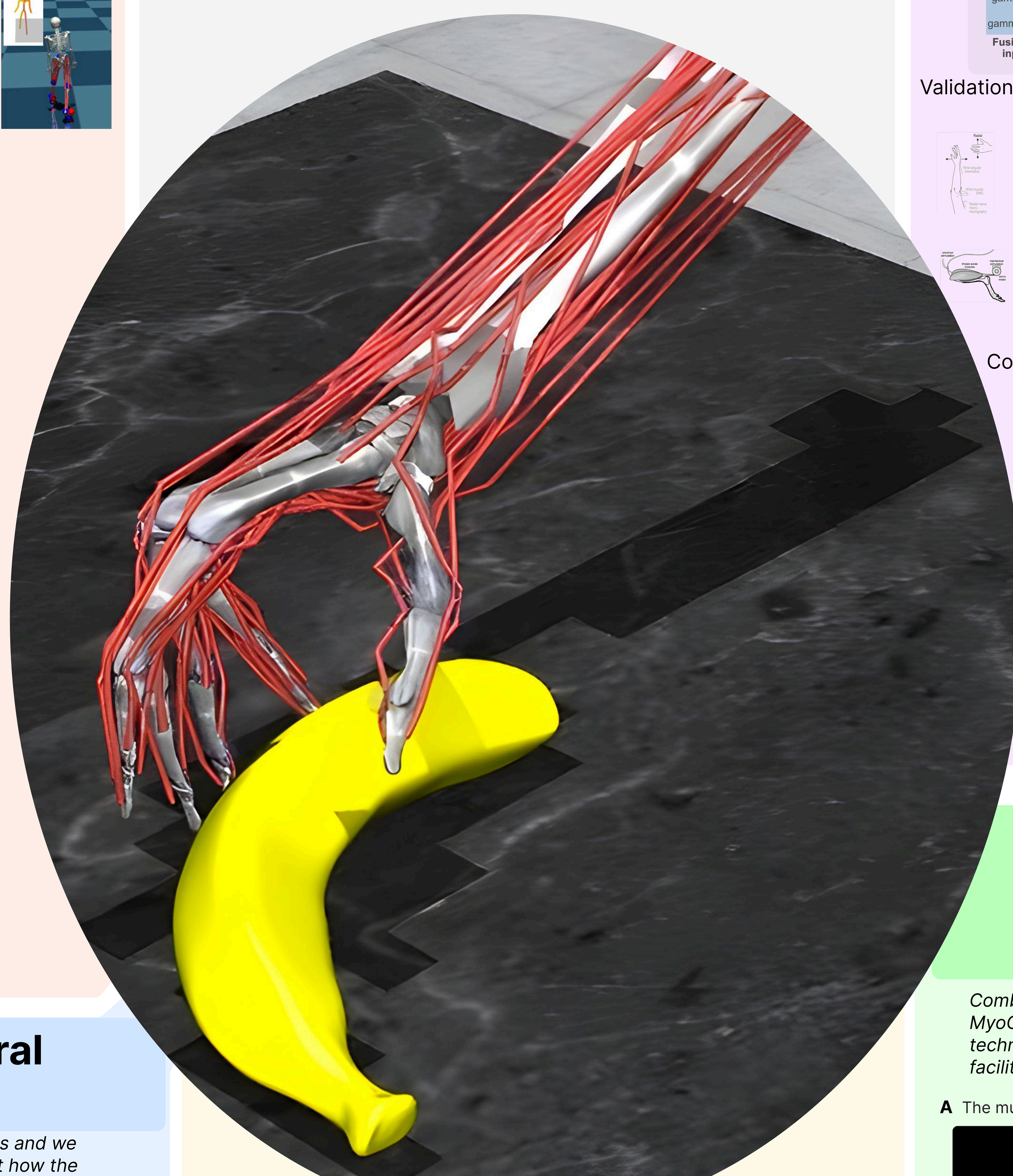

## RESEARCH QUESTIONS

What are the principles of proprioception?

What are the neural mechanisms underlying robust motor control?

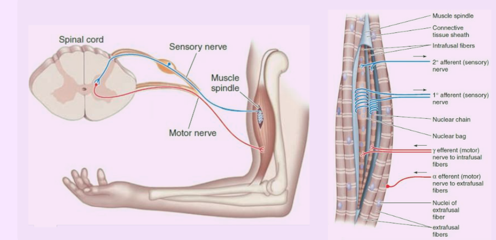
How does the brain integrate sensory inputs to execute movements?

How does expert behavior emerge?

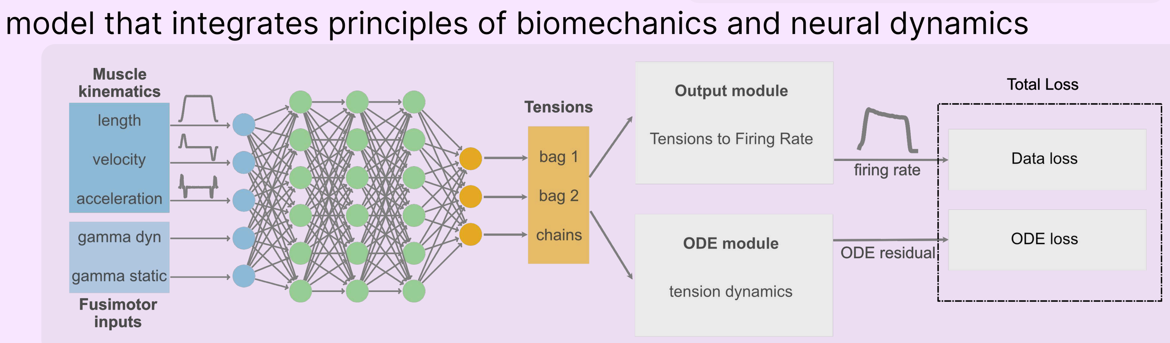


## Modeling muscle spindles with Physics-Informed Neural Networks (PINNs)

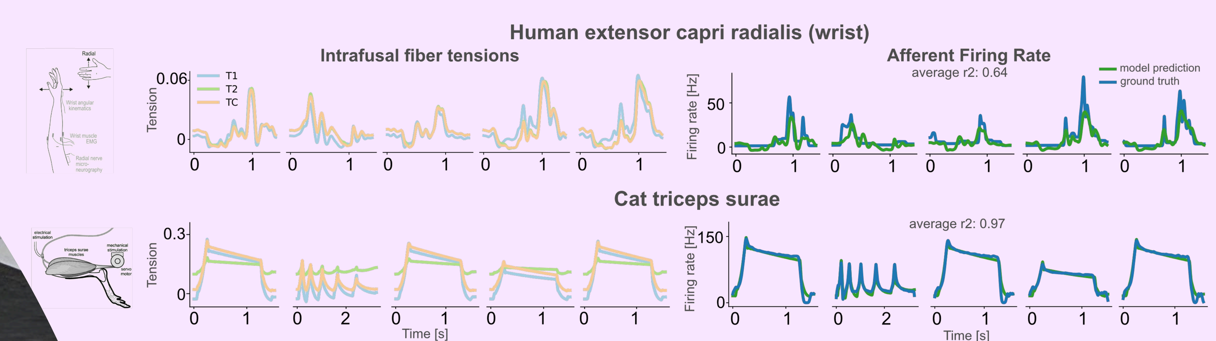
*Muscle spindles convey information about the body position and movement to the central nervous system.*
*By leveraging the power of PINNs we propose a model of muscle spindles that merges structural fidelity with computational efficiency.*



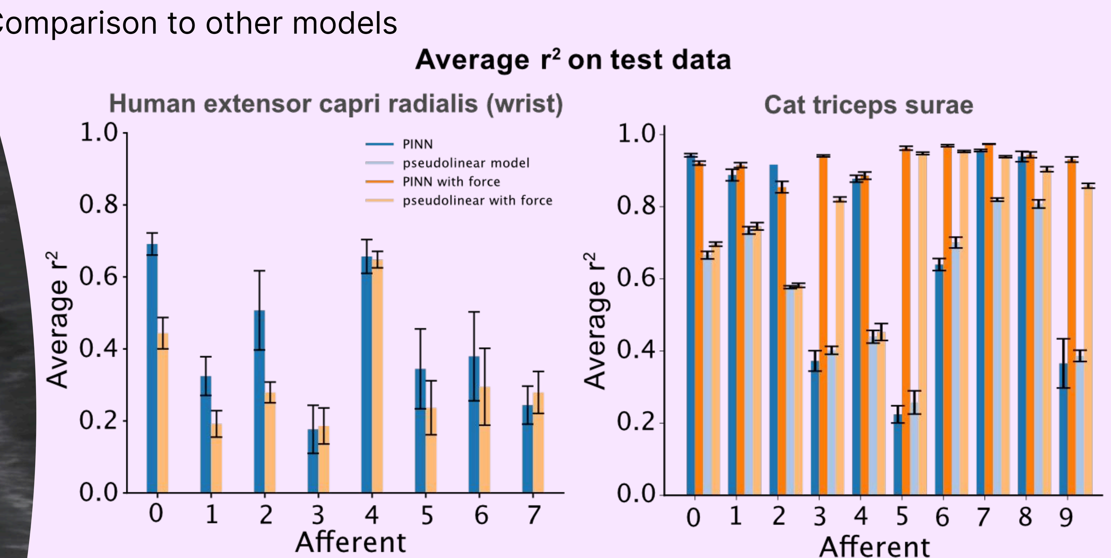
A model that integrates principles of biomechanics and neural dynamics




Validation on single trials from multiple datasets



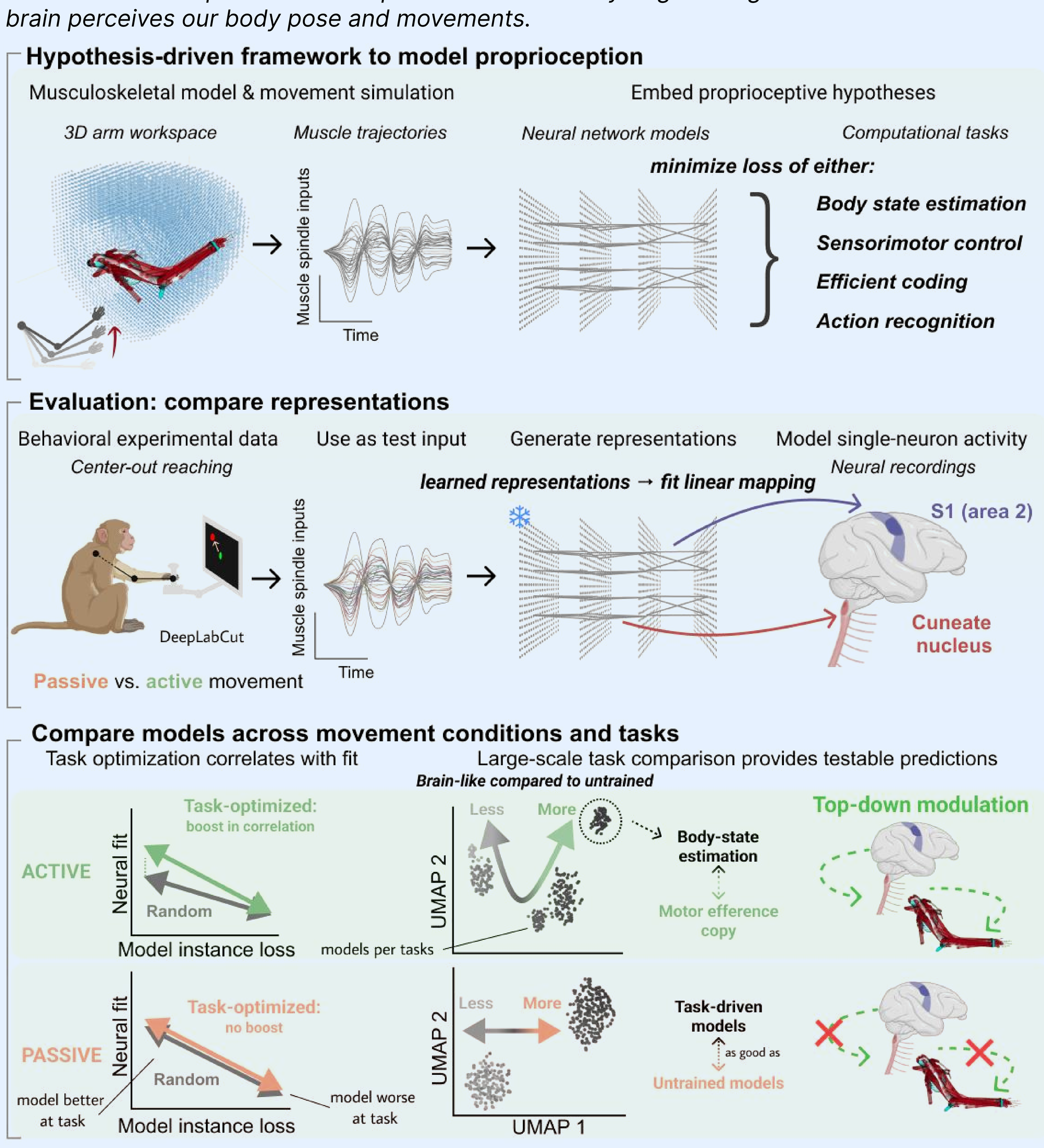

Comparison to other models




A. Perez Rotondo, M. Dimitriou, A., Mathis, A. "Modeling Sensorimotor Processing with Physics-Informed Neural Networks." (In preparation)

## Modeling Proprioception with neural network models

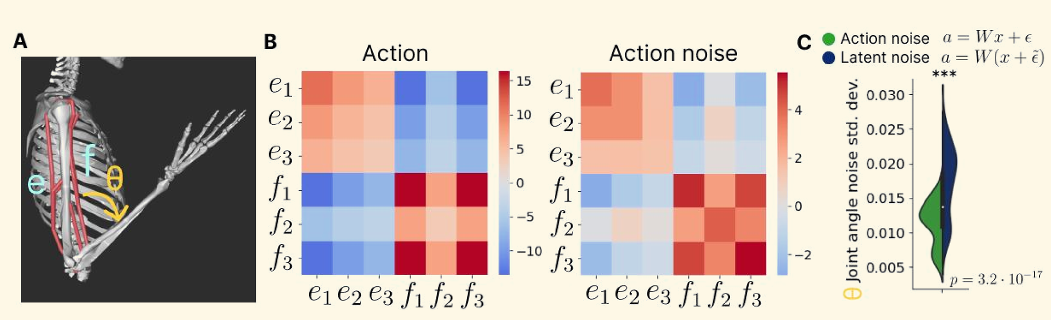
*We trained neural network models to solve proprioceptive computational tasks and we use the learned representation to predict neural activity to gain insights about how the brain perceives our body pose and movements.*



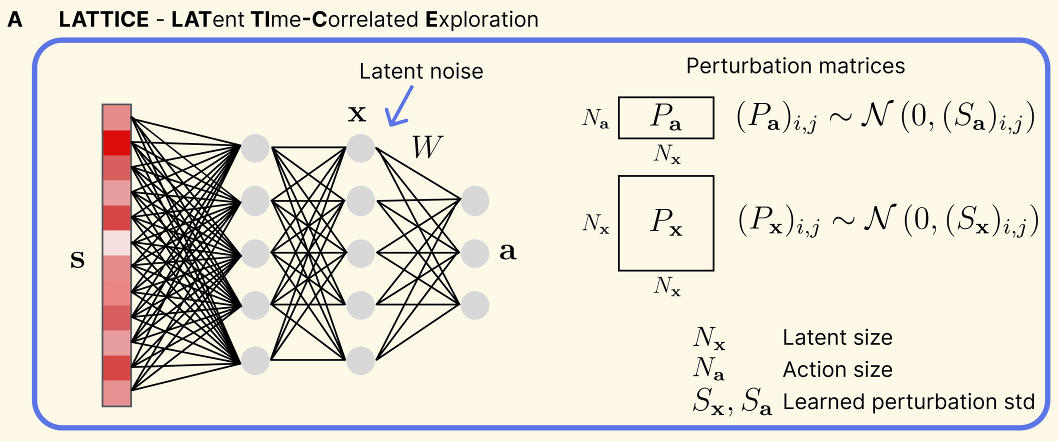

Marin Vargas*, A., Bisi*, A., Chiappa, A. S., Versteeg, C., Miller, L. E., & Mathis, A. "Task-driven neural network models predict neural dynamics of proprioception". Cell, 2024.

## Latent exploration for reinforcement learning (Lattice)

*Lattice is an exploration method which helps learning complex skills in complex environments through reinforcement learning. It uses the correlation across actuators learnt by the policy to give a structure to the exploration noise.*




This is achieved by perturbing the latent state of the policy network.

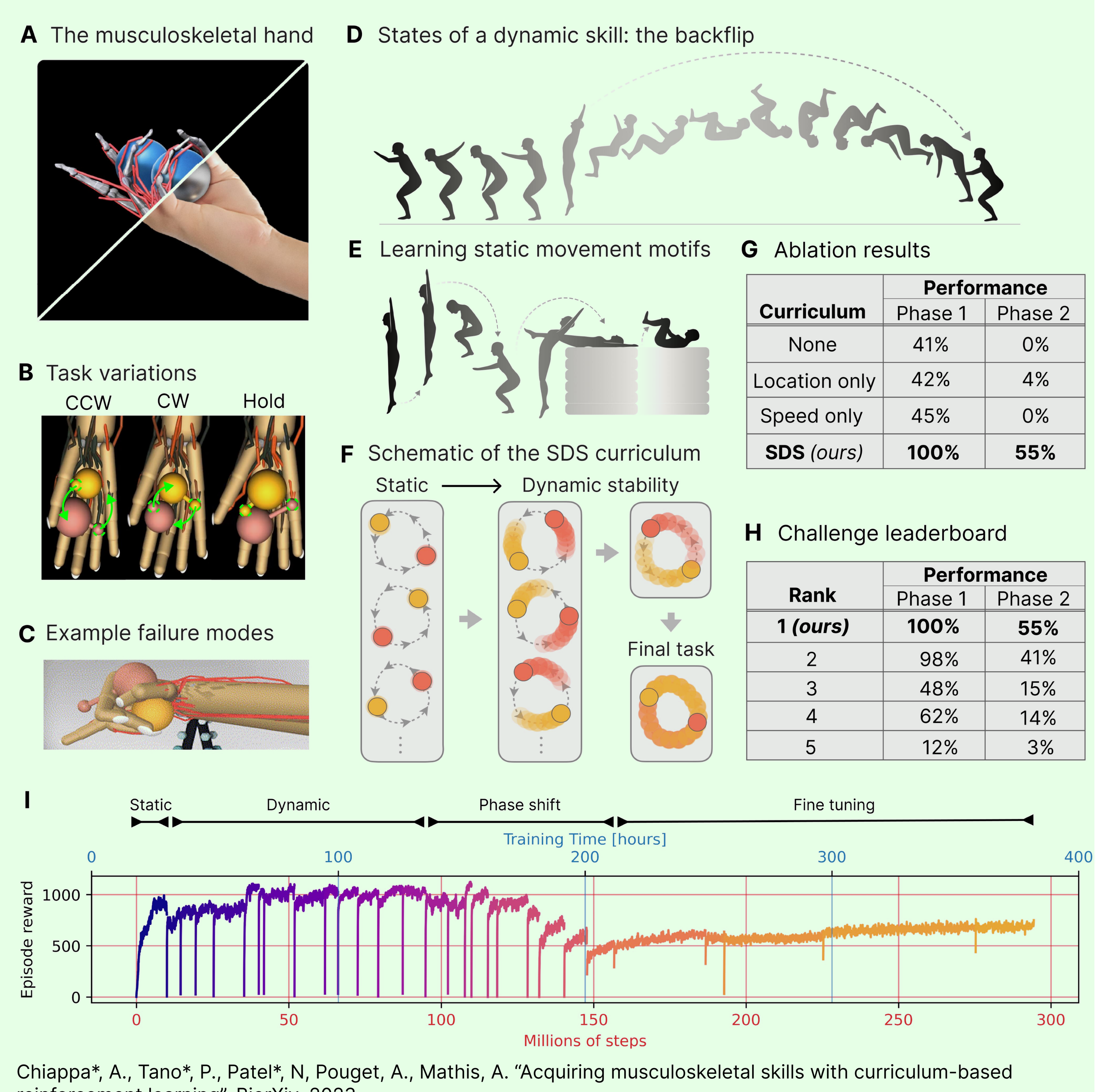



Chiappa, A., Marin Vargas, A., Huang, A. Z., and Mathis, A. "Latent exploration for reinforcement learning". NeurIPS, 2023.

We used LATTICE to win the **2023 MyoChallenge**. Check out our solution!

## Acquiring musculoskeletal skills with curriculum-based reinforcement learning

*Combining reinforcement and curriculum learning, we managed to win the NeurIPS MyoChallenge both in 2022 and 2023. Curriculum learning, similarly to coaching techniques used to train athletes, introduces progressively more complex task which facilitate the acquisition of sophisticated skills.*




G Ablation results

| Curriculum | Performance Phase 1 | Performance Phase 2 |
|---|---|---|
| None | 41% | 0% |
| Location only | 42% | 4% |
| Speed only | 45% | 0% |
| **SDS (ours)** | **100%** | **55%** |

H Challenge leaderboard

| Rank | Performance Phase 1 | Performance Phase 2 |
|---|---|---|
| **1 (ours)** | **100%** | **55%** |
| 2 | 98% | 41% |
| 3 | 48% | 15% |
| 4 | 62% | 14% |
| 5 | 12% | 3% |

Chiappa*, A., Tano*, P., Patel*, N, Pouget, A., and Mathis, A. "Acquiring musculoskeletal skills with curriculum-based reinforcement learning". BiorXiv, 2023.

We love open source!

Check out our website!

Swiss National Science Foundation

Neuro X Institute

BRAIN MIND INSTITUTE

**Selected collaborators:**
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