

Inferring cerebellar computations with probabilistic machine learning approaches

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Growing evidence is suggesting that vertebrate adaptability relies on the cerebellum’s capacity to channel information well beyond its traditionally known motor pathways. In particular, researchers in the field have discovered novel projections to sub-cortical and reward related regions (Washburn et al. 2024; Ohmae and Medina 2015; Washburn et al. 2024; Wagner et al. 2017), observing that the cerebellum is involved in a plethora of tasks not directly related to movement tuning (Strick, Dum, and Fiez 2009; Overwalle et al. 2014). Despite this improvement in phenomenological understanding, the grounding theoretical principles driving cerebellar computations are still strongly debated.

To address this question, several computational models have been proposed, dissecting specific functional aspects and leveraging different mathematical frameworks (Schepper et al. 2021; D’Angelo et al. 2016; Diedrichsen et al. 2019). We plan to build on top of this work and propose a unified theoretical framework of cerebellar computation by integrating model selection and inference theory with experimental validation and neuromorphic applications.

We will start by studying the equivalence of the proposed models with respect to their emerging behaviour, framing the question as a model degeneracy (or robustness) problem (Calaim et al. 2022; Gonçalves et al. 2019). To tackle this problem, we will start by characterizing the models’ parameter space using simulation-based inference (Lueckmann et al. 2017), leveraging the latest toolkit developments achieved in our group (Tejero-Cantero et al. 2020; Deistler et al. 2024). Coupling this approach with summary statistic design and dimensionality reduction techniques (Pellegrino, Stein, and Cayco-Gajic 2024; Cenedese et al. 2022) we will characterize these parameter spaces in terms of their computational features, low-dimensional dynamics, and other optimality metrics such as energy efficiency (Jedlicka, Bird, and Cuntz 2022). With the aid of variational inference techniques (Bishop 2006; Luo 2022), we will search for common latent factors that underpin these emerging features across different models, ultimately separating a healthy neuronal circuit from a pathological one.

Building on these insights, we will develop a new computational model, and test the predictions of our theoretical framework on existing human and animal cerebellar datasets (Kumar et al. 2022; Mayoral-Palarz et al. 2022). Moreover, in strict collaboration with experts in the field (Ribar and Sepulchre 2020), we will investigate how the newly discovered factors can be applied to neuromorphic networks to achieve a superior degree of robustness in motor control tasks.

In summary, by bridging advanced parameter inference, model selection and experimental data analysis, this project will unveil the foundational principles underlying cerebellar computations. This will ultimately pave the way to novel diagnostic approaches and resilient, brain-inspired computational motor controllers.

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