Dendritic gated networks: A rapid and efficient learning rule for biological neural circuits

Dimitar Kostadinov[1]*, Eren Sezener[2*], Agnieszka Grabska-Barwińska[2*], Maxime Beau[1], Sanjukta Krishnagopal[3], David Budden[2], Marcus Hutter[2], Joel Veness[2], Matthew Botvinick[2,3], Claudia Clopath[4], Michael Häusser[1], Peter E. Latham[3]
1. Wolfson Institute for Biomedical Research, University College London, 2. DeepMind, 3. Gatsby Computational Neuroscience Unit, University College London, 4. Department of Bioengineering, Imperial College London *Equal contribution

UCL

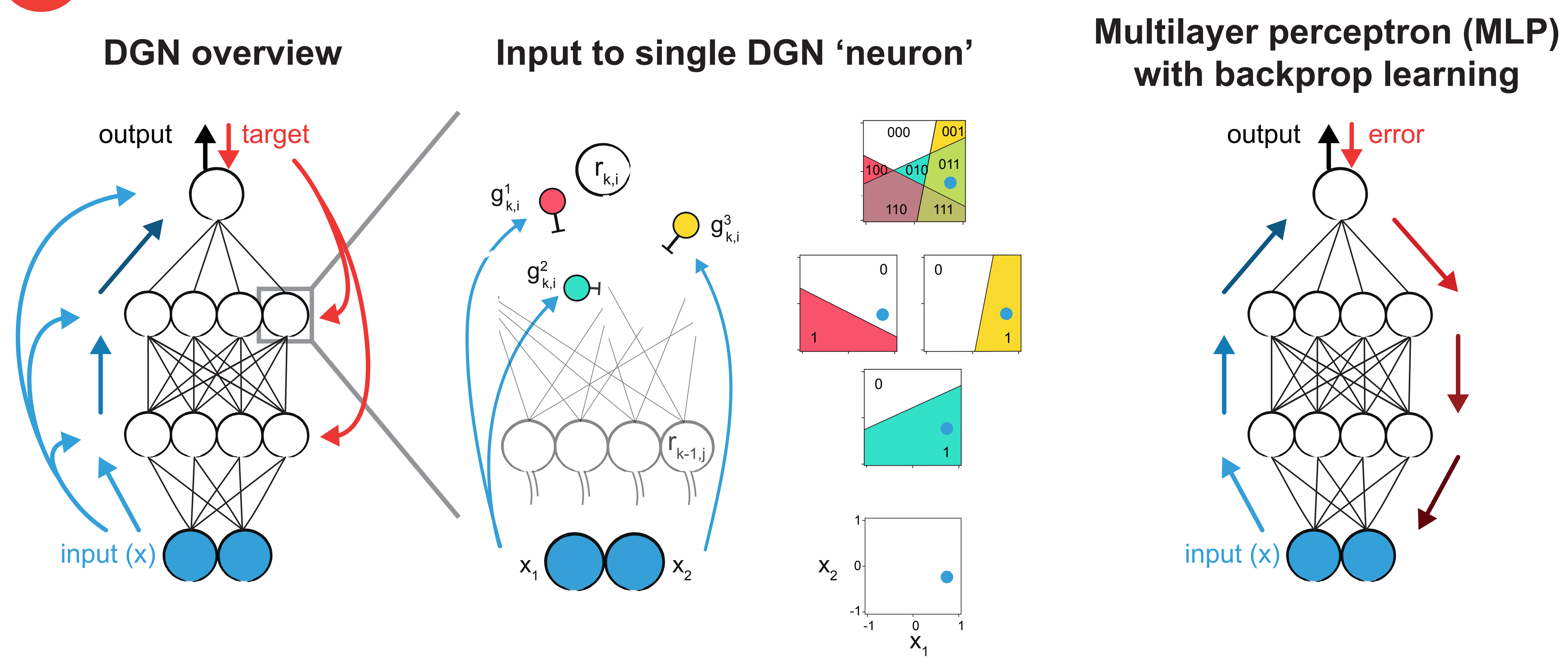
Introduction

The dominant view in neuroscience is that changes in synaptic weights underlie learning. It is not clear, however, how the brain is able to determine which synapses should change and by how much. This uncertainty stands in sharp contrast to deep learning, where changes in weights are explicitly engineered to optimize performance[1]. However, the dominant algorithm used for learning in artificial networks, backpropagation, is not directly applicable to biological systems[2]. The biological implausibility of backpropagation has motivated several proposals for architectures and learning rules that may be more relevant to the brain. These include feedback alignment, creative use of dendrites, multiplexing, and methods in which the feedback signal is fed directly to each layer rather than propagating backwards from the output layer back through the network, including Gated Linear Networks (GLNs)[3].

Here, we introduce a powerful new biologically plausible alternative to backpropagation: the Dendritic Gated Network (DGN), a variant of the Gated Linear Network. DGNs combine dendritic 'gating' - whereby interneurons target dendrites to shape neuronal responses - with local learning rules to yield provably robust performance. In particular, DGNs are more data efficient than other artificial networks, and are highly resistant to forgetting.

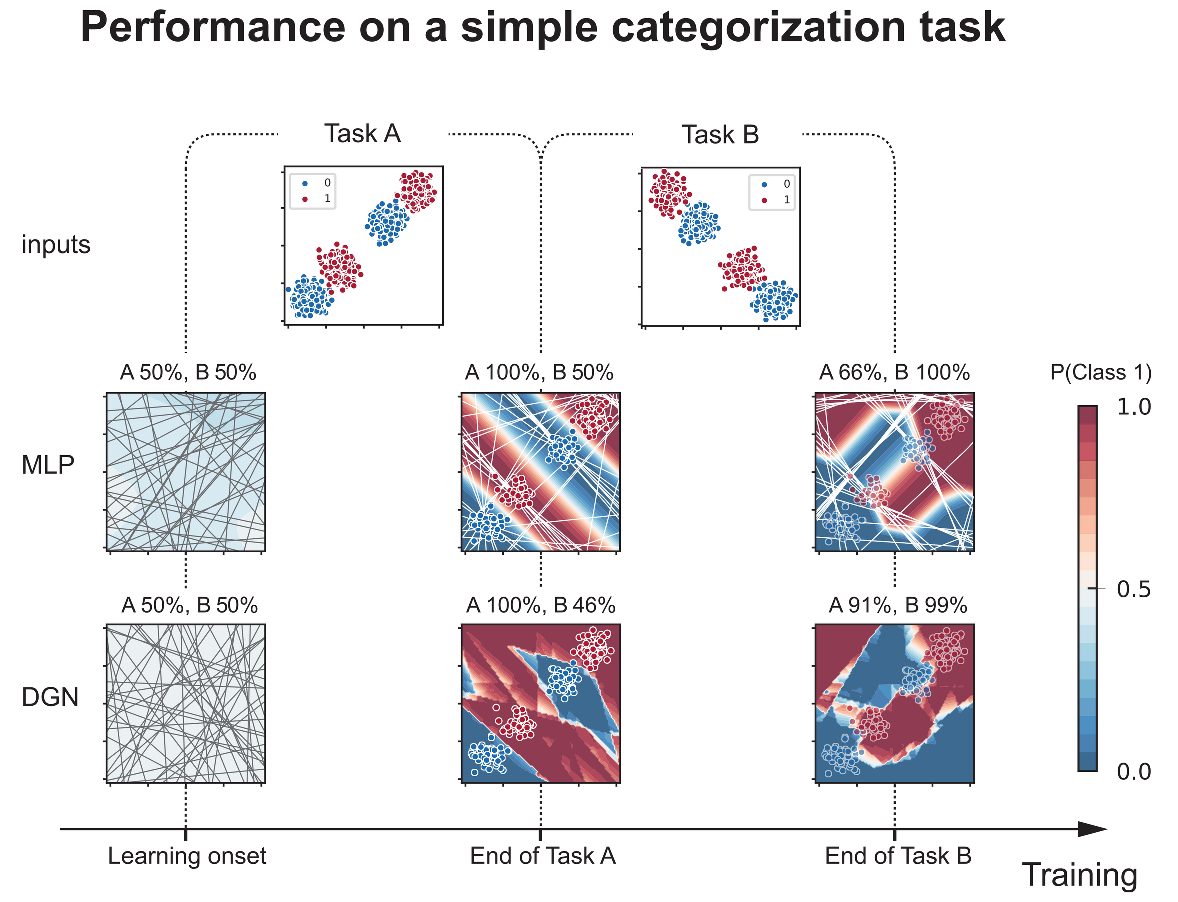
The generality of the DGN architecture should allow this algorithm to be implemented in a range of networks in the brain. In particular, DGNs exhibit several structural and functional similarities to cerebellar circuits. To make this link explicit, we have performed two-photon calcium imaging of Purkinje cell dendrites and molecular layer interneurons in awake mice to test a key prediction of the DGN: that interneurons should gate activity in single dendritic branches of principal cells.

1 Dendritic Gated Network architecture

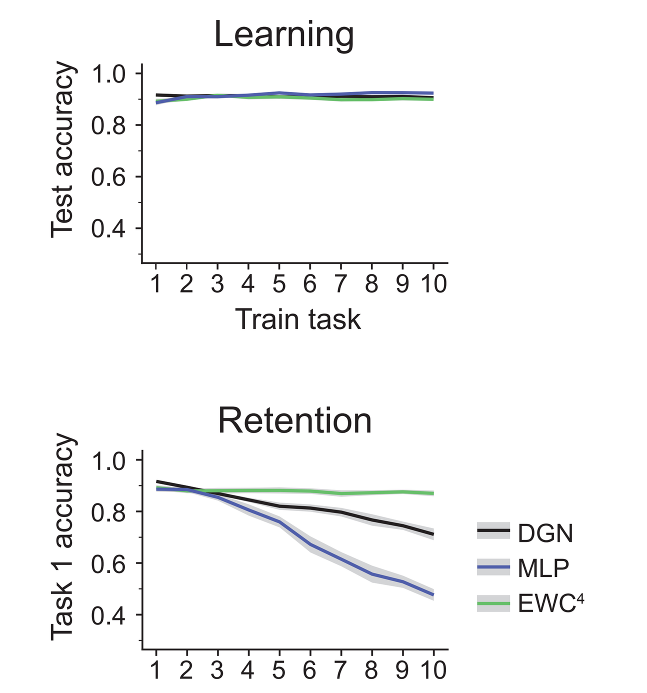


Key features:
1. Goal of each 'neuron' in each layer is to predict ultimate target, so no error propagation is necessary
→ Learning occurs locally (more biologically plausible)
2. Signal propagation and learning is subject to input-dependent gating, so not all weights are used and updated in all tasks
→ Learning new tasks does not cause forgetting of old tasks

2 DGNs are resistant to catastrophic forgetting

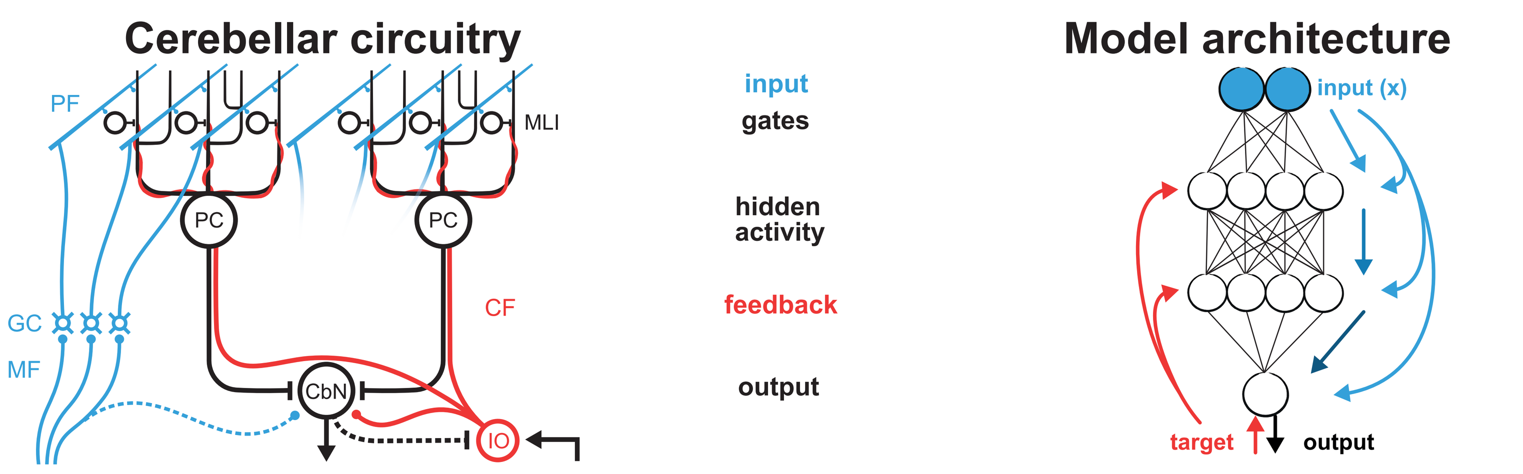


Performance on Task A is maintained, even after learning Task B



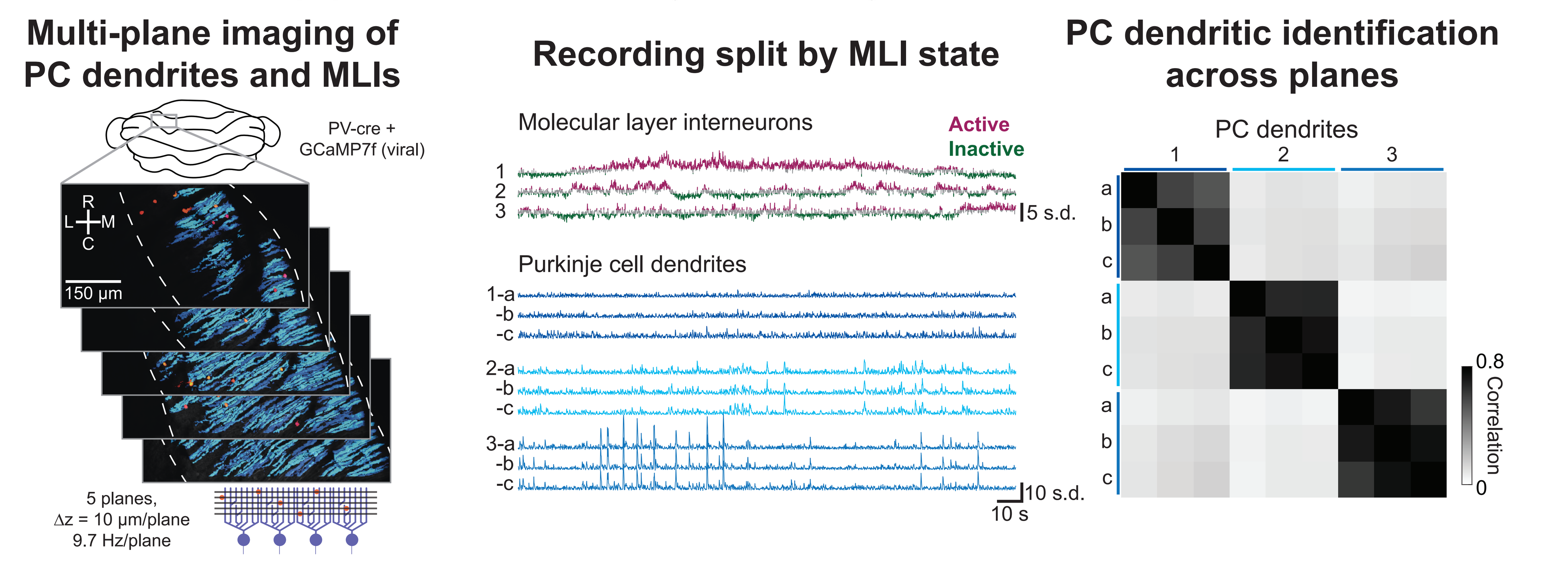
DGNs exhibit similar levels of learning and superior retention to MLPs

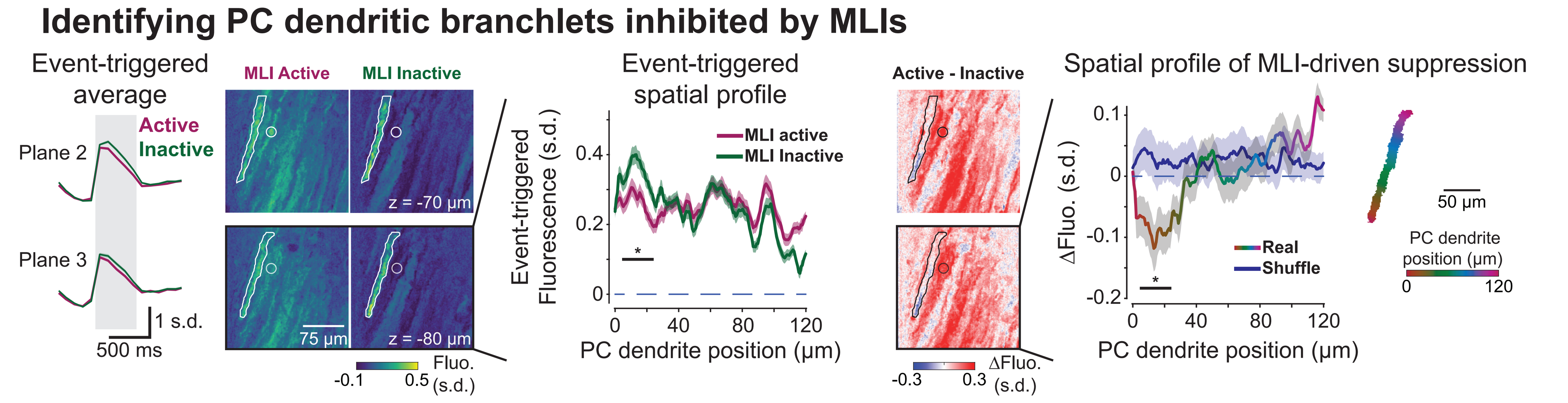
3 Cerebellar circuitry resembles DGNs

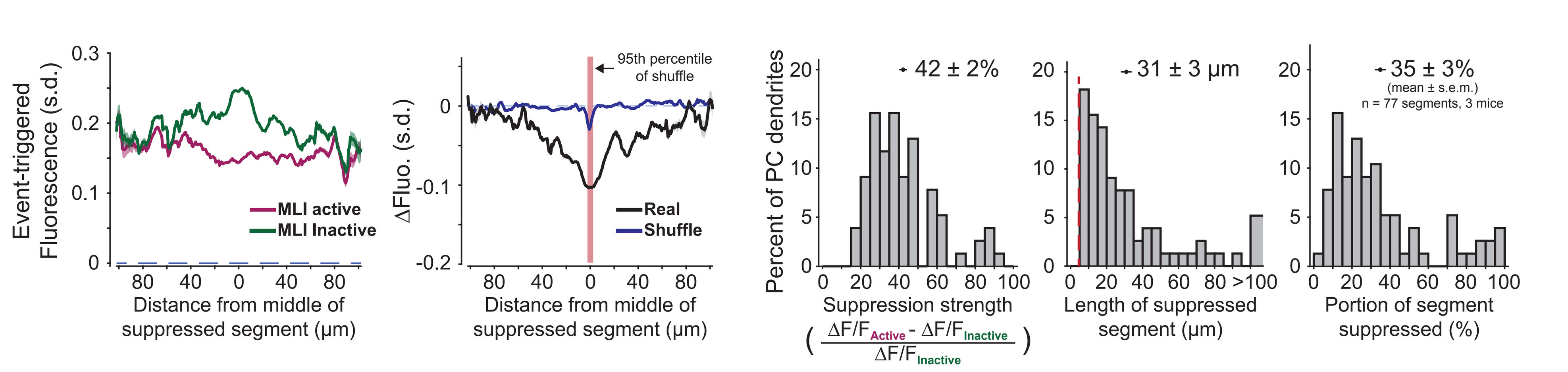


Crucial similarities between DGNs and cerebellar circuits:
1. Climbing fibers provide a well-defined feedback signal[5]
2. The input-output transformation of Purkinje cells (PCs) is linear[6-7]
3. Molecular layer interneurons (MLIs) could act as local gates on learning[8-10]

4 Testing predictions of DGN *in vivo*: MLIs suppress activity locally in PC dendrites







Conclusions

Dendritic gated networks (DGNs) are a novel learning algorithm that represent a biologically plausible alternative to backpropagation

DGNs utilize local learning and input-dependent dendritic gating to yield efficent learning and resistance to catastrophic forgetting

The network architecture of DGNs exhibits features that resemble cerebellar circuitry, generating testable predictions that support their relevance to biological neural circuits

In vivo, molecular layer interneurons gate activity in dendritic branches of cerebellar Purkinje cells, validating a key prediction of DGNs in a canonical biological neural circuit

The generality of the DGN architecture should also allow this agorithm to be implemented in a range of networks throughout the nervous system, including the mammalian neocortex

References:
1. Schmidhuber J (2015) *Neural networks*, 61, 85-117.
2. Lillicrap TP et al. (2020) *Nature Rev. Neurosci.*, 21(6), 335-46.
3. Veness J et al. (2019) *arXiv*:1910.01526.
4. Kirkpatrick J et al. (2017) *PNAS*, 114(13), 3521-6.
5. Raymond JL & Medina JF (2018) *Annual Rev. Neurosci*, 41, 233-53.
6. Llinás R & Sugimori M (1980) *Journal of physiology*, 305(1), 171-95.
7. Walter JT & Khodakhah K (2006) *Journal of Neuroscience*, 26(50), 12861-72.
8. Callaway JC et al. (1995) *Journal of Neuroscience*, 15(4), 2777-87.
9. Gaffield MA et al. (2018) *Elife*, 7, e36246
10. Jörntell et al. (2010) *Trends in neurosciences*, 33(11), 524-532.

This research is supported by
EMBO
wellcome
erc European Research Council
GATSBY