

Introduction:

- > Catastrophic forgetting is an issue common to artificial neural networks in stark contrast with the brain.
- > Neuroscience suggest that real synapses are complex and metaplastic.
- Hidden weights of Binarized Neural Networks are discarded for inference, but what difference does their hidden magnitudes make?

Binary Optimization:

 \succ We consider the quadratic binary task:





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Consolidation strategy:

> The higher the hidden magnitude of the binarized weight, the more difficult to switch to the opposite sign.

 $W^{\rm h} \leftarrow W^{\rm h} - \eta U_W \cdot f_{\rm meta}(m, W)$

 $W^{\rm h} \leftarrow W^{\rm h} - \eta U_W$ otherwise.



Continual learning:

- Our approach performs similarly to Elastic Weight Consolidation on the permuted MNIST continual learning benchmark.
- Can also learn more complex sequences like MNIST -> Fashion MNIST (see paper).
- No need for tasks boundaries.





$$^{\mathrm{h}}$$
) if $U_W W^{\mathrm{h}} > 0$

Stream Learning:

- The network is a learning a given task by **learning** sequentially subsets of the whole dataset.
- The accuracy of the Vanilla network plateaus because of it forgets previous subsets.



Also works on CIFAR-10.

Summary/Conclusion

- continual learning.
- learning.

Paper: https://www.nature.com/articles/s41467-021-22768-y Code: <u>https://github.com/Laborieux-Axel/SynapticMetaplasticityBNN</u> Contact: axel.laborieux@c2n.upsaclay.fr



. Binarized Neural Networks hidden weights are relevant for

2. We show a **principled explanation** for a tractable sub problem. 3. The resulting consolidation strategy **does not need task boundaries** and can be applied to Continual learning and Stream