PyTorch-Hebbian: facilitating local learning in a deep learning framework

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NEURAL INFORMATION PROCESSING SYSTEMS

Unsupervised local learning in neural networks

Recently, unsupervised local learning, based on Hebb's idea that change in synaptic efficacy depends on the activity of the pre- and postsynaptic neuron only [1], has shown potential as an alternative training mechanism to backpropagation. Unfortunately, Hebbian learning remains experimental and rarely makes its way into standard deep learning frameworks. In this work, we:

- Propose a PyTorch framework for thorough and systematic evaluation of local learning rules.
- Investigate the potential of Hebbian learning in the context of standard deep learning workflows.
- Expand the Krotov-Hopfield learning rule to CNNs.
- Illustrate the potential of Hebbian learned feature extractors for image classification.

The Krotov-Hopfield learning rule

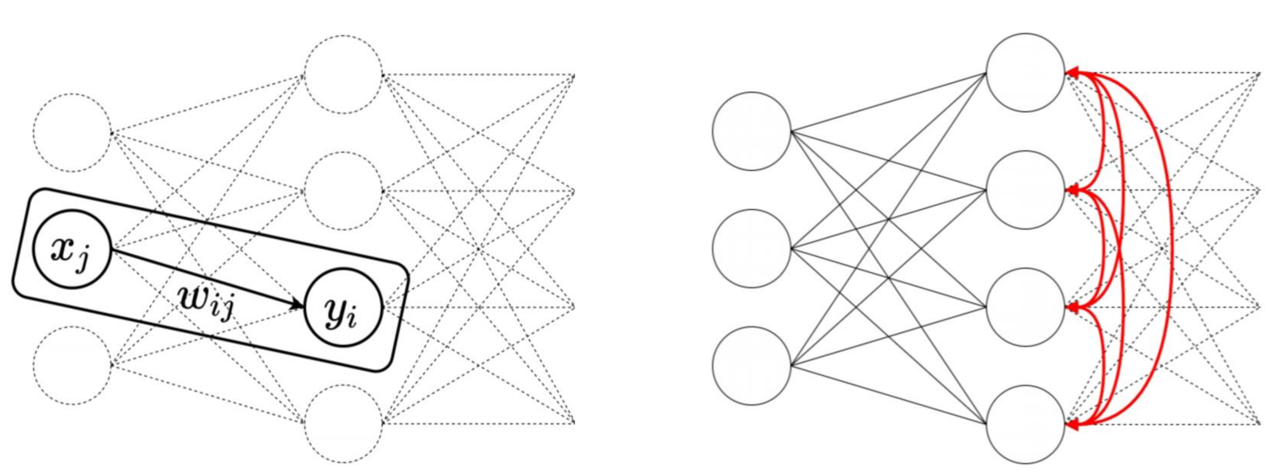
A computationally feasible Hebbian learning rule

Krotov and Hopfield propose a biologically inspired learning rule that combines both normalization and lateral Inhibition [2]. They introduce their learning rule in the context of feedforward neural networks with a single hidden layer, consisting of M hidden neurons or units (m, p and Δ are hyperparameters):

$$\Delta w_{ij} = g(\mathrm{rank}(\langle \boldsymbol{w_i}, \boldsymbol{x}\rangle_i))(x_j - \langle \boldsymbol{w_i}, \boldsymbol{x}\rangle_i w_{ij})$$

$$\langle \boldsymbol{w_i}, \boldsymbol{x}\rangle_i = \sum_j |w_{ij}|^{p-2} w_{ij} x_j$$

$$g(\mu) = \begin{cases} 1 & \mu = M \\ -\Delta & \mu = M - m \\ 0 & \text{otherwise} \end{cases}$$



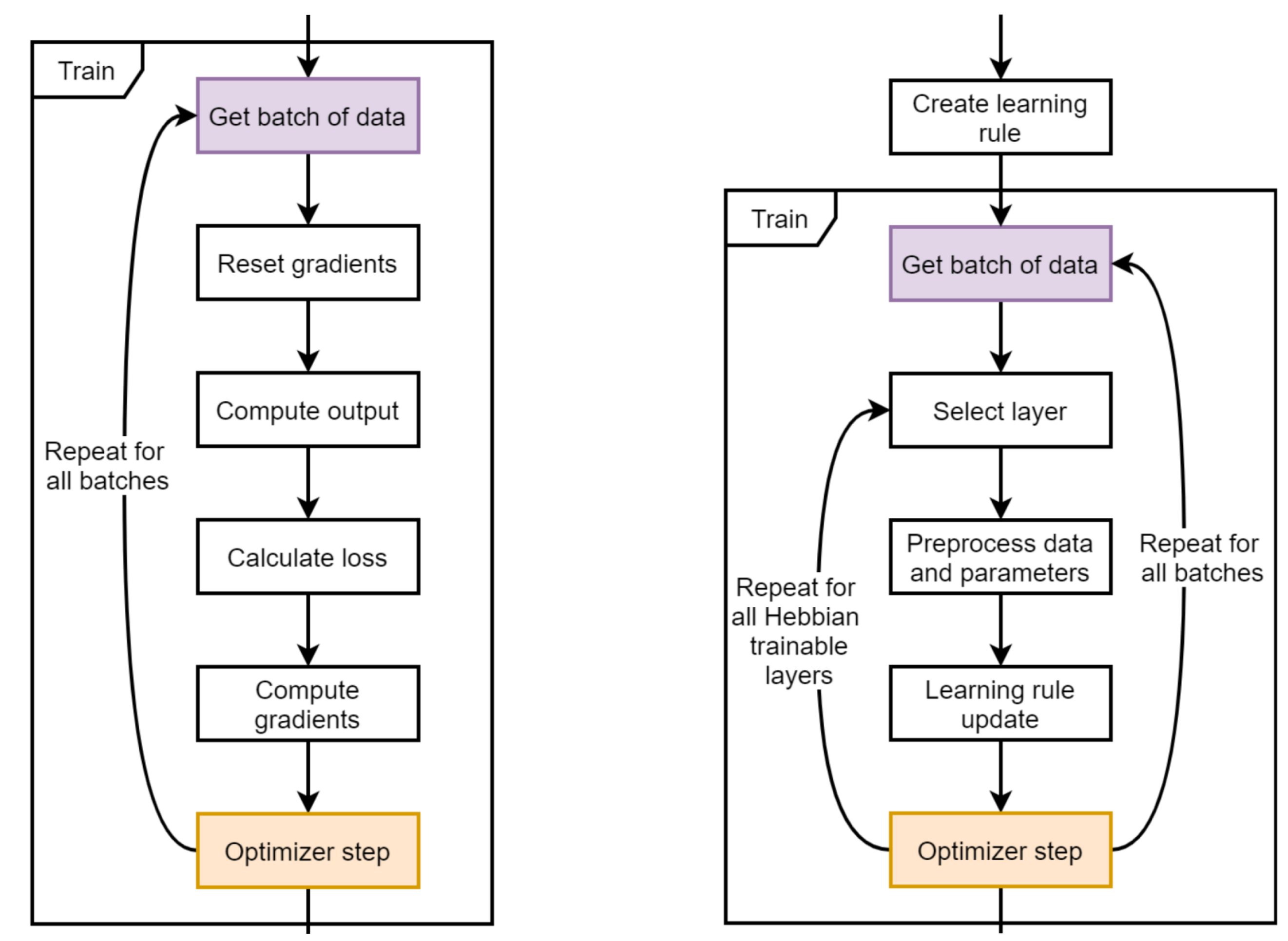
(a) (b)

(a) A connection with weight w_{ij} between pre- and postsynaptic neuron, j and i. (b) Competition between neurons is introduced by adding inhibitory lateral connections (red arrows) between all neurons.

A PyTorch framework for local learning rules

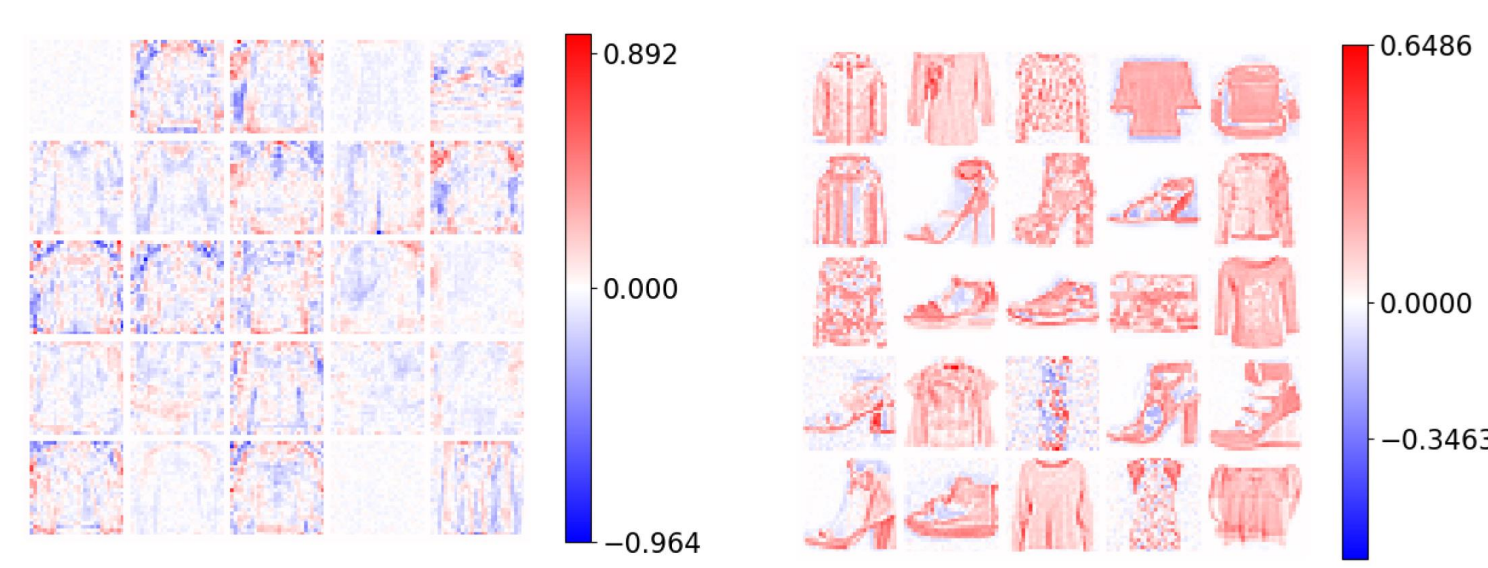
Introducing local learning into standard deep learning workflows

Hebbian learning introduces a new learning paradigm with an accompanying shift in execution flow. The flow for a single epoch, compared to the classical backpropagation execution flow, is illustrated below. For Hebbian learning, there is no single forward pass and the Hebbian trainable layers are trained separately. The Hebbian paradigm thus introduces a second loop.



A comparison of the learning flow of backpropagation (left) and Hebbian learning (right).

The proposed framework fully supports **CUDA** and offers more room for **parallelism** compared to backpropagation. For the Krotov-Hopfield learning rule on the MNIST digits dataset, our proposed framework is **14 times faster** with only 3 seconds per epoch compared to 44 seconds for the original numpy implementation [3].

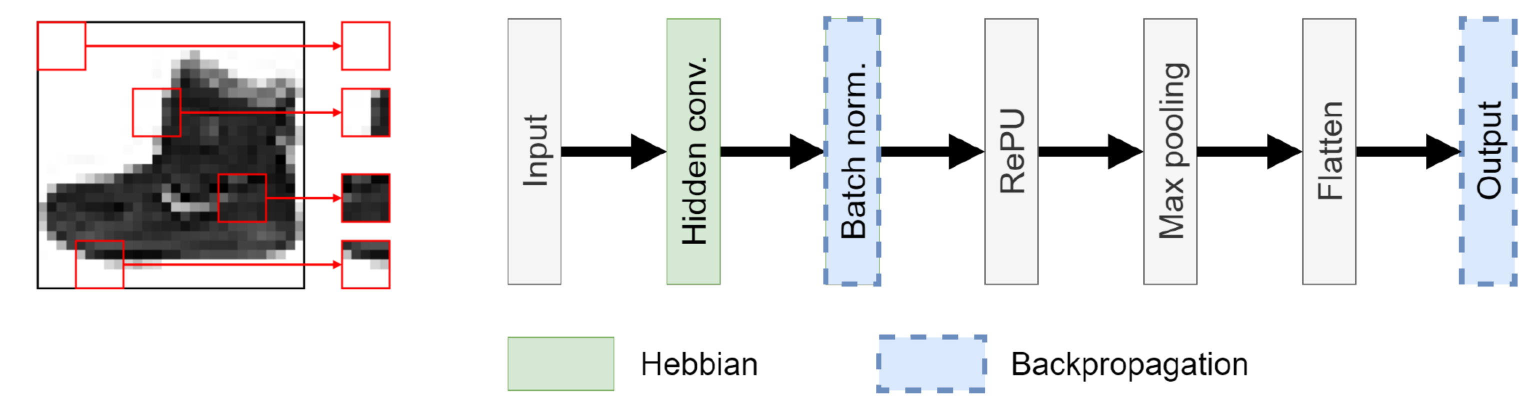


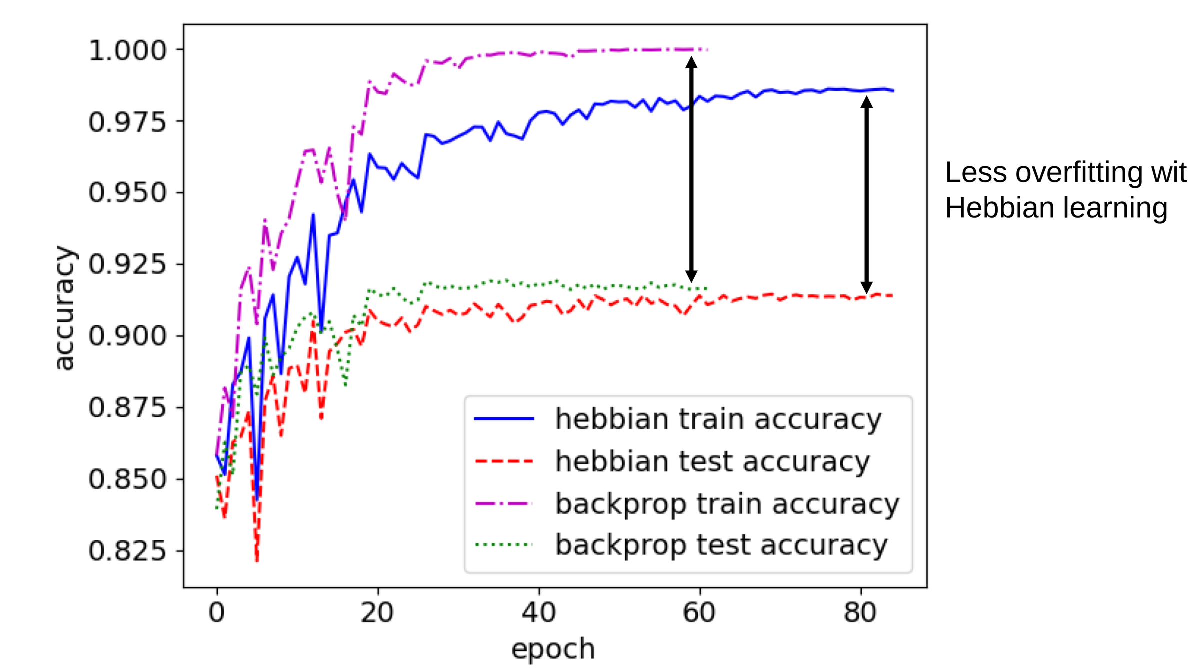
(a) (b)

The incoming weights for 25 (out of 2000) randomly sampled fully connected hidden units trained end-to-end with backpropagation (a) and the Krotov-Hopfield learning rule (b) on the MNIST fashion dataset.

Experimental results and analysis

Using the novel framework, a convolutional layer was trained with the Krotov-Hopfield learning rule on the MNIST fashion dataset. The output layer was then trained with backpropagation. The resulting network achieves 91.44% test accuracy, which is **only 0.5% lower compared to the same network trained end-to-end with backpropagation**.





Train and test accuracy curves for the CNN trained on MNIST fashion with end-to-end backpropagation compared to backpropagation for the final layer only, with a Hebbian learned hidden layer.

	Hebb + backprop	End-to-end backprop
train accuracy (%)	98.64	99.98
test accuracy (%)	91.44	91.94

https://github.com/Joxis/pytorch-hebbian (available for your experiments)

References

[1] D. O. Hebb, *The Organization of Behavior: A Neuropsychological Theory*. Psychology Press,1949.

[2] D. Krotov and J. J. Hopfield, "Unsupervised learning by competing hidden units," *Proceedings of the National Academy of Sciences*, vol. 116, pp. 7723–7731, Apr. 2019.

[3] D.Krotov,"DimaKrotov/Biological_learning." https://github.com/DimaKrotov/Biological_Learning, Apr. 2020.

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GHENT UNIVERSITY

BEYOND BACKPROPAGATION

Novel Ideas for Training Neural Architectures

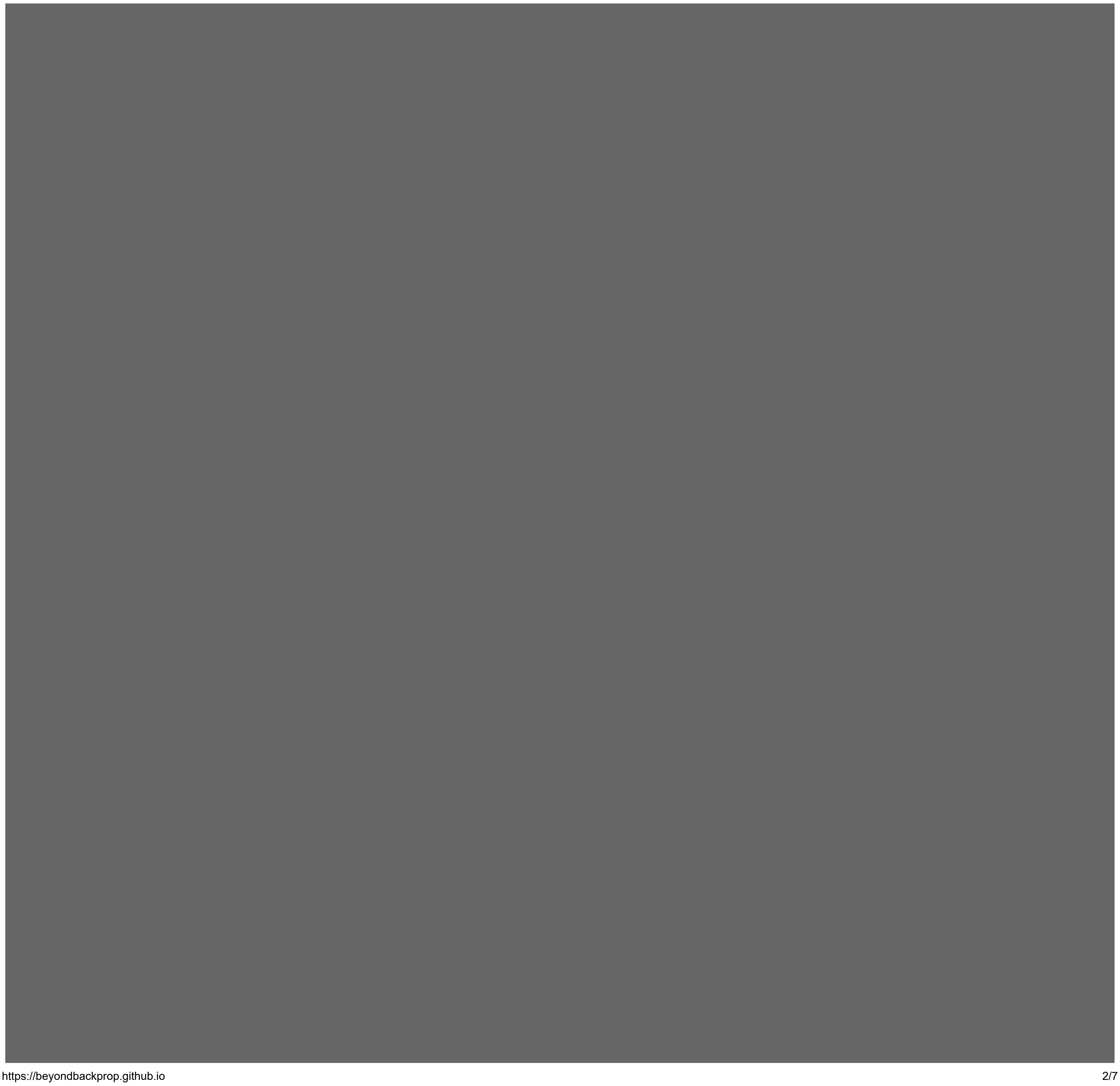
Workshop at NeurIPS, 12th of December 2020

Overview

Is backpropagation the ultimate tool on the path to achieving artificial intelligence as its success and widespread adoption would suggest?

Many have questioned the biological plausibility of backpropagation as a learning mechanism since its discovery. The weight transport and timing problems are the most disputable. The same properties of backpropagation training also have practical consequences. For instance, backpropagation training is a global and coupled procedure that limits the amount of possible parallelism and yields high latency.

These limitations have motivated us to discuss possible alternative directions. In this workshop, we want to promote such discussions by bringing together researchers from various but related disciplines, and to discuss possible solutions from engineering, machine learning and neuroscientific perspectives.



Accepted Papers

We will have two poster sessions in [Gather.Town]. The numbers correspond to the papers' locations during these poster sessions. See map below.

Papers accepted for oral presentations

19. Hardware Beyond Backpropagation: a Photonic Co-Processor for Direct Feedback Alignment - *Julien Launay, Iacopo Poli, Kilian Müller, Igor Carron, Laurent Daudet, Florent Krzakala, Sylvain Gigan* [Video]
36. Policy Manifold Search for Improving Diversity-based Neuroevolution - *Nemanja Rakicevic, Antoine Cully, Petar Kormushev* [Video]
39. Randomized Automatic Differentiation - *Deniz Oktay, Nick B McGreivy, Joshua Aduol, Alex Beatson, Ryan P Adams* [Video]

ZORB: A Derivative-Free Backpropagation Algorithm for Neural Networks - *Varun Ranganathan, Alex Lewandowski* [Video]

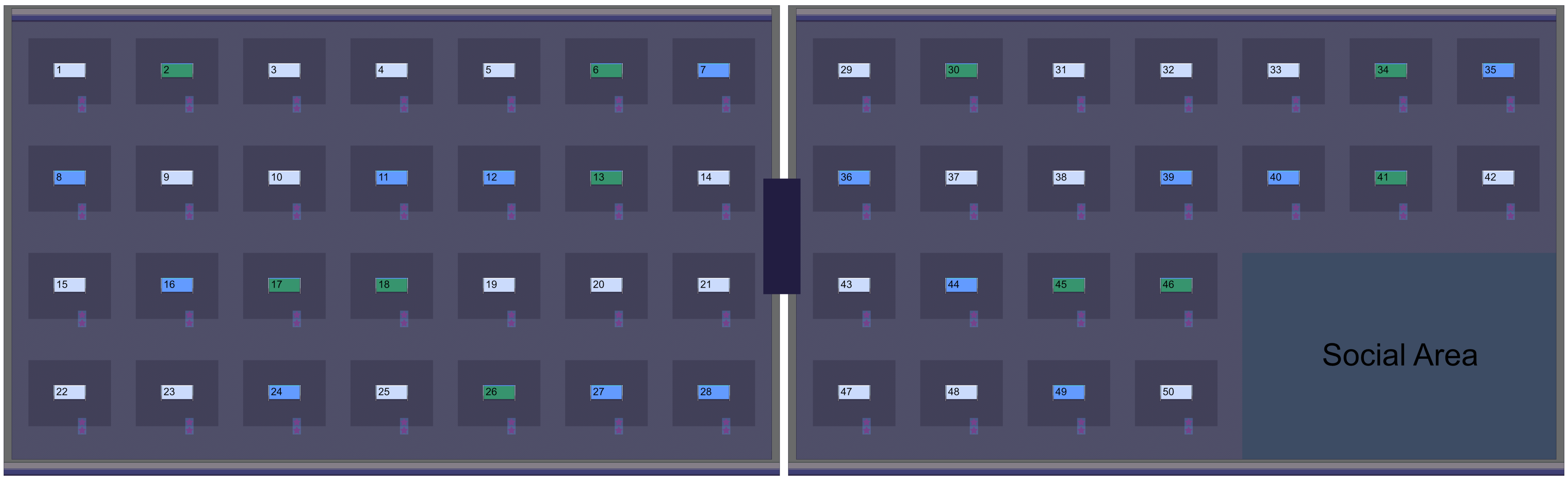
Papers accepted for poster presentations

1. A biologically plausible neural network for local supervision in cortical microcircuits - *Siavash Golkar, David Lipshutz, Yanis Bahroun, Anirvan Sengupta, Dmitri Chklovskii*
2. A More Biologically Plausible Local Learning Rule for ANNs - *Shashi Kant Gupta*
3. A Theoretical Framework for Target Propagation - *Alexander Meulemans, Francesco S Carzaniga, Johan Suykens, João Sacramento, Benjamin F. Grewe*
4. Align, then Select: Analysing the Learning Dynamics of Feedback Alignment - *Maria Refinetti, Stéphane d'Ascoli, Ruben Ohana, Sebastian Goldt*
5. Architecture Agnostic Neural Networks - *Sabera Talukder, Guruprasad Raghavan, Yisong Yue*
6. Backpropagation Free Transformers - *Dinko D Franceschi*
7. Biophysical Neural Networks Provide Robustness and Versatility over Artificial Neural Networks - *James Hazelden, Michael I Ivanitskiy, Daniel Forger*
8. BP2T2: Moving towards Biologically-Plausible BackPropagation Through Time - *Arna Ghosh, Jonathan Cornford, Blake Richards*
9. Convolutional Neural Networks from Image Markers - *Barbara C Benato, Italos Estilon de Souza, Felipe L Galvao, Alexandre X Falcão* [Video]

10. Deep Networks from the Principle of Rate Reduction - *Kwan Ho Ryan Chan, Yaodong Yu, Chong You, Haozhi Qi, John Wright, Yi Ma*
11. Deep Neural Network Training without Multiplications - *Tsuguo Mogami*
12. Deep Neural Networks Are Congestion Games - *Nina Vesseron, Ievgen Redko, Charlotte Laclau*
13. Deep Reservoir Networks with Learned Hidden Reservoir Weights using Direct Feedback Alignment - *Matthew S Evanusa, Aloimonos Yiannis, Cornelia Fermuller* [Video]
14. Direct Feedback Alignment Scales to Modern Deep Learning Tasks and Architectures - *Julien Launay, François Boniface, Iacopo Poli, Florent Krzakala*
15. Feature Whitening via Gradient Transformation for Improved Convergence - *Shmulik Markovich-Golan, Barak Battash, Amit Bleiweiss*
16. Front Contribution instead of Back Propagation - *Swaroop Ranjan Mishra, Anjana Arunkumar* [Video]
17. Gated Linear Networks and Extensions - *Eren Sezener, David Budden, Marcus Hutter, Christopher Mattern, Jianan Wang, Joel Veness*
18. Generalized Stochastic Backpropagation - *Amine Echraibi, Joachim Flocon-Cholet, Stéphane W Gosselin, Sandrine Vaton*
20. HebbNet: A Simplified Hebbian Learning Framework to do Biologically Plausible Learning - *Manas Gupta, ArulMurugan Ambikapathi, Ramasamy Savitha* [Video]
21. Hindsight Network Credit Assignment - *Kenny Young* [Video]
22. How and When does Feedback Alignment Work? - *Stéphane d'Ascoli, Maria Refinetti, Ruben Ohana, Sebastian Goldt*
23. Ignorance is Bliss: Adversarial Robustness by Design through Analog Computing and Synaptic Asymmetry - *Alessandro Cappelli, Ruben Ohana, Julien Launay, Iacopo Poli, Florent Krzakala*
24. Improving Multimodal Accuracy Through Modality Pre-training and Attention - *Aya Abdelsalam A Ismail, Faisal Ishtiaq, Mahmudul Hasan*
25. Investigating Coagent Networks for Supervised Learning - *Dhawal Gupta, Matthew Schlegel, James Kostas, Gabor Mihucz, Martha White*
26. Investigating the Scalability and Biological Plausibility of the Activation Relaxation Algorithm - *Beren Millidge, Alexander D Tschanz, Anil Seth, Christopher Buckley*
27. Layer-wise Learning of Kernel Dependence Networks - *Chieh Tzu Wu, Aria Masoomi, Arthur Gretton, Jennifer Dy* [Video]
28. Layer-wise Learning via Kernel Embedding - *Aria Masoomi, Chieh Tzu Wu, Arthur Gretton, Jennifer Dy* [Video]
29. Learning Flows By Parts - *Manush Bhatt, David I Inouye* [Video]
30. MEAL V2: Boosting Vanilla ResNet-50 to 80%+ Top-1 Accuracy on ImageNet without Tricks - *Zhiqiang Shen, Marios Savvides*
31. Menger: Large-Scale Distributed Reinforcement Learning - *Amir Yazdanbakhsh, Junchao Chen, Yu Zheng*
32. Meta-Learning Backpropagation And Improving It - *Louis Kirsch, Jürgen Schmidhuber* [Video]
33. MPLP: Learning a Message Passing Learning Protocol - *Ettore Randazzo, Eyvind Niklasson, Alexander Mordvintsev* [Video]
34. Neighbourhood Distillation: On the benefits of non end-to-end distillation - *Laëtitia M Shao, Max Moroz, Elad Eban, Yair Movshovitz-Attias*
35. Optimizing Neural Networks via Koopman Operator Theory - *William T Redman, Akshunna S. Dogra*
37. Predicting Pretrained Weights of Large-scale CNNs - *Boris Knyazev, Michal Drozdzal, Graham Taylor, Adriana Romero* [Video]
38. PyTorch-Hebbian: facilitating local learning in a deep learning framework - *Jules Talloen*
40. Scaling Equilibrium Propagation to Deep ConvNets by Drastically Reducing its Gradient Estimator Bias - *Axel Laborieux, Maxence M ERNOULT, Benjamin Scellier, Yoshua Bengio, Julie Grollier, Damien Querlioz* [Video]
41. Scaling up learning with GAIT-prop - *Sander Dalm*
42. Self Normalizing Flows - *Thomas A Keller, Jorn W.T. Peters, Priyank Jaini, Emiel Hoogeboom, Patrick Forré, Max Welling* [Video]
43. Short-Term Memory Optimization in Recurrent Neural Networks by Autoencoder-based Initialization - *Antonio Carta, Alessandro Sperduti, Davide Bacciu* [Video]
44. Slot Machines: Discovering Winning Combinations of Random Weights in Neural Networks - *Maxwell M Aladago, Lorenzo Torresani*
45. Supervised Learning with Brain Assemblies - *Akshay Rangamani, Anshula Gandhi* [Video]
46. Symbiotic Learning of Dual Discrimination andReconstruction Networks - *Tahereh Toosi, Elias B Issa*

47. The Interplay of Search and Gradient Descent in Semi-stationary Learning Problems - *Shibhansh Dohare, Rupam Mahmood, Richard S Sutton* [Video]
48. Towards self-certified learning: Probabilistic neural networks trained by PAC-Bayes with Backprop - *Maria Perez-Ortiz, Omar Rivasplata, John Shawe-Taylor, Csaba Szepesvari*
49. Towards truly local gradients with CLAPP: Contrastive, Local And Predictive Plasticity - *Bernd Illing, Guillaume Bellec, Wulfram Gerstner* [Video]
50. Unintended Effects on Adaptive Learning Rate for Training Neural Network with Output Scale Change - *Ryuichi Kanoh, Mahito Sugiyama* [Video]

Accepted papers will be presented during the poster sessions in [Gather.Town]. This is the map:



[This document] provides guidelines on the Gather.Town virtual platform used for the Beyond Backpropagation Workshop.

Reviewers

We would like to thank all of our reviewers for their great work:

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