Layer-skipping connections facilitate training of layered networks using equilibrium propagation.

Jimmy Gammell Sae Woo Nam Adam N. McCaughan

July 28, 2020

- Equilibrium propagation:[1] biologically-motivated learning framework

[1] Benjamin Scellier and Yoshua Bengio. *Equilibrium Propagation: Bridging the Gap Between Energy-Based Models and Backpropagation*. 2016. arXiv: 1602.05179 [cs.LG].

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- We will show that adding layer-skipping connections can help solve the problem
  - Still biologically-plausible
  - Simple to implement in hardware with configurable connectivity

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- For same reasons, appealing for implementation on neuromorphic analog hardware

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  - Seems unlikely to happen in biological systems

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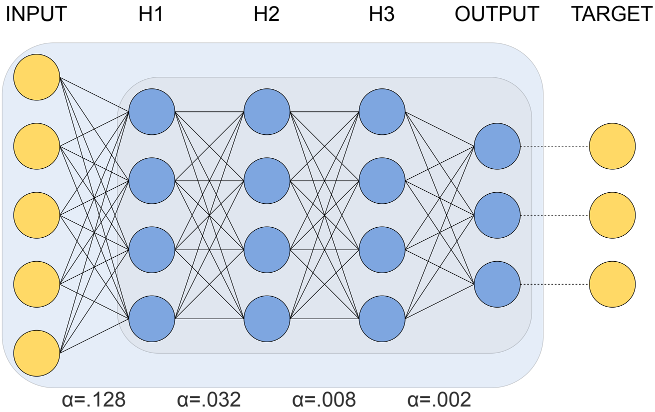
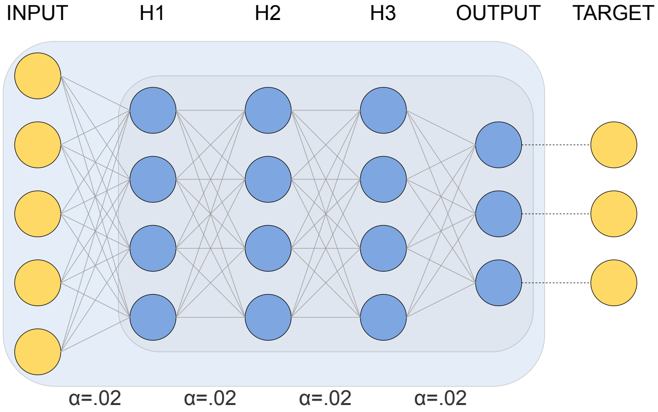
- Our solution: modify layered topology by adding random layer-skipping connections
  - Inspired by small-world topology, but little correlation with common small-worldness metrics (e.g. characteristic path length, clustering coefficient, small-world coefficient)
  - Could be conveniently implemented in neuromorphic systems with configurable connectivity

Conventional layered topology



- Topology used in original paper
- Independently-tuned learning rates for each layer

Our topological modifications



- Use original topology as starting point
- Single global learning rate across all layers

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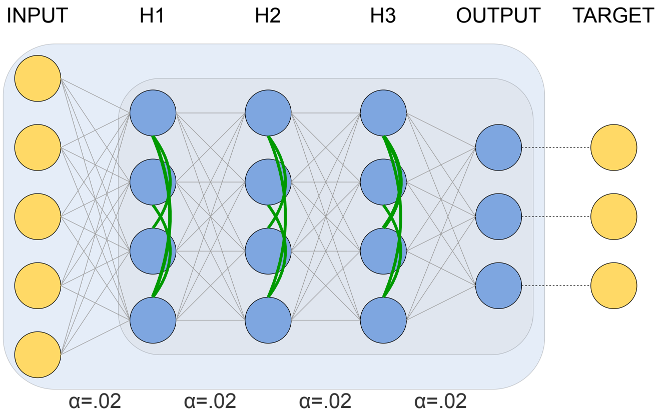

- Make hidden layers fully-connected

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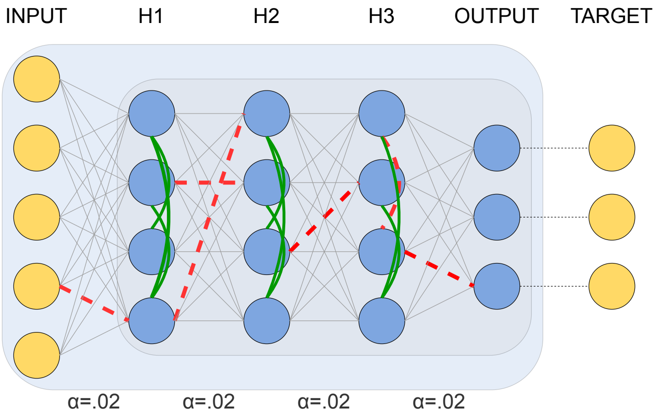

- Consider each connection and remove with probability p

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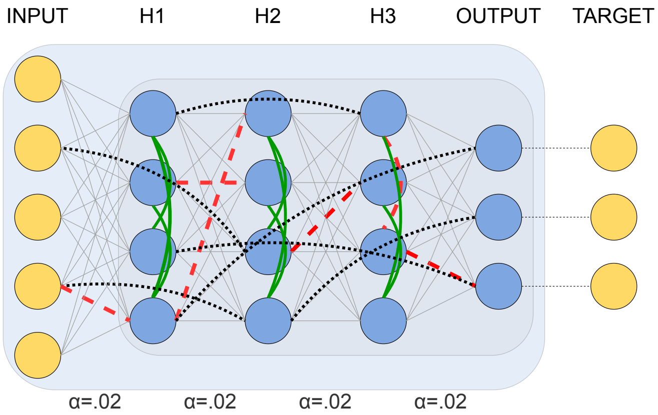
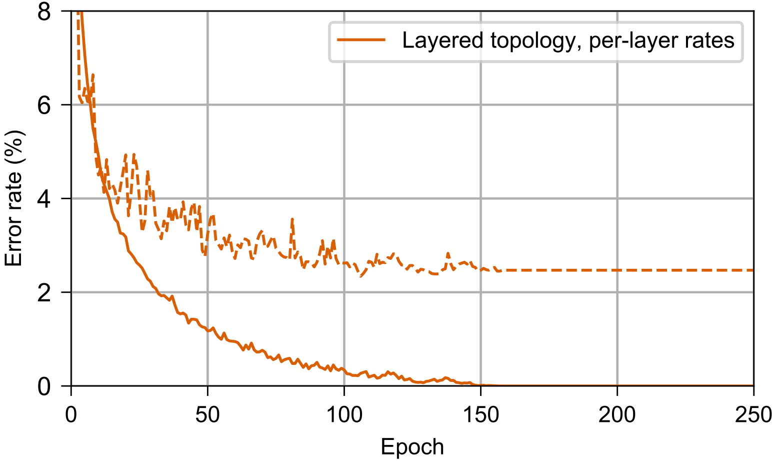


- For each removed connection, randomly connect two separated neurons
  - Only 1 connection per pair
  - No connections within input or output layers

Results: performance of network with layer-skipping connections



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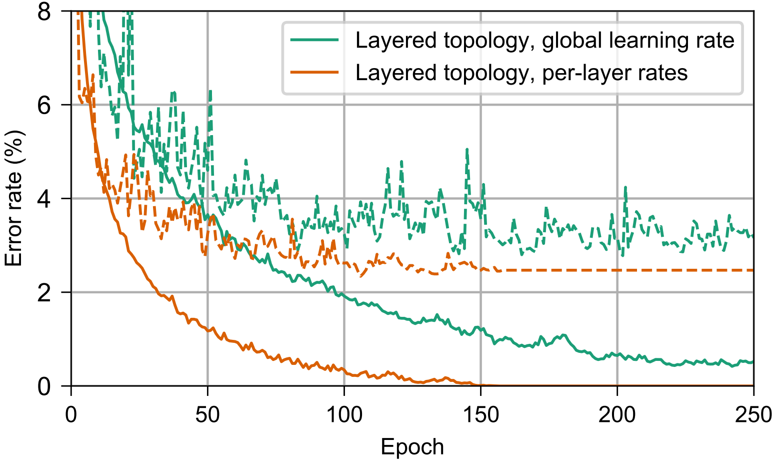

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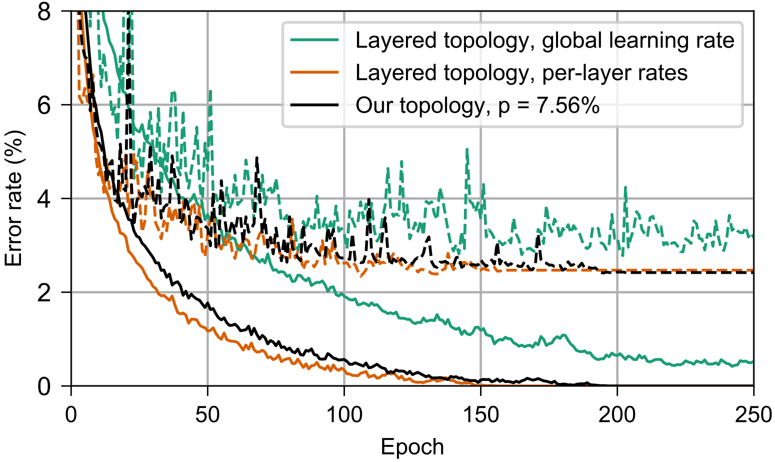

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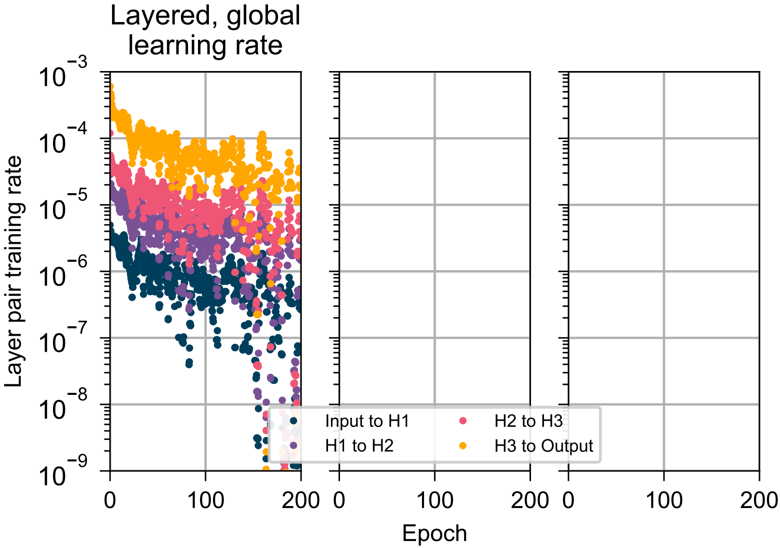

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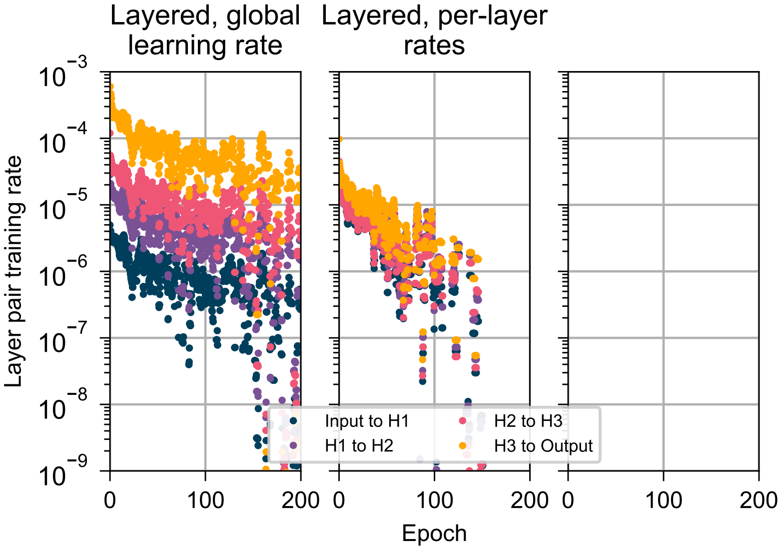

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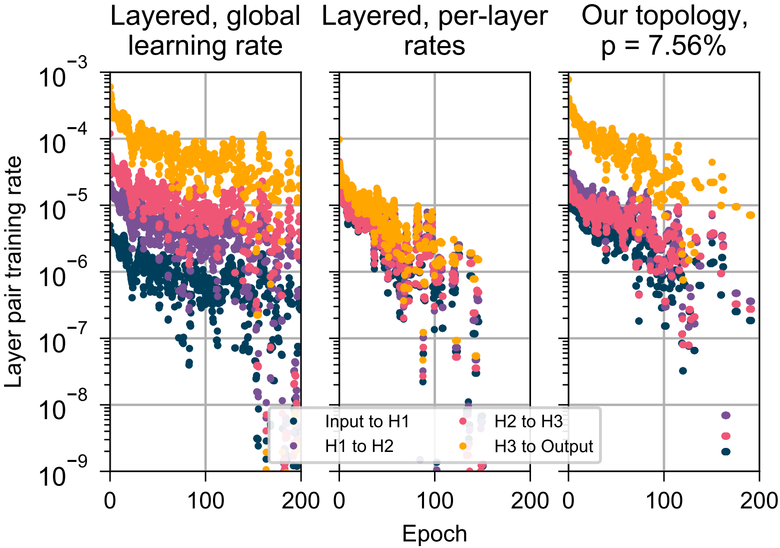

Results: takeaways

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- Evaluate effect of p on network test error
- Evaluate effectiveness on deeper networks
- Try training a network with added layer-skipping connections, then removing them afterwards