Two Routes to Scalable Credit Assignment without Weight Symmetry

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ICML 2020

Stanford
Neuro AI Lab
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Agenda

- Motivation
  - The problems with backpropagation
  - Breaking weight symmetry: some previous proposals
- Regularization-inspired framework
  - Evaluation criteria
- Results
  - Local Learning Rules
  - Non-local Learning Rules
- Conclusion

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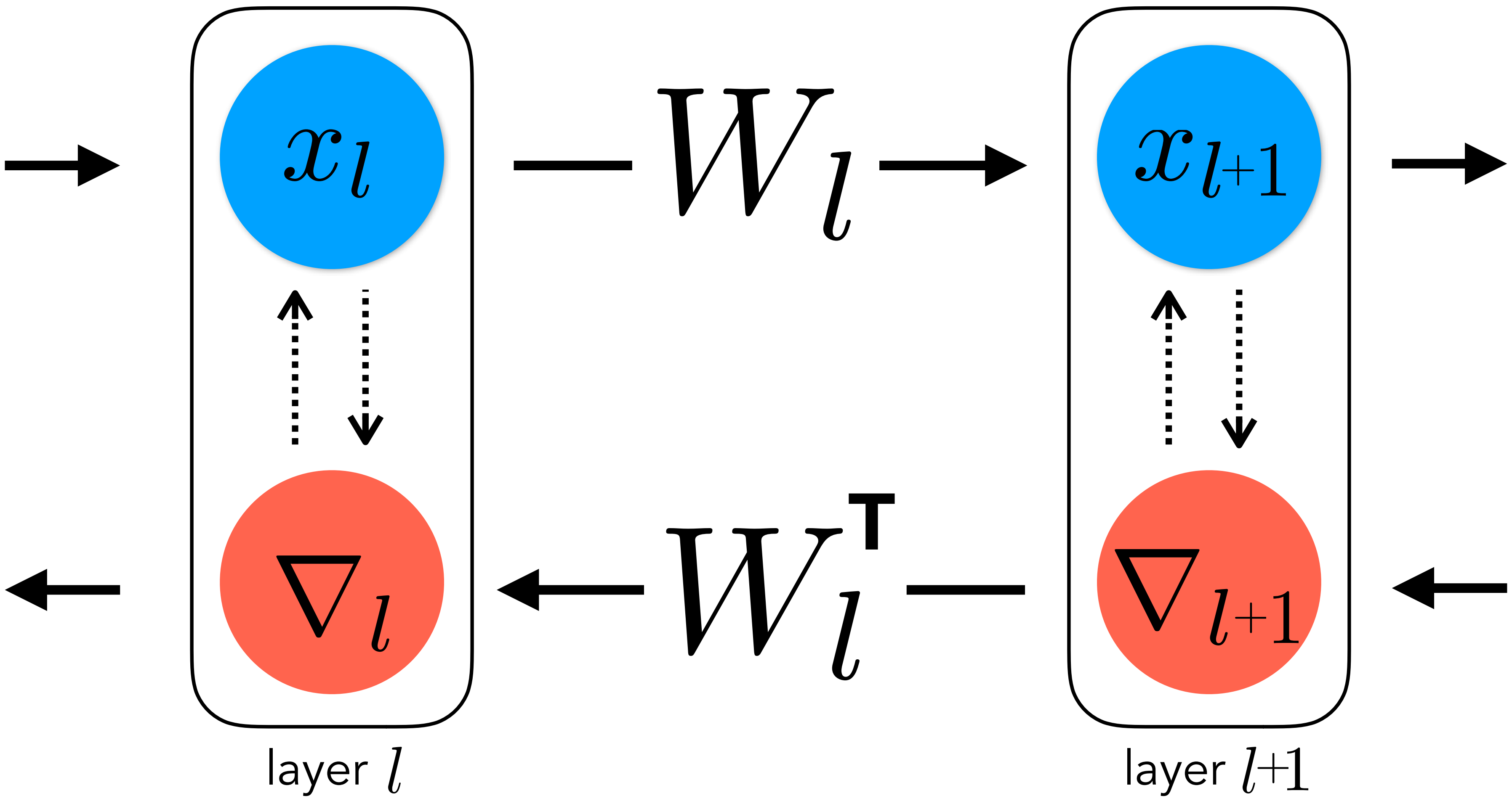

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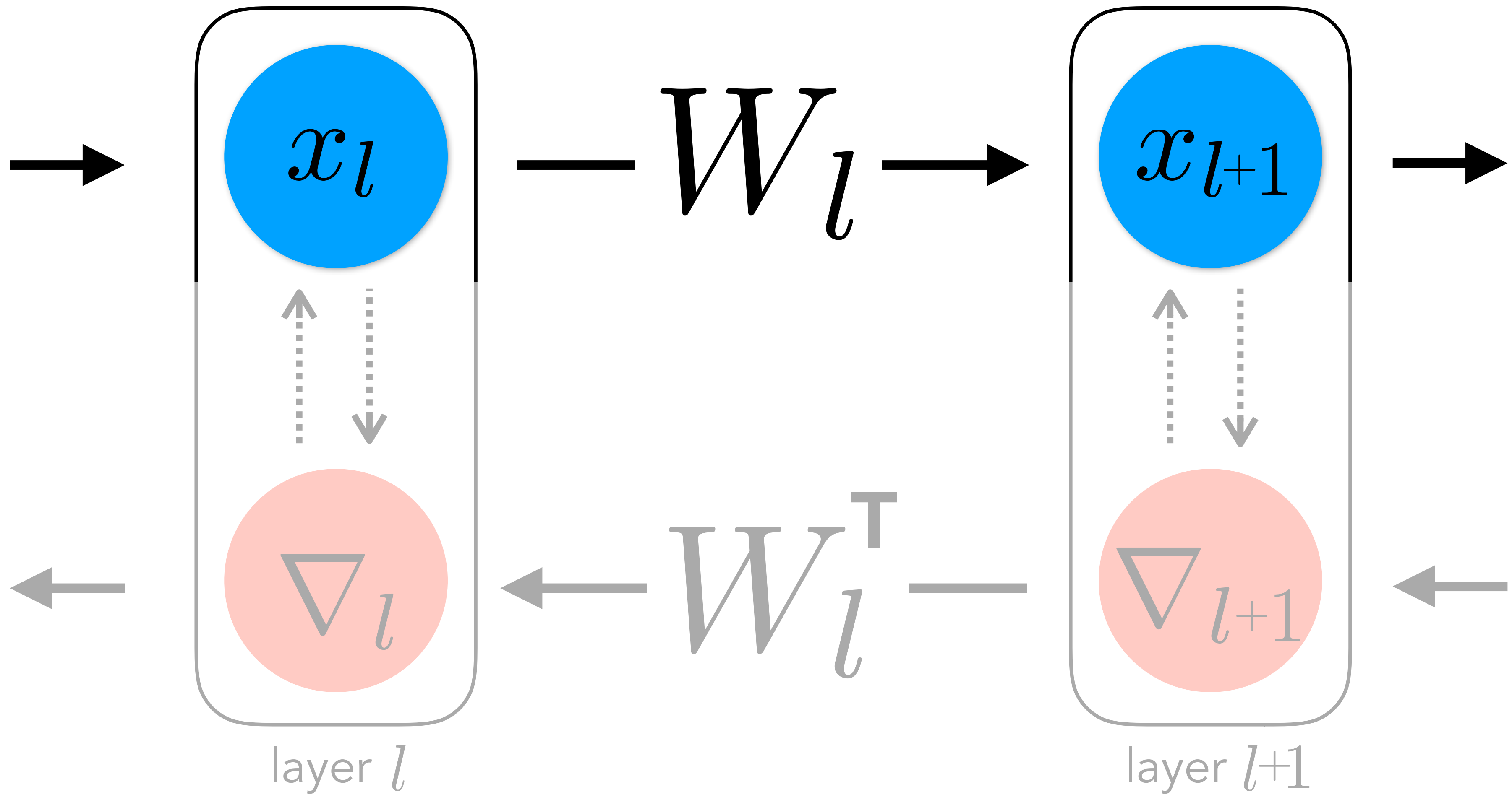

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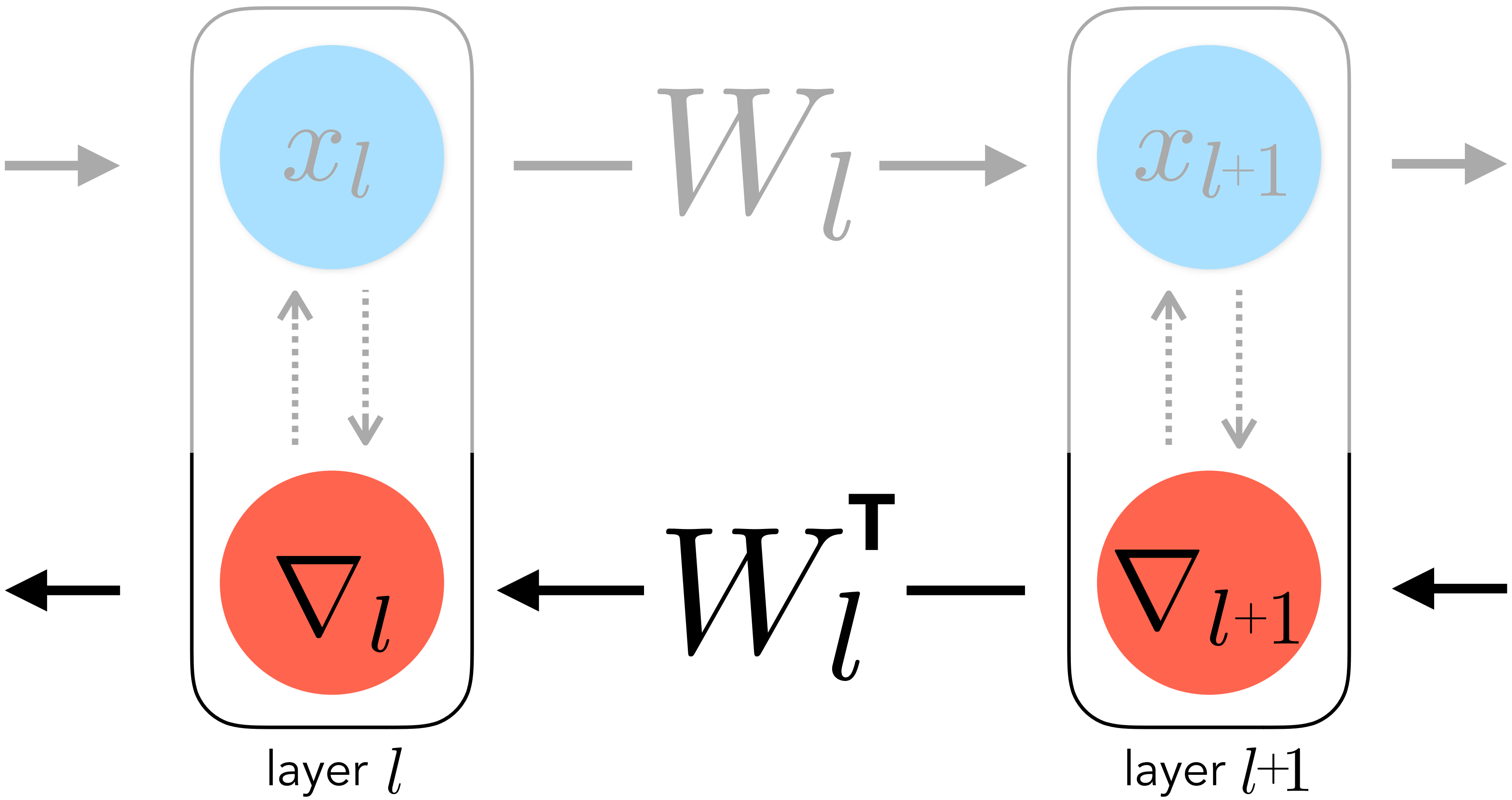

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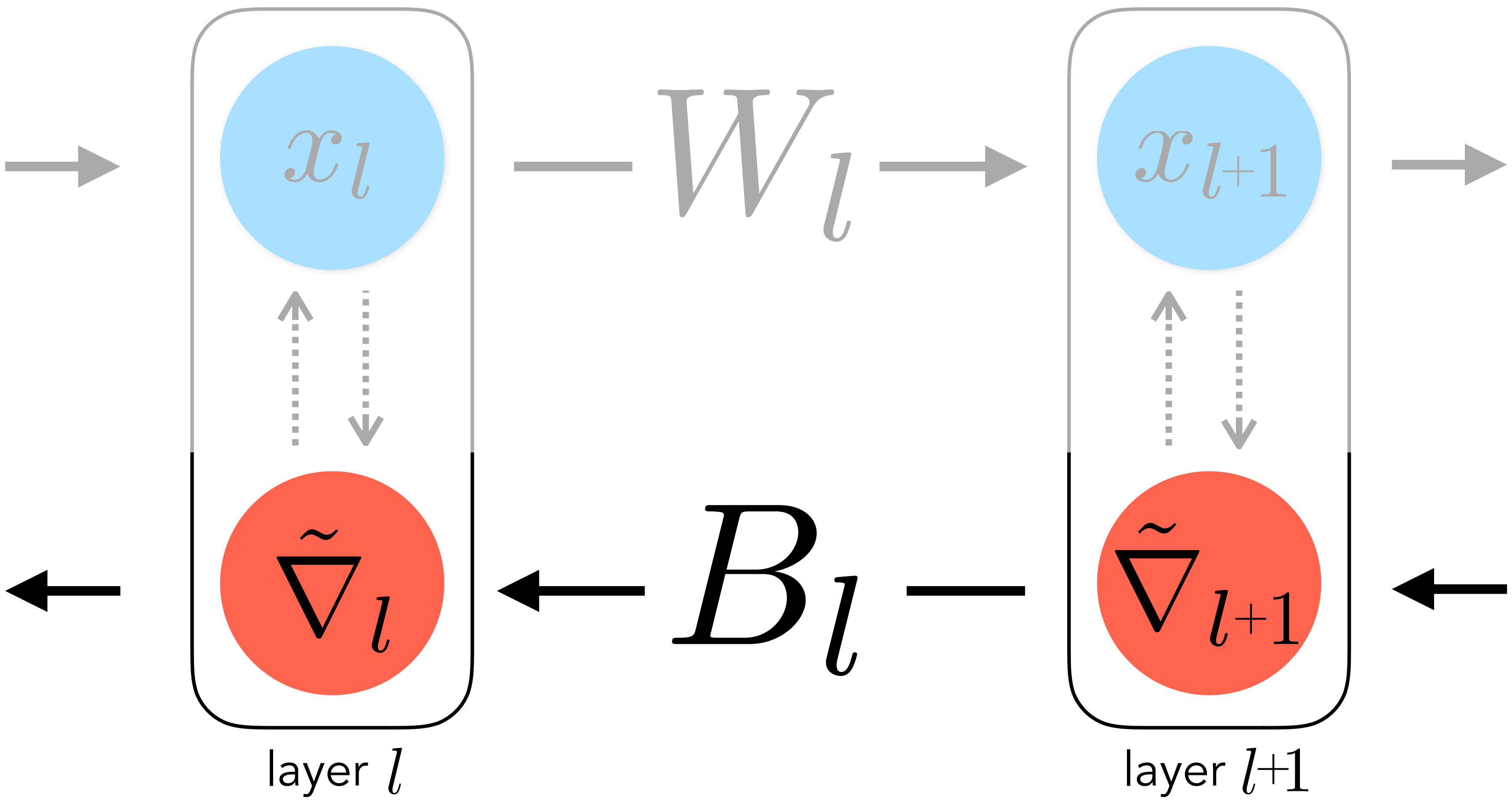

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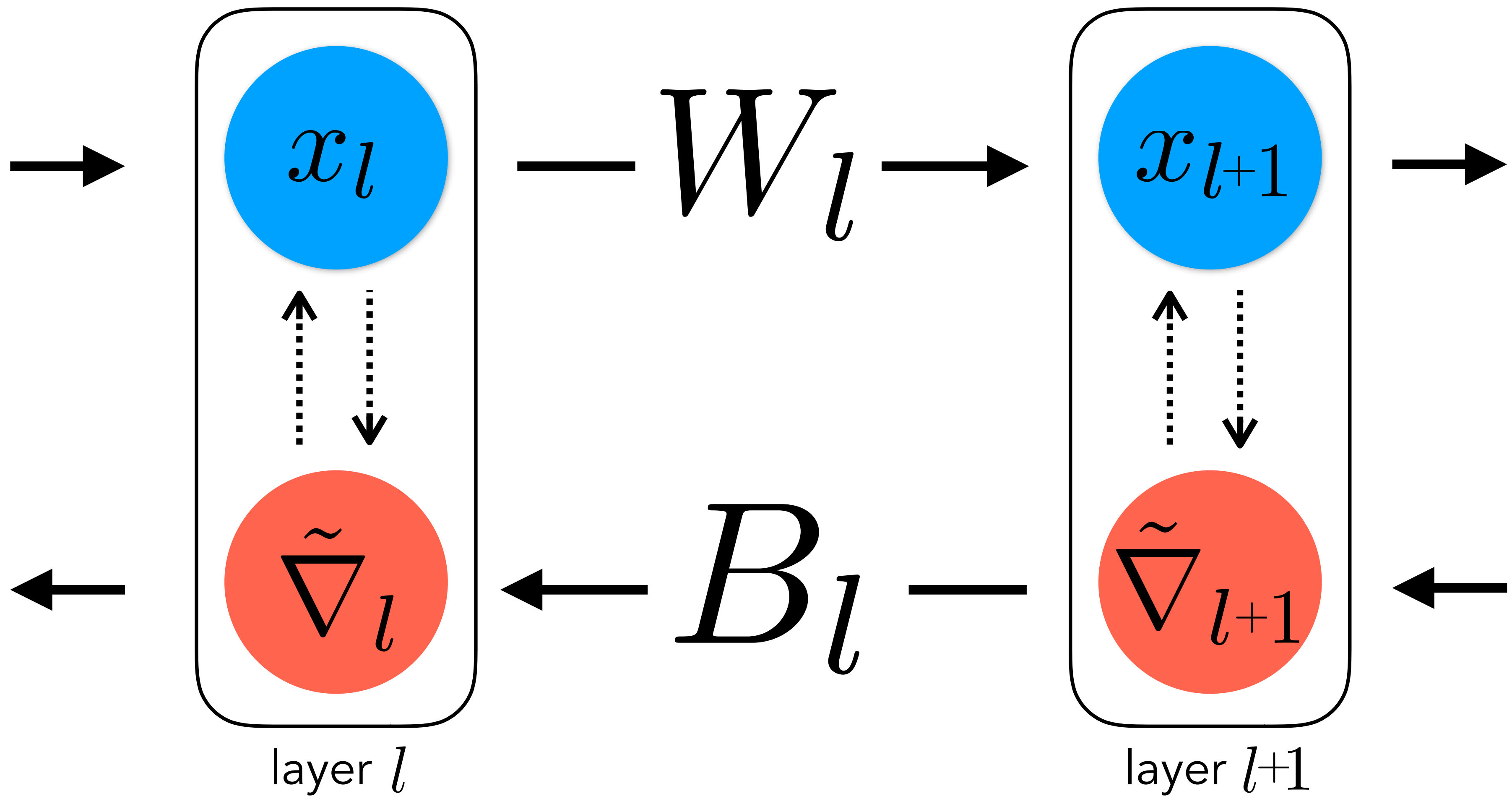

- What should the dynamics on the backward weights be?

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- **Idea:** think of backwards weights updates as derivatives of a loss function
  - Integrates well with the current Deep Learning stack

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Regularization Inspired Learning Rule Framework

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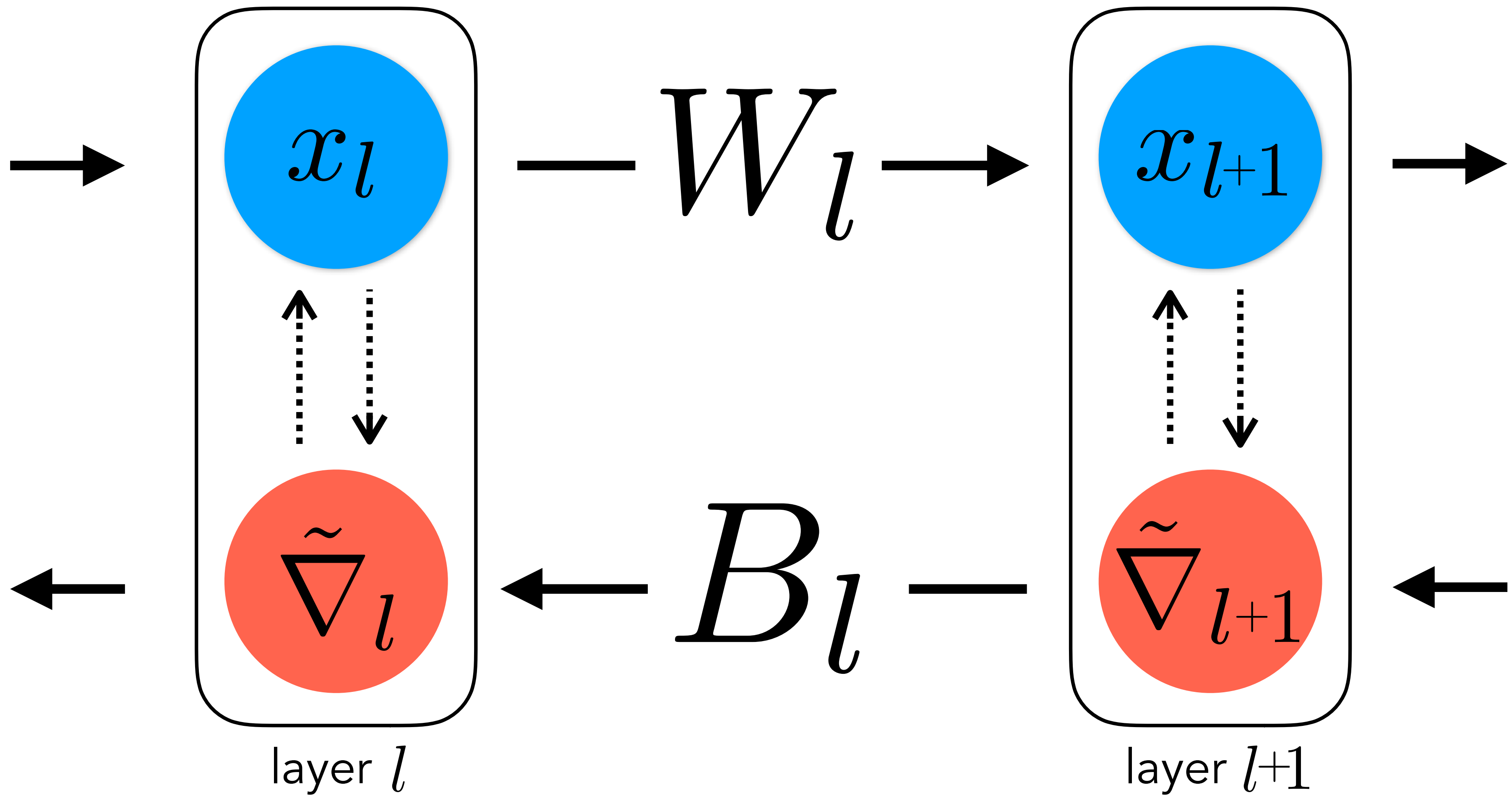

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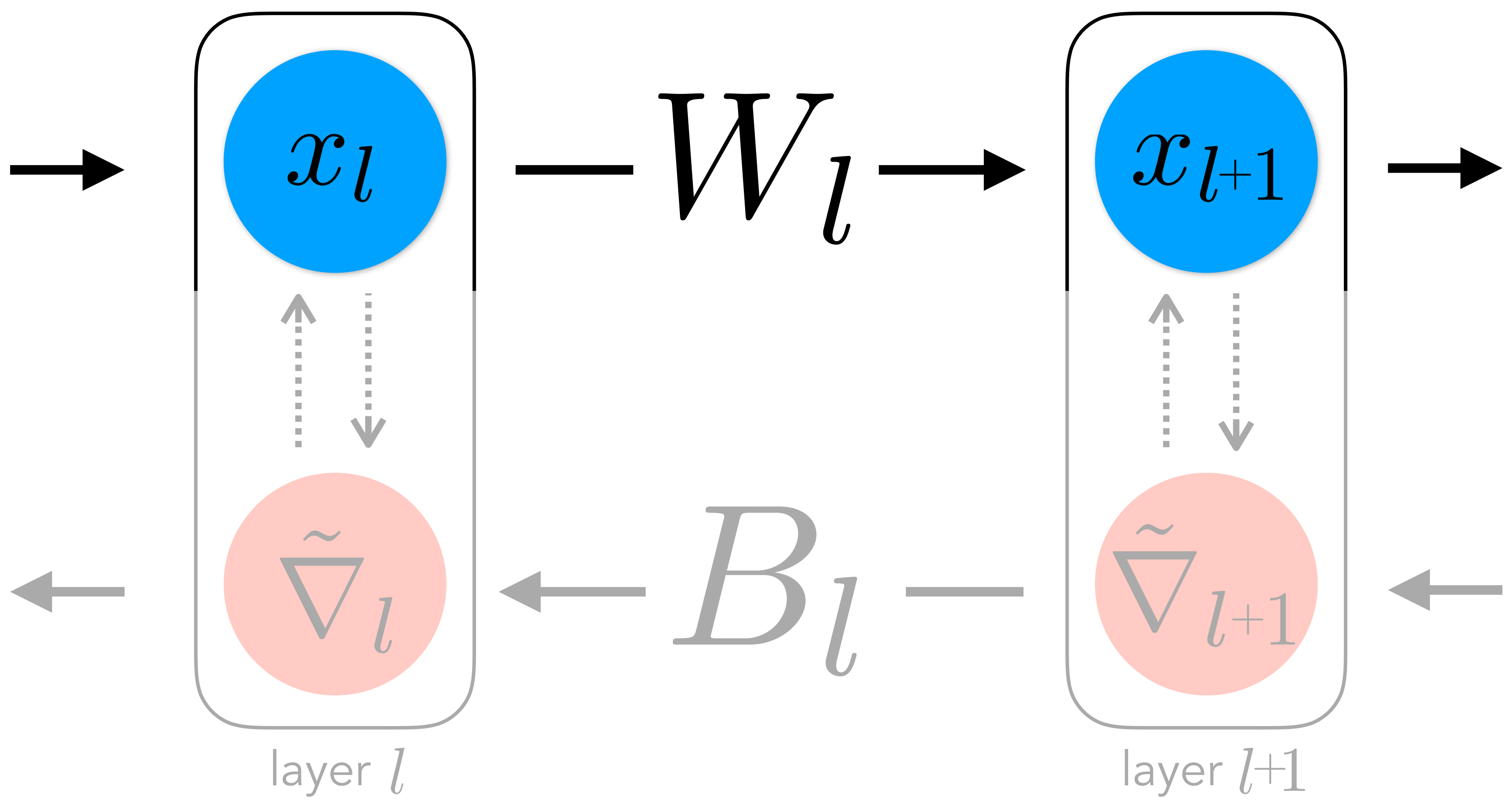

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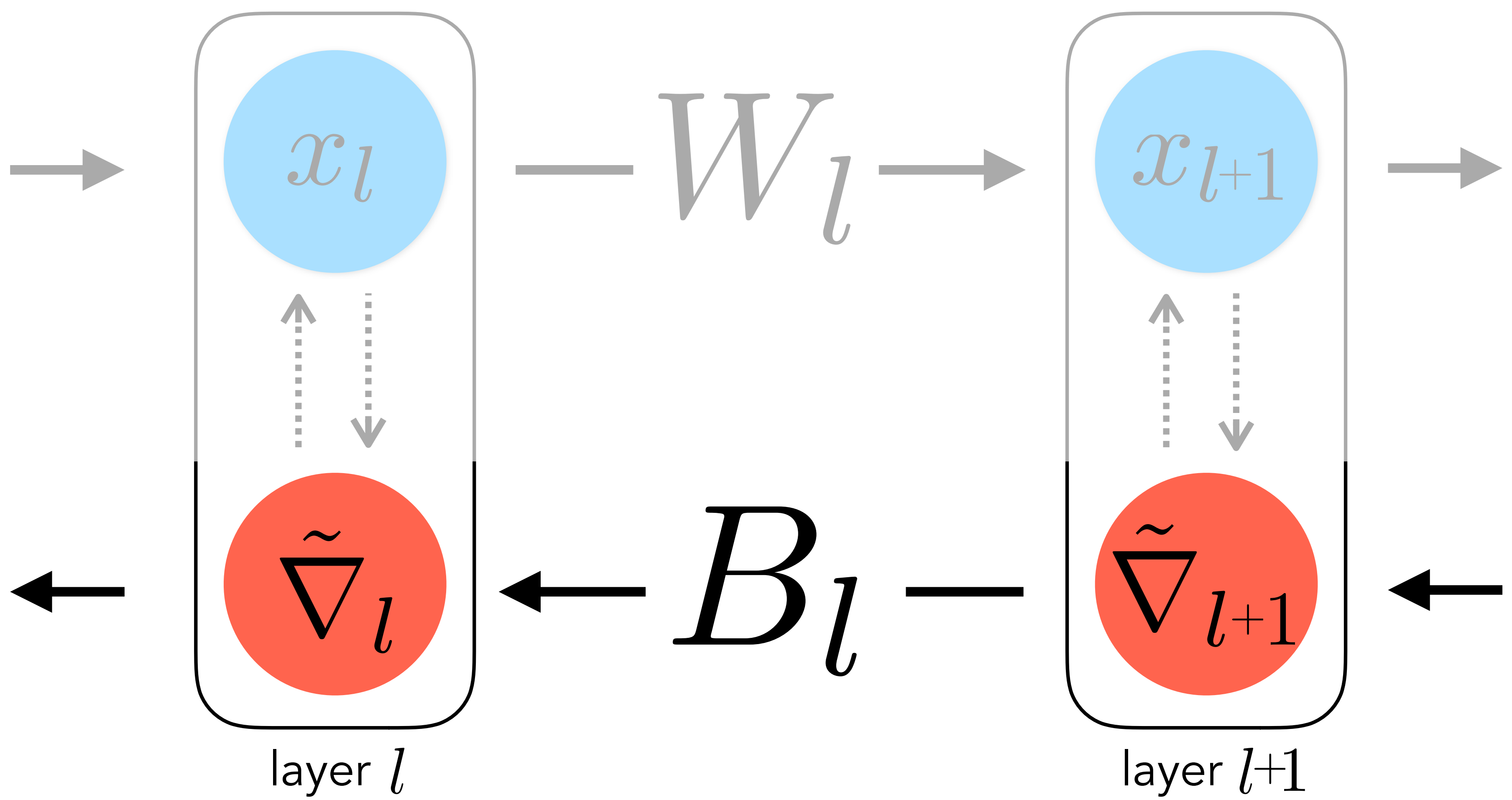

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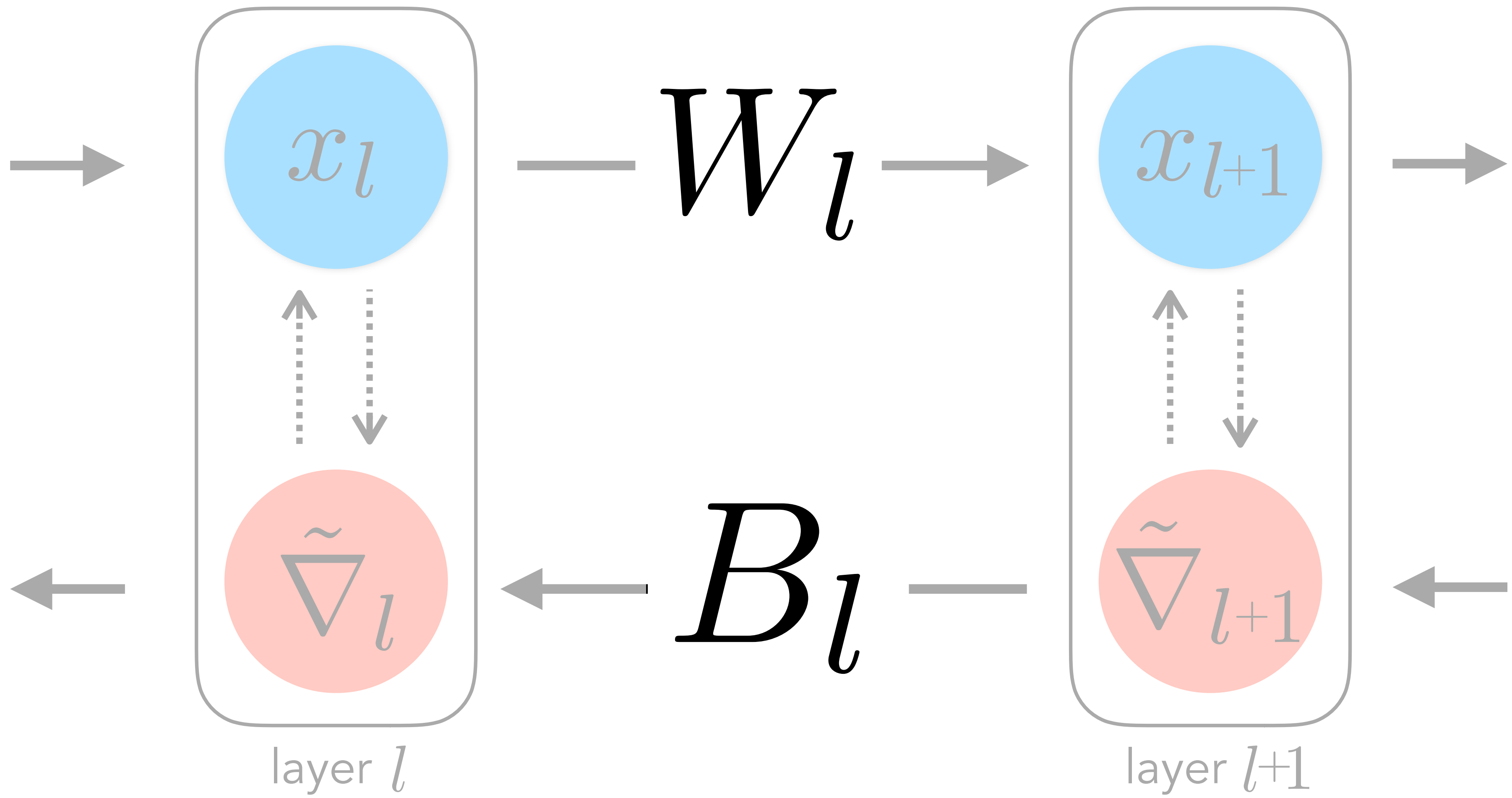

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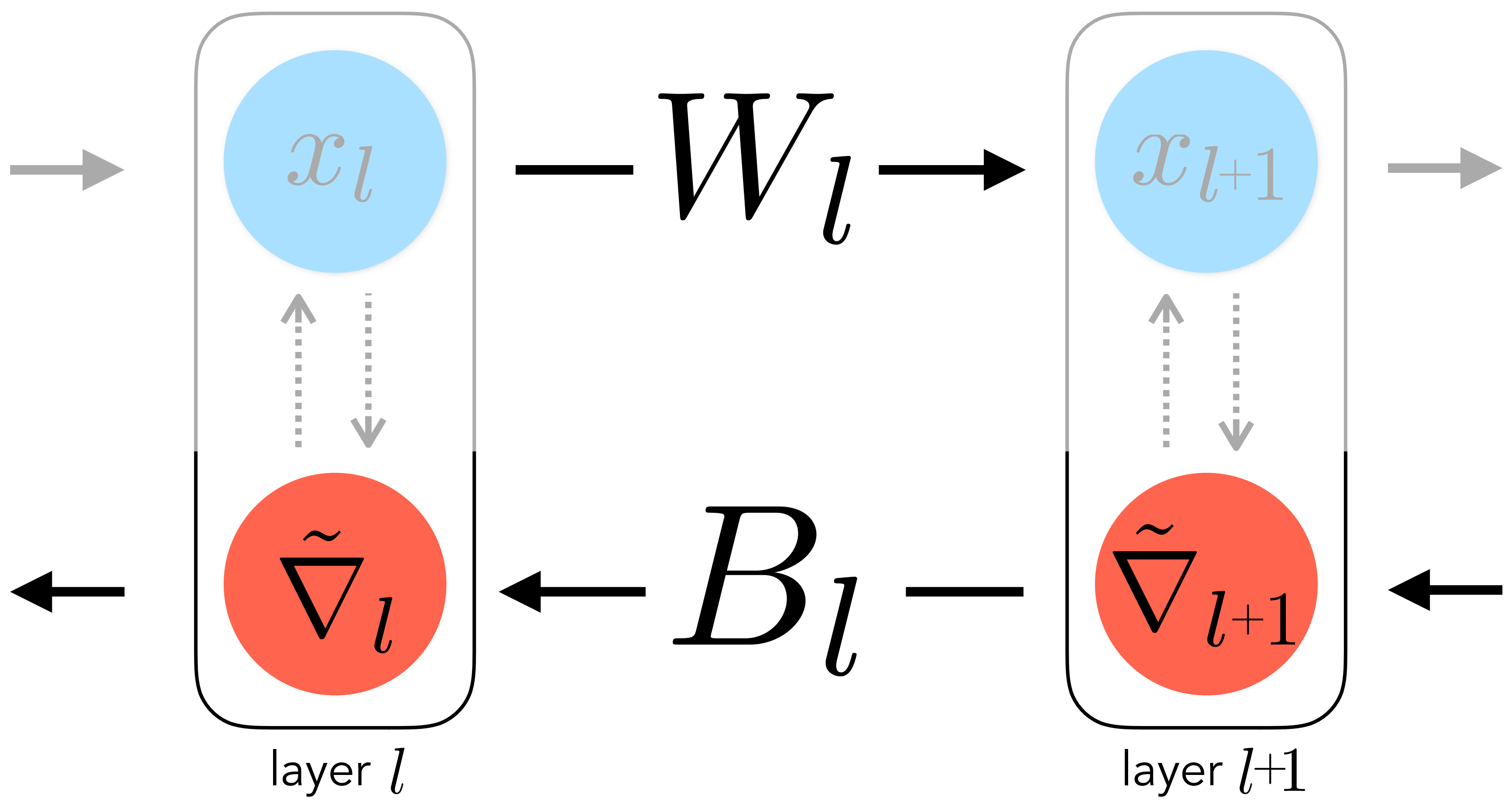

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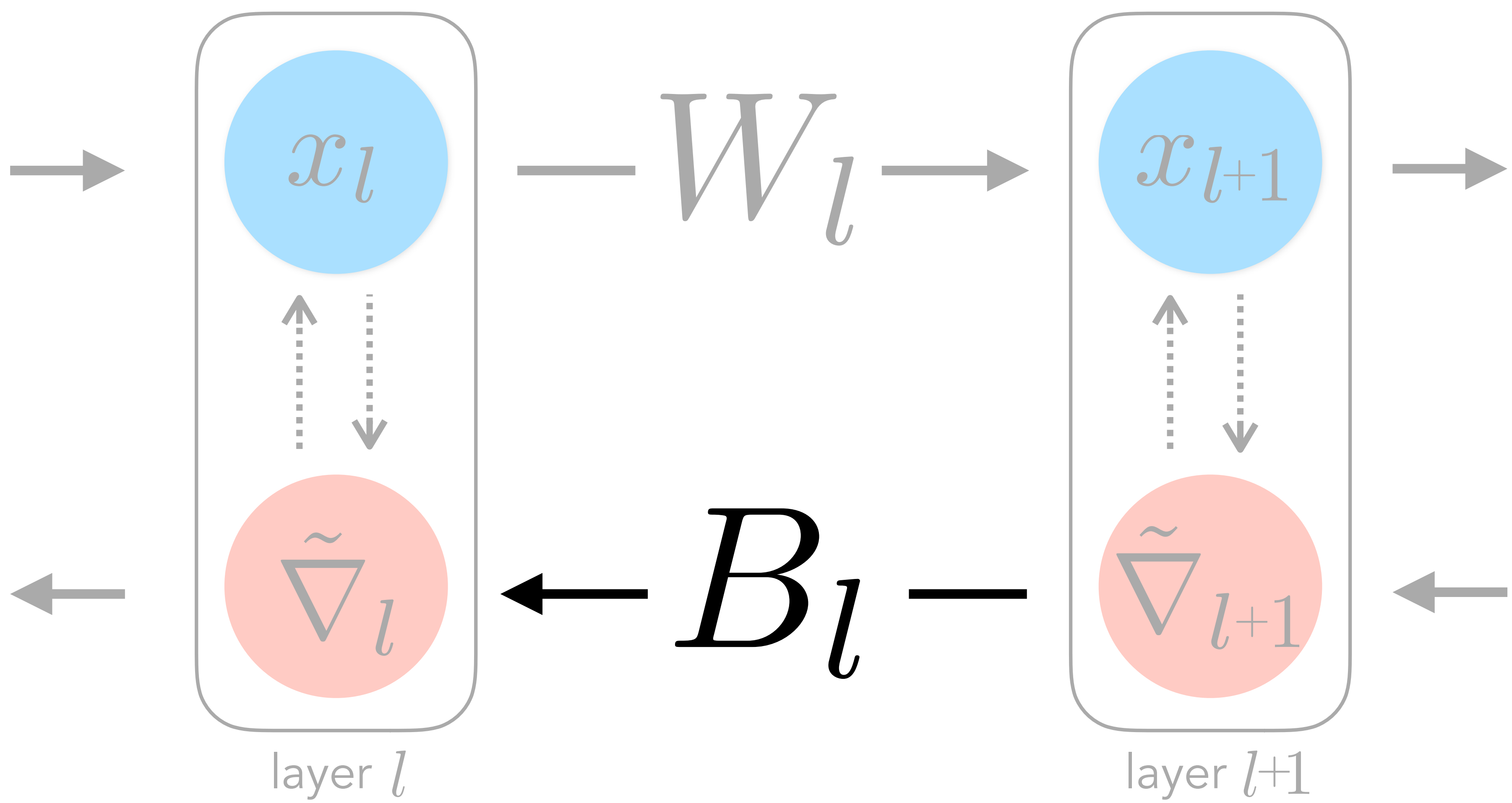

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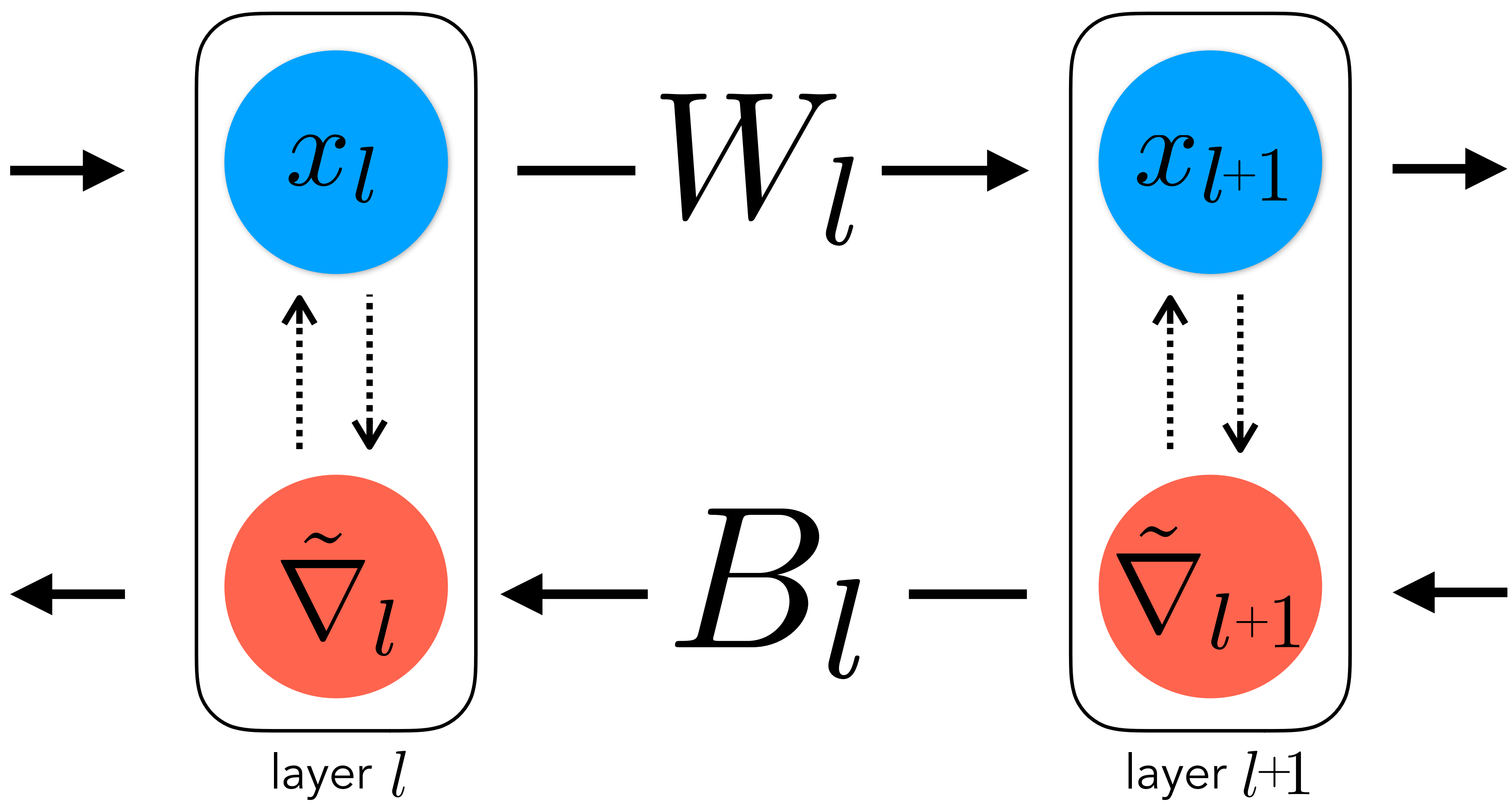

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Novel proposals

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- **II. Metaparameter Robustness**
  - Metaparameters that work well for a particular learning rule should transfer well to different and deeper architectures.
  - ImageNet top-1 validation accuracy *across* models for *fixed* metaparameters.

Route I: Local Learning Rules

Local Learning Rules: Weight Mirror

Weight Mirror: literature

$$\mathcal{R}_{\text{WM}} = \sum_{l \in \text{layers}} \alpha \mathcal{P}_l^{\text{amp}} + \beta \mathcal{P}_l^{\text{decay}}$$

Learning Rule	Top-1 Val Accuracy
Backprop.	70.06%
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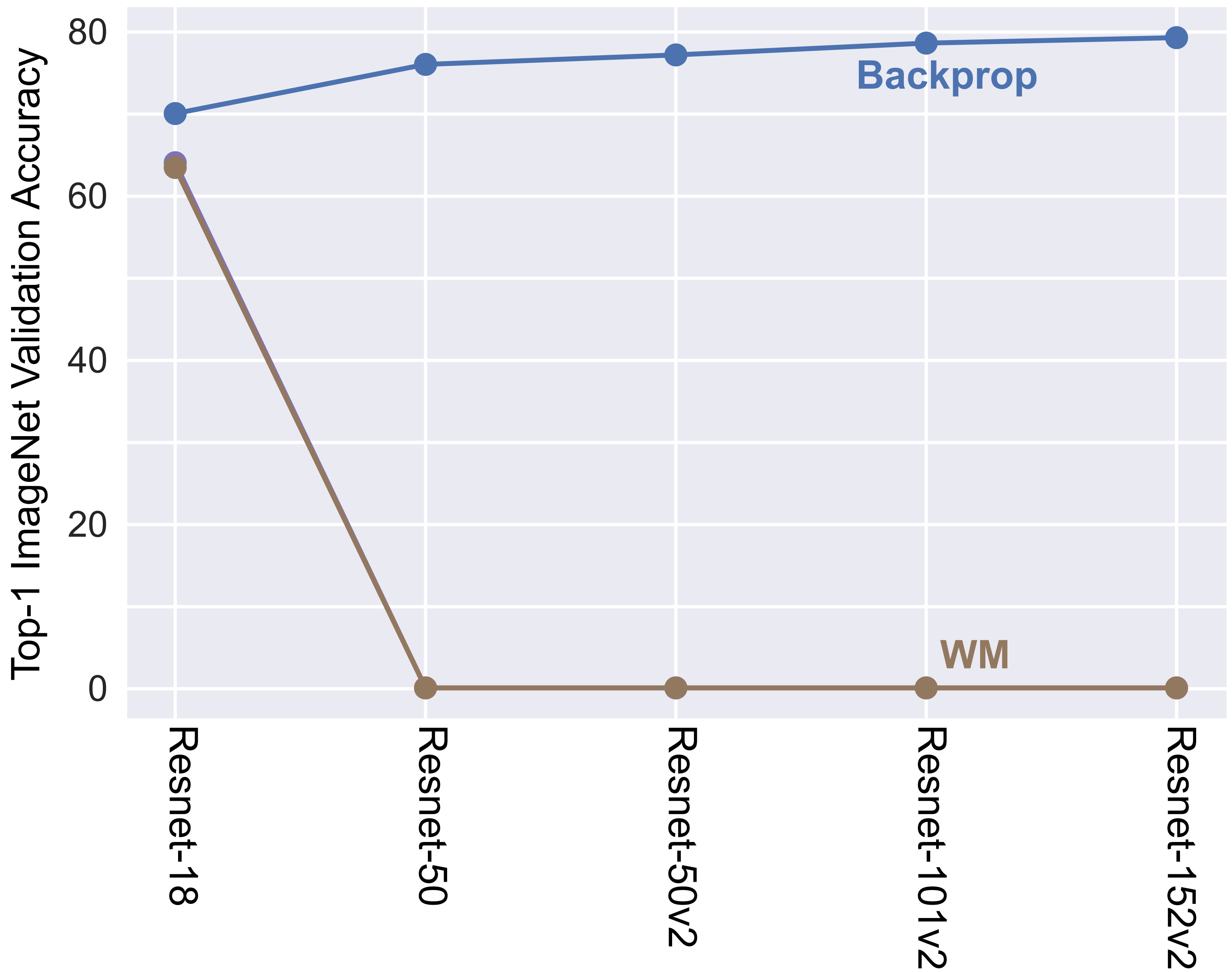

Local Learning Rules: Weight Mirror

Weight Mirror: optimized metaparameters

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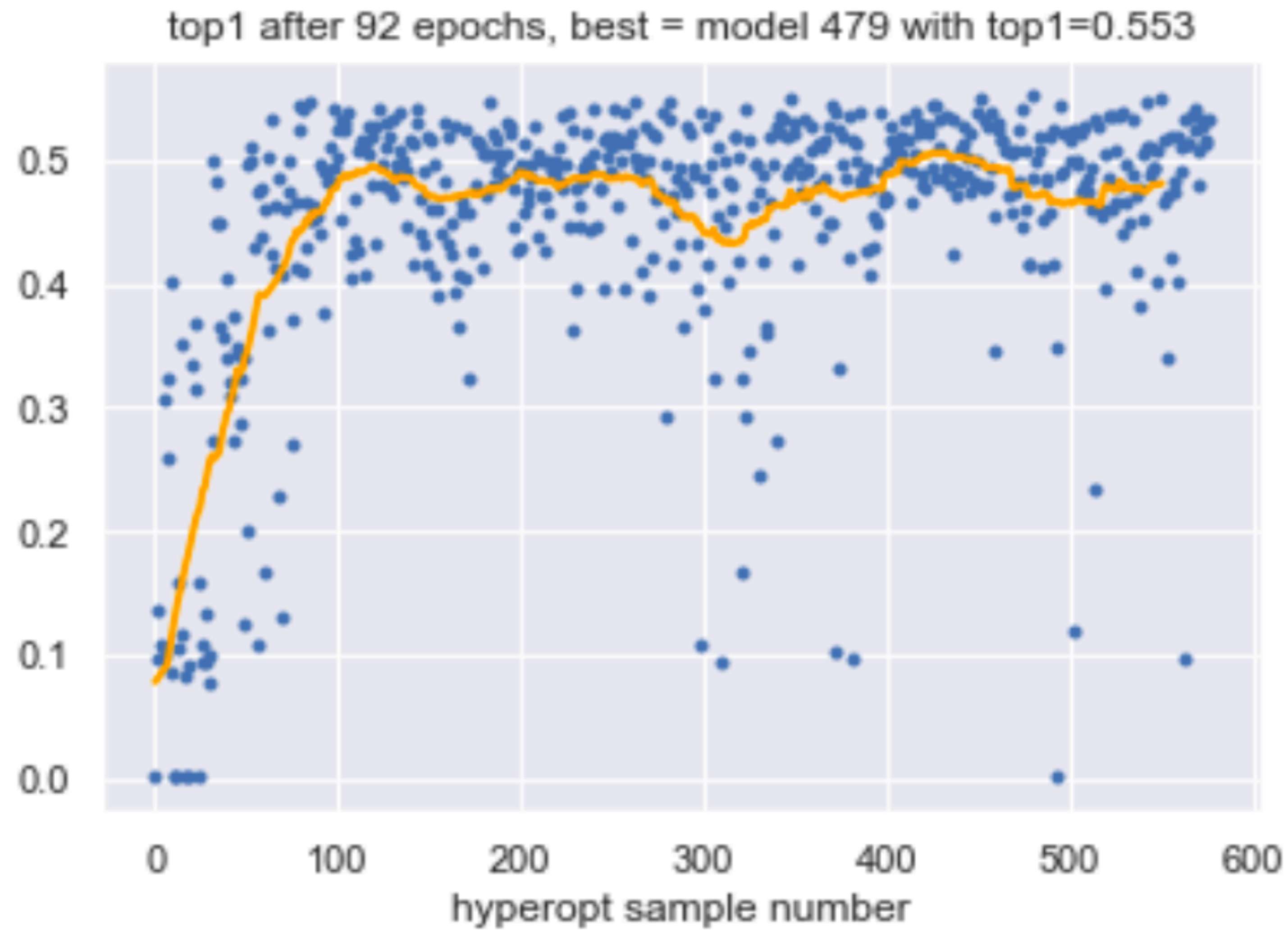
- TPE Search over alpha, beta and the variance of the noise used in mirror mode on ResNet-18.



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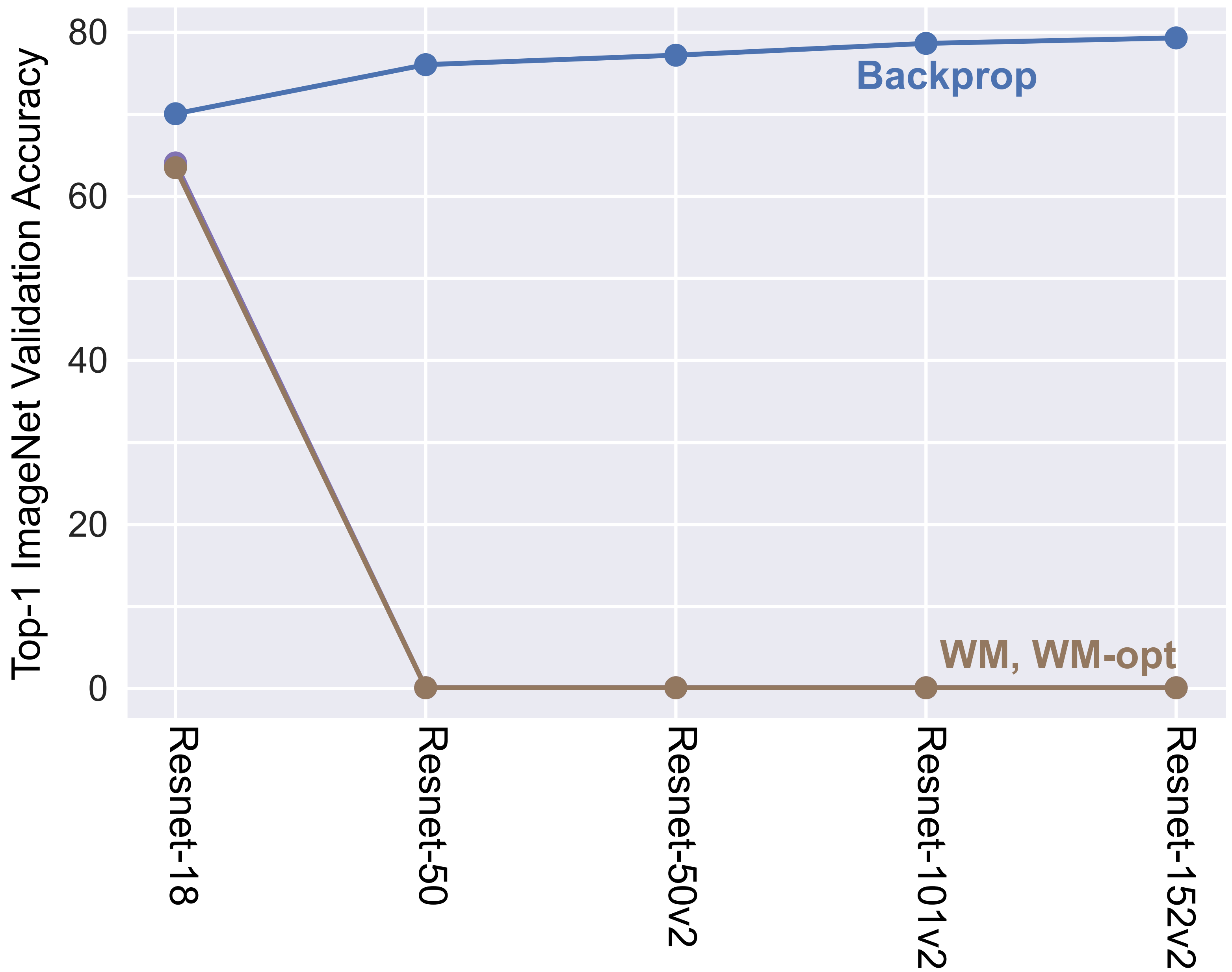

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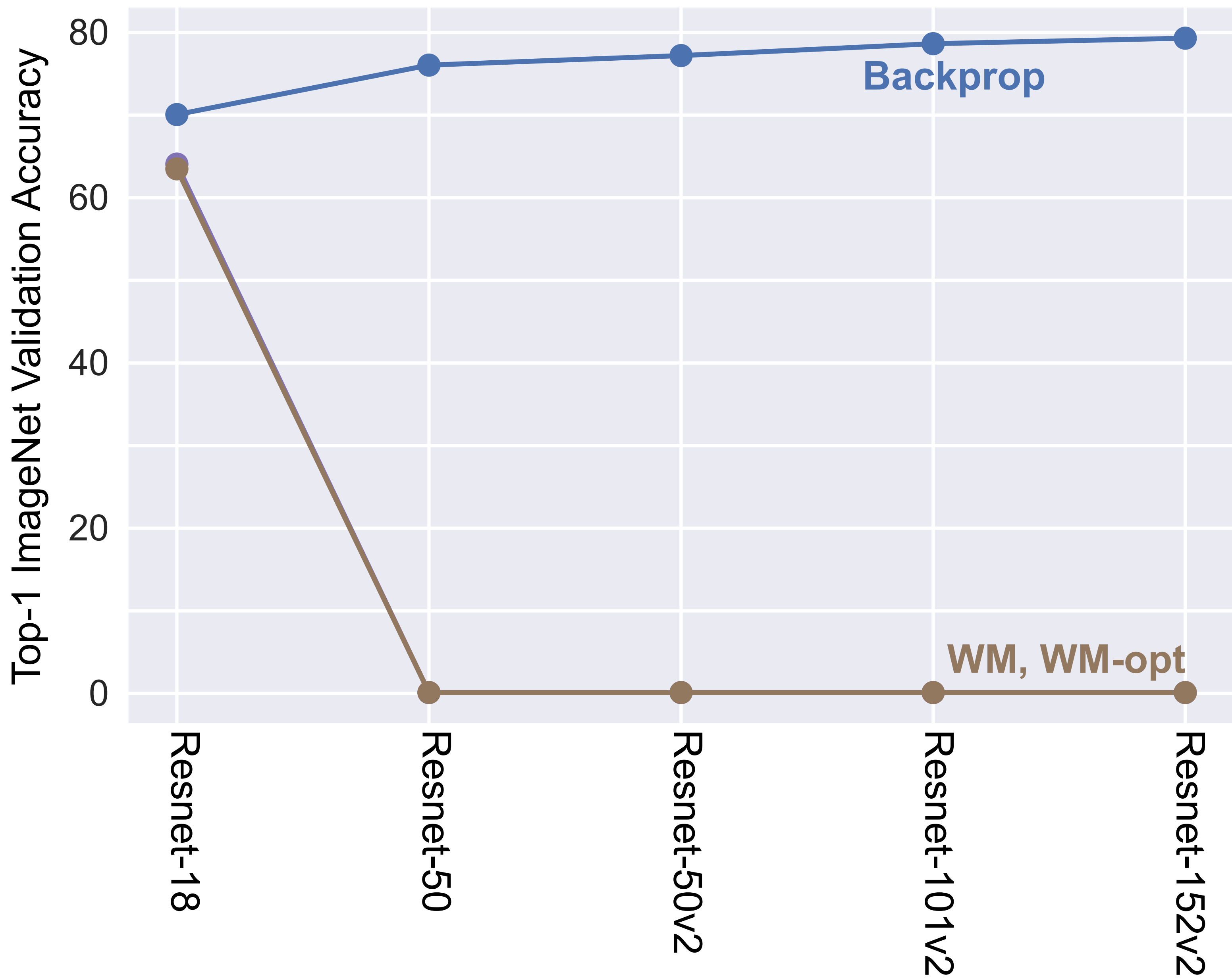
- Why is weight mirror unstable?



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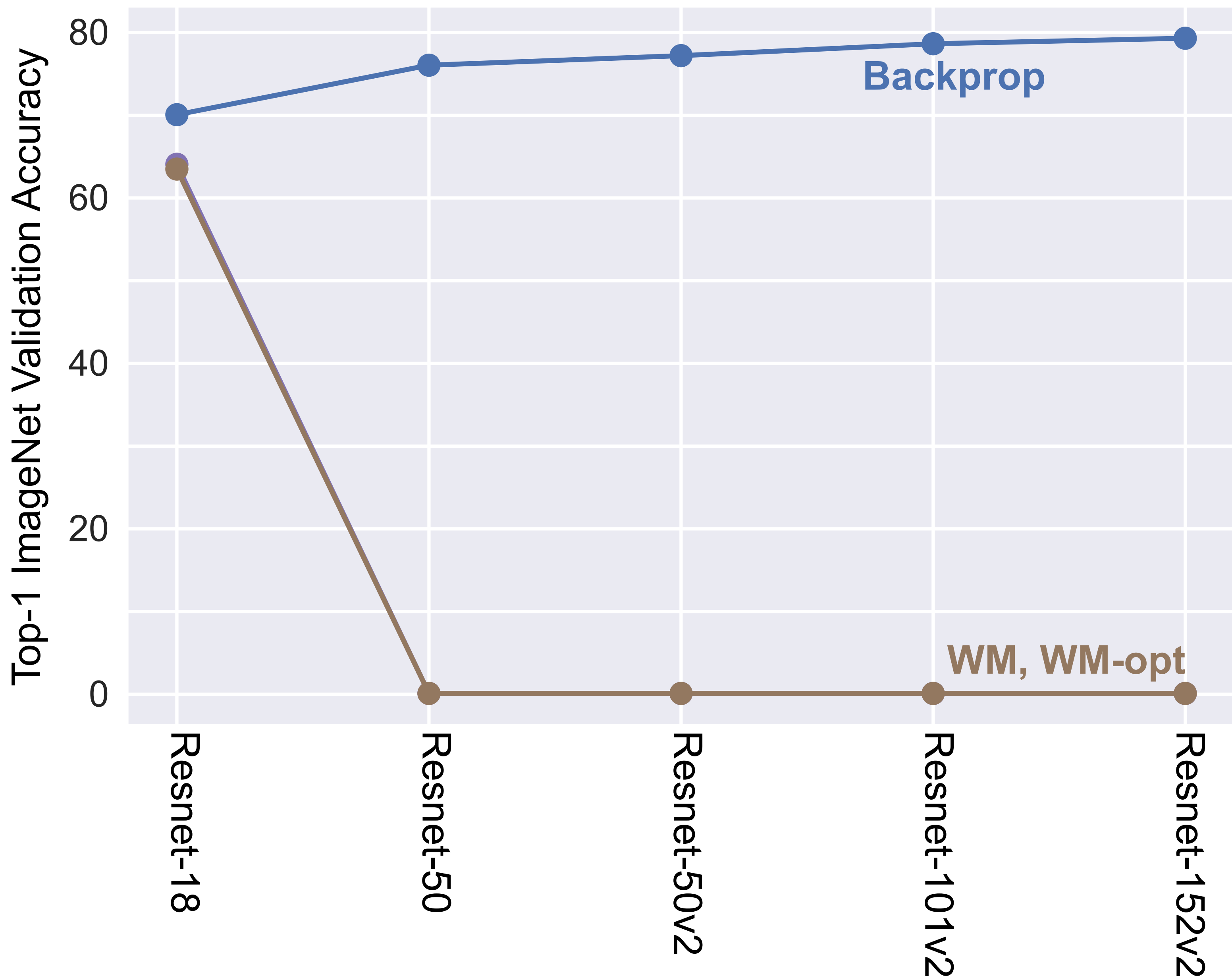
- Why is weight mirror unstable?
- Could this be helped by using an adaptive optimizer?



Local Learning Rules: Improved Metaparameter Robustness

Weight Mirror: adding an adaptive optimizer

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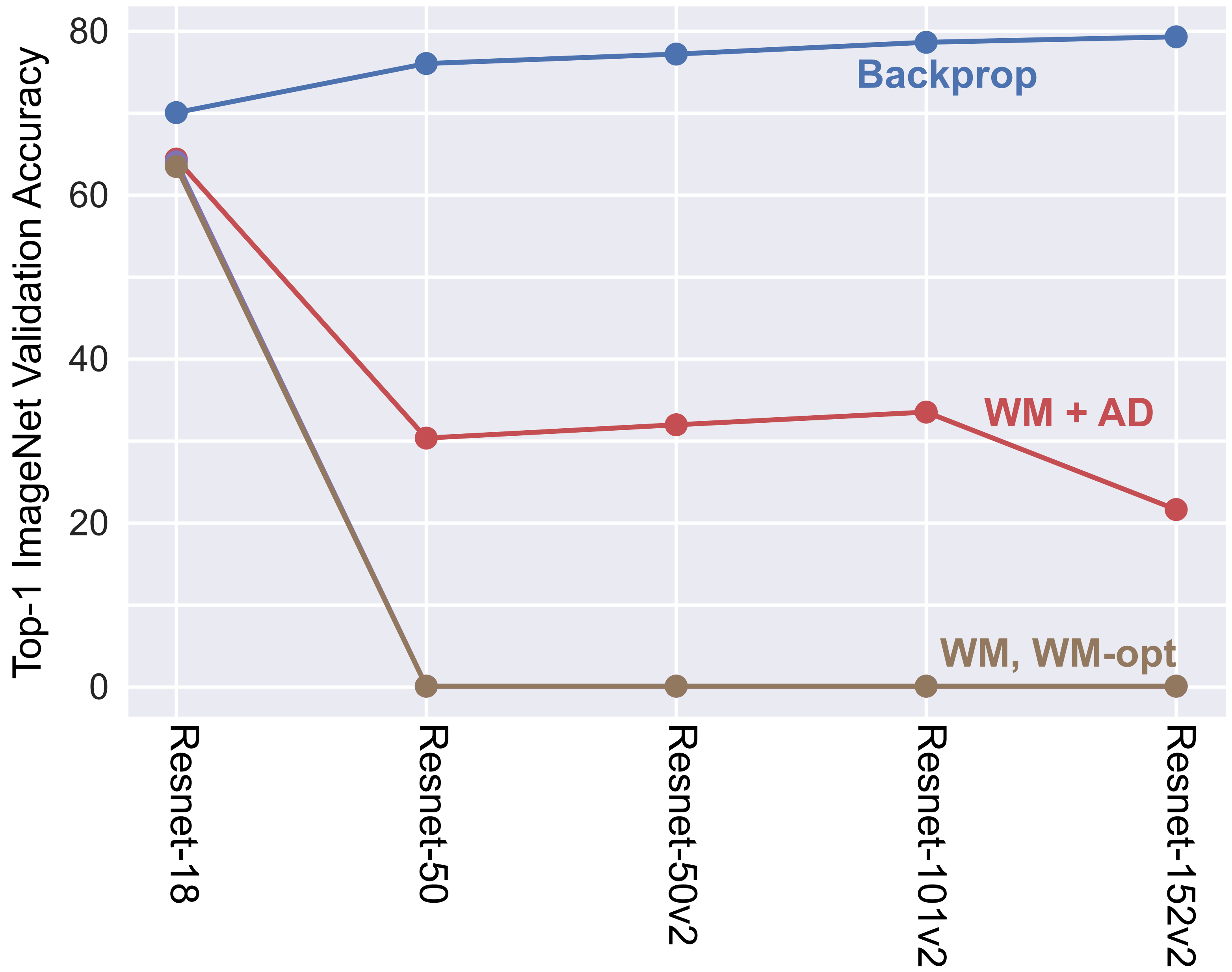
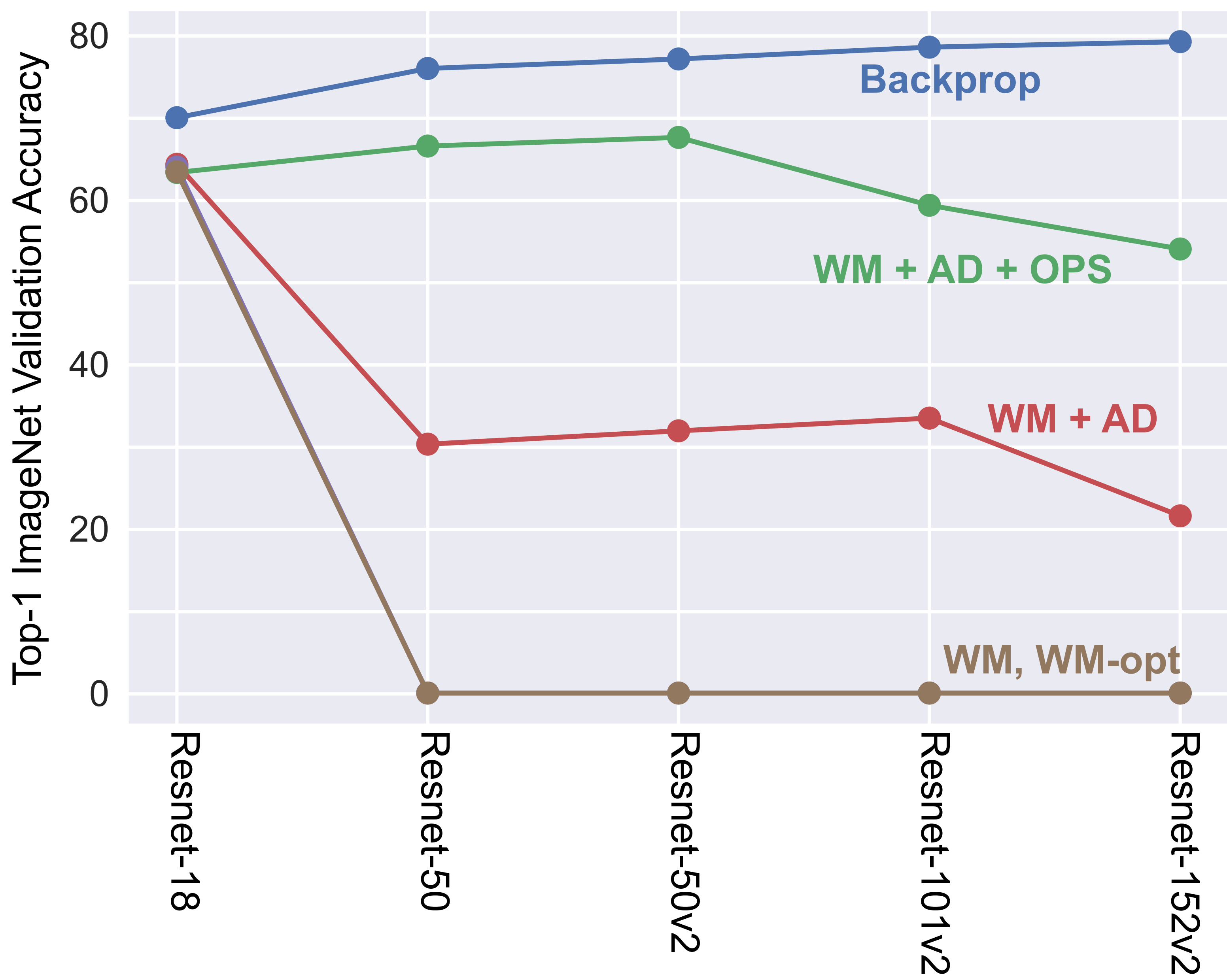


Local Learning Rules: Improved Metaparameter Robustness

Weight Mirror: adding an adaptive optimizer and normalizing operations

$$\mathcal{R}_{\mathrm{WM}} = \sum_{l \in \mathrm{layers}} \alpha \mathcal{P}_l^{\mathrm{amp}} + \beta \mathcal{P}_l^{\mathrm{decay}}$$



Oja-style Stabilization of Weight Mirror

- The update given by WM (without decay) is Hebbian
- Purely Hebbian learning rules are unstable
- WM adds weight decay to prevent diverging norms
- An alternative strategy to stabilizing Hebbian dynamics given by Oja (1982) for learning dynamics of linear neurons

Normalizing operation:

$$B_l^{(t+1)} = \frac{B_l^{(t)} + \eta x_l x_{l+1}^\intercal}{||B_l^{(t)} + \eta x_l x_{l+1}^\intercal||}$$

Taylor series expansion:

$$B_l^{(t+1)} = B_l^{(t)} + \eta \left(x_l x_{l+1}^\intercal - B_l^{(t)} x_l^\intercal B_l^{(t)} x_{l+1} \right) + O(\eta^2)$$

New update:

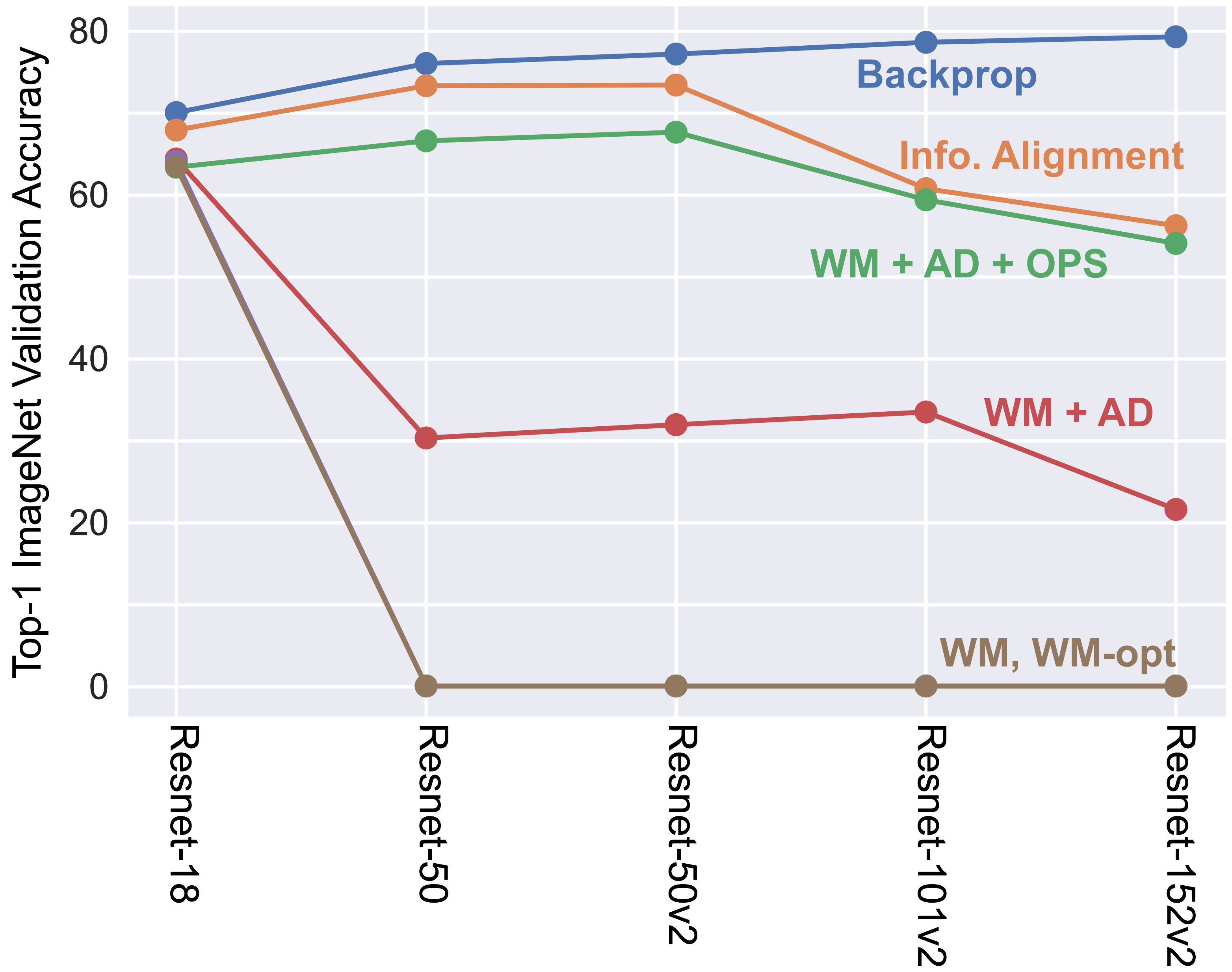
$$\Delta B_l = \eta \left(x_l x_{l+1}^\intercal - \underbrace{B_l x_l^\intercal B_l x_{l+1}}_{\approx \nabla \mathcal{P}_{\text{null}}} \right)$$

A More Robust Local Learning Rule

Weight Mirror

Information Alignment

$$\mathcal{R}_{\mathrm{WM}} = \sum_{l \in \mathrm{layers}} \alpha \mathcal{P}_l^{\mathrm{amp}} + \beta \mathcal{P}_l^{\mathrm{decay}}$$



Route II: Non-Local Learning Rules

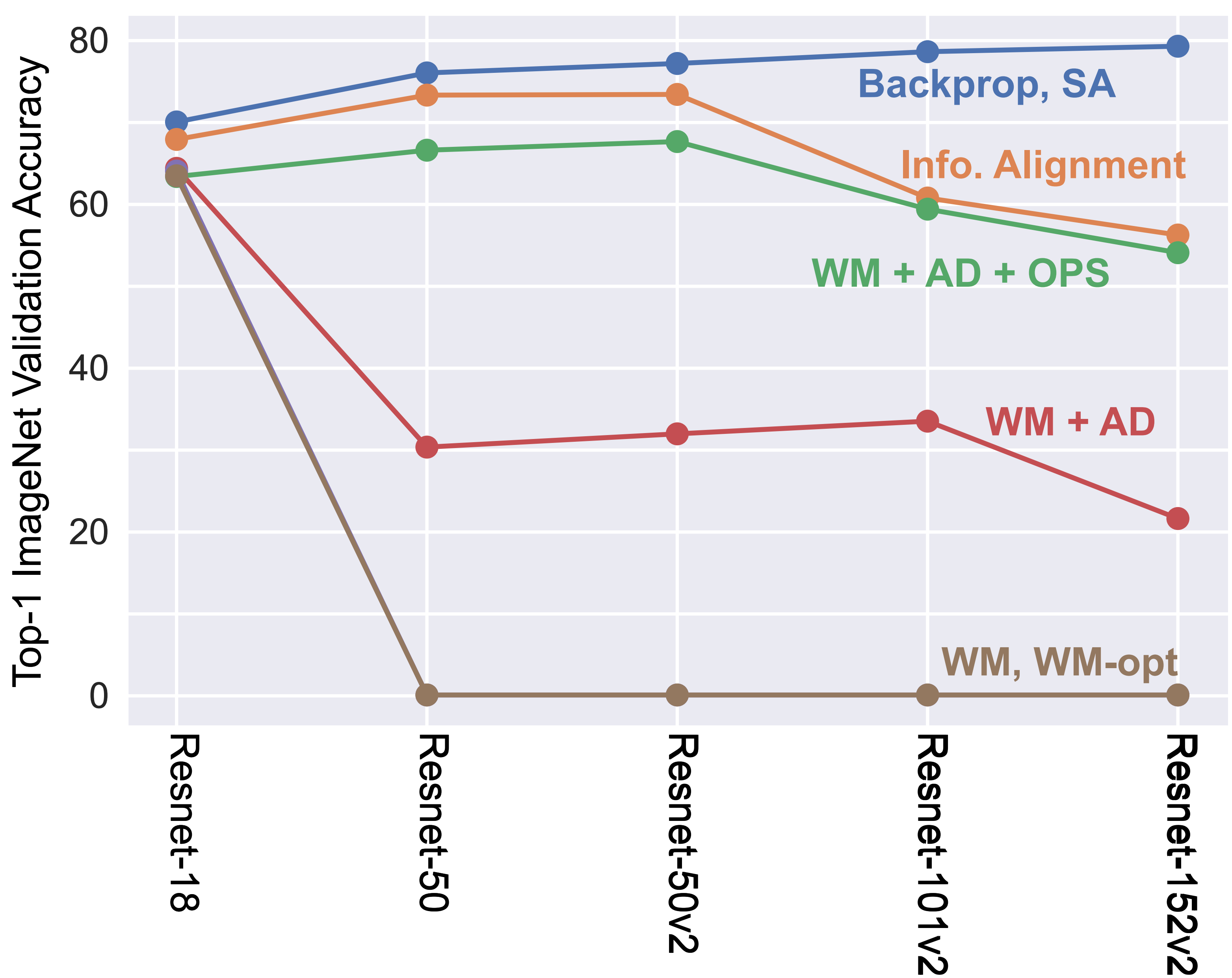
Non-Local Learning Rules

Weight Mirror

Symmetric Alignment

$$\mathcal{R}_{\text{WM}} = \sum_{l \in \text{layers}} \alpha \mathcal{P}_l^{\text{amp}} + \beta \mathcal{P}_l^{\text{decay}}$$

$$\propto \sum_{l \in \text{layers}} \frac{1}{2} ||W_l - B_l^{\intercal}||^2$$



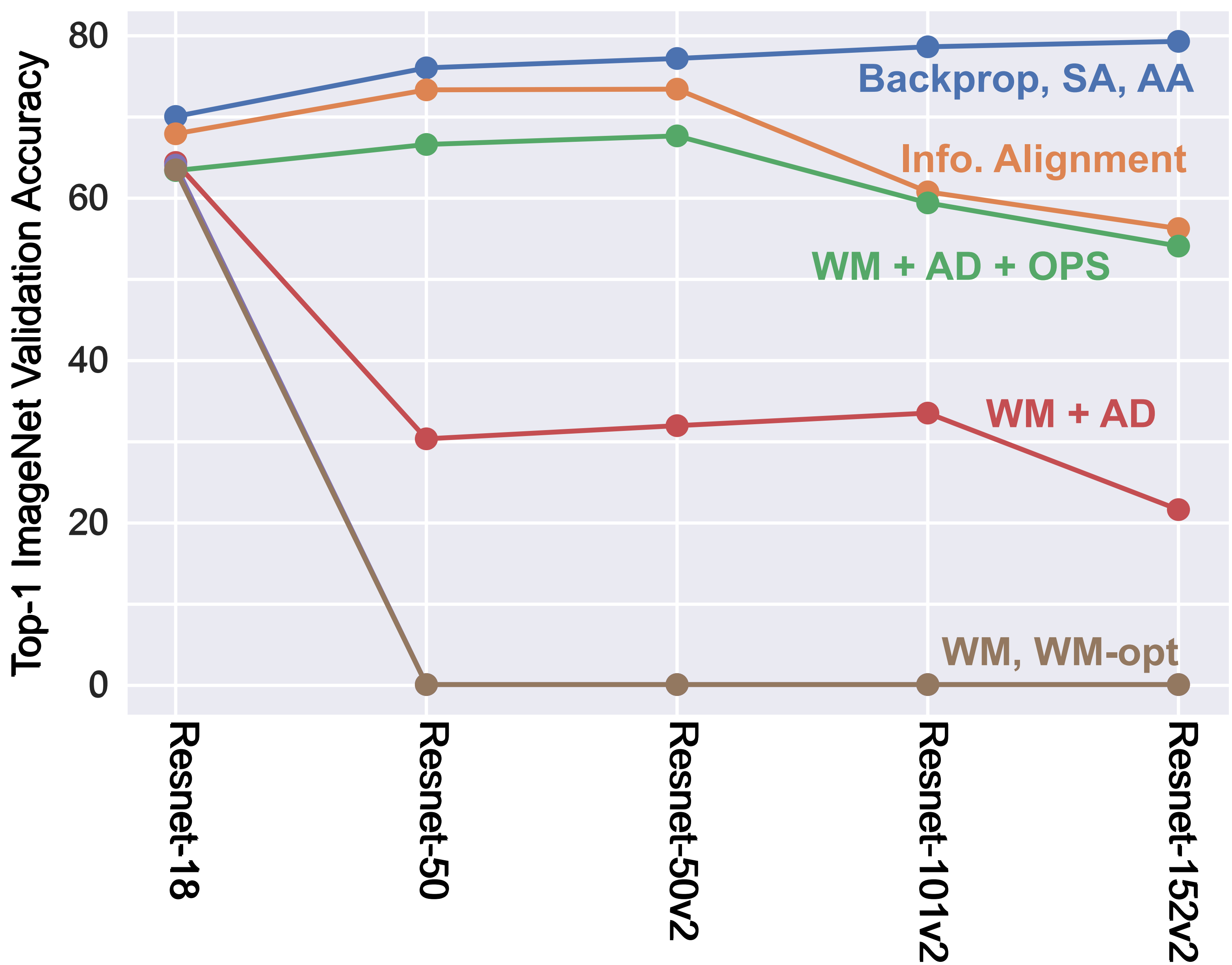
Non-Local Learning Rules

Weight Mirror

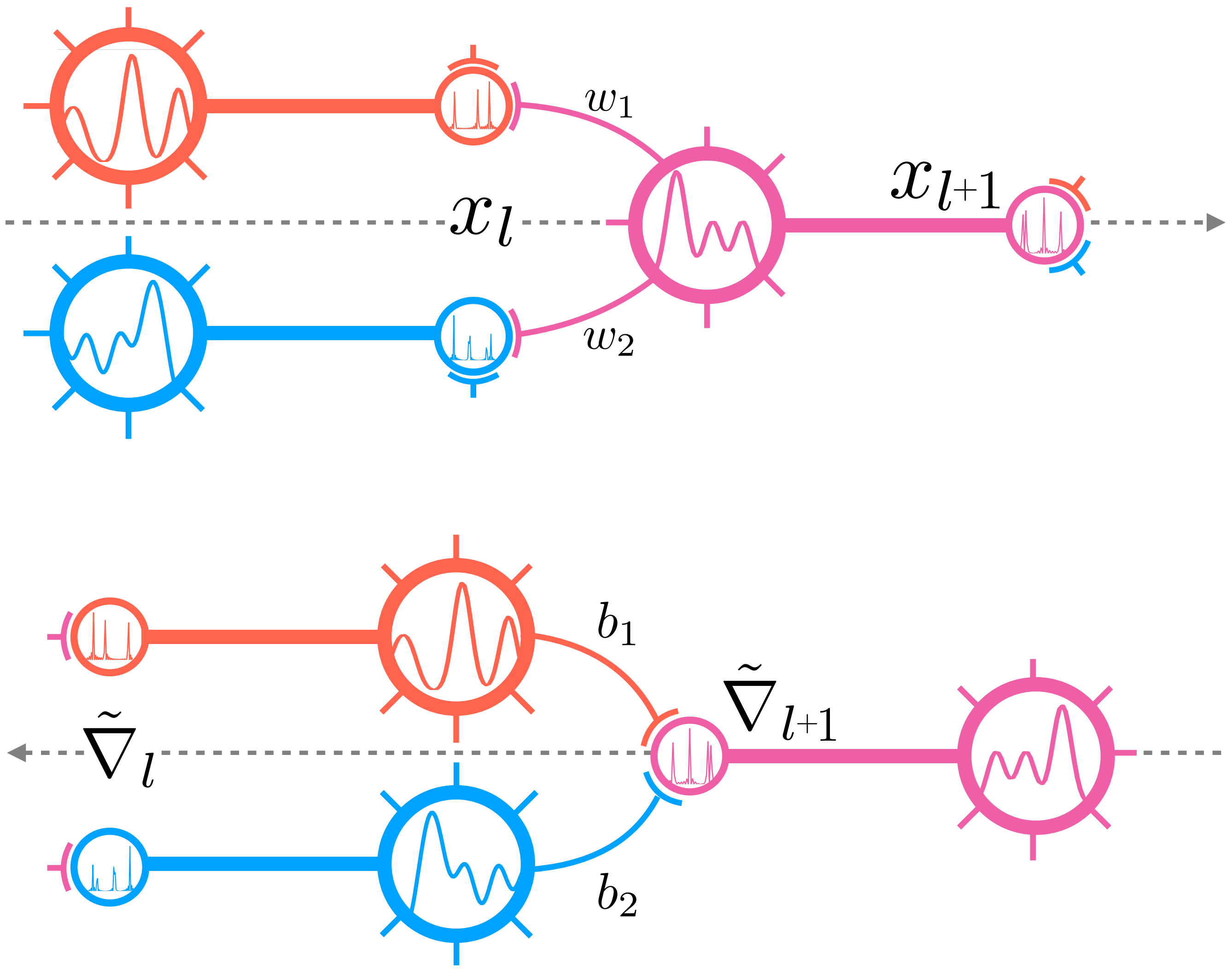
$$\mathcal{R}_{\text{WM}} = \sum_{l \in \text{layers}} \alpha \mathcal{P}_l^{\text{amp}} + \beta \mathcal{P}_l^{\text{decay}}$$

Activation Alignment

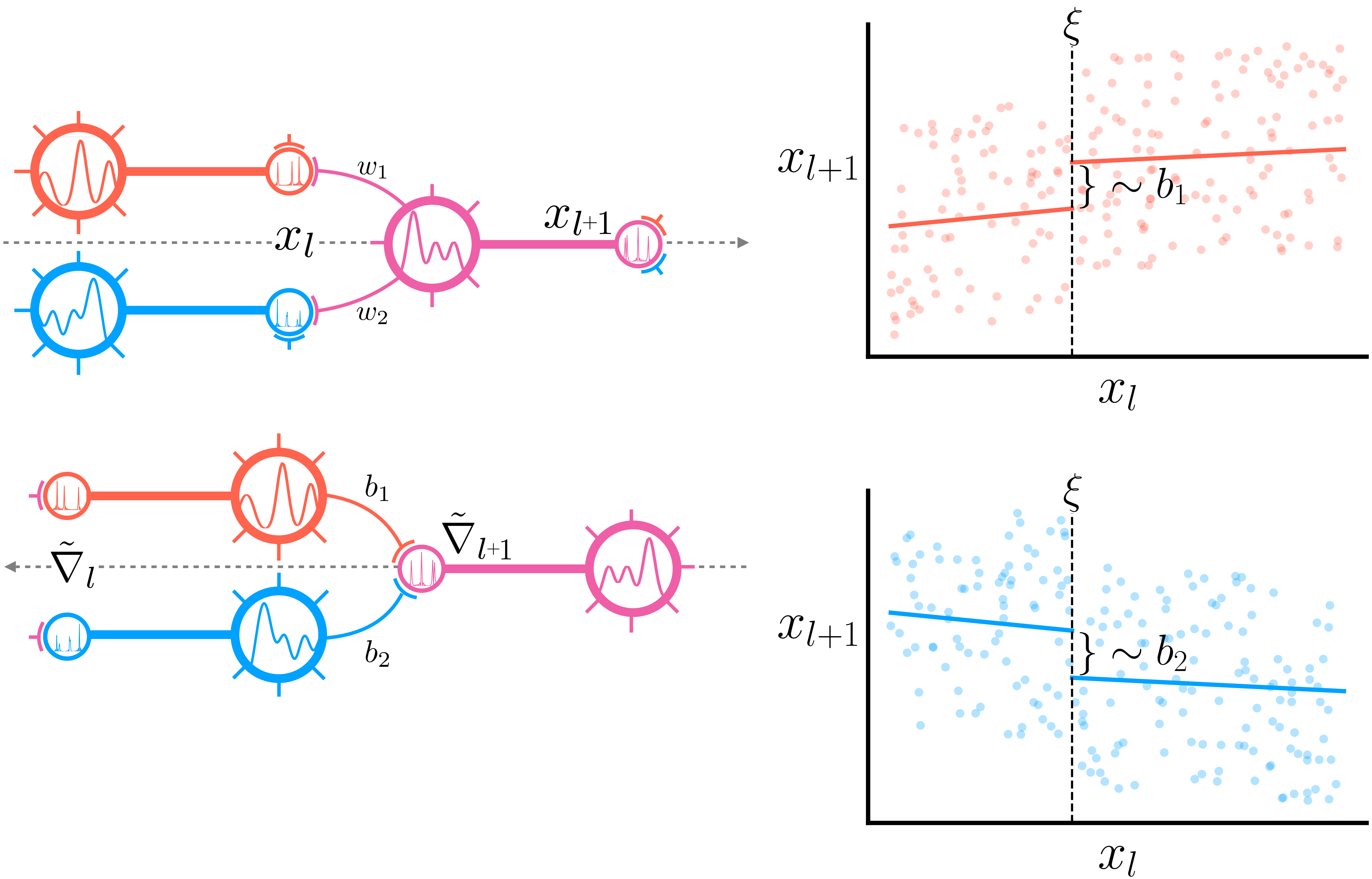
$$\propto \sum_{l \in \text{layers}} \frac{1}{2} ||W_l x_l - B_l^{\intercal} x_l||^2$$



Weight Estimation



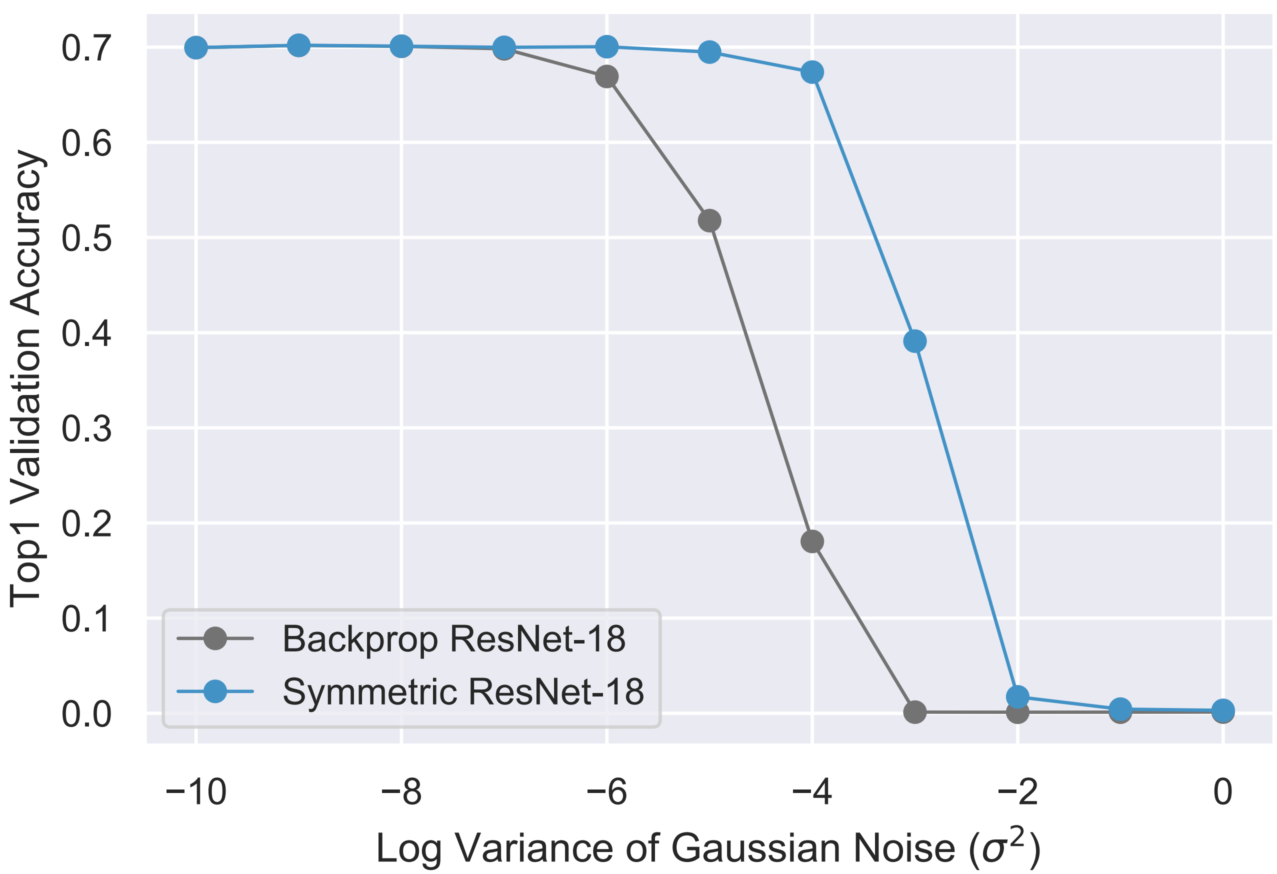
Weight Estimation: Regression Discontinuity Design



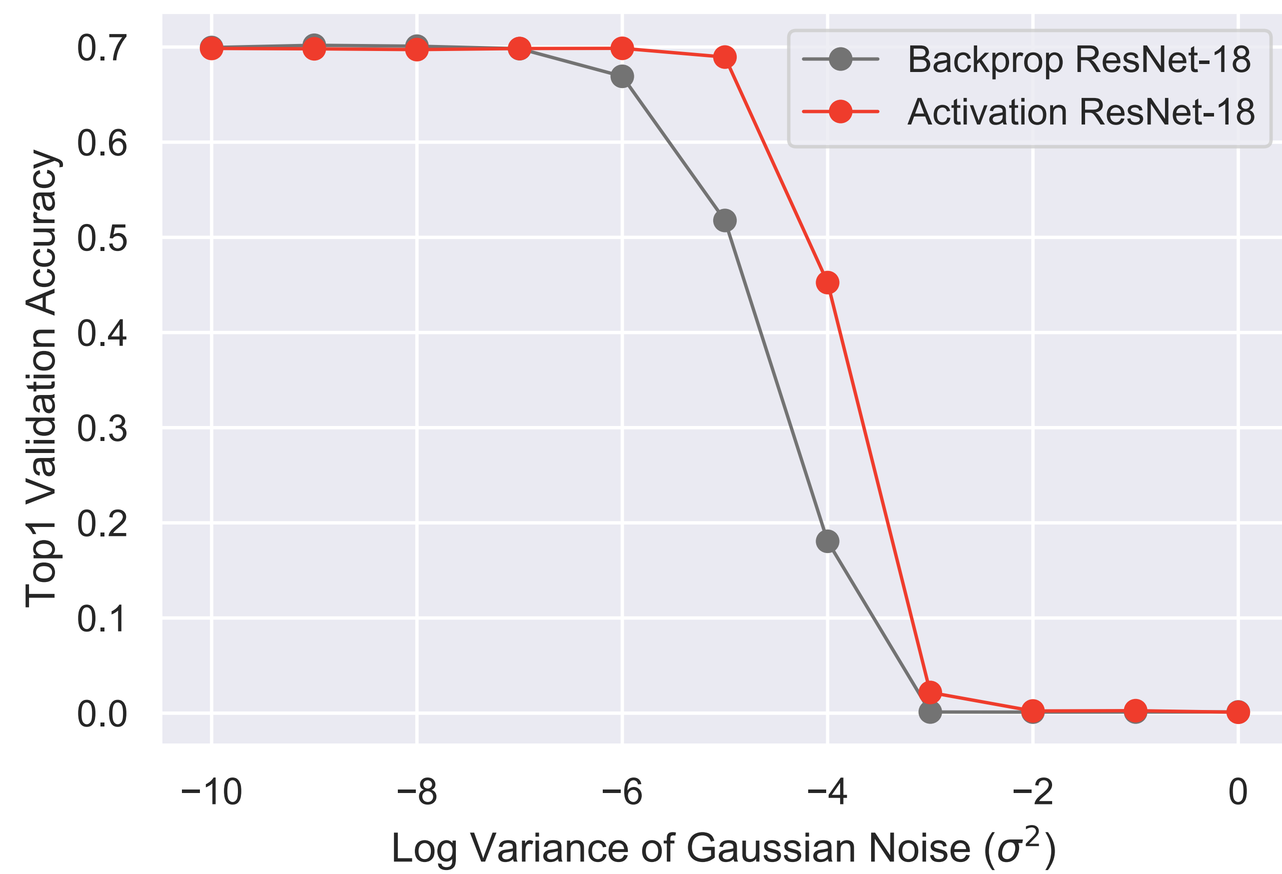
[1] Lansdell, B. J. and Kording, K. P. Spiking allows neurons to estimate their causal effect. bioRxiv, pp. 253351, 2019.
[2] Guerguiev, J., Kording, K. P., and Richards, B. A. Spike-based causal inference for weight alignment. arXiv:1910.01689 [cs, q-bio], October 2019.

Non-Local Learning Rules: Robust to noisy updates

Symmetric Alignment



Activation Alignment



$$\Delta B = \nabla \mathcal{R} + \mathcal{N}(0, \sigma^2)$$

Conclusions

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Conclusions

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- **Route I:** further improvement of local rules to close the gap with respect to backpropagation
- **Route II:** further refinement and characterization of scalable biological implementations of weight estimation mechanisms for non-local rules
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