THE UNIVERSITY *of* EDINBURGH

Multitrate Training of Neural Networks

Tiffany Vlaar and Ben Leimkuhler

Get in touch at: Tiffany.Vlaar@ed.ac.uk

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Latent Multiple Time Scales in Deep Learning

WideResNet-16 trained on patch-augmented [Li, Wei & Ma, NeurIPS 2019] CIFAR-10 data:

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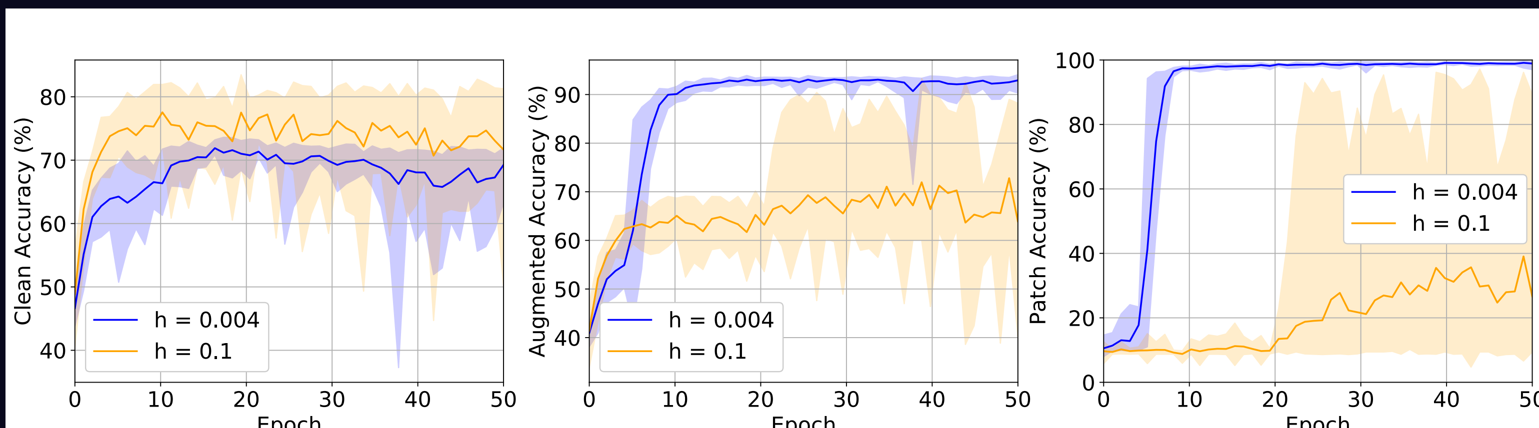

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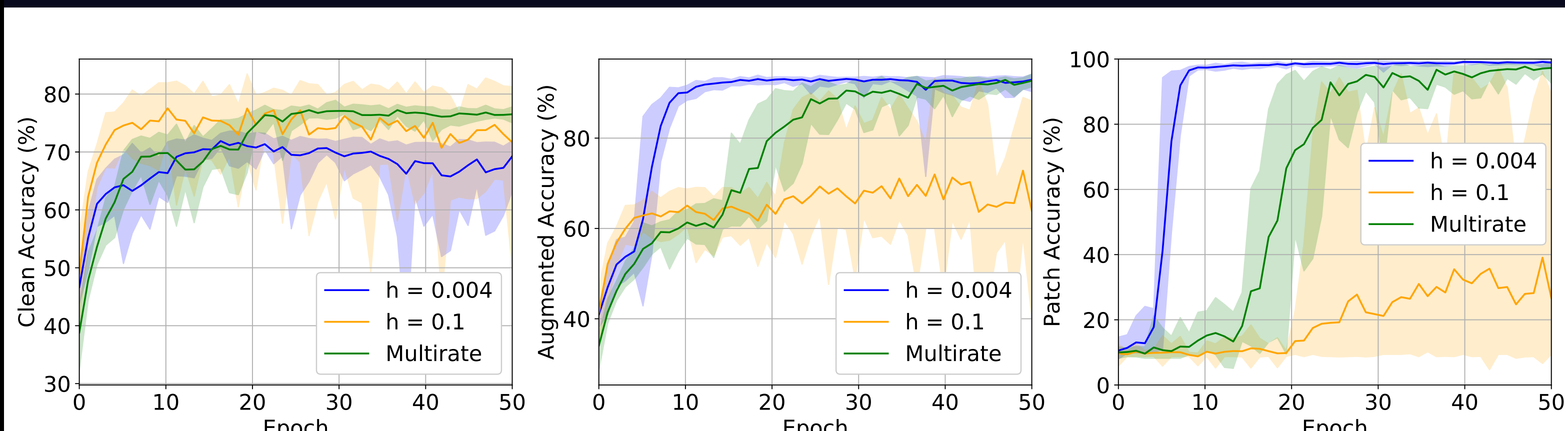

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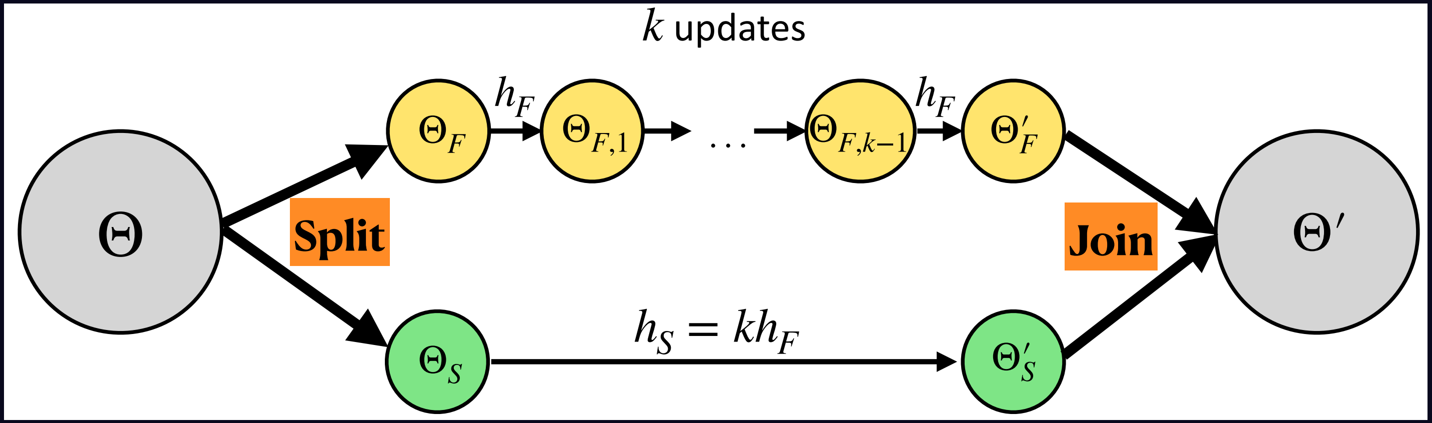
- Our multirate approach (green) can perform well on both.

Multirate Methods

Two time-scales example:

Partition model (+ accompanying momentum) parameters $\Theta = (\Theta_F, \Theta_S)$.



Fast components Θ_F are updated every step with step size h_F
Slow components Θ_S are updated every k steps with step size $h_S = kh_F$

Partition-based Multirate Approach

Separate neural network parameters into different parts.
You have a choice!

Examples: layer-wise, weight vs. biases, or random subgroups.

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Act as an add-on to existing optimization schemes: they can be combined with any desired base algorithm.

If base algorithm SGD (as used in PyTorch code):

$p_S := \mu p_S + \nabla_{\theta_S} \mathcal{L}(\theta_S, \theta_F)$
$\theta_S := \theta_S - h p_S$
for $i = 1, 2, ..., k$ **do**
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end

with momentum p and loss $\mathscr{L}$

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We compare convergence properties with vanilla SGD.

Application: Transfer Learning

Basics of transfer learning:

- Start with pre-trained model on large datasets, e.g., ImageNet.
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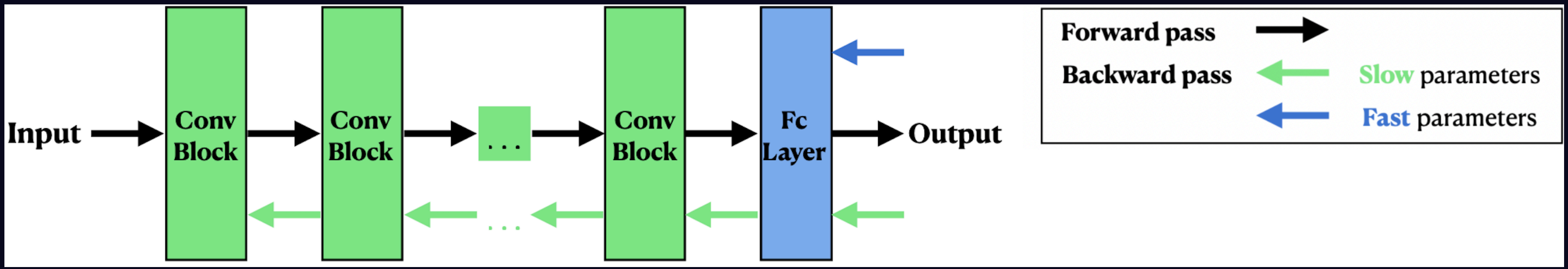
Example for a ResNet architecture:



For a ResNet-34 architecture fast parameters are only 0.024% of total.

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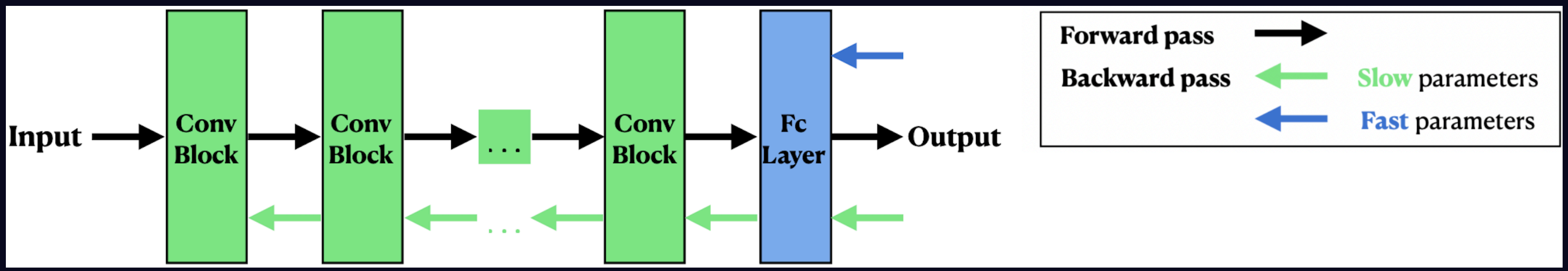
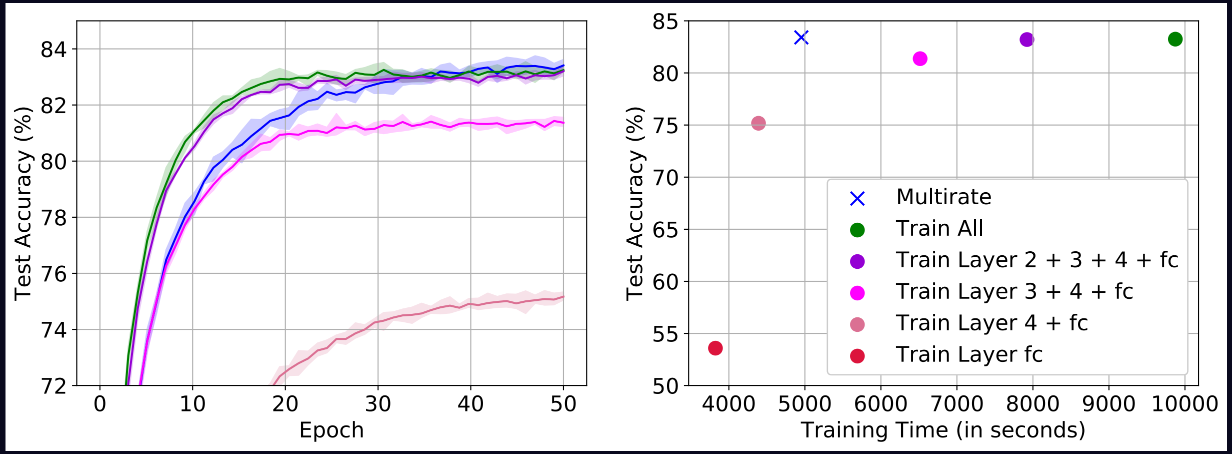


ResNet-50, CIFAR-100 data



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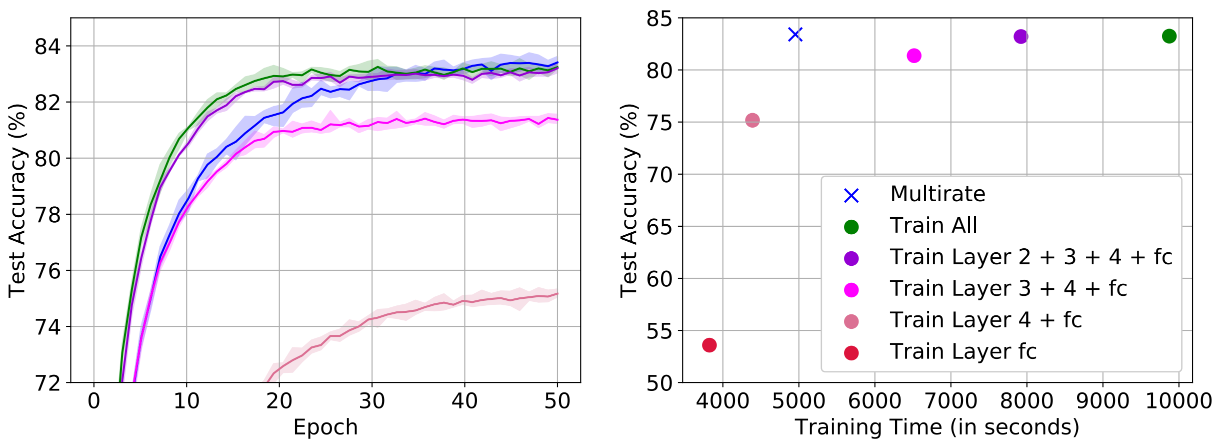
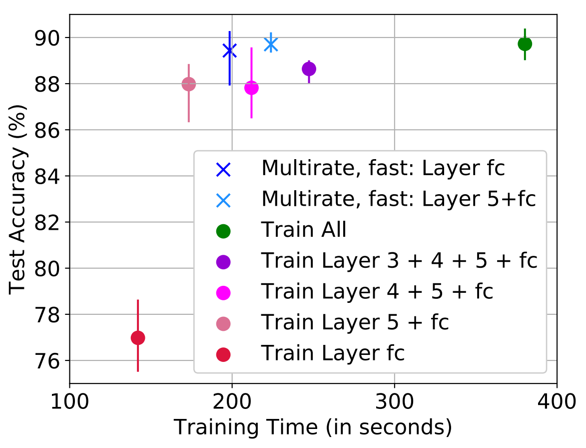


DistilBERT, SST-2 data



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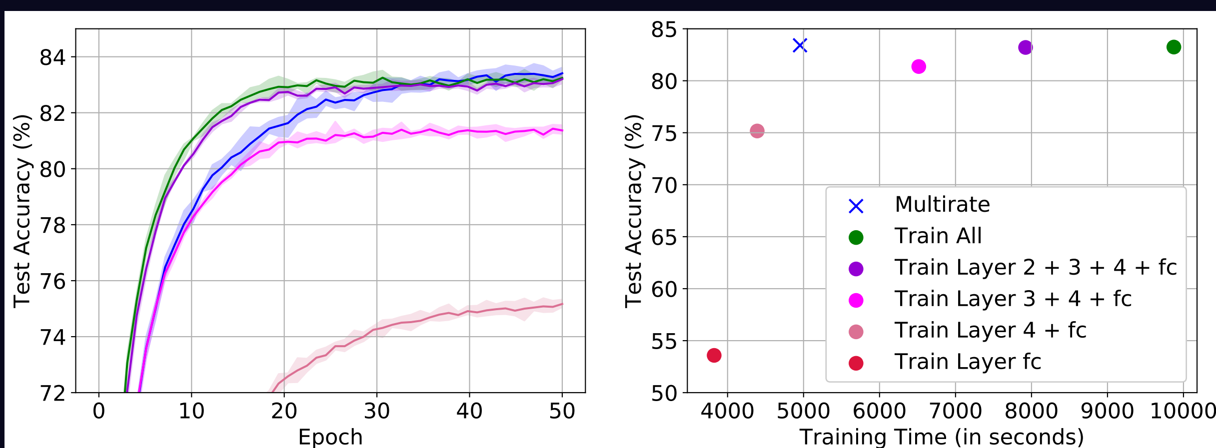

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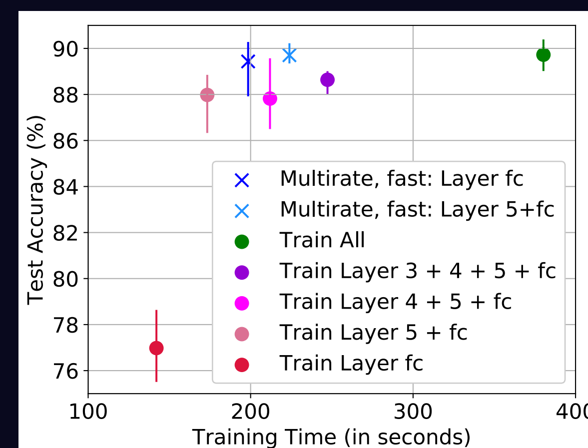

Can train in half the time, without losing performance!

Full ablation studies in paper.

Take-aways

Multirate methods can be used to enhance current neural network training techniques!

The proposed techniques:

- Act as add-on to existing optimizers.
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Random Subgroups Partitioning

Transformer, Penn Treebank