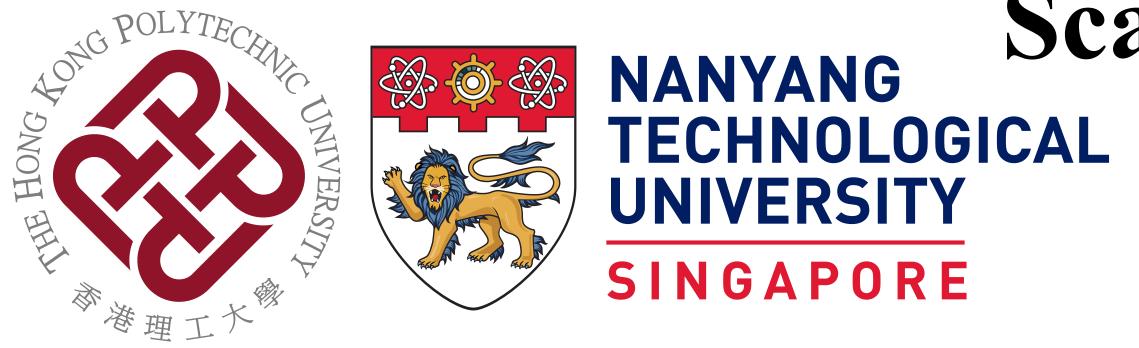
## Scaling Supervised Local Learning with Augmented Auxiliary Networks

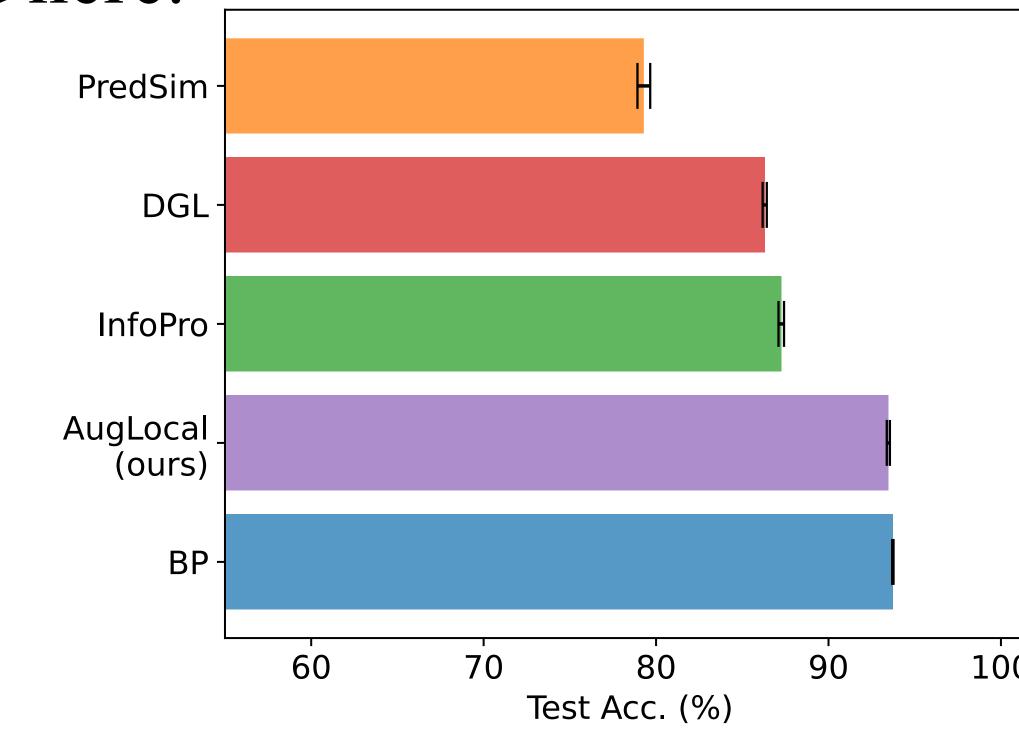


Chenxiang Ma¹, Jibin Wu¹⊠, Chenyang Si², Kay Chen Tan¹
¹The Hong Kong Polytechnic University, Hong Kong SAR, China
²Nanyang Technological University, Singapore

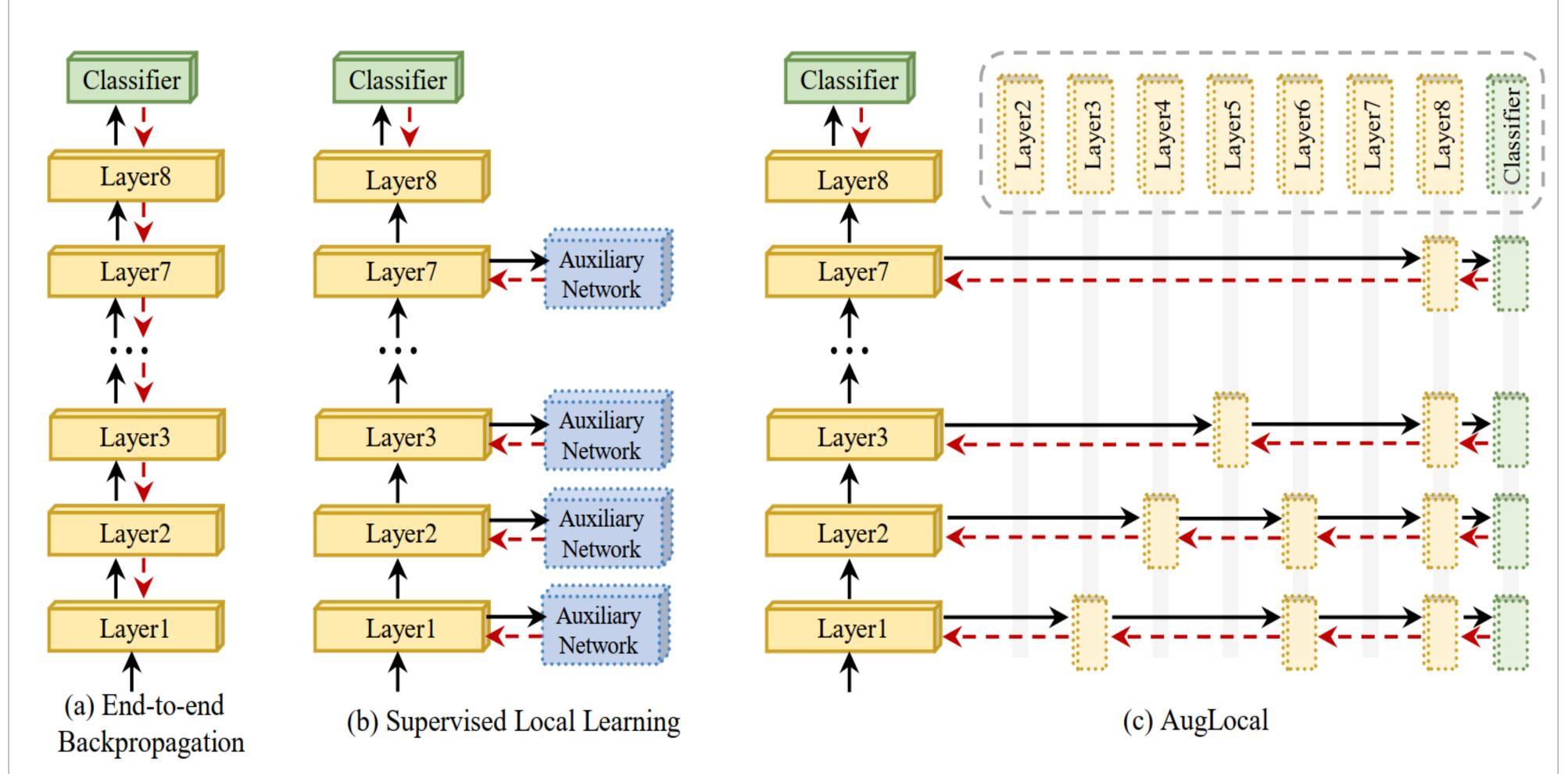
# ICLR

### Background & Motivation

- Backpropagation (BP)
- Biological implausibility
- Update locking
- > Huge memory requirement
- Local learning:
- Independent training of each layer
- Addressing of all the above issues of BP
- > Lower accuracy compared to BP
- Short-sightedness problem: Hidden layers learn representations for their local targets rather than benefiting subsequent layers
- Comparison of local learning rules and BP on CIFAR-10. ResNet32, with 16 local layers, is used here.



#### Method



- To strengthen the synergy between local layers and their subsequent layers, we propose an augmented local learning rule, namely AugLocal, which builds each local layer's auxiliary network using a uniformly sampled small subset of its subsequent layers.
- To reduce the additional computational cost of auxiliary networks, we propose a pyramidal structure that linearly decreases the depth of auxiliary networks as the local layer approaches the output.

#### Results

#### > Results on image classification datasets

Network	Method	CIFAR-10	SVHN	STL-10
	BP	$93.73 \pm 0.04$	$97.01 \pm 0.03$	$80.80 \pm 0.17$
	PredSim (Nøkland & Eidnes, 2019)	$79.29 \pm 0.37$	$92.02\pm0.35$	$70.67 \pm 0.39$
	InfoPro (Wang et al., 2021)	$87.26 \pm 0.16$	$93.30 \pm 0.73$	$70.85 \pm 0.14$
ResNet-32	DGL (Belilovsky et al., 2020)	$86.30 \pm 0.12$	$95.14 \pm 0.09$	$73.13 \pm 1.08$
	AugLocal (d = 2)	$91.12 \pm 0.24$	$95.86 \pm 0.04$	$78.58 \pm 0.66$
(L=16)	AugLocal (d = 3)	$92.26 \pm 0.20$	$96.43 \pm 0.02$	$79.79 \pm 0.27$
	AugLocal (d = 4)	$93.08 \pm 0.10$	$96.79 \pm 0.08$	$80.65 \pm 0.16$
	AugLocal $(d=5)$	$93.38 \pm 0.11$	$96.87 \pm 0.03$	$80.73 \pm 0.18$
	AugLocal (d = 6)	$93.47 \pm 0.09$	$96.85 \pm 0.08$	$80.95 \pm 0.55$
	BP	$94.61 \pm 0.18$	97.10±0.05	$80.41 \pm 0.74$
	PredSim (Nøkland & Eidnes, 2019)	$74.95 \pm 0.36$	$89.90\pm0.76$	$68.91 \pm 0.48$
	InfoPro (Wang et al., 2021)	$86.95 \pm 0.46$	$92.26 \pm 0.59$	$70.61 \pm 0.50$
ResNet-110	DGL (Belilovsky et al., 2020)	$85.69 \pm 0.32$	$95.12 \pm 0.06$	$72.27 \pm 0.51$
	AugLocal (d = 2)	$90.98 \pm 0.05$	$95.92 \pm 0.10$	$78.29 \pm 0.37$
(L=55)	AugLocal (d = 3)	$92.62 \pm 0.22$	$96.45 \pm 0.08$	$79.30 \pm 0.26$
	AugLocal (d = 4)	$93.22 \pm 0.17$	$96.74 \pm 0.11$	$80.77 \pm 0.33$
	AugLocal $(d=5)$	$93.75 \pm 0.20$	$96.85 \pm 0.05$	$80.20 \pm 0.56$
	AugLocal ( $d = 6$ )	93.96±0.15	$96.96 \pm 0.01$	$80.40 \pm 0.17$

#### > Results on ImageNet > GPU Memory Efficiency

	Network	Method	Top-1 Acc.	Top-5 Acc.
	VGG13	BP	71.59	90.37
-		DGL	67.32	87.81
	(L=10)	AugLocal	70.92	90.13
	ResNet-34	BP	74.28	91.76
	(L = 17)	AugLocal	73.95	91.70
	ResNet-101	BP	77.34	93.71
	(L = 34)	AugLocal	76.70	93.29

ResNet-32 BP 3.15 $(L = 16) \text{ AugLocal } 1.67 (\downarrow \textbf{47.0\%})$ CIFAR-10 $ResNet-110 \\ (L = 55) \\ GC \\ 3.03 (\downarrow 67.3\%)$	Dataset	Network	Method	GPU Memory (GB)
CIFAR-10 BP 9.27 ResNet-110 BP 2.22 (1.27.20%)		ResNet-32	BP	3.15
ResNet-110 BP 9.27	<b>-</b> 10:	(L=16)	AugLocal	1.67 (\psi 47.0%)
		ResNet-110	BP	9.27
				$3.03 (\downarrow 67.3\%)$
$(L = 55) \begin{array}{ccc} & GC & 3.03 (\downarrow 67.3\%) \\ & \text{AugLocal} & 1.72 (\downarrow \textbf{81.5\%}) \end{array}$			AugLocal	1.72 ( <b>\ 81.5</b> %)
ResNet-34 BP 42.95		ResNet-34	BP	42.95
ImageNet $(L = 17)$ AugLocal 29.04 ( $\downarrow$ <b>32.4%</b> )	nageNet.	(L=17)	AugLocal	29.04 ( <b>\ 32.4%</b> )
ResNet-101 BP 157.12		ResNet-101	BP	157.12
$(L = 34)$ AugLocal 97.65 ( $\downarrow$ <b>37.9%</b> )		(L=34)	AugLocal	97.65 ( <b>\ 37.9</b> %)

#### Representation Similarity Analysis

