Backprop with Approximate Activations for Memory-efficient Network Training

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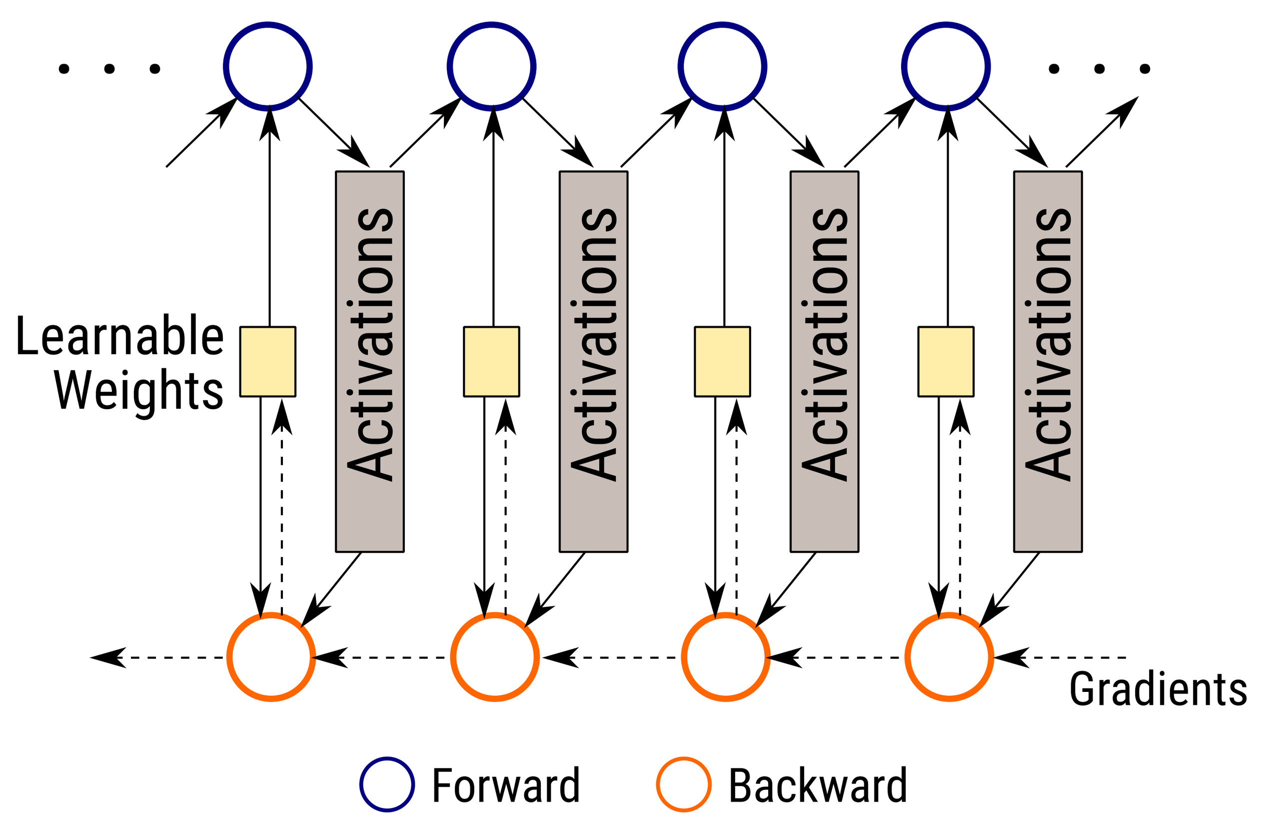
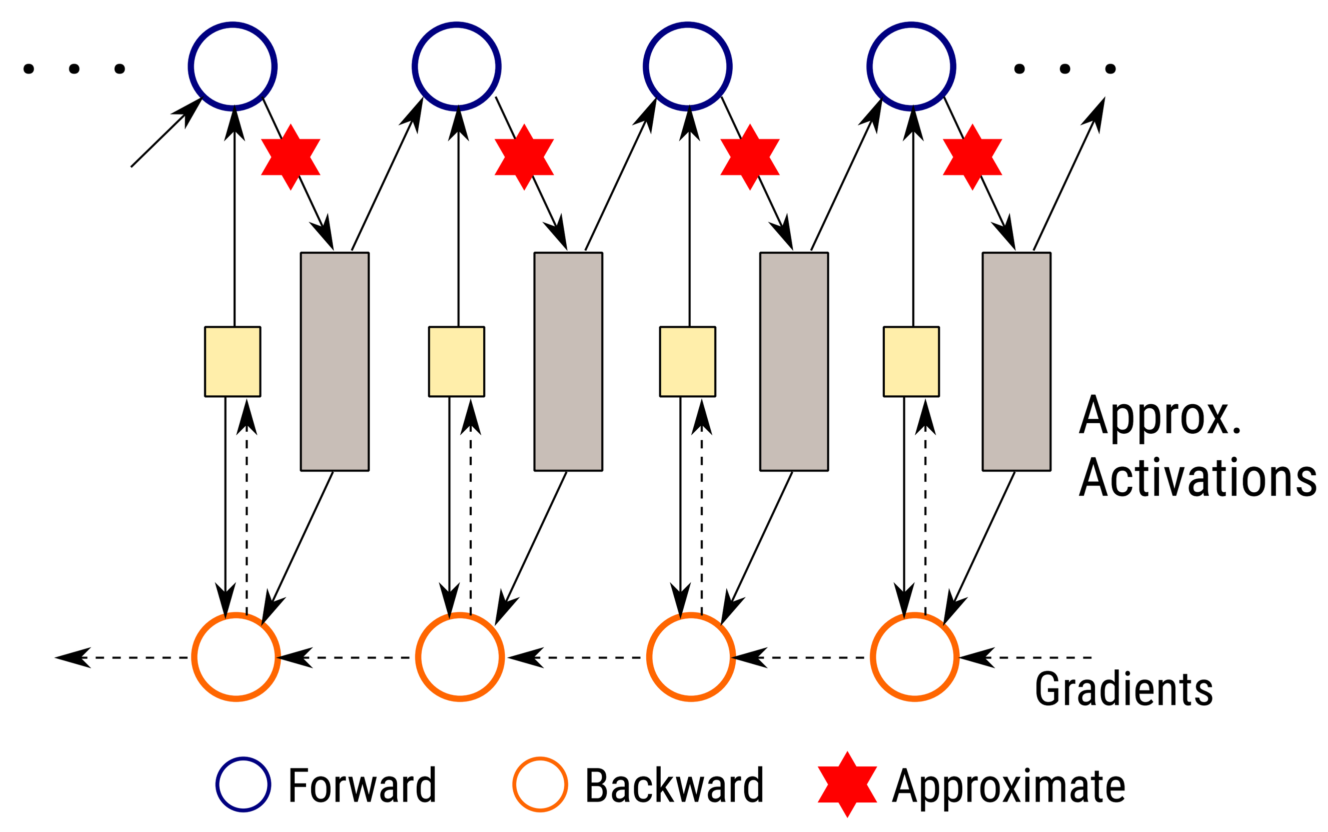
https://projects.ayanc.org/blpa

Standard Backprop



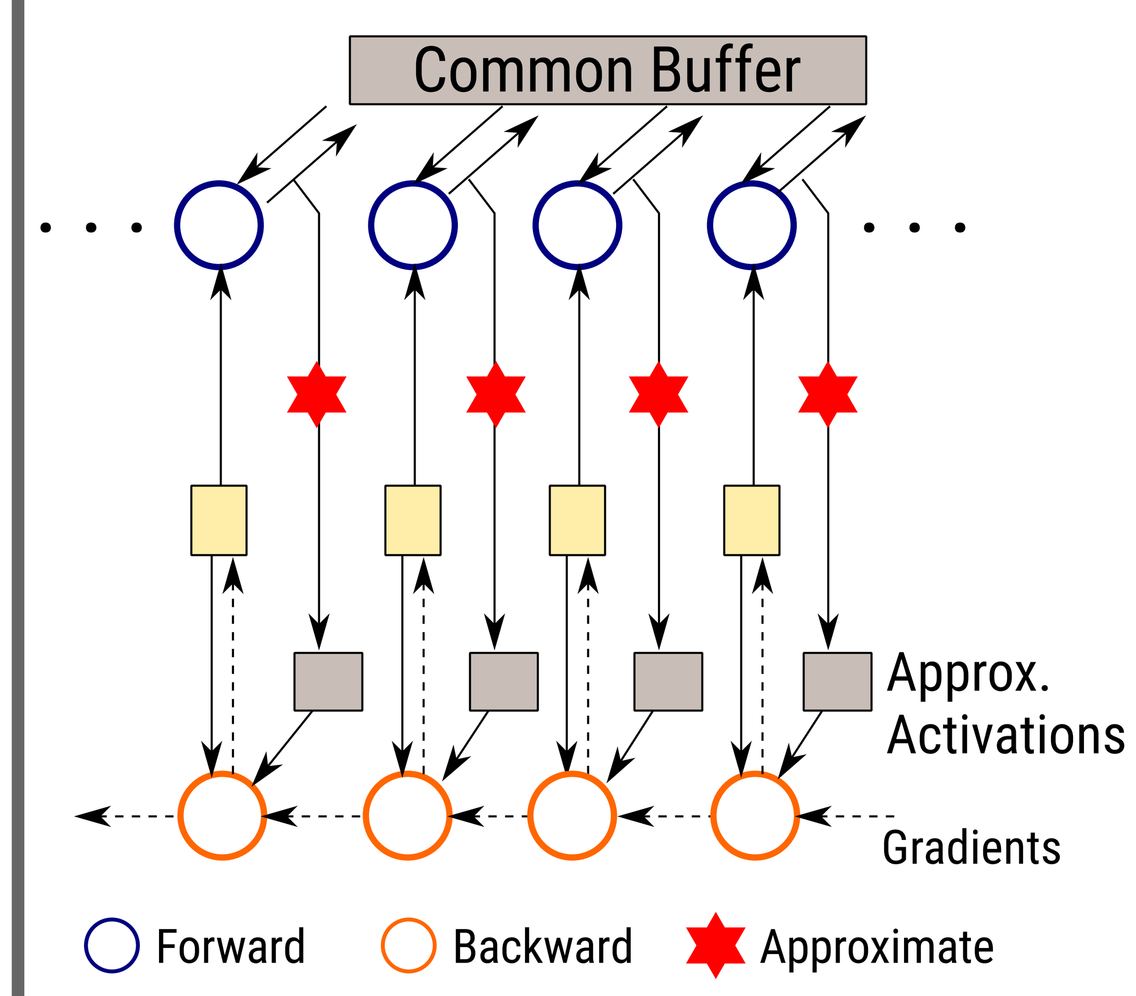
- Need to store all intermediate activations in device memory.
- Compute becomes memory bound !
  - Limits batch size per device.
  - Underutilizes available cores on GPUs / TPUs.

Direct Approximation



- Approximating / quantizating activations can save memory.
  [Gupta et al., 2015], [Micikevicius et al., 2017], [Banner et al., 2018].
- But when we do this *within* every layer to approximate outputs:
  Approximation error compounds across layers.

Proposed Method

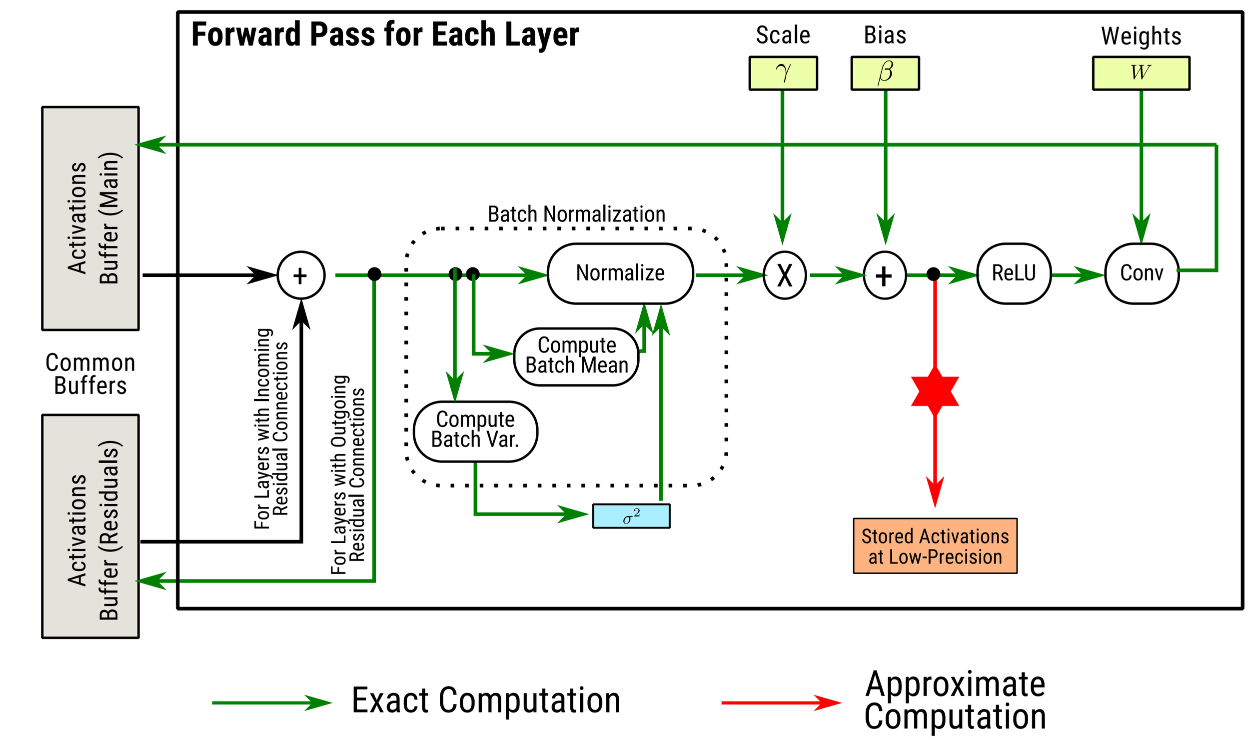


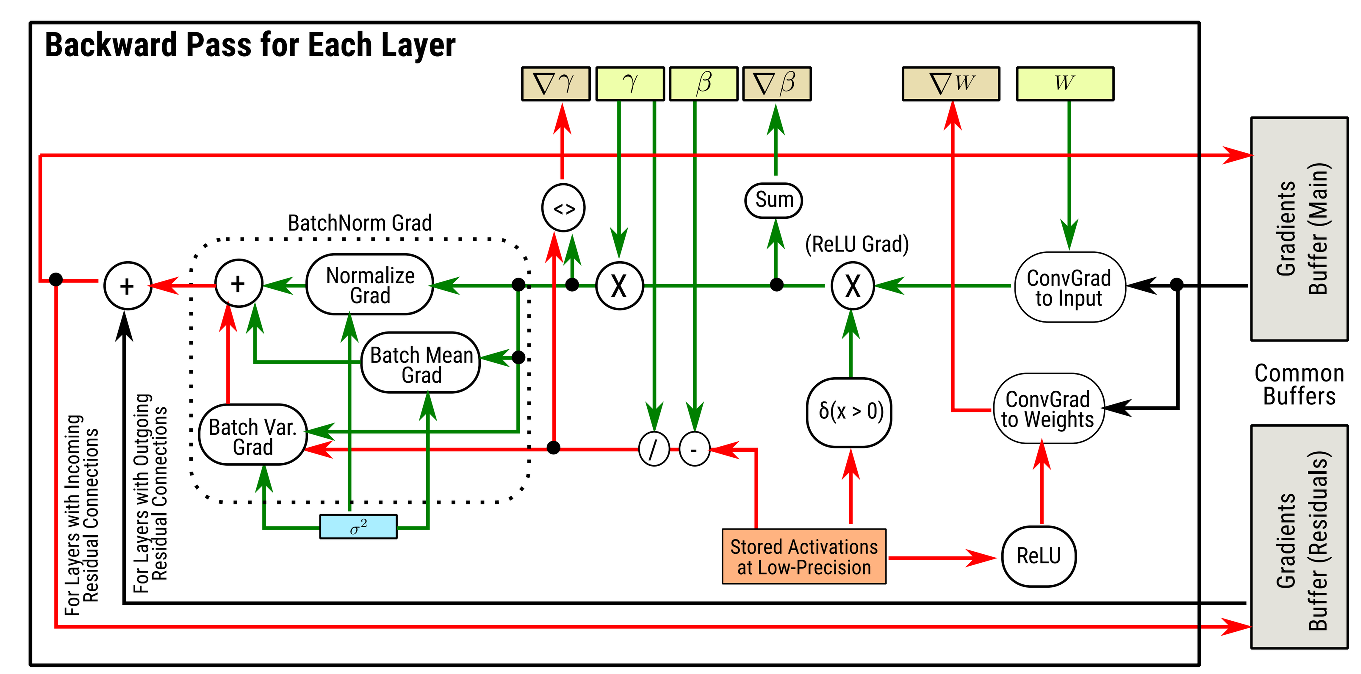
Discard exact activations *after* use in forward, store approximate versions for use in backward.

- Forward pass happens at full precision,
  no approximation errors in forward pass !
- Discard exact activations after use,
  saving memory !
- Use approximate activations to compute gradients:
  For ReLU layers & sign-preserving approximation:
  minimal error compounding in backward pass !

Allows for much higher approximation rate, and thus much more memory savings !

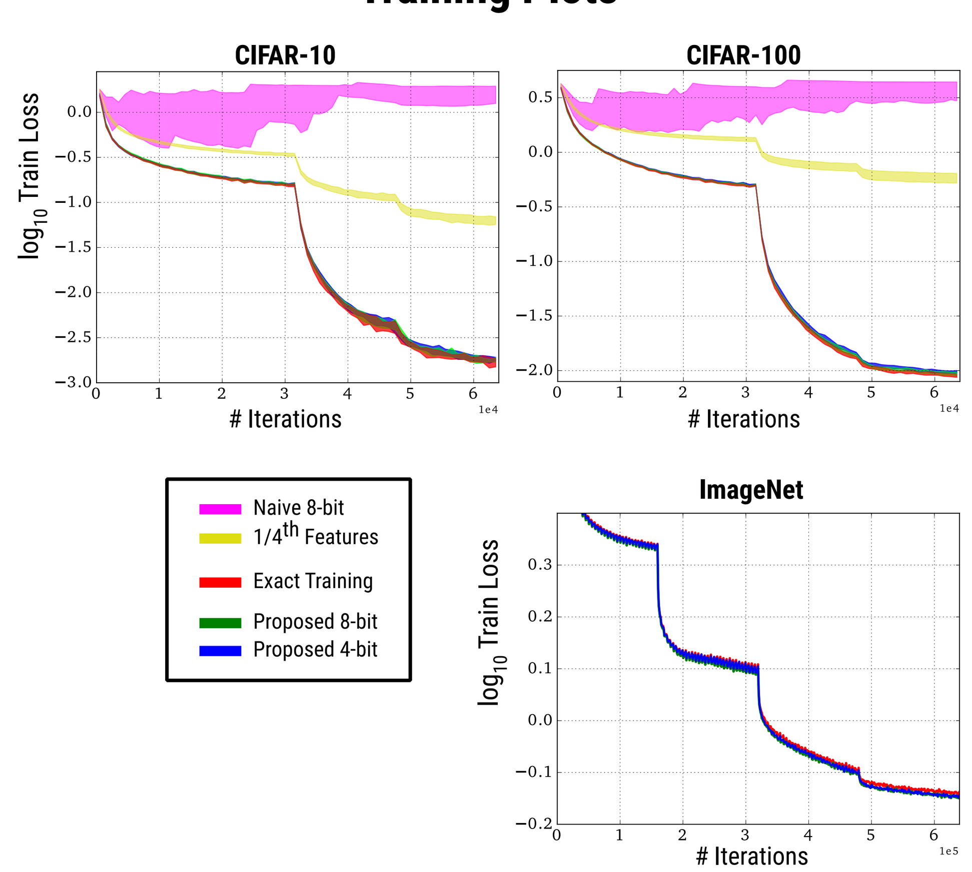
32-bit Float ⇨ 8 or 4-bit fixed point
≈ 4x - 8x less memory





Results

Training Plots



Accuracy of Trained Models

(α = approximation/memory-savings rate)

		CIFAR-10 Test Set Error	*CIFAR-100* Test Set Error	*ImageNet* Val Set Top-5 Error
Exact	$(\alpha = 1)$	5.36%±0.15	23.44%±0.26	7.20%
Exact w/ fewer features	$(\alpha = 1/4)$	9.49%±0.12	33.47%±0.50	-
Naive 8-bit Approx.	$(\alpha = 1/4)$	75.49%±9.09	95.41%±2.16	-
Proposed Method				
8-bit	$(\alpha = 1/4)$	5.48%±0.13	23.63%±0.32	7.70%
4-bit	$(\alpha = 1/8)$	5.49%±0.16	23.58%±0.30	7.72%

Maximum Batch-size & Run-time per Sample

# Layers		1001 (4x)	1001	488	254	164
Maximum Batch-size	Exact	26	134	264	474	688
	4-bit	**182**	**876**	**1468**	**2154**	**2522**
Run-time per Sample	Exact	130.8 ms	31.3 ms	13.3 ms	**6.5 ms**	**4.1 ms**
	4-bit	**101.6 ms**	**26.0 ms**	**12.7 ms**	6.7 ms	4.3 ms

Gradient Errors