Online Normalization for Training Neural Networks

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Motivation and Background

- Normalization accelerates learning
- Normalization transforms a neural network from a function to a statistical operator that depends on its input distribution.
- Batches are commonly used to approximate the input distribution[1]
- We propose an online process that eliminates batches to:
  - Decrease memory usage
  - Compute unbiased gradients
  - Provide training/inference symmetry
- Online Norm is compatible with automatic differentiation, so it can be integrated into any deep learning framework.

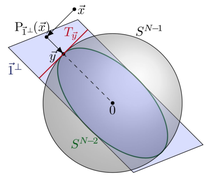
Network	Online Norm	Batch Norm 32	Batch Norm 128
ResNet-50, ImageNet, theory	1	2	4
ResNet-50, ImageNet, measured[a]	2	5	15
3D U-Net, $150 \times 150 \times 150$ voxels, theory	1	29	115
3D U-Net, $250 \times 250 \times 250$ voxels, theory	6	195	785
2D U-Net, 1024×1024 pixels, theory	2	31	123
2D U-Net, 2048×2048 pixels, theory	5	137	546

[a] PyTorch implementation stores multiple copies of activations for improved performance.

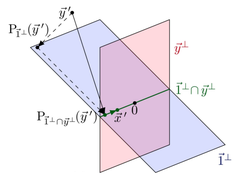
Principles of Normalization

- Normalization and its derivative are statistical operators
  - Notation: $(\cdot)' = \nabla_{(\cdot)} L$

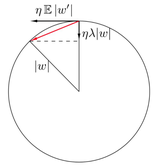
$$y = f_{\mathbb{X}}[x] \equiv (x - \mu[x])/\sigma[x] \quad \text{and} \quad x' = (\nabla_x f_{\mathbb{X}}[x])\, y', \quad x \sim \mathbb{X}$$



FWD: Projection and rescaling s.t. normalized output lies in the zero-centered unit sphere:
$\mu[y] = 0 \quad \text{and} \quad \mu[y^2] = 1$



BWD: Two projections [2] st. gradient satisfies the orthogonality conditions that follow from the backward eqs:
$\mu[x'] = 0 \quad \text{and} \quad \mu[x'y] = 0$



Normalized networks are invariant to gradient scale

Weight decay is required to prevent magnitude growth

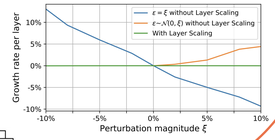
Online Normalization

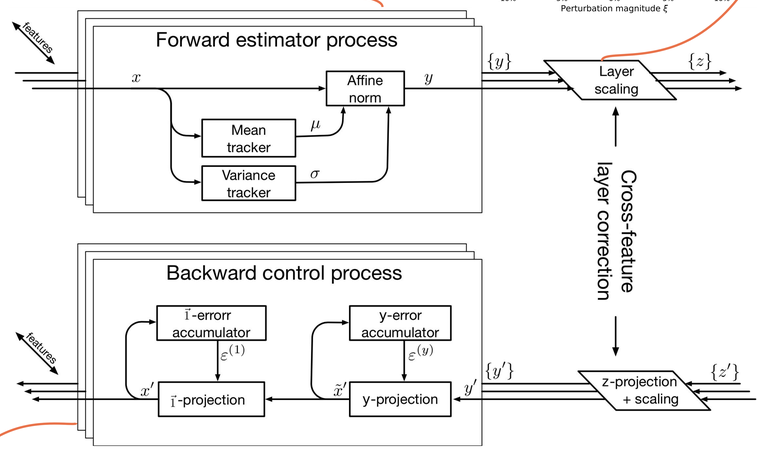
Forward Pass : Tracking process

- Exponential moving average
- Maintains mean zero, unit variance in expectation

Layer-wide correction

- Cross-Feature second moment correction
- Avoids exponential growth of activations





Backward Pass: Control Process

- Basic controller to enforce backward pass orthogonality constraints:
  $\langle x', 1 \rangle = 0 \quad \text{and} \quad \langle x', y \rangle = 0$
- Leads to uniformly bounded error in gradient calculation

Controller

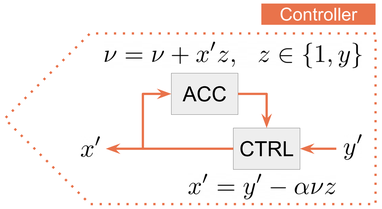
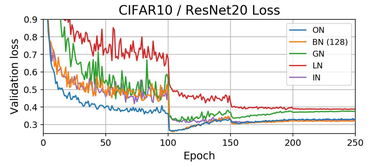
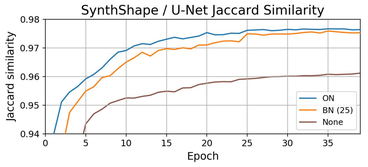
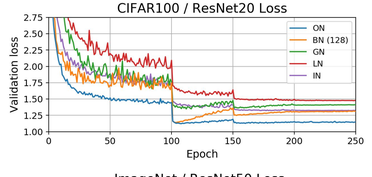
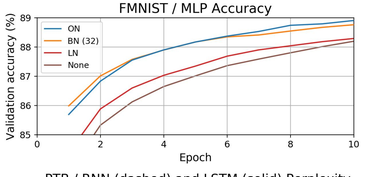


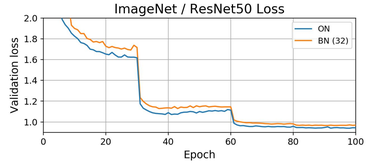
Image / Language / Generative Models

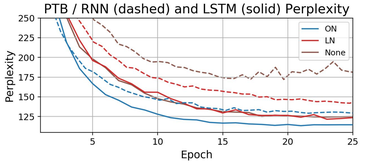








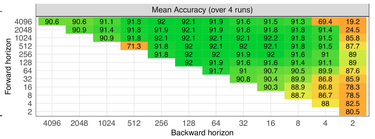




Normalizer	CIFAR-10 ResNet-20		CIFAR-100 ResNet-20		ImageNet ResNet-50	
Online	**0.26**	(**92.3%**)	**1.12**	(**68.6%**)	**0.94**	(76.3%)
Batch[a]	**0.26**	(92.2%)	1.14	(**68.6%**)	0.97	(**76.4%**)
Group	0.32	(90.3%)	1.35	(63.3%)		(75.9%)[b]
Instance	0.31	(90.4%)	1.32	(63.1%)		(71.6%)[b]
Layer	0.39	(87.4%)	1.47	(59.2%)		(74.7%)[b]
Weight Propagation	-		-			(67 %)[b] (71.9%)[b]

[a] Batch size 128 for CIFAR and 32 for ImageNet.
[b] Data from [3,4,5].

HyperParam Robustness



References

[1] Sergey Ioffe and Christian Szegedy. "Batch normalization: Accelerating deep network training by reducing internal covariate shift."
[2] Sergey Ioffe. "Batch renormalization: Towards reducing minibatch dependence in batch-normalized models."
[3] Yuxin Wu and Kaiming He. "Group normalization."
[4] Igor Gitman and Boris Ginsburg. "Comparison of batch normalization and weight normalization algorithms for the large-scale image classification."
[5] Wenling Shang, Justin Chiu, and Kihyuk Sohn. "Exploring normalization in deep residual networks with concatenated rectified linear units."