Wed Jun 12th 06:30 -- 09:00 PM Room Pacific Ballroom

Poster

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Differentiable Dynamic Normalization for Learning Deep Representation

Ping Luo*[1 2]

Zhanglin Peng*[3]

Wenqi Shao[2 3]

Ruimao Zhang[2 3]

Jiamin Ren[3]

Lingyun Wu[3]

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What is Dynamic Normalization (DN)?

1. DN adapts to various networks, tasks, and batch sizes.
2. DN can be easily implemented and trained in a **Differentiable** end-to-end manner with merely **small number of parameters**, by replacing the original normalizers.
3. DN has **matrix formulation**, representing a wide range of normalization methods (e.g. GroupNorm with any numbers of groups), shedding light on **analyzing them theoretically**.

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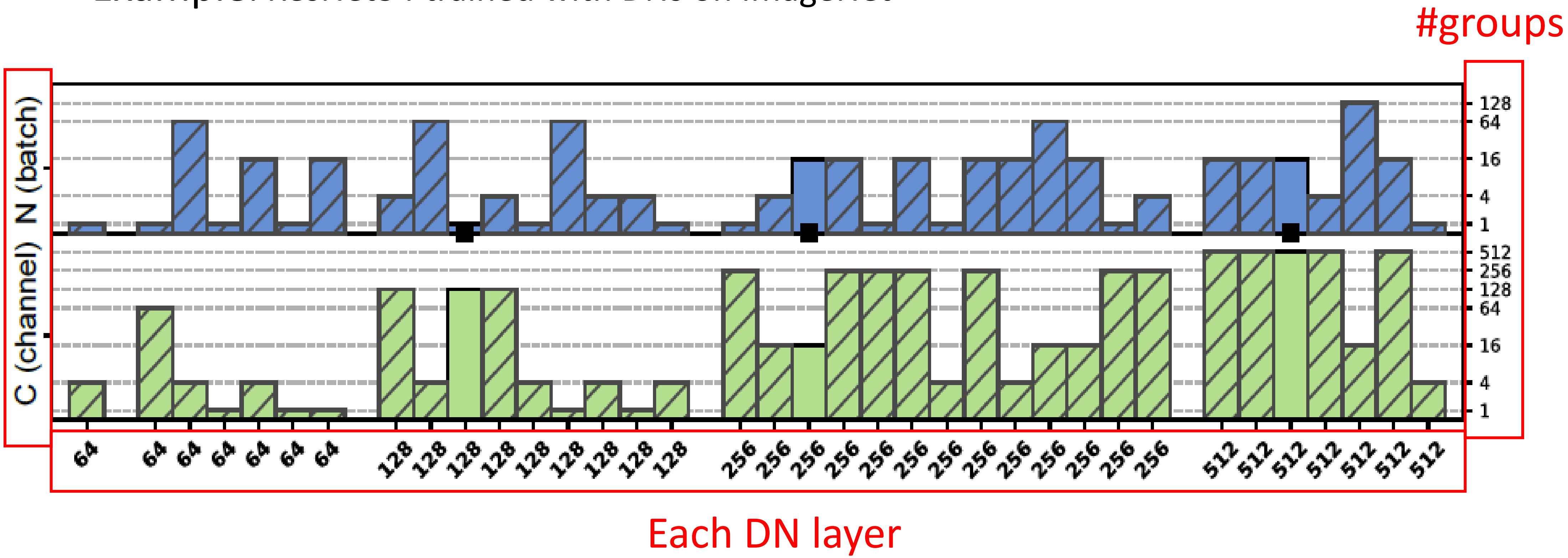
Dynamic Normalization (DN)

- Example: ResNet34 trained with DNs on ImageNet



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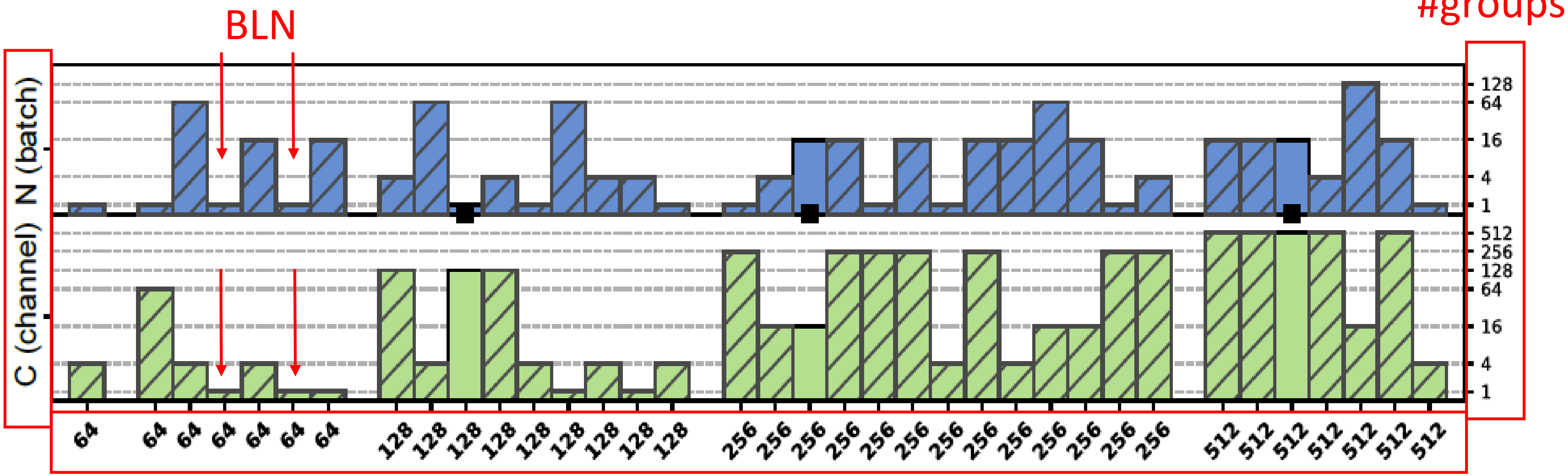

Each DN layer

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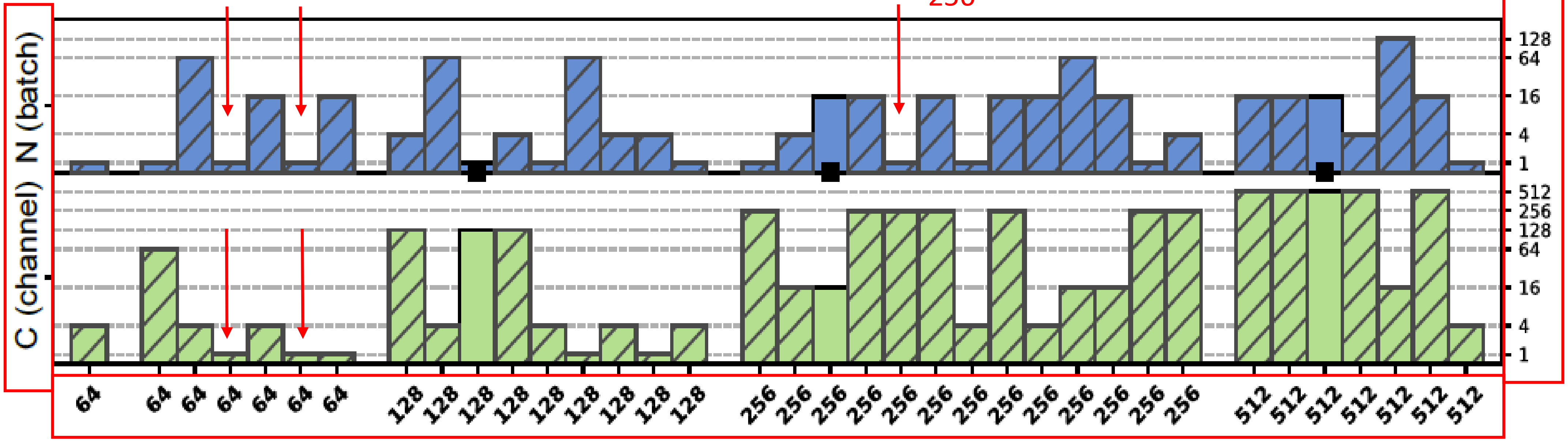

BLN

GN_{256}

#groups

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Dynamic Normalization (DN)

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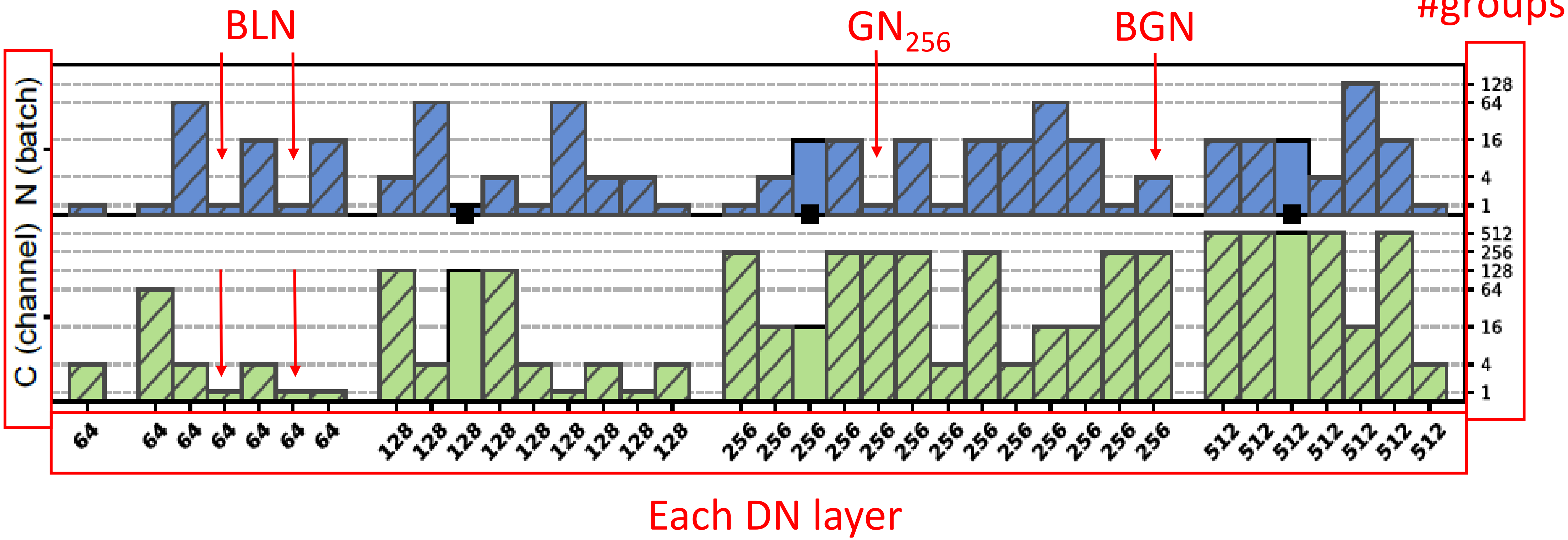

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A General Form *vs.* Switchable Normalization (SN)

A General Normalization Form

- Remove means and reduce by variance

normalized feature map

feature map

mean

$$\hat{h} = \frac{h - \mu^k}{\sqrt{(\sigma^k)^2 + \epsilon}}$$

standard deviation

Switchable Normalization: Discrete Learning-to-Normalize

- Learn a linear combination of Batch Norm, Instance Norm, Layer Norm and Group Norm

importance ratio, sum to 1

$$\hat{h} = \frac{h - \sum_{k \in \{\mathrm{BN}, \mathrm{IN}, \mathrm{LN}, \mathrm{GN}, \ldots\}} \lambda^k \mu^k}{\sqrt{\sum_{k \in \{\mathrm{BN}, \mathrm{IN}, \mathrm{LN}, \mathrm{GN}, \ldots\}} \lambda^k (\sigma^k)^2 + \epsilon}}$$

- **Problem: enumerate a large pool of candidate normalizers**

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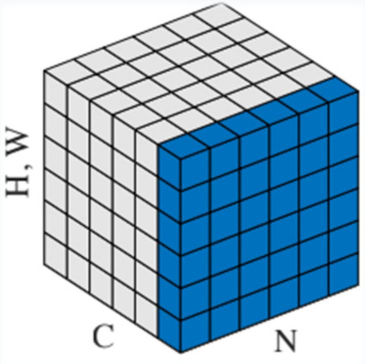
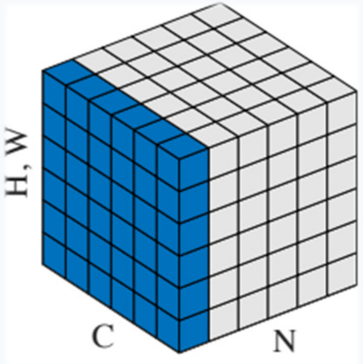
Dynamic Normalization (DN): Continuous Learning-to-Normalize



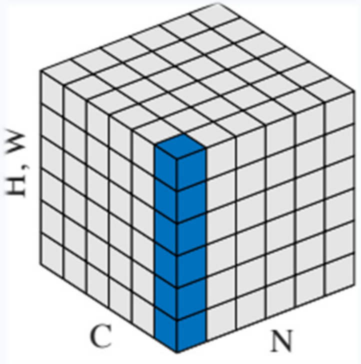
average pixels: {H,W,N}

(a) Batch Norm (BN)



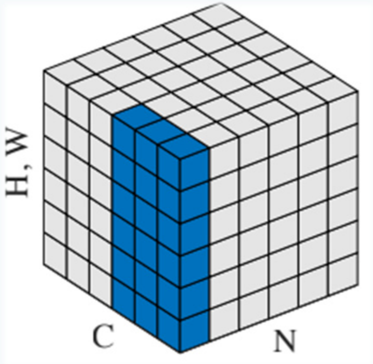
{H,W,C}

(b) Layer Norm (LN)



{H,W}

(c) Instance Norm (IN)



{H,W,C/2}

(d) Group Norm (GN)

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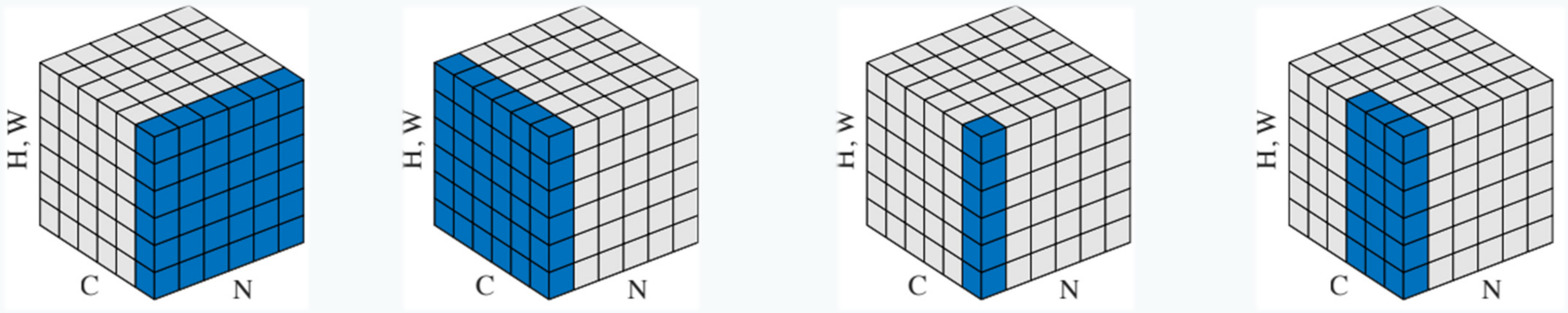
Dynamic Normalization (DN): Continuous Learning-to-Normalize



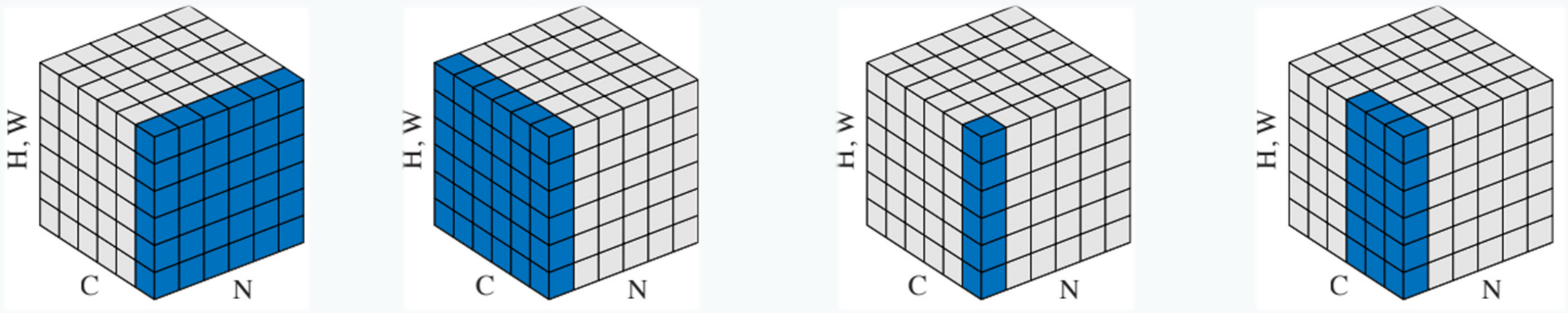
average pixels: {H,W,N} {H,W,C} {H,W} {H,W,C/2}

(a) Batch Norm (BN) **(b) Layer Norm (LN)** **(c) Instance Norm (IN)** **(d) Group Norm (GN)**

Dynamic Normalization: $$\hat{\boldsymbol{h}} = \gamma \frac{\boldsymbol{h} - \boldsymbol{U}\boldsymbol{\mu}\boldsymbol{V}}{\boldsymbol{U}\boldsymbol{\sigma}\boldsymbol{V}} + \beta$$

- $\boldsymbol{U} \in \mathbb{R}^{N\times N}, \boldsymbol{V} \in \mathbb{R}^{C\times C}$: two binary diagonal-block matrices
- $\boldsymbol{\mu}, \boldsymbol{\sigma} \in \mathbb{R}^{N\times C}$: means and stds of Instance Normalization (IN), implying that we learn to combine statistics of IN

Dynamic Normalization (DN): Continuous Learning-to-Normalize



average pixels: {H,W,N} {H,W,C} {H,W} {H,W,C/2}

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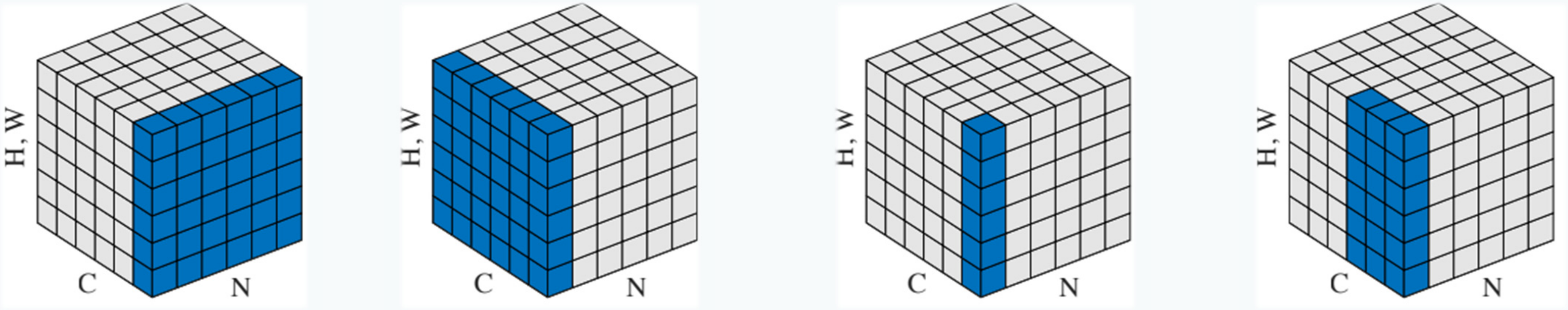

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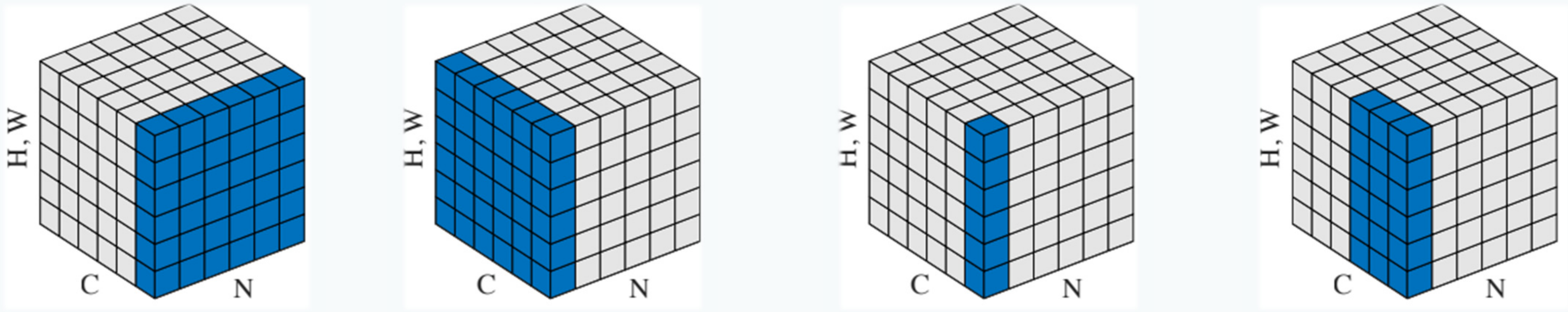
Dynamic Normalization (DN): Continuous Learning-to-Normalize

$\boldsymbol{U}=\mathbf{1}, \boldsymbol{V}=\boldsymbol{I}$ $\quad$ $\boldsymbol{U}=\boldsymbol{I}, \boldsymbol{V}=\mathbf{1}$ $\quad$ $\boldsymbol{U}=\boldsymbol{I}, \boldsymbol{V}=\boldsymbol{I}$ $\quad$ $\boldsymbol{U}=\boldsymbol{I}, \boldsymbol{V}$ is block-diagonal



$$\begin{bmatrix} 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \end{bmatrix}$$

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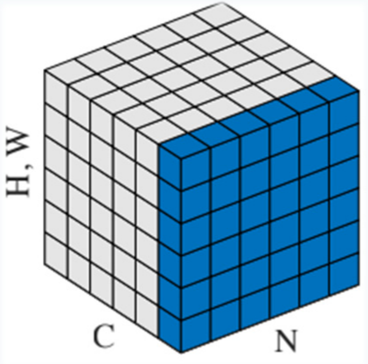

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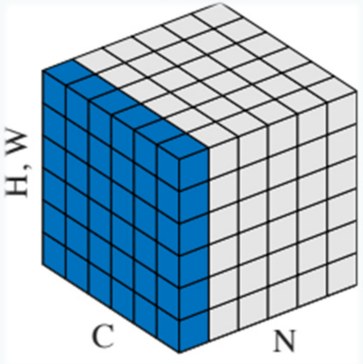
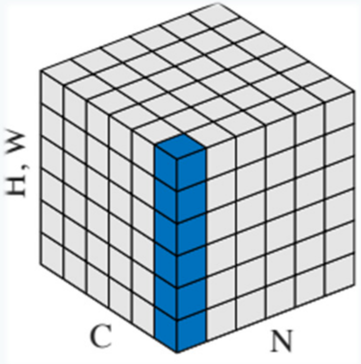


{H,W,C}

(b) Layer Norm (LN)

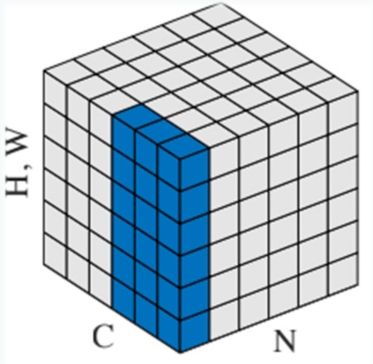
$\boldsymbol{U} = \boldsymbol{I}, \boldsymbol{V} = \boldsymbol{I}$



{H,W}

(c) Instance Norm (IN)

$\boldsymbol{U} = \boldsymbol{I}, \boldsymbol{V}$ is block-diagonal



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{H,W,C/2}

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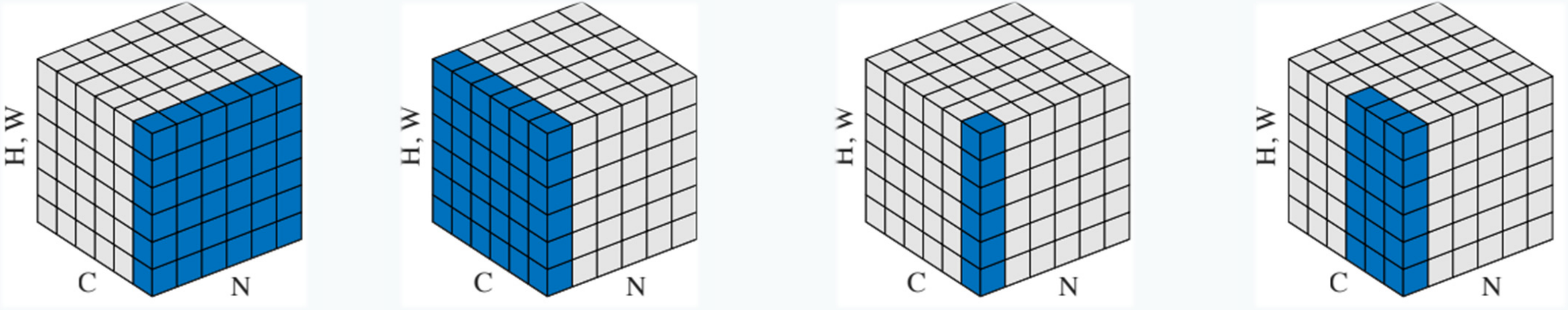

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average pixels: {H,W,N} {H,W,C} {H,W} {H,W,C/2}

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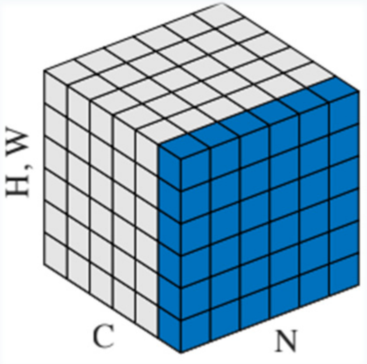

average pixels: {H,W,N}

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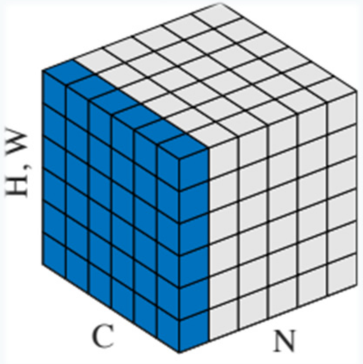
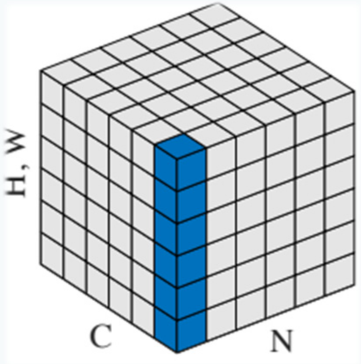


{H,W,C}

(b) Layer Norm (LN)

$\boldsymbol{U} = \boldsymbol{I}, \boldsymbol{V} = \boldsymbol{I}$



{H,W}

(c) Instance Norm (IN)

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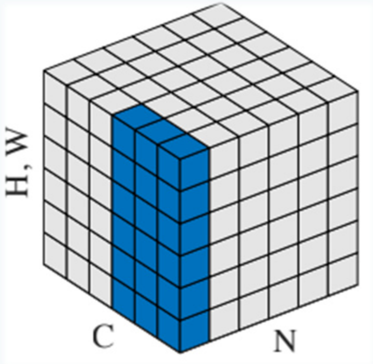

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{H,W,C/2}

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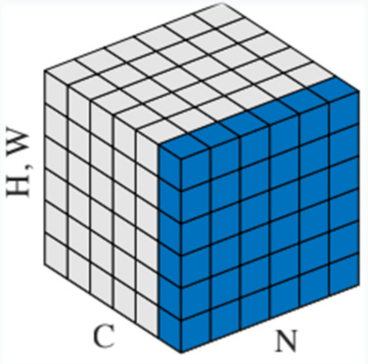

average pixels: {H,W,N}

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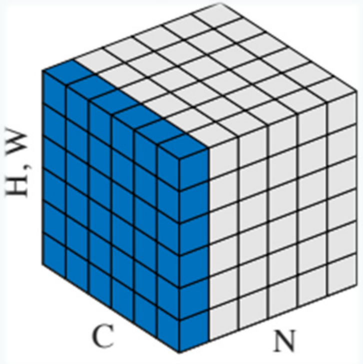

{H,W,C}

(b) Layer Norm (LN)

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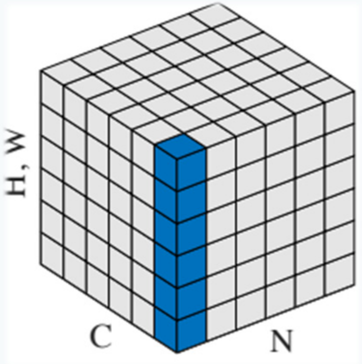

{H,W}

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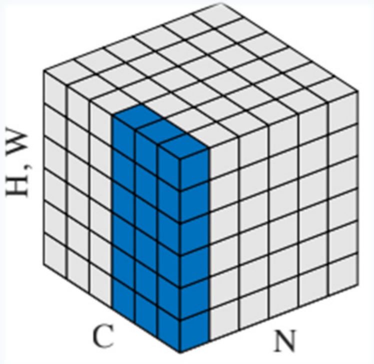

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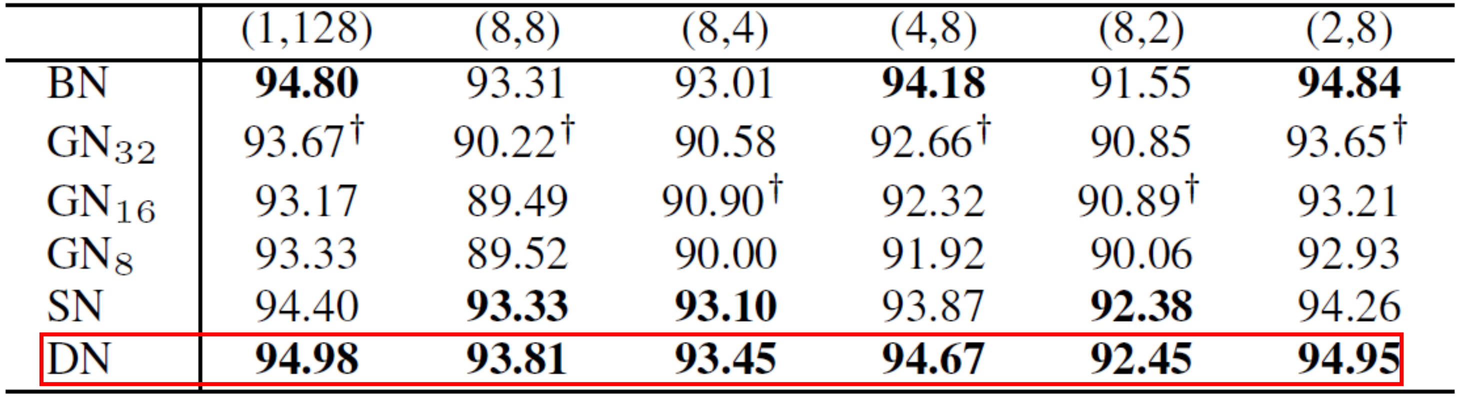
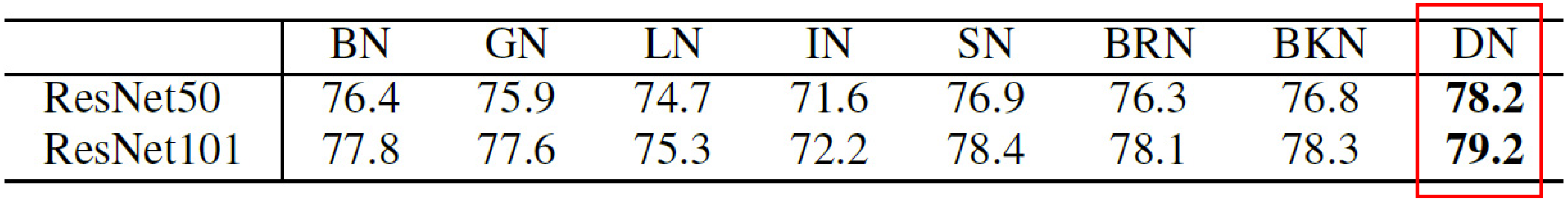
Experimental Results

- ResNet18 on CIFAR10



	(1,128)	(8,8)	(8,4)	(4,8)	(8,2)	(2,8)
BN	**94.80**	93.31	93.01	**94.18**	91.55	**94.84**
GN$_{32}$	93.67†	90.22†	90.58	92.66†	90.85	93.65†
GN$_{16}$	93.17	89.49	90.90†	92.32	90.89†	93.21
GN$_{8}$	93.33	89.52	90.00	91.92	90.06	92.93
SN	94.40	**93.33**	**93.10**	93.87	**92.38**	94.26
DN	**94.98**	**93.81**	**93.45**	**94.67**	**92.45**	**94.95**

- ImageNet



	BN	GN	LN	IN	SN	BRN	BKN	DN
ResNet50	76.4	75.9	74.7	71.6	76.9	76.3	76.8	**78.2**
ResNet101	77.8	77.6	75.3	72.2	78.4	78.1	78.3	**79.2**

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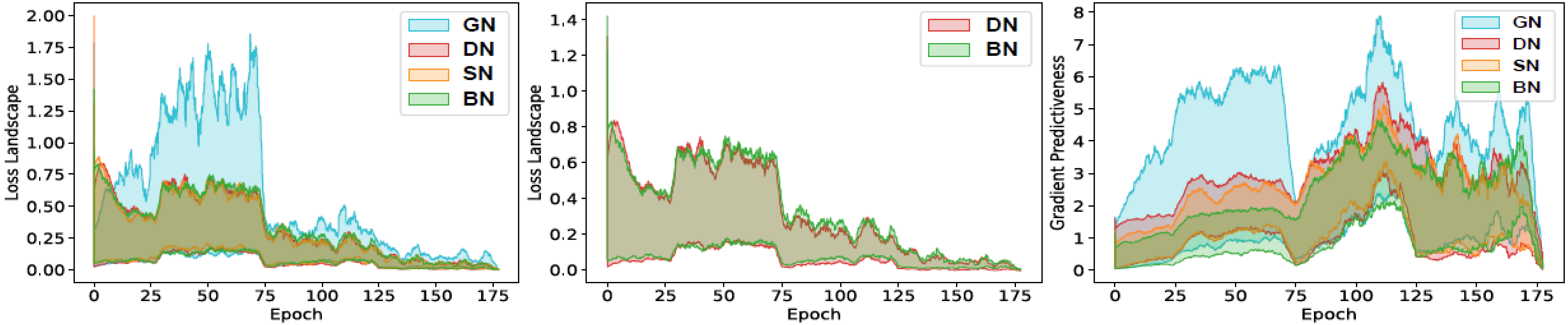
Comparisons of Loss Landscapes

- ResNet18 on CIFAR10



(a) variations of loss values

(b) variations of losses of DN *v.s.* BN

(c) variations of gradient values

$GN \gg DN \approx SN \approx BN$

$GN \gg DN > SN \approx BN$

Thank You

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Differentiable Dynamic Normalization for Learning Deep Representation

Wed Jun 12th 06:30 -- 09:00 PM Room Pacific Ballroom

Poster