

NLP Seminar

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# Batch Normalization & Layer Normalization

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2022. 04. 29

KISTI - UST **IKJE CHOI**



# CONTENTS

01

**Batch Normalization (ICS)**

02

**Batch Normalization (Smoothing)**

03

**Layer Normalization**

04

**Reference**

## Batch Normalization

- Title : Batch normalization: Accelerating deep network training by reducing internal covariate shift

- Google Scholar

**Batch normalization:** Accelerating deep network training by reducing internal covariate shift

[S Ioffe](#), [C Szegedy](#) - International conference on machine ..., 2015 - proceedings.mlr.press

Abstract Training Deep Neural Networks is complicated by the fact that the distribution of each layer's inputs changes during training, as the parameters of the previous layers ...

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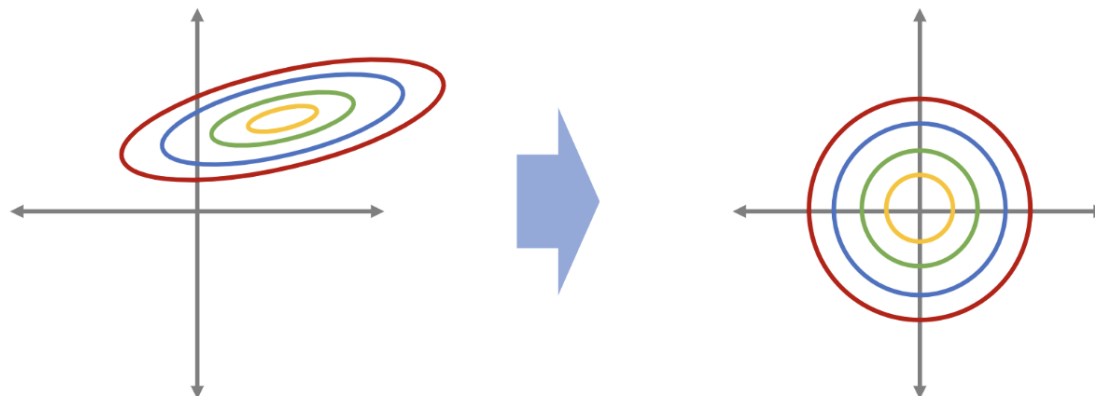
## Batch Normalization

### ➤ Batch

- ✓ Epoch : one pass over the full training set
- ✓ Batch : use all data to compute the gradient during one iteration.
- ✓ Mini-batch : take a subset of all data during one iteration.

### ➤ Normalization

- ✓ Gets rid of a variety of irregularities that can make it more difficult to interpret the data.



# Batch Normalization

What is the advantages of using Batch Normalization?

- Reducing Training Time
- Reducing significant changes in Weight Initialization
- Provide Regularization effect of the model

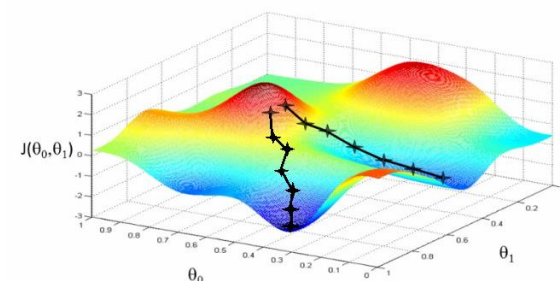
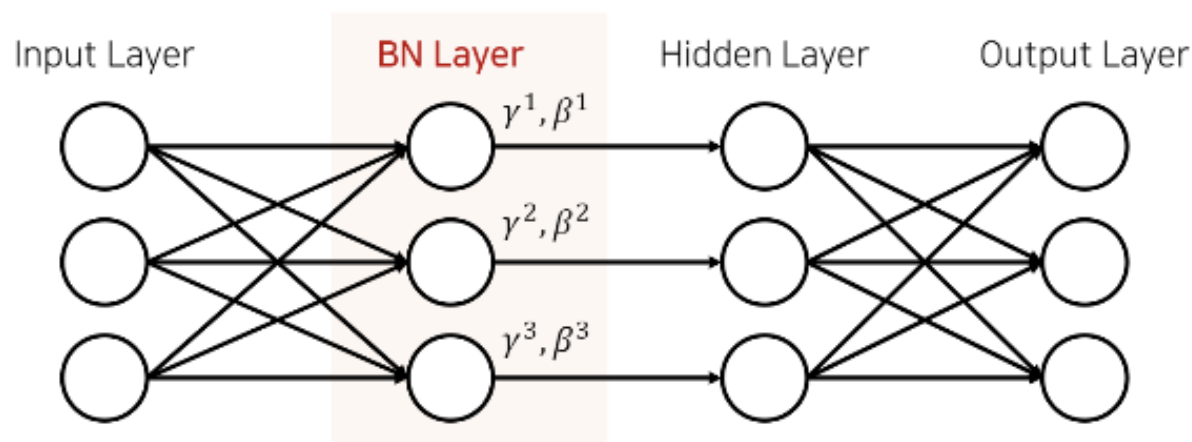
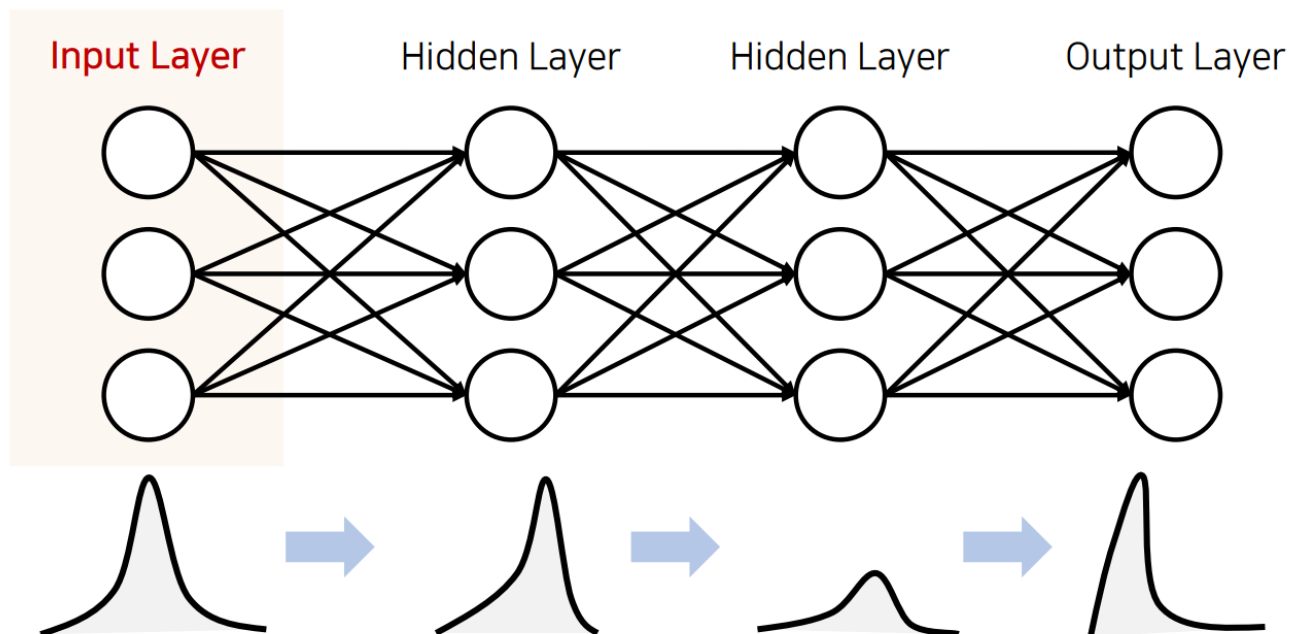


Image from DatumBox



## Motivation

- Scaling(Normalizing) data then it gives better accuracy and faster speed.
- If this is applied to hidden Layer then It might give same advantages.



## Normalization Equation

➤ Mean

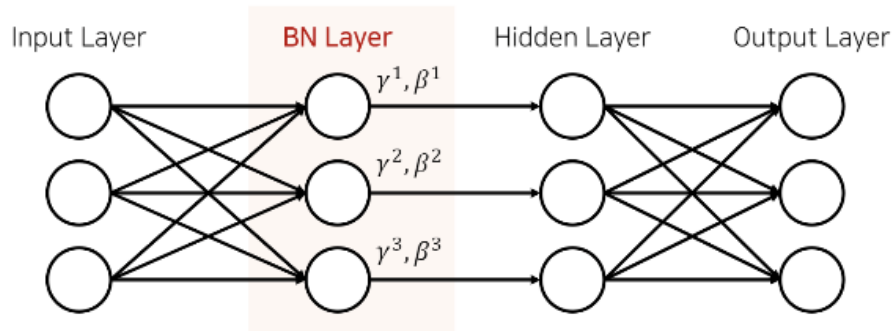
$$\mu_{Batch} \leftarrow \frac{1}{m} \sum_{i=1}^m x_i$$

➤ Variance

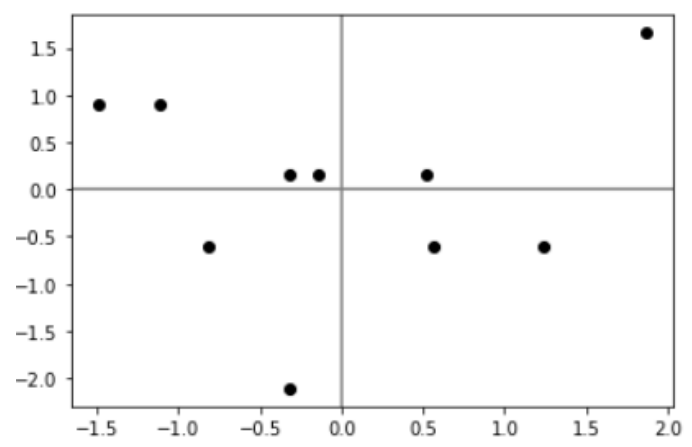
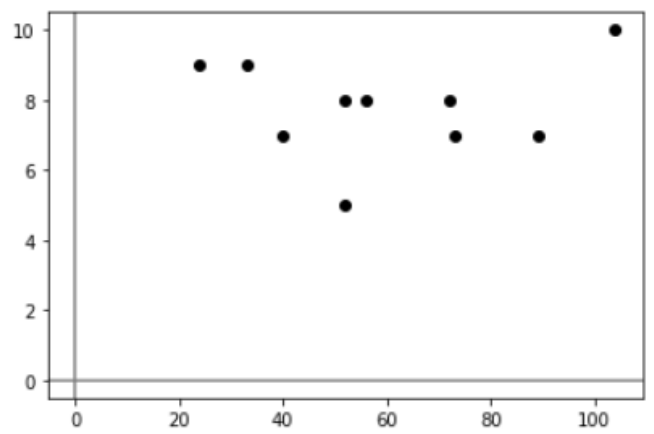
$$\sigma_{Batch}^2 \leftarrow \frac{1}{m} \sum_{i=1}^m (x_i - \mu_{Batch})^2$$

➤ Normalization

$$\hat{x}_i \leftarrow \frac{x_i - \mu_{Batch}}{\sqrt{\sigma_{Batch}^2 + \epsilon}}$$



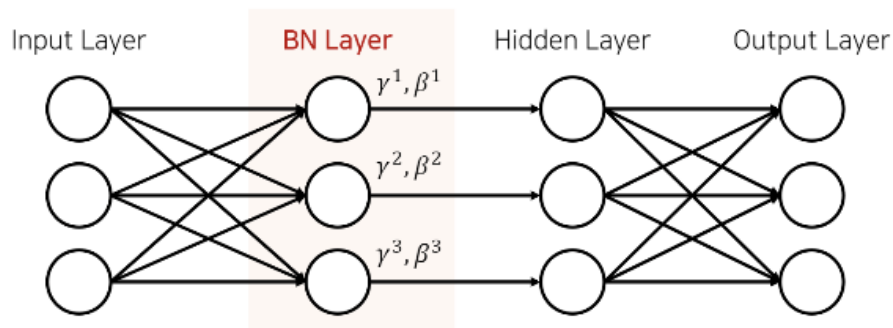
```
x1 = np.asarray([33, 72, 40, 104, 52, 56, 89, 24, 52, 73])
x2 = np.asarray([9, 8, 7, 10, 5, 8, 7, 9, 8, 7])
```



# Batch Normalization

## Batch Normalization

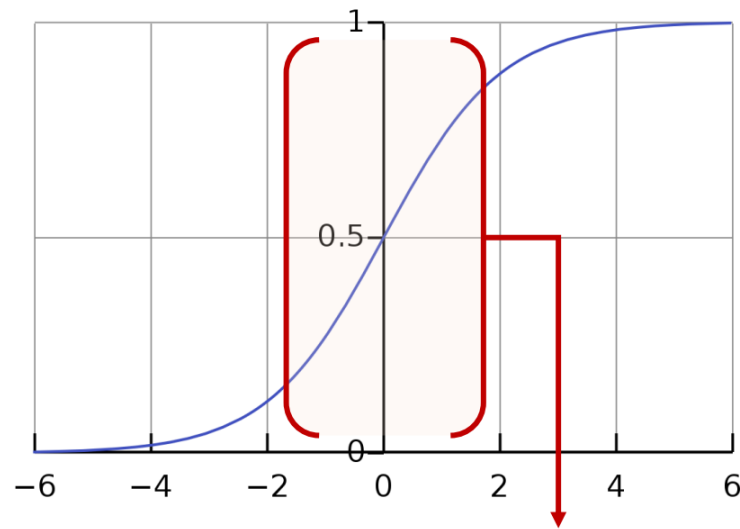
➤ Normalization  $\hat{x}_i \leftarrow \frac{x_i - \mu_{Batch}}{\sqrt{\sigma_{Batch}^2 + \epsilon}}$



Why two parameters ( $\gamma, \beta$ ) learning?

➤ Equation  $y_i \leftarrow \gamma \hat{x}_i + \beta \equiv BN_{\gamma, \beta}(x_i)$

- Loosing Non-linearity (example : Sigmoid)
- ✓ Linearity  $\rightarrow$  Non-linearity by learning ( $\gamma, \beta$ )



Almost Linear in Sigmoid



## Batch Normalization for Train

- Mean

$$\mu_{Batch} \leftarrow \frac{1}{m} \sum_{i=1}^m x_i$$

- Variance

$$\sigma_{Batch}^2 \leftarrow \frac{1}{m} \sum_{i=1}^m (x_i - \mu_{Batch})^2$$

- Normalization

$$\hat{x}_i \leftarrow \frac{x_i - \mu_{Batch}}{\sqrt{\sigma_{Batch}^2 + \epsilon}}$$

$$y_i \leftarrow \gamma \hat{x}_i + \beta \equiv BN_{\gamma, \beta}(x_i)$$

## Batch Normalization for Test

- No mini batch at test

- But we still need to apply BN at test

- Then How?

- Mean

$$E[x] \leftarrow E_{Batch}[\mu_{Batch}]$$

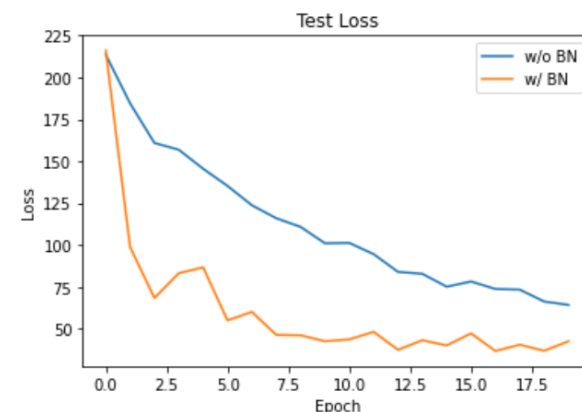
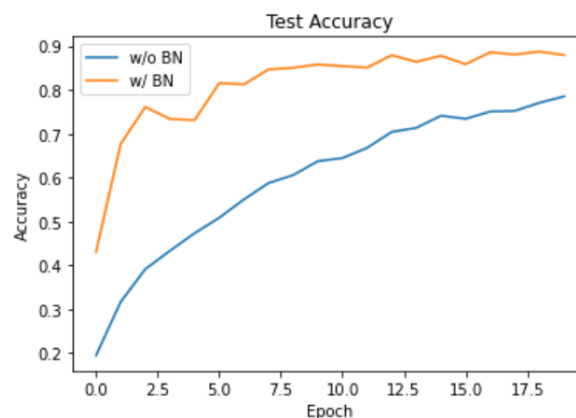
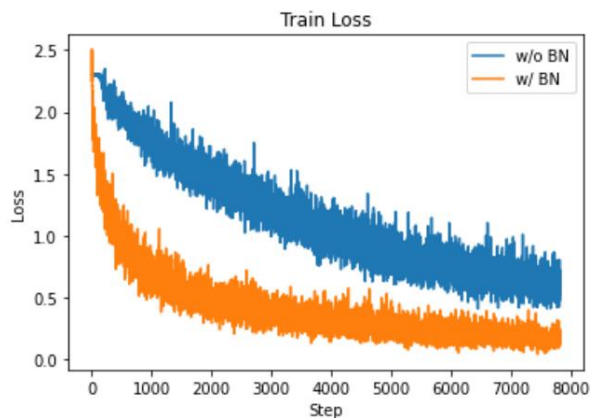
- Variance  $Var[x] \leftarrow \frac{m}{m-1} E_{Batch}[\sigma_{Batch}^2]$

$$y = BN_{\gamma, \beta}(x) \text{ with } y = \frac{\gamma}{\sqrt{Var[x] + \epsilon}} \cdot x + \left( \beta - \frac{\gamma E[x]}{\sqrt{Var[x] + \epsilon}} \right)$$

# Batch Normalization

What is the advantages of using Batch Normalization?

- Reducing Training Time (14 times)
- Reducing significant changes in Weight Initialization
- Provide Regularization effect of the model




## Batch Normalization

### ➤ Google Scholar

**Batch normalization:** Accelerating deep network training by reducing internal covariate shift

[S Ioffe](#), [C Szegedy](#) - International conference on machine ..., **2015** - proceedings.mlr.press

Abstract Training Deep Neural Networks is complicated by the fact that the distribution of each layer's inputs changes during training, as the parameters of the previous layers ...

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How does **batch normalization** help optimization?

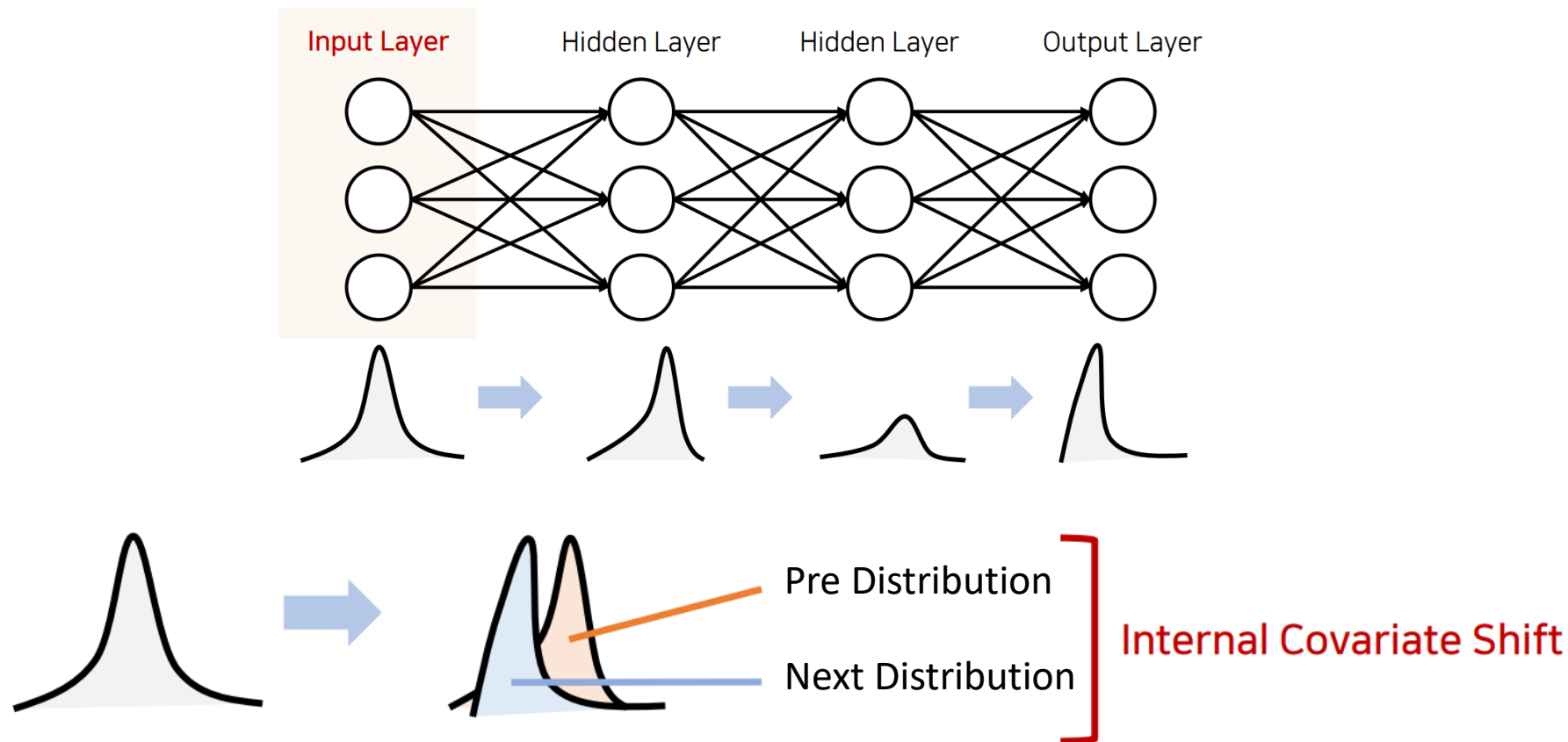
[S Santurkar](#), [D Tsipras](#), [A Ilyas](#)... - Advances in neural ..., **2018** - proceedings.neurips.cc

... We show that **batch normalization** causes this landscape to be more well-behaved, inducing favourable properties in Lipschitz-continuity, and predictability of the gradients. We then ...

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## Internal Covariate Shift

### ➤ Original Paper



## Batch Internal Covariate Shift

### ➤ Later Paper

How does **batch normalization** help optimization?

[S Santurkar](#), [D Tsipras](#), [A Ilyas](#)... - Advances in neural ..., 2018 - [proceedings.neurips.cc](#)

... We show that **batch normalization** causes this landscape to be more well-behaved, inducing favourable properties in Lipschitz-continuity, and predictability of the gradients. We then ...

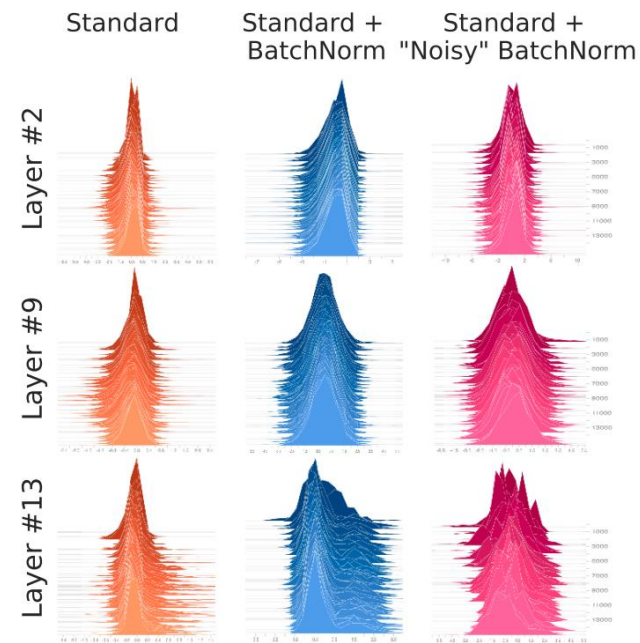
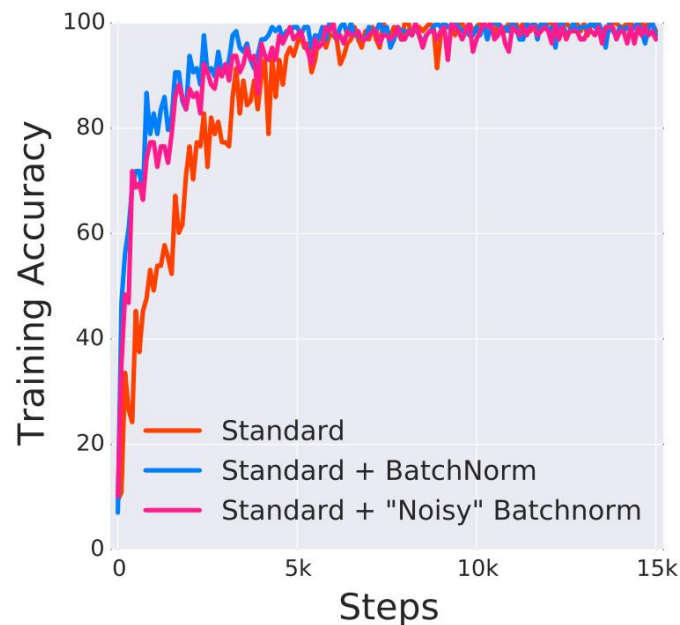
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### ➤ This paper agrees about all technical advantages of BN

### ➤ But it does not relate any to Internal Covariate Shift

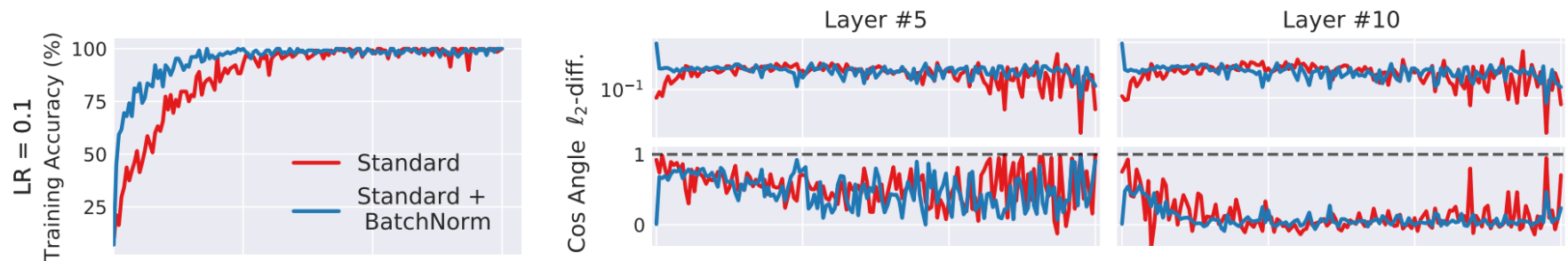
## Internal Covariate Shift

- Intentionally add noise and test accuracy -> increase internal covariate shift
- Still BN with noise is better than Standard



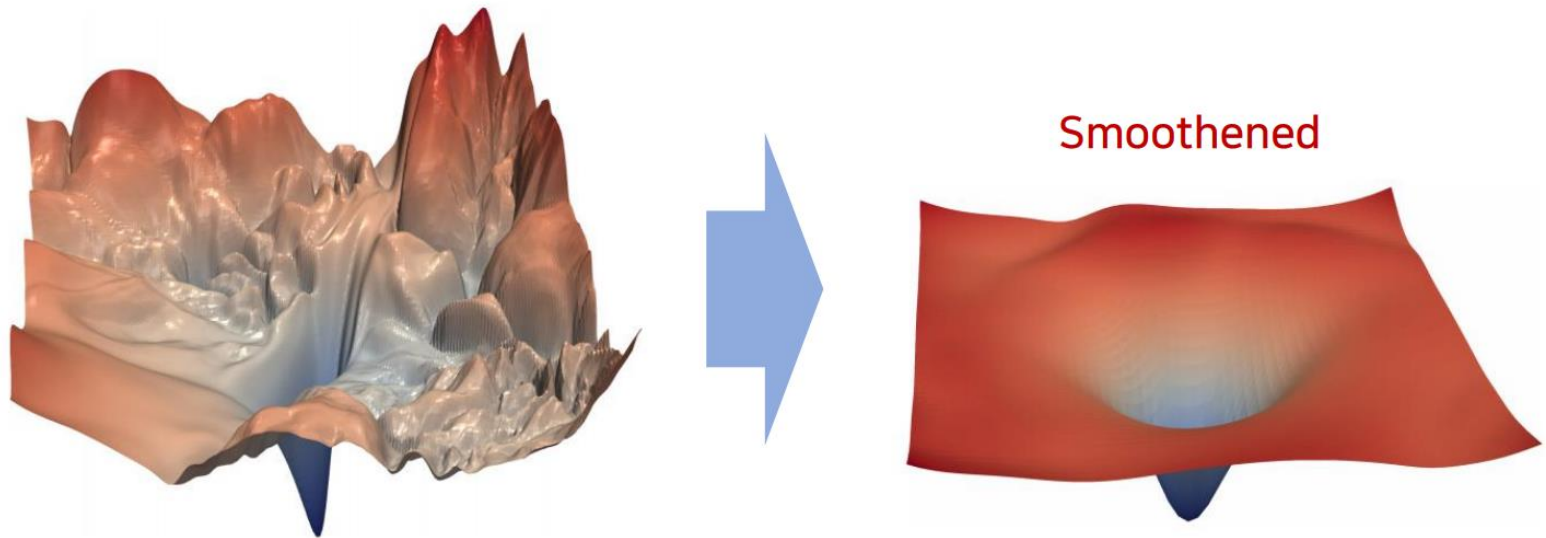
## Internal Covariate Shift calculation

- Every Weight update and calculate similarity
- Plot between with BN and without BN



## What is reason that BN works well?

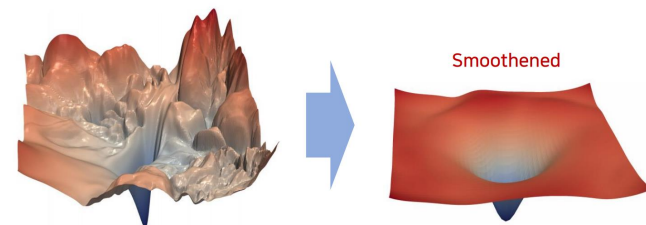
- Smoothing Effect!



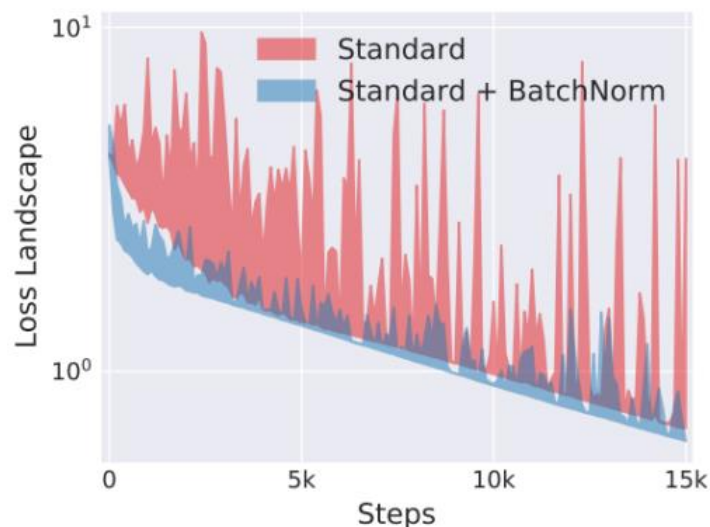


## Batch Internal Covariate Shift

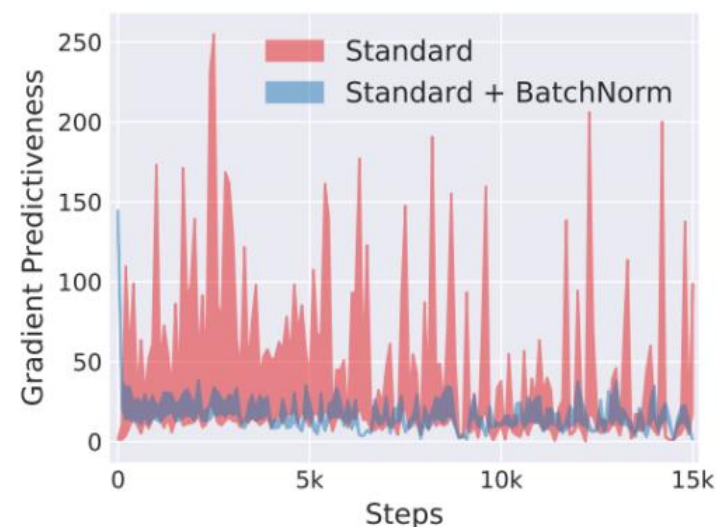
- Every Steps calculating Loss and Gradient
  - ✓ Big differences imply less reliable gradients
  - ✓ Large Fluctuation make optimization hard



### Variation in Loss ( $L(W)$ )



### Change in Gradient ( $\nabla_W L(W)$ )





## Layer Normalization

### ➤ Google Scholar

#### Layer normalization

[JL Ba](#), [JR Kiros](#), [GE Hinton](#) - arXiv preprint arXiv:1607.06450, 2016 - arxiv.org

... , we transpose batch **normalization** into **layer normalization** by computing the mean and variance used for **normalization** from all of the summed inputs to the neurons in a **layer** on a ...

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## Layer Normalization

### ➤ Batch Normalization

- ✓ Hard to use with Sequence data as Sequence data has varying length
- ✓ Batch means Mini-Batch in Batch Normalization  
It is hard to parallelization as it BN has dependency on its batches.

### ➤ Layer Normalization

- ✓ LN remove dependency as it applies normalization based on layer.

## Batch Normalization

➤ Mean

$$\mu_{Batch} \leftarrow \frac{1}{m} \sum_{i=1}^m x_i$$

➤ Variance

$$\sigma_{Batch}^2 \leftarrow \frac{1}{m} \sum_{i=1}^m (x_i - \mu_{Batch})^2$$

➤ Normalization

$$\hat{x}_i \leftarrow \frac{x_i - \mu_{Batch}}{\sqrt{\sigma_{Batch}^2 + \epsilon}}$$

## Layer Normalization

➤ Mean

$$\mu^l = \frac{1}{H} \sum_{i=1}^H a_i^l$$

➤ Variance

$$\sigma^l = \sqrt{\frac{1}{H} \sum_{i=1}^H (a_i^l - \mu^l)^2}$$

➤ Normalization

$$\mathbf{h}^t = f \left[ \frac{\mathbf{g}}{\sigma^t} \odot (\mathbf{a}^t - \mu^t) + \mathbf{b} \right]$$

## Layer Normalization

➤ Normalization  $\mathbf{h}^t = f \left[ \frac{\mathbf{g}}{\sigma^t} \odot (\mathbf{a}^t - \mu^t) + \mathbf{b} \right]$

➤ Weight re-scaling and re-centering

$$\begin{aligned}\mathbf{h}' &= f\left(\frac{\mathbf{g}}{\sigma'} (W' \mathbf{x} - \mu') + \mathbf{b}\right) = f\left(\frac{\mathbf{g}}{\sigma'} ((\delta W + \mathbf{1}\gamma^\top) \mathbf{x} - \mu') + \mathbf{b}\right) \\ &= f\left(\frac{\mathbf{g}}{\sigma} (W \mathbf{x} - \mu) + \mathbf{b}\right) = \mathbf{h}.\end{aligned}$$

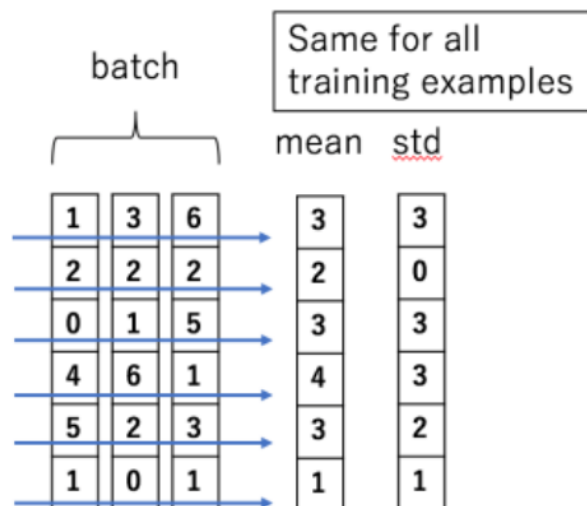
Where bias for  $\mathbf{b}$ , gain for  $\mathbf{g}$

➤ Easy to see re-scaling individual data points does not change the model's prediction under layer normalization

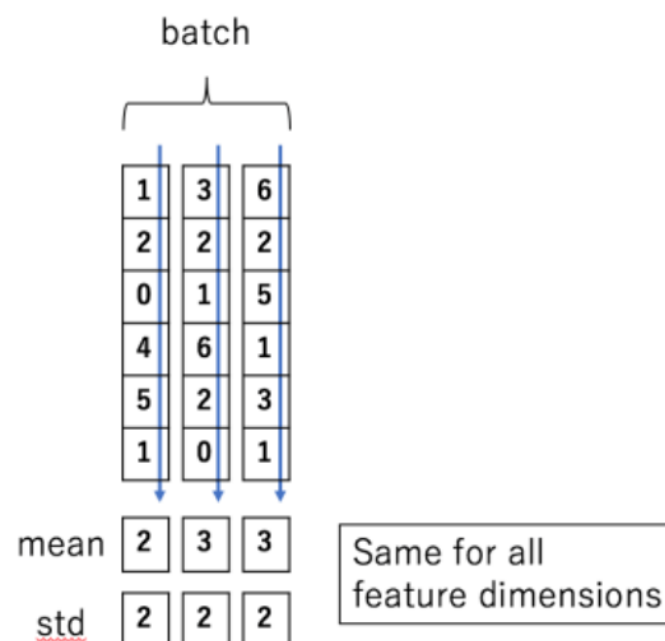
## Layer Normalization

- Layer Normalization is effective at longer sequences data
- Suitable with RNN but not CNN (BN is recommended)

Batch Normalization



Layer Normalization



## Paper

- 2015, “Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift” by Sergey Ioffe
- 2018, “How Does Batch Normalization Help Optimization?” by Shibani Santurkar
- 2016, “Layer Normalization” by Jimmy Lei Ba

## Extra

- <https://github.com/ndb796/Deep-Learning-Paper-Review-and-Practice>



The image features a central white circle containing the text "THANK YOU" in a blue, serif, all-caps font. This circle is surrounded by several triangles of varying sizes and colors. A large, light gray triangle points downwards from the top left, partially overlapping the circle. A small, solid blue triangle points upwards from the top right, also partially overlapping the circle. Two medium-sized, medium-blue triangles point downwards from the bottom left and bottom right, flanking the circle. Additionally, there are two small, solid blue triangles at the bottom: one pointing upwards on the left and one pointing upwards on the right. The overall composition is balanced and modern, using a limited color palette of white, blue, and gray.

**THANK  
YOU**