## Tanh Works Better with Asymmetry

## Dongjin Kim<sup>1,3</sup>, Woojeong Kim<sup>2</sup>, Suhyun Kim<sup>3</sup>

<sup>1</sup>Korea University, <sup>2</sup>Cornell University, <sup>3</sup>Korea Institute of Science and Technology





# An activation function with two boundaries

#### $\circ$ It has a saturation state.

The activation is close to the asymptotic value.

 The saturated output suffered from the vanishing gradients problem

 Due to poor performance, Tanh becomes forgotten.





Glorot, Xavier, and Yoshua Bengio. "Understanding the difficulty of training deep feedforward neural networks." Proceedings of the thirteenth international conference on artificial intelligence and statistics. JMLR Workshop and Conference Proceedings, 2010.

## 02 Motivation — Order of Batch Normalization

Batch Normalization(BN) places between the weight and activation function(AF).



#### 02 Motivation **Order of Batch Normalization**

Batch Normalization(BN) places between the weight and activation function(AF).

| Weight     | Weight |
|------------|--------|
| BN         | AF     |
| AF         | BN     |
| Convention | Swap   |

order

order

ReLU

The layer order does not dramatically change accuracy.



Models

Datasets

**ReLU** 

Swap

Convention

V: VGG16, M: MobileNet, PR: PreAct-ResNet

## 02 Motivation — Order of Batch Normalization

Batch Normalization(BN) places between the weight and activation function(AF).



order

order

| Datasets | Models                     | ReLU            |            | Tanh  |            |       |
|----------|----------------------------|-----------------|------------|-------|------------|-------|
|          | Dutubets                   | in out is       | Convention | Swap  | Convention | Swap  |
|          |                            | VGG16           | 93.69      | 93.04 | 91.75      | 92.90 |
|          | CIFAR-10                   | MobileNet       | 92.48      | 91.93 | 91.66      | 92.53 |
|          |                            | PreAct-ResNet18 | 94.94      | 94.86 | 92.46      | 94.41 |
|          | CIFAR-100                  | VGG16           | 73.68      | 71.79 | 64.95      | 70.93 |
|          |                            | MobileNet       | 70.27      | 69.49 | 64.50      | 70.39 |
|          |                            | PreAct-ResNet18 | 78.06      | 77.39 | 73.26      | 75.76 |
|          | Tiny ImageNet Mo<br>PreAct | VGG16           | 59.37      | 59.05 | 49.29      | 57.05 |
|          |                            | MobileNet       | 51.90      | 50.25 | 45.38      | 52.05 |
|          |                            | PreAct-ResNet34 | 67.28      | 66.21 | 59.06      | 64.94 |
|          | ImageNet                   | VGG16           | 73.83      | 72.95 | 60.85      | 67.04 |
|          |                            | MobileNet       | 68.27      | 71.1  | 64.26      | 72.07 |



The layer order does not dramatically change accuracy.

#### Tanh

The Swap order significantly outperforms the Convention order.



V: VGG16, M: MobileNet, PR: PreAct-ResNet

## 02 Motivation — Order of Batch Normalization

|                               |        |        | Datasets  | Datasets Models    | ReLU           |                | Tanh           |                |
|-------------------------------|--------|--------|-----------|--------------------|----------------|----------------|----------------|----------------|
|                               |        |        |           |                    | Convention     | Swap           | Convention     | Swap           |
| Datah Narmalizatian (DN)      | Weight | Weight |           | VGG16              | 93.69          | 93.04          | 91.75          | 92.90          |
| Batch Normalization(BN)       |        |        | CIFAR-10  | MobileNet          | 92.48          | 91.93          | 91.66          | 92.53          |
| places between the weight     | BN     | AF     |           | PreAct-Residents   | 94.94          | 94.80          | 92.40          | 94.41          |
| and activation function(AF) . |        |        | CIFAR-100 | VGG16<br>MobileNet | 73.68<br>70.27 | 71.79<br>69.49 | 64.95<br>64.50 | 70.93<br>70.39 |

### Goal

#### 1. Reveal a hidden property

Why is the Swap order effective on Tanh?

#### 2. Modified Activation Function

How can we redesign the order-agnostic Tanh with improved accuracy?

#### Tanh

The Swap order significantly outperforms the Convention order.



## 03 Intuition ——— Layer-wise Activations of Tanh



#### 03 Intuition

#### **Channel-wise Activation of Tanh**



Channel-wise activation of the Swap order is asymmetrically distributed.

The Reason for Low Asymmetry in the Convention Order

 Batch Normalization shifts the biased weighted sum outputs to zero.

 In the Convention order, the zero mean distribution generates
symmetric activation on Tanh.



The Reason for Low Asymmetry in the Convention Order



What Brings Asymmetry in the Swap Order?

The elimination of the preceding Batch Normalization

The biased distribution to Tanh encourages asymmetric saturation in the Swap order.





Additional Improvement incurred by Asymmetry

The elimination of Batch Normalization before the Tanh

The biased distribution to Tanh encourages asymmetric saturation in the Swap order. Asymmetric saturation in the Swap order incurs sparsity

Asymmetric saturation incurs sparsity by a zero mean shifting in normalization.



The Effect of Asymmetry and Sparsity on Accuracy



#### **Convention order**



#### The Effect of Asymmetry and Sparsity on Accuracy





The shifted Tanh introduce asymmetric and sparse activation easily.



05 Extended Experiments — Shifted Tanh

The properties of the shifted Tanh

 It shows improved accuracy comparable with the ReLU model.

• The accuracy discrepancy between orders decreased.



### 05 Extended Experiments — Other Activation Functions

17

#### Other Bounded Activation Functions

- The Swap model with other bounded functions outperforms the Convention model.
- Softsign, which is a slower approach to its asymptotes than Tanh, underperforms Tanh on the Swap order, even if it performs better on the Convention order.

| Activation functions | Order      | •     | $\Delta$ avg. Skewness |  |  |
|----------------------|------------|-------|------------------------|--|--|
|                      | Convention | Swap  | (Swap - Convention)    |  |  |
| Tanh                 | 69.5       | 74.11 | 2.38                   |  |  |
| Softsign             | 70.01      | 73.65 | 1.28                   |  |  |
| LeCun Tanh           | 67.82      | 74.46 | 1.90                   |  |  |
|                      |            |       |                        |  |  |

#### Other Bounded Activation Functions

- The Swap model with other bounded functions outperforms the Convention model.
- Softsign, which is a slower approach to its asymptotes than Tanh, underperforms Tanh on the Swap order, even if it performs better on the Convention order.

| Activation functions | Order      | r     | $\Delta$ avg. Skewness |  |  |
|----------------------|------------|-------|------------------------|--|--|
|                      | Convention | Swap  | (Swap - Convention)    |  |  |
| Tanh                 | 69.5       | 74.11 | 2.38                   |  |  |
| Softsign             | 70.01      | 73.65 | 1.28                   |  |  |
| LeCun Tanh           | 67.82      | 74.46 | 1.90                   |  |  |

#### Dominance Between Asymmetry and Sparsity

 The NWDBN model with encouraged asymmetry outperforms the Convention model even if the sparsity is decreased.



# **Thank You!**

npclinic3@gmail.com