Understanding and Improving Layer Normalization

Jingjing Xu, Xu Sun, Zhiyuan Zhang, Guanxiang Zhao, Junyang Lin

MOE Key Lab of Computational Linguistics, School of EECS, Peking University

{jingjingxu,xusun,zzy1210,zhaoguangxiang,linjunyang}@pku.edu.cn

What is layer normalization?

- Layer Normalization (LayerNorm) is a widely-used technique that scales the distributions of intermediate layers to have zero mean and unit standard deviation.
- It enables smoother gradients, faster training, and better generalization accuracy.

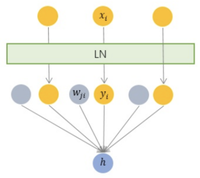


Figure 1:Illustration of LayerNorm.

How does LayerNorm work?

- The widely accepted explanation is that forward normalization brings distribution stability.
- However, recent studies show that the effects of normalization have nothing to do with the stability of input distribution.
- It is still unclear where the success of LayerNorm stems from.

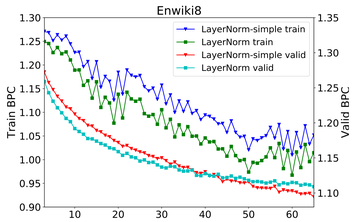
How do we explore LayerNorm?

To investigate how LayerNorm works, we conduct a series of experiments on different tasks.

- **Machine translation** includes three widely-used datasets, WMT English-German, IWSLT 14 German-English and IWSLT 15 English-Vietnamese.
- **Language modeling** includes a large dataset, Enwiki8.
- **Text classification** includes two sentence classification datasets: RT, and SST5.
- **Image classification** includes a widely-used dataset, MNIST.
- **Dependency parsing** uses English Penn TreeBank.

Observation 1: The bias and gain do not work in most cases.

- Dropping the bias and gain ("LayerNorm-simple") does not decrease the performance on six datasets. Surprisingly, it outperforms LayerNorm on four datasets and achieves SOTA on En-Vi translation.
- From convergence curves, we can see that current affine transformation mechanism has a potential risk of over-fitting and needs to be further improved.



	Machine Translation			Language Modeling	Classification			
	En-De(+)	De-En(+)	En-Vi(+)	Enwiki8(-)	RT(+)	SST5(+)	MNIST(+)	
Model Layers	12	12	12	12	4	4	3	
w/o Norm	Diverge	34.0	28.4	**1.04**	76.85	38.55	**99.14**	
LayerNorm	28.3	**35.5**	31.2	1.07	**77.21**	39.23	99.13	
LayerNorm-simple	**28.4**	**35.5**	**31.6**	1.07	76.66	**40.54**	99.09	

Table 1:The bias and gain do not work in most cases.

Observation 2: The derivatives of the mean and variance are more important than forward normalization.

- To evaluate the effects of the derivatives, we design a new method, called DetachNorm. It treats the mean and variance as changeable constants, rather than variables. The difference between LayerNorm and DetachNorm is that DetachNorm detaches the derivatives of the mean and variance.
- The derivatives of the mean and variance bring higher improvements than forward normalization does.
- The derivative of mean μ re-centers $\frac{\partial \ell}{\partial x}$ to zero. The derivative of variance σ reduces the variance of $\frac{\partial \ell}{\partial x}$, which can be seen a kind of re-scaling.
- The derivative of variance is more important than that of mean for deeper networks.

Given $\frac{\partial \ell}{\partial y} = (g_1, g_2, ..., g_H)^{\mathrm{T}}$, let $\bar{g}$ and D_g be the mean and variance of $g_1, g_2, ..., g_H$. For the case of detaching the derivatives of μ and σ, suppose $\frac{\partial \ell}{\partial x} = (a_1, a_2, ..., a_H)^{\mathrm{T}}$ is the gradient of x with mean $\bar{a}$ and variance D_a. We have $\bar{a} = \bar{g}/\sigma$ and $D_a = D_g/(\sigma^2)$.

(1) For the case of standard LayerNorm-simple, suppose $\frac{\partial \ell}{\partial x} = (b_1, b_2, ..., b_H)^{\mathrm{T}}$ is the gradient of x with mean $\bar{b}$ and variance D_b.

We have $\bar{b} = 0$ and $D_b \leq D_g/(\sigma^2)$.

(2) For the case of detaching the derivative of μ, suppose $\frac{\partial \ell}{\partial x} = (c_1, c_2, ..., c_H)^{\mathrm{T}}$ is the gradient of x with mean $\bar{c}$ and variance D_c.

We have $\bar{c} = \bar{g}/\sigma$ and $D_c \leq D_g/(\sigma^2)$.

(3) For the case of detaching the derivative of σ, suppose $\frac{\partial \ell}{\partial x} = (d_1, d_2, ..., d_H)^{\mathrm{T}}$ is the gradient of x with mean $\bar{d}$ and variance D_d.

We have $\bar{d} = 0$ and $D_c = D_g/(\sigma^2)$.

Models	Machine Translation			Language Modeling	Classification			Parsing
	En-De	De-En(+)	En-Vi(+)	Enwiki8(-)	RT(+)	SST5(+)	MNIST(+)	PTB(+)
Model Layers	12	12	12	12	4	4	3	3
w/o Norm	Diverge	**34.0**	**28.4**	**1.04**	**76.85**	38.55	**99.14**	88.31
DetachNorm	Diverge	33.9	27.7	1.12	76.40	**40.04**	99.10	**89.79**
Improvement	–	-0.1	-0.7	-0.08	-0.45	1.49	-0.04	**1.48**
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	En-De	De-En(+)	En-Vi(+)	Enwiki8(-)	RT(+)	SST5(+)	MNIST(+)	PTB(+)
Model Layers	12	12	12	12	4	4	3	3
DetachNorm	Diverge	33.9	27.7	1.12	76.40	40.04	**99.10**	**89.79**
LayerNorm-simple	**28.4**	**35.5**	**31.6**	**1.07**	**76.66**	**40.54**	99.09	89.19
Improvement	–	**1.6**	**3.9**	**0.05**	**0.26**	**0.50**	-0.01	-0.60

Table 2:The derivatives of the mean and variance matter.

AdaNorm

To address the over-fitting problem, we propose a normalization method, Adaptive Normalization.

$$z = \phi(y) \odot y = \phi(N(x)) \odot N(x) \tag{1}$$

It achieves better results on seven out of eight datasets.

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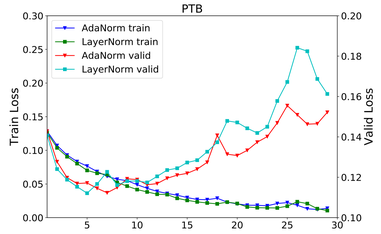
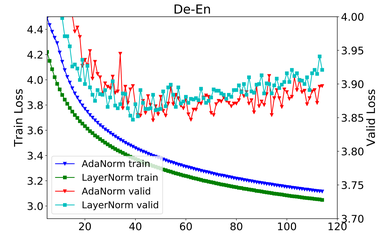
LayerNorm-simple	28.4	35.5	**31.6**	1.07	76.66	**40.54**	99.09	89.19
AdaNorm	**28.5**	**35.6**	31.4	1.07	**77.50**	**40.54**	**99.35**	**89.23**

Table 3:Results of LayerNorm and AdaNorm.

Better Convergence

- Compared to AdaNorm, LayerNorm has lower training loss but higher validation loss. Lower validation loss proves that AdaNorm has better convergence.





Couclusions

- In this paper, we investigate how layer normalization works.
- Based on a series of experiments and theoretical analysis, we summarize some interesting conclusions.
- We find that the derivatives of the mean and variance are important to the success of LayerNorm by re-centering and re-scaling backward gradients. Furthermore, the bias and gain increase the risk of over-fitting and do not work in most cases.
- To address the over-fitting problem, we propose a normalization method AdaNorm. Experiments show that AdaNorm outperforms LayerNorm on seven datasets.
- In the future work, we would like to explore more alternatives to LayerNorm from the perspective of gradient normalization.