Understanding and Improving Layer Normalization

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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.

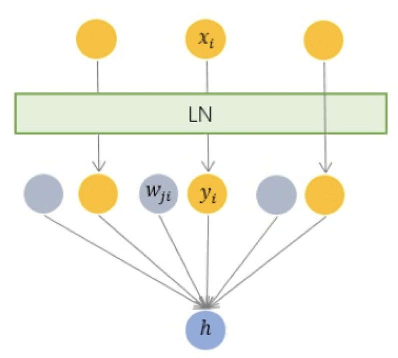

Figure 1:Illustration of LayerNorm.

How does LayerNorm work?

- The widely accepted explanation is that forward normalization brings distribution stability.
- However, recent studies show that the effects of batch normalization is closed related to optimization landscape, rather than 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 models and 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.

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.
- Experimental results show that current affine transformation mechanism has a potential risk of over-fitting and needs to be further improved.

	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
LayerNorm	28.3	**35.5**	31.2	1.07	**77.21**	39.23	99.13	89.12
LayerNorm-simple	**28.4**	**35.5**	**31.6**	1.07	76.66	**40.54**	99.09	**89.19**

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

The derivatives of the mean and variance are more important to LayerNorm than forward normalization.

- We design a new method, called DetachNorm. It treats the mean and variance as changeable constants, rather than variables.
- The derivatives of the mean and variance bring higher improvements than forward normalization does. The derivative of variance is more important than that of mean for deeper networks.
- 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.

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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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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.

$$z = \phi(y) \odot y = \phi(N(x)) \odot N(x) \quad (1)$$

It achieves better results on seven out of eight datasets.

Table 3:Results of LayerNorm and AdaNorm.

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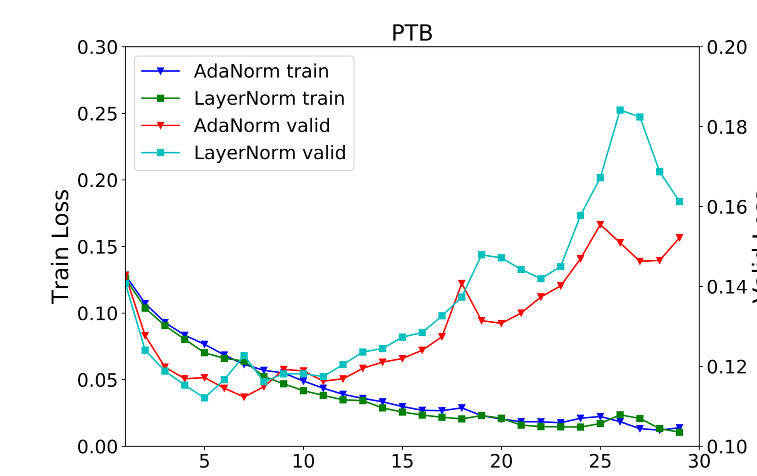
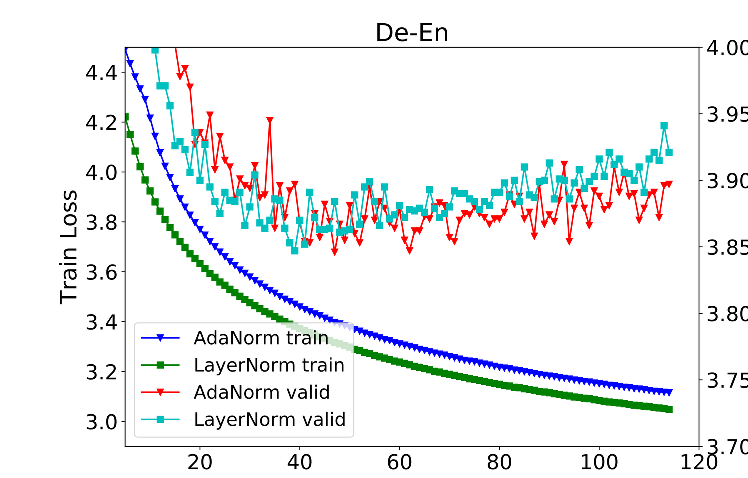
AdaNorm	**28.5**	**35.6**	31.4	1.07	**77.50**	**40.54**	**99.35**	**89.23**

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 this 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.