Layer-normalized LSTM for Hybrid-HMM and End-to-End ASR

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Introduction

Layer normalization is a critical component for training deep models

- Experiments showed that Transformer [Vaswani & Shazeer+ 17, Irie & Zeyer+ 19, Wang & Li+ 19] **does not converge** without layer normalization
- RNMT+ [Chen & Firat+ 18], deep encoder-decoder LSTM RNN model, also depends crucially on layer normalization for convergence.

Contribution of this work

- Investigation of layer normalization variants for LSTMs
- Improvement of the **overall performance** of ASR systems
- Improvement of the **stability** of training (deep) models
- Models become **more robust** to hyperparameter tuning
- Models can work well even without pretraining when using layer-normalized LSTMs

Introduction

Layer normalization (LN) [Ba & Kiros$^+$ 16] is defined as:

$$\mathrm{LN}(x;\gamma,\beta) = \gamma \odot \frac{x - \mathbb{E}[x]}{\sqrt{\mathrm{Var}[x] + \epsilon}} + \beta$$

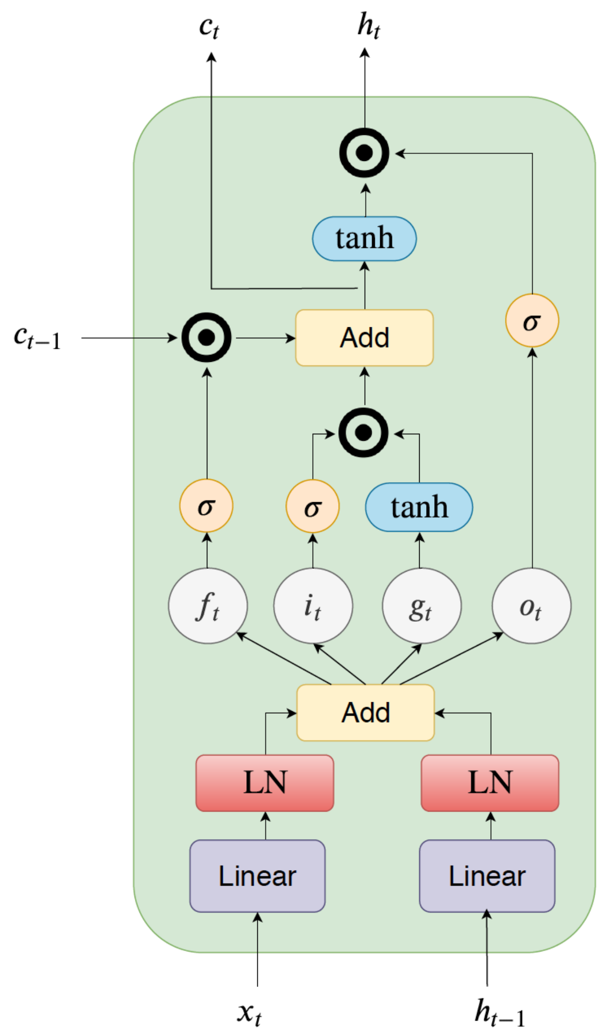
- $\mathbb{E}[x]/\mathrm{Var}[x]$ are mean/variance computed over the **feature dimension**
- $\gamma \in \mathbb{R}^D$ and $\beta \in \mathbb{R}^D$ are the gain and shift respectively (trainable parameters)
- $\odot$ is an element-wise multiplication operator
- ϵ is a small value used to avoid dividing by very small variance
- In the next slides, LN LSTM denotes layer-normalized LSTM

Layer-normalized LSTM Variants

Global Norm [Ba & Kiros+ 16]

$$\begin{pmatrix} f_t \\ i_t \\ o_t \\ g_t \end{pmatrix} = \mathrm{LN}(W_{hh}h_{t-1}) + \mathrm{LN}(W_{hx}x_t) + b$$

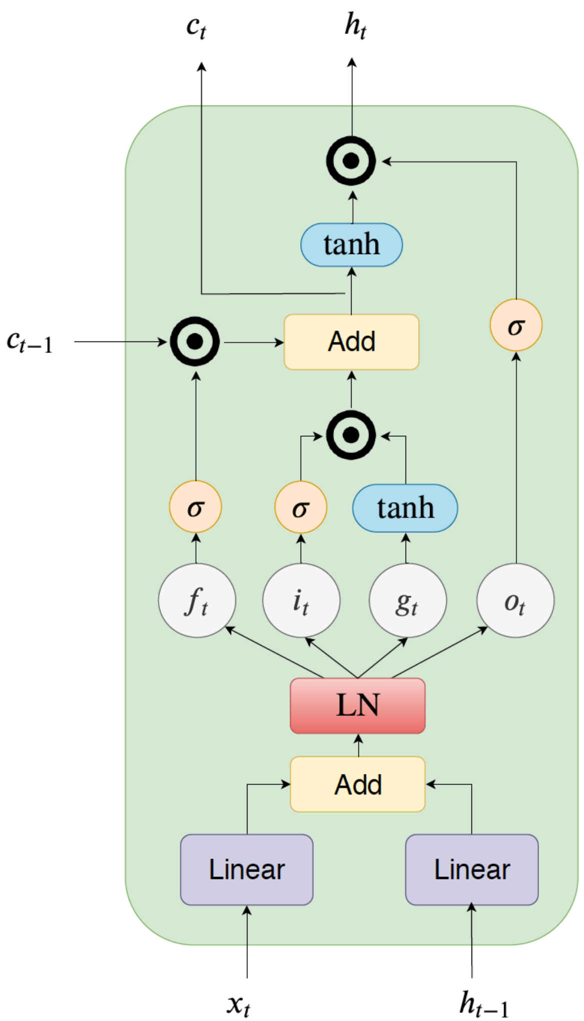
- LN is applied **separately** to each of the forward and recurrent inputs
- Gives the model the flexibility of learning two relative normalized distributions



Global Joined Norm

$$\begin{pmatrix} f_t \\ i_t \\ o_t \\ g_t \end{pmatrix} = \mathrm{LN}(W_{hx}x_t + W_{hh}h_{t-1})$$

- To our best knowledge, this variant was not used in any work
- LN is applied **jointly** to the forward and recurrent inputs after adding them together
- There is a single globally normalized distribution

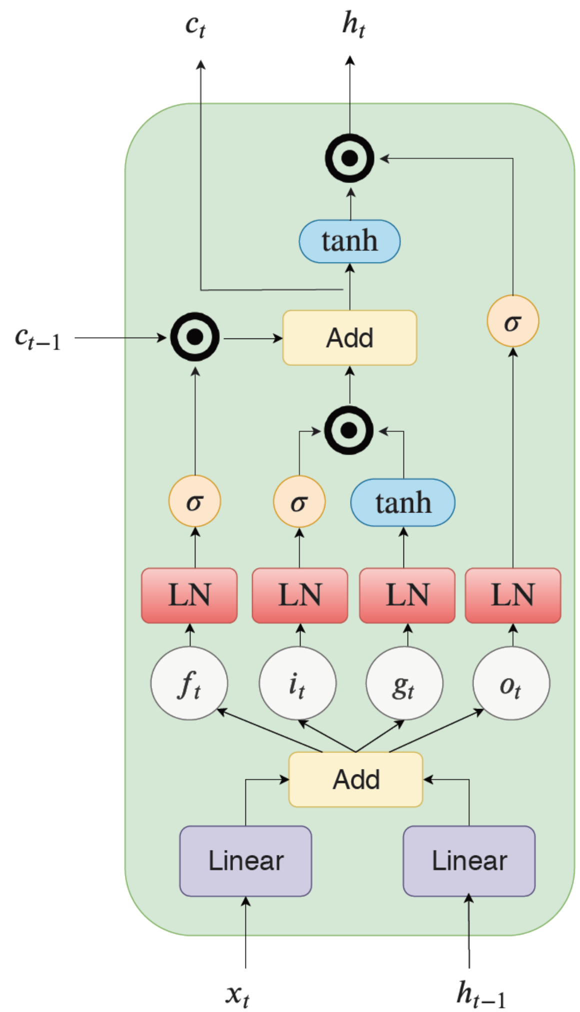


Layer-normalized LSTM Variants

Per Gate Norm [Chen & Firat⁺ 18]

$$\begin{pmatrix} f_t \\ i_t \\ o_t \\ g_t \end{pmatrix} = \begin{pmatrix} \mathrm{LN}(f_t) \\ \mathrm{LN}(i_t) \\ \mathrm{LN}(o_t) \\ \mathrm{LN}(g_t) \end{pmatrix}$$

- LN is applied separatly to each LSTM gate
- There are learned distributions for each gate

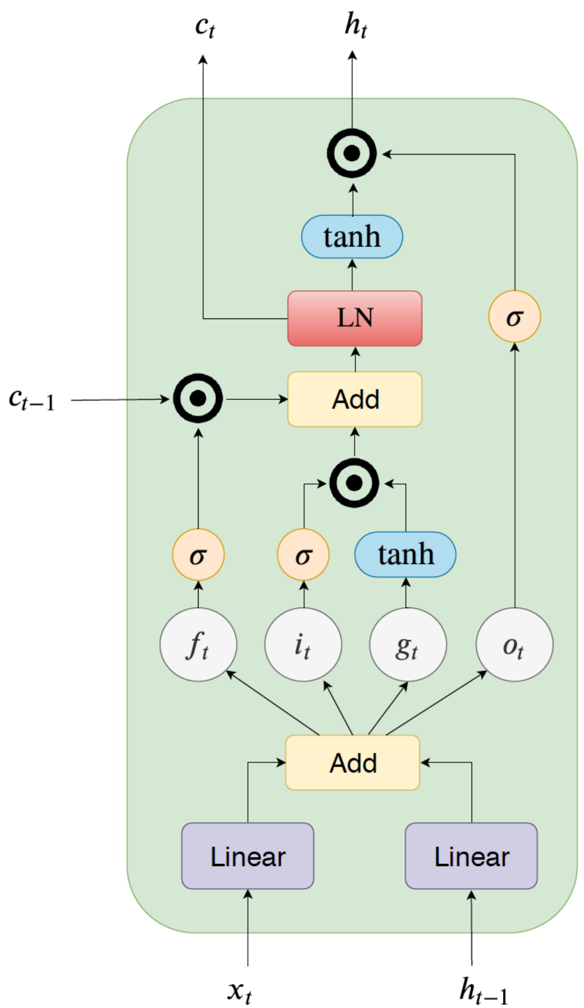


Layer-normalized LSTM Variants

Cell Norm [Ba & Kiros+ 16]

$$c_t = \mathrm{LN}(\sigma(f_t) \odot c_{t-1} + \sigma(i_t) \odot \tanh(g_t))$$

- LN is applied to the LSTM cell output



Experimental Setups

Data

- Switchboard 300h (English telephone speech)
- For testing, Hub5'00 (Switchboard + CallHome) and Hub5'01 are used

Hybrid baseline

- For NN training, alignments from a triphone CART-based GMM are used as ground truth labels
- The NN acoustic model consists of L bidirectional LSTM RNN layers
- The number of units in each direction is 500
- A 4-gram count-based language model is used for recognition

End-to-end baseline

- Attention based end-to-end baseline [Zeyer & Irie+ 18, Chan & Jaitly+ 16]
- 6 bidirectional LSTM RNN layers encoder with 1024 units for each direction
- 1 unidirectional LSTM RNN layer decoder with 1024 units
- Multi-layer perceptron attention is used
- Uses byte-pair-encoding as subword units with an alphabet size of 1k
- No utilization of a language model or any data augmentation methods

LN-LSTM for Hybrid-HMM ASR

L	Layer Norm Variant	Layer Norm Cell	WER [%] Hub5'00 $\sum$	Hub5'00 SW	Hub5'00 CH	Hub5'01 $\sum$	Epoch
6	-	-	14.3	9.6	19.0	14.5	12.8
	Joined	Yes	**14.1**	9.5	**18.8**	**14.1**	12.8
	Global	Yes	**14.1**	**9.3**	18.9	14.2	12.6
	Per Gate	Yes	14.5	9.8	19.2	14.6	12.8
	Joined	No	14.4	9.7	19.1	14.5	13.2
	Global	No	14.2	9.5	18.9	**14.1**	12.8
	Per Gate	No	14.7	10.0	19.4	14.6	12.8
8	-	-	14.4	9.8	19.1	14.3	12.6
	Joined	Yes	14.4	9.6	19.2	14.4	12.8
	Global	Yes	**14.0**	9.6	**18.5**	**14.1**	12.8
	Per Gate	Yes	14.2	9.5	18.9	14.3	12.8
	Joined	No	14.5	9.9	19.1	14.7	11.0
	Global	No	**14.0**	**9.4**	18.6	14.4	12.8
	Per Gate	No	14.5	9.8	19.2	14.8	10.8

- L: number of layers
- Training is often stable so we do not expect significant improvement
- Small improvement with deeper models
- **Global Norm** reports the best results

Experiments

LN-LSTM for end-to-end ASR[1]

Pre-train	Layer Norm		WER [%]				Epoch
	Variant	Cell	Hub5'00			Hub5'01	
			$\sum$	SW	CH	$\sum$	
Y	-	-	19.1	12.9	25.2	18.8	13.0
	Joined	Yes	18.3	12.1	24.5	17.8	10.8
	Global		22.2	14.9	29.4	20.7	20.0
	Per Gate		18.1	**11.7**	24.4	17.8	13.0
	Joined	No	**17.9**	11.8	**23.9**	**17.6**	11.8
	Global		19.1	12.8	25.5	18.5	12.3
	Per Gate		18.4	12.0	24.8	18.1	13.3
N	-	-	19.2	12.9	25.5	18.6	<u>20.0</u>
	Joined	Yes	*	*	*	*	
	Global		19.0	12.5	25.4	18.4	11.0
	Per Gate		*	*	*	*	
	Joined	No	**17.2**	**11.1**	**23.2**	**16.7**	<u>13.3</u>
	Global		18.9	12.2	25.4	18.1	16.0
	Per Gate		18.4	12.0	24.8	18.1	13.3

[1] LN is applied to both encoder and decoder

- 10% relative improvement in terms of WER
- **Global Joined Norm** reports the best results and even without pretraining
- Baseline without pretraining requires **heavy hyperparameter tuning**
- LN LSTM models require **less hyperparameter** tuning to converge and often from the first run
- **Faster convergence** is observed with LN LSTM
- *: model broken

Training variance

- Run same model with multiple random seeds
- Run multiple times same model with same random seed

Layer Norm	Variant	WER [%] (min-max, μ, σ) Hub5'00	Hub5'01
No	5 seeds	19.4-20.7, 20.2, **0.19**	19.1-20.2, 19.7, 0.18
Yes	5 seeds	17.1-17.6, 17.3, **0.08**	16.7-16.9, 16.8, 0.03
No	5 runs	19.2-19.7, 19.4, 0.08	18.6-19.4, 19.0, 0.14
Yes	5 runs	17.2-17.4, 17.3, 0.03	16.7-17.0, 16.8, 0.04

- Applied for the attention-based end-to-end model
- For LN LSTM, Global Joined Norm is used
- No pretraining is applied
- LN LSTM model is **robust to parameter initialization**

Experiments

Deeper encoder

Layer Norm	encN	WER [%] Hub5'00 $\sum$	SW	CH	Hub5'01 $\sum$
No	6	19.2	12.9	25.5	18.6
Yes		**17.2**	11.1	23.2	16.7
No	7	∞	∞	∞	∞
Yes		17.4	11.4	23.4	16.8
No	8	∞	∞	∞	∞
Yes		17.5	11.3	23.7	16.9

- Applied for the attention-based end-to-end model
- encN: number of encoder layers
- Global Joined Norm is used and no pretraining is applied
- ∞: no convergence
- Worse results due to **overfitting**
- LN LSTM allows training **deeper** models **without pretraining**

Conclusion & Outlook

Summary

- Investigated different variants of LN LSTM
- Successful training with **better stability**, and **better overall system performance** for ASR using LN LSTM
- Experiments show that LN LSTM models require **less hyperparameter** tuning, in addition to being **robust** to training variance
- Showed that in some cases there is no need for pretraining with LN LSTMs
- LN LSTM allows for training deeper models

Future work

- How much layer normalization do we need?
- Implementing an optimized LN-LSTM kernel for speed-up
- Applying SpecAugment [Park & Chan^{+} 19] for data augmentation

Thank you for your attention

Apendix

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