Transformers without Normalization

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March 14, 2025

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Introduction

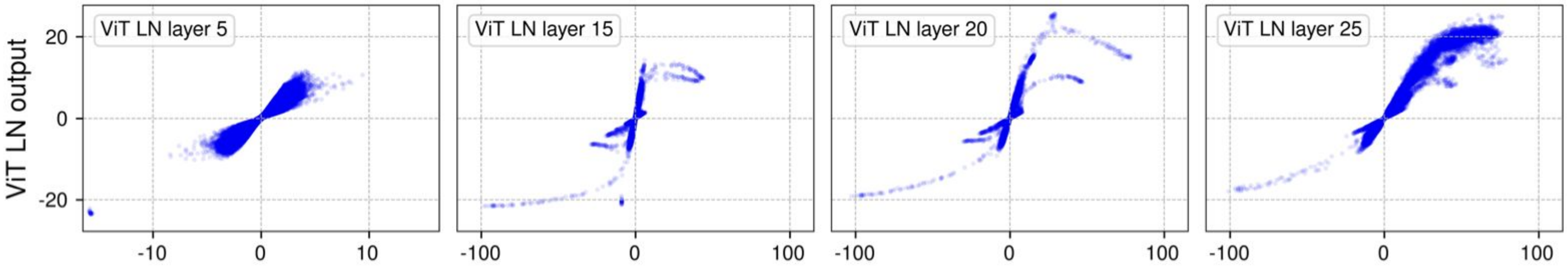
Normalization Layer often produces tanh-like input-output mapping

↓

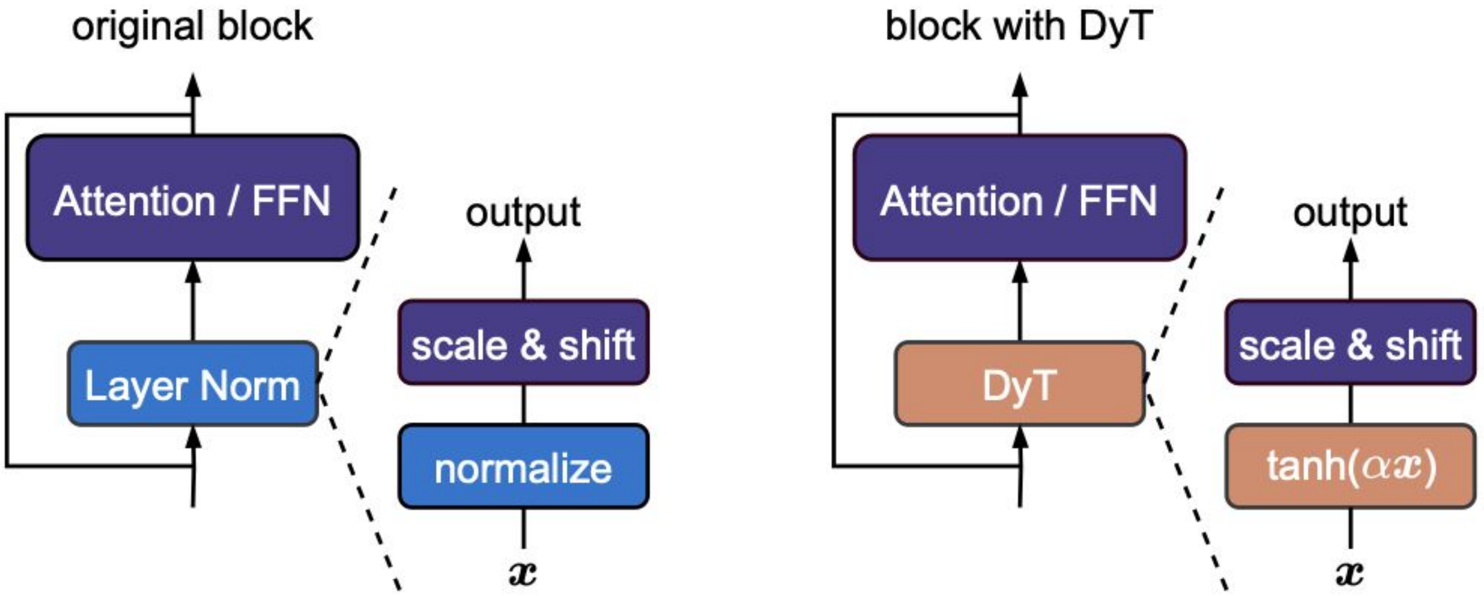
Dynamic Dynamic Tanh (DyT) drop-in replacement for normalization layers in Transformers

$$DyT(x) = \tanh(\alpha x)$$

LN output (y axis) vs. LN input (x axis)



Introduction



Normalization Layers

Layer normalization is a crucial technique in transformer models that helps **stabilize convergence** and **accelerate training** by **normalizing the inputs to each layer**. Due to that, **the model processes information consistently**, regardless of the input's scale or distribution.

Given an input x with shape (B,T,C), where B is the batch size, T is the number of tokens, and C is the embedding dimension per token:

$$\text{normalization}(\boldsymbol{x}) = \boldsymbol{\gamma} * \left(\frac{\boldsymbol{x} - \boldsymbol{\mu}}{\sqrt{\boldsymbol{\sigma}^2 + \epsilon}} \right) + \boldsymbol{\beta}$$

Batch Normalization (BN)

The first modern normalization layer

It is specifically designed to address **internal covariate shift** : the distribution of activations changes during training due to the constant updates to the network's weights

Batch normalization normalize the activations within each layer, ensuring they follow a consistent distribution with a **mean of zero** and a **standard deviation of one**

Layer Normalization (LN), Root Mean Square Normalization

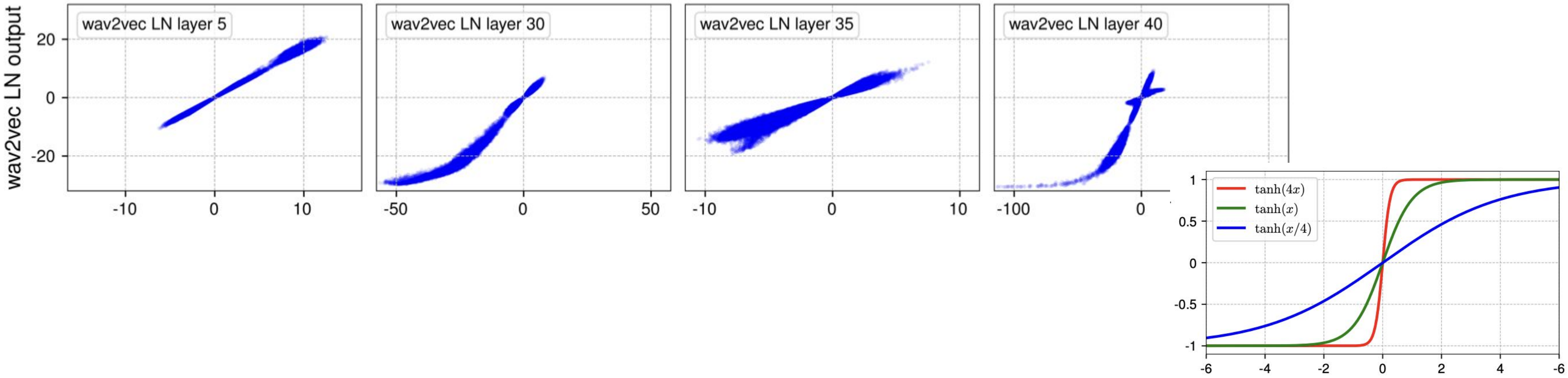
The major types of normalization layers in Transformer architectures

BN does not work effectively with self-attention mechanisms of transformers as it struggles with sequential data, therefore, LN

LN computes the **mean** and **standard deviation for each row across all features**, while in BN the normalization is done across the batch

Tanh-like Mappings with Layer Normalization

For all three models, the input-output relationship in **earlier LN layers** are mostly **linear**, resembling a straight line in an x-y plot. However, the **deeper LN layers** represent **curves** highly resemble **S-shaped curves** represented by a tanh function.



For such an S-shaped curve, the central part represented by points with x values close to zero, is still mainly in a linear shape. However, there are points (“extreme” values) that clearly fall out of this range. Normalization layers’ main effect for these values is to **squash** them into **less extreme values**, more in line with the majority of points.

Dynamic Tanh (DyT)

Given an input tensor x, a DyT layer is defined as follows:

$$DyT(x) = \gamma * \tanh(\alpha x) + \beta$$

- ❏ α is a learnable scalar parameter that allows scaling the input differently based on its range, accounting for varying x scales
- ❏ γ and β are learnable, per-channel vector parameters

Integrating DyT layers into an existing architecture is straightforward: one DyT layer replaces one normalization layer. Other parts of the activation functions or networks themselves remain intact.

Important: DyT is **not** a new type of normalization layer. However, it preserves the effect of normalization layers in **squashing the extreme values** in a non-linear fashion while almost **linearly transforming the very central parts** of the input.

DyT Experiments

Supervised learning in vision (classification accuracy):

model	LN	DyT	change
ViT-B	82.3%	82.5%	↑0.2%
ViT-L	83.1%	83.6%	↑0.5%
ConvNeXt-B	83.7%	83.7%	-
ConvNeXt-L	84.3%	84.4%	↑0.1%

Self-supervised learning in vision (accuracy):

model	LN	DyT	change
MAE ViT-B	83.2%	83.2%	-
MAE ViT-L	85.5%	85.4%	↓0.1%
DINO ViT-B (patch size 16)	83.2%	83.4%	↑0.2%
DINO ViT-B (patch size 8)	84.1%	84.5%	↑0.4%

DyT Experiments

Diffusion Transformer (DiT) models (image generation quality, lower is better):

model	LN	DyT	change
DiT-B	64.9	63.9	↓1.0
DiT-L	45.9	45.7	↓0.2
DiT-XL	19.9	20.8	↑0.9

Large Language Models
(training loss and average performance):

score / loss	RMSNorm	DyT	change
LLaMA 7B	0.513 / 1.59	0.513 / 1.60	- / ↑0.01
LLaMA 13B	0.529 / 1.53	0.529 / 1.54	- / ↑0.01
LLaMA 34B	0.536 / 1.50	0.536 / 1.50	- / -
LLaMA 70B	0.549 / 1.45	0.549 / 1.45	- / -

DyT Experiments

Self-supervised learning in speech (validation loss):

model	LN	DyT	change
wav2vec 2.0 Base	1.95	1.95	-
wav2vec 2.0 Large	1.92	1.91	↓0.01

DNA sequence modeling (classification accuracy):

model	LN	DyT	change
HyenaDNA (Nguyen et al., 2024)	85.2%	85.2%	-
Caduceus (Schiff et al., 2024)	86.9%	86.9%	-

Efficiency of DyT

Time evaluation

To compare and evaluate inference and training time of DyT and LN:
LLaMA 7B with RMSNorm vs LLaMA 7B with DyT to measure the total time taken for inference and for training using a single sequence of 4096 tokens

	inference		training	
LLaMA 7B	layer	model	layer	model
RMSNorm	2.1s	14.1s	8.3s	42.6s
DyT	1.0s	13.0s	4.8s	39.1s
reduction	↓52.4%	↓7.8%	↓42.2%	↓8.2%

Ablations of tanh and α

Removing and replacing tanh by other squashing functions lead to a significant drop in performance (e.g., classification accuracy):

model	identity	tanh	hardtanh	sigmoid
ViT-S	58.5% → failed	**80.3%**	79.9%	79.6%
ViT-B	61.0% → failed	**82.5%**	82.2%	81.6%

Removing the learnable α while retaining the squashing functions (tanh, hardtanh, and sigmoid) results in performance degradation across all squashing functions:

model	tanh	hardtanh	sigmoid
without α	81.1%	80.7%	80.7%
with α	**82.5%**	**82.2%**	**81.6%**

Comparison with Other Methods

- Initialization-based methods: *Fixup* and *SkipInit* ⟶ **adjust the initial parameter values** to prevent large gradients and activations at the start of training enabling stable learning without normalization layers
- Weight-normalization-based methods: *σReparam* ⟶ impose **constraints on network weights** throughout training to maintain stable learning dynamics in the absence of normalization layers

model	LN	Fixup	SkipInit	σReparam	DyT
ViT-B	82.3%	77.2%	74.1%	82.5%	**82.8%**
ViT-L	83.1%	78.1%	75.6%	83.0%	**83.6%**
MAE ViT-B	83.2%	73.7%	73.1%	83.2%	**83.7%**
MAE ViT-L	85.5%	74.1%	74.0%	85.4%	**85.8%**

Conclusion

☆Transformers can be trained without normalization layers☆

★DyT captures the behavior of NLs, thus, it can replace them ★

☆DyT adjusts the input activation range via a learnable scaling factor α☆

★DyT squashes the extreme values through an S-shaped tanh function★