Going deeper with Image Transformers

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Abstract

Transformers have been recently adapted for large scale image classification, achieving high scores shaking up the long supremacy of convolutional neural networks. However the optimization of vision transformers has been little studied so far. In this work, we build and optimize deeper transformer networks for image classification. In particular, we investigate the interplay of architecture and optimization of such dedicated transformers. We make two architecture changes that significantly improve the accuracy of deep transformers. This leads us to produce models whose performance does not saturate early with more depth, for instance we obtain 86.5% top-1 accuracy on Imagenet when training with no external data, we thus attain the current sate of the art with less floating-point operations and parameters. Our best model establishes the new state of the art on Imagenet with Reassessed labels and Imagenet-V2 / match frequency, in the setting with no additional training data. We share our code and models[1].

1. Introduction

Residual architectures are prominent in computer vision since the advent of ResNet [27]. They are defined as a sequence of functions of the form

$$x_{l+1} = g_l(x_l) + R_l(x_l), \tag{1}$$

where the function g_l and R_l define how the network updates the input x_l at layer l. The function g_l is typically identity, while R_l is the main building block of the network: many variants in the literature essentially differ on how this residual branch R_l is constructed or parametrized [51, 63, 73]. Residual architectures highlight the strong interplay between optimization and architecture design. As pointed out by He *et al*. [27], residual networks do not offer a better representational power. They achieve better performance because they are easier to train: shortly after their seminal work, He *et al*. discussed [28] the importance of having a clear path both forward and backward, and advocate setting g_l to the identity function.

The vision transformers [19] instantiate a particular form of residual architecture: after casting the input image into a set x_0 of vectors, the network alternates self-attention layers (SA) with feed-forward networks (FFN), as

$$\begin{aligned} x'_l &= x_l + \mathrm{SA}(\eta(x_l)) \\ x_{l+1} &= x'_l + \mathrm{FFN}(\eta(x'_l)) \end{aligned} \tag{2}$$

where η is the LayerNorm operator [1]. This definition follows the original architecture of Vaswani *et al*. [67], except the LayerNorm is applied before the block (*pre-norm*) in the residual branch, as advocated by He *et al*. [28]. Child *et al*. [13] adopt this choice with LayerNorm for training deeper transformers for various media, including for image generation where they train transformers with 48 layers.

How to normalize, weigh, or initialize the residual blocks of a residual architecture has received significant attention both for convolutional neural networks [7, 8, 28, 76] and for transformers applied to NLP or speech tasks [2, 34, 76]. In Section 2, we revisit this topic for transformer architectures solving image classification problems. Examples of approaches closely related to ours include Fixup [76], T-Fixup [34], ReZero [2] and SkipInit [16].

Following our analysis of the interplay between different initialization, optimization and architectural design, we propose an approach that is effective to improve the training of deeper architecture compared to current methods for image transformers. Formally, we add a learnable diagonal matrix on the output of each residual block, initialized close to (but not at) 0. Adding this simple layer after each residual block improves the training dynamic, allowing us to train deeper high-capacity image transformers that benefit from depth. We refer to this approach as **LayerScale**.

Section 3 introduces our second contribution, namely **class-attention layers,** that we present in Figure 2. It is akin to an encoder/decoder architecture, in which we explicitly separate the transformer layers involving self-attention between patches, from class-attention layers that are devoted to extract the content of the processed patches into a single vector so that it can be fed to a linear classifier. This explicit separation avoids the contradictory objective of guiding the attention process while processing the class embedding. We refer to this new architecture as **CaiT** (Class-Attention in Image Transformers).

[1]`https://github.com/facebookresearch/deit`

In the experimental Section 4, we empirically show the effectiveness and complementary of our approaches:

- LayerScale significantly facilitates the convergence and improves the accuracy of image transformers at larger depths. It adds a few thousands of parameters to the network at training time (negligible with respect to the total number of weights).
- Our architecture with specific class-attention offers a more effective processing of the class embedding.
- Our best CaiT models establish the new state of the art on Imagenet-Real [6] and Imagenet V2 matched frequency [53] with no additional training data. On ImageNet1k-val [55], our model is on par with the state of the art (86.5%) while requiring less FLOPs (329B vs 377B) and having less parameters than the best competing model (356M vs 438M).
- We also achieve competitive results on Transfer Learning, see Section C in supplemental material.

We discuss related works along this paper and in the dedicated Section 5, before we conclude in Section 6.

2. Deeper image transformers with LayerScale

Our goal is to increase the stability of the optimization when training transformers for image classification derived from the original architecture by Vaswani *et al.* [67], and especially when we increase their depth. We consider more specifically the vision transformer (ViT) architecture proposed by Dosovitskiy *et al.* [19] as the reference architecture and adopt the data-efficient image transformer (DeiT) optimization procedure of Touvron *et al.* [64]. In both works, there is no evidence that depth can bring any benefit when training on Imagenet only: the deeper ViT architectures have a lower performance, while DeiT only considers transformers with 12 blocks of layers. Section 4 will confirm that DeiT does not train deeper models effectively.

Figure 1 depicts the main variants we compare to facilitate the optimization. They cover recent choices from the literature: as discussed in the introduction, the architecture (a) of ViT and DeiT is a pre-norm architecture [19, 64], in which the layer-normalisation η occurs at the beginning of the residual branch. Note that the original architecture of Vaswani *et al.* [67] applies the normalization after the block, but in our experiments the DeiT training does not converge with post-normalization.

Fixup [76], ReZero [2] and SkipInit [16] introduce learnable scalar weighting α_l on the output of residual blocks, while removing the pre-normalization and the warmup, see Figure 1(b). This amounts to modifying Eqn. 2 as

$$\begin{aligned} x'_l &= x_l + \alpha_l \, \mathrm{SA}(x_l) \\ x_{l+1} &= x'_l + \alpha'_l \, \mathrm{FFN}(x'_l). \end{aligned} \tag{3}$$

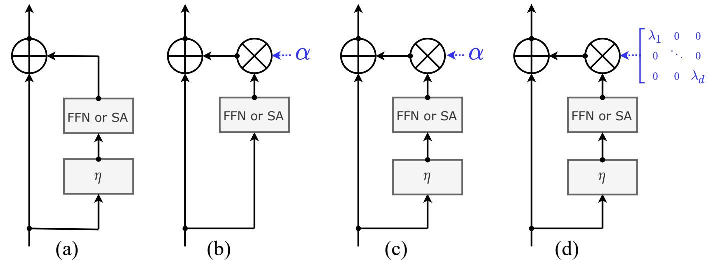

Figure 1. Normalization strategies for transformer blocks. (a) The ViT image classifier adopts pre-normalization like Child *et al.* [13]. (b) ReZero/Skipinit and Fixup remove the η normalization and the warmup (i.e., a reduced learning rate in the early training stage) and add a learnable scalar initialized to $\alpha = 0$ and $\alpha = 1$, respectively. Fixup additionally introduces biases and modifies the initialization of the linear layers. Since these methods do not converge with deep vision transformers, (c) we adapt them by re-introducing the pre-norm η and the warmup. Our main proposal (d) introduces a per-channel weighting (i.e, multiplication with a diagonal matrix $\mathrm{diag}(\lambda_1, \ldots, \lambda_d)$, where we initialize each weight with a small value as $\lambda_i = \varepsilon$.

ReZero simply initializes this parameter to $\alpha = 0$. Fixup initializes this parameter $\alpha = 1$ and makes other modifications: it adopts different policies for the initialization of the block weights, and adds several weights to the parametrization. In our experiments, these approaches do not converge even with some adjustment of the hyper-parameters.

Our empirical observation is that removing the warmup and the layer-normalization is what makes training unstable in Fixup and T-Fixup. Therefore we re-introduce these two ingredients so that Fixup and T-Fixup converge with DeiT models, see Figure 1(c). As we see in the experimental section, these amended variants of Fixup and T-Fixup help with convergence. The main contributing factor is the learnable α_l, which when initialized at a small value do help the convergence when we increase the depth.

Our proposal LayerScale is a per-channel multiplication of the vector produced by each residual block, as opposed to a single scalar, see Figure 1(d). Our objective is to group the updates of the weights associated with the same output channel. Formally, LayerScale is a multiplication by a diagonal matrix on output of each residual block. In other terms, we modify Eqn. 2 as

$$\begin{aligned} x'_l &= x_l + \mathrm{diag}(\lambda_{l,1}, \ldots, \lambda_{l,d}) \times \mathrm{SA}(\eta(x_l)) \\ x_{l+1} &= x'_l + \mathrm{diag}(\lambda'_{l,1}, \ldots, \lambda'_{l,d}) \times \mathrm{FFN}(\eta(x'_l)), \end{aligned} \tag{4}$$

where the parameters $\lambda_{l,i}$ and $\lambda'_{l,i}$ are learnable weights. The diagonal values are all initialized to a fixed small value ε: we set it to $\varepsilon = 0.1$ until depth 18, $\varepsilon = 10^{-5}$ for 24 and $\varepsilon = 10^{-6}$ for deeper networks. This formula is akin to other normalization strategies ActNorm [37] or LayerNorm but executed on output of the residual block. Yet we seek a different effect: ActNorm is a data-dependent initialization that calibrates activations so that they have zero-mean and unit variance, like batchnorm [35]. In contrast, we initialize the diagonal with small values so that the initial contribution of the residual branches to the function implemented by the transformer is small. In that respect our motivation is therefore closer to that of ReZero [2], SkipNorm [16], Fixup [76] and TFixup [34]: we start to train closer to the identity function and let the network integrate the additional parameters progressively during the training. However, LayerScale offers more diversity in the optimization than just adjusting the whole layer by a single learnable scalar as in ReZero/SkipNorm, Fixup and T-Fixup. As we will show empirically, offering the freedom to do so per channel is a decisive advantage of LayerScale over existing approaches.

Formally, adding these weights does not change the expressive power of the architecture since they can be integrated into the previous matrix of the SA and FFN layers.

3. Specializing layers for class attention

In this section, we introduce the CaiT architecture, depicted in Figure 2 (right). This design aims at circumventing one of the problems of the ViT architecture: the learned weights are asked to optimize two contradictory objectives: (1) guiding the self-attention between patches while (2) summarizing the information useful to the linear classifier. Our proposal is to explicitly separate the two stages.

Later class token. As an intermediate step towards our proposal, we insert the so-called class token, denoted by CLS, later in the transformer. This choice eliminates the discrepancy on the first layers of the transformer, which are therefore fully employed for performing self-attention between patches only. As a baseline that does not suffer from the contradictory objectives, we also consider **average pooling** of all the patches on output of the transformers, as typically employed in convolutional architectures.

Architecture. Our CaiT network consists of two distinct processing stages visible in Figure 2:

1. The *self-attention* stage is identical to the ViT transformer, but with no class embedding (CLS).

2. The *class-attention* stage is a set of layers that compiles the set of patch embeddings into a class embedding CLS that is subsequently fed to a linear classifier.

This class-attention alternates in turn a layer that we refer to as a multi-head class-attention (CA), and a FFN layer. In this stage, only the class embedding is updated. Similar to the one fed in ViT and DeiT on input of the transformer, it is a learnable vector. The main difference is that, in our architecture, we do no copy information from the class embedding to the patch embeddings during the forward pass.

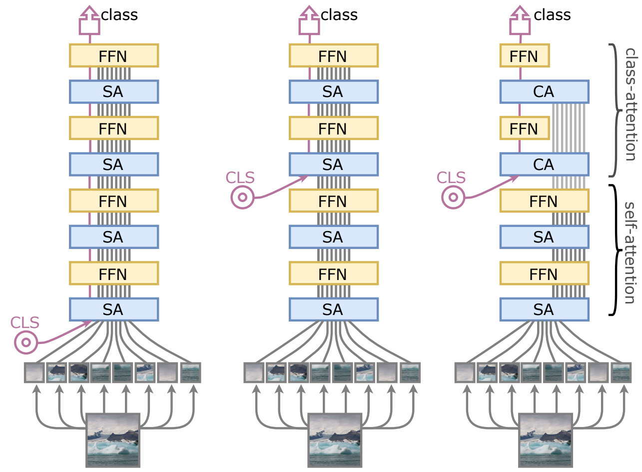

Figure 2. In the ViT transformer (*left*), the class embedding (CLS) is inserted along with the patch embeddings. This choice is detrimental, as the same weights are used for two different purposes: helping the attention process, and preparing the vector to be fed to the classifier. We put this problem in evidence by showing that inserting CLS later improves performance (*middle*). In the **CaiT** architecture (*right*), we further propose to freeze the patch embeddings when inserting CLS to save compute, so that the last part of the network (typically 2 layers) is fully devoted to summarizing the information to be fed to the linear classifier.

Only the class embedding is updated by residual in the CA and FFN processing of the summarize stage.

Multi-heads class attention. The role of the CA layer is to extract the information from the set of processed patches.It is identical to a SA layer, except that it relies on the attention between (i) the class embedding x_{class} (initialized at CLS in the first CA) and (ii) itself plus the set of frozen patch embeddings x_{patches}.

Considering a network with h heads and p patches, and denoting by d the embedding size, we parametrize the multi-head class-attention with several projection matrices, $W_q, W_k, W_v, W_o \in \mathbf{R}^{d\times d}$, and the corresponding biases $b_q, b_k, b_v, b_o \in \mathbf{R}^d$. With this notation, the computation of the CA residual block proceeds as follows. We first augment the patch embeddings (in matrix form) as $z = [x_{\text{class}}, x_{\text{patches}}]$, which makes the CA closer to a SA layer in that we guarantee that there is at least a key corresponding to the query. We then perform the projections:

$$Q = W_q\, x_{\text{class}} + b_q, \tag{5}$$
$$K = W_k\, z + b_k, \tag{6}$$
$$V = W_v\, z + b_v. \tag{7}$$

The class-attention weights are given by

$$A = \text{Softmax}(Q.K^T/\sqrt{d/h}) \tag{8}$$

where $Q.K^T \in \mathbf{R}^{h\times 1\times p}$. This attention is involved in the weighted sum $A \times V$ to produce the residual output vector

$$\mathrm{out}_{\mathrm{CA}} = W_o\, A\, V + b_o, \tag{9}$$

which is in turn added to x_{class} for subsequent processing.

The CA layers extract the useful information from the patches embedding to the class embedding. In preliminary experiments, we empirically observed that the first CA and FFN give the main boost, and a set of 2 blocks of layers (2 CA and 2 FFN) is sufficient to cap the performance. In the experimental section, we denote by 12+2 a transformer when it consists of 12 blocks of SA+FFN layers and 2 blocks of CA+FFN layers.

Complexity. The layers contain the same number of parameters in the class-attention and self-attention stages: CA is identical to SA in that respect, and we use the same parametrization for the FFNs. However the processing of these layers is much faster: the FFN only processes matrix-vector multiplications.

The CA function is also less expensive than SA in term of memory and computation because it computes the attention between the class vector and the set of patch embeddings: $Q \in \mathbf{R}^d$ means that $Q.K^T \in \mathbf{R}^{h\times 1\times p}$. In contrast, in the "regular self-attention" layers SA, we have $Q \in \mathbf{R}^{p\times d}$ and therefore $Q.K^T \in \mathbf{R}^{h\times p\times p}$. In other words, the initially quadratic complexity in the number of patches becomes linear in our extra CaiT layers.

4. Experiments

In this section, we report our experimental results related to LayerScale and CaiT. Note that we provide complementary results in supplemental material: in Appendix A we provide some experiments that have guided our architecture design and hyper-parameter optimization. Experiment in Transfer learning are reported in Appendix C and we show additional visualizations in Appendix D.

Experimental setting. Our implementation is based on the Timm library [69]. Unless specified otherwise, for this analysis we make minimal changes to hyper-parameters compared to the DeiT training scheme [64], except for minor adjustments of the learning rate in case we do not observe convergence. All our experiments are carried out on ImageNet [55], and also evaluated on two variations of it: ImageNet-Real [6] that corrects and give a more detailed annotation, and ImageNet-V2 [53] (matched frequency) that provides a separate test set.

4.1. Preliminary analysis with deeper architectures

We first carry out an empirical study of the normalization methods discussed in Section 2. At this stage we consider a Deit-Small model during 300 epochs to allow a direct comparison with the results reports by Touvron *et al*. [64]. For all the variants we adjust the drop-rate of stochastic depth to the depth of the network, see Appendix A for a more detailed discussion. This is required to achieve convergence when increasing the depth to 36 layers. We measure the performance on the Imagenet1k [17, 55] classification dataset as a function of the depth.

Table 1. **Improving convergence at depth** on ImageNet-1k. The baseline is DeiT-S. Several methods include a fix scalar learnable weight α per layer as in Figure 1(c). We have adapted Rezero, Fixup, T-Fixup, since the original methods do not converge: we have re-introduced the Layer-normalization η and warmup. We have adapted the drop rate d_r for all the methods, including the baseline (otherwise it does not converge). The column $\alpha = \varepsilon$ reports the performance when initializing the scalar with the same value as for LayerScale.

depth	baseline	scalar α weighting				LayerScale
	$[d_r]$	Rezero	T-Fixup	Fixup	$\alpha=\varepsilon$	
12	79.9 [*0.05*]	78.3	79.4	80.7	80.4	80.5
18	80.7 [*0.10*]	80.1	81.7	82.0	81.6	81.7
24	81.0 [*0.20*]	80.8	81.5	82.3	81.1	82.4
36	81.9 [*0.25*]	81.6	82.1	82.4	81.6	82.9

4.1.1 Comparison of normalization strategies

As discussed in Section 2, Rezero, Fixup and T-Fixup do not converge when training DeiT off-the-shelf. However, if we re-introduce LayerNorm[2] and warmup, Fixup and T-Fixup achieve congervence and even improve training compared to the baseline DeiT. We report the results for these "adaptations" of Fixup and T-Fixup in Table 1.

The modified methods are able to converge with more layers without saturating too early. ReZero converges, we show (column $\alpha = \varepsilon$) that it is better to initialize α to a small value instead of 0, as in LayerScale. Fixup and t-Fixup are competitive with LayerScale in the regime of a relatively low number of blocks (12–18). However, they are more complex than LayerScale: they employ different initialization rules depending of the type of layers, and they require more changes of the transformer architecture. Therefore we only use LayerScale in subsequent experiments, which is much simpler as it only makes a single change and is parametrized by a single hyper-parameter ε.

Note, all the methods have a beneficial effect on convergence and they tend to reduce the need for stochastic depth, therefore we adjust these drop rate accordingly per method. Figure 3 provides the performances as the function of the drop rate d_r for LayerScale. We empirically use the following formula to set up the

[2]Bachlechner *et al*. report that batchnorm is complementary to ReZero, while removing LayerNorm in the case of transformers.

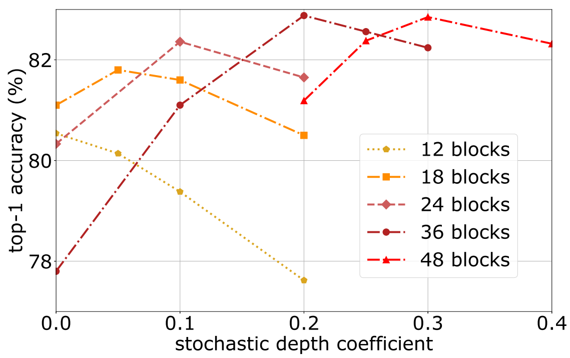

Figure 3. We measure the impact of stochastic depth on ImageNet with a DeiT-S with LayerScale for different depths. The drop rate of stochastic depth needs to be adapted to the network depth.

drop-rate for the CaiT-S models derived from on Deit-S: $d_r = \min\left(0.1 \times \frac{\text{depth}}{12} - 1, 0\right)$. This formulaic choice avoids cross-validating this parameter and overfitting. We further increase (resp. decrease) it by a constant for larger (resp. smaller) working dimensionality d.

4.1.2 Analysis of Layerscale

Statistics of branch weighting. We evaluate the impact of Layerscale for a 36-layer transformer by measuring the ratio between the norm of the residual activations and the norm of the activations of the main branch $\|g_l(x)\|_2/\|x\|_2$. The results are shown in Figure 4. We can see that training a model with Layerscale makes this ratio more uniform across layers, and seems to prevent some layers from having a disproportionate impact on the activations. While translating this empirical observation to a provable conclusion, similar to prior works [2, 76] we hypothetize that the benefit is mostly the impact on optimization, which we try to support by the control experiment below.

Re-training. LayerScale makes it possible to get increased performance by training deeper models. At the end of training we obtain a specific set of scaling factors for each layer. Inspired by the lottery ticket hypothesis [23], one question that arises is whether what matters is to have the right scaling factors, or to include these learnable weights in the optimization procedure. In other terms, what happens if we re-train the network with the scaling factors obtained by a previous training?

The table below empirically answers that question.

Depth →	12	18	24	36
LayerScale	80.5	81.7	82.4	82.9
Re-trained with fixed weights	80.6	81.5	81.2	81.6

In this experiment, we compare the performance (top-1 validation accuracy, %) on ImageNet-1k with DeiT-S architectures of differents depths. Everything being identical otherwise, in the first experiment we use LayerScale, i.e. we have learnable weights initialized at a small value ε. In the control experiment we use fixed scaling factors initialised at values obtained by the LayerScale training.

We can see that the control training with fixed weights also converges without suffering from instabilities with the deepest architectures. Nevertheless, the results are lower than those obtained with the learnable weighting factors. This suggests that the evolution of the parameters during training has a beneficial effect on the deepest models.

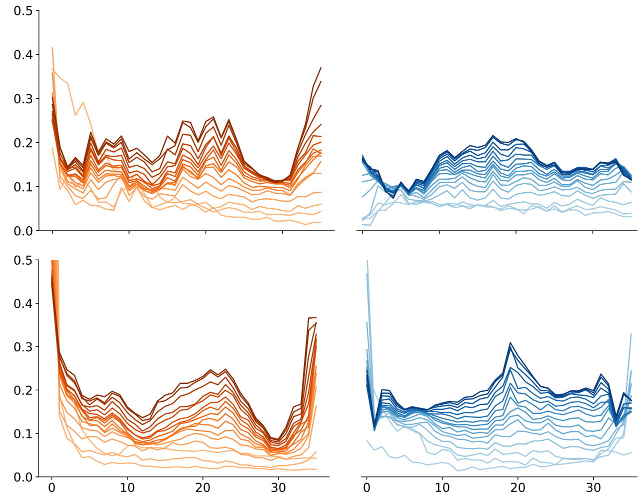

Figure 4. Analysis of the contribution of the residual branches (*Top:* Self-attention ; *Bottom:* FFN) for a network comprising 36 layers, without (red) or with (blue) Layerscale. The ratio between the norm of the residual and the norm of the main branch is shown for each layer of the transformer and for various epochs (darker shades correspond to the last epochs). For the model trained with layerscale, the norm of the residual branch is on average 20% of the norm of the main branch. We observe that the contribution of the residual blocks fluctuates more for the model trained without layerscale and in particular is lower for some of the deeper layers.

4.2. Class-attention layers

In Table 2 we study the impact on performance of the design choices related to class embedding. We depict some of them in Figure 2. As a baseline, average pooling of patches embeddings with a vanilla DeiT-Small achieves a better performance than using a class token. This choice, which does not employ any class embedding, is typical in convolutional networks, but possibly weaker with transformers when transferring to other tasks [20].

Late insertion. The performance increases when we insert the class embedding later in the transformer. It is maximized two layers before the output. Our interpretation is that the attention process is less perturbed in the 10 first lay-

Table 2. Variations on CLS with Deit-Small (no LayerScale): we change the layer at which the class embedding is inserted. In ViT and DeiT, it is inserted at layer 0 jointly with the projected patches. We evaluate a late insertion of the class embedding, as well as our design choice to introduce specific class-attention layers.

depth: SA+CA	insertion layer	top-1 acc.	#params	FLOPs
Baselines: DeiT-S and average pooling				
12: 12 + 0	0	79.9	22M	4.6B
12: 12 + 0	n/a	80.3	22M	4.6B
Late insertion of class embedding				
12: 12 + 0	2	80.0	22M	4.6B
12: 12 + 0	4	80.0	22M	4.6B
12: 12 + 0	8	80.0	22M	4.6B
12: 12 + 0	10	80.5	22M	4.6B
12: 12 + 0	11	80.3	22M	4.6B
DeiT-S with class-attention stage (SA+FFN)				
12: 9 + 3	9	79.6	22M	3.6B
12: 10 + 2	10	80.3	22M	4.0B
12: 11 + 1	11	80.6	22M	4.3B
13: 12 + 1	12	80.8	24M	4.7B
14: 12 + 2	12	80.8	26M	4.7B
15: 12 + 3	12	80.6	27M	4.8B

ers, yet it is best to keep 2 layers for compiling the patches embedding into the class embedding via the class-attention, otherwise the processing gets closer to a weighted average.

Our class-attention layers are designed on the assumption that there is no benefit in copying information from the class embedding back to the patch embeddings in the forward pass. Table 2 supports that hypothesis: if we compare the performance for a total number of layers fixed to 12, the performance of CaiT with 10 SA and 2 CA layers is identical to average pooling and better than the DeiT-Small baseline with a lower number of FLOPs. If we set 12 layers in the self-attention stage, which dominates the complexity, we increase the performance significantly by adding two blocks of CA+FFN.

Visualization of class-attention maps. In Figure 5 we show the attention map related to our first class-attention layer. In CaiT, the first class-attention layer conveniently concentrates all the spatial-class relationship. The second class-attention layer seems to focus more on the context, see Appendix D for complementary visualizations.

4.3. Our CaiT models

Our CaiT models are built upon ViT: the only difference is that we incorporate LayerScale in each residual block (see Section 2) and the two-stages architecture with class-attention layers described in Section 3. Table 3 describes our different models. The design parameters governing the capacity are the depth and the working dimensionality d. In

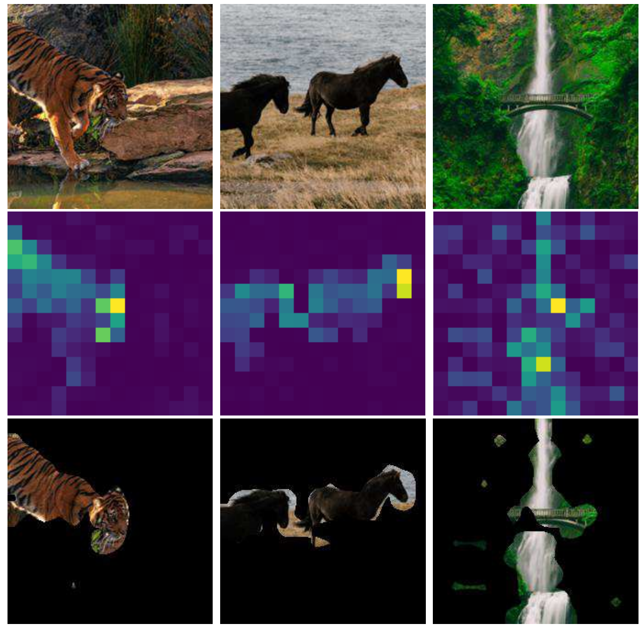

Figure 5. Visualization of the class-attention (first CA layer) obtained with a CaiT XXS-12 model. We show the attention map for each head in appendix. *top:* original image; *middle:* attention between all patches and class token; *bottom:* thresholded map.

our case is related to the number of heads h as $d = 48 \times h$, since we fix the **number of components per head** to 48. This choice is a bit smaller than the value used in DeiT. We also adopt the **crop-ratio** of 1.0 optimized for DeiT by Wightman [69]. Table A.4 and A.5 in Appendix support these choices.

We incorporate talking-heads attention [56] into our model. It increases the performance on Imagenet of DeiT-Small from 79.9% to 80.3%.

The hyper-parameters are identical to those provided in DeiT [64], except mentioned otherwise. The main parameters are as follows: we use a batch size of 1024 samples and train during 400 epochs with repeated augmentation [5, 29]. The learning rate of the AdamW optimizer [44] is set to 0.001 and associated with a cosine training schedule, 5 epochs of warmup and a weight decay of 0.05.

We report in Table 3 the two hyper-parameters that we modify depending on the model complexity, namely the drop rate d_r associated with uniform stochastic depth, and the initialization value ε associated with LayerScale.

Fine-tuning at higher resolution (↑) and distillation (Υ). We train all our models at resolution 224, and optionally fine-tune them at a higher resolution to trade performance against accuracy [19, 64, 65]: we denote the model by ↑384 models fine-tuned at resolution 384×384. We also train models with distillation (Υ) as suggested by Touvron *et*

Table 3. CaiT models: The design parameters are depth and d. The mem columns correspond to the memory usage. The speed is the throughput at inference time for a batch of 128 images with FP16 precision on one GPU V100 32GB (PyTorch 1.8 [48], CUDA 11). The only parameters that we adjust per model are the drop rate d_r of stochastic depth and the LayerScale initialization ε. All models are initially trained at resolution 224 during 400 epochs, the complexity measures (FLOPs, speed and mem) are reported for this resolution. We also fine-tune these models at resolution 384 (identified by $\uparrow$384) or train them with distillation (Υ).

CAIT	depth	d	#params	FLOPs ($\times 10^9$)		speed (im/s)		mem. (MB)		hparams		Top-1 acc. (%) on Imagenet1k-val			
model $\downarrow$	(SA+CA)		($\times 10^6$)	@224	@384	@224	@384	@224	@384	d_r	ε	@224	$\uparrow$384	@224Υ	$\uparrow$384Υ
XXS-24	24 + 2	192	12.0	2.5	9.6	1012.8	182.3	403	2126	0.1	10^{-5}	77.6	80.4	78.4	80.9
XXS-36	36 + 2	192	17.3	3.7	14.3	680.9	122.0	434	2156	0.1	10^{-6}	79.1	81.8	79.7	82.2
XS-24	24 + 2	288	26.6	5.4	19.3	737.6	134.8	614	3130	0.1	10^{-5}	81.8	83.8	82.0	84.1
XS-36	36 + 2	288	38.6	8.1	28.8	496.7	90.2	682	3198	0.2	10^{-6}	82.6	84.3	82.9	84.8
S-24	24 + 2	384	46.9	9.4	32.2	573.6	104.1	860	4165	0.1	10^{-5}	82.7	84.3	83.5	85.1
S-36	36 + 2	384	68.2	13.9	48.0	386.6	69.8	983	4287	0.2	10^{-6}	83.3	85.0	84.0	85.4
S-48	48 + 2	384	89.5	18.6	63.8	291.5	52.5	1106	4410	0.3	10^{-6}	83.5	85.1	83.9	85.3
M-24	24 + 2	768	185.9	36.0	116.1	262.9	38.3	2165	8634	0.2	10^{-5}	83.4	84.5	84.7	85.8
M-36	36 + 2	768	270.9	53.7	173.3	176.8	25.6	2661	9128	0.3	10^{-6}	83.8	84.9	85.1	86.1

Table 4. Ablation: we present the ablation path from DeiT-S to our CaiT models. We highlight the complementarity of our approaches and optimized hyper-parameters †: training failed.

Improvement	top-1 acc.	#params	FLOPs
DeiT-S [*d=384,300 epochs*]	79.9	22M	4.6B
+ More heads [*8*]	80.0	22M	4.6B
+ Talking-heads	80.5	22M	4.6B
+ Depth [*36 blocks*]	69.9†	64M	13.8B
+ Layer-scale [*init $\varepsilon = 10^{-6}$*]	80.5	64M	13.8B
+ Stochastic depth adaptation [*d_r=0.2*]	83.0	64M	13.8B
+ CA [CaiT]	83.2	68M	13.9B
+ Longer training [*400 epochs*]	83.4	68M	13.9B
+ Inference at higher resolution [*256*]	83.8	68M	18.6B
+ Fine-tuning at higher resolution [*384*]	84.8	68M	48.0B
+ Hard distillation [*teacher: RegNetY-16GF*]	85.2	68M	48.0B
+ Adjust crop ratio [*0.875 → 1.0*]	85.4	68M	48.0B

al. [64]. We use a RegNet-16GF [51] as teacher and adopt the simple "hard distillation" [64] for its simplicity.

4.4. Results

Table 3 provides different complexity measures for our models. As a general observation, we observe a subtle interplay between the width and the depth, both contribute to the performance as reported by Dosovitskiy *et al.* [19] with longer training schedules. But if one parameter is too small the gain brought by increasing the other is not worth the additional complexity.

Fine-tuning to size 384 ($\uparrow$) systematically offers a large boost in performance without changing the number of parameters. It also comes with a higher computational cost. In contrast, leveraging a pre-trained convnet teacher with hard distillation as suggested by Touvron *et al.* [64] provides a boost in accuracy without affecting the number of parameters nor the speed.

Comparison with the state of the art. In Table 5 we compare some of our models with the state of the art on Imagenet classification without external data. We focus on the models CaiT-S36 and CaiT-M36, at different resolutions and with or without distillation.

On Imagenet-val, we achieve 86.5% of top-1 accuracy, which is a significant improvement over DeiT (85.2%). It is the state of the art except for a very recent concurrent work [8] that also reports a top-1 accuracy of 86.5%. Our CaiT-M36$\uparrow$384Υ model obtains 85.9% top-1 accuracy on Imagenet-1k-val: this network is more efficient that the best performing NFNet convnets w.r.t. FLOPs and even more in terms of throughput (images processed per second on a V100 GPU), thanks to the lower memory usage.

Our approach is on par with the state of the art on Imagenet with reassessed labels, and outperforms it on Imagenet-V2, which has a distinct validation set which makes it harder to overfit.

Ablation. In Table 4 we present how to gradually transform the Deit-S [64] architecture to CaiT-36, and measure at each step the performance/complexity changes. One can see that CaiT is complementary with LayerScale and offers an improvement without significantly increasing the FLOPs. As already reported in the literature, the resolution is another important step for improving the performance and fine-tuning instead of training the model from scratch saves a lot of computation at training time. Last but not least, our models benefit from longer training schedules.

5. Related work

Since AlexNet [40], convolutional neural networks (CNN) are the standard in image classification [27, 63, 65], and more generally in computer vision. While a deep CNN can theoretically model long range interaction between pixels across many layers, there has been research in increas-

Table 5. **Complexity vs accuracy** on Imagenet [55], Imagenet Real [6] and Imagenet V2 matched frequency [53] for models trained without external data. We compare CaiT with DeiT [64], Vit-B [19], TNT [26], T2T [75] and to several state-of-the-art convnets: Regnet [51] improved by Touvron et al. [64], EfficientNet [14, 63, 72], Fix-EfficientNet [66] and NFNets [8]. Most reported results are from corresponding papers, and therefore the training procedure differs for the different models. For Imagenet V2 matched frequency and Imagenet Real we report the results provided by the authors. When not available (like NFNet), we report the results measured by Wigthman [69] with converted models, which may be suboptimal. The RegNetY-16GF is the teacher model that we trained for distillation. We report the best result in **bold** and the second best result(s) underlined.

Network	nb of param.	nb of FLOPs	image size train	image size test	ImNet top-1	Real top-1	V2 top-1
RegNetY-16GF	84M	16B	224	224	82.9	88.1	72.4
EfficientNet-B5	30M	10B	456	456	83.6	88.3	73.6
EfficientNet-B7	66M	37B	600	600	84.3	_	_
EfficientNet-B5 RA	30M	10B	456	456	83.7	_	_
EfficientNet-B7 RA	66M	37B	600	600	84.7	_	_
Fix-EfficientNet-B8	87M	90B	672	800	85.7	90.0	75.9
NFNet-F0	72M	12B	192	256	83.6	88.1	72.6
NFNet-F1	133M	36B	224	320	84.7	88.9	74.4
NFNet-F2	194M	62B	256	352	85.1	88.9	74.3
NFNet-F3	255M	115B	320	416	85.7	89.4	75.2
NFNet-F4	316M	215B	384	512	85.9	89.4	75.2
NFNet-F5	377M	290B	416	544	86.0	89.2	74.6
NFNet-F6+SAM	438M	377B	448	576	**86.5**	89.9	75.8
Transformers							
ViT-B/16	86M	55B	224	384	77.9	83.6	_
ViT-L/16	307M	191B	224	384	76.5	82.2	_
T2T-ViT t-14	21M	5B	224	224	80.7	_	_
TNT-S	24M	5B	224	224	81.3	_	_
TNT-S + SE	25M	5B	224	224	81.6	_	_
TNT-B	66M	14B	224	224	82.8	_	_
DeiT-S	22M	5B	224	224	79.8	85.7	68.5
DeiT-B	86M	18B	224	224	81.8	86.7	71.5
DeiT-B↑384	86M	55B	224	384	83.1	87.7	72.4
DeiT-B↑384⚗	87M	56B	224	384	85.2	89.3	75.2
Our deep transformers							
CaiT-S36	68M	14B	224	224	83.3	88.0	72.5
CaiT-S36↑384	68M	48B	224	384	85.0	89.2	75.0
CaiT-S48↑384	89M	64B	224	384	85.1	89.5	75.5
CaiT-S36⚗	68M	14B	224	224	84.0	88.9	74.1
CaiT-S36↑384⚗	68M	48B	224	384	85.4	89.8	76.2
CaiT-M36↑384⚗	271M	173B	224	384	86.1	90.0	76.3
CaiT-M36↑448⚗	271M	248B	224	448	86.3	**90.2**	76.7
CaiT-M48↑448⚗	356M	330B	224	448	**86.5**	**90.2**	**76.9**

ing the range of interactions within a single layer. Some approaches adapt the receptive field of convolutions dynamically [15, 42]. At another end of the spectrum, attention can be viewed as a general form of non-local means, which was used in filtering (e.g. denoising [10]), and more recently in conjunction with convolutions [68]. Various other attention mechanism have been used successfully to give a global view in conjunction with (local) convolutions [4, 52, 12, 77, 79], most mimic *squeeze-and-excitate* [32] for leveraging global features. Lastly, LambdaNetworks [3] decomposes attention into an approximated content attention and a batch-amortized positional attention component.

Hybrid architectures combining CNNs and transformers blocks have also been used on ImageNet [58, 70] and on COCO [11]. Originally, transformers without convolutions were applied on pixels directly [47], even scaling to hundred of layers [13], but did not perform at CNNs levels. More recently, a transformer architecture working directly on small patches has obtained state of the art results on ImageNet [19]. Nevertheless, the state of the art has since returned to CNNs [8, 49]. While some small improvements have been applied on the transformer architecture with encouraging results [75], their performance is below the one of DeiT [64], which uses a vanilla ViT architecture.

Encoder/decoder architectures. Transformers were originally introduced for machine translation [67] with encoder-decoder models, and gained popularity as masked language model encoders (BERT) [18, 43]. They yielded impressive results as scaled up language models, e.g. GPT-2 and 3 [50, 9]. They became a staple in speech recognition too [45, 36], being it in encoder and sequence criterion or encoder-decoder seq2seq [61] conformations, and hold the state of the art to this day [74, 78] with models 36 blocks deep. Note, transforming only the class token with frozen trunk embeddings in CaiT is reminiscent of non-autoregressive encoder-decoders [25, 41], where a whole sequence (we have only one prediction) is produced at once by iterative refinements.

Deeper architectures usually lead to better performance [27, 57, 62], however this complicates their training process [59, 60]. One must adapt the architecture and the optimization procedure to train them correctly. Some approaches focus on the initialization schemes [24, 27, 71], others on multiple stages training [54, 57], multiple loss at different depth [62], adding components in the architecture [2, 76] or regularization [33]. As pointed in our paper, in that respect our LayerScale approach is more related to Rezero [2] and Skipinit [16], Fixup [76], and T-Fixup [34].

6. Conclusion

In this paper, we have shown how train deeper transformer-based image classification neural networks when training on Imagenet only. We have also introduced the simple yet effective CaiT architecture designed in the spirit of encoder/decoder architectures. Our work further demonstrates that transformer models offer a competitive alternative to the best convolutional neural networks when considering trade-offs between accuracy and complexity.

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