Better plain ViT baselines for ImageNet-1k

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https://github.com/google-research/big_vision

Abstract

It is commonly accepted that the Vision Transformer model requires sophisticated regularization techniques to excel at ImageNet-1k scale data. Surprisingly, we find this is not the case and standard data augmentation is sufficient. This note presents a few minor modifications to the original Vision Transformer (ViT) vanilla training setting that dramatically improve the performance of plain ViT models. Notably, 90 epochs of training surpass 76% top-1 accuracy in under seven hours on a TPUv3-8, similar to the classic ResNet50 baseline, and 300 epochs of training reach 80% in less than one day.

1. Introduction

The ViT paper [4] focused solely on the aspect of large-scale pre-training, where ViT models outshine well tuned ResNet [6] (BiT [8]) models. The addition of results when pre-training only on ImageNet-1k was an afterthought, mostly to ablate the effect of data scale. Nevertheless, ImageNet-1k remains a key testbed in the computer vision research and it is highly beneficial to have as simple and effective a baseline as possible.

Thus, coupled with the release of the big vision codebase used to develop ViT [4], MLP-Mixer [14], ViT-G [19], LiT [20], and a variety of other research projects, we now provide a new baseline that stays true to the original ViT’s simplicity while reaching results competitive with similar approaches [15, 17] and concurrent [16], which also strives for simplification.

2. Experimental setup

We focus entirely on the ImageNet-1k dataset (ILSVRC-2012) for both (pre)training and evaluation. We stick to the original ViT model architecture due to its widespread acceptance [1, 2, 5, 9, 15], simplicity and scalability, and revisit only few very minor details, none of which are novel. We choose to focus on the smaller ViT-S/16 variant introduced by [15] as we believe it provides a good tradeoff between iteration velocity with commonly available hardware and final accuracy. However, when more compute and data is available, we highly recommend iterating with ViT-B/32 or ViT-B/16 instead [12,19], and note that increasing patch-size is almost equivalent to reducing image resolution.

All experiments use “inception crop” [13] at 224px² resolution, random horizontal flips, RandAugment [3], and Mixup augmentations. We train on the first 99% of the training data, and keep 1% for minival to encourage the community to stop selecting design choices on the validation (de-facto test) set. The full setup is shown in Appendix A.

3. Results

The results for our improved setup are shown in Figure 1, along with a few related important baselines. It is clear that a simple, standard ViT trained this way can match both the seminal ResNet50 at 90 epochs baseline, as well as more modern ResNet [17] and ViT [16] training setups. Furthermore, on a small TPUv3-8 node, the 90 epoch run takes only
6h30, and one can reach 80% accuracy in less than a day when training for 300 epochs.

The main differences from [4, 12] are a batch-size of 1024 instead of 4096, the use of global average-pooling (GAP) instead of a class token [2, 11], fixed 2D sin-cos position embeddings [2], and the introduction of a small amount of RandAugment [3] and Mixup [21] (level 10 and probability 0.2 respectively, which is less than [12]). These small changes lead to significantly better performance than that originally reported in [4].

Notably absent from this baseline are further architectural changes, regularizers such as dropout or stochastic depth [7], advanced optimization schemes such as SAM [10], extra augmentations such as CutMix [18], repeated augmentations [15], or blurring, “tricks” such as high-resolution fine-tuning or checkpoint averaging, as well as supervision from a strong teacher via knowledge distillation.

Table 1 shows an ablation of the various minor changes we propose. It exemplifies how a collection of almost trivial changes can accumulate to an important overall improvement. The only change which makes no significant difference in classification accuracy is whether the classification head is a single linear layer, or an MLP with one hidden tanh layer as in the original Transformer formulation.

4. Conclusion

It is always worth striving for simplicity.

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A. big_vision experiment configuration

```python
def get_config():
    config = mlc.ConfigDict()
    config.dataset = 'imagenet2012'
    config.train_split = 'train[:99%]'
    config.cache_raw = True
    config.shuffle_buffer_size = 250_000
    config.num_classes = 1000
    config.loss = 'softmax_xent'
    config.batch_size = 1024
    config.num_epochs = 90
    config.log_training_steps = 50
    config.log_eval_steps = 1000
    config.checkpoint_steps = 1000

    # Model section
    config.model_name = 'vit'
    config.model = dict(
        variant='S/16',
        rep_size=True,
        pool_type='gap',
        posemb='sincos2d',
    )

    config.log_eval_steps = 1000
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Listing 1. Full recommended config