TResNet: High Performance GPU-Dedicated Architecture

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Abstract

Many deep learning models, developed in recent years, reach higher ImageNet accuracy than ResNet50, with fewer or comparable FLOPS count. While FLOPs are often seen as a proxy for network efficiency, when measuring actual GPU training and inference throughput, vanilla ResNet50 is usually significantly faster than its recent competitors, offering better throughput-accuracy trade-off.

In this work, we introduce a series of architecture modifications that aim to boost neural networks’ accuracy, while retaining their GPU training and inference efficiency. We first demonstrate and discuss the bottlenecks induced by FLOPs-optimizations. We then suggest alternative designs that better utilize GPU structure and assets. Finally, we introduce a new family of GPU-dedicated models, called TResNet, which achieve better accuracy and efficiency than previous ConvNets.

Using a TResNet model, with similar GPU throughput to ResNet50, we reach 80.7% top-1 accuracy on ImageNet. Our TResNet models also transfer well and achieve state-of-the-art accuracy on competitive datasets such as Stanford cars (96.0%), CIFAR-10 (99.0%), CIFAR-100 (91.5%) and Oxford-Flowers (99.1%). Implementation is available at: https://github.com/mrT23/TResNet

1. Introduction

The seminal ResNet models [5], introduced in 2016, revolutionized the world of deep learning. ResNet models use repeated well-designed residual blocks, allowing training of very deep networks to high accuracy while maintaining high GPU utilization. ResNet models are also easy to train, and converge fast and consistent even with plain SGD optimizer [34]. NVIDIA Volta tensor cores [18] further improved ResNet models GPU utilization, up to quadrupling their GPU throughput on mixed-precision training and inference [33]. Among the ResNet models, ResNet50 established himself as a prominent model in terms of speed-accuracy trade-off, and became a leading backbone model for many computer vision tasks [4, 15, 31, 9].

Since ResNet50, many newer models were developed, which achieve better ImageNet accuracy with fewer or comparable FLOPs. Surprisingly, even though most deep learning models are trained, and sometimes deployed, on GPUs, few models try explicitly to find an optimal design in terms of GPU throughput. Since FLOPs are not an accurate proxy for GPU speed [1], sub-optimal design for GPUs might occur. This is especially true for GPU training speed, which is rarely measured and documented in academic literature, and can be severely hindered by some modern architecture design tricks [17].

Table 1 compares ResNet50 to popular newer networks like ResNet50-D [6], ResNetXt50 [32], SEResNeXt50 [8], EfficientNet-B1 [28] and MixNet-L [29], which have similar top-1 ImageNet accuracy. We see from Table 1 that the reduction of FLOPs and the usage of new tricks in modern networks, compared to ResNet50, is not translated to improvement in GPU throughput. This is especially evi-
Stem Design - Most neural networks start with a stem unit - a component whose goal is to quickly reduce the input resolution. ResNet50 stem is comprised of a stride-2 conv7x7 followed by a max pooling layer \([5]\), which reduces the input resolution by a factor of 4 (224 → 56). ResNet50-D stem design \([6]\), for comparison, is more elaborate - the conv7x7 is replaced by three conv3x3 layers. The new ResNet50-D stem design did improve accuracy, but at a cost of lowering the training throughput - see Table\([1]\) where the new stem design is responsible for almost all the decline in the training throughput.

We wanted to create a fast, seamless stem layer, with little information loss as possible, and let the simple well-designed residual blocks do all the actual processing work. The stem sole functionality should be to downscale the input resolution to match the rest of the architecture, e.g., by a factor of 4. We met these goals by using a dedicated SpaceToDepth transformation layer \([25]\), that rearranges blocks of spatial data into depth. The SpaceToDepth transformation layer is followed by simple 1x1 convolution to match the number of wanted channels, as can be seen in Figure\([1]\).

Anti-Alias Downsampling (AA) - \([35]\) proposed to replace all downsampling layers in a network by an equivalent AA component, to improve the shift-equivariance of deep networks. We implemented an economic variant of AA, similar to \([14]\), that gives a better speed-accuracy tradeoff - all our stride-2 convolutions are replaced by stride-1 convolutions followed by 3x3 blur kernel filter with stride 2, as described in Figure\([2]\).

In-Place Activated BatchNorm (Inplace-ABN) - Along the architecture, we replaced all BatchNorm+ReLU layers by Inplace-ABN \([24]\) layers, which implements BatchNorm with activation as a single, inplace operation, allowing to reduce significantly the memory required for training deep networks, with a negligible increase in computational cost. As an activation function for the Inplace-ABN, we chose to use Leaky-ReLU instead of ResNet50’s plain ReLU.

Using Inplace-ABN in TResNet models offers the following advantages:

- BatchNorm layers are major consumers of GPU mem-
ory. Replacing BatchNorm layers with Inplace-ABN enables to practically double the maximal possible batch size, which improves the GPU throughput.

- For TResNet models, Leaky-ReLU provides better accuracy than plain ReLU. While some modern activation, like Swish and Mish [19], might also give better accuracy than ReLU, their GPU memory consumption is higher, as well as their computational cost. In contrast, Leaky-ReLU has exactly the same GPU memory consumption and computational cost as plain ReLU.

**Blocks Selection** - ResNet34 and ResNet50 share the same architecture, with one difference: ResNet34 uses solely 'BasicBlock' layers, which comprise of two conv3x3 as the basic building block, while ResNet50 uses 'Bottleneck' layers, which comprise of two conv1x1 and one conv3x3 as the basic building block [5]. 'Bottleneck' layers have higher GPU usage than 'BasicBlock' layers, but usually give better accuracy.

For TResNet models, we found that using a mixture of 'BasicBlock' and 'Bottleneck' layers gives the best speed-accuracy tradeoff. Since 'BasicBlock' layers have larger receptive field, they are usually more effective at the beginning of a network. Hence, we placed 'BasicBlock' layers at the first two stages of the network, and 'Bottleneck' layers at the last two stages. Compared to ResNet50, we also modified the number of channels and the depth of the 3rd stage for the different TResNet models. Full specification of TResNet networks, including width and number of blocks per stage, appears in Table 2.

**SE Layers** - We added dedicated squeeze-and-excitation [8] layers (SE) to TResNet architecture. In order to reduce the computational cost of the SE blocks, and gain the maximal speed-accuracy benefit, we placed SE layers only in the first three stages of the network. Compared to standard SE design [8], TResNet SE placement and hyper-parameters are also optimized: For Bottleneck units we added the SE module after the conv3x3 operation, with reduction factor of 8, and for BasicBlock units we added SE module just before the residual sum, with reduction factor of 4. The complete blocks design, with SE and Inplace-ABN, is presented in Figure 3.

### 2.2. Code Optimizations

We designed TResNet using the popular PyTorch [21] package. We find that PyTorch enables easy code prototyping and debugging, while remaining efficient and fast on GPU. In this section, we will describe some code optimizations we did to enhance the GPU throughput of TResNet models. While code optimizations are sometimes over-
| Layer     | Block Type         | Output  | Stride | TResNet M | TResNet L | TResNet XL |
|-----------|--------------------|---------|--------|-----------|-----------|------------|
| Stem      | SpaceToDepth Conv1x1 | 56×56   | -      | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  |
| Stage1    | BasicBlock+SE      | 56×56   | 1      | 1  | 48 | 1  | 48 | 1  | 48 | 1  | 48 | 1  |
| Stage2    | BasicBlock+SE      | 28×28   | 3      | 3  | 64 | 4  | 76 | 4  | 84 | 4  | 84 | 4  |
| Stage3    | Bottleneck+SE      | 14×14   | 11     | 11 | 128| 5  | 152| 5  | 168| 5  | 168| 5  |
| Stage4    | Bottleneck         | 7×7     | 3      | 3  | 2048| 3  | 2432| 3  | 2688| 3  | 2688| 3  |
| Pooling   | GlobalAvgPool      | 1×1     | 1      | 1  | 2048| 1  | 2432| 1  | 2688| 1  | 2688| 1  |

#Params.                  | 29.4M | 54.7M | 77.1M |

Table 2. Overall architecture of the three TResNet models.

We found that a simple dedicated implementation of GAP, using PyTorch View and Mean tensor operations, can be up to 5 times faster than AvgPool2d on GPU. Another optimization we offer is flattening the average pooling in the final layer, thus avoiding additional reshaping. Our TResNet implementation for fixed GAP appears in appendix A.

### 2.2.3 Inplace Operations

In PyTorch, inplace operations change directly the content of a given tensor, without making a copy. They reduce the memory access cost of an operation, and also prevent creation of unneeded activation maps for backward propagation, hence increasing the maximal possible batch size. In TResNet code, inplace operations were used as much as possible. All TResNet BatchNorms are done inplace (Inplace-ABN), and there are also inplace operations for the residual connection, SE layers, blocks' final activation and more. This is a key factor in enabling large batch size - TResNet-M maximal batch size is almost twice of ResNet50 - 512, as can be seen in Table 1. For full review of TResNet inplace operations, see the public code.

### 3. Results

In this section, we will evaluate TResNet models on standard ImageNet training (input resolution 224), and compare their top-1 accuracy and GPU throughput to other known models. We will also perform an ablation study, and show results for fine-tuning TResNet to higher ImageNet resolution. In addition, we will present transfer learning results of TResNet models on four well-known downstream datasets.

#### 3.1 ImageNet Results

##### 3.1.1 Basic Training

Our main benchmark for evaluating TResNet models is the popular ImageNet dataset. We trained the models on input resolution 224, for 300 epochs, using a SGD optimizer and 1-cycle policy [26]. For regularization, we used Auto-augment [2], Cutout [3], Label-smooth [27] and True-weight-decay [16]. We found that the common ImageNet statistics normalization [14, 2, 28] does not improve the training accuracy, and instead normalized all the RGB channels to be between 0 and 1. For comparison, we repeated the same training procedure for ResNet50. Results appear in Table 3.

![Table 3. TResNet models accuracy and GPU throughput on ImageNet, compared to ResNet50. All measurements were done on Nvidia V100 GPU, with mixed precision. All models are trained on input resolution of 224.](image)

We can see from Table 3 that TResNet-M, which has similar GPU throughput to ResNet50, has significantly higher validation accuracy on ImageNet (+1.7%). It also outperforms all the other models that appear in Table 1 both in terms of GPU throughput and ImageNet top-1 accuracy. Note that our ResNet50 ImageNet accuracy, 79.0%, is significantly higher than the accuracy stated in previous articles [5, 6, 10], demonstrating the effectiveness of our training procedure. In addition, training TResNet-M and ResNet50 models takes less than 24 hours on an 8xV100 GPU machine, showing that our training scheme is also efficient and practical.

Another strength of the TResNet models, as reflected by Table 3, is the ability to work with significantly larger batch sizes than previous models. In general, large batch size leads to better GPU utilization, and allows easier scaling to large inputs. For distributed learning, it also reduces the number of synchronization needed in an epoch between the
different GPUs.

### 3.1.2 Ablation Study

We performed an ablation study to investigate the impact of the different refinements in TResNet-M model on the validation accuracy, and the model inference speed. Results appear in Table 4. We can see from Table 4 that in terms of contribution to top-1 accuracy, dedicated SE layers and AA are the most dominate refinements, but with a price of reducing the model throughput. We were able to compensate for this decrease with refinements like SpaceToDepth stem, Inplace-ABN and new blocks selection, that in addition to increasing to top-1 accuracy, actually improve the inference throughput.

| Refinement          | Top-1 Accuracy | Inference speed (img/sec) |
|---------------------|----------------|---------------------------|
| Original ResNet50   | 79.0           | 2830                      |
| + Stem → SpaceToDepth | 79.1           | 2950                      |
| + Blocks selection  | 79.4           | 3320                      |
| + Inplace-ABN       | 79.5           | 3470                      |
| + Dedicated SE      | 80.3           | 3280                      |
| + AA                | 80.7           | 2930                      |

Table 4. Ablation study - The impact of refinements in TResNet-M model on ImageNet top-1 accuracy and inference speed.

### 3.1.3 High-Resolution Fine-Tuning

We tested the scaling of TResNet models to higher input resolutions. We used the pre-trained TResNet models that appear in Table 3 as a starting point, and fine-tuned them for 10 epochs on input resolution of 448. The results appear in Table 5.

| Model          | Input Resolution | Top-1 Accuracy [%] |
|----------------|------------------|--------------------|
| TResNet-M      | 224              | 80.7               |
| TResNet-M      | 448              | 83.2               |
| TResNet-L      | 224              | 81.4               |
| TResNet-L      | 448              | 83.8               |
| TResNet-XL     | 224              | 82.0               |
| TResNet-XL     | 448              | **84.3**           |

Table 5. Impact of the input resolution on the top1 ImageNet accuracy for TResNet models. All TResNet 448 input-resolution accuracies are obtained with 10 epochs of fine-tuning.

We see from Table 5 that TResNet models scale well to high resolutions. Even TResNet-M, which is a relatively small and compact model, can achieve top-1 accuracy of 83.3% on ImageNet with high-resolution input. TResNet largest variant, TResNet-XL, achieves 84.3% top-1 accuracy on ImageNet.

### 3.1.4 Comparison to EfficientNet Models

EfficientNet models, which are based on MobileNetV3 architecture [7], propose to balance the resolution, height, and width of a base network for generating a series of larger networks. They are considered state-of-the-art architectures, that provide efficient networks for all ImageNet top-1 accuracy spectrum [28]. In Figure 4 and Figure 5 we compare the inference and training speed of TResNet models to the different EfficientNet models respectively.

![Top-1 Accuracy [%] Vs Inference Speed](image)

Figure 4. TResNet Vs EfficientNet models inference speed comparison.

We can see from Figure 4 and Figure 5 that all along the top-1 accuracy curve, TResNet models give better inference-speed-accuracy and training-speed-accuracy tradeoff than EfficientNet models. Note that Each EfficientNet model was bundled and optimized to a specific resolution, while TResNet models were trained and tested on multi-resolutions, which makes this comparison biased toward EfficientNet models; Yet, TResNet models show superior results. Also note that EfficientNet models were trained for 450 epochs and not for 300 epochs like TResNet models, and that EfficientNet training procedure included more GPU intensive tricks (RMSProp optimizer, drop-block) [28], so the actual gap in training times is even higher than stated in Figure 5.

### 3.2. Transfer Learning Results

We also evaluated TResNet on four commonly used, competitive transfer learning datasets: Stanford-cars [11], CIFAR-10 [12], CIFAR-100 [12] and Oxford-Flowers [20].
Figure 5. TResNet Vs EfficientNet models training speed comparison.

For each dataset, we used ImageNet pre-trained checkpoints, and fine-tuned the models for 80 epochs using 1-cycle policy \[26\]. For the fine-grained classification tasks (Stanford-cars and Oxford-Flowers), in addition to Cross Entropy loss we used weighted Triplet loss with Soft-margin \[23, 13\] which emphasizes hard examples by focusing of the most difficult positives and negatives samples in the batch. Table 6 shows the transfer learning performance of TResNet, compared to the known state-of-the-art models.

| Dataset        | Model      | Top-1 Acc. | Speed (img/sec) | Input |
|----------------|------------|------------|-----------------|-------|
| CIFAR-10       | Gpipe      | 99.0       | -               | 480   |
|                | TResNet-XL | 99.0       | 1060            | 224   |
| CIFAR-100      | EfficientNet-B7 | 91.7       | 70              | 600   |
|                | TResNet-XL | 91.5       | 1060            | 224   |
| Stanford Cars  | EfficientNet-B7 | 94.7       | 70              | 600   |
|                | TResNet-L  | 96.0       | 500             | 368   |
| Oxford-Flowers | EfficientNet-B7 | 98.8       | 70              | 600   |
|                | TResNet-L  | 99.1       | 500             | 368   |

Table 6. Comparison of TResNet to state-of-the-art models on transfer learning datasets (only ImageNet-based transfer learning results). Models inference speed is measured on a mixed precision V100 GPU. Since no official implementation of Gpipe was provided, its inference speed is unknown.

We can see from Table 6 that TResNet surpasses or matches the state-of-the-art accuracy on 3 of the 4 datasets, with x8-15 faster GPU inference speed. Note that all TResNet’s results are from single-crop single-model evaluation.

4. Conclusion

In this paper, we point out a possible blind-spot of latest developments in neural network design patterns. They tend not to consider actual GPU inference and training throughput, which are two critical factors in many real-world deep learning applications. To address this issue, we propose a set of design refinements, which are highly effective in utilizing typical GPU resources - SpaceToDepth stem cell, economical AA downsampling and attention-like layers, block selection redesign and Inplace-ABN operations. Powered by this carefully selected set, we suggested a family of new models which we call TResNet. We demonstrate that TResNet surpass state-of-the-art accuracy, with improved GPU training and inference throughput, on both ImageNet and four commonly used downstream datasets.

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Appendices

A. Code for Different Modules in TResNet

JIT accelerated SpaceToDepth module

```python
@torch.jit.script
class SpaceToDepthJIT(object):
    def __call__(self, x: torch.Tensor):
        N, C, H, W = x.size()
        x = x.view(N, C, H // 4, 4, W // 4, 4)
        x = x.permute(0, 3, 5, 1, 2, 4).contiguous()
        x = x.view(N, C * 16, H // 4, W // 4)
        return x
```

JIT accelerated AA downsampling module

```python
@torch.jit.script
class AADownsamplingJIT(object):
    def __call__(self, input: torch.Tensor):
        input_pad = F.pad(input, (1, 1, 1, 1), 'reflect')
        return F.conv2d(input_pad, self.filt, stride=2,
                        padding=0, groups=input.shape[1])
```
class FastGlobalAvgPool2d:
    def __init__(self, flatten=False):
        self.flatten = flatten
    def __call__(self, x):
        if self.flatten:
            in_size = x.size()
            return x.view((in_size[0], in_size[1], -1)).mean(dim=2)
        else:
            return x.view(x.size(0), x.size(1), -1).mean(-1).view(x.size(0), x.size(1), 1, 1)