Lowering PyTorch's Memory Consumption for Selective Differentiation



Samarth Bhatia, Felix Dangel

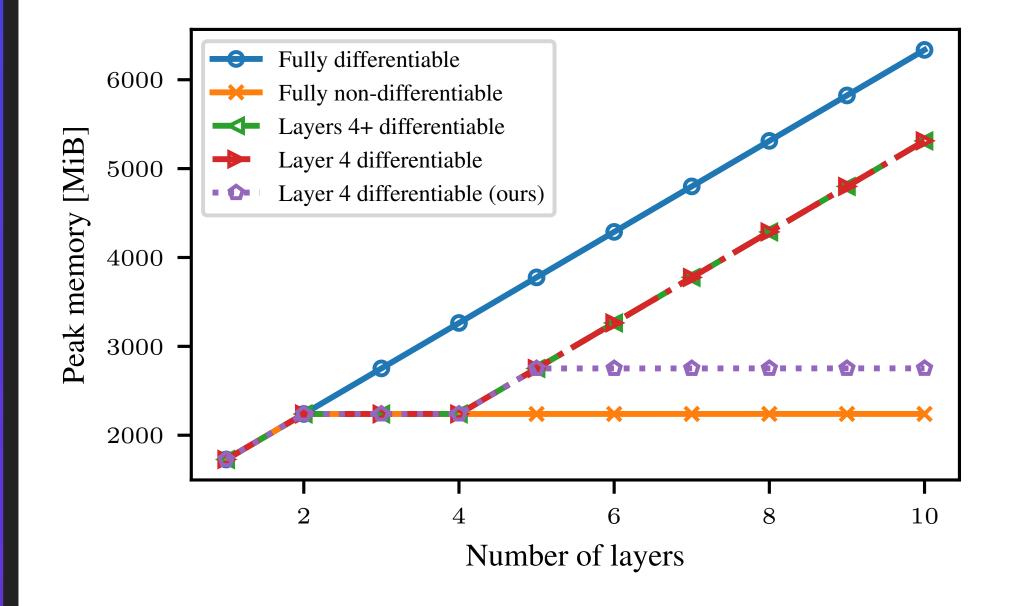


We identify that some PyTorch layers save unnecessary tensors when parameters have requires_grad = False and provide a fix to reduce memory without affecting runtime.

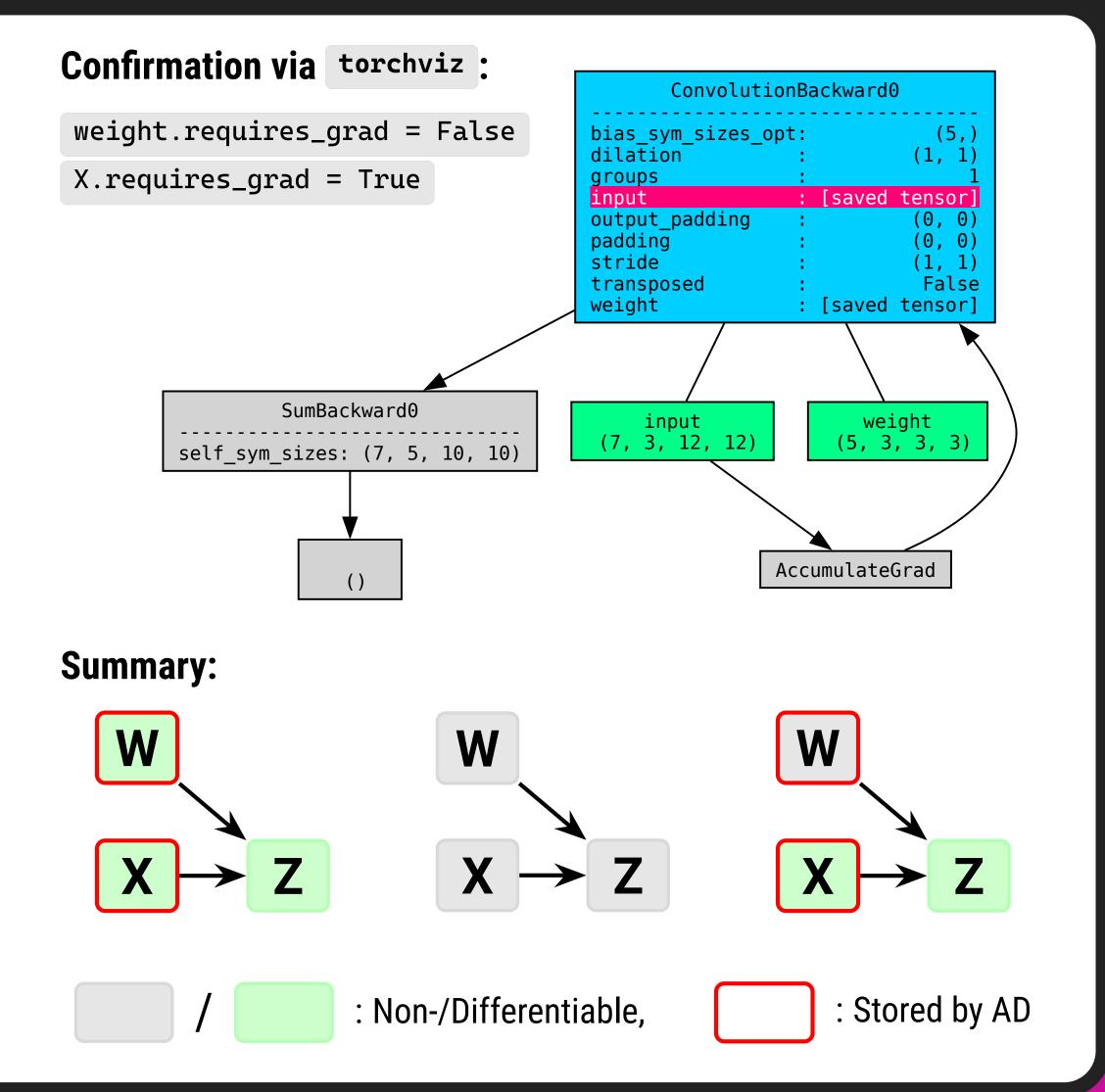
This is useful for fine-tuning setups that only compute gradients for a sub-set of parameters.

PyTorch sometimes retains tensors which are not required for backpropagation

Toy example: Let's look at a CNN without pooling/activations. We feed a mini-batch which consumes 512 MiB memory. Each intermediate tensor requires 512 MiB memory. Here is the forward pass's memory consumption when different parameters are trainable (approximates computation graph size).



Conclusion: PyTorch's convolution stores the layer input if it is differentiable, *irrespective* of the weight's differentiability. But we don't need the input if the weight is non-differentiable!



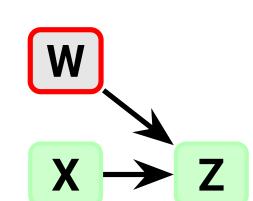
Fix: We provide a drop-in implementation which stores only the required tensors

Affected layers:

- Convolutions (nn.ConvNd)
- Batch norm in eval mode (nn.BatchNormNd)
- Transpose convolution (nn.ConvTransposeNd)

Interestingly, nn.Linear is optimized already!

Ours



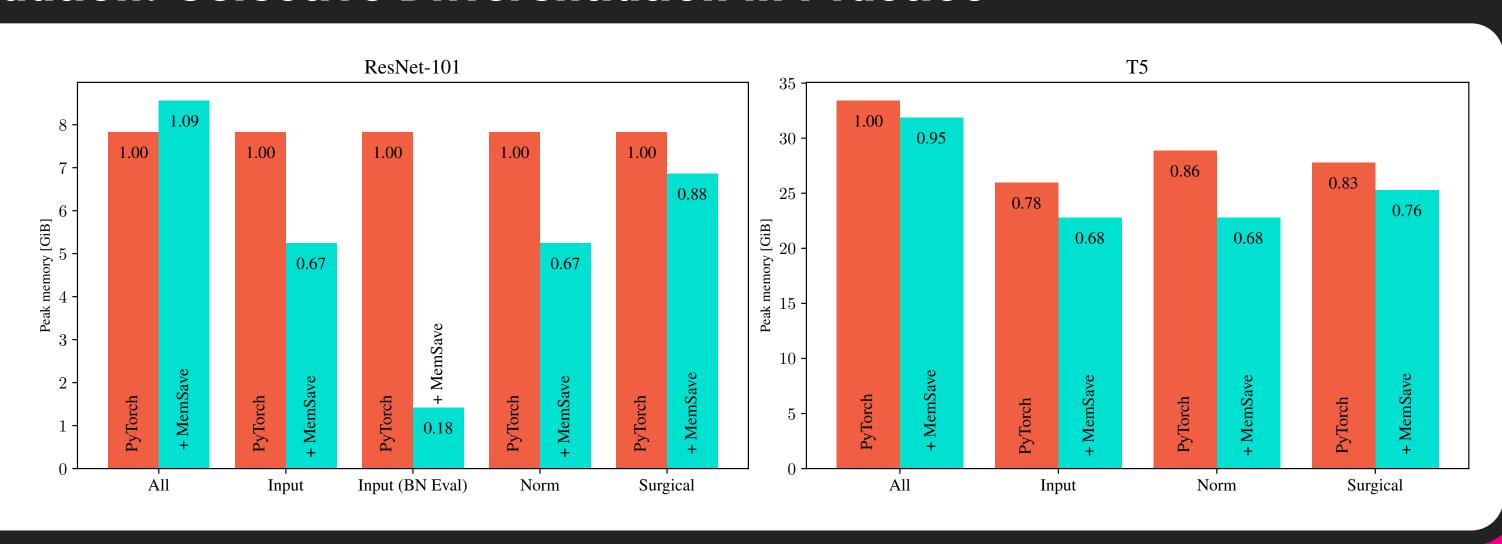
Other memory optimizations:

- nn.Relu: Store boolean mask instead of floating point tensor (4x reduction, soon 32x when torch.bit is implemented)
- nn.Dropout: Only save random number generator state and re-compute dropout mask

Evaluation: Selective Differentiation in Practice

We evaluate on practical scenarios:

- 'All': Training the full net (baseline)
- 'Input': Only input differentiable (style transfer, adversarial data)
- 'Norm': Only normalization layers trainable (layer-norm fine-tuning)
- 'Surgical': Only trainable subnetwork (surgical fine-tuning)



\$ pip install memsave
\$ model = memsave.convert(model)

Samarth is looking for a PhD position: samarth.bhatia23@alumni.iitd.ac.in





code