Deep learning

6.6. Using GPUs

François Fleuret

https://fleuret.org/dlc/
The size of current state-of-the-art networks makes computation a critical issue, in particular for training and optimizing meta-parameters.

Although they were historically developed for mass-market real-time CGI, the highly parallel architecture of GPUs is extremely fitting to signal processing and high dimension linear algebra.

Their use is instrumental in the success of deep-learning (Raina et al., 2009; Ciresan et al., 2010; Krizhevsky et al., 2012; Shi et al., 2016).
A standard NVIDIA GTX 3090 has 10,500 computing cores clocked at 1.5GHz, and delivers a peak performance of $\approx 35$ TFlops.

The precise structure of a GPU memory and how its cores communicate with it is a complicated topic that we will not cover here.

Notes

The thickness of the arrows illustrate the speed of the communication between components. Thin arrows mean slow access while thick arrows mean fast.

Each core of the CPU is able to run its own program and has access to the CPU memory (CPU RAM) at high speed, and to the disk and network through a slower bus. A CPU may have up to tens of cores (16, 32, sometimes 64).

A GPU comes with its own memory (GPU RAM) and thousands of cores. The GPU cores have a very fast access to the GPU memory, while the access between the CPU and GPU memories is quite slow: moving data from the CPU memory to the GPU memory is inefficient.

We will not cover the organization of the GPU memory (groups of cores, groups of groups, cache, etc.) but it is worth mentioning that properly programming a GPU at a low level is an extremely difficult task that requires strong expertise.
## TABLE 7. COMPARATIVE EXPERIMENT RESULTS (TIME PER MINI-BATCH IN SECOND)

<table>
<thead>
<tr>
<th>Network</th>
<th>Mini-batch size</th>
<th>Desktop CPU (Threads used)</th>
<th>Server CPU (Threads used)</th>
<th>Single GPU</th>
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</thead>
<tbody>
<tr>
<td>FCN-S</td>
<td>128</td>
<td>Caffe 0.700 0.378 0.1544</td>
<td>1.355 0.774 0.1208</td>
<td>1.130</td>
</tr>
<tr>
<td></td>
<td></td>
<td>CNTK 0.960 1.035</td>
<td>1.340 0.909 0.643</td>
<td>0.441</td>
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<tr>
<td></td>
<td></td>
<td>Torch 0.710 0.425</td>
<td>1.270 1.211 0.595</td>
<td>0.382</td>
</tr>
<tr>
<td></td>
<td>64</td>
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<td>1.355 0.774 0.1208</td>
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</table>

Notes

The table shows the results of a detailed benchmark between desktop CPU, server CPU, and single GPU for several deep learning libraries. The reported values are the time in seconds is takes to process one mini-batch. The take-home message is that GPUs provide a speed up of an order of magnitude or more.

(Shi et al., 2016)
The current standard to program a GPU is through the CUDA (“Compute Unified Device Architecture”) model, defined by NVIDIA.

Alternatives are OpenCL, backed by several CPU/DSP manufacturers, and more recently AMD’s HIP/ROCm.

Google developed its own line of processors for deep learning dubbed TPU (“Tensor Processing Unit”) which offer excellent flops/watt performance.

In practice, as of today (29.03.2022), NVIDIA hardware remains the default choice for deep learning, and CUDA is the reference framework in use.
From a practical perspective, libraries interface the framework (e.g. PyTorch) with the “computational backend” (e.g. CPU or GPU)

- BLAS (“Basic Linear Algebra Subprograms”): vector/matrix products, and the cuBLAS implementation for NVIDIA GPUs,
- LAPACK (“Linear Algebra Package”): linear system solving, Eigen-decomposition, etc.
- cuDNN (“NVIDIA CUDA Deep Neural Network library”) computations specific to deep-learning on NVIDIA GPUs.
Using GPUs in PyTorch
The use of the GPUs in PyTorch is done by creating or copying tensors into their memory.

Operations on tensors in a device’s memory are done by the said device.

Notes

Multiplying two tensors which are on the CPU (resp. GPU) memory is done by the CPU (resp. GPU).
Basic tensor operators, and virtually all functions require operand to be on the same device. E.g. when a forward pass has been done on the GPU, the output is on the GPU. Computing a loss with the target values would require the targets to also be on the GPU.
As for the type, the device can be specified to the creation operations as a device, or as a string that will implicitly be converted to a device.

```python
>>> x = torch.zeros(10, 10)
>>> x.device
device(type='cpu')

>>> x = torch.zeros(10, 10, device = torch.device('cuda'))
>>> x.device
device(type='cuda', index=0)

>>> x = torch.zeros(10, 10, device = torch.device('cuda:1'))
>>> x.device
device(type='cuda', index=1)

>>> x = torch.zeros(10, 10, device = 'cuda:0')
>>> x.device
device(type='cuda', index=0)
```
The `torch.Tensor.to(device)` returns a clone on the specified device if the tensor is not already there or returns the tensor itself if it was already there.

The argument `device` can be either a string, or a device.

Alternatives are `torch.Tensor.cuda([gpu_id])` and `torch.Tensor.cpu()`.

⚠️ Moving data between the CPU and the GPU memories is far slower than moving it inside the GPU memory.
>>> u = torch.tensor([1, 2, 3])
>>> u.device
device(type='cpu')
>>> v = u.to('cuda')  # copy of u
>>> v
tensor([1, 2, 3], device='cuda:0')
>>> v[0] = 5
>>> u
tensor([1, 2, 3])

Notes

Here, changing v does not change u because v was a copy.
But w points to the same data as u because the latter was already on the device.
```python
>>> m = torch.randn(10, 10)
>>> m.device
device(type='cpu')
>>> x = torch.randn(10, 100)
>>> q = m@x
>>> q.device
device(type='cpu')
>>> m = m.to('cuda')
>>> x = x.to('cuda')
>>> q = m@x # This is done on GPU (#0)
>>> q.device
device(type='cuda', index=0)
```
Since operations maintain the types and devices of the tensors, you generally do not need to worry about making your code generic regarding these aspects.

To explicitly create new tensors you can use a tensor’s `new_*()` methods.

```python
>>> u = torch.randn(3, 5, dtype = torch.float64)
>>> v = u.new_zeros(1, 2)

>>> v
tensor([[0., 0.]], dtype=torch.float64)

>>> w = torch.empty(3, 5, dtype = torch.float16,
...                  device = 'cuda:1').fill_(1.0)

>>> w.new_full((2, 3), 1.4)

  tensor([[1.4004, 1.4004, 1.4004],
          [1.4004, 1.4004, 1.4004]], device='cuda:1', dtype=torch.float16)
```

**Notes**

`new_*` methods allow to create tensors which are of the same type and on the same device as the object which we call them on:

- `u` is of type `float64` on the CPU, and so is `u.new_*`.
- `w` is of type `float16` on the GPU, and so is `w.new_*`. 

Apart from `copy_()` operations cannot mix different tensor types or devices:

```python
>>> import torch
>>> x = torch.randn(3, 5)
>>> y = torch.randn(3, 5).to('cuda')
>>> x.copy_(y)
tensor([[ 0.4071, 0.7589, -0.5321, 0.9103, -1.4985],
        [-0.1059, 2.1554, -0.0774, -0.4520, 1.5123],
        [ 0.1322, 0.1002, -0.4071, 1.8927, -0.5800]])
```

```python
>>> x + y
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
RuntimeError: Expected object of type torch.FloatTensor but found type torch.cuda.FloatTensor for argument #3 'other'
```

Similarly if multiple GPUs are available, cross-GPUs operations are not allowed by default, with the exception of `copy_()`.

Another exception to this rule are 0d tensors, which act as scalars and can be combined without device constraint.

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**Notes**

One has to explicitly move the objects to the same device before making an operation.

`x + y` fails because `x` is located on the CPU while `y` is on the GPU.
The method \texttt{torch.Module.to(device)} moves all the parameters and buffers of the module (and registered sub-modules recursively) to the specified device.

Although they do not have a “_” in their names, these \texttt{Module} operations make changes in-place.

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**Notes**

A tensor can be moved to a device with \( x = x.\text{to}(...) \). This is the case for minibatches and target values.

A module (network, criterion) can be moved to a device by simply calling \texttt{model.to(...) and criterion.to(...)}.
The method `torch.cuda.is_available()` returns a Boolean value indicating if a GPU is available, so a typical GPU-friendly code would start with:

```python
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

and then have some `device = device` in some places, and/or

```python
model.to(device)
criterion.to(device)
train_input, train_target = train_input.to(device), train_target.to(device)
test_input, test_target = test_input.to(device), test_target.to(device)
```
Multiple GPUs with \texttt{nn.DataParallel}
A very simple way to leverage multiple GPUs is to wrap the model in a `nn.DataParallel`.

The forward of `nn.DataParallel(my_module)` will

1. split the input mini-batch along the first dimension in as many mini-batches as there are GPUs,
2. send them to the forwards of clones of `my_module` located on each GPU,
3. concatenate the results.

And it is (of course!) autograd-compliant.
If we define a simple module to printout the calls to forward.

class Dummy(nn.Module):
    def __init__(self, m):
        super().__init__()
        self.m = m

    def forward(self, x):
        print('Dummy.forward', x.size(), x.device)
        return self.m(x)
```python
x = torch.randn(50, 10)
model = Dummy(nn.Linear(10, 5))

print('On CPU')
y = model(x)

x = x.to('cuda')
model.to('cuda')

print('On GPU w/o nn.DataParallel')
y = model(x)

print('On GPU w/ nn.DataParallel')
parallel_model = nn.DataParallel(model)
y = parallel_model(x)
```

will print, on a machine with two GPUs:

```
On CPU
  Dummy.forward torch.Size([50, 10]) cpu
On GPU w/o nn.DataParallel
  Dummy.forward torch.Size([50, 10]) cuda:0
On GPU w/ nn.DataParallel
  Dummy.forward torch.Size([25, 10]) cuda:0
  Dummy.forward torch.Size([25, 10]) cuda:1
```

Notes

This little example shows that on a machine with two GPUs, the input batch of fifty samples is split in two batches of twenty-five samples. `nn.DataParallel` allows to leverage multiple GPUs with a minimal change of the code, by simply wrapping the model.
References


