Lecture 28 - GPU and Distributed Training

DSE 512

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2022-05-10

From Last Time

- Homework 5 is assigned: due tomorrow
- Last day today!
- Questions?

Training with PyTorch

Example

We will be using modifications of a horovod example

https://github.com/horovod/horovod/blob/master/examples/pytorch/pytorch_mnist.py

MNIST Data

- handwritten digits
- 60,000 examples

Getting the Data

```python
from torchvision import datasets

data_dir = '/tmp/mnist'
datasets.MNIST(data_dir, train=False, download=True)
```

Loading the Data

```
train_dataset = datasets.MNIST(data_dir, train=True, download=False,
    transform=transforms.Compose([
       transforms.ToTensor(),
       transforms.Normalize((0.1307,), (0.3081,))
    ]))

test_dataset = datasets.MNIST(data_dir, train=False,
    transform=transforms.Compose([
        transforms.ToTensor(),
        transforms.Normalize((0.1307,), (0.3081,))
    ]))
```

Defining the Network

```python
import torch.nn as nn
import torch.nn.functional as F

class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 10, kernel_size=5)
        self.conv2 = nn.Conv2d(10, 20, kernel_size=5)
        self.conv2_drop = nn.Dropout2d()
        self.fc1 = nn.Linear(320, 50)
        self.fc2 = nn.Linear(50, 10)

    def forward(self, x):
        x = F.relu(F.max_pool2d(self.conv1(x), 2))
        x = F.relu(F.max_pool2d(self.conv2_drop(self.conv2(x)), 2))
        x = x.view(-1, 320)
        x = F.relu(self.fc1(x))
        x = F.dropout(x, training=self.training)
        x = self.fc2(x)
        return F.log_softmax(x, dim=-1)
```

The Outline

```
torch.manual_seed(1234)
torch.set_num_threads(8)

model = Net()
optimizer = optim.SGD(model.parameters(), lr=learning_rate, momentum=momentum)

for epoch in range(1, epochs + 1):
    train(epoch)
    test()
```

Defining the Training/Test Loops

Training

- Iterate over the data
  - Apply model (forward propagation)
  - Compute loss
  - Backpropagation
  - Update optimizer

Test

- Iterate over the data
  - Apply model (forward propagation)
  - Compute loss
  - Make prediction
  - Compute accuracy

Using a GPU

- Relatively easy these days
- Operations mostly fp32 (fp16 acceleration if supported)
- Gamer cards can be used!

Using a GPU

```
torch.cuda.is_available()
```

```
True
```

```
device = torch.device(0)
print(device)
```

```
device(type='cuda', index=0)
```

```
torch.cuda.current_device()
```

```
0
```

```
torch.cuda.device_count()
```

```
1
```

```
torch.cuda.get_device_name(0)
```

```
'NVIDIA GeForce GTX 1070 Ti'
```

GPU Tensor Computing

```
x = torch.FloatTensor([1, 2])
x_gpu = x.cuda()
x_gpu
```

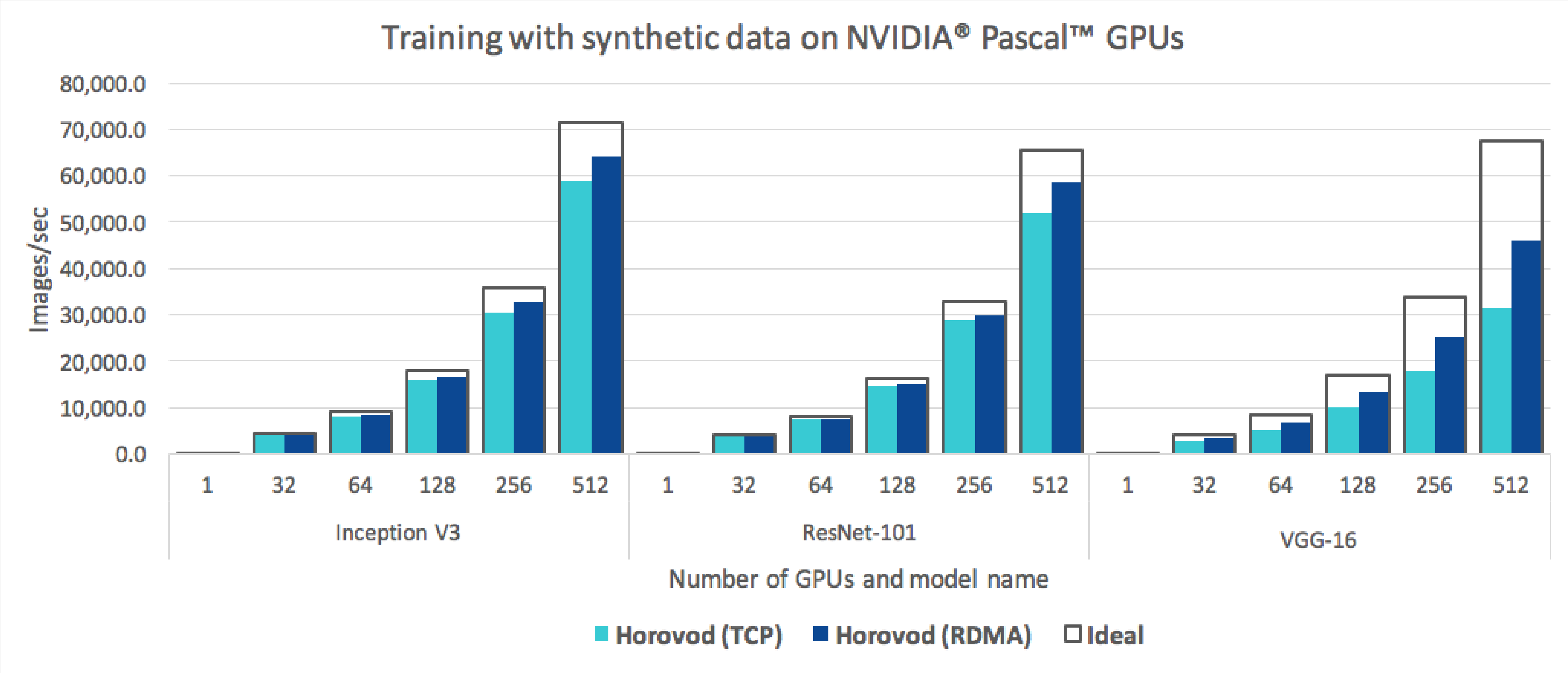
```
tensor([1., 2.], device='cuda:0')
```

Distributed Training with Horovod

What Is Horovod?

- Enables distributed training
- Named after a Russian dance
- Uses MPI!
- Powered by `allreduce()`

Horovod Scaling



Source: https://horovod.readthedocs.io/en/stable/summary_include.html

Why Use Horovod

- Runs on a laptop (need MPI installed)
- Runs on a cluser
- Easily integrates with GPUs
- Faster than

For any serious project, you should be using Horovod *from the start*.

Using Horovod: Major Changes

```python
import horovod
import horovod.torch as hvd

# Tensor averaging
def metric_average(val, name):
    tensor = torch.tensor([val])
    avg_tensor = hvd.allreduce(tensor, name=name)
    return avg_tensor.item()

# Wrap the optimizer
optimizer = hvd.DistributedOptimizer(optimizer,
    named_parameters = model.named_parameters(),
    compression = hvd.Compression.none,
    op = hvd.Average,
    gradient_predivide_factor = 1.0
)
```

Distributed Training (Data Parallelism)

```
train_dataset = datasets.MNIST(data_dir, train=True, download=False,
    transform=transforms.Compose([
        transforms.ToTensor(),
        transforms.Normalize((0.1307,), (0.3081,))
    ]))

train_sampler = torch.utils.data.distributed.DistributedSampler(
    train_dataset, num_replicas=hvd.size(), rank=hvd.rank())
train_loader = torch.utils.data.DataLoader(
    train_dataset, batch_size=batch_size, sampler=train_sampler)
```

Distributed Training (Data Parallelism)

```
test_dataset = \
    datasets.MNIST(data_dir, train=False, transform=transforms.Compose([
        transforms.ToTensor(),
        transforms.Normalize((0.1307,), (0.3081,))
    ]))
# Horovod: use DistributedSampler to partition the test data.
test_sampler = torch.utils.data.distributed.DistributedSampler(
    test_dataset, num_replicas=hvd.size(), rank=hvd.rank())
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=test_batch_size,
                                          sampler=test_sampler)
```

The Training Loop

```
def train(epoch):
    model.train()
    train_sampler.set_epoch(epoch)
    for batch_idx, (data, target) in enumerate(train_loader):
        optimizer.zero_grad()
        output = model(data)
        loss = F.nll_loss(output, target)
        loss.backward()
        optimizer.step()
```

The Test Loop

```
def test():
    model.eval()
    test_loss = 0.
    test_accuracy = 0.
    for data, target in test_loader:
        output = model(data)
        test_loss += F.nll_loss(output, target, size_average=False).item()
        pred = output.data.max(1, keepdim=True)[1]
        test_accuracy += pred.eq(target.data.view_as(pred)).cpu().float().sum()

    test_loss /= len(test_sampler)
    test_accuracy /= len(test_sampler)

    test_loss = metric_average(test_loss, 'avg_loss')
    test_accuracy = metric_average(test_accuracy, 'avg_accuracy')

    if hvd.rank() == 0:
        print('Test set: Average loss: {:.4f}, Accuracy: {:.2f}%\n'.format(
            test_loss, 100. * test_accuracy))
```

Launching

```python
def main():
    # setup omitted
    for epoch in range(1, epochs + 1):
        train(epoch)
        test()

num_proc = 8
horovod.run(main, np=num_proc, use_mpi=True)
```

Distributed Training

Training Without Horovod

```
Test: Avg loss: 0.2169, Acc: 93.45%
Test: Avg loss: 0.1334, Acc: 96.02%
Test: Avg loss: 0.1006, Acc: 96.99%
Test: Avg loss: 0.0833, Acc: 97.29%
Test: Avg loss: 0.0738, Acc: 97.68%
Test: Avg loss: 0.0682, Acc: 97.89%
Test: Avg loss: 0.0634, Acc: 97.99%
Test: Avg loss: 0.0588, Acc: 98.18%
Test: Avg loss: 0.0525, Acc: 98.35%
Test: Avg loss: 0.0512, Acc: 98.36%

real	3m9.633s
user	13m1.501s
sys	0m2.505s
```

Training With Horovod

```
Running training through horovod.run
[1,0]<stdout>:Test: Avg loss: 0.2353, Acc
[1,0]<stdout>:Test: Avg loss: 0.1405, Acc
[1,0]<stdout>:Test: Avg loss: 0.1088, Acc
[1,0]<stdout>:Test: Avg loss: 0.0822, Acc
[1,0]<stdout>:Test: Avg loss: 0.0766, Acc
[1,0]<stdout>:Test: Avg loss: 0.0652, Acc
[1,0]<stdout>:Test: Avg loss: 0.0650, Acc
[1,0]<stdout>:Test: Avg loss: 0.0560, Acc
[1,0]<stdout>:Test: Avg loss: 0.0618, Acc
[1,0]<stdout>:Test: Avg loss: 0.0505, Acc

real	1m16.417s
user	17m25.743s
sys	0m49.709s
```

What About GPUs?

- As before: set your tensors to use GPU
- Recommendation: one GPU $\longleftrightarrow$ one MPI rank
- Not just true for DL!
- Horovod makes this easy

```
torch.cuda.set_device(hvd.local_rank())
```

Wrapup

Wrapup

- Use Horovod for distributed training
- Can also be used for multi-core parallelism on a laptop
- GPU acceleration is fairly straight-forward
- A lot of these pieces can be abstracted and repurposed
  - Data loader class
  - Train/test

Where We've Been

Module 1: Basic Cloud and HPC

- Lecture 1 - Introduction
- Lecture 2 - Overview of HPC and the Cloud
- Lecture 3 - Introduction to Remote Computing
- Lecture 4 - Introduction to Containers
- Lecture 5 - Introduction to ISAAC
- Lecture 6 - MPI and Singularity

Where We've Been

Module 2: Performance Optimization

- Lecture 7 - Introduction to Performance Optimization
- Lecture 8 - High Level Language Optimizations
- Lecture 9 - Computational Linear Algebra Part 1
- Lecture 10 - Computational Linear Algebra Part 1
- Lecture 11 - GPGPU (The Easy Parts) Part 1
- Lecture 12 - GPGPU (The Easy Parts) Part 2
- Lecture 13 - Utilizing Compiled Code
- Lecture 14 - I/O

Where We've Been

Module 3: Parallelism

- Lecture 15 - Introduction to Parallelism
- Lecture 16 - Forks and Threads Part 1
- Lecture 17 - Forks and Threads Part 2
- Lecture 18 - MPI Part 1
- Lecture 19 - MPI Part 2
- Lecture 20 - MPI Part 3
- Lecture 21 - MapReduce

Where We've Been

Module 4: Profiling

- Lecture 22 - Profiling Basics
- Lecture 23 - Debugging Story
- Lecture 24 - HLL Profiling
- Lecture 25 - Advanced Profiling (Hardware and MPI)

Module 5: Deep Learning

- Lecture 26 - Basic Intro
- Lecture 27 - DL for Practitioners
- Lecture 28 - GPU and Distributed Training

Questions?