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# Writing Distributed Applications with PyTorch

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## Abstract

In this short tutorial, we will be going over the distributed package of PyTorch. We'll see how to set up the distributed setting, use the different communication strategies, and go over part of the internals of the package.

## 1 Setup

The distributed package included in PyTorch (i.e., `torch.distributed`) enables researchers and practitioners to easily distribute their computations across processes and clusters of machines. To do so, it leverages the messaging passing semantics allowing each process to communicate data to any of the other processes. As opposed to the multiprocessing (`torch.multiprocessing`) package, processes can use different communication backends and are not restricted to being executed on the same machine.

In order to get started we should thus be able to run multiple processes simultaneously. If you have access to compute cluster you should check with your local sysadmin or use your favorite coordination tool. (e.g., [pdsh](#), [clustershell](#), or [others](#)) For the purpose of this tutorial, we will use a single machine and can fork multiple processes using the following template.

```
"""run.py: """
#!/usr/bin/env python
import os
import torch
import torch.distributed as dist
from torch.multiprocessing import Process

def run(rank, size):
    """ Distributed function to be implemented later. """
    pass
```

```
def init_processes(rank, size, fn, backend='tcp'):
    """ Initialize the distributed environment. """
    os.environ['MASTER_ADDR'] = '127.0.0.1'
    os.environ['MASTER_PORT'] = '29500'
    dist.init_process_group(backend, rank=rank, world_size=size)
    fn(rank, size)

if __name__ == "__main__":
    size = 2
    processes = []
    for rank in range(size):
        p = Process(target=init_processes, args=(rank, size, run))
        p.start()
        processes.append(p)

    for p in processes:
        p.join()
```

In the above, the script spawns two processes who will each setup the distributed environment, initialize the process group (`dist.init_process_group`), and finally execute the given function.

The `init_processes` function is what interests us for now. It ensures that every process will be able to coordinate through a master, using the same ip address and port. Note that we used the TCP backend, but we could have used [MPI](#) or [Gloo](#) instead, provided they are installed. We will go over the magic happening in `dist.init_process_group` at the end of this tutorial, but it essentially allows processes to communicate with each other by sharing their locations.

## 2 Point-to-Point Communication

### Send and Recv

A transfer of data from one process to another is called a point-to-point communication. These are achieved through the `send` and `recv` functions or their *immediate* counter-parts, `isend` and `irecv`.

```
"""Blocking point-to-point communication."""

def run(rank, size):
    tensor = torch.zeros(1)
    if rank == 0:
        tensor += 1
        # Send the tensor to process 1
```

```
dist.send(tensor=tensor, dst=1)
else:
    # Receive tensor from process 0
    dist.recv(tensor=tensor, src=0)
    print('Rank ', rank, ' has data ', tensor[0])
```

In the above example, both processes start with a zero tensor, then process 0 increments the tensor and sends it to process 1 so that they both end up with 1.0. Notice that process 1 needs to allocate memory in order to store the data it will receive.

Also notice that `send/recv` are **blocking**: both processes stop until the communication is completed. Immediate's on the other hand are **non-blocking**, the script continues its execution and the methods return a `DistributedRequest` object upon which we can choose to `wait()`.

```
"""Non-blocking point-to-point communication."""

def run(rank, size):
    tensor = torch.zeros(1)
    req = None
    if rank == 0:
        tensor += 1
        # Send the tensor to process 1
        req = dist.isend(tensor=tensor, dst=1)
        print('Rank 0 started sending')
    else:
        # Receive tensor from process 0
        req = dist.irecv(tensor=tensor, src=0)
        print('Rank 1 started receiving')
        print('Rank 1 has data ', tensor[0])
    req.wait()
    print('Rank ', rank, ' has data ', tensor[0])
```

Running the above function a couple of times will sometimes result in process 1 still having 0.0 while having already started receiving. However, after `req.wait()` has been executed we are guaranteed that the communication took place.

Point-to-point communication is useful when we want a fine-grained control over the communication of our processes. They can be used to implement fancy algorithms, such as the one used in [Baidu's DeepSpeech](#) or [Facebook's large-scale experiments](#).

### 3 Collective Communication

Broadcast

AllGather

Reduce

AllReduce

Scatter

Gather

As opposed to point-to-point communication, collectives allow for communication patterns across all processes in a **group**. A group is a subset of all our processes. To create a group, we can pass a list of ranks to `dist.new_group(group)`. By default, collectives are executed on the all processes, also known as the **world**. Then, in order to obtain the sum of all tensors at all processes, we can use the `dist.all_reduce(tensor, op, group)` collective.

```
""" All-Reduce example."""
def run(rank, size):
    """ Simple point-to-point communication. """
    group = dist.new_group([0, 1])
    tensor = torch.ones(1)
    dist.all_reduce(tensor, op=dist.reduce_op.SUM, group=group)
    print('Rank ', rank, ' has data ', tensor[0])
```

Since we wanted the sum of all tensors in the group, we used `dist.reduce_op.SUM` as the reduce operator. Generally speaking, any commutative mathematical operation can be used as an operator. PyTorch comes with 4 out-of-the-box, all working at the element-wise level:

- `dist.reduce_op.SUM`,
- `dist.reduce_op.PRODUCT`,
- `dist.reduce_op.MAX`,
- `dist.reduce_op.MIN`.

In addition to `dist.all_reduce(tensor, op, group)`, there are a total of 6 collectives that are currently implemented in PyTorch.

- `dist.broadcast(tensor, src, group)`: Copies tensor from `src` to all other processes.
- `dist.reduce(tensor, dst, op, group)`: Applies `op` to all tensor and stores the result at `dst`.

- `dist.all_reduce(tensor, op, group)`: Same as `reduce`, but the result is stored at all processes.
- `dist.scatter(tensor, src, scatter_list, group)`: Copies `scatter_list[i]` to the  $i^{\text{th}}$  process.
- `dist.gather(tensor, dst, gather_list, group)`: Copies tensor from all processes to `dst`.
- `dist.all_gather(tensor_list, tensor, group)`: Copies tensor from all processes to `tensor_list`, on all processes.

## 4 Distributed Training

**Note:** You can find the full script of this example [here](#).

Now that we understand how the distributed module works, let us write something useful with it. Our goal will be to replicate the functionality of `DistributedDataParallel`. Of course, this will be a didactic example and in a real-world situation you should use the official, well-tested and well-optimized version linked above.

Quite simply we want to implement a distributed version of stochastic gradient descent. Our script will let all processes compute the gradients of their model on their batch of data and then average their gradients. In order to ensure replicability across runs, we will first have to partition our dataset. (You could also use `tnt.dataset.SplitDataset`)

```
""" Dataset partitioning helper """
class Partition(object):

    def __init__(self, data, index):
        self.data = data
        self.index = index

    def __len__(self):
        return len(self.index)

    def __getitem__(self, index):
        data_idx = self.index[index]
        return self.data[data_idx]

class DataPartitioner(object):

    def __init__(self, data, sizes=[0.7, 0.2, 0.1], seed=1234):
        self.data = data
        self.partitions = []
        rng = Random()
        rng.seed(seed)
```

```

data_len = len(data)
indexes = [x for x in range(0, data_len)]
rng.shuffle(indexes)

for frac in sizes:
    part_len = int(frac * data_len)
    self.partitions.append(indexes[0:part_len])
    indexes = indexes[part_len:]

def use(self, partition):
    return Partition(self.data, self.partitions[partition])

```

With the above snippet, we can now simply partition any dataset using the following few lines:

```

""" Partitioning MNIST """
def partition_dataset():
    dataset = datasets.MNIST('./data', train=True, download=True,
                             transform=transforms.Compose([
                                 transforms.ToTensor(),
                                 transforms.Normalize((0.1307,), (0.3081,))
                             ]))
    size = dist.get_world_size()
    bsz = 128 / float(size)
    partition_sizes = [1.0 / size for _ in range(size)]
    partition = DataPartitioner(dataset, partition_sizes)
    partition = partition.use(dist.get_rank())
    train_set = torch.utils.data.DataLoader(partition,
                                              batch_size=bsz,
                                              shuffle=True)

    return train_set, bsz

```

Assuming that we have 2 replicas, then each process will have a `train_set` of  $60000 / 2 = 30000$  samples. We also divide the batch size by the number of replicas in order to maintain the overall batch size of 128.

We can now write our usual forward-backward-optimize training code, and include a method to average the gradients of our models. (The following is largely inspired from the official [PyTorch MNIST example](#).)

```

""" Distributed Synchronous SGD Example """
def run(rank, size):
    torch.manual_seed(1234)
    train_set, bsz = partition_dataset()
    model = Net()

```

```

optimizer = optim.SGD(model.parameters(),
                       lr=0.01, momentum=0.5)

num_batches = ceil(len(train_set.dataset) / float(bsz))
for epoch in range(10):
    epoch_loss = 0.0
    for data, target in train_set:
        data, target = Variable(data), Variable(target)
        optimizer.zero_grad()
        output = model(data)
        loss = F.nll_loss(output, target)
        epoch_loss += loss.data[0]
        loss.backward()
        average_gradients(model)
        optimizer.step()
    print('Rank ', dist.get_rank(), ', epoch ',
          epoch, ': ', epoch_loss / num_batches)

```

It remains to implement the `average_gradients(model)` function, which simply takes in a model and averages its gradients across the group.

```

""" Gradient averaging. """
def average_gradients(model):
    size = float(dist.get_world_size())
    for param in model.parameters():
        dist.all_reduce(param.grad.data, op=dist.reduce_op.SUM, group=0)
        param.grad.data /= size

```

*Et voilà !* We successfully implemented distributed synchronous SGD and could train any model on a large computer cluster.

**Note:** While the last sentence is *technically* true, there are **a lot more tricks** required to implement a production-level implementation of synchronous SGD. Again, use what **has been tested**.

## 4.1 Our Own Ring-Allreduce

As an additional challenge, imagine that we wanted to implement DeepSpeech's efficient ring allreduce. This is fairly easily implemented using point-to-point collectives.

```

""" Implementation of a ring-reduce with addition. """
def allreduce(send, recv):

```

```
rank = dist.get_rank()
size = dist.get_world_size()
send_buff = th.zeros(send.size())
recv_buff = th.zeros(send.size())
accum = th.zeros(send.size())
accum[:] = send[:]

left = ((rank - 1) + size) % size
right = (rank + 1) % size

for i in range(size - 1):
    if i % 2 == 0:
        # Send send_buff
        send_req = dist.isend(send_buff, right)
        dist.recv(recv_buff, left)
        accum[:] += recv[:]
    else:
        # Send recv_buff
        send_req = dist.isend(recv_buff, right)
        dist.recv(send_buff, left)
        accum[:] += send[:]
    send_req.wait()
recv[:] = accum[:]
```

In the above script, the `allreduce(send, recv)` function has a slightly different signature than the ones in PyTorch. It takes a `recv` tensor and will store the sum of all `send` tensors in it. There is still one difference between our version and the one in DeepSpeech, which is left as an exercise to the reader: in their implementation they divide the reduced tensor into *chunks*, so as to optimially utilize the communication bandwidth.

## 5 Advanced Topics

We are now ready to discover some of the more advanced functionalities of `torch.distributed`. Since there is a lot to cover, this section is divided into three subsections:

1. Communication Backends: where we learn how to use MPI and Gloo for GPU-GPU communication.
2. Initialization Methods: where we understand how to best setup the initial coordination phase in `dist.init_process_group()`.
3. Internals: where we take a look at what is happening under the hood.



## 5.1 Communication Backends

One of the most elegant aspects of `torch.distributed` is its ability to use different backends. As mentioned before, there are currently three backends implemented in PyTorch: TCP, MPI, and Gloo. They all support different functions, depending on whether you use CPUs or GPUs. A comparative table can be found [here](#).

### 5.1.1 TCP Backend

So far, we have only been using the TCP backend. It is quite handy as a development platform, as it is guaranteed to work on most machines and operating systems. It also supports all point-to-point and collective functions on CPU. However, there is no support for GPUs and its communication routines are not as optimized as MPI.

### 5.1.2 Gloo Backend

The [Gloo backend](#) provides an optimized implementation of collective communication procedures, both for CPUs and GPUs. It particularly shines with GPUs as it can perform communication without transferring data to the CPU's memory using [GPUDirect](#). It is also capable of using [NCCL](#) to perform fast intra-node communication and its [own algorithms](#) for inter-node routines.

Since version 0.2.0, the Gloo backend is automatically included with the pre-compiled binaries of PyTorch. As you have surely noticed, our distributed SGD example above does not if you put `model` on the GPU. Let's fix it by first replacing `backend='gloo'` in `init_processes(rank, size, fn, backend='tcp')`. At this point, the script will still run on CPU, but uses the Gloo backend behind the scenes. In order to use multiple GPUs, let us also do the following modifications:

0. `init_processes(rank, size, fn, backend='tcp') → init_processes(rank, size, fn, backend='gloo')`
1. `model = Net() → model = Net().cuda(rank)`
2. `data, target = Variable(data), Variable(target) → data, target = Variable(data.cuda(rank)), Variable(target.cuda(rank))`

With the above modifications, our model is now training on two GPUs and you can monitor their utilization with `watch nvidia-smi`.

### 5.1.3 MPI Backend

The Message Passing Interface (MPI) is a standardized tool from the field of high-performance computing. It allows to do point-to-point and collective communications and was the main inspiration for the interface of `torch.distributed`. Several implementations of MPI exist (e.g. [Open-MPI](#), [MVAPICH2](#), [Intel MPI](#)) each optimized for different purposes. The advantage of using the MPI backend lies in MPI's wide availability - and high-level of optimization - on large clusters. [Some recent implementations](#) are also able to take advantage of CUDA IPC and GPU Direct technologies in order to avoid memory copies through the CPU.

Unfortunately, PyTorch's binaries can not include an MPI implementation and we'll have to recompile it by hand. Fortunately this process is fairly simple given that upon compilation, PyTorch will look *by itself* for an available MPI implementation. The following steps install the MPI backend, by installing PyTorch [from sources](#).

1. Create and activate your Anaconda environment, install all the pre-requisites following [the guide](#), but do not run `python setup.py install` yet.
2. Choose and install your favorite MPI implementation. Note that enabling CUDA-aware MPI might require some additional steps. In our case, we'll stick to Open-MPI *without* GPU support: `conda install -c mpi4py openmpi`
3. Now, go to your cloned PyTorch repo and execute `python setup.py install`.

In order to test our newly installed backend, a few modifications are required.

1. Replace `backend='mpi'` in `init_processes(rank, size, fn, backend='tcp')`.
2. Change `size = 4` to `size = 1`, right before creating the list of processes.
3. Run `mpirun -n 4 python myscript.py`.

The reason for changes 2. and 3. is that MPI needs to create its own environment before spawning the processes. This is actually quite powerful as you can pass additional arguments to `mpirun` in order to tailor computational resources for each process. (Things like number of cores per process, hand-assigning machines to specific ranks, and some more) Doing so, you should obtain the same familiar output as with the other communication backends.

## **5.2 Initialization Methods**

### **5.2.1 Environment Variable**

### **5.2.2 TCP Init & Multicast**

### **5.2.3 Shared File System**

### **5.2.4 Acknowledgements**

I'd like to thank the PyTorch developers for doing such a good job on their implementation. When the code was unclear, I could always count on the docs or the tests to find an answer. In particular, I'd like to thank Soumith Chintala, Adam Paszke, and Natalia Gimelshein for providing insightful comments and answering questions on early drafts.