Horovod: Distributed training framework

Khemraj Shukla

Division of Applied Mathematics, Brown University



Outline

➤ What's Horovod?

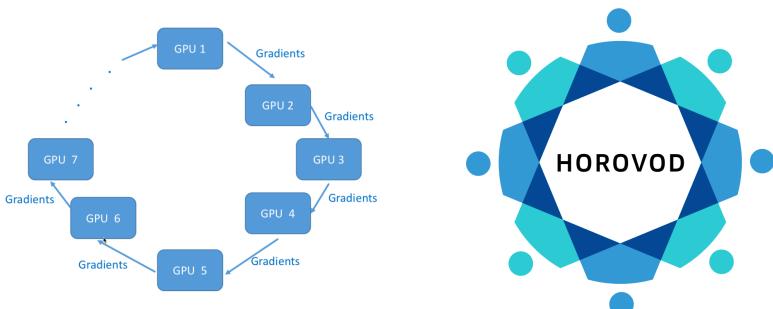
- > How to use?
 - 1. Data parallelism
 - 2. Ensemble training
- Examples for function approximation/PINN
 - 1. Data parallelism
 - 2. Ensemble training











Horovod

TensorFlow

MPI

NCCL-2

Computing Platform



Data parallelism & Ensemble training

| J n |
|-----|
| |
| |
| N |
| |
| J n |
| |
| l |

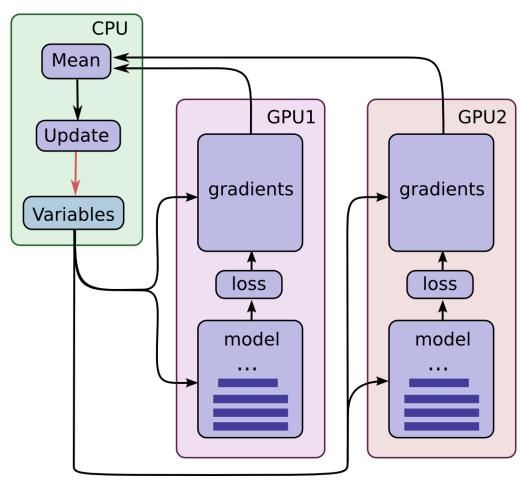
Outline

➤ What's Horovod?

- > How to use?
 - 1. Data parallelism
 - 2. Ensemble training
- Examples for function approximation/PINN
 - 1. Data parallelism
 - 2. Ensemble training



How to use Horovod – Data parallelism



- 1. Run multiple copies of the training scripts, and each copy:
 - Reads a chunk of data
 - Train the model
 - Compute the gradients
- 2. Average the gradients from all the copies
- 3. Update the model
- 4. Repeat 1-3

Show me the code: Data parallelism

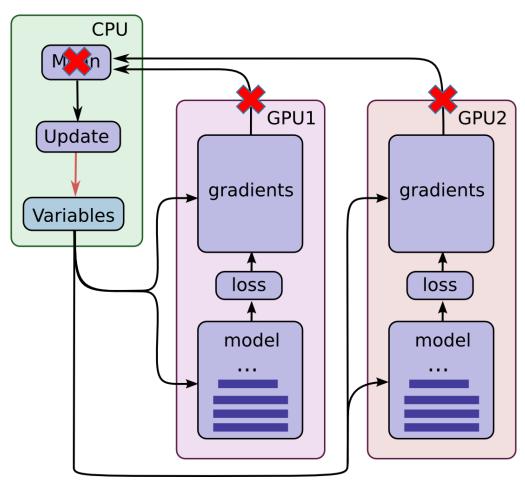
```
import tensorflow as tf
                                                init = tf.global_variables_initializer()
import horovod.tensorflow ad hvd
                                                sess.run(init)
hvd.init() #initialize the environment
                                                #broadcast the initialization to all processes
                                                bcast = hvd.broadcast global variables(0)
#pin one GPU to each tensorflow process
                                                sess.run(bcast)
config = tf.ConfigProto()
config.gpu_options.visible_device_list
                                               while train_step < step_max:
= str(hvd.local rank())
                                                         sess.run([train, loss], feed dict=...)
if hvd.rank() == 0: #read data
         read chunk 0
else:
                                                  horovodrun/mpirun –np NP –H
         read chunk n...
                                                  localhost:np
                                                  python *.py
# Build model...
loss = ...
                                                  mpirun –np NP –H
opt = tf.train.AdamOptimizer(learning rate *
                                                  server 1:np...server n: np
hvd.size())
                                                  python *.py
# Add Horovod Distributed Optimizer
opt = hvd.DistributedOptimizer(opt)
train = opt.minimize(loss)
```

Show me the code: Data parallelism

train = opt.minimize(loss)

```
import tensorflow as tf
                                                 init = tf.global_variables_initializer()
import horovod.tensorflow ad hvd 1
                                                 sess.run(init)
hvd.init() 2
                                                 bcast = hvd.broadcast global variables(0)
                                                 sess.run(bcast)
config = tf.ConfigProto()
config.gpu_options.visible_device_list
                                                 while train step < step max:
= str(hvd.local rank())
                                                           sess.run([train, loss], feed dict=...)
if hvd.rank() == 0:
         read chunk 0
else:
         read chunk n...
loss = ...
opt = tf.train.AdamOptimizer(learning rate *
hvd.size())
opt = hvd.DistributedOptimizer(opt)
```

How to use Horovod – Ensemble training



- 1. Run multiple copies of the training scripts, and each copy:
 - Reads a chunk of data
 - Train the model
 - Compute the gradients
- Update the model using their own gradient
- 3. Repeat 1-2

Show me the code: Ensemble training

```
import tensorflow as tf
import horovod.tensorflow ad hvd
hvd.init() #initialize the environment
#pin one GPU to each tensorflow process
config = tf.ConfigProto()
config.gpu_options.visible_device_list
= str(hvd.local rank())
if hvd.rank() == 0: #read data
         read chunk 0
else:
         read chunk n...
# Build model...
loss = ...
opt = tf.train.AdamOptimizer(learning rate)
# Add Horovod Distributed Optimizer
#opt = hvd.DistributedOptimizer(opt)
train = opt.minimize(loss)
```



Show me the code: Ensemble training

```
import tensorflow as tf
import horovod.tensorflow ad hvd 1
hvd.init() 2
config = tf.ConfigProto()
config.gpu_options.visible_device_list
= str(hvd.local rank())
if hvd.rank() == 0:
         read_chunk_0
else:
         read chunk n...
loss = ...
opt = tf.train.AdamOptimizer(learning rate)
#opt = hvd.DistributedOptimizer(opt)
train = opt.minimize(loss)
```



Outline

➤ What's Horovod?

- > How to use?
 - 1. Data parallelism
 - 2. Ensemble training
- Examples for function approximation/PINN
 - 1. Data parallelism
 - 2. Ensemble training

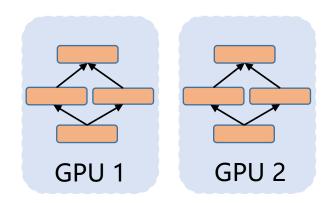


Example 1: Function approximation (Data parallelism)

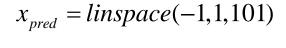
$$y = \sin(2\pi x) + \sin(4\pi x), x \in [-1, 1]$$

GPU 1 x = linspace(-1, 0, N)

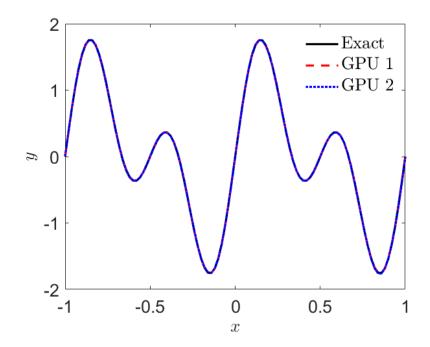
GPU 2 x = linspace(0,1,N)

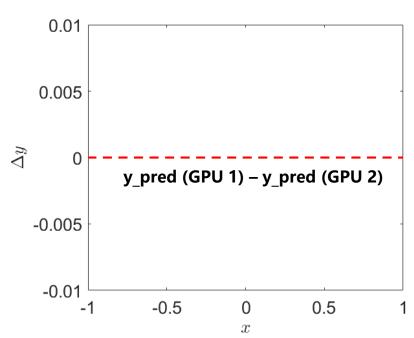


$$depth \times width = 16 \times 2$$



N = 16





Example 2: Function approximation (Ensemble training)

N = 16

$$y = \sin(2\pi x) + \sin(4\pi x), x \in [-1, 1]$$

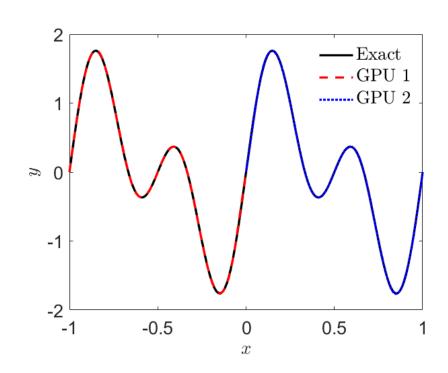
GPU 1
$$x = linspace(-1, 0, N)$$

GPU 2
$$x = linspace(0,1,N)$$

 $depth \times width = 16 \times 2$

GPU 1
$$x_{pred} = linspace(-1, 0, 101)$$

GPU 2 $x_{pred} = linspace(0, 1, 101)$



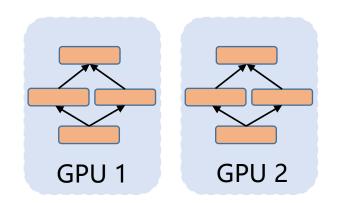
Example 2: Function approximation (Ensemble training)

$$y = \sin(2\pi x) + \sin(4\pi x), x \in [-1, 1]$$

GPU 1
$$x = linspace(-1, 0, N)$$

$$N = 16$$

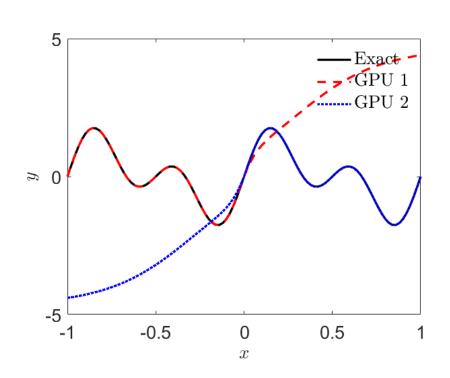
GPU 2
$$x = linspace(0,1,N)$$



 $depth \times width = 16 \times 2$

GPU 1
$$x_{pred} = linspace(-1,1,101)$$

GPU 2
$$x_{pred} = linspace(-1,1,101)$$



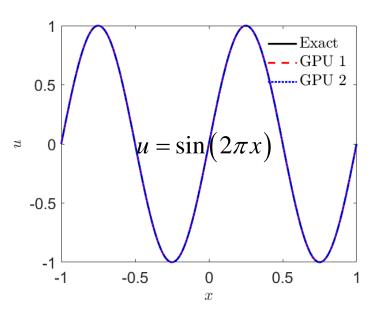
Example 3: PINNs (Data parallelism)

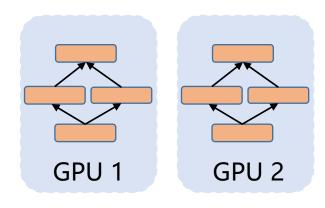
$$-\partial_{xx}u = f, x \in [-1,1]$$

$$f = 4\pi^2 \sin\left(2\pi x\right)$$

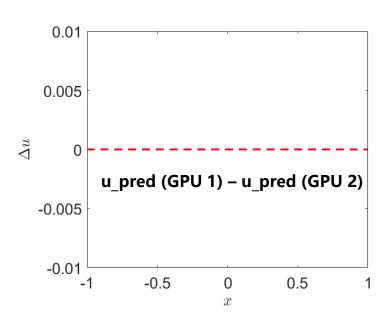
GPU 1
$$x = linspace(-1, 0, 51)$$

GPU 2
$$x = linspace(0,1,51)$$





 $depth \times width = 16 \times 2$



GPU 1
$$x = linspace(-1, 1, 201)$$

GPU 2
$$x = linspace(-1, 1, 201)$$

Example 4: PINNs (Ensemble training)

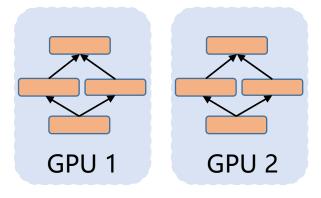
$$-\partial_{xx}u = f, x \in [-1,1]$$

GPU 1
$$f = \pi^2 \sin(\pi x)$$

GPU 2
$$f = 4\pi^2 \sin(2\pi x)$$

GPU 1
$$u = \sin(\pi x)$$

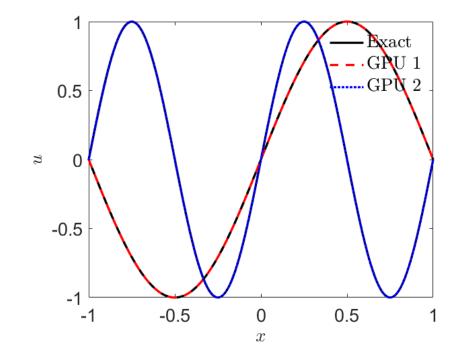
GPU 2
$$u = \sin(2\pi x)$$



 $depth \times width = 16 \times 2$

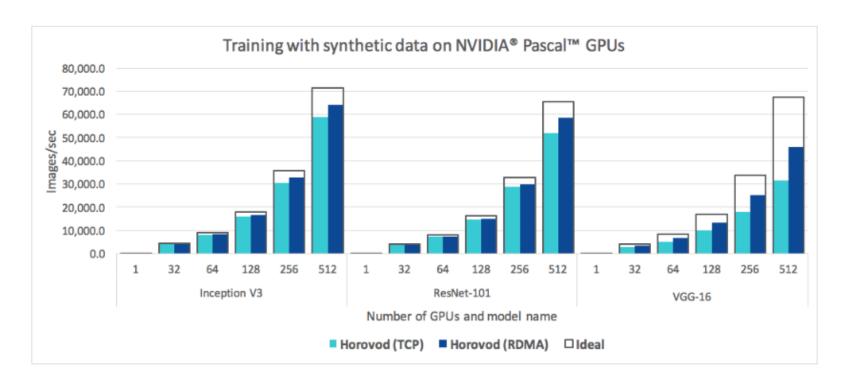
GPU 1
$$x = linspace(-1,1,101)$$

GPU 2
$$x = linspace(-1, 1, 101)$$





Scaling efficiency



The above benchmark was done on 128 servers with 4 Pascal GPUs each connected by a RoCE-capable 25 Gbit/s network. Horovod achieves 90% scaling efficiency for both Inception V3 and ResNet-101, and 68% scaling efficiency for VGG-16.



Installation & Code

Installation
https://github.com/horovod/horovod

CCV: Oscar module load horovod/0.16

Code download

https://github.com/XuhuiM/Distributed-training-Horovod.git



Thank you!

