

# multiple-gpus

April 9, 2019

## 1 Multi-GPU Computation with Data Parallelism

```
In [1]: import d2l
import mxnet as mx
from mxnet import autograd, nd
from mxnet.gluon import loss as gloss
import time
```

```
!nvidia-smi
```

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NVIDIA-SMI 396.37				Driver Version: 396.37							
+-----+											
GPU		Name		Persistence-M		Bus-Id		Disp.A		Volatile Uncorr. ECC	
Fan		Temp		Perf		Pwr:Usage/Cap		Memory-Usage		GPU-Util Compute M.	
+=====+											
0		Tesla M60		Off		00000000:00:1D.0		Off		0	
N/A		31C		P0		38W / 150W		2639MiB / 7618MiB		0% Default	
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1		Tesla M60		Off		00000000:00:1E.0		Off		0	
N/A		33C		P8		13W / 150W		11MiB / 7618MiB		0% Default	
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Processes:										GPU Memory	
GPU		PID		Type		Process name				Usage	
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### 1.1 Define the Model: LeNet

```
In [3]: scale = 0.01
W1 = nd.random.normal(scale=scale, shape=(20, 1, 3, 3))
b1 = nd.zeros(shape=20)
W2 = nd.random.normal(scale=scale, shape=(50, 20, 5, 5))
```

```

b2 = nd.zeros(shape=50)
W3 = nd.random.normal(scale=scale, shape=(800, 128))
b3 = nd.zeros(shape=128)
W4 = nd.random.normal(scale=scale, shape=(128, 10))
b4 = nd.zeros(shape=10)
params = [W1, b1, W2, b2, W3, b3, W4, b4]

def lenet(X, params):
    h1_conv = nd.Convolution(data=X, weight=params[0], bias=params[1],
                             kernel=(3, 3), num_filter=20)
    h1_activation = nd.relu(h1_conv)
    h1 = nd.Pooling(data=h1_activation, pool_type='avg', kernel=(2, 2),
                    stride=(2, 2))
    h2_conv = nd.Convolution(data=h1, weight=params[2], bias=params[3],
                             kernel=(5, 5), num_filter=50)
    h2_activation = nd.relu(h2_conv)
    h2 = nd.Pooling(data=h2_activation, pool_type='avg', kernel=(2, 2),
                    stride=(2, 2))
    h2 = nd.flatten(h2)
    h3_linear = nd.dot(h2, params[4]) + params[5]
    h3 = nd.relu(h3_linear)
    y_hat = nd.dot(h3, params[6]) + params[7]
    return y_hat

loss = gloss.SoftmaxCrossEntropyLoss()

```

## 1.2 Copy Parameter to a Device

```

In [4]: def get_params(params, ctx):
        new_params = [p.copyto(ctx) for p in params]
        for p in new_params:
            p.attach_grad()
        return new_params

new_params = get_params(params, mx.gpu(0))
print('b1 weight:', new_params[1])
print('b1 grad:', new_params[1].grad)

```

## 1.3 Sum Over All Devices and then Broadcast

```

In [6]: def allreduce(data):
        for i in range(1, len(data)):
            data[0][:] += data[i].copyto(data[0].context)
        for i in range(1, len(data)):
            data[0].copyto(data[i])

data = [nd.ones((1, 2), ctx=mx.gpu(i)) * (i + 1) for i in range(2)]
print('before allreduce:', data)

```

```
allreduce(data)
print('after allreduce:', data)
```

## 1.4 Split a Data Batch into Each GPUs

```
In [8]: def split_and_load(data, ctx):
        n, k = data.shape[0], len(ctx)
        m = n // k # For simplicity, we assume the data is divisible.
        assert m * k == n, '# examples is not divided by # devices.'
        return [data[i * m: (i + 1) * m].as_in_context(ctx[i]) for i in range(k)]

batch = nd.arange(24).reshape((6, 4))
ctx = [mx.gpu(0), mx.gpu(1)]
splitted = split_and_load(batch, ctx)
print('input: ', batch)
print('load into', ctx)
print('output:', splitted)
```

## 1.5 Multi-GPU Training on a Single Mini-batch

```
In [10]: def train_batch(X, y, gpu_params, ctx, lr):
        # When ctx contains multiple GPUs, mini-batches of data instances are divided and
        gpu_Xs, gpu_ys = split_and_load(X, ctx), split_and_load(y, ctx)
        with autograd.record(): # Loss is calculated separately on each GPU.
            ls = [loss(lenet(gpu_X, gpu_W), gpu_y)
                   for gpu_X, gpu_y, gpu_W in zip(gpu_Xs, gpu_ys, gpu_params)]
        for l in ls: # Back Propagation is performed separately on each GPU.
            l.backward()
        # Add up all the gradients from each GPU and then broadcast them to all the GPUs.
        for i in range(len(gpu_params[0])):
            allreduce([gpu_params[c][i].grad for c in range(len(ctx))])
        for param in gpu_params: # The model parameters are updated separately on each GPU.
            d2l.sgd(param, lr, X.shape[0]) # Here, we use a full-size batch.
```

## 1.6 Training Functions

```
In [11]: def train(num_gpus, batch_size, lr):
        train_iter, test_iter = d2l.load_data_fashion_mnist(batch_size)
        ctx = [mx.gpu(i) for i in range(num_gpus)]
        print('running on:', ctx)
        # Copy model parameters to num_gpus GPUs.
        gpu_params = [get_params(params, c) for c in ctx]
        for epoch in range(4):
            start = time.time()
            for X, y in train_iter:
                # Perform multi-GPU training for a single mini-batch.
                train_batch(X, y, gpu_params, ctx, lr)
            nd.waitall()
```

```

train_time = time.time() - start

def net(x): # Verify the model on GPU 0.
    return lenet(x, gpu_params[0])

test_acc = d2l.evaluate_accuracy(test_iter, net, ctx[0])
print('epoch %d, time: %.1f sec, test acc: %.2f'
      % (epoch + 1, train_time, test_acc))

```

## 1.7 Multi-GPU Training Experiment

```
In [12]: train(num_gpus=1, batch_size=256, lr=0.2)
```

```

running on: [gpu(0)]
epoch 1, time: 2.7 sec, test acc: 0.10
epoch 2, time: 2.2 sec, test acc: 0.66
epoch 3, time: 2.2 sec, test acc: 0.75
epoch 4, time: 2.2 sec, test acc: 0.71

```

```
In [13]: train(num_gpus=2, batch_size=256, lr=0.2)
```

```

running on: [gpu(0), gpu(1)]
epoch 1, time: 2.5 sec, test acc: 0.10
epoch 2, time: 2.2 sec, test acc: 0.61
epoch 3, time: 2.2 sec, test acc: 0.75
epoch 4, time: 2.2 sec, test acc: 0.76

```