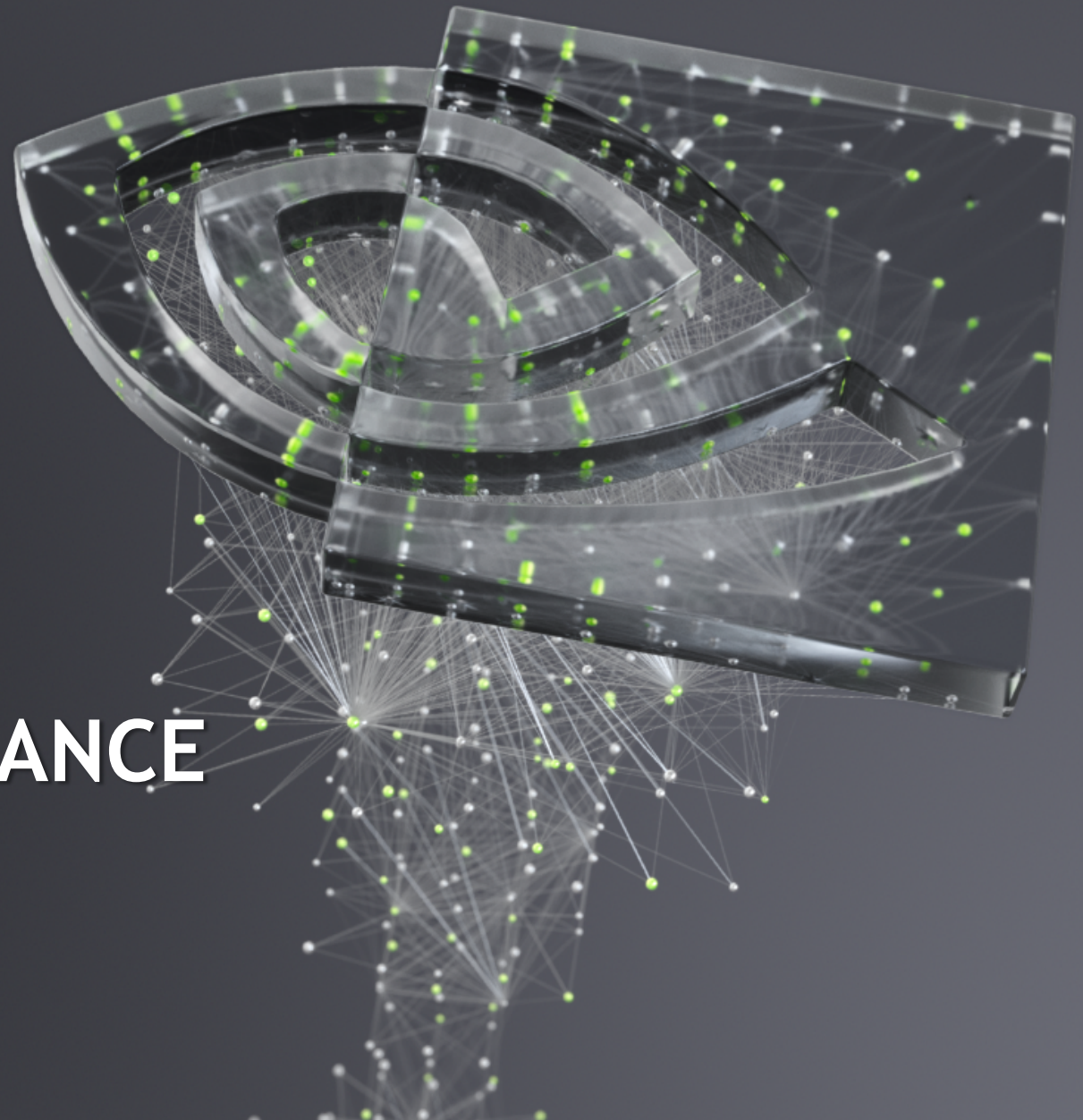


PYTORCH PERFORMANCE TUNING GUIDE

Szymon Migacz, 04/12/2021

CONTENT

PyTorch Performance Tuning Guide

- Simple techniques to improve training performance
- Implement by changing a few lines of code

GENERAL OPTIMIZATIONS

ENABLE ASYNC DATA LOADING & AUGMENTATION

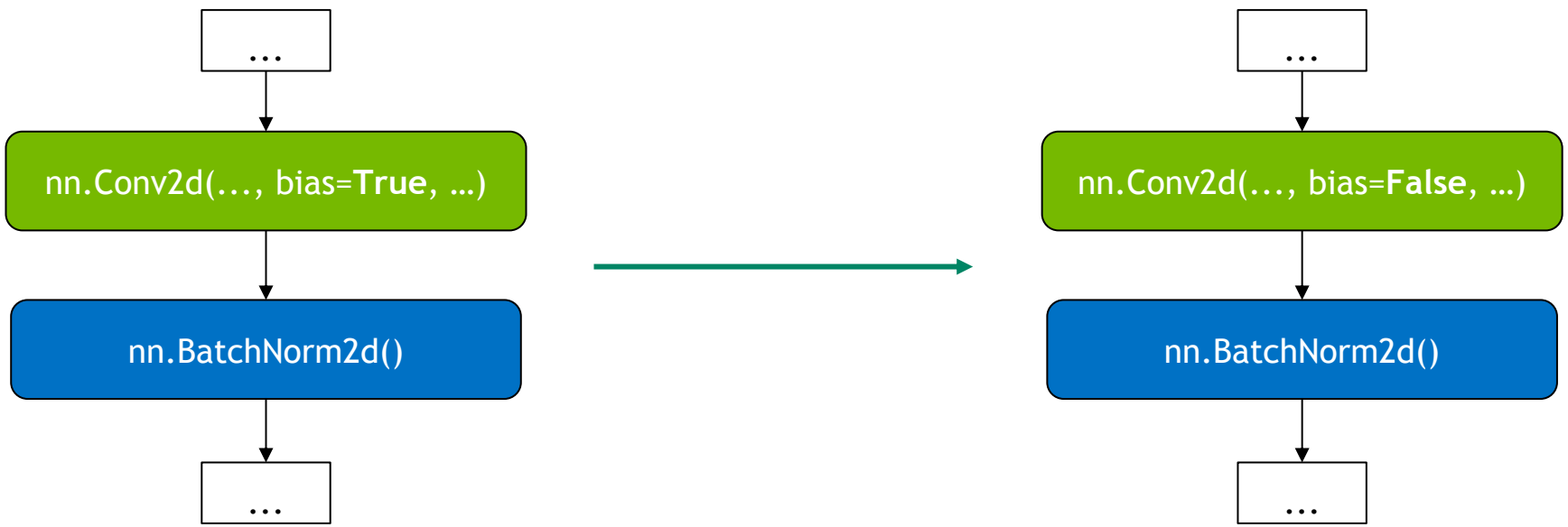
- PyTorch DataLoader supports asynchronous data loading / augmentation
  - Default settings: `num_workers=0, pin_memory=False`
- Use `num_workers > 0` to enable asynchronous data processing
- Use `pin_memory=True`

Example: PyTorch MNIST example: DataLoader with default `{'num_workers': 1, 'pin_memory': True}`.

Setting for the training DataLoader	Time for one training epoch
`{'num_workers': 0, 'pin_memory': False}`	8.2 s
`{'num_workers': 1, 'pin_memory': False}`	6.75 s
`{'num_workers': 1, 'pin_memory': True}`	6.7 s
`{'num_workers': 2, 'pin_memory': True}`	4.2 s
`{'num_workers': 4, 'pin_memory': False}`	4.5 s
`{'num_workers': 4, 'pin_memory': True}`	4.1 s
`{'num_workers': 8, 'pin_memory': True}`	4.5 s

PyTorch 1.6, NVIDIA Quadro RTX 8000

DISABLE BIAS FOR CONVOLUTIONS DIRECTLY FOLLOWED BY A BATCH NORM



Also applicable to Conv1d, Conv3d if BatchNorm normalizes on the same dimension as convolution's bias.

EFFICIENTLY SET GRADIENTS TO ZERO

```
model.zero_grad()

# or

optimizer.zero_grad()
```

```
for param in model.parameters():
    param.grad = None

# or (in PyT >= 1.7)

model.zero_grad(set_to_none=True)
```

- executes memset for every parameter in the model
- backward pass updates gradients with "+=" operator (read + write)

- doesn't execute memset for every parameter
- memory is zeroed-out by the allocator in a more efficient way
- backward pass updates gradients with "=" operator (write)

DISABLE GRADIENT CALCULATION FOR INFERENCE

```
# torch.no_grad() as a context manager:
with torch.no_grad():
      output = model(input)

# torch.no_grad() as a function decorator:
@torch.no_grad()
def validation(model, input):
      output = model(input)
      return output
```

FUSE POINTWISE OPERATIONS

- PyTorch JIT can fuse pointwise operations into a single CUDA kernel.
- Unfused pointwise operations are memory-bound, for each unfused op PyTorch:
  - launches a separate kernel
  - loads data from global memory
  - performs computation
  - stores results back into global memory

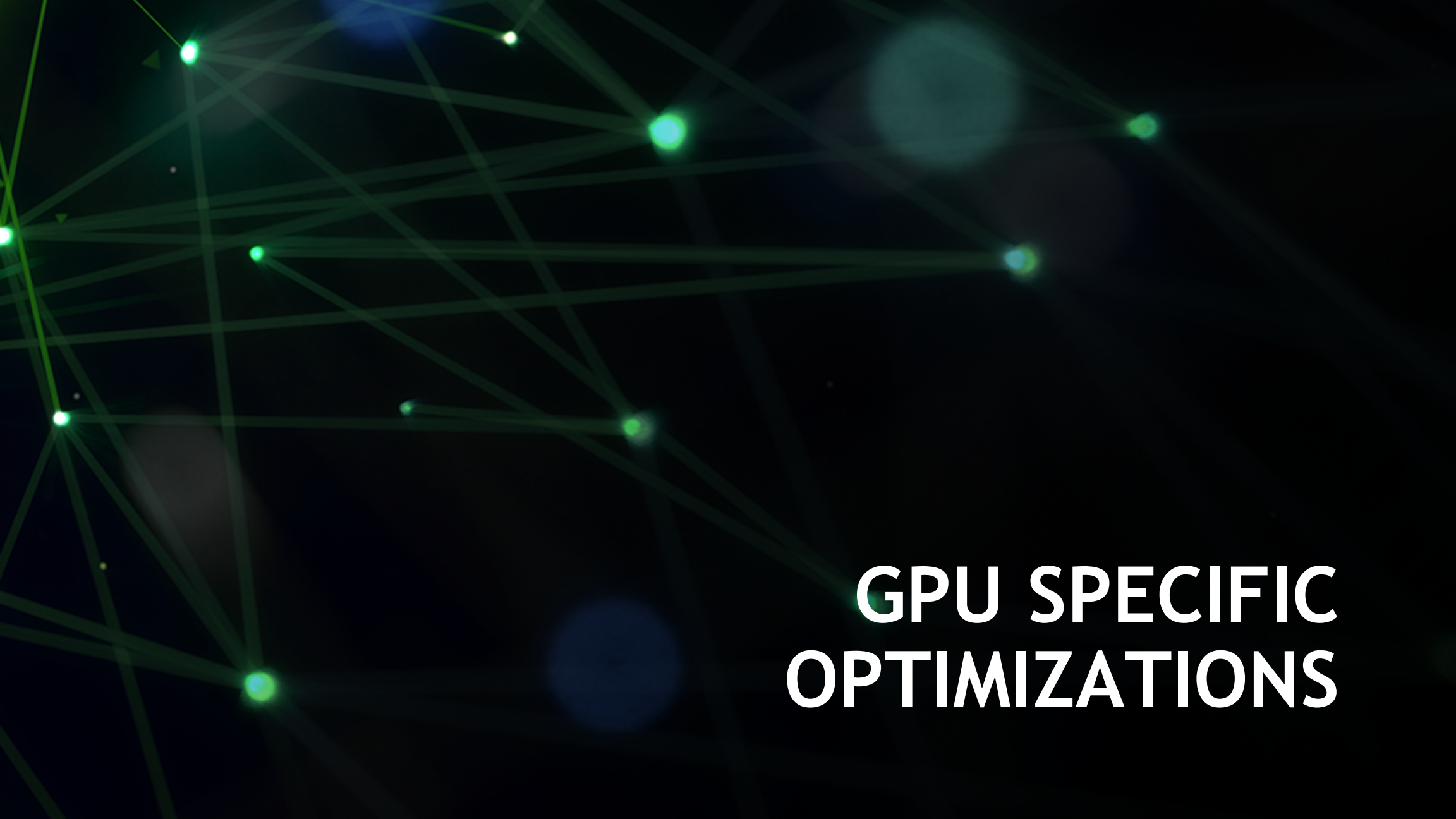
Example:

```
def gelu(x):
    return x * 0.5 * (1.0 + torch.erf(x / 1.41421))
```

```
@torch.jit.script
def fused_gelu(x):
    return x * 0.5 * (1.0 + torch.erf(x / 1.41421))
```

Function name	Number of CUDA kernels launched	Execution time [us] (input vector with 1M elements)
`gelu(x)`	5	65
`fused_gelu(x)`	1	16

PyTorch 1.6, NVIDIA Quadro RTX 8000


GPU SPECIFIC
OPTIMIZATIONS

USE MIXED PRECISION AND AMP

- Set sizes to multiples of 8
  - See Deep Learning Performance Documentation for more details and guidelines specific to layer type
  - Use explicit padding when necessary (e.g. vocabulary size in NLP)
- Enable AMP
  - Introduction to Mixed Precision Training and AMP: video, slides
  - Native PyTorch AMP is available starting from PyTorch 1.6: documentation, examples, tutorial

ENABLE cuDNN AUTOTUNER

For convolutional neural networks, enable cuDNN autotuner by setting:

```
torch.backends.cudnn.benchmark = True
```

- cuDNN supports many algorithms to compute convolution
- autotuner runs a short benchmark and selects algorithm with the best performance

Example:
nn.Conv2d with 64 3x3 filters applied to an input with batch size = 32, channels = width = height = 64.

Setting	`cudnn.benchmark = False` (the default)	`cudnn.benchmark = True`	**Speedup**
Forward propagation (FP32) [us]	1430	840	1.70
Forward + backward propagation (FP32) [us]	2870	2260	1.27

PyTorch 1.6, NVIDIA Quadro RTX 8000

CREATE TENSORS DIRECTLY ON TARGET DEVICE

```
torch.rand(size).cuda()
```

```
torch.rand(
    size,
    device=torch.device('cuda'),
)
```

Also applicable to:

```
torch.empty(), torch.zeros(), torch.full(), torch.ones(),
torch.eye(), torch.randint(), torch.randn()
```

and similar functions.

AVOID CPU-GPU SYNC

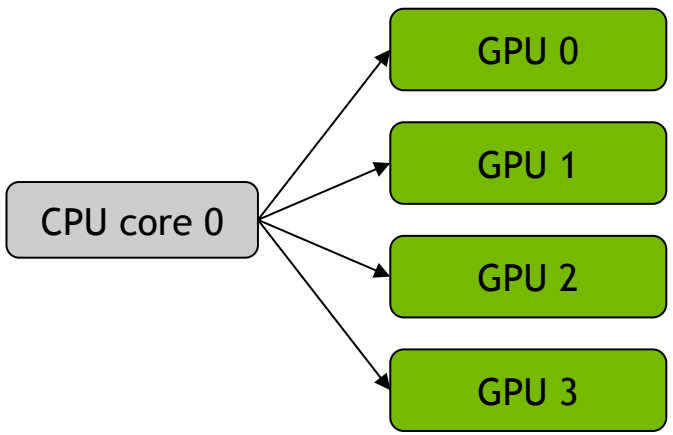
- Operations which require synchronization:
  - `print(cuda_tensor)`
  - `cuda_tensor.item()`
  - memory copies: `tensor.cuda()`, `cuda_tensor.cpu()` and `tensor.to(device)` calls
  - `cuda_tensor.nonzero()`
  - python control flow which depends on operations on CUDA tensors e.g.

```
if (cuda_tensor != 0).all()
```


DISTRIBUTED
OPTIMIZATIONS

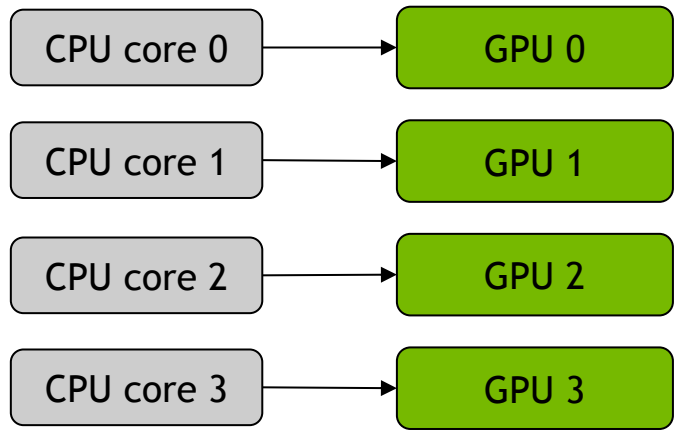
USE EFFICIENT MULTI-GPU BACKEND

DataParallel



- 1 CPU core drives multiple GPUs
- 1 python process drives multiple GPUs (GIL)
- only up to a single node

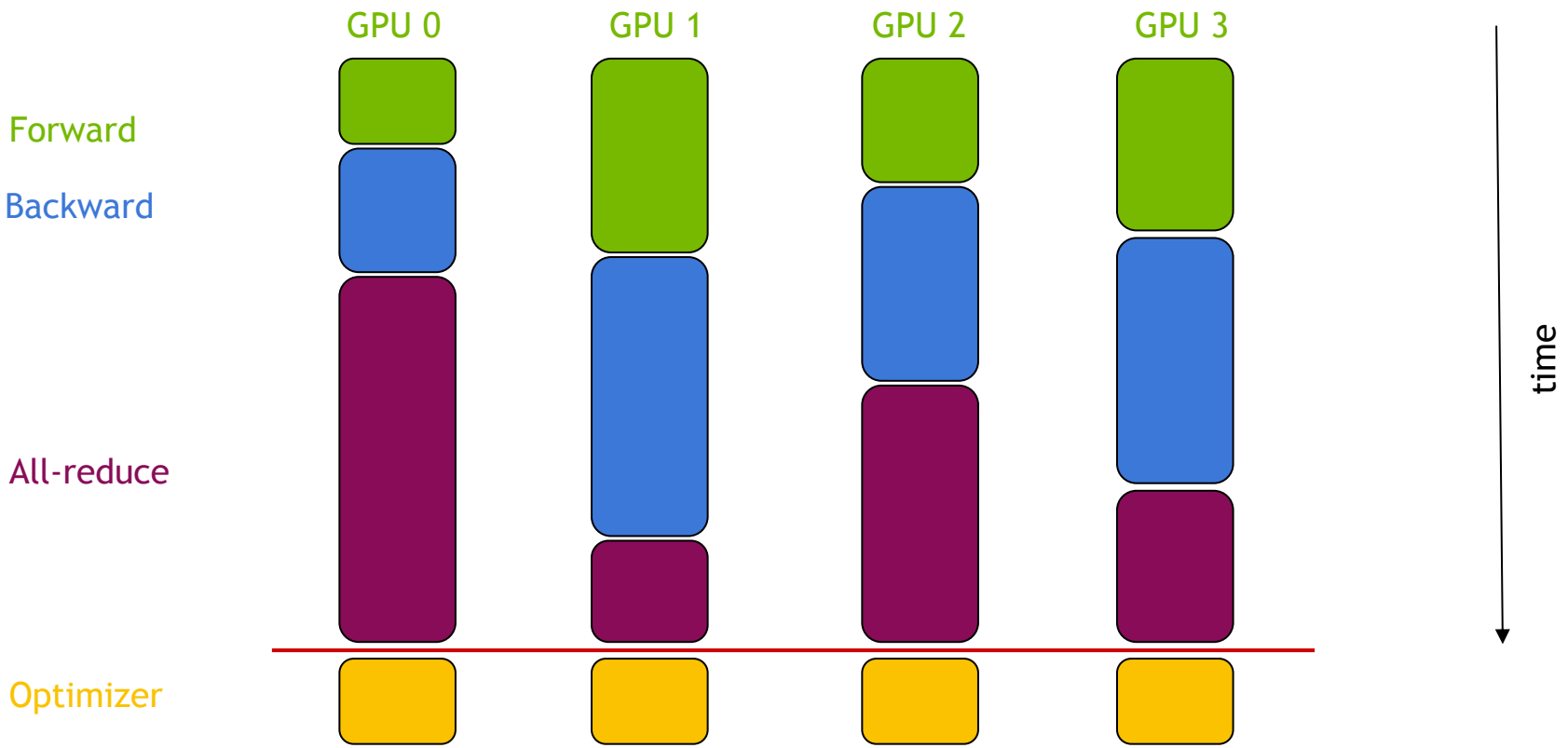
DistributedDataParallel



- 1 CPU core for each GPU
- 1 python process for each GPU
- single-node and multi-node (same API)
- efficient implementation:
  - automatic bucketing for grad all-reduce
  - all-reduce overlapped with backward pass
- multi-process programing

LOAD-BALANCE WORKLOAD ON MULTIPLE GPUs

Gradient all-reduce after backward pass is a synchronization point in a multi-GPU setting



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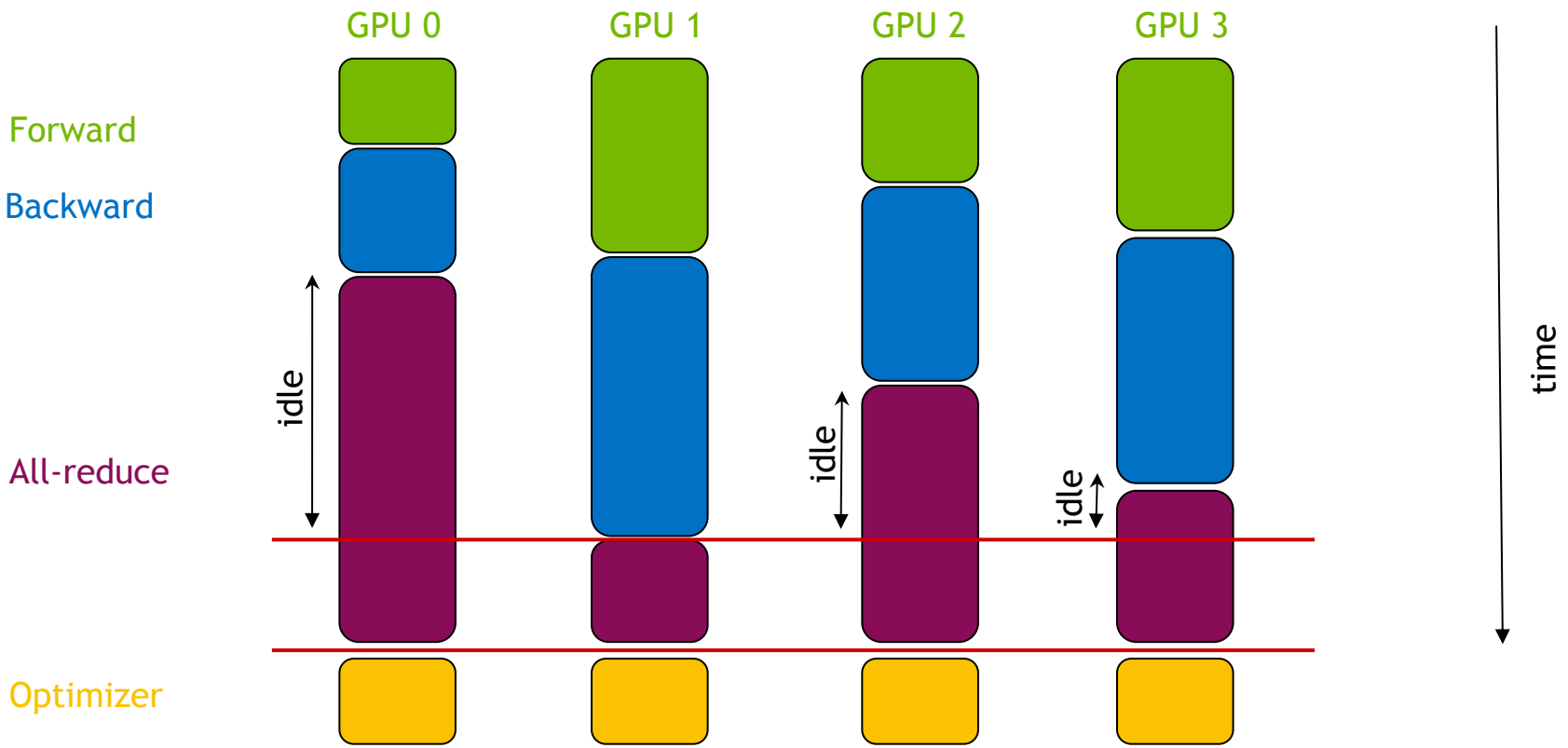

SUMMARY

- General optimizations:
  - Use asynchronous data loading
  - Disable bias for convolutions directly followed by batch norm
  - Efficiently set gradients to zero
  - Disable gradient calculation for validation/inference
  - Fuse pointwise operations with PyTorch JIT
- GPU specific optimizations:
  - Use mixed precision and AMP
  - Enable cuDNN autotuner
  - Create tensors directly on a GPU
  - Avoid CPU-GPU sync
- Distributed optimizations
  - Use DistributedDataParallel
  - Load-balance workload on all GPUs

ADDITIONAL RESOURCES

- PyTorch Tutorial: Performance Tuning Guide
  - Check for more optimizations
- NVIDIA Deep Learning Performance Documentation
- Introduction to Mixed Precision Training and AMP: video, slides
- Using Nsight Systems to profile GPU workload (PyTorch Dev forum)