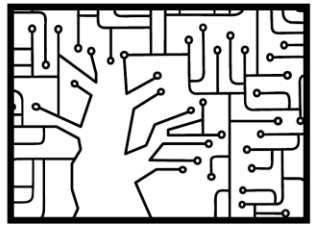
Training Large Models

Shai Bagon



Training Large Models

- Make the mem footprint smaller

  Fewer bits/variable

- Utilize more memory

  Parallel GPUs

Mixed Precision

Binary Variables

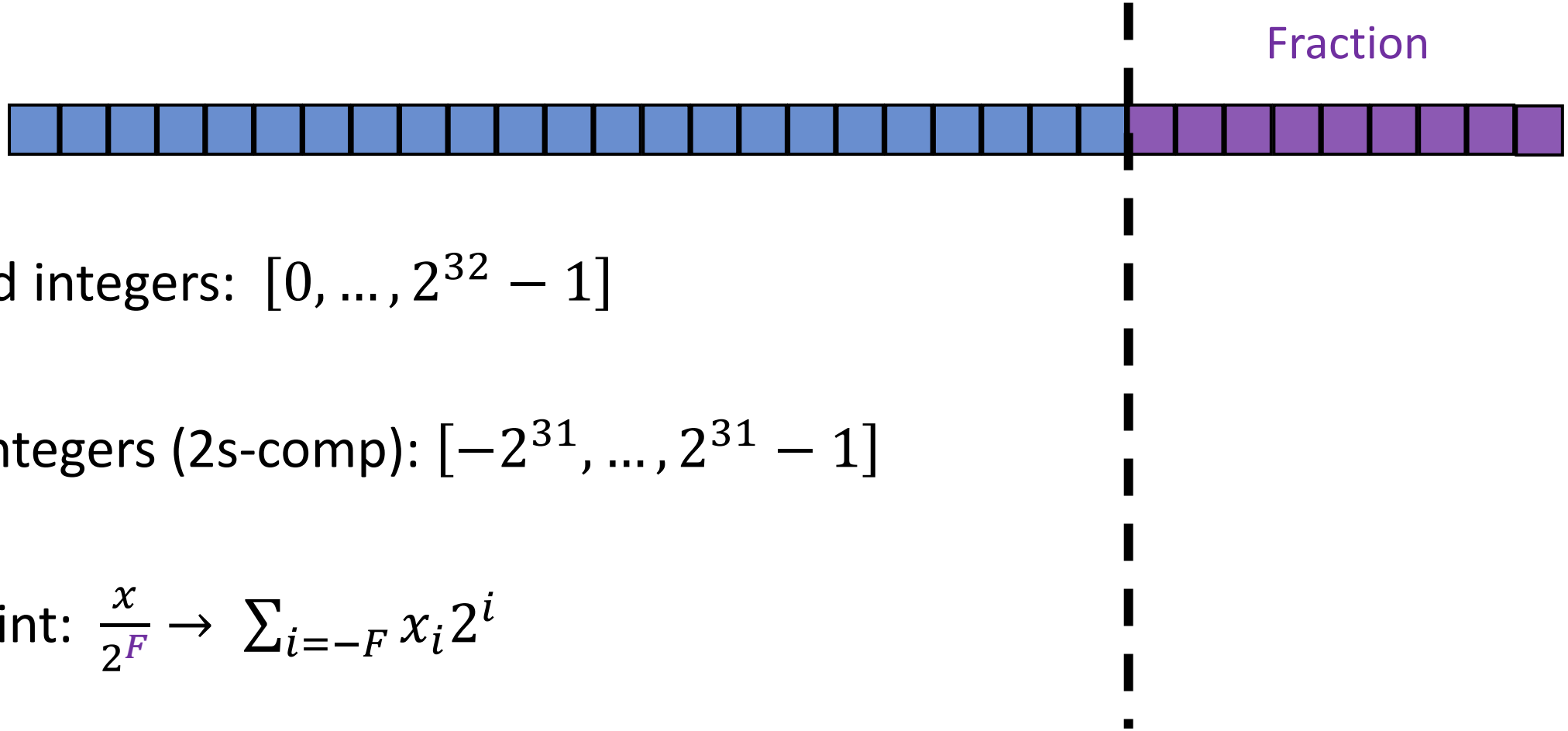
32bits

Unsigned integers: $[0, \ldots, 2^{32} - 1]$

Signed integers (2s-comp): $[-2^{31}, \ldots, 2^{31} - 1]$

Slide credit: Justin Johnson (EECS-498-007, UMich)

Binary Variables



Unsigned integers: $[0, \ldots, 2^{32} - 1]$

Signed integers (2s-comp): $[-2^{31}, \ldots, 2^{31} - 1]$

Fixed point: $\frac{x}{2^F} \rightarrow \sum_{i=-F} x_i 2^i$

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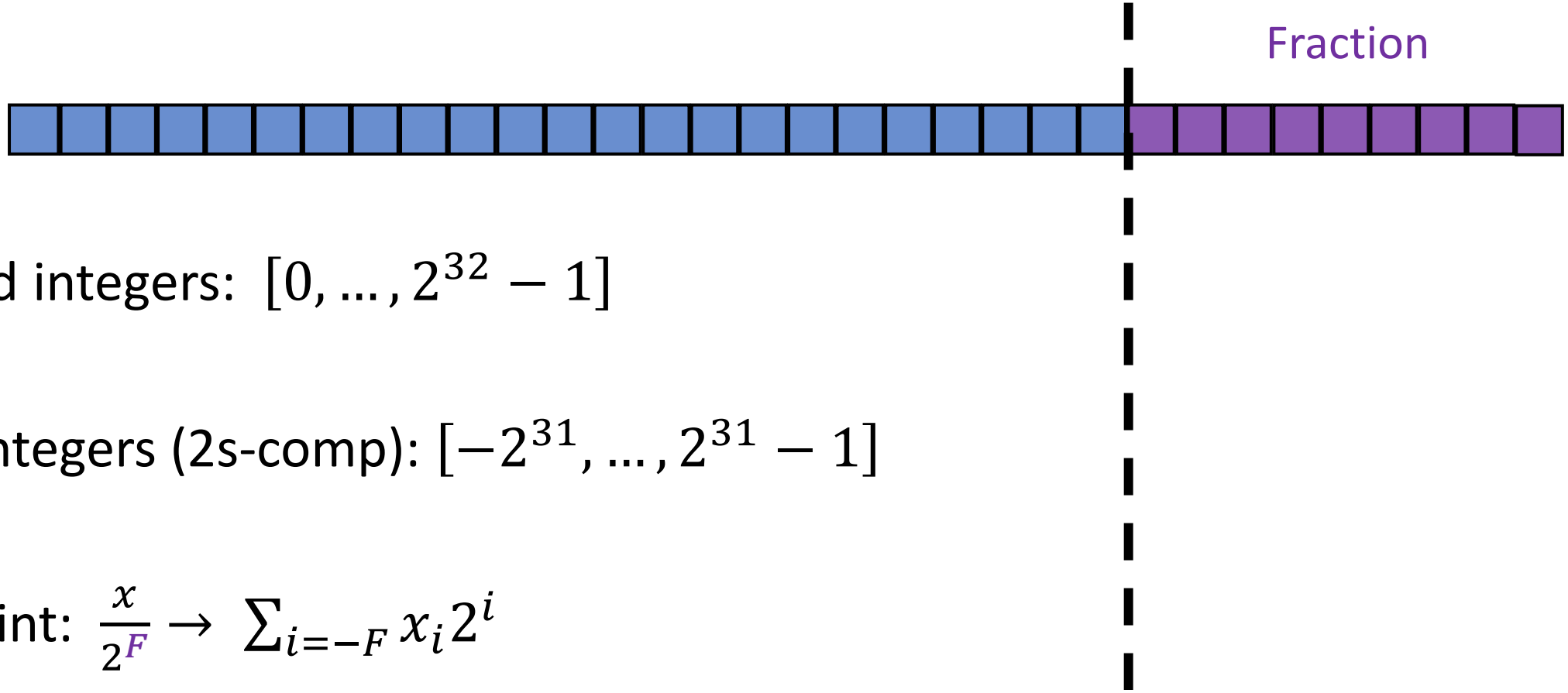
Binary Variables



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Signed integers (2s-comp): $[-2^{31}, \ldots, 2^{31} - 1]$

Fixed point: $\frac{x}{2^F} \rightarrow \sum_{i=-F} x_i 2^i$

100,000,000,000,000,000.000006 vs. 100,000,000,000,000,000.000007

Slide credit: Justin Johnson (EECS-498-007, UMich)

Binary Variables

Fixed point: $\frac{x}{2^F} \rightarrow \sum_{i=-F} x_i 2^i = 2^{-F} \sum_{i=0} x_i 2^i$

Fixed

All bits

Floating point:

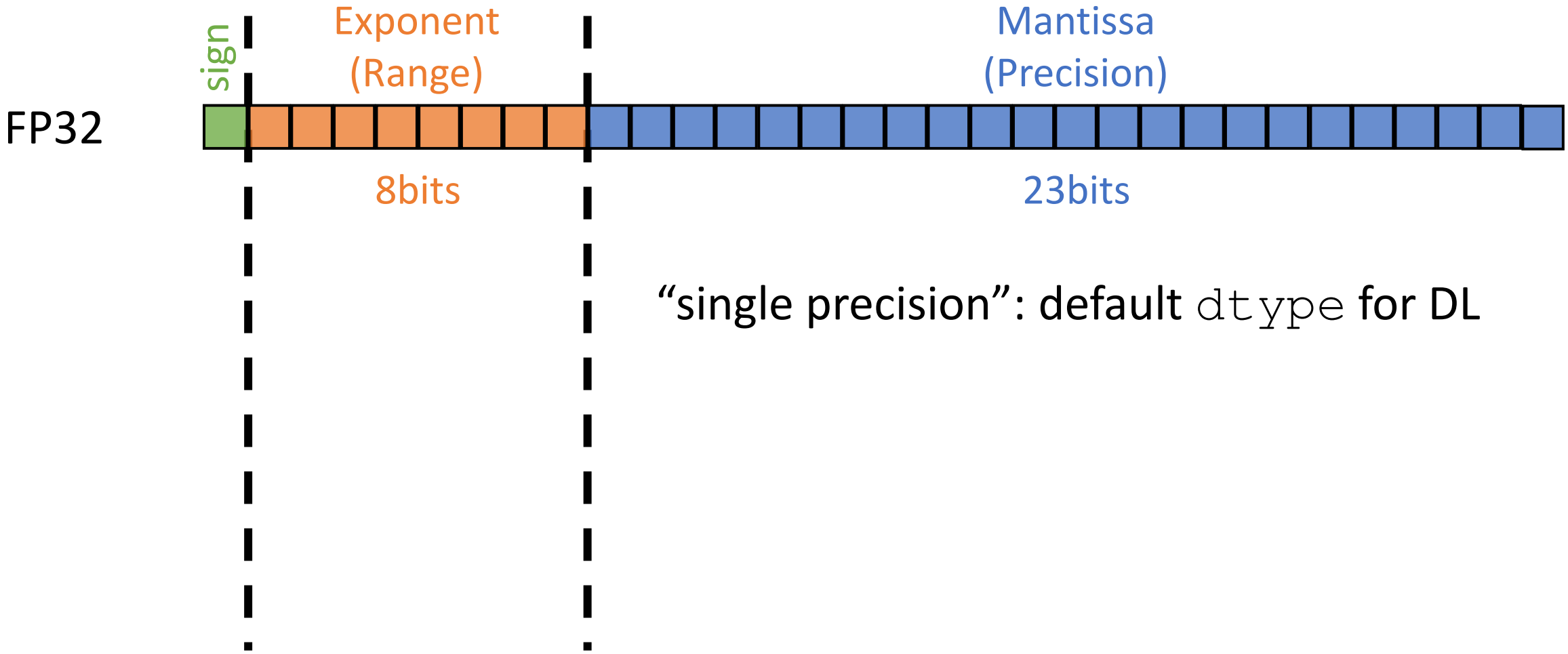
$2^{-e} \sum_{i=0} x_i 2^i$

Allocate E bits

Remaining bits

Floating Point Variables

$$(-1)^s\left(2^{E+bias}\right)\left(1+\frac{M}{2^{|M|}}\right)$$

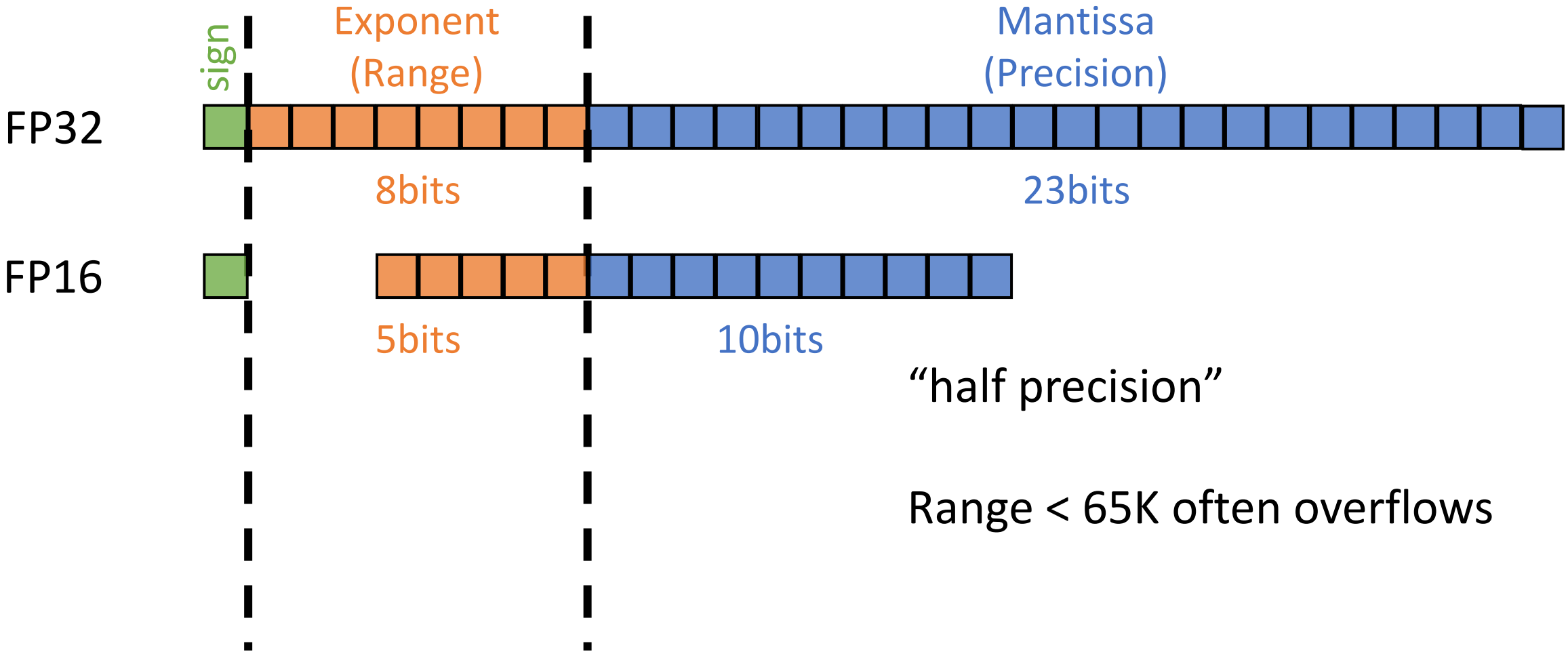


"single precision": default `dtype` for DL

Slide credit: Justin Johnson (EECS-498-007, UMich)

Floating Point Variables

$$(-1)^s\left(2^{E+bias}\right)\left(1+\frac{M}{2^{|M|}}\right)$$



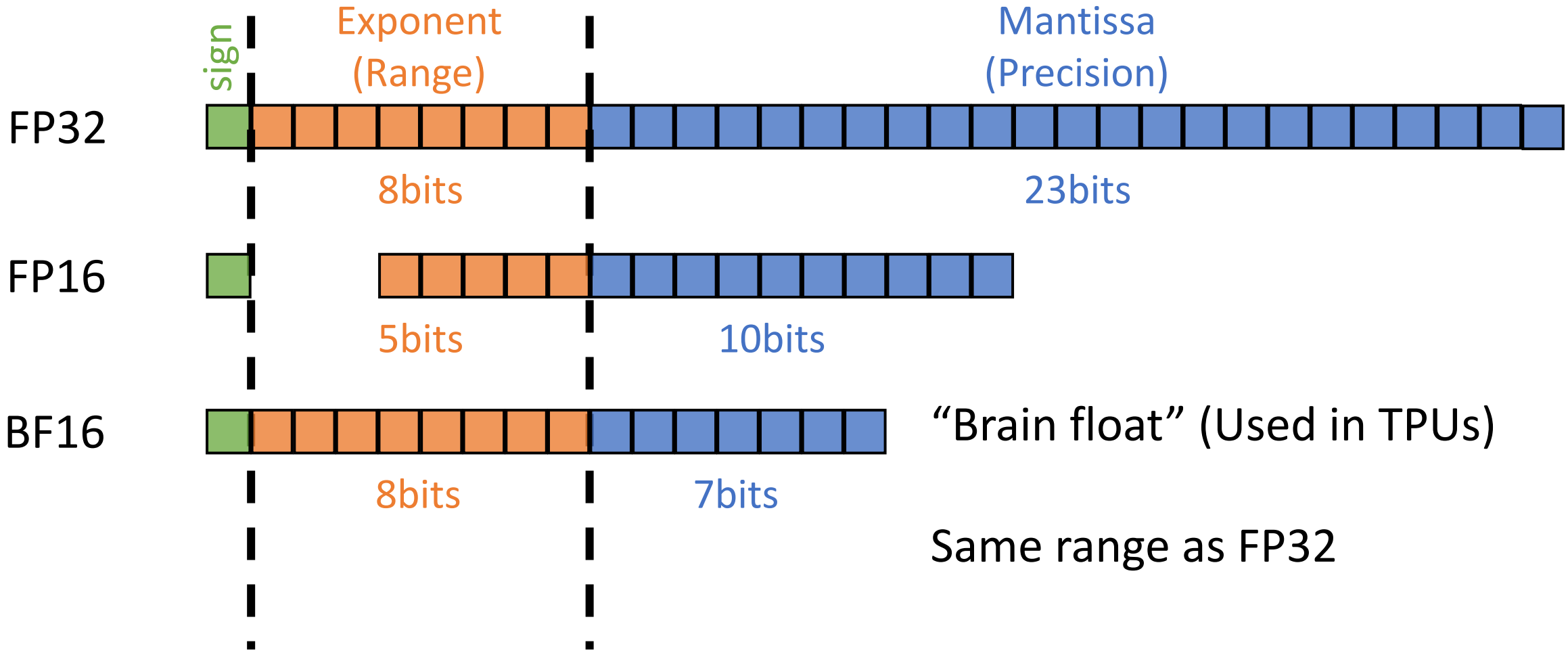
"half precision"

Range < 65K often overflows

Slide credit: Justin Johnson (EECS-498-007, UMich)

Floating Point Variables

$$(-1)^s\left(2^{E+bias}\right)\left(1+\frac{M}{2^{|M|}}\right)$$



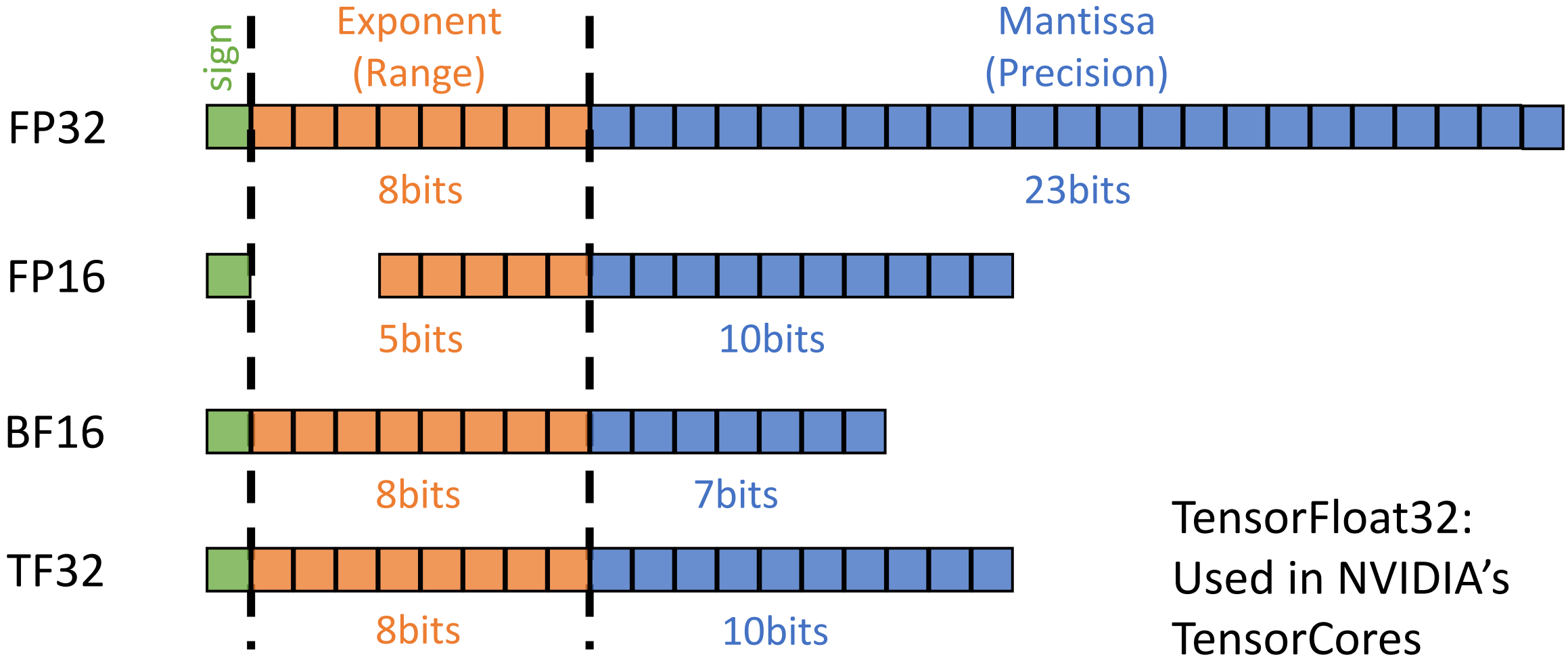
"Brain float" (Used in TPUs)

Same range as FP32

Slide credit: Justin Johnson (EECS-498-007, UMich)

Floating Point Variables

$$(-1)^{s}\left(2^{E+bias}\right)\left(1+\frac{M}{2^{|M|}}\right)$$

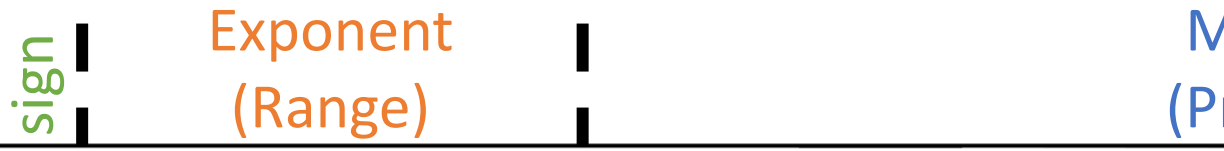


TensorFloat32:
Used in NVIDIA's
TensorCores

Slide credit: Justin Johnson (EECS-498-007, UMich)

Floating Point Variables

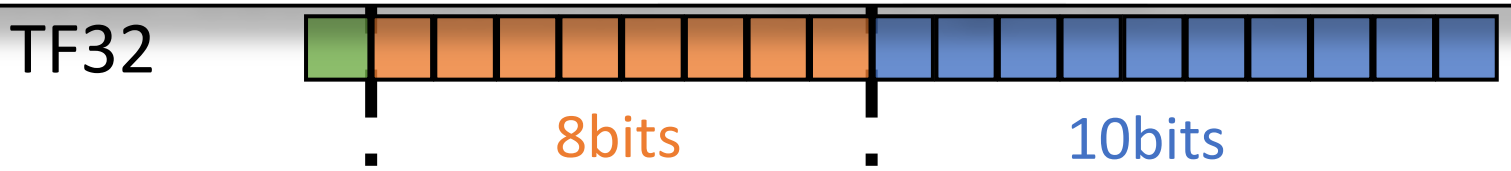
$$(-1)^{s}\left(2^{E+bias}\right)\left(1+\frac{M}{2^{|M|}}\right)$$



Using `TensorFloat32` in PyTorch (Ampere GPU only):

```
# The flag below controls whether to allow TF32 on matmul.
# defaults to False in PyTorch 1.12 and later.
torch.backends.cuda.matmul.allow_tf32 = True

# The flag below controls whether to allow TF32 on cuDNN.
# This flag defaults to True.
torch.backends.cudnn.allow_tf32 = True
```



Slide credit: Justin Johnson (EECS-498-007, UMich)

Mixed Precision

"Half precision" is enough for DL weights

What about computations? $y_i = \sum_j w_{ij} x_j$

Inputs: low-precision x, w

Output: FP32 y

$$y_i = \sum_j FP32(w_{ij} x_j)$$

Mixed Precision

```
with torch.autocast(dtype=torch.float16):
    pred = net(x)
    loss = loss_fn(pred, target)
    loss.backward()
```

Mixed Precision

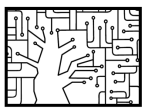
```
scaler = torch.cuda.amp.GradScaler(enabled=use_amp)

for x, target in train_data:
    opt.zero_grad()
    with torch.autocast(dtype=torch.float16):
        pred = net(x)
        loss = loss_fn(pred, target)
    scaler.scale(loss).backward()
    scaler.step(opt)
    scaler.update()
```

Mixed Precision

- Floating point numbers can be represented with less than 32bits
- Using AMP to alternate between float `dtype`s
- FP16 vs. BF16: range vs. precision
- `GradScaler`
- Saves space and time

Training with Multiple GPUs



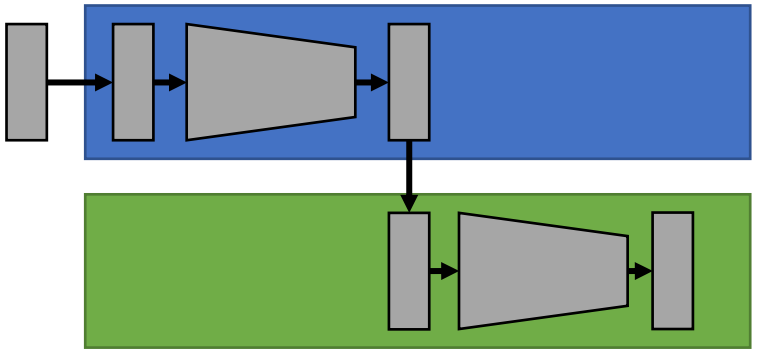
Why?

- More compute power
- More GPU memory

How to parallel?

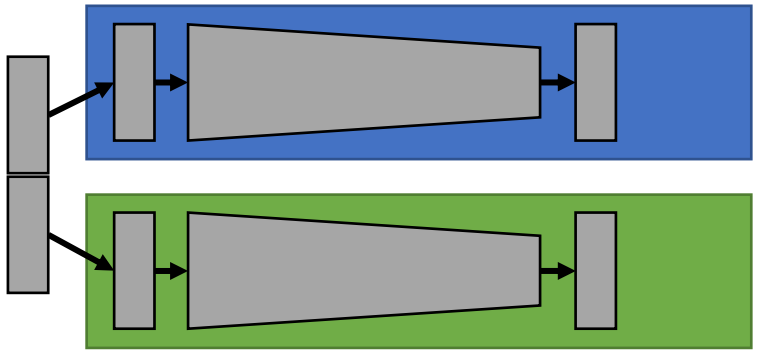
Model parallel

- Different parts of the **model** on parallel GPUs
- When GPU mem is the issue



Data parallel

- Different parts of the **data** on parallel GPUs
- When GPU compute is the issue



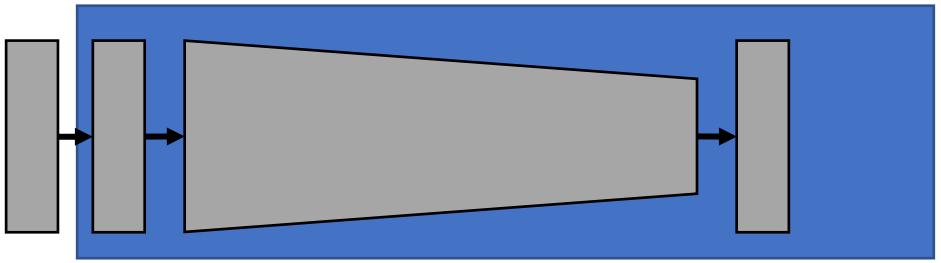
Model Parallel

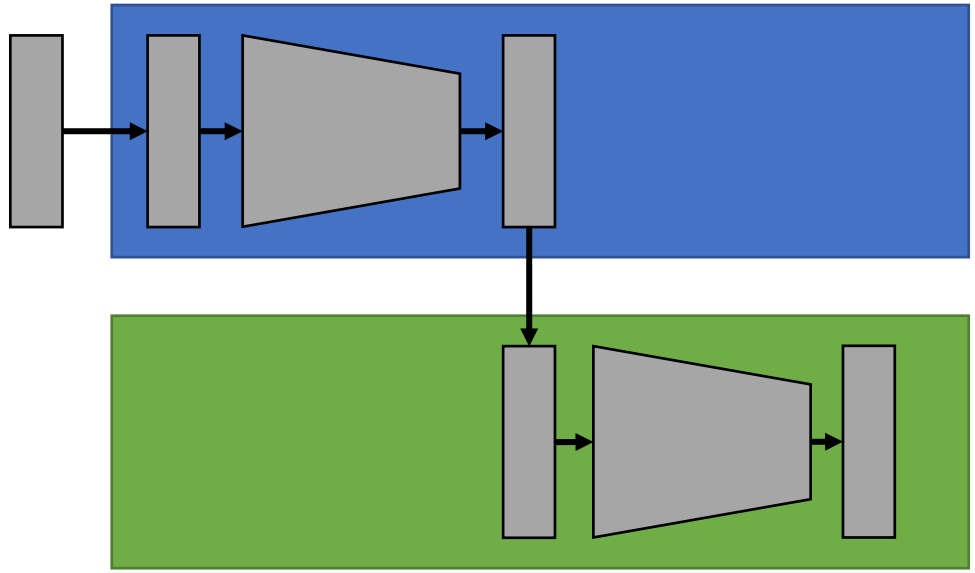
Bottleneck is GPU mem

Model Parallel

GPU memory is not enough

Split processing between GPUs

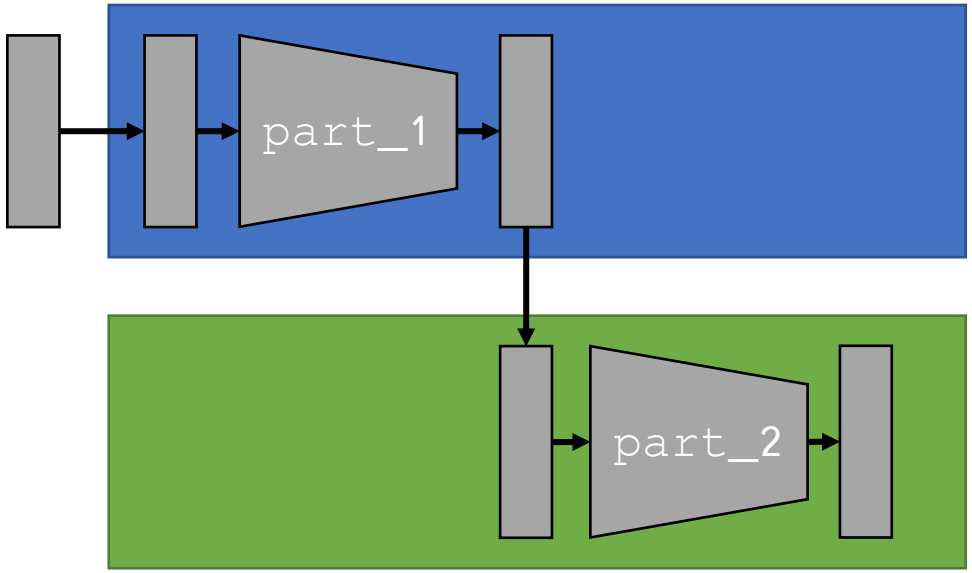




Model Parallel

```python
class ModelParallel(nn.Module):
    def __init__(self, ...):
        super(ModelParallel, self).__init__()
        self.part_1 = nn.Sequential(
            ...
        )
        self.part_2 = nn.Sequential(
            ...
        )
        # put each part on a different device
        self.part_1.to(torch.device('cuda:0'))
        self.part_2.to(torch.device('cuda:1'))

    def forward(self, x):
        x = x.to(torch.device('cuda:0'))
        x1 = self.part_1(x)
        # move to second device
        x1 = x1.to(torch.device('cuda:1'))
        y = self.part_2(x1)
        return y
```



Model Parallel

- Takes advantage of GPU mem of several devices

- Tailored specific to each model
- Requires “bookkeeping” of tensors/devices

Gradient Accumulation

Regular training

```
for x, y_gt in data:
    opt.zero_grad()
    y_pred = model(x)
    loss = criterion(y, y_gt)
    loss.backward()
    opt.step()
```

Gradient accumulation

```
for x, y_gt in data:
    opt.zero_grad()
    for sub_x, sub_y_gt in split(x, y_gt):
        sub_y_pred = model(sub_x)
        loss = criterion(sub_y_pred, sub_y_gt)
        loss.backward()
    opt.step()
```

Minimal code change

Serial processing of sub-batches

Data Parallel

Bottleneck is GPU compute

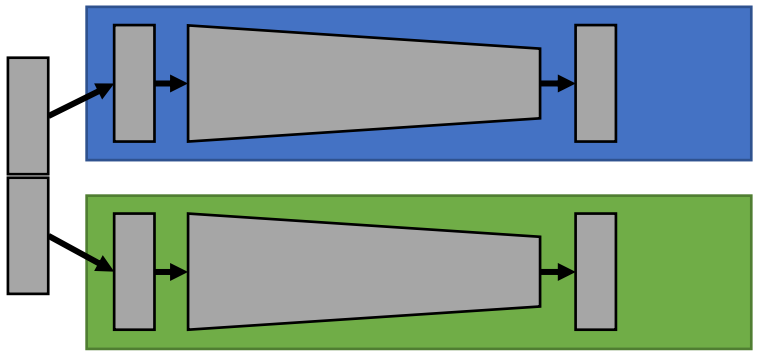
Data Parallel

When?

Process large batches **in parallel**

Key components

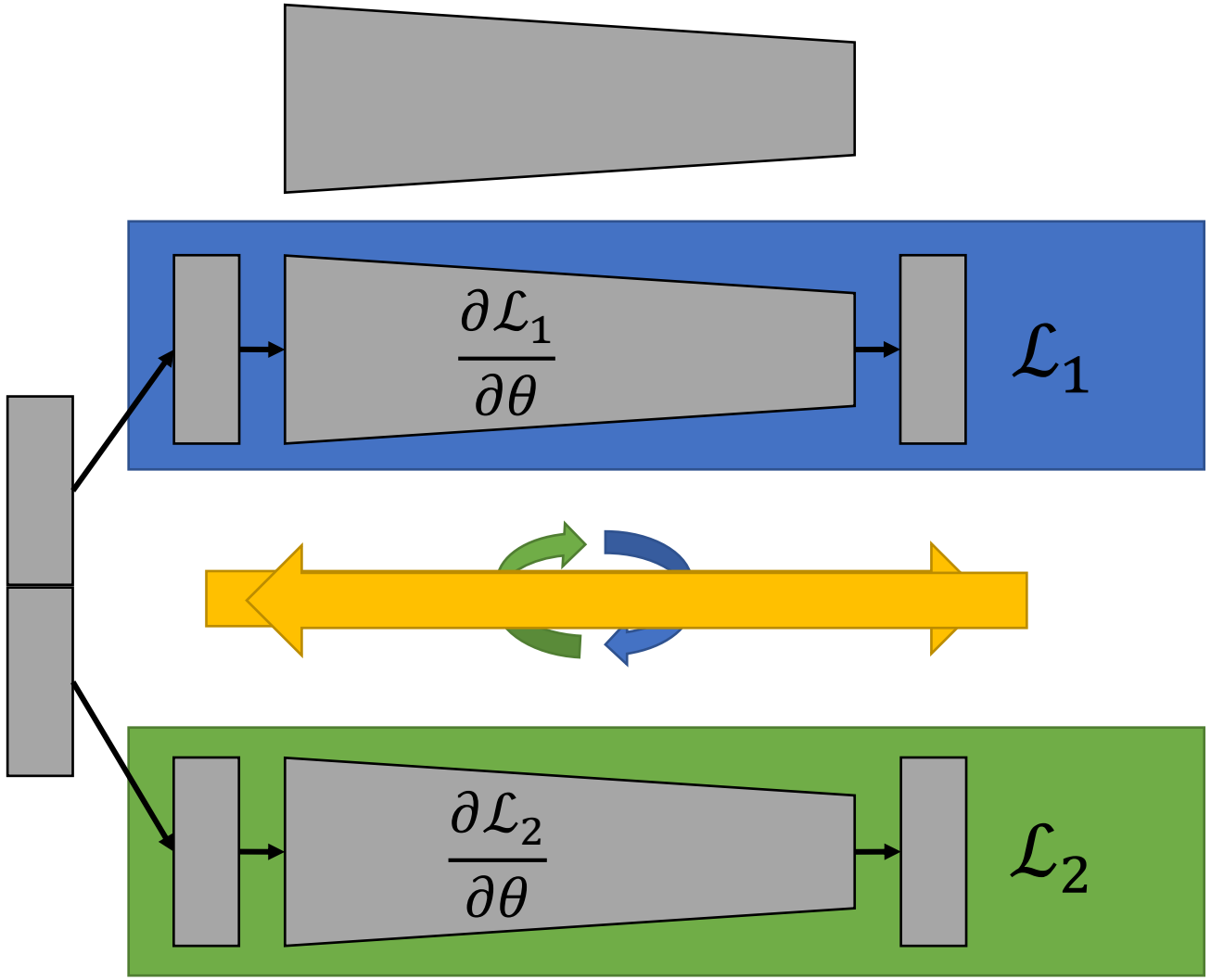
- **Identical** copies of the model
- **Different** sub-batches
- **Synchronized** updates



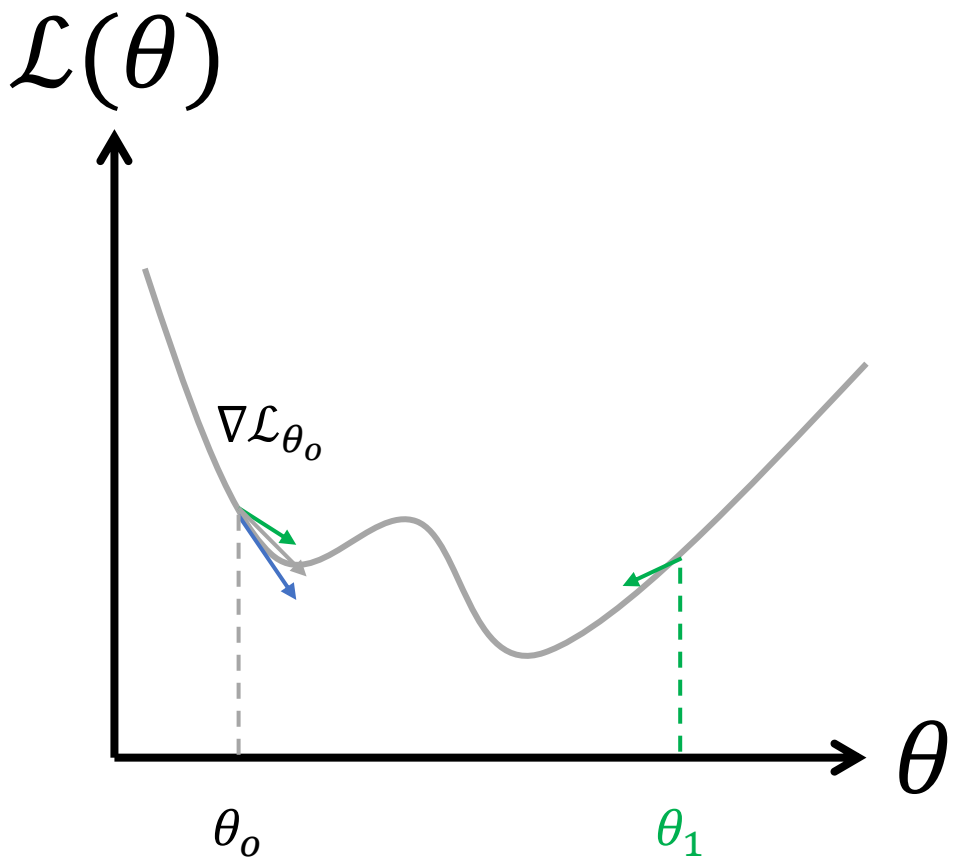
Data Parallel – How does it work?

Key components

- **Identical** copies of the model
- **Different** sub-batches
- **Synchronized** updates



Why Identical?



Data Parallel – How does it work?

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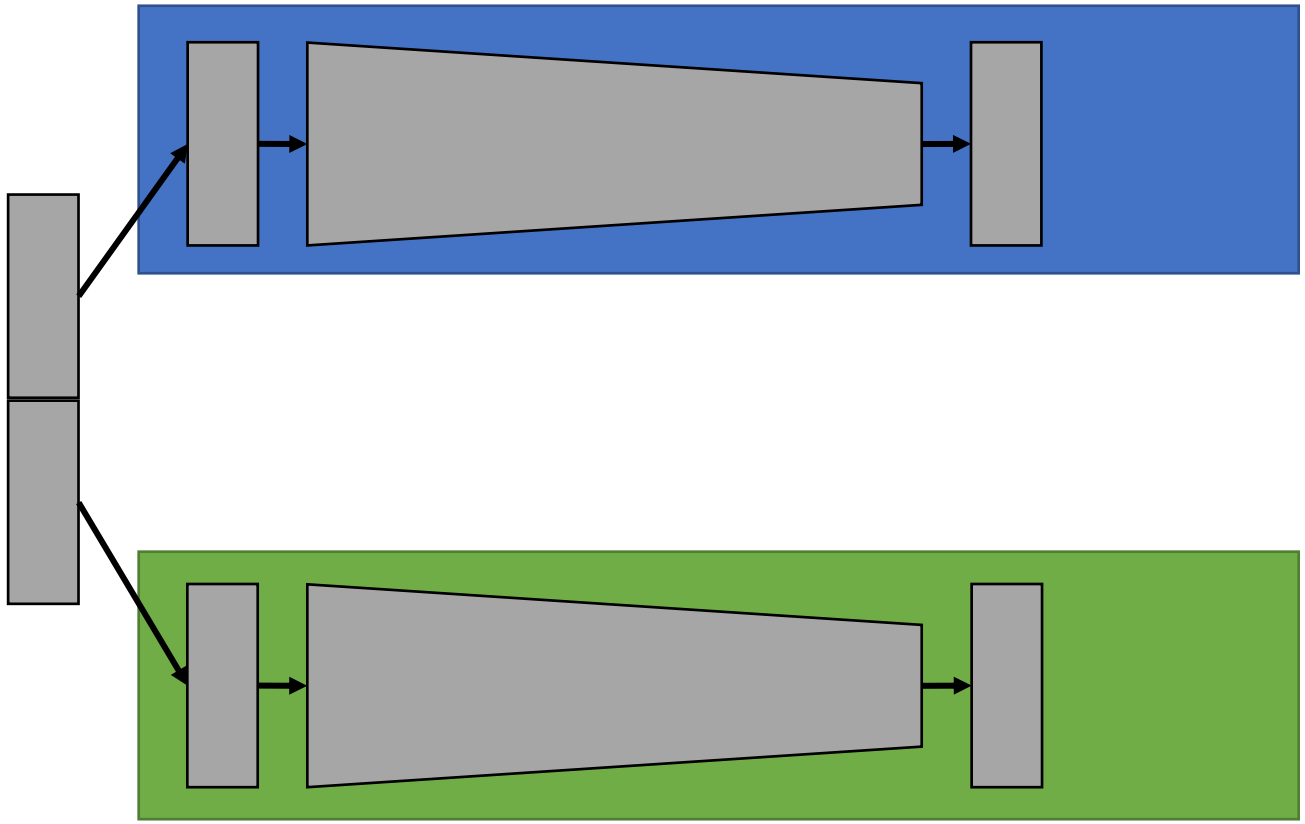


Data Parallel `nn.DataParallel`

```
model = MyModel()
# make it parallel
model = nn.DataParallel(model)
```

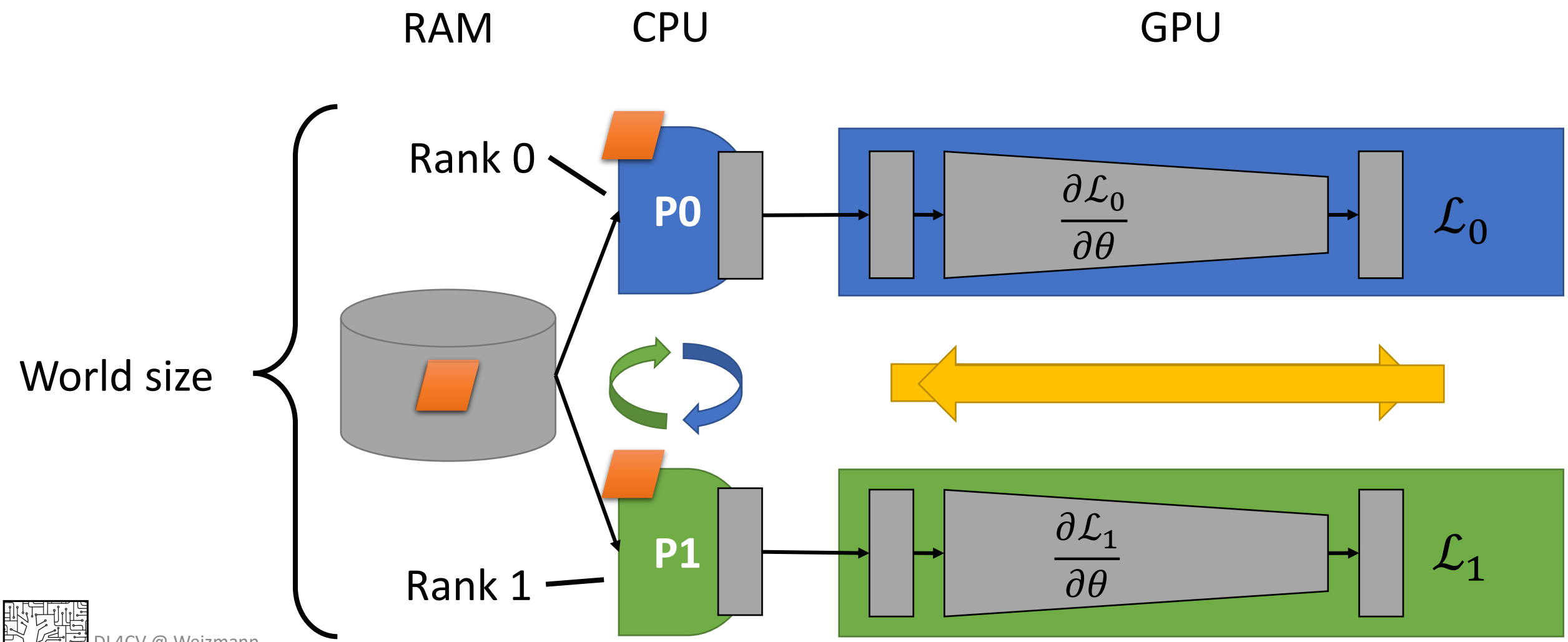
At each iteration:

1. Replicates model to all GPUs
2. Splits the batch to the GPUs
3. Sync updates

Handles everything for you

Increased overhead

Data Parallel `DistributedDataParallel`



Data Parallel `DistributedDataParallel`

```
def train(rank, args):
    # init the process in context
    torch.distributed.init_process_group(backend='nccl', init_method='tcp://127.0.0.1:54263', world_size, rank)
    ...
    # wrap the model
    model = nn.parallel.DistributedDataParallel(model, device_ids=[rank])

    # use "distributed aware" sampler
    sampler = torch.utils.data.distributed.DistributedSampler(
                train_dataset,
                num_replicas=world_size,
                rank=rank)

    loader = DataLoader(train_dataset, batch_size,
                        shuffle=False, sampler=train_sampler)
```

Data Parallel `DistributedDataParallel`

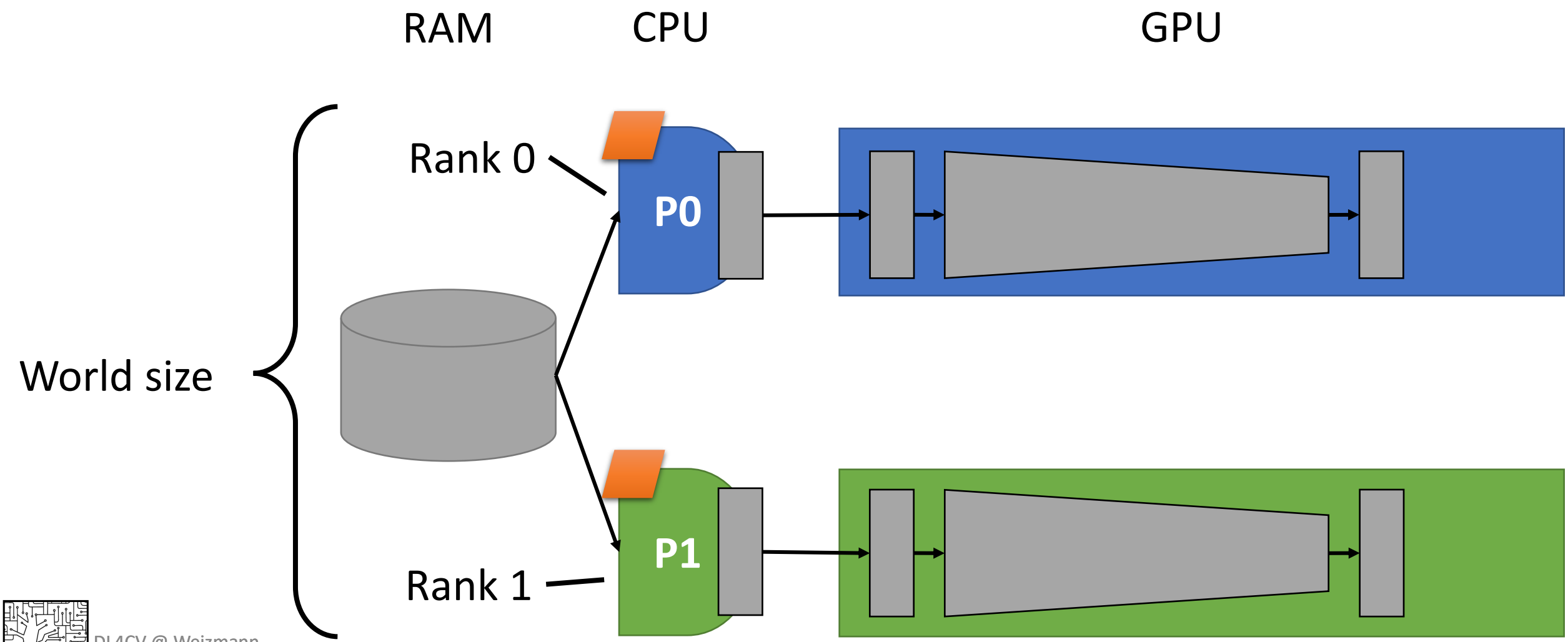
```
def main():
    ...
    torch.multiprocessing.spawn(train,
                                nproc=world_size,
                                args=args)

def train(rank, args):
    # init the process in context
```

Data Parallel `DistributedDataParallel`

Same code – multiple processes

- Print/log only from rank 0
- Do eval only from rank 0

Data Parallel `DistributedDataParallel`



Data Parallel with PyTorch

DataParallel

```
model = MyModel()
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model = nn.DataParallel(model)
```

Handles everything for you

Increased overhead

DistributedDataParallel

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```
def main():
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                                nproc=world_size,
                                args=args)

def train(rank, args):
    # init the process in context
```

Requires coding effort

Significant speedup

Scales to multiple machines

Flexible parallel scenarios

On WAIC

```
bsub -gpu num=2:j_exclusive=yes
     -q waic-medium
     -R rusage[mem=128000] -R affinity[thread*20]
     -Is /bin/bash
```

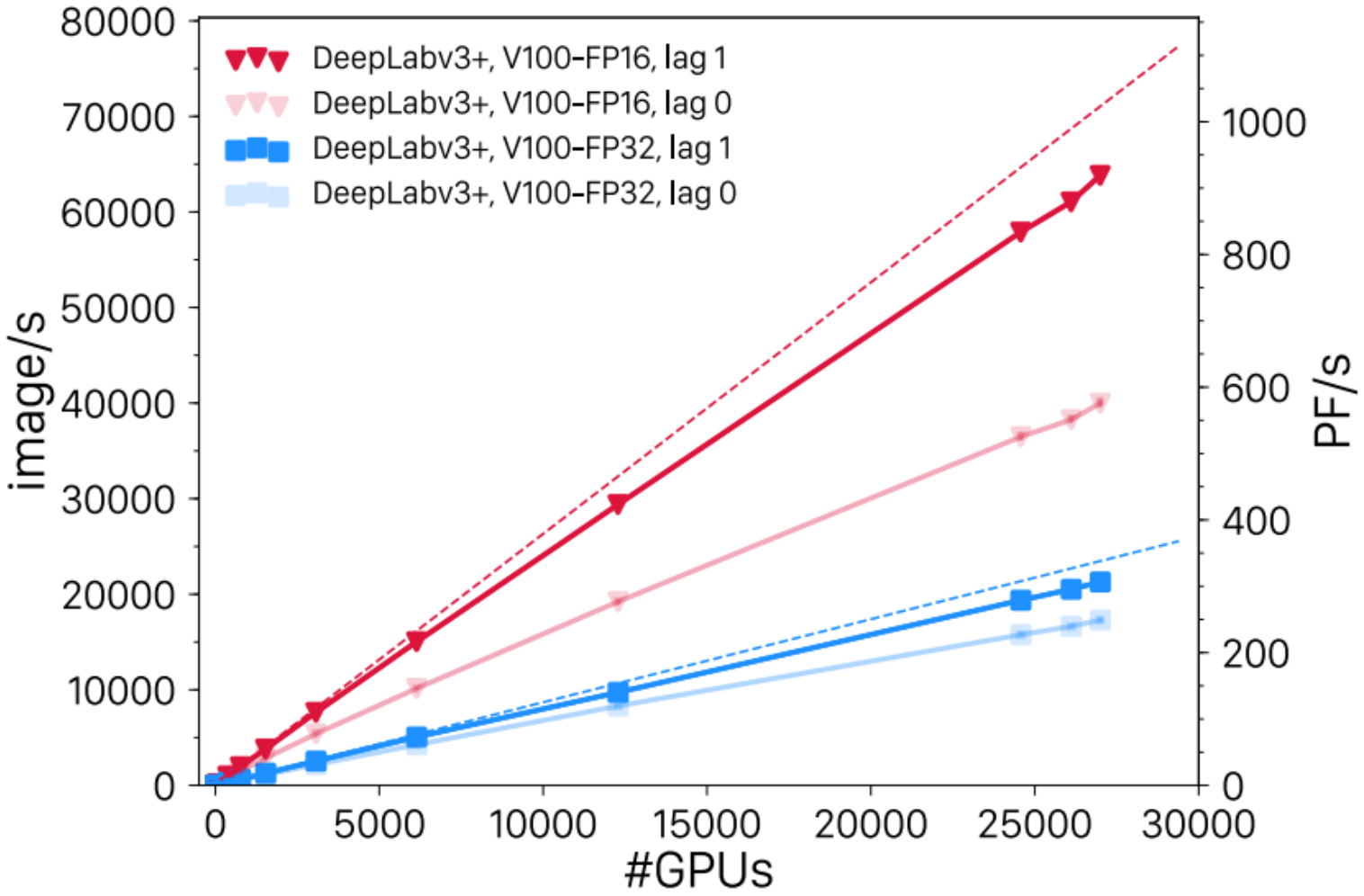
```
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 440.64.00    Driver Version: 440.64.00    CUDA Version: 10.2     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|===============================+======================+======================|
|   0  Tesla V100-DGXS...  Off  | 00000000:08:00.0 Off |                    0 |
| N/A   29C    P0    36W / 300W |      0MiB / 32508MiB |      0%      Default |
+-------------------------------+----------------------+----------------------+
|   1  Tesla V100-DGXS...  Off  | 00000000:0E:00.0 Off |                    0 |
| N/A   29C    P0    38W / 300W |      0MiB / 32508MiB |      0%      Default |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                       GPU Memory |
|  GPU       PID   Type   Process name                             Usage      |
|=============================================================================|
|  No running processes found                                                 |
+-----------------------------------------------------------------------------+
```


WAIC

Before you leave…

Do we always want larger batches?

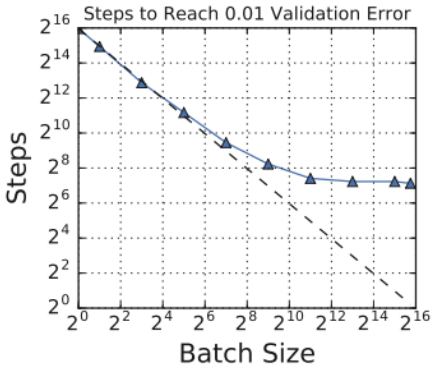
Images/sec **YES!**



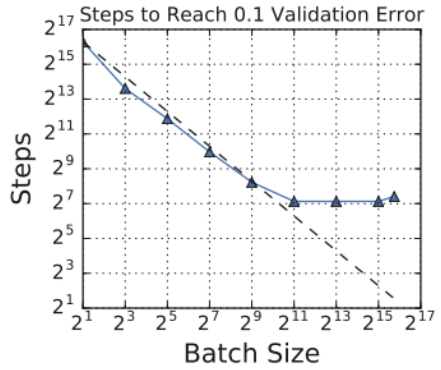
Kurth, Thorsten, Sean Treichler, Joshua Romero, Mayur Mudigonda, Nathan Luehr, Everett Phillips, Ankur Mahesh et al. "**Exascale deep learning for climate analytics**" (2018)

Do we always want larger batches?

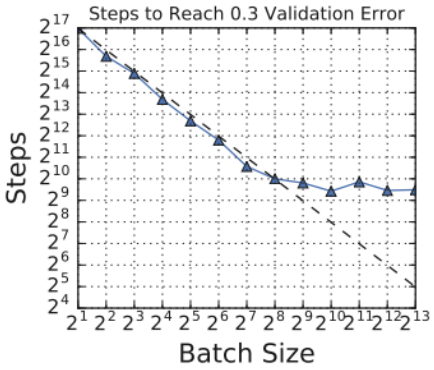
Steps to converge - **NO!**



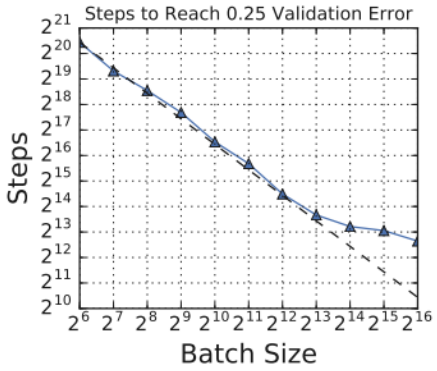
(a) Simple CNN on MNIST



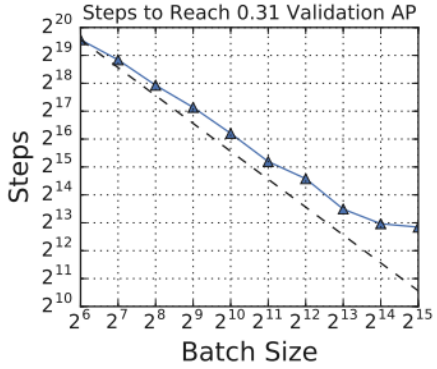
(b) Simple CNN on Fashion MNIST



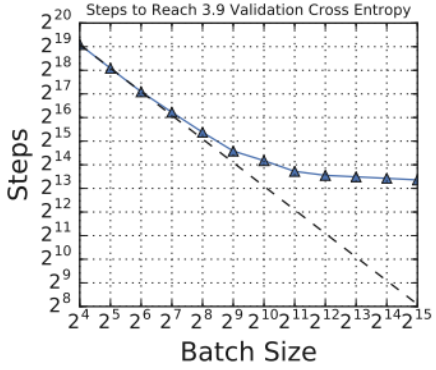
(c) ResNet-8 on CIFAR-10



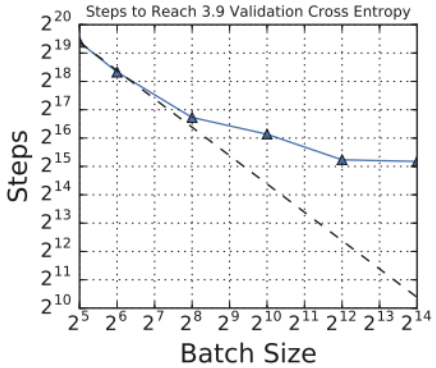
(d) ResNet-50 on ImageNet



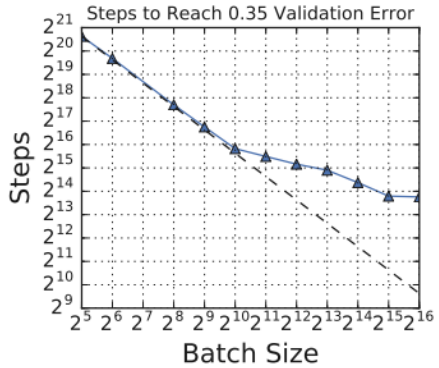
(e) ResNet-50 on Open Images



(f) Transformer on LM1B



(g) Transformer on Common Crawl

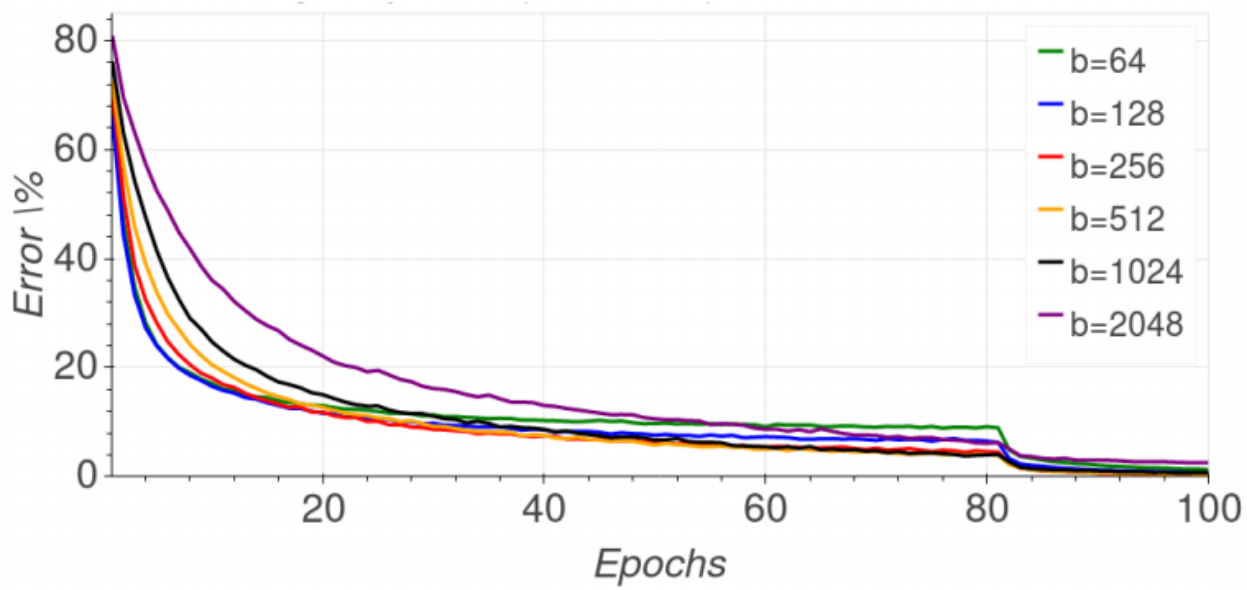


(h) VGG-11 on ImageNet

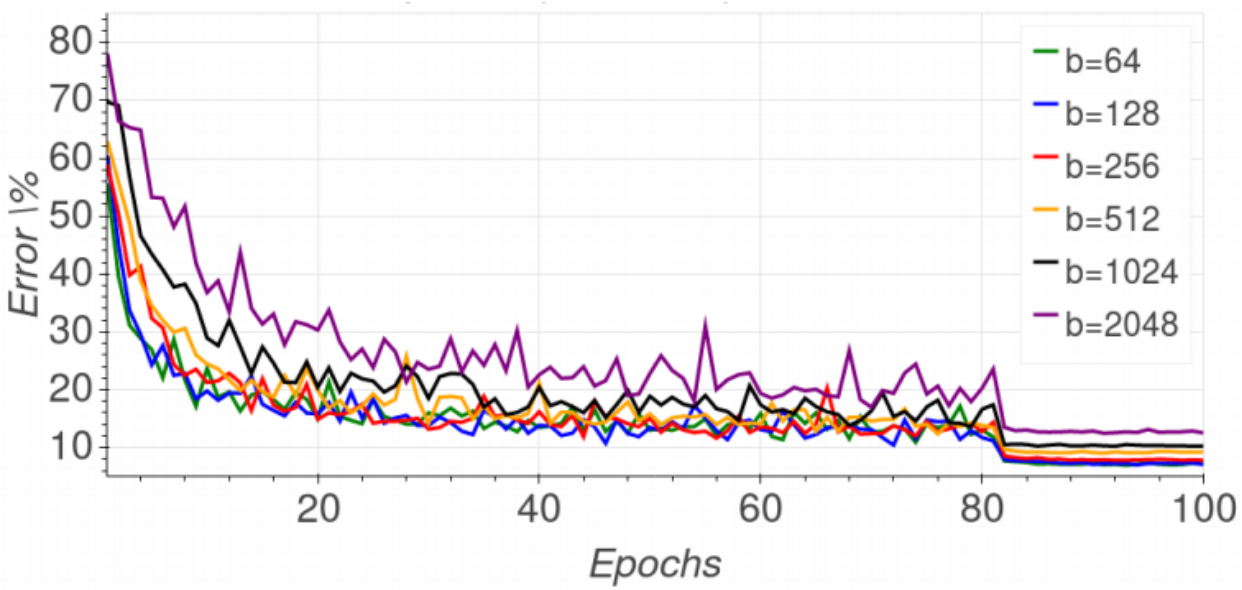
Shallue, Christopher J., Jaehoon Lee, Joseph Antognini, Jascha Sohl-Dickstein, Roy Frostig, and George E. Dahl. "Measuring the effects of data parallelism on neural network training" (2018).

Do we want larger batches?

Generalization **NO!**



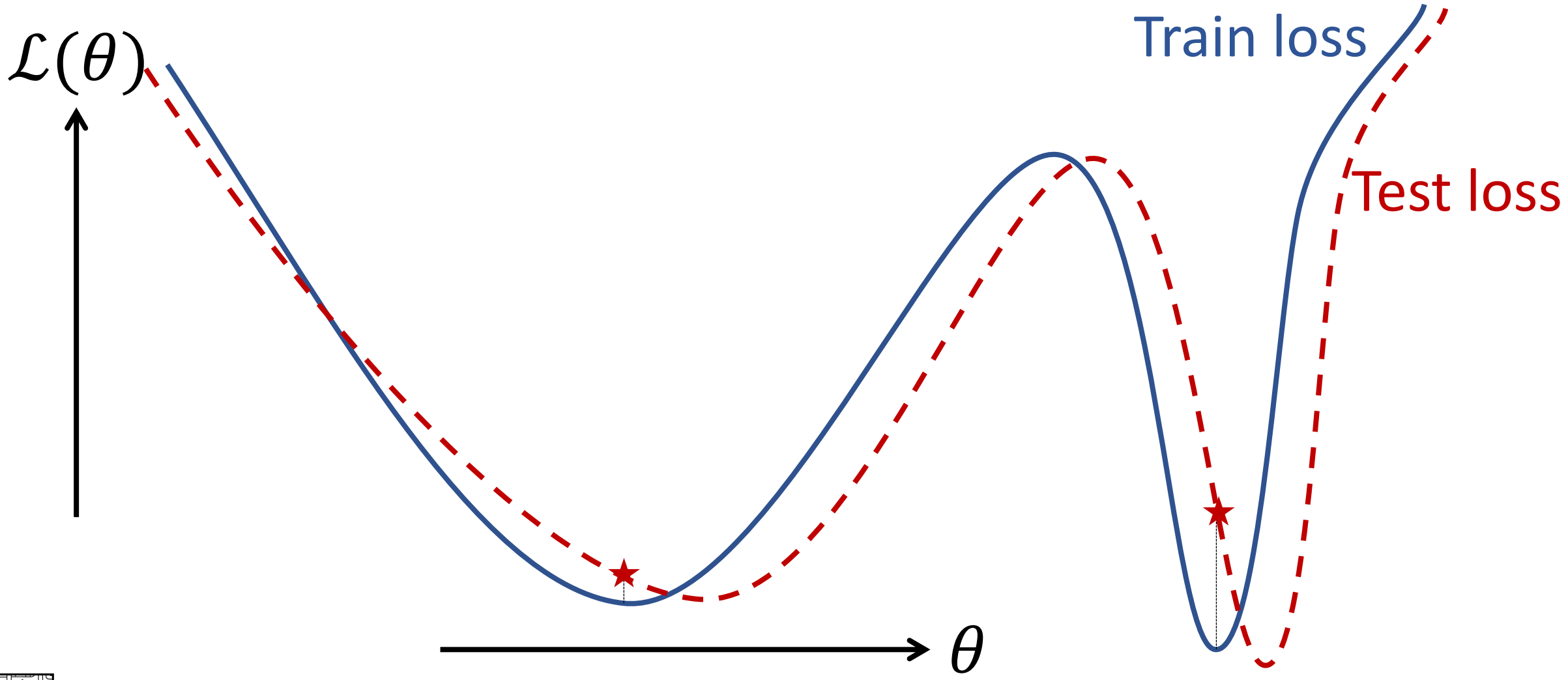
(a) Training error



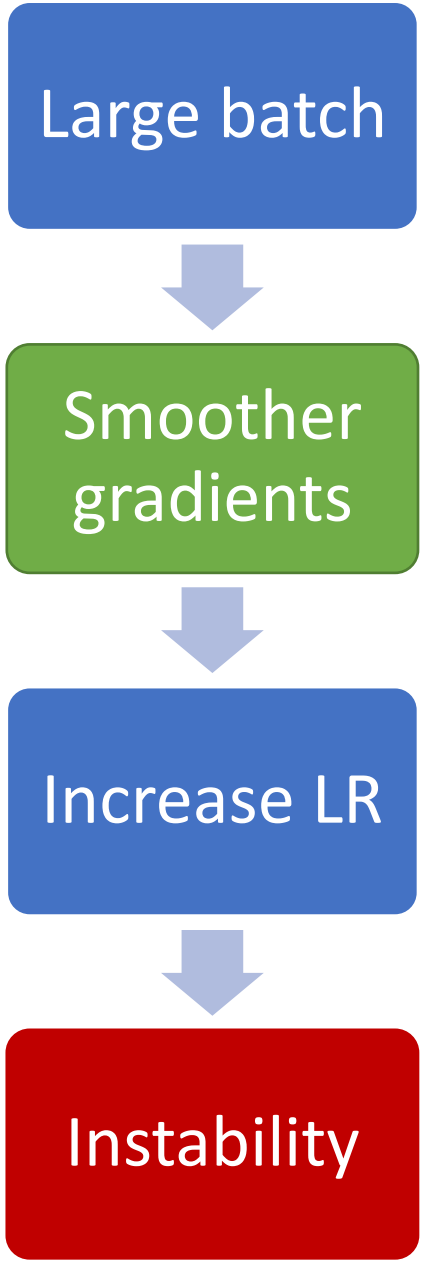
(b) Validation error

Hoffer, E., Hubara, I. and Soudry, D., "Train longer, generalize better: closing the generalization gap in large batch training of neural networks". (2017)

Why?



Do we want larger batches?



You, Y., Gitman, I. and Ginsburg, B., "Large batch training of convolutional networks" *(2017)*

Multiple GPU - Summary

- Parallel GPUs – when more compute/memory is needed
- Model Parallel – when GPU mem is required
- Data Parallel – when GPU compute is required
- Data Parallel – ready made in PyTorch
- Accumulating gradients – when many GPUs are not available

Multiple GPU - Summary