Distributed Training

02457 Machine Learning Operations

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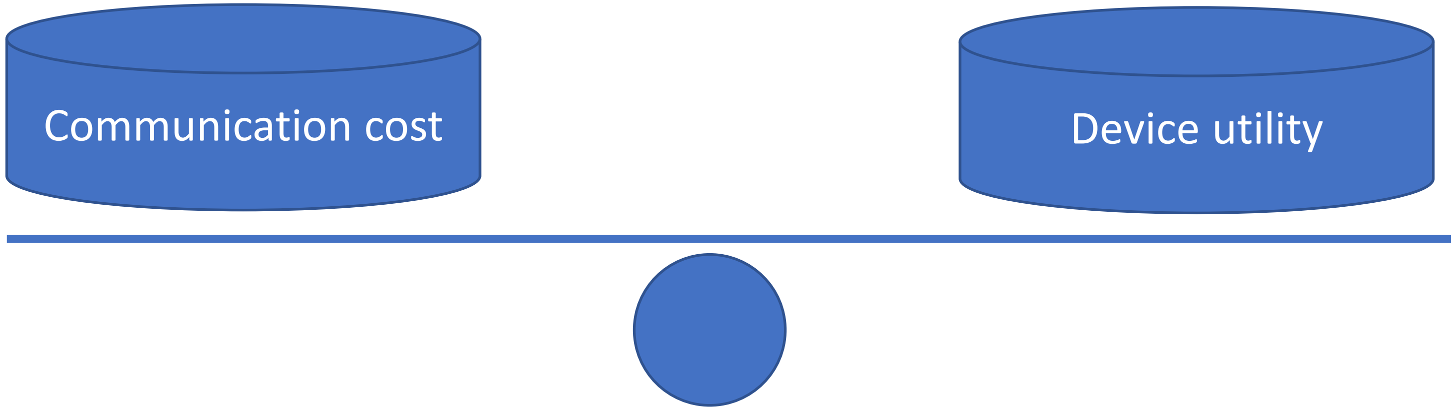
What is distributed computations?

Computing on multiple threads/devices/nodes in parallel

We focus on training as it is the most computationally expensive part but doing testing or inference can also be done in distributed manner

Distributed computing is not always beneficial:

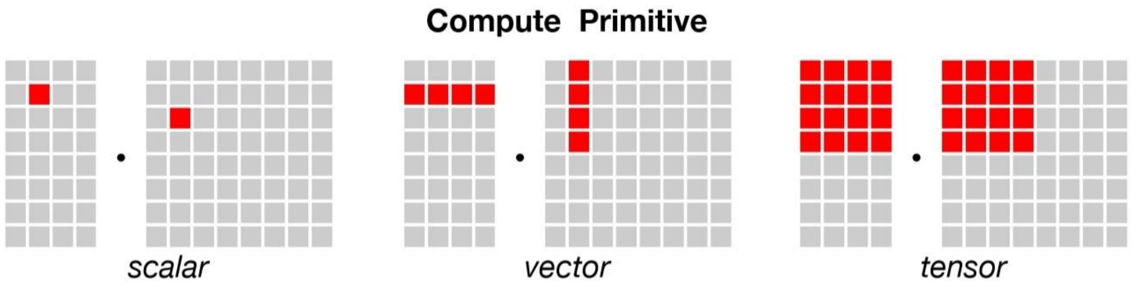


Devices

- Three types of devices
  - CPU
    - General compute unit
    - 2-128 threads
  - GPU
    - Rendering unit
    - 1000-10000 threads
  - TPU
    - Specialized unit
    - 8-2048 threads

Note that we are comparing apples to bananas!

CPU GPU TPU



Memory

Equally important to what device you are using, is the amount of memory that you have available

With more memory

- Faster data transfer
- Higher data modality
- Larger models

	CPU	GPU	TPU
Standard	32-64 GiB	12 GiB	64 GiB
Maximum	256 GiB	24 GiB	32 TiB

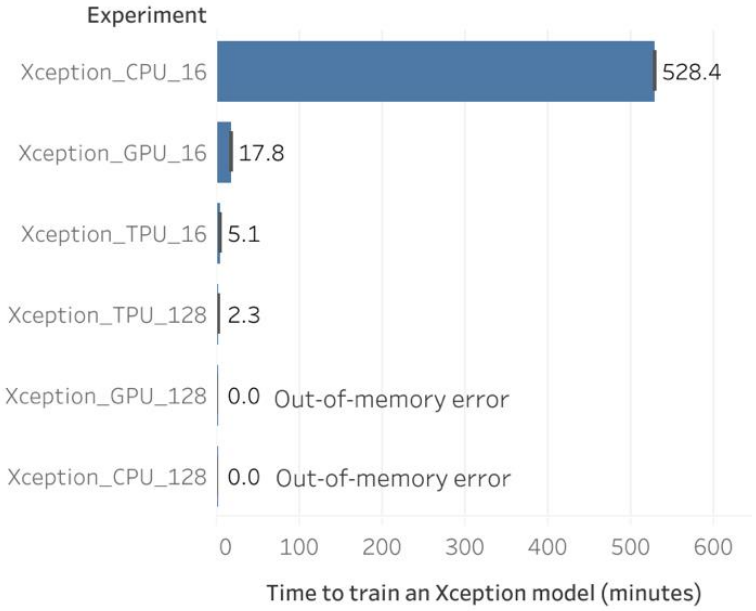
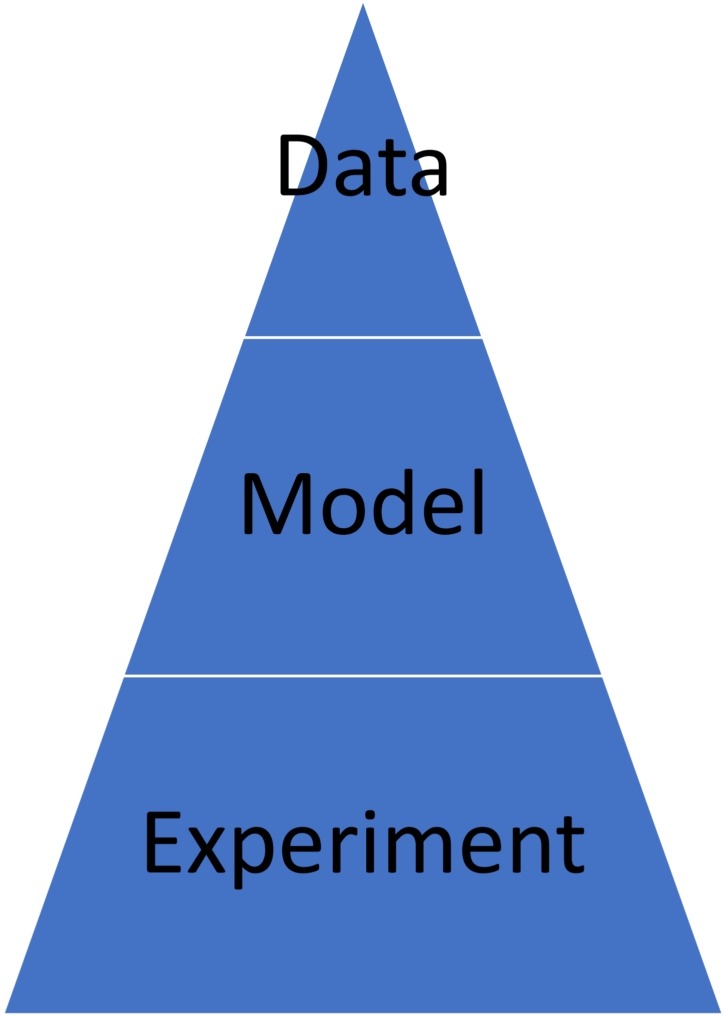


Figure 3: CPUs vs GPUs vs TPUs for training an Xception model for 12 epochs. Y-Axis labels indicate the choice of model, hardware, and batch size for each experiment. Increasing the batch size to 128 for TPUs resulted in an additional ~2x speedup.

https://towardsdatascience.com/when-to-use-cpus-vs-gpus-vs-tpus-in-a-kaggle-competition-9af708a8c3eb

Many layers of distributed computations



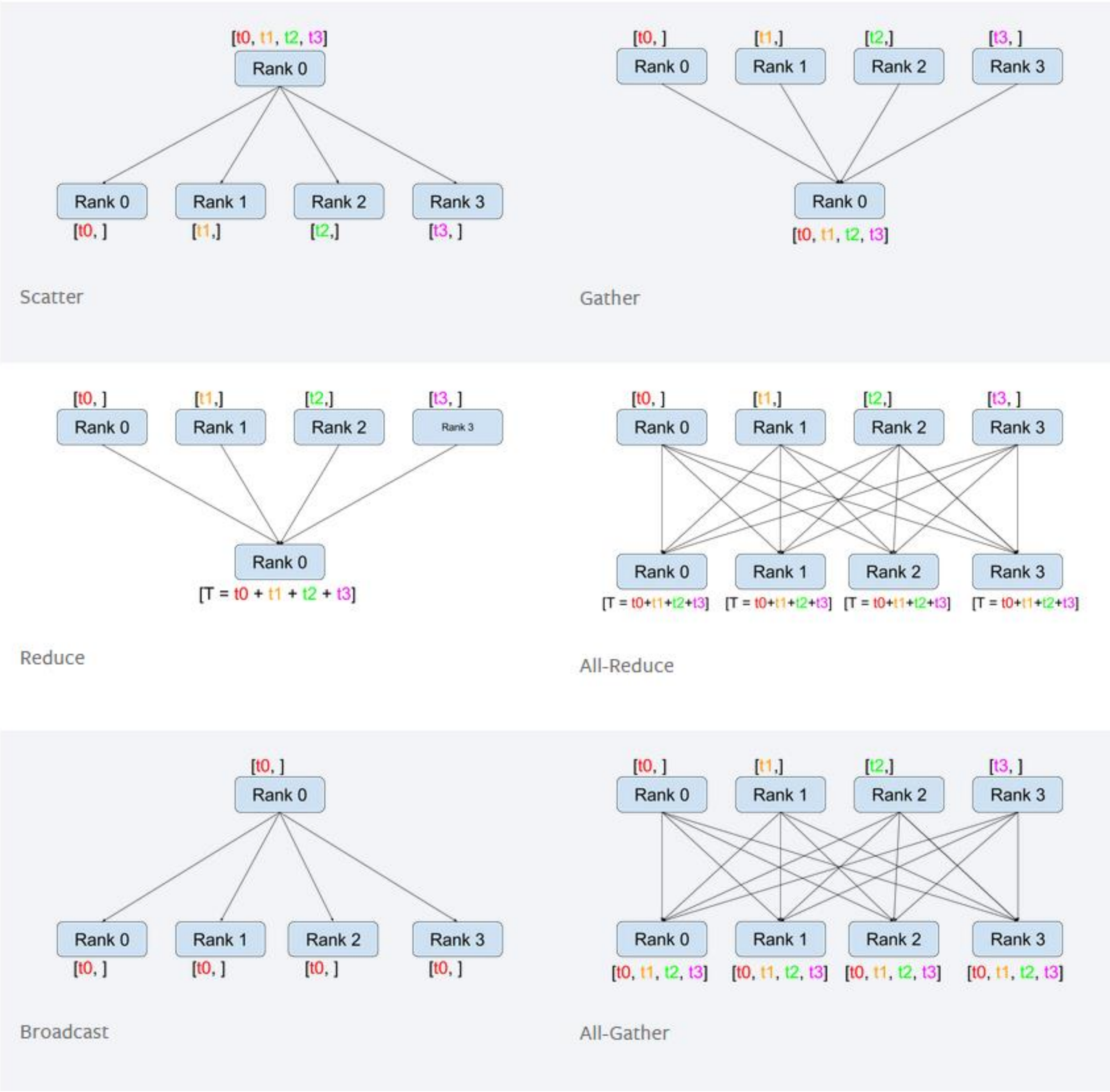
Load data in paralle
Inference on data in parallel

Stack models in parallel

Launch multiple experiments at once

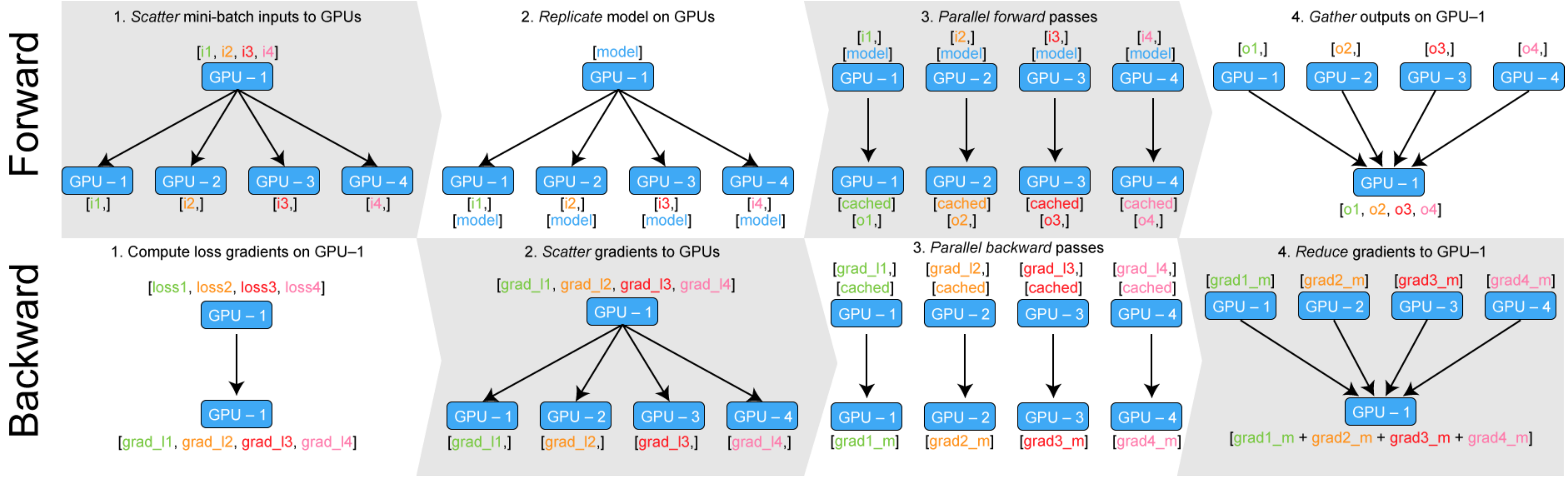
You may use multiple of these at the same time

The six imporatnt communication types



Data Parallel: one process controls all

Simple as parallel_model = torch.nn.DataParallel(model)



Note that only GPU-1 parameters are updated, the replicas are destroyed after backward

Distributed Data Parallel

In Distributed Data Parallel (DDP) all processes gets equal workload

Distributed Data Parallel

No master GPUs

Implemented in PyTorch DistributedDataParallel module

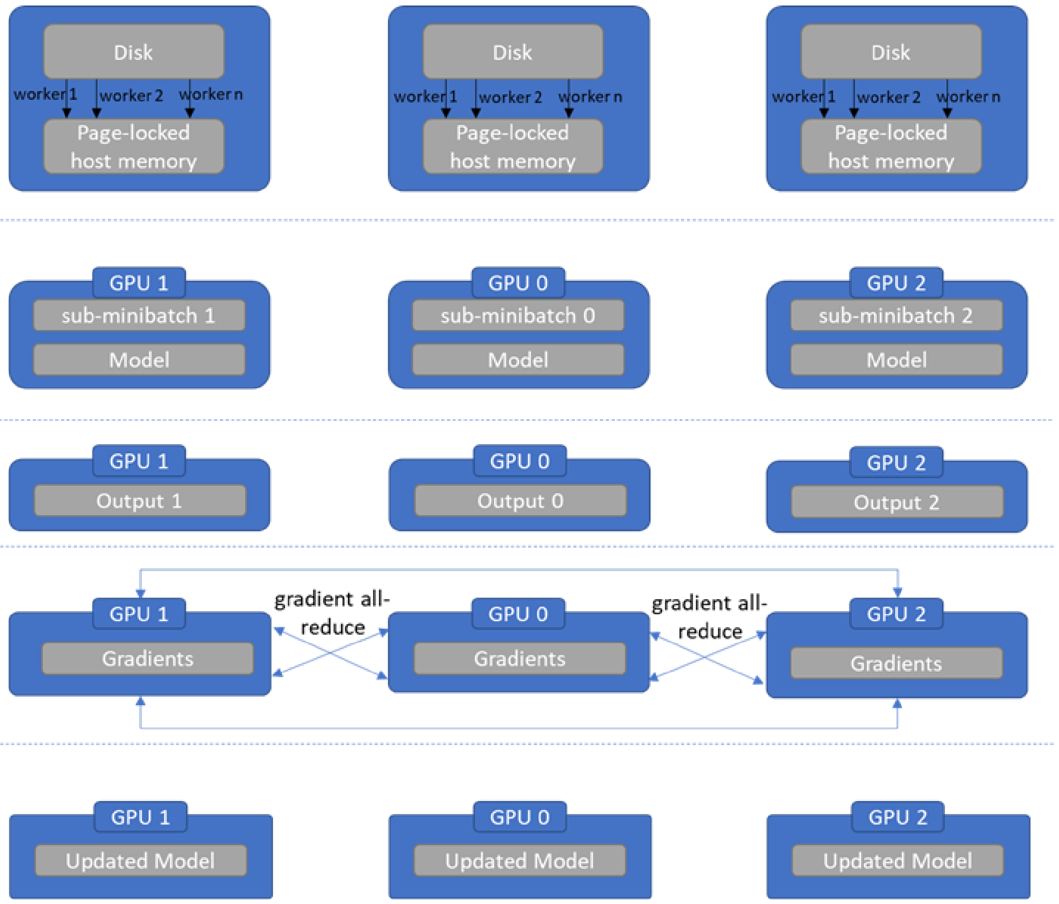
1. Load data from disk into page-locked memory on the host. Use multiple worker processes to parallelize data load. Distributed minibatch sampler ensures that each process loads non-overlapping data

2. Transfer minibatch data from page-locked memory to each GPU concurrently. No data broadcast is needed. Each GPU has an identical copy of the model and no model broadcast is needed either

3. Run forward pass on each GPU, compute output

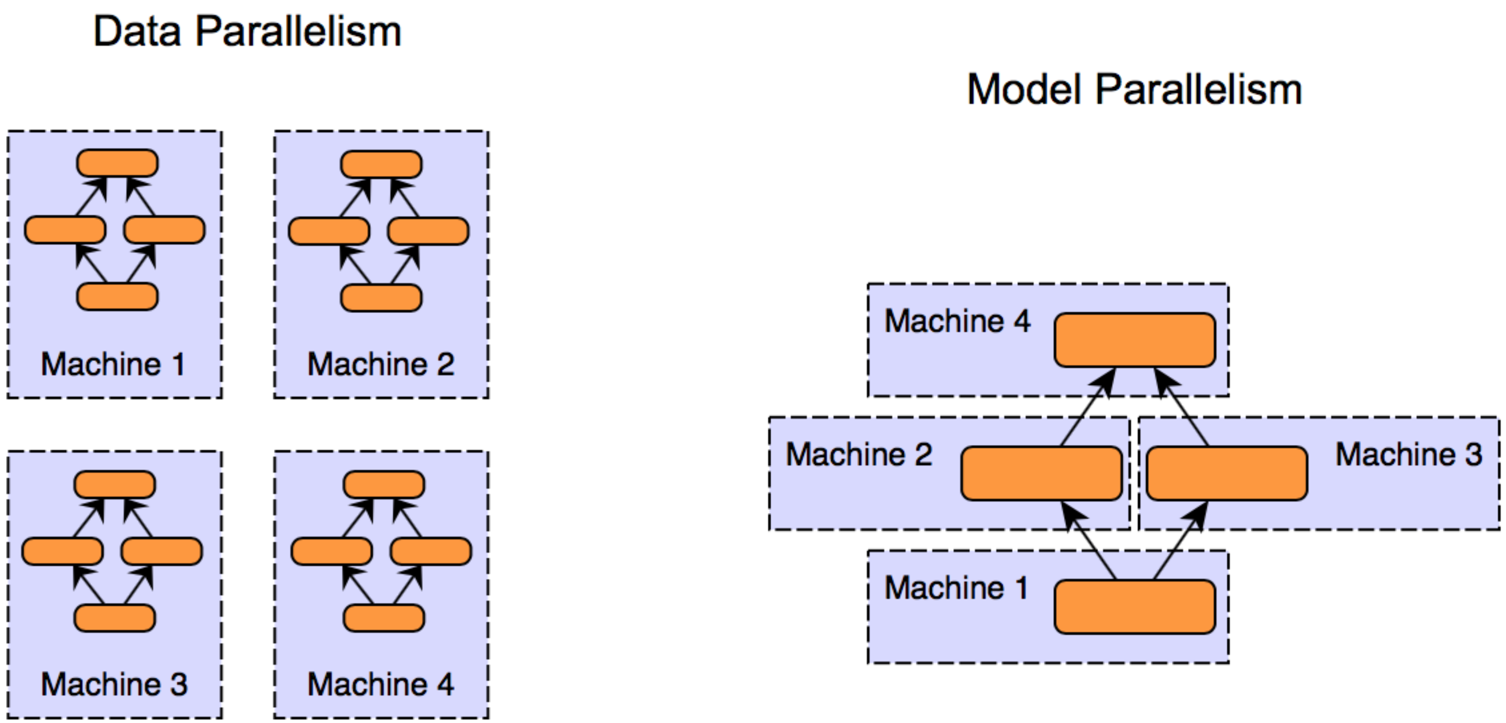
4. Compute loss, run backward pass to compute gradients. Perform gradient all-reduce in parallel with gradient computation

5. Update Model parameters. Because each GPU started with an identical copy of the model and gradients were all-reduced, weights updates on all GPUs are identical. Thus no model sync is required



Model paralliseme

When your model is too big for one device



How to do this in practise

- DataParallel
  - parallel_model = torch.nn.DataParallel(model)

- Distributed Data Parallel
  - Set a enviroment MASTER_ADDR and MASTER_PORT
  - Init a process group
  - parallel_model = nn.parallel.DistributedDataParallel(model, device_ids=[gpu]
  - Use mp.spawn to spawn multiple processes
  - ...

- Model parallizeme
  - A shit ton of tensor.to('cuda:x') calls

Seperating engineering and research code

Getting code to run in parallel has somewhat become a research task!

However maybe it should not be like that?

Research Code

```
l1 = nn.Linear(...)
l2 = nn.Linear(...)
decoder = Decoder()

x1 = l1(x)
x2 = l2(x2)
out = decoder(features, x)

loss = perceptual_loss(x1, x2, x) + CE(out, x)
```

Engineering code

```
model.cuda(0)
x = x.cuda(0)

distributed = DistributedParallel(model)

with gpu_zero:
    download_data()

dist.barrier()
```

Spend time on research code and not engineering code!

Why using a training framework

Spend time on research code and not engineering code

➡ Why training frameworks exist!

- Reduce boilerplate = increase turn-around time
- Focus on what is important
- Reproducibility
- Shareability
- Consistency
- Scalability

Training Fremworks

MLOps

Disclaimer

Many frameworks exist for reducing boilerplate

fast.ai

PyTorch Ignite

PyTorch Lightning

Many frameworks for accelerating training

RAY

HOROVOD

microsoft/ DeepSpeed

Pytorch Lightning

PyTorch

```
class MNISTClassifier(nn.Module):

  def __init__(self):
      self.layer_1 = torch.nn.Linear(28 * 28, 128)
      self.layer_2 = torch.nn.Linear(128, 10)

  def forward(self, x):
    x = x.view(x.size(0), -1)
    x = self.layer_1(x)
    x = F.relu(x)
    x = self.layer_2(x)
    return x

# download data
if global_rank == 0:
  mnist_train = MNIST(os.getcwd(), train=True, download=True)
  mnist_test = MNIST(os.getcwd(), train=False, download=True)

dist.barrier()

# transforms
transform=transforms.Compose([transforms.ToTensor(),
                              transforms.Normalize((0.1307,), (0.3081,))])
mnist_train = MNIST(os.getcwd(), train=True, transform=transform)
mnist_test = MNIST(os.getcwd(), train=False, transform=transform)

# split dataset
mnist_train, mnist_val = random_split(mnist_train, [55000, 5000])
mnist_test = MNIST(os.getcwd(), train=False, download=True)

# build dataloaders
mnist_train = DataLoader(mnist_train, batch_size=64)
mnist_val = DataLoader(mnist_val, batch_size=64)
mnist_test = DataLoader(mnist_test, batch_size=64)

optimizer = torch.optim.Adam(pytorch_model.parameters(), lr=1e-3)

def cross_entropy_loss(logits, labels):
  return F.nll_loss(logits, labels)

num_epochs = 1
for epoch in range(num_epochs):
  for train_batch in mnist_train:
    x, y = train_batch
    logits = pytorch_model(x)
    loss = cross_entropy_loss(logits, y)
    print('train loss: ', loss.item())
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()

  model.eval()
  with torch.no_grad():
    val_loss = []
    for val_batch in mnist_val:
      x, y = val_batch
      logits = pytorch_model(x)
      val_loss.append(cross_entropy_loss(logits, y).item())

    avg_val_loss = torch.stack(val_loss).mean()
  model.train()
```

Its just reorganized Pytorch code!

Two core objects

- Lightning Module
  - Training, validation, test logic
  - Optimizer
- Trainer
  - The ”rest”

trainer.fit(model) does the heavy lifting

What you get for free

Multi-GPU, multi-node

```
# 8 GPUs
# no code changes needed
trainer = Trainer(max_epochs=1, gpus=8)

# 256 GPUs
trainer = Trainer(max_epochs=1, gpus=8, num_nodes=32)
```

TPU training

```
# no code changes needed
trainer = Trainer(tpu_cores=8)
```

16 bit precision

```
# no code changes needed
trainer = Trainer(precision=16)
```

Experiment managers

```
from pytorch_lightning import loggers

logger = loggers.TensorBoardLogger('logs/')
logger = loggers.WandbLogger()
logger = loggers.CometLogger()
logger = loggers.MLFlowLogger()
logger = loggers.NeptuneLogger()
# ... and many more

trainer = Trainer(logger=logger)
```

What you get for free

Early stopping

```
es = EarlyStopping(monitor='val_loss')
trainer = Trainer(callbacks=[es])
```

Model Checkpoint

```
checkpointing = ModelCheckpoint(monitor='val_loss')
trainer = Trainer(callbacks=[checkpointing])
```

40+ tricks and extensions

```
trainer = Trainer(
    max_epochs=10,
    auto_lr_find=True,
    gradient_clip_val=1.0,
    accumulate_grad_batches=10,
    max_steps=1000
    #... 40+ tricks and extensions

)
```

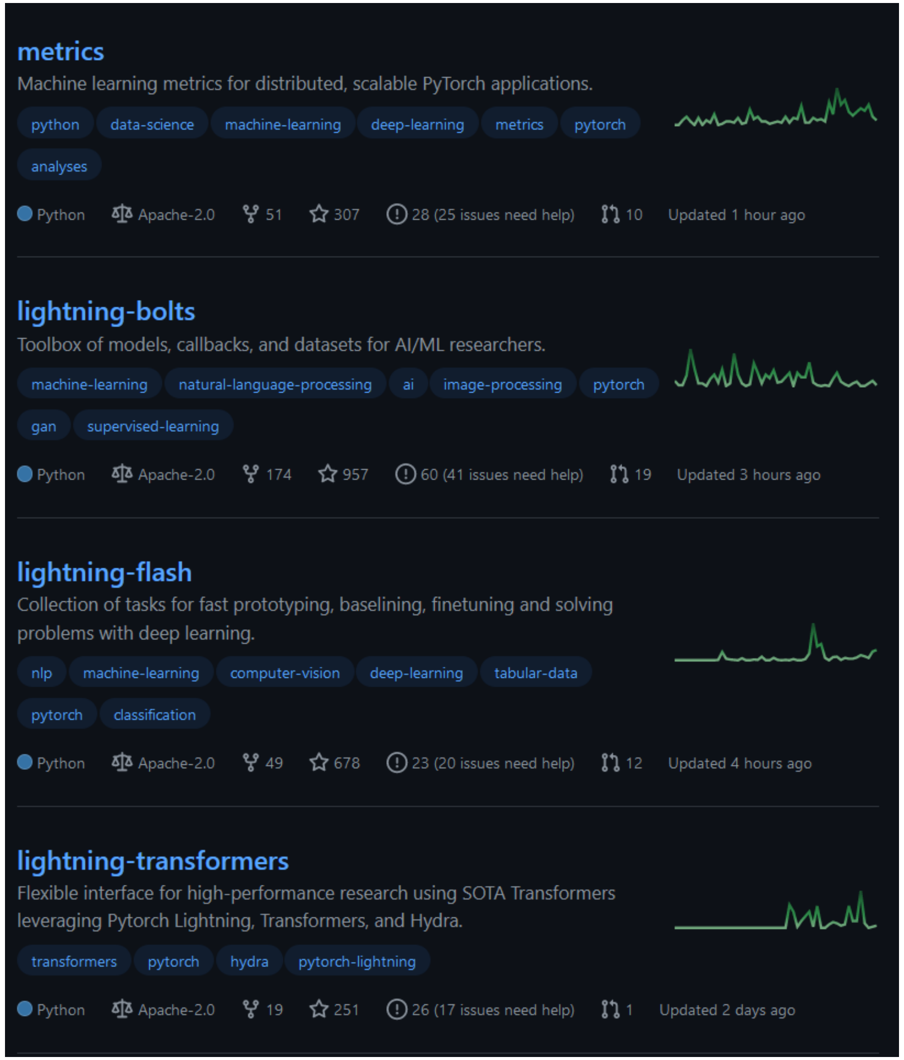
Arbitrary functionality

```
# add arbitrary functionality
class MyNotifier(pl.Callback):

    def on_train_epoch_start(trainer, pl_module):
      slack.post('training started!')

notifier = MyNotifier()
trainer = Trainer(callbacks=[notifier])
```

What else do we offer?



All the metrics you need to measure the quality of your ML model in Pytorch

SOTA implementation of selected models

Easy-to-get-started tasks and models for fast prototyping

Transformer models in Lightning (for all NLP lovers)

Todays exercises

- Format your code using pytorch-lightning
  - https://pytorch-lightning.readthedocs.io/en/latest/
  - https://pytorch-lightning.readthedocs.io/en/latest/starter/converting.html

- Make it run on multi-gpu

Meme of the day