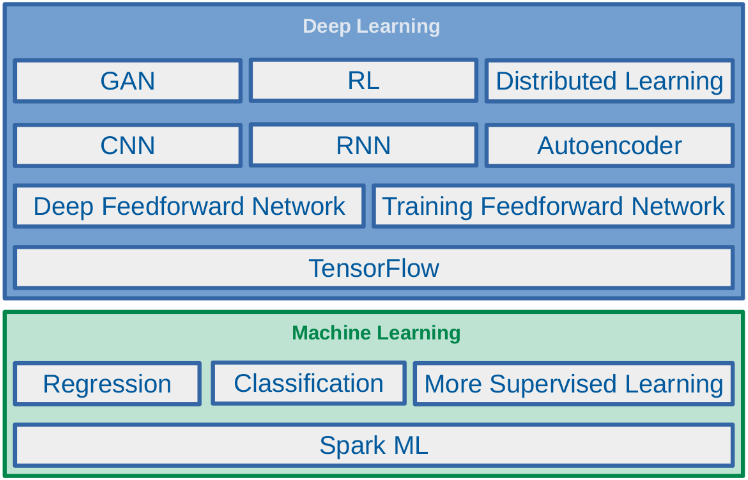
Distributed Learning

Amir H. Payberah
payberah@kth.se
10/12/2019

The Course Web Page

`https://id2223kth.github.io`

Where Are We?


Deep Learning
GAN
RL
Distributed Learning
CNN
RNN
Autoencoder
Deep Feedforward Network
Training Feedforward Network
TensorFlow
Machine Learning
Regression
Classification
More Supervised Learning
Spark ML

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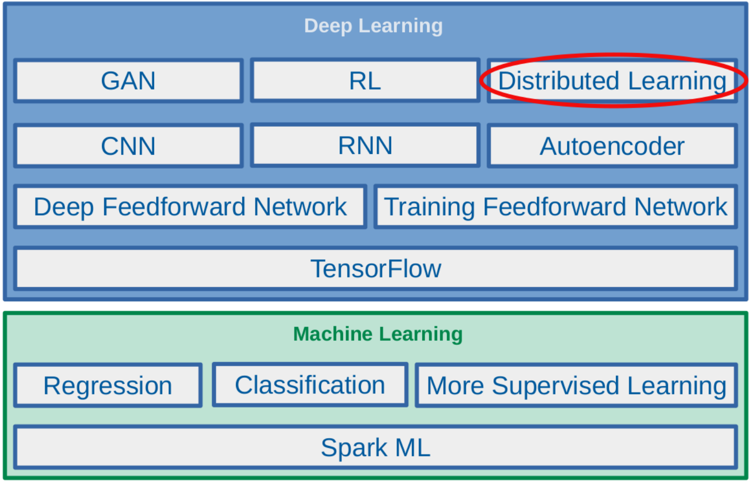
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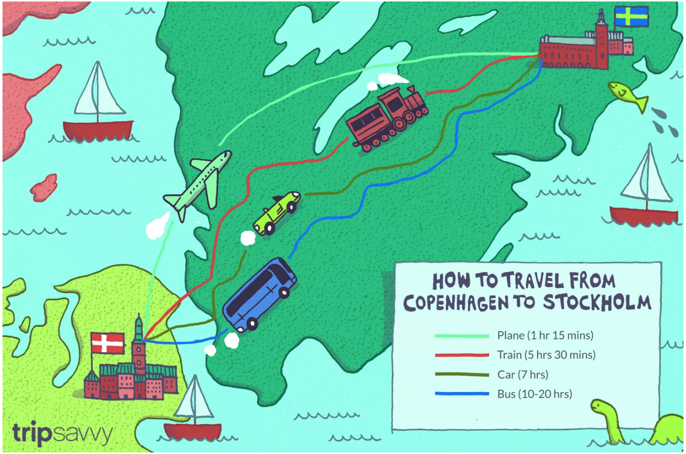
A few Words about CPU and GPU



[https://www.tripsavvy.com/how-to-get-from-copenhagen-to-stockholm-1626275]

Ferrari or Truck?

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- Pick up your partner?

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- Moving the furniture?

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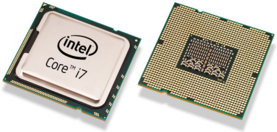
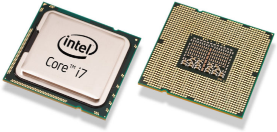
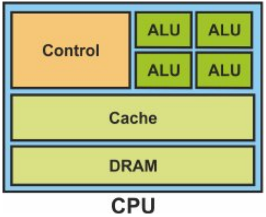
CPU vs GPU

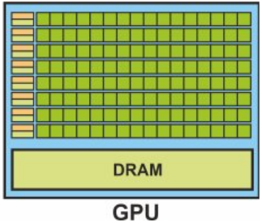


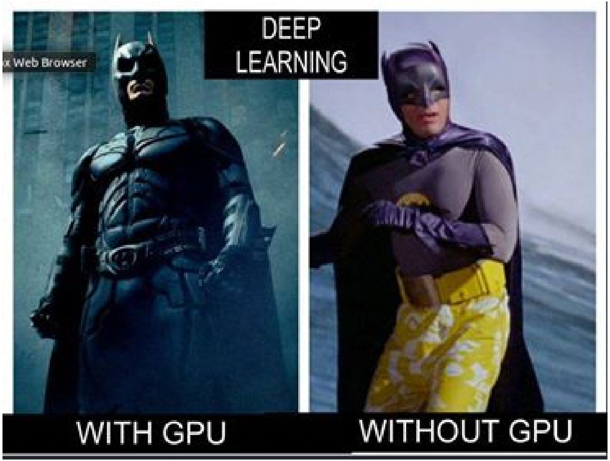
CPU vs GPU


intel
Core™ i7


TITAN Z


Control
ALU
ALU
ALU
ALU
Cache
DRAM
CPU


DRAM
GPU


DEEP LEARNING
x Web Browser
WITH GPU
WITHOUT GPU

Do We Need GPU for Deep Learning?

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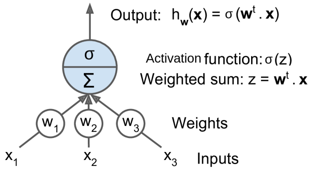
Training a Model

- **Forward pass:** input is passed through the DNN and an output is generated.
- **Backward pass:** weights are updated on the basis of error we get in forward pass.



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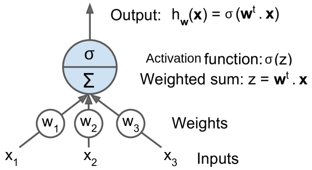
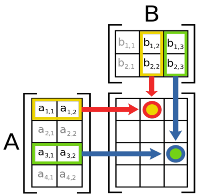
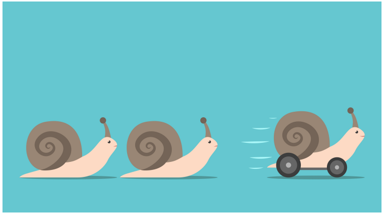


- Both of these operations are essentially matrix multiplications.



How to Train a Model Faster?

- The computationally intensive part of neural network is made up of multiple matrix multiplications.
- How can we make it faster?



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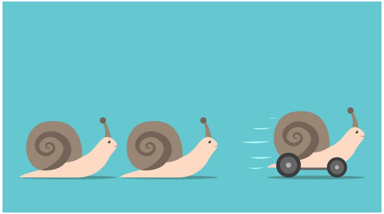
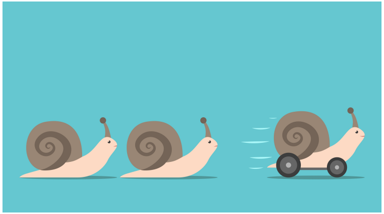
- Do these operations at the same time, instead of doing it one after the other.



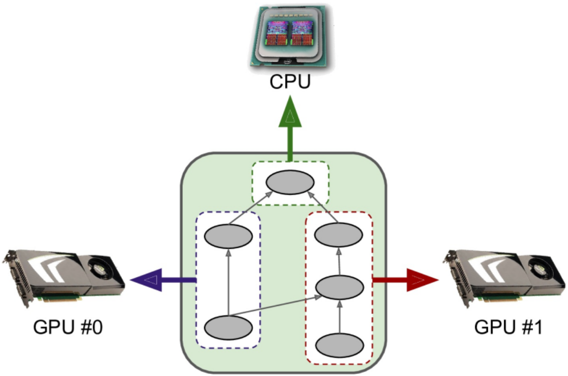
How to Train a Model Faster?

- The computationally intensive part of neural network is made up of multiple matrix multiplications.
- How can we make it faster?
- Do these operations at the same time, instead of doing it one after the other.
- This is in a nutshell why we use GPU instead of a CPU for training a neural network.



Placing Operations and Variables on Devices (1/4)

- For now, lets asume to run everything on a single machine.



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- Place the data preprocessing operations on CPUs, and the NN operations on GPUs.
- Adding more CPU RAM to a machine is simple and cheap, whereas the GPU RAM is an expensive and limited resource.
  - If a variable is not needed in the next few training steps, it should probably be placed on the CPU (e.g., datasets generally belong on the CPU).
- GPUs usually have a fairly limited communication bandwidth, so it is important to avoid unnecessary data transfers in and out of the GPUs.

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- Variables/operations that do not have a GPU kernel are placed on the CPU: `/cpu:0`.
- A kernel is a variable or operation's implementation for a specific data and device type.
  - For example, there is a GPU kernel for the `float32 tf.matmul()` operation, but there is no GPU kernel for `int32 tf.matmul()` (only a CPU kernel).

Placing Operations and Variables on Devices (4/4)

- TensorFlow automatically decides which device to execute an operation and copies tensors to that device.

- However, TensorFlow operations can be explicitly placed on specific devices using the `tf.device` context manager.

Manual Device Placement (1/3)

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Output:
Executing op MatMul in device /job:localhost/replica:0/task:0/device:GPU:0
tf.Tensor(
[[22. 28.]
 [49. 64.]], shape=(2, 2), dtype=float32)
```

Manual Device Placement (2/3)

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tf.debugging.set_log_device_placement(True)

with tf.device('/cpu:0'):
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- Here, `a` and `b` are assigned to `CPU:0`.
- Since a device was not explicitly specified for the `matmul` operation, it will be run on the default device `GPU:0`.

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Executing op MatMul in device /job:localhost/replica:0/task:0/device:CPU:0
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Parallel Execution Across Multiple Devices

Parallelization

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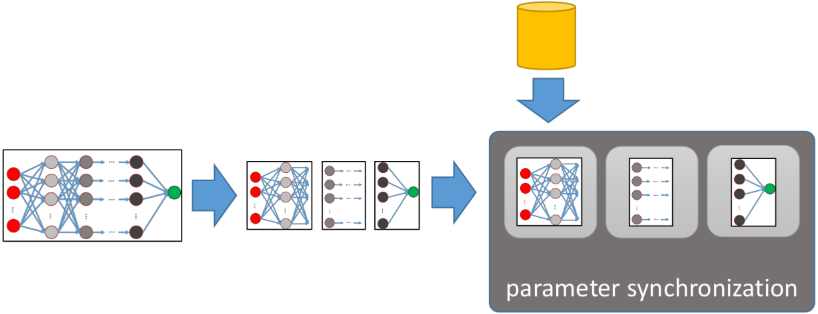
- Train large deep learning models with huge amounts of training data.
- Parallelization and distribution are essential.
- Two main approaches to training a single model across multiple devices:
  - Model parallelization
  - Data parallelization

Model Parallelization

Model Parallelization

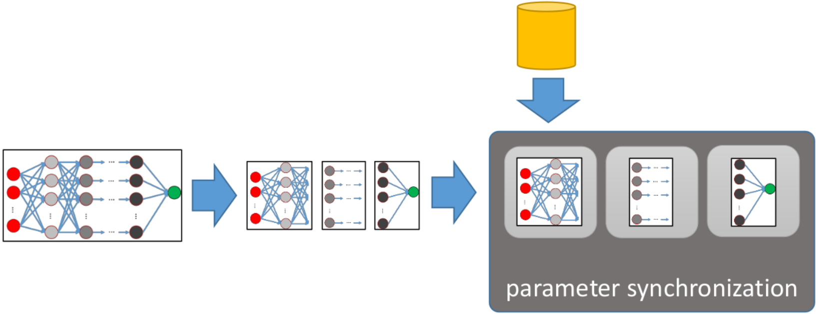
- The model is split across multiple devices.



[Mayer, R. et al., arXiv:1903.11314, 2019]

Model Parallelization

- The model is split across multiple devices.
- Depends on the architecture of the NN.



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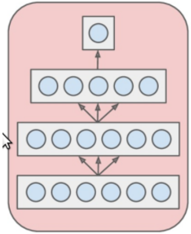
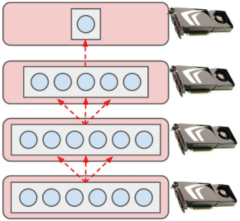
Fully Connetected Model Parallelization (1/2)

- To place each layer on a different device.



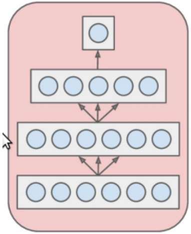
Fully connected neural network



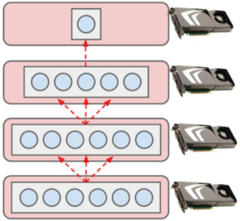
One layer per device

Fully Connetected Model Parallelization (1/2)

- To place each layer on a different device.
- Not good: each layer needs to wait for the output of the previous layer before it can do anything.



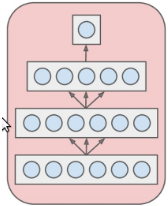
Fully connected
neural network



One layer per device

Fully Connetected Model Parallelization (2/2)

- Slice the model vertically.
  - E.g., the left half of each layer on one device, and the right part on another device.



Fully connected
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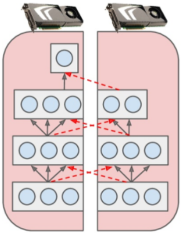

Vertical split

Fully Connetected Model Parallelization (2/2)

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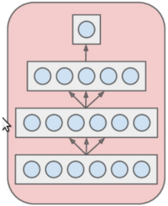
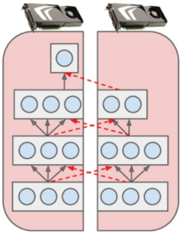
- Slightly better: both halves of each layer can indeed work in parallel.



Fully connected neural network



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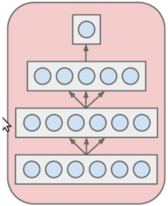
- Each half of the next layer requires the output of both halves: lot of cross-device communication.



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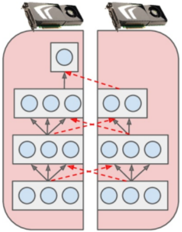
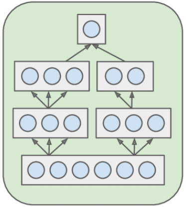


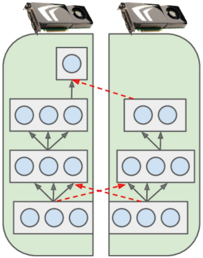
Vertical split

CNN Model Parallelization

- Some NN, such as CNN, contains layers that are only partially connected to the lower layers.



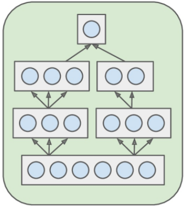
Partially connected
neural network



Vertical split

CNN Model Parallelization

- Some NN, such as CNN, contains layers that are only partially connected to the lower layers.
- Easier to distribute the model across devices in an efficient way.



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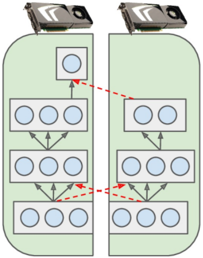
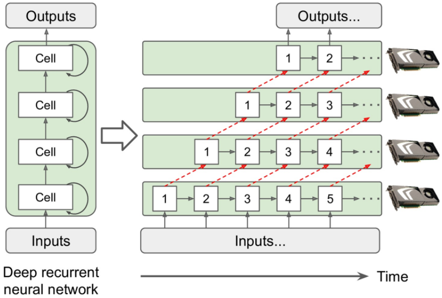


Vertical split

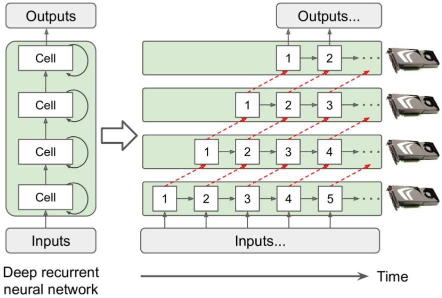
RNN Model Parallelization

- Split the NN **horizontally** by placing **each layer** on a **different device**.



RNN Model Parallelization

- Split the NN horizontally by placing each layer on a different device.
- At the first step, only one device will be active.



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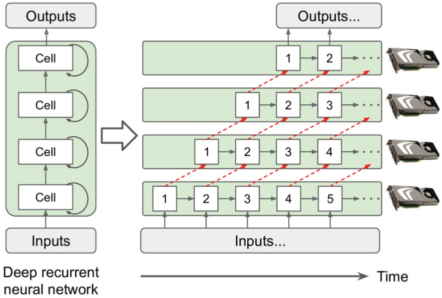

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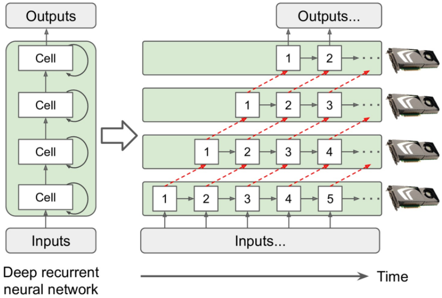
- While the first layer will be handling the second value, the second layer will be handling the output of the first layer for the first value.



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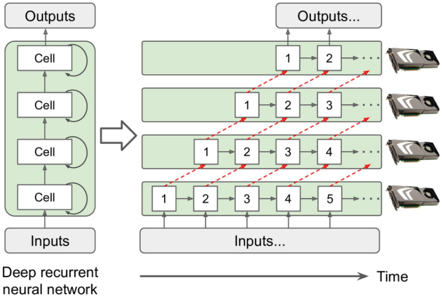
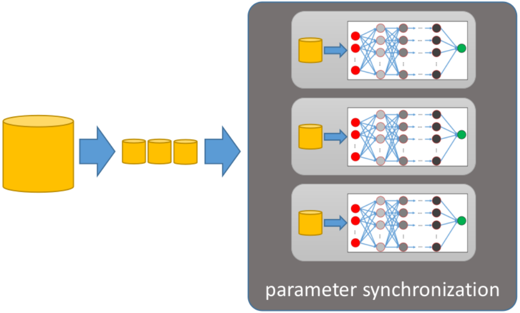
- By the time the signal propagates to the output layer, all devices will be active simultaneously.



Data Parallelization

Data Parallelization (1/2)

- Replicate a whole model on every device.
- Train all replicas simultaneously, using a different mini-batch for each.



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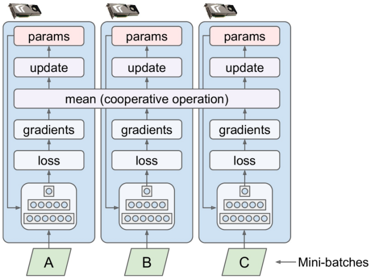
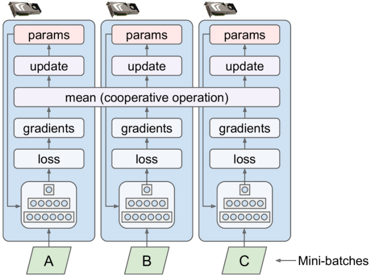
Data Parallelization (2/2)

1. Compute the gradient of the loss function using a mini-batch on each GPU.



Data Parallelization (2/2)

1. Compute the gradient of the loss function using a mini-batch on each GPU.
2. Compute the mean of the gradients by inter-GPU communication.



Data Parallelization (2/2)

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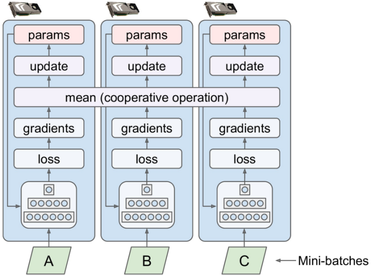
3. Update the model.



Data Parallelization Design Issues

- System Architecture: how to synchronize the parameters

Data Parallelization Design Issues

- System Architecture: how to synchronize the parameters
- Synchronization: when to synchronize the parameters

System Architecture

System Architecture - Centralized

- How to aggregate gradients (compute the mean of the gradients)?
- How the parameters of the different replicas are synchronized?

System Architecture - Centralized

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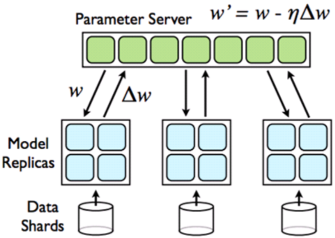
- Workers periodically report their computed parameters or parameter updates to a (set of) parameter server(s) (PSs).



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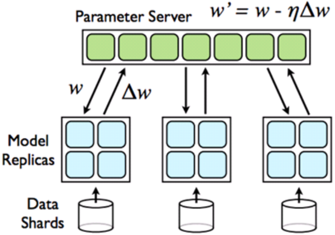

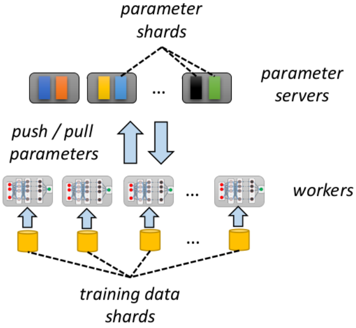

System Architecture - Decentralized

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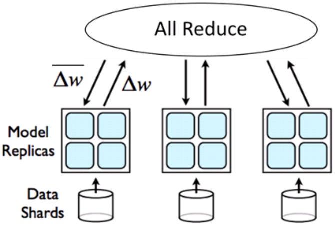
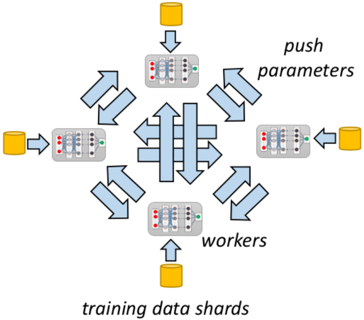
System Architecture - Decentralized

- Mirror all the model parameters across all workers (No PS).
- Workers exchange parameter updates directly via an allreduce operation.





Reduce and AllReduce (1/2)

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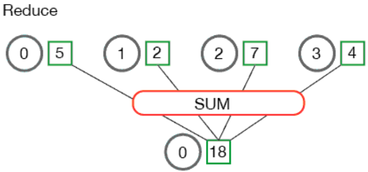

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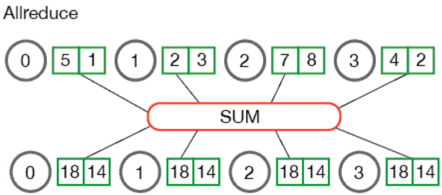
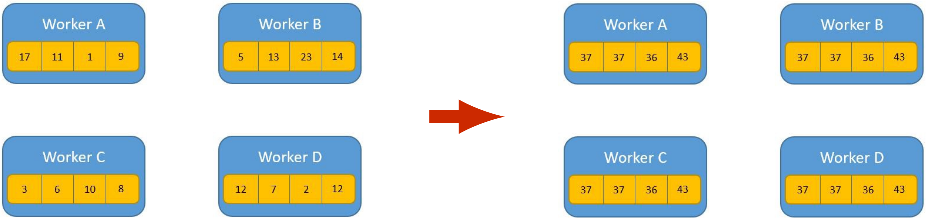


[https://mpitutorial.com/tutorials/mpi-reduce-and-allreduce]

AllReduce Example

Initial state

After AllReduce operation



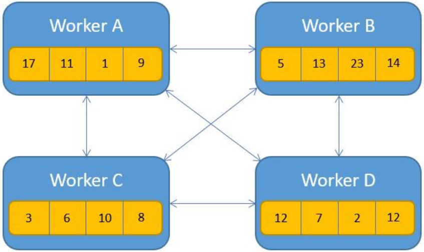
[https://towardsdatascience.com/visual-intuition-on-ring-allreduce-for-distributed-deep-learning-d1f34b4911da]

AllReduce Implementation

- All-to-all allreduce
- Master-worker allreduce
- Tree allreduce
- Round-robin allreduce
- Butterfly allreduce
- Ring allreduce

AllReduce Implementation - All-to-All AllReduce

- Send the array of data to each other.
- Apply the reduction operation on each process.



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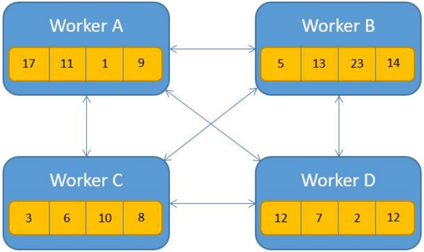
AllReduce Implementation - All-to-All AllReduce

- Send the array of data to each other.
- Apply the reduction operation on each process.
- Too many unnecessary messages.



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AllReduce Implementation - Master-Worker AllReduce

- Selecting one process as a master, gather all arrays into the master.
- Perform reduction operations locally in the master.
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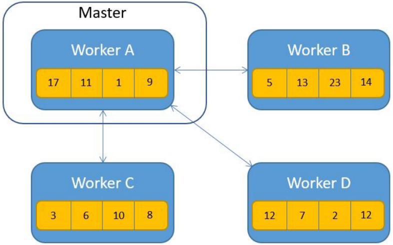

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AllReduce Implementation - Master-Worker AllReduce

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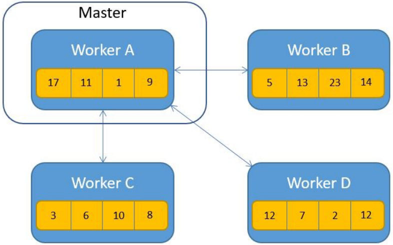
- Distribute the result to the other processes.
- The master becomes a bottleneck (not scalable).



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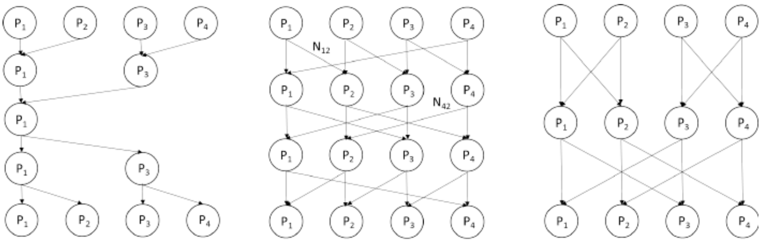
AllReduce Implementation - Other implementations

- Some try to minimize bandwidth.
- Some try to minimize latency.



(a) Tree AllReduce (b) Round-robin AllReduce (c) Butterfly AllReduce

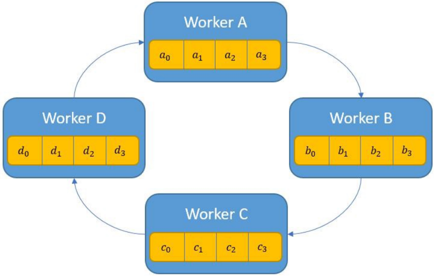
[Zhao H. et al., arXiv:1312.3020, 2013]

AllReduce Implementation - Ring-AllReduce (1/6)

- The Ring-Allreduce has two phases:
  1. First, the share-reduce phase
  2. Then, the share-only phase

AllReduce Implementation - Ring-AllReduce (2/6)

- In the share-reduce phase, each process `p` sends data to the process `(p+1) % m`
  - `m` is the number of processes, and `%` is the modulo operator.



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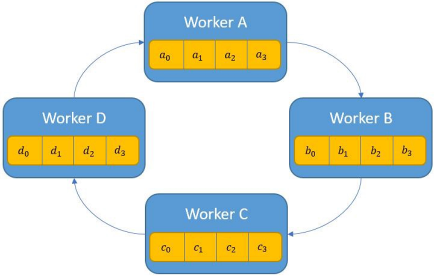

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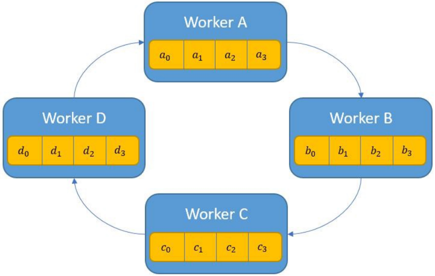
- Each one of these chunks will be indexed by `i` going forward.



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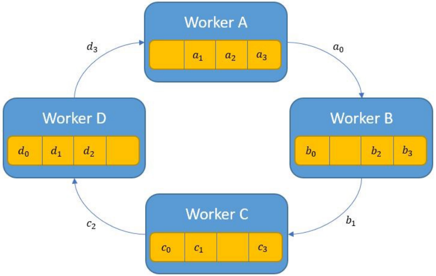
AllReduce Implementation - Ring-AllReduce (3/6)

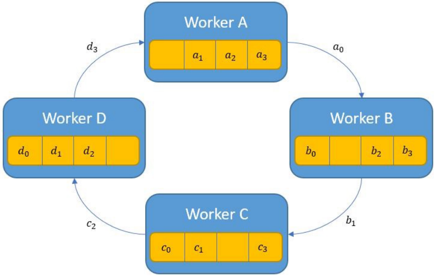
- In the first share-reduce step, process `A` sends a_0 to process `B`.



[https://towardsdatascience.com/visual-intuition-on-ring-allreduce-for-distributed-deep-learning-d1f34b4911da]

AllReduce Implementation - Ring-AllReduce (3/6)

- In the first share-reduce step, process `A` sends $\mathtt{a}_0$ to process `B`.
- Process `B` sends $\mathtt{b}_1$ to process `C`, etc.



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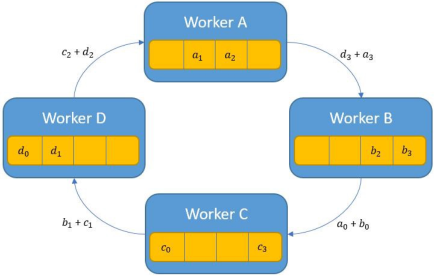
AllReduce Implementation - Ring-AllReduce (4/6)

- When each process receives the data from the previous process, it applies the reduce operator (e.g., sum or mean)



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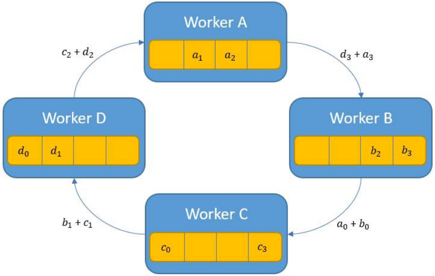

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AllReduce Implementation - Ring-AllReduce (4/6)

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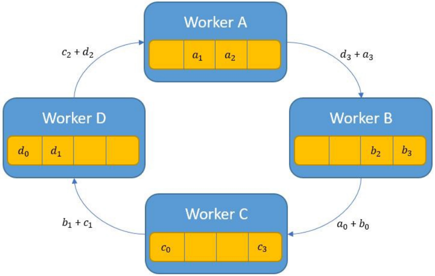
- It then proceeds to send it to the next process in the ring.



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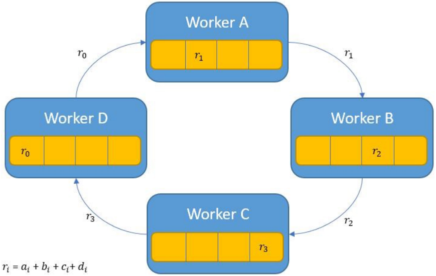
AllReduce Implementation - Ring-AllReduce (5/6)

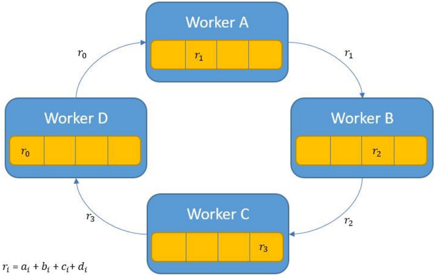
- The share-reduce phase finishes when each process holds the complete reduction of chunk `i`.



[https://towardsdatascience.com/visual-intuition-on-ring-allreduce-for-distributed-deep-learning-d1f34b4911da]

AllReduce Implementation - Ring-AllReduce (5/6)

- The share-reduce phase finishes when each process holds the complete reduction of chunk `i`.
- At this point each process holds a part of the end result.



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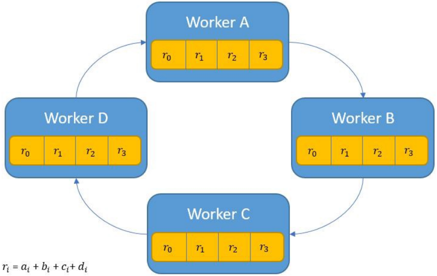
AllReduce Implementation - Ring-AllReduce (6/6)

- The share-only step is the same process of sharing the data in a ring-like fashion without applying the reduce operation.



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AllReduce Implementation - Ring-AllReduce (6/6)

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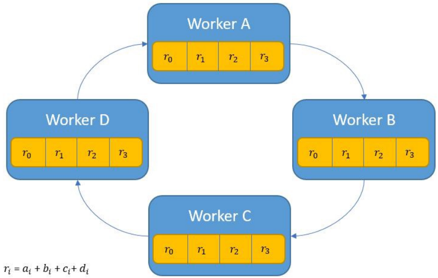
- This consolidates the result of each chunk in every process.



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Master-Worker AllReduce vs. Ring-AllReduce

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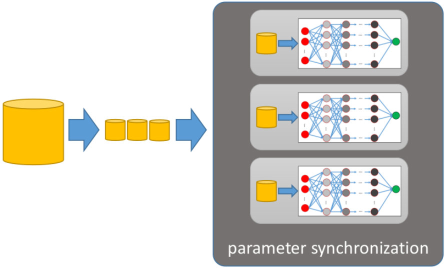
Synchronization

Synchronization

- When to synchronize the parameters among the parallel workers?

Synchronization - Synchronous

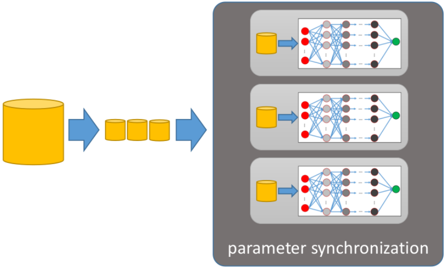
- After each iteration (processing of a mini-batch), the workers synchronize their parameter updates.



[Mayer, R. et al., arXiv:1903.11314, 2019]

Synchronization - Synchronous

- After each iteration (processing of a mini-batch), the workers synchronize their parameter updates.
  - Easy to reason about the model convergence.



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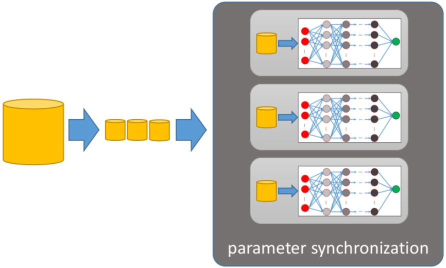
Synchronization - Synchronous

- After each iteration (processing of a mini-batch), the workers synchronize their parameter updates.
  - Easy to reason about the model convergence.
  - The training process prone to the straggler problem, where the slowest worker slows down all the others.



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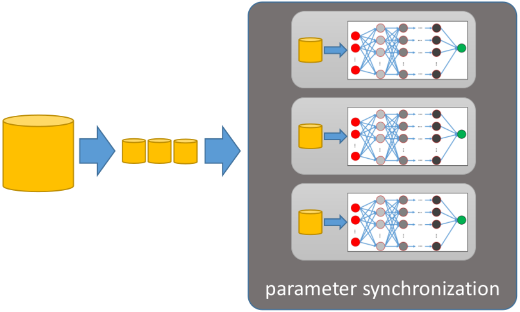
Synchronization - Asynchronous

- Workers update their model independently from each other.



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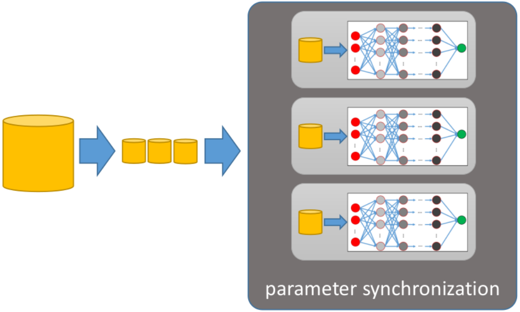

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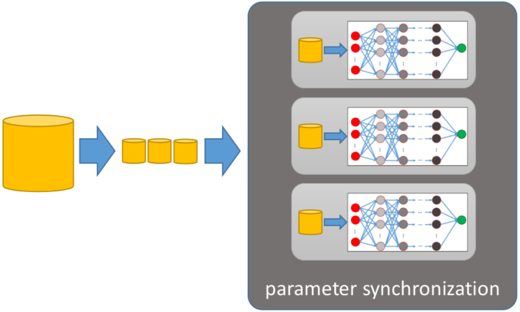

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Synchronization - Asynchronous

- Workers update their model independently from each other.
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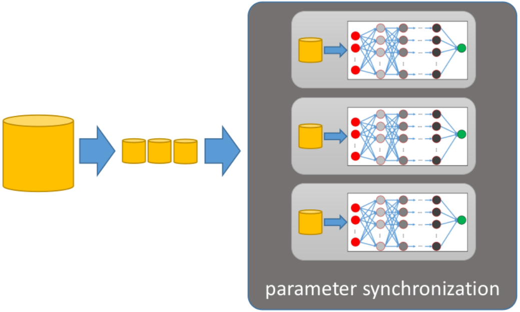
  - This makes it hard to mathematically reason about the model convergence.
  - It provides the workers flexibility in their training process, completely avoiding all straggler problems.



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Data Parallelization in TensorFlow

TensorFlow Distribution Strategies

- `tf.distribute.Strategy` is a TensorFlow API to distribute training.
- Supports both parameter server and allreduce models.

Single Server

Single Server Training - MirroredStrategy (1/2)

- Synchronous distribute training training on multiple GPUs on one machine.

```
mirrored_strategy = tf.distribute.MirroredStrategy()

# to use only some of the GPUs on your machine
mirrored_strategy = tf.distribute.MirroredStrategy(devices=["/gpu:0", "/gpu:1"])
```

Single Server Training - MirroredStrategy (1/2)

- Synchronous distribute training training on multiple GPUs on one machine.
- One replica per GPU.

```
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# to use only some of the GPUs on your machine
mirrored_strategy = tf.distribute.MirroredStrategy(devices=["/gpu:0", "/gpu:1"])
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Single Server Training - MirroredStrategy (1/2)

- Synchronous distribute training training on multiple GPUs on one machine.
- One replica per GPU.
- The parameters of the model are mirrored across all the replicas.

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- These parameters are kept in sync with each other by applying identical updates.
- The parameters updates are communicated using allreduce algorithms.

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Single Server Training - MirroredStrategy (2/2)

- There are different implementation of allreduce.
- You can override the cross GPU communication:
  - `tf.distribute.NcclAllReduce` (the default)
  - `tf.distribute.ReductionToOneDevice`
  - `tf.distribute.HierarchicalCopyAllReduce`

```
mirrored_strategy = tf.distribute.MirroredStrategy(
    cross_device_ops=tf.distribute.HierarchicalCopyAllReduce())
```

Single Server Training - CentralStorageStrategy

- Parameters are not mirrored, instead they are placed on the CPU.

```
central_storage_strategy = tf.distribute.experimental.CentralStorageStrategy()
```

Single Server Training - CentralStorageStrategy

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- Operations are replicated across all local GPUs.

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Single Server Training - CentralStorageStrategy

- Parameters are not mirrored, instead they are placed on the CPU.
- Operations are replicated across all local GPUs.
- Does synchronous training.

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central_storage_strategy = tf.distribute.experimental.CentralStorageStrategy()
```

Single Server Trainings - Example

- Creat a strategy, e.g., `MirroredStrategy` or `CentralStorageStrategy`.

```
distribution = tf.distribute.MirroredStrategy()

with distribution.scope():
    model = keras.models.Sequential([...])
    model.compile(...)

model.fit(...)
model.predict(...)
```

Single Server Trainings - Example

- Creat a strategy, e.g., `MirroredStrategy` or `CentralStorageStrategy`.
- Call its `scope()` method to get a distribution context.

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- Creat a strategy, e.g., `MirroredStrategy` or `CentralStorageStrategy`.
- Call its `scope()` method to get a distribution context.
- Wrap the creation and compilation of the model inside that context.

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Single Server Trainings - Example

- Creat a strategy, e.g., `MirroredStrategy` or `CentralStorageStrategy`.
- Call its `scope()` method to get a distribution context.
- Wrap the creation and compilation of the model inside that context.
- Call the model's `fit()` and `predict()` method normally (outside the context).

```
distribution = tf.distribute.MirroredStrategy()

with distribution.scope():
    model = keras.models.Sequential([...])
    model.compile(...)

model.fit(...)
model.predict(...)
```

Multi Servers

Multi Servers Trainings - MultiWorkerMirroredStrategy (1/2)

- Very similar to `MirroredStrategy`.

```
multiworker_strategy = tf.distribute.experimental.MultiWorkerMirroredStrategy()
```

Multi Servers Trainings - MultiWorkerMirroredStrategy (1/2)

- Very similar to `MirroredStrategy`.
- Synchronous distributed training across multiple workers, each with potentially multiple GPUs.

```
multiworker_strategy = tf.distribute.experimental.MultiWorkerMirroredStrategy()
```

Multi Servers Trainings - MultiWorkerMirroredStrategy (1/2)

- Very similar to `MirroredStrategy`.
- Synchronous distributed training across multiple workers, each with potentially multiple GPUs.
- Makes copies of all parameters of the model on each device across all workers.

```
multiworker_strategy = tf.distribute.experimental.MultiWorkerMirroredStrategy()
```

Multi Servers Trainings - MultiWorkerMirroredStrategy (2/2)

- Two different implementations:
  - `CollectiveCommunication.RING` (ring-based implementation)
  - `CollectiveCommunication.NCCL` (Nvidia's NCCL implementation)

```
# ring-based collectives
multiworker_strategy = tf.distribute.experimental.MultiWorkerMirroredStrategy(
    tf.distribute.experimental.CollectiveCommunication.RING)
```

Multi Servers Trainings - MultiWorkerMirroredStrategy (2/2)

- Two different implementations:
  - CollectiveCommunication.RING (ring-based implementation)
  - CollectiveCommunication.NCCL (Nvidia's NCCL implementation)
- CollectiveCommunication.AUTO defers the choice to the runtime.

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Multi Servers Trainings - MultiWorkerMirroredStrategy (2/2)

- Two different implementations:
  - `CollectiveCommunication.RING` (ring-based implementation)
  - `CollectiveCommunication.NCCL` (Nvidia's NCCL implementation)
- `CollectiveCommunication.AUTO` defers the choice to the runtime.
- The best choice of collective implementation depends upon the number and kind of GPUs, and the network interconnect in the cluster.

```
# ring-based collectives
multiworker_strategy = tf.distribute.experimental.MultiWorkerMirroredStrategy(
    tf.distribute.experimental.CollectiveCommunication.RING)
```

Multi Servers Trainings - ParameterServerStrategy

- Supports parameter servers training on multiple machines.

```
ps_strategy = tf.distribute.experimental.ParameterServerStrategy()
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- Each parameter of the model is placed on one parameter server.

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```

Multi Servers Trainings - ParameterServerStrategy

- Supports parameter servers training on multiple machines.
- Some machines are designated as workers and some as parameter servers.
- Each parameter of the model is placed on one parameter server.
- Computation is replicated across all GPUs of all the workers.

```
ps_strategy = tf.distribute.experimental.ParameterServerStrategy()
```

Multi Servers Trainings - More Details

- A TensorFlow cluster is a group of TensorFlow processes running in parallel.

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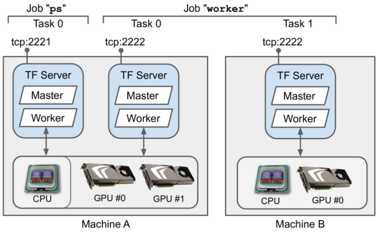
- A TensorFlow cluster is a group of TensorFlow processes running in parallel.
- Each TF process (a.k.a task) in the cluster has a type:
  - Worker: performs computations, usually on a machine with one or more GPUs.
  - Parameter Server (ps): keeps track of parameters values, it is usually on a CPU-only machine.
- The set of tasks that share the same type is often called a job. For example, the worker job is the set of all workers.

Multi Servers Trainings - Example (1/3)

- Assume a cluster with 3 tasks (2 workers and 1 parameter server).

```
cluster_spec = tf.train.ClusterSpec({
    "worker": [
        "machine-a.example.com:2222", # /job:worker/task:0
        "machine-b.example.com:2222"  # /job:worker/task:1
    ],
    "ps": ["machine-a.example.com:2221"] # /job:ps/task:0
})
```



Multi Servers Trainings - Example (2/3)

- To start a task, you must give it the cluster spec and define its type and index (ID), e.g., worker 0.

```
ps0 = tf.distribute.Server(cluster_spec, job_name="ps", task_index=0)
```

Multi Servers Trainings - Example (2/3)

- To start a task, you must give it the cluster spec and define its type and index (ID), e.g., worker 0.

```
ps0 = tf.distribute.Server(cluster_spec, job_name="ps", task_index=0)
```

```
worker0 = tf.distribute.Server(cluster_spec, job_name="worker", task_index=0)
```

Multi Servers Trainings - Example (2/3)

- To start a task, you must give it the cluster spec and define its type and index (ID), e.g., worker 0.

```
ps0 = tf.distribute.Server(cluster_spec, job_name="ps", task_index=0)
```

```
worker0 = tf.distribute.Server(cluster_spec, job_name="worker", task_index=0)
```

```
worker1 = tf.distribute.Server(cluster_spec, job_name="worker", task_index=1)
```

Multi Servers Trainings - Example (3/3)

- Alternative way to specify a cluster spec is to use the TF_CONFIG environment variable before starting the program.
- For example to run worker 1:

```
distribution = tf.distribute.experimental.ParameterServerStrategy()

os.environ["TF_CONFIG"] = json.dumps({
   "cluster": {
     "worker": ["machine-a.example.com:2222", "machine-b.example.com:2222"],
     "ps": ["machine-a.example.com:2221"]},
   "task": {"type": "worker", "index": 1}
})

with distribution.scope():
    model = keras.models.Sequential([...])
    model.compile(...)

model.fit(...)
```

Communication Overhead

Communication Overhead in Data Parallelization

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- Synchronizing the model replicas in data-parallel training requires communication between workers (in allreduce)
- Between workers and parameter servers (in the centralized architecture).
- Such communication can easily become the bottleneck of the overall training process.

Approaches for Communication Efficiency

- Reducing the model precision
- Compressing the model updates
- Improving the communication scheduling

Reducing the Model Precision

- Reduce the precision of the parameters' data types, e.g., from double precision to single floating point.

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- Reduce the precision of the parameters' data types, e.g., from double precision to single floating point.
- It saves communication bandwidth when parameter updates need to be transferred over the network.
- It reduces the model size, which can be useful when the model is deployed on resource-constrained hardware such as GPUs.

Compressing the Model Updates

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- Gradient quantization: reducing the number of bits per gradient.
- Gradient sparsification: communicating only important gradients that have a significant value.

Improving the Communication Scheduling

- Communication patterns in data-parallel are typically bursty, especially in synchronous systems.

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- To prevent that the network bandwidth is exceeded and communication is delayed, the communication of the different workers can be scheduled such that it does not overlap.

Improving the Communication Scheduling

- Communication patterns in data-parallel are typically bursty, especially in synchronous systems.
    - All workers may share their updated parameters at the same time with their peer workers or parameter servers.

- To prevent that the network bandwidth is exceeded and communication is delayed, the communication of the different workers can be scheduled such that it does not overlap.
    - Prioritize specific messages over others.

Summary

Summary

- CPU vs. GPU
- Parallelization
- Model-parallel
- Data-parallel
  - Parameter server vs. AllReduce
  - Synchronized vs. asynchronoused
- Communication challenges

Reference

- Aurélien Géron, Hands-On Machine Learning (Ch. 19)
- Mayer, R. et al., "Scalable Deep Learning on Distributed Infrastructures: Challenges, Techniques and Tools", 2019.

Questions?