Distributed Learning - Data Parallelization

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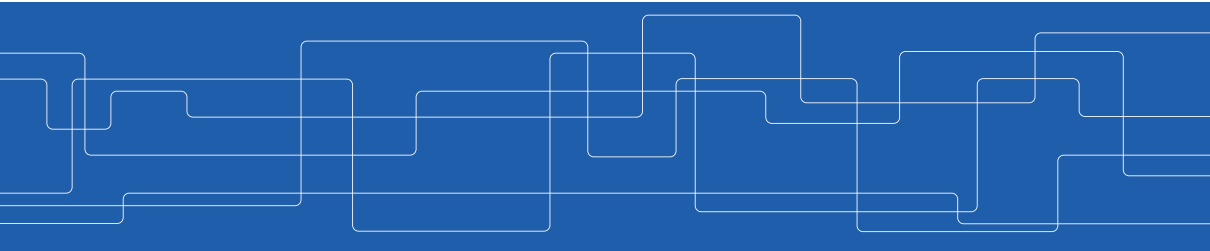
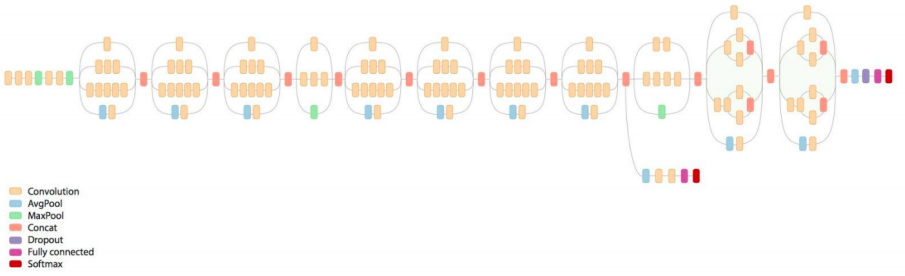


Training Deep Neural Networks

- Computationally intensive
- Time consuming

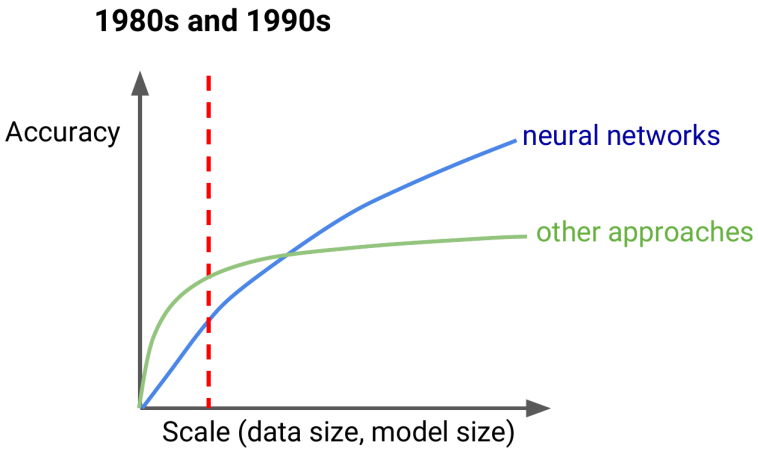


[https://cloud.google.com/tpu/docs/images/inceptionv3onc--oview.png]

Why?

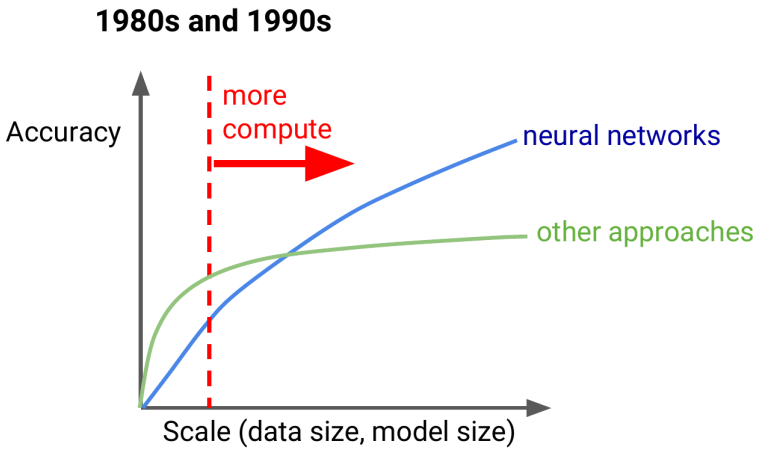
- Massive amount of training dataset
- Large number of parameters

Accuracy vs. Data/Model Size



[Jeff Dean at AI Frontiers: Trends and Developments in Deep Learning Research]

Accuracy vs. Data/Model Size



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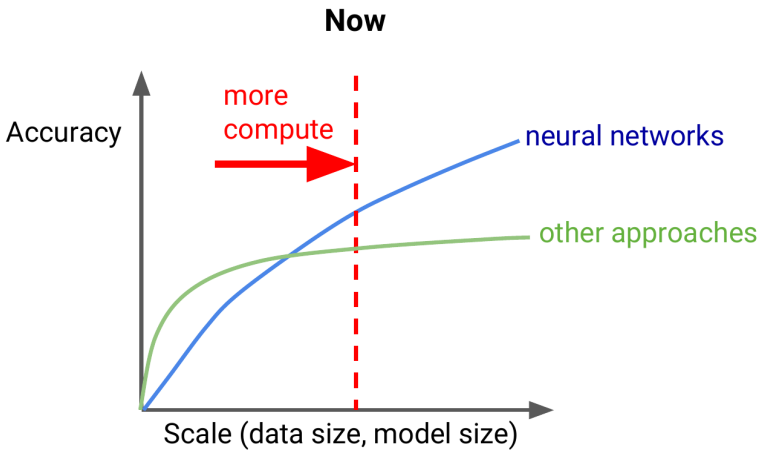

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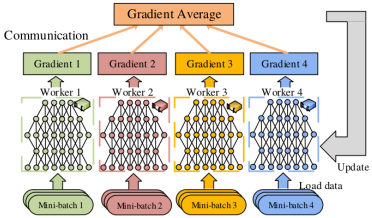
Scale Matters

Data Parallelization (1/4)

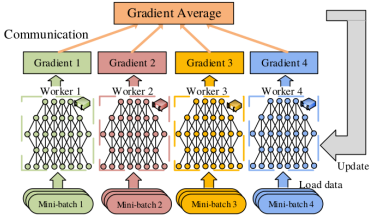
- Replicate a whole model on every device.



[Tang et al., Communication-Efficient Distributed Deep Learning: A Comprehensive Survey, 2020]

Data Parallelization (1/4)

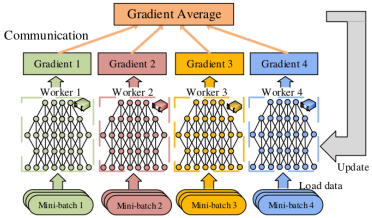
- Replicate a whole model on every device.
- Train all replicas simultaneously, using a different mini-batch for each.



[Tang et al., Communication-Efficient Distributed Deep Learning: A Comprehensive Survey, 2020]

Data Parallelization (2/4)

- k devices



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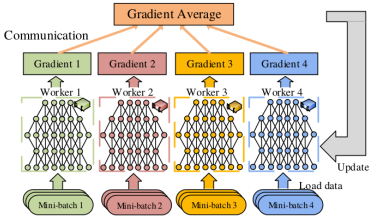
Data Parallelization (2/4)

- k devices
- $J_i(\mathbf{w}) = \frac{1}{|\beta_i|} \sum_{\mathbf{x} \in \beta_i} l(\mathbf{x}, \mathbf{w})$, $\forall i = 1, 2, \cdots, k$



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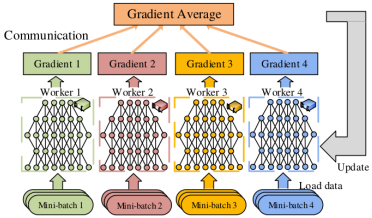
- k devices
- $J_i(w) = \frac{1}{|\beta_i|} \sum_{x \in \beta_i} l(x, w)$, $\forall i = 1, 2, \cdots, k$
- $G_i(w, \beta_i) = \frac{1}{|\beta_i|} \sum_{x \in \beta_i} \nabla l(w, x)$



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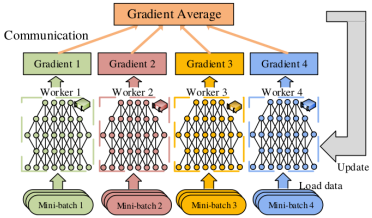
Data Parallelization (2/4)

- $\mathtt{k}$ devices
- $\mathtt{J_i}(\mathbf{w}) = \frac{1}{|\beta_\mathtt{i}|} \sum_{\mathbf{x} \in \beta_\mathtt{i}} \mathtt{l}(\mathbf{x}, \mathbf{w})$, $\forall \mathtt{i} = 1, 2, \cdots, \mathtt{k}$
- $\mathtt{G_i}(\mathbf{w}, \beta_\mathtt{i}) = \frac{1}{|\beta_\mathtt{i}|} \sum_{\mathbf{x} \in \beta_\mathtt{i}} \nabla \mathtt{l}(\mathbf{w}, \mathbf{x})$
- $\mathtt{G_i}(\mathbf{w}, \beta_\mathtt{i})$: the local estimate of the gradient of the loss function $\nabla \mathtt{J_i}(\mathbf{w})$.



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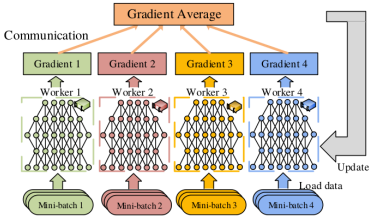
Data Parallelization (3/4)

- Compute the gradients aggregation (e.g., mean of the gradients).
- $F(G_1, \cdots, G_k) = \frac{1}{k} \sum_{i=1}^{k} G_i(\mathbf{w}, \beta_i)$



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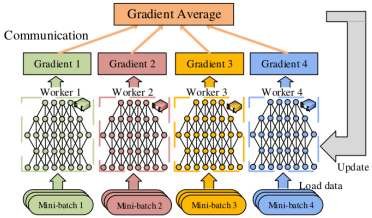
Data Parallelization (4/4)

- Update the model.
- $\mathbf{w} := \mathbf{w} - \eta \mathrm{F}(\mathrm{G}_1, \cdots, \mathrm{G}_k)$



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Data Parallelization Design Issues

- The aggregation algorithm
- Communication synchronization and frequency
- Communication compression
- Parallelism of computations and communications

The Aggregation Algorithm

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- Decentralized - all-reduce

The Aggregation Algorithm

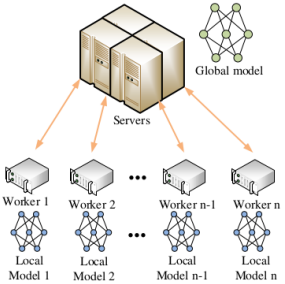
- How to aggregate gradients (compute the mean of the gradients)?
- Centralized - parameter server
- Decentralized - all-reduce
- Decentralized - gossip

Aggregation - Centralized - Parameter Server

- Store the model parameters outside of the workers.

Aggregation - Centralized - Parameter Server

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



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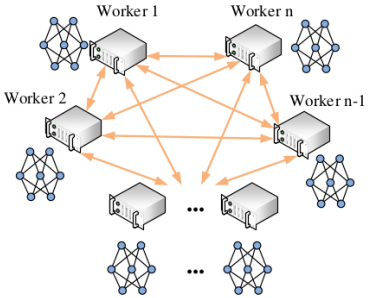
Aggregation - Distributed - All-Reduce

- Mirror all the model parameters across all workers (no PS).

Aggregation - Distributed - All-Reduce

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



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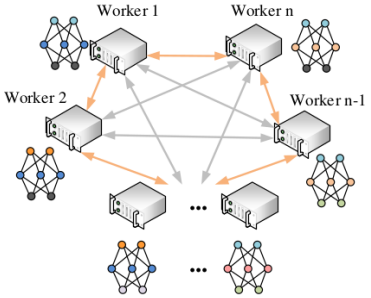
Aggregation - Distributed - Gossip

- No PS, and no global model.



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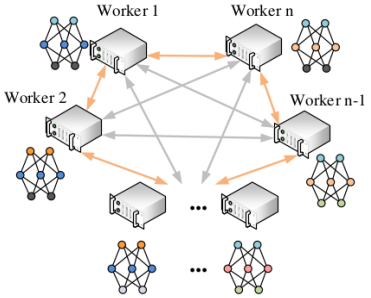

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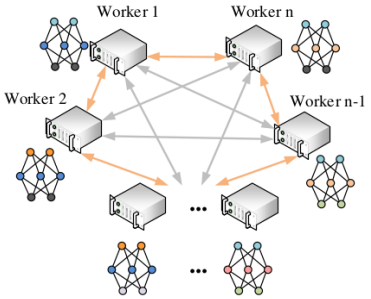
Aggregation - Distributed - Gossip

- No PS, and no global model.
- Every worker communicates updates with their neighbors.
- The consistency of parameters across all workers only at the end of the algorithm.



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Reduce and AllReduce (1/2)

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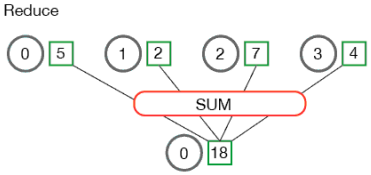

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[https://mpitutorial.com/tutorials/mpi-reduce-and-allreduce]

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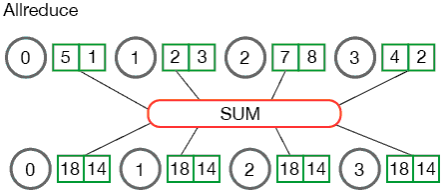

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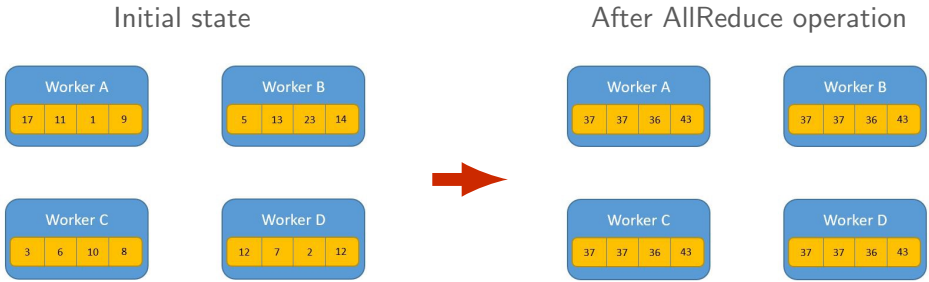
AllReduce Example



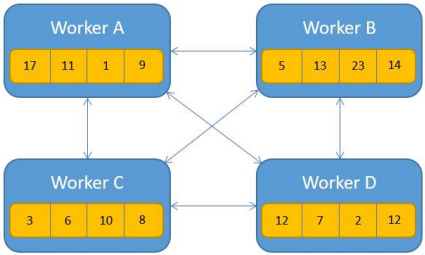
[https://towardsdatascience.com/visual-intuition-on-ring-allreduce-for-distributed-deep-learning-d1f34b4911da]

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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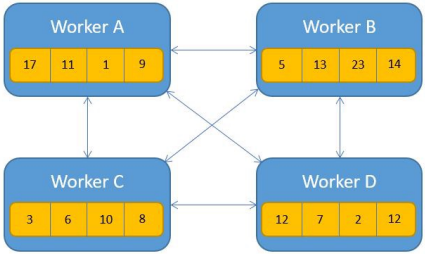
AllReduce Implementation - All-to-All AllReduce

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



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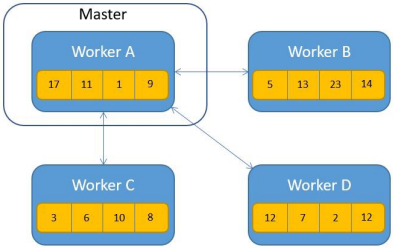
AllReduce Implementation - Master-Worker AllReduce

- Selecting one process as a master, gather all arrays into the master.
- Perform reduction operations locally in the master.
- Distribute the result to the other processes.



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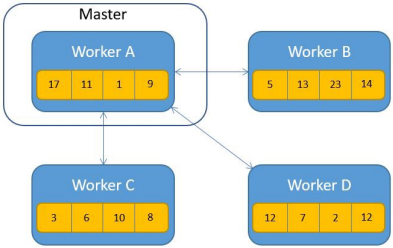
AllReduce Implementation - Master-Worker AllReduce

- Selecting one process as a master, gather all arrays into the master.
- Perform reduction operations locally in the master.
- Distribute the result to the other processes.
- The master becomes a bottleneck (not scalable).



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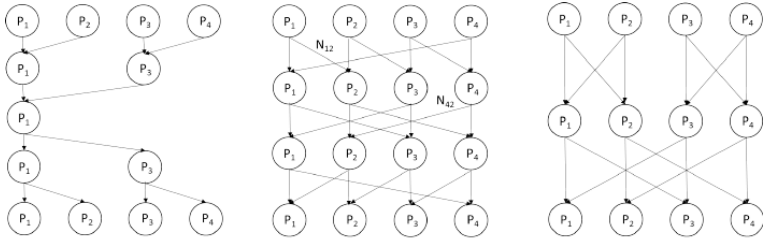
AllReduce Implementation - Other implementations

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



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

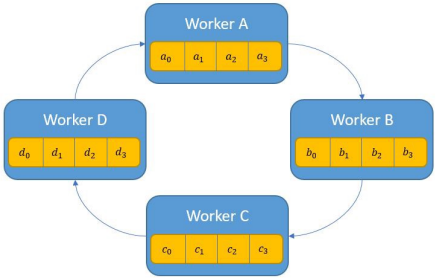
[Zhao H. et al., arXiv:1312.3020, 2013]

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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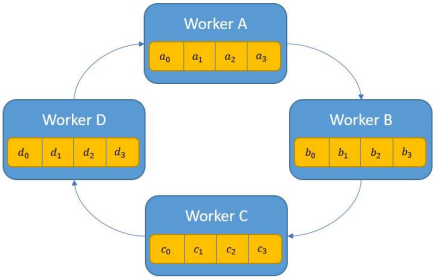

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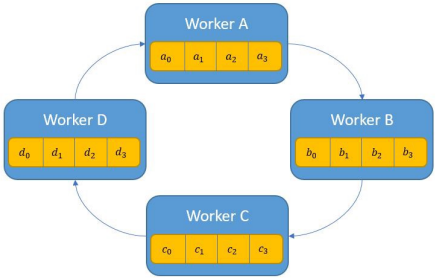
- Each one of these chunks will be indexed by `i` going forward.



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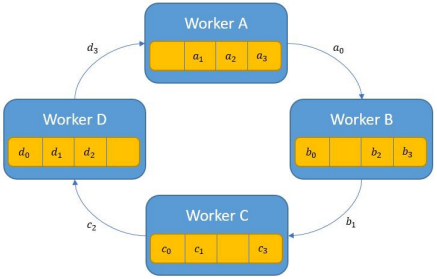
AllReduce Implementation - Ring-AllReduce (3/6)

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



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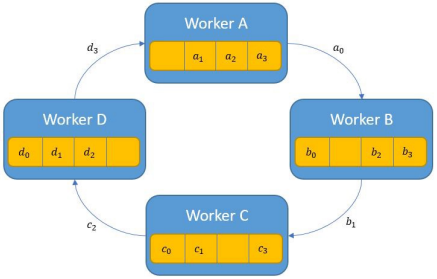
AllReduce Implementation - Ring-AllReduce (3/6)

- In the first share-reduce step, process `A` sends a_0 to process `B`.
- Process `B` sends b_1 to process `C`, etc.



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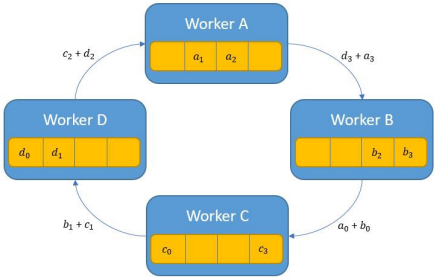
AllReduce Implementation - Ring-AllReduce (4/6)

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



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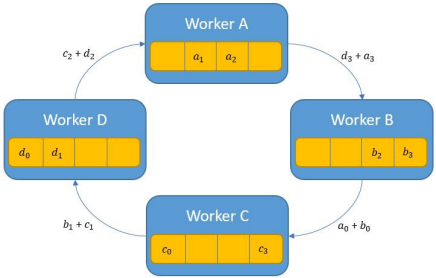
AllReduce Implementation - Ring-AllReduce (4/6)

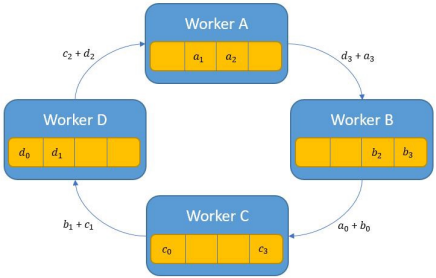
- When each process receives the data from the previous process, it applies the reduce operator (e.g., sum)
  - The reduce operator should be associative and commutative.



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

AllReduce Implementation - Ring-AllReduce (4/6)

- When each process receives the data from the previous process, it applies the reduce operator (e.g., sum)
  - The reduce operator should be associative and commutative.
- It then proceeds to send it to the next process in the ring.



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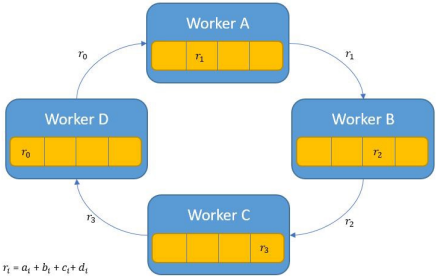
AllReduce Implementation - Ring-AllReduce (5/6)

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



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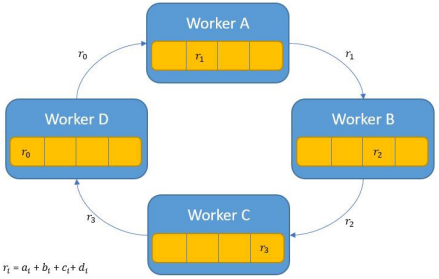
AllReduce Implementation - Ring-AllReduce (5/6)

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



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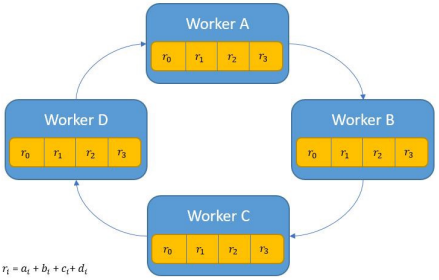
AllReduce Implementation - Ring-AllReduce (6/6)

- 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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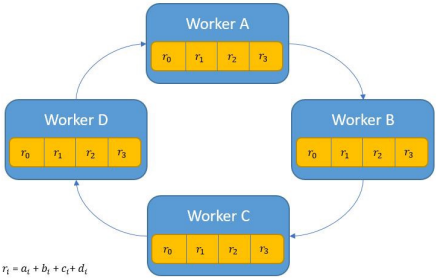
AllReduce Implementation - Ring-AllReduce (6/6)

- The share-only step is the same process of sharing the data in a ring-like fashion without applying the reduce operation.
- This consolidates the result of each chunk in every process.



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Master-Worker AllReduce vs. Ring-AllReduce

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  - First each process sends `N` elements to the master: $\mathtt{N} \times (\mathtt{m} - 1)$ messages.

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Master-Worker AllReduce vs. Ring-AllReduce

- N: number of elements, m: number of processes
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  - First each process sends N elements to the master: $N \times (m - 1)$ messages.
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  - Total network traffic is $2(N \times (m - 1))$, which is proportional to m.

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  - In the share-reduce step each process sends $\frac{N}{m}$ elements, and it does it $m-1$ times: $\frac{N}{m} \times (m-1)$ messages.

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Communication Synchronization and Frequency

Synchronization

- When to synchronize the parameters among the parallel workers?

Communication Synchronization (1/2)

- Synchronizing the model replicas in data-parallel training requires communication
  - between workers, in allreduce
  - between workers and parameter servers, in the centralized architecture

Communication Synchronization (1/2)

- Synchronizing the model replicas in data-parallel training requires communication
  - between workers, in allreduce
  - between workers and parameter servers, in the centralized architecture
- The communication synchronization decides how frequently all local models are synchronized with others.

Communication Synchronization (2/2)

- It will influence:
  - The communication traffic
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Communication Synchronization (2/2)

- It will influence:
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  - The performance
  - The convergence of model training
- There is a trade-off between the communication traffic and the convergence.

Reducing Synchronization Overhead

- Two directions for improvement:

Reducing Synchronization Overhead

- Two directions for improvement:
  1. To relax the synchronization among all workers.

Reducing Synchronization Overhead

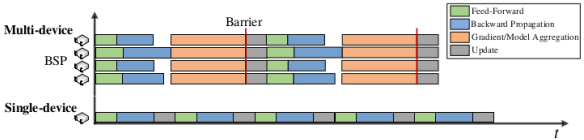
- Two directions for improvement:
  1. To relax the synchronization among all workers.
  2. The frequency of communication can be reduced by more computation in one iteration.

Communication Synchronization Models

- Synchronous
- Stale-synchronous
- Asynchronous
- Local SGD

Communication Synchronization - Synchronous

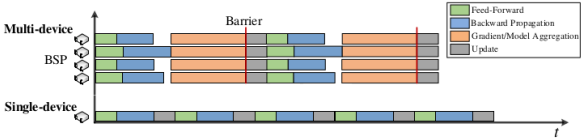
- After each iteration, the workers synchronize their parameter updates.



[Tang et al., Communication-Efficient Distributed Deep Learning: A Comprehensive Survey, 2020]

Communication Synchronization - Synchronous

- After each iteration, the workers synchronize their parameter updates.
- Every worker must wait for all workers to finish the transmission of all parameters in the current iteration, before the next training.



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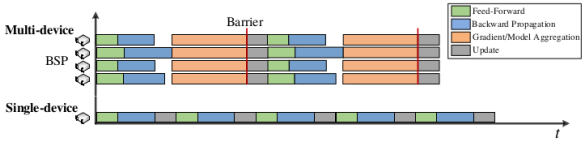

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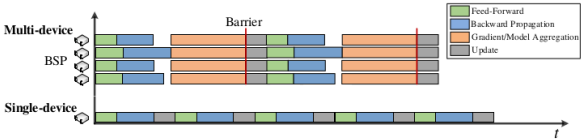
- High communication cost that limits the system scalability.



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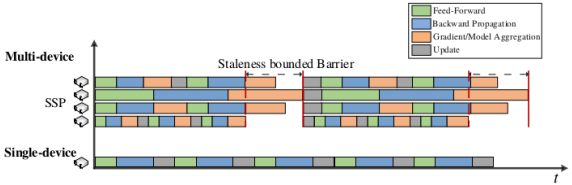

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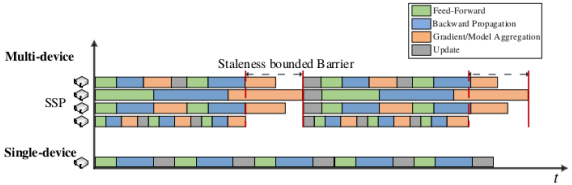

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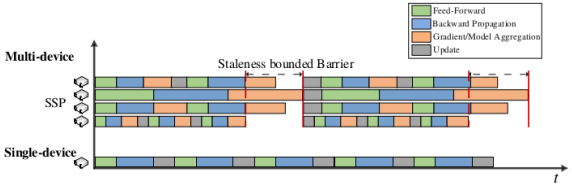
- Staleness bounded barrier to limit the iteration gap between the fastest worker and the slowest worker.



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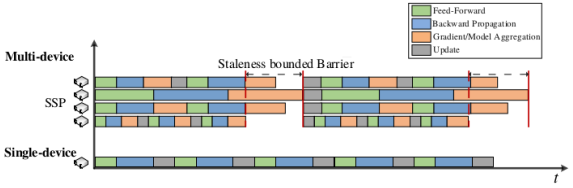
Communication Synchronization - Stale Synchronous (2/2)

- For a maximum staleness bound s, the update formula of worker i at iteration $t+1$:
- $\mathbf{w}_{i,t+1} := \mathbf{w}_0 - \eta(\sum_{k=1}^{t}\sum_{j=1}^{n} G_{j,k} + \sum_{k=t-s}^{t} G_{i,k} + \sum_{(j,k)\in S_{i,t+1}} G_{j,k})$



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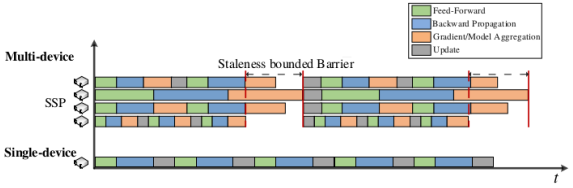

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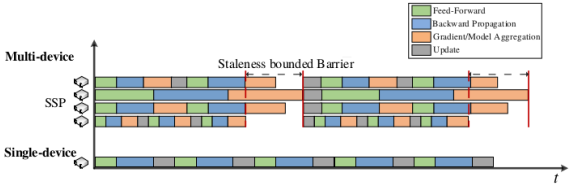
- The update has three parts:
  1. Guaranteed pre-window updates from clock 1 to t over all workers.



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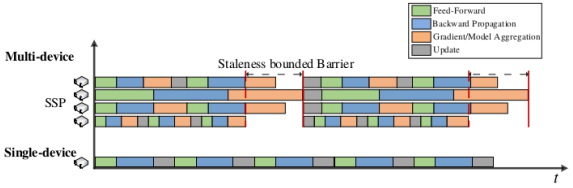

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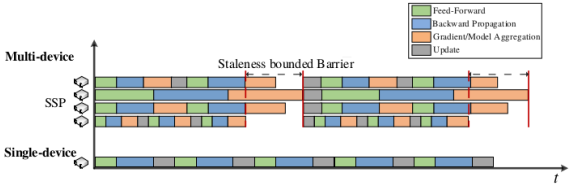
  2. Guaranteed read-my-writes in-window updates made by the querying worker i.
  3. Best-effort in-window updates. $S_{i,t+1}$ is some subset of the updates from other workers during period $[t-s]$.



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Communication Synchronization - Asynchronous (1/2)

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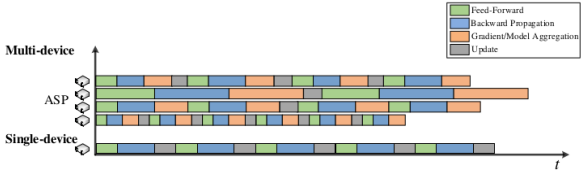

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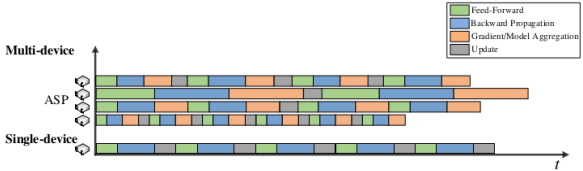

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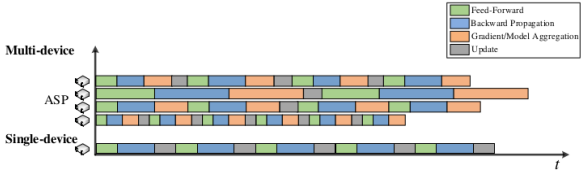
Communication Synchronization - Asynchronous (1/2)

- It completely eliminates the synchronization.
- Each work transmits its gradients to the PS after it calculates the gradients.
- The PS updates the global model without waiting for the other workers.



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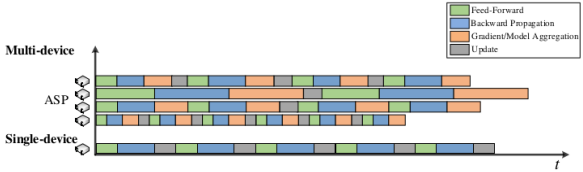
- $\mathbf{w}_{t+1} := \mathbf{w}_t - \eta \sum_{i=1}^{n} G_{i,t-\tau_{k,i}}$



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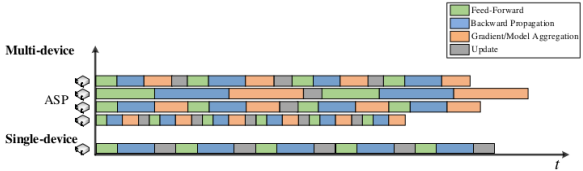
- $\mathbf{w}_{t+1} := \mathbf{w}_t - \eta \sum_{i=1}^{n} G_{i,t-\tau_{k,i}}$
- $\tau_{k,i}$ is the time delay between the moment when worker i calculates the gradient at the current iteration.



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Communication Synchronization - Local SGD

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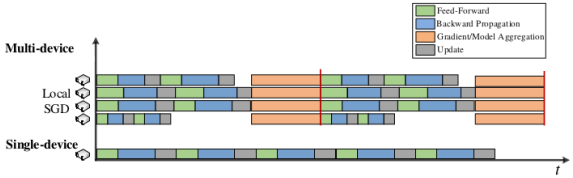

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Communication Synchronization - Local SGD

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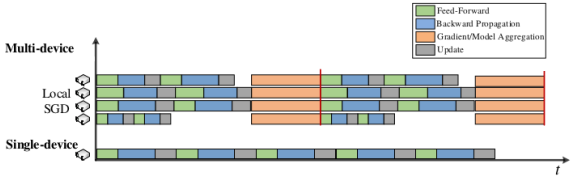
- If $\mathcal{I}_{\mathtt{T}}$ represents the synchronization timestamps, then:

$$\mathbf{w}_{\mathtt{i},\mathtt{t}+1} = \begin{cases} \mathbf{w}_{\mathtt{i},\mathtt{t}} - \eta \mathtt{G}_{\mathtt{i},\mathtt{t}} & \text{if} \quad \mathtt{t}+1 \notin \mathcal{I}_{\mathtt{T}} \\ \mathbf{w}_{\mathtt{i},\mathtt{t}} - \eta \frac{1}{\mathtt{n}} \sum_{\mathtt{i}=1}^{\mathtt{n}} \mathtt{G}_{\mathtt{i},\mathtt{t}} & \text{if} \quad \mathtt{t}+1 \in \mathcal{I}_{\mathtt{T}} \end{cases}$$



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- Quantization
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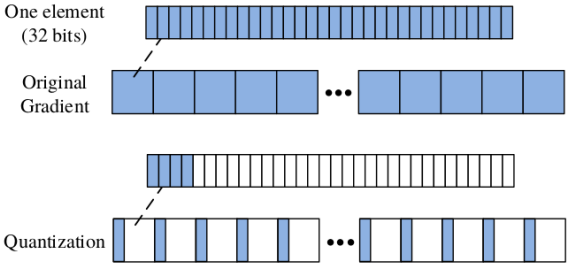
Communication Compression - Quantization

- Useing lower bits to represent the data.



[Tang et al., Communication-Efficient Distributed Deep Learning: A Comprehensive Survey, 2020]

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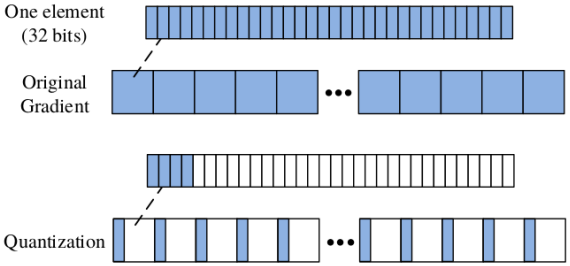

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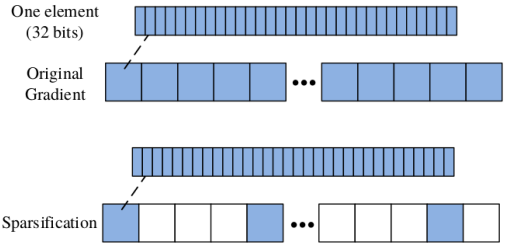

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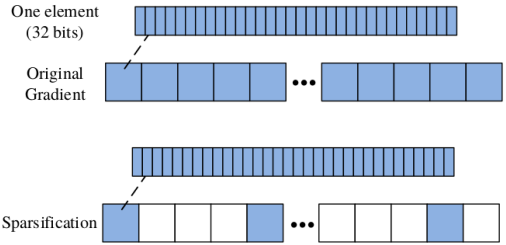

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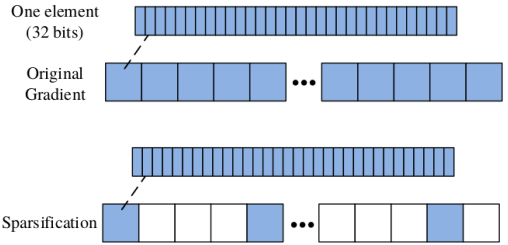
- E.g., the zero-valued elements are no need to transmit.



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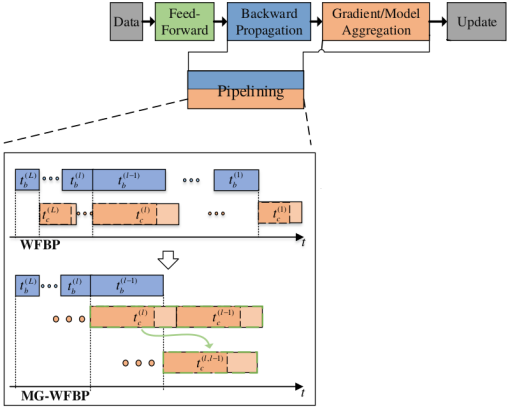
- Optimizing the order of computation and communication such that the communication cost can be minimized

Parallelism of Computations and Communications (2/3)

- Wait-free backward propagation (WFBP)
- Merged-gradient WFBP (MG-WFBP)



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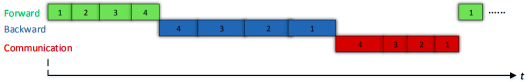

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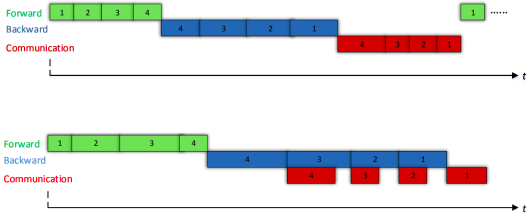

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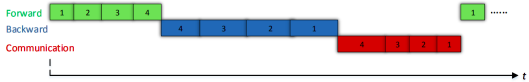

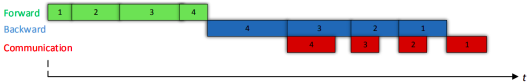

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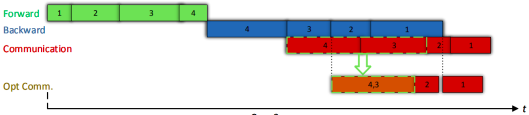

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TicTac: Accelerating Distributed Deep Learning with Communication Scheduling

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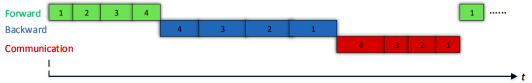

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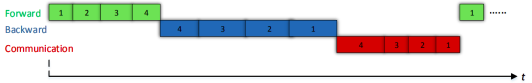

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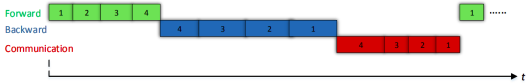

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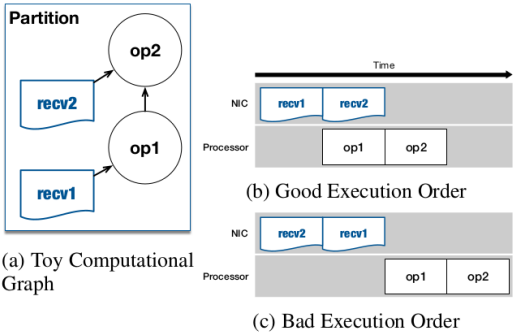
Good vs. Bad Execution Order



(a) Toy Computational Graph

(b) Good Execution Order

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[Hashemi et al., TicTac: Accelerating Distributed Deep Learning with Communication Scheduling, 2019]

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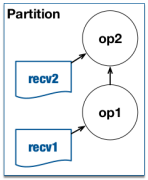
- E.g., $\text{op}_1.\text{M} = \texttt{Time}(\texttt{recv}_1)$ and $\text{op}_2.\text{M} = \texttt{Time}(\texttt{recv}_1) + \texttt{Time}(\texttt{recv}_2)$.



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- To achieve this goal, the algorithm focuses on two cases:
  1. Any communication and computation overlapping?
  2. If no, choose one which eliminates the computation block sooner.

CARAMEL: Accelerating Decentralized Distributed Deep Learning with Computation Scheduling

CARAMEL

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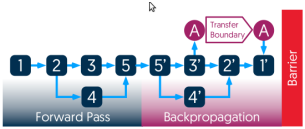

(a) Example DAG

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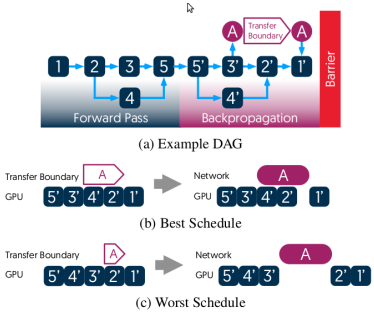

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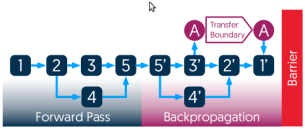

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- Network Transfer Scheduler
- Parameter Batcher
- Adaptive Depth Enforcer

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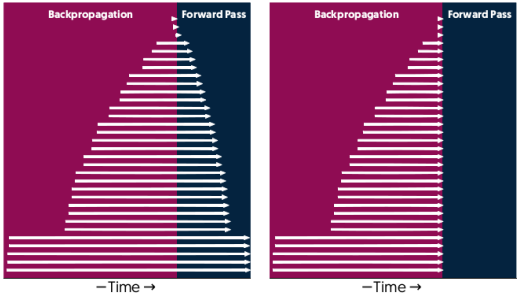
  - Ensureing that at each given time, only ops needed for the target parameter update can be executed.

Network Transfer Scheduler

- Increasing the overlap coefficient α by scheduling parameter transfers efficiently.
- Transfers are scheduled in both backward pass and forward pass.



(a) Parameter Server (b) Decentralized aggregation

[Hashemi et al., CARAMEL: Accelerating Decentralized Distributed Deep Learning with Model-Aware Scheduling, 2020]

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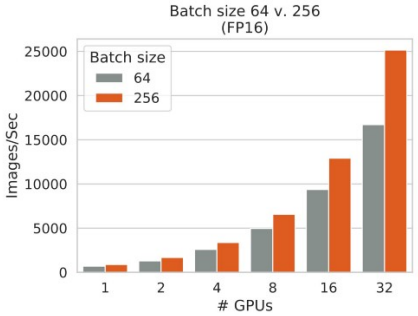
- While one chunk is being reduced on the CPU, another chunk can be sent over the network: this enables pipelining of network transfer and application-level processing across various chunks.

Distributed SGD and Batch Size

Batch Size vs. Number of GPUs

- $\mathbf{w} \leftarrow \mathbf{w} - \eta \frac{1}{|\beta|} \sum_{\mathbf{x} \in \beta} \nabla \mathtt{l}(\mathbf{x}, \mathbf{w})$



[https://medium.com/@emwatz/lessons-for-improving-training-performance-part-1-b5efd0f0dcea]

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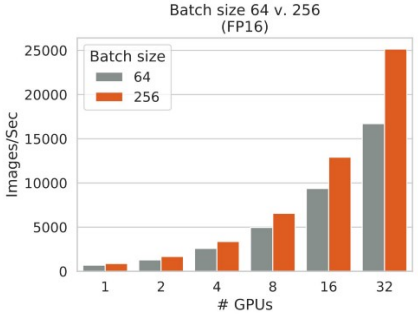
- The more samples processed during each batch, the faster a training job will complete.



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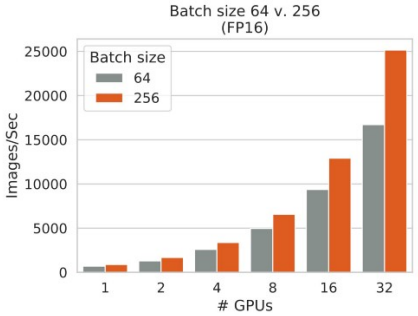
- The more samples processed during each batch, the faster a training job will complete.
- E.g., ImageNet + ResNet-50



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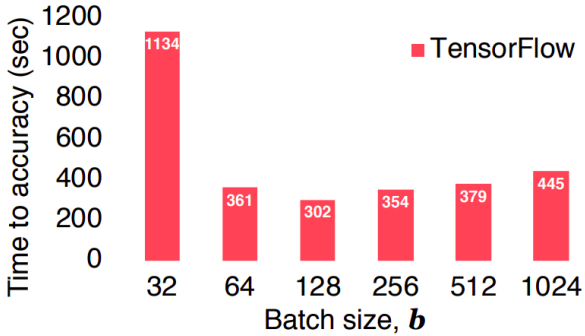
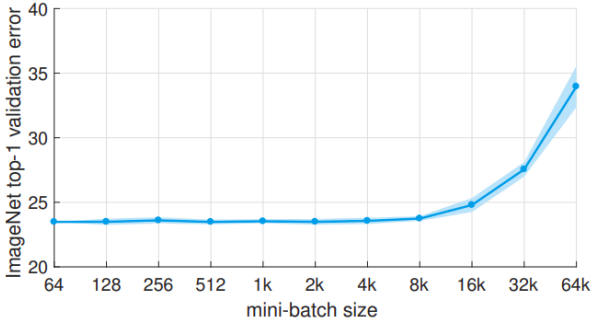
Batch Size vs. Time to Accuracy

- ResNet-32 on Titan X GPU



[Peter Pietzuch - Imperial College London]

Batch Size vs. Validation Error



[Goyal et al., Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour, 2018]

Improve the Validation Error

Improve the Validation Error

- Scaling learning rate
- Batch normalization
- Label smoothing
- Momentum

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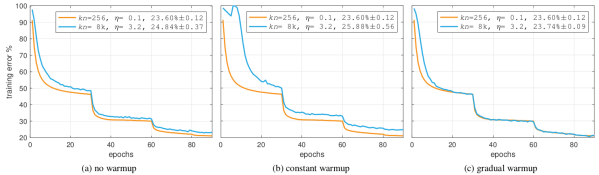

(a) no warmup (b) constant warmup (c) gradual warmup

[Goyal et al., Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour, 2018]

Batch Normalization (1/2)

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- Batch Normalization computes statistics along the minibatch dimension.

$$\mu_\beta = \frac{1}{|\beta|} \sum_{\mathbf{x} \in \beta} \mathbf{x}$$

$$\sigma_\beta^2 = \frac{1}{|\beta|} \sum_{\mathbf{x} \in \beta} (\mathbf{x} - \mu_\beta)^2$$

Batch Normalization (2/2)

- Zero-centering and normalizing the inputs, then scaling and shifting the result.

$$\hat{\mathbf{x}} = \frac{\mathbf{x} - \mu_\beta}{\sqrt{\sigma_\beta^2 + \epsilon}}$$

$$\mathbf{z} = \alpha \hat{\mathbf{x}} + \gamma$$

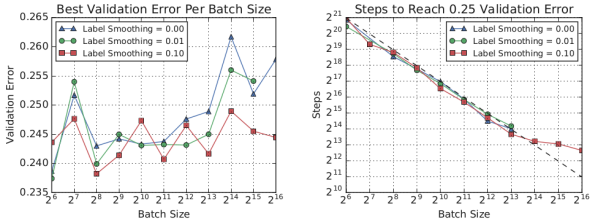
- $\hat{\mathbf{x}}$: the zero-centered and normalized input.
- $\mathbf{z}$: the output of the BN operation, which is a scaled and shifted version of the inputs.
- α: the scaling parameter vector for the layer.
- γ: the shifting parameter (offset) vector for the layer.
- ϵ: a tiny number to avoid division by zero.

Label Smoothing

- A generalization technique.
- Replaces one-hot encoded label vector $\mathbf{y}_{\mathtt{hot}}$ with a mixture of $\mathbf{y}_{\mathtt{hot}}$ and the uniform distribution.

$$\mathbf{y}_{\mathtt{ls}} = (1 - \alpha)\mathbf{y}_{\mathtt{hot}} + \alpha/\mathrm{K}$$

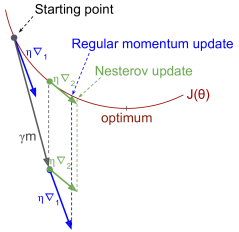
- K is the number of label classes, and α is a hyperparameter.



[Shallue et al., Measuring the Effects of Data Parallelism on Neural Network Training, 2019]

Momentum (1/3)

- Regular gradient descent optimization: $\mathbf{w} \leftarrow \mathbf{w} - \eta \nabla J(\mathbf{w})$

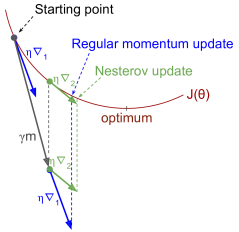


[Aurélien Géron, Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, 2019]

Momentum (1/3)

- Regular gradient descent optimization: $\mathbf{w} \leftarrow \mathbf{w} - \eta \nabla \mathrm{J}(\mathbf{w})$
- At each iteration, momentum optimization adds the local gradient to the momentum vector $\mathbf{m}$.

$$\mathbf{m} \leftarrow \beta \mathbf{m} + \eta \nabla \mathrm{J}(\mathbf{w})$$
$$\mathbf{w} \leftarrow \mathbf{w} - \mathbf{m}$$

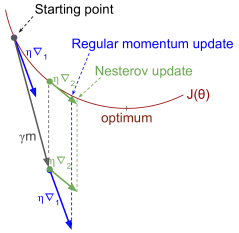


[Aurélien Géron, Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, 2019]

Momentum (2/3)

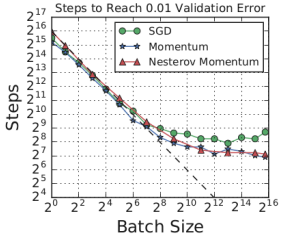
- Nesterov momentum measure the gradient of the cost function slightly ahead in the direction of the momentum.

$$\mathbf{m} = \beta\mathbf{m} + \eta\nabla \mathrm{J}(\mathbf{w} + \beta\mathbf{m})$$
$$\mathbf{w} \leftarrow \mathbf{w} - \mathbf{m}$$

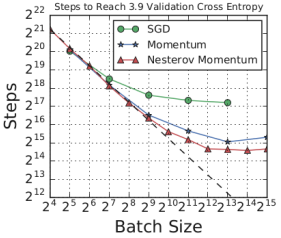


[Aurélien Géron, Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, 2019]

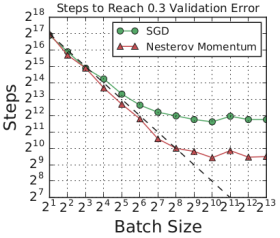
Momentum (3/3)



(a) Simple CNN on MNIST



(b) Transformer Shallow on LM1B



(c) ResNet-8 on CIFAR-10

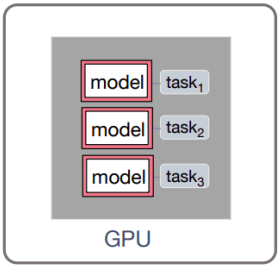
[Shallue et al., Measuring the Effects of Data Parallelism on Neural Network Training, 2019]

CROSSBOW: Scaling Deep Learning with Small Batch Sizes on Multi-GPU Servers

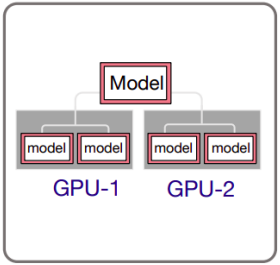
- How to design a deep learning system that scales training with multiple GPUs, even when the preferred batch size is small?

Crossbow

(1) How to increase efficiency with small batches?



(2) How to synchronise model replicas?



[Peter Pietzuch - Imperial College London]

Problem: Small Batches

- Small batch sizes underutilise GPUs.

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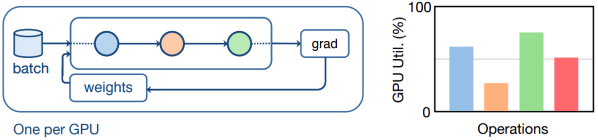
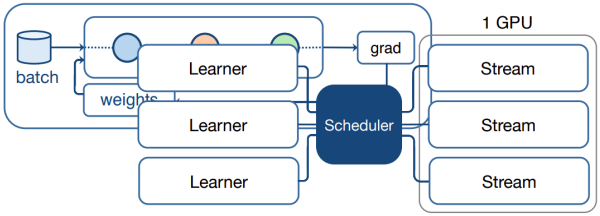
- Small batch sizes underutilise GPUs.
- One batch per GPU: not enough data and instruction parallelism for every operator.



[Peter Pietzuch - Imperial College London]

Idea: Multiple Replicas Per GPU

- Train multiple model replicas per GPU.
- A learner is an entity that trains a single model replica independently with a given batch size.



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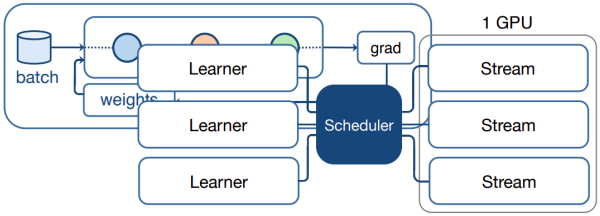
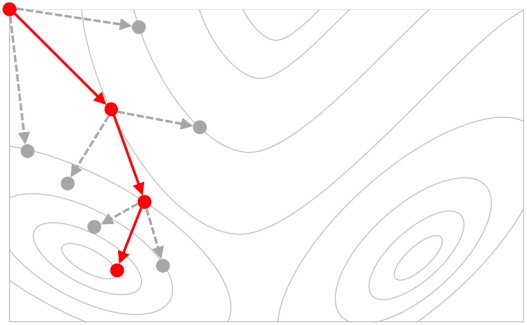


[Peter Pietzuch - Imperial College London]

- But, now we must synchronise a large number of model replicas.

Problem: Similiar Starting Point

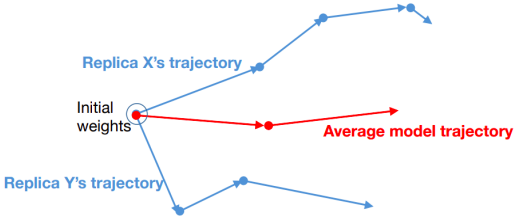
- All learners always start from the same point.
- Limited exploration of parameter space.



[Peter Pietzuch - Imperial College London]

Idea: Independent Replicas

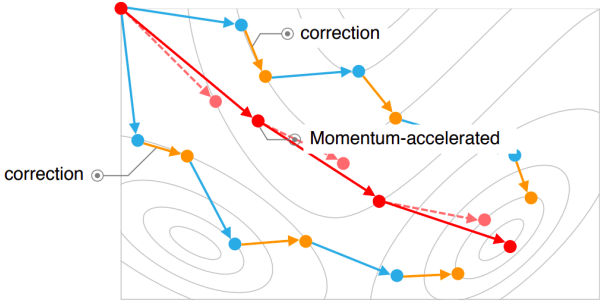
- Maintain independent model replicas.
- Increased exploration of space through parallelism.
- Each model replica uses small batch size.



[Peter Pietzuch - Imperial College London]

Crossbow: Synchronous Model Averaging

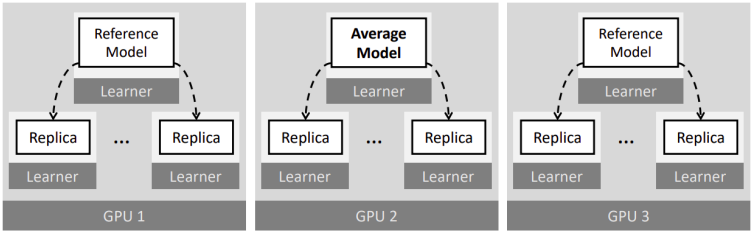
- Allow learners to diverge, but correct trajectories based on average model.
- Accelerate average model trajectory with momentum to find minima faster.



[Peter Pietzuch - Imperial College London]

GPUs with Synchronous Model Averaging

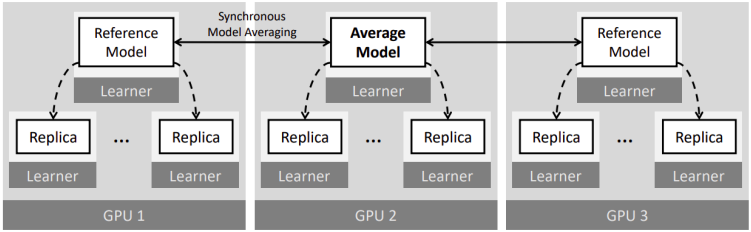
- Synchronously apply corrections to model replicas.



[Peter Pietzuch - Imperial College London]

GPUs with Synchronous Model Averaging

- Ensures consistent view of average model.
- Takes GPU bandwidth into account during synchronisation.



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Crossbow

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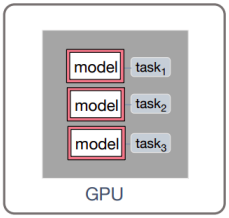

Train multiple model replicas per GPU

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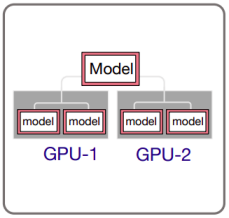

Use synchronous model averaging

[Peter Pietzuch - Imperial College London]

Summary

Summary

- Data-parallel
- The aggregation algorithm
- Communication synchronization
- Communication compression
- Parallelism of computations and communications
- TicTac and Caramel
- Batch Size

Reference

- Tang et al., Communication-Efficient Distributed Deep Learning: A Comprehensive Survey, 2020
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- C. Shallue et al., Measuring the effects of data parallelism on neural network training, 2018
- A. Koliousis et al. CROSSBOW: scaling deep learning with small batch sizes on multi-gpu servers, 2019

Questions?