Distributed Deep Learning

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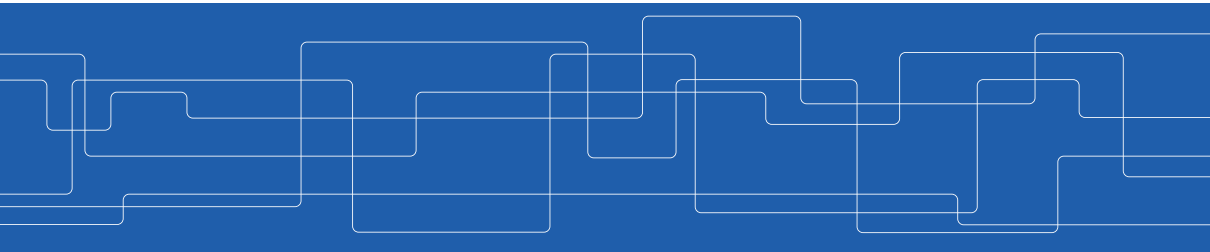
2021-12-08

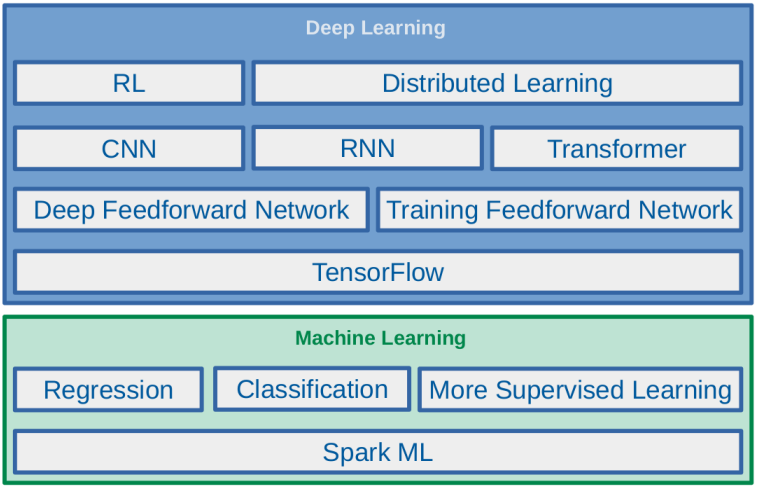


The Course Web Page

https://id2223kth.github.io

https://tinyurl.com/6s5jy46a

Where Are We?


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

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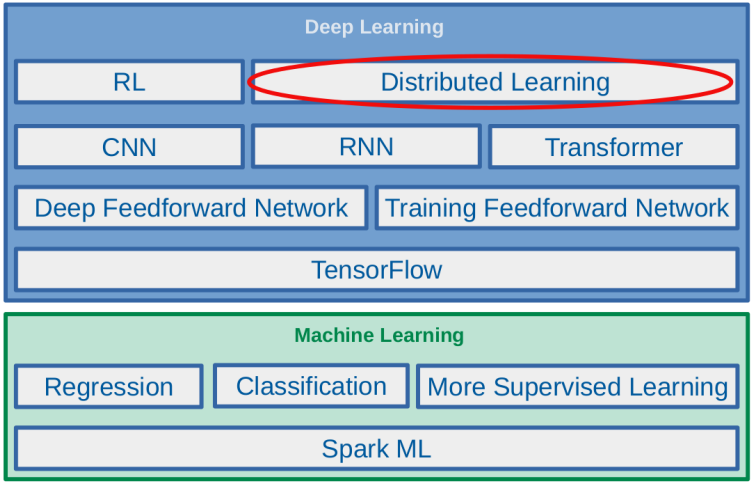
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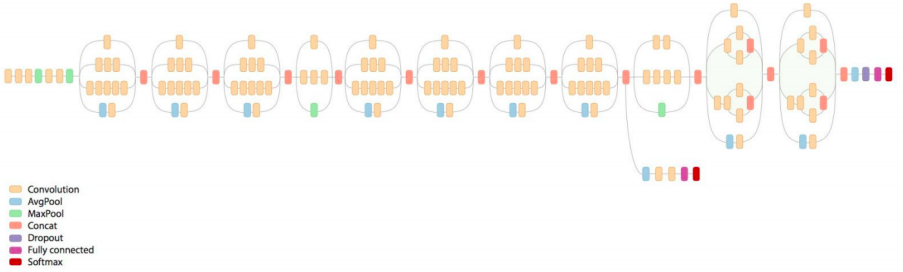
What is the problem?

Training Deep Neural Networks

- Computationally intensive
- Time consuming

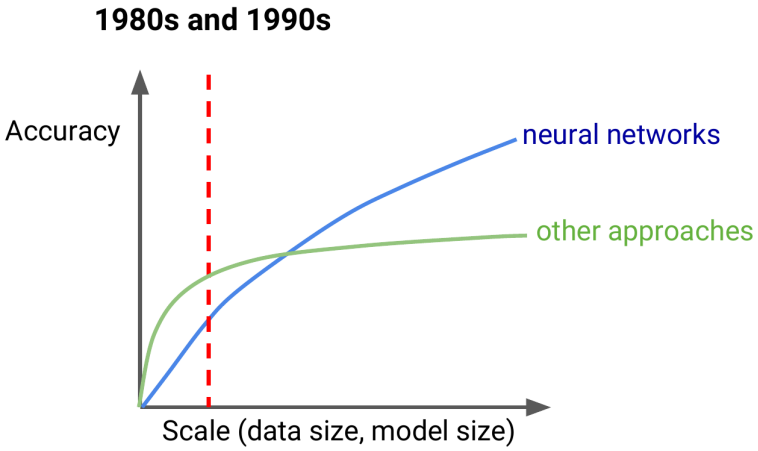


[https://cloud.google.com/tpu/docs/images/inceptionv3onc--oview.png]

Why?

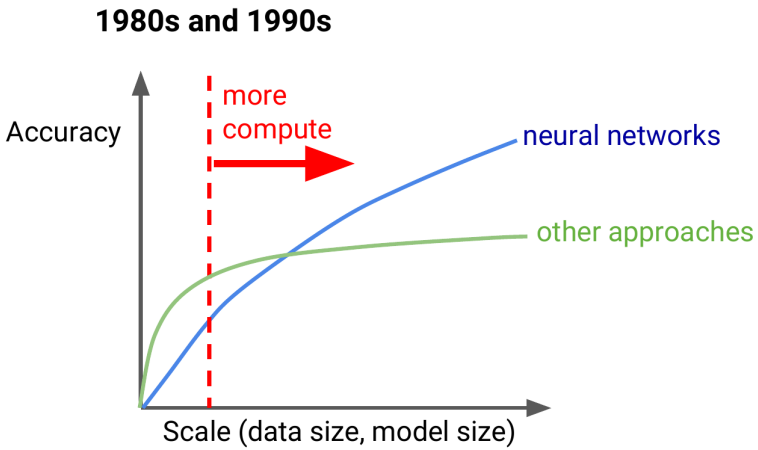
- Massive amount of training dataset
- Large number of parameters

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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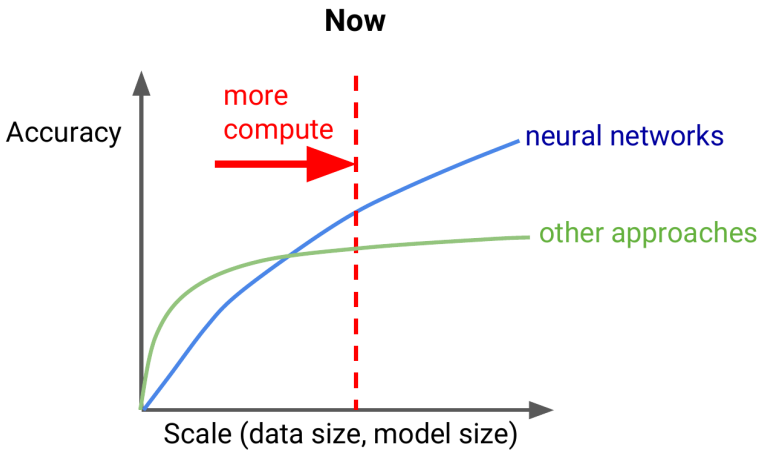
Accuracy vs. Data/Model Size



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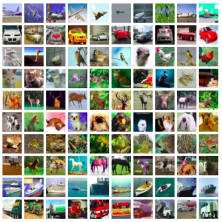
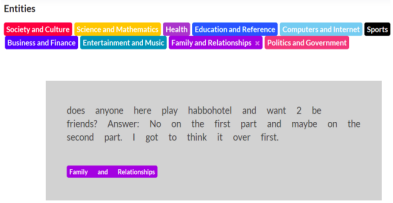
Scale Matters

Fundamentals of Machine Learning

Training Dataset

- E.g., tabular data, image, text, etc.





Date	Cost	Actions	Offsite conversions	Impressions	Clicks
2017-04-04	29.44	461	4	5655	477
2017-04-03	74.08	1331	16	18170	1340
2017-04-02	76.09	1349	12	16877	1357
2017-04-01	76.79	1382	8	19757	1378
2017-03-31	77.28	1141	21	18598	1116
2017-03-30	68.62	1065	18	14847	1046
2017-03-29	64.9	1111	25	13994	1094
2017-03-28	65.12	1137	12	15952	1145
2017-03-27	66.98	1185	7	17970	1190
2017-03-26	64.94	1118	5	14410	1116
2017-03-25	66.3	1208	6	15123	1204
2017-03-24	67.38	1143		15298	1159
2017-03-23	65.59	1147	13	14972	1143
2017-03-22	68.19	1129	4	17959	1116
2017-03-21	64.78	1081		25810	1059

Model

- E.g., linear models, neural networks, etc.

Model

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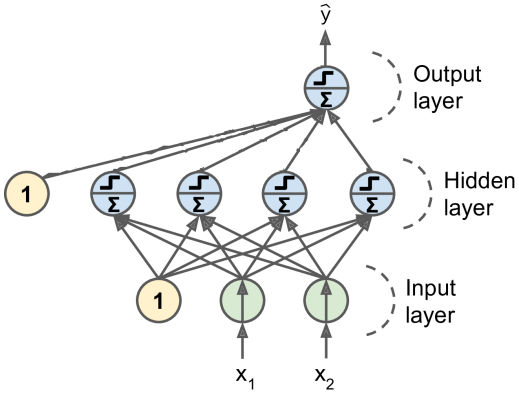
- $\hat{y} = \mathtt{f}_{\mathtt{w}}(\mathbf{x})$



Loss function

- How good $\hat{y}$ is able to predict the expected outcome y.

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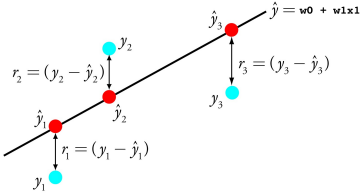

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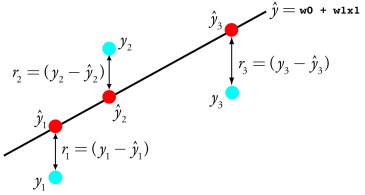

- E.g., $J(\mathbf{w}) = \frac{1}{m} \sum_{i=1}^{m} (y_i - \hat{y}_i)^2$

Objective

- Minimize the loss function

Objective

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- $\arg\min_w J(w)$
- $J(w) = \sum_{i=1}^{m} l(y_i, \hat{y}_i)$

Training

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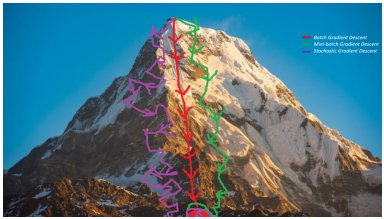
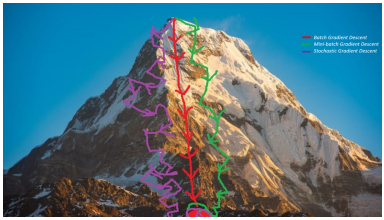


Training

- $J(w) = \sum_{i=1}^{m} l(y_i, \hat{y}_i)$
- Gradient descent, i.e., $w := w - \eta \nabla J(w)$



Training

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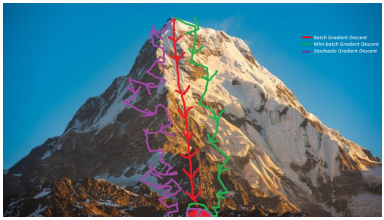
- Gradient descent, i.e., $w := w - \eta \nabla J(w)$
- Stochastic gradient descent, i.e., $w := w - \eta \tilde{g} J(w)$
  - $\tilde{g}$: gradient at a randomly chosen point.



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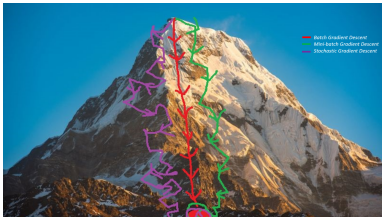
  - $\tilde{g}$: gradient at a randomly chosen point.
- Mini-barch gradient descent, i.e., $w := w - \eta \tilde{g}_B J(w)$
  - $\tilde{g}$: gradient with respect to a set of B randomly chosen points.



Let's Scale the Learning

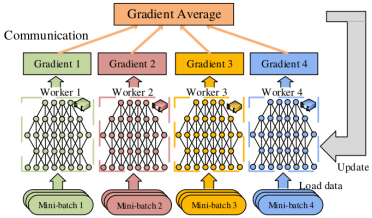
Scalable Training

- Data parallelism
- Model parallelism

Data Parallelism

Data Parallelization (1/4)

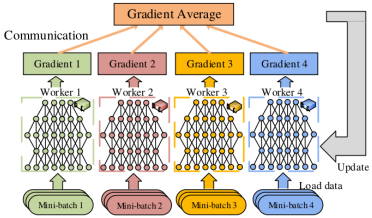
- Replicate a whole model on every device.



[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.



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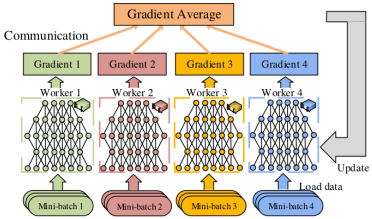
Data Parallelization (2/4)

- k devices



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Data Parallelization (2/4)

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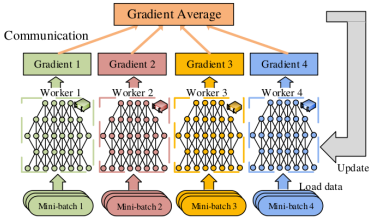
- $J_j(w) = \sum_{i=1}^{b_j} l(y_i, \hat{y}_i)$, $\forall j = 1, 2, \cdots, k$



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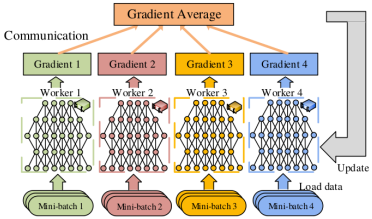
- $\tilde{g}_B J_j(w)$: gradient of $J_j(w)$ with respect to a set of B randomly chosen points at device j.



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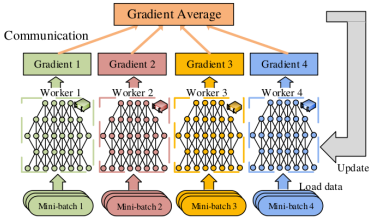
- $\tilde{g}_B J_j(w)$: gradient of $J_j(w)$ with respect to a set of B randomly chosen points at device j.
- Compute $\tilde{g}_B J_j(w)$ on each device j.



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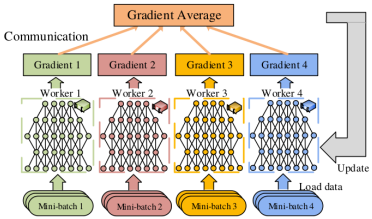
Data Parallelization (3/4)

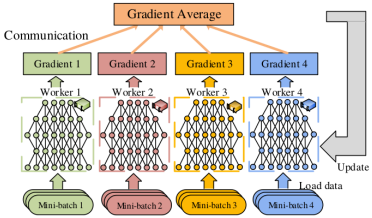
- Compute the mean of the gradients.
- $\tilde{g}_B J(w) = \frac{1}{k} \sum_{j=1}^{k} \tilde{g}_B J_j(w)$



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

Data Parallelization (4/4)

- Update the model.
- $w := w - \eta \tilde{g}_B J(w)$



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

Data Parallelization Design Issues

- The aggregation algorithm
- Communication synchronization and frequency
- Communication compression

The Aggregation Algorithm

The Aggregation Algorithm

- How to aggregate gradients (compute the mean of the gradients)?

The Aggregation Algorithm

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- Centralized - parameter server

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- Decentralized - all-reduce

The Aggregation Algorithm

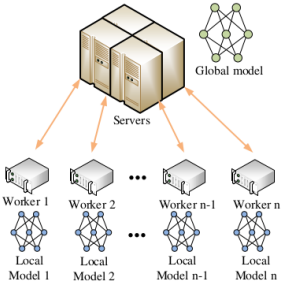
- How to aggregate gradients (compute the mean of the gradients)?
- Centralized - parameter server
- Decentralized - all-reduce
- Decentralized - gossip

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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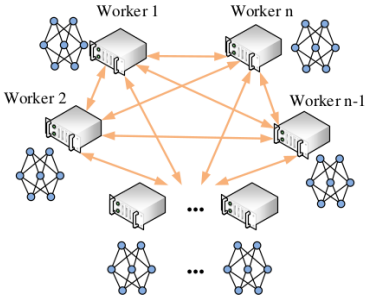
Aggregation - Distributed - All-Reduce

- 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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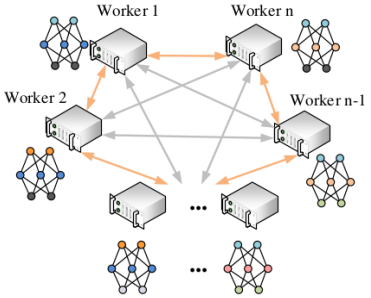
Aggregation - Distributed - Gossip

- No PS, and no global model.



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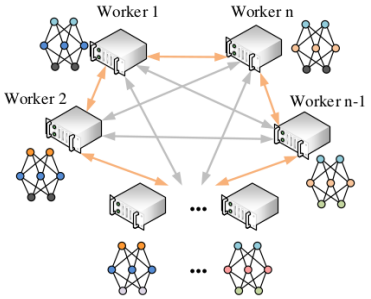
Aggregation - Distributed - Gossip

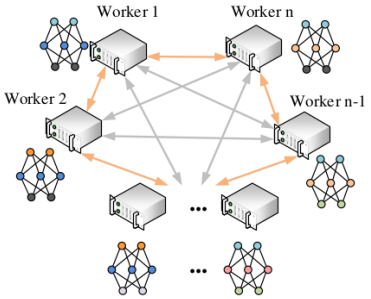
- No PS, and no global model.
- Every worker communicates updates with their neighbors.



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

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)

- Reduce: reducing a set of numbers into a smaller set of numbers via a function.

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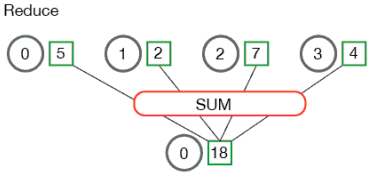

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[https://mpitutorial.com/tutorials/mpi-reduce-and-allreduce]

Reduce and AllReduce (2/2)

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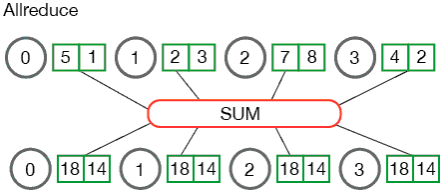


[https://mpitutorial.com/tutorials/mpi-reduce-and-allreduce]

AllReduce Example

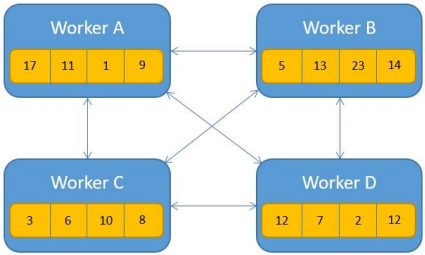
[https://towardsdatascience.com/visual-intuition-on-ring-allreduce-for-distributed-deep-learning-d1f34b4911da]

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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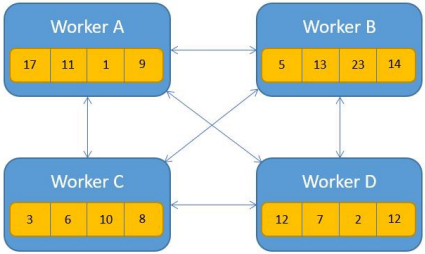
AllReduce Implementation - All-to-All AllReduce

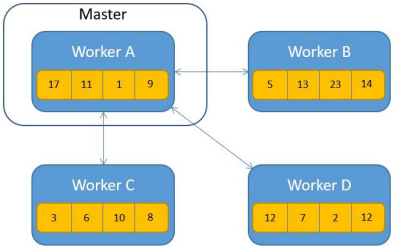
- Send the array of data to each other.
- Apply the reduction operation on each process.
- Too many unnecessary messages.



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

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.
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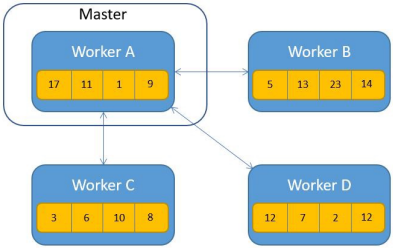
- The master becomes a bottleneck (not scalable).



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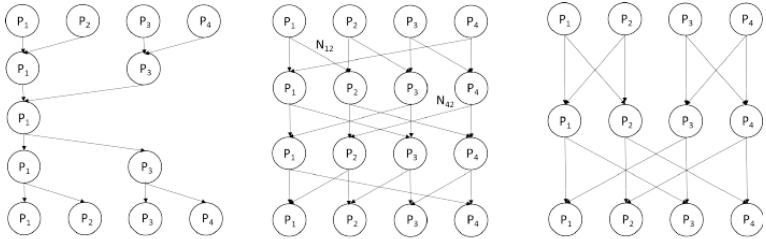
AllReduce Implementation - Other implementations

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



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

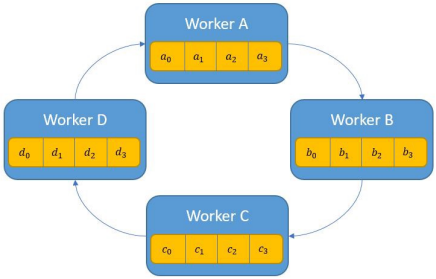
[Zhao H. et al., arXiv:1312.3020, 2013]

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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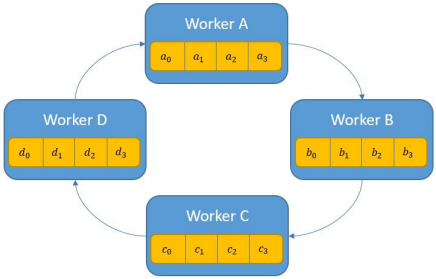

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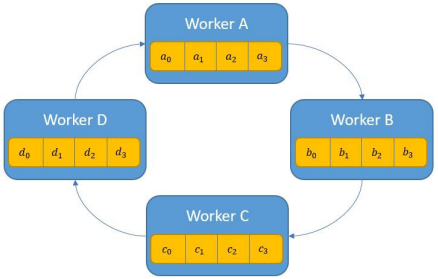
- Each one of these chunks will be indexed by `i` going forward.



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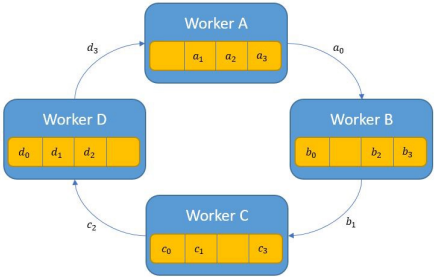
AllReduce Implementation - Ring-AllReduce (3/6)

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



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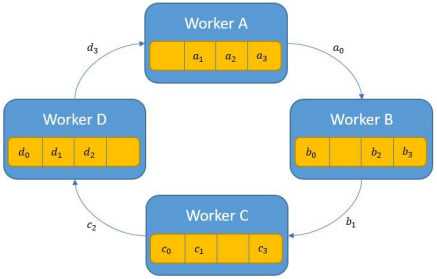
AllReduce Implementation - Ring-AllReduce (3/6)

- 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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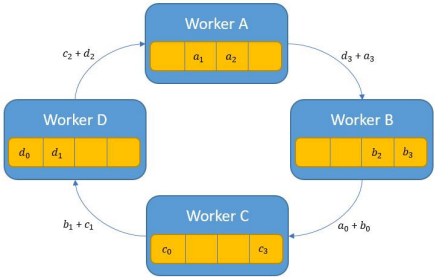
AllReduce Implementation - Ring-AllReduce (4/6)

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



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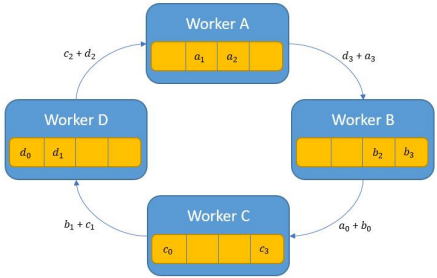

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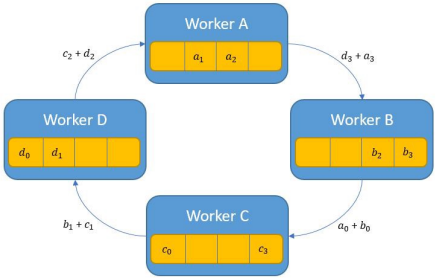
AllReduce Implementation - Ring-AllReduce (4/6)

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



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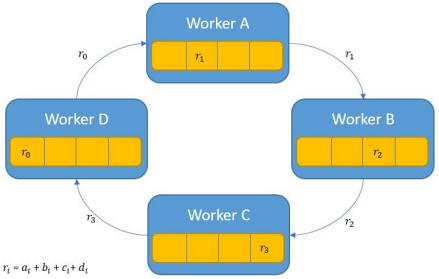
AllReduce Implementation - Ring-AllReduce (5/6)

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



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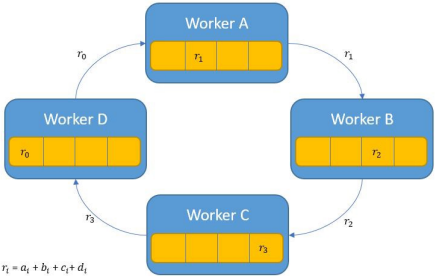
AllReduce Implementation - Ring-AllReduce (5/6)

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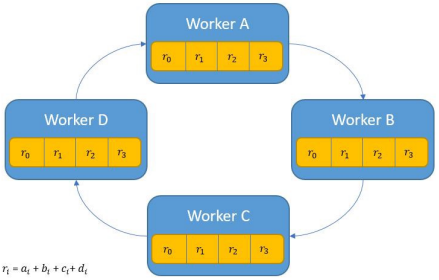
AllReduce Implementation - Ring-AllReduce (6/6)

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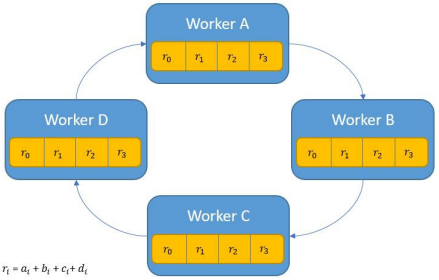
AllReduce Implementation - Ring-AllReduce (6/6)

- 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: $N \times (m - 1)$ messages.

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  - First each process sends N elements to the master: $N \times (m-1)$ messages.
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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
  - The performance
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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

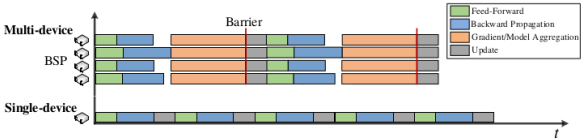
- Two directions for improvement:
  1. To relax the synchronization among all workers.
  2. The frequency of communication can be reduced by more computation in one iteration.

Communication Synchronization Models

- Synchronous
- Stale-synchronous
- Asynchronous
- Local SGD

Communication Synchronization - Synchronous

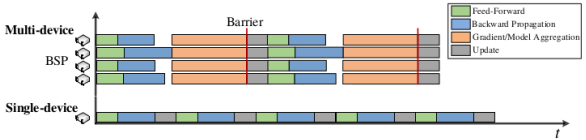
- After each iteration, the workers synchronize their parameter updates.



[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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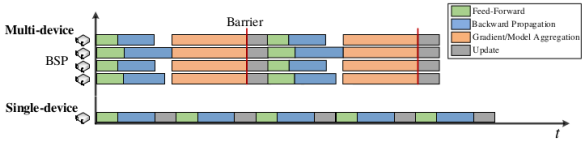

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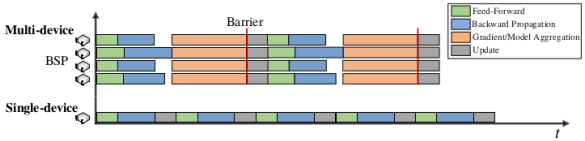
- High communication cost that limits the system scalability.



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Communication Synchronization - Stale Synchronous (1/2)

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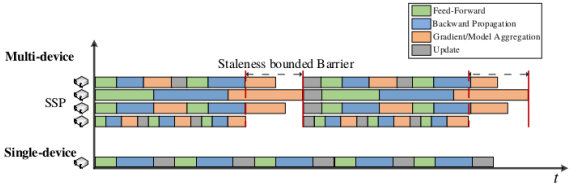

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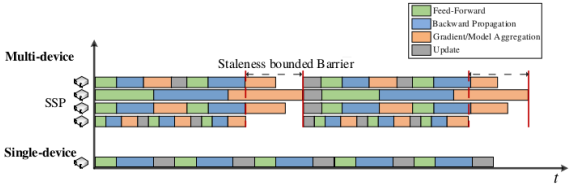

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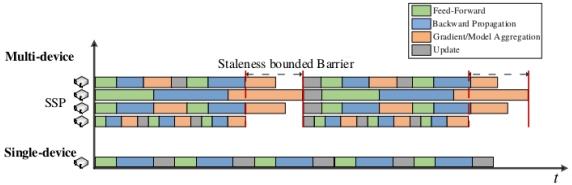
- Staleness bounded barrier to limit the iteration gap between the fastest worker and the slowest worker.



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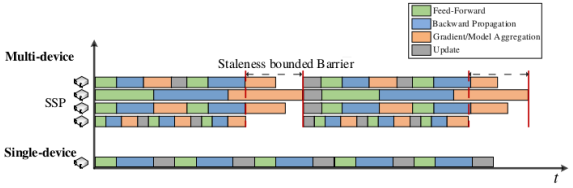
Communication Synchronization - Stale Synchronous (2/2)

- For a maximum staleness bound s, the update formula of worker i at iteration $t+1$:
- $w_{i,t+1} := w_0 - \eta(\sum_{k=1}^{t}\sum_{j=1}^{n} G_{j,k} + \sum_{k=t-s}^{t} G_{i,k} + \sum_{(j,k)\in S_{i,t+1}} G_{j,k})$



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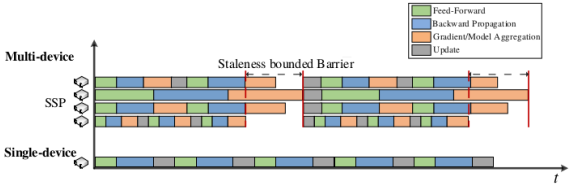

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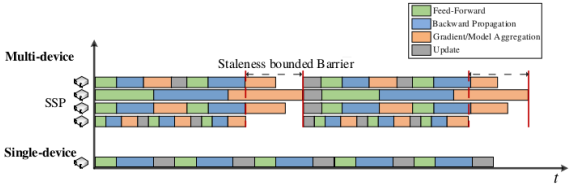
  1. Guaranteed pre-window updates from clock 1 to t over all workers.



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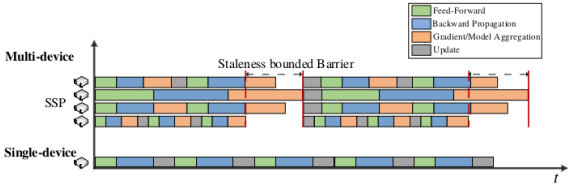
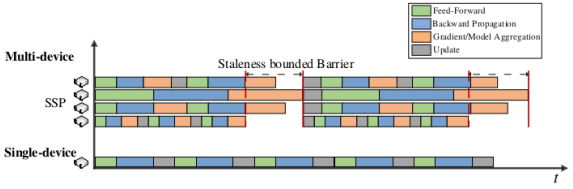
  1. Guaranteed pre-window updates from clock 1 to t over all workers.
  2. Guaranteed read-my-writes in-window updates made by the querying worker i.



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

Communication Synchronization - Stale Synchronous (2/2)

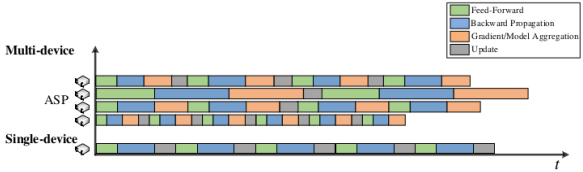
- For a maximum staleness bound s, the update formula of worker i at iteration $t+1$:
- $w_{i,t+1} := w_0 - \eta(\sum_{k=1}^{t}\sum_{j=1}^{n} G_{j,k} + \sum_{k=t-s}^{t} G_{i,k} + \sum_{(j,k)\in S_{i,t+1}} G_{j,k})$
- The update has three parts:
  1. Guaranteed pre-window updates from clock 1 to t over all workers.
  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 $[t-s]$.



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

Communication Synchronization - Asynchronous (1/2)

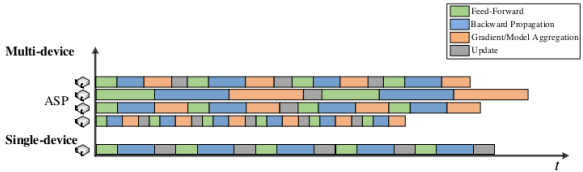
- It completely eliminates the synchronization.



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

Communication Synchronization - Asynchronous (1/2)

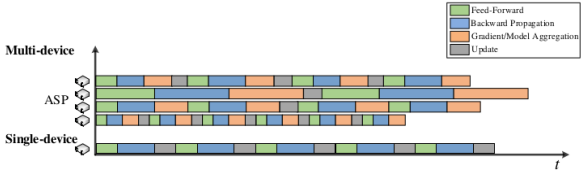
- It completely eliminates the synchronization.
- Each work transmits its gradients to the PS after it calculates the gradients.



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

Communication Synchronization - Asynchronous (1/2)

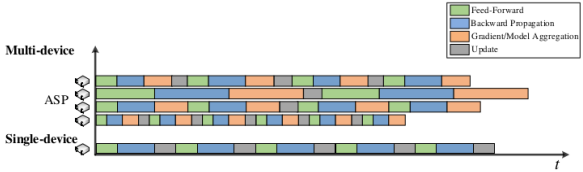
- It completely eliminates the synchronization.
- Each work transmits its gradients to the PS after it calculates the gradients.
- The PS updates the global model without waiting for the other workers.



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

Communication Synchronization - Asynchronous (2/2)

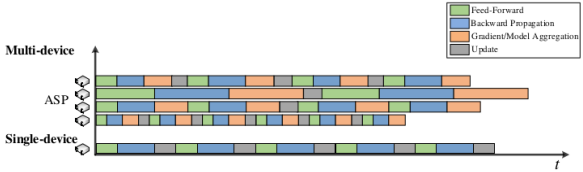
- $w_{t+1} := w_t - \eta \sum_{i=1}^{n} G_{i,t-\tau_{k,i}}$



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

Communication Synchronization - Asynchronous (2/2)

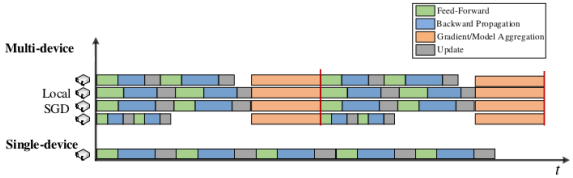
- $w_{t+1} := w_t - \eta \sum_{i=1}^{n} G_{i,t-\tau_{k,i}}$
- $\tau_{k,i}$ is the time delay between the moment when worker i calculates the gradient at the current iteration.



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

Communication Synchronization - Local SGD

- All workers run several iterations, and then averages all local models into the newest global model.

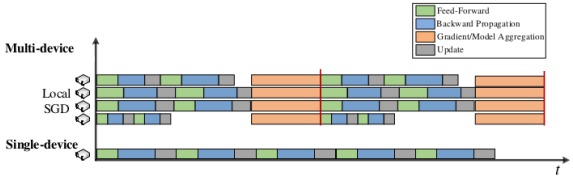


[Tang et al., Communication-Efficient Distributed Deep Learning: A Comprehensive Survey, 2020]

Communication Synchronization - Local SGD

- All workers run several iterations, and then averages all local models into the newest global model.
- If $\mathcal{I}_T$ represents the synchronization timestamps, then:

$$w_{i,t+1} = \begin{cases} w_{i,t} - \eta G_{i,t} & \text{if} \quad t+1 \notin \mathcal{I}_T \\ w_{i,t} - \eta \frac{1}{n} \sum_{i=1}^{n} G_{i,t} & \text{if} \quad t+1 \in \mathcal{I}_T \end{cases}$$



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

Communication Compression

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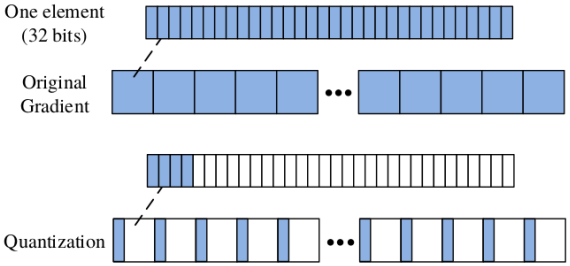
- Compress the exchanged gradients or models before transmitting across the network.
- Quantization
- Sparsification

Communication Compression - Quantization

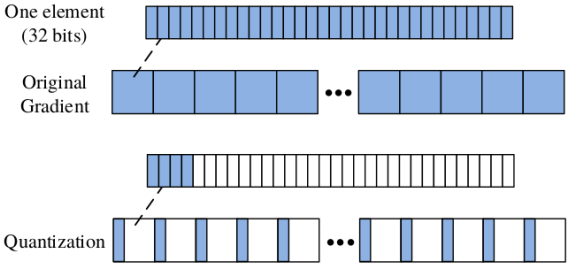
- Useing lower bits to represent the data.



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

Communication Compression - Quantization

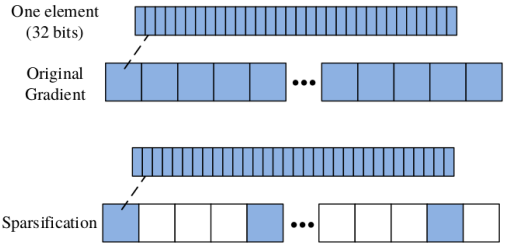
- Useing lower bits to represent the data.
- The gradients are of low precision.



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

Communication Compression - Sparsification

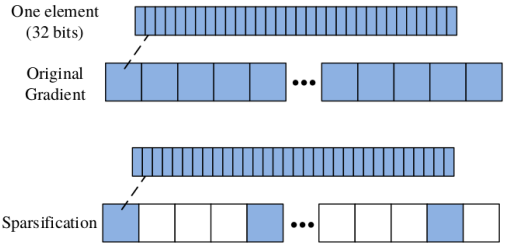
- Reducing the number of elements that are transmitted at each iteration.



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

Communication Compression - Sparsification

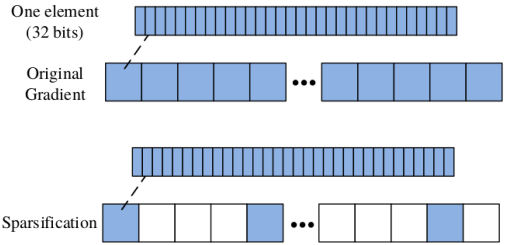
- Reducing the number of elements that are transmitted at each iteration.
- Only significant gradients are required to update the model parameter to guarantee the convergence of the training.



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

Communication Compression - Sparsification

- Reducing the number of elements that are transmitted at each iteration.
- Only significant gradients are required to update the model parameter to guarantee the convergence of the training.
- E.g., the zero-valued elements are no need to transmit.



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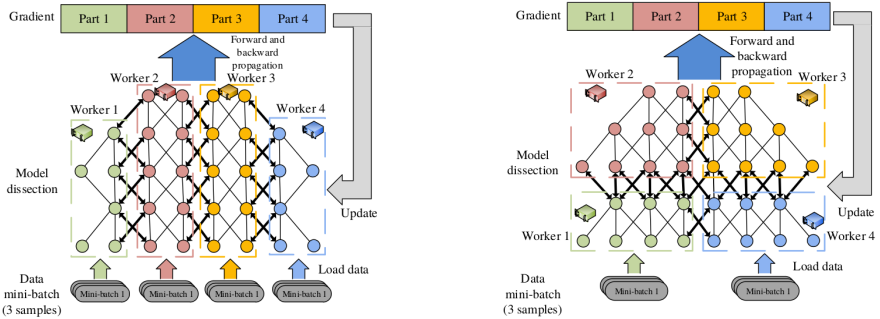
Model Parallelism

Model Parallelization

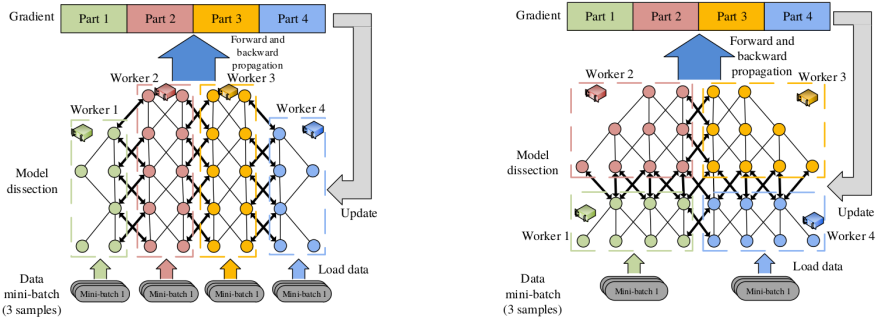
- The model is split across multiple devices.



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

Model Parallelization

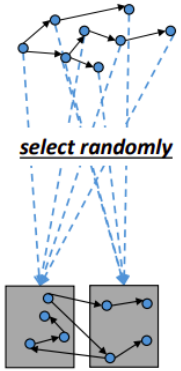
- The model is split across multiple devices.
- Depends on the architecture of the NN.



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

Model Parallelization - Hash Partitioning

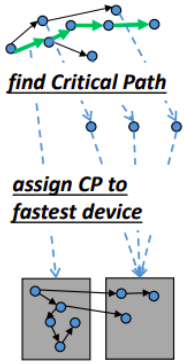
- Randomly assign vertices to devices proportionally to the capacity of the devices by using a hash function.



[Mayer, R. et al., The TensorFlow Partitioning and Scheduling Problem, 2017]

Model Parallelization - Critical Path

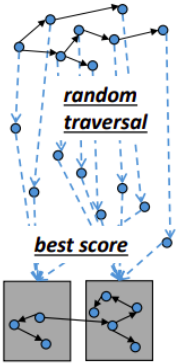
- Assigning the complete critical path to the fastest device.
- Critical path: the path with the longest computation time from source to sink vertex.



[Mayer, R. et al., The TensorFlow Partitioning and Scheduling Problem, 2017]

Model Parallelization - Multi-Objective Heuristics

- Different objectives, e.g., memory, importance, traffic, and execution time



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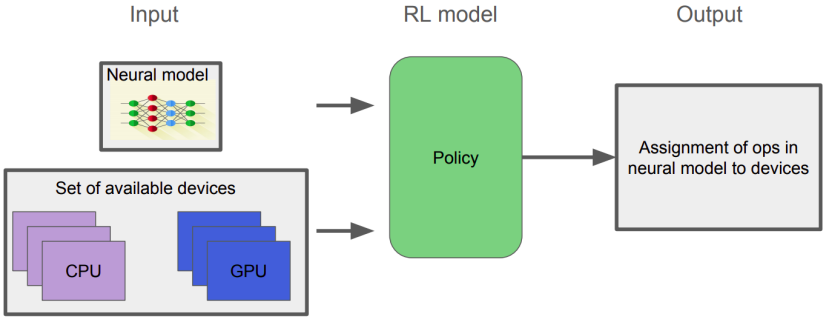
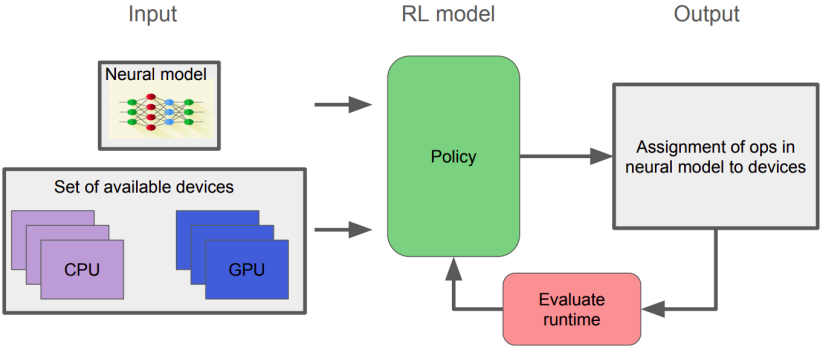
Model Parallelization - Reinforcement Learning (1/5)



[Mirhoseini et al., Device Placement Optimization with Reinforcement Learning, 2017]

Model Parallelization - Reinforcement Learning (2/5)



[Mirhoseini et al., Device Placement Optimization with Reinforcement Learning, 2017]

Model Parallelization - Reinforcement Learning (3/5)

- $\mathtt{J}(\mathtt{w}) = \mathbb{E}_{\mathcal{P}\sim\pi(\mathcal{P}|\mathcal{G},\mathtt{w})}[\mathtt{R}(\mathcal{P})|\mathcal{G}]$
- Objective: $\arg\min_{\mathtt{w}} \mathtt{J}(\mathtt{w})$

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- $\mathtt{J}(\mathtt{w})$: expected runtime

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Model Parallelization - Reinforcement Learning (3/5)

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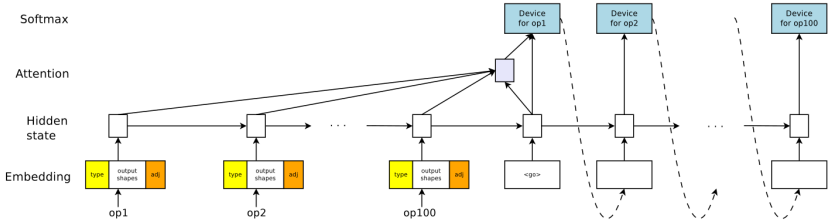
- $\mathtt{J}(\mathtt{w})$: expected runtime
- $\mathtt{w}$: trainable parameters of policy
- $\pi(\mathcal{P}|\mathcal{G},\mathtt{w})$: policy
- $\mathcal{P}$: output placements $\in \{1, 2, ..., num\_ops\}^{num\_devices}$

Model Parallelization - Reinforcement Learning (4/5)

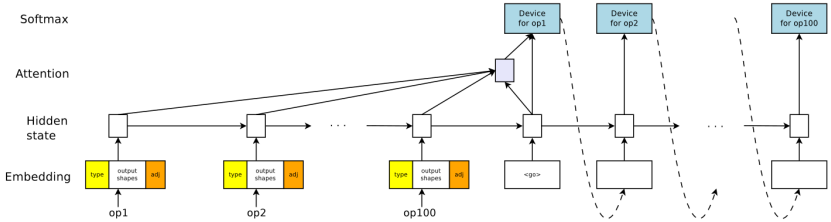
- RL reward function based on execution runtime.



[Mirhoseini et al., Device Placement Optimization with Reinforcement Learning, 2017]

Model Parallelization - Reinforcement Learning (4/5)

- RL reward function based on execution runtime.
- The RL policy is defined as a seq-to-seq model.



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Model Parallelization - Reinforcement Learning (4/5)

- RL reward function based on execution runtime.
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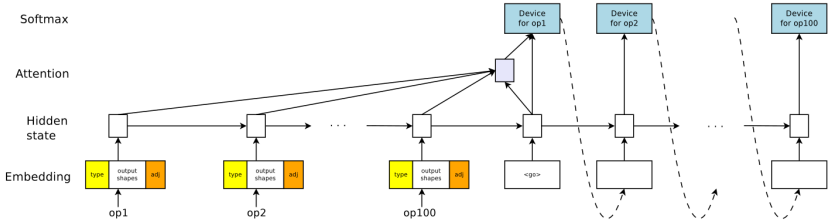
- RNN Encoder receives graph embedding for each operation.



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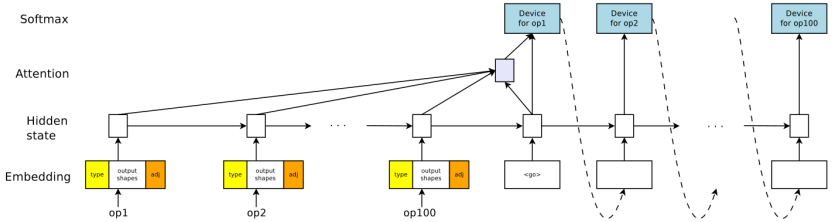
Model Parallelization - Reinforcement Learning (4/5)

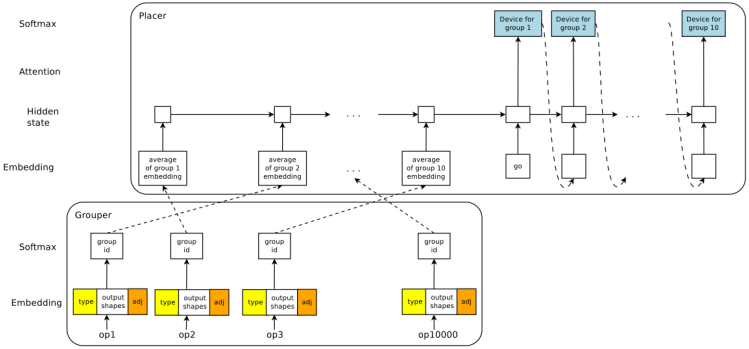
- RL reward function based on execution runtime.
- The RL policy is defined as a seq-to-seq model.
- RNN Encoder receives graph embedding for each operation.
- RNN Decoder predicts a device placement for each operation.



[Mirhoseini et al., Device Placement Optimization with Reinforcement Learning, 2017]

Model Parallelization - Reinforcement Learning (5/5)

- Grouping operations.
- Prediction is for group placement, not for a single operation.



[Mirhoseini et al., A Hierarchical Model for Device Placement, 2018]

Summary

Summary

- Scalability matters
- Parallelization
- Data Parallelization
  - Parameter server vs. AllReduce
  - Synchronized vs. asynchronized
- Model Parallelization
  - Random, critical path, multi-objective, RL

Thanks!