HPC16 4th Presentation

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Selected Papers

- P. Watcharapichat, V. L. Morales, R. C. Fernandez, P. Pietzuch.
- ***Ako: Decentralised Deep Learning with Partial Gradient Exchange***.
- SoCC '16 Proceedings of the Seventh ACM Symposium on Cloud Computing.

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1. Introduction
2. Resource Allocation in DNN Systems
3. Partial Gradient Exchange
4. Ako Architecture
5. Evaluation
6. Related work
7. Conclusion

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§1 Introduction

- DNNs in distributed systems

- A common architecture for DNN systems takes advantage of data-parallelism which a set of *workers* train model replicas.
- By using *parameter servers*, model replicas are kept synchronised.

- DNN systems employing parameter server must balance the use of compute and network resources to achieve fastest model.
  - However, an optimal resource allocation depends on many factors, and users must decide it empirically, by trial-and-error approach.

§1 Introduction
- Described system

- Goal is to design a DNN system that always utilises the full CPU resources and network bandwidth of a cluster.

- Paper describe ***Ako***, a decentralised DNN system.
  - Homogeneous workers train model replicas without parameter server.
  - Synchronise directly with each other in a peer-to-peer fashion.

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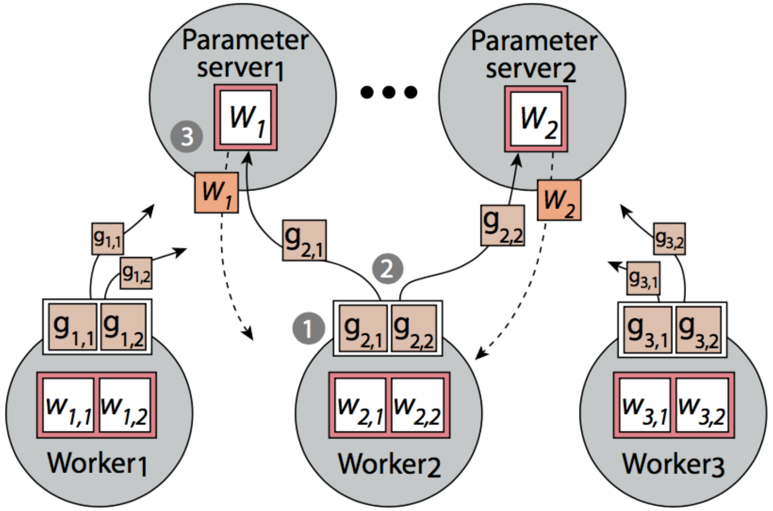
§2 Resource Allocation in DNN Systems

- DNN systems with parameter servers

- A scalable approach for training DNNs is to use *parameter server*
  1. The training data is split across *worker*.
  2. Each worker calculate the gradient over its data partition.
  3. Worker sends the local gradient g to parameter servers.
  4. Parameter servers aggregate the gradients and update the global model W.
  5. And return the new model W to the workers.



For more detail about parameter server architecture, read [24, 2, 19, 26, 49].

§2 Resource Allocation in DNN Systems

- DNN systems with parameter servers

- To reach fastest time-to-convergence, DNN systems must achieve:
    1. High hardware efficiency,
        - Which is time to complete a single iteration.
    2. High statistical efficiency,
        - Which is the improvement in the model per iteration.

- There is a trade-off between these two aspects.
    - In practice, modern distributed DNN systems require such decision on resource allocation.

§2 Resource Allocation in DNN Systems

- Resource allocation problem

- The best allocation should result in fastest time-to-convergence.
  - However, the best allocation depends on many factors which make prediction difficult.

- This difficulty can be checked through some experiments.
  - Deployed a DNN system with parameter servers on 64-machines, training a model for **ImageNet** benchmark (explained later).

§2 Resource Allocation in DNN Systems

- Resource allocation problem

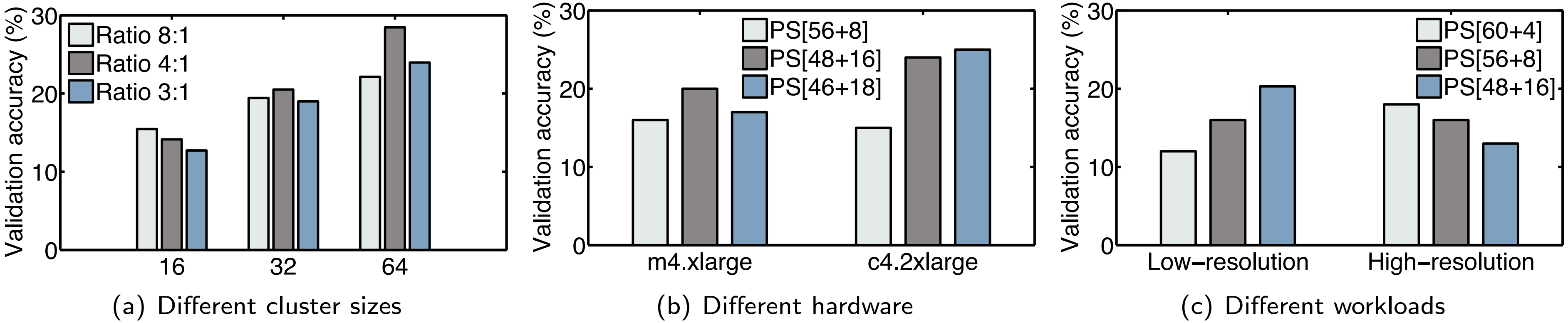
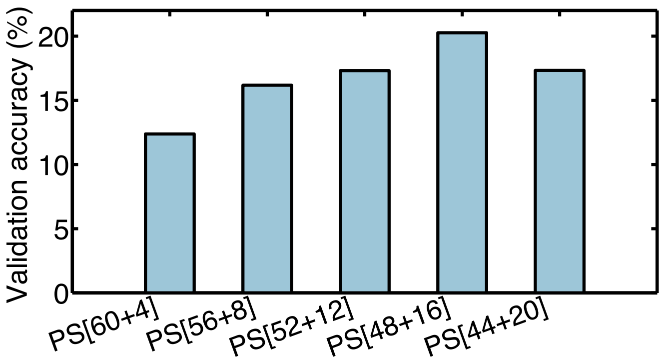


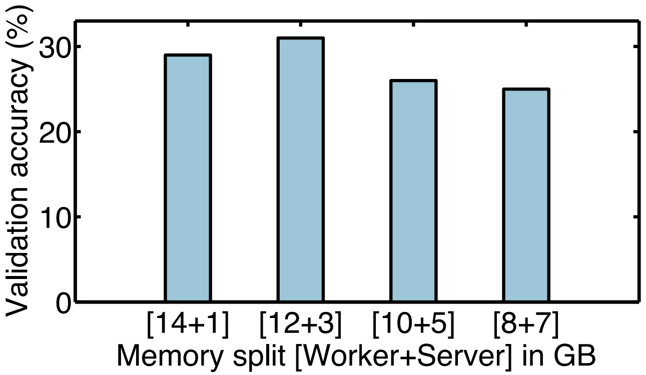
Figure 3: Effect of system and workload changes on best resource allocation

- Accuracy with different (a) **cluster size**, (b) **hardware**, and (c) **workloads**.
- In (b), comparing “m4.xlarge” and “c4.2xlarge” VMS on a 64-machine Amazon EC2 deployment.
- In (c), low-resolution is 100x100 pixels, and high-resolution is 200x200 pixels.

§2 Resource Allocation in DNN Systems

- Resource allocation problem





- Accuracy with different worker and parameter server **allocation** (left), and **memory allocation** in co-located parameter server (right).
  - Both are accuracy after one hour training.
- In co-located [44], worker and parameter server are located on same node.

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§3 Partial Gradient Exchange

- Adopting decentralised synchronisation scheme

- Instead of using parameter server, the author adopts a decentralised synchronisation scheme.
  - which workers communicate directly with each other, without intermediate nodes.

- Some decentralised solutions are…
  - All-to-All communication
  - Relaying updates
- However, these are not “good” as parameter server.

§3 Partial Gradient Exchange
- Partial gradient exchange algorithm

- A new decentralised synchronisation approach called ***partial gradient exchange***.
  - In this approach, worker sends only one partition to each other worker.

- For each worker, there are three steps which refer as ***synchronisation round***.
  - Calculating & accumulating local gradient
  - Partitioning local gradient
  - Sending local gradient

§3 Partial Gradient Exchange

- Partitioning gradients at synchronization round t

$$^{(t)}\mathbf{g}_j$$

Creates the local gradients from (a part of) data points in mini-batch.

$$\Downarrow$$

$$^{(t)}\mathbf{g}_j^*$$

Accumulates the gradient with previous-unsent local gradients.

$$^{(t)}\mathbf{g}_j^* \leftarrow {}^{(t)}\mathbf{g}_j + {}^{(t-1)}\mathbf{g}_j + {}^{(t-2)}\mathbf{g}_j + \cdots$$

To do so, worker needs to store previous local gradients some how.

$$\Downarrow$$

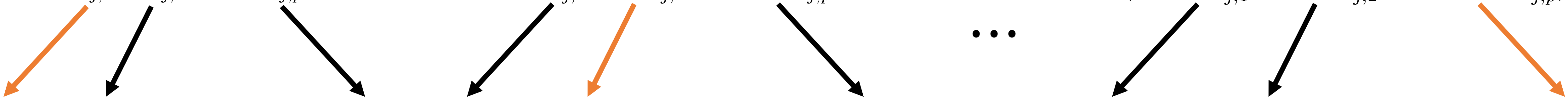
$$\left({}^{(t)}\mathbf{g}_{j,1}^*, {}^{(t)}\mathbf{g}_{j,2}^*, \cdots, {}^{(t)}\mathbf{g}_{j,p}^*\right)$$

Partitions the accumulated gradient into p disjoint ***gradient partitions***.

§3 Partial Gradient Exchange

- Sending gradients at synchronization round t

$$({}^{(t)}\mathbf{g}^*_{j,1}, {}^{(t)}\mathbf{g}^*_{j,2}, \cdots, {}^{(t)}\mathbf{g}^*_{j,p}) \quad ({}^{(t+1)}\mathbf{g}^*_{j,1}, {}^{(t+1)}\mathbf{g}^*_{j,2}, \cdots, {}^{(t+1)}\mathbf{g}^*_{j,p}) \quad \cdots \quad ({}^{(t+p-1)}\mathbf{g}^*_{j,1}, {}^{(t+p-1)}\mathbf{g}^*_{j,2}, \cdots, {}^{(t+p-1)}\mathbf{g}^*_{j,p})$$



Sending to other workers

- Sends each gradient partitions to other workers in round-robin fashion.
- It takes p synchronization rounds to send complete gradient which calculated at synchronization round t.

§3 Partial Gradient Exchange

- Accumulating gradients

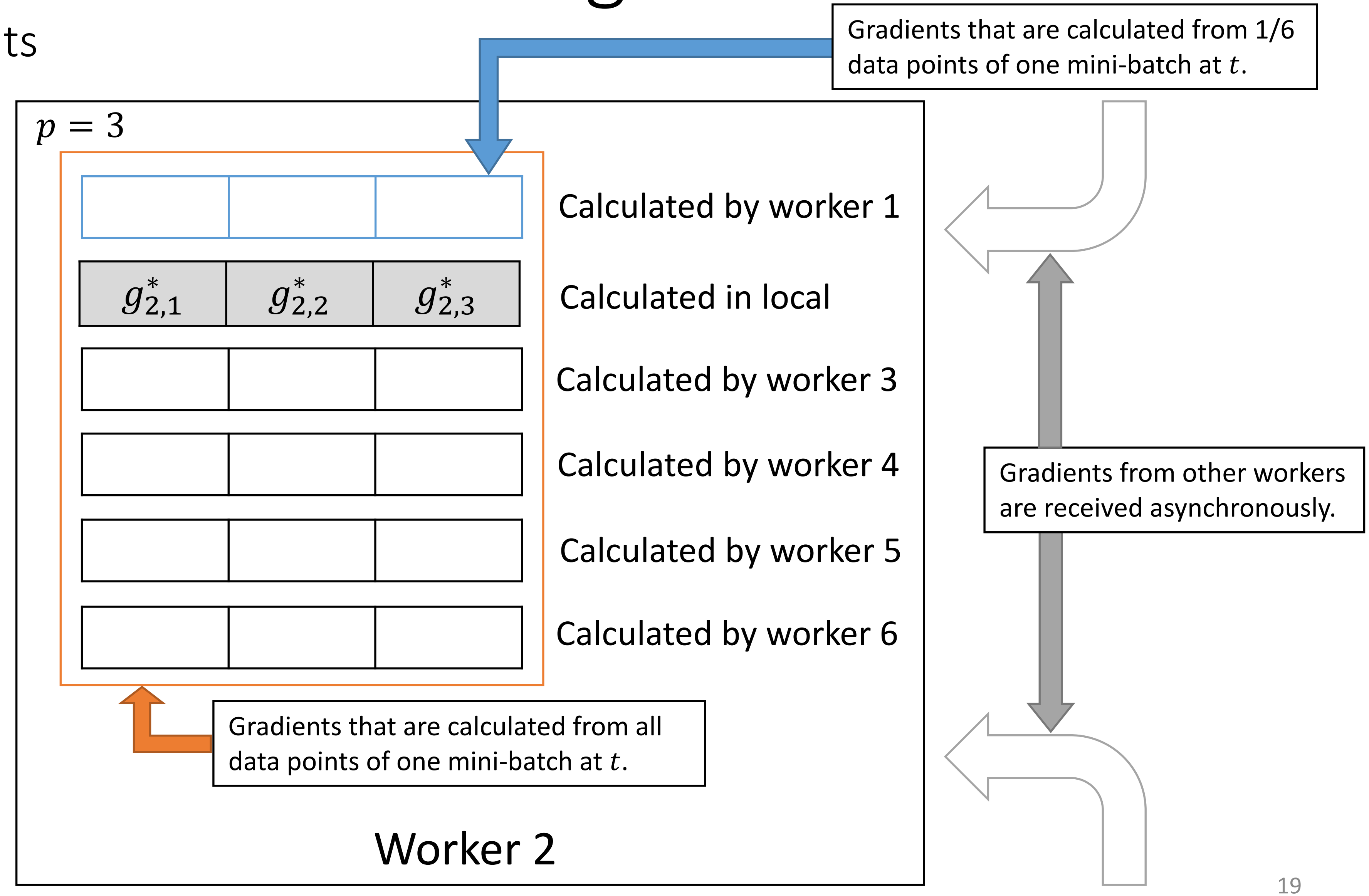
- According to the previous slide, only last p gradients are needed to be accumulated.
  - Thus, the relational expression will be:

$$\begin{cases} {}^{(1)}\mathbf{g}_j^* \leftarrow {}^{(1)}\mathbf{g}_j & \\ {}^{(t)}\mathbf{g}_j^* \leftarrow {}^{(t-1)}\mathbf{g}_j^* + {}^{(t)}\mathbf{g}_j & \text{if } 2 \leq t \leq p \\ {}^{(t)}\mathbf{g}_j^* \leftarrow {}^{(t-1)}\mathbf{g}_j^* + {}^{(t)}\mathbf{g}_j - {}^{(t-p)}\mathbf{g}_j & \text{if } t > p \end{cases}$$

  - Subtracting ${}^{(t-p)}\mathbf{g}_j$ is needed to avoid sending already-sent gradient partitions.
  - This improves the training quality when compared with no accumulation.

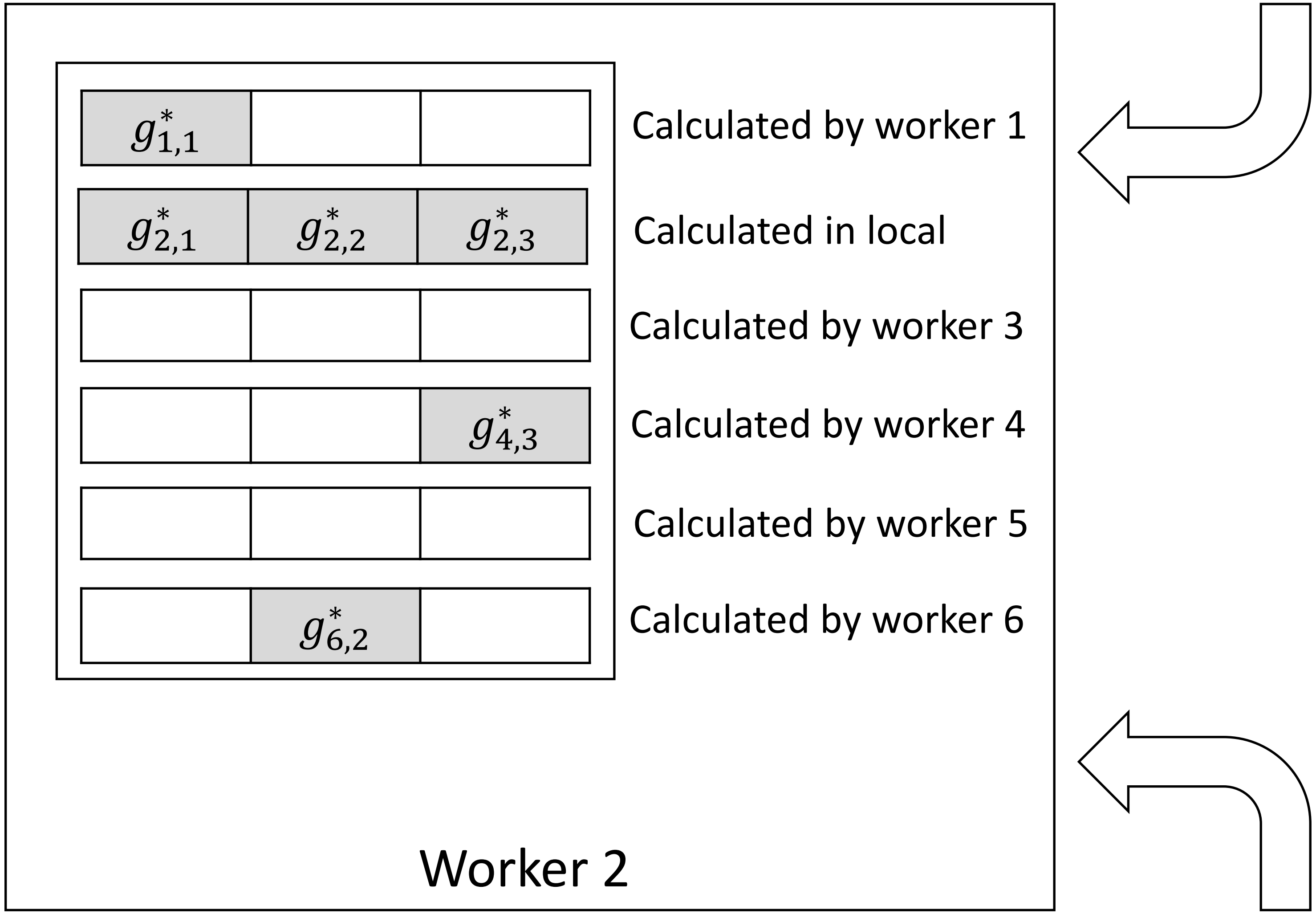
§3 Partial Gradient Exchange

- Receiving gradients



§3 Partial Gradient Exchange

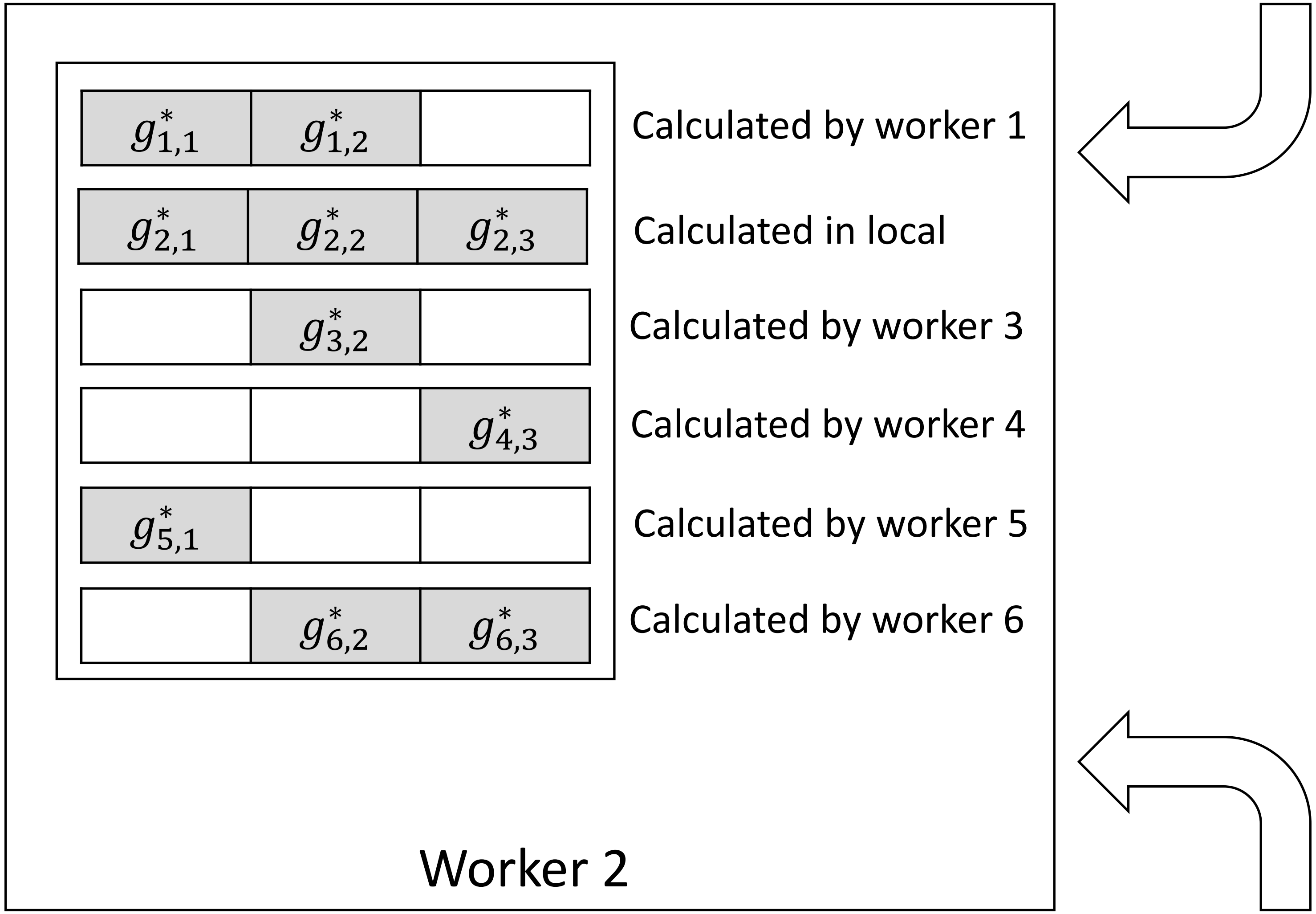
- Receiving gradients (cont.)



synchronization round : t

§3 Partial Gradient Exchange

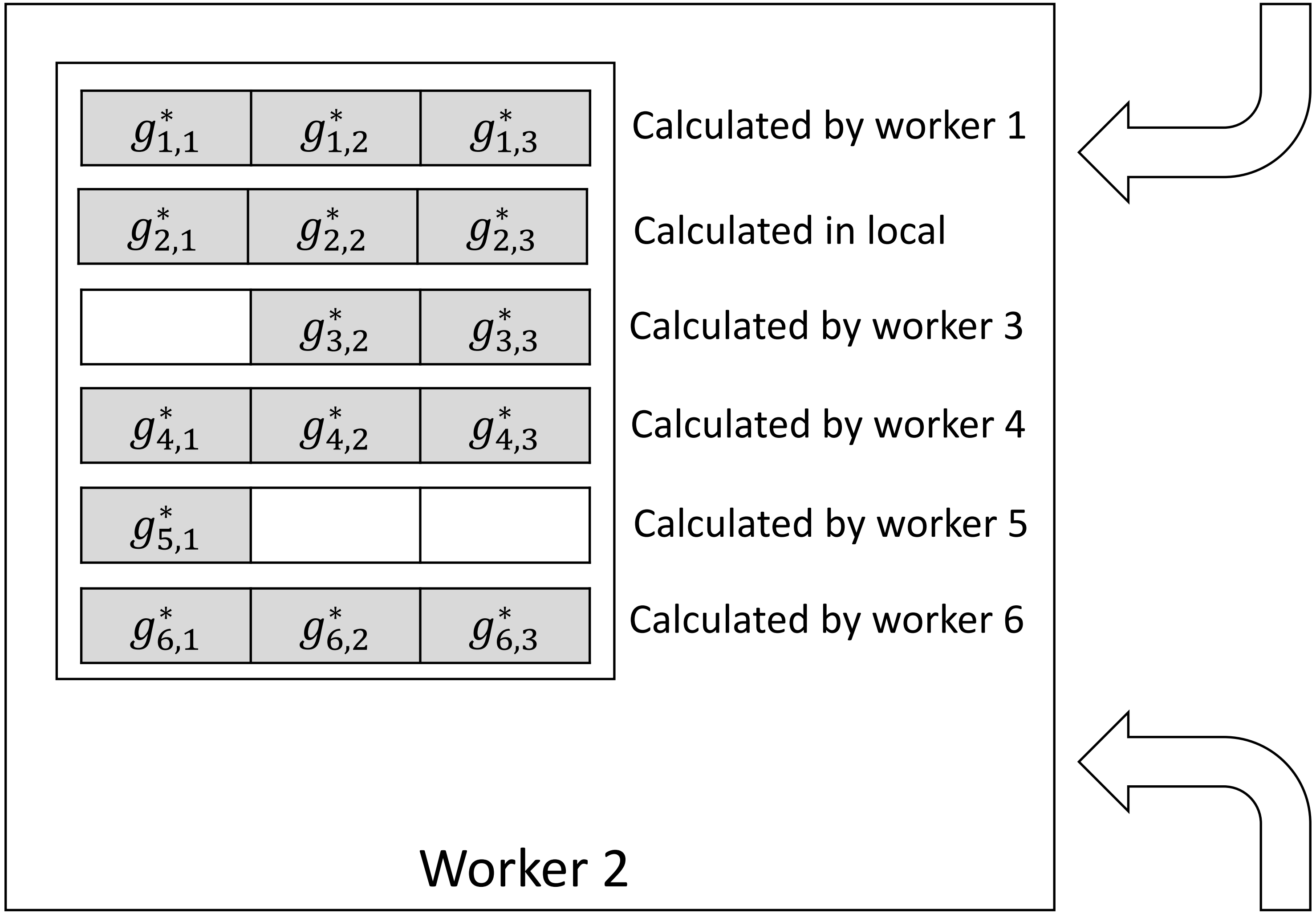
- Receiving gradients (cont.)



synchronization round : $t+1$

§3 Partial Gradient Exchange

- Receiving gradients (cont.)



synchronization round : $t + 2$

§3 Partial Gradient Exchange

- Receiving gradients (cont.)

- Since the communication is asynchronous, accumulated gradient partitions may not be received in their expected synchronisation rounds.
  - Expected to be received in p synchronisation rounds.
  - Although this introduce staleness in the local model, it does not compromise convergence (mentioned later).

§3 Partial Gradient Exchange

- Algorithm

- Each worker executes two functions, `generateGradients` and `updatePartialModel`, **asynchronously**.
  - c_j, $s_{j,i}$, and τ are used for bounding staleness (mentioned later).
  - The `updatePartialModel` function is executed when an gradient partition is received by a worker.

Algorithm 1: Partial gradient exchange

function `generateGradients` *(j, d, t, η, τ)*
  input : worker index j, mini-batch data points d, gradient computation timestamp t, learning rate η, staleness bound τ
  while $\neg$`converged` **do**
    if $c_j \leq \mathit{min}\,(s_{j,1}, \ldots, s_{j,n}) + p + \tau$ **then**
      ${}^{t}g_j \leftarrow$ `computeGradient` $({}^{t}w_j, d)$
      ${}^{(t+1)}w_j \leftarrow {}^{t}w_j + \eta \cdot {}^{t}g_j$
      ${}^{t}g_j^* \leftarrow {}^{(t-1)}g_j^* + {}^{t}g_j - {}^{(t-p)}g_j$
      $({}^{t}g_{j,1}^*, \ldots, {}^{t}g_{j,p}^*) \leftarrow$ `partitionGrad` $({}^{t}g_j^*, p)$
      for $i = 1 \ldots n$ ***in parallel*** **do**
        $k \leftarrow i \bmod p$
        `sendGradient` $(i, {}^{t}g_{j,k}^*)$
      $c_j \leftarrow c_j + 1$

function `updatePartialModel` *(j, i, $g_{j,p}$, η)*
  input : receiver worker index j, origin worker index i, gradient partition $g_{j,p}$, learning rate η
  $w_{j,p} \leftarrow w_{j,p} + \eta \cdot g_{j,p}$
  $s_{j,i} \leftarrow s_{j,i} + 1$

§3 Partial Gradient Exchange

- Deciding the number of gradient partitions (*p*)

- The number of gradient partitions p impacts the statistical efficiency.
  - Workers can use cost model to select p when training begins:

$$p = \left\lceil \frac{\gamma m(n-1)}{B} \right\rceil$$

  - Where, m is the local model size, n is the number of the workers, γ is the rate which workers compute new gradient partitions[?], and B is the given available full-bisection bandwidth.

§3 Partial Gradient Exchange

- Deciding the number of gradient partitions (p) (cont.)

- The reason of this cost model
  - The amount of data to send the full gradient is $m(n-1)$ per worker.
  - With partial gradient exchange, it is $m(n-1)/p$.
  - And only γ of the whole workers need to communicate, thus $\gamma m(n-1)/p$.
  - And this $\gamma m(n-1)/p$ is the required bandwidth usage of partial gradient exchange.
  - This means,

$$B = \frac{\gamma m(n-1)}{p}$$

Assuming system has a $m \times m$ network with bandwidth B.

  - Therefore, integer p will be represented as:

$$p = \left\lceil \frac{\gamma m(n-1)}{B} \right\rceil$$

§3 Partial Gradient Exchange

- Bounding staleness

- The gradients computed by each worker may use weights from previous mini-batch, which introduces ***staleness***.
- To guarantee convergence, Ako imposes a **staleness bound** τ.
  - Limits the generation of new local gradients when a worker has advanced in the computation further than τ compared to all other workers.
  - To do so, each worker j maintain,
    - *Staleness clock* $s_{j,i}$ for each other worker i.
    - *Local staleness clock* c_j.
  - As p synchronisation rounds are necessary to fully propagate model, staleness bound is $p + \tau$.

§3 Partial Gradient Exchange

- Bounding staleness (cont.)

Algorithm 1: Partial gradient exchange

function `generateGradients` (j, d, t, η, τ)
  input : worker index j, mini-batch data points d, gradient computation timestamp t, learning rate η, staleness bound τ
  while $\neg$`converged` **do**
    if $c_j \leq min\,(s_{j,1}, \ldots, s_{j,n}) + p + \tau$ **then**
      ${}^{t}g_j \leftarrow$ `computeGradient` $({}^{t}w_j, d)$
      ${}^{(t+1)}w_j \leftarrow {}^{t}w_j + \eta \cdot {}^{t}g_j$
      ${}^{t}g_j^* \leftarrow {}^{(t-1)}g_j^* + {}^{t}g_j - {}^{(t-p)}g_j$
      $({}^{t}g_{j,1}^*, \ldots, {}^{t}g_{j,p}^*) \leftarrow$ `partitionGrad` $({}^{t}g_j^*, p)$
      for $i = 1 \ldots n$ ***in parallel*** **do**
        $k \leftarrow i \bmod p$
        `sendGradient` $(i, {}^{t}g_{j,k}^*)$
      $\boxed{c_j \leftarrow c_j + 1}$

function `updatePartialModel` $(j, i, g_{j,p}, \eta)$
  input : receiver worker index j, origin worker index i, gradient partition $g_{j,p}$, learning rate η
  $w_{i,p} \leftarrow w_{i,p} + \eta \cdot g_{j,p}$
  $\boxed{s_{j,i} \leftarrow s_{j,i} + 1}$

Local staleness bound is incremented after one synchronisation round ended.

Staleness bound for worker i is incremented when partial gradient is received.

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§4 Ako Architecture

- Implementation of the Ako architecture

- The Ako architecture follows a stateful distributed dataflow model.
- Execution is broken into a series of short ***tasks***.
  - Compute tasks have one work
    - Gradient computation
  - Network tasks have four works
    - Gradient accumulation
    - Gradient partitioning
    - Gradient sending
    - Gradient receiving

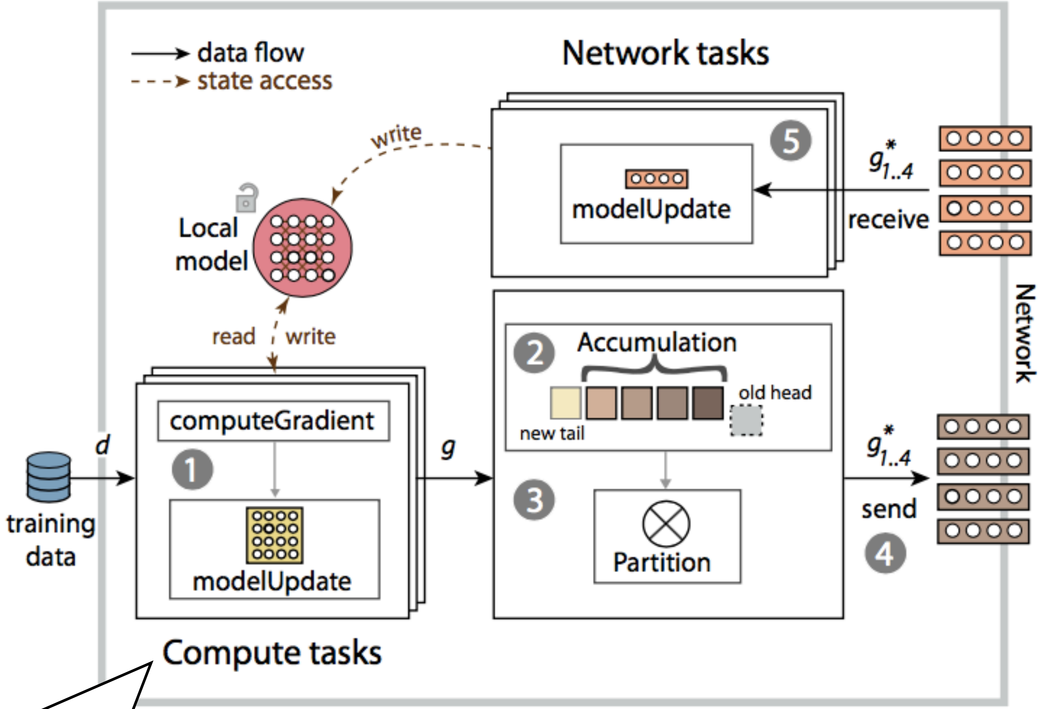

Figure 7: Architecture of an Ako worker

Computation is parallel.
Each task has exclusive
access to the local model.

§4 Ako Architecture

- Implementation of the Ako architecture (cont.)

- Gradient computation
  - Local computation is in parallel and each task has exclusive access to a partition of the local model.
  - When the gradient computation is at the end of the mini-batch, the computed (local) gradients are aggregated and updates the (local) model.
  - Update occurs concurrently with other compute task reading the (local) model.

- Gradient accumulation
  - The computed gradients at the end of a mini-batch are accumulated by a pool of network task.

§4 Ako Architecture
- Implementation of the Ako architecture (cont.)

- Gradient partitioning
  - Before sending the gradients, it is partitioned using range-partitioning.
- Gradient sending
  - Send the gradient partitions, tagged by the partitioning range, to other workers in round-robin.
  - After p rounds, complete gradients have been sent to all workers.
- Gradient receiving
  - Concurrently, workers receive gradient partitions from other worker.
  - Network task apply the gradients immediately without locking.

§4 Ako Architecture
- Fault tolerance

- Ako uses checkpointing for fault tolerance.
  - Each worker saves their local models and the staleness counter.
  - Similar to SEEP [14] and TensorFlow [1].
  - SEEP's master node notifies the other workers and let them remove the staleness counter.
    - Counters are re-added when worker recover.

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§5 Evaluation

- Setting-up datasets and DNNs

- Datasets
  - MNIST
  - ImageNet
- DNNs
  - 3 convolutional (with max-pooling) and 2 fully-connected layers.
    - For MNIST, 10/20/100 convolutional kernels (filters) with 200 neurons
    - For ImageNet 32/64/256 convolutional kernels (filters) with 800 neurons.
- Prior to training
  - Datasets are partitioned evenly across the workers.
  - The model parameters are initialized using warm-start.

§5 Evaluation

- Setting-up systems

- Ako vs. PS[w+p] (parameter server) vs. Al-to-All
  - All are implemented on top of the **SEEP** stateful distributed data platform with the same optimizations.
- Ako vs. TF (TensorFlow) vs. SG (Singa)
  - For TF and SG, asynchronous **Downpour algorithm** architecture is used to train DNNs.

- Staleness bound τ
  - Decided according to the used data set and DNN models.
  - As a heuristic, τ is increased proportionally to the # of used workers.

§5 Evaluation

- Short intro of MNIST and ImageNet

- MNIST
  - Dataset of handwritten digits (0 to 9).
  - 60,000 training sets, and 10,000 test sets.
  - Each image has 28x28 pixels which have 0 to 255 value.
  - http://yann.lecun.com/exdb/mnist/

- ImageNet
  - Dataset of images that illustrate synonym set (synset) nouns.
  - More than 14,000,000 images that have been indexed.
  - http://image-net.org/

§5 Evaluation

- Short intro to SEEP and Downpour SGD

- SEEP [14] (http://lsds.doc.ic.ac.uk/projects/SEEP)
  - An experimental parallel data processing system developed by LSDS.
  - Handles large scale stream data processing in cloud architectures with stateful operator.

- Downpour SGD [12]
  - Asynchronous SGD algorithm on parameter server deployment.
  - Using AdaGrad learning rate.

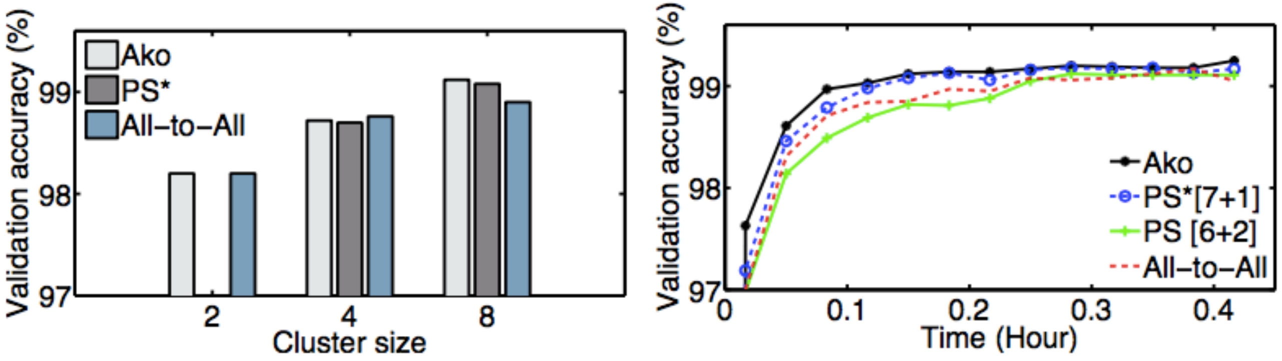
§5 Evaluation
- Performance metrics & cluster hardware

- Validation of the DNN models
  - Based on top-1 accuracy with the validation data, not the top-5.

- Hardware environment
  1. For MNIST, 16-machine cluster with 4-core Intel Xeon E3-1220 3.1GHz CPUs with 8GB RAM and 1Gbps Ethernet
  2. For ImageNet, 64-machine Amazon EC2 cluster with "m4.xlarge" Intel Xeon instances, each with 4 vCPU cores at 2.4GHz and 16GB RAM

§5 Evaluation

- Results of convergence and scalability (MNIST)

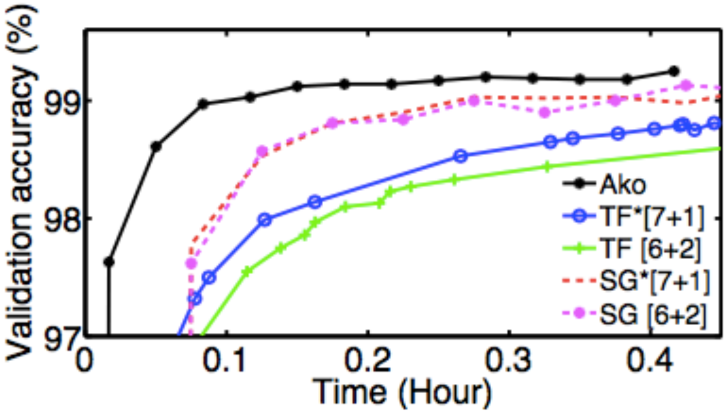


(a) Accuracy after 10 minutes of training (b) Convergence with 8 machines

- Fig. (a) shows that Ako achieves similar convergence as PS*.
  - PS*[1+3] for 4 machines and PS*[7+1] for 8 machines.
- Fig. (b) shows that Ako achieves similar convergence as PS* and converges faster than All-to-All.
  - All-to-All is not “too bad” since the data that need to communicate is not too large.

§5 Evaluation

- Results of convergence and scalability (MNIST)



(c) Comparison with TensorFlow and Singa

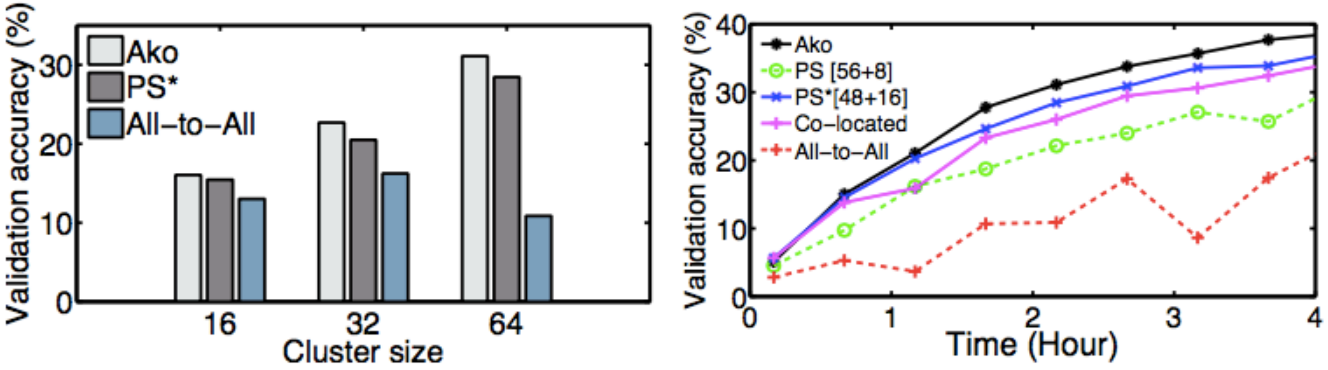
Dataset	Accuracy	TensorFlow	All-to-All	Ako
MNIST	99%	> 20 min	14 min	7 min
ImageNet	30%	3.3 h	> 4 h	1.5 h

Table 1: Time to reach target validation accuracy

- Fig. (c) shows that Ako converges faster than both TF and SG.
- From table 1, it takes Ako 7 minutes and TF* more than 20 minutes to achieve validation accuracy of 99%.
  - Author speculates this difference is caused from synchonisation under downpour SGD.

§5 Evaluation

- Results of convergence and scalability (ImageNet)



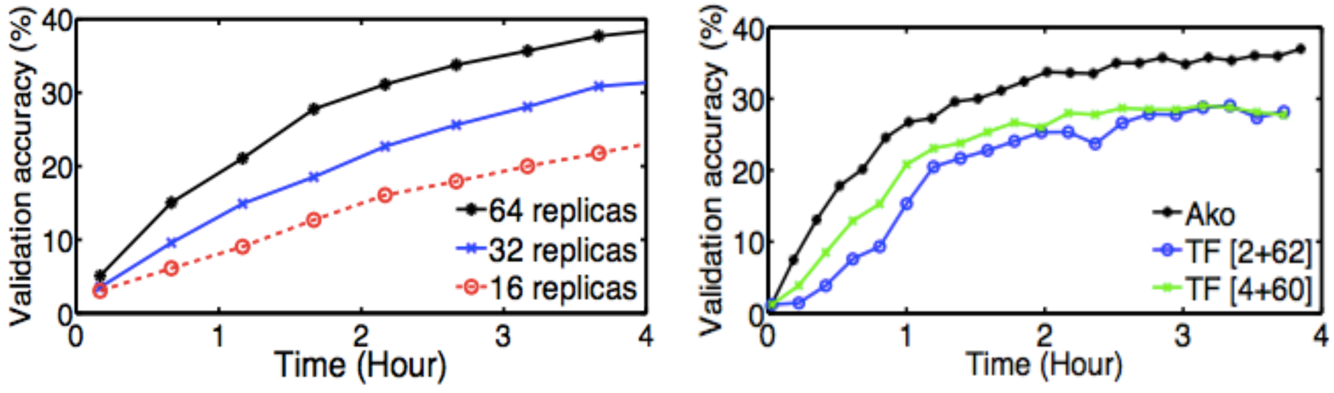
(a) Accuracy after 2-hours of training

(b) Convergence with 64 machines

- Fig. (a) shows that Ako achieves a higher validation accuracy than PS*, and with more machines, Ako and PS* convergence improves.
  - Any Ako worker can be used for validation, as difference between them are negligible.
- Fig. (b) shows that Ako requires less training time than PS*.
  - As Ako has more worker nodes than PS has.

§5 Evaluation

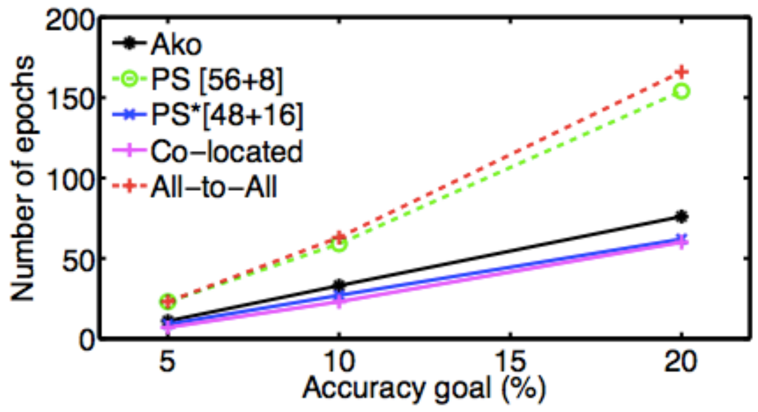
- Results of convergence and scalability (ImageNet)



(c) Convergence with different cluster sizes (a) Comparison with TensorFlow

- Fig. (c) shows that Ako scales gracefully.
  - Ako keeps the communication cost constant with p.
- Fig. (a) shows that Ako achieves higher accuracy from the begging of training.

§5 Evaluation
- Results of statistical efficiency

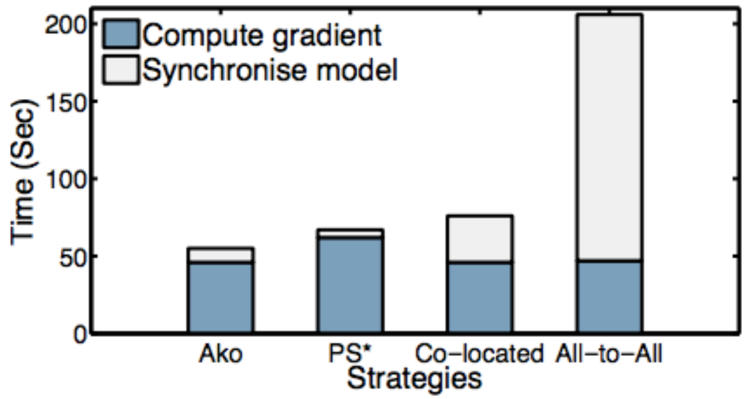


(b) Epoch number for given accuracy goal

- Number of epochs to achieve 5, 10, 15, 20% accuracy in ImageNet.
- Fig. shows that the PS approach requires the fewest passes.
  - Ako requires extra epochs, which is less statistically efficient than PS.
  - Workers receive incomplete gradients but with low latency.

§5 Evaluation

- Results of hardware efficiency



(c) Break-down of epoch time

- Collected time per epoch with two aspects.
- Fig. shows that Ako has shorter epoch time than PS.

§5 Evaluation
- Results of resource utilisation

- Average CPU resource utilisations on 16-machines were
  - Worker of Ako: 87%
  - Worker of PS*[12+4]: 84%, parameter server of PS*[12+4]: 17%
  - Worker of All-to-All: 85%

§5 Evaluation

- Results of resource utilisation

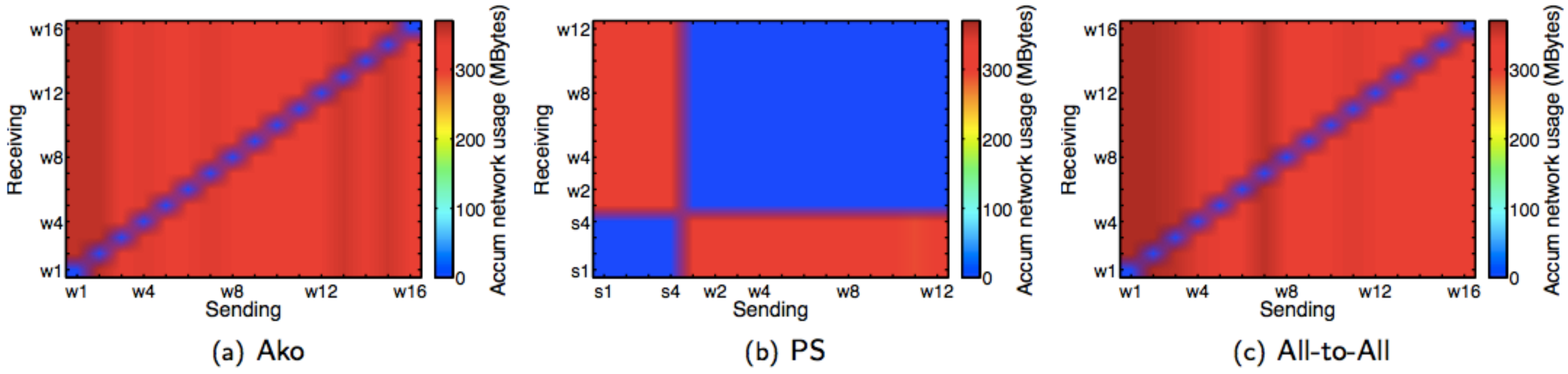
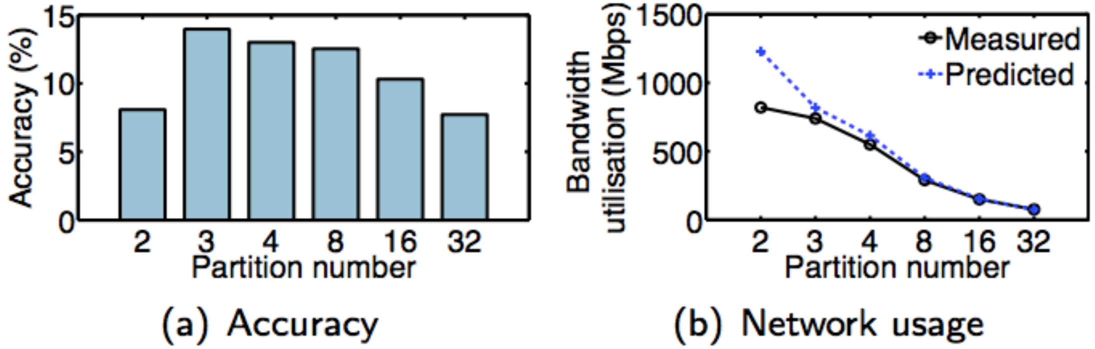


Figure 11: Average network usage with 16 machines (ImageNet)

- Fig. shows the accumulated network usage utilisation in MBs.
  - For Ako, usage is high while still achieving a low synchronisation delay.
  - For PS*, worker-worker networks are unused.
  - All-to-All also saturates the network, but suffers from a high delay.

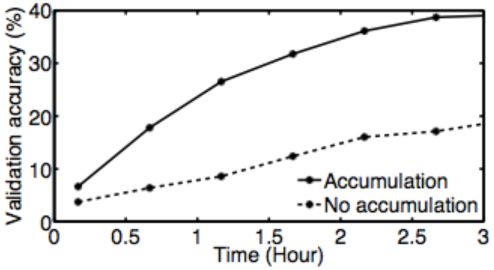
§5 Evaluation

- Effectiveness of gradient partitions and accumulation



(a) Accuracy (b) Network usage

Figure 12: Effect of gradient partitions



- Fig. (a) shows how partition number effects accuracy in Ako.
- Fig. (b) shows how partition number effects bandwidth usage in Ako.
- Right fig. shows how accumulation of gradient effects accuracy in Ako.
  - Without accumulation, workers do not receive complete gradients, make the statistical efficiency low.

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§6 Related Work
- DNN systems with parameter servers

- DistBelief [12]
- TensorFlow [1]
- Project Adam [5]
- Singa [27, 42, 43]
- Poseidon [48]
- SparkNet [25]
- Bösen [44]
- Yan et al. [47]

§6 Related Work
- DNN systems without parameter servers

- Wang et al. [41]
- MALT [23]
- CNTK [32, 33]
- Mariana [50]
- Deep Image [45]

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§7 Conclusions

- To achieve the best performance, distributed DNN systems must fully utilise the system resources.
- This paper described Ako, a decentralised DNN system that does not use parameter servers.
- In the experiment of Ako implementation on a fixed-size cluster, it achieved better performance than one with parameter servers.