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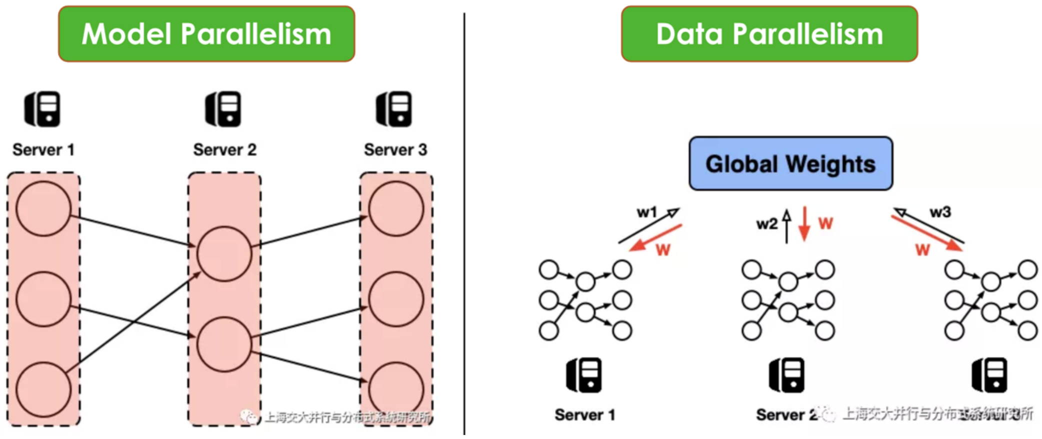
Abstract idea- Distributed deep learning using iterative pair-wise averaging

About

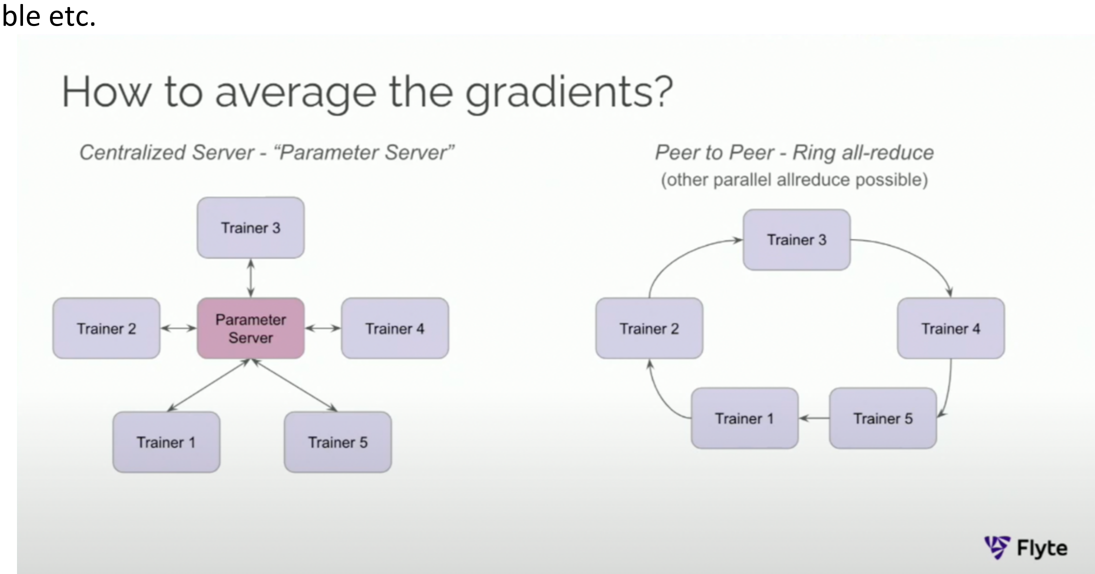
2 ways to achieve parallelism-

1) Data Parallelism: Splitting data into multiple chunks, training the model on all nodes. Each model learns a different set of weights. Hence, the workers communicate with each other to make sure they are training a consistent model- "Synchronous training".
2) Model Parallelism: Splitting the network in multiple sub-networks, training the same data on each sub-network.



Source: http://www.juyang.co/distributed-model-training-ii-parameter-server-and-allreduce/

Data parallelism is preferred over model parallelism mostly because of the ease of implementation. But it does have one drawback- the sync step after every iteration i.e., gradient averaging step. The parameter sever approach [2] mitigates this problem by storing the model parameters centrally and allowing worker nodes to read/write to it. But this creates a single point of failure, the parameter server itself [1,2,3,4]. It has to be highly available etc.



Source: https://www.youtube.com/watch?v=gF3cVTdgLUY

A peer-to-peer alternative approach (called ring all-reduce[4,5,6,7,8]) mitigates the above bottleneck problem and is currently used by the industry. In this approach, the weights learned by each worker travel in a ring format twice: once to calculate the average and then to propagate the average. Although, it's significant improvement over its predecessors; solving the bottleneck issue, it still has a long synchronous step. This takes finite time and is directly proportional to the number of worker nodes in the ring, to calculate aggregated weights.

Proposition

I propose to study a *plausible* improvement over the above-described technique, where the weights in the iteration steps are an aggregation of its current weight and the previous node's weight only.

Example- say workers A, B and C each produce a, b and c weights after the first iteration

	Subset Data 1 Worker A Node	→	Subset Data 2 Worker B Node	→	Subset Data 3 Worker C Node	
Weights: (first pass)	a		b		c	
	(c+a)/2		(a+b)/2		(b+c)/2	
	(c+a+b+c)/4		(a+b+c+a)/4		(b+c+a+b)/4	
	…		…		…	And so on…

The weights should eventually converge is my claim.
Pros: Network activity is expensive and can be reduced to pair wise communication only.
Cons: Same cons as for ring all-reduce. No new ones.

Queries

- Is this feasible? :)
- Anything I'm not foreseeing or planning for?
- Is it in scope for this course?
- Is a proof of concept with 3 VM spark cluster and a modification of the horvord sufficient?

I solicit your guidance/suggestion/thoughts for this topic or any other topic if you'd prefer me to pick something else.

References

1) http://learningsys.org/papers/LearningSys_2015_paper_14.pdf - Huawei's asynchronous distributed learning
2) https://www.cs.cmu.edu/~muli/file/ps.pdf - parameter server related paper
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6) http://www.cs.fsu.edu/~xyuan/paper/09jpdc.pdf - Peer-to-peer model for distributed deep learning
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