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Parallelism in Training Deep Neural Networks

DPHPC Guest Lecture

With contributions from Tal Ben-Nun, Torsten Hoefler, Dan Alistarh, and others at SPCL, LLNL, UIUC, IST Austria, and Tokyo Tech

Overview

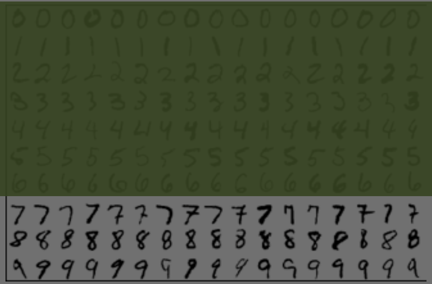
- **What is deep learning?**
- **Some deep neural networks**
- **Parallelizing and distributing training**
- **Communication for training**
- **Applications**

Some General References

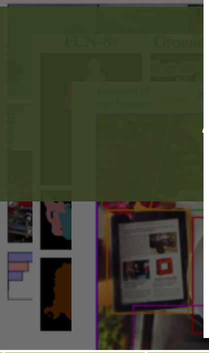
- **Russell & Norvig, *Artificial Intelligence: A Modern Approach***
- **Goodfellow, Bengio, & Courville, *Deep Learning***
  - Freely available online: http://www.deeplearningbook.org/
- **Ben-Nun & Hoefler, *Demystifying Parallel and Distributed Deep Learning***
  - https://arxiv.org/abs/1802.09941
- **Many slides adapted from Tal Ben-Nun, Torsten Hoefler, Svetlana Lazebnik, and prior talks**

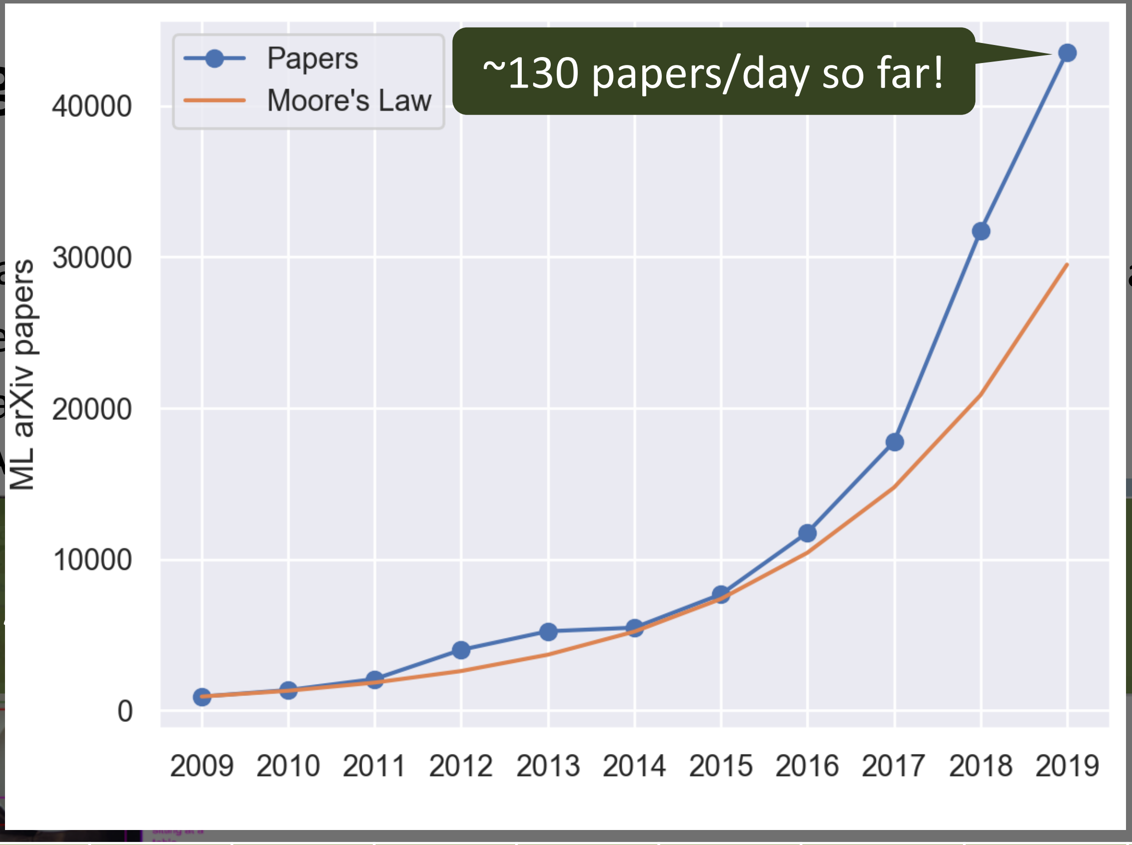
What is Deep Learning

Digit Recognition

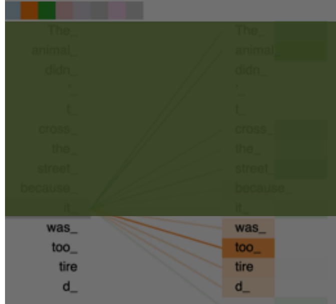


Object Cla
Segme
Image Ca
GA





anguage Models



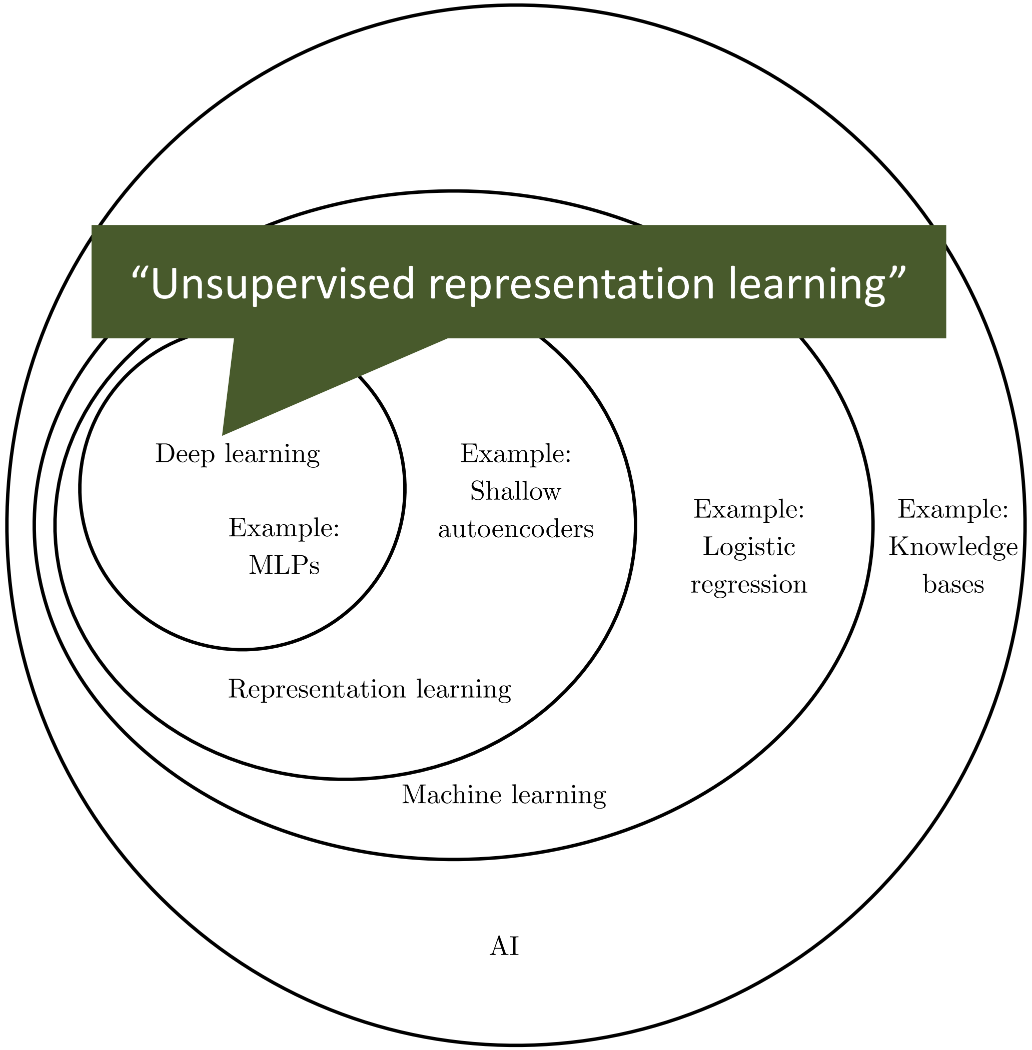
Towards
Real Physics
RTS

Subject	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
cs.AI	380	479	789	1082	1768	1028	1106	1938	2820	4263	4371
cs.CV	148	286	385	577	852	1349	2262	3631	5704	8599	10353
cs.LG	231	333	469	1222	1418	1742	2485	3564	5225	10472	17267
stat.ML	164	256	439	1131	1203	1360	1827	2628	4021	8376	11551
Total	923	1354	2082	4012	5241	5479	7680	11761	17770	31710	43542

1989

2019

Classes of AI Problems



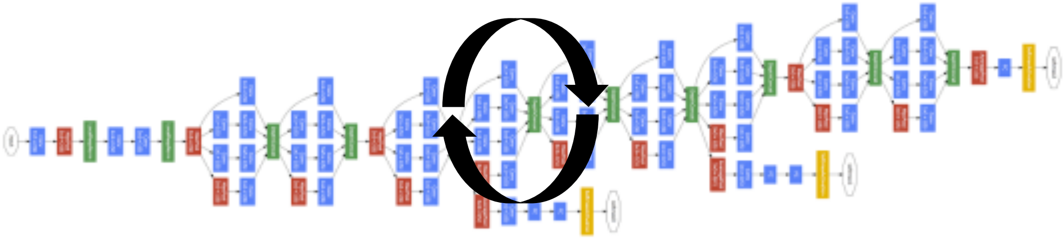
- **Supervised learning**
  - Learn mapping from labeled inputs
    $$\mathrm{argmin}_{f \in \mathcal{H}} \; \mathbb{E}_{x,y \sim \mathcal{D}}[\ell(f(x), y)]$$
- **Unsupervised learning**
  - Learn patterns in inputs
    $$\mathrm{argmin}_{f \in \mathcal{H}} \; \mathbb{E}_{x \sim \mathcal{D}}[\ell(f(x))]$$
- **Reinforcement learning**
  - Learn policy to maximize reward
    $$\mathrm{argmax}_{\pi \in \mathcal{H}} \; \mathbb{E}_{O \sim \Omega}[R(\pi, O)]$$
- **Many others…**

Deep

A brief theory of supervised deep learning (mini-batch SGD)

labeled samples $x \in X \subset \mathcal{D}$

$f(x)$



layer-wise parameter update
(backpropagation)

label	label domain Y	true label $l(x)$
Cat	0.54	1.00
Dog	0.28	0.00
Airplane	0.07	0.00
Horse	0.33	0.00
Banana	0.02	0.00
Truck	0.02	0.00

label domain Y true label $l(x)$

$f(x): X \to Y$

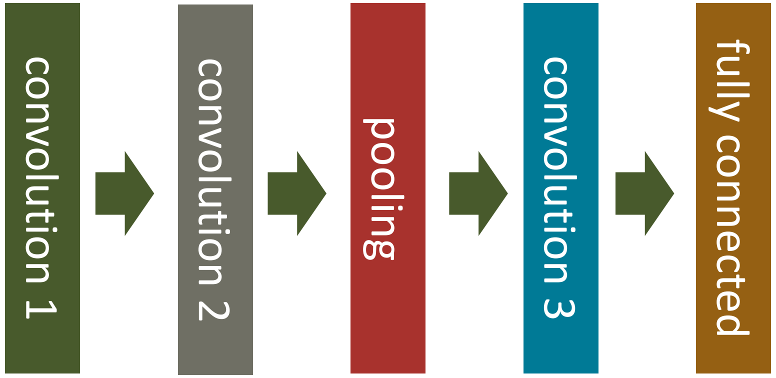
network structure (fixed)

weights w (learned)

$$w^* = \text{argmin}_{w \in \mathbb{R}^d} \mathbb{E}_{x \sim \mathcal{D}}[\ell(w,x)]$$

$$f(x) = f_n\left(f_{n-1}\left(f_{n-2}\left(\ldots f_1(x) \ldots\right)\right)\right)$$

$f_1(x)$ $f_2(f_1(x))$ … $f(x)$



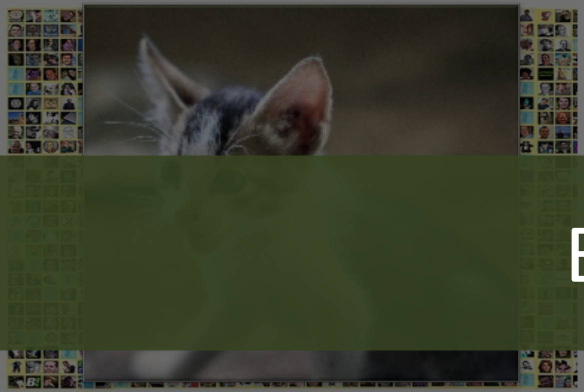
$$\ell_{sq}(w,x) = \left(f(x) - l(x)\right)^2$$

$$\ell_{0-1}(w,x) = \begin{cases} 0 & f(x) = l(x) \\ 1 & f(x) \neq l(x) \end{cases}$$

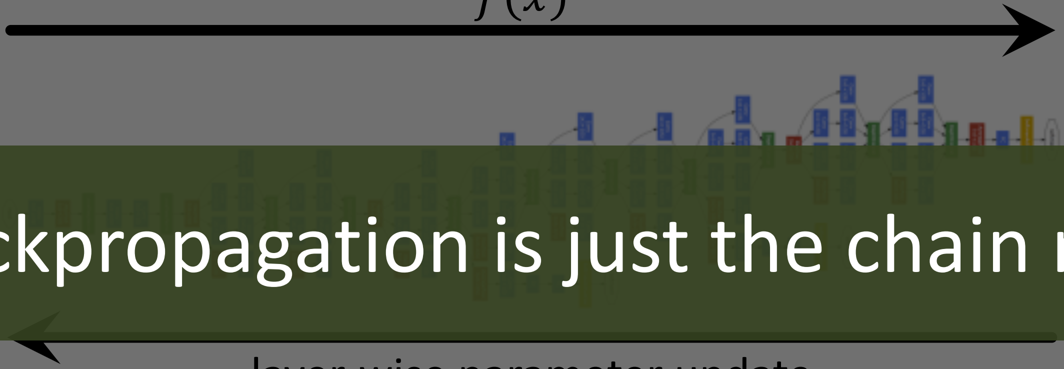
$$\ell_{ce}(w,x) = -\sum_i l(x)_i \cdot \log \frac{e^{f(x)_i}}{\sum_k e^{f(x)_k}}$$

A brief digression on backpropagation

- ”Backward propagation of errors” (Rumelhart, Hinton, & Williams 1986)



$f(x)$



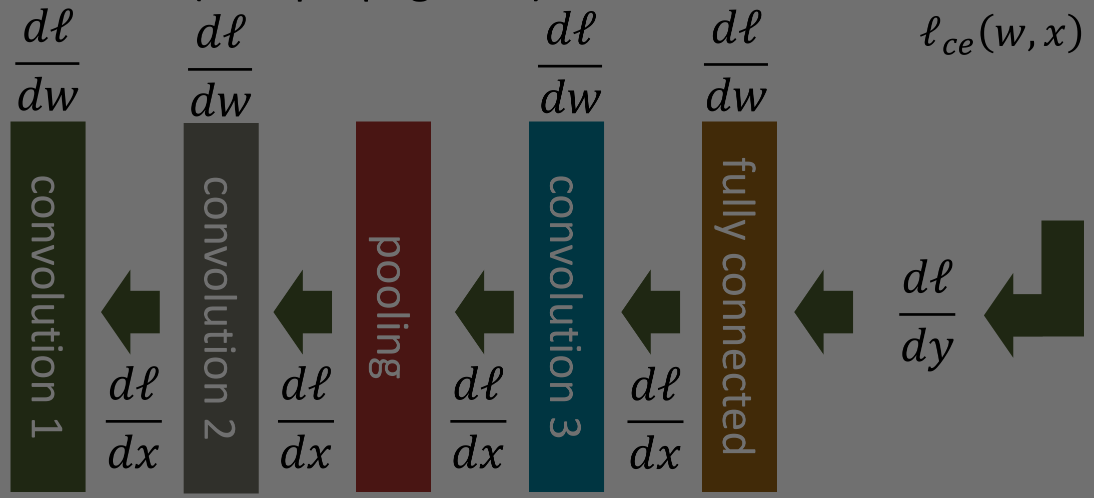
Cat	0.54
Dog	0.28
Airplane	0.07
Horse	0.33
Banana	0.02
Truck	0.02

Cat	1.00
Dog	0.00
Airplane	0.00
Horse	0.00
Banana	0.00
Truck	0.00

Backpropagation is just the chain rule!

layer-wise parameter update
(backpropagation)

$$\ell_{ce}(w,x) = -\sum_i l(x)_i \cdot \log \frac{e^{f(x)_i}}{\sum_k e^{f(x)_k}}$$



Stochastic Gradient Descent

$$w^* = \text{argmin}_{w \in \mathbb{R}^d} \mathbb{E}_{x \sim \mathcal{D}}[\ell(w, x)]$$

$f_1(x)$ convolution 1

$f_2(f_1(x))$ convolution 2

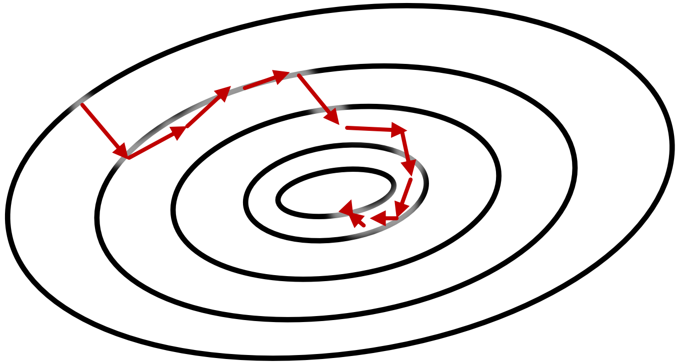
pooling

…

convolution 3

$f(x)$ fully connected

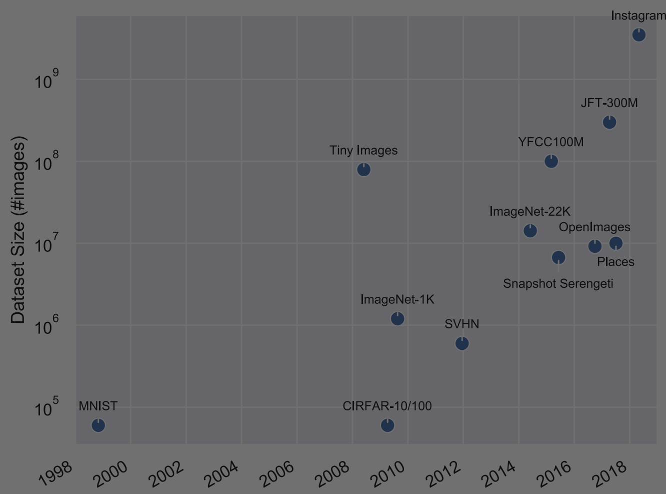
- Layer storage = $|w_l| + |f_l(o_{l-1})| + |\nabla w_l| + |\nabla o_l|$

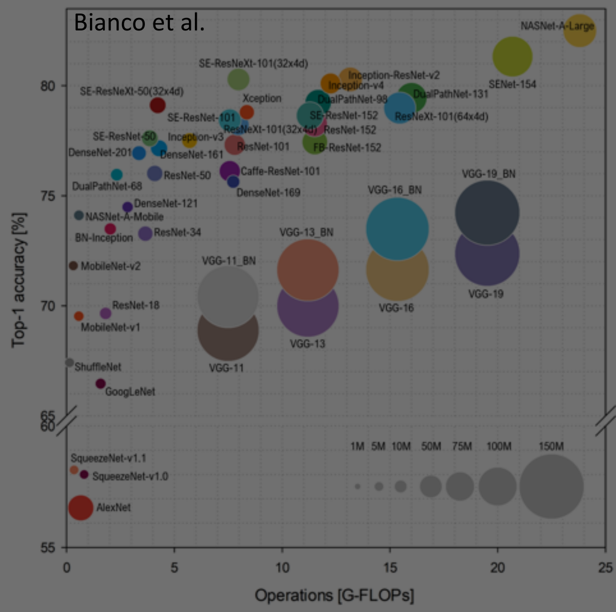


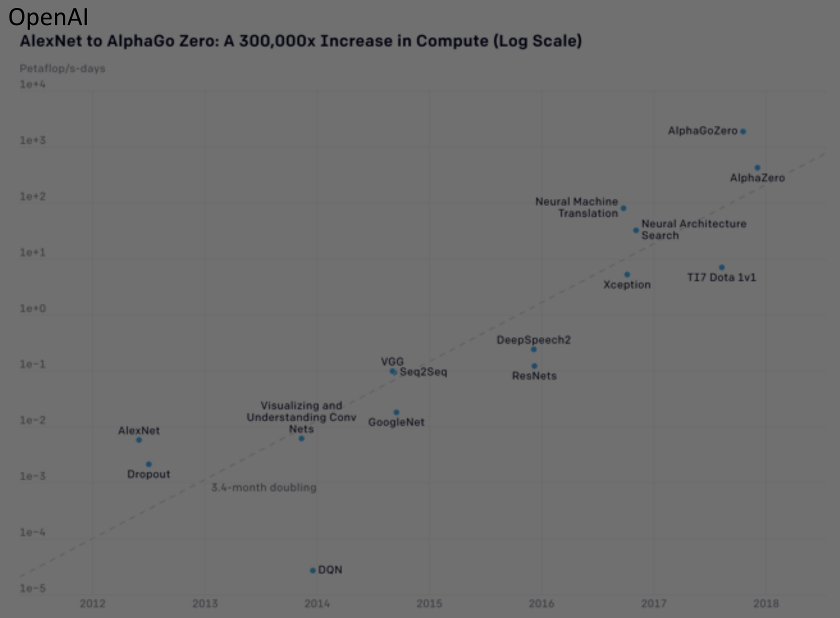
Learning Rate	$w^{(t+1)} = w^{(t)} - \eta \cdot \nabla \ell(w^{(t)}, z) \quad = w^{(t)} - \eta \cdot \nabla w^{(t)}$
Adaptive Learning Rate	$w^{(t+1)} = w^{(t)} - \eta_t \cdot \nabla w^{(t)}$
Momentum [Qian 1999]	$w^{(t+1)} = w^{(t)} + \mu \cdot (w^{(t)} - w^{(t-1)}) - \eta \cdot \nabla w^{(t)}$
Nesterov Momentum [Nesterov 1983]	$w^{(t+1)} = w^{(t)} + v_t; \quad v_{t+1} = \mu \cdot v_t - \eta \cdot \nabla \ell(w^{(t)} - \mu \cdot v_t, z)$
AdaGrad [Duchi et al. 2011]	$w_i^{(t+1)} = w_i^{(t)} - \frac{\eta \cdot \nabla w_i^{(t)}}{\sqrt{A_{i,t} + \varepsilon}}; \quad A_{i,t} = \sum_{\tau=0}^{t} \left(\nabla w_i^{(t)}\right)^2$
RMSProp [Hinton 2012]	$w_i^{(t+1)} = w_i^{(t)} - \frac{\eta \cdot \nabla w_i^{(t)}}{\sqrt{A'_{i,t} + \varepsilon}}; \quad A'_{i,t} = \beta \cdot A'_{t-1} + (1 - \beta)\left(\nabla w_i^{(t)}\right)^2$
Adam [Kingma and Ba 2015]	$w_i^{(t+1)} = w_i^{(t)} - \frac{\eta \cdot M_{i,t}^{(1)}}{\sqrt{M_{i,t}^{(2)} + \varepsilon}}; \quad M_{i,t}^{(m)} = \frac{\beta_m \cdot M_{i,t-1}^{(m)} + (1-\beta_m)\left(\nabla w_i^{(t)}\right)^m}{1 - \beta_m^t}$

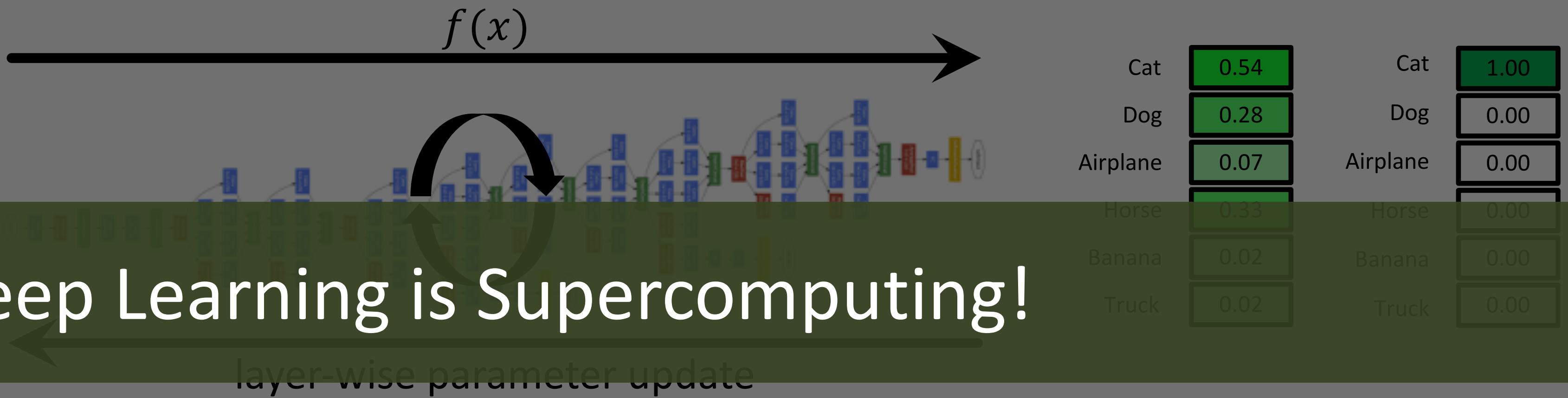
T. Ben-Nun, T. Hoefler: Demystifying Parallel and Distributed Deep Learning: An In-Depth Concurrency Analysis, CSUR 2019

The scale of deep learning









Deep Learning is Supercomputing!

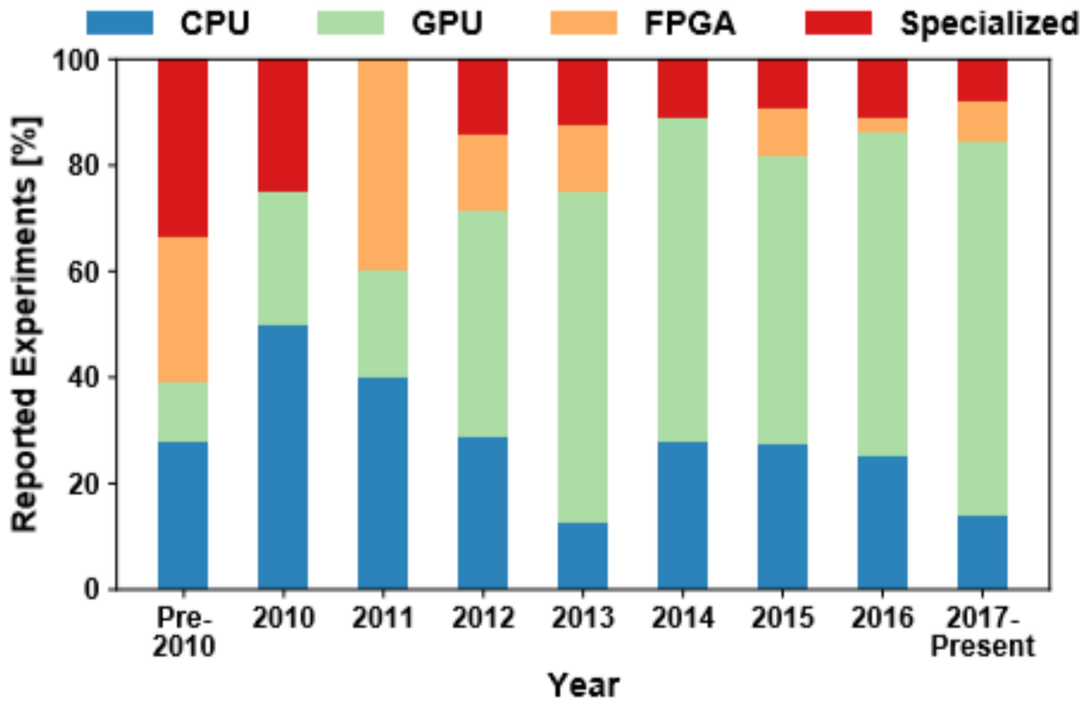
- ImageNet 1k: 150 GB
- ImageNet 22k: ~2 TB
- Industry: Much larger

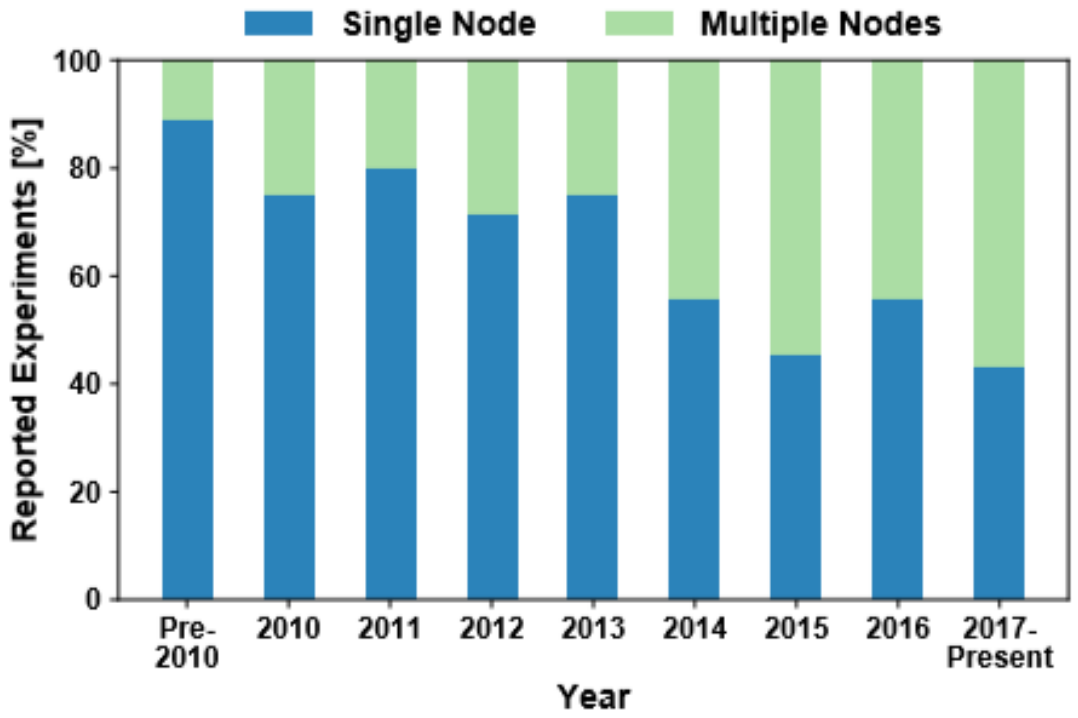
- >100 layers deep
- ~25M – >10B parameters
- 0.1 – 40 GiB storage

- 10-22k labels
- Growing
- Weeks to train

Trends in deep learning: hardware and multi-node

The field is moving fast – trying everything imaginable – survey results from 252 papers in the area of parallel deep learning



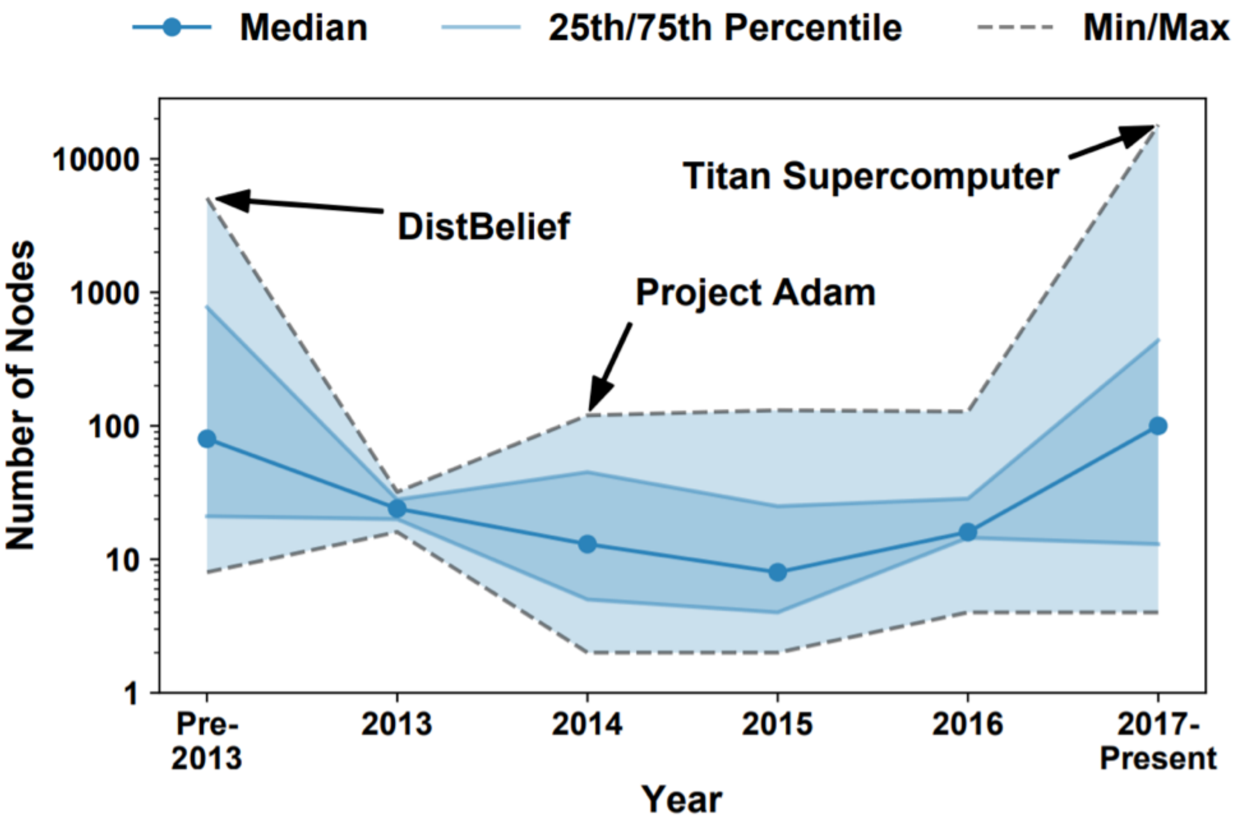


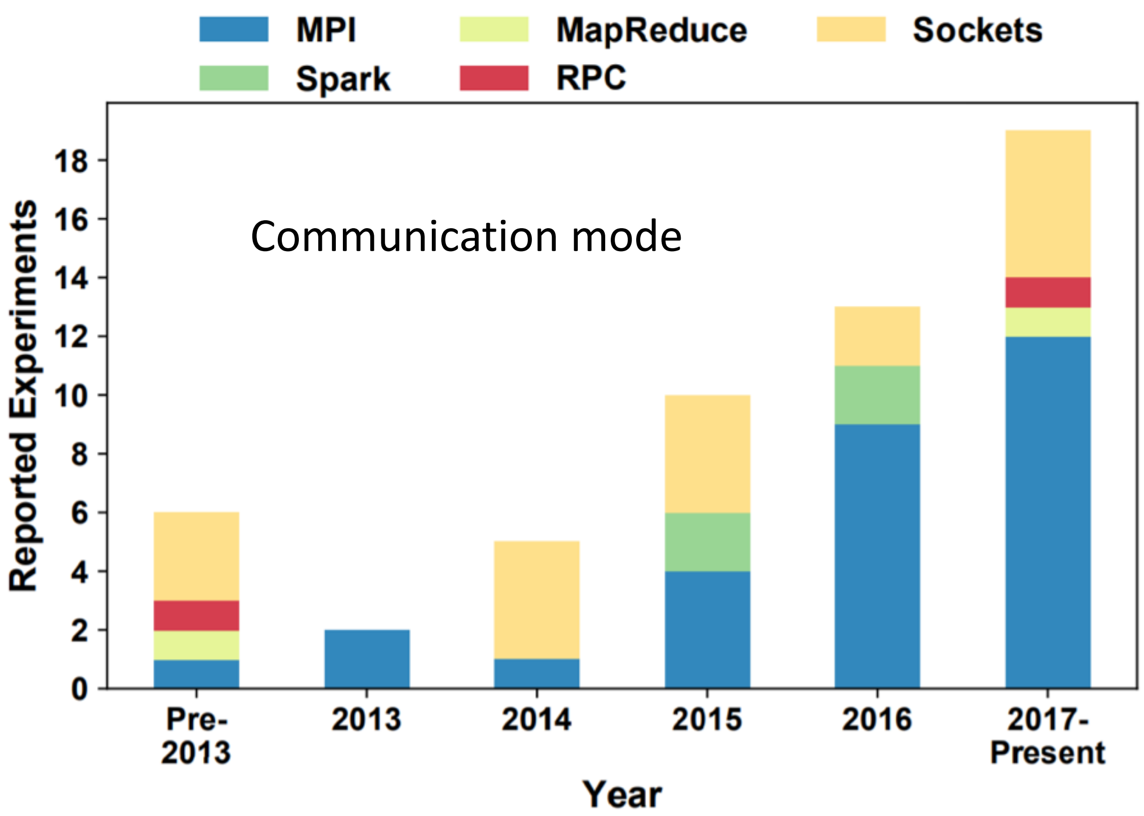
Deep Learning is largely on distributed memory today!

T. Ben-Nun, T. Hoefler: Demystifying Parallel and Distributed Deep Learning: An In-Depth Concurrency Analysis, CSUR 2019

Trends in distributed deep learning: node count and communication

The field is moving fast – trying everything imaginable – survey results from 252 papers in the area of parallel deep learning

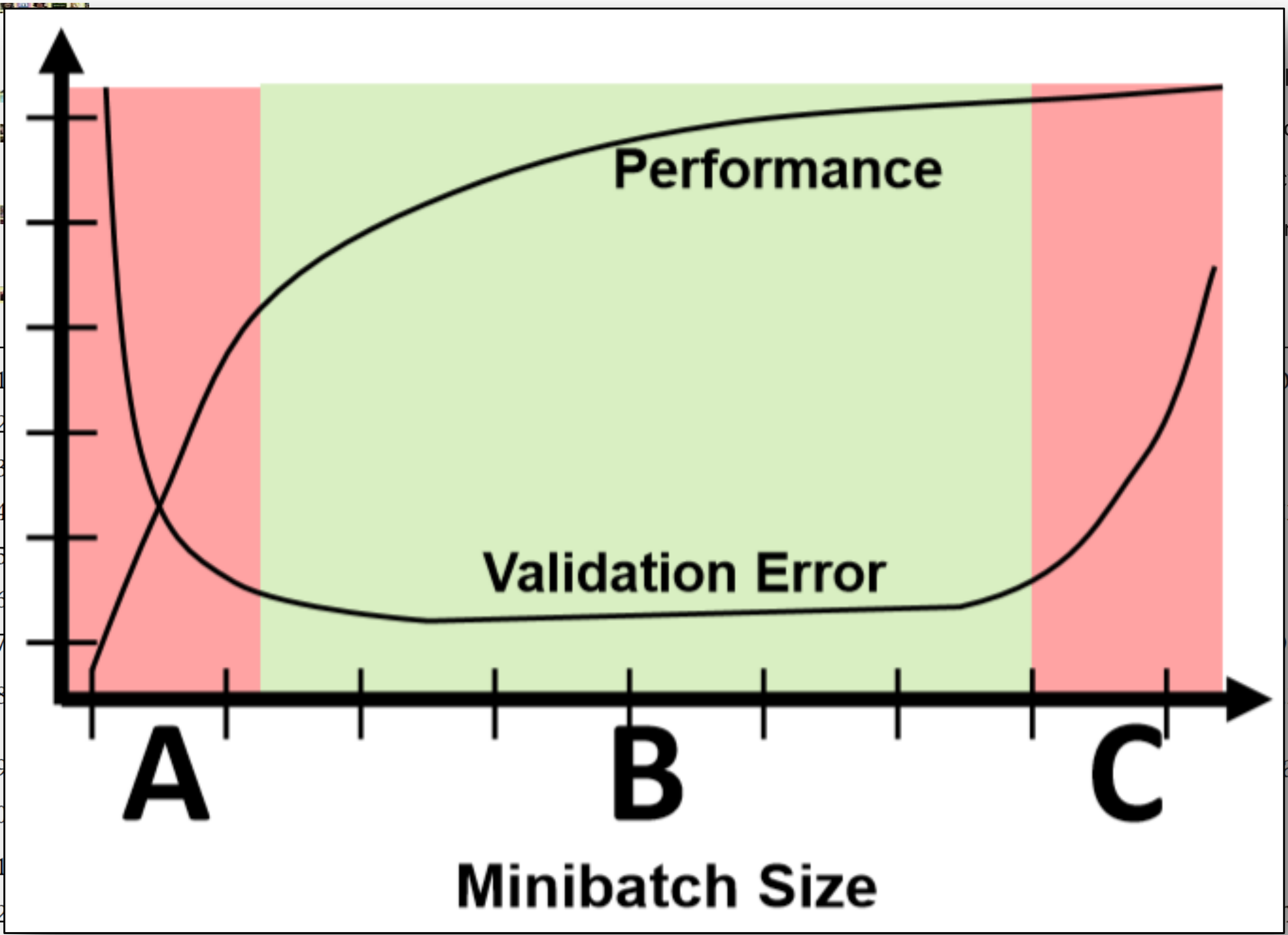




Deep Learning research is converging to MPI!

T. Ben-Nun, T. Hoefler: Demystifying Parallel and Distributed Deep Learning: An In-Depth Concurrency Analysis, CSUR 2019

Minibatch Stochastic Gradient Descent (SGD)



Cat	0.54
Dog	0.28
lane	0.07
orse	0.04
ycle	0.03
ruck	0.02
	0.02

Cat	1.00
Dog	0.00
Airplane	0.00
Horse	0.00
Bicycle	0.00
Truck	0.00

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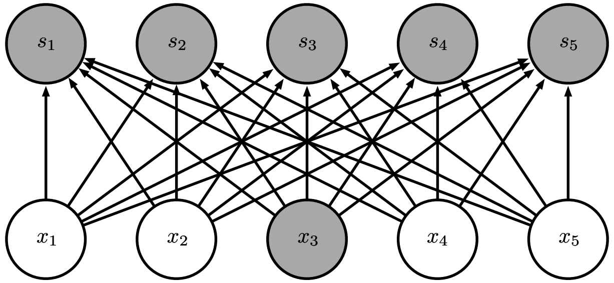
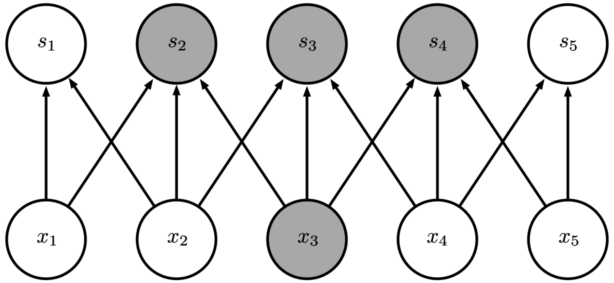
Ingredients of a neural network: Operators

- **Fully-connected layers (multi-layer perceptrons)**

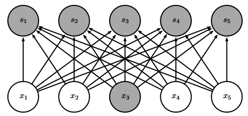


- **Convolution**

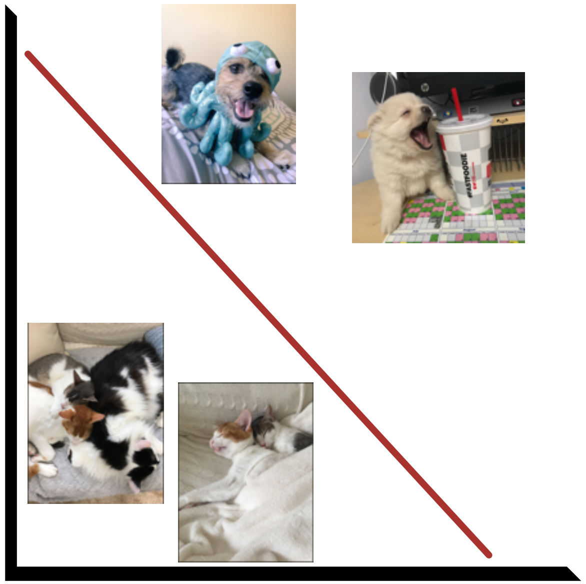


- **Many other moving parts:**
  - Pooling
  - Batch normalization [Ioffe & Szegedy 2015]
  - ReLU activations [Glorot, Bordes, & Bengion 2011]
  - …

Fully-connected layers



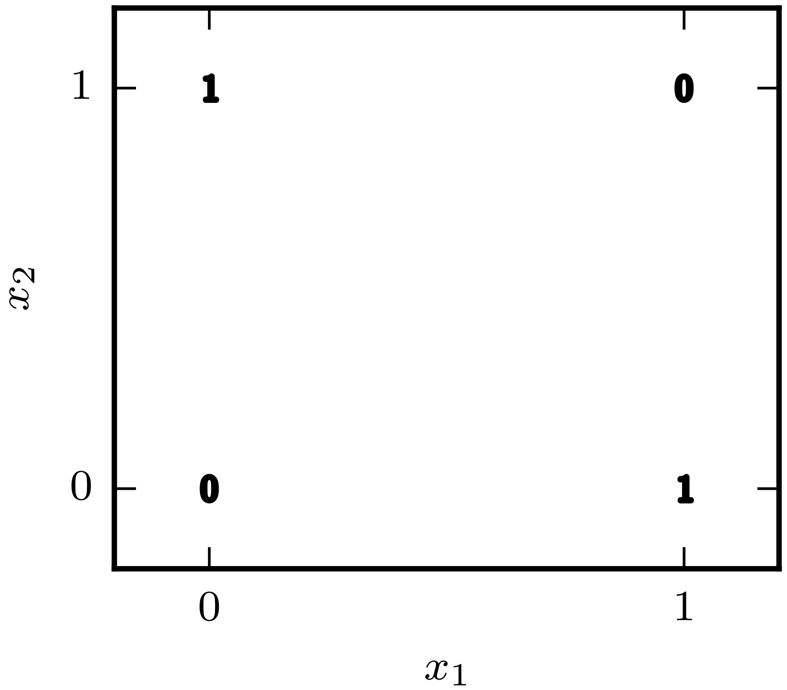
Perceptron [Rosenblatt 1958]



$$y = wx + b$$

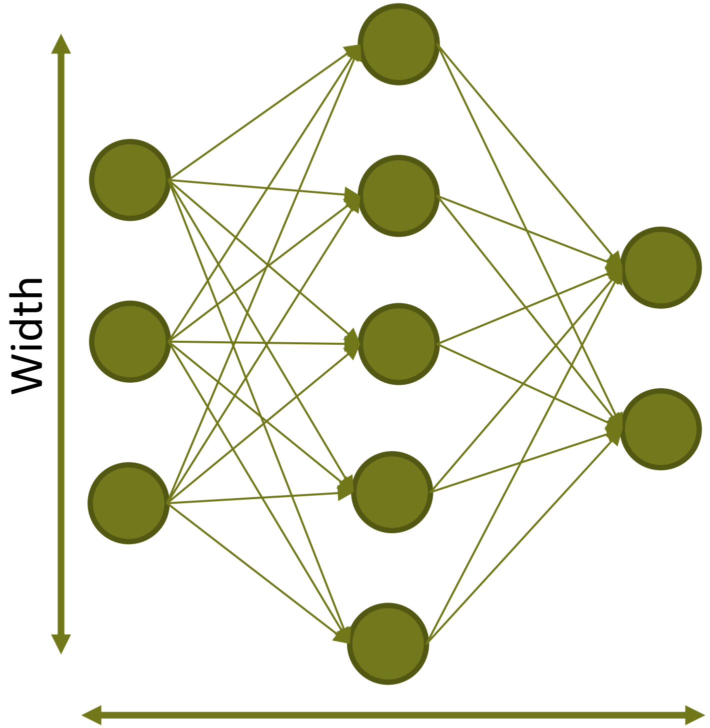
Learned weights and bias

Exclusive OR



Not linearly seperable!

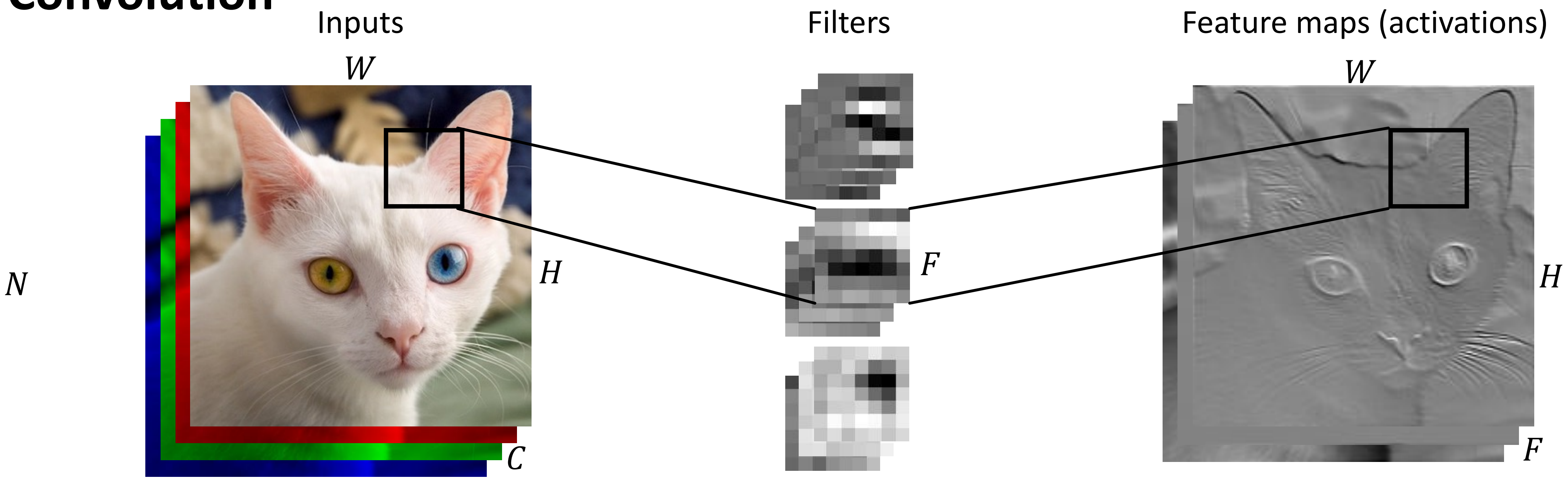
Multi-layer Perceptron

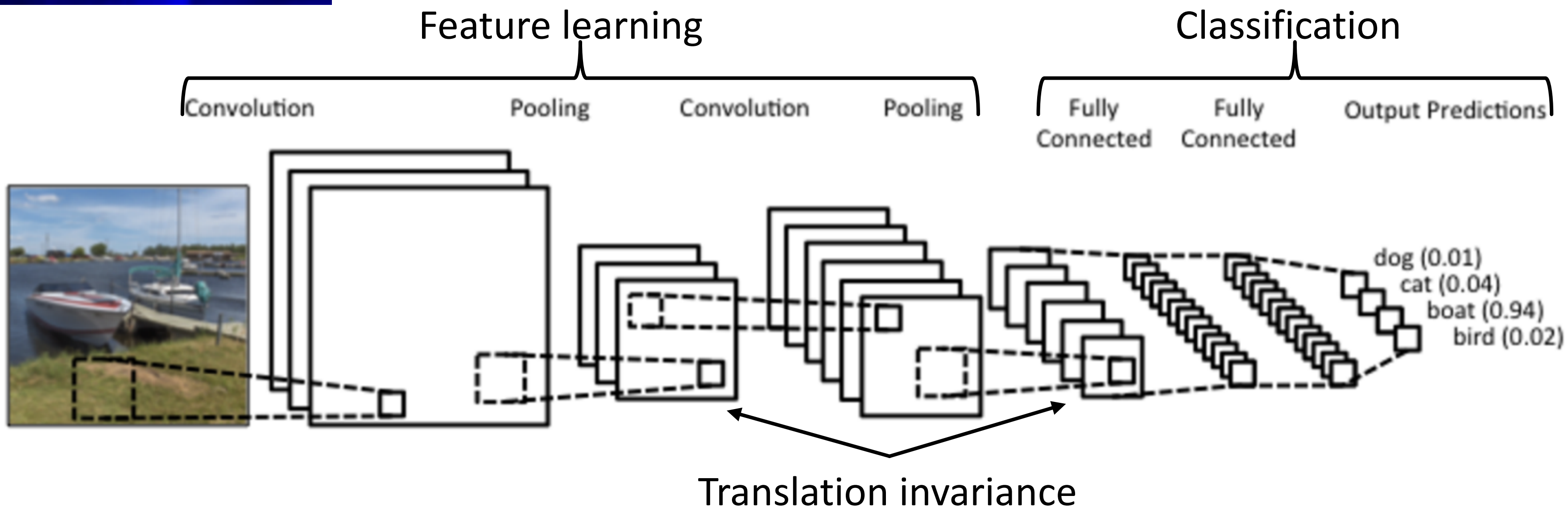


$$y = \sigma(Wx + b)$$

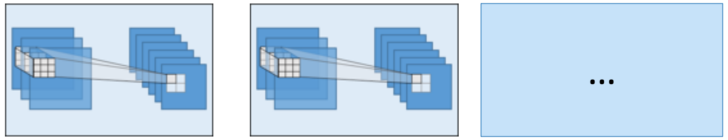
Universal!

Convolution





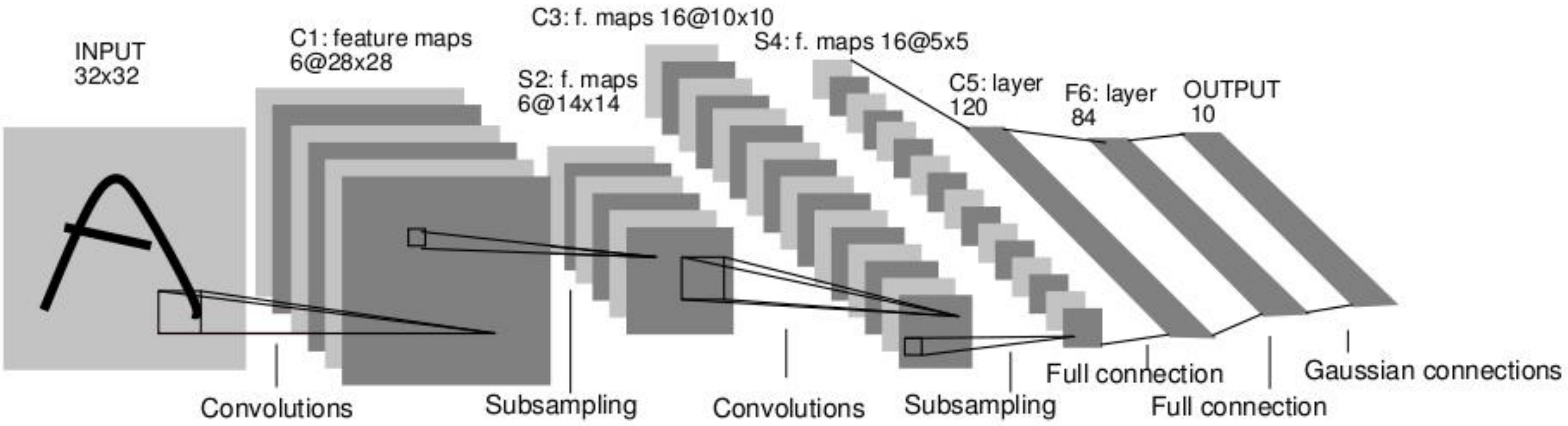
Operators



Operators

A short history of (old) CNNs

LeNet-5 [LeCun, Bottou, Bengio, & Haffner 1998]



- Average pooling
- Sigmoid/tanh nonlinearites
- Fully-connected layers at end
- Trained on MNIST (60k samples)

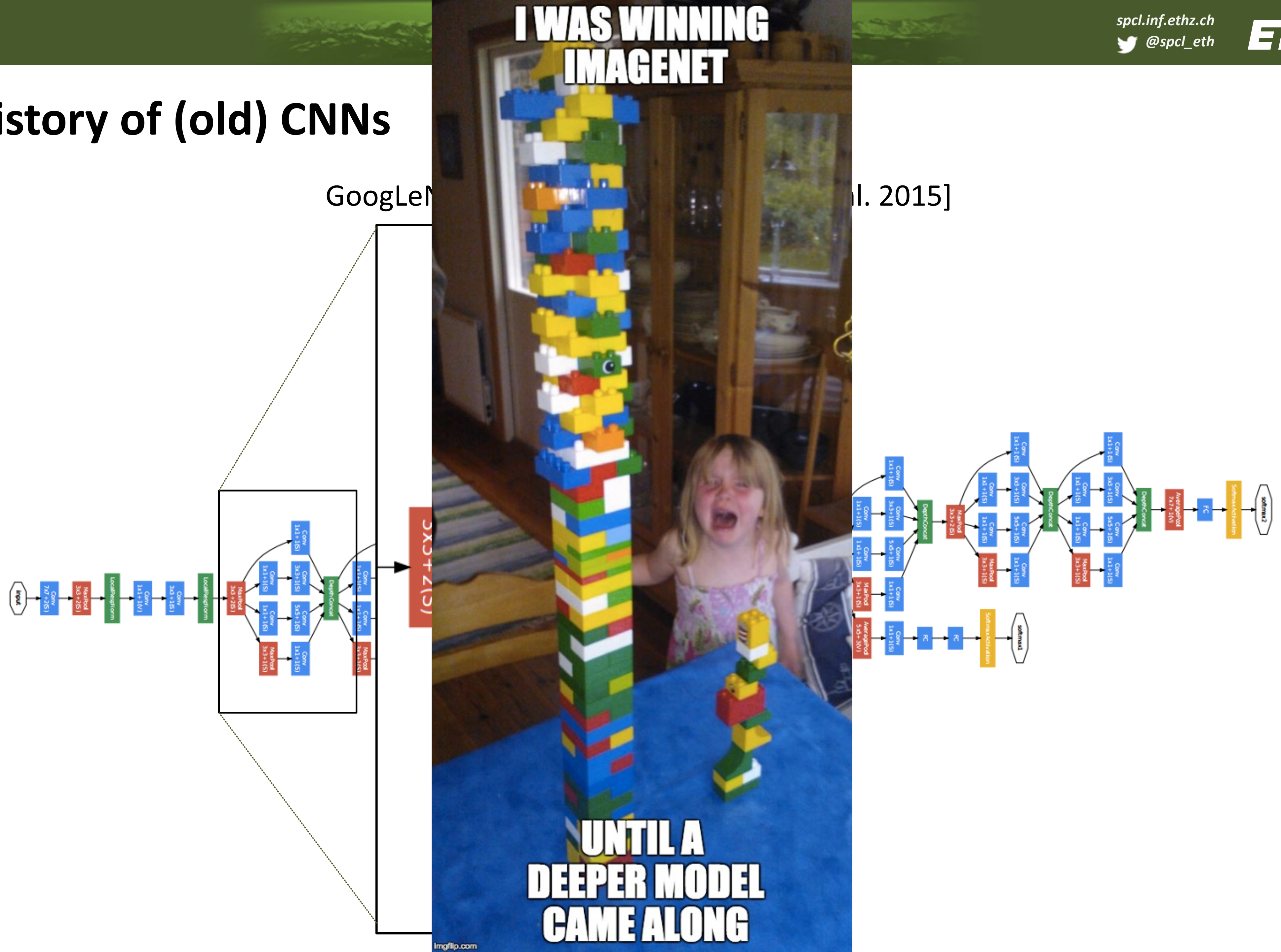
A short history of (old) CNNs

AlexNet [Krizhevsky, Sutskever, & Hinton 2012]

- Deeper, bigger model
- Dropout
- Trained on ImageNet (1.2M images)
- GPU implementation (2 GPUs for a week)

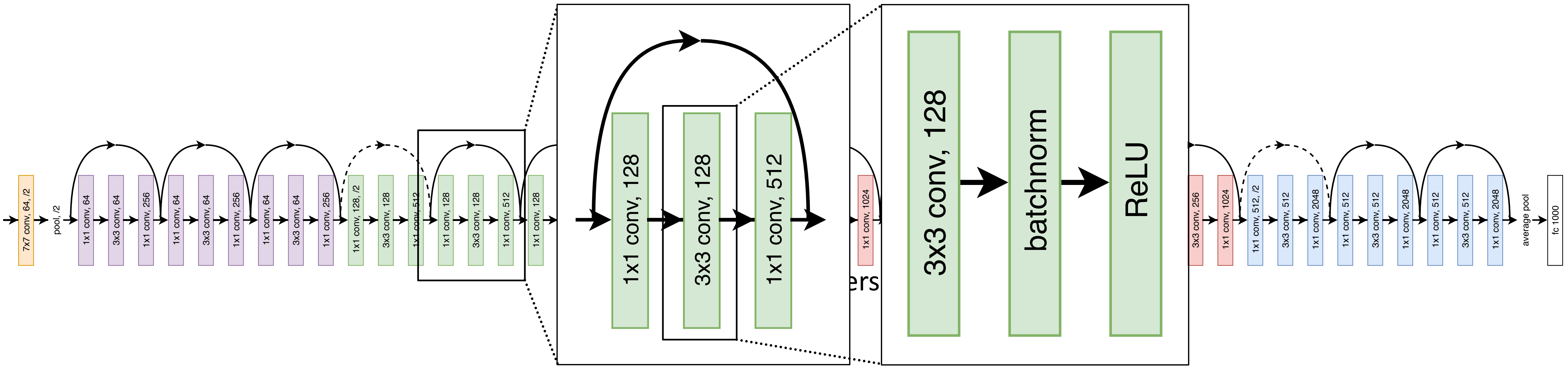
A short history of (old) CNNs

GoogLeN l. 2015]



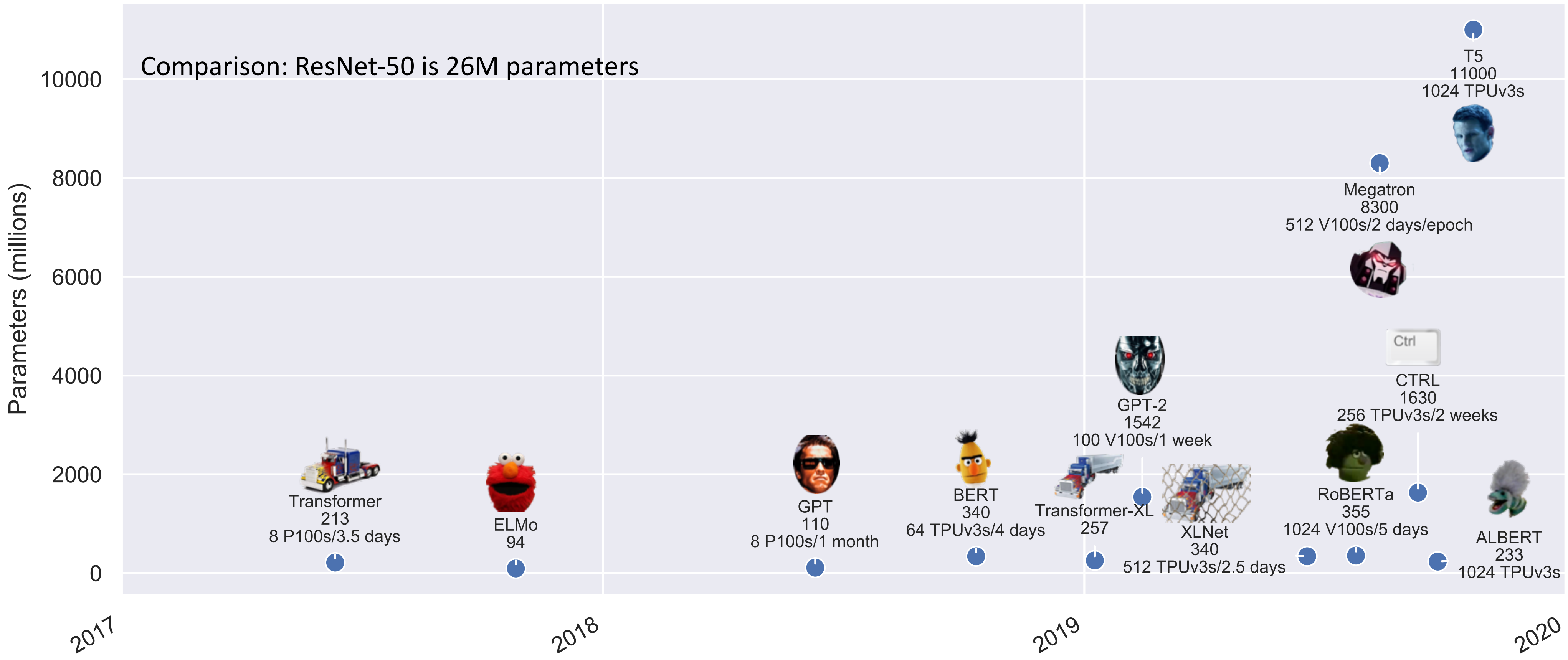
ResNet-50

ResNets [He, Zhang, Ren, & Sun, 2016]



GPT-2 (transformers)

- Sequence-to-sequence models (like RNNs but with more parallelism)
- Revolutionizing NLP like AlexNet &co. did for computer vision



GPT-2 (transformers)

(From Tensor2Tensor intro notebook)

Scaled Dot-product Attention

Layer: 5 Attention: Input - Input

Decoder (w/o enco

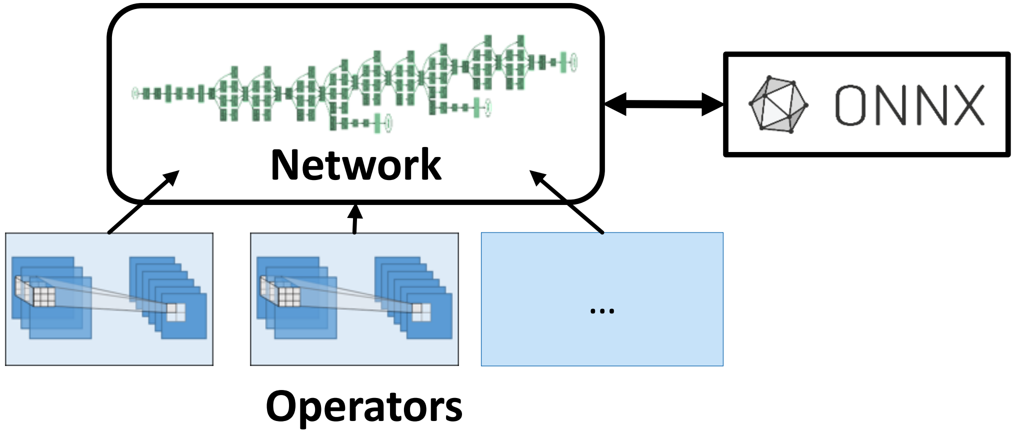
Stacked N times

Prompt (human-written):
Recycling is good for the world.
NO! YOU COULD NOT BE MORE WRONG!!

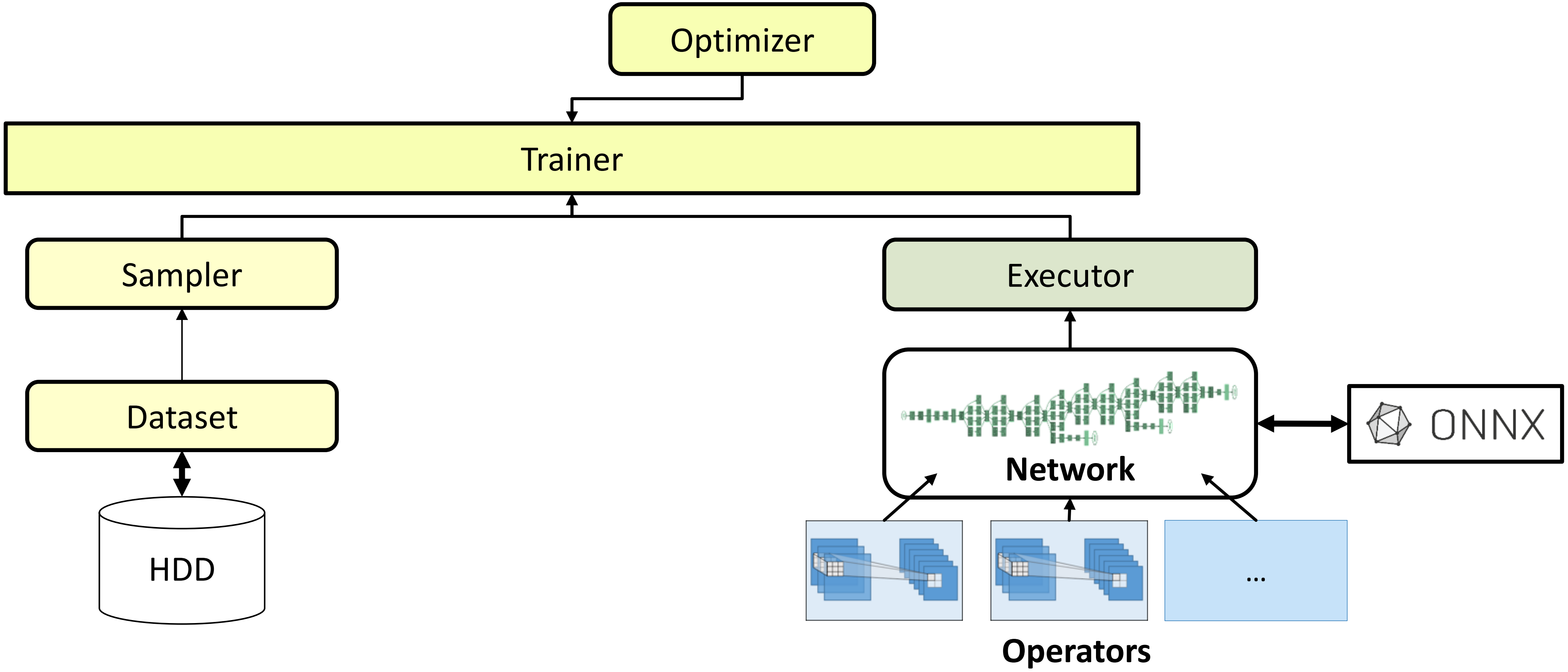
GPT-2-xlarge generated text:
Recycling is NOT good for the world. It is bad for the environment, it is bad for our health, and it is bad for our economy. I'm not kidding. Recycling is not good for the environment. It is destructive to the earth and it is a major contributor to global warming. Recycling is not good for our health. It contributes to obesity and diseases like heart disease and cancer. Recycling is bad for our economy. It increases the cost of a product, and in turn, the price of everything that is made with that product. Recycling is not good for our nation. We pay a tremendous price for the privilege of having the world's most advanced and efficient recycling system. Recycling is a huge, colossal waste of time, energy, money, and resources. And THAT is why we need to get back to basics and get back to basics in our recycling efforts. One of the best ways to start is to look at the process of creating a paper product. When you make a paper product, it is basically a long chain of materials. Everything from the raw materials (wood, cardboard, paper, etc.), to the reagents (dyes, solvents, etc.) to the printing equipment (chemicals, glue, paper, ink, etc.), to the packaging, to the packaging materials (mercury, chemicals, etc.) to the processing equipment (heating, cooling, etc.), to the packaging materials, to the packaging materials that are shipped overseas and to the packaging materials that are used in the United States. Each step along the way creates tons of waste that we constantly have to clean up. The process of making a paper product is a very wasteful one. But the end result is something that all of us need to consume. And if we want to keep the recycling process running efficiently, then we really need to think about each and every step that goes into making a paper product.

https://openai.com/blog/better-language-models/#sample8

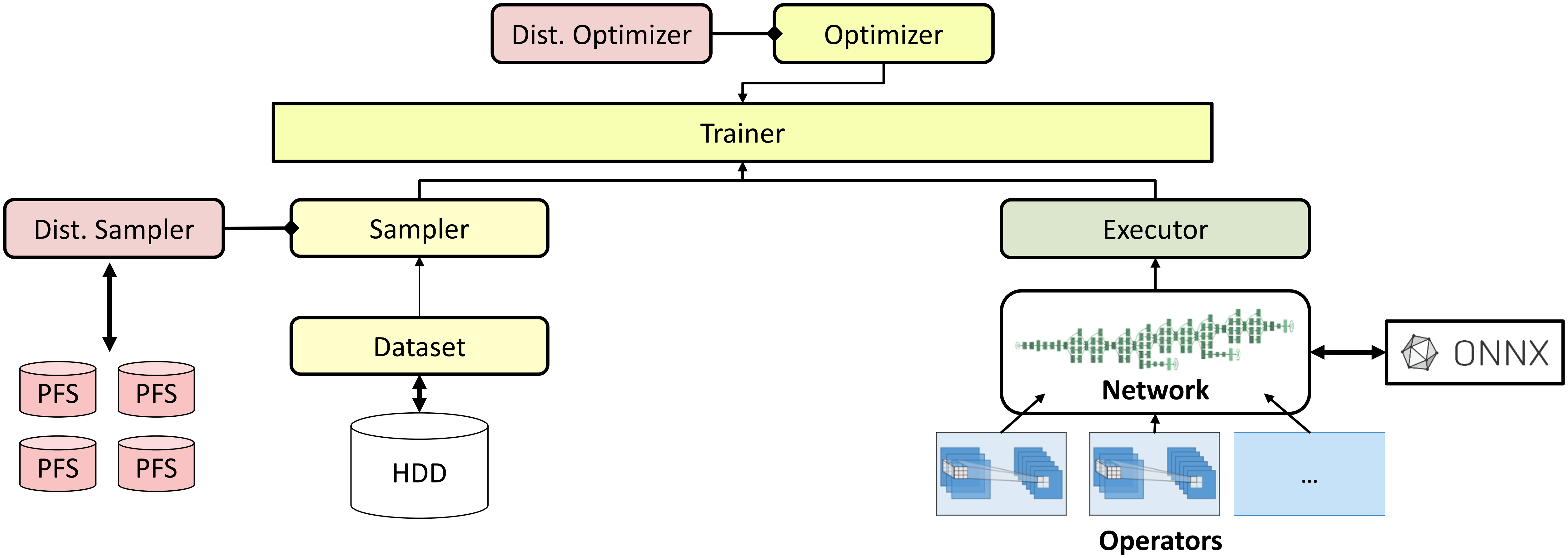
Networks

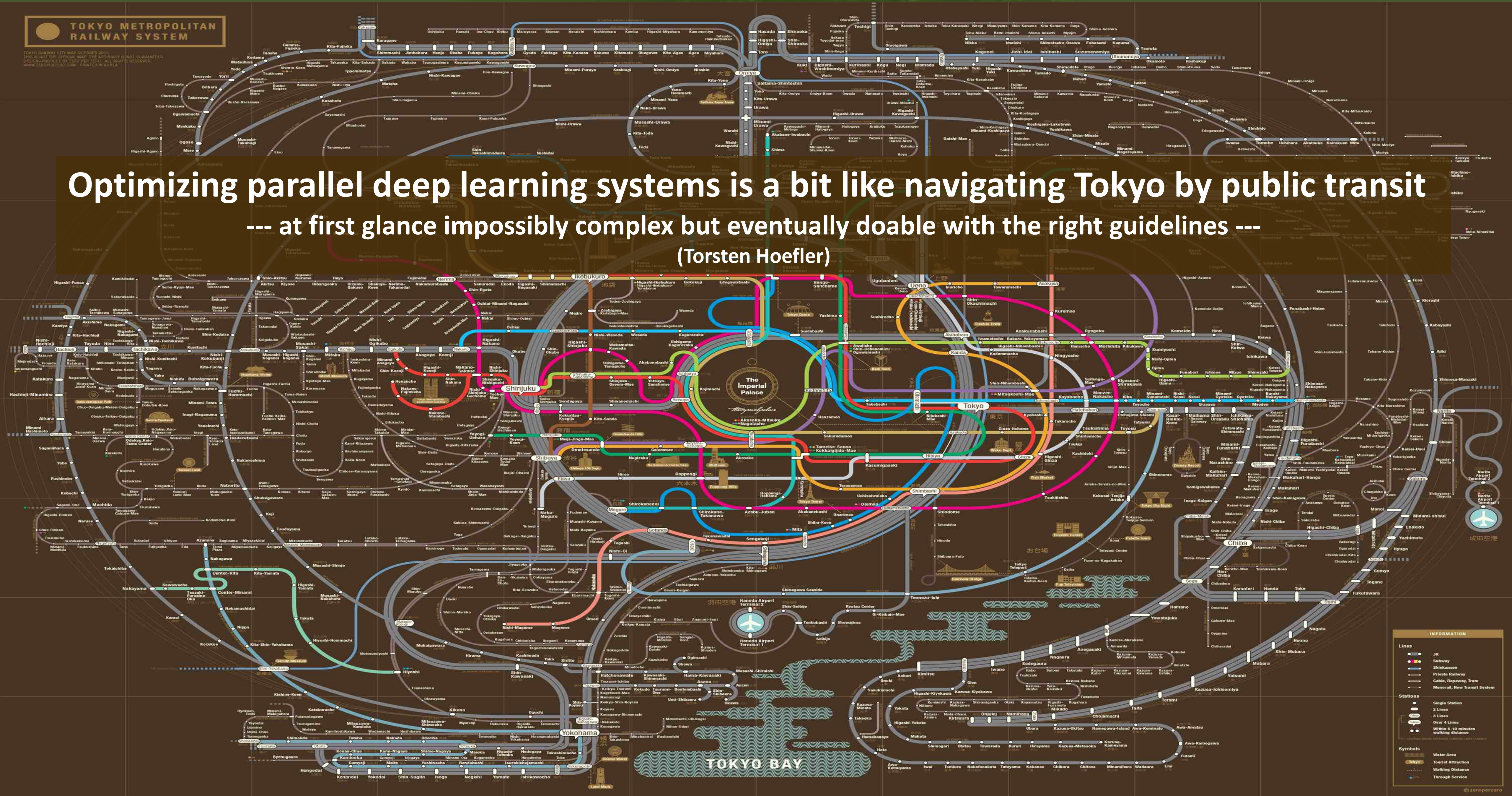


Training


Optimizer
Trainer
Sampler
Executor
Dataset
Network
ONNX
HDD
...
Operators

Distributed training





Optimizing parallel deep learning systems is a bit like navigating Tokyo by public transit

--- at first glance impossibly complex but eventually doable with the right guidelines ---

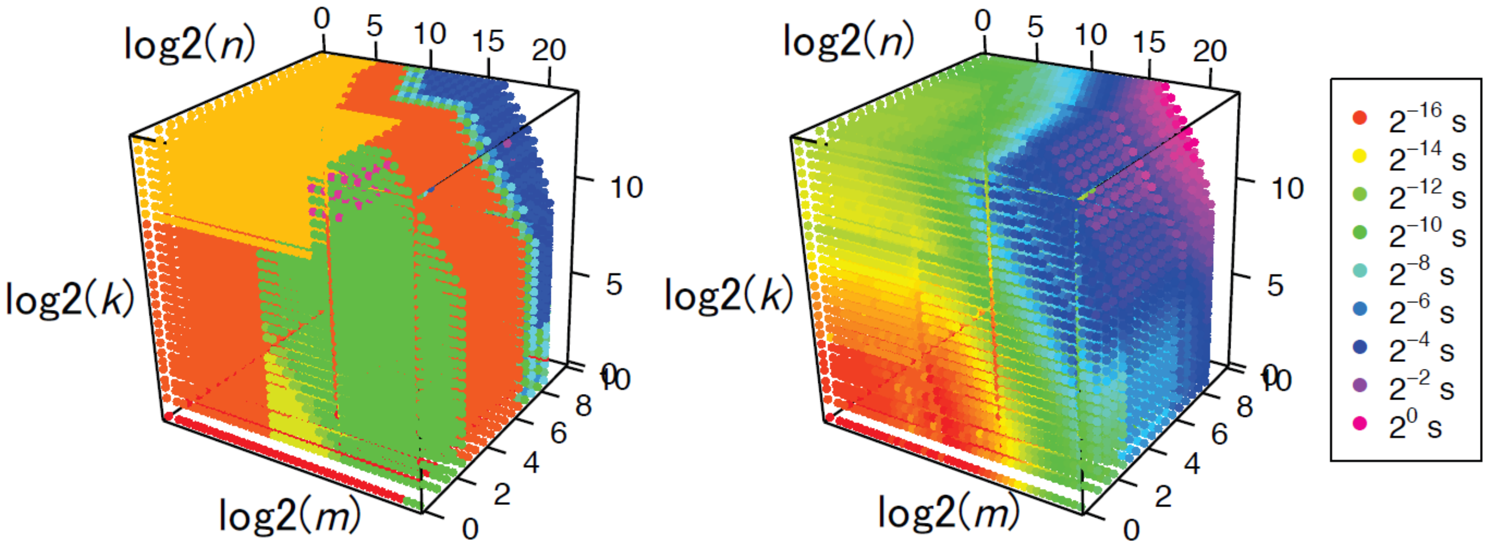
(Torsten Hoefler)

Operator implementations: fully-connected layers

$$Y = \sigma(WX + b)$$

- **Dominated by matrix-matrix multiplication**
  - Standard tricks: vectorize, tile, fusion, …
- **BLAS3 GEMM**
  - cuBLAS, MKL, …

Performance is not consistent!



[Oyama et al.]

Operator implementations: convolution

$$Y_{k,f,i,j} = \sum_{c=0}^{C-1} \sum_{a=-O}^{O} \sum_{b=-O}^{O} X_{k,c,i+a,j+b} w_{f,c,a+O,b+O}$$

Direct

Direct

4	1	9	8
5	9	9	8
0	7	3	4
2	6	3	1

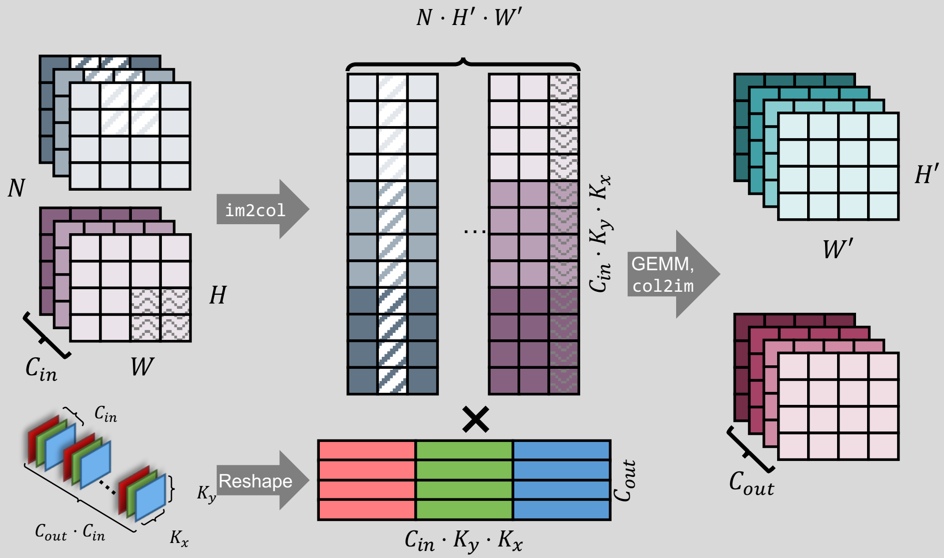
*

1	-1	0
0.1	-2	0
3	4	1.1

=

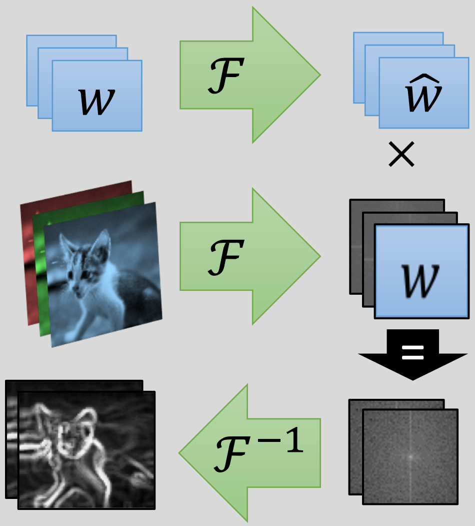
21.9	59.3	53.9	43.9
-6.3	16.8	12.3	12
9.6	15.3	25.8	14
0.4	7.1	52.1	53.1

im2col

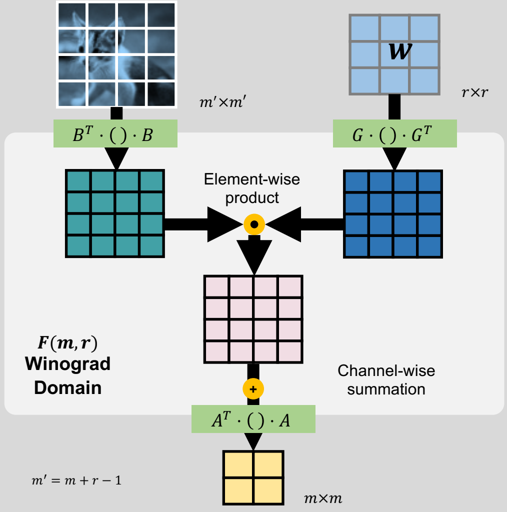


Indirect

FFT



Winograd



[Chellapilla et al. 2006; Mathieu et al. 2014; Lavin & Gray 2016; Liu et al. 2017]

Microbatching (μ-cuDNN) – how to implement layers best in practice?

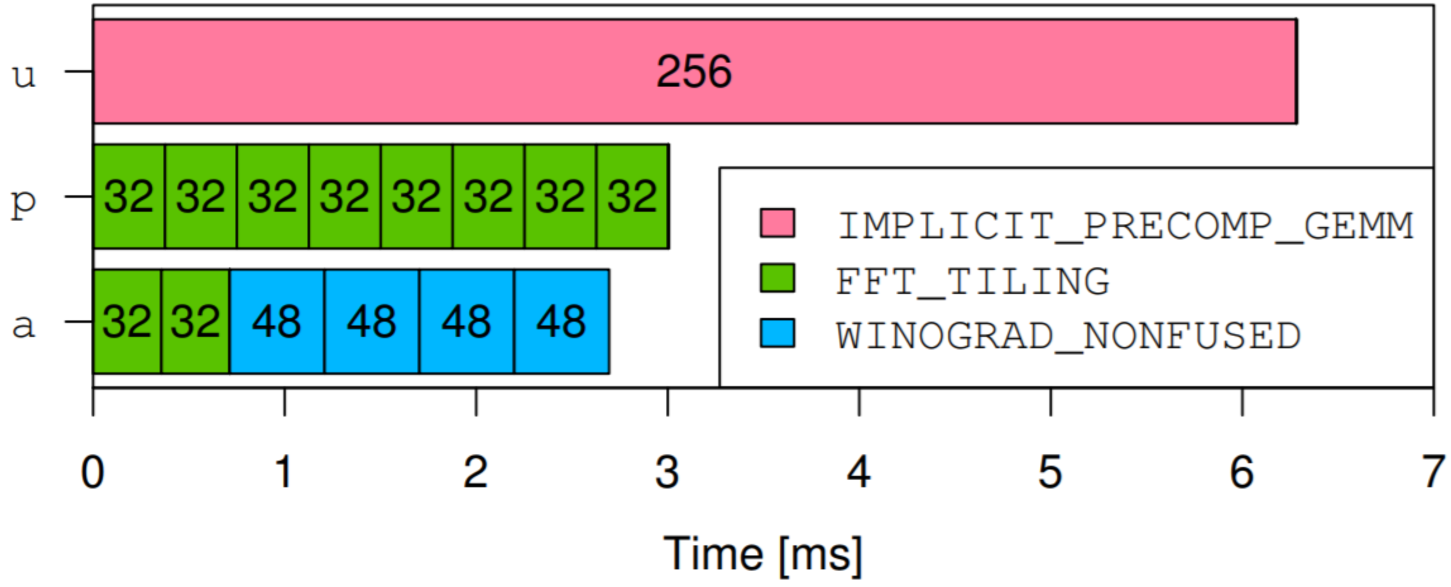
Microbatching Strategy

Fast (up to 4.54x faster on DeepBench)

none (undivided)

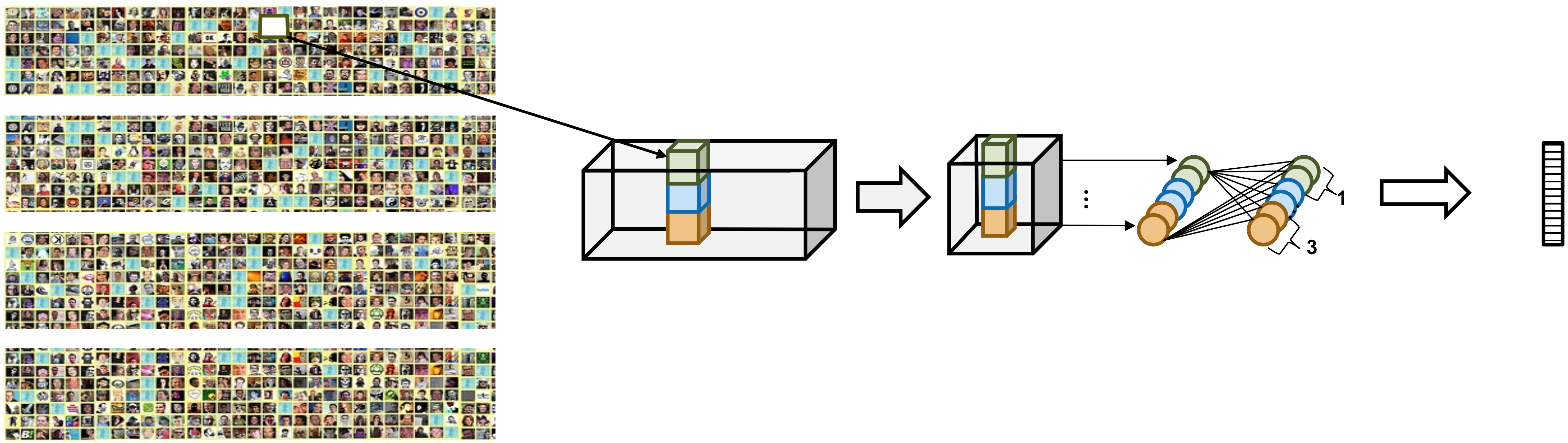
powers-of-two only

any (unrestricted)



[Oyama et al. 2018]

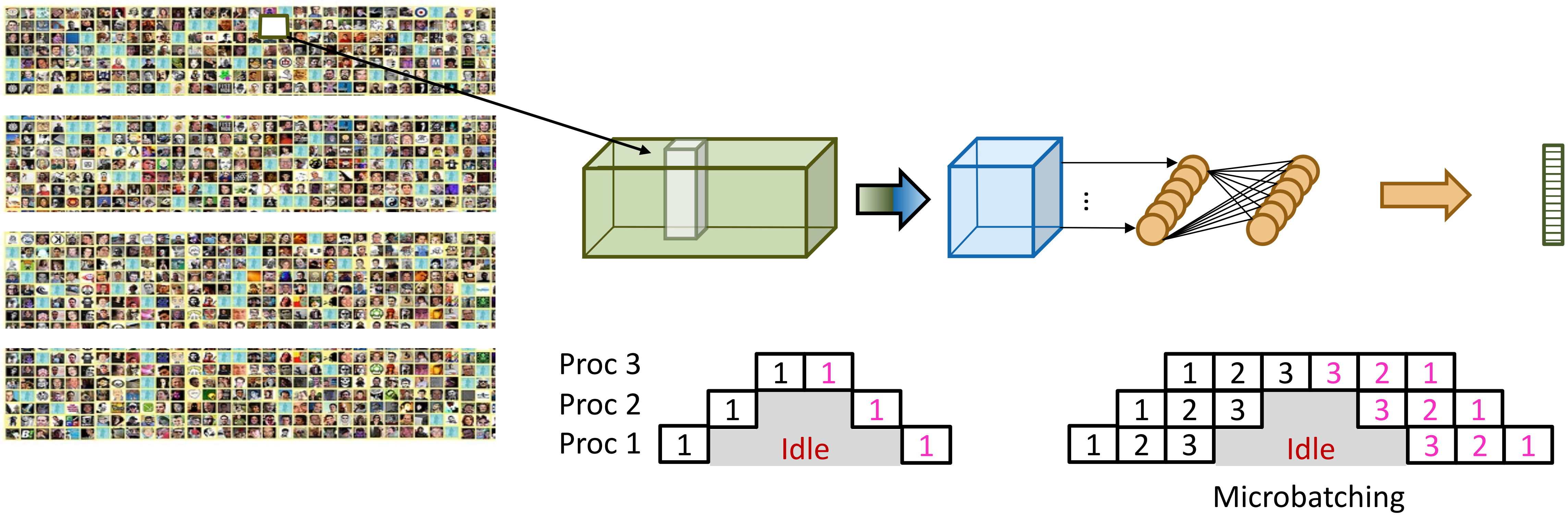
Model parallelism – limited by network size



- Parameters can be distributed across processors
- Mini-batch has to be copied to all processors
- Backpropagation requires complex communication every layer

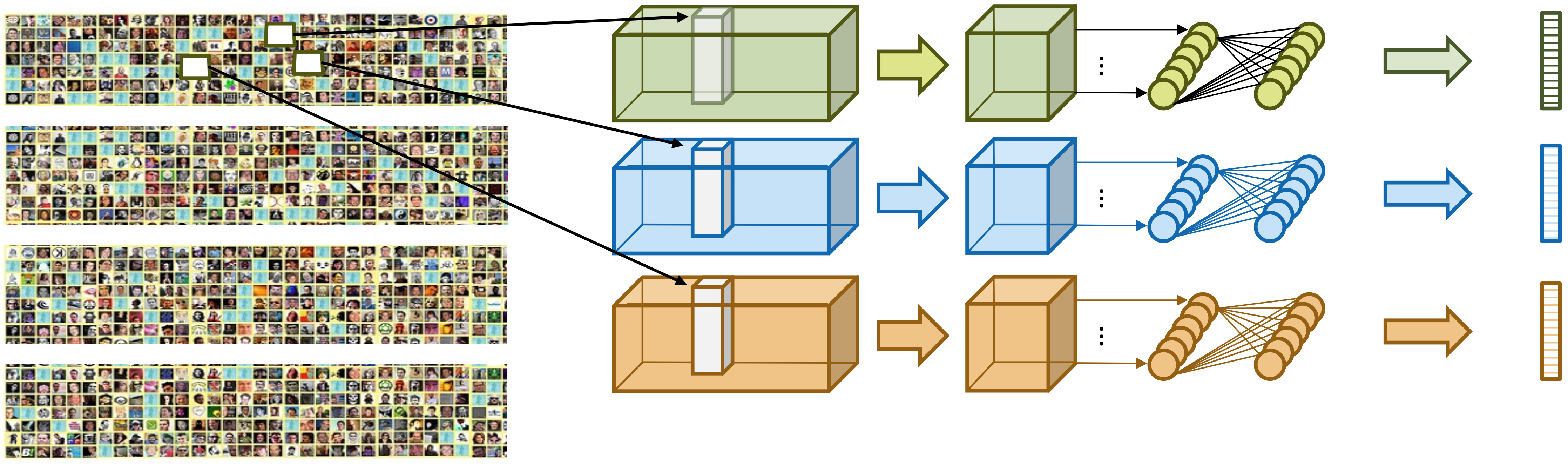
[Forrest et al. 1987]

Pipeline parallelism – limited by network size



- Layers/parameters can be distributed across processors
- Sparse communication pattern (only pipeline stages)
- Mini-batch has to be copied through all processors
- Consistent model introduces idle-time "bubble"

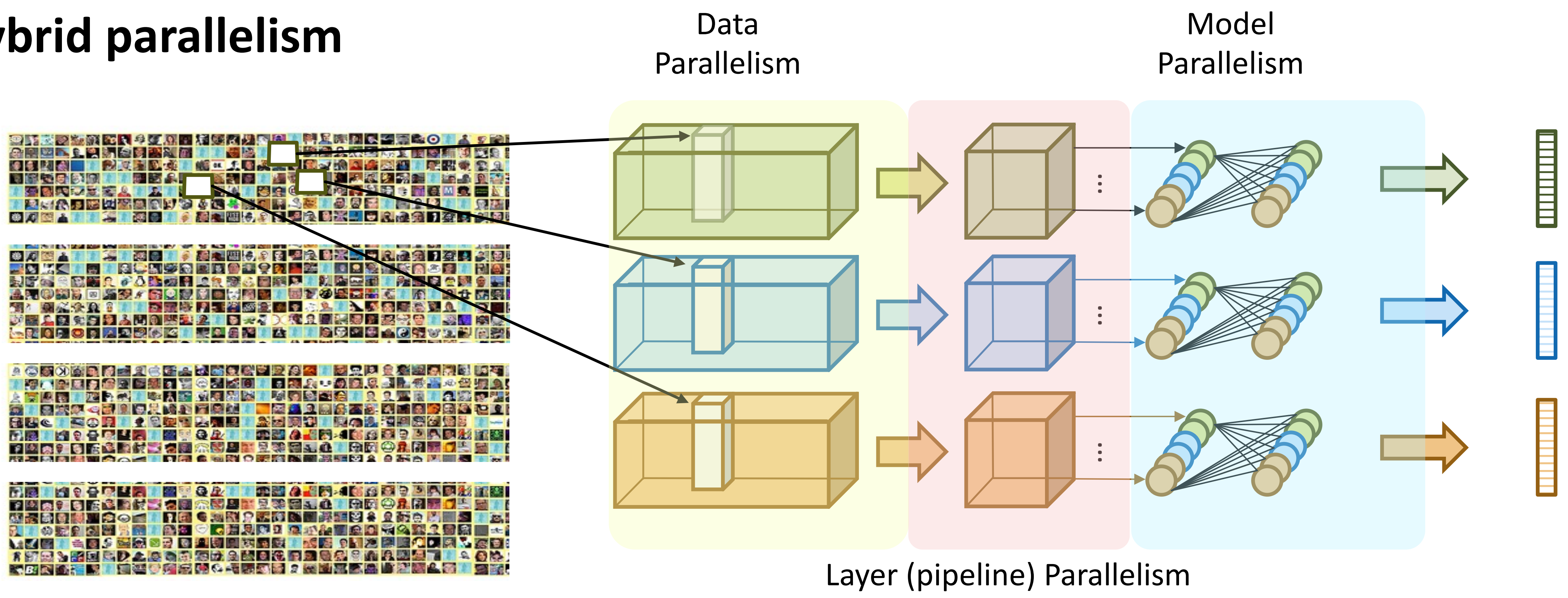
Data parallelism – limited by batch-size



- Simple and efficient solution, easy to implement
- Duplicate parameters at all processors
- Affects generalization

[Zhang et al. 1989]

Hybrid parallelism



- **Layers/parameters can be distributed across processors**
- **Can distribute minibatch**
- **Often specific to layer-types (e.g., distribute fc layers but handle conv layers data-parallel)**
  - Enables arbitrary combinations of data, model, and pipeline parallelism – very powerful!

[Krizhevsky 2014; Dean et al. 2012; Ben-Nun & Hoefler 2019]

Other ways to think about parallelism

- **All definitions are fuzzy (including this 🙂)**

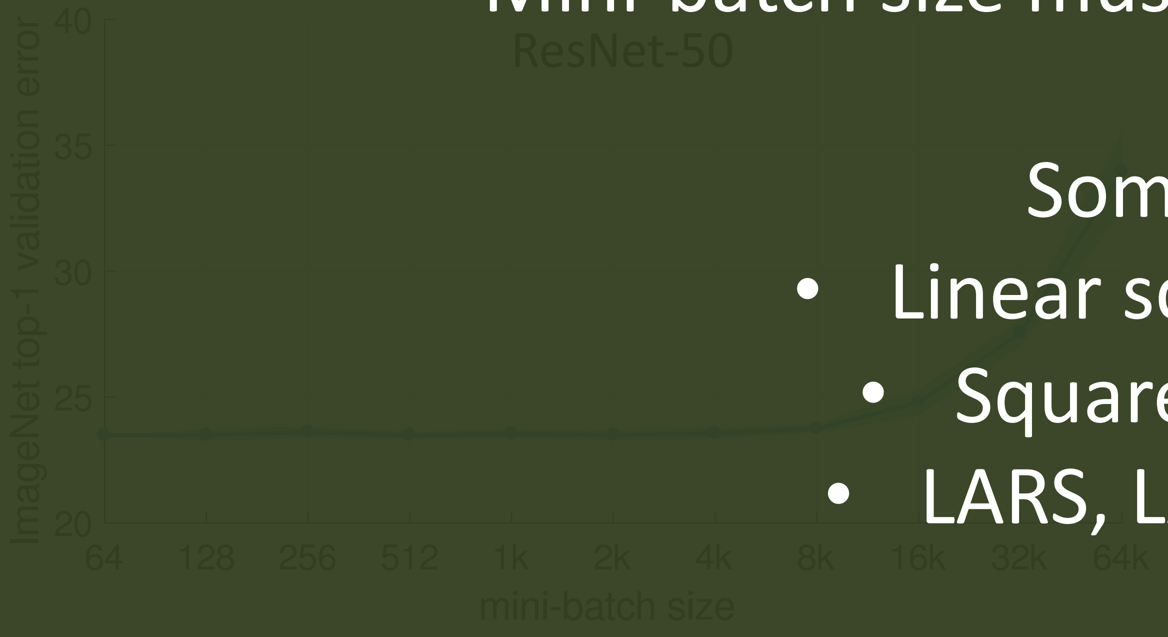
- **Data-, model-, pipeline-, hybrid-parallelism**

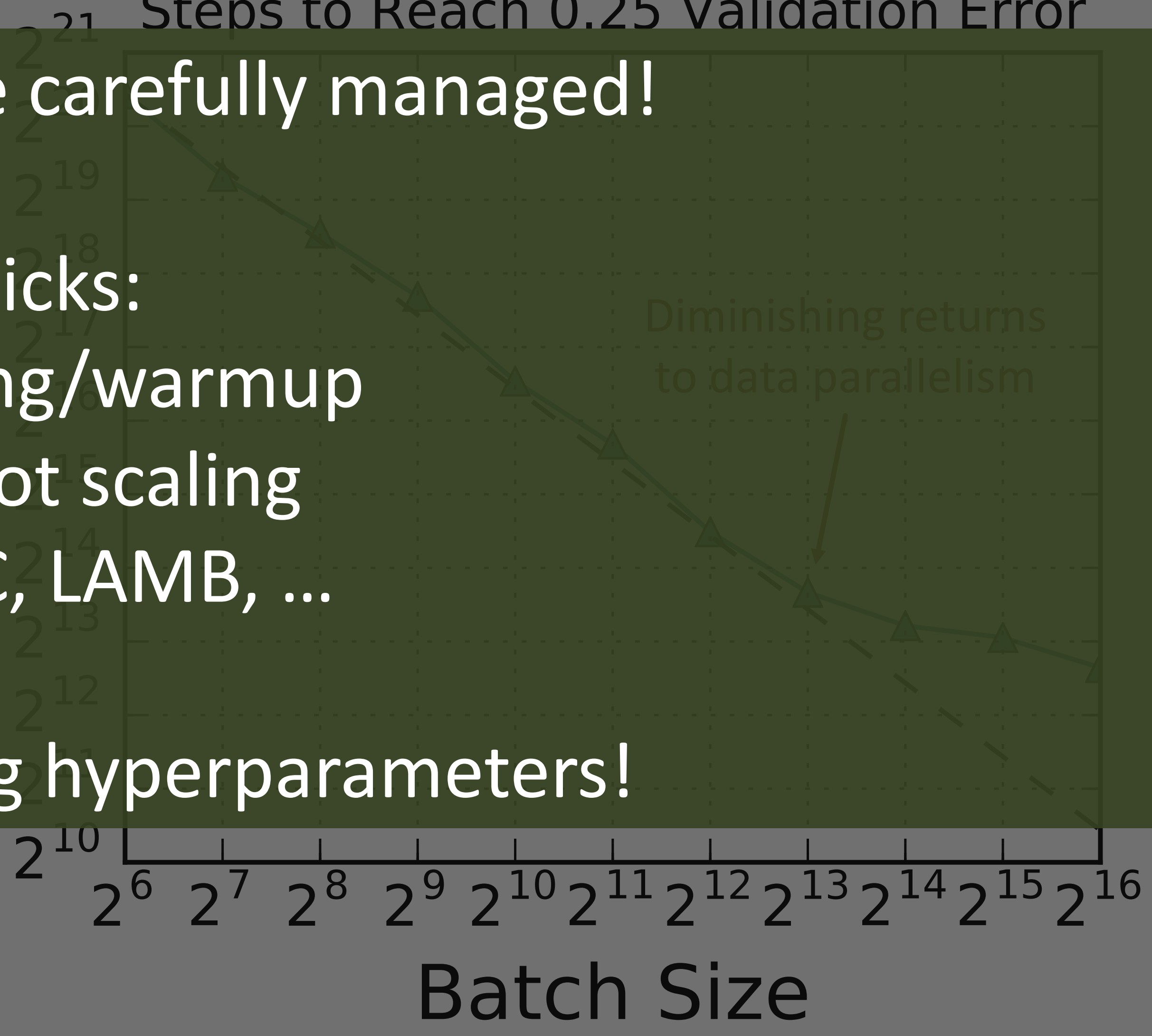
- **Weak vs strong scaling**
  - What do you keep the same vs what do change?
  - Mini-batch weak scaling: grow the mini-batch
  - Mini-batch model scaling: grow the model size (not so useful in general…)
  - Strong scaling: Fix everything, use more GPUs

- **For convolution: based on partitioned tensor dimensions**
  - Sample-, spatial-, channel-, filter-parallelism

Large mini-batches

- **Make the mini-batch really big!**





Mini-batch size must be carefully managed!

Some tricks:

- Linear scaling/warmup
- Square root scaling
- LARS, LARC, LAMB, …

Often requires retuning hyperparameters!

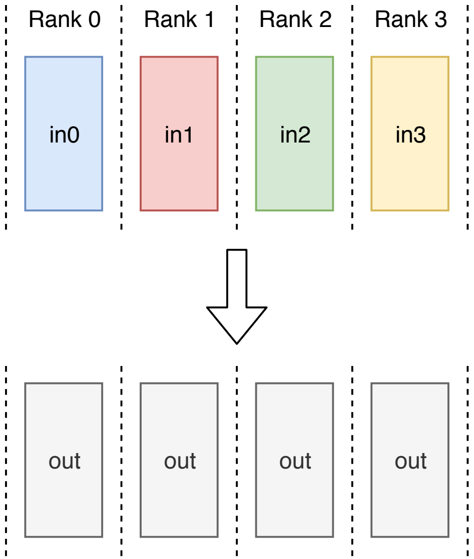
[Goyal et al. 2017; Shallue et al. 2019]

Collectives for deep learning

- **Certain communication patterns can be optimized**
- **People keep reinventing MPI**
  - Baidu Allreduce, NCCL, Gloo, Horovod, …

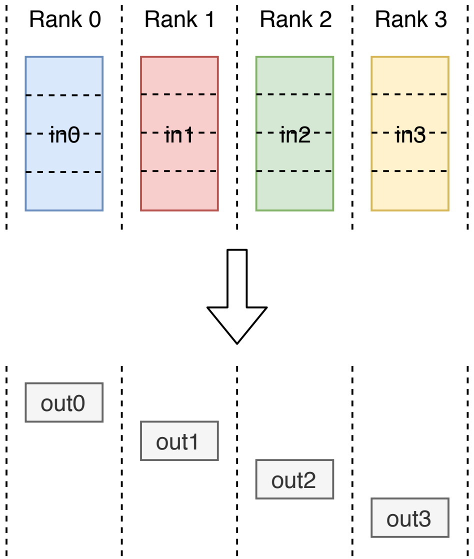
- **What we need (for this talk):**

Allreduce



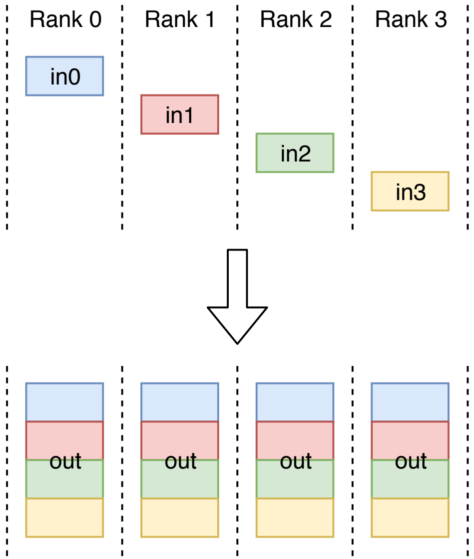
`out[i] = sum(inX[i])`

Reduce-scatter



`outY[i] = sum(inX[Y*count+i])`

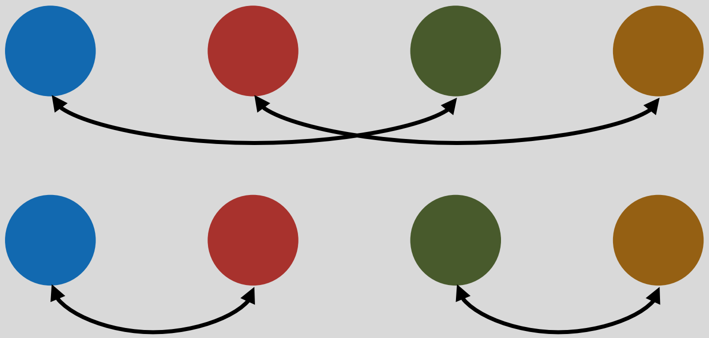
Allgather



`out[Y*count+i] = inY[i]`

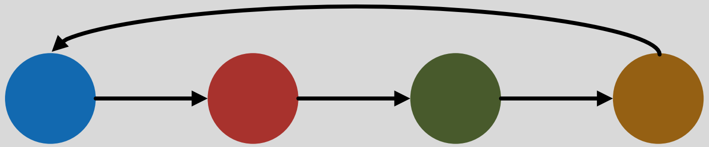
Reduce-scatter

Recursive-halving

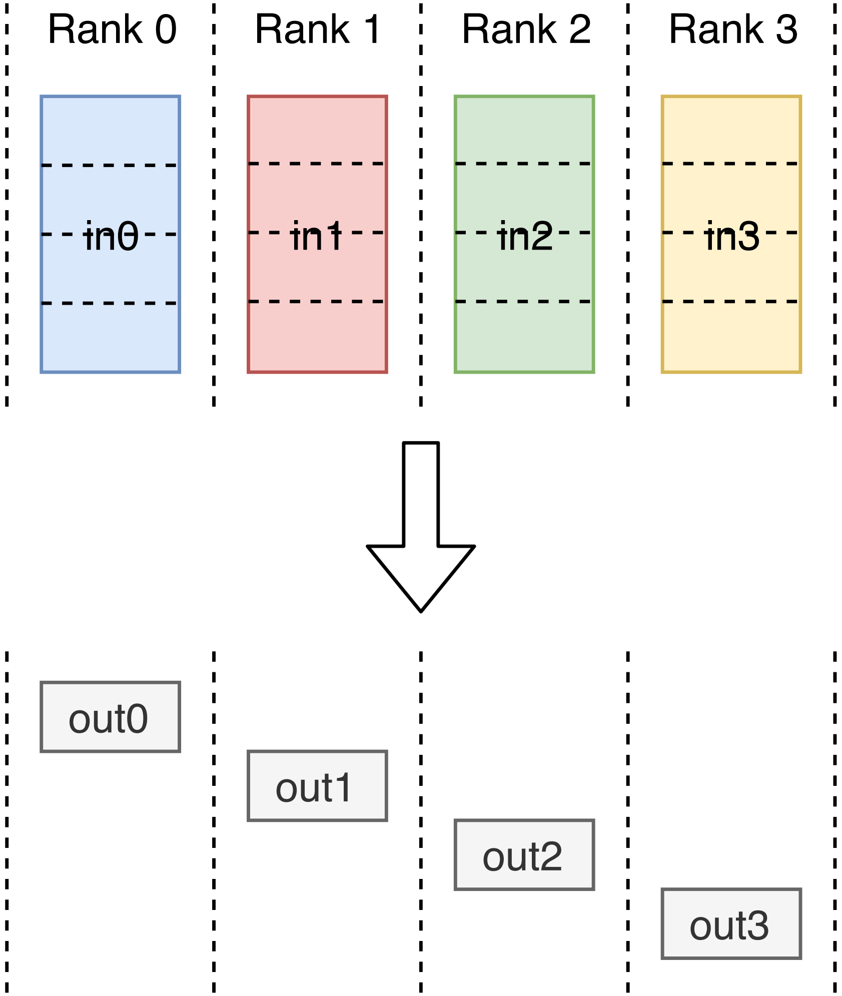


$$\alpha \lg p + \frac{p-1}{p} n\beta + \frac{p-1}{p} n\gamma$$

Ring



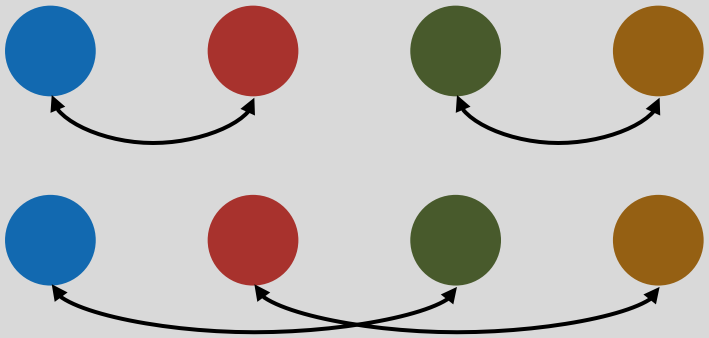
$$(p-1)\alpha + \frac{p-1}{p} n\beta + \frac{p-1}{p} n\gamma$$




```
outY[i] = sum(inX[Y*count+i])
```

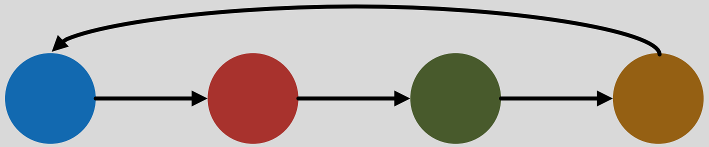
Allgather

Recursive-doubling

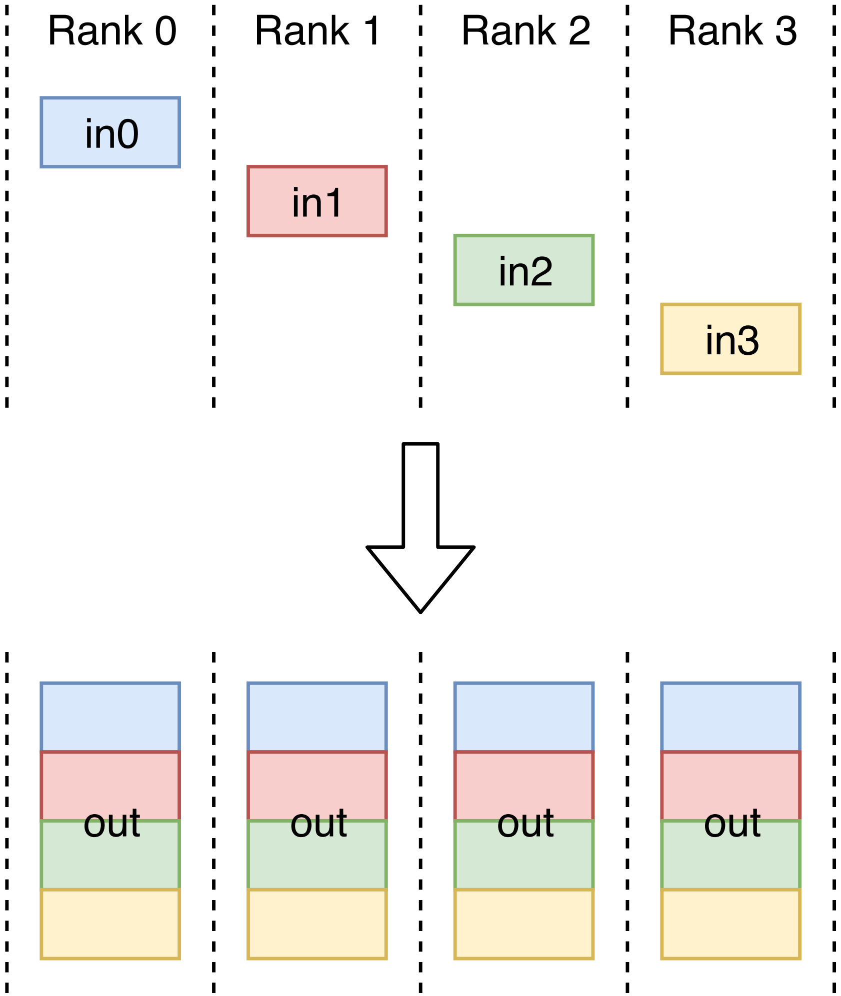


$$\alpha \lg p + \frac{p-1}{p} n\beta$$

Ring



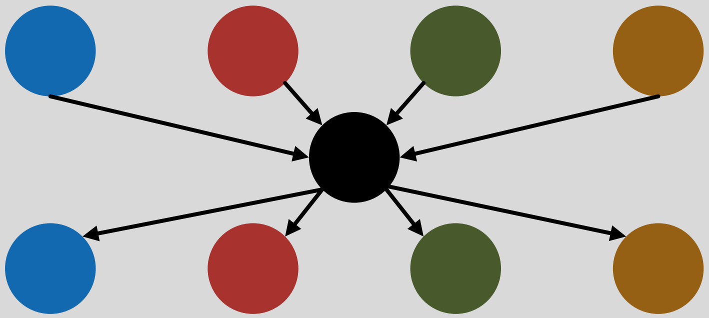
$$(p-1)\alpha + \frac{p-1}{p} n\beta$$



`out[Y*count+i] = inY[i]`

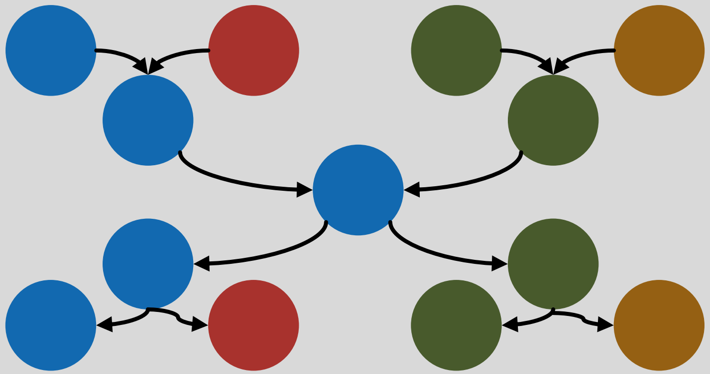
Allreduce

Parameter Server

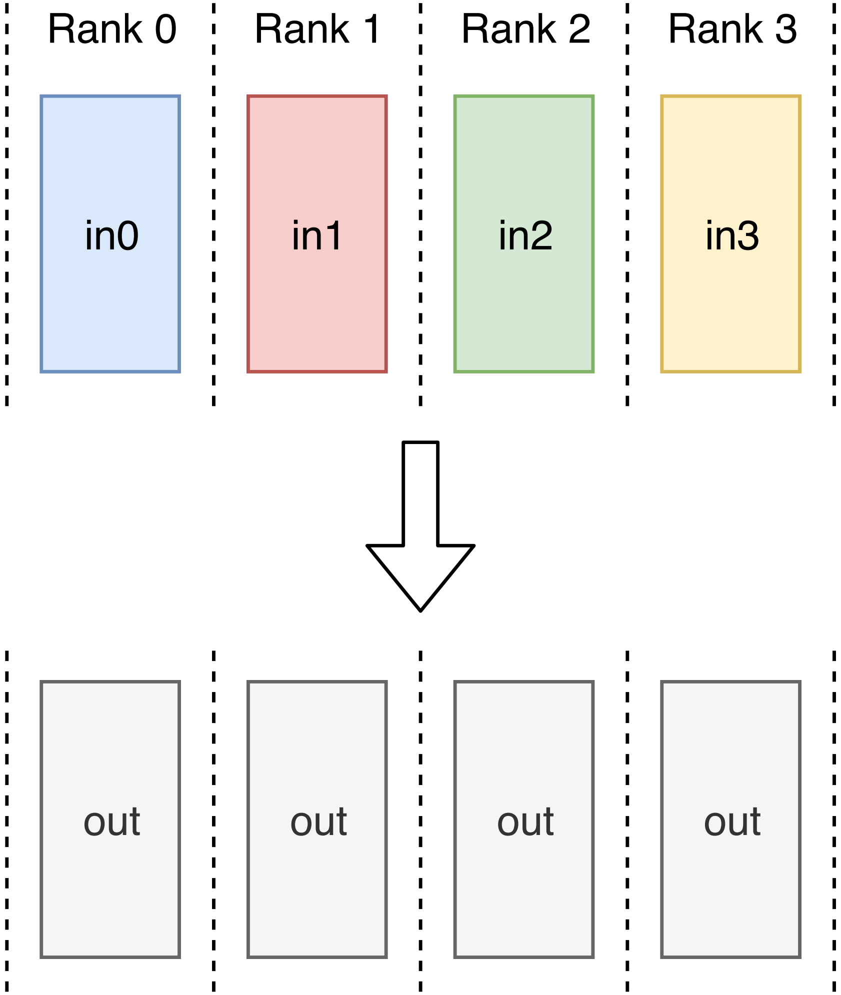


$$2p\alpha + 2pn\beta + pn\gamma$$

Tree (reduce/broadcast)



$$2\alpha \lg p + 2\beta n \lg p + \gamma n \lg p$$



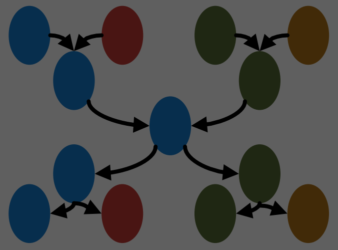
`out[i] = sum(inX[i])`

Allreduce

Parameter Server

$2p\alpha + 2pn\beta + pn\gamma$

Tree



$2\alpha \lg p + 2\beta n \lg p + \gamma n \lg p$

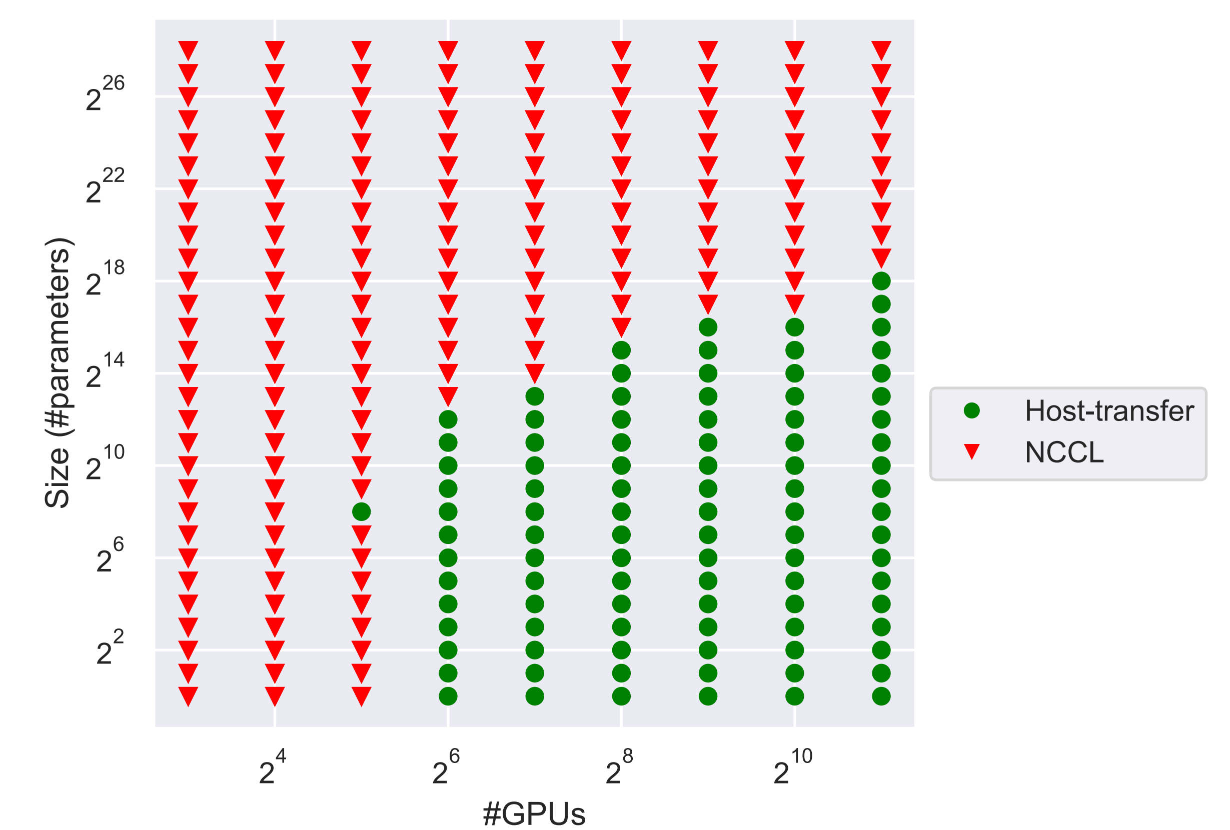
Butterfly (doubling)

$\alpha \lg p + \beta n \lg p + \gamma n \lg p$

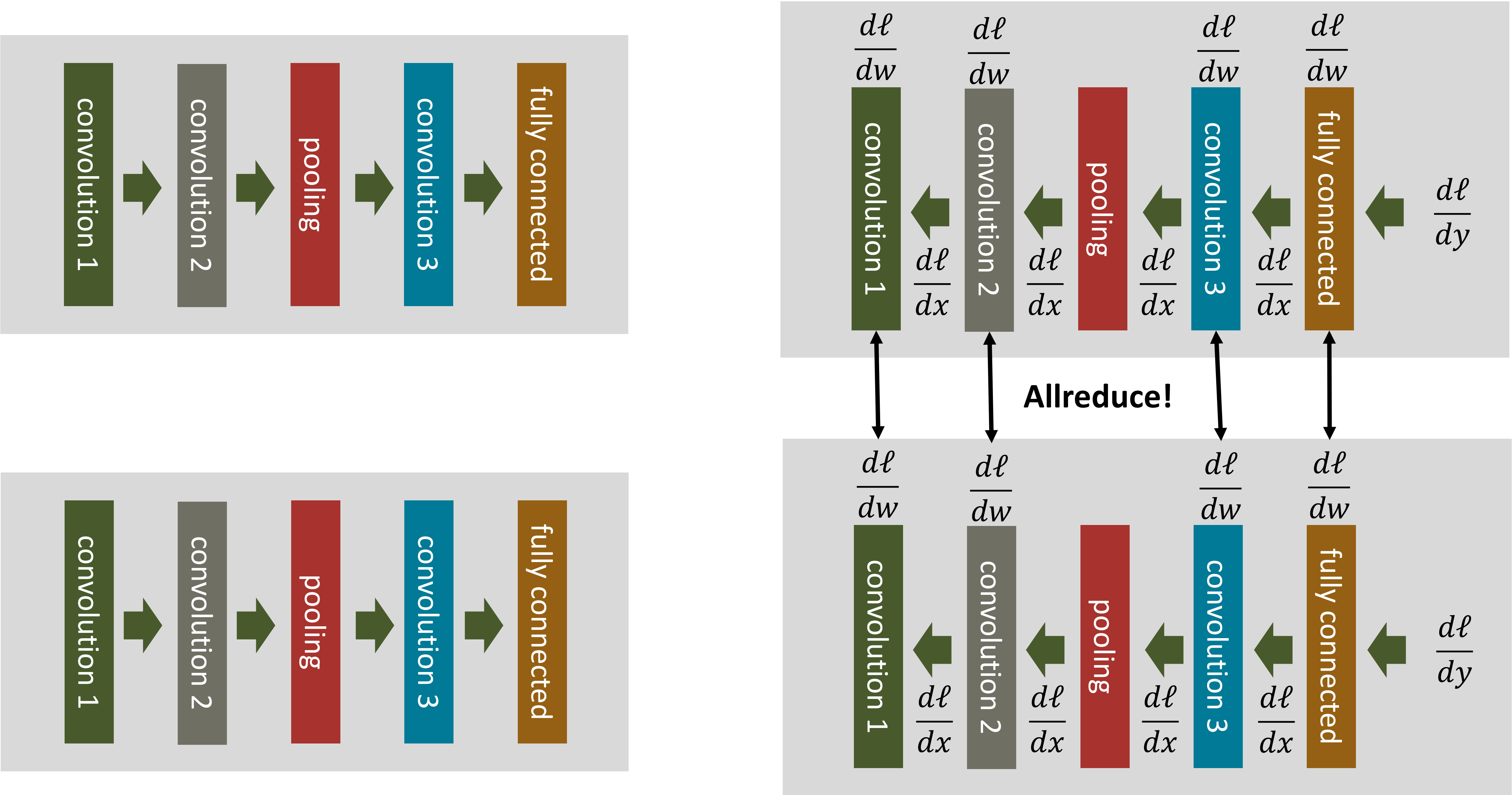
$n\beta + \frac{p-1}{p} n\gamma$

$n\beta + \frac{p-1}{p} n\gamma$

Implementation matters!

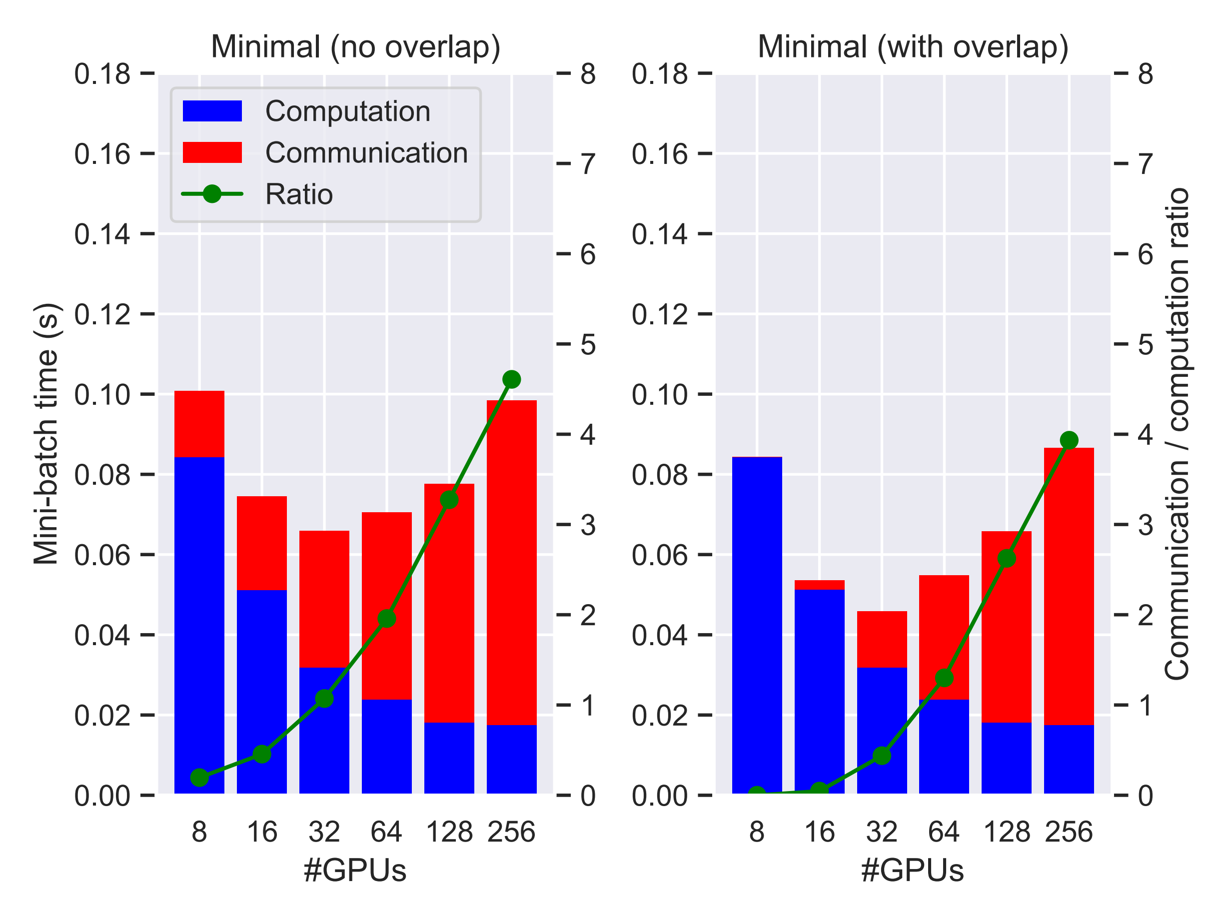


Distributed data-parallelism

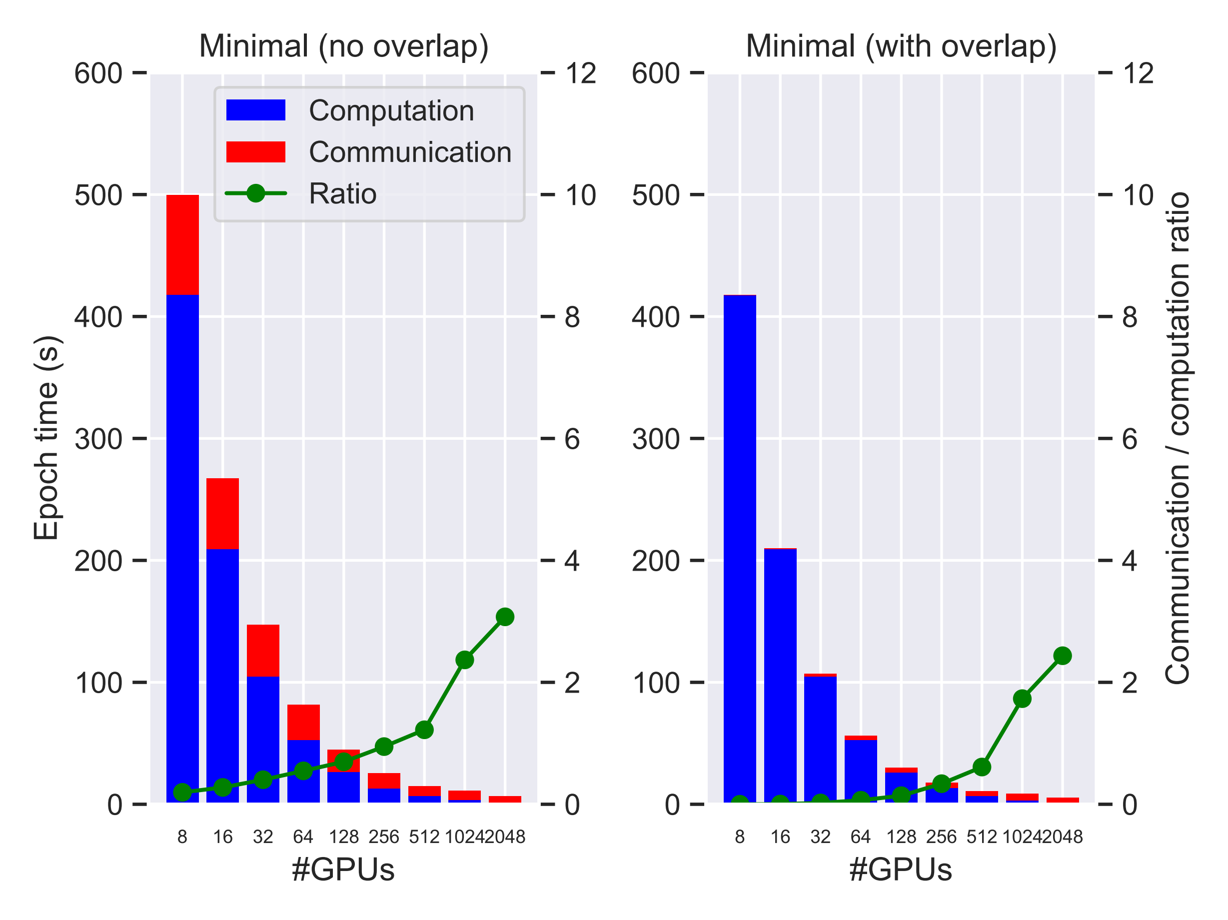


Distributed data-parallelism

Strong scaling

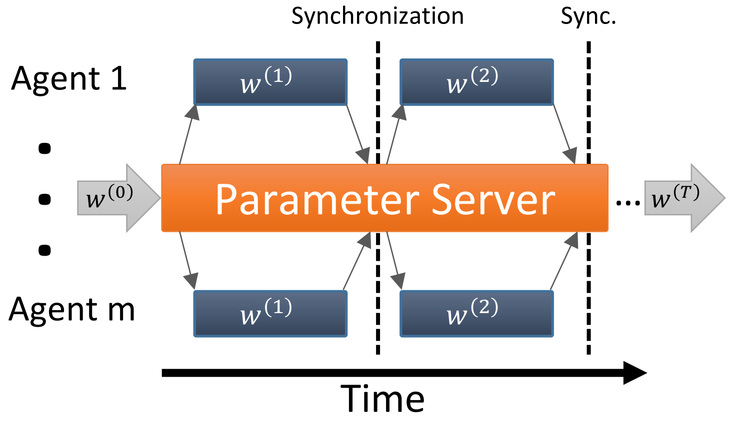


Weak scaling

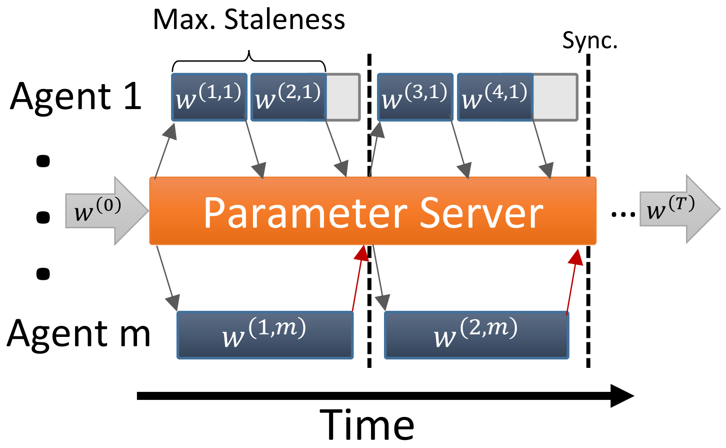


Parameter (and model) consistency - centralized

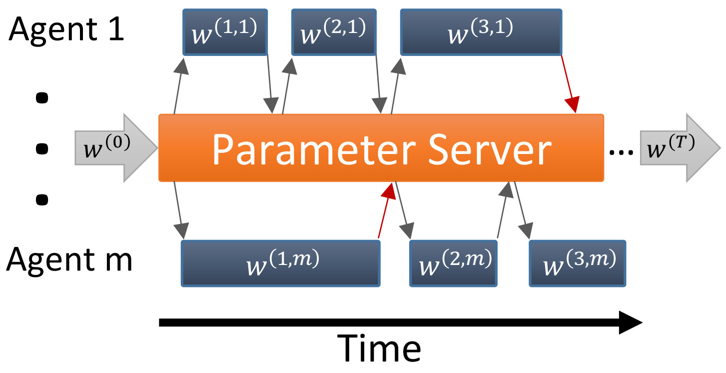
- **Parameter exchange frequency can be controlled, while still attaining convergence:**



Synchronous



Stale Synchronous / Bounded Asynchronous



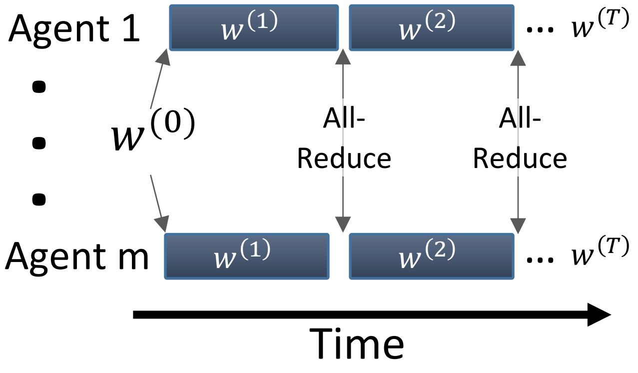
Asynchronous

- **Trades off "statistical performance" for "hardware performance"**

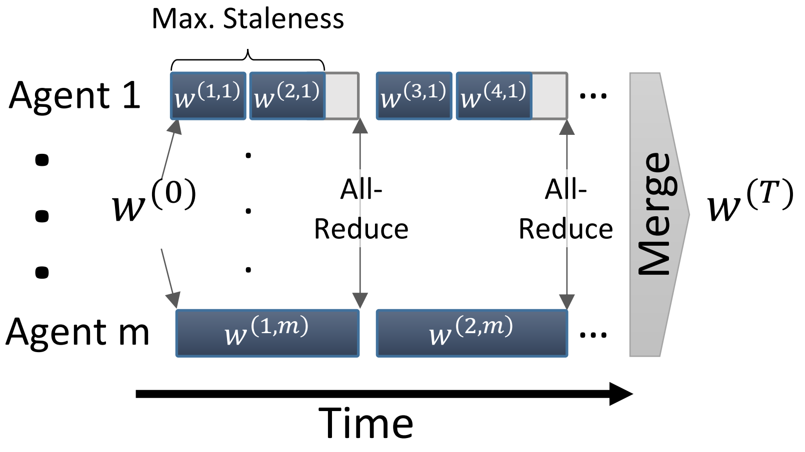
[Dean et al. 2012; Niu et al. 2011]

Parameter (and model) consistency - decentralized

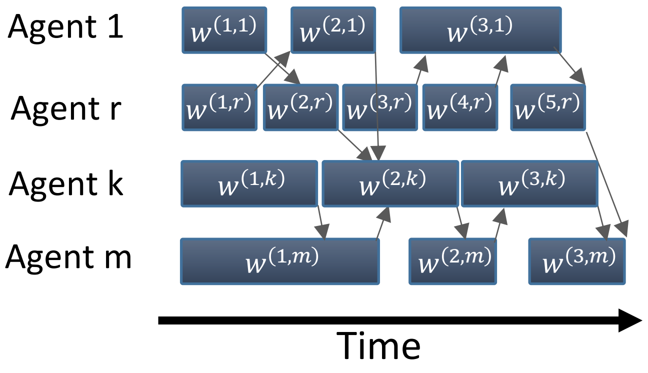
- **Parameter exchange frequency can be controlled, while still attaining convergence:**



Synchronous



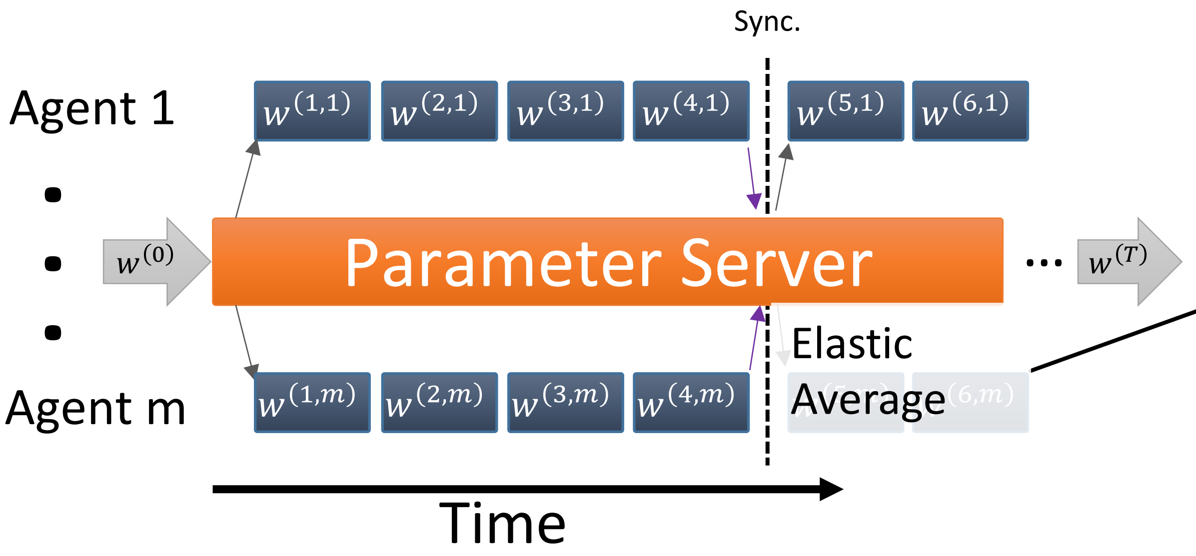
Stale Synchronous / Bounded Asynchronous



Asynchronous

- **May also consider limited/slower distribution – gossip [Jin et al. 2016]**

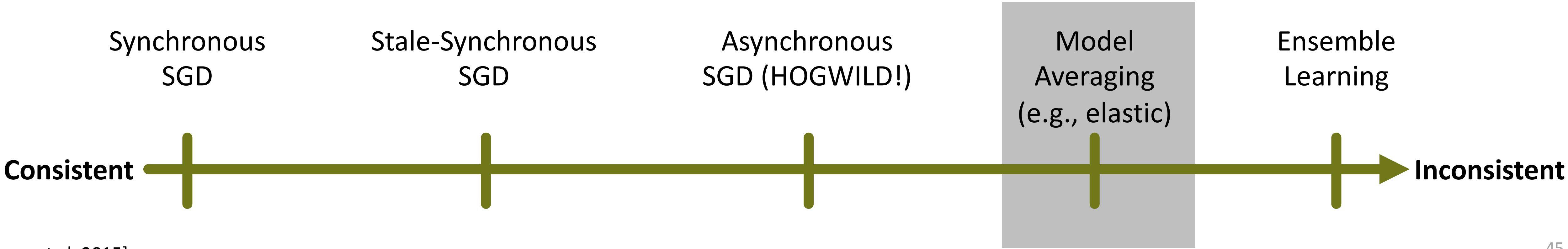
Parameter consistency in deep learning



Using physical forces between different versions of w:

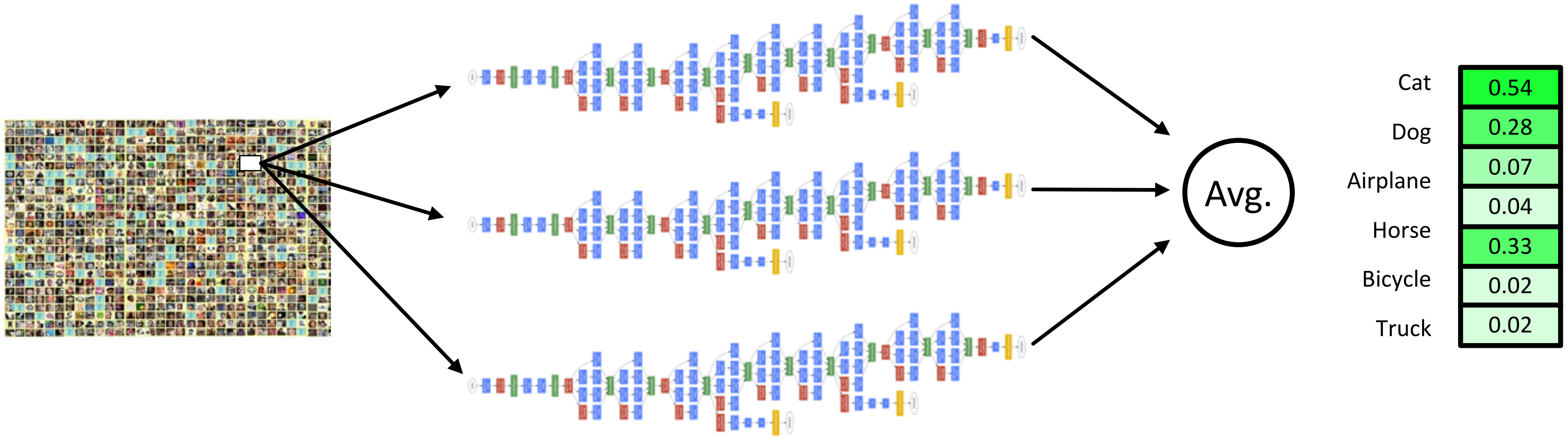
$$w^{(t+1,i)} = w^{(t,i)} - \eta \nabla w^{(t,i)} - \alpha\left(w^{(t,i)} - \widetilde{w}_t\right)$$

$$\widetilde{w}_{t+1} = (1-\beta)\widetilde{w}_t + \frac{\beta}{m}\sum_{i=1}^{m} w^{(t,i)}$$



[Zhang et al. 2015]

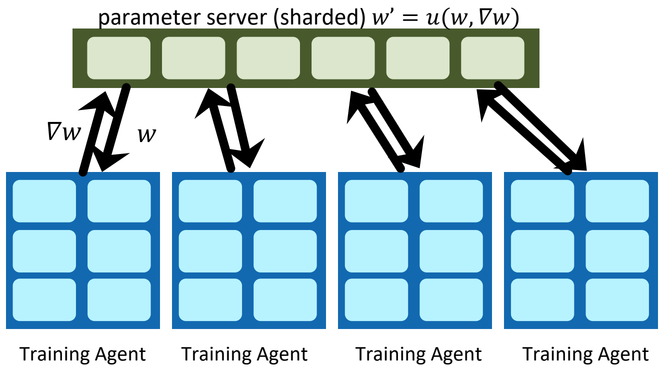
Parameter consistency in deep learning

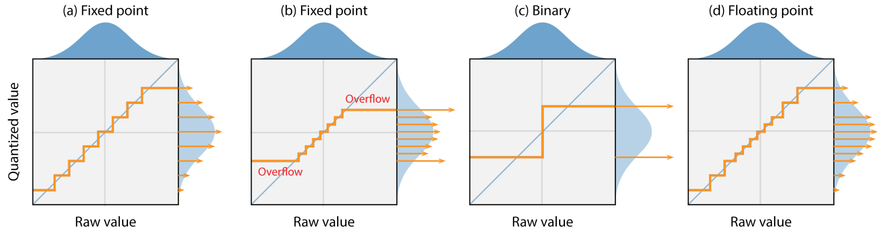


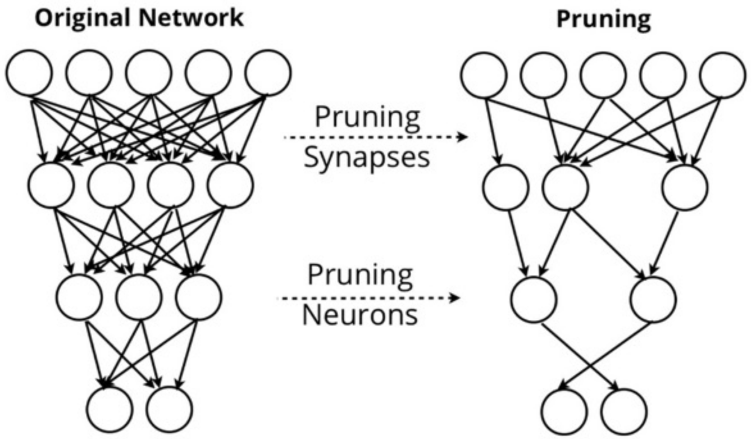
[Dietterich 2000]

Communication optimization

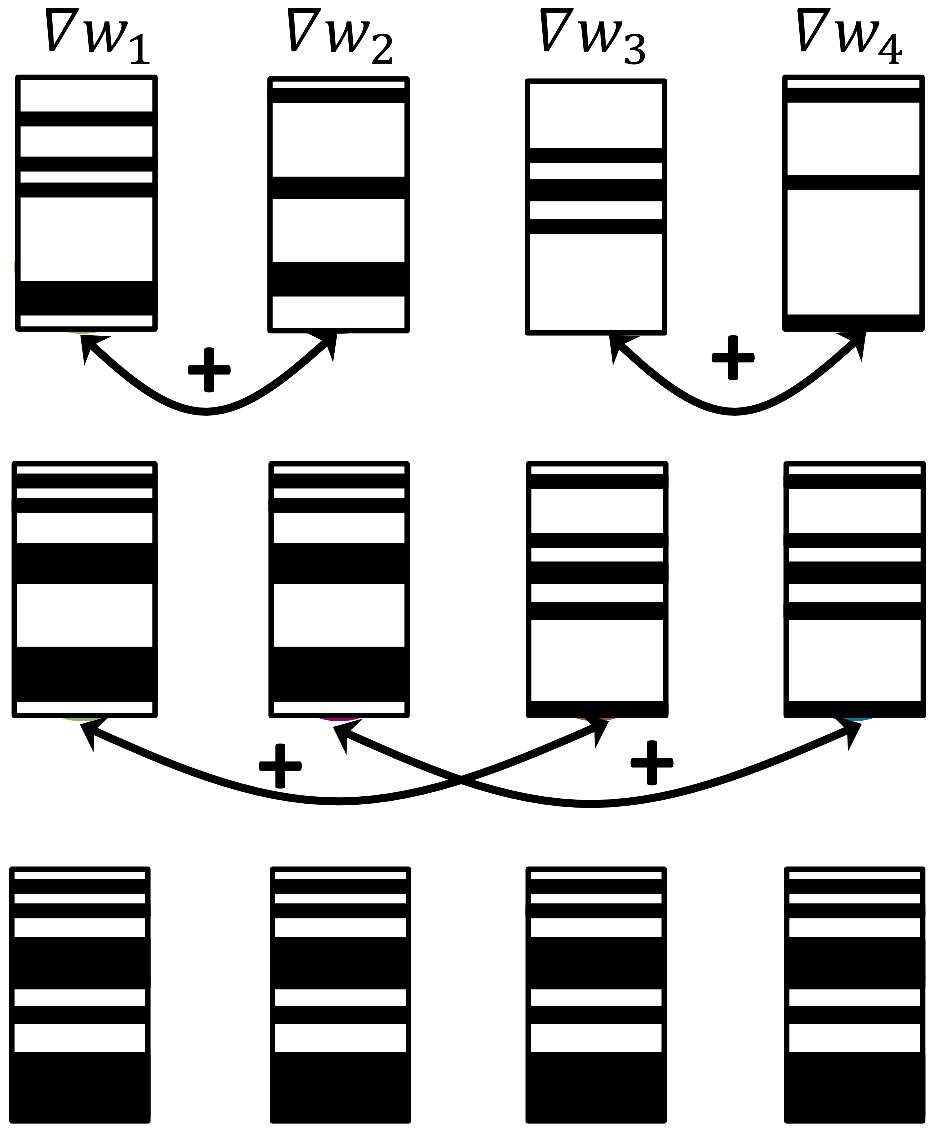
- **Lossy compression: trade off latency (local compute) for bandwidth**
- **Sufficient factor broadcasting**
- **Quantization:**
  - 16-bit (IEEE FP16, bfloat16) becoming standard
  - QSGD (stochastic rounding) [Alistarh et al. 2016]
  - 1-bit SGD [Seide et al. 2014; Dryden et al. 2016]
  - Error feedback is important!
- **Sparsification:**
  - Top-k SGD [Renggli et al. 2019]
  - Skip small weight updates



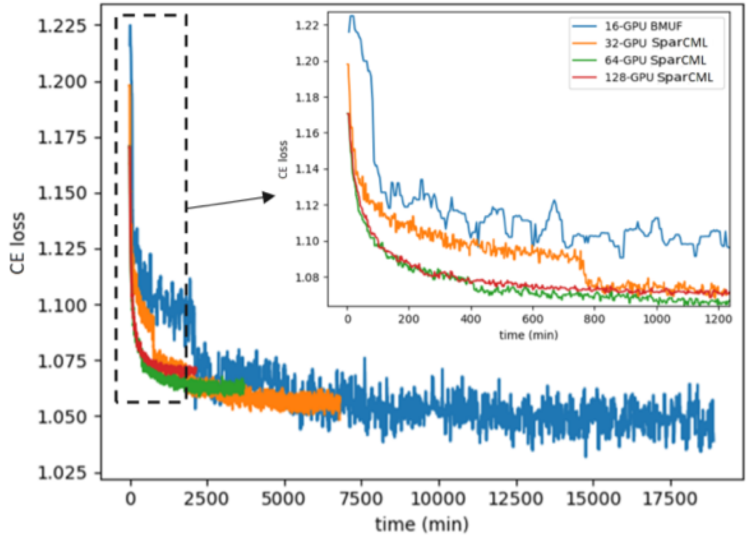


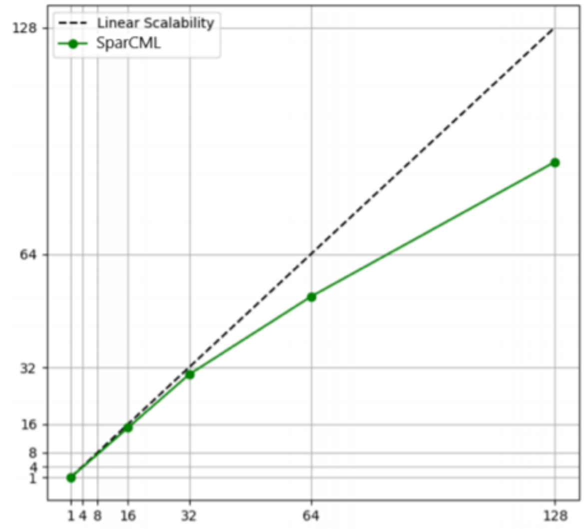


SparCML – Quantized sparse allreduce



Six epochs, 60 million params





Microsoft Speech Production Workload Results – **2 weeks → 2 days**!

System	Dataset	Model	# of nodes	Algorithm	Speedup
Piz Daint	ImageNet	VGG19	8	Q4	1.55 (3.31)
Piz Daint	ImageNet	AlexNet	16	Q4	1.30 (1.36)
Piz Daint EC2	MNIST	MLP	8	Top16_Q4 Top16_Q4	3.65 (4.53) 19.12 (22.97)

[Renggli et al. 2019]

The limits to data parallelism

- When does data parallelism break down?

- Communication overheads
- Hyperparameter tuning

- Memory for one sample
- More GPUs than samples in a mini-batch

Need to strong scale!

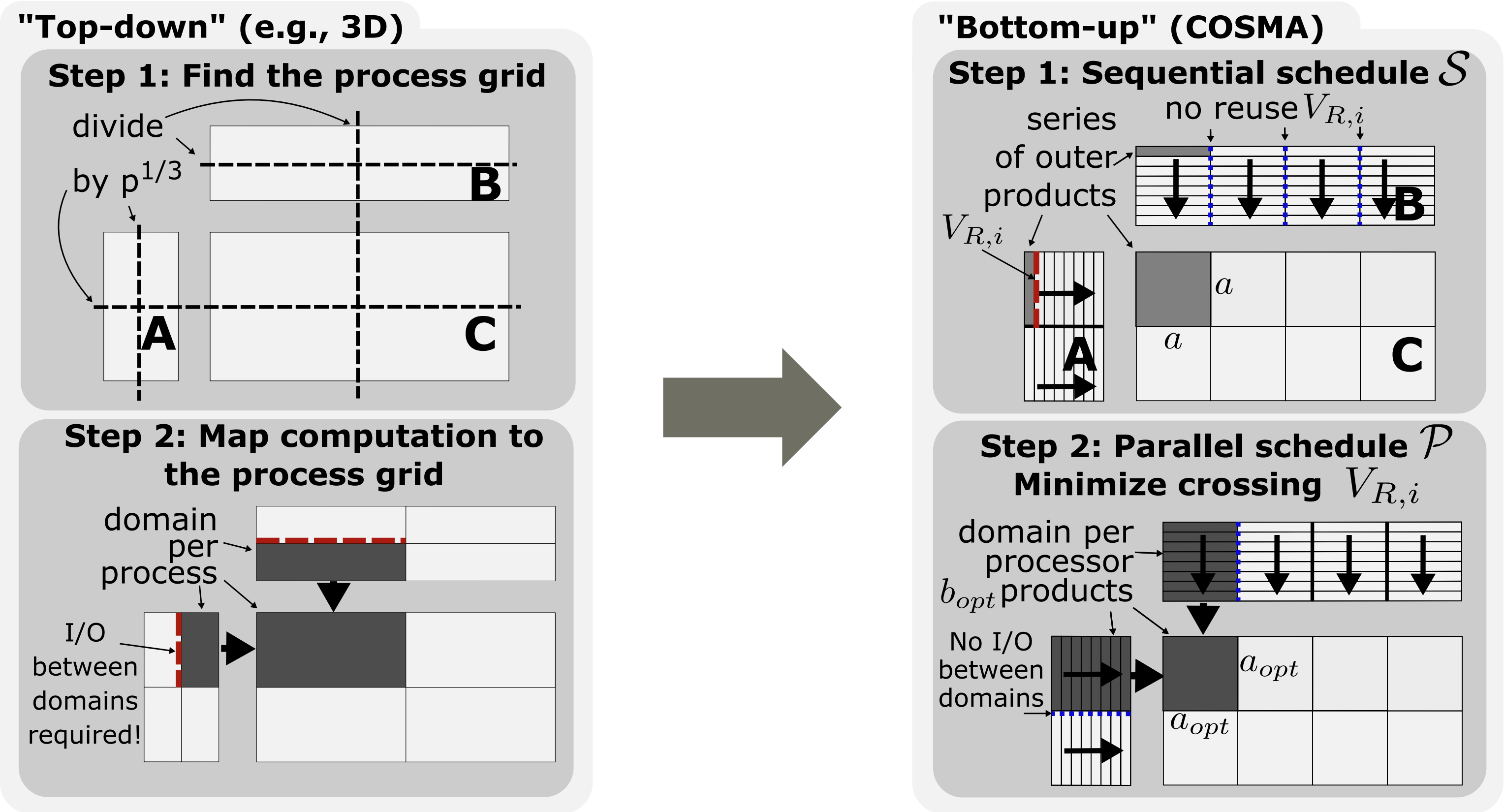
Distributed-memory fully-connected layers

$$Y = \sigma(WX + b)$$

- **Just a distributed matrix-matrix multiplication!**

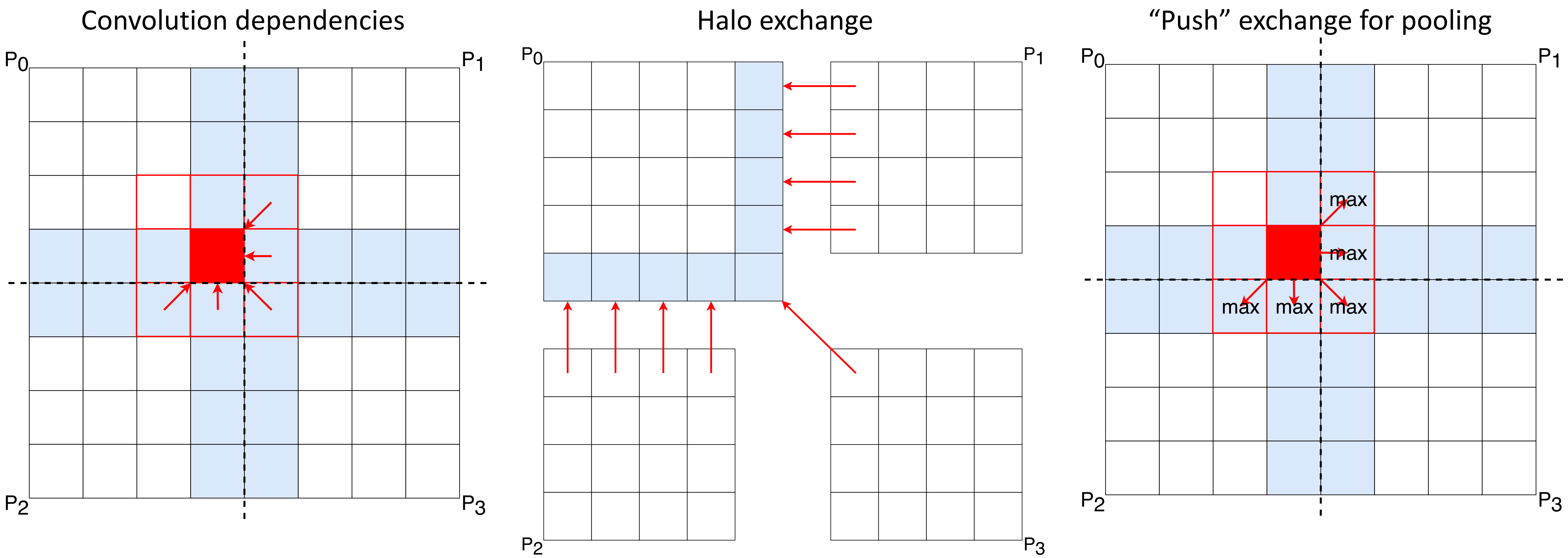
Use SUMMA [Van Essen et al. 2015]

New: COSMA [Kwasniewski et al. 2019]

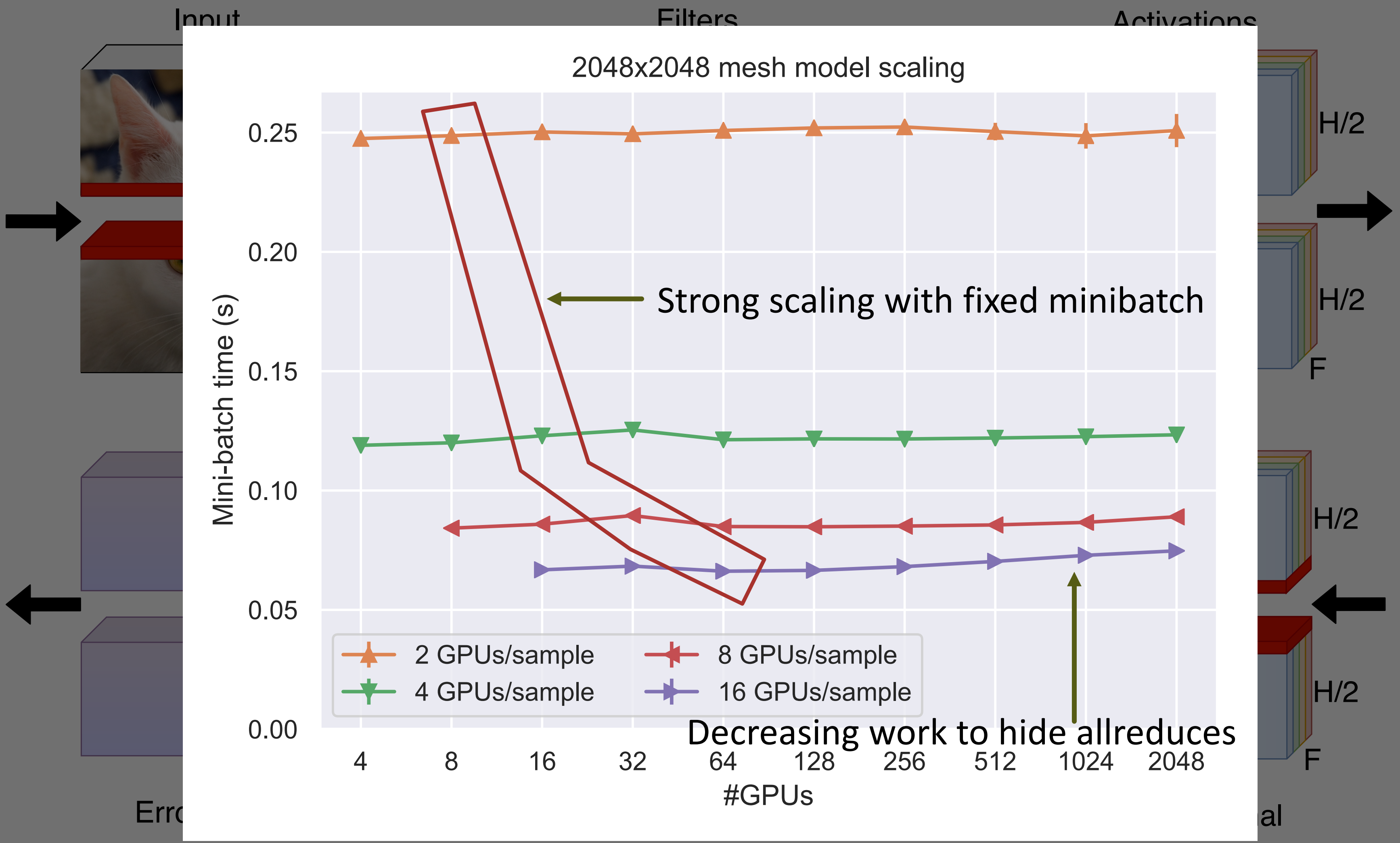


Spatial parallelism [Dryden et al. 2019]

- **Observation: Convolution is just a funny stencil operation**
- **Domain decomposition with a halo exchange!**

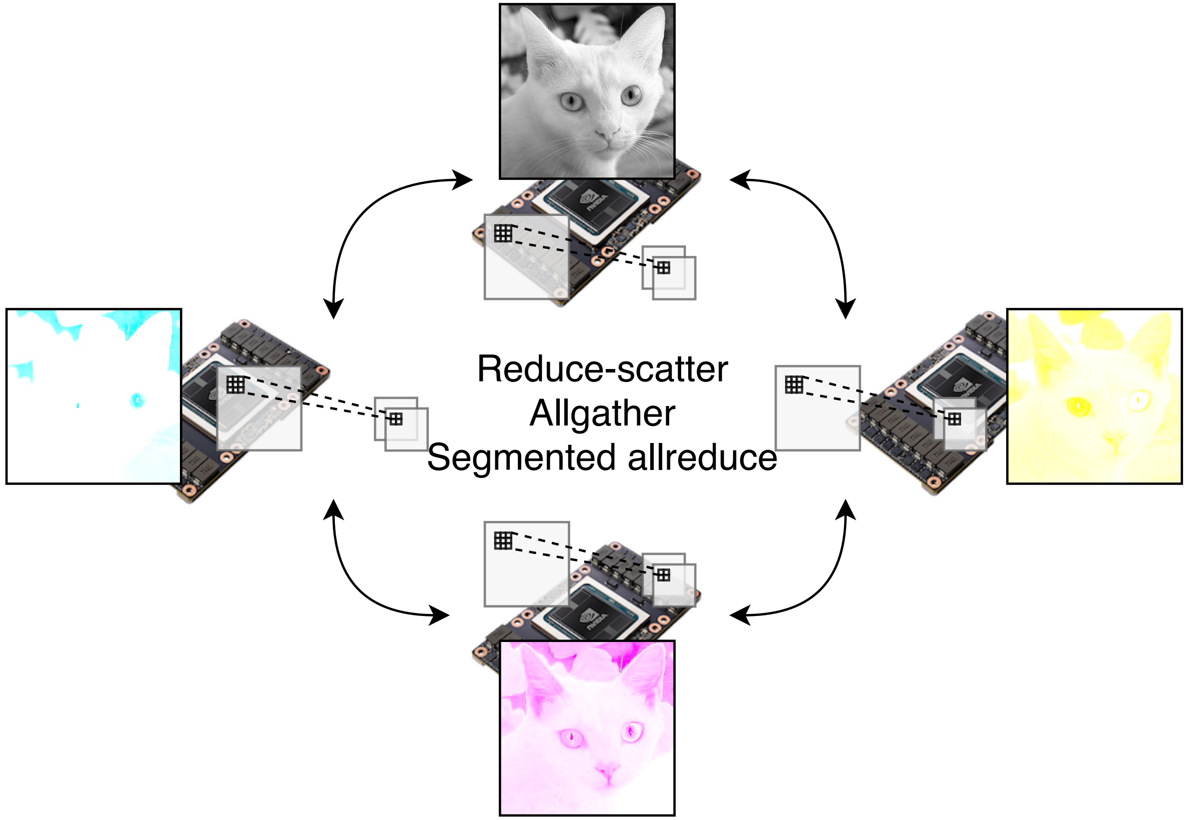


Spatial parallelism [Dryden et al. 2019]

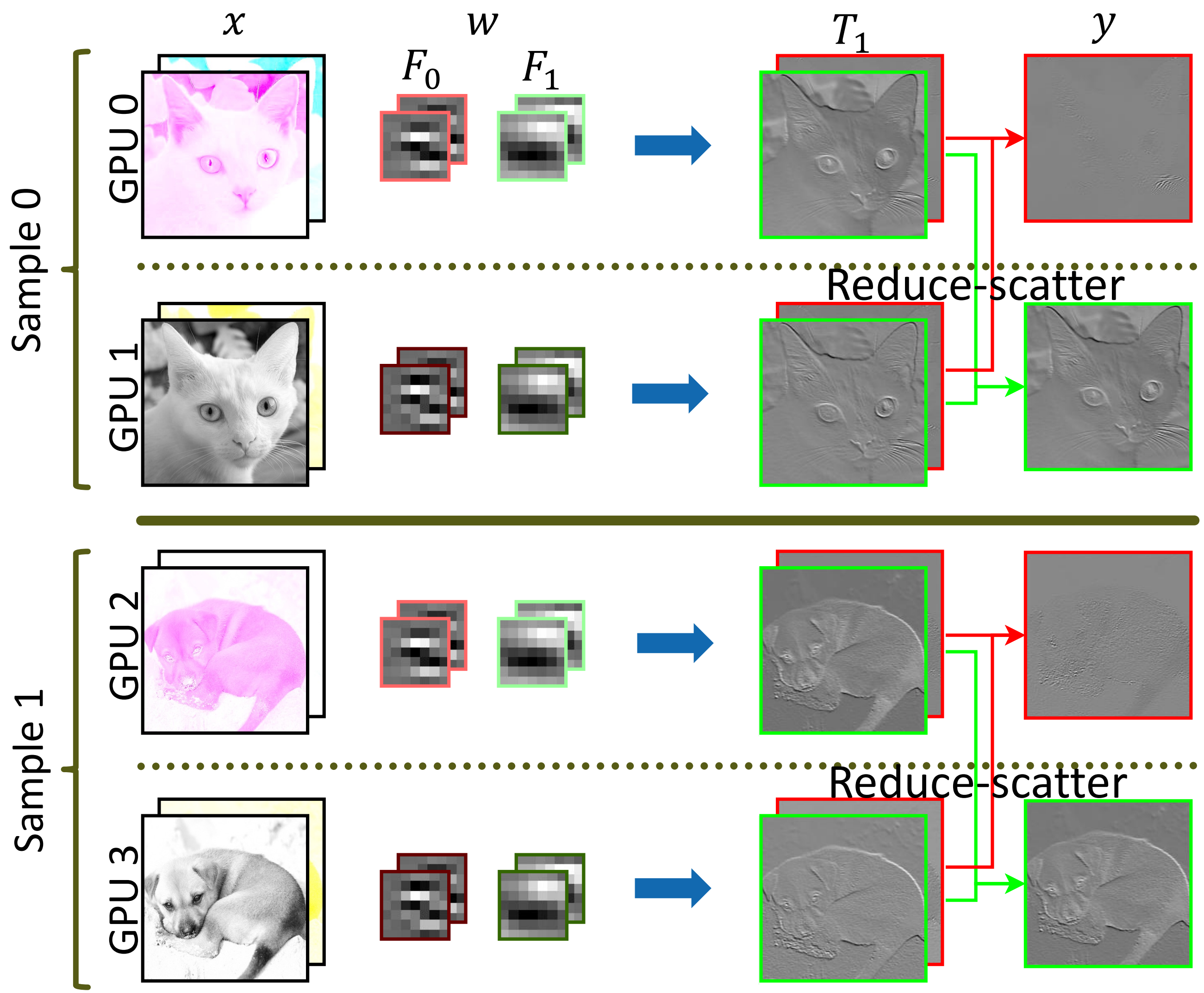


Channel/filter parallelism [Dryden et al. 2019]

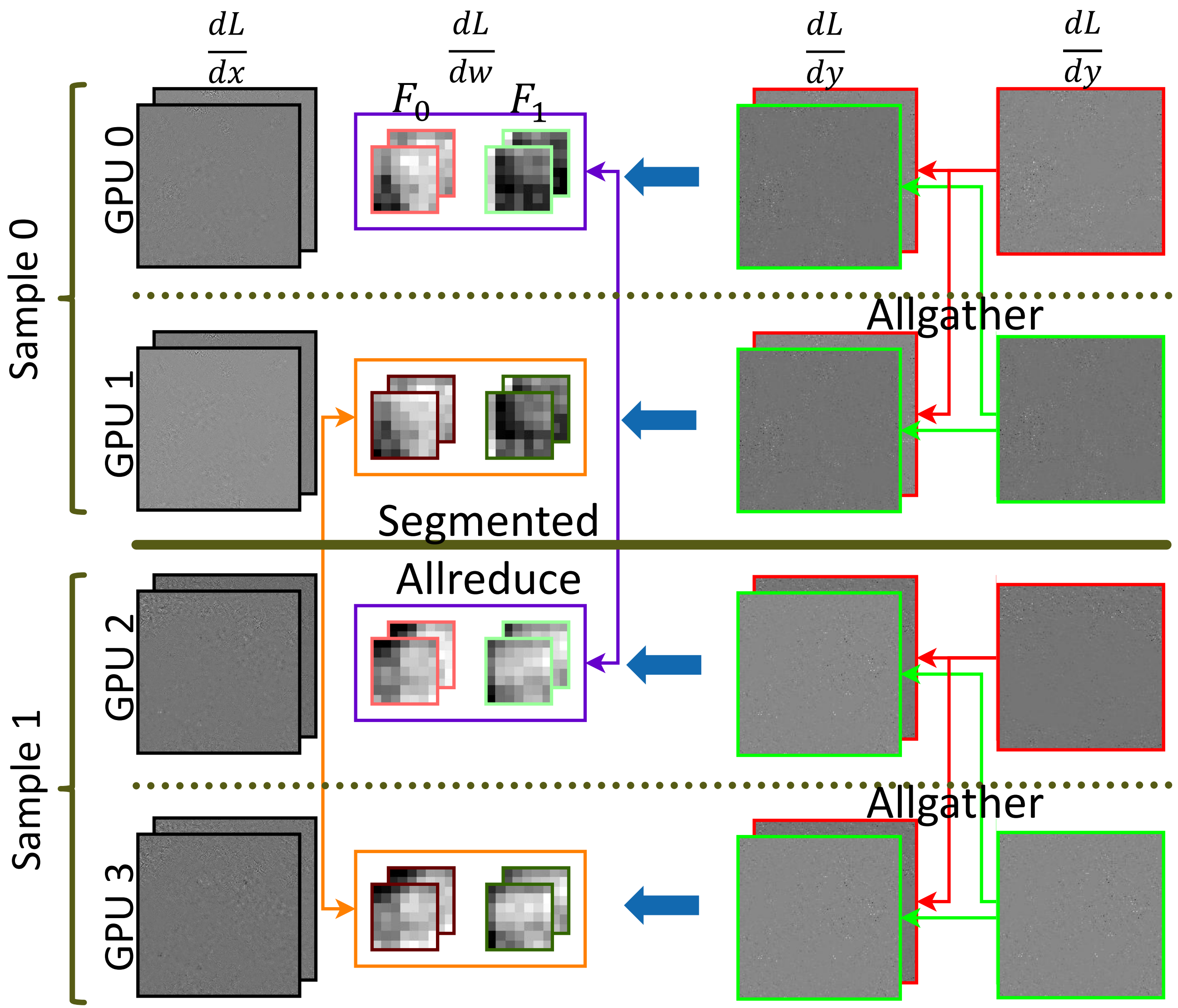
- **Family of algorithms for jointly partitioning channels and filters in convolution**



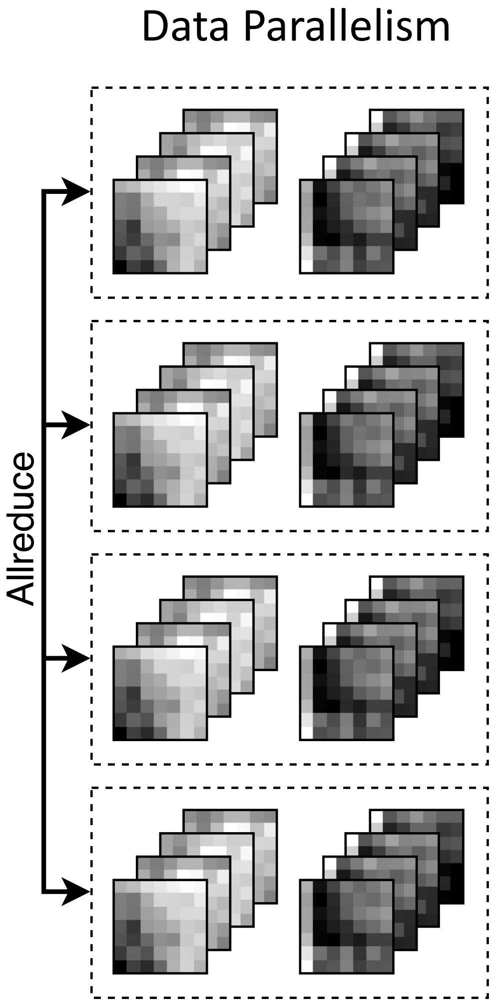
Stationary-x: Forward

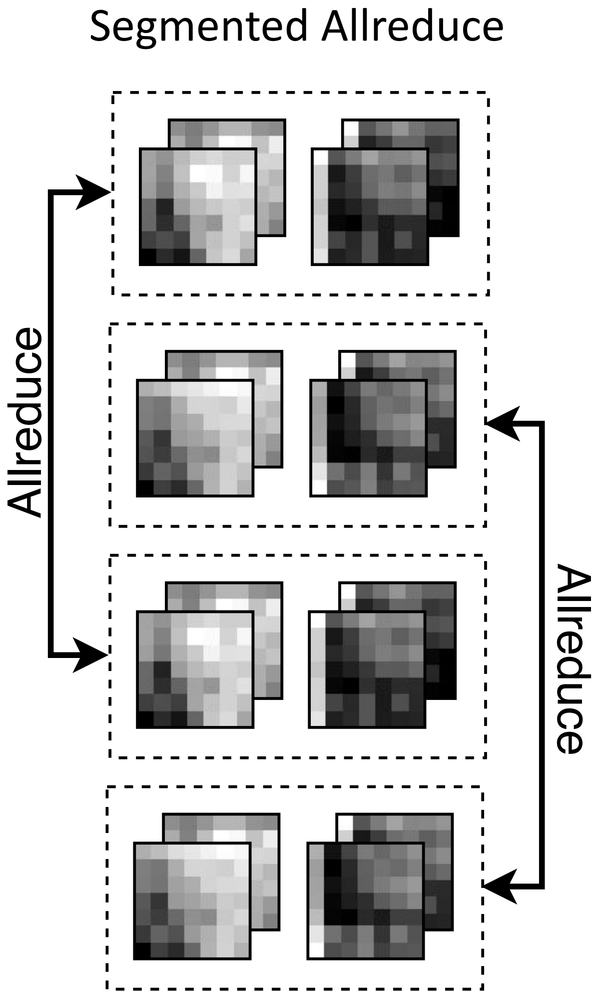


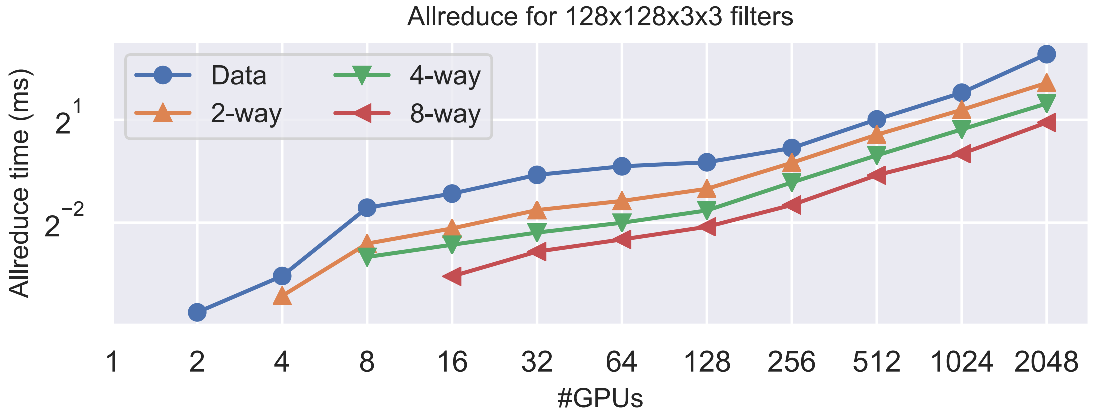
Stationary-x: Backward



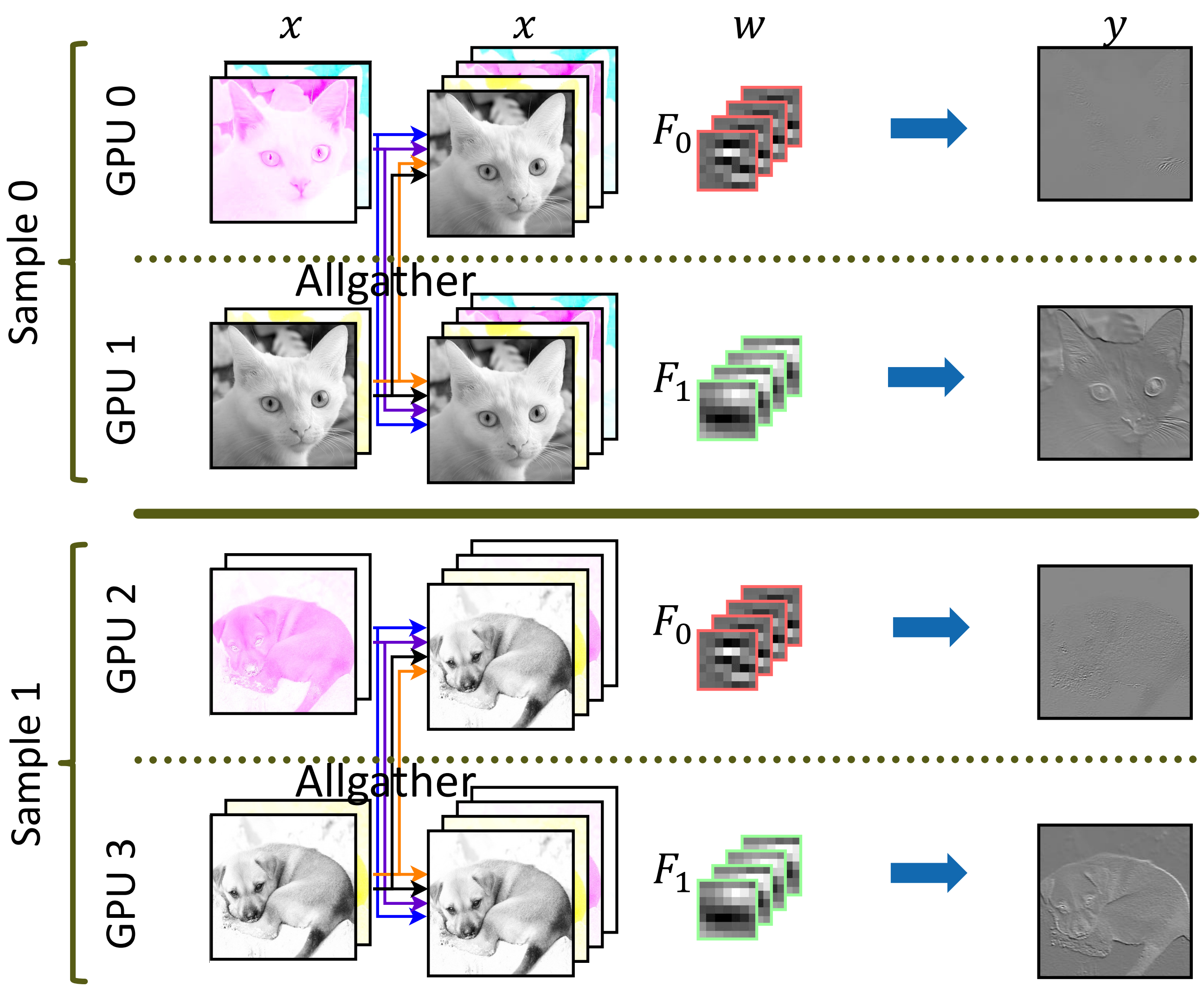
Segmented allreduce



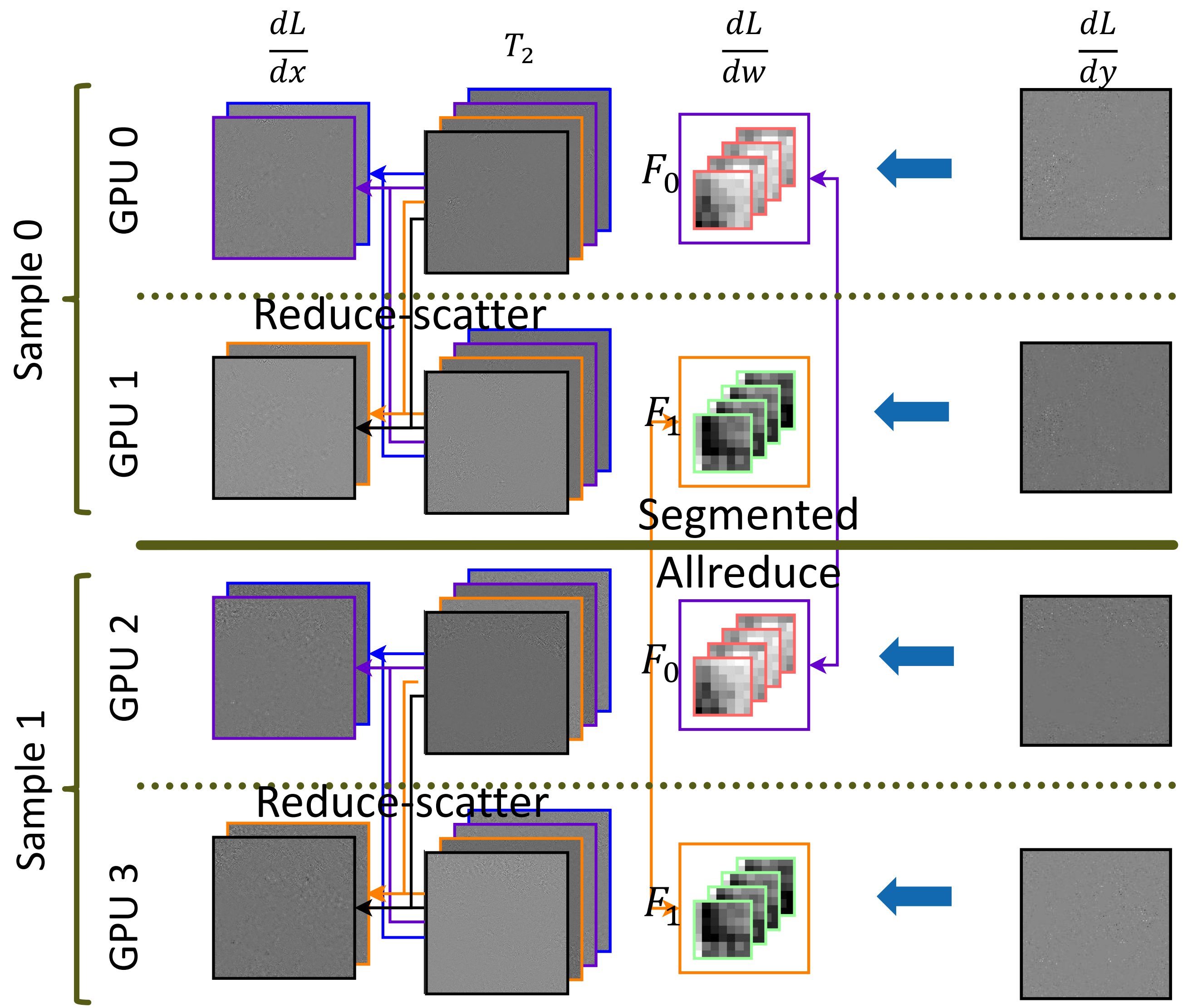




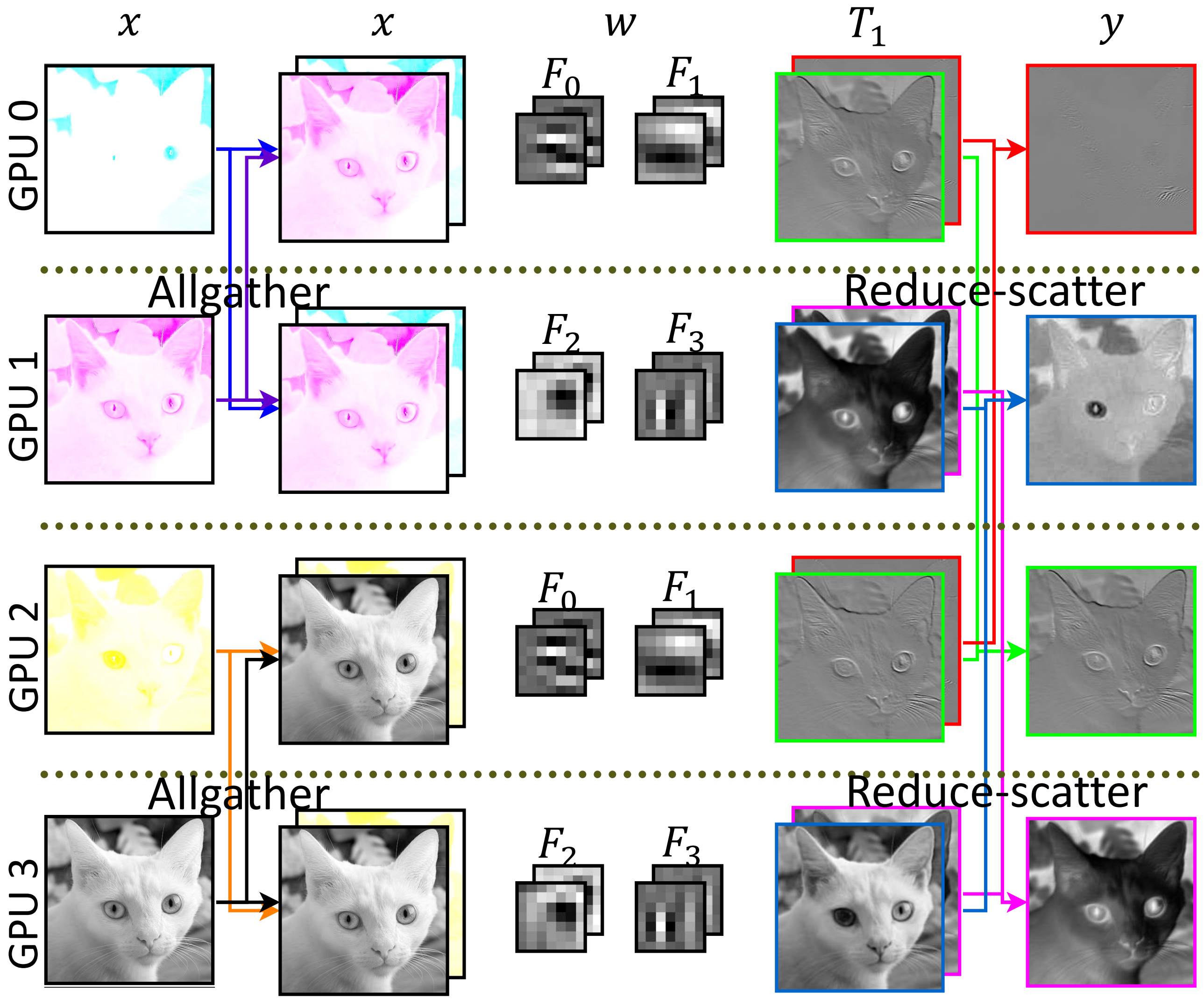
Stationary-y: Forward



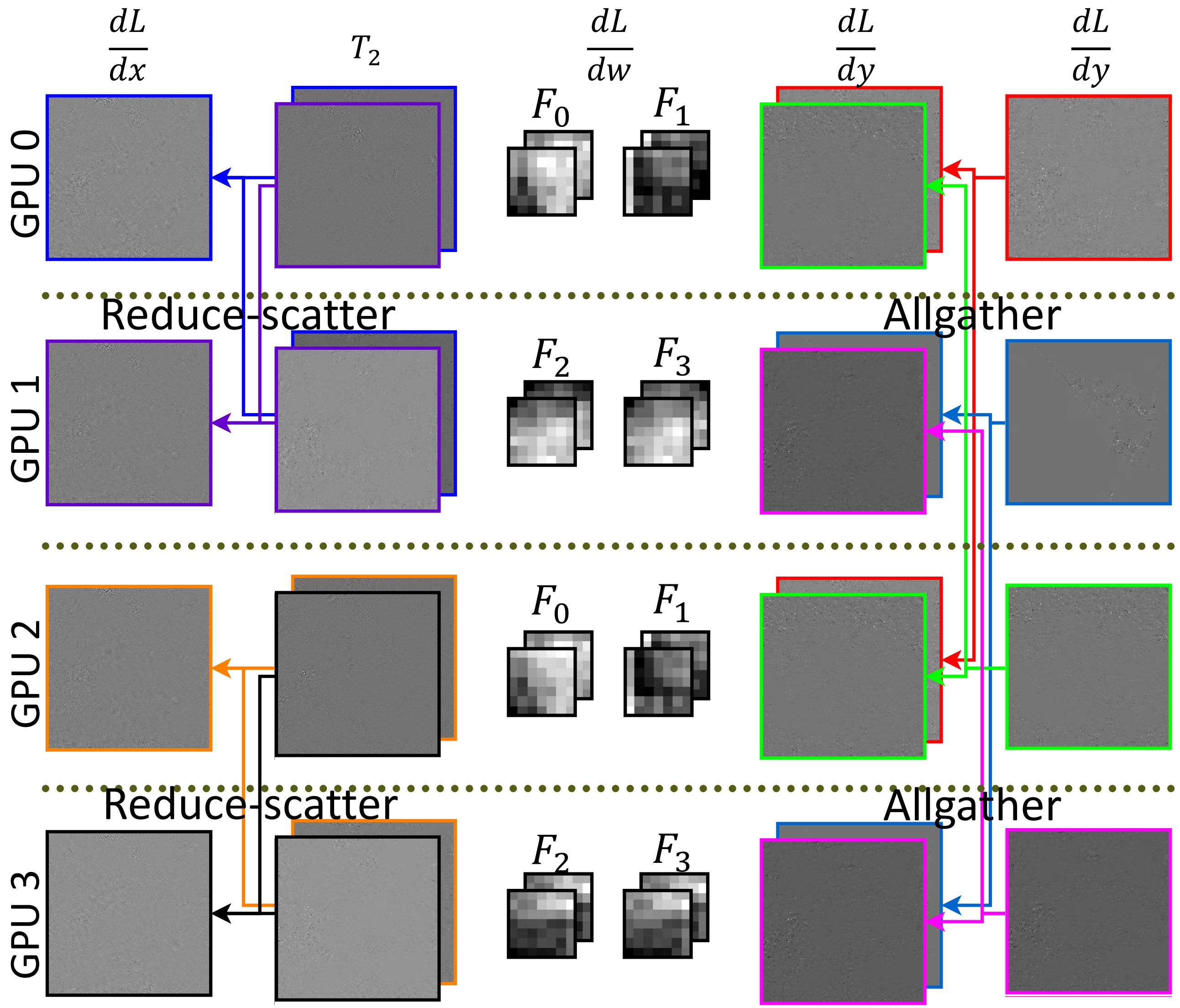
Stationary-y: Backward



Stationary-w: Forward



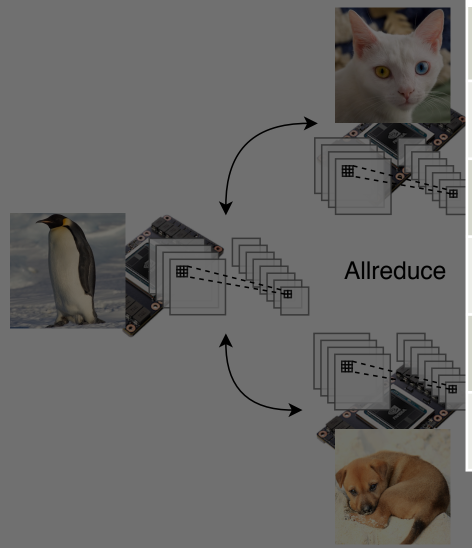
Stationary-w: Backward



General distributed convolution

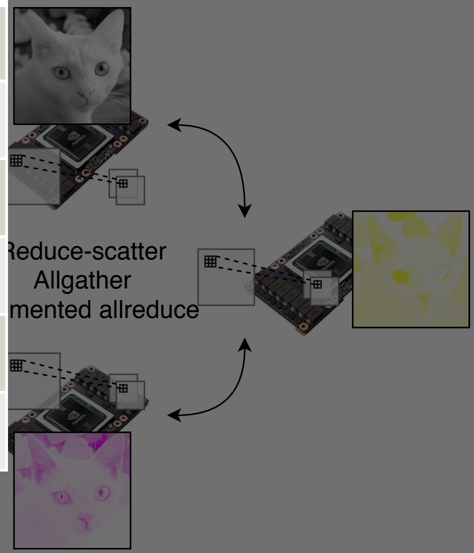
- Provide a variety of options to enable and improve strong and weak scaling
- Support a full spectrum of data and model types

Data paralle



Model/Algorithm	Mini-batch	Top-1	Top-5	Runtime (min)
ResNet-50 (data)	8192	77.3%	93.6%	34.1
+ spatial + 4-way x, y				19.9 (1.7x)
WRN-50-2 (data)	4096	78.4%	94.3%	106.9
+ spatial + 8-way x, y				45.5 (2.3x)
WRN-50-4 (data)	2048	80.0%	95.1%	432.3
+ spatial + 4×2 w				105.0 (4.1x)

ilter parallelism



Allreduce

N

~100-1000 GPUs

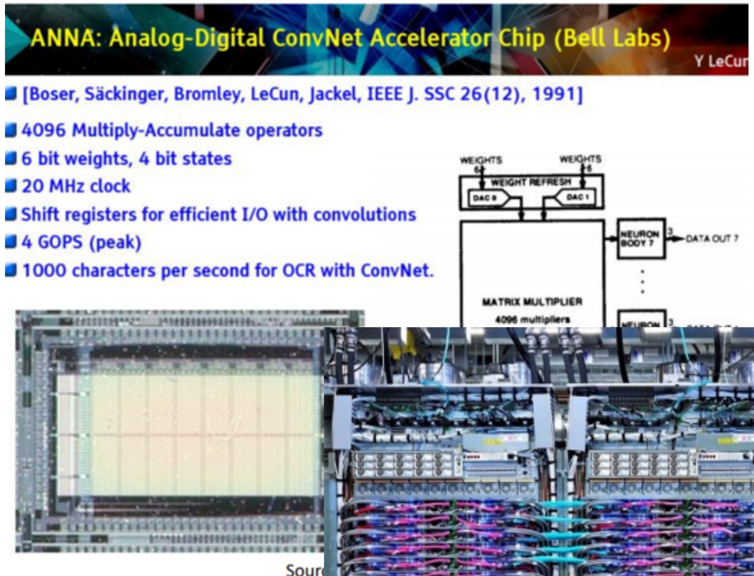
$H\times W$

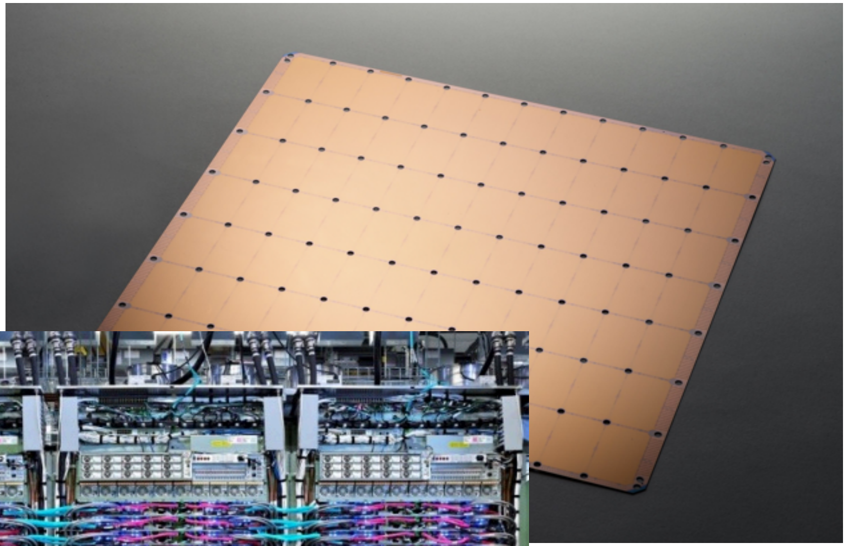
~10 GPUs

$C\times F$

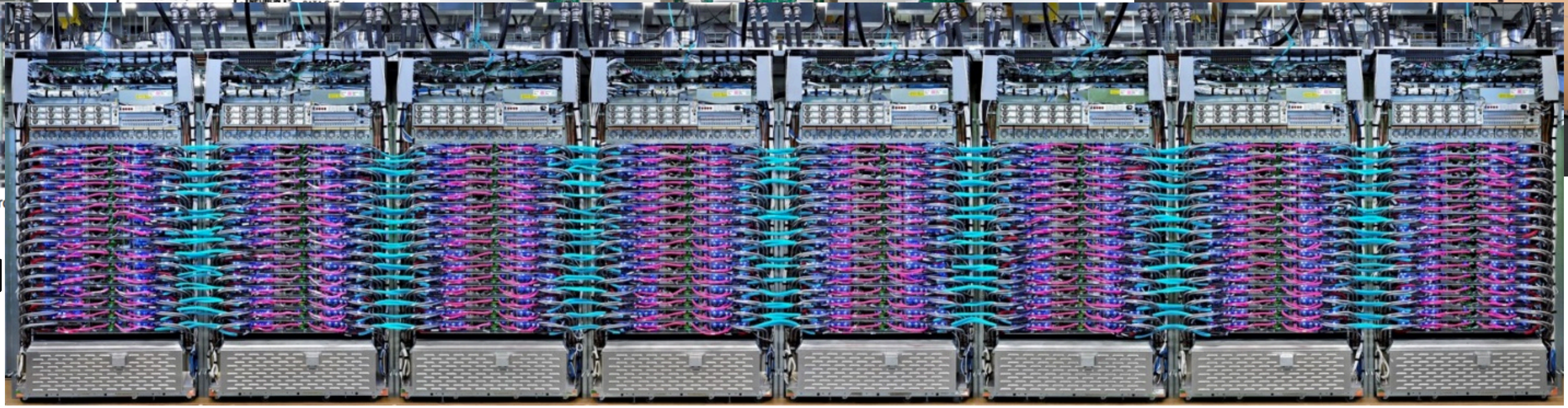
~10 GPUs

Specialized hardware





These form large supercomputers



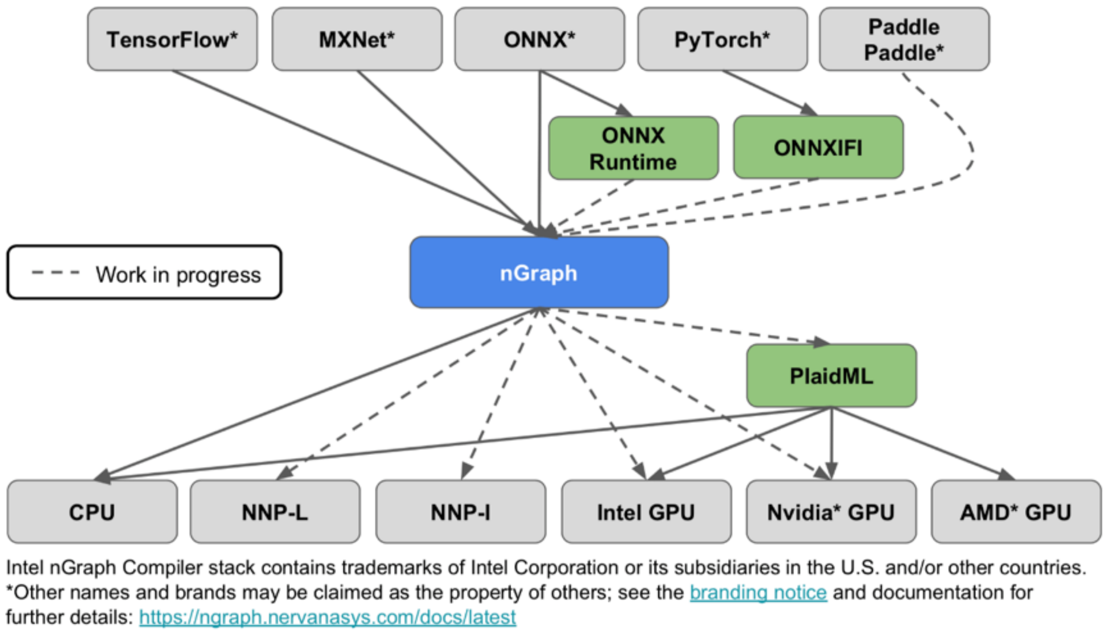
ANN

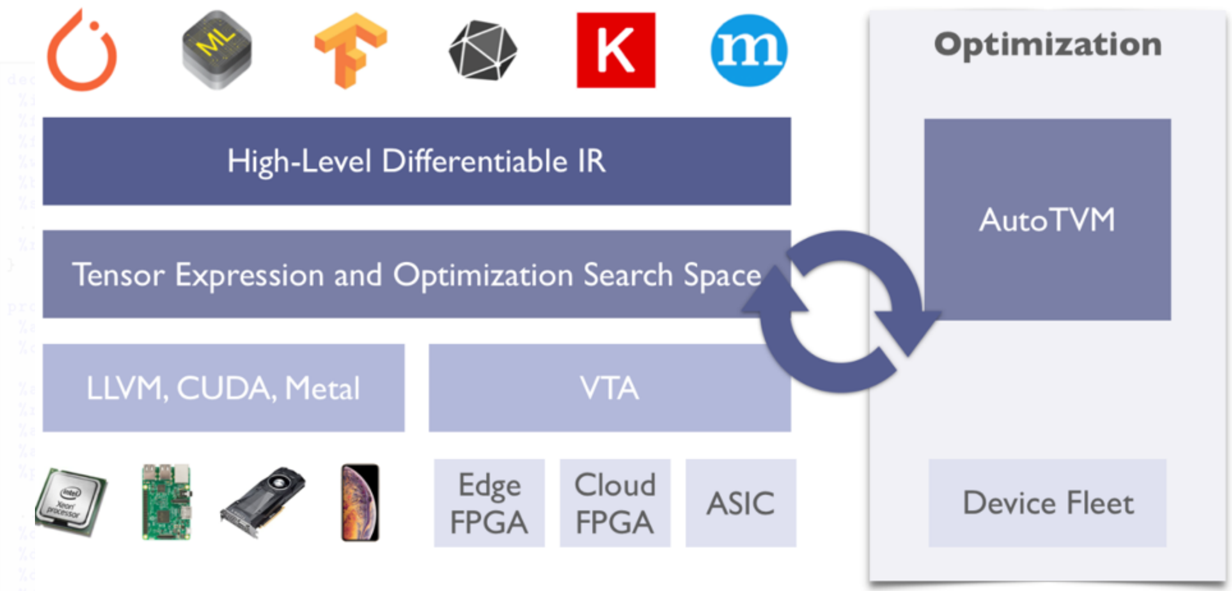
[2019]

Literally hundreds of other startups in this space

DNN Compilers

- Use techniques from compiler construction: DNN → Graph → IR → Transformations → HW Mapping





Intel nGraph

TVM Stack

How to not do this

"Twelve ways to fool the masses when reporting performance of deep learning workloads"

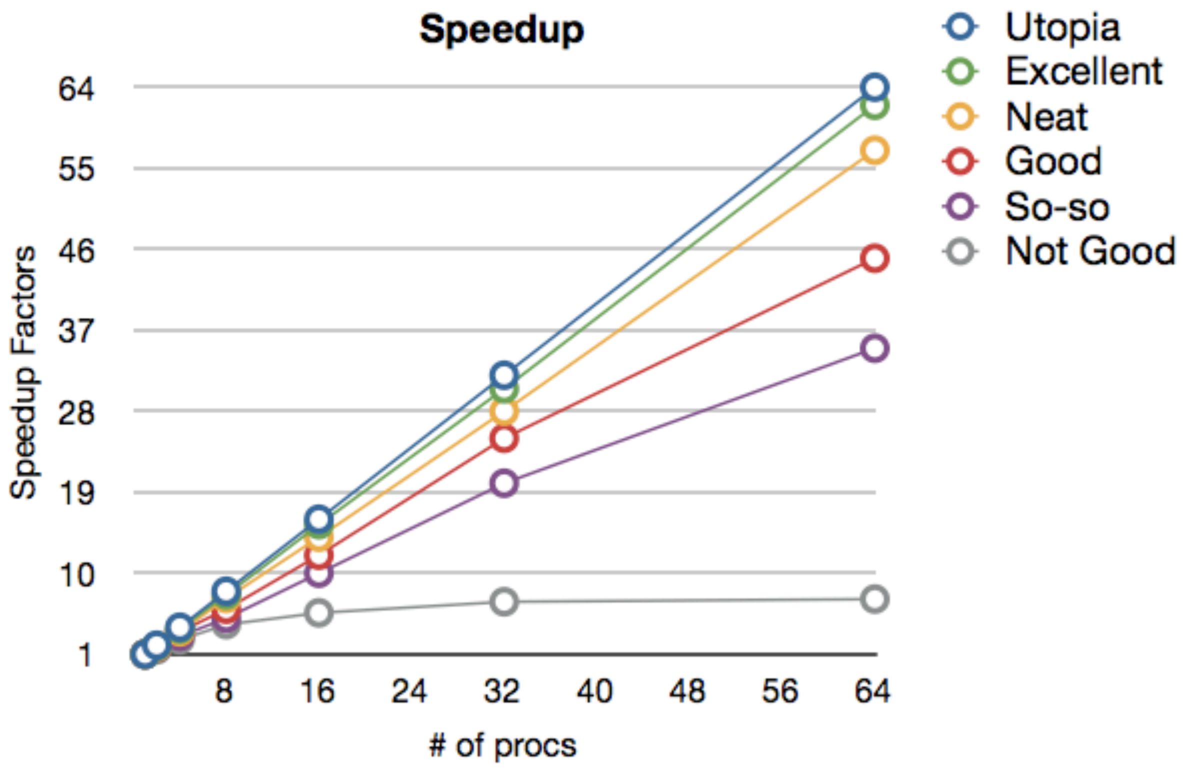
(A humorous guide to floptimize deep learning)

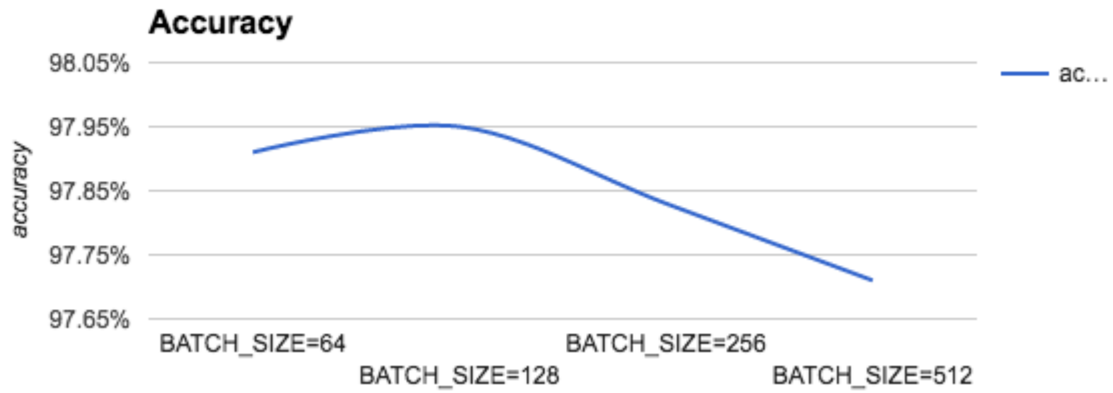
https://htor.inf.ethz.ch/blog/index.php/2018/11/08/twelve-ways-to-fool-the-masses-when-reporting-performance-of-deep-learning-workloads/

8) Show performance when enabling option set A and show accuracy when enabling option set B!

- **Pretty cool idea isn't it? Hyperparameters sometimes conflict**

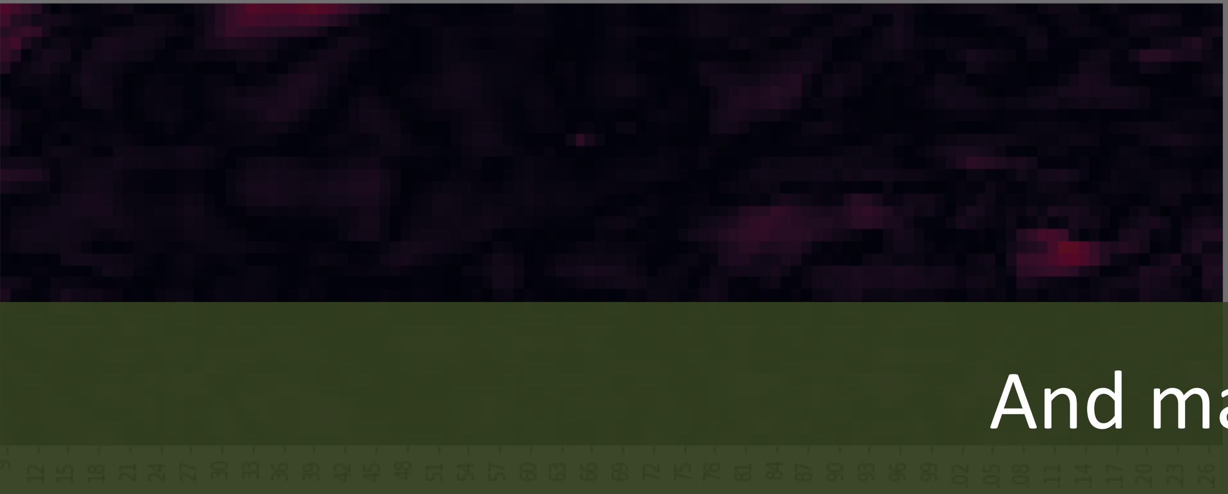
  So always tune the to show the best result, whatever the result shall be!



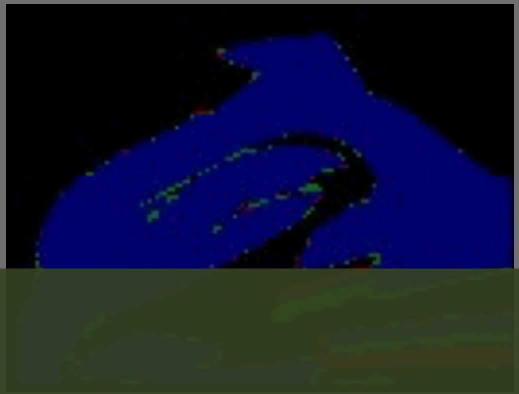


Some big deep learning applications

UQ for weather prediction [Grönquist et al. 2019]



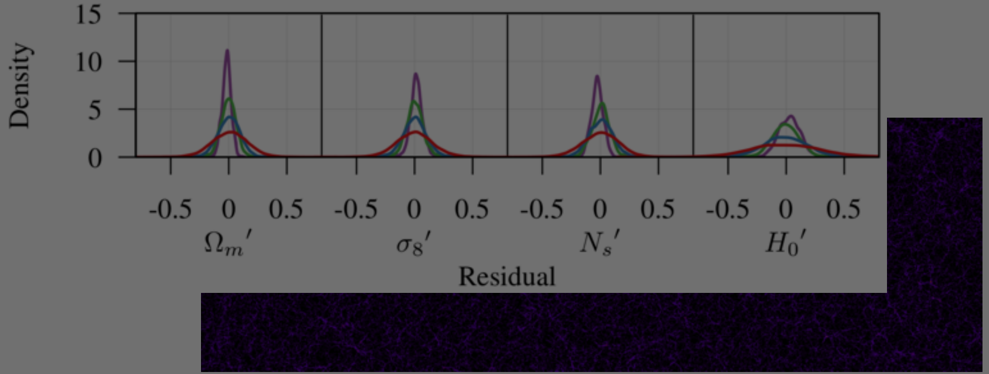
Predicting mesh tangling [Dryden et al. 2019]

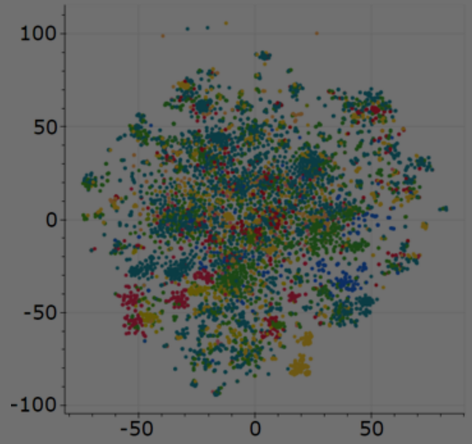


And many more!

Code comprehension [Ben-Nun et al. 2018]

Cosmology [Oyama et al. 2019]





Big seq2seq models

Research opportunities

https://spcl.inf.ethz.ch/SeMa/

ndryden@ethz.ch

	Project Name	Category
+	Efficient partial collective operations for distributed deep learning training	Parallel Algorithms
+	Clairvoyant Prefetching for Machine Learning I/O	Machine Learning
+	Transformers: More than Meets the Eye (of the Hurricane)	Machine Learning
+	Scalable Deep Learning for Weather and Climate Prediction	Machine Learning
+	Fastest Matrix Multiplication in the West (Europe)	Parallel Algorithms
+	Efficient Collective Operations On Reconfigurable Hardware	Architecture
+	Quantized Allreduces for Distributed Deep Learning Training	Machine Learning
+	Who Optimizes the Optimizers? Performance Programming Made Easy	Toolchains
+	Analytical Cache Model for Parallel Programs	Compilation

+	Automatic Algorithm Detection for Readability and Performance Rewriting	Compilation
+	Data-Centric Deep Learning Framework (or: how to beat TensorFlow)	Machine Learning
+	Authenticated Deep Learning	Machine Learning
+	Kernel/Network Offloading of Streaming Data Processing Tasks	Networking
+	Performance Counters for Interactive Bottleneck Identification in Large-Scale Applications	Compilation
+	Automatic Learning of GPU Code Generation Parameters	Compilation
+	Array Partitioning to Exploit High-Bandwidth Block-RAM on FPGA	Compilation
+	Proofably optimal loop scheduling using MINLP	Compilation
+	Cache as RAM to accelerate x86 computations	Compilation
+	Visualization Techniques for Performance-Guided Programming	Compilation
+	Large Scale Framework for Code Analysis	Compilation
+	Deep Learning for Large-Scale Graph Analytics	Machine Learning

Parallelism in training DNNs – Summary

- **Deep learning is HPC – very similar – mainly dense linear algebra**
  - Amenable to our usual set of tricks, sometimes with a twist
- **Main bottleneck is communication – reduction by trading off**

Parameter Consistency	Parameter Accuracy
• Bounded synchronous SGD • Central vs. distributed parameter server • EASGD to ensemble learning	• Lossless compression of gradient updates • Quantization of gradient updates • Sparsification of gradient updates

- **Strong scaling requires effort**
- **Very different environment from traditional HPC**
  - Trade-off accuracy for performance!
- **Performance-centric view in HPC can be harmful for accuracy!**