Efficient & Scalable Deep Learning and Beyond

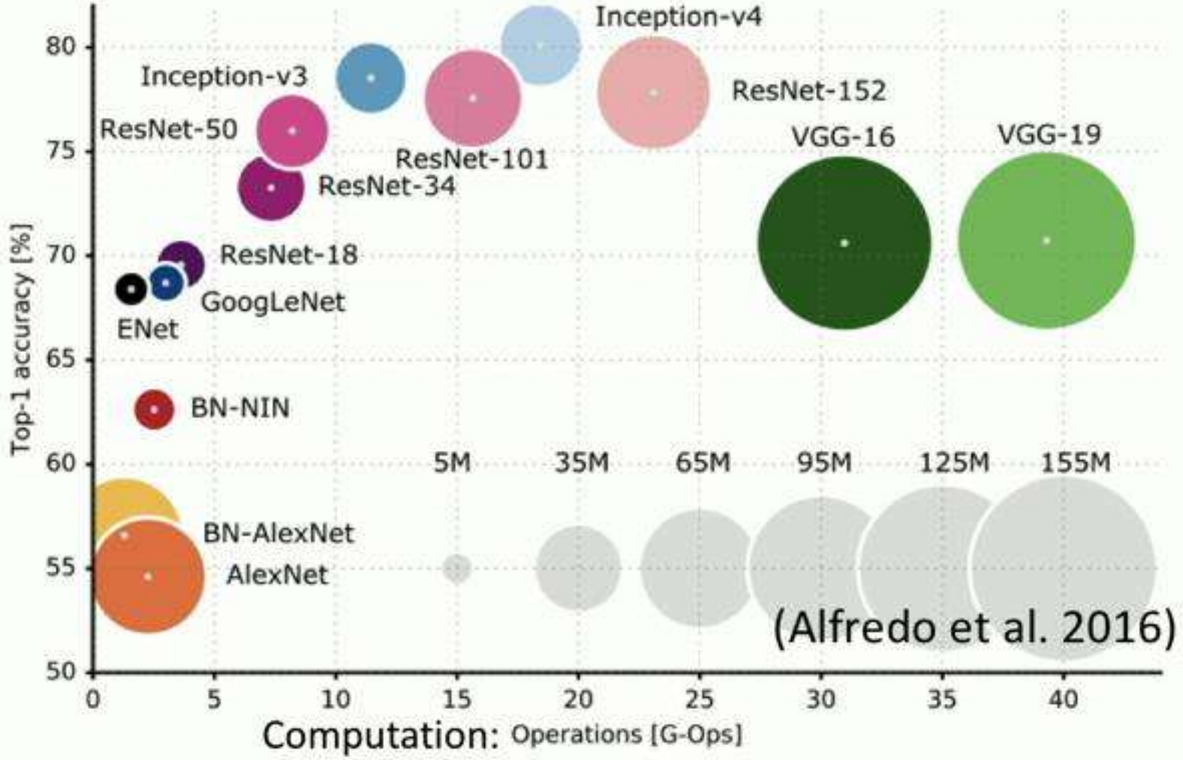
Wei Wen

Duke University

http://www.pittnuts.com/

Deep Learning Model Scaling

Image Classification on ImageNet



Trend: we can obtain better prediction using larger models

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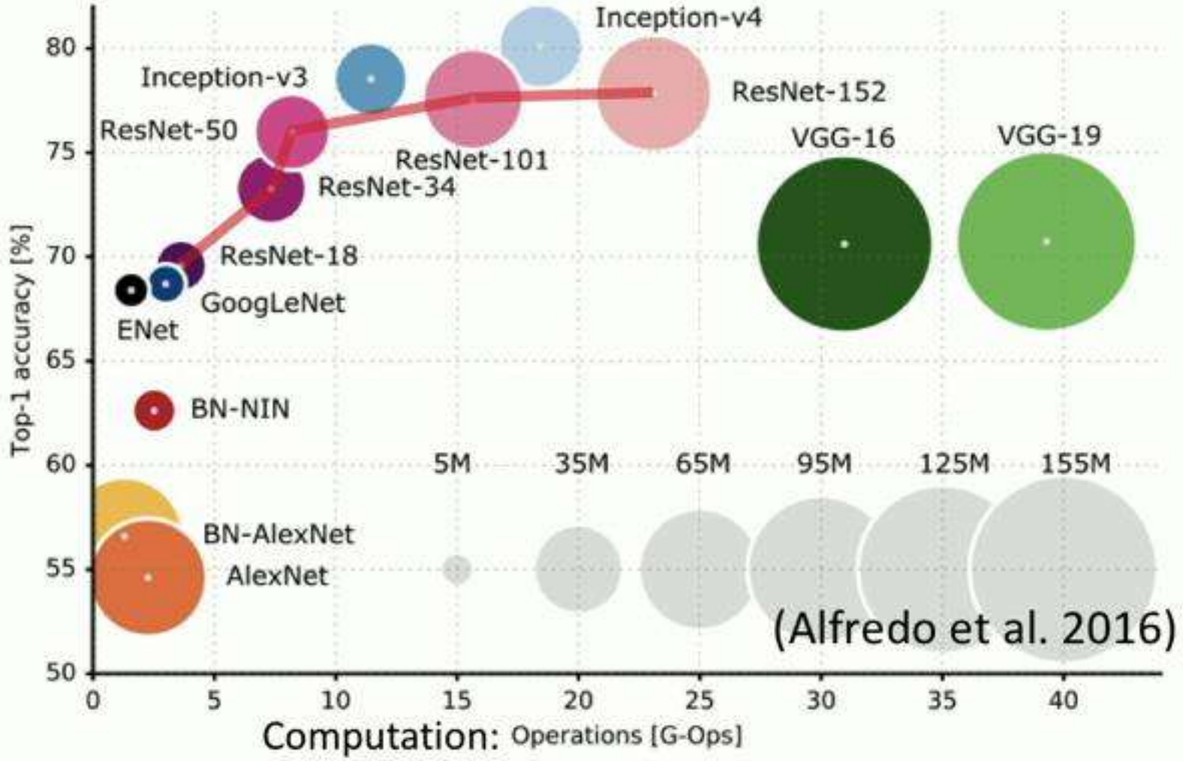

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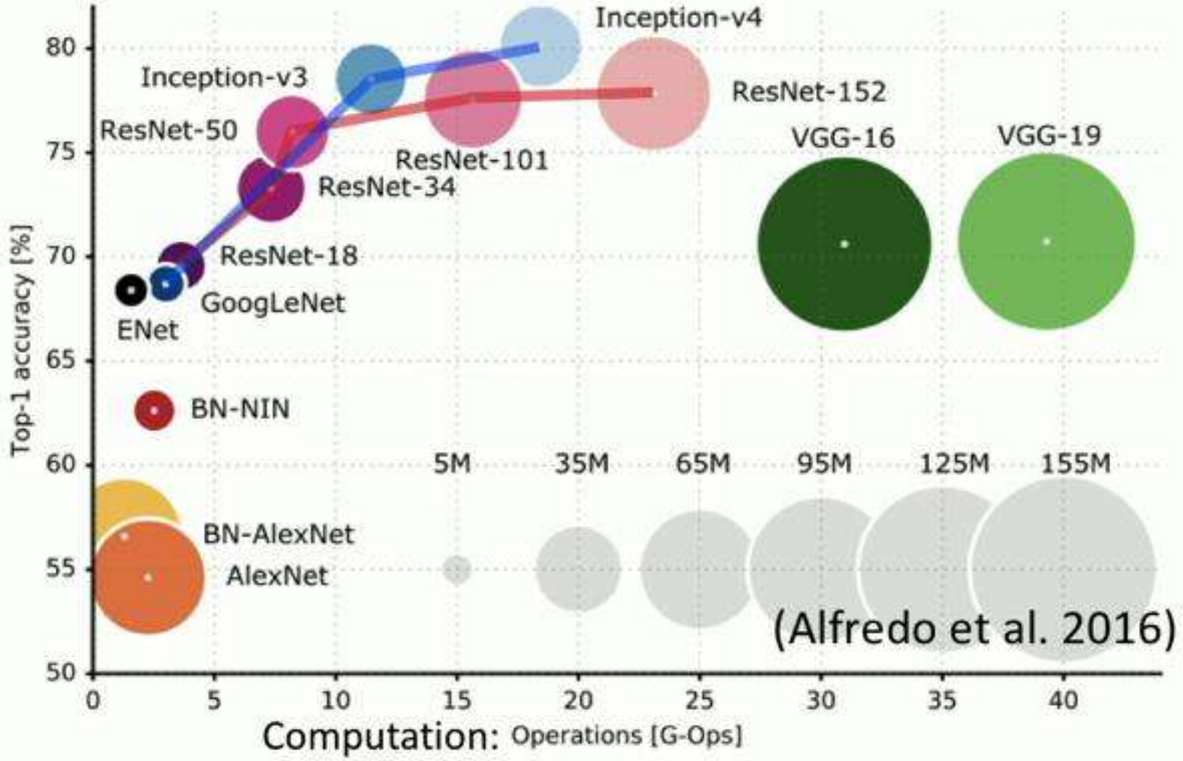

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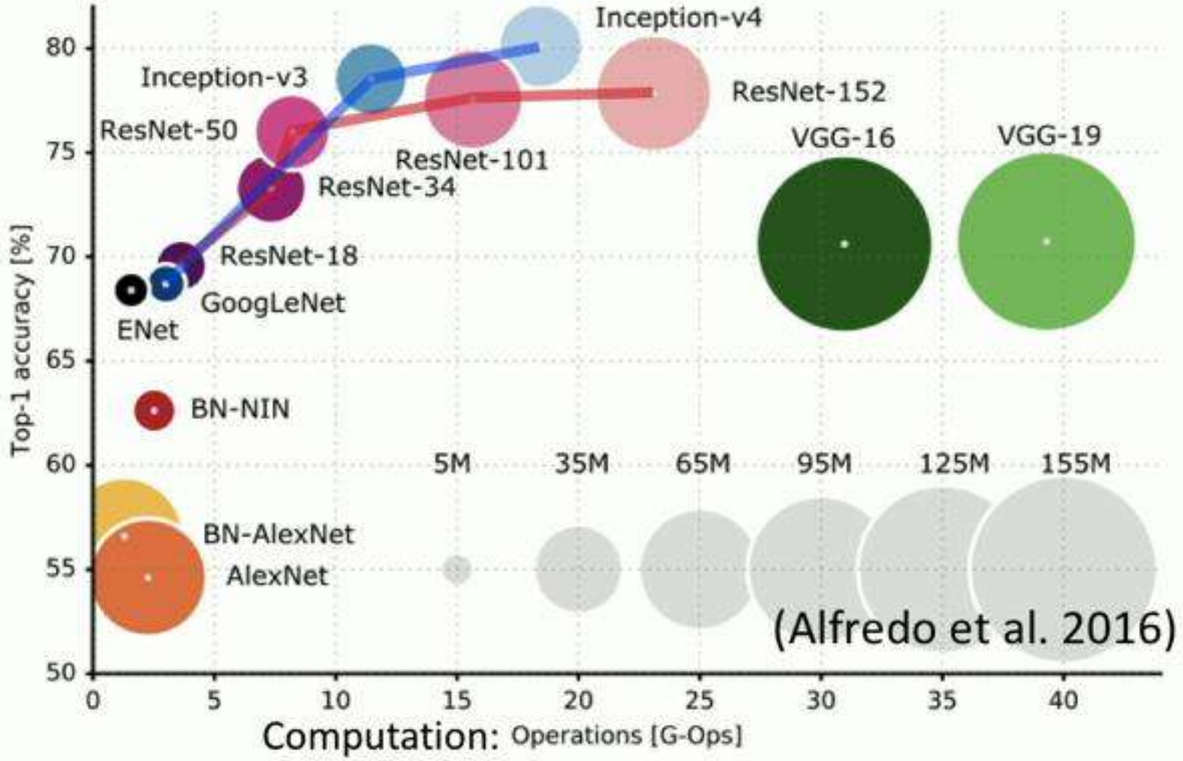
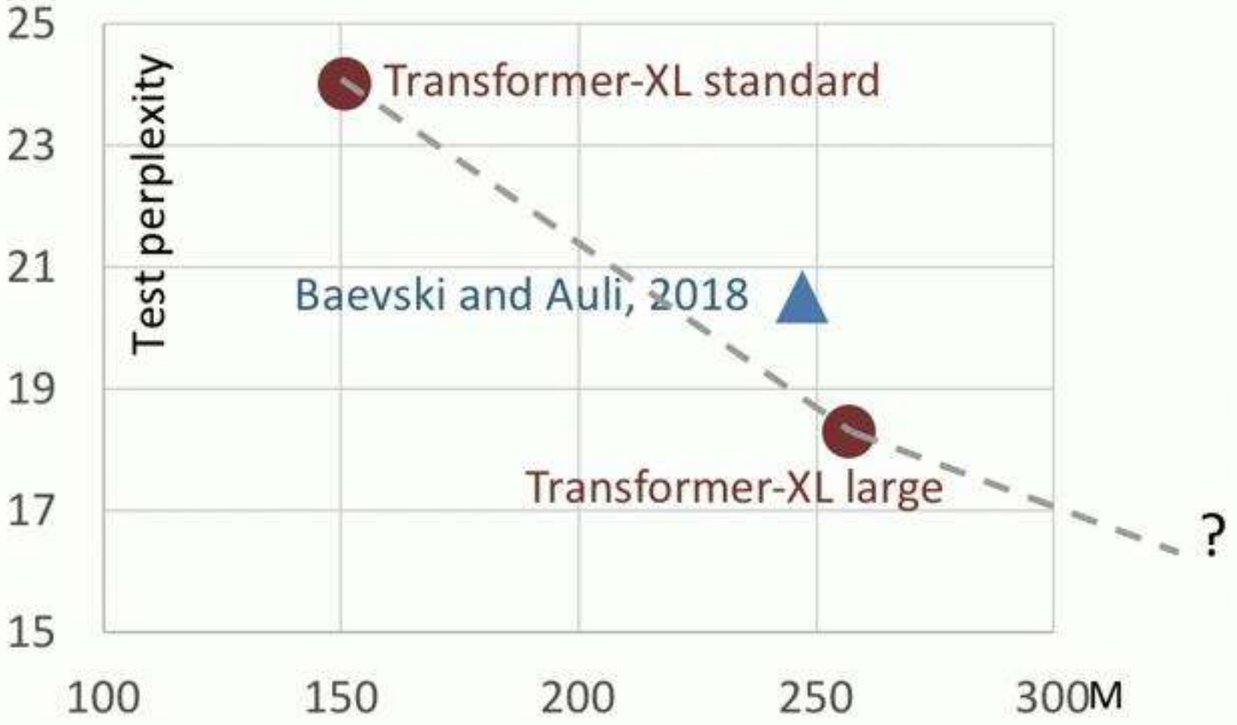
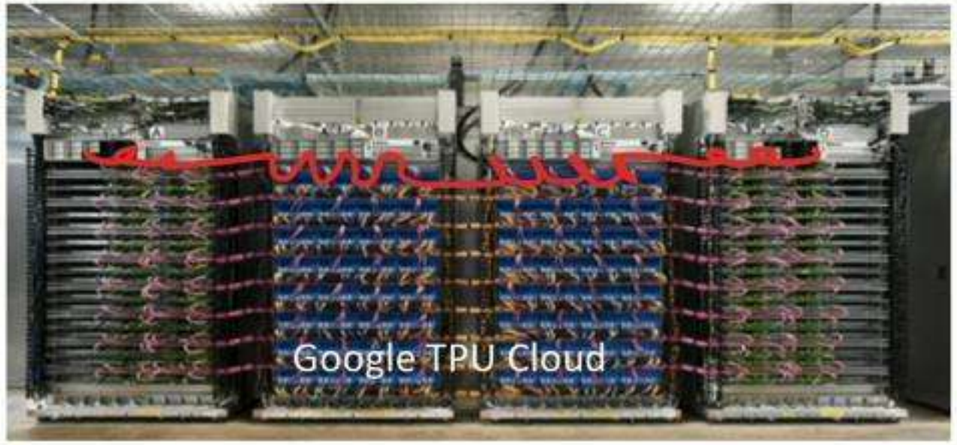


Language Modeling on Wikitext-103



Trend: we can obtain better prediction using larger models

Obstacles of Building Larger Models



- Training larger models is slower
- Longer research & production cycles

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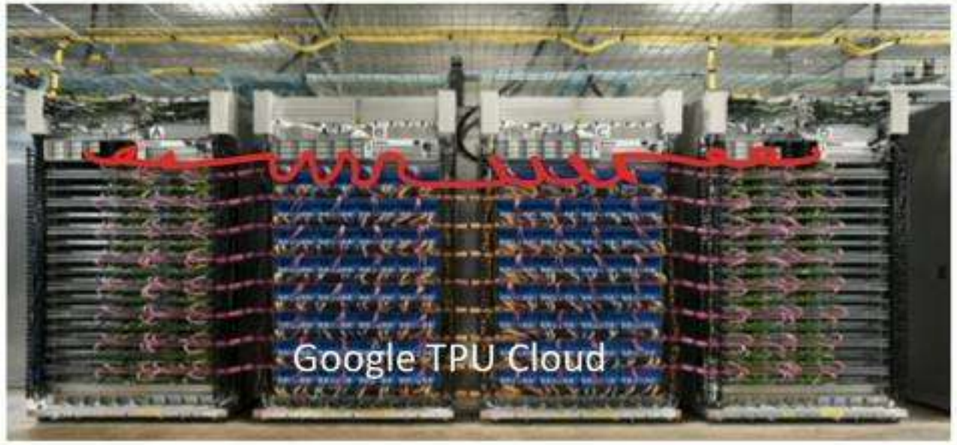

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- Inference speed is slow
- Challenging to deploy large models to applications with compute and memory constraints

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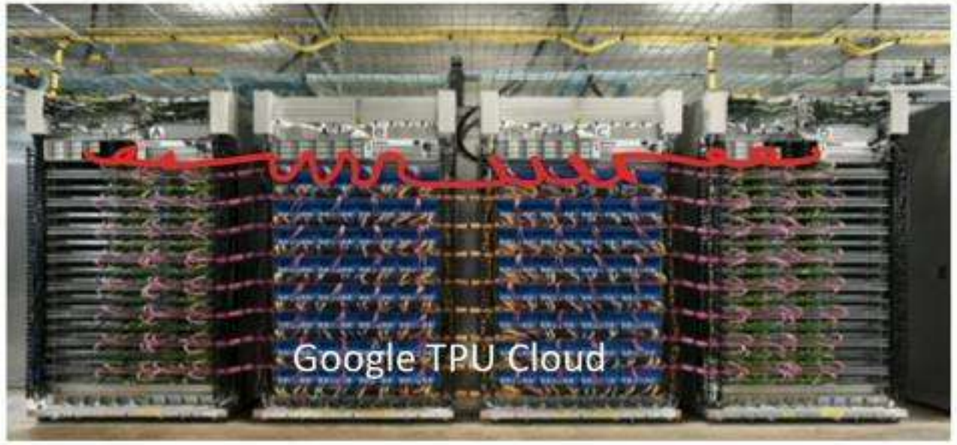

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- Challenging to deploy large models to applications with compute and memory constraints

My research: make training and inference faster.

Outline

- Previous Research
  - Distributed deep learning acceleration (15 min)
  - Sparse deep neural networks (20 min)
- Future Research (6 min)

TernGrad: Ternary Gradients to Reduce Communication in Distributed Deep Learning

NeurIPS 2017 (Oral)

Wen, Wei, Cong Xu, Feng Yan, Chunpeng Wu, Yandan Wang, Yiran Chen, and Hai Li. "Terngrad: Ternary gradients to reduce communication in distributed deep learning." In *Advances in neural information processing systems*, pp. 1509-1519. 2017.

Communication Bottleneck in Distributed Deep Learning

Synchronous SGD

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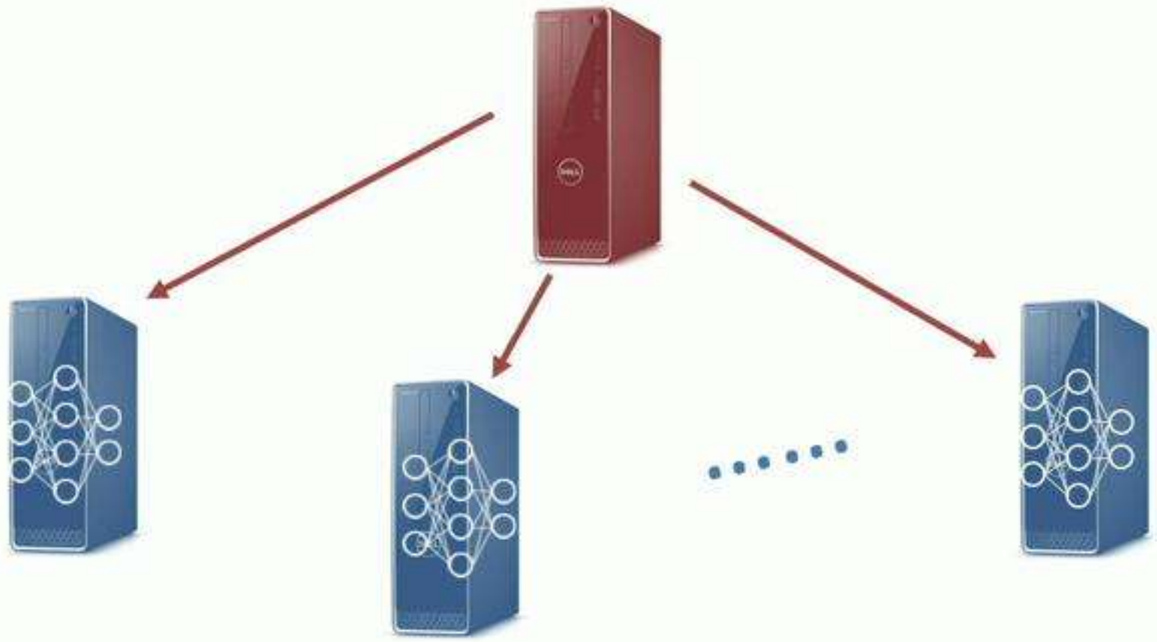

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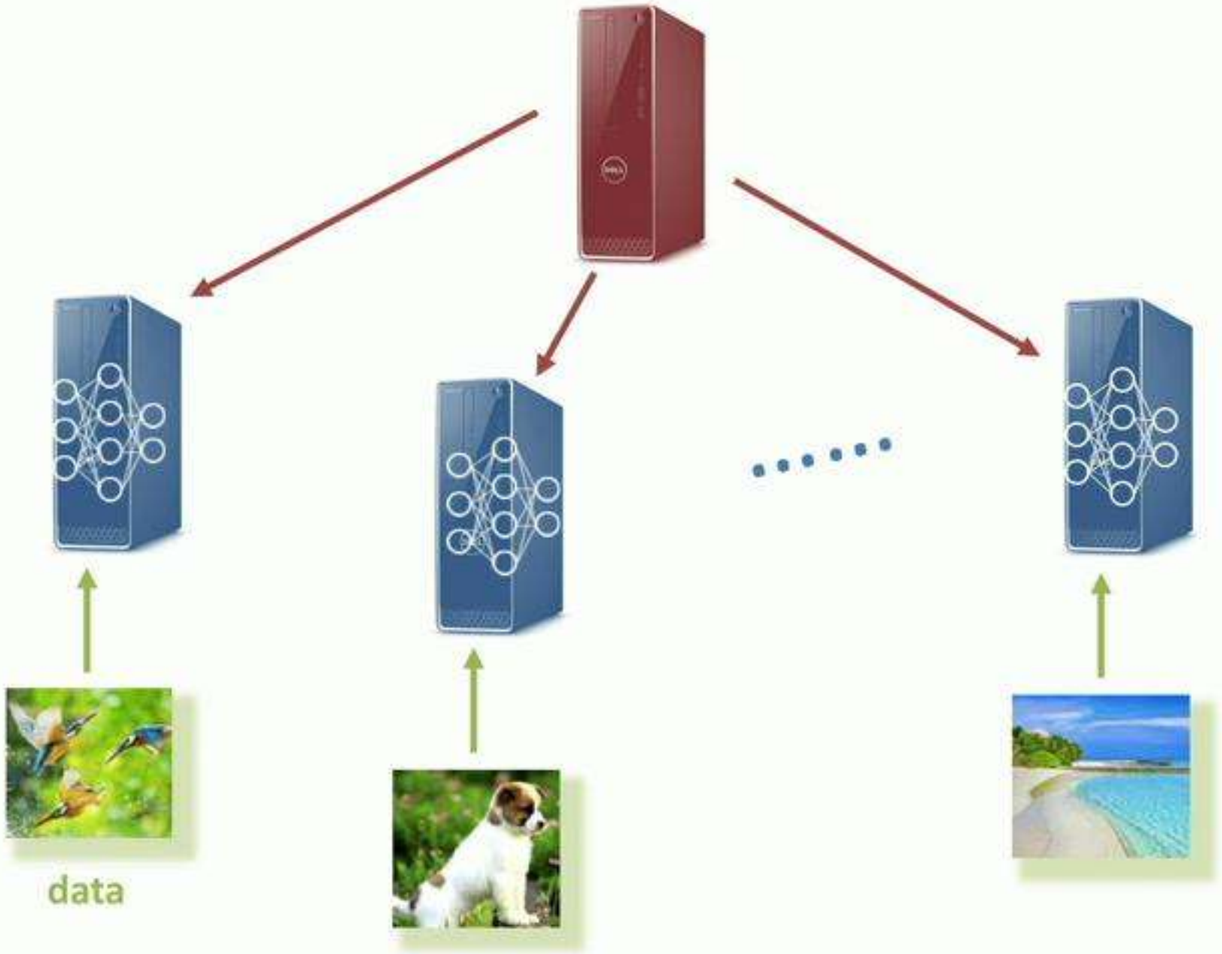

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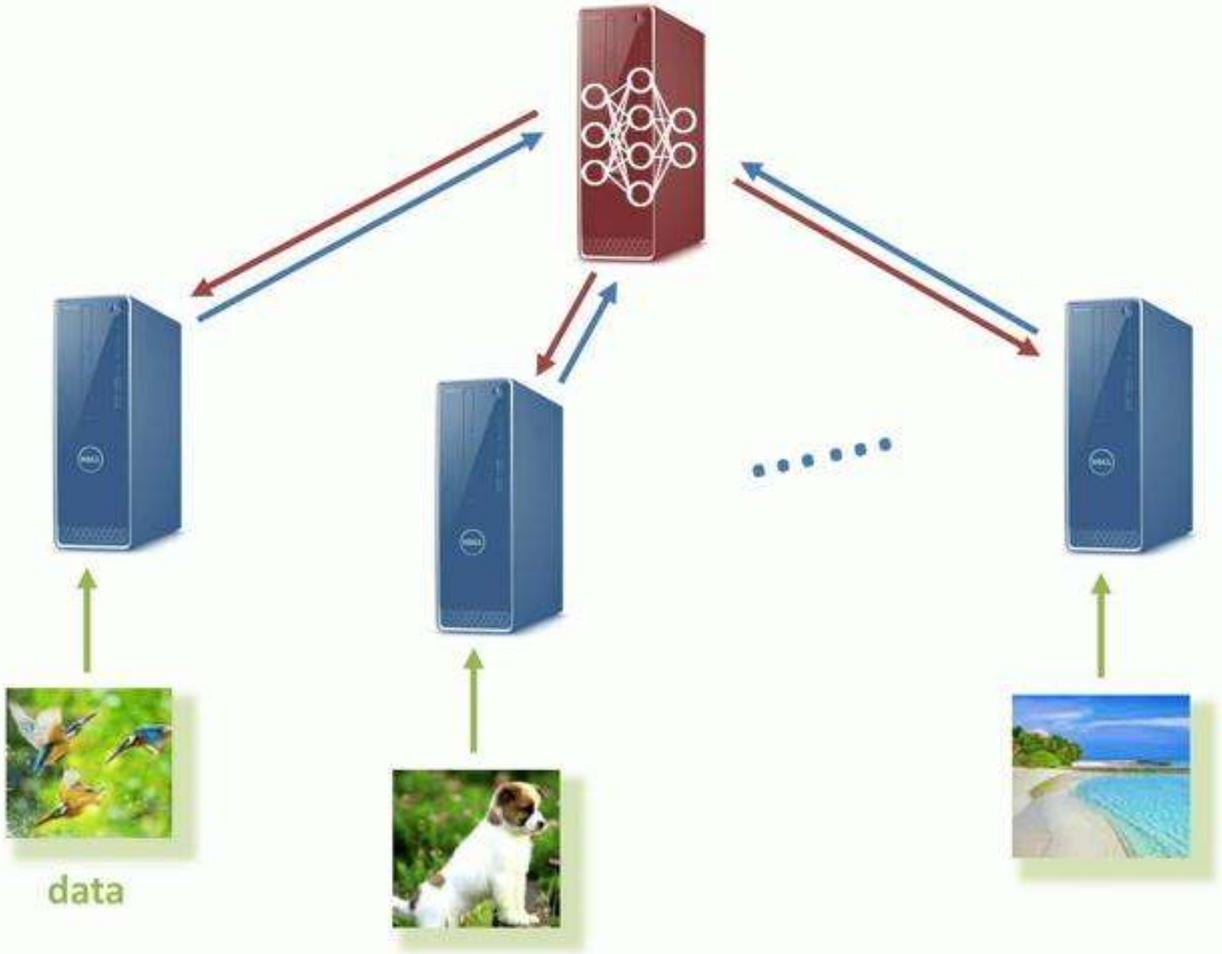

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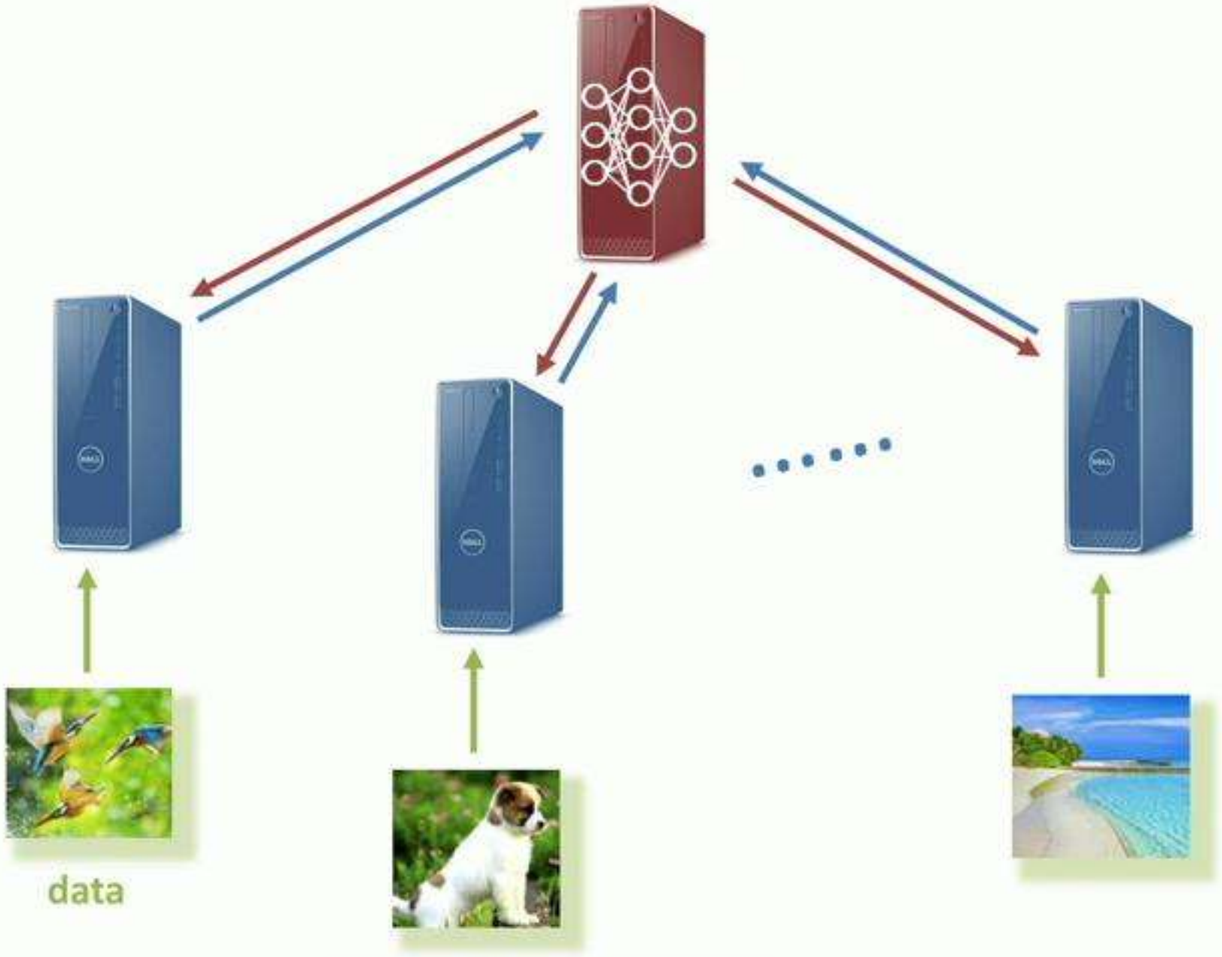

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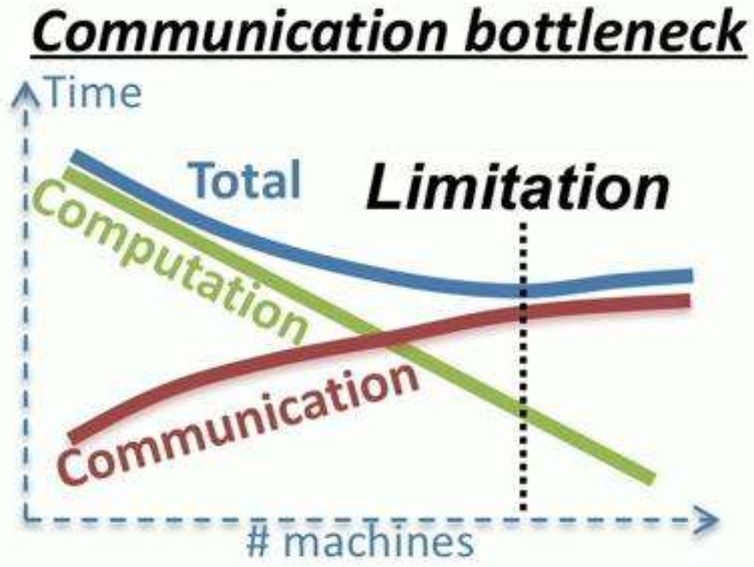

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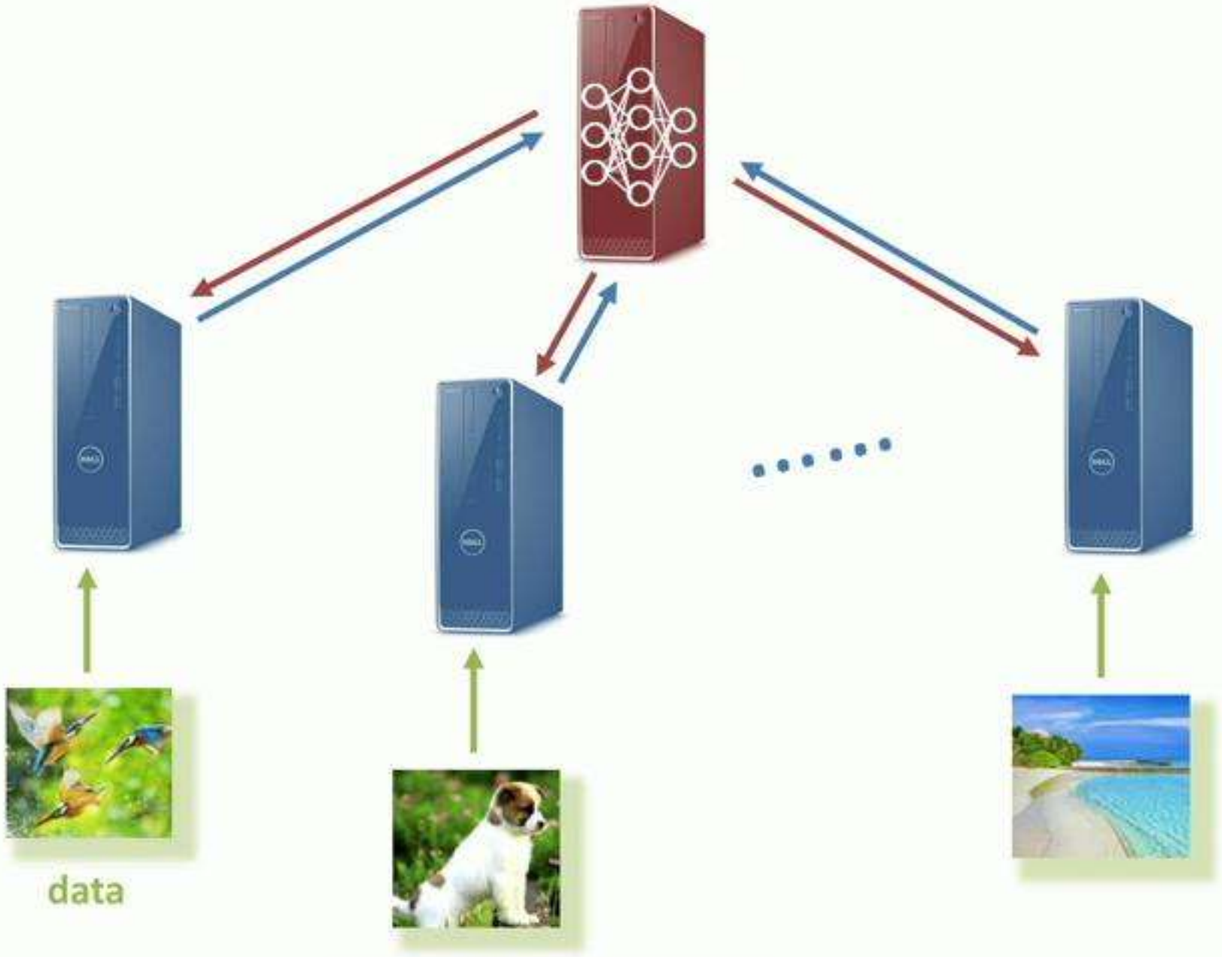

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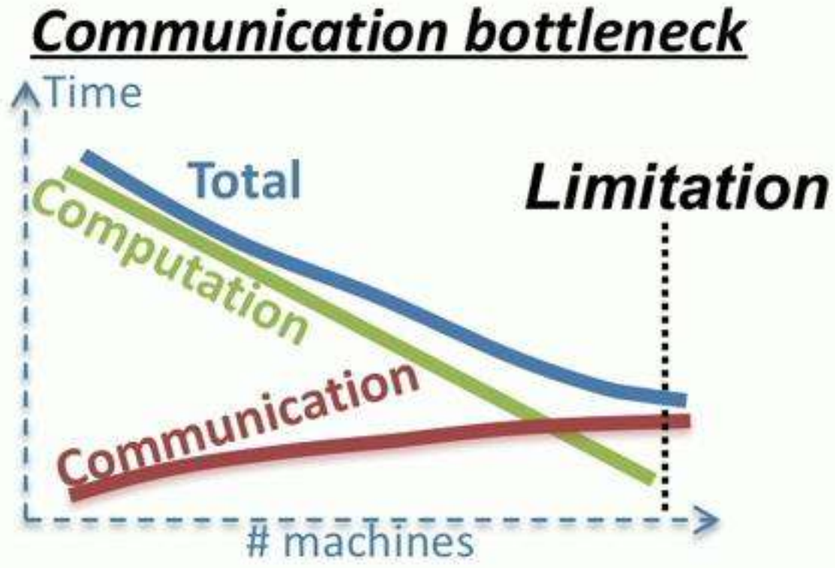
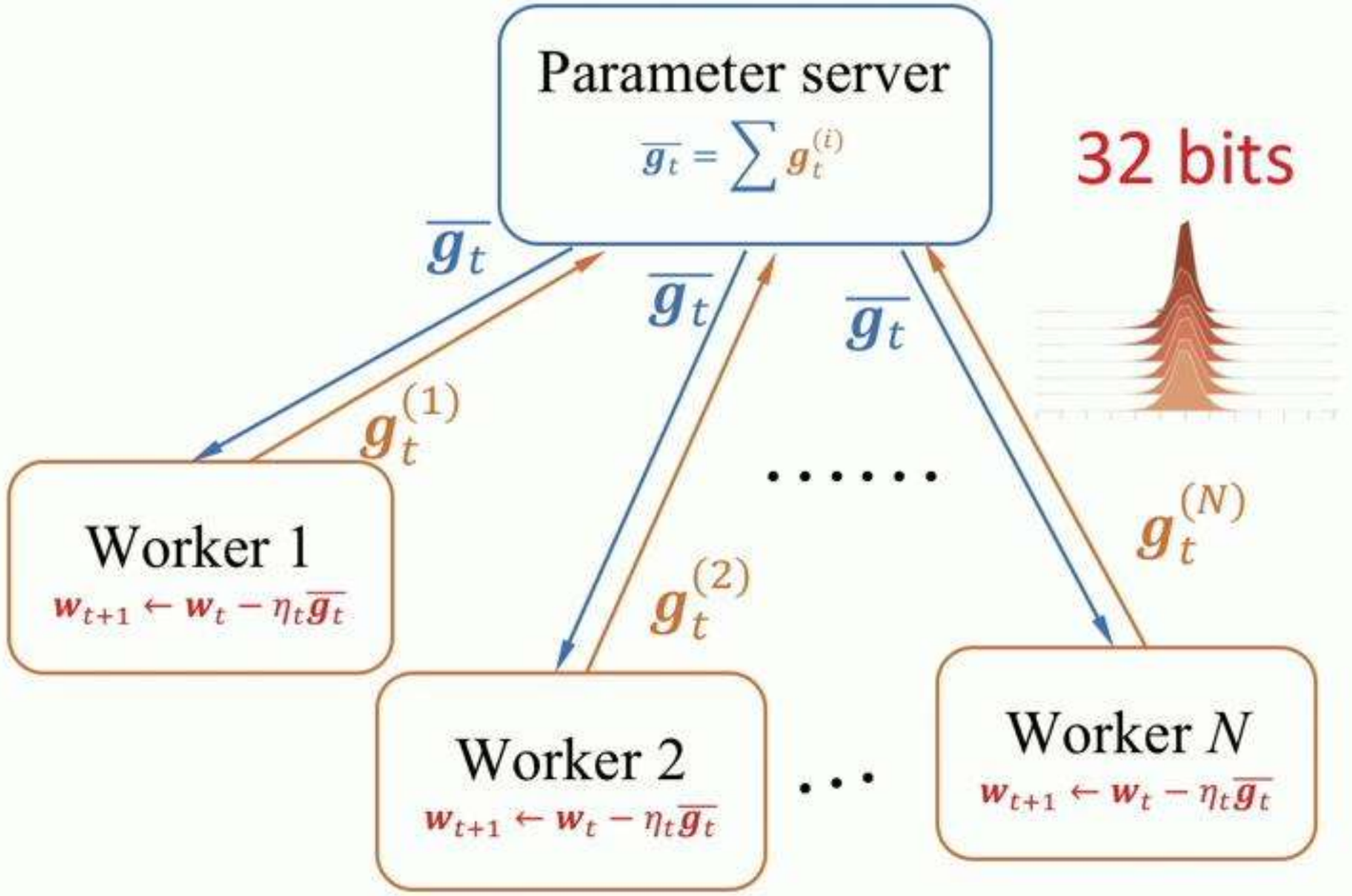


Gradient Quantization for Communication Reduction



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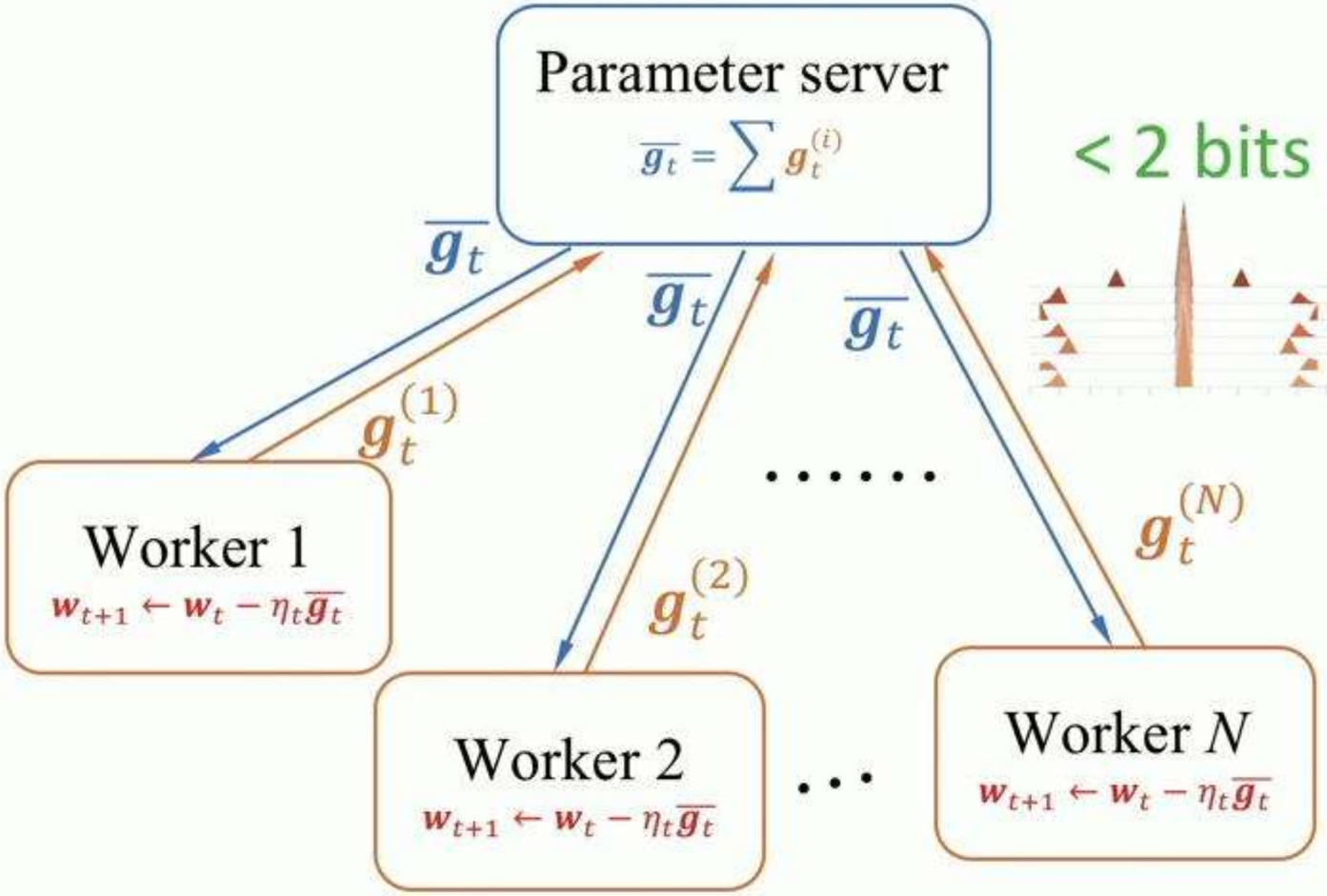

< 2 bits (>16x reduction)

ternary gradients (TernGrad)

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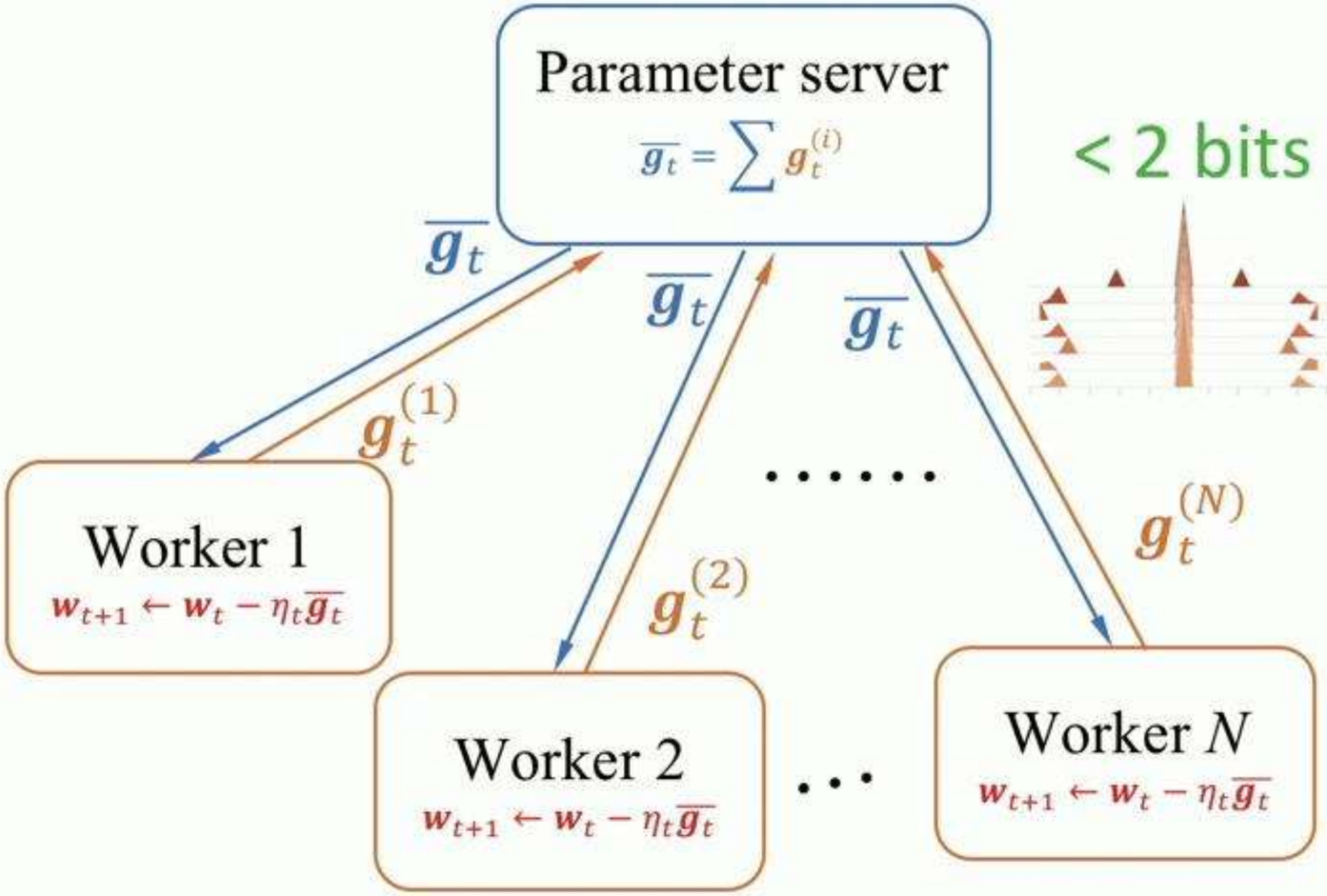

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ternary gradients (TernGrad)

It's challenging because it loses precision in the learning.

Basic Idea: Stochastic Gradients without Bias

Batch Gradient Descent

$$C(\boldsymbol{w}) \triangleq \frac{1}{n}\sum_{i=1}^{n} Q(\boldsymbol{z}_i, \boldsymbol{w})$$

$$\boldsymbol{w}_{t+1} = \boldsymbol{w}_t - \frac{\eta_t}{n}\sum_{i=1}^{n} g_t^{(i)}$$

SGD

$$\boldsymbol{w}_{t+1} = \boldsymbol{w}_t - \eta_t \cdot g_t^{(I)}$$

I is randomly drawn from [1,n]

$$\mathrm{E}\left\{g_t^{(I)}\right\} = \nabla C(\boldsymbol{w})$$

No bias

TernGrad

$$\boldsymbol{w}_{t+1} = \boldsymbol{w}_t - \eta_t \cdot ternarize\left(g_t^{(I)}\right)$$

$$\mathrm{E}\left\{ternarize\left(g_t^{(I)}\right)\right\} = \nabla C(\boldsymbol{w})$$

No bias

TernGrad is Simple

$$\tilde{\boldsymbol{g}}_t = ternarize(\boldsymbol{g}_t) = s_t \cdot sign\left(\boldsymbol{g}_t\right) \circ \boldsymbol{b}_t$$

$$s_t \triangleq ||\boldsymbol{g}_t||_\infty \triangleq max\left(abs\left(\boldsymbol{g}_t\right)\right)$$

$$\begin{cases} P(b_{tk} = 1 \mid \boldsymbol{g}_t) = |g_{tk}|/s_t \\ P(b_{tk} = 0 \mid \boldsymbol{g}_t) = 1 - |g_{tk}|/s_t \end{cases}$$

Example:

$\boldsymbol{g}_t^{(i)}$: [0.30, -1.20, ..., 0.9]

s_t: 1.20

Signs: [1, -1, ..., 1]

$P(b_{tk} = 1|g_t)$: $[\frac{0.3}{1.2}, \frac{1.2}{1.2}, \ldots, \frac{0.9}{1.2}]$

$\boldsymbol{b}_t$: [0,1,...,1]

$\widetilde{\boldsymbol{g}_t^{(i)}}$: [0, -1, ..., 1]*1.20

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$$\mathbf{E}_{\boldsymbol{z},\boldsymbol{b}}\left\{\tilde{\boldsymbol{g}}_t\right\} = \mathbf{E}_{\boldsymbol{z},\boldsymbol{b}}\left\{s_t \cdot sign\left(\boldsymbol{g}_t\right) \circ \boldsymbol{b}_t\right\}$$

$$= \mathbf{E}_{\boldsymbol{z}}\left\{s_t \cdot sign\left(\boldsymbol{g}_t\right) \circ \mathbf{E}_{\boldsymbol{b}}\left\{\boldsymbol{b}_t|\boldsymbol{z}_t\right\}\right\} = \mathbf{E}_{\boldsymbol{z}}\left\{\boldsymbol{g}_t\right\} = \nabla_{\boldsymbol{w}} C(\boldsymbol{w}_t)$$

No bias

Convergence

Standard SGD almost truly converges under assumptions (Fisk 1965, Metivier 1981&1983, Bottou 1998)

Assumption 1:

$C(\boldsymbol{w})$ has a single minimum $\boldsymbol{w}^*$ and $\forall \epsilon > 0, \inf_{||\boldsymbol{w}-\boldsymbol{w}^*||^2>\epsilon} (\boldsymbol{w}-\boldsymbol{w}^*)^T \nabla_{\boldsymbol{w}} C(\boldsymbol{w}) > 0$

Assumption 2:

Learning rate γ_t decreases neither very fast nor very slow $\begin{cases} \sum_{t=0}^{+\infty} \gamma_t^2 < +\infty \\ \sum_{t=0}^{+\infty} \gamma_t = +\infty \end{cases}$

Assumption 3 (gradient bound):

$\mathbf{E}\left\{||\boldsymbol{g}||^2\right\} \leq A + B\,||\boldsymbol{w}-\boldsymbol{w}^*||^2$

Standard SGD *almost-truly* converges

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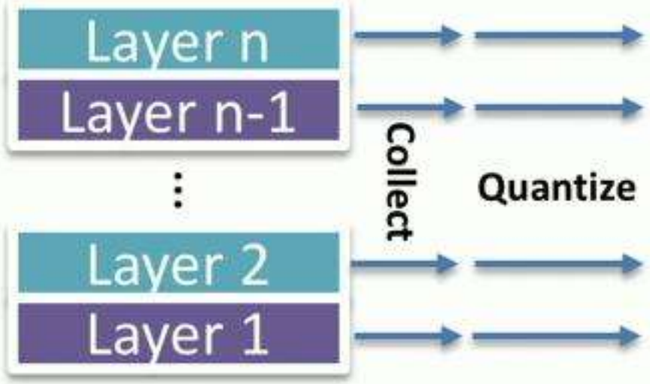
Stronger gradient bound in *TernGrad*

Closing Bound Gap

Two methods to push the gradient bound of *TernGrad* closer to the bound of standard SGD

Layer-wise ternarizing



Gradient clipping

Histogram of gradients

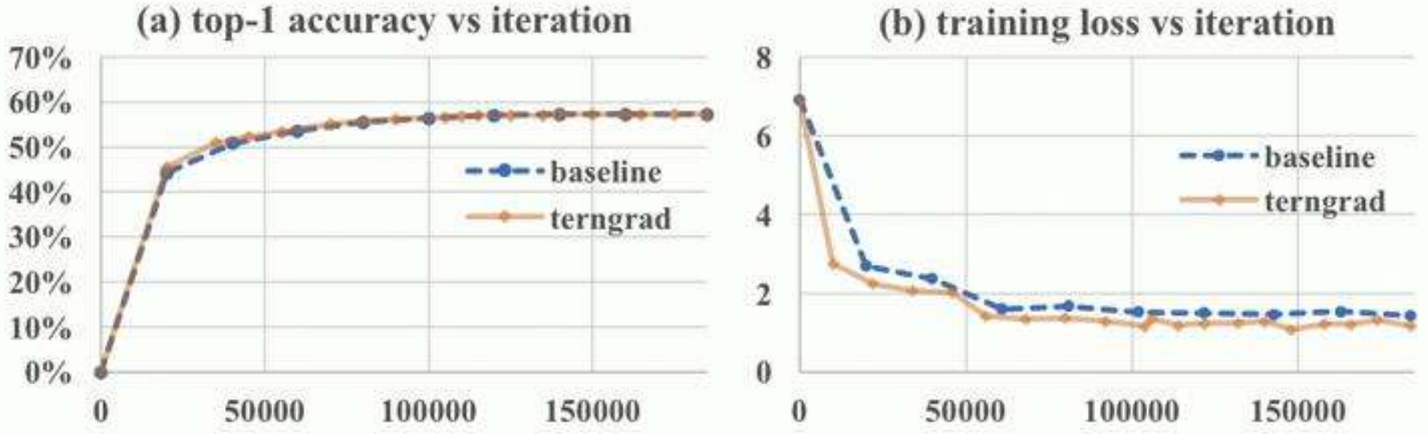
Training ImageNet with Ternary Gradients

AlexNet

base LR	mini-batch size	workers	gradients	top-1
0.01	256	2	floating	57.33%
			TernGrad	57.61%
			TernGrad-noclip	54.63%
0.02	512	4	floating	57.32%
			TernGrad	57.28%
0.04	1024	8	floating	**56.62%**
			TernGrad	**57.54%**

Keskar, et al., 2017

4 workers



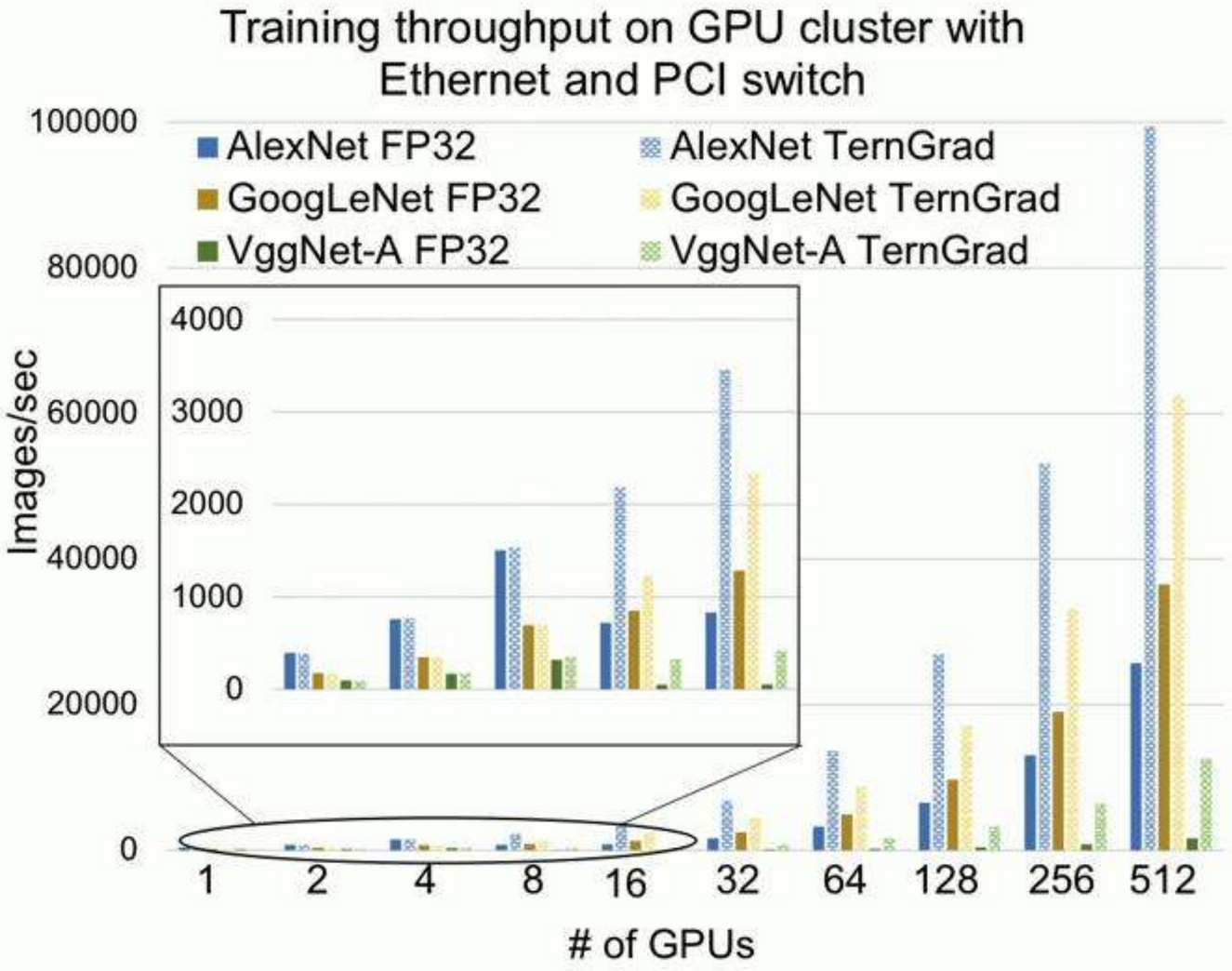
Training ImageNet with Ternary Gradients

GoogLeNet accuracy loss is <2% on avgerage.

base LR	mini-batch size	workers	gradients	top-5
0.04	128	2	floating	88.30%
			TernGrad	86.77%
0.08	256	4	floating	87.82%
			TernGrad	85.96%
0.10	512	8	floating	89.00%
			TernGrad	86.47%

All hyper-parameters in standard SGD are directed used in *TernGrad* (such as learning rate, batch size, total epochs, etc.)

Speedup



TernGrad gives higher speedup when communication time occupies a higher ratio, such as:

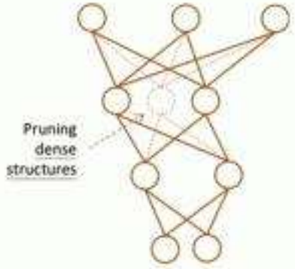
1. using more machines;
2. having smaller communication bandwidth, e.g., Ethernet vs. InfiniBand;
3. training a DNN with a higher "parameter #: computation #"
4. using GPU-based distributed systems vs. CPU-based

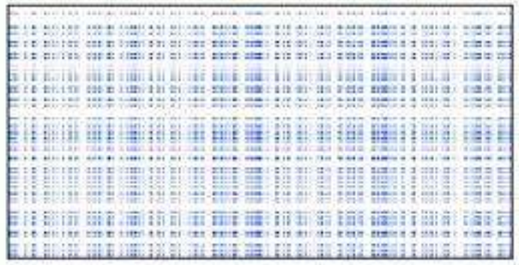
TernGrad in Production

- Facebook is using *TernGrad* to overcome communication bottleneck in AI Infra
- Effectiveness is evaluated by ad ranking models, which have zero toleration on prediction loss
- Available in PyTorch/Caffe2

Inference Acceleration

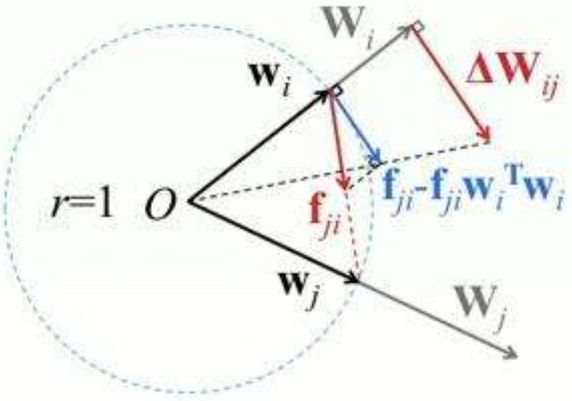
Wen et al. NeurIPS 2016



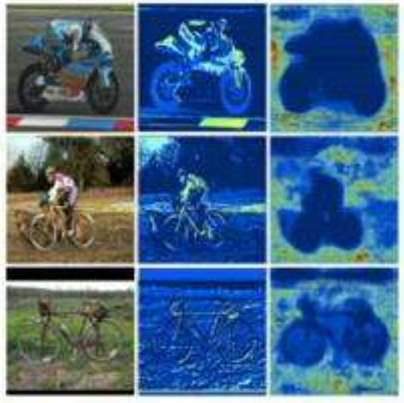


Wen et al. ICLR 2018

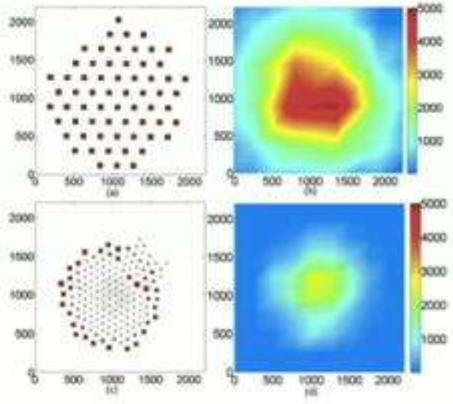
Wang et al. ASP-DAC 2017
(Best Paper Award)



Wen et al. ICCV 2017



Wu et al. CVPR 2017



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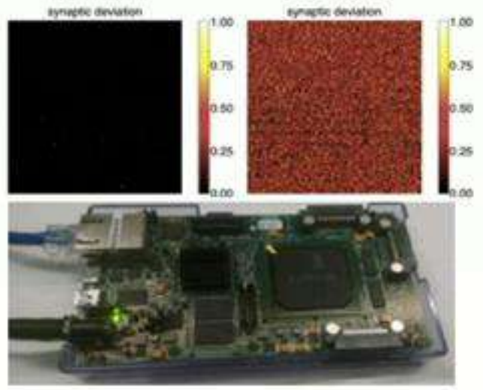

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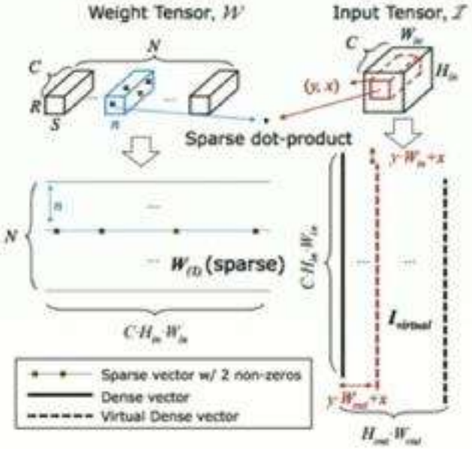

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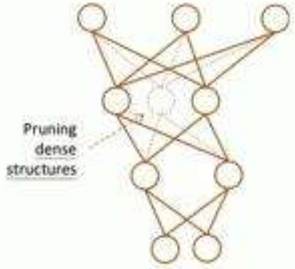

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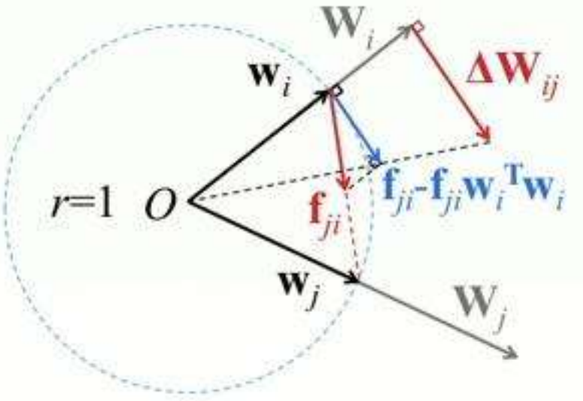
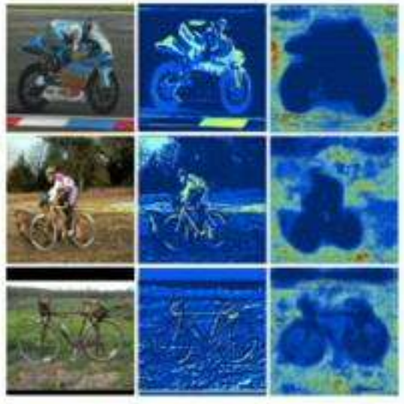
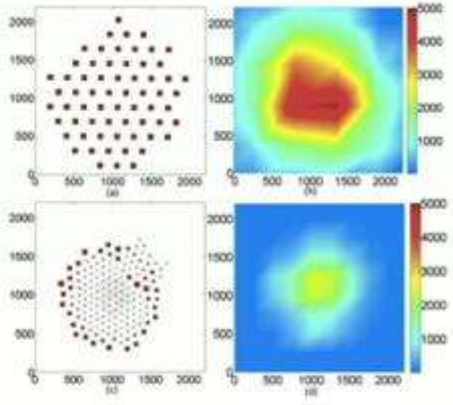


Wen et al. ICCV 2017



Wu et al. CVPR 2017



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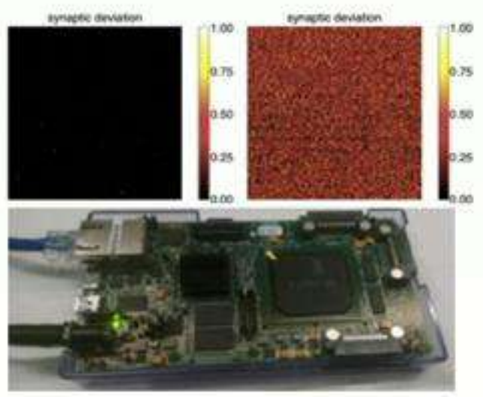

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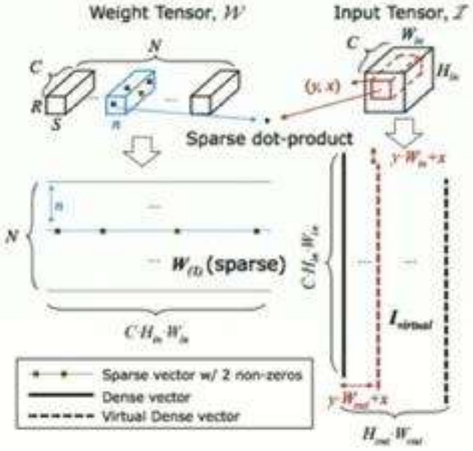

Park et al. ICLR 2017

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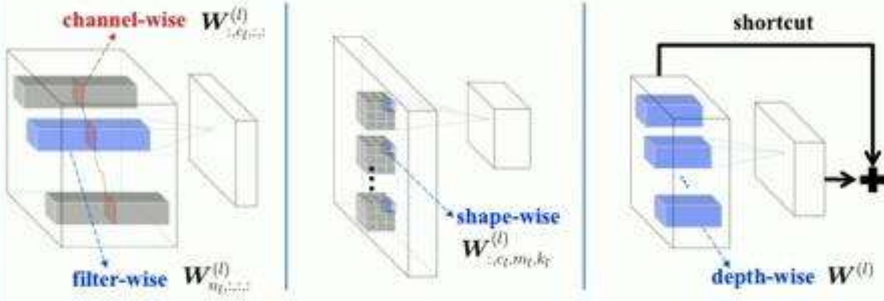
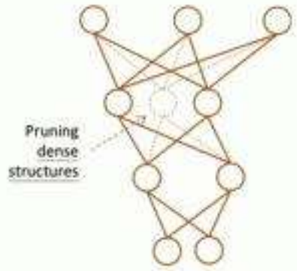


Wen et al. NeurIPS 2016

This presentation



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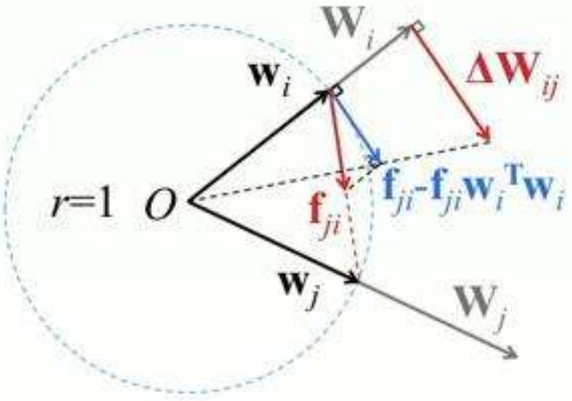
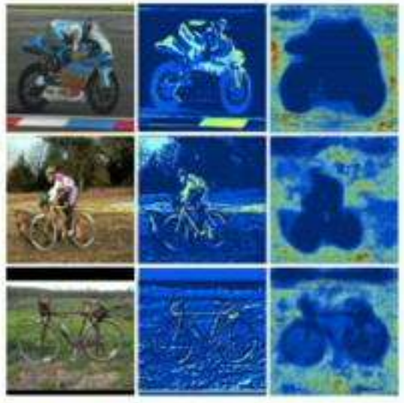
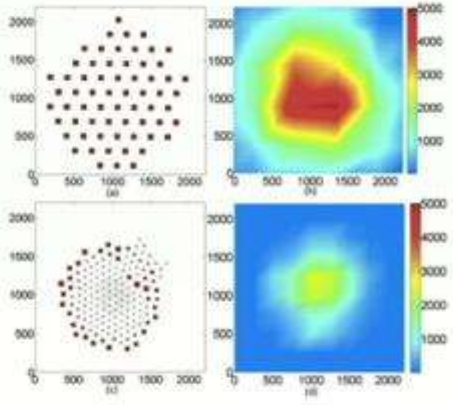
Wang et al. ASP-DAC 2017
(Best Paper Award)



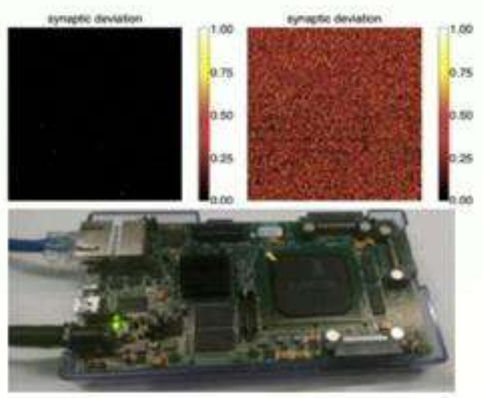
Wen et al. ICCV 2017



Wu et al. CVPR 2017



Wen et al. DAC 2015
(Best Paper Nomination)



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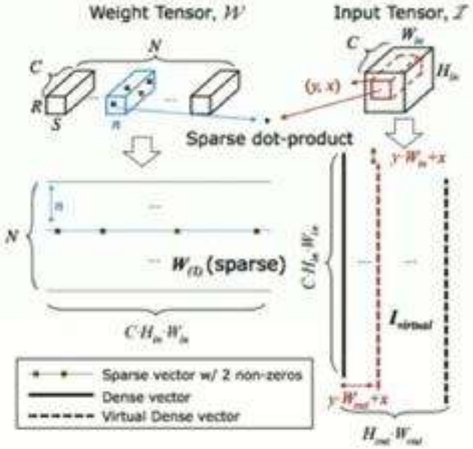
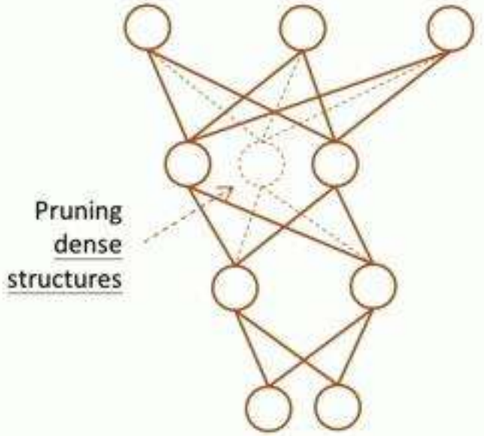


Park et al. ICLR 2017

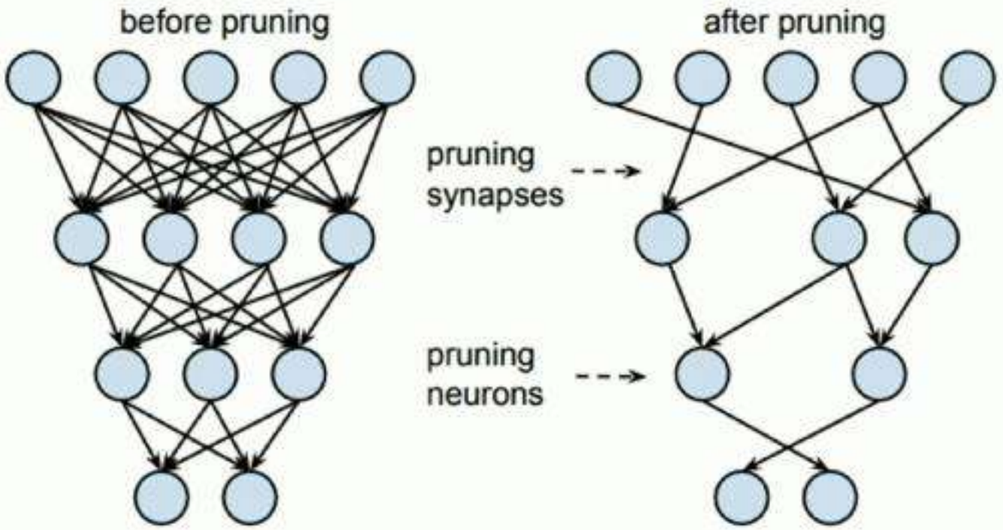


Sparse Deep Neural Networks

Wen, Wei, Chunpeng Wu, Yandan Wang, Yiran Chen, and Hai Li. "Learning structured sparsity in deep neural networks." In *Advances in neural information processing systems*, pp. 2074-2082. 2016.

Wen, Wei, Yuxiong He, Samyam Rajbhandari, Minjia Zhang, Wenhan Wang, Fang Liu, Bin Hu, Yiran Chen, and Hai Li. "Learning intrinsic sparse structures within long short-term memory." *ICLR* 2018.

Inefficiency of Sparse Convolutional Neural Networks



Significantly reduces the storage size of DNNs [1]
Good speedup with customized hardware [2]

[1] S. Han et. al. NeurIPS 2015
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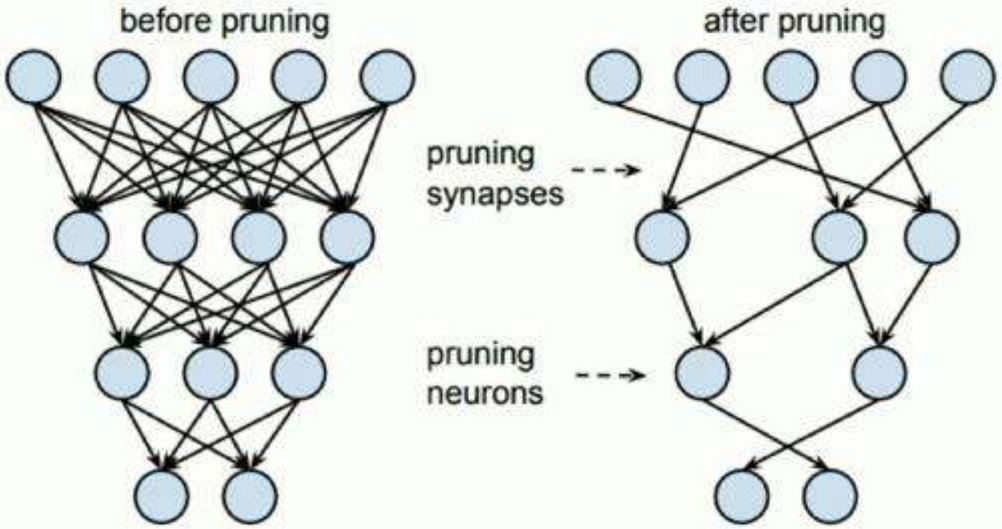
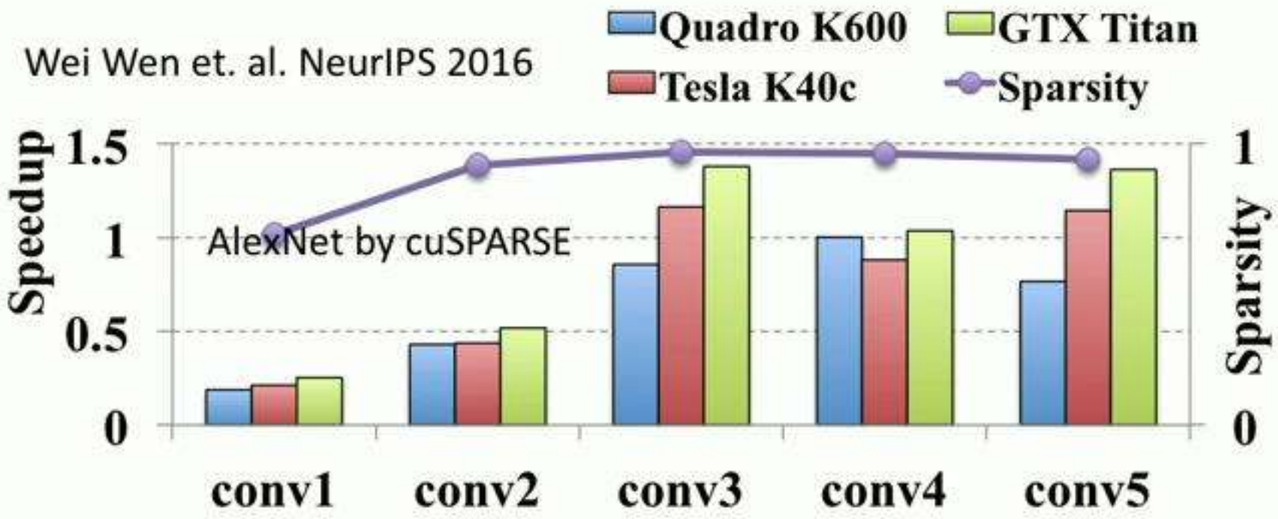
Inefficiency of Sparse Convolutional Neural Networks





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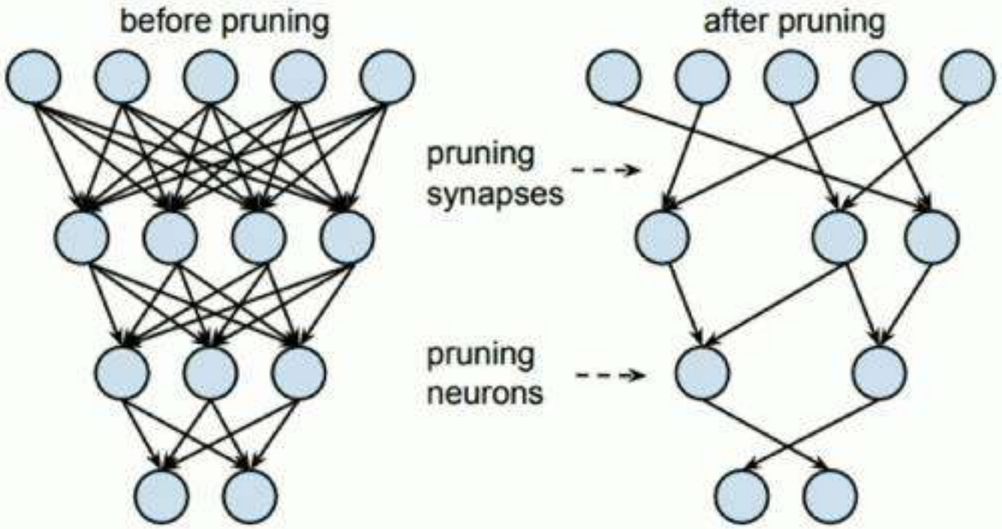

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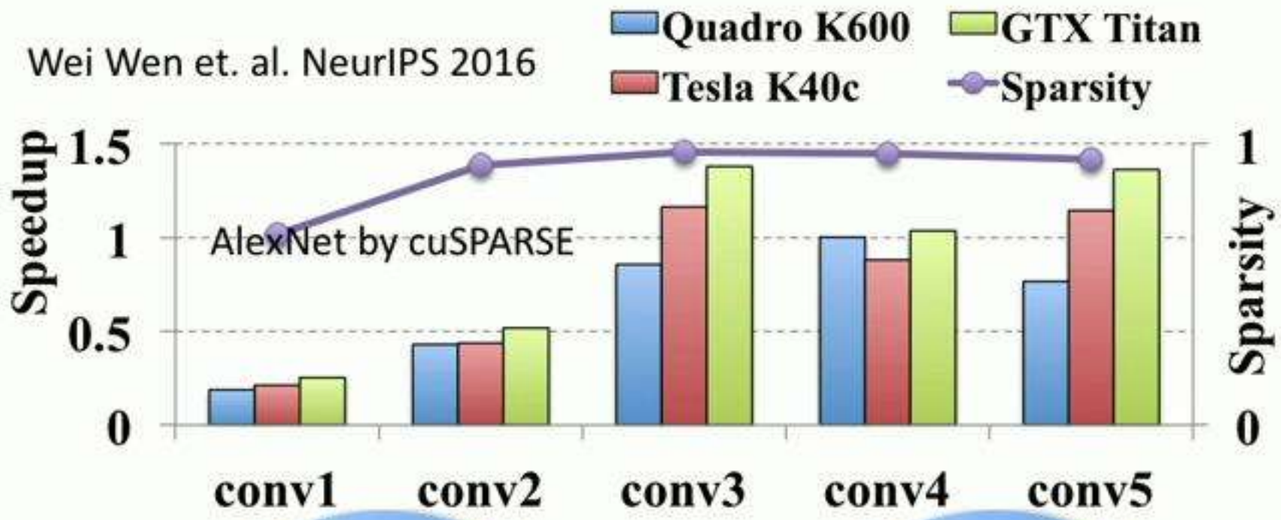
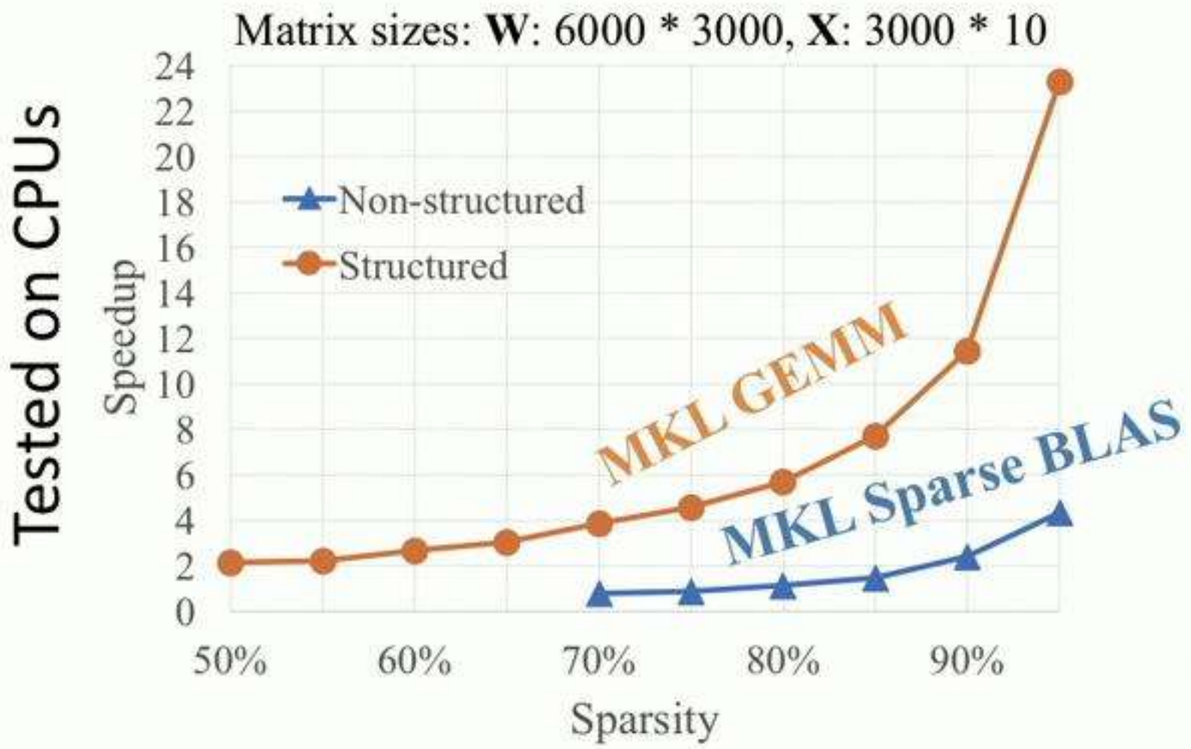


Efficiency of Structured Sparsity

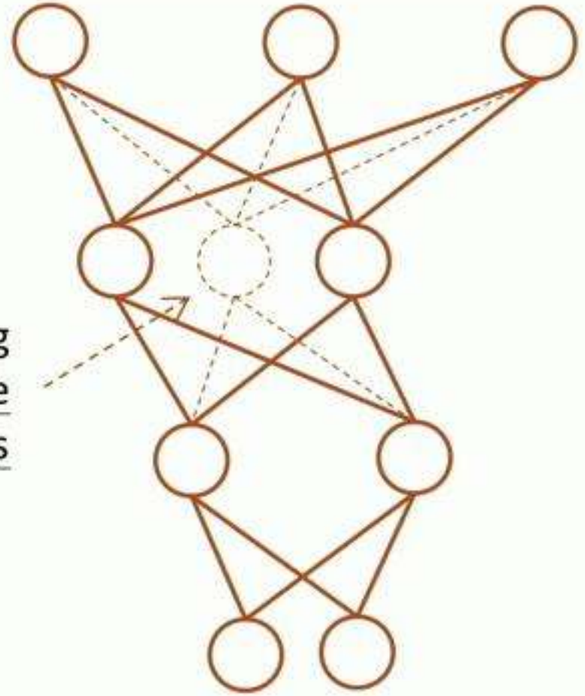
Structured sparsity

Non-structured sparsity



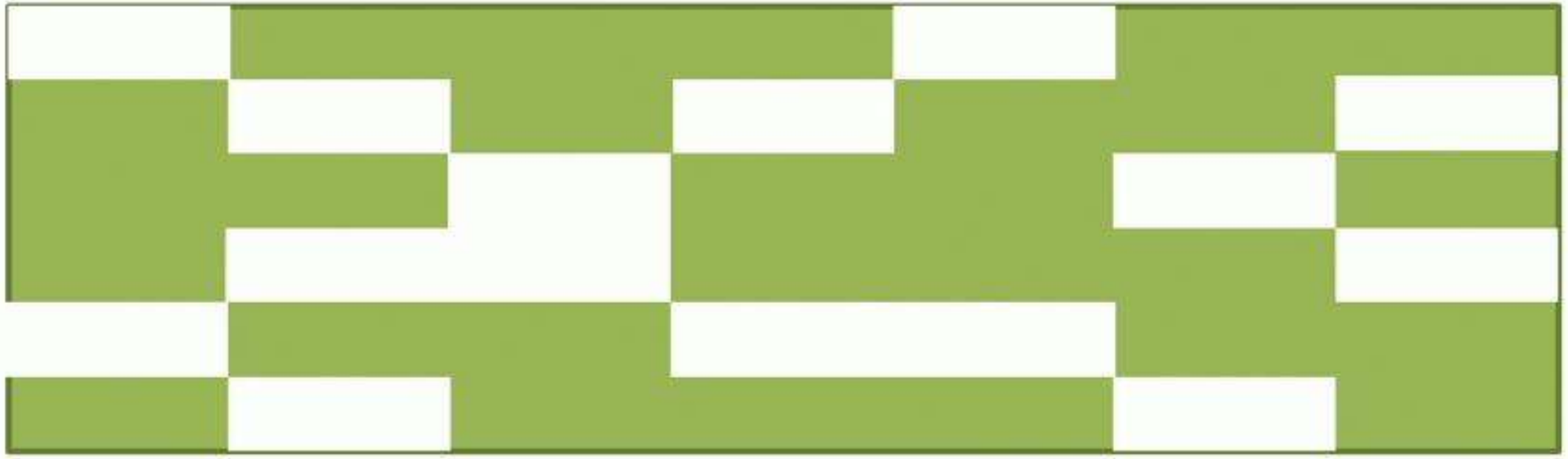
Structurally Sparse DNNs (SSDNNs)

Neural Architecture



Pruning dense structures

Weight matrix



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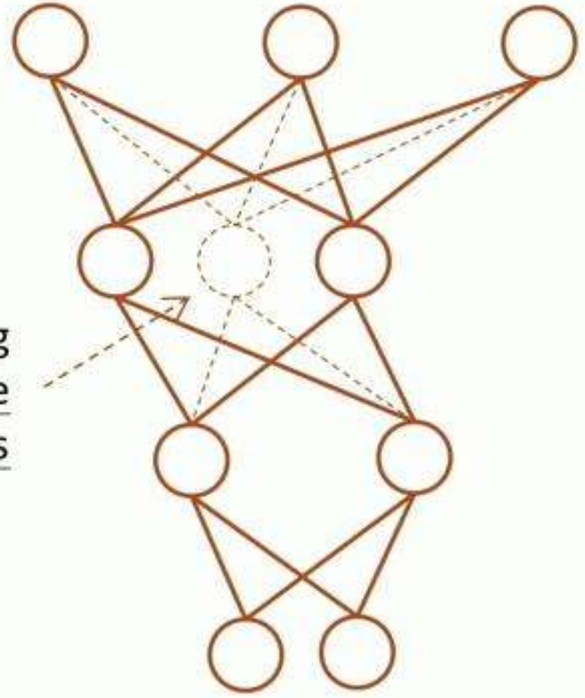

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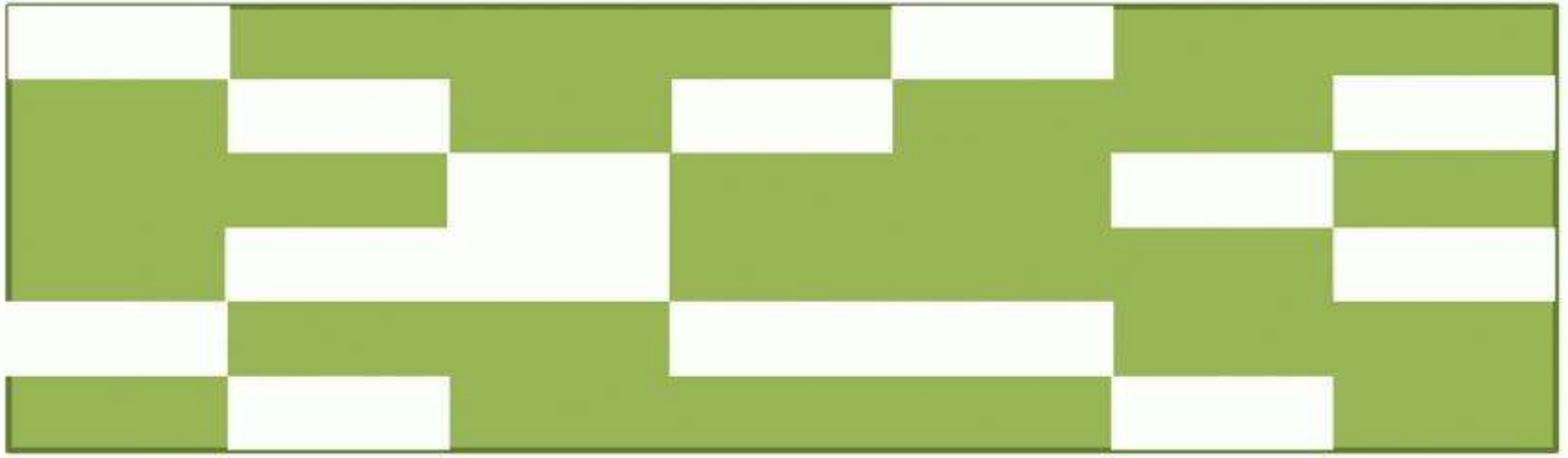

Connections/Weights are removed group by group.

In neural architecture: a group can be a neuron, a layer, a filter, a hidden state, etc.

In weight matrix: a group can be a rectangle block, a row, a column or even the whole matrix

Group Lasso [1] Regularization is All you Need for SSDNNs

Step 1: Weights are split to G groups $\mathbf{w}^{(1..G)}$

e.g. $(w_1, w_2, w_3, w_4, w_5)$ -> group 1: $\mathbf{w}^{(1)} = (w_1, w_2, w_3)$, group 2: $\mathbf{w}^{(2)} = (w_4, w_5)$

[1] Yuan et al. 2006

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Step 2: Add group Lasso on each group $\mathbf{w}^{(g)}$ $||\boldsymbol{w}^{(g)}||_g = \sqrt{\sum_{i=1}^{|\boldsymbol{w}^{(g)}|} \left(w_i^{(g)}\right)^2}$ i.e. vector length

sqrt($w_1^2 + w_2^2 + w_3^2$), sqrt($w_4^2 + w_5^2$)

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We refer to our method as ***Structured Sparsity Learning (SSL)***

[1] Yuan et al. 2006

Structured Sparsity Learning (*SSL*)

- Why can SSL learn to remove weights group by group?

The gradient-based explanation:

$$\mathbf{w}^{(g)} \leftarrow \mathbf{w}^{(g)} - \eta \left(\frac{\partial E_D(\mathbf{w})}{\partial \mathbf{w}^{(g)}} + \lambda_g \frac{\mathbf{w}^{(g)}}{\|\mathbf{w}^{(g)}\|_2} \right)$$

A group of weights

Regular gradients to minimize error

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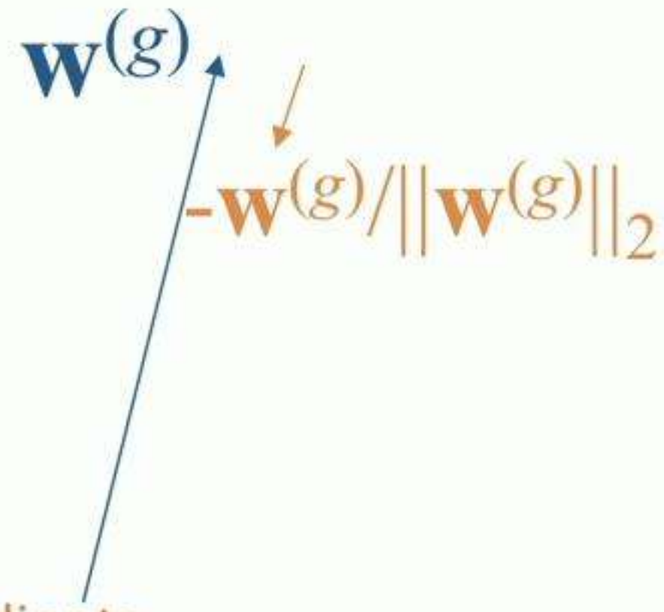
Additional gradients to learn sparsity



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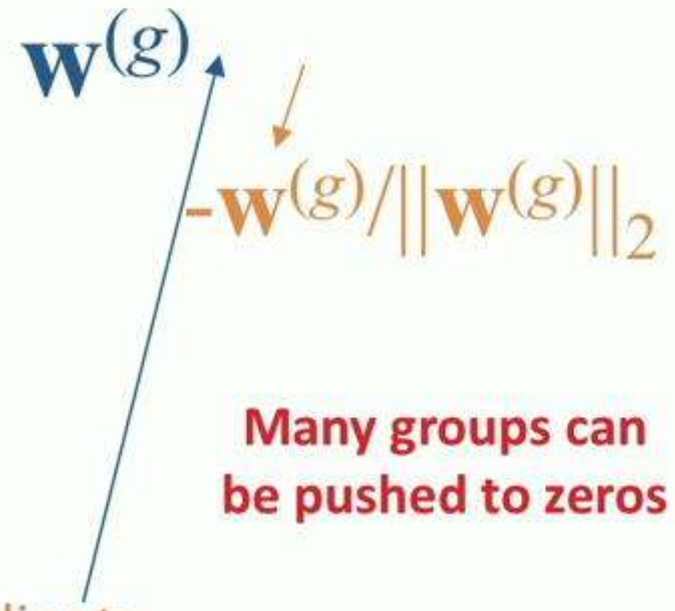
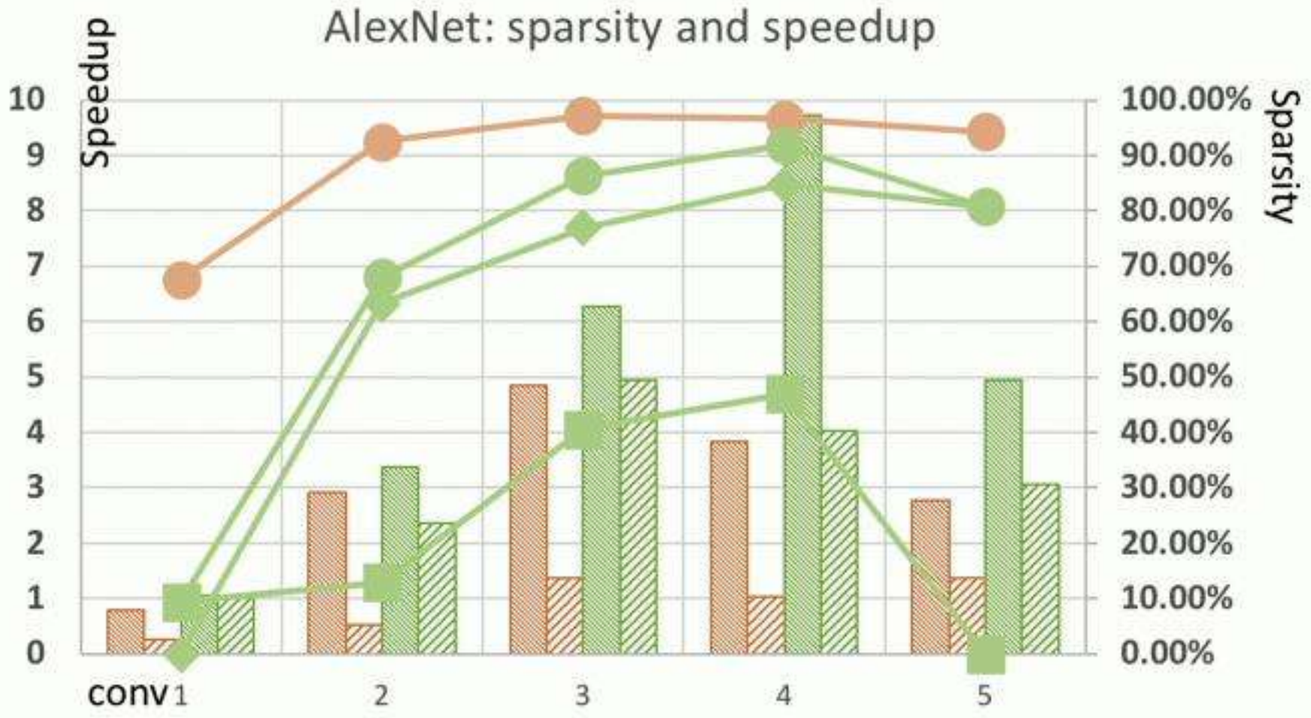


Many groups can be pushed to zeros

Structurally Sparse *AlexNet*

Structured Sparsity (removing columns and rows):

Non-structured sparsity



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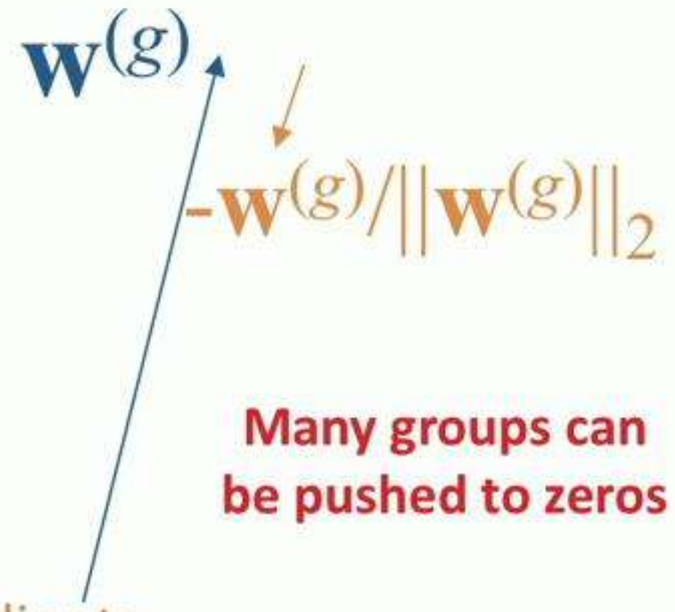

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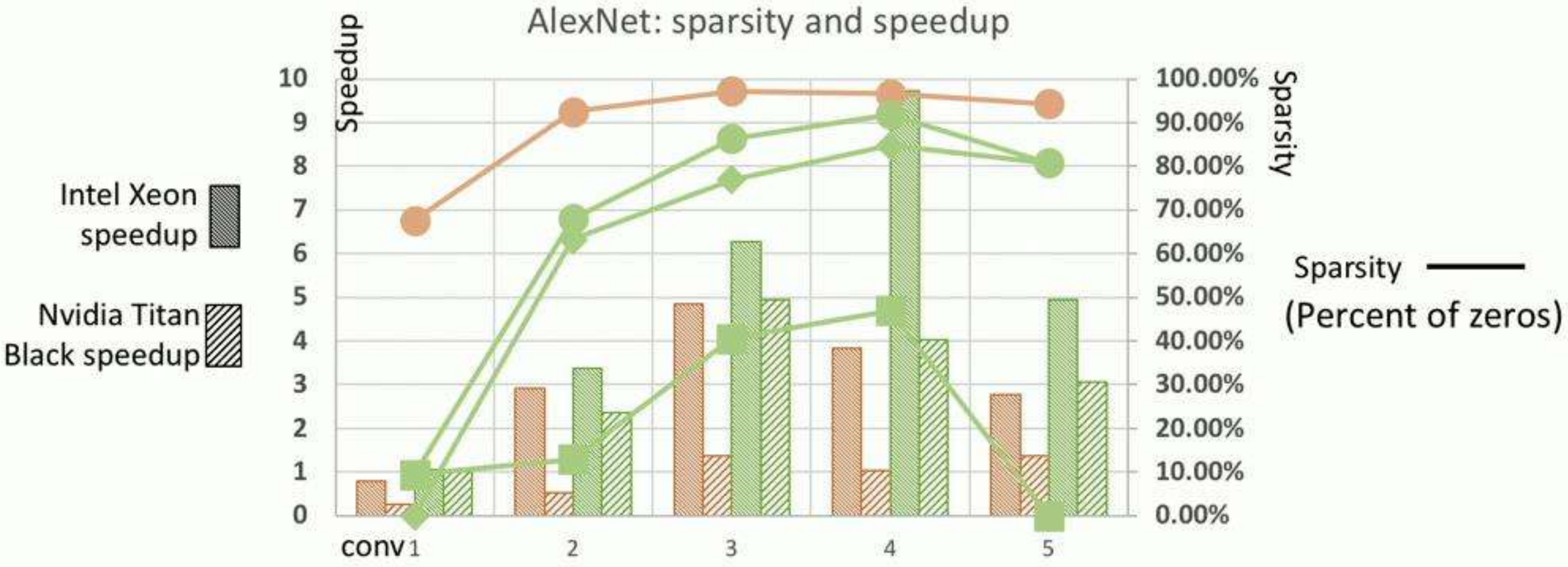

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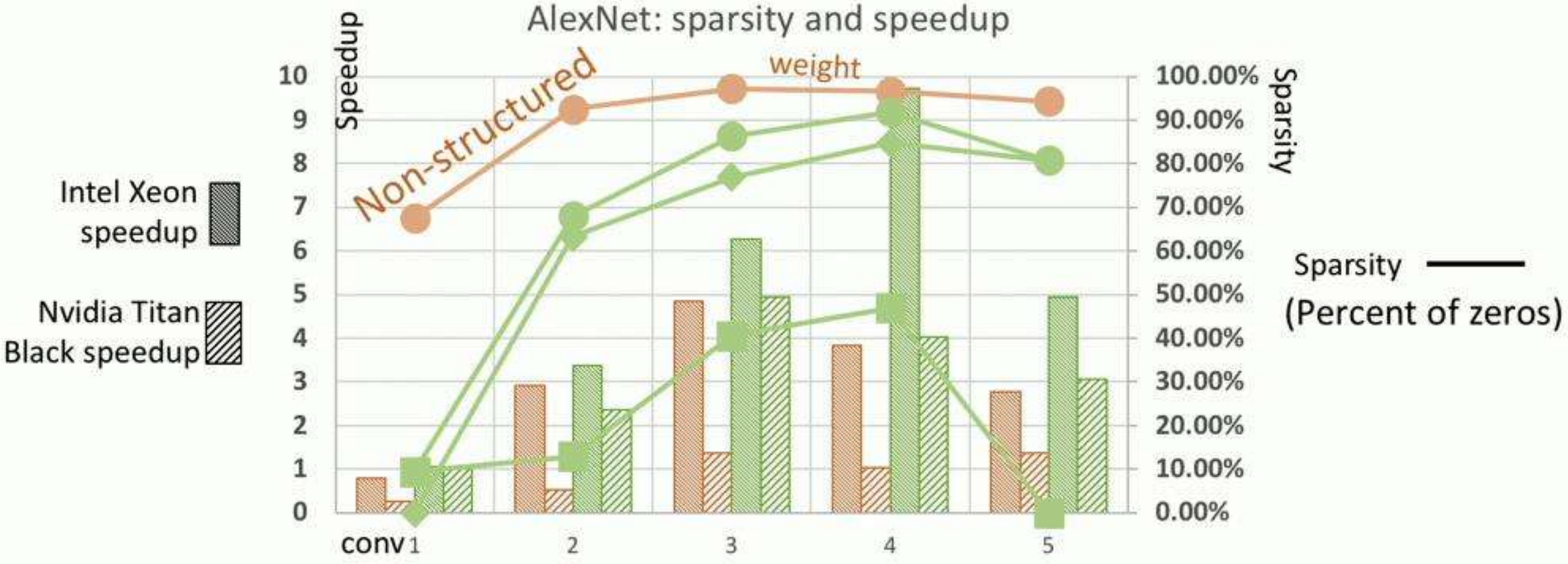

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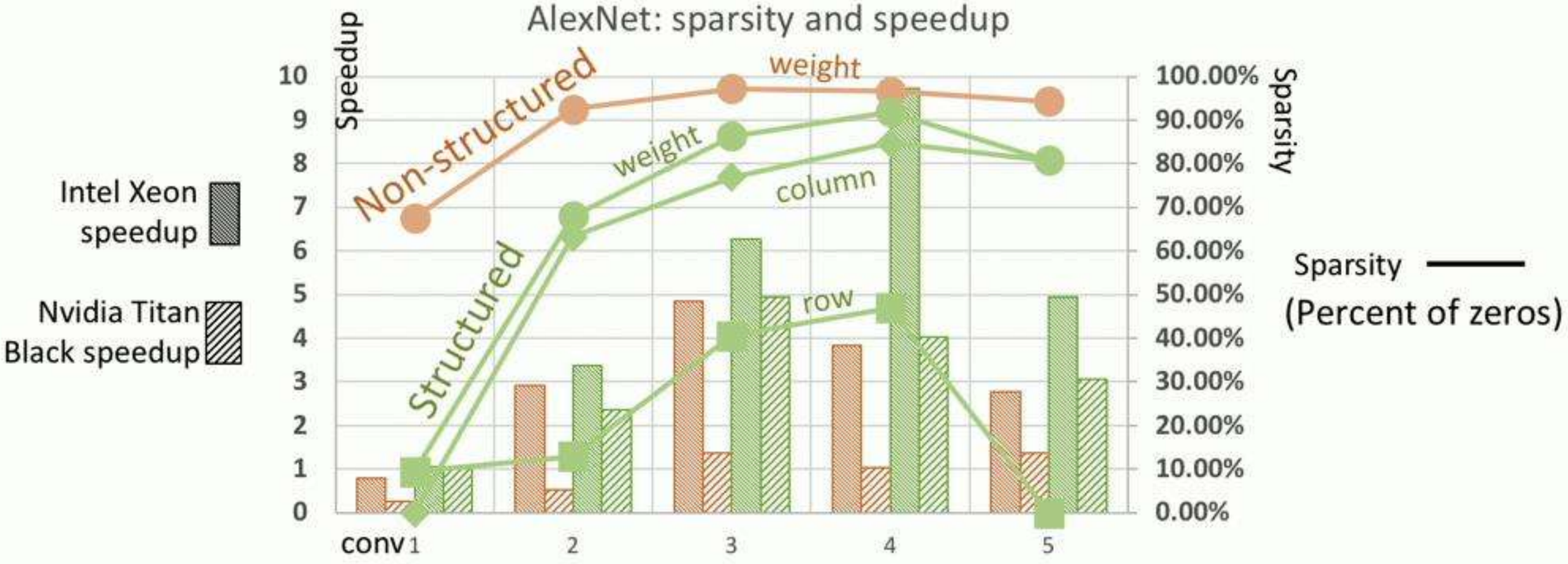
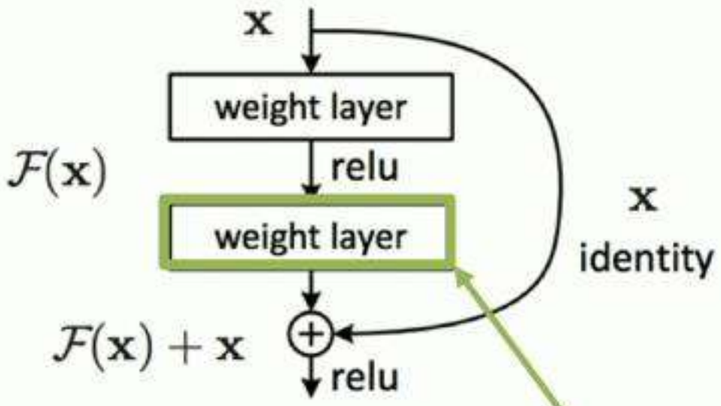


Structurally Sparse *ResNets* – Removing Layers

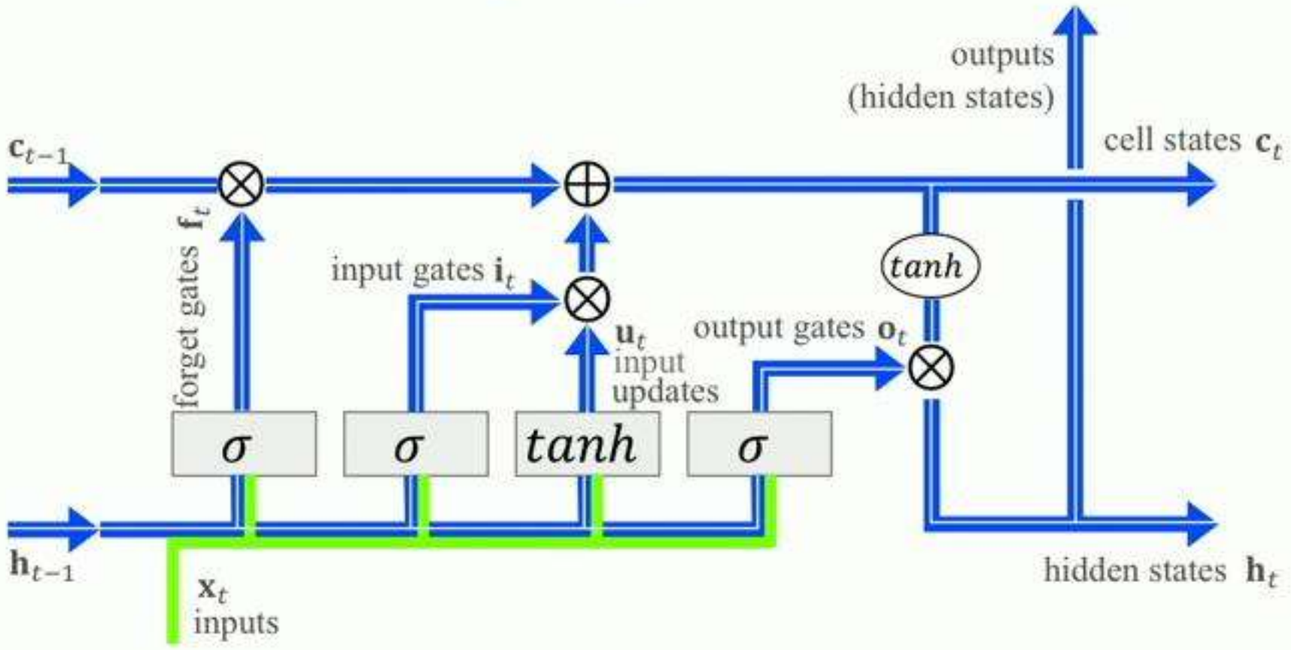


K. He et al. CVPR 2016.

One layer is one group.

	# layers	error
ResNet	20	8.82%
SSL-ResNet	14	8.54%
Reduced	**6/20**	
ResNet	32	7.51%
SSL-ResNet	18	7.40%
Reduced	**14/32**	

Structurally Sparse LSTMs: Removing Hidden Structures



$$\mathbf{i}_t = \sigma\left(\mathbf{x}_t \cdot \mathbf{W}_{xi} + \mathbf{h}_{t-1} \cdot \mathbf{W}_{hi} + \mathbf{b}_i\right)$$
$$\mathbf{f}_t = \sigma\left(\mathbf{x}_t \cdot \mathbf{W}_{xf} + \mathbf{h}_{t-1} \cdot \mathbf{W}_{hf} + \mathbf{b}_f\right)$$
$$\mathbf{o}_t = \sigma\left(\mathbf{x}_t \cdot \mathbf{W}_{xo} + \mathbf{h}_{t-1} \cdot \mathbf{W}_{ho} + \mathbf{b}_o\right)$$
$$\mathbf{u}_t = tanh\left(\mathbf{x}_t \cdot \mathbf{W}_{xu} + \mathbf{h}_{t-1} \cdot \mathbf{W}_{hu} + \mathbf{b}_u\right)$$
$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \mathbf{u}_t$$
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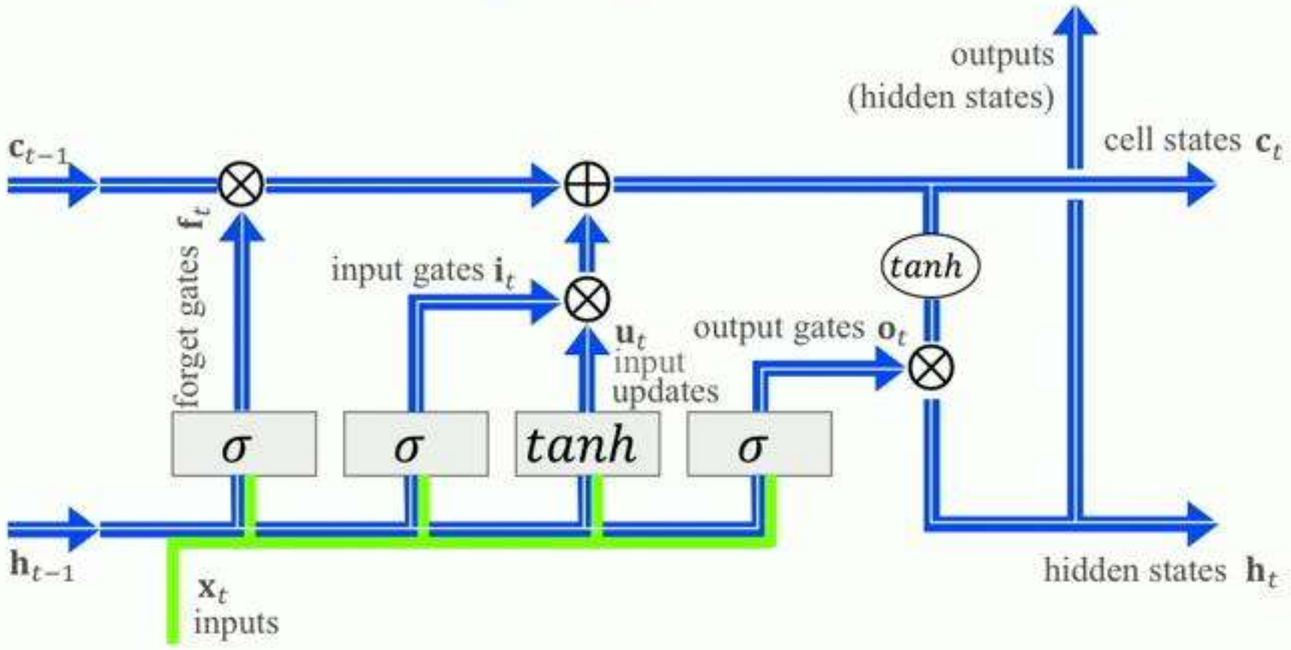

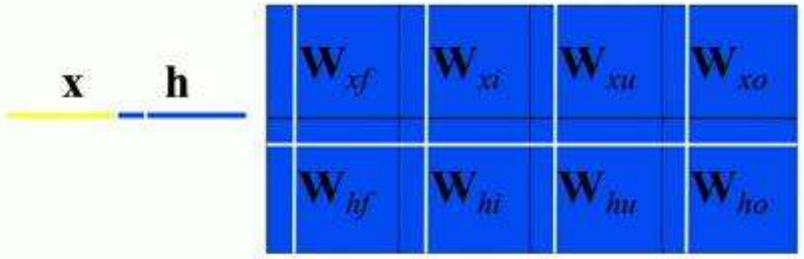

Weights matrices in LSTM

Weights in next layer(s)

$$\mathbf{i}_t = \sigma\left(\mathbf{x}_t \cdot \mathbf{W}_{xi} + \mathbf{h}_{t-1} \cdot \mathbf{W}_{hi} + \mathbf{b}_i\right)$$
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White strips = *one* group of weights in SSL

Removing one group = reducing hidden size by one

Structurally Sparse *LSTMs*

Method	Test perplexity	Hidden size of (1st, 2nd) LSTMs	Real-time speedup
Zaremba et. al. 2014	78.57	(1500, 1500)	1.00X
Ours (sparsifying Zaremba et. al. 2014)	78.64	(373, 315)	10.59X
	76.03	(381, 535)	7.10X
Train a smaller one	85.66	(373, 315)	10.59X

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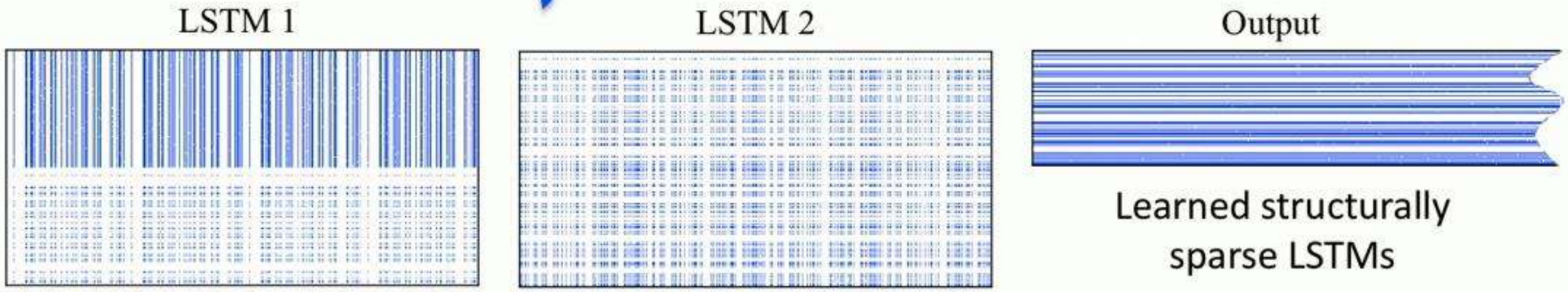

Learned structurally sparse LSTMs

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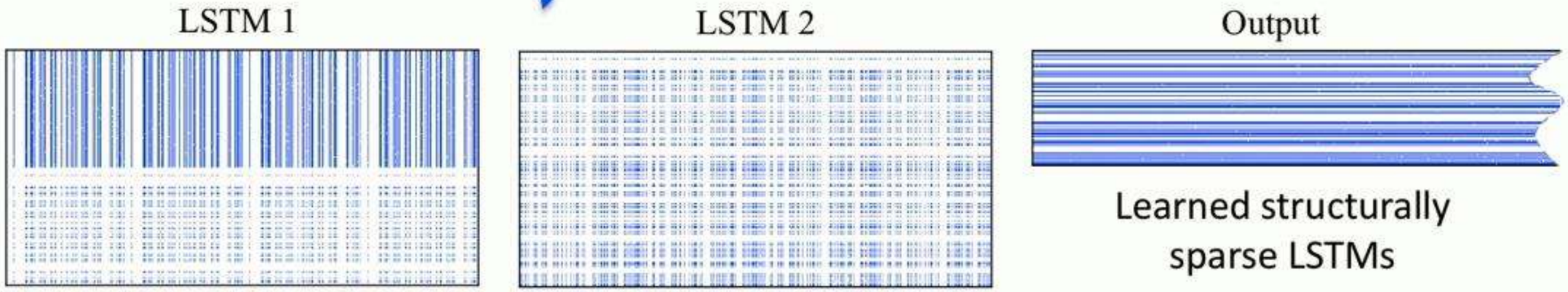
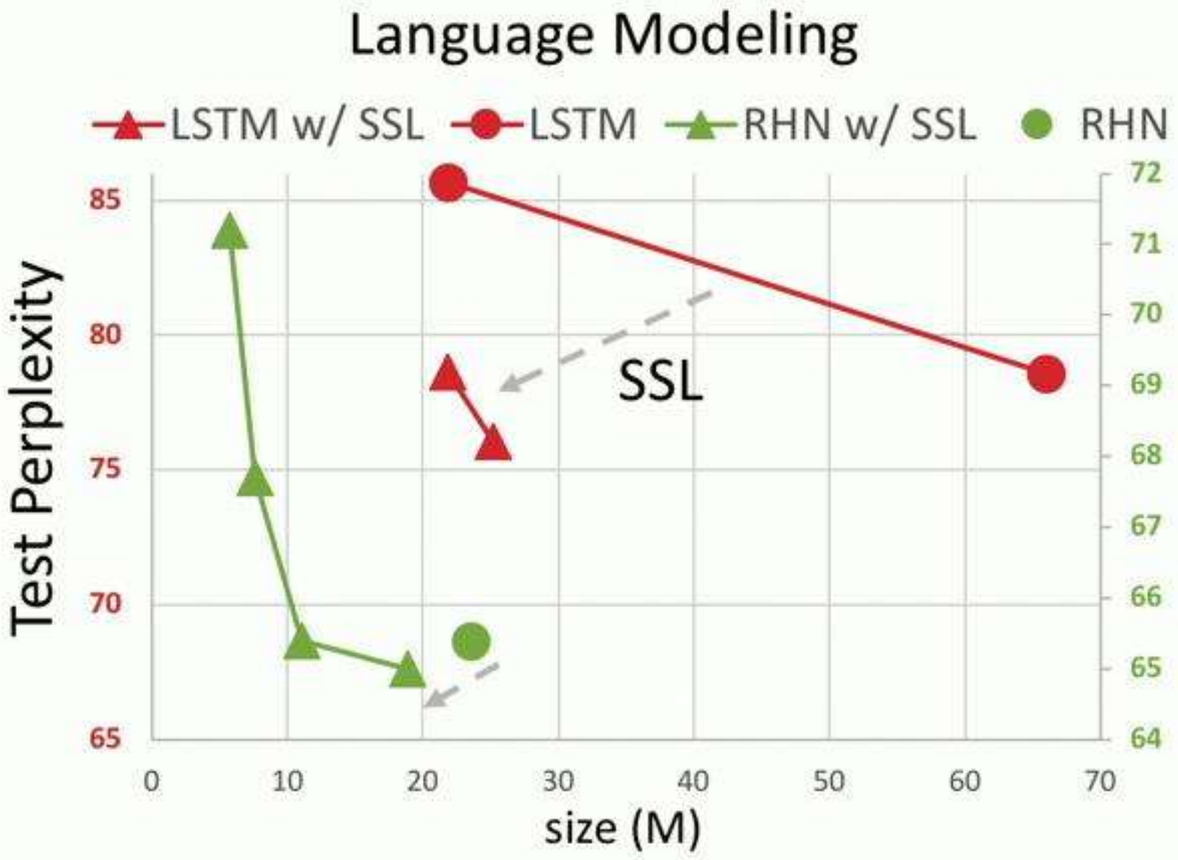
1. Reduce size while maintaining perplexity
2. Achieve lower perplexity
3. Better than training a smaller one



Learned structurally sparse LSTMs

Generalization vs. Model Complexity under SSL



☺ Start from redundant models and sparsify by SSL

RHN: Zilly et al. 2017. BiDAF: Seo et al. 2016

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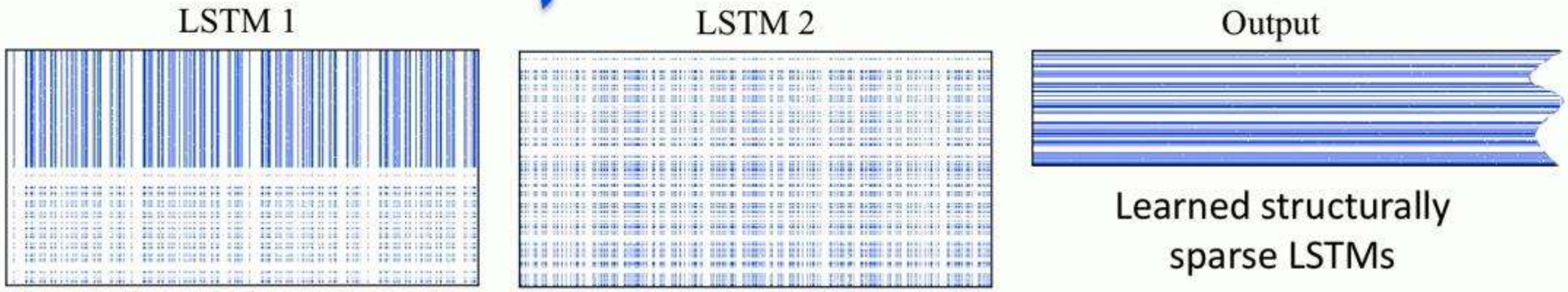
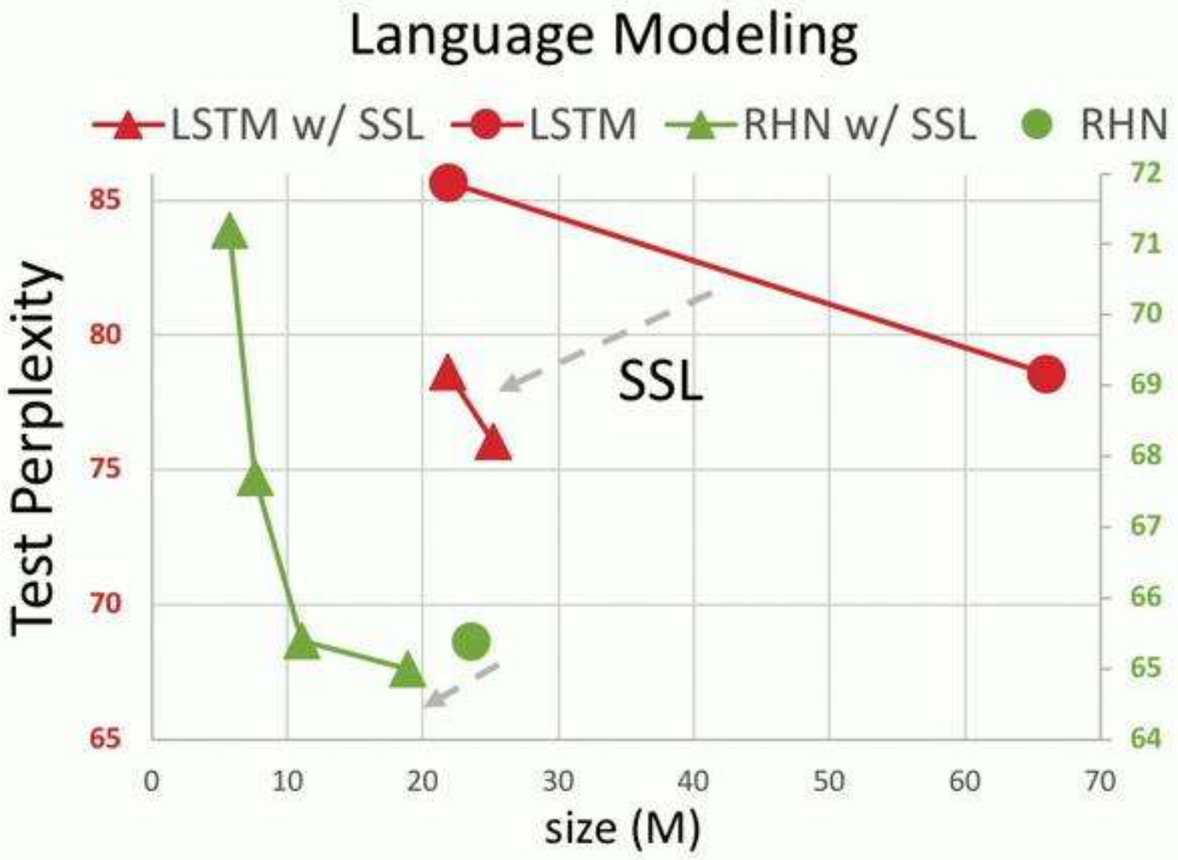


Learned structurally sparse LSTMs

Generalization vs. Model Complexity under SSL



☺ Start from redundant models and sparsify by SSL

RHN: Zilly et al. 2017. BiDAF: Seo et al. 2016

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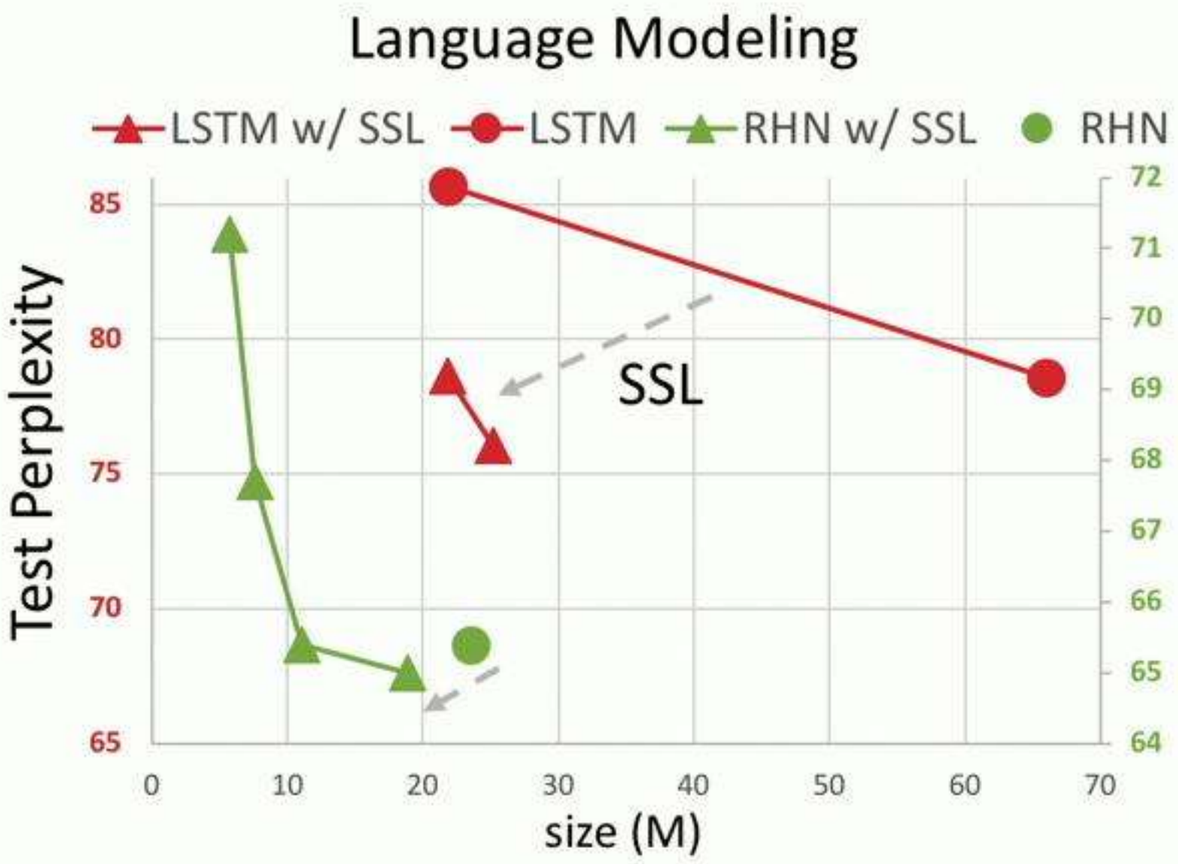

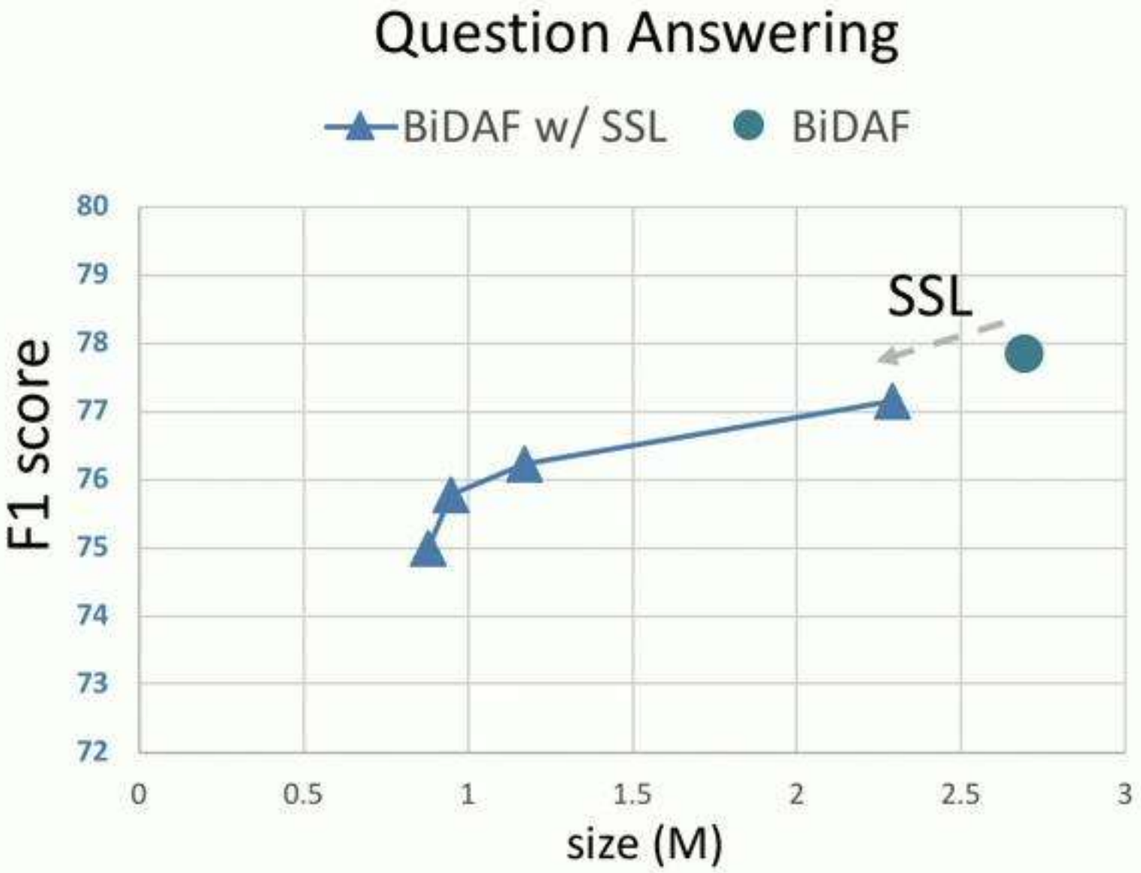

☺ Start from redundant models and sparsify by SSL

☺ Trade-off for compact models with SSL

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Summary of Previous Research

- More scalable distributed deep learning with stochastic low-precision gradients
  - *Effectiveness verified by AI productions*
  - *Can reduce research and production cycle by reducing evaluation/training time of each new model*
  - *More scalable to train larger models*
- Sparse deep neural networks
  - *Enable more ubiquitous AI on edge devices (such as mobile phones, drones, self-driving cars, VR devices, etc)*
  - *Performance gain by starting from a large model and sparsify it down*

Future Research

- Connections to previous research and going beyond
- Scaling Natural Language Processing
- Automated machine learning

SSL Implications and Beyond

Lottery Ticket Hypothesis

(Frankle et al 2019)

"dense, randomly-initialized, feed-forward networks contain subnetworks (winning tickets) that—when trained in isolation— reach test accuracy comparable to the original network in a similar number of iterations. "

SSL identifies winning tickets in the early stage?

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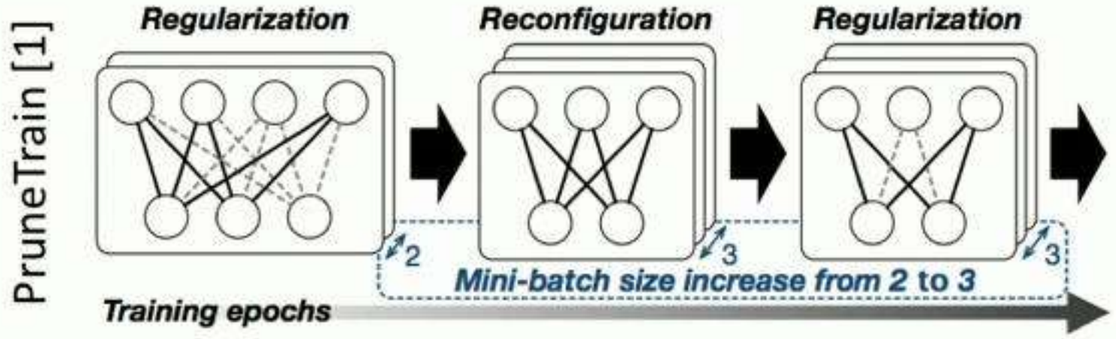

39% training time reduction of ResNet50 for ImageNet.

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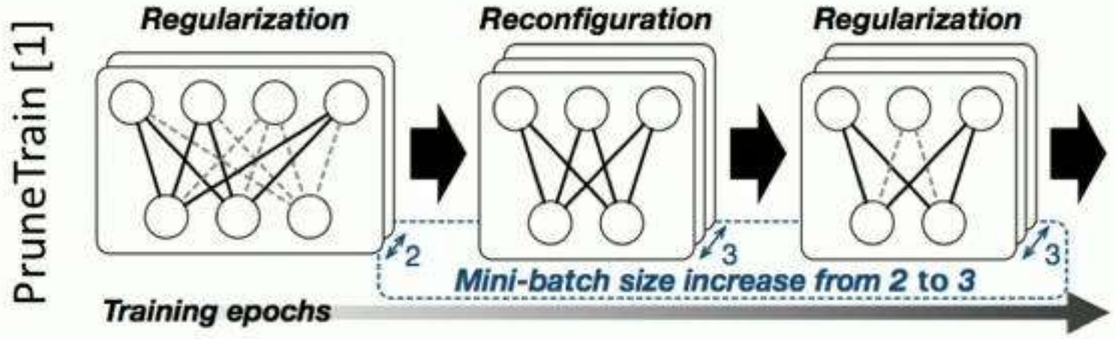

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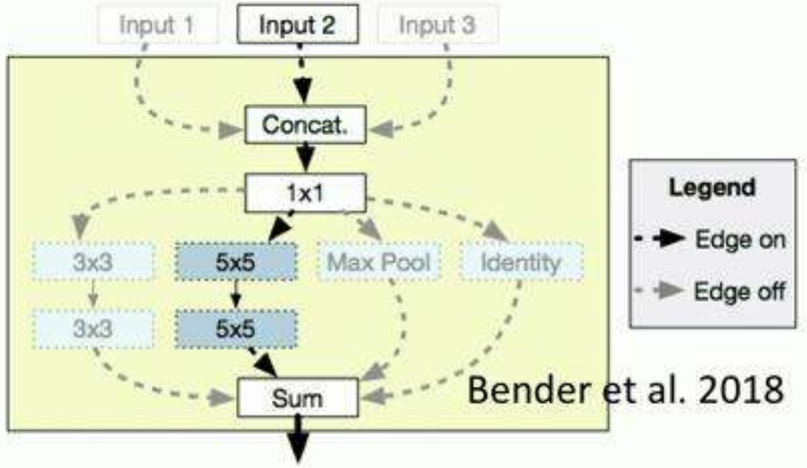

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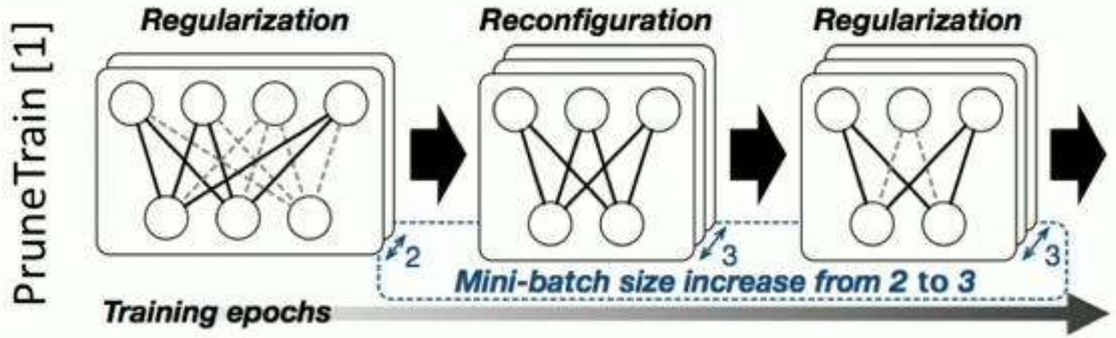

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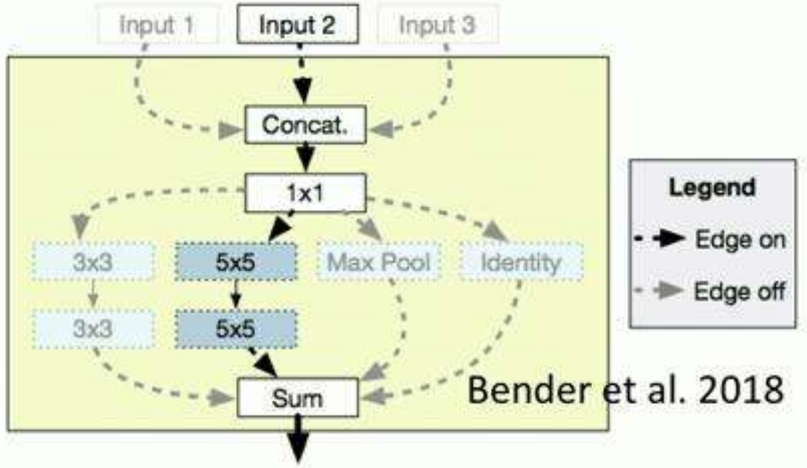

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Scaling Natural Language Processing

#L: layer, #H: hidden size, #A: attention head

Devlin et al. 2018

Hyperparams				Dev Set Accuracy		
#L	#H	#A	LM (ppl)	MNLI-m	MRPC	SST-2
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6	768	3	5.24	80.6	82.2	90.7
6	768	12	4.68	81.9	84.8	91.3
12	768	12	3.99	84.4	86.7	92.9
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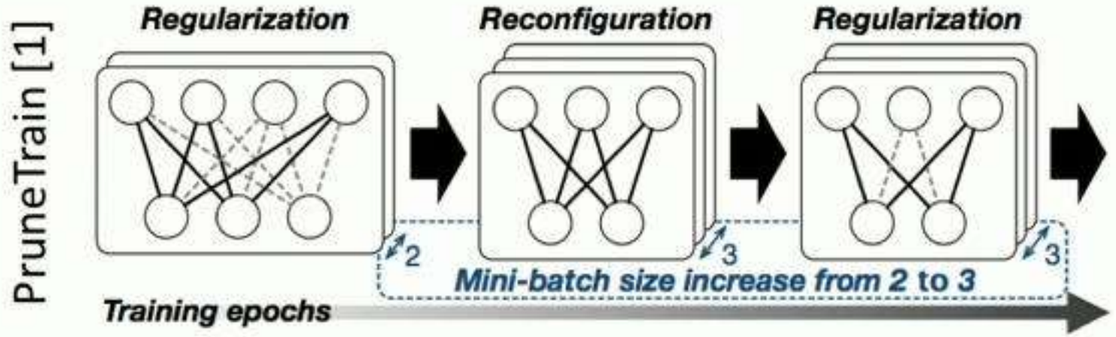

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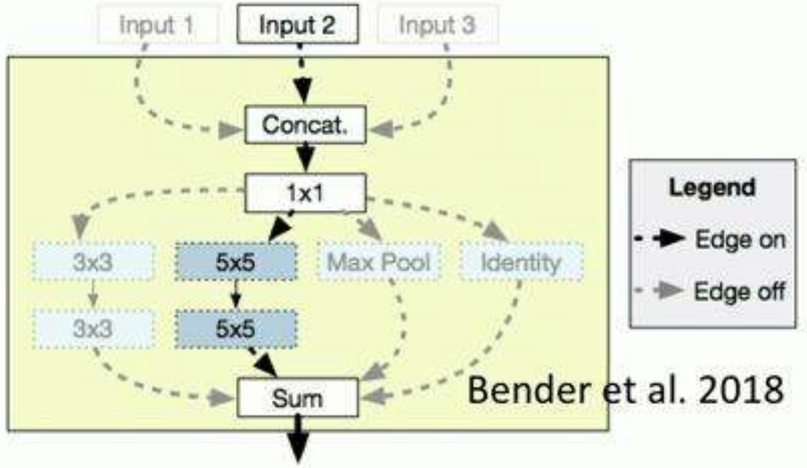

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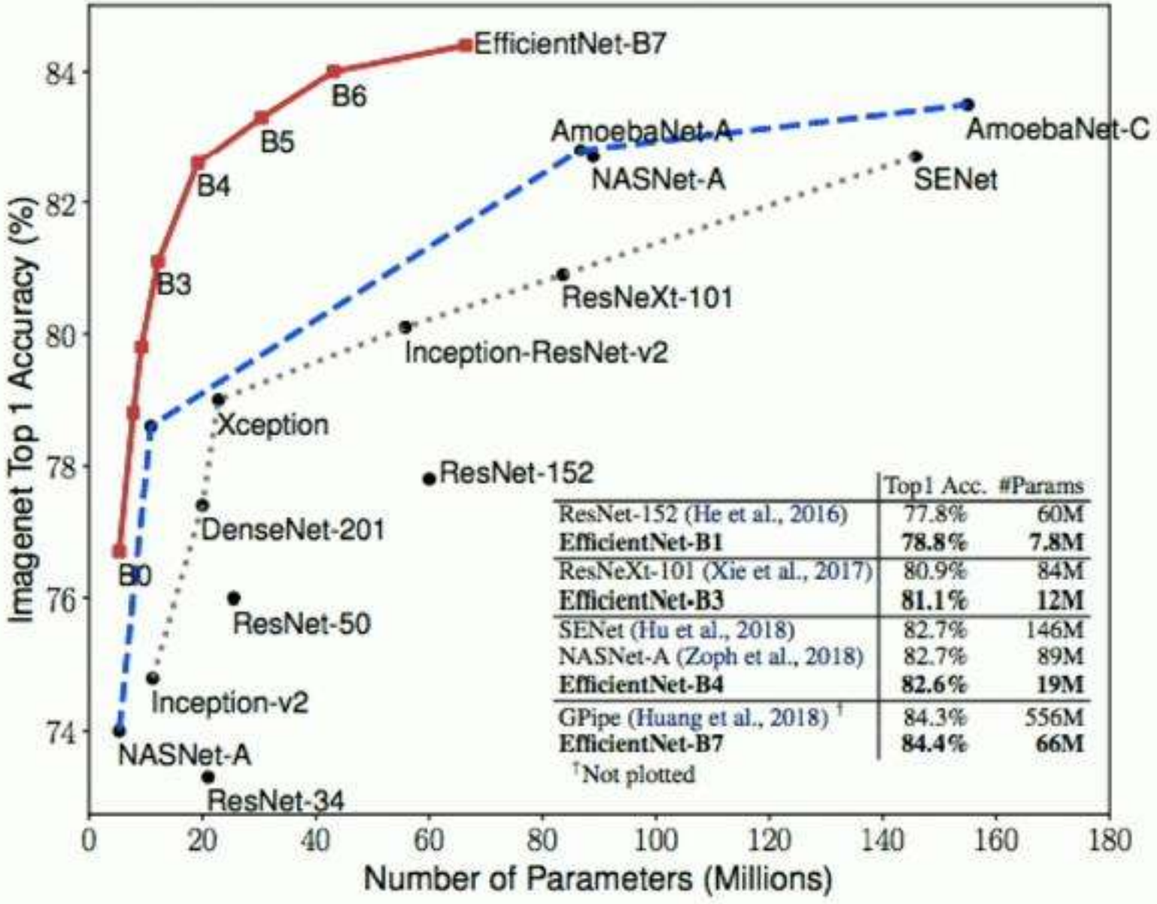

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Tan & Le, 2019

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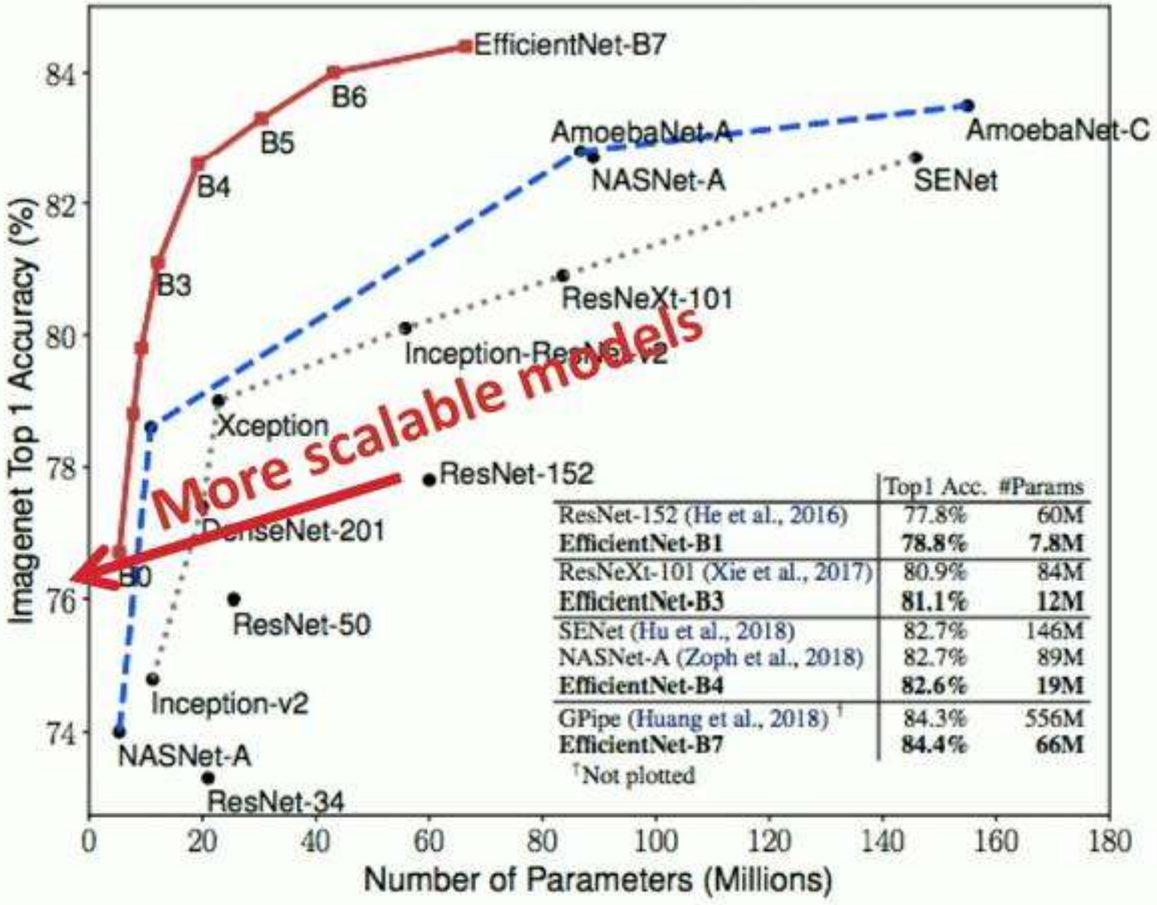

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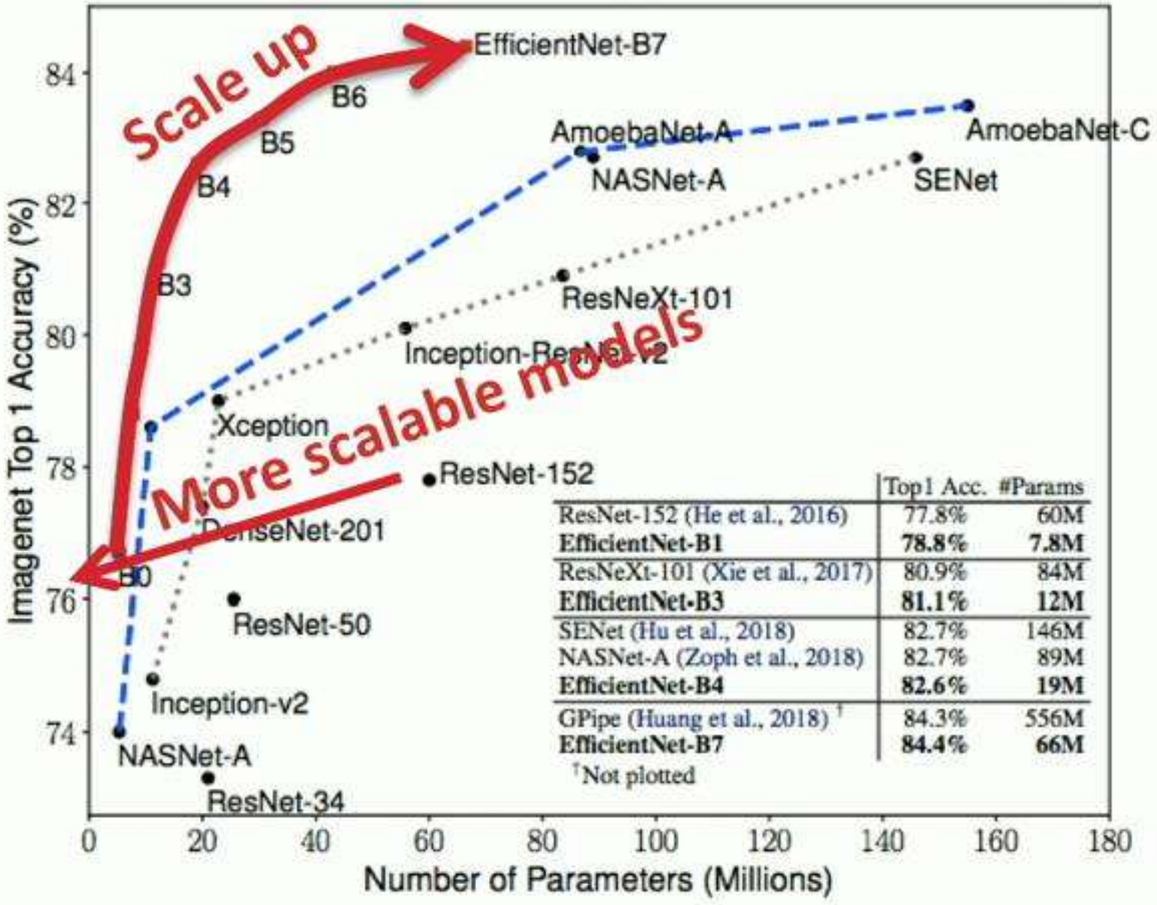

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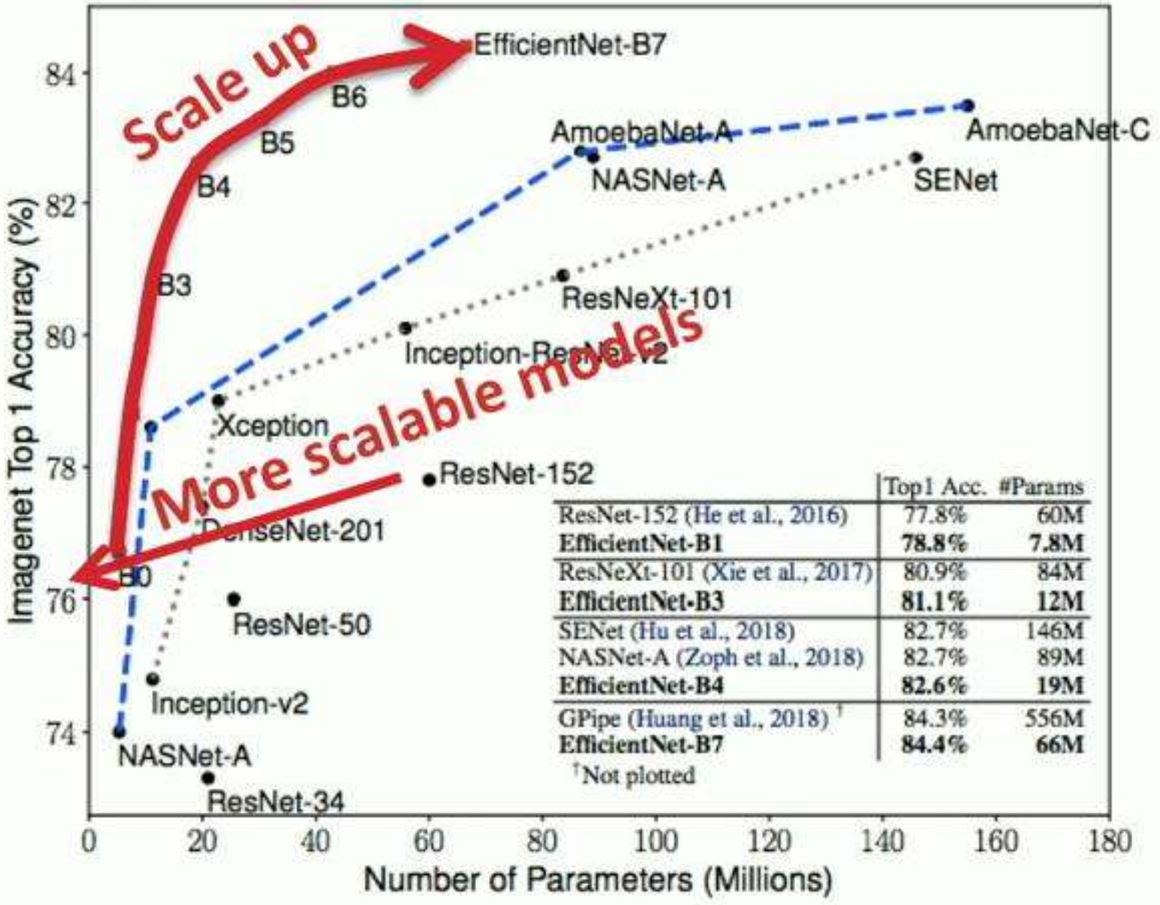

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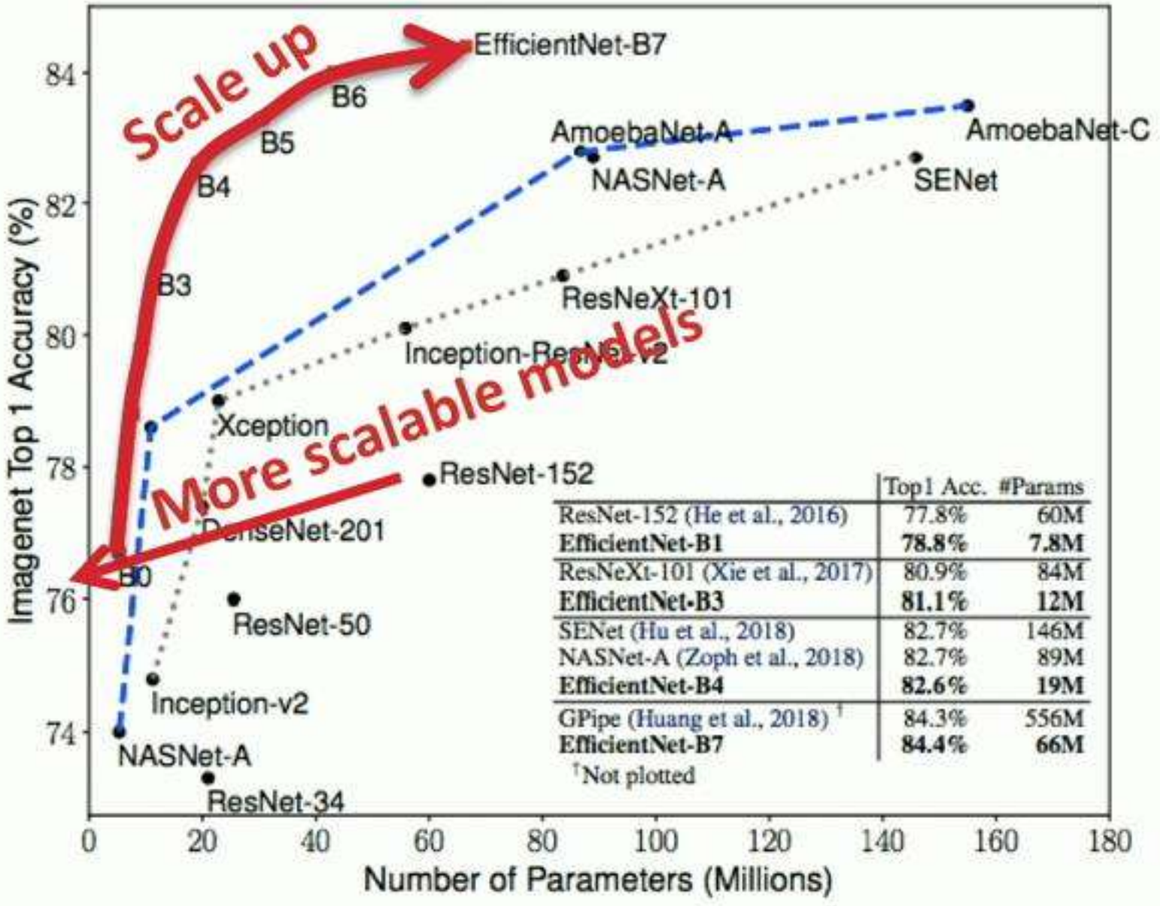

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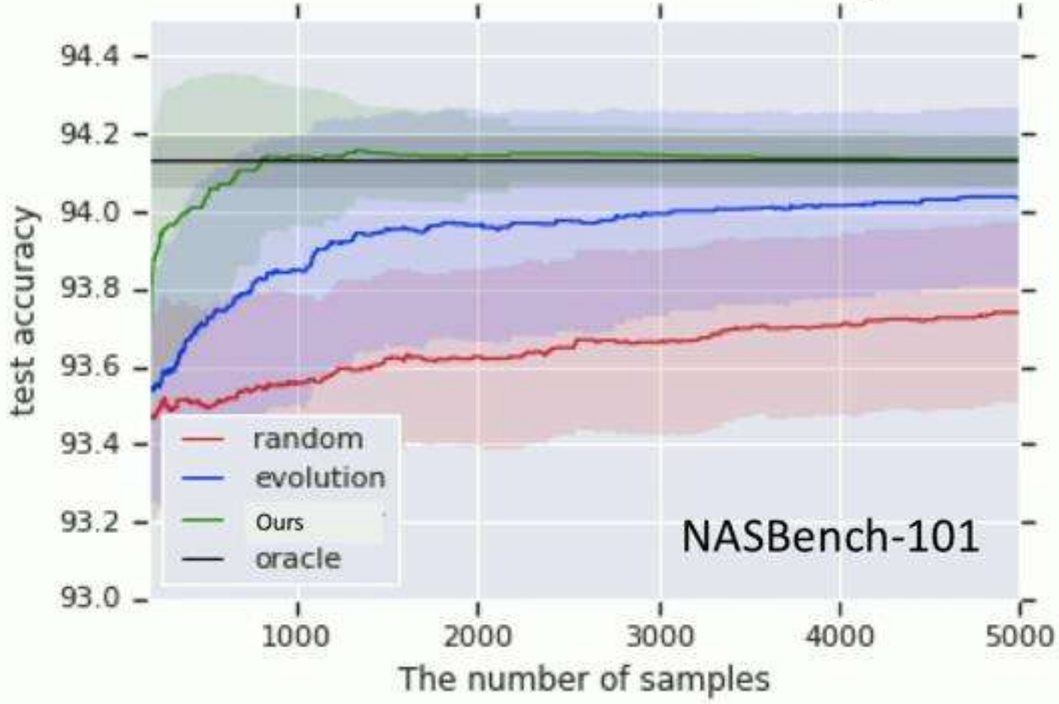

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THANKS! Q&A?

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