The University of Texas at Austin
Electrical and Computer Engineering
Cockrell School of Engineering

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ADVANCED TOPICS IN COMPUTER VISION

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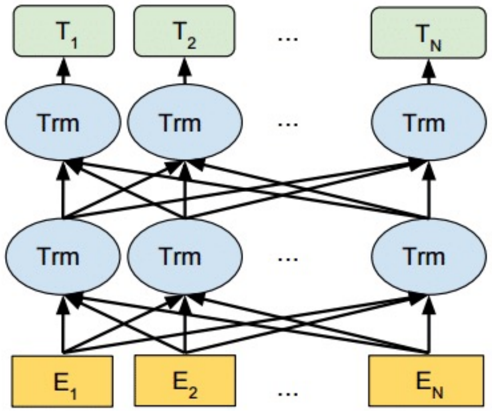
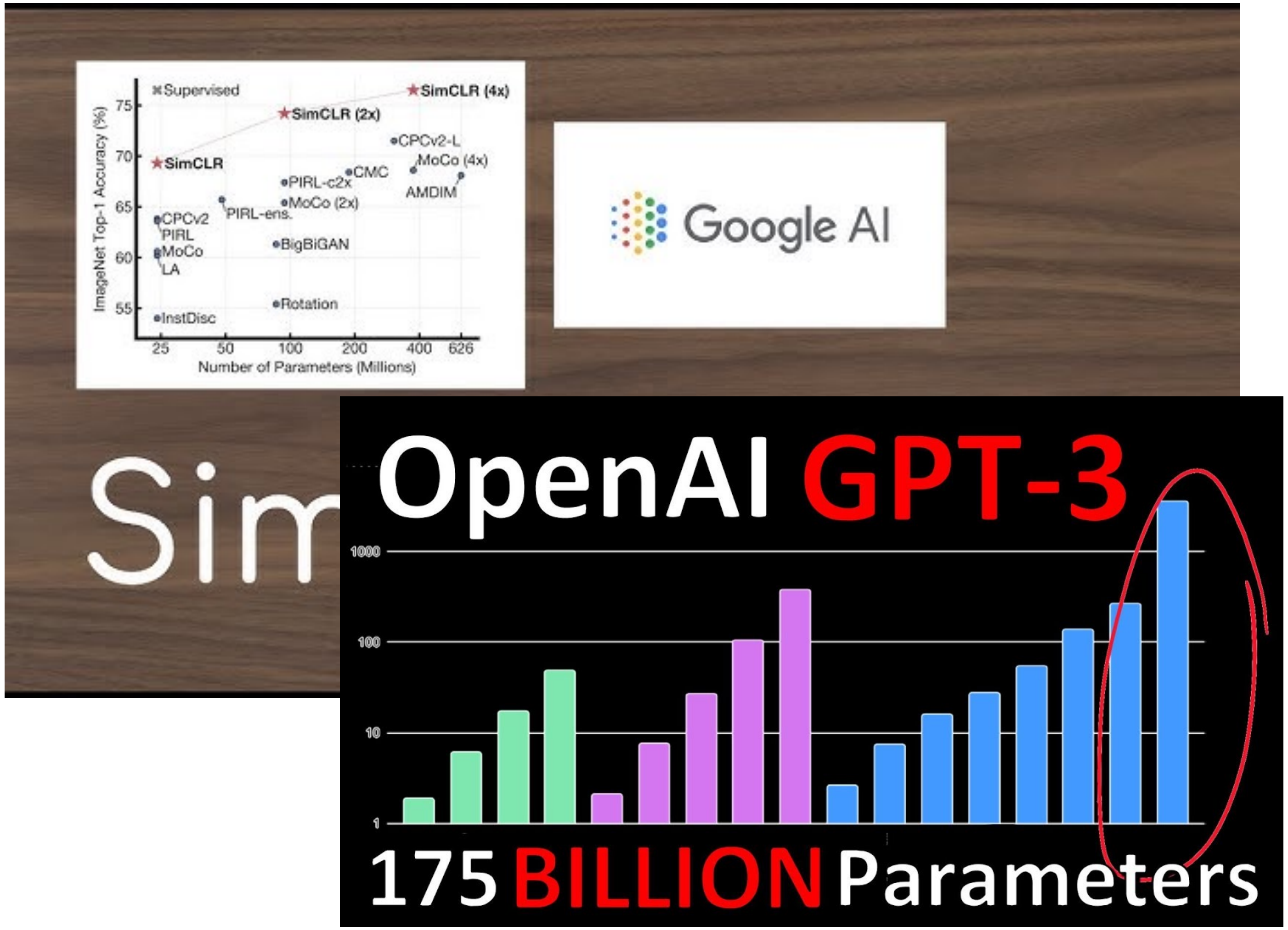
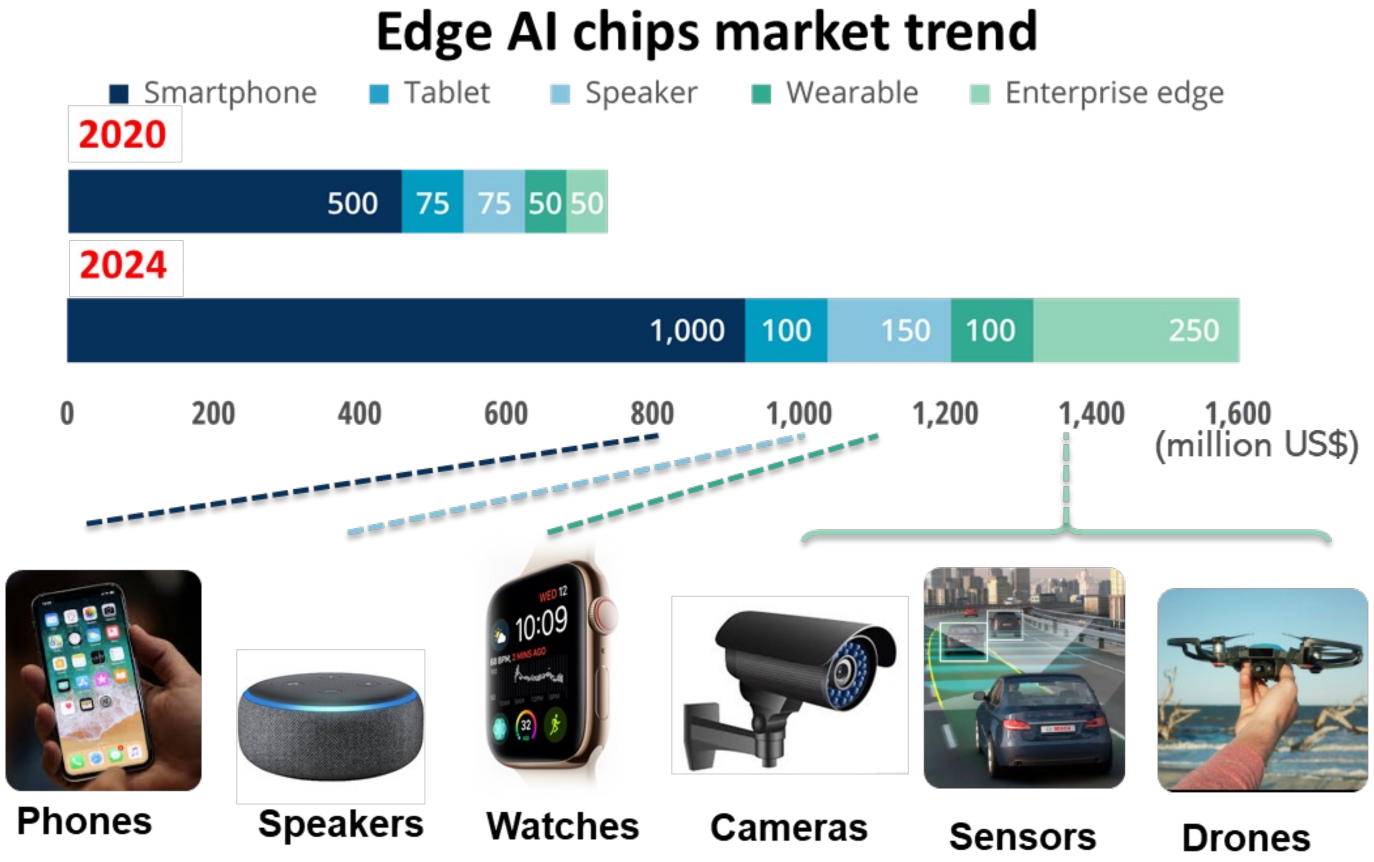
ML researchers like to go BIG



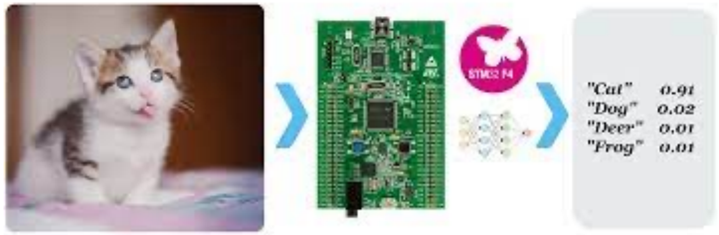


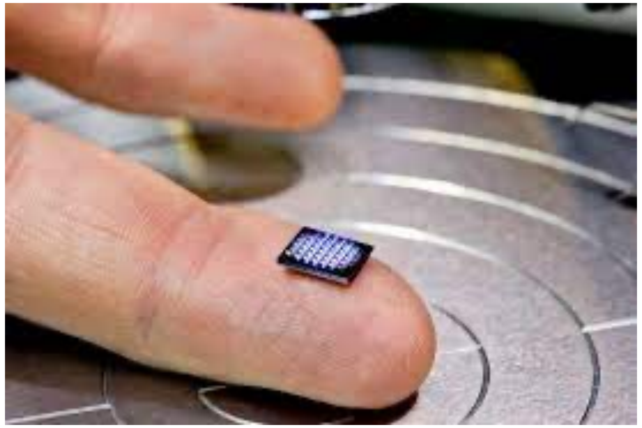
Big NNs seem to be more capable at everything…

….While the world prefers going TINY

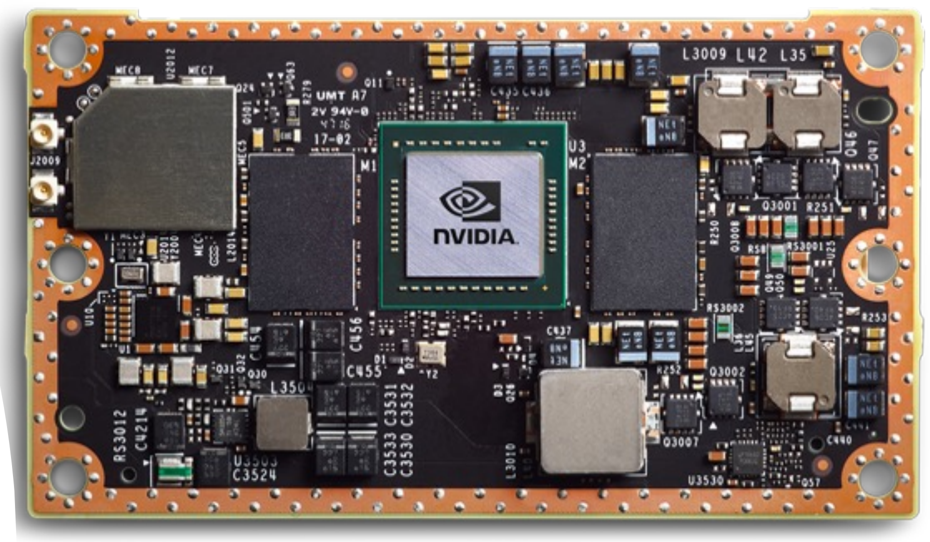


[Deloitte'19]





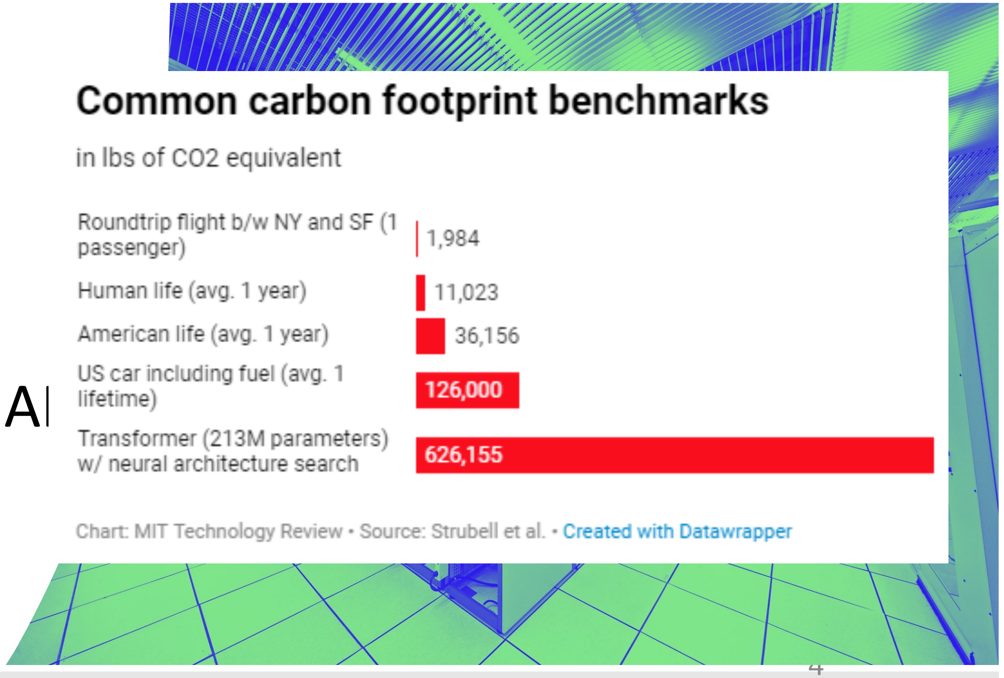
Deep Learning on a Budget



- Three Top Concerns:
  - **Storage and Memory**
  - **Speed or Latency**
  - **Energy Efficiency**

- The three goals all pursue “light weight”
- … but they are often **not aligned***
- … so need to **consider all** in implementation
- … and for both **Inference** and **Training**

- Broad economic viability requires energy efficient AI
- Energy efficiency of a brain is **100x better** than current SOTA hardware!



* Eyeriss: An Energy-Efficient Reconfigurable Accelerator for Deep Convolutional Neural Networks, IEEE ISSCC 2016

Model Compression

- Training Phase:
  - The easiest way to extract a lot of knowledge from the training data is to learn many different models in parallel.
  - 3B: Big Data, Big Model, Big Ensemble
  - Imagenet: 1.2 million pictures in 1,000 categories.
  - AlexNet: ~ 240Mb, VGG16: ~550Mb
- Testing Phase:
  - Want small and specialist models.
  - Minimize the amount of computation and the memory footprint.
  - Real time prediction
  - Even able to run on mobile devices.

Two Main Streams

- **“Transfer”:** How to transfer knowledge from big general model (teacher) to small specialist models (student)?
  - Example: “Distilling the Knowledge in a Neural Network”, G. Hinton et. al., 2015

- **“Compress”:** How to reduce the size of the same model, during or after training, without losing much accuracy.
  - Example: “Deep Compression: Compressing Deep Neural Networks with Pruning, Trained Quantization and Huffman Coding”, S. Han et. al., 2016

- **Comparison:** Knowledge Transfer provides a way to train a <u>new small model</u> inheriting from big general models, while Deep Compression Directly does the surgery on big models, using a pipeline: pruning, quantization & Huffman coding.

Knowledge Transfer/“Distillation”: Main Idea

- Introduce “Soft targets” as one way to transfer the knowledge from big models.
  - Classifiers built from a softmax function have a great deal more information contained in them than just a classifier;
  - The correlations in the softmax outputs are very informative.

- Hard Target: the ground truth label (one-hot vector)
- Soft Target: T is “temperature”, z is logit

$$q_i = \frac{exp(z_i/T)}{\sum_j exp(z_j/T)}$$

- More information in soft targets

cow	dog	cat	car	
0	1	0	0	original hard targets

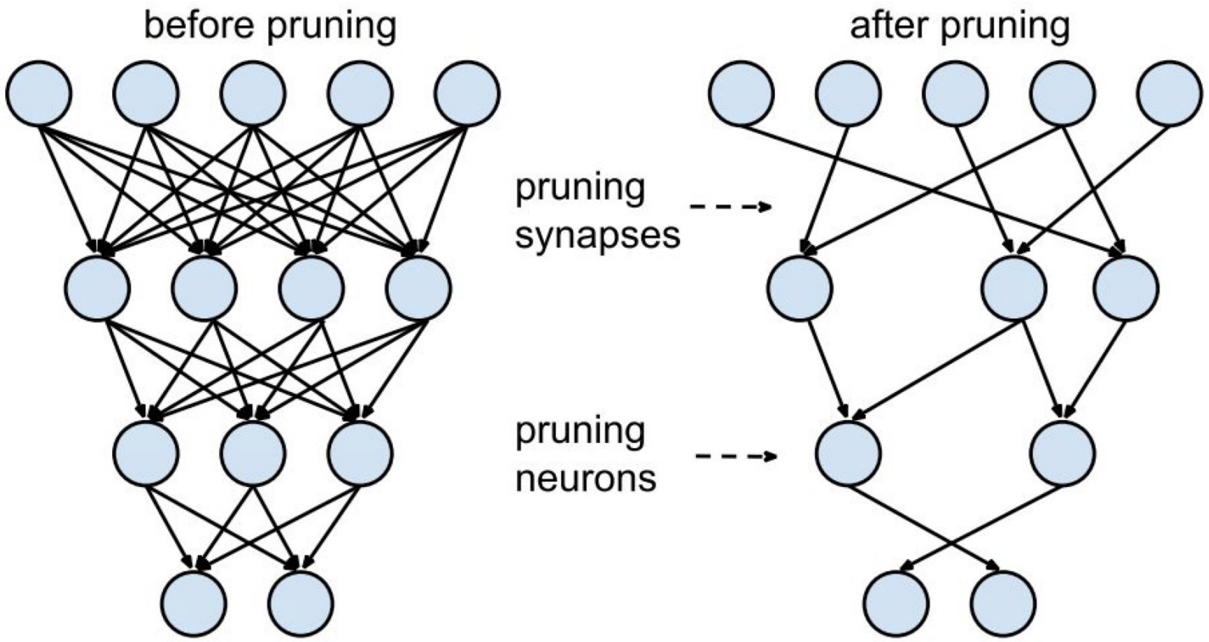
cow	dog	cat	car	
.05	.3	.2	.005	softened output of ensemble

Hinton’s Observation: If we can extract the knowledge from the data using very big models or ensembles of models, it is quite easy to distill most of it into a much smaller model for deployment.

More follow-up observations: teachers can be weak, or even the same as student …

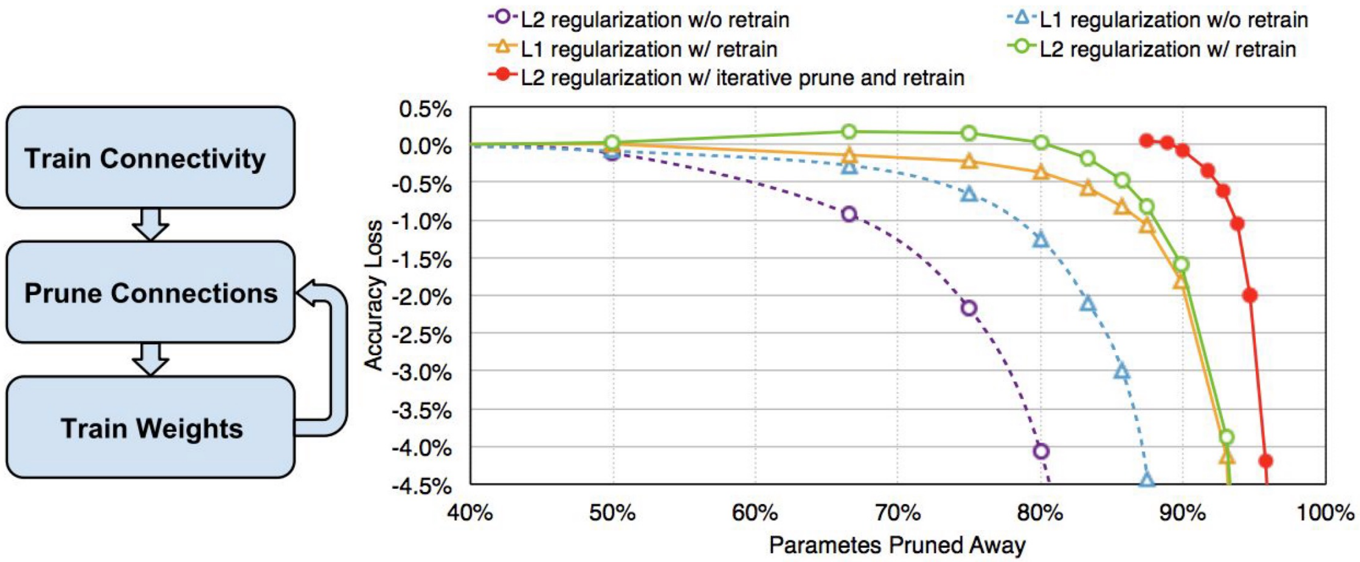
Deep Compression: Main Idea (i)

Pruning



Deep Compression: Main Idea (ii)

Retrain to Recover Accuracy



Network pruning can save 9x to 13x parameters without drop in accuracy

Deep Compression: Main Idea (iii)

Weight Sharing (Trained Quantization)

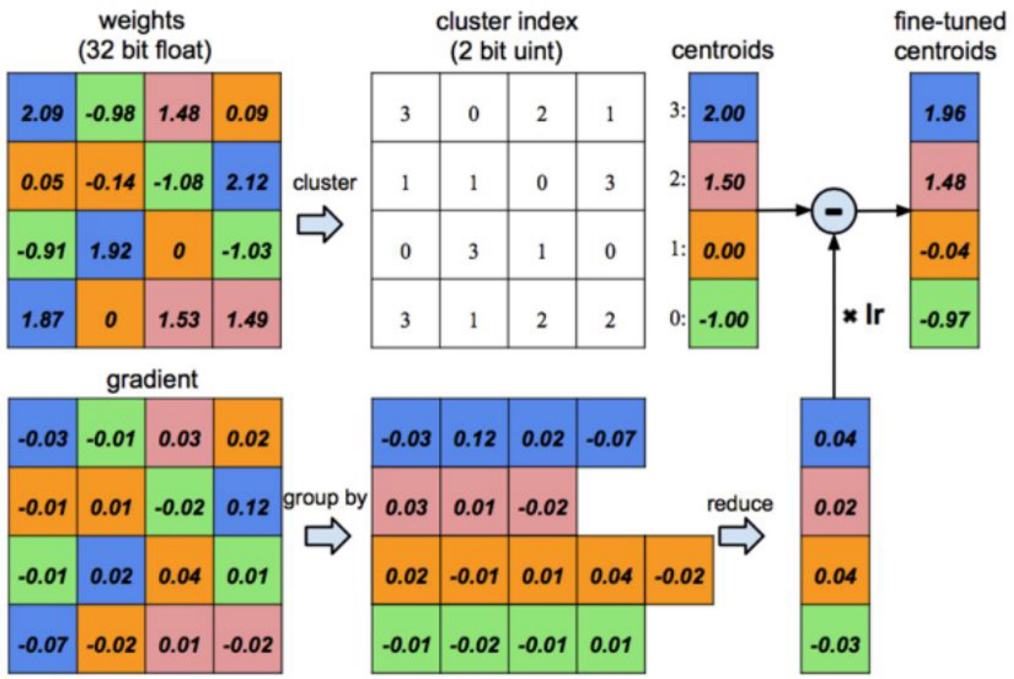
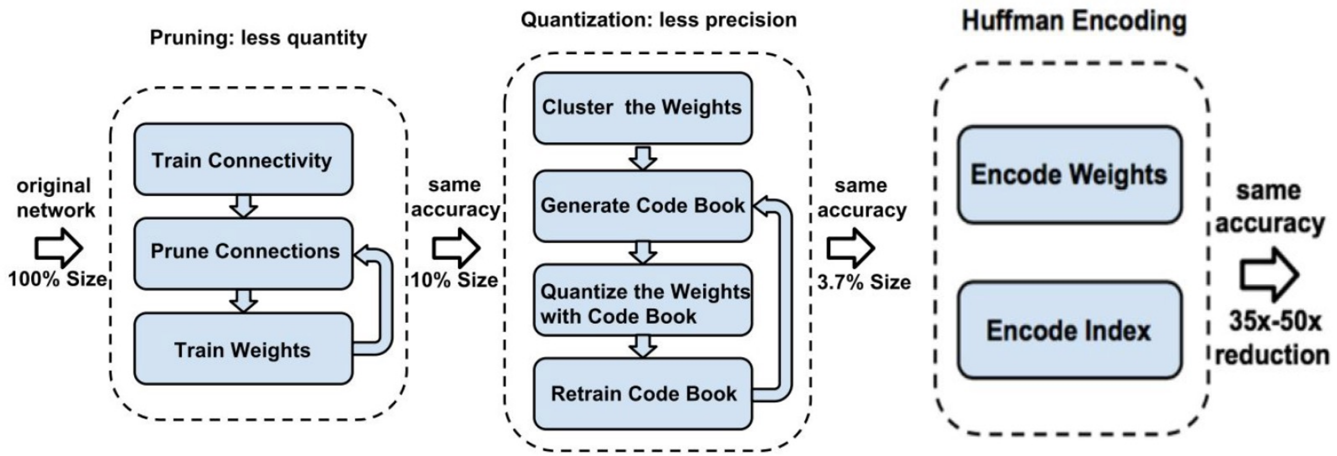


Figure 3: Weight sharing by scalar quantization (top) and centroids fine-tuning (bottom)

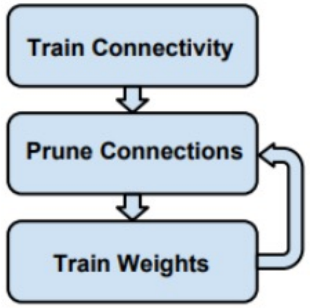
Deep Compression: Main Idea (iv)

Huffman Coding



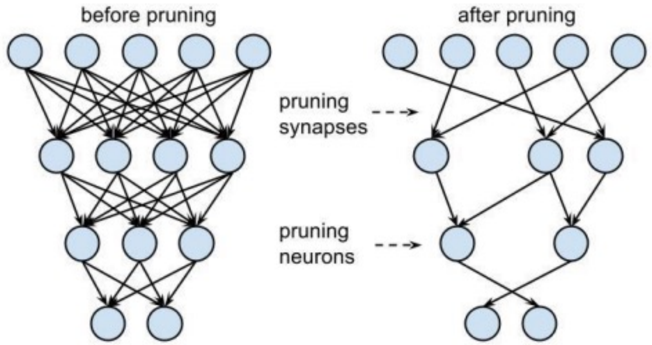
More About Pruning

- Determining **low-saliency parameters**, given a pre-trained network
- Follows the framework proposed by LeCun et al. (1990):



> 1. **Train** a deep model until convergence
> 2. **Delete** “unimportant” connections w.r.t. a certain criteria
> 3. **Re-train** the network
> 4. **Iterate** to step 2, or stop

- Defining which connection is unimportant can vary
  - Weight magnitudes (L^2, L^1, …)
  - Mean activation [Molchanov et al., 2016]
  - Avg. % of Zeros (APoZ) [Hu et al., 2016]
  - Low entropy activation [Luo et al., 2017]
  - …



Human Brain Prunes too!

50 Trillion Synapses

1000 Trillion Synapses

500 Trillion Synapses

This image is in the public domain

Newborn

This image is in the public domain

1 year old

This image is in the public domain

Adolescent

Optimal Brain Damage (OBD)

- Network pruning **perturbs weights $\mathbf{W}$** by **zeroing** some of them
- How the loss L would be changed when $\mathbf{W}$ is perturbed?

- **OBD** approximates L by the 2nd order Taylor series:

$$\delta L \simeq \underbrace{\sum_i \frac{\partial L}{\partial w_i}\delta w_i}_{\text{1st order}} + \underbrace{\frac{1}{2}\sum_i \frac{\partial^2 L}{\partial {w_i}^2}\delta w_i^2 + \frac{1}{2}\sum_{i,j}\frac{\partial^2 L}{\partial w_i \partial w_j}\delta w_i \delta w_j}_{\text{2nd order}} + O(||\delta \mathbf{W}||^3)$$

- **Problem:** Computing $H = \left(\frac{\partial L}{\partial w_i \partial w_j}\right)_{i,j}$ is usually intractable
  - Requires $O(n^2)$ on # weights
  - Neural networks usually have enormous number of weights
    - e.g. AlexNet: **60M** parameters ⇒ H consists $\approx \mathbf{3.6 \times 10^{15}}$ elements

Optimal Brain Damage (OBD)

- **Problem:** Computing $H = \left(\frac{\partial L}{\partial w_i \partial w_j}\right)_{i,j}$ is usually intractable
- Two additional assumptions for tractability

1. **Diagonal** approximation: $H = \frac{\partial^2 L}{\partial w_i \partial w_j} = 0 \quad \text{if} \quad i \neq j$
2. **Extremal** assumption: $\frac{\partial L}{\partial w_i} = 0 \quad \forall i$
   - **W** would be in a local minima if it's pre-trained

- Now we get: $\delta L \simeq \frac{1}{2} \sum_i \frac{\partial^2 L}{\partial {w_i}^2} \delta w_i^2 + O(||\delta \mathbf{W}||^3)$
  - It only needs $\mathrm{diag}(H) := \left(\frac{\partial^2 L}{\partial w_i^2}\right)_i$

- $\mathbf{diag}(\boldsymbol{H})$ can be computed in $O(n)$, allowing a backprop-like algorithm
  - For details, see [LeCun et al., 1987]

Optimal Brain Damage (OBD)

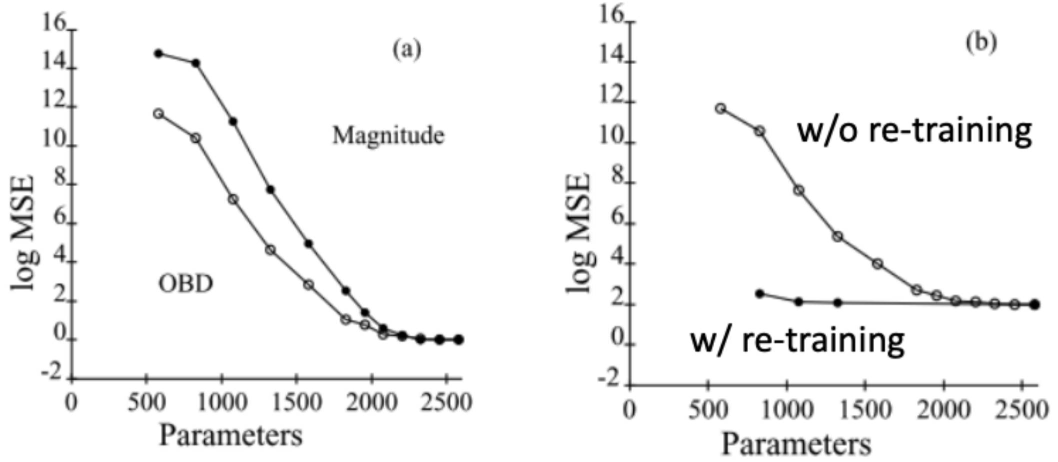
- How the loss L would be changed when $\mathbf{W}$ is perturbed?

$$L(\delta \mathbf{W}) \simeq \frac{1}{2}\sum_i \frac{\partial^2 L}{\partial {w_i}^2}\delta w_i^2 =: \sum_i \frac{1}{2} h_{ii}\delta w_i^2$$

- The **saliency** for each weight ⇒ $s_i := \frac{1}{2} h_{ii}|w_i|^2$

$\boxed{s_i := |w_i|}$

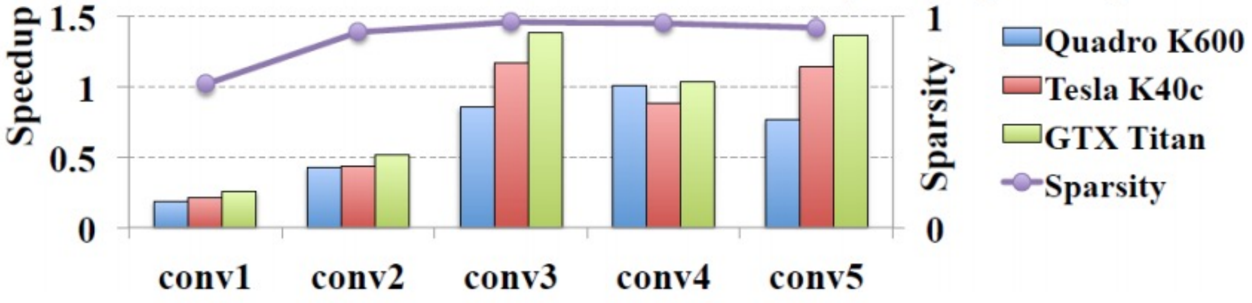
- OBD shows robustness on pruning compared to magnitude-based deletion
- After re-training, the original test accuracy is recovered



Structured Sparsity

- "Un-structured" **weight-level pruning** may not engage a **practical speed-up**
  - Despite of extremely high sparsity, actual speed-ups in GPU is limited

sparsity = percentage of zeros



Speed-up ratio of weight-level pruning

5× speedup after concatenation of nonzero rows and columns

Structured sparsity

- **Structured sparsity** can be induced by adding group-lasso regularization

$$\min_{\mathbf{W}} \mathcal{L}(\mathbf{W}) + \lambda \sum_{l=1}^{L} R_g(\mathbf{W}^{(l)}), \;\; R_g(\mathbf{w}) = \sum_{g=1}^{G} \|\mathbf{w}^{(g)}\|_2$$

- **Filter-wise** and **channel-wise:**

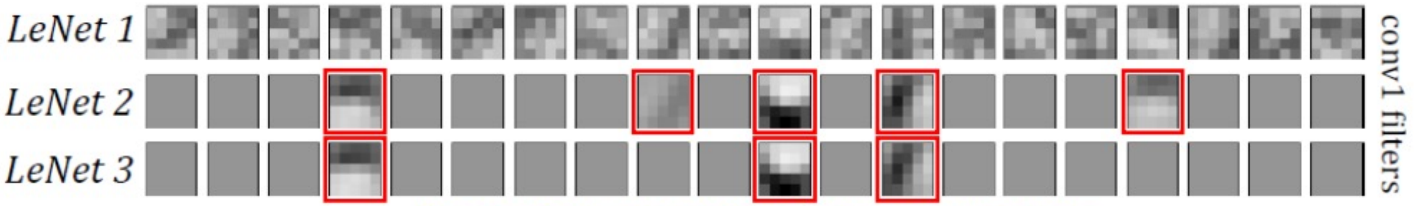
filters # channels

$$R_g(\mathbf{W}^{(l)}) = \sum_{n_l=1}^{N_l} \|\mathbf{W}^{(l)}_{n_l,:,:,:}\|_2 + \sum_{c_l=1}^{C_l} \|\mathbf{W}^{(l)}_{:,c_l,:,:}\|_2$$

Table 1: Results after penalizing unimportant filters and channels in *LeNet*

LeNet #	Error	Filter # §	Channel # §	FLOP §	Speedup §
1 (*baseline*)	0.9%	20—50	1—20	100%—100%	1.00×—1.00×
2	0.8%	5—19	1—4	25%—7.6%	1.64×—5.23×
3	1.0%	3—12	1—3	15%—3.6%	1.99×—7.44×

§In the order of *conv1—conv2*



Fewer but smoother feature extractors

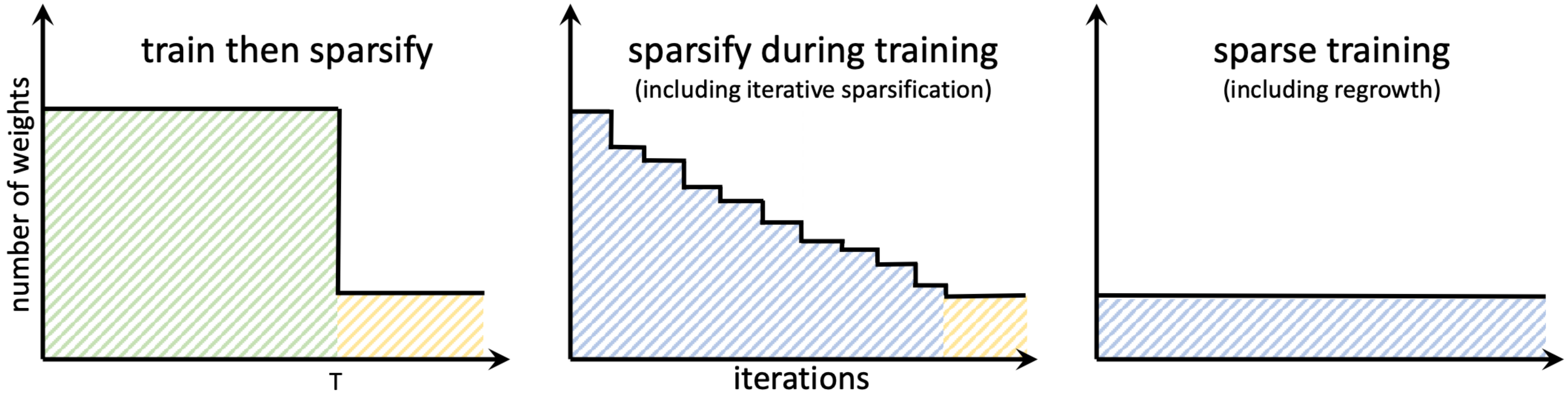


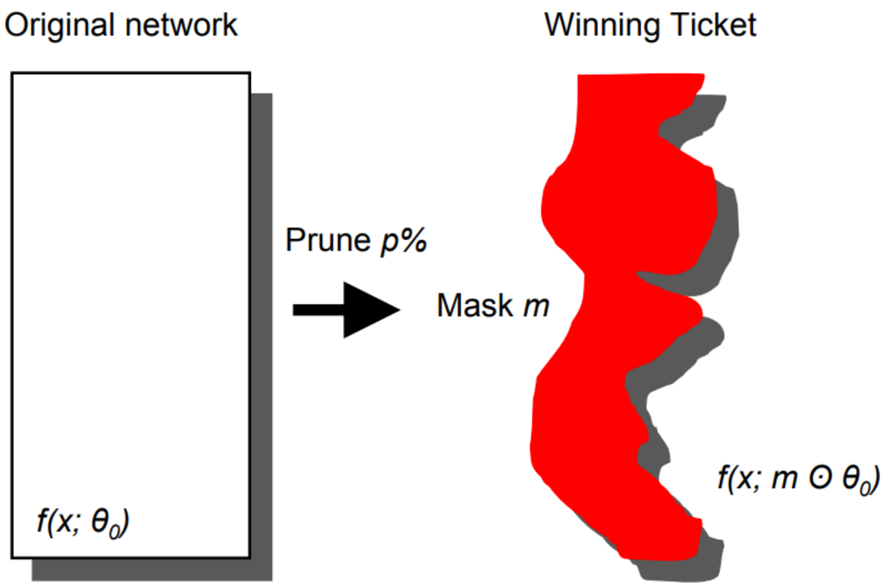
Figure 7: Overview of structural sparsification schedules.

Sparsity beyond post-training compression

- *Hoefler, T., Alistarh, D., Ben-Nun, T., Dryden, N., & Peste, A. (2021). Sparsity in Deep Learning: Pruning and growth for efficient inference and training in neural networks. J. Mach. Learn. Res., 22(241), 1-124.*

Lottery Ticket Hypothesis

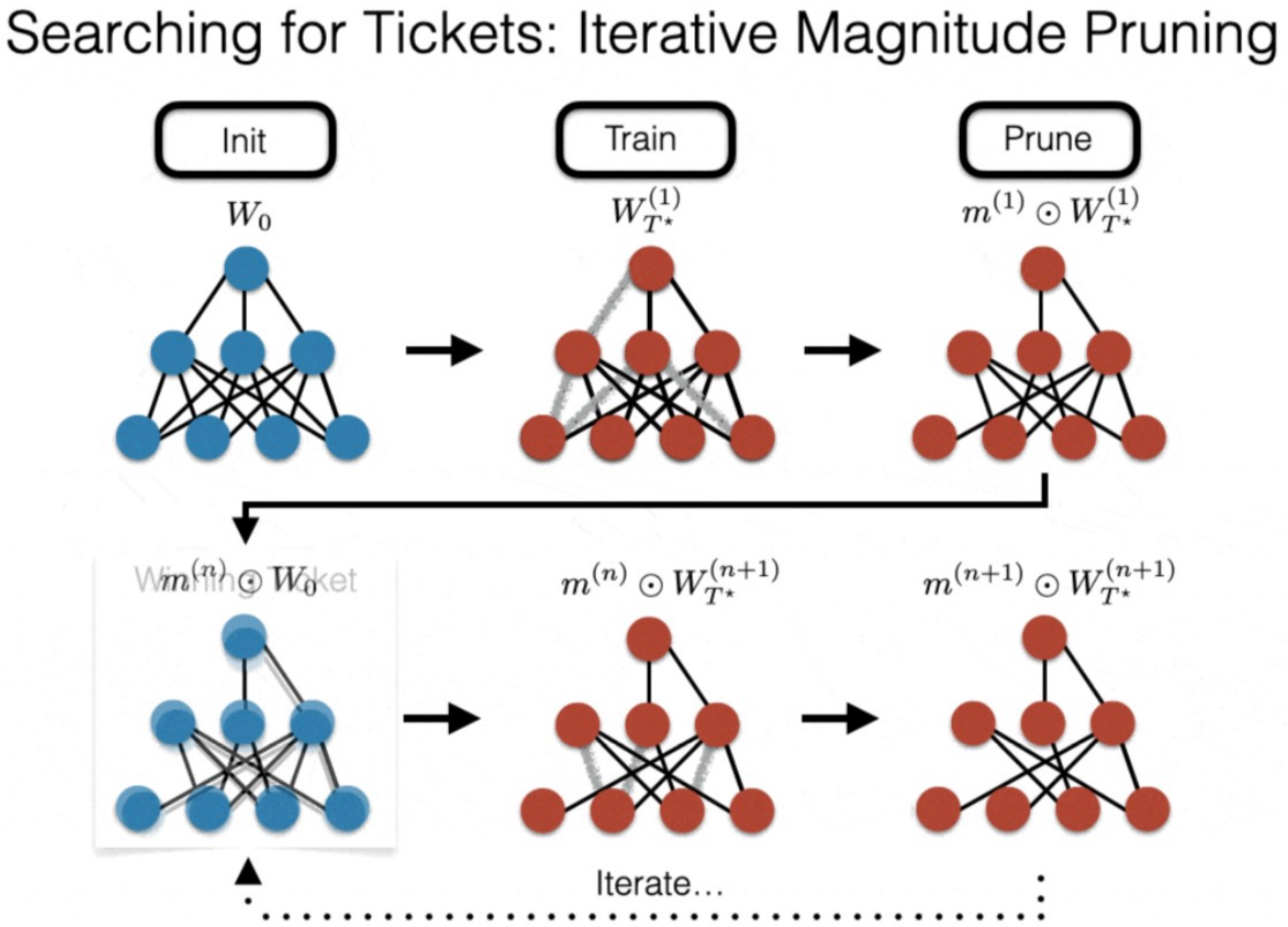
The Lottery Ticket Hypothesis. *A randomly-initialized, dense neural network contains a subnetwork that is initialized such that—when trained in isolation—it can match the test accuracy of the original network after training for at most the same number of iterations.*



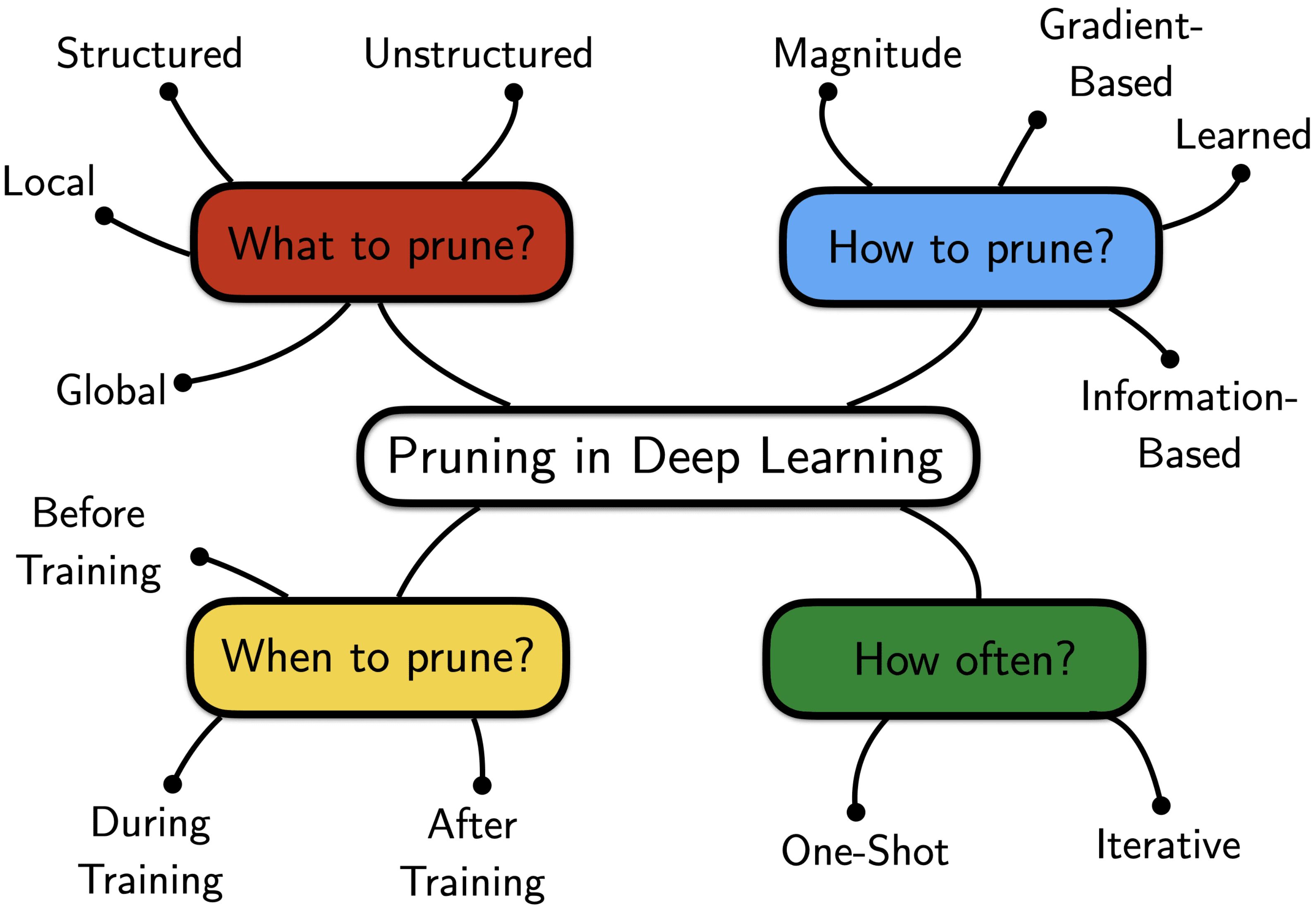
- Winning Ticket gives
  - Better or same results
  - Shorter or same training time
  - Notably fewer parameters
  - Is trainable from the beginning

Frankle, Jonathan, and Michael Carbin. "The lottery ticket hypothesis: Finding sparse, trainable neural networks." *ICLR 2019*

Lottery Ticket Hypothesis



Summary of Pruning



End-to-End (Dynamic) Sparse Training

- **Sparsity distribution**. The simplest is “uniform” - every layer has the same sparsity. More advanced ones work better, e.g., bigger layers are pruned more than small layers (called “ERK’)
- **Update schedule**. Sparsification happens at a certain frequency during training (btw, sparse training usually costs more epochs to converge)
- **Drop criterion**. The weights with the **lowest magnitude** are dropped.
- **Grow criterion**. The weights receiving the **highest gradient** will be re-added (zero-init). The number grown connections is the same as the dropped.

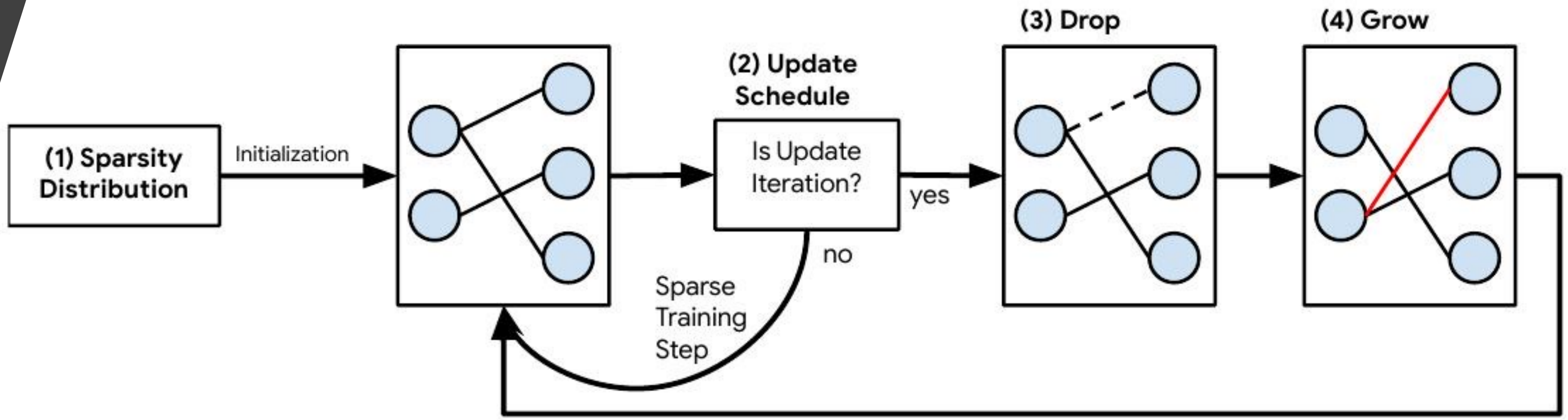
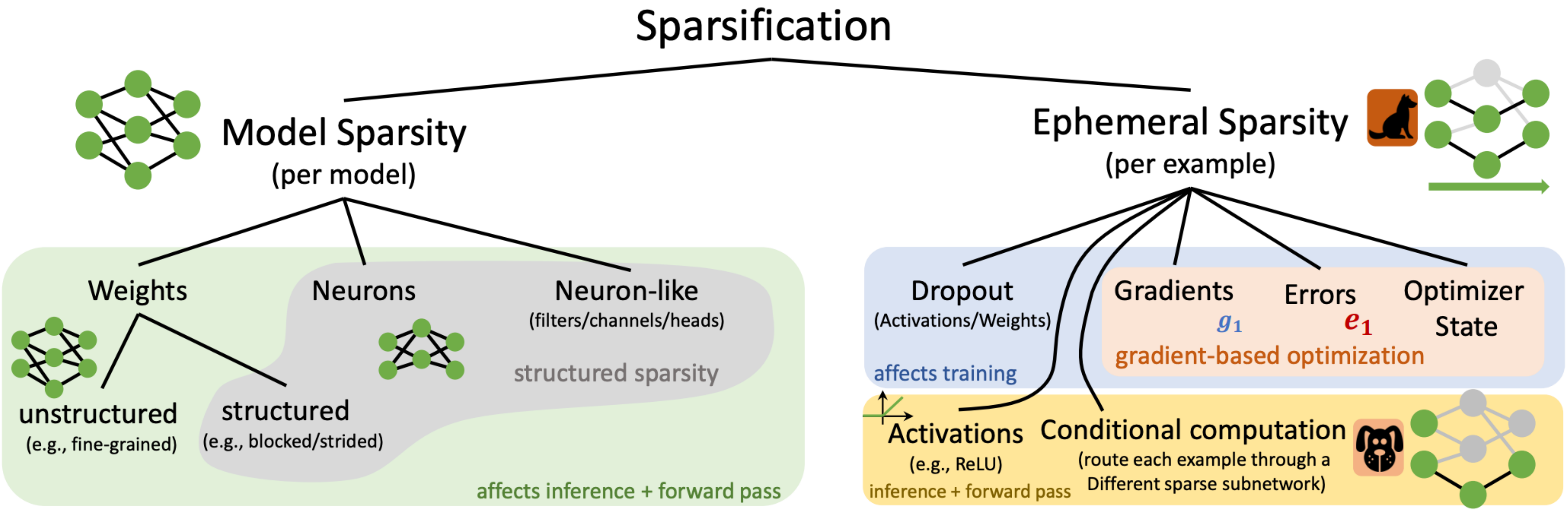


Figure 1: Dynamic sparse training changes connectivity during training to aid optimization.

Evci, Utku, Trevor Gale, Jacob Menick, Pablo Samuel Castro, and Erich Elsen. "Rigging the lottery: Making all tickets winners." *ICML 2020*



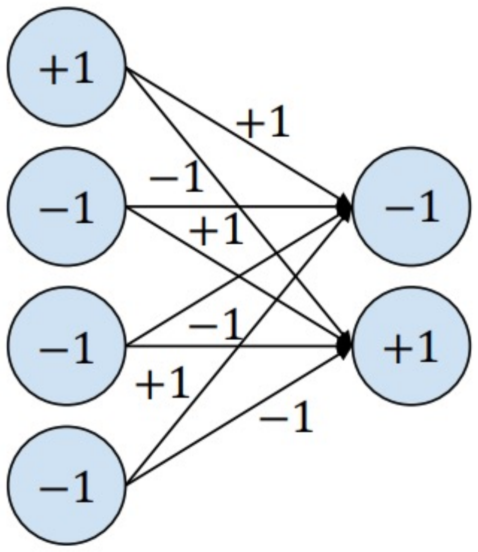
”Sparsity”, in broader terms

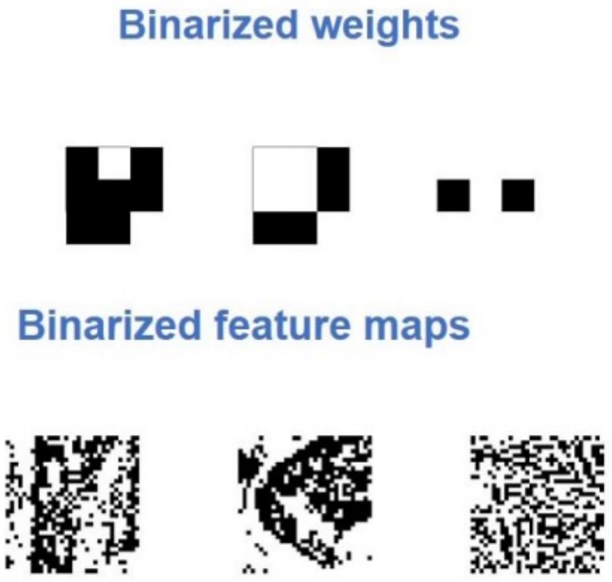
- *Hoefler, T., Alistarh, D., Ben-Nun, T., Dryden, N., & Peste, A. (2021). Sparsity in Deep Learning: Pruning and growth for efficient inference and training in neural networks. J. Mach. Learn. Res., 22(241), 1-124.*

More About Quantization

- Neural networks can be even **binarized** (**+1** or **-1**)
  - DNNs trained to use binary weights and binary activations
- Expensive **32-bit MAC** (**M**ultiply-**AC**cumulate) ⇒ Cheap **1-bit XNOR-Count**
  - "MAC == XNOR-Count": when the weights and activations are ± 1

\# 1s in bits





Binary Neural Networks

- **Idea**: Training real-valued nets (W_r) treating binarization (W_b) as noise
  - Training W_r is done by **stochastic gradient descent**

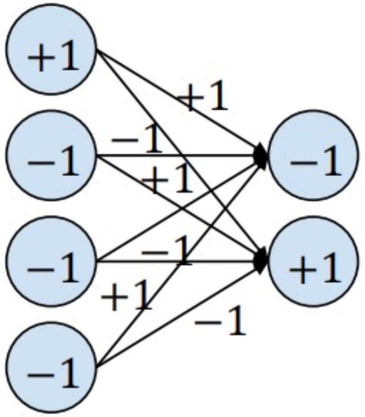
- **Binarization** ($W_r \rightarrow W_b$) occurs for each forward propagation
  - On each of **weights**: $W_b = \mathrm{sign}(W_r)$
  - … also on each **activation**: $a_b = \mathrm{sign}(a_r)$

- Gradients for W_r is estimated from $\frac{\partial L}{\partial W_b}$ [Bengio et al., 2013]
  - "Straight-through estimator": Ignore the binarization during backward!

$$\frac{\partial L}{\partial W_r} = \frac{\partial L}{\partial W_b} \mathbf{1}_{|W_r| \leq 1}$$

$$\frac{\partial L}{\partial a_r} = \frac{\partial L}{\partial a_b} \mathbf{1}_{|a_r| \leq 1}$$

  - Cancelling gradients for better performance
    - When the value is too large

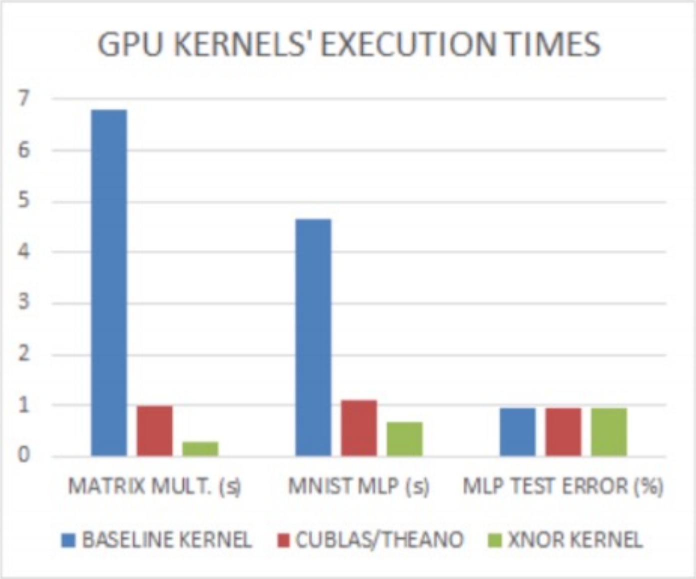


Binary Neural Networks

- BNN yields **32x less memory** compared to the baseline 32-bit DNNs
  - … also expected to reduce energy consumption drastically

- **23x faster** on kernel execution times
  - BNN allows us to use XNOR kernels
  - **3.4x** faster than cuBLAS

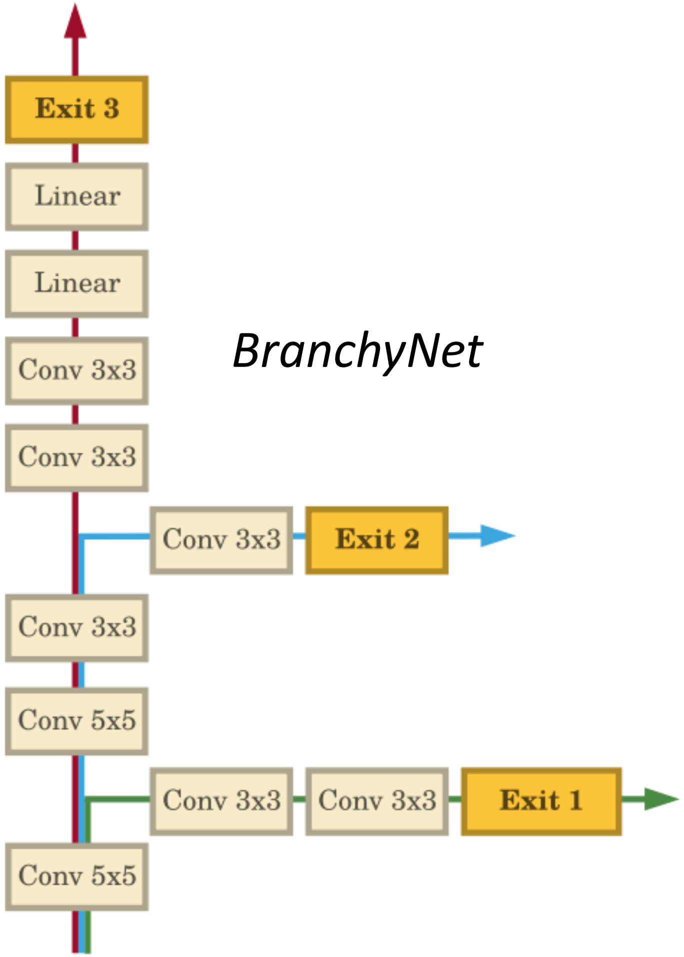
Operation	MUL	ADD
8bit Integer	0.2pJ	0.03pJ
32bit Integer	3.1pJ	0.1pJ
16bit Floating Point	1.1pJ	0.4pJ
32tbit Floating Point	3.7pJ	0.9pJ



- **BNN** achieves comparable error rates over existing DNNs

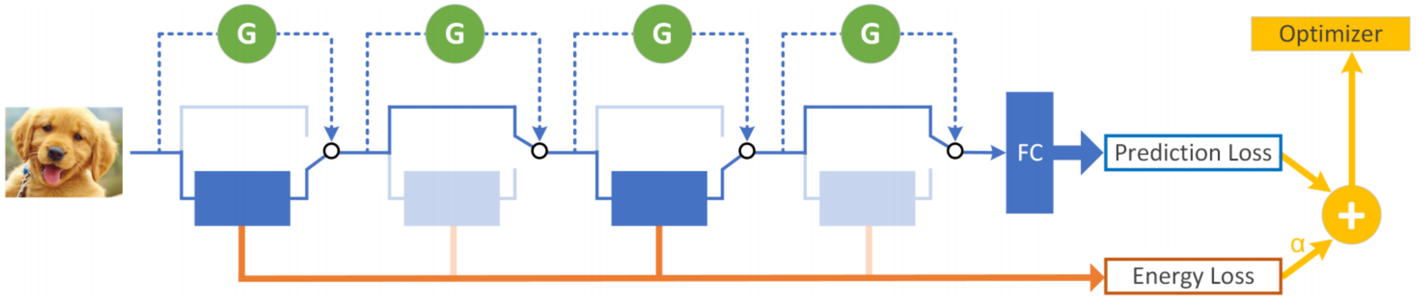
Dynamic Inference

- Only execute a fraction of the network per needed
- Can enable both “input-dependent” and “resource-dependent” forms



BranchyNet

SkipNet



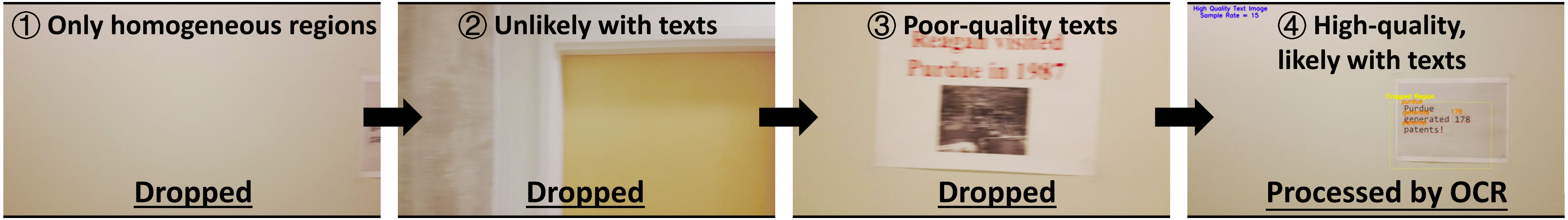
Real-World Efficient ML: Way to Go

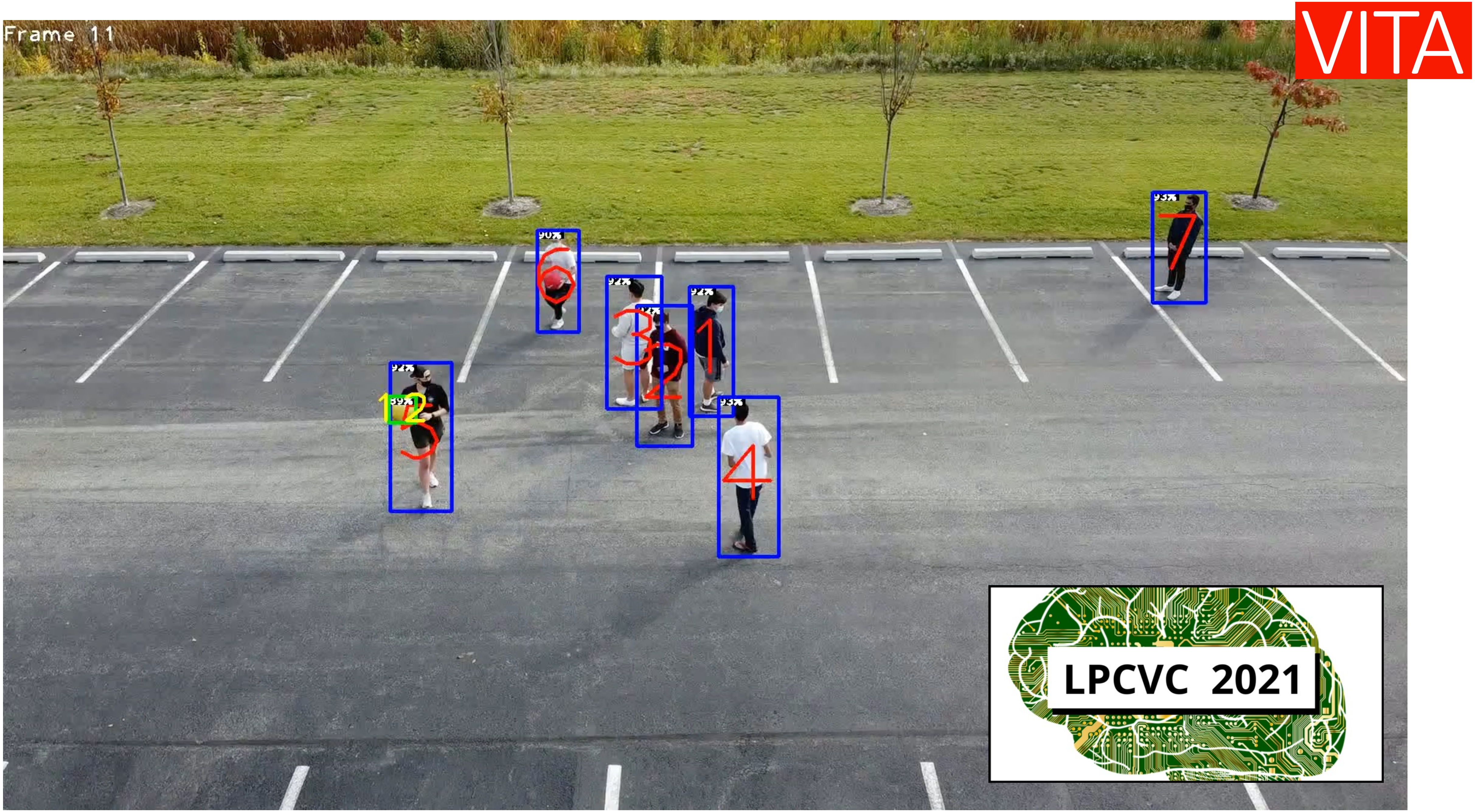
- Jointly utilizing several compression means
  - Also, can choose efficient “by-design” models (MobileNets, or even non-deep models, etc.)
  - Channel pruning is in fact very similar to NAS
- **Data processing** is often a key concern, maybe more important
- **Hardware co-design** is another key concern
- Resource constraints & user demands often **change over time**
- From single task to multi-task and lifelong learning …

Demo: Energy-Efficient UAV-Based Text Spotting System

- **Task:** UAV-based low-energy video understanding (Raspberry Pi 3B+)
- Our group has been leading the show!
    - **2021 IEEE Low-Power Computer Vision (LPCV) Challenge, 1st prize (video track)** among 31 university & company teams that submitted 249 independent solutions
    - **2020 IEEE Low-Power Computer Vision (LPCV) Challenge, 2nd prize (video track**), among ~ 90 solutions

2020 Low-Power Computer Vision Challenge




Frame 11
VITA
LPCVC 2021

From Efficient Inference to Efficient Training

Two type of demands dominate:

- ”Personalization” (or adaptation, continual learning) at the **edge** (resource-constrained device): saving communication bandwidth /energy & protecting data privacy etc.
    - Mostly **fine-tuning** (new unseen data, etc.)
- “Scaling up” bigger models at the **data center** (resource-rich cloud server), while keep relatively affordable training budget & suppressing carbon footprint, etc.
    - Both **training from scratch**, and **transfer learning** (new task type, new data, etc.)

Edge-based Training: Lessons from Efficient Inference?

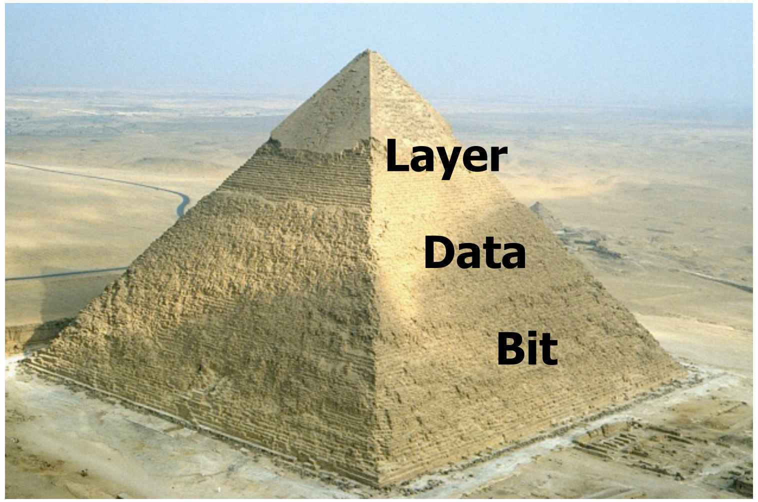
- **Training v.s. Inference:** one-pass feedforward v.s. iterative forward + backward

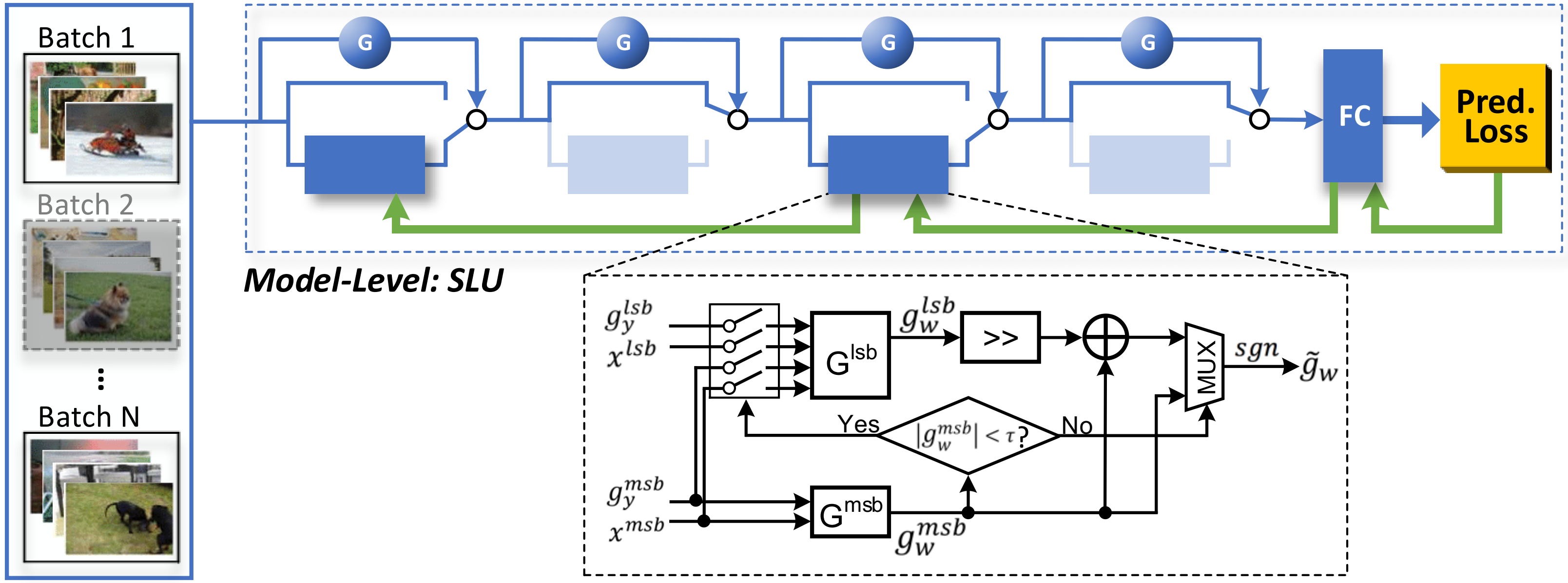
- **Lessons that we learned from Inference:**
  - Model parameters are not born equally, and many redundancies do exist
  - *Know your specific goal:* saving memory, latency and energy are often not aligned
  - To achieve energy goal, realistic energy models and/or hardware measurements are very helpful
  - Consider a more "end-to-end" effort beyond just the model itself (data, hardware, architecture…)

- **New Challenges posed for Training:**
  - Saving per-sample (mini-batch) complexity (both feed-forward and backward)
  - The empirical convergence (how many iterations needed) matters more than per-MB complexity
  - Data access/movement bottlenecks are (even more) crucial

E2-Train: Energy-Efficient CNN Training (NeurIPS’19)

Motivation:





Data-Level: SMD

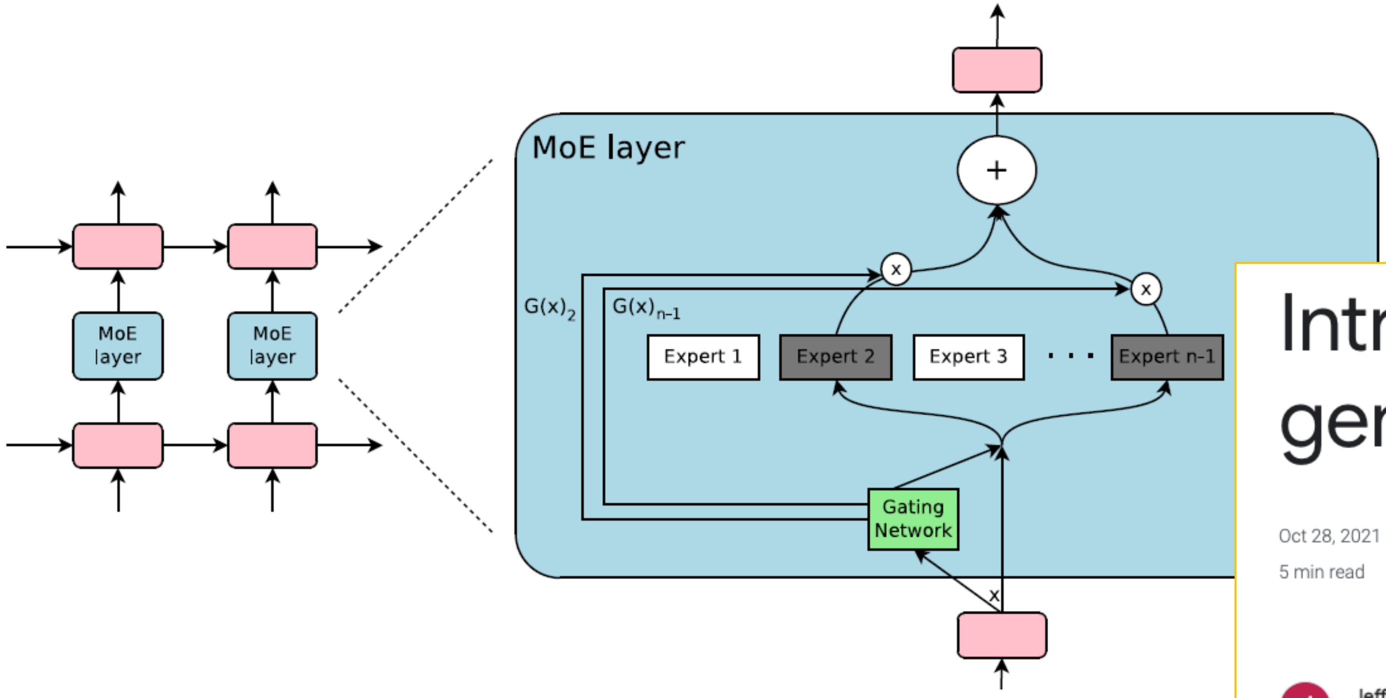
Bit-level: PSG

“Three-Pronged” Approach:

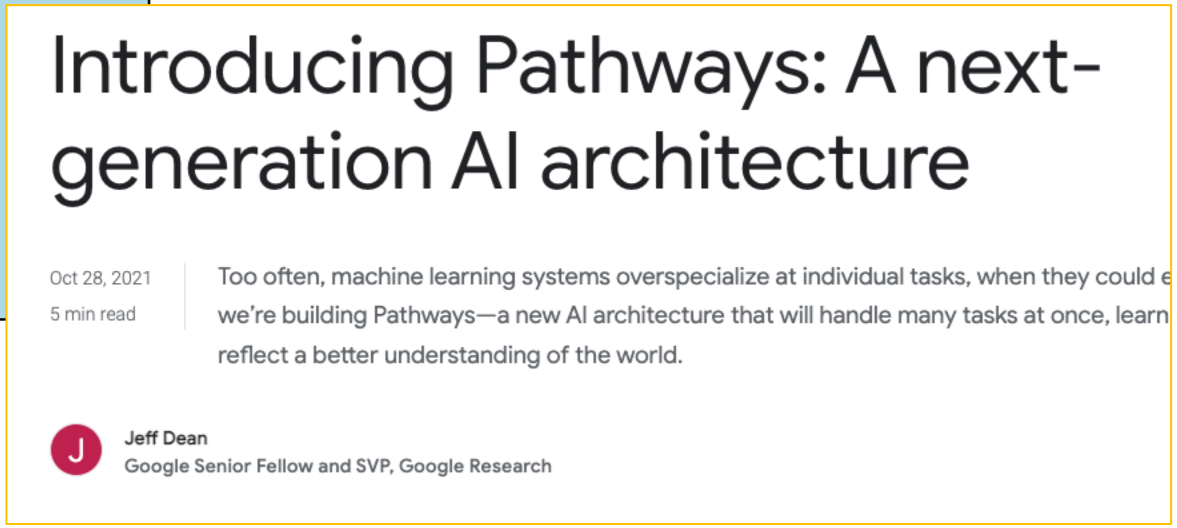
- **Data-Level:** stochastic mini-batch dropping
- **Layer-Level:** selective layer update
- **Bit-Level:** predictive sign gradient descent

Datasets	Models	Accuracy (vs. Original One)	Energy Savings
CIFAR-10	MobileNetV2	92.06% (vs. 92.47%)	88%
	ResNet-110	93.01% (vs. 93.57%)	83%
CIFAR-100	MobileNetV2	71.61% (vs. 71.91%)	88%
	ResNet-110	71.63% (vs. 71.60%)	84%

Efficiently Scaling and Training from Scratch:
Mixture of Experts (MoEs)



Shazeer M. et. al. "Outrageously Large Neural Networks: The Sparsely-Gated Mixture-of-Experts



Introducing Pathways: A next-generation AI architecture

Oct 28, 2021
5 min read

Too often, machine learning systems overspecialize at individual tasks, when they could e
we're building Pathways—a new AI architecture that will handle many tasks at once, learn
reflect a better understanding of the world.

Jeff Dean
Google Senior Fellow and SVP, Google Research

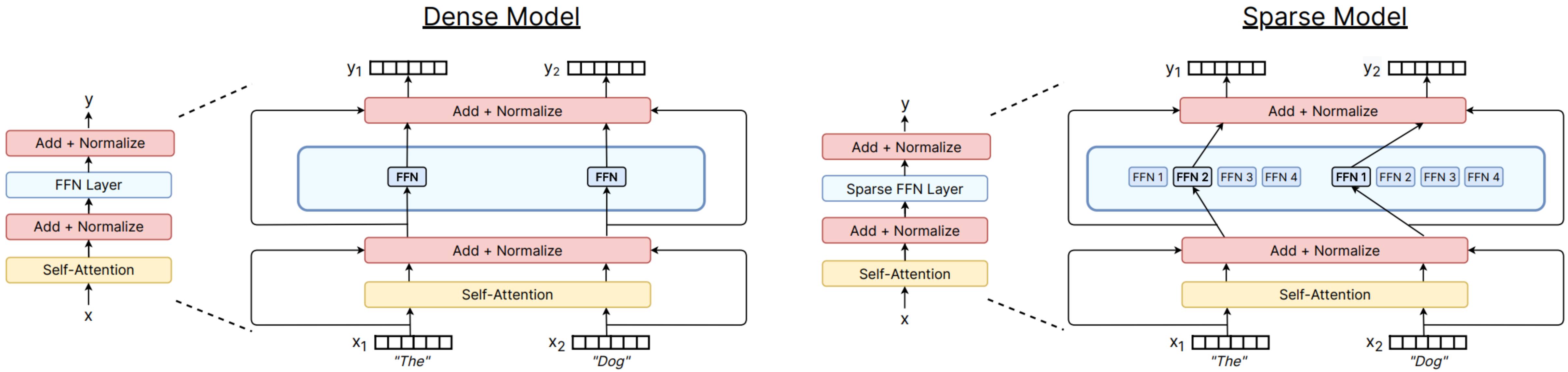
Why MoE?

- MoE is a special type of sparsity (**dynamic, structured, end-to-end**)
  - "Modalized" structure is naturally good for distributed training/parallelism
  - "Block-level" sparsity is hardware-friendly
  - "End-to-end" sparsity keeps the memory /compute low at any point of training

- MoE is also a special type of dynamic inference
  - Dynamically activate an "input-dependent" subnetwork for a new test sample
  - The activation is controlled by a **routing network** (top-*k* classifier, RL, hashing…)

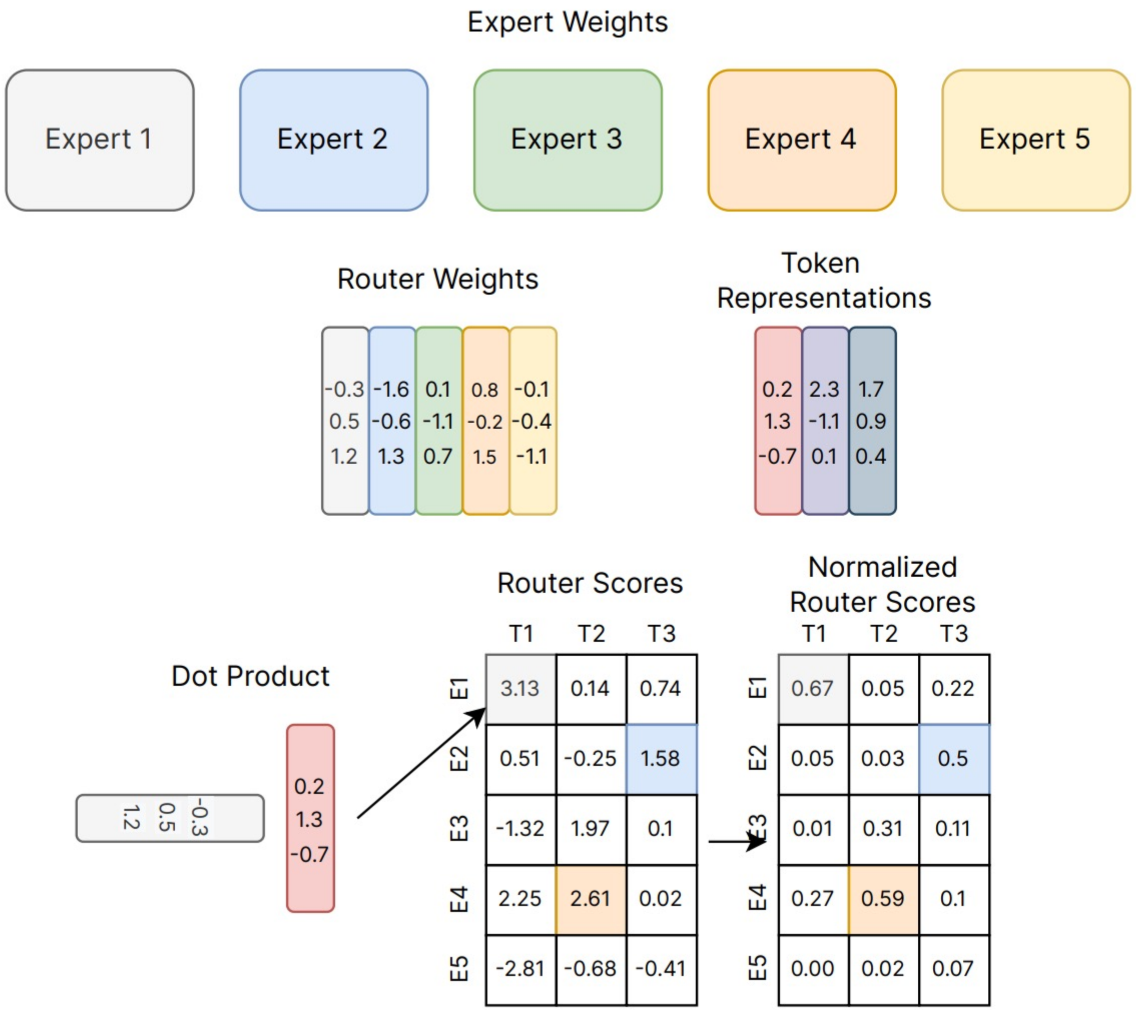
- MoE can be straightforwardly extended to "divide and conquer"…
  - Multi-task learning
  - Multi-modality learning

Dense versus Sparse MoE Transformer



Fedus, William, Jeff Dean, and Barret Zoph. "A review of sparse expert models in deep learning." *arXiv preprint arXiv:2209.01667* (2022).

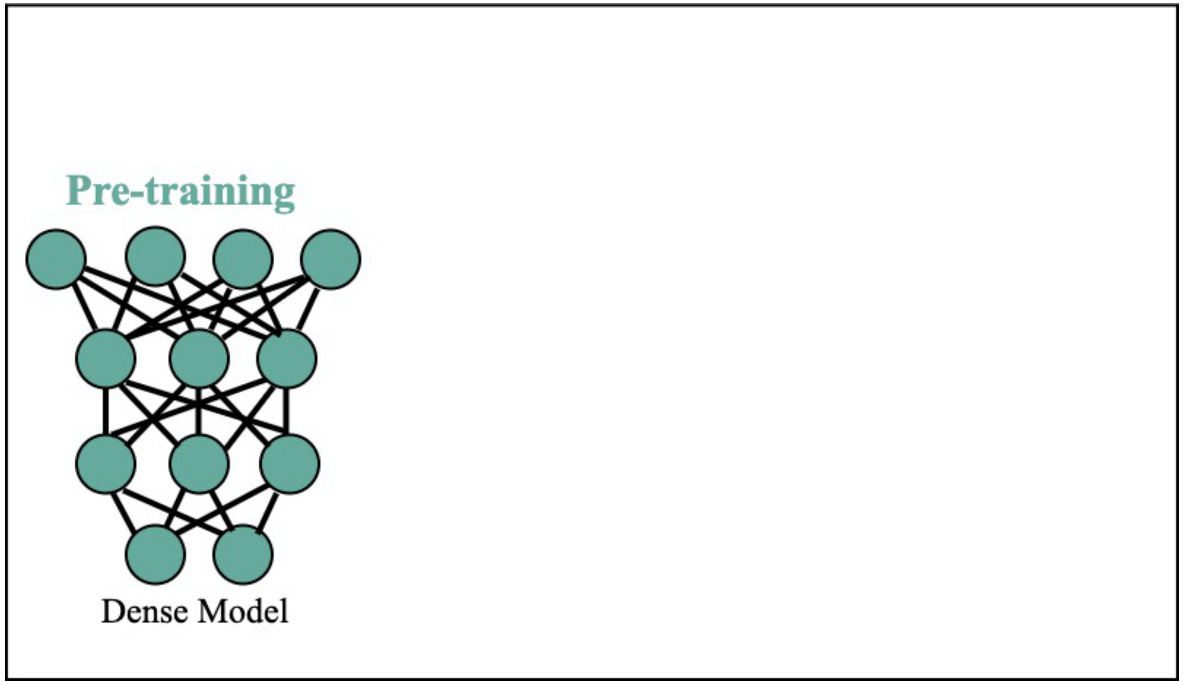
Schematic of Routing Network (using top-k as example)



Many open challenges remain on routing!

- Expert load balancing
- Representational Collapse
- ”In-situ” change sparsity k?
- …

Sparse Transfer Learning using Lottery Ticket Hypothesis (NeurIPS'20, ICLR'21, CVPR'21, ...)



Take Home Message: *LTH can find you a good mask on pre-trained models (supervised or self-supervised), in NLP, CV and even multi-modality, so the sparse subnetwork is* ***the same transferrable****!*

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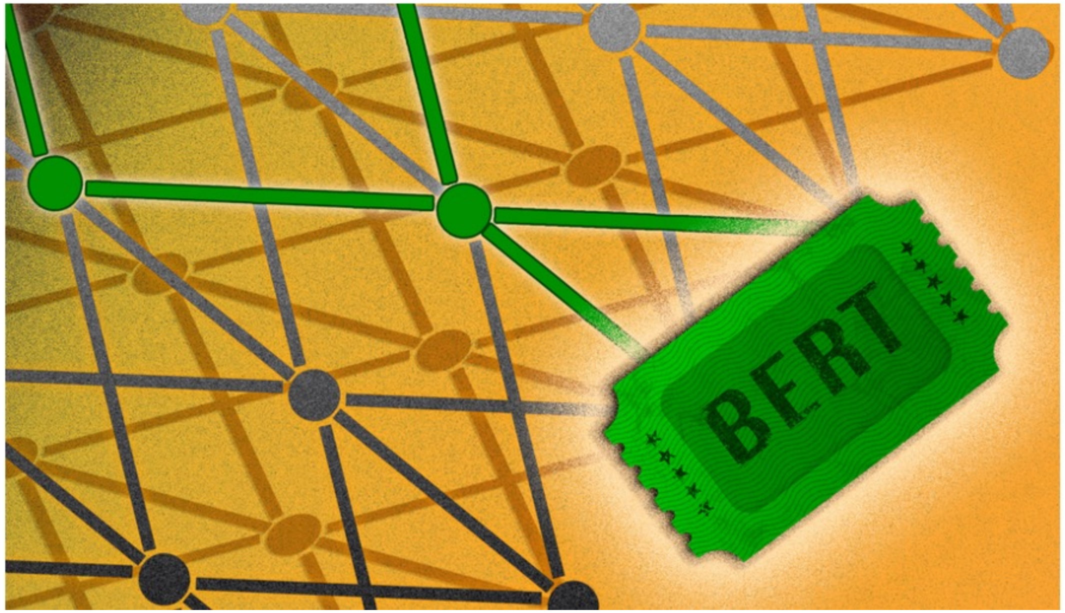
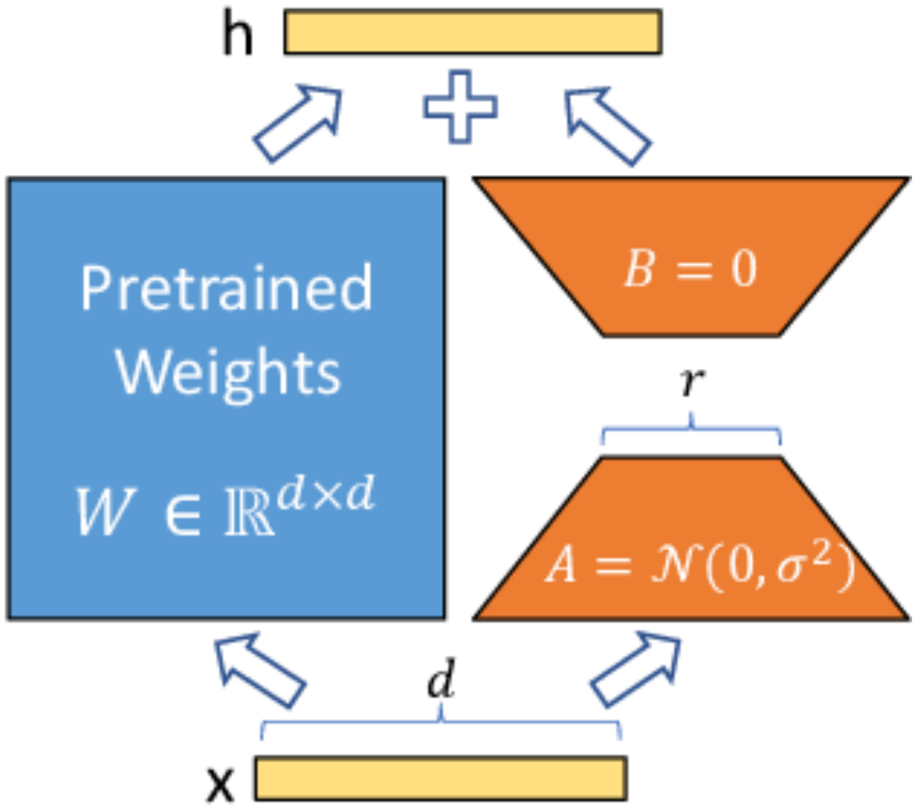
Shrinking massive neural networks used to model language

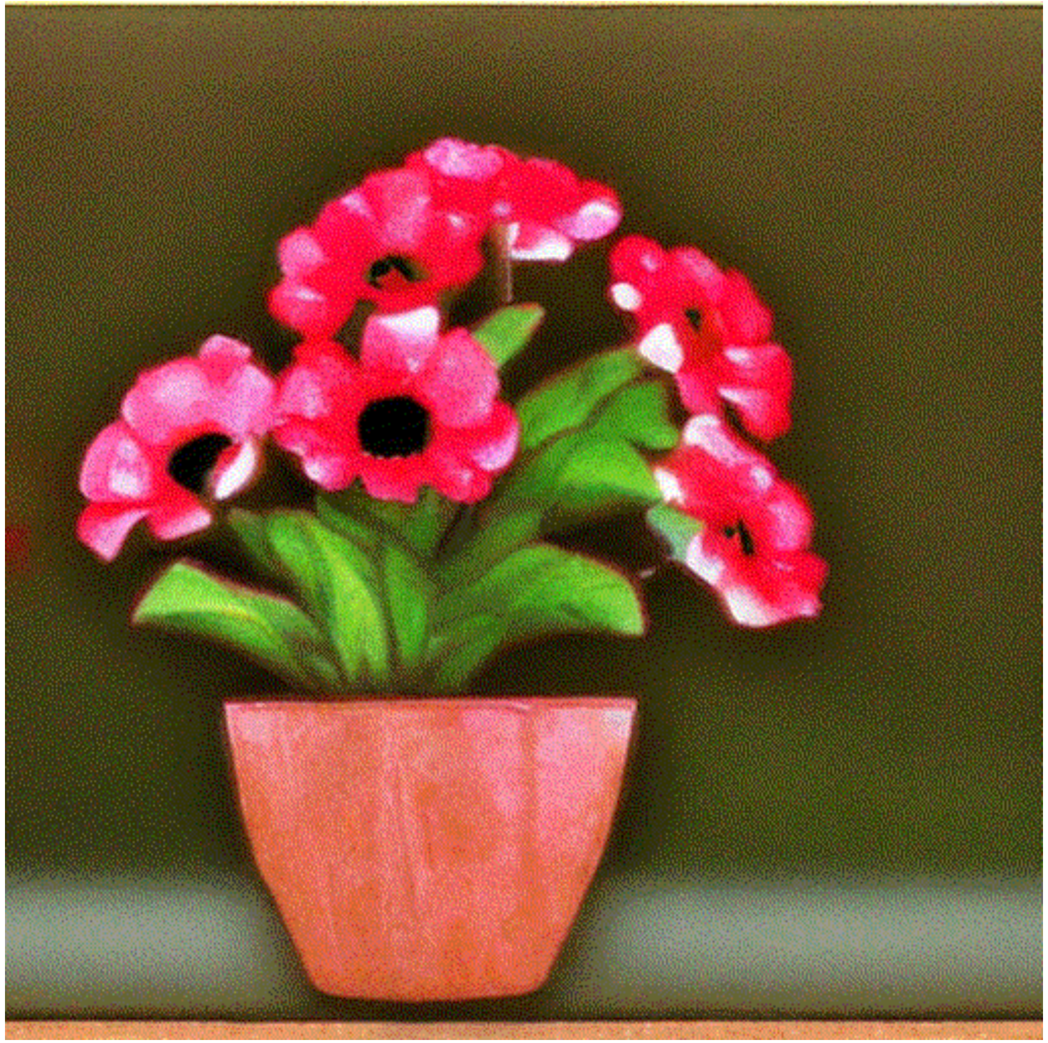
A new approach could lower computing costs and increase accessibility to state-of-the-art natural language processing.

Daniel Ackerman | MIT News Office
December 1, 2020



LoRA: Low-Rank Fine-Tuning





Hu, Edward J., Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. "LoRA: Low-Rank Adaptation of Large Language Models." ICLR 2022

Recent success: fine-tune GenAI Text2Image Models! (https://github.com/cloneofsimo/lora)

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