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Optimizing Deep Learning Systems for Hardware

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Part III : Model-level Optimization

- PIII.a : Model compression
- PIII.b : Efficient architectures

Optimizing a DL model on HW

	Model-Level	System-Level
Scope	Neural network structure & parameters	Hardware, runtime, parallelism strategies
Examples	Pruning, quantization, distillation…	Pipeline parallelism, compiler optimizations
Target	Model size, accuracy-efficiency tradeoff	Latency, throughput, hardware utilization
Who applies it?	ML researchers & algorithm designers	Systems engineers, ML infra-teams

Part III: Model-Level Optimizations

- Definition: Techniques applied directly to the neural network architecture or weights to improve efficiency.
- Focus: Reduce computation, memory, and power usage without significantly impacting accuracy.
- Why it matters?
  - No system-level change
  - Smaller models = faster inference
  - Better fit for resource-constrained devices (edge, mobile)
  - Lower energy and deployment costs

Part III.a: Compression

- a) Model Compression
  - Pruning
  - Quantization
  - Knowledge Distillation
- b) Architecture Optimization
  - Case: Efficient CNNs (e.g., MobileNet)

Model Compression?

- Definition: Techniques that reduce the size and complexity of a deep learning model
- Goal: **Maintain** accuracy while improving:
  - Inference speed
  - Memory footprint
  - Energy efficiency

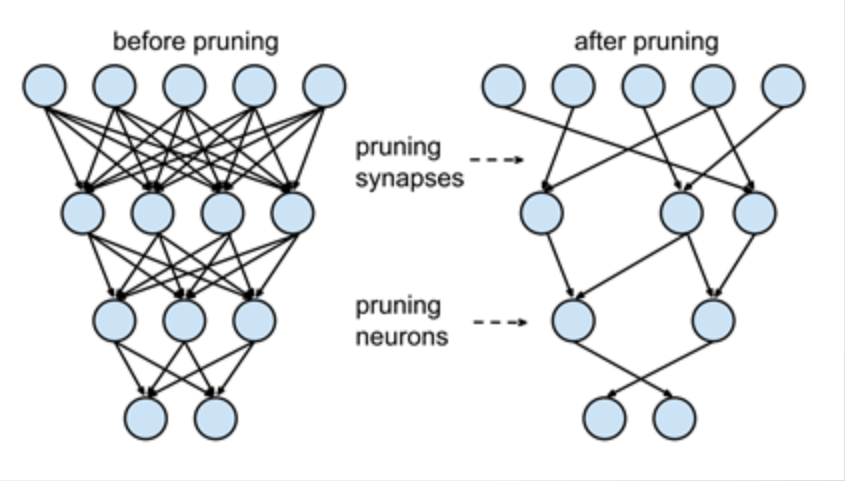
Why Model Compression?

- Real-world drivers:
  - Edge deployment (IoT, smartphones)
  - Faster inference in production systems
  - Lower costs in datacenters (compute + energy)

- Compression ≠ just "shrinking". It's about smart tradeoffs.

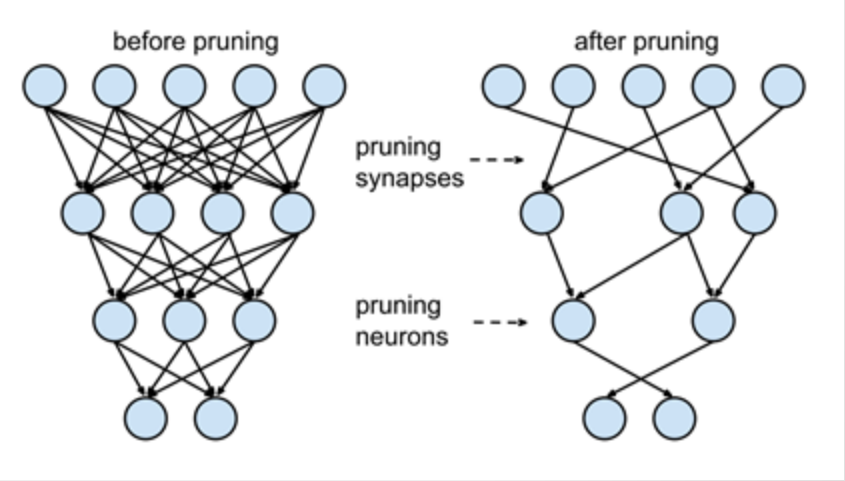
Pruning

- Definition: Eliminate weights or entire neurons that contribute little to output
- Types:
  - Weight pruning (unstructured)
  - Neuron/channel pruning (structured)
  - Visualization:



Pruning

- Pros:
  - Reduces parameter count and computation
  - Works well post-training ("fine-tune" stage)
- Cons:
  - May require retraining/fine-tuning
  - Unstructured pruning may not lead to real speedups without specialized libraries/hardware



Pruning - but how?

- Magnitude-Based Pruning
  - Remove weights with smallest absolute values
  - Simple and effective; often used post-training
- Structured Pruning
  - Remove entire filters, channels, or layers
  - Hardware-friendly → leads to real speedups
- Dynamic / Iterative Pruning
  - Gradually prune during training (e.g., Lottery Ticket Hypothesis)
  - Allows the network to adapt and recover
- Learning-Based Pruning
  - Use optimization or learn mask weights (e.g., L0 regularization)
  - More complex but can yield better performance

Pruning - but how?

Method	Pros	Cons
Magnitude-Based	Simple, fast, widely used	May not accelerate inference without support
Structured Pruning	Leads to real speedups on hardware	Can reduce accuracy more if not carefully tuned
Iterative/Dynamic	Allows model to adapt gradually	Requires longer training/fine-tuning cycles
Learning-Based	Can find better pruning masks	Computationally complex and harder to tune

Quantization

- Definition: Replace high-precision floats with lower-bit representations

- Common types:
  - Post-training quantization (PTQ)
  - Quantization-aware training (QAT)
- Popular formats:
  - int8, float16, bfloat16

Post-Training Quantization

- Definition: Apply quantization to a trained model without retraining
- Workflow:
  - Train model as usual (float32)
  - Convert weights/activations to lower precision (e.g., int8)

✓ Fast and easy to apply
✓ Doesn’t require access to training data (in some versions)
× May suffer accuracy drop, especially for sensitive models (e.g., Transformers)
× Limited control over quantization effects

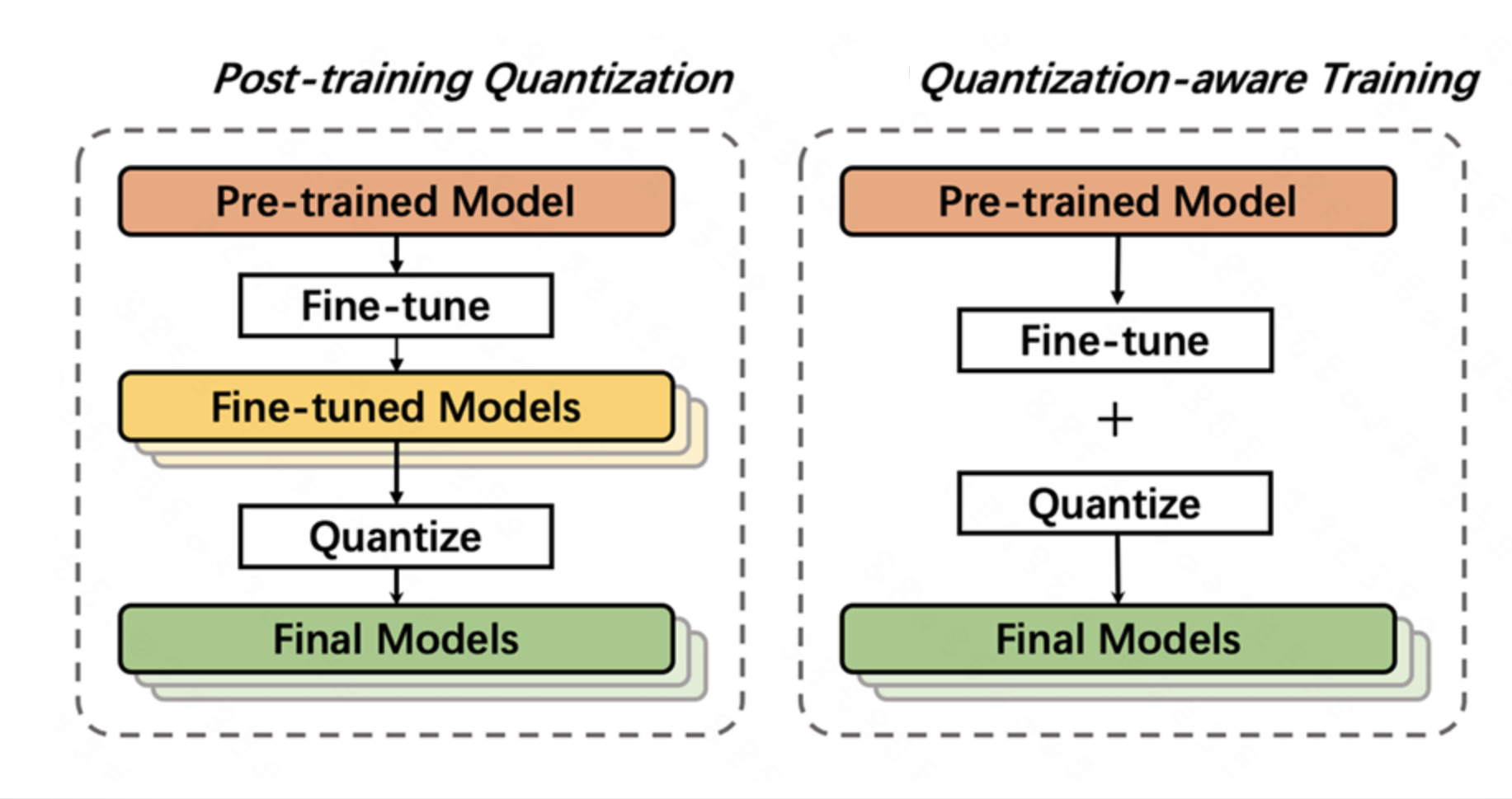
Quantization-aware Training

- Definition: Simulate quantization effects during training
- Workflow:
  - Insert fake quantization ops during training (e.g., simulate int8 rounding)
  - Model learns to be robust to quantization noise

✓ Much smaller accuracy drop vs. PTQ
✓ Works well for complex tasks (e.g., NLP, object detection)

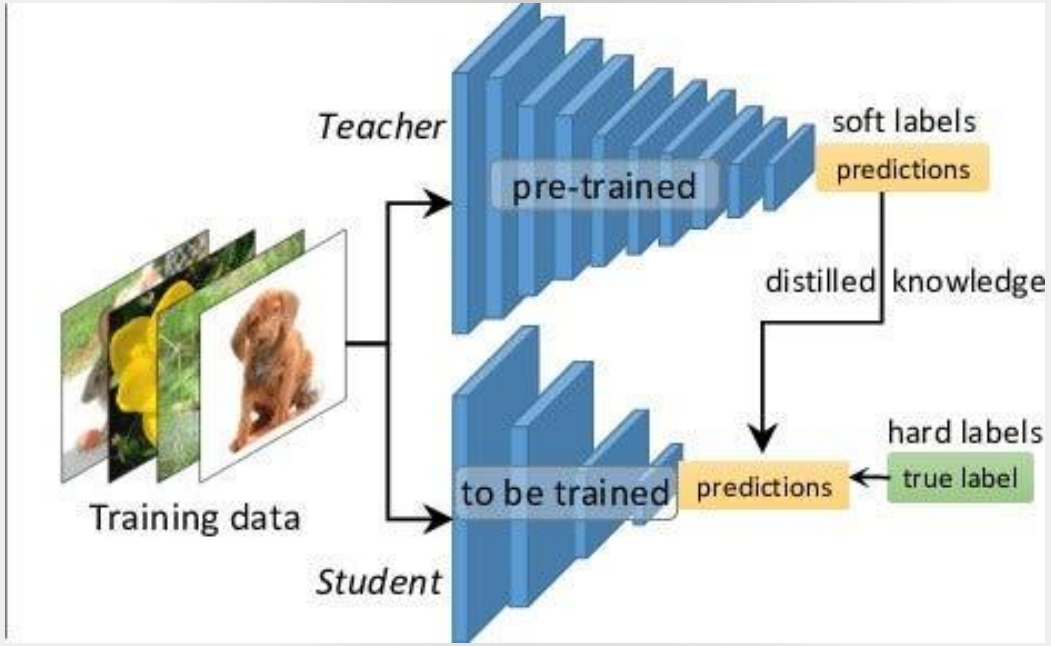
✗ Requires access to training pipeline and data
✗ Slower training due to extra ops
✗ Usually applied to a trained model

PQT vs QAT


Post-training Quantization
Pre-trained Model
Fine-tune
Fine-tuned Models
Quantize
Final Models
Quantization-aware Training
Pre-trained Model
Fine-tune
+
Quantize
Final Models

Knowledge Distilation

- Train a "student" model to mimic a larger, pre-trained "teacher" model



Knowledge Distilation

- Benefits:
  - Student model is smaller and faster
  - Retains much of teacher's performance

- Use Cases:
  - Deploying large LLMs in mobile settings (e.g., TinyBERT from BERT)
  - Ensembles distilled into single model for efficiencyTrain a "student" model to mimic a larger, pre-trained "teacher" model

Model Compression Trade-offs

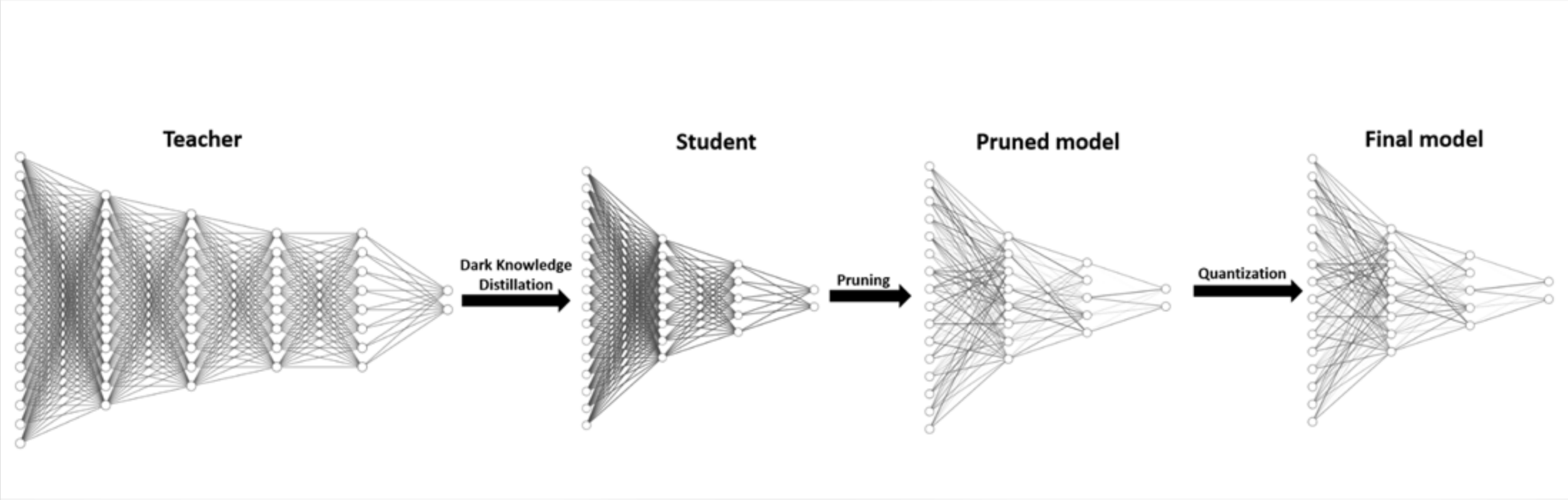
Technique	Description	When to Use
Pruning	Remove unnecessary weights/connections	Overparameterized models
Quantization	Lower precision (e.g., float32 → int8)	Speed + memory critical environments
Knowledge Distillation	Train small model to mimic large one	When deploying compact models

Model Compression Trade-offs

Technique	Size ↓	Speed ↑	Accuracy Impact
Pruning	✅✅	✅	Medium
Quantization	✅✅✅	✅✅	Low–Medium
Knowledge Distill.	✅✅	✅✅	Low

Combined?

- Yes, if you have a pre-trained teacher



Next: Part III.b

- PIII.a : Model compression
- PIII.b : Efficient architectures

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Thanks!

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