Monarch: Expressive Structured Matrices for Efficient and Accurate Training

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Sparse Training for Large Models

Challenges with structured linear maps (low-rank, sparse, Fourier):

Sparse end-to-end training   Dense-to-sparse finetuning

Efficiency-quality tradeoffs:

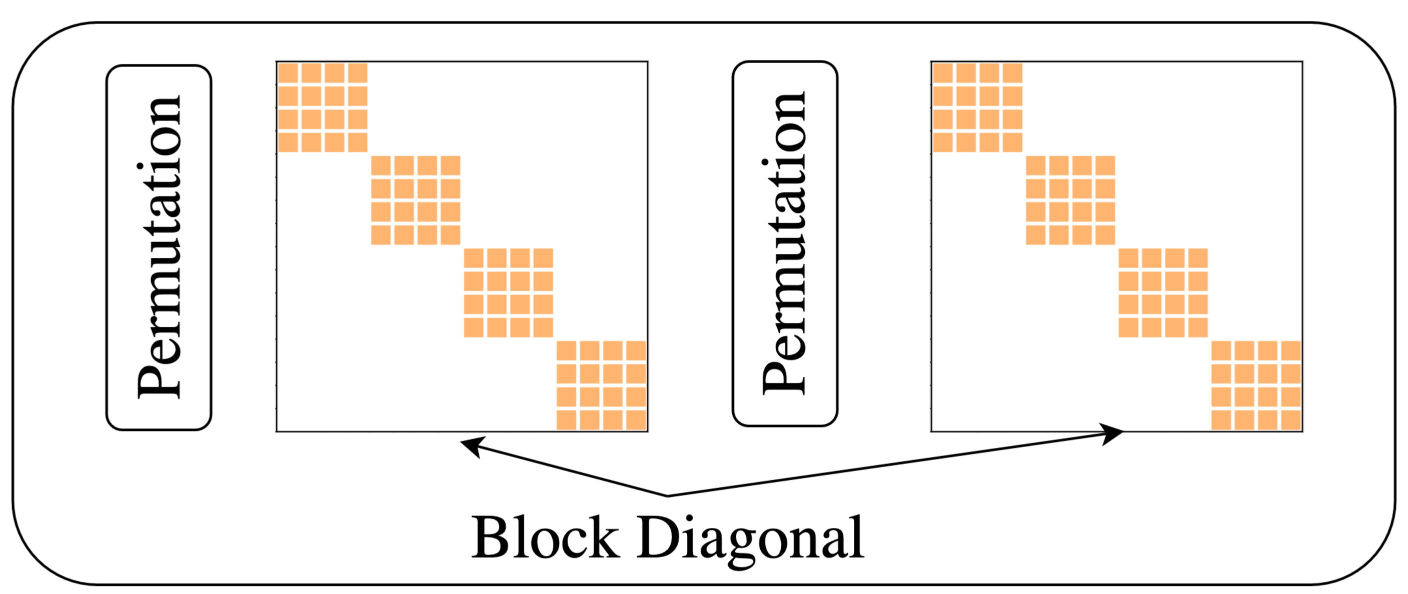
1. Efficiency: on modern hardware (GPU)

2. Quality: how expressive are the weight matrices (can they represent commonly used transforms)

3. Projection: How to find a sparse/structured matrices closest to a pretrained dense weight matrix

Are there structured matrices that are efficient, expressive, and with tractable projection algorithm? Yes

Monarch Matrices: Efficient and Expressive

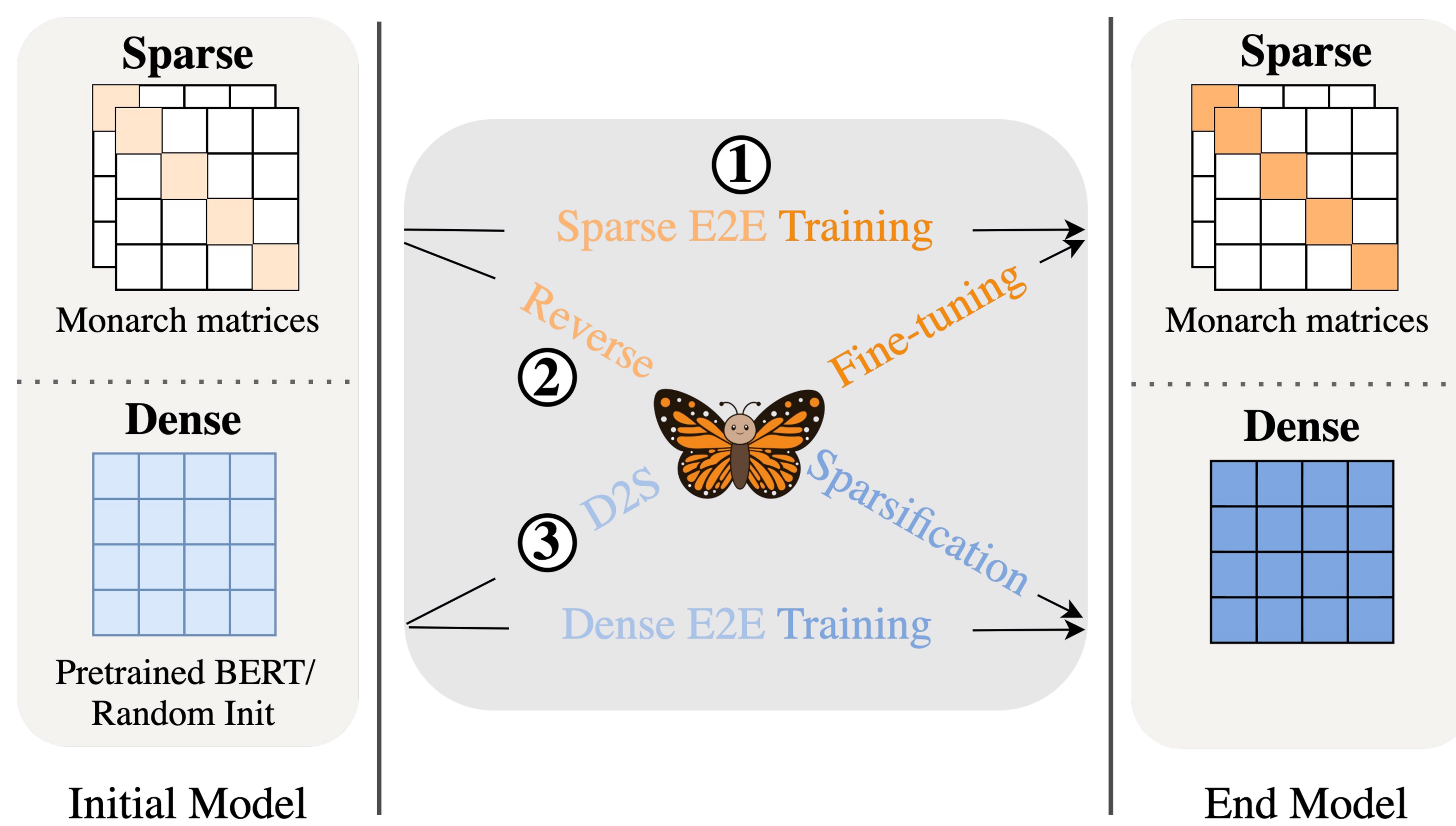


1. Hardware-efficient: Block-diagonal leverages efficient batch-matrix-multiply on GPU.

2. Expressive: contains butterfly matrices (and Fourier, DST, DCT, convolution, Hadamard, etc.)

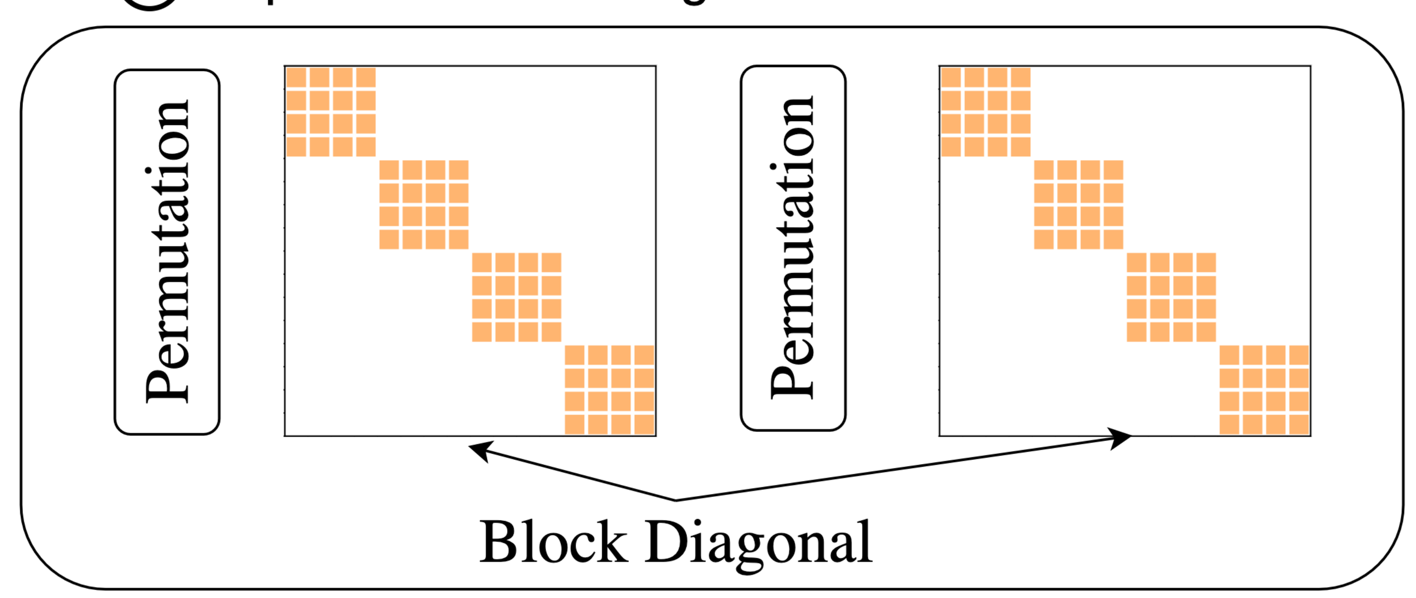
3. Tractable projection: find a Monarch matrix closest to a given dense matrix.

Three Ways to Use Sparse Models



Sparse End-to-End Training

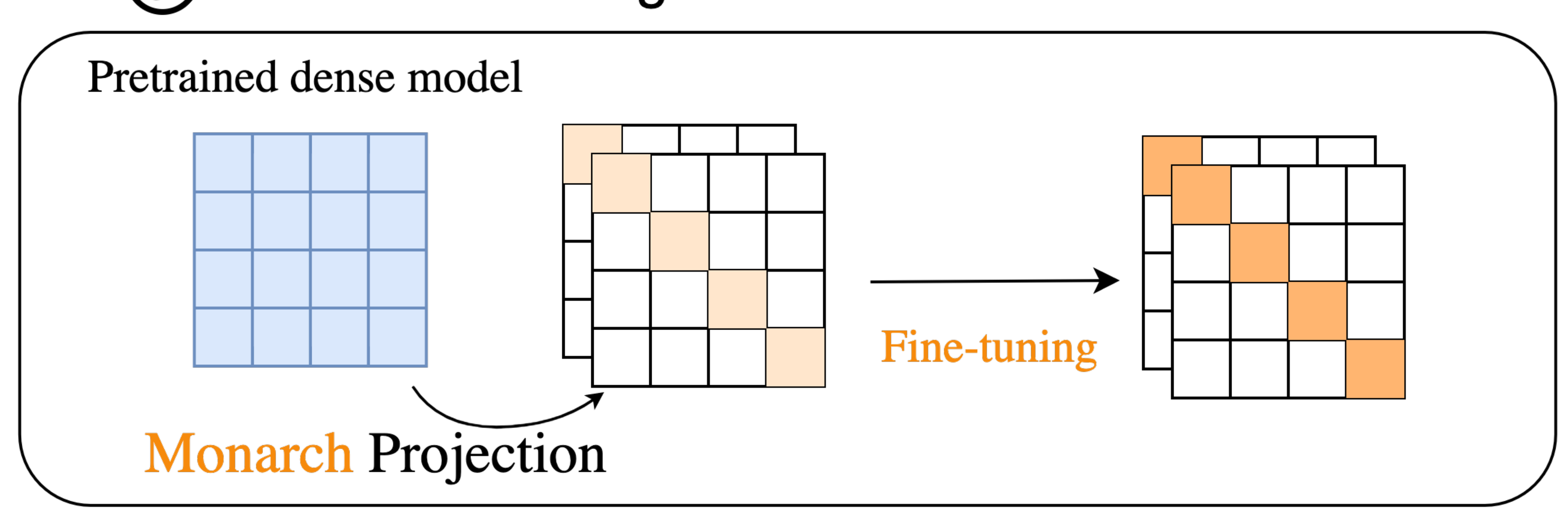
① Sparse E2E Training



Replace dense weight matrices (e.g., attention & FFN) with Monarch matrices for efficiency.

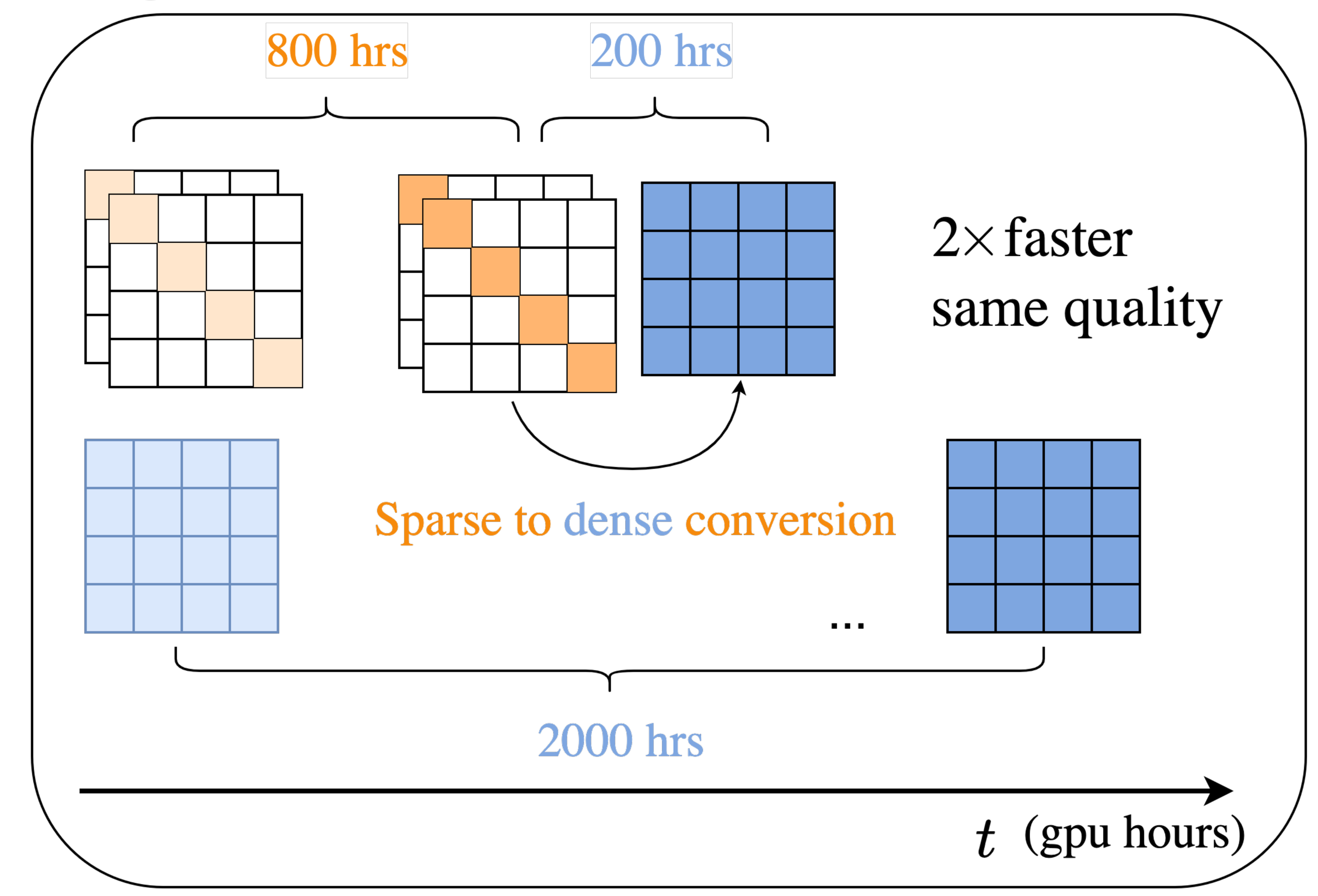
Dense-to-sparse Finetuning

③ D2S Fine-tuning



Sparse-to-Dense Training

② Reverse Sparsification



Sparse-to-dense speeds up training without losing performance 🚀!

Results: Monarch speeds up training from scratch and Finetuning

Sparse end-to-end training

Model	WikiText 103(ppl)	Speedup
GPT-2 Small	20.6	-
Monarch GPT-2-small	20.7	**1.8 x**

Sparse-to-dense training

Implementation	BERT-large training time on 8xA100s (h)
HuggingFace	84.5
MegaTron	52.5
Nvidia MLPerf 1.1	30.2
Monarch	**23.8**

Dense-to-sparse finetuning

Model	GLUE (avg)	Speedup
BERT-large	80.4	-
Monarch BERT-large	79.6	**1.7 x**

Up to 3.5x training speedup without performance loss.