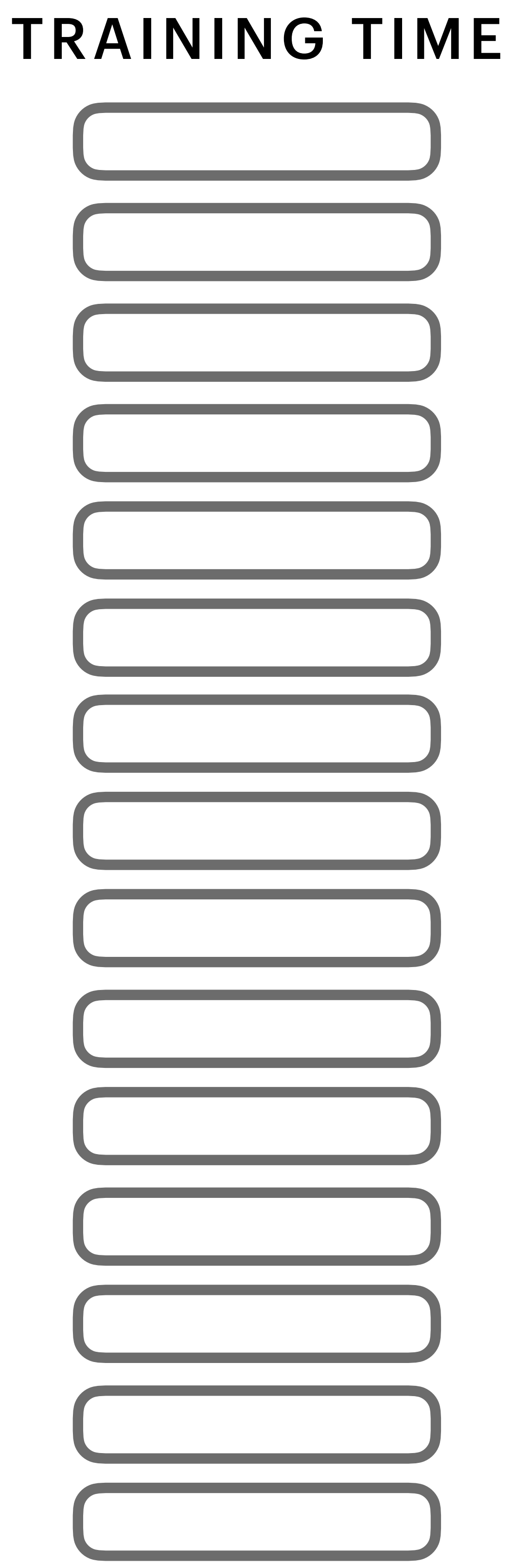
Efficient Transformers

Angela Fan

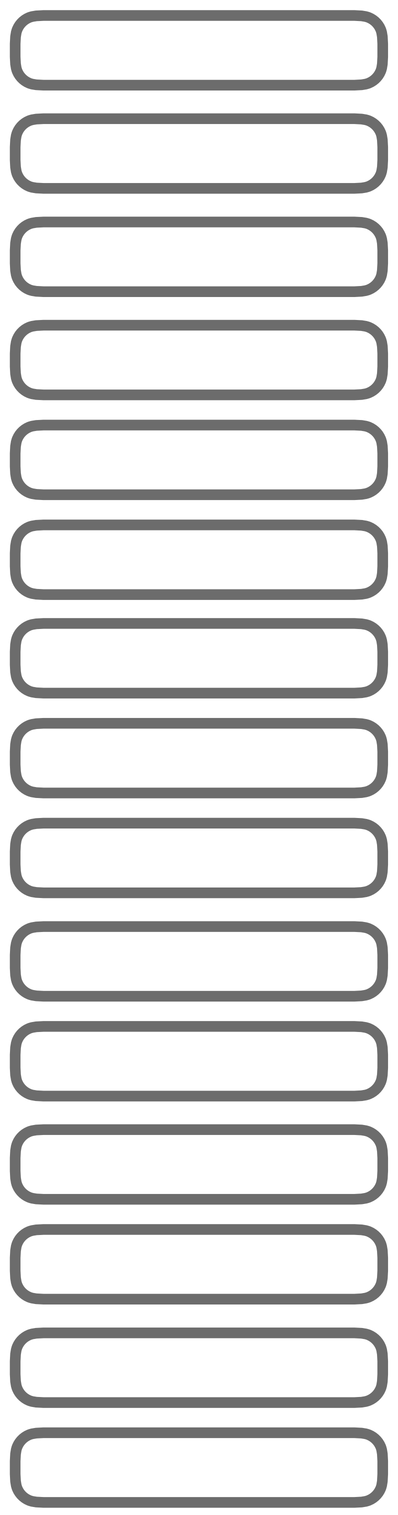
Standard Neural Networks



- Overparameterized

Standard Neural Networks

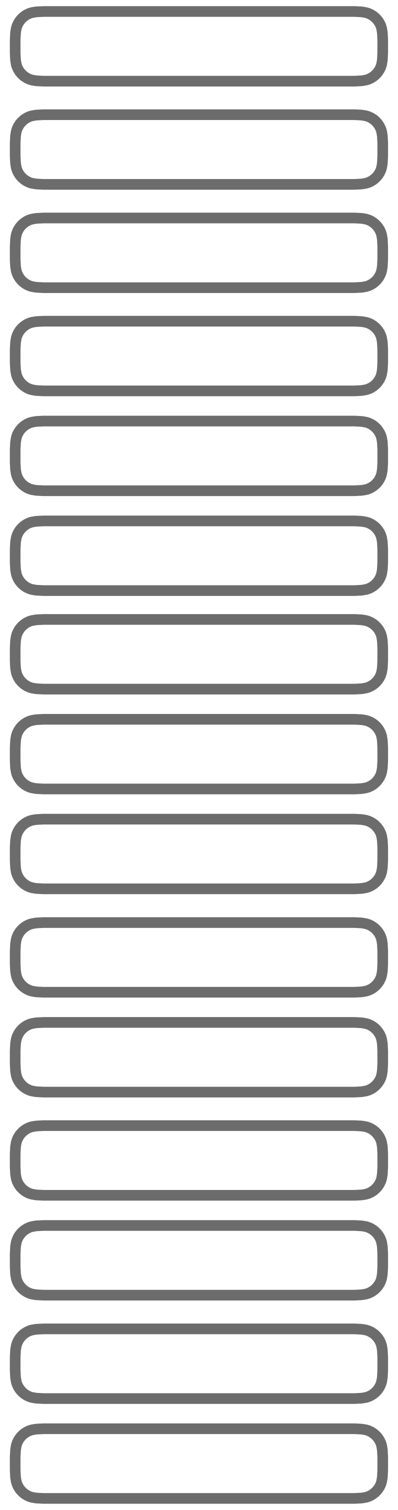
TRAINING TIME



- Overparameterized
- Redundant

Standard Neural Networks

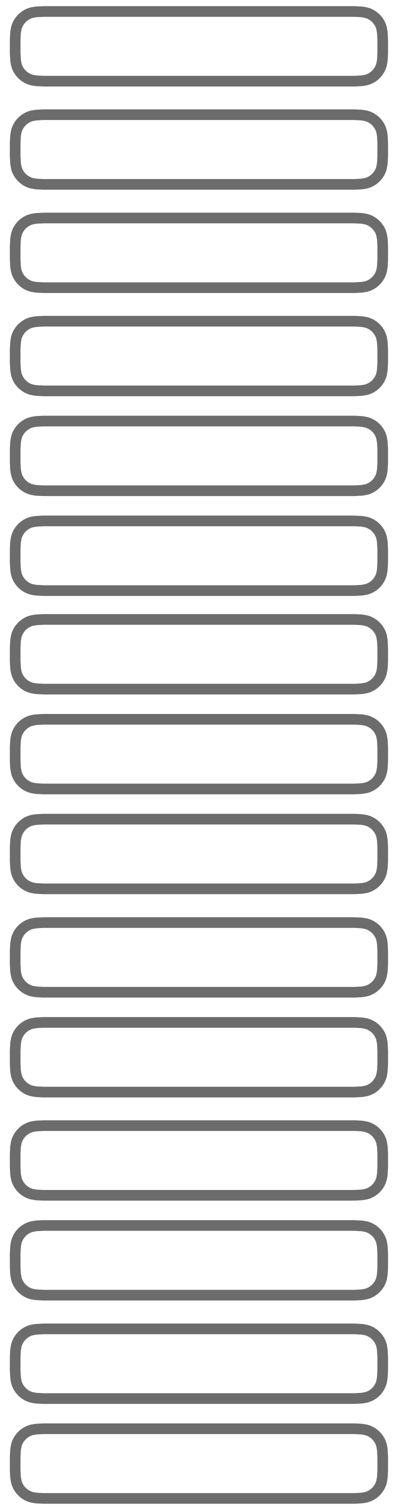
TRAINING TIME



- Overparameterized
- Redundant
- Overfitting

Standard Neural Networks

TRAINING TIME



- Overparameterized
- Redundant
- Overfitting
- Too Large for Practical Applications

Techniques for Smaller Networks

- Train Smaller Network from Scratch

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- Sparsity Inducing Training

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- More efficient architectures

Caveat: this is a **brief** overview focused on **Transformers**

What to think about when talking about efficiency?

- Training Time
- Inference Time
- Model size
- Energy

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not all techniques improve all of these areas

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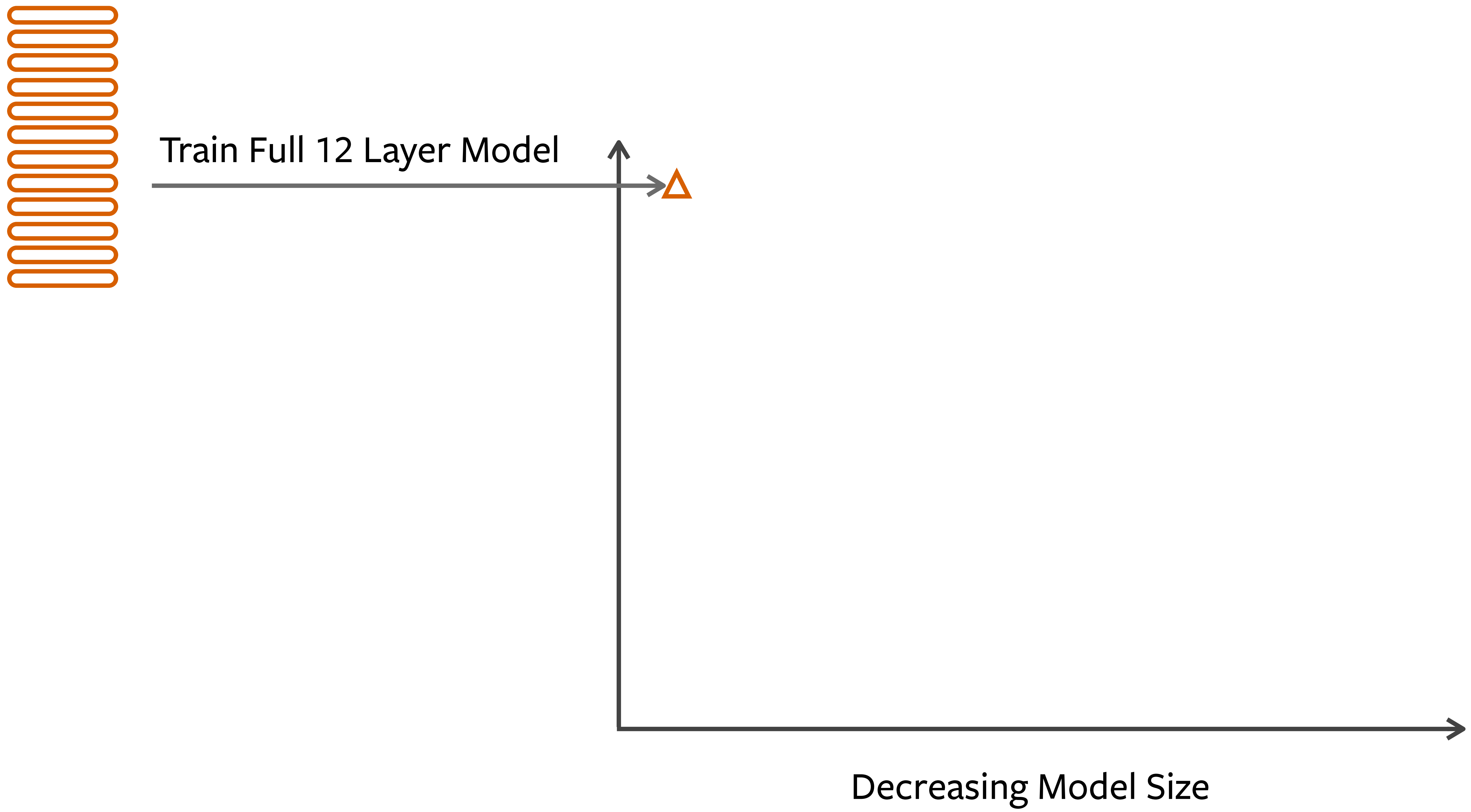
Training a Smaller Model from Scratch



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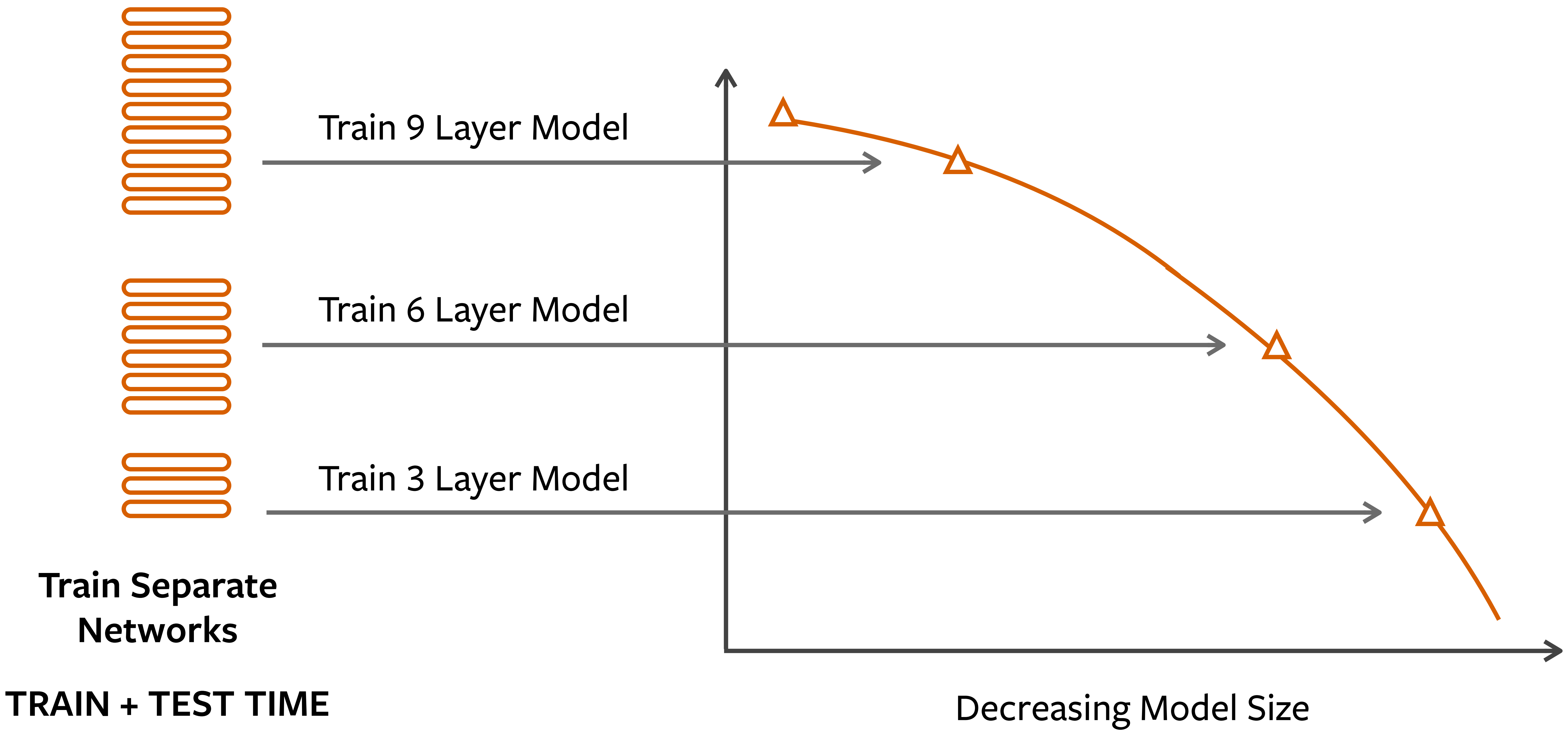

Training a Smaller Model from Scratch

- Training Time ✓
- Inference Time ✓
- Model size ✓
- Performance ✗

Techniques for Smaller Networks

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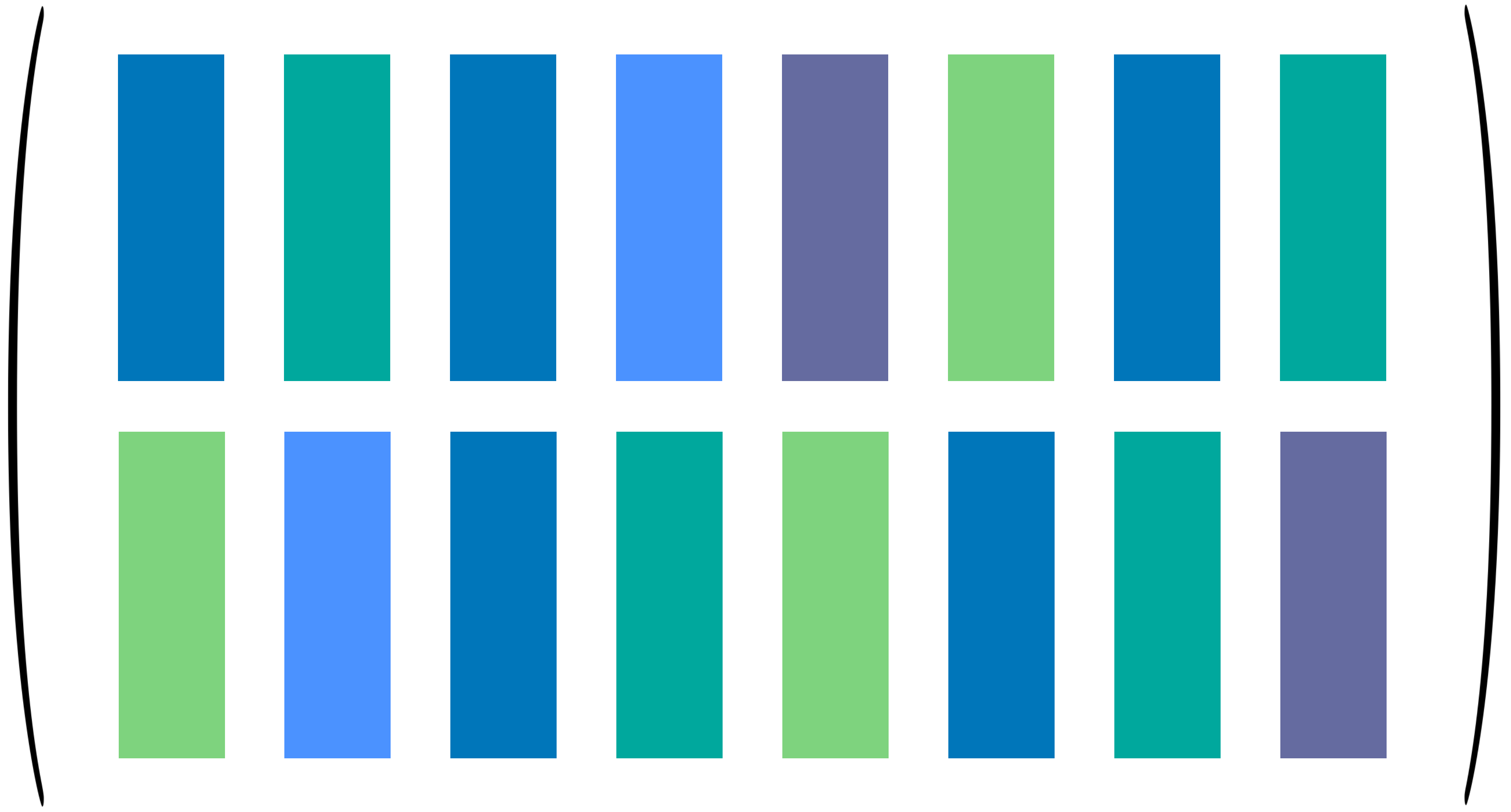
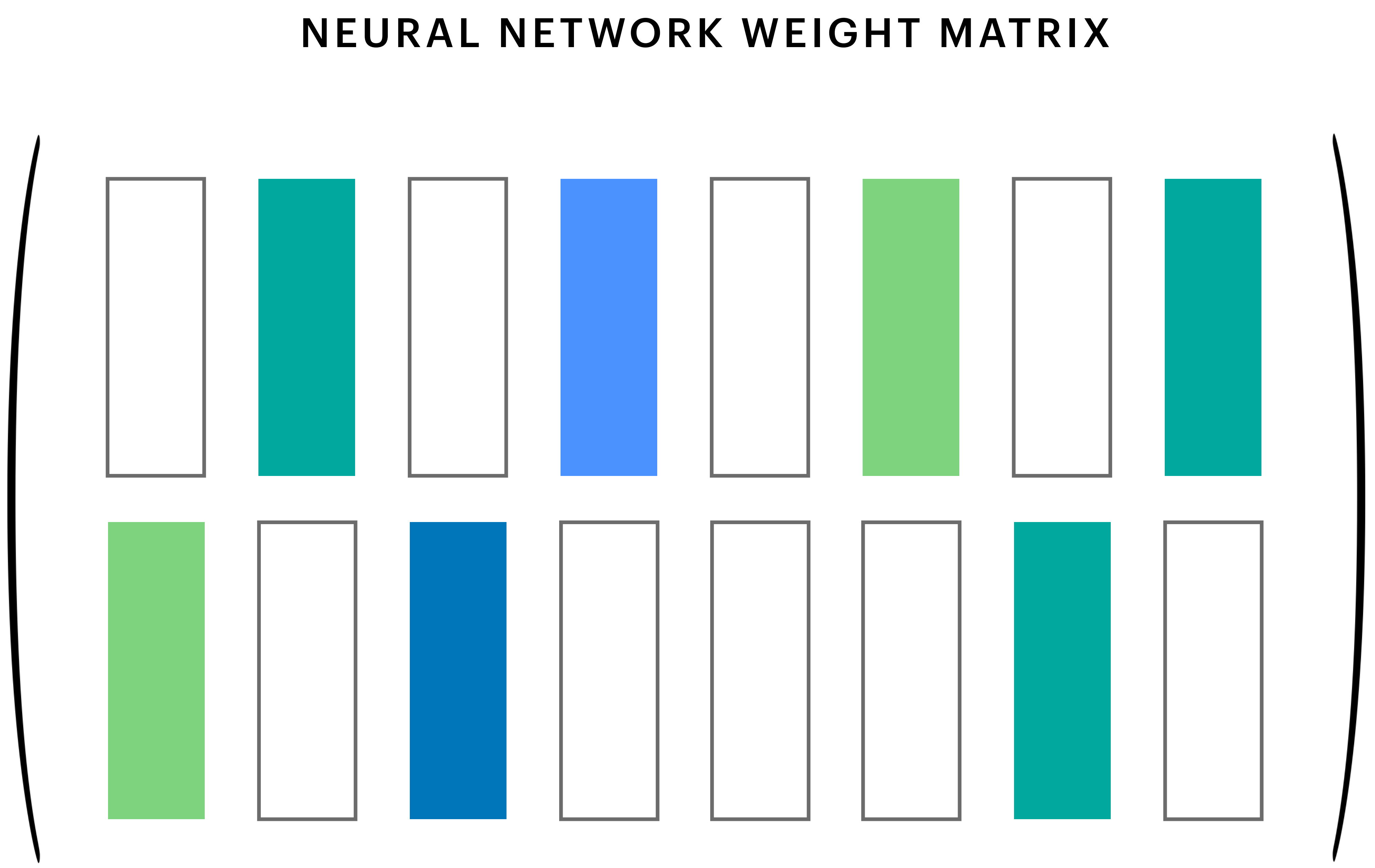
Sparsity Inducing Training

NEURAL NETWORK WEIGHT MATRIX



Sparsity Inducing Training

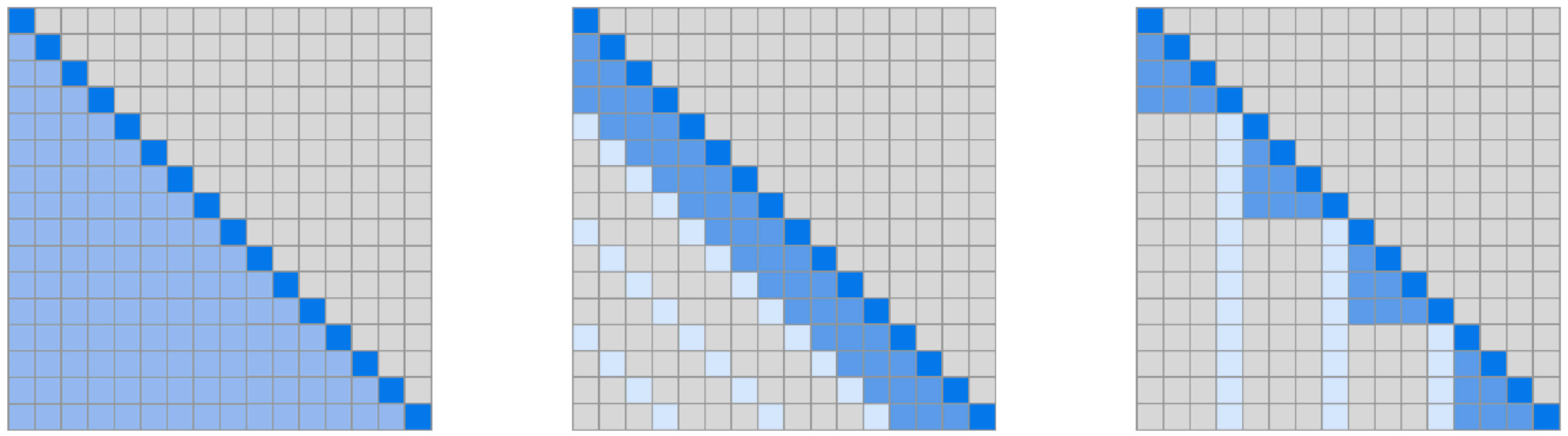


sparsify the weight matrix to include many zeroes

Advantages

- Sparse matrix multiplication - takes advantage of the zeroes
- Specialized kernels - everywhere you see a zero, don’t need to compute that row/column, so less multiplications
- Important for on-device

Sparsity Inducing Training via Attention Matrices



GENERATING LONG SEQUENCES WITH SPARSE TRANSFORMERS

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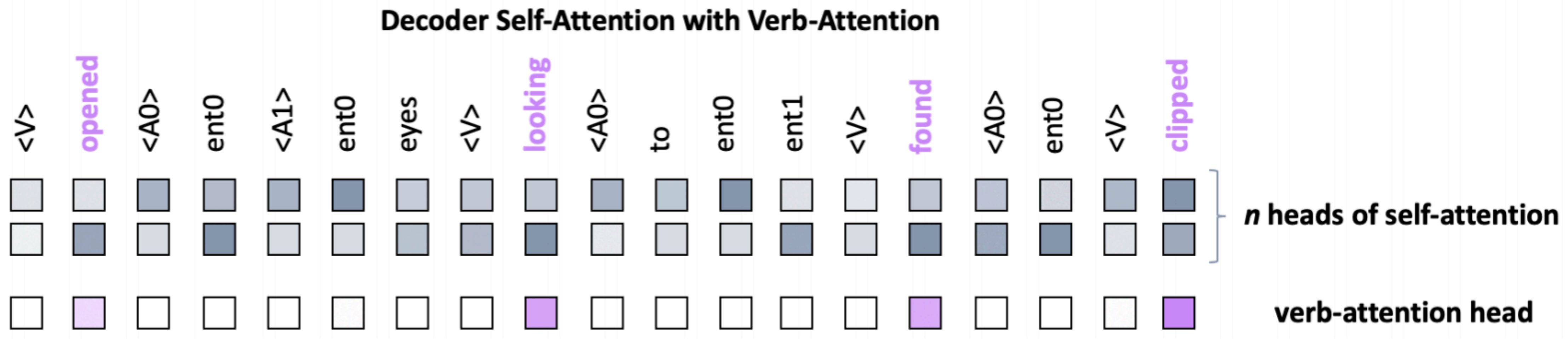

STRATEGIES FOR STRUCTURING STORY GENERATION

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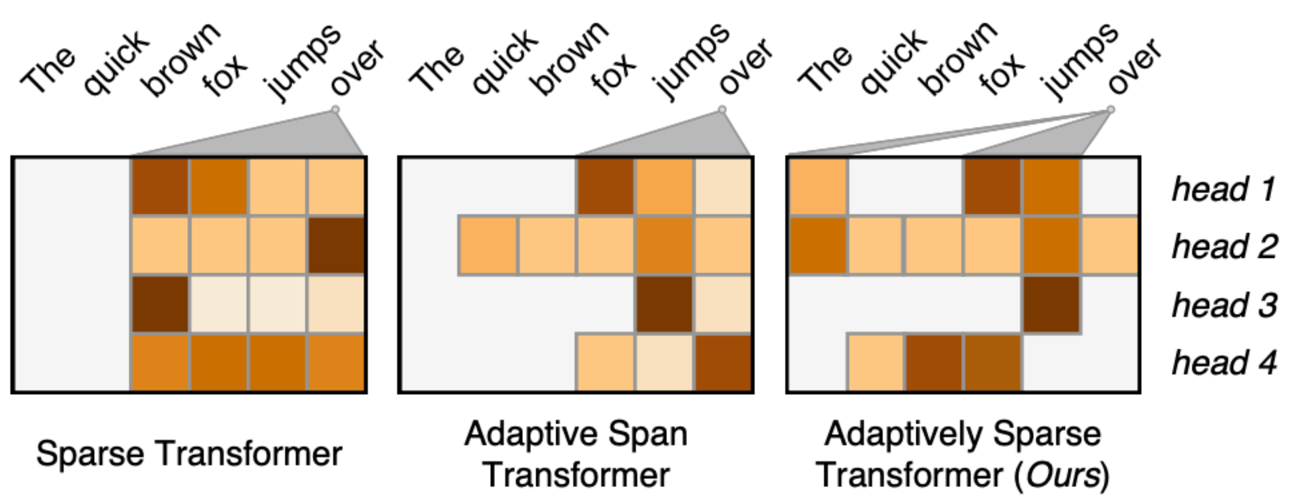

ADAPTIVELY SPARSE TRANSFORMERS

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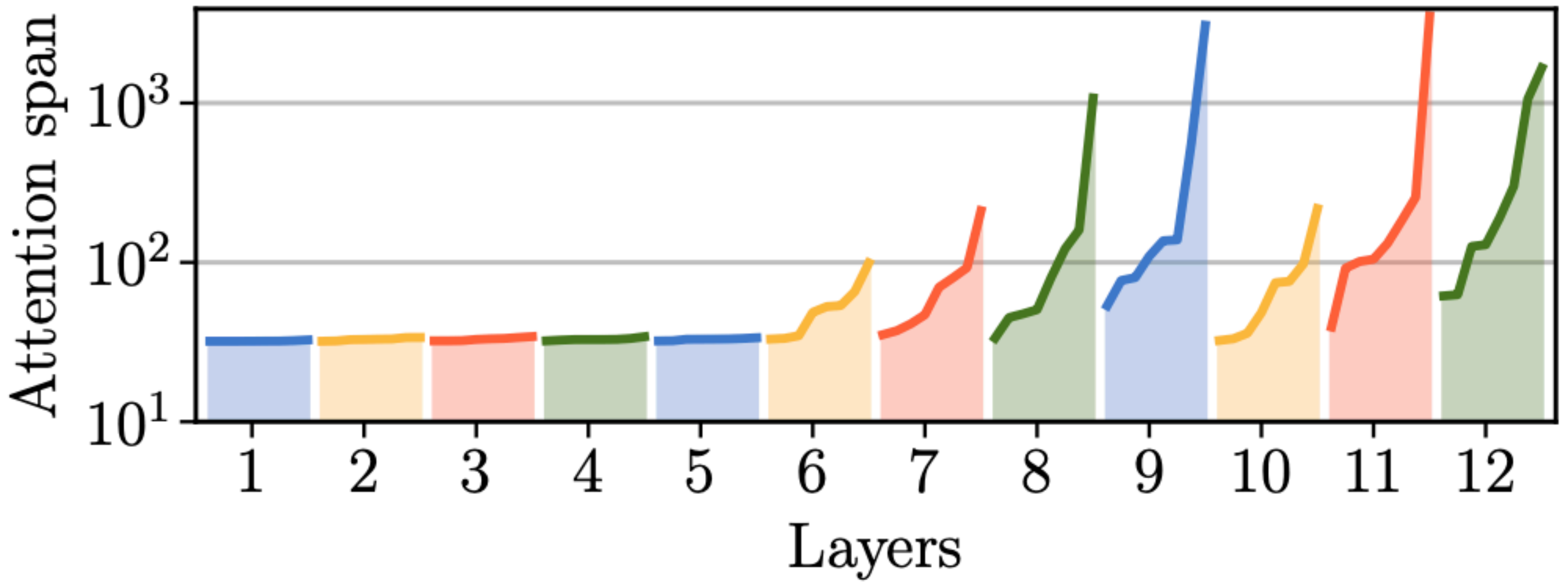
Sparsity Inducing Training via Network Losses

penalize network for using parameters by increasing loss



ADAPTIVE ATTENTION SPAN IN TRANSFORMERS

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Sparsity Inducing Training

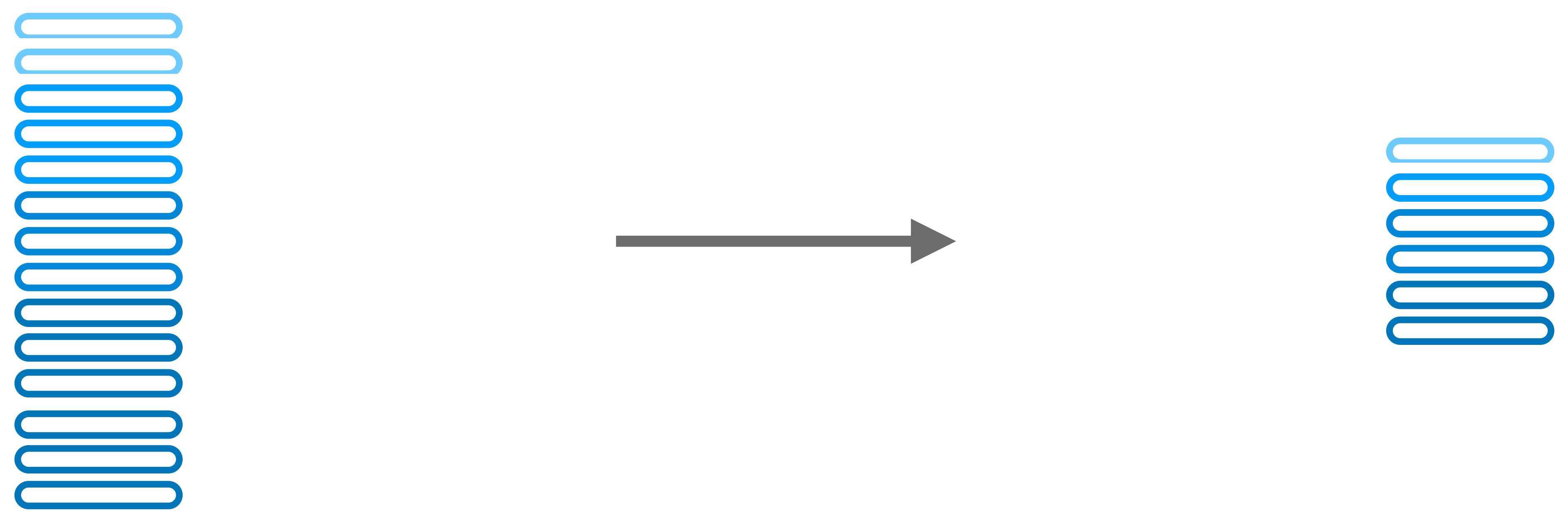
- Inference Time ✓
- Energy ✓
- Performance ✓

at least, often no performance drop

Techniques for Smaller Networks

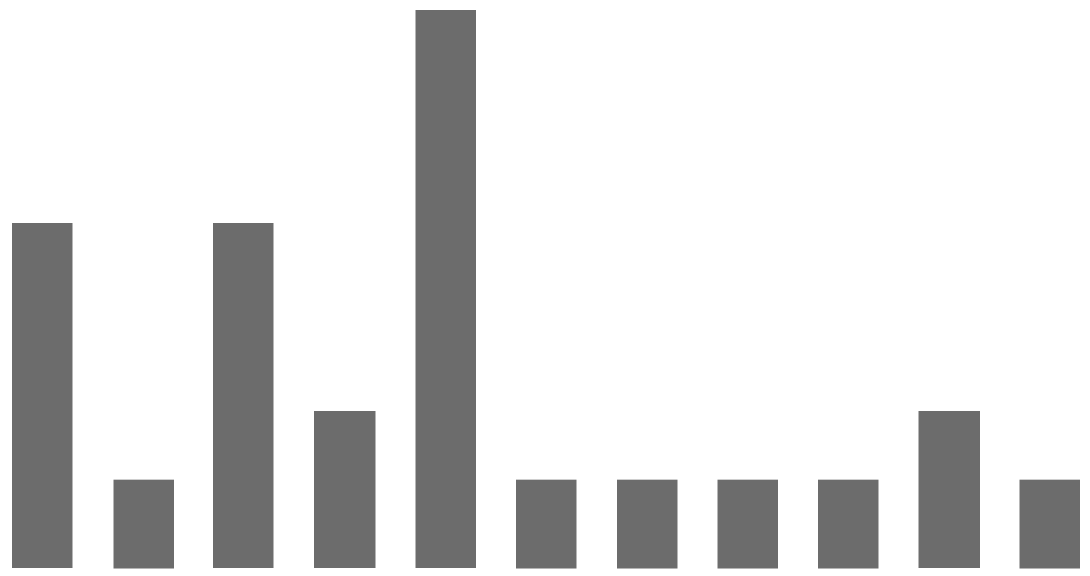
- Train Smaller Network from Scratch
- Sparsity Inducing Training
- **Knowledge Distillation**
- Pruning
- Weight Sharing
- Quantization
- More efficient architectures

Knowledge Distillation

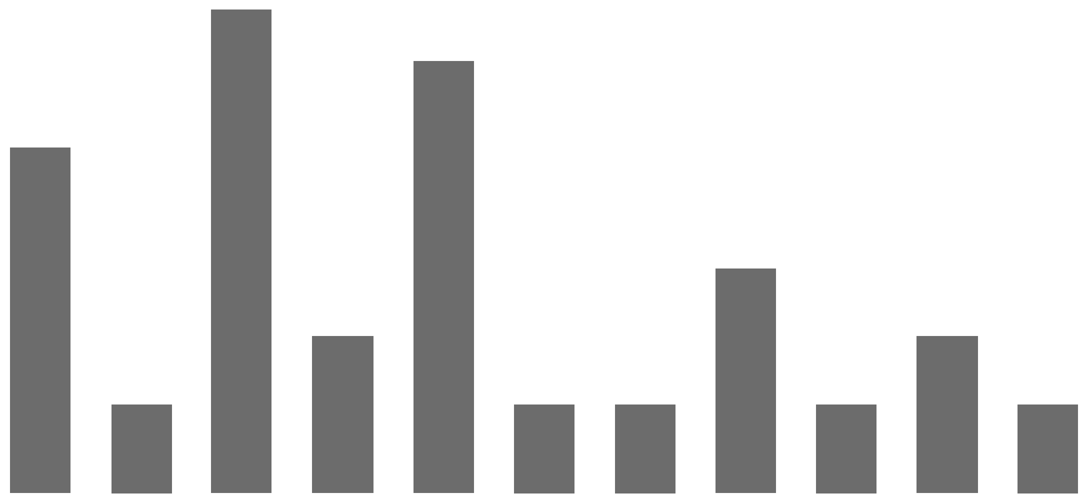


Knowledge Distillation

student model learns to mimic the output of the teacher model



TEACHER MODEL



STUDENT MODEL

Knowledge Distillation

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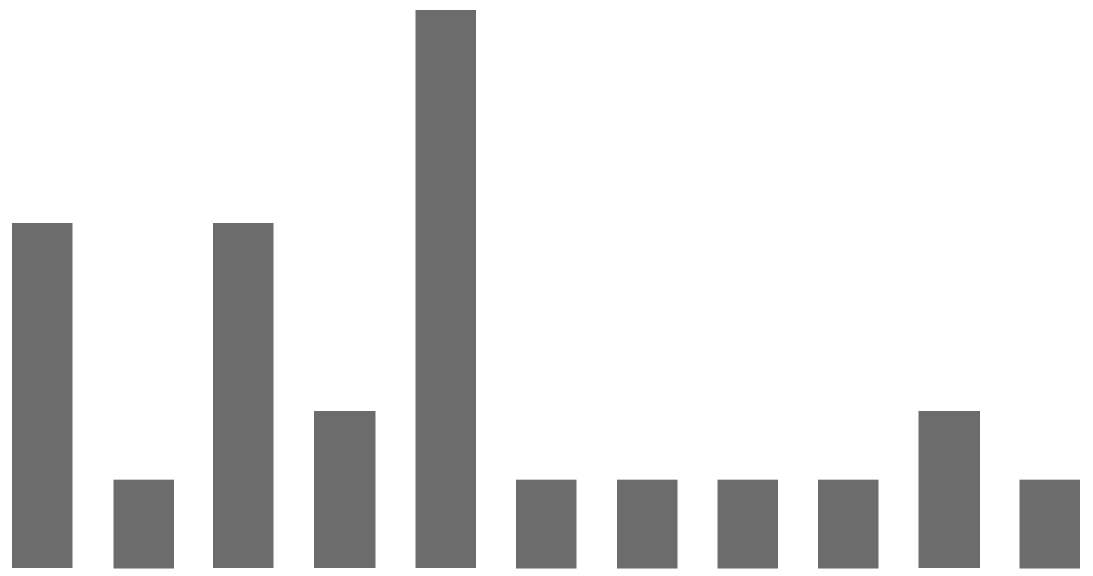

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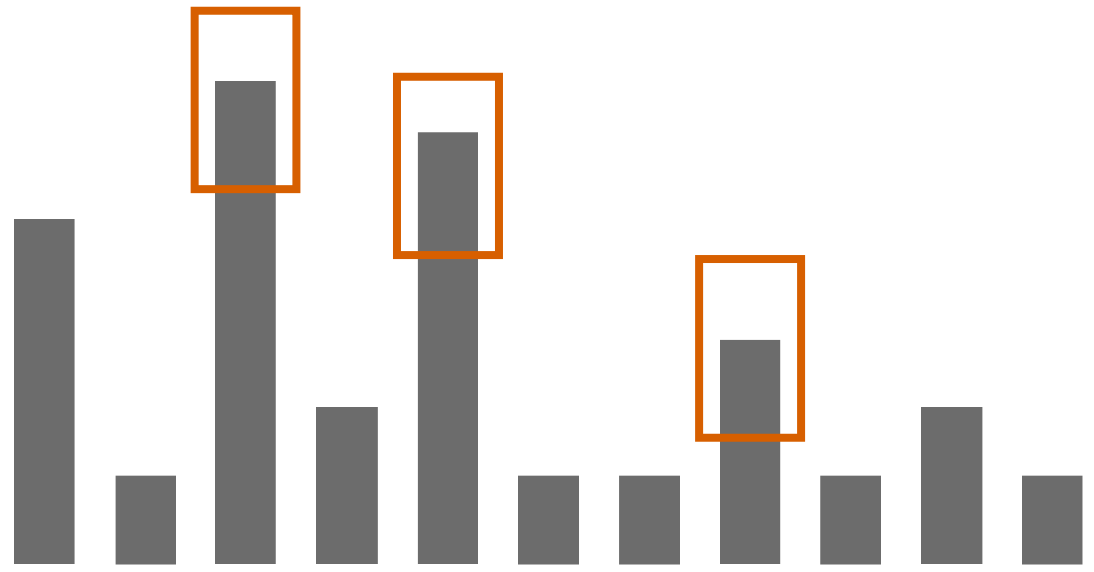

STUDENT MODEL

CALCULATE DIFFERENCE BETWEEN THE TWO PREDICTIONS

Advantages

- Flexibility over size - teacher and student can both be any size

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- Not limited to the training data - any data can be used to distill
  - data augmentation is **very powerful**

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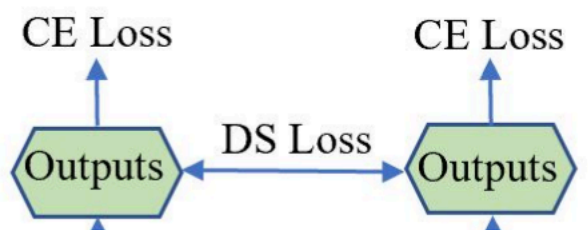
- Can also learn from intermediate layers



PATIENT KNOWLEDGE DISTILLATION FOR BERT MODEL COMPRESSION

SUN ET AL

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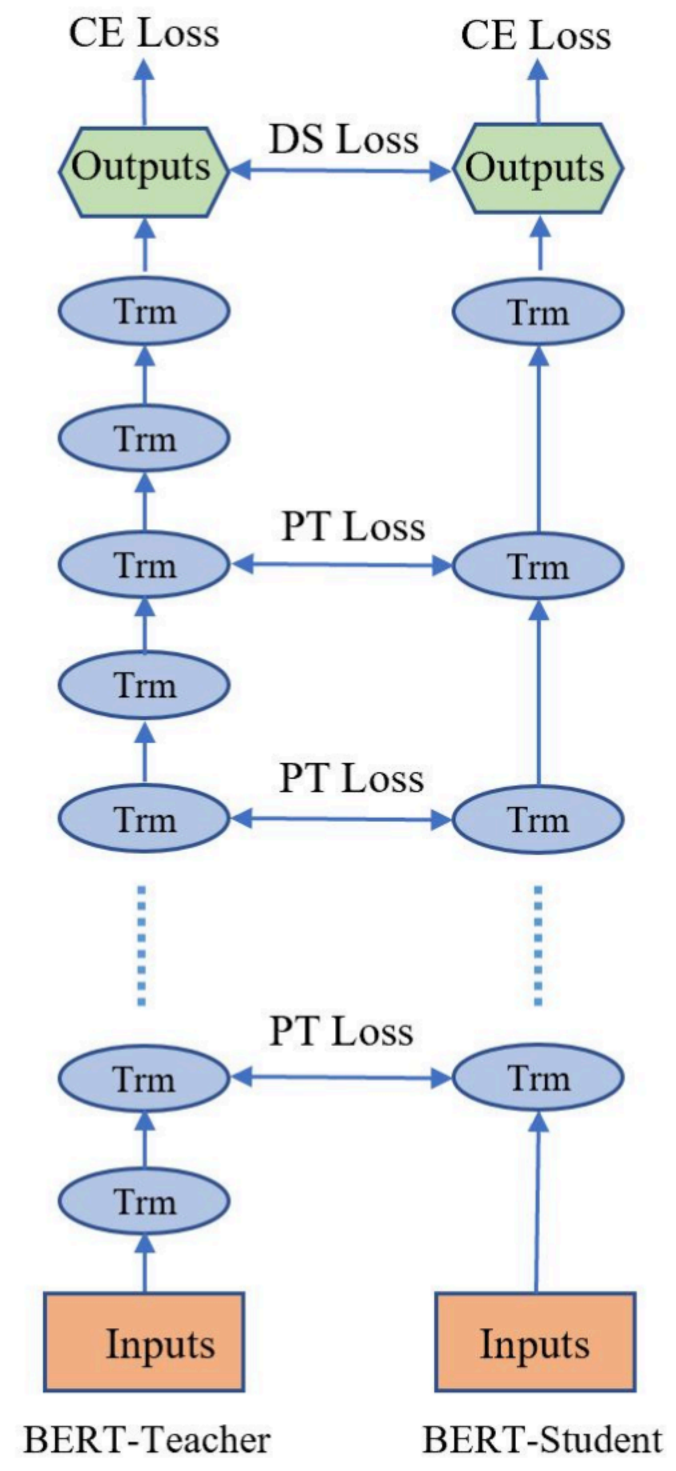

PATIENT KNOWLEDGE DISTILLATION FOR BERT MODEL COMPRESSION

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Knowledge Distillation

- Training Time ✓
- Inference Time ✓
- Performance ✓

training time: need pre-trained teacher, but often state of the art large models can be downloaded

Knowledge Distillation

people love knowledge distillation!

TINYBERT: DISTILLING BERT FOR NATURAL LANGUAGE UNDERSTANDING
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DISTILBERT, A DISTILLED VERSION OF BERT: SMALLER, FASTER, CHEAPER AND LIGHTER
SANH ET AL

WELL-READ STUDENTS LEARN BETTER: ON THE IMPORTANCE OF PRE-TRAINING COMPACT MODELS
TURC ET AL

MOBILEBERT: TASK-AGNOSTIC COMPRESSION OF BERT BY PROGRESSIVE KNOWLEDGE TRANSFER
SUN ET AL

AND MORE!

Techniques for Smaller Networks

- Train Smaller Network from Scratch
- Sparsity Inducing Training
- Knowledge Distillation
- **Pruning** remove layers from a trained model
- Weight Sharing
- Quantization
- More efficient architectures

Techniques for Smaller Networks

- Train Smaller Network from Scratch
- Sparsity Inducing Training

if you want a smaller model size, need to re-train

- Knowledge Distillation
- **Pruning (with LayerDrop)**
- Weight Sharing
- Quantization
- More efficient architectures

How can we make models smaller without re-training?

Goal: Train One Network, Prune to Any Depth at Inference Time

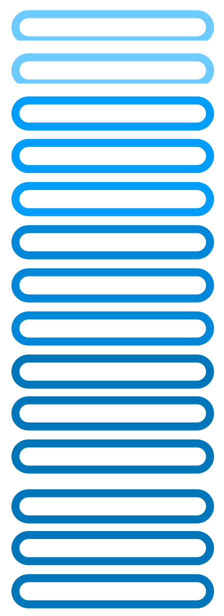
How can we make models smaller without re-training?

Goal: Train One Network, Prune to Any Depth at Inference Time

↓

Drop Any Layer and Model Remains the Same

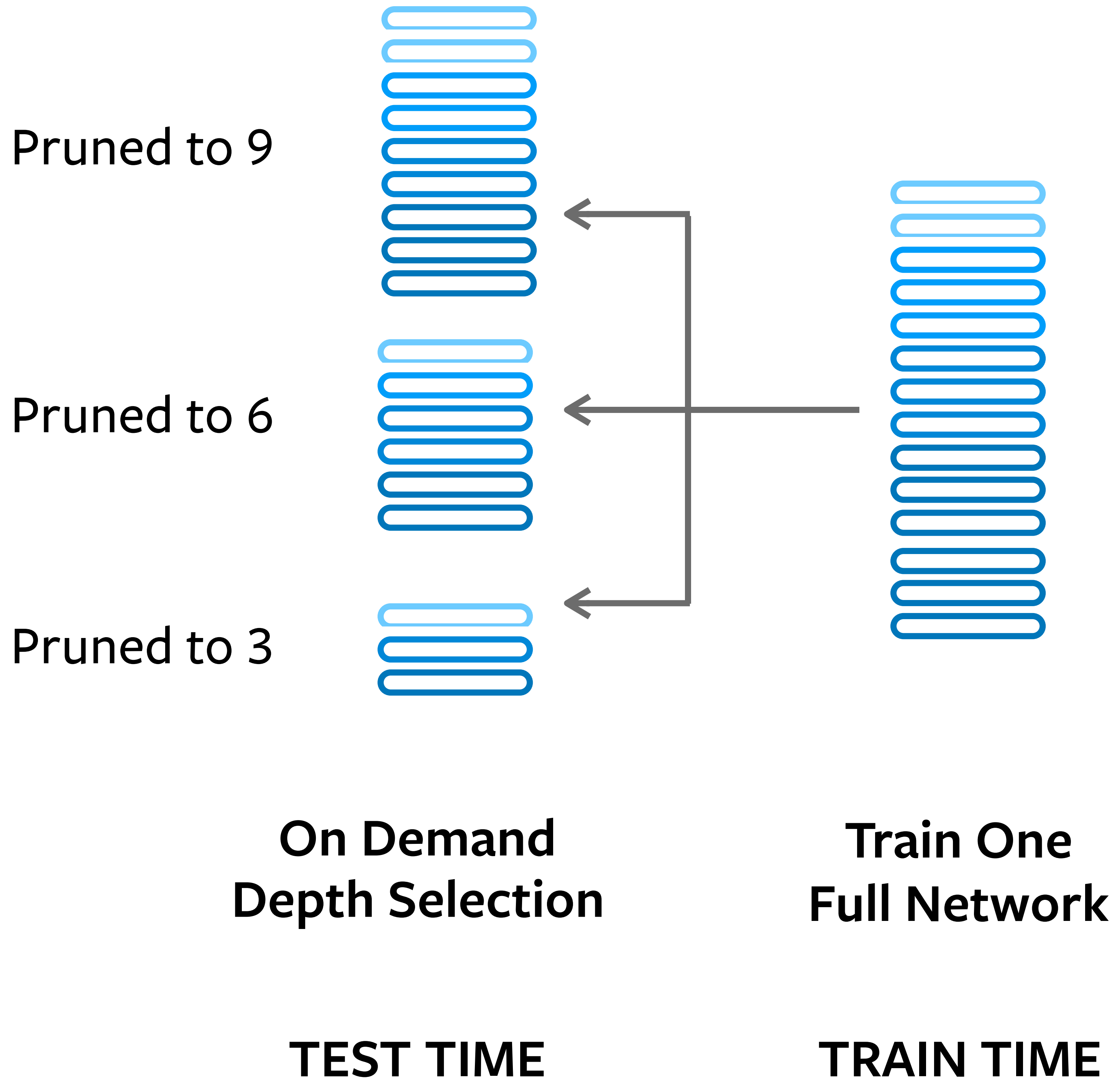
How can we make models smaller without re-training?



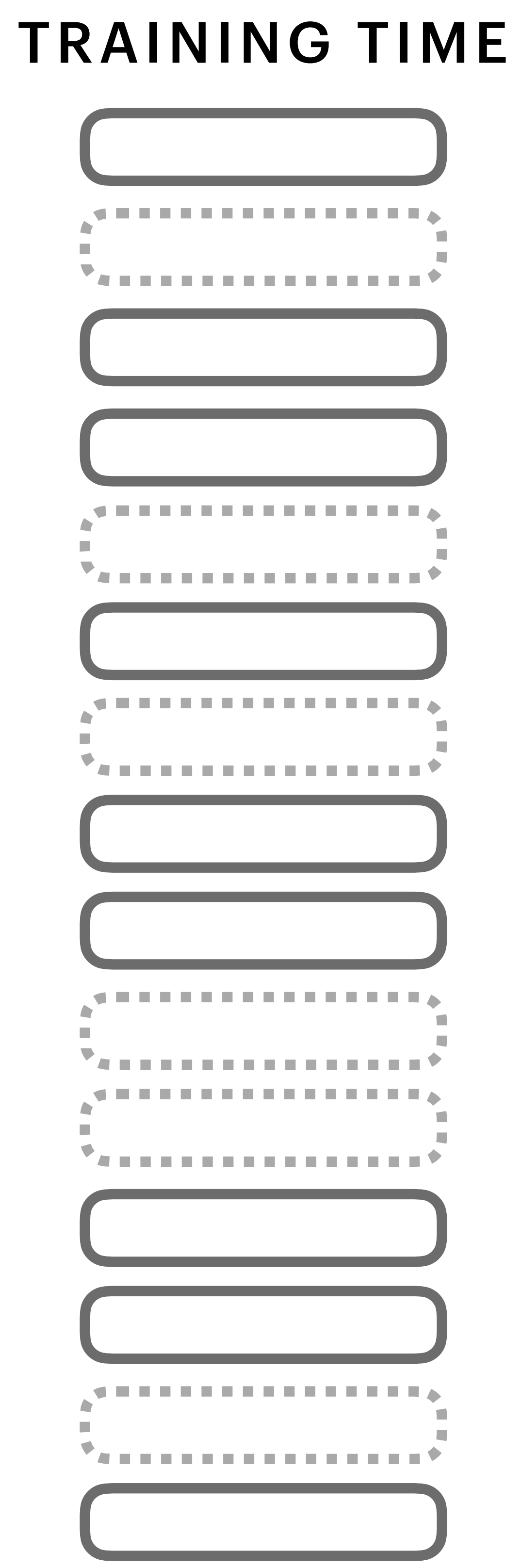
Train One
Full Network

TRAIN TIME

How can we make models smaller without re-training?



Our Proposal: LayerDrop



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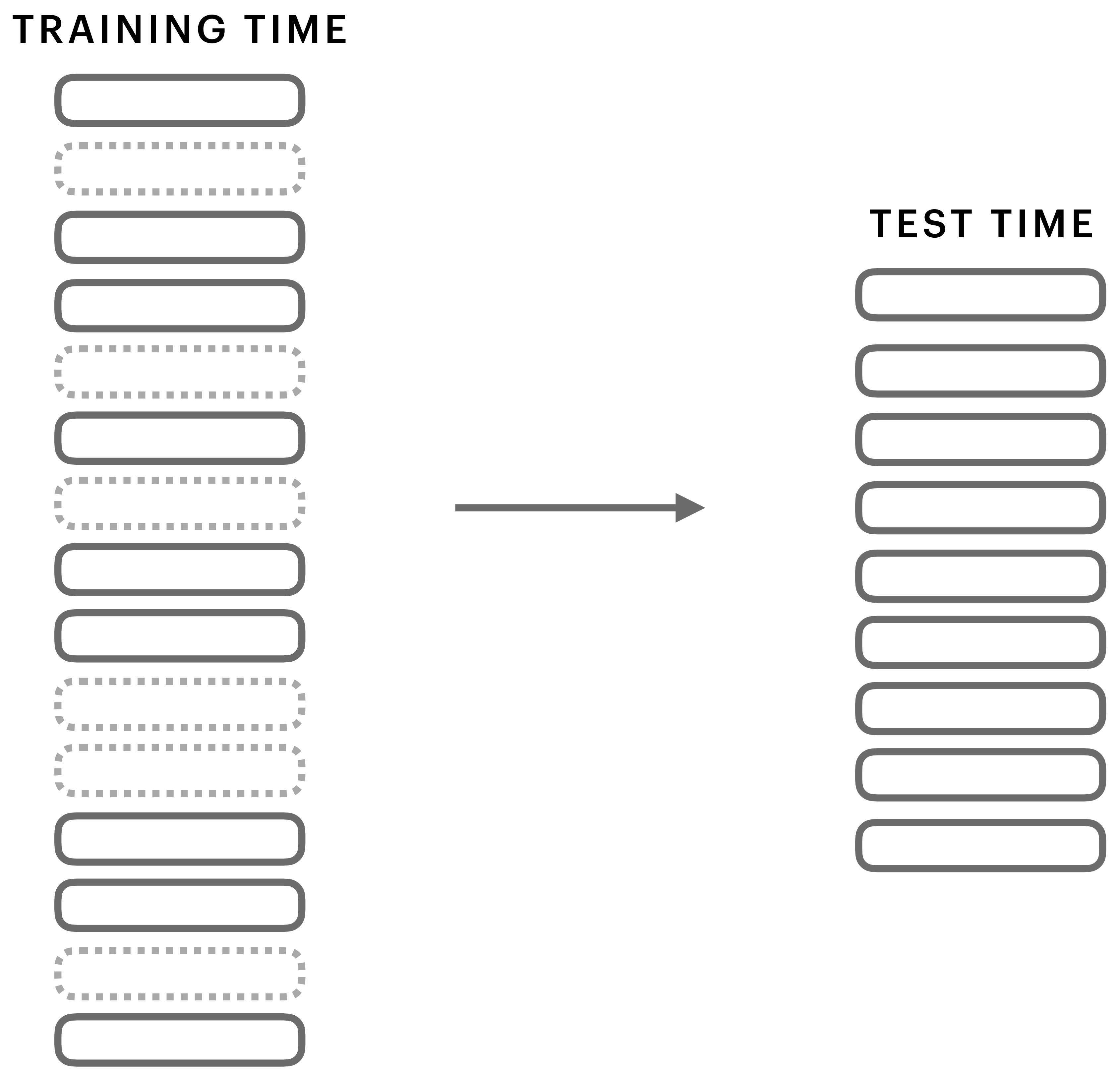

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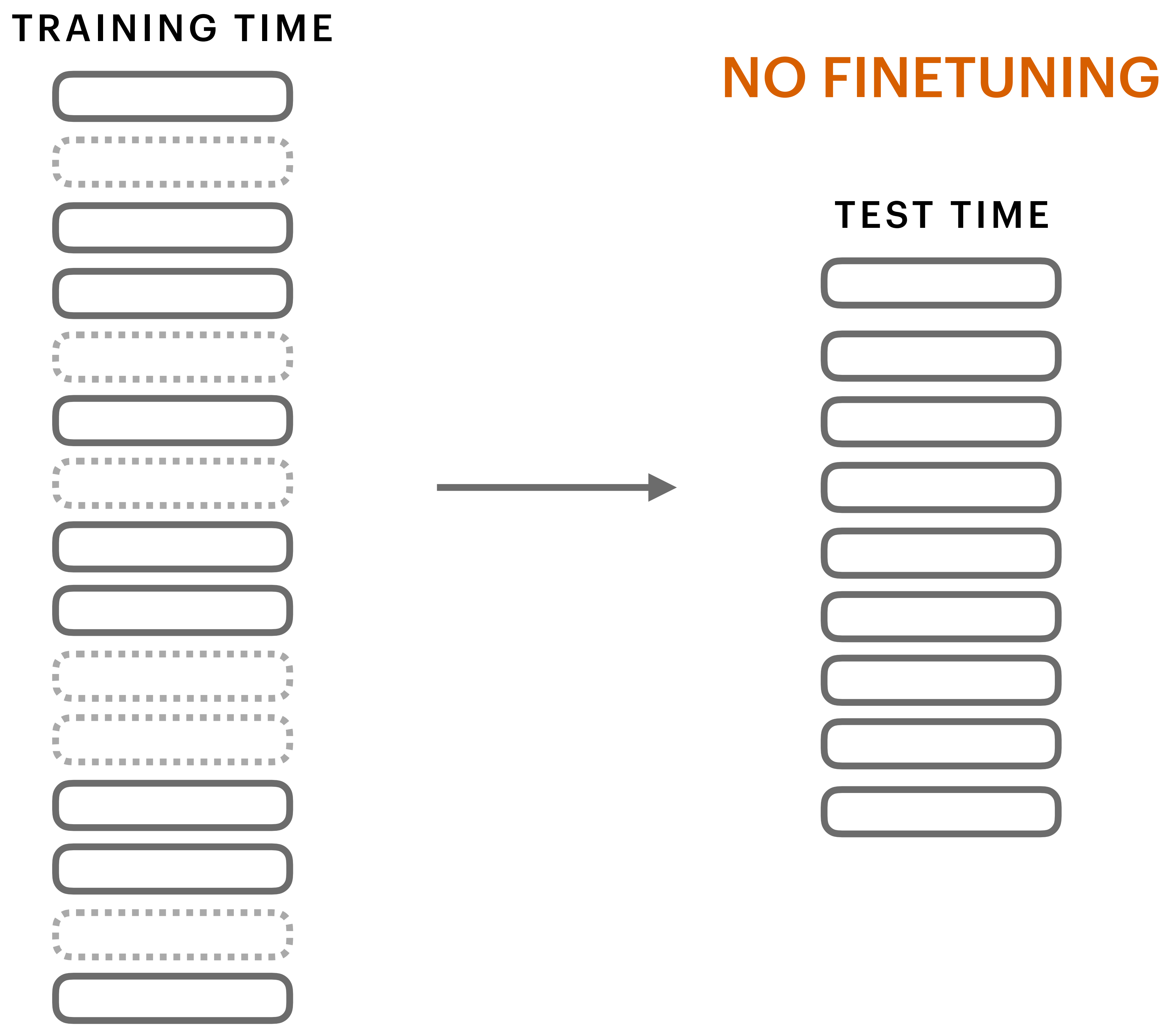
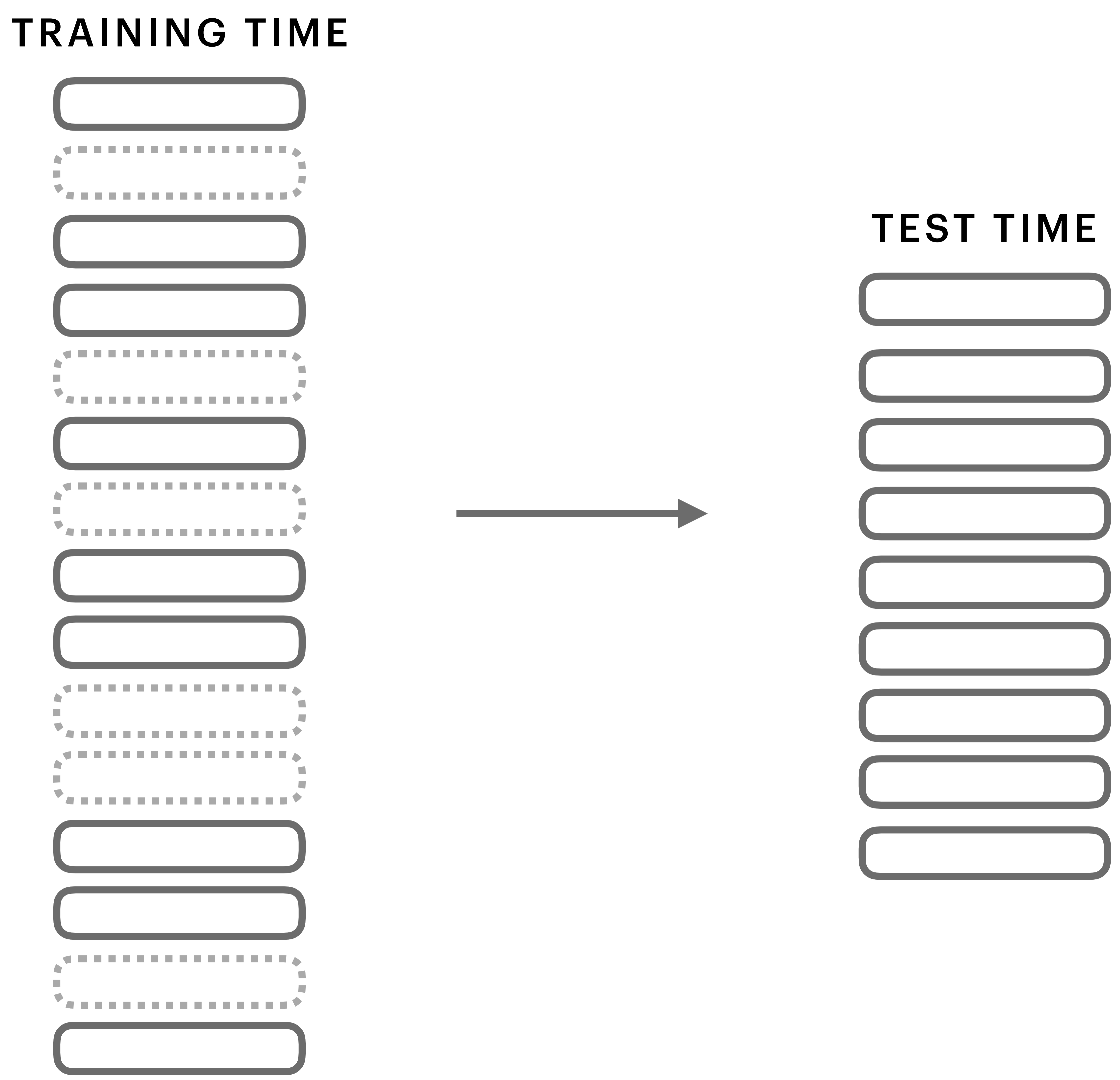
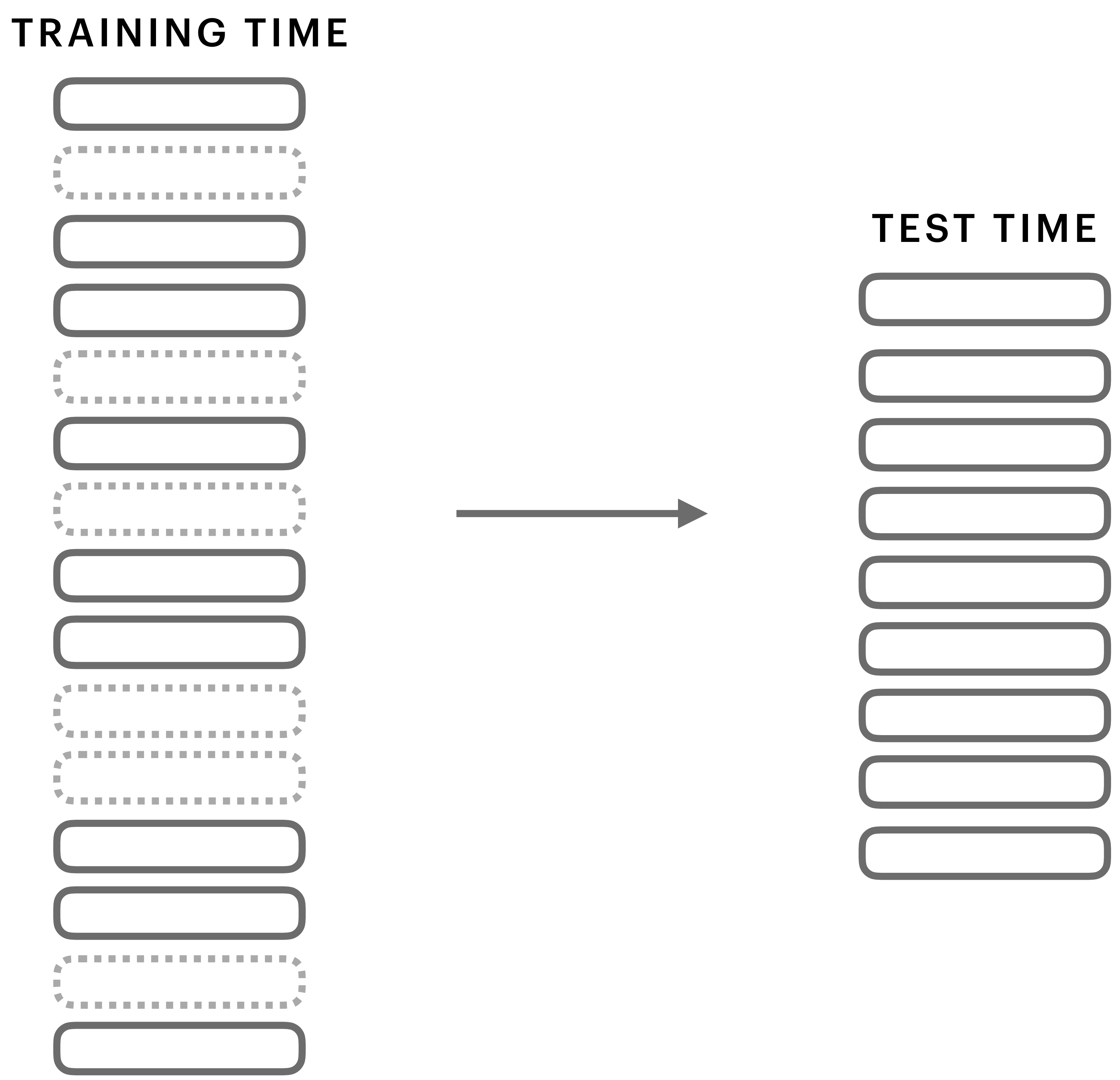


Structured Dropout can be More General



- Layers (our focus)

Structured Dropout can be More General

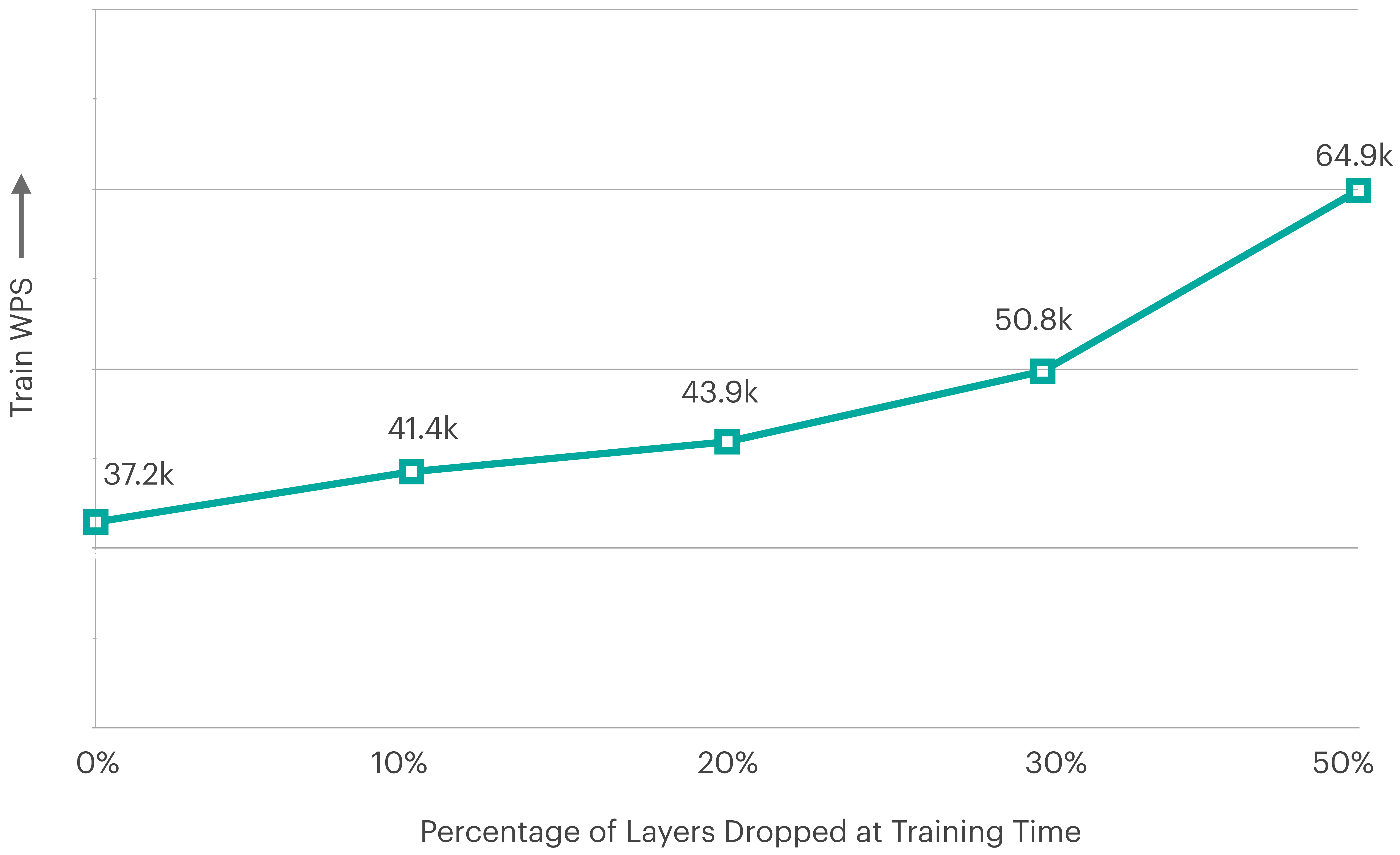


- Layers
- Attention Heads
- FFN, Attention Sub-Layers
- Portions of Matrices
- etc

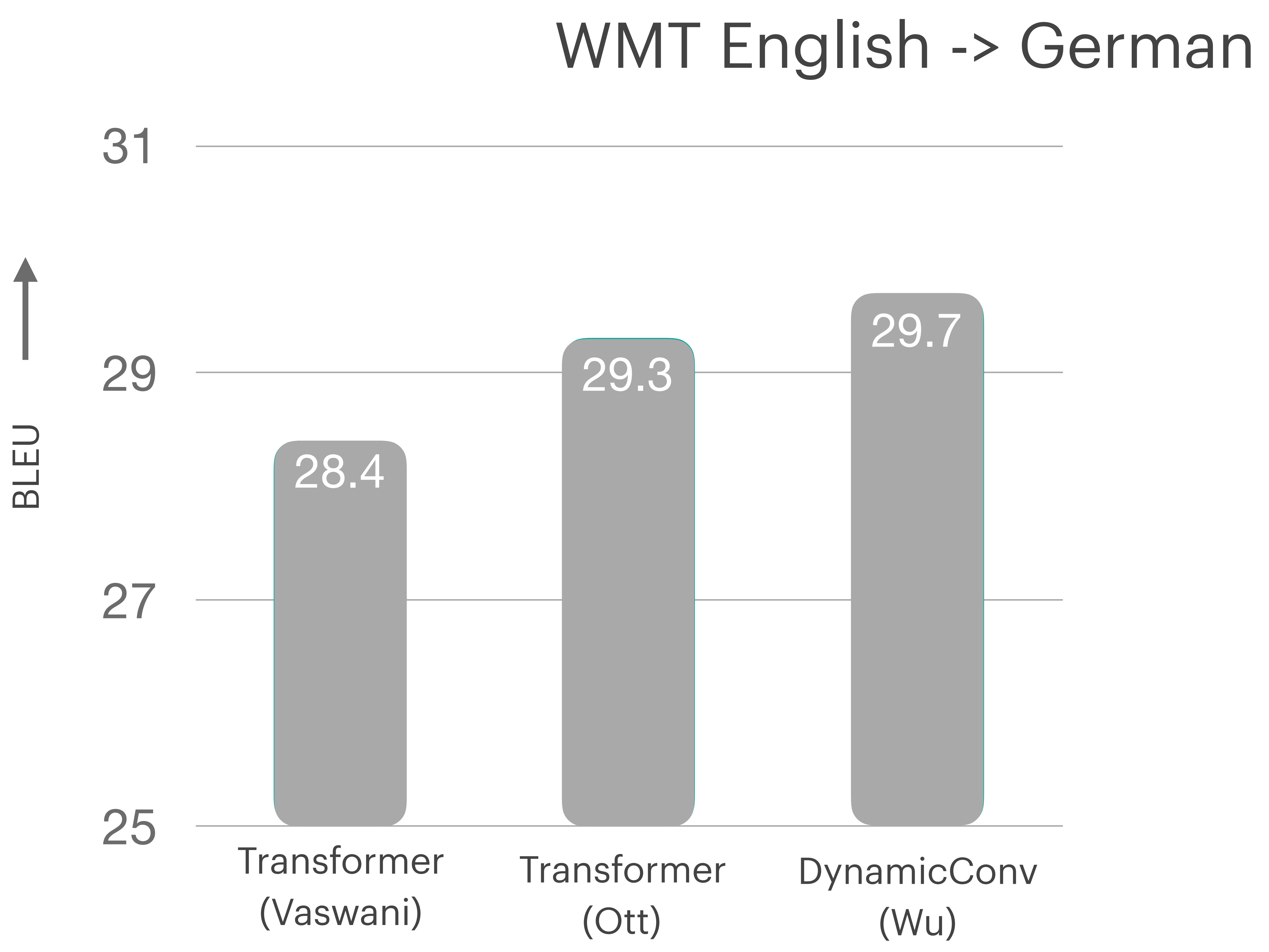
Advantages

- Training Speed
- Regularization
- Reduction

(1) LayerDrop Increases Training Speed



(2) LayerDrop is an effective regularizer - Neural Machine Translation



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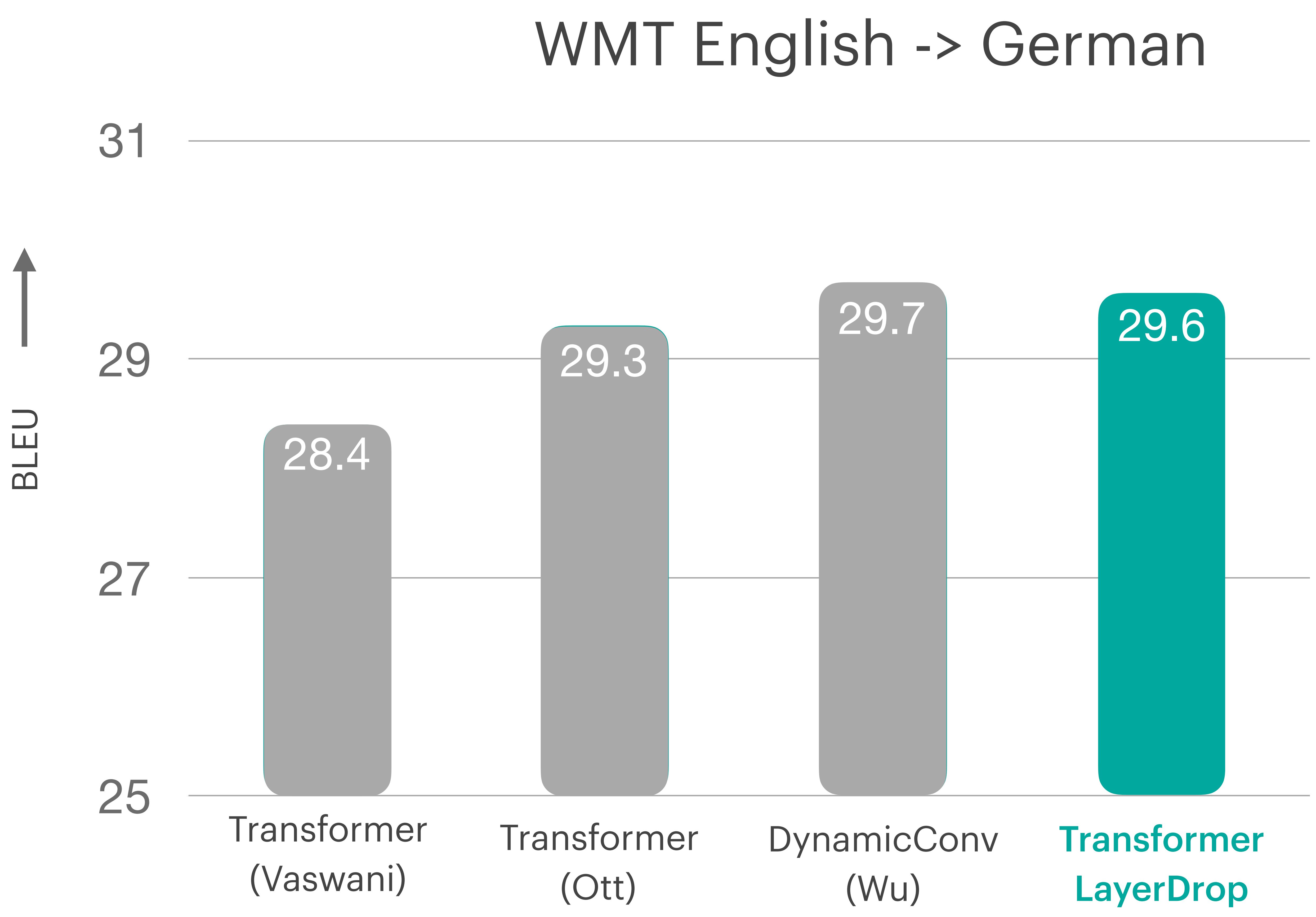

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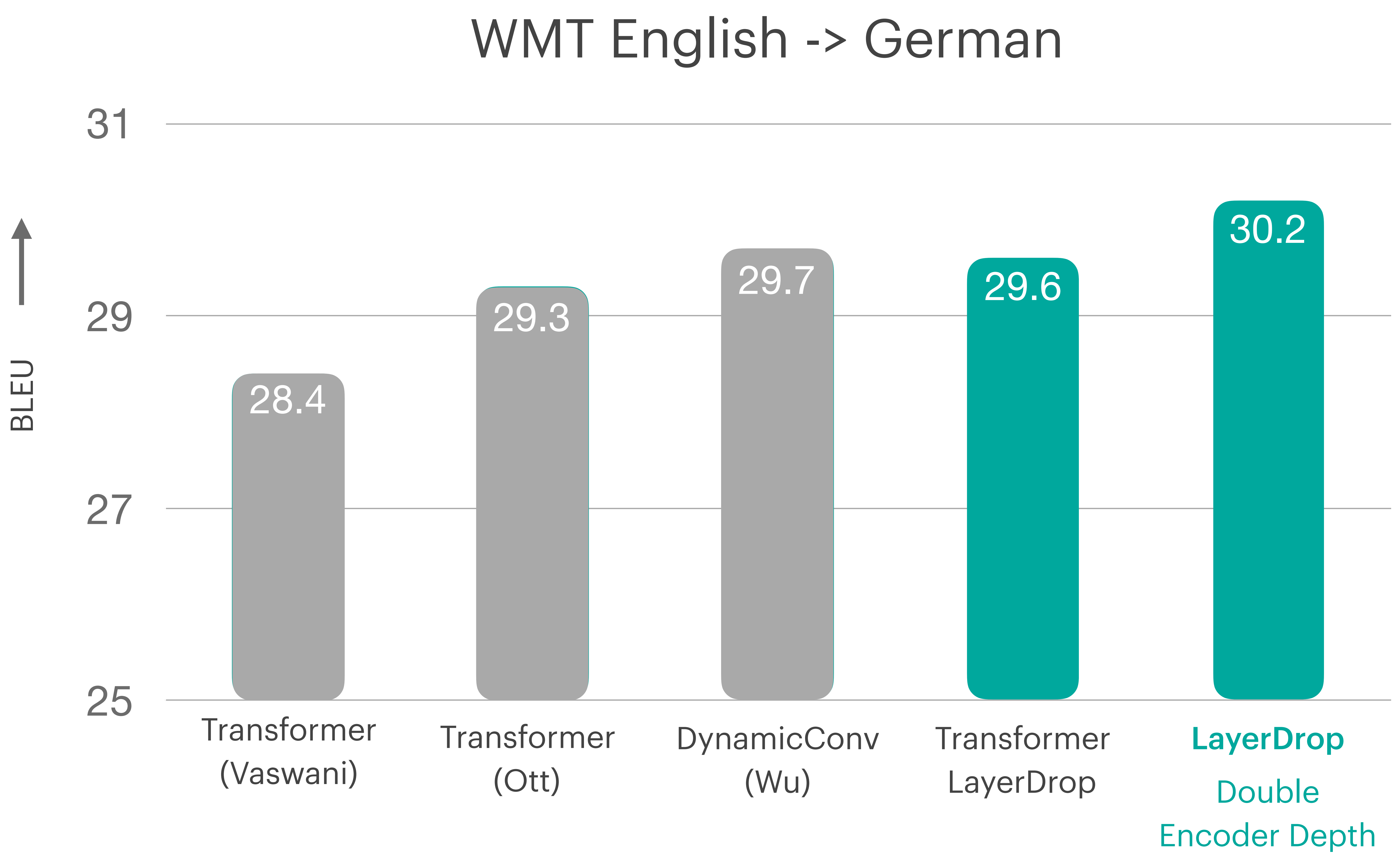

(3) Our Main Focus: LayerDrop for Pruning

- Train once, prune to any desired depth

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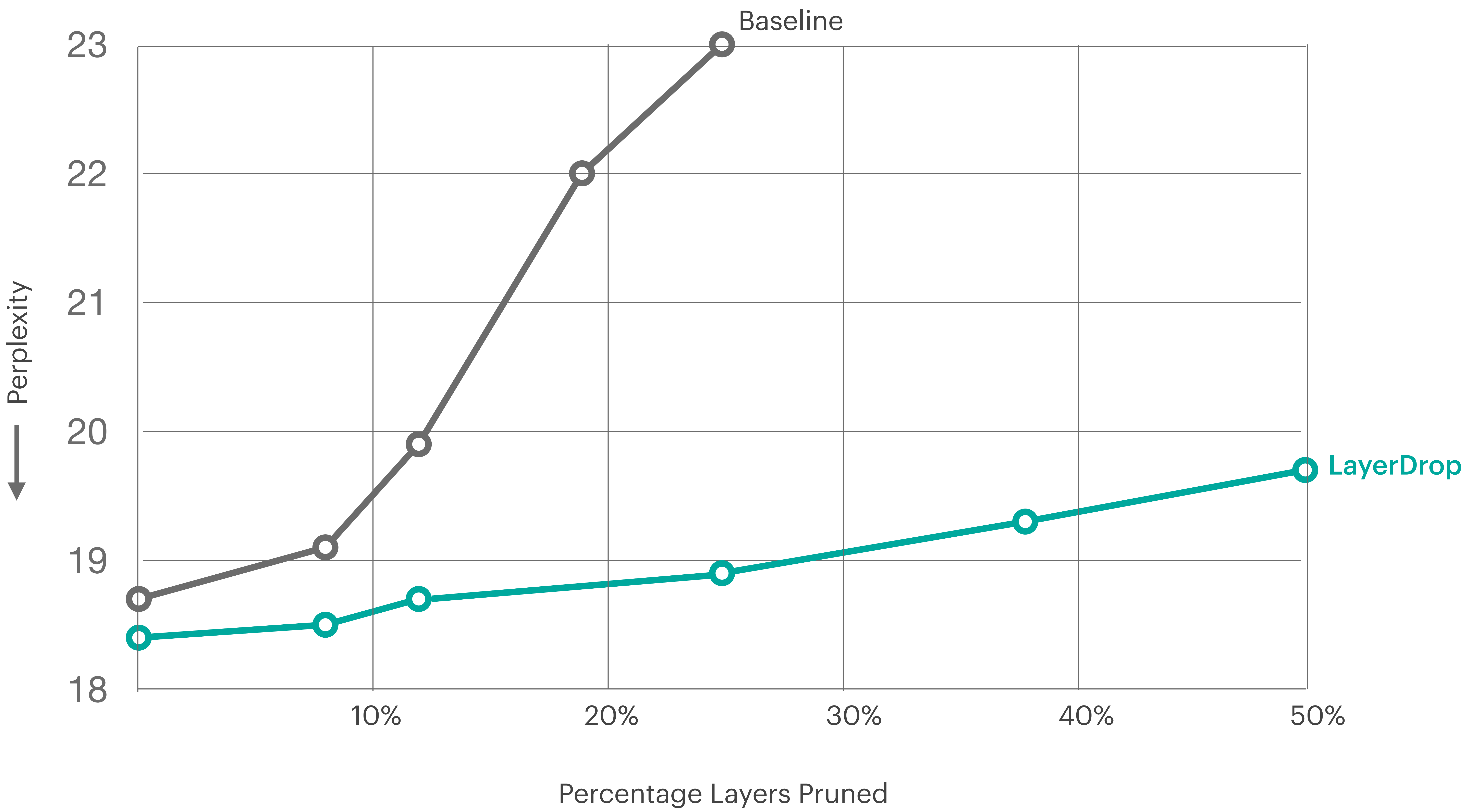
- Robust to parameter setting
  - use the same value for all experiments

(3) Our Main Focus: LayerDrop for Pruning

- Train once, prune to any desired depth
- Robust to parameter setting
- Specific Pruning Strategy is not Important

(3) LayerDrop for Pruning - Language Modeling



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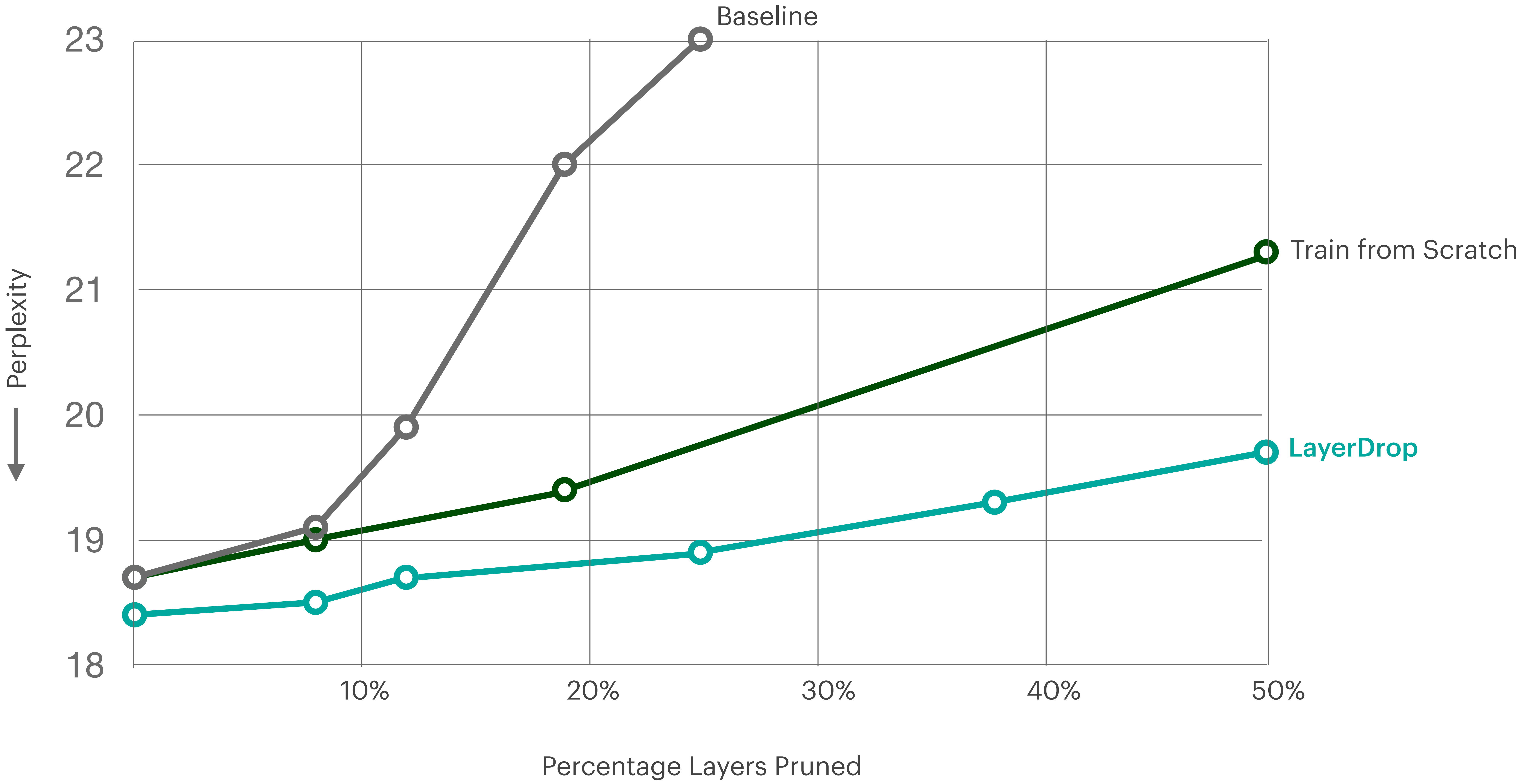
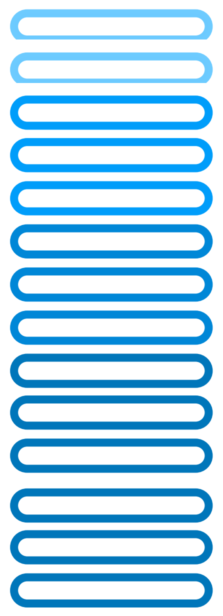
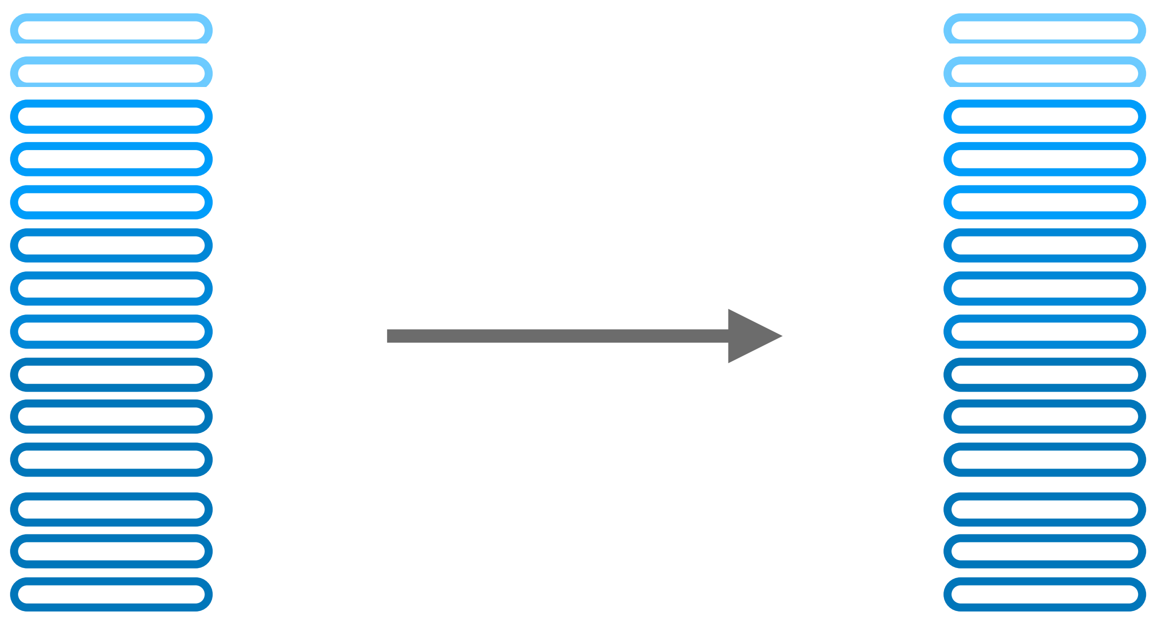


(3) LayerDrop for Pruning - BERT Pre-Training



Train BERT
+ LayerDrop

(3) LayerDrop for Pruning - BERT Pre-Training



Train BERT + LayerDrop

Fine-tune BERT + LayerDrop

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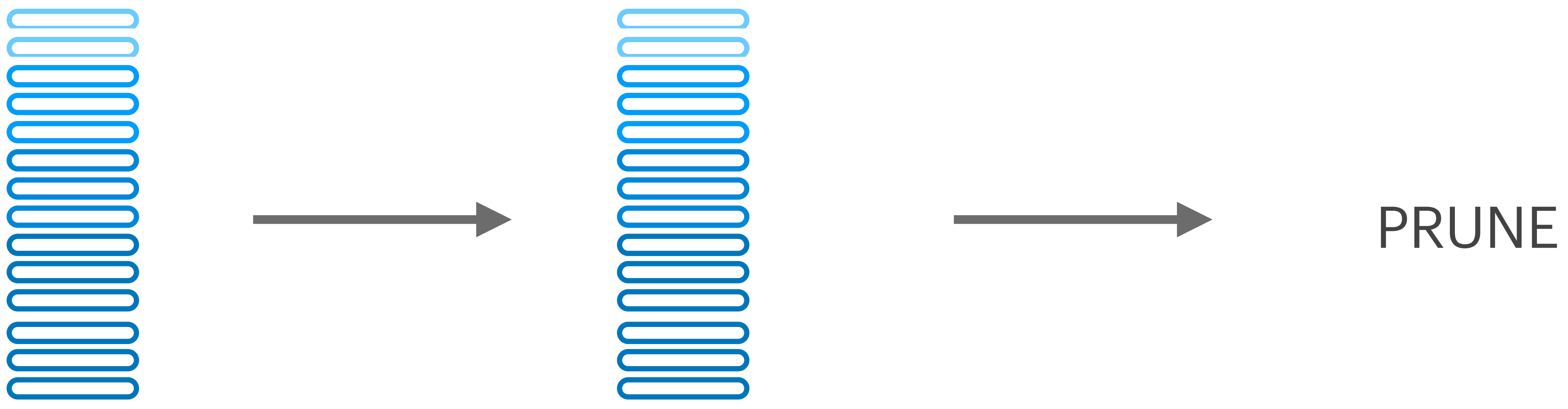

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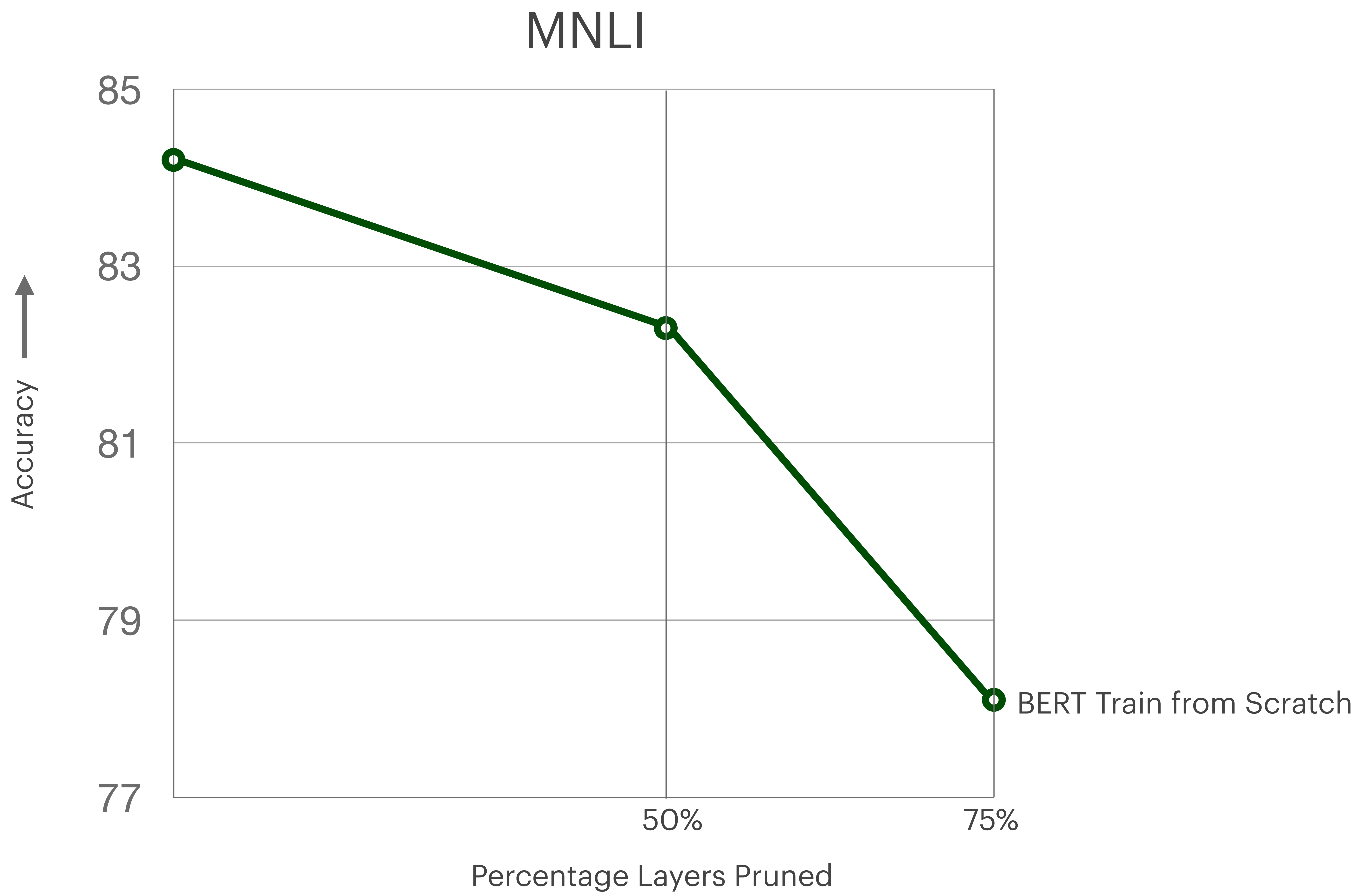

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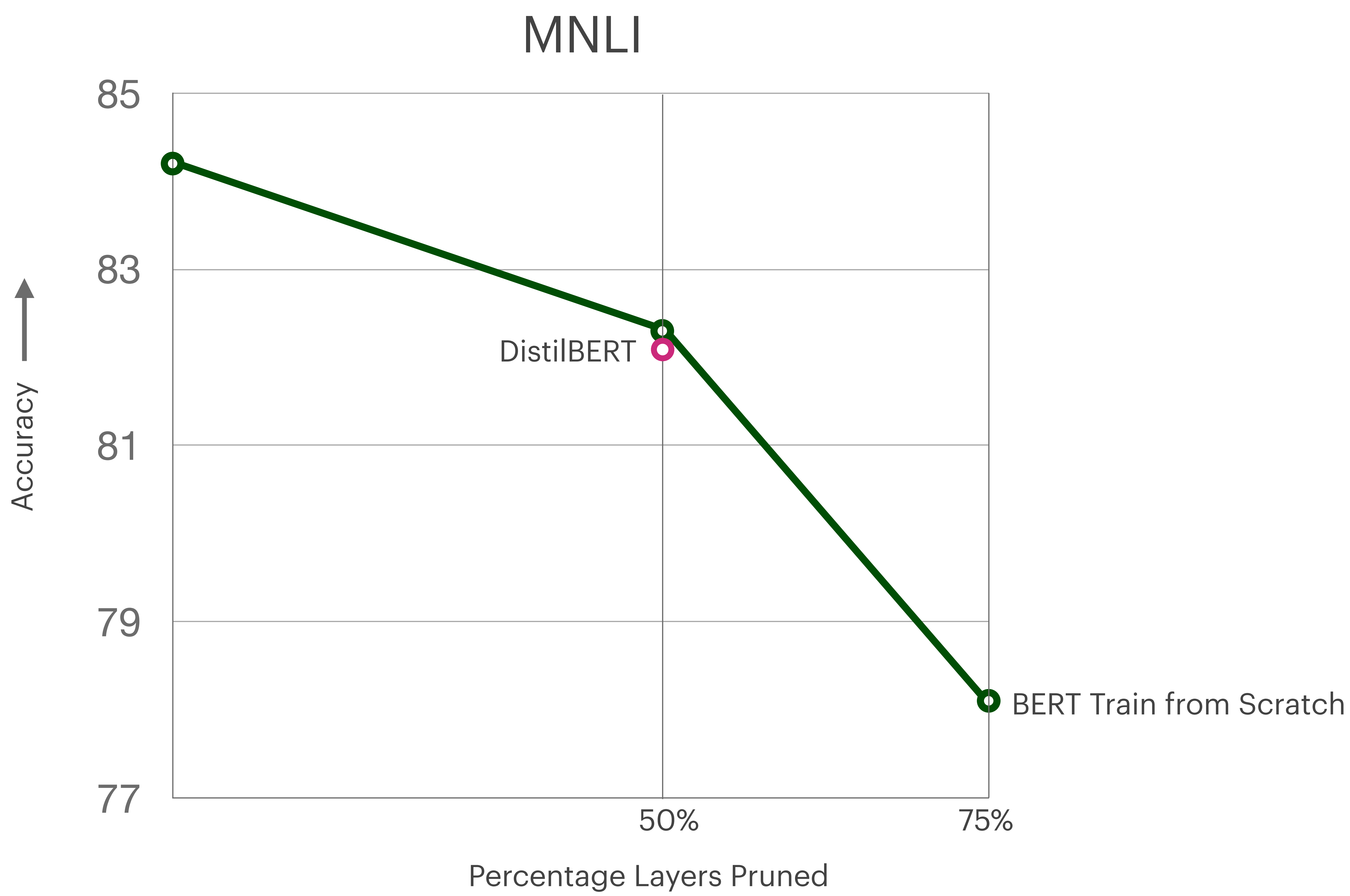

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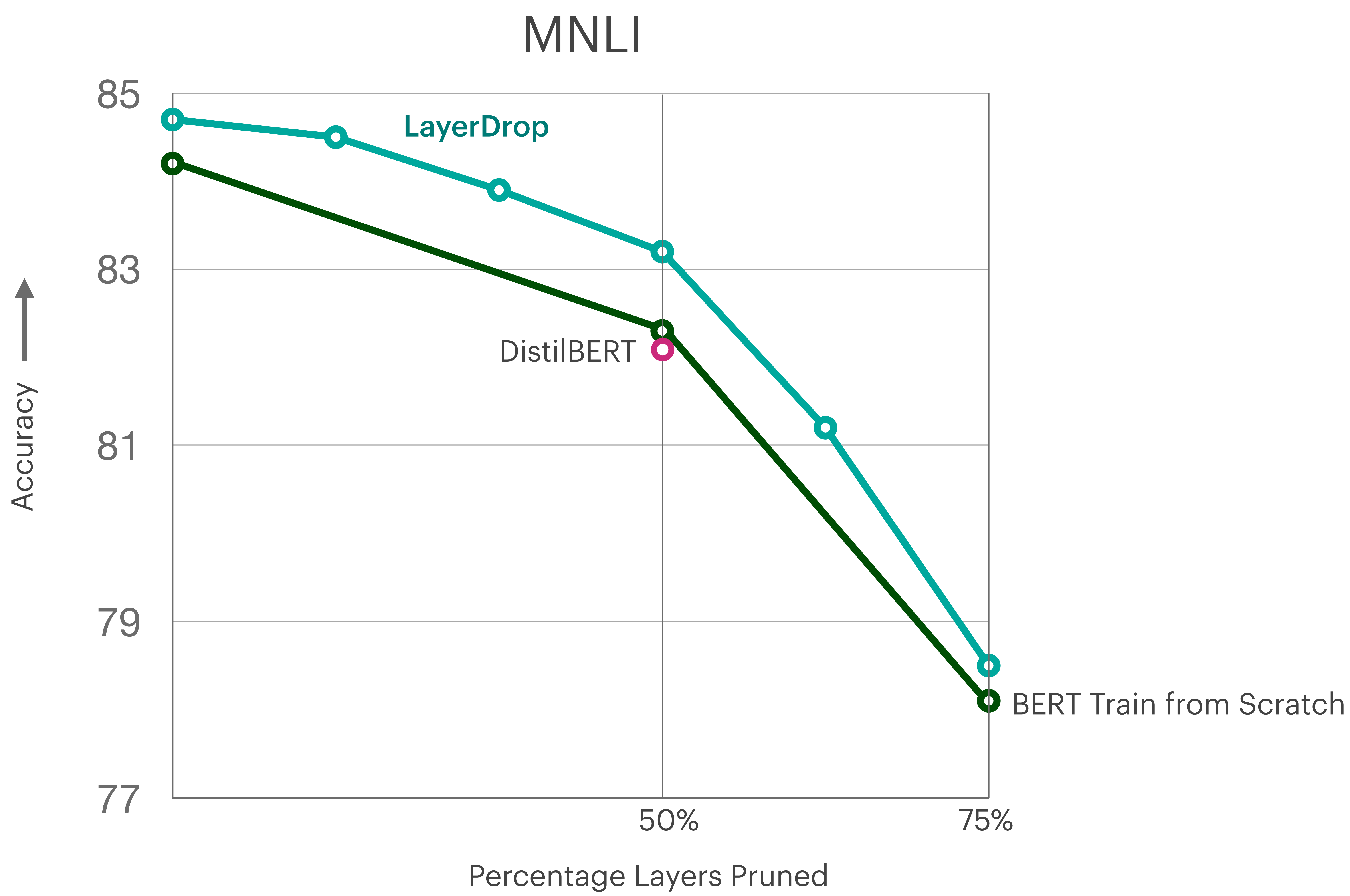

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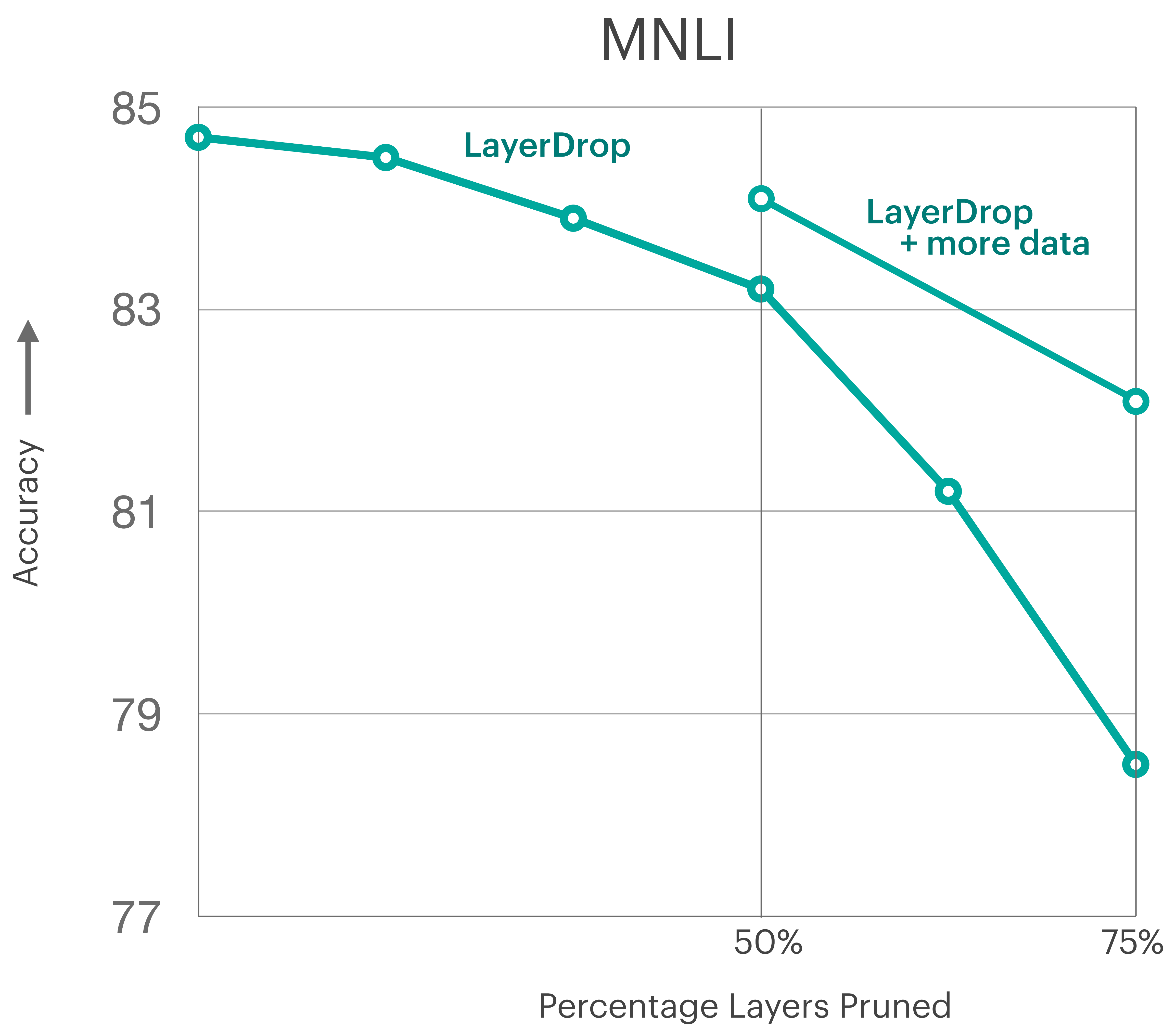
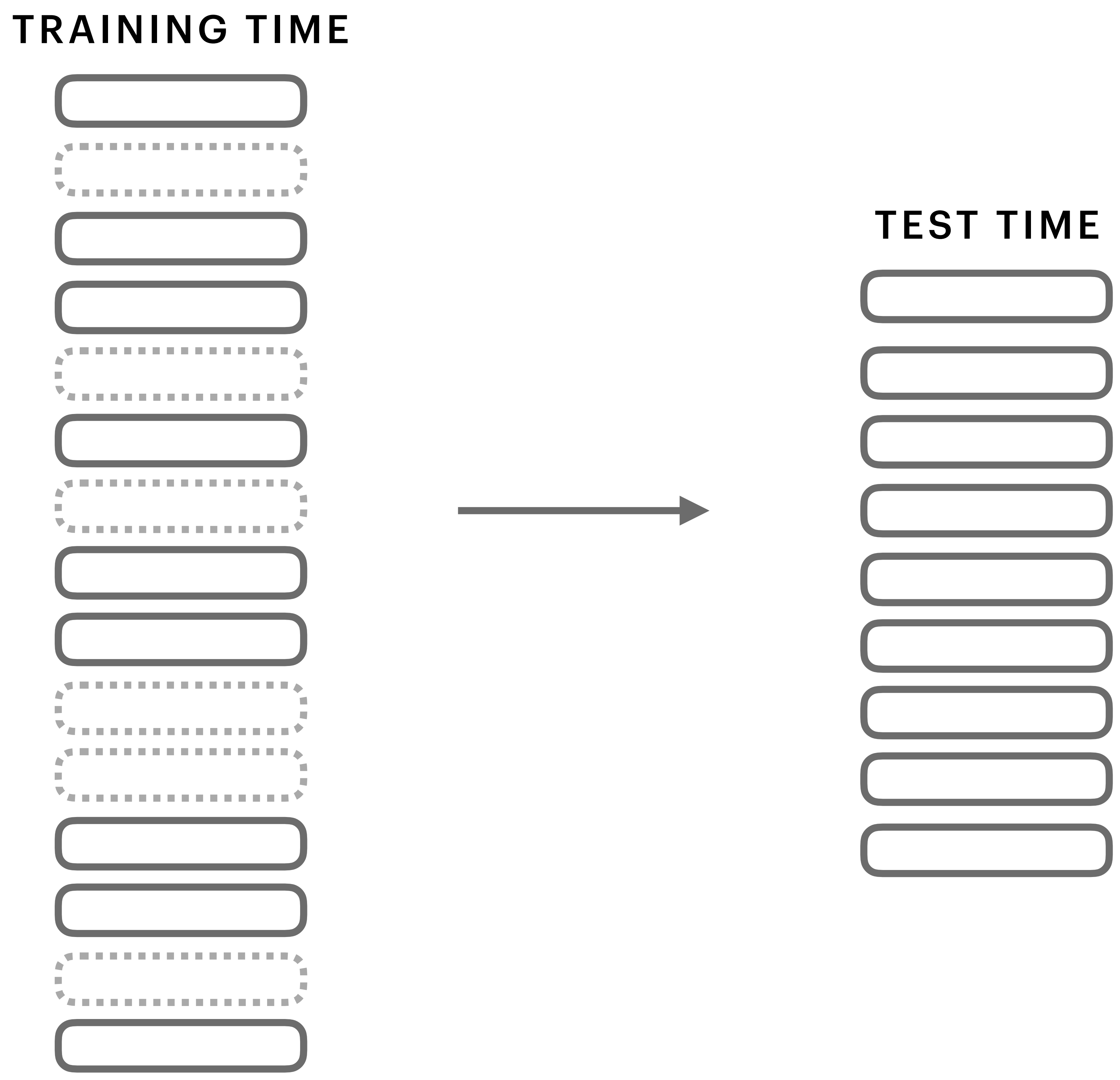


Different Pruning Strategies - Does it Matter?



Add LayerDrop to Your Transformer Training

```
for layer in transformer.layers:
     x = layer(x)
```

Add LayerDrop to Your Transformer Training

```
for layer in transformer.layers:
     if random(0,1) > layer_drop and self.training:
          x = layer(x)
```

Pruning with LayerDrop

- Training Time ✓
- Inference Time ✓
- Performance ✓
- Model Size ✓

Techniques for Smaller Networks

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- Quantization
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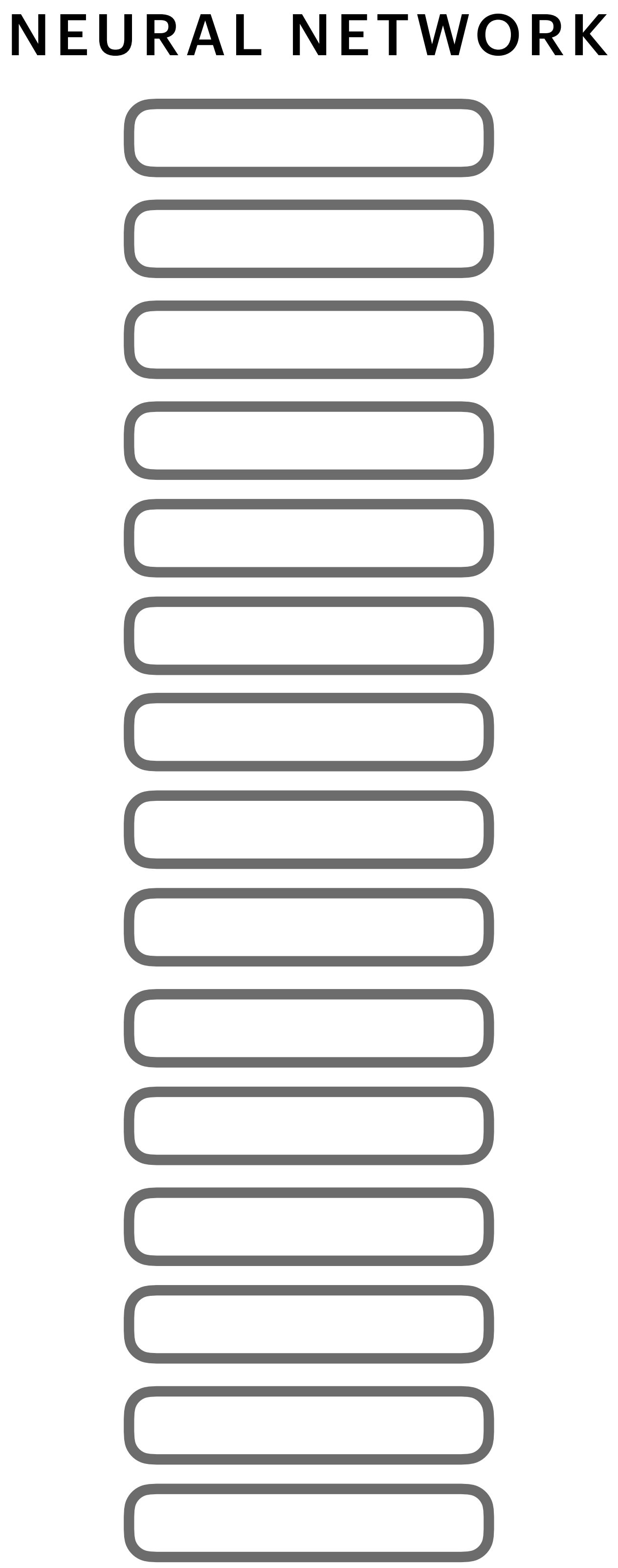
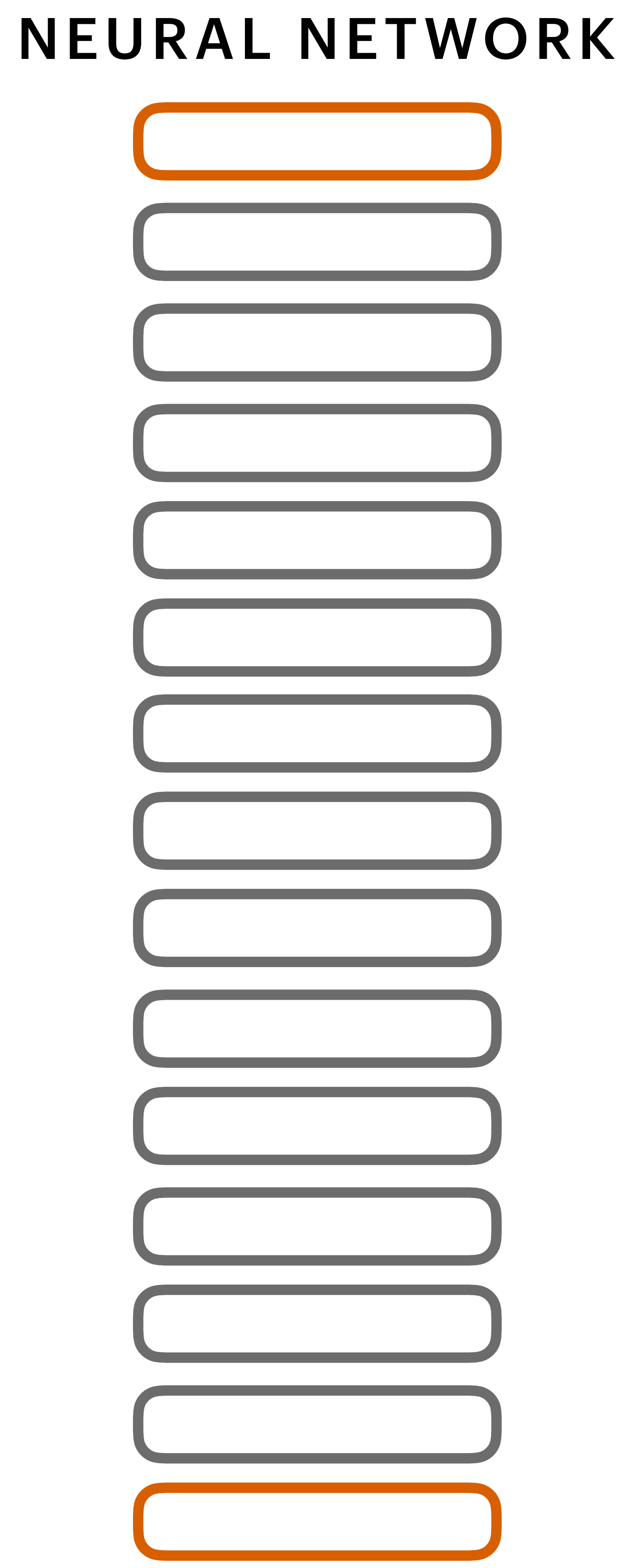
Weight Sharing



re-use weights in multiple places

Weight Sharing



input and output embeddings tied (common)

EXTREME LANGUAGE MODEL COMPRESSION WITH OPTIMAL SUBWORDS AND SHARED PROJECTIONS

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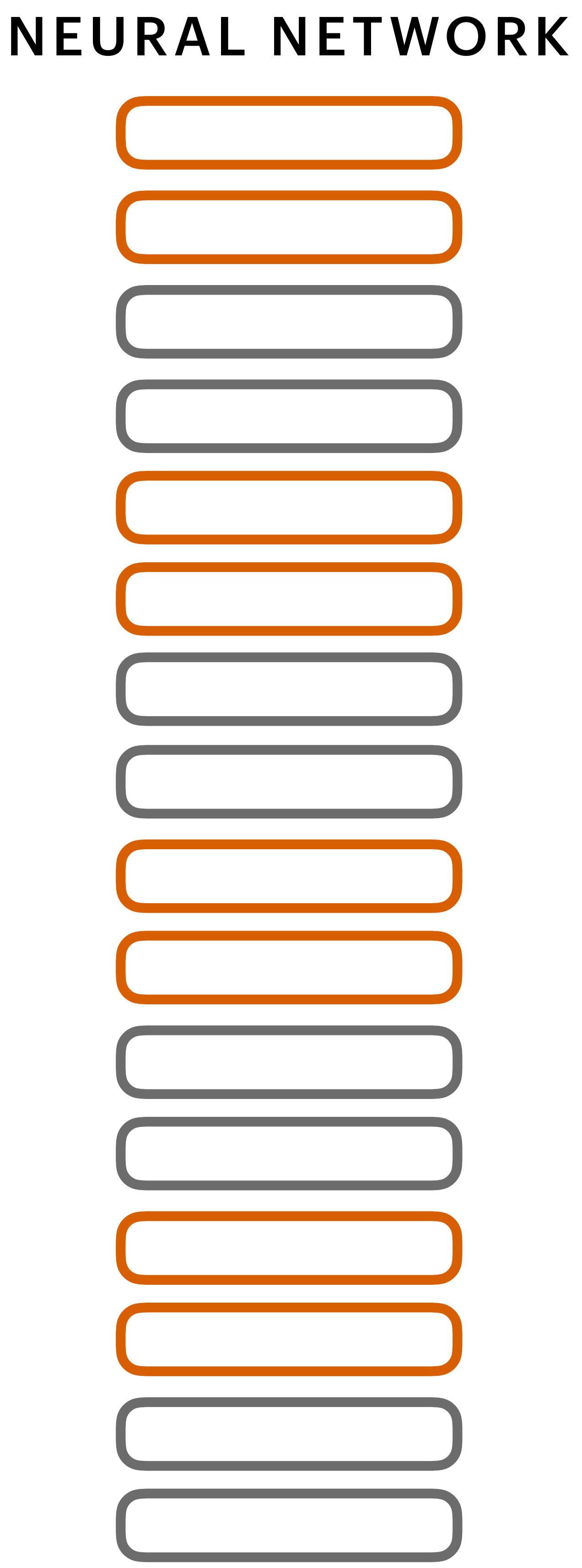
Weight Sharing



share the weights of chunks of layers

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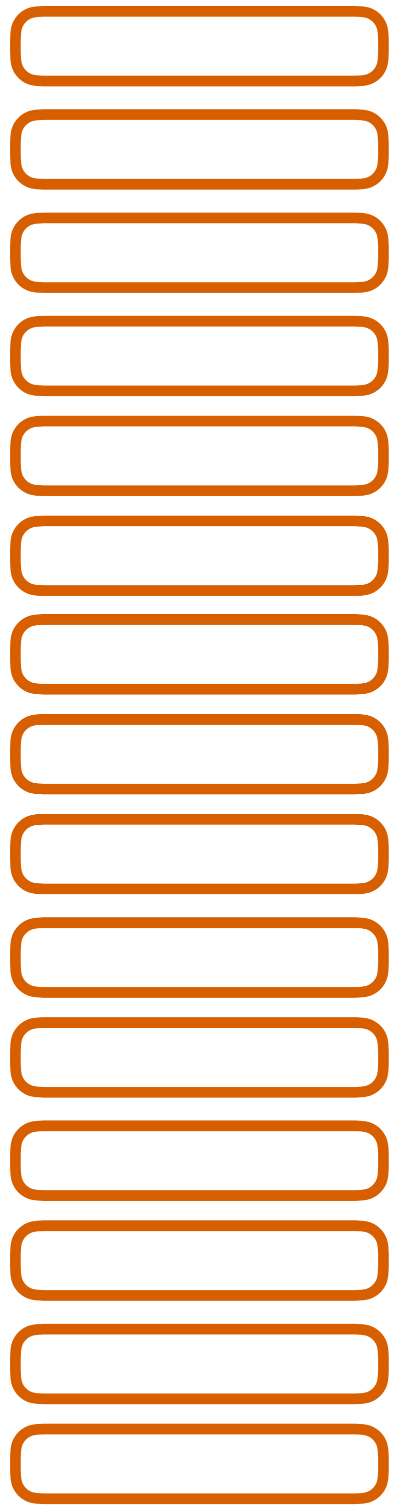
Weight Sharing

NEURAL NETWORK



share the weights of chunks ALL layers

ALBERT: A LITE BERT FOR SELF-SUPERVISED LEARNING OF LANGUAGE REPRESENTATIONS

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UNIVERSAL TRANSFORMER

DEGHANI ET AL

Weight Sharing

- Model Size
- Performance

unless you increase model size

Techniques for Smaller Networks

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Advantages of Quantization

- Easily combined with existing techniques
  - you can quantize a pruned model, quantize a distilled model, etc

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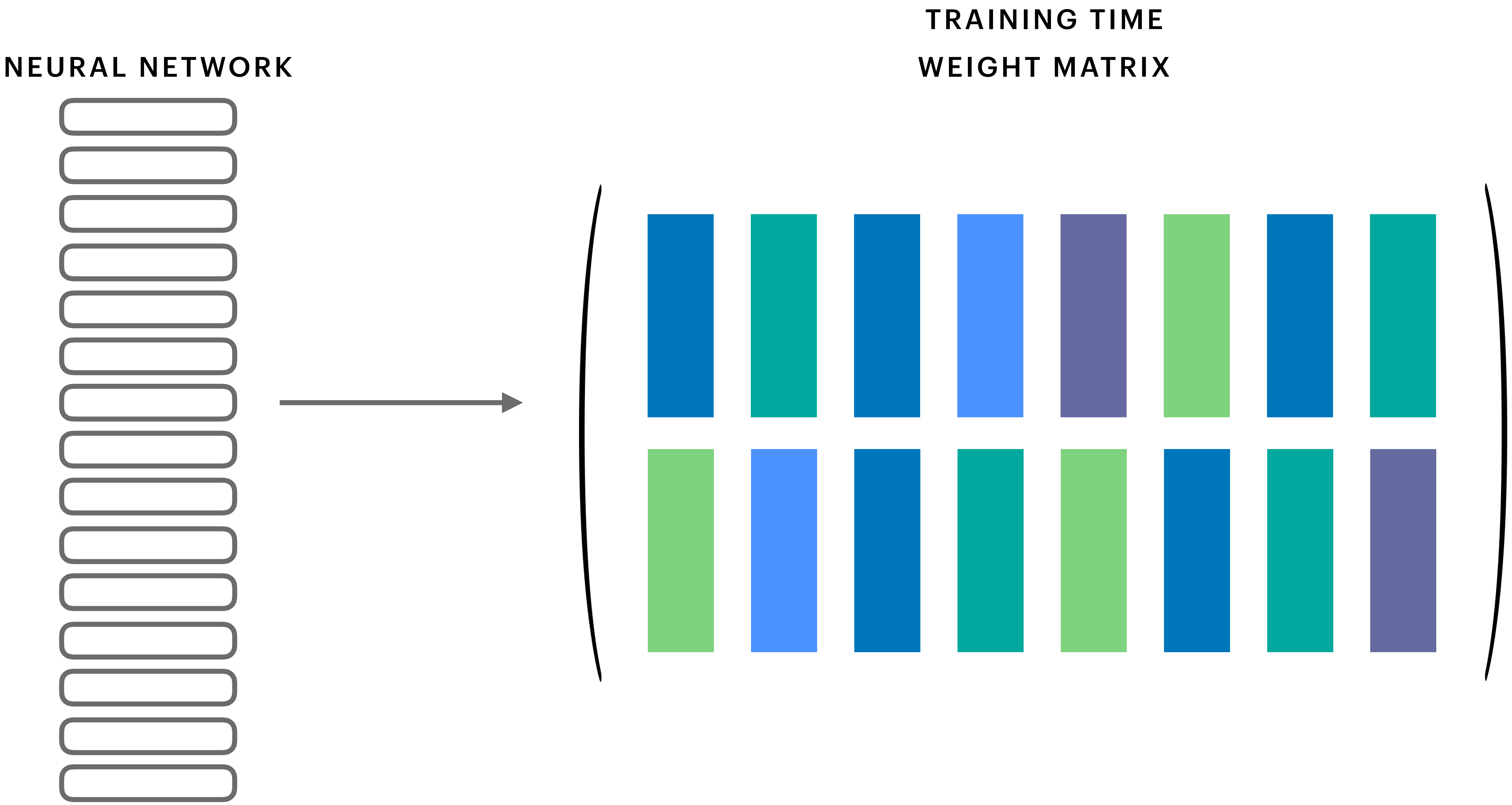
  - easy to apply

- Can offer drastic compression

How much Model Size do you want to decrease?

• Train Smaller Network from Scratch	maybe model will be 2-4x smaller
• Sparsity Inducing Training	probably less...
• Knowledge Distillation	2-10x smaller
• Pruning	2x smaller
• Weight Sharing	2-8x smaller
• **Quantization**	**4-25x smaller** 50 - 100x in combination

How does Quantization offer such extreme compression?



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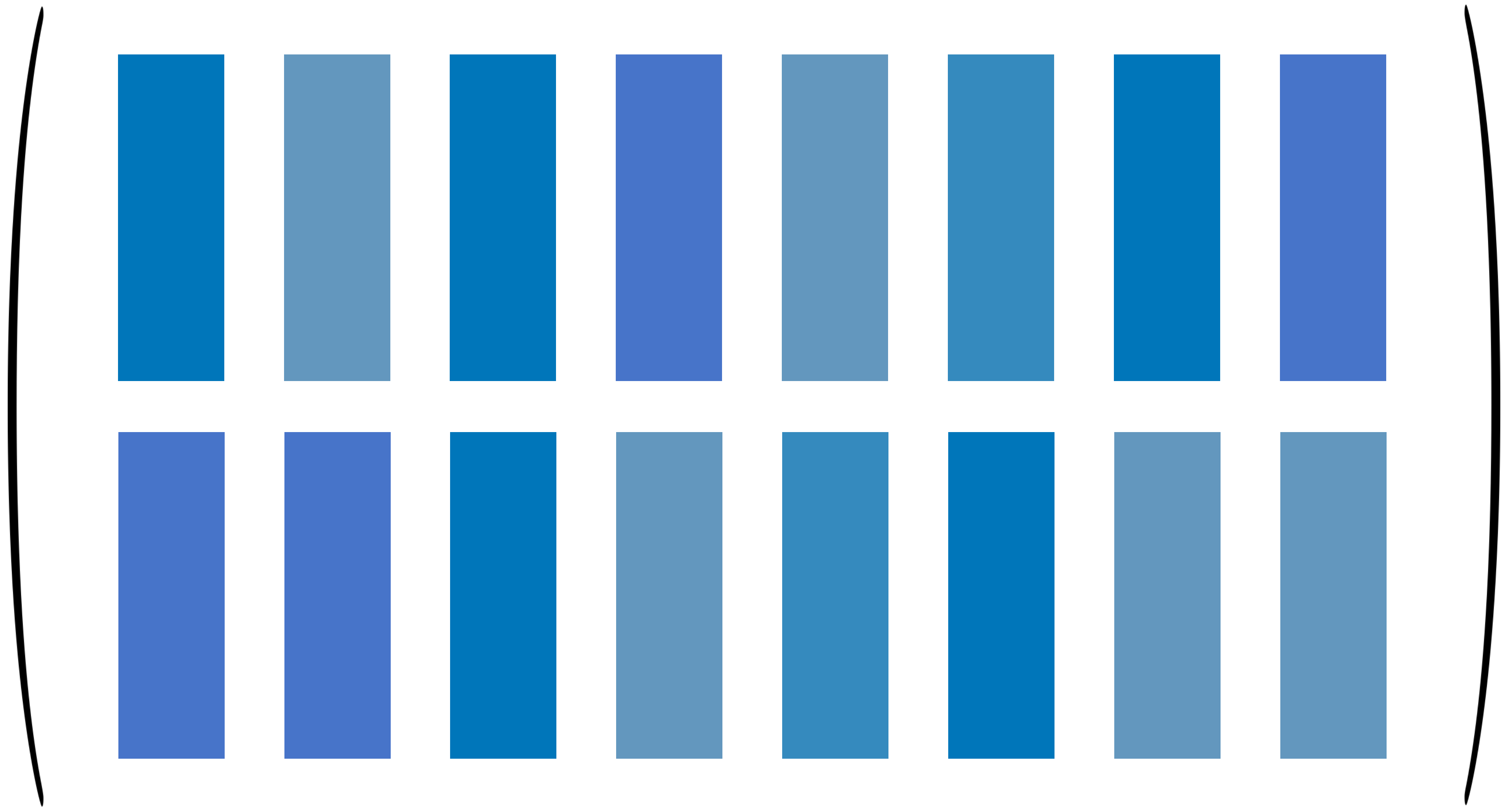
INFERENCE TIME

QUANTIZED WEIGHT MATRIX



QUANTIZATION OPERATIONS CHANGE THE WEIGHT VALUES
IN ORDER TO COMPRESS NETWORK SIZE

Different Types of Quantization

- Scalar Quantization (int8, int4, binary)
- Vector Quantization (Product Quantization)

Scalar Quantization

4x compression from int8

8x compression from int4

32x compression from binary… so far not working for Transformers

Scalar Quantization

- Neural Networks are often stored in fp32. We save space by going to int8 or int4.
- Take real numbers and instead store them as integers with scaling factors

0.0269
real number

Scalar Quantization

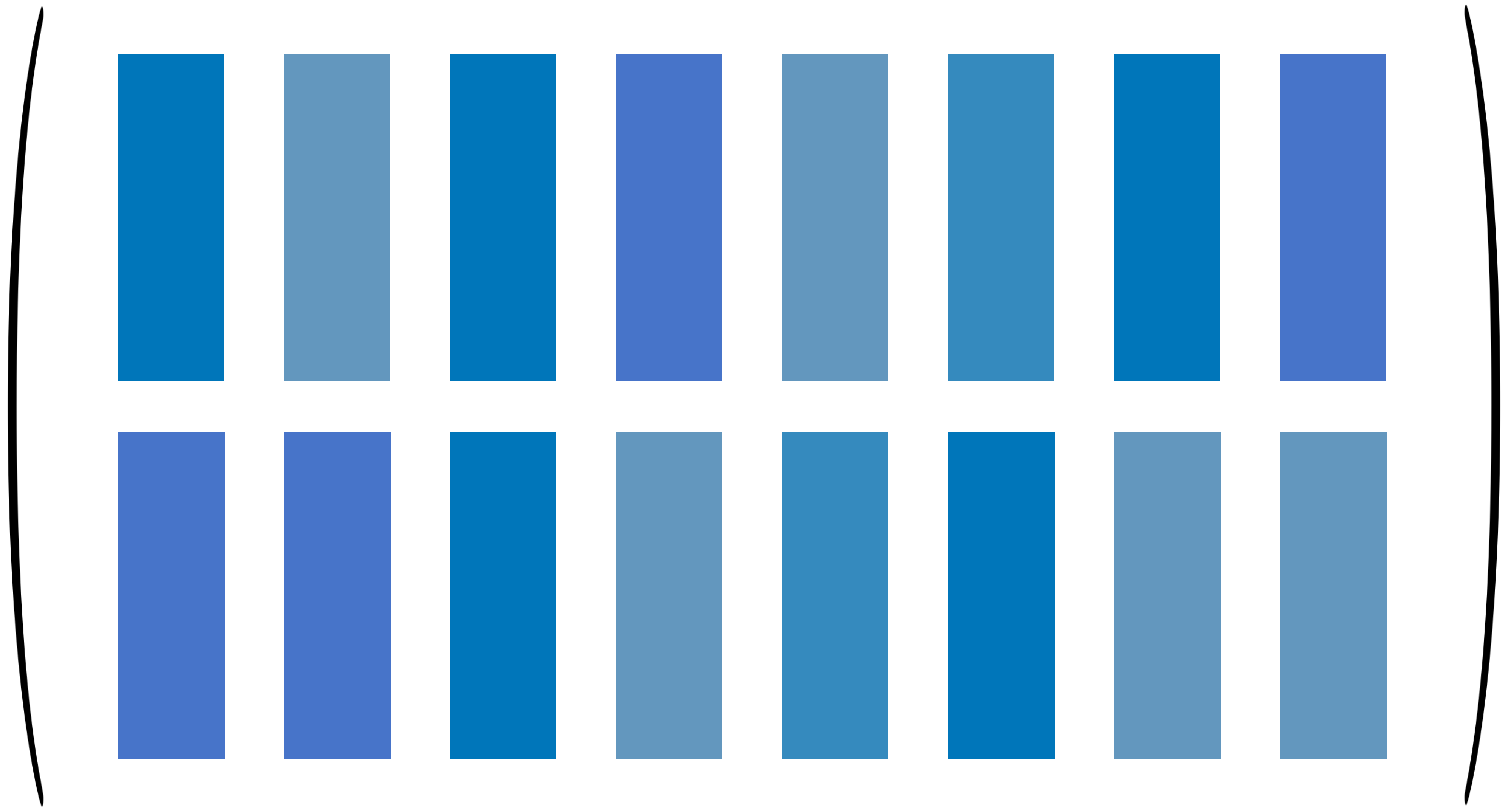
- Neural Networks are often stored in fp32. We save space by going to int8 or int4.
- Take real numbers and instead store them as integers with scaling factors

0.0269	=	110	*	2^ -12
real number		integer		scaling factor

How to apply to an entire matrix?

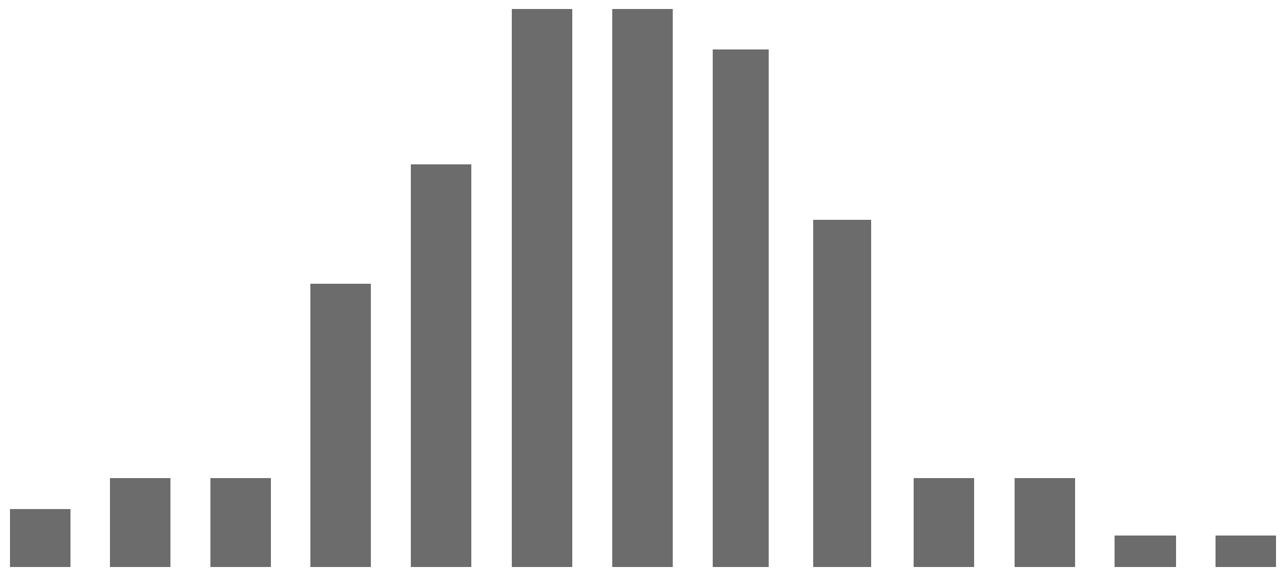
INFERENCE TIME

QUANTIZED WEIGHT MATRIX



QUANTIZATION OPERATIONS CHANGE THE WEIGHT VALUES
IN ORDER TO COMPRESS NETWORK SIZE

Calculate Scaling Factor across all values

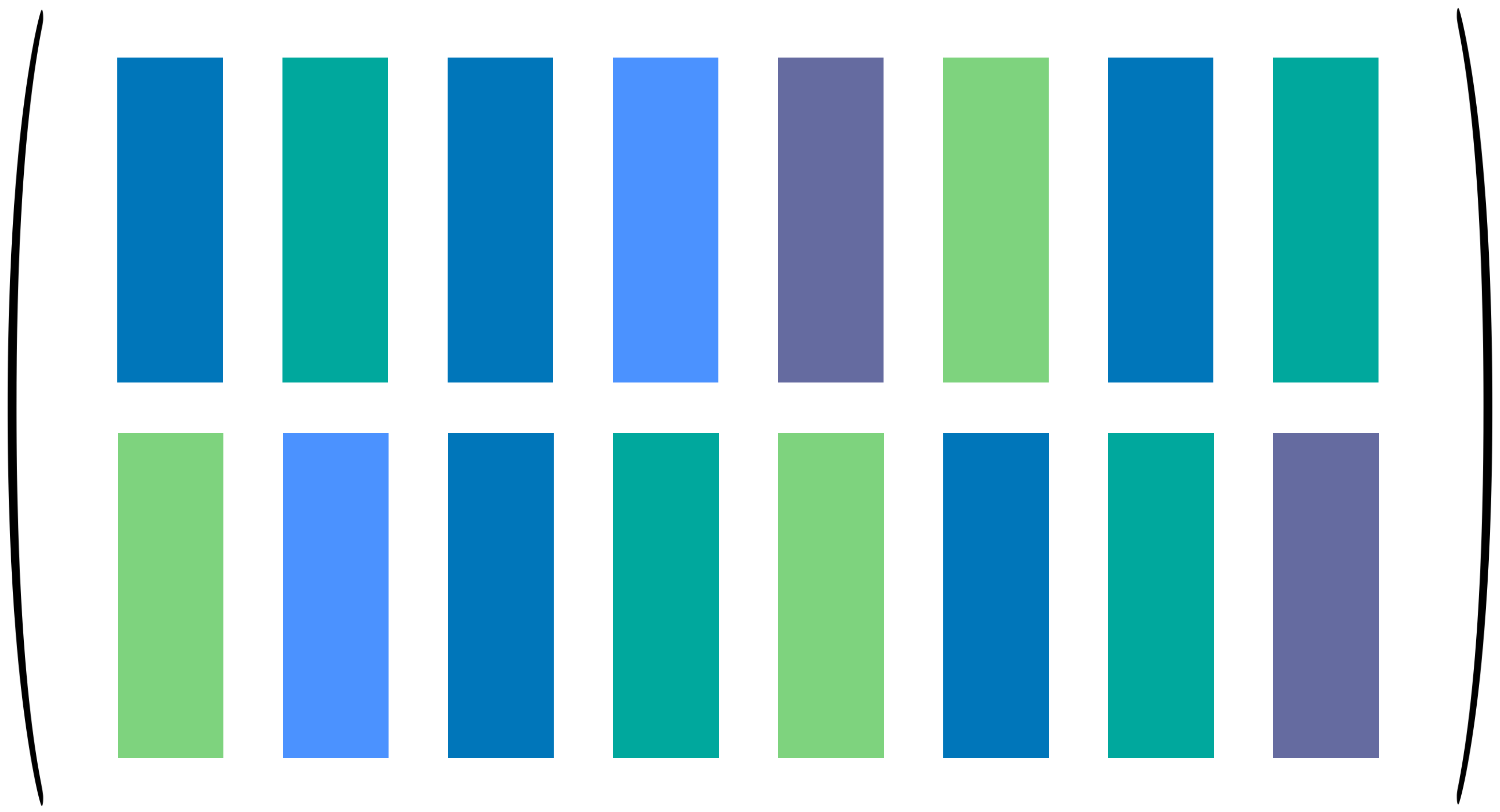


HISTOGRAM OF SCALING FACTORS

Vector Quantization: Product Quantization

25x compression or more

TRAINING TIME
WEIGHT MATRIX



Vector Quantization: Product Quantization

25x compression or more

Vector Quantization: Product Quantization

can combine scalar and vector quantization

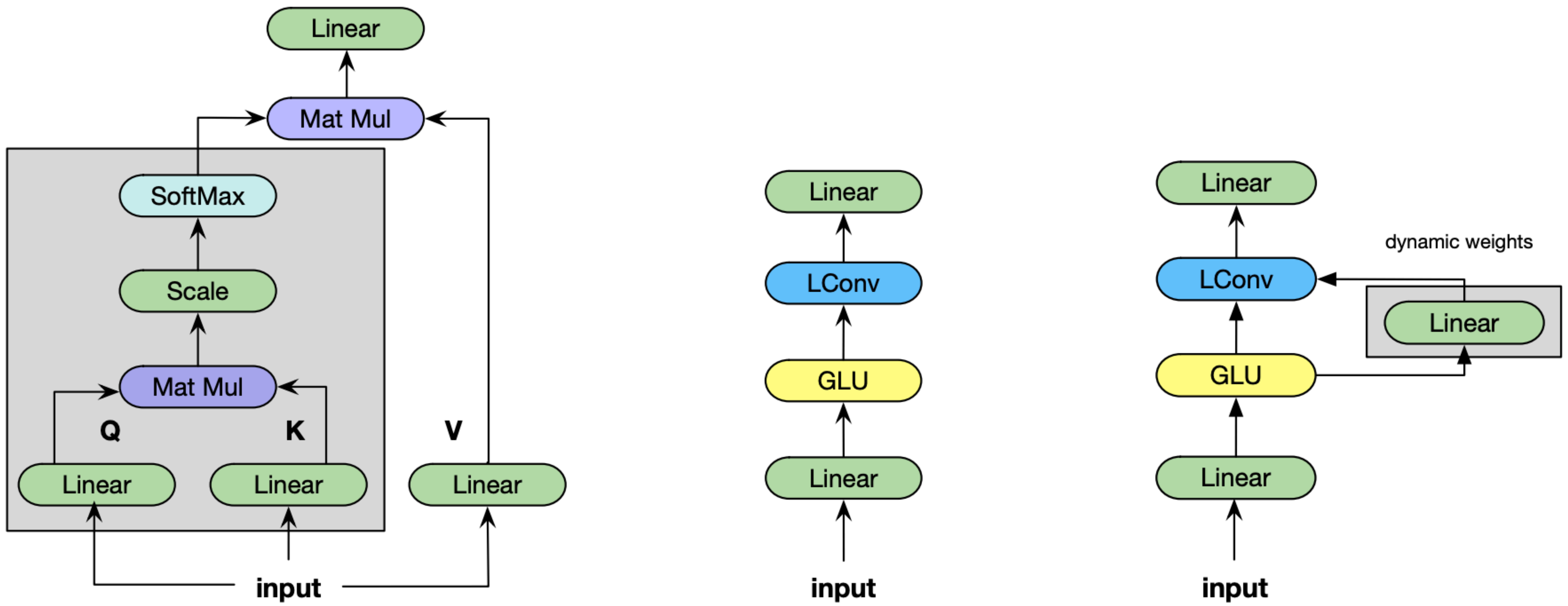
Quantization

- Inference Time ✓ if scalar quantization
- Performance ✓ depending on how compressed
- Model Size ✓ critical for on-device

Techniques for Smaller Networks

- Train Smaller Network from Scratch
- Sparsity Inducing Training
- Knowledge Distillation
- Pruning
- Weight Sharing
- Quantization
- **More efficient architectures**

Variant Transformer Architectures

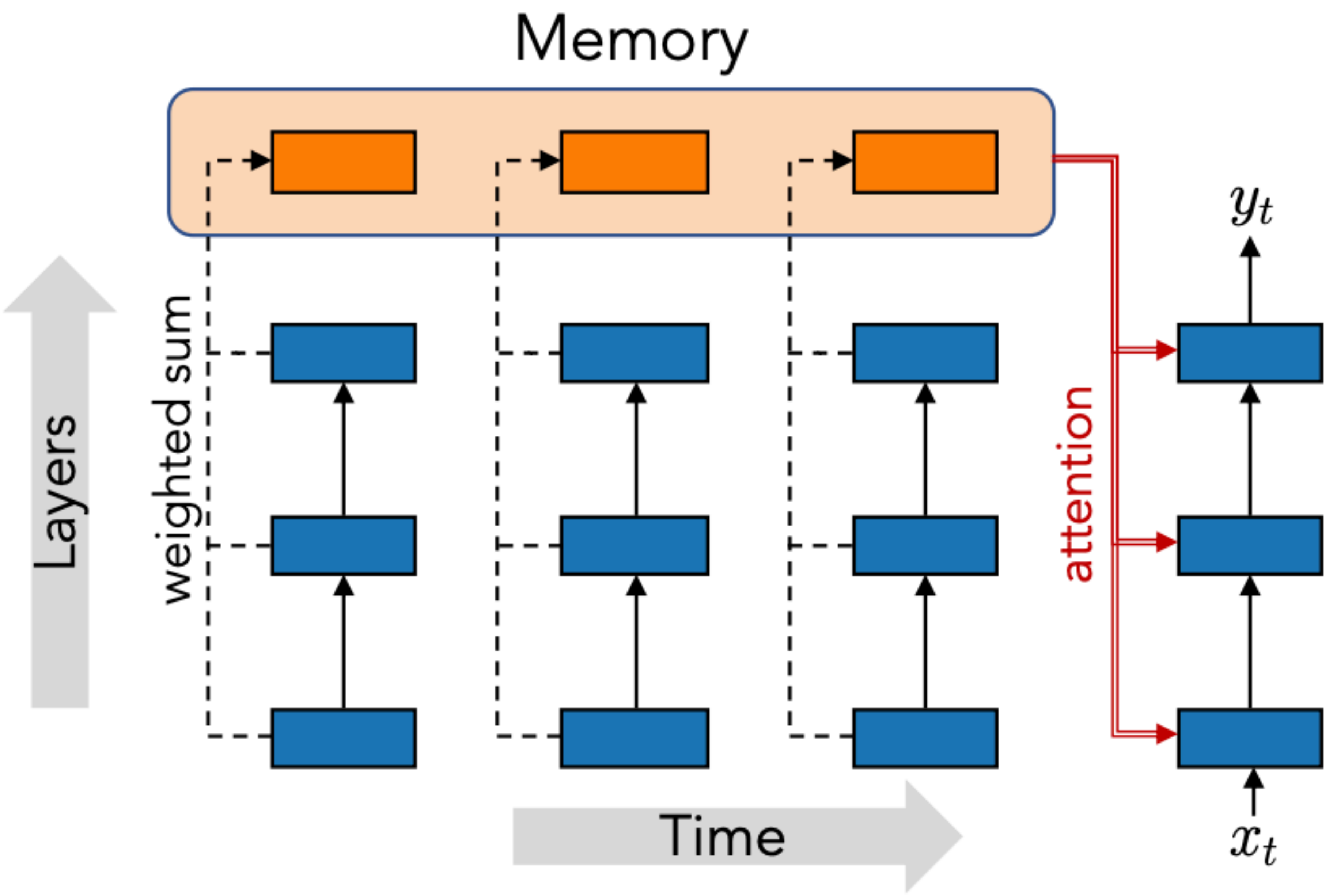


(a) Self-attention (b) Lightweight convolution (c) Dynamic convolution

PAY LESS ATTENTION WITH LIGHTWEIGHT AND DYNAMIC CONVOLUTIONS

WU ET AL

Variant Transformer Architectures



ACCESSING HIGHER-LEVEL REPRESENTATIONS IN SEQUENTIAL TRANSFORMERS WITH FEEDBACK MEMORY
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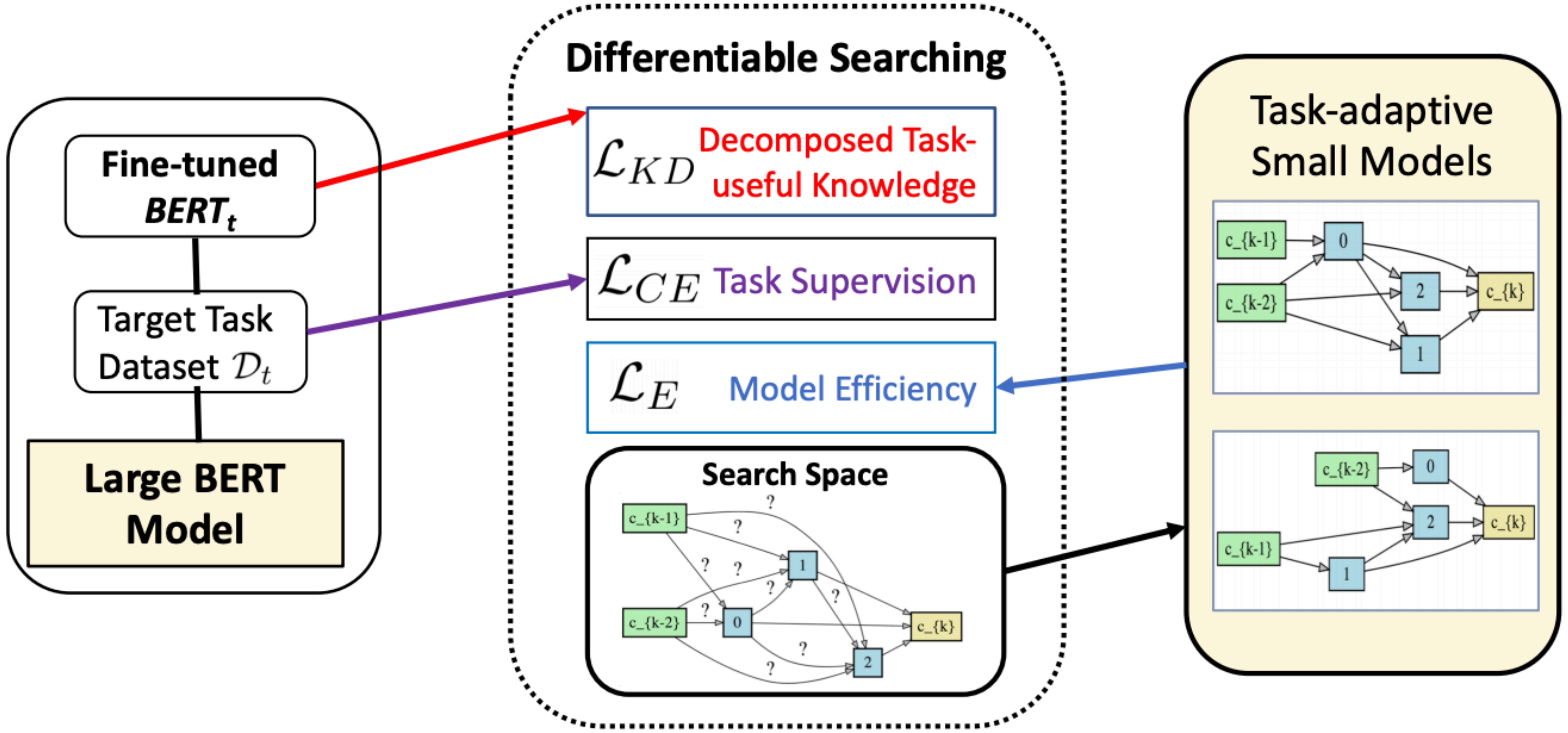
Variant Transformer Architectures



ADABERT: TASK-ADAPTIVE BERT COMPRESSION WITH DIFFERENTIABLE NEURAL ARCHITECTURE SEARCH

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In Summary...

- Train Smaller Network from Scratch

strong baseline. would not discount.

- Sparsity Inducing Training
- Knowledge Distillation
- Pruning
- Weight Sharing
- Quantization
- More efficient architectures

In Summary...

- Train Smaller Network from Scratch
- Sparsity Inducing Training
- Knowledge Distillation
- Pruning
- Weight Sharing
- Quantization
- More efficient architectures

important for on-device

In Summary...

- Train Smaller Network from Scratch
- Sparsity Inducing Training
- Knowledge Distillation — a lot of recent improvements, very flexible
- Pruning
- Weight Sharing
- Quantization
- More efficient architectures

In Summary...

- Train Smaller Network from Scratch
- Sparsity Inducing Training
- Knowledge Distillation
- Pruning
- Weight Sharing
- Quantization
- More efficient architectures

easy and straightforward gains

In Summary...

- Train Smaller Network from Scratch
- Sparsity Inducing Training
- Knowledge Distillation
- Pruning
- Weight Sharing
- Quantization
- More efficient architectures

depends on how much you share

In Summary...

- Train Smaller Network from Scratch
- Sparsity Inducing Training
- Knowledge Distillation
- Pruning
- Weight Sharing
- Quantization
- More efficient architectures

important for on-device. easily combinable.
can be used for aggressive compression

In Summary...

- Train Smaller Network from Scratch
- Sparsity Inducing Training
- Knowledge Distillation
- Pruning
- Weight Sharing
- Quantization
- More efficient architectures

exciting direction

And of course, even more considerations...

- Latency (faster decoding)
- Models that fit on Specialized Hardware
    - specific block sizes
    - battery life and heat from device

Interested in Efficient NLP?

Simple and Efficient Natural Language Processing

Workshop at EMNLP 2020 in Punta Cana

Thanks for listening!