Train Large, Then Compress:
Rethinking Model Size for Efficient Training and Inference of Transformers

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State-of-the-art NLP models require millions of dollars to train

Devlin et al. (2019). We pretrain our model using 1024 V100 GPUs for approximately one day.

$4,600,000: The full cost of training GPT-3

Consumption	CO_2e (lbs)
Air travel, 1 passenger, NY↔SF	1984
Human life, avg, 1 year	11,023
American life, avg, 1 year	36,156
Car, avg incl. fuel, 1 lifetime	126,000
Training one model (GPU)	
NLP pipeline (parsing, SRL)	39
w/ tuning & experimentation	78,468
Transformer (big)	192
w/ neural architecture search	626,155

Artificial intelligence / Machine learning

Training a single AI model can emit as much carbon as five cars in their lifetimes

Why is training so expensive?

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  - ⬆ Larger model size
  - ⬆ Larger datasets
  - ⬆ More training iterations
- **Computational constraints** are increasingly the bottleneck

Maximizing Computational Efficiency

- The goal → maximize **computational efficiency**
  - highest possible accuracy given fixed hardware and training time

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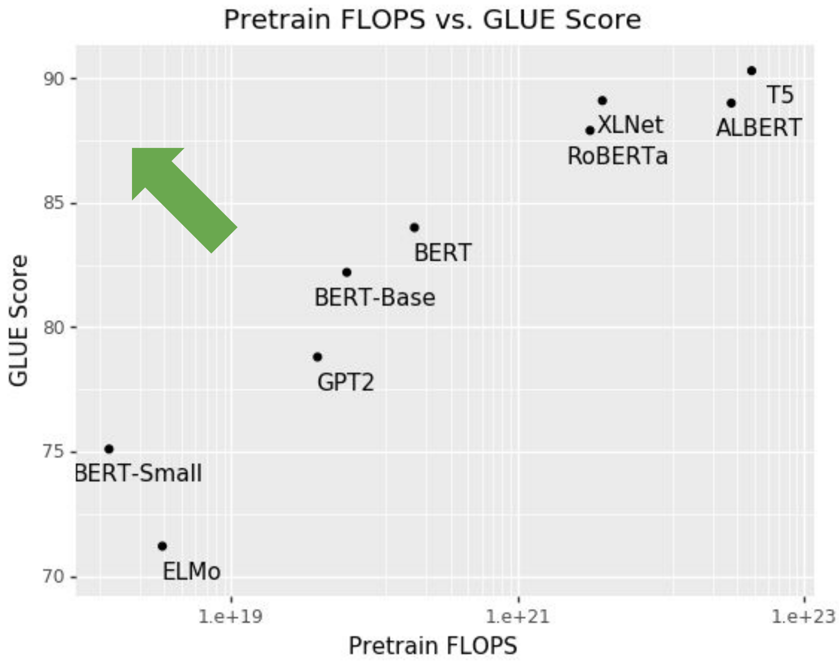

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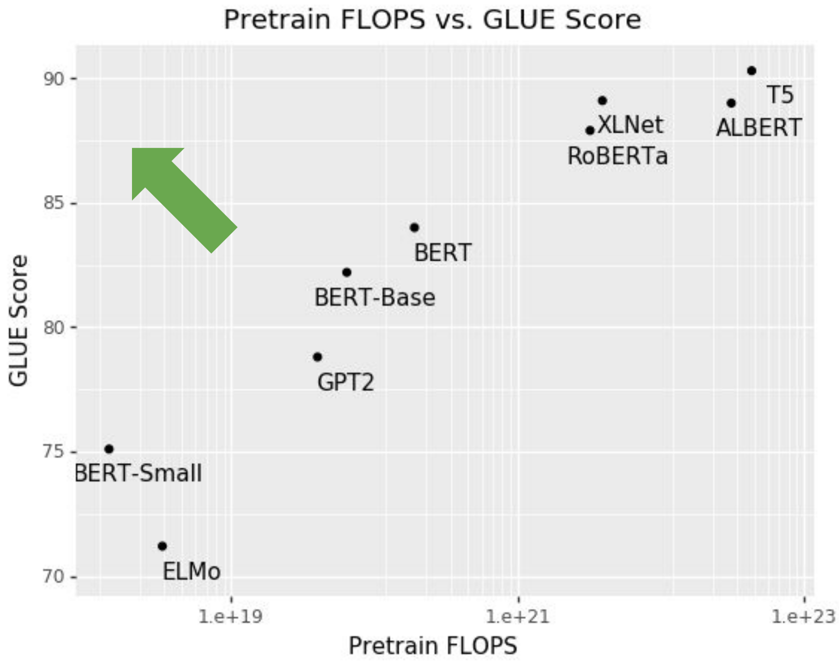

Rethinking Common Assumptions

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- Results:
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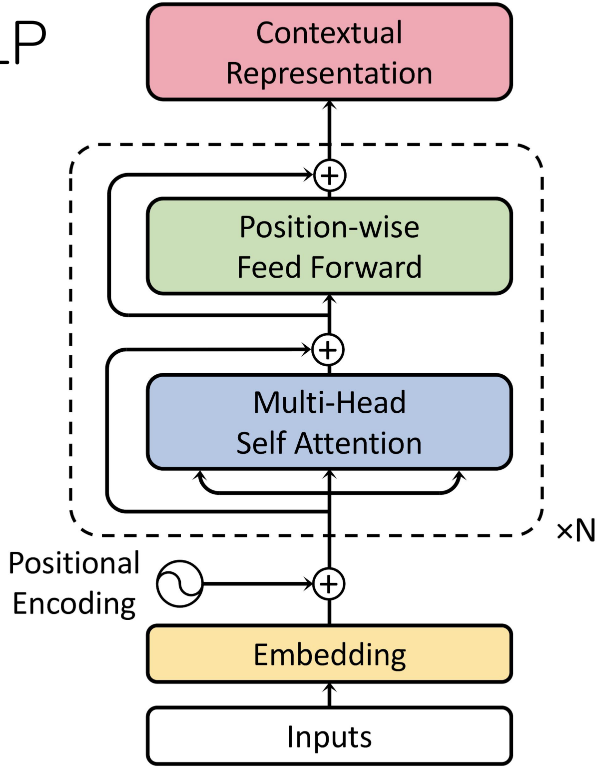
- Results:
  - **Large** models **train faster**
  - **Large** models are **efficient** at **inference** time
- Key idea: stop training early & compress heavily

Training Efficiency

Experimental Setup

- Transformer models
  - feedforward architecture, SoTA for NLP



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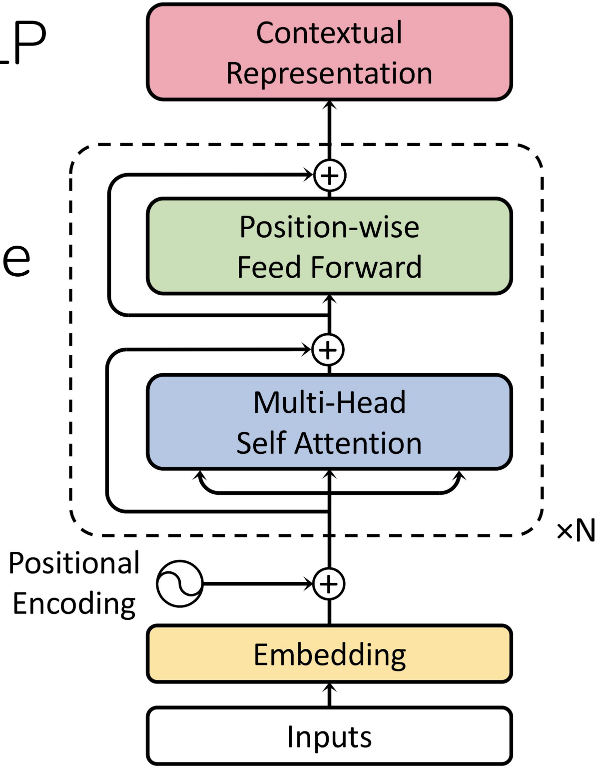
- We vary hidden size + model depth
  - measure loss at a given wall clock time
  - increase batch size to fill the GPU



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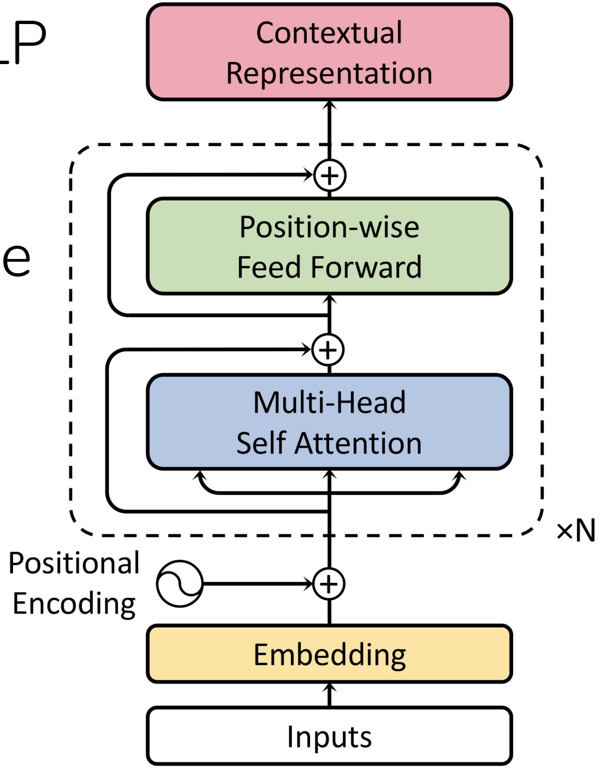
- Task 1: **MLM pretraining + finetuning (RoBERTa)**
- Task 2: **machine translation**



Deeper and Wider Models Converge in Fewer Steps

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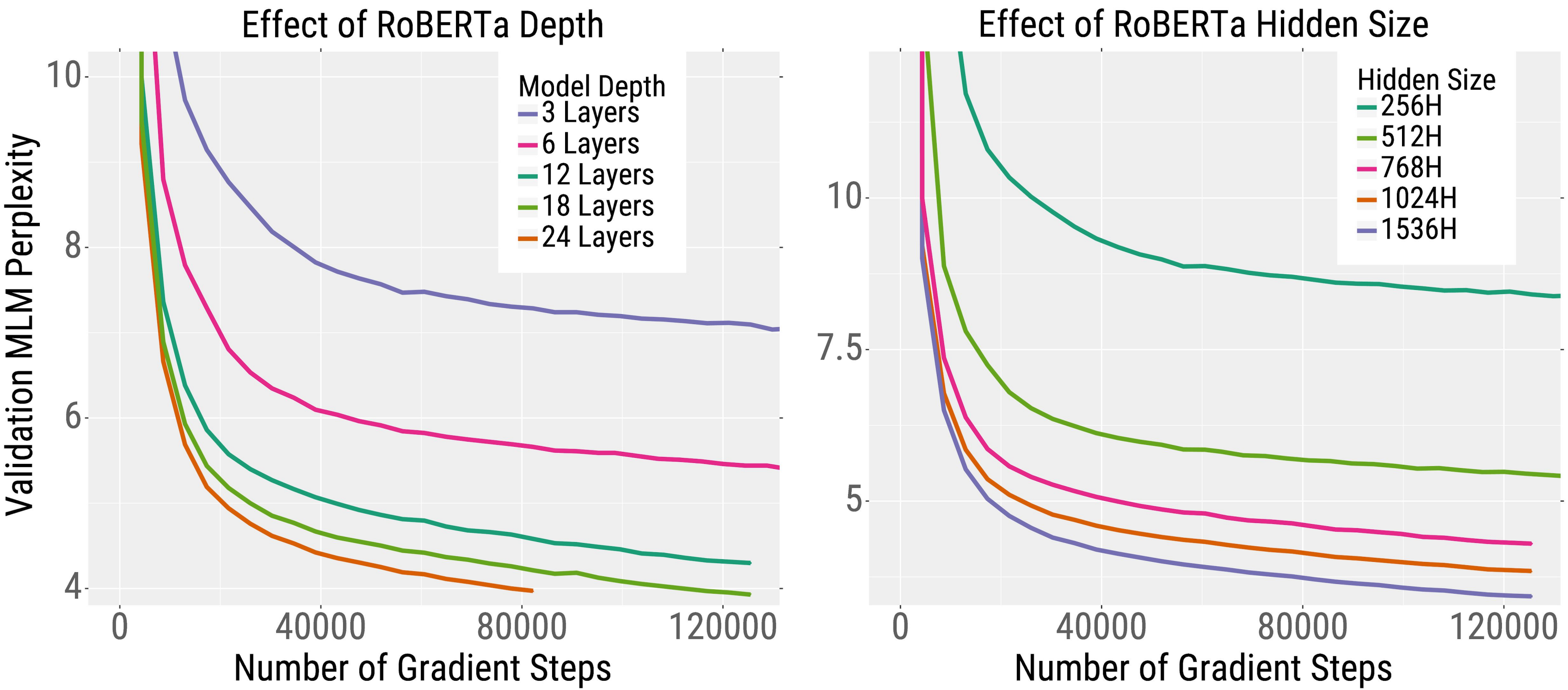

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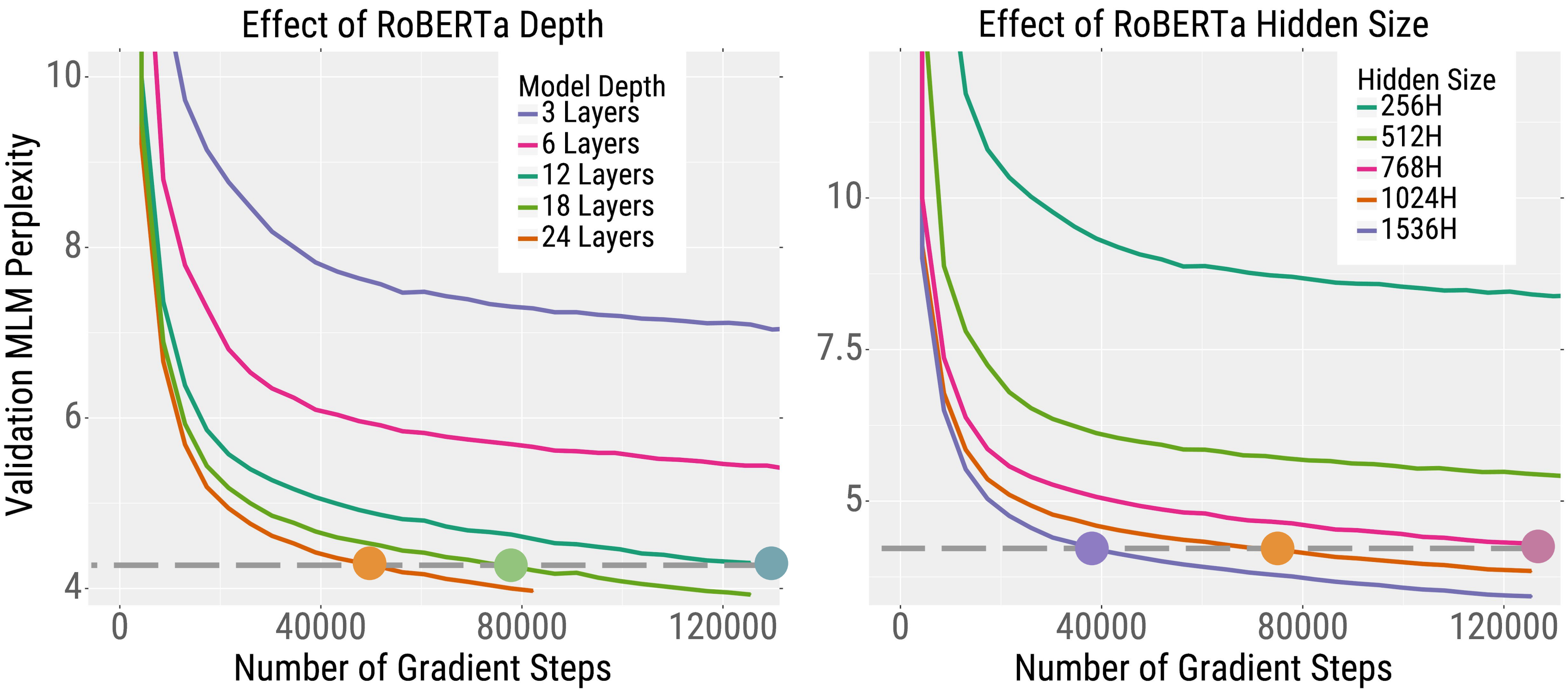
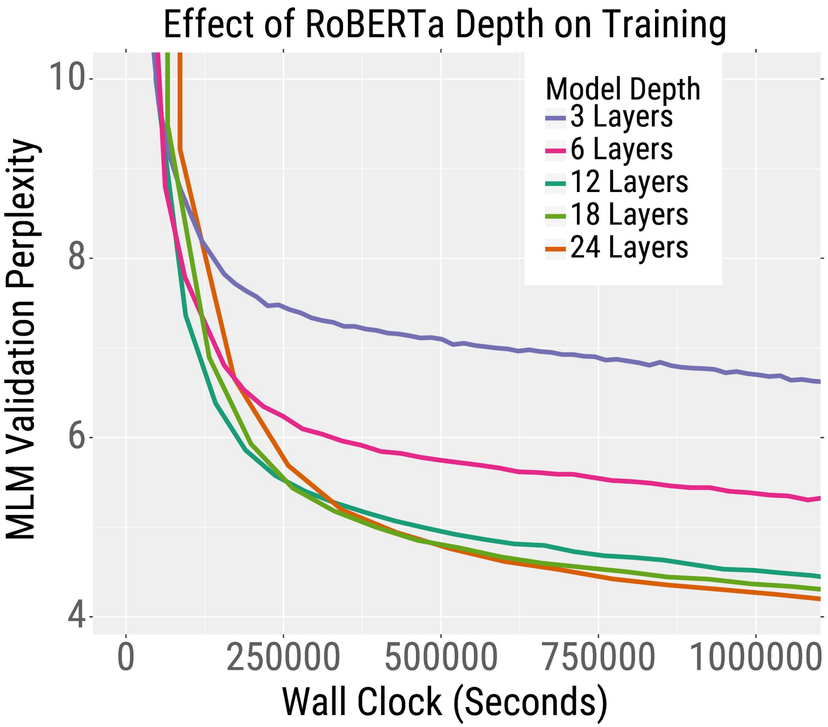
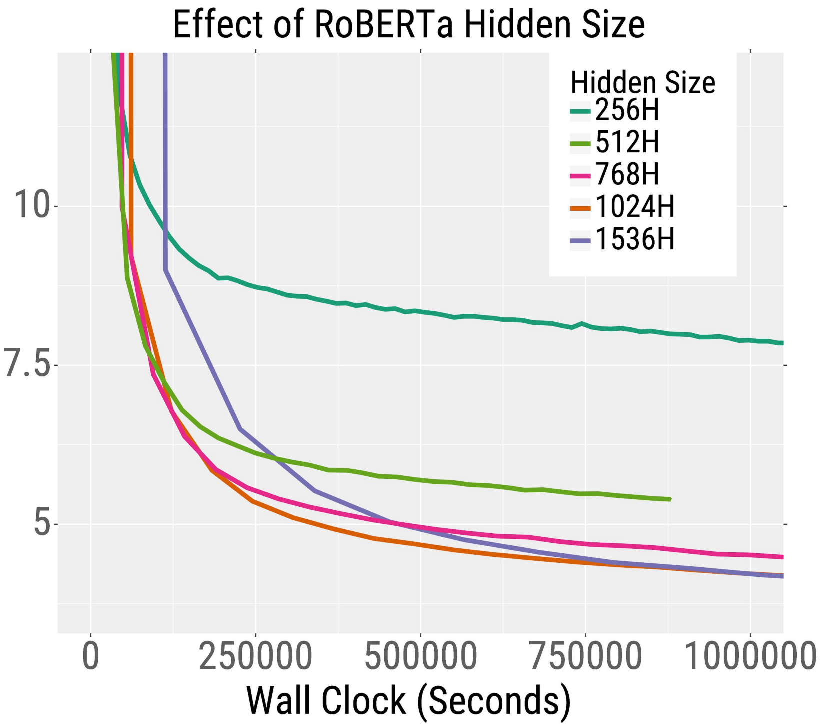


Deeper and Wider Models Converge in Less Wall Clock Time





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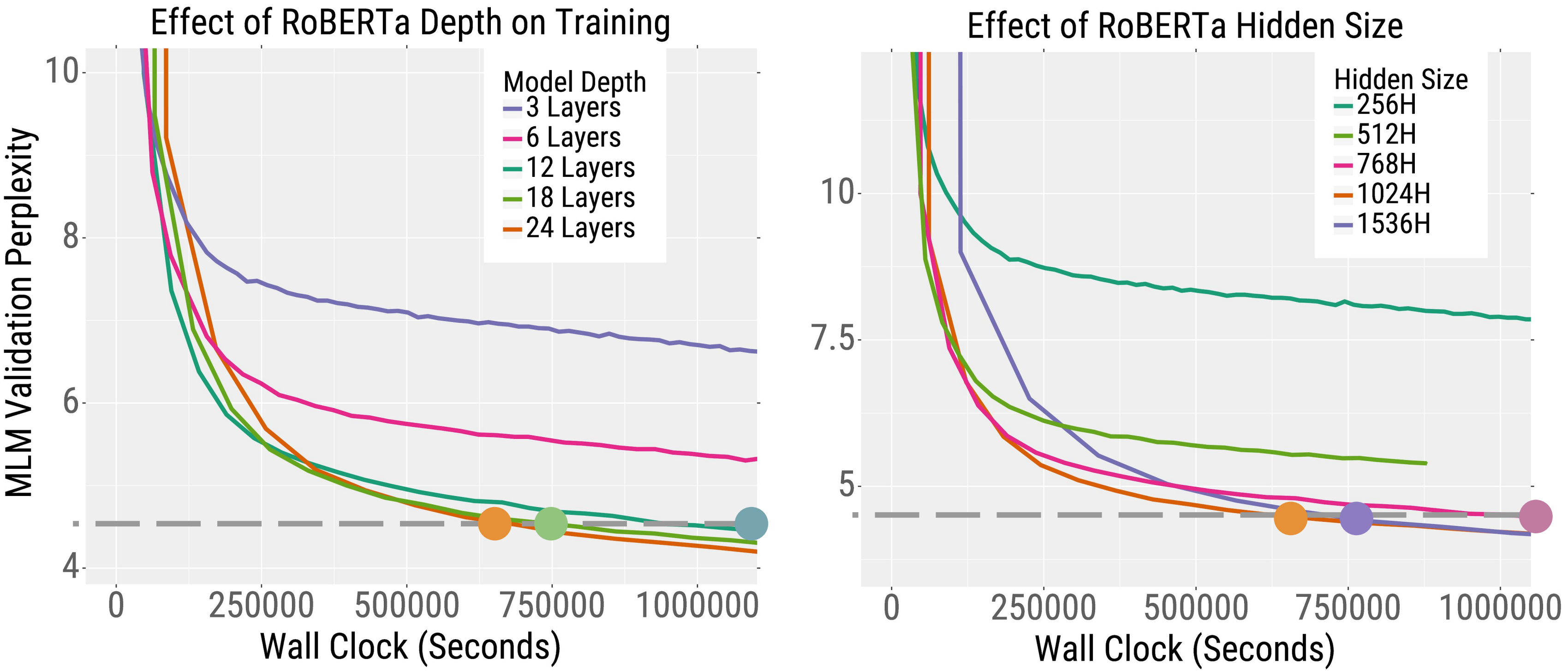
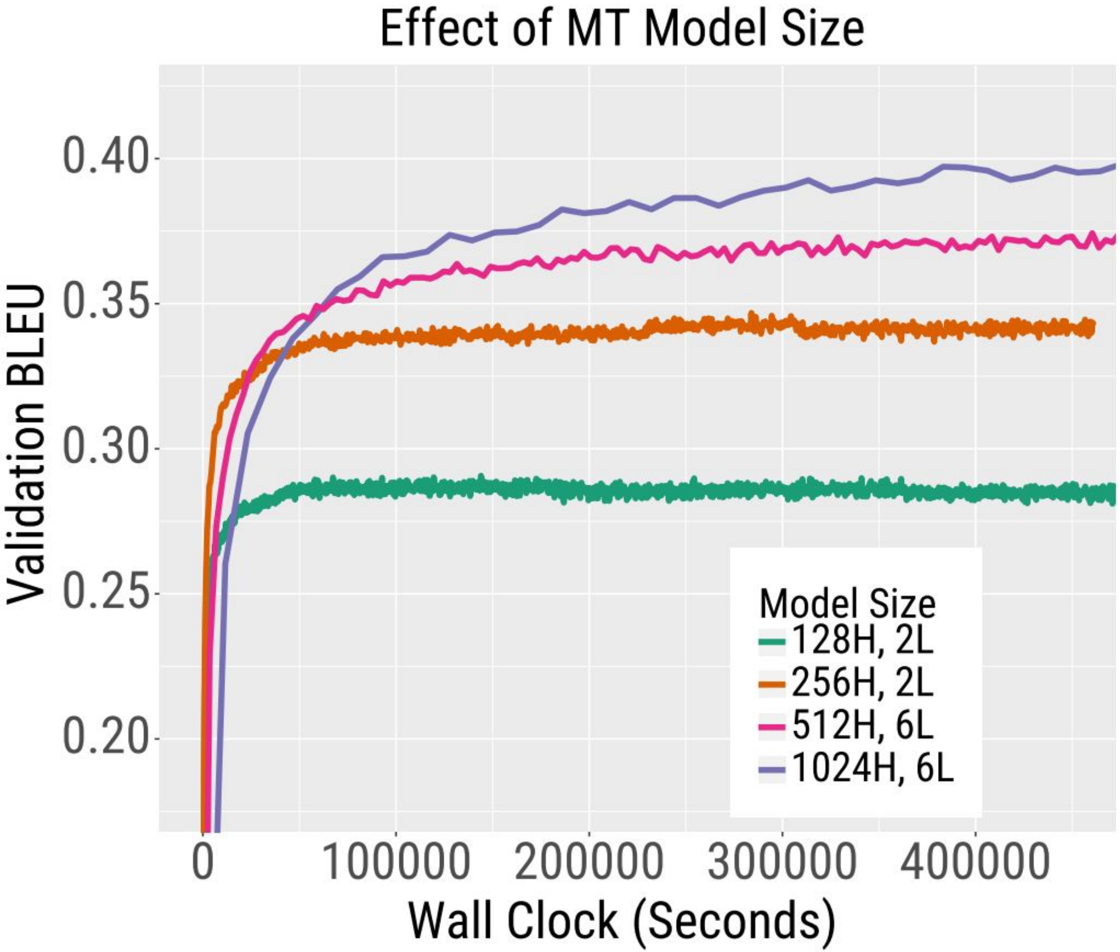


Same Trends Hold for Machine Translation



Why Do Larger Models Train Faster?

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- MLM training has "**unlimited**" data → overfitting <u>*not*</u> a concern
- Thus, larger models also minimize **validation** error faster

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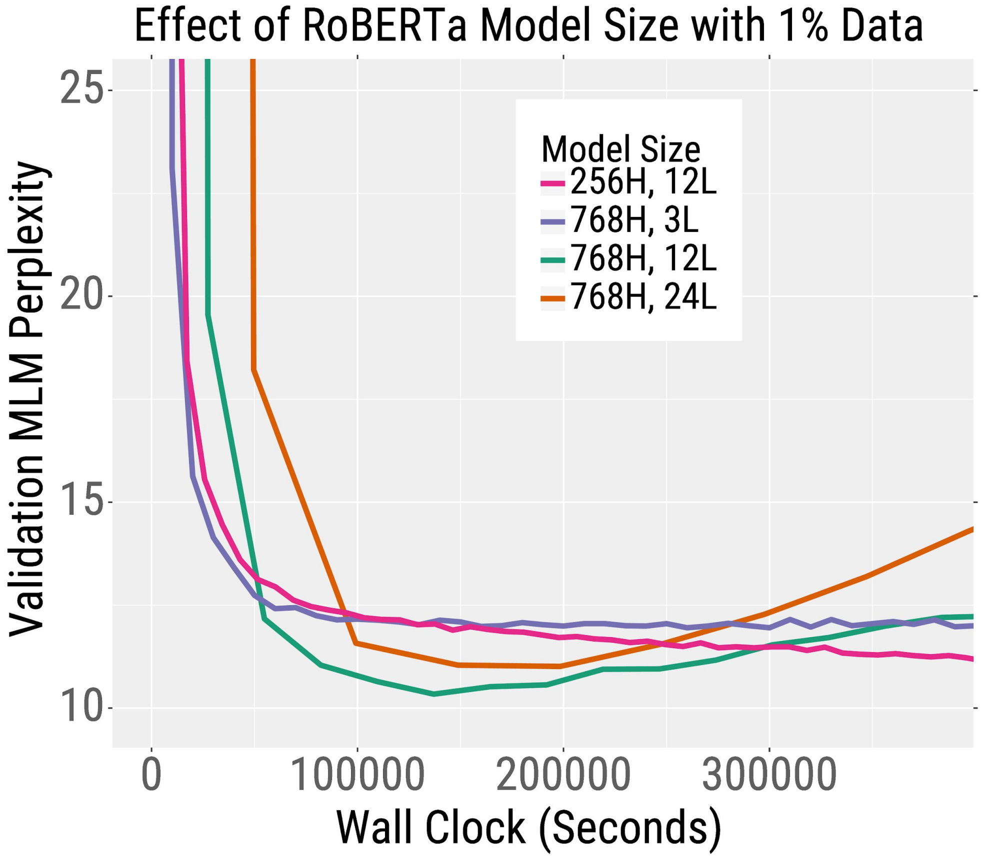

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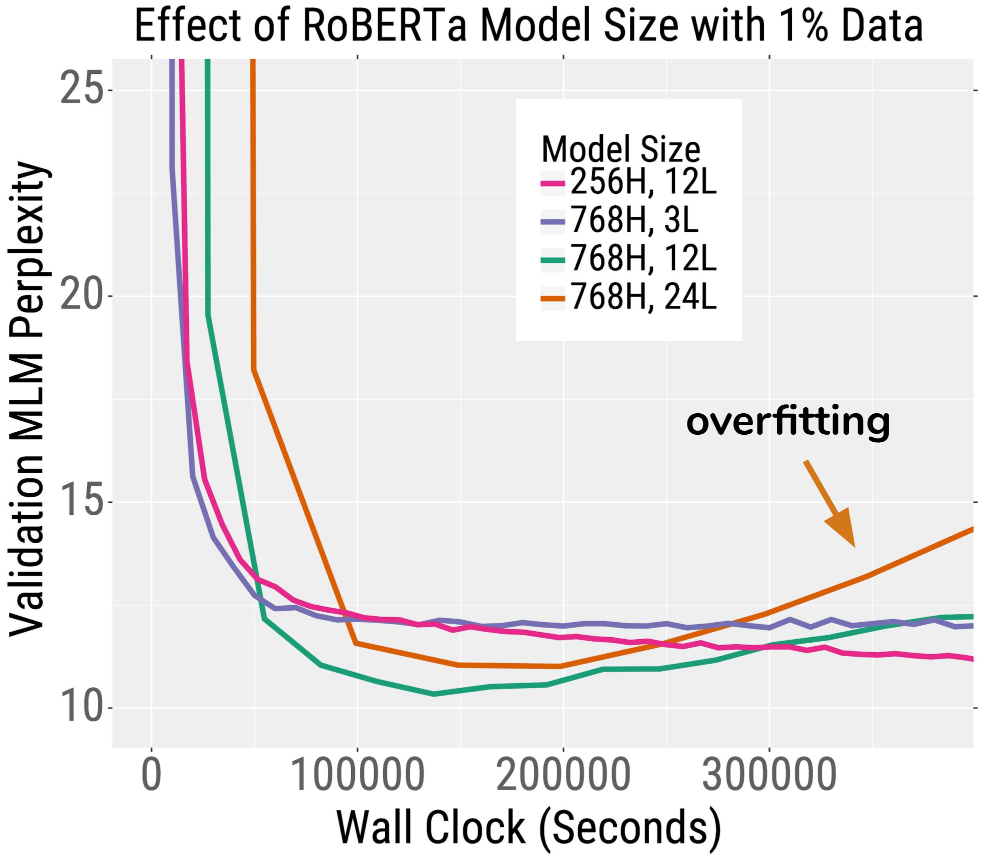

Inference Efficiency

Large models are **fast** at **training** time

Large models are **slow** at **inference** time

Trade-off between large and small models?

✓ Large models are **fast** at **training** time

✗ Large models are **slow** at **inference** time

Trade-off between large and small models? **No!**

✓ We show that larger models are **more** *compressible*

Experimental Setup

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- Two compression techniques: pruning & quantization

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  - ➔ Set weights to 0
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    - ◆ Reduces FP operations

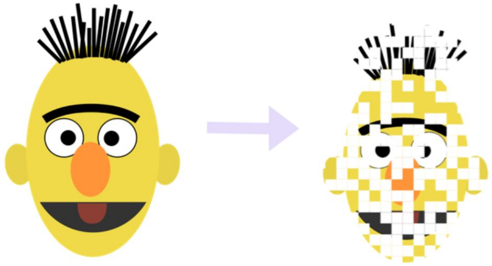

Image: Rasa

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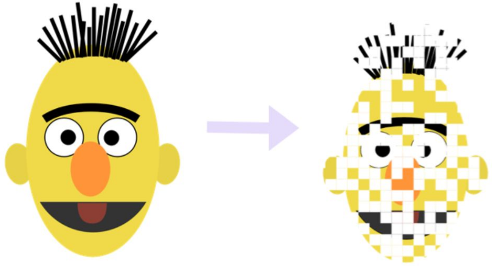

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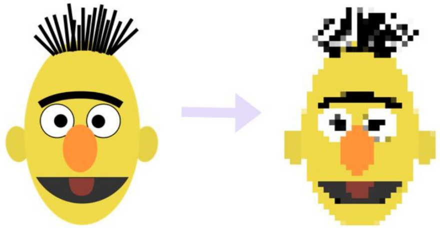
Experimental Setup

- Fix training time for models of different sizes
- Two compression techniques: pruning & **quantization**
  - ➔ Store weights in low precision
    - ◆ Reduces memory
    - ◆ Accelerates speed on certain hardware
    - ◆ Post-hoc quantize with no additional training time



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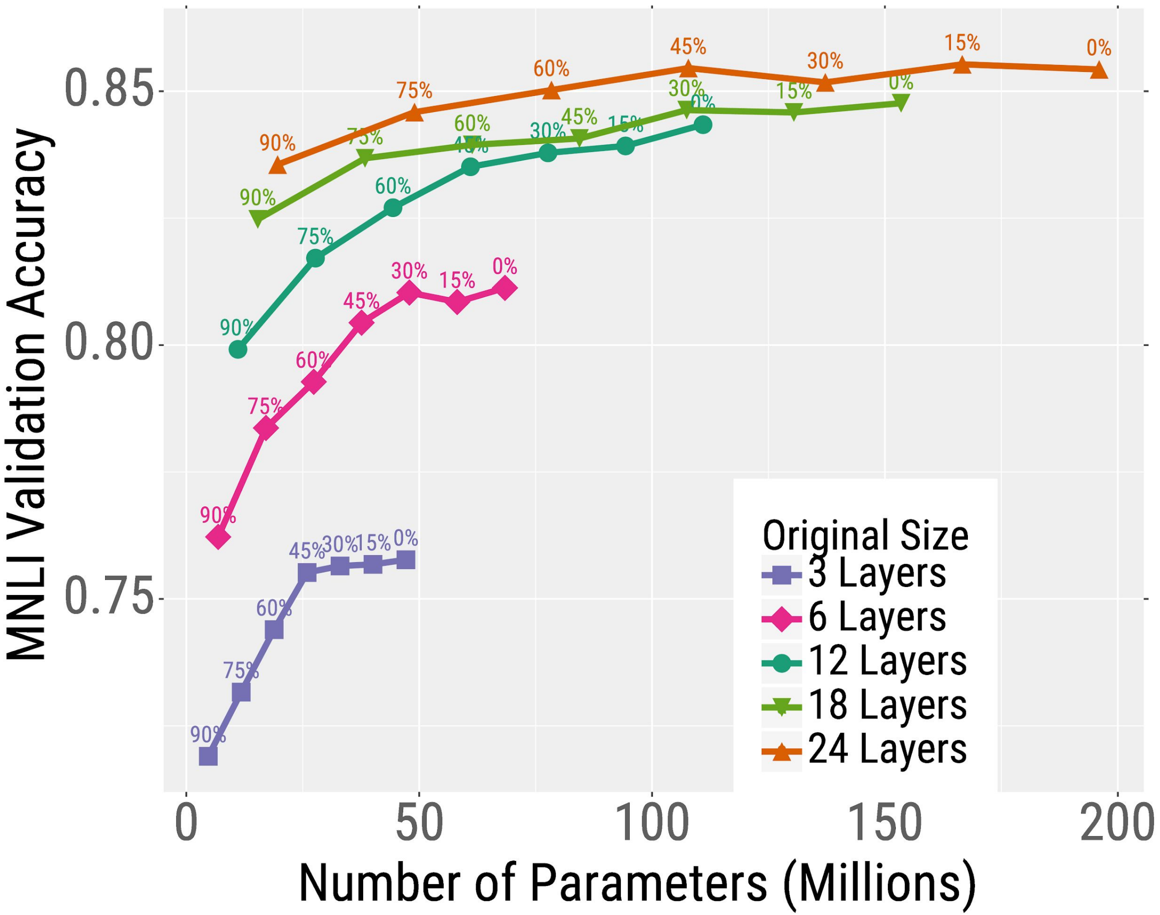
Deeper and Wider Models are More Robust to Pruning



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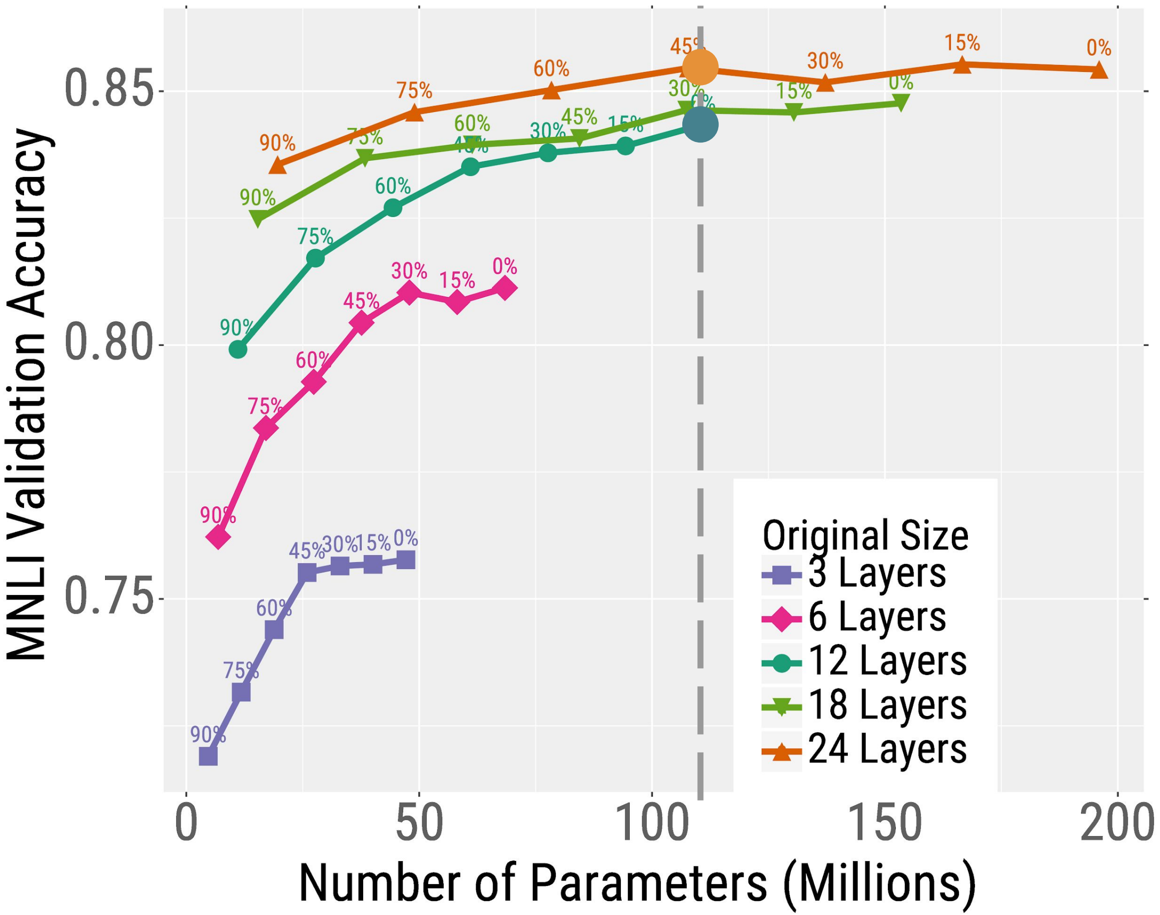

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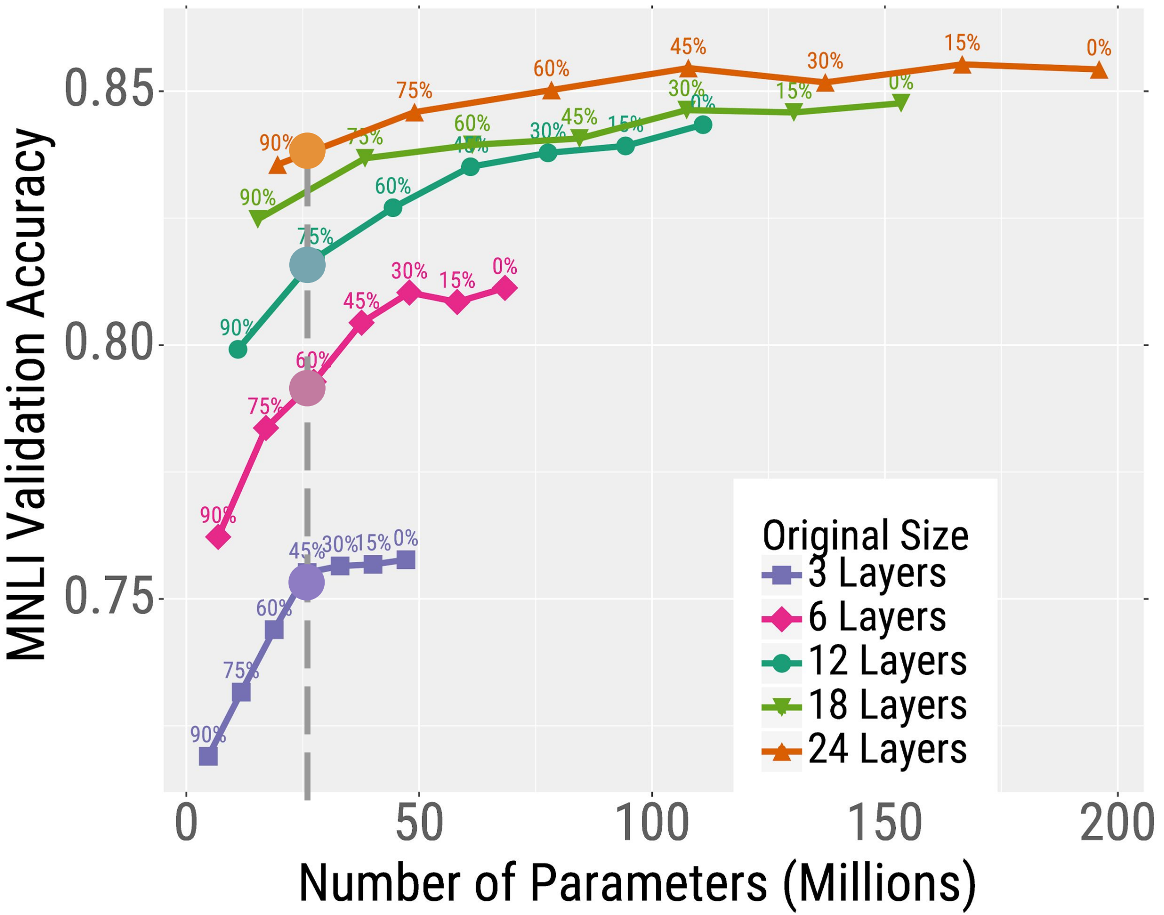
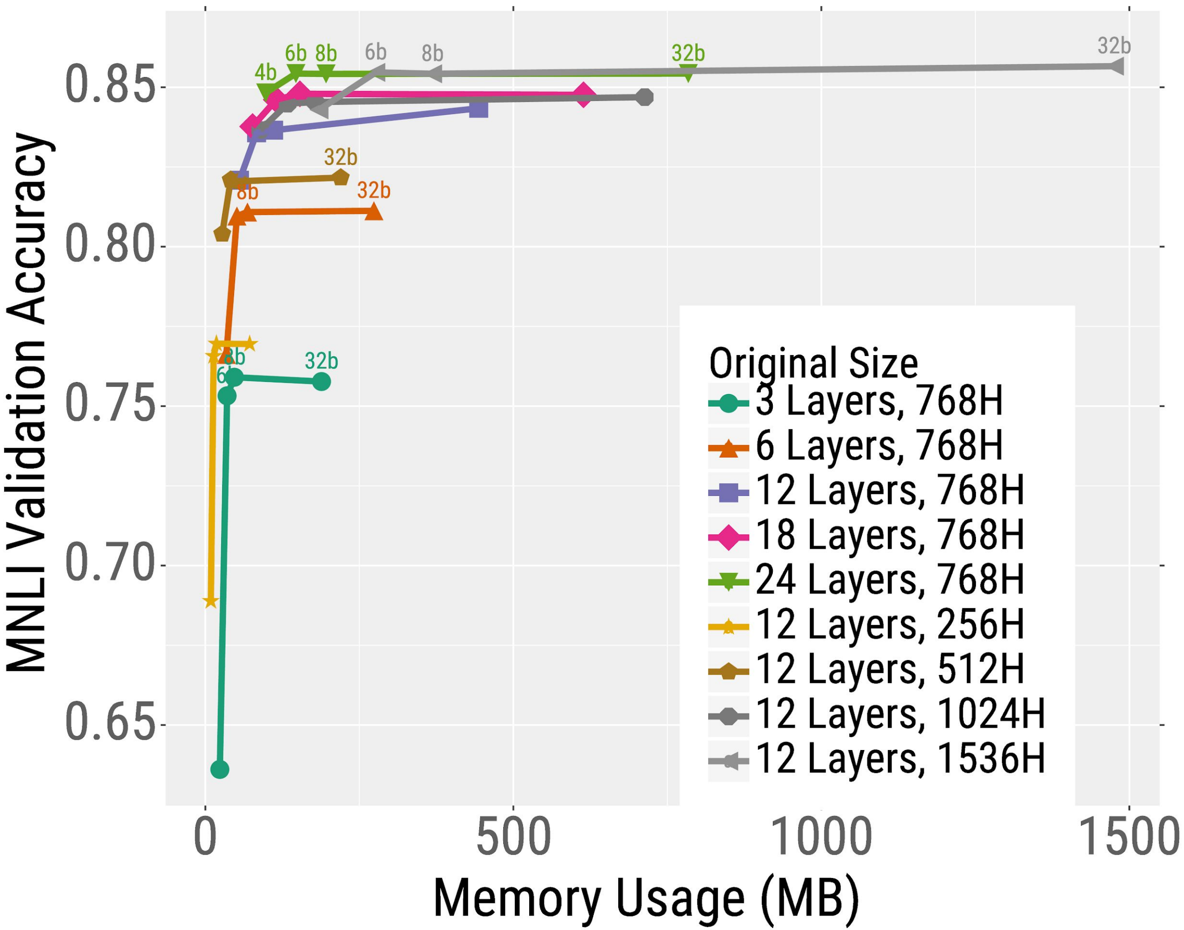
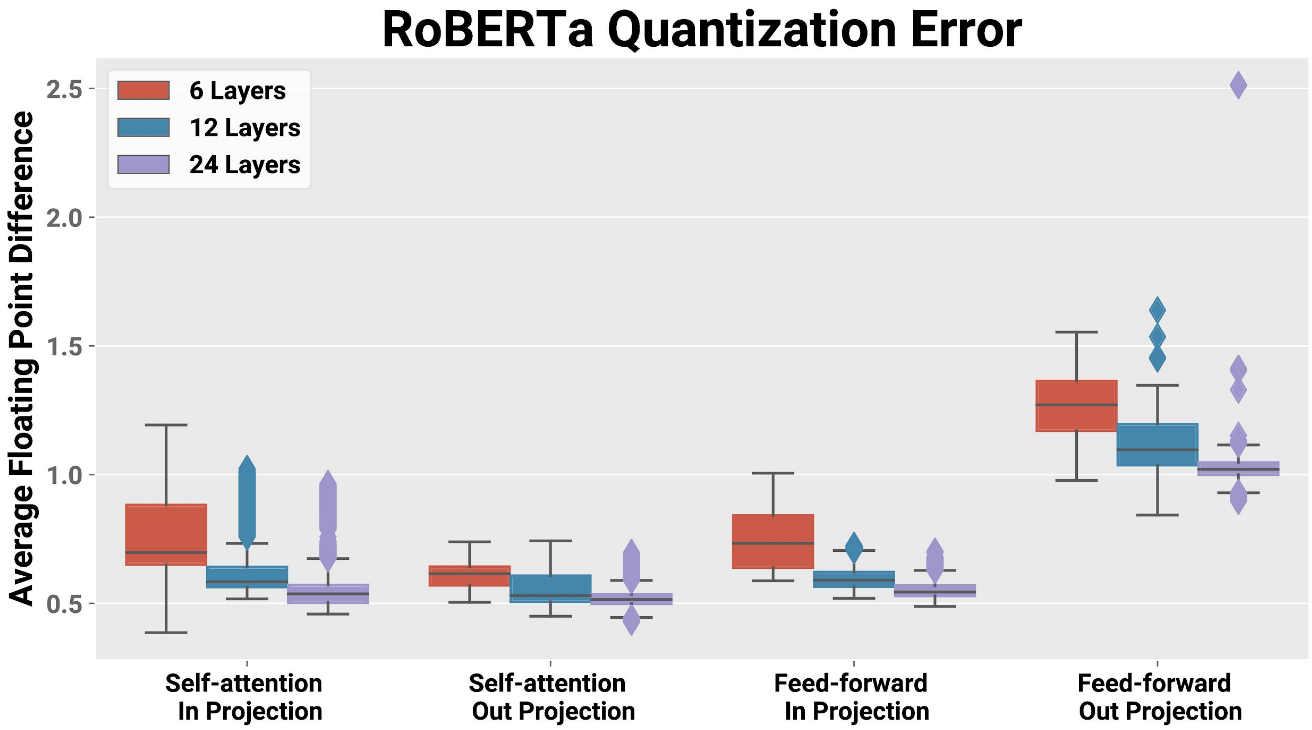


Deeper and Wider Models are More Robust to Quantization



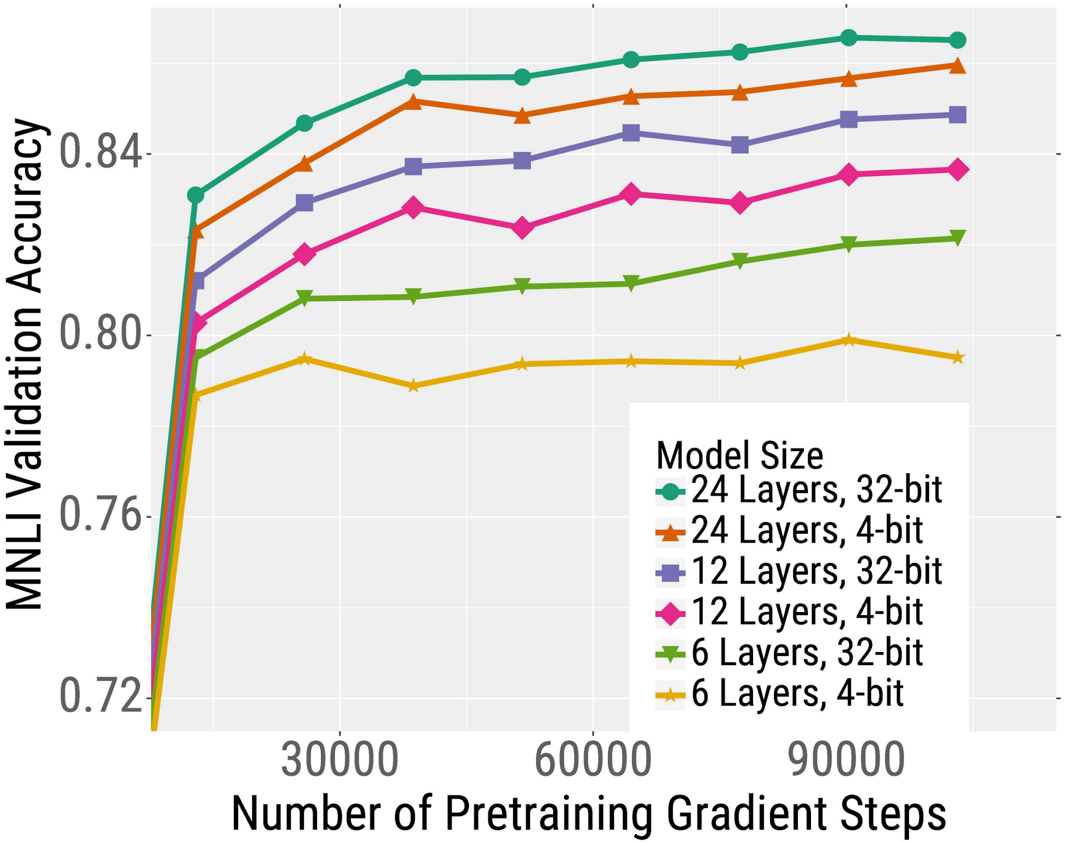
Why Do Larger Models Compress Better?

- Quantization/Pruning error is smaller for larger models



Why Do Larger Models Compress Better?

- Size, not convergence, determines compressibility



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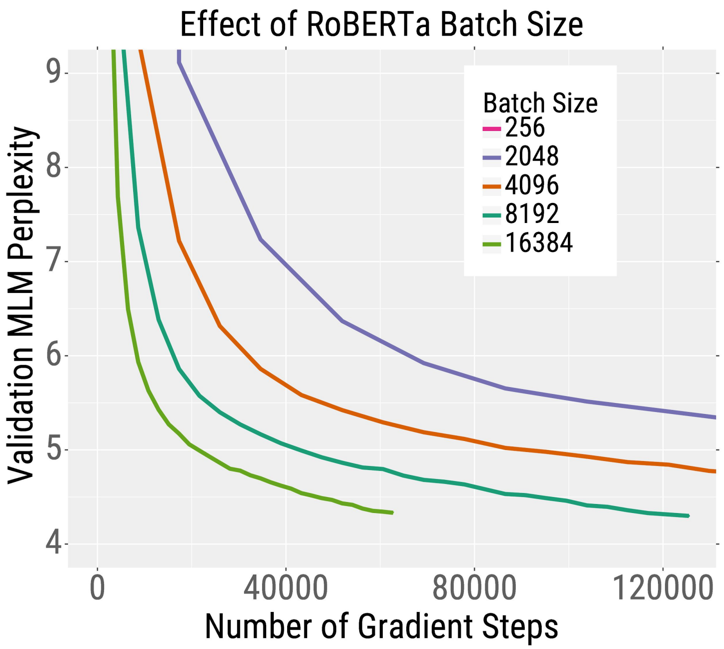
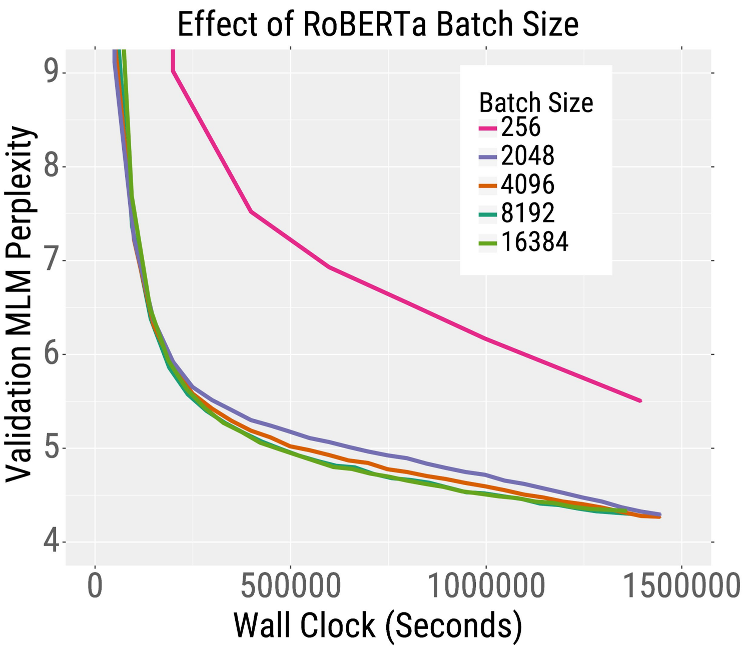




Practical Takeaways

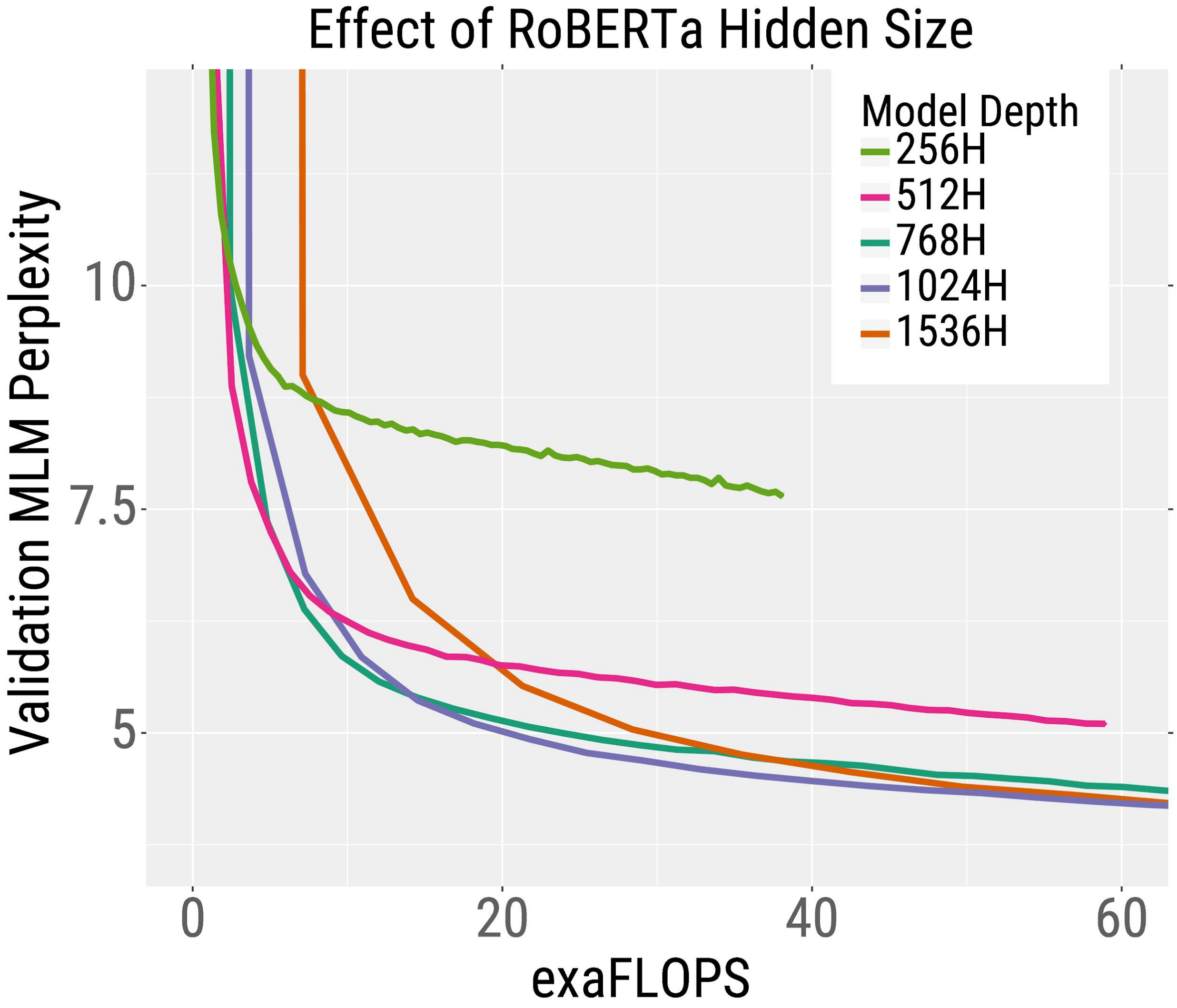
- Increase model width, sometimes depth
- Increase model size not batch size
- **Apply compression methods like pruning/quantization**
  - little to no training overhead
  - compress model up to 8x without hurting performance

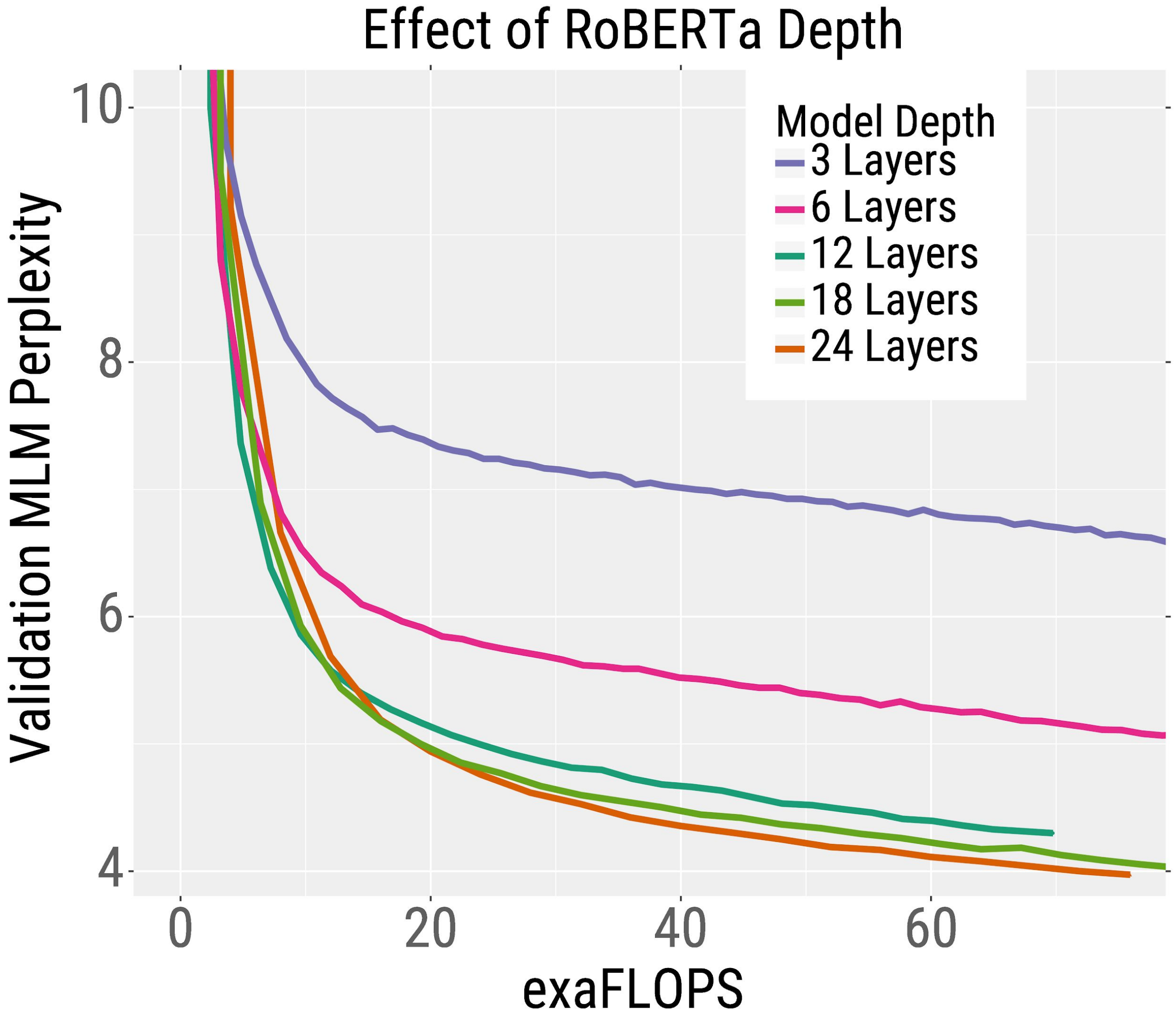
Conclusion

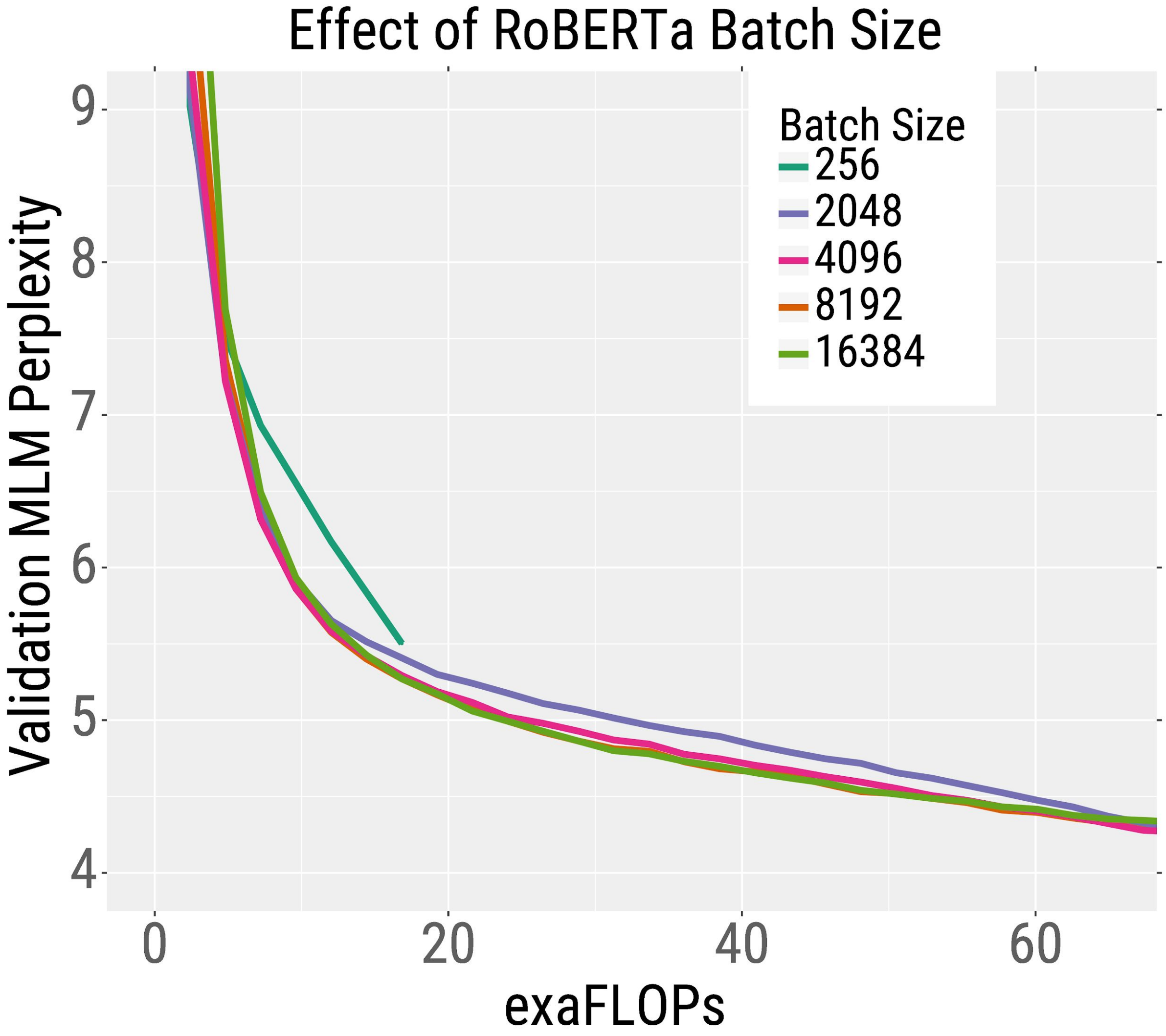
Common Practice	Train Small Model →	Stop Training When Converged →	Lightly Compress
Optimal	Train Large Model →	Stop Training Early →	Heavily Compress

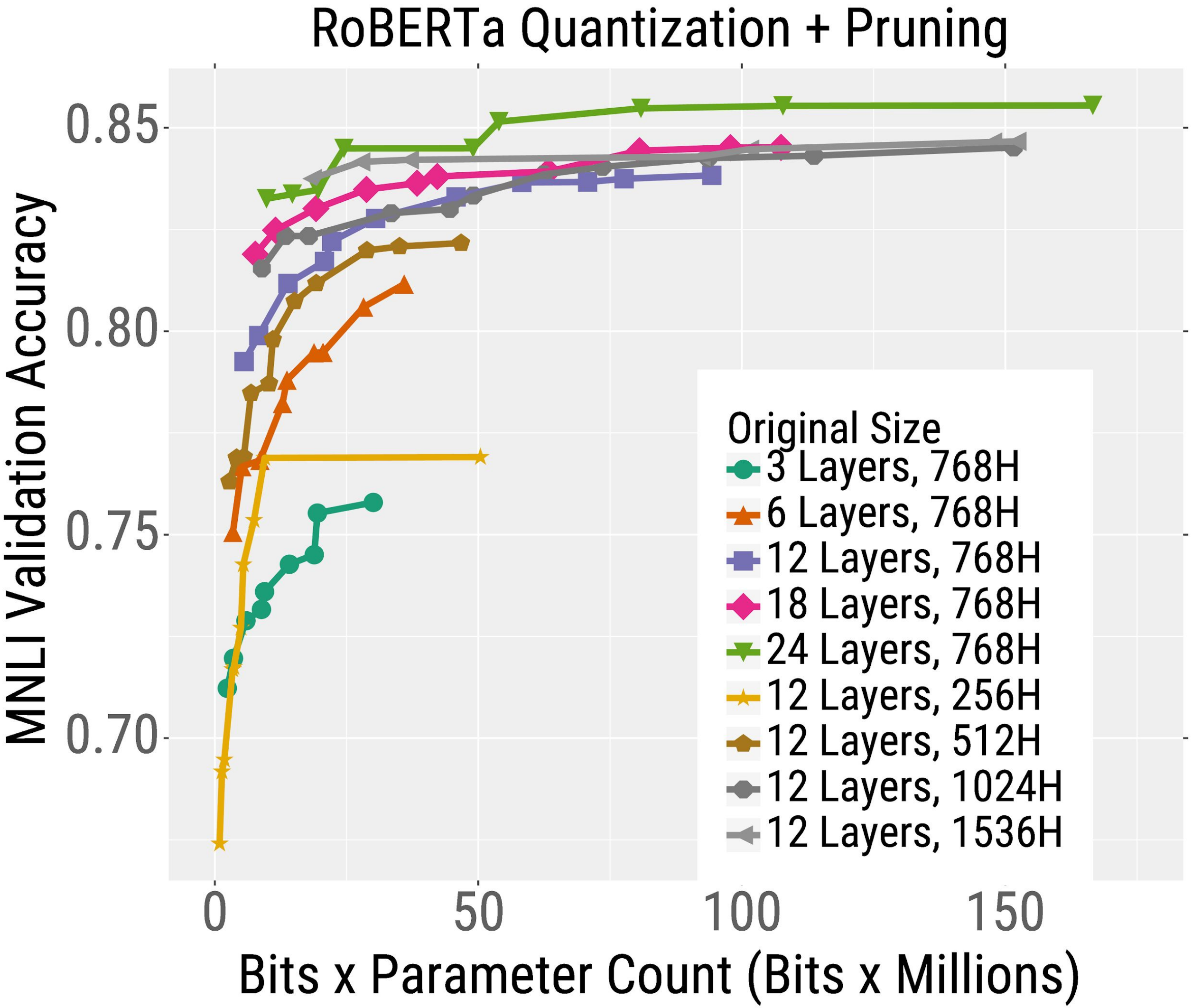
Blog and Paper available

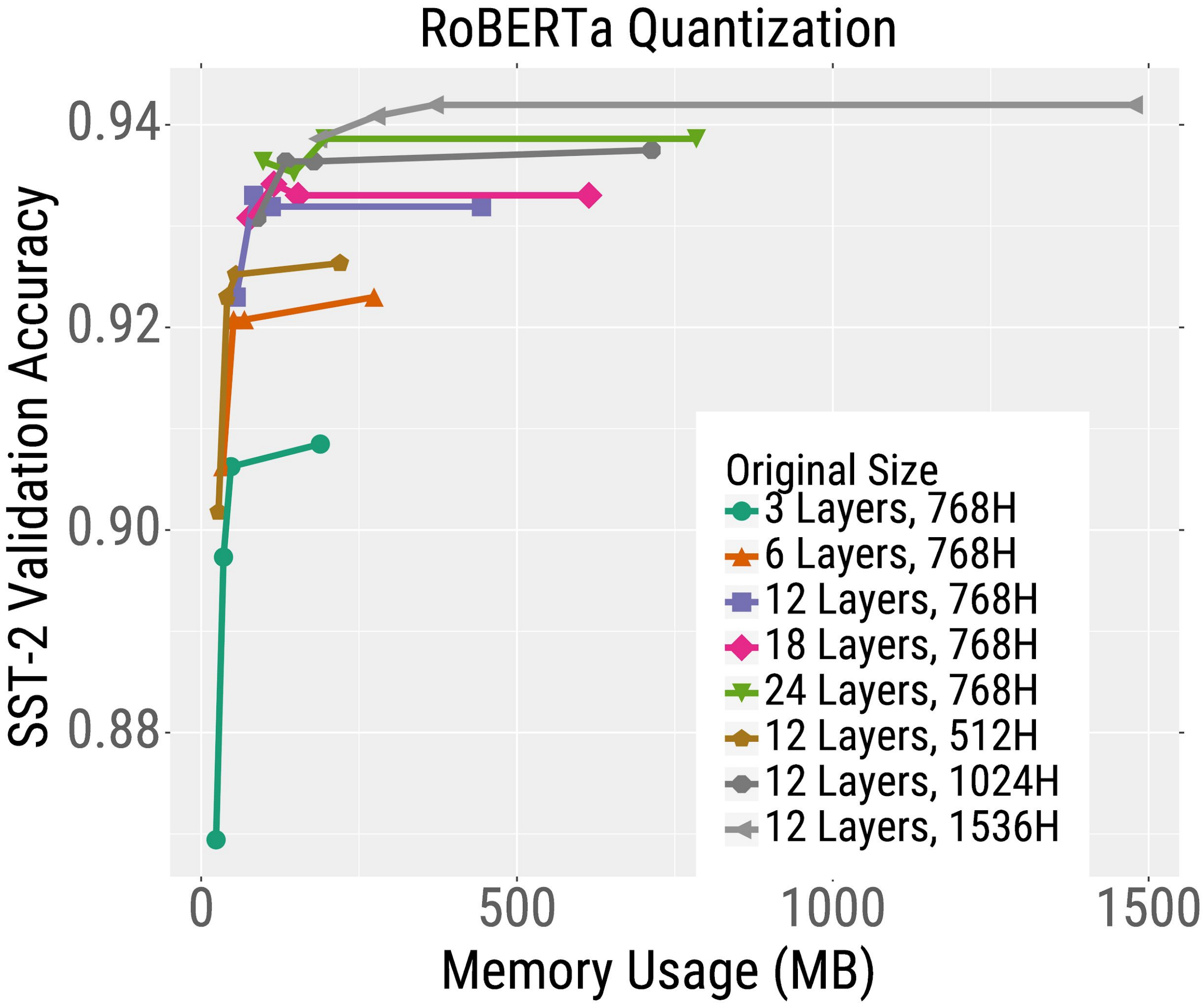
Bonus Slides

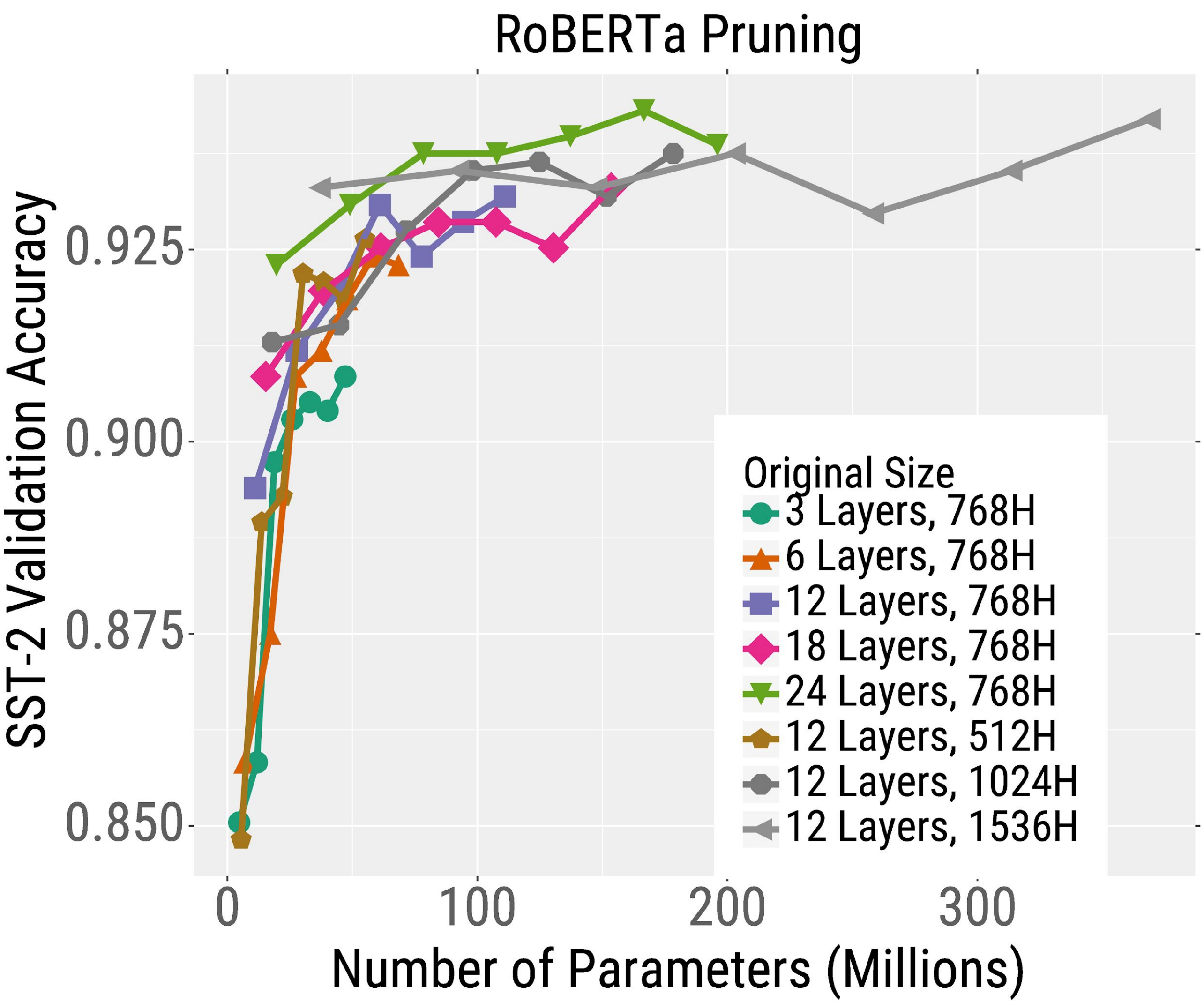

Effect of RoBERTa Hidden Size
Model Depth
256H
512H
768H
1024H
1536H
Validation MLM Perplexity
10
7.5
5
0
20
40
60
exaFLOPS


Effect of RoBERTa Depth
Model Depth
3 Layers
6 Layers
12 Layers
18 Layers
24 Layers
Validation MLM Perplexity
10
8
6
4
0
20
40
60
exaFLOPS


Effect of RoBERTa Batch Size
Validation MLM Perplexity
exaFLOPs
Batch Size
256
2048
4096
8192
16384
9
8
7
6
5
4
0
20
40
60


RoBERTa Quantization + Pruning
MNLI Validation Accuracy
0.85
0.80
0.75
0.70
0
50
100
150
Bits x Parameter Count (Bits x Millions)
Original Size
3 Layers, 768H
6 Layers, 768H
12 Layers, 768H
18 Layers, 768H
24 Layers, 768H
12 Layers, 256H
12 Layers, 512H
12 Layers, 1024H
12 Layers, 1536H


RoBERTa Quantization
SST-2 Validation Accuracy
0.94
0.92
0.90
0.88
0
500
1000
1500
Memory Usage (MB)
Original Size
3 Layers, 768H
6 Layers, 768H
12 Layers, 768H
18 Layers, 768H
24 Layers, 768H
12 Layers, 512H
12 Layers, 1024H
12 Layers, 1536H


RoBERTa Pruning
SST-2 Validation Accuracy
0.850
0.875
0.900
0.925
0
100
200
300
Number of Parameters (Millions)
Original Size
3 Layers, 768H
6 Layers, 768H
12 Layers, 768H
18 Layers, 768H
24 Layers, 768H
12 Layers, 512H
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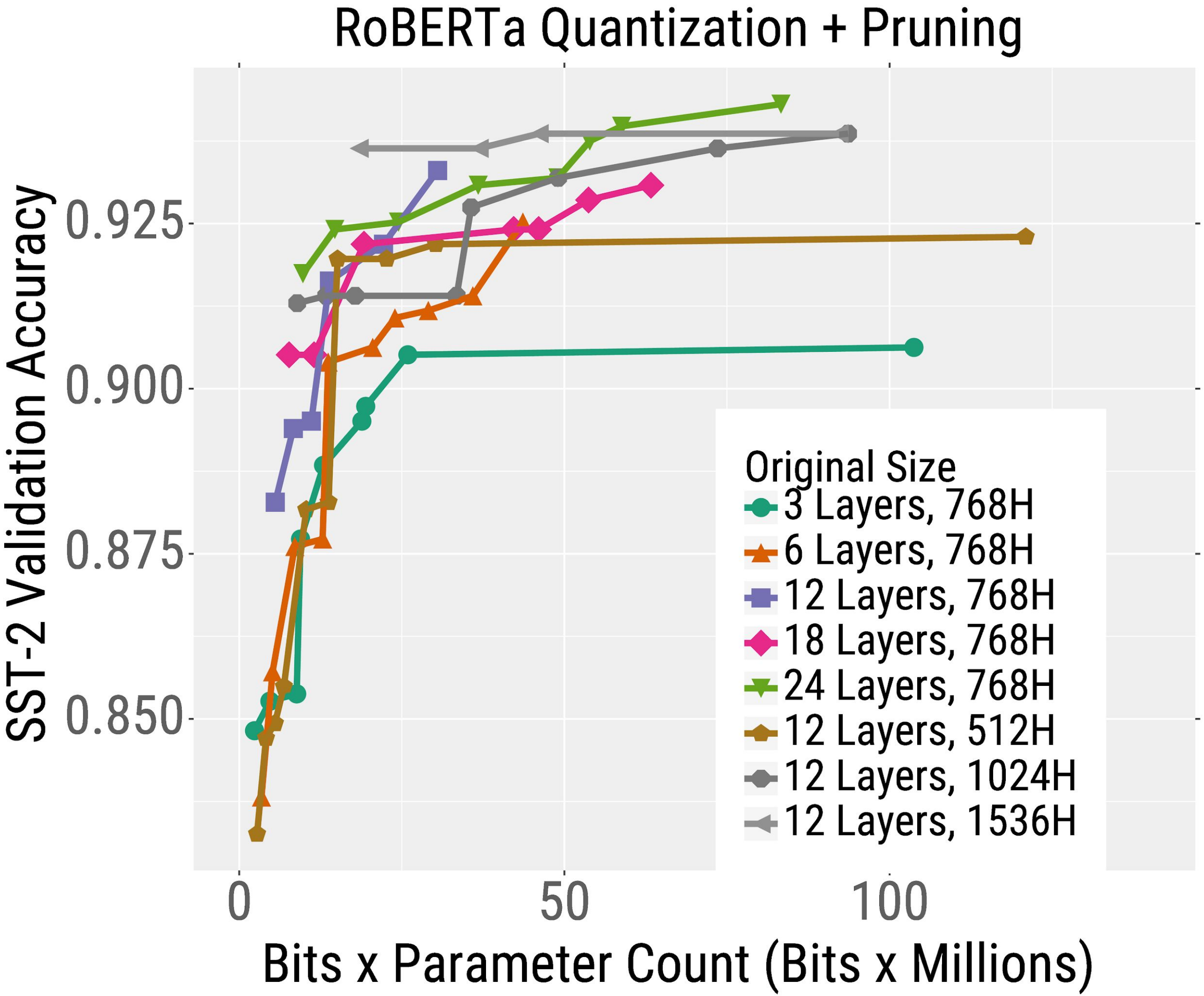
RoBERTa Quantization + Pruning
SST-2 Validation Accuracy
0.925
0.900
0.875
0.850
0
50
100
Bits x Parameter Count (Bits x Millions)
Original Size
3 Layers, 768H
6 Layers, 768H
12 Layers, 768H
18 Layers, 768H
24 Layers, 768H
12 Layers, 512H
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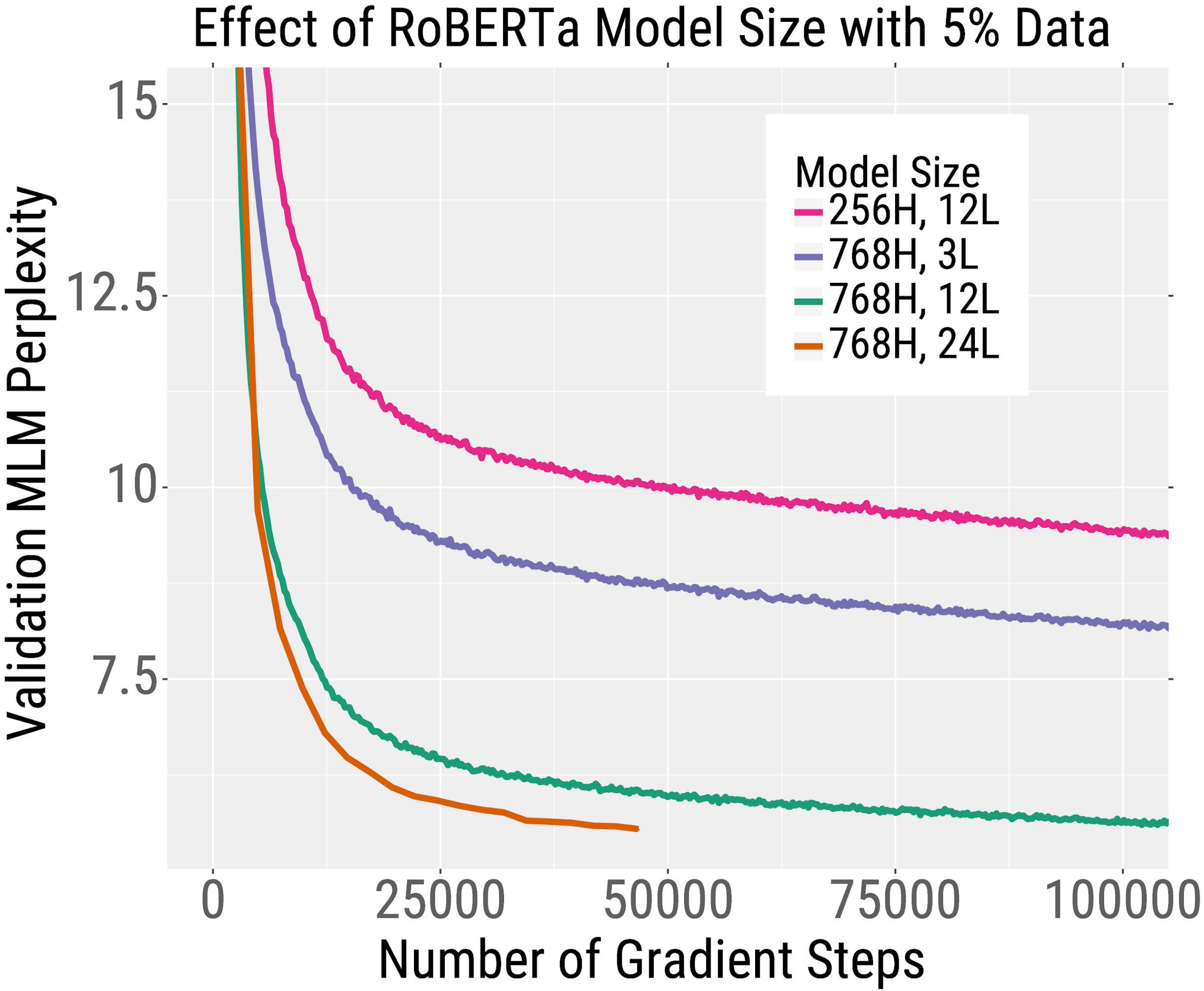
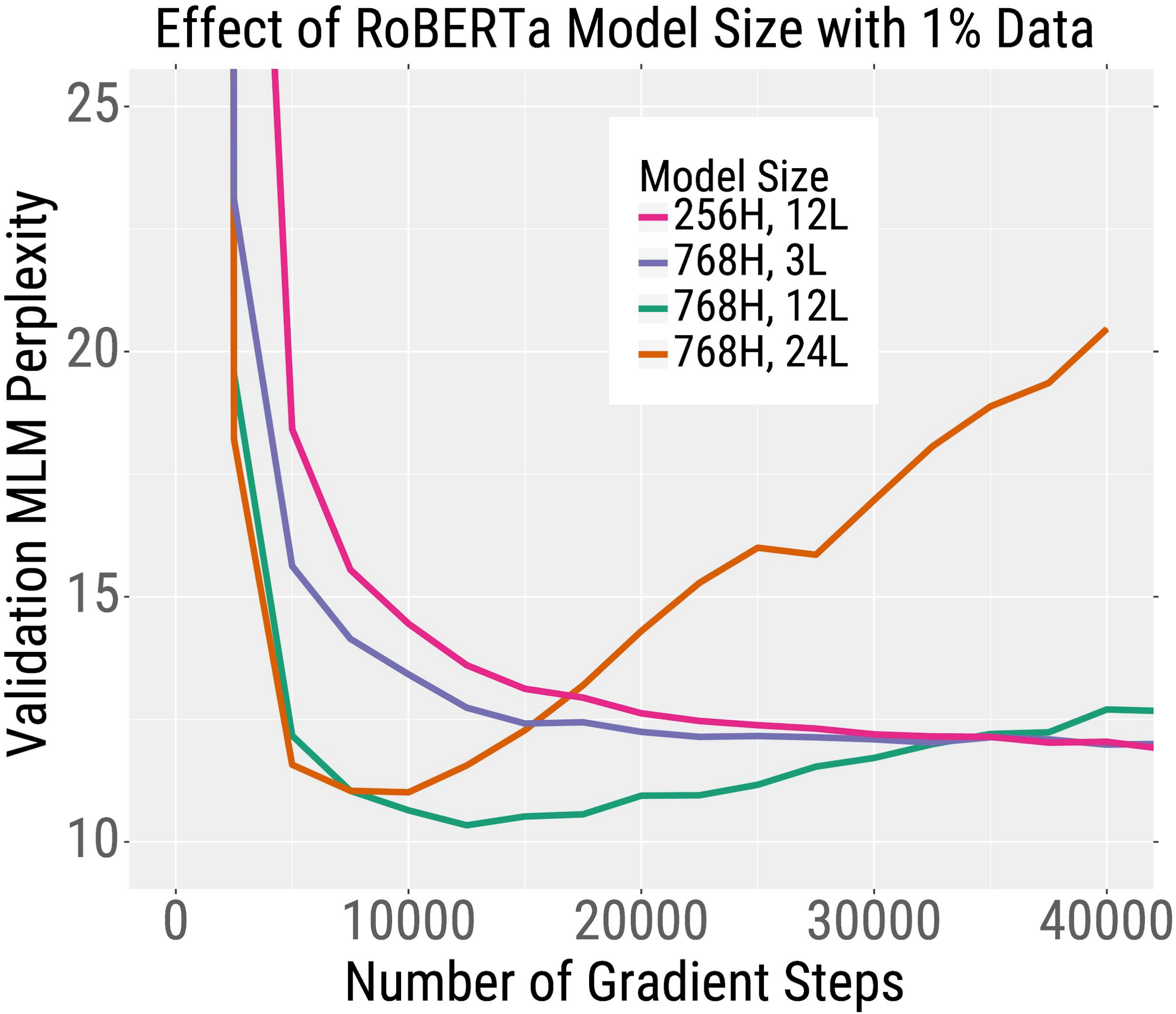
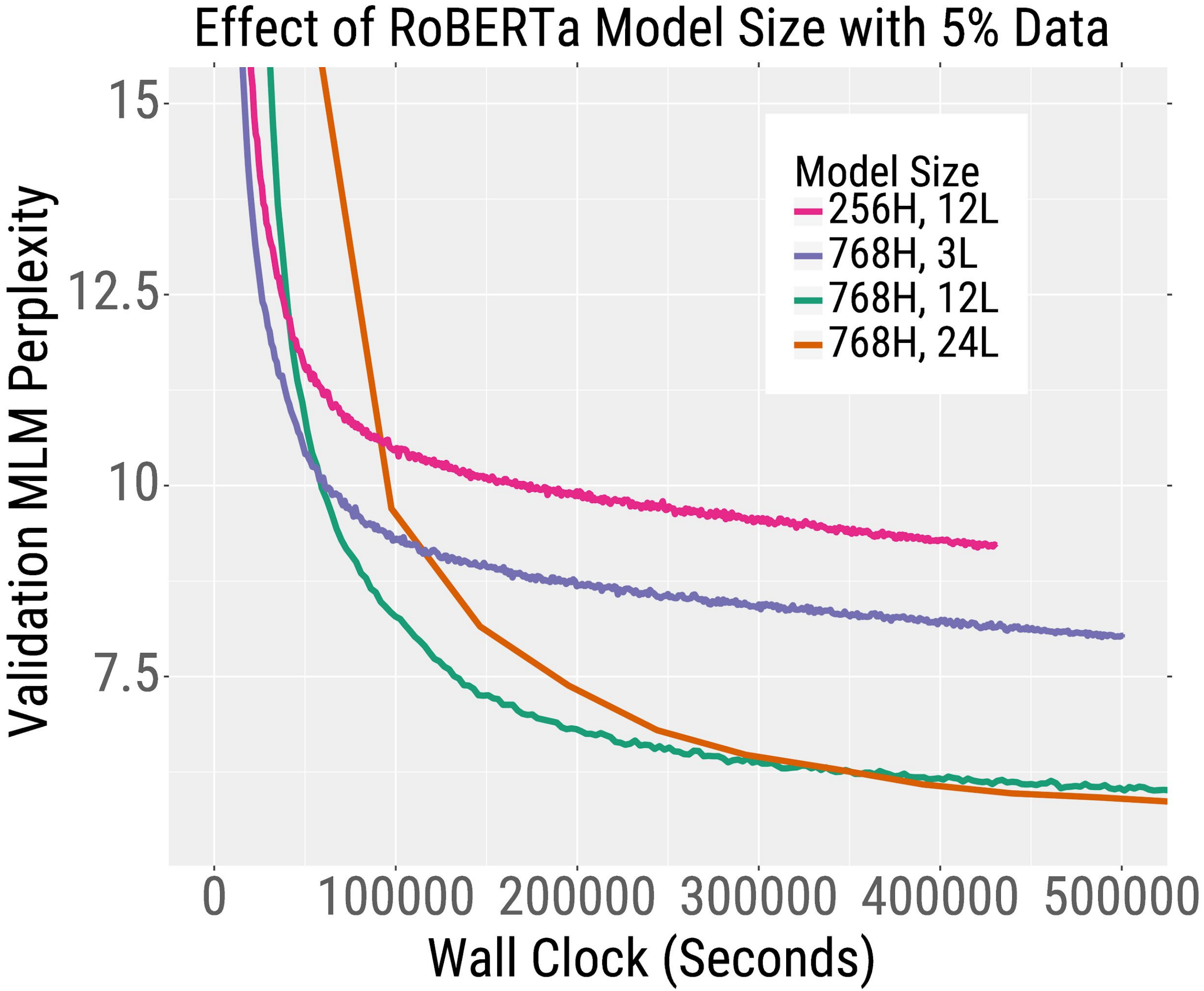
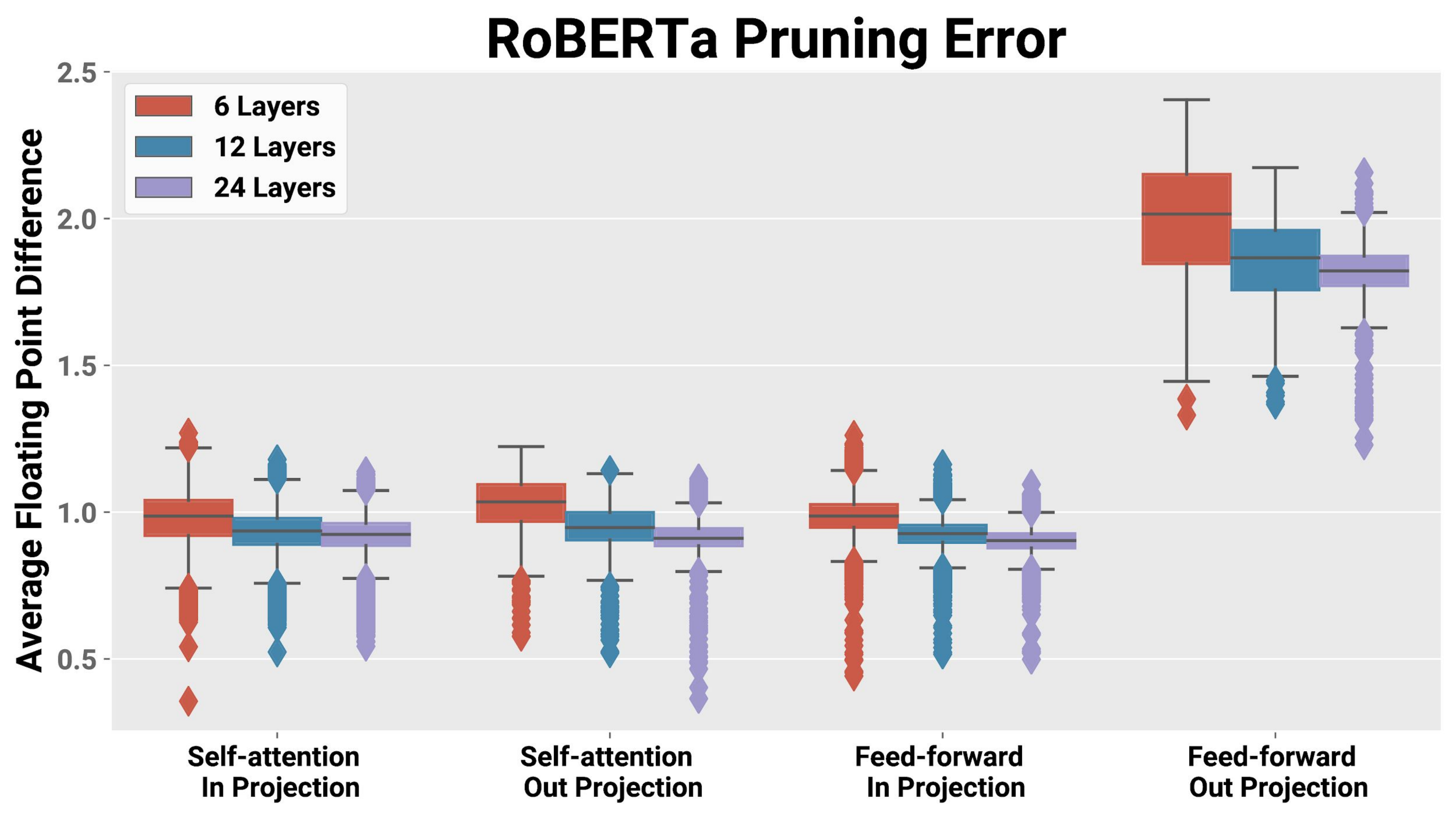


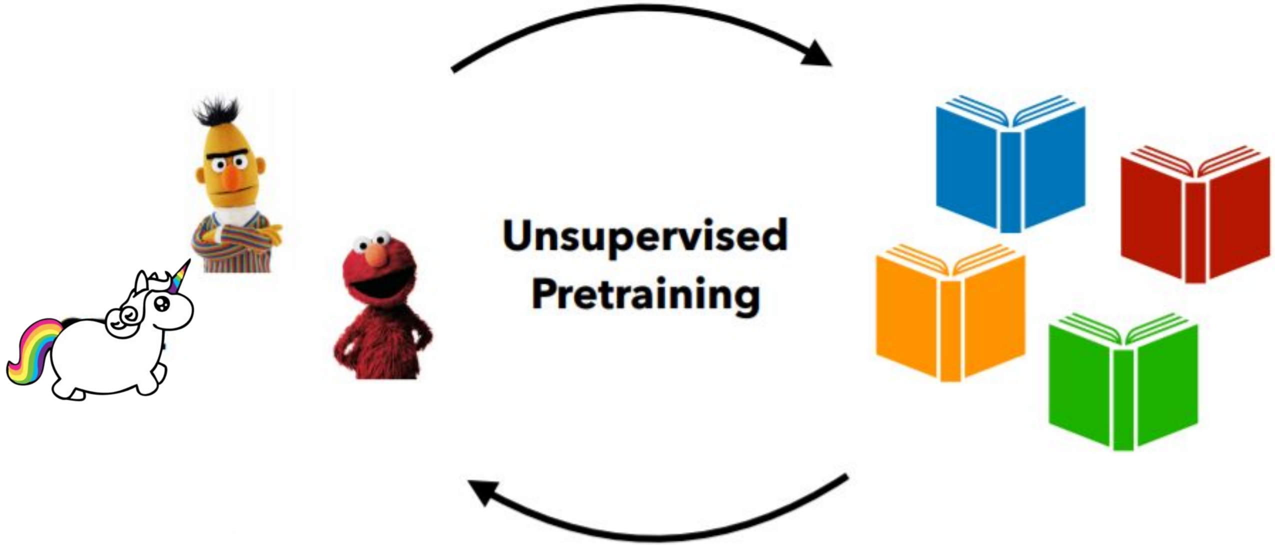
Effect of RoBERTa Model Size with 5% Data
Validation MLM Perplexity
15
12.5
10
7.5
0
25000
50000
75000
100000
Number of Gradient Steps
Model Size
256H, 12L
768H, 3L
768H, 12L
768H, 24L



Effect of RoBERTa Model Size with 1% Data
Model Size
256H, 12L
768H, 3L
768H, 12L
768H, 24L
Validation MLM Perplexity
25
20
15
10
0
10000
20000
30000
40000
Number of Gradient Steps


Effect of RoBERTa Model Size with 5% Data
Validation MLM Perplexity
15
12.5
10
7.5
0
100000
200000
300000
400000
500000
Wall Clock (Seconds)
Model Size
256H, 12L
768H, 3L
768H, 12L
768H, 24L


RoBERTa Pruning Error
6 Layers
12 Layers
24 Layers
Average Floating Point Difference
2.5
2.0
1.5
1.0
0.5
Self-attention In Projection
Self-attention Out Projection
Feed-forward In Projection
Feed-forward Out Projection


Unsupervised
Pretraining