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

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- One can **trade compute for accuracy**
  - Larger model size
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- **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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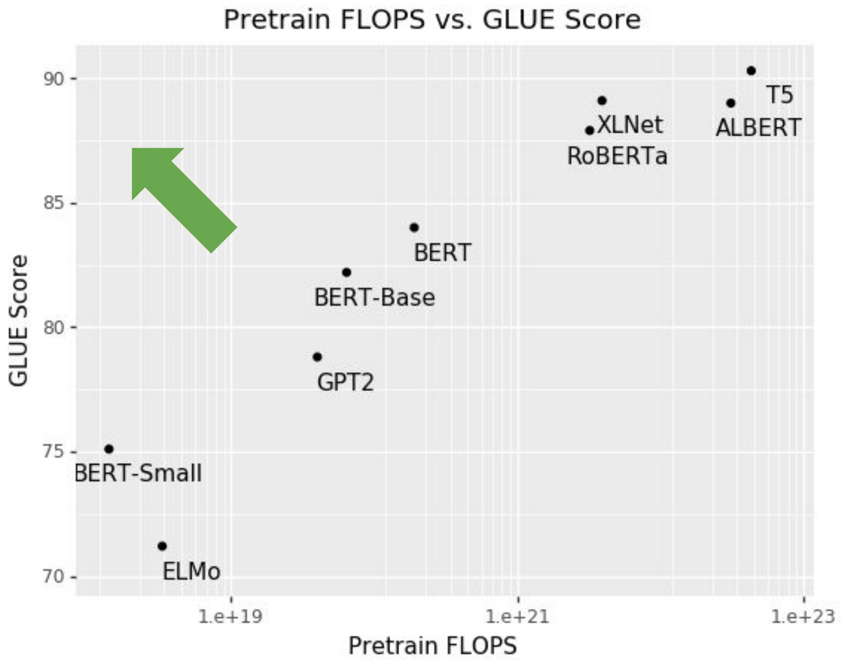

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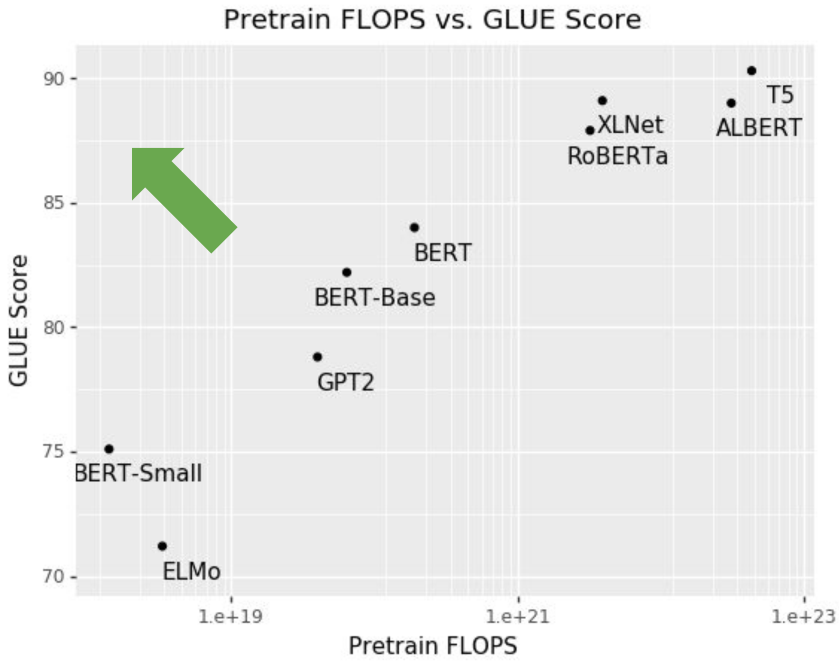

Rethinking Common Assumptions

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    - *Small* models **train** *faster*

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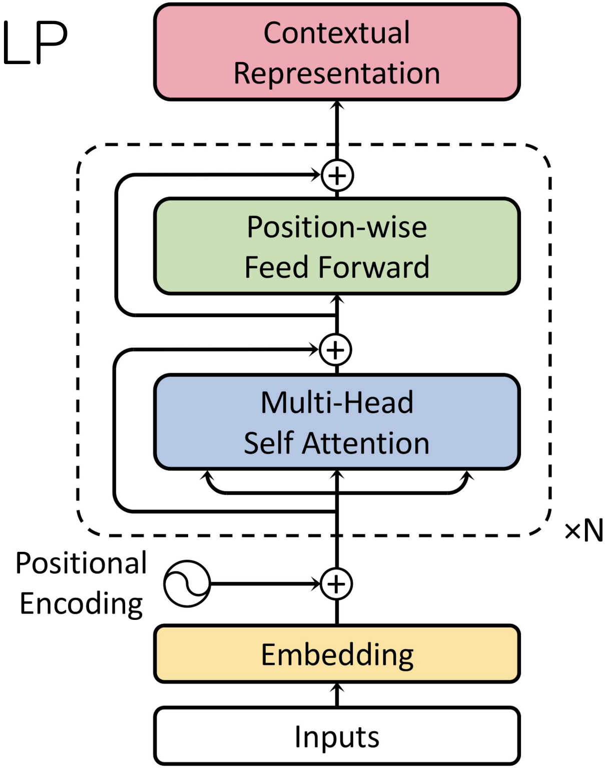
- Key idea: stop training early & compress heavily

Training Efficiency

Experimental Setup

- Transformer models
  - Feedforward architecture, SoTA for NLP



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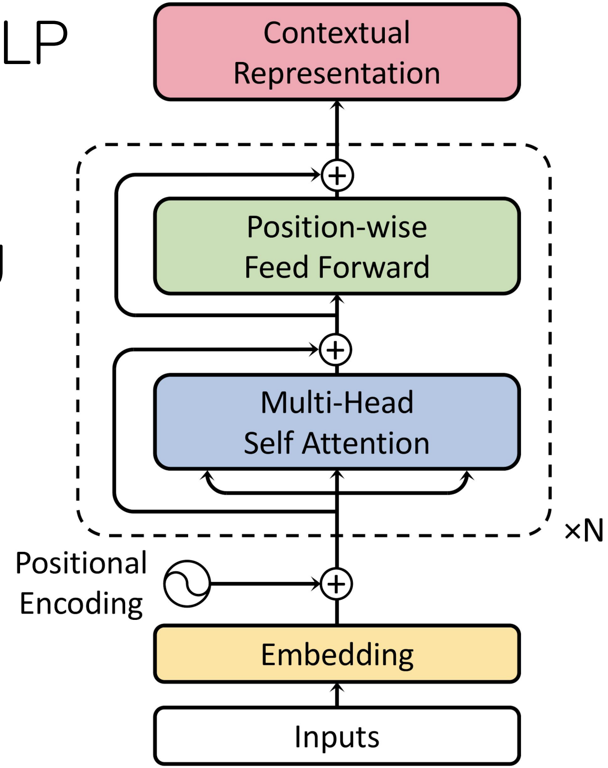
  increase batch size to fill the GPU



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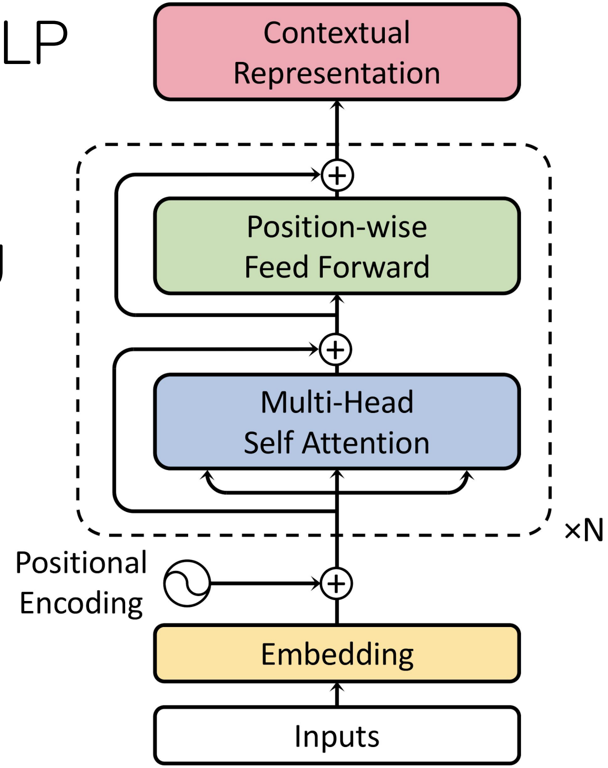
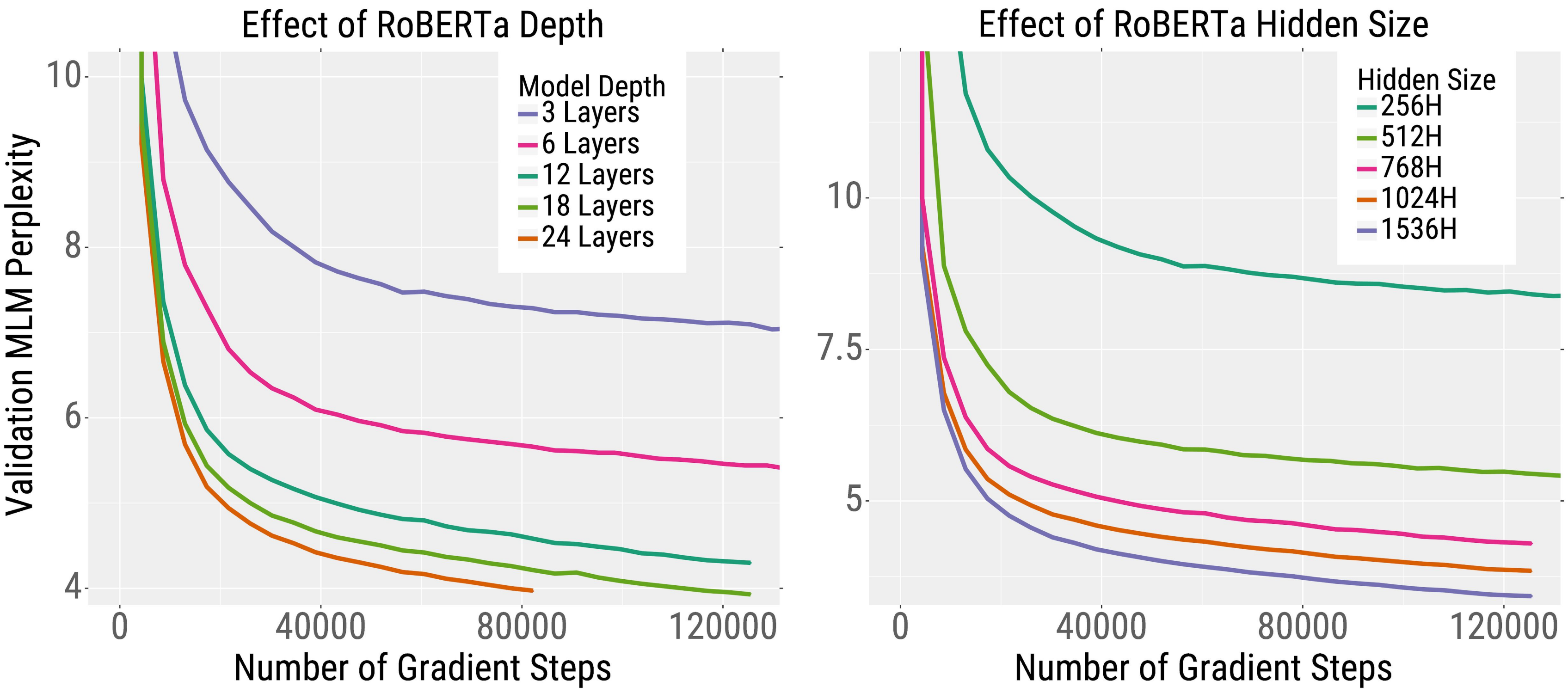
- Task 1: **MLM pretraining + finetuning (RoBERTa)**
- Task 2: **machine translation**



Deeper and Wider Models Converge in Fewer Steps



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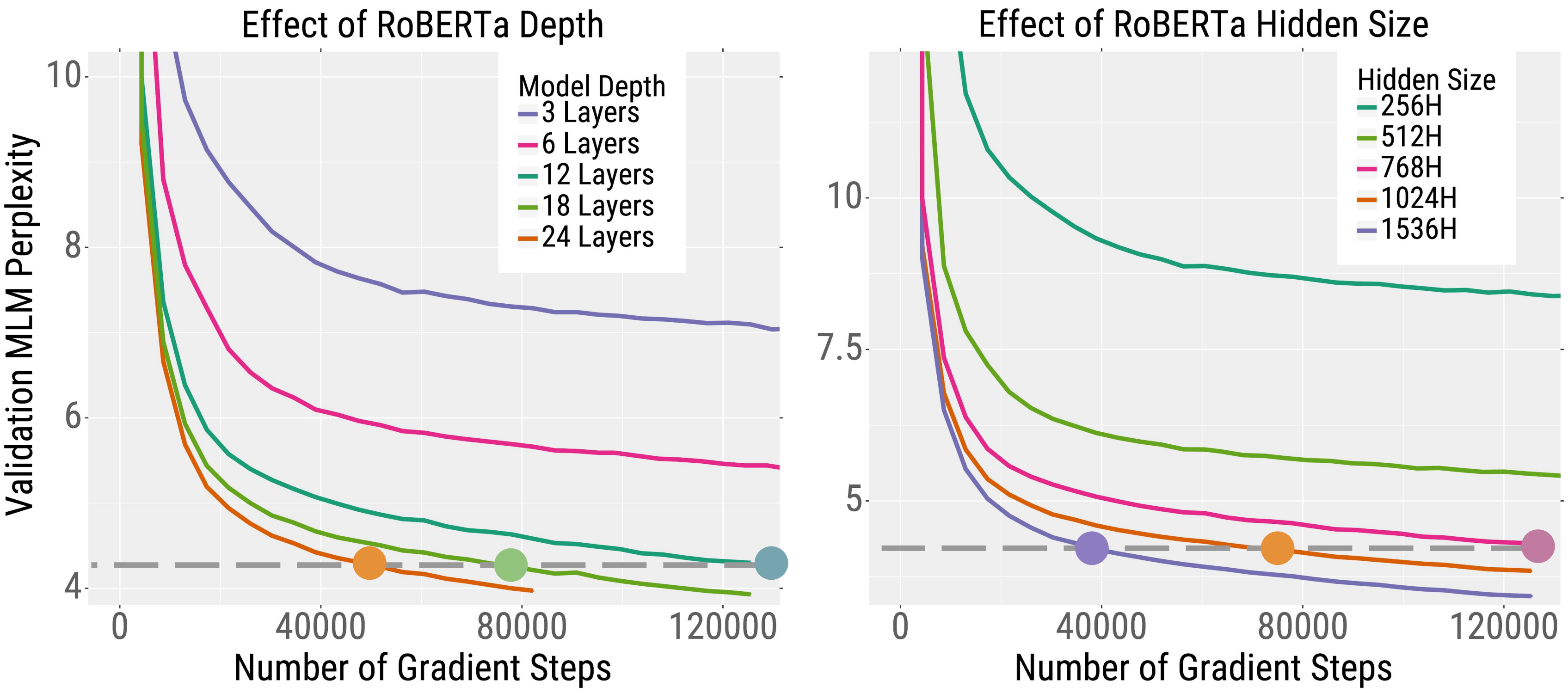
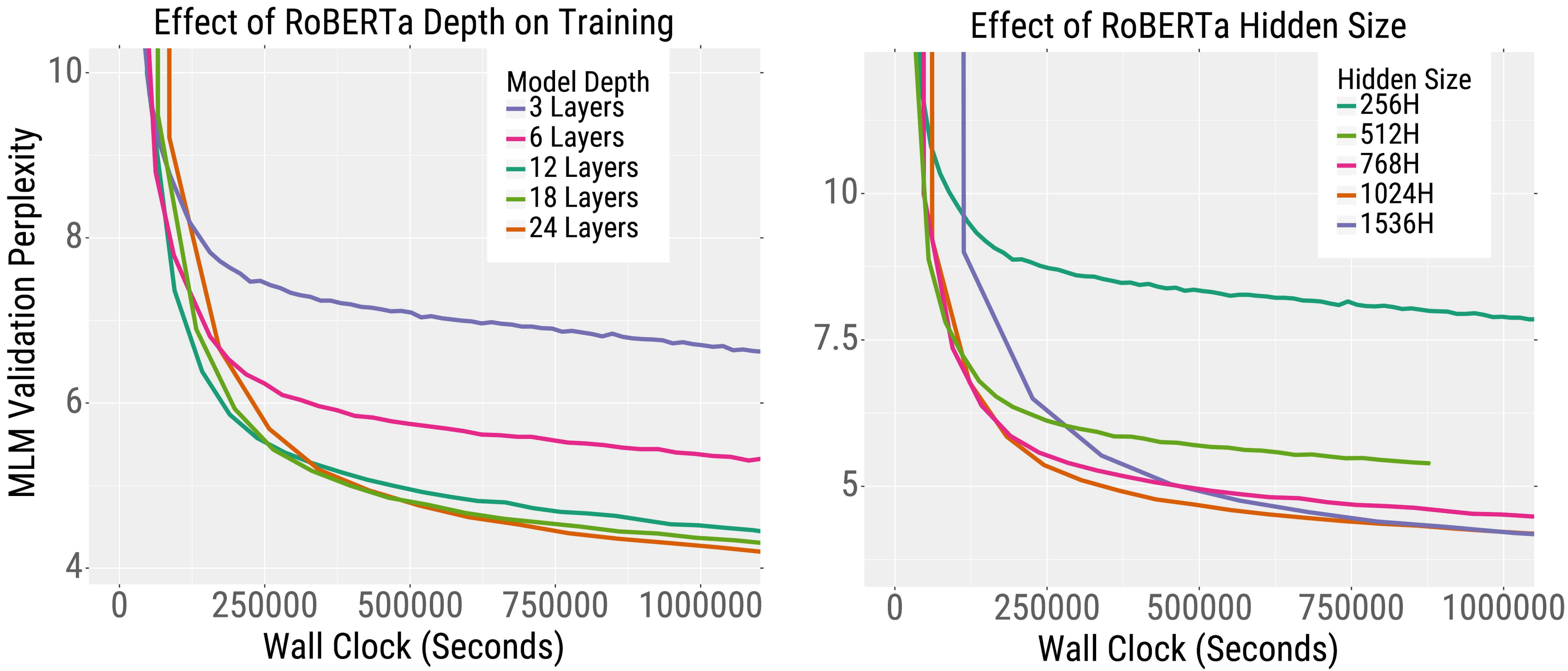


Deeper and Wider Models Converge in Less Wall Clock Time



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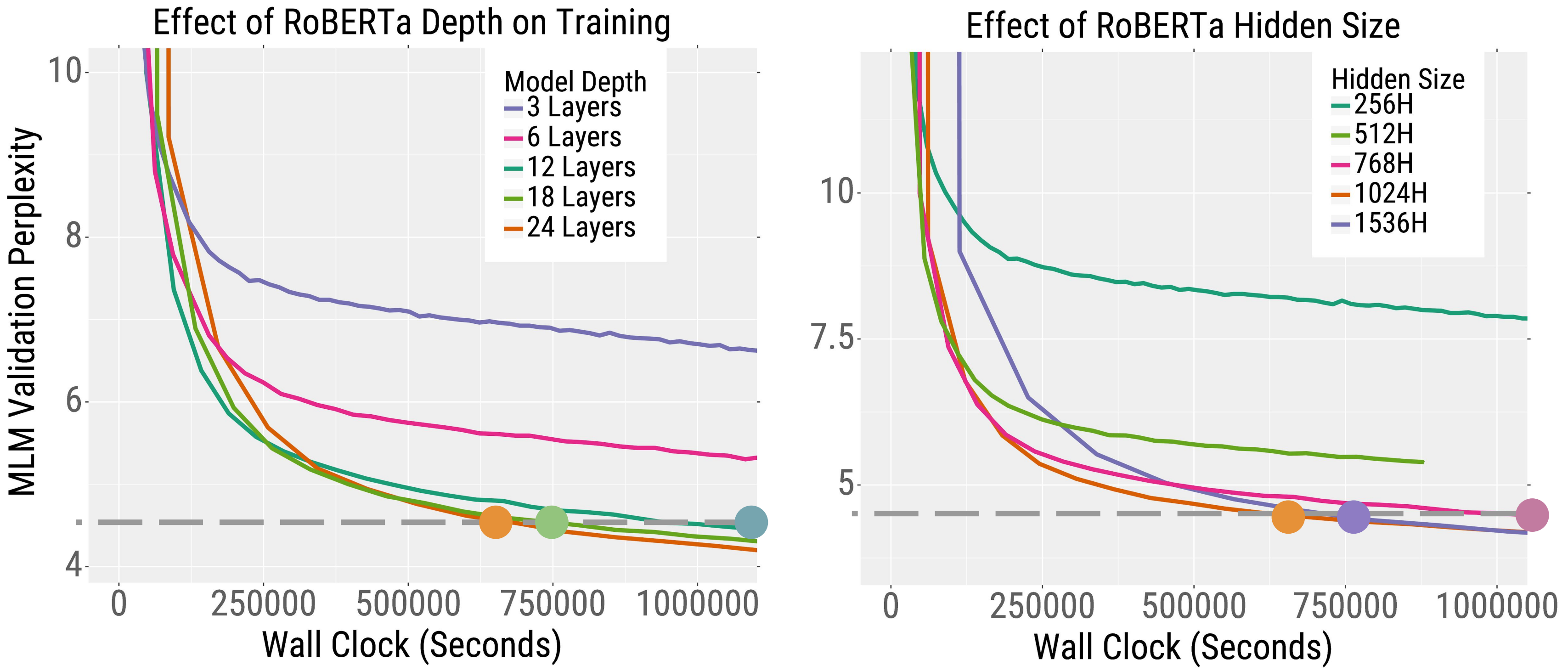
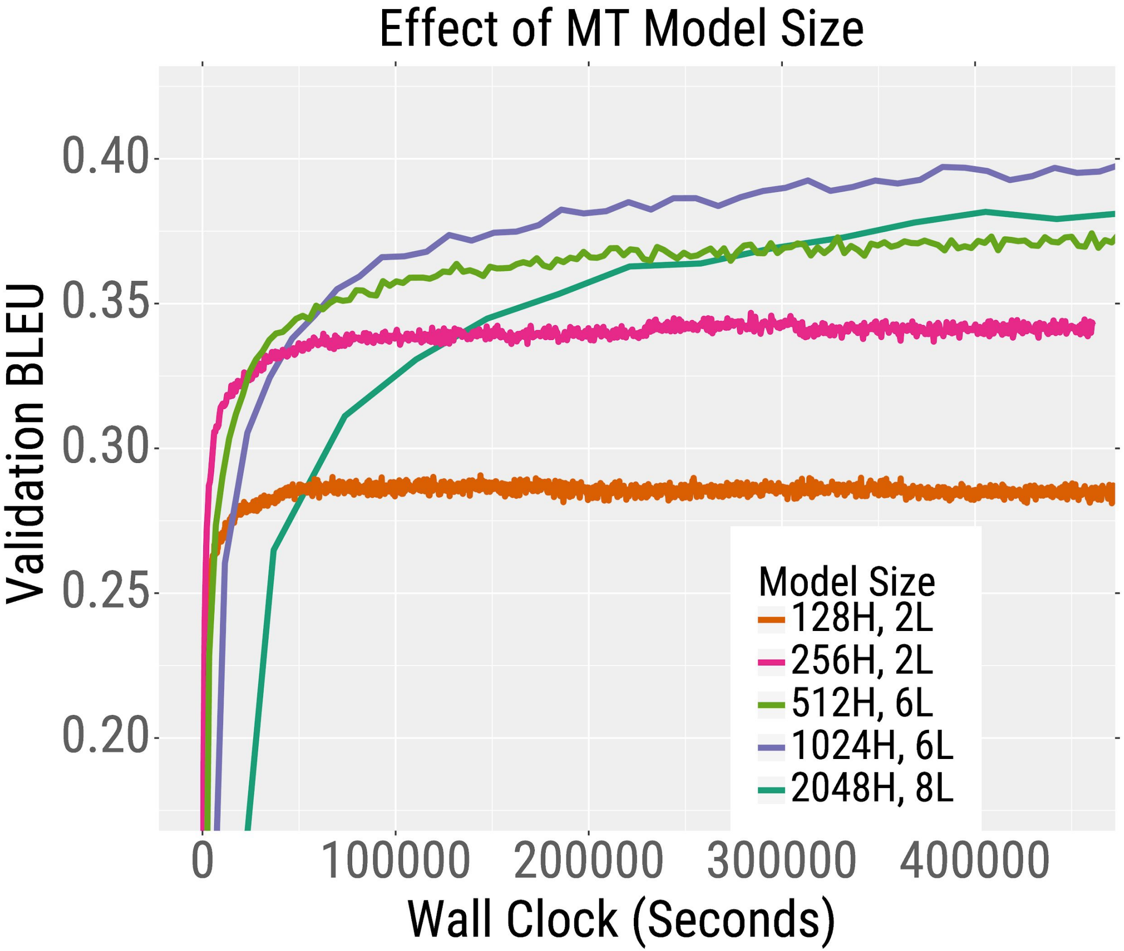


Same Trends Hold for Machine Translation



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- Larger models reduce **training** error faster
- MLM training has "**unlimited**" data ⟶ overfitting *not* a concern
- Thus, larger models also minimize **validation** error faster

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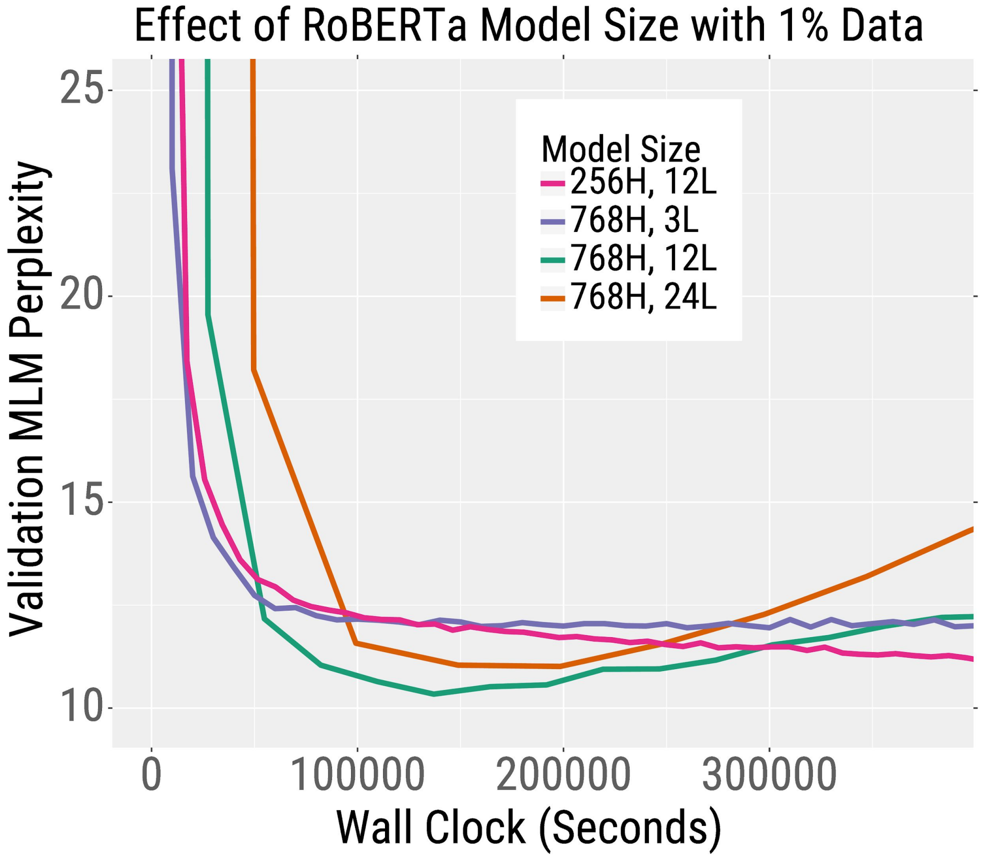
- When overfitting *is* a concern, be careful of how big you go



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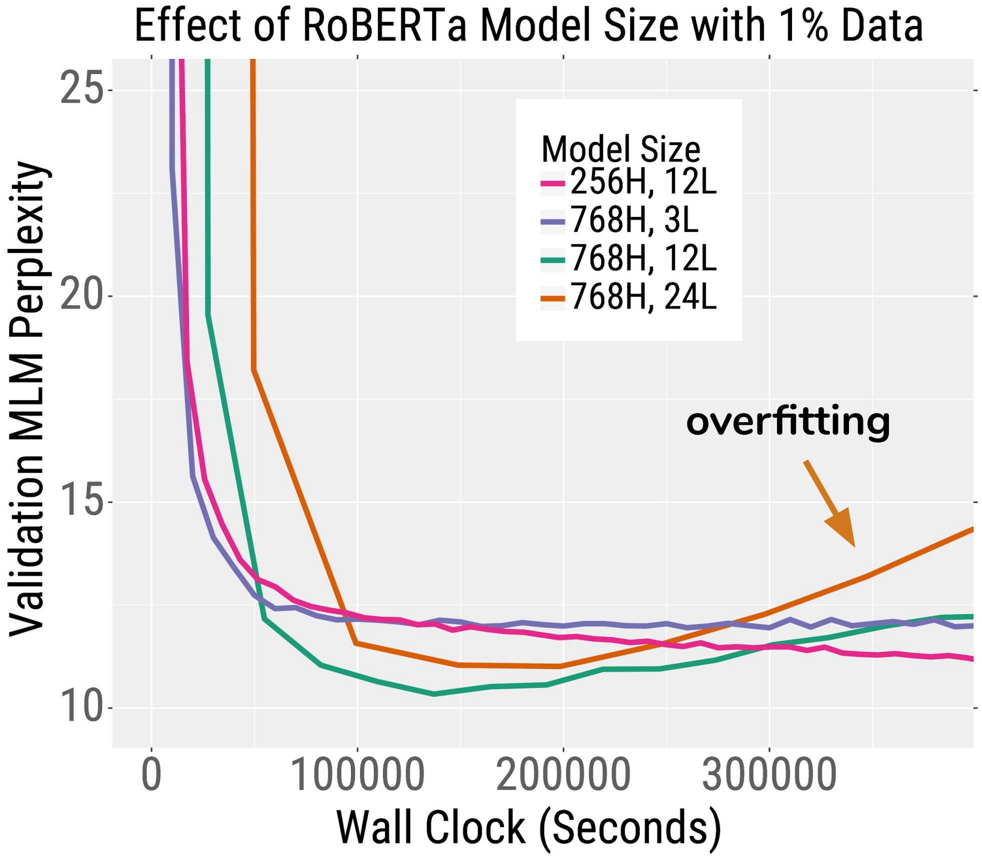

Inference Efficiency

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

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

Trade-off between large and small models?

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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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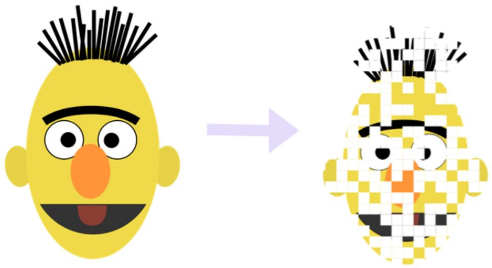

Image: Rasa

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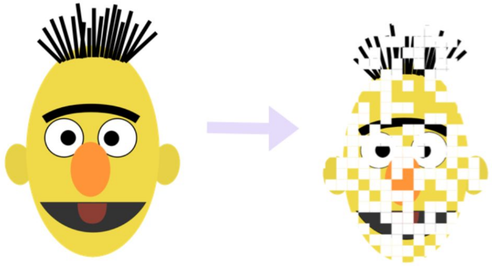

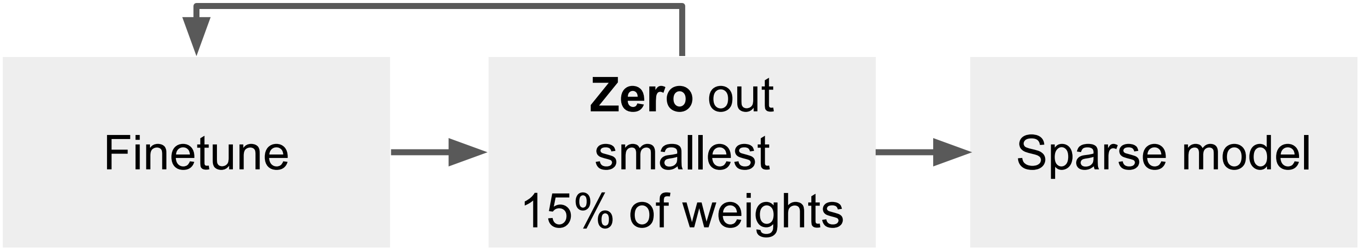

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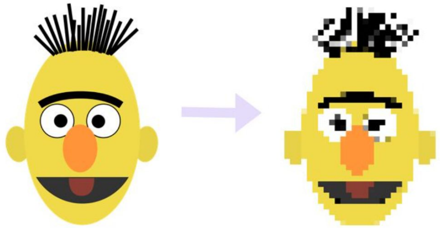
Experimental Setup

- 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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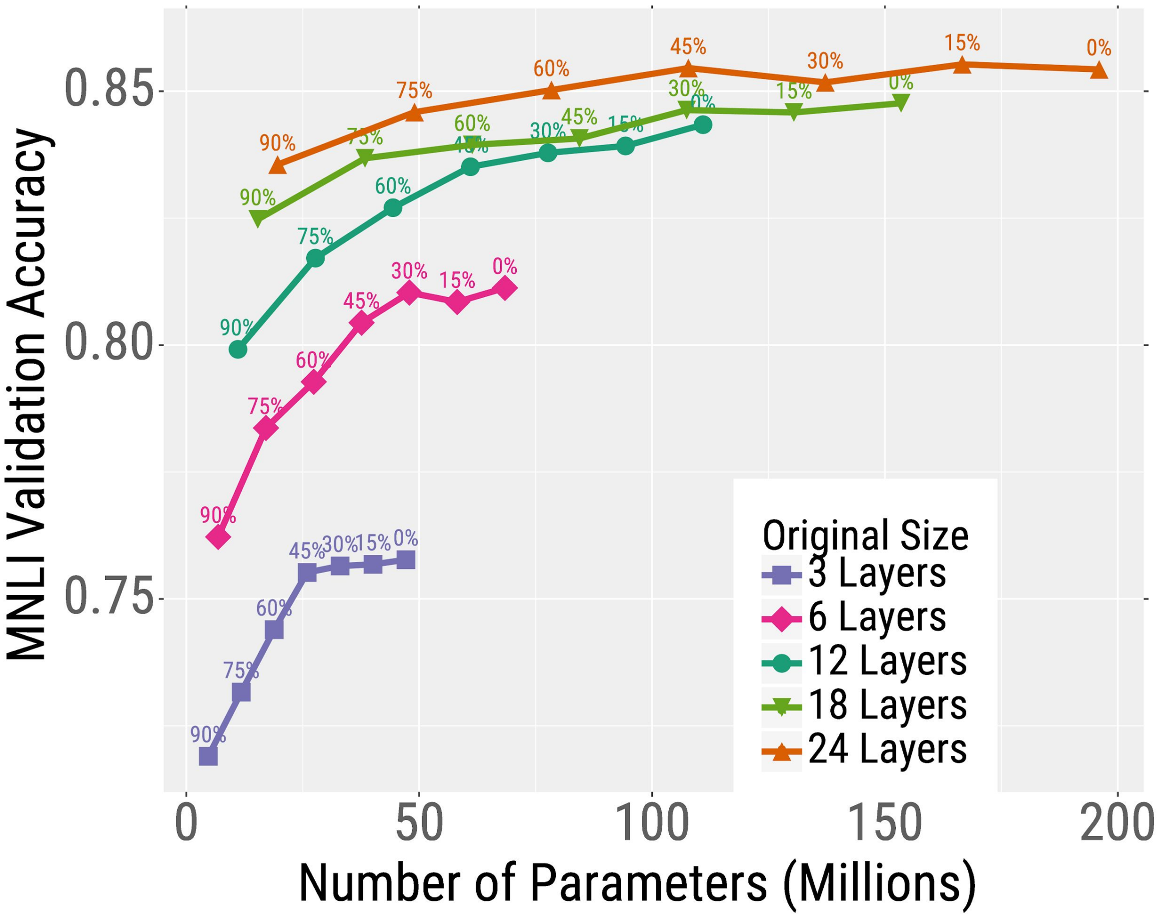
Deeper and Wider Models are More Robust to Pruning



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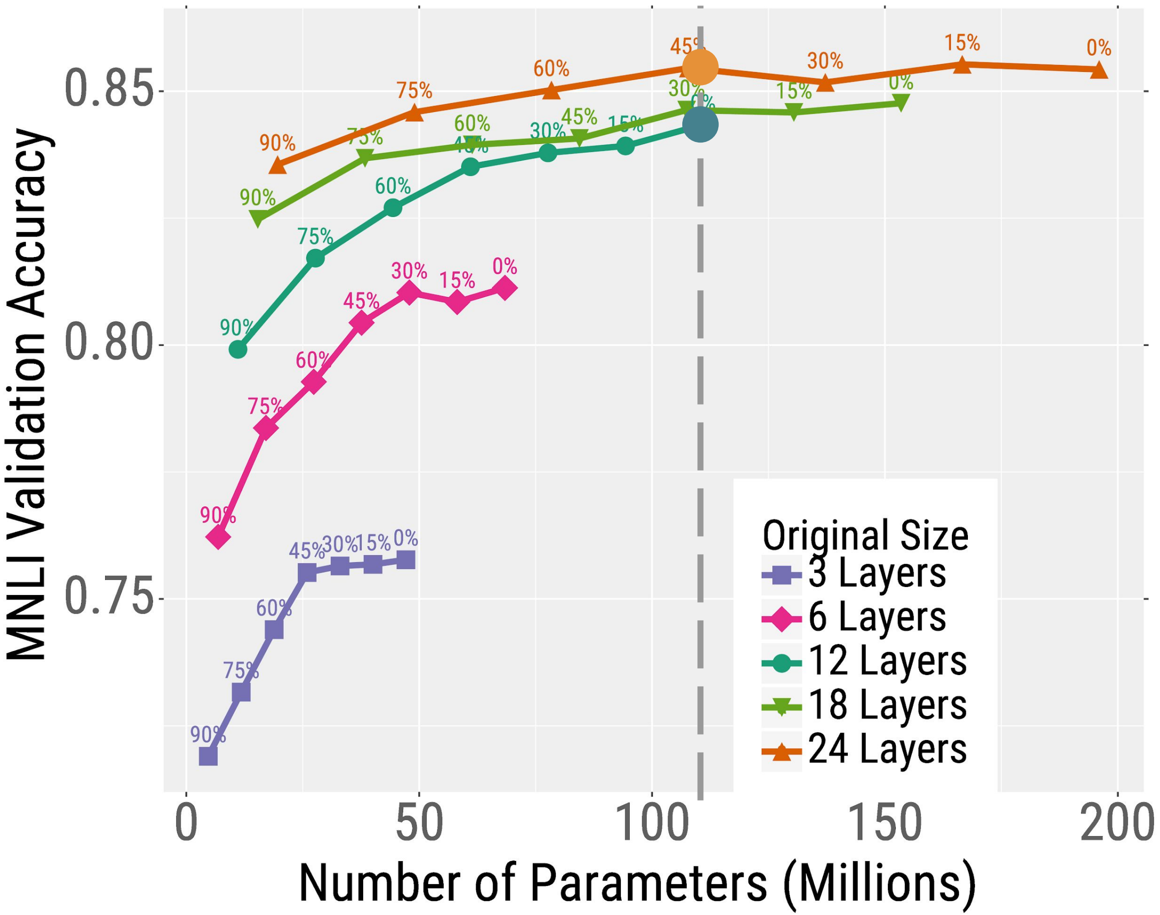

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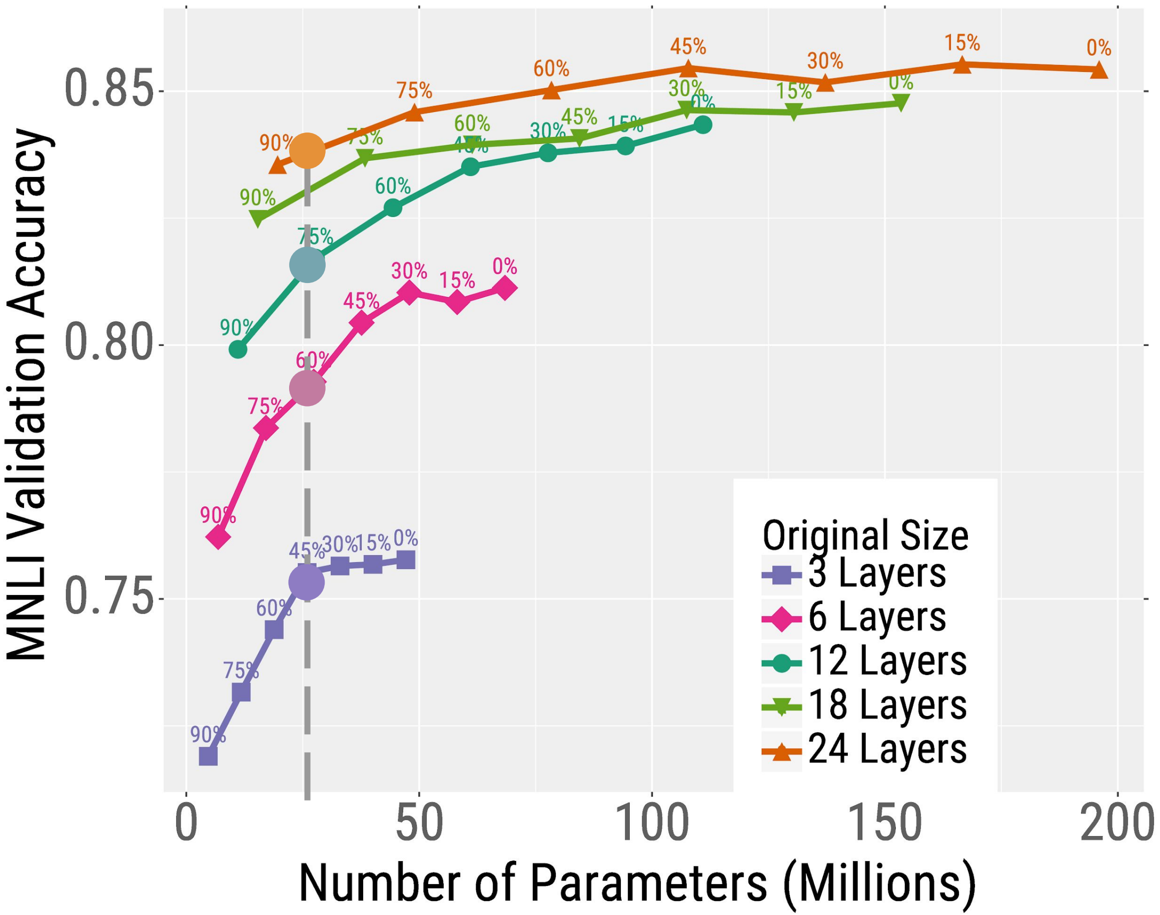
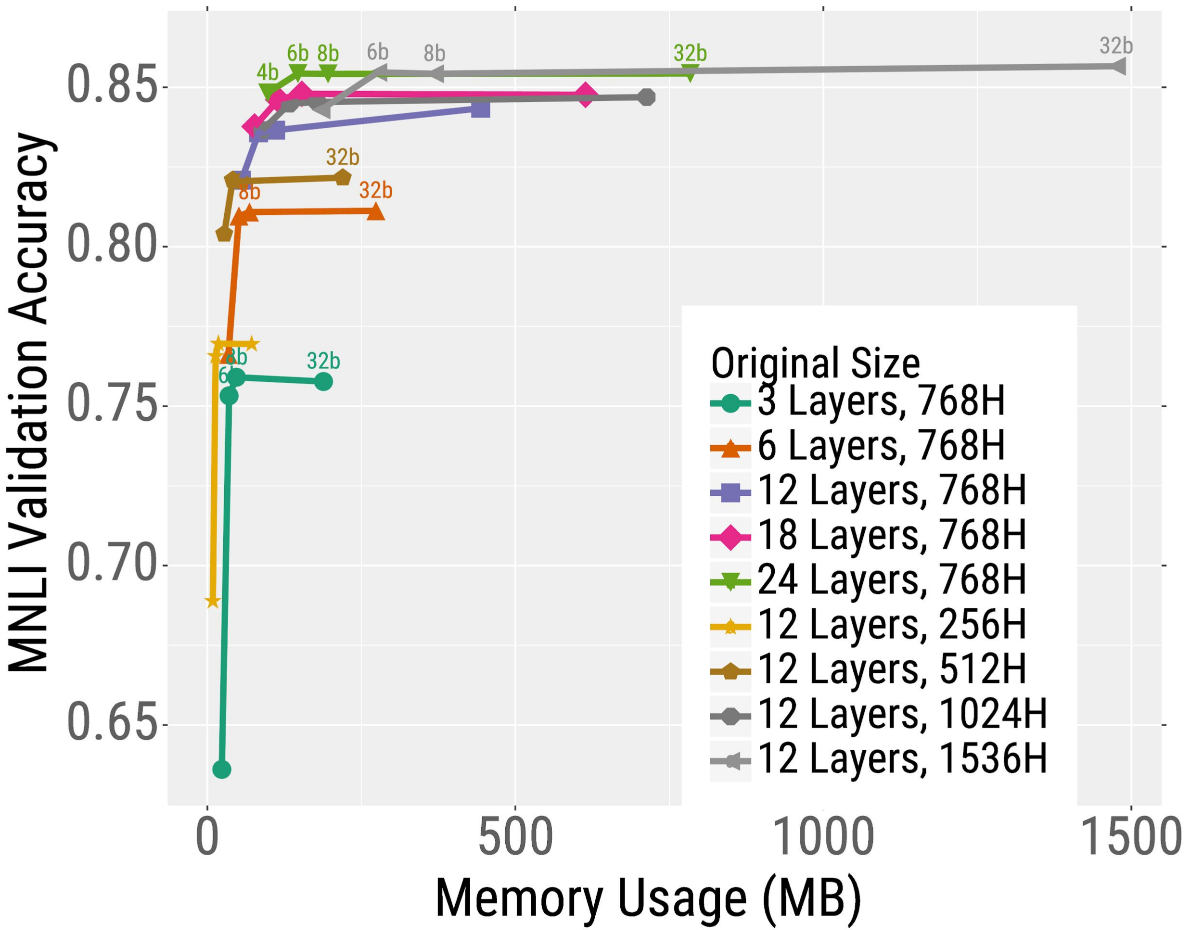
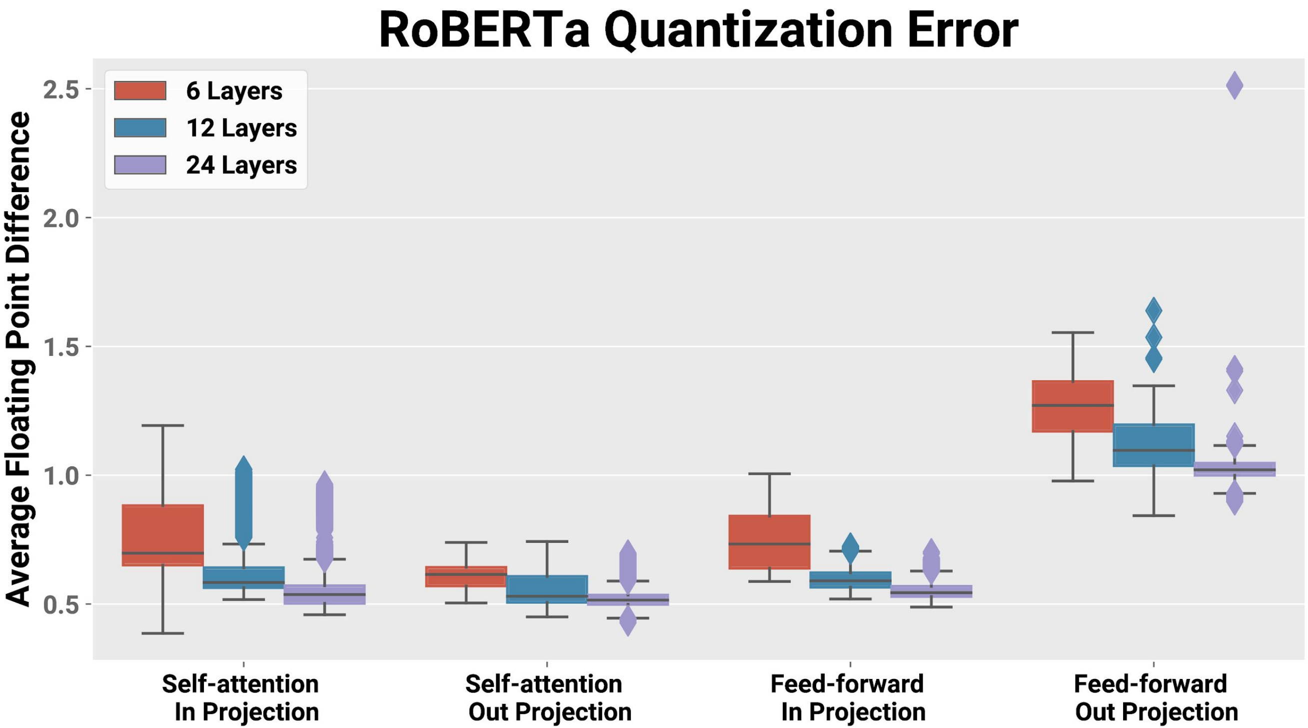


Deeper and Wider Models are More Robust to Quantization



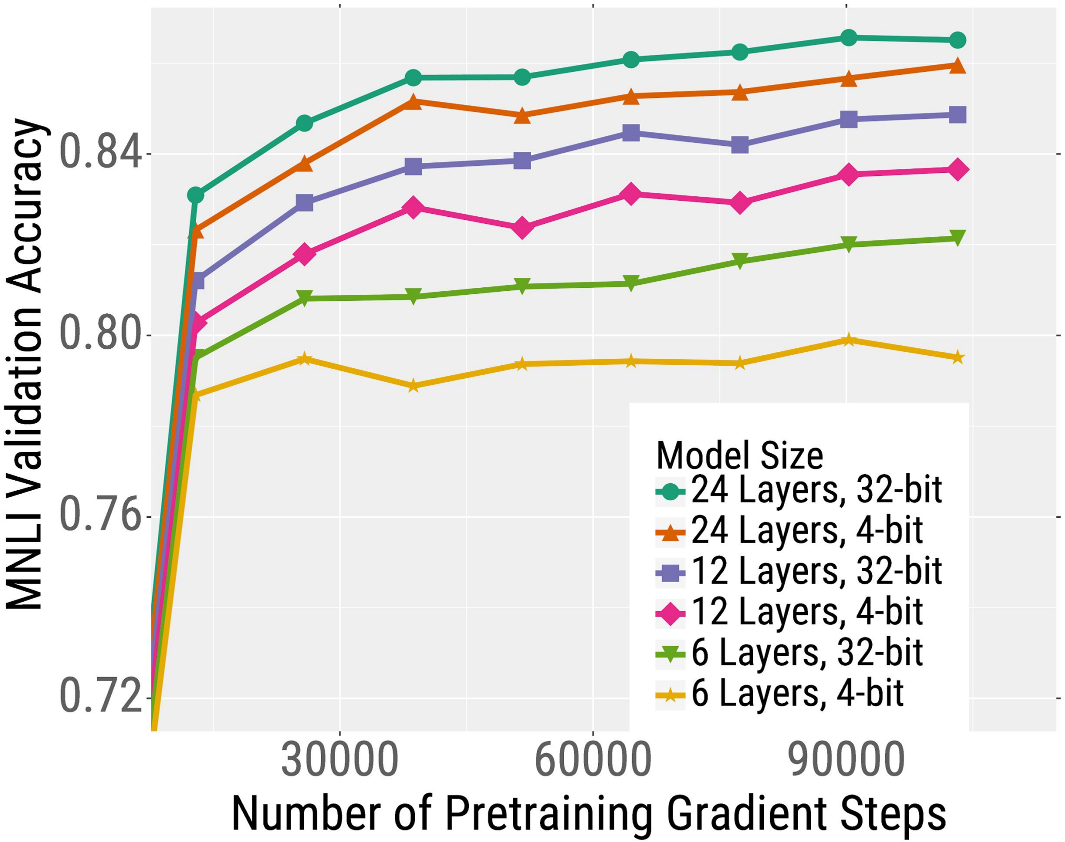
Why Do Larger Models Compress Better?

- Quantization/Pruning error is smaller for larger models



Why Do Larger Models Compress Better?

- Size, not convergence, determines compressibility



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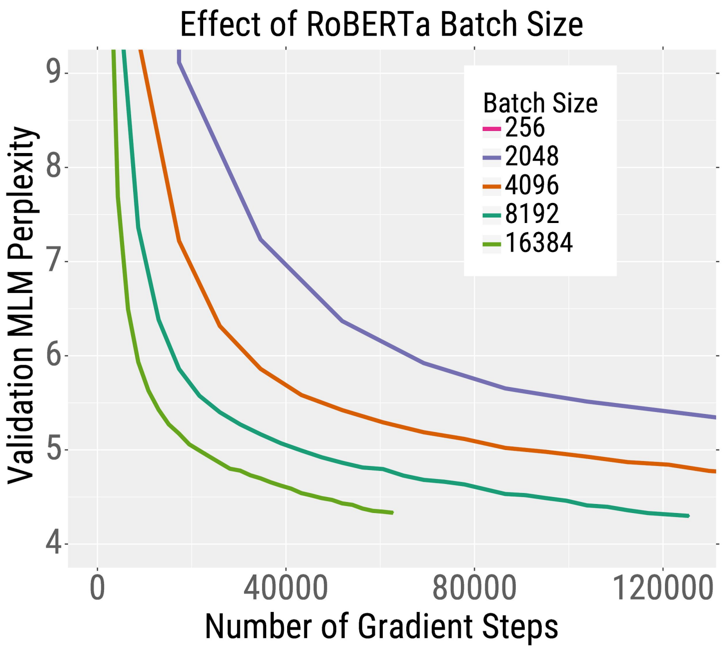

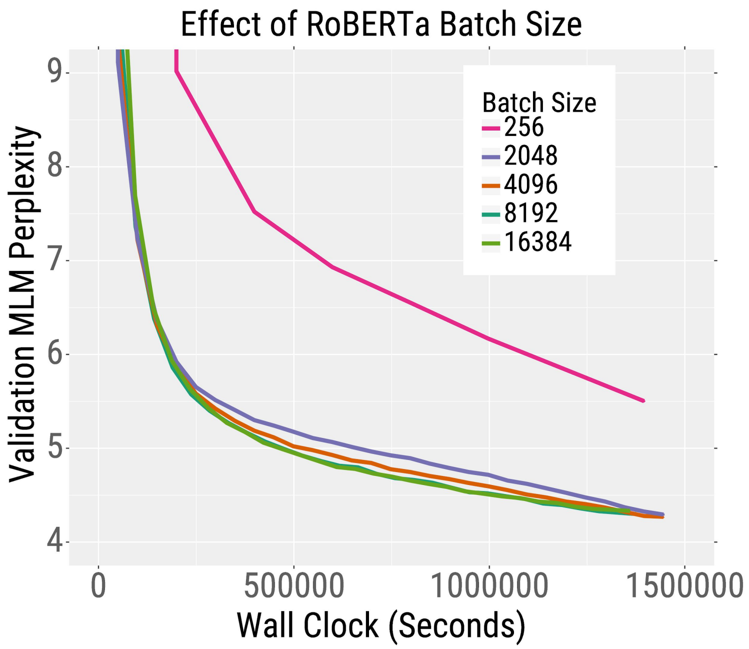

Practical Takeaways

- 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