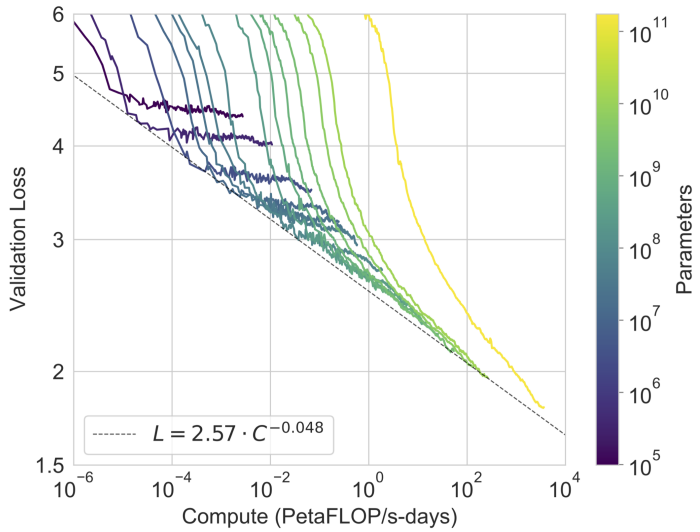
Deep Learning for NLP

Training LLMs
Scaling laws



Learning goals

- Understand scaling laws

NUMBER OF PARAMETERS: NOTATION

- In this slide set, we use N for the number of parameters.
- (Unfortunately, we use P for the number of parameters in other slide sets.)

SCALING LAWS PROPOSED BY KAPLAN ET AL. (2020)

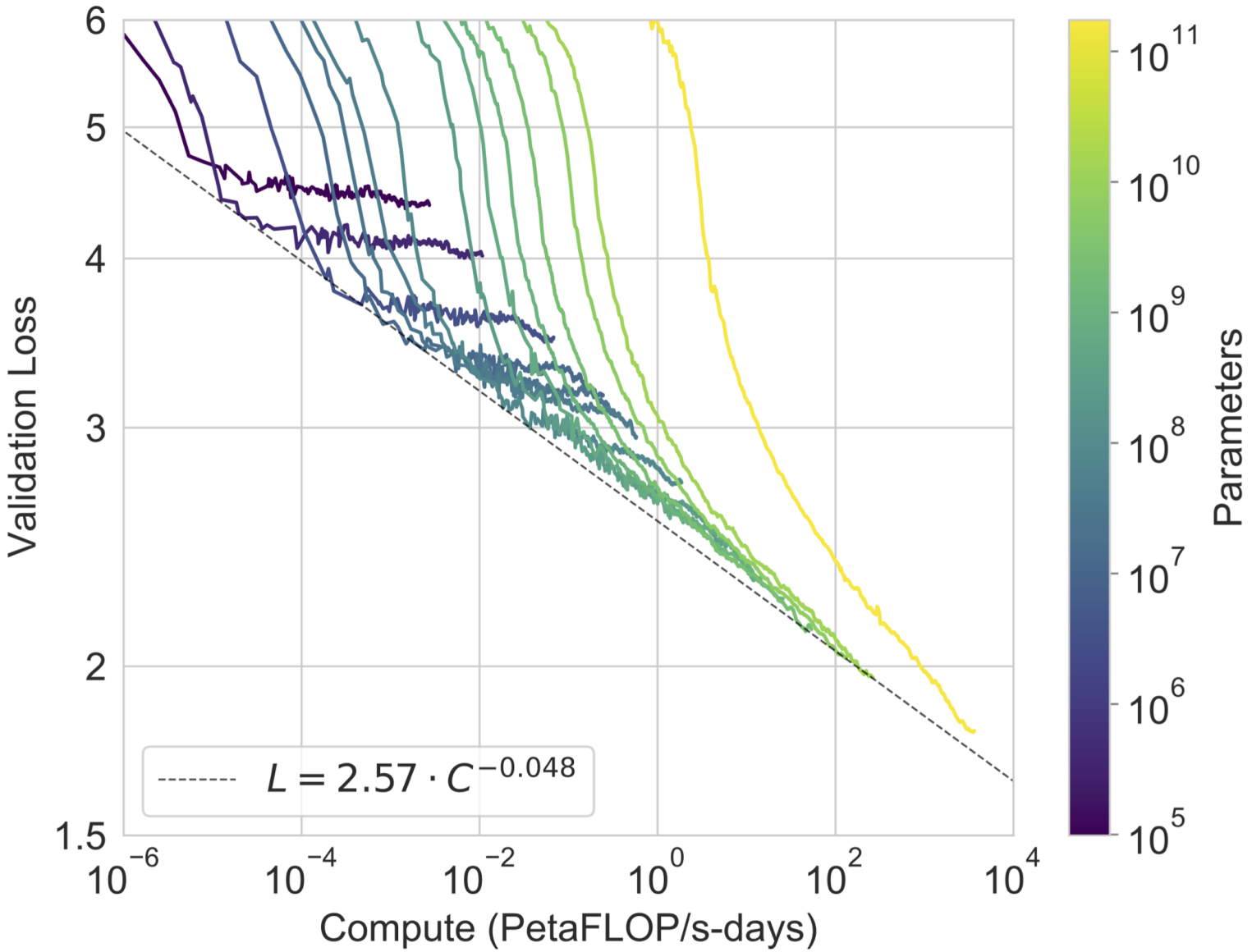
▸ Kaplan et al. (2020)

- Performance depends strongly on scale, weakly on model shape
  - Scale means: parameters N, data D, and compute C
  - Shape means: depth and width
- Power laws
  - Performance has power law relation with each factor N, D, C
  - Trend spanning more than six orders of magnitude
- Limits of power laws
  - Power law for one variable only holds when not bottlenecked by the other two
  - Performance enters regime of diminishing returns if N or D held fixed while the other increases

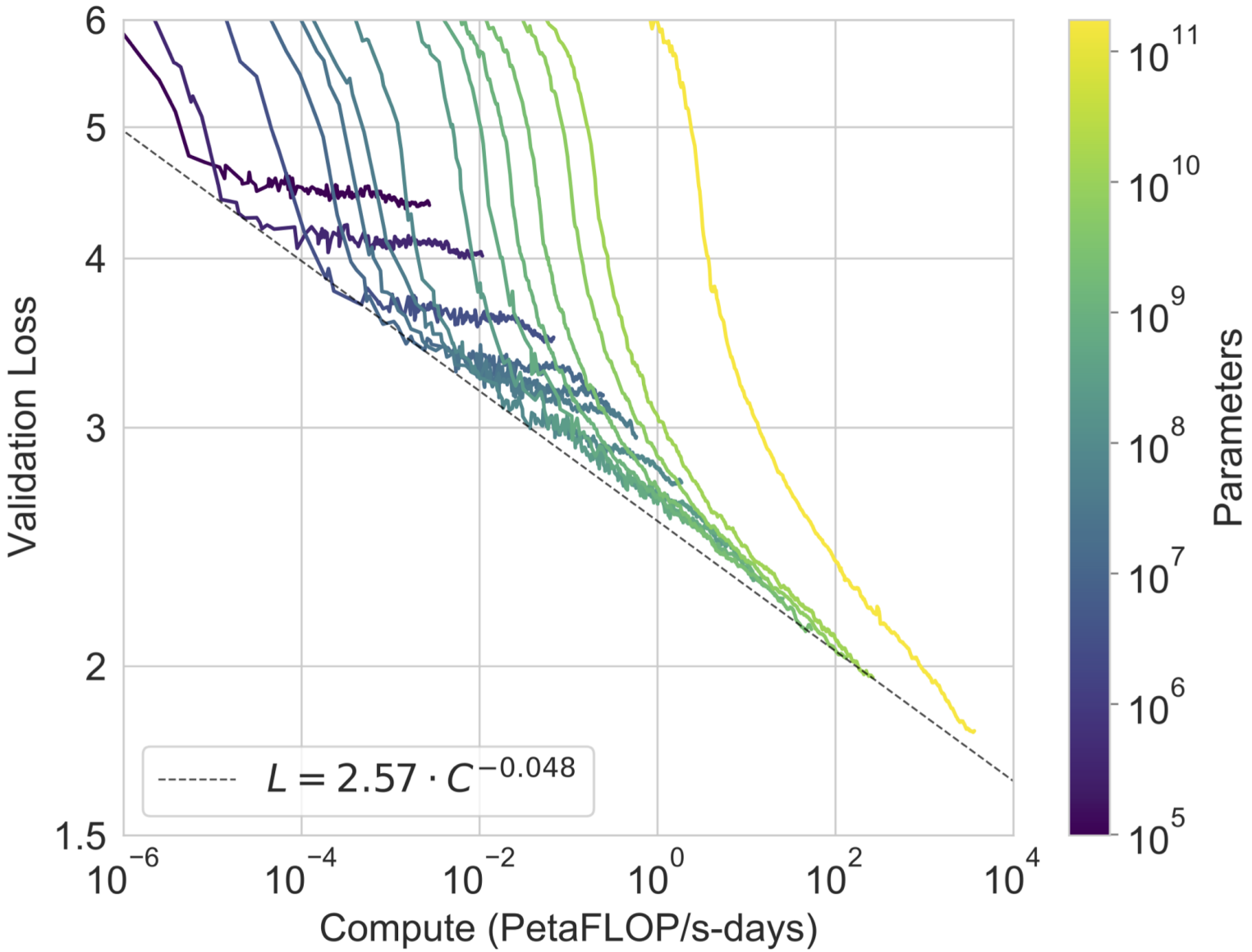
SCALING LAWS PROPOSED BY KAPLAN ET AL. (2020)

- These power laws were huge news in 2020!
- Easy way to improve AI
- We can predict by extrapolating the early part of the training curve
- Power law parameters are roughly independent of model size
- Transfer improves with test performance
  - When evaluating on text with different distribution from training text, results are strongly correlated to those on the validation set
  - Transfer to different distribution incurs a constant penalty but improves in line with performance on training set
- Sample efficiency
  - Large models are more sample-efficient than small models
  - They reach same performance with fewer optimization steps

POWER LAW (GPT3 PAPER)



POWER LAW (GPT3 PAPER): QUESTIONS?



SCALING LAWS

- “Convergence is inefficient”
  - When C is fixed but N and D are not, optimal performance is achieved by training very large models and stopping significantly short of convergence
  - That is: early stopping
  - So the claim is: Larger language models will perform better and be more sample efficient than smaller models.
- Optimal batch size
  - Claim: “Optimal batch size: The ideal batch size for training these models is roughly a power of the loss only, and continues to be determinable by measuring the gradient noise scale [MKAT18]; it is roughly 1-2 million tokens at convergence for the largest models we can train.”
  - gradient noise scale = a measure of the signal-to-noise ratio of gradient across training examples

OPTIMAL BATCH SIZE

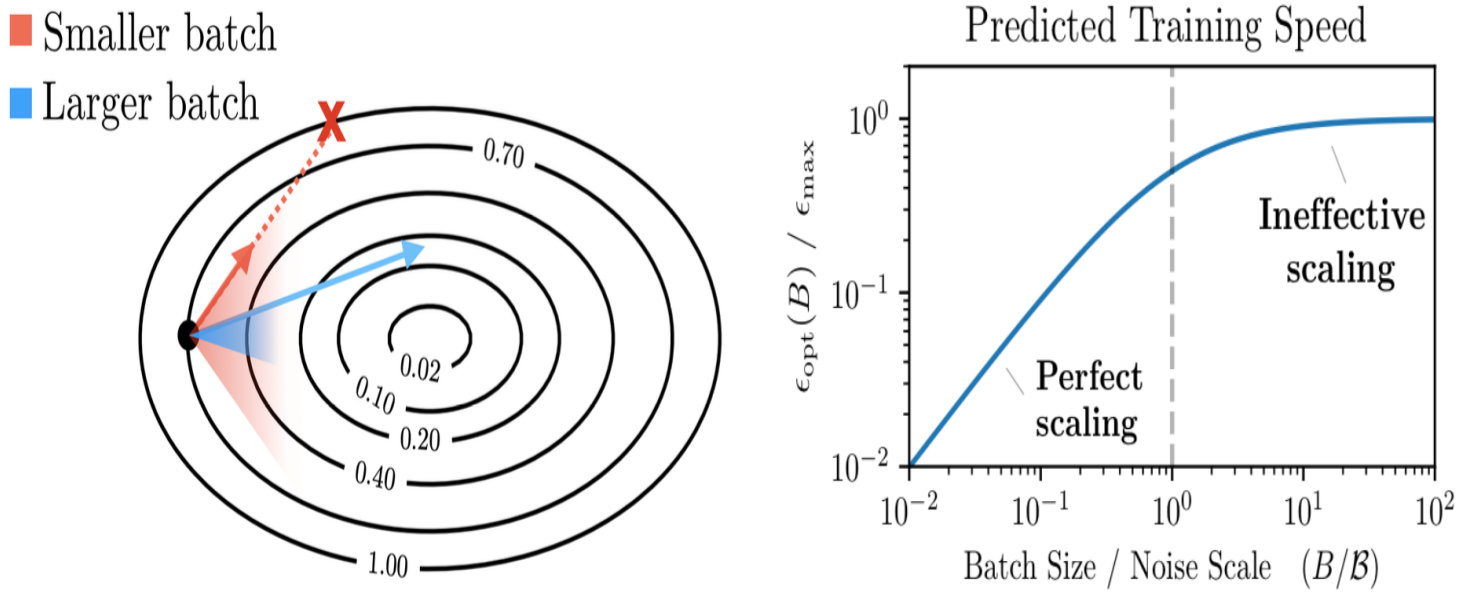


Figure 3: Larger batch sizes yield estimated gradients that are closer to the true gradient, on average. Larger step sizes can be used when the estimated gradient is closer to the true gradient, so more progress can be made per step. **Left:** A large step size used with a small batch size can lead to instability, as illustrated for a quadratic loss. **Right:** Equation 2.6 predicts that the 'turning point' after which larger batch sizes become less helpful is the noise scale $\mathcal{B}$, where the training speed drops to 50% of the maximum possible.

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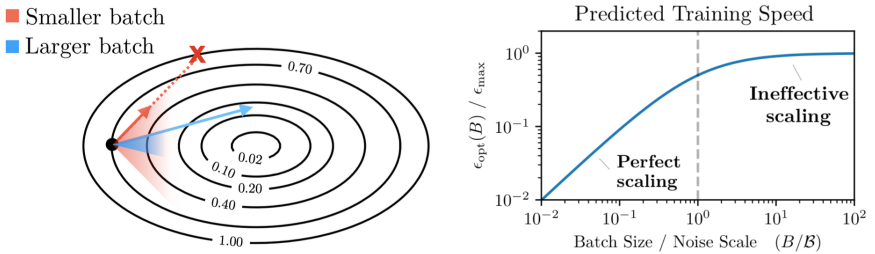


Figure 3: Larger batch sizes yield estimated gradients that are closer to the true gradient, on average. Larger step sizes can be used when the estimated gradient is closer to the true gradient, so more progress can be made per step. **Left:** A large step size used with a small batch size can lead to instability, as illustrated for a quadratic loss. **Right:** Equation 2.6 predicts that the 'turning point' after which larger batch sizes become less helpful is the noise scale $\mathcal{B}$, where the training speed drops to 50% of the maximum possible.

- The ideal batch size increases over the course of training.
- Estimate gradient as accurately as possible $\rightarrow$ large batch
- Exploit stochasticity (epoch batches would not be a good thing even if we could compute them efficiently) $\rightarrow$ small batch
- Increase training speed as much as possible $\rightarrow$ large step size
- Based on the estimated gradient, choose a step size such that the cost of the landing position does not deviate too much from the cost of the ideal landing position $\rightarrow$ small step size

SCALING LAW FOR NEXT WORD PREDICTION

- $L(N, D) = 1.61 + \frac{406.4}{N^{0.34}} + \frac{410.7}{D^{0.28}}$
- $L(N, D)$ is cross entropy on new text
- Source: ▸ Hoffmann et al., 2022

SCALING LAW FOR NEXT WORD PREDICTION

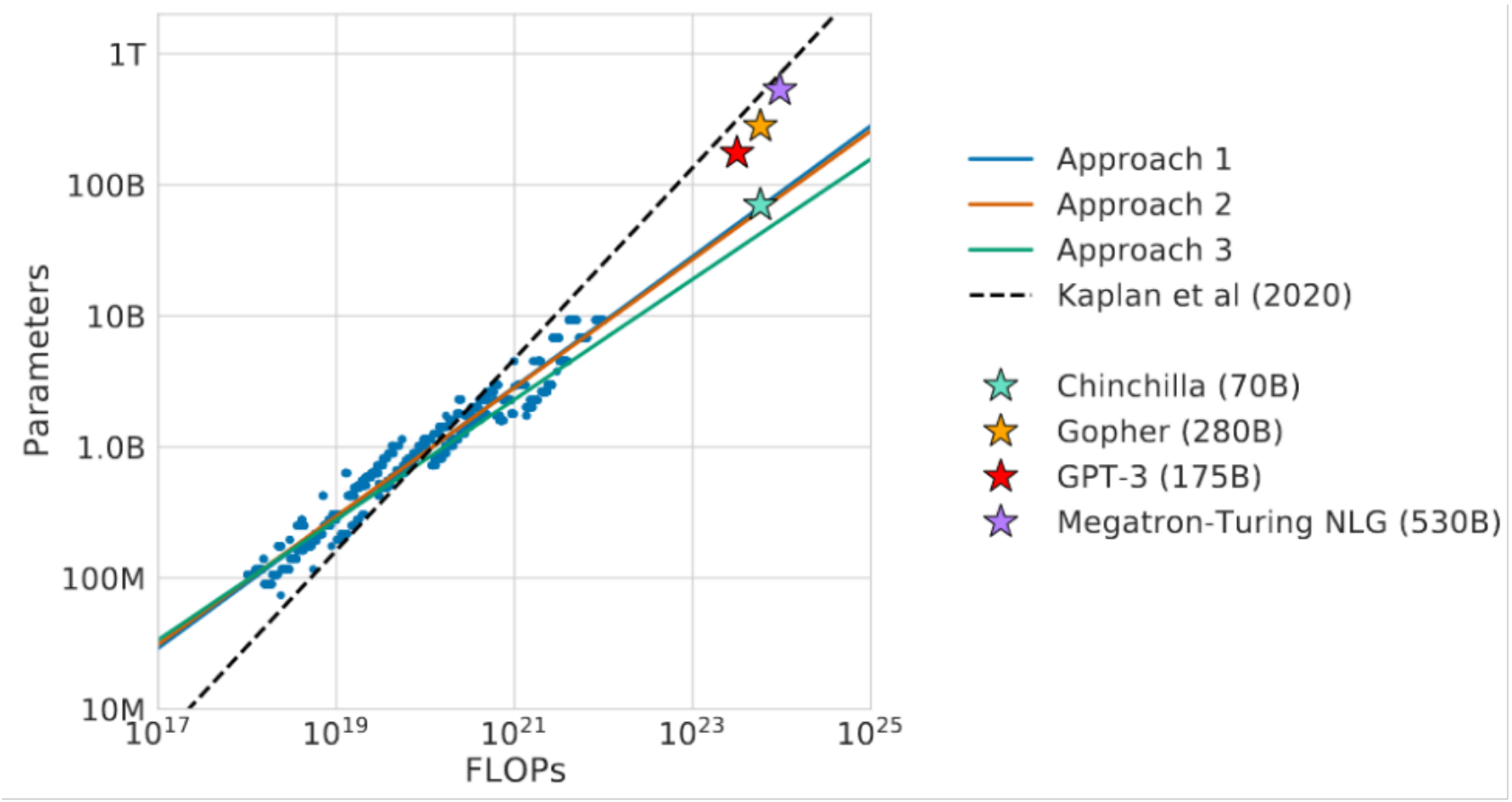
- $L(N, D) = 2 + \frac{1000}{N^{1/3}} + \frac{1000}{D^{1/4}}$
- **Question:** Compute $L(N, D)$ for $N = 10^9, D = 10^8$, $N = 10^{12}, D = 10^{16}$, $N = 10^3, D = 10^{100}$ and $N = 10^{100}, D = 10^4$
- **Question:** Which configuration is best?
- **Question:** Why is it best?
- **Question:** Which values of N and D would you choose to create an even more powerful model?
- Of course, the last question is relative to the available compute budget, so try and find a reasonable answer.

COMPUTE-OPTIMAL LLMs

Given a fixed FLOP budget C, how should we trade-off model size and text size to optimize performance? ▸ Hoffmann et al., 2022

- Find N and D so that $FLOP(N, D) = C$ and $L(N, D)$ is minimal
- Empirical estimates of N and D based on 400 models.
  - Ranging from 70 M to 16 B parameters
  - Trained on 5 B to 400 B tokens
- Different results from those of ▸ Kaplan et al., 2020
- Results verified using Chinchilla
  - Chinchilla has 70 B parameters and is trained on 1.4 T tokens
  - 4x less parameters and 4x more tokens than Gopher
  - Chinchilla outruns Gopher and has reduced memory footprint and inference cost

COMPUTE-OPTIMAL LLMs: ARE GPT3 ETC TOO LARGE?



▸ Source: Hoffmann et al., 2022

COMPUTE-OPTIMAL LLMs (2)

Given a fixed FLOPs budget, how should one trade off model size and the number of training tokens? We find that all three methods predict that current large models should be substantially smaller and therefore trained much longer than is currently done. Based on our estimated compute-optimal frontier, we predict that for the compute budget used to train Gopher, an optimal model should be 4 times smaller, while being training on 4 times more tokens. We verify this by training a more compute-optimal 70B model, called Chinchilla, on 1.4 trillion tokens. Not only does Chinchilla outperform its much larger counterpart, Gopher, but its reduced model size reduces inference cost considerably and greatly facilitates downstream uses on smaller hardware. The energy cost of a large language model is amortized through its usage for inference and fine-tuning. The benefits of a more optimally trained smaller model, therefore, extend beyond the immediate benefits of its improved performance.

CHINCHILLA AND THE OTHER LLMs

Model	Size (# Parameters)	Training Tokens
LaMDA (Thoppilan et al., 2022)	137 Billion	168 Billion
GPT-3 (Brown et al., 2020)	175 Billion	300 Billion
Jurassic (Lieber et al., 2021)	178 Billion	300 Billion
Gopher (Rae et al., 2021)	280 Billion	300 Billion
MT-NLG 530B (Smith et al., 2022)	530 Billion	270 Billion
Chinchilla	70 Billion	1.4 Trillion

▸ Source: Hoffmann et al., 2022

Model	Layers	Number Heads	Key/Value Size	d_{model}	Max LR	Batch Size
Gopher 280B	80	128	128	16,384	4×10^{-5}	3M $\rightarrow$ 6M
Chinchilla 70B	80	64	128	8,192	1×10^{-4}	1.5M $\rightarrow$ 3M

▸ Source: Hoffmann et al., 2022

CHINCHILLA OUTPERFORMS OTHER LLMs: MMLU

Random	25.0%
Average human rater	34.5%
GPT-3 5-shot	43.9%
Gopher 5-shot	60.0%
***Chinchilla* 5-shot**	**67.6%**
Average human expert performance	*89.8%*
June 2022 Forecast	57.1%
June 2023 Forecast	63.4%

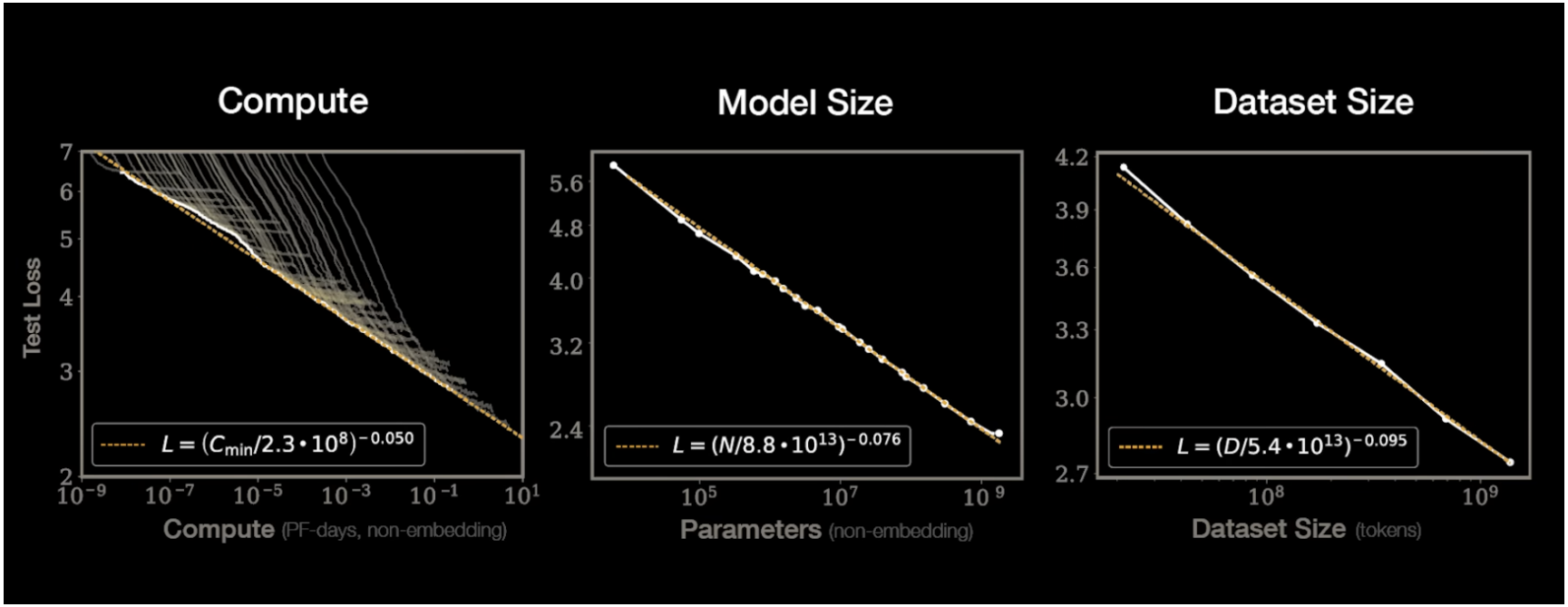
▸ Source: Hoffmann et al., 2022, compared with human forecasts

CHINCHILLA OUTPERFORMS OTHER LLMs: QA

	Method	*Chinchilla*	*Gopher*	GPT-3	SOTA (open book)
Natural Questions (dev)	0-shot	16.6%	10.1%	14.6%	54.4%
	5-shot	31.5%	24.5%	-	
	64-shot	35.5%	28.2%	29.9%	
TriviaQA (unfiltered, test)	0-shot	67.0%	52.8%	64.3 %	-
	5-shot	73.2%	63.6%	-	
	64-shot	72.3%	61.3%	71.2%	
TriviaQA (filtered, dev)	0-shot	55.4%	43.5%	-	72.5%
	5-shot	64.1%	57.0%	-	
	64-shot	64.6%	57.2%	-	

▸ Source: Hoffmann et al., 2022

SCALING LAWS: DISCUSSION



Question: Any doubts?

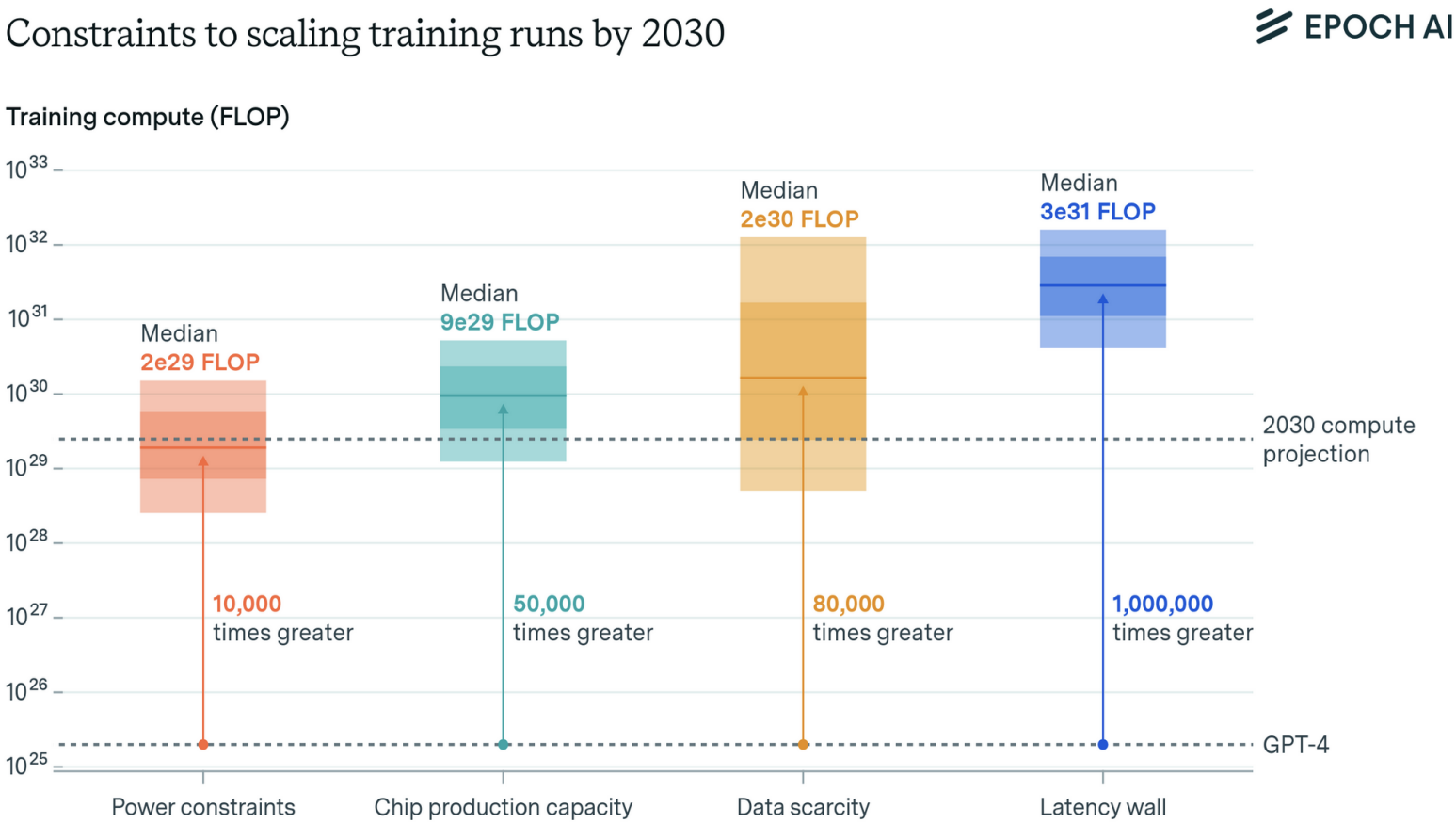
BEYOND BRUTE-FORCE SCALING OF DATASETS

- If you run out of data, then increase # epochs
- The Stack v2 already contains all public code! arxiv.org/abs/2305.16264
- data quality/model size tradeoff: Training a smaller model on a smaller high-quality dataset may be better than training a huge model on a huge medium-quality dataset.
- For higher quality datasets, allocate more compute to model size. arxiv.org/abs/2401.02954
- See Stanford CS25: StarCoder Use Case

MORE RECENT THOUGHTS ON SCALING

- ▸ Reuters, 2024-11-15
- Ilya Sutskever: “results from scaling up pre-training . . . have plateaued.”
- “The 2010s were the age of scaling, now we’re back in the age of wonder and discovery once again. Everyone is looking for the next thing,” Sutskever said. “Scaling the right thing matters more now than ever.”

EPOCH AI PROJECTIONS



▸ Epoch AI

TRAIN/TEST TRADEOFF (1)

- Current models cost order of magnitude $100 million to train, and this number could reach $100 billion within a few years, according to Anthropic's Dario Amodei. Rising costs could lead companies to reallocate their gargantuan training budgets and researchers to focus on more cost-effective, application-specific approaches. (Andrew Ng)

TRAIN/TEST TRADEOFF (2)

- Phi4: released by Microsoft Dec 2024
- 14 billion parameters (small!)
- pretraining data: 9.8 trillion tokens (pretty big)
- pretraining data curated / synthesized

TRAIN/TEST TRADEOFF (3)

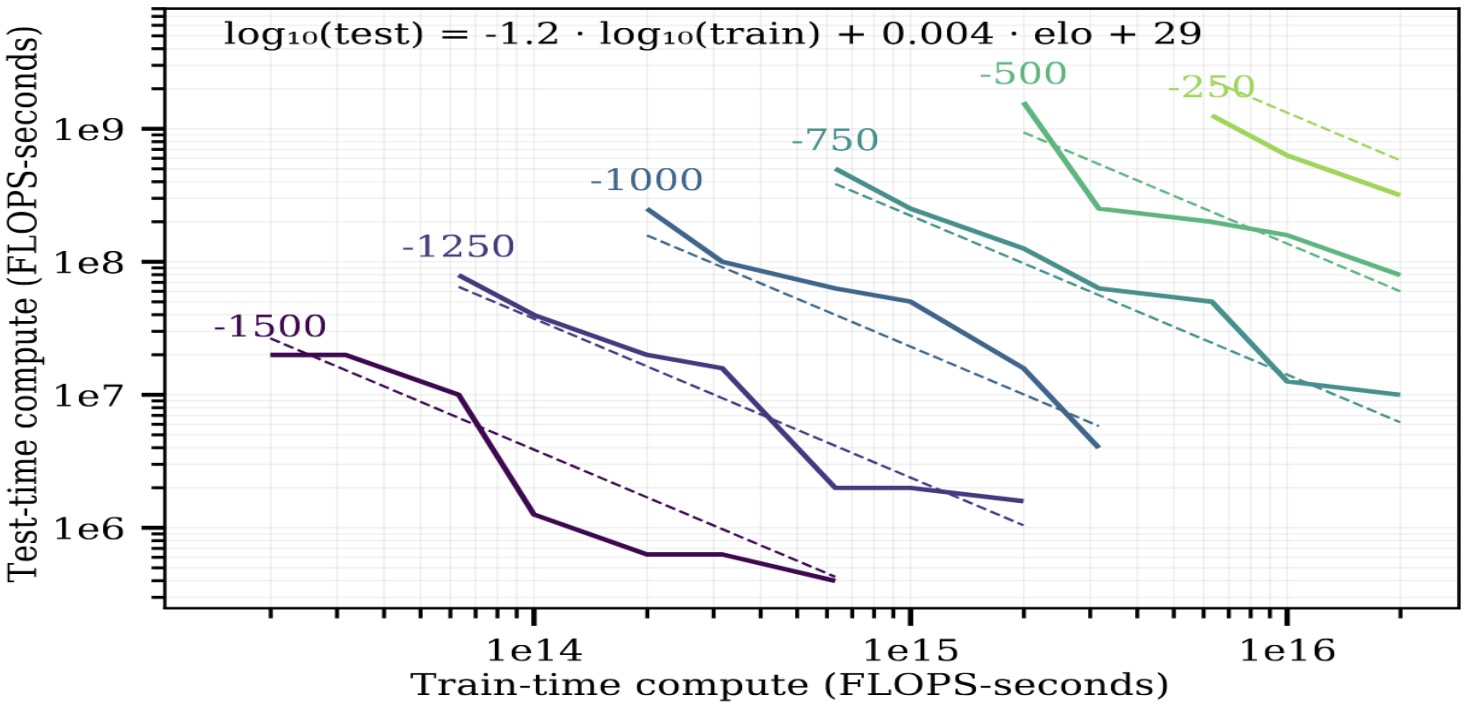
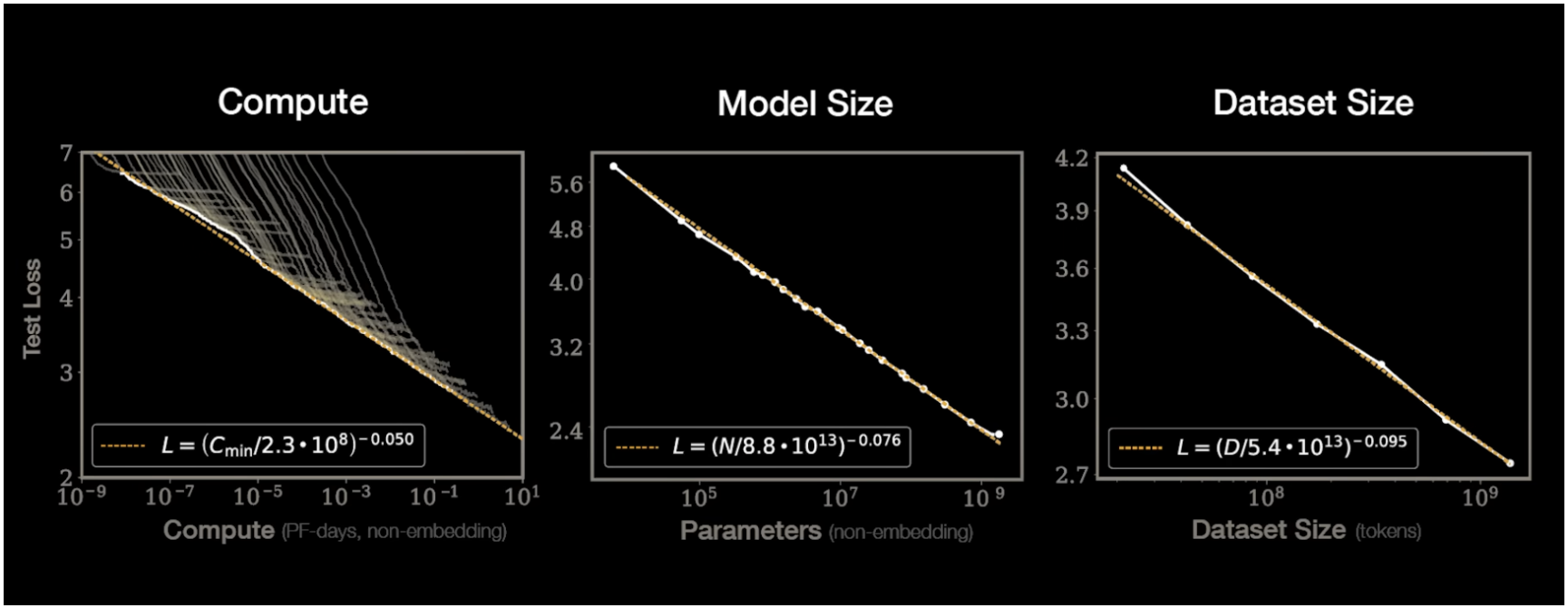


Fig. 9. The trade-off between train-time compute and test-time compute. Each dotted line gives the minimum train-test compute required for a certain Elo on a 9×9 board

▸ Andy L. Jones

MAIN TAKEAWAY (1)



MAIN TAKEAWAY (2)

- The original scaling laws were exclusively about (pre)training: What is the best model I can pretrain given constraints such as compute budget?
- This has shifted to a more holistic view of what we want to achieve, e.g., even if a trillion parameter model is the optimal model given pretraining constraints, a much smaller model may be preferable since it is so much cheaper at inference time.
- In the future: compound systems of many smaller models/agents rather than a single huge monolithic model?
- MoE is a version of that.

WHAT IS A TRILLION?

▸ https://www.youtube.com/watch?v=QgUj09K7vx4 (1:30)