Scaling laws for LLMs

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Advanced Natural Language Processing

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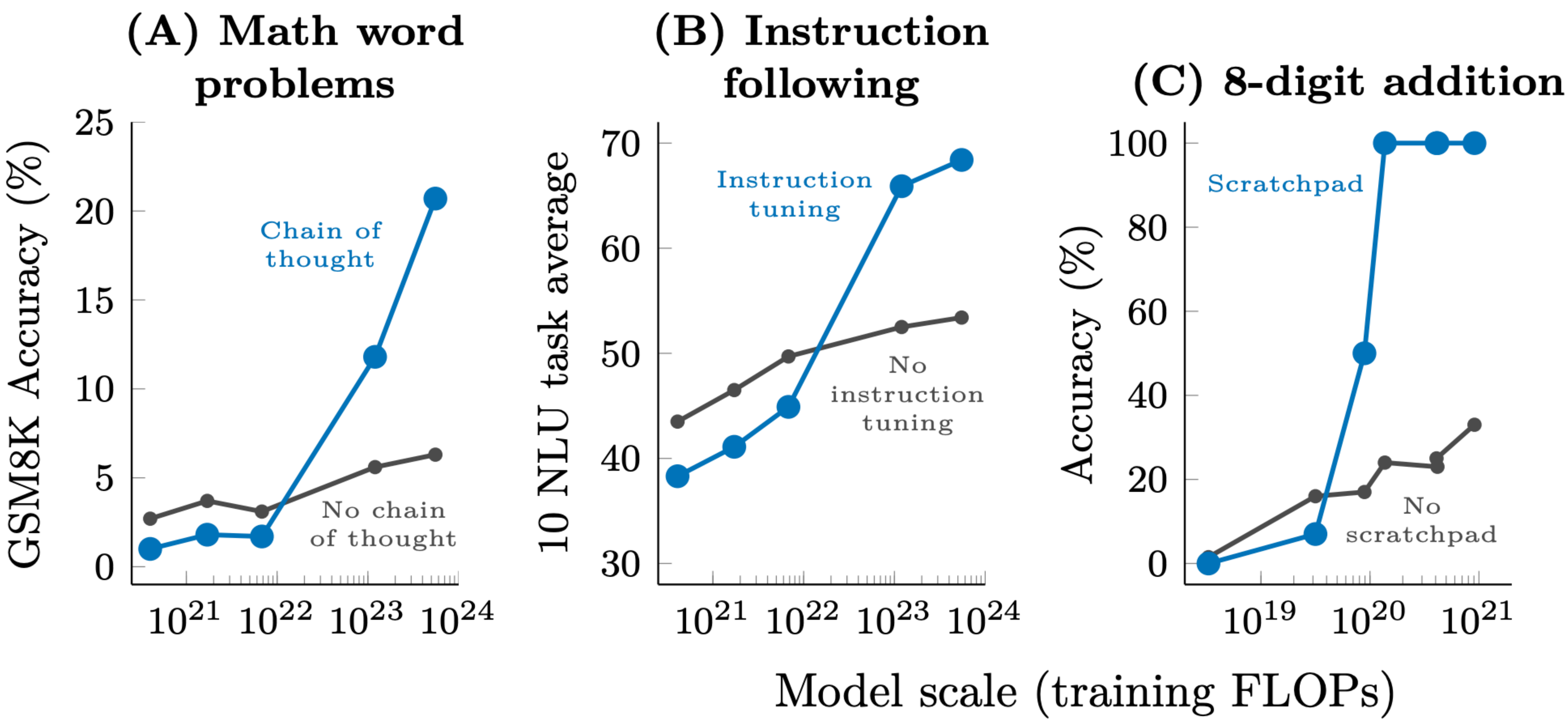
What do bigger LMs buy us?

- "In-context" learning, chain-of-thought prompting, instruction following, more memorized knowledge and patterns from the training data, etc

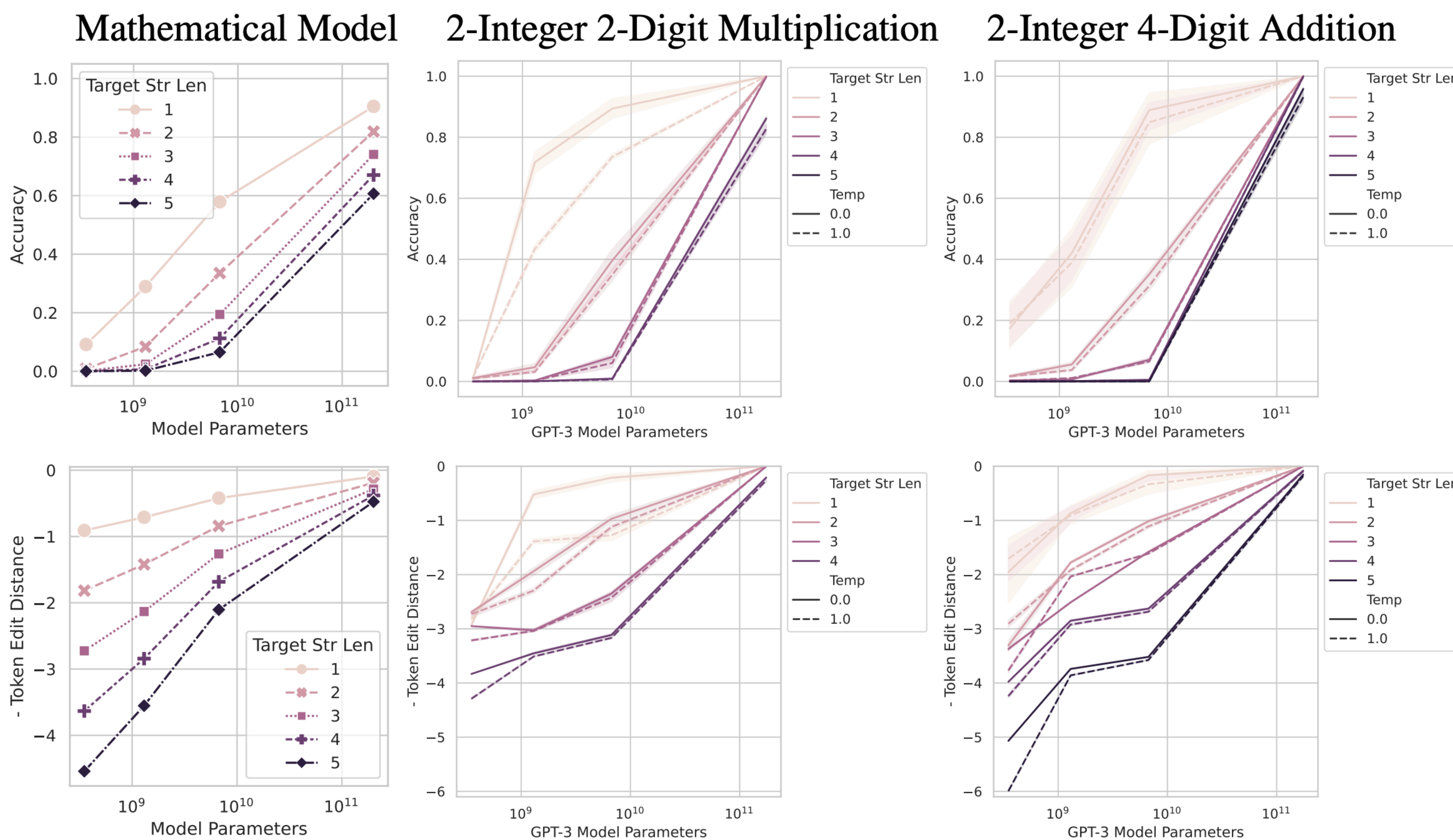
- Broadly, **"emergent properties"**, which may only appear with larger LMs but not smaller ones

"The ability to perform a task via few-shot prompting is emergent when a model has random performance until a certain scale, after which performance increases to well-above random." (Wei et al., 2022)



Emergent Abilities of Large Language Models, Wei et al., TMLR 2022

Are “emergent properties” really emergent?



Are Emergent Abilities of Large Language Models a Mirage?, Schaeffer et al., NeurIPS 2023

What can we scale?

- Model size
- Dataset size
- Amount of total compute used during training (e.g., number of training steps)

Given a fixed compute budget, what is the optimal model size and training dataset size for training a Transformer LM?

Let’s say you can use one GPU for one day

- Would you train a 5 million parameter LM on 100 books?
- What about a 500 million parameter LM on one book?
- Or a 100k parameter LM on 5k books?

Observations from Kaplan et al., 2020

- Performance depends strongly on scale (model params, data size, and compute used for training), weakly on model shape (e.g., depth, width)
- Perf vs scale can be modeled with power laws
- Perf improves most if model size and dataset size are scaled up together. Increasing one while keeping the other fixed leads to diminishing returns
- Larger models are more sample efficient than smaller models, take fewer steps / data points to reach same loss

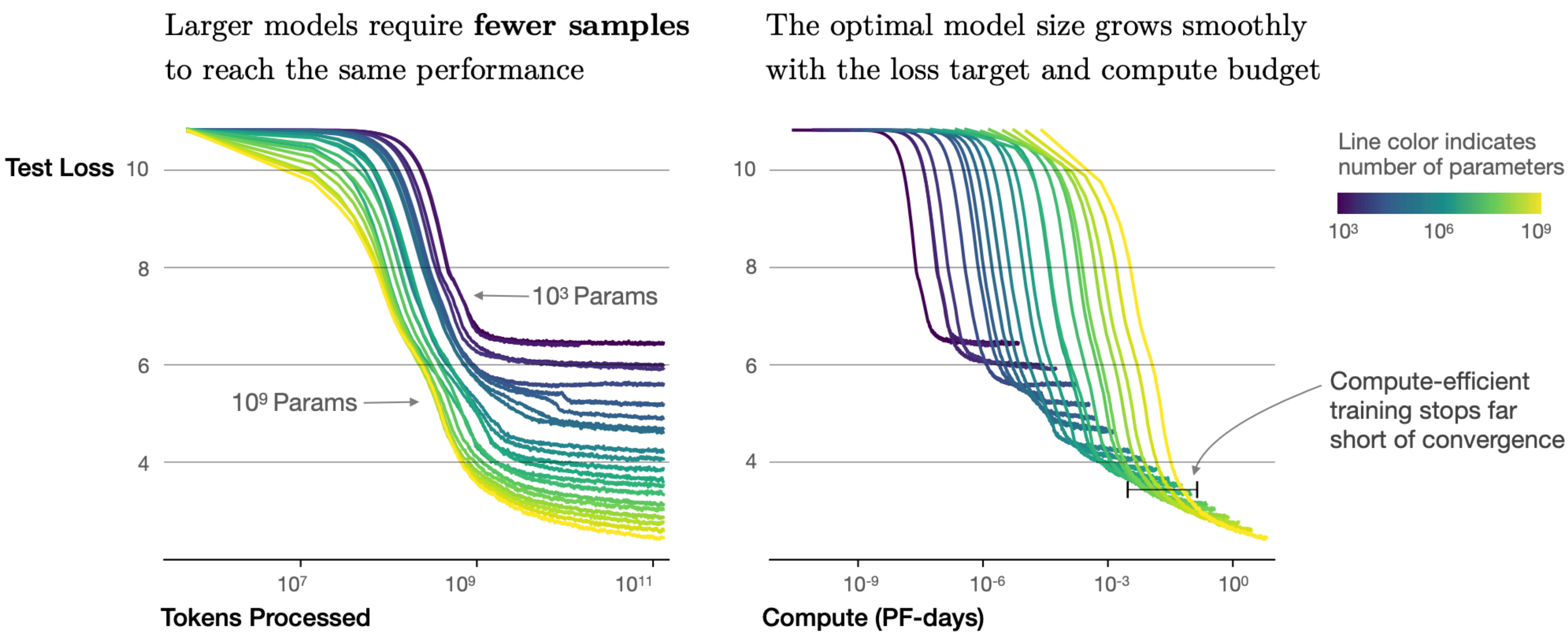


Figure 2 We show a series of language model training runs, with models ranging in size from 10^3 to 10^9 parameters (excluding embeddings).

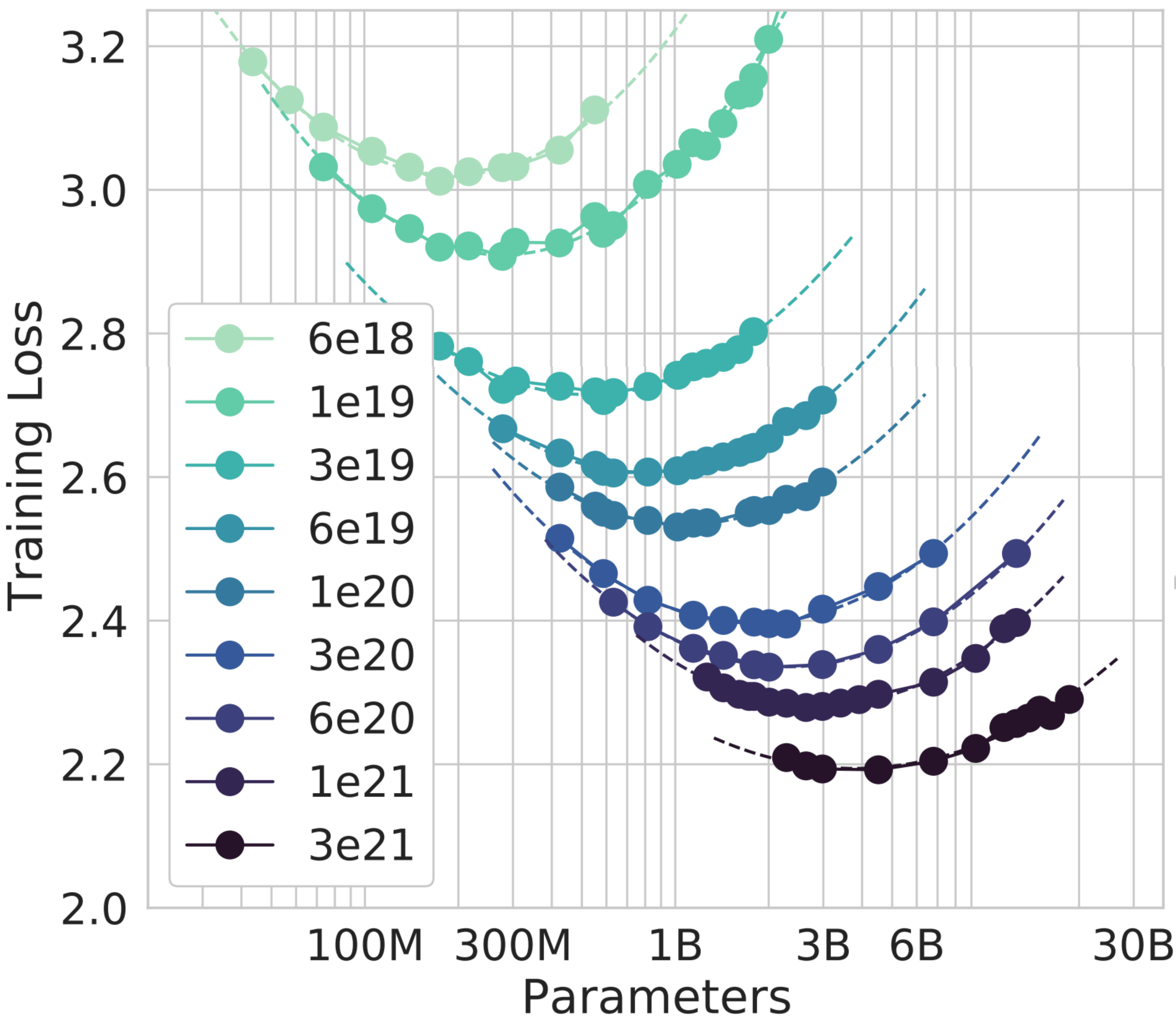
Issues with Kaplan laws

- Used same learning rate schedule for all training runs, regardless of how many training tokens / batches!
- This schedule needs to be adjusted based on the number of training steps; otherwise, it can impair performance
- The resulting “scaling laws” from Kaplan et al., are flawed because of this!

Chinchilla (Hoffmann et al., 2022)

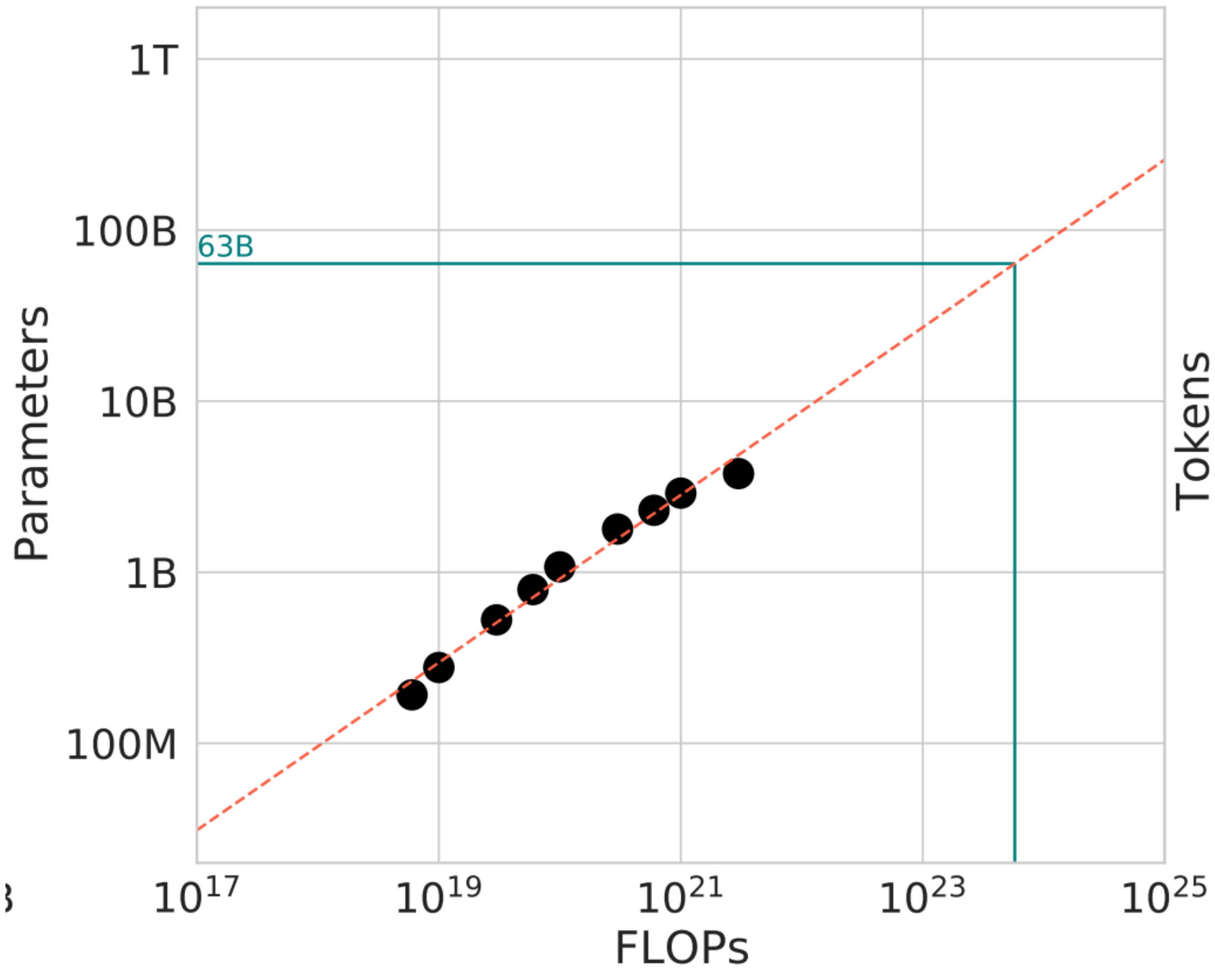
Quick takeaways

- **Kaplan et al., 2020**: if you're able to increase your compute budget, you should prioritize increasing model size over data size
  - With a 10x compute increase, you should increase model size by 5x and data size by 2x
  - With a 100x compute increase, model size 25x and data 4x
- **Hoffmann et al., 2022**: you should increase model and data size at the same rate
  - With a 10x compute increase, you should increase both model size and data size by 3.1x
  - With a 100x compute increase, both model and data size 10x

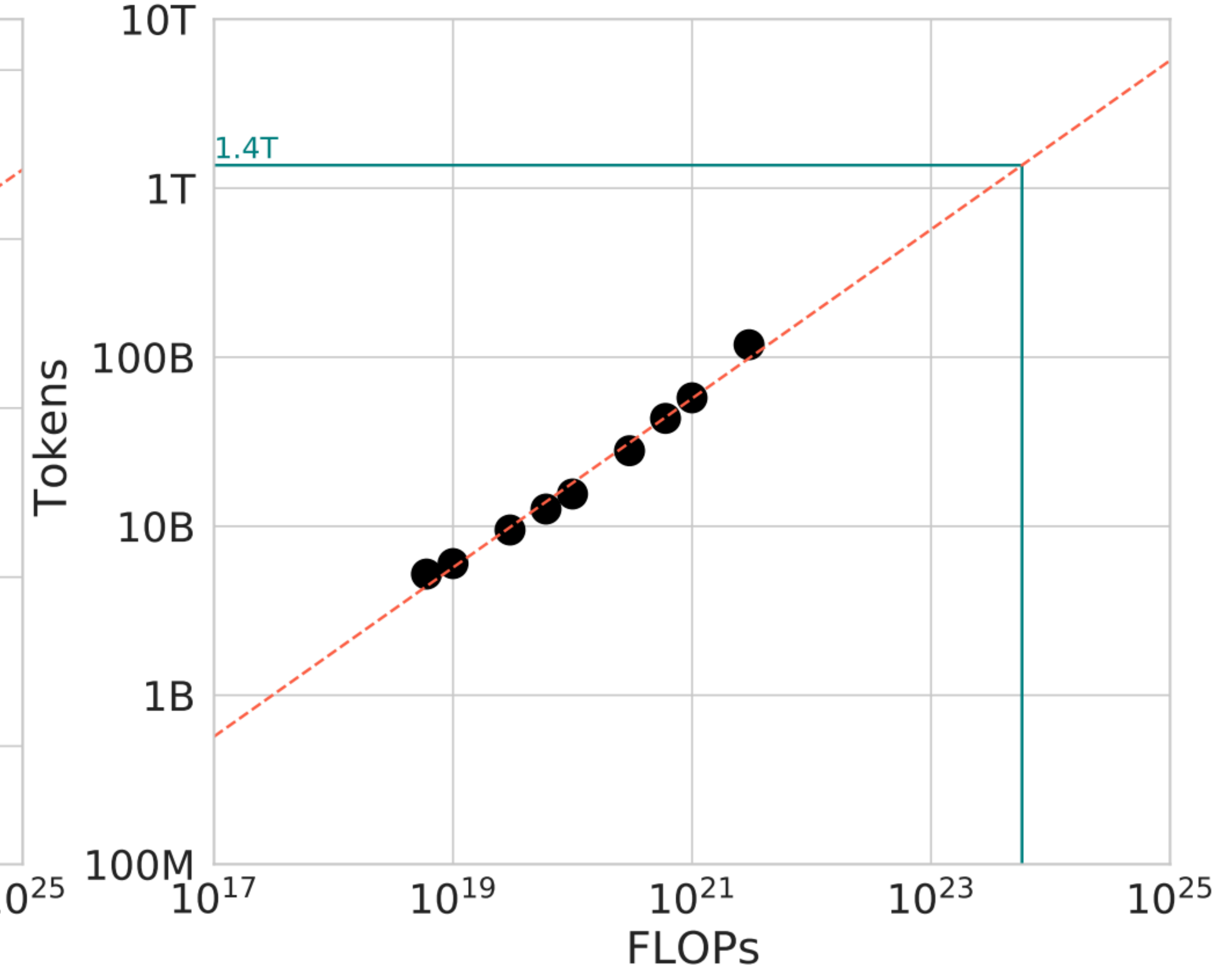


Training Loss
Parameters
3.2
3.0
2.8
2.6
2.4
2.2
2.0
100M
300M
1B
3B
6B
30B
6e18
1e19
3e19
6e19
1e20
3e20
6e20
1e21
3e21

Model size



Data size



iPad

Given a fixed compute budget, what is the optimal model size and training dataset size for training a Transformer LM?

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

- N – the number of model parameters, *excluding all vocabulary and positional embeddings*
- $C \approx 6NBS$ – an estimate of the total non-embedding training compute, where B is the batch size, and S is the number of training steps (ie parameter updates). We quote numerical values in PF-days, where one PF-day $= 10^{15} \times 24 \times 3600 = 8.64 \times 10^{19}$ floating point operations.

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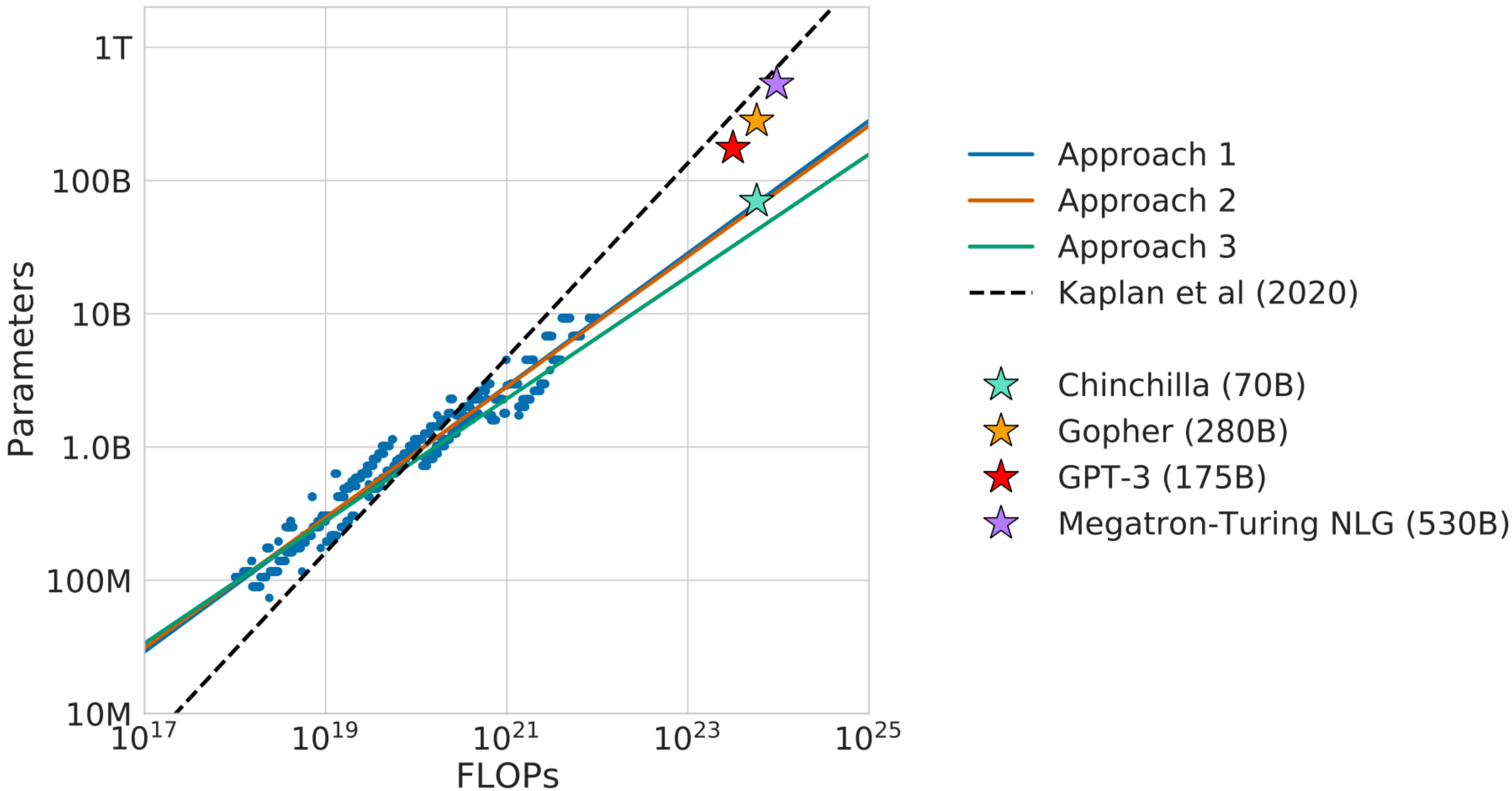

Hoffmann et al., 2022, *Chinchilla*

What about the *type* of data?

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- The internet contains a huge amount of text, but it's extremely noisy! Copyrighted text (e.g. published books) are much higher-quality, but is it legal to train on them?

- What is the impact of *repeated* data?
  - Repeated data can lead to severe degradation in performance (Brown et al., 2022)
    - *"For instance, performance of an 800M parameter model can be degraded to that of a 2x smaller model (400M params) by repeating 0.1% of the data 100 times, despite the other 90% of the training tokens remaining unique."*
  - Repeated data is helpful (Taylor et al., 2022; Galactica)
    - *"We train the models for 450 billion tokens, or approximately 4.25 epochs. We find that performance continues to improve on validation set, in-domain and out-of-domain benchmarks with multiple repeats of the corpus."*
    - *"We note the implication that the "tokens → ∞" focus of current LLM projects may be overemphasised versus the importance of filtering the corpus for quality."*

Google Books Search

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Thursday, August 05, 2010 at 8:26 AM

Posted by Leonid Taycher, software engineer

When you are part of a company that is trying to digitize all the books in the world, the first question you often get is: “Just how many books are out there?”

http://booksearch.blogspot.com/2010/08/books-of-world-stand-up-and-be-counted.html