Scaling Data-Constrained Language Models

Niklas Muennighoff

Twitter: @Muennighoff

arxiv.org/abs/2305.16264

Niklas Muennighoff, Alexander M. Rush, Boaz Barak, Teven Le Scao, Aleksandra Piktus, Nouamane Tazi, Sampo Pyysalo, Thomas Wolf & Colin Raffel

Outline

(1) Scaling language models
Background on what, why &
how of scaling

(2) Data-constrained scaling
Scaling with repeated data
Mixing modalities & revising filtering

Please interrupt with questions / thoughts anytime!

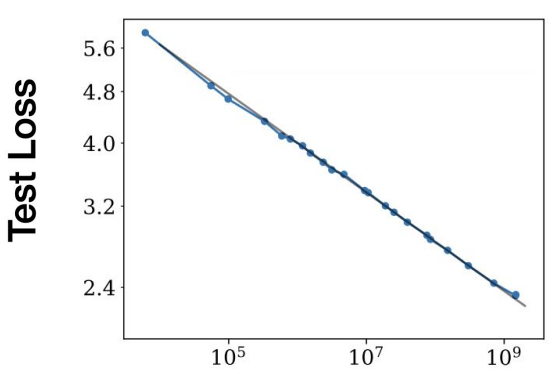
What is scaling?

α x Model size  x Training data  = Training compute 

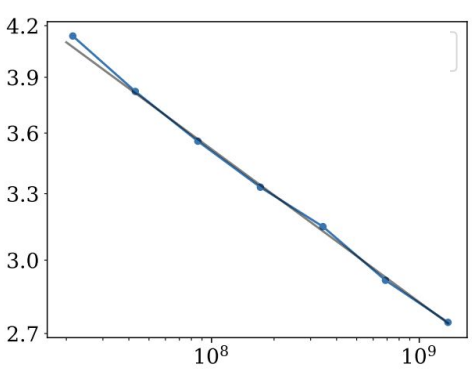
	Model size (# parameters)	Training data (# tokens)	Training compute (FLOPs)	Resources
BERT-base (2018)	109M	250B	1.6e20	64 TPU v2 for 4 days (16 V100 GPU for 33 hrs)
GPT-3 (2020)	175B	300B	3.1e23	~1,000x BERT-base
PaLM (2022)	540B	780B	2.5e24	6k TPU v4 for 2 months

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding (2018)
Language Models are Few-Shot Learners (2020)
PaLM: Scaling Language Modeling with Pathways (2022)

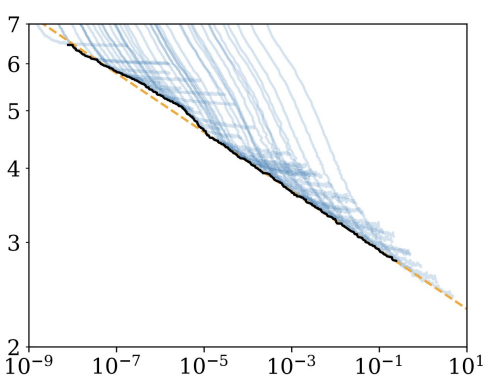
How important is scaling? **(Return)**



Model size



Training data



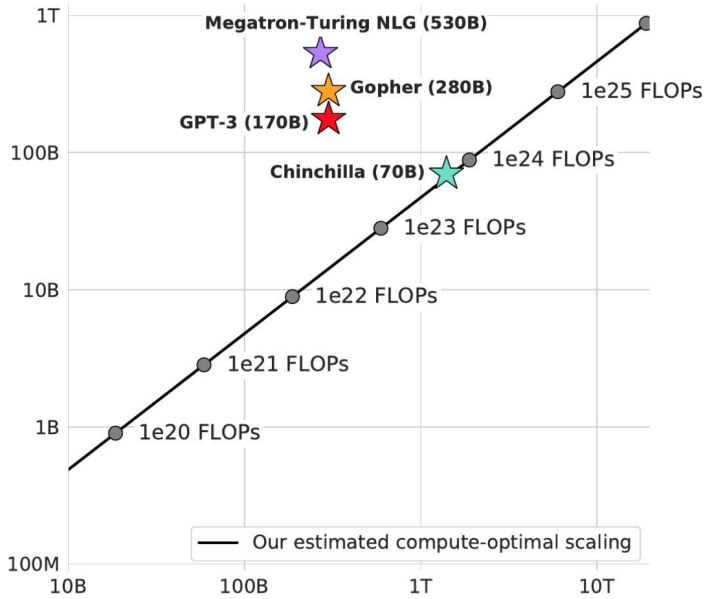
Compute

*Language models improve as a **power-law** with model size, training data, and amount of compute used for training.*

Scaling laws for neural language models (2020)

How to scale? **(Allocation)**

Model size (# parameters)



Training data (# tokens)

*Optimal compute allocation is scaling model size & training data **equally** (Chinchilla).*

Training compute-optimal large language models (2022)

Predictive formula

We can estimate loss (L) given **model size (N),** training data (D), and learned constants:

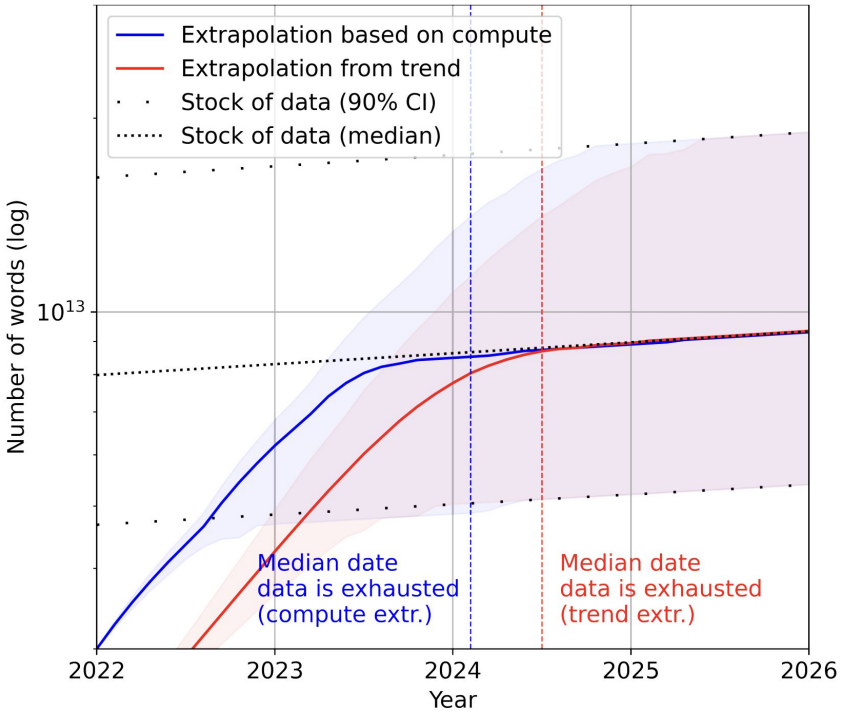
$$L(N, D) = \frac{A}{N^{\alpha}} + \frac{B}{D^{\beta}} + E$$

Fitting the constants, yields: $\alpha \approx \beta$

i.e. equal scaling of **N** and **D**.

Training compute-optimal large language models (2022)

Scaling is **data**-constrained



High-quality language data
Papers: ~1T tokens
Books: ~1.6T tokens
\+ Other sources (Wikipedia etc)

Code data
GitHub: ~14T tokens

Low-resource languages
Finnish 🇫🇮 (6M speakers): 38B tokens
(across public and closed sources incl. libraries, social media, web crawls etc.)

Will we run out of data? An analysis of the limits of scaling datasets in Machine Learning (2022)
chinchilla's wild implications (2022)
FinGPT: Large Generative Models for a Small Language (2023)

Outline

(1) Scaling language models
Background on what, why & how of scaling

(2) Data-constrained scaling
Scaling with repeated data
Mixing modalities & revising filtering

Repeating data considered harmful for LLMs

GPT-3: “Data are sampled **without replacement** during training...”

PaLM: “We train all three models on exactly one epoch of the data ... and choose the mixing proportions **to avoid repeating data in any subcomponent**.”

Is repeating 📚data really so bad?

Language Models are Few-Shot Learners (2020)
PaLM: Scaling Language Modeling with Pathways (2022)

Experimental setup

💻 Training compute (FLOPs)	🤖 Model size (# parameters)	📚 Training data (# tokens)
9.3e20	2.8B	55B
2.1e21	4.2B	84B
9.3e21	8.7B	178B

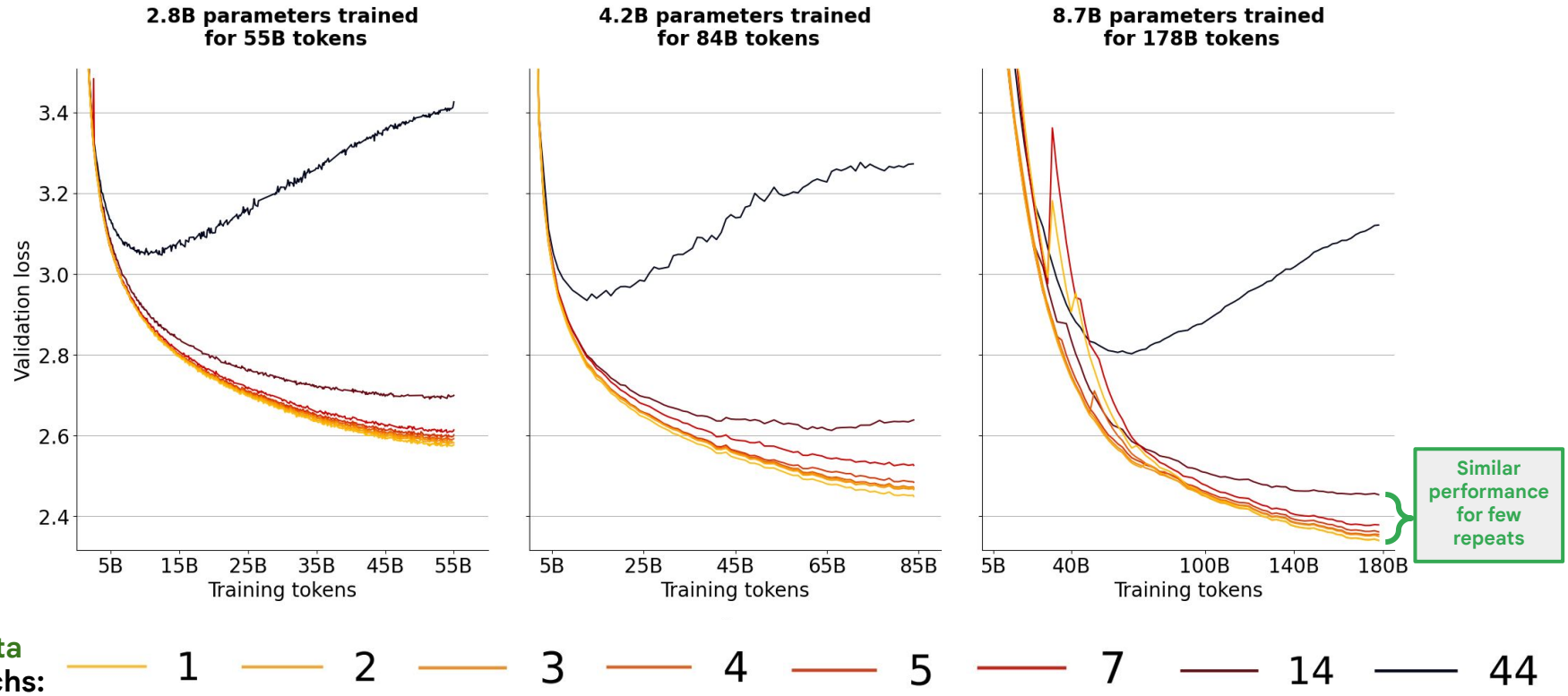
For each setup, train 8 models with different amounts of unique training data that is repeated

\+ ~300 miscellaneous runs

Use common large language modeling presets:

- architecture (GPT-2 transformer)
- hyperparameters (Chinchilla)
- datasets (web crawls like C4)

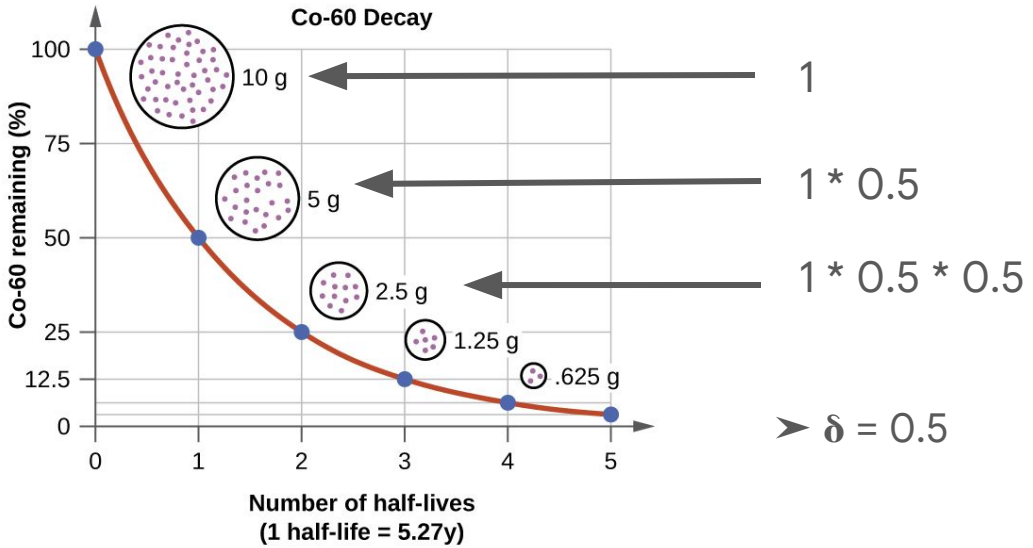
Repeating data (**Return**)



Hypothesis: 📚Data repeating as exponential decay

Intuitively, each time unique data is repeated it loses a fraction (δ) of its original value.

Radioactive decay is an example of exponential decay:



Sum up the value at each 📚data repeat

D′ = value of total data, U = unique data, R_D = number of repetitions

$$D' = U + (1-\delta)U + (1-\delta)^2 U + \cdots + (1-\delta)^{R_D} U$$

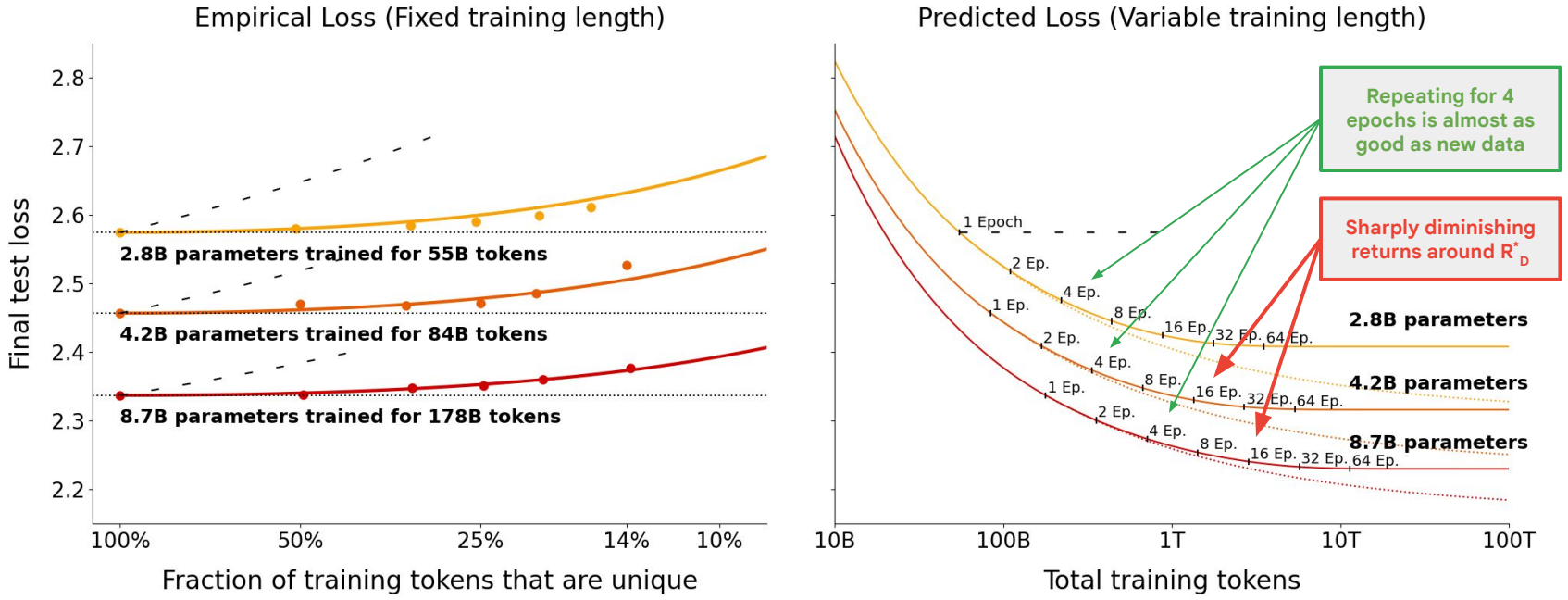
- If δ = 1: repeated data is worth nothing (only first U counts)
- If δ = 0: repeated data is as good as new data
- If δ = 0.5: repeated data retains 50% of its prior value at each repeat

Approximation: $$D' = U + U \cdot R_D^* \cdot (1 - e^{-R_D / R_D^*})$$

R^*_D= learned parameter, number of times you can repeat before **sharply diminishing returns**

- If R^*_D = 0: repeated data is worth nothing
- If R^*_D = infinity: repeated data is as good as new data

Predicting loss (**Return**)



- Loss of models trained
- Loss assuming training is stopped when exhausting all unique data
- Loss assuming repeated data is worth the same as new data
- Loss predicted by our data-constrained scaling laws

Estimate loss given parameters and repeated data

$$L(N, D) = \frac{A}{N^{\alpha}} + \frac{B}{D^{\beta}} + E$$

$$N' = U_N + U_N R_N^* (1 - e^{\frac{-R_N}{R_N^*}})$$

$$U_N = \min\{N_{opt}, N\}$$

$$D' = U_D + U_D R_D^* (1 - e^{\frac{-R_D}{R_D^*}})$$

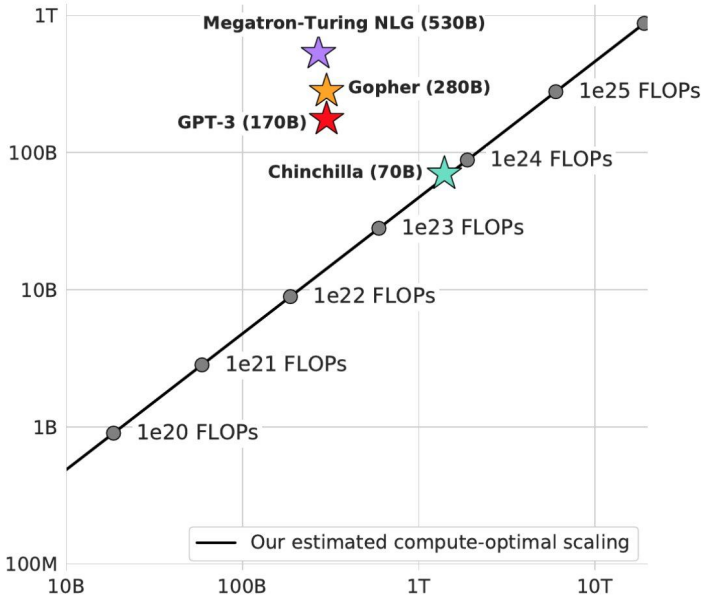
Fit on data from ~200 training runs to learn R^*_D and R^*_N

$R^*_D = 15.4$ ($\delta \approx 0.06$)

$R^*_N = 5.3$ ($\delta \approx 0.19$)

Reminder: Equal scaling when **not repeating data**

Model size (# parameters)

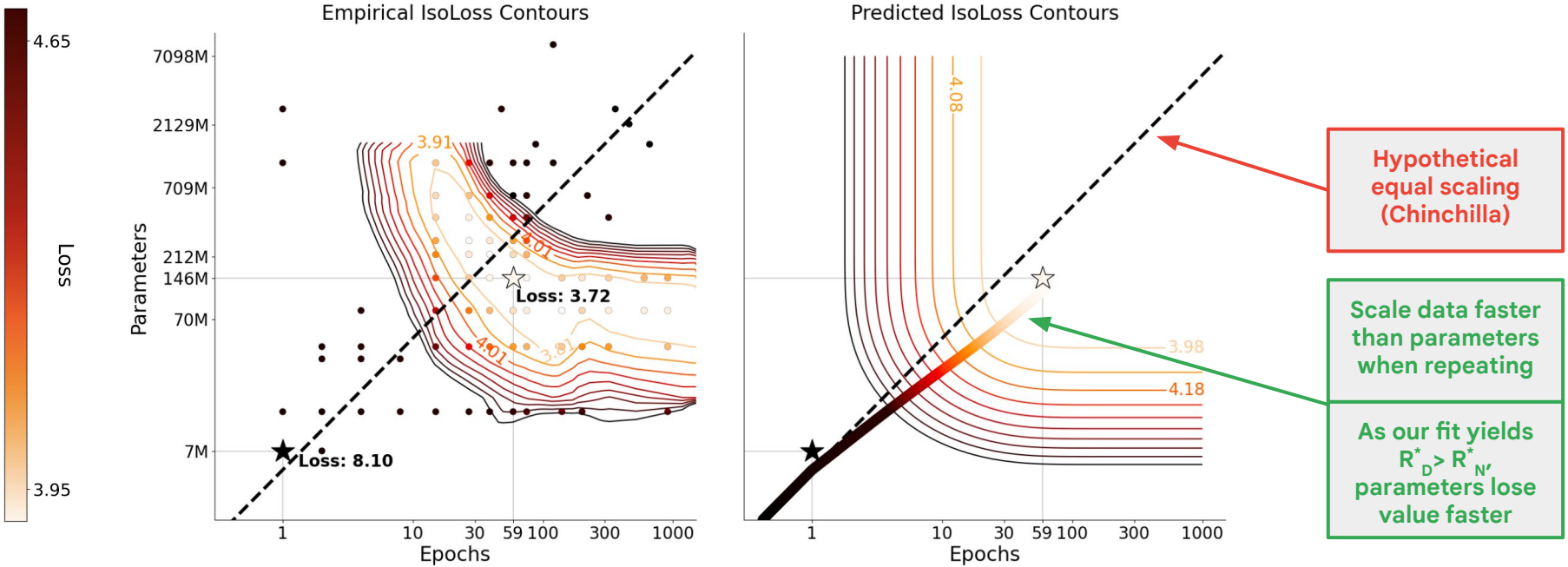


Training data (# tokens)

[Training compute-optimal large language models (2022)]

How to scale when repeating? (**Allocation**)

Training on 100M tokens of unique data with varying model size and data repetitions



- Models trained

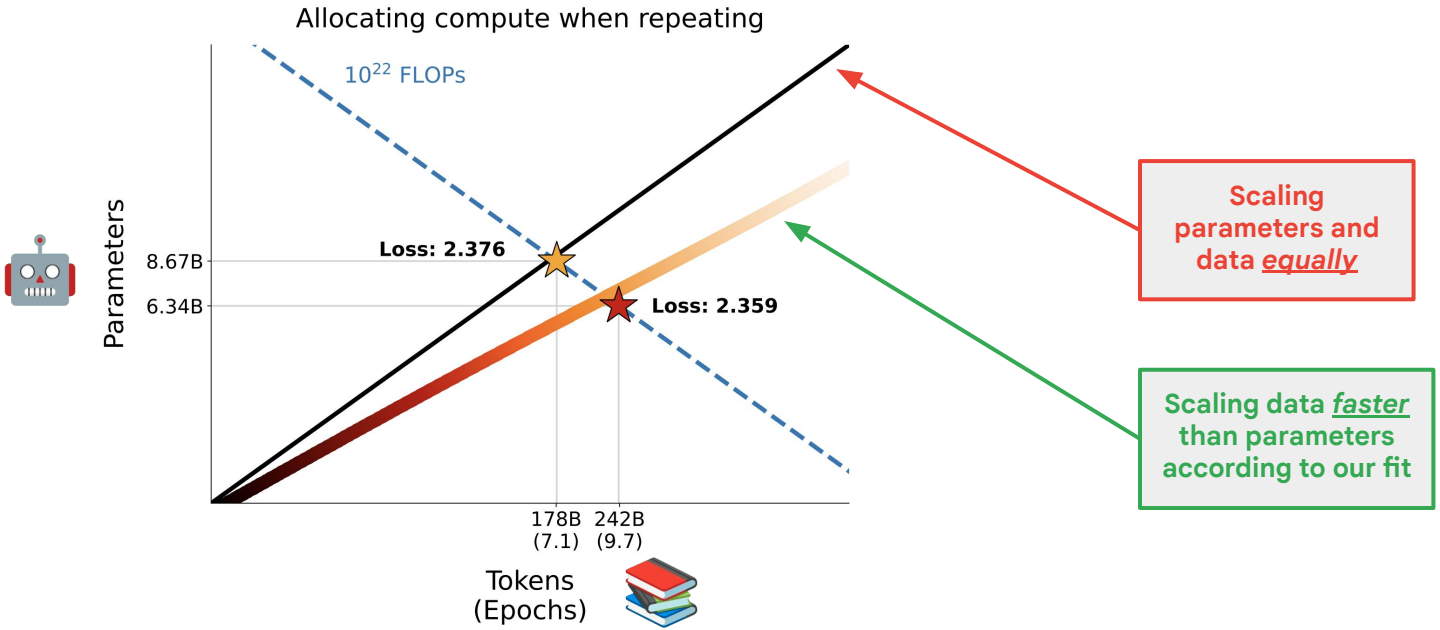
★ Compute-optimal model for 100M tokens and one epoch

☆ Lowest loss for 100M tokens

Chinchilla scaling laws efficient frontier

Data-constrained scaling laws efficient frontier

Testing our predictions at scale (**Allocation**)



Testing our predictions at scale - Downstream (**Allocation**)

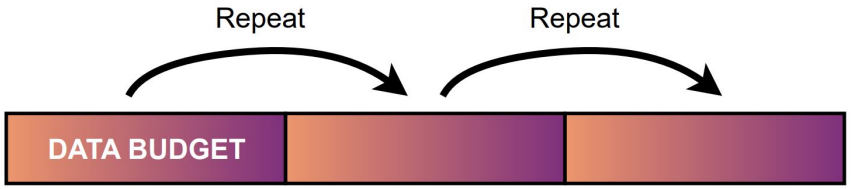
Task	**Chinchilla: 8.7B parameters & 7 epochs**	**Data-Constrained: 6.3B parameters & 10 epochs**
HellaSwag*	37.5	38.1
StoryCloze*	66.8	68.4
XSum*	3.0	3.8
...16 other NLP tasks...		
Average	**23.5**	**25.9**

*Average across 0-5 fewshots & rescaled

Complementary strategies to solve 📚data constraints

Thus far:

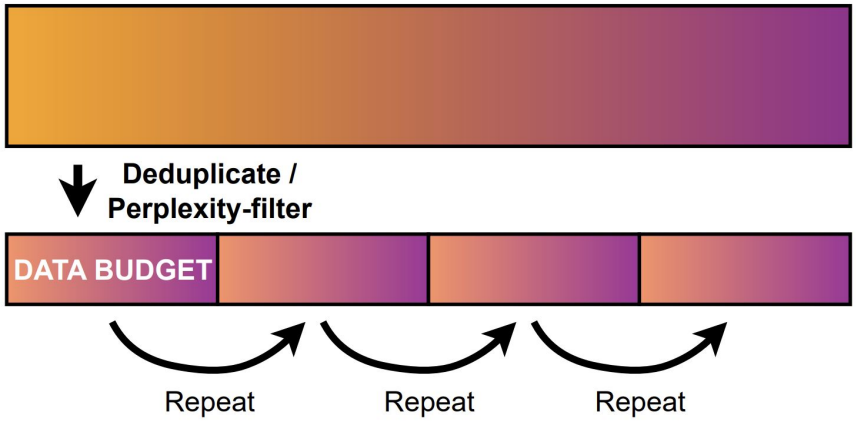
Repeating



Other strategies:

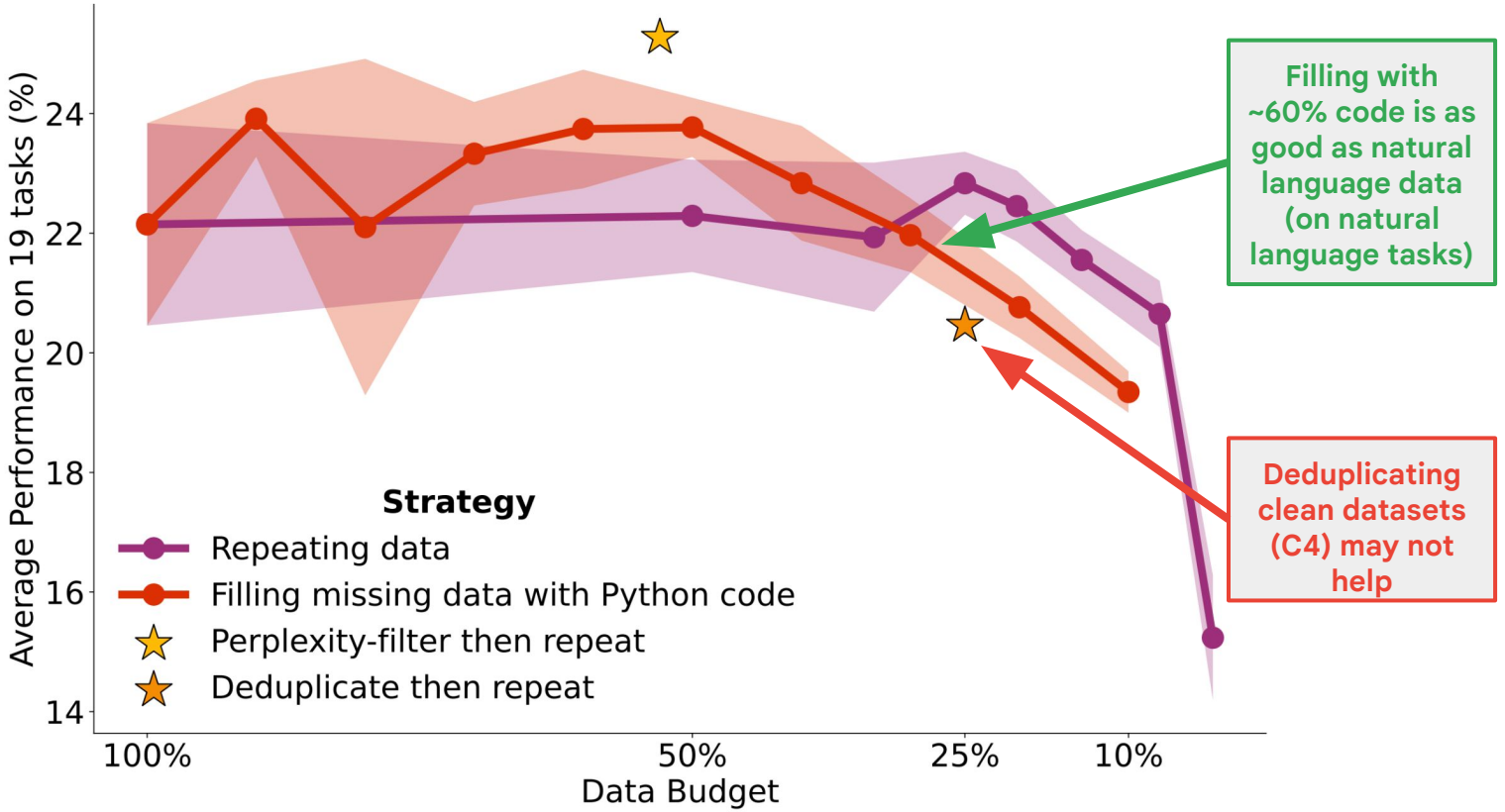
Filling with code

Revise filtering



Complementary strategies to solve 📚data constraints

💻
97 models trained for 2.1e21 FLOPs each



Takeaway #1

Repeating LLM data ~4x is fine.

Takeaway #2

50% code data is fine.

Takeaway #3

Quality-filtering + repeating can be a good strategy

Scaling Data-Constrained Language Models - Impact

NEURAL INFORMATION PROCESSING SYSTEMS

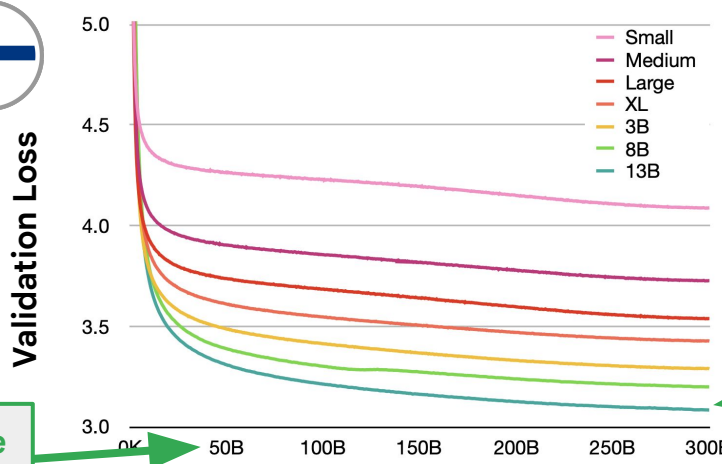
Outstanding Main Track Runner-Ups

Scaling Data-Constrained Language Models

Authors: Niklas Muennighoff · Alexander Rush · Boaz Barak · Teven Aleksandra Piktus · Sampo Pyysalo · Thomas Wolf · Colin Raffel

Poster session 2: Tue 12 Dec 5:15 p.m. — 7:15 p.m. CST, **#813**

Oral: Tue 12 Dec 3:40 p.m. — 4:40 p.m. CST, Hall C2 (level 1)



FinGPT: Large Generative Models for a Small Language

38B unique tokens

8 epochs of data

"Textbooks Are All You Need" Microsoft Phi-1

Llama 3

天工

StarCoder2 built by BigCode supported by servicenow × × NVIDIA

PORO

SILO Language Models

S.

AI2 OLMo Open Language Model

Thanks!

Twitter: @Muennighoff

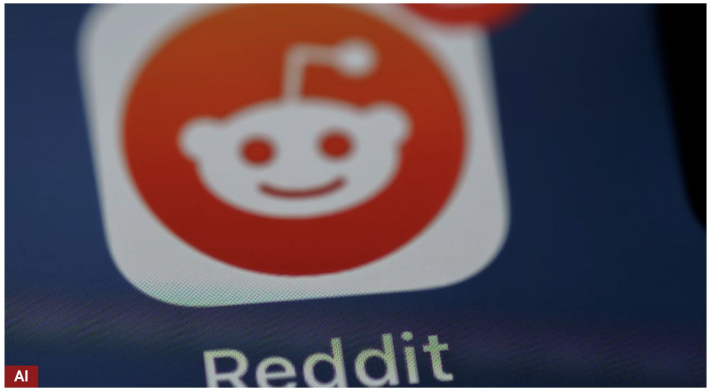
Niklas Muennighoff, Alexander M. Rush, Boaz Barak,
Teven Le Scao, Aleksandra Piktus, Nouamane Tazi,
Sampo Pyysalo, Thomas Wolf, Colin Raffel

Acknowledgements: This work was co-funded by the European Union under grant agreement No 101070350. The authors wish to acknowledge CSC – IT Center for Science, Finland, for generous computational resources on the LUMI supercomputer. We are thankful for the immense support from teams at LUMI and AMD, especially Samuel Antao. Hugging Face provided storage and additional compute instances. This work was supported by a Simons Investigator Fellowship, NSF grant DMS-2134157, DARPA grant W911NF2010021, and DOE grant DE-SC0022199. We are grateful to Harm de Vries, Woojeong Kim, Mengzhou Xia and the EleutherAI community for exceptional feedback. We thank Loubna Ben Allal for help with the Python data and Big Code members for insightful discussions on scaling laws. We thank Thomas Wang, Helen Ngo and TurkuNLP members for support on early experiments. Thanks to Jason Wei for inspiration on some slides.

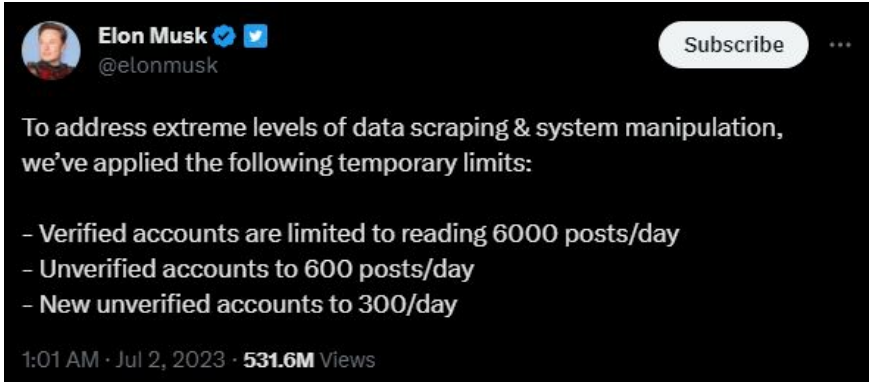
Appendix

Scaling is data-constrained

UPDATED 22:38 EDT / APRIL 18 2023



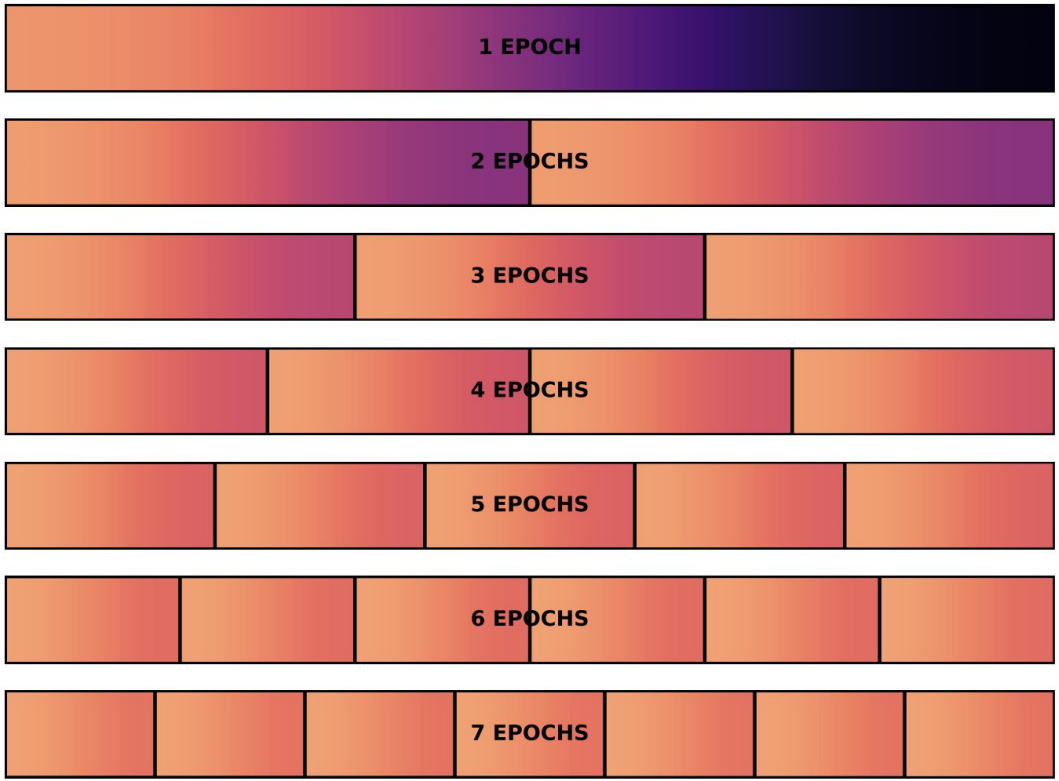
Reddit to charge for access to its API to counter free data scraping by AI companies



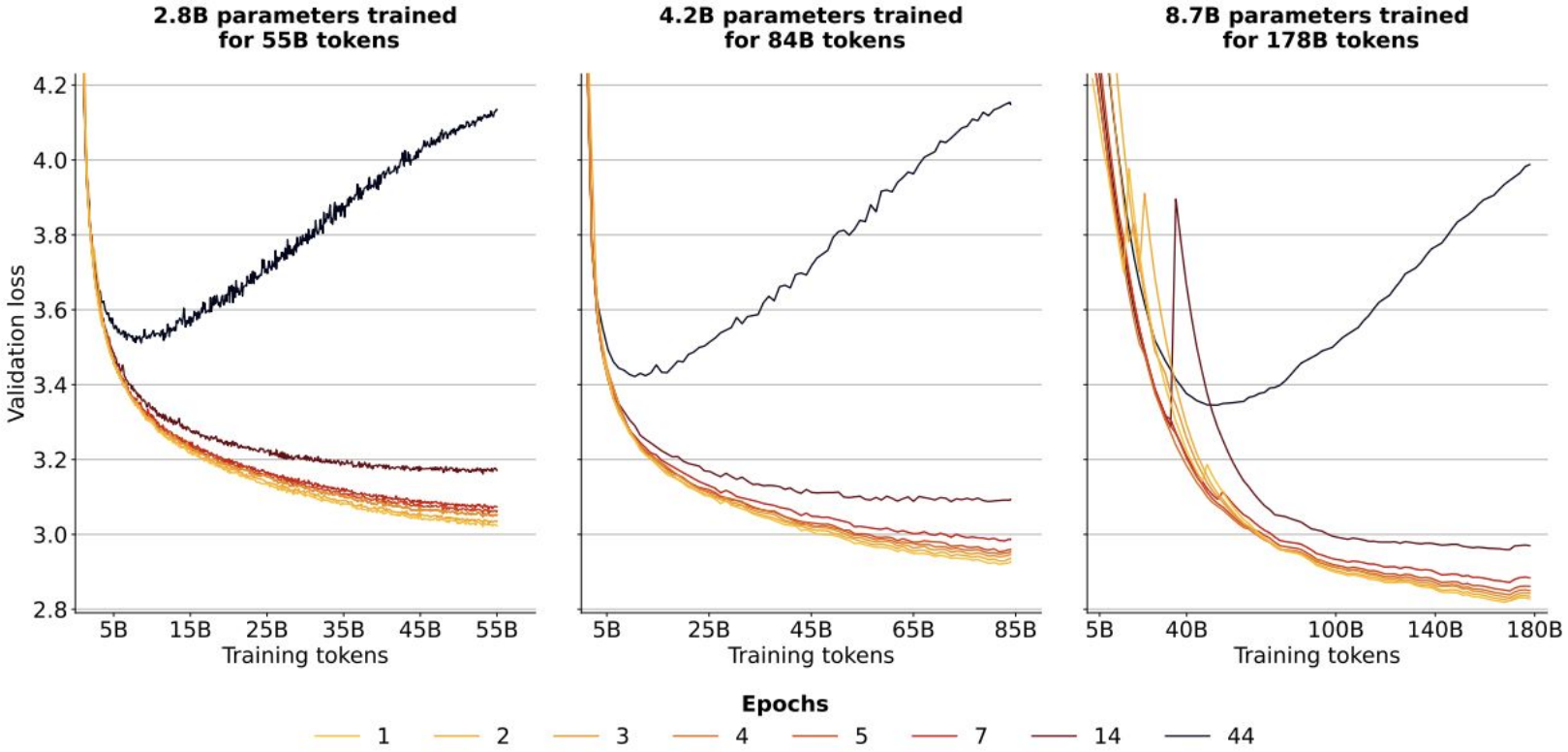
Google Books

Pages 362 to 556 are not shown in this preview.

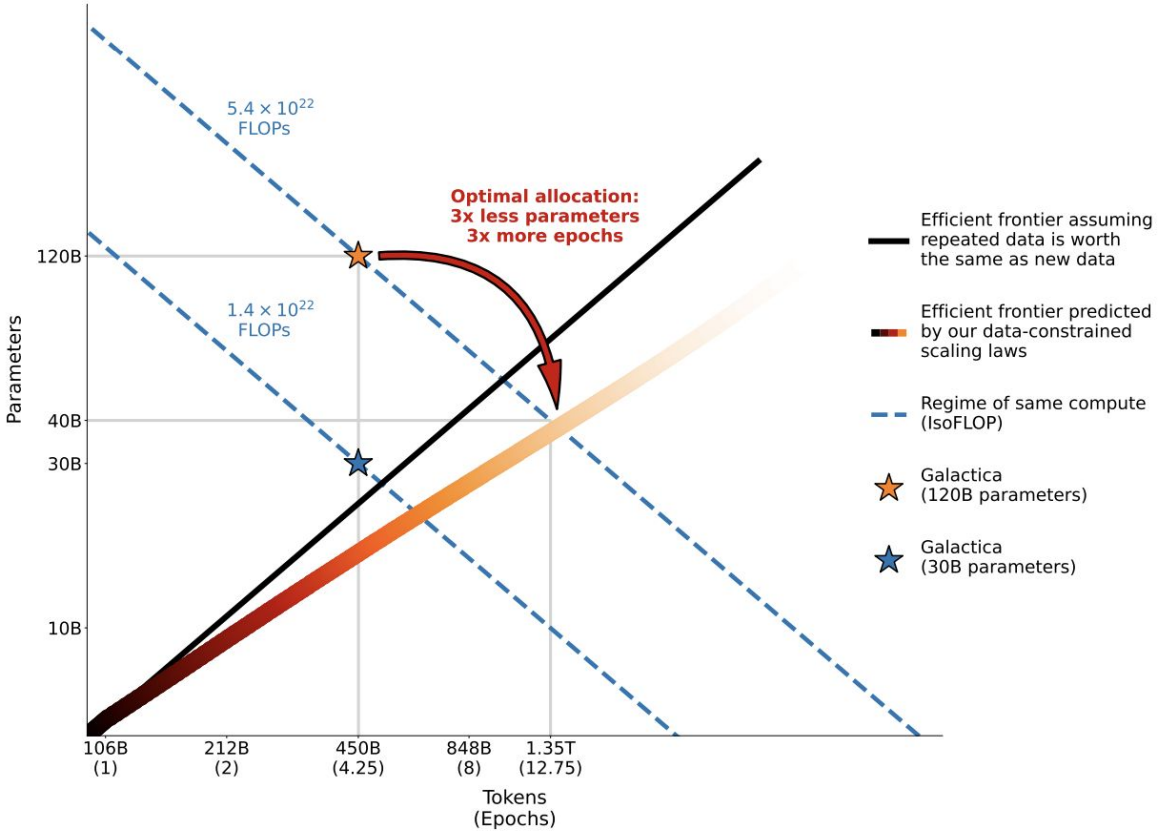
Dataset Setup



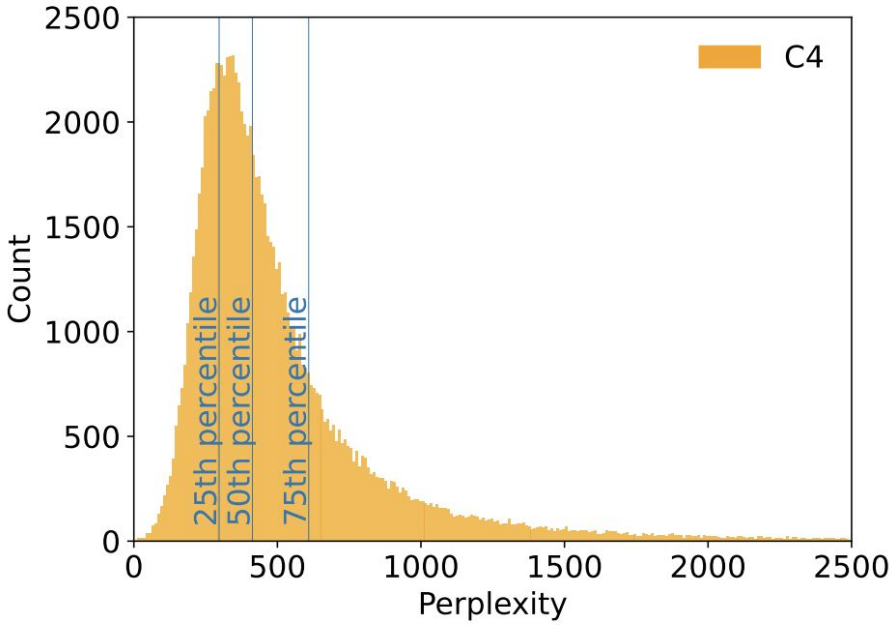
Repeating data on OSCAR (**Return**)

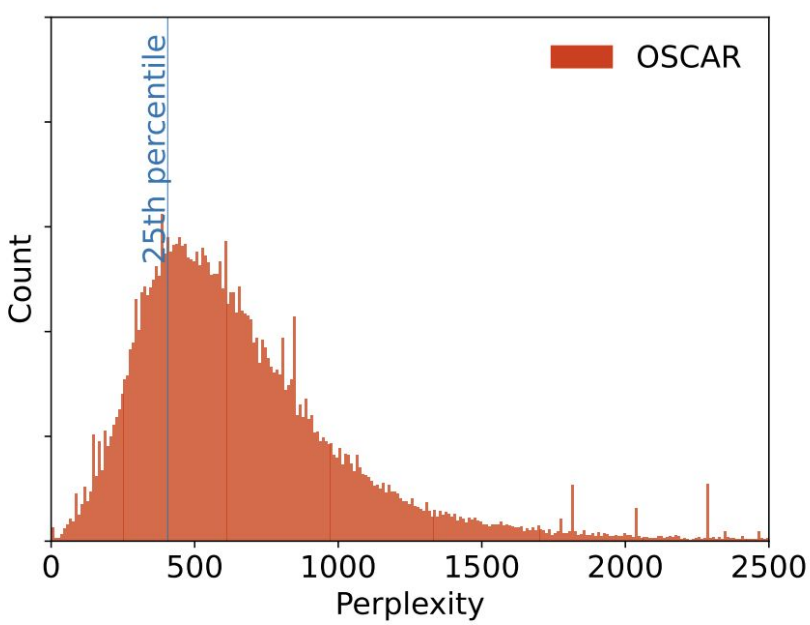


Case Study: Galactica



Perplexity filtering





Approximations

$$D' = U + (1-\delta)U + (1-\delta)^2 U + \cdots + (1-\delta)^{R_D} U$$

$$= U + (1-\delta)U \frac{(1-(1-\delta)^{R_D})}{\delta}$$ *(Geometric Series)*

Let $R_D^* = \frac{1-\delta}{\delta}$ &

$$(1-\delta) \approx e^{-\delta} \approx e^{-1/R_D^*}$$

$$D' = U + U \cdot R_D^* \cdot (1 - e^{-R_D/R_D^*})$$