What do We Need to Learn Before Burning the Next One Million GPU Hours?

Iz Beltagy
Allen Institute for AI

Julien Launay
LightOn

What we did for the past year in architecture & scaling…

What Language Model to Train if You Have One Million GPU Hours?
Le Scao et al. (2022).

What Language Model Architecture and Pretraining Objective Work Best for Zero-Shot Generalization?
Wang et al. (ICML 2022).

…but this talk is about what we learned and what open questions we still need to answer?

Overview

Evaluation

Architecture and Pretraining Objective

Scaling

Datasets

Engineering

Efficient Pretraining

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What evaluation setup to use to make modeling decisions?

Many settings

- LM loss vs. downstream
- Zero-shot vs. few-shot
- Prompting vs. finetuning
- Parameter-efficient vs. full finetuning
- With/without multi-task finetuning

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- Fast and easy to run

- Representative of how the model will be used in practice

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Open question

- Better understanding of the relation between different setup, and why the results differ

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Narang et. al., 2021: Do Transformer Modifications Transfer Across Implementations and Applications?

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Tay et. al., 2022: Unifying Language Learning Paradigms

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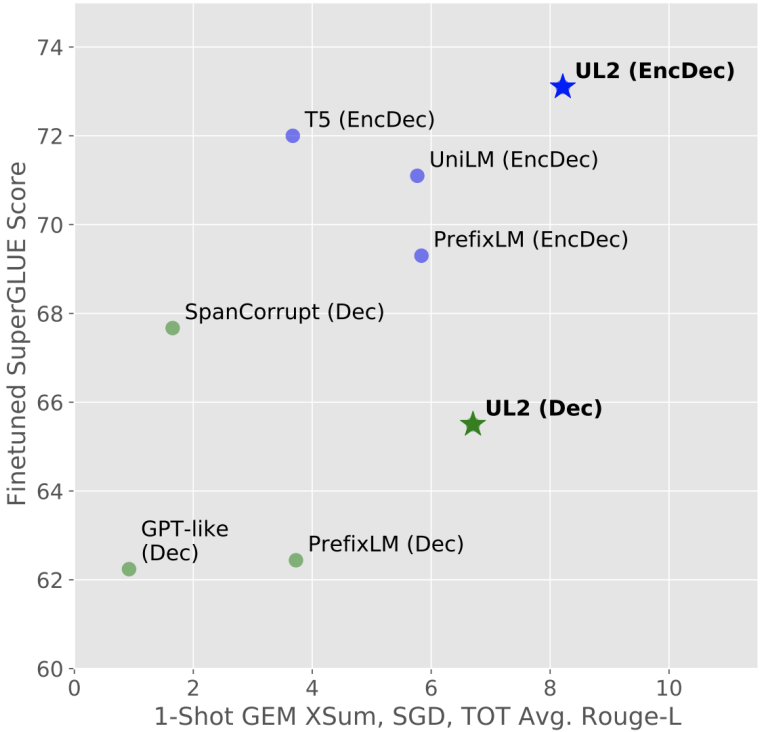

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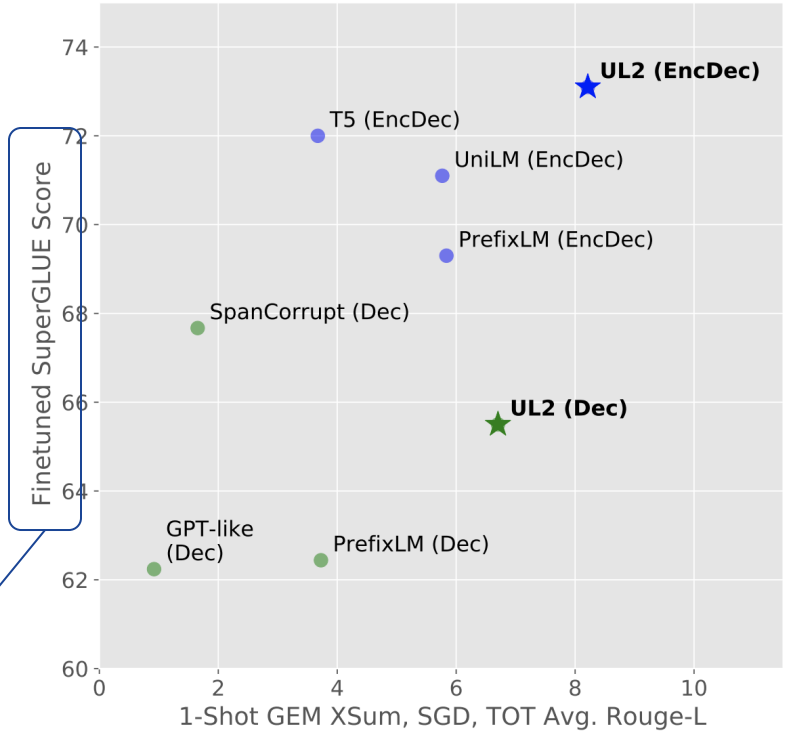

T5-style are usually better

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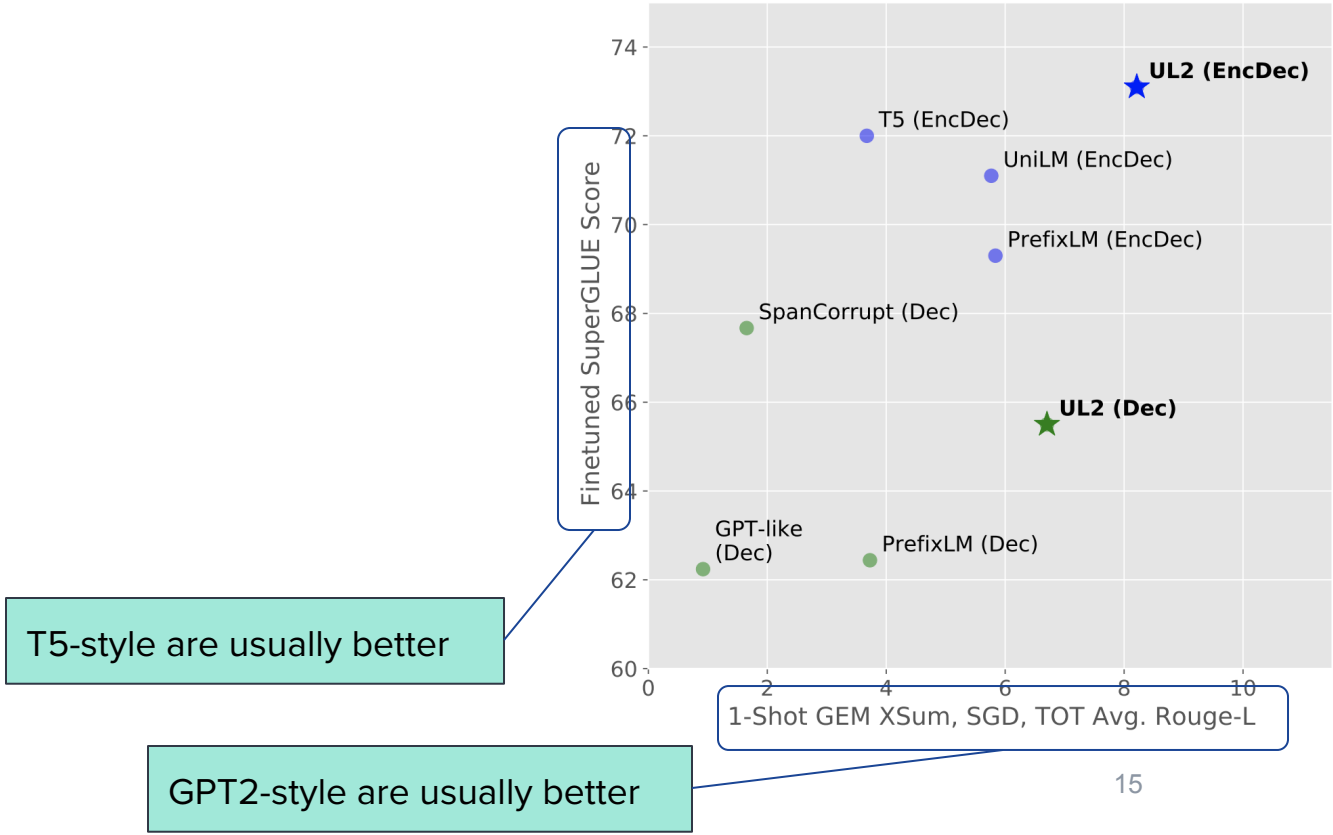

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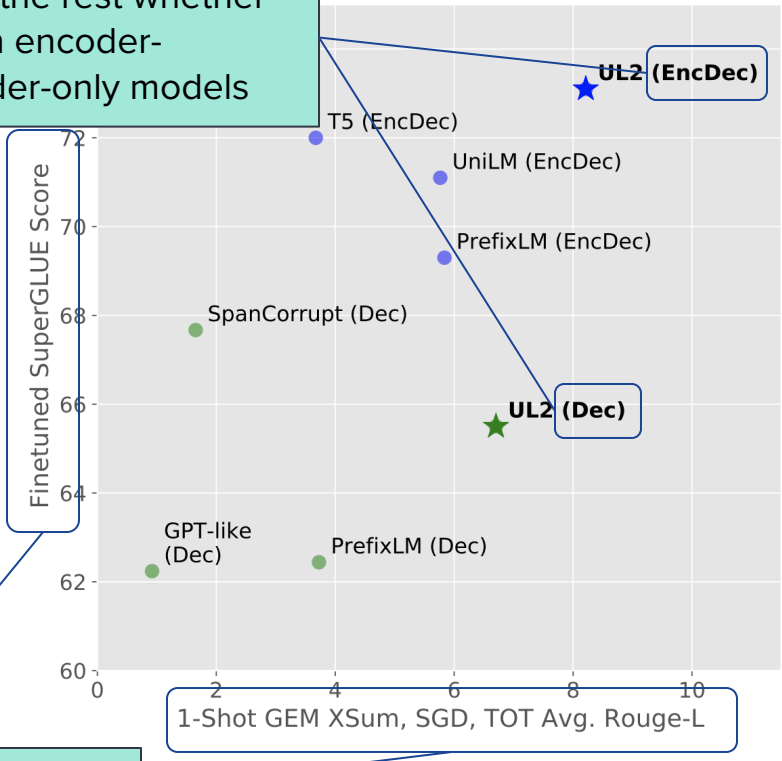
UL2 outperforms the rest whether implemented with encoder-decoder or decoder-only models



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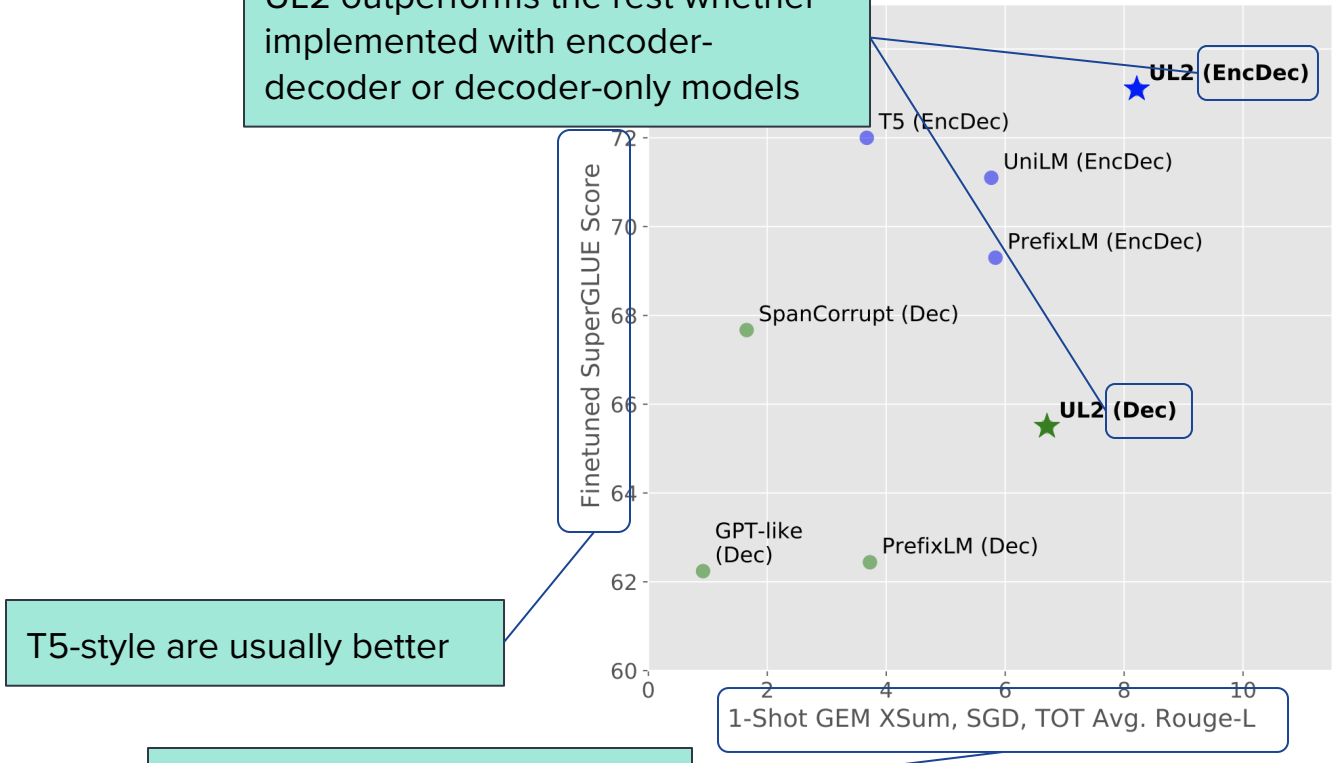

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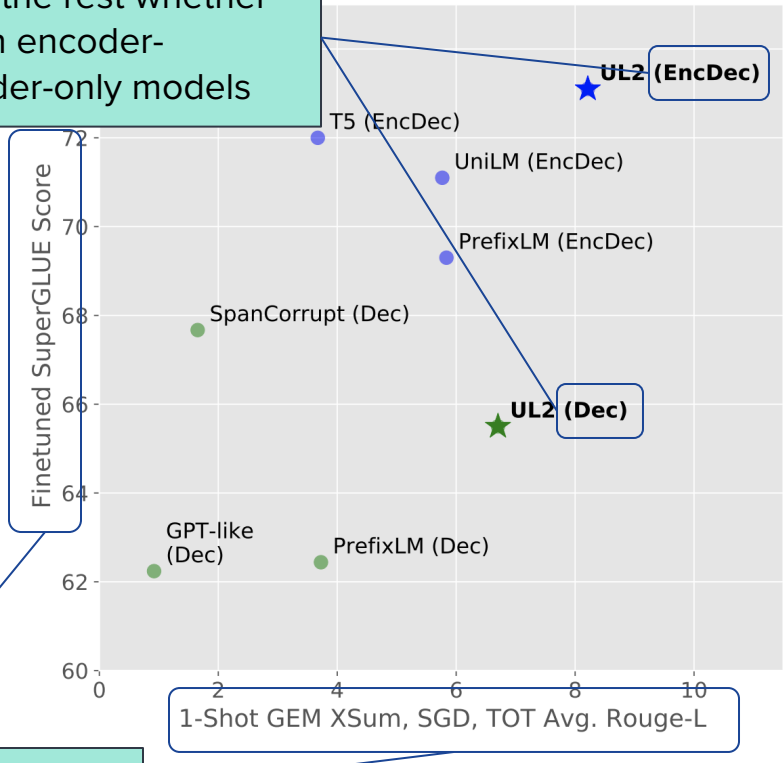

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- Ignored causal LM
  - Claimed that Prefix LM is generally better

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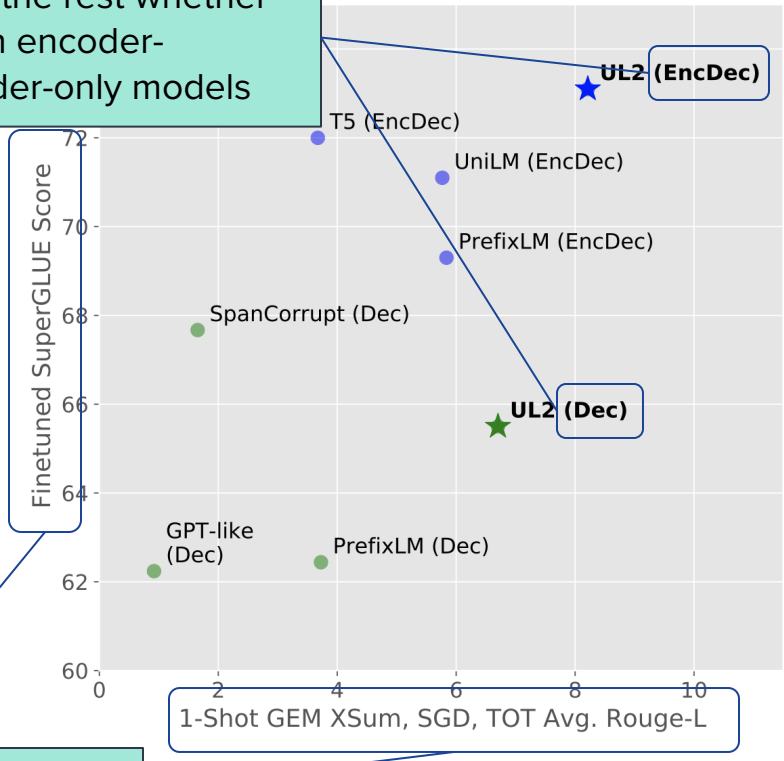

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We don’t know, but we are getting closer

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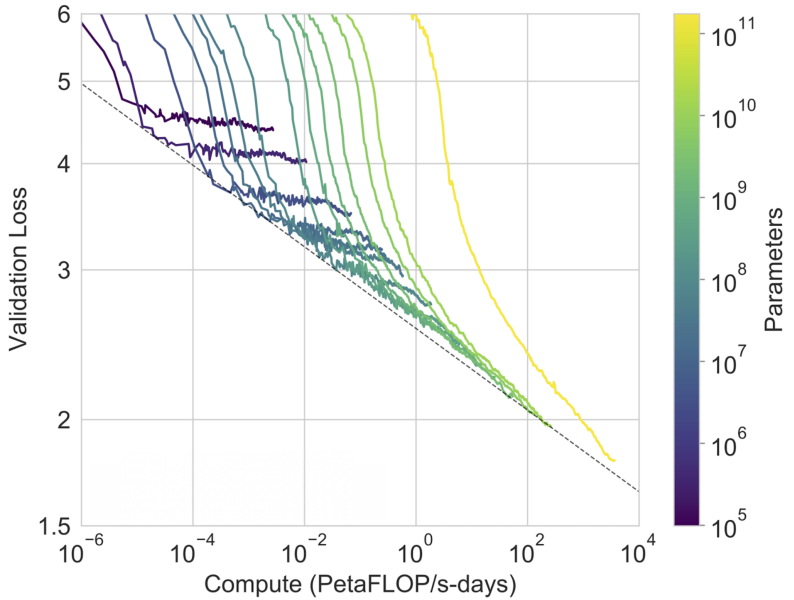

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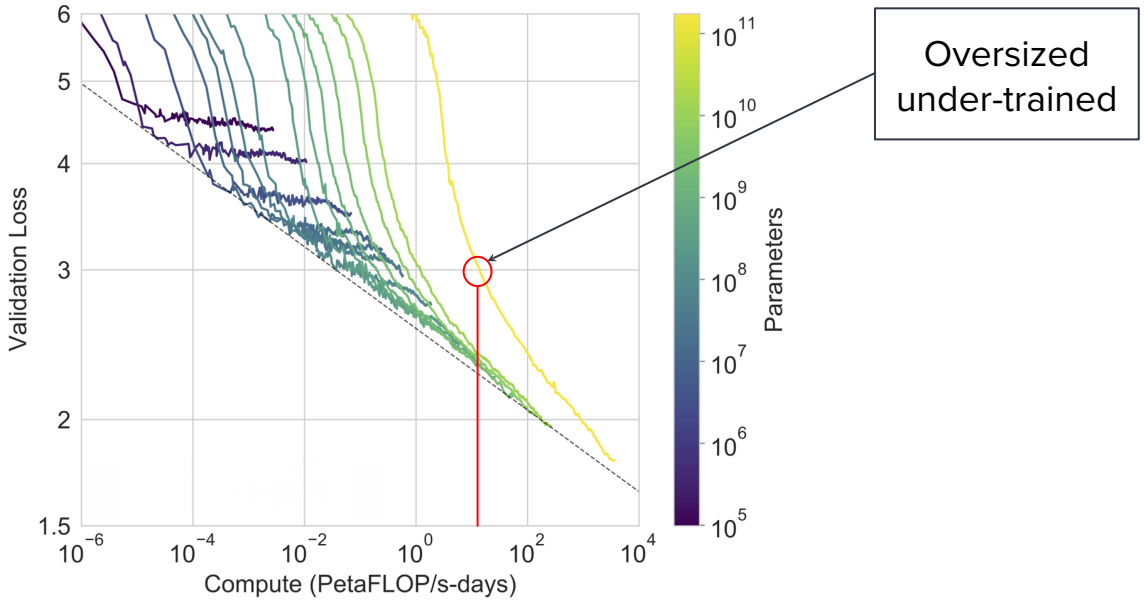

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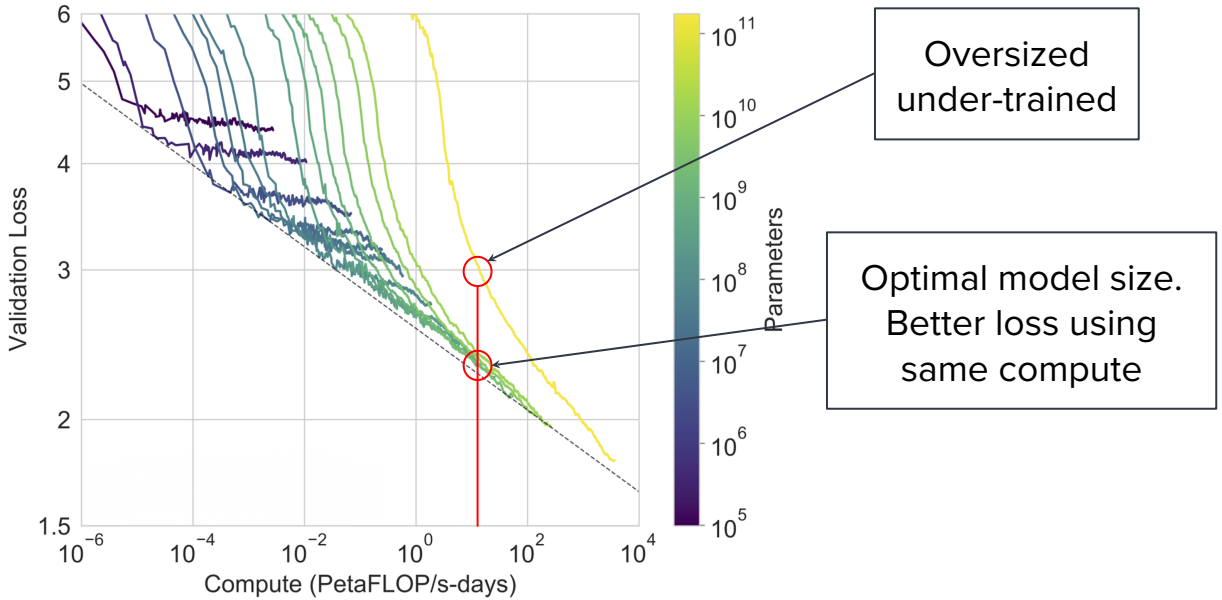

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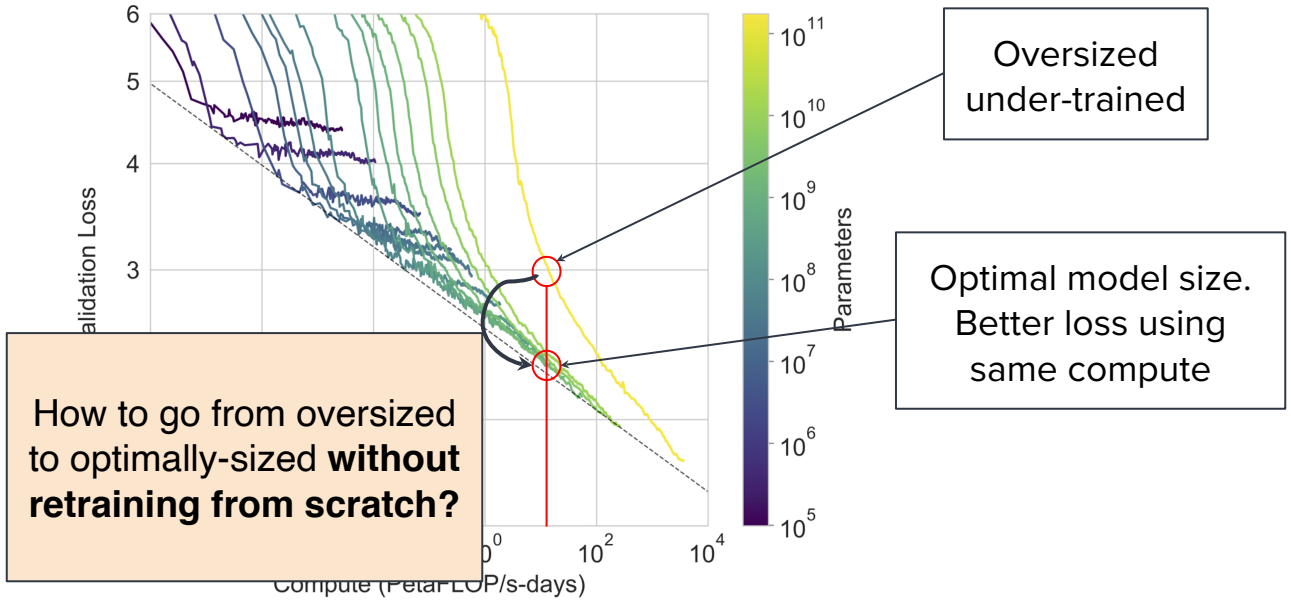

Chonk' me up Scotty

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(more than most modeling choices?)

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Aggregated performance on EAI harness

Model	Parameters	Pretraining tokens			
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OpenAI — Babbage	1.3B				**45.30**
EleutherAI — GPT-Neo	1.3B	The Pile			42.94
Ours	13B	OSCAR			47.09
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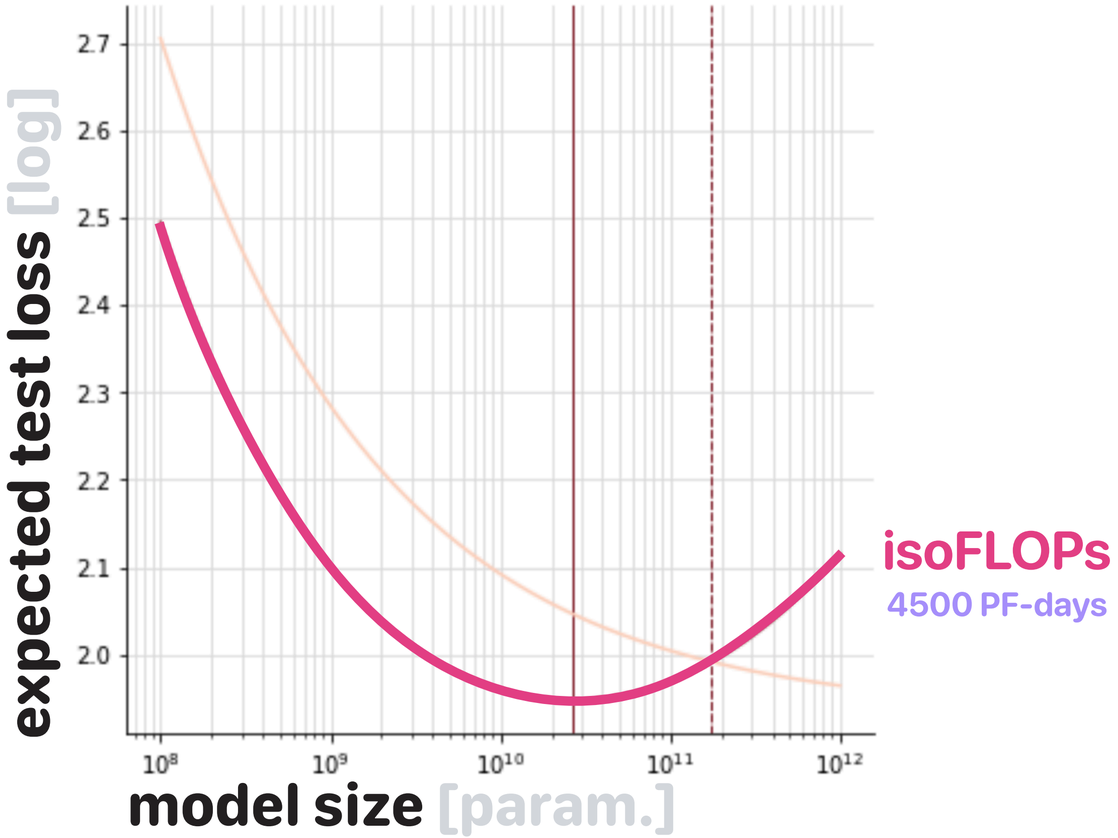

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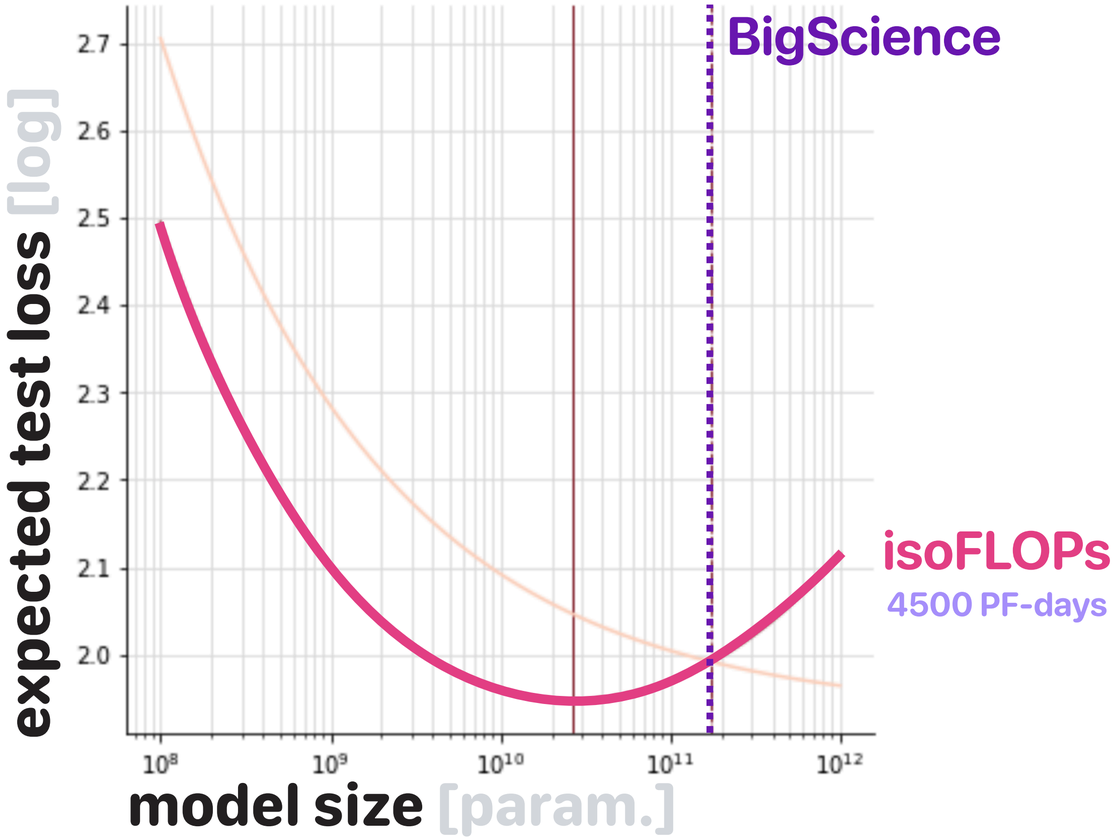

We are gonna need a bigger dataset!

Bad news: we need a lot more data than expected...

Previously... Kaplan et al., 2020

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isoFLOPs 50B parameters → 1000B tokens

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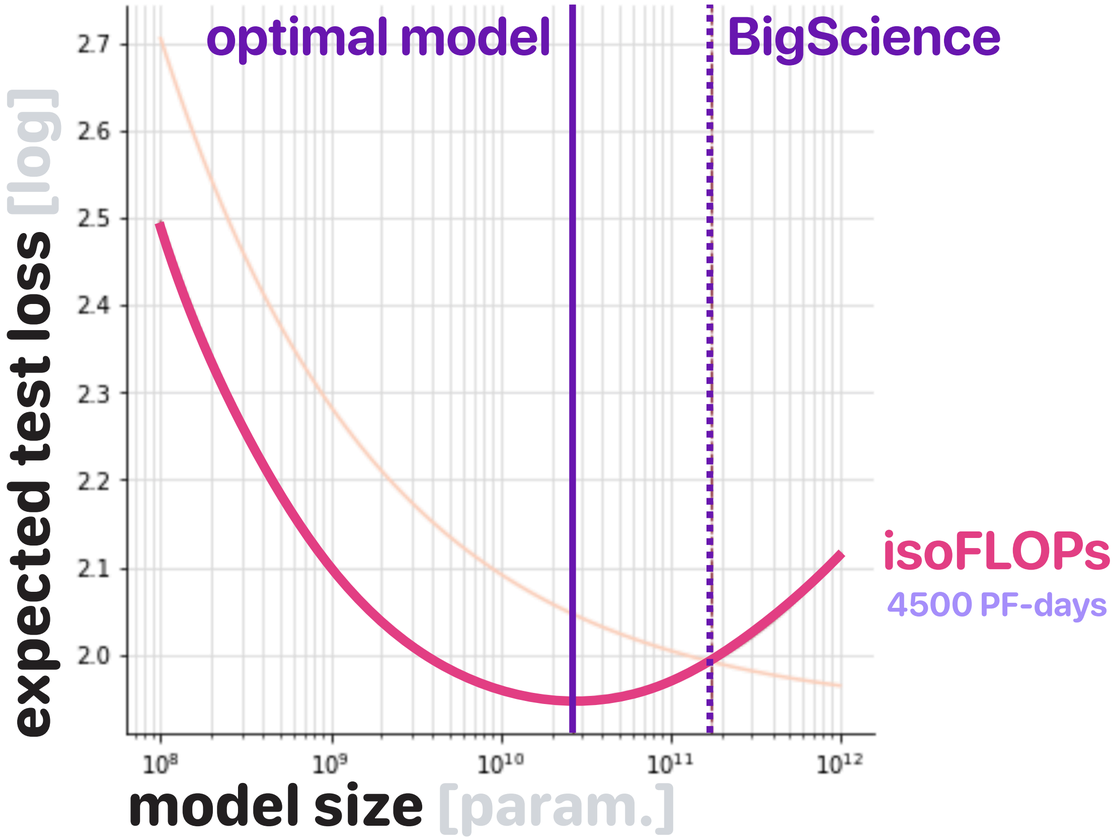

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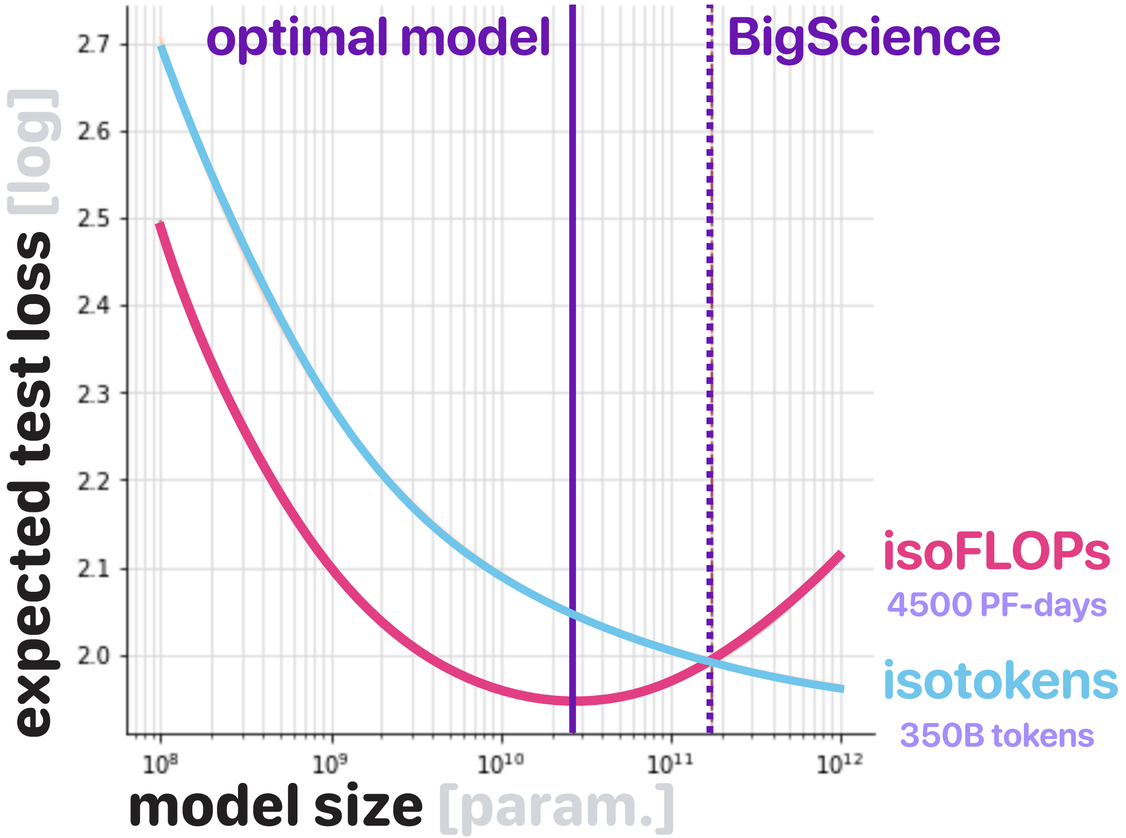

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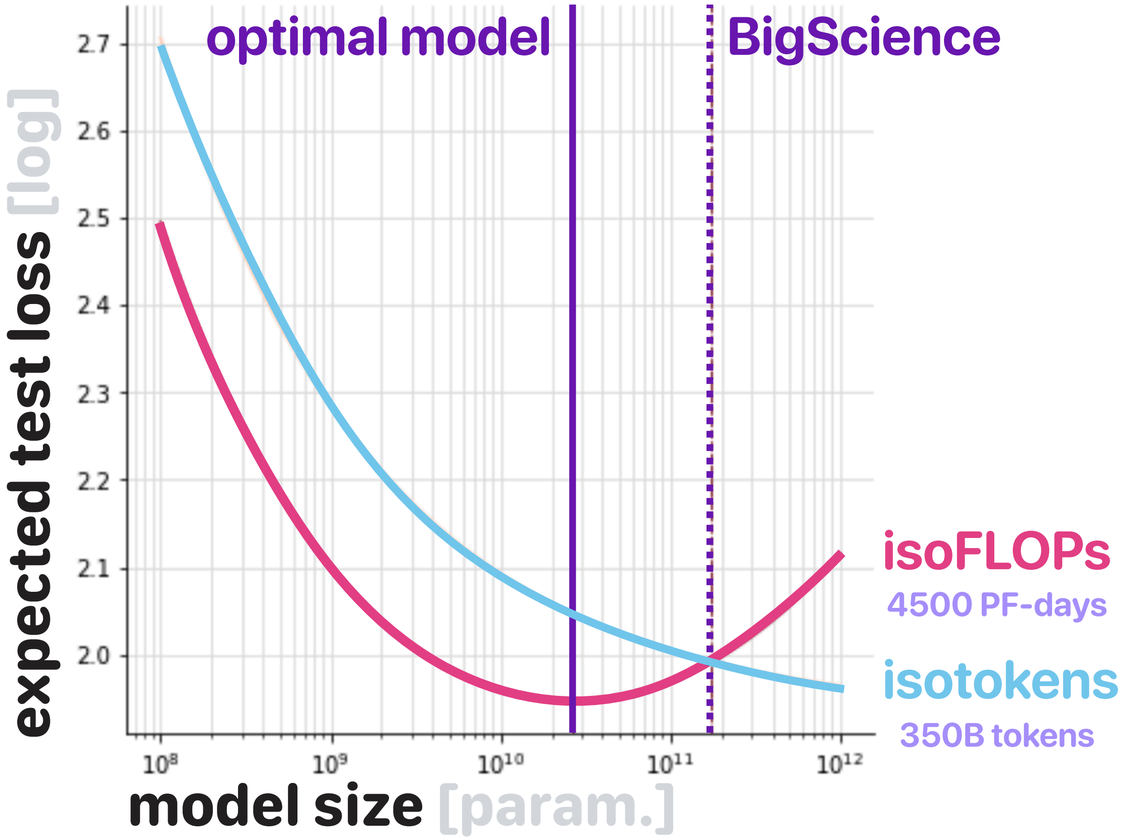

Will we be data-bound instead of compute-bound?

Fantastic training data and where to find it

🔬 What even is high-quality data?

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Fantastic training data and where to find it

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technical filtering	deduplication, lack of artefacts, etc.
curation	diverse, cross-domain, etc.

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"social media conversations"

Total dataset size = 780 billion tokens	
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Chowdhery et al.,2022.

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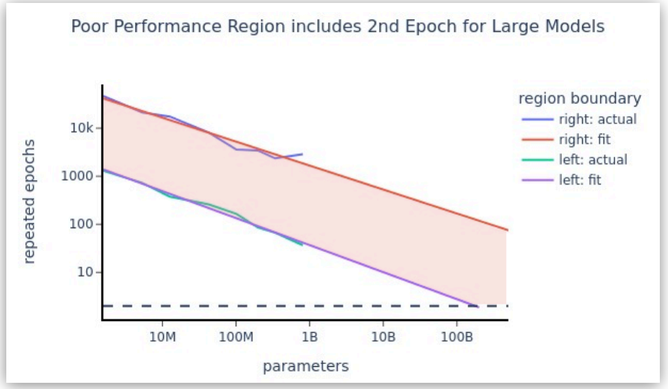
double descent for duplication?



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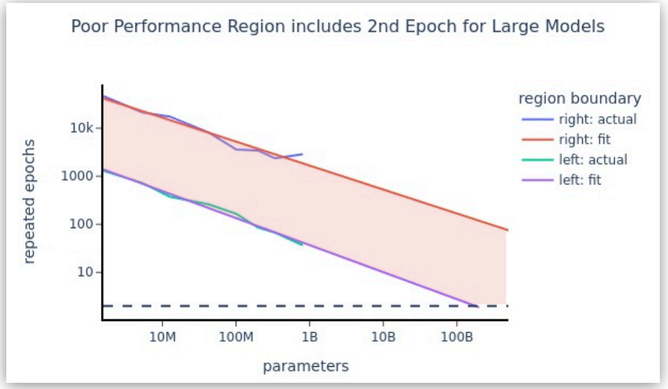

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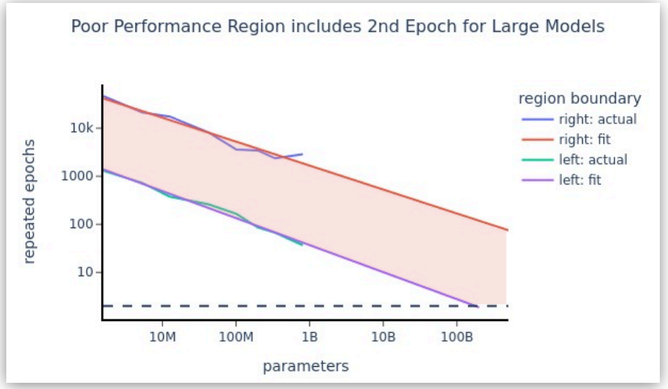

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⚠️ Emergence of data moats which could stand in the way of research.

Fantastic training data and where to find it

Oh and by the way...

We need this in >100 languages!

We are doing Big Science, and this comes with challenges...

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🚀 LLMs are a true big science and require significant engineering efforts...

state-of-the-art HPC challenges

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BLOOM: >100 configurations tested!

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e.g. tile/wave quantization, distributed hyperparameters, etc.

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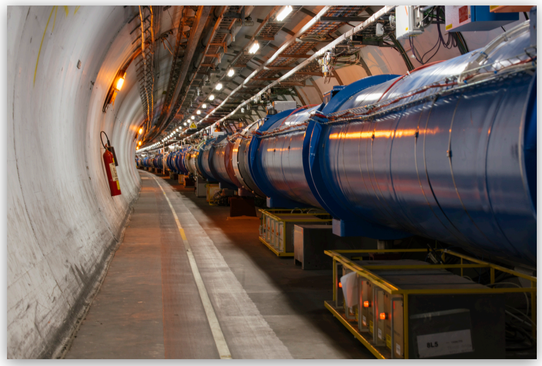

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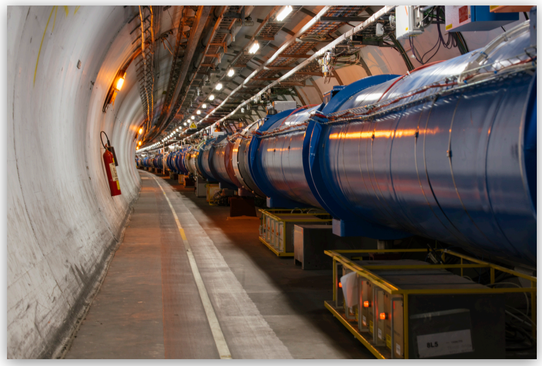

(let's avoid this)

Case-study of how hard it can get: Meta's OPT

OPT: Open Pre-Trained Transformer Language Models

Zhang et al., 2022

Case-study of how hard it can get: Meta's OPT

OPT: Open Pre-trained Transformer Language Models

Susan Zhang* Stephen Roller* Naman Goyal*
Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona Diab, Xian Li,
Xi Victoria Lin, Todor Mihaylov, Myle OtC Sam Shleifer, Kurt Shuster, Daniel Simig,
Punit Singh Koura, Anjali Sridhar, Tianlu Wang, Luke Zettlemoyer
Meta AI
{susanz,roller,namangoyal}@fb.com

Abstract

Large language models, which are often trained for hundreds of thousands of compute days, have shown remarkable capabilities for zero- and few-shot learning. Given their computational cost, these models are difficult to replicate without significant capital. For the few that are available through APIs, no access is granted to the full model weights, making them difficult to study. We present Open Pre-trained Transformers (OPT), a suite of decoder-only pre-trained transformers ranging from 125M to 175B parameters, which we aim to fully and responsibly share with interested researchers. We show that OPT-175B is comparable to GPT-3, while requiring only 1/7th the carbon footprint to develop. We are also releasing our logbook detailing the infrastructure challenges we faced, along with code for experimenting with all of the released models.

1 Introduction

Large language models (LLMs) trained on massive text collections have shown surprising emergent capabilities to generate text and perform zero- and few-shot learning (Brown et al., 2020; Lieber et al., 2021; Smith et al., 2022; Rae et al., 2021; Chowdhery et al., 2022). While in some cases the public can interact with these models through paid APIs, full model access is currently limited to only a few highly resourced labs.[1] This restricted access has limited researchers' ability to study how and why these large language models work, hindering progress on improving known challenges in areas such as robustness, bias, and toxicity.

We present Open Pre-trained Transformers (OPT), a suite of decoder-only pre-trained transformers ranging from 125M to 175B parameters, which we aim to fully and responsibly share with interested researchers. We show that OPT-175B is comparable to GPT-3, while also applying the latest best practices in data collection and efficient training. Our aim in developing this suite of OPT models is to enable reproducible and responsible research at scale, and to bring more voices to the table in studying the impact of these LLMs. Definitions of risk, harm, bias, and toxicity, etc., should be articulated by the collective research community as a whole, which is only possible when models are available for study.

We are releasing all of our models between 125M and 30B parameters, and will provide full research access to OPT-175B upon request. Access will be granted to academic researchers; those affiliated with organizations in government, civil society, and academia; and those in industry research laboratories. We are also releasing both the logbook of our model creation as well as our codebase, metaseq,[2] which enabled training OPT-175B on 992 80GB A100 GPUs, reaching 147 TFLOP/s utilization per GPU. From this implementation, and from using the latest generation of NVIDIA hardware, we are able to develop OPT-175B using only 1/7th the carbon footprint of GPT-3. While this is a substantial improvement, the resources required for such a model is still nonetheless significant for many to replicate a model of this size will only amplify the growing compute footprint of these LLMs.

We believe the entire AI community — academic researchers, civil society, policymakers, and industry — must work together to develop clear

[2] https://github.com/facebookresearch/metaseq

OPT: Open Pre-Trained Transformer Language Models

Zhang et al., 2022

😅 Meta's open "reproduction" of GPT-3 was... a challenging experience!

Case-study of how hard it can get: Meta's OPT


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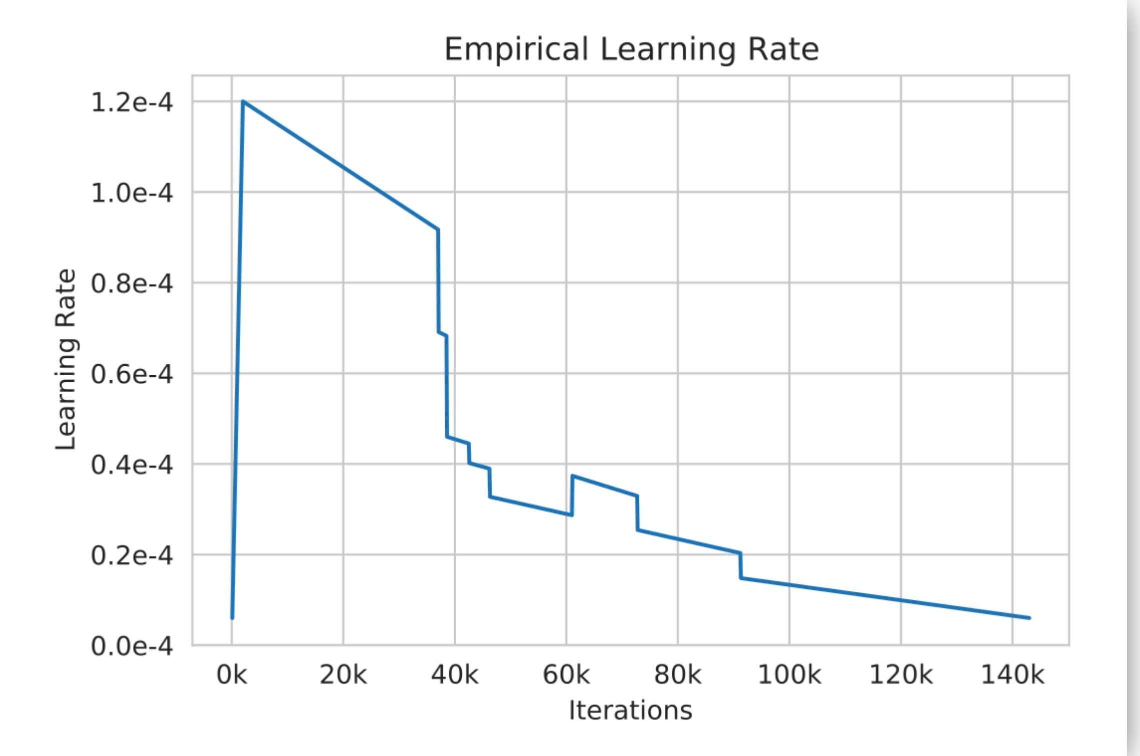

manually tuned learning rate

hundreds of restarts, spikes, etc.

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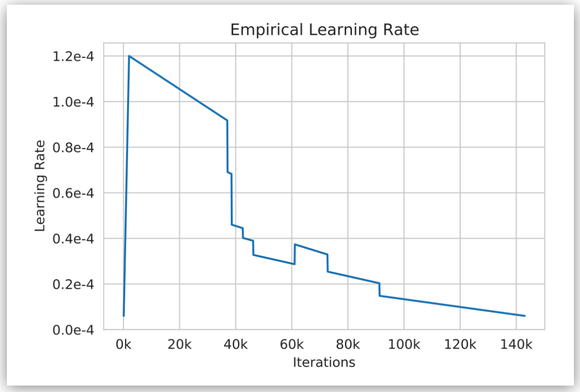


manually tuned learning rate

hundreds of restarts, spikes, etc.

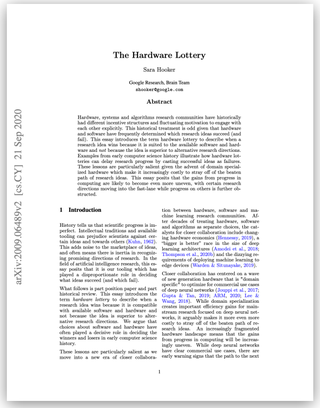
But why?

FP16

BF16

template: Karpathy, 2020

He who controls the chips controls the LLMs



The Hardware Lottery

Sara Hooker

Google Research, Brain Team
shooker@google.com

Abstract

Hardware, systems and algorithms research communities have historically had different incentive structures and fluctuating motivation to engage with each other explicitly. This historical tension has led to a lack of collaboration and software have frequently determined which research ideas succeed (and fail). This essay introduces the term hardware lottery to describe when a research idea wins because it is suited to the available software and hardware and not because the idea is superior to alternative research directions. Examples from early computer science history illustrate how hardware lotteries can delay research progress by casting successful ideas as failures. These lessons are particularly salient given the advent of domain specialized hardware which makes it increasingly costly to stray off of the beaten path of research ideas. This essay posits that the gains from progress in computing are likely to become even more uneven, with certain research directions moving into the fast-lane while progress on others is further obstructed.

1 Introduction

History tells us that scientific progress is imperfect. Intellectual traditions and available tooling can prejudice scientists against certain research directions (Sutton, 2019; Mattson et al., 2020). This adds noise to the marketplace of ideas, and often means there is inertia in recognizing promising directions of research. In the field of artificial intelligence research, this essay argues that the tools for research have played a disproportionate role in deciding what ideas succeed (and which fail).

What follows is part position paper and part historical review. This essay introduces the term hardware lottery to describe when a research idea wins because it is compatible with available software and hardware and not because the idea is superior to alternative research directions. We argue that choices about software and hardware have often played a decisive role in deciding the winners and losers in early computer science history.

These lessons are particularly salient as we move into a new era of closer collaboration between hardware, software and machine learning research communities. After decades of treating hardware, software and algorithms as separate choices, the catalysts for closer collaboration include changing hardware economics (Hennessy, 2019), a "bigger is better" race in the size of deep learning architectures (Amodei et al., 2018; Thompson et al., 2020) and the dissolution of requirements of deploying machine learning to edge devices (Warden & Situnayake, 2019).

Closer collaboration has centered on a wave of new generation hardware that is "domain specific" to optimize for commercial use cases of current neural networks (Jouppi et al., 2017; Ignatov et al., 2019; Fowers et al., 2018; Wang, 2018). While domain specialization creates important efficiency gains for mainstream research focused on a fixed set of deep learning workloads, it makes it more even more costly to stray off of the beaten path of research ideas. An increasingly fragmented hardware landscape means that the gains from algorithmic improvements will be unevenly enjoyed. While deep neural networks have clear commercial use cases, there are early warning signs that the path to the next

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arXiv:2009.06489v2 [cs.CY] 21 Sep 2020

Hardware progress is secretly shaping machine learning

The Hardware Lottery

Sara Hooker, 2020

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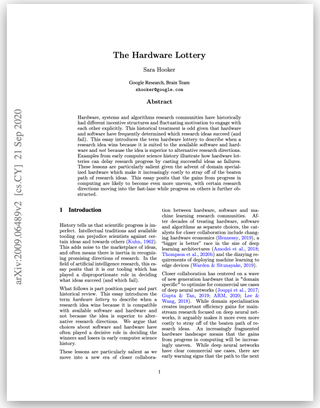

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- pure data/model parallelism
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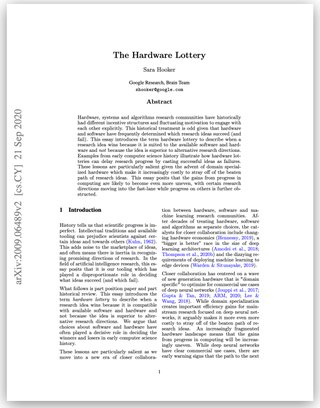

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- data/model/pipeline/sequence parallelism
- diversity in HPC platforms
  - network topology, etc.

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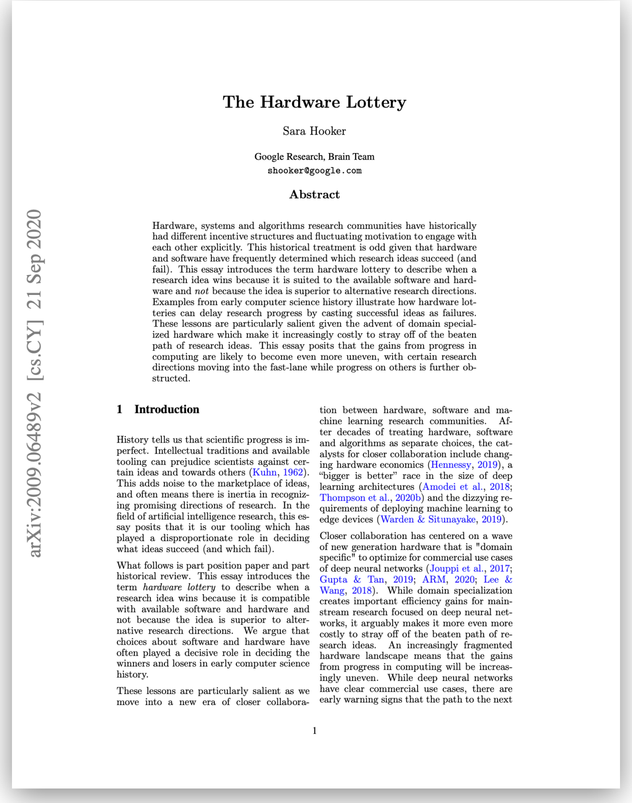

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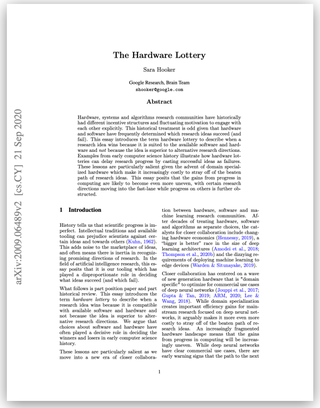

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Google, Facebook, Tesla, Amazon are all making their own chips!

Can better modeling & more efficient pretraining change the playing field?

- 💨 We can gain in efficiency...

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💨 We can gain in efficiency... current approaches, ~50% GPU FLOPs usage

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reduced numerical precision: down to int8

see Transformer engine in H100

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But can we also fundamentally change scaling behaviour?

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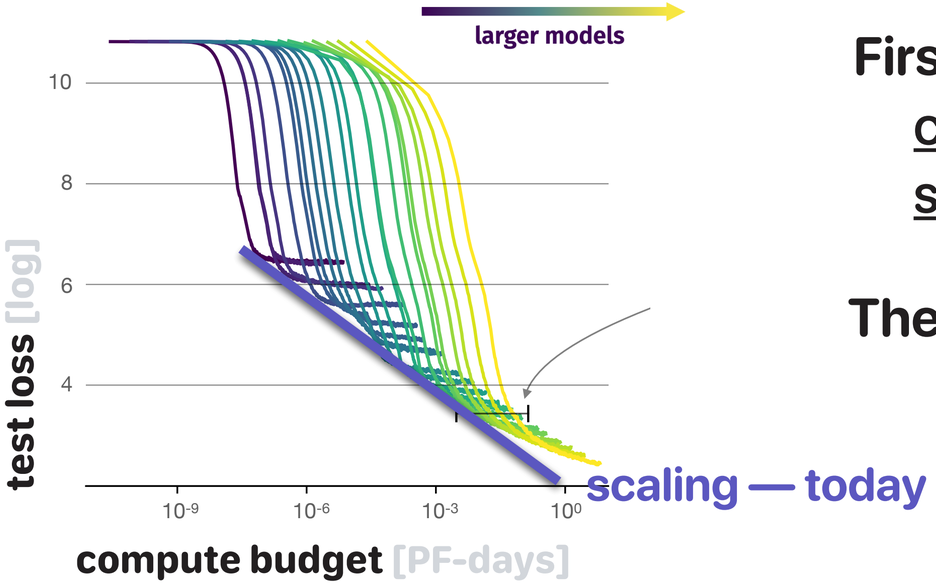

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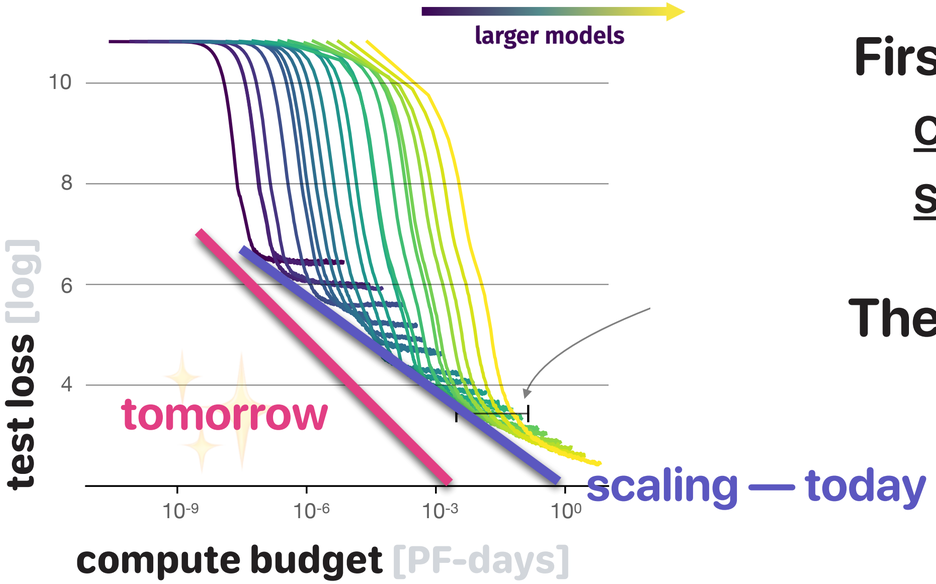

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🤗 Thank you to all contributors!