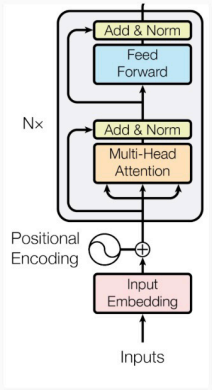
03

Notable LLMs

Three Easy Pieces

BERT

[*] [*] **[sat_]** [*] **[the_]** [*]



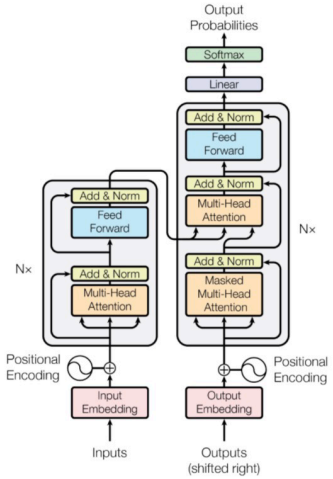
[The_] [cat_] **[MASK]** [on_] **[MASK]** [mat_]

T5

Das ist gut.

A storm in Attala caused 6 victims.

This is not toxic.



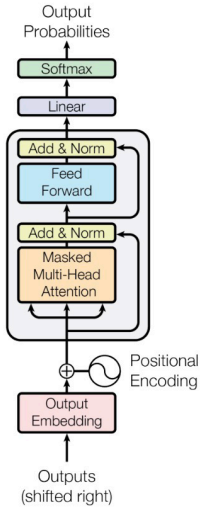
Translate EN-DE: This is good.

Summarize: state authorities dispatched…

Is this toxic: You look beautiful today!

GPT

[sat_]



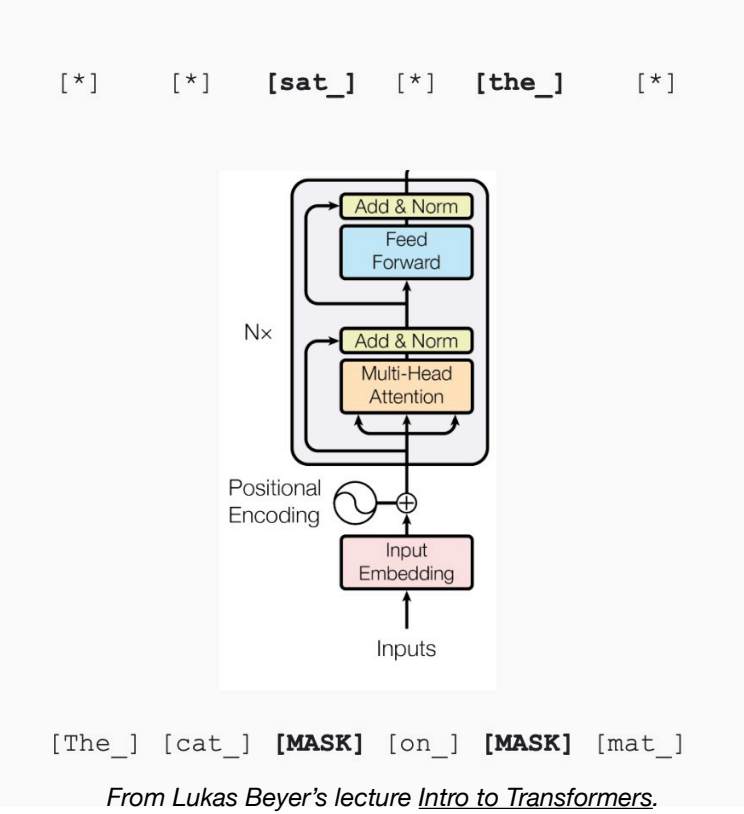
[START] [The_] [cat_]

Transformer image source: "Attention Is All You Need" paper

From Lukas Beyer's lecture Intro to Transformers.

BERT (2019)

- *Bidirectional* Encoder Representations from Transformers
- Encoder-only (no attention masking)
- 110M params
- 15% of all words masked out
- Was great, now dated



From Lukas Beyer's lecture Intro to Transformers.

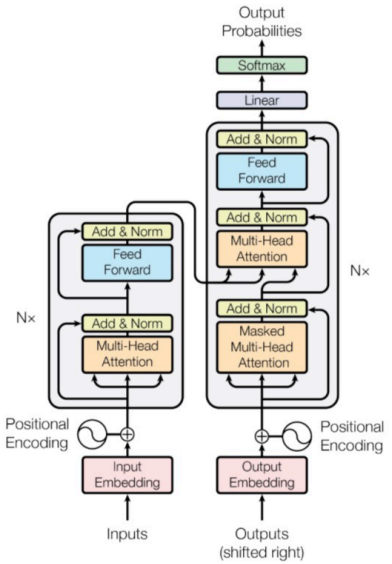
T5: Text-to-Text Transfer Transformer (2020)

- Input and output are both text strings
- Encoder-Decoder architecture
- 11B parameters
- Still could be a good choice for fine-tuning!

Das ist gut.

A storm in Attala caused 6 victims.

This is not toxic.



Translate EN-DE: This is good.

Summarize: state authorities dispatched…

Is this toxic: You look beautiful today!

From Lukas Beyer's lecture Intro to Transformers.

T5 Training Data

- Unsupervised pre-training on Colossal Clean Crawled Corpus (C4)
  - Start with Common Crawl (over 50TB of compressed data, 10B+ web pages)
  - Filtered down to ~800GB, or ~160B tokens
- Also trained on academic supervised tasks

- We discarded any page with fewer than 5 sentences and only retained lines that contained at least 3 words.
- We removed any page that contained any word on the "List of Dirty, Naughty, Obscene or Otherwise Bad Words".[6]
- Some pages inadvertently contained code. Since the curly bracket "{" appears in many programming languages (such as Javascript, widely used on the web) but not in natural text, we removed any pages that contained a curly bracket.
- To deduplicate the data set, we discarded all but one of any three-sentence span occurring more than once in the data set.

https://paperswithcode.com/dataset/c4

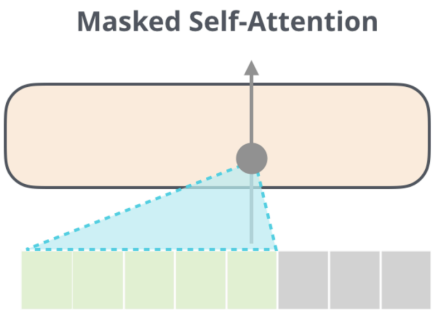
2. **Datasets used for Supervised text-to-text language modeling objective**

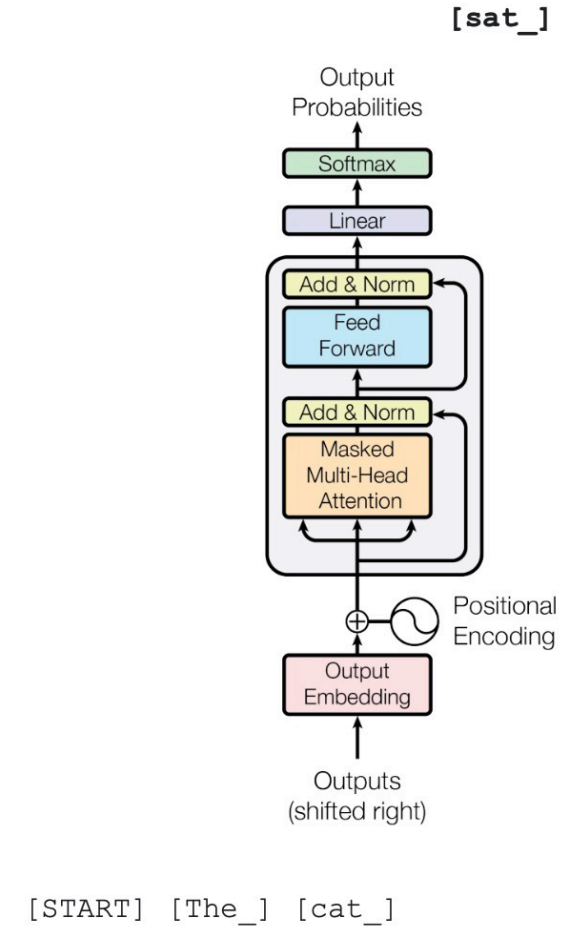
- Sentence acceptability judgment
  - CoLA Warstadt et al., 2018
- Sentiment analysis
  - SST-2 Socher et al., 2013
- Paraphrasing/sentence similarity
  - MRPC Dolan and Brockett, 2005
  - STS-B Ceret al., 2017
  - QQP Iyer et al., 2017
- Natural language inference
  - MNLI Williams et al., 2017
  - QNLI Rajpurkar et al.,2016
  - RTE Dagan et al., 2005
  - CB De Marneff et al., 2019
- Sentence completion
  - COPA Roemmele et al., 2011
- Word sense disambiguation
  - WIC Pilehvar and Camacho-Collados, 2018
- Question answering
  - MultiRC Khashabi et al., 2018
  - ReCoRD Zhang et al., 2018
  - BoolQ Clark et al., 2019

https://stanford-cs324.github.io/winter2022/lectures/data/

GPT / GPT-2 (2019)

- Generative Pre-trained Transformer
- Decoder-only (uses masked self-attention)
- Largest model is 1.5B





From Lukas Beyer's lecture Intro to Transformers.

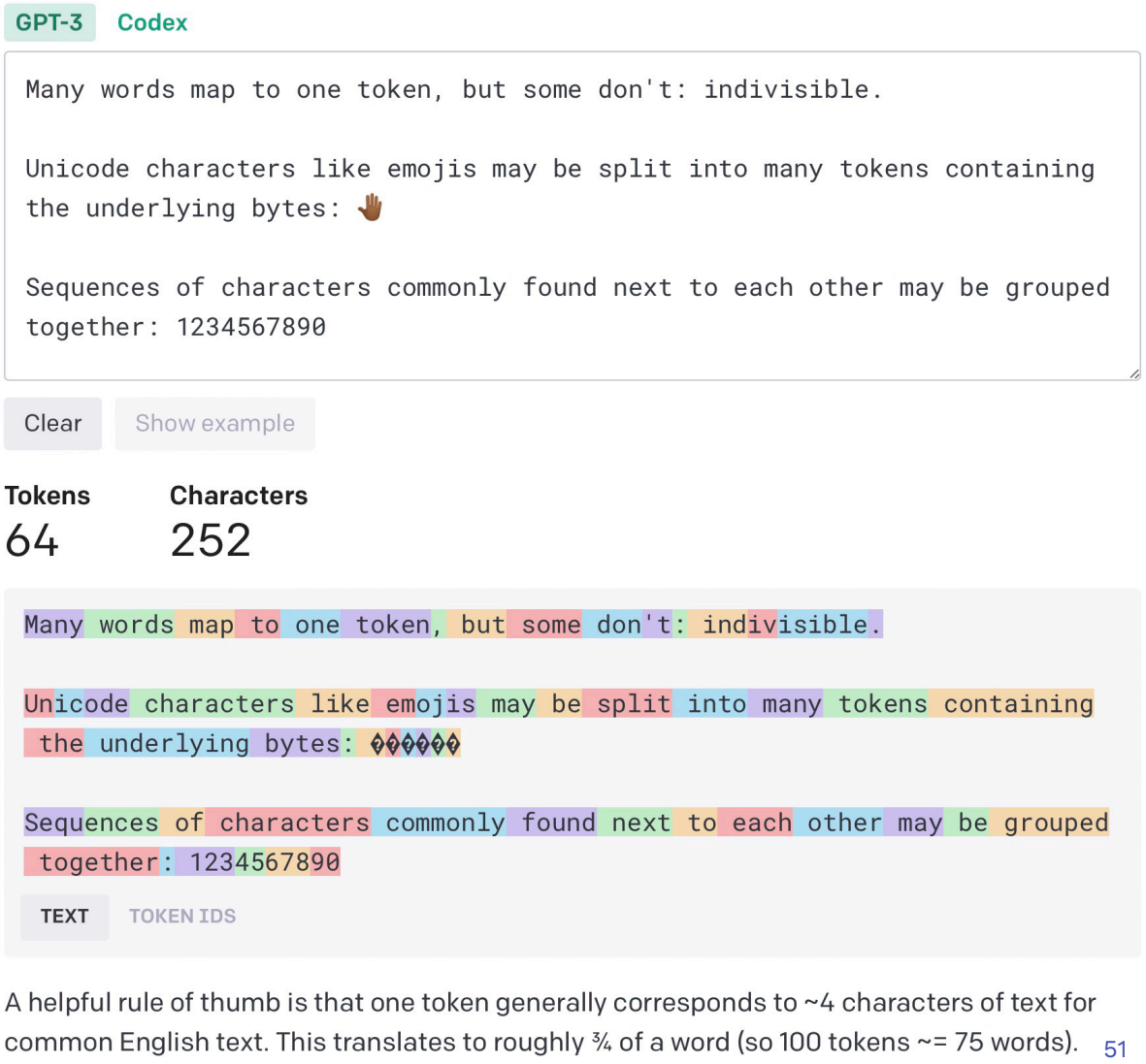
GPT-2 Training Data

- Found that Common Crawl has major data quality issues
- Formed the WebText dataset
  - scraped all outbound links (45M) from Reddit which received at least 3 karma
- After de-duplication and some heuristic filtering, left with 8M documents for a total of 40GB of text

https://cdn.openai.com/better-language-models/language_models_are_unsupervised_multitask_learners.pdf

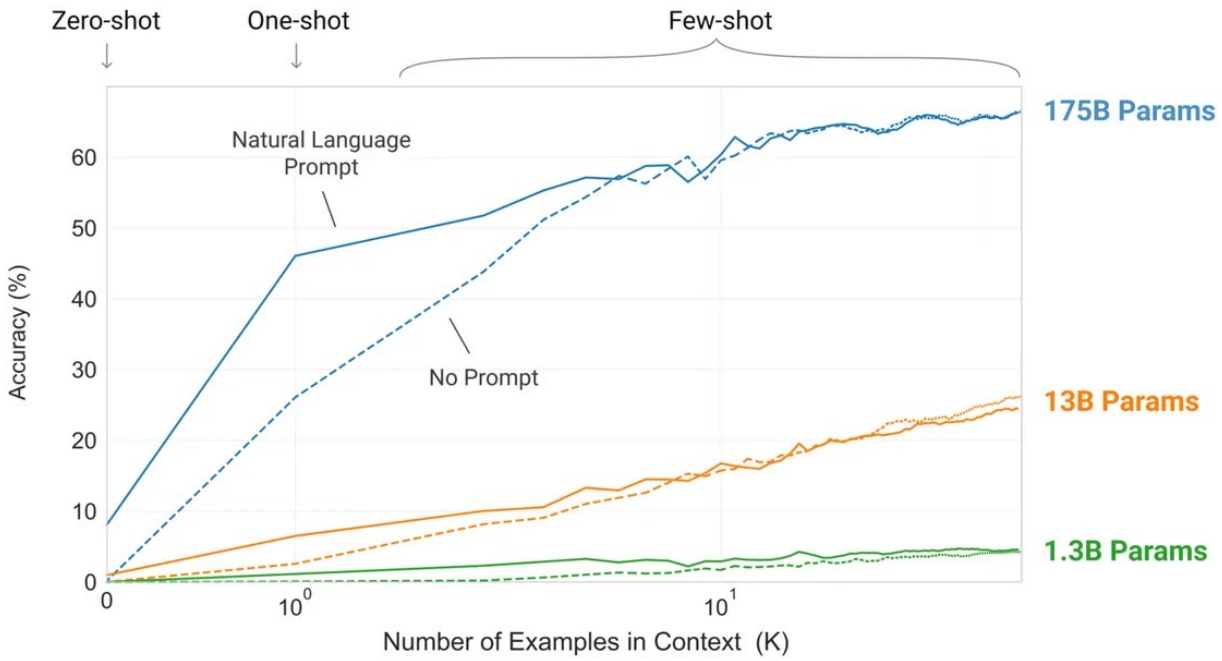
Byte Pair Encoding

- How does GPT tokenize?
- Middle ground between
  - old-school NLP tokenization, where out-of-vocab words would be replaced by a special token
  - UTF-8 bytes



GPT-3 (2020)

- Just like GPT-2, but 100x larger (175B params)
- Exhibited unprecedented few-shot and zero-shot learning



Zero-shot

The model predicts the answer given only a natural language discription of the task. No gradient updates are performed.

```
Translate English to French:    ← task description
cheese =>                       ← prompt
```

One-shot

In addition to the task description, the model sees a single example of the task. No gradient updates are performed.

```
Translate English to French:    ← task description
sea otter => loutre de mer      ← example
cheese =>                       ← prompt
```

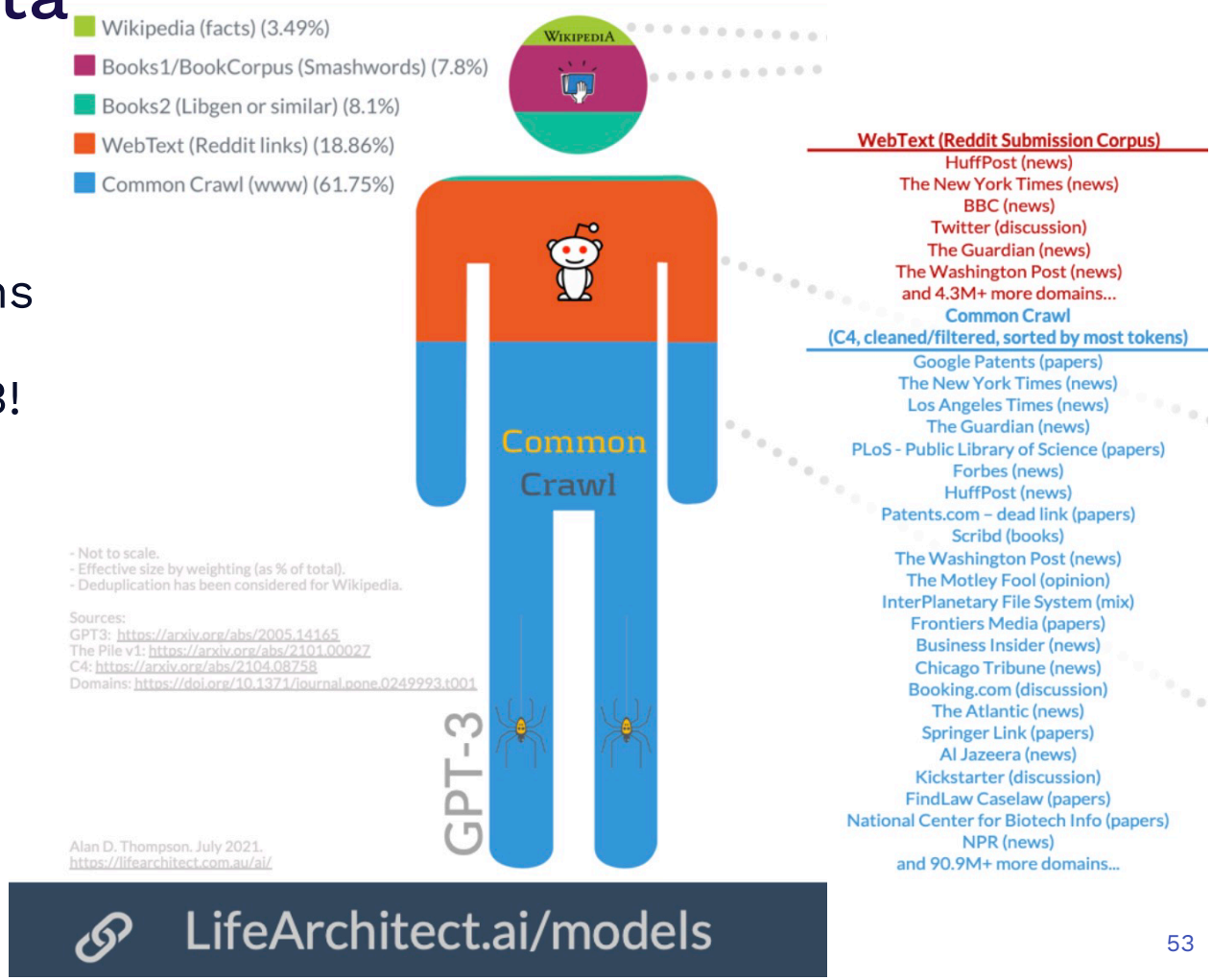
Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

```
Translate English to French:    ← task description
sea otter => loutre de mer      ← examples
peppermint => menthe poivrée    ←
plush girafe => girafe peluche  ←
cheese =>                       ← prompt
```

GPT-3 Training Data

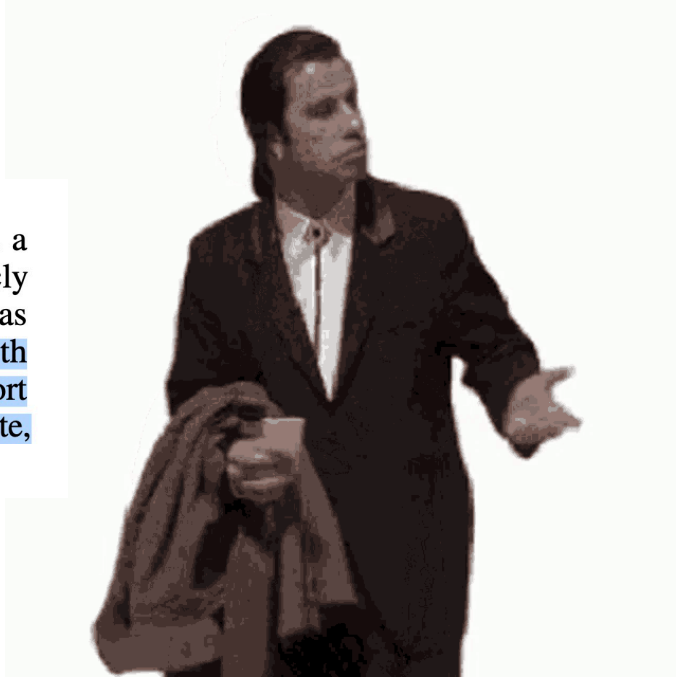
- For a total of 500B tokens
- But trained on only 300B!



https://arxiv.org/pdf/2005.14165.pdf

GPT-4 (2023)

This report focuses on the capabilities, limitations, and safety properties of GPT-4. GPT-4 is a Transformer-style model [39] pre-trained to predict the next token in a document, using both publicly available data (such as internet data) and data licensed from third-party providers. The model was then fine-tuned using Reinforcement Learning from Human Feedback (RLHF) [40]. Given both the competitive landscape and the safety implications of large-scale models like GPT-4, this report contains no further details about the architecture (including model size), hardware, training compute, dataset construction, training method, or similar.

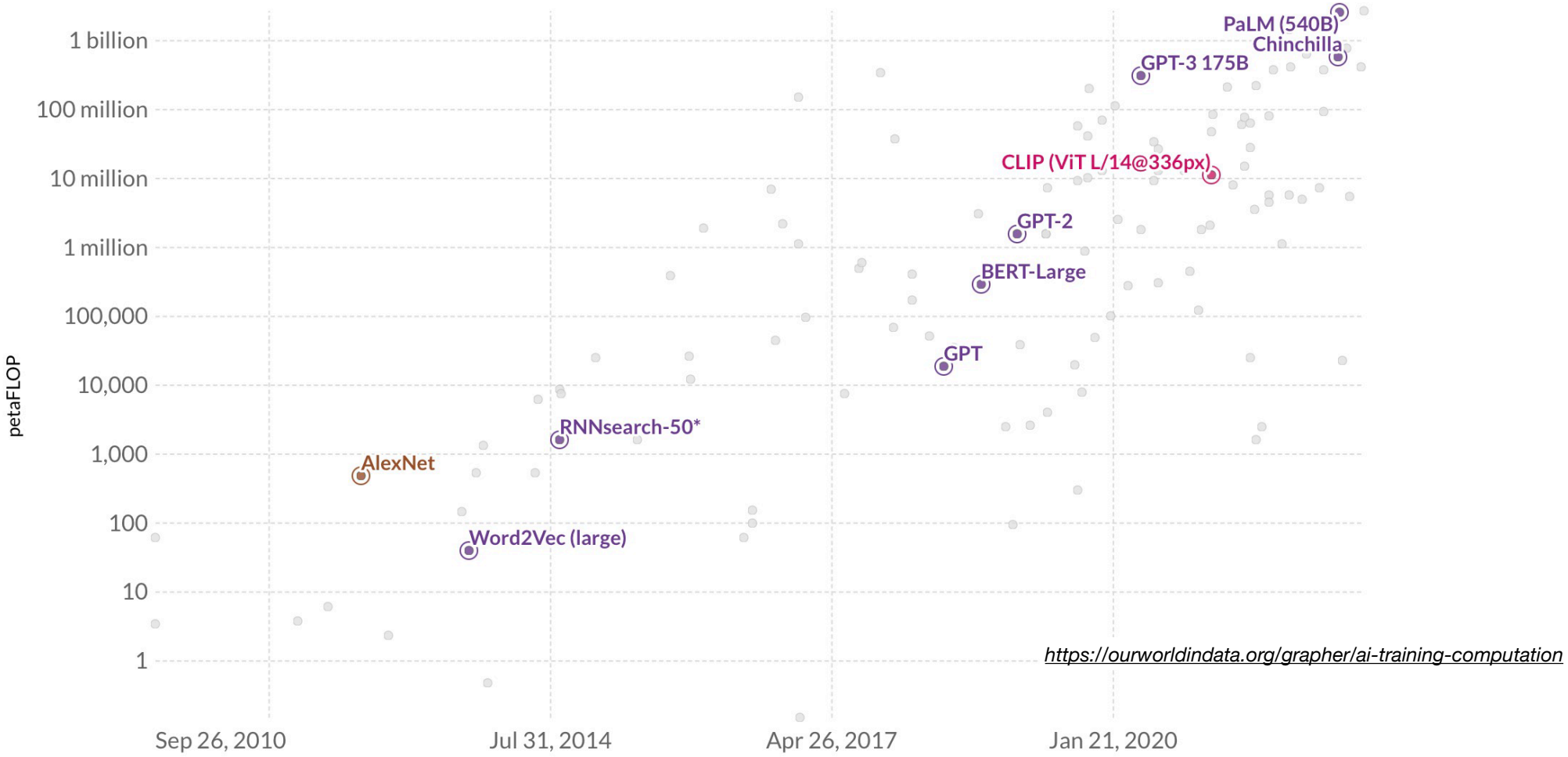


Computation used to train notable AI systems

Computation is measured in petaFLOP, which is 10^{15} floating-point operations.

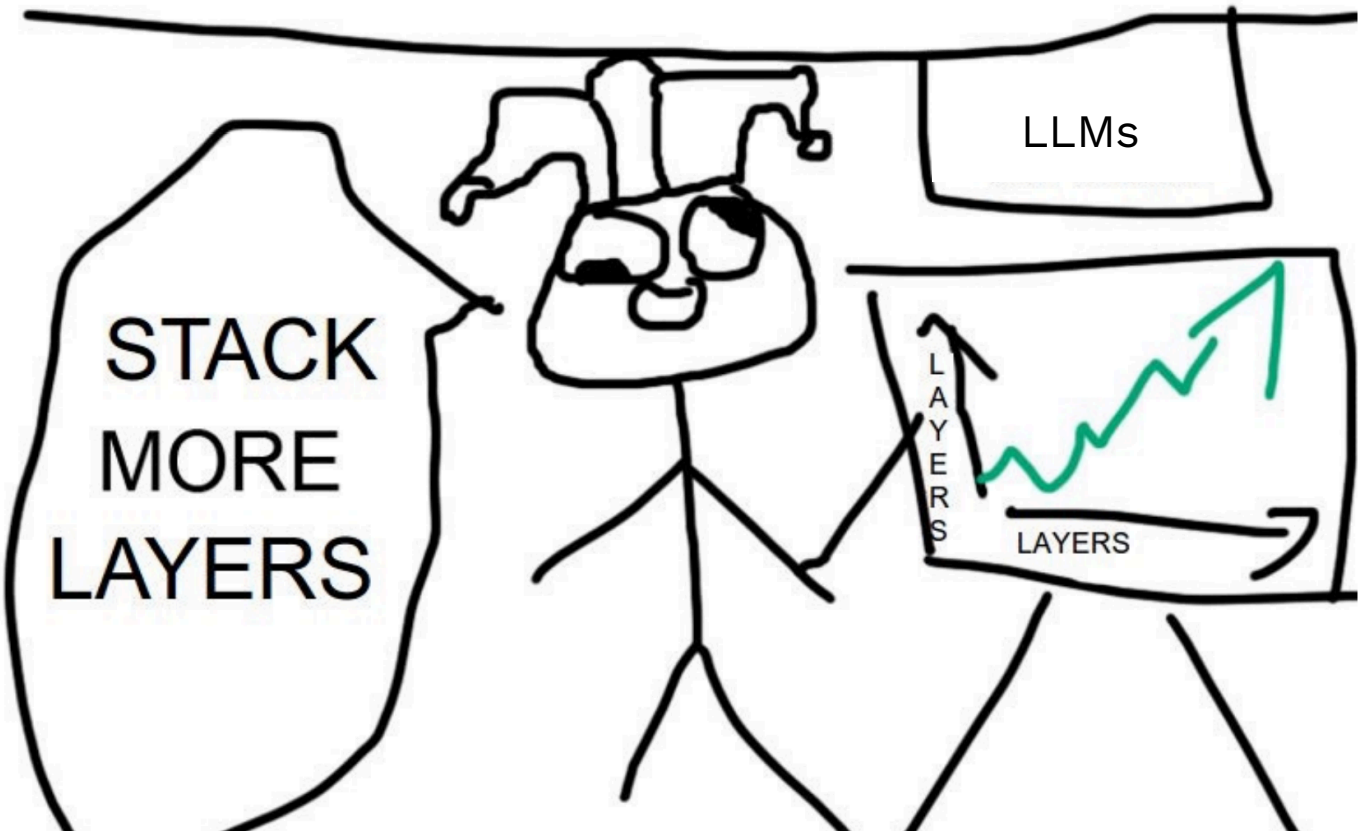
LLMBC 2023

LINEAR | LOG | Select systems | Zoom to selection



https://ourworldindata.org/grapher/ai-training-computation

The Bitter Lesson



But what exactly is the relationship between model size and dataset size?

Chinchilla (2022)

- Empirically derived formulas for optimal model and training set size given a fixed compute budget
- Found that most LLMs are "undertrained"
- Trained Chinchilla (70B) vs Gopher (280B) at the same compute budget, by using 4x fewer params and 4x more data
- (Note that this is for one epoch)

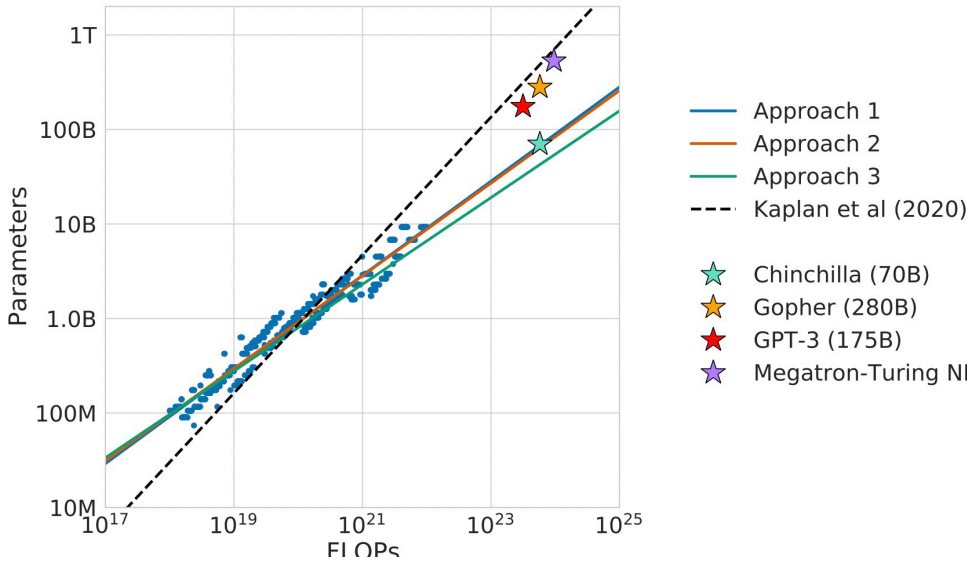
https://arxiv.org/pdf/2203.15556.pdf

DeepMind

Training Compute-Optimal Large Language Models

Jordan Hoffmann*, Sebastian Borgeaud*, Arthur Mensch*, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, Tom Hennigan, Eric Noland, Katie Millican, George van den Driessche, Bogdan Damoc, Aurelia Guy, Simon Osindero, Karen Simonyan, Erich Elsen, Jack W. Rae, Oriol Vinyals and Laurent Sifre*

*Equal contributions



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

LLaMA (2023)

- "Chinchilla-optimal" open-source LLMs from Meta
- Several sizes from 7B to 65B, trained on at least 1T tokens
- Benchmarks competitively against GPT-3 and other LLMs
- Open-source, but non-commercial

params	dimension	n heads	n layers	learning rate	batch size	n tokens
6.7B	4096	32	32	$3.0e^{-4}$	4M	1.0T
13.0B	5120	40	40	$3.0e^{-4}$	4M	1.0T
32.5B	6656	52	60	$1.5e^{-4}$	4M	1.4T
65.2B	8192	64	80	$1.5e^{-4}$	4M	1.4T

Table 2: **Model sizes, architectures, and optimization hyper-parameters.**

		Humanities	STEM	Social Sciences	Other	Average
GPT-NeoX	20B	29.8	34.9	33.7	37.7	33.6
GPT-3	175B	40.8	36.7	50.4	48.8	43.9
Gopher	280B	56.2	47.4	71.9	66.1	60.0
Chinchilla	70B	63.6	54.9	79.3	**73.9**	67.5
PaLM	8B	25.6	23.8	24.1	27.8	25.4
	62B	59.5	41.9	62.7	55.8	53.7
	540B	**77.0**	**55.6**	**81.0**	69.6	**69.3**
LLaMA	7B	34.0	30.5	38.3	38.1	35.1
	13B	45.0	35.8	53.8	53.3	46.9
	33B	55.8	46.0	66.7	63.4	57.8
	65B	61.8	51.7	72.9	67.4	63.4

Table 9: **Massive Multitask Language Understanding (MMLU).** Five-shot accuracy.

LLaMA Training Data

- Custom quality-filtering of CommonCrawl + some C4 + Github + Wikipedia + Books + ArXiV + Stack Exchange
- RedPajama: open-source recreation

	RedPajama	LLaMA*
CommonCrawl	878 billion	852 billion
C4	175 billion	190 billion
Github	59 billion	100 billion
Books	26 billion	25 billion
ArXiv	28 billion	33 billion
Wikipedia	24 billion	25 billion
StackExchange	20 billion	27 billion
Total	1.2 trillion	1.25 trillion

https://www.together.xyz/blog/redpajama

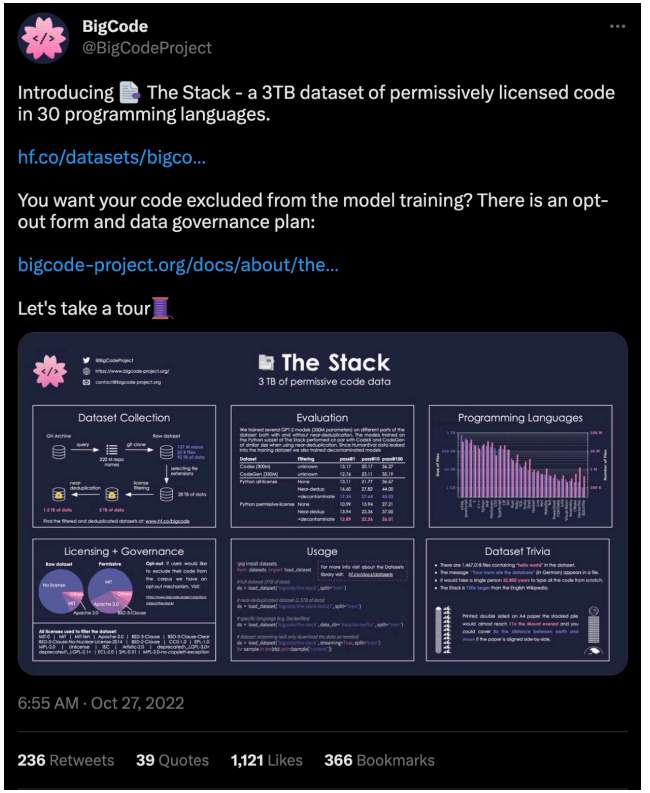
Dataset	Sampling prop.	Epochs	Disk size
CommonCrawl	67.0%	1.10	3.3 TB
C4	15.0%	1.06	783 GB
Github	4.5%	0.64	328 GB
Wikipedia	4.5%	2.45	83 GB
Books	4.5%	2.23	85 GB
ArXiv	2.5%	1.06	92 GB
StackExchange	2.0%	1.03	78 GB

Table 1: **Pre-training data.** Data mixtures used for pre-training, for each subset we list the sampling proportion, number of epochs performed on the subset when training on 1.4T tokens, and disk size. The pre-training runs on 1T tokens have the same sampling proportion.

https://arxiv.org/pdf/2302.13971.pdf

Including code in training data

- T5 and GPT-3 (2020) specifically removed code. But most recent models are trained on ~5% code. Why?
- Code-specific models such as OpenAI Codex (2021) was GPT-3 further trained on public GitHub code.
- Empirically, this improved performance on non-code tasks!
- Open-source dataset: The Stack (3TB of permissively licensed source code)



Yao Fu et al. How does GPT Obtain its Ability?

And there's another important part of the story: Instruction Tuning

Few-shot vs Zero-shot

- At the time of GPT-3 (2020), the mindset was mostly few-shot
  - e.g. text completion
- By the time of ChatGPT (2022), the mindset was all zero-shot
  - e.g. instruction-following

Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

```
1  Translate English to French:        ← task description
2  sea otter => loutre de mer          ← examples
3  peppermint => menthe poivrée        ←
4  plush girafe => girafe peluche      ←
5  cheese =>                           ← prompt
```

Zero-shot

The model predicts the answer given only a natural language discription of the task. No gradient updates are performed.

```
1  Translate English to French:        ← task description
2  cheese =>                           ← prompt
```

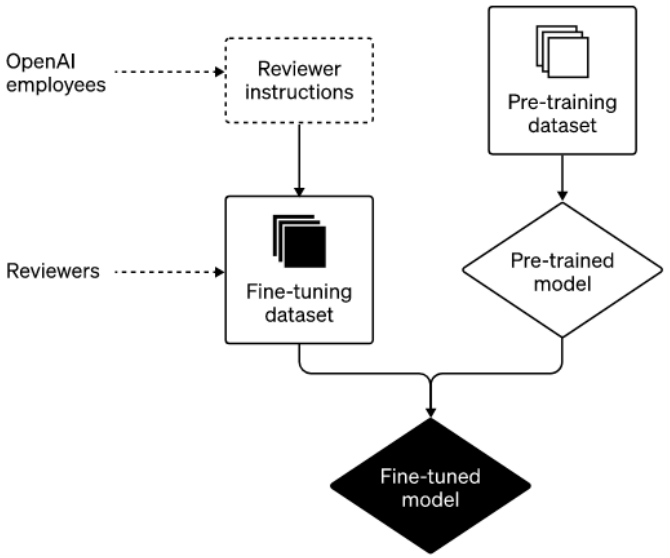
Supervised Fine-tuning

- Very little text in the original GPT-3 dataset is of the zero-shot form.
- To improve performance on zero-shot inputs, fine-tuned on a smaller high-quality dataset of instructions-completions
- (Sourced from thousands of contractors)

Zero-shot

The model predicts the answer given only a natural language discription of the task. No gradient updates are performed.

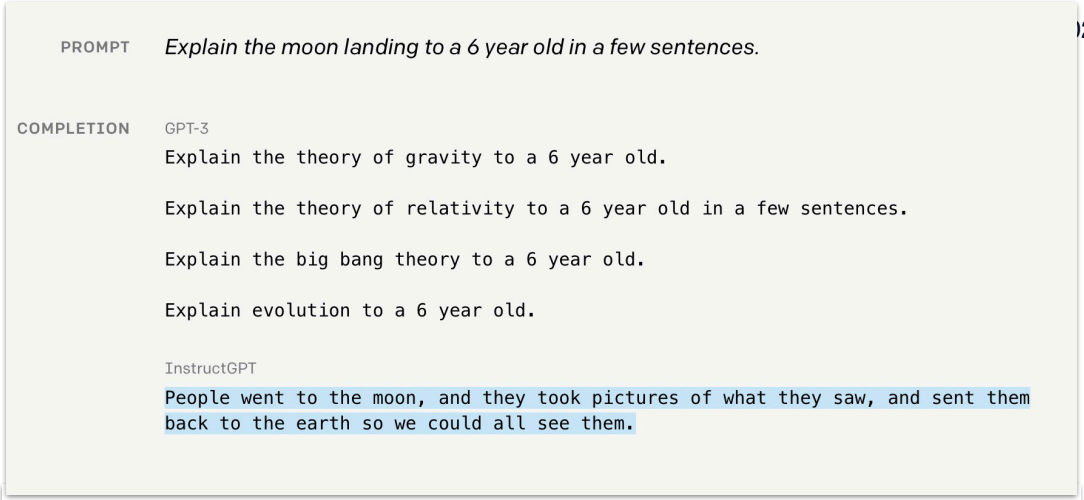
```
1  Translate English to French:        ← task description
2  cheese =>                           ← prompt
```

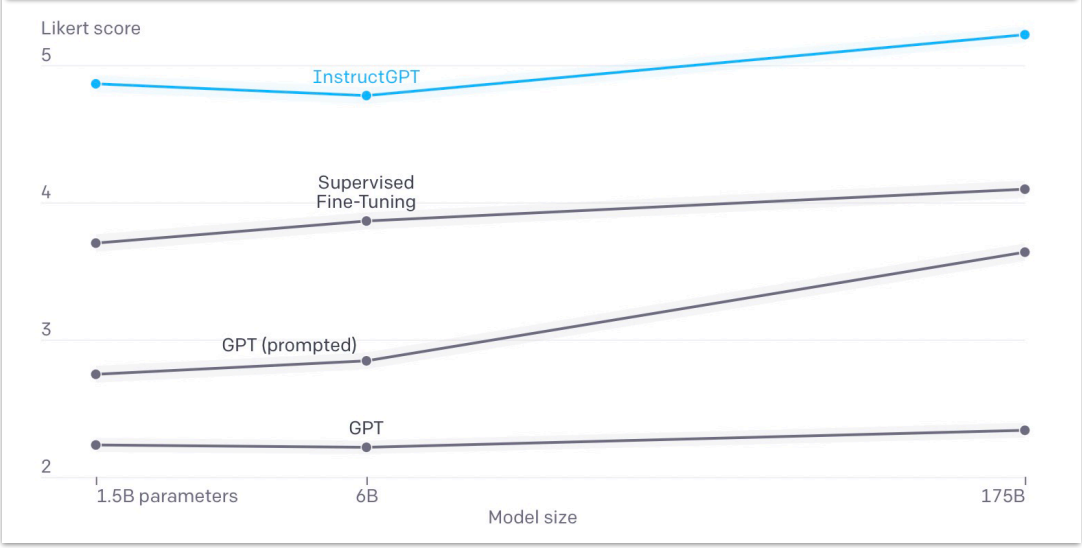


https://openai.com/blog/how-should-ai-systems-behave

InstructGPT/GPT-3.5

- Had humans rank different GPT-3 outputs, and used RL to further fine-tune the model
- **Much** better at following instructions
- Released as text-davinci-002 in OpenAI API





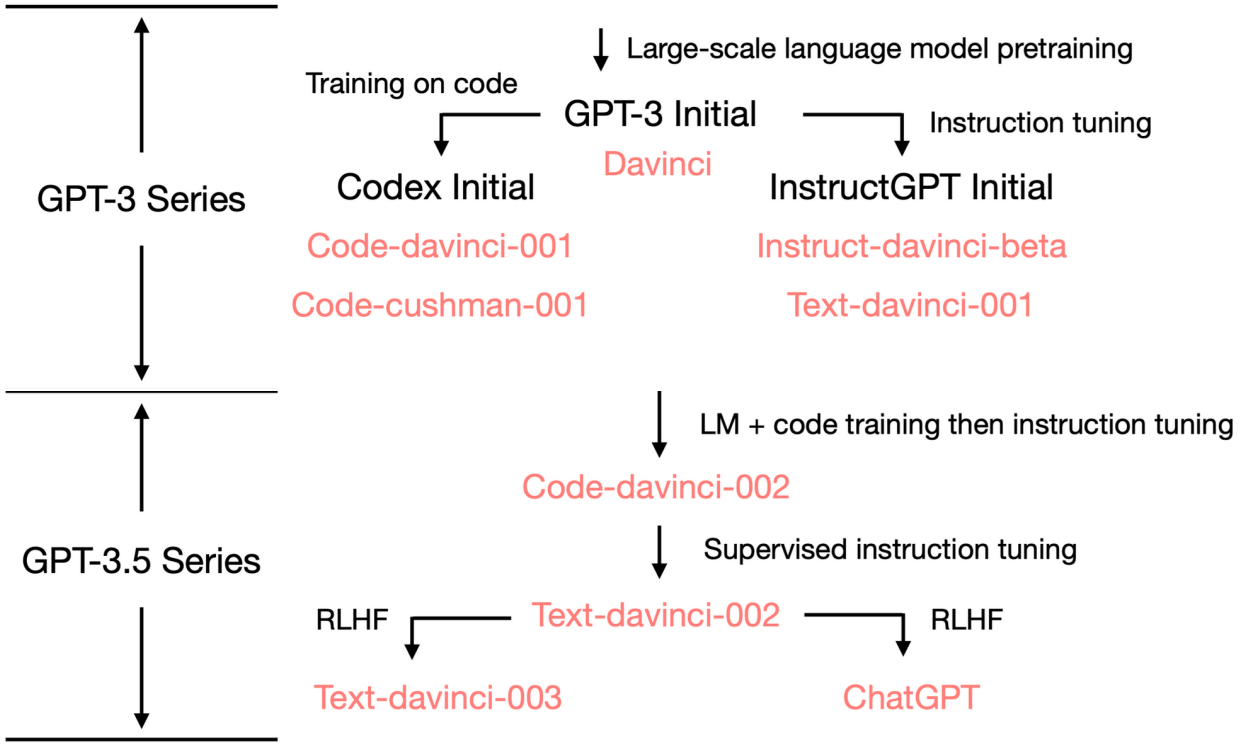
https://openai.com/blog/instruction-following/

ChatGPT

- Further RLHF on **conversations**
- ChatML format (messages from system, assistant, user roles)

```
openai.ChatCompletion.create(
  model="gpt-3.5-turbo",
  messages=[
        {"role": "system", "content": "You are a helpful assistant."},
        {"role": "user", "content": "Who won the world series in 2020?"},
        {"role": "assistant", "content": "The Los Angeles Dodgers won the Worl
        {"role": "user", "content": "Where was it played?"}
    ]
)
```

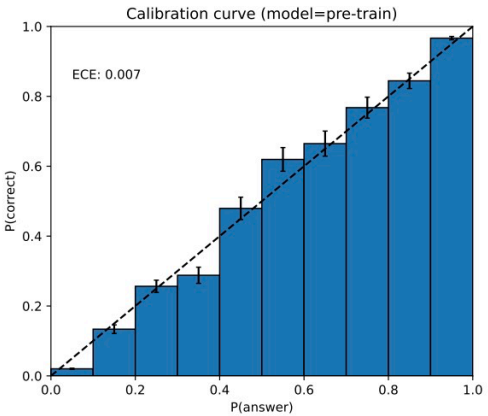
The GPT Lineage



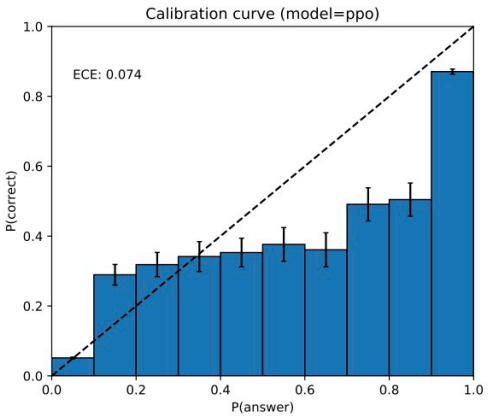
Yao Fu's How does GPT Obtain its Ability?

"Alignment Tax"

- Instruction-tuning increases the model's zero-shot ability, but at a cost
  - Confidence becomes less calibrated
  - Few-shot ability suffers



Base GPT-4



RLHF GPT-4

GPT-4 Technical Report - https://arxiv.org/pdf/2303.08774.pdf

It's possible to "steal" RLHF

*We introduce **Alpaca 7B**, a model fine-tuned from the LLaMA 7B model on 52K instruction-following demonstrations. On our preliminary evaluation of single-turn instruction following, Alpaca behaves qualitatively similarly to OpenAI's text-davinci-003, while being surprisingly small and easy/cheap to reproduce (<600$).*

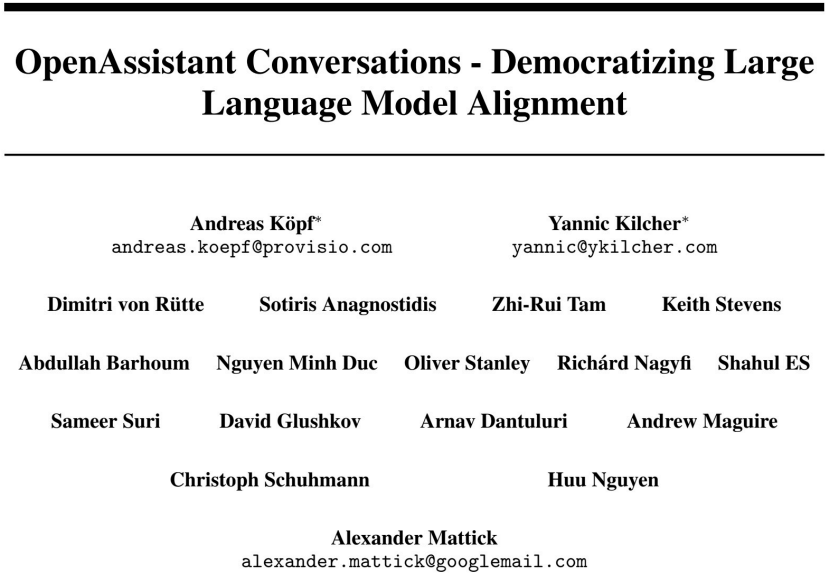
Web Demo GitHub

Stanford Alpaca

- Got 52K instruction-following demonstrations from text-davinci-003, then fine-tuned LLaMA on them.

OpenAssistant

- April 2023 dataset release
- 160K messages across 66K conversation trees, 35 languages, 460K quality ratings, 13.5K volunteers



OpenAssistant Conversations - Democratizing Large Language Model Alignment

Andreas Köpf* andreas.koepf@provisio.com
Yannic Kilcher* yannic@ykilcher.com
Dimitri von Rütte **Sotiris Anagnostidis** **Zhi-Rui Tam** **Keith Stevens**
Abdullah Barhoum **Nguyen Minh Duc** **Oliver Stanley** **Richárd Nagyfi** **Shahul ES**
Sameer Suri **David Glushkov** **Arnav Dantuluri** **Andrew Maguire**
Christoph Schuhmann **Huu Nguyen**
Alexander Mattick alexander.mattick@googlemail.com

https://huggingface.co/datasets/OpenAssistant/oasst1

And one last idea

Retrieval-enhanced Transformer (2021)

- Instead of both learning language and memorizing facts in the model's params, why not just learn language in params, and retrieve facts from a large database?
- BERT-encode sentences, store them in large DB (>1T tokens)
- Then, fetch matching sentences and attend to them.
- Doesn't work as well as large LLMs. Yet.

DeepMind

Improving language models by retrieving from trillions of tokens

Sebastian Borgeaud[†], Arthur Mensch[†], Jordan Hoffmann[†], Trevor Cai, Eliza Rutherford, Katie Millican, George van den Driessche, Jean-Baptiste Lespiau, Bogdan Damoc, Aidan Clark, Diego de Las Casas, Aurelia Guy, Jacob Menick, Roman Ring, Tom Hennigan, Saffron Huang, Loren Maggiore, Chris Jones, Albin Cassirer, Andy Brock, Michela Paganini, Geoffrey Irving, Oriol Vinyals, Simon Osindero, Karen Simonyan, Jack W. Rae[‡], Erich Elsen[‡] and Laurent Sifre[†,‡]

All authors from DeepMind, [†]Equal contributions, [‡]Equal senior authorship

https://arxiv.org/pdf/2112.04426.pdf Dec 2021

Resources

- Lillian Weng's "The Transformer Family v2" megapost
- Xavier Amatriain's Transformer Models Catalog
- Yao Fu's How does GPT Obtain its Ability?

Questions?

04

Training & Inference

Problems with training LLMs

- Massive amounts of data
- Massive models don't fit on a single GPU or even a single multi-GPU machine
- Long training runs are painful

Problems with training LLMs

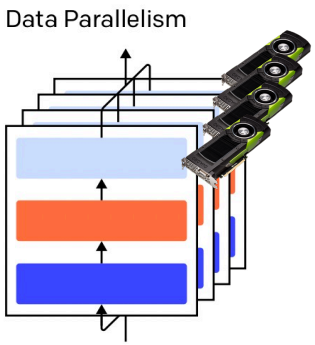
- **Massive amounts of data**
- Massive models don't fit on a single GPU or even a single multi-GPU machine
- Long training runs are painful

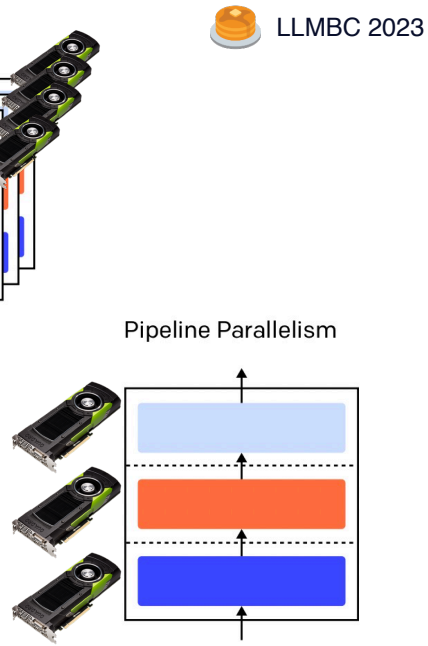
Problems with training LLMs

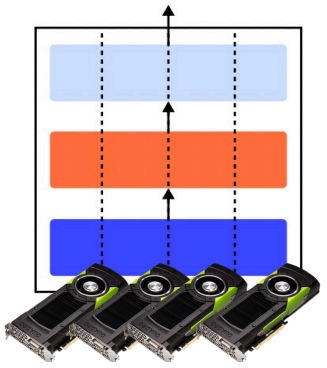
- Massive amounts of data
- **Massive models don't fit on a single multi-GPU machine**
- Long training runs are painful

Parallelism

- Data parallelism: spread a single batch of data across GPUs
- Model parallelism: spread the model's layers across GPUs
- Tensor parallelism: spread a single matrix op across GPUs



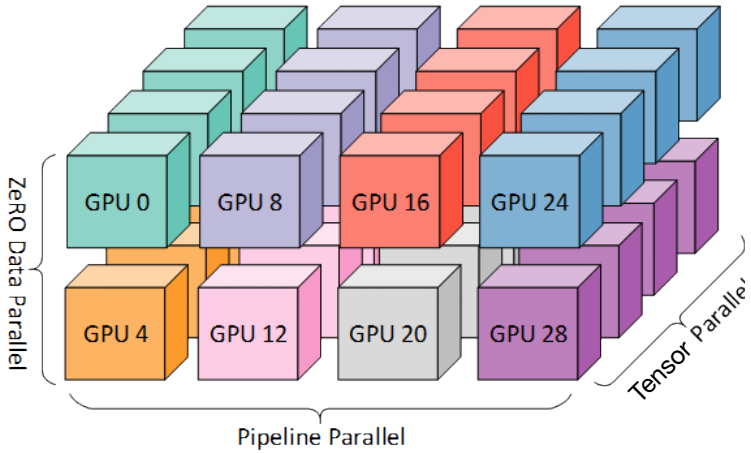




https://openai.com/blog/techniques-for-training-large-neural-networks/

BLOOM (GPT-3 sized LM)

Component	DeepSpeed	Megatron-LM
ZeRO Data Parallelism	V	
Tensor Parallelism		V
Pipeline Parallelism	V	
BF16Optimizer	V	
Fused CUDA Kernels		V
DataLoader		V

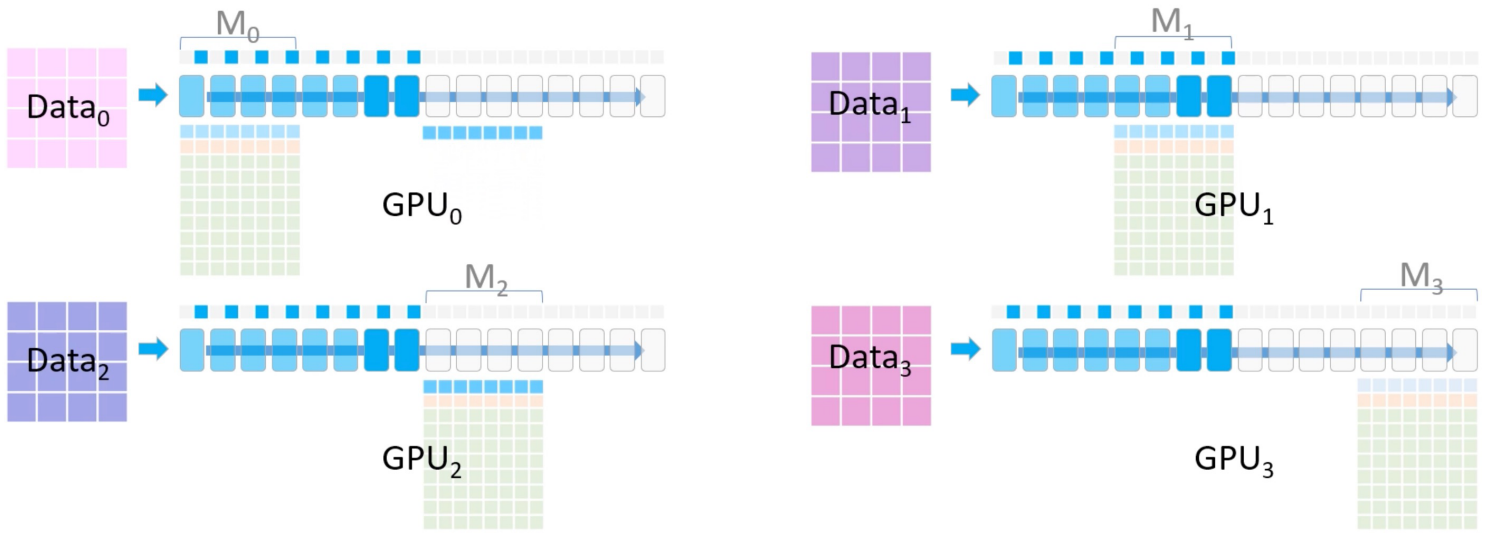


Had to use multiple tricks ("3D parallelism")
from two great libraries: DeepSpeed and Megatron-LM

https://huggingface.co/blog/bloom-megatron-deepspeed

https://www.deepspeed.ai/training/

Sharded Data-Parallelism



GPU_2 broadcasts the parameters for M_2

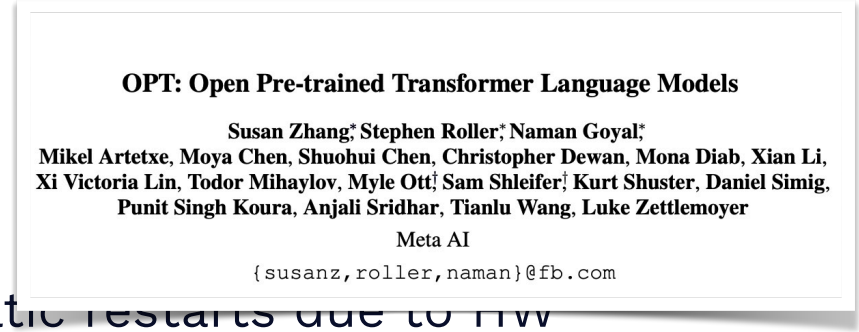
Literally pass around model params between GPUs as computation is proceeding!

Helpful video:
https://www.microsoft.com/en-us/research/blog/zero-deepspeed-new-system-optimizations-enable-training-models-with-over-100-billion-parameters/

Problems with training LLMs

- Massive amounts of data
- Massive models don't fit on a single GPU or even a single multi-GPU machine
- **Long training runs are painful**

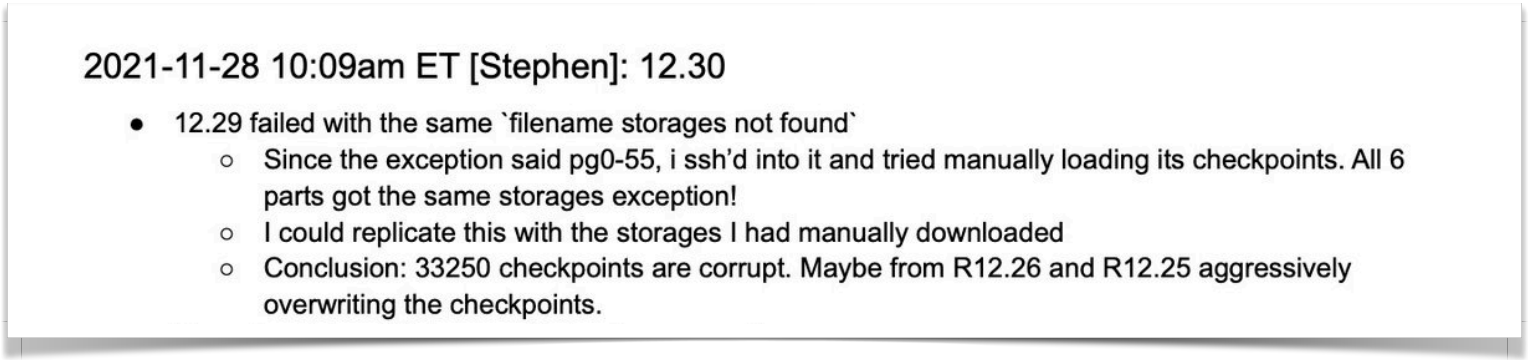
A glimpse into training hell



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 Ott[‡] Sam Shleifer[‡] Kurt Shuster, Daniel Simig, Punit Singh Koura, Anjali Sridhar, Tianlu Wang, Luke Zettlemoyer
Meta AI
{susanz,roller,naman}@fb.com

- Dozens of manual restarts, 70+ automatic restarts due to HW failures
- Manual restarting from checkpoints when loss would diverge
- Switching optimizers and software versions in the middle of training



2021-11-28 10:09am ET [Stephen]: 12.30

- 12.29 failed with the same `filename storages not found`
  - Since the exception said pg0-55, i ssh'd into it and tried manually loading its checkpoints. All 6 parts got the same storages exception!
  - I could replicate this with the storages I had manually downloaded
  - Conclusion: 33250 checkpoints are corrupt. Maybe from R12.26 and R12.25 aggressively overwriting the checkpoints.

https://arxiv.org/pdf/2205.01068.pdf

"Training run babysitting"

GPT-4 contributions

Pretraining

Core contributors
Christopher Berner *Supercomputing lead*
Greg Brockman *Infrastructure lead*
Trevor Cai *Throughput lead*
David Farhi *Manager of optimization team*
Chris Hesse *Infrastructure usability co-lead*
Shantanu Jain *Infrastructure usability co-lead*
Kyle Kosic *Uptime and stability lead*
Jakub Pachocki *Overall lead, optimization lead*
Alex Paino *Architecture & data vice lead*
Mikhail Pavlov *Software correctness lead*
Michael Petrov *Hardware correctness lead*
Nick Ryder *Architecture & data lead*
Szymon Sidor *Optimization vice lead*
Nikolas Tezak *Execution lead*
Phil Tillet *Triton lead*
Amin Tootoonchian *Model distribution, systems & networking lead*
Qiming Yuan *Dataset sourcing and processing lead*
Wojciech Zaremba *Manager of dataset team*

Compute cluster scaling
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Emy Parparita, Henri Roussez, Eric Sigler, Akila Welihinda

Data
Sandhini Agarwal, Suchir Balaji, Mo Bavarian, Che Chang, Sheila Dunni
Gordon, Peter Hoeschele, Shawn Jain, Shantanu Jain, Roger Jiang, Hee
Kaiser, Nitish Shirish Keskar, Jong Wook Kim, Aris Konstantinidis, Chak
Bianca Martin, David Mély, Oleg Murk, Hyeonwoo Noh, Long Ouyang, A
Pong, Alec Radford, Nick Ryder, John Schulman, Daniel Selsam, Ian So
Weng, Clemens Winter, Tao Xu, Qiming Yuan, Wojciech Zaremba

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Amin Tootoonchian, Qiming Yuan

Hardware correctness
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Optimization & architecture
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Training run babysitting
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Vision

Core contributors
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Mark Chen *Vision team co-lead, Deployment lead*
Casey Chu *Initial prototype lead*
Chris Hesse *Data load balancing & developer tooling lead*
Shengli Hu *Vision Safety Evaluations lead*
Yongjik Kim *GPU performance lead*
Jamie Kiros *Overall vision co-lead, deployment research & evaluation lead*
Daniel Levy *Overall vision co-lead, optimization lead*
Christine McLeavey *Vision team lead*
David Mély *Data lead*
Hyeonwoo Noh *Overall vision co-lead, research lead*
Mikhail Pavlov *Scaling engineering lead*
Raul Puri *Overall vision co-lead, engineering lead*
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Compute cluster scaling
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Hardware correctness
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Data
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Alignment Data
Long Ouyang

Training run babysitting
Trevor Cai, Kyle Kosic, Daniel Levy, David Mély, Reiichiro Nakano, Hyeonwoo Noh, Mikhail Pavlov, Raul Puri, Amin Tootoonchian

Deployment & post-training
Ilge Akkaya, Mark Chen, Jamie Kiros, Rachel Lim, Reiichiro Nakano, Raul Puri, Jiayi Weng

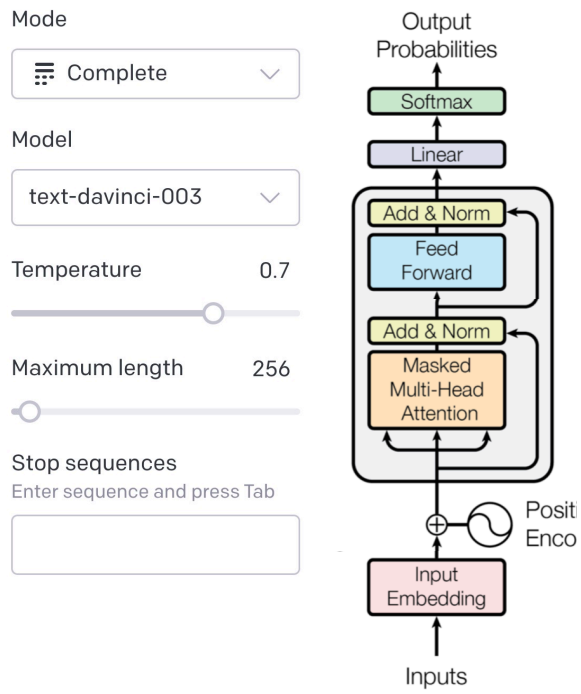
https://openai.com/contributions/gpt-4

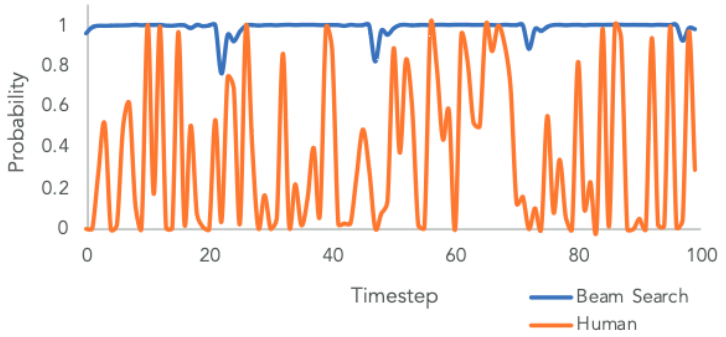
Considerations for LLM inference

- Understanding auto-regressive sampling
- Improving (or not) runtime complexity
- Dealing with large model size

Auto-regressive Sampling

- Remember that we sample tokens one at a time
  - [It's, a, blue, …
- The softmax outputs a peaky probability distribution over possible next tokens
- Temperature parameter makes it less peaky
  - t=0 will always sample the most likely next token;
  - t=1 will often sample less-likely ones
- Human text is not all high-probability next words!

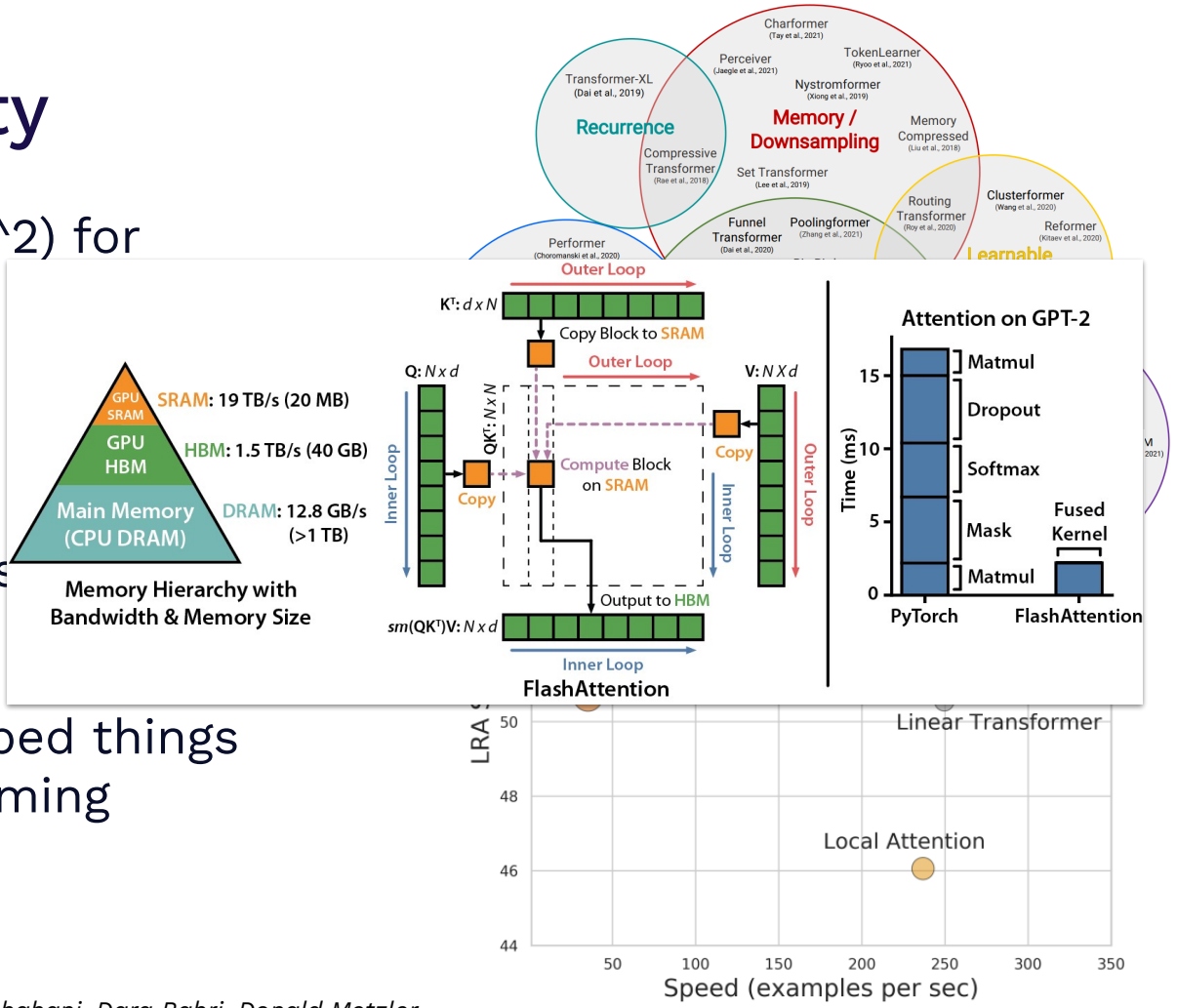




https://arxiv.org/abs/1904.09751

Runtime Complexity

- Self-attention runs in O(N^2) for sequence length N
- Many O(N) approximations developed
- But none have provided a s improvement
- Recently, FlashAttention sped things up via smart GPU programming



Based on "Efficient Transformers: A Survey" by Yi Tay, Mostafa Dehghani, Dara Bahri, Donald Metzler and "Long Range Arena: A Benchmark for Efficient Transformers" by Y Tay, M Dehghani, S Abnar, Y Shen, D Bahri, P Pham, J Rao, L Yang, S Ruder, D Metzler

http://lucasb.eyer.be/transformer *https://github.com/HazyResearch/flash-attention*

Dealing with Large Model Sizes

- Large subject! Lilian Weng from OpenAI has a thorough post
- Quantization is most relevant to us
  - LLM weights are usually in float32 or 16
  - Recent work (LLM.int8) has shown that 8-bit post-quantization is basically fine
  - Even 4-bit seems fine!

The case for 4-bit precision: k-bit Inference Scaling Laws

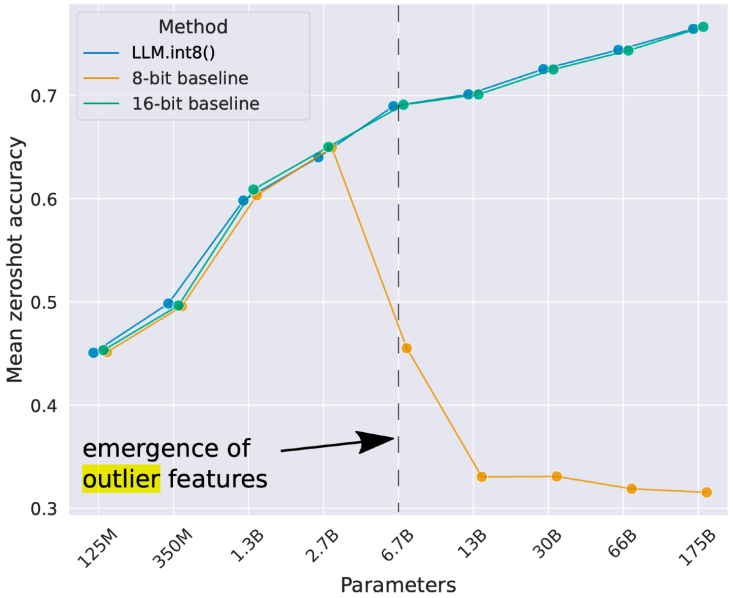
Tim Dettmers [1] Luke Zettlemoyer [1]

https://arxiv.org/pdf/2212.09720.pdf

LLaMA Quantization

model	original size	quantized size (4-bit)
7B	13 GB	3.9 GB
13B	24 GB	7.8 GB
30B	60 GB	19.5 GB
65B	120 GB	38.5 GB

https://github.com/ggerganov/llama.cpp



https://arxiv.org/pdf/2208.07339.pdf

Resources

- Megatron-LM (GitHub): probably still the best insights into training LLMs at scale.
- OpenAI post Techniques for Training Large Neural Networks
- Lillian Weng's "Large Transformer Model Inference Optimization"

Questions?

Questions?

Thanks!

@sergeykarayev

@full_stack_dl

/imagine green tropical parrot eating stack of pancakes, flapjack breakfast, hyper-realistic portrait, DSLR Canon R5, chromatic aberration, accent lighting, super resolution, hyper-detailed, cinematic, OpenGL - Shaders