Fast data loaders and Foundation/Frontier Models

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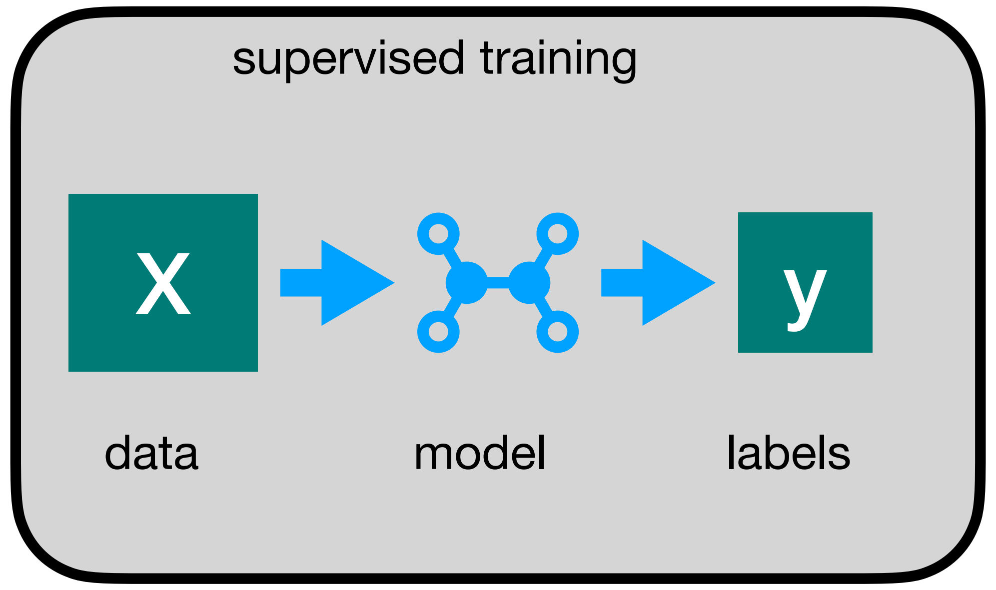
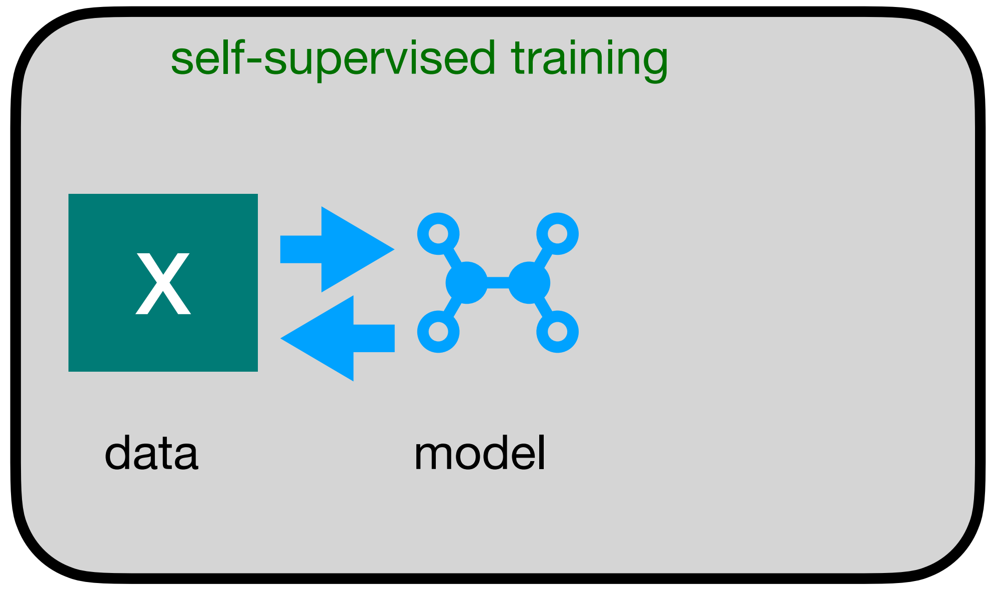
Plan

- Self-supervised Learning
- Scaling laws, Frontier and Foundation Models
- The Data Challenge
- Fast Data Loaders: Keeping the GPUs Fed

Supervised and Self-supervised Learning

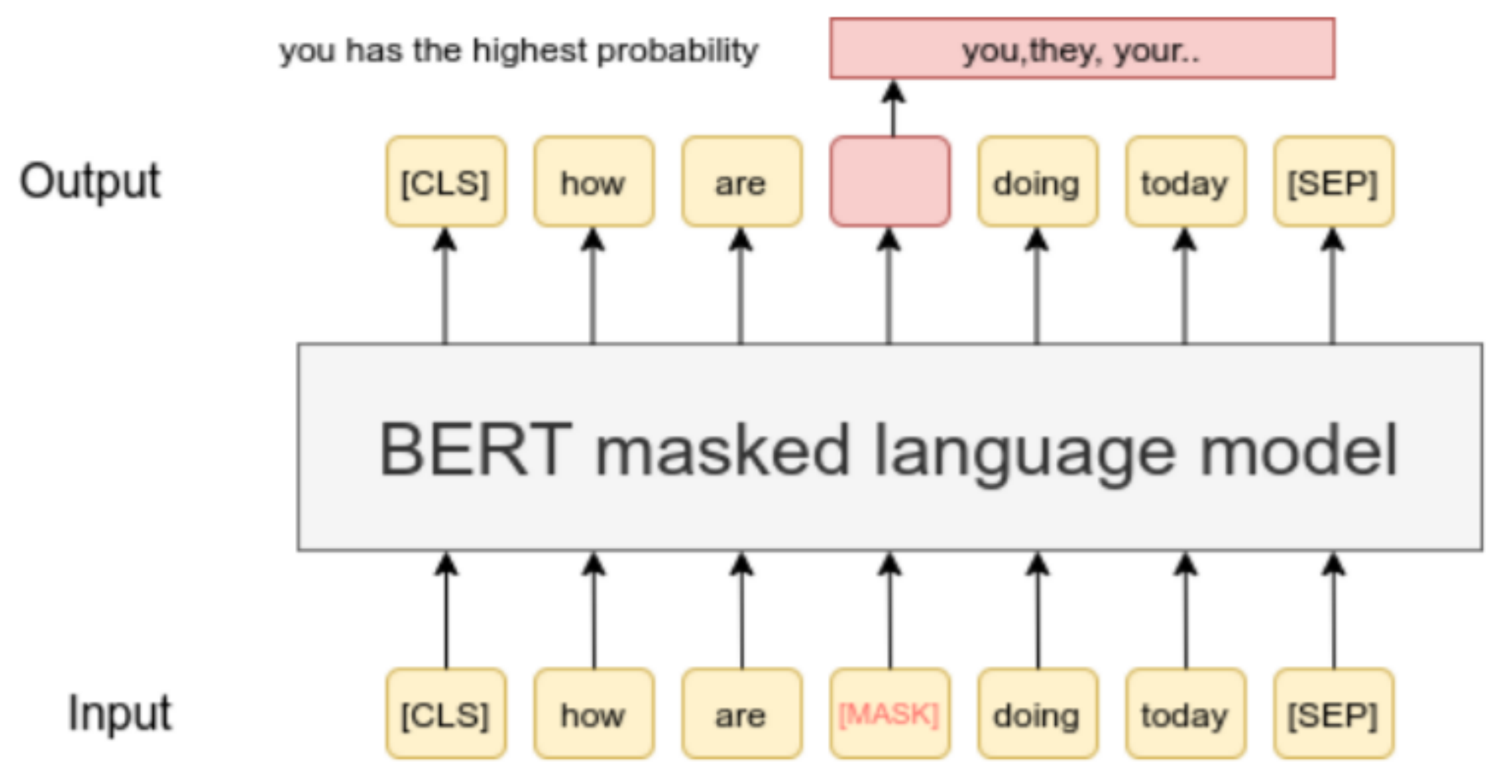
- Supervised learning: we have data and labels. The model is trained to predict the labels.
- Unlabeled data is abundant. Can we do without the labels?
- Self-supervised learning

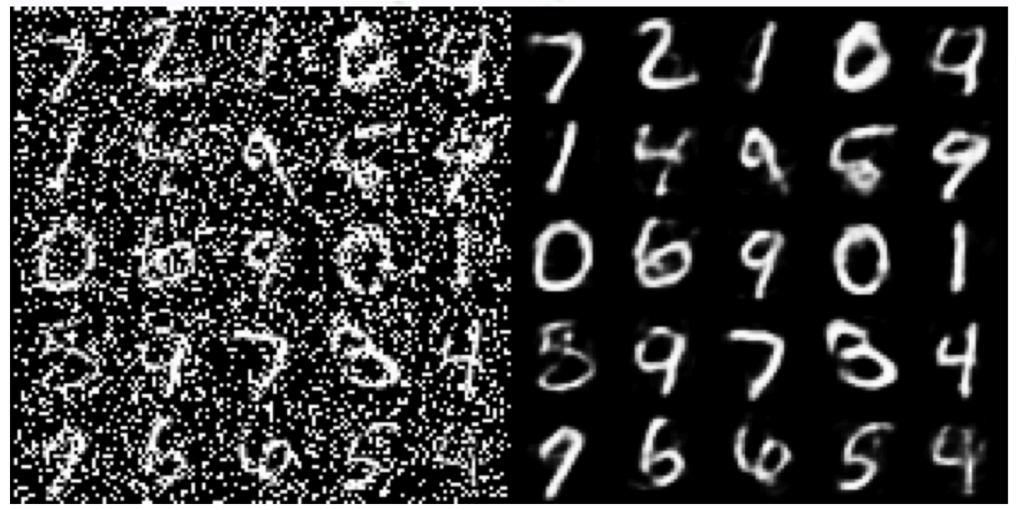




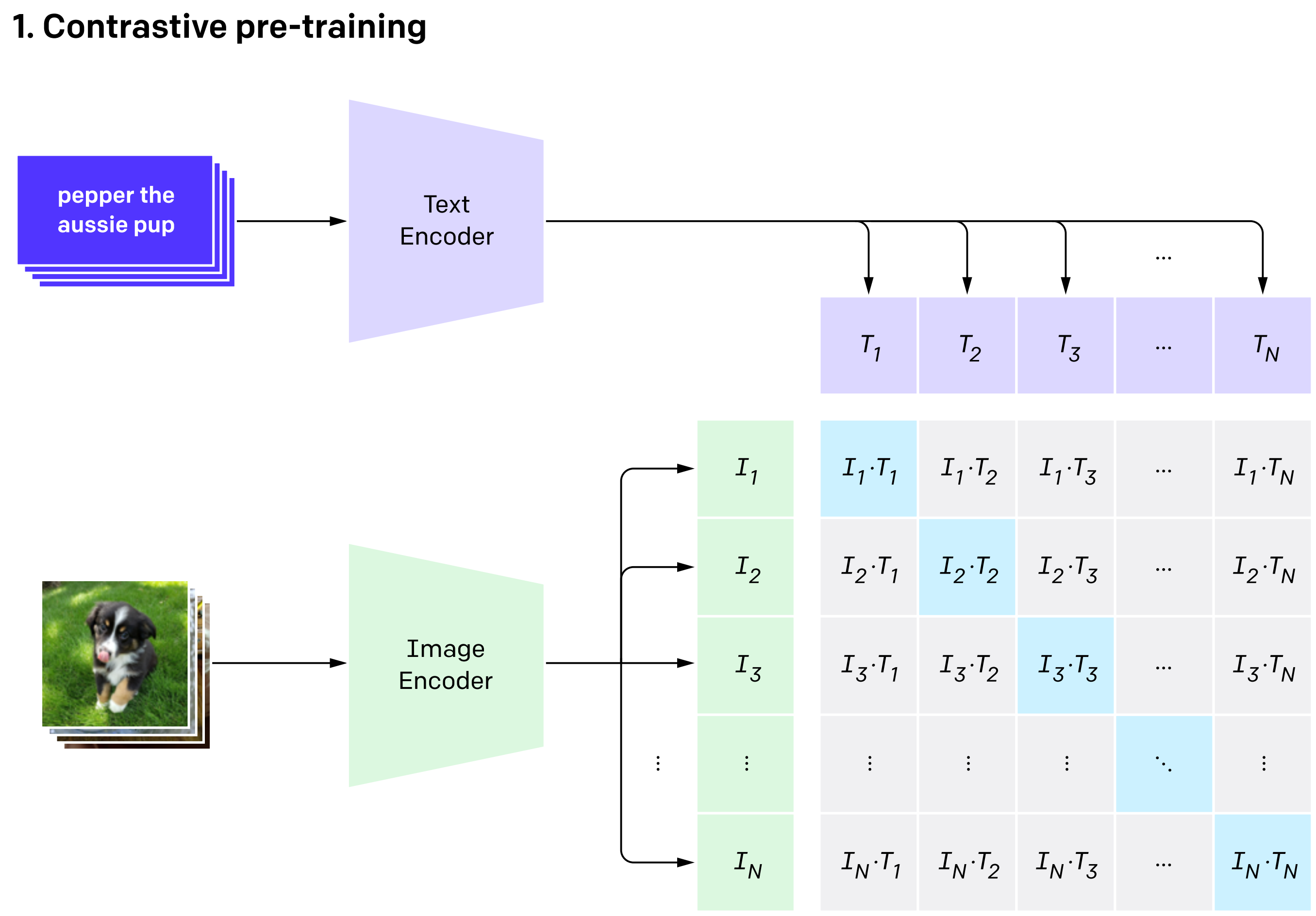
How can we train without labels?

- **Masked Prediction:** We train models to predict hidden or "masked" parts of the input data (e.g., words in a sentence or patches in an image).
- **Denoising:** The model learns to reconstruct original, clean data from a corrupted or noisy version we create.
- **Contrastive Learning:** We teach the model to pull representations of similar (e.g., augmented) data points closer and push dissimilar ones further apart.





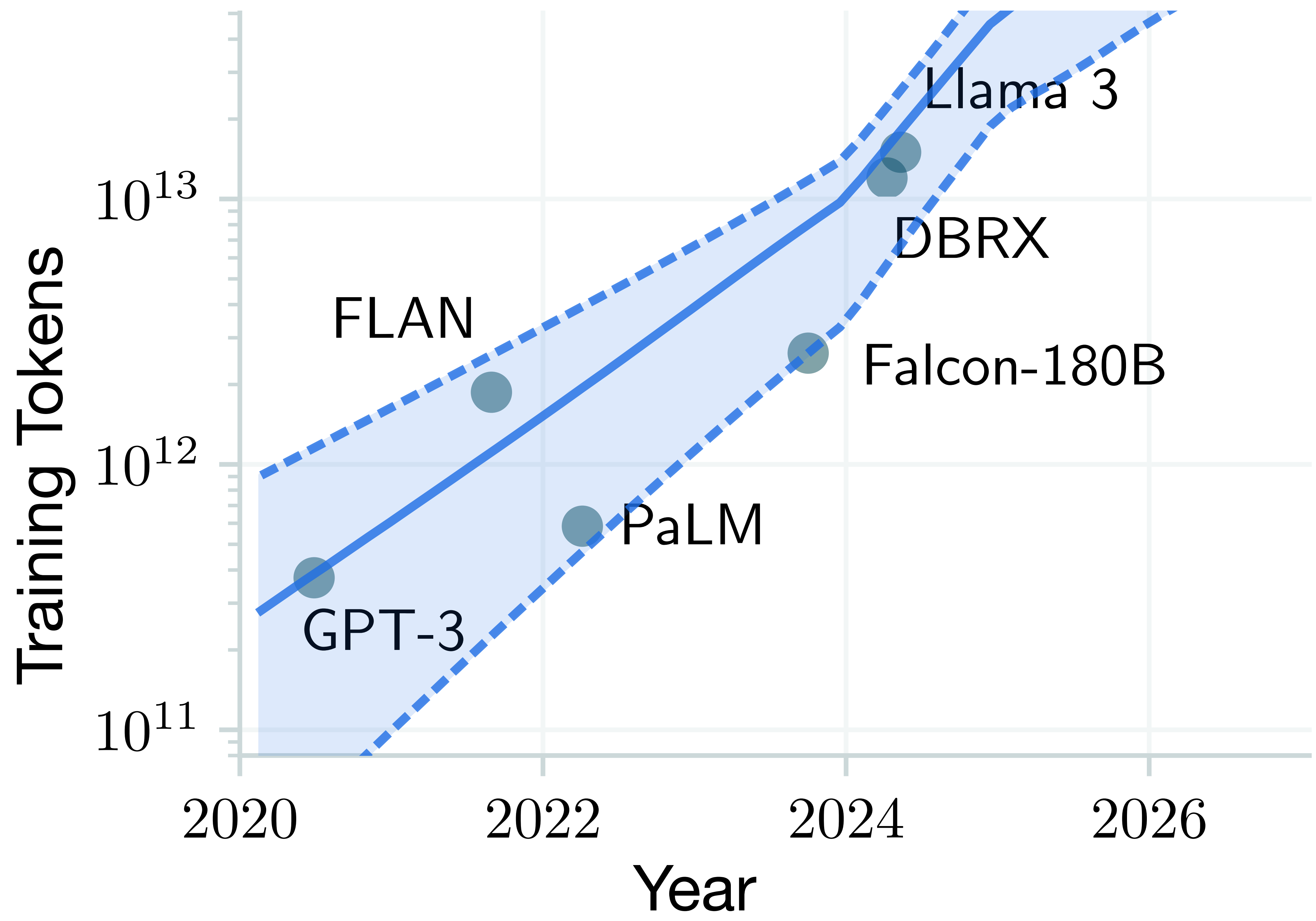
Denoising Autoencoder



OpenAI CLIP
(Contrastive Language-Image Pre-training)

Success of self-supervise training

- Labeled data is limited
- Unlabeled data is abundant (text, image, video)
- Led to GenAI revolution
- Some recent models were trained on 30 trillion tokens!



source:
2211.04325 "Will we run out of data?
Limits of LLM scaling based on human-generated data"

BERT - 3.3B tokens

1810.04805 "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding"

Self-supervise training: Scaling Laws

Performance predictably improves with scale

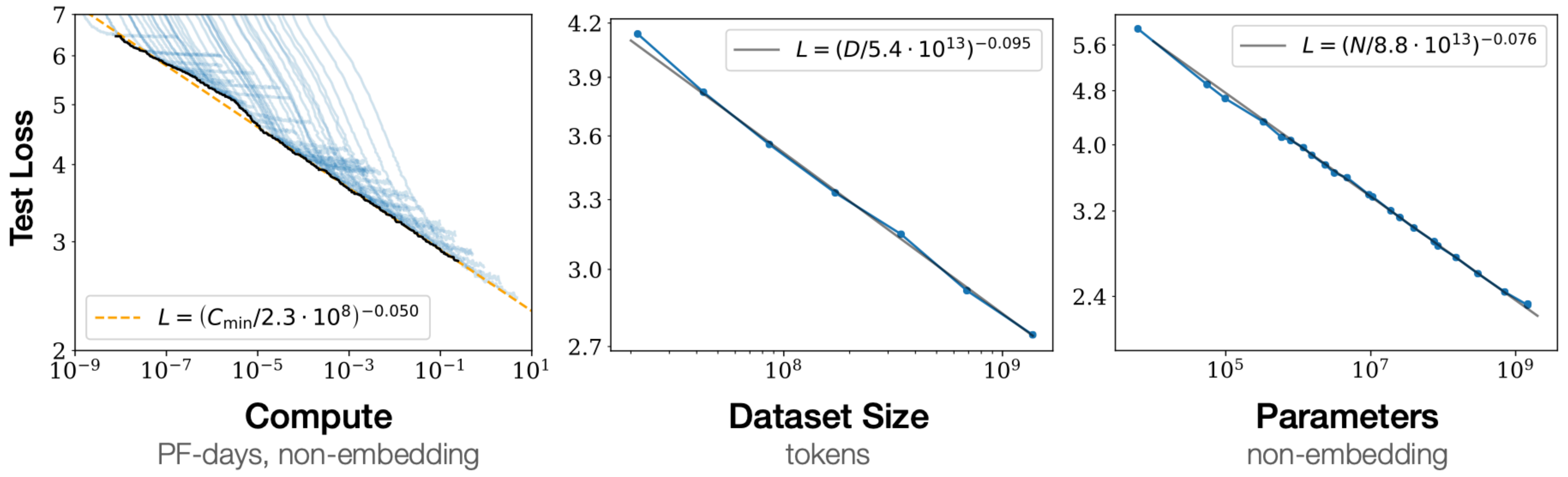
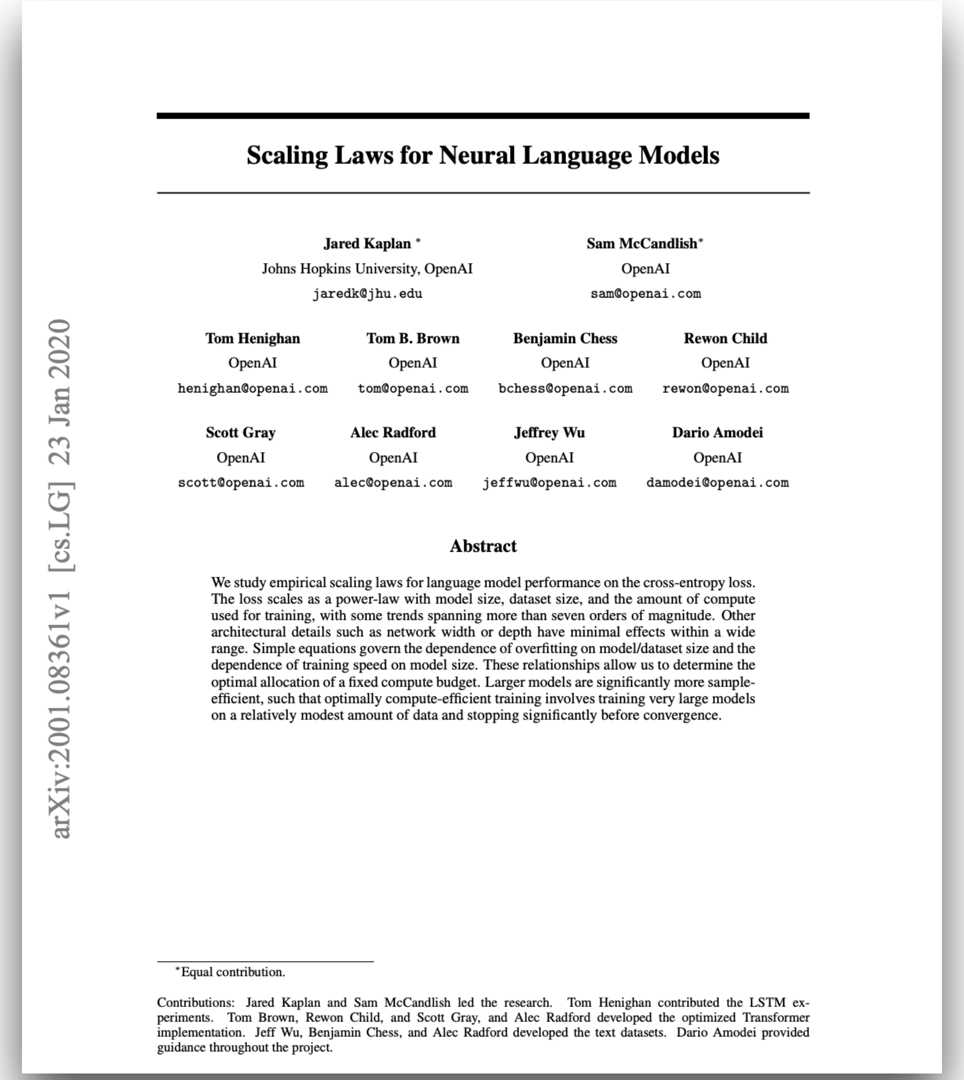


Figure 1 Language modeling performance improves smoothly as we increase the model size, datasetset size, and amount of compute[2] used for training. For optimal performance all three factors must be scaled up in tandem. Empirical performance has a power-law relationship with each individual factor when not bottlenecked by the other two.

https://arxiv.org/pdf/2001.08361
Scaling Laws for Neural Language Models

The effect of the scaling laws



arXiv:2001.08361v1 [cs.LG] 23 Jan 2020

Scaling Laws for Neural Language Models

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Abstract

We study empirical scaling laws for language model performance on the cross-entropy loss. The loss scales as a power-law with model size, dataset size, and the amount of compute used for training, with some trends spanning more than seven orders of magnitude. Other architectural details such as network width or depth have minimal effects within a wide range. Simple equations govern the dependence of overfitting on model/dataset size and the dependence of training speed on model size. These relationships allow us to determine the optimal allocation of a fixed compute budget. Larger models are significantly more sample-efficient, such that optimally compute-efficient training involves training very large models on a relatively modest amount of data and stopping significantly before convergence.

*Equal contribution.

Contributions: Jared Kaplan and Sam McCandlish led the research. Tom Henighan contributed the LSTM experiments. Tom Brown, Rewon Child, and Scott Gray, and Alec Radford developed the optimized Transformer implementation. Jeff Wu, Benjamin Chess, and Alec Radford developed the text datasets. Dario Amodei provided guidance throughout the project.

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Scaling Laws for Neural Language Models

ACTUAL SPENDING — real capital deployed in 2026

Amazon	Microsoft	Alphabet	Meta	NVIDIA inv.	Total
$200B	$190B	$185B	$135B	$45B+	$725B

CASH RAISED — injected into AI labs

OpenAI total	Anthropic total	xAI
~$186B	~$40B	$20B
incl. $122B, Mar '26	incl. $30B, Feb '26	Jan '26

REVENUE — annualized run rates, Apr 2026

NVIDIA datacenter	Anthropic ARR	OpenAI ARR
$197B	~$30–43B	~$30B
FY2026 actual	80x in 28 mo	900M weekly users

VALUATIONS — paper value, can evaporate overnight

NVIDIA mkt cap	Anthropic	OpenAI	DeepSeek est.
$5.4T	~$900B	$852B	~$50B
#1 globally	targeting, May '26	Mar '26 round	private

SUMMARY Real spend 2026: **~$775B** Revenue: **~$260B** Valuations: **~$7T**

Origin: $L \propto C^{-\alpha}$, Kaplan et al. 2020

Foundation Models

- **Definition:** Models pre-trained on broad data at massive scale, designed to be adapted (e.g., fine-tuned) to a wide range of downstream tasks.
  (Stanford HAI definition)

- **Scale:** Data (petabytes), Parameters (billions to trillions).

- **Generality:** Adaptable to diverse tasks, often beyond their explicit training objectives

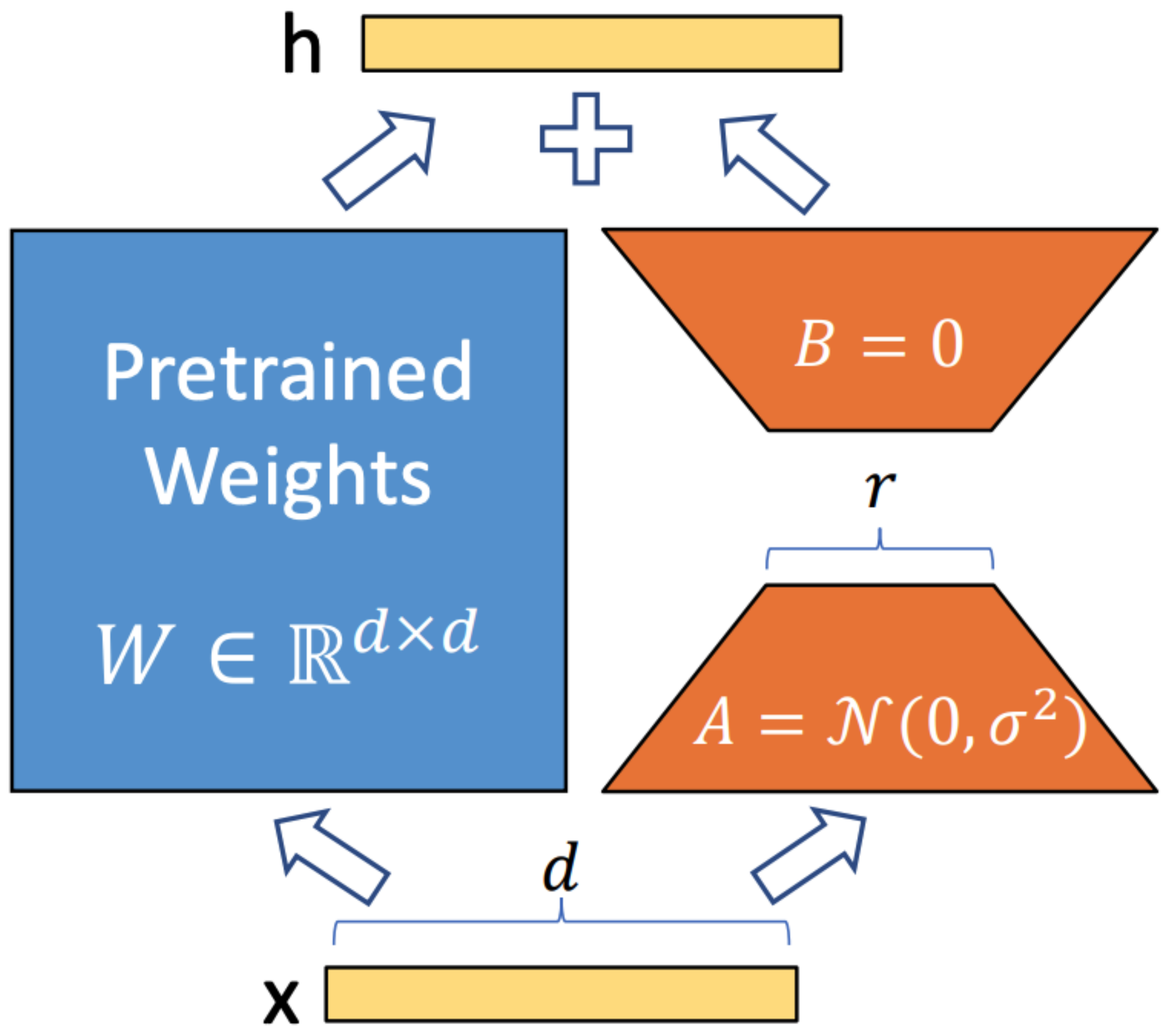
  - **Examples:** Bert, CLIP,…

- Another term: **Frontier Models** — zero shot capabilities, no fine-tuning

  Examples: GPT, Claude, Gemini, Grok, Llama, DeepSeek, Qwen

Parameter-Efficient Fine-Tuning (PEFT)

- Sometimes it is enough to tune just a subset of parameters.
- One can freeze early layers, or the full backbone.
- One can also apply techniques like **LoRA** (Low-Rank Adaptation).
- See this nice guide for LLMs: https://docs.unsloth.ai/get-started/fine-tuning-guide



$$h = Wx + BAx$$

BA is a low rank matrix

Foundation Models

LANGUAGE (DENSE)

Llama 3.1 405B

405B params, 15.6T tokens
Meta, 2024 — 16K H100s × 100 days
Reference scale for dense frontier LLMs

LANGUAGE (MOE)

DeepSeek V4-Pro

1.6T total / 49B active, 33T tokens
Apr 2026 — on Huawei Ascend, not NVIDIA
Matches Claude Opus at 7× lower price

PROTEIN DESIGN

ESM3

98B params, 2.78B proteins, 10^{24} FLOPs
EvolutionaryScale, 2024 — H100 cluster
Generated protein 500M yr from nature

GENOMICS

Evo 2

40B params, 9.3T nucleotides, 1M context
Arc Institute, 2025 — 2,048 H100s, ~$10M
Zero-shot BRCA1 variant prediction

PROTEIN STRUCTURE

AlphaFold 2 / 3

93M / 500M params, PDB + MSAs
DeepMind, 2021/2024 — 128 TPUv3 × 11 days
Solved protein structure prediction

WEATHER (DIFFUSION)

GenCast

Diffusion model, 40 yr ERA5, 0.25° res
DeepMind, Nature 2024 — 32 TPUv5 × 5 days
Beats ECMWF ENS on 97% of targets

PHYSICS SIMULATION

Walrus

1.3B params, 15 TB, 19 physics scenarios
Polymathic AI, 2025 — neutron stars to bacteria
Cross-domain transfer across physics

TABULAR DATA

TabPFN v2

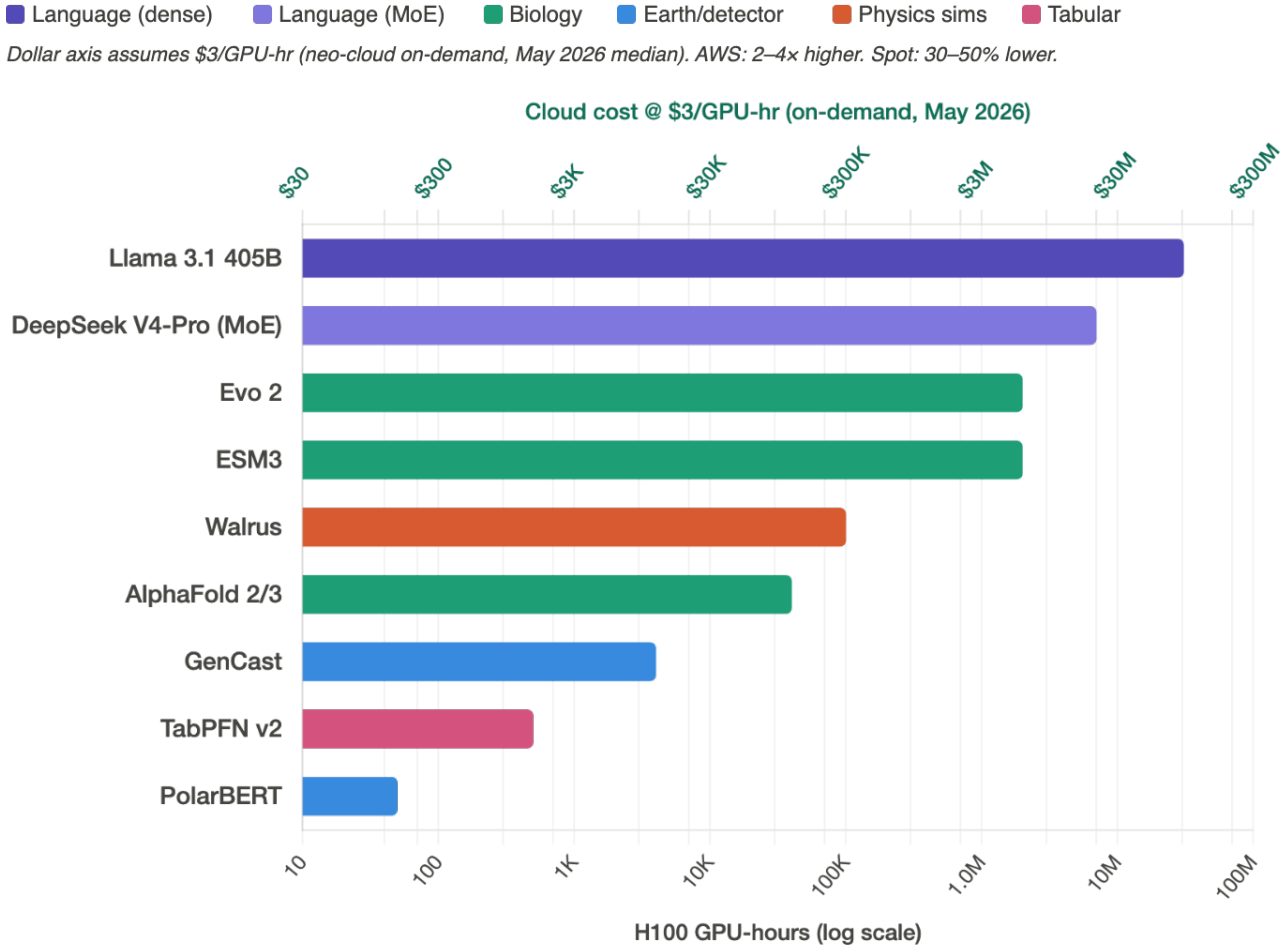
Transformer, 130M synthetic datasets
Prior Labs, Nature 2025 — single A100
100% win rate vs XGBoost (≤10K samples)

NEUTRINO TELESCOPE

PolarBERT

BERT-style, IceCube detector events
Timiryasov et al., 2024 — ~50 H100-hrs
Power-law scaling $\alpha \approx 0.62$ on detector data

Foundation Models



The Data Challenge

- Scale is crucial for foundation models

- Large model — GPU parallelism (data, pipeline, tensor)
  - Data parallelism evenly distributes data across multiple GPUs.
  - Model parallelism distributes a model across multiple GPUs.
  - Tensor parallelism distributes large tensor computations across multiple GPUs.

- Large datasets — quickly loading it and transferring on GPU(s) is critical.

  If your GPU is sitting idle waiting for data, you're wasting resources and time.

DL specific compute requirements

- NNs rely on massive matrix multiplies.
  $x' = Wx$
  # multiplies is the same as the number of parameters in W

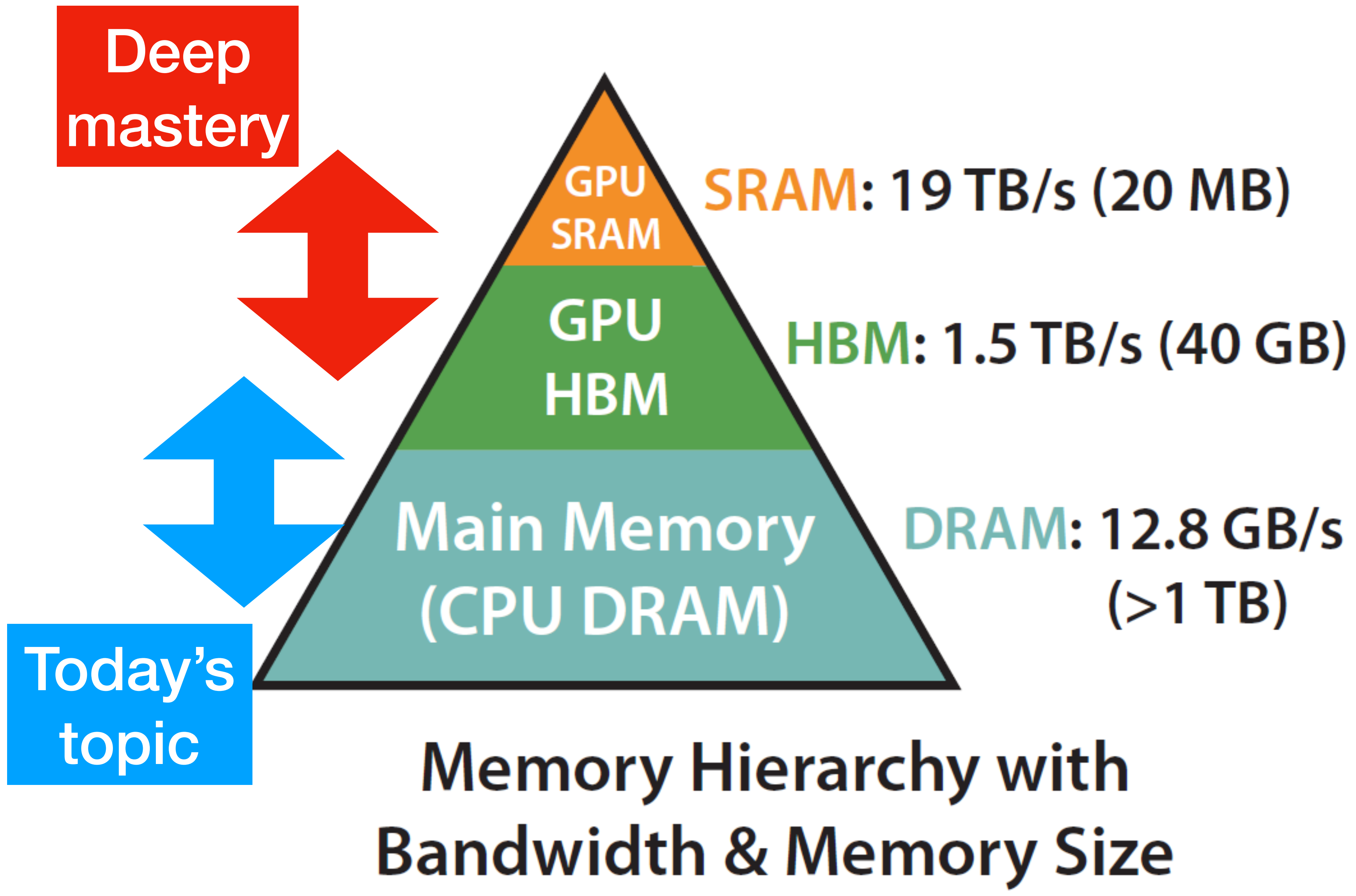
- CPUs.

- CPUs can execute ~ one instruction at a time.

- GPUs perform many operations in parallel, so they give a significant speed up. Moreover, the modern GPUs have specialized tensor cores (TPUs have only those).

- GPUs have fast memory, but it is limited, so we need to transfer data to them.

https://jax-ml.github.io/scaling-book/



The I/O Bottleneck

- **Definition**: The **I/O (Input/Output) bottleneck** happens when your system's ability to read/write data is slower than its ability to process that data.
- **The Core Issue:** Your powerful CPU or GPU is often idle, waiting for data to be loaded from storage (like an SSD/HDD) or transferred to its memory.
- **Key Symptoms:**
  - **Low CPU/GPU utilization** during computationally intensive phases.
  - Tasks take much longer to complete than theoretically expected.
  - Data loading/preprocessing steps visibly consume a large portion of the total time.

GPU Utilization

`**nvidia-smi**` terminal command is your friend!
(System Management Interface)

```
|-----------------------------------------+------------------------+----------------------+
| GPU  Name                 Persistence-M | Bus-Id          Disp.A | Volatile Uncorr. ECC |
| Fan  Temp   Perf          Pwr:Usage/Cap |           Memory-Usage | GPU-Util  Compute M. |
|                                         |                        |               MIG M. |
|=========================================+========================+======================|
|   0  NVIDIA GeForce RTX 3090        Off |   00000000:21:00.0 Off |                  N/A |
| 71%   67C    P0             283W /  350W |    4733MiB /  24576MiB |     54%      Default |
|                                         |                        |                  N/A |
+-----------------------------------------+------------------------+----------------------+
```

- **GPU-Util:** Percentage of time the GPU's processing cores were actively computing.
  - Aim for consistently high values (e.g., >90%) during intensive training.
  - Low Util (like 54%): Strong indicator the GPU is often idle, typically waiting for data (I/O bound) or CPU tasks.
  - **Caveat:** 100% util doesn't always mean *peak theoretical* performance. Throughput can still be limited by memory bandwidth bottlenecks or suboptimal kernel execution.

- **Memory-Usage:** Shows GPU video RAM (VRAM) currently allocated versus total available

- **Perf:** The GPU's current performance state. P0 means maximum performance. Other states (e.g., P2, P8) mean reduced performance/power.

- **Pwr:Usage/Cap:** Current GPU power consumption versus its maximum rated capacity.

GPU Utilization

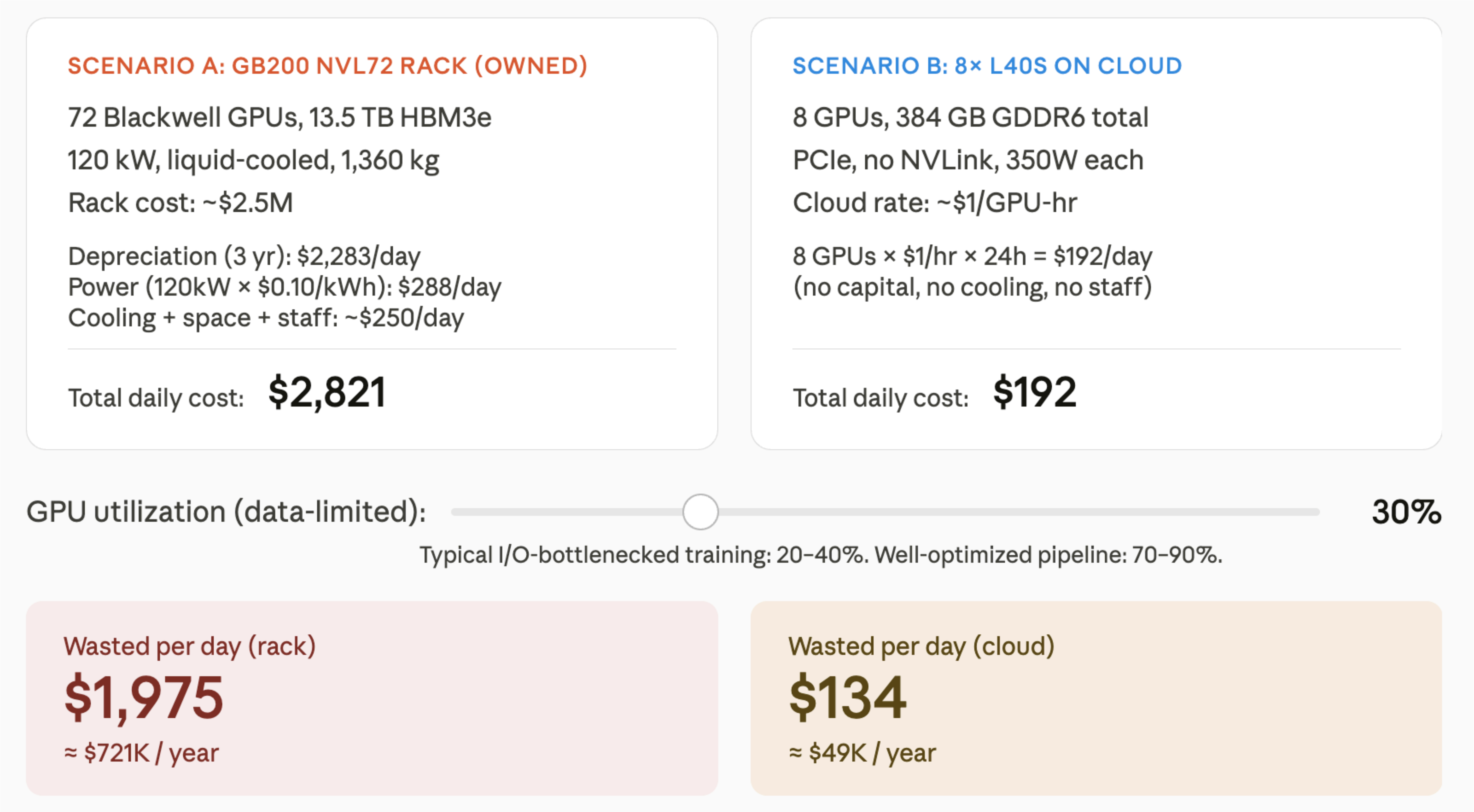
```
+-----------------------------------------------------------------------------------------+
(base) [inar@hep04 ~]$ nvidia-smi
Tue May 20 17:52:08 2025
+-----------------------------------------------------------------------------------------+
| NVIDIA-SMI 555.42.06              Driver Version: 555.42.06      CUDA Version: 12.5     |
|-----------------------------------------+------------------------+----------------------+
| GPU  Name                 Persistence-M | Bus-Id          Disp.A | Volatile Uncorr. ECC |
| Fan  Temp   Perf          Pwr:Usage/Cap |           Memory-Usage | GPU-Util  Compute M. |
|                                         |                        |               MIG M. |
|=========================================+========================+======================|
|   0  NVIDIA GeForce RTX 3090        Off |   00000000:21:00.0 Off |                  N/A |
| 30%   35C    P8             10W /  350W |       4MiB /  24576MiB |      0%      Default |
|                                         |                        |                  N/A |
+-----------------------------------------+------------------------+----------------------+
|   1  NVIDIA GeForce RTX 3090        Off |   00000000:4D:00.0 Off |                  N/A |
| 47%   52C    P0            149W /  350W |    4276MiB /  24576MiB |    100%      Default |
|                                         |                        |                  N/A |
+-----------------------------------------+------------------------+----------------------+


+-----------------------------------------------------------------------------------------+
| Processes:                                                                              |
|  GPU   GI   CI        PID   Type   Process name                              GPU Memory |
|        ID   ID                                                               Usage      |
|=========================================================================================|
+-----------------------------------------------------------------------------------------+
```

The I/O Bottleneck

- Slow storage media (e.g., hard disk drives vs. faster SSDs, distributed filesystems like LUSTRE could be unpredictable).
- Inefficient data access patterns (e.g., reading many small files repeatedly).
- Data formats not optimized for quick loading or random access.
- Limited bandwidth between storage, CPU memory, and GPU memory.
- CPU-bound data preprocessing or augmentation that stalls the pipeline.
- Insufficient parallelism in the data loading process (e.g., single-threaded loading).

Why are we doing this?



torch.utils.data.Dataset (Code on GitHub)

- An abstract class in PyTorch representing your collection of data samples.
- Separates data loading and preprocessing logic from your model training loop.
- Seamlessly works with torch.utils.data.DataLoader for efficient batching, shuffling, and parallel data loading.
- Key Requirement: To create your own dataset, you subclass torch.utils.data.Dataset and must override two methods:
  - __len__(self): Returns the total number of samples in the dataset. Used by DataLoader to know the dataset size.
  - __getitem__(self, idx): Fetches and returns the sample (e.g., data tensor and label tensor) at the given index idx. This is where you'll typically load data from disk, apply transformations, etc.

real world example: https://github.com/timinar/BabyLlama/blob/main/babylm_dataset.py

torch.utils.data.DataLoader (Code on GitHub)

- Input: A torch.utils.data.Dataset object

- Batching: Automatically groups individual samples from the Dataset into batches of a specified size.

- Shuffling: Optionally shuffles the order of data at the start of each epoch to improve model training.

- Parallel Loading: Can use multiple CPU worker processes (num_workers) to load data in the background, preventing I/O bottlenecks and keeping the GPU fed.

- Memory Management: Offers options like pin_memory for faster CPU-to-GPU data transfers.

more details: https://docs.pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader

Other types of Datasets

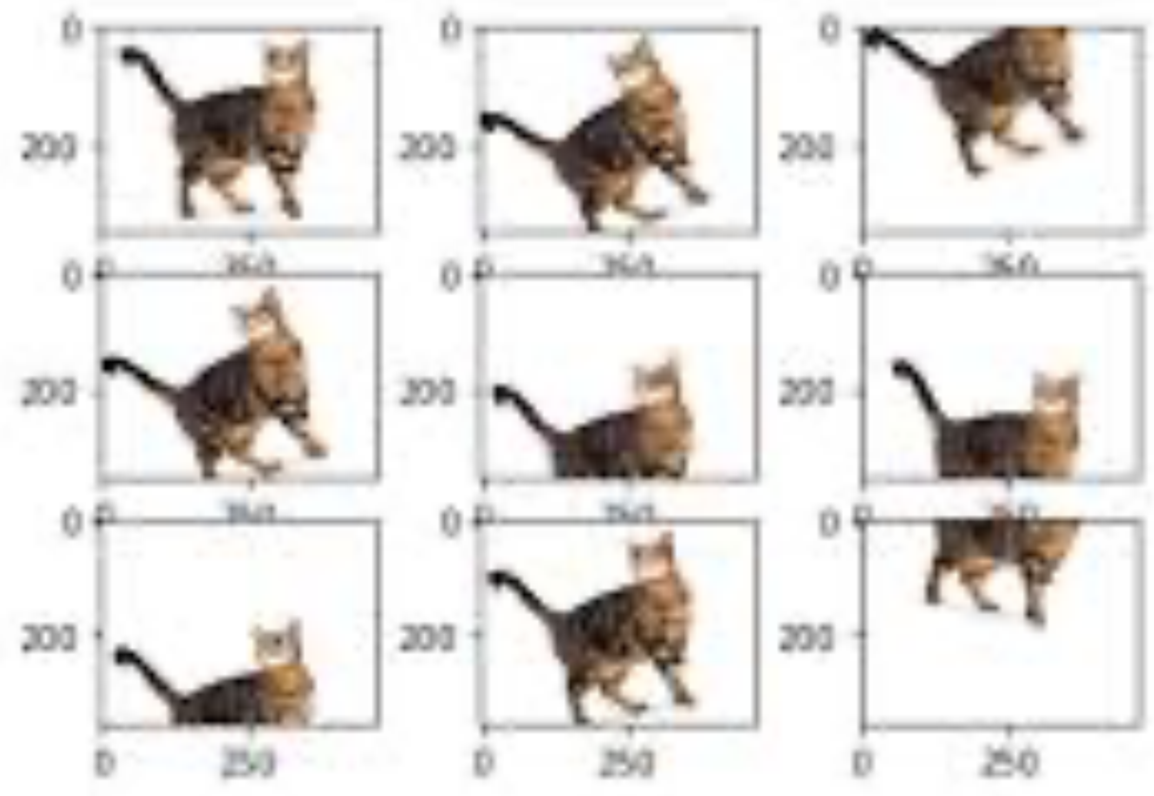
- Iterable-style Datasets (torch.utils.data.IterableDataset)
  - For datasets where data is read sequentially, like a data stream, rather than by random access using an index.
  - You implement __iter__(self) (which yields samples).
  - Note: DataLoader handles these differently (e.g., num_workers has specific considerations, shuffling is typically done within __iter__).
  - Example: https://github.com/timinar/PolarBERT/blob/main/src/polarbert/icecube_dataset.py
- Working with Image Folders (torchvision.datasets.ImageFolder)
  - You have images organized in a directory structure like: dataset_root/class_A/image1.jpg, dataset_root/class_B/image2.jpg
  - ImageFolder automatically discovers images, infers class labels from subfolder names, and can apply specified transformations.

Data Handling Technicalities & Performance Tips

- **Useful torch.utils.data Utilities:**
    - ConcatDataset: Merges multiple datasets sequentially (e.g., combining data from different sources or augmentation passes).
    - Subset: Extracts a specific portion of a dataset using a provided list of indices (useful for specific selections or k-fold cross-validation).
    - random_split: Conveniently splits a dataset into random, non-overlapping new datasets (ideal for creating train/validation/test sets).
- **Strategies for Large Datasets & Performance:**
    - Implement an Efficient __getitem__ (for map-style Dataset):
    - Lazy Loading: Crucially, load data (e.g., image from disk, specific rows from a large file) only when that specific item is requested by __getitem__.
    - Lightweight __init__: Avoid loading the entire dataset into RAM during __init__. Instead, store file paths, metadata, or pointers.
- **Specialized Data Storage Formats:**
    - WebDataset (.tar files): Excellent for streaming large image or sequence datasets, reads data sequentially from TAR archives.
    - HDF5: Hierarchical format, good for large numerical arrays; supports chunking, compression, and partial reads.
    - Apache Parquet: Columnar storage format, highly efficient for tabular data, offers good compression and predicate pushdown (filtering) when reading with libraries like pyarrow.
- Memory-Mapped Files

Data Augmentation: Where?

- Idea: Artificially create diverse training samples from your existing data (e.g., flipping images, altering text) to improve model robustness and reduce overfitting.
- Where:
  - Offline (Pre-processing): Generate and save augmented versions before training. Uses more disk space; simpler loading logic.
  - Online (On-the-fly): Apply augmentations dynamically during data loading for each epoch. More flexible; less disk space.
    - CPU-based: Common (e.g., in DataLoader workers using torchvision.transforms). Can be a bottleneck if transformations are heavy.
    - GPU-based: For faster, complex augmentations.



Caching & Buffering

- Idea: Store frequently accessed data or pre-loaded items in faster memory (e.g., RAM, fast SSD) to avoid repeated slow reads from primary storage (HDD, network).
- Common Strategies:
  - Full Dataset in RAM: If your dataset is small enough, load it entirely into memory at the start.
  - Selective Caching: Cache only the most frequently used samples or pre-process and cache transformed items.
  - Prefetch Buffers (e.g., in DataLoader): Automatically load upcoming batches into a memory buffer while the current batch is being processed.
  - Disk Caching: Use a fast local SSD as a cache for data originating from slower network storage or HDDs. Usually GPU nodes have they own fast storage

```
#!/bin/bash

if [ ! -e /dev/shm/filtered_all_big_data.db ]; then
  echo "Stage to /dev/shm/"
  time cp filtered_all_big_data.db /dev/shm/
else
  echo "File already staged to /dev/shm"
  ls -al /dev/shm/filtered_all_big_data.db
  du -skh /dev/shm/filtered_all_big_data.db
fi
```

Profiling & Tools

- Profiling — measuring time and memory consumption.
- nvidia-smi, htop / top, iotop
- PyTorch Profiler (torch.profiler)

Summary of Data Loading Best Practices

- Use num_workers wisely.
- Consider pin_memory and prefetching.
- Choose appropriate data formats for your dataset size and access patterns.
- Profile your pipeline!

- For perspective, big labs have they own **filesystems**! https://github.com/deepseek-ai/3FS

Useful resources

- The best lecture on transformers (Karpathy)
  Let's build GPT: from scratch, in code, spelled out.
- 3B1B videos on transformers
- How to Scale Your Model — the best technical dive on TPU/GPU practices at the frontier scale
- How GPT, Claude, and Gemini are actually trained and served – Reiner Pope (Dwarfish Patel’s channel, blackboard derivations!)