Decentralized Deep Learning

Running Large Neural Networks Together

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Talk outline

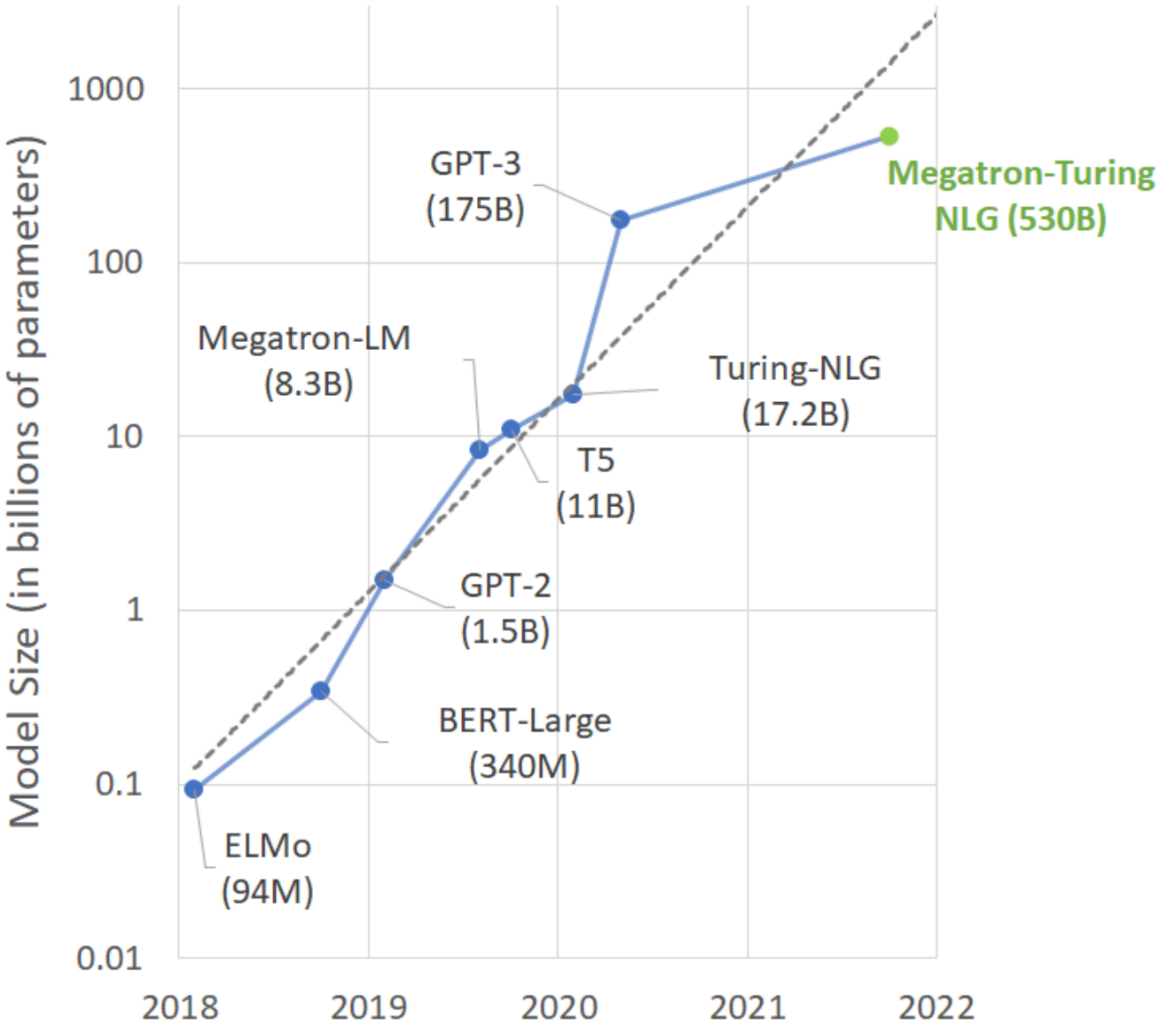
- Motivation and key challenges
- Decentralized training
  - Specialized architectures
  - General data-parallel training
  - Pipeline-parallel training
- Decentralized inference of pretrained models

The state of deep learning in 2023

〉 Large-scale training becomes more popular

〉 Scaling laws promise continued gains

〉 Larger models have emergent abilities (e.g. in-context learning)



img: arxiv.org/abs/2201.11990

Implications of scaling

〉 Some models cost hundreds of thousands to train — or more!

〉 GPT-3 training costs millions of $

〉 Hard to train for an average researcher and advance the field

110-340M parameters in most work

img: jalammar.github.io/illustrated-bert

Solution: share the effort

- Collaboration has worked in other sciences
- Let's use idle volunteer resources for DL as well!

Challenges of volunteer deep learning

- **Node failures**: PC turns off, Internet gets disabled, ...
- **Communication over Internet:** magnitudes slower than clusters
- **Heterogeneous hardware:** different GPUs, connection speeds etc.

Existing approaches for distributed DL

Training method	Size limit	Throughput	Scalability	Fault tolerance	Worker hot-join	Network bandwidth	Network latency
Data parallel	Worker	**High**	Medium	**Full**	**Yes**	High	Low
Asynchronous	Worker	**High**	High	Only workers	**Yes**	Medium	**Any**
Model parallel	**System**	Medium	Low	No	No	High	Low
Federated	Worker	Low	**High**	Only workers	**Yes**	**Low**	**Any**
Desired	**System**	**High**	**High**	**Full**	**Yes**	**Low**	**Any**

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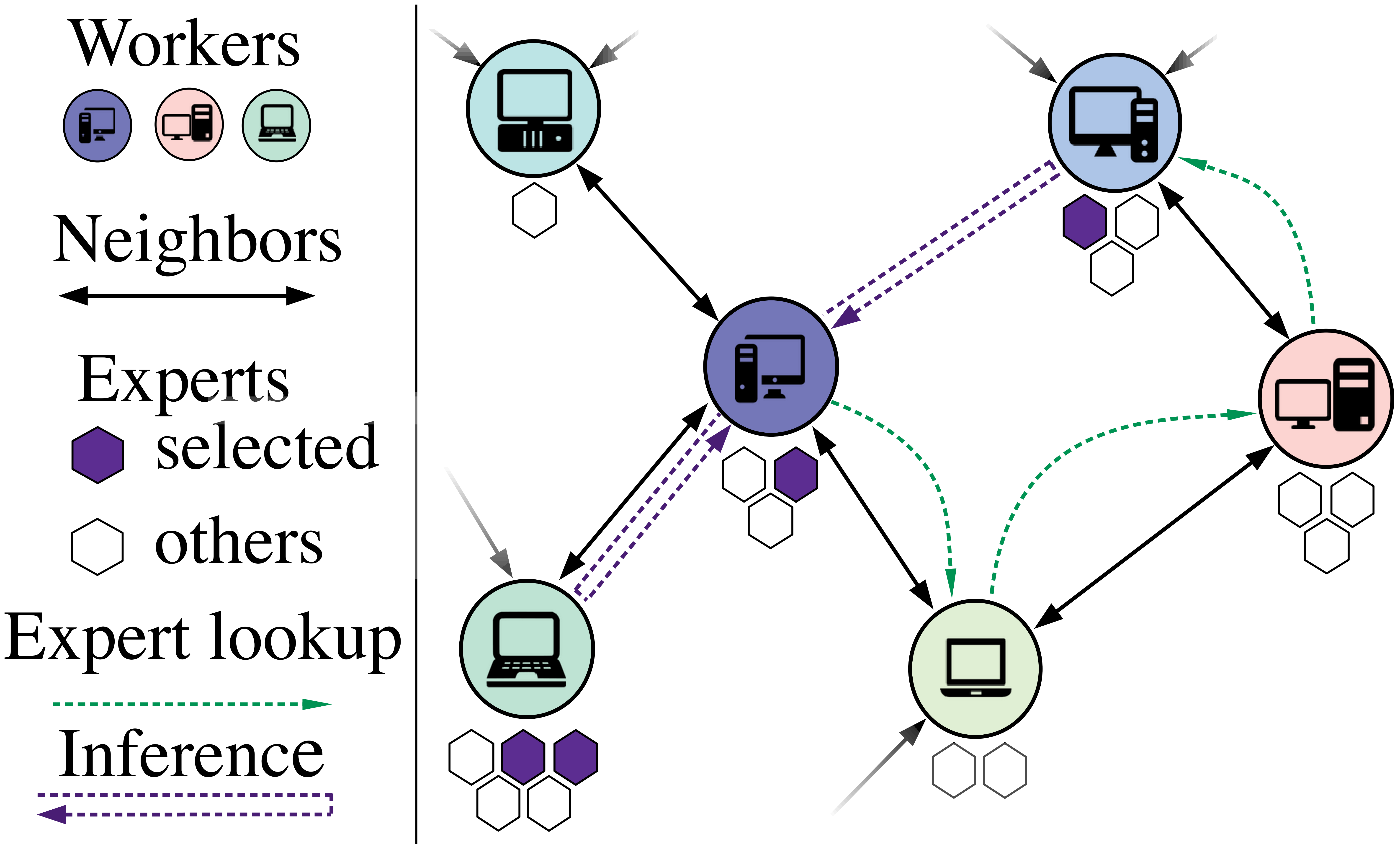
Learning@home (NeurIPS’20)

Towards Crowdsourced Training of Large Neural Networks
using Decentralized Mixture-of-Experts



DMoE (Decentralized Mixture-of-Experts)

Training over the Internet

DHT request

Data transfer

Trainer process

Available expert
(unused)

Expert selected
by gating function

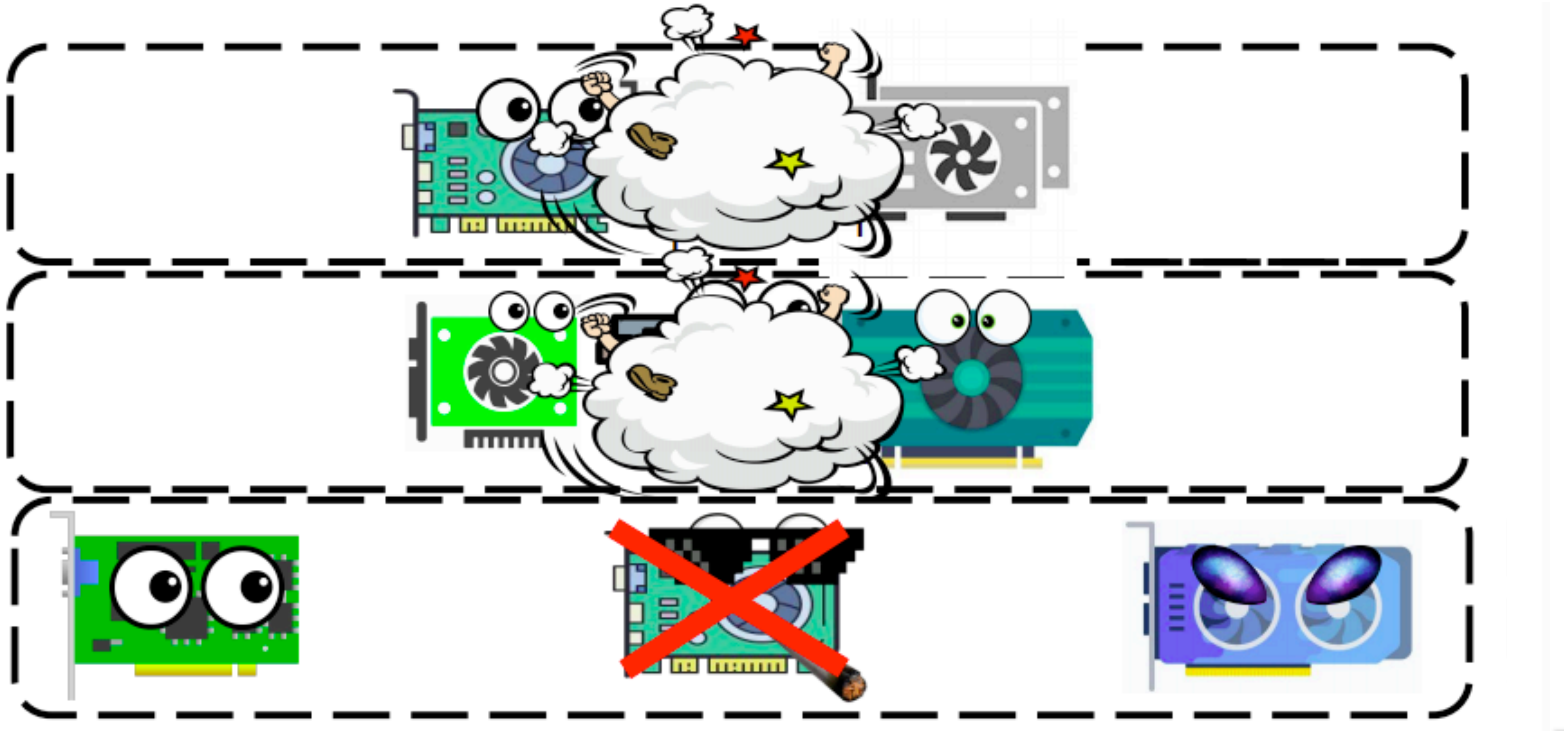
Failed expert
(e.g. disconnected)

Moshpit SGD (NeurIPS’21)

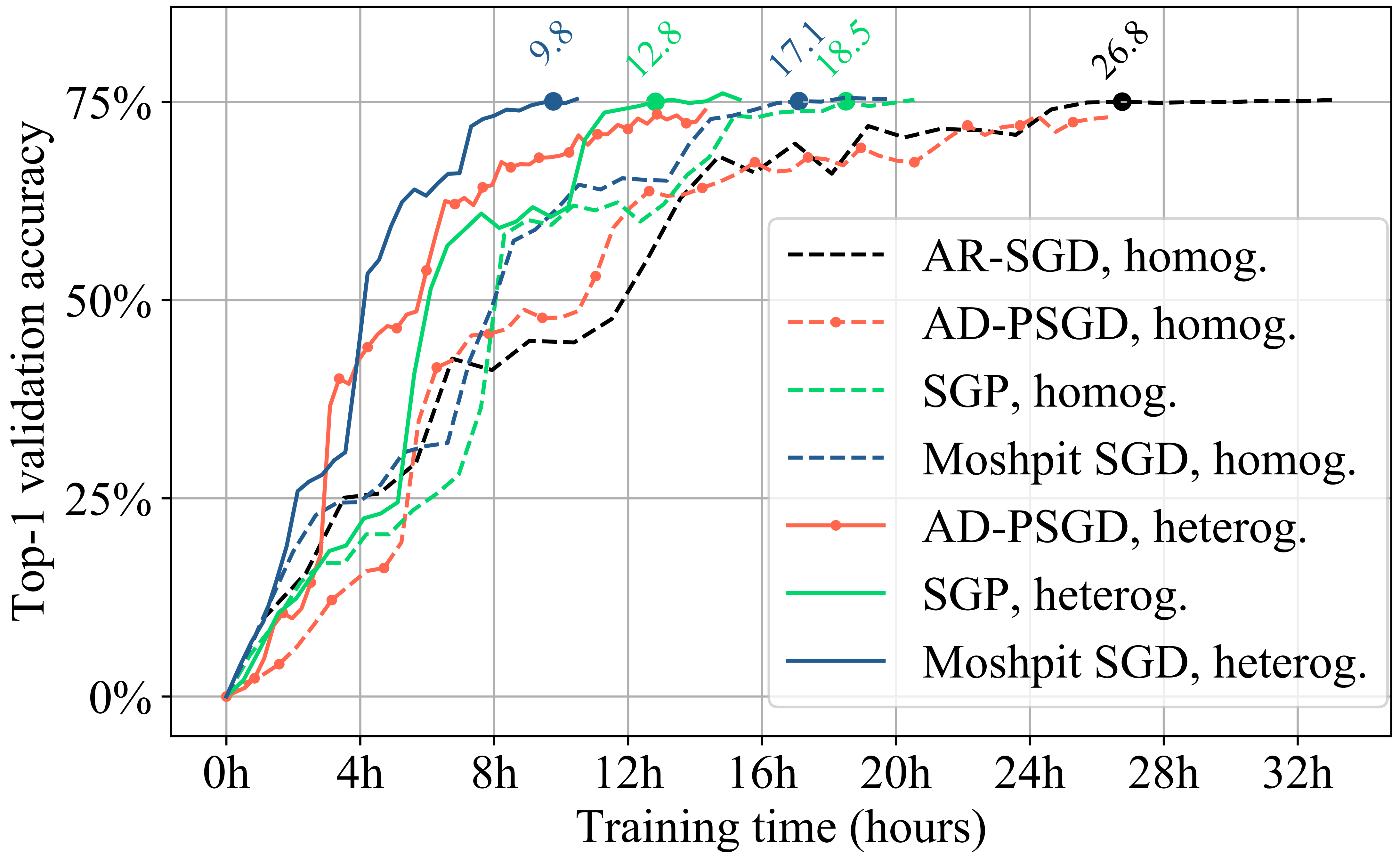
Communication-Efficient Decentralized Training
on Heterogeneous Unreliable Devices

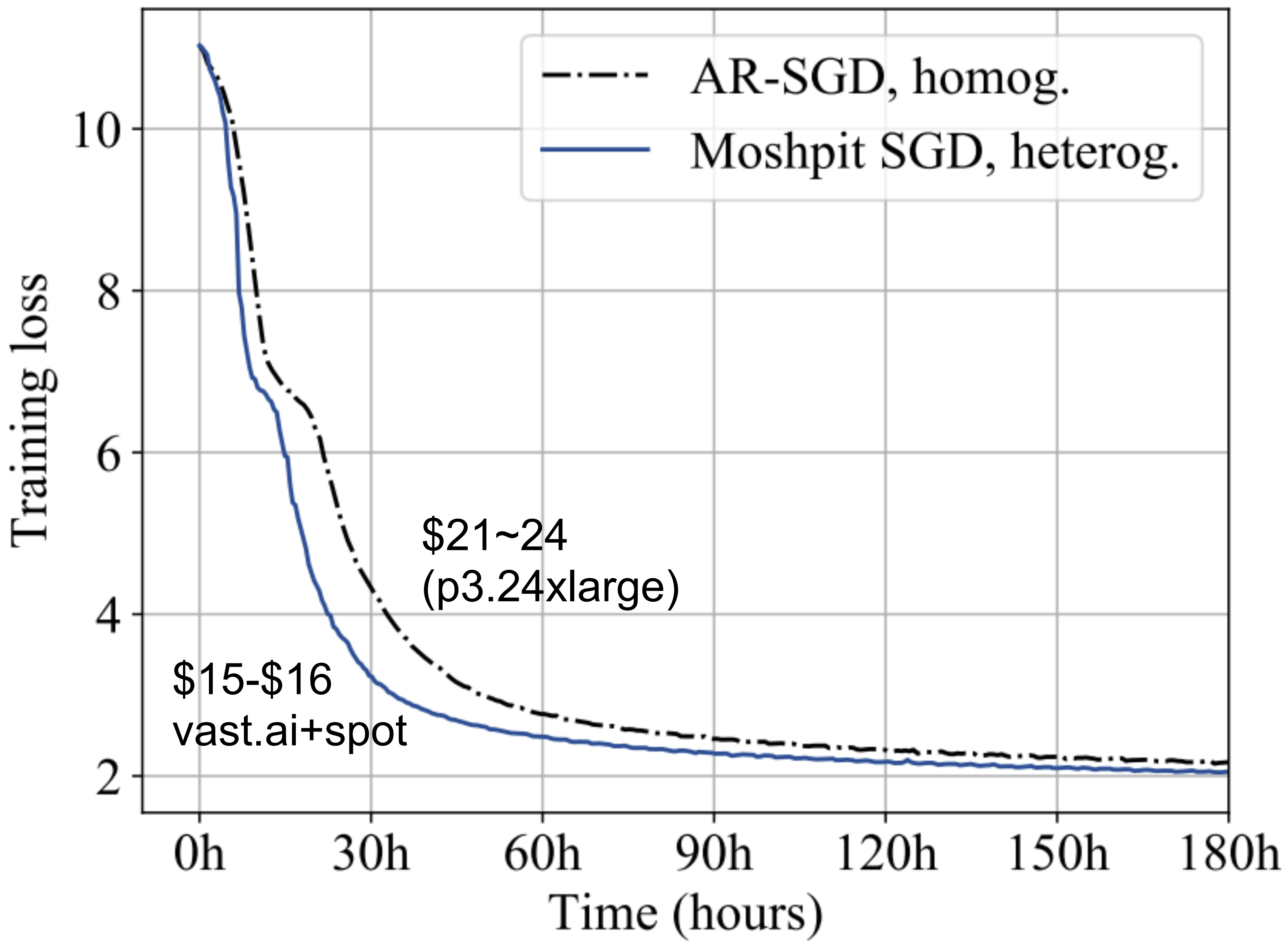
- How to average the gating function/embeddings?
- We propose a new algorithm for decentralized AllReduce-like averaging
- Main idea: average in smaller non-overlapping groups
- Communication-efficient and fault-tolerant, useful even on its own

Moshpit All-Reduce: core idea



Experiments





Analysis TL;DR

- The averaging converges exponentially quickly

Theorem 3.2. *Consider a modification of Moshpit All-Reduce that works as follows: at each iteration $k \geq 1$, 1) peers are randomly split in r disjoint groups of sizes $M_1^k, \ldots, M_r^k$ in such a way that $\sum_{i=1}^r M_i^k = N$ and $M_i^k \geq 1$ for all $i = 1, \ldots, r$ and 2) peers from each group compute their group average via All-Reduce. Let $\theta_1, \ldots, \theta_N$ be the input vectors of this procedure and $\theta_1^T, \ldots, \theta_N^T$ be the outputs after T iterations. Also, let $\overline{\theta} = \frac{1}{N}\sum_{i=1}^N \theta_i$ Then,*

$$\mathbb{E}\left[\frac{1}{N}\sum_{i=1}^{N}\|\theta_i^T - \overline{\theta}\|^2\right] = \left(\frac{r-1}{N} + \frac{r}{N^2}\right)^T \frac{1}{N}\sum_{i=1}^{N}\|\theta_i - \overline{\theta}\|^2. \tag{5}$$

- For Moshpit SGD — equivalent results to Local SGD

Theorem 3.4 (Non-convex case). *Let $f_1 = \ldots = f_N = f$, function f be L-smooth and bounded from below by f_*, and Assumptions 3.1 and 3.2 hold with $\Delta_{pv}^k = \delta_{pv,1}\gamma\mathbb{E}[\|\nabla f(\theta^k)\|^2] + L\gamma^2\delta_{pv,2}^2$, $\delta_{pv,1} \in [0, 1/2)$, $\delta_{pv,2} \geq 0$. Then there exists such choice of γ that $\mathbb{E}\left[\|\nabla f(\theta_{rand}^K)\|^2\right] \leq \varepsilon^2$ after K iterations of Moshpit SGD, where K equals*

$$\mathcal{O}\left(\frac{L\Delta_0}{(1-2\delta_{pv,1})^2\varepsilon^2}\left[1+\tau\sqrt{1-2\delta_{pv,1}}+\frac{\delta_{pv,2}^2+\sigma^2/N_{\min}}{\varepsilon^2}+\frac{\sqrt{(1-2\delta_{pv,1})(\delta_{aq}^2+(\tau-1)\sigma^2)}}{\varepsilon}\right]\right),$$

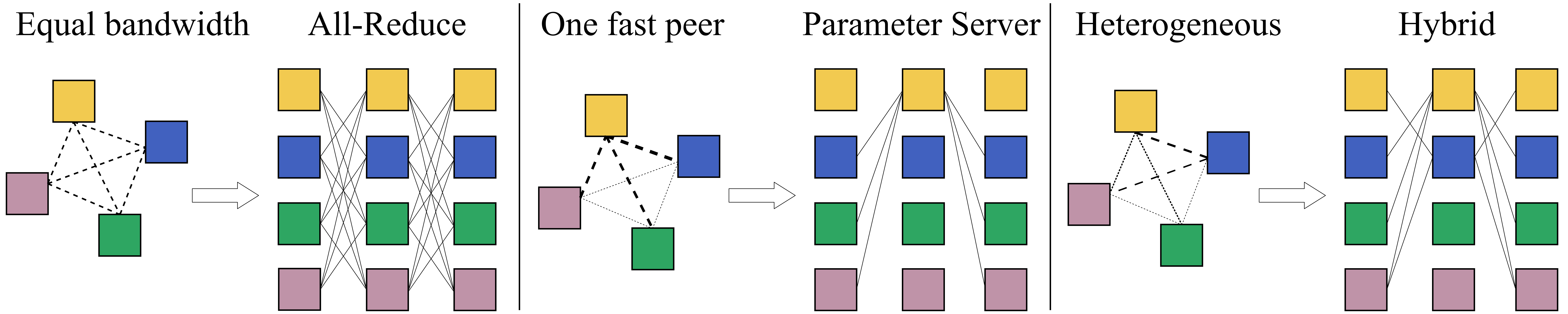
$\Delta_0 = f(\theta^0) - f(\theta^*)$ and θ_{rand}^K is chosen uniformly from $\{\theta^0, \theta^1, \ldots, \theta^{K-1}\}$ defined in As. 3.2.

Again, if $\delta_{pv,1} \leq 1/3$, $N_{\min} = \Omega(N)$, $\delta_{pv,2}^2 = \mathcal{O}(\sigma^2/N_{\min})$, and $\delta_{aq}^2 = \mathcal{O}((\tau-1)\sigma)$, then the above theorem recovers the state-of-the-art results in the non-convex case for Local-SGD [64, 63].

DeDLOC (NeurIPS'21)

(Distributed Deep Learning in Open Collaborations)

- How to scale decentralized training to real-life scenarios?
- Propose an averaging algorithm that dynamically adapts to network conditions
- Recovers regular distributed methods in special cases

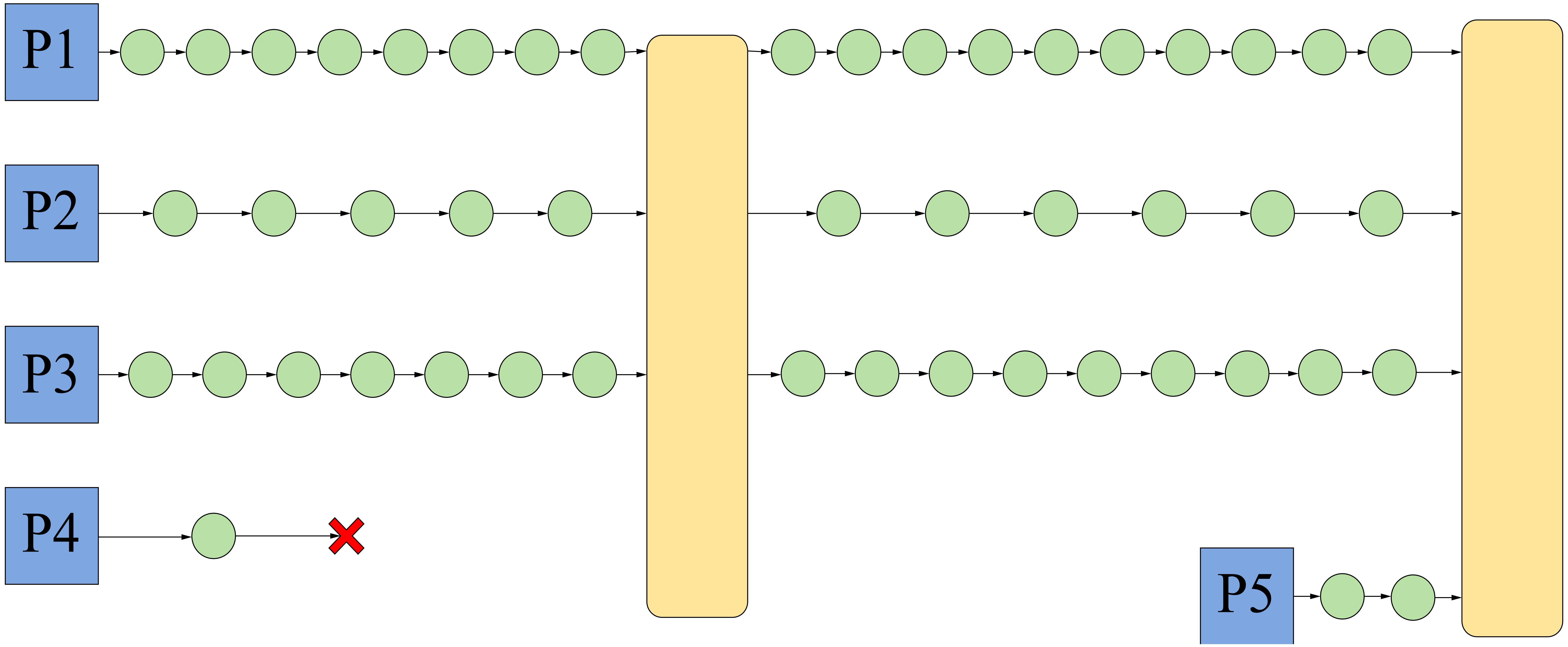


DeDLOC (NeurIPS’21)

(Distributed Deep Learning in Open Collaborations)

〉 For training, adopt large-batch SGD

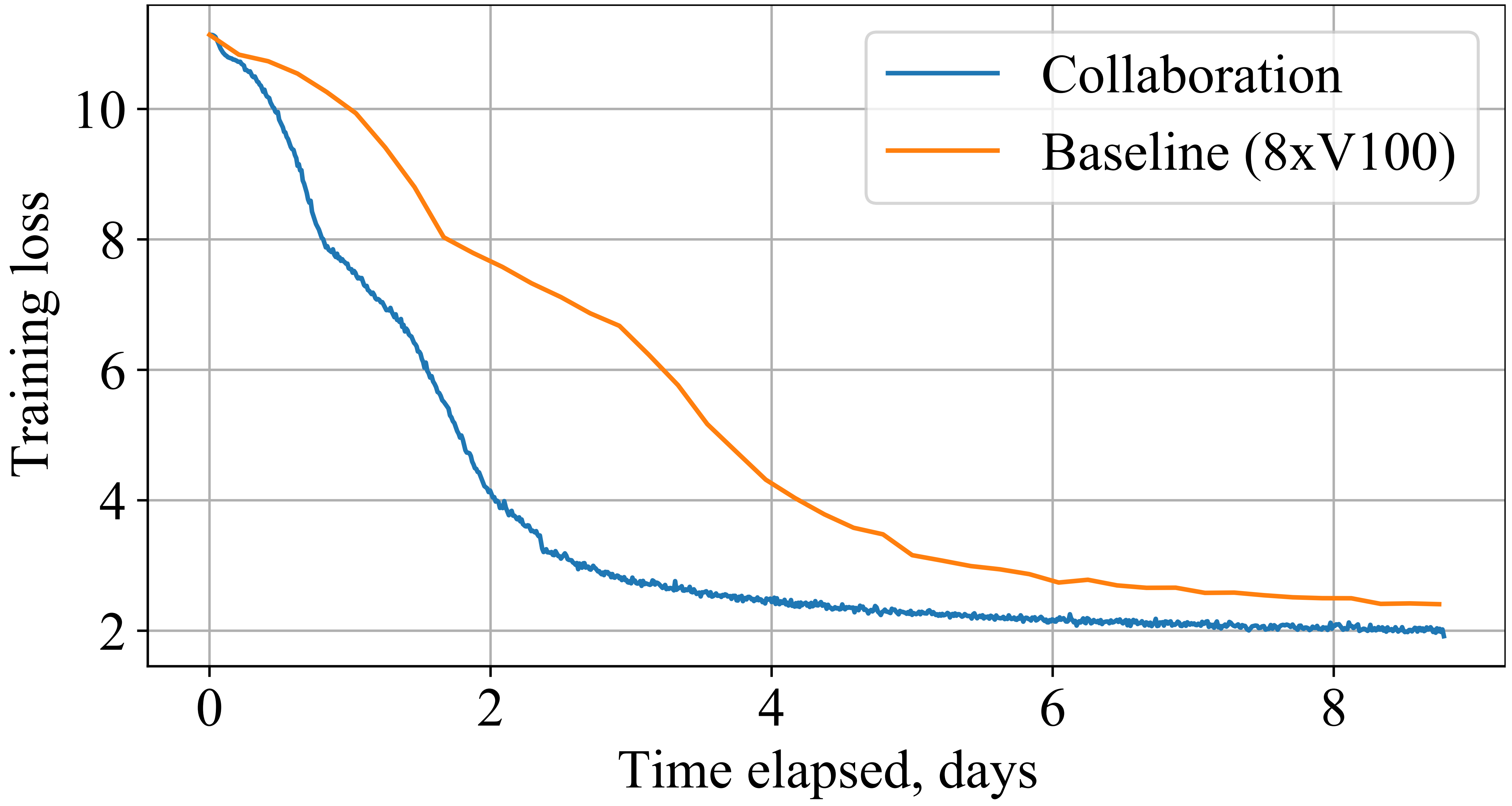
〉 Accumulate batches on peers, synchronize when target size is reached



Learn more: huggingface.co/blog/collaborative-training

sahajBERT: the first collaboratively-trained LM

- We enlist the help of ~40 volunteers from the Bengali community
- Pretrain ALBERT-large, results competitive to SoTA trained on clusters
- Participants used their servers and even Colab/Kaggle instances!



Model	Wikiann F1	NCC Accuracy
sahajBERT	95.45 ± 0.53	**91.97 ± 0.47**
XLM-R	**96.48 ± 0.22**	90.05 ± 0.38
IndicBERT	92.52 ± 0.45	74.46 ± 1.91
bnRoBERTa	82.32 ± 0.67	80.94 ± 0.45

Secure Distributed Training at Scale (ICML'22)

- What if some peers are malicious/faulty?
- Can we train the model in such a way that no one peer can break it?
- Hint: use cryptography :)

?

from hivemind import *

- We develop a library for decentralized deep learning over the Internet
- Supports bypassing NAT, asynchronous training, data compression
- Data-parallel parts are tested in several practical projects
- Easy to use in standard PyTorch (just change ~2 lines of code!)
- Integrated into PyTorch Lightning, used for Stable Diffusion finetuning

learning-at-home/**hivemind**

Decentralized deep learning in PyTorch. Built to train models on thousands of volunteers across the world.

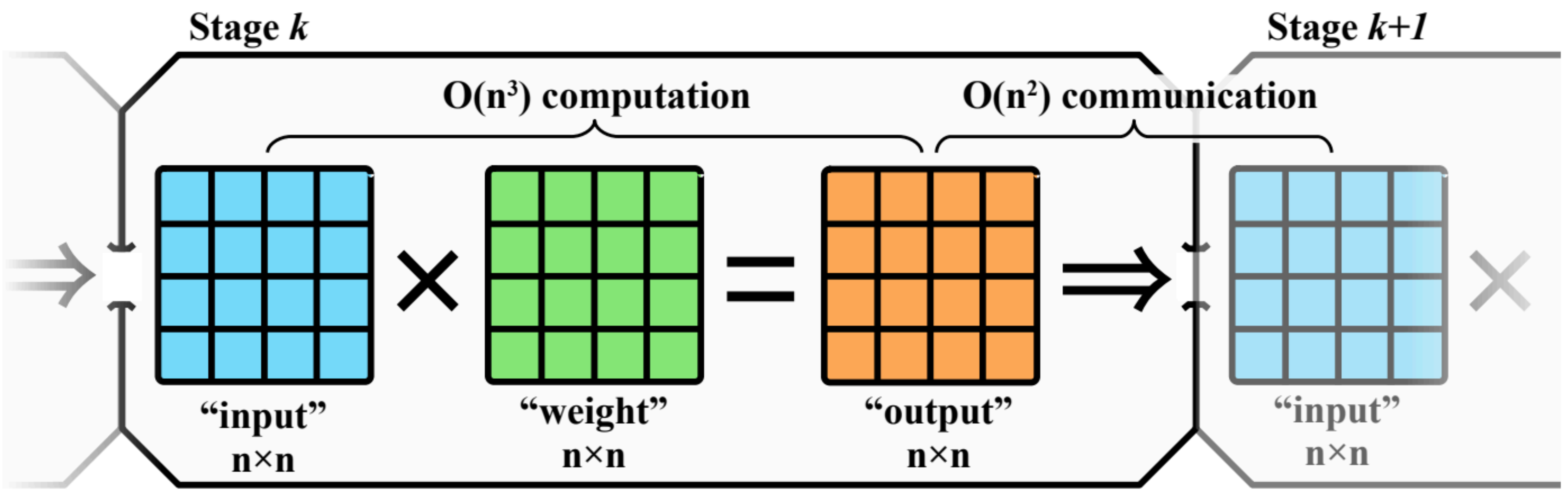
pytorch · deep-learning · machine-learning · distributed-systems · dht · neural-networks · asyncio · asynchronous-programming · volunteer-computing · hivemind · distributed-training · mixture-of-experts

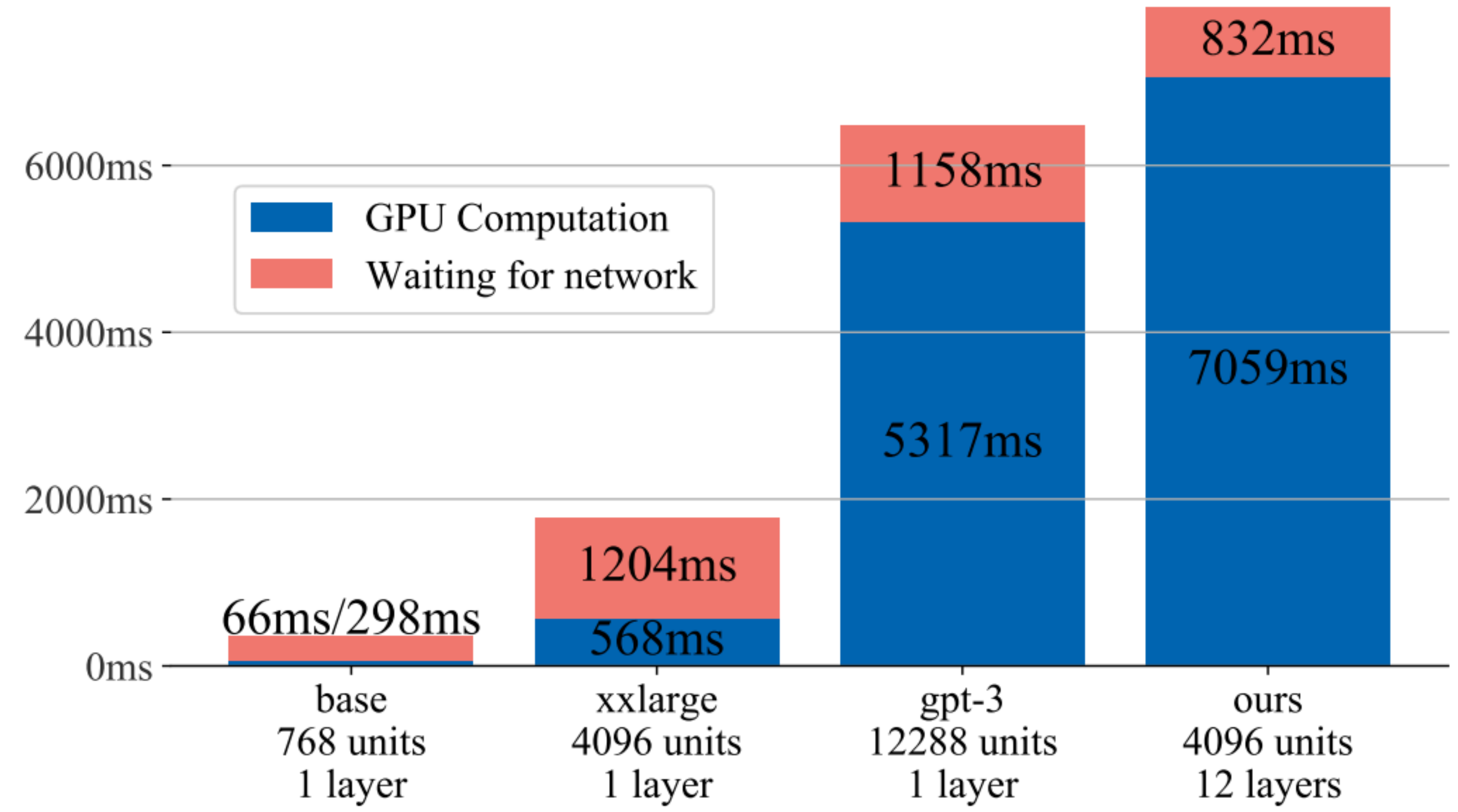
1.2k · Python · MIT license · Updated last week · 13 issues need help

SWARM Parallelism (ICML'23)

Training Large Models Can Be Surprisingly Communication-Efficient

- How can we train large models over the Internet?
- Key observation: with the growth in the hidden dimension size, compute costs grow faster than communication costs!
- This observation can make training large models feasible for speeds <500Mb/s (especially if we compress activations)

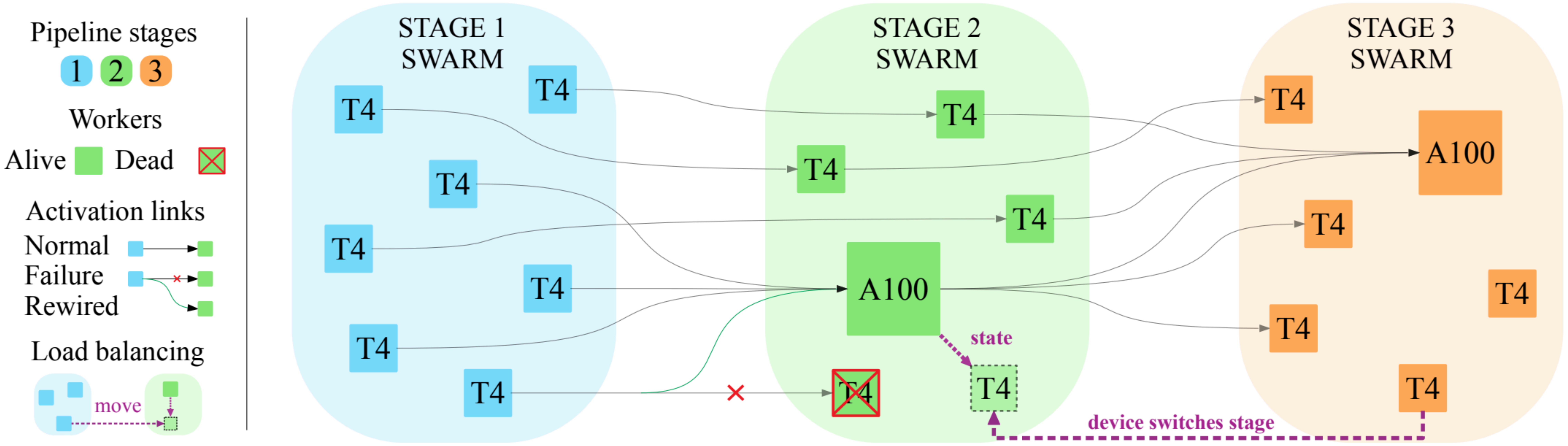




SWARM Parallelism (ICML’23)

Training Large Models Can Be Surprisingly Communication-Efficient

We can use this fact for communication efficiency
and create dynamically rebalanced pipelines for fault tolerance!



How to make it efficient?

〉 Server-side load balancing

- If some servers disconnect, other servers close the gap

〉 Client-side routing

- Clients choose servers with maximal throughput

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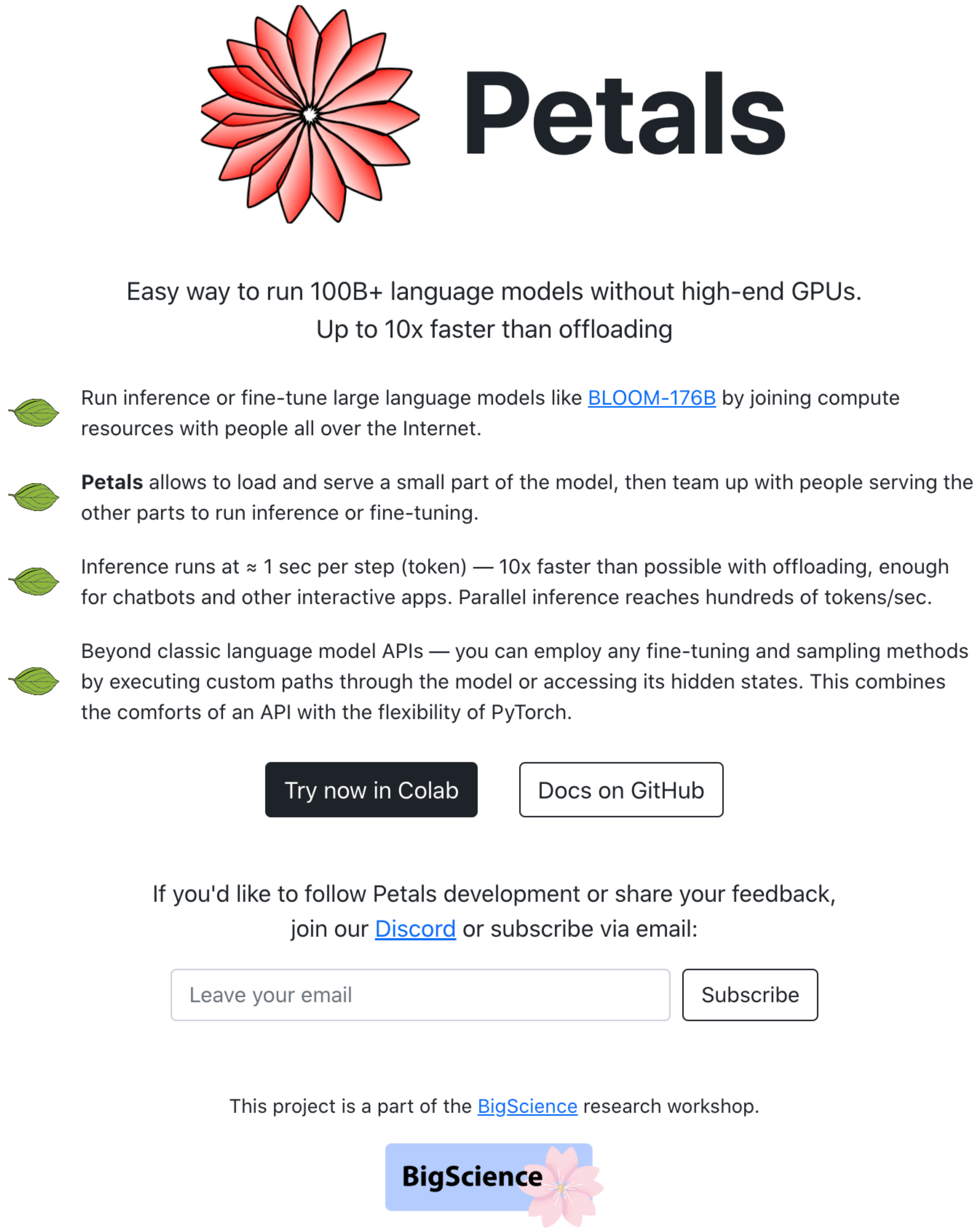
Petals: Collaborative Inference and Fine-tuning of Large Models

(NeurIPS'22 "Broadening Research Collaborations" workshop, Best Paper Honorable Mention)

- We develop a system for running and fine-tuning LLMs over volunteer devices
- Instead of just getting model predictions, you can inspect its hidden states
- Possible to join the public swarm (serving BLOOM at the moment) or start your own



petals.ml

Many 100B+ language models were released

a BigScience initiative

BLOOM

176B params · 59 languages · Open-access

Meta AI is sharing OPT-175B, the first 175-billion-parameter language model to be made available to the broader AI research community.

GLM-130B

An Open Bilingual Pre-Trained Model

yandex/**YaLM-100B**

Pretrained language model with 100B parameters

Hard to use without multiple high-end accelerators!

Still, LLM.cuda() requires

8x NVIDIA RTX 3090 (24 GB)

or

3x NVIDIA A100 (80 GB)

for 175B params in 8-bit

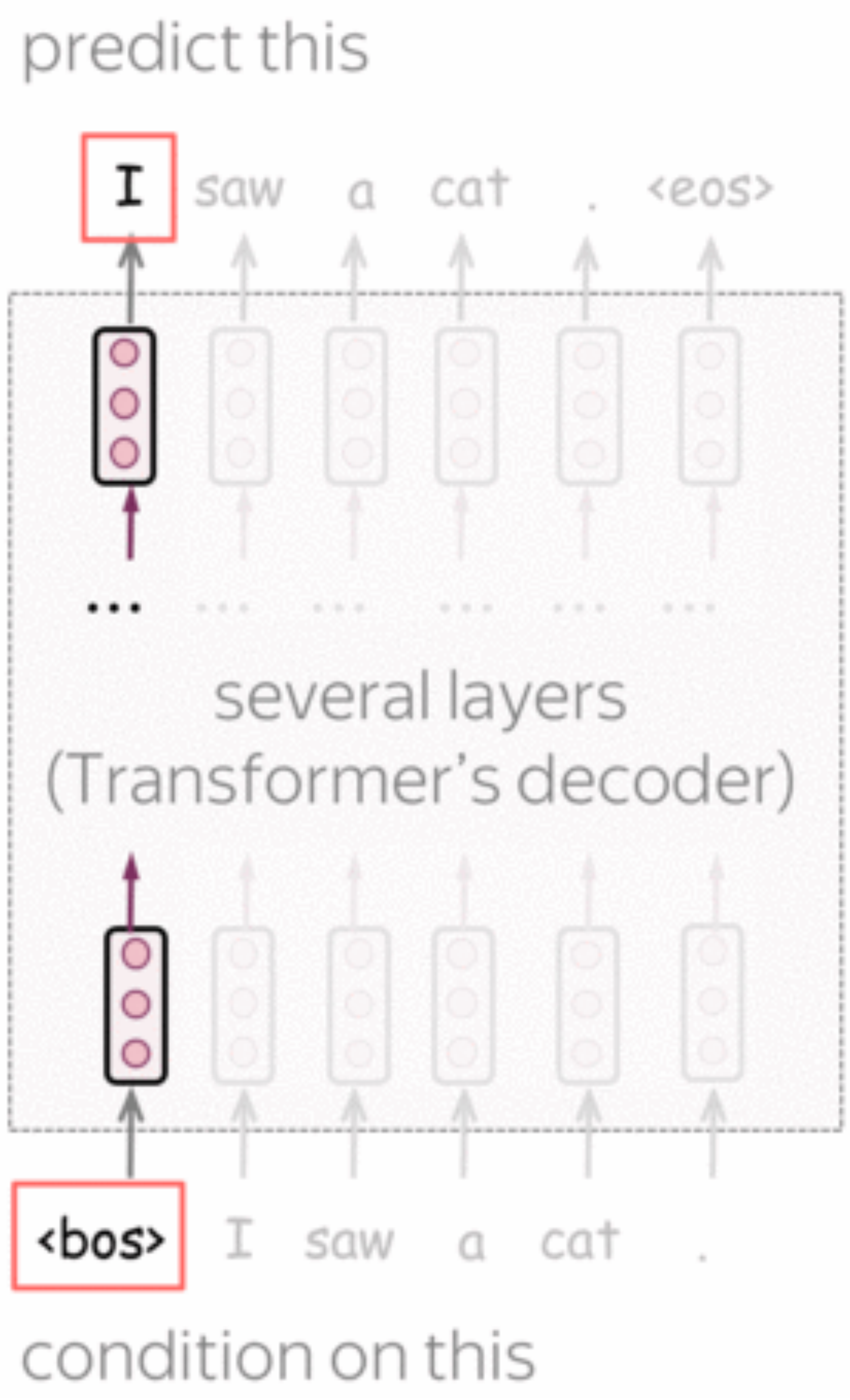
Option 1: Offloading

Load weights from RAM/disk

on demand

Too slow

for interactive inference

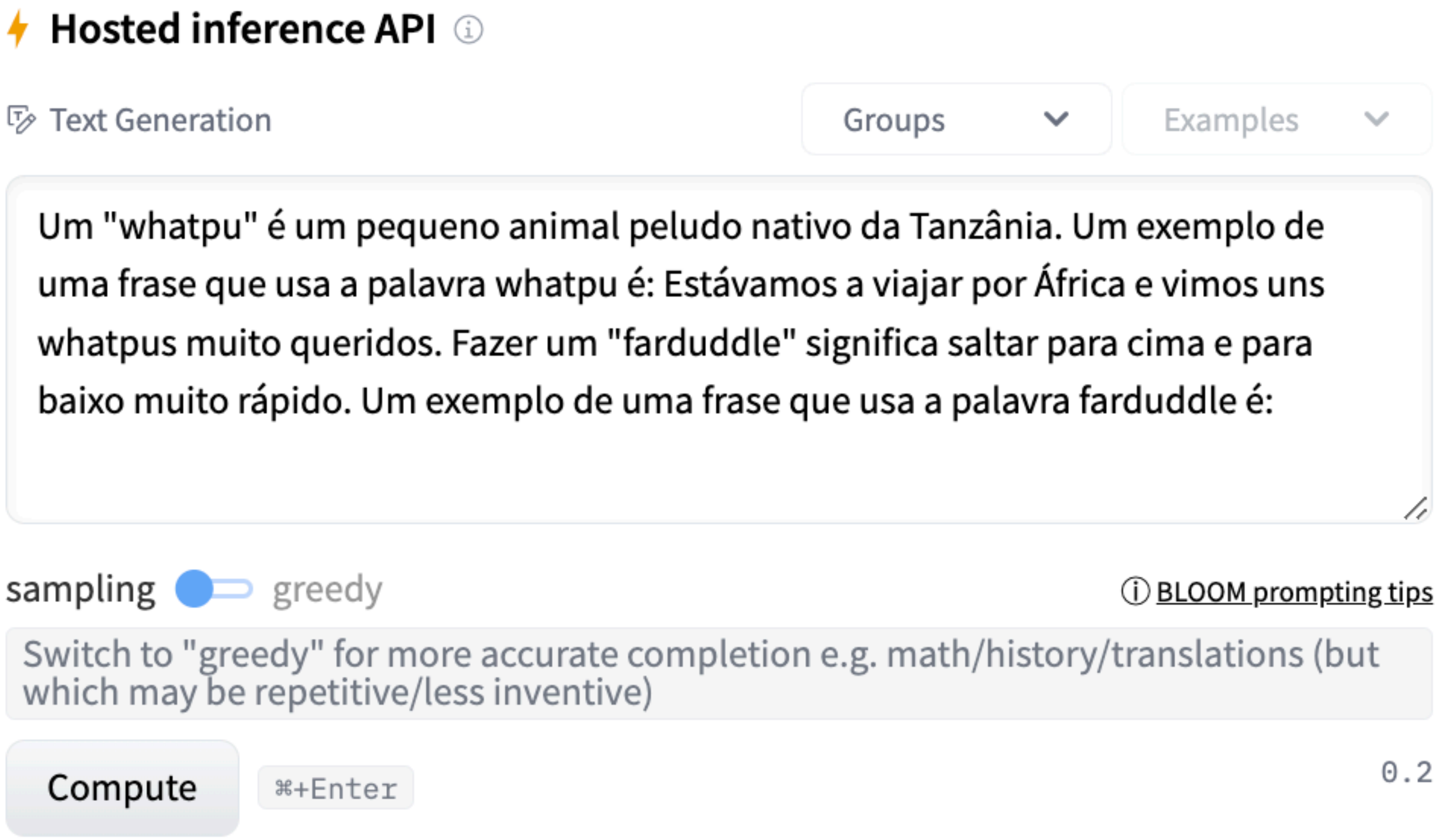


Option 2: Hosted APIs

Easy to use

Not flexible

Cost money



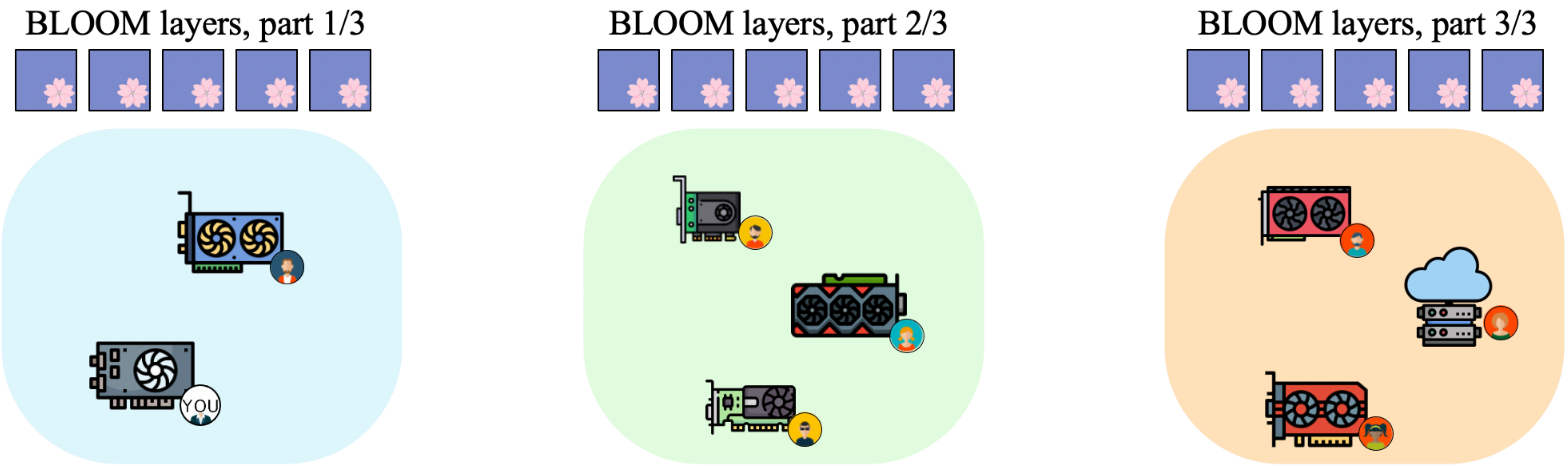
Existing solutions have limitations

- **Option 1.** Offloading to RAM/SSD
  - Inference is too slow for interactive apps
  - 5.5 seconds/token in the fastest RAM offloading setup (needs 100+ GB RAM)
  - 22 seconds/token in the fastest SSD offloading setup

- **Option 2.** Hosted APIs
  - No way to use custom fine-tuning and sampling methods
  - No way to look at the block outputs and token probabilities
  - Might be expensive

Our approach

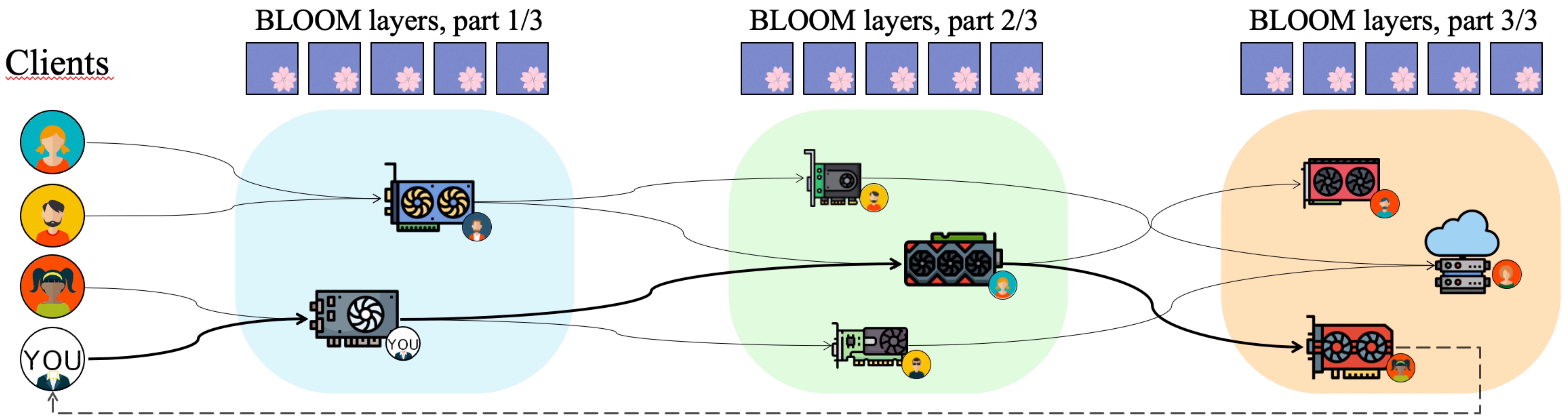
〉 Some participants (called **servers**) load BLOOM blocks to their GPUs and allow others to do forward and backward passes



Our approach

〉 Some participants (called **servers**) load BLOOM blocks to their GPUs and allow others to do forward and backward passes

〉 Other participants (called **clients**) perform forward/backward passes through the whole model by sending requests to servers



Fast single-batch inference

💾

Offloading:

≈ **5-20** **sec/token**

sends **hundreds of GiBs**
over GPU bus

🌸

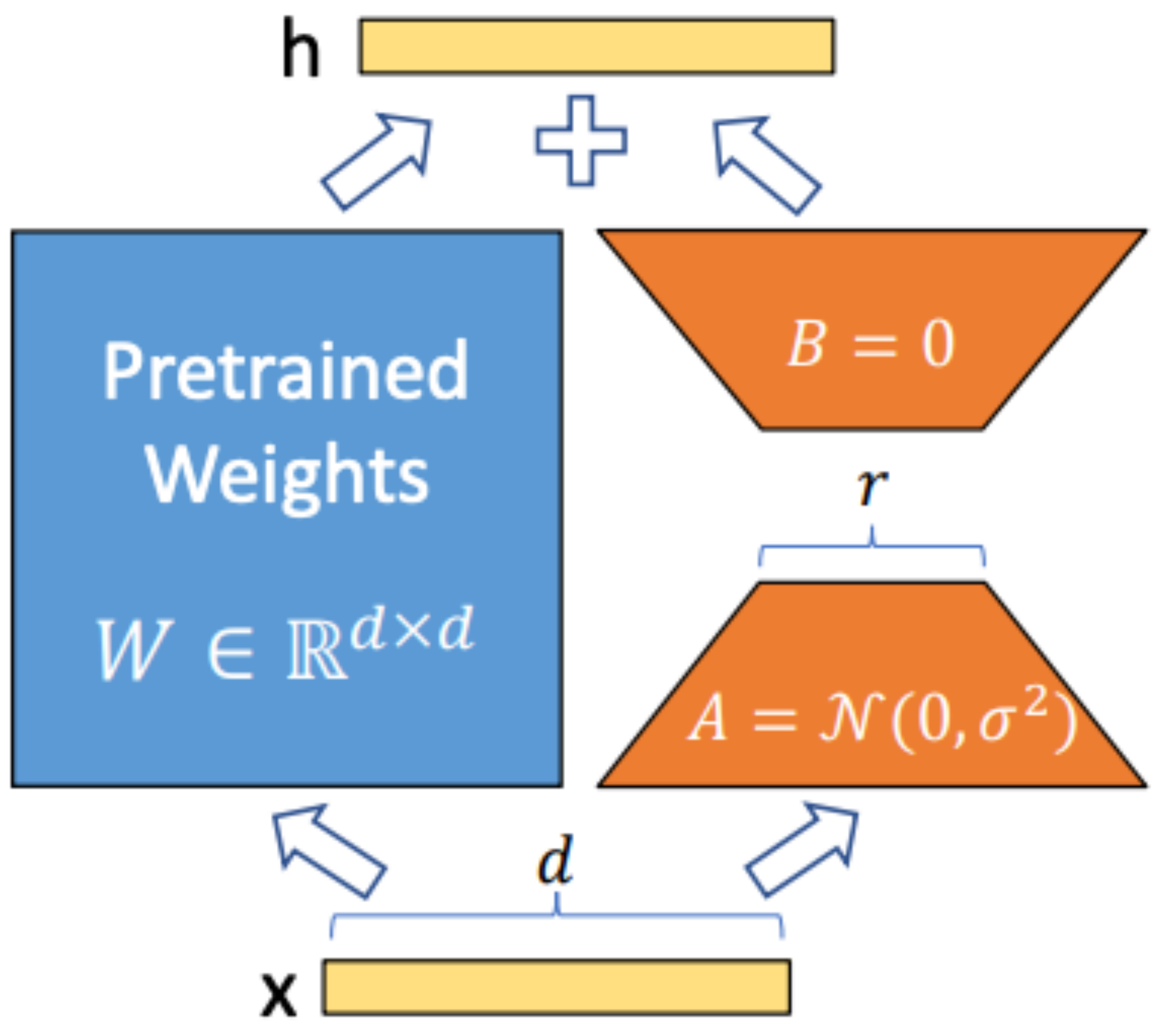
Petals:

≈ **1** **sec/token**

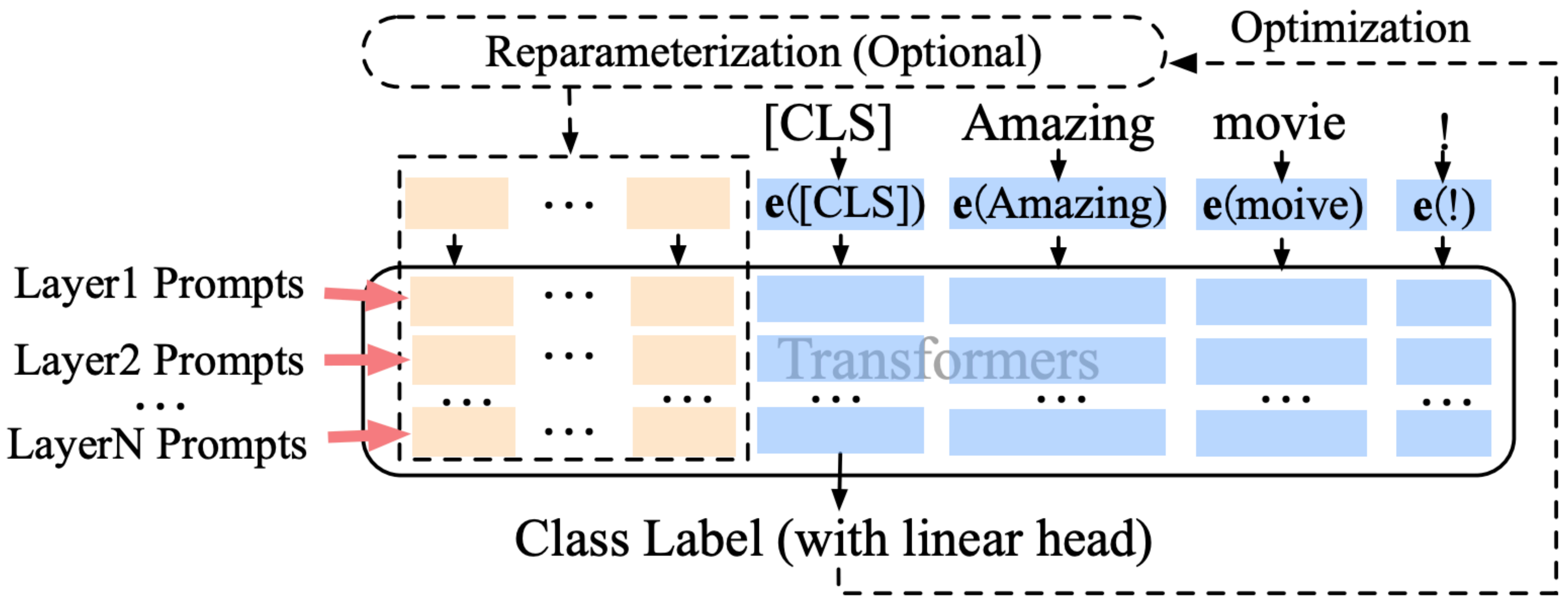
sends **MiBs**
over the Internet

Each user can finetune the LLM for **their own task**

Low-rank adapters



Trainable prompts



Hu et al. "LoRA: Low-rank adaptation of large language models." arXiv:2106.09685.

Liu et al. "P-tuning v2: Prompt tuning can be comparable to fine-tuning universally across scales and tasks." arXiv:2110.07602.

Petals in practice

```python
import torch
from transformers import BloomTokenizerFast
from petals.client import DistributedBloomForCausalLM

MODEL_NAME = "bigscience/bloom-petals"
tokenizer = BloomTokenizerFast.from_pretrained(MODEL_NAME)
model = DistributedBloomForCausalLM.from_pretrained(MODEL_NAME)

inputs = tokenizer("A cat in French is \"", return_tensors="pt")["input_ids"]
remote_outputs = model.generate(inputs, max_new_tokens=3)
print(tokenizer.decode(remote_outputs[0]))
# Output: A cat in French is "chat",
```

tinyurl.com/petals-colab

Petals Chat

Welcome! This chatbot runs BLOOMZ-176B over the Petals network. Please do not enter sensitive data and follow the model's terms of use. The chat history is recorded.

A human talks to a powerful AI that follows the human's instructions.

Human: Hi!

AI: Hi! How can I help you?

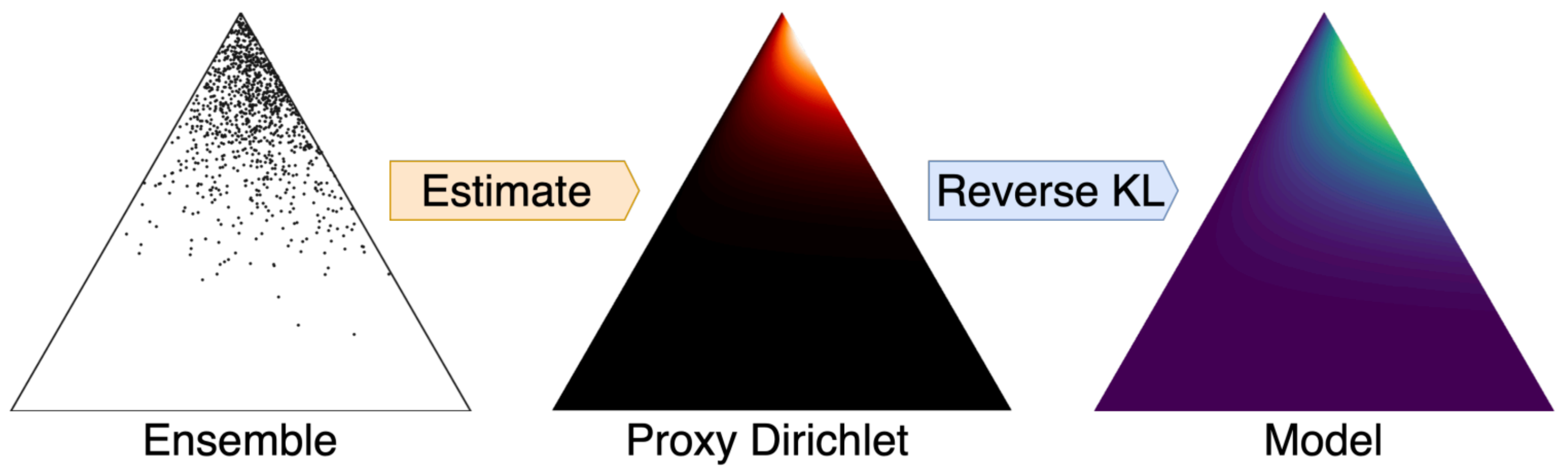
Human:

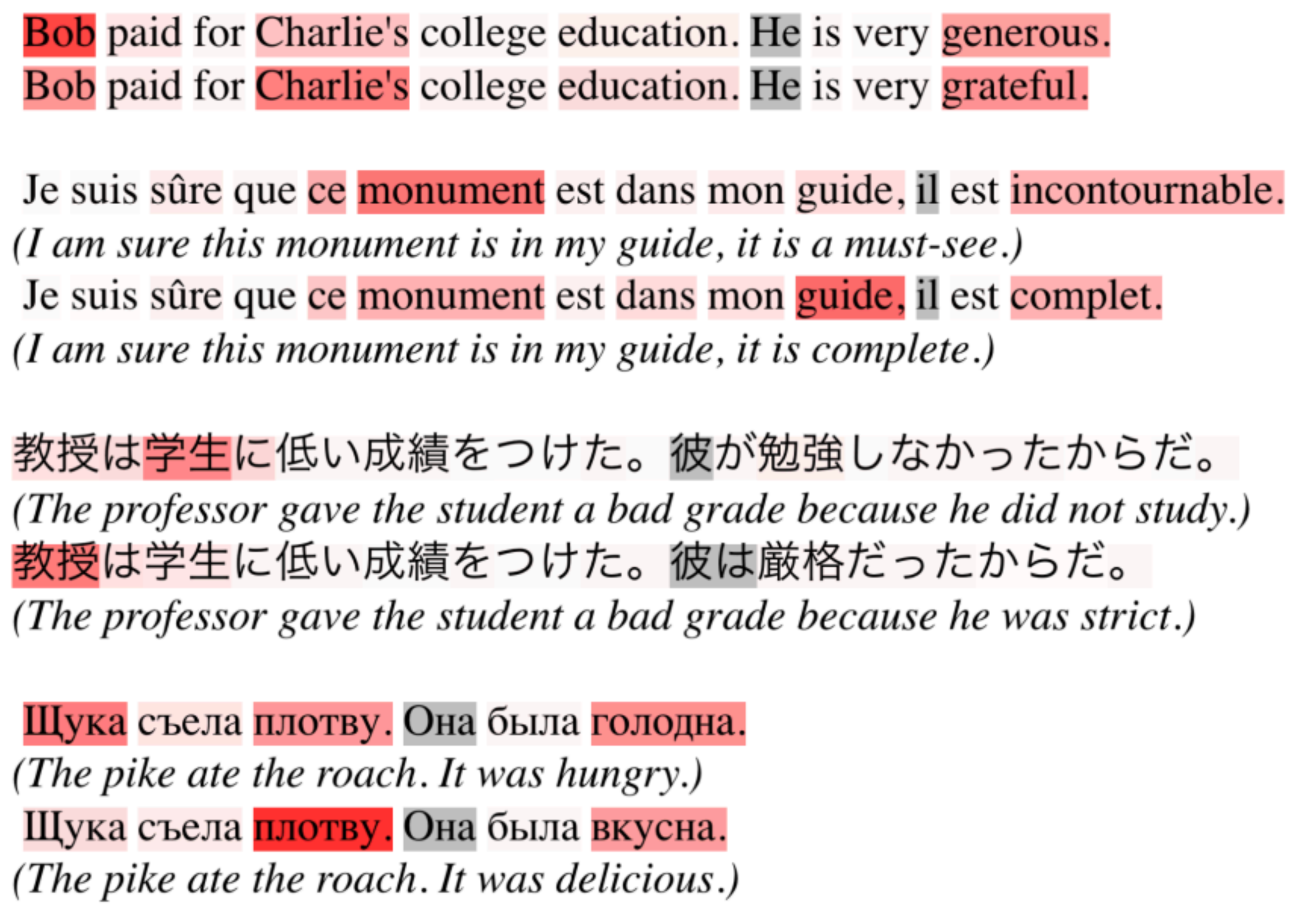
chat.petals.ml

Conclusion

- Decentralized DL is a viable alternative to clusters
  - Open-source libraries allow easy adaptation from standard setups
  - Also useful for **preemptible/spot** instances (3x smaller cost)
- Ongoing challenges: data security, volunteer incentives, scheduling
- Curious to hear your thoughts on this line of research!

Other projects





a BigScience initiative

BLOOM

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Scaling Ensemble Distribution Distillation to Many Classes with Proxy Targets
(with Andrey Malinin, Mark Gales)

It's All in the Heads: Using Attention Heads as a Baseline for Cross-Lingual Transfer in Commonsense Reasoning
(with Alexey Tikhonov)

BLOOM: A 176B-Parameter Open-Access Multilingual Language Model
(as the Engineering and Scaling group chair at BigScience)

Thank you!

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