ML Training with Cloud GPU Shortages: Is Cross-Region the Answer?

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Increased demand for GPUs

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➡ The size of models reaches trillions of parameters!

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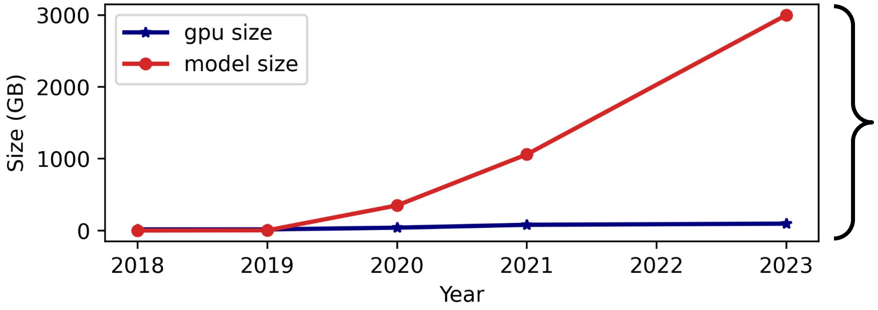

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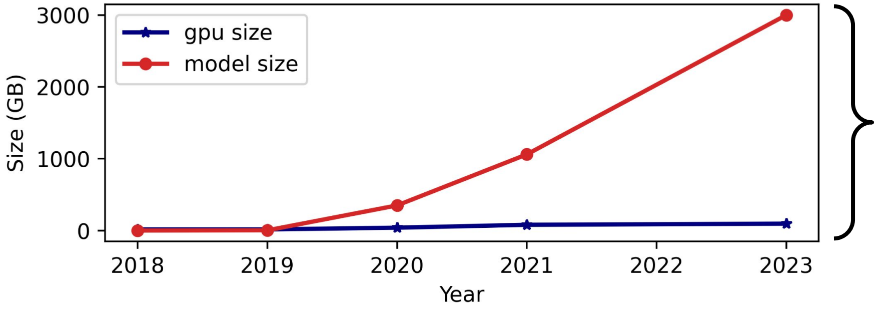
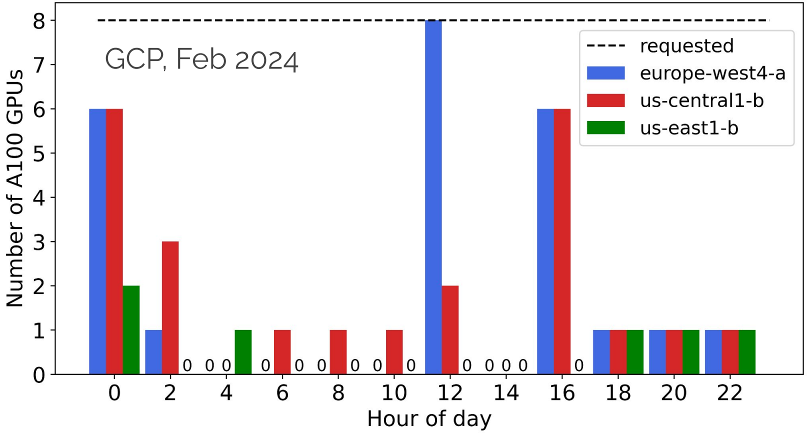


More and more GPUs are needed to train these models

GPU scarcity in the public cloud

This increased GPU demand has led to a **GPU scarcity** in the public cloud



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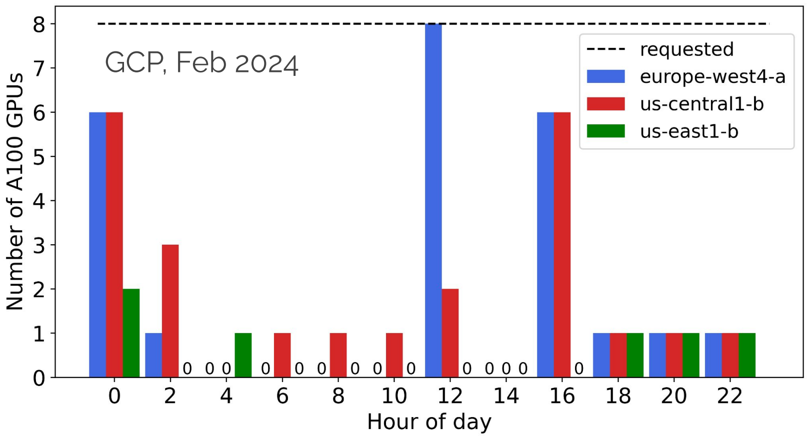

We found failover to be especially valuable for scarce resources (e.g., large CPU or GPU VMs). For example, depending on request timing, it took 3–5 and 2–7 location attempts to allocate 8 V100 and 8 T4 GPUs on AWS, respectively.

SkyPilot, NSDI'23

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pools generally have lower utilization. We conjecture that this is due to the greater scarcity of GPUs in the public cloud.

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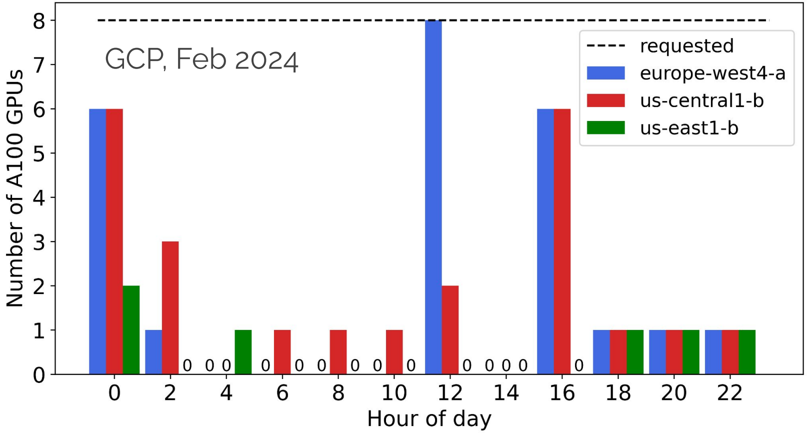

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A natural way to acquire more GPUs would be to spread across cloud regions

Implications of geo-distributed training

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1. **Reduced Network bandwidth and increased latency**

Traffic between	Bandwidth (GB/sec)	Latency (ms)
Same AZ (US)	1.45	< 1
Diff. AZ, same region (US)	1.42	0.9
Diff. regions (US)	0.63	31
Diff. continents (US/EU)	0.18	102

a2-highgpu-1g, GCP

Implications of geo-distributed training

However, when crossing the cloud zone boundaries there are two main implications:

1. Reduced Network bandwidth and increased latency
2. **Charges for data exchange**

Traffic between	Bandwidth (GB/sec)	Latency (ms)	Cost/GB ($)
Same AZ (US)	1.45	< 1	0
Diff. AZ, same region (US)	1.42	0.9	0.01
Diff. regions (US)	0.63	31	0.02
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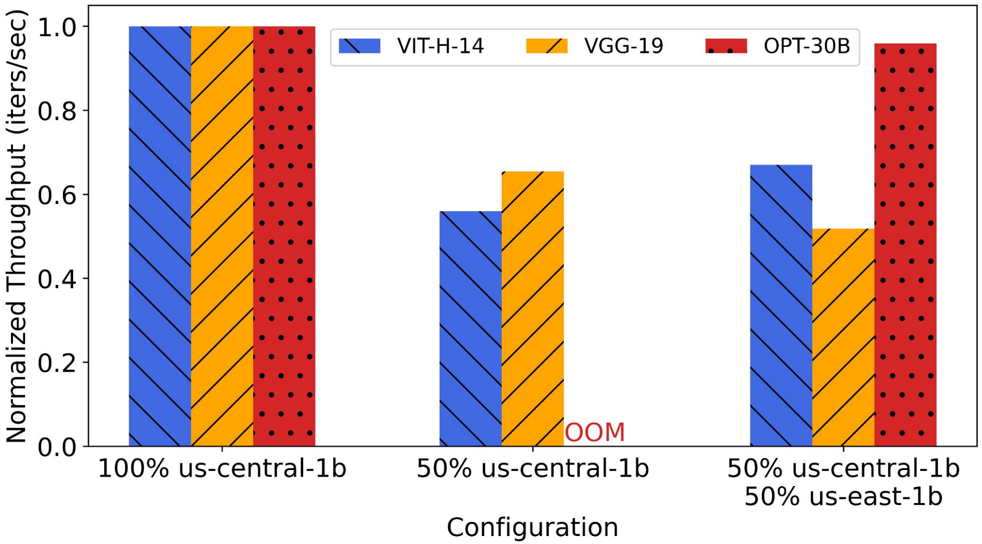
Implications of geo-distributed training

The impact on training throughput and cost depends on the model and cluster configuration



Our work

We study **when and how it makes sense to use GPUs across zones and regions for large-scale, distributed training**

Methodology

2-step approach:

1. **Profiling** (model + cloud-specific info)
2. **Throughput and cost estimation for data and pipeline parallelism**

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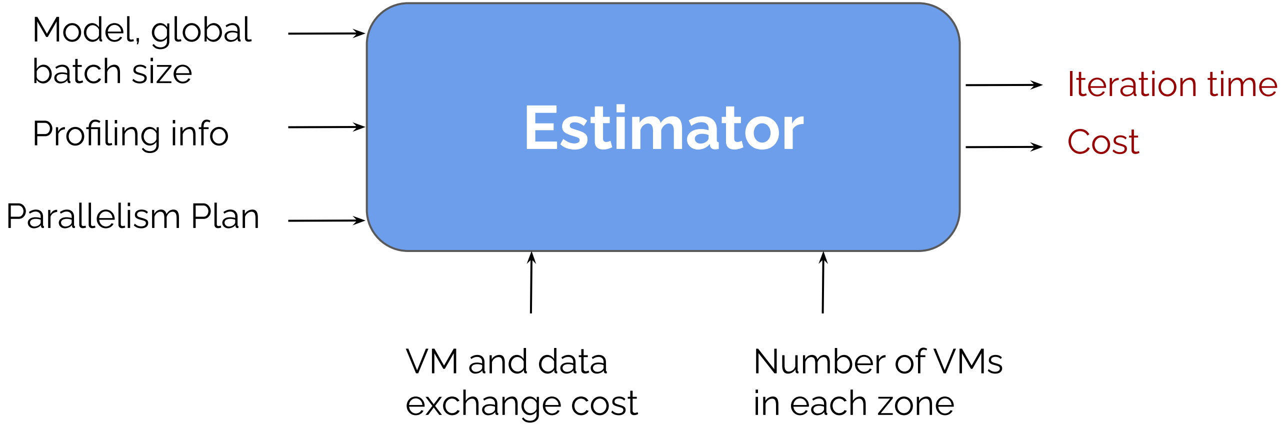
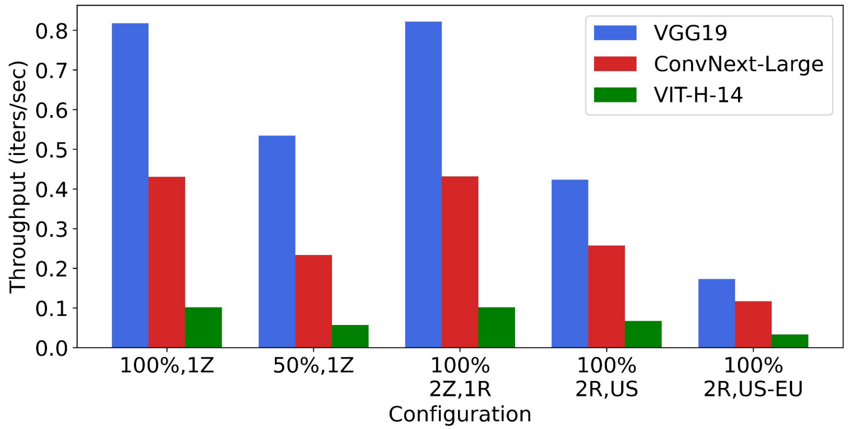
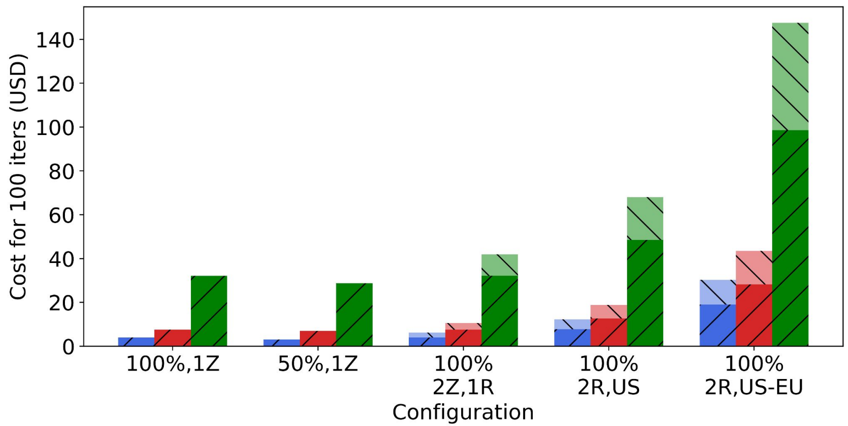


Evaluation and Key Insights

Data Parallelism

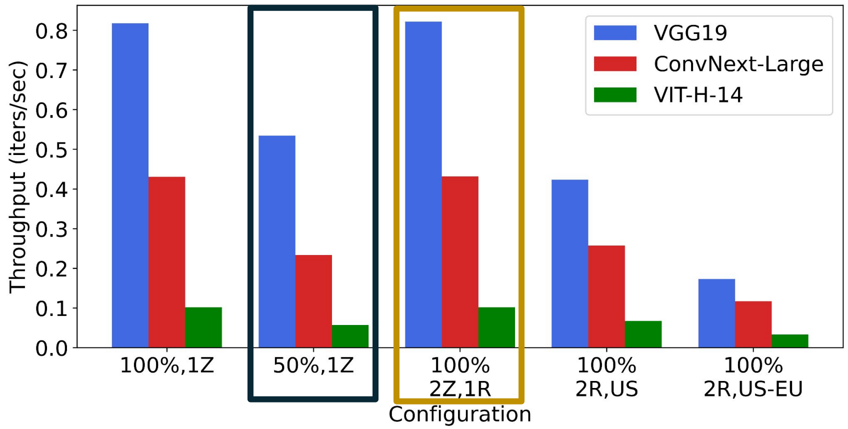
If only λ*N GPUs are available in one zone (e.g. λ=0.5), when to use GPUs from multiple zones?

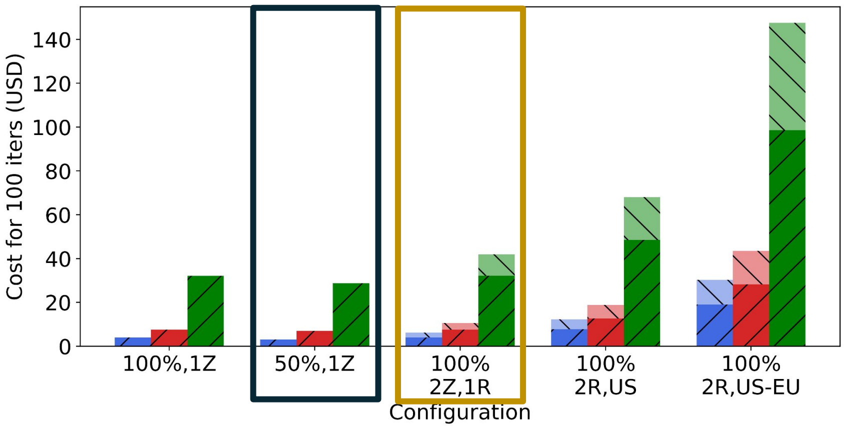




Data Parallelism

If only λ*N GPUs are available in one zone (λ=0.5 or λ=0.75), when to use GPUs from multiple zones?





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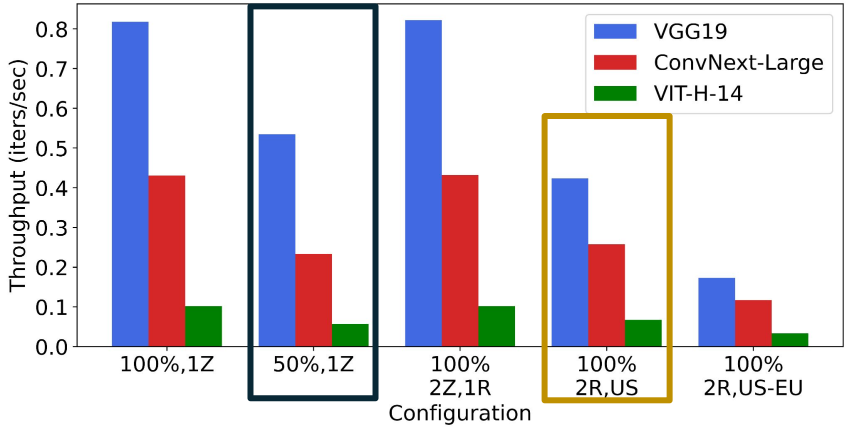

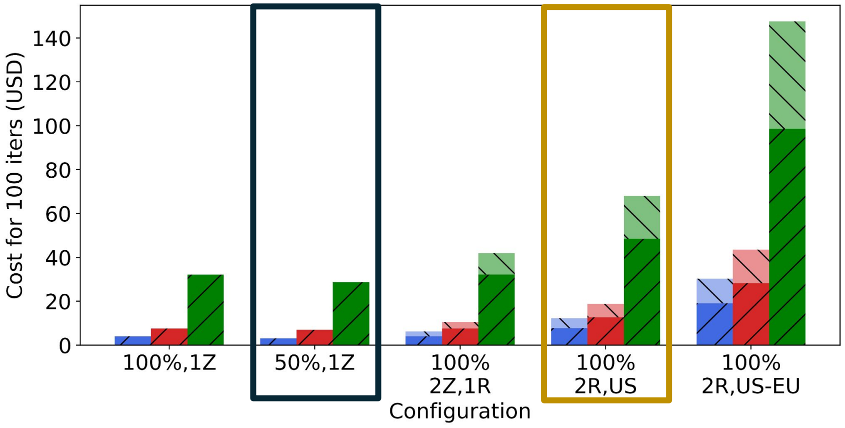

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- **Multiple regions in the same continent (e.g. US) has varying effects depending on the model (ratio of compute to communication)**

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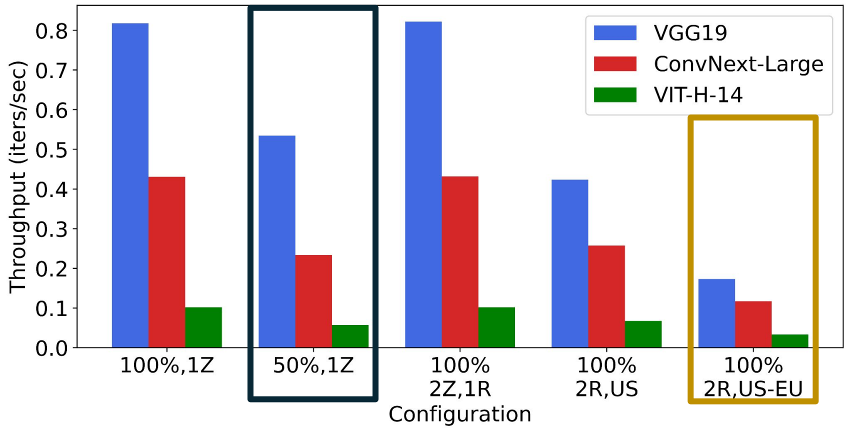
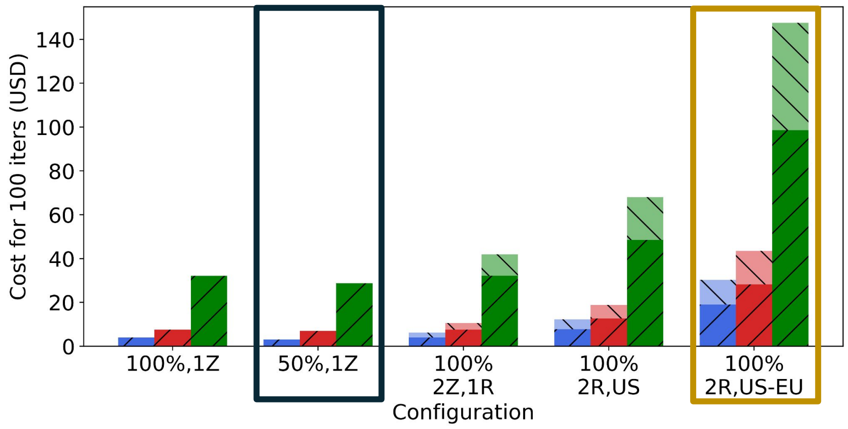
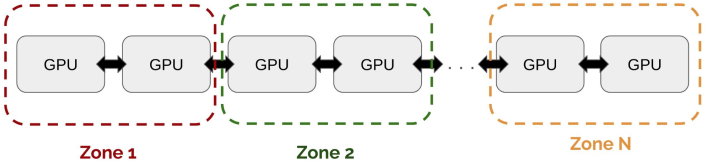
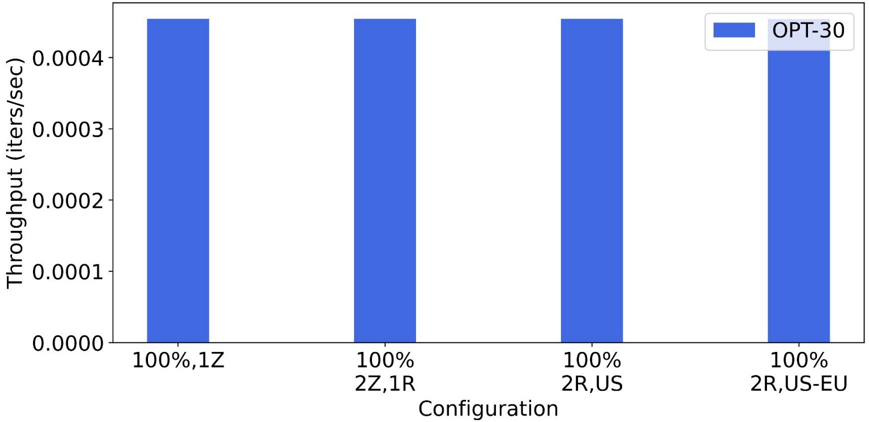


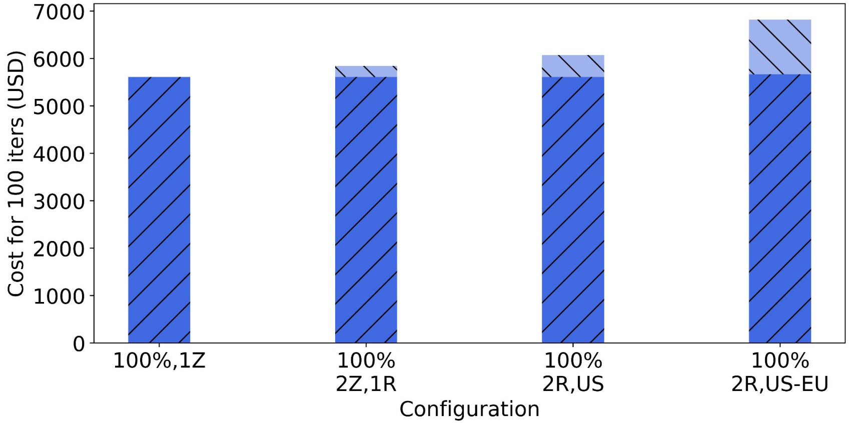


- Using zones from the same region is always beneficial
- Multiple regions in the same continent (e.g. US) has varying effects depending on the model (ratio of compute to communication)
- **Inter-continental training is detrimental to both throughput and cost**

Pipeline Parallelism

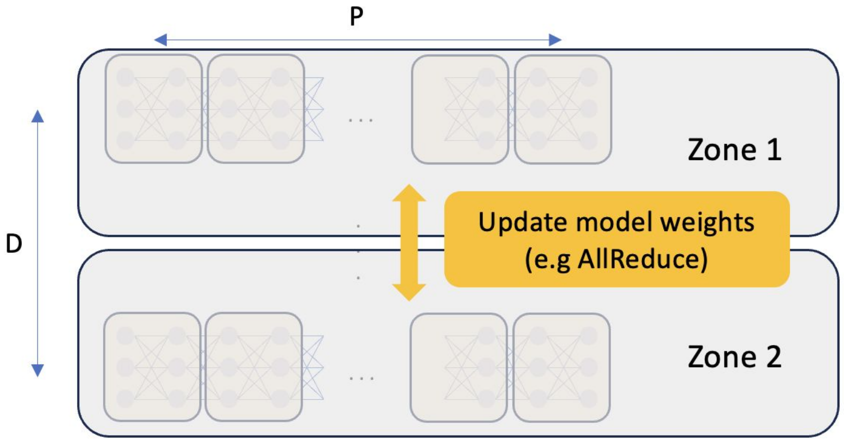




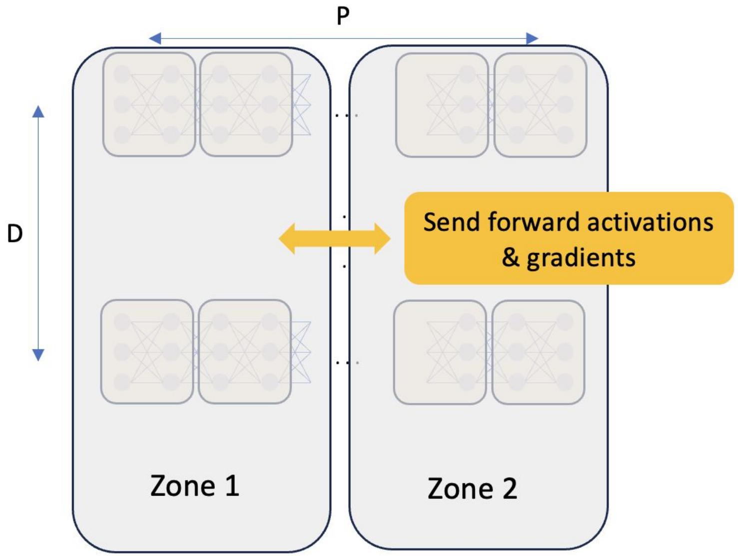


- Using multiple regions for pipeline parallelism has **marginal effects on throughput**:
    - Pipelining of computation with activation/gradient exchange
    - Small-sized per-layer activations even for big models
- However, the cost for multi-region or inter-continental setups is significant

Data + Pipeline Parallelism



DP-Cut



PP-Cut

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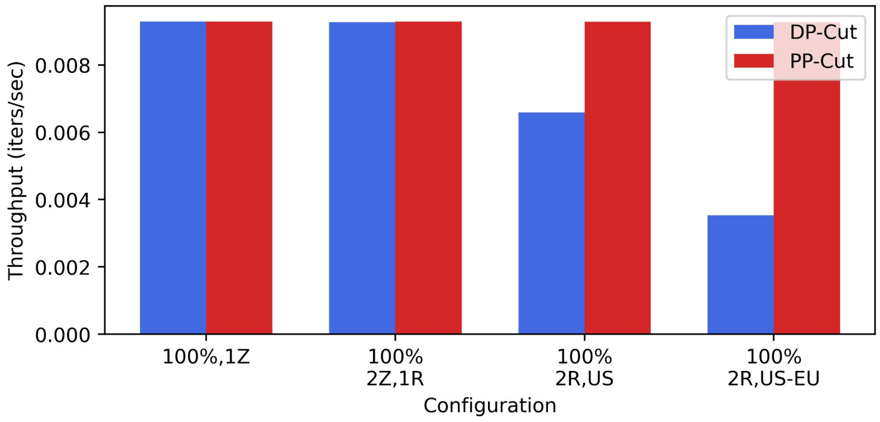
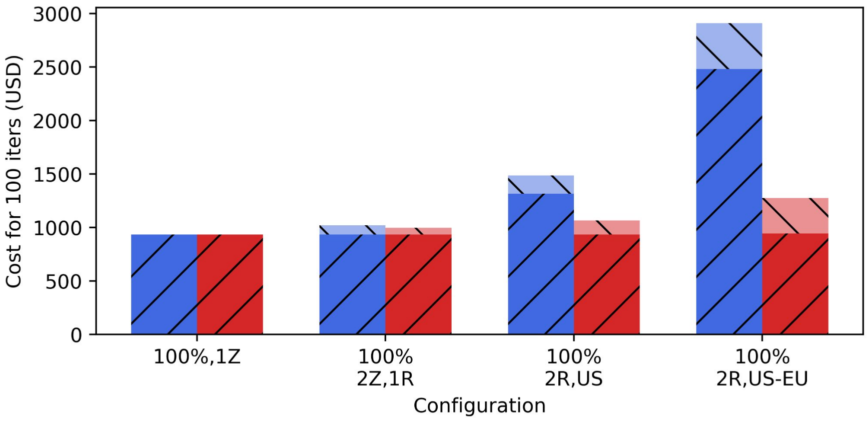


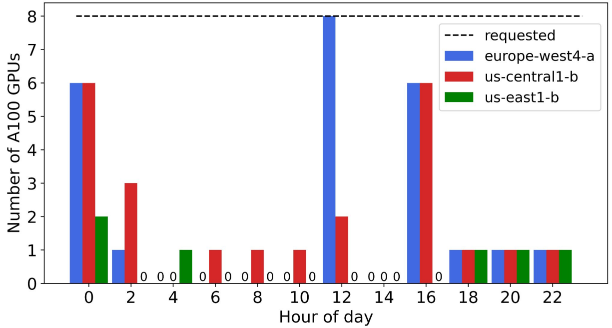


- **If we keep all the All-Reduce traffic in a single zone, multi-region training is beneficial**

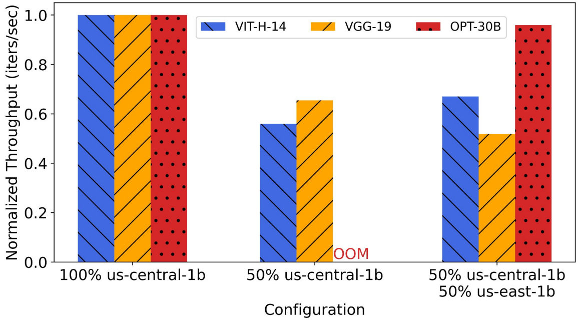
Key Insights

- Spreading training **across zones** in the same region has **minimal effects in training throughput**
- **Pipeline parallelism is much more tolerant to crossing zone boundaries compared to data parallelism**
- **Across-continental training is detrimental** to data parallelism
- **With 2D parallelism, maintain data parallel traffic within one region**

Advances in ML have led to GPU shortage in the public cloud



Using GPUs from multiple cloud regions can help the training of large models, but has 2 implications:
reduced network bandwidth and **data exchange charges**



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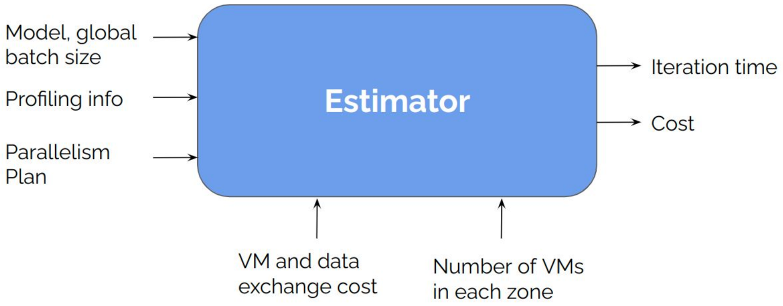

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Backup Slides

Iteration time estimation

- **Data parallelism**

$$T_i = (t_f + t_b) \cdot (ga - 1) + max((t_f + t_b), 2 \cdot (N - 1) \cdot \frac{M}{N \cdot b}) + t_u$$

Iteration time estimation

- **Data parallelism**

We consider:

- **Computation (with gradient accumulation)**
- All-reduce based synchronization
- Computation-Communication overlap

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We adapt the formula followed by [1] for 1F1B [2] microbatch scheduling

[1] Li et al, AMP: Automatically Finding Model Parallel Strategies with Heterogeneity Awareness, NeurIPS'22

[2] Narayanan et al, PipeDream: Generalized Pipeline Parallelism for DNN Training, SOSP'19

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- **Data + Pipeline parallelism**

We assume a grid of *D* pipelines, each with *P* stages

$$t_{sync} = 2 \cdot (D - 1) \cdot \frac{M}{D \cdot P \cdot b_{min}}$$

$$t_{iter} = t_{pp} + t_{sync}$$

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Cost estimation

- **Computation cost:** $C_{comp} = t_{iter} * \sum_{\text{zone } i} (num\_vm_i \cdot cost_i)$
- **Communication cost:** $C_{comm} = \sum data_{ij} \cdot c_{ij}$
- **Total cost:** $C_{comp} + C_{comm}$

t_{iter}	Iteration time
$data_{ij}$	Data exchanged between workers i and j
c_{ij}	Cost of exchanging data between workers i and j
num_vm_i	Numbers of VMs at zone i
$cost_i$	Cost of a VM at zone i