Cloud Computing
GPUs and GPU cloud

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SCHOOL OF
DATA SCIENCE
數據科學學院

Outline

GPU introduction and architecture

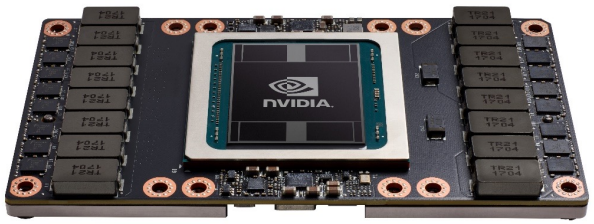
GPU virtualization

GPU cluster in the cloud

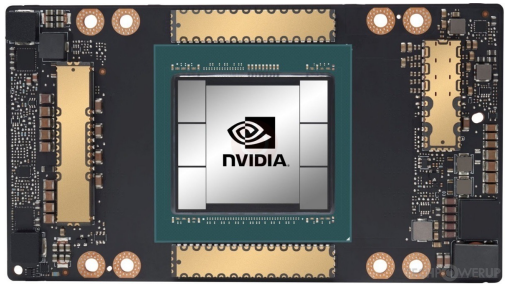
GPU introduction

What is a GPU?

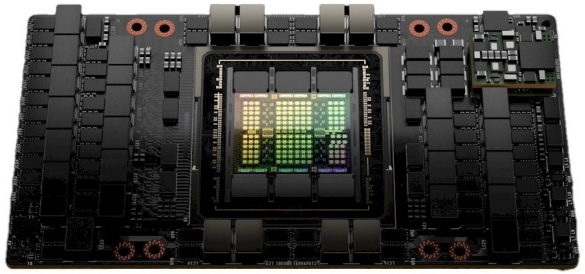
- GPU = Graphics Processing Unit
  - Accelerator for raster based graphics (OpenGL, DirectX)
  - Highly programmable
  - Commodity hardware
  - 100s of ALUs; 10s of 1000s of concurrent threads



NVIDIA Volta: V100



NVIDIA Ampere: A100



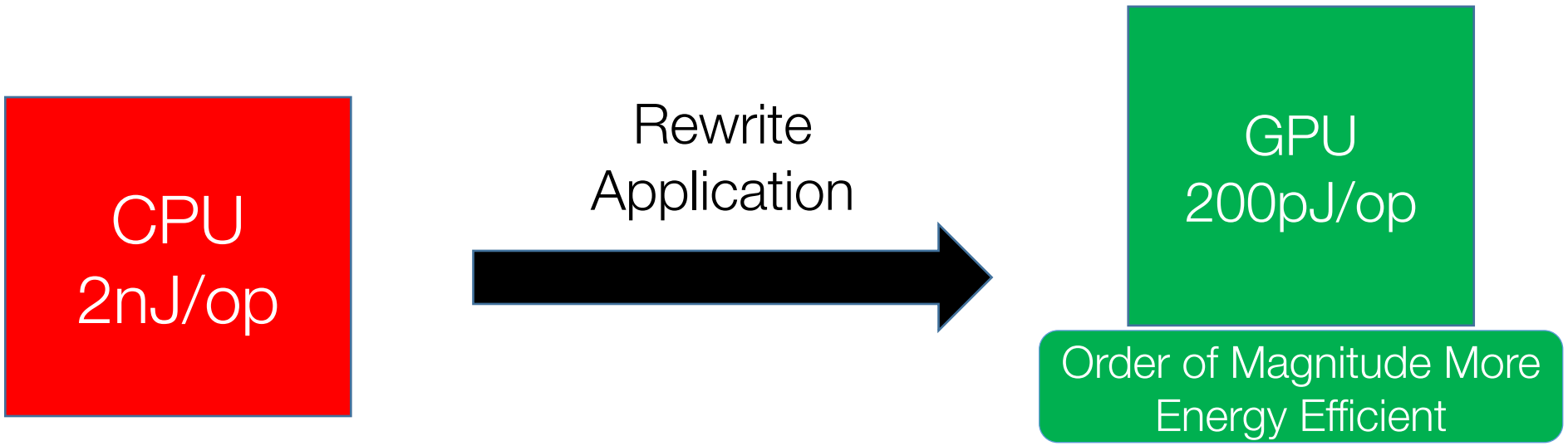
NVIDIA Hopper: H100

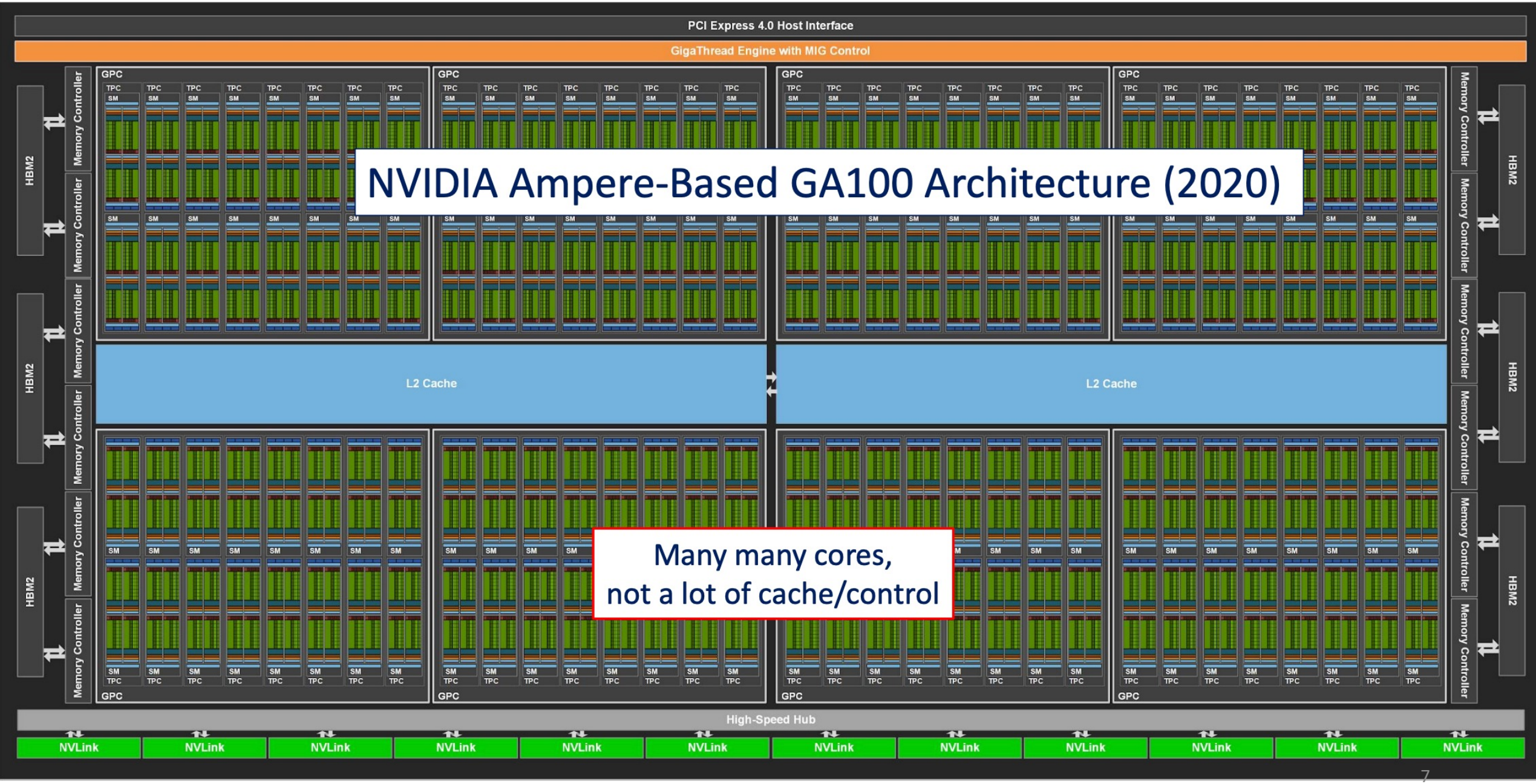
Graphic Processing – Some History

- 1990s: Real-time 3D rendering for video games were becoming common
- 3D graphics processing is immensely computation-intensive
- Before 3D accelerators (GPUs) were common, CPUs had to do all graphics computation, while maintaining framerate!
  - Many tricks were played
- Much of 3D processing is short algorithms repeated on a lot of data
  - pixels, polygons, textures, …
- Dedicated accelerators with simple, massively parallel computation

Why GPU?

- GPU uses larger fraction of silicon for computation than CPU.
- At peak performance GPU uses order of magnitude less energy per operation than CPU.

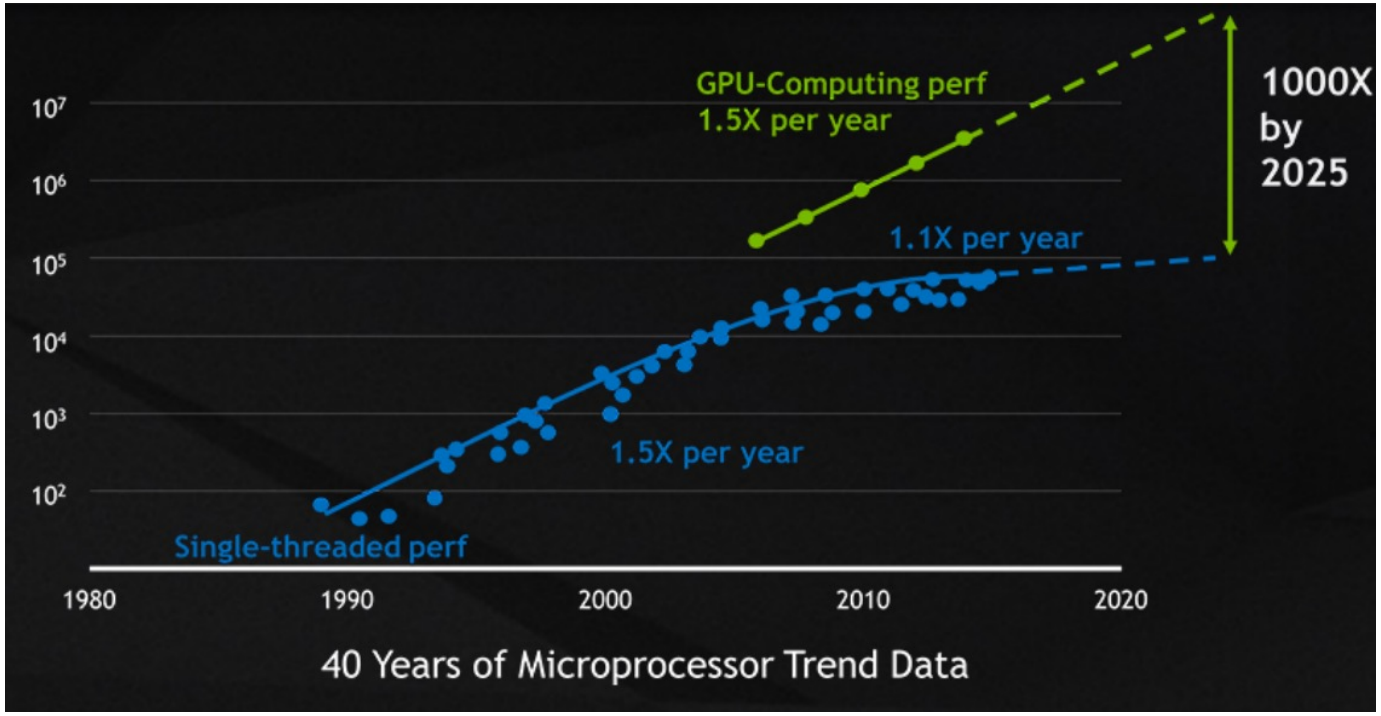



PCI Express 4.0 Host Interface
GigaThread Engine with MIG Control
NVIDIA Ampere-Based GA100 Architecture (2020)
GPC
TPC
SM
L2 Cache
Memory Controller
HBM2
Many many cores,
not a lot of cache/control
High-Speed Hub
NVLink

Peak Performance vs. CPU

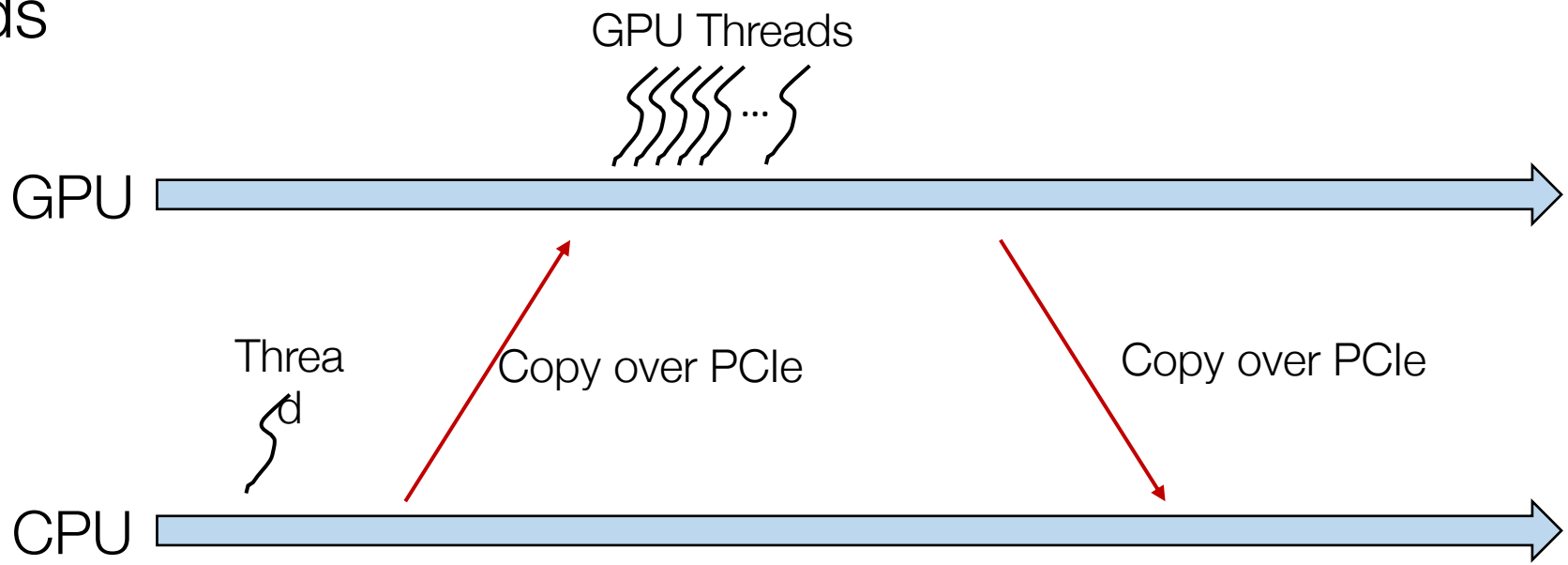
	Throughput	Power	Throughput/Power
Intel Skylake	128 SP GFLOPS/4 Cores	100+ Watts	~1 GFLOPS/Watt
NVIDIA V100	15 TFLOPS	200+ Watts	~75 GFLOPS/Watt

Also,



Massively Parallel Architecture For Massively Parallel Workloads!

- NVIDIA CUDA (Compute Uniform Device Architecture) – 2007
  - A way to run custom programs on the massively parallel architecture!
- OpenCL specification released – 2008
- Both platforms expose synchronous execution of a massive number of threads



GPU and deep learning

- Good match between GPU and deep learning
- DNNs are matrix multiplication-intensive
- Back to CNNs
  - “Building High-Level Features Using Large Scale Unsupervised Learning” 16,000 CPU cores in 2012
  - “Deep learning with COTS HPC systems” Two CPU cores and two GPUs in 2013
- Now widely used in modern deep learning models (e.g., LLMs, etc.)

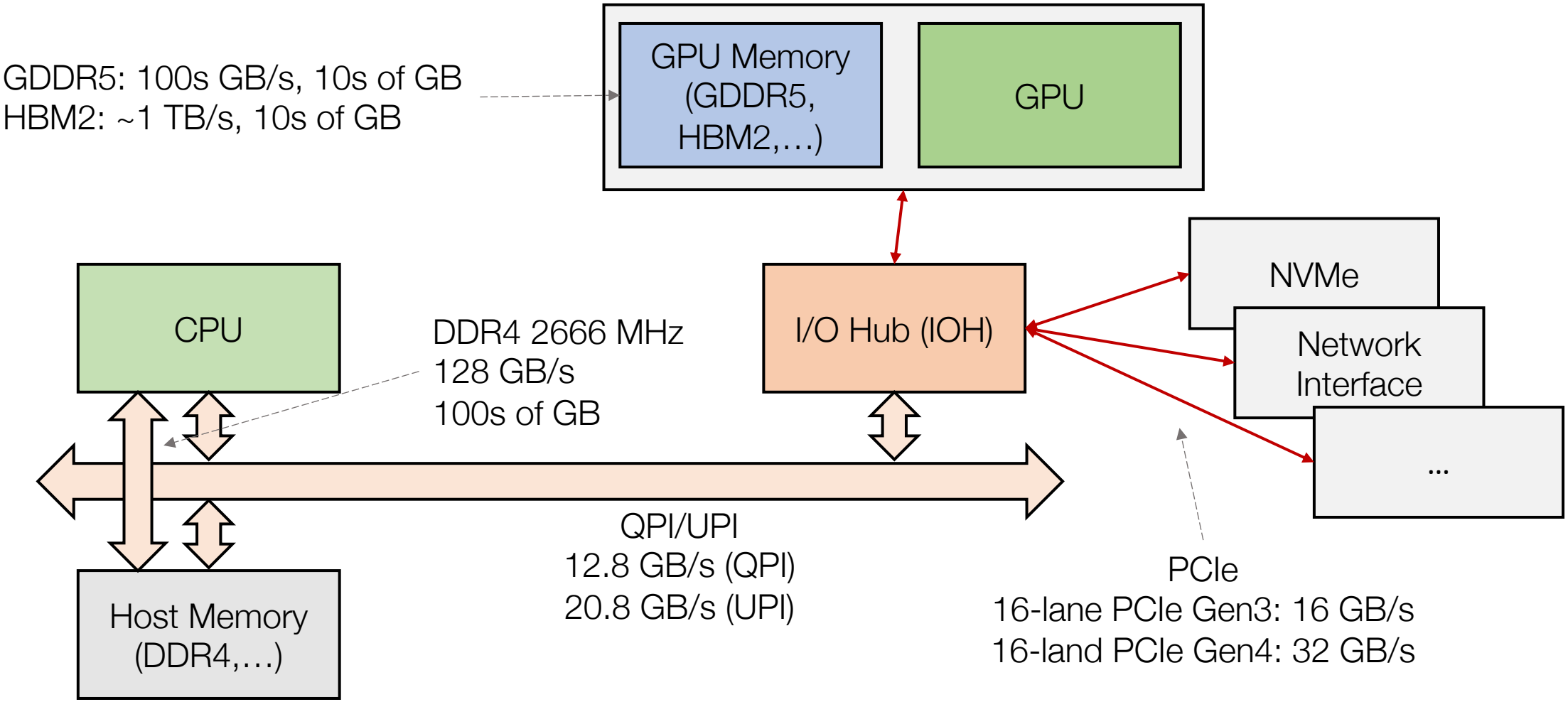
GPU architecture

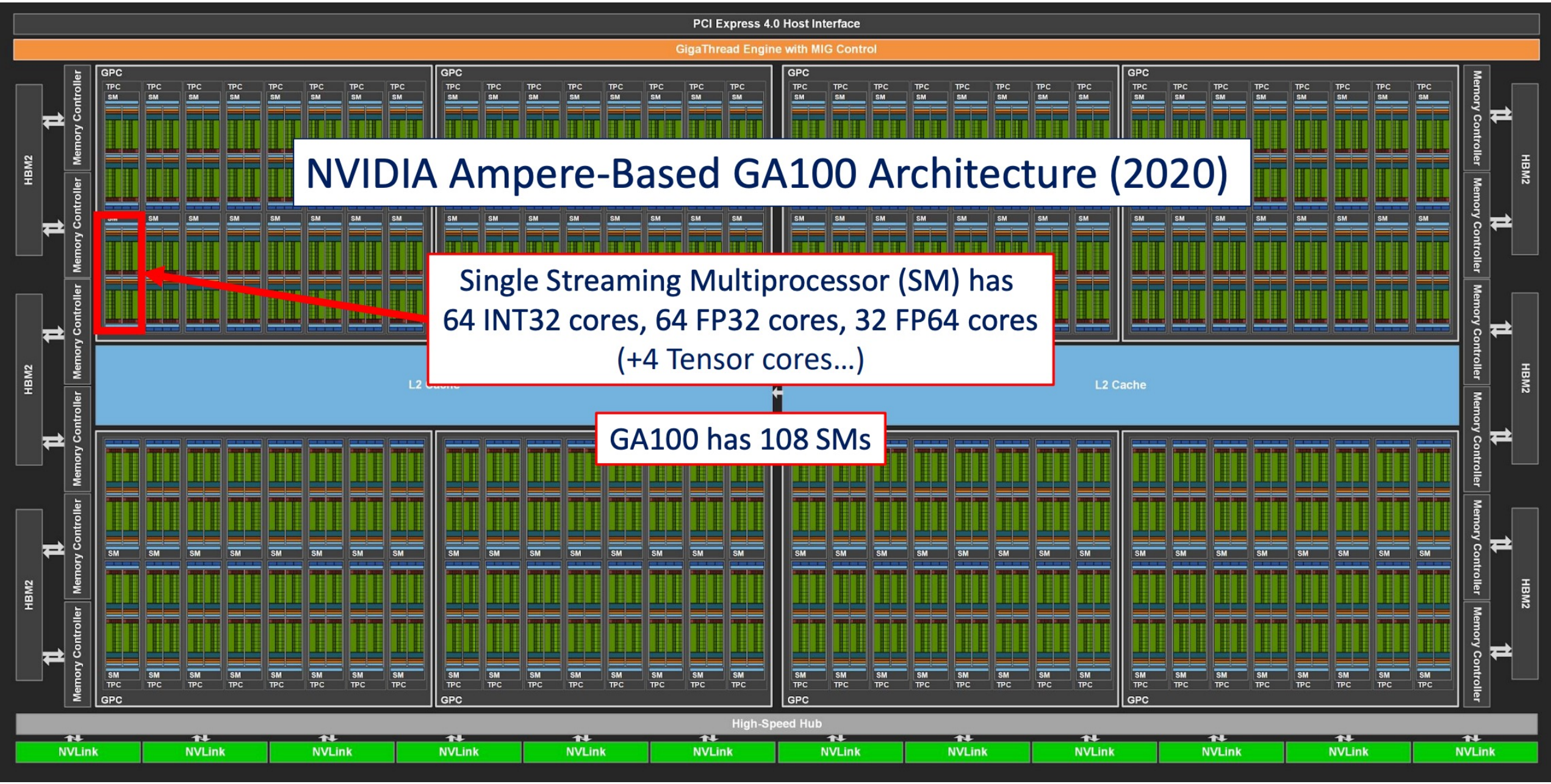
GPU architecture

- GPUs have thousands of threads running concurrently at GHzs
- Much simpler processor architecture
  - Dozens of threads scheduled together in a SIMD fashion
  - Much simpler microarchitecture (doesn't need to boot Linux)
- Much higher power budget
  - CPUs try to maintain 100 W power budget (Pentium 4 till now)
  - Thermal design power (TDP) for modern GPUs around 300 W
    - TDP: Safe level of power consumption for effective cooling

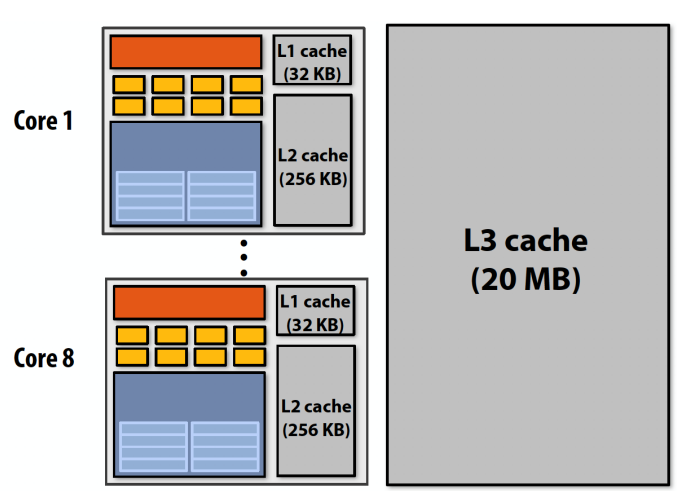
CPU (i7) adding 1 Billion floats: 2.14s, NVIDIA Turing with only one thread: 29.16s

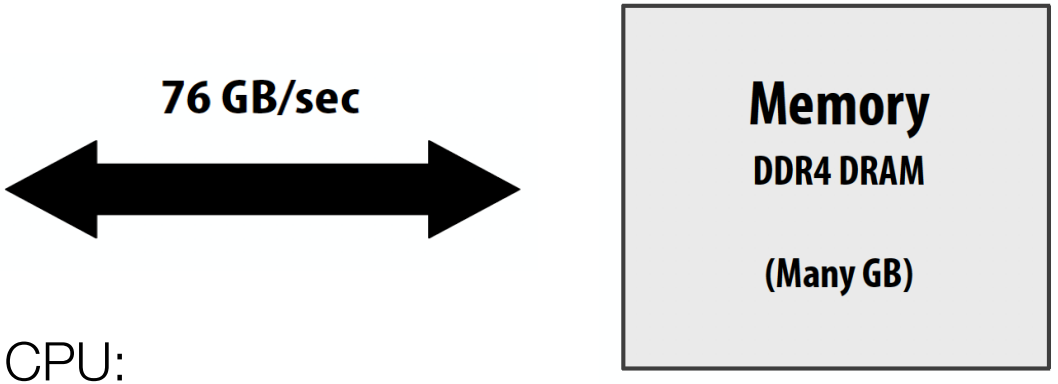
System Architecture Snapshot With a GPU




PCI Express 4.0 Host Interface
GigaThread Engine with MIG Control
NVIDIA Ampere-Based GA100 Architecture (2020)
Single Streaming Multiprocessor (SM) has
64 INT32 cores, 64 FP32 cores, 32 FP64 cores
(+4 Tensor cores…)
GA100 has 108 SMs
L2 Cache
GPC
TPC
SM
HBM2
Memory Controller
High-Speed Hub
NVLink

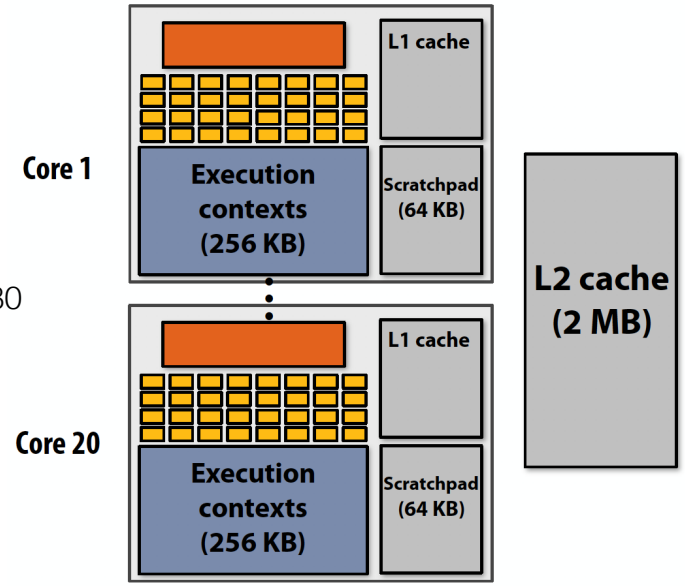
CPU v.s. GPU Memory Hierarchies

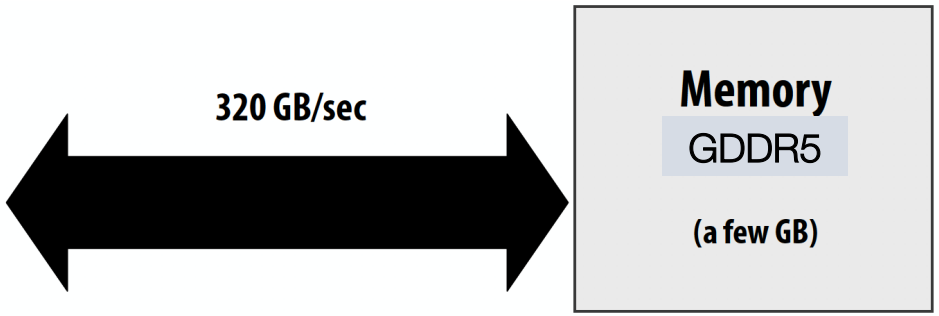




CPU:
Big caches, few threads per core, modest memory BW
Rely mainly on caches and prefetching

NVIDIA GTX 1080 (Pascal)

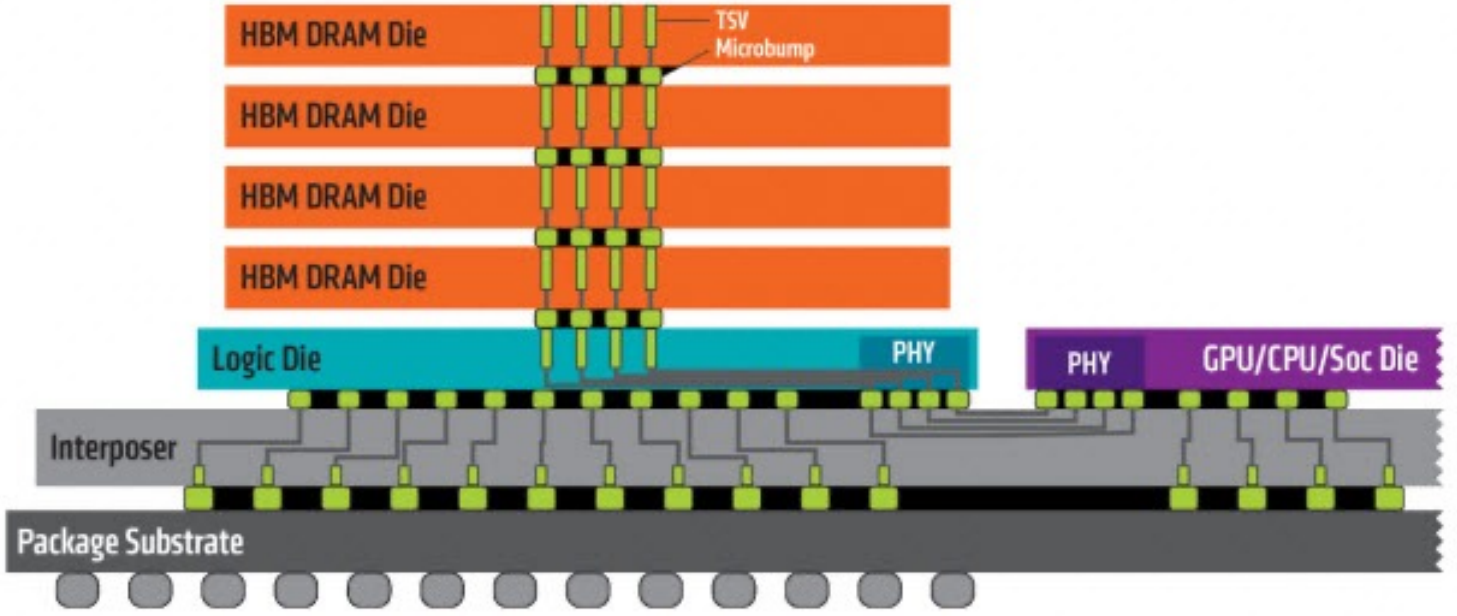




GPU:
Small caches, many threads, huge memory BW
Rely heavily on multi-threading for performance

High-Performance Graphics Memory

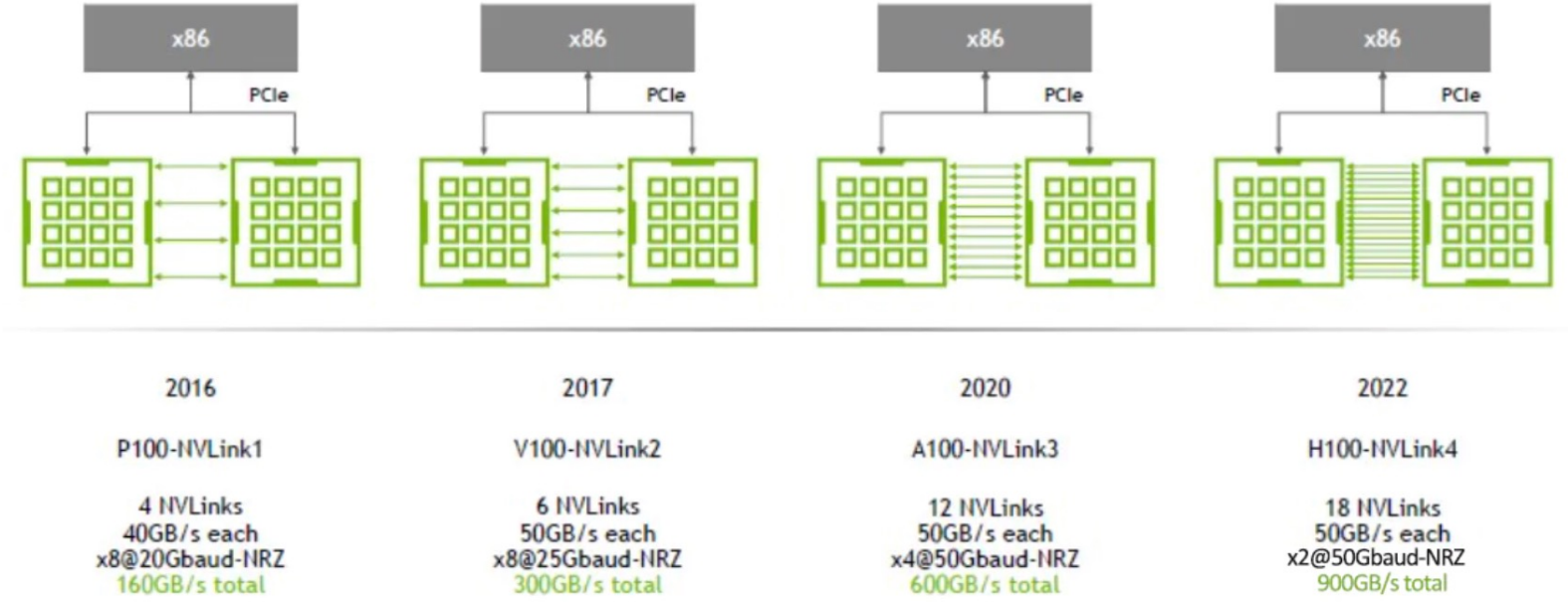
- Modern GPUs even employing 3D-stacked memory via silicon interposer
  - Very wide bus, very high bandwidth
  - e.g., HBM2 in Volta



Graphics Card Hub, “GDDR5 vs GDDR5X vs HBM vs HBM2 vs GDDR6 Memory Comparison,” 2019

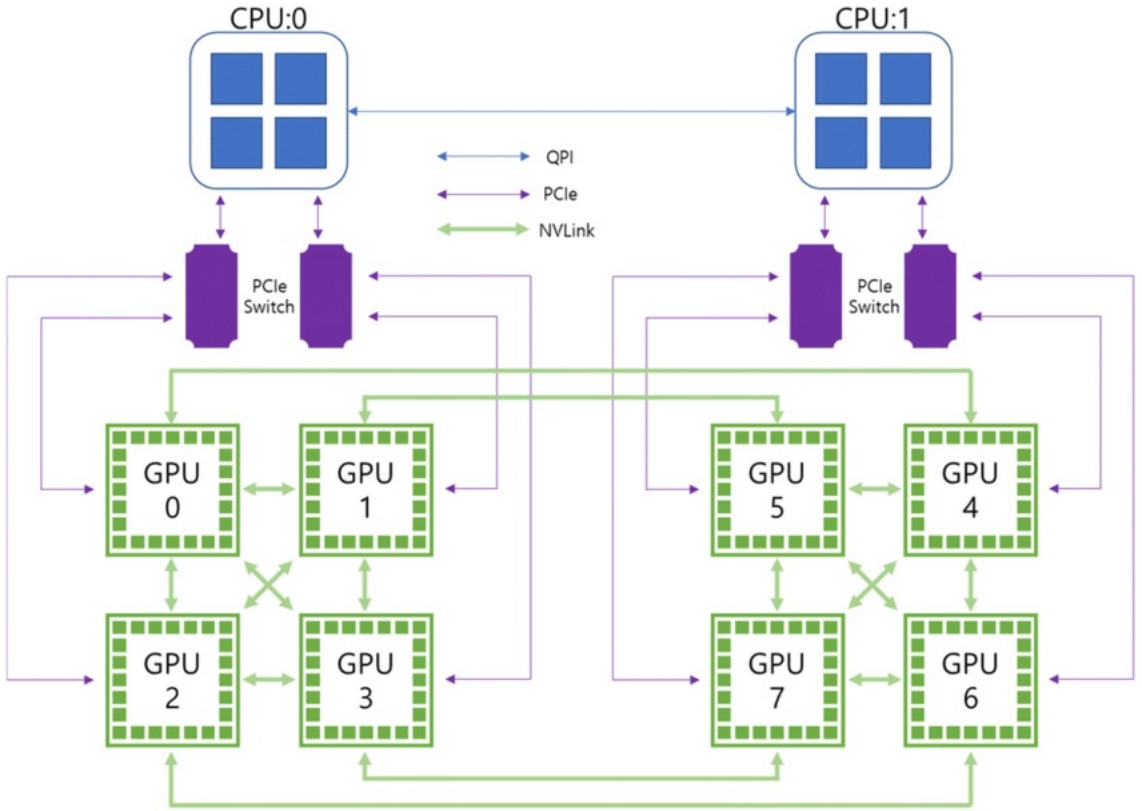
High-speed interconnect between GPUs

- NVLink
  - bidirectional, direct GPU-to-GPU interconnect



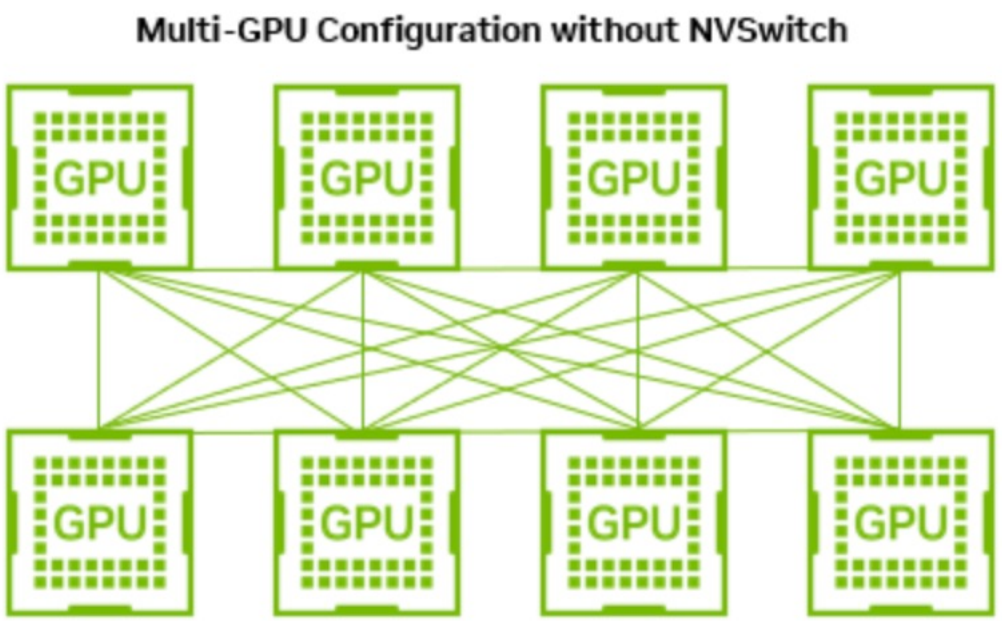
Multi-GPU topology

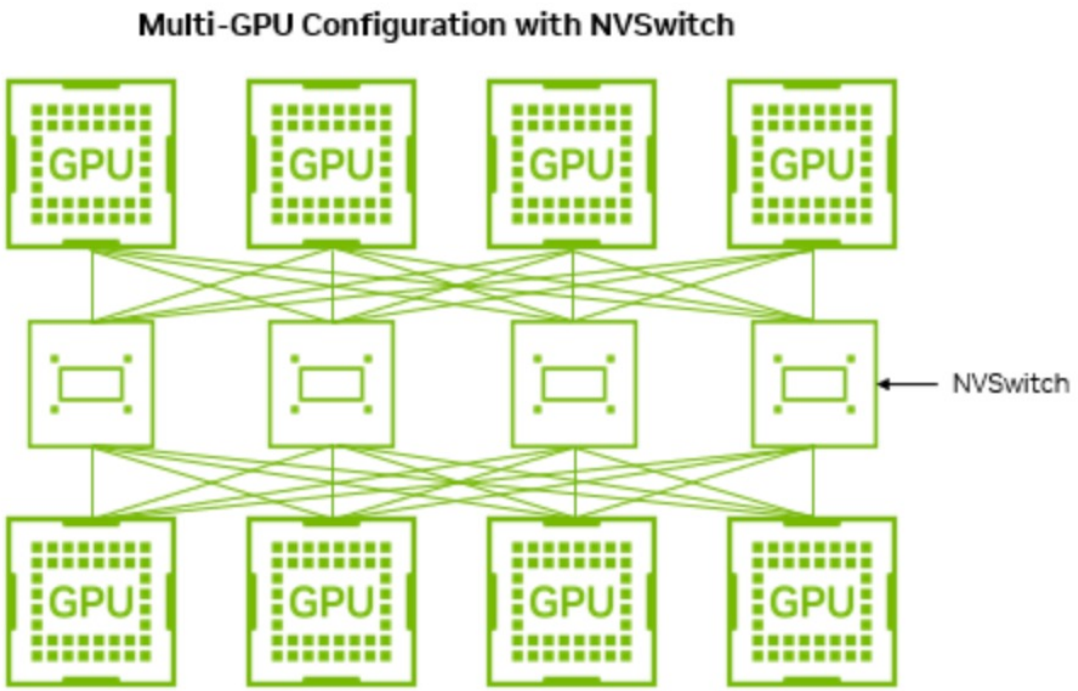
- Multi-GPU topology before DGX-A100



Multi-GPU topology

- NVSwitch (NVLink Switch) connects multiple NVLinks to provide all-to-all GPU communication at full NVLink speed



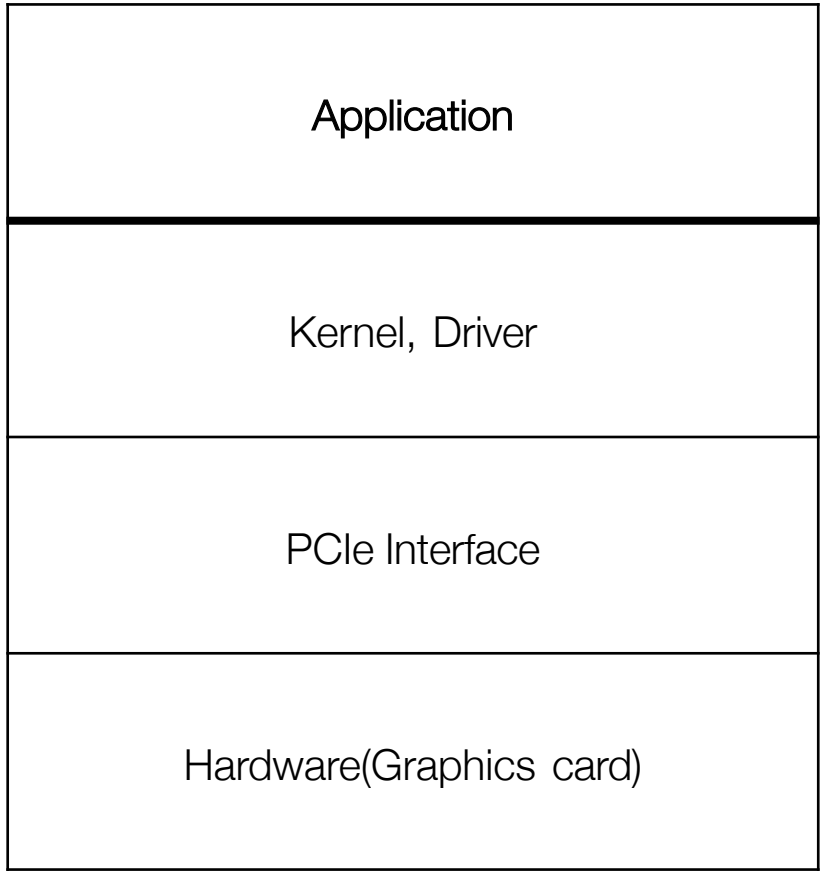


GPU virtualization

GPU virtualization

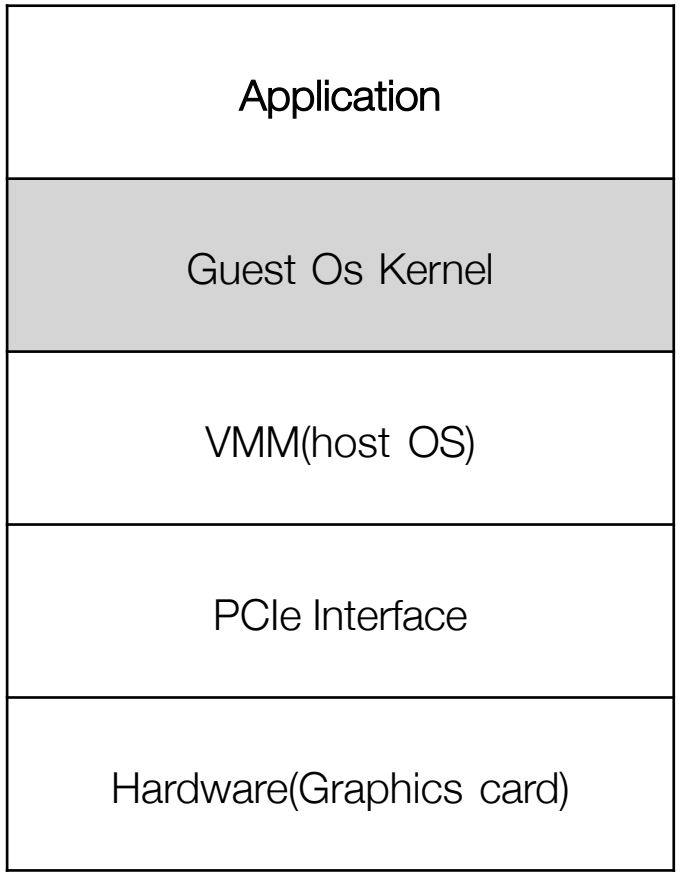
- Hot direction in today's cloud
  - GPU sharing among cloud users
- Some solutions at various levels
  - Provided by hardware vendors, e.g., Nvidia MPS, MIG
  - Enabled at application level, e.g., vCUDA
  - …

Without Virtualization



GPU virtualization is more like I/O virtualization

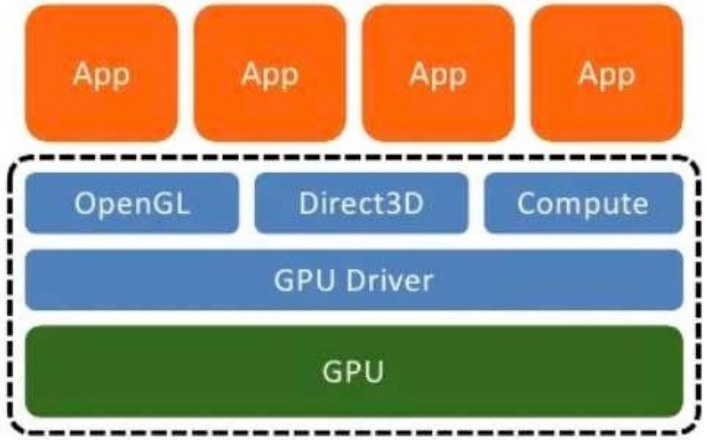
- GPU is connected to CPU via PCIe



CPU	GPU
Fidelity Performance Safety	Fidelity Performance (safety)Multiplexing (safety)Interposition

Unique challenges

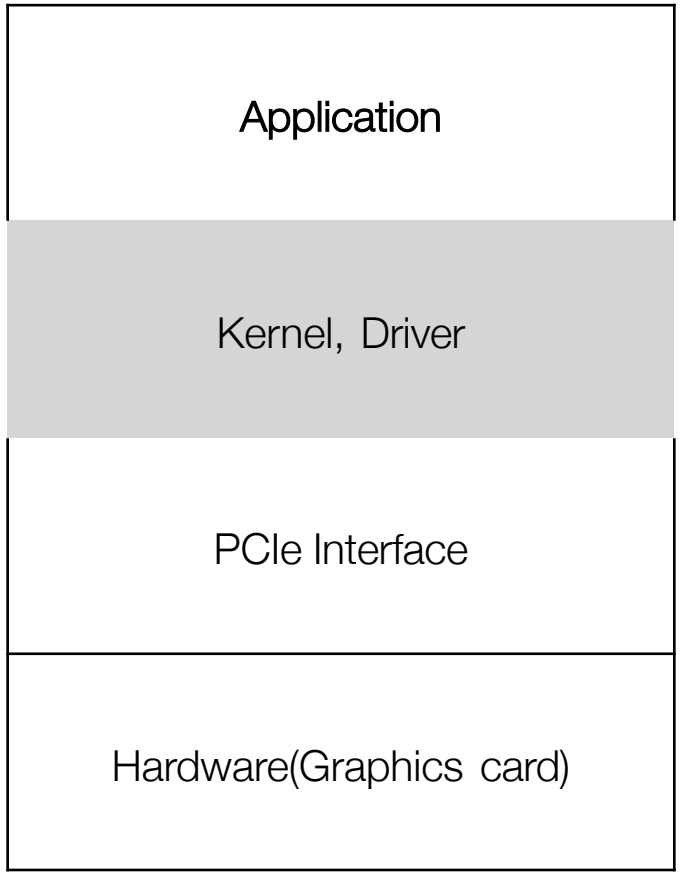
- Hardware specs
  - Diverse, changes frequently
  - Closely guarded secret
  - Speed vs. portability
- Hardware state
  - Up to gigabytes of data
  - Highly device-specific format
  - In-progress DMA and computation

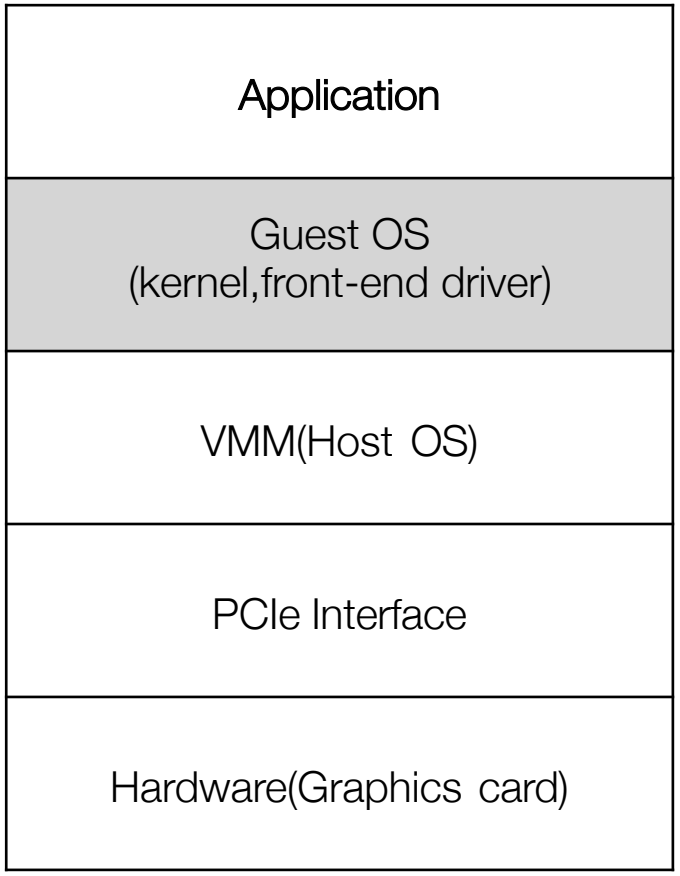


Taxonomy of GPU virtualization

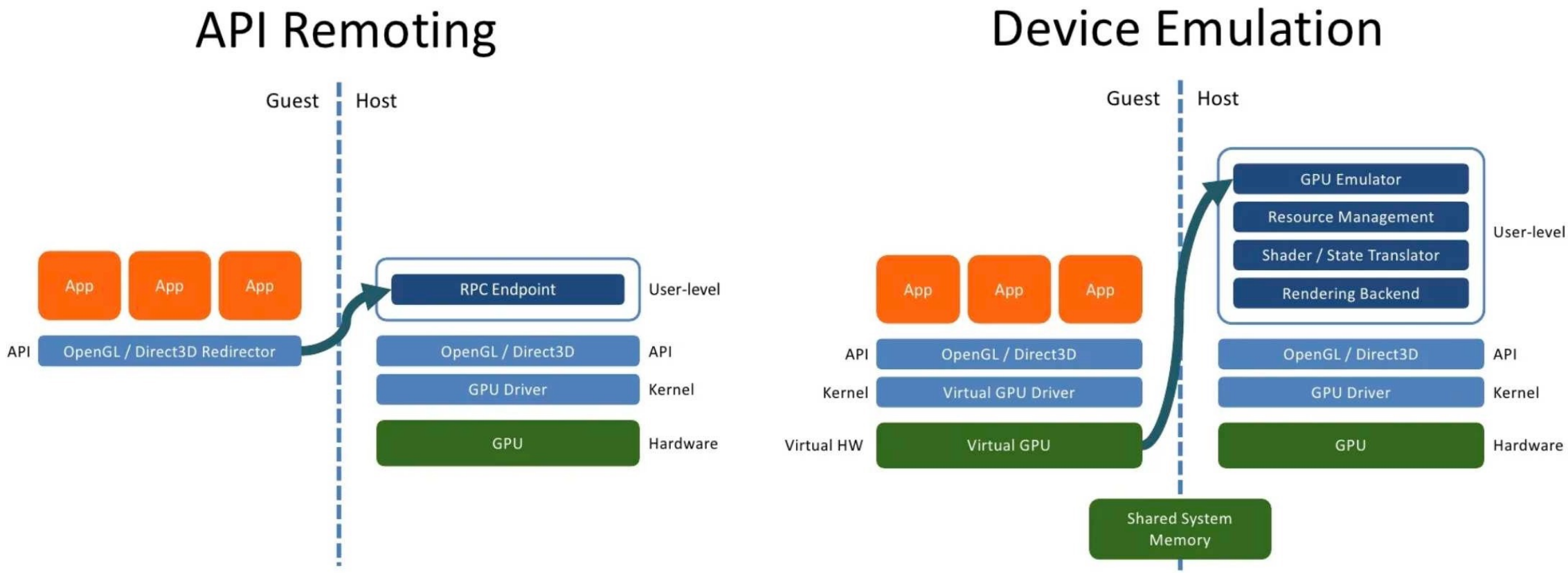
- Front-end
- Back-end

Front-end Virtualization





Front-end Virtualization

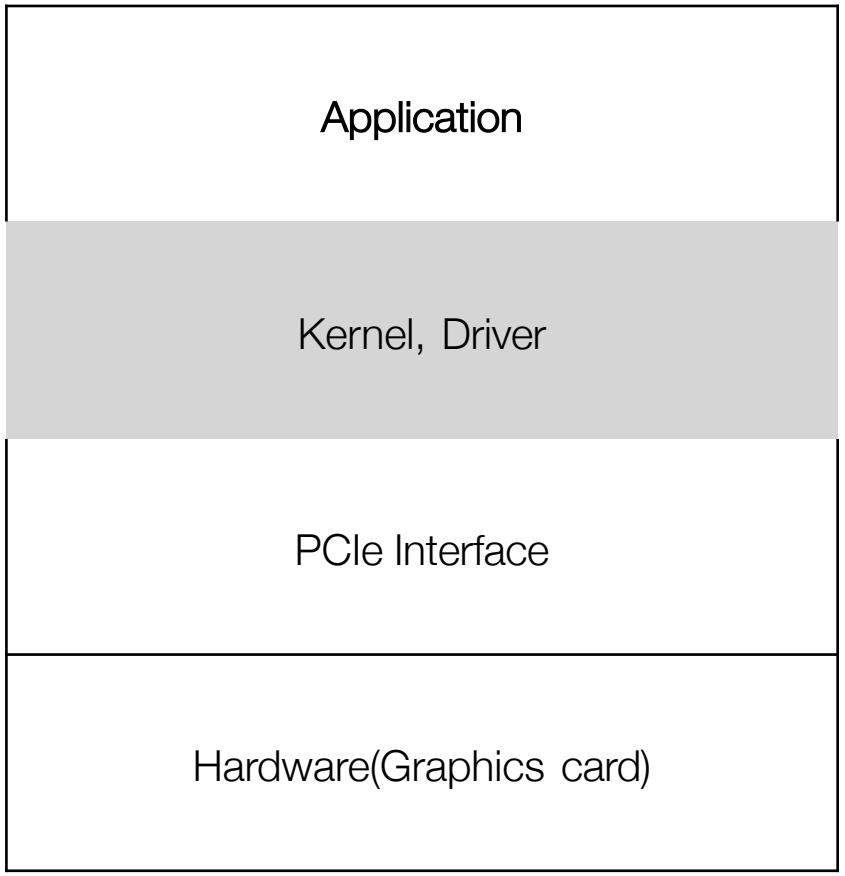


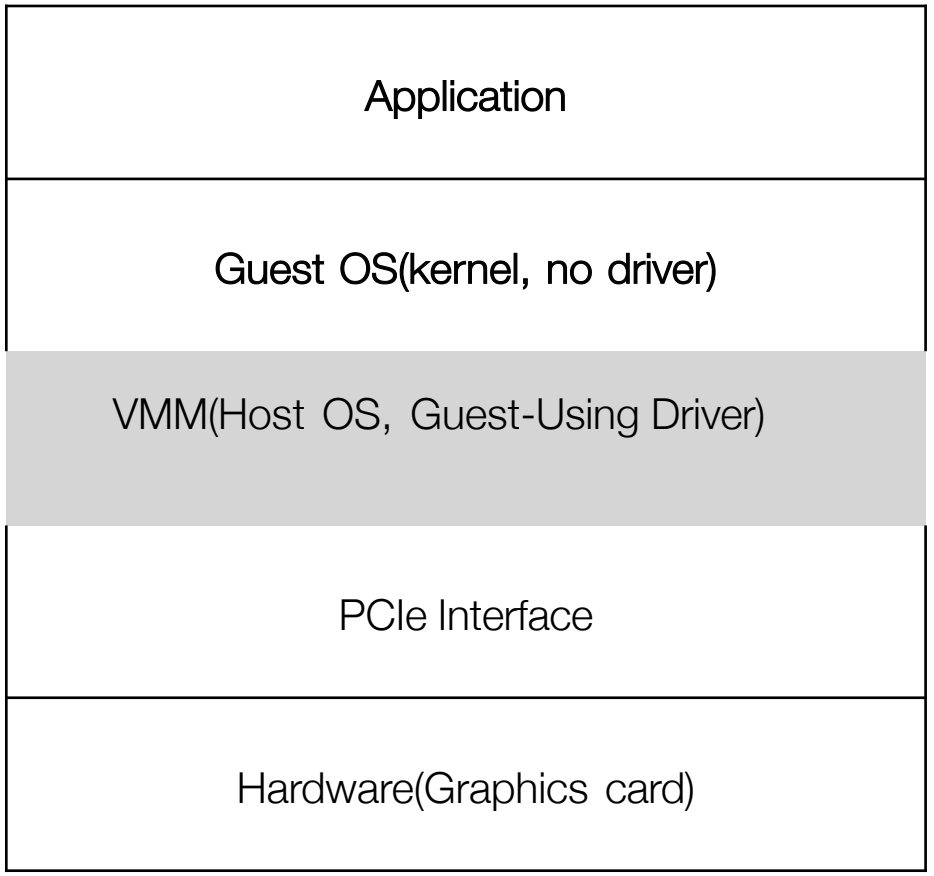
https://www.slideshare.net/guestb3fc97/gpu-virtualization-on-vmwares-hosted-io-architecture-presentation

Front-end Virtualization

- Two ways to enable the designed driver in the guest OS
- Pure API remoting
  - Put the api ability to somewhere else. Could be vmm, could be not.
  - Large data transfer, Low interposition. Easy implementation.
- Pure device emulation
  - Emulate the graphics card behavior by cpu.
  - Highly complicated and undocumented behavior. Good interposition.

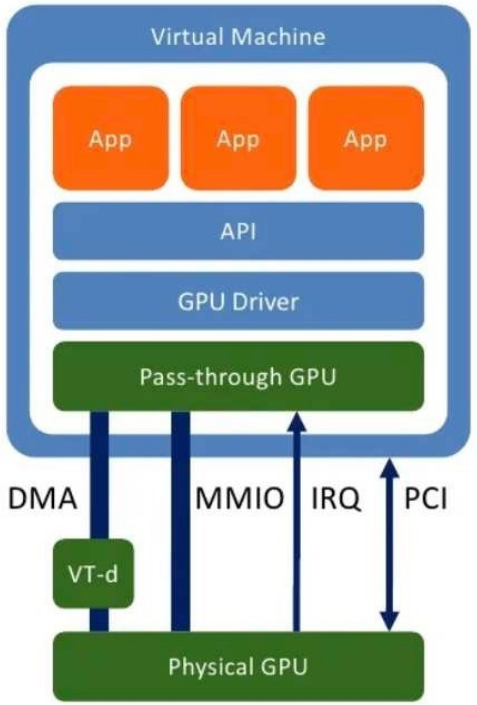
Back-end Virtualization



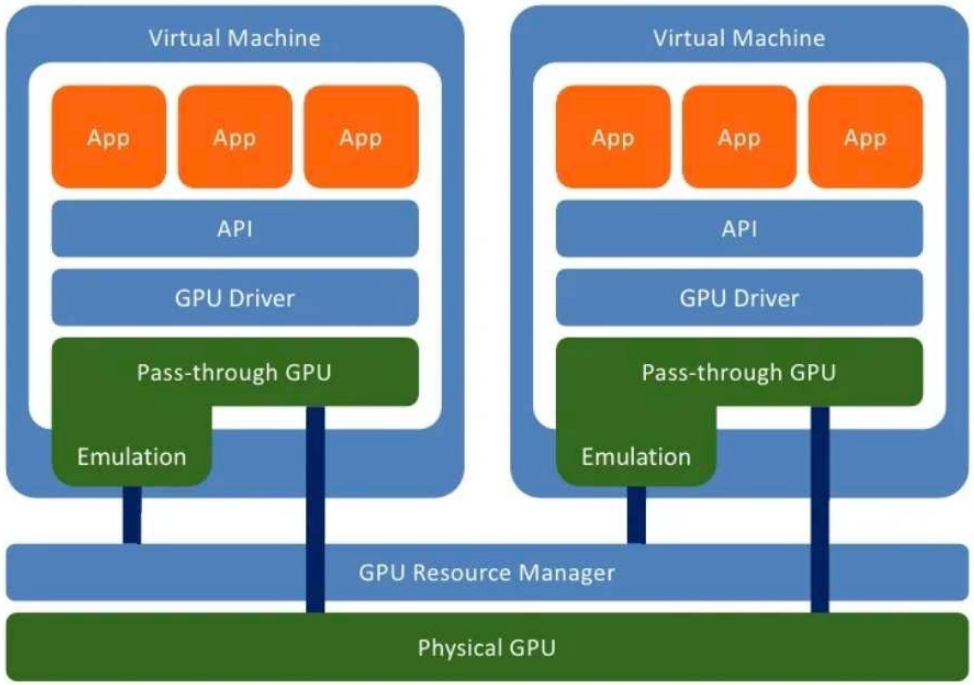


Back-end Virtualization

Fixed pass-through



Mediated pass-through



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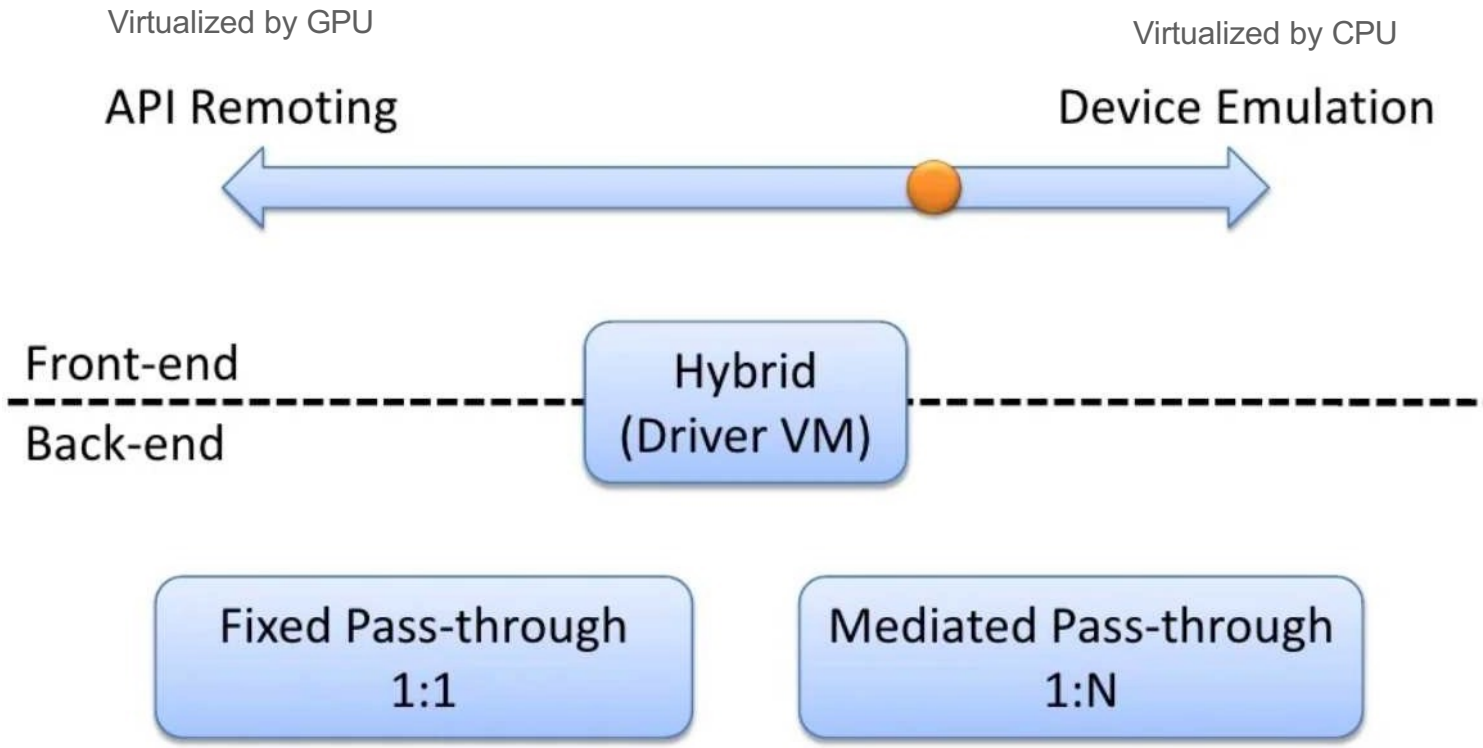
Back-end Virtualization

- Hard to multiplex and interposition
- Multiplex strategy
  - fixed pass-through: the permanent association of a virtual machine with full exclusive access to a physical GPU.
  - mediated pass-through: just give different vm different context. So they can multiplex.
    - Hard to map to different virtual machines with low overheads and the host/hypervisor must have enough of a hardware driver to allocate and manage GPU contexts.

GPU Virtualization Taxonomy



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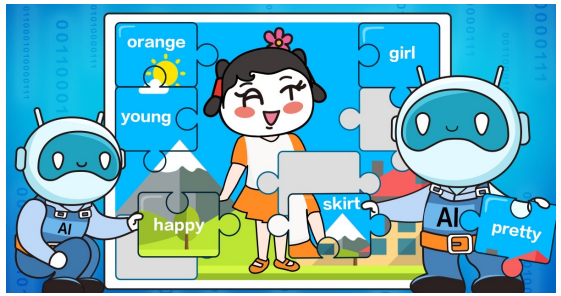
GPU cluster in the cloud

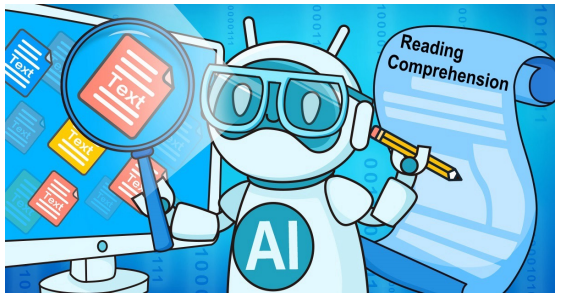
“MLaaS in the Wild: Workload Analysis and Scheduling in Large-Scale Heterogeneous GPU Clusters” in NSDI’22

Qizhen Weng, Wencong Xiao, Yinghao Yu, Wei Wang, Cheng Wang, Jian He, Yong Li, Liping Zhang, Wei Lin, Yu Ding

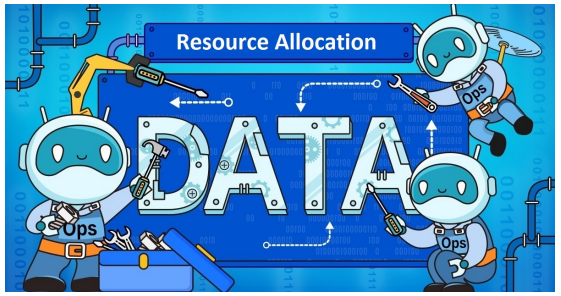
Production ML Workloads

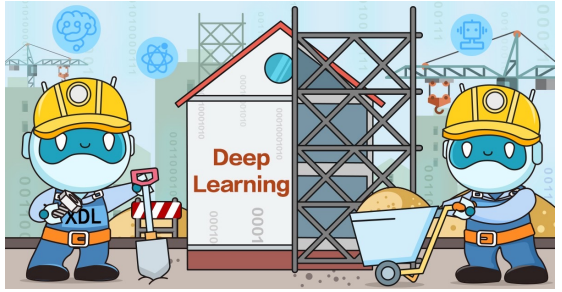
- Machine Learning (ML) is ubiquitous: CV, NLP, Recommend ...





- ML jobs can scale to hundreds of GPUs, requesting TBs of data.

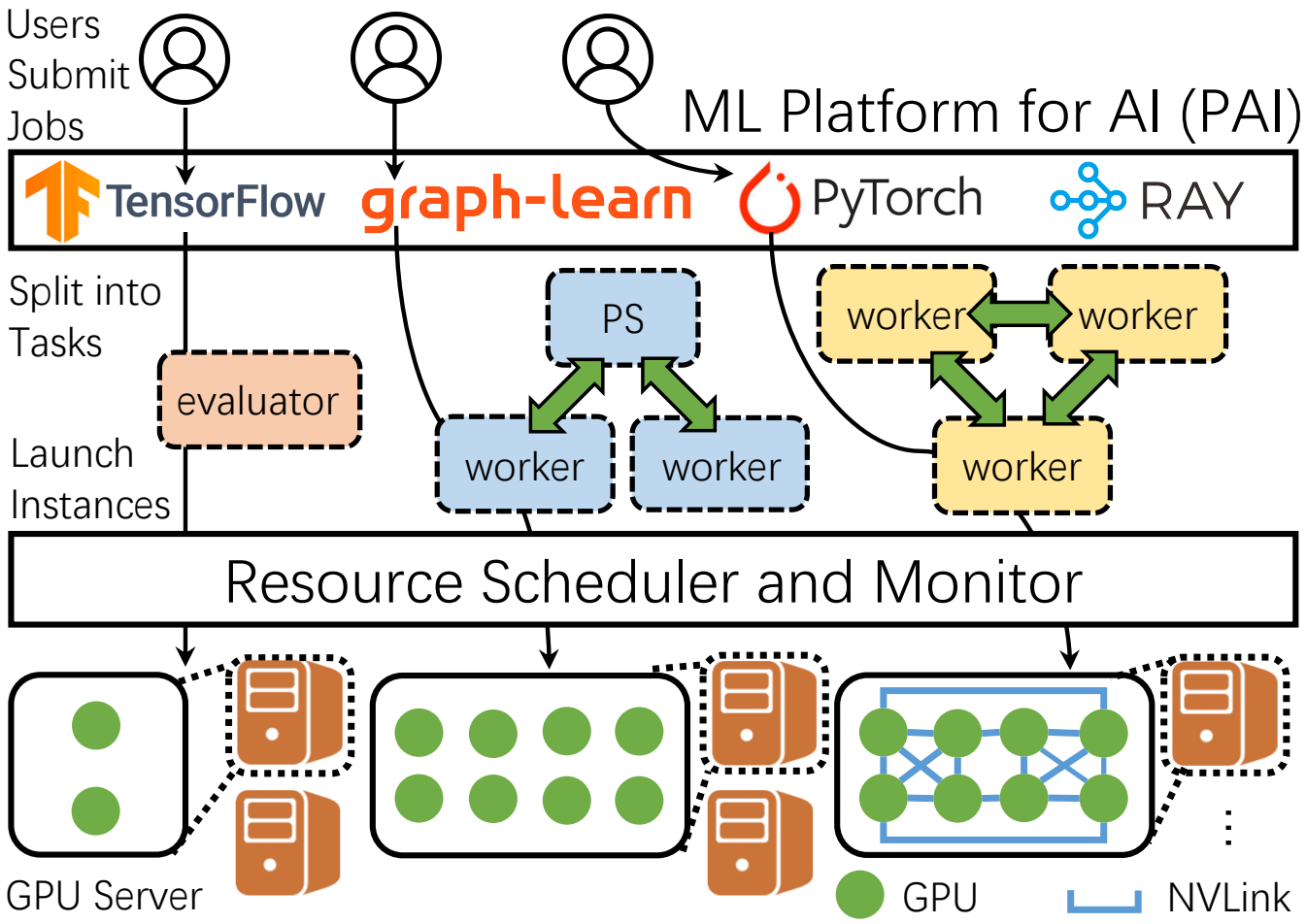




Images credit to: https://alibabatech.medium.com/

PAI: a Cloud-based MLaaS Platform

- All-in-one platform for training & inference
- Support a variety of ML frameworks
- Allocate containerized instances to hetero. nodes



Trace Basics

Traces are released at: https://github.com/alibaba/clusterdata/tree/master/cluster-trace-gpu-v2020

Trace Overview

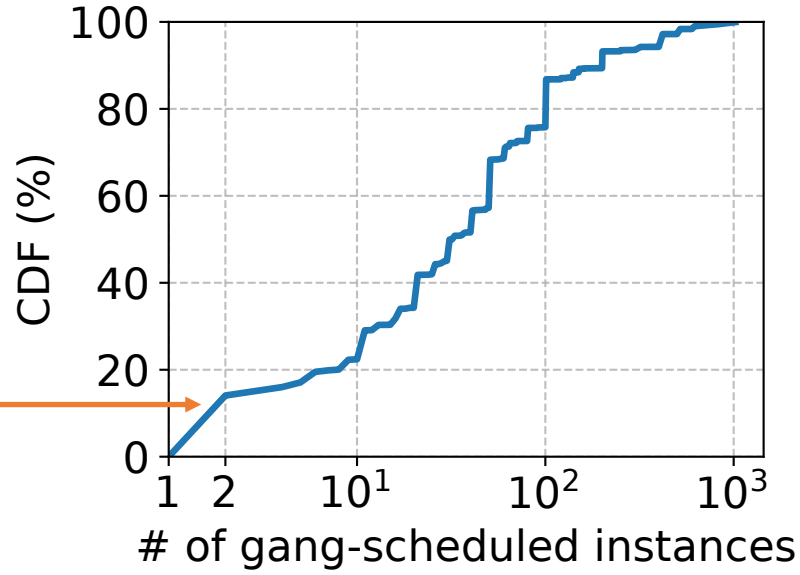
- Collected in Jul. and Aug. 2020 on 1800+ nodes, 6700+ GPUs

† are equipped with NVLink

System	#CPUs	Mem (GiB)	#GPUs	GPU type	#Nodes
PAI	64	512	2	P100	798
	96	512	2	T4	497
	96	512	8	Misc.	280
	96	384	8	V100M32†	135
	96	512/384	8	V100†	104
	96	512	0	N/A	83

Trace Overview

- Over 1300 users submitted 1.2M tasks with 7.5M instances
  - Allow GPU sharing & type specifying
  - 85% Instances are gang-scheduled

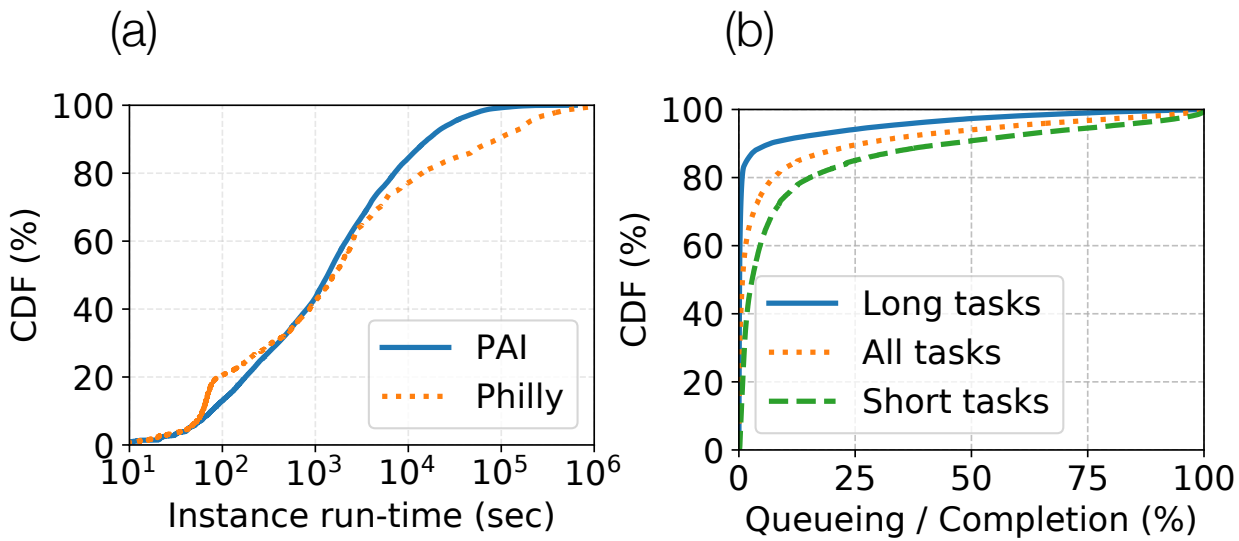


A sample job

task_name	num_inst	plan_cpu	plan_mem	plan_gpu	gpu
worker	20	800	30000	100	T4
ps	25	1500	40000	N/A	N/A

Run-time and Queueing delays

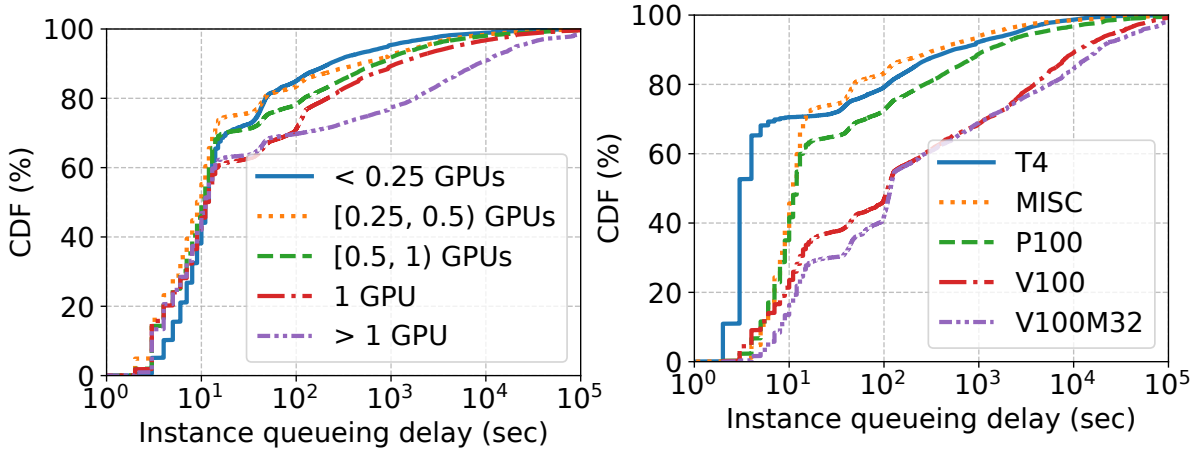
- Instance run-time ranges from seconds to hours (c.f. Philly[1]) (a)
- Short tasks wait for a larger proportion of their runtime (b)



[1] Jeon, Myeongjae et al. “Analysis of Large-Scale Multi-Tenant GPU Clusters for DNN Training Workloads.” ATC ‘19 https://github.com/msr-fiddle/philly-traces

Run-time and Queueing delays

- Tasks requesting full and/or high-end GPUs wait longer



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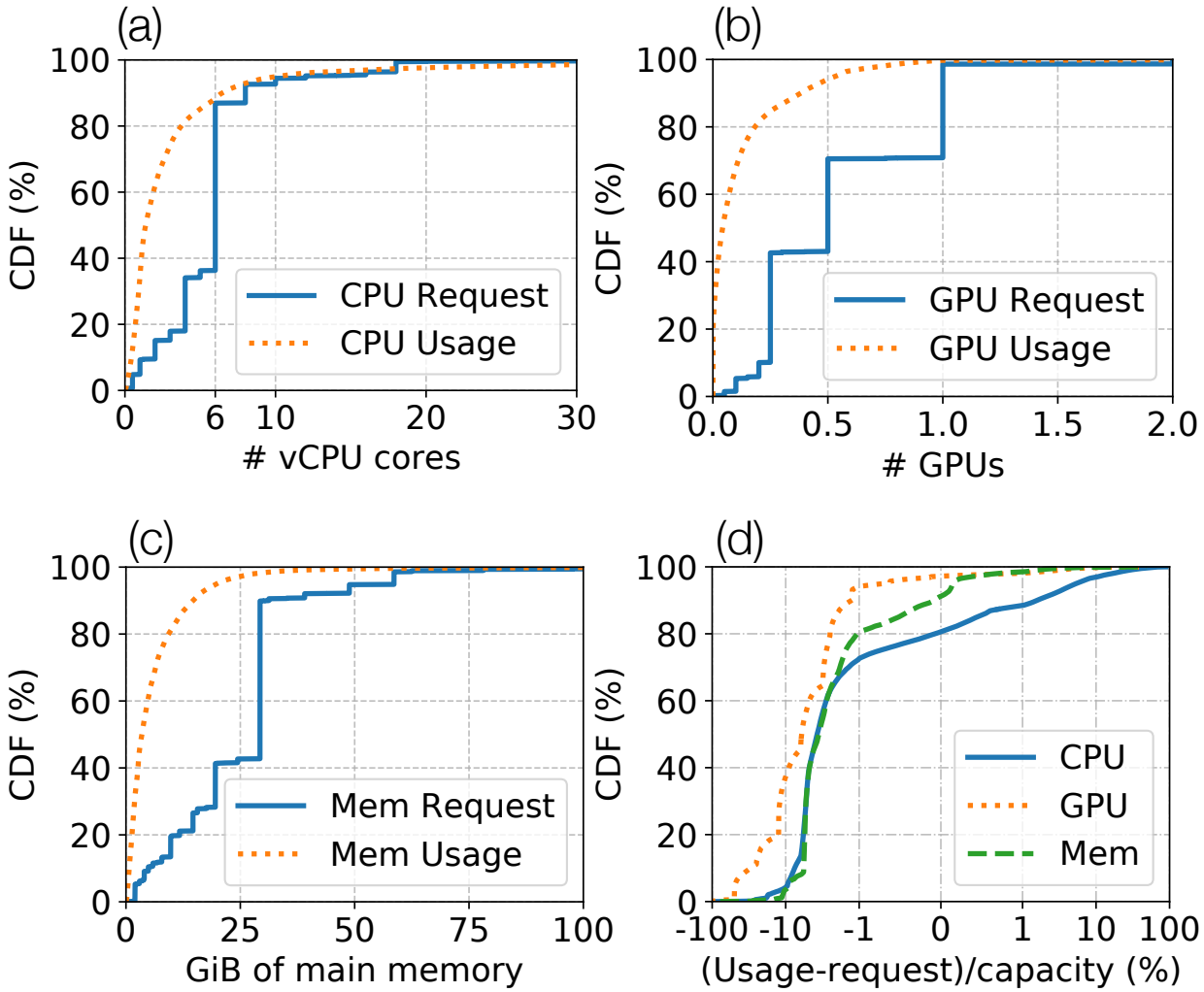
Resource Requests & Usage

- Heavy-tailed distribution of requests: ~20% are “elephants” (solid lines in (a) (b) (c))
- Uneven resource usage: High on CPUs but low on GPUs (dotted lines in (a) (b) (c))
- Usage / Request: 19% instances overuse CPUs (solid lines in (d)); only 3% instances overuse GPUs (dotted lines in (d)).

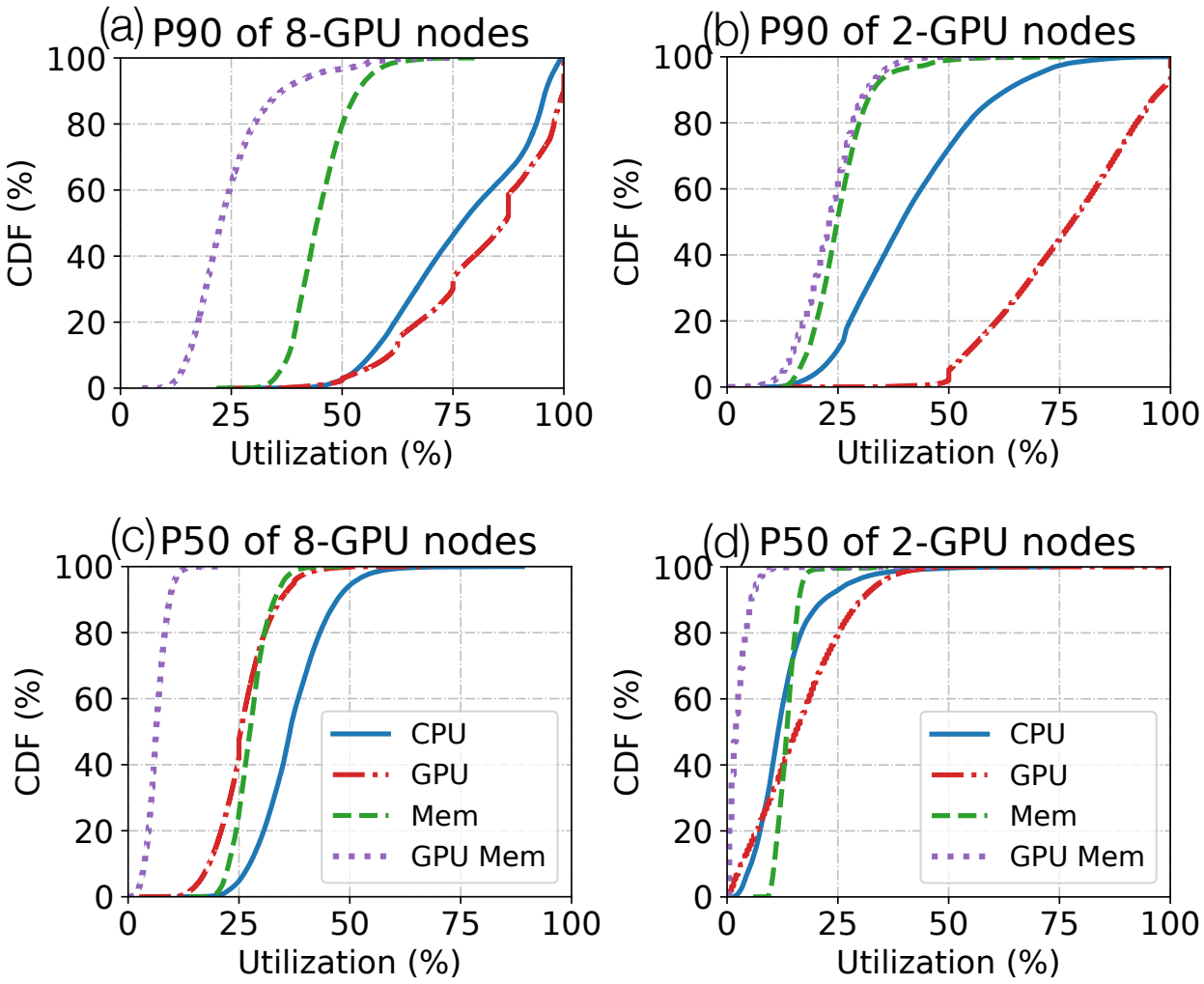


Machine Resource Utilization

- 8-GPU machines (a) (c)
  - High GPU, high CPU utilization
- 2-GPU machines (b) (d)
  - High GPU, medium CPU utilization

- Gap between P90 and P50 (median) util. is large for GPUs

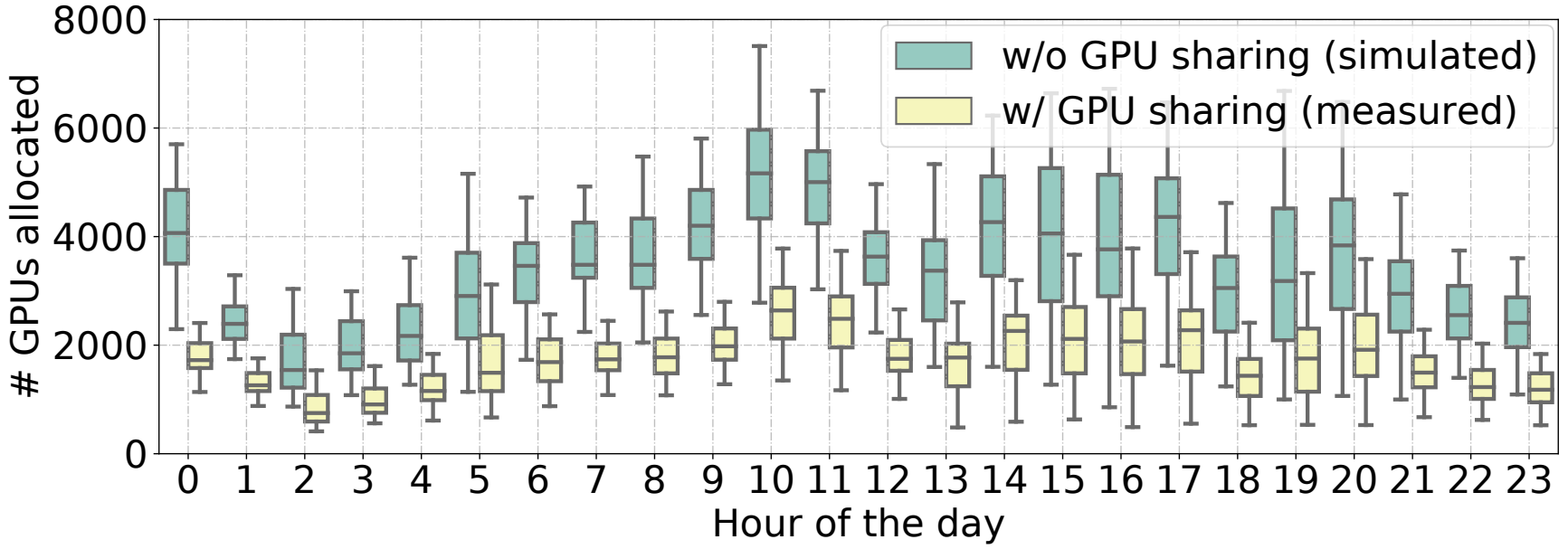
- Main memory and GPU memory are sufficient.



Opportunities

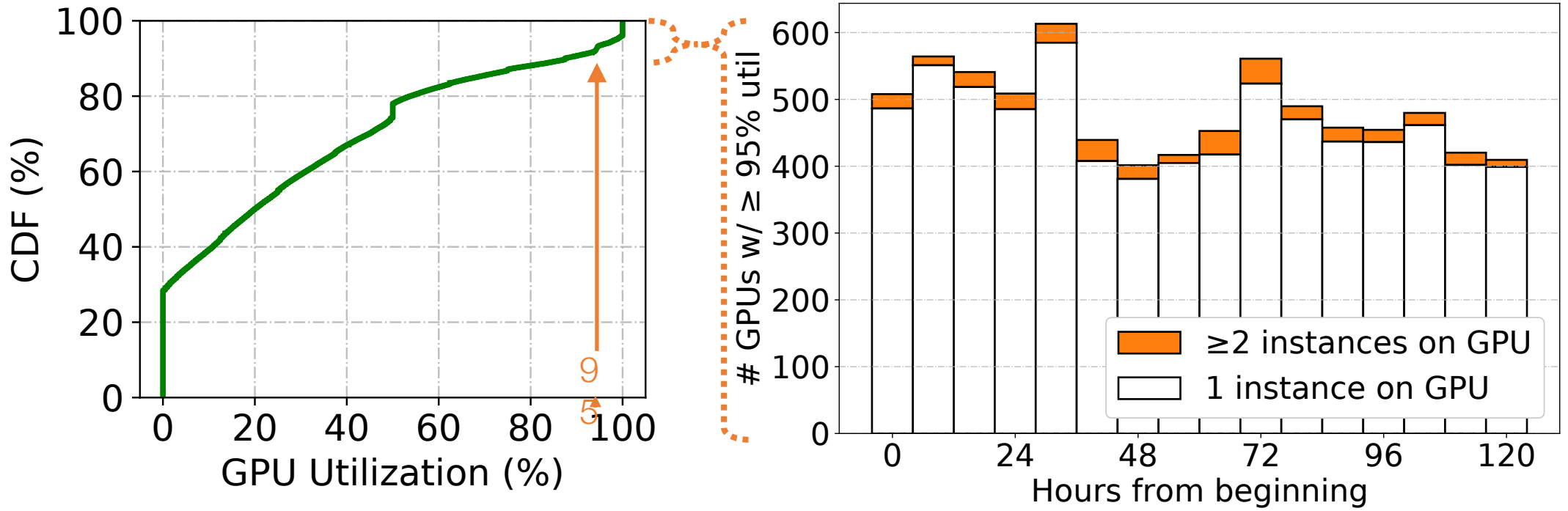
GPU Sharing

- Space-multiplex: GPU memory. Time-multiplex: GPU compute units.
- Sharing saves 50% GPUs on avg. and 2,500 GPUs in peak hrs.



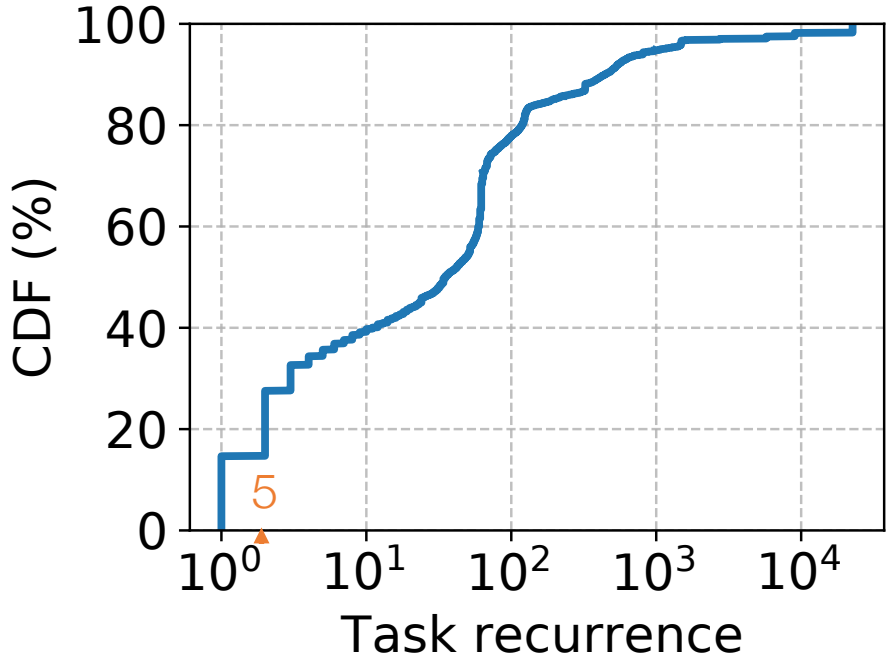
GPU Sharing

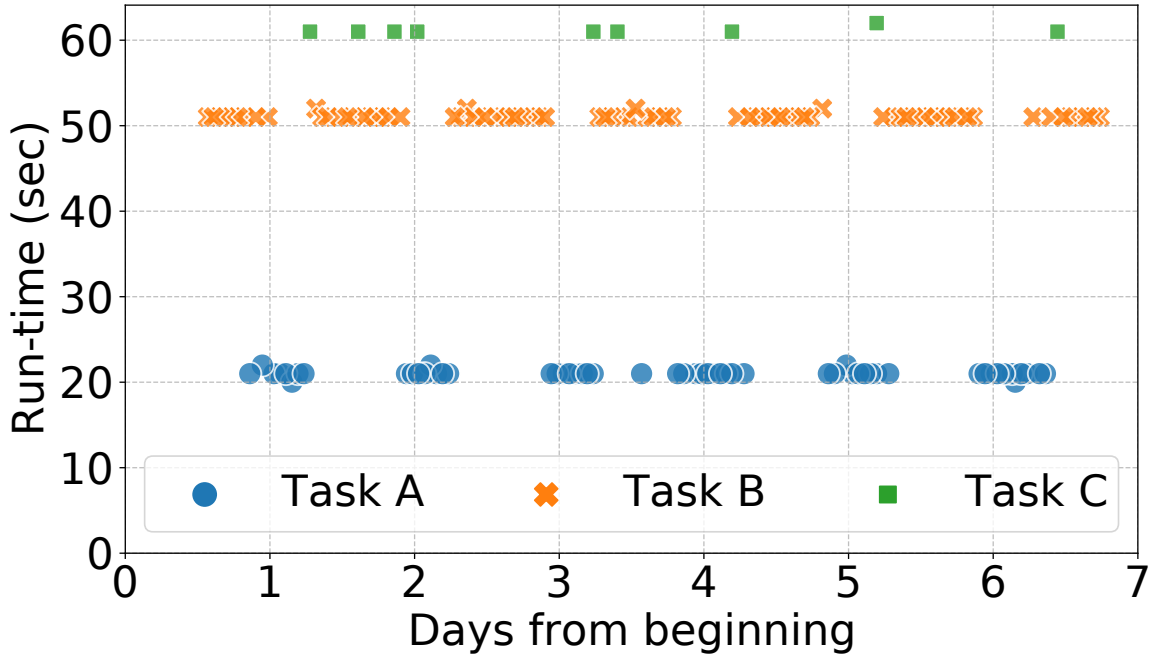
- Current GPU sharing does not cause severe GPU contention
  - On ≥ 95% utilized GPUs, only ~4% of them have ≥ 2 workers run simultaneously



Duration Predict for Recurring Tasks

- Recurring tasks are prevalent (65% tasks repeat ≥ 5 times)
  - Criteria of repetition: Group tag—hash value of jobs' customized input (e.g., entry scripts, command-line params, data sources and sinks)

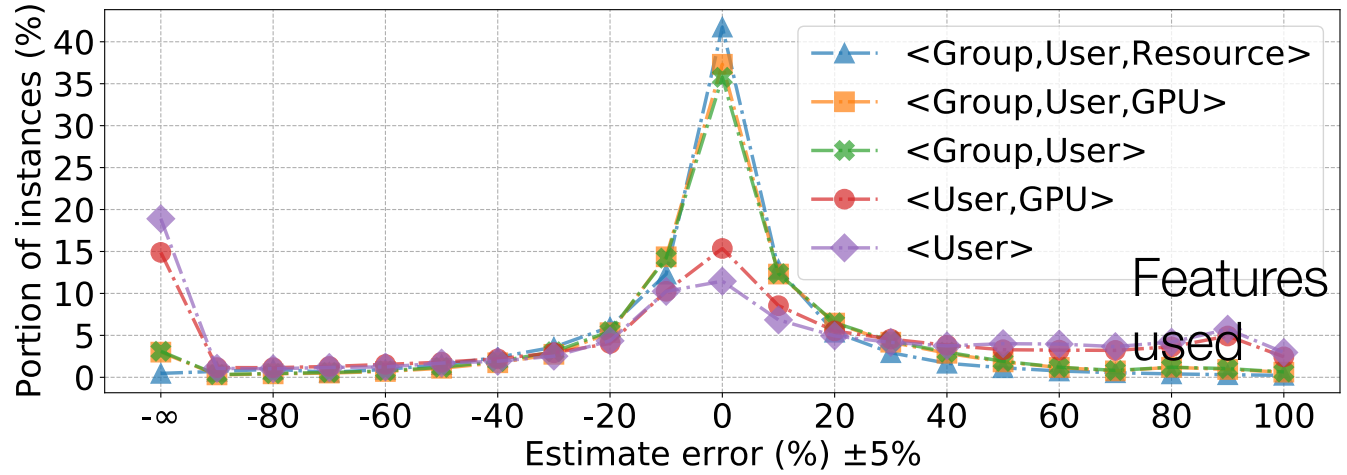


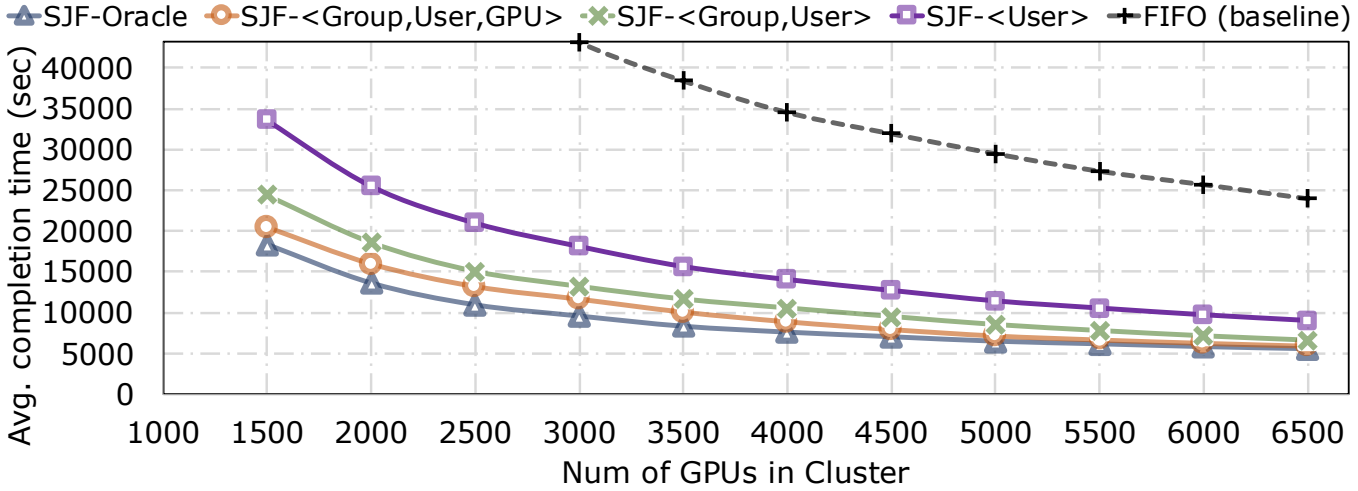


Sample inference tasks

Duration Predict for Recurring Tasks

- Predictor: Regression tree
  - Predict 78% instances duration within ±25% error
- Scheduling: SJF vs. FIFO
  - Speedup by 63%-77% with different predictors



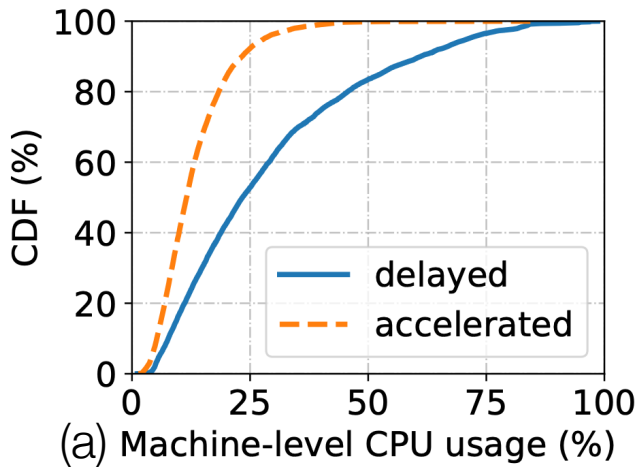


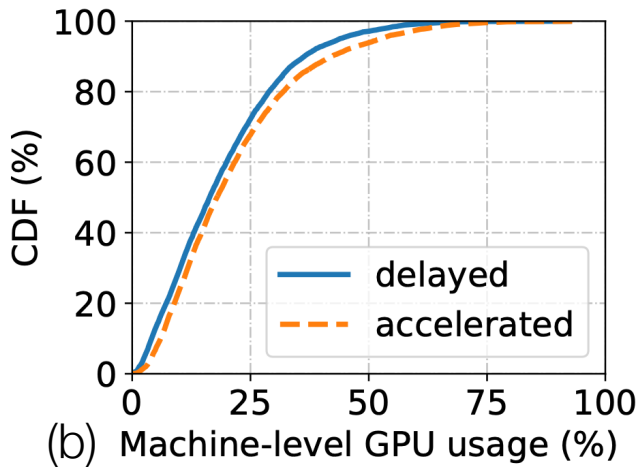
Challenges

CPU can be the bottleneck

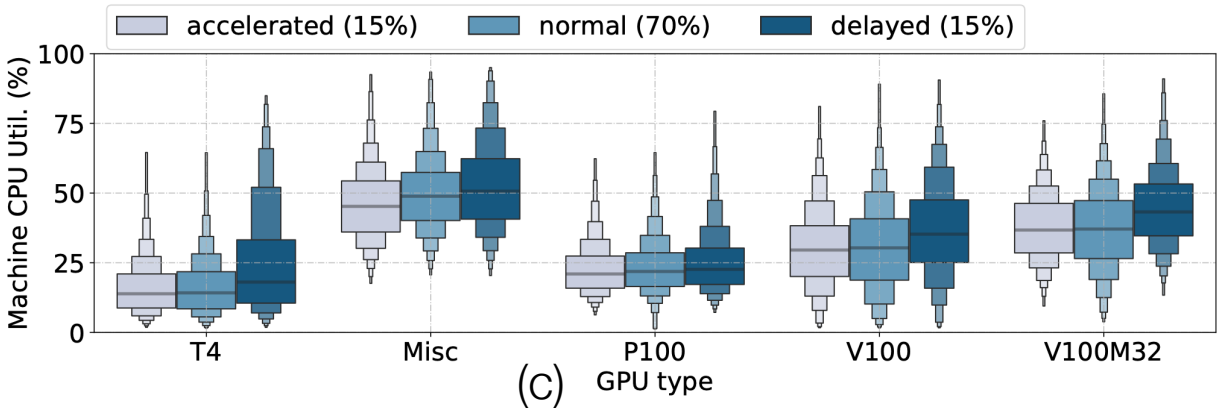
- Task delays are more likely to be observed under high CPU util. (a) (c), rather than high GPU util. (b) (d)

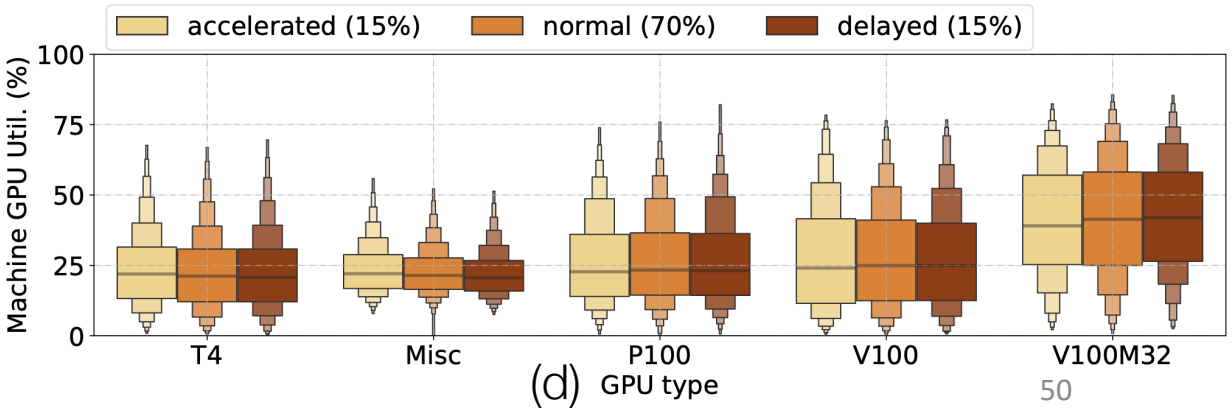
A sample Click-Through Rate (CTR) prediction task





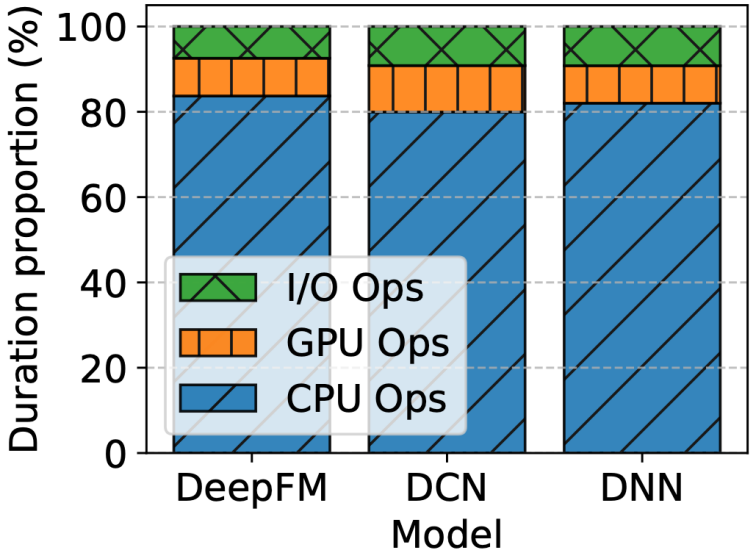
General tasks on various GPU nodes



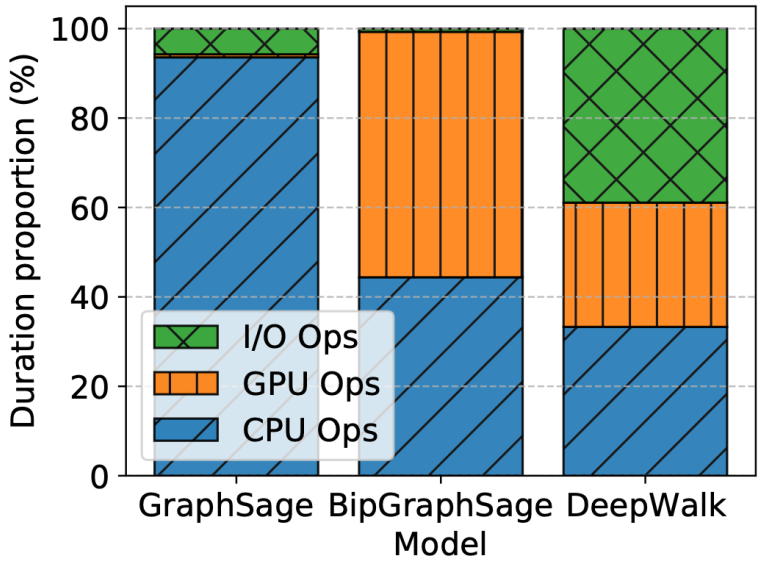


Majority of High-CPU-Low-GPU Tasks

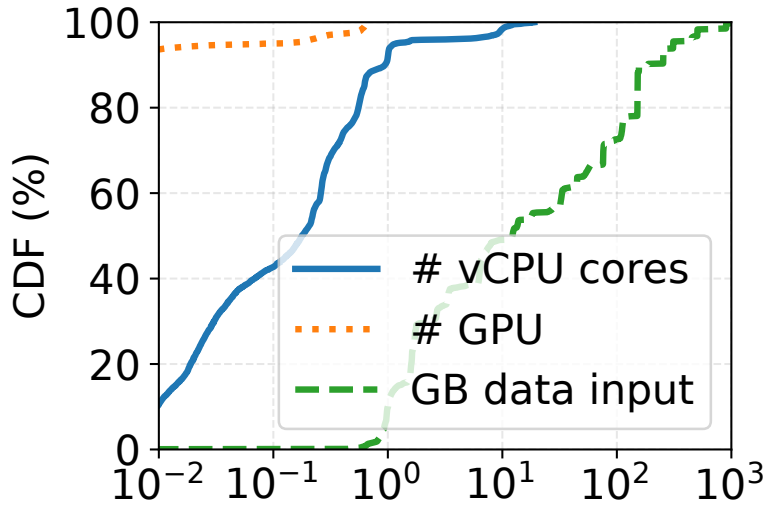
- CTR tasks could spend ~80% time on CPU (fetch and pre-process)
- GNNs spend 30-90% time on Edge Iteration, Neighbor Sampling, …
- RL launches massive CPU-intensive instances to run simulations



(a) Recommending: CTR models



(b) Graph Neural Networks (GNNs)

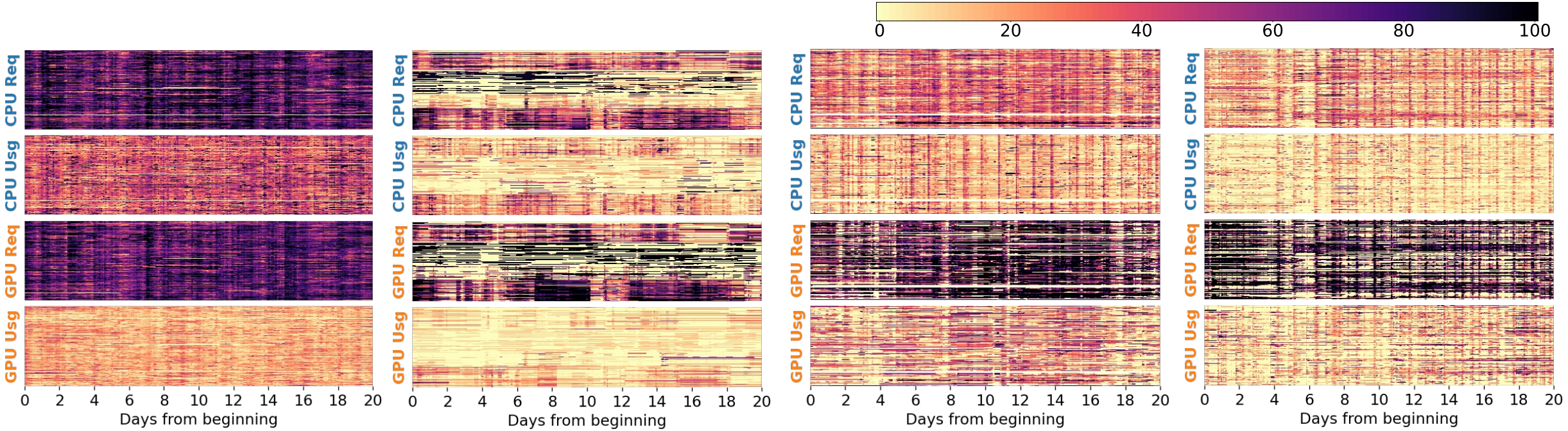


(c) Reinforcement Learning (RL)

Imbalanced Scheduling

- Overcrowding weak 8-GPU nodes (a)
- Packing on high-end V100 nodes (b)
- Underutilizing 2-GPU nodes (c) (d)

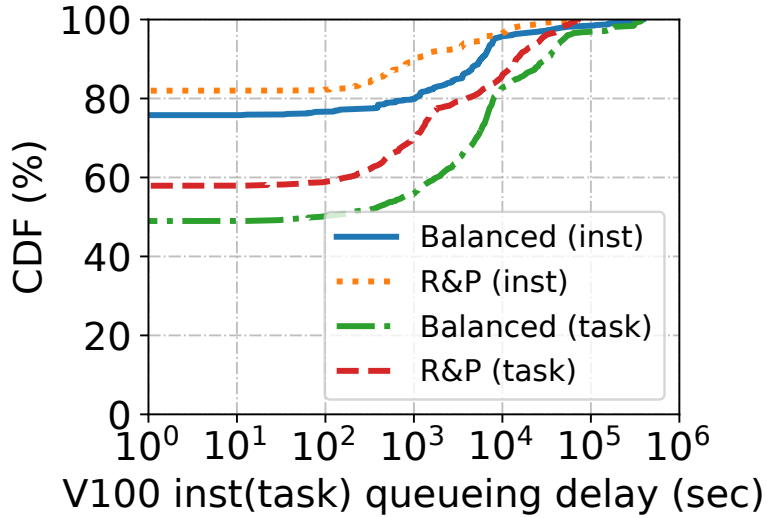
vCPU cores per GPU	All nodes	8-GPU nodes	2-GPU nodes
Machine specs	23.2	12.0	38.1
Instance requests	21.4	22.8	18.1



(a) 8-Misc-GPU Nodes (b) 8-V100-GPU Nodes (c) 2-P100-GPU Nodes (d) 2-T4-GPU Nodes

The Deployed Scheduling Policy

- Reserving-and-packing
  - Reserves high-end GPUs for high-GPU tasks
  - Packs other workloads to less-advanced GPUs
- Load-balancing
  - Assigns instances to nodes with low allocation rate



- Our scheduler prioritizes reserving-and-packing over load-balancing
  - Avoids extremely long latency for multi-GPU training jobs.
  - Simulation: V100 instances wait 68% shorter time in avg. with R&P than Balanced.

Takeaways

- A majority of tasks have gang-scheduled instances, mostly small in GPU
- GPU sharing and duration prediction of recurring tasks can help
- CPU could be the bottleneck, esp. under imbalanced scheduling

Open problems in GPU cloud

- Reduce GPU fragmentation
- GPU virtualization and GPU pooling
- Efficiency for prevalent domain applications (e.g., LLMs)

…

Credits

- Some slides are adapted from course slides of CSE291 in UCSD
- Some slides are adapted from course slides of CS 250B in UCI
- Q. Weng, W. Xiao, Y. Yu, et al., MLaaS in the Wild: Workload Analysis and Scheduling in Large-Scale Heterogeneous GPU Clusters. In USENIX NSDI, 2022.