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Optimizing Facebook AI Workloads for NVIDIA GPUs

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Facebook AI Infrastructure

S9866

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NVIDIA GPUs at Facebook

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Data-Driven Efficiency

You can’t improve what you can’t measure

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Issues and Solutions

Commonly observed reasons for poor utilization and how to address them

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NVIDIA GPUs at Facebook

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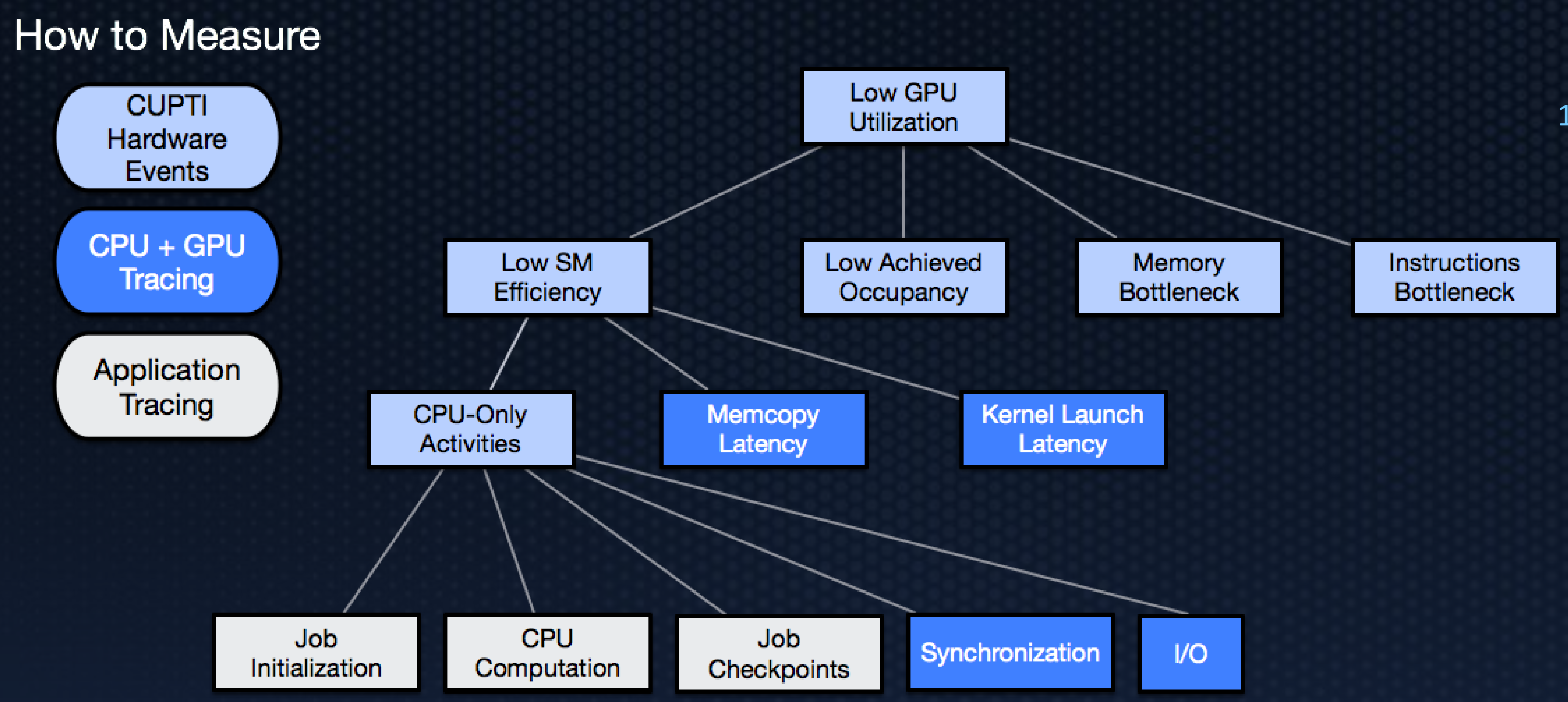

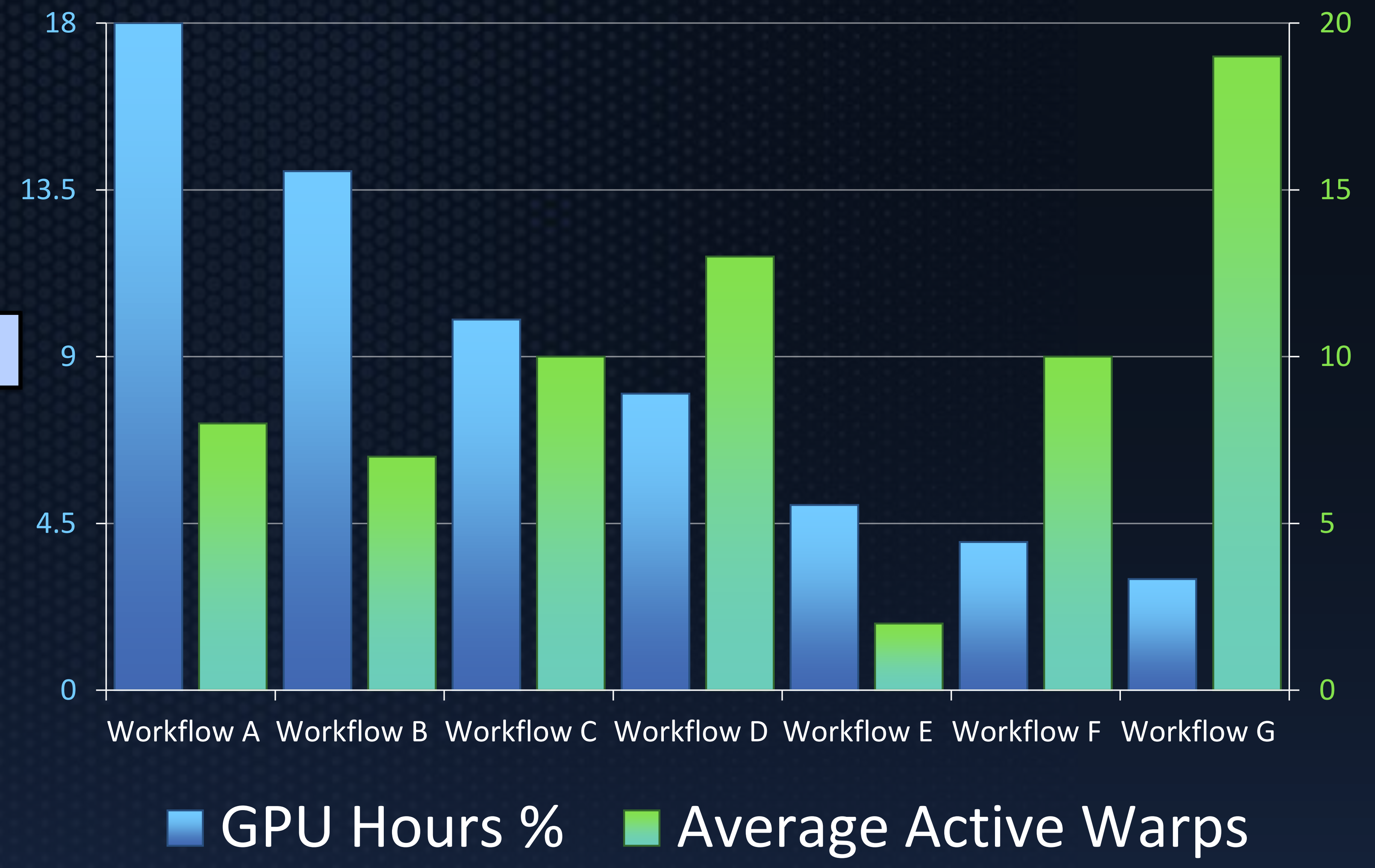

Outline

— 1

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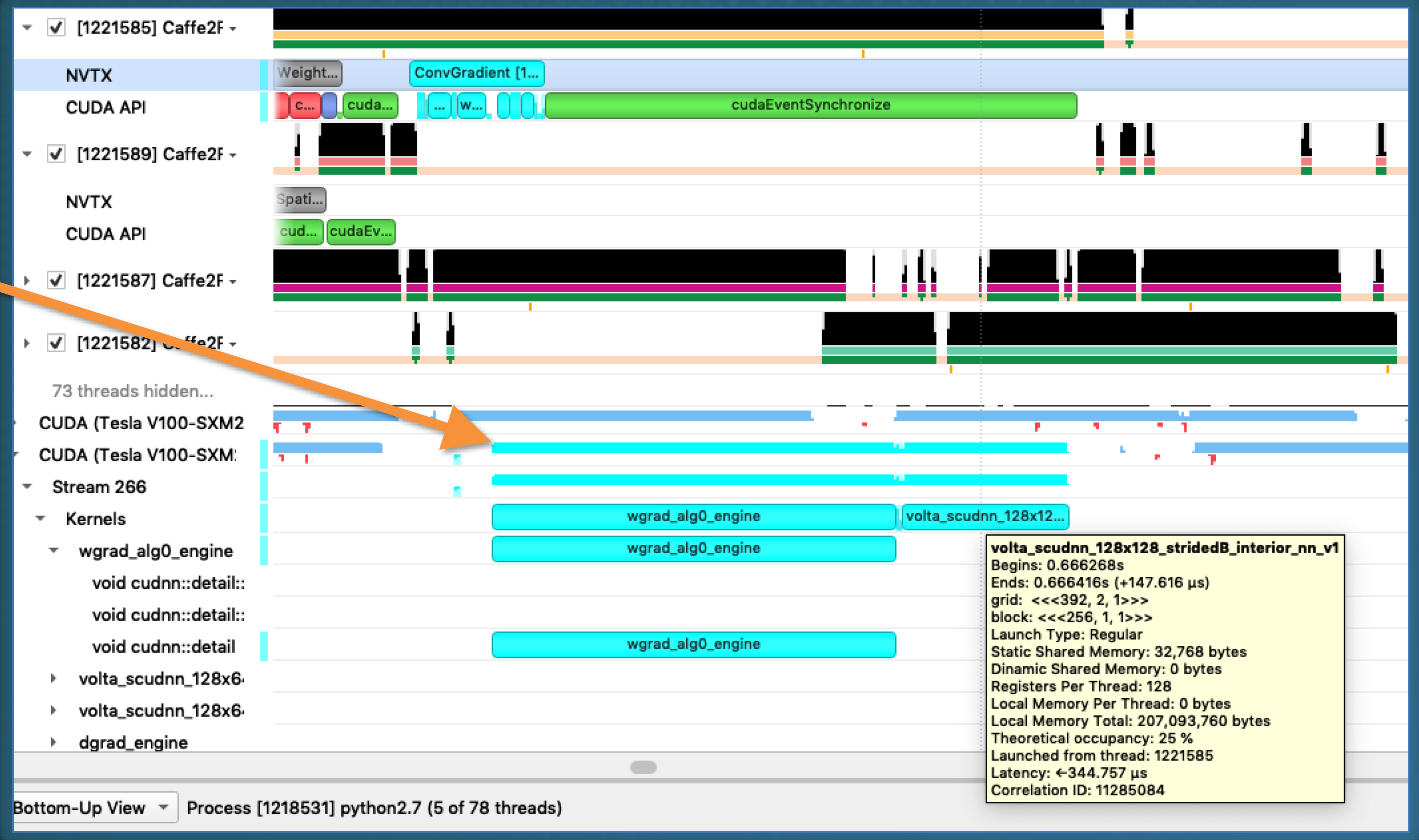
NVIDIA GPU Timeline Analysis

Understanding low utilization

Low utilization



Outline

— 1 — 2 — 3 — 4

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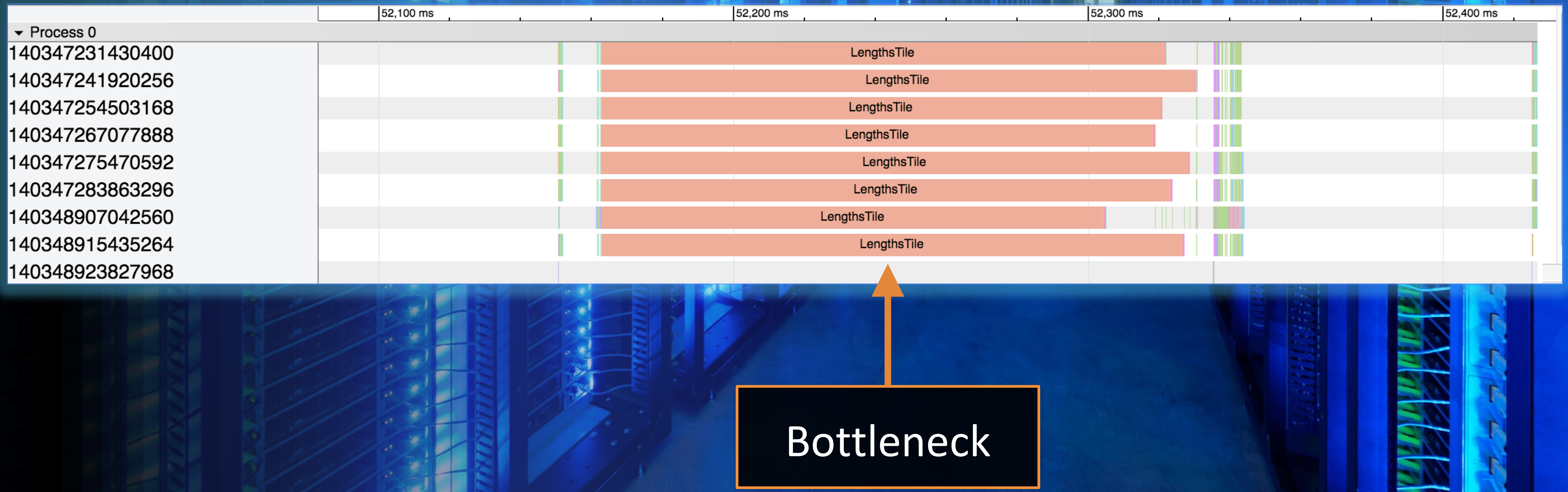
Commonly observed reasons for poor utilization and how to address them



NVIDIA GPUs at Facebook

Context

Why the need for a dedicated efficiency effort

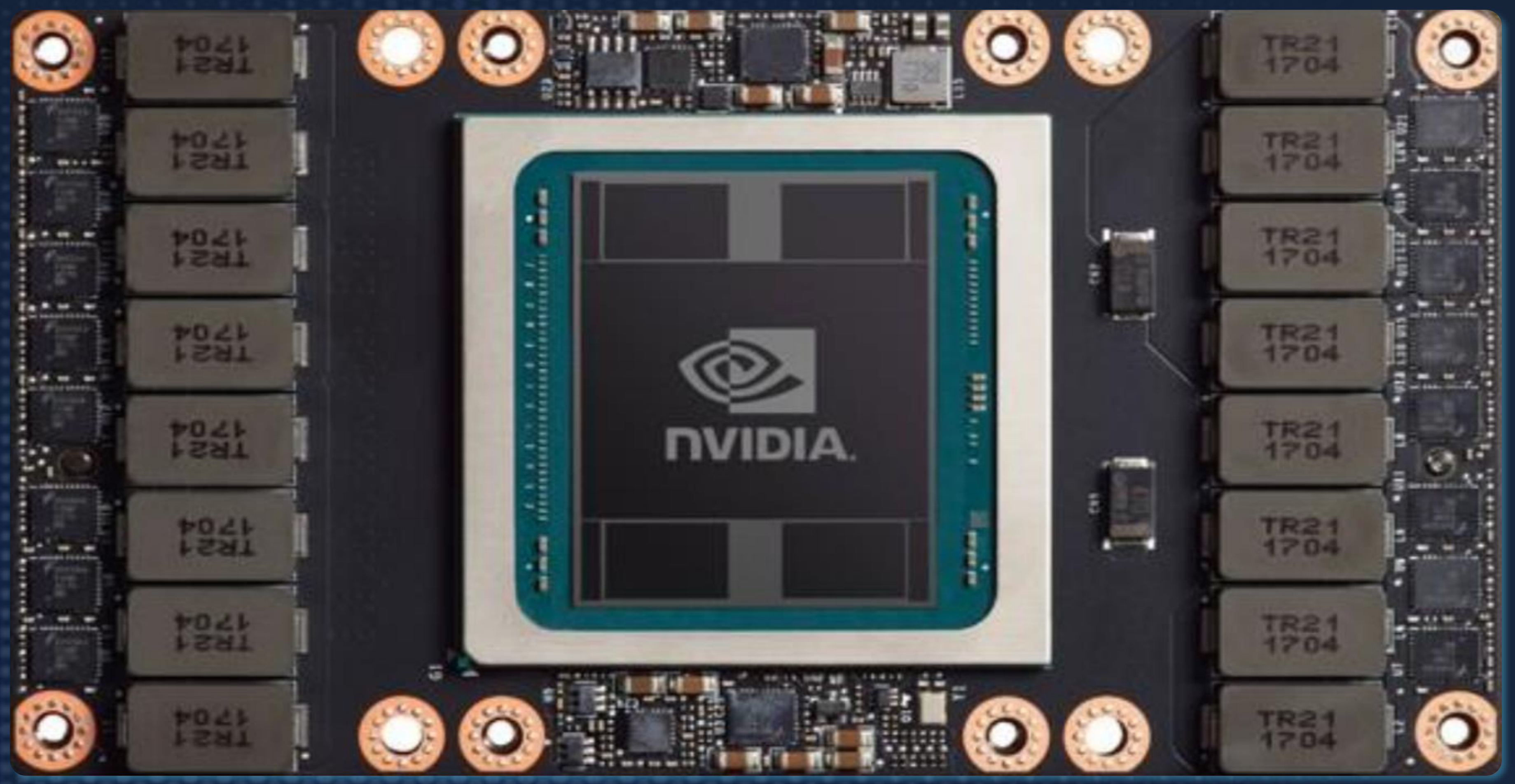
Large shared GPU pool for training

- Mainly Pascal and Volta GPUs, 8 per server
- CUDA 9 (soon 10)
- Mix of CUDA libraries (cuDNN, cuBLAS, …) & custom kernels

Various users across several teams

- Their own distinct use cases, changes over time
- Computer vision, speech, translation and many more
- Many machine learning experts, not as many GPU experts

Caffe2 and PyTorch 1.0 in containers



Enable GPU experts to improve efficiency across teams with minimal workload context

Data-Driven Efficiency

You can’t improve what you can’t measure

Efficiency

Efficient Algorithms

Machine learning domain experts

Domain-specific efficiency metrics

Focused on correctness, model experimentation time, and model launch time

Efficient Execution

GPU performance experts

System-centric efficiency metrics

Focused on maximizing use of resources given particular choice of algorithm

Efficiency

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Efficient Execution

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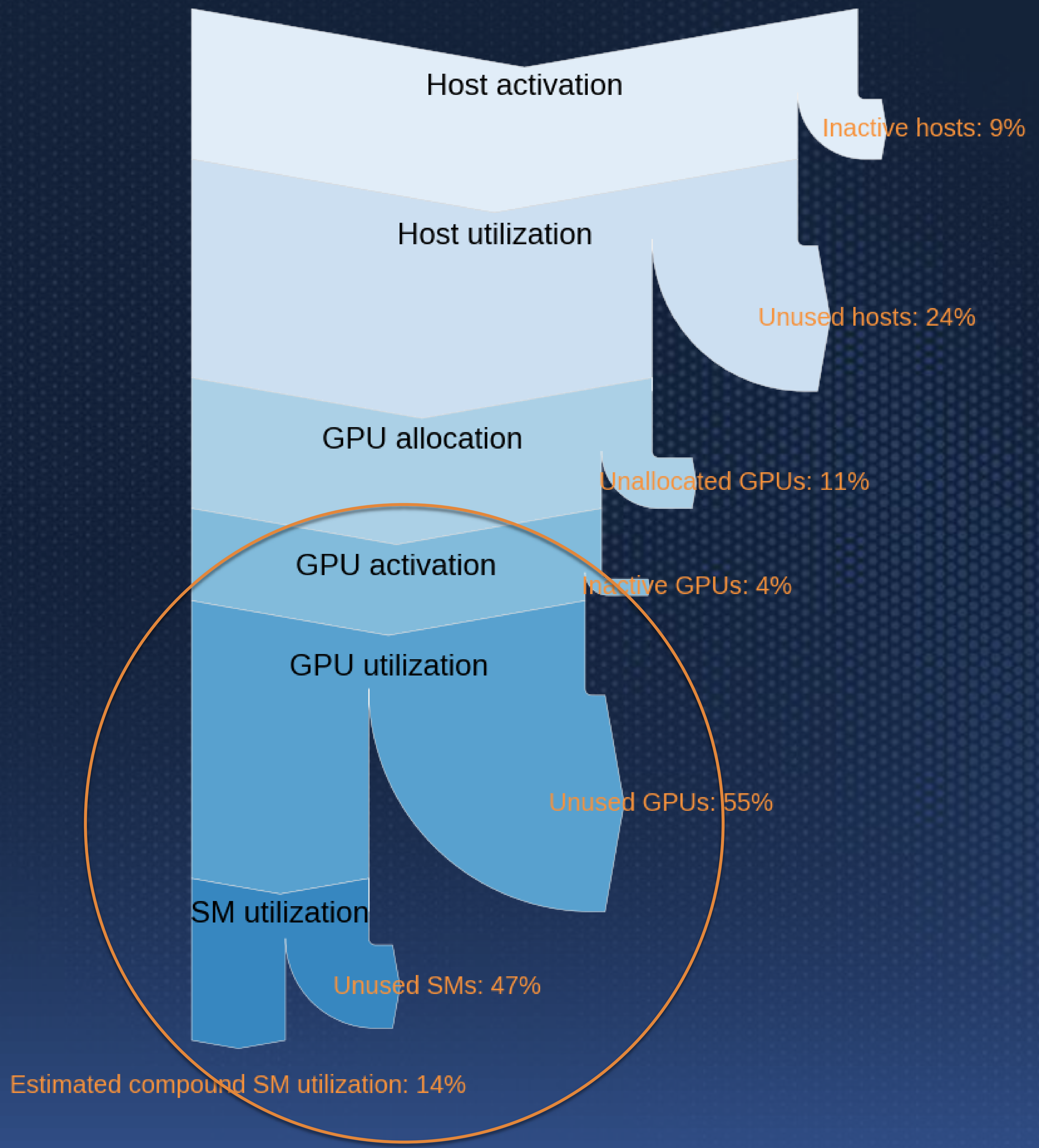
Focused on maximizing use of resources given particular choice of algorithm

This is us

Efficient Resource Utilization - A Complete Picture

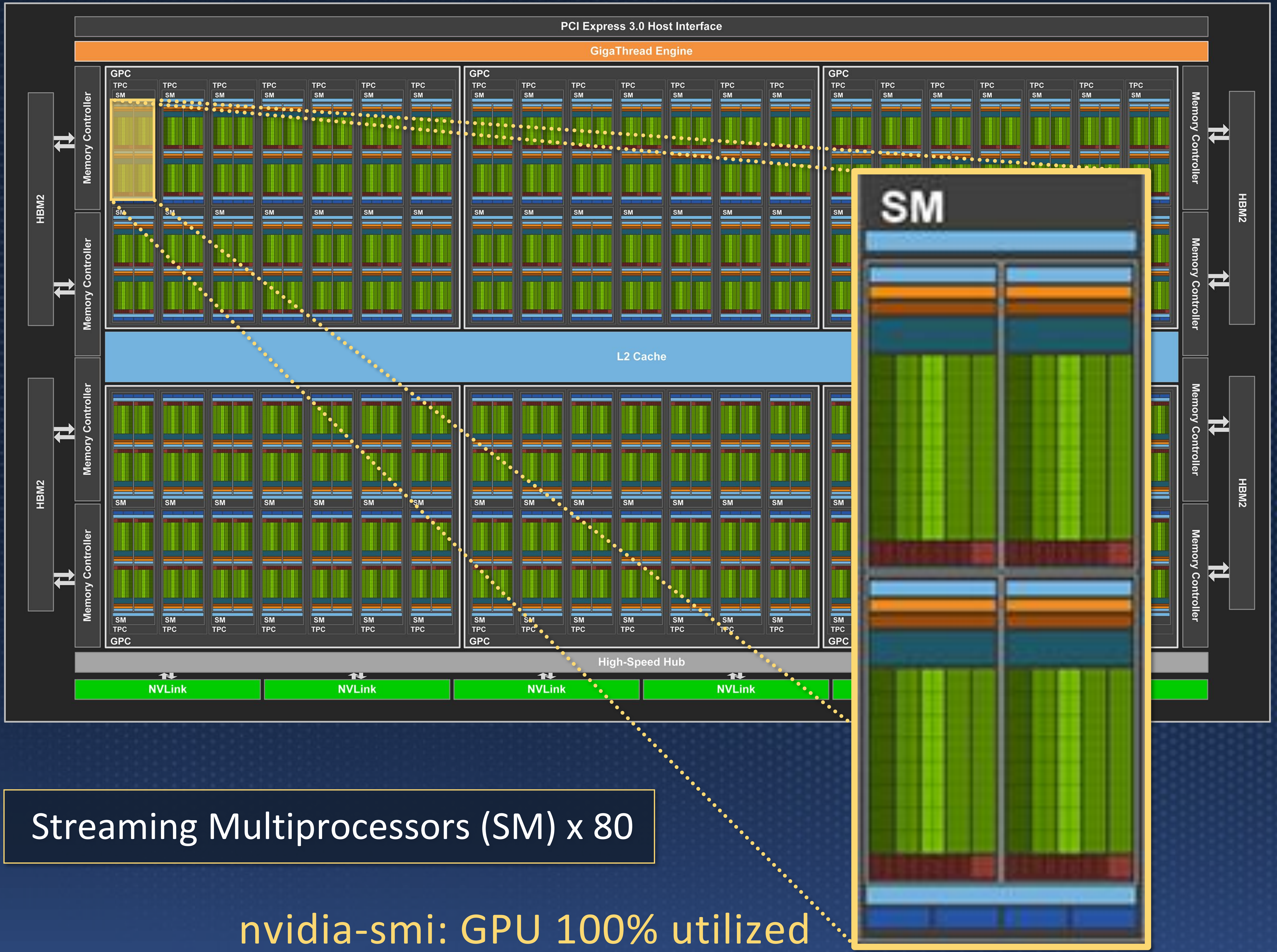


Many layers of inefficiency

The top part could fill another talk

We will focus on the portion of time when GPUs have been allocated to a job

Zooming in on NVIDIA GPU Utilization



Streaming Multiprocessors (SM) x 80

nvidia-smi: GPU 100% utilized

SM Efficiency: GPU ~1% utilized

What does utilization mean?

High-level utilization metric is coarse (GPU in use?)

Doesn’t show how many SMs / functional units in use

A kernel with a single thread running continuously will get 100% GPU utilization

Even if it only uses 0.1% of available GPU resources!

H/W Event: SM Active Cycles:

Cycles where SM had > 0 active warps

Metric: SM Efficiency:

SM Active Cycles / SM Elapsed Cycles

Zooming in on SM Utilization

What does utilization mean?

SM Efficiency does not tell the whole story

Single active warp will not utilize SM to anywhere near its potential

Active Warps:

Number of warps in-flight on an SM concurrently (0-64)

Achieved Occupancy:

Active Warps / Active Cycles

Even more detail:

*_fu_utilization - Per-functional unit utilizationInstructions per cycle (IPC)

FLOPS / peak FLOPS

CUPTI – the CUDA Profiler Tools Interface

Dynamic library for writing profiling and tracing tools

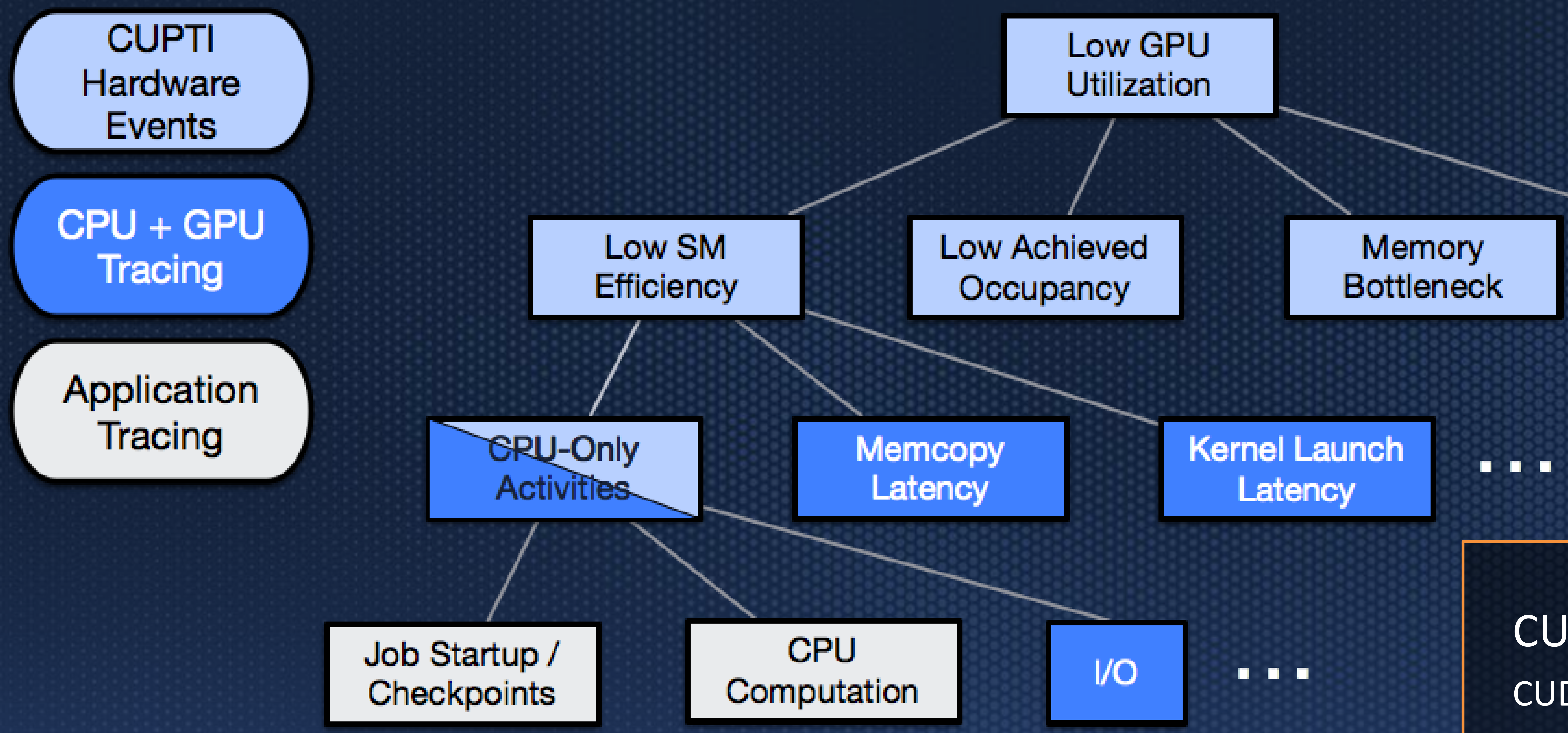
Provides multiple APIs:

- **Activity API:** GPU tracing, e.g. kernel launches, memcopies
- **Callback API:** Driver and library API tracing
- **Event API:** GPU events, e.g. cycles, instructions, active warps
- **Metric API**: Predefined metrics, e.g. SM Efficiency, Achieved Occupancy
- **Profiler API:** Kernel replays, range profiling

Library (libcupti) must be linked into application to be profiled

Contributors to Low GPU Utilization

How to Measure



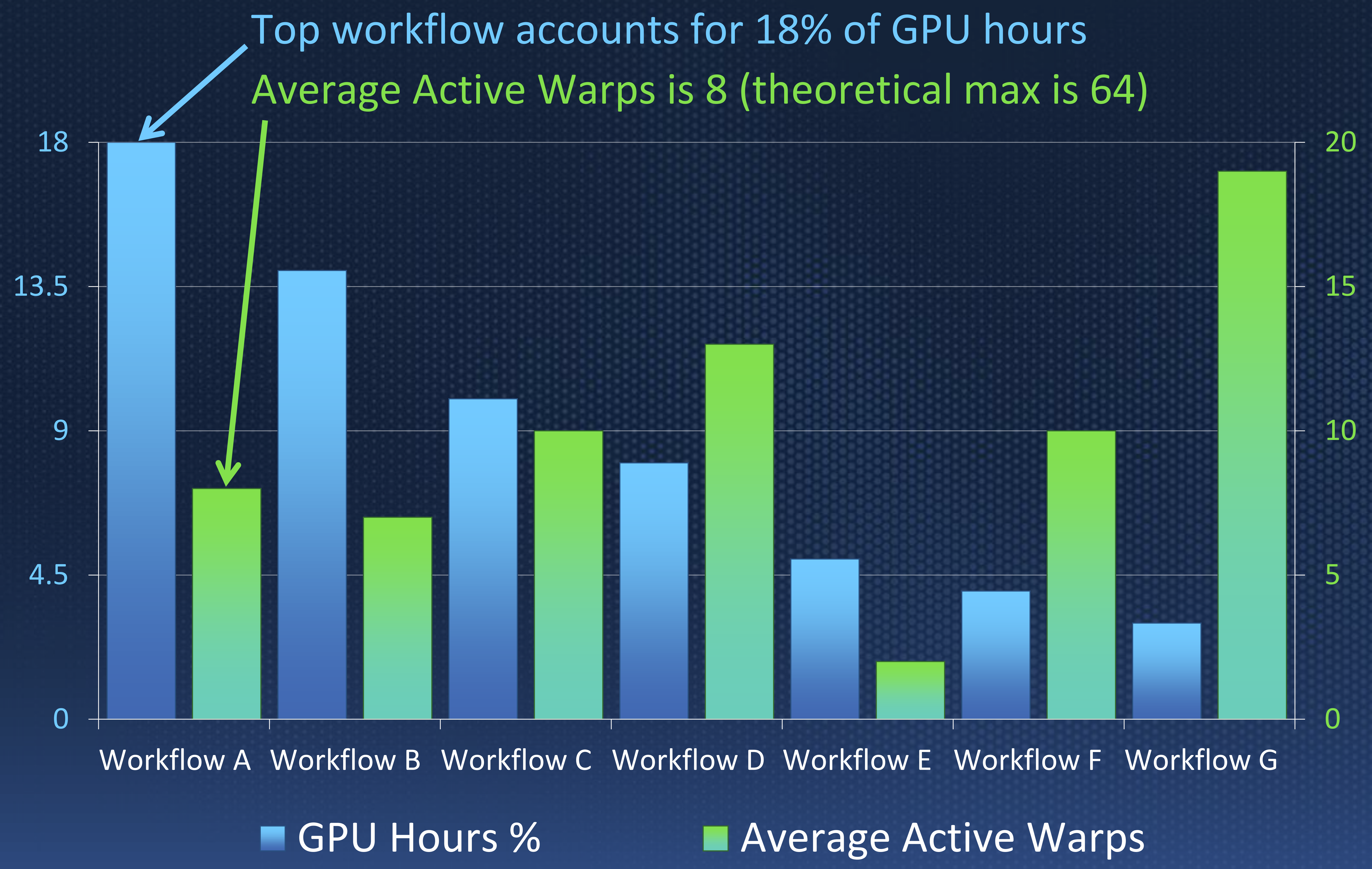
CUPTI:

CUDA Profiling Tools Interface

APIs we use:

Events API, Activities API, Callback API

%GPU Hours and Average Active Warps by Workflow



$$\textit{Average Active Warps} = \frac{\textit{Active Warps}}{\textit{Elapsed Cycles}} = \textit{SM Efficiency} \cdot \textit{Achieved Occupancy}$$

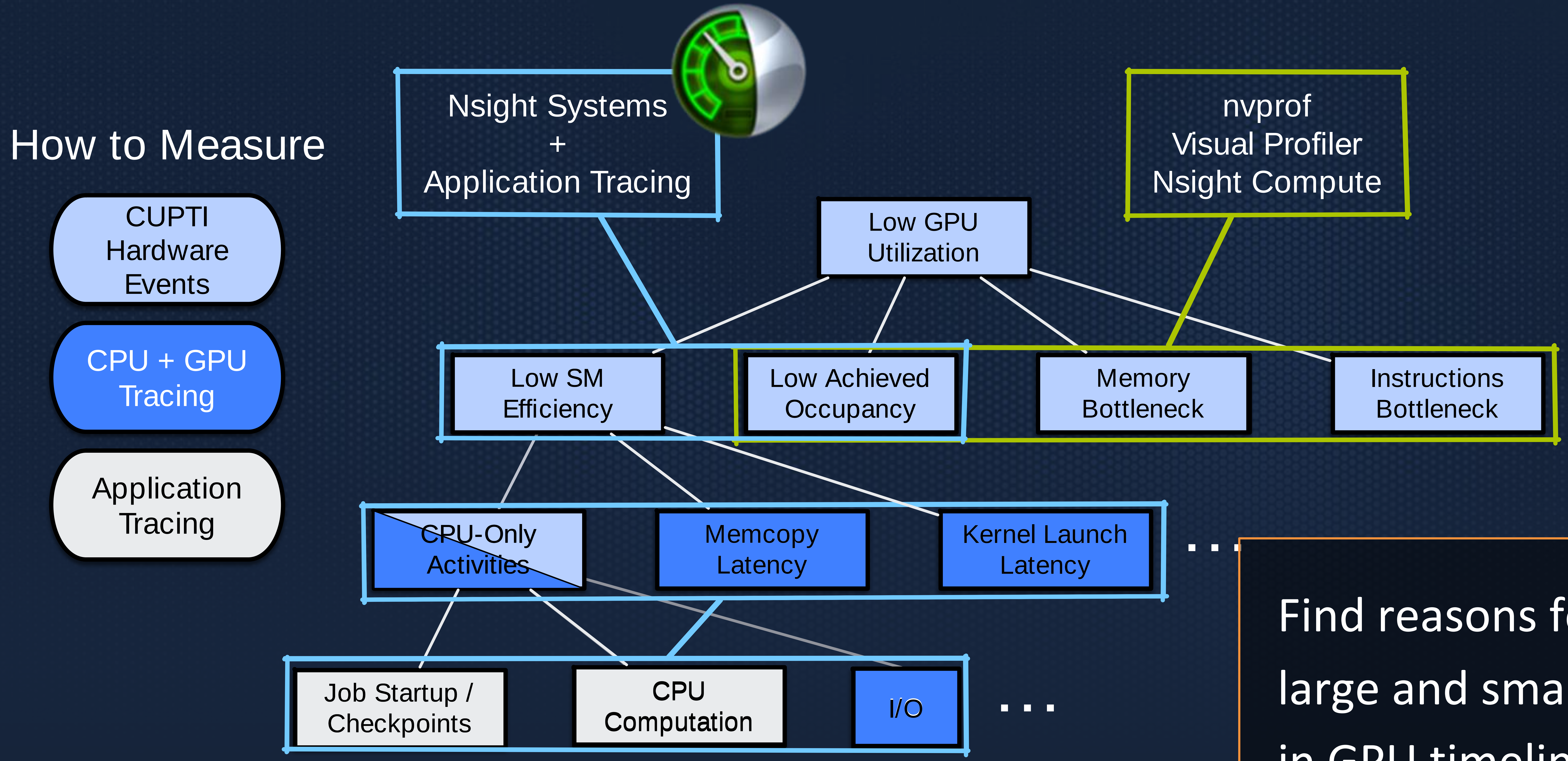
Active Warps per SM

vary from 0 to 64

"Active"

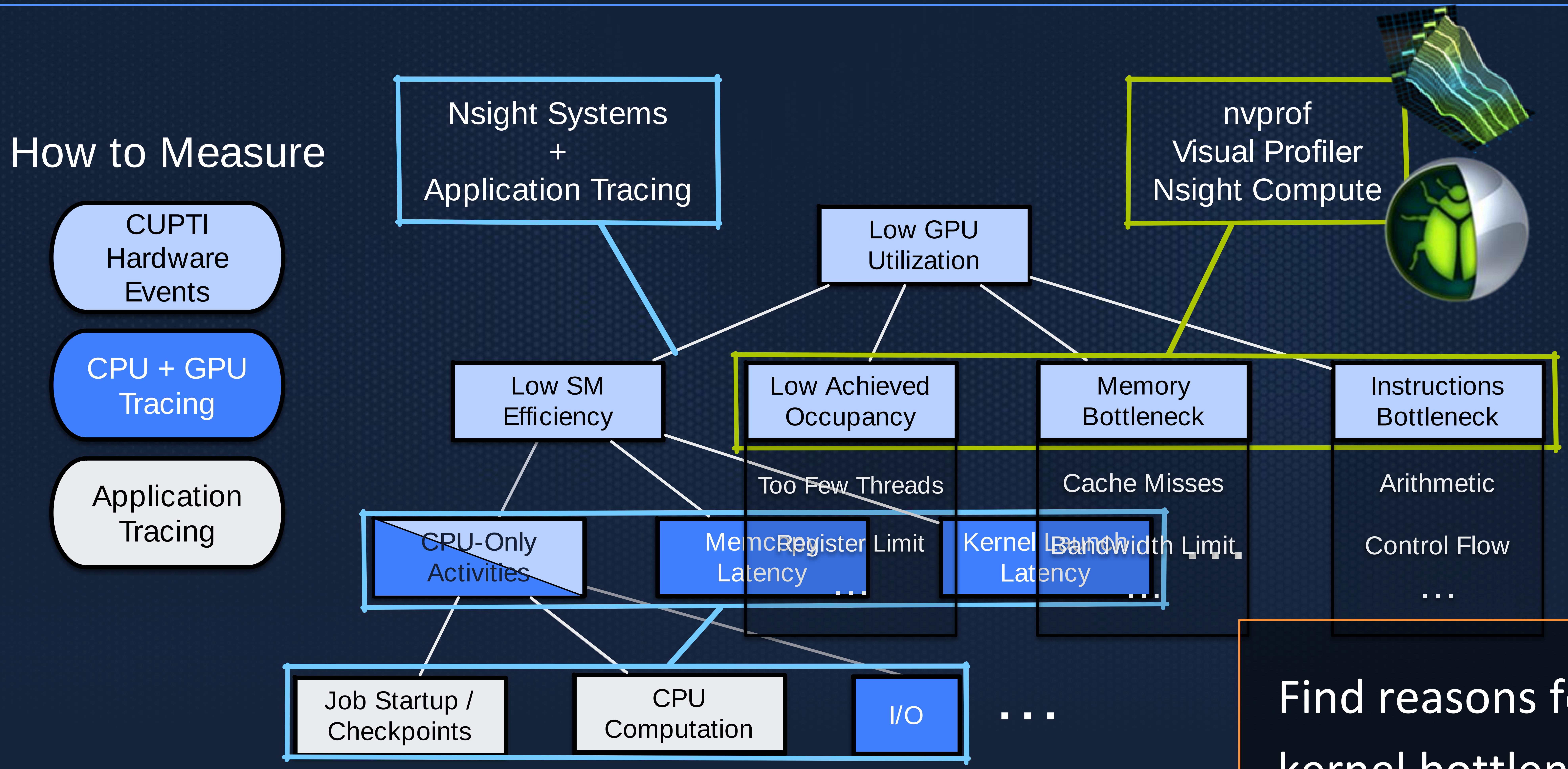
means the warp has been issued and is in-flight

Profiling Deep Dive



Find reasons for large and small gaps in GPU timeline

Profiling Deep Dive



Find reasons for GPU kernel bottlenecks

GPU Timeline Analysis

Understanding low utilization

NVIDIA Nsight Systems

Source: NVIDIA

CPU (80)
Threads (78)
[1221583] Caffe2F
NVTX
CUDA API
[1221585] Caffe2F
NVTX
CUDA API
[1221589] Caffe2F
NVTX
CUDA API
[1221587] Caffe2F
[1221582] Caffe2F
73 threads hidden...
CUDA (Tesla V100-SXM2
CUDA (Tesla V100-SX
NVIDIA Tools Extension API (NVTX)
Caffe2
Operator
WeightedSum
cu...
cuda...
Weight...
ConvGradient [1...
c...
cuda...
w...
Spati...
cud...
cudaEv...
void FacebookGPUOperatorObserver::Start(){
nvtxRangePush(opDetails_->opType);
}
void FacebookGPUOperatorObserver::Stop() {
nvtxRangePop();
}
CUDA Kernel running
Time: 0.666129s


[1221585] Caffe2F
NVTX
Weight...
ConvGradient [1...
CUDA API
c...
cuda...
w...
cudaEventSynchronize
[1221589] Caffe2F
NVTX
Spati...
CUDA API
cud...
cudaEv...
[1221587] Caffe2F
[1221582] Caffe2F
73 threads hidden...
CUDA (Tesla V100-SXM2
CUDA (Tesla V100-SXM:
Stream 266
Kernels
wgrad_alg0_engine
void cudnn::detail::
void cudnn::detail::
void cudnn::detail
volta_scudnn_128x6
volta_scudnn_128x6
dgrad_engine
volta_scudnn_128x12...
volta_scudnn_128x128_stridedB_interior_nn_v1
Begins: 0.666268s
Ends: 0.666416s (+147.616 µs)
grid: <<<392, 2, 1>>>
block: <<<256, 1, 1>>>
Launch Type: Regular
Static Shared Memory: 32,768 bytes
Dinamic Shared Memory: 0 bytes
Registers Per Thread: 128
Local Memory Per Thread: 0 bytes
Local Memory Total: 207,093,760 bytes
Theoretical occupancy: 25 %
Launched from thread: 1221585
Latency: ←344.757 µs
Correlation ID: 11285084
Bottom-Up View
Process [1218531] python2.7 (5 of 78 threads)

Fleetwide On-Demand Training

Always available tracing at the push of a button

We use our own tracing library today for the following reasons:

- Always available **on-demand** (no workload config or build mode)
- Available in **production** (at very low overhead)
- **Integrated** with job management UI and other relevant perf tools
- **Browser-based** (including visualization)

We use CUPTI Activities API to implement on-demand tracing for production workflows. In the future, we hope to expand our use of Nsight Systems.

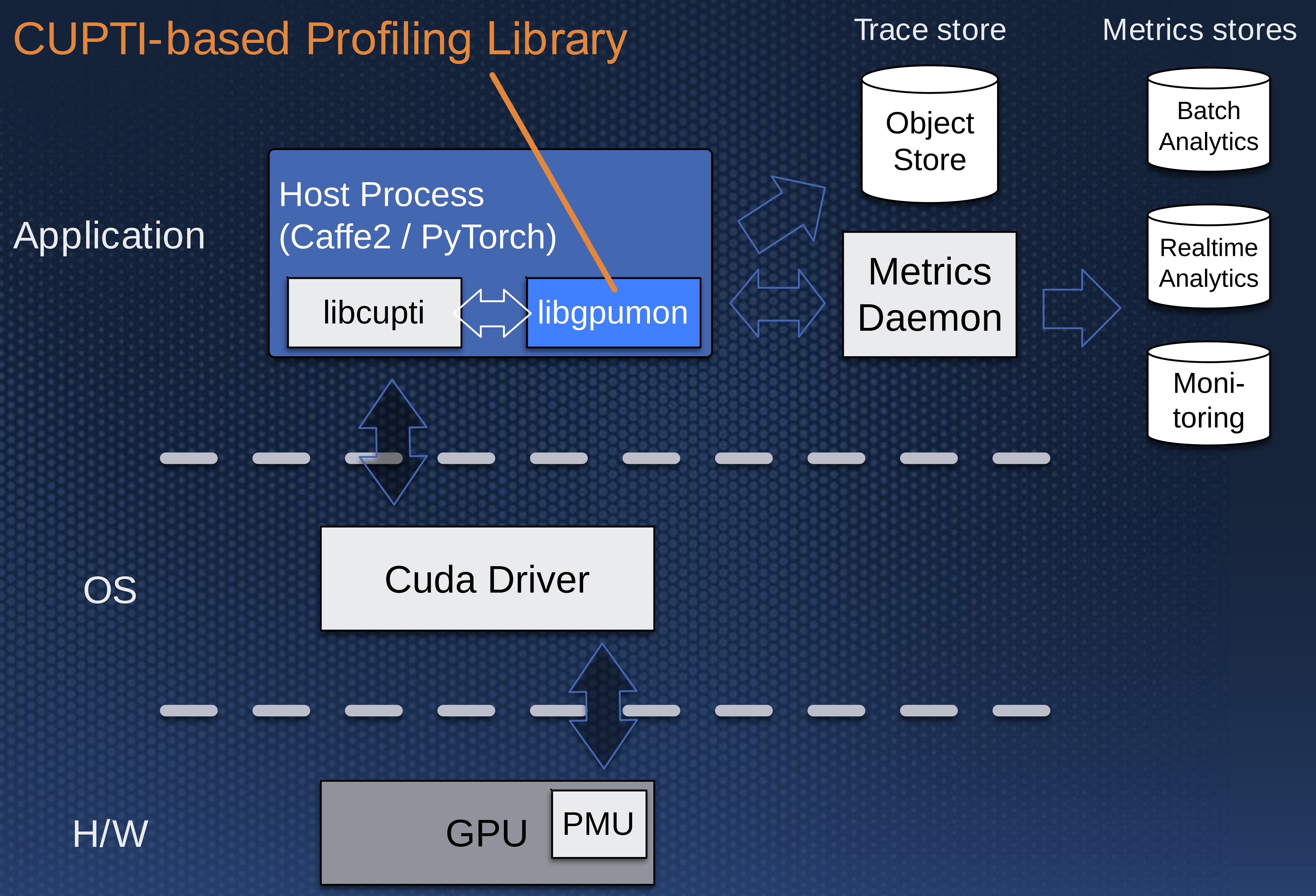
In-House Tracing Infrastructure

Visualized in Chrome

Libgpumon

Profiling and tracing library

Detailed utilization metrics and tracing on-demand for all production workflows



Telemetry and Profiling Takeaways

Visibility, top-down, full coverage

Best experience when all these integrate smoothly

Collect metrics deep and wide

- Hierarchical top-down breakdown
- Detailed utilization metrics
- Break down by team, user, package, workflow, GPU kernels etc.

Systematically address low utilization with on-demand tracing

- Nsight Systems and CUPTI Activity API for CPU-GPU interactions
- Application level tracing for big picture

Target frequently used GPU kernels with nvprof and Nsight Compute

- What to target: Use periodic tracing to rank kernels across fleet

Issues and Solutions

Commonly observed reasons for poor utilization and how to address them

Fleetwide Performance Optimization

Aggregate occupancy and resource use stats by workflow

Select the set of workflows with occupancy < 8

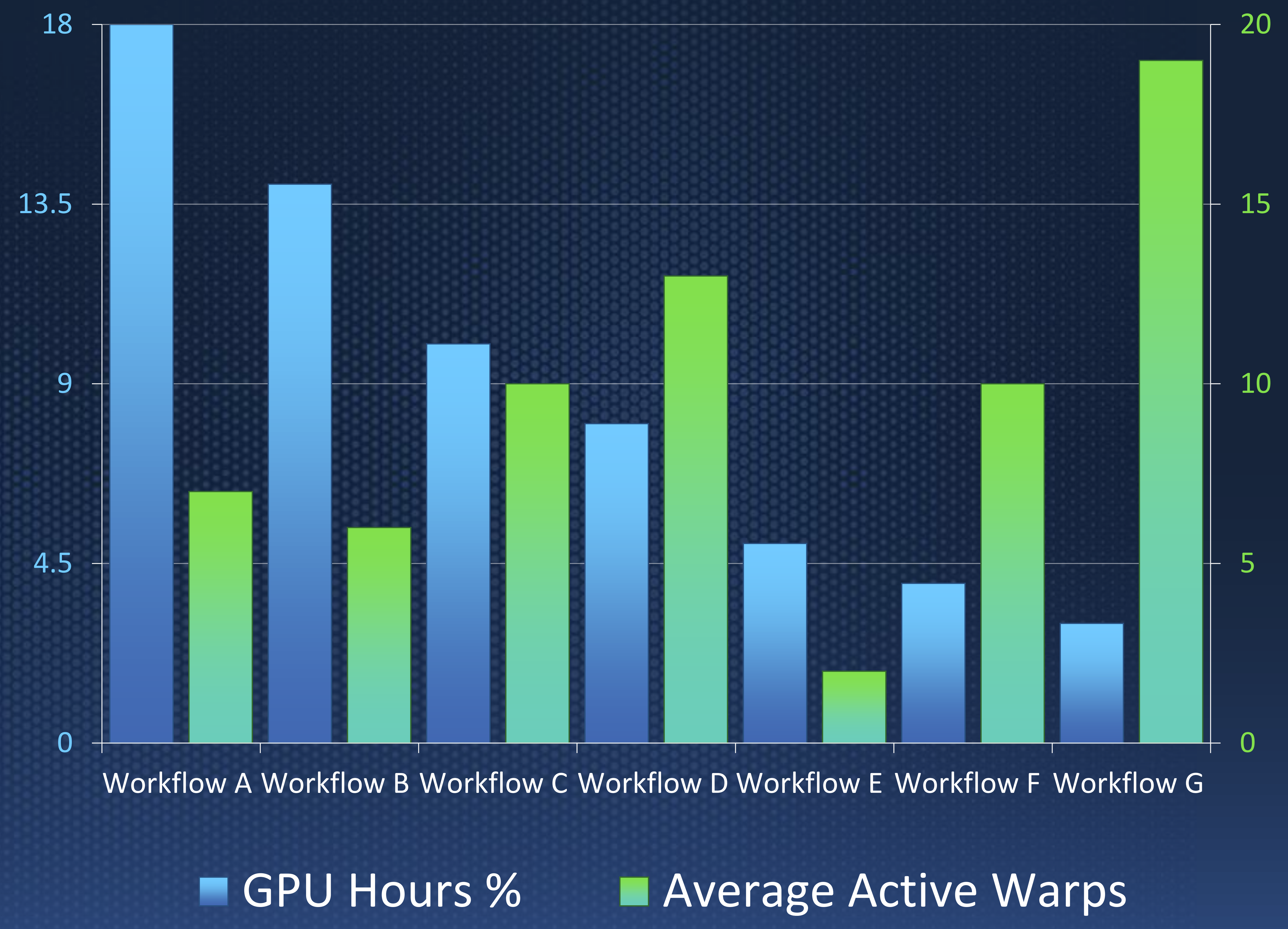
Rank resulting workflows by aggregate resources consumed

Select top workflow

Collect timeline trace

Identify and fix bottleneck

Repeat



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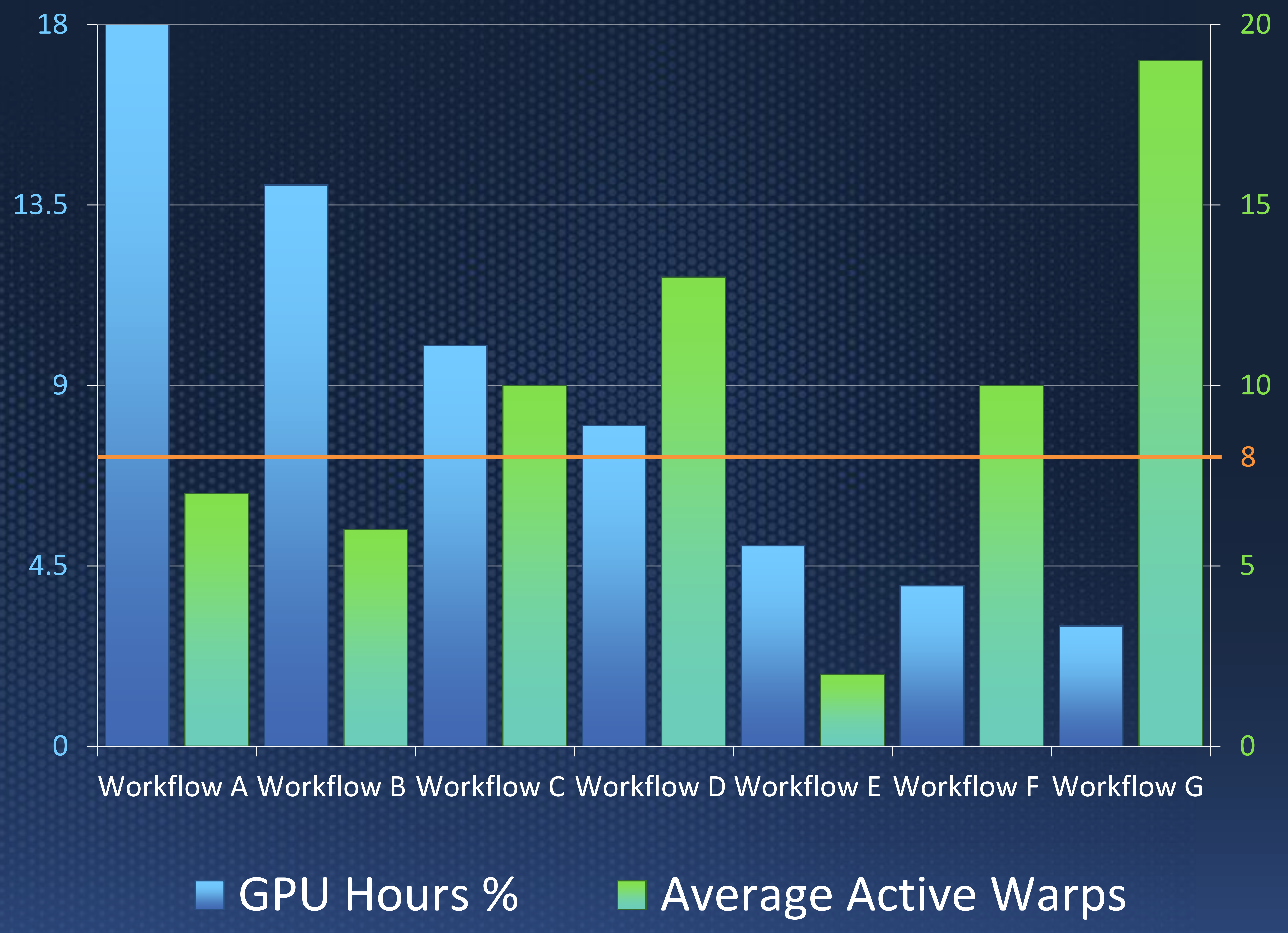

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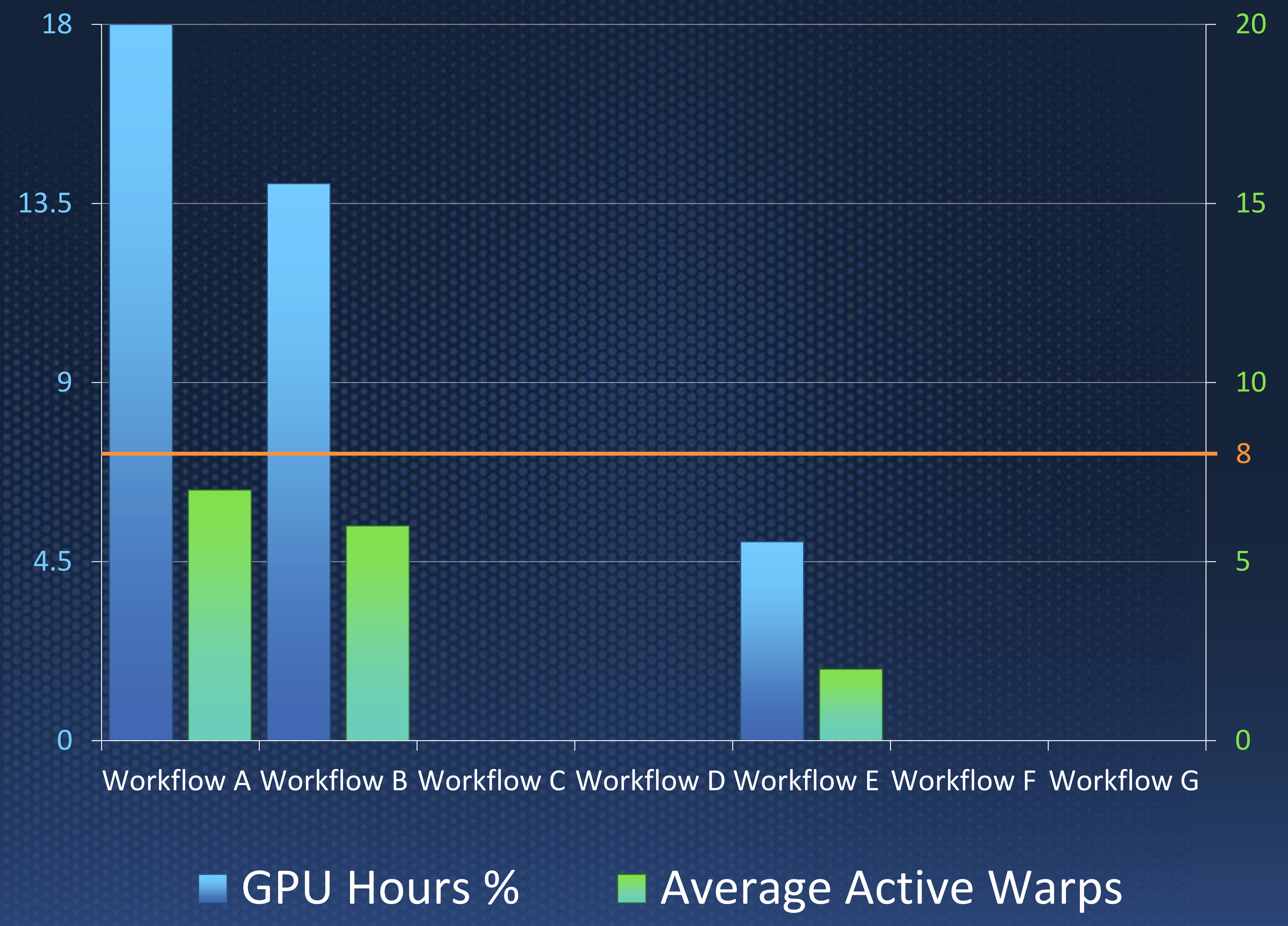

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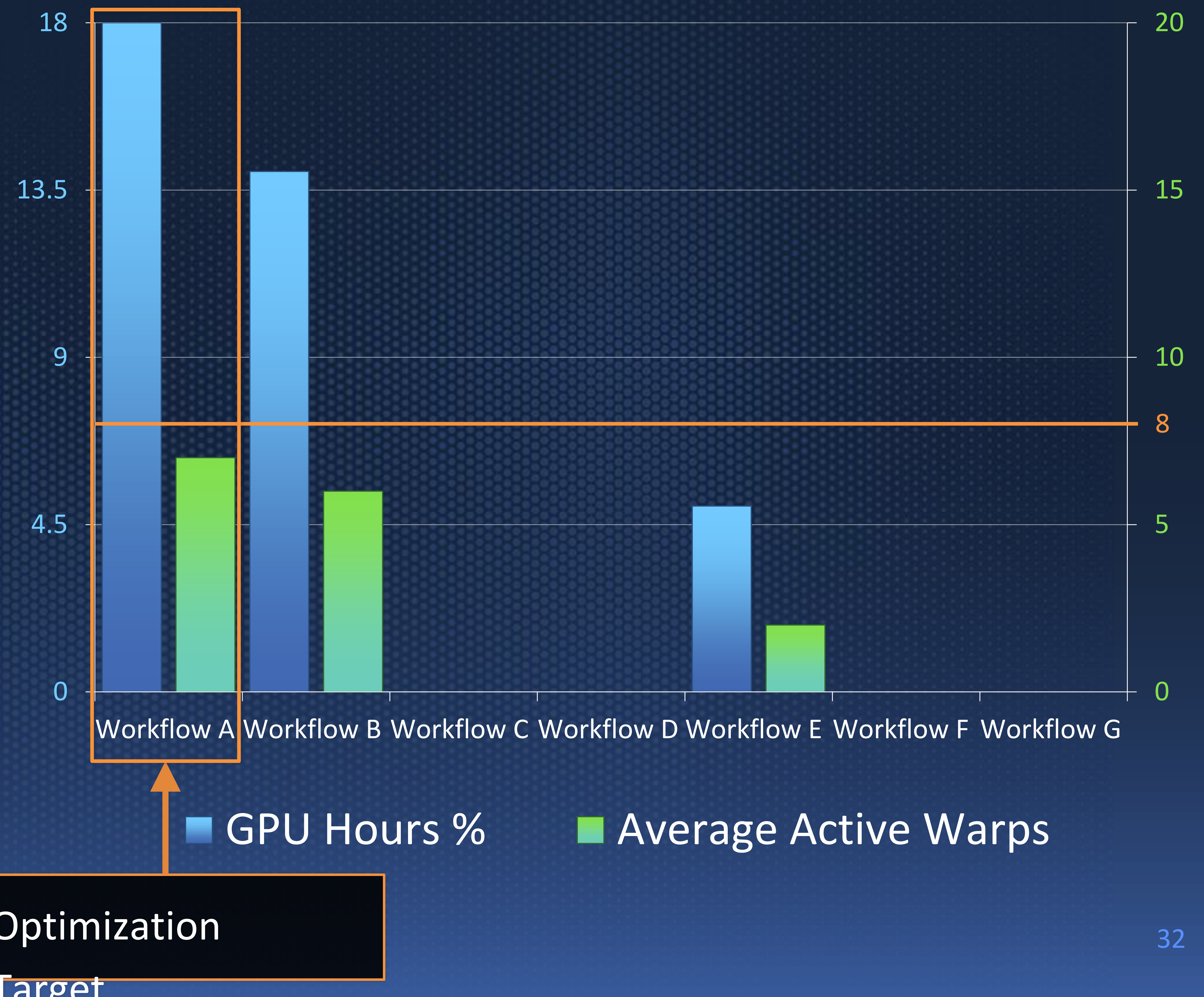

Fleetwide Performance Optimization

Aggregate occupancy and resource use stats by workflow

Select the set of workflows with occupancy < 8 (12.5% of max)

Rank resulting workflows by aggregate resources consumed

Select top workflow

Collect timeline trace

Identify and fix bottleneck

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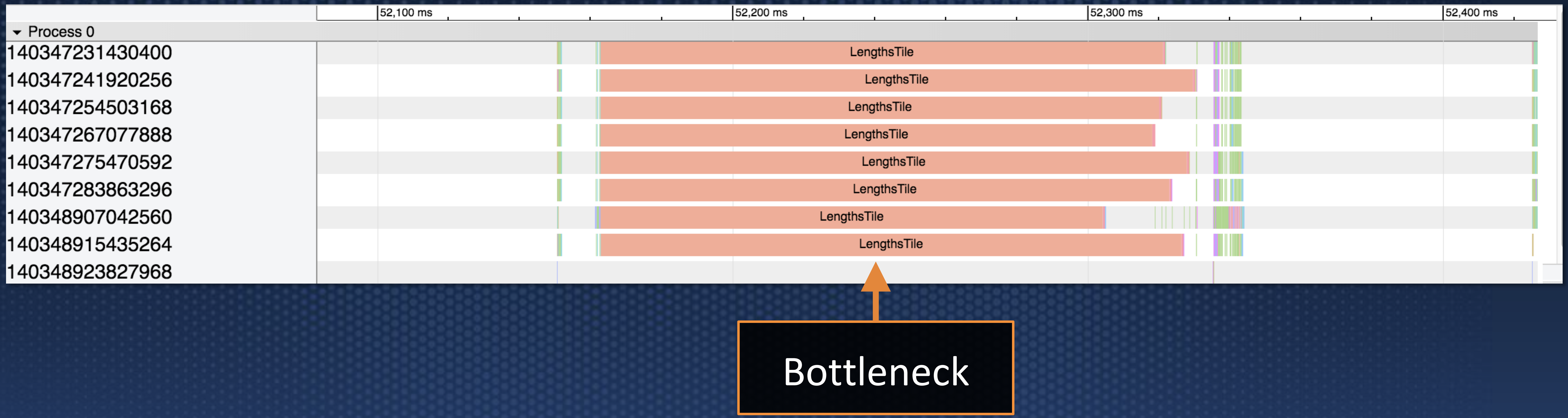
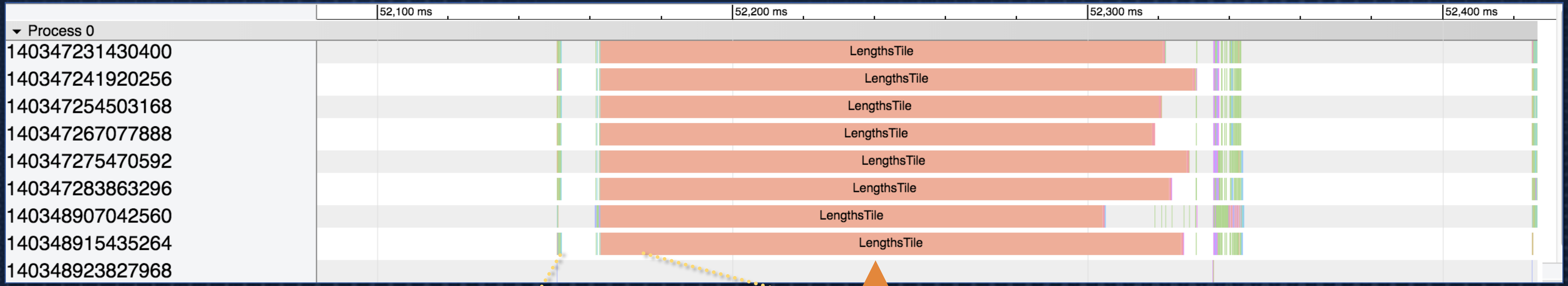


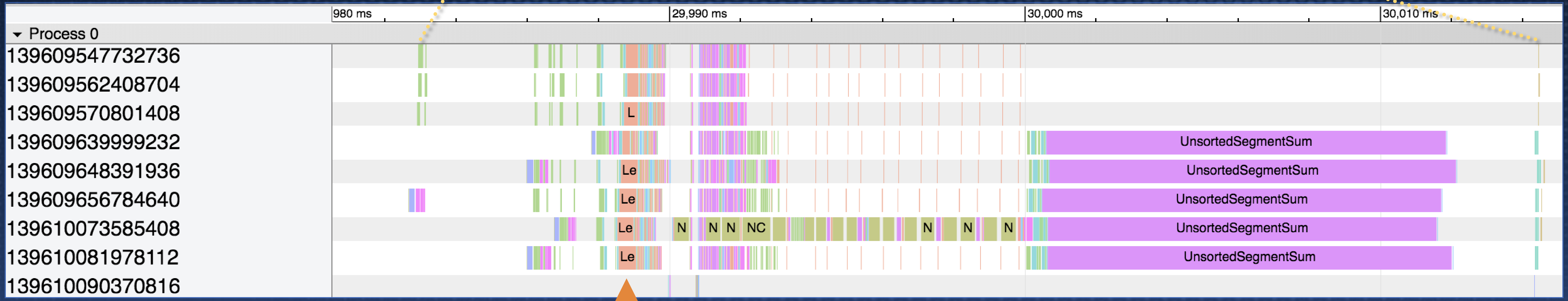
Fleetwide Performance Optimization

Before optimization



Bottleneck

After optimization



200x operator speedup

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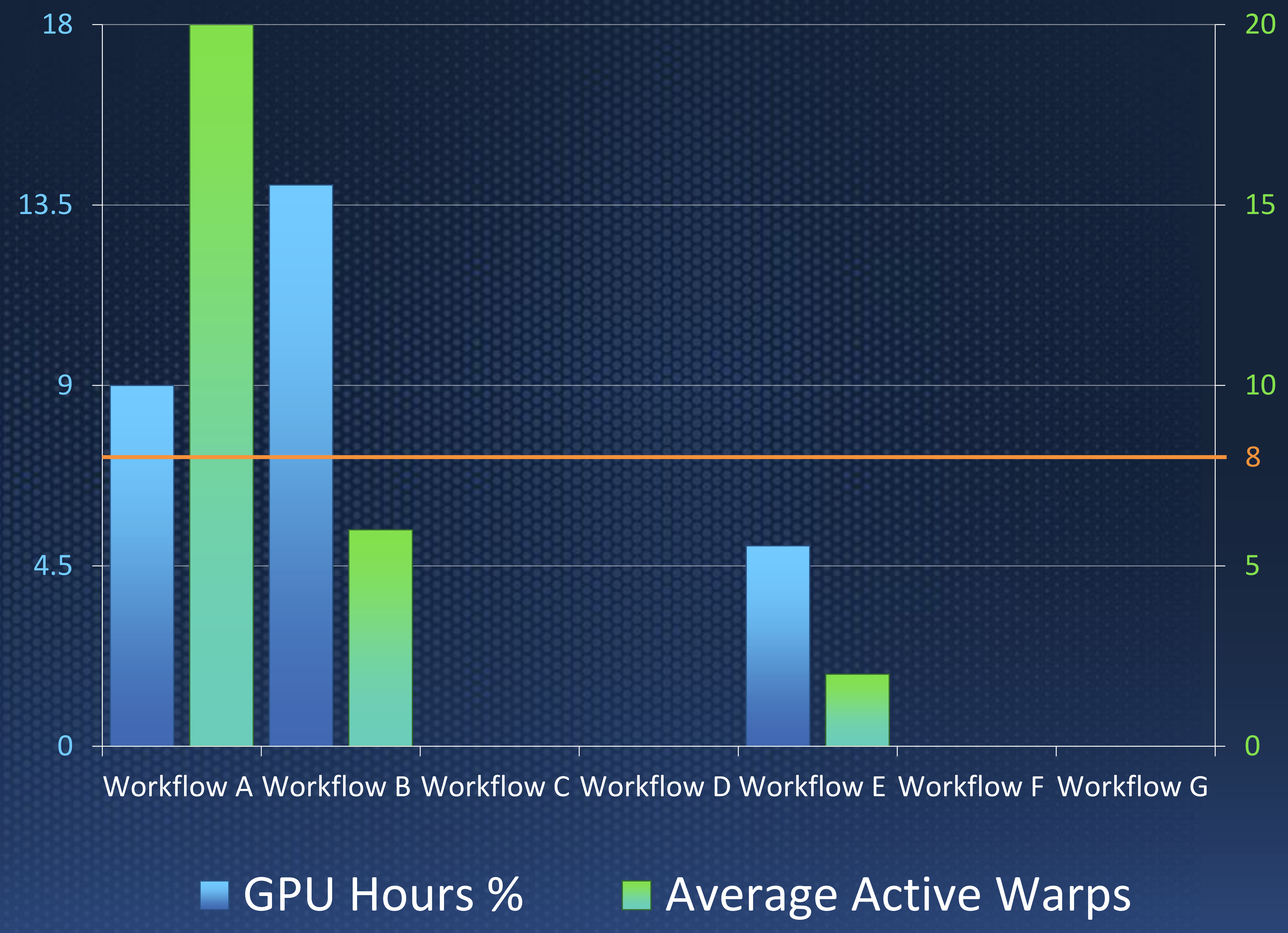

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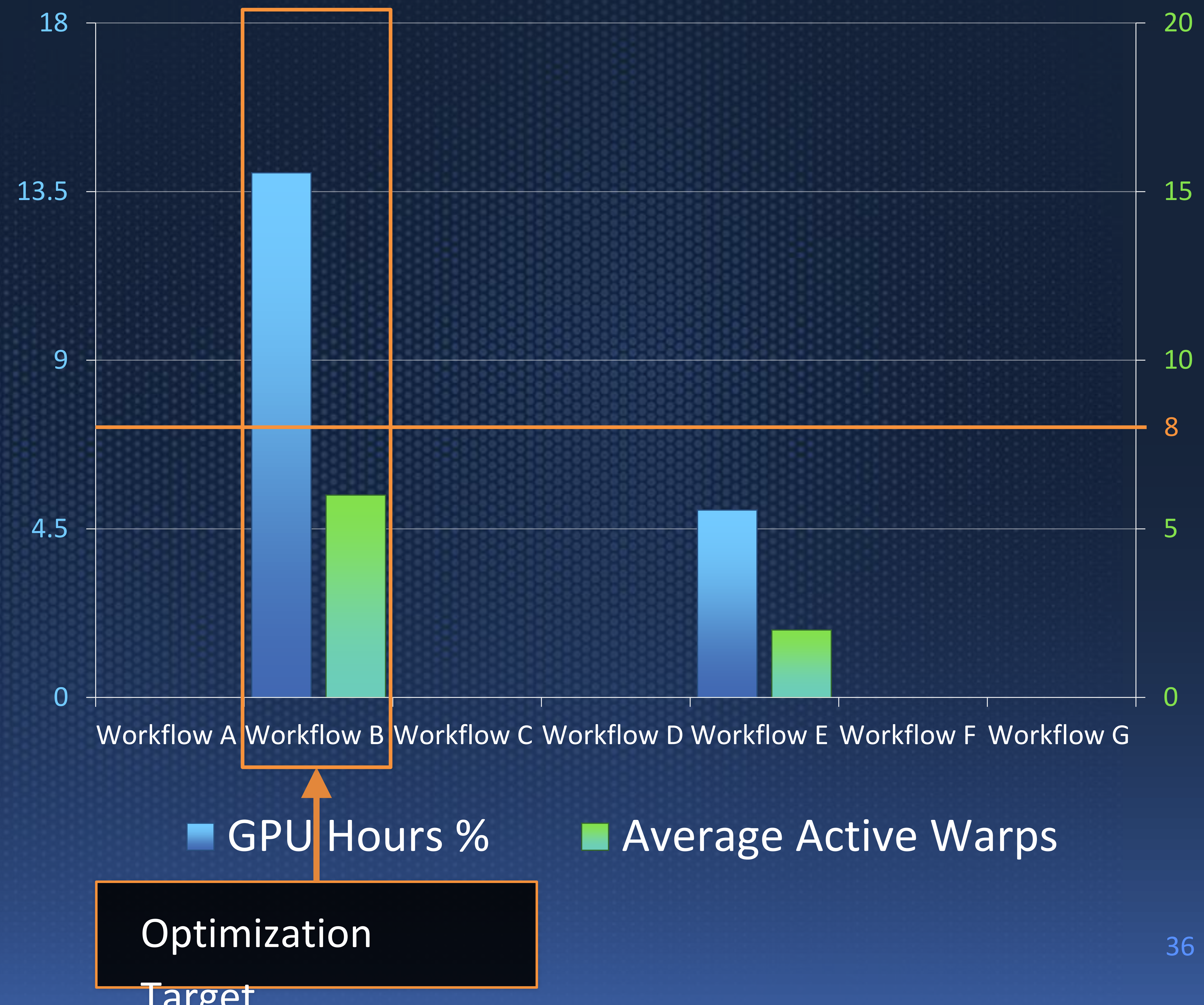
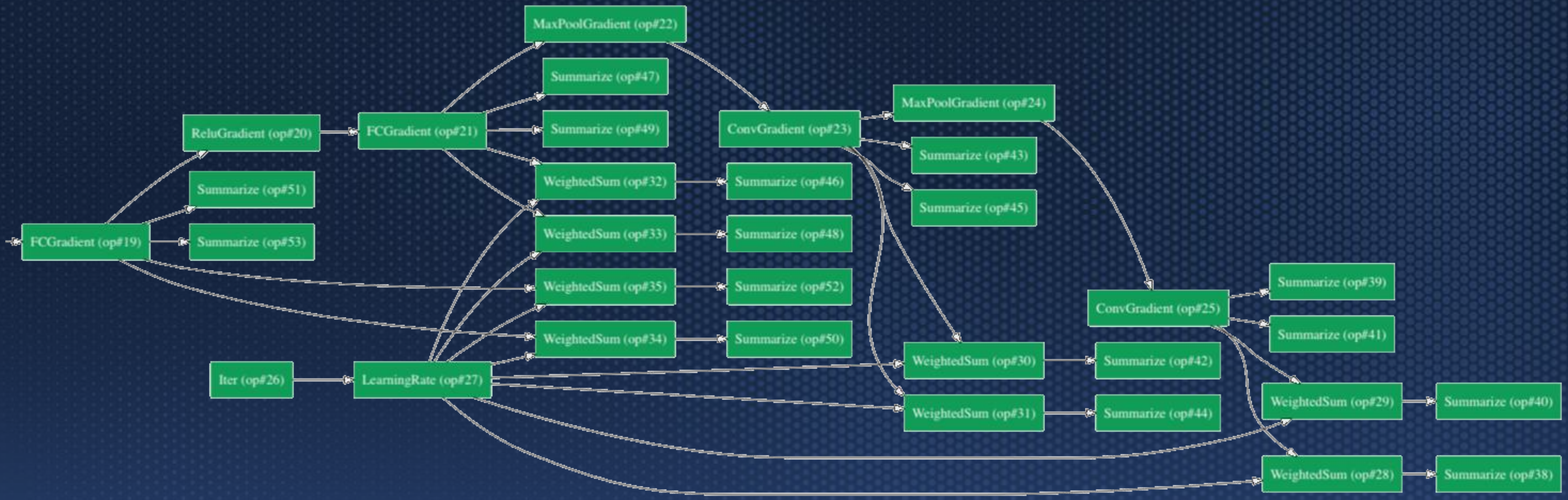


A One-Minute Primer to Caffe2 and PyTorch

The vast majority of GPUs at FB are used for training machine learning models using Caffe2 or PyTorch

Caffe2 and PyTorch are open source deep learning platforms that facilitate expression, training, and inference of neural network models

In Caffe2 models are expressed by defining a graph for the neural network whose nodes are operators



PyTorch supports eager mode in which the graph is expressed implicitly through control flow in an imperative program

In practice the graph can usually be automatically generated to facilitate optimizations and tracing support similar to Caffe2

API and Platform Design Choices that Improve Performance

Caffe2 platform support

For translating loops into kernel code with proper block sizes; helps improve SM utilization and occupancy

Dependency-tracking system for operators

Performs memory copies into and out of GPU memory generally only when required

Automatic fusion of operators

Prevents unnecessary copies and kernel invocations

CUDA's similarity to C++

Reduces the barrier of entry for writing GPU code

Causes of Performance Issues in GPU Code

A case of mistaken assumptions

GPUs differ significantly from CPUs

- Much higher number of execution units
- Data-parallel code and execution
- Lower single-thread performance
- Accelerator managed by the CPU

Each difference requires an adaptation in code patterns for good performance

Most new GPU programmers are experienced CPU programmers

- They often use common CPU practices and coding patterns, which may not work well on the GPU

Patterns of GPU Misuse

Most GPU performance issues result from a **Blind Spot** or mistaken assumptions about key GPU architectural aspects

As a result, the programmer writes **Anti-Pattern** code that performs poorly

Often, a simple **Solution** is available to a whole class of problems

Issue 1: CPU to GPU Communication Latency

So close, yet so far away

Blind Spot: Overhead of kernel launches and cudaMemcpy is relatively high

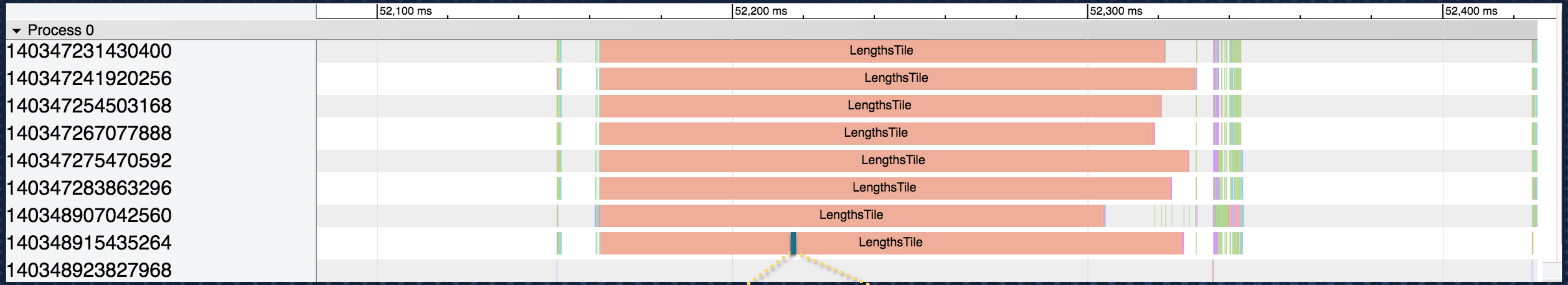
And GPUs are not designed to allow executing a large number of cudaMemcpy calls concurrently

Anti-Pattern: Code that transforms GPU data using CPU loops containing fine-grained cudaMemcpy calls

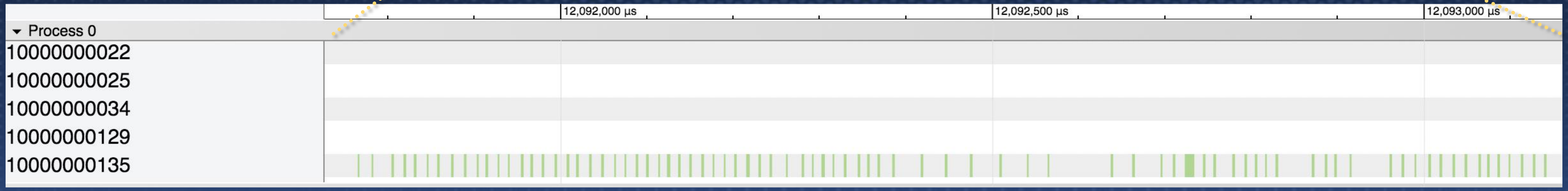
Solution: Rewrite these operations as GPU kernels that transform the data using blocks of GPU threads

Example: The Case of the 14k cudaMemcpy Calls

CPU Timeline

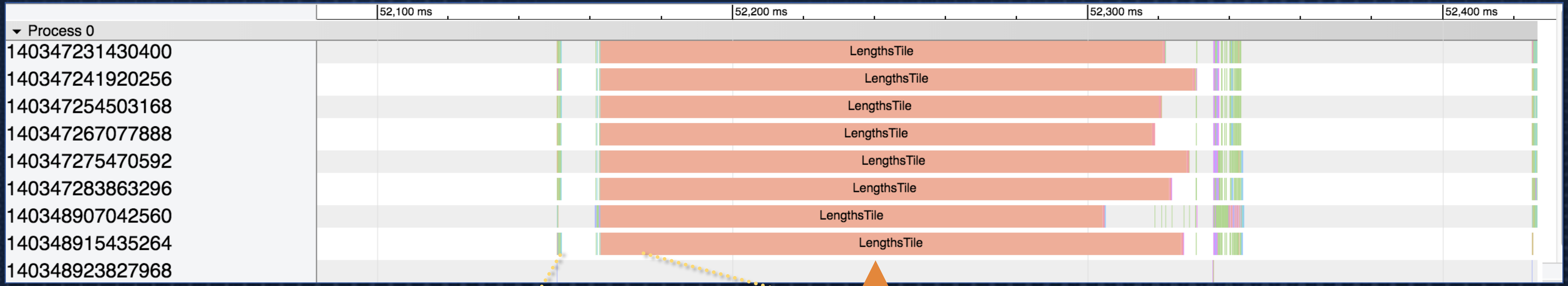


GPU Timeline Zoomed In



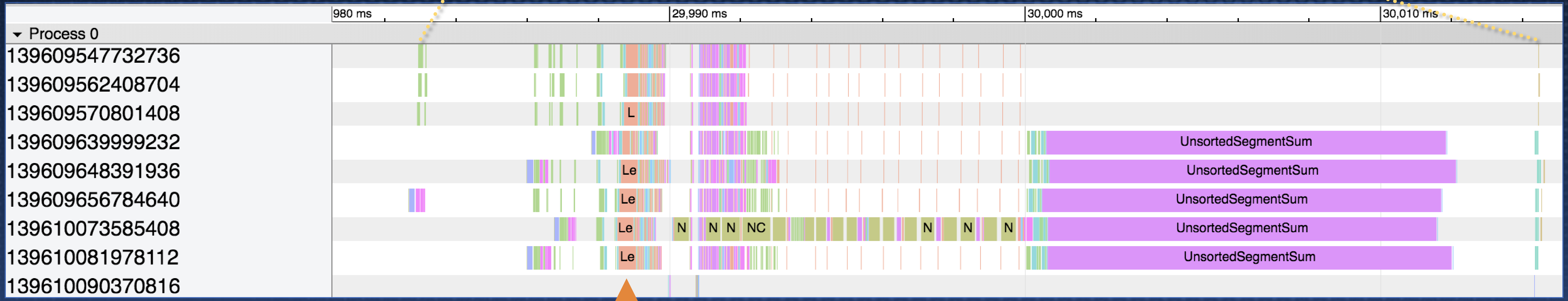
Before and After Optimization

Before optimization



Bottleneck

After optimization



200x op speedup, 3.5x workflow speedup

Issue 2: Bottlenecks at the CPU Cause High GPU Idle Time

Feeding the beast

Blind Spot: Peak throughput is much higher on GPU than on CPU

Anti-Pattern: Code that performs expensive data transformations on the CPU, causing GPU to go idle for extended time

Solution 1: Do as much as possible of the expensive work on the GPU with kernels that take advantage of the available concurrency

Solution 2: Run more threads on the CPU to concurrently prepare work for GPU execution to help feed the GPU more effectively

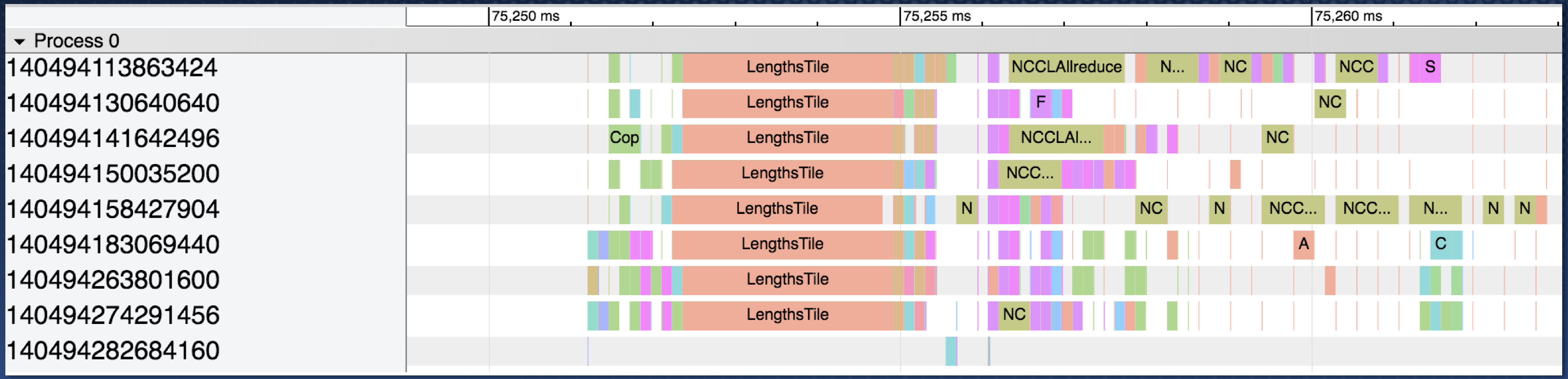
Example: The Case of the Well-Utilized CPU Threads

... and poorly utilized GPUs

A workflow used 8 CPU threads to manage the 8 GPUs on the server

CPU timeline showed good thread utilization, GPU timeline showed gaps

Increasing the number of threads on the CPU (from 8 to 64) to concurrently prepare more GPU work improved overall throughput by 40%



Issue 3: Improper Grain Size per GPU Thread

The more the merrier

Blind Spot: On the CPU, the work per thread needs to be substantial (e.g. to absorb context-switch overhead), but GPUs switch between warps of threads very efficiently, so keeping grain size very low is fine

Anti-Pattern: GPU code with too much work per thread artificially limits concurrency, yielding low block count and SM efficiency

Solution: Rewrite kernels to expose more concurrency and increase number of blocks per kernel

Issue 4: Improper Memory Access Patterns

Blind Spot: GPU memory data access patterns between threads in the same warp can affect achieved memory bandwidth by more than an order of magnitude

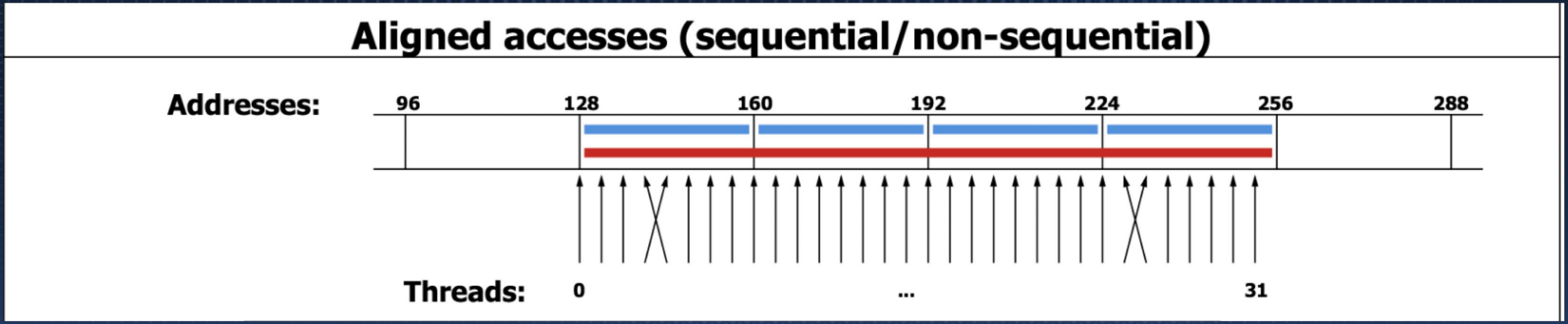
Anti-Pattern: Code with inefficient memory access patterns, where threads access different memory segments or individual threads copy large chunks of memory

Solution: Rewrite kernels to structure memory access patterns in the proper way to utilize bandwidth effectively

Proper GPU Global Memory Access Patterns

Threads access addresses in the same segments

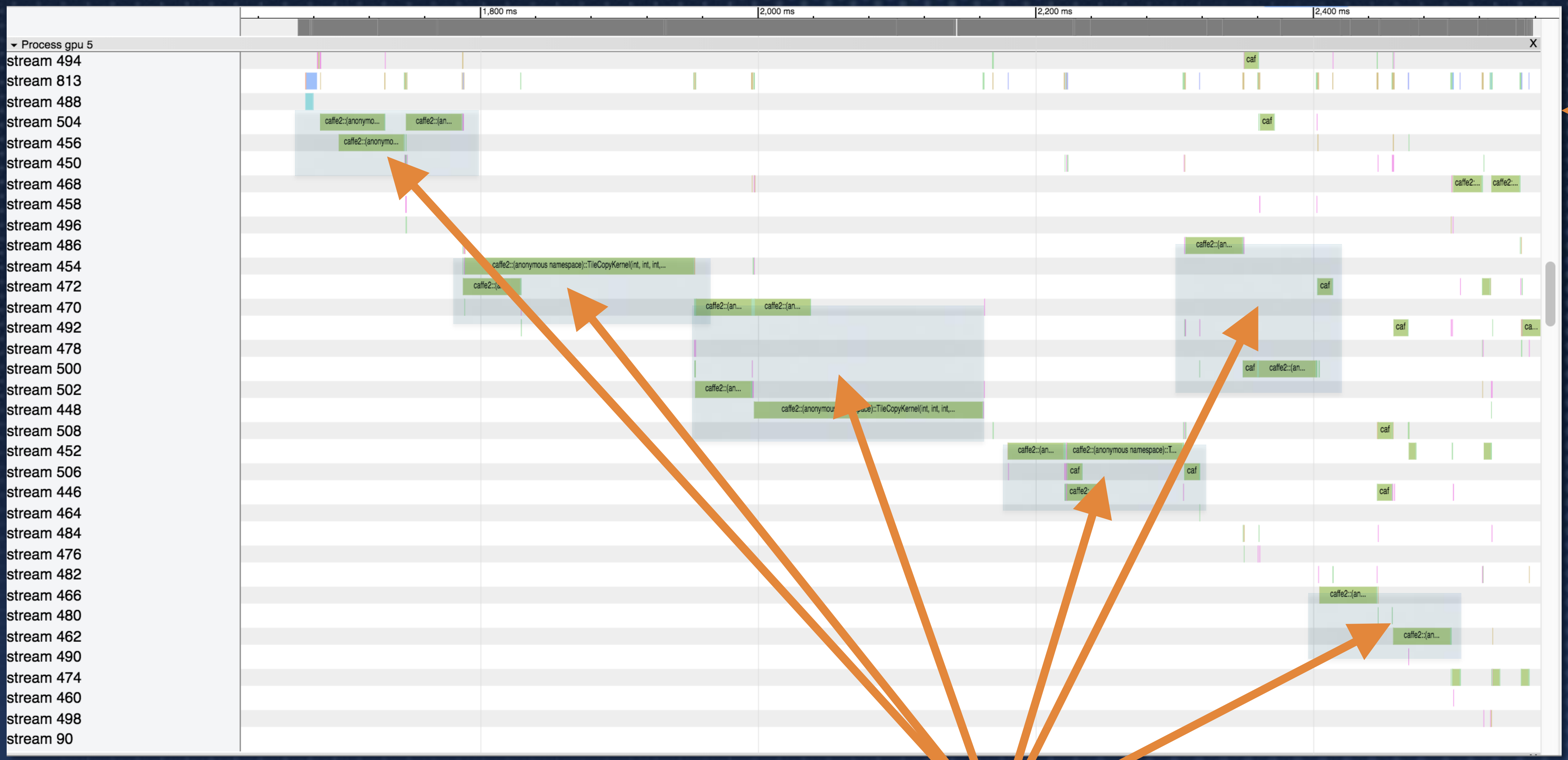
Each thread fetches one word (fine grain)



Source: CUDA Programming Guide

Example: Increase Concurrency and Improve Memory Access Pattern

A timeline for a workflow showed 95% of GPU active time in one operator that performed a data transformation



GPU Summary indicates good utilization

95% of active time spent executing one kernel type

Example: Increase Concurrency and Improve Memory Access Pattern

Two birds with one stone

A timeline for a workflow showed 95% of GPU active time in one operator that performed a data transformation

Each thread in the kernel block was issuing a memcpy inside GPU global memory to replicate a large portion of the input tensor

We rewrote the kernel code so each thread would write a single value of the output tensor

```
memcpy(output_ptr, input_ptr, inner_dim * item_size);
↓
output_data[index] = input_data[row * inner_dim + col];
```

3x speedup in operator and workflow

Issue 5: Insufficient Concurrency

When a GPU for your workload is overkill

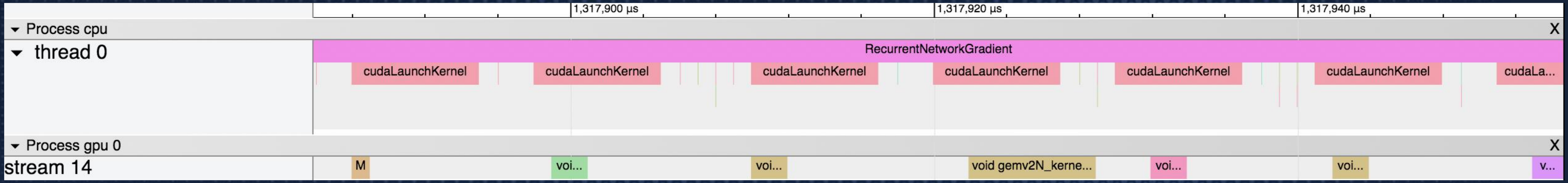
Blind Spot: Modern GPUs contain thousands of arithmetic units, so code must expose that much concurrency for proper utilization

Anti-Pattern: Code that runs a few kernel blocks at a time with only a small fraction of SMs utilized

Solution: If the problem inherently has low concurrency, consider running on CPU instead

Example: Too Little Work

You know you are in trouble when it takes longer to launch a kernel than to run it



Optimization Takeaways

Platform abstractions allow our workflow developers to make use of GPUs and help with some performance aspects

Timeline tracing is the first tool you should use for identifying bottlenecks in parallel workflows

To become a better GPU programmer, understand the key differences between GPU and CPU architectures

- Very high parallelism – requires high concurrency and efficiently feeding work from CPU
- Accelerator - minimize CPU to GPU communication
- Zero-cost “context switch” – don’t be afraid to keep grain size very low
- Access patterns – learn the optimal access patterns for the various memory/cache types on the GPU

Don't reinvent the wheel - use optimized libraries like cuDNN whenever possible

Q&A

Thank you for watching

facebook
Artificial Intelligence

NVIDIA Nsight Systems

Understanding the work*flow*

A tracing tool such as NSight Systems is what we use to investigate low utilization cases

- Collects both CPU and GPU traces
- API for adding application-level trace events
- Great at highlighting system-wide bottlenecks

In addition, we use CUPTI Activities API directly

- NVIDIA's tools are built on top of CUPTI APIs
- Allows greater flexibility
- Derive metrics on-the-fly, aggregate per-kernel stats etc

Use off-the-shelf tracing tools or use CUPTI APIs to build your own

%GPU Hours and Average Active Warps by Workflow

$$Efficiency = \frac{\text{"Goodput"}}{Cost}$$

$$Utilization = \frac{Resources_{Used}}{Resources_{Available}}$$

Goodput is not easily measurable - workload and context dependent

From images processed to user engagement rates

Cost is standardized and measurable

E.g. GPU hours

Used resources is measurable in context independent manner

Various levels of system metrics

From GPU hours to FLOPs / instructions

Available resources is measurable

Available GPU hours, peak FLOPs / instructions

Poor utilization = waste of expensive resource   TODO: clarify

Focus on improving utilization - lower cost for the same goodput

Contributors to Low GPU Utilization