Practical Performance Optimization for Deep Learning Applications

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GPUs are Underutilized

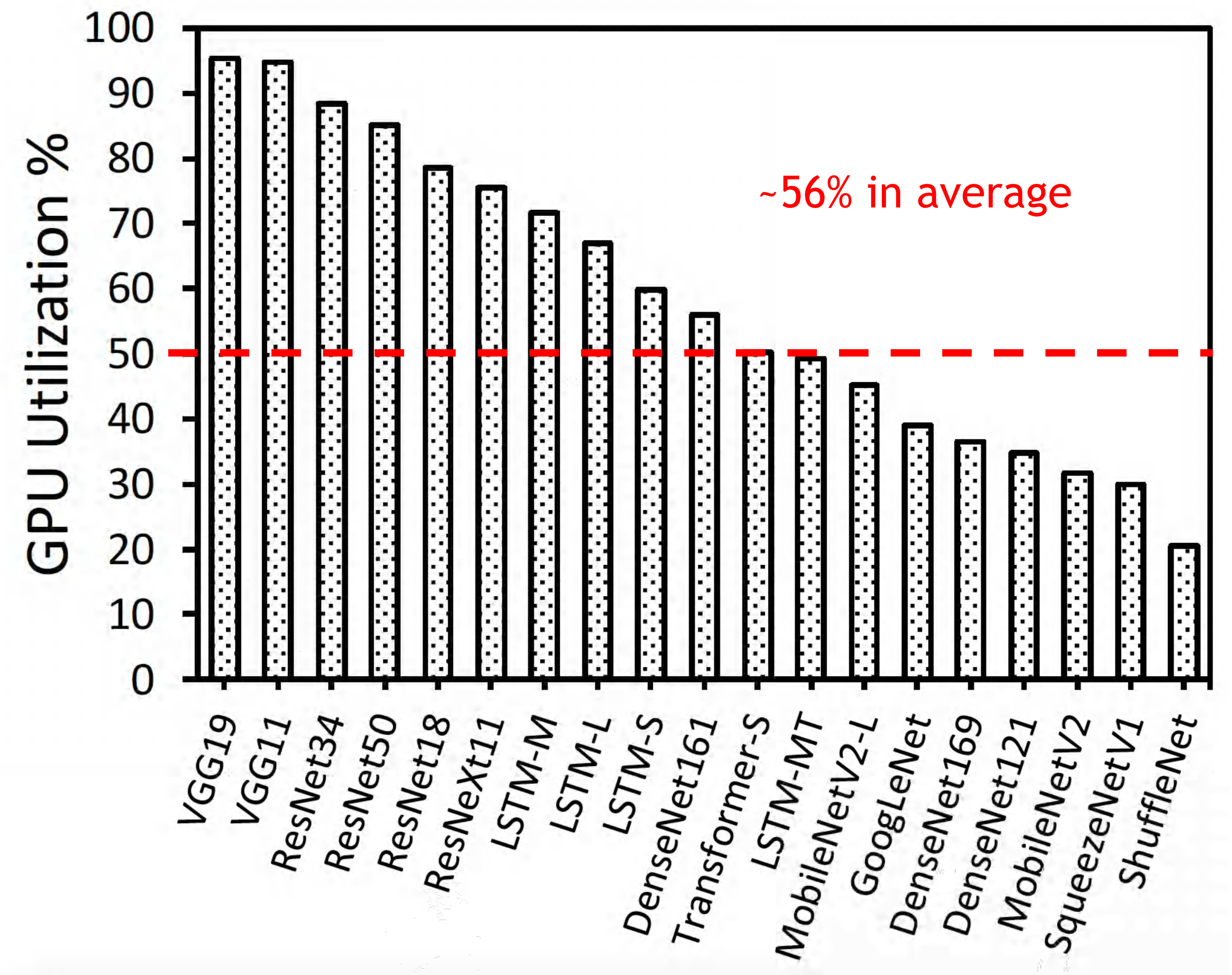
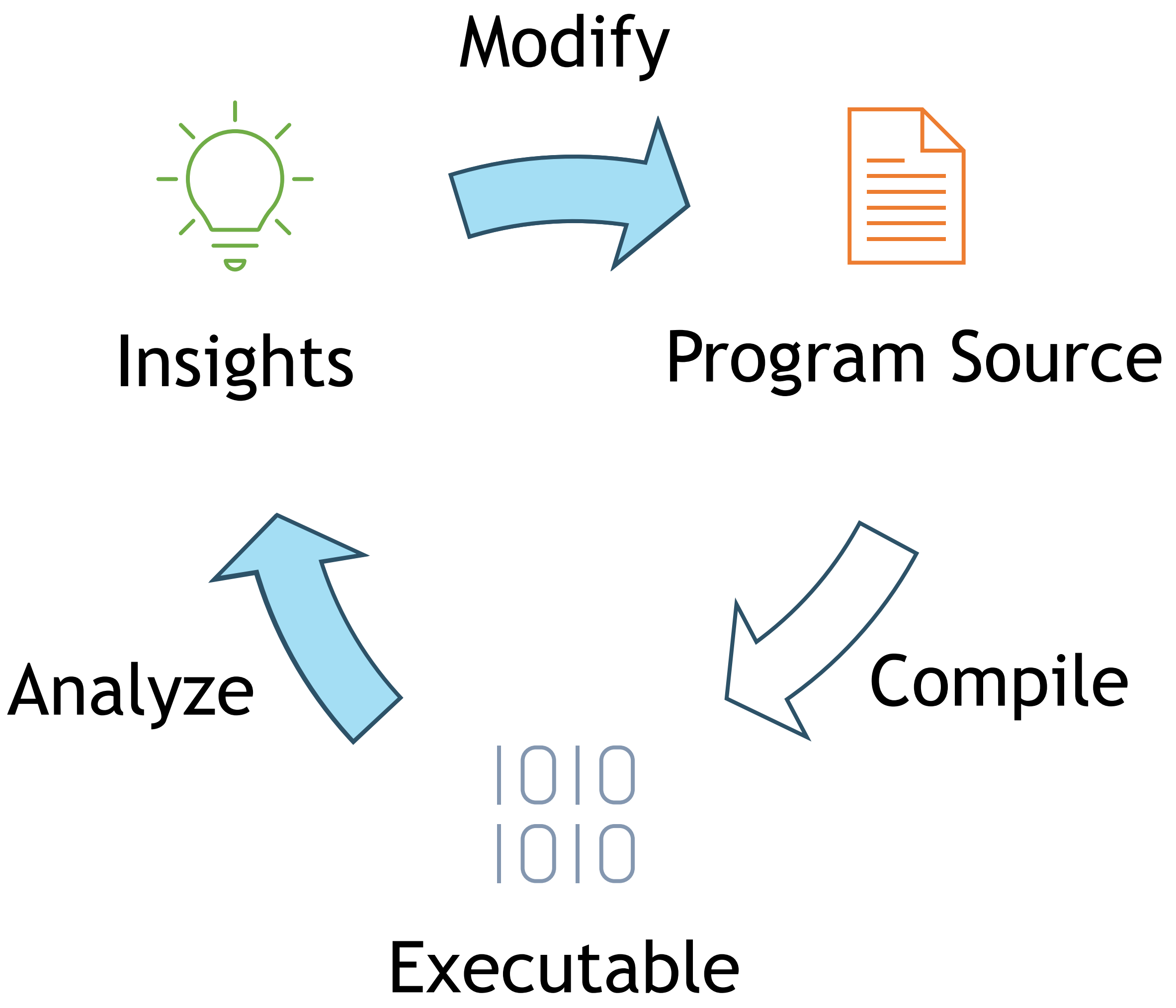


Image source:
Yeung, Gingfung, et al. "Towards GPU utilization prediction for cloud deep learning." 12th USENIX Workshop on Hot Topics in Cloud Computing (HotCloud 20). 2020.

GPU Program Optimization Process



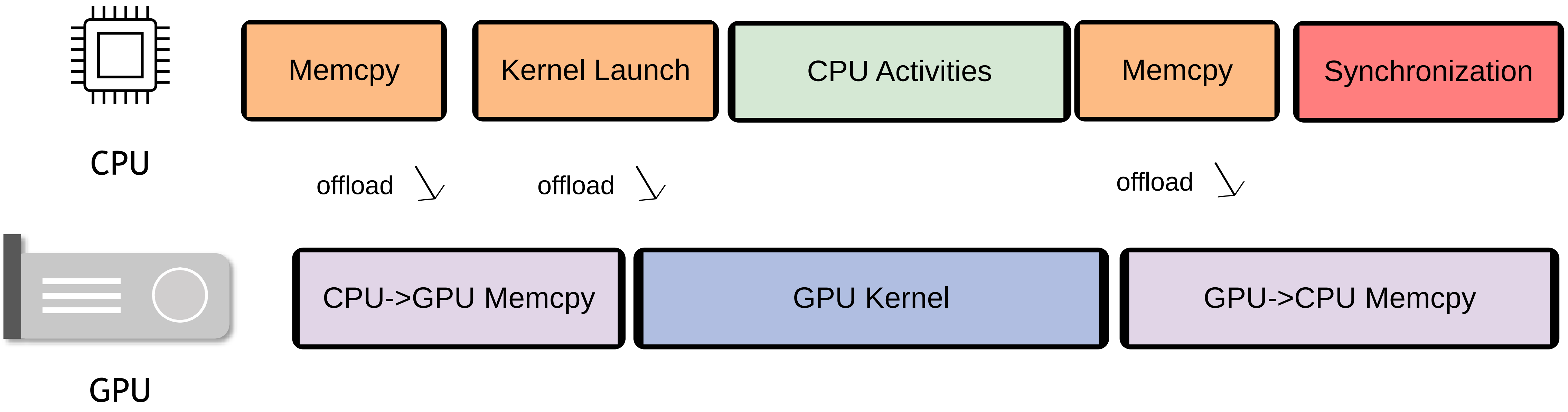
Optimization Techniques

- What will not be covered today
  - Quantization
  - Compression
  - Pruning
  - Sparse computation
- What will be covered today

Given a GPU kernel, how do you optimize its implementation?

Given a PyTorch script, how do you pinpoint its performance bottlenecks?

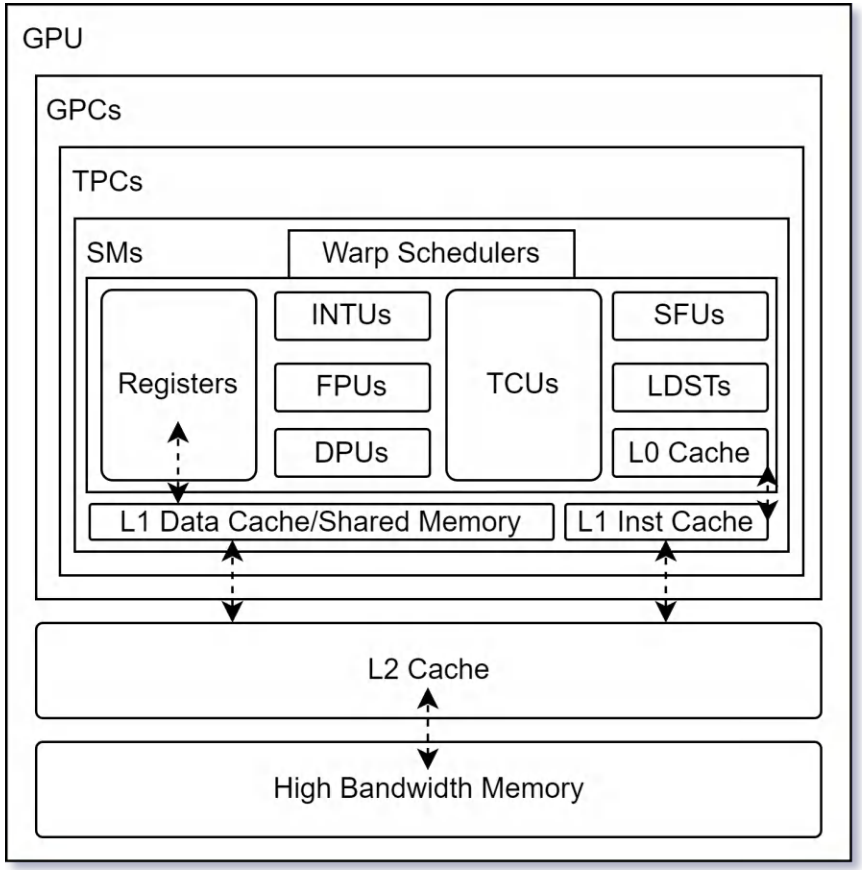
GPU-accelerated Application Sketch



GPU-accelerated Application Sketch

GPU

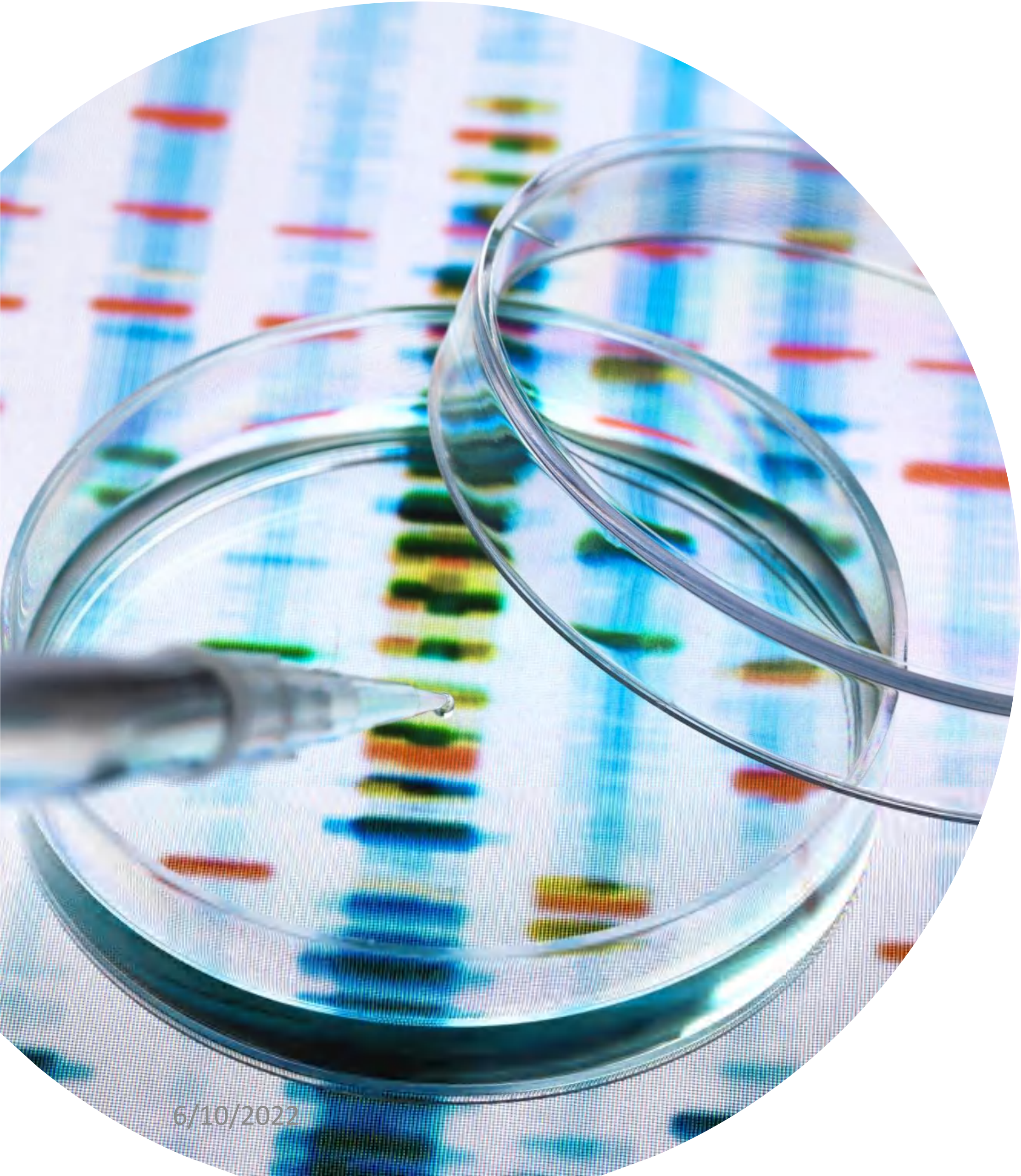
CPU->GPU Memcpy	GPU Kernel	GPU->CPU Memcpy



NVIDIA GA100 architecture

Performance Analysis and Optimization for GPU Code is Challenging

- Sophisticated programming models
  - Tensorflow, PyTorch, RAJA, and Kokkos
- Complicated hardware
  - Multiple compute units
  - Multiple memory spaces
  - Thread synchronization/divergence
- Frequent communication
  - Data transfers between GPUs and CPUs
  - Internode communication



GPU Kernel Optimization

Inefficiencies of Existing PyTorch Operators

- Native PyTorch operators (e.g., torch.add)
  - Can be very slow
  - Can run out-of-memory
- Graph compilers (e.g., TorchScript)
  - Don't support custom data-structures
    - block-sparse tensors
    - lists/trees of tensors
  - Don't support custom precision format
    - FP8
  - Automatic kernel fusion is limited

Customize GPU kernel implementation!

How Difficult It Is to Optimize a GEMM Kernel?

Difficulty

- Vanilla (1-10% fp32 peak)
- NVIDIA CUDA Programming Guide (30%-50% fp32 peak)
  - +global memory coalesce
  - +shared memory

C/C++

- CUTLASS (80%-90% tf32 peak)
  - +tf32 tensor core
  - +vectorization
  - +shared bank conflict reduction
  - +thread layout autotune
  - +async shared memory transfer
  - +multi-stage shared memory

C++ Template & PTX

- cuBLAS (>90% tf32 peak)
  - +register bank conflict reduction
  - +control code optimization

SASS

Problems with Handwritten GPU Kernels

- Hard to recruit new Machine Learning Engineers
- Difficult to maintain libraries in a small company
- A black box to Machine Learning researchers
  - They want to understand how kernels work
  - They want to fast validate new ideas at scale

Triton - Agile Development of Fast GPU Kernels

- PyTorch compatible
  - Tensors are stored on-chip rather than off-chip
  - Custom data-structures using tensors of pointers
- Python syntax
  - All standard python control flow structure (for/if/while) are supported
  - Highly optimized GPU code is generated
    - +tf32 tensor core
    - +vectorization
    - +shared bank conflict reduction
    - +thread layout autotune
    - +async shared memory transfer
    - +multi-stage shared memory

Automatic apply with minimal annotations

Triton vs CUDA

	CUDA	Triton
Memory	Global/Shared/Local	Automatic
Parallelism	Threads/Blocks/Warps	Mostly Blocks
Tensor Core	Manual	Automatic
Vectorization	.8/.16/.32/.64/.128	Automatic
Async SIMT	Support	Limited
Device Function	Support	Not Available

Vector Addition

- Z[:] = X[:] + Y[:]
  - Without boundary check
- @triton.jit
  - Kernel decorator
- tl.load()
  - Load values from global memory to shared memory/registers
- _add[grid](num_warps=*K*)
  - grid = (*G*,)
    - *G* thread block
  - num_warps = *K*
    - *K* = 4 by default

```python
import triton.language as tl
import triton

@triton.jit
def _add(z_ptr, x_ptr, y_ptr, N):
    # same as torch.arange
    offsets = tl.arange(0, 1024)
    # create 1024 pointers to X, Y, Z
    x_ptrs = x_ptr + offsets
    y_ptrs = y_ptr + offsets
    z_ptrs = z_ptr + offsets
    # load 1024 elements of X, Y, Z
    x = tl.load(x_ptrs)
    y = tl.load(y_ptrs)
    # do computations
    z = x + y
    # write-back 1024 elements of X, Y, Z
    tl.store(z_ptrs, z)

N = 1024
x = torch.randn(N, device='cuda')
y = torch.randn(N, device='cuda')
z = torch.randn(N, device='cuda')
grid = (1, )
_add[grid](z, x, y, N)
```

Vector Addition – Boundary Check

- Z[:] = X[:] + Y[:]
  - With boundary check
- program_id()
  - Get the block id
- mask
  - if mask[idx] is false, do not load the data at address pointer[idx]
- triton.cdiv(N, 1024)
  - (N – 1)//1024 + 1

```python
import triton.language as tl
import triton

@triton.jit
def _add(z_ptr, x_ptr, y_ptr, N):
    # same as torch.arange
    offsets = tl.arange(0, 1024)
    offsets += tl.program_id(0)*1024
    # create pointers to X, Y, Z
    x_ptrs = x_ptr + offsets
    y_ptrs = y_ptr + offsets
    z_ptrs = z_ptr + offsets
    # load elements of X, Y, Z
    x = tl.load(x_ptrs, mask=offset<N)
    y = tl.load(y_ptrs, mask=offset<N)
    # do computations
    z = x + y
    # write-back elements of X, Y, Z
    tl.store(z_ptrs, z, mask=offset<N)

N = 192311
x = torch.randn(N, device='cuda')
y = torch.randn(N, device='cuda')
z = torch.randn(N, device='cuda')
grid = (triton.cdiv(N, 1024), )
_add[grid](z, x, y, N)
```

Vector Addition – Custom Tile Size

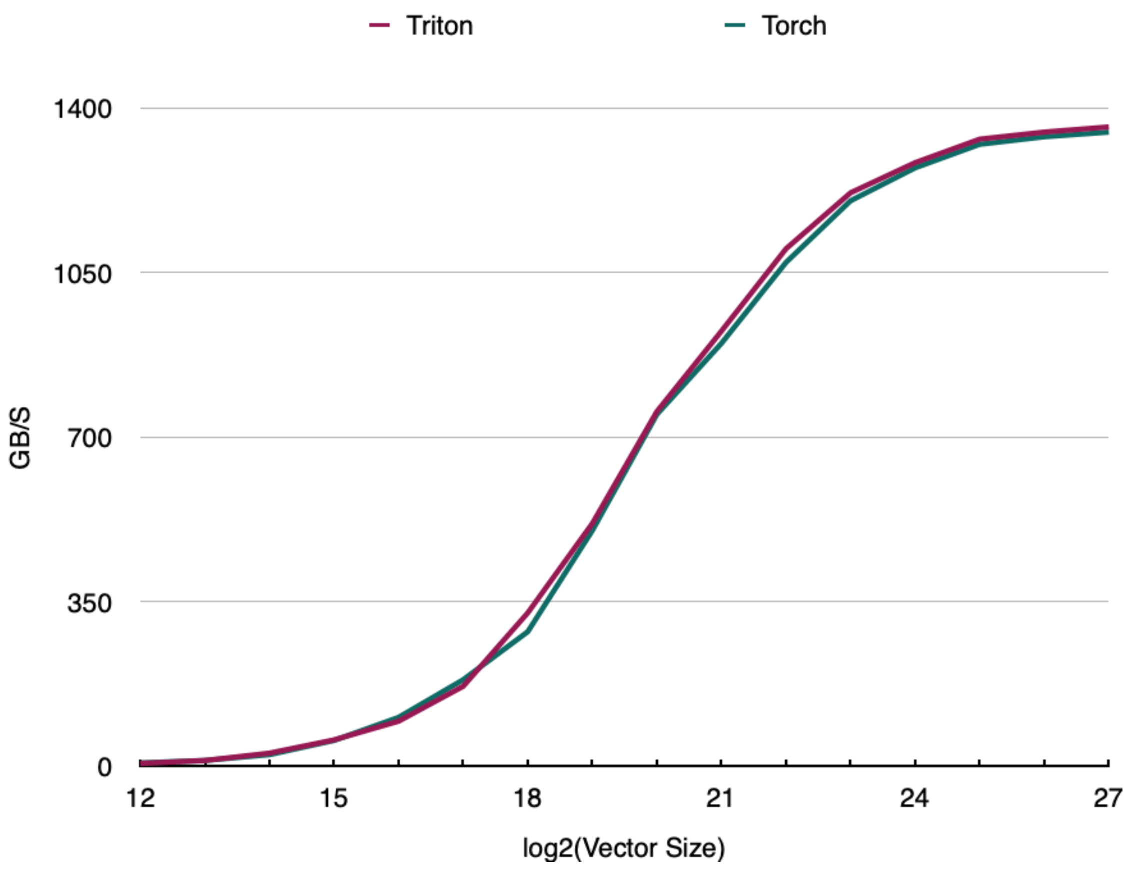
- Z[:] = X[:] + Y[:]
  - Each block computes *TILE* elements
- @triton.autotune
  - Instantiate kernels using configs
  - Select the best config based on the execution time
- lambda
  - Calculate grid dim based on *TILE*

```
import triton.language as tl
import triton
@triton.autotune(configs=
    [triton.Config(‘TILE’: 128),
     triton.Config(‘TILE’: 256)]
@triton.jit
def _add(z_ptr, x_ptr, y_ptr, N, TILE: tl.constexpr):
    # same as torch.arange
    offsets = tl.arange(0, TILE)
    offsets += tl.program_id(0)*TILE
    # create pointers to X, Y, Z
    x_ptrs = x_ptr + offsets
    y_ptrs = y_ptr + offsets
    z_ptrs = z_ptr + offsets
    # load elements of X, Y, Z
    x = tl.load(x_ptrs, mask=offset<N)
    y = tl.load(y_ptrs, mask=offset<N)
    # do computations
    z = x + y
    # write-back elements of X, Y, Z
    tl.store(z_ptrs, z, mask=offset<N)

N = 192311
x = torch.randn(N, device='cuda')
y = torch.randn(N, device='cuda')
z = torch.randn(N, device='cuda')
grid = lambda args: (triton.cdiv(N, args[“TILE”]), )
_add[grid](z, x, y, N)
```

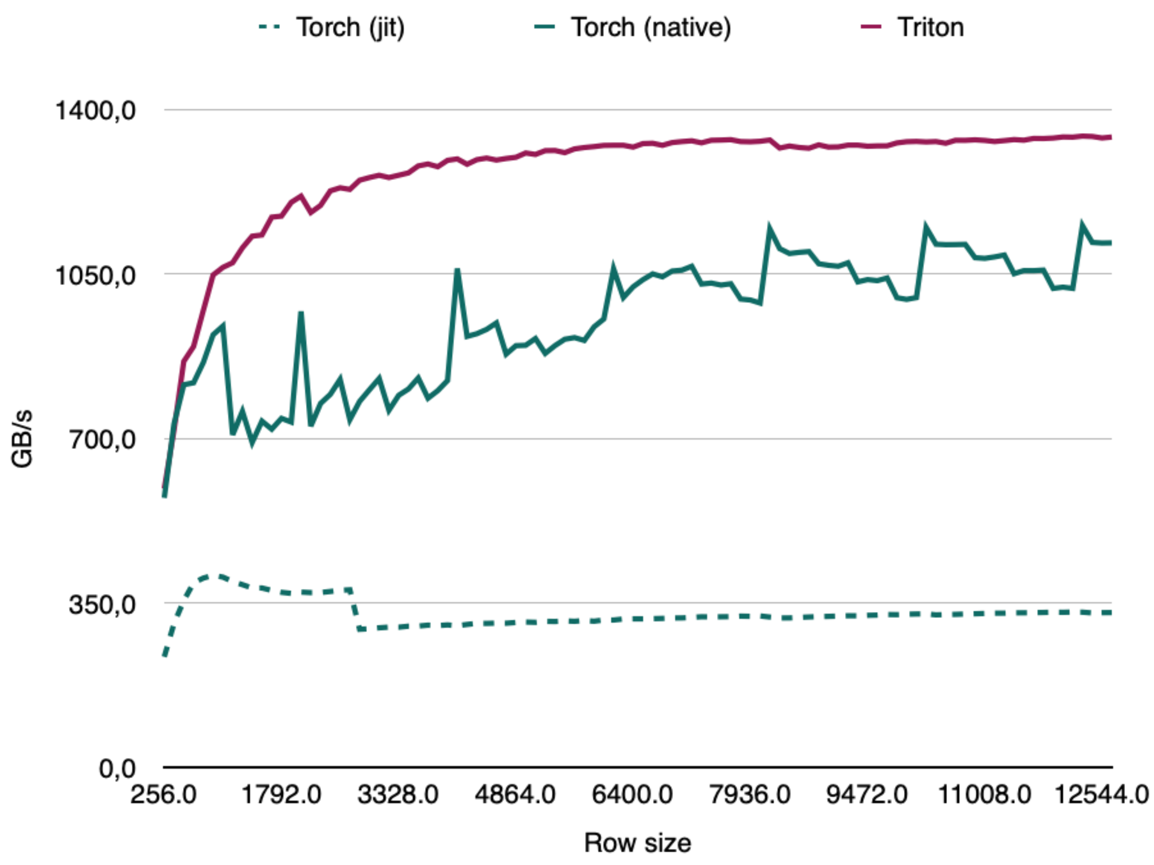
Element-wise OP Performance

- Triton and Torch both achieve peak bandwidth
- Researchers can write *fused element-wise* operations easily using Triton



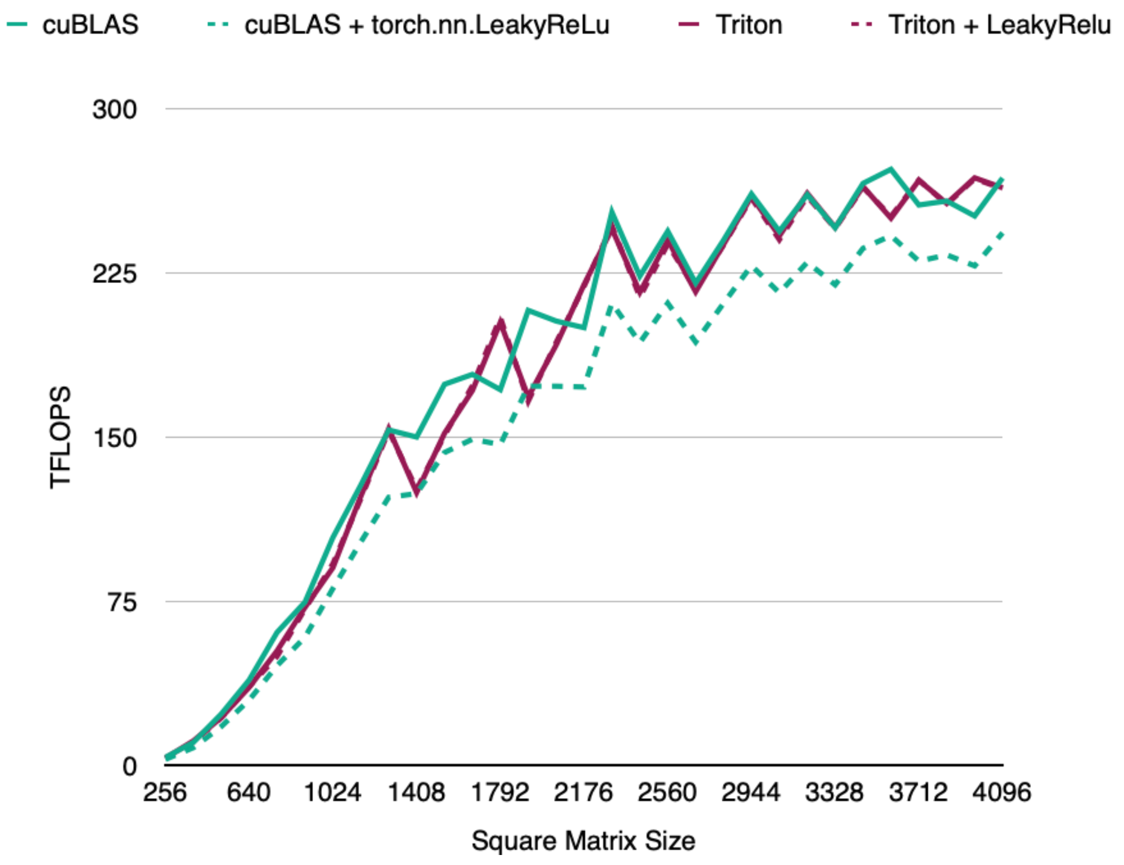
Row-wise Normalization Performance

- Triton kernels can keep data on-chip throughout the entire normalization
- PyTorch JIT could in theory do that but in practice doesn't
- The native PyTorch op is designed to work for every input shape and is slower in cases where we care



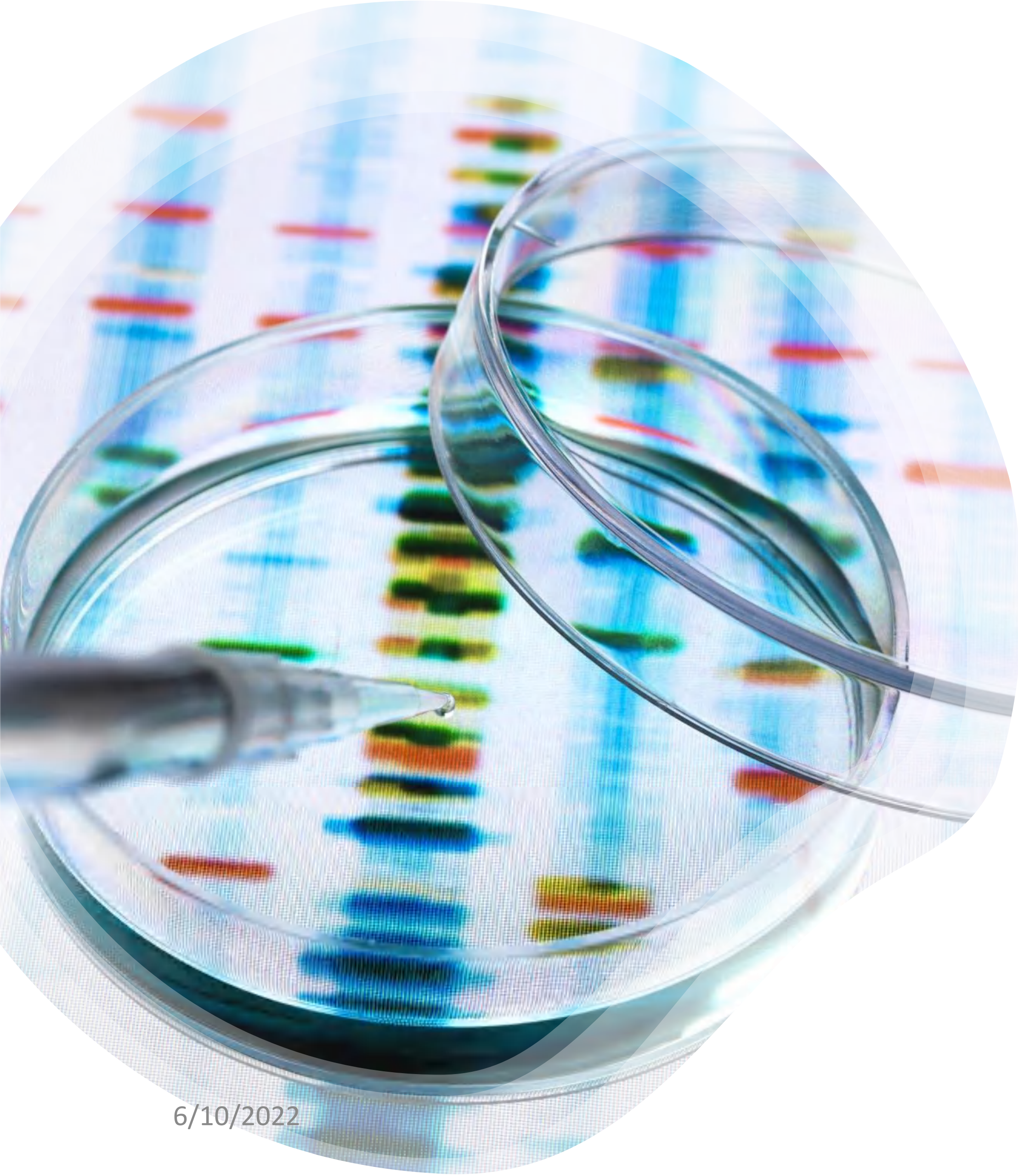
Matrix Multiplication Performance

- It takes <25 lines of code to write a Triton kernel on par with cuBLAS
- Arbitrary ops can be "fused" before/after the GEMM while the data is still on-chip, leading to large speedups over PyTorch
- More examples
  - [Tutorials — Triton documentation (triton-lang.org)]()



Triton Future Work

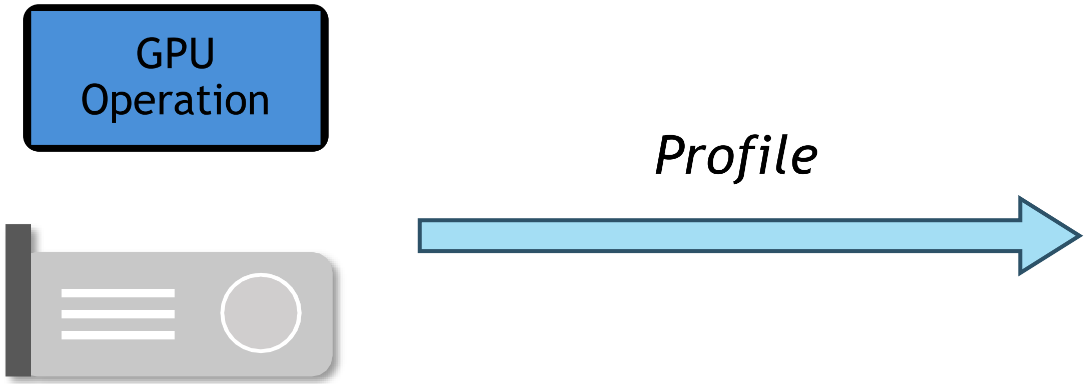
- Rewrite with MLIR
- Enhance debugging utility
- Support Hopper GPUs



GPU Performance Analysis

GPU Performance Tools

- Measurement Modalities
  - Interception of GPU operations
  - Instrumentation within GPU kernels
  - Instruction sampling in GPU kernels



- Metrics
  - GPU/CPU time
  - Memory movement
  - GPU utilization
  - …

- NVIDIA Nsight Systems/Compute
- AMD RocTracer/RocProfiler
- Intel VTune
- …

Flat Profile View

API Statistics

Reset | Export to CSV

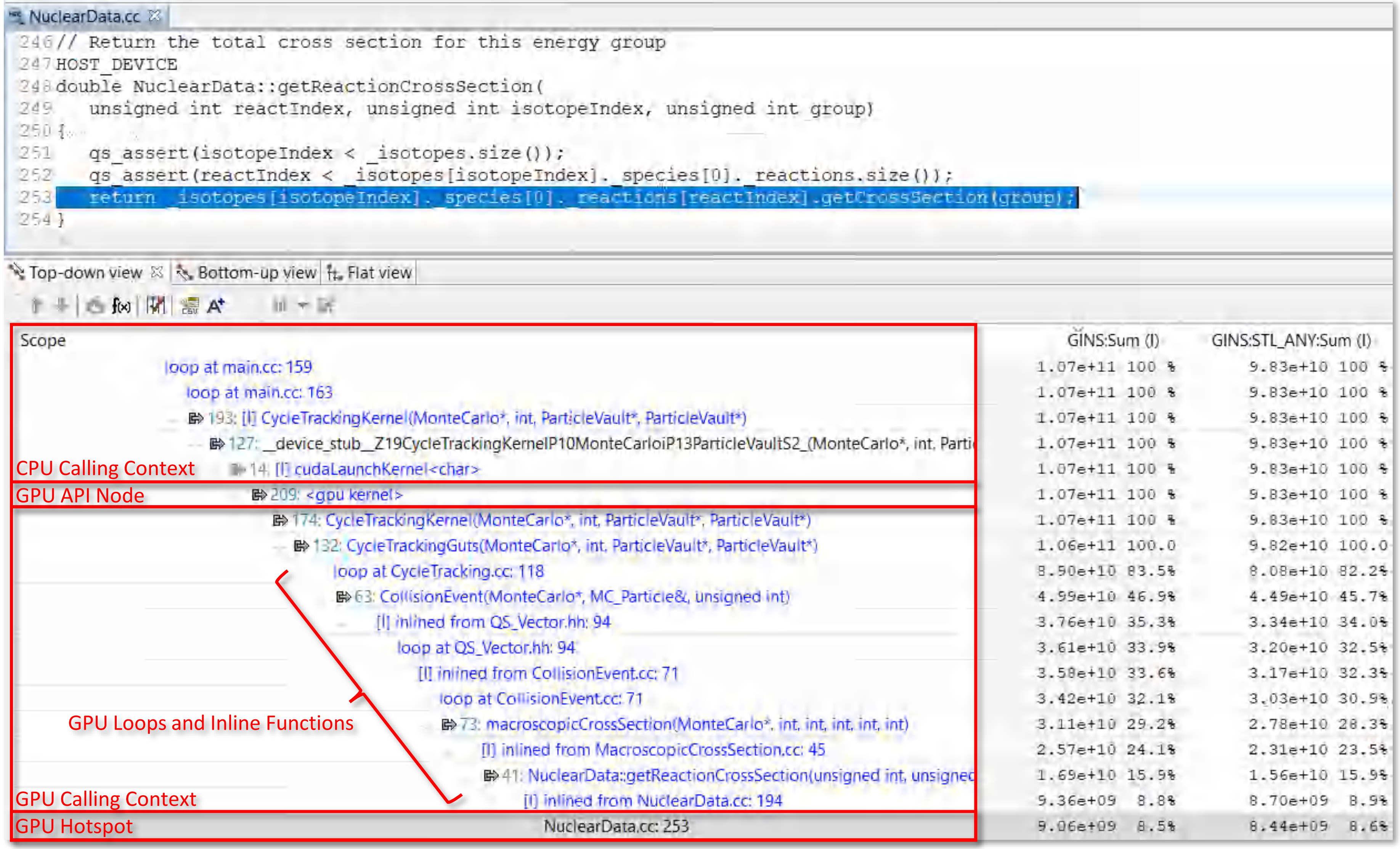
Enter filter, e.g. $('Name') == 'MyAPIName'

Name	Number of Calls	Total Duration	Average Duration	Minimum Duration	Maximum Duration
cudaMemcpy	1	71.41us	71.41us	71.41us	71.41us
cudaMalloc	2	123.224ms	61.612ms	41.294us	123.183ms
cudaGetLastError	1	931ns	931ns	931ns	931ns
cuModuleGetFunction	4	12.106us	3.0265us	931ns	9.003us
cuMemcpyHtoD_v2	1	29.806us	29.806us	29.806us	29.806us
cuMemAlloc_v2	2	428.154us	214.077us	9.935us	418.219us
cuInit	1	191.568ms	191.568ms	191.568ms	191.568ms
cuDriverGetVersion	1	8.693us	8.693us	8.693us	8.693us
cuDeviceTotalMem_v2	3	34.152us	11.384us	8.693us	15.524us
cuDevicePrimaryCtxRetain	1	120.4ms	120.4ms	120.4ms	120.4ms
cuDeviceGetUuid	3	1.55us	516.667ns	310ns	620ns
cuDeviceGetName	3	1.861us	620.333ns	310ns	931ns
cuDeviceGetCount	1	4.657us	4.657us	4.657us	4.657us
cuDeviceGetAttribute	279	2.88614ms	10.3446us	0ns	498.013us

Nsight Compute Profiling

Image source: *https://docs.nvidia.com/nsight-compute/NsightCompute/index.html*

Profile View Using HPCToolkit



HPCToolkit for Deep Learning Applications

PyTorch-MNIST

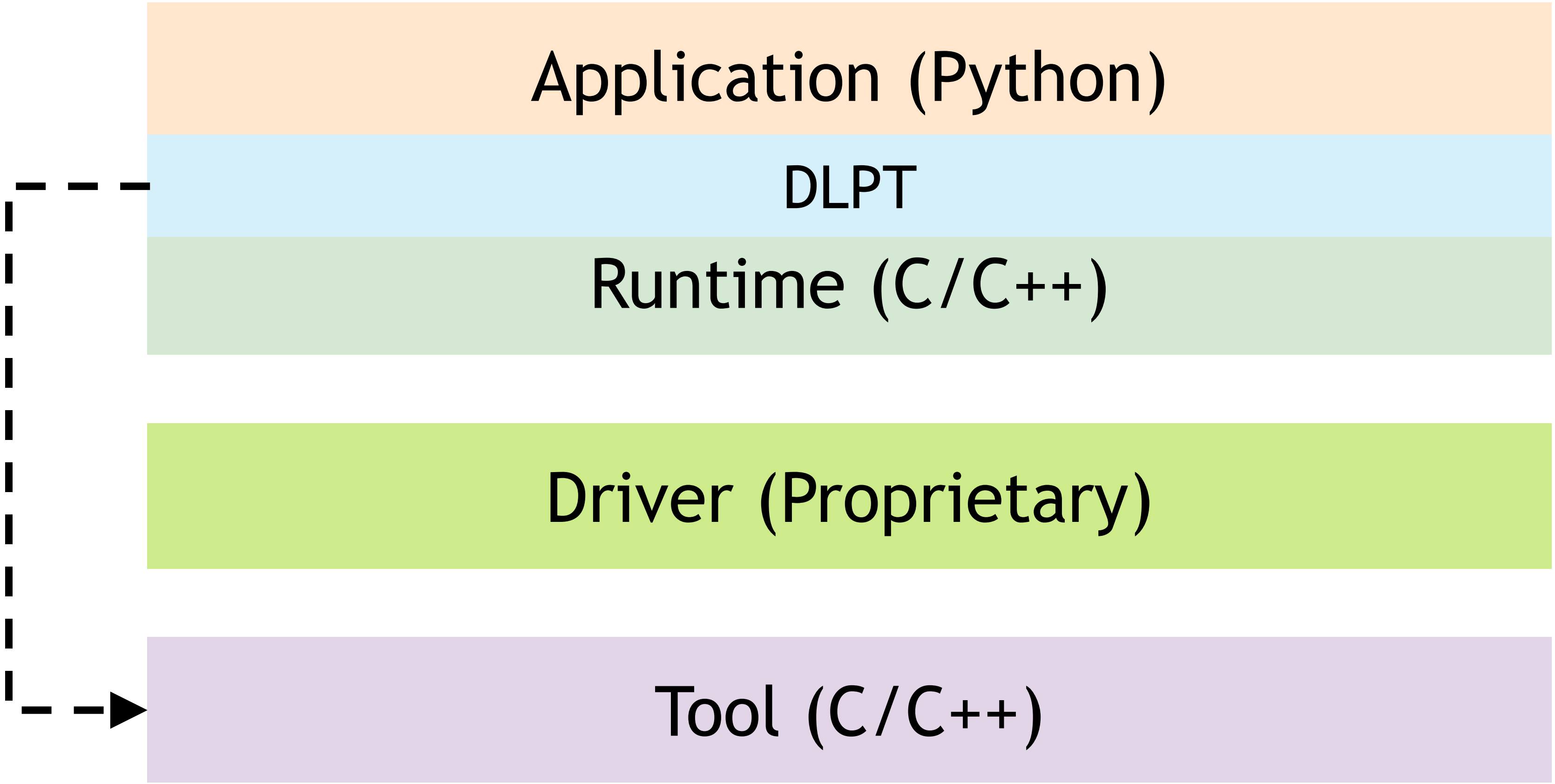
Top-down view | Bottom-up view | Flat view

Scope	GKER (sec):Sum (I)	
Experiment Aggregate Metrics	1.27e-02	100.0%
<thread root>	7.62e-03	60.0%
<program root>	5.08e-03	40.0%
530: Py_BytesMain [python3.8]	5.08e-03	40.0%
1137: Py_RunMain.cold.2916 [python3.8]	5.08e-03	40.0%
[I] pymain_run_python	5.08e-03	40.0%
[I] pymain_run_file	5.08e-03	40.0%
[I] inlined from main.c: 347	5.08e-03	40.0%
387: PyRun_SimpleFileExFlags [python3.8]	5.08e-03	40.0%
428: PyRun_FileExFlags [python3.8]	5.08e-03	40.0%
1063: run_mod [python3.8]	5.08e-03	40.0%
1147: run_eval_code_obj [python3.8]	5.08e-03	40.0%
1125: PyEval_EvalCode [python3.8]	5.08e-03	40.0%
718: PyEval_EvalCodeEx [python3.8]	5.08e-03	40.0%
4327: _PyEval_EvalCodeWithName [python3.8]	5.08e-03	40.0%
4298: _sre_SRE_Match_expand [python3.8]	5.08e-03	40.0%
[I] inlined from ceval.c: 1239	5.08e-03	40.0%
loop at ceval.c: 1239	5.08e-03	40.0%
loop at ceval.c: 1239	5.08e-03	40.0%
loop at ceval.c: 1323	5.08e-03	40.0%
[I] call_function	5.08e-03	40.0%
[I] _PyObject_Vectorcall	5.08e-03	40.0%
[I] inlined from abstract.h: 123	5.08e-03	40.0%
127: _PyFunction_Vectorcall.localalias.355 [python3.8]	5.08e-03	40.0%
[I] function_code_fastcall	5.08e-03	40.0%
[I] inlined from call.c: 279	5.08e-03	40.0%
283: _sre_SRE_Match_expand [python3.8]	5.08e-03	40.0%
[I] inlined from ceval.c: 1239	5.08e-03	40.0%

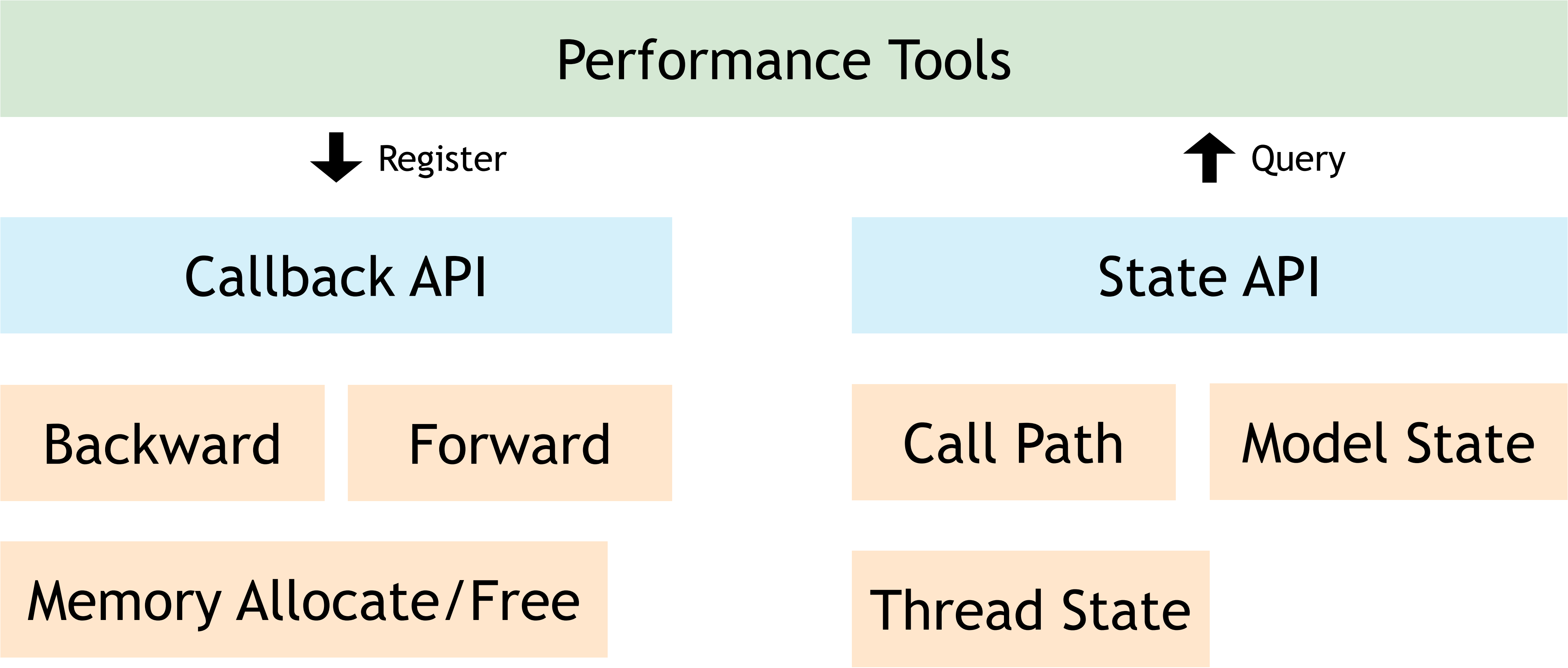
Low level Calling Context

No Application-level Information

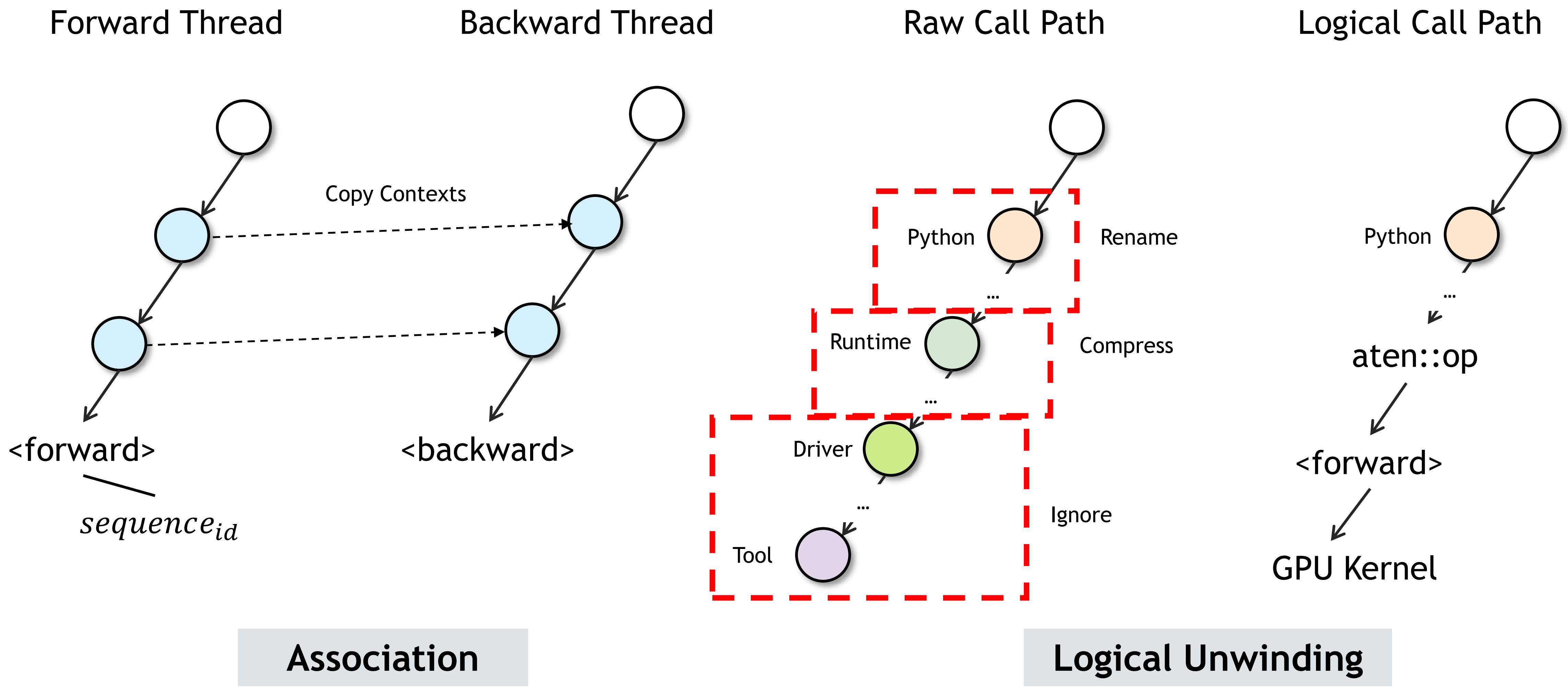
Deep Learning Profiling Interface (DLPT)



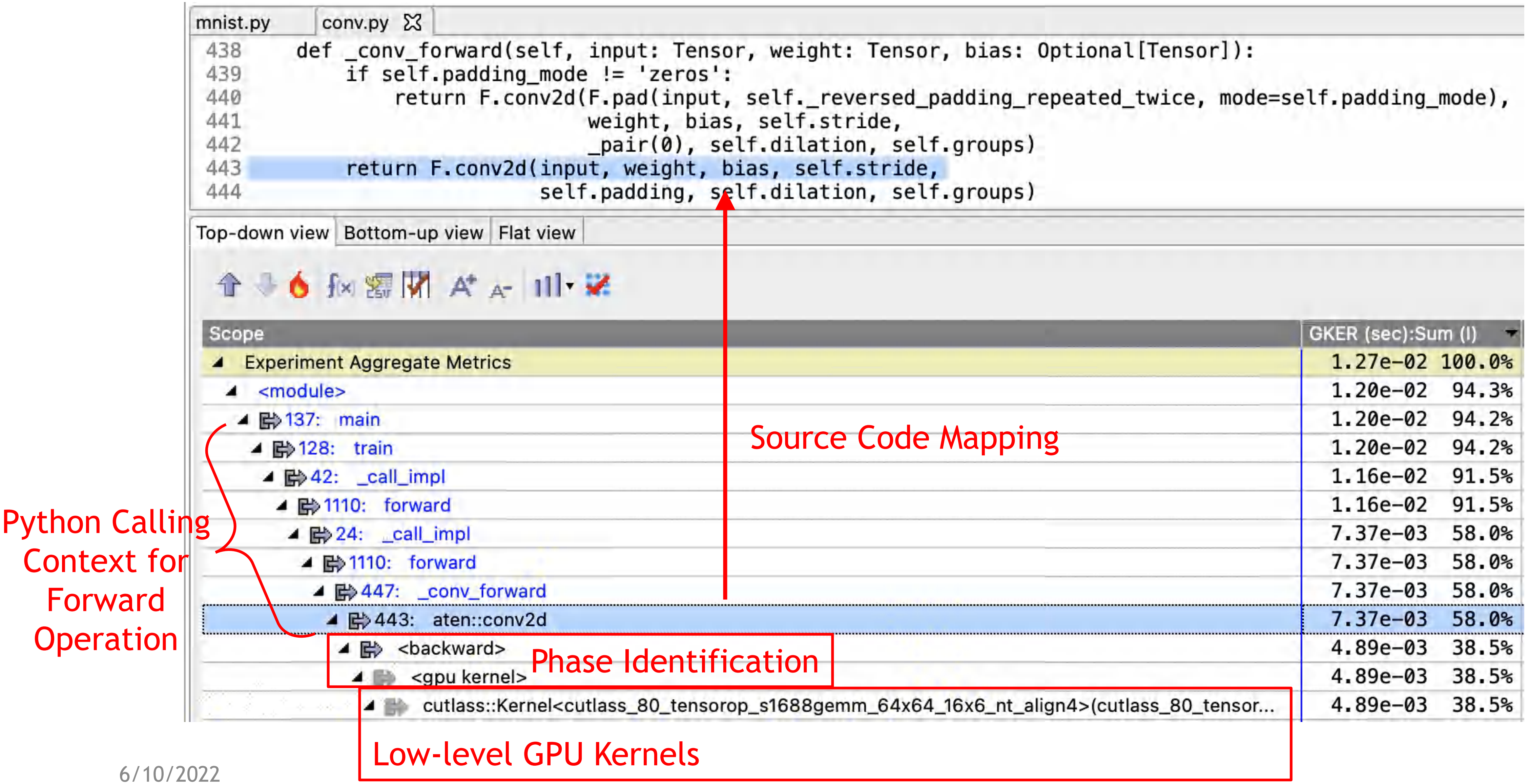
DLPT Components



Calling Context Manipulation



Profile View Using DLPT



ResNet – Nsight Systems

- GPU memory time

Time (%)	Total Time (ns)	Count	Avg (ns)	Med (ns)	Min (ns)	Max (ns)	StdDev (ns)	Operation
97.1	10,745,609	322	33,371.5	2,496.0	2,240	1,097,704	137,703.2	[CUDA memcpy HtoD]
2.8	309,316	54	5,728.1	5,568.5	4,865	6,656	408.1	[CUDA memcpy DtoD]
0.1	15,809	6	2,634.8	2,512.5	2,400	3,104	294.3	[CUDA memset]

- GPU kernel time

Time (%)	Total Time (ns)	Instances	Avg (ns)	Med (ns)	Min (ns)	Max (ns)	StdDev (ns)	Name
31.6	1,529,706	6	254,951.0	254,913.5	254,018	256,450	902.5	void cutlass::Kernel<cutlass_80_tensorop_s1688gemm_128x128_32x3_nn_align$ >(T1::Params)
10.5	507,041	53	9,566.8	9,281.0	7,392	19,680	1,869.7	void at::native::batch_norm_transform_input_kernel<float, float, float, $ bool)1, int>(at::GenericPa…
9.3	449,157	20	22,457.9	19,616.0	11,776	49,344	8,777.1	void at::native::im2col_kernel<float>(long, const T1 *, long, long, long$ long, long, long, long, l…
7.3	351,456	49	7,172.6	7,008.0	6,496	9,376	717.1	void at::native::vectorized_elementwise_kernel<(int)4, at::native::<unna$ ed>::launch_clamp_scalar(a…
7.2	350,882	19	18,467.5	18,432.0	16,608	24,672	1,924.8	void cutlass::Kernel<cutlass_80_tensorop_s1688gemm_64x64_32x6_nn_align4>$ T1::Params)

ResNet – DLPT – Kernel Time

resnet.py

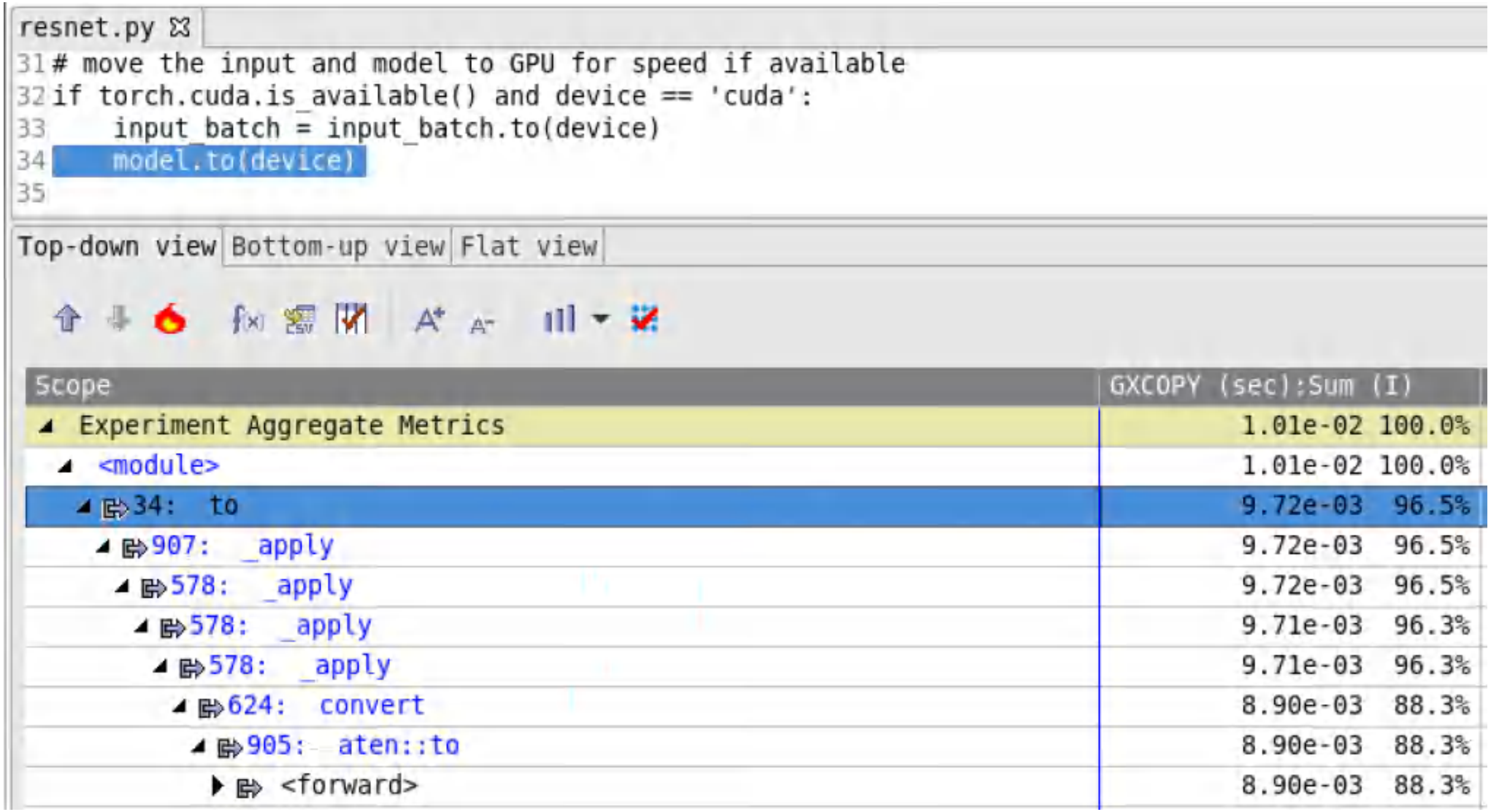
```
264    def _forward_impl(self, x: Tensor) -> Tensor:
265        # See note [TorchScript super()]
266        x = self.conv1(x)
267        x = self.bn1(x)
268        x = self.relu(x)
269        x = self.maxpool(x)
270
271        x = self.layer1(x)
272        x = self.layer2(x)
273        x = self.layer3(x)
274        x = self.layer4(x)
275
276        x = self.avgpool(x)
277        x = torch.flatten(x, 1)
278        x = self.fc(x)
```

Source Code/Network Topology Mapping

Top-down view | Bottom-up view | Flat view

Scope	GKER (sec):Sum (I)	
283: _forward_impl	4.84e-03	100.0%
273: _call_impl	2.52e-03	52.0%
272: _call_impl	7.98e-04	16.5%
274: _call_impl	6.99e-04	14.5%
271: _call_impl	6.50e-04	13.4%

ResNet – DLPT – Memory Time



DLPT Future Work

- Profile distributed systems
- Semantic analysis on calling context

More case studies on production deep learning applications are welcome!