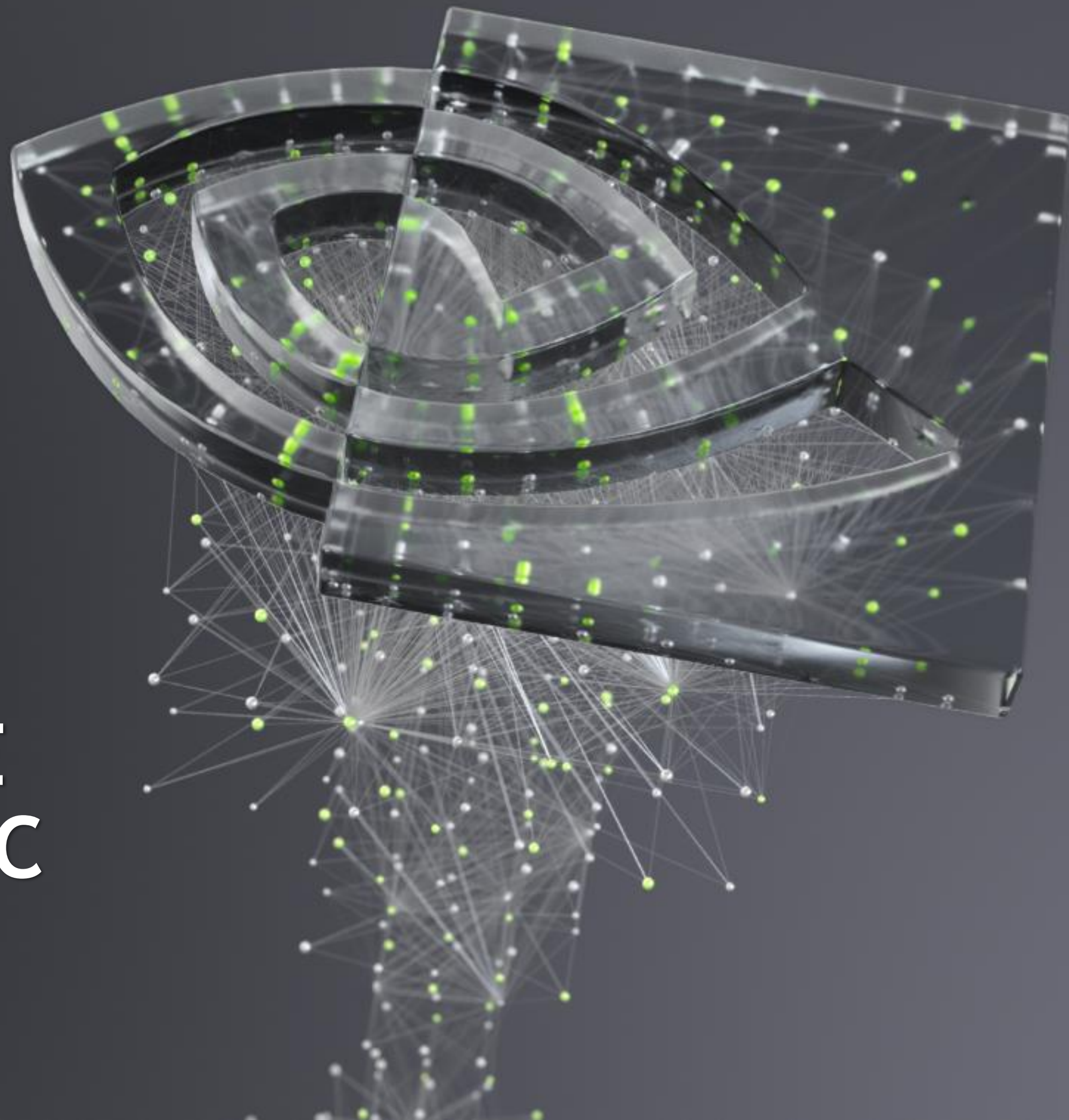




NVIDIA'S SOFTWARE ECOSYSTEM FOR HPC

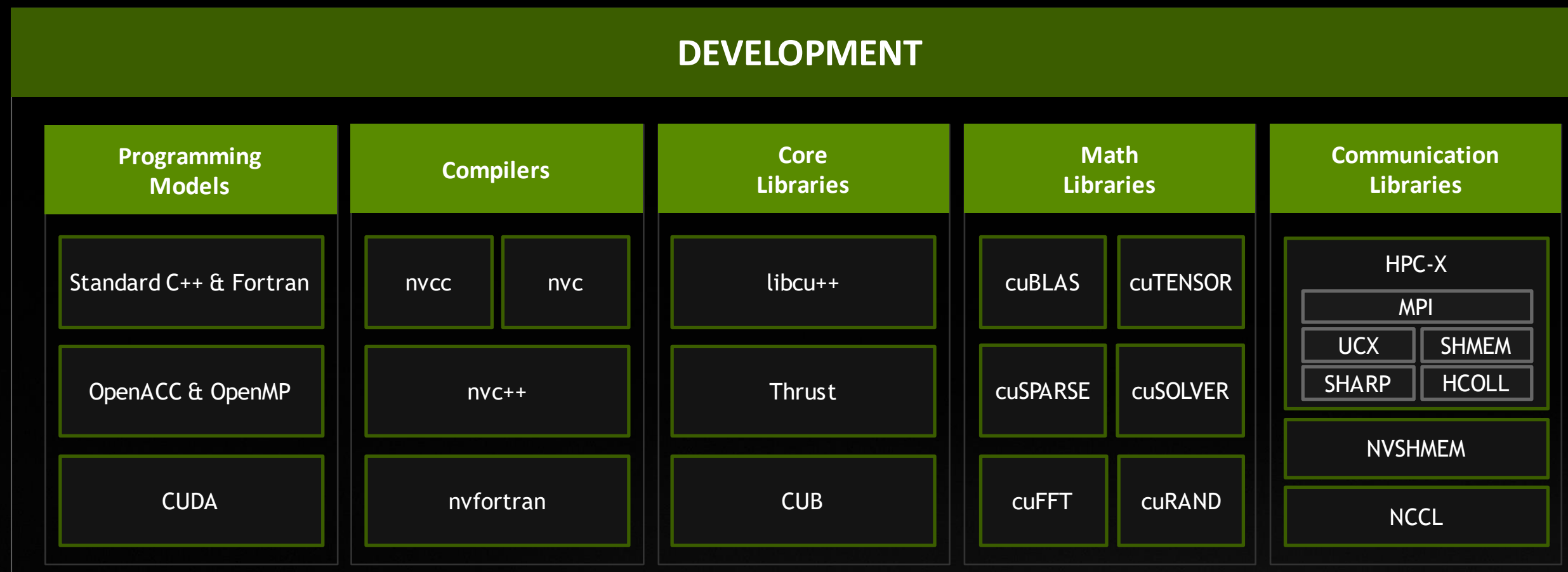
Max Katz

May 5, 2021

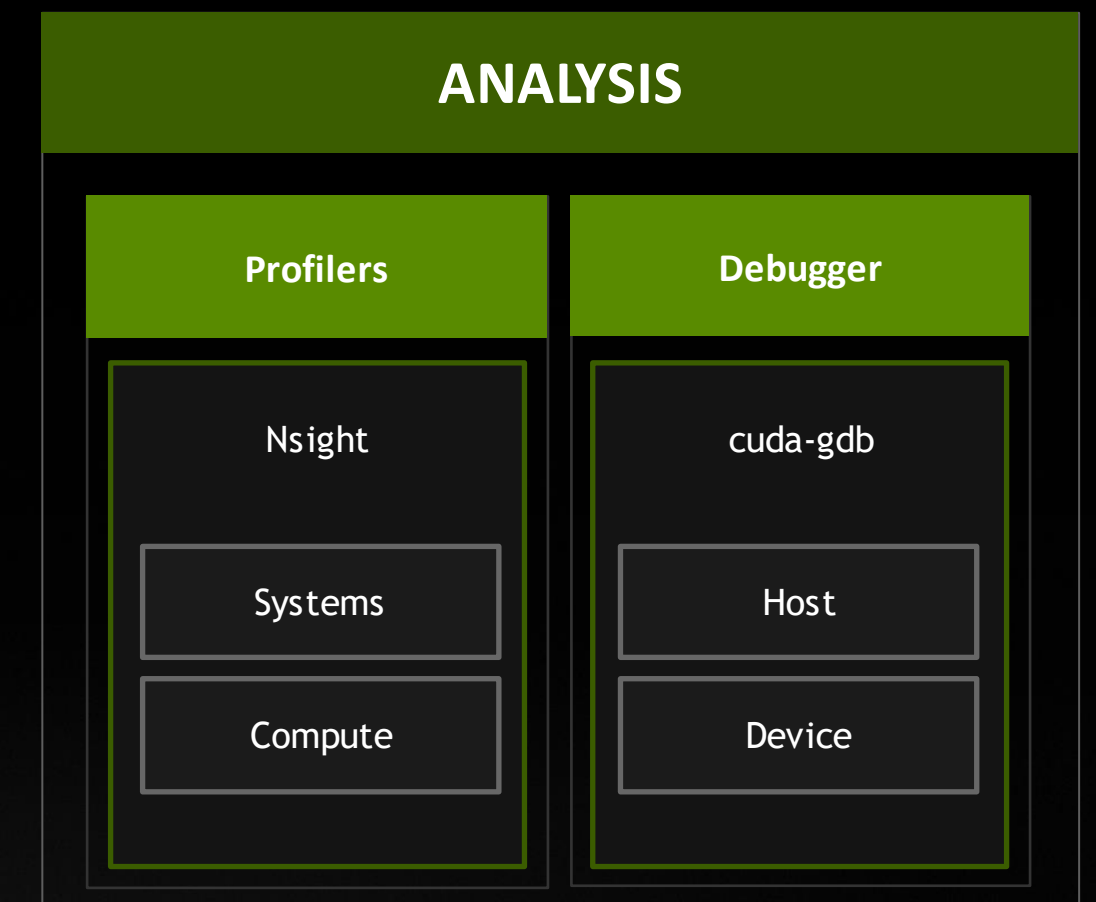


NVIDIA HPC SDK

DEVELOPMENT



ANALYSIS



Develop for the NVIDIA Platform: GPU, CPU and Interconnect
Libraries | Accelerated C++ and Fortran | Directives | CUDA
7-8 Releases Per Year | Freely Available

PROGRAMMING THE NVIDIA PLATFORM

CPU, GPU and Network

Accelerated Standard Languages

```
std::transform(par, x, x+n, y, y,  
              [=] (float x, float y) { return y + a*x; }  
);
```

```
do concurrent (i = 1:n)  
  y(i) = y(i) + a*x(i)  
enddo
```

```
import legate.numpy as np  
...  
def saxpy(a, x, y):  
  y[:] += a*x
```

Incremental Portable Optimization

```
#pragma acc data copy(x,y)  
{  
...  
std::transform(par, x, x+n, y, y,  
              [=] (float x, float y) {  
                return y + a*x;  
              });  
...  
}
```

Platform Specialization

```
__global__  
void saxpy(int n, float a,  
          float *x, float *y) {  
  int i = blockIdx.x*blockDim.x +  
         threadIdx.x;  
  if (i < n) y[i] += a*x[i];  
}  
  
int main(void) {  
  ...  
  cudaMemcpy(d_x, x, ...);  
  cudaMemcpy(d_y, y, ...);  
  
  saxpy<<<(N+255)/256,256>>>(...);  
  
  cudaMemcpy(y, d_y, ...);  
}
```

Core

Math

Communication

Data Analytics

AI

Acceleration Libraries

ACCELERATED STANDARDS

Parallel performance for wherever you code needs to run

```
std::transform(std::execution::par, x, x+n, y, y,  
 [=] (auto xi, auto yi) { return y + a*xi; });
```

```
do concurrent (i = 1:n)  
  y(i) = y(i) + a*x(i)  
enddo
```

CPU



```
nvc++ -stdpar=multicore  
nvfortran -stdpar=multicore
```

GPU



```
nvc++ -stdpar=gpu  
nvfortran -stdpar=gpu
```

ACCELERATED PROGRAMMING IN ISO FORTRAN

NVFORTRAN Accelerates Fortran Intrinsic with cuTENSOR Backend

```
real(8), dimension(ni,nk) :: a
real(8), dimension(nk,nj) :: b
real(8), dimension(ni,nj) :: c
...
!$acc enter data copyin(a,b,c) create(d)

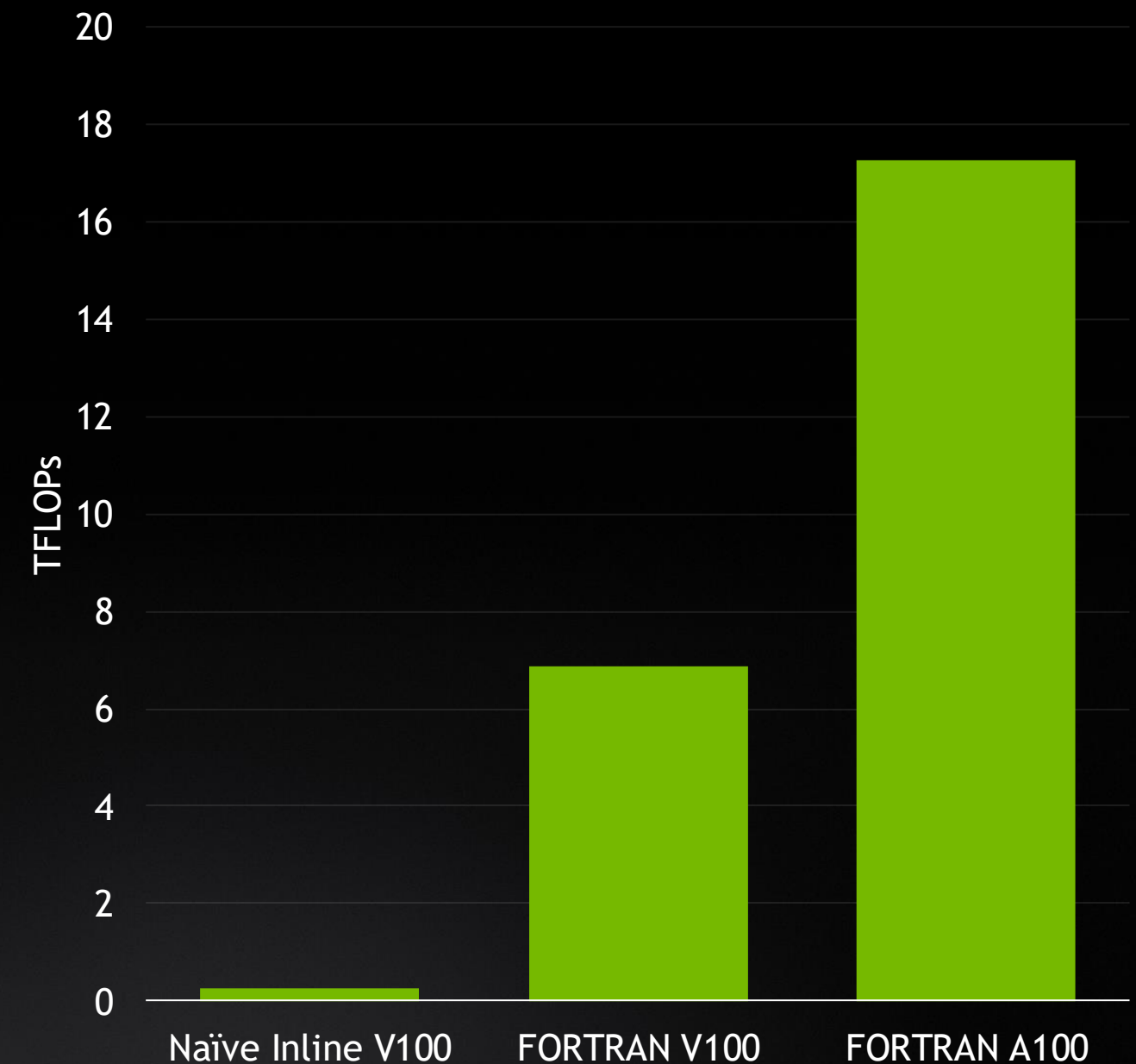
do nt = 1, ntimes
  !$acc kernels
  do j = 1, nj
    do i = 1, ni
      d(i,j) = c(i,j)
      do k = 1, nk
        d(i,j) = d(i,j) + a(i,k) * b(k,j)
      end do
    end do
  end do
  !$acc end kernels
end do

!$acc exit data copyout(d)
```

Inline FP64 matrix multiply

```
real(8), dimension(ni,nk) :: a
real(8), dimension(nk,nj) :: b
real(8), dimension(ni,nj) :: c
...
do nt = 1, ntimes
  d = c + matmul(a,b)
end do
```

MATMUL FP64 matrix multiply



HPC PROGRAMMING IN ISO FORTRAN

Examples of Patterns Accelerated in NVFORTRAN

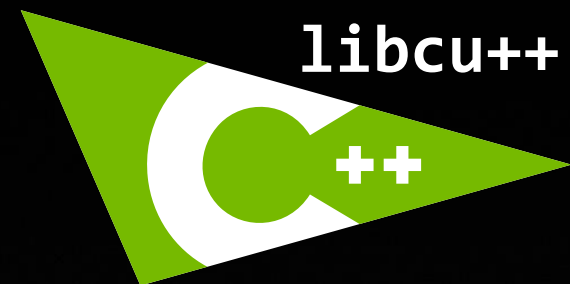
```
d = 2.5 * ceil(transpose(a)) + 3.0 * abs(transpose(b))
d = 2.5 * ceil(transpose(a)) + 3.0 * abs(b)
d = reshape(a, shape=[ni, nj, nk])
d = reshape(a, shape=[ni, nk, nj])
d = 2.5 * sqrt(reshape(a, shape=[ni, nk, nj], order=[1, 3, 2]))
d = alpha * conjg(reshape(a, shape=[ni, nk, nj], order=[1, 3, 2]))
d = reshape(a, shape=[ni, nk, nj], order=[1, 3, 2])
d = reshape(a, shape=[nk, ni, nj], order=[2, 3, 1])
d = reshape(a, shape=[ni*nj, nk])
d = reshape(a, shape=[nk, ni*nj], order=[2, 1])
d = reshape(a, shape=[64, 2, 16, 16, 64], order=[5, 2, 3, 4, 1])
d = abs(reshape(a, shape=[64, 2, 16, 16, 64], order=[5, 2, 3, 4, 1]))
c = matmul(a, b)
c = matmul(transpose(a), b)
c = matmul(reshape(a, shape=[m, k], order=[2, 1]), b)
c = matmul(a, transpose(b))
c = matmul(a, reshape(b, shape=[k, n], order=[2, 1]))
```

```
c = matmul(transpose(a), transpose(b))
c = matmul(transpose(a), reshape(b, shape=[k, n], order=[2, 1]))
d = spread(a, dim=3, ncopies=nk)
d = spread(a, dim=1, ncopies=ni)
d = spread(a, dim=2, ncopies=nx)
d = alpha * abs(spread(a, dim=2, ncopies=nx))
d = alpha * spread(a, dim=2, ncopies=nx)
d = abs(spread(a, dim=2, ncopies=nx))
d = transpose(a)
d = alpha * transpose(a)
d = alpha * ceil(transpose(a))
d = alpha * conjg(transpose(a))
c = c + matmul(a, b)
c = c - matmul(a, b)
c = c + alpha * matmul(a, b)
d = alpha * matmul(a, b) + c
d = alpha * matmul(a, b) + beta * c
```

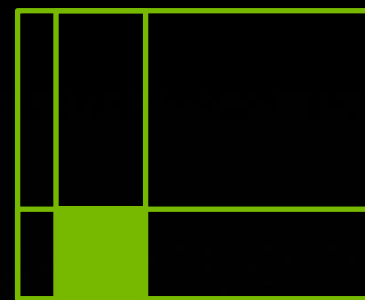
NVIDIA PERFORMANCE LIBRARIES

Core and Math

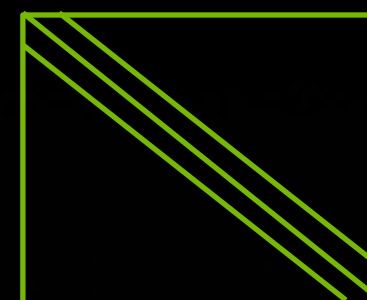
Core



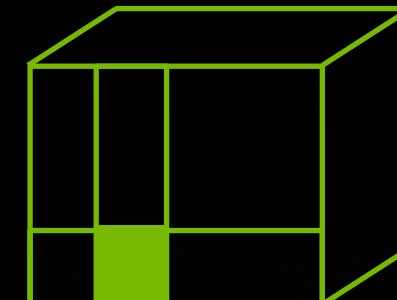
Math



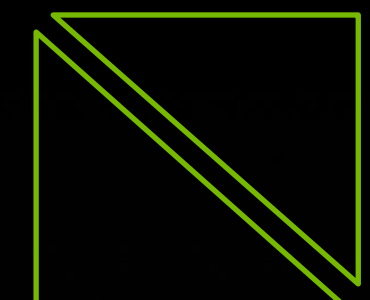
cuBLAS



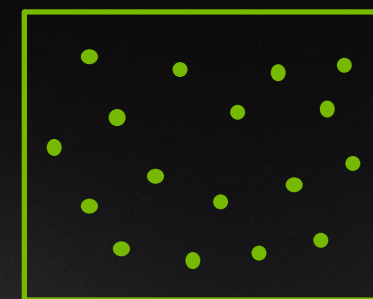
cuSPARSE



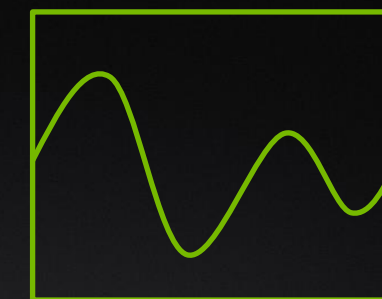
cuTENSOR



cuSOLVER



cuRAND

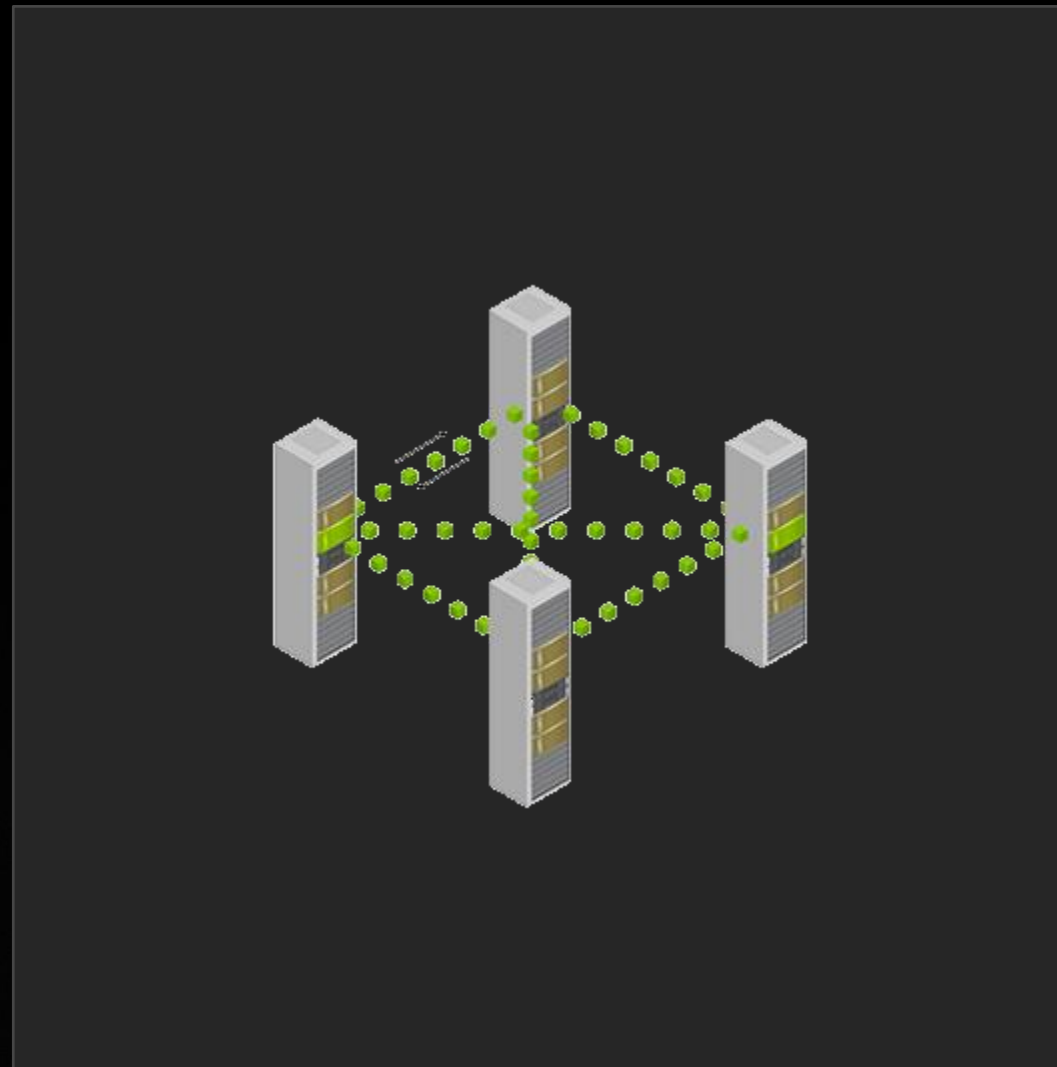


cuFFT



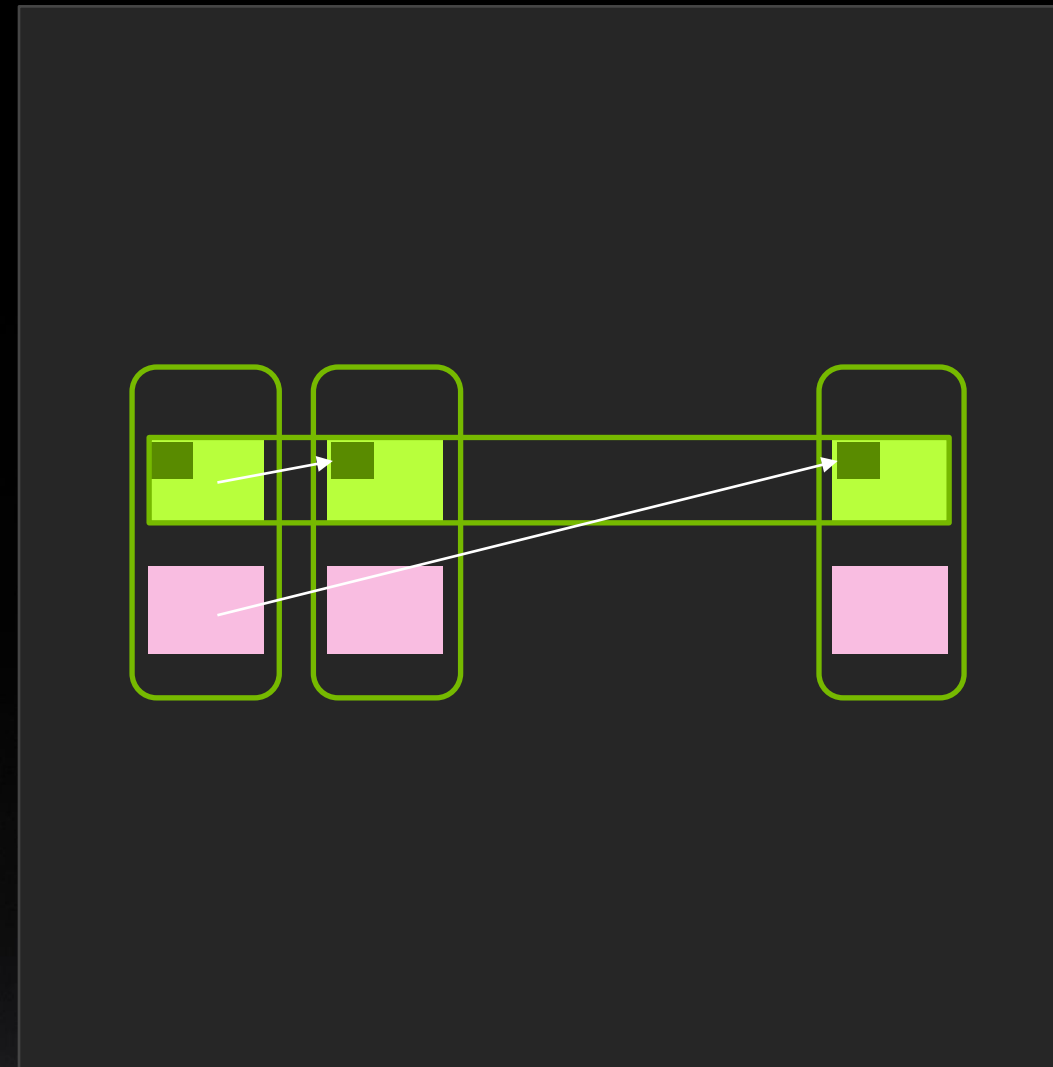
CUDA Math API

NVIDIA COMMUNICATION LIBRARIES



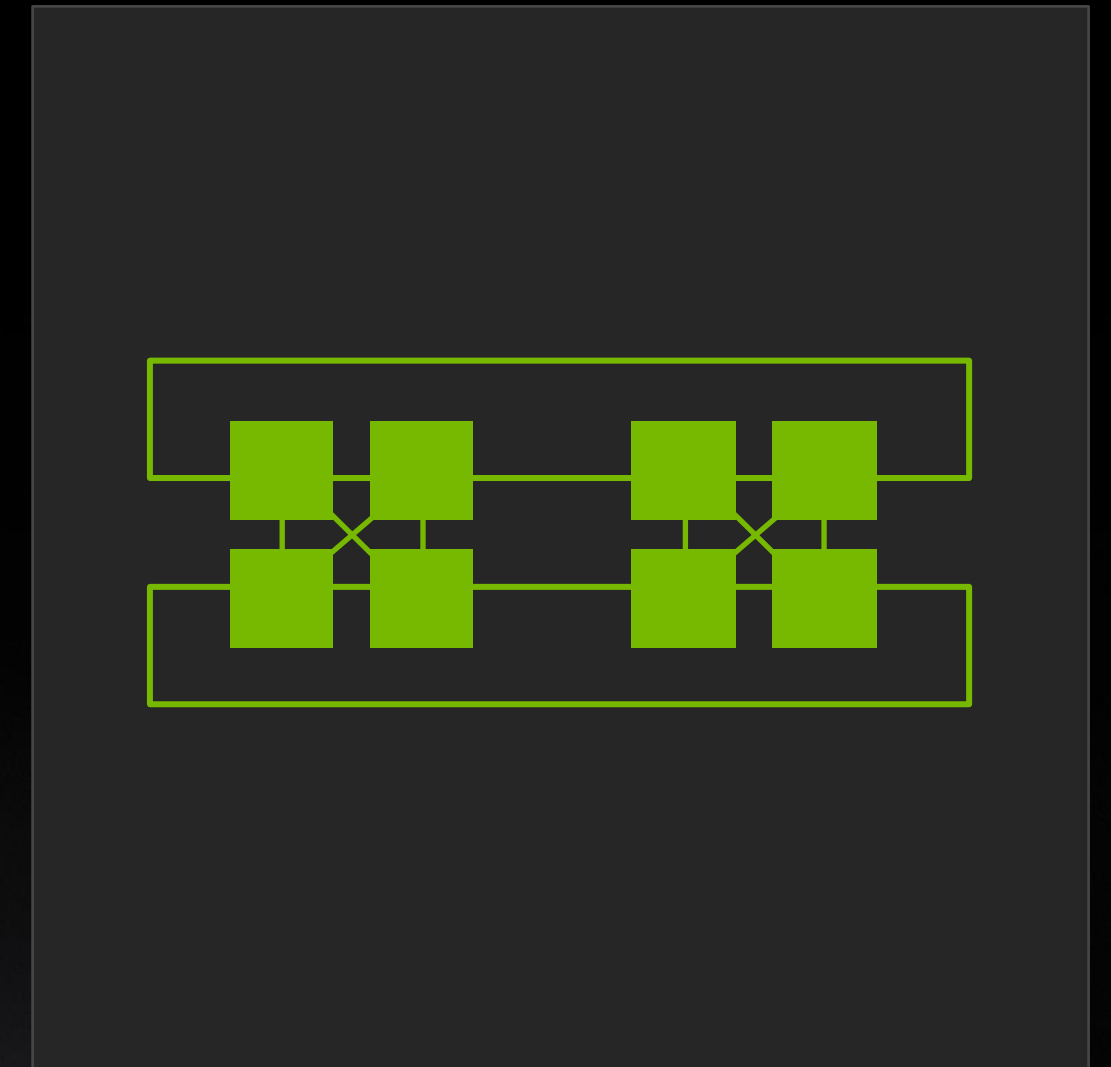
HPC-X

Optimized whole-system communications



NVSHMEM

Low-latency PGAS programming



NCCL

Multi-node collectives for accelerators

INTRODUCING LEGATE

Accelerated and Distributed

A framework for programming large numbers of GPUs as if they were a single processor

Pass data between Legate libraries without worrying about distribution or synchronization requirements

Legate NumPy and Pandas aim to transparently scale existing Numpy and Pandas workloads

Legate Numpy and Legate Pandas available now and opensource!

```
import legate.numpy as np

def cg_solve(A, b, tol=1e-10):
    x = np.zeros(A.shape[1])
    r = b - A.dot(x)
    p = r
    rsold = r.dot(r)
    for i in xrange(b.shape[0]):
        Ap = A.dot(p)
        alpha = rsold / (p.dot(Ap))
        x = x + alpha * p
        r = r - alpha * Ap
        rsnew = r.dot(r)
        if np.sqrt(rsnew) < tol:
            break
        beta = rsnew / rsold
        p = r + beta * p
        rsold = rsnew
    return x
```



LEGATE NUMPY

Results from “CFD Python”

<https://github.com/barbagroup/CFDPython>

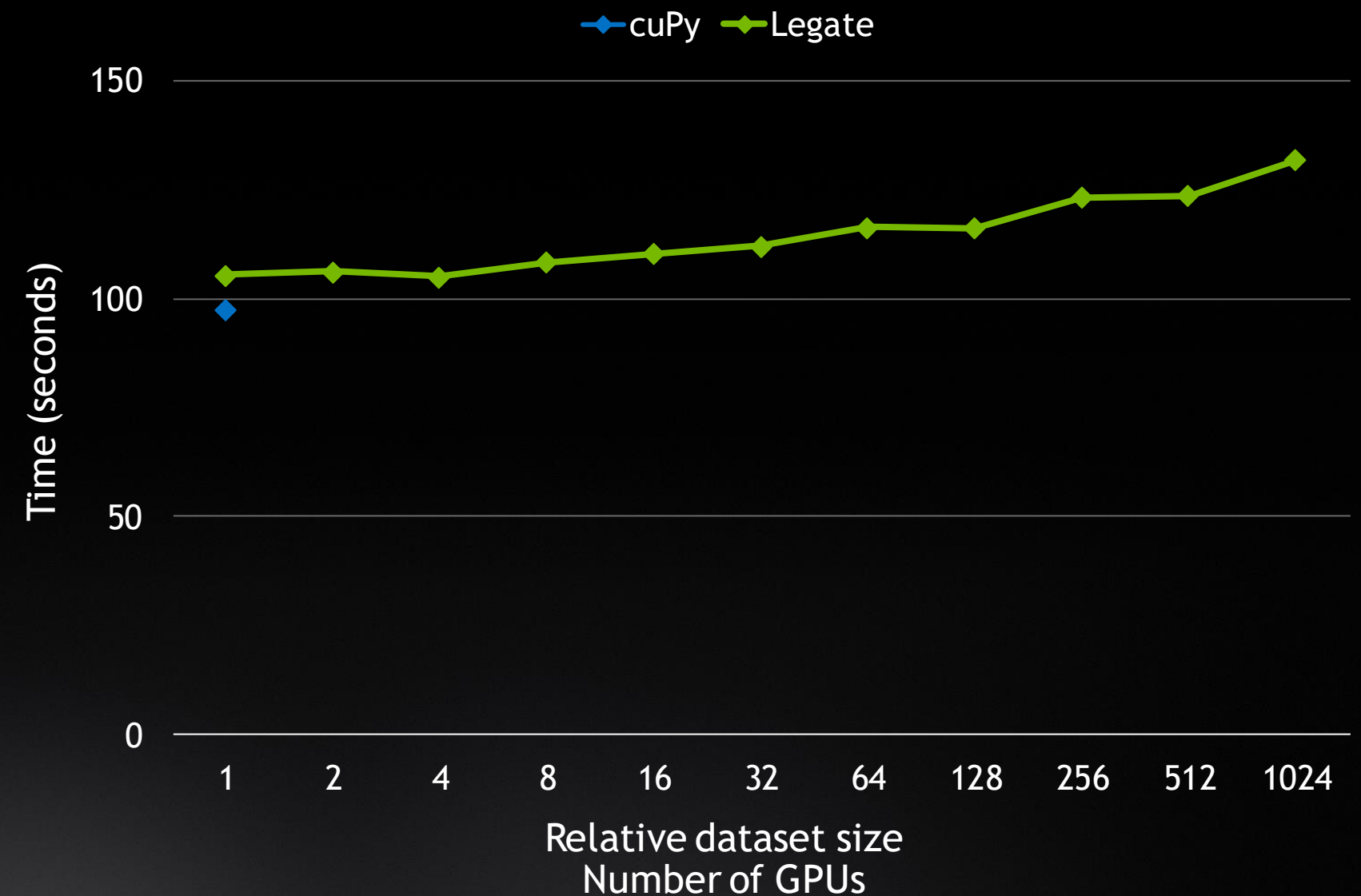
```
import legate.numpy as np

for _ in range(iter):
    un = u.copy()

    vn = v.copy()
    b = build_up_b(rho, dt, dx, dy, u, v)
    p = pressure_poisson_periodic(b, nit, p, dx, dy)

    u[1:-1, 1:-1] = (
        un[1:-1, 1:-1]
        - un[1:-1, 1:-1] * dt / dx * (un[1:-1, 1:-1] - un[1:-1, 0:-2])
        - vn[1:-1, 1:-1] * dt / dy * (un[1:-1, 1:-1] - un[0:-2, 1:-1])
        - dt / (2 * rho * dx) * (p[1:-1, 2:] - p[1:-1, 0:-2])
        + nu
        * (
            dt
            / dx ** 2
            * (un[1:-1, 2:] - 2 * un[1:-1, 1:-1] + un[1:-1, 0:-2])
            + dt
            / dy ** 2
            * (un[2:, 1:-1] - 2 * un[1:-1, 1:-1] + un[0:-2, 1:-1])
        )
        + F * dt
    )
```

Distributed NumPy Performance (weak scaling)



LEGATE PANDAS

Pandas join micro-benchmark - 300M rows/GPU

```
import legate.numpy as np
import legate.pandas as pd

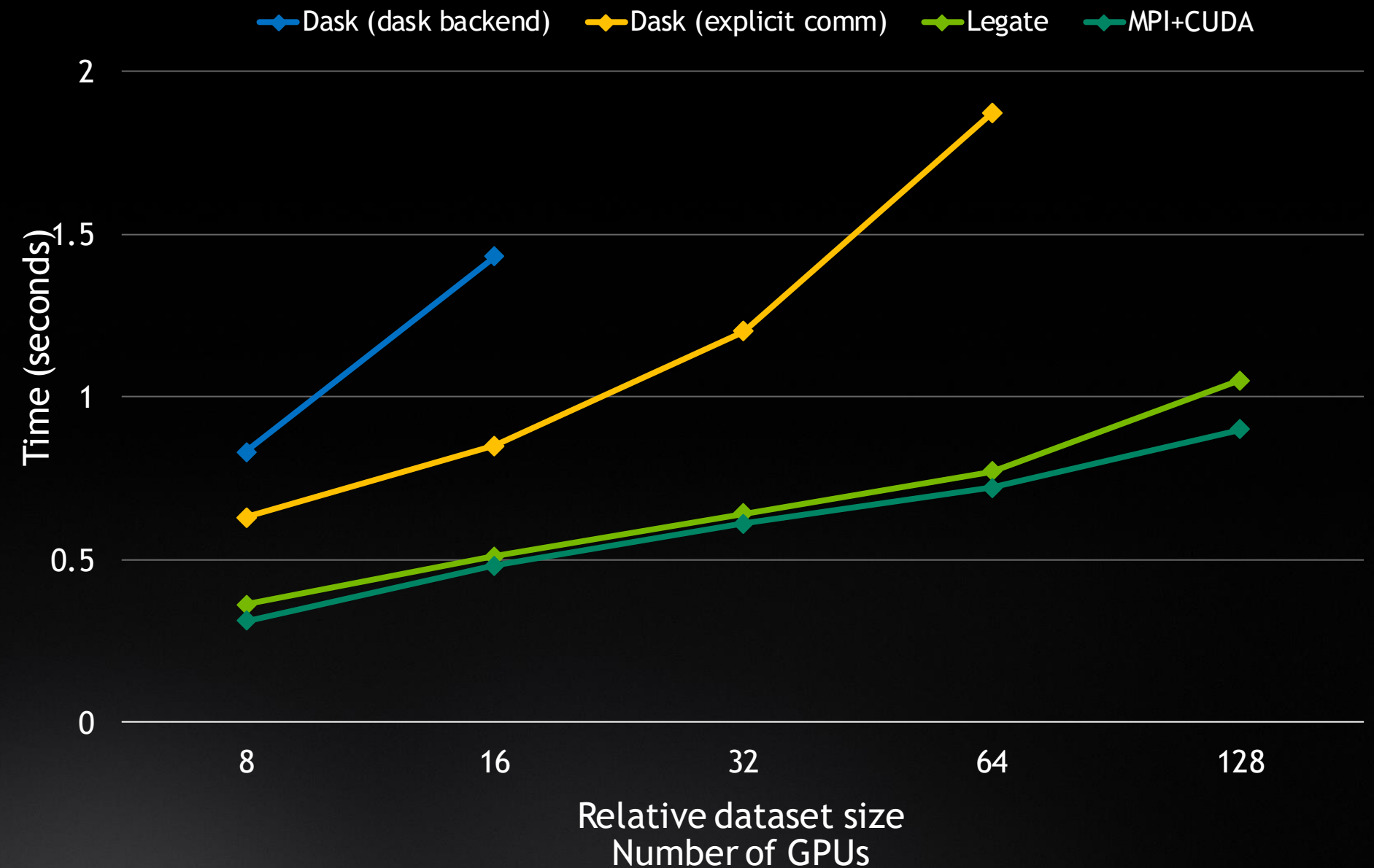
size = num_rows_per_gpu * num_gpus

key_l = np.arange(size)
payload_l = np.random.randn(size) * 100.0
lhs = pd.DataFrame({"key": key_l, "payload": payload_l})

key_r = key_l // 3 * 3 # selectivity: 0.33
payload_r = np.random.randn(size) * 100.0
rhs = pd.DataFrame({"key": key_r, "payload": payload_r})

out = lhs.merge(rhs, on="key")
```

Distributed Pandas Performance (weak scaling)



NSIGHT PRODUCT FAMILY

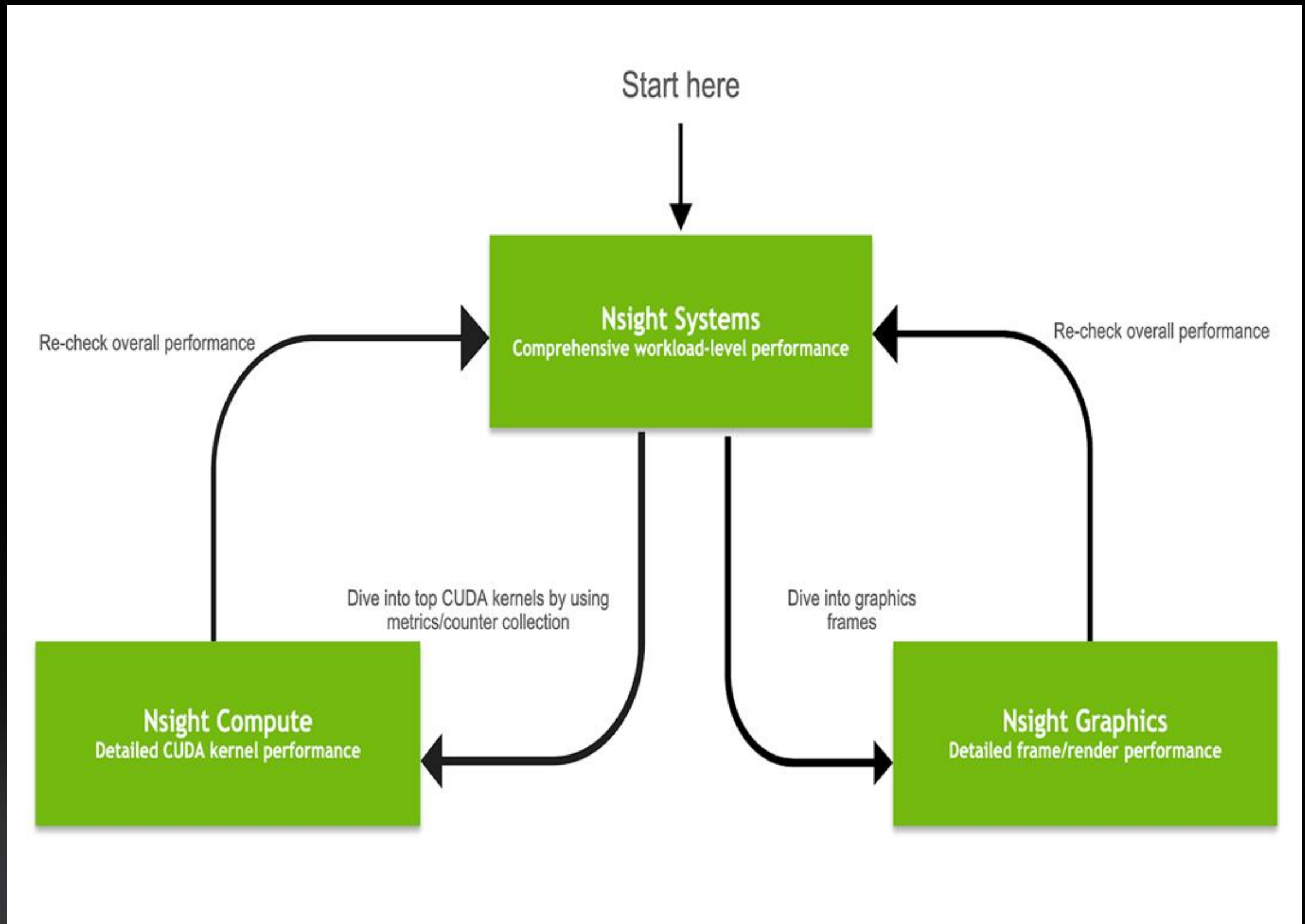
Nsight Systems - Analyze application performance (system-wide)

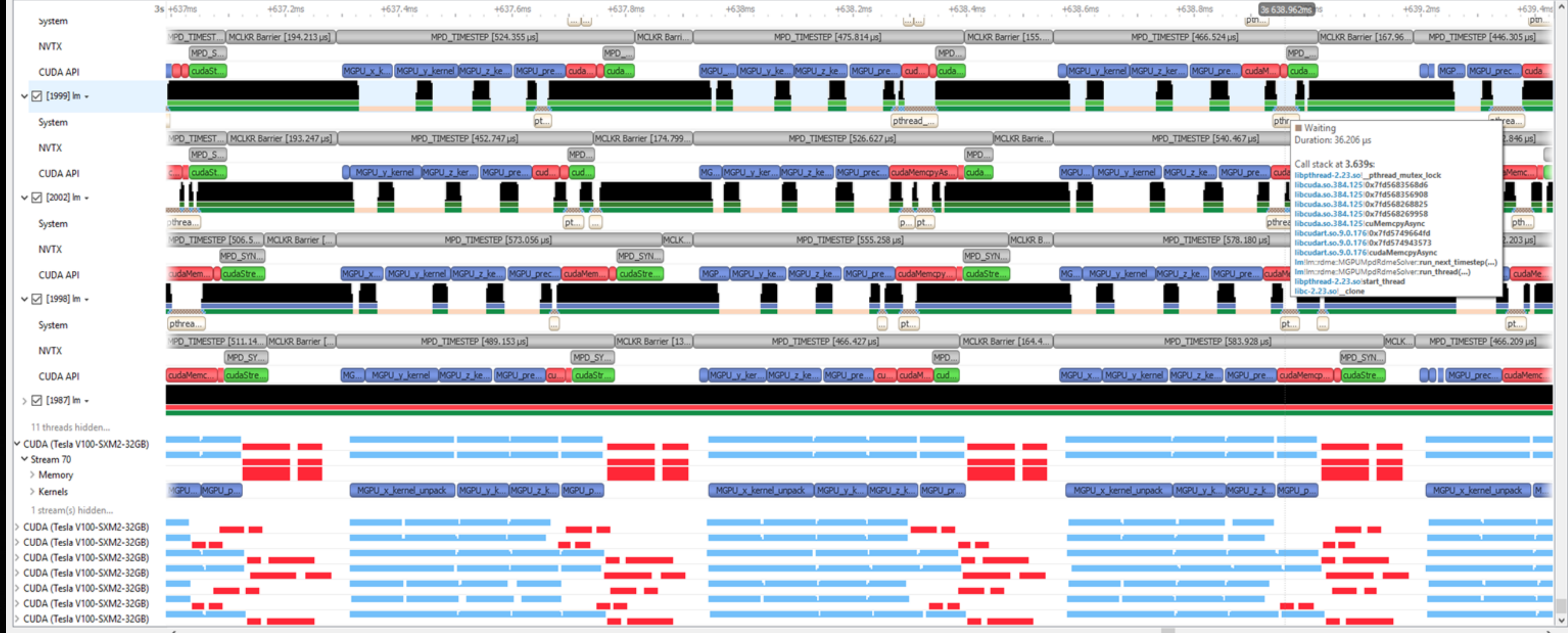
Nsight Compute - Optimize CUDA kernel

Other developer tools:

Compute Sanitizer: memory debugging similar to valgrind for GPUs

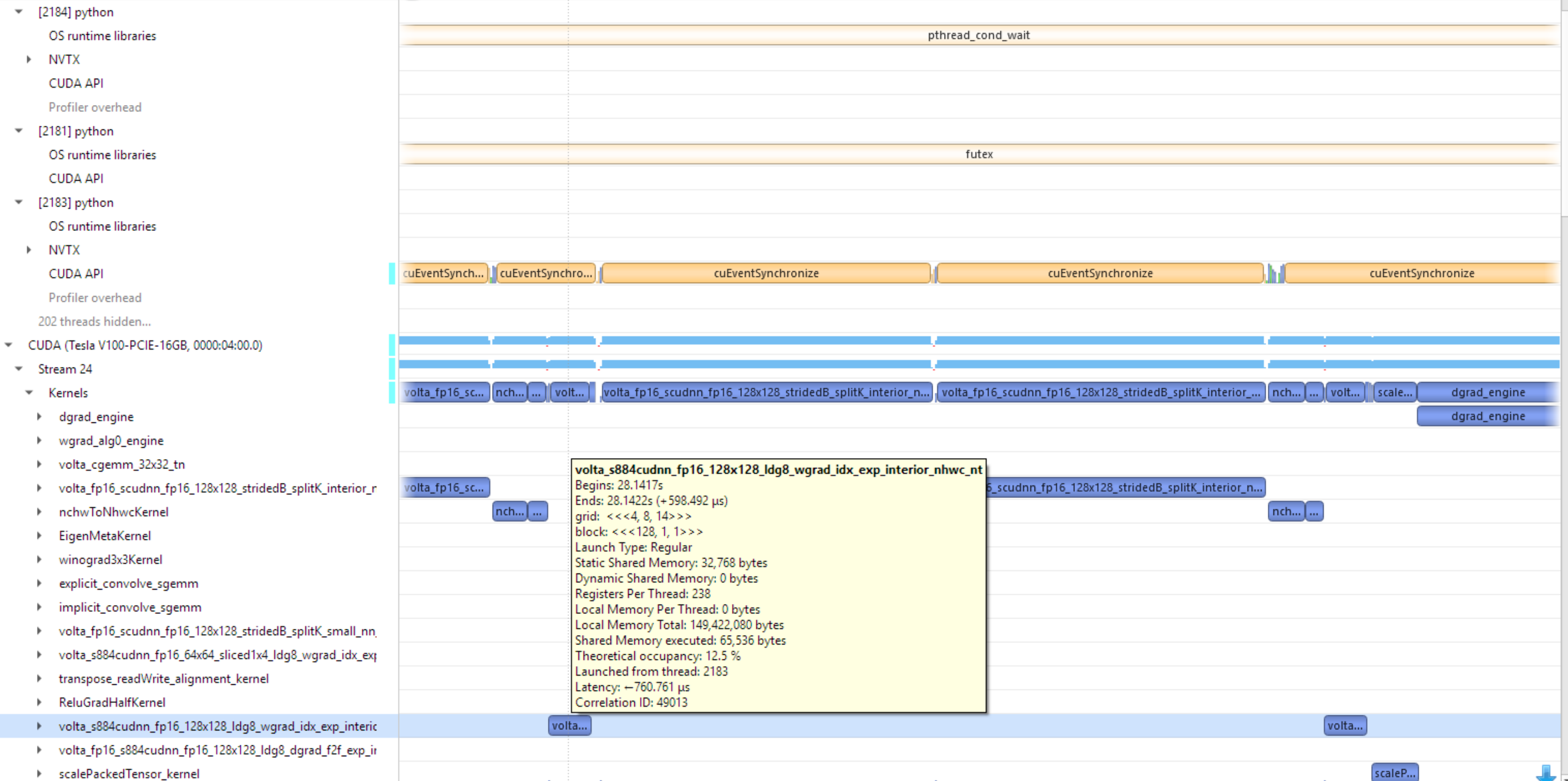
cuda-gdb: CUDA-aware extension of gdb





Symbol Name	Self, %	Module Name
> lm::rdme:MGPUMpdRdmeSolver::run_thread(int)	38.59	/opt/lm/bin/lm
> 0x7fd568442726	8.26	/usr/lib/x86_64-linux-gnu/libcuda.so.384.125
> 0x7fd568373448	2.97	/usr/lib/x86_64-linux-gnu/libcuda.so.384.125
> 0x7fd568373436	2.25	/usr/lib/x86_64-linux-gnu/libcuda.so.384.125

28s 40ms 28s 141.92ms +144ms +146ms +148ms +150ms +152ms +154ms



NVTX

NVIDIA Tools Extension for Profiling

NVTX can be used to manually instrument applications, for example in C:

```
nvtxRangePush("region_name");
```

```
nvtxRangePop();
```

These names are then shown on the nsys timeline (can also be used with ncu)

Headers provided with CUDA toolkit for C/C++; can also be used with Fortran, generic Python (e.g. provided by CuPy), TensorFlow, and PyTorch

COLLECT A PROFILE WITH NSIGHT SYSTEMS

```
$ nsys profile -o report --stats=true ./myapp.exe
```

Generated file: `report.qdrep`; open for viewing in the Nsight Systems UI

Can be done inside a container if the container has `nsys`:

```
$ mpirun -n 4 singularity run --nv -B $CONTAINER_IMG nsys profile python train.py
```


NSIGHT COMPUTE

The screenshot displays the NVIDIA Nsight Compute application window. The title bar reads "NVIDIA Nsight Compute". The menu bar includes "File", "Connection", "Debug", "Profile", "Tools", "Window", and "Help". The toolbar contains icons for "Connect", "Disconnect", "Terminate", "Profile Kernel", and various playback controls. The main window shows a report for a kernel named "old_2_fusion_on_softmax.nsisight-cuprof-report". The current kernel is "64291 - softmax_compute_kernel (1966...)" with a duration of 15.65 usecond, 16,235 cycles, and 28 registers. The GPU is a Tesla V100-SXM2-16GB with an SM frequency of 1.04 cycle/nsecond and a CC of 7.0. The process is [944] python3.5.

The "GPU Speed Of Light" section provides a high-level overview of GPU utilization. It includes a table with the following data:

Metric	Value	Unit	Value	Unit
SOL SM [%]	45.88	Duration [usecond]	15.65	
SOL Memory [%]	43.42	Elapsed Cycles [cycle]	16,235	
SOL TEX [%]	55.37	SM Active Cycles [cycle]	12,110.30	
SOL L2 [%]	13.66	SM Frequency [cycle/nsecond]	1.04	
SOL FB [%]	43.42	Memory Frequency [cycle/usecond]	701.94	

Below the table is a "GPU Utilization" chart showing Speed of Light [%] on the x-axis (0.0 to 100.0) and SM [%] and Memory [%] on the y-axis. The SM utilization is approximately 46% and Memory utilization is approximately 43%.

A "Bottleneck" warning is displayed: "[Warning] This kernel exhibits low compute throughput and memory bandwidth utilization relative to the peak performance of this device. Achieved compute throughput and/or memory bandwidth below 60.0% of peak typically indicate latency issues. Look at 'Scheduler Statistics' and 'Warp State Statistics' for potential reasons."

The "Compute Workload Analysis" section provides a detailed analysis of the compute resources of the streaming multiprocessors (SM), including the achieved instructions per dock (IPC) and the utilization of each available pipeline. It includes a table with the following data:

Metric	Value	Metric	Value
Executed Ipc Elapsed [inst/cycle]	1.83	SM Busy [%]	61.39
Executed Ipc Active [inst/cycle]	2.44	Issue Slots Busy [%]	61.39
Issued Ipc Active [inst/cycle]	2.46		-

CUDA kernel profiler

Targeted metric sections for various performance aspects

Customizable data collection and presentation (tables, charts, ...)

UI and Command Line

Python-based rules for guided analysis (or post-processing)

NSIGHT COMPUTE

The screenshot displays the NSIGHT COMPUTE interface with the following components:

- Source Code (Left Panel):** C++ code for a softmax kernel. Line 249 is highlighted: `cuda::Reduce1D<red::maximum, x_bits>(smem);`
- Sampling Data (Middle Panel):** A heatmap showing sampling data for the highlighted instruction. A tooltip is visible with the following data:
 - Total Sample Count: 111
 - Barrier: 43 (38.7%)
 - Mio Throttle: 21 (18.9%)
 - Not Selected: 8 (7.2%)
 - Selected: 7 (6.3%)
 - Short Scoreboard: 16 (14.4%)
 - Wait: 16 (14.4%)
- PTX Instructions (Right Panel):** A list of PTX instructions with their execution counts. The first instruction, `BSYNC B0`, has a count of 6,144. Other instructions include `NOP`, `BAR.SYNC 0x0`, and various `ISETP.GT.AND`, `LDS.U`, `STL`, `FMNMX`, and `STS` instructions.

Source/PTX/SASS analysis and correlation

Source metrics per instruction and aggregated (e.g. PC sampling data)

Metric heatmap

KERNEL PROFILES WITH NSIGHT COMPUTE

```
$ ncu -k mykernel -o report ./myapp.exe
```

Generated file: `report.ncu-rep`; open for viewing in the Nsight Compute UI

(Without the `-k` option, Nsight Compute will profile everything and take a long time!)

