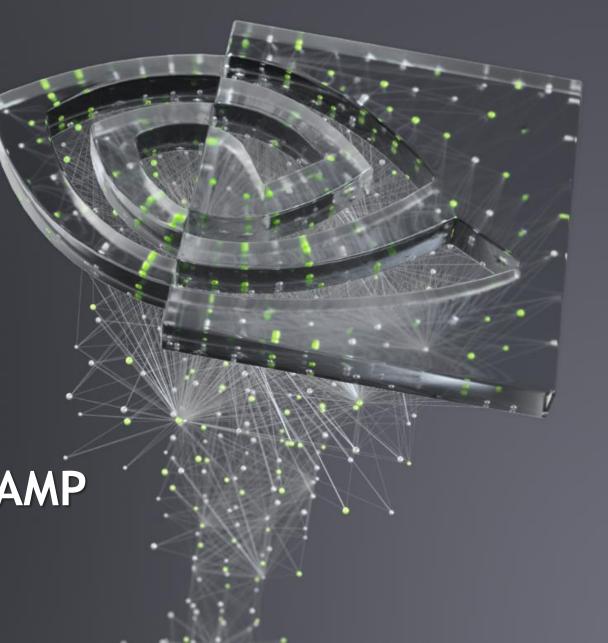


N-WAYS GPU BOOTCAMP



OUT OF SCOPE

 This session should not be considered as extensive guide covering all the API of respective parallel programming model

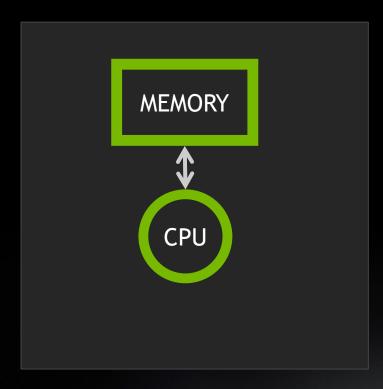
This session is focused on the introduction and no detail optimization will covered

INTRODUCTION TO GPU COMPUTING

What to expect?

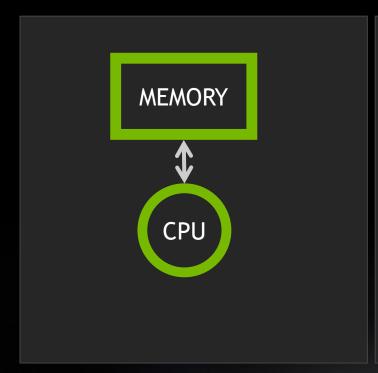
- Broad view on GPU Stack
- Fundamentals of GPU Architecture
- Good starting point

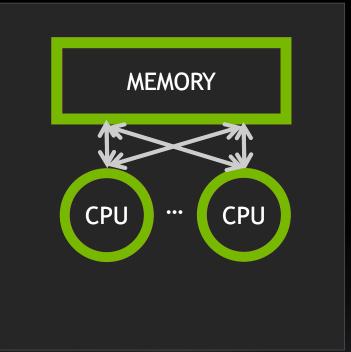
HPC SYSTEM EVOLUTION



Sequential

HPC SYSTEM EVOLUTION

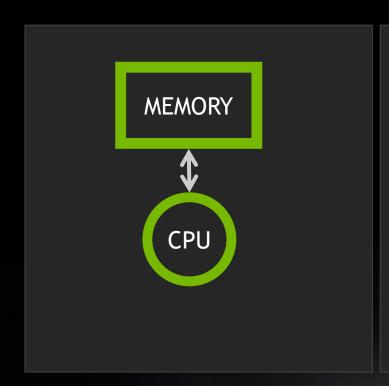


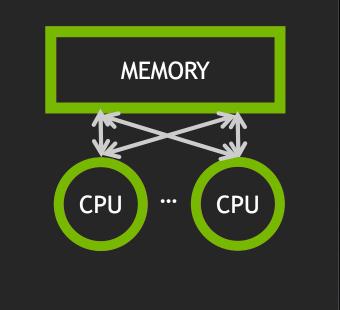


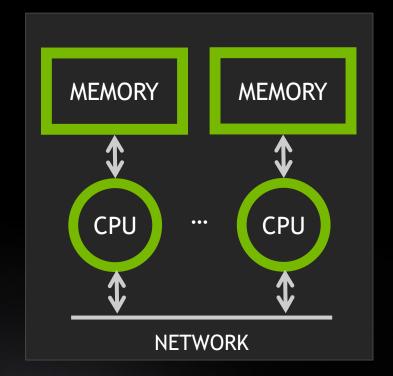
Sequential

Multithreaded P-Thread/OpenMP

HPC SYSTEM EVOLUTION



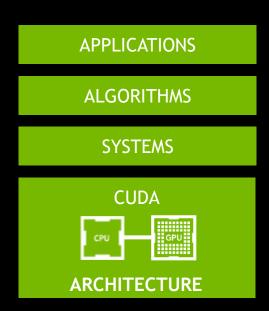


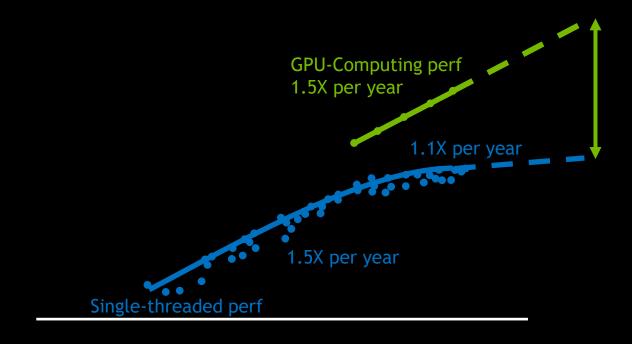


Sequential

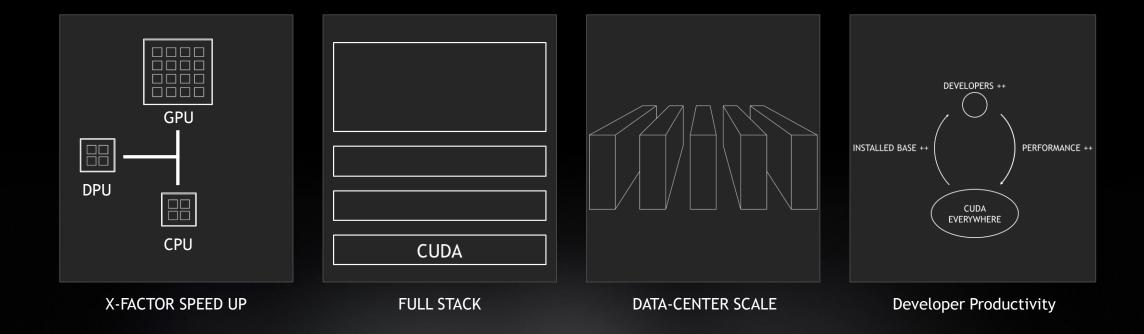
Multithreaded P-Thread/OpenMP Distributed MPI

GPU ARCHITECTURE CONTINUES TO DELIVER PERFORMANCE

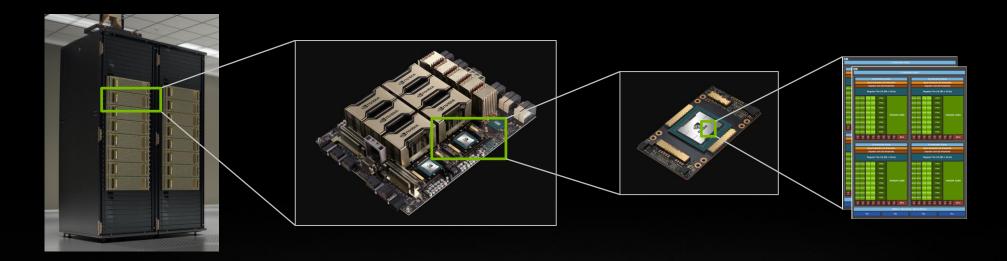




ACCELERATED COMPUTING PILLARS



HIERARCHY OF SCALES



Multi-System Rack
Unlimited Scale

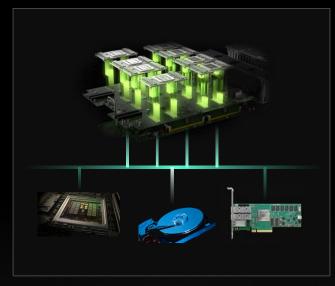
Multi-GPU System 8 GPUs Multi-SM GPU
108 Multiprocessors

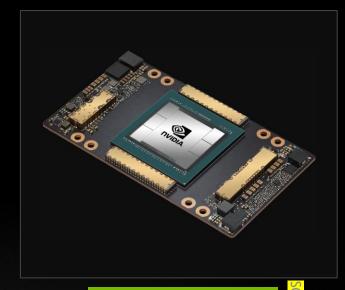
Multi-Core SM 2048 threads

CUDA PLATFORM: TARGETS EACH LEVEL OF THE HIERARCHY

The CUDA Platform Advances State Of The Art From Data Center To The GPU







System Scope

FABRIC MANAGEMENT
DATA CENTER OPERATIONS
DEPLOYMENT
MONITORING
COMPATIBILITY
SECURITY

Node Scope

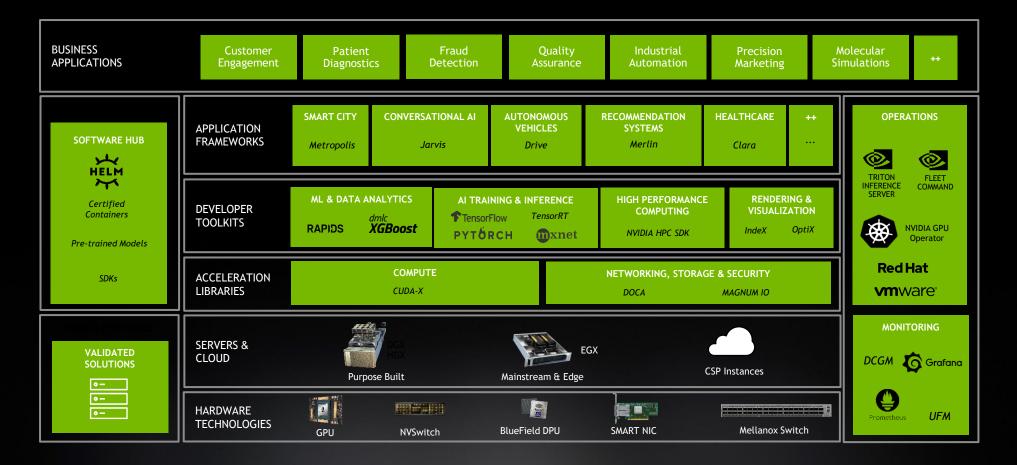
GPU-DIRECT NVLINK LIBRARIES UNIFIED MEMORY ARM

Program Scope

CUDA C++
OPENACC
STANDARD LANGUAGES
SYNCHRONIZATION
PRECISION

O INVIDIA

ACCELERATED PLATFORM



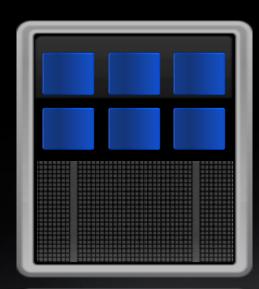
HOW GPU ACCELERATION WORKS



ACCELERATED COMPUTING

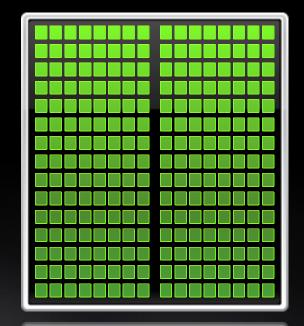
CPU

Optimized for Serial Tasks



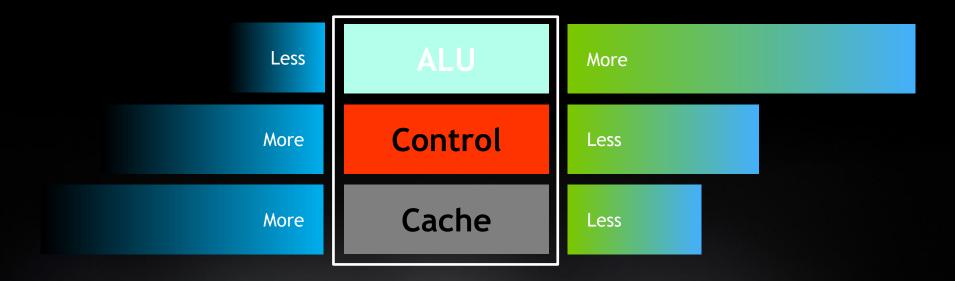
GPU Accelerator

Optimized for Parallel Tasks



SILICON BUDGET

The three components of any processor



CPU IS A LATENCY REDUCING ARCHITECTURE

CPU

Optimized for Serial Tasks



CPU Strengths

- Very large main memory
- Very fast clock speeds
- Latency optimized via large caches
- Small number of threads can run very quickly

CPU Weaknesses

- Relatively low memory bandwidth
- Cache misses very costly
- Low performance/watt

GPU IS ALL ABOUT HIDING LATENCY

GPU Strengths

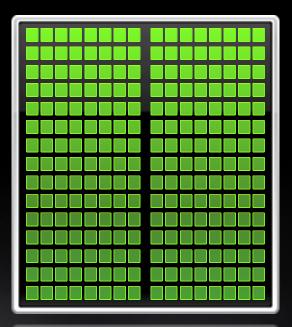
- High bandwidth main memory
- Significantly more compute resources
- Latency tolerant via parallelism
- High throughput
- High performance/watt

GPU Weaknesses

- Relatively low memory capacity
- · Low per-thread performance

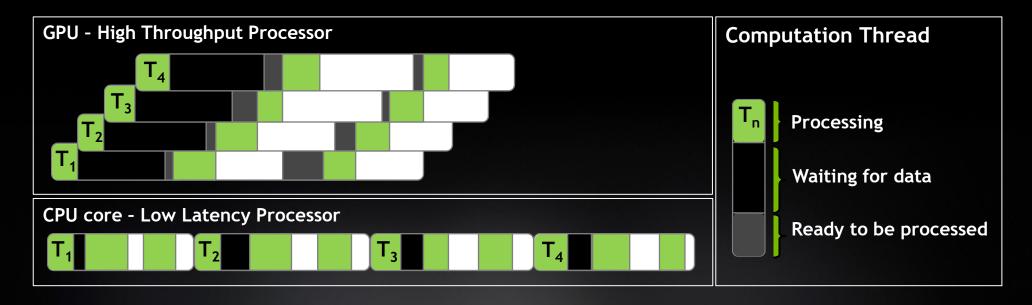
GPU Accelerator

Optimized for Parallel Tasks



LOW LATENCY VS HIGH THROUGHPUT

- CPU architecture must minimize latency within each thread
- GPU architecture hides latency with computation (data-parallelism, to 30k threads!)



SPEED V. THROUGHPUT

Speed

Throughput



Which is better depends on your needs...

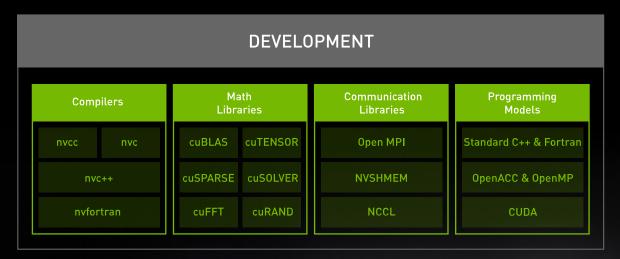
HUGE BREADTH OF PLATFORMS, SYSTEMS, LANGUAGES

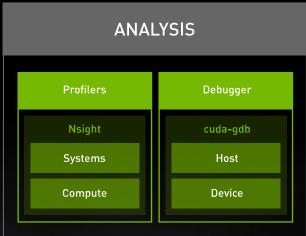


NVIDIA HPC SDK

Download at developer.nvidia.com/hpc-sdk

NVIDIA HPC SDK







Develop for the NVIDIA HPC Platform: GPU, CPU and Interconnect HPC Libraries | GPU Accelerated C++ and Fortran | Directives | CUDA

N-WAYS TO GPU PROGRAMMING

Math Libraries | Standard Languages | Directives | CUDA

```
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
```

GPU Accelerated C++ and Fortran

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

Incremental Performance
Optimization with Directives

Maximize GPU Performance with CUDA C++/Fortran

GPU Accelerated Math Libraries



GPU ACCELERATED MATH LIBRARIES



cuBLAS

BF16, TF32 and FP64 **Tensor Cores**



nvJPEG

Hardware Decoder



cuSPARSE

Increased memory BW, Shared Memory & L2



cuTENSOR

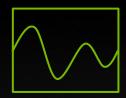
BF16, TF32 and FP64 **Tensor Cores**



cuSOLVER

BF16, TF32 and **FP64 Tensor Cores**





cuFFT

BF16, TF32 and FP64 Tensor Cores



CUDA Math API

Increased memory BW, Shared Memory & L2



CUTLASS

BF16 & TF32 Support

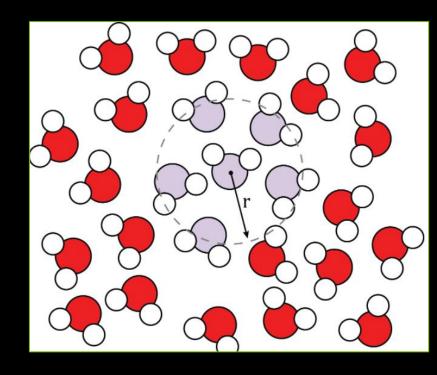
APPLICATION

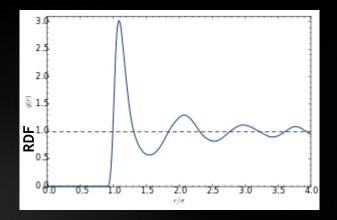
Molecular Simulation

RDF

The radial distribution function (RDF) denoted in equations by g(r) defines the probability of finding a particle at a distance r from another tagged particle.

https://en.wikipedia.org/wiki/Radial_distribution_function





RDF

Pseudo Code - C

```
for (int frame=0;frame<nconf;frame++){</pre>
      for(int id1=0;id1<numatm;id1++)</pre>
            for(int id2=0;id2<numatm;id2++)</pre>
                  dx=d_x[]-d_x[];
                  dy=d_y[]-d_y[];
                  dz=d_z[]-d_z[];
                  r=sqrtf(dx*dx+dy*dy+dz*dz);
                  if (r<cut) {</pre>
                        ig2=(int)(r/del);
                        d_g2[ig2] = d_g2[ig2] +1;
```

Across Frames

Find Distance

Reduction

RDF

Pseudo Code - Fortran

```
do iconf=1,nframes
  if (mod(iconf,1).eq.0) print*,iconf
  do i=1,natoms
     do j=1,natoms
           dx=x(iconf,i)-x(iconf,j)
           dy=y(iconf,i)-y(iconf,j)
           dz=z(iconf,i)-z(iconf,j)
           r=dsqrt(dx**2+dy**2+dz**2)
           if(r<cut)then
                g(ind)=g(ind)+1.0d0
           endif
     enddo
  enddo
enddo
```

Across Frames

Find Distance

Reduction

SINGLE PRECISION ALPHA X PLUS Y (SAXPY)

GPU SAXPY in multiple languages and libraries

Part of Basic Linear Algebra Subroutines (BLAS) Library

$$z = \alpha x + y$$

x, y, z: vector

 α : scalar

SAXPY: OPENACC COMPILER DIRECTIVES

Parallel C Code

```
void saxpy(int n,
           float a,
           float *x,
           float *y)
#pragma acc kernels
  for (int i = 0; i < 0
    y[i] = a*x[i] + y[i];
// Perform SAXPY on 1M elements
saxpy(1 << 20, 2.0, x, y);
```

Parallel Fortran Code

```
subroutine saxpy(n, a, x, y)
  real :: x(:), y(:), a
 integer :: n, i
!$acc kernels
 do i=1,n
   y(i) = a*x(i)+y(i)
 enddo
!$acc end kernels
end subroutine saxpy
! Perform SAXPY on 1M elements
```

SAXPY: CUBLAS LIBRARY

Serial BLAS Code

```
int N = 1<<20;
....
// Use your choice of blas library
// Perform SAXPY on 1M elements
blas_saxpy(N, 2.0, x, 1, y, 1);</pre>
```

Parallel cuBLAS Code

```
int N = 1 << 20;
cublasInit();
cublasSetVector(N, sizeof(x[0]), x, 1, d_x, 1);
cublasSetVector(N, sizeof(y[0]), y, 1, d_y, 1);
// Perform SAXPY on 1M elements
cublasSaxpy(N, 2.0, d_x, 1, d_y, 1);
cublasGetVector(N, sizeof(y[0]), d_y, 1, y, 1);
cublasShutdown();
```

You can also call cuBLAS from Fortran, C++, Python, and other languages:

http://developer.nvidia.com/cublas



SAXPY: CUDA C

Standard C

Parallel C

```
__global__
void saxpy(int n, float a,
      float *x, float *y)
  int i = blockIdx.x*blockDim.x + threadIdx
           ) y[i] = a*x[i] + y[i];
int N = 1 << 20:
cudaMemcpy(d_x, x, N, cudaMemcpyHostToDevice);
cudaMemcpy(d_y, y, N, cudaMemcpyHostToDevice);
// Perform SAXPY on 1M elements
saxpy <<< 4096, 256>>> (N, 2.0, d_x, d_y);
cudaMemcpy(y, d_y, N, cudaMemcpyDeviceToHost);
```

SAXPY: CUDA FORTRAN

Standard Fortran

```
module mymodule contains
  subroutine saxpy(n, a, x, y)
    real :: x(:), y(:), a
    integer :: n, i
    do i=1,n
     y(i) = a*x(i)+y(i)
    enddo
  end subroutine saxpy
end module mymodule
program main
  use mymodule
  real :: x(2**20), y(2**20)
  x = 1.0, y = 2.0
  ! Perform SAXPY on 1M elements
  call saxpy(2**20, 2.0, x, y)
end program main
```

Parallel Fortran

```
module mymodule contains
  attributes(global) subroutine saxpy(n, a, x, y)
    real :: x(:), y(:), a
    integer :: n, i
    attributes(value) :: a, n
    i = threadIdx%x+(blockIdx%x-1)*blockDim%x
    if (i \le n) y(i) = a \times x(i) + y(i)
  end subroutine saxpy
end module mymodule
program main
  use cudafor; use mymodule
  real, device :: x_d(2**20), y_d(2**20)
  x_d = 1.0, y_d = 2.0
  ! Perform SAXPY on 1M elements
  call saxpy <<<4096,256>>>(2**20, 2.0, x_d, y_d)
end program main
```

SAXPY: PYTHON

Standard Python

```
import numpy as np
def saxpy(a, x, y):
  return [a * xi + yi
          for xi, yi in zip(x, y)]
x = np.arange(2**20, dtype=np.float32)
y = np.arange(2**20, dtype=np.float32)
cpu_result = saxpy(2.0)
```

Numba: Parallel Python

```
import numpy as np
from numba import vectorize
@vectorize(['float32(float32, float32,
float32)'], target='cuda')
def saxpy(a, x, y):
    return a * x + y
N = 1048576
# Initialize arrays
A = np.ones(N, dtype=np.float32)
B = np.ones(A.shape, dtype=A.dtype)
C = np.empty_like(A, dtype=A.dtype)
# Add arrays onGPU
C = saxpy(2.0, X, Y)
```

SAXPY: PYTHON

Standard Python

```
import numpy as np

x = np.ones(2**20, dtype=np.float32)
y = np.ones(2**20, dtype=np.float32)

def saxpy(a, x, y):
    return a * x + y

cpu_result = saxpy(2.0, x, y )
```

CUPY: GPU accelerated NumPy Python

```
import cupy as cp
# Initialize arrays
x = cp.ones(2**20, dtype=cp.float32)
y = cp.ones(2**20, dtype=cp.float32)
def saxpy(a, x, y):
  return a * x + y
qpu_result = saxpy(2.0, x, y)
```

SAXPY: MATLAB

Parallel C Code

```
void saxpy(int n,
           float a,
           float *x,
           float *y)
#pragma acc kernels
  for (int i = 0; i <
   y[i] = a*x[i] + y[i];
// Perform SAXPY on 1M elements
saxpy(1 << 20, 2.0, x, y);
```

Parallel C++ Code

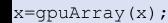
```
<<initialize>>
p = parpool
parfor i = 1:numel(N)
   y(i) = 2.0 * x(i) + y(i)
end
<<pre><<post process>
delete(p)
```

SAXPY: MATLAB

500+ GPU-enabled MATLAB functions

Transfer Data To GPU From

- Additional GPU-enabled Toolboxes
 - Neural Networks
 - Image Processing and Computer Vision
 - Communications
 - Signal Processing
 - Stats Toolbox

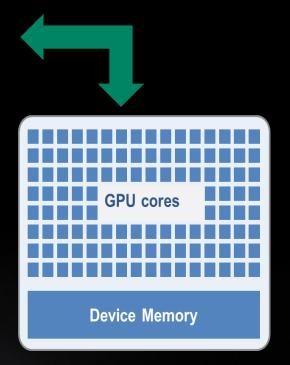


Perform Calculation on GPU

X = saxpy(N, 2.0, x, 0, 1, y, 0, 1);

Gather Data or Plot

y=gather(y)



MATLAB GPU computing

SAXPY: PSTL

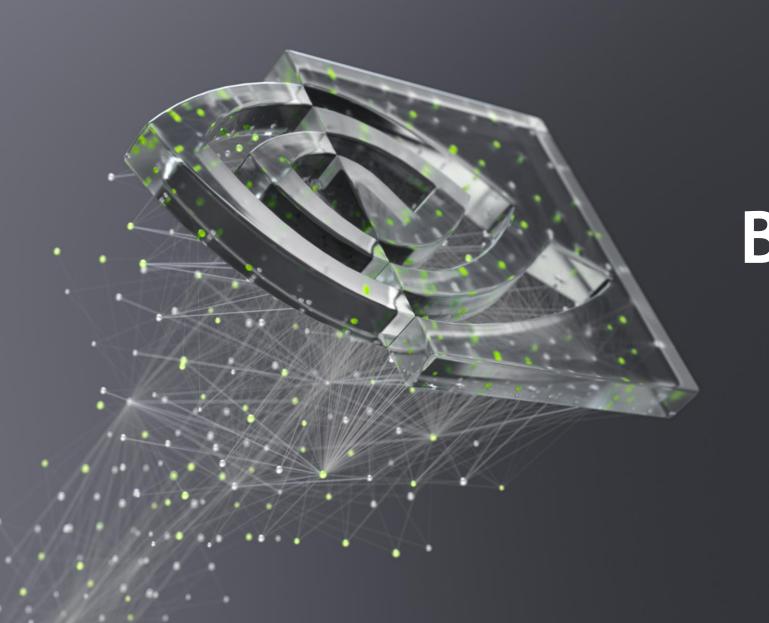
Serial C++ Code (with STL and Boost)

```
int N = 1 << 20;
std::vector<float> x(N), y(N);
// Perform SAXPY on 1M elements
std::transform(x.begin(), x.end(),
               y.begin(), y.end(),
          2.0f * _1 + _2):
```

Parallel C++ Code

```
int N = 1 << 20;
std::vector<float> x(N), y(N);
// Perform SAXPY on 1M elements
std::transform(std::execution::par
, x.begin(), x.end(),
               y.begin(), y.end(),
          2.0f * _1 + _2);
```





BACKUP

