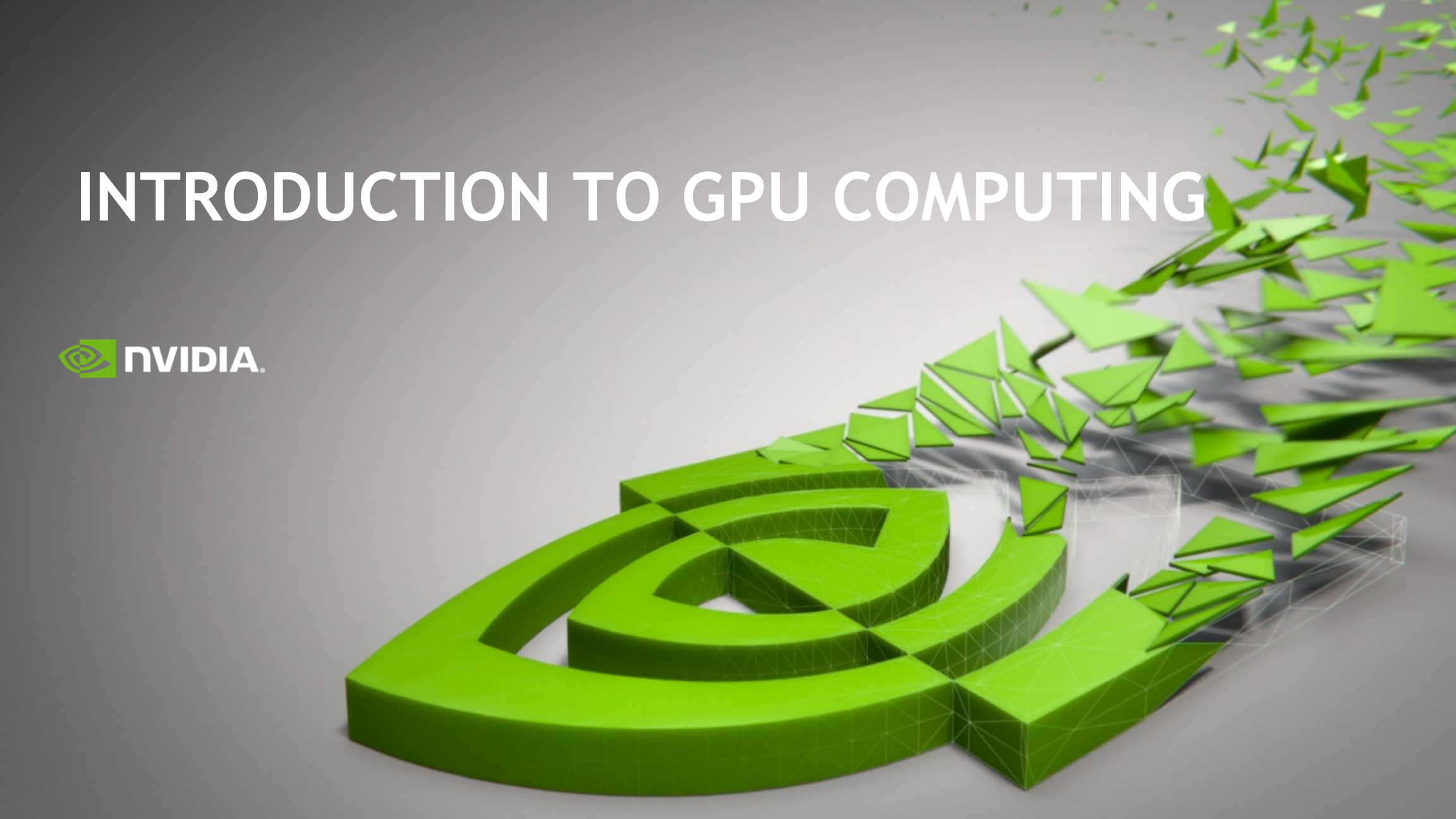
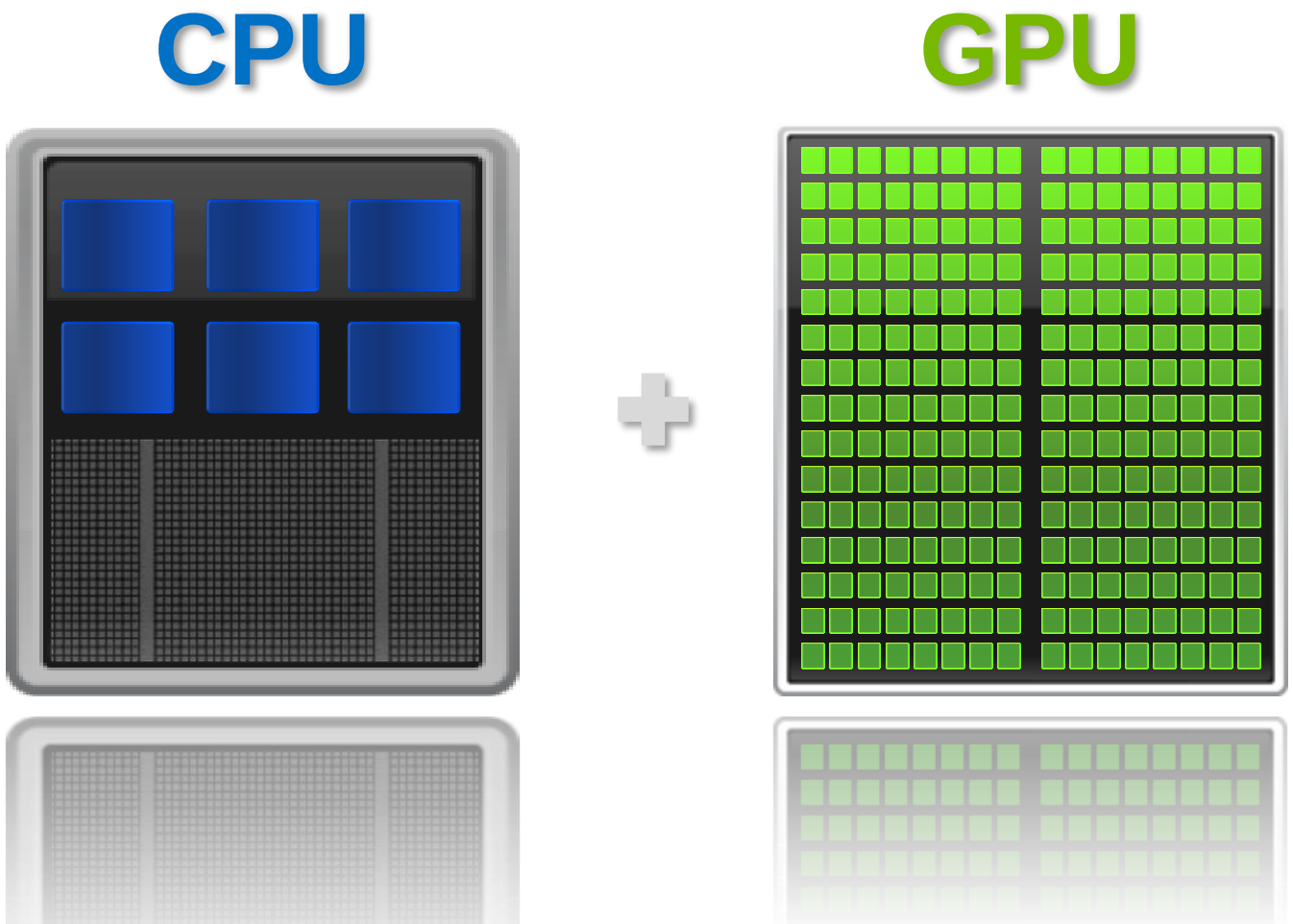
INTRODUCTION TO GPU COMPUTING

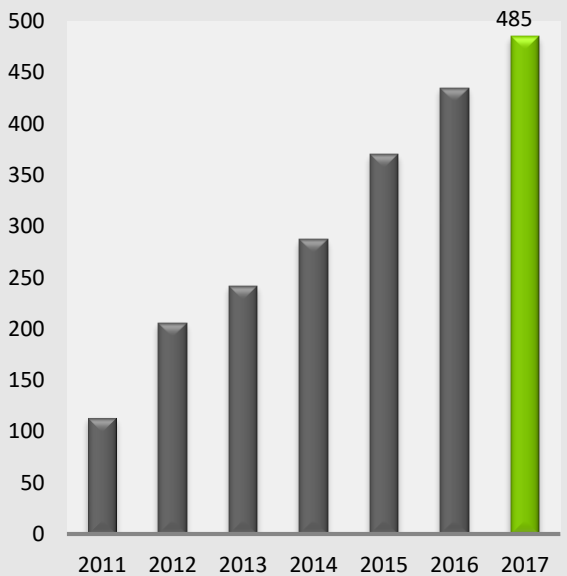


Add GPUs: Accelerate Science Applications

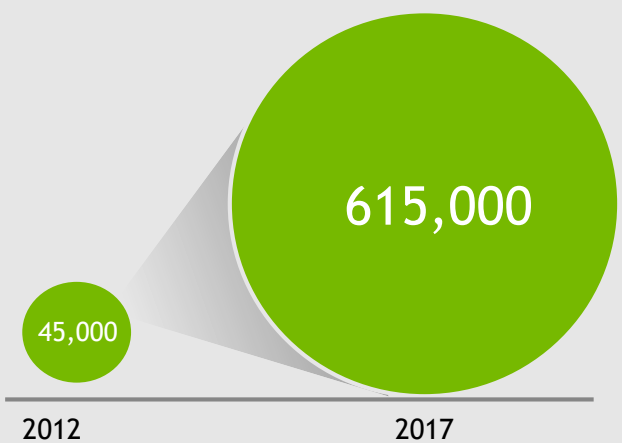


ACCELERATED COMPUTING IS GROWING RAPIDLY

450+ Applications Accelerated



11x GPU Developers



Available Everywhere

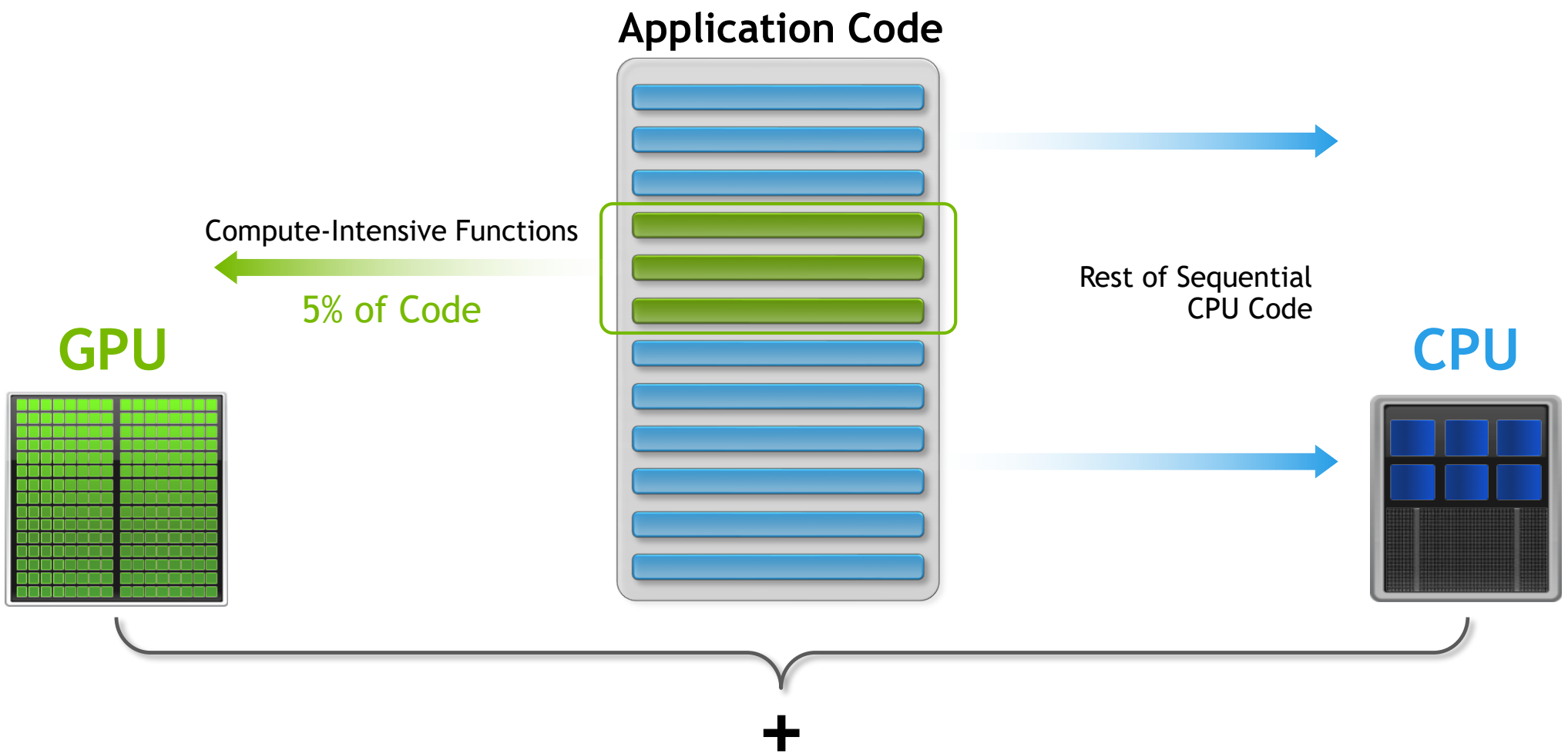
>730M

CUDA Enabled GPUs

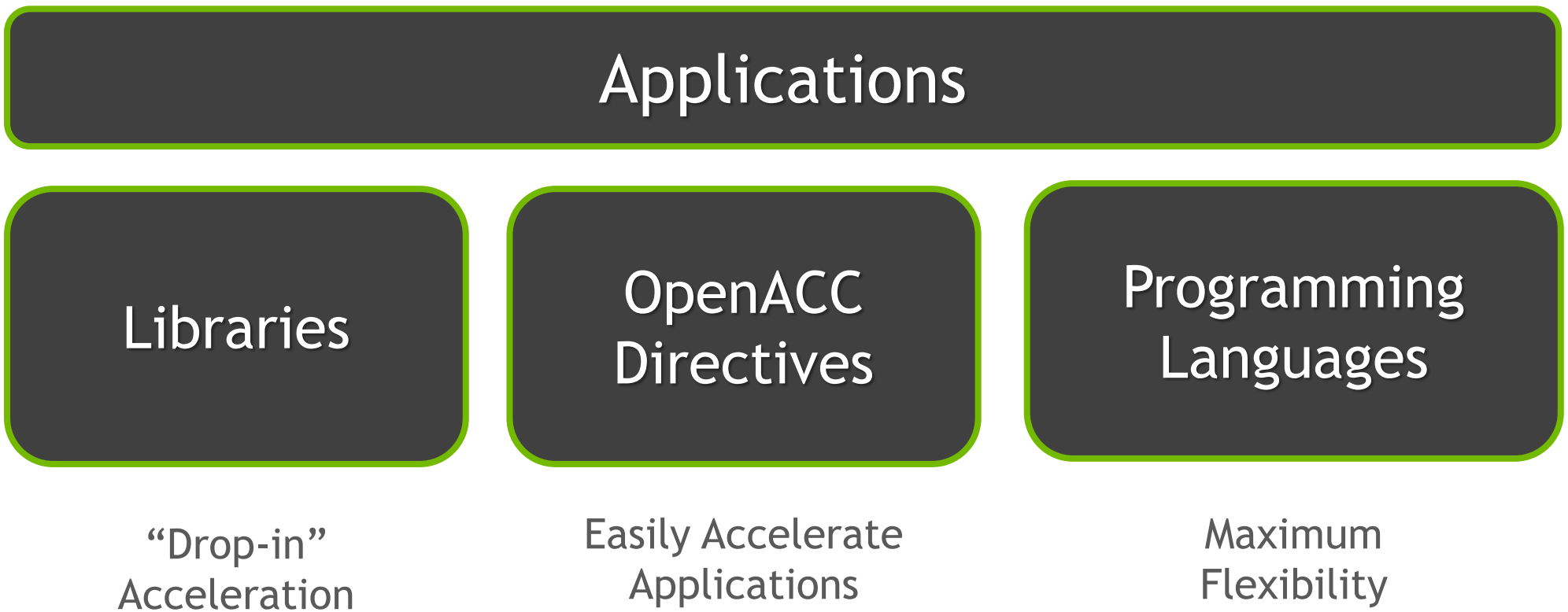
>2200

Universities Teaching CUDA

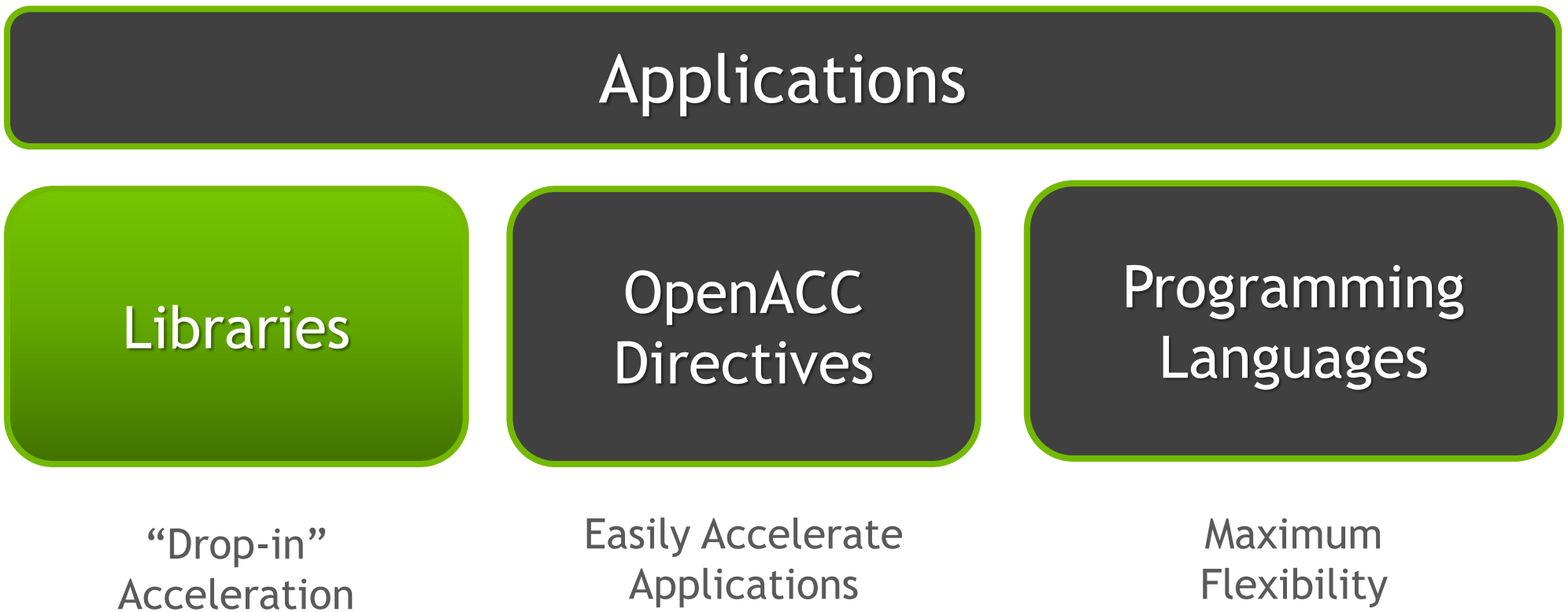
SMALL CHANGES, BIG SPEED-UP



3 WAYS TO ACCELERATE APPLICATIONS



3 WAYS TO ACCELERATE APPLICATIONS



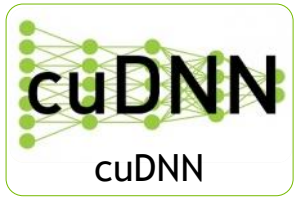
LIBRARIES: EASY, HIGH-QUALITY ACCELERATION

EASE OF USE	Using libraries enables GPU acceleration without in-depth knowledge of GPU programming
"DROP-IN"	Many GPU-accelerated libraries follow standard APIs, thus enabling acceleration with minimal code changes
QUALITY	Libraries offer high-quality implementations of functions encountered in a broad range of applications
PERFORMANCE	NVIDIA libraries are tuned by experts

GPU ACCELERATED LIBRARIES

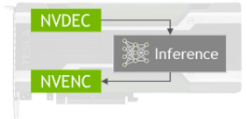
"Drop-in" Acceleration for Your Applications

DEEP LEARNING



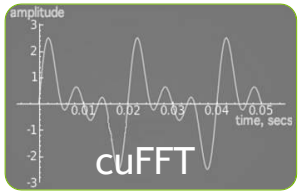
cuDNN


TensorRT

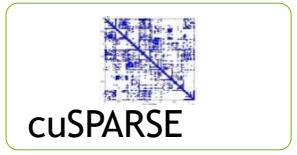


DeepStream SDK

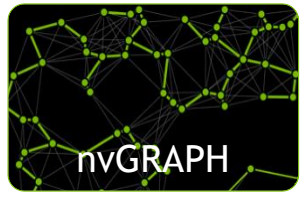
SIGNAL, IMAGE & VIDEO

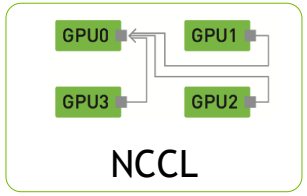


LINEAR ALGEBRA



PARALLEL ALGORITHMS





NCCL

3 STEPS TO CUDA-ACCELERATED APPLICATION

Step 1: Substitute library calls with equivalent CUDA library calls

```
saxpy ( … ) ► cublasSaxpy ( … )
```

Step 2: Manage data locality

- with CUDA: `cudaMalloc(), cudaMemcpy(), etc.`
- with CUBLAS: `cublasAlloc(), cublasSetVector(), etc.`

Step 3: Rebuild and link the CUDA-accelerated library

```
gcc myobj.o –l cublas
```

DROP-IN ACCELERATION (STEP 1)

```
int N = 1 << 20;




// Perform SAXPY on 1M elements: y[]=a*x[]+y[]
saxpy(N, 2.0, d_x, 1, d_y, 1);
```

DROP-IN ACCELERATION (STEP 1)

```
int N = 1 << 20;

// Perform SAXPY on 1M elements: d_y[]=a*d_x[]+d_y[]
cublasSaxpy(N, 2.0, d_x, 1, d_y, 1);
```

Add “cublas” prefix
and use device variables

DROP-IN ACCELERATION (STEP 2)

```
int N = 1 << 20;
cublasInit();




// Perform SAXPY on 1M elements: d_y[]=a*d_x[]+d_y[]
cublasSaxpy(N, 2.0, d_x, 1, d_y, 1);




cublasShutdown();
```

Initialize cuBLAS

Shut down cuBLAS

DROP-IN ACCELERATION (STEP 3)

```
int N = 1 << 20;
cublasInit();
cublasAlloc(N, sizeof(float), (void**)&d_x);
cublasAlloc(N, sizeof(float), (void*)&d_y);



// Perform SAXPY on 1M elements: d_y[]=a*d_x[]+d_y[]
cublasSaxpy(N, 2.0, d_x, 1, d_y, 1);



cublasFree(d_x);
cublasFree(d_y);
cublasShutdown();
```

Allocate device vectors

Deallocate device vectors

DROP-IN ACCELERATION (STEP 4)

```
int N = 1 << 20;
cublasInit();
cublasAlloc(N, sizeof(float), (void**)&d_x);
cublasAlloc(N, sizeof(float), (void*)&d_y);

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: d_y[]=a*d_x[]+d_y[]
cublasSaxpy(N, 2.0, d_x, 1, d_y, 1);

cublasGetVector(N, sizeof(y[0]), d_y, 1, y, 1);

cublasFree(d_x);
cublasFree(d_y);
cublasShutdown();
```

Transfer data to GPU

Read data back GPU

ACCELERATING OCTAVE

Scientific Programming Language

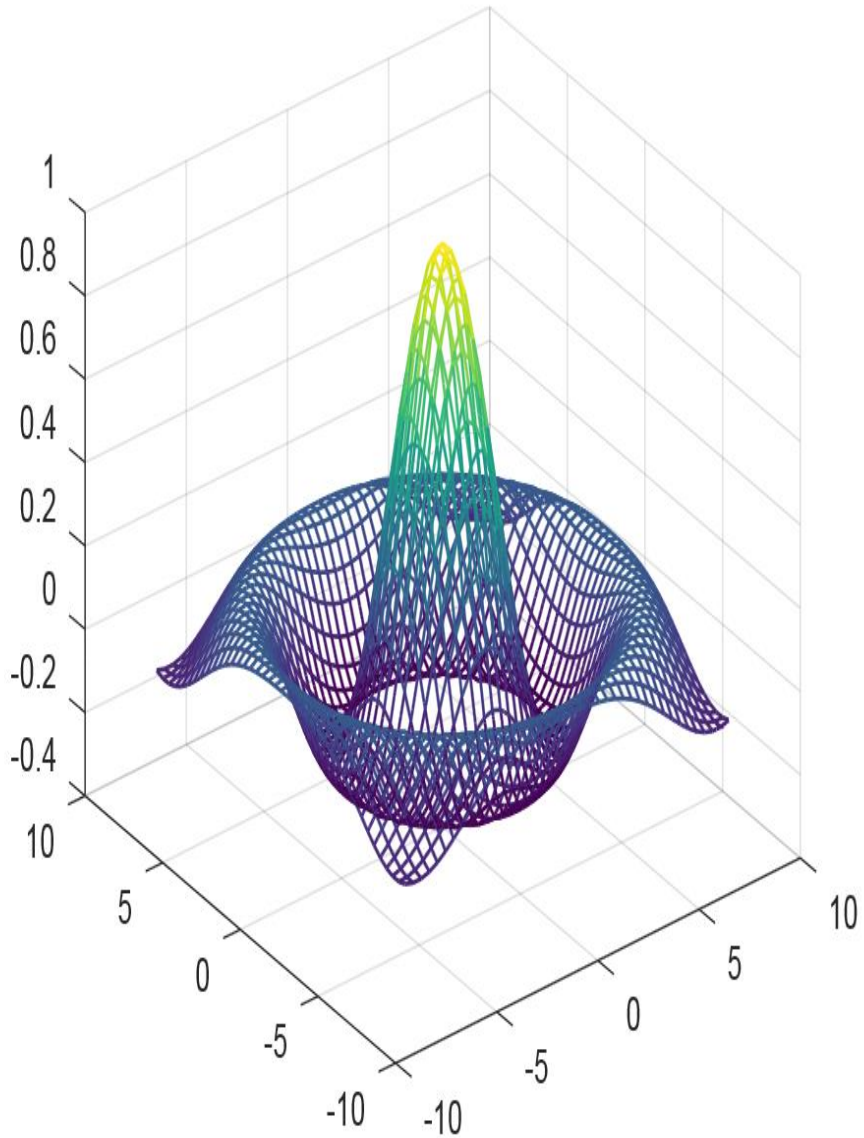
Mathematics-oriented syntax

Drop-in compatible with many MATLAB scripts

Built-in plotting and visualization tools

Runs on GNU/Linux, macOS, BSD, and Windows

Free Software

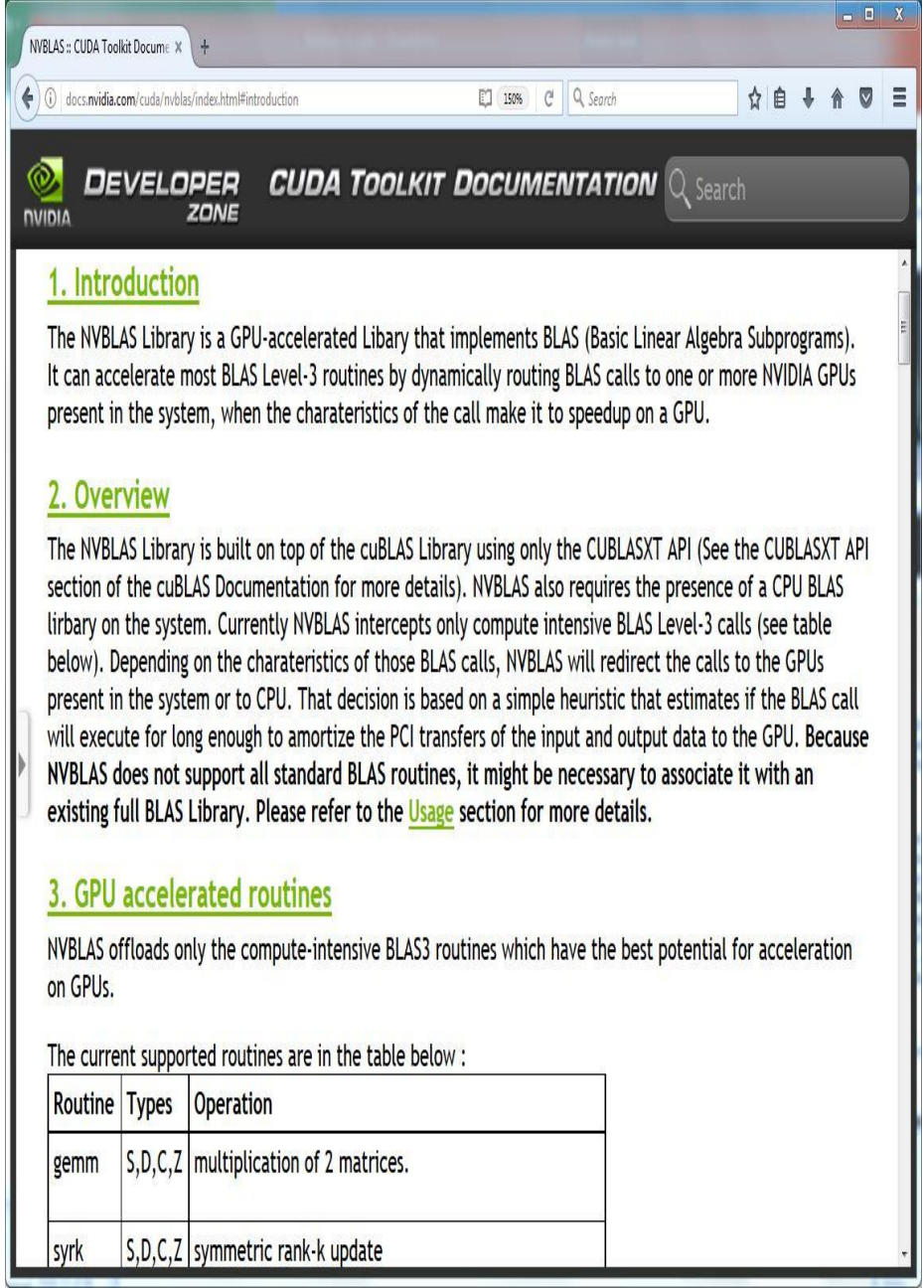


Source: http://www.gnu.org/software/octave/

NVBLAS

Drop-in GPU Acceleration

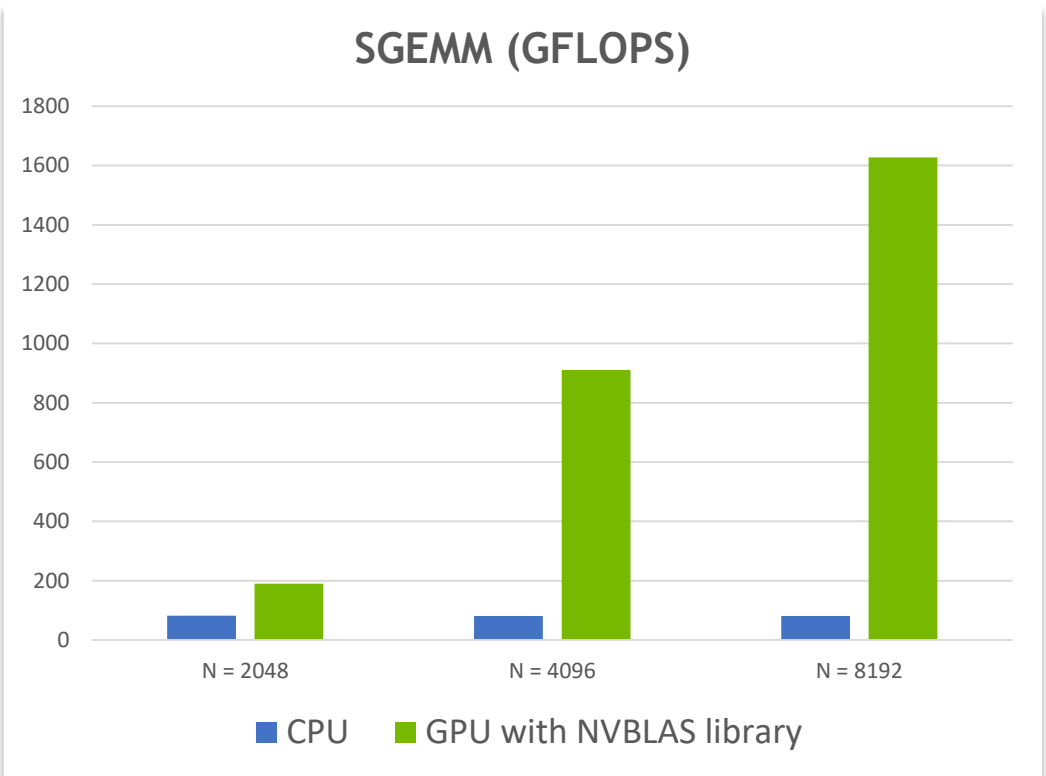
Routines	Types	Operation
gemm	S,D,C,Z	Multiplication of 2 matrices
syrk	S,D,C,Z	Symmetric rank-k update
herk	C,Z	Hermitian rank-k update
syr2k	S,D,C,Z	Symmetric rank-2k pdate
her2k	C,Z	Hemitian rank-2k update
trsm	S,D,C,Z	Triangular solve, mult right-hand
trmm	S,D,C,Z	Triangular matrix-matrix mult
symm	S,D,C,Z	Symmetric matrix-matrix mult
hemm	C,Z	Hermitian matrix-matrix mult

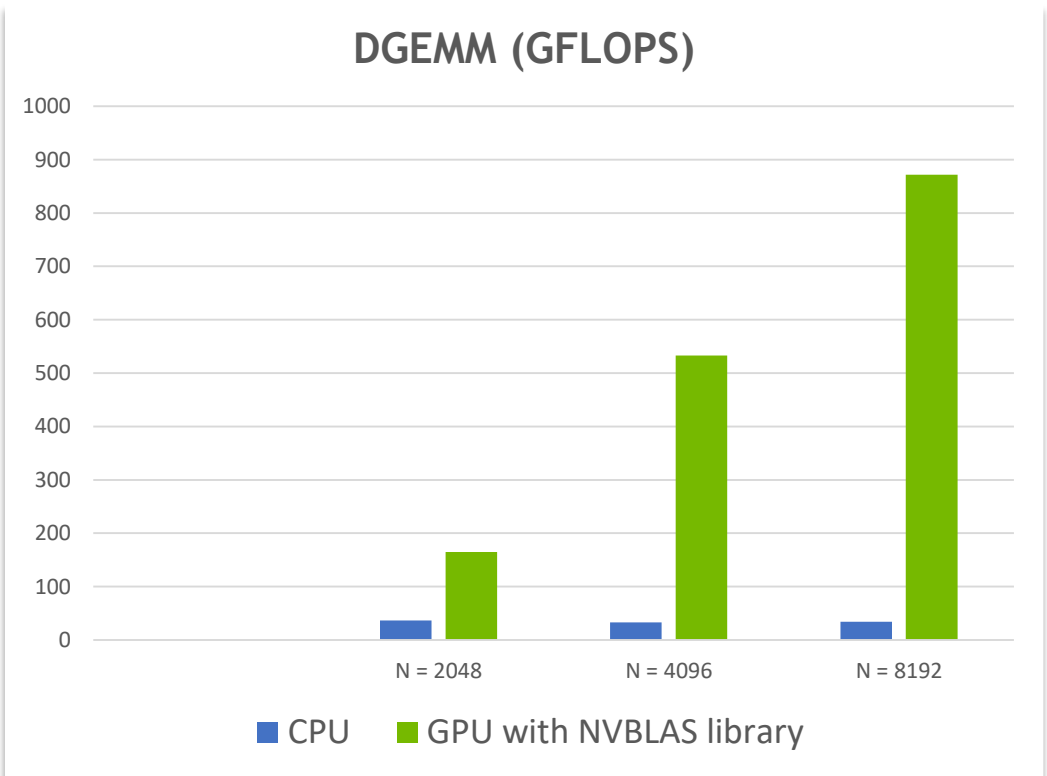


PERFORMANCE COMPARISON

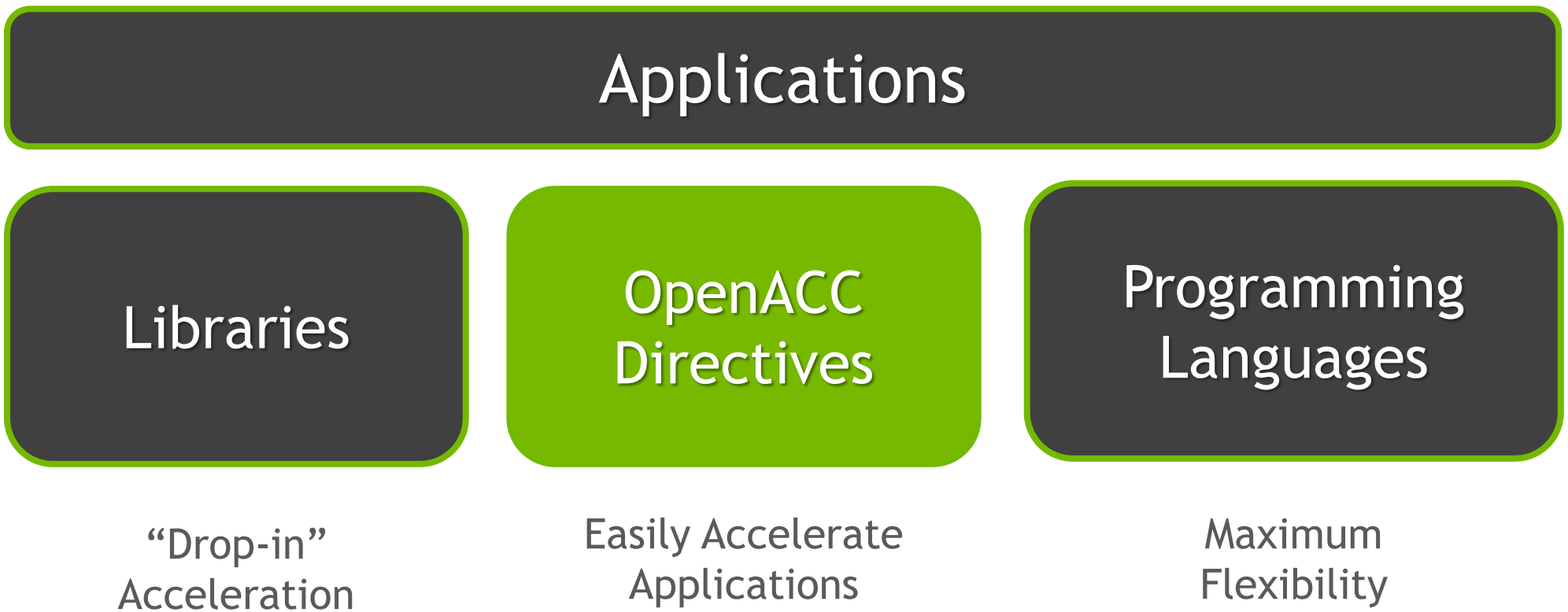
CPU (openblas) vs GPU (NVBLAS)

Dell C4130 | 128 GB | 36-core, E5-2697 v4 @ 2.30GHz | 4x NVIDIA Tesla P100-SXM2 + NVLINK





3 WAYS TO ACCELERATE APPLICATIONS



OpenACC is a directives-based programming approach to **parallel computing** designed for **performance** and **portability** on CPUs and GPUs for HPC.

Add Simple Compiler Directive

```
main()
 {
  <serial code>
  #pragma acc kernels
  {
    <parallel code>
  }
}
```

TOP HPC APPS ADOPTING OPENACC

OpenACC – Performance Portability And Ease of Programming

ANSYS Fluent
VASP
Gaussian

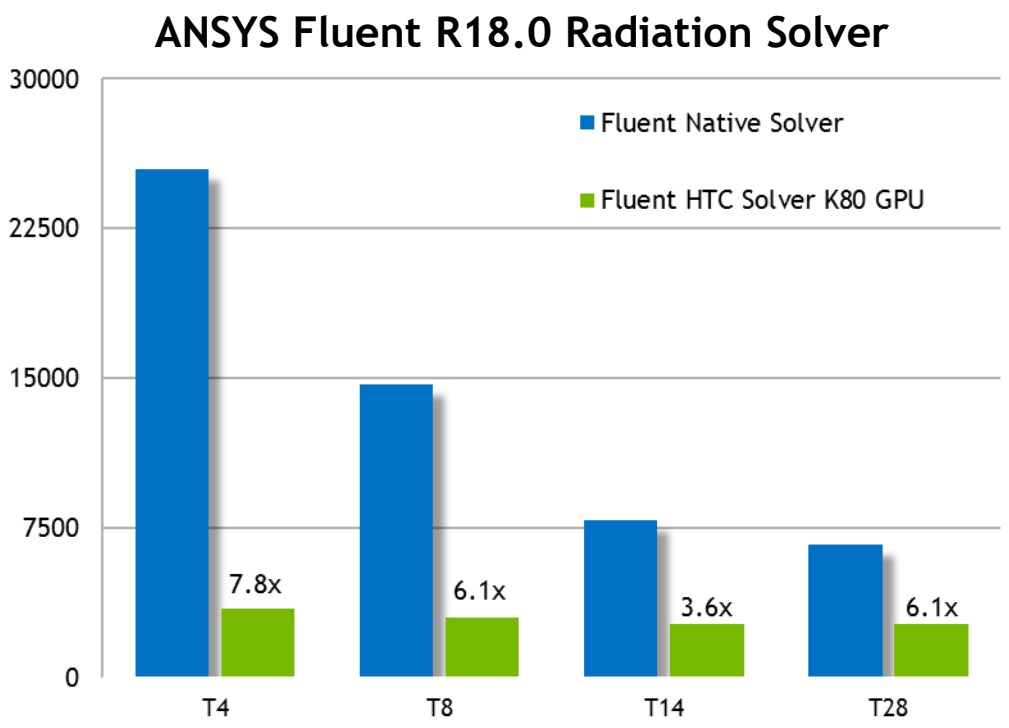
3 of Top 10 Apps

GTC
XGC
ACME
FLASH
LSDalton

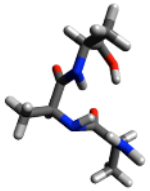
5 ORNL CAAR Codes

COSMO
ELEPHANT
RAMSES
ICON
ORB5

5 CSCS Codes



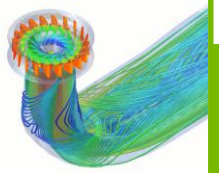
CPU: (Haswell EP) Intel(R) Xeon(R) CPU E5-2695 v3 @2.30GHz, 2 sockets, 28 cores
GPU: Tesla K80 12+12 GB, Driver 346.46



LSDalton

Quantum Chemistry

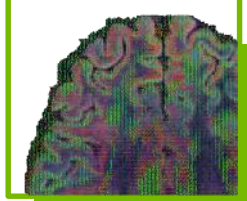
12X speedup
in 1 week



Numeca

CFD

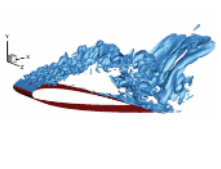
10X faster kernels
2X faster app



PowerGrid

Medical Imaging

40 days to
2 hours



INCOMP3D

CFD

3X speedup

NekCEM

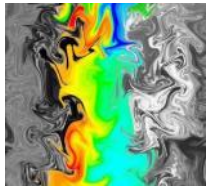
Computational Electromagnetics

2.5X speedup
60% less energy

COSMO

Climate Weather

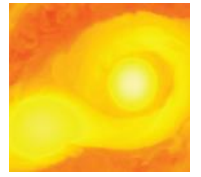
40X speedup
3X energy efficiency



CloverLeaf

CFD

4X speedup
Single CPU/GPU code



MAESTRO CASTRO

Astrophysics

4.4X speedup
4 weeks effort

2 BASIC STEPS TO GET STARTED

Step 1:

```
!$acc data copy(util1,util2,util3) copyin(ip,scp2,scp2i)
  !$acc parallel loop
  …
  !$acc end parallel
!$acc end data
```

Step 2:

```
pgf90 -ta=nvidia -Minfo=accel file.f
```

OpenACC DIRECTIVES EXAMPLE

```
!$acc data copy(A,Anew)
 iter=0
 do while ( err > tol .and. iter < iter_max )

  iter = iter +1
  err=0._fp_kind

!$acc kernels
   do j=1,m
    do i=1,n
     Anew(i,j) = .25_fp_kind *( A(i+1,j  ) + A(i-1,j  ) &
                               +A(i  ,j-1) + A(i  ,j+1))
     err = max( err, Anew(i,j)-A(i,j))
    end do
   end do
!$acc end kernels
   IF(mod(iter,100)==0 .or. iter == 1)    print *, iter, err
   A= Anew

 end do
!$acc end data
```

Copy arrays into GPU memory within data region

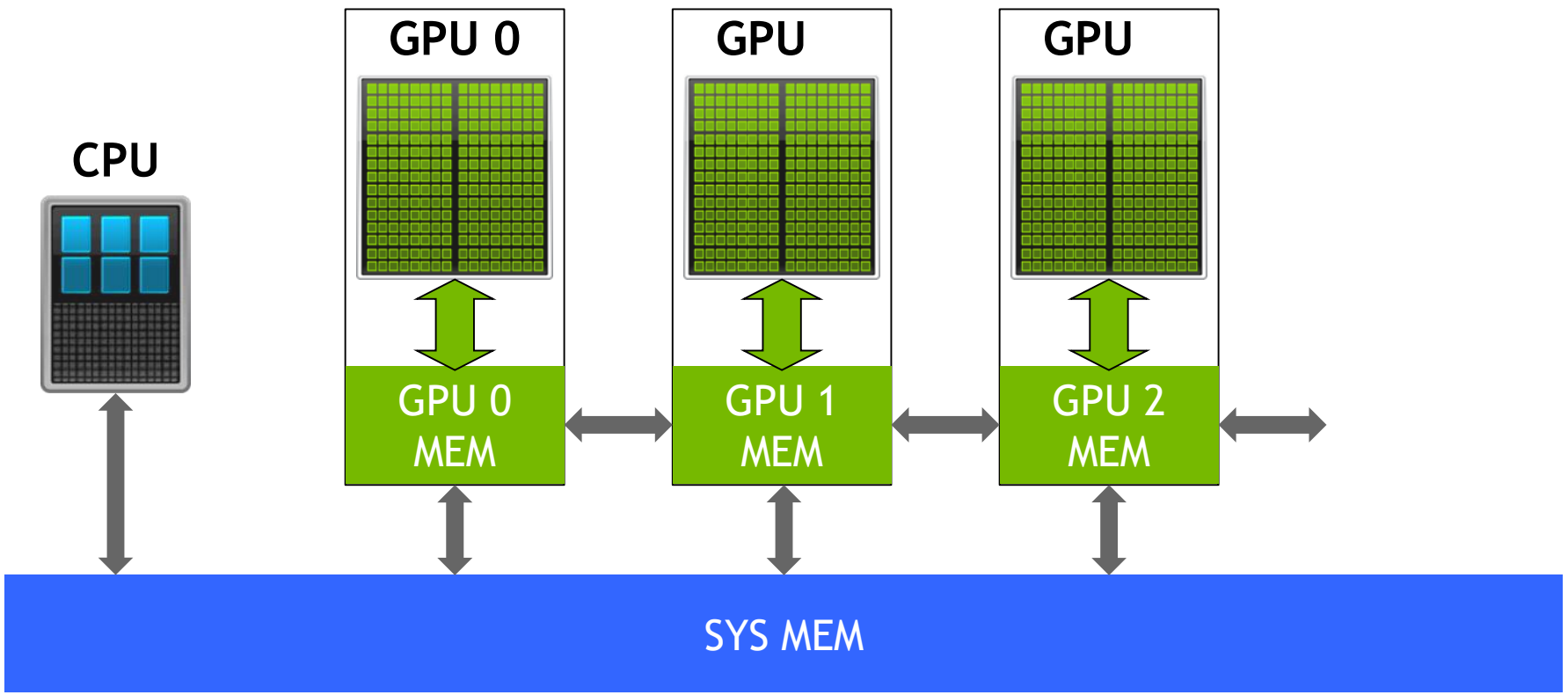
Parallelize code inside region

Close off parallel region

Close off data region, copy data back

HETEROGENEOUS ARCHITECTURES

Unified Memory



OPENACC FOR EVERYONE

New PGI Community Edition Now Available

FREE

	PGI Community Edition	PGI Professional Edition	PGI Enterprise Edition
PROGRAMMING MODELS OpenACC, CUDA Fortran, OpenMP, C/C++/Fortran Compilers and Tools	✓	✓	✓
PLATFORMS X86, OpenPOWER, NVIDIA GPU	✓	✓	✓
UPDATES	1-2 times a year	6-9 times a year	6-9 times a year
SUPPORT	User Forums	PGI Support	PGI Professional Services
LICENSE	Annual	Perpetual	Volume/Site

RESOURCES

FREE Compiler

Success stories

Guides

Tutorials

Videos

Courses

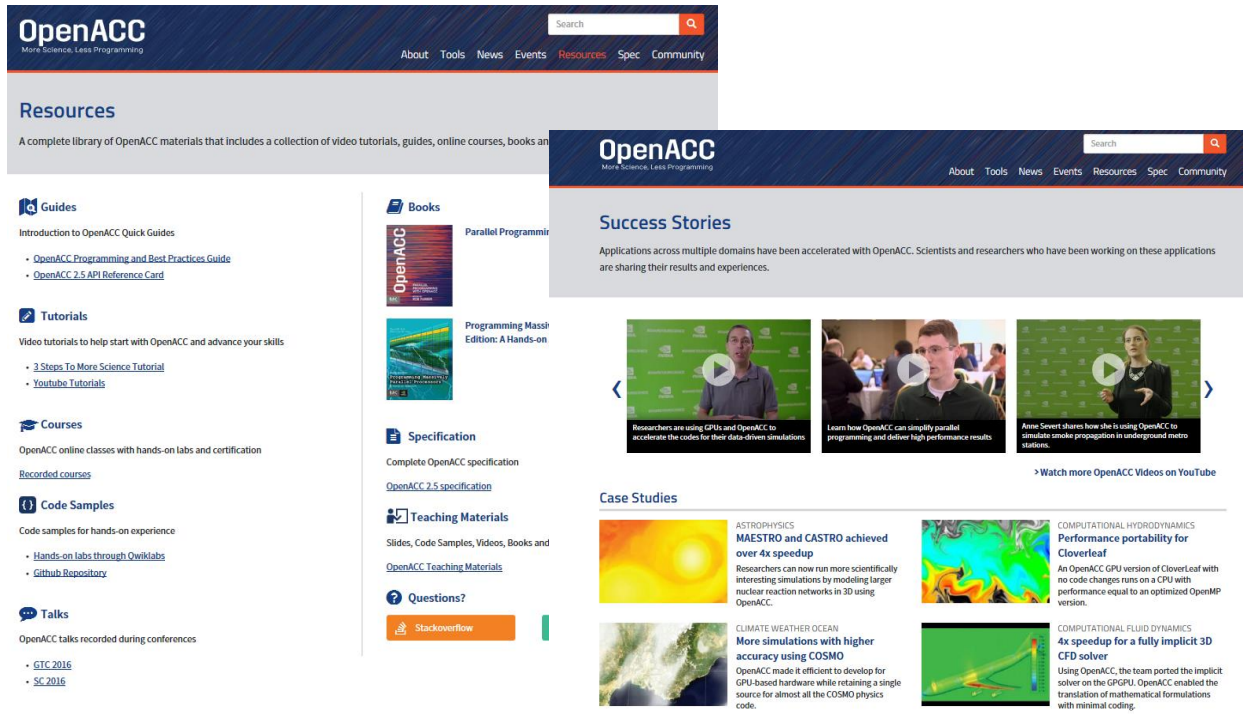
Code Samples

Talks

Books Specification

Teaching Materials

Slack&StackOverflow



Success stories: https://www.openacc.org/success-stories
Resources: https://www.openacc.org/resources
Free Compiler: https://www.pgroup.com/products/community.htm

CUDA PROGRAMMING LANGUAGES

GPU PROGRAMMING LANGUAGES

Numerical analytics	MATLAB, Mathematica, LabVIEW, Octave
Fortran	CUDA Fortran, OpenACC
C, C++	CUDA C++, OpenACC
Python	CUDA Python, PyCUDA, Numba, PyCulib
C#	Altimesh Hybridizer, Alea GPU
Other	R, Julia

CUDA C

```
void saxpy_serial(int n,
                  float a,
                  float *x,
                  float *y)
{

  for (int i = 0; i < n; ++i)
    y[i] = a*x[i] + y[i];
}

// Perform SAXPY on 1M elements
saxpy_serial(4096*256, 2.0, x, y);
```

```
__global__
void saxpy_parallel(int n,
                    float a,
                    float *x,
                    float *y)
{
  int i = blockIdx.x*blockDim.x +
          threadIdx.x;
  if (i < n) y[i] = a*x[i] + y[i];
}

// Perform SAXPY on 1M elements
saxpy_parallel<<<4096,256>>>(n,2.0,x,y);
```

http://developer.nvidia.com/cuda-toolkit

CUDA C++: DEVELOP GENERIC PARALLEL CODE

CUDA C++ features enable sophisticated and flexible applications and middleware

- Class hierarchies
- __device__ methods
- Templates
- Operator overloading
- Functors (function objects)
- Device-side new/delete
- More…

http://developer.nvidia.com/cuda-toolkit

```
template <typename T>
struct Functor {
  __device__ Functor(_a) : a(_a) {}
  __device__ T operator(T x) { return a*x; }
  T a;
}

template <typename T, typename Oper>
__global__ void kernel(T *output, int n) {
  Oper op(3.7);
  output = new T[n]; // dynamic allocation
  int i = blockIdx.x*blockDim.x + threadIdx.x;
  if (i < n)
    output[i] = op(i);  // apply functor
}
```

CUDA FORTRAN

- Program GPU using Fortran
  - Key language for HPC
- Simple language extensions
  - Kernel functions
  - Thread / block IDs
  - Device & data management
  - Parallel loop directives
- Familiar syntax
  - Use allocate, deallocate
  - Copy CPU-to-GPU with assignment (=)

http://developer.nvidia.com/cuda-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<=n) y(i) = a*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
  call saxpy<<<4096,256>>>(2**20,3.0,x_d,y_d,)
  y = y_d
  write(*,*) 'max error=', maxval(abs(y-5.0))
end program main
```

PYTHON

- Numba, a just-in-time compiler for Python functions (open-source!)
  - Numba runs inside the standard Python interpreter
  - Can compile for GPU or CPU!
- Includes Pyculib

```
import numpy as np
from numba import vectorize

@vectorize(['float32(float32, float32)'], target='cuda')
def Add(a, b):
  return a + b

# Initialize arrays
N = 100000
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 on GPU
C = Add(A, B)
```

PYTHON - PYCULIB

- Python interface to CUDA libraries:
  - cuBLAS (dense linear algebra), cuFFT (Fast Fourier Transform), and cuRAND (random number generation)
- Code generates a million uniformly distributed random numbers on the GPU using the “XORWOW” pseudorandom number generator

```
import numpy as np
from pyculib import rand as curand

prng = curand.PRNG(rndtype=curand.PRNG.XORWOW)
rand = np.empty(100000)
prng.uniform(rand)
print rand[:10]
```

JULIA

- Up and coming scientific language
- Cross between Python and Matlab
- Interpreter (like Python) –or- compiled (like C/Fortran)
- New approach to multi-processing/multi-node
  - Or use MPI
- Easy to combine it with other languages
- Works with Jupyter Notebooks!

JULIA - SIMPLE EXAMPLE

- Simple matrix multiplication example (integers)
  - Double precision (Int64)
- Can also do elementwise multiplication (just like Matlab)
  - `A .* B`

```
julia> A = [1 2 ; 3 4]
  2x2 Array{Int64,2}:
  1  2
  3  4
julia> B = [10 11 ; 12 13]
  2x2 Array{Int64,2}:
  10  11
  12  13
julia> A * B
 2x2 Array{Int64,2}:
  34  37
  78  85
```

JULIA - GPU EXAMPLE

- Options:
  - JuliaGPU (github)
  - Native CUDA (new)
  - GPUarrays
- Simple native GPU example

```
using CUDAdrv, CUDAnative

function kernel_vadd(a, b, c)
    # from CUDAnative: (implicit) CuDeviceArray type,
    #                  and thread/block intrinsics
    i = (blockIdx().x-1) * blockDim().x + threadIdx().x
    c[i] = a[i] + b[i]
    return nothing
end

dev = CuDevice(0)
ctx = CuContext(dev)

# generate some data
len = 512
a = rand(Int, len)
b = rand(Int, len)

# allocate & upload on the GPU
d_a = CuArray(a)
d_b = CuArray(b)
d_c = similar(d_a)

# execute and fetch results
@cuda (1,len) kernel_vadd(d_a, d_b, d_c)    # from CUDAnative.jl
c = Array(d_c)

using Base.Test
@test c == a + b

destroy(ctx)
```

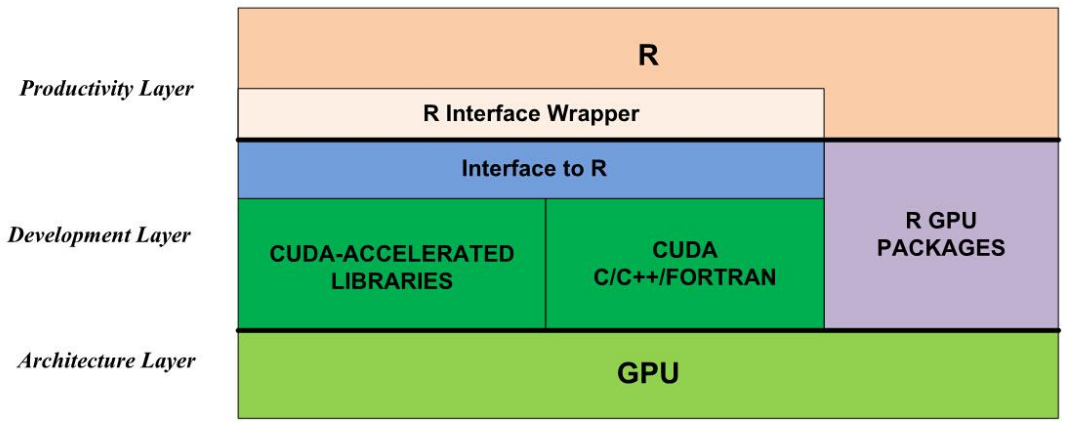
JULIA - GPU EXAMPLE

- GPUarrays example
  - Convolution

```
using GPUArrays, Colors, FileIO, ImageFiltering
using CLArrays
using GPUArrays: synchronize_threads
import GPUArrays: LocalMemory
using CLArrays


img =
RGB{Float32}.(load(homedir()*"/Desktop/backround.jpg"));

a = CLArray(img);
out = similar(a);
k = CLArray(Float32.(collect(Kernel.gaussian(3))));
imgc = similar(img)

# convolution!(a, out, k);
# Array(out)
# outc = similar(img)
# copy!(outc, out)
```

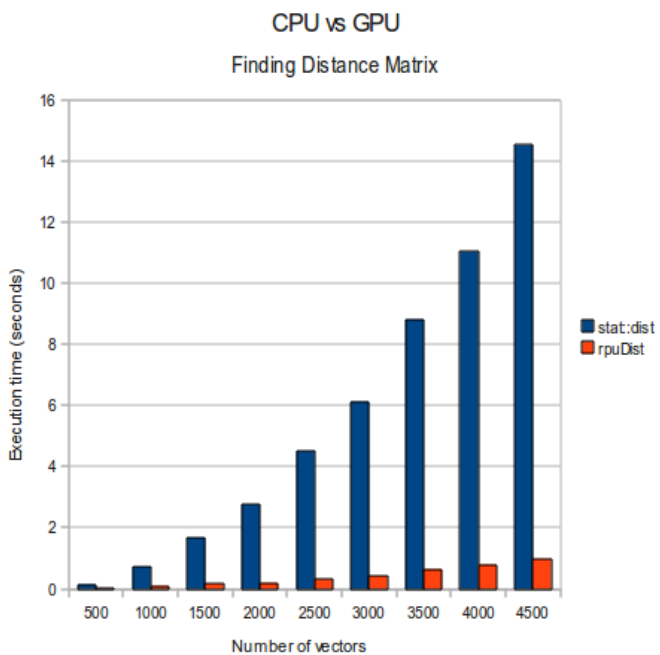
R

- Very popular Statistics language
  - Used heavily in Machine Learning
- gpuR package



R - GPUR

- gpuR package
- Simple integer addition of two vectors with 1,000 values




```
A <- seq.int(from=0, to=999)
B <- seq.int(from=1000, to=1)
gpuA <- gpuVector(A)
gpuB <- gpuVector(B)

C <- A + B
gpuC <- gpuA + gpuB

all(C == gpuC)
```

MATLAB

- Native support for most operations/functions
- Next speaker will cover this ☺

GET STARTED TODAY

These languages are supported on all CUDA-capable GPUs.

You might already have a CUDA-capable GPU in your laptop or desktop PC!

CUDA C/C++
http://developer.nvidia.com/cuda-toolkit

CUDA Python
http://developer.nvidia.com/how-to-cuda-python

Thrust C++ Template Library
http://developer.nvidia.com/thrust

CUDA Fortran
http://developer.nvidia.com/cuda-toolkit

MATLAB
http://www.mathworks.com/discovery/matlab-gpu.html

Mathematica
http://www.wolfram.com/mathematica/new-in-8/cuda-and-opencl-support/

THANK YOU

SIX WAYS TO SAXPY

Programming Languages for GPU Computing

SINGLE PRECISION ALPHA X PLUS Y (SAXPY)

Part of Basic Linear Algebra Subroutines (BLAS) Library

$$z = \alpha x + y$$

x, y, z : vector

α : scalar

GPU SAXPY in multiple languages and libraries

A menagerie* of possibilities, not a tutorial

*technically, a *program chrestomathy*: http://en.wikipedia.org/wiki/Chrestomathy

OpenACC COMPILER DIRECTIVES

Parallel C Code

```
void saxpy(int n,
           float a,
           float *x,
           float *y)
{
#pragma acc kernels
  for (int i = 0; i < n; ++i)
    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
call saxpy(2**20, 2.0, x_d, y_d)
...
```

http://developer.nvidia.com/openacc or http://openacc.org

2

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);
```

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

CUDA C

```
void saxpy(int n, float a,
           float *x, float *y)
{
  for (int i = 0; i < n; ++i)
    y[i] = a*x[i] + y[i];
}

int N = 1<<20;



// Perform SAXPY on 1M elements
saxpy(N, 2.0, x, y);
```

```
__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] + 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);
```

http://developer.nvidia.com/cuda-toolkit

THRUST C++ TEMPLATE LIBRARY

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);
```

www.boost.org/libs/lambda

Parallel C++ Code

```
int N = 1<<20;
thrust::host_vector<float> x(N), y(N);

...

thrust::device_vector<float> d_x = x;
thrust::device_vector<float> d_y = y;


// Perform SAXPY on 1M elements
thrust::transform(d_x.begin(), d_x.end(),
                  d_y.begin(),d_y.begin(),
                  2.0f * _1 + _2)
```

http://thrust.github.com

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<=n) y(i) = a*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
```

http://developer.nvidia.com/cuda-fortran

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, x, y)
```

http://numpy.scipy.org

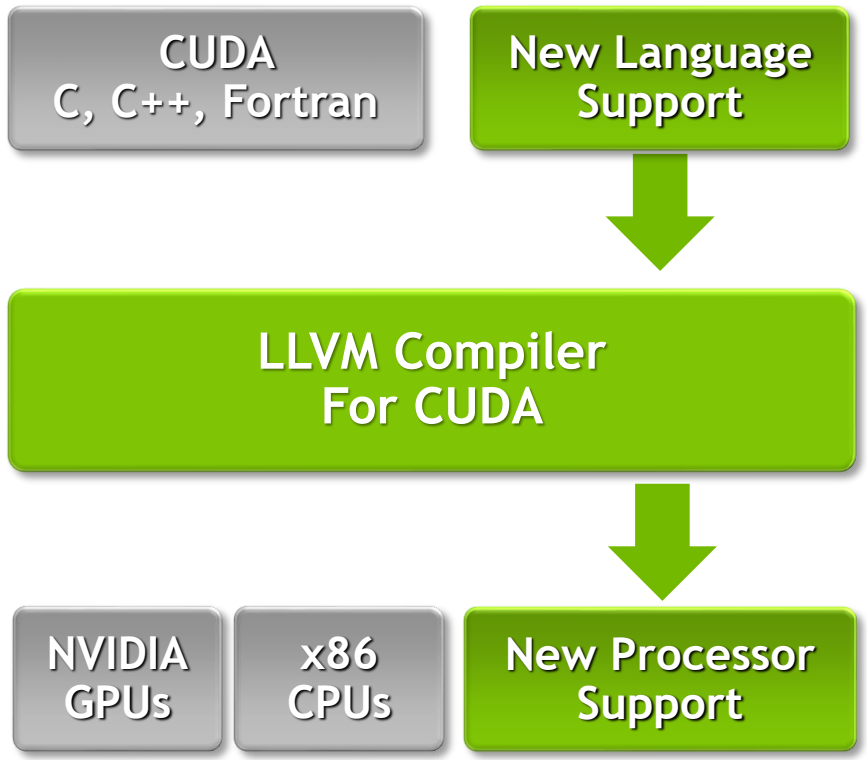
Numba Parallel Python

```
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)
```

https://numba.pydata.org

ENABLING ENDLESS WAYS TO SAXPY

- Build front-ends for Java, Python, R, DSLs
- Target other processors like ARM, FPGA, GPUs, x86



CUDA Compiler Contributed to Open Source LLVM

LLVM COMPILER INFRASTRUCTURE

GPU-ACCELERATED LIBRARIES

cuBLAS

Dense Linear Algebra on GPUs

Complete BLAS Library Plus Extensions

Supports all 152 standard routines for single, double, complex, and double complex

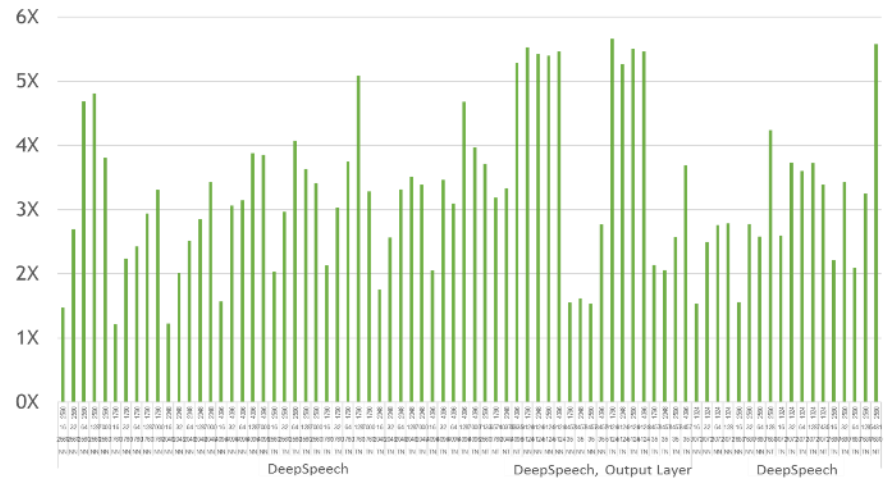
Supports half-precision (FP16) and integer (INT8) matrix multiplication operations

Batched routines for higher performance on small problem sizes

Host and device-callable interface

XT interface supports distributed computations across multiple GPUs

Up To 5x Faster DeepBench SGEMM Than CPU



- CUDA 8 (cuBLAS 8.0.88); Driver 375.66; P100 (PCIe, 16GB, Base Clocks). ECC OFF
- Host System: Intel Xeon Broadwell Dual E5-2690v4 with Ubuntu 14.04.5 and 256GB DDR4 memory
- MKL 2017.3, Compiler v17.0.4; FP32 Input, Output and Compute
- CPU system; Intel Xeon Broadwell Dual E5-2699v4 (Turbo Enabled) with Ubuntu 14.04.5 and 256GB DDR4 memory

https://developer.nvidia.com/cublas

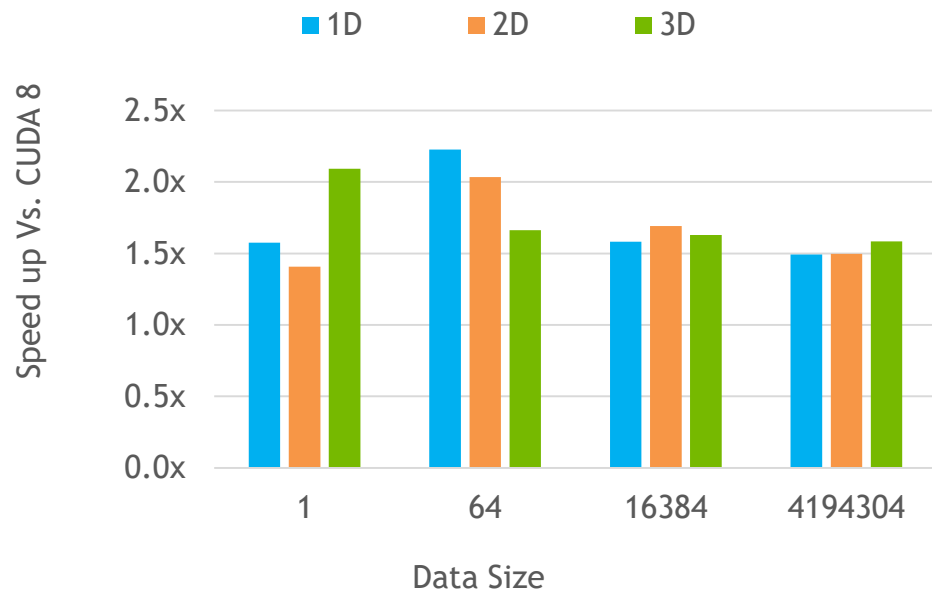
cuFFT

Complete Fast Fourier Transforms Library

Complete Multi-Dimensional FFT Library

- “Drop-in” replacement for CPU FFTW library
- Real and complex, single- and double-precision data types
- Includes 1D, 2D and 3D batched transforms
- Support for half-precision (FP16) data types
- Supports flexible input and output data layouts
- XT interface now supports up to 8 GPUs

2x Faster Image & Signal Processing than CUDA 8



* V100 and CUDA 9 (r384); Intel Xeon Broadwell, dual socket, E5-2698 v4@ 2.6GHz, 3.5GHz Turbo with Ubuntu 14.04.5 x86_64 with 128GB System Memory
* P100 and CUDA 8 (r361); For cublas CUDA 8 (r361): Intel Xeon Haswell, single-socket, 16-core E5-2698 v3@ 2.3GHz, 3.6GHz Turbo with CentOS 7.2 x86-64 with 128GB System Memory

https://developer.nvidia.com/cufft

NPP

NVIDIA Performance Primitives Library

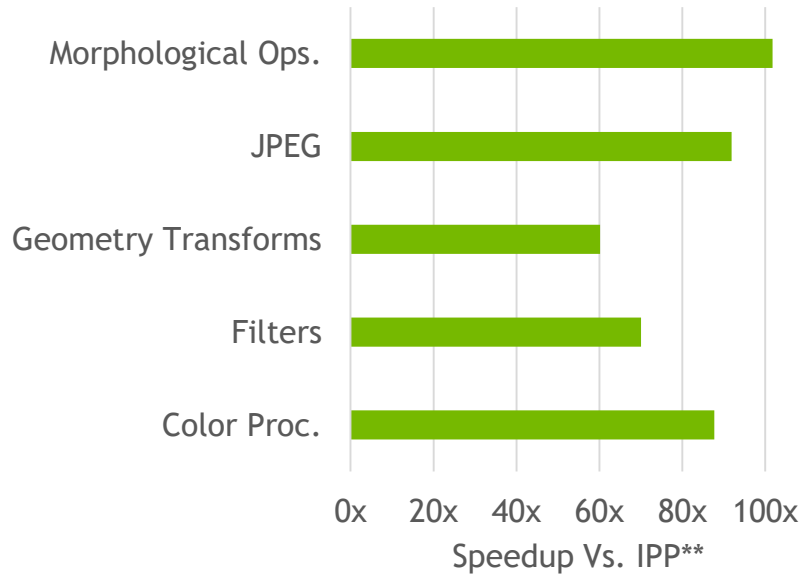
GPU-accelerated Building Blocks for Image, Video Processing & Computer Vision

Over 2500 image, signal processing and computer vision routines

Color transforms, geometric transforms, move operations, linear filters, image & signal statistics, image & signal arithmetic, building blocks, image segmentation, median filter, BGR/YUV conversion, 3D LUT color conversion

Eliminate unnecessary copying of data to/from CPU memory

Up to 100x faster than IPP



* V100 and CUDA 9 (r384); Intel Xeon Broadwell, dual socket, E5-2698 v4@ 2.6GHz, 3.5GHz Turbo with Ubuntu 14.04.5 x86_64 with 128GB System Memory
* P100 and CUDA 8 (r361); For cublas CUDA 8 (r361): Intel Xeon Haswell, single-socket, 16-core E5-2698 v3@ 2.3GHz, 3.6GHz Turbo with CentOS 7.2 x86-64 with 128GB System Memory
** CPU system running IPP: Intel Xeon Haswell single-socket 16-core E5-2698 v3@ 2.3GHz, 3.6GHz Turbo Ubuntu 14.04.5 x86_64 with 128GB System Memory

https://developer.nvidia.com/npp

cuSPARSE

Sparse Linear Algebra on GPUs

Optimized Sparse Matrix Library

Optimized sparse linear algebra BLAS routines for matrix-vector, matrix-matrix, triangular solve

Support for variety of formats (CSR, COO, block variants)

Incomplete-LU and Cholesky preconditioners

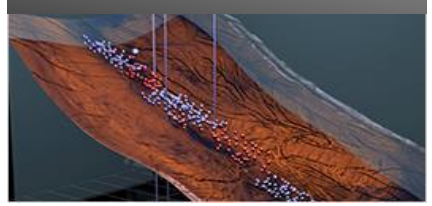
Support for half-precision (fp16) sparse matrix-vector operations

NLP

RECOMMENDATION ENGINES

COMPUTATIONAL FLUID DYNAMICS

SEISMIC EXPLORATION

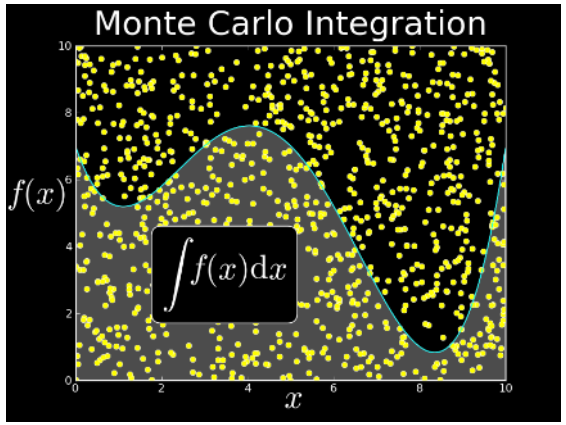


CAD/CAM/CAE

https://developer.nvidia.com/cusparse

CURAND

Random Number Generation (RNG) Library



High Performance Random Number Generation

Flexible interfaces for RNG on the host or within GPU kernels

Pseudo- and Quasi-RNGs — MRG32k3a, MTGP Mersenne Twister, XORWOW, Sobol

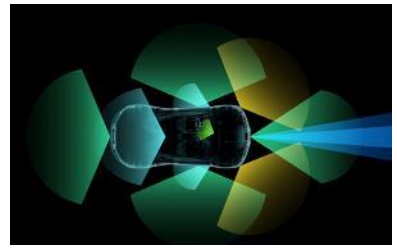
Supports several output distributions

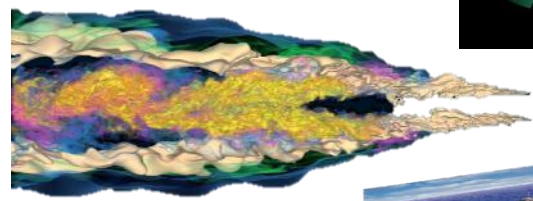
Tested against well-known statistical test batteries (test results available in documentation)

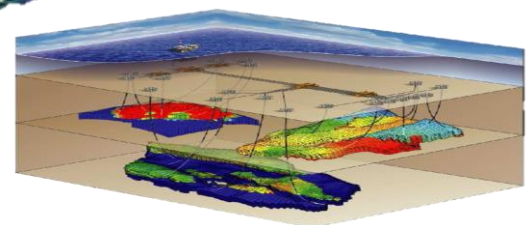
https://developer.nvidia.com/curand

cuSOLVER

Linear Solver Library







Library for Dense and Sparse Direct Solvers

Supports Dense Cholesky, LU, (batched) QR, SVD and Eigenvalue solvers (new in CUDA 8)

Sparse direct solvers & Eigen solvers

Includes a sparse refactorization solver for solving sequences of matrices with a shared sparsity pattern

Used in a variety of applications such as circuit simulation and computational fluid dynamics

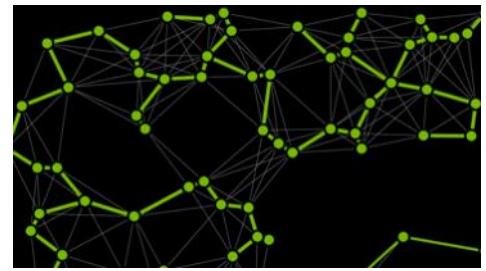
Sample Applications

- Computer Vision
- CFD
- Newton's method
- Chemical Kinetics
- Chemistry
- ODEs
- Circuit Simulation

https://developer.nvidia.com/cusolver

nvGRAPH

GPU Accelerated Graph Analytics



Parallel Library for Interactive and High Throughput Graph Analytics

Solve graphs with up to 2.5 Billion edges on a single GPU (Tesla M40)

Includes — PageRank, Single Source Shortest Path and Single Source Widest Path algorithms

Semi-ring SPMV operations provides building blocks for graph traversal algorithms

PageRank	Single Source Shortest Path	Single Source Widest Path
Search	Robotic Path Planning	IP Routing
Recommendation Engines	Power Network Planning	Chip Design / EDA
Social Ad Placement	Logistics & Supply Chain Planning	Traffic sensitive routing

https://developer.nvidia.com/nvgraph

AmgX

Algebraic Multi-Grid Solvers

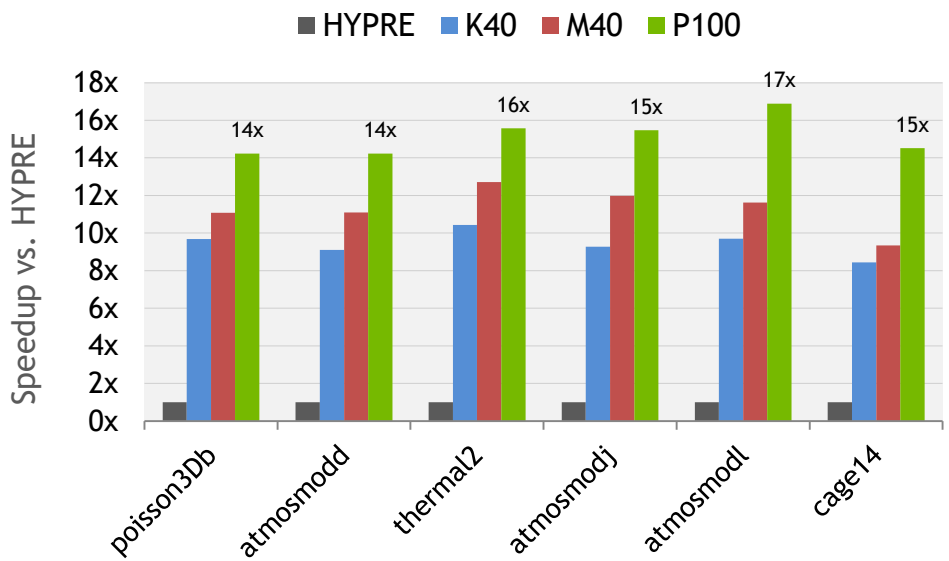
Flexible Solver Composition System

Easy construction of complex nested solvers and pre-conditioners

Flexible and simple high level C API that abstracts parallelism and GPU implementation

Includes Ruge-Steuben, un-smoothed aggregation, Krylov methods and different smoother algorithms

> 15x Speedup vs HYPRE



- Florida Matrix Collection; Total Time to Solution
- HYPRE AMG Package (http://acts.nersc.gov/hypre) on Intel Xeon E5-2697 v4@2.3GHz, 3.6GHz Turbo, Hyperthreading off
- AmgX on K40, M40, P100 (SXM2); Base clocks
- Host system: Intel Xeon Haswell single-socket 16-core E5-2698 v3 @ 2.3GHz, 3.6GHz Turbo
- CentOS 7.2 x86-64 with 128GB System Memory

https://developer.nvidia.com/amgx