

# Using CUDA Libraries with OpenACC



# 3 Ways to Accelerate Applications

Applications

Libraries

OpenACC  
Directives

Programming  
Languages

CUDA Libraries are  
interoperable with OpenACC

“Drop-in”  
Acceleration

Easily Accelerate  
Applications

Maximum  
Flexibility

# 3 Ways to Accelerate Applications

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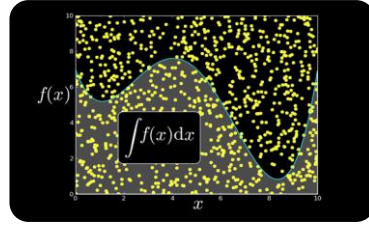
CUDA Languages are  
interoperable with OpenACC,  
too!



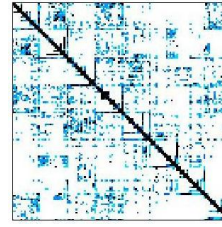
# CUDA Libraries Overview



NVIDIA cuBLAS



NVIDIA cuRAND



NVIDIA cuSPARSE



NVIDIA NPP

**GPU VSIPL**

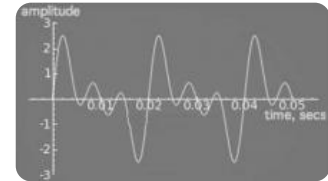
Vector Signal  
Image Processing

**CULA** | tools

GPU Accelerated  
Linear Algebra



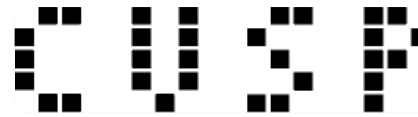
Matrix Algebra on  
GPU and Multicore



NVIDIA cuFFT



Building-block  
Algorithms for CUDA



Sparse Linear  
Algebra



C++ STL Features  
for CUDA



**GPU Accelerated Libraries**  
“Drop-in” Acceleration for Your Applications

# CUDA Math Libraries



High performance math routines for your applications:

- cuFFT - Fast Fourier Transforms Library
- cuBLAS - Complete BLAS Library
- cuSPARSE - Sparse Matrix Library
- cuRAND - Random Number Generation (RNG) Library
- NPP - Performance Primitives for Image & Video Processing
- Thrust - Templated C++ Parallel Algorithms & Data Structures
- math.h - C99 floating-point Library

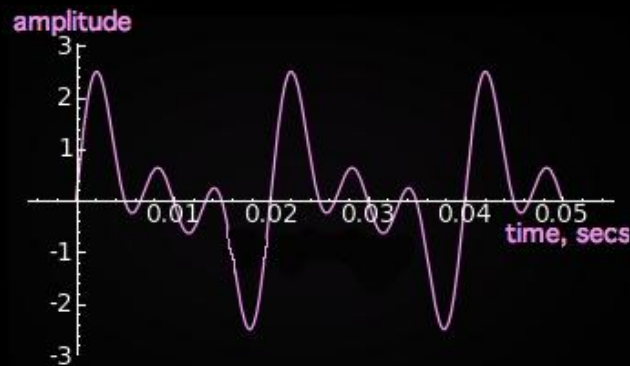
Included in the CUDA Toolkit    Free download @ [www.nvidia.com/getcuda](http://www.nvidia.com/getcuda)

More information on CUDA libraries:

<http://www.nvidia.com/object/gtc2010-presentation-archive.html#session2216>

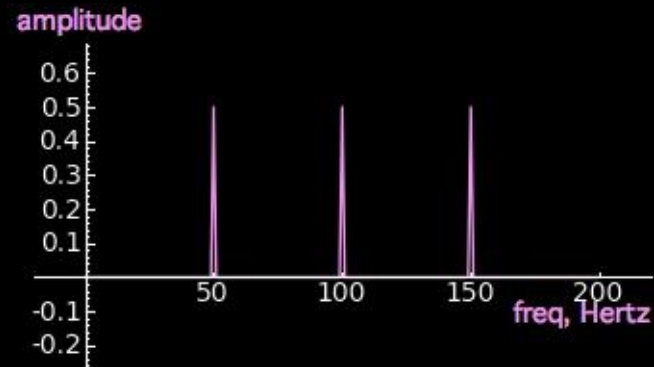
# cuFFT: Multi-dimensional FFTs

- New in CUDA 4.1
  - Flexible input & output data layouts for all transform types
    - Similar to the FFTW “Advanced Interface”
    - Eliminates extra data transposes and copies
  - API is now thread-safe & callable from multiple host threads
  - Restructured documentation to clarify data layouts



$$F(x) = \sum_{n=0}^{N-1} f(n) e^{-j2\pi(x\frac{n}{N})}$$

$$f(n) = \frac{1}{N} \sum_{x=0}^{N-1} F(x) e^{j2\pi(x\frac{n}{N})}$$

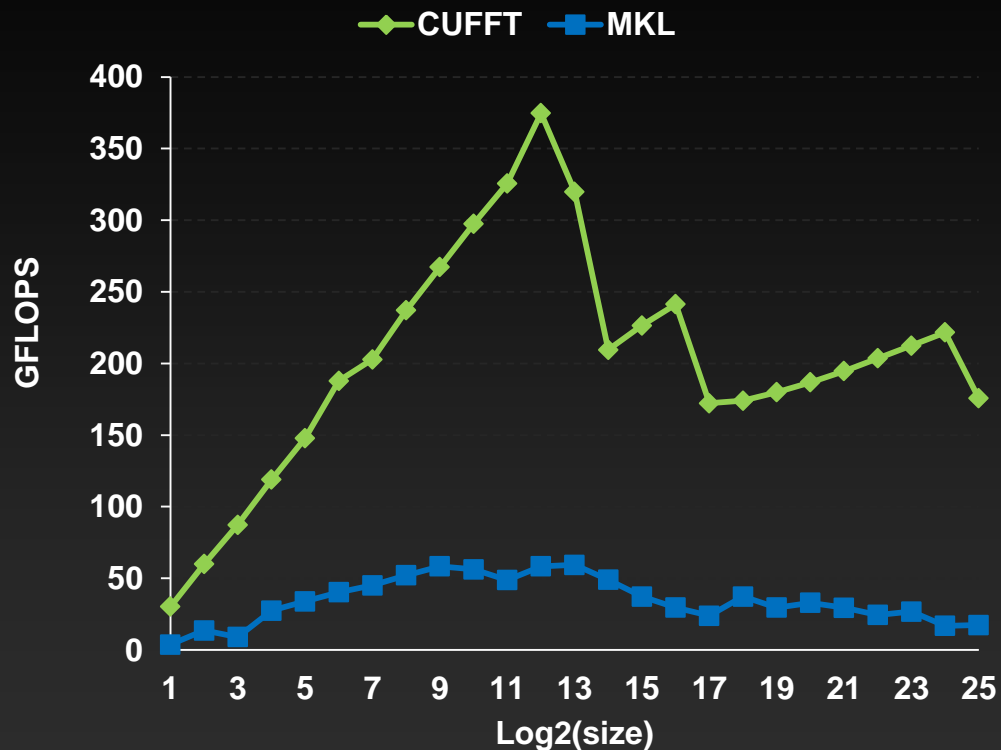


# FFTs up to 10x Faster than MKL

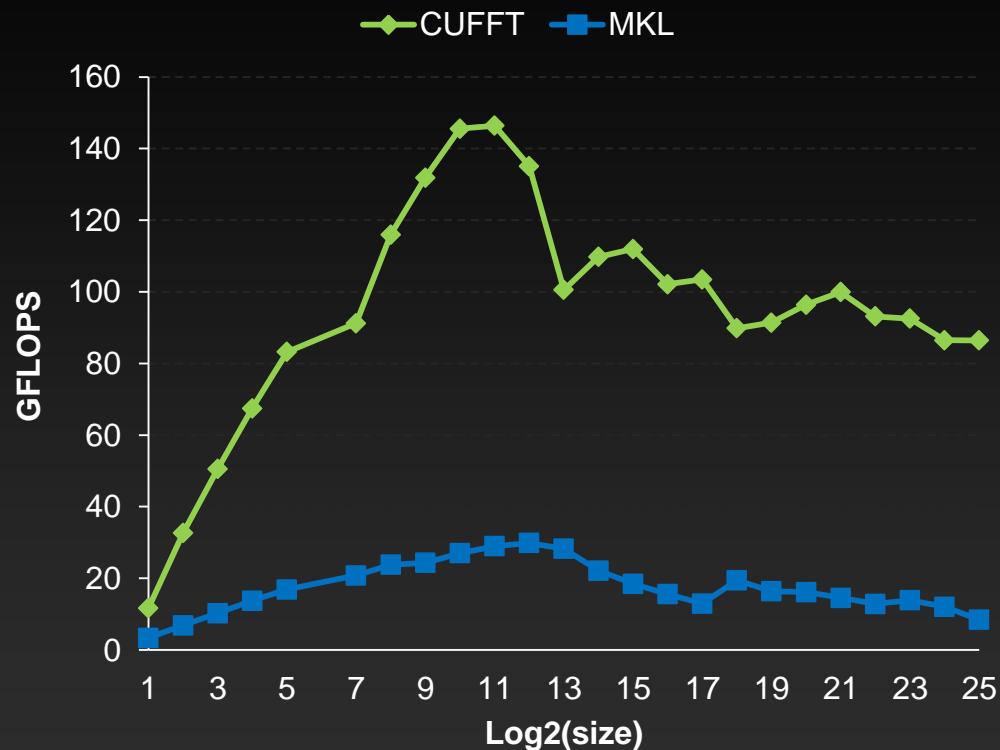
1D used in audio processing and as a foundation for 2D and 3D FFTs



## cuFFT Single Precision



## cuFFT Double Precision



- Measured on sizes that are exactly powers-of-2
- cuFFT 4.1 on Tesla M2090, ECC on
- MKL 10.2.3, TYAN FT72-B7015 Xeon x5680 Six-Core @ 3.33 GHz

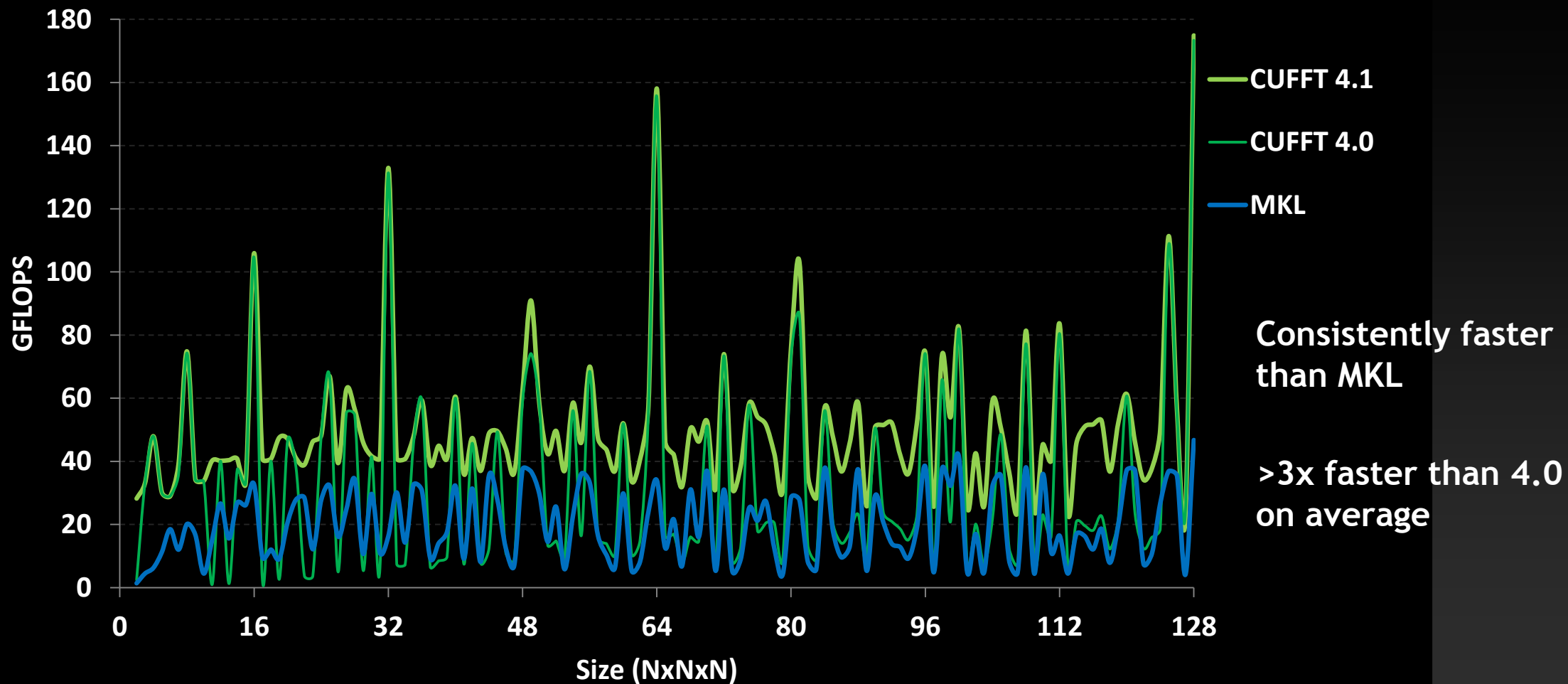
Performance may vary based on OS version and motherboard configuration



# CUDA 4.1 optimizes 3D transforms



Single Precision All Sizes 2x2x2 to 128x128x128



- cuFFT 4.1 on Tesla M2090, ECC on
- MKL 10.2.3, TYAN FT72-B7015 Xeon x5680 Six-Core @ 3.33 GHz

# cuBLAS: Dense Linear Algebra on GPUs

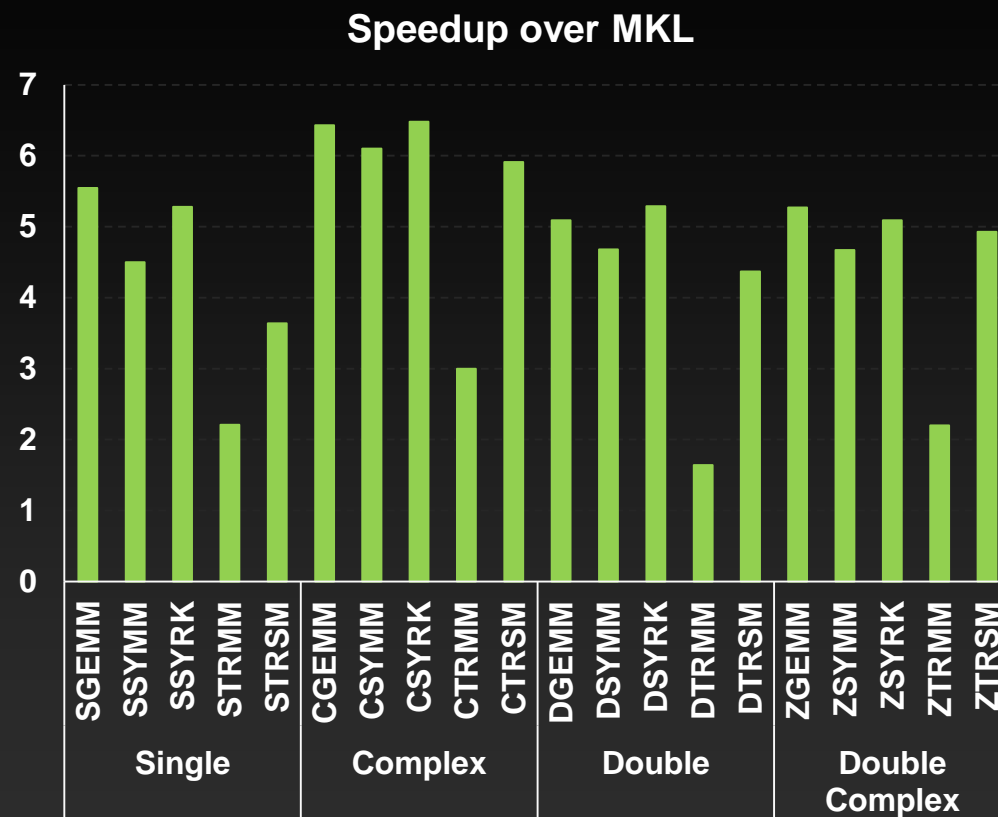
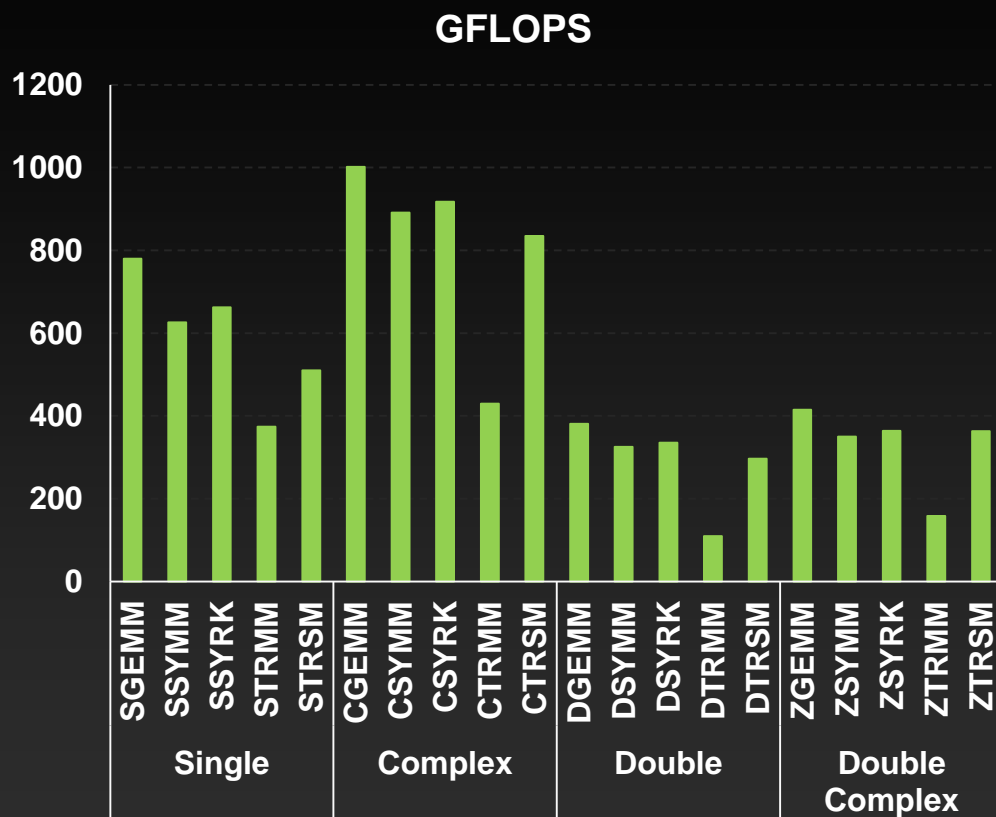


- **Complete BLAS implementation plus useful extensions**
  - Supports all 152 standard routines for single, double, complex, and double complex
- **New in CUDA 4.1**
  - New batched GEMM API provides >4x speedup over MKL
    - Useful for batches of 100+ small matrices from 4x4 to 128x128
  - 5%-10% performance improvement to large GEMMs

# cuBLAS Level 3 Performance

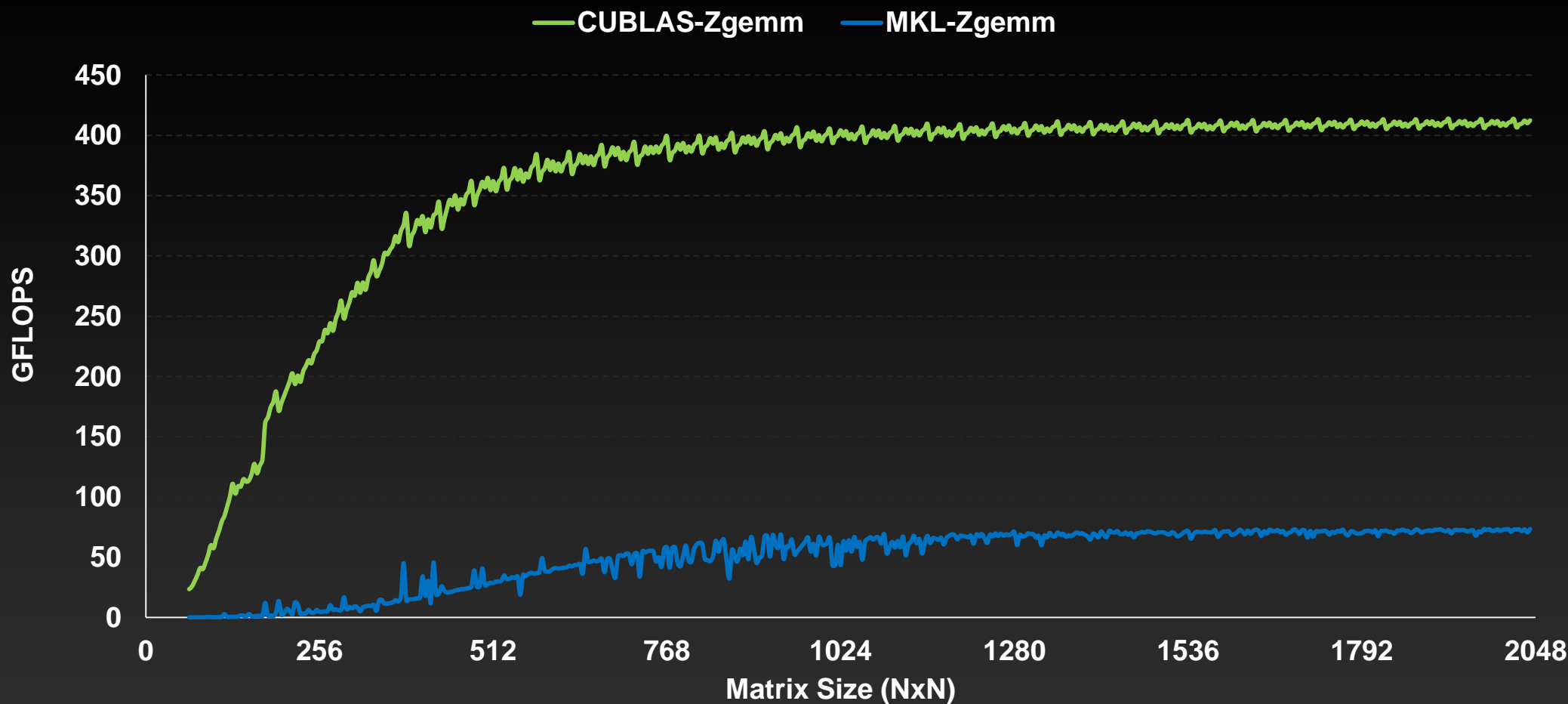


Up to 1 TFLOPS sustained performance and **>6x** speedup over Intel MKL



- 4Kx4K matrix size
- cuBLAS 4.1, Tesla M2090 (Fermi), ECC on
- MKL 10.2.3, TYAN FT72-B7015 Xeon x5680 Six-Core @ 3.33 GHz

# ZGEMM Performance vs Intel MKL

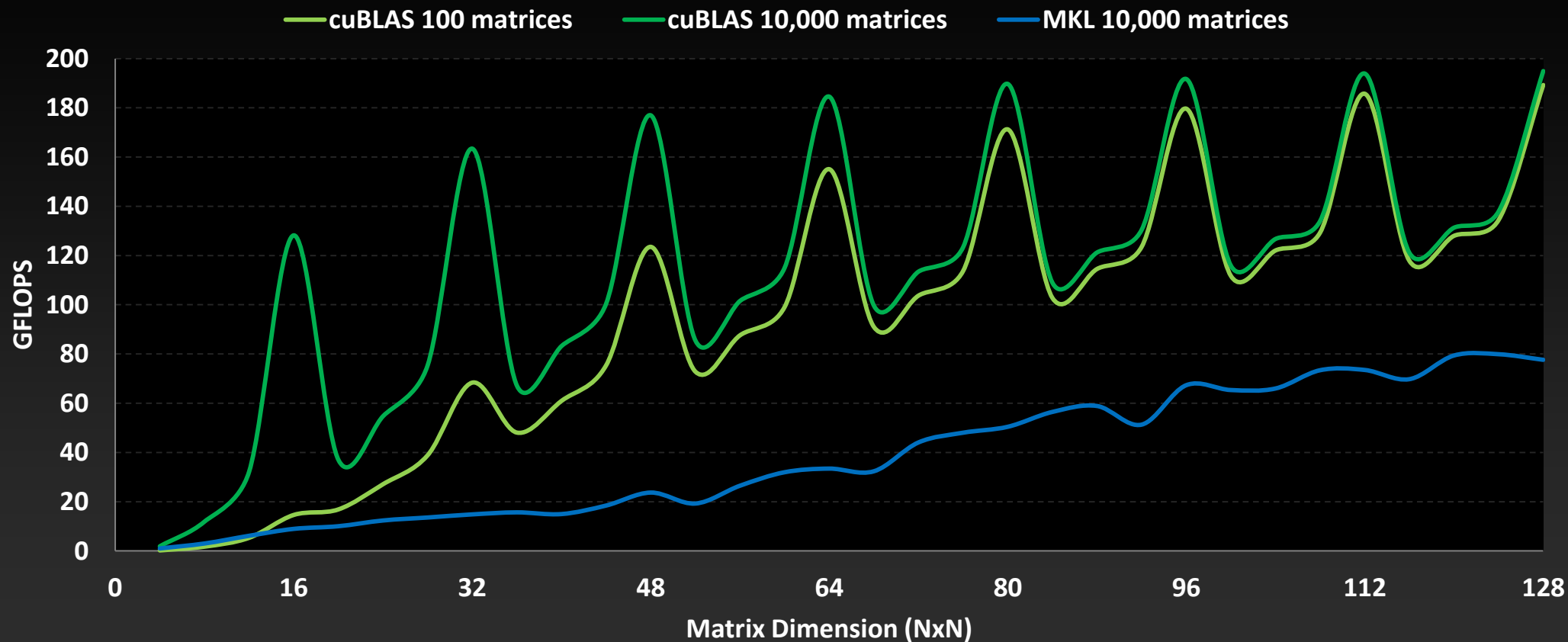


Performance may vary based on OS version and motherboard configuration

- cuBLAS 4.1 on Tesla M2090, ECC on
- MKL 10.2.3, TYAN FT72-B7015 Xeon x5680 Six-Core @ 3.33 GHz



# cuBLAS Batched GEMM API improves performance on batches of small matrices



Performance may vary based on OS version and motherboard configuration

- cuBLAS 4.1 on Tesla M2090, ECC on
- MKL 10.2.3, TYAN FT72-B7015 Xeon x5680 Six-Core @ 3.33 GHz

# cuSPARSE: Sparse linear algebra routines



- Sparse matrix-vector multiplication & triangular solve
  - APIs optimized for iterative methods
- New in 4.1
  - Tri-diagonal solver with speedups up to 10x over Intel MKL
  - ELL-HYB format offers 2x faster matrix-vector multiplication

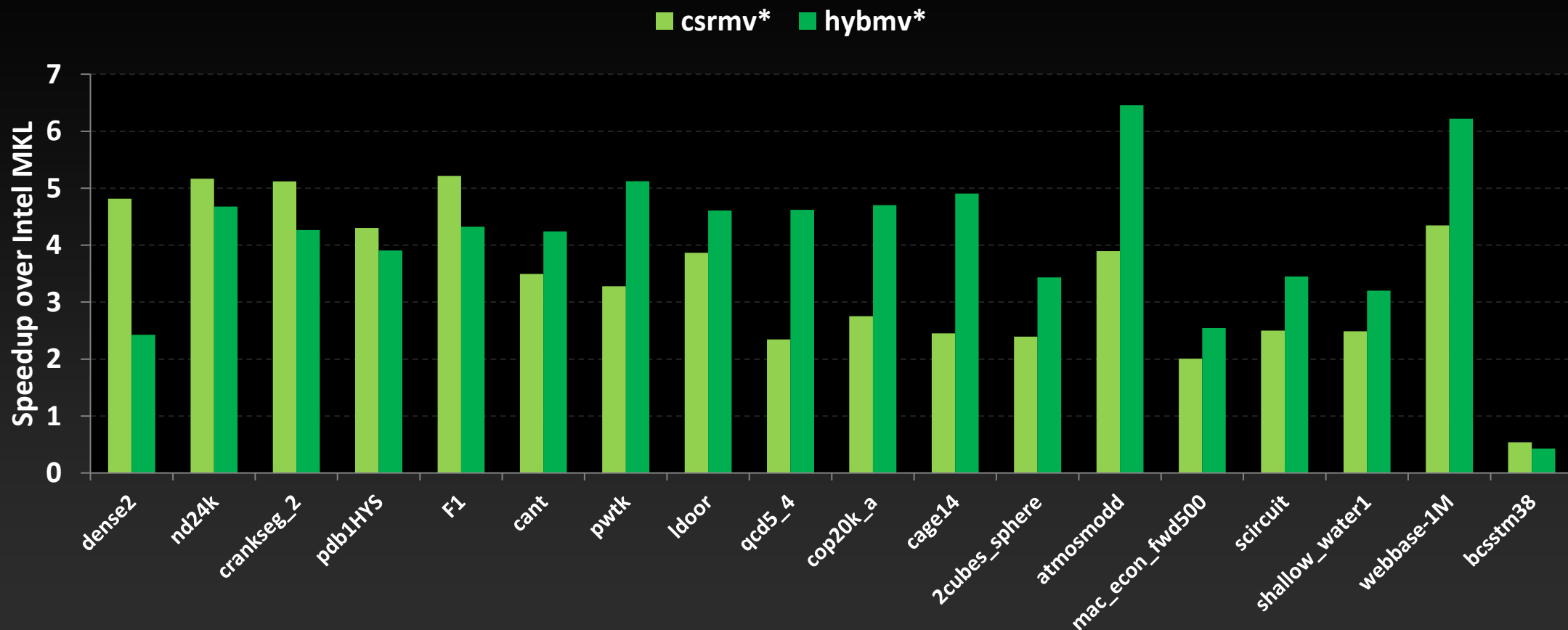
$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \alpha \begin{bmatrix} 1.0 & \dots & \dots & \dots \\ 2.0 & 3.0 & \dots & \dots \\ \dots & \dots & 4.0 & \dots \\ 5.0 & \dots & 6.0 & 7.0 \end{bmatrix} \begin{bmatrix} 1.0 \\ 2.0 \\ 3.0 \\ 4.0 \end{bmatrix} + \beta \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix}$$

$$\begin{bmatrix} \lambda^T \\ \lambda^T \\ \lambda^T \end{bmatrix} = \begin{bmatrix} 2.0 & \dots & 6.0 & 7.0 \\ \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots \end{bmatrix} \begin{bmatrix} 4.0 \\ \dots \\ \dots \\ \dots \end{bmatrix} + \begin{bmatrix} \lambda^T \\ \lambda^T \\ \lambda^T \end{bmatrix}$$

# cuSPARSE is >6x Faster than Intel MKL



## Sparse Matrix x Dense Vector Performance



*\*Average speedup over single, double, single complex & double-complex*

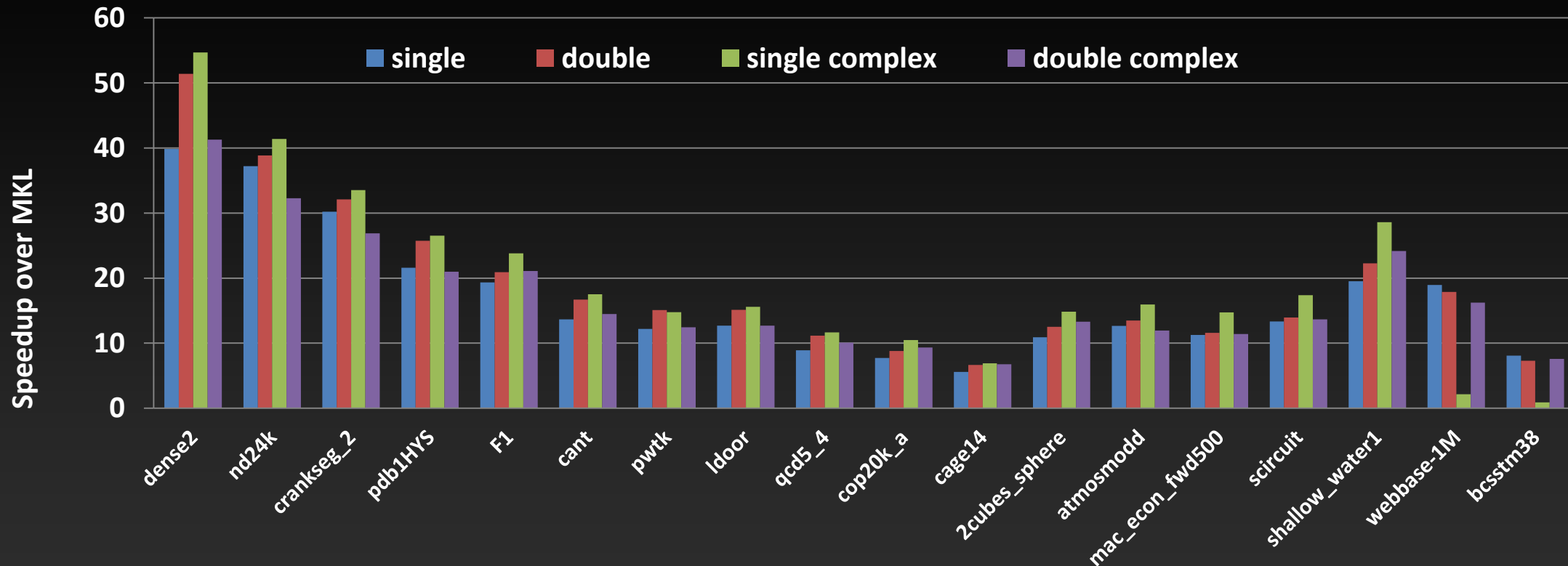
Performance may vary based on OS version and motherboard configuration

• cuSPARSE 4.1, Tesla M2090 (Fermi), ECC on  
• MKL 10.2.3, TYAN FT72-B7015 Xeon x5680 Six-Core @ 3.33 GHz

# Up to 40x faster with 6 CSR Vectors



cuSPARSE Sparse Matrix x 6 Dense Vectors (csrmm)  
Useful for block iterative solve schemes

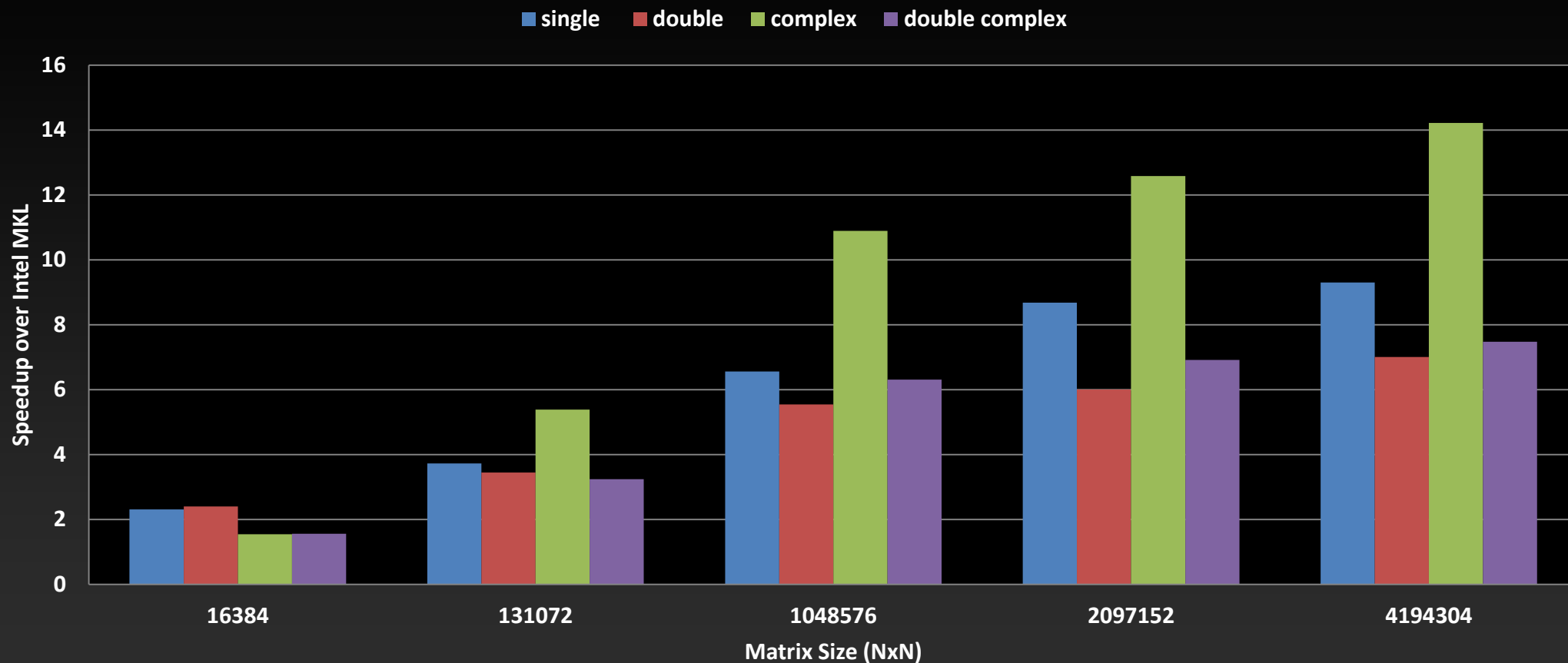




# Tri-diagonal solver performance vs. MKL



Speedup for Tri-Diagonal solver (gtsv)\*



*\*Parallel GPU implementation does not include pivoting*

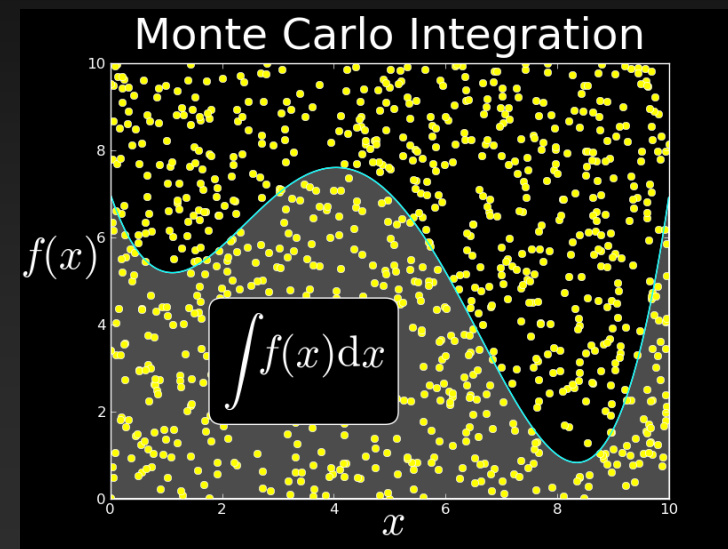
Performance may vary based on OS version and motherboard configuration

- cuSPARSE 4.1, Tesla M2090 (Fermi), ECC on
- MKL 10.2.3, TYAN FT72-B7015 Xeon x5680 Six-Core @ 3.33 GHz

# cuRAND: Random Number Generation



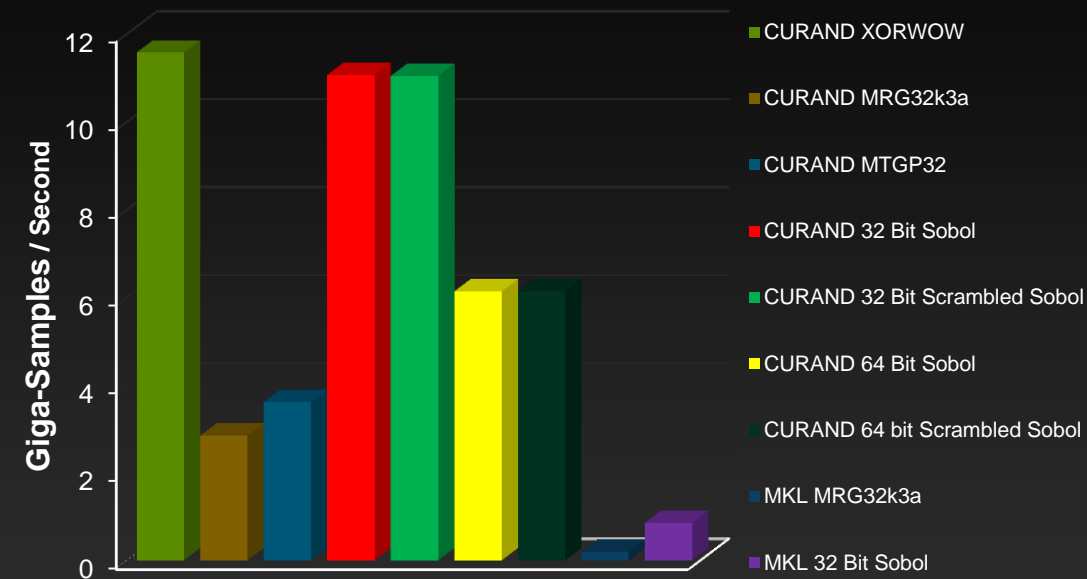
- Pseudo- and Quasi-RNGs
- Supports several output distributions
- Statistical test results reported in documentation
- New commonly used RNGs in CUDA 4.1
  - MRG32k3a RNG
  - MTGP11213 Mersenne Twister RNG



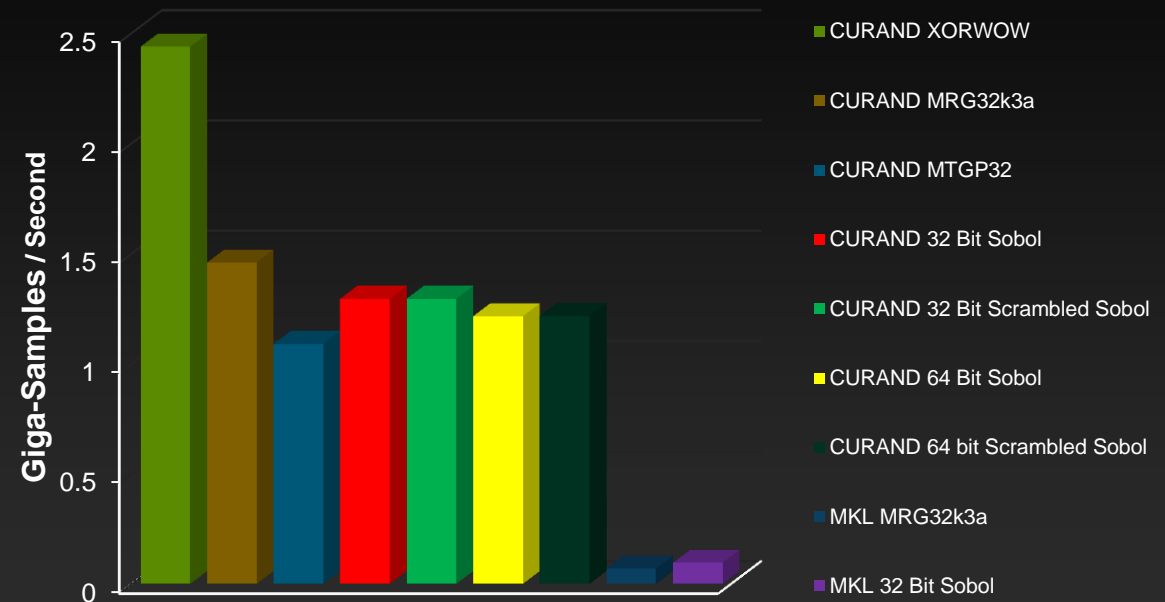
# cuRAND Performance compared to Intel MKL



## Double Precision Uniform Distribution



## Double Precision Normal Distribution



Performance may vary based on OS version and motherboard configuration

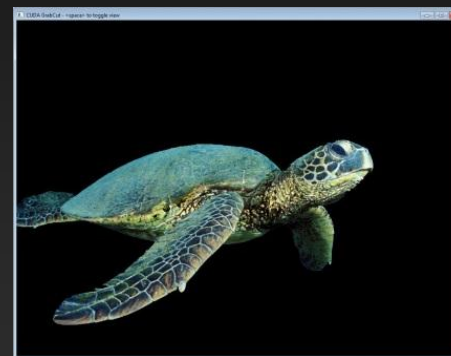
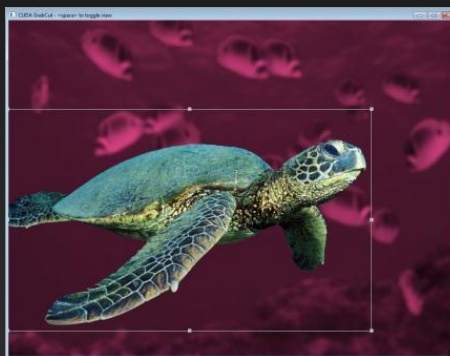
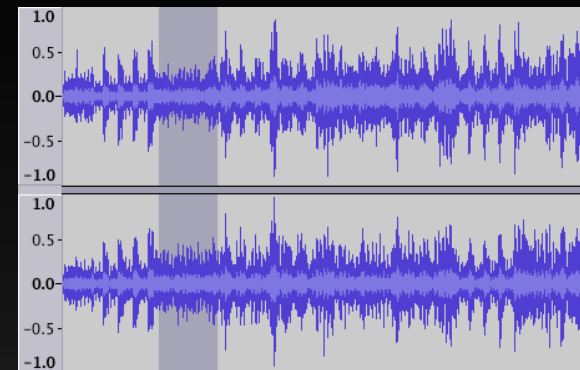
• cuRAND 4.1, Tesla M2090 (Fermi), ECC on  
• MKL 10.2.3, TYAN FT72-B7015 Xeon x5680 @ 3.33 GHz

# 1000+ New Imaging Functions in NPP 4.1



Up to **40x** speedups

- NVIDIA Performance Primitives (NPP) library includes over 2200 GPU-accelerated functions for image & signal processing  
Arithmetic, Logic, Conversions, Filters, Statistics, etc.
- Most are 5x-10x faster than analogous routines in Intel IPP



<http://developer.nvidia.com/content/graphcuts-using-npp>

\* NPP 4.1, NVIDIA C2050 (Fermi)

\* IPP 6.1, Dual Socket Core™ i7 920 @ 2.67GHz



# Using CUDA Libraries with OpenACC



# Sharing data with libraries



- CUDA libraries and OpenACC both operate on device arrays
- OpenACC provides mechanisms for interop with library calls
  - deviceptr data clause
  - host\_data construct
- Note: same mechanisms useful for interop with custom CUDA C/C++/Fortran code

# deviceptr Data Clause



`deviceptr( list )` Declares that the pointers in *list* refer to device pointers that need not be allocated or moved between the host and device for this pointer.

Example:

C

```
#pragma acc data deviceptr(d_input)
```

Fortran

```
$!acc data deviceptr(d_input)
```

# host\_data Construct



Makes the address of device data available on the host.

`deviceptr( list )` Tells the compiler to use the device address for any variable in *list*. Variables in the list must be present in device memory due to data regions that contain this construct

## Example

C

```
#pragma acc host_data use_device(d_input)
```

Fortran

```
$!acc host_data use_device(d_input)
```



# Example: 1D convolution using CUFFT



- Perform convolution in frequency space
  1. Use CUFFT to transform input signal and filter kernel into the frequency domain
  2. Perform point-wise complex multiply and scale on transformed signal
  3. Use CUFFT to transform result back into the time domain
- We will perform step 2 using OpenACC
- Code walk-through follows. Code available with exercises.
  - In `exercises/cufft-acc`

# Source Excerpt



```
// Transform signal and kernel
error = cufftExecC2C(plan, (cufftComplex *)d_signal,
                      (cufftComplex *)d_signal, CUFFT_FORWARD);
error = cufftExecC2C(plan, (cufftComplex *)d_filter_kernel,
                      (cufftComplex *)d_filter_kernel, CUFFT_FORWARD);

// Multiply the coefficients together and normalize the result
printf("Performing point-wise complex multiply and scale.\n");
complexPointwiseMulAndScale(new_size,
                             (float *restrict)d_signal,
                             (float *restrict)d_filter_kernel);

// Transform signal back
error = cufftExecC2C(plan, (cufftComplex *)d_signal,
                      (cufftComplex *)d_signal, CUFFT_INVERSE);
```

This function  
must execute on  
device data

# OpenACC convolution code



```
void complexPointwiseMulAndScale(int n, float *restrict signal,
                                float *restrict filter_kernel)
{
    // Multiply the coefficients together and normalize the result
    #pragma acc data deviceptr(signal, filter_kernel)
    {
        #pragma acc kernels loop independent
        for (int i = 0; i < n; i++) {
            float ax = signal[2*i];
            float ay = signal[2*i+1];
            float bx = filter_kernel[2*i];
            float by = filter_kernel[2*i+1];
            float s = 1.0f / n;
            float cx = s * (ax * bx - ay * by);
            float cy = s * (ax * by + ay * bx);
            signal[2*i] = cx;
            signal[2*i+1] = cy;
        }
    }
}
```

Note: The PGI C compiler does not currently support structs in OpenACC loops, so we cast the Complex\* pointers to float\* pointers and use interleaved indexing

# Linking CUFFT



- `#include "cufft.h"`
- Compiler command line options:

```
CUDA_PATH = /usr/local/pgi/linux86-64/2012/cuda/4.0  
CCFLAGS = -I$(CUDA_PATH)/include -L$(CUDA_PATH)/lib64  
          -lcudart -lcufft
```

Must use  
PGI-provided  
CUDA toolkit paths

Must link libcudart  
and libcufft

# Results



```
[harrism@kollman0 cufft-acc]$ ./cufft_acc  
Transforming signal cufftExecC2C  
Performing point-wise complex multiply and scale.  
Transforming signal back cufftExecC2C  
Performing Convolution on the host and checking correctness  
  
Signal size: 500000, filter size: 33  
Total Device Convolution Time: 11.461152 ms (0.242624 for point-wise convolution)  
Test PASSED
```

CUFFT + cudaMemcpy

OpenACC

# Summary



- Use deviceptr data clause to pass pre-allocated device data to OpenACC regions and loops
- Use host\_data to get device address for pointers inside acc data regions
- The same techniques shown here can be used to share device data between OpenACC loops and
  - Your custom CUDA C/C++/Fortran/etc. device code
  - Any CUDA Library that uses CUDA device pointers

Thank you

