EC500 E1: Parallel Programming and HPC

# Parallelizing 2D Convolutions on GPUs

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# Outline

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- Introduction - What Is a Convolution and Why is it important
- Work Planned vs Work Accomplished
- Parallelization Strategy
- Results
- Road Blocks
  - Time Complexity
  - Memory Issues
- Lessons Learned
- Next Steps
- Conclusion

# Goal

**The goal of our project is to work with 2D convolution, a widely-used and simple, yet computationally inefficient algorithm, and explore methods to speed it up by implementing parallelization with GPU's**

# What is a Convolution?

$$(f * g)[n] = \sum_{m=-\infty}^{\infty} f[m]g[n-m]$$

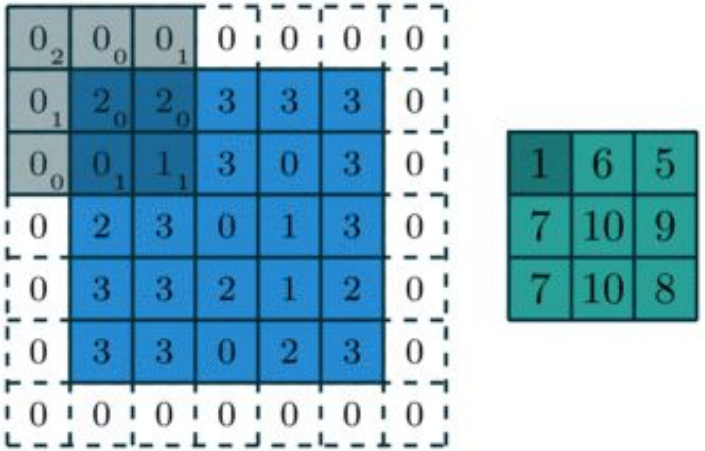
A 1D convolution is a linear combination of two functions: ***f,*** some **signal** that you have recorded and ***g***, a **filter** to process the signal data in some desired fashion (i.e. smoothing, edge detection, or lowpass). You can extend the convolution into 2, 3, … N dimension. Convolution is a common data processing method that is used in a wide variety of domains.

The 2D convolution has a worst case time complexity of **O($n^4$)**. So finding methods to improve performance is key.



Image from Wikipedia

# The 2D Convolution Example




$$\mathbf{g}_{mn} = \sum_{m'=0}^{N-1} \sum_{n'=0}^{N-1} \mathbf{a}_{m-m',n-n'} \mathbf{f}_{m',n'}$$

2D convolutions generate new representations of the original data matrix based on a linear combination of its elements with that of a filter matrix or “Kernel” as it moves through the original data.

One relevant reason for exploring parallelizing this operation is its wide use in modern computer vision and current deep learning applications.

# The 2D Convolution Example

64x64 grayscale input image

64x64 edge detection output image

Example of using our 2D convolution function for edge detection on a 64x64 grayscale image of a dogs using a 3x3 local filter.

# Work Planned vs Work Accomplished

- Build the 2D convolution function, FFT and the resulting matrices in both serial and  parallel fashion
  - Building the 2D convolution matrix follows a specific pattern and can be parallelized
  - Reshaping the image, performing matrix math, and reshaping back to original size are all also parallelizable operations.
- Compare direct convolution to FFT2
  - Parallelize FFT
  - Test both parallelized methods and compare/contrast for different inputs (different sized images and kernels)
- Use OpenACC for GPU parallelization
  - Use OpenACC on the SCC

# Work Planned vs Work Accomplished

- Built 2D convolution functions in C++
  - Built Circulant Matrix Variant
  - Built Direct Variant
  - Built 2D FFT method for comparison
  - Used built-in image libraries for reading images
  - Built function to generate 2D black and white noise images to test scaling
  - Parallelized code for Direct Variant
- Compared direct variant with multiple compiling methods on SCC
  - Serial, Multicore CPU and GPU
  - Required porting much of the code from C++ to C.
- Used OpenACC for GPU and parallelization
  - Use OpenACC on the SCC

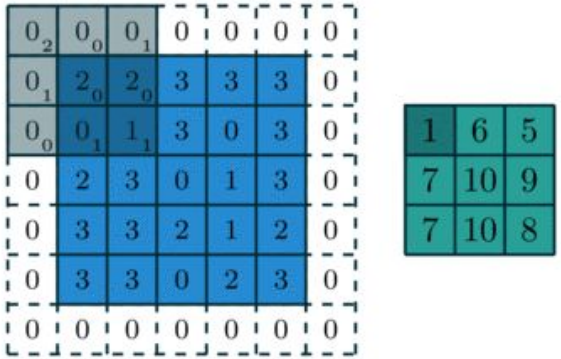
# Parallelization Strategy

- Initial strategy looked to parallelize each helper function required to perform the entire convolution as well as the convolution function itself
  - Generating the Circulant Matrix
  - Converting 2D matrices into 1D Vectors
  - Generating Images and Filters to Convolve
  - The main convolution function

# Parallelization Strategy

- The convolution operation is highly parallelizable due to each step in the algorithm being independent of the rest.
- Each KxK block can be computed correctly without information from any of the others.
- Our plan was to compute all KxK blocks simultaneously using the openACC library

OpenACC



# Parallelization Strategy

```
61
62    #pragma acc kernels copy(image[0:IMAGE_N][0:IMAGE_N]), copyout(output[0:IMAGE_N][0:IMAGE_N])
63    {
64      for(int x = 0; x < IMAGE_N; x++)
65        for(int y = 0; y < IMAGE_N; y++)
66          for(int x_pos = 0; x_pos <filter_N; x_pos++)
67            for(int y_pos = 0 ; y_pos < filter_N; y_pos++)
68              if (x+x_pos < IMAGE_N && y+y_pos < IMAGE_N){ //improve
69                // printf("%d %d \n", x, y);
70                output[x][y] += image[x+x_pos][y+y_pos]*filter[x_pos][y_pos];
71              }
72    }
```

# Parallelization Strategy

```
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62    #pragma acc kernels copy(image[0:IMAGE_N][0:IMAGE_N]), copyout(output[0:IMAGE_N][0:IMAGE_N])
63    {
64      for(int x = 0; x < IMAGE_N; x++)
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70                output[x][y] += image[x+x_pos][y+y_pos]*filter[x_pos][y_pos];
71              }
72    }
```

**Each KxK block is run in parallel**

# Parallelization with OpenACC

```
pgcc -DUSE_DOUBLE -Minfo=accel -fast -acc -ta=tesla:cc20 -c main.c  -g
main:
     62, Generating implicit copyin(filter[:][:])
         Generating copyout(output[:][:])
         Generating copy(image[:][:])
     64, Loop is parallelizable
     65, Loop is parallelizable
     66, Loop carried dependence of output prevents parallelization
         Loop carried backward dependence of output prevents vectorization
     67, Complex loop carried dependence of output prevents parallelization
         Loop carried dependence of output prevents parallelization
         Loop carried backward dependence of output prevents vectorization
         Inner sequential loop scheduled on accelerator
         Accelerator kernel generated
         Generating Tesla code
         64, #pragma acc loop gang /* blockIdx.y */
         65, #pragma acc loop gang, vector(128) /* blockIdx.x threadIdx.x */
         66, #pragma acc loop seq
         67, #pragma acc loop seq
```

# Results

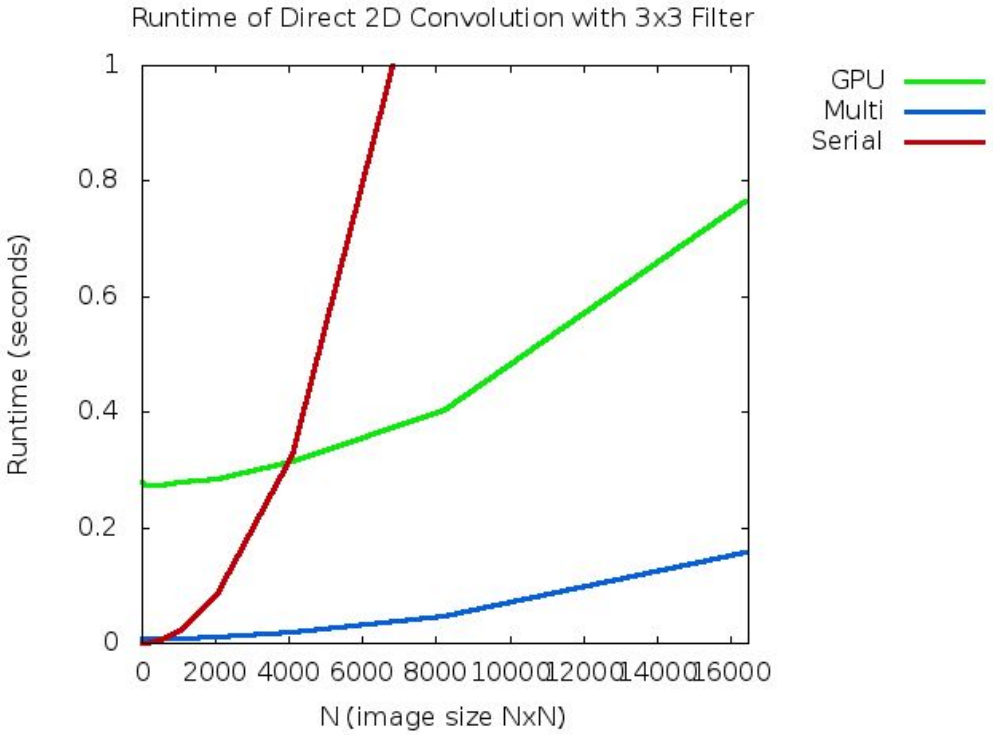
- Parallel Code is Faster Than Serial Code! But how much faster, and in what cases?

- We ran the following **3 Experiments**:

    - 3x3 kernel on grayscale images ranging from 16x16 to 16384x16384
    - 16x16 kernel on grayscale images ranging from 16 x16 to 16384x16384
    - All-to-All kernel on grayscale images ranging from 16x16 to 1024x1024

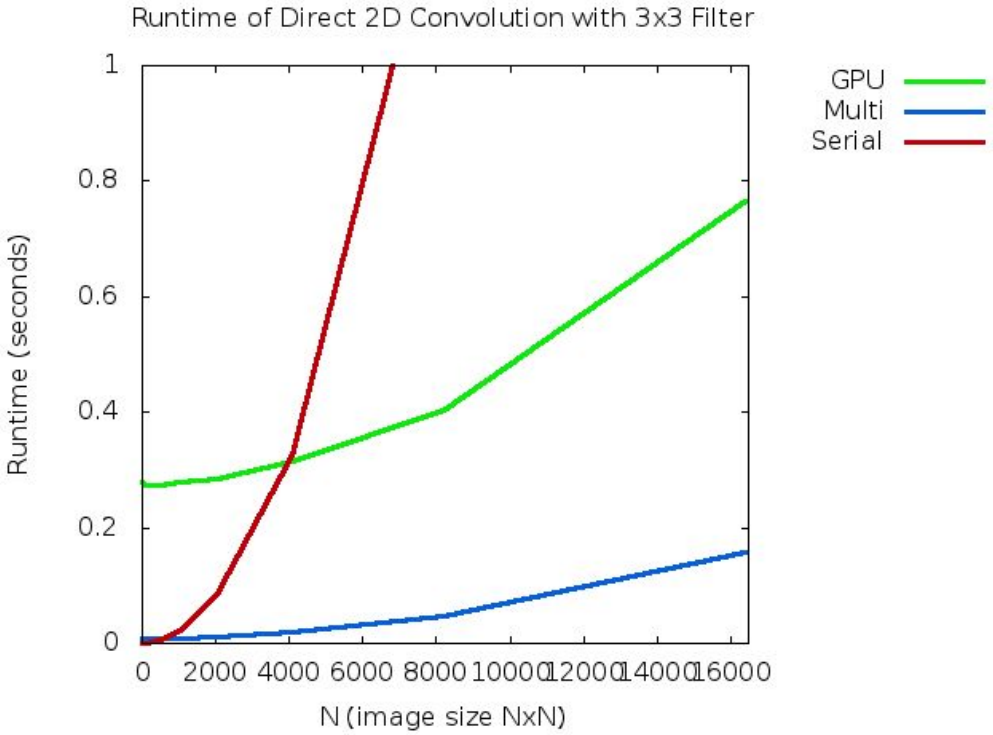
- We compared the performance of serial code run on a CPU, parallelized multicore CPU and parallelized GPU. All were run in an interactive session on the SCC with 1 GPU.

# Results: 3x3 Kernel



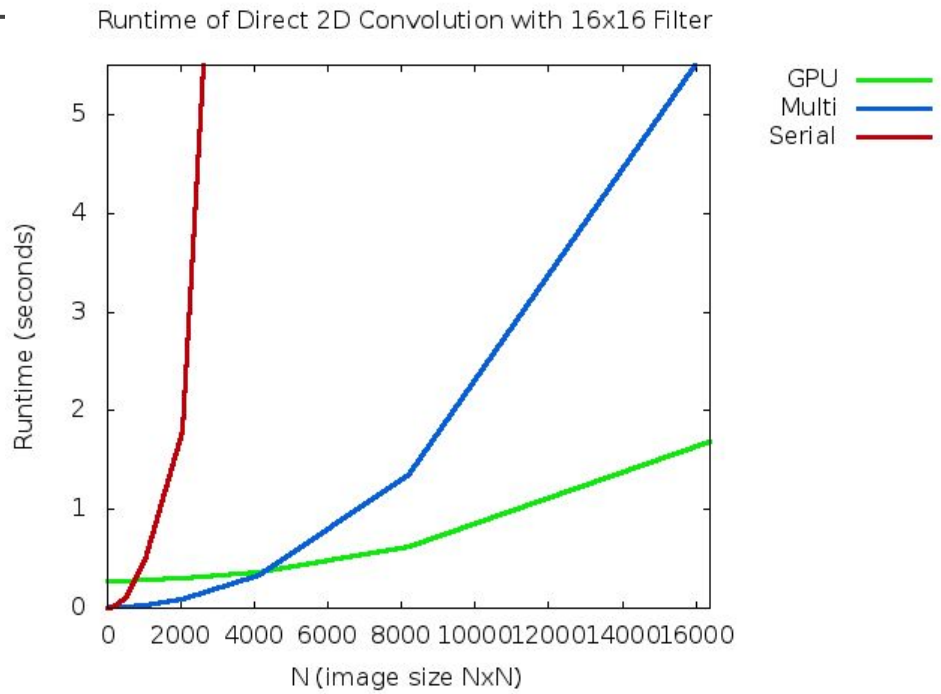

- Due to GPU data passing procedures, the serial code is actually much faster than using a GPU until we reach an image size of around 4000 x 4000 pixels.
- Use of GPU has a constant start up time of about ~0.27 seconds. Making it slower than serial code for small convolutions.
- Without any data passing overhead multi-core achieves by far the best performance here.

# Results: 3x3 Kernel



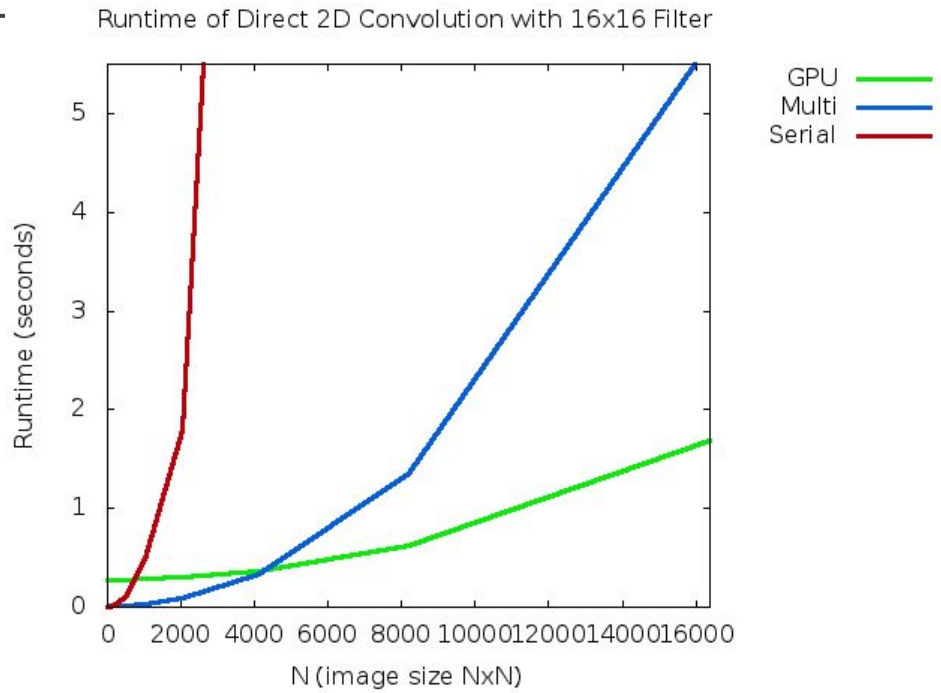

- Endpoint Performance (16384 pix):
  - GPU: 0.7649 seconds
  - Multi: 0.1583 seconds
  - Serial: 4.3467 seconds
- With these dimensions GPU is approximately **5.6** times faster and Multi-core is about **27.4** times faster.

# Results: 16x16 Kernel



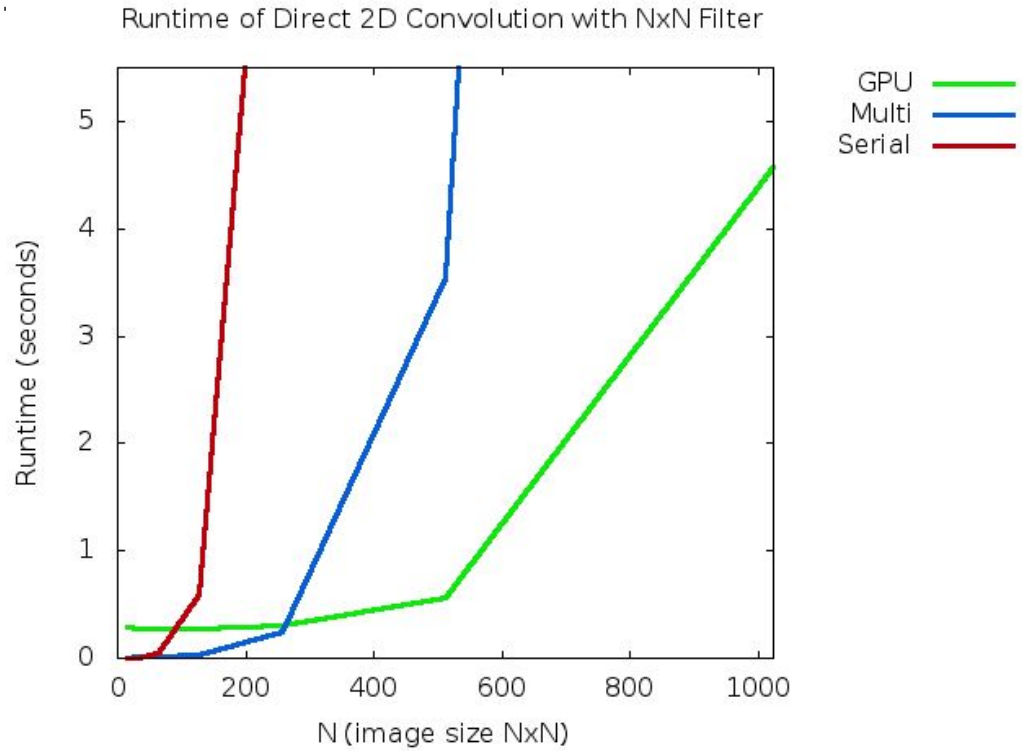

- With a larger kernel,however, we see the benefits of using the GPU much earlier. Around 1024 x 1024.
- Although GPU still has constant overhead with smaller matrices, we can see that it vastly outperforms both Serial and Multi-core processing for larger operations.

# Results: 16x16 Kernel



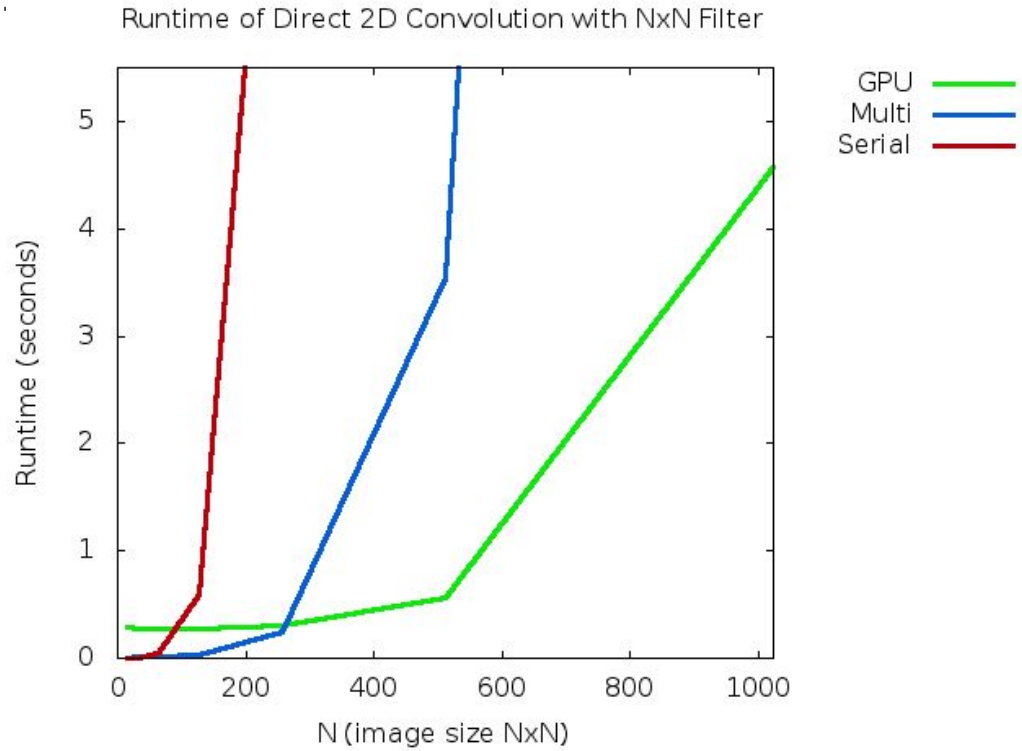

- Endpoint Performance (16384 pix):
  - GPU: 1.6843 seconds
  - Multi: 5.7168 seconds
  - Serial: 102.6549 seconds
- With these dimensions GPU is approximately **60.9** times faster and Multi-core is about **17.95** times faster.

# Results: NxN Kernel




- All-to-All convolutions require large amounts of memory. Only ran these to 1024 x 1024
- These were guaranteed to provide us with worst case running time for each method

# Results: NxN Kernel



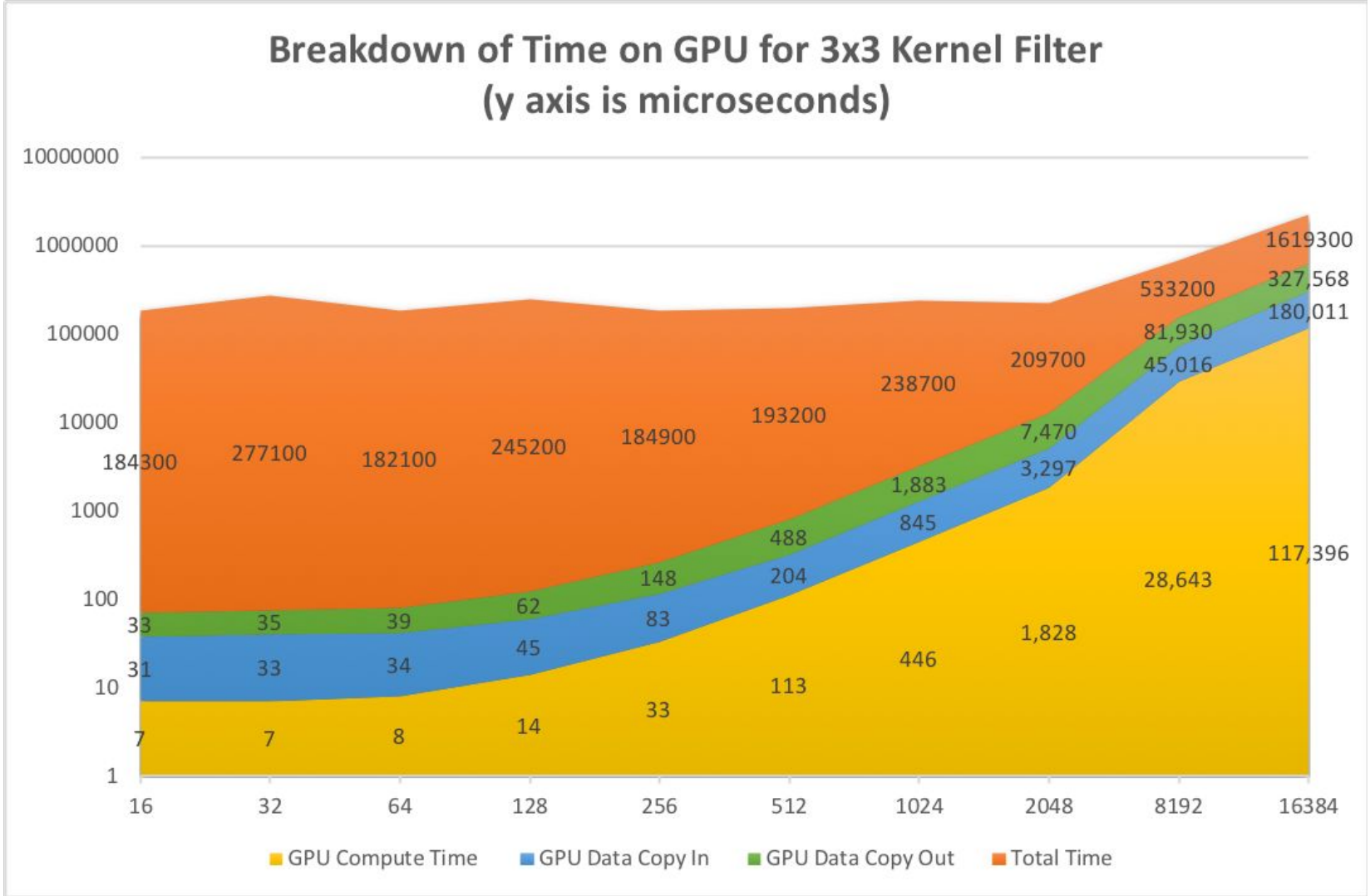

- Endpoint Performance (1024 pix):
  - GPU: 4.5761 seconds
  - Multi: 54.7941seconds
  - Serial: 2347.54 seconds
- With these dimensions GPU is approximately **513** times faster and Multi-core is about **42.84** times faster.

# A Closer Look at GPU Timing

Set the PGI_ACC_TIME environment variable to receive detailed timing info regarding GPU:

```
Accelerator Kernel Timing data

main  NVIDIA  devicenum=0
    time(us): 625,121
    62: compute region reached 1 time
        67: kernel launched 1 time
            grid: [128x256]  block: [128]
             device time(us): total=117,676 max=117,676 min=117,676 avg=117,676
            elapsed time(us): total=117,736 max=117,736 min=117,736 avg=117,736
    62: data region reached 4 times
        62: data copyin transfers: 65
             device time(us): total=179,962 max=2,820 min=8 avg=2,768
        81: data copyout transfers: 130
             device time(us): total=327,483 max=2,605 min=25 avg=2,519
```


Breakdown of Time on GPU for 3x3 Kernel Filter
(y axis is microseconds)
10000000
1000000
100000
10000
1000
100
10
1
16
32
64
128
256
512
1024
2048
8192
16384
184300
277100
182100
245200
184900
193200
238700
209700
533200
1619300
33
35
39
62
148
488
1,883
7,470
81,930
327,568
31
33
34
45
83
204
845
3,297
45,016
180,011
7
7
8
14
33
113
446
1,828
28,643
117,396
GPU Compute Time
GPU Data Copy In
GPU Data Copy Out
Total Time

# Road Blocks: PGCC compiler on SCC

- Initial code was in C++ and used the CImg library
- Unfortunately could not compile on PGCC
- PGCC has dependence on GCC and referenced GCC 4.4. Attempted fixes:
  - Switching between Evan's PGCC install and SCC install
  - Changing localrc files to point to newer version
- We gave up on getting existing code and rewrote
- Removed any dependencies for GCC > 4.4 in both a C and a C++ version

# Road Blocks: PGCC compiler on SCC

- In C++ we had to remove image library. Attempted hacks:
  - Separating into different files and using different compilers
  - Compiling as a library and linking
  - This should be possible, but became a distraction
- C we used lodepng library but abandoned it because of difficulty debugging
- Went with C version because it was easier to locate parallelization

# Road Blocks: Memory Issues

- Memory Issues:
  - Initial circular convolution method required massive memory overhead to store secondary matrices. Memory needs became untenable at around 512 x 512 pixel images. At this point we switched to the direct convolution method.
  - Despite modified approach, unless a reasonably sized local kernel was used, memory issues remained.

# Lessons Learned

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- In real-world applications, memory bandwidth can be as important (if not more so) than computational complexity. We quickly ran into memory allocation issues that we had not originally considered when focusing solely on parallelizing the computations.
- OpenACC is an extremely powerful tool that can generate orders of magnitude speedups with a single line of code.

# Future Work

- Parallelize FFT and compare performance on similar tests.
- Implement image reading function and use more interesting filters
- Create matrices on GPU to minimize data movement (this would only work for certain kinds of matrices--not images)

# Conclusion

- GPU’s can be expensive to initialize and so provide little benefit on smaller tasks. However the economy of scale quickly becomes realized (1024 x 1024 convolution runs over 500x faster than serial variant!)
- OpenACC is amazing (once you get it working)
- Despite GPU’s massive speed up at larger scales, more work is needed to intelligently manage data allocation and movement.

# THANKS!!!!!!


Any questions?

# Coding Plan

- Begin coding of sequential algorithm
  - Creation of circulant matrix and 2D representation
  - Convolution via matrix multiplication
- In parallel, install plumbing…
  - Library for I/O of images as 2D matrices (CImg may be an option)
  - Setup script for OpenACC on SCC (BU Help article)
  - Devise plan for testing against FFT
- Turn sequential algorithm into parallel
  - First step is to parallelize convolution/matrix multiplication
  - May also be able to parallelize creation of kernel matrices

# Testing, Results, & Other Ideas

- A simple kernel, blur filter, to average pixel values
- We can subsequently develop a more sophisticated kernels
- *Concrete Mathematics* has other interesting convolution applications (e.g. samplesort)
- The work we are proposing could be the beginning of a convolutional neural network

# The 1D Convolution Matrix (Circulant Matrix)

$$\mathbf{g} = \mathbf{A}\mathbf{f} = \mathbf{a} * \mathbf{f}$$

$$\mathbf{g} = \begin{bmatrix} a_0 & a_{N-1} & a_{N-2} & \cdots & \cdots & a_1 \\ a_1 & a_0 & a_{N-1} & \ddots & & \vdots \\ a_2 & a_1 & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & a_{N-1} & a_{N-2} \\ \vdots & & \ddots & a_1 & a_0 & a_{N-1} \\ a_{N-1} & \cdots & \cdots & a_2 & a_1 & a_0 \end{bmatrix} \begin{pmatrix} \mathbf{f}_0 \\ \mathbf{f}_1 \\ \\ \vdots \\ \\ \mathbf{f}_{N-1} \end{pmatrix}$$

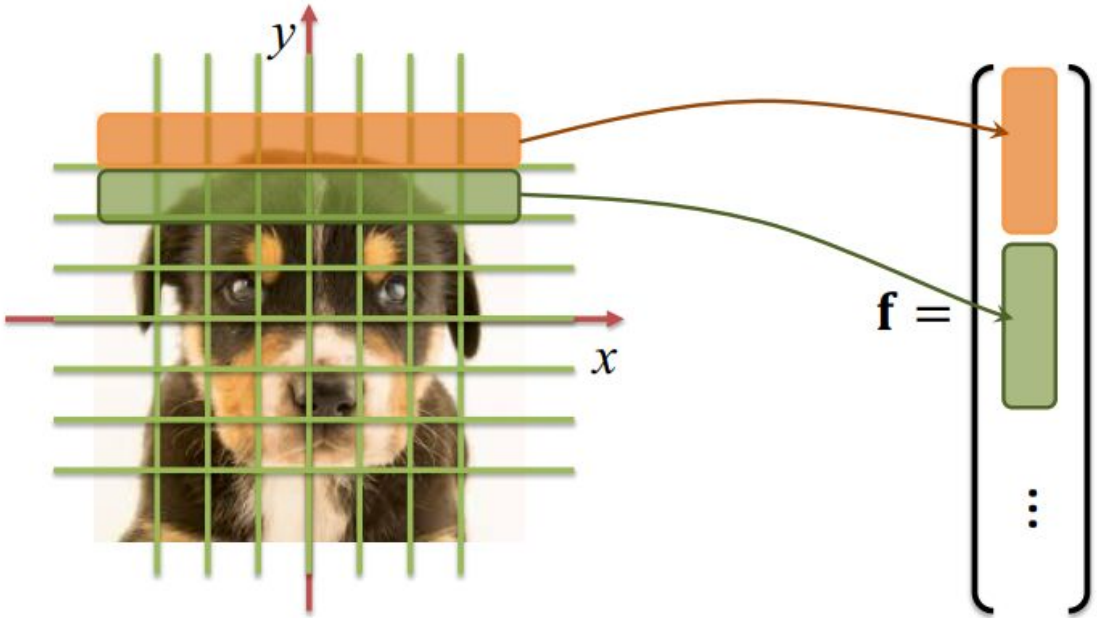
PSF

- Here, **PSF** is the **Point Spread Function**, which is also called the transfer function, kernel, filter, etc.



Image from Professor Lei Tian, BU Dept. ECE

# Extending into the 2D Space…



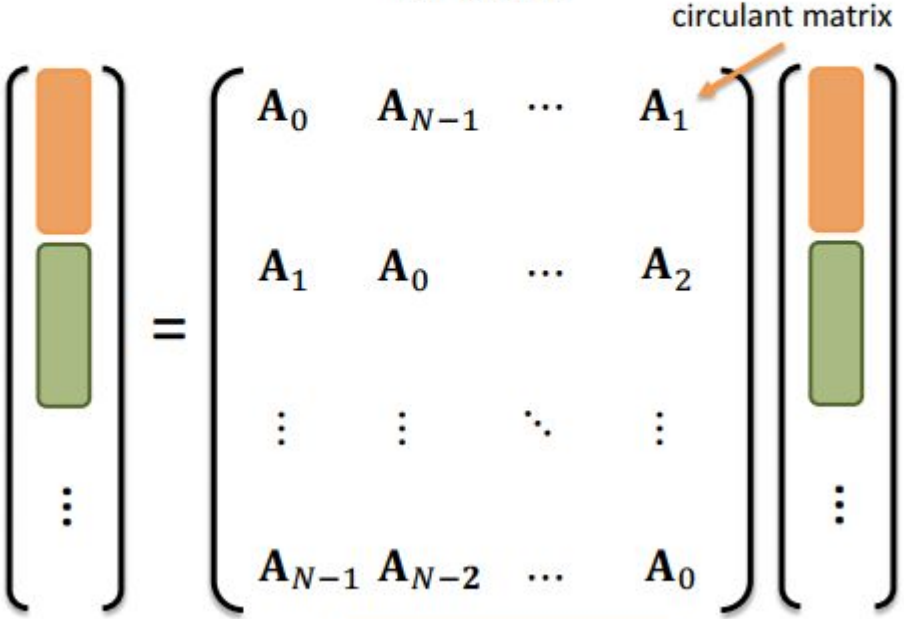

- We can represent the entire image as a column vector of stacked pixel-rows of the image



Image from Professor Lei Tian, BU Dept. ECE

# Using Our Stacked Column Representation…

$$\mathbf{g} = \mathbf{Af} \qquad \mathbf{g}_{mn} = \sum_{m'=0}^{N-1} \sum_{n'=0}^{N-1} \mathbf{a}_{m-m',n-n'} \mathbf{f}_{m',n'}$$




- Here, we can perform the 2D convolution image in a similar way to the 1D convolution, except here each $A_n$ is itself a circulant matrix.
- If image is NxN, then A will be $N^2$x$N^2$ which can get rather large and take up a lot of memory.

Our Image Column Vector



Image from Professor Lei Tian, BU Dept. ECE