



Optimization 101

Christopher Blanton

PACE

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Introduction

Motivation

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- ***There are many reasons why we want to do this, but here are two common ones:***
 - ① ***To get work done faster.***
 - ② ***To approach larger and more complex versions of the problems.***

Code Optimization

There are many ways to optimize code, but common methods include

- ***Automatic compiler optimization***
- ***Use of profilers***
- ***Algorithm analysis***
- ***Library use***

Optimization process

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- ***Take action to address the bottleneck. Optimization proper***

Warning



Avoid assuming what the bottleneck is!

Optimization process

- ***Establish the correctness of your solution.***
- ***Establish a baseline performance. Benchmarking***
- ***Find the bottleneck for performance. Profiling***
- ***Take action to address the bottleneck. Optimization proper***
- ***Go back to step 2, if needed.***

The $\mathbf{Ax} = \mathbf{b}$ in science

Problems that can be expressed as systems of linear equations can be found in many areas of science and computing.

- ***Chemistry***
- ***Network Analysis***
- ***Fiance***
- ***Electrical Engineering***
- ***Chemical Engineering***
- ***Mechanical Engineering***
- ***And Many more***

The problem

We want to solve large systems of linear equations; that is

$$a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n = b_1$$

$$a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n = b_2$$

$$a_{31}x_1 + a_{32}x_2 + \cdots + a_{3n}x_n = b_3$$

⋮

$$a_{n1}x_1 + a_{n2}x_2 + \cdots + a_{nn}x_n = b_n$$

Matrix Representation

- ***The coefficients can be represented as a matrix***

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{1n} & a_{2n} & \cdots & a_{nn} \end{bmatrix}, \quad (1)$$

Matrix representation

- ***the variables***

$$\mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}, \quad (2)$$

- ***and solutions as***

$$\mathbf{b} = \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{pmatrix}. \quad (3)$$

Solving Linear Equations Directly

- **We may think that we want to solve the equation in the same way as we would solve a single linear equation $ax = b$:**

$$x = a^{-1}b$$

- **However, the calculation of matrix inverses is a costly process that involved many calculations.**
- **In essence, it involves more operations than solving the system directly.**
- **Even a sparse matrix A may generate a dense A^{-1} .**
- **Direct solvers are rarely used for these reasons.**

Iterative Solvers

- ***Alternatively, we can use a trial solution to generate a better approximation to the “true” solution.***

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- *That is*

$$\mathbf{A}\mathbf{x}^{trial} = \mathbf{b}^{trial}$$

- *Which can then be used to generate further refined answers until $|\mathbf{b}^{trial} - \mathbf{b}|$ is small enough.*

Iterative Solvers

- *Alternatively, we can use a trial solution to generate a better approximation to the “true” solution.*
- *That is*

$$\mathbf{A}\mathbf{x}^{trial} = \mathbf{b}^{trial}$$

- *Which can then be used to generate further refined answers until $|\mathbf{b}^{trial} - \mathbf{b}|$ is small enough.*
- *The method for generating new \mathbf{x} vary .*

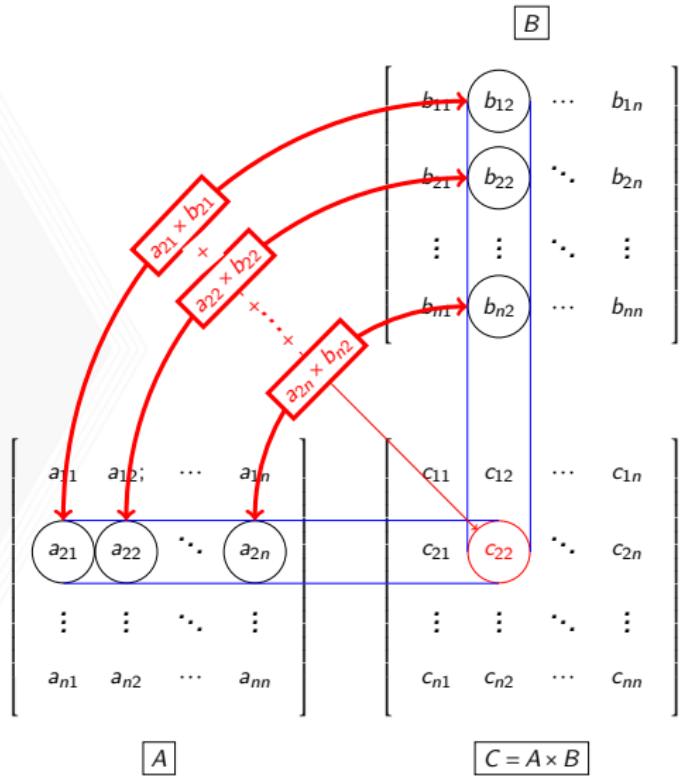
Jacobi method

- ① **Choose a convergence value, ϵ . (What is the difference between solutions that will be accurate enough?) Choose a maximum number of iterations N**
- ② **Decompose A into L,D,U.**
- ③ **Select a guess for the solution x^0 .**
- ④ **Calculate the next iterative of the solution as**

$$x^{k+1} = -D^{-1}(L + U)x^k + D^{-1}b \quad (4)$$

- ⑤ **Calculate the $r = |x^{k+1} - x^k|$.**
- ⑥ **Continue until $r \leq \epsilon$ or the number of iterations is greater than N .**

Matrix Multiplication



Some decompositions of a matrix

Decompose A

$$\mathbf{A} = (\mathbf{L} + \mathbf{U}) + \mathbf{D}, \quad (5)$$

Some decompositions of a matrix

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with the strictly lower matrix

$$\mathbf{L} = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ a_{21} & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ a_{1n} & a_{2n} & \cdots & 0 \end{bmatrix} \quad (6)$$

Some decompositions of a matrix

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with the strictly upper matrix

$$\mathbf{U} = \begin{bmatrix} 0 & a_{12} & \cdots & a_{1n} \\ 0 & 0 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \end{bmatrix} \quad (6)$$

Some decompositions of a matrix

Decompose A

$$\mathbf{A} = (\mathbf{L} + \mathbf{U}) + \mathbf{D}, \quad (5)$$

with the diagonal component

$$\mathbf{D} = \begin{bmatrix} a_{11} & 0 & \cdots & 0 \\ 0 & a_{22} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & a_{nn} \end{bmatrix}, \quad (6)$$

Working on PACE Resources

- **If you have PACE resources that you wish to work on, you should connect with X11 forwarding, like this**

```
$ ssh -XY userid@login-s.pace.gatech.edu
```

- **Let's start a VNC session like this**

```
$ pace-vnc-job -q pace-training -l walltime=02:00:00 -l nodes=1:ppn  
=1
```

Then, we'll follow the off-screen prompts.

Git Repository for Presentation and Code

- **The presentation and code are available at**

`https://github.com/chrisblanton/gatech_optimization101`

- **The code can be obtained by**

```
$ module load git
```

```
$ git clone https://github.com/chrisblanton/gatech_optimization101
```

Building the code

- Once you are in a compute session, load the GCC module like this

```
$ module load gcc
```

- Then change into the desired directory and run

```
$ make benchmark_solver.out
```

- To run,

```
$ cd ./bin
```

```
$ ./benchmark_solver.out
```

Enter n: 1000

Computation_time: 2.52361608

Number_iterations: 9

Error: 1.5088572462296224E-007

Number_of_ops: 19990000000.000000

Operations per second: 7921173190.3057709

Let's do this!

Let's try some cases to see!

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- About 4 seconds with my implementation.

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- We implement the standard matrix multiplication algorithm ourselves. I'll talk more about what that is later.
- We want to do 1.0×10^6 in production so let's see how long 1000 takes.
- About 4 seconds with my implementation.
- Let's try 2000 then.

Let's do this!

Let's try some cases to see!

- We implement the standard matrix multiplication algorithm ourselves. I'll talk more about what that is later.
- We want to do 1.0×10^6 in production so let's see how long 1000 takes.
- About 4 seconds with my implementation.
- Let's try 2000 then.
- It took about 60 seconds.

Let's do this!

Let's try some cases to see!

- We implement the standard matrix multiplication algorithm ourselves. I'll talk more about what that is later.
- We want to do 1.0×10^6 in production so let's see how long 1000 takes.
- About 4 seconds with my implementation.
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What does that mean for my bigger cases

It didn't take twice as long, it took 15 times as long!

Taking action

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- ***Then we'll try to find ways to improve the performance while getting the same answer.***

Benchmarking

- ***The most basic benchmarking is use the time command to determine the amount of time that is being used.***
- ***The way to run this on most Unix-like systems is to run it in this manner:***

```
$ /usr/bin/time ./benchmark_solver.out < mytemp
```

Enter n:

Number_iterations: 23

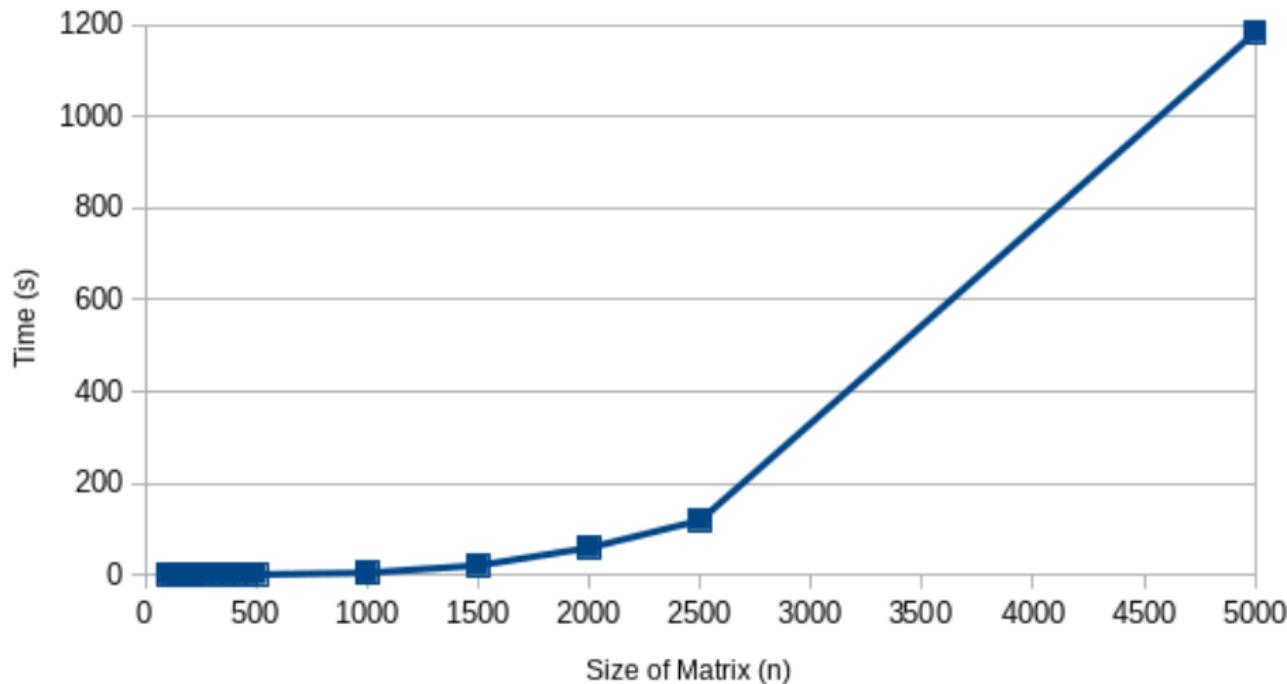
Error: 5.0284740371608905E-007

Number_of_ops: 45600.000000000000

0.00 real *0.00 user* *0.00 sys*

Benchmarking results

Naive O0 Benchmarking



Profiling and Optimization

Methods for optimizing

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- ***Profiling***
- ***Simple alterations to the algorithm.***
- ***Using a library***

Compiler Optimizations

Compilers may, when directed, perform a number of optimizations such as

- ***Unroll loops (since loops require a logic check for each iteration).***
- ***Fuse loops.***
- ***Interchange loops.***
- ***Eliminate dead code (remove logic checks for a branch which will never be taken).***
- ***Reorder instructions to improve register reuse and more.***
- ***Strength reduction (turn instructions into simpler equivalent instructions).***

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Warning

All my problems are solved! No, sometimes it does the best thing possible, other times it does not.

Compiler flags

- ***Optimization Flags***

- O0 No optimization, used for debugging generally***
- O1 Minimal optimization, some***
- O2 Standard optimization***
- O3 High optimization***

- ***Debugging Flags***

This are changed in the Makefile.

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Effects of optimization flags on naïve MM

<i>N</i>	<i>O0</i>	<i>O1</i>	<i>O2</i>	<i>O3</i>
1000	4.3	2.0	2.1	2.1
1500	20.3	19.6	19.7	19.4
2000	58.8	53.5	55.4	54.2
2500	118.5	111.9	109.3	110.4
5000	1184.2	1127.0	1131.9	1132.0

*Changing of optimization levels did not have a large effect on the walltime, particularly as the systems increased in size.
We need to do something ourselves!*

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Profiling with gprof

- **The GNU project profiler is a freely available profiling tool.**
- **It has several modes:**

Flat profile: which shows the CPU time spent in each function, number of calls for function, and finds hotspots.

Call Graph: which shows the number of times a function was called by other functions, useful to find function relations.

Annotated source: indicates the number of times a line was executed.

Instruction on using gprof

① ***Build the program like this***

```
$ gcc -g -pg -o exeFile ./srcFile.c  
$ gfortran -g -pg -o exeFile ./srcFile.f90
```

② ***Run the executable to generate gmon.out.***

③ ***Execute gprof. The output comes to stdout, so you may wish to redirect.***

```
$ gprof ./exeFile gmon.out > profile.txt  
$ gprof -l ./exeFile gmon.out > profile_line.txt  
$ gprof -A ./exeFile gmon.out > profile_anotated.txt
```

Profile of our MM with gprof

Flat profile:

Each sample counts as 0.01 seconds.

% time	cumulative seconds	self seconds	calls	self s/call	total s/call	name
99.38	4.27	4.27	12	0.36	0.36	<u>__mod_matops_MOD_dgemm</u>
0.23	4.28	0.01	1	0.01	0.01	<u>__mod_matops_MOD_generatediagdommat</u>
0.23	4.29	0.01	1	0.01	0.01	<u>__mod_matops_MOD_strictlowerpart</u>
0.23	4.30	0.01	1	0.01	0.01	<u>__mod_matops_MOD_strictupperpart</u>
0.00	4.30	0.00	1001082	0.00	0.00	<u>__mod_random_MOD_generate_random_a_b</u>
0.00	4.30	0.00	1	0.00	4.30	<u>MAIN</u>

#Snip

The main function that takes most of the time is the dgemm (which is the matrix multiplication).

Profiling with Intel Vtune Amplifier

- ***Intel Vtune Amplifier is a commercial component of the Intel Parallel Studio suite.***
- ***Amplifier offers a GUI for setting up runs and for analyzing results.***
- ***There are many options and good documentation***
<https://software.intel.com/en-us/vtune-amplifier-help>

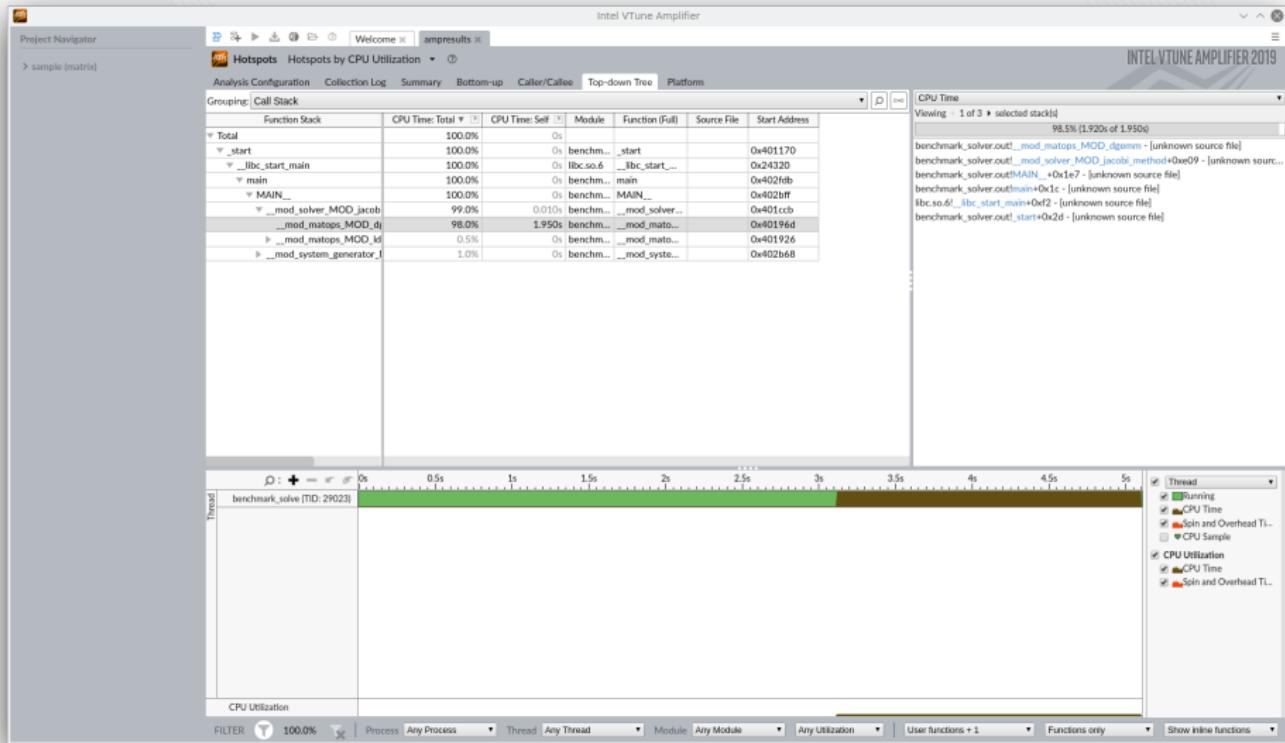
Using Amplifier on the command-line

- **We will do a hotspot analysis of the naïve code using Amplifier.**
- **With the `amplxe-cl` in our path**

```
$ module purge
$ module load intel/19.0
$ amplxe-cl -collect hotspots -result-dir ampresults ./
benchmark_solver.out
```

- **The program will run and results will be collected in the `ampresults` (in this case) directory.**
- **It is often to then analyze results using the GUI.**

Profile of our MM with Amplifier



The Issue

- ***We have seen that the issue appears to be the matrix multiplication function within the code.***

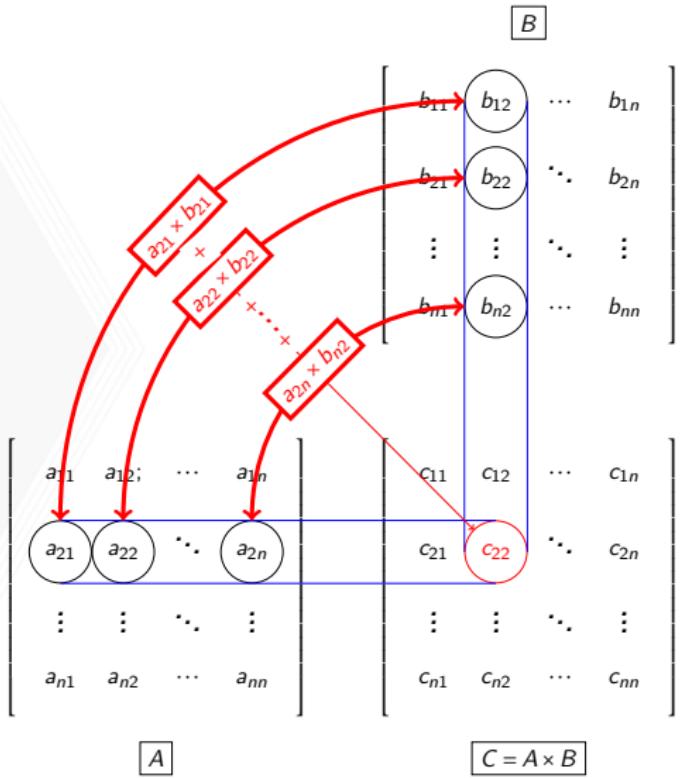
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- ***We will have to change the function to improve the performance.***

Matrix Multiplication



How many operations in a Matrix Multiplication

For a pair of $n \times n$ matrices, we must perform

Multiplication Operations n^3

Addition Operations $n^3 - n^2$

Total number of Operations $2n^3 - n^2$

Considering the Algorithm

The math that is implemented in the matrix multiplication is

$$C_{ij} = \alpha \times \sum_{k=1}^n A_{ik} B_{kj} + \beta \times C_{ij} \quad (7)$$

This is a little different, but it was used align with BLAS (more on that later!)

Considering the Algorithm

```
do i = 1, n
    do j = 1, n
        do k = 1, n
            C(i,j) = alpha*A(i,k)*B(k,j) + beta*C(i,j)
        end do
    end do
end do
```

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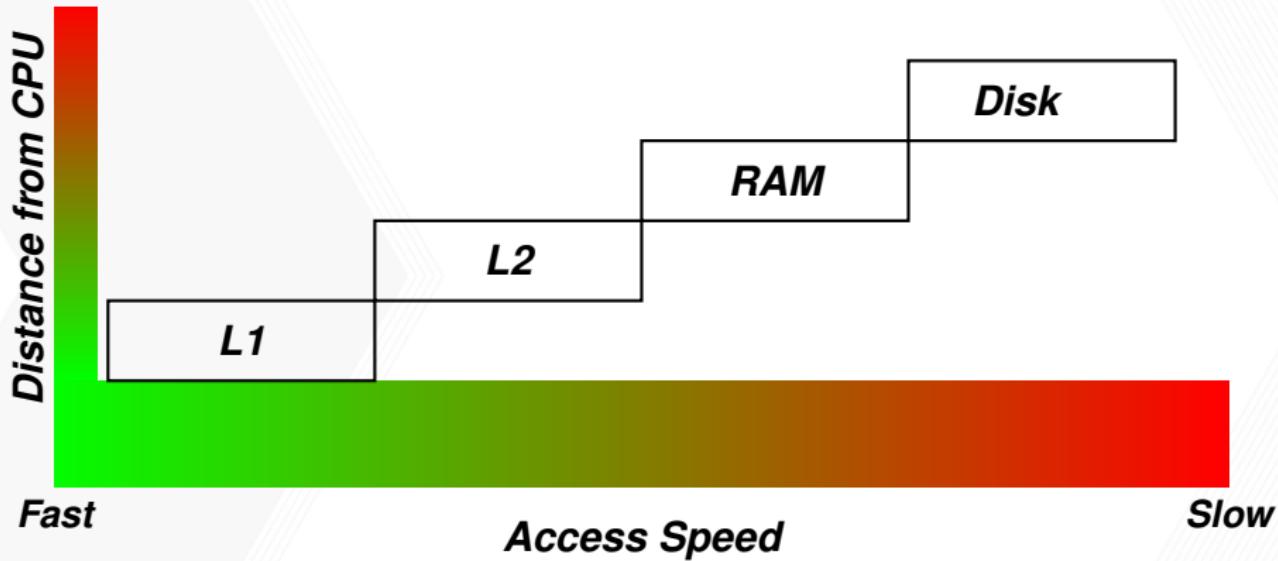
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        end do
    end do
end do
```

- ***This algorithm does not take into account how the values are stored in memory.***
- ***Analysis of the algorithm shows that it scales as $O(n^3)$***

Computer memory speeds



Slow memory access in the naïve MM

Analysis of a simple model that assumes two speeds of memory-fast and slow.

$$\begin{aligned}m &= n^3 \\&+ n^2 \\&+ 2n^2 \\&= n^3 + 3n^2\end{aligned}$$

to read each column of B n times

to reach each row of A once

to read and write each element of C once

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Analysis of a simple model that assumes two speeds of memory-fast and slow.

$$\begin{aligned} m &= n^3 && \text{to read each column of } B_n \text{ times} \\ &+ n^2 && \text{to reach each row of } A \text{ once} \\ &+ 2n^2 && \text{to read and write each element of } C \text{ once} \\ &= n^3 + 3n^2 \end{aligned}$$

This is a bottleneck to address.

Considerations

- *There are multiple layers of memory, called cache, with varying degrees of speed.*
- *When a variable is not in fastest memory, this is called a cache-miss.*
- *Cache-misses require multiple instructions to free space and load the needed variable.*
- *This can proceed for several cache levels.*

Tiling of the MM algorithm

- ***In order to take the cache behavior into account, we can use tiling.***

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- ***This is an implementation of a block matrix multiplication***

$$\begin{bmatrix} \mathbf{A}_{11} & \mathbf{A}_{12} \\ \mathbf{A}_{21} & \mathbf{A}_{22} \end{bmatrix} \begin{bmatrix} \mathbf{B}_{11} & \mathbf{B}_{12} \\ \mathbf{B}_{21} & \mathbf{B}_{22} \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{11}\mathbf{B}_{11} + \mathbf{A}_{12}\mathbf{B}_{21} & \mathbf{A}_{11}\mathbf{B}_{12} + \mathbf{A}_{12}\mathbf{B}_{22} \\ \mathbf{A}_{21}\mathbf{B}_{11} + \mathbf{A}_{22}\mathbf{B}_{21} & \mathbf{A}_{21}\mathbf{B}_{12} + \mathbf{A}_{22}\mathbf{B}_{22} \end{bmatrix}$$

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- ***We do this by converting the three-loop implementation into a six-loop implementation with loops to handle the tiling.***

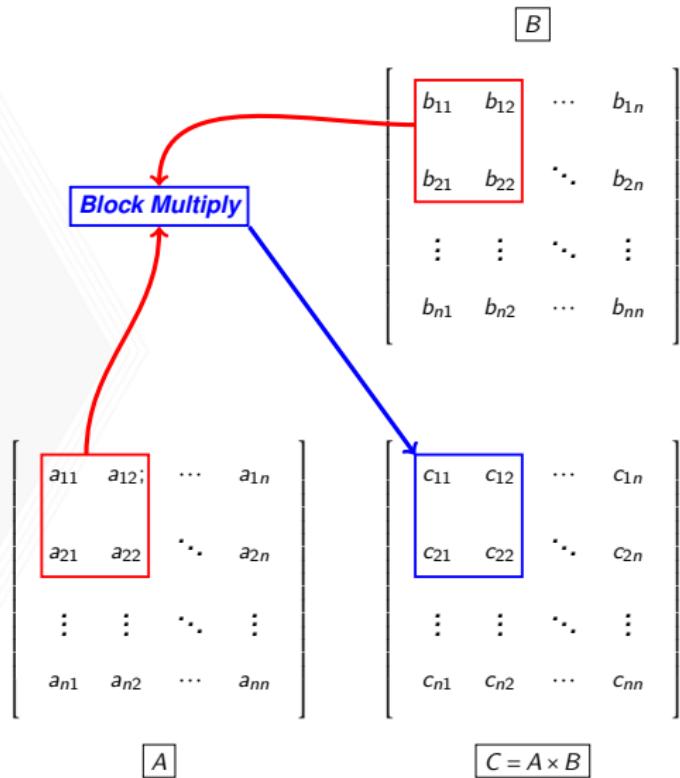
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- ***We do this by converting the three-loop implementation into a six-loop implementation with loops to handle the tiling.***
- ***This still has the same number of operations as the naïve implementation.***

Graphical tiling of MM



Tiled version of MM

```
do i0 = 1, n, tile_size
do j0 = 1, m, tile_size
do k0 = 1, k, tile_size
  do i1 = i0, min(i0+tile_size-1,m)
    do j1 = j0, min(j0+tile_size-1,n)
      do k1 = k0, min(k0+tile_size-1,k)
        C(i1,j1) = alpha*(A(i1,k1)*B(k1,j1))+beta*C(i1,j1)
      end do
    end do
  end do
end do
end do
end do
```

Memory access in the tiled version of MM

The memory traffic m between slow and fast memory is

$$\begin{aligned}m &= Nn^2 && \text{read each block of } B \quad N^3 \quad \text{times} \\&+ Nn^2 && \text{read each block of } A \quad N^3 \quad \text{times} \\&+ 2n^2 && \text{read and write each block of } C \quad \text{once} \\&= (2N + 2)n^2\end{aligned}$$

$$(N^2 b^2 = N^3(n/N)^2 = Nn^2)$$

Building and running the tiled version of the solver

- **To build the optimized code**

```
$ cd ${GITROOT}/opt1  
$ module purge; module load gcc  
$ make benchmark_solver_tilesize.out
```

- **To run**

```
$ cd ./bin  
$ ./benchmark_solver_tilesize.out
```

Enter n:

1000

Enter tile_size:

4

Computation_time: 1.90570998

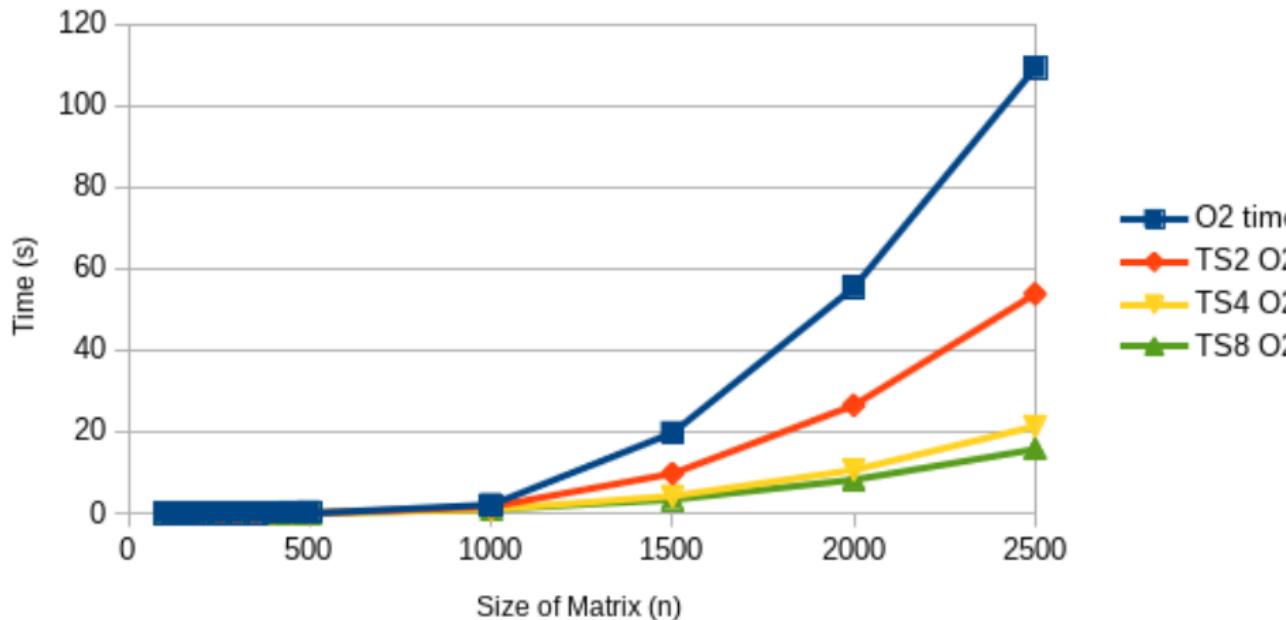
Number_iterations: 5

Error: 2.3059705256400775E-009

Number_of_ops: 11994000000.000000

Results of using tiled MM

Comparsion of Tiled and Naive



Using a library

- *When possible, using a library is very good idea.*
- *Matrix operations have been optimized in the BLAS (Basic Linear Algebra System) library.*
- *There are several implementations of the standard, but many give much better performance than a naïve or optimization outside of specialist knowledge.*

How to use BLAS with GCC on PACE

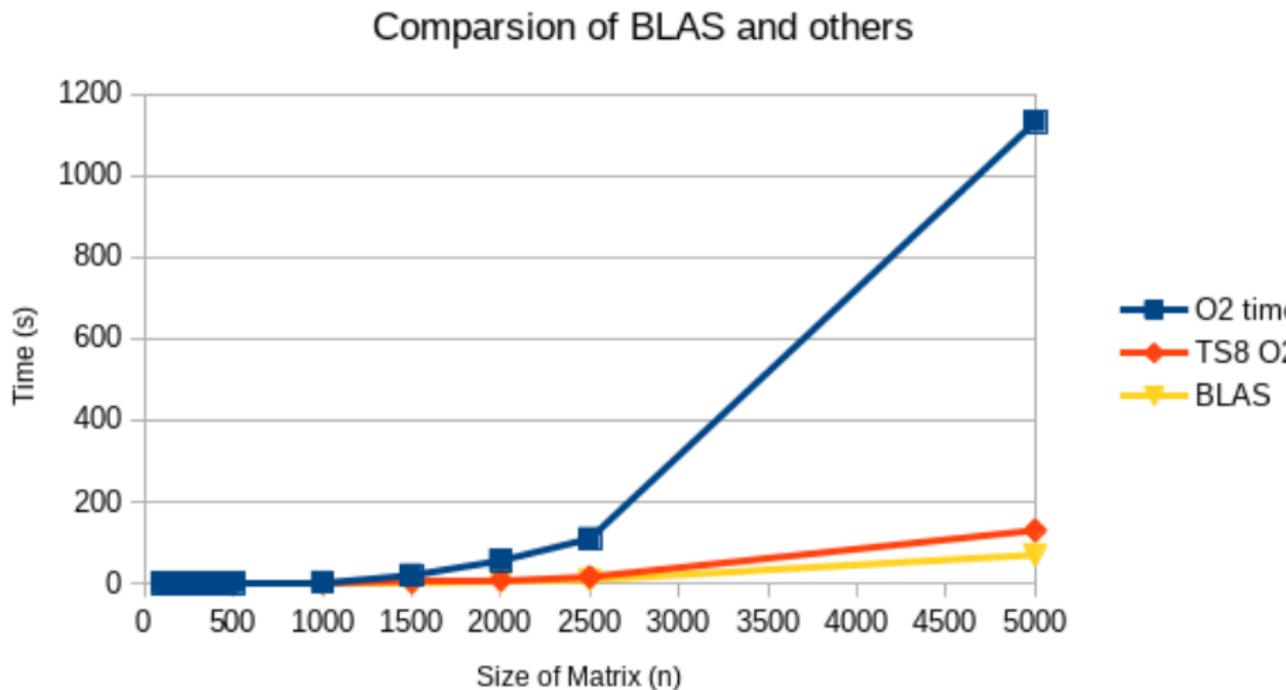
- ***Load the environment using the module system***

```
$ cd ${GITROOT}/blas  
$ module purge; module load gcc  
$ make benchmark_solver.out
```

- ***To run the application,***

```
$ cd ./bin  
$ ./benchmark_solver.out  
Enter n:  
1000  
Number_iterations: 9  
Error: 1.5088572462296224E-007  
Number_of_ops: 19990000000.000000  
Total_execution_time: 0.666899025  
Operations per second: 29974552724.536854
```

Results of using library



Conclusion

Conclusions

- ***In this workshop, some basics the following topics where covered.***
 - ▶ ***Benchmarking***
 - ▶ ***Profiling***
 - ▶ ***Code Optimization***
 - ▶ ***Library use***

Future training

- ***Shared-memory parallelization***
- ***Distributed-memory parallelization***
- ***GPU programming***

Please fill out the survey

Please fill out the survey

<https://b.gatech.edu/2lke9g8>