**HW1: Optimizing Matrix Multiply Report**

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**Results:**

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自動產生的描述一張含有 文字, 螢幕擷取畫面, 功能表 的圖片

自動產生的描述

My best try is around 41% of the peak. To get this result, I have tried two main approaches. The main difference is that one initially realigns and fixes the size to memory; the other one doesn’t realign it and keeps the size then deals with a tail. For me, the approach of dealing with the tail is better, which is 40%. And I combine two of them to get the 41%

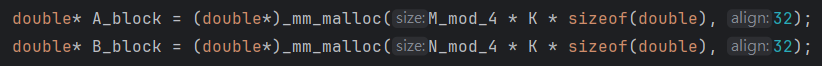
**optimizations attempt:**

Based on the HW1 doc. I tried to implement multi-level blocking. I just simply added one more layer with 3 for-loop. 一張含有 文字, 螢幕擷取畫面, 字型 的圖片

自動產生的描述

Use the same logic to add a second layer. The result is positive, but not increase speed much from just one level of blocking.

Next one is Repack and Realign



I set 32 bytes because my avx is 256. 256/32=8 which is double’s size.

I didn’t do the Repack. I think it can potentially increase the speed with blocking.

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自動產生的描述

Here is in small block(C is M-by-N, A is M-by-K, and B is K-by-N)

I copied the matrix within the loop. Step is 4 because memory size is 32 and double is 8, 32/8=4. I only do Realign for A and B because it is slower to add C. I have tried to implement C\_block in small blocks or initials, but they are slower. I guess because they are not really aligned since I didn’t fix the size before getting the microkernel.

My micro-kernel is inspired by doc 一張含有 文字, 螢幕擷取畫面, 字型 的圖片

自動產生的描述

But I use \_\_m256d is not supported in Perlmutter. My loop for K is unrolling for every 2 steps. 一張含有 文字, 螢幕擷取畫面, 字型 的圖片

自動產生的描述

I added them while in the loop and combined them in the end, then wrote to C.

After implementing the Micro-kernel, the speed increased a lot. This verified the results from some HPC papers which blocking and micro-kernel are most effective.

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自動產生的描述

For the tail. Just simply access the original A,B, and C to deal. I tried to make them aligned to avoid tail, but it didn’t work out.

Other small optimizations:

I read that an “inline” function can help with optimization because the compiler attempts to embed the function's code directly into the calling site, rather than generating a function call. However, I don’t see any difference after adding them to my function.

Same as “restrict” I don’t see any difference after adding them to my Matrix.

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自動產生的描述

This is the critical factor for performance. Is decided whether the blocking size or represented as L1 and L2 cache. (128,64) is my best set to my code.

Note: because my other approach is better on size 31. So I only run it if the size is smaller than 32

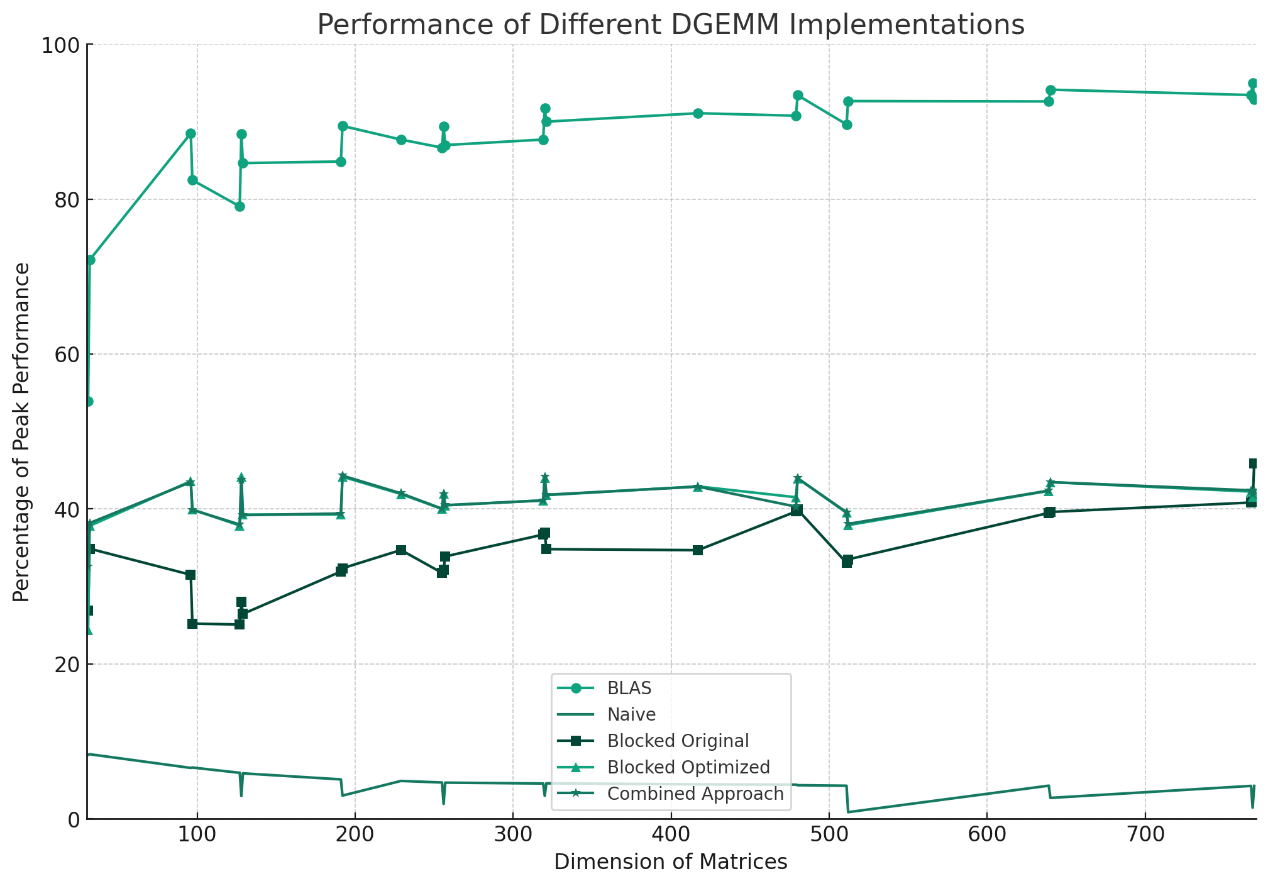
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自動產生的描述

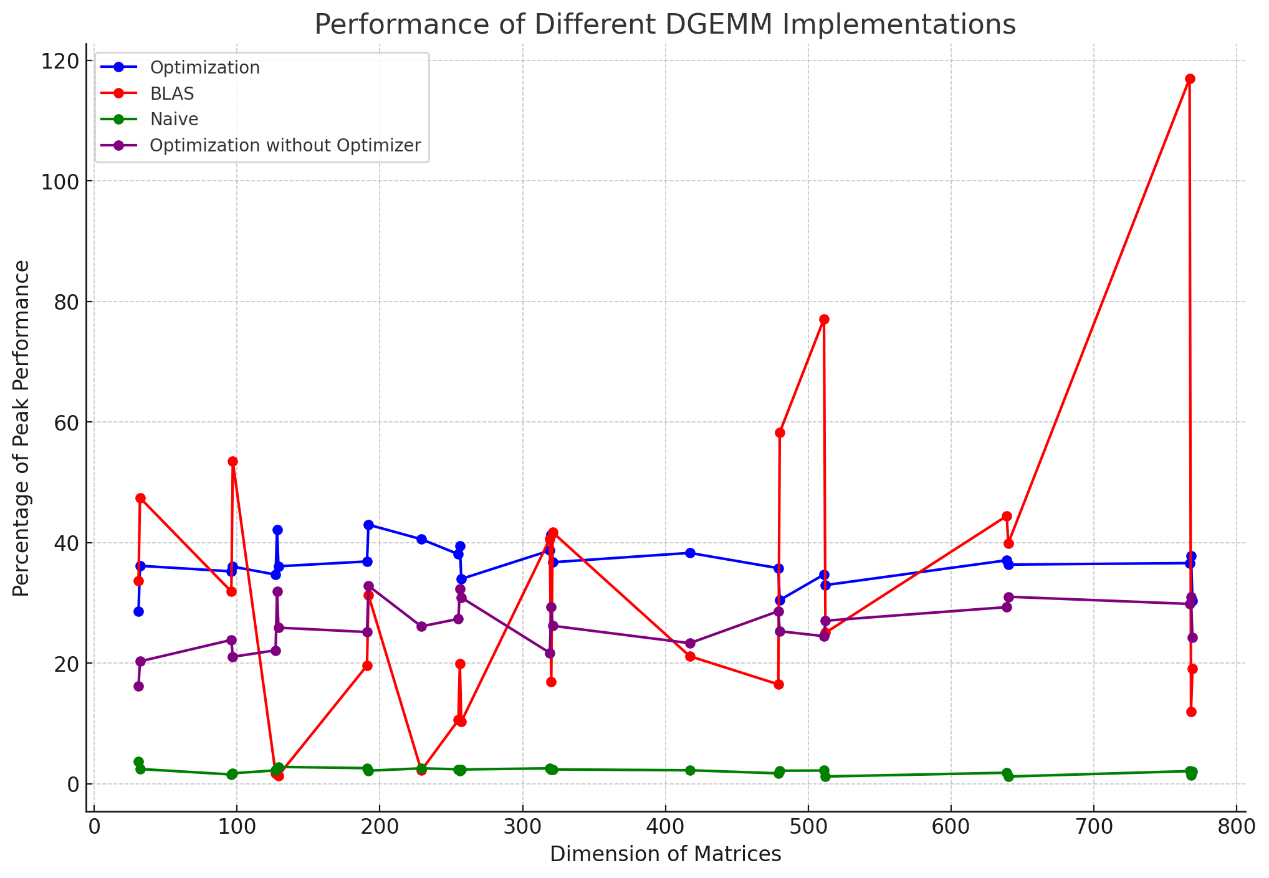
Those are optimizers I found. They can help my local computer dramatically speed up, but not for Perlmutter. The interesting thing is that with optimizers, my computer is faster than in Perlmutter; without them, it is way slower than in Perlmutter.

Update: I didn’t edit the max\_speed on my desktop. After I changed it, the percentage of the peak was around 36%, which is a little bit slower than Perlmutter. My max\_speed calculation is:

3.9 Processor frequency \* 2 cores \*2 vector pipelines \* 2 flops for FMA=93.6



This is my plot for the final performance on Perlmutter. My curve is flat at around 40%



My performance on my desktop. It has a lot of fluctuations compared to Perlmutter

Conclusion:

The optimization attempts on matrix multiplication yielded a significant performance increase, achieving approximately 41% of the peak. The critical factor for performance optimization was the cache-aware blocking size, indicating the profound impact of memory hierarchy on computational efficiency (speed would drop a lot if I forgot to free it). Despite the various strategies employed, a performance gap remains at the theoretical peak.

References

Jiang, Xuan, et al. “Optimizing Matrix Multiplication on Nersc’s High Performance Computer Cori.” OSF Preprints, 26 Feb. 2022. Web.