CS 267 Homework 1 Part 1

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1 General Optimizations

For almost all of our trials and codes, we tried common techniques. Ultimately we specifically tailored each of these methods for different implementations, however.

1.1 Switching for loop variables

Note that in the original code, the main code within the 3 nested loops (for do_block, and to a magnified extent, square_dgemm) was: $C[i,j]+=A[i,k]*B[k,j]$. The original order for the nested do_block function was, from outer to inner order: i,j,k. For the B matrix, this ordering moved the entries downward on the columns of B, but moved the entries row-wise on A, which was cache-inefficient. By instead using j,k,i ordering, this also allowed the i variable to move downwards on the columns of A. This inspired essentially ways to reorganize the for loops to allow for better cache access.

1.2 Buffer Copying

Because the do_block function uses blocks of matrices A,B,C, this leads to only columns of a block being consecutive in memory, which leads to redundant cache loads (i.e. a cache line may be much longer than the column size of a block). Thus, every time we used the do_block function, we would load in the input A-block and B-blocks into temporary contiguous memory.

1.2.1 Transposition of A-blocks

While copying, we also considered transposition of the elements for a given A-block, allowing the A-block to be row-major in temporary memory. This would allow the writes to be consecutive: $C[i,j]+=A[i,1]*B[1,j], C[i,j]+=A[i,2]*B[2,j], ...$

[*]xsong@berkeley.edu - Xingyou wrote the report, presented techniques and strategies for optimization, and coded some parts

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[‡]Our Third Partner, Zhiwei Yao, dropped the course.

1.2.2 Padding

To allow for cache-alignment, we also padded 0's into the buffers. Cache alignment allows for consecutive address access, to prevent any cache-misses.

1.3 Vectorization

To allow for the Intel compiler to detect vectorization, we unrolled parts of computation within the inner-most loop. In theory, this should allow the compiler to use the AVX 4-vector commands, as well as its FMA (Fused Multiply-Add) operation for speedup. In code, this would mean unrolling loops in order for the inner-most portion to have multiply and add operations on 4, consecutive doubles in memory.

1.4 Parameter Tuning

The above methods imply that the size-parameters (for block sizes) must be carefully adjusted. Essentially, there should be a balance among the following aspects:

1. Larger copies are expensive because of more memory operations, as reading from memory is expensive, with writing even more expensive.

2. The parameters should be fine tuned in order to match with the $L1, L2$ cache sizes (both total memory sizes and cache-line lengths). L1 cache is considered when making a second blocking function (e.g. do_block_L1 inside do_block).

3. Having too low block sizes generates more overhead overall, and especially for boundary mismatches (for cache lines as well as inner blocking functions).

1.5 Code Tweaks

We also made small code improvements that sometimes improved performance by small increments. These include:

- Removing redundant calculations (e.g. removing a line out of a for-loop if it remains constant over the entire loop)

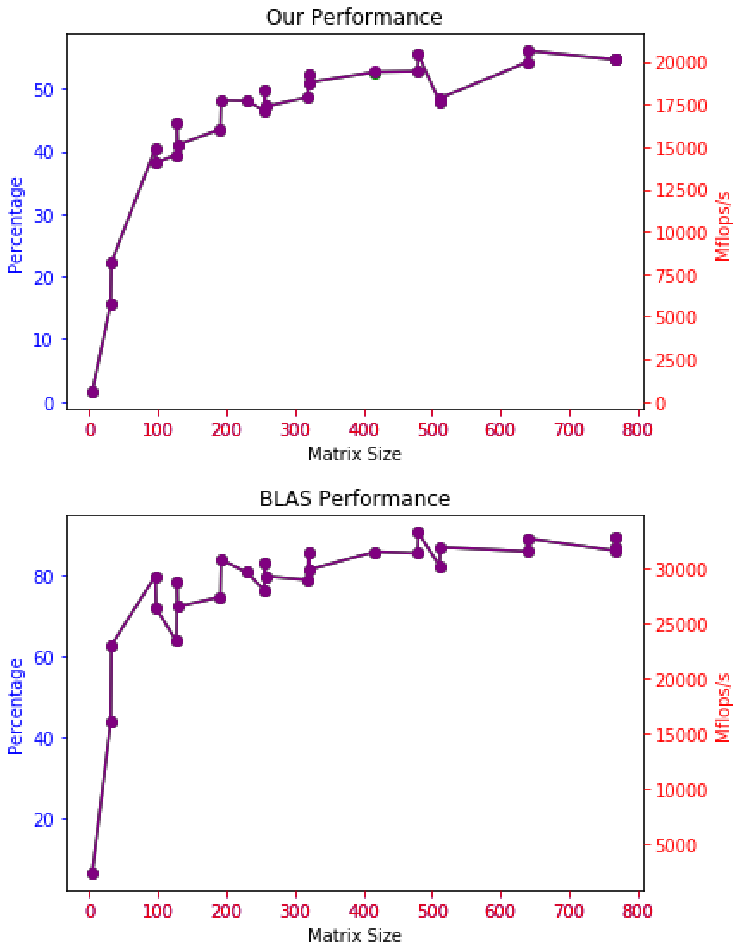
- Preprocessing calculations - Since multiplications are relatively expensive, it makes sense to only precalculate an index $(i + j * stride)$ once, store this value, and use it as often as possible.

2 (Submitted) dgemm-blocked.c

2.1 Performance

Overall, our submission gave an average of 44% over the normal test cases. Note that the asymptotic performance is above 50% for large matrices, while there is less performance for smaller matrices. The major explanation for this is due to the use of the transpose function on A early on, rather than later - This gives a large boost for larger matrices than it does for smaller matrices.

Figure 1: Performance for our submission vs. BLAS



2.2 Methods

Our submission consists of the following functions:

- weird_transformation - This transforms the input matrix by stretching its columns by STRIDE times, while reducing its rows by STRIDE times (and padding the last row accordingly if there is uneven divisibility).
- compute - This performs AVX vectorization to update each 8x4 block of the C-matrix, given input as ”smaller blocks”, using the FMA intrinsic.
- do_block_large - This cuts an input block into smaller blocks, with each smaller block passed into compute.
- square_dgemm - This cuts the entire matrix inputs into blocks to be passed into do_block_large.

- vectorized_FMA - This takes in 8x4 matrix from C and performs the correct updates.

Note that the ordering of the 3 nested for loops in each of the functions (square_dgemm, do_block_large, compute) are subtly not the same. For notation purposes (i.e. i,j,k representing columns and rows), suppose that computation is always performed using the update rule (where $C[i,j]$ may represent a larger block, smaller block, or individual element): $C[i,j] += A[i,k] * B[k,j]$. Furthermore, we may define, roughly speaking, 'large blocks' data intended to fit in L2 cache, while "small blocks" data intended to fit in L1 cache. The 8x4 AVX vectorization is therefore intended for the CPU registers.

Then we have the following orderings:

- square_dgemm is in i-j-k ordering. The reason for this is to fill in a large block of C in one pass as the data is in L2, to prevent too many DRAM passes if we kept making passes over larger blocks in intervals.
- do_block_large is in k-j-i ordering. Because A has been made row major early on, this allows cache lines to also follow the order of the blocking movement of A.
- compute is in i-j-k ordering. This is also explained by the fact that i must be before j for AVX memory loads from the C matrix, with k moving consecutively.

Thus the pseudocode for the algorithm is presented below (ignoring boundary cases, small tweaks, etc.)

Algorithm 1 SQUARE-DGEMM(lda, A,B,C)

$A_{weird} \leftarrow weird\_transformation(A)$
$LARGE\_M = 128$
$LARGE\_N = 256$
$LARGE\_K = 512$
for $i = 0, i < lda, i += LARGE\_M$ **do**
  for $j = 0, j < lda, j += LARGE\_N$ **do**
    for $k = 0, k < lda, k += LARGE\_K$ **do**
      do_block_large(block(i,j,k))
    end for
  end for
end for

Algorithm 2 do_block_large(M, N, K)

$A_{weird} \leftarrow weird\_transformation(A)$
$SMALL\_M = 128$
$SMALL\_N = 128$
$SMALL\_K = 128$
for $k = 0, k < K, k+ = SMALL\_K$ **do**
  for $j = 0, j < N, j+ = SMALL\_N$ **do**
    for $i = 0, i < M, i+ = SMALL\_M$ **do**
      compute(small_block(i, j, k))
    end for
  end for
end for

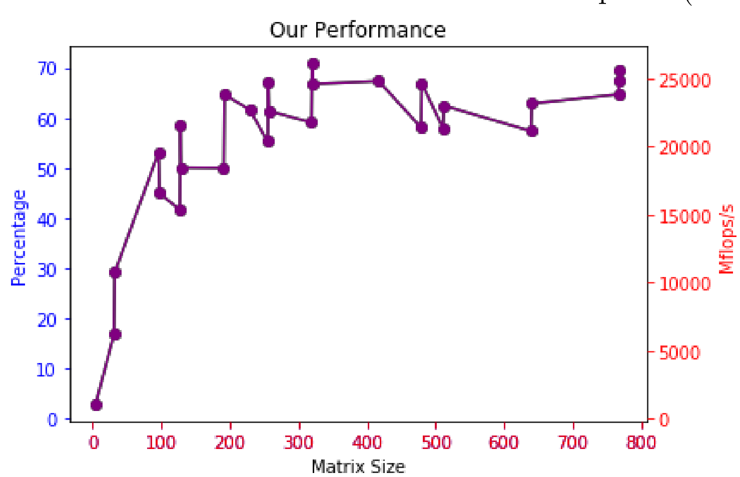
Algorithm 3 compute(M, N, K)

for $i = 0, i < M, i+ = 8$ **do**
  for $j = 0, j < N, j+ = 4$ **do**
    Vectorized_FMA(8×4 $C_{i,j}$)
  end for
end for

2.3 Performance On Local Computer

We performed the same code on a personal laptop, Lenovo Y510p with Intel i7 4700MQ 2.4 GHz, which allows AVX/AVX2 instructions. It also had the same cache specifications as Cori. The CPU allows for maximum frequency 3.4 GHz, but this was disabled. Thus this implies that the theoretical optimum is 2.4 GHz * 8 vector width * 2 flops for FMA = 38.4 GF/s, similar to the benchmark on Cori as well. This gave an average of 53 % over all test trials, with more percentages given larger matrix sizes. The performance seemed to be

Figure 2: Performance for our submission on local computer (Lenovo Y510p)



slightly better than Cori - this is possibly due to using the GCC compiler rather than the

ICC compiler, as this is the only significant difference between the two machines.

3 Other Methods Considered

In this section, we briefly describe some of the other methods which failed, as well as how our code's performance progressed as we added more features. Note that some of the other trials performed approximately 20% on smaller test cases, such as sizes 1-32, while our code performs poorly on smaller sizes. This is expected, because our submission performs 2 layers of blocking, which creates a large overhead for small matrices.

3.1 GEPP

One of the methods implemented was a reimplementation of the paper [1], which used recursive functions GEPP and GEBP, which partitioned blocks into columns, which were also sub-partitioned. This implemented the buffer-copying transpose aspect, but was only optimized for the L2-cache. Transposition and manual SSE instructions were also implemented in a 4x4 fashion. Ultimately however, this achieved only 16% - 20% average performance on the Cori supercomputer. The cause of this failure might have been due to lack of usage of the FMA instructions, as well as disregard for the L1 cache.

3.2 SSE-4x4, 2x2

SSE instructions were also used for vectorizing two doubles ignoring L1 cache optimization and transpose., early on for the code. A blocked kernel of size 4x4 and 2x2's were used. Unfortunately, this also only achieved approximately 14 %. It seemed that use of the L1 cache is highly critical to optimization. Furthermore, any further optimizations for loops **other** than $i - j - k$ ordering for calling do_block had a very large overhead for DRAM access, which enforced that every block of matrix C needed to be filled immediately.

[1] Goto, K., and van de Geijn, R. A. 2008. Anatomy of High-Performance Matrix Multiplication, ACM Transactions on Mathematical Software 34, 3, Article 12