# ${\rm HPC~4MA~2021/2022}$

## Members

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Date

 $12~\mathrm{Dec},\,2021$ 

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### Chapter 1

### **OpenMP**

#### 1.1 Optimization techniques

#### 1.1.1 Naive dot

We first mention here the original naive\_dot function. This function serves as an anchor (or base case) for performance comparision as well as for making sure we have the right result when using other techniques.

```
for (i = 0; i < M; i++)
  for (j = 0; j < N; j++)
   for (k = 0; k < K; k++) C[i + ldc * j] += A[i + lda * k] * B[k + ldb *
    j];</pre>
```

Below is the output of naive\_dot for M = 1, K = 2 and N = 2:

```
## ( 1.00 1.50 )
##
## ( 1.00 1.50 )
## ( 1.50 2.00 )
##
## Frobenius Norm = 5.550901
## Total time naive = 0.000001
## Gflops = 0.013333
##
## ( 3.25 4.50 )
```

As

$$\begin{pmatrix} 1 & 1,5 \end{pmatrix} \begin{pmatrix} 1 & 1,5 \\ 1,5 & 2 \end{pmatrix} = \begin{pmatrix} 3,25 & 4,5 \end{pmatrix}$$

The result of this function is correct. We move on to the next technique.

#### 1.1.2 Spatial locality

Spatial locality refers to the following scenario: if a particular storage location is referenced at a particular time, then it is likely that nearby memory locations will be referenced in the near future. In order to take advantages of this property, we notice that:

- In memory, A, B, C are stored in contiguous memory block.
- When using the index order i, j, k, we access B consecutively (as we access B by B[k + ldb \* j]), but not A and C.
- Data from A, B, C are loaded in a memory block consisting of severals consecutive elements to cache. Thus, we could make use of spatial locality when reading data continuously.

From 3 points above, we decide to switch the index order to k, j, i. Now we see that both reading and writing operations on C are in cache, this brings us a critical gain in performance. In addition, reading operations on A are in cache too but those on B are not.

```
for (k = 0; k < K; k++)
  for (j = 0; j < N; j++)
  for (i = 0; i < M; i++) C[i + ldc * j] += A[i + lda * k] * B[k + ldb *
  j];</pre>
```

For comparision, we have a table below with M = 4, K = 8 and N = 4.

Table 1.1: naive vs saxpy when M, N, K is small

| algo  | time     | norm     | gflops   |
|-------|----------|----------|----------|
| naive | 0.000002 | 3.461352 | 0.111304 |
| saxpy | 0.000001 | 3.461352 | 0.182857 |

We have the frobenius norm of both techniques are 3,461352 which indicate we have the right computation result. In addition, calculating time is already significantly small ( $\approx$  0 second in both methods) and the difference between these two can therefore be ommitted.

However, if we set M=2048, K=2048 and N=2048, there will be a huge performance gain as in the table shown below. In addition, from now, for an easier comparision between results, we will consider the default value of M, K and N is M=2048, K=2048 and N=2048 if not explicitly mentioned.

Table 1.2: naive vs saxpy when M, N, K is big

| algo           | time                    | norm  | gflops  |
|----------------|-------------------------|---|---|
| naive<br>saxpy | $149.30573 \\ 62.04563$ | $\begin{array}{c} 2.323362 \\ 2.323362 \end{array}$ | $\begin{array}{c} 0.115065 \\ 0.276891 \end{array}$ |

Here, the naive\_dot function is approximately 2,41 times slower than the saxpy\_dot function.

#### 1.1.3 OpenMP parallelization

In this section, we will analyse the main technique of this chapter: OpenMP. First, we show how we enable it on each function. We add a directive above each loop we want to parallelize whose general form is as below:

- Variables inside private are tied to one specific thread (each thread has their own copies of those variables).
- SCHEDULE\_HPC is replaced by the schedule we want.
- NUM\_THREADS\_HPC is corresponding to the number of threads to use for parallel regions.

```
#pragma omp parallel for schedule(SCHEDULE_HPC) default(shared) private(i, j
   ) \
   num_threads(NUM_THREADS_HPC)
```

In addition, inside norm function, we add a reduction clause reduction(+ : norm) as we want to sum up every norm from each thread to one final norm and taking square of that final sum. Finally, we have to add #pragma omp atomic above each line that updating the result matrix (C). It is because that matrix is shared among threads, atomic makes sure that there is only one += operation (which is essentially reading and writing) on one specific pair of indices at a given time. Note that norm does not need atomicity thank to reduction.

Here, we show a comparision between with and without OpenMP. Default OpenMP options will be SCHEDULE\_HPC = static and NUM\_THREADS\_HPC = 4.

| algo  | time      | norm     | gflops   | omp |
|-------|-----------|----------|----------|-----|
| naive | 45.08355  | 2.323362 | 0.381067 | X   |
| naive | 149.30573 | 2.323362 | 0.115065 |     |
| saxpy | 15.29221  | 2.323362 | 1.123440 | X   |
| saxpy | 62.04563  | 2.323362 | 0.276891 |     |

Table 1.3: naive vs saxpy with OpenMP

Thank to OpenMP, naive approach is faster than 0,3 times while the saxpy\_dot took less 0,25 times than before. Both approachs performance are significantly improved.

#### 1.1.4 Cache blocking (Tiled)

The main idea of the cache blocking technique (or tiled) is breaking the whole matrices into smaller sub-matrices so the data needed for one multiplication operation could fit into the cache, therefore leads to a much faster calculation. Furthermore, if we enable <code>OpenMP</code>, the computation would be even faster as each sub-matrice is processed by a separate thread. However, if we set <code>BLOCK</code> size too small, the benefit of dividing

matrix is overshadowed by the additional loops and operations. Meanwhile, a too large BLOCK size leads to an overfitting (data for one operation can not be fitted into the cache), and therefore a slower operation. The principal source code is shown below:

The above code will work only if M, N and K are divisible by BLOCK. A more generic version could be found in full source-code.

We have a table comparision between all techniques we are dicussing so far below. Also, we set the default size of BLOCK = 4.

|  | Table | 1.4: | naive | vs | saxpy | vs | tiled |
|--|-------|------|-------|----|-------|----|-------|
|--|-------|------|-------|----|-------|----|-------|

| algo  | time                    | norm  | gflops  | omp |
|---|-------------------------|---|---|-----|
| naive<br>naive  | $45.08355 \\ 149.30573$ | $\begin{array}{c} 2.323362 \\ 2.323362 \end{array}$ | $\begin{array}{c} 0.381067 \\ 0.115065 \end{array}$ | х   |
| saxpy<br>saxpy  | $15.29221 \\ 62.04563$  | $\begin{array}{c} 2.323362 \\ 2.323362 \end{array}$ | $\begin{array}{c} 1.123440 \\ 0.276891 \end{array}$ | x   |
| $\begin{array}{c} \text{tiled} \\ \text{tiled} \end{array}$ | $17.01662 \\ 17.14018$  | $\begin{array}{c} 2.323362 \\ 2.323362 \end{array}$ | $1.009594 \\ 1.002316$                              | X   |

In the table above, cache blocking technique is already fast enough. However, OpenMP does not help speeding it up as the default BLOCK size is not optimized in this case.