Assignment 1

Foundations of HPC 2021-2022

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Section 1

Ring

In order to solve the exercise I provide two different implementation: one it uses only blocking operations while the other one uses non-blocking operations.

Implementation

In the blocking implementation I have divided the cores in two subsets based on the parity of ranks. The odd processors send to right and left, and then they receive from left and right. Instead, the even processors first receive from left and right and subsequently send to right and left. In this way the program avoid deadlock. Obviously, when the cardinality of the processors is an odd number I had to modify the behaviour of one processor, like the one with rank 0. In these cases, the processor 0 send to left and receive from right, and after send to right and receive from left. The execution in the two cases is shown in figure 1.

The implementation that use only non-blocking operations is simpler: each processor send and receive from e to its neighbours. Then, there is an *MPI_barrier* in order to prevent a processor from update its message before it has received it. This barrier implicitly makes the execution "blocking", however, as seen in the next section, this implementation is one time faster then the other one.

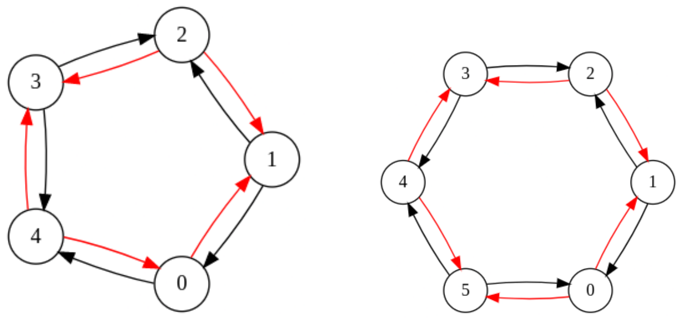


Figure 1: The blocking implementation with an odd and an even numbers of processors. In black there are the first operation executed while in red the second one.

Runtime analysis

Since each processor send and receive $2n$ messages, where n is the total number of processors, the runtime is expected to grow linearly on n. Meanwhile, the total number of messages exchanged between processors grows as $O(n^2)$.

The runtime is calculated as the time of the slowest core. In addition, to obtain significant data, I have taken the mean over 10000 repetition. The figure 2 show the time as a function of the number of processors used, i.e the number of vertices of the ring. As we expected, the time grows linearly and the non blocking implementation is faster then the blocking one. It can be notice that, when it has been added a socket, there is a step in the runtime; the biggest one is between 24 and 25 core, since the program starts using two nodes. The trivial reason is that the bandwidth and the latency decrease with more sockets and nodes used. However, after a first peak the time goes back down each time, and that is probably because after the first time that the program use a new socket or node, the channel is already open.

To estimate the runtime it is possible to consider the following model: each processors send $2n$ messages, so the time it takes will be

$$T = n\left(\lambda + \frac{\text{2*size of the msg}}{\text{bandwidth}}\right)$$

where I considered the bandwidth and the latency of the slowest network involved in the computation. In the figure 2, it is possible to see the trend of the model.

The model seems to be quite good for the non-blocking implementation. The blocking implementation should take around two times the other one, because processors take turns exchanging messages.

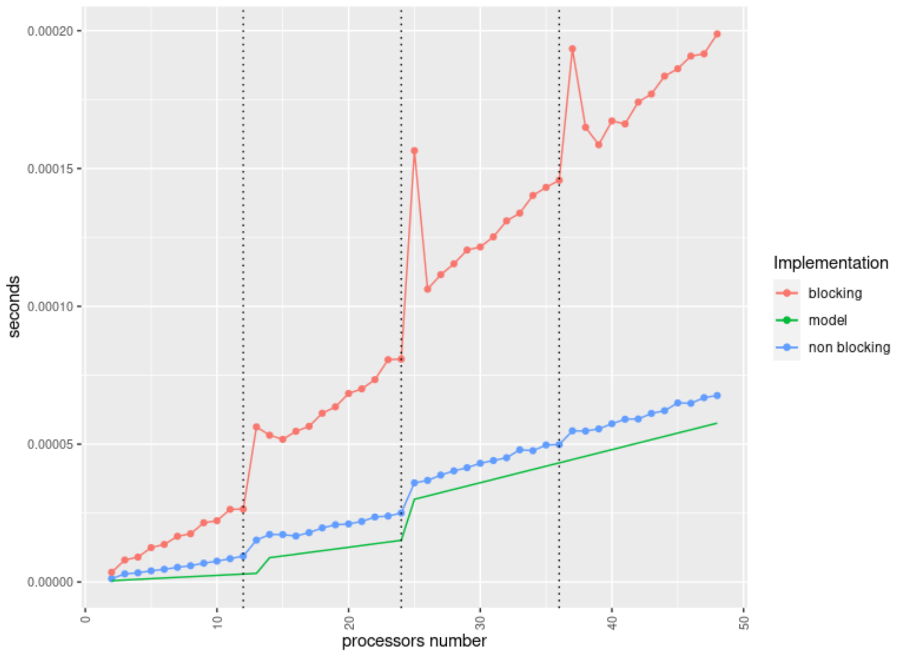
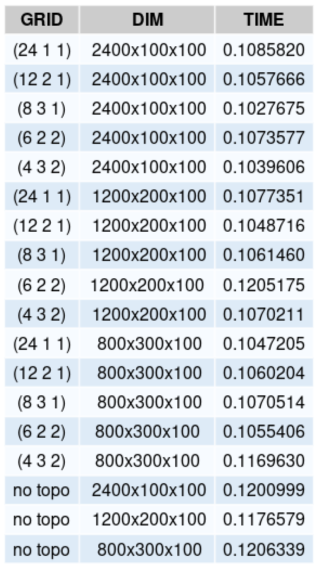


Figure 2: Walltime of the ring as a function of the number of processors.

Matrix-Matrix sum

I implemented the matrix-matrix sum program both with topology and not. As the figure 3 shown, the topology is useless to gain more performance in this exercise. In fact, since there are not halo or communications between processors, the domain decomposition can not result in a speed up.



GRID	DIM	TIME
(24 1 1)	2400x100x100	0.1085820
(12 2 1)	2400x100x100	0.1057666
(8 3 1)	2400x100x100	0.1027675
(6 2 2)	2400x100x100	0.1073577
(4 3 2)	2400x100x100	0.1039606
(24 1 1)	1200x200x100	0.1077351
(12 2 1)	1200x200x100	0.1048716
(8 3 1)	1200x200x100	0.1061460
(6 2 2)	1200x200x100	0.1205175
(4 3 2)	1200x200x100	0.1070211
(24 1 1)	800x300x100	0.1047205
(12 2 1)	800x300x100	0.1060204
(8 3 1)	800x300x100	0.1070514
(6 2 2)	800x300x100	0.1055406
(4 3 2)	800x300x100	0.1169630
no topo	2400x100x100	0.1200999
no topo	1200x200x100	0.1176579
no topo	800x300x100	0.1206339

Figure 3: Execution of the 3Dmatrix sum with different topologies and sizes.

In both implementation, the *master* allocates three matrix with random numbers. Then, it send to the other their sub-matrices to sum, where the sub-matrices are simply allocated as an array of dimension $\frac{size}{n}$. Even if I used the topology, I did not split the data in the right way, because I always cut the domain in slices. That because the topology is not useful at all in this program and I only implemented the topology to have a feedback about that. Anyway, a possible way to divide the data is by use of *MPI Scatterv* and/or *MPI Type*.

Since in provided code there are three collective operation (2 *MPI_Scatter*, 1 *MPI_Gather*), a simple communication model could be

$$T_{comm} = 3 * \left(lambda + \frac{size}{band} \right)$$

where $size$ is the dimension of the matrices. However, the real behaviour of the program is may different and the results obtained with this model are far from the experimental times.

Section 2

I ran the PingPong benchmark on THIN and GPU nodes, both with OpenMPI and IntelMPI. The first thing I noticed is that, as I expected, there are not big differences between GPU and THIN: the PingPong measure networks performance, so the differences between CPUs are not such relevant.

In the folder */fast/dssc/francescortu/2021Assignement01/section2* there are plenty of csv files and plots that describe what I found. In addition to the experimental data, as requested, the plots shown the simple communication model discussed during lessons

$$T = \lambda + \frac{size}{band}$$

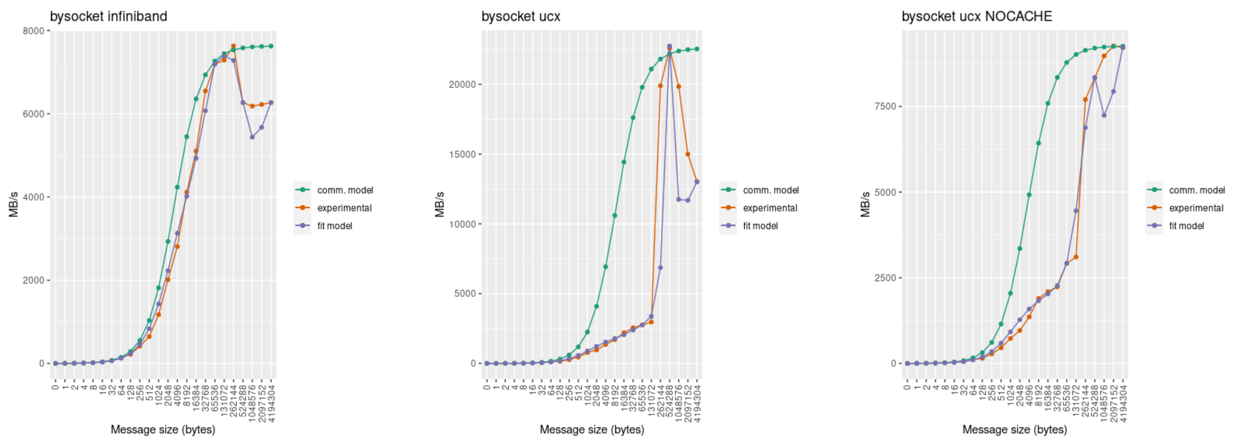
computed taken the latency and the bandwidth from the experimental data. Furthermore, in the plots there is the fitted model, which is reported also on the csv files.

The most interesting thing is the difference between the data obtained with OpenMPI and IntelMPI while measuring the connection inter-socket. As it shown in figure 4 (a) (b) using infiniband, the PingPong ran with IntelMPI has the peak at 8000 MB/s, while the other one performed with OpenMPI reaches 20000 MB/s. It is possible to observed similar difference also in intra-socket communication and with all the other network tried. The possible explanation of this behaviour is that with IntelMPI there are more cache missing than with OpenMPI.

Another thing is that all intra-node communications shown a big step in the bandwidth when the message size is around 1MB. That could be caused by the use of the L2 cache, and it is visible for instance in figure 4 (b). If it is specified to not to use the cache I obtain lower bandwidth but with a less steep jump, as it possible to see in figure 4 (c).

Moreover, again in intra-node communication we can observe that, after a certain point, there is drop of the bandwidth: probably, after the message size becomes larger than the L2 cache, there are a lot of cache missing. In addition, as it explained in the book *Introduction to High Performance Computing for Scientists and Engineers, G.H., G.W.*, the design of the benchmarks could affect the performance when the number of repetitions start decreasing.

In conclusion, the intra-node communications are harder to understand because of the cache missing and other behaviour releted to shared memory. In addition, OpenMPI behave slightly better than IntelMPI.



(a) IntelMPI

(b) OpenMPI

(c) OpenMPI without using cache

Figure 4: Difference behaviour between OpenMPI and IntelMPI while measuring the bandwidth.

Section 3

The tables 5, 6 summarize the data collected running the Jacobi solver on THIN and GPU nodes and their respective performance model keeping the total size of the problem fixed to 1200^3. In particular I used the model discussed in class:

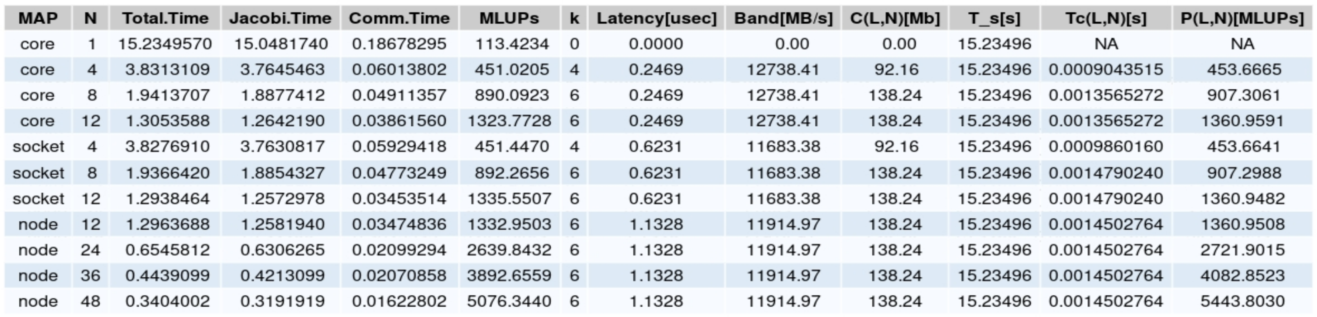
$$P(L,N) = \frac{L^3 N}{T_s + T_c(L,N)}$$

$$T_c(L,N) = \frac{C(L,N)}{B} + k\lambda$$

$$C(L,N) = 16kL^2$$

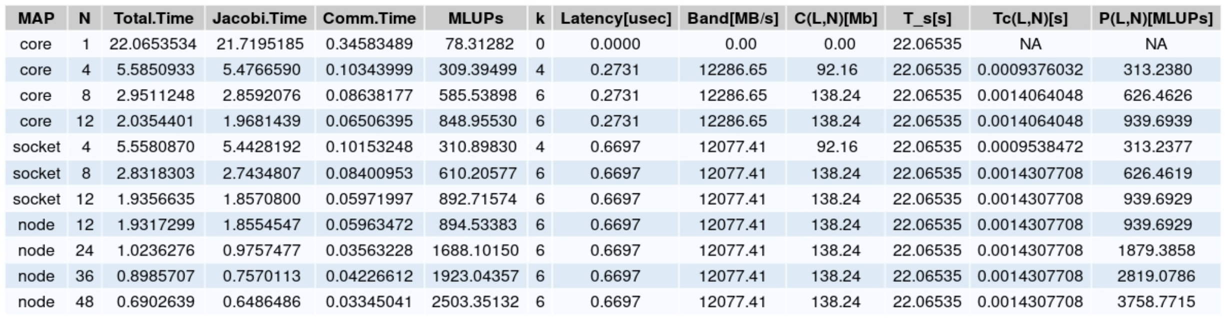
where N is the number of the processors, L is the size of each subdomain and T_s is the sequential time. T_s is calculated as the ratio between the Total Time with N equal to 1 and N. I used the bandwidth B and the latency λ computed from the fitted model of the *Section 2*.

In THIN nodes, the performance $P(L,N)$ predicted form the theoretical model reflect quite well the real performance obtained from the computation. Instead, in the GPU node, there is an overestimation from the model. Probably this happens because of the *hyper-threading* enabled on this node: in the Jacobi program each core do the same kind of operations, while the *hyper-threading* is designed to work well when cores are doing different tasks. It is possible to see this behaviour in figure 7. Notice that performance begin decreasing when the program use more than 24 cores, i.e. when it start to use *hyper-threading*.



MAP	N	Total.Time	Jacobi.Time	Comm.Time	MLUPs	k	Latency[usec]	Band[MB/s]	C(L,N)[Mb]	T_s[s]	Tc(L,N)[s]	P(L,N)[MLUPs]
core	1	15.2349570	15.0481740	0.18678295	113.4234	0	0.0000	0.00	0.00	15.23496	NA	NA
core	4	3.8313109	3.7645463	0.06013802	451.0205	4	0.2469	12738.41	92.16	15.23496	0.0009043515	453.6665
core	8	1.9413707	1.8877412	0.04911357	890.0923	6	0.2469	12738.41	138.24	15.23496	0.0013565272	907.3061
core	12	1.3053588	1.2642190	0.03861560	1323.7728	6	0.2469	12738.41	138.24	15.23496	0.0013565272	1360.9591
socket	4	3.8276910	3.7630817	0.05929418	451.4470	4	0.6231	11683.38	92.16	15.23496	0.0009860160	453.6641
socket	8	1.9366420	1.8854327	0.04773249	892.2656	6	0.6231	11683.38	138.24	15.23496	0.0014790240	907.2988
socket	12	1.2938464	1.2572978	0.03453514	1335.5507	6	0.6231	11683.38	138.24	15.23496	0.0014790240	1360.9482
node	12	1.2963688	1.2581940	0.03474836	1332.9503	6	1.1328	11914.97	138.24	15.23496	0.0014502764	1360.9508
node	24	0.6545812	0.6306265	0.02099294	2639.8432	6	1.1328	11914.97	138.24	15.23496	0.0014502764	2721.9015
node	36	0.4439099	0.4213099	0.02070858	3892.6559	6	1.1328	11914.97	138.24	15.23496	0.0014502764	4082.8523
node	48	0.3404002	0.3191919	0.01622802	5076.3440	6	1.1328	11914.97	138.24	15.23496	0.0014502764	5443.8030

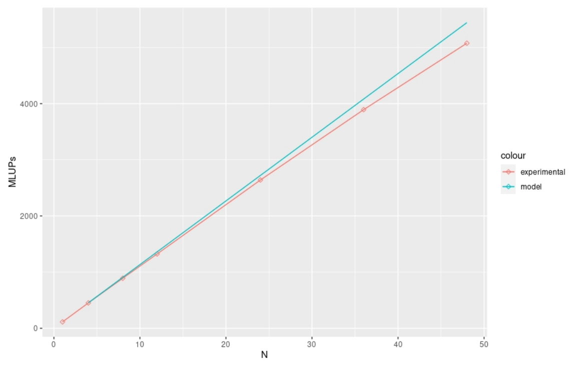
Figure 5: Strong scalability performance table of 3D Jacobi solve for thin nodes



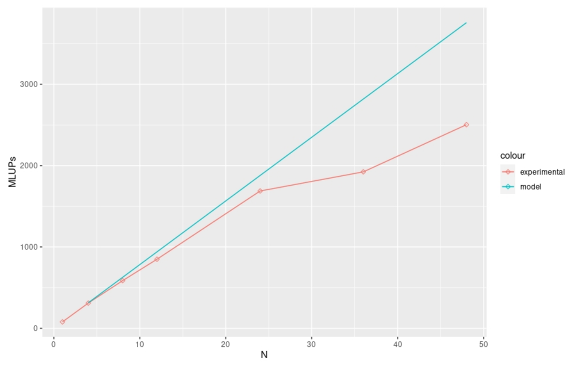
MAP	N	Total.Time	Jacobi.Time	Comm.Time	MLUPs	k	Latency[usec]	Band[MB/s]	C(L,N)[Mb]	T_s[s]	Tc(L,N)[s]	P(L,N)[MLUPs]
core	1	22.0653534	21.7195185	0.34583489	78.31282	0	0.0000	0.00	0.00	22.06535	NA	NA
core	4	5.5850933	5.4766590	0.10343999	309.39499	4	0.2731	12286.65	92.16	22.06535	0.0009376032	313.2380
core	8	2.9511248	2.8592076	0.08638177	585.53898	6	0.2731	12286.65	138.24	22.06535	0.0014064048	626.4626
core	12	2.0354401	1.9681439	0.06506395	848.95530	6	0.2731	12286.65	138.24	22.06535	0.0014064048	939.6939
socket	4	5.5580870	5.4428192	0.10153248	310.89830	4	0.6697	12077.41	92.16	22.06535	0.0009538472	313.2377
socket	8	2.8318303	2.7434807	0.08400953	610.20577	6	0.6697	12077.41	138.24	22.06535	0.0014307708	626.4619
socket	12	1.9356635	1.8570800	0.05971997	892.71574	6	0.6697	12077.41	138.24	22.06535	0.0014307708	939.6929
node	12	1.9317299	1.8554547	0.05963472	894.53383	6	0.6697	12077.41	138.24	22.06535	0.0014307708	939.6929
node	24	1.0236276	0.9757477	0.03563228	1688.10150	6	0.6697	12077.41	138.24	22.06535	0.0014307708	1879.3858
node	36	0.8985707	0.7570113	0.04226612	1923.04357	6	0.6697	12077.41	138.24	22.06535	0.0014307708	2819.0786
node	48	0.6902639	0.6486486	0.03345041	2503.35132	6	0.6697	12077.41	138.24	22.06535	0.0014307708	3758.7715

Figure 6: Strong scalability performance table of 3D Jacobi solver for GPU node

The biggest difference between model and data is the communication time. In fact, the time $T_c(L,N)$ predicted from the model is hundred time smaller then the observed one. However, the simple model used is enough good to predict the performance of the program.



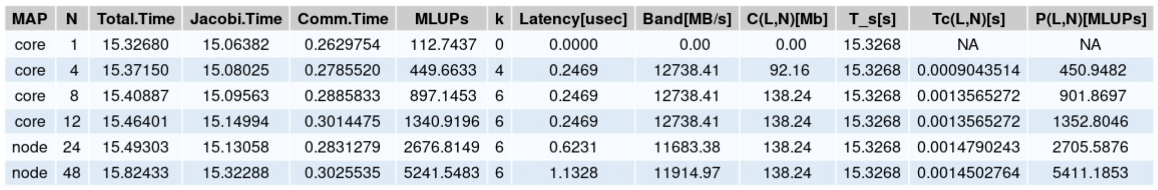
(a) THIN



(b) GPU

Figure 7: Strong scalability of Jacobi solver again the theoretical model, both with GPU and THIN node.

I ran also the Jacobi solver on THIN nodes keeping constant the subsize L instead the total size. The results obtained and the relative performance model is shown in figure 8 and 9. The model used is the same of the strong scalability.



MAP	N	Total.Time	Jacobi.Time	Comm.Time	MLUPs	k	Latency[usec]	Band[MB/s]	C(L,N)[Mb]	T_s[s]	Tc(L,N)[s]	P(L,N)[MLUPs]
core	1	15.32680	15.06382	0.2629754	112.7437	0	0.0000	0.00	0.00	15.3268	NA	NA
core	4	15.37150	15.08025	0.2785520	449.6633	4	0.2469	12738.41	92.16	15.3268	0.0009043514	450.9482
core	8	15.40887	15.09563	0.2885833	897.1453	6	0.2469	12738.41	138.24	15.3268	0.0013565272	901.8697
core	12	15.46401	15.14994	0.3014475	1340.9196	6	0.2469	12738.41	138.24	15.3268	0.0013565272	1352.8046
node	24	15.49303	15.13058	0.2831279	2676.8149	6	0.6231	11683.38	138.24	15.3268	0.0014790243	2705.5876
node	48	15.82433	15.32288	0.3025535	5241.5483	6	1.1328	11914.97	138.24	15.3268	0.0014502764	5411.1853

Figure 8: Weak scalability performance for Jacobi solver on THIN node.

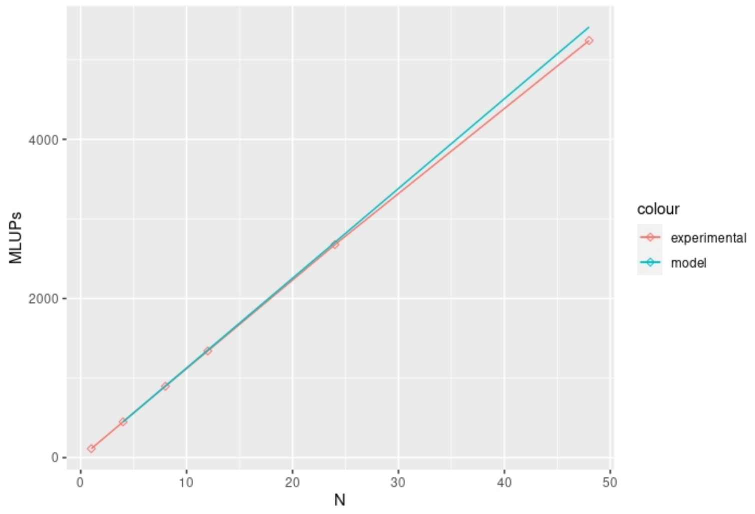


Figure 9: Weak scalability of Jacobi solver