# Parallel Computing Exercise 1 (April 18, 2023) 

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The result is to be submitted by the deadline stated above via the Moodle interface. The result is submitted as a .zip or .tgz file which contains

- a single PDF (.pdf) file with
- a cover page with the title of the course, your name(s), Matrikelnummer(s), and emailaddress(es),
- the source code of the sequential program,
- the demonstration of a sample solution of the program,
- the source code of the parallel program,
- the demonstration of a sample solution of the program,
- a benchmark of the sequential and of the parallel program.
- the source (.c/.cpp/.java) files of the sequential and of the parallel program.


## Shared Memory Programming in C/C++ with OpenMP or in Java

Develop a sequential and a parallel solution to one of the subsequently stated problems, either in C/C++ with OpenMP or in Java using the Java basic thread/high-level concurrency API.

Instrument the source code of your program to measure the real ("wall clock") time spent (only) in that part of your program that you are interested in (the core function without initialization of input data and output of results) and print this time to the standard output. In $\mathrm{C} / \mathrm{C}++$ with OpenMP, you can determine wall clock times by the function omp_get_wtime(), in Java you can determine it by System. currentTimeMillis().

When running the parallel programs, make sure that threads are pinned to freely available cores; use top to verify the applied thread/core mapping and the thread's share of CPU time (which should be close to $100 \%$ ). In a C/C++ solution with OpenMP, make sure that both your sequential and parallel program are compiled with all optimizations switched on (option -03).

When benchmarking the parallel program, make sure that you run the parallel program with the same actual inputs (not only the same input sizes) as the sequential one by using the same random number generator seeds in the generation of inputs (if applicable).

Repeat each benchmark (at least) five times, collect all results, drop the smallest and the highest value and take the average of the remaining three values. For automating this process, the use of a shell script is recommended. For instance, a shell script loop. sh with content

```
#!/bin/sh
for P in 1 2 4 8 16 32 ; do
    echo $P
done
```

can be run as sh loop. sh >log.txt to print a sequence of values into file log.txt.
Present all timings in an adequate form in the report by

- a numerical table with the (average) execution times of sequential and parallel programs for varying input sizes and processor numbers, (absolute) speedups and (absolute) efficiencies;
- diagrams that illustrate execution times, speedups, and efficiencies with both linear and algorithmic axes, as shown in class (multiple runs should be shown in the same diagram by different curves, if the scales are comparable);
- ample verbal explanations that explain your compilation/execution settings, how you interpret the results, how you judge the performance/scalability of your programs.

Hint In Assignment 3, you will be asked for an MPI solution of this problem in C/C++, you may consider this when choosing the problem and the implementation language for this assignment.

Tip For a C/C++ program, the tool valgrind ${ }^{1}$ is useful to debug invalid memory accesses; this package is included in many Linux distributions (Debian: apt-get install valgrind).

Presentation Please be prepared to give a short ( 10 min ) presentation of your results on April 25; you will be notified by April 20 whether such a presentation is requested from you.

[^0]
## Alternative A: Matrix Inversion by Gauss-Jordan Elimination

Given a regular matrix $A=\left(a_{i j}\right)$ with $n$ rows and $n$ columns, our goal is to compute the inverse of $A$, i.e., that matrix $B=\left(b_{i j}\right)$ with $n$ rows and $n$ columns that satisfies $A \cdot B=I$ where $I$ is the identity matrix:

$$
\left(\begin{array}{ccc}
a_{11} & \ldots & a_{1 n} \\
\vdots & \ddots & \vdots \\
a_{n 1} & \ldots & a_{n n}
\end{array}\right) \cdot\left(\begin{array}{ccc}
b_{11} & \ldots & b_{1 n} \\
\vdots & \ddots & \vdots \\
b_{n 1} & \ldots & b_{n n}
\end{array}\right)=\left(\begin{array}{ccc}
1 & \ldots & 0 \\
\vdots & \ddots & \vdots \\
0 & \ldots & 1
\end{array}\right)
$$

This problem can be solved by Gauss-Jordan Elimination ${ }^{2}$, a variant of Gaussian Elimination that transforms in a sequence of steps the matrix $(A \mid I)$ with $n$ rows and $2 n$ columns into the corresponding matrix $(I \mid B)$ :

$$
\left(\begin{array}{ccc|ccc}
a_{11} & \ldots & a_{1 n} & 1 & \ldots & 0 \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
a_{n 1} & \ldots & a_{n n} & 0 & \ldots & 1
\end{array}\right) \rightsquigarrow \ldots \rightsquigarrow\left(\begin{array}{ccc|ccc}
1 & \ldots & 0 & b_{11} & \ldots & b_{1 n} \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
0 & \ldots & 1 & b_{n 1} & \ldots & b_{n n}
\end{array}\right)
$$

The algorithm proceeds in $n$ iterations where in iteration $i$, for $i=1, \ldots n$, the element $a_{i i}$ serves as the pivot element: we divide line $i$ by $a_{i i}$ and subtract from every row $j \neq i$ the multiple $a_{j i} / a_{i i}$ of row $i$; thus column $i$ gets 1 in row $i$ and 0 in every row $j \neq i$. Please note that $A$ is already in diagonal form in every column $j<i$ such that it is thus not necessary to consider this part any more. For instance, for $n=6$ and $i=4$, we have the following situation:

$$
\left(\begin{array}{llllll|llllll}
1 & 0 & 0 & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\
0 & 1 & 0 & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\
0 & 0 & 1 & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\
0 & 0 & 0 & a_{4,4} & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\
0 & 0 & 0 & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\
0 & 0 & 0 & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots
\end{array}\right)
$$

While Gauss-Jordan Elimination is typically not used when the matrix coefficients are floating point numbers (here mainly iterative methods are used for determining approximate solutions), it may play a role if the coefficients are from a domain where the equation is to be solved exactly (as in computer algebra systems). In this assignment we will consider the domain $\mathbb{Z} / p=\{0,1, \ldots, p-1\}$ where $p$ is a prime number and arithmetic is integer arithmetic modulo $p$ as implemented by the following C functions:

```
static long mAdd(long a, long b) { return (a+b)%p; }
static long mSub(long a, long b) { return (a+p-b)%p; }
static long mMul(long a, long b) { return (a*b)%p; }
static long mDiv(long a, long b) { return mMul(a, mInv(b)); }
```

Here $m \operatorname{Inv}(a)$ computes the modular inverse of $a$ (i.e., the value $a^{\prime}$ for which $a \cdot a^{\prime} \equiv 1(\bmod p)$ holds) by applying the extended Euclidean algorithm:

[^1]```
static long mInv(long a)
{
    long r = p; long old_r = a;
    long s = 0; long old_s = 1;
    while (r != 0)
    {
        long q = old_r/r;
        long r0 = r; r = old_r-q*r; old_r = r0;
        long sQ = s; s = old_s-q*s; old_s = s0;
    }
    return old_s >= 0 ? old_s : old_s+p;
}
```

Please note that for computing multiple modular quotients $a_{i} / b$, one may compute once the modular inverse $b^{-1}$ and then compute multiple modular products $a_{i} \cdot b^{-1}$.

## Sequential Program

Your first task is to implement a sequential program solving the problem for a randomly generated matrix $A$ and $p=982451653\left(\approx 2^{30}\right)$.

You may construct a "straight-forward" version of the algorithm that aborts with a corresponding message, if matrix $A$ is not regular. Since arithmetic is exact, any non-zero coefficient may serve as a pivot element in the diagonalization (i.e., is not necessary to take the element with the maximum absolute value).

Demonstrate the correctness of your program by inverting a random $4 \times 4$ matrix for, e.g., $p=11$, and giving the output of the program (system and solution). Benchmark the execution time of your solution (the time for solving the system not including the initialization time) for randomly initialized matrices with at least two different dimensions that let the program run at least 1 min and at least 3 min , respectively.

Please note that the input of the algorithm is $A$ and its output of $B$; it is the task of the algorithm to convert $A$ into the intermediate form $(A \mid I)$ and $(I \mid B)$ into $B$; the times for these conversions therefore have to be attributed to the algorithm.

## Parallel Program (Basic Version)

In iteration $i$ of the outermost loop, all coefficients of $(A \mid I)$ in all rows and all columns $j \geq i$ have to be processed; this can be done independently for each coefficient, i.e., in parallel. A simple strategy to increase the task granularity is to utilize the parallelism just across rows: consequently modify the sequential program (if necessary) such that the iterations of the loop that runs over matrix rows can be performed independently of each other:

- $\mathrm{C} / \mathrm{C}++$ : use OpenMP pragmas to ensure that the loop gets executed in parallel; do not forget to mark "private" variables appropriately. Compile the program with options -03 -openmp -openmp-report 1. Experiment with different scheduling strategies respectively chunk sizes to determine the one that gives best performance.
- Java: use the high-level Java concurrency API for creating a thread pool among which tasks are scheduled each of which processes a block of $B$ rows of the matrix; experiment with suitable values for the block size $B$. Please note that the pool is created only once and reused
in every iteration of the triangulation (you may use the method invokeAll ${ }^{3}$ which blocks until all tasks have been processed).

Benchmark your program for $P=1,2,4,8,16,32$ cores (and potentially more).

## Parallel Program (Advanced Version)

Most likely the basic program will not scale well beyond 16 cores ( 1 blade on the UV 1000) due to the higher latency of memory access across blades. In particular, in every outermost iteration of the algorithm, each matrix row may be accessed by a thread running on another node, which leads to a transfer of the row to another blade in every iteration step. Therefore write another version of the program that addresses this problem: every row is assigned to the same thread (pinned to a node blade) across multiple iterations: if we have $P$ threads, thread 0 processes rows $0, P, 2 P, \ldots$, thread 1 processes rows $1, P+1,2 P+1, \ldots$ and so on (generally rows are distributed to threads in a "round-robin" fashion to ensure that the work load of a thread is not influenced by a particular distribution of data in the matrix).

In Java, this may be achieved by explicitly creating $P$ threads that stay alive during the whole computation. Each thread allocates (in the heap of the node on which it runs) the matrix rows which it subsequently processes; after the allocation phase, the original main thread initializes the matrix with the coefficients. Then the program runs in $n$ iterations where in every iteration each thread processes the rows it is in charge of. For synchronizing all threads after every iteration, you may use class CyclicBarrier ${ }^{4}$.

In OpenMP this may be achieved by using (like in Java) a matrix representation that stores in an array the start addresses of each row and using repeated execution of omp parallel to let each thread process a part of a matrix: in the first execution each thread allocates the memory of the rows for which it is in charge, in every subsequent execution, it processes theses rows.

Benchmark the program in the same way as the original version.
Note: there is no guarantee that the advanced version of the program will indeed scale better than the basic one. However, the effort to achieve such an improvement and its evaluation will be judged.

[^2]
## Alternative B: Counting the Satisfying Assignments of a Formula

The goal is to develop a parallel program for determining the number of satisfying assignments of a propositional formula in conjunctive normal form.

## Preliminaries

A propositional formula $F$ in conjunctive normal form is a conjunction of clauses where each clause $C$ is a disjunction of literals and each literal $L$ is a positive or negative occurrence of a propositional variable $V . F$ is thus formed according to the following extended BNF grammar:

$$
\begin{aligned}
& F::=\left[C(\wedge C)^{*}\right] \\
& C::=\left[L(\vee L)^{*}\right] \\
& L::=V \mid \neg V
\end{aligned}
$$

An example of such a formula is

$$
(x \vee \neg y \vee z) \wedge(\neg x \vee y) \wedge(y \vee \neg z)
$$

which can be also represented by the set

$$
\{\{x, \neg y, z\},\{\neg x, y\},\{y, \neg z\}\} .
$$

If a clause has both a positive occurrence $V$ and a negative occurrence $\neg V$ of the same variable $V$, it is equivalent to "true" and can be discarded; we thus may assume that no clause has such conflicting occurrences.
An assignment $A$ is a set of $n$ literals such that every variable $V$ occurs in $A$ either in positive or in negative form: $V \in A$ indicates that variable $V$ is assigned the truth value "true" while $\neg V \in A$ indicates that it is assigned the truth value "false". An assignment $A$ satisfies a formula $F$, if the formula becomes true when all the variables are replaced by the truth values indicated by the assignment. In more detail, assignment $A$ satisfies clause $C$, if there exists a literal $L$ in $A$ that also occurs in $C$; $A$ satisfies $F$, if it satisfies every clause in $C$. For instance, above formula is satisfied by the assignment $A=\{x, y, z\}$.

In order to determine whether there exists any satisfying assignment for a formula $F$ with $n$ variables, the DPLL algorithm ${ }^{5}$ depicted (in a simplified form) as Algorithm 1 may be applied: if $F$ is empty, the formula represents "true" and is thus satisfiable; if $F$ has an empty clause, this clause represents "false", and the formula is not satisfiable. Otherwise, we choose some literal $L$ that occurs in $F$ and apply the algorithm recursively, first to formula $F \wedge L$ and, if necessary, also to formula $F \wedge \neg L$. Each of these formulas has $n-1$ variables, because the computation of $F \wedge L$ removes every negative occurrence of $L$ from $F$ and removes every clause $C$ from $F$ that has a positive occurrence of $L$ (dually for the computation of $F \wedge \neg L$ ). Thus the recursive call $\operatorname{DPPL}(F \wedge L)$ determines whether there exists any satisfying assignment for $F$ which sets $L$ to "true"; the recursive call $\operatorname{DPPL}(F \wedge \neg L)$ determines whether there exists any satisfying assignment for $F$ which sets $L$ to "false". The execution of the algorithm can be described by a binary tree with $2^{n}$ leaves that represent all possible assignments; it thus represents an exhaustive search for a satisfying assignment in the space of all possible assignments.

The algorithm can be easily extended to return the number of satisfying assignments by the following changes:

[^3]```
Algorithm 1 DPLL Algorithm (simplified)
    function \(\operatorname{DPLL}(F, n) \quad \triangleright\) Formula \(F\) has \(n\) variables
        if \(F\) is empty then
            return true
        else if \(F\) has an empty clause then
            return false
        else
            choose literal \(L\) in \(F\)
            return \(\operatorname{DPPL}(F \wedge L, n-1)\) or \(\operatorname{DPPL}(F \wedge \neg L, n-1)\)
        end if
    end function
```

1. In first base case, it returns $2^{n}$ (if there are still $n$ unassigned variables, there are $2^{n}$ possible assignments to these variables).
2. In the second base case, it returns 0 (since there is no assignment).
3. In the recursive case, it returns the sum of the values returned by the two recursive calls.

In the actual implementation of the algorithm by a computer program, a formula $F$ with $c$ clauses in $v$ variables can be represented by a $c \times v$ matrix of elements $\{-1,0,+1\}$ where $F[i, j]$ has value +1 , if clause $i$ has a positive occurrence of variable $j$, value -1 , if it has a negative occurrence, and value 0 , if variable $j$ does not occur in clause $i$. Above formula can be thus represented by the matrix

$$
\left[\begin{array}{ccc}
1 & -1 & 1 \\
-1 & 1 & 0 \\
0 & 1 & -1
\end{array}\right]
$$

Rather than constructing a new formula matrix $F$ for every recursive invocation of the algorithm, we may pass to every invocation just a triple $c^{\prime}, l, a$ where

- $c^{\prime}$ is the number of clauses that are still in $F$,
- $l$ is an array of length $c$ where $l[i]$ is the number of literals in clause $i$ of $F$ (the special value $l[i]=-1$ indicates that clause $i$ has been deleted from $F$; there are $c-c^{\prime}$ such lines);
- a represents the partial assignment computed so far: it is a vector of length $v$ of values $\{-1,0,+1\}$ (initially 0 everywhere): $a[i]=+1$ indicates that variable $i$ has been assigned the truth value "true", $a[i]=-1$ indicates that it has been assigned the truth value "false"; $a[i]=0$ indicates that it has not been assigned a truth value yet.

All necessary operations of the algorithm may be expressed in terms of these three variables.

Sequential Solution Implement a sequential solution that solves the problems for parameters $c$, $v, d, s$, where $c$ is the number of clauses, $v$ is the number of variables, $d$ is a density value between 0 and 1 , and $s$ is an integer that represents the seed for the random number generator. The program shall generate a random formula matrix of dimension $c \times v$ of which a fraction $d$ is filled with random literals using seed $s$ for the random number generator (to save space, use type byte for the elements
of the matrix). Demonstrate the correctness of your solution by showing the result for some (small) formula and then benchmark the solution for three different inputs of reasonable size.

The parallel solution shall also use a parameter $T$ that representes the number of concurrent threads to be applied for the solution. Demonstrate also the correctness of the parallel solution by showing that it computes the same result as the sequential one.

Java-Based Parallel Solution The program may be based on the Java concurrency framework using the classes ForkJoinTask and ForkJoinPool ${ }^{6}$.

However, you may also apply the strategy sketched for the OMP-based solution below which lets a fixed set of worker threads operate on a shared stack (this may or may not be more efficient).

OMP-based Parallel Solution The program creates $T$ worker threads that simultaneously process the space of possible solutions:

```
#pragma omp parallel ... num_threads(T)
```

The space of possible solutions to be processed is represented by:

- a global stack of partial assignments (access to this stack is protected by a critical section or a lock variable);
- for every thread a local stack of partial assignments (since the thread has exclusive access to its stack, the lockal stacks need not be protected).

Initially, the global stack holds only the empty assignment $a=$ [] and all local stacks are empty.
Each thread primarily processes assignments from its local stack by a doubly nested loop:

1. in the outer loop, the thread pops a partial assignment $a$ from its local stack and determines from $F, n, a$ the values $l$ and $c$ with which it starts the execution of the inner loop;
2. in the inner loop, the thread proceeds as follows:
a) the thread performs the checks for the "base cases" and only proceeds with the loop, if they are not successful;
b) for one of the "recursive" cases, the thread pushes a new partial assignment $a$ ' to its local stack;
c) the other "recursive" case with assignment $a^{\prime}$ is processed by the thread itself in the next iteration of the loop;
3. the thread leaves the inner loop when it reaches the "base case" where it can determine the number of total assignments arising from the current partial assignment $a^{\prime \prime}$; the thread correspondingly increments a local counter that keeps track of the number of satisfying assignments that the thread has found so far.
[^4]If the local stack becomes empty, the thread pops instead an assignment $a$ from the global stack and continues with processing this assignment. However, if by the removal of $a$ the global stack becomes empty, the thread extends $a$ by setting $t \geq 1$ previously unassigned variables to all possible combinations of their truth values; it thus generates $2^{t}$ new assignments from which the thread keeps itself one for further processing and leaves the other ones on the global stack for processing by the other threads (experiment with different values of $t$ to see which one gives best performance).

Furthermore, to prevent an early permanent idling of some threads, every busy thread checks from time to time (e.g. after it has popped a certain number of assignments from its local stack), whether the global queue is empty. If yes, it fills the global stack with the $2^{t}-1$ oldest assignments (the assignment with the fewest variables set) from its local stack (the local stack should be thus implemented with the help of two index variables as a cyclic queue).

If a thread runs out of assignments to process and also finds the global stack empty, it increments a protected shared variable that denotes the number of threads that are waiting on the global stack for assignments. If this variable indicates that all threads are waiting, the total number of satisfying assignments may be computed as the sum of all local counters and all threads may terminate.

Please note that a local stack may hold at most $n-1$ assignments (where $n$ is the maximum number of variables in a formula) and that the global stack may only hold at most $2^{t}-1$ assignments. Furthermore, since each assignment can be represented by $n$ truth values, each local stack can be represented by an array of $(n-1) \cdot n$ truth values and the global stack can be represented by an array of $\left(2^{t}-1\right) \cdot n$ truth values. All these arrays can be allocated in advance; to improve data locality, let each thread allocate its local stack on its own.

Finally, please note that the (exponentially many) satisfying assignments must not be actually stored; it is only their number that is to be determined. Also please note that different formulas of the same size may lead to different speedups; you may thus want to experiment with different seed values of the random number generator.


[^0]:    ${ }^{1}$ http://valgrind.org/

[^1]:    ${ }^{2}$ https://de.wikipedia.org/wiki/Inverse_Matrix\#Gau\%C3\%9F-Jordan-Algorithmus https://en.wikipedia.org/wiki/Gaussian_elimination\#Finding_the_inverse_of_a_matrix

[^2]:    ${ }^{3}$ https://docs.oracle.com/en/java/javase/11/docs/api/java.base/java/util/concurrent/ ExecutorService.html\#invokeAll(java.util.Collection)
    ${ }^{4}$ https://docs.oracle.com/en/java/javase/11/docs/api/java.base/java/util/concurrent/ CyclicBarrier.html

[^3]:    5https://en.wikipedia.org/wiki/DPLL_algorithm

[^4]:    ${ }^{6}$ See https://docs.oracle.com/javase/tutorial/essential/concurrency/forkjoin.html and the documentation of these classes

