## Matrix Multiplication in Theory and Practice Math, Concurrency, and High-Performance Implementation (Final)

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## Contents

1	Overview	2
2	Mathematical background (concise)  2.1 Definition and rationale	2 2 2 2
3	Algorithms and practical optimizations 3.1 Blocking / tiling	2 2 3
4	Production-grade concurrent Java: implementation and explanation 4.1 Key design notes	<b>3</b>
5	Alternatives: invokeAll, Phaser, ForkJoin sketches 5.1 invokeAll + Callable	5 5 5
6	Verification, numeric tolerances, and correctness         6.1 Verification          6.2 Numeric tolerances	<b>5</b> 5
7	Benchmarking and profiling 7.1 Warm-up	<b>5</b> 5
8	Memory layout, cache and false sharing8.1 Row-major indexing8.2 False sharing mitigation8.3 Tile sizing	5 5 5
9	Error handling and production patterns	6

10 Advanced notes (brief)	6
11 Production deployment recommendations	6
12 References & resources	6
13 Checklist: prototype $\rightarrow$ production	6

#### 1 Overview

This document collects theory, practical algorithms, and production-grade parallel implementation guidance for matrix multiplication. It includes:

- concise mathematical foundations and worked examples,
- complexity analysis and practical optimizations (tiling, Strassen),
- detailed Java concurrency patterns (ExecutorService, CyclicBarrier, Phaser, ForkJoin),
- verification, benchmarking, memory-layout, and deployment notes.

## 2 Mathematical background (concise)

#### 2.1 Definition and rationale

Let  $A \in \mathbb{R}^{n \times m}$  and  $B \in \mathbb{R}^{m \times p}$ . The product C = AB is the  $n \times p$  matrix with entries

$$C_{ij} = \sum_{k=1}^{m} A_{ik} B_{kj}, \qquad 1 \le i \le n, \ 1 \le j \le p.$$

This corresponds to composition of linear maps and the row-column (dot-product) view.

#### 2.2 Worked example

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix}, \quad B = \begin{bmatrix} 7 & 8 \\ 9 & 10 \\ 11 & 12 \end{bmatrix} \implies C = \begin{bmatrix} 58 & 64 \\ 139 & 154 \end{bmatrix}.$$

#### 2.3 Complexity recap

Naive arithmetic cost for  $A \in \mathbb{R}^{n \times m}$  and  $B \in \mathbb{R}^{m \times p}$ :

$$T(n, m, p) = \Theta(nmp).$$

For square  $N \times N$  matrices,  $T(N) = \Theta(N^3)$ . Practical work focuses on lowering constants (tiling, vectorization, BLAS) or asymptotics (Strassen and theoretical research).

## 3 Algorithms and practical optimizations

#### 3.1 Blocking / tiling

Partition matrices into  $b \times b$  tiles and compute block multiplications

$$C_{(i,j)} += A_{(i,k)} \cdot B_{(k,j)}.$$

Choose b to maximize reuse in L1/L2 caches — tune empirically per hardware.

#### 3.2 Strassen (2x2 block sketch)

Strassen reduces the number of half-size multiplications from 8 to 7, giving exponent  $\log_2 7 \approx 2.807$ . For two-by-two block matrices A, B, compute 7 M matrices (see main text) and combine them to form C. Strassen trades multiplications for additions and is worthwhile only for large enough matrices due to overhead and numerical care.

# 4 Production-grade concurrent Java: implementation and explanation

Below is a robust, production-minded Java example using flat arrays, row-block partitioning, and two CyclicBarrier phases. Compile and run in a modern JDK.

```
/* MatrixMultiplyParallel.java */
   import java.util.*;
   import java.util.concurrent.*;
   public class MatrixMultiplyParallel {
6
       public static void main(String[] args) throws Exception {
           final int N = 600; // rows of A and C
8
           final int M = 500; // cols of A, rows of B
9
           final int P = 400; // cols of B and C
           final int numWorkers = Math.min(8, Runtime.getRuntime().availableProcessors());
11
13
           double[] A = randomMatrix(N, M, 42L);
14
           double[] B = randomMatrix(M, P, 99L);
           double[] C = new double[N * P];
           double[] rowNorms = new double[N];
17
           ExecutorService executor = Executors.newFixedThreadPool(numWorkers);
18
19
           CyclicBarrier barrierAfterMultiply = new CyclicBarrier(numWorkers);
20
           CyclicBarrier barrierAfterNorms = new CyclicBarrier(numWorkers);
21
22
           int rowsPerWorker = (N + numWorkers - 1) / numWorkers;
23
           List<Future<?>> futures = new ArrayList<>();
           for (int w = 0; w < numWorkers; w++) {</pre>
               final int startRow = w * rowsPerWorker;
27
               final int endRow = Math.min(N, startRow + rowsPerWorker);
28
               if (startRow >= endRow) break;
29
30
               futures.add(executor.submit(new Worker(A, B, C, rowNorms,
31
                      startRow, endRow, N, M, P, barrierAfterMultiply, barrierAfterNorms)));
32
33
34
           for (Future<?> f : futures) f.get(); // surface exceptions
           executor.shutdown();
           if (!executor.awaitTermination(2, TimeUnit.MINUTES))
37
               executor.shutdownNow();
38
39
           System.out.println("Parallel multiply+norms complete.");
40
41
42
       static class Worker implements Runnable {
43
           private final double[] A, B, C, norms;
44
           private final int startRow, endRow, N, M, P;
           private final CyclicBarrier barrier1, barrier2;
47
           Worker(double[] A, double[] B, double[] C, double[] norms,
```

```
49
                  int startRow, int endRow, int N, int M, int P,
                  CyclicBarrier barrier1, CyclicBarrier barrier2) {
50
               this.A = A; this.B = B; this.C = C; this.norms = norms;
51
               this.startRow = startRow; this.endRow = endRow;
52
               this.N = N; this.M = M; this.P = P;
53
               this.barrier1 = barrier1; this.barrier2 = barrier2;
54
56
57
           @Override
           public void run() {
               try {
                    // Phase 1: compute assigned rows of {\it C}
60
                   for (int i = startRow; i < endRow; i++) {</pre>
61
                       int rowA = i * M;
62
                       int rowC = i * P;
63
                       for (int k = 0; k < M; k++) {
64
                           double a = A[rowA + k];
65
66
                           int rowB = k * P;
                           for (int j = 0; j < P; j++) {
67
                               C[rowC + j] += a * B[rowB + j];
68
70
                       }
71
                   }
72
                   barrier1.await(); // memory fence + sync
73
                   // Phase 2: compute row norms
74
                   for (int i = startRow; i < endRow; i++) {</pre>
75
                       int rowC = i * P;
76
                       double s = 0.0;
77
                       for (int j = 0; j < P; j++) {
78
79
                           double v = C[rowC + j];
                           s += v * v;
80
                       }
81
                       norms[i] = Math.sqrt(s);
82
                   }
83
                   barrier2.await();
84
85
               } catch (InterruptedException ie) {
86
                   Thread.currentThread().interrupt();
87
               } catch (BrokenBarrierException bbe) {
88
                   System.err.println("Barrier broken in worker for rows "
                       + startRow + "-" + (endRow - 1));
91
               }
           }
92
       }
93
94
        static double[] randomMatrix(int rows, int cols, long seed) {
95
           Random rnd = new Random(seed);
96
           double[] m = new double[rows * cols];
97
           for (int i = 0; i < m.length; i++) m[i] = rnd.nextDouble();</pre>
98
           return m;
99
        }
   }
```

Listing 1: Parallel matrix multiplication with CyclicBarrier

#### 4.1 Key design notes

- Flat arrays: one-dimensional 'double []' with row-major indexing 'i\*cols + j'.
- Row-block partitioning: lower synchronization and simple ownership semantics.
- Barriers: barrier.await() acts as a synchronization point and memory fence.

• Diagnostics: stored separately to avoid clobbering results.

### 5 Alternatives: invokeAll, Phaser, ForkJoin sketches

#### 5.1 invokeAll + Callable

Each task returns its computed chunk (no shared writes during computation). Main thread merges results.

#### 5.2 Phaser

Use 'Phaser' for dynamic registration and many iterative phases. API: 'phaser.arriveAndAwaitAdvance()'.

#### 5.3 ForkJoin recursive tiling

Implement 'RecursiveAction' that splits blocks until base-case, then multiplies. Leverages work-stealing for load balance.

#### 6 Verification, numeric tolerances, and correctness

#### 6.1 Verification

Compare parallel result to a sequential reference for small matrices. Use checksums for quick detection.

#### 6.2 Numeric tolerances

Use absolute and relative tolerances:

$$|x - y| \le \operatorname{atol} + \operatorname{rtol} \cdot |y|$$
.

Typical values depend on application; start with 'atol=1e-12', 'rtol=1e-9' for double.

## 7 Benchmarking and profiling

#### 7.1 Warm-up

Run several warm-up iterations to allow JIT optimizations.

#### 7.2 Measurement

Use 'System.nanoTime()' for rough timing; use JMH for rigorous microbenchmarks. Collect wall-clock, CPU, memory, and cache metrics.

## 8 Memory layout, cache and false sharing

#### 8.1 Row-major indexing

Store matrices as 'double []' and index by 'i\*cols + j' for contiguous row access.

#### 8.2 False sharing mitigation

Assign coarser-grain chunks, add padding to per-thread buffers, avoid threads writing adjacent small regions.

#### 8.3 Tile sizing

Rough heuristic:

$$b \approx \sqrt{\frac{\text{cacheBytes}}{3 \times 8}}.$$

Tune experimentally.

## 9 Error handling and production patterns

- Surface worker exceptions via 'Future.get()'.
- If barrier breaks, abort centrally with 'executor.shutdownNow()'.
- Use timed 'await(timeout, unit)' if stalls are possible.

## 10 Advanced notes (brief)

Cache-oblivious recursion offers multi-level cache friendliness without explicit tile tuning, but tuned BLAS kernels still outperform general recursive code on most CPUs.

## 11 Production deployment recommendations

For critical workloads:

- Prefer vendor BLAS (MKL/OpenBLAS) or GPU libraries (cuBLAS).
- Profile to find whether compute, memory bandwidth, or synchronization is the bottleneck.
- Keep concurrency coarse-grained; use proven libraries for heavy lifting.

#### 12 References & resources

- V. Strassen, "Gaussian elimination is not optimal", Numerische Mathematik, 1969.
- BLAS: http://www.netlib.org/blas/
- Intel MKL: https://software.intel.com/onemkl
- NVIDIA cuBLAS: https://developer.nvidia.com/cublas
- JMH: Java Microbenchmark Harness documentation.

## 13 Checklist: prototype $\rightarrow$ production

- 1. Validate correctness on small matrices.
- 2. Warm-up and benchmark (JMH for accuracy).
- 3. Profile (CPU, memory, cache).
- 4. Tune tile size and loop order.
- 5. Check for false sharing and widen granularity if needed.
- 6. Consider native BLAS for production.