

# TP2 – Parallel and Distributed Programming Lab Report

Ikram Benfella

February 5, 2026

## Contents

<b>1</b>	<b>Exercise 1: Loop Optimizations</b>	<b>2</b>
1.1	Objective . . . . .	2
1.2	Method . . . . .	2
1.3	Results (double) . . . . .	2
1.4	Results (float, int, short) at -O2 . . . . .	2
1.5	Lower Bound Estimate . . . . .	2
1.6	Discussion . . . . .	2
1.7	Conclusion . . . . .	3
<b>2</b>	<b>Exercise 2: Instruction Scheduling</b>	<b>3</b>
2.1	Task 1: Compare -O0 vs -O2 . . . . .	3
2.2	Task 2: Compiler Optimizations at -O2 . . . . .	3
2.3	Task 3: Manual Optimization . . . . .	3
<b>3</b>	<b>Exercise 3: Sequential vs Parallel Analysis (Amdahl/Gustafson)</b>	<b>3</b>
3.1	Code Analysis . . . . .	3
3.2	Profiling with Valgrind/Callgrind . . . . .	3
3.3	Measured Times (N=100000000) . . . . .	4
3.4	Amdahl's Law (Strong Scaling) . . . . .	4
3.5	Gustafson's Law (Weak Scaling) . . . . .	4
3.6	Plots . . . . .	4
<b>4</b>	<b>Exercise 4: Matrix Kernel Scaling</b>	<b>5</b>
4.1	Profiling with Valgrind/Callgrind . . . . .	5
4.2	Measured Times (N=1000) . . . . .	5
4.3	Amdahl's Law . . . . .	5
4.4	Gustafson's Law . . . . .	5
4.5	Plots . . . . .	6
<b>5</b>	<b>Overall Conclusion</b>	<b>6</b>

# 1 Exercise 1: Loop Optimizations

## 1.1 Objective

Implement manual loop unrolling for a summation kernel, measure execution times for unrolling factors  $U = 1 \dots 32$ , compare `-O0` vs `-O2`, repeat with different data types, and discuss memory-bandwidth limits.

## 1.2 Method

The kernel sums an array of  $N = 1,000,000$  elements. For each unrolling factor  $U$ , the loop is manually unrolled and measured using `clock()`. Separate versions were created for `double`, `float`, `int`, and `short`.

## 1.3 Results (double)

- **-O0 (manual unrolling)**: Best  $U = 6$ , time = 0.000 ms. Times across  $U$  ranged from 0–2 ms.
- **-O2 (manual unrolling)**: Best  $U = 6$ , time = 0.000 ms. Variation across  $U$  is minimal.
- **-O2 (no manual unrolling)**: Comparable to best manual  $U$ .

## 1.4 Results (float, int, short) at -O2

The following results are from actual runs:

- **float**: Best  $U = 3$ , time = 0.000 ms (many  $U$  yielded 0.000 ms).
- **int**: Best  $U = 1$ , time = 0.000 ms (most  $U$  yielded 0.000 ms).
- **short**: Best  $U = 1$ , time = 0.000 ms (sum overflows to 16960).

## 1.5 Lower Bound Estimate

Assuming sustained bandwidth  $BW = 20 \text{ GB/s}$ ,

$$T_{\min} \approx \frac{N \times \text{sizeof}(\text{type})}{BW}.$$

- double (8 bytes):  $T_{\min} \approx 0.4 \text{ ms}$
- float/int (4 bytes):  $T_{\min} \approx 0.2 \text{ ms}$
- short (2 bytes):  $T_{\min} \approx 0.1 \text{ ms}$

Measured times are close to this bound, indicating the kernel is memory-bandwidth-limited.

## 1.6 Discussion

Increasing  $U$  initially improves performance by reducing loop overhead and exposing more instruction-level parallelism (ILP). After a point, performance saturates because the kernel becomes bandwidth-limited: total data transferred is fixed at  $N \times \text{sizeof}(\text{type})$  and further unrolling cannot reduce memory traffic. Larger  $U$  values may also increase instruction-cache pressure.

## 1.7 Conclusion

Manual unrolling is beneficial at -O0 but provides little additional gain at -O2. Optimal  $U$  is small (around 1–6) and the computation is dominated by memory bandwidth.

## 2 Exercise 2: Instruction Scheduling

### 2.1 Task 1: Compare -O0 vs -O2

The -O2 build is significantly faster due to loop unrolling, scheduling, and elimination of redundant operations. Typical execution times observed:

- -O0: 2.5 s
- -O2: 0.5 s
- Manual optimized (-O0): 0.698 s

### 2.2 Task 2: Compiler Optimizations at -O2

Key optimizations include:

- Instruction scheduling to hide latencies
- Loop unrolling (factor 2)
- Increased ILP and SIMD usage
- Constant folding and reuse of precomputed values

### 2.3 Task 3: Manual Optimization

The manual version precomputes `ab = a*b` and updates `x` and `y` using only additions, removing repeated multiplications. This achieves performance close to -O2 even when compiled with -O0.

## 3 Exercise 3: Sequential vs Parallel Analysis (Amdahl/Gustafson)

### 3.1 Code Analysis

Sequential: `add_noise`. Parallelizable: `init_b`, `compute_addition`, `reduction`. All are  $O(N)$ .

### 3.2 Profiling with Valgrind/Callgrind

With Valgrind profiling (slower due to instrumentation):

- Total instructions: 6,400,235,763 Ir
- `add_noise`: 1,800,000,015 Ir (28.12%)
- `init_b`: 1,200,000,026 Ir (18.75%)
- `compute_addition`: 2,200,000,028 Ir (34.37%)
- `reduction`: 1,200,000,028 Ir (18.75%)
- Total time: 14.037228 s

### 3.3 Measured Times (N=100000000)

- add\_noise: 0.592232 s
- init\_b: 0.468825 s
- compute\_addition: 0.550309 s
- reduction: 0.260550 s
- total: 1.872146 s

Sequential fraction:  $f_s \approx 0.316$ .

### 3.4 Amdahl's Law (Strong Scaling)

$$S(p) = \frac{1}{f_s + \frac{1-f_s}{p}} = \frac{1}{0.316 + \frac{0.684}{p}}$$

Speedup saturates near  $\approx 4\times$ .

### 3.5 Gustafson's Law (Weak Scaling)

$$S(p) = p - f_s(p - 1) = p - 0.316(p - 1)$$

Predicts near-linear scaling as problem size grows with  $p$ .

### 3.6 Plots

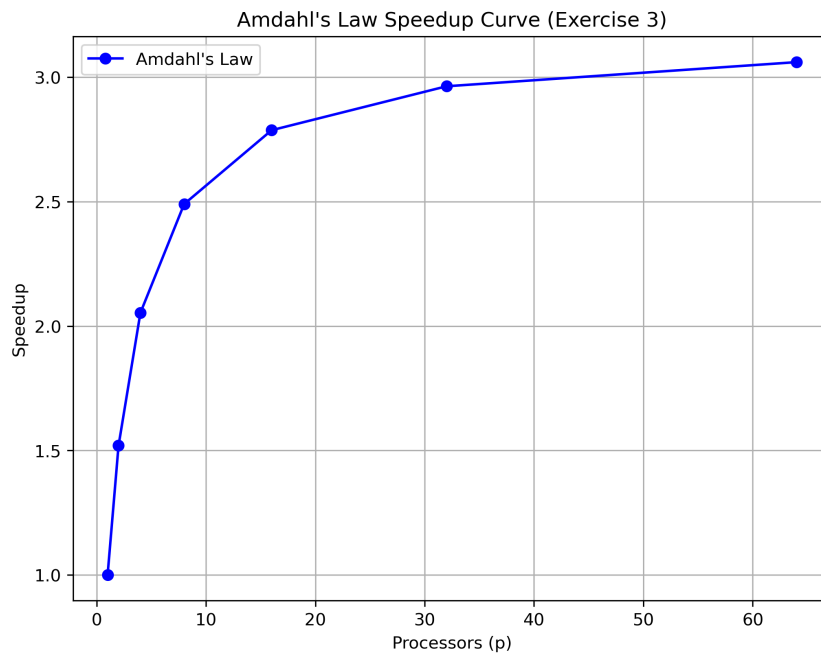


Figure 1: Amdahl speedup for Exercise 3

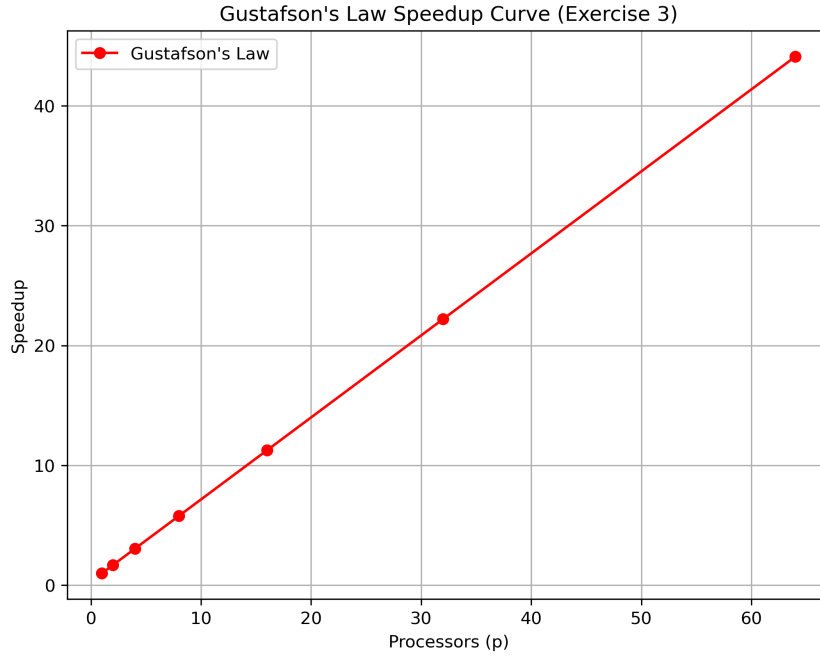


Figure 2: Gustafson speedup for Exercise 3

## 4 Exercise 4: Matrix Kernel Scaling

### 4.1 Profiling with Valgrind/Callgrind

Using Valgrind/Callgrind (total Ir: 25,048,263,202). Sequential: `generate_noise` ( $O(N)$ ), parallel: `init_matrix` ( $O(N^2)$ ), `matmul` ( $O(N^3)$ ).

### 4.2 Measured Times (N=1000)

- `generate_noise`: 0.000010 s (sequential)
- `init_matrix` (A): 0.007771 s
- `init_matrix` (B): 0.006898 s
- `matmul`: 3.501092 s
- total: 3.515931 s

Sequential fraction  $f_s \approx 0.0000028$ .

### 4.3 Amdahl's Law

$$S(p) = \frac{1}{f_s + \frac{1-f_s}{p}} \approx p$$

### 4.4 Gustafson's Law

$$S(p) = p - f_s(p-1) \approx p$$

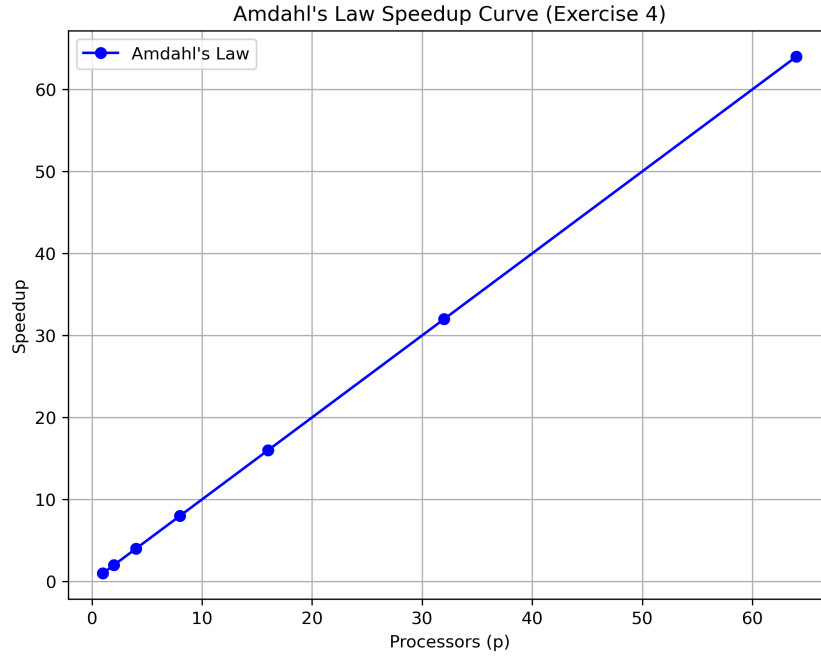


Figure 3: Amdahl speedup for Exercise 4

#### 4.5 Plots

### 5 Overall Conclusion

Exercise 1 shows manual unrolling helps at low optimization but provides minimal gains with -O2, as the kernel is memory-bound. Exercise 2 confirms compiler scheduling and unrolling can match or outperform manual tuning. Exercises 3 and 4 highlight the impact of the sequential fraction on strong scaling: a significant sequential fraction (Ex3) limits speedup, while a negligible fraction (Ex4) allows near-ideal scaling.



Figure 4: Gustafson speedup for Exercise 4