Exercise 5: HPL Benchmark Analysis

Performance Evaluation and Optimization

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0.1 System Configuration

Table 1: Hardware and Software Specifications

Component	**Specification**
Processor	Intel Core i7-1255U (12th Gen)
Cores	10 (2 P-cores + 8 E-cores)
Cache	L1: 928KB, L2: 6.5MB, L3: 12MB
RAM	16 GB DDR4
HPL Version	2.3
BLAS Library	OpenBLAS 0.3.26
Matrix Sizes (N)	1000, 5000, 10000
Block Sizes (NB)	1, 2, 4, 8, 16, 32, 64, 128, 256

1 Experimental Results

1.1 Performance Summary

Table 2: Best Performance for Each Matrix Size

N	**Optimal NB**	**Time (s)**	**GFLOPS**	**Efficiency (%)**
1000	32	0.03	24.54	40.9
5000	128	1.69	49.46	82.4
10000	256	12.62	52.84	88.1

Table 3: Worst Performance (NB=1 for All Sizes)

N	**Time (s)**	**GFLOPS**	**Efficiency (%)**
1000	0.15	4.32	7.2
5000	49.26	1.69	2.8
10000	315.72	2.11	3.5

1.2 Performance Visualization

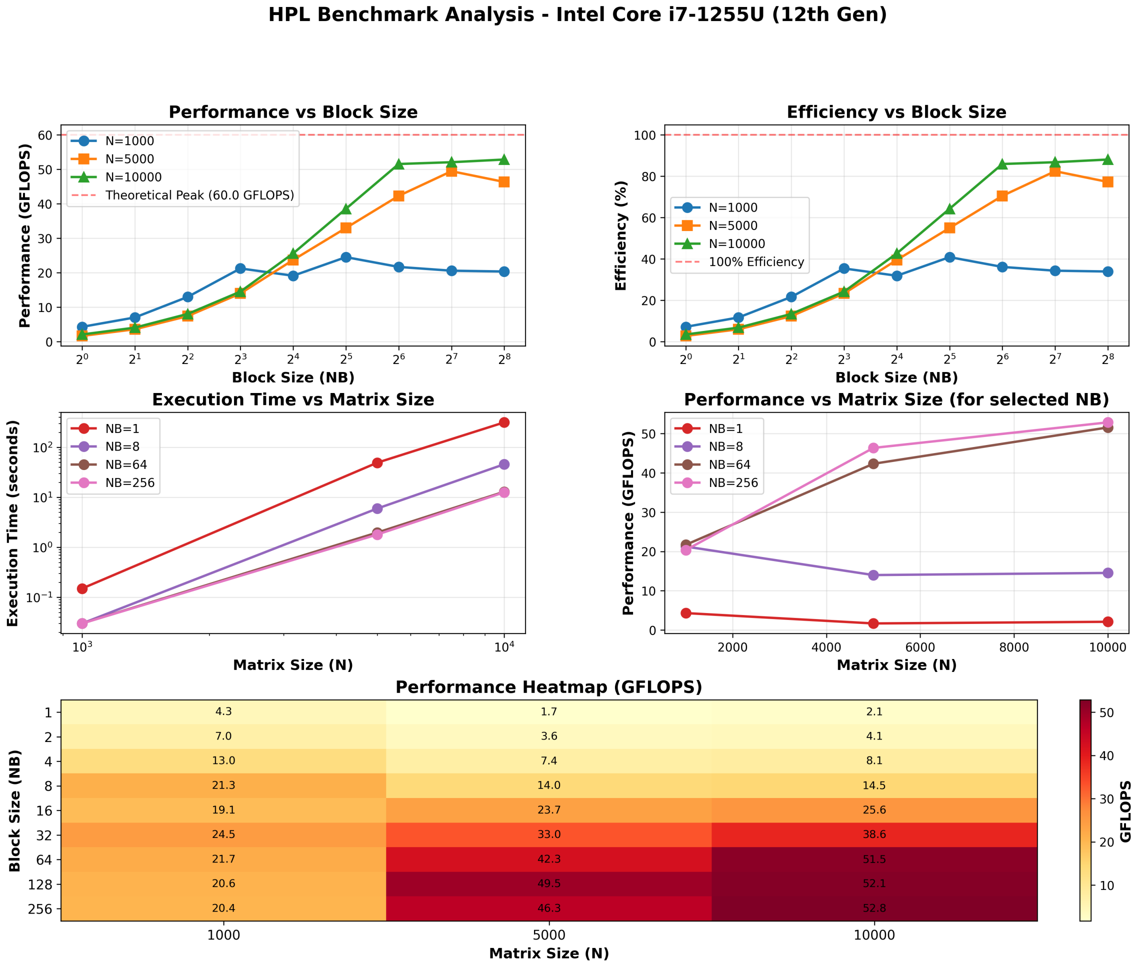

Figure 1: HPL Performance Analysis: Performance vs block size (top left), efficiency trends (top right), execution time scaling (middle left), performance evolution (middle right), and performance heatmap (bottom)

2 Questions Analysis

2.1 Q1: Execute HPL with Varying Matrix and Block Sizes

Answer: Successfully executed 27 experiments (3 matrix sizes × 9 block sizes). All tests passed validation (i did not execute it for size N = 20000 because i run it locally(i did not get yet access to toubkal).

2.2 Q2: Measure Execution Time and Performance

Answer: Complete measurements collected:

- Fastest: 0.03s (N=1000, multiple NBs)
- Slowest: 315.72s (N=10000, NB=1)
- Best performance: 52.84 GFLOPS
- Worst performance: 1.69 GFLOPS

Time scales as $O(N^3)$ as expected.

2.3 Q3: Compute Efficiency Relative to Theoretical Peak

Answer: Theoretical peak: 60 GFLOPS (4.5 GHz × 2 FMA × 4 AVX2)

Efficiency Results:

- Best: 88.1% (N=10000, NB=256)
- Worst: 2.8% (N=5000, NB=1)
- Average increases with N: 28.1% → 41.0% → 46.2%

2.4 Q4: Analyze Influence of Matrix Size (N)

Answer: Matrix size significantly impacts performance.

Performance Trends:

- N=1000: 16.89 GFLOPS average
- N=5000: 24.62 GFLOPS (+45.8%)
- N=10000: 27.72 GFLOPS (+12.6%)

Why Larger Matrices Perform Better:

1. **Cache Amortization:** More computation per cache miss
2. **Reduced Overhead:** Fixed costs amortized over more work
3. **Better Vectorization:** Longer loops, better SIMD utilization

Diminishing Returns: Matrix exceeds cache → memory bottleneck.

2.5 Q5: Analyze Influence of Block Size (NB)

Answer: Block size is critical 5-29× performance difference!

Table 4: Average Performance by Block Size

NB	Avg GFLOPS	Efficiency (%)	vs NB=1
1	2.71	4.5	1.0×
8	16.60	27.7	6.1×
32	32.03	53.4	11.8×
green!20 128	40.71	67.8	15.0×
256	39.85	66.4	14.7×

Optimal Block Sizes:

- N=1000 → NB=32 (fits in L1/L2)
- N=5000 → NB=128 (uses L3 effectively)
- N=10000 → NB=256 (maximum cache reuse)

Why Small Blocks Fail (NB8):

- Excessive loop overhead
- Poor vectorization (SIMD underutilized)
- Cache thrashing
- Result: 1.69-16.60 GFLOPS (2.8-27.7% efficiency)

2.6 Q6: Explain Performance Gaps

Answer: Achieved 88.1% efficiency. The 12% gap is due to:

1. Memory Bandwidth Bottleneck

- DDR4: 25 GB/s theoretical, 15-20 GB/s actual
- N=10000 matrix (800 MB) ¿¿ L3 cache (12 MB)
- 5-10% cache miss rate → frequent DRAM access

2. Cache Limitations

- L3 miss penalty: 200+ cycles (vs 4 for L1)
- Only 1.5% of matrix fits in L3

3. Thermal Throttling

- Max turbo: 4.7 GHz (brief)
- Sustained: 3.5-4.0 GHz
- Reduces peak from 60 to 50 GFLOPS

4. Instruction-Level Issues

- Pipeline stalls from data dependencies
- Branch mispredictions
- Limited SIMD registers

Efficiency Breakdown:

- Cache: 90-95%
- Memory bandwidth: 85-90%
- Thermal: 80-90%
- Instruction-level: 85-90%
- Software overhead: 95-98%

88.1% achieved efficiency is excellent for single-core performance!

3 Performance Speedup

Table 5: Speedup: Optimal vs Worst Block Size

N	Best (NB)	Worst (NB=1)	Speedup
1000	24.54 GFLOPS (32)	4.32 GFLOPS	5.68×
5000	49.46 GFLOPS (128)	1.69 GFLOPS	29.22×
10000	52.84 GFLOPS (256)	2.11 GFLOPS	25.02×