CS4402-9535: Parallel and Distributed Systems

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CS4402-9535



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2 Optimizing Code for Data Locality: A Case Study

3 Multicore Programming





Electronic Numerical Integrator And Computer (ENIAC). The first general-purpose, electronic computer. It was a Turing-complete, digital computer capable of being reprogrammed and was running at 5,000 cycles per second for operations on the 10-digit numbers.



The IBM Personal Computer, commonly known as the IBM PC (Introduced on August 12, 1981).



The Pentium Family.







Main Memory







The CPU-Memory Gap

The increasing gap between DRAM, disk, and CPU speeds.



Once uopn a time, every thing was slow in a computer

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A typical matrix multiplication C code

```
#define IND(A, x, y, d) A[(x)*(d)+(y)]
uint64_t testMM(const int x, const int y, const int z)
Ł
  double *A: *B: *C:
        long started, ended;
        float timeTaken;
        int i, j, k;
        srand(getSeed());
        A = (double *)malloc(sizeof(double)*x*y);
        B = (double *)malloc(sizeof(double)*x*z);
        C = (double *)malloc(sizeof(double)*v*z);
        for (i = 0; i < x*z; i++) B[i] = (double) rand();</pre>
        for (i = 0; i < y*z; i++) C[i] = (double) rand() ;</pre>
        for (i = 0; i < x*y; i++) A[i] = 0;
        started = example_get_time();
        for (i = 0; i < x; i++)
          for (j = 0; j < y; j++)
             for (k = 0; k < z; k++)
                    // A[i][i] += B[i][k] + C[k][i];
                    IND(A,i,j,y) += IND(B,i,k,z) * IND(C,k,j,y);
        ended = example_get_time();
        timeTaken = (ended - started)/1.f;
  return timeTaken;
```

}

Issues with matrix representation



• Contiguous accesses are better:

- Data fetch as cache line (Core 2 Duo 64 byte per cache line)
- With contiguous data, a single cache fetch supports 8 reads of doubles.
- Transposing the matrix C should reduce L1 cache misses!

}

Transposing for optimizing spatial locality

```
float testMM(const int x. const int v. const int z)
ſ
  double *A; double *B; double *C; double *Cx;
        long started, ended; float timeTaken; int i, j, k;
        A = (double *)malloc(sizeof(double)*x*y);
        B = (double *)malloc(sizeof(double)*x*z):
        C = (double *)malloc(sizeof(double)*y*z);
        Cx = (double *)malloc(sizeof(double)*v*z);
        srand(getSeed());
        for (i = 0; i < x*z; i++) B[i] = (double) rand();</pre>
        for (i = 0; i < y*z; i++) C[i] = (double) rand();</pre>
        for (i = 0; i < x*y; i++) A[i] = 0;
        started = example_get_time();
        for(j =0; j < y; j++)</pre>
          for(k=0: k < z: k++)
            IND(Cx, j, k, z) = IND(C, k, j, y);
        for (i = 0; i < x; i++)
          for (j = 0; j < y; j++)
             for (k = 0; k < z; k++)
                IND(A, i, j, y) \models IND(B, i, k, z) \models IND(Cx, j, k, z);
        ended = example_get_time();
        timeTaken = (ended - started)/1.f:
  return timeTaken;
```

Issues with data reuse



- Naive calculation of a row of A, so computing 1024 coefficients: 1024 accesses in A, 384 in B and $1024 \times 384 = 393, 216$ in C. Total = 394, 524.
- Computing a 32×32 -block of A, so computing again 1024 coefficients: 1024 accesses in A, 384×32 in B and 32×384 in C. Total = 25,600.
- The iteration space is traversed so as to reduce memory accesses.

Blocking for optimizing temporal locality

```
float testMM(const int x, const int y, const int z)
{
        double *A: double *B: double *C:
        long started, ended; float timeTaken; int i, j, k, i0, j0, k0;
        A = (double *)malloc(sizeof(double)*x*y);
        B = (double *)malloc(sizeof(double)*x*z);
        C = (double *)malloc(sizeof(double)*v*z);
        srand(getSeed());
        for (i = 0; i < x*z; i++) B[i] = (double) rand();</pre>
        for (i = 0; i < y*z; i++) C[i] = (double) rand();</pre>
        for (i = 0; i < x*y; i++) A[i] = 0;
        started = example_get_time();
        for (i = 0; i < x; i += BLOCK_X)</pre>
          for (j = 0; j < y; j += BLOCK_Y)
            for (k = 0; k < z; k += BLOCK_Z)
              for (i0 = i: i0 < min(i + BLOCK X, x); i0++)
                for (j0 = j; j0 < min(j + BLOCK_Y, y); j0++)</pre>
                   for (k0 = k; k0 < min(k + BLOCK_Z, z); k0++)
                        IND(A,i0,j0,y) += IND(B,i0,k0,z) * IND(C,k0,j0,y);
         ended = example_get_time();
         timeTaken = (ended - started)/1.f:
  return timeTaken:
}
```

Transposing and blocking for optimizing data locality

```
float testMM(const int x, const int y, const int z)
ſ
        double *A; double *B; double *C, double *Cx;
        long started, ended; float timeTaken; int i, j, k, i0, j0, k0;
        A = (double *)malloc(sizeof(double)*x*y);
        B = (double *)malloc(sizeof(double)*x*z);
        C = (double *)malloc(sizeof(double)*y*z);
        srand(getSeed());
        for (i = 0; i < x*z; i++) B[i] = (double) rand();</pre>
        for (i = 0; i < y*z; i++) C[i] = (double) rand();</pre>
        for (i = 0; i < x*y; i++) A[i] = 0;
        started = example_get_time();
        for(j =0; j < y; j++)</pre>
          for (k=0: k < z: k++)
            IND(Cx,j,k,z) = IND(C,k,j,y);
        for (i = 0; i < x; i += BLOCK_X)
          for (j = 0; j < y; j += BLOCK_Y)
            for (k = 0; k < z; k += BLOCK_Z)
              for (i0 = i; i0 < min(i + BLOCK_X, x); i0++)</pre>
                for (j0 = j; j0 < min(j + BLOCK_Y, y); j0++)
                   for (k0 = k; k0 < min(k + BLOCK_Z, z); k0++)
                        IND(A,i0,j0,y) += IND(B,i0,k0,z) * IND(Cx,j0,k0,z);
        ended = example_get_time();
        timeTaken = (ended - started)/1.f;
```

Experimental results

Computing the product of two $n \times n$ matrices on my laptop (Quad-core Intel i7-3630QM CPU @ 2.40GHz L2 cache 6144 KB, 8 GBytes of RAM)

n	naive	transposed	8×8 -tiled	t. & t.
1024	7854	1086	1105	999
2048	8335	8646	10166	7990
4096	747100	69149	100538	69745
8192	6914349	546585	823525	562433

Timings are in milliseconds.

The cache-oblivious multiplication (more on this later) and the titled multiplication have similar performance.

Other performance counters

Hardware count events

- CPI Clock cycles Per Instruction: the number of clock cycles that happen when an instruction is being executed. With pipelining we can improve the CPI by exploiting instruction level parallelism
- L1 and L2 Cache Miss Rate.
- Instructions Retired: In the event of a misprediction, instructions that were scheduled to execute along the mispredicted path must be canceled.

	СРІ	L1 Miss Rate	L2 Miss Rate	Percent SSE Instructions	Instructions Retired
In C	4.78	0.24	0.02	43%	13,137,280,000
	- 5x	- 2x			- 1x
Transposed	1.13	0.15	0.02	50%	13,001,486,336
	- 3x	- 8x			-0.8x
Tiled	0.49	0.02	0	39%	18,044,811,264

Analyzing cache misses in the naive and transposed multiplication



- Let A, B and C have format (m, n), (m, p) and (p, n) respectively.
- A is scanned once, so mn/L cache misses if L is the number of coefficients per cache line.
- B is scanned n times, so mnp/L cache misses if the cache cannot hold a row.
- C is accessed "nearly randomly" (for m large enough) leading to mnp cache misses.
- Since 2m n p arithmetic operations are performed, this means roughly one cache miss per flop!
- If C is transposed, then the ratio improves to 1 for L.

Analyzing cache misses in the tiled multiplication



- \bullet Let $A,\,B$ and C have format $(m,n),\,(m,p)$ and (p,n) respectively.
- Assume all tiles are square of order b and three fit in cache.
- If C is transposed, then loading three blocks in cache cost $3b^2/L$.
- This process happens n^3/b^3 times, leading to $3n^3/(bL)$ cache misses.
- Three blocks fit in cache for $3b^2 < Z$, if Z is the cache size.
- So $O(n^3/(\sqrt{Z}L))$ cache misses, if b is well chosen, which is optimal.

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Cilk and CilkPlus

- Cilk has been developed since 1994 at the MIT Laboratory for Computer Science by Prof. Charles E. Leiserson and his group, in particular by Matteo Frigo.
- Cilk has been integrated into Intel C compiler under the name CilkPlus, see http://www.cilk.com/
- CilkPlus (resp. Cilk) is a small set of linguistic extensions to C++ (resp. C) supporting fork-join parallelism
- Both Cilk and CilkPlus feature a provably efficient work-stealing scheduler.
- CilkPlus provides a hyperobject library for parallelizing code with global variables and performing reduction for data aggregation.
- CilkPlus includes the Cilkscreen race detector and the Cilkview performance analyzer.

Nested Parallelism in CilkPlus

```
int fib(int n)
{
    if (n < 2) return n;
    int x, y;
    x = cilk_spawn fib(n-1);
    y = fib(n-2);
    cilk_sync;
    return x+y;
}</pre>
```

- The named child function cilk_spawn fib(n-1) may execute in parallel with its parent
- CilkPlus keywords cilk_spawn and cilk_sync grant permissions for parallel execution. They do not command parallel execution.

Scheduling



A **scheduler**'s job is to map a computation to particular processors. Such a mapping is called a **schedule**.

- If decisions are made at runtime, the scheduler is *online*, otherwise, it is *offline*
- Cilk++'s scheduler maps strands onto processors dynamically at runtime.

The CilkPlus Platform



Benchmarks for the parallel version of the divide-n-conquer mm

Multiplying a 4000x8000 matrix by a 8000x4000 matrix

- on 32 cores = 8 sockets x 4 cores (Quad Core AMD Opteron 8354) per socket.
- The 32 cores share a L3 32-way set-associative cache of 2 Mbytes.

#core	Elision (s)	Parallel (s)	speedup
8	420.906	51.365	8.19
16	432.419	25.845	16.73
24	413.681	17.361	23.83
32	389.300	13.051	29.83

Benchmarks using Cilkview



Speedup for 'multiply 5000x10000 matrix by 10000x5000 matrix'

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What are the prerequisites?

- Some familiarity with algorithms and their analysis.
- Elementary linear algebra (matrix multiplication).
- Ideas about multithreaded programming.
- Some ideas about multi-core processors and GPUs.

What are the objectives of this course?

- Understand why data locality can have a huge impact on code performances.
- Acquire techniques for analyzing and improving data locality.
- Understand the concepts of work, span, parallelism, burdened parallelism in multithreaded programming.
- Acquire techniques for analyzing and improving parallelism in multithreaded programming.
- Understand issues related to parallelism overheads in GPU programming
- Acquire techniques for reducing parallelism overheads of a GPU kernel.

Course Topics

- Week 1: Introduction to Multicore Programming
- Week 2: Multithreaded Parallelism and the CilkPlus concurrency platform
- Week 3: Analysis of Multithreaded Algorithms
- Week 4: Issues with data locality and code parallelization
- Week 5: Cache complexity
- Week 6: Synchronizing without Locks and Concurrent Data Structures
- Week 7: Pipelining (Cilk-P, TBB)
- Weeks 8: CUDA Programming model
- Week 9-10: CUDA Implementation on the GPU
 - Week 11: Code optimization with CUDA
 - Weeks 12: Multiprocessed parallelism, message passing (MPI)
 - Week 13: Course project presentations

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High-performance computing and symbolic computation





www.regularchains.org

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