Advanced Computer Architecture

Chapter 4: Caches and Memory Systems Part 2: miss rate reduction using software

October 2023 Paul H J Kelly

These lecture notes are partly based on the course text, Hennessy and Patterson's Computer Architecture, a quantitative approach (3rd, 4^{th,} 5th and 6th eds), and on the lecture slides of David Patterson and John Kubiatowicz's Berkeley course

Average memory access time:

AMAT = HitTime + MissRate × MissPenalty

There are three ways to improve AMAT:

- 1. Reduce the miss rate,
 - 2. Reduce the miss penalty, or
 - 3. Reduce the time to hit in the cache

We now look at each of these in turn...

In hardware

In software

Reducing misses by software prefetching

1:

- Some processors have instructions to trigger prefetching explicitly, in software
- Almost never worth using on sophisticated processors with good hardware prefetching
- May be useful on simpler processors —
- Some care is needed to ensure prefetch accesses don't have unwanted side effects
 - Eg memory-mapped i/o registers
 - (this is the function of the R10KCBARRIER macro) —
- Prefetch instructions may target addresses that would cause a page fault or protection violation
 - Prefetches of addresses that would result in a page fault or exception are silently squashed

R10KCBARRIER(0(ra))
LOAD(t0, UNIT(0)(src), .Ll_exc\@)
<pre>LOAD(t1, UNIT(1)(src), .Ll_exc_copy\@)</pre>
<pre>LOAD(t2, UNIT(2)(src), .Ll_exc_copy\@)</pre>
<pre>LOAD(t3, UNIT(3)(src), .Ll_exc_copy\@)</pre>
SUB len, len, 8*NBYTES
<pre>LOAD(t4, UNIT(4)(src), .Ll_exc_copy\@)</pre>
<pre>LOAD(t7, UNIT(5)(src), .Ll_exc_copy\@)</pre>
<pre>STORE(t0, UNIT(0)(dst), .Ls_exc_p8u\@)</pre>
<pre>STORE(t1, UNIT(1)(dst), .Ls_exc_p7u\@)</pre>
<pre>LOAD(t0, UNIT(6)(src), .Ll_exc_copy\@)</pre>
<pre>LOAD(t1, UNIT(7)(src), .Ll_exc_copy\@)</pre>
ADD src, src, 8*NBYTES
ADD dst, dst, 8*NBYTES
<pre>STORE(t2, UNIT(-6)(dst), .Ls_exc_p6u\@)</pre>
<pre>STORE(t3, UNIT(-5)(dst), .Ls_exc_p5u\@)</pre>
<pre>STORE(t4, UNIT(-4)(dst), .Ls_exc_p4u\@)</pre>
STORE(t7, UNIT (-3)(dst), .Ls exc p3u\@)
<pre>STORE(t0, UNIT(-2)(dst), .Ls_exc_p2u\@)</pre>
<pre>STORE(t1, UNIT(-1)(dst), .Ls_exc_p1u\@)</pre>
PREFS (0, 8*32(src))
<pre>PREFD(1, 8*32(dst))</pre>
bne len, rem , 1b
nop

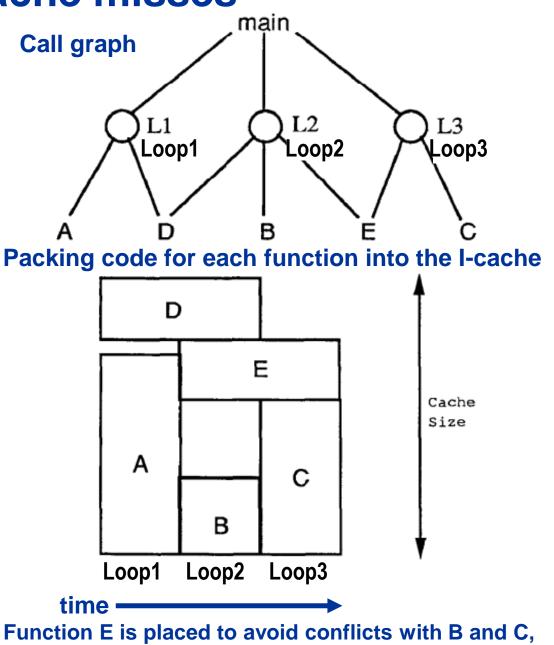
- Example: MIPS "memcpy" library code handwritten assembler unrolled 12 times, manually scheduled, with prefetching to initiate loading the source and destination cache lines into cache (heavy use of macros)
- From https://elixir.bootlin.com/linux/v5.9.2/source/arch/mips/lib/memcpy.S

Reducing instruction-cache misses

McFarling [1989]* reduced instruction cache misses by 75% on 8KB direct mapped cache, 4 byte blocks in software

Instructions

- By choosing instruction memory layout based on callgraph, branch structure and profile data
- Reorder procedures in memory so as to reduce conflict misses
- (actually this really needs the whole program – a link-time optimisation)



* "Program optimization for instruction caches", ASPLOS89, http://doi.acm.org/10.1145/70082.68200

Storage layout transformations

- Merging Arrays: improve spatial locality by single array of compound elements vs. 2 arrays
- Permuting a multidimensional array: improve spatial locality by matching array layout to traversal order

Improve spatial locality

Iteration space transformations

- Loop Interchange: change nesting of loops to access data in order stored in memory
- Loop Fusion: Combine 2 independent loops that have same looping and some variables overlap
- Blocking: Improve temporal locality by accessing "blocks" of data repeatedly vs. going down whole columns or rows (wait for Chapter 4)

Can also improve temporal locality

```
/* Before: 2 sequential arrays */
int val[SIZE];
int key[SIZE];
```

/* After: 1 array of stuctures */ struct merge { int val; int key; }; struct merge merged_array[SIZE];

Array Merging - example

"Array of Structs" vs "Struct of Arrays"

(AoS vs SoA)

Reducing conflicts between val & key (example?) Improve spatial locality (counter-example?)

 whether this is a good idea depends on access pattern

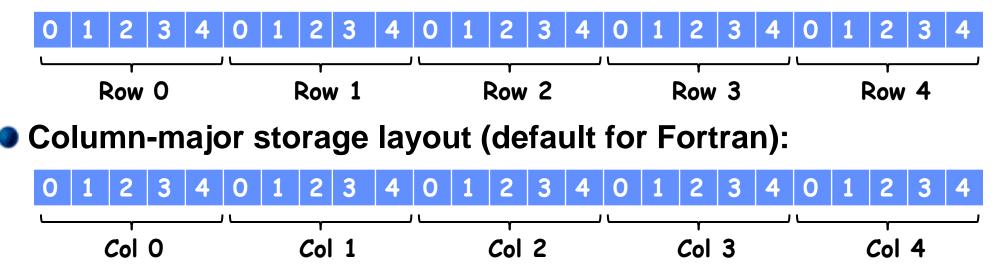
(actually this is a transpose: 2*SIZE -> SIZE*2)

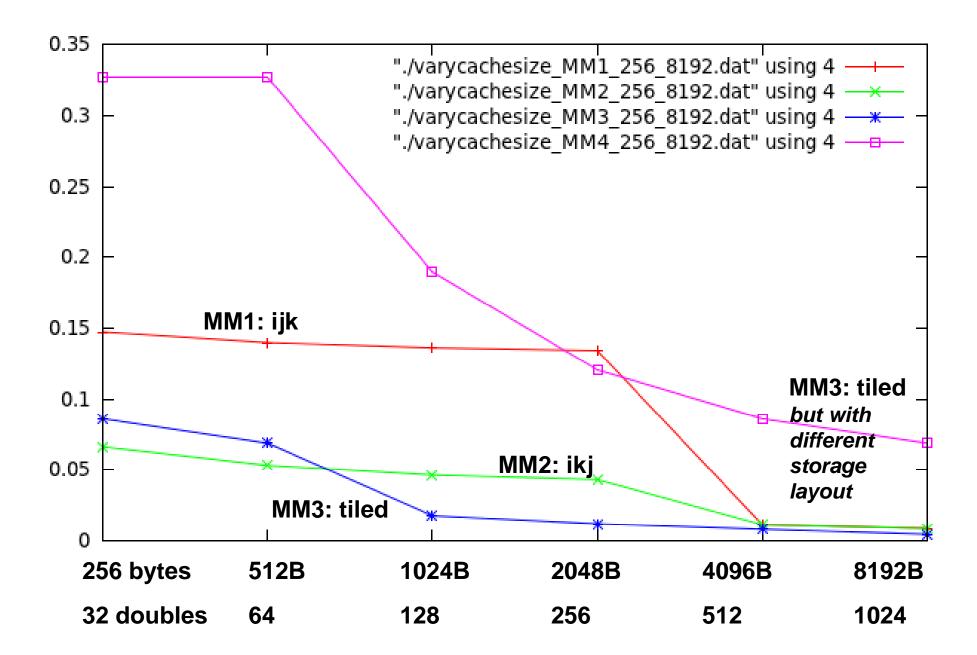
Consider matrix-matrix multiply (tutorial ex)

MM1:
 MM2:
 for (i=0;i<N;i++)
 for (j=0;j<N;j++)
 for (k=0;k<N;k++)
 for (k=0;k<N;k++)
 for (j=0;j
 C[i][j] += A[i][k] * B[k][j];

MM2: for (i=0;i<N;i++) for (k=0;k<N;k++) for (j=0;j<N;j++)</p>
C[i][j] += A[i][k] * B[k][j];

Row-major storage layout (default for C):

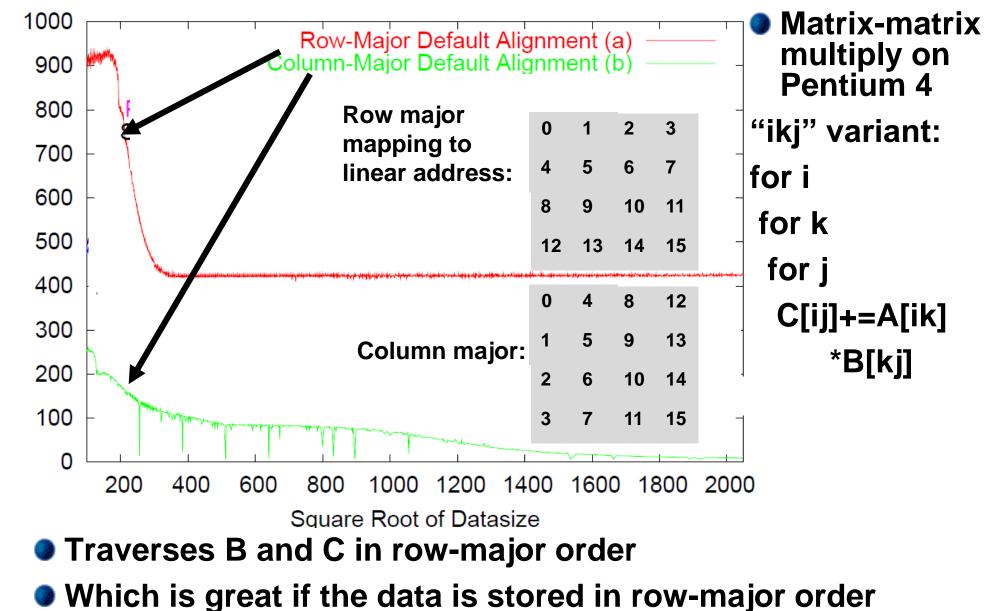




Problem size: 192 doubles, 1536 bytes per row

Permuting multidimensional arrays to improve spatial locality

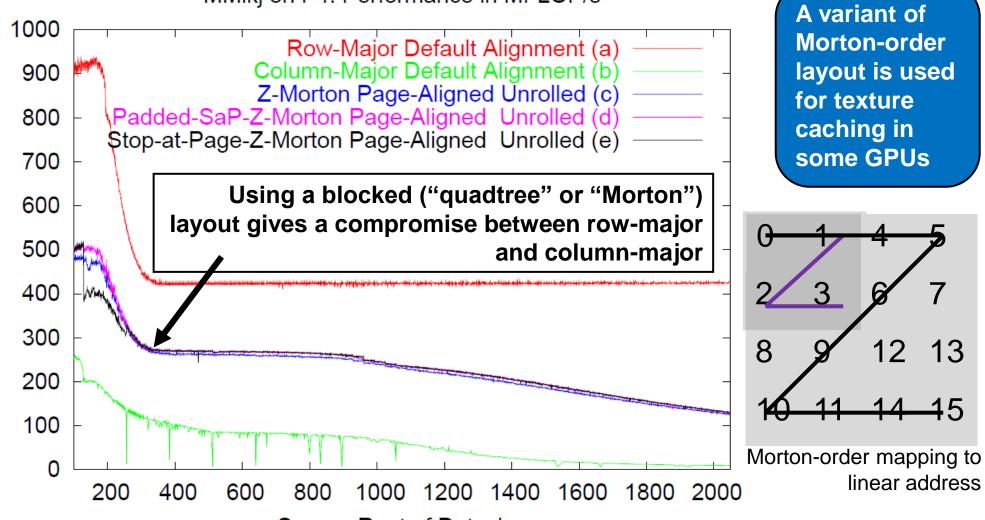
MMikj on P4: Performance in MFLOP/s



If data is actually in column-major order...

Permuting multidimensional arrays to improve spatial locality

MMikj on P4: Performance in MFLOP/s



Square Root of Datasize

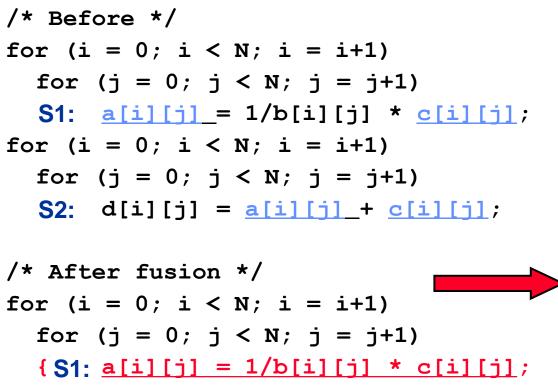
- Blocked layout offers compromise between row-major and columnmajor
- Some care is needed in optimising address calculation to make this work (Jeyan Thiyagalingam's Imperial PhD thesis)

Loop Interchange: example

```
/* Before */
for (k = 0; k < 100; k = k+1)
  for (j = 0; j < 100; j = j+1)
        for (i = 0; i < 5000; i = i+1)
                x[i][j] = 2 * x[i][j];
/* After */
for (k = 0; k < 100; k = k+1)
  <u>for (i = 0; i < 5000; i = i+1)</u>
     → <u>for (j = 0; j < 100; j = j+1)</u>
                x[i][j] = 2 * x[i][j];
```

Sequential accesses: instead of striding through memory every 100 words; improved spatial locality

Loop Fusion: example



S2: d[i][j] = a[i][j] + c[i][j];

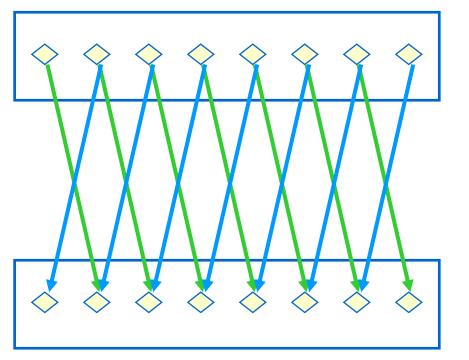
2 misses per access to a & c vs. one miss per access; improve spatial locality

<mark>(51</mark> **S1 S1** (51) (51 (51) **S1** (<mark>\$</mark>2) **S**2 **S2** /* After array contraction */ for (i = 0; i < N; i = i+1)for (j = 0; j < N; j = j+1) $\{ cv = c[i][j]; \}$ S1: a = 1/b[i][j] * cv;S2: d[i][j] = a + cv;

The real payoff comes if fusion enables Array Contraction: values transferred in scalar instead of via array

Fusion is not always so simple

- Dependences might not align nicely
- Example: one-dimensional convolution filters

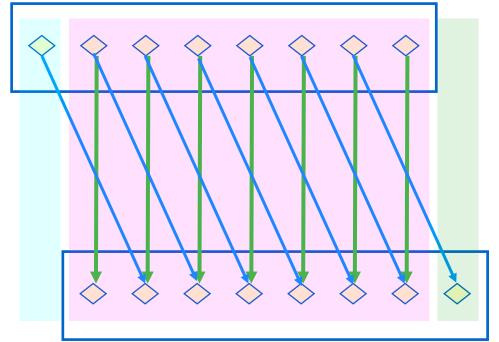


for (i=1; i<N; i++) V[i] = (U[i-1] + U[i+1])/2

• "Stencil" loops are not directly fusable

Loop fusion – code expansion

We make them fusable by shifting:



$$V[1] = (U[0] + U[2])/2$$

for (i=2; i V[i] = (U[i-1] + U[i+1])/2
 W[i-1] = (V[i-2] + V[i])/2
}

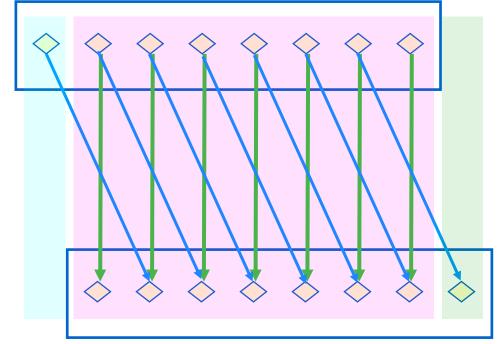
W[N-1] = (V[N-2] + V[N])/2

The middle loop is fusableWe get lots of little edge bits

Loop fusion – code expansion

We make them fusable by shifting:

This transformation is important in image-processing filters, finite difference solvers, and convolutional neural networks



The middle loop is fusableWe get lots of little edge bits

V[1] = (U[0] + U[2])/2for (i=2; i<N; i++) { V[i%4] = (U[i-1] + U[i+1])/2 W[i-1] = (V[(i-2)%4] + V[i%4])/2

W[N-1] = (V[(N-2)%4] + V[N%4])/2

- Contraction is trickier
- We need the last two Vs
- We need 3 V locations
- Quicker to round up to four

Summary

We can reduce the miss rate at the software level

By using prefetch instructions
If they work better than predictive prefetch hardware

- By transforming storage layout
 Might help with *spatial* locality
 Might help with associativity conflicts
 Can't help with *temporal* locality
- Storage layout optimisations are disruptive they affect all the code that might use that data
- Loop interchange, fusion, tiling

Can get really messy to implement by hand

Can lead to a large space of possible schedules – it can be hard to know what will work best

Loop fusion can be very powerful but often breaks abstraction boundaries

Further reading

Algorithms and locality: cache-oblivious algorithms:

https://en.wikipedia.org/wiki/Cache-oblivious_algorithm

Compilers that optimise for locality:

- Michael E. Wolf and Monica S. Lam. 1991. A data locality optimizing algorithm. PLDI91.
- Kathryn S. McKinley, Steve Carr, and Chau-Wen Tseng. 1996. Improving data locality with loop transformations. ACM Trans. Program. Lang. Syst. 18, 4 (July 1996)
- Uday Bondhugula, Albert Hartono, J. Ramanujam, and P. Sadayappan. 2008. A practical automatic polyhedral parallelizer and locality optimizer. PLDI08
- Programming Abstractions for Data Locality
- https://sites.google.com/a/lbl.gov/padal-workshop/
- Optimisations for convolutional neural networks
- Yizhi Liu, Yao Wang, Ruofei Yu, Mu Li, Vin Sharma, Yida Wang. Optimizing CNN model inference on CPUs. USENIX ATC'19.