

# Andrew Faulring

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- Office hours:
  - NSH 2504 (lab) / 2507 (conference room)
  - Thursday 5–6
- Lab 4
  - due Thursday, 24 Oct @ 11:59pm
  - Submission is online
    - <http://www2.cs.cmu.edu/afs/cs/academic/class/15213-f02/www/L4.html>

## Recitation 7: Memory Access Patterns

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15213 Section A  
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## Today's Plan

- Loop Unrolling
- Blocking

## Loop Unrolling

```
void combine5(vec_ptr v, int *dest)
{
    int length = vec_length(v);
    int limit = length-2;
    int *data = get_vec_start(v);
    int sum = 0;
    int i;
    /* Combine 3 elements at a time */
    for (i = 0; i < limit; i+=3) {
        sum += data[i] + data[i+1]
            + data[i+2];
    }
    /* Finish any remaining elements */
    for (; i < length; i++) {
        sum += data[i];
    }
    *dest = sum;
}
```

- Optimization
  - Combine multiple iterations into single loop body
  - Amortizes loop overhead across multiple iterations
  - Finish extras at end

# Practice Problem

- Problem 5.12 and 5.13

## Solution 5.12

- A. We must perform two loads per element to read values for **udata** and **vdata**. There is only one unit to perform these loads, and it requires one cycle.
- B. The performance for floating point is still limited by the 3 cycle latency of the floating-point adder.

## Solution 5.12

```
void inner5(vec_ptr u, vec_ptr v, data_t *dest)
{
    int i;
    int length = vec_length(u);
    int limit = length-3;
    data_t *udata = get_vec_start(u);
    data_t *vdata = get_vec_start(v);
    data_t sum = (data_t) 0;

    /* Do four elements at a time */
    for (i = 0; i < limit; i += 4) {
        sum += udata[i] * vdata[i] + udata[i+1] * vdata[i+1]
            + udata[i+2] * vdata[i+2] + udata[i+3] * vdata[i+3];
    }

    /* Finish off any remaining elements */
    for (; i < length; i++)
        sum += udata[i] * vdata[i];

    *dest = sum;
}
```

## Solution 5.13

```
void inner6(vec_ptr u, vec_ptr v, data_t *dest)
{
    int i;
    int length = vec_length(u);
    int limit = length-3;
    data_t *udata = get_vec_start(u);
    data_t *vdata = get_vec_start(v);
    data_t sum0 = (data_t) 0;
    data_t sum1 = (data_t) 0;

    /* Do four elements at a time */
    for (i = 0; i < limit; i+=4) {
        sum0 += udata[i] * vdata[i];
        sum1 += udata[i+1] * vdata[i+1];
        sum0 += udata[i+2] * vdata[i+2];
        sum1 += udata[i+3] * vdata[i+3];
    }

    /* Finish off any remaining elements */
    for (; i < length; i++)
        sum0 = sum0 + udata[i] * vdata[i];

    *dest = sum0 + sum1;
}
```

# Solution 5.13

- For each element, we must perform two loads with a unit that can only load one value per clock cycle.
- We must also perform one floating-point multiplication with a unit that can only perform one multiplication every two clock cycles.
- Both of these factors limit the CPE to 2.

# Summary of Matrix Multiplication

## ijk (& jik):

- 2 loads, 0 stores
- misses/iter = 1.25

```
for (i=0; i<n; i++) {
    for (j=0; j<n; j++) {
        sum = 0.0;
        for (k=0; k<n; k++) {
            sum += a[i][k]
                * b[k][j];
            c[i][j] = sum;
        }
    }
}
```

## kij (& ikj):

- 2 loads, 1 store
- misses/iter = 0.5

```
for (k=0; k<n; k++) {
    for (i=0; i<n; i++) {
        r = a[i][k];
        for (j=0; j<n; j++)
            c[i][j] += r
                * b[k][j];
    }
}
```

## jki (& kji):

- 2 loads, 1 store
- misses/iter = 2.0

```
for (j=0; j<n; j++) {
    for (k=0; k<n; k++) {
        r = b[k][j];
        for (i=0; i<n; i++)
            c[i][j] +=
                a[i][k] * r;
    }
}
```

# Improving Temporal Locality by Blocking

- Example: Blocked matrix multiplication
  - “block” (in this context) does not mean “cache block”.
  - Instead, it means a sub-block within the matrix.
  - Example: N = 8; sub-block size = 4

$$\begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \times \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} = \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix}$$

Key idea: Sub-blocks (i.e.,  $A_{xy}$ ) can be treated just like scalars.

$$C_{11} = A_{11}B_{11} + A_{12}B_{21} \quad C_{12} = A_{11}B_{12} + A_{12}B_{22}$$

$$C_{21} = A_{21}B_{11} + A_{22}B_{21} \quad C_{22} = A_{21}B_{12} + A_{22}B_{22}$$

# Blocked Matrix Multiply (bijk)

```
for (jj=0; jj<n; jj+=bsize) {
    for (i=0; i<n; i++)
        for (j=jj; j < min(jj+bsize,n); j++)
            c[i][j] = 0.0;
    for (kk=0; kk<n; kk+=bsize) {
        for (i=0; i<n; i++) {
            for (j=jj; j < min(jj+bsize,n); j++) {
                sum = 0.0
                for (k=kk; k < min(kk+bsize,n); k++)
                    sum += a[i][k] * b[k][j];
                c[i][j] += sum;
            }
        }
    }
}
```

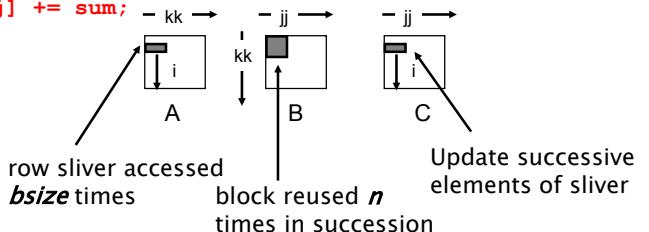
- Provides temporal locality as block is reused multiple times
- Constant cache performance

# Blocked Matrix Multiply

## Analysis

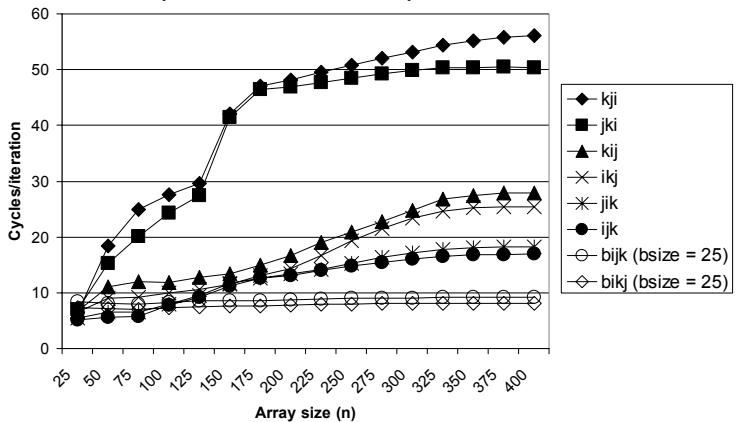
- Innermost loop pair multiplies a  $1 \times bsize$  sliver of  $A$  by a  $bsize \times bsize$  block of  $B$  and accumulates into  $1 \times bsize$  sliver of  $C$
- Loop over  $i$  steps through  $n$  row slivers of  $A$  &  $C$ , using same  $B$

```
for (i=0; i<n; i++) {
    for (j=jj; j < min(jj+bsize,n); j++) {
        sum = 0.0
        for (k=kk; k < min(kk+bsize,n); k++) {
            sum += a[i][k] * b[k][j];
        }
        c[i][j] += sum;
    }
}
```



# Pentium Blocked Matrix Multiply Performance

- Blocking (bijk and bikj) improves performance by a factor of two over unblocked versions (ijk and jik)
  - relatively insensitive to array size.



## Summary

- All systems favor “cache friendly code”
  - Getting absolute optimum performance is very platform specific
    - Cache sizes, line sizes, associativities, etc.
  - Can get most of the advantage with generic code
    - Keep working set reasonably small (temporal locality)
    - Use small strides (spatial locality)