



PROGRAMMING AND OPTIMIZATION FOR INTEL[®] ARCHITECTURE

Hands-On Workshop (HOW) Series "Deep Dive"

Session 7

Colfax International — colfaxresearch.com

February 2017

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- ▶ **Module I. Programming**
 - 01. Intel Architecture and Modern Code – Feb 13
 - 02. Xeon Phi, Coprocessors, Omni-Path – Feb 14
- ▶ **Module II. Expressing Parallelism**
 - 03. Automatic vectorization – Feb 15
 - 04. Multi-threading with OpenMP – Feb 16
 - 06. Distributed Computing, MPI – Feb 17
- ▶ **Module III. Optimization**
 - 06. Optimization Overview: N-body – Feb 20
 - 07. Scalar tuning, Vectorization – Feb 21
 - 08. Common Multi-threading Problems – Feb 22
 - 09. Multi-threading, Memory Aspect – Feb 23
 - 10. Access to Caches and Memory – Feb 24

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Course page:

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- ▶ Slides
- ▶ Code
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Forum

Colfax Cluster

Discussion of Colfax Cluster usage policies, troubleshooting.

Modern Code

Discuss with Colfax Research and colleagues any topics related to computational science, parallel programming, performance optimization and code modernization.

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Questions about any of the Colfax trainings? Usage of training servers, experience with specific exercises, inquiries on what's inside, suggestions for future trainings - post them here.

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colfaxresearch.com/discussion

- ▶ All registrants receive an invitation from `cluster@colfaxresearch.com`
- ▶ Queue-based access to Intel Xeon E5, Intel Xeon Phi (KNC and KNL)
- ▶ Can access the cluster the entire 2 weeks of the workshop





§2. PERFORMANCE OPTIMIZATION

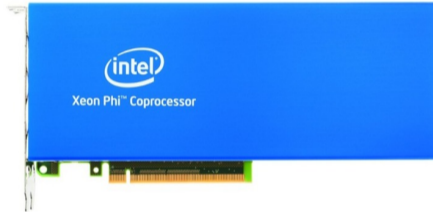
Intel Xeon Processor



Current: Broadwell
Upcoming: Skylake

Multi-Core Architecture

Intel Xeon Phi Coprocessor, 1st generation



Knights Corner (KNC)

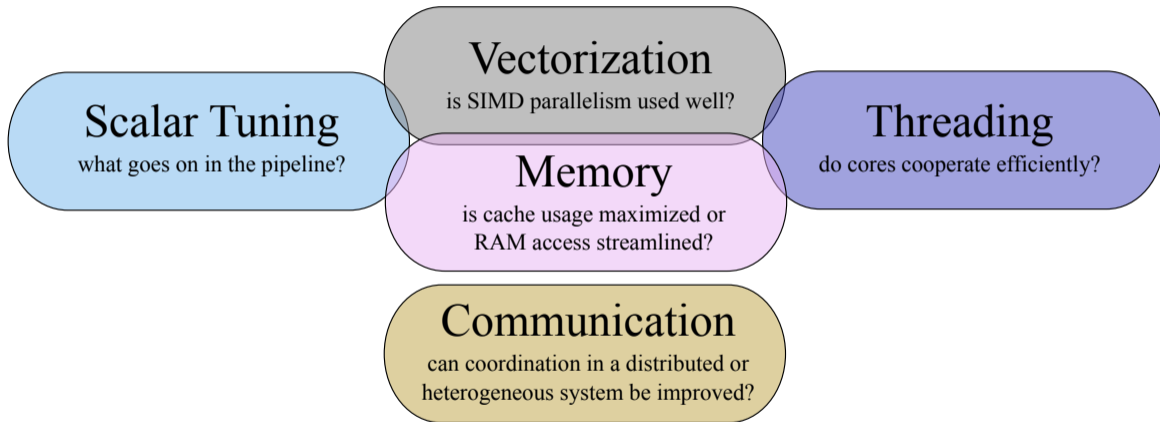
Intel Xeon Phi Processor, 2nd generation*



* socket and coprocessor versions

Knights Landing (KNL)

Intel Many Integrated Core (MIC) Architecture



§3. SCALAR TUNING



COMPILER ARGUMENTS

PERFORMANCE-RELATED ARGUMENTS FOR INTEL COMPILERS

- O<n> – optimization level (n=0, 1, 2, 3 or s)
 - g – debugging symbols (resets optimization to -O0)
- fp-model <model> – floating-point semantics (model=strict, precise, fast=1 or fast=2)
- fimf-precision=<value> – transcendental function precision (value=high, medium or low)
- x<code> – target arch. (code=MIC-AVX512, CORE-AVX2, etc., or host)
- ax<code> – dispatch for multiple target architectures
 - ipo – inter-procedural optimization

Click above for links in the [Intel C++ Compiler User and Reference Guide](#)

OPTIMIZATION LEVEL

Default optimization level -O2

- ▶ optimization for speed
- ▶ automatic vectorization
- ▶ inlining
- ▶ constant propagation
- ▶ dead-code elimination
- ▶ loop unrolling

Optimization level -O3

- ▶ aggressive optimization
- ▶ loop fusion
- ▶ block-unroll-and-jam
- ▶ if-statement collapse
- ▶ *may or may not be better than -O2*

SETTING OPTIMIZATION LEVEL

For the entire file:

```
vega@lyra% icpc -o mycode -O3 source.cc
```

For a specific function:

```
1 #pragma intel optimization_level 3
2 void my_function() {
3     //...
4 }
```



PROGRAMMING PRACTICES

STRENGTH REDUCTION

Common Subexpression Elimination.

```

1  for (int i = 0; i < n; i++) {
2      A[i] /= B;
3  }
```

```

1  const float Br = 1.0f/B;
2  for (int i = 0; i < n; i++)
3      A[i] *= Br;
```

Replace division with multiplication.

```

1  for (int i = 0; i < n; i++) {
2      P[i] = (Q[i]/R[i])/S[i];
3  }
```

```

1  for (int i = 0; i < n; i++) {
2      P[i] = Q[i]/(R[i]*S[i]);
3  }
```

Use functions with Hardware support.

```

1  double r = pow(r2, -0.5);
2  double v = exp(x);
3  double y = y0*exp(log(x/x0)*
4              log(y1/y0)/log(x1/x0));
```

```

1  double r = 1.0/sqrt(r2);
2  double v = exp2(x*1.44269504089);
3  double y = y0*exp2(log2(x/x0)*
4              log2(y1/y0)/log2(x1/x0));
```

PERFORMANCE OF VECTOR INSTRUCTIONS IN KNL

All values in cycles. Lower is better.

Instruction	Latency	1/Throughput
Most vector math and FMA	6	0.5
64-bit exp2a23, rcp28 and rsqrt28	7	2
32-bit exp2a23, rcp28 and rsqrt28	8	3
Floating-point division and sqrt	38	10
Simple integer math	2	2
32-bit scalar division	25	20
64-bit scalar division	40	30
Type conversion (same width)	2	1
Type conversion (different widths)	6	5

CONSISTENCY OF PRECISION: CONSTANTS

```
1 // Bad: 2 is "int"
2 long b=a*2;
3
4 // Bad: overflow
5 long n=100000*100000;
6
7 // Bad: excessive
8 float p=6.283185307179586;
9
10 // Bad: 2 is "int"
11 float q=2*p;
12
13 // Bad: 1e9 is "double"
14 float r=1e9*p;
15
16 // Bad: 1 is "int"
17 double t=s+1;
```

```
1 // Good: 2L is "long"
2 long b=a*2L;
3
4 // Good: correct
5 long n=100000L*100000L;
6
7 // Good: accurate
8 float p=6.283185f;
9
10 // Good: 2.0f is "float"
11 float q=2.0f*p;
12
13 // Good: 1e9f is "float"
14 float r=1e9f*p;
15
16 // Good: 1.0 is "double"
17 double t=s+1.0;
```

CONSISTENCY OF PRECISION: FUNCTIONS

```
1 // Bad: 3.14 is a double
2 float x = 3.14;
3
4 // Bad: sin() is a
5 // double precision function
6 float s = sin(x);
7
8 // Bad: round() takes double
9 // and returns double
10 long v = round(x);
11
12 // Bad: abs() is not from IML
13 // it takes int and returns int
14 int v = abs(x);
```

```
1 // Good: 3.14f is a float
2 float x = 3.14f;
3
4 // Good: sin() is a
5 // single precision function
6 float s = sinf(x);
7
8 // Good: lroundf() takes float
9 // and returns long
10 long v = lroundf(x);
11
12 // Good: fabsf() is from IML
13 // It takes and returns a float
14 float v = fabsf(x);
```

CONSISTENCY OF PRECISION: FUNCTIONS

Transcendental functions are *not* overloaded (unless in namespace `std` in C++).

```
vega@lyra% ./Scalar-TestF0verload
Proof that exp() is not overloaded:
exp (1.0f)=2.7182818284590451
exp (1.0 )=2.7182818284590451
Exact:    e=2.71828182845904523536...

Proof that expf() gives lower precision:
expf(1.0f)=2.7182817459106445
expf(1.0 )=2.7182817459106445
Exact:    e=2.71828182845904523536...

Overloading in namespace std:
std::exp(1.0f)=2.7182817459106445
std::exp(1.0 )=2.7182818284590451
Exact:    e=2.71828182845904523536...
```

MOVE BRANCHES OUTSIDE OF LOOPS

```
1 // Elegant, but bad for performance
2 for (i = 0; i < n; i++) {
3     if (i == 0) {
4         // Absorbing boundary
5         B[i] = 0.0;
6     } else if (i == n - 1) {
7         // Injection at boundary
8         B[i] = A[i] + 1.0;
9     } else {
10        // Diffusion between boundaries
11        B[i] = 0.25*(A[i-1] +
12                    2.0*A[i] + A[i+1]);
13    }
14 }
```

```
1 // Moving branches out of loops
2
3
4 // Absorbing boundary
5 B[i] = 0.0;
6
7 for (i = 1; i < n - 1; i++) {
8     // Diffusion between boundaries
9     B[i] = 0.25*(A[i-1] + 2.0*A[i] +
10                 A[i+1]);
11 }
12
13 // Injection at boundary
14 B[n-1] = A[n-1] + 1.0;
```

REDUNDANT CODE IS OK

```
1 // Elegant, but bad for performance
2 for (ii = 0; ii < n; ii+=16) {
3     for (i = ii; i < ii+16; i++)
4         // Branch causes unnecessary
5         // masking of vector iterations
6         if (i < n) {
7             A[k*n + i] = ...
8         }
9 }
```

```
1 // Redundant code, but faster
2 const int nTrunc = n - n%16;
3 for (ii = 0; ii < nTrunc; ii+=16) {
4     for (i = ii; i < ii+16; i++)
5         A[k*n + i] = ...
6
7     for (i = nTrunc; i < n; i++)
8         A[k*n + i] = ...
9 }
```



§4. VECTORIZATION

SHORT VECTOR SUPPORT

Vector instructions – one of the implementations of SIMD (Single Instruction Multiple Data) parallelism.

Scalar Instructions

$$\begin{array}{r} 4 + 1 = 5 \\ 0 + 3 = 3 \\ -2 + 8 = 6 \\ 9 + -7 = 2 \end{array}$$

Vector Instructions

$$\begin{array}{r} 4 \\ 0 \\ -2 \\ 9 \end{array} + \begin{array}{r} 1 \\ 3 \\ 8 \\ -7 \end{array} = \begin{array}{r} 5 \\ 3 \\ 6 \\ 2 \end{array}$$

↑ Vector Length ↓



DATA STRUCTURES AND MEMORY ACCESS

UNIT-STRIDE ACCESS

Unit-stride access is optimal:

```
1 for (int i = 0; i < n; i++)
2   A[i] += B[i];
```

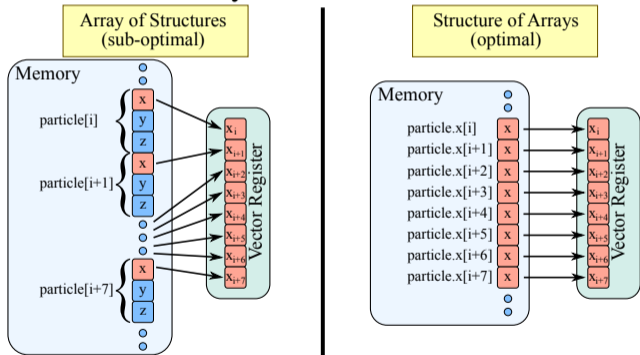
Non-unit stride is slower:

```
1 for (int i = 0; i < n; i++)
2   A[i*stride] += B[i];
```

Stochastic access may be vectorized (but not efficient):

```
1 for (int i = 0; i < n; i++)
2   A[offset[i]] += B[i];
```

It may be a question of changing the order of loop nesting, but sometimes you need to modify data structures:



SUGGESTED EXERCISE

Review lab 4.01 (N-body simulation) or perform lab 4.02 (Coulomb's law calculation) to re-visit the AoS to SoA conversion.



ALIGNMENT AND PADDING

DATA ALIGNMENT REQUIREMENTS

Array `char* p` is `n`-byte aligned if `((size_t)p%n==0)`.

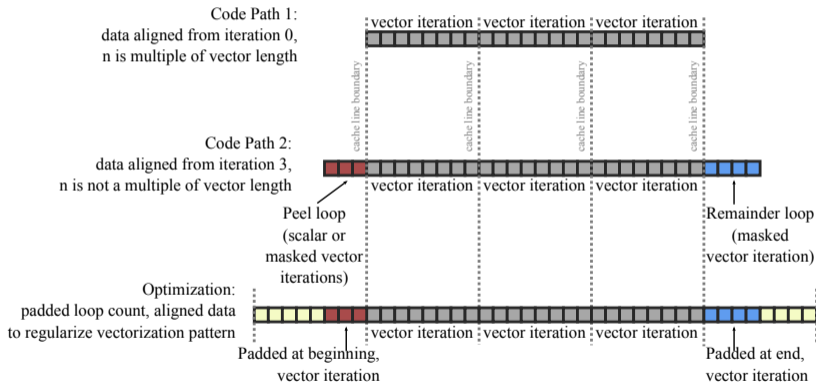
Processor	Operation	Alignment
Xeon (Westmere and earlier)	SSE load, store	16-byte
Xeon (Sandy Bridge and later)	AVX load, store	32-byte (relaxed)
Xeon Phi (1st gen)	IMCI load, store	64-byte (strict)
Xeon Phi (1st gen)	DMA transfer in offload	4096-byte (preferred)
Xeon Phi (2nd gen)	AVX-512 load, store	64-byte (relaxed)

Why align: speed up vector load/stores, avoid false sharing, accelerate RDMA.

WHAT HAPPENS WITHOUT ALIGNMENT

Compiler may implement peel and remainder loops:

```
for (i = 0; i < n; i++) A[i] = ...
```



CREATING ALIGNED DATA CONTAINERS

- ▶ Data alignment on the stack

```
1 float A[n] __attribute__((aligned(64))); // 64-byte alignment applied
```

- ▶ Data alignment on the heap

```
1 float *A = (float*) _mm_malloc(sizeof(float)*n, 64);
```

- ▶ A[0] is aligned on a 64-byte boundary.
- ▶ Very high alignment value may lead to wasted virtual memory.
- ▶ Fortran: directive or compiler argument `-align array64byte`

PADDING MULTI-DIMENSIONAL CONTAINERS FOR ALIGNMENT

To use aligned instructions, you may need to pad inner dimension of multi-dimensional arrays to a multiple of 16 (in SP) or 8 (DP) elements.

Incorrect:

```
1 // A - matrix of size (n x n)
2 // n is not a multiple of 16
3 float* A =
4   _mm_malloc(sizeof(float)*n*n, 64);
5
6 for (int i = 0; i < n; i++)
7   // A[i*n + 0] may be unaligned
8   for (int j = 0; j < n; j++)
9     A[i*n + j] = ...
```

Correct:

```
1 // ... Padding inner dimension
2 int lda=n + (16-n%16); // lda%16==0
3 float* A =
4   _mm_malloc(sizeof(float)*n*lda, 64);
5
6 for (int i = 0; i < n; i++)
7   // A[i*lda + 0] aligned for any i
8   for (int j = 0; j < n; j++)
9     A[i*lda + j] = ...
```

DATA ALIGNMENT HINTS

Programmer may promise to the compiler (under penalty of segmentation fault) that alignment has been taken care of:

```
1 // Promising that A[i*lda + 0] is aligned for every i
2 // and the same for every other array in this loop
3 #pragma vector aligned
4     for (int j = 0; j < n; j++)
5         A[i*lda + j] -= ...
```

This can lead to significant speedups, because compiler will not implement runtime checks for alignment situation and *peel loops*.



EXAMPLE: LU DECOMPOSITION

EXAMPLE: LU DECOMPOSITION

```

1 void LU_decomp(const int n, float* const A) {
2     // LU decomposition (Doolittle algorithm)
3     // In-place decomposition of form A=LU
4     // L is returned below main diagonal of A
5     // U is returned at and above main diagonal
6     for (int b = 0; b < n; b++) {
7         // Strength reduction:
8         const float recAbb = 1.0f/A[b*n + b];
9         for (int i = b+1; i < n; i++) {
10            A[i*n + b] = A[i*n + b]*recAbb;
11        #pragma simd
12            for (int j = b+1; j < n; j++)
13                A[i*n + j] -= A[i*n + b]*A[b*n + j];
14        }
15    }
16 }

```

LU decomposition for small matrices. ($n \approx 128$)

Based on publication:

<http://xeonphi.com/papers/>

Non-optimal
Vectorization Pattern.

- ▶ Unaligned
- ▶ Irregular loop count

LU DECOMPOSITION: REGULARIZING VECTORIZATION

Before:

```

1 for (int b = 0; b < n; b++) {
2     // ...
3     // ...
4     for (int i = b+1; i < n; i++) {
5         // ...
6         for (int j = b+1; j < n; j++)
7             A[i*n+j] -= A[i*n+b]*A[b*n+j];
8     }
9 }

```

After:

```

1 for (int b = 0; b < n; b++) {
2     // ...
3     const int jMin = (b+1) - (b+1)%16;
4     for (int i = b+1; i < n; i++) {
5         // ...
6         for (int j = jMin; j < n; j++)
7             A[i*n+j] -= L[i*n+b]*A[b*n+j];
8     }
9 }

```

Loop in j always starts on a multiple of 64 →
aligned access to A and L

LU DECOMPOSITION: COMPILER HINTS

- ▶ Data alignment hint: `#pragma vector aligned`

Before:

```

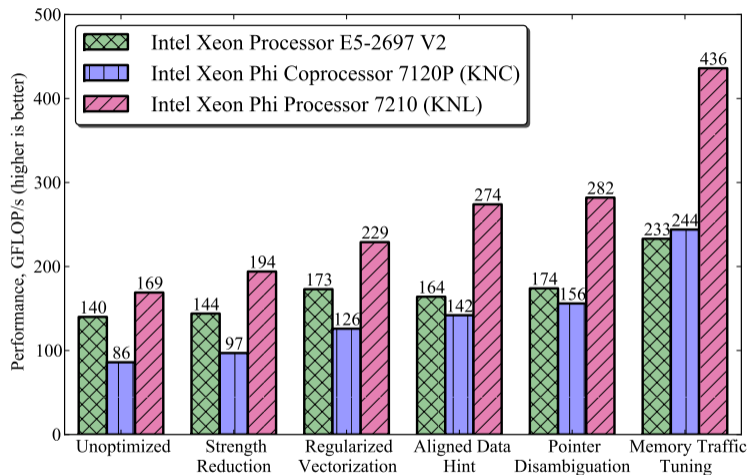
1  for (int b = 0; b < n; b++) {
2      const int jMin = (b+1)-(b+1)%tile;
3      const float recAbb = 1.0f/A[b*n+b];
4      for (int i = b+1; i < n; i++) {
5          L[i*n + b] = A[i*n + b]*recAbb;
6
7
8      #pragma simd
9          for (int j = jMin; j < n; j++)
10             A[i*n+j] -= L[i*n+b]*A[b*n+j];
11     }
12 }
```

After:

```

1  for (int b = 0; b < n; b++) {
2      const int jMin = (b+1)-(b+1)%tile;
3      const float recAbb = 1.0f/A[b*n+b];
4      for (int i = b+1; i < n; i++) {
5          L[i*n + b] = A[i*n + b]*recAbb;
6
7          #pragma vector aligned
8          #pragma ivdep
9          #pragma simd
10             for (int j = jMin; j < n; j++)
11                 A[i*n+j] -= L[i*n+b]*A[b*n+j];
12     }
13 }
```

LU DECOMPOSITION: PERFORMANCE



Paper: <http://xeonphi.com/papers/lu>



STRIP-MINING FOR VECTORIZATION

EXAMPLE: BINNING

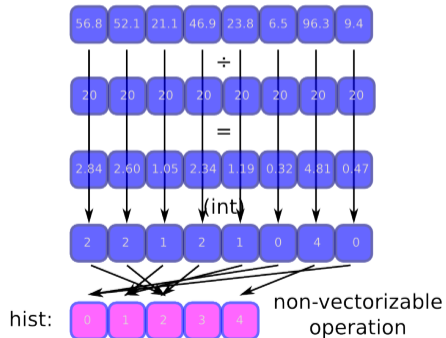
EXAMPLE: BINNING PROBLEM

Computing a histogram ($m \ll n$):

```

1 void Histogram(
2     // Ages, values from 0.0f to 100.0f:
3     const float* age,
4     // Size of array age, n=100000000:
5     const int n,
6     // Output: counts in groups:
7     int* const hist,
8     // Size of array hist, m=5:
9     const int m,
10    const float group_width) {
11    for (int i = 0; i < n; i++) {
12        const int j = int(age[i]/group_width);
13        hist[j]++;
14    }
15 }
  
```

- ▶ Vector dependence in `hist[j]++`
- ▶ Strip-mine or use conflict detection

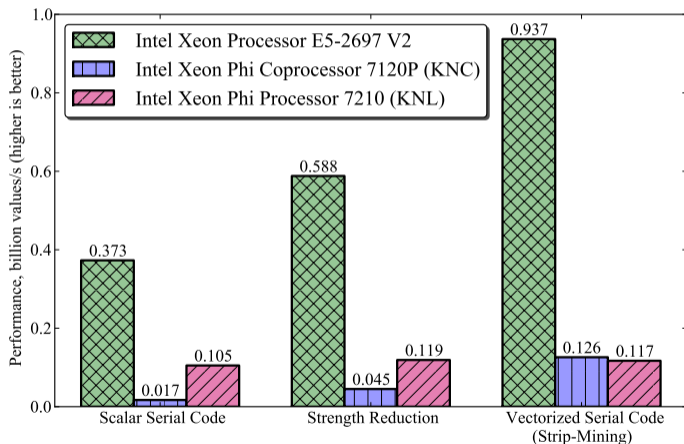


THE SAME CALCULATION, STRIP-MINED, VECTORIZED

```
1 void Histogram(const float* age, int* const hist, const int n,  
2 const float group_width, const int m) {  
3     const int vecLen = 16; // Length of vectorized loop  
4     const float invGroupWidth = 1.0f/group_width; // Pre-compute the reciprocal  
5     // Strip-mining the loop in order to vectorize the inner short loop  
6     // Note: this algorithm assumes n%vecLen == 0.  
7     for (int ii = 0; ii < n; ii += vecLen) { //Temporary store vecLen indices  
8         int index[vecLen] __attribute__((aligned(64)));  
9         // Vectorize the multiplication and rounding  
10    #pragma vector aligned  
11        for (int i = ii; i < ii + vecLen; i++)  
12            index[i-ii] = (int) ( age[i] * invGroupWidth );  
13        // Scattered memory access, does not get vectorized  
14        for (int c = 0; c < vecLen; c++)  
15            hist[index[c]]++;  
16    }  
17 }
```

STRIP-MINING FOR VECTORIZATION

Vectorization improves performance on both platforms. However, more work is needed to take advantage of the MIC architecture. See materials on multi-threading.





§5. REVIEW AND WHAT'S NEXT

SUMMARY

1. Vector-Friendly Data Structures
 - Use data structures that allow for unit-stride vector load.
2. Regularization of Vectorization Pattern
 - Align data to 64-byte boundaries
 - Pad data containers and loop bounds
3. Remove Run-time Checks
 - Disable run-time checks for alignment and aliasing with compiler hints
4. Strip-Mining for Vectorization
 - Use strip-mining expose vectorization opportunities.

LOOP WAS VECTORIZED, NOW WHAT?

1. Ensure unit stride access
2. Align data
3. Pad multi-dimensional containers
4. Eliminate peel loops
5. Eliminate multiversioning
6. **Optimize data re-use in caches**

Good to Know

Vector FLOPs are cheap compared to memory access.

If your data is served by RAM and not caches, it does not matter if you have vectorization: you will be bottlenecked by memory access.

Next class: optimization of thread parallelism, common issues.

1. Controlling synchronization in parallel reduction
2. Eliminating false sharing
3. Dealing with insufficient parallelism

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Parallel Programming Book

Introduction to parallel programming, deep discussion of optimization techniques, exercises.

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Research and Educational Publications

Introduction to Intel DAAL, Part 1: Polynomial Regression with Batch Mode Computation

Software Developer's Introduction to the HGST Ultrastar Archive H700 SMR Drives

Optimization Techniques for the Intel MIC Architecture, Part 3 of 3: False Sharing and Padding

Optimization Techniques for the Intel MIC Architecture, Part 2 of 3: Strip-Mining for Vectorization

Optimization Techniques for the Intel MIC Architecture, Part 1 of 3: Multi-Threading and Parallel Reduction

Featured Video

See Research material re-creation in a streaming video

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- Accelerate your application using coprocessor tech
- Investigate the potential system configurations that satisfy your cost, power, performance requirements.
- Take a clean slate to develop a novel approach to solve your computing problem

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Episode 2.1 — Purpose of the MIC architecture

▶

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Fluid Dynamics with Fortran on Intel Xeon Phi coprocessors

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- Take a clean slate to develop a novel approach to solve your computing problem

Configuration and Benchmarks of Peer-to-Peer Communication over Gigabit Ethernet and InfiniBand in a Cluster with Intel Xeon Phi Coprocessors

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- Optimize your existing application to take advantage of parallelism, from vectors to cores to clusters and
- Future-proof your application for upcoming innovations
- Accelerate your application using coprocessor tech
- Investigate the potential system configurations that satisfy your cost, power, performance requirements.
- Take a clean slate to develop a novel approach to solve your computing problem

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REVIEW AND WHAT'S NEXT

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