PROGRAMMING AND OPTIMIZATION FOR INTEL® ARCHITECTURE

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

Session 3

Colfax International — *colfaxresearch.com*

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COURSE ROADMAP

- Module I. Programming Models
  - 01. Intel Architecture and Modern Code
  - 02. Xeon Phi, Coprocessors, Omni-Path
- Module II. Expressing Parallelism
  - 03. Automatic vectorization
  - 04. Multi-threading with OpenMP
  - 05. Distributed Computing, MPI
- Module III. Performance Optimization
  - 06. Optimization Overview: N-body
  - 07. Scalar tuning, Vectorization
  - 08. Common Multi-threading Problems
  - 09. Multi-threading, Memory Aspect
  - 10. Access to Caches and Memory

HOW SERIES ONLINE

Course page:
colfaxresearch.com/how-series

- Slides
- Code
- Video
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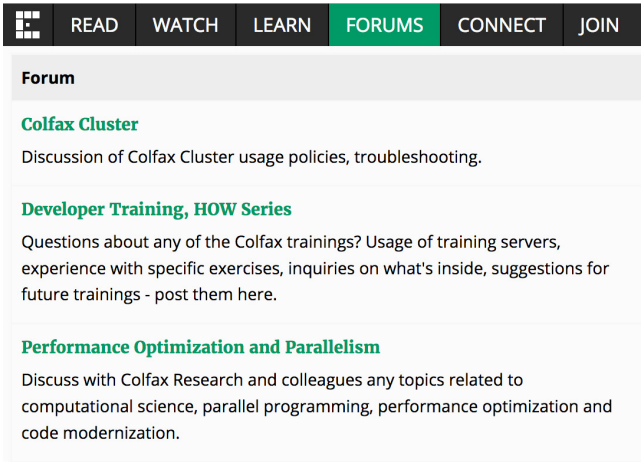


colfaxresearch.com/forum

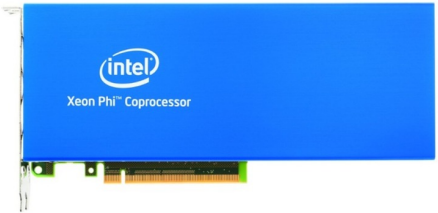
HANDS-ON EXERCISES AND REMOTE ACCESS

- 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. SIMD PARALLELISM AND VECTORIZATION

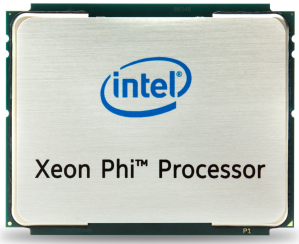
VECTOR INSTRUCTIONS IN INTEL ARCHITECTURE

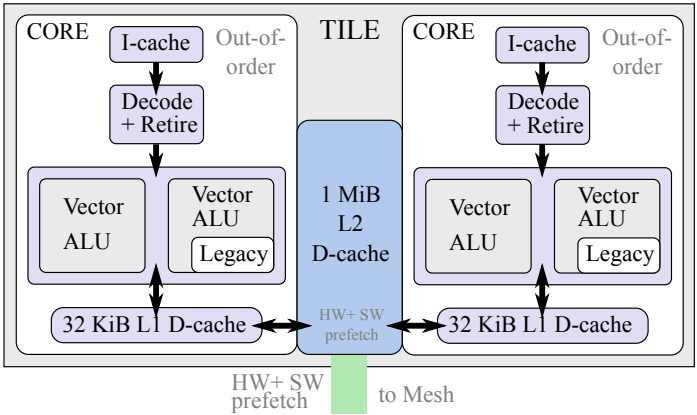
COMPUTING PLATFORMS

Intel Xeon Processor	Intel Xeon Phi Coprocessor, 1st generation	Intel Xeon Phi Processor, 2nd generation*
		
Current: Broadwell Upcoming: Skylake	Knights Corner (KNC)	* socket and coprocessor versions Knights Landing (KNL)
Multi-Core Architecture	Intel Many Integrated Core (MIC) Architecture	

KNL CORES

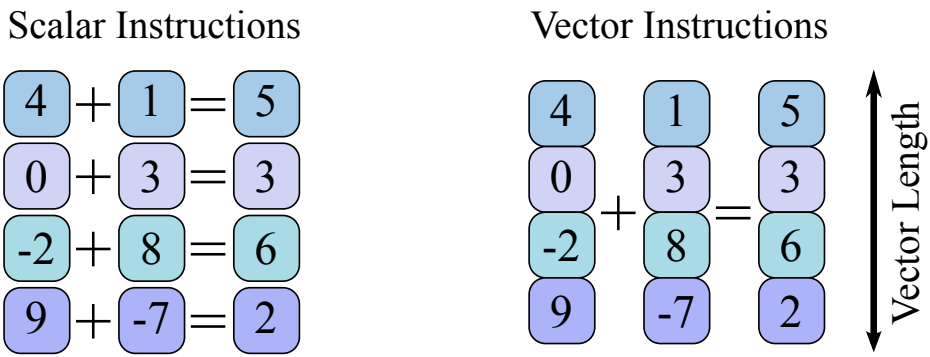
- Even more power in vector units
- Binary compatible with Xeon, but in legacy mode



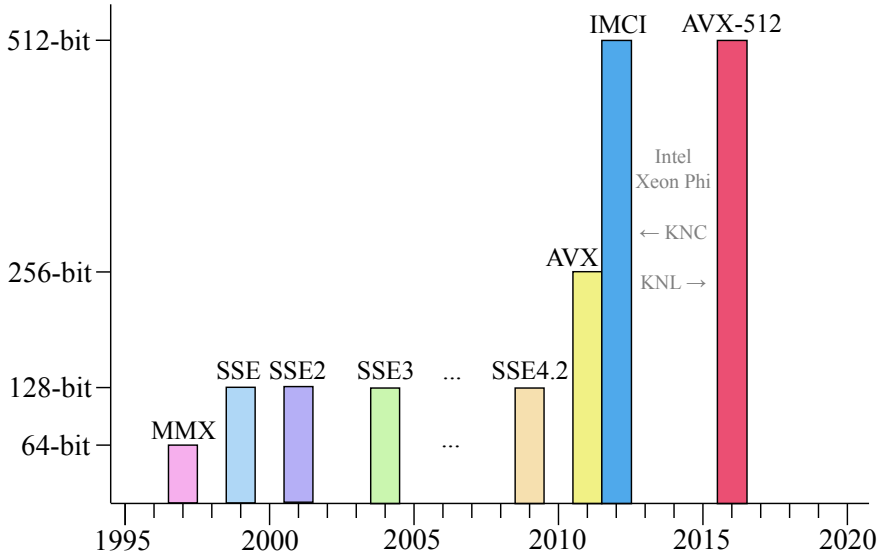


SHORT VECTOR SUPPORT

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

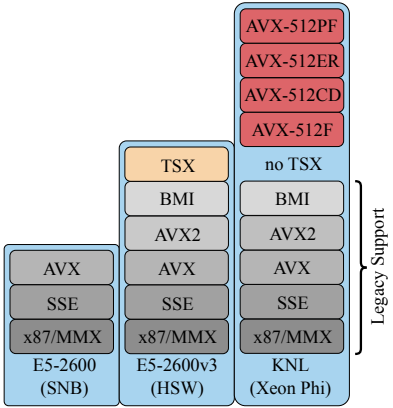


INSTRUCTION SETS IN INTEL ARCHITECTURE



AVX-512 IN INTEL XEON PHI PROCESSORS

- Intel® Advanced Vector Extensions 512 (AVX-512)
  - 512-bit vector registers.
  - Hardware gather/scatter, DP transcendental functions support and more.
  - Supported by non-Intel compilers like GCC.
- ≤ Intel® AVX2
  - Legacy mode operation.
  - Binary compatibility with Xeon.
  - Does *not* include IMCI (from KNC).



AVX-512 MODULES

- AVX-512F (Fundamentals)
  - Extension of most AVX2 instructions to 512-bit vector registers.
- AVX-512CD (Conflict Detection)
  - Efficient conflict detection (application: binning).
- AVX-512ER (Exponential and Reciprocal)
  - Transcendental function (`exp`, `rcp` and `rsqrt`) support.
- AVX-512PF (Prefetch)
  - Prefetch for scatter and gather.

Learn more: colfaxresearch.com/knl-avx512

VECTOR INTRINSICS

USING VECTOR INSTRUCTIONS: TWO APPROACHES

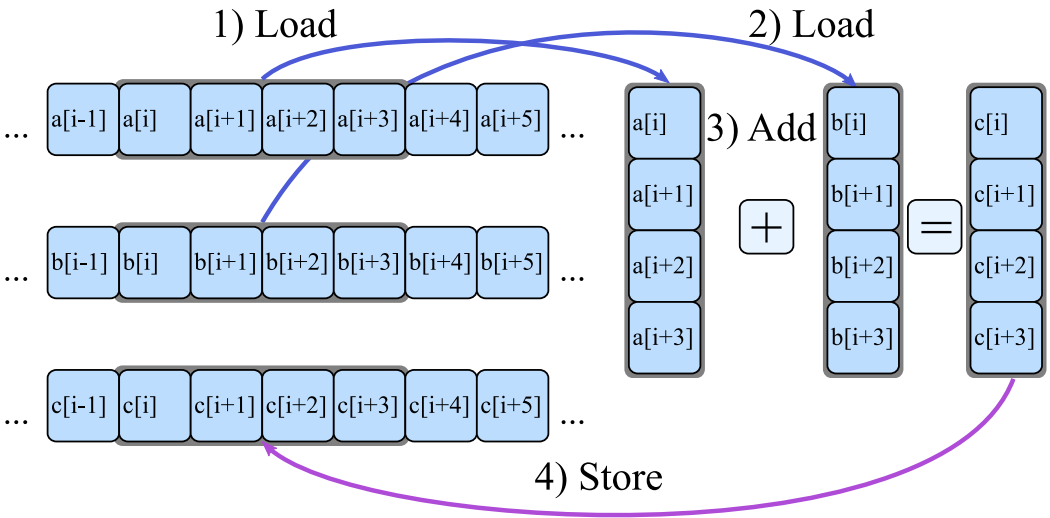
Automatic Vectorization →

```
1 double A[vec_width], B[vec_width];
2 // ...
3 for(int i = 0; i < vec_width; i++)
4   A[i]+=B[i];
```

```
1 double A[8], B[8];
2 __m512d A_v = _mm512_load_pd(A);
3 __m512d B_v = _mm512_load_pd(B);
4 A_v = _mm512_add_pd(A_v,B_v);
5 _mm512_store_pd(A, A_v);
```

← Explicit Vectorization

WORKFLOW OF VECTOR COMPUTATION



DETECTING AVAILABLE INSTRUCTIONS

In the OS:

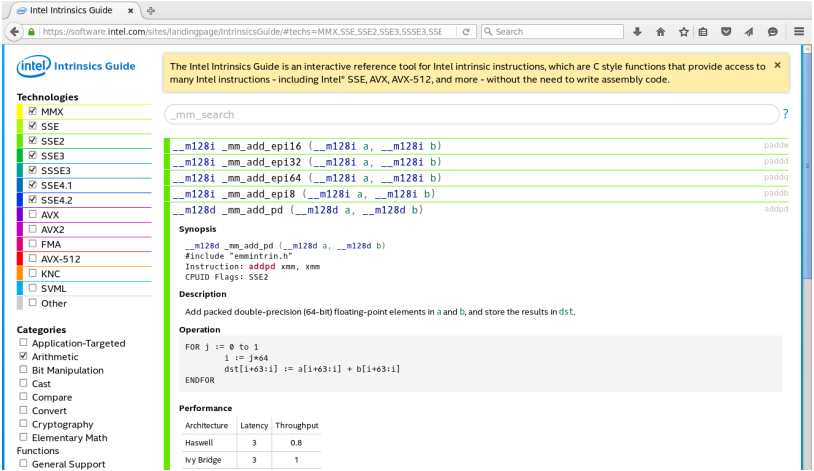
```
[student@cdt ~]% cat /proc/cpuinfo
...
fpu_exception   : yes
cpuid level     : 11
wp              : yes
flags           : fpu vme de pse tsc msr pae mce
cx8 apic mtrr pge mca cmov pat pse36 clflush mmx
fxsr sse sse2 ss ht syscall nx lm constant_tsc
unfair_spinlock pni ssse3 cx16 sse4_1 sse4_2
x2apic popcnt aes hypervisor lahf_lm fsgsbase
bogomips        : 5985.17
clflush size    : 64
cache_alignment: 64
address sizes   : 46 bits physical, 48 bits virtual
...
```

In code (see also):

```
1  // Intel compiler
2  // preprocessor macros:
3
4  #ifdef __SSE__
5  // ...SSE code path
6  #endif
7
8  #ifdef __SSE4_2__
9  // ...SSE code path
10 #endif
11
12 #ifdef __AVX__
13 // ...AVX code path
14 #endif
```

INTEL INTRINSICS GUIDE

https://software.intel.com/sites/landingpage/IntrinsicsGuide



EXAMPLE: NUMERICAL INTEGRATION

$$I(a,b) = \int_0^a \frac{1}{\sqrt{x}} \mathrm{d}x$$

Rectangle method:

$$\begin{aligned} \Delta x &= \frac{a}{n}, \\ x_i &= (i+1)\Delta x, \\ I(a,b) &= \sum_{i=0}^{n-1} \frac{1}{\sqrt{x_i}} \Delta x + O(\Delta x). \end{aligned}$$

```
1  float Integrate(const float a,
2                  const int N) {
3    const float dx = a/float(n);
4    float S = 0.0f;
5    for (int i = 0; i < n; i++) {
6      const float xi = dx*float(i+1);
7      S += 1.0f/sqrtf(xi) * dx;
8    }
9    return S;
10 }
```

IMPLEMENTATION WITH SSE4.2

```
1  float Integrate(const float a, const int n) {
2    __m128 dx = _mm_set1_ps(a/float(n));
3    __m128 S  = _mm_set1_ps(0.0f);
4    for (int i = 0; i < n; i += 4) {
5      __m128i ip1  =
6                _mm_set_epi32(i+4, i+3, i+2, i+1);
7      __m128  ip1f = _mm_cvtepi32_ps(ip1);
8      __m128  xi = _mm_mul_ps(dx, ip1f);
9      __m128  fi = _mm_rsqrt_ps(xi);
10     __m128  dS = _mm_mul_ps(fi, dx);
11     S  = _mm_add_ps(S, dS);
12   }
13   ConverterType c;
14   c.v = S;
15   return c.f[0] + c.f[1] + c.f[2] + c.f[3];
16 }
```

That is fine, *but*...

- Assuming `n` is a multiple of 4
- Only for SSE4.2 (circa 2011)
- No memory access. If we had some, peeling may be needed

§3. AUTOMATIC VECTORIZATION

LOOPS

AUTOMATIC VECTORIZATION OF LOOPS

```
1  #include <cstdio>
2
3  int main(){
4    const int n=1024;
5    int A[n] __attribute__((aligned(64)));
6    int B[n] __attribute__((aligned(64)));
7
8    for (int i = 0; i < n; i++)
9      A[i] = B[i] = i;
10
11   // This loop will be auto-vectorized
12   for (int i = 0; i < n; i++)
13     A[i] = A[i] + B[i];
14
15   for (int i = 0; i < n; i++)
16     printf("%2d %2d %2d\n",i,A[i],B[i]);
17 }
```

```
vega@lyra% icpc autovec.cc -qopt-report
vega@lyra% cat autovec.optrpt
...
LOOP BEGIN at autovec.cc(12,3)
remark #15399: vectorization support:
unroll factor set to 2 [autovec.cc(12,3)]
remark #15300: LOOP WAS VECTORIZED
[autovec.cc(12,3)]
LOOP END
...
vega@lyra% ./a.out
0  0  0
1  2  1
2  4  2
3  6  3
4  8  4
...
```

TARGETING A SPECIFIC INSTRUCTION SET

`-x[code]` to target specific processor architecture

`-ax[code]` for multi-architecture dispatch

`code`	Target architecture
MIC-AVX512	Intel Xeon Phi processors (KNL)
CORE-AVX512	Future Intel Xeon processors
CORE-AVX2	Intel Xeon processor E3/E5/E7 v3, v4 family
AVX	Intel Xeon processor E3/E5 and E3/E5/E7 v2 family
SSE4.2	Intel Xeon processor 55XX, 56XX, 75XX and E7 family
host	architecture on which the code is compiled

GCC SUPPORT FOR AVX-512

GCC ≥ 4.9.1 supports AVX-512 instruction set.

```
user@knl% g++ -v
gcc version 4.9.2 (GCC)
user@knl% g++ foo.cc -mavx512f -mavx512er -mavx512cd -mavx512pf
```

Basic automatic vectorization support: add -O3.

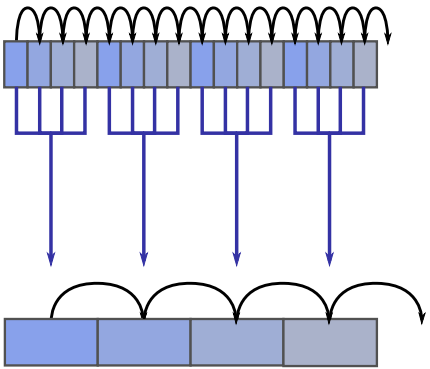
```
1 // ... foo.cc ... //
2 for(int i = 0; i < n; i++)
3   B[i] = A[i] + B[i];
```

```
user@knl% g++ -s foo.cc -mavx512f -O3
user@knl% cat foo.s
...
  vmovapd -16432(%rbp,%rax), %zmm0
  vaddpd -8240(%rbp,%rax), %zmm0, %zmm0
  vmovapd %zmm0, -8240(%rbp,%rax)
```

LIMITATIONS ON AUTOMATIC VECTORIZATION

- Innermost loops*
- Known number of iterations
- No vector dependence
- Functions must be SIMD-enabled

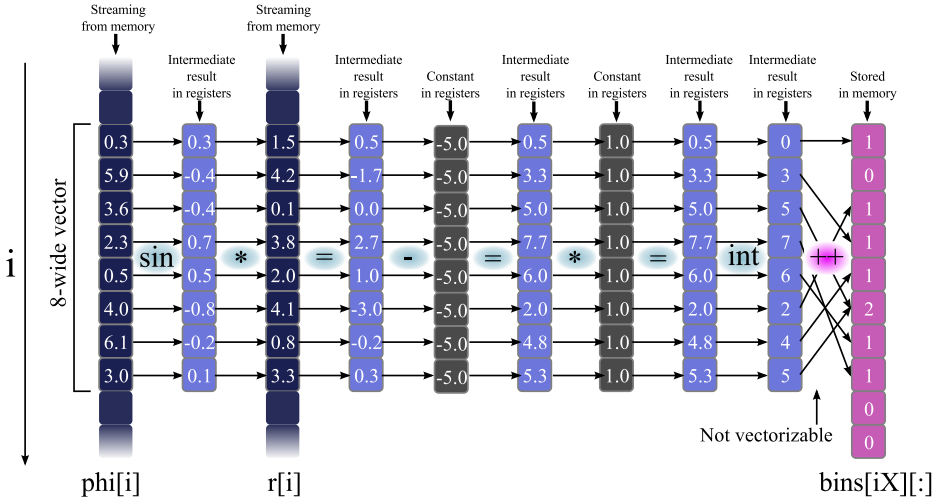
* `#pragma omp simd` to override



AUTO-VECTORIZED LOOPS MAY BE COMPLEX

```
1  for (int i = ii; i < ii + tileSize; i++) { // Auto-vectorized
2
3    // Newton's law of universal gravity
4    const float dx = particle.x[j] - particle.x[i]; // x[j] is a const
5    const float dy = particle.y[j] - particle.y[i]; // x[i] -> vector
6    const float dz = particle.z[j] - particle.z[i];
7    const float rr = 1.0f/sqrtf(dx*dx + dy*dy + dz*dz + softening);
8    const float drPowerN32  = rr*rr*rr;
9
10   // Calculate the net force
11   Fx[i-ii] += dx * drPowerN32;
12   Fy[i-ii] += dy * drPowerN32;
13   Fz[i-ii] += dz * drPowerN32;
14 }
```

AUTO-VECTORIZED LOOPS MAY BE COMPLEX (EXAMPLE 2)



See this paper for more details

PRAGMA SIMD

VECTORIZE MORE LOOPS: `#pragma omp simd`

Used to “enforce vectorization of loops”, which includes:

- Loops with SIMD-enabled functions
- Second innermost loops
- Failed vectorization due to compiler decision
- Where guidance is required (vector length, reduction, etc.)

See OpenMP reference for syntax; `#pragma simd`

EXAMPLE FOR #pragma omp simd

```
const int N=128, T=4;
float A[N*N], B[N*N], C[T*T];

for (int jj = 0; jj < N; jj+=T) // Tile in j
  for (int ii = 0; ii < N; ii+=T) // and tile in i
#pragma omp simd   // Vectorize outer loop
  for (int k = 0; k < N; ++k) // long loop, vectorize it
    for (int i = 0; i < T; i++) { // Loop between ii and ii+T
      // Instead of a loop between jj and jj+T, unrolling that loop:
      C[0*T + i] += A[(jj+0)*N + k]*B[(ii+i)*N + k];
      C[1*T + i] += A[(jj+1)*N + k]*B[(ii+i)*N + k];
      C[2*T + i] += A[(jj+2)*N + k]*B[(ii+i)*N + k];
      C[3*T + i] += A[(jj+3)*N + k]*B[(ii+i)*N + k];
}
```

ARRAY NOTATION

EXTENSIONS FOR ARRAY NOTATION

Array notation is a method for specifying

- slices of arrays (begin, length)

```
A[0:16] += B[32:16]; // B[32]...B[47] added to A[0]...A[15]
```

- a stride (begin, length, stride)

```
A[0:16:2] += B[32:16:4]; // B[32],B[36]...B[92] added A[0],A[2]...A[30]
```

- Multi-dimensional arrays

```
A[:][:] += B[:][:]; // Add B to A; arrays are of the same shape
```

Better than strided loops (e.g., this paper).

EXPRESSIONS WITH ARRAY NOTATION MAY BE COMPLEX

Example from https://colfaxresearch.com/efft

```
evenrek[:] = evens[kk  :kTILE:2];
evenimk[:] = evens[kk+1:kTILE:2];
oddrek [:] = odds [kk  :kTILE:2];
oddimk [:] = odds [kk+1:kTILE:2];

evens[kk  :kTILE:2] = evenrek[:] + coslist[:]*oddrek[:] - sinlist[:]*oddimk[:];
evens[kk+1:kTILE:2] = evenimk[:] + sinlist[:]*oddrek[:] + coslist[:]*oddimk[:];

oddmirrek[:] = odds[size-kk  :kTILE:-2];
oddmirimk[:] = odds[size-kk+1:kTILE:-2];

odds[size-kk  :kTILE:-2] =
                      evenrek[:] - coslist[:]*oddrek[:] + sinlist[:]*oddimk[:];
odds[size-kk+1:kTILE:-2] =
                     -evenimk[:] + sinlist[:]*oddrek[:] + coslist[:]*oddimk[:];
// ...
```

SIMD-ENABLED FUNCTIONS

SIMD-ENABLED FUNCTIONS

Define function in one file (e.g., library), use in another

```
// Compiler will produce 3 versions:
#pragma omp declare simd
float my_simple_add(float x1, float x2){
  return x1 + x2;
}
```

```
// May be in a separate file
#pragma omp simd
for (int i = 0; i < N, ++i) {
  output[i] = my_simple_add(inputa[i], inputb[i]);
}
```

SIMD-ENABLED FUNCTIONS MAY BE COMPLEX

```
#pragma omp declare simd
float MyErfElemental(const float inx){
    const float x = fabsf(inx); // Absolute value (in each vector lane)
    const float p = 0.3275911f; // Constant parameter across vector lanes
    const float t = 1.0f/(1.0f+p*x); // Expression in each vector lanes
    const float l2e = 1.442695040f; // log2f(expf(1.0f))
    const float e = exp2f(-x*x*l2e); // Transcendental in each vector lane
    float res = -1.453152027f + 1.061405429f*t; // Computing a polynomial
    res = 1.421413741f + t*res;                 // in each vector lane
    res =-0.284496736f + t*res;
    res = 0.254829592f + t*res;
    res *= e;
    res = 1.0f - t*res; // Analytic approximation in each vector lane
    return copysignf(res, inx); // Copy sign in each vector lane
}
```

MULTIVERSIONING, POINTER DISAMBIGUATION

TRUE VECTOR DEPENDENCE

- True vector dependence – vectorization impossible:

```
1 for (int i = 1; i < n; i++)
2   a[i] += a[i-1]; // dependence on the previous element
```

- Safe to vectorize:

```
1 for (int i = 0; i < n-1; i++)
2   a[i] += a[i+1]; // no dependence on the previous element
```

- May be safe to vectorize:

```
1 for (int i = 16; i < n; i++)
2   a[i] += a[i-16]; // no dependence if vector length <=16
```

ASSUMED VECTOR DEPENDENCE

Not enough information to confirm or rule out vector dependence:

```
1 void AmbiguousFunction(int n, int *a, int *b) {
2   for (int i = 0; i < n; i++)
3     a[i] = b[i];
4 }
```

- If `a`, `b` are not aliased or `b>a`, then safe to vectorize
- If `a`, `b` are aliased (e.g., `b==a-1`), requires scalar computation

MULTIVERSIONING

```
user@host% icpc -c code.cc -qopt-report
user@host% cat code.optrpt
...
LOOP BEGIN at code.cc(4,1)
<Multiversioned v1>
   remark #25228: LOOP WAS VECTORIZED
LOOP END
...
LOOP BEGIN at code.cc(4,1)
<Multiversioned v2>
   remark #15304: loop was not vectorized: non-vectorizable loop instance ....
LOOP END
```

Pointers checked for aliasing *runtime* to choose code path.

POINTER DISAMBIGUATION

Prevent multiversioning or allow vectorization with a directive:

```
1 #pragma ivdep
2   for (int i = 0; i < n; i++)
3     // ...
```

```
user@host% icpc -c code.cc -qopt-report -qopt-report-phase:vec
user@host% cat vdep.optrpt
...
LOOP BEGIN at code.cc(4,1)
   remark #25228: LOOP WAS VECTORIZED
LOOP END
...
```

Alternative: keyword `restrict` – more fine-grained, weaker.

ADDTIONAL CONTROLS

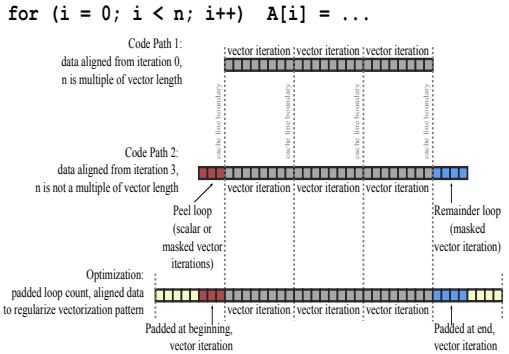
VECTORIZATION DIRECTIVES

- `#pragma omp simd`
- `#pragma vector always`
- `#pragma vector aligned | unaligned`
- `__assume_aligned` keyword
- `#pragma vector nontemporal | temporal`
- `#pragma novector`
- `#pragma ivdep`
- `restrict` qualifier and `-restrict` command-line argument
- `#pragma loop count`

LOOP WAS VECTORIZED, WHAT NOW?

LOOP WAS VECTORIZED, NOW WHAT?

1. Unit-stride access
2. Data alignment
3. Container padding
4. Eliminate peel loops
5. Eliminate multiversioning
6. **Optimize data re-use in caches**



LOOP WAS VECTORIZED, NOW WHAT?

1. Unit-stride access
2. Data alignment
3. Container padding
4. Eliminate peel loops
5. Eliminate multiversioning
6. **Optimize data re-use in caches**

Vector Arithmetics is Cheap, Memory Access is Expensive

If you don't optimize cache usage, vectorization will not matter.
You will be bottlenecked by memory access.

REVIEW AND WHAT'S NEXT

Discussed today:

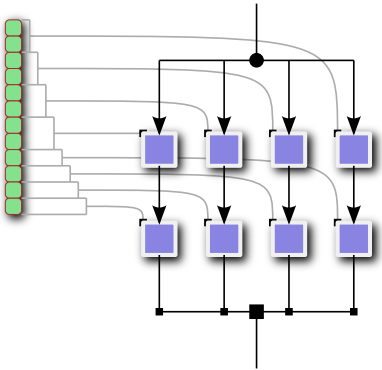
- Vectorization – support for data parallelism in each core
- Automatic vectorization enabled at default optimization level
- Loops, SIMD-enabled functions, array notation
- Argument `-qopt-report` produces a report on vectorization success

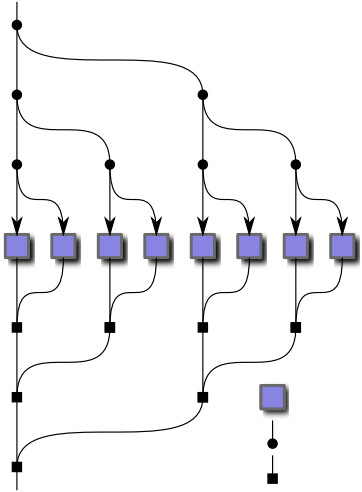
Later in the course – tuning automatic vectorization:

- alignment
- unit-stride data structures
- vectorization pattern regularization
- programming techniques for exposing automatic vectorization
- compiler hints.

WHAT'S NEXT

Next session: expressing thread parallelism with OpenMP.





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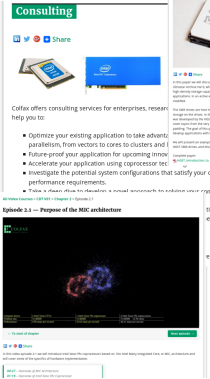

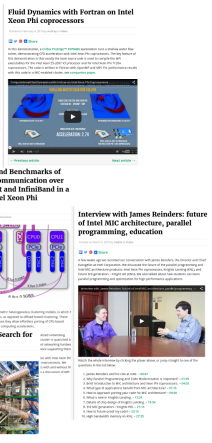

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