Vector Processing
(aka, Single Instruction Multiple Data, or SIMD)

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What is Vectorization/SIMD and Why do We Care?

Performance!

Many hardware architectures today, both CPU and GPU, allow you to perform arithmetic operations on multiple array elements simultaneously.

(Thus the label, "Single Instruction Multiple Data").

We care about this because many problems, especially scientific and engineering, can be cast this way. Examples include convolution, Fourier transform, power spectrum, autocorrelation, etc.

SIMD in Intel Chips

<table>
<thead>
<tr>
<th>Year Released</th>
<th>Name</th>
<th>Width (bits)</th>
<th>Width (FP words)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996</td>
<td>MMX</td>
<td>64</td>
<td>2</td>
</tr>
<tr>
<td>1999</td>
<td>SSE</td>
<td>128</td>
<td>4</td>
</tr>
<tr>
<td>2011</td>
<td>AVX</td>
<td>256</td>
<td>8</td>
</tr>
<tr>
<td>2013</td>
<td>AVX-512</td>
<td>512</td>
<td>16</td>
</tr>
</tbody>
</table>

Xeon Phi
Note: one complete cache line!
Note: also a 4x4 transformation matrix!

If you care:
• MMX stands for “MultiMedia Extensions”
• SSE stands for “Streaming SIMD Extensions”
• AVX stands for “Advanced Vector Extensions”

Intel SSE

Intel and AMD CPU architectures support vectorization. The most well-known form is called Streaming SIMD Extension, or SSE. It allows four floating point operations to happen simultaneously.

Normally a scalar floating point multiplication instruction happens like this:

\[ \text{mulss } r1, r0 \]

“ATT form”:
\[ \text{muls } \text{src}, \text{dst} \]

r0*
r1

r1
The SSE version of the multiplication instruction happens like this:

```
mulps xmm1, xmm0
```

"ATT form":

```
mulps src, dst
```

Note that the construct:

```
a[0 : ArraySize ]
```

is meant to be read as:

"The set of elements in the array \( a \) starting at index 0 and going for \( ArraySize \) elements".

**not as:**

"The set of elements in the array \( a \) starting at index 0 and going through index \( ArraySize \)".

### Array * Array

```
void SimdMul( float *a, float *b, float *c, int len )
{
    c[0:len] = a[0:len] * b[0:len];
}
```

### Array * Scalar

```
void SimdMul( float *a, float b, float *c, int len )
{
    c[0:len] = a[0:len] * b;
}
```

```
void SimdMul( float *a, float b, float *c, int len )
{
    #pragma omp simd
    for( int i = 0; i < len; i++ )
    c[ i ] = a[ i ] * b[ i ];
}
```
You would think it would always be 4.0 ± noise effects, but it's not. Why?

**Requirements for a For-Loop to be Vectorized**

- If there are nested loops, the one to vectorize must be the inner one.
- There can be no jumps or branches. “Masked assignments” (an if-statement-controlled assignment) are OK, e.g.,
  
  \[
  \text{if}( A[ i ] > 0. ) \\
  B[ i ] = 1. ;
  \]
- The total number of iterations must be known at runtime when the loop starts
- There can be no inter-loop data dependencies such as:
  
  \[
  a[ i ] = a[ i-1 ] + 1. ;
  \]

- It helps performance if the elements have contiguous memory addresses.

**Prefetching**

Prefetching is used to place a cache line in memory before it is to be used, thus hiding the latency of fetching from off-chip memory.

There are two key issues here:

1. Issuing the prefetch at the right time
2. Issuing the prefetch at the right distance

**The right time:**

If the prefetch is issued too late, then the memory values won’t be back when the program wants to use them, and the processor has to wait anyway.

If the prefetch is issued too early, then there is a chance that the prefetched values could be evicted from cache by another need before they can be used.

**The right distance:**

The “prefetch distance” is how far ahead the prefetch memory is than the memory we are using right now.

Too far, and the values sit in cache for too long, and possibly get evicted.

Too near, and the program is ready for the values before they have arrived.
The Effects of Prefetching on SIMD Computations

Array Multiplication
Length of Arrays (NUM): 1,000,000
Length per SIMD call (ONETIME): 256

for ( int i = 0; i < NUM; i += ONETIME )
{
    __builtin_prefetch ( &A[i+PD], WILL_READ_ONLY, LOCALITY_LOW );
    __builtin_prefetch ( &B[i+PD], WILL_READ_ONLY, LOCALITY_LOW );
    __builtin_prefetch ( &C[i+PD], WILL_READ_AND_WRITE, LOCALITY_LOW );

    SimdMul( A, B, C, ONETIME );
}

Getting at the full SIMD power until compilers catch up

This all sounds great!
What is the catch?

The catch is that compilers haven't caught up to producing really efficient
SIMD code. So, while there are great ways to express the desire for SIMD in
code, you won't get the full potential speedup … yet.

One way to get a better speedup is to use assembly language.
Don't worry – you wouldn't need to write it.

Here are two assembly functions:


Warning – due to the nature of how different compilers and systems
handle local variables, these two functions only work on flip using
gcc/g++, without –O3 !!!
Getting at the full SIMD power until compilers catch up

```c
float
SimdMulSum( float *a, float *b, int len )
{
    float sum[4] = { 0., 0., 0., 0. };
    int limit = ( len/SSE_WIDTH ) * SSE_WIDTH;
    __asm(
        "movq -40(%rbp), %r8
        movq -48(%rbp), %rcx
        leaq -32(%rbp), %rdx
        movups (%rdx), %xmm2
    )
    for( int i = 0; i < limit; i += SSE_WIDTH )
    {
        __asm(
            "movups (%r8), %xmm0
            movups (%rcx), %xmm1
            mulps %xmm1, %xmm0
            addps %xmm0, %xmm2
            addq $16, %r8
            addq $16, %rcx
        )
    }
    __asm(
        "movups %xmm2, (%rdx)
    )
    for( int i = limit; i < len; i++ )
    {
        sum[0] += a[ i ] * b[ i ];
    }
}
```

This only works on flip using gcc/g++, without -O3 !!!

Combining SIMD with Multicore

```c
#define NUM_ELEMENTS_PER_CORE ( ARRSIZE / NUMT )

omp_set_num_threads( NUMT );
maxMegaMultsPerSecond = 0.;
double time0 = omp_get_wtime();
#pragma omp parallel
{
    int thisThread = omp_get_thread_num();
    int first = thisThread * NUM_ELEMENTS_PER_CORE;
    SimdMul( &A[first], &B[first], &C[first], NUM_ELEMENTS_PER_CORE );
}
double time1 = omp_get_wtime();
double megaMultsPerSecond = (double)ARRSIZE / ( time1 - time0 ) / 1000000.;
```

Notes:

- Remember that `#pragma omp parallel` creates a thread team and that all threads execute everything in the curly braces.
- The variable `thisThread` is the thread number of the thread who is executing this code right now. There will eventually be NUMT threads who get to execute this code. Thus, all the instances of `thisThread` will be between 0 and NUMT-1.
- The variable `first` is the first array element number that `thisThread` will execute.
- Starting the SIMD multiplications at `&A[first]`, `&B[first]`, and `&C[first]` gives each thread its very own set of contiguous array elements to work on. The `SimdMul` function depends on this.

<table>
<thead>
<tr>
<th>Array Size</th>
<th>SpeedUp</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 core alone</td>
<td>1x</td>
</tr>
<tr>
<td>2 cores alone</td>
<td>2x</td>
</tr>
<tr>
<td>4 cores alone</td>
<td>4x</td>
</tr>
<tr>
<td>8 cores alone</td>
<td>8x</td>
</tr>
<tr>
<td>16 cores alone</td>
<td>16x</td>
</tr>
</tbody>
</table>

- Speedups are with respect to a for-loop with no multicore or SIMD.
- "cores alone" = a for-loop with "#pragma omp parallel for".
- "cores + SIMD" = as the code looks on the previous page.
Avoiding Assembly Language: the Intel Intrinsics

Intel has a mechanism to get at the SSE SIMD without resorting to assembly language. These are called **Intrinsics**.

<table>
<thead>
<tr>
<th>Intrinsic</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>__m128</td>
<td>Declaration for a 128 bit 4-float word</td>
</tr>
<tr>
<td>_mm_loadu_ps</td>
<td>Load a __m128 word from memory</td>
</tr>
<tr>
<td>_mm_storeu_ps</td>
<td>Store a __m128 word into memory</td>
</tr>
<tr>
<td>_mm_mul_ps</td>
<td>Multiply two __m128 words</td>
</tr>
<tr>
<td>_mm_add_ps</td>
<td>Add two __m128 words</td>
</tr>
</tbody>
</table>

SimdMul using Intel Intrinsics

```c
#include <xmmintrin.h>
#define SSE_WIDTH 4

void SimdMul( float *a, float *b, float *c, int len )
{
    int limit = ( len/SSE_WIDTH ) * SSE_WIDTH;
    register float *pa = a;
    register float *pb = b;
    _mm_storeu_ps( c, _mm_mul_ps( _mm_loadu_ps( pa ), _mm_loadu_ps( pb ) ) );
    pa += SSE_WIDTH;
    pb += SSE_WIDTH;
    for( int i = 0; i < limit; i += SSE_WIDTH )
    {
        _mm_storeu_ps( pc, _mm_mul_ps( _mm_loadu_ps( pa ), _mm_loadu_ps( pb ) ) );
        pc += SSE_WIDTH;
    }
    for( int i = limit; i < len; i++ )
    {
        c[i] = a[i] * b[i];
    }
}
```

SimdMulSum using Intel Intrinsics

```c
float SimdMulSum( float *a, float *b, int len )
{
    float sum[4] = { 0., 0., 0., 0. };
    int limit = ( len/SSE_WIDTH ) * SSE_WIDTH;
    register float *pa = a;
    register float *pb = b;
    __m128 ss = _mm_loadu_ps( &sum[0] );
    for( int i = 0; i < limit; i += SSE_WIDTH )
    {
        ss = _mm_add_ps( ss, _mm_mul_ps( _mm_loadu_ps( pa ), _mm_loadu_ps( pb ) ) );
        pa += SSE_WIDTH;
        pb += SSE_WIDTH;
    }
    _mm_storeu_ps( &sum[0], ss );
    for( int i = limit; i < len; i++ )
    {
        sum[i] += a[i] * b[i];
    }
}
```

Intel Intrinsics

![Speed-ups for Array Multiply-Add](image.png)
Why do the Intrinsics do so well with a small dataset size?

It’s not due to the code in the inner-loop:

C/C++

for( int i = 0; i < len; i++ )
{
  c[i] = a[i] * b[i];
}

Assembly Intrinsics

movups (%r8), %xmm0
movups (%rcx), %xmm1
mulps %xmm1, %xmm0
movups %xmm0, (%rdx)
addq $16, %r8
addq $16, %rcx
addq $16, %rdx
addl $4, -4(%rbp)

It’s actually due to the setup time. The intrinsics have a tighter coupling to the setting up of the registers. A smaller setup time makes the small dataset size speedup look better.

A preview of things to come:
OpenCL and CUDA have SIMD Data Types

The whole thing will look like this:

constant float4 G = (float4) ( 0., -9.8, 0., 0.);
constant float DT = 0.1;
kernelparticle( global float4 * dPobj, global float4 * dVel, global float4 * dCobj )
{
  int gid = get_global_id( 0 ); // particle #
  float4 p = dPobj[gid]; // particle #gid’s position
  float4 v = dVel[gid]; // particle #gid’s velocity
  float4 pp = p + v*DT + .5*DT*DT*G; // p’
  float4 vp = v + G*DT; // v’
  dPobj[gid] = pp;
  dVel[gid] = vp;
}

A preview of things to come:
OpenCL and CUDA have SIMD Data Types

When we get to OpenCL, we could compute projectile physics like this:

float4 pp; // p’
pp.x = p.x + v.x*DT;
pp.y = p.y + v.y*DT + .5*DT*DT*G.y;
pp.z = p.z + v.z*DT;

But, instead, we will do it like this:

float4 pp = p + v*DT + .5*DT*DT*G; // p’

We do it this way for two reasons:
1. Convenience and clean coding
2. Some hardware can do multiple arithmetic operations simultaneously

• SIMD is an important way to achieve speed-ups on a CPU
• For now, you might have to write in assembly language or use Intel intrinsics to get to all of it
• I suspect that #pragma omp simd will eventually catch up
• Prefetching can really help SIMD