Code Generation for Data Processing Lecture 13: Vectorization

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Parallel Data Processing

Sequential execution has inherently limited performance

- Clock rate, data path lengths, speed of light, ...
- ▶ Parallelism is the key to substantial and scalable perf. improvements
- Modern systems have many levels of parallelism:
 - Multiple nodes/systems, connected via network
 - ▶ Different compute units (CPU, GPU, etc.), connected via PCIe
 - Multiple CPU sockets, connected via QPI (Intel) or HyperTransport (AMD)
 - Multiple CPU cores
 - Multiple threads per core
 - Instruction-level parallelism (superscalar out-of-order execution)
 - Data parallelism (SIMD)

Single Instruction, Multiple Data (SIMD)

Idea: perform same operations on multiple data in parallel

- ► First computer with SIMD operations: MIT Lincoln Labs TX-2, 1957⁵⁶
- Wider use in HPC in 1970s with vector processors (Cray et al.)
 - Ultimately replaced by much more scalable distributed machines
- SIMD-extensions for multimedia processing from 1990s onwards
 Often include comparial instructions for increase (video (and in processing))
 - Often include very special instructions for image/video/audio processing
- Shift towards HPC and data processing around 2010
- Extensions for machine learning/AI in late 2010s

SIMD: Idea

Multiple data elements are stored in vectors

- Size of data may differ, vector size is typically constant
- Single elements in vector referred to as *lane*
- (Vertical) Operations apply the same operation to all lanes



Horizontal operations work on neighbored elements

SIMD ISAs: Design

- Vectors are often implemented as fixed-size wide registers
 - ► Examples: ARM NEON 32×128-bit, Power QPX 32×256-bit
 - Data types and element count is defined by instruction
- Some ISAs have dynamic vector sizes: ARM VFP, ARM SVE, RISC-V V
 - Problematic for compilers: variable spill size, less constant folding
- Data types vary, e.g. i8/i16/i32/i64/f16/bf16/f32/f64/f128
 - Sometimes only conversion, sometime with saturating arithmetic
- Masking allows to suppress operations for certain lanes
 - Dedicated mask registers (AVX-512, SVE, RVV) allow for hardware masking
 - Can also apply for memory operations, optionally suppressing faults
 - Otherwise: software masking with another vector register



SIMD: Use Cases

Dense linear algebra: vector/matrix operations

- Implementations: Intel MKL, OpenBLAS, ATLAS, ...
- Sparse linear algebra
 - Needs gather/scatter instructions
- Image and video processing, manipulation, encoding
- String operations
 - Implemented, e.g., in glibc, simdjson



SIMD ISAs: Usage Considerations

Very easy to implement in hardware

- Simple replication of functional units and larger vector registers
- ▶ Too large vectors, however, also cause problems (AVX-512)
- Offer significant speedups for certain applications
 With 4x parallelism, speed-ups of ~3x are achievable
- Caveat: non-trivial to program
 - Optimized routines provided by libraries
 - Compilers try to auto-vectorize, but often need guidance

SIMD Programming: (Inline) Assembly

► Idea: SIMD is too complicated, let programmer handle this

- Programmer specifies exact code (instrs, control flow, and registers)
- Inline assembly allows for integration into existing code
 - Specification of register constraints and clobbers needed
- "Popular" for optimized libraries
- + Allows for best performance
- Very tedious to write, manual register allocation, non-portable
- No optimization across boundaries

SIMD Programming: Intrinsics

Idea: deriving a SIMD schema is complicated, delegate to programmer

- Intrinsic functions correspond to hardware instructions
 - __m128i _mm_add_epi32 (__m128i a, __m128i b)
- Programmer explicitly specifies vector data processing instructions compiler supplements registers, control flow, and scalar processing
- $+\,$ Allows for very good performance, still exposes all operations
- + Compiler can to some degree optimize intrinsics
 - GCC does not; Clang/LLVM does intrinsics often lowered to LLVM-IR vectors
- Tedious to write, non-portable

Intrinsics for Unknown Vector Size

Size not known at compile-time, but can be queried at runtime

- SVE: instruction incd adds number of vector lanes to register
- ▶ In C: behave like an incomplete type, except for parameters/returns
- Flexible code often slower than with assumed constant vector size
- Consequences:
 - Cannot put such types in structures, arrays, sizeof
 - Stack spilling implies variably-sized stack
- Instructions to set mask depending on bounds: whilelt, ...
 - No loop peeling for tail required

Fault Suppression

► Variable-length vectors are problematic for buffers of unknown size

- Example: NUL-terminated C strings
- Classical approach: ensure alignment to prevent page faults
 - > These types of out-of-bounds reads are guaranteed to be non-harmful
 - Downside: needs loop peeling code for start/end
- More recent approach: make hardware suppress exceptions
 - Option 1: specify that masked out lanes do not produce faults
 - Option 2: stop loading after first fault, store as mask in register
 - Downside 1: increased complexity in hardware, may use microcode
 - Downside 2: permits speculative vectorization at cost of more instructions

SIMD Programming: Target-independent Vector Extensions

Idea: vectorization still complicated, but compiler can choose instrs.

- Programmer still specifies exact operations, but in target-independent way
- Often mixable with target-specific intrinsics
- Compiler maps operations to actual target instructions
- ▶ If no matching target instruction exists, use replacement code
 - Inherent danger: might be less efficient than scalar code
- Often relies on explicit vector size

GCC Vector Extensions

```
#include <stdint.h>
```

```
typedef uint32_t uint32x4_t
__attribute__((vector_size(16)));
```

```
uint32x4_t
addvec(uint32x4_t a, uint32x4_t b) {
    return a + b;
}
```

```
uint32x4_t
modvec(uint32x4_t a, uint32x4_t b) {
    return a % b;
}
```

```
addvec:
paddd xmm0, xmm1
ret
<sup>modvec:</sup>
movd ecx, xmm1
movd eax, xmm0
```

```
xor edx, edx
pextrd edi, xmm1, 1
div ecx
pextrd eax, xmm0, 1
pextrd ecx, xmm1, 2
mov esi, edx
xor edx. edx
div edi
pextrd eax, xmm0, 2
mov r8d. edx
xor edx. edx
div ecx
pextrd ecx, xmm1, 3
pextrd eax, xmm0, 3
movd xmm0. esi
pinsrd xmm0, r8d, 1
mov edi. edx
xor edx. edx
div ecx
movd xmm1. edi
pinsrd xmm1, edx, 1
```

SIMD Programming: Single Program, Multiple Data (SPMD)

- So far: manual vectorization
- Observation: same code is executed on multiple elements
- Idea: tell compiler to vectorize handling of single element
 - Splice code for element into separate function
 - Tell compiler to generate vectorized version of this function
 - Function called in vector-parallel loop
- Needs annotation of variables
 - Varying: variables that differ between lanes
 - Uniform: variables that are guaranteed to be the same (basically: scalar values that are broadcasted if necessary)

SPMD: Example (OpenMP)

```
#pragma omp declare simd
int add(int x, int y) {
  return x + y;
}
```

 Compiler generates version that operates on vector foo: add edi, esi mov eax, edi ret

_ZGVxN4vv_foo: paddd xmm0, xmm1 ret

SPMD: Example (OpenMP)

```
#pragma omp declare simd uniform(y)
int add(int x, int y) {
  return x + y;
}
```

Uniform: always same value

foo:
 add edi, esi
 mov eax, edi
 ret

_ZGVxN4vu_foo: movd xmm1, eax pshufd xmm2, xmm1, 0 paddd xmm0, xmm2 ret

SPMD: Example (OpenMP) - if/else

```
#pragma omp declare simd
int foo(int x, int y) {
    int res;
    if (x > y) res = x;
    else res = y - x;
    return res;
}
```

 Diverging control flow: all paths are executed foo:

mov eax, esi sub eax, edi cmp edi, esi cmovg eax, edi ret

_ZGVxN4vv_foo: movdqa xmm2, xmm0 pcmpgtd xmm0, xmm1 psubd xmm1, xmm2 pblendvb xmm1, xmm2, xmm0 movdqa xmm0, xmm1 ret

SPMD to SIMD: Handling if/else

Control flow solely depending on uniforms: nothing different

- Otherwise: control flow may diverge
 - Different lanes may choose different execution paths
 - ▶ But: CPU has only one control flow, so all paths must execute
- Condition becomes mask, mask determines result
- After insertion of masks, linearize control flow
 - Relevant control flow now encoded in data through masks

SPMD to SIMD: Handling Loops

- Uniform loops: nothing different
- Otherwise: need to retain loop structure
 - "active" mask added to all loop iterations
 - Loop only terminates once all lanes terminate (active is zero)
 - Lanes that terminated early need their values retained
- Approach also works for nested loops/conditions
- Irreducible loops need special handling⁵⁷

SPMD Implementations on CPUs

OpenMP SIMD functions

Need to be combined with #pragma omp simd loops

- ▶ Intel ispc⁵⁸ (Implicit SPMD Program Compiler)
 - Extension of C with keywords uniform, varying
 - Still active and interesting history⁵⁹

OpenCL on CPU

- Very similar programming model
- But: higher complexity for communicating with rest of application

⁵⁸ M Pharr and WR Mark. "ispc: A SPMD compiler for high-performance CPU programming". In: InPar. 2012, pp. 1–13.
⁵⁹ https://pharr.org/matt/blog/2018/04/30/ispc-all

SIMD Programming: SPMD on CPUs

Semi-explicit vectorization

Programmer chooses level of vectorization

E.g., inner vs. outer loop

- Compiler does actual work
- $+\,$ Allows simple formulation of complex control flow
- Compilers often fail at handling complex control flow well
 - Loops are particularly problematic

SIMD Programming: Auto-vectorization

Idea: programmer is too incompetent/busy, let compiler do vectorization

- ► Inherently difficult and problematic, after decades of research
 - Recognizing and matching lots of patterns
 - Instruction selection becomes more difficult
 - Compiler lacks domain knowledge about permissible transformations
- Executive summary of the state of the art:
 - Auto-vectorization works well for very simple cases
 - For "medium complexity", code is often suboptimal
 - In many cases, auto-vectorization fails on unmodified code

Auto-vectorization is Hard

- Biggest problem: data dependencies
 - Resolving loop-carried dependencies is difficult
- Memory aliasing
 - Overlapping arrays, or worse loop counter
- Loop body *might* impact loop count
- Function calls, e.g. for math functions
- Strided memory access (e.g., only every n-th element)
- Choosing vectorization level (outer loop *might* be better)
- Is vectorization profitable at all?
- Often black box to programmer, preventing fine-grained tuning

Auto-vectorization Strategies

- Inner Loop Vectorization: unroll innermost loop *n* times
 Try to compact loop body into vectors with *n* lanes
- Outer Loop Vectorization: unroll outer loop *n* times
 Try to compact loop body into vectors with *n* lanes
 Generally does not support diverging control flow in loop body
- Superword-level Parallelism (SLP): packing series of scalar stores
 - Detect neighbored stores, try to fold operations into vectors

Vectorization – Summary

- SIMD is an easy way to improve performance numbers of CPUs
- Most general-purpose ISAs have one or more SIMD extensions
- Recent trend: variably-length vectors
- ▶ Inline Assembly: easiest for compiler, but extremely tedious
- Intrinsics: best trade-off towards performance and usability
- Target-independent operations: slightly increase portability
- SPMD: strategy dominant for GPU programming
- > Auto-vectorization: very hard, unsuited for complex code