Autovectorisation

L25: Modern Compiler Design
• Single Instruction, Multiple Data
• Single Register Multiple Data
• 2-8 values are loaded at once, operated on, stored.
• Operations must be grouped
• Modern SIMD units support scatter-gather, but slower than contiguous data
Characteristics of Modern Vector Units

- Multiple pipelines for different kinds of operation
- Independent operations dispatched in parallel
- Usually one instruction (e.g. add two four-lane vectors in parallel) per pipeline dispatched per cycle
- Multi-cycle (2-20) latency before results are available
- ISA vector width does not necessarily imply microarchitectural vector width! (e.g. Early Intel Atom had 128-bit vectors but 64-bit ALUs, dispatches half of the vector instruction each cycle)
Explicit Language Support

• Fortran, APL, GNU C and OpenCL C provide vector types
• Compiles to scalar operations or vector operations if available
• Lots of work for the programmer
Explicit Language Support

- Fortran, APL, GNU C and OpenCL C provide vector types
- Compiles to scalar operations or vector operations if available
- Lots of work for the programmer

```c
typedef __attribute__((vector_size(16))) int v4;
v4 vadd(v4 a, v4 b) {
    return a+b;
}
```
Explicit Language Support

- Fortran, APL, GNU C and OpenCL C provide vector types
- Compiles to scalar operations or vector operations if available
- Lots of work for the programmer

```c
typedef __attribute__ ((vector_size(16))) int v4;
v4 vadd(v4 a, v4 b) {
    return a+b;
}
```

```assembly
define <4 x i32> @vadd(<4 x i32> %a,
              <4 x i32> %b) {
    %1 = add <4 x i32> %b, %a
    ret <4 x i32> %1
}
```
Explicit Language Support

- Fortran, APL, GNU C and OpenCL C provide vector types
- Compiles to scalar operations or vector operations if available
- Lots of work for the programmer

```c
typedef __attribute__((vector_size(16))) int v4;

v4 vadd(v4 a, v4 b) {
    return a+b;
}
```

```assembly
define <4 x i32> @vadd(<4 x i32> %a,
               <4 x i32> %b) {
    %1 = add <4 x i32> %b, %a
    ret <4 x i32> %1
}
```

```assembly
paddd %xmm1, %xmm0
retq
```
Autovectorisation

- Take scalar source code
- ???
- Profit!
- Run high-performance vector code
Aside: Vector Types in LLVM

- LLVM IR supports arbitrary-sized vectors
- All scalar arithmetic operations are defined for vectors
- Type legalisation (before code generation) splits them into smaller vectors for the target
- Autovectorisation algorithms can be target independent, converting scalar IR into vector IR
- Target-specific cost model is important for deciding which transforms make sense
Prerequisites for Vectorisation:

Example:

```
a = b+c;
d = e+f;
```

• Can this be vectorised?
Prerequisites for Vectorisation: Alias Analysis

Example:

\[
\begin{align*}
  a &= b+c; \\
  d &= e+f;
\end{align*}
\]

- Can this be vectorised?
- Only if \( a \) doesn’t alias \( e \) or \( f \) (e.g. C++ `int &a = e`)
- `restrict` keyword is helpful in this context
- Why might the resulting code be slower?
Prerequisites for Vectorisation: Alignment

- Many vector units depend on vectors having natural alignment for loads and stores
- Unaligned loads and stores can be done by loading as scalar and copying to vector register
- Alternatively by two vector loads and a permute
- This is very slow
- For on-stack allocations, we can modify the alignment
- For loops, we can special-case the unaligned first / last elements
Pattern-Based Loop Vectorisation

- Recognise common loop patterns
- Transform to vector equivalents
- Used by GCC, XLC
- Works well for specific cases that match patterns
- Not general - no benefit for near misses (pattern must match exactly)
Example Loop Pattern

for (int i=0 ; i<x; i++)
    a[i] = b[i] + c[i];

Transforms to (pseudocode):

int i=0;
while (insufficiently_aligned(&a[i]))
    a[i] = b[i] + c[i];
for (; i+4<x; i+=4)
    vector4_add(&a[i], &b[i], &c[i]);
for (; i<x; i++)
    a[i] = b[i] + c[i];
Loop Nest Optimisation (LNO)

- Generic family of optimisations
- Transform nested loops into canonical forms
- Expose many future optimisation opportunities
- Most auto-vectorisation works on loops and depends on loops being in a comprehensible form
- Heuristic: 90% of all program execution is spent in relatively tight loops
General Loop Vectorisation

- Unroll the loop (a multiple of $n$ times for $n$-way vectors)
- Perform *if conversion* to eliminate branches
- Canonicalise induction variables / pointers
- Vectorise instructions within the resulting basic block
- Re-roll the loop
Canonicise induction variables

- Canonical form for induction loops (‘for loops’) has value that is incremented on each iteration
- Transform loop induction variables such that:
  - Induction variable starts at 0
  - Is incremented by 1 each iteration
- Followed by Loop Strength Reduction
  - Turns all array accesses into GEPs on array base for first iteration and loop increment

Before:
```
for (i=7 ; i<j ; i+=2)
  bar(y[i]);
```

After:
```
int t = j - 7;
for (i=0 ; i<t ; i++)
  bar(y[(i*2)+7]);
```
Aside: Do-Loop Transform

• Some targets (especially DSPs) have very simple loop branch predictors or ‘zero cost’ loops
• Loop induction variable should count down to 0, decrementing by 1 each time
• Loop branch always predicted taken when induction variable is non-zero
• Loop branch always predicted not-taken when induction variable is zero
• No branch predictor misses for loop in this form
Loop Invariant Code Motion (LICM)

- Hoist values that don’t depend on any $\phi$ nodes inside the loop to the start
- Avoids redundant computations within loop
- Reduces the amount of code that loop optimisations need to look at
- Very easy with SSA form: dependencies are explicit in the IR

Before:

```c
for (i=0 ; i<j ; i++){
    x = a + b;
    bar(y[i] + x);
}
```

After:

```c
x = a + b;
for (i=0 ; i<j ; i++){
    bar(y[i] + x);
}
```
Loop Unswitching

- Transform loops containing conditionals into conditionals containing loops
- Dramatically reduces number of conditional branches executed
- Exposes parallelism between iterations more cleanly
- Dual of LICM

Before:
```c
for (i=0 ; i<j ; i++){
  if (x) 
    foo(y[i]);
  else 
    bar(y[i]);
}
```

After:
```c
if (x) {
  for (i=0 ; i<j ; i++)
    foo(y[i]);
} else {
  for (i=0 ; i<j ; i++)
    bar(y[i]);
}
```
Loop Unrolling

- Expands loops to be a smaller number of loops with multiple copies of the body
- Less useful when loop branch predictors are competent
- Increases instruction cache usage
- ...but exposes more optimisation opportunities

Before:

```c
for (i=0 ; i<32 ; i++)
    bar(y[i]);
```

After:

```c
for (i=0 ; i<32 ; i++){
    bar(y[i++]);
    bar(y[i++]);
    bar(y[i++]);
    bar(y[i]);
}
```
Superword Level Parallelism (SLP)

- Identify pairs / tuples of the same instruction
- Combine into vector operations
- Inspect operands, try to perform the same combination
- Bottom-up, works across basic blocks
Padded SLP vectorisation

- Observe that there are lots of near-misses for SLP opportunities (e.g. same operation done to 3 adjacent things, not to the 4th)
- Pad vectors
- Insert data into one operand to perform a nop on one lane:
  - Multiply by one
  - Add zero
- More opportunities for vectorisation
Polyhedral Optimisation (Polytope Model)

- Create dependency graph of array elements for array iterations
- Perform affine transform on graph
- Rewrite loop
Dithering:

```c
for (int j = 0; j < h; ++j) {
    for (int i = 0; i < w; ++i) {
        int v = src[i][j];
        v -= (dst[i-1][j] - src[i-1][j]) / 2;
        v -= (dst[i][j-1] - src[i][j-1]) / 4;
        v -= (dst[i+1][j-1] - src[i+1][j-1]) / 2;
        dst[i][j] = (v < 128) ? 0 : 255;
        src[i][j] = (v < 0) ? 0 : (v < 255) ? v : 255;
    }
}
```
Loop Data Dependencies

Each iteration reads:

```
src[i][j]
dst[i-1][j], src[i-1][j]
dst[i][j-1], src[i][j-1]
dst[i+1][j-1], src[i+1][j-1];
```

Each iteration writes:

```
dst[i][j]
src[i][j]
```
Loop Iteration Dependencies

Each iteration depends on the results from:

(i-1,j)
(i,j-1)
(i+1,j-1)

As a polyhedron (arrows show data flow between loop iterations):
Applying an Affine Transform

- Affine transforms are matrices that change coordinate spaces
- Can skew, rotate, scale (not relevant in this context)
- Skew and rotate applied here to the dependencies:
- \((p, t) = (i, 2j + i)\)
Changing the Execution Order

- $t$ becomes the outer loop
- $p$ becomes the inner loop

$t = 2j - i$

$p = i$
Why?

- Polyhedral transformations allow various reorderings of the loop
- Dependencies between iterations are preserved
- May expose better parallelism opportunities
- May expose better locality of reference
- Factor of $10 \times$ speedup or more for some algorithms
Parallel Execution

- First and last two iterations are scalar
- All of the rest are 2-element vectors

\[
t = 2j - i
\]

\[
p = i
\]
Questions?