# Autovectorisation

L25: Modern Compiler Design

# SIMD

- 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)

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- Lots of work for the programmer

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  ret <4 x i32> %1
}
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```

```
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:

```
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d = e+f;
```

- 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 autovectorisation 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:

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

After:

```
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:

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

After:

```
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

# Polyhedral Example

Dithering:

```
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:

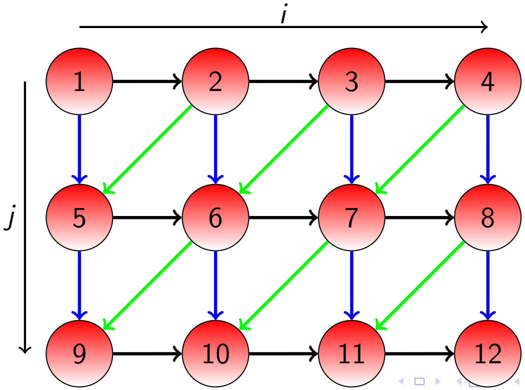
```
dst[i][j]
src[i][j]
```

# Loop Iteration Dependencies

Each iteration depends on the results from:

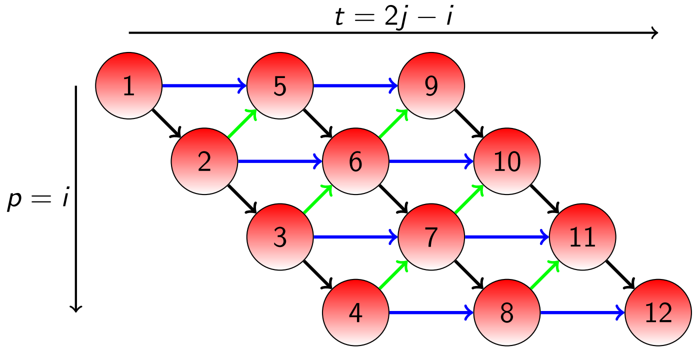
```
(i-1,j)
(i,j-1)
(i+1,j-1)
```

As a polyhedron (arrows show data flow between loop iterations):



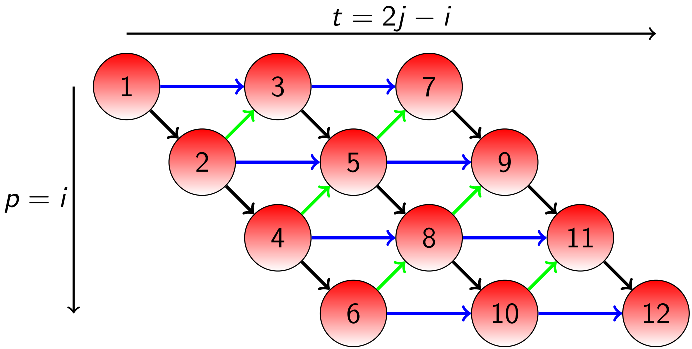
# Applying an Affine Transform

- 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

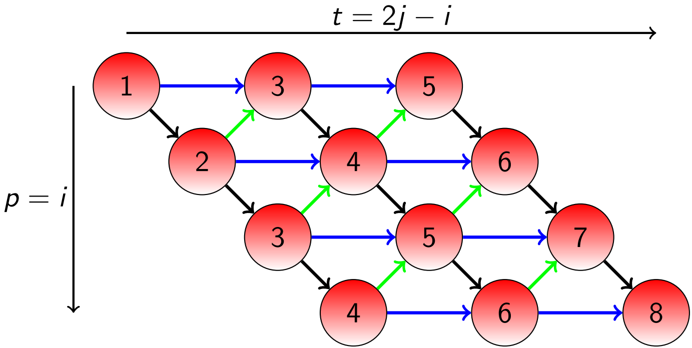


# Why?

- 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



Questions?