

CS614: Advanced Compilers

Loop Parallelization

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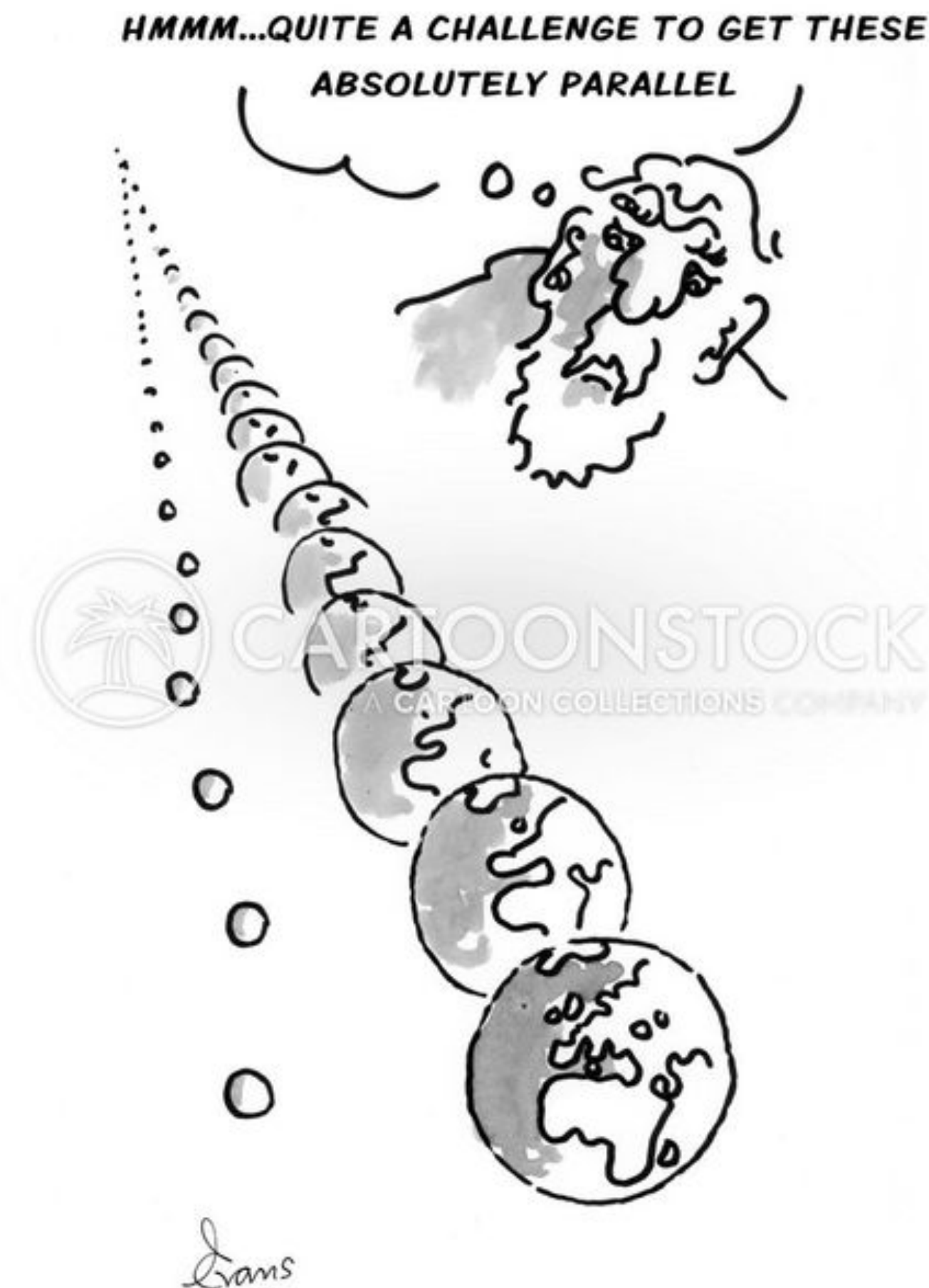


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Things we have learnt post midsem

CS402899

- Instruction scheduling (pipelines)
- Memory optimizations (cache)
- Loop transformations (cache)
- Now lets move to compute units!
 - *We have lots of them nowadays.*
 - Utilize them effectively
 - **Parallelize**, **vectorize**



Parallelization

- What's not parallel?
 - **Concurrent:** Execute code sequences in an interleaved manner
- What is **parallel**?
 - Actually execute simultaneously (on different hardware)
- Why?
 - **Moore's law** is fading
 - Free lunch is over
- How?
 - Learn to code in concurrent frameworks
 - Parallelize code portions during compilation!



How much can we benefit from parallelization?

- Amdahl's law:

- The **speed-up** achievable using parallelization is **limited by the sequential portion** of the code.
- For a 10-hour program, if we can parallelize 9 hours of computation, we will still take at least 1 hour.
 - That is, maximum 10x speed-up even with a 1000-core GPU!
- Thus, parallel computing with a large number of processors is straightforwardly useful only for **highly parallelizable** programs.
 - What's better than to target loops!!



When can't we parallelize?

- Dependencies inhibit parallelism

- Control dependency:

```
if (a < b)
    x = 10;
else
    x = 20;
```

- Usually explicit in the syntax
- Easier to identify

- Data dependency:

- Quite often needs analyses to identify
- Can foo and bar execute simultaneously?
- Are both the f's same?
- More involved with pointers (alias analysis!)

```
foo() {
    f = 10;
}
bar() {
    print f;
}
```

```
foo() {
    x = 10;
}
bar() {
    print *y;
}
```



Kinds of data dependencies

- RAW / True / Flow:

- $x = 2; y = x + 1;$

- WAR / Anti:

- $y = x + 1; x = 5;$

- WAW / Output:

- $x = 2; x = 3;$

- RAR (not critical)

- $y = x; \text{print } x;$

True dependencies are real dependencies; anti and output dependencies can often be elided with variable/register renaming.



Kinds of loop dependencies

1. Loop-carried dependencies

- Arise because of iterations of the loop
- On every (except first) iteration, S2 uses a value of A that was computed in the previous iteration by S1
- S2 has a *true* dependence on S1, and vice-versa

```
    for (i=0; i<N; i++) {  
S1:    A[i+1] = B[i];  
S2:    B[i+1] = A[i];  
    }
```

2. Loop-independent dependencies

- Arise because of relative statement position
- S2 refers to the same memory location as S1
- There is a control-flow path from S1 to S2

```
    for (i=0; i<N; i++) {  
S1:    A[i] = ...;  
S2:    ... = A[i];  
    }
```

Which of the following loops can be parallelized?

```
for (k=0; k<n; ++k) {  
    a[k] = b[k];  
    b[k] = a[k] + 1;  
}
```



```
for (k=0; k<n; ++k) {  
    a[k] = a[k+1];  
}
```

```
for (k=0; k<n; ++k) {  
    a[x] = a[y];  
}
```



Loop Parallelization. It is valid to convert a sequential loop to a parallel loop if the loop carries no dependence.

Array Data-Dependence Analysis

- Step 1: Express relations among array indices and loop bounds as **linear inequations**.
- Step 2: Determine whether solution exists using **GCD test**.
- Step 3: Solve after simplification if need solution values.

```
for (k=0; k<n; ++k) {  
    a[x] = a[y];  
}
```

```
for (i=1; i<=10; i++) {  
    Z[i] = Z[i-1];  
}
```

Dependence between $Z[i-1]$ and $Z[i]$:

- $1 \leq i_r \leq 10; 1 \leq i_w \leq 10; i_r - 1 = i_w; i_r \neq i_w$
- 9 solutions: $(i_r=2, i_w=1), (i_r=3, i_w=2), \dots$

Dependence between $Z[i]$ and itself:

- $1 \leq i_{w1} \leq 10; 1 \leq i_{w2} \leq 10; i_{w1} = i_{w2}; i_{w1} \neq i_{w2}$
- No solution

Array Data-Dependence Analysis (Cont.)

GCD Test. The linear *Diophantine* equation

$$a_1x_1 + a_2x_2 + \dots + a_nx_n = c$$

has an integer solution for x_1, x_2, \dots, x_n if and only if $\gcd(a_1, a_2, \dots, a_n)$ divides c .

```
for (i = 1; i < 10; i++) {  
    Z[2*i] = 10;  
}  
for (j = 1; j < 10; j++) {  
    Z[2*j+1] = 20;  
}
```

- In order for the two Z accesses to write to the same location, $2*i = 2*j+1$.
- Canonical form: $2*i - 2*j = 1$.
- $\text{GCD}(2, -2) = 2$, which does not divide 1.
- Thus there is no dependency.
- Hence the **two loops can run in parallel**.



Loop Parallelization: Practice

```
for (i = 1; i <= 4; i++) {  
    B[i] = A[3*i-5] + 2.0;  
    A[2*i+1] = 1.0/i;  
}
```

- $2*i_1+1 = 3*i_2-5$
- $2*i_1 - 3*i_2 = -6$
- $\text{GCD}(2, -3) = 1$, which divides -6
- Hence the **loop cannot be parallelized**.
- $a[7]$ is written to in iteration 4 and used in iteration 3.

```
for (i = 1; i <= 4; i++) {  
    B[i] = A[4*i] + 2.0;  
    A[2*i+1] = 1.0/i;  
}
```

- $2*i_1+1 = 4*i_2$
- $2*i_1 - 4*i_2 = -1$
- $\text{GCD}(2, -4) = 2$, which does not divide -1
- Hence the **loop can be parallelized**.



Reordering within a loop

- A less obvious loop-independent dependence:

```
    for (i=1; i<9; i++) {  
S1:    A[i] = ...;  
S2:    ... = A[10-i];  
    }
```

- Dependence in 5th iteration.

Why this requirement?

If there is a loop-independent dependence from S1 to S2, any reordering transformation that **does not move statement instances across iterations** and preserves the relative order of S1 and S2 in the loop body preserves that dependence.

Reordering within a loop (Cont.)

- Some compiler optimization may perform this transformation:

```
for (i=1; i<N; i++) {  
S1:   A[i] = B[i] + C;  
S2:   D[i] = A[i] + E;  
}
```



```
D[1] = A[1] + E;  
for (i=2; i<N; i++) {  
S1:   A[i-1] = B[i-1] + C;  
S2:   D[i] = A[i] + E;  
}  
A[N] = B[N] + C;
```

- Order of statements within the body preserved, but **loop-independent true dependence converted to anti-dependence** ==> *invalid transformation*.

A loop-carried dependence is satisfied so long as loops are iterated in the original order, regardless of the statement order within a specific iteration. A loop-independent dependence is satisfied so long as the statement order is maintained, regardless of the order in which the loops are iterated.

Loop Vectorization



Vector Operation

- An operation that can be performed simultaneously on multiple registers
- SIMD (Single Instruction, Multiple Data) processors

Scalar Operation

$$\begin{array}{l} A_1 \times B_1 = C_1 \\ A_2 \times B_2 = C_2 \\ A_3 \times B_3 = C_3 \\ A_4 \times B_4 = C_4 \end{array}$$

SIMD Operation

$$\begin{array}{l} A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \times \begin{array}{l} B_1 \\ B_2 \\ B_3 \\ B_4 \end{array} = \begin{array}{l} C_1 \\ C_2 \\ C_3 \\ C_4 \end{array}$$

- Most modern hardware support vector instructions (sometimes, of varied lengths)
 - Intel has AVX; AMD has 3DNow!; ARM has NEON; GPUs.
 - Some also support “predicated” (masked) vectorization.



Compiling for Vector Pipelines

- Some programming languages provide capability for manual vectorization
 - `#pragma omp simd` in OpenMP; `_mm_add_ps` in C
 - Java? Programmer shouldn't bother with tricky stuff; offload to compiler ;-)
- Many compilers perform auto-vectorization as a machine-dependent optimization

```
for (i=0; i<1024; i++) {  
    C[i] = A[i] * B[i];  
}
```



```
for (i=0; i<1024; i+=4) {  
    C[i:i+3] = A[i:i+3] * B[i:i+3];  
} // remaining array, if needed
```

- How is this different from loop unrolling?
 - *The four multiplications must have the effect of getting performed in parallel.*

```
for (i=0; i<1024; i+=4) {  
    C[i] = A[i] * B[i];  
    C[i+1] = A[i+1] * B[i+1];  
    C[i+2] = A[i+2] * B[i+2];  
    C[i+3] = A[i+3] * B[i+3];  
}
```

Vectorization

➤ Valid transformation:

```
for (i=1; i<N; i++) {  
    X[i] = X[i] + C;  
}
```



```
X[1:N] = X[1:N] + C
```

➤ Invalid transformation:

```
for (i=1; i<N; i++) {  
    X[i+1] = X[i] + C;  
}
```



```
X[2:N+1] = X[1:N] + C
```

- Sequential version uses a value of X that is computed in the previous iteration, while the vectorized version uses old values of X.

Which loops can be vectorized?

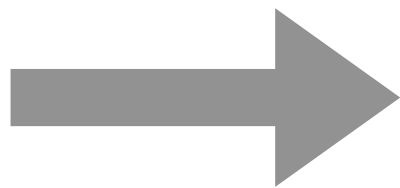
```
for (i=1; i<N; i++) {  
S1:   A[i+1] = B[i] + C;  
S2:   D[i] = A[i] + E;  
}
```



```
S1: A[2:N+1] = B[1:N] + C  
S2: D[1:N] = A[1:N] + E
```

- Valid vectorization even though the loop carries a dependence!
- We had an implicit *loop distribution/fission*:

```
for (i=1; i<N; i++) {  
S1:   A[i+1] = B[i] + C;  
S2:   D[i] = A[i] + E;  
}
```



```
for (i=1; i<N; i++) {  
S1:   A[i+1] = B[i] + C;  
}  
for (i=1; i<N; i++) {  
S2:   D[i] = A[i] + E;  
}
```

- Did you say it worked because the loop-carried dependence was *forward*?

Which loops can be vectorized? (Cont.)

- The **fission magic** can sometimes be made to work even when the loop-carried dependence is *backward*, with reordering within the loop body:

```
for (i=1; i<N; i++) {  
S2:   D[i] = A[i] + E;  
S1:   A[i+1] = B[i] + C;  
}
```



```
for (i=1; i<N; i++) {  
S1:   A[i+1] = B[i] + C;  
S2:   D[i] = A[i] + E;  
}
```

- However, this case has a backward-carried dependence as well as a loop-independent dependence, and hence interchange will not work:

```
for (i=1; i<N; i++) {  
S1:   B[i] = A[i] + E;  
S2:   A[i+1] = B[i] + C;  
}
```

Loop Vectorization. A statement contained in at least one loop can be vectorized by direct rewriting if the statement is not included in any cycle of dependences.

Which reorderings are valid compiler transformations?

- We have studied (at least) the following reordering transformations:
 - *Software pipelining; data prefetching; LICM; loop interchange, tiling, fusion, fission, parallelization, vectorization.*
- Any general notion that describes which ones are valid?
- Interestingly, validity depends (quite a bit) on the programming language!
- The **memory model** for a language L determines how much “reordering freedom” do compiler implementations and hardware have for programs written in L.
- Decided by PL designers (often continuously improvised by PL researchers).

Next Class: *Memory Models* and Valid Reordering Transformations.

