# Lecture 13—Speculation; Parallelization Patterns

## ECE 459: Programming for Performance

January 30, 2015

# Estimating Impact of Speculative Execution

$T_1$: time to run `longCalculatuion`.
$T_2$: time to run `secondLongCalculation`.
$p$: probability that `secondLongCalculation` executes.

In the normal case we have:

$$T_{\text{normal}} = T_1 + pT_2.$$

$S$: synchronization overhead.
Our speculative code takes:

$$T_{\text{speculative}} = \max(T_1, T_2) + S.$$

Exercise. When is speculative code faster? Slower?
How could you improve it?

# Shortcomings of Speculative Execution

Consider the following code:

```
void doWork(int x, int y) {
    int value = longCalculation(x, y);
    return secondLongCalculation(value);
}
```

Now we have a true dependency; can't use speculative execution.

But: if the value is predictable, we can execute `secondLongCalculation` using the predicted value.

This is value speculation.

# Value Speculation Implementation

This Pthread code does value speculation:

```
void doWork(int x, int y) {
    thread_t t1, t2;
    point p(x,y);
    int v1, v2, last_value;
    thread_create(&t1, NULL, &longCalculation, &p);
    thread_create(&t2, NULL, &secondLongCalculation,
                  &last_value);
    thread_join(t1, &v1);
    thread_join(t2, &v2);
    if (v1 == last_value) {
      return v2;
    } else {
      last_value = v1;
      return secondLongCalculation(v1);
    }
}
```

Note: this is like memoization (plus parallelization).

# Estimating Impact of Value Speculation

$T_1$: time to run `longCalculatuion`.
$T_2$: time to run `secondLongCalculation`.
$p$: probability that `secondLongCalculation` executes.
$S$: synchronization overhead.

In the normal case, we again have:

$$T = T_1 + pT_2.$$

This speculative code takes:

$$T = \max(T_1, T_2) + S + pT_2.$$

Exercise. Again, when is speculative code faster? Slower? How could you improve it?

# When Can We Speculate?

Required conditions for safety:

- `longCalculation` and `secondLongCalculation` must not call each other.
- `secondLongCalculation` must not depend on any values set or modified by `longCalculation`.
- The return value of `longCalculation` must be deterministic.

General warning: Consider side effects of function calls.

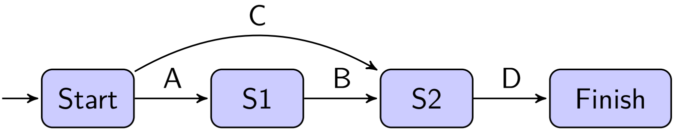
# Part I

# Parallelization Patterns

# Critical Paths

Should be familiar with critcal paths from other courses (Gantt charts).

Consider the following diagram (edges are tasks):




- B depends on A, C has no dependencies, and D depends on B and C.
- Can execute A-then-B in parallel with C.
- Keep dependencies in mind when calculating speedups for more complex programs.

# Data and Task Parallelism

Data parallelism is performing *the same* operations on different input.
**Example:** doubling all elements of an array.

Task parallelism is performing *different* operations on different input.
**Example:** playing a video file: one thread decompresses frames, another renders.

# Data Parallelism: Single Instruction, Multiple Data

We'll discuss SIMD in more detail later. An overview:

- You can load a bunch of data and perform arithmetic.
- Intructions process multiple data items simultaneously. (Exact number is hardware-dependent).

For x86-class CPUs, MMX and SSE extensions provide SIMD instructions.

# SIMD Example

Consider the following code:

```
void vadd(double * restrict a, double * restrict b,
          int count) {
  for (int i = 0; i < count; i++)
    a[i] += b[i];
}
```

In this scenario, we have a regular operation over block data.

We could use threads, but we'll use SIMD.

# SIMD Example—Assembly without SIMD

If we compile this without SIMD instructions on a 32-bit x86, (flags `-m32 -march=i386 -S`) we might get this:

```
loop:
  fldl   (%edx)
  faddl  (%ecx)
  fstpl  (%edx)
  addl   8, %edx
  addl   8, %ecx
  addl   1, %esi
  cmp    %eax, %esi
  jle    loop
```

Just loads, adds, writes and increments.

# SIMD Example—Assembly with SIMD

Instead, compiling to SIMD instructions
(`-m32 -mfpmath=sse -march=prescott`) gives:

```
loop:
  movupd  (%edx),%xmm0
  movupd  (%ecx),%xmm1
  addpd   %xmm1,%xmm0
  movpd   %xmm0,(%edx)
  addl    16,%edx
  addl    16,%ecx
  addl    2,%esi
  cmp     %eax,%esi
  jle     loop
```

- Now processing two elements at a time on the same core.
- Also, no need for stack-based x87 code.

# SIMD Overview

- Operations *packed*: operate on multiple data elements at the same time.
- On modern 64-bit CPUs, SSE has 16 128-bit registers.
- Very good if your data can be *vectorized* and performs math.
- Usual application: image/video processing.
- We'll see more SIMD as we get into GPU programming: GPUs excel at these types of applications.

# Task-Based Patterns: Overview

- We'll now look at thread and process-based parallelization.
- Although threads and processes differ, we don't care for now.

# Pattern 1: Multiple Independent Tasks

Only useful to maximize system utilization.

- Run multiple tasks on the same system
  (e.g. database and web server).

  If one is memory-bound and the other is I/O-bound, for example, you'll get maximum utilization out of your resources.

  **Example:** cloud computing, each task is independent and can tasks can spread themselves over different nodes.

- Performance can increase linearly with the number of threads.

# Pattern 2: Multiple Loosely-Coupled Tasks

Tasks aren't quite independent, so there needs to be some inter-task communication (but not much).

- Communication might be from the tasks to a controller or status monitor.

Refactoring an application can help with latency. For instance: split off the CPU-intensive computations into a separate thread—your application may respond more quickly.

**Example:** A program (1) receives/forwards packets and (2) logs them. You can split these two tasks into two threads, so you can still receive/forward while waiting for disk. This will increase the throughput of the system.

# Pattern 3: Multiple Copies of the Same Task

Variant of multiple independent tasks: run multiple copies of the same task (probably on different data).

- No communcation between different copies.

Again, performance should increase linearly with number of tasks.

**Example:** In a rendering application, each thread can be responsible for a frame (gain throughput; same latency).

# Pattern 4: Single Task, Multiple Threads

Classic vision of "parallelization".

**Example:** Distribute array processing over multiple threads—each thread computes results for a subset of the array.

- Can decrease latency (and increase throughput), as we saw with Amdahl's Law.
- Communication can be a problem, if the data is not nicely partitioned.
- Most common implementation is just creating threads and joining them, combining all results at the join.