18-447 Lecture 22: 1 Lecture Worth of Parallel Programming Primer

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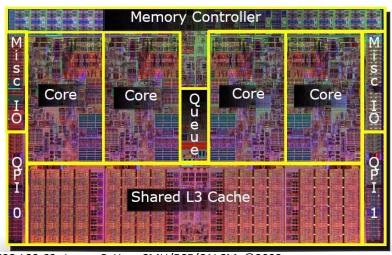
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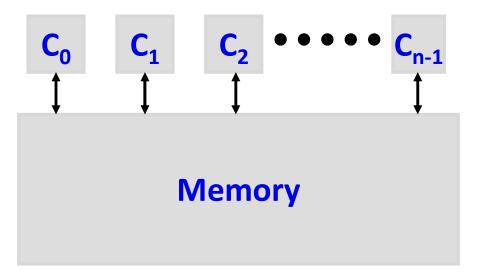
Housekeeping

- Your goal today
 - see basic concepts in shared-memory multithreading (context for topics to come)
 - appreciate how easy parallel programming can be
 - appreciate how difficult "good" parallel programming can be
- Notices
 - Lab 4, due week 14
 - HW6, due Monday 5/2 noon
 - Midterm 2 Regrade, due Monday, 4/25
- Readings
 - P&H Ch 6

Shared-Memory Multicores

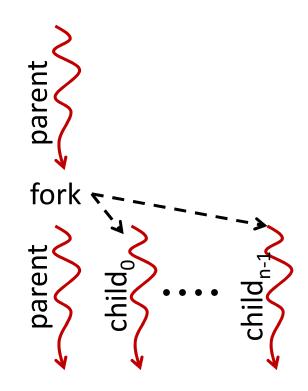
- Today's general-purpose multicore processors are MIMD, symmetric, shared memory
 - individual cores follow classic von Neuman
 - common access to physical address space and mem
 - processes/threads on different cores communicate
 by writing and reading agreed-upon mem locations





Single Program Multiple Data

- SPMD is MIMD except all threads based on the same program image
- On SMP, SPMD starts as a singlethread process and its memory
- Independent "threads of execution" (think program counters, regfile and stacks) spawned
 - **same process memory**
 —same
 EA in different threads refers to
 shared program and data locations
 - different threads run concurrently (on different cores) or interleaved



SPMD just one of many options; prevalent and easy to start on

E.g., POSIX Threads Create and Join

```
// globals are in memory and shared!!
long count=0;
void *foo(void *arg) { return count = count + (long)arg; }
int main(){
 pthread t tid[HOWMANY];
                                // array of thread IDs
 long i;
 void *retval;
 // spawn children threads
 for(i=0; i<HOWMANY; i++ )</pre>
   NULL,
                              // attribute (default)
                  foo, // fxn to run by thread
                  (void*)i);  // ptr-size arg to fxn
 // wait for children threads to exit
 for (i=0; i<HOWMANY; i++ )</pre>
   pthread join( tid[i],
                                // ID to wait on
                &retval);
                                // ptr-size return value
```

Memory Consistency

- Memory consistency model says for each read which write bound the value to be returned
 - intuitively: a read should return value of "most recent" write to the same address
 - straight forward for a single thread
- In a shared-memory multicore, cores C1/C2/C3 perform following streams of reads and writes

```
C1: ..... W(x)......

C2: .... W(x), W(y), R(x), R(y)...

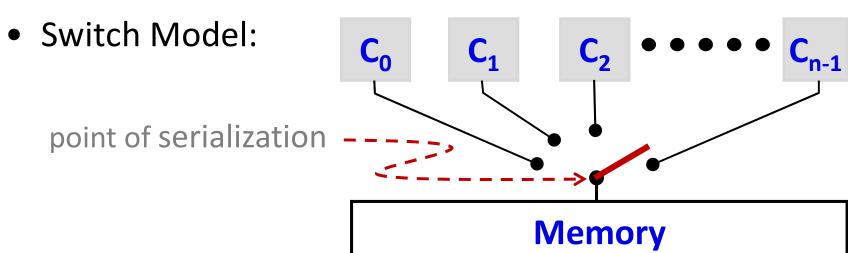
C3: ..... W(x), W(y), W(x)...
```

Which is the last write to x before R(x) by C2?

Ordering determines what can be seen by reads, but what is observed by reads determines ordering!!

Sequential Consistency (SC)

- A thread perceives its own memory ops in program order (of course)
- Memory ops from threads in program order can be interleaved arbitrarily; different interleaving allowed on different runs, i.e., nondeterminism
- For each run, all threads must not disagree on any orderings observed



SC Example: what can and cannot be

 Threads T1 and T2 and shared locations X and Y (initially X = 0, Y = 0)

```
T1: .... store(X, 1); vy = load(Y); store(Y, 1); vx = load(X); ....
```

- SC says
 - vy and vx may get different values from run to run

e.g.,
$$(vy=0, vx=0)$$
, $(vy=0, vx=1)$, or $(vy=1, vx=1)$

but if vy is 1 then vx cannot be 0

An Useful Example

- Threads T1 and T2 communicate via shared memory locations X and Y
 - T1 produces result in X to be consumed by T2
 - T1 signals readiness to T2 by setting Y

```
Y is initially 0
.....

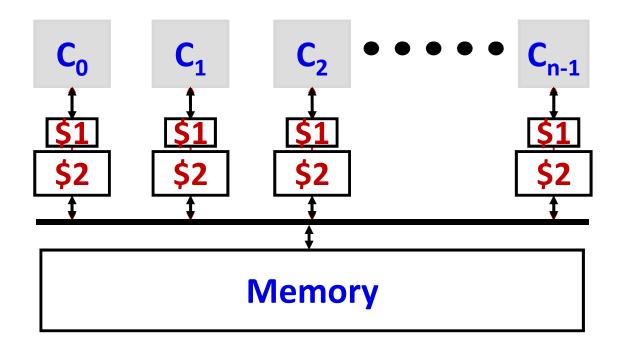
compute v
store (X, v)
store (Y, 1)
.....

T2:

ready=load Y
} while (!ready)
data = load X reorder?
```

 This works because SC says T1 and T2 must see the stores to X and Y in the same order

Easy to think about hard to build



- Where is "point of serialization" if memory ops don't always go to memory or even onto a bus?
- SC restricts many memory reordering optimizations taken-for-granted in sequential execution (e.g., non-blocking miss)

Weak Consistency (WC)

- WC imposes only uniprocessor memory ordering requirements: R(x)<W(x); W(x)<R(x); W(x)<W(x)
- Program inserts explicit memory fence instructions to force serialization when it matters

```
Y is initially 0
.....

compute v
store (X, v)

fence
store (Y, 1)

T2:
.....

do {
ready=load Y
} while (!ready)

fence
data = load X
```

 If serialization is rare, cheap(hw)/slow fences okay, e.g., completely drain/restart pipeline

Intermediate models exist between SC and WC

Embarrassingly Parallel Processing

- Summing 10,000 numbers from array A []
- In sequential algorithm

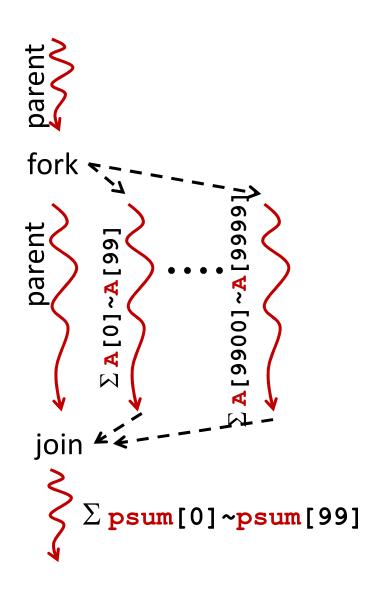
```
for (i=0; i<10000; i=i+1)
sum = sum "+" A[i];</pre>
```

- Assuming "+" is 1 unit-time; everything else free
 - $-T_1=10,000$
 - $-T_{\infty} = \lceil \log_2 10,000 \rceil = 14$ (using associativity of "+")
 - $P_{avg} = T_1/T_{\infty} = 714$
- Ideally, at p=100 << T₁/T∞

expect
$$T_{100} \approx T_1/p = 100$$
 or $S_{100} \approx p = 100$

Shared-Memory Pthreads Strategy 1

- Fork p=100 threads on a p-way shared memory multiprocessor
 - A[10000] is in shared memory
 - psum[100] is also in shared memory
- Child thread-i uses psum[i] to compute its portion of the partial sum
- When all threads finish, parent sums psum [0] ~psum [99]



Children Thread Code

```
double A[ARRAY SIZE];
double psum[p];
void *sumParallel(void * id) {
  long id=(long) id;
  long i;
  psum[id]=0;
  for (i=0;i<(ARRAY SIZE/p);i++)</pre>
     psum[id]+=A[id*(ARRAY_SIZE/p) + i];
  return NULL;
```

Parent Code

```
double A[ARRAY SIZE];
double psum[p];
double sum=0;
int main(){
  ... skipped pthreads boilerplate ...
  for(i=0; i<p; i++)
     pthread create( &tid[i],
                     NULL,
                     sumParallel,
                      (void*)i);
  for (i=0; i<p; i++) {
     pthread_join( tid[i], &retval);
     sum+=psum[i];
```

Performance Analysis

- Summing 10,000 numbers on 100 cores
 - 100 threads performs 100 +'s each in parallel
 - parent thread performs 100 +'s sequentially

$$-T_{100} = 100 + 100$$

$$S_{100} = 50$$

• If <u>100,000</u> num on 100 cores

$$-T_{100} = 1000 + 100$$

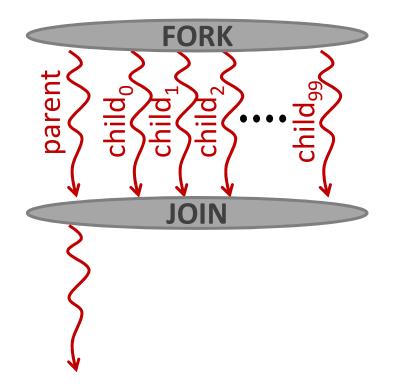
$$-S_{100} = 90.9$$

• If 10,000 num on <u>10</u> cores

$$-T_{10} = 1000 + 10$$

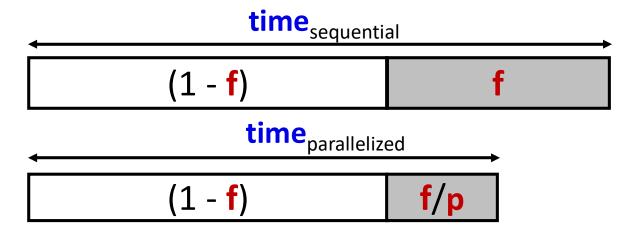
$$S_{10}$$
 = 9.9

- Don't forget,
 - fork and join are not free
 - moving data (even thru shared memory) not free



The Actual Amdahl's Law

If only a fraction f (by time) is parallelizable by p



time_{parallelized} = time_{sequential}·(
$$(1-f) + f/p$$
)
 $S_{effective} = 1 / ((1-f) + f/p)$

- if f is small, p doesn't matter
- even when f is large, diminishing return on p;
 eventually "1-f" dominates

Strategy 2: parallelizing the reduction

 How about asking each thread to do a bit of the reduction, i.e.,

```
void *sumParallel(void * id) {
  long id=(long) id;
  long i;
  psum[id]=0;
  for (i=0;i<(ARRAY SIZE/p);i++)</pre>
      psum[id]+=A[id*ARRAY SIZE/p+i];
  sum=sum+psum[id];
  return NULL;
```

Data Races

- On last slide sum is read and updated by all threads at around the same time
- Let's try just 2 threads T1 and T2, sum is initially 0

```
T1: compute v
temp=load sum
temp=temp+v
store (sum, temp)

T2: compute w
temp=load sum
temp=load sum
temp=temp+w
store (sum, temp)
```

- What are the possible final values of sum?
 - v+w or v or w depending on the interleaving of the read/modify/write sequence in T1 and T2
- To work, RMW regions needs to be atomic

i.e., no intervening reads/writes by other threads

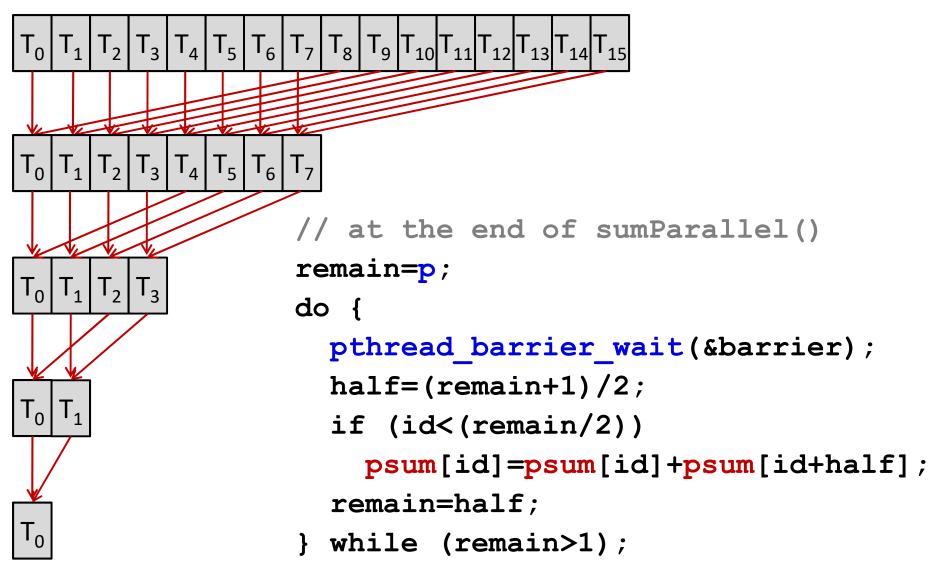
Critical Sections

 Special "lock" variables and lock/unlock operators to demarcate a "critical section" that only one thread can enter at a time, e.g.,

- lock() blocks until lockvar is free or freed (released by previous owner)
- on unlock(), if multiple lock() pending, only 1 should succeed; the rest keep waiting
- Strategy 2 is now correct but actually slower

Reduction still sequential plus extra cost of locking and unlocking

Strategy 3: Parallel Reduction (assume "+" associative and commutative)



Performance Analysis

- Summing 10,000 on 100 cores
 - 100 threads performs 100 +'s each in parallel, and
 - between 1~7 +'s each in the parallel reduction

$$-T_{100} = 100 + 7$$

$$S_{100} = 93.5$$

• If summing <u>100,000</u> on 100 cores

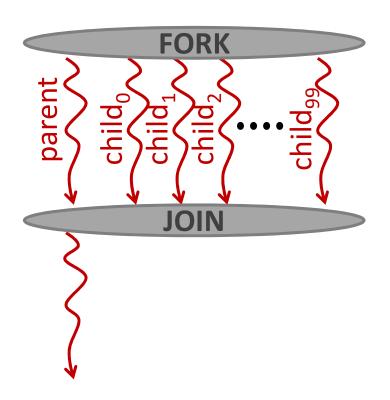
$$-T_{100} = 1000 + 7$$

$$-S_{100} = 99.3$$

• If summing 10,000 on <u>10</u> cores

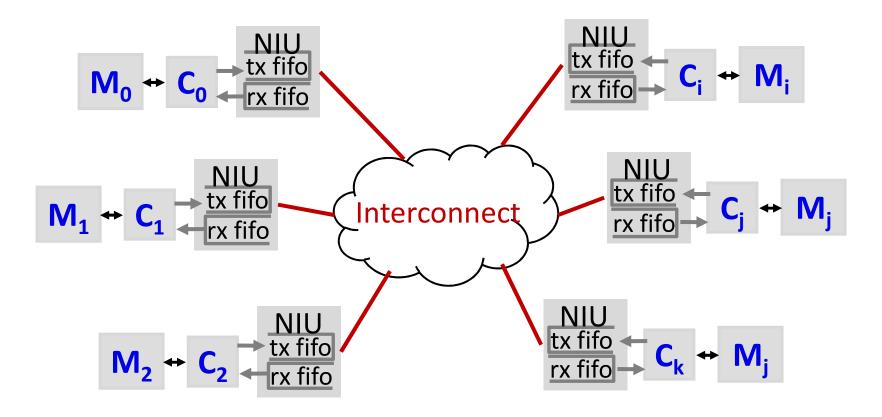
$$-T_{10} = 1000 + 4$$

$$S_{10} = 10.0$$



First-order analysis! Don't bet on this.

Message Passing



Private address space and memory per processor
 Parallel threads on different processors communicate
 v explicit sending and receiving of messages

Example using Matched Send/Receive

```
if (id==0)
                   //assume node-0 has A initially
   for (i=1;i<p;i=i+1)</pre>
      SEND(i, &A[SHARE*i], SHARE*sizeof(double));
else
   RECEIVE(0,A[]) //receive into local array
sum=0;
for(i=0;i<SHARE;i=i+1) sum=sum+A[i];</pre>
remain=p;
do {
    BARRIER();
    half=(remain+1)/2;
    if (id>=half&&id<remain) SEND(id-half,sum,8);</pre>
    if (id<(remain/2)) {</pre>
       RECEIVE (id+half, &temp);
       sum=sum+temp;
    remain=half;
  while (remain>1);
                               [based on P&H Ch 6 example]
```

Communication Cost

- Communication cost is a part of parallel execution
- Easier to perceive communication cost in message passing
 - overhead: takes time to send and receive data
 - latency: takes time for data to go from A to B
 - gap (1/bandwidth): takes time to push successive data through a finite bandwidth
- Same cost was also there in shared memory

To be continued