

Thread-Level Parallelism

14-513 / 18-613: Computer Systems 27th Lecture, July 28th, 2020

Today

Parallel Computing Hardware

- Multicore
 - Multiple separate processors on single chip
- Hyperthreading
 - Efficient execution of multiple threads on single core

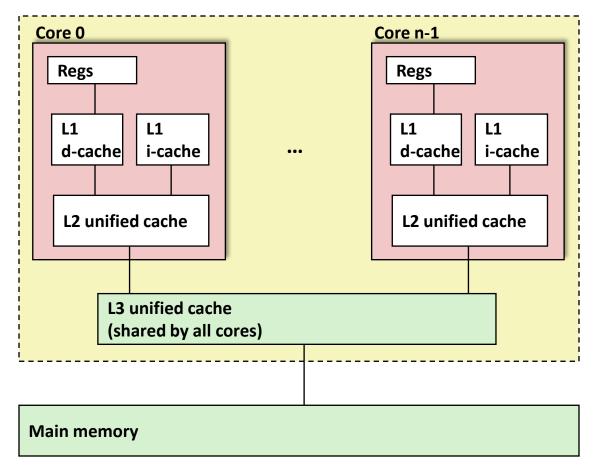
Consistency Models

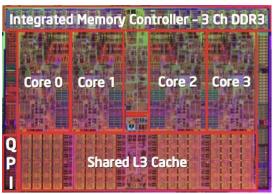
What happens when multiple threads are reading & writing shared state

Thread-Level Parallelism

- Splitting program into independent tasks
 - Example: Parallel summation
 - Examine some performance artifacts
- Divide-and conquer parallelism
 - Example: Parallel quicksort

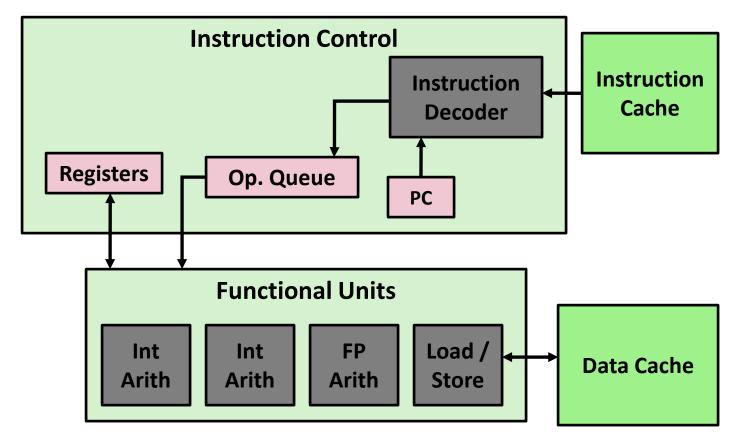
Typical Multicore Processor





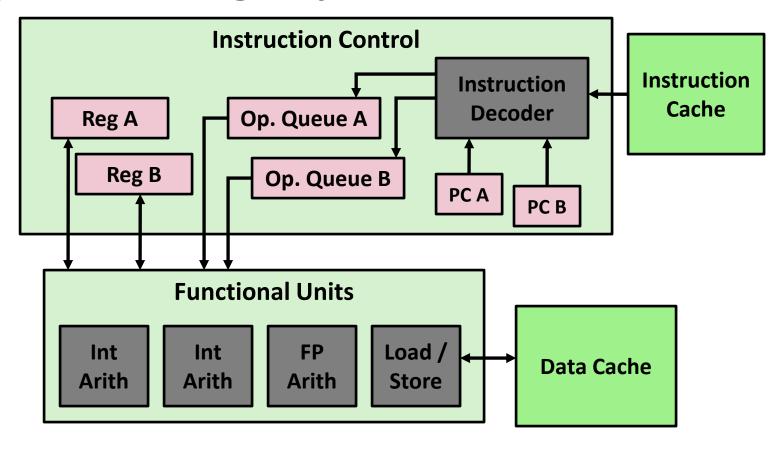
Multiple processors operating with coherent view of memory

Out-of-Order Processor Structure



- Instruction control dynamically converts program into stream of operations
- Operations mapped onto functional units to execute in parallel

Hyperthreading Implementation



- Replicate instruction control to process K instruction streams
- K copies of all registers
- Share functional units

Benchmark Machine

- Get data about machine from /proc/cpuinfo
- Shark Machines
 - Intel Xeon E5520 @ 2.27 GHz
 - Nehalem, ca. 2010
 - 8 Cores
 - Each can do 2x hyperthreading

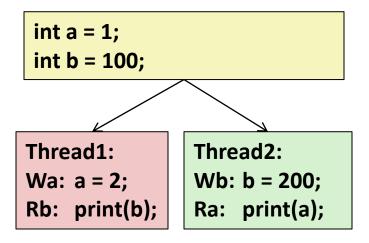
Exploiting parallel execution

- So far, we've used threads to deal with I/O delays
 - e.g., one thread per client to prevent one from delaying another
- Multi-core CPUs offer another opportunity
 - Spread work over threads executing in parallel on N cores
 - Happens automatically, if many independent tasks
 - e.g., running many applications or serving many clients
 - Can also write code to make one big task go faster
 - by organizing it as multiple parallel sub-tasks

Shark machines can execute 16 threads at once

- 8 cores, each with 2-way hyperthreading
- Theoretical speedup of 16X
 - never achieved in our benchmarks

Memory Consistency

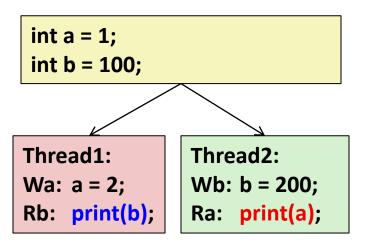


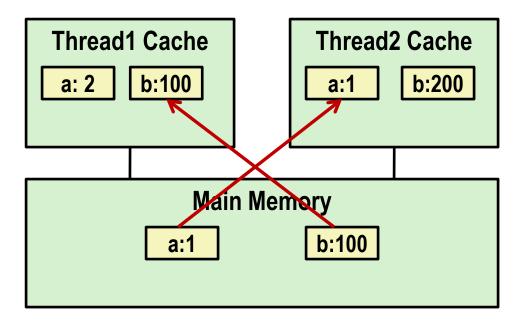
What are the possible values printed?

- Depends on memory consistency model
- Abstract model of how hardware handles concurrent accesses.

Non-Coherent Cache Scenario

Write-back caches, without coordination between them





print 1

print 100

At later points, a:2 and b:200 are written back to main memory

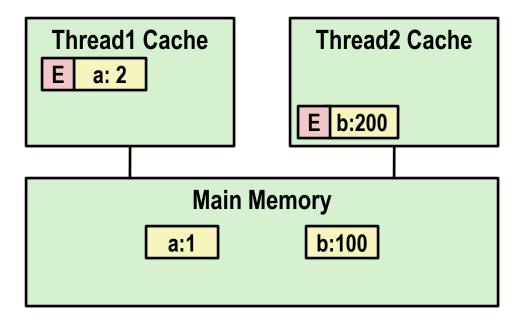
Snoopy Caches

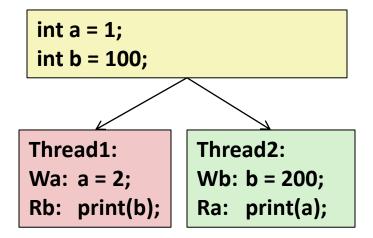
Tag each cache block with state

Invalid Cannot use value

Shared Readable copy

Exclusive Writeable copy





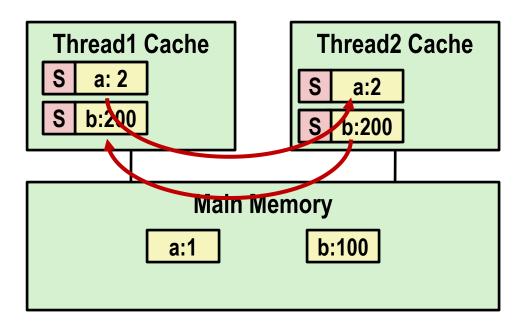
Snoopy Caches

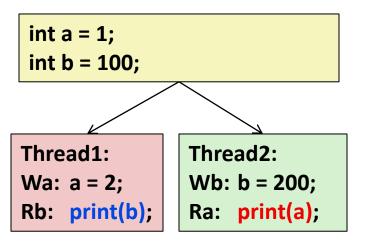
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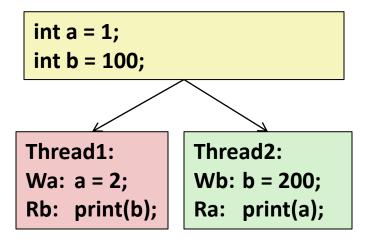


print 2

print 200

- When cache sees request for one of its E-tagged blocks
 - Supply value from cache (Note: value in memory may be stale)
 - Set tag to S

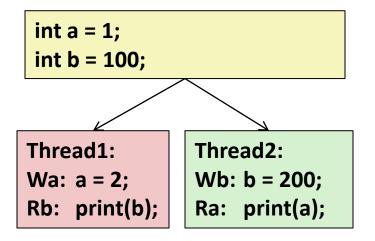
Memory Consistency



Thread consistency constraints
Wa → Rb
Wb → Ra

- What are the possible values printed?
 - Depends on memory consistency model
 - Abstract model of how hardware handles concurrent accesses

Memory Consistency



Thread consistency constraints
Wa → Rb
Wb → Ra

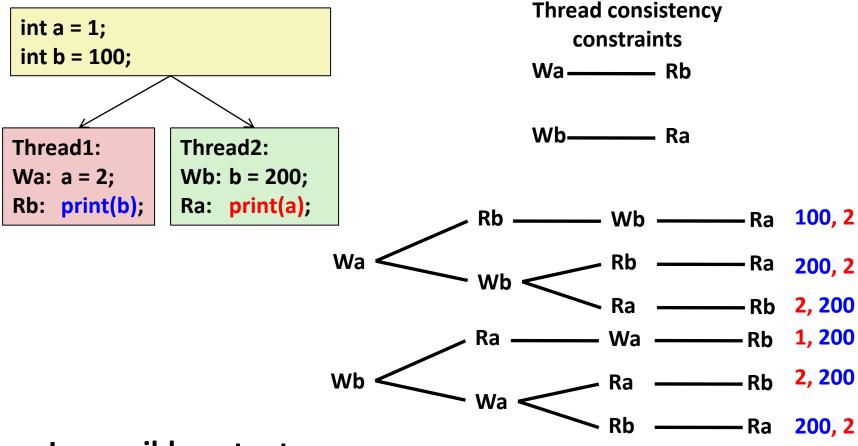
What are the possible values printed?

- Depends on memory consistency model
- Abstract model of how hardware handles concurrent accesses

Sequential consistency

- As if only one operation at a time, in an order consistent with the order of operations within each thread
- Thus, overall effect consistent with each individual thread but otherwise allows an arbitrary interleaving

Sequential Consistency Example

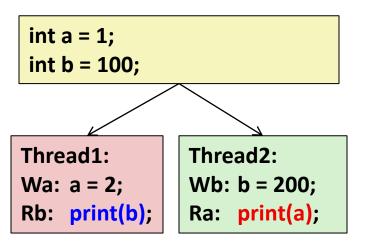


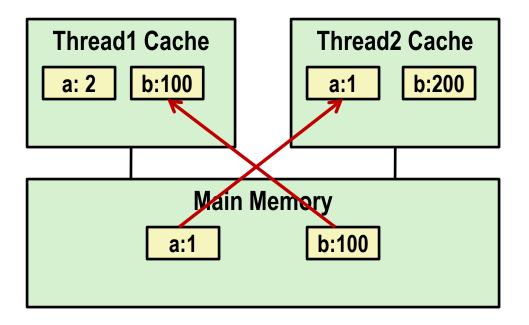
Impossible outputs

- 100, 1 and 1, 100
- Would require reaching both Ra and Rb before either Wa or Wb

Non-Coherent Cache Scenario

Write-back caches, without coordination between them





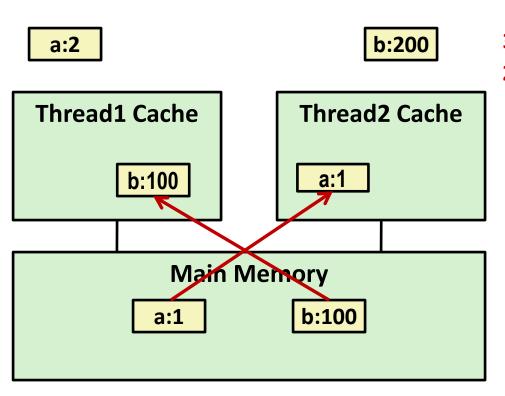
print 1

print 100

Sequentially consistent? No

Non-Sequentially Consistent Scenario

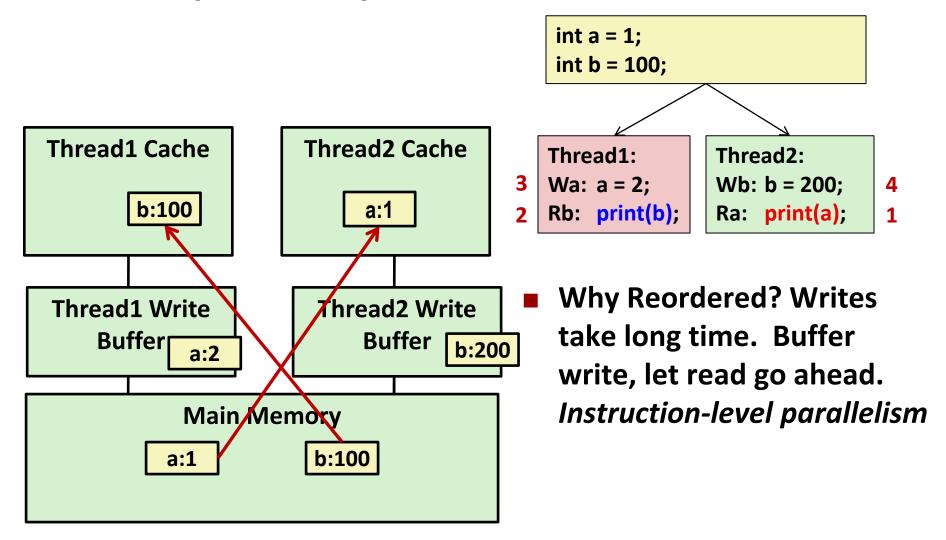
 Coherent caches, but thread consistency constraints violated due to operation reordering



```
int a = 1;
 int b = 100;
Thread1:
                 Thread2:
                 Wb: b = 200;
Wa: a = 2;
Rb: print(b);
                 Ra: print(a);
    print 1
    print 100
```

 Arch lets reads finish before writes b/c single thread accesses different memory locations

Non-Sequentially Consistent Scenario



■ Fix: Add SFENCE instructions between Wa & Rb and Wb & Ra

Memory Models

- Sequentially Consistent:
 - Each thread executes in proper order, any interleaving
- To ensure, requires
 - Proper cache/memory behavior
 - Proper intra-thread ordering constraints

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Consistency Models

What happens when multiple threads are reading & writing shared state

Thread-Level Parallelism

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 - Examine some performance artifacts
- Divide-and conquer parallelism
 - Example: Parallel quicksort

Summation Example

- Sum numbers 0, ..., N-1
 - Should add up to (N-1)*N/2
- Partition into K ranges
 - LN/K values each
 - Each of the t threads processes 1 range
 - Accumulate leftover values serially
- Method #1: All threads update single global variable
 - 1A: No synchronization
 - 1B: Synchronize with pthread semaphore
 - 1C: Synchronize with pthread mutex
 - "Binary" semaphore. Only values 0 & 1

Accumulating in Single Global Variable: Declarations

```
typedef unsigned long data t;
/* Single accumulator */
volatile data_t global_sum;
```

Accumulating in Single Global Variable: Declarations

```
typedef unsigned long data t;
/* Single accumulator */
volatile data t global sum;
/* Mutex & semaphore for global sum */
sem t semaphore;
pthread mutex t mutex;
```

Accumulating in Single Global Variable: Declarations

```
typedef unsigned long data t;
/* Single accumulator */
volatile data t global sum;
/* Mutex & semaphore for global sum */
sem t semaphore;
pthread mutex t mutex;
/* Number of elements summed by each thread */
size t nelems per thread;
/* Keep track of thread IDs */
pthread t tid[MAXTHREADS];
/* Identify each thread */
int myid[MAXTHREADS];
```

Accumulating in Single Global Variable: Operation

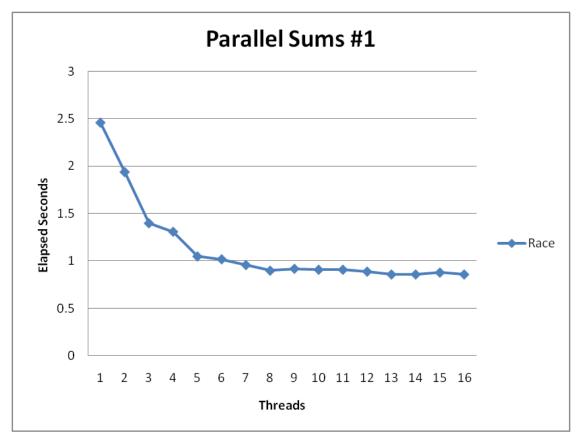
```
nelems per thread = nelems / nthreads;
/* Set global value */
                                                     Thread routine
global sum = 0;
                                      Thread ID
/* Create threads and wait for them to finish */
for (i = 0; i < nthreads; 1++) {</pre>
   myid[i] = i;
   Pthread create(&tid[i], NULL, thread fun, &myid[i]);
for (i = 0; i < nthreads; i++)</pre>
                                                   Thread arguments
   Pthread join(tid[i], NULL);
                                                       (void *p)
result = global sum;
/* Add leftover elements */
for (e = nthreads * nelems per thread; e < nelems; e++)</pre>
    result += e;
```

Thread Function: No Synchronization

```
void *sum_race(void *vargp)
{
    int myid = *((int *)vargp);
    size_t start = myid * nelems_per_thread;
    size_t end = start + nelems_per_thread;
    size_t i;

for (i = start; i < end; i++) {
        global_sum += i;
    }
    return NULL;
}</pre>
```

Unsynchronized Performance



- $N = 2^{30}$
- Best speedup = 2.86X
- Gets wrong answer when > 1 thread! Why?

Thread Function: Semaphore / Mutex

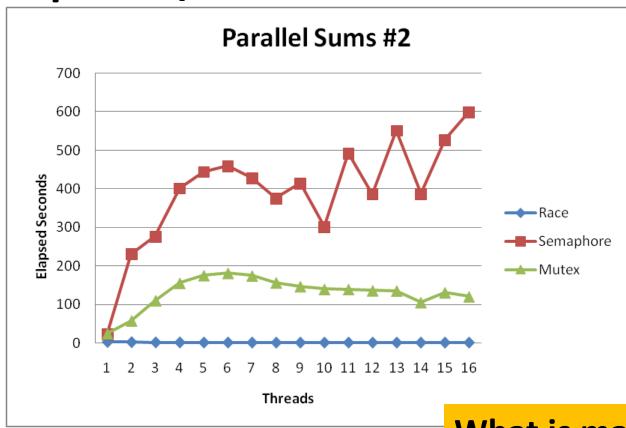
Semaphore

```
void *sum sem(void *varqp)
{
    int myid = *((int *)varqp);
    size t start = myid * nelems per thread;
    size t end = start + nelems per thread;
    size t i;
    for (i = start; i < end; i++) {
       sem wait(&semaphore);
       global sum += i;
       sem post(&semaphore);
    return NULL;
```

Mutex

```
pthread_mutex_lock(&mutex);
global_sum += i;
pthread_mutex_unlock(&mutex);
```

Semaphore / Mutex Performance



- Terrible Performance
 - 2.5 seconds → ~10 minutes
- Mutex 3X faster than semaphore
- Clearly, neither is successful

What is main reason for poor performance?

Separate Accumulation

- Method #2: Each thread accumulates into separate variable
 - 2A: Accumulate in contiguous array elements
 - 2B: Accumulate in spaced-apart array elements
 - 2C: Accumulate in registers

```
/* Partial sum computed by each thread */
data_t psum[MAXTHREADS*MAXSPACING];

/* Spacing between accumulators */
size_t spacing = 1;
```

Separate Accumulation: Operation

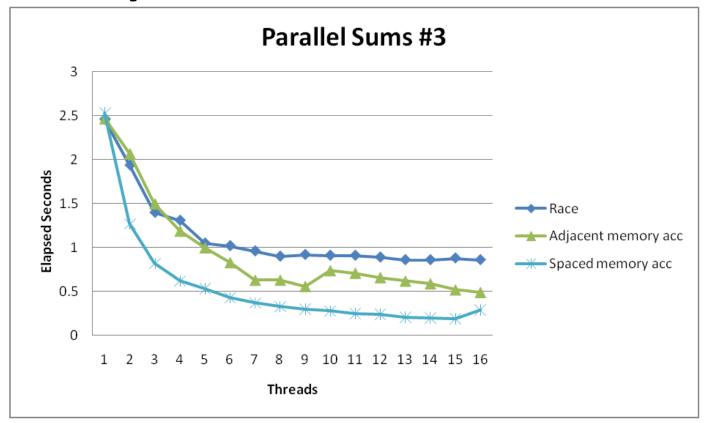
```
nelems per thread = nelems / nthreads;
/* Create threads and wait for them to finish */
for (i = 0; i < nthreads; i++) {</pre>
   myid[i] = i;
   psum[i*spacing] = 0;
   Pthread create(&tid[i], NULL, thread fun, &myid[i]);
for (i = 0; i < nthreads; i++)
   Pthread join(tid[i], NULL);
result = 0;
/* Add up the partial sums computed by each thread */
for (i = 0; i < nthreads; i++)</pre>
   result += psum[i*spacing];
/* Add leftover elements */
for (e = nthreads * nelems per thread; e < nelems; e++)</pre>
    result += e;
```

Thread Function: Memory Accumulation

Where is the mutex?

```
void *sum global(void *vargp)
    int myid = *((int *)varqp);
    size t start = myid * nelems per thread;
    size t end = start + nelems per thread;
    size t i;
    size t index = myid*spacing;
    psum[index] = 0;
    for (i = start; i < end; i++) {</pre>
       psum[index] += i;
    return NULL;
```

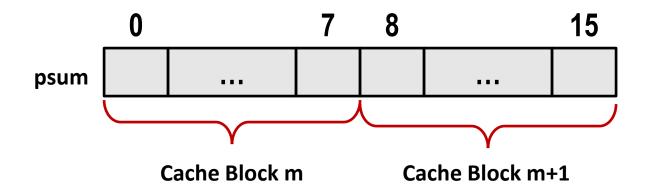
Memory Accumulation Performance



Clear threading advantage

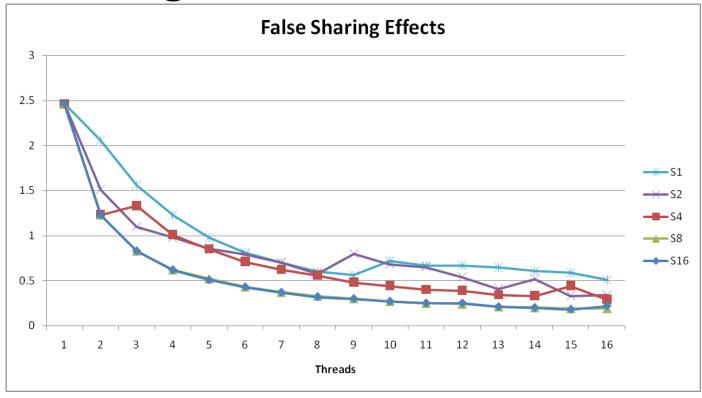
- Adjacent speedup: 5 X
- Spaced-apart speedup: 13.3 X (Only observed speedup > 8)
- Why does spacing the accumulators apart matter?

False Sharing



- Coherence maintained on cache blocks
- To update psum[i], thread i must have exclusive access
 - Threads sharing common cache block will keep fighting each other for access to block

False Sharing Performance

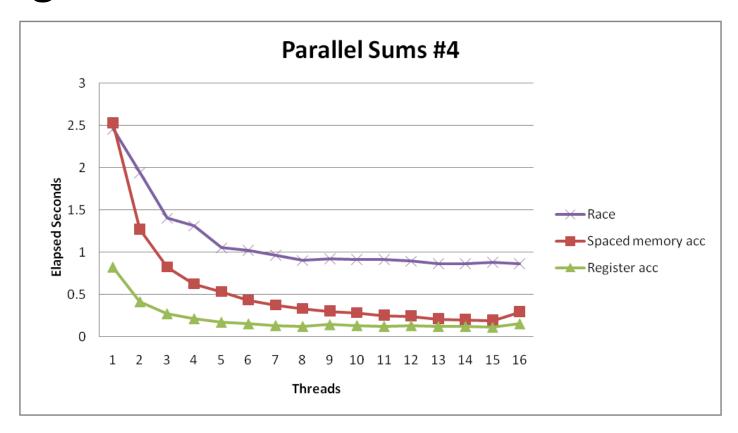


- Best spaced-apart performance 2.8 X better than best adjacent
- Demonstrates cache block size = 64
 - 8-byte values
 - No benefit increasing spacing beyond 8

Thread Function: Register Accumulation

```
void *sum local(void *vargp)
{
    int myid = *((int *)vargp);
    size t start = myid * nelems per thread;
    size t end = start + nelems per thread;
    size t i;
    size t index = myid*spacing;
    data t sum = 0;
    for (i = start; i < end; i++) {</pre>
       sum += i;
    psum[index] = sum;
    return NULL;
```

Register Accumulation Performance



- Clear threading advantage
 - Speedup = 7.5 X

Beware the speedup metric!

2X better than fastest memory accumulation

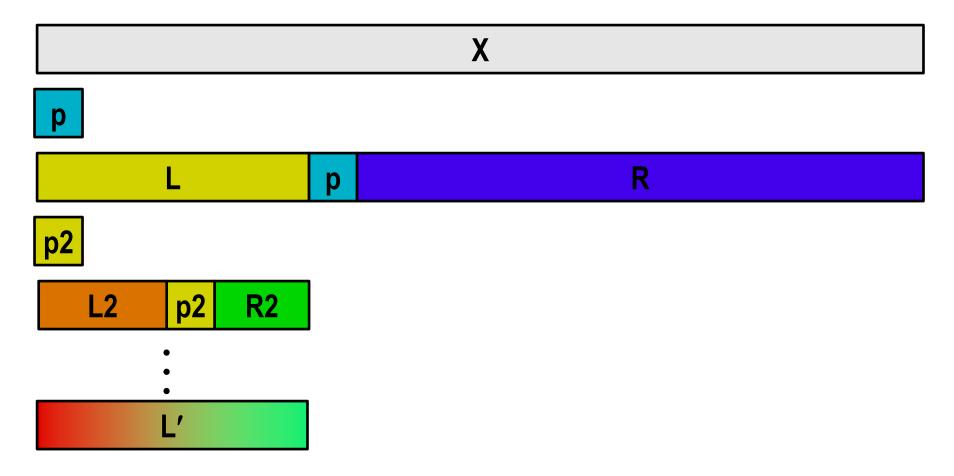
Lessons learned

- Sharing memory can be expensive
 - Pay attention to true sharing
 - Pay attention to false sharing
- Use registers whenever possible
 - (Remember cachelab)
 - Use local cache whenever possible
- Deal with leftovers
- When examining performance, compare to best possible sequential implementation

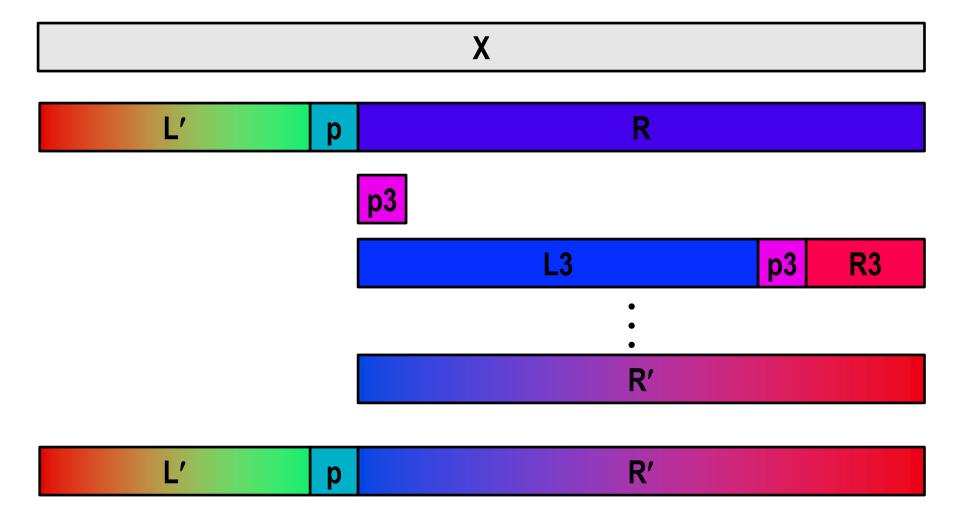
A More Substantial Example: Sort

- Sort set of N random numbers
- Multiple possible algorithms
 - Use parallel version of quicksort
- Sequential quicksort of set of values X
 - Choose "pivot" p from X
 - Rearrange X into
 - L: Values ≤ p
 - R: Values \geq p
 - Recursively sort L to get L'
 - Recursively sort R to get R'
 - Return L' : p : R'

Sequential Quicksort Visualized



Sequential Quicksort Visualized



Sequential Quicksort Code

```
void qsort serial(data t *base, size t nele) {
  if (nele <= 1)
    return:
  if (nele == 2) {
    if (base[0] > base[1])
      swap(base, base+1);
    return;
  }
  /* Partition returns index of pivot */
  size t m = partition(base, nele);
  if (m > 1)
   qsort serial(base, m);
  if (nele-1 > m+1)
   qsort serial(base+m+1, nele-m-1);
```

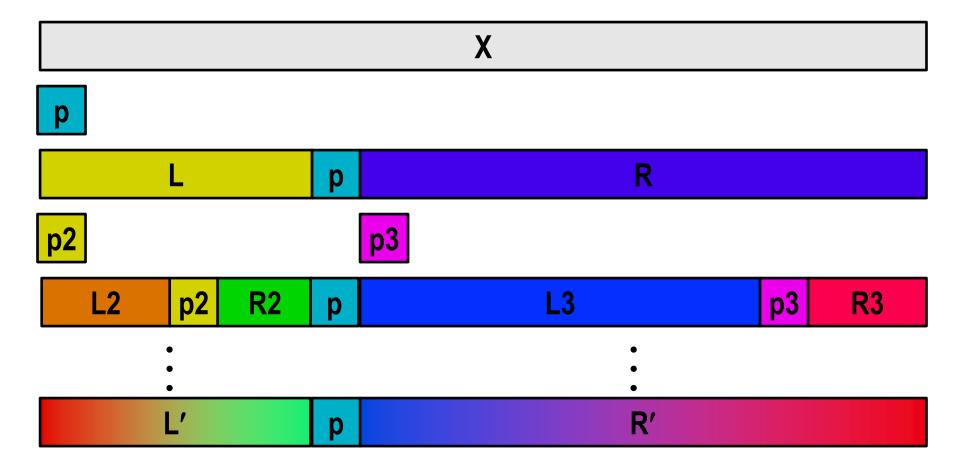
Sort nele elements starting at base

Recursively sort L or R if has more than one element

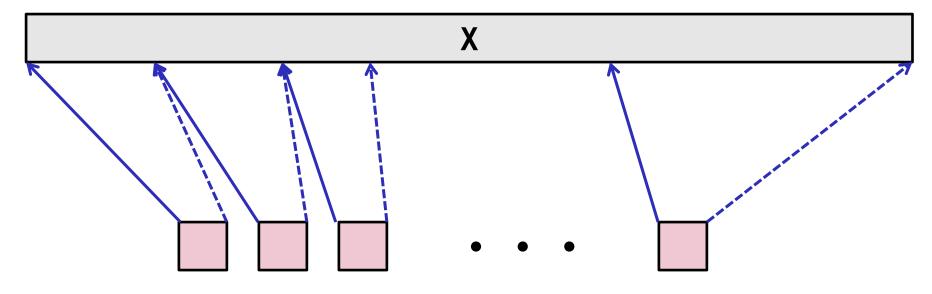
Parallel Quicksort

- Parallel quicksort of set of values X
 - If N ≤ Nthresh, do sequential quicksort
 - Else
 - Choose "pivot" p from X
 - Rearrange X into
 - L: Values \leq p
 - R: Values ≥ p
 - Recursively spawn separate threads
 - Sort L to get L'
 - Sort R to get R'
 - Return L' : p : R'

Parallel Quicksort Visualized



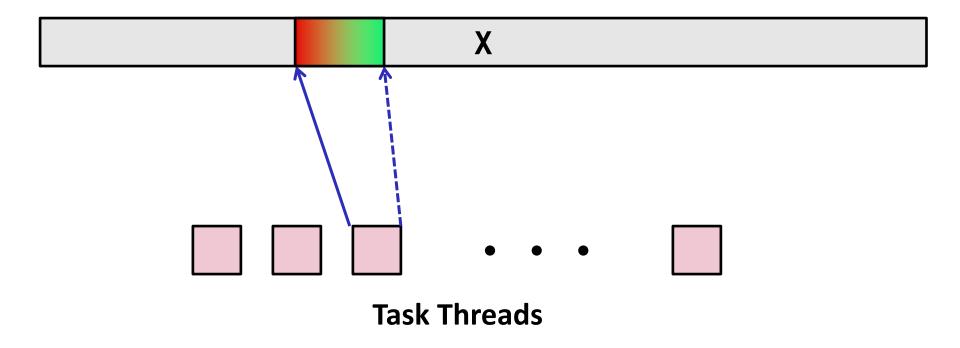
Thread Structure: Sorting Tasks



Task Threads

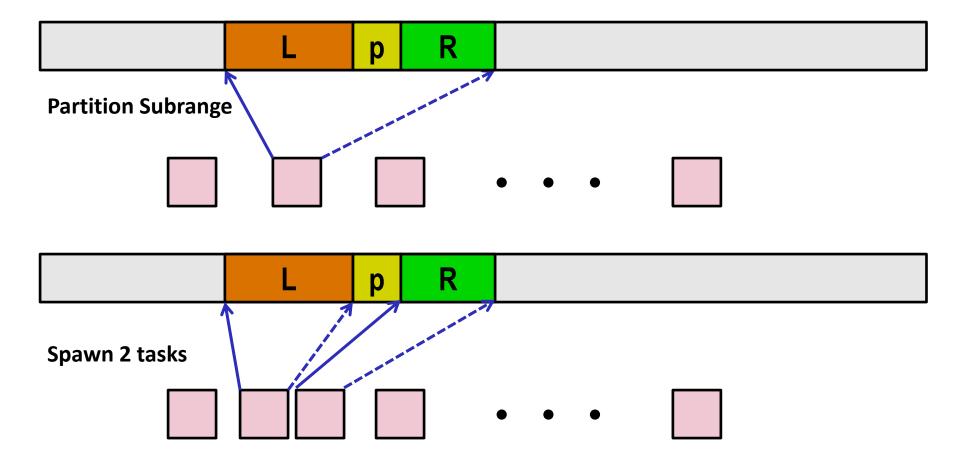
- Task: Sort subrange of data
 - Specify as:
 - base: Starting address
 - nele: Number of elements in subrange
- Run as separate thread

Small Sort Task Operation



Sort subrange using serial quicksort

Large Sort Task Operation



Top-Level Function (Simplified)

```
void tqsort(data_t *base, size_t nele) {
   init_task(nele);
   global_base = base;
   global_end = global_base + nele - 1;
   task_queue_ptr tq = new_task_queue();
   tqsort_helper(base, nele, tq);
   join_tasks(tq);
   free_task_queue(tq);
}
```

- Sets up data structures
- Calls recursive sort routine
- Keeps joining threads until none left
- Frees data structures

Recursive sort routine (Simplified)

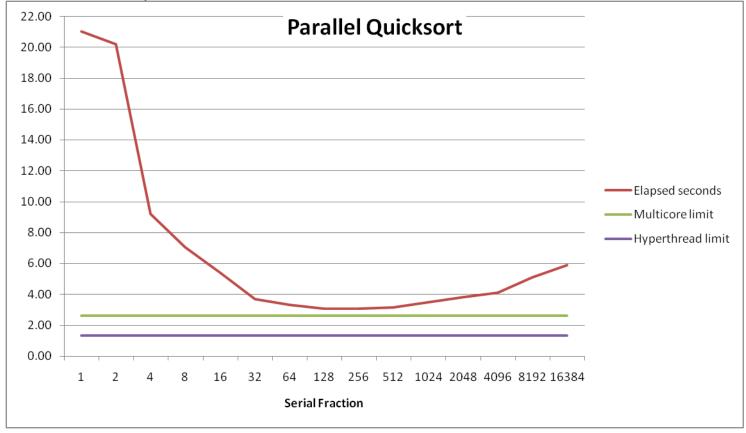
- Small partition: Sort serially
- Large partition: Spawn new sort task

Sort task thread (Simplified)

```
/* Thread routine for many-threaded quicksort */
static void *sort thread(void *vargp) {
    sort task t *t = (sort task t *) varqp;
    data t *base = t->base;
    size t nele = t->nele;
    task queue ptr tq = t->tq;
    free (varqp);
    size t m = partition(base, nele);
    if (m > 1)
        tqsort helper(base, m, tq);
    if (nele-1 > m+1)
        tqsort helper(base+m+1, nele-m-1, tq);
    return NULL;
```

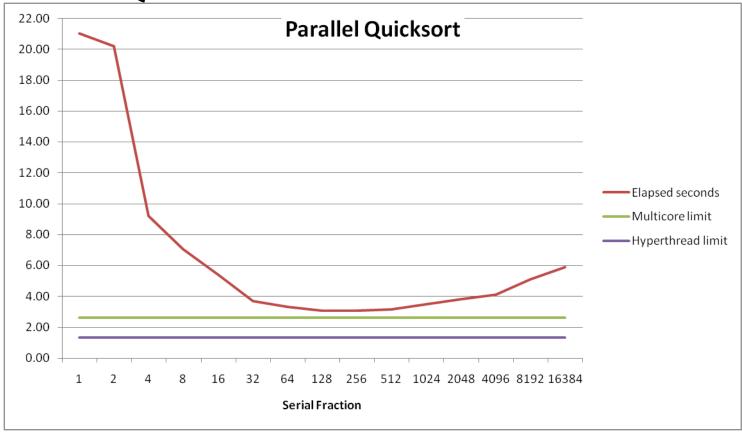
- Get task parameters
- Perform partitioning step
- Call recursive sort routine on each partition (if size of part > 1)

Parallel Quicksort Performance



- Serial fraction: Fraction of input at which do serial sort
- Sort 2²⁷ (134,217,728) random values
- Best speedup = 6.84X

Parallel Quicksort Performance



Good performance over wide range of fraction values

- F too small: Not enough parallelism
- F too large: Thread overhead too high

Amdahl's Law

Overall problem

- T Total sequential time required
- p Fraction of total that can be sped up $(0 \le p \le 1)$
- k Speedup factor

Resulting Performance

- $T_k = pT/k + (1-p)T$
 - Portion which can be sped up runs k times faster
 - Portion which cannot be sped up stays the same
- Maximum possible speedup
 - $k = \infty$
 - $T_{\infty} = (1-p)T$

Amdahl's Law Example

Overall problem

- T = 10 Total time required
- p = 0.9 Fraction of total which can be sped up
- k = 9 Speedup factor

Resulting Performance

T₉ =
$$0.9 * 10/9 + 0.1 * 10 = 1.0 + 1.0 = 2.0$$
 (a 5x speedup)

Maximum possible speedup

- $T_{\infty} = 0.1 * 10.0 = 1.0$ (a 10x speedup)
 - With infinite parallel computing resources!
- Limit speedup shows algorithmic limitation

Amdahl's Law & Parallel Quicksort

Sequential bottleneck

- Top-level partition: No speedup
- Second level: ≤ 2X speedup
- k^{th} level: $\leq 2^{k-1}X$ speedup

Implications

- Good performance for small-scale parallelism
- Would need to parallelize partitioning step to get large-scale parallelism
 - Parallel Sorting by Regular Sampling
 - H. Shi & J. Schaeffer, J. Parallel & Distributed Computing, 1992

Lessons Learned

Must have parallelization strategy

- Partition into K independent parts
- Divide-and-conquer

Inner loops must be synchronization free

Synchronization operations very expensive

Watch out for hardware artifacts

- Need to understand processor & memory structure
- Sharing and false sharing of global data

Beware of Amdahl's Law

Serial code can become bottleneck

You can do it!

- Achieving modest levels of parallelism is not difficult
- Set up experimental framework and test multiple strategies