Thread-Level Parallelism

15-213/15-513: Introduction to Computer Systems 26th Lecture, July 26, 2024

Instructors:

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Logistics

Proxy and SFS due Friday August 2 at 11:59pm

- NO late submissions
- No extensions except for exceptional circumstances

Final Exam

- Final will be on Thursday, August 1 at 12:30-3:30pm
 - Unless 8/24 at ?
 - Unless 12/? at ?
- You can bring two 8.5"x11" / A4 cheat sheets, written or printed

Disclaimer

We do not have time to fully cover the following content

Take -346, -410, -418 ...

Valuable to know as you start writing parallel programs

Today

Parallel Computing Hardware

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

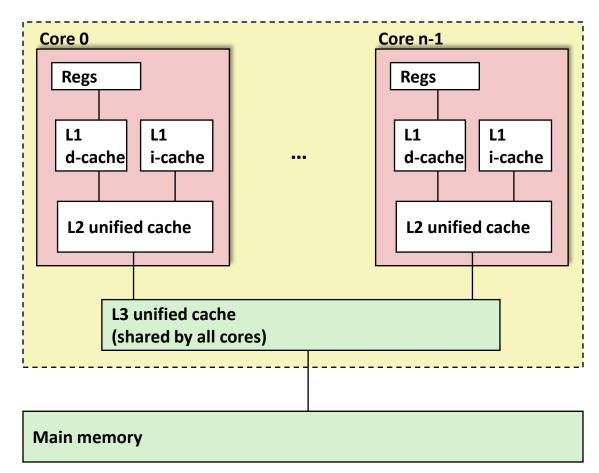
Consistency Models

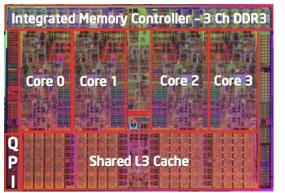
• What happens when multiple threads are reading & writing shared state

Thread-Level Parallelism

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

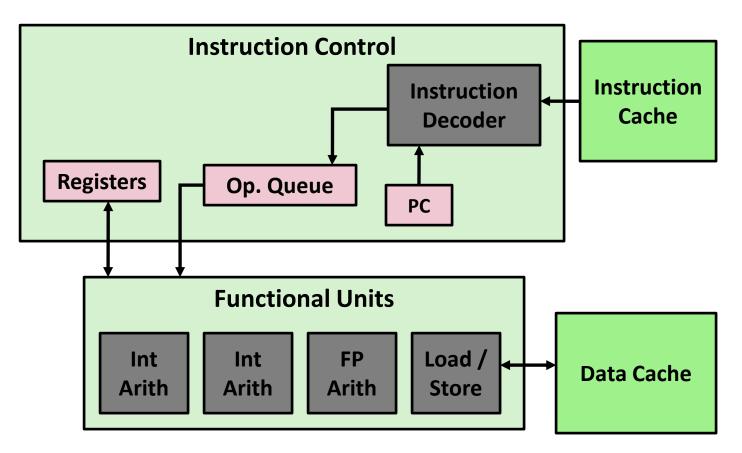
Typical Multicore Processor





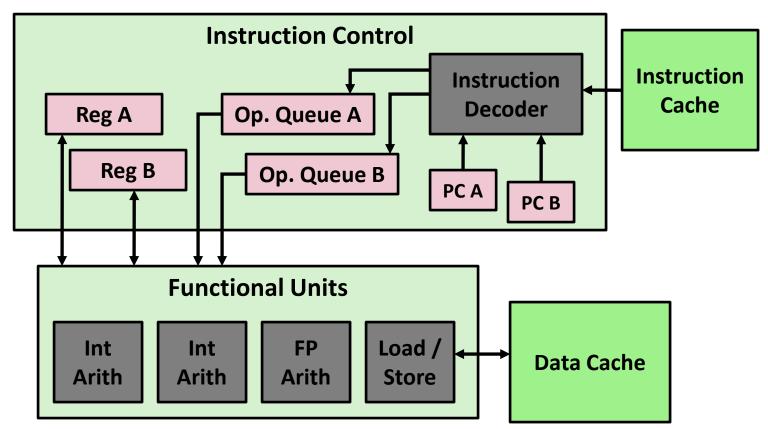
Multiple processors operating with coherent view of memory

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

Powerful, Parallel Computing Is

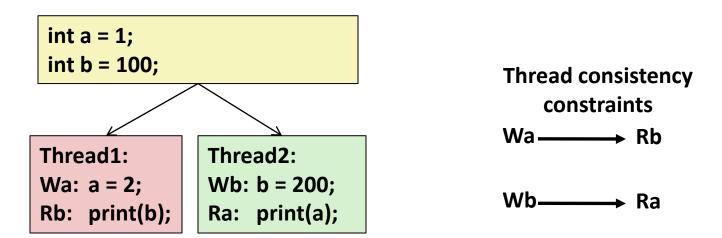
Two threads, with X and Y initialized to 0

 X = 1
 Y = 1

 if (Y == 0) print Hello
 if (X == 0) print World



Memory Coherence / Consistency

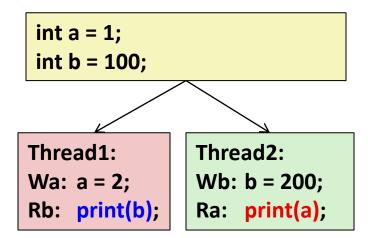


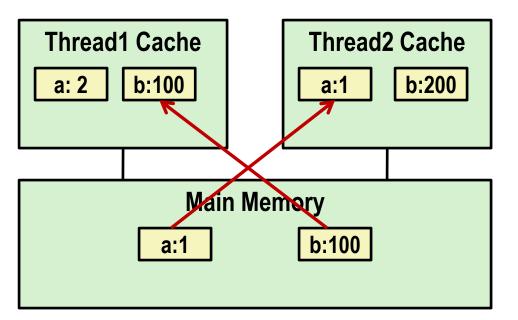
What are the possible values printed?

- Depends on memory consistency model
- Abstract model of how hardware handles concurrent accesses
- How do the two threads really see the writes?

Non-Coherent Cache Scenario

 Write-back caches, without coordination between them







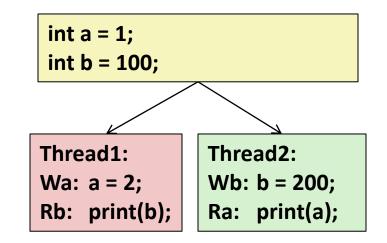
print 100

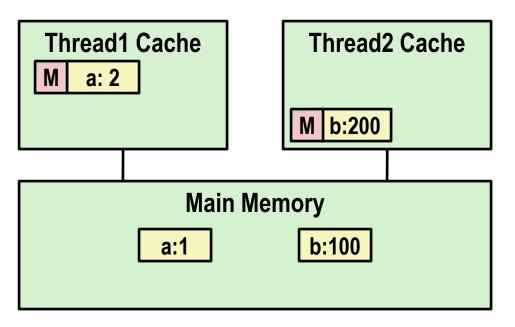
At later points, a:2 and b:200 are written back to main memory

Snoopy Caches

Tag each cache block with state

- InvalidCannot use valueSharedReadable copy
- Modified Writeable copy

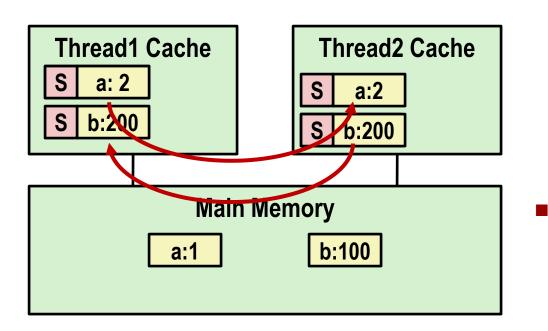


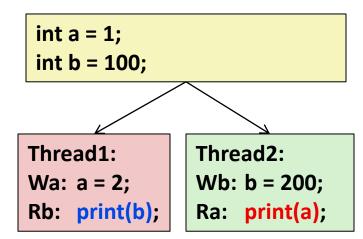


Snoopy Caches

Tag each cache block with state

InvalidCannot use valueSharedReadable copyModifiedWriteable copy

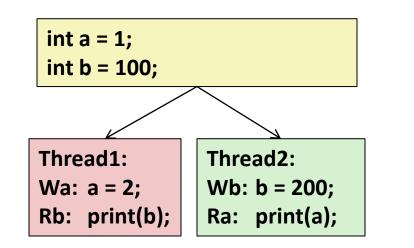


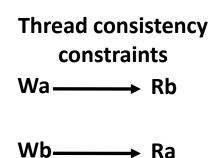


print 2
print 200
When cache sees request for one of its M-tagged blocks

- Supply value from cache (Note: value in memory may be stale)
- Set tag to S

Memory Consistency

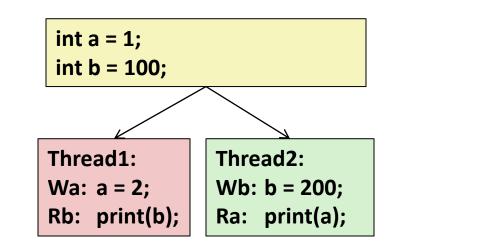


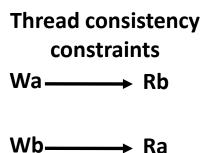


What are the possible values printed?

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Memory Consistency





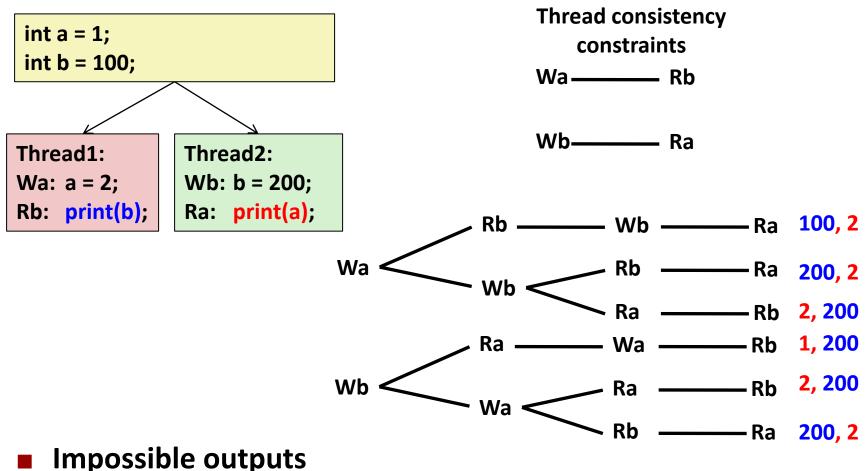
What are the possible values printed?

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- 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

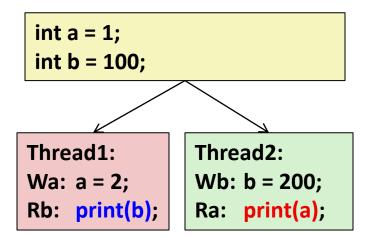
Sequential Consistency Example

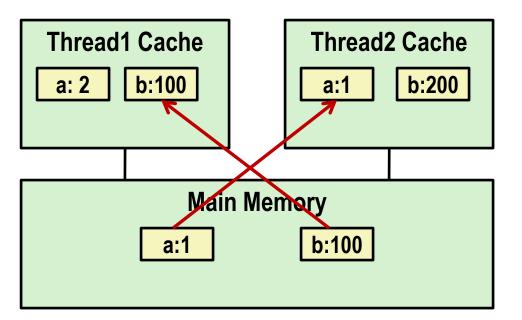


- 100, 1 and 1, 100
- Would require reaching *both* Ra and Rb before *either* Wa or Wb

Non-Coherent Cache Scenario

Write-back caches, without coordination between them





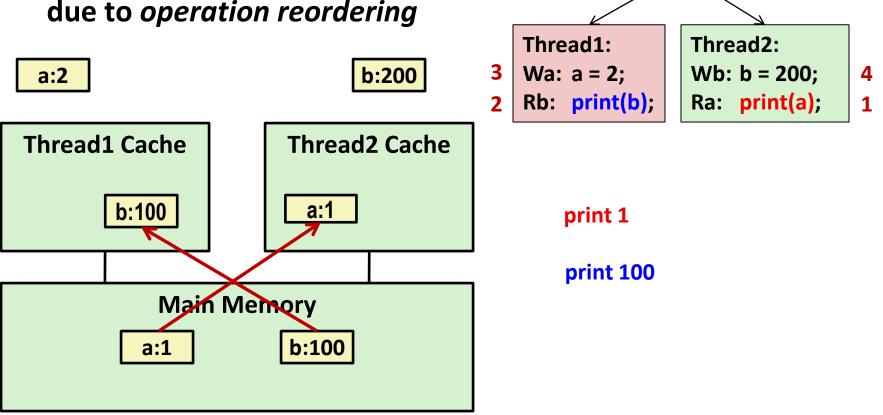
print 1

print 100

Sequentially consistent? No!

Non-Sequentially Consistent Scenario

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

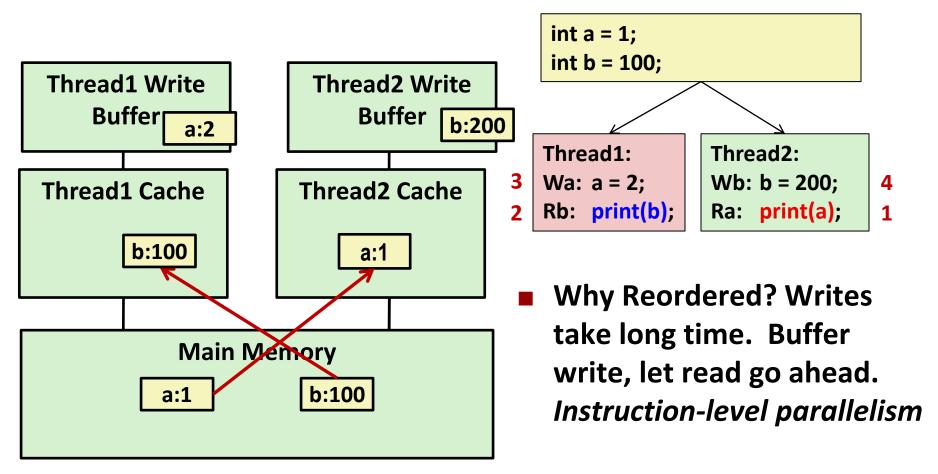


int a = 1;

int b = 100;

Architecture lets reads finish before writes because single thread accesses different memory locations

Non-Sequentially Consistent Scenario



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

Fix: Use synchronization (properly written, it fences)

Memory Models

Sequentially Consistent:

Each thread executes in proper order, any interleaving

To ensure, requires

- Proper cache/memory behavior
- Proper intra-thread ordering constraints

Thread ordering constraints

Use synchronization to ensure the program is free of data races

Today

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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

Summation Example

Sum numbers 0, ..., N-1

Should add up to (N-1)*N/2

Partition into K ranges

- N/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
- IC: 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;

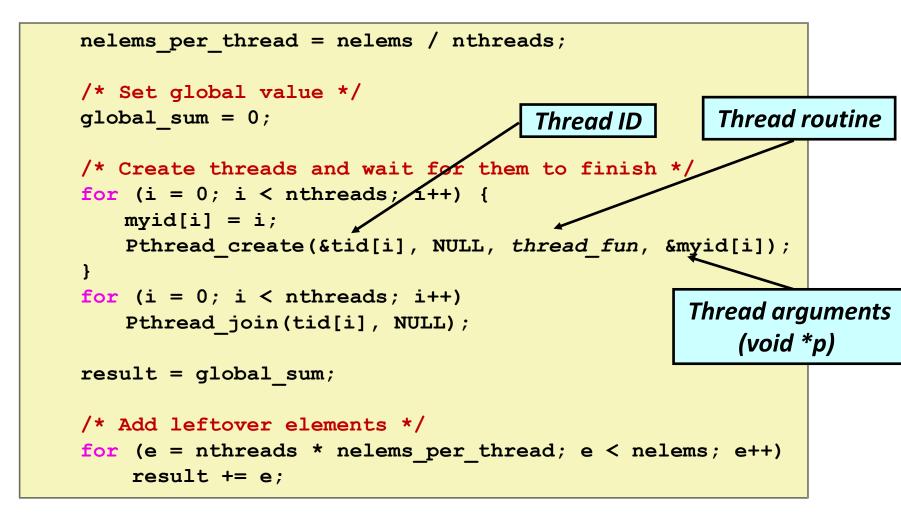
Accumulating in Single Global Variable: Declarations

```
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];
```

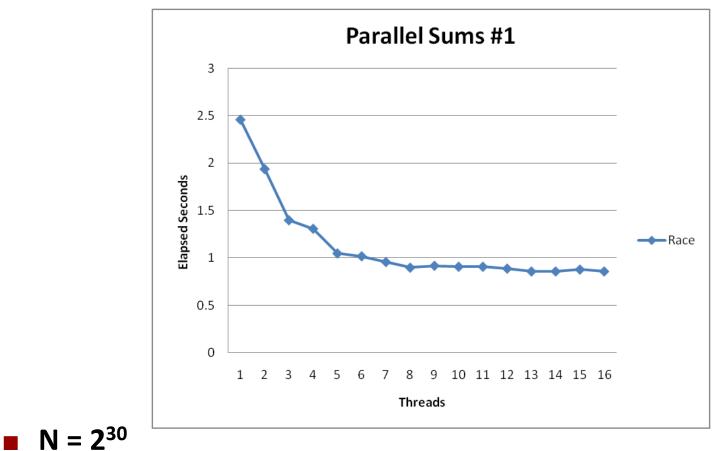
Accumulating in Single Global Variable: Operation



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



Best speedup = 2.86X

Gets wrong answer when > 1 thread! Why?

Thread Function: Semaphore / Mutex

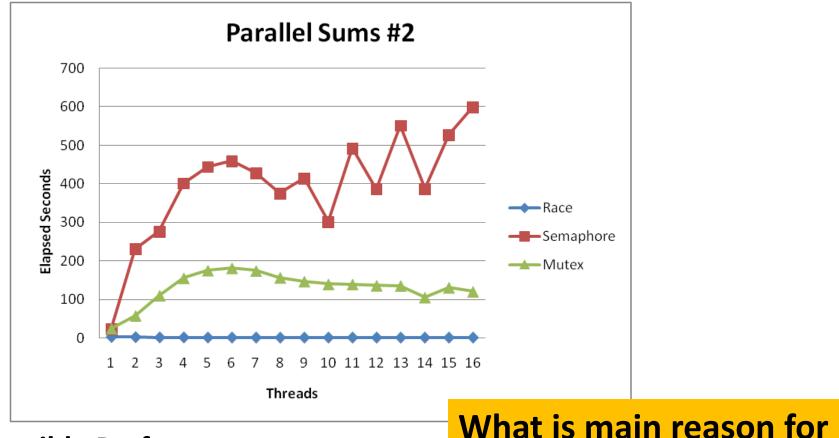
Semaphore

```
void *sum sem(void *varqp)
{
    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++) {
       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



poor performance?

Terrible Performance

- Mutex 3X faster than semaphore
- Clearly, neither is successful

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

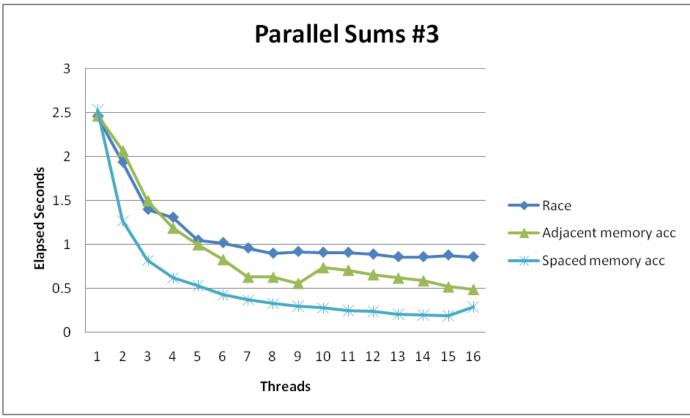
```
nelems per thread = nelems / nthreads;
/* Create threads and wait for them to finish */
for (i = 0; i < nthreads; i++) {</pre>
   myid[i] = i;
   psum[i*spacing] = 0;
   Pthread create(&tid[i], NULL, thread fun, &myid[i]);
for (i = 0; i < nthreads; i++)
   Pthread join(tid[i], NULL);
result = 0;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

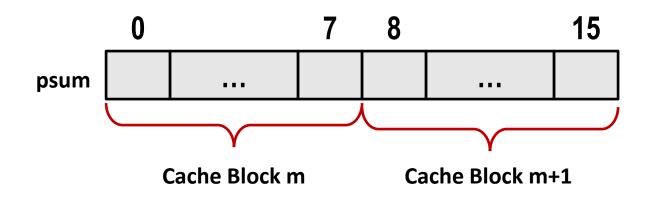
Memory Accumulation Performance



Clear threading advantage

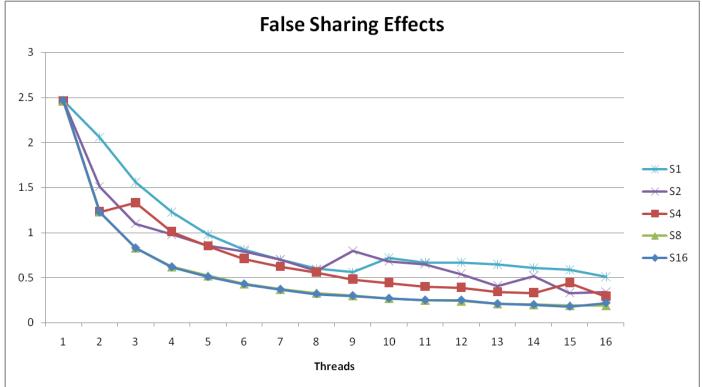
- Adjacent speedup: 5 X
- Spaced-apart speedup: 13.3 X (Only observed speedup > 8)
- Why does spacing the accumulators apart matter?

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

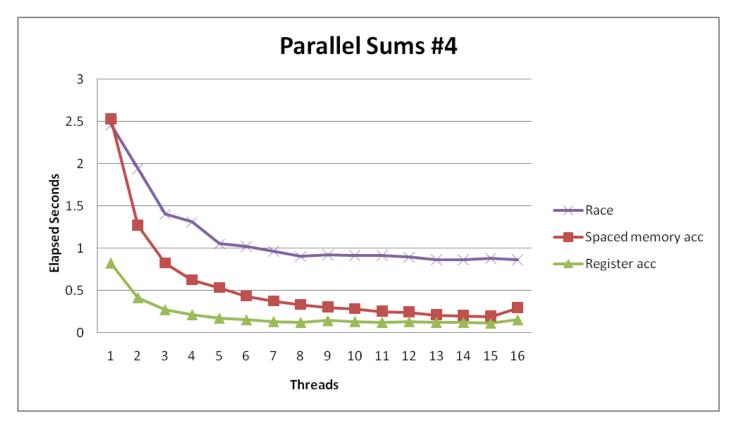
Demonstrates cache block size = 64

- 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++) {
        sum += i;
    }
    psum[index] = sum;
    return NULL;
}</pre>
```

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

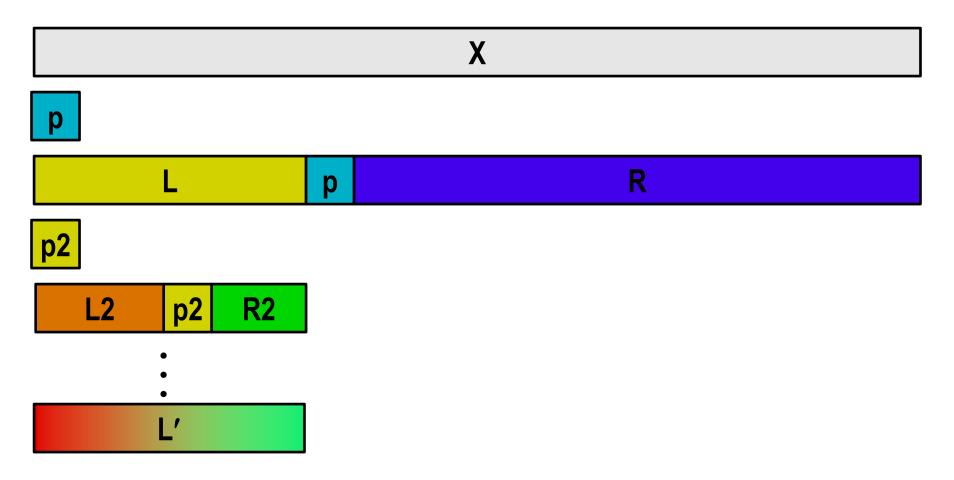
A More Substantial Example: Sort

- Sort set of N random numbers
- Multiple possible algorithms
 - Use parallel version of quicksort

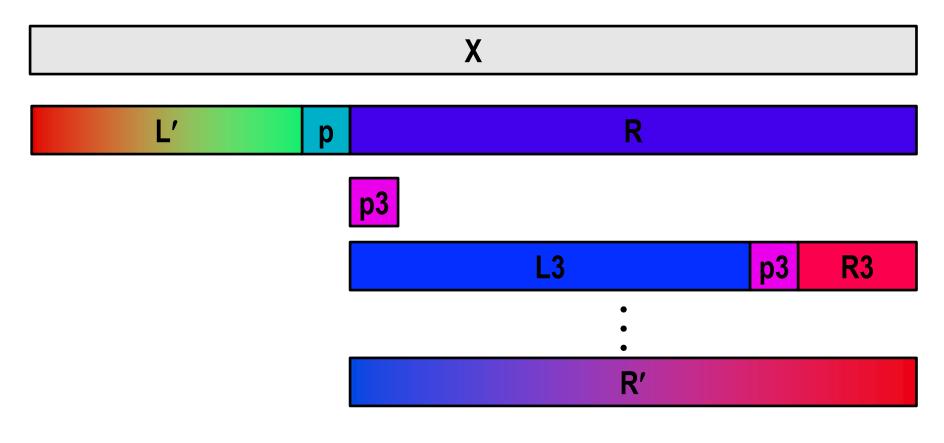
Sequential quicksort of set of values X

- Choose "pivot" p from X
- Rearrange X into
 - L: Values $\leq p$
 - 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



L'	р	R'
----	---	----

Sequential Quicksort Code

```
void qsort serial(data t *base, size t nele) {
  if (nele \leq 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

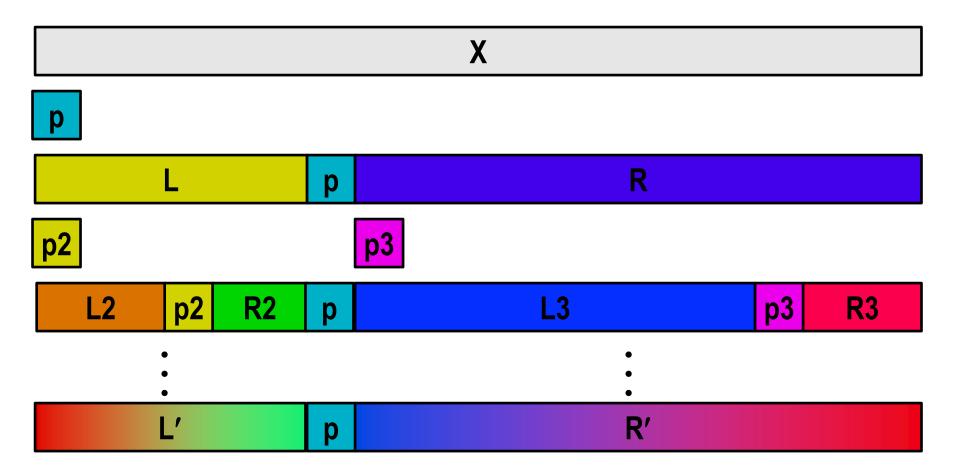
Recursively sort L or R if has more than one element

Parallel Quicksort

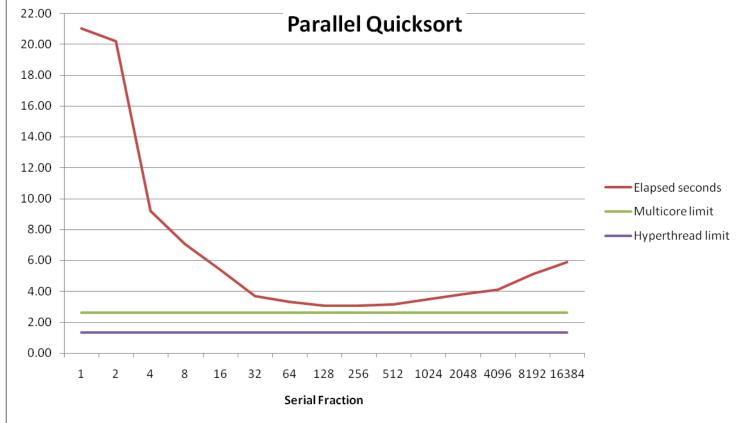
Parallel quicksort of set of values X

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

Parallel Quicksort Visualized



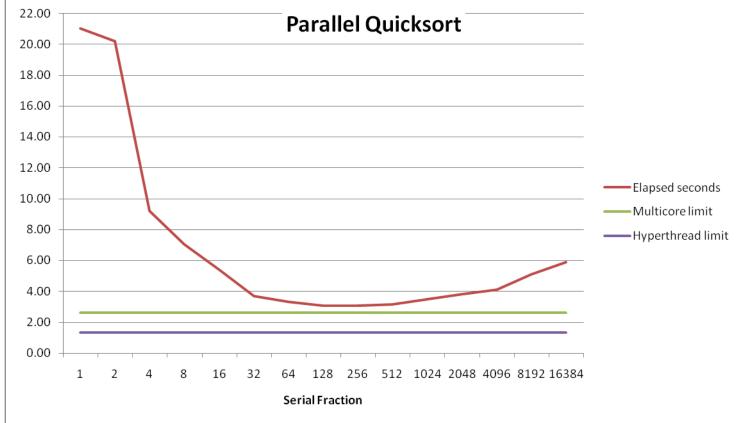
Parallel Quicksort Performance



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 (Travel Analogy)

Speed-Up

- Flying jet non-stop from PIT -> LHR: 7.5 Hours 1
- Or, old fashioned SST way:
 - Fly jet from PIT -> JFK: 1.5 Hours
 - Fly SST from JFK -> LHR: 3.5 Hours
 5 Hours
 1.5x

Or, Using FTL:

- Fly jet from PIT -> JFK: 1.5 Hours
- Fly FTL from JFK -> LHR: .01 Hours 1.51 Hours ~5x
- Best possible speed up is 5X, even with FTL because have to get to New York.

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 = ∞
 - T_∞ = (1-p)T

Amdahl's Law (Travel Analogy)

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- Fly jet from PIT -> JFK: 1.5 Hours
- Fly FTL from JFK -> LHR: .01 Hours 1.51 Hours ~5x
- Best possible speed up is 5X, even with FTL because have to get to New York.
 - T=7.5, p=6/7.5=.8, k= $\infty \Rightarrow T_{\infty} = (1-p)T=1.5$ max speed-up =5x

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