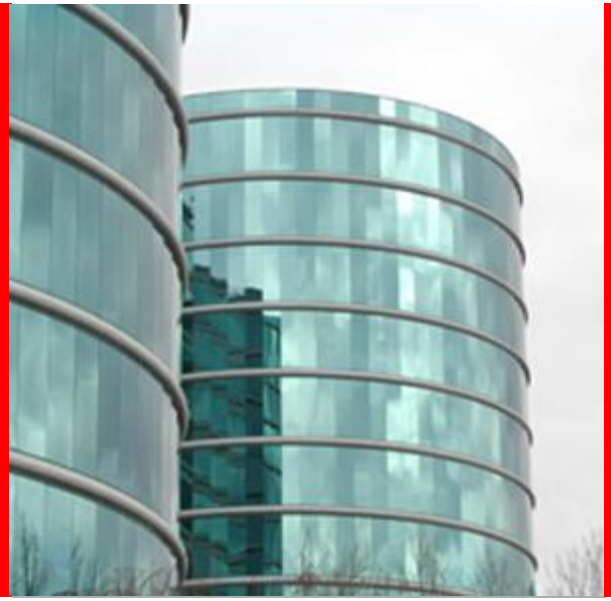

ORACLE

Data Parallelism in Java

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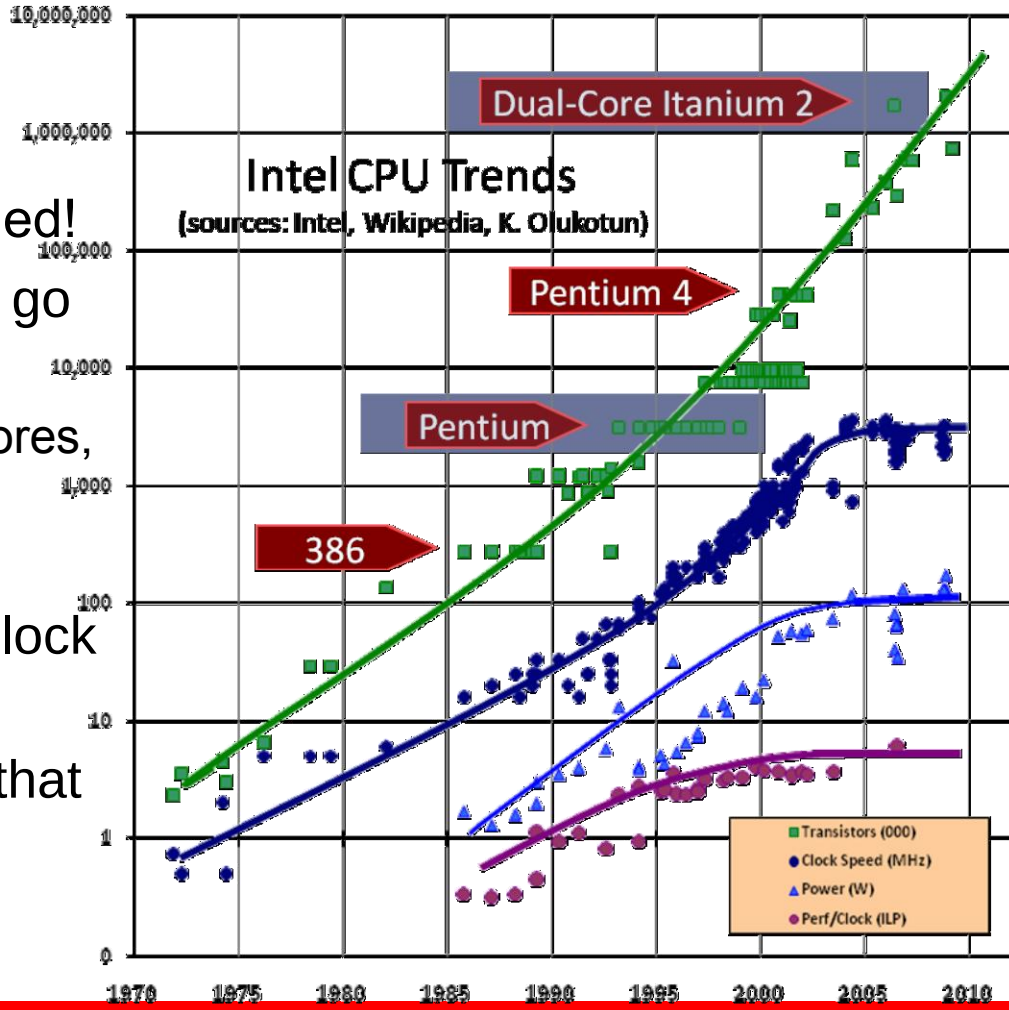
Hardware trends

- As of ~2003, we stopped seeing increases in CPU clock rate
- Moore's law has not been repealed!
- Chip designers have nowhere to go but parallel
  - Moore's Law now gives more cores, not faster cores
- Hit the wall in power dissipation, instruction-level parallelism, clock rate, and chip scale
- We must learn to write software that parallelizes gracefully

(Graphic courtesy Herb Sutter)



Hardware trends

- “The free lunch is over”
  - For years, we had it easy
    - Always a faster machine coming out in a few months
  - Can no longer just buy a new machine and have our program run faster
    - Even true of many so-called concurrent programs!
- Challenge #1: decomposing your application into units of work that can be executed concurrently
- Challenge #2: Continuing to meet challenge #1 as processor counts increase
  - Even so-called scalable programs often run into scaling limits just by doubling the number of available CPUs
  - Need coding techniques that parallelize efficiently across a wide range of processor counts

Hardware trends

- Primary goal of using threads has always been to achieve *better CPU utilization*
  - But those hardware guys just keep raising the bar
- In the old days – only one CPU
  - Threads were largely about *asynchrony*
    - Utilization improved by doing other work during I/O operations
- More recently – handful (or a few handfuls) of cores
  - Coarse-grained parallelism usually enough for reasonable utilization
    - Application-level requests made reasonable task boundaries
    - Thread pools were a reasonable scheduling mechanism
- The future – all the cores you can eat
  - May not be enough concurrent user requests to keep CPUs busy
  - May need to dig deeper to find latent parallelism
  - Shared work queues become a bottleneck

Hardware trends drive software trends

- Languages, libraries, and frameworks shape how we program
  - All languages are Turing-complete, but…the programs we *actually* write reflect the idioms of the languages and frameworks we use
- Hardware shapes language, library, and framework design
  - The Java language had thread support from day 1
    - But early support was mostly useful for asynchrony, not concurrency
    - Which was just about right for the hardware of the day
- As MP systems became cheaper, platform evolved better library support for *coarse-grained* concurrency (JDK 5)
  - Principal user challenge was identifying reasonable task boundaries
- Programmers now need to exploit *fine-grained* parallelism
  - We need to learn to spot latent parallelism
  - No single technique works in all situations

Finding finer-grained parallelism

- User requests are often too coarse-grained a unit of work for keeping many-core systems busy
  - May not be enough concurrent requests
  - Possible solution: find parallelism *within* existing task boundaries
- One promising candidate is *sorting and searching*
  - Amenable to parallelization
    - Sorting can be parallelized with merge sort
    - Searching can be parallelized by searching sub-regions of the data in parallel and then merging the results
  - Can improve response time by using more CPUs
    - May actually use more total CPU cycles, but less wall-clock time
    - Response time may be more important than total CPU cost
      - Human time is valuable!

Finding finer-grained parallelism

Example: stages in the life of a database query

- Parsing and analysis
- Plan selection (may evaluate many candidate plans)
- I/O (already reasonably parallelized)
- Post-processing (filtering, sorting, aggregation)

```
SELECT first, last FROM Names ORDER BY last, first

SELECT SUM(amount) FROM Orders

SELECT student, AVG(grade) as avg FROM Tests
    GROUP BY student
    HAVING avg > 3.5
```

Plan selection and post-processing phases are CPU-intensive

- Could be sped up with more parallelism

Point solutions

Work queues + thread pools

Divide and conquer (fork-join)

Parallel collection libraries

Map/Reduce

Actors / Message passing

Software Transactional Memory (STM)

GPU-based computation

Point solution: Thread pools / work queues

- A reasonable solution for coarse-grained concurrency
  - Typical server applications with medium-weight requests
    - Database servers
    - File servers
    - Web servers
- Library support added in JDK 5
- Works well in SMP systems
  - Even when tasks do IO
- Shared work queue is eventually source of contention

Running example: select-max

Simplified example: find the largest element in a list

- O(n) problem
- Obvious sequential solution: iterate the elements
  - For very small lists the sequential solution is obviously fine
  - For larger lists a parallel solution will clearly win
    - Though still O(n)

```
class MaxProblem {
    final int[] nums;
    final int start, end, size;

    public int solveSequentially() {
        int max = Integer.MIN_VALUE;
        for (int i=start; i<end; i++)
            max = Math.max(max, nums[i]);
        return max;
    }

    public MaxProblem subproblem(int subStart, int subEnd) {
        return new MaxProblem(nums, start+subStart, start+subEnd);
    }
}
```

First attempt: Executor+Future

We can divide the problem into N disjoint subproblems and solve them independently

- Then compute the maximum of the result of all the subproblems
- Can solve the subproblems concurrently with invokeAll()

```
Collection<Callable<Integer>> tasks = ...
for (int i=0; i<N; i++)
   tasks.add(makeCallableForSubproblem(problem, N, i));
List<Future<Integer>> results = executor.invokeAll(tasks);
int max = -Integer.MAX_VALUE;
for (Future<Integer> result : results)
   max = Math.max(max, result.get());
```

First attempt: Executor+Future

- A reasonable choice of N is Runtime.availableProcessors()
  - Will prevent threads from competing with each other for CPU cycles
  - Problem is “embarassingly parallel”
- But has inherent scalability limits
  - Shared work queue in Executor eventually becomes a bottleneck
  - If some subtasks finish faster than others, may not get ideal utilization
    - Can address by using smaller subproblems
    - But this increases contention costs
- Code is clunky!
  - Subproblem extraction prone to fencepost errors
  - Find-maximum loop duplicated
- Clunky code => people won’t bother with it

Point solution: divide and conquer

- Divide-and-conquer breaks down a problem into subproblems, solves the subproblems, and combines the result
  - Apply recursively until subproblems are so small that sequential solution is faster
  - Scales well – can keep 100s of CPUs busy
  - Good for fine-grained tasks
- Example: merge sort
  - Divide the data set into pieces
  - Sort the pieces
  - Merge the results
  - Result is still *O(n log n)*, but subproblems can be solved in parallel
    - Parallelizes fairly efficiently – subproblems operate on disjoint data
- Divide-and-conquer applies this process recursively
  - Until subproblems are so small that sequential solution is faster
  - Scales well – can keep many CPUs busy

Divide-and-conquer

Divide-and-conquer algorithms take this general form

```
Result solve(Problem problem) {
     if (problem.size < SEQUENTIAL_THRESHOLD)
         return problem.solveSequentially();
     else {
         Result left, right;
         INVOKE-IN-PARALLEL {
             left = solve(problem.extractLeftHalf());
             right = solve(problem.extractRightHalf());
         }
         return combine(left, right);
     }
 }
```

The invoke-in-parallel step waits for both halves to complete

- Then performs the combination step

Fork-join parallelism

- The key to implementing divide-and-conquer is the invoke-in-parallel operation
  - Create two or more new tasks (fork)
  - Suspend the current task until the new tasks complete (join)
- Naïve implementation creates a new thread for each task
  - Invoke Thread() constructor for the fork operation
  - Thread.join() for the join operation
  - Don’t actually want to do it this way
    - Thread creation is expensive
    - Requires O(log n) idle threads
- Of course, non-naïve implementations are possible
  - Package java.util.concurrent.forkjoin proposed for JDK 7 offers one
  - For now, download package jsr166y from
    `http://gee.cs.oswego.edu/dl/concurrency-interest/index.html`

Fork-join libraries: coming in JDK 7

There are good libraries for fork-join decomposition

One such library is Doug Lea's "jsr166y" library

- Scheduled for inclusion in JDK 7
- Also can be used with JDK 5, 6 as a standalone library

Solving select-max with fork-join

The RecursiveAction class in the fork-join framework is ideal for representing divide-and-conquer solutions

```
class MaxSolver extends RecursiveAction {
    private final MaxProblem problem;
    int result;

    protected void compute() {
        if (problem.size < THRESHOLD)
            result = problem.solveSequentially();
        else {
            int m = problem.size / 2;
            MaxSolver left, right;
            left = new MaxSolver(problem.subproblem(0, m));
            right = new MaxSolver(problem.subproblem(m,
                                  problem.size));
            forkJoin(left, right);
            result = Math.max(left.result, right.result);
        }
    }
}

ForkJoinExecutor pool = new ForkJoinPool(nThreads);
MaxSolver solver = new MaxSolver(problem);
pool.invoke(solver);
```

Fork-join example

- Example implements RecursiveAction
  - forkJoin() creates two new tasks and waits for them
  - ForkJoinPool is like an Executor, but optimized for fork-join task
    - Waiting for other pool tasks risks *thread-starvation deadlock* in standard executors
    - While waiting for the results of a task, pool threads find other tasks to work on
- Implementation can avoid copying elements
  - Different subproblems work on disjoint portions of the data
    - Which also happens to have good cache locality
    - Data copying would impose a significant cost
  - In this case, data is read-only for the entirety of the operation

Performance considerations

- How low should the sequential threshold be set?
- Two competing performance forces
  - Making tasks smaller enhances parallelism
    - Increased load balancing, improves throughput
  - Making tasks larger reduces coordination overhead
    - Must create, enqueue, dequeue, execute, and wait for tasks
- Fork-join task framework is designed to minimize per-task overhead for *compute-intensive* tasks
  - The lower the task-management overhead, the lower the sequential threshold can be set
  - Traditional Executor framework works better for tasks that have a mix of CPU and I/O activity

Performance considerations

- Fork-join offers a *portable* way to express many parallel algorithms
  - Code is independent of the execution topology
  - Reasonably efficient for a wide range of CPU counts
  - Library manages the parallelism
    - Frequently no additional synchronization is required
- Still must set number of threads in fork-join pool
  - Runtime.availableProcessors() is usually the best choice
    - Larger numbers won't hurt much, smaller numbers will limit parallelism
- Must also determine a reasonable sequential threshold
  - Done by experimentation and profiling
  - Mostly a matter of avoiding "way too big" and "way too small"

Performance considerations

- Table shows speedup relative to sequential for various platforms and thresholds for 500K run (bigger is better)
  - Pool size always equals number of HW threads
    - No code differences across HW platforms
  - Can't expect perfect scaling, because framework and scheduling introduce some overhead
- Reasonable speedups for wide range of threshold

	Threshold=500k	Threshold=50K	Threshold=5K	Threshold=500	Threshold=50
Dual Xeon HT (4)	.88	3.02	3.2	2.22	.43
8-way Opteron (8)	1.0	5.29	5.73	4.53	2.03
8-core Niagara (32)	.98	10.46	17.21	15.34	6.49

Under the hood

- Already discussed naïve implementation – use Thread
  - Problem is it uses a lot of threads, and they mostly just wait around
- Executor is similarly a bad choice
  - Likely deadlock if pool is bounded – standard thread pools are designed for *independent* tasks
  - Standard thread pools can have high contention for task queue and other data structures when used with fine-grained tasks
- An ideal solution minimizes
  - Context switch overhead between worker threads
    - Have as many threads as hardware threads, and keep them busy
  - Contention for data structures
    - Avoid a common task queue

Work stealing

Fork-join framework is implemented using *work-stealing*

- Create a limited number of worker threads
- Each worker thread maintains a private double-ended work queue (deque)
  - Optimized implementation, not the standard JUC deques
- When forking, worker pushes new task at the *head* of its deque
- When waiting or idle, worker pops a task off the *head* of its deque and executes it
  - Instead of sleeping
- If worker's deque is empty, steals an element off the *tail* of the deque of another randomly chosen worker

Work stealing

- Work-stealing is efficient – introduces little per-task overhead
- Reduced contention compared to shared work queue
  - No contention ever for head
    - Because only the owner accesses the head
  - No contention ever between head and tail access
    - Because good queue algorithms enable this
  - Almost never contention for tail
    - Because stealing is infrequent, and steal collisions more so
- Stealing is infrequent
  - Workers put and retrieve items from their queue in LIFO order
  - Size of work items gets smaller as problem is divided
  - So when a thread steals from the tail of another worker's queue, it generally steals a big chunk!
    - This will keep it from having to steal again for a while

Work stealing

- When pool.invoke() is called, task is placed on a random deque
  - That worker executes the task
    - Usually just pushes two more tasks onto its deque – very fast
    - Starts on one of the subtasks
  - Soon some other worker steals the other top-level subtask
  - Pretty soon, most of the forking is done, and the tasks are distributed among the various work queues
  - Now the workers start on the meaty (sequential) subtasks
    - If work is unequally distributed, corrected via stealing
- Result: reasonable load balancing
  - With no central coordination
  - With little scheduling overhead
  - With minimal synchronization costs
    - Because synchronization is almost never contended

Example: Traversing and marking a graph

```
class GraphVisitor extends RecursiveAction {
       private final Node node;
       private final Collection<ForkJoinTask> children =
           new ArrayList<>();

      GraphVisitor(Node node) {
           this.node = node;
       }

       protected void compute() {
         if (node.mark.compareAndSet(false, true)) {
            // Do node-visiting action here
            for (Edge e : node.edges()) {
               Node dest = e.getDestination();
               if (!dest.mark.get()) {
                  children.add(new GraphVisitor(dest));
               }
            }
            ForkJoinTask.invokeAll(children);
         }

     }
   }
```

Other applications

- Fork-join can be used for parallelizing many types of problems
  - Matrix operations
    - Multiplication, LU decomposition, etc
  - Finite-element modeling
  - Numerical integration
  - Game playing
    - Move generation
    - Move evaluation
    - Alpha-beta pruning

Point solution: parallel collection libraries

One can build on the fork/join approach to add parallel aggregate operations to collection-like classes

Doug Lea's ParallelArray (from extra166y) is one example

- Collections will likely acquire bulk data operations in JDK 8

Aim is to enable code that has a functional / query-like feel

Example: ParallelArray

```
class Student {
    String name;
    int graduationYear;
    double gpa;
}

ParallelArray<Student> students
       = ParallelArray.createUsingHandoff(studentsArray, forkJoinPool);

double highestGpa = students.withFilter(new Ops.Predicate<Student>() {
                                            public boolean op(Student s) {
                                                return s.graduationYear == 2010;
                                            }
                                        })
                            .withMapping(new Ops.ObjectToDouble<Student>() {
                                            public double op(Student student) {
                                                return student.gpa;
                                            })
                            .max();
```

ParallelArray

Bulk data operations offer opportunities for library-directed parallelism and laziness

- More functional style, code reads more like problem statement
- Except that inner classes make it *painful*

With closures in the language (JDK 8), gets much better:

```
double highestGpa
    = students.withFilter(#{ s -> s.graduationYear == 2010 })
              .withMapping(#{ s -> student.gpa })
              .max();
```

Point solution: Map / Reduce

- Map / Reduce is a distributed generalization of fork/join
- Decomposes data queries across a cluster
  - Designed for very large input data sets (usually distributed)
  - “Map” tasks each search a portion of the data set
    - Map task often runs on node where the data is, for locality
  - “Reduce” tasks combine results of map tasks
  - Framework handles distribution, reliability, scheduling
- Scales to thousands of nodes
- High quality open-source implementations available (e.g., Hadoop)

Point solution: Actors

- Actors are a computing model where state is not shared – all mutable state is confined to actors
  - Actors communicate by sending messages to each other
  - To access another actor's state, send it a request, and it sends a response, containing a *read-only copy* of the state
  - No shared mutable state → less error-prone
  - Immutable messages → easy distribution across cluster
- Works well in Erlang and Scala
  - Possible in Java, but clunkier and requires more discipline

Point solution: Software Transactional Memory

- STM has been sold as “garbage collection for concurrency”
  - Some might say oversold
- Programmer demarcates transaction boundaries
  - System figures out what is modified, and prevents interference
- Performance of current general-purpose systems is poor
  - But...seems to work very well in Clojure
  - Because Clojure is mostly functional and greatly limits mutable state

Point solution: GPU computing

- GPUs have zillions of simple cores
  - Great for doing the same operation to lots of data (SIMD)
  - Designed for graphics, but can be programmed for general-purpose computations too
  - “Vector processors on steroids”
- Significant latency moving data between CPU / GPU
  - But enough parallelism makes up for that
- Works well on certain types of problems
- Widely supported APIs – CUDA, OpenCL, DirectCompute
- Java bindings starting to appear – jCuda, JOCL

Conclusion

We have not yet identified a general framework for parallel computing in Java

- But there are lots of point solutions that work on specific problem types
- Each point solution introduces a specific style of programming and program organization