CS 267: Applications of Parallel Computers

Dynamic Load Balancing

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Outline

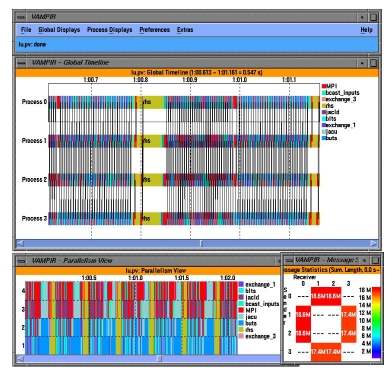
- Motivation for Load Balancing
- Recall graph partitioning as static load balancing technique
- Overview of load balancing problems, as determined by
  - Task costs
  - Task dependencies
  - Locality needs
- Spectrum of solutions
  - Static - all information available before starting
  - Semi-Static - some info before starting
  - Dynamic - little or no info before starting
  - Or: how rapidly do costs/dependencies/locality needs change?
- Survey of solutions
  - How each one works
  - Theoretical bounds, if any
  - When to use it, tools

Sources of inefficiency in parallel codes

- Poor single processor performance
  - Typically in the memory system (recall matmul homework)
- Too much parallelism overhead
  - Thread creation, synchronization, communication
- Load imbalance
  - Different amounts of work across processors
    - Computation and communication
  - Different speeds (or available resources) for the processors
    - Possibly due to load on shared machine
    - Heterogeneous resources (eg CPU + GPU)
- How to recognize load imbalance
  - Time spent at synchronization is high and is uneven across processors, but not always so simple …

Measuring Load Imbalance

- Challenges:
  - Can be hard to separate from high synchronization overhead
  - Especially subtle if not bulk-synchronous
  - "Spin locks" can make synchronization look like useful work
  - Note that imbalance may change over phases
  - Insufficient parallelism always leads to load imbalance
  - Tools like IPM,TAU can help (acts.nersc.gov)



Review of Graph Partitioning – static case

- Partition G(N,E) so that
  - $N = N_1 \cup \ldots \cup N_p$, with each $|N_i| \sim |N|/p$
  - As few edges connecting different N_i and N_k as possible
- If N = {tasks}, each unit cost, edge e=(i,j) means task i has to communicate with task j, then partitioning means
  - balancing the load, i.e. each $|N_i| \sim |N|/p$
  - minimizing communication volume
- Optimal graph partitioning is NP complete, so we use heuristics (see earlier lectures)
  - Spectral, Kernighan-Lin, Multilevel …
- Good software available
  - (Par)METIS, Scotch, Zoltan, …
- Speed of partitioner trades off with quality of partition
  - Better load balance costs more; may or may not be worth it
- Need to know tasks, communication pattern before starting
  - What if you don't? Can redo partitioning, but not frequently

Load Balancing Overview

Load balancing differs with properties of the tasks

- Tasks costs
  - Do all tasks have equal costs?
  - If not, when are the costs known?
    - Before starting, when task created, or only when task ends
- Task dependencies
  - Can all tasks be run in any order (including parallel)?
  - If not, when are the dependencies known?
    - Before starting, when task created, or only when task ends
    - One task may prematurely end another task (eg search)
- Locality (may tradeoff with load balance)
  - Is it important for some tasks to be scheduled on the same processor (or nearby) to reduce communication cost?
  - When is the information about communication known?
- If properties known only when tasks end
  - Are statistics fixed, change slowly, change abruptly?

Task Cost Spectrum

Schedule a set of tasks under one of the following assumptions:

Easy: The tasks all have equal (unit) cost. branch-free loops

n items p bins

Harder: The tasks have different, but known, times. sparse matrix-vector multiply

n items p bins

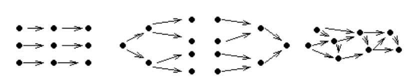
Hardest: The task costs unknown until after execution. GCM, circuits, search

Task Dependency Spectrum

Schedule a graph of tasks under one of the following assumptions:

Easy: The tasks can execute in any order. dependence free loops

Harder: The tasks have a predictable structure. matrix computations (dense, and some sparse, Cholesky)



wave-front out-tree in-tree general dag
balanced or unbalanced

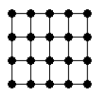
Hardest: The structure changes dynamically (slowly or quickly) search, sparse LU

Task Locality Spectrum (Communication)

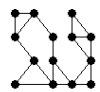
Schedule a set of tasks under one of the following assumptions:

Easy: The tasks, once created, do not communicate. — embarrassingly parallel

Harder: The tasks communicate in a predictable pattern. — PDE solver



regular



irregular

Hardest: The communication pattern is unpredictable. — discrete event simulation

Spectrum of Solutions

A key question is when certain information about the load balancing problem is known.

Leads to a spectrum of solutions:

- Static scheduling. All information is available to scheduling algorithm, which runs before any real computation starts.
  - Off-line algorithms, eg graph partitioning, DAG scheduling
  - Still might use dynamic approach if too much information
- Semi-static scheduling. Information may be known at program startup, or the beginning of each timestep, or at other well-defined points. Offline algorithms may be used even though the problem is dynamic.
  - eg Kernighan-Lin, as in Zoltan
- Dynamic scheduling. Information is not known until mid-execution.
  - On-line algorithms – main topic today

Dynamic Load Balancing

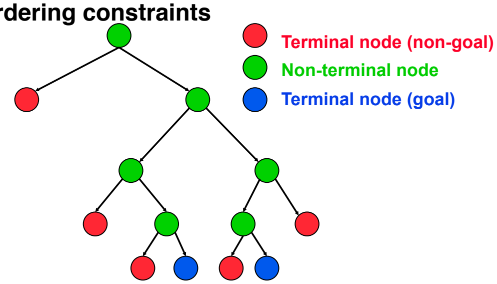
- Motivation for dynamic load balancing
  - Search algorithms as driving example
- Centralized load balancing
  - Overview
  - Special case for schedule independent loop iterations
  - Makes most sense in shared memory environment
  - Hard to scale to large numbers of processors
- Distributed load balancing
  - Overview – randomization often used
  - Engineering
  - Theoretical results

Search

- Search problems are often:
  - Computationally expensive
  - Have very different parallelization strategies than physical simulations.
  - Require dynamic load balancing
- Examples:
  - Optimal layout of VLSI chips
  - Robot motion planning
  - Chess and other games (N-queens)
  - Speech processing
  - Constructing phylogeny tree from set of genes

Example Problem: Tree Search

- In Tree Search the tree unfolds dynamically
- May be a graph if there are common sub-problems along different paths
- Graphs unlike meshes which are precomputed and have no ordering constraints



Depth vs Breadth First Search (Review)

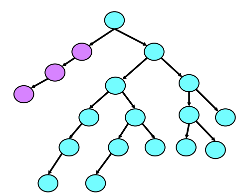
- DFS with Explicit Stack – little parallelism
  - Put root into Stack
    - Stack is data structure where items added to and removed from the top only
  - While Stack not empty
    - If node on top of Stack satisfies goal of search, return result, else
      - Mark node on top of Stack as "searched"
      - If top of Stack has an unsearched child, put child on top of Stack, else remove top of Stack
- BFS with Explicit Queue – lots of parallelism (depending on graph)
  - Put root into Queue
    - Queue is data structure where items added to end, removed from front
  - While Queue not empty
    - If node at front of Queue satisfies goal of search, return result, else
      - Mark node at front of Queue as "searched"
      - If node at front of Queue has any unsearched children, put them all at end of Queue
      - Remove node at front from Queue

Sequential Search Algorithms

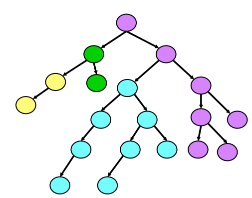
- Depth-first search (DFS)
  - Simple backtracking
    - Search to bottom, backing up to last choice if necessary
  - Depth-first branch-and-bound
    - Keep track of best solution so far ("bound")
    - Cut off sub-trees that are guaranteed to be worse than bound
  - Iterative Deepening ("in between" DFS and BFS)
    - Choose a bound d on search depth, and use DFS up to depth d
    - If no solution is found, increase d and start again
    - Can use an estimate of cost-to-solution to get bound on d
- Breadth-first search (BFS)
  - Search all nodes at distance 1 from the root, then distance 2, and so on

Parallel Search

- Consider simple backtracking search
- Try static load balancing: spawn each new task on an idle processor, until all have a subtree



Load balance on 2 processors

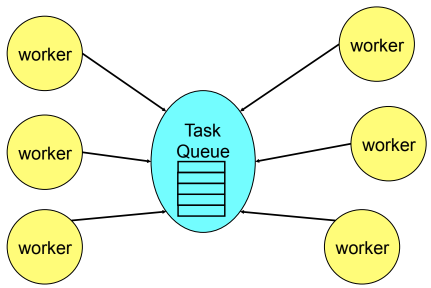


Load balance on 4 processors

- We can and should do better than this …

Centralized Scheduling

- Keep a queue of task waiting to be done
  - May be done by manager task
  - Or a shared data structure protected by locks



Centralized Task Queue: Scheduling Loops

- When applied to loops, often called **self scheduling**:
  - Tasks may be range of loop indices to compute
  - Assumes independent iterations
  - Loop body has unpredictable time (branches) or the problem is not interesting
- Originally designed for:
  - Scheduling loops by compiler (or runtime-system)
  - Original paper by Tang and Yew, ICPP 1986
- Properties
  - Dynamic, online scheduling algorithm
  - Good for a small number of processors (centralized)
  - Special case of task graph – independent tasks, known at once

Centralized Task Queue: Scheduling Loops

- When applied to loops, often called **self scheduling**
  - Assume independent loop iterations, varying run times
- Typically, don't want to grab smallest unit of parallel work, i.e., a single loop iteration
  - Too much contention at shared queue
- Instead, choose a chunk of tasks of size K.
  - If K is large, access overhead for task queue is small
  - If K is small, we are likely to have even finish times (load balance)
- (at least) Four Variations:
  1. Use a fixed chunk size
  2. Guided self-scheduling
  3. Tapering
  4. Weighted Factoring

Variation 1/4: Fixed Chunk Size

- Kruskal and Weiss give a technique for computing the optimal chunk size (IEEE Trans. Software Eng., 1985)
- Requires a lot of information about the problem characteristics
  - e.g., task costs, number of tasks, cost of scheduling
  - Probability distribution of runtime of each task (same for all)
  - Assumes distribution is IFR = "Increasing Failure Rate"
    - For any t>0, P(X > x+t | X > x) is a decreasing function of x
  - $K_{opt} = (2^{1/2} * \#tasks * time\_to\_access\_queue/(\sigma * p * (\log p)^{1/2}))^{2/3}$
- Not very useful in practice
  - Distribution must be known at loop startup time

Variation 2/4: Guided Self-Scheduling

- Idea: use larger chunks at the beginning to avoid excessive overhead and smaller chunks near the end to even out the finish times.
  - The chunk size K_i at the i^{th} access to the task pool is given by

    K_i = ceiling(R_i/p)
  - where R_i is the total number of tasks remaining and
  - p is the number of processors
- See Polychronopoulos & Kuck, "Guided Self-Scheduling: A Practical Scheduling Scheme for Parallel Supercomputers," IEEE Transactions on Computers, Dec. 1987.

Variation 3/4: Tapering

- Idea: the chunk size, K_i is a function of not only the remaining work, but also the task cost variance
  - variance is estimated using history information
  - high variance => small chunk size should be used
  - low variance => larger chunks OK
- See S. Lucco, "Adaptive Parallel Programs," PhD Thesis, UCB, CSD-95-864, 1994.
  - Gives analysis (based on workload distribution)
  - Also gives experimental results -- tapering always works at least as well as GSS, although difference is often small

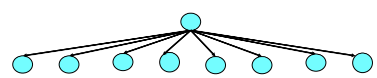
Variation 4/4: Weighted Factoring

- Idea: similar to self-scheduling, but divide task cost by computational power of requesting node
- Useful for heterogeneous systems
- Also useful for shared resource clusters, e.g., built using all the machines in a building
  - as with Tapering, historical information is used to predict future speed
  - "speed" may depend on the other loads currently on a given processor
- See Hummel, Schmit, Uma, and Wein, SPAA '96
  - includes experimental data and analysis

Summary: When is Self-Scheduling a Good Idea?

Useful when:

- A batch (or set) of tasks without dependencies
  - can also be used with dependencies, but most analysis has only been done for task sets without dependencies



- The cost of each task is unknown
- Locality is not important
- Shared memory machine, or at least number of processors is small – centralization is OK

Cilk: A Language with Built-in Load balancing

A C language for programming dynamic multithreaded applications on shared-memory multiprocessors.

CILK (Leiserson et al) (supertech.lcs.mit.edu/cilk)
- **Created startup company called CilkArts**
- **Acquired by Intel**

Example applications:

- virus shell assembly
- graphics rendering
- *n*-body simulation
- heuristic search
- dense and sparse matrix computations
- friction-stir welding simulation
- artificial evolution

Fibonacci Example: Creating Parallelism

C elision

```
int fib (int n) {
if (n<2) return (n);
  else {
    int x,y;
    x = fib(n-1);
    y = fib(n-2);
    return (x+y);
  }
}
```

Cilk code

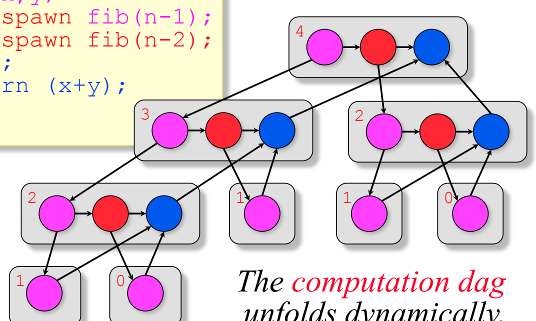
```
cilk int fib (int n) {
  if (n<2) return (n);
  else {
    int x,y;
    x = spawn fib(n-1);
    y = spawn fib(n-2);
    sync;
    return (x+y);
  }
}
```

Cilk is a *faithful* extension of C. A Cilk program's *serial elision* is always a legal implementation of Cilk semantics. Cilk provides *no* new data types.

Dynamic Multithreading

```
cilk int fib (int n) {
  if (n<2) return (n);
  else {
    int x,y;
    x = spawn fib(n-1);
    y = spawn fib(n-2);
    sync;
    return (x+y);
  }
}
```

Example: `fib(4)`

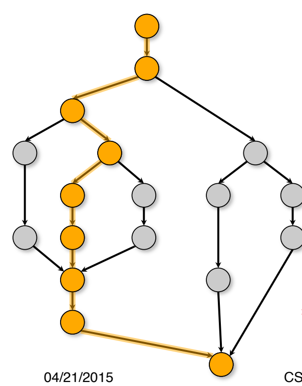


processors are virtualized

The computation dag unfolds dynamically.

Algorithmic Complexity Measures

T_P = execution time on P processors



T_1 = *work*

T_∞ = *span**

LOWER BOUNDS
- $T_P \geq T_1/P$
- $T_P \geq T_\infty$

*Also called *critical-path length* or *computational depth*.

Speedup

Definition: T_1/T_P = *speedup* on P processors.

If $T_1/T_P = \Theta(P) \le P$, we have *linear speedup*;
$= P$, we have *perfect linear speedup*;
$> P$, we have *superlinear speedup*,
which is not possible in our model, because of the lower bound $T_P \ge T_1/P$.

T_1/T_∞ = *available parallelism*
= *the average amount of work per step along the span (critical path).*

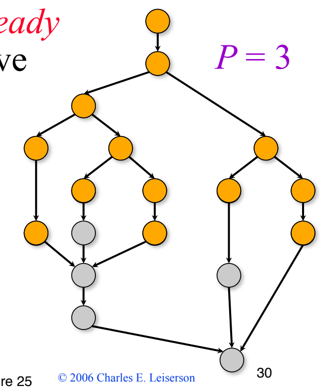
Greedy Scheduling

IDEA: Do as much as possible on every step.

Definition: A thread is *ready* if all its predecessors have *executed*.

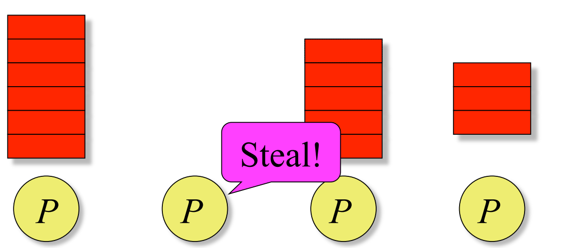
Complete step
- $\ge P$ threads ready.
- Run any P.

Incomplete step
- $< P$ threads ready.
- Run all of them.

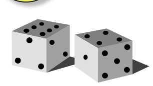


Cilk's Work-Stealing Scheduler

Each processor maintains a *work deque* of ready threads, and it manipulates the bottom of the deque like a stack.



When a processor runs out of work, it *steals* a thread from the top of a *random* victim's deque.



Performance of Work-Stealing

Theorem: Cilk's work-stealing scheduler achieves an expected running time of

$$T_P \le T_1/P + O(T_\infty)$$

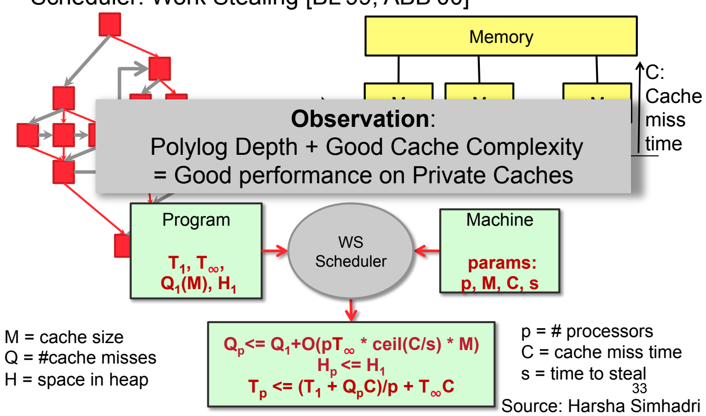
on P processors.

Pseudoproof. A processor is either *working* or *stealing*. The total time all processors spend working is T_1. Each steal has a $1/P$ chance of reducing the span by 1. Thus, the expected cost of all steals is $O(PT_\infty)$. Since there are P processors, the expected time is

$$(T_1 + O(PT_\infty))/P = T_1/P + O(T_\infty)\ . \ \blacksquare$$

Analysis of work-stealing (WS) with private caches

Scheduler: Work Stealing [BL'99, ABB'00]



Source: Harsha Simhadri

Further analyses of Cilk's Performance

- Bounds on #cache misses caused by work stealing if each processor has private cache, single shared (slow) memory
- Bounds extended to hierarchical memories
- Space needed (for stacks) by P processors at most P times space needed by one processor
- General conclusions:
  - Work stealing good idea if execution DAG not too deep, and sequential implementation would not generate too many cache misses

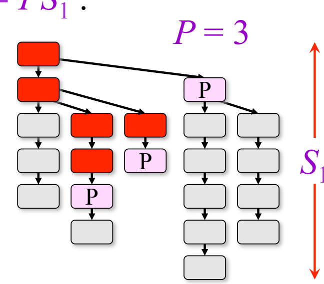
Extensions/variations on work stealing

- Parallel-Depth First Schedule
  - Assume Depth First order of tasks known, prioritize in this order
  - Greedy work schedule where "ready tasks" executed in priority order
  - Better bounds on parallel space, locality on shared caches
- Space Bounded schedulers
  - Anchor tasks to preserve locality
  - Do not allow tasks to move, once assigned
  - Assignments must not allow caches to overflow

Space Bounds

Theorem. Let S_1 be the stack space required by a serial execution of a Cilk program. Then, the space required by a P-processor execution is at most $S_P = PS_1$.

Proof (by induction). The work-stealing algorithm maintains the *busy-leaves property*: *every extant procedure frame with no extant descendents has a processor working on it.* ■



DAG Scheduling software

- QUARK (U. Tennessee)
  - Library developed to support PLASMA for pipelining ("synchronization avoiding") dense linear algebra
- SMPss (Barcelona)
  - Compiler based; Data usage expressed via pragmas; Proposal to be in OpenMP; Recently added GPU support
- StarPU (INRIA)
  - Library based; GPU support; Distributed data management; Codelets=tasks (map CPU, GPU versions)
- DAGUE/DPLASMA (MPI group work)
  - Needs a compact DAG representation; Distributed memory; Designed to be very, very scalable
- Other tools (e.g., fork-join graphs only)
  - Cilk, Intel Threaded Building Blocks (TBB); Microsoft CCR, …

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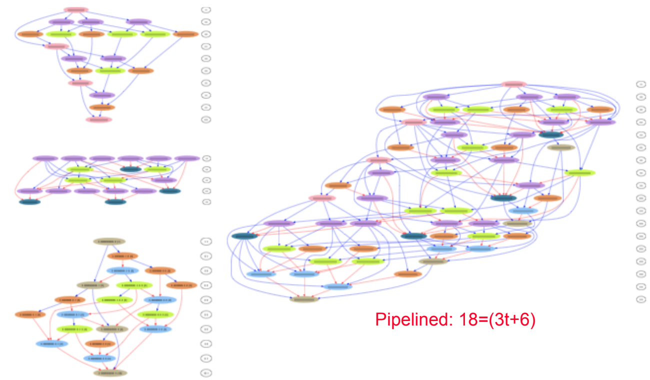
Pipelining: Cholesky Inversion



Pipelined: 18=(3t+6)

POTRF+TRTRI+LAUUM: 25=(7t-3)
Cholesky Factorization alone: 3t-2

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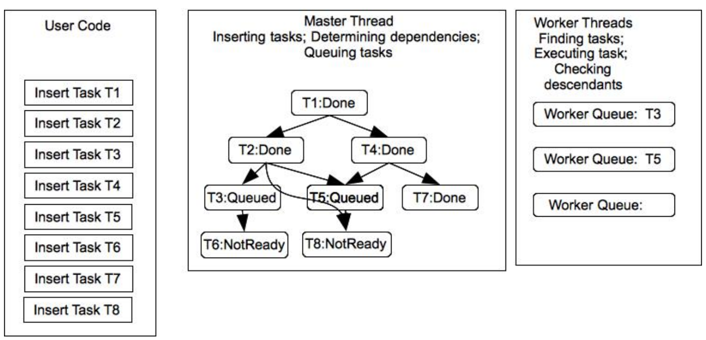
Source: Julien Langou: ICL presentation 2011/02/04

Simplified QUARK architecture



Scheduling is done using a combination of task assignment to workers (via locality reuse, etc) and work stealing.

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Basic QUARK API

Setup QUARK data structures
QUARK_New [standalone] or
QUARK_Setup [part of external library]

For each kernel routine, insert into QUARK runtime
QUARK_Insert_Task(quark, function, task_flags,
arg_size, arg_ptr, arg_flags,
..., ..., ..., 0);

When done, exit QUARK
QUARK_Delete[standalone] or
QUARK_Waitall [return to external library]

Other basic calls
QUARK_Barrier
QUARK_Cancel_Task
QUARK_Free (used after QUARK_Waitall)

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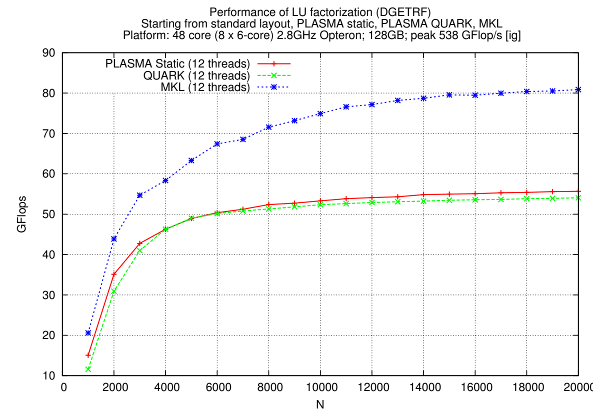
Scalability of DAG Schedulers

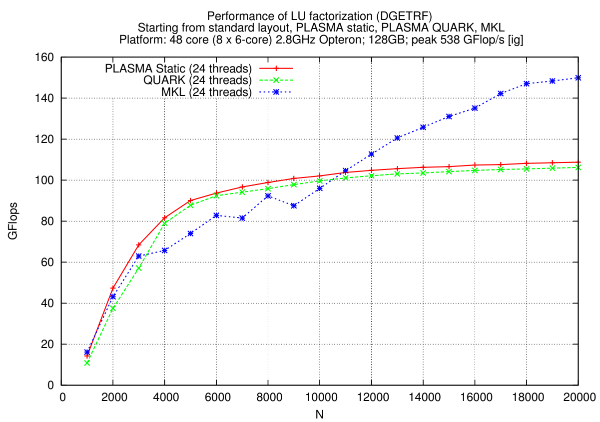
- How many tasks are there in DAG for dense linear algebra operation on an n x n matrix with b x b blocks?
- $O((n/b)^3)$ = 1M, for n=10,000 and b = 100
- Creating, scheduling entire DAG does not scale
- PLASMA: static scheduling of entire DAG
- QUARK: dynamic scheduling of "frontier" of DAG at any one time

Performance – 12 core



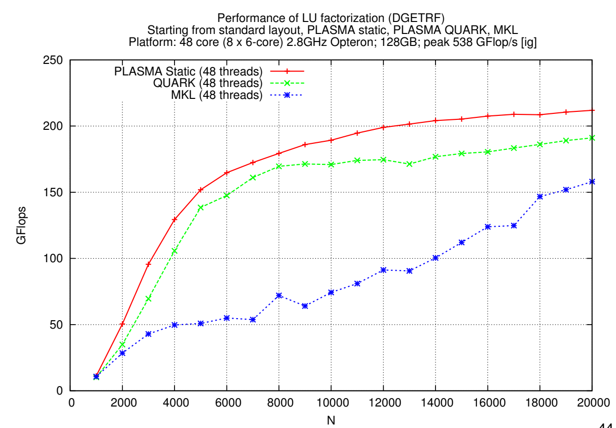
MKL is really good when there are a few cores

Performance – 24 core



QUARK is pretty close to static PLASMA

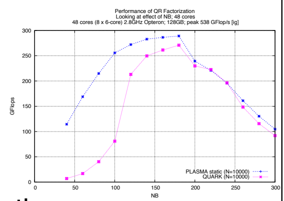
Performance – 48 core



QUARK is approx 10% less than static; MKL scales up more slowly.

Limitations: Future Work

- VERY sensitive to task size
  - For PLASMA, small tile sizes give bad performance, need NB around 180
  - Overhead kills performance for small tasks.



- Master handles serial task insertion
  - This is a hurdle for large scale scalability
  - Some work may be delegated in future versions
- Scalability
  - Largest tests are for 48 cores
  - Large scale scalability is untested
  - For ongoing work see icl.cs.utk.edu/iclprojects/

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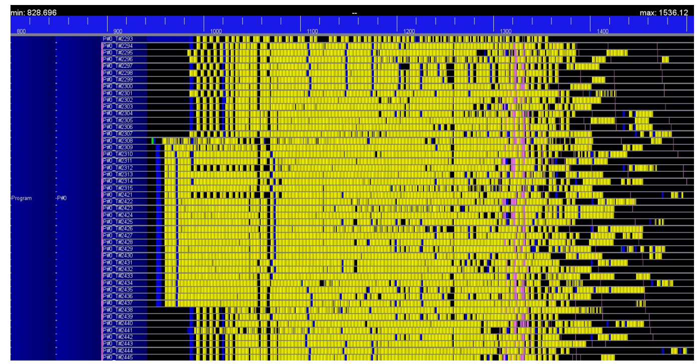
Trace: LU factorization



LU factorization (dgetrf) of N=5000 on 48 cores using dynamic QUARK runtime

Trace created using EZTrace and visualized using ViTE

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Distributed Task Queues

- **The obvious extension of task queue to distributed memory is:**
  - **a distributed task queue (or "bag")**
  - **Idle processors can "pull" work, or busy processors "push" work**
- **When are these a good idea?**
  - **Distributed memory multiprocessors**
  - **Or, shared memory with significant synchronization overhead**
  - **Locality is not (very) important**
  - **Tasks may be:**
    - **known in advance, e.g., a bag of independent ones**
    - **dependencies exist, i.e., being computed on the fly**
  - **The costs of tasks is not known in advance**

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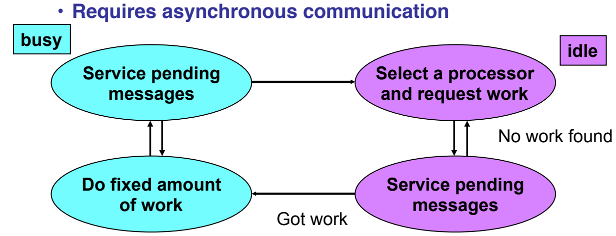
Distributed Dynamic Load Balancing

- **Dynamic load balancing algorithms go by other names:**
  - **Work stealing, work crews, …**
- **Basic idea, when applied to tree search:**
  - **Each processor performs search on disjoint part of tree**
  - **When finished, get work from a processor that is still busy**
  - **Requires asynchronous communication**



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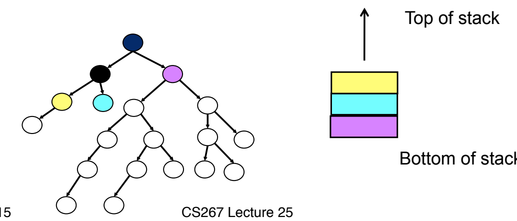
How to Select a Donor/Acceptor Processor

- Three basic techniques:
  1. Asynchronous round robin
     - Each processor k, keeps a variable "$target_k$"
     - When a processor runs out of work, requests work from $target_k$
     - Set $target_k = (target_k + 1) \bmod procs$
  2. Global round robin
     - Proc 0 keeps a single variable "target"
     - When a processor needs work, gets target, requests work from target
     - Proc 0 sets target = (target + 1) mod procs
  3. Random polling/stealing
     - When a processor needs work, select a random processor and request work from it
  4. Random distribution of work
     - When a processor has too much work, select a random processor to take it
- Repeat if no work is found

How to Split Work

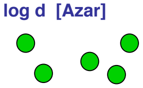
- First parameter is number of tasks to give when asked
  - Related to the self-scheduling variations, but total number of tasks is now unknown
- Second question is which one(s)
  - Send tasks near the bottom of the stack (oldest)
  - Execute from the top (most recent)
  - May be able to do better with information about task costs



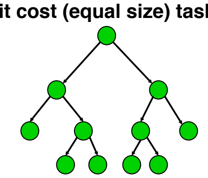
Theoretical Results (1)

Main result: Simple randomized algorithms are optimal with high probability

- Others show this for independent, equal sized tasks
  - "Throw n balls into random bins": Θ (log n / log log n) in fullest bin
  - Throw d times and pick the emptiest bin: log log n / log d [Azar]
  - Extension to parallel throwing [Adler et all 95]
  - Shows p log p tasks leads to "good" balance



- Karp and Zhang show this for a tree of unit cost (equal size) tasks
  - Parent must be done before children
  - Tree unfolds at runtime
  - Task number/priorities not known a priori
  - Children "pushed" to random processors



Theoretical Results (2)

Main result: Simple randomized algorithms are optimal with high probability

- Blumofe and Leiserson [94] show this for a fixed task tree of variable cost tasks
  - their algorithm uses task pulling (stealing) instead of pushing, which is good for locality
  - I.e., when a processor becomes idle, it steals from a random processor
  - also have (loose) bounds on the total memory required
  - Used in Cilk
  - "better to receive than to give"
- Chakrabarti et al [94] show this for a dynamic tree of variable cost tasks
  - works for branch and bound, i.e. tree structure can depend on execution order
  - uses randomized pushing of tasks instead of pulling, so worse locality

Distributed Task Queue References

- Introduction to Parallel Computing by Kumar et al (text)
- Multipol library (See C.-P. Wen, UCB PhD, 1996.)
  - Part of Multipol (www.cs.berkeley.edu/projects/multipol)
  - Try to push tasks with high ratio of cost_to_compute/cost_to_push
    - Ex: for matmul, ratio = $2n^3$ cost(flop) / $2n^2$ cost(send a word)
- Goldstein, Rogers, Grunwald, and others (independent work) have all shown
  - advantages of integrating into the language framework
  - very lightweight thread creation

Diffusion-Based Load Balancing

- In the randomized schemes, the machine is treated as fully-connected.
- Diffusion-based load balancing takes topology into account
  - Send some extra work to a few nearby processors
    - Average work with nearby neighbors
    - Analogy to diffusion (Jacobi for solving Poisson equation)
  - Locality properties better than choosing random processor
  - Load balancing somewhat slower than randomized
  - Cost of tasks must be known at creation time
  - No dependencies between tasks
- See Ghosh et al, SPAA96 for a second order diffusive load balancing algorithm
  - takes into account amount of work sent last time
  - avoids some oscillation of first order schemes

Diffusion-based load balancing

- The machine is modeled as a graph
- At each step, we compute the weight of task remaining on each processor
  - This is simply the number if they are unit cost tasks
- Each processor compares its weight with its neighbors and performs some averaging
  - Analysis using Markov chains
- See Ghosh et al, SPAA96 for a second order diffusive load balancing algorithm
  - takes into account amount of work sent last time
  - avoids some oscillation of first order schemes
- Note: locality is still not a major concern, although balancing with neighbors may be better than random

Charm++
Load balancing based on Overdecomposition

- Context: "Iterative Applications"
  - Repeatedly execute similar set of tasks
- Idea: decompose work/data into chunks (*chares* in Charm++) , and migrate chares for balancing loads
  - Chares can be split or merged, but typically less frequently (or unnecessary in many cases)
- How to predict the computational load and communication between objects?
  - Could rely on user-provided info, or based on simple metrics
    - (e.g. number of elements)
  - Alternative: *principle of persistence*
    - Statistics change slowly, can rebalance occasionally
- Software, documentation at charm.cs.uiuc.edu
  - Many applications: NAMD, LeanMD, OpenAtom, ChaNGa, …

Source: Laxmikant Kale

Measurement Based Load Balancing in Charm++

- Principle of persistence (A Heuristic)
  - *Object communication patterns and computational loads tend to persist over time, so recent past good predictor of future*
  - In spite of dynamic behavior
    - Abrupt but infrequent changes
    - Slow and small changes
  - Only a heuristic, but applies on many applications
- Measurement based load balancing
  - Runtime system (in Charm++) schedules objects and mediates communication between them, so can measure load
  - Use the instrumented data-base periodically to make new decisions, and migrate objects accordingly
- Charm++ provides a suite of strategies, and plug-in capability for user-defined ones
  - Also, a meta-balancer for deciding how often to balance, and what type of strategy to use

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Periodic Load Balancing Strategies

- Many alternative strategies can use the same database
  - OCG: Object communication graph
  - Or simply #loads of each object, if communication unimportant
- Centralized strategies: collect data on one processor
  - Feasible on up to a few thousand cores, because number of objects is typically small (10-100 per core?)
  - Use Graph partitioners, or greedy strategies
  - Or refinement strategies: mandated to keep most objects on the same processors
  - Charm++ provides a suite of strategies, and plug-in capability for user-defined ones
    - Also, a meta-balancer for deciding how often to balance, and what type of strategy to use

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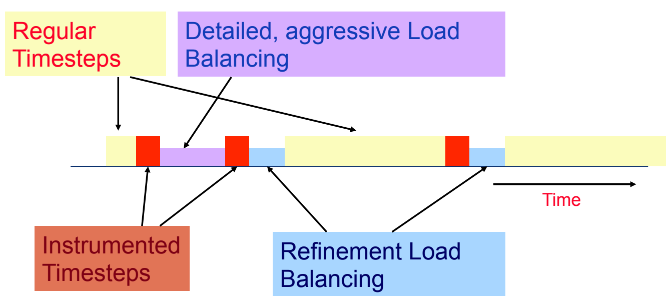
Load Balancing Steps



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Periodic Load Balancing for Large machines

- Two Challenges:
- Object communication graph cannot be brought to one processor
  - A solution : Hierarchical load balancer (next slide)
- Interconnection topology must be taken into account
  - Limited bisection bandwidth (on Torus networks, for example)
  - Solution: topology-aware balancers (later slides)

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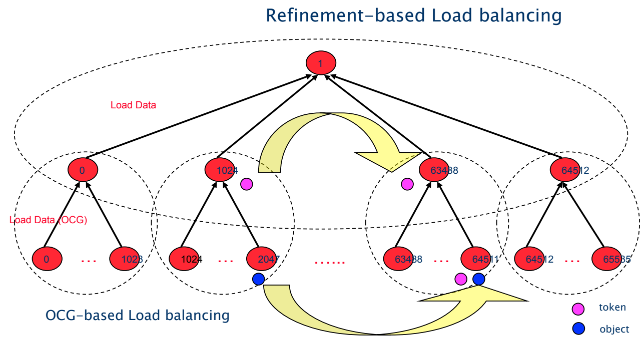
Charm++ Hierarchical Load Balancer Scheme



Source: Laxmikant Kale 61

Topology-aware load balancing

- With wormhole routing, the number of hops a message takes has very little impact on transit time
  - But: On an unloaded network!
- But bandwidth is a problem
  - Especially on torus networks
  - More hops each message takes, more bandwidth they occupy
  - Leading to contention and consequent delays
- So, we should place communicating objects nearby
  - Many current systems are "in denial" (no topo-aware allocation)
    - Partly because some applications do well
  - Lot of research in the 1980's
    - But not very relevant because of technological assumptions and topologies considered
  - Ex: Take advantage of physical proximity (domain decomp.)

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Topology aware load balancing (2/2)

- Metric: Average dilation (equivalently, sum of hop-bytes)
- Object-based over-decomposition helps balancing
- When (almost) near-neighbor communication dominates
  - And geometric information available
  - Simplest case, but challenges: Aspect ratios, load variations,
  - Strategies: ORB, many heuristic placement strategies
    - (A. Bhatele Phd. Thesis)
  - Variation: A set of pairwise interactions (e.g. Molecular dynamics) among geometrically placed primary objects:
    - Strategy: place within the "brick" formed by the two primary objs
- When application has multiple phases:
  - Strategy: often blocking helps. Alternatively, optimize one phase (better than optimizing neither)
  - Example: *OpenAtom* for Quantum Chemistry

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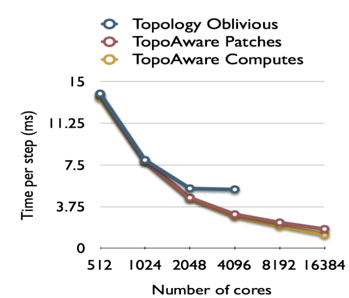
Efficacy of Topology aware load balancing



NAMD biomolecular simulation running on BG/P

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Summary and Take-Home Messages

- There is a fundamental trade-off between locality and load balance
- Many algorithms, papers, & software for load balancing
- Key to understanding how and what to use means understanding your application domain and their target
  - Shared vs. distributed memory machines
  - Dependencies among tasks, tasks cost, communication
  - Locality oblivious vs locality "encouraged" vs locality optimized
    - Computational intensity: ratio of computation to data movement cost
  - When you know information is key (static, semi, dynamic)
- Open question: will future architectures lead to so much load imbalance that even "regular" problems need dynamic balancing?