Parallel Programming

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CS 740
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Topics

- **Motivating Examples**
- **Parallel Programming for High Performance**
- **Impact of the Programming Model**
- **Case Studies**
  - Ocean simulation
  - Barnes-Hut N-body simulation

Motivating Problems

Simulating Ocean Currents

- **Regular structure, scientific computing**

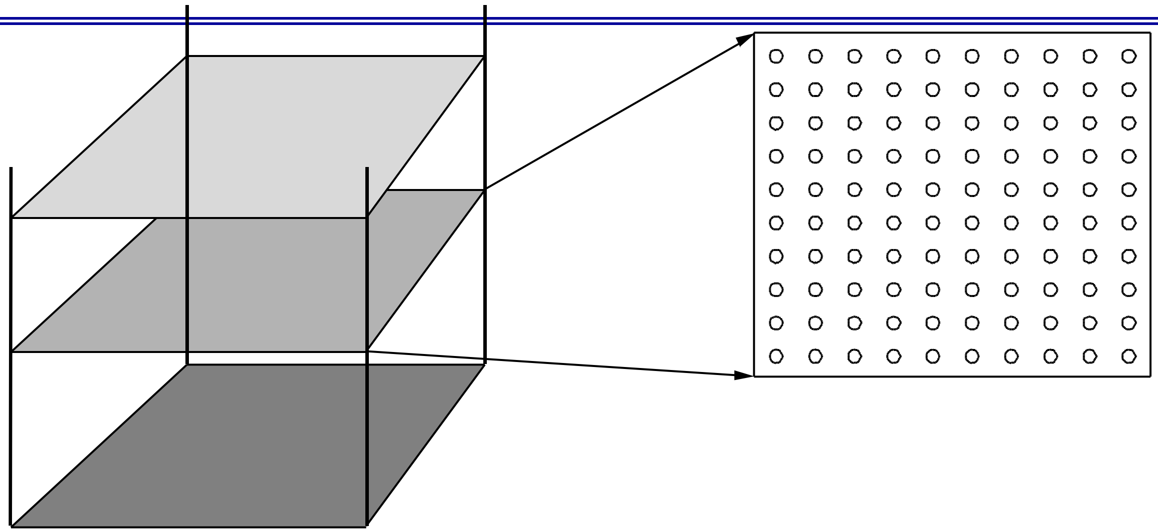
Simulating the Evolution of Galaxies

- **Irregular structure, scientific computing**

Rendering Scenes by Ray Tracing

- **Irregular structure, computer graphics**
- **Not discussed here (read in book)**

Simulating Ocean Currents

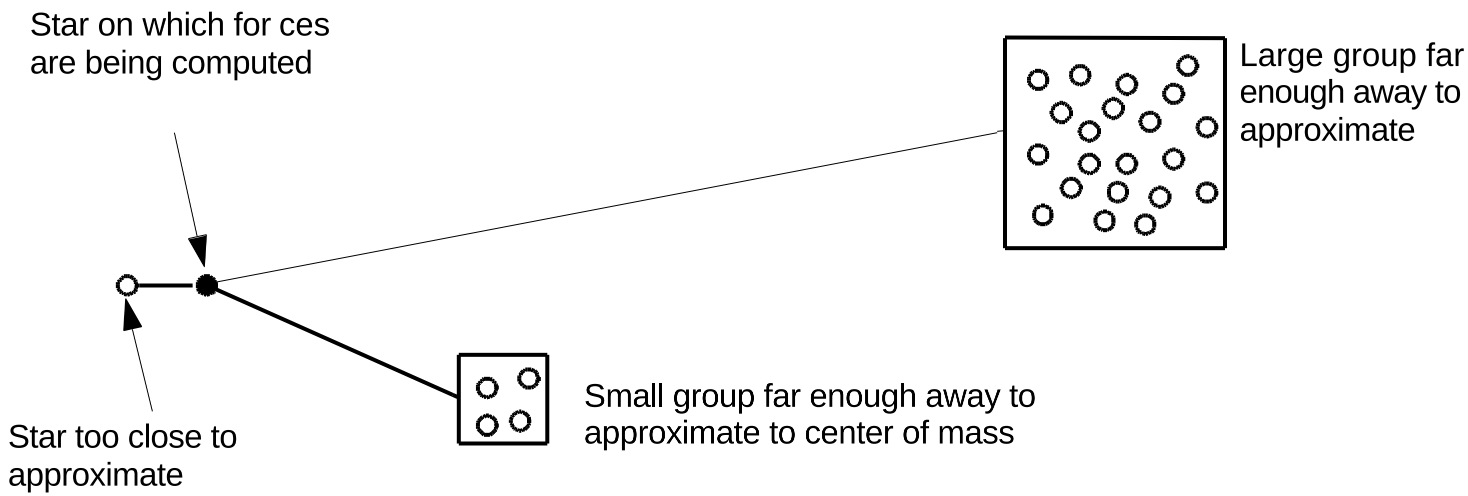


(a) Cross sections (b) Spatial discretization of a cross section

- **Model as two-dimensional grids**
- **Discretize in space and time**
  - finer spatial and temporal resolution => greater accuracy
- **Many different computations per time step**
  - set up and solve equations
- **Concurrency across and within grid computations**

Simulating Galaxy Evolution

- **Simulate the interactions of many stars evolving over time**
- **Computing forces is expensive**
- **O(n²) brute force approach**
- **Hierarchical Methods take advantage of force law: *G*** $\frac{m_1 m_2}{r^2}$



•Many time-steps, plenty of concurrency across stars within one

Rendering Scenes by Ray Tracing

- **Shoot rays into scene through pixels in image plane**
- **Follow their paths**
  - they bounce around as they strike objects
  - they generate new rays: ray tree per input ray
- **Result is color and opacity for that pixel**
- **Parallelism across rays**

All case studies have abundant concurrency

Parallel Programming Task

Break up computation into tasks

- **assign tasks to processors**

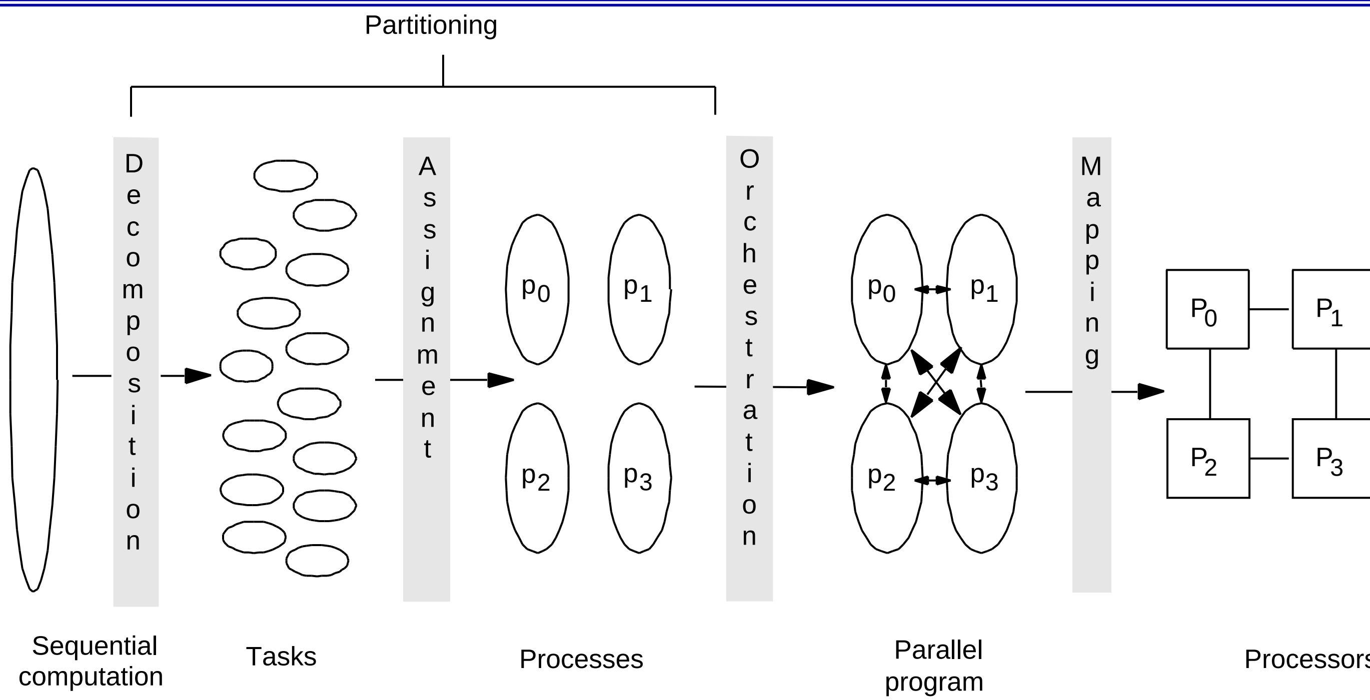
Break up data into chunks

- **assign chunks to memories**

Introduce synchronization for:

- **mutual exclusion**
- **event ordering**

Steps in Creating a Parallel Program



4 steps: Decomposition, Assignment, Orchestration, Mapping

- **Done by programmer or system software (compiler, runtime, ...)**
- **Issues are the same, so assume programmer does it all explicitly**

Partitioning for Performance

Balancing the workload and reducing wait time at synch points

Reducing inherent communication

Reducing extra work

Even these algorithmic issues trade off:

- **Minimize comm. => run on 1 processor => extreme load imbalance**
- **Maximize load balance => random assignment of tiny tasks => no control over communication**
- **Good partition may imply extra work to compute or manage it**

Goal is to compromise

- **Fortunately, often not difficult in practice**

Load Balance and Synch Wait Time

Limit on speedup: $\textit{Speedup}_{problem}(p) \leq \dfrac{\text{Sequential Work}}{\textit{Max}\text{ Work on any Processor}}$

- **Work includes data access and other costs**
- **Not just equal work, but must be busy at same time**

Four parts to load balance and reducing synch wait time:

1. **Identify enough concurrency**
2. **Decide how to manage it**
3. **Determine the granularity at which to exploit it**
4. **Reduce serialization and cost of synchronization**

Deciding How to Manage Concurrency

Static **versus** ***Dynamic*** **techniques**

Static:

- **Algorithmic assignment based on input; won't change**
- **Low runtime overhead**
- **Computation must be predictable**
- **Preferable when applicable (except in multiprogrammed/heterogeneous environment)**

Dynamic:

- **Adapt at runtime to balance load**
- **Can increase communication and reduce locality**
- **Can increase task management overheads**

Dynamic Assignment

Profile-based (semi-static):

- **Profile work distribution at runtime, and repartition dynamically**
- **Applicable in many computations, e.g. Barnes-Hut, some graphics**

Dynamic Tasking:

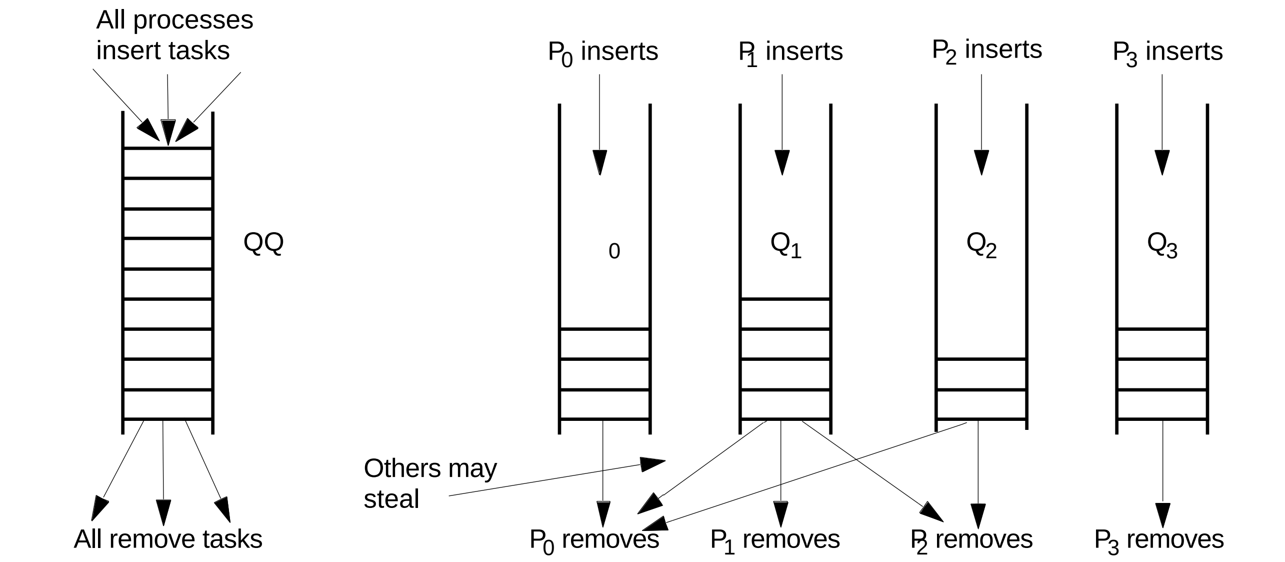
- **Deal with unpredictability in program or environment (e.g. Raytrace)**
  - computation, communication, and memory system interactions
  - multiprogramming and heterogeneity
  - used by runtime systems and OS too
- **Pool of tasks; take and add tasks until done**
- **E.g. “self-scheduling” of loop iterations (shared loop counter)**

Dynamic Tasking with Task Queues

Centralized versus distributed queues

Task stealing with distributed queues

- **Can compromise comm and locality, and increase synchronization**
- **Whom to steal from, how many tasks to steal, ...**
- **Termination detection**
- **Maximum imbalance related to size of task**



(a) Centralized task queue

(b) Distributed task queues (one per pr ocess)

Determining Task Granularity

Task granularity: amount of work associated with a task

General rule:

- **Coarse-grained => often less load balance**
- **Fine-grained => more overhead; often more communication and contention**

Communication and contention actually affected by assignment, not size

- **Overhead by size itself too, particularly with task queues**

Reducing Serialization

Careful about assignment and orchestration (including scheduling)

Event synchronization

- **Reduce use of conservative synchronization**
  - e.g. point-to-point instead of barriers, or granularity of pt-to-pt
- **But fine-grained synch more difficult to program, more synch ops.**

Mutual exclusion

- **Separate locks for separate data**
  - e.g. locking records in a database: lock per process, record, or field
  - lock per task in task queue, not per queue
  - finer grain => less contention/serialization, more space, less reuse
- **Smaller, less frequent critical sections**
  - don't do reading/testing in critical section, only modification
  - e.g. searching for task to dequeue in task queue, building tree
- **Stagger critical sections in time**

Reducing Inherent Communication

Communication is expensive!

Measure: *communication to computation ratio*

Focus here on inherent communication

- **Determined by assignment of tasks to processes**
- **Later see that actual communication can be greater**

Assign tasks that access same data to same process

Solving communication and load balance NP-hard in general case

But simple heuristic solutions work well in practice

- **Applications have structure!**

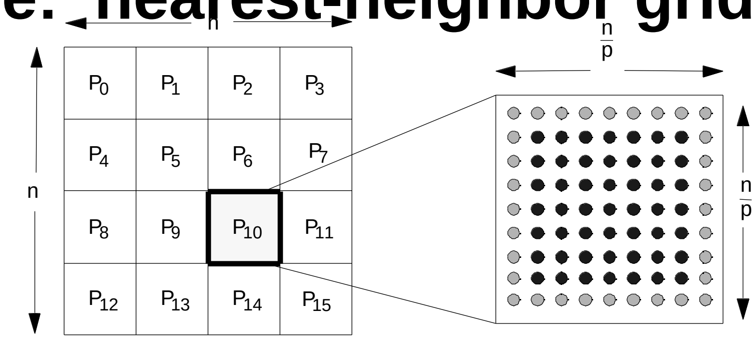
Domain Decomposition

Works well for scientific, engineering, graphics, ... applications

Exploits local-biased nature of physical problems

- **Information requirements often short-range**
- **Or long-range but fall off with distance**

Simple example: nearest-neighbor grid computation



Perimeter to Area comm-to-comp ratio (area to volume in 3-d)

- Depends on *n*,*p*: decreases with *n*, increases with *p*

Reducing Extra Work

Common sources of extra work:

- **Computing a good partition**
  - e.g. partitioning in Barnes-Hut or sparse matrix
- **Using redundant computation to avoid communication**
- **Task, data and process management overhead**
  - applications, languages, runtime systems, OS
- **Imposing structure on communication**
  - coalescing messages, allowing effective naming

Architectural Implications:

- **Reduce need by making communication and orchestration efficient**

$$\text{Speedup} \leq \frac{\text{Sequential Work}}{\mathit{Max}\,(\text{Work} + \text{Synch Wait Time} + \text{Comm Cost} + \text{Extra Work})}$$

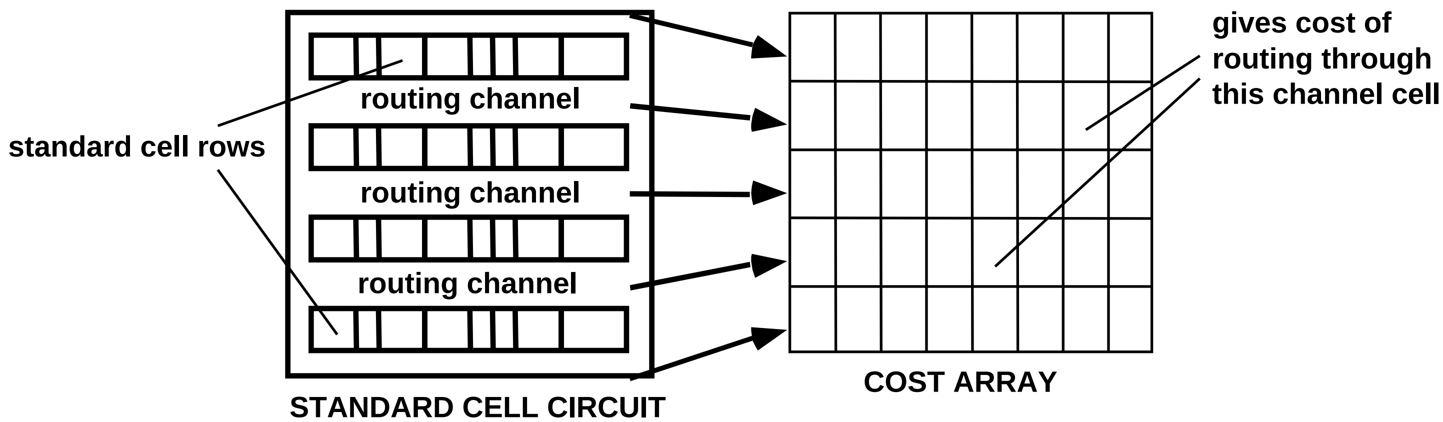
Summary of Tradeoffs

Different goals often have conflicting demands

- **Load Balance**
  - fine-grain tasks
  - random or dynamic assignment
- **Communication**
  - usually coarse grain tasks
  - decompose to obtain locality: not random/dynamic
- **Extra Work**
  - coarse grain tasks
  - simple assignment
- **Communication Cost:**
  - big transfers: amortize overhead and latency
  - small transfers: reduce contention

Impact of Programming Model

- **Example: LocusRoute (standard cell router)**




```
while (route_density_improvement > threshold)
  {
    for (i = 1 to num_wires) do
       {
         - rip old wire route out
         - explore new routes
         - place wire using best new route
       }
  }
```

Shared-Memory Implementation

Shared memory algorithm:

- Divide cost-array into regions (assign regions to PEs)
- Assign wires to PEs based on the region in which center lies
- Do load balancing using stealing when local queue empty

Good points:

- Good load balancing
- Mostly local accesses
- High cache-hit ratio

Message-Passing Implementations

Solution-1:

- **Distribute wires and cost-array regions as in sh-mem implementation**
- **Big overhead when wire-path crosses to remote region**
  - send computation to remote PE, or
  - send messages to access remote data

Solution-2:

- **Wires distributed as in sh-mem implementation**
- **Each PE has copy of full cost array**
  - one owned region, plus potentially stale copy of others
  - send frequent updates so that copies not too stale
- **Consequences:**
  - waste of memory in replication
  - stale data => poorer quality results or more iterations

=> In either case, lots of thinking needed on the programmer's part

Case Studies

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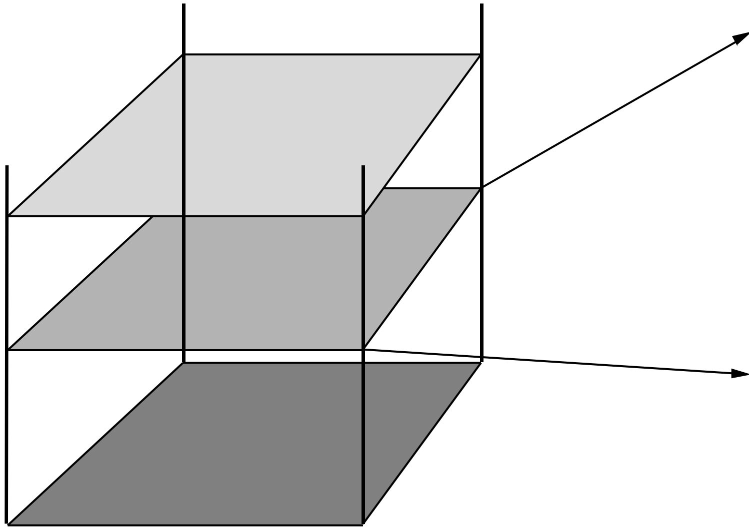
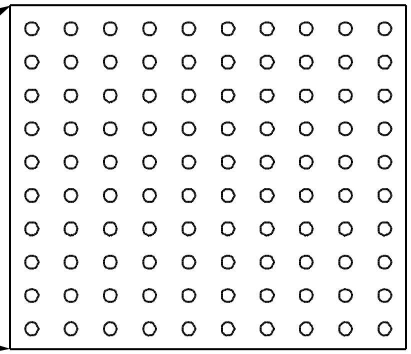
Case 1: Simulating Ocean Currents



(a) Cross sections



(b) Spatial discretization of a cross section

- **Model as two-dimensional grids**
- **Discretize in space and time**
  - finer spatial and temporal resolution => greater accuracy
- **Many different computations per time step**
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Steps in Ocean Simulation

Put Laplacian of Ψ_1 in $W1_1$	Put Laplacian of Ψ_3 in $W1_3$	Copy Ψ_1, Ψ_3 into T_1, T_3	Put $\Psi_1 - \Psi_3$ in W2	Put computed Ψ_2 values in W3	Initialize γ_a and γ_b
Add f values to columns of $W1_1$ and $W1_3$		Copy Ψ_{1M}, Ψ_{3M} into Ψ_1, Ψ_3			Put Laplacian of Ψ_{1M}, Ψ_{3M} in $W7_{1,3}$
Put Jacobians of ($W1_1$, T_1), ($W1_3$, T_3) in $W5_1$, $W5_3$		Copy T_1, T_3 into Ψ_{1M}, Ψ_{3M}			Put Laplacian of $W7_{1,3}$ in $W4_{1,3}$
			Put Jacobian of (W2, W3) in W6		Put Laplacian of $W4_{1,3}$ in $W7_{1,3}$
UPDATE THE γ EXPRESSIONS					
SOLVE THE EQUATION FOR Ψ_a AND PUT THE RESULT IN γ_a					
COMPUTE THE INTEGRAL OF Ψ_a					
Compute $\Psi = \Psi_a + C(t)\Psi_b$ (note: Ψ_a and now Ψ are maintained in γ_a matrix)			Solve the equation for Φ and put result in γ_b		
Use Ψ and Φ to update Ψ_1 and Ψ_3					
Update streamfunction running sums and determine whether to end program					

Note: Every box is a computation on an entire grid(s). Horizontal lines represent synchronization points among all processes, and vertical lines spanning phases demarcate threads of dependence.

Computations in a Time-step

Partitioning

Exploit data parallelism

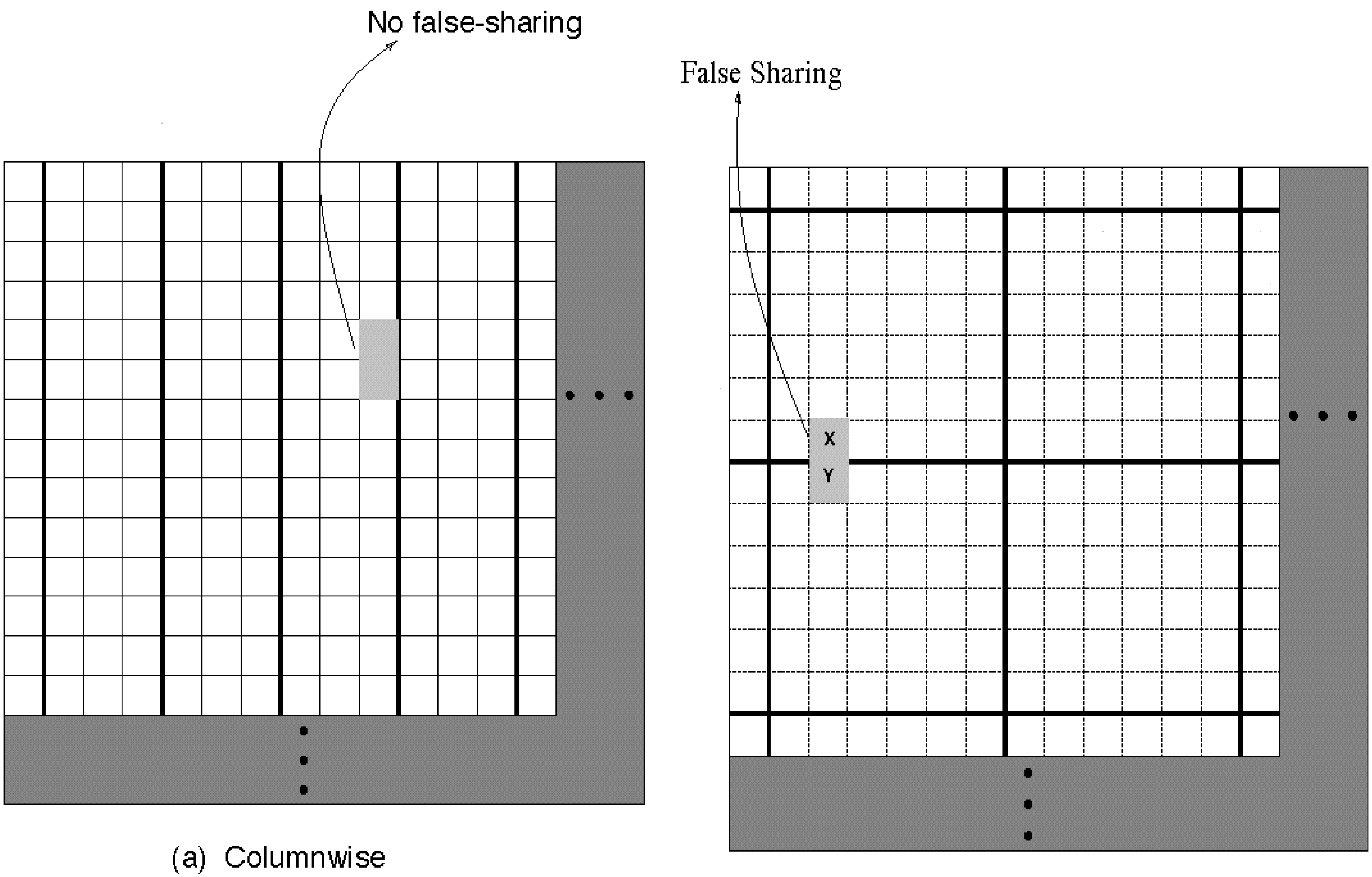
- **Function parallelism only to reduce synchronization**

Static partitioning within a grid computation

- **Block versus strip**
  – inherent communication versus spatial locality in communication
- **Load imbalance due to border elements and number of boundaries**

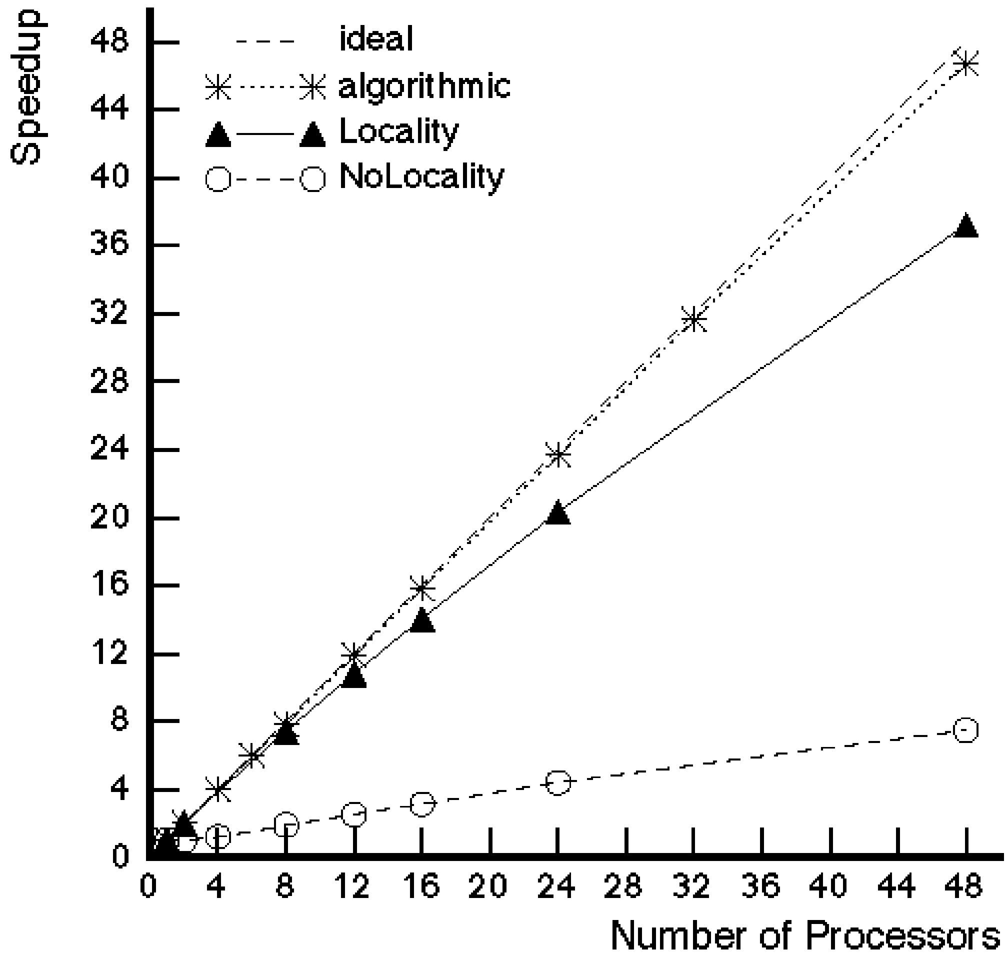
Solver has greater overheads than other computations

Ocean Simulation



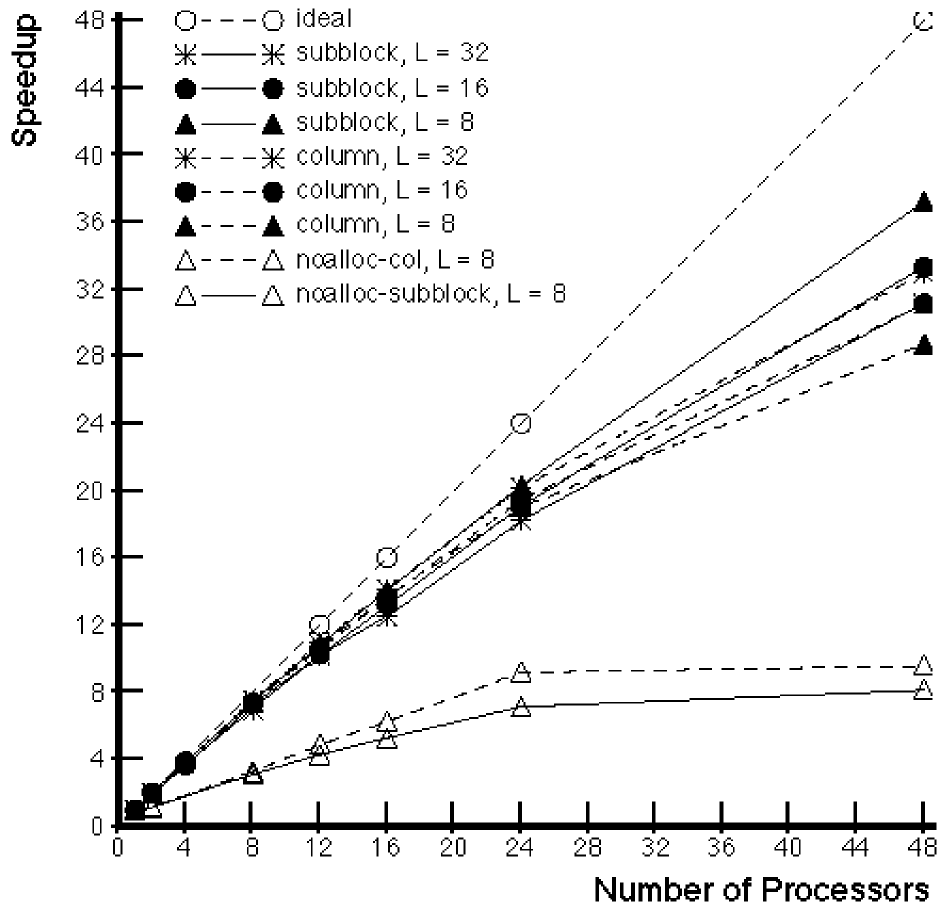
Two Static Partitioning Schemes

Impact of Memory Locality



algorithmic = perfect memory system; No Locality = dynamic assignment of columns to processors; Locality = static subgrid assigment (infinite caches)

Impact of Line Size & Data Distribution



(a) 16 KByte Cache, Grid_98

no-alloc = round-robin page allocation; otherwise, data assigned to local memory.
L = cache line size.

Case 2: Simulating Galaxy Evolution

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- **Computing forces is expensive**
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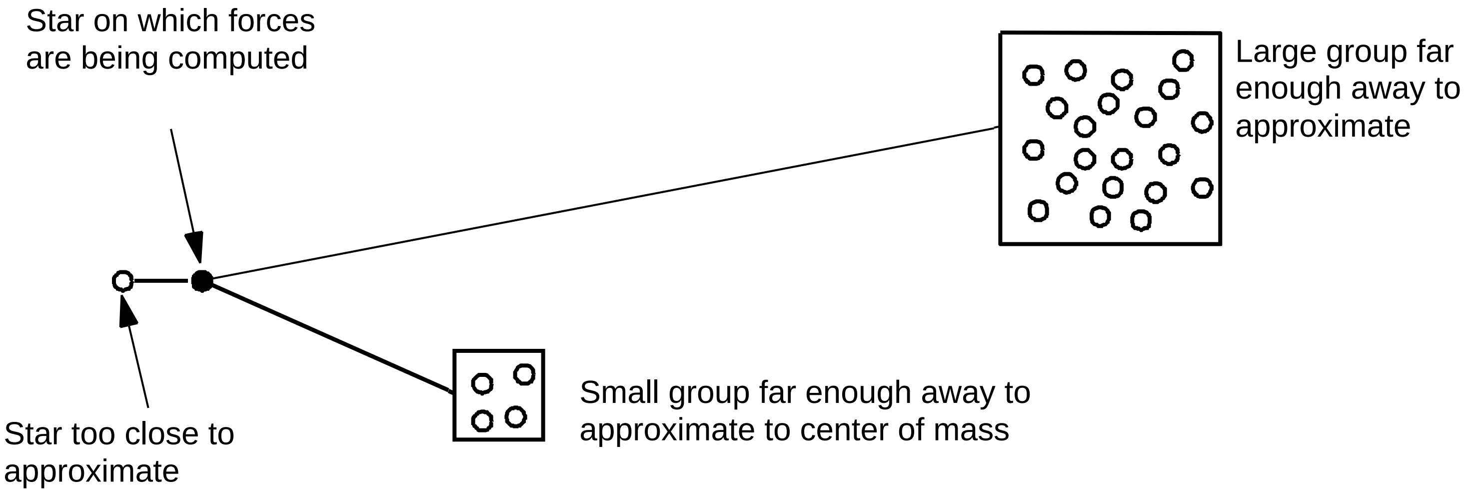
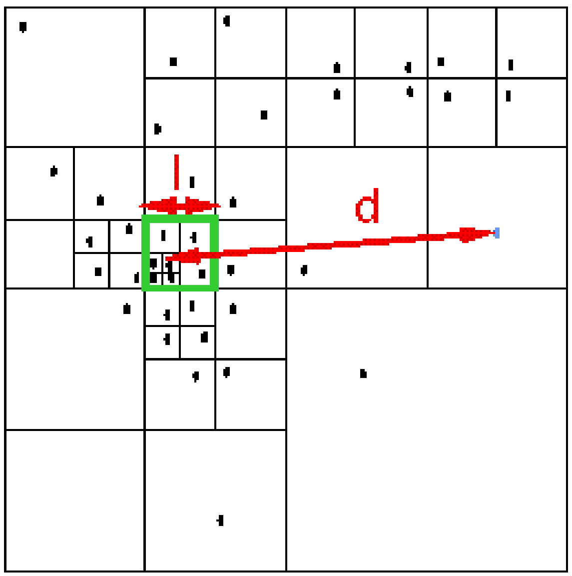
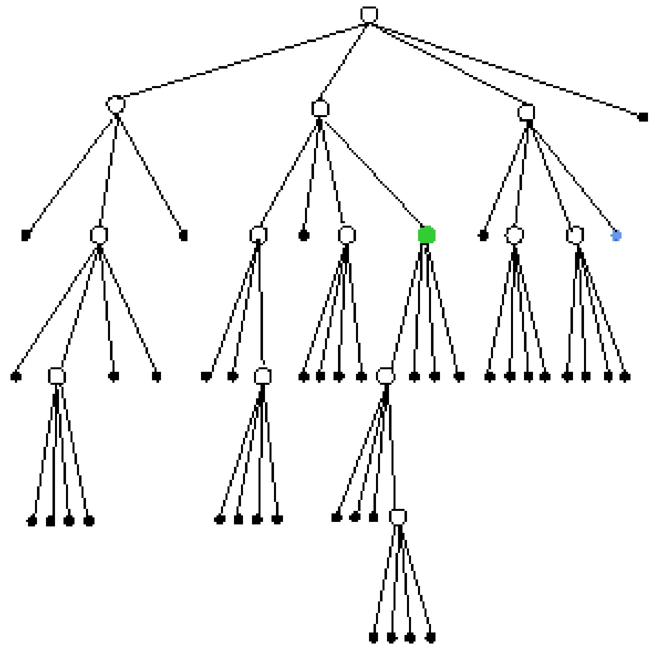


- **Many time-steps, plenty of concurrency across stars within one**

Barnes-Hut



2 d Spatial Domain



Quadtree Representation

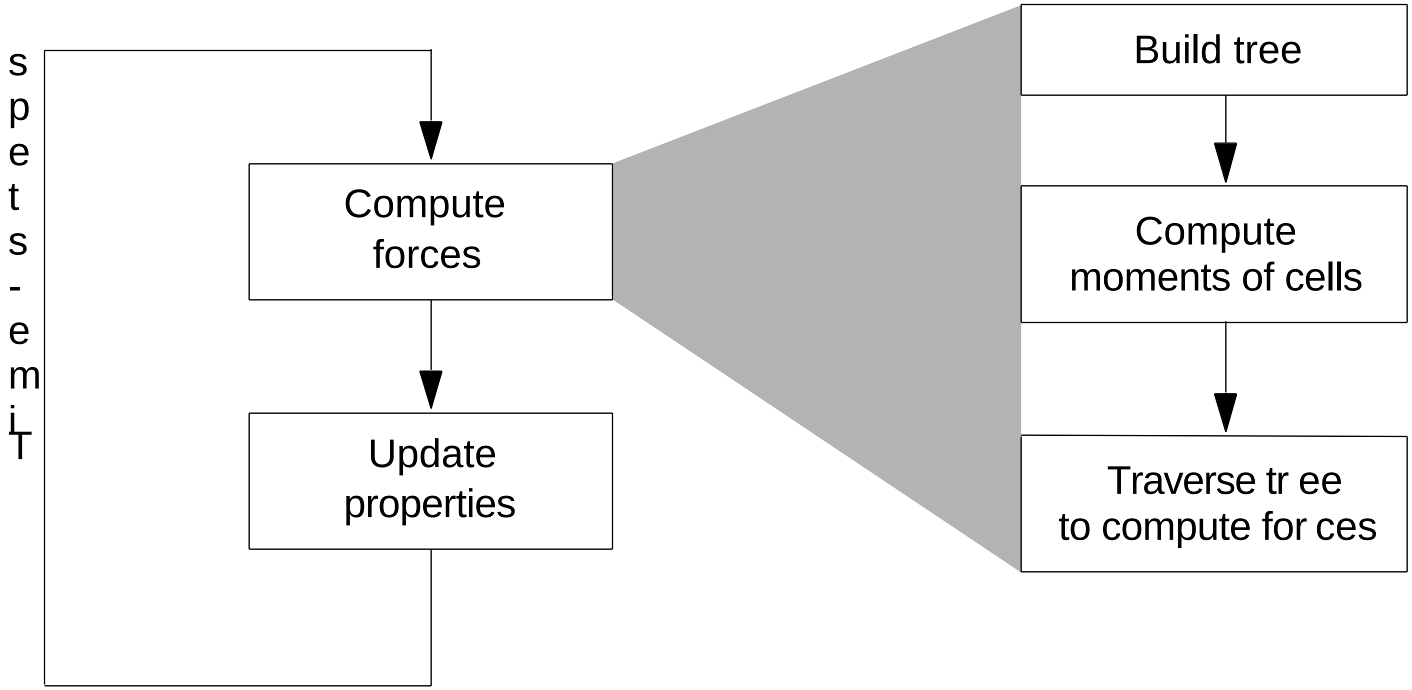
Locality Goal:

- **particles close together in space should be on same processor**

Difficulties:

- **nonuniform, dynamically changing**

Application Structure



- **Main data structures: array of bodies, of cells, and of pointers to them**
  - Each body/cell has several fields: mass, position, pointers to others
  - pointers are assigned to processes

Partitioning

Decomposition: bodies in most phases, cells in computing moments

Challenges for assignment:

- **Nonuniform body distribution => work and comm. nonuniform**
  - Cannot assign by inspection
- **Distribution changes dynamically across time-steps**
  - Cannot assign statically
- **Information needs fall off with distance from body**
  - Partitions should be spatially contiguous for locality
- **Different phases have different work distributions across bodies**
  - No single assignment ideal for all
  - Focus on force calculation phase
- **Communication needs naturally fine-grained and irregular**

Load Balancing

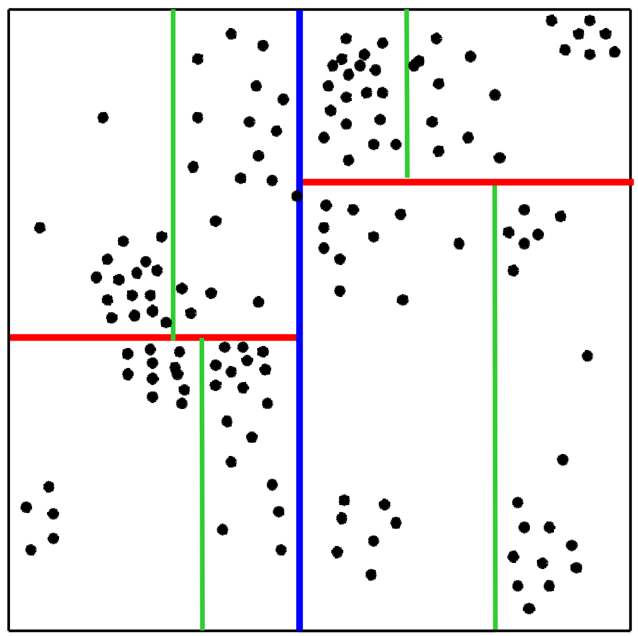
- **Equal particles ≠ equal work.**
  - Solution: Assign costs to particles based on the work they do
- **Work unknown and changes with time-steps**
  - Insight : System evolves slowly
  - Solution: ***Count*** work per particle, and use as cost for next time-step.

Powerful technique for evolving physical systems

A Partitioning Approach: ORB

Orthogonal Recursive Bisection:

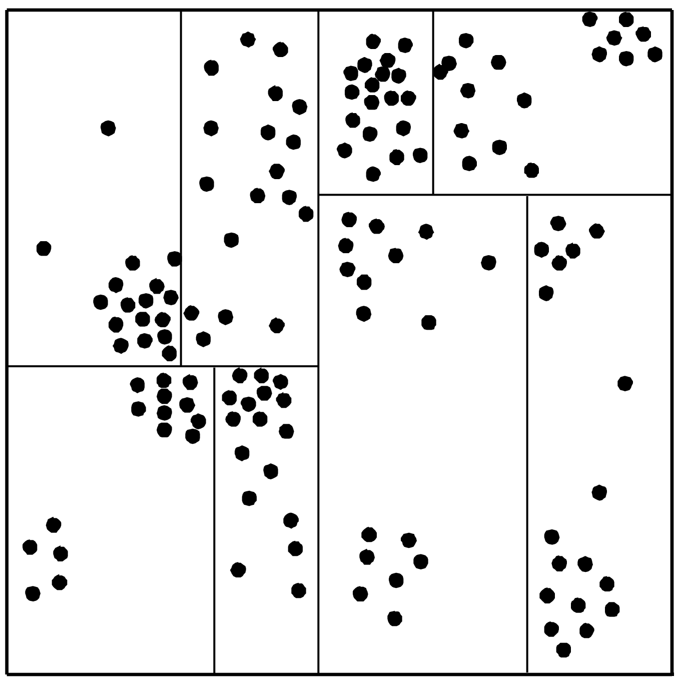
- **Recursively bisect space into subspaces with equal work**
  - Work is associated with bodies, as before
- **Continue until one partition per processor**



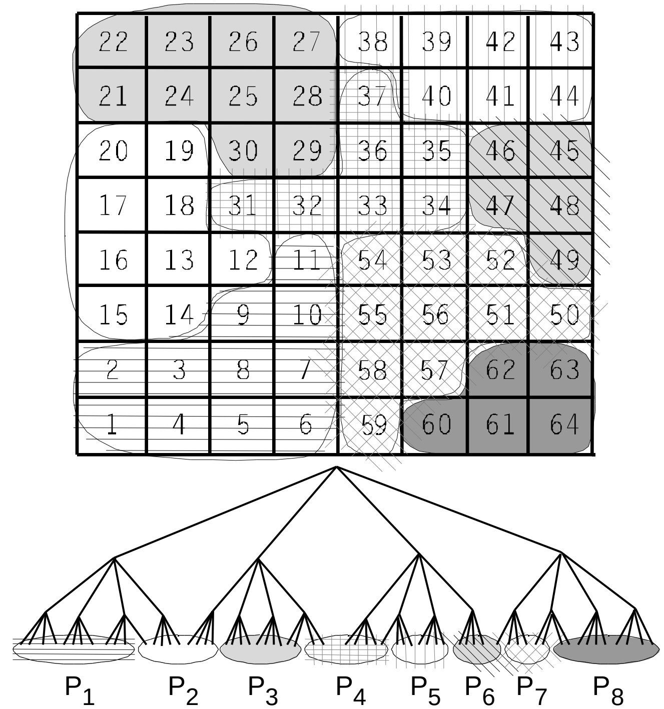
- **High overhead for large number of processors**

Another Approach: Costzones

Insight: Tree already contains an encoding of spatial locality.



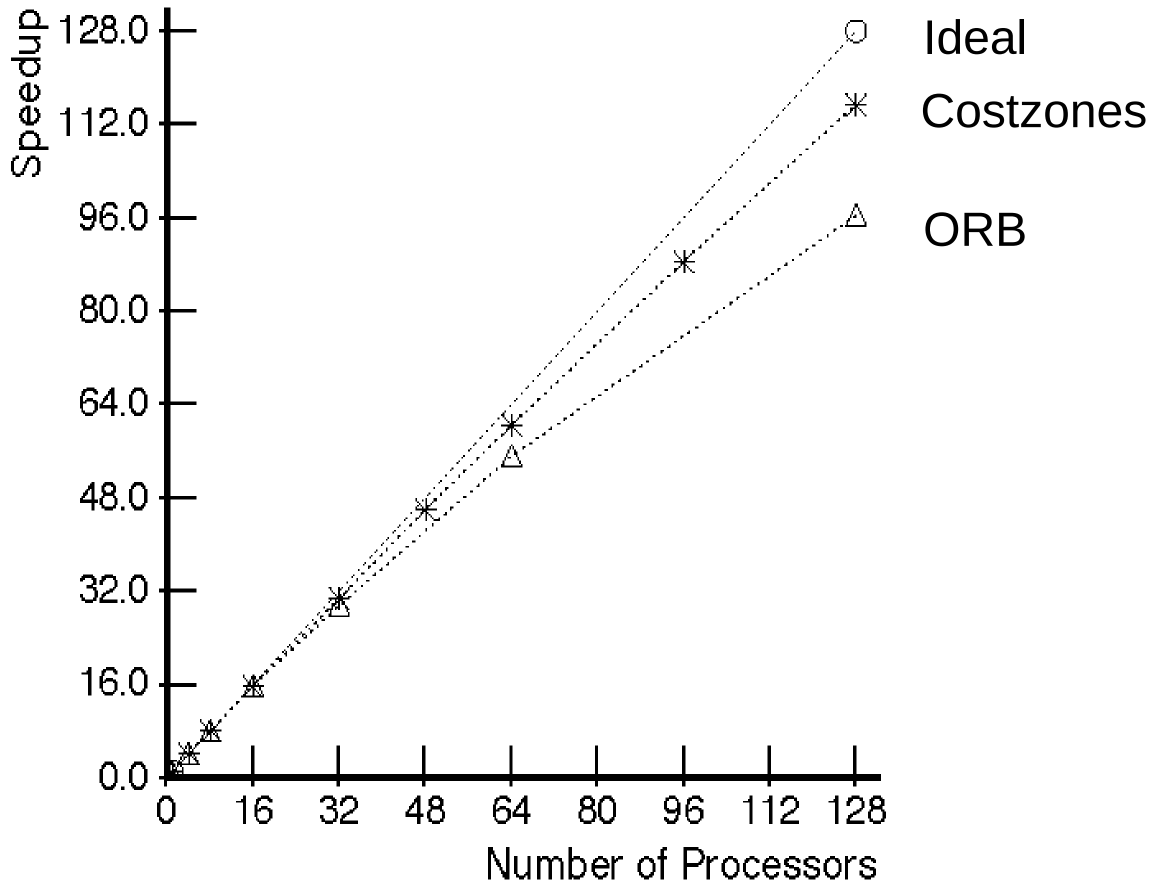
(a) ORB



(b) Costzones

- **Costzones is low-overhead and very easy to program**

Barnes-Hut Performance



- **Speedups on simulated multiprocessor**
- **Extra work in ORB is the key difference**