CS 5220: Load Balancing

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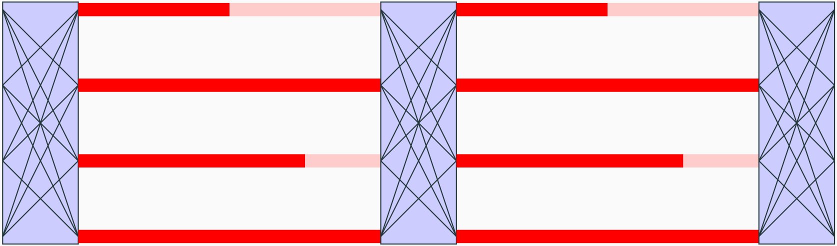
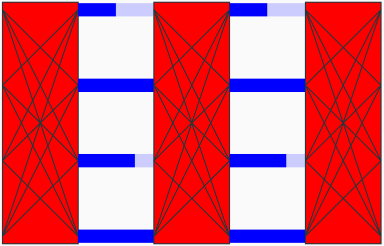
Inefficiencies in parallel code



Poor single processor performance

- Typically in the memory system
- Saw this in matrix multiply assignment

Inefficiencies in parallel code



Overhead for parallelism

- Thread creation, synchronization, communication
- Saw this in moshpit and shallow water assignments

Inefficiencies in parallel code

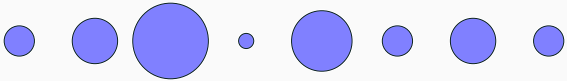
Load imbalance

- Different amounts of work across processors
- Different speeds / available resources
- Insufficient parallel work
- All this can change over phases

Where does the time go?

- Load balance looks like large sync cost
- … maybe so does ordinary synchronization overhead!
- And spin-locks may make sync look like useful work
- And ordinary time sharing can confuse things more
- Can get some help from profiling tools

Many independent tasks



- Simplest strategy: partition by task index
    - What if task costs are inhomogeneous?
    - Worse: what if expensive tasks all land on one thread?
- Potential fixes
    - Many small tasks, randomly assigned to processors
    - Dynamic task assignment
- Issue: what about scheduling overhead?

Variations on a theme

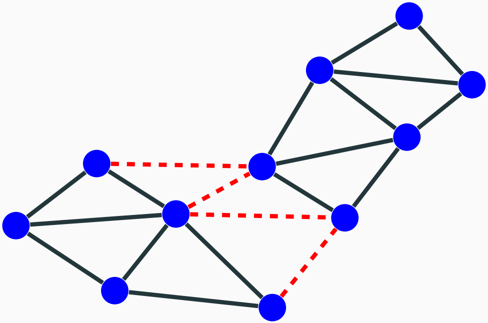
How to avoid overhead? Chunks! (Think OpenMP loops)

- Small chunks: good balance, large overhead
- Large chunks: poor balance, low overhead

Variants:

- Fixed chunk size (requires good cost estimates)
- Guided self-scheduling (take $\lceil(\text{tasks left})/p\rceil$ work)
- Tapering (size chunks based on variance)
- Weighted factoring (GSS with heterogeneity)

Static dependency and graph partitioning



- Graph $G = (V, E)$ with vertex and edge weights
- Goal: even partition with small edge cut (comm volume)
- Optimal partitioning is NP complete – use heuristics
- Tradeoff quality vs speed
- Good software exists (e.g. METIS)

The limits of graph partitioning

What if

- We don't know task costs?
- We don't know the communication/dependency pattern?
- These things change over time?

May want *dynamic* load balancing?

Even in regular case: not every problem looks like an undirected graph!

Dependency graphs

So far: Graphs for dependencies between *unknowns*.

For dependency between tasks or computations:

- Arrow from A to B means that B depends on A
- Result is a *directed acyclic graph* (DAG)

Example: Longest Common Substring

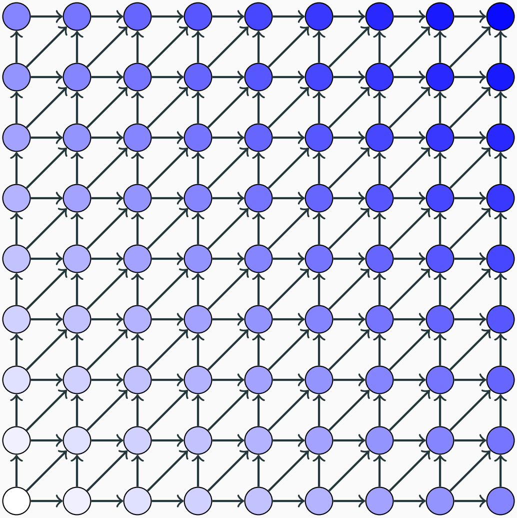
Goal: Longest sequence of (not necessarily contiguous) characters common to strings S and T.

Recursive formulation:

$$\mathrm{LCS}[i,j] = \begin{cases} \max(\mathrm{LCS}[i-1,j], \mathrm{LCS}[j,i-1]), & S[i] \neq T[j] \\ 1 + \mathrm{LCS}[i-1,j-1], & S[i] = T[j] \end{cases}$$

Dynamic programming: Form a table of $\mathrm{LCS}[i,j]$

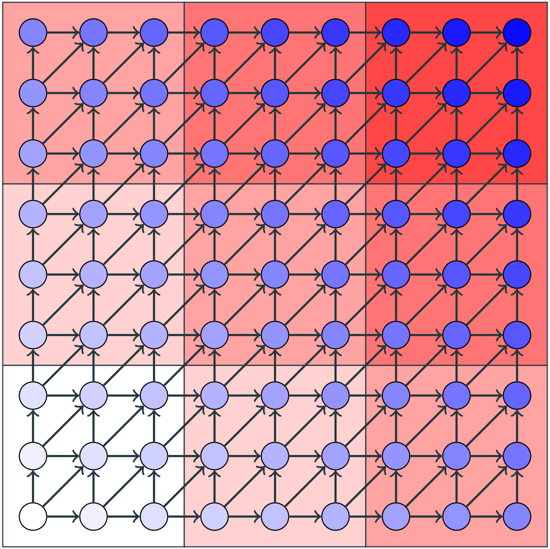
Dependency graphs



Can process in any order consistent with dependencies.

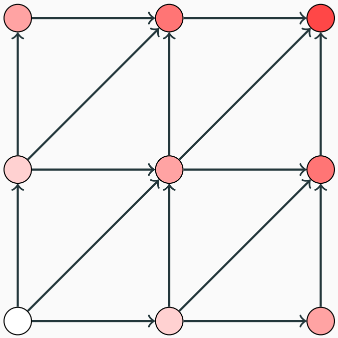
Limits to available parallel work early on or late!

Dependency graphs



Partition into coarser-grain tasks for locality?

Dependency graphs



Dependence between coarse tasks limits parallelism.

Alternate perspective

Recall LCS

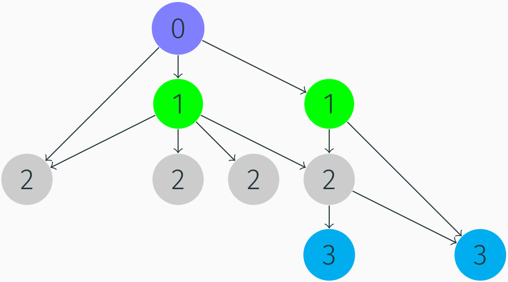
$$\mathrm{LCS}[i,j] = \begin{cases} \max(\mathrm{LCS}[i-1,j], \mathrm{LCS}[j,i-1]), & S[i] \neq T[j] \\ 1 + \mathrm{LCS}[i-1,j-1], & S[i] = T[j] \end{cases}$$

Two approaches to LCS:

- Solve subproblems from bottom up
- Solve from top down and *memoize* common subproblems

Parallel question: shared memoization (and synchronize) or independent memoization (and redundant computation)?

Load balancing and task-based parallelism



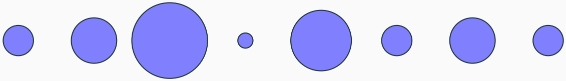
- Task DAG captures data dependencies
- May be known at outset or dynamically generated
- Topological sort reveals parallelism opportunities

Basic parameters

- Task costs
  - Do all tasks have equal costs?
  - Costs known statically, at creation, at completion?
- Task dependencies
  - Can tasks be run in any order?
  - If not, when are dependencies known?
- Locality
  - Should tasks be co-located to reduce communication?
  - When is this information known?

Task costs

Easy: equal unit cost tasks (branch-free loops)

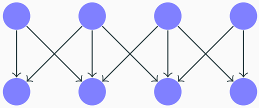


Harder: different, known times (sparse MVM)

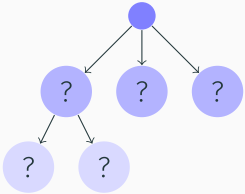
Hardest: costs unknown until completed (search)

Dependencies

Easy: dependency-free loop (Jacobi sweep)



Harder: tasks have predictable structure (some DAG)



Hardest: structure is dynamic (search, sparse LU)

Locality/communication

When do you communicate?

- Easy: Only at start/end (embarrassingly parallel)
- Harder: In a predictable pattern (elliptic PDE solver)
- Hardest: Unpredictable (discrete event simulation)

A spectrum of solutions

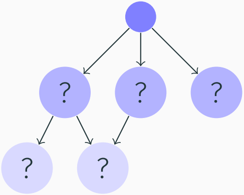
How much we can do depends on cost, dependency, locality

- Static scheduling
  - Everything known in advance
  - Can schedule offline (e.g. graph partitioning)
  - Example: Shallow water solver
- Semi-static scheduling
  - Everything known at start of step (for example)
  - Can use offline ideas (e.g. Kernighan-Lin refinement)
  - Example: Particle-based methods
- Dynamic scheduling
  - Don't know what we're doing until we've started
  - Have to use online algorithms
  - Example: most search problems

Search problems

- Different set of strategies from physics sims!
- Usually require dynamic load balance
- Example:
    - Optimal VLSI layout
    - Robot motion planning
    - Game playing
    - Speech processing
    - Reconstructing phylogeny
    - …

Example: Tree search



- Tree unfolds dynamically during search
- May be common problems on different paths (graph)
- Graph may or may not be explicit in advance

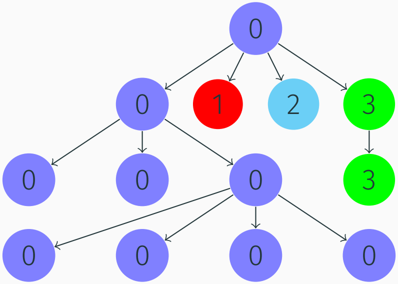
Search algorithms

Generic search:

Put root in stack/queue
while stack/queue has work
  remove node *n* from queue
  if *n* satisfies goal, return
  mark *n* as searched
  add viable unsearched children of *n* to stack/queue
    (Can branch-and-bound)

Variants: DFS (stack), BFS (queue), A* (priority queue), ...

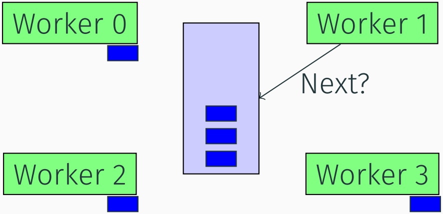
Simple parallel search



Static load balancing:

- Each new task on an idle processor until all have a subtree
- Not very effective without work estimates for subtrees!
- How can we do better?

Centralized scheduling



Idea: obvious parallelization of standard search

- Locks on shared data structure (stack, queue, etc)
- Or might be a manager task

Centralized scheduling

Teaser: What could go wrong with this parallel BFS?

```
Put root in queue
fork
   obtain queue lock
   while queue has work
      remove node n from queue
      release queue lock
      process n, mark as searched
      obtain queue lock
      enqueue unsearched children of n
   release queue lock
join
```

Centralized scheduling

Teaser: What could go wrong with this parallel BFS?

Put root in queue; **workers active = 0**

fork

    obtain queue lock

    while queue has work **or workers active > 0**

        remove node *n* from queue; **workers active ++**

        release queue lock

        process *n*, mark as searched

        obtain queue lock

        enqueue unsearched children of *n*; **workers active --**

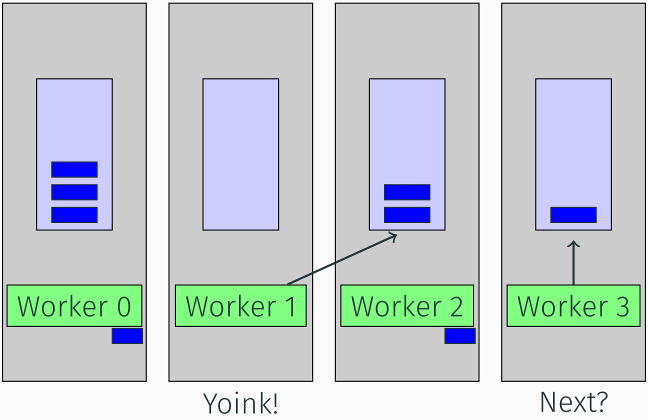
    release queue lock

join

Centralized task queue

- Called *self-scheduling* when applied to loops
    - Tasks might be range of loop indices
    - Assume independent iterations
    - Loop body has unpredictable time (or do it statically)
- Pro: dynamic, online scheduling
- Con: centralized, so doesn't scale
- Con: high overhead if tasks are small

Beyond centralized task queue



Beyond centralized task queue

Basic *distributed* task queue idea:

- Each processor works on part of a tree
- When done, get work from a peer
- *Or* if busy, push work to a peer
- Requires asynch communication

Also goes by work stealing, work crews...

Implemented in OpenMP, Cilk, X10, CUDA, QUARK, SMPss, ...

Picking a donor

Could use:

- Asynchronous round-robin
- Global round-robin (keep current donor pointer at proc 0)
- Randomized – optimal with high probability!

Diffusion-based balancing

- Problem with random polling: communication cost!
    - But not all connections are equal
    - Idea: prefer to poll more local neighbors
- Average out load with neighbors $\implies$ diffusion!

Mixed parallelism

- Today: mostly coarse-grain *task* parallelism
- Other times: fine-grain *data* parallelism
- Why not do both? *Switched* parallelism.

Takeaway

- Lots of ideas, not one size fits all!
- Axes: task size, task dependence, communication
- Dynamic tree search is a particularly hard case!
- Fundamental tradeoffs
  - Overdecompose (load balance) vs
    keep tasks big (overhead, locality)
  - Steal work globally (balance) vs
    steal from neighbors (comm. overhead)
- Sometimes hard to know when code should stop!