Plan

Last time

- some terminology
- parallel computing models (SISD, SIMD, MIMD)
- measures of "goodness" (speedup, efficiency, scalability)
- Amdahl law and its variations (parallel fraction)

Today

- Functional decomposition and task scheduling
- Domain decomposition applied to matrix operations
- Gaussian elimination

Parallelization of applications

Partitioning (or decomposition)

- break the problem into "chunks" that can be assigned to concurrent tasks
- functional decomposition and domain decomposition.

Functional Decomposition:

• the problem is decomposed according to the types of work that must be performed, different types are assigned to different tasks.

Domain Decomposition:

• the data associated with the problem is decomposed, tasks works on portions of the data

Scheduling

$Functional\ decomposition$

Execute several functions on the same data array:

- average,
- minimum,
- geometric mean
- etc.

No dependencies between the tasks, so all can run in parallel Video streaming

- Read data from server
- Parse data
- decode sound and decode video
- play sound and draw video frame

$Domain\ deomposition$

- Add two matrices
- Local filtering (convolve with a mask)
- Integration via Riemann sums
- etc.

PRAM - scheduling

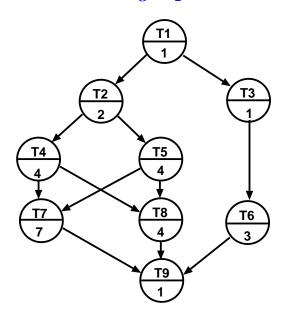
Scheduling is a scheme for assigning tasks to PEs

• so the parallel execution time is less than sequential execution time.

Task graph G = (V, E)

- $V = \{T_i\}$ set of nodes with $T_i \in V$ representing task i
- $E = \{e_{ij}\} = \{(i, j)\}$ set of directed edges representing dependencies among the tasks
- $w(T_i)$ is the (sequential) execution cost of T_i (or weight of T_i)
 - may include the cost of communicating data,
 - $w(T_i)$ determines the **granularity** of the dependence graph.
- no circular dependencies (DAG)

Task graph



For $e_{ij} \in E$

- T_i is a **predecessor** of T_j ,
- the number of predecessors of T_j is called the **indegree** of T_j ,
- T_j is a **successor** of T_i .
- the number of successors of T_i is called the outdegree of T_i ,

Scheduling problem: assign T_i 's to P PEs "optimally".

Task scheduling heuristic

In general a very difficult problem (NP-problem). Good heuristics exists.

List scheduling

- 1. assign tasks to **levels** dynamic programming
- 2. based on levels create a **priority queue**
- 3. extract from the priority queue a ready queue
- 4. assign idle PEs to tasks from the ready queue (in some order)
- 5. after finishing a task update the priority and ready queues
- 6. repeat from (4) until done

Critical path

Assume one start node T_0 and one terminal node T_{end} .

Def 3.1: A path p(s, e) joining T_s and T_e is a chain of edges $(i_k, i_{k+1}), k = 0, ..., n$ s.t. $i_0 = s$ and $i_{n+1} = e$,

$$p(s,e) = \{(i_0, i_1), ..., (i_n, i_{n+1})\}.$$

The **length** of p(s, e) is the number of edges in p(s, e),

$$length(p(s, e)) \stackrel{def}{=} |p(s, e)| = n + 1.$$

Critical path

Def 3.2: The **weight** w(p(s,e)) of $p(s,e) = \{(i_0,i_1),...,(i_n,i_{n+1})\}$ is

$$w(p(s,e)) = \sum_{j=0}^{n+1} w(T_{i_j})$$

. **Def 3.3**: Let $\mathcal{P}(s,e)$ be the set of all paths between T_s and T_e . A **critical path** between T_s and T_e is a path of the largest weight,

$$p_{crit}(s, e) = \operatorname{argmax}_{p(s, e) \in \mathcal{P}(s, e)} w(p(s, e))$$

Def 3.4: The **level** l_i of task T_i is defined as

$$l_i = |p_{crit}(T_i, T_{end})|$$

Step 1: Get the critical path for all tasks. Use Dynamic Programming.

Task level - dynamic programming (DP)

In stage s of DP nodes from set $V^{(s)}$ are considered.

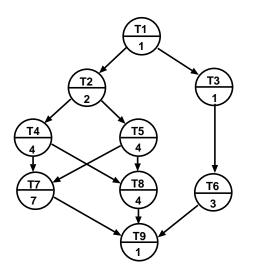
Start with stage s = 0 and set $V^{(0)} = \{T_{end}\}$. Loop:

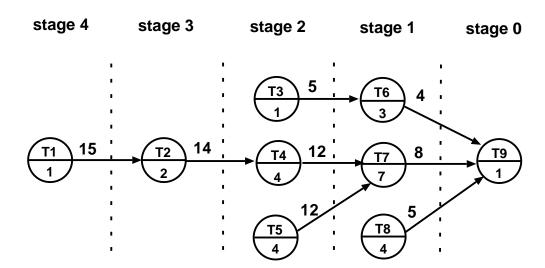
- 1. if the nodes in stage s have indegree 0 then exit
- $2. \ s = s + 1,$
- 3. set $V^{(s)}$ as the set of all predecessor of nodes in $V^{(s-1)}$ (whose successors had their critical path already evaluated)
- 4. for $T_i^{(s)} \in V^{(s)}$ set

$$w(p_{crit}(T_i^{(s)}, T_{end})) = w(T_i^{(s)}) + \max_{T_j^{(s-1)}, (T_i^{(s)}, T_j^{(s-1)}) \in E} w(p_{crit}(T_j^{(s-1)}, T_{end}))$$

5. go back to loop

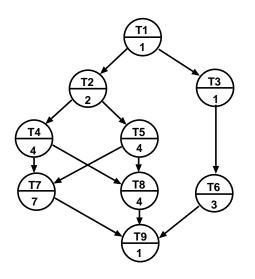
Task levels

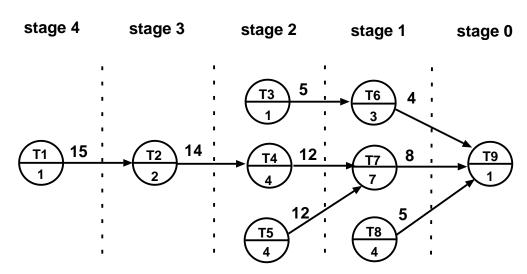




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Priority queue





Order task by stage (level) Within level order by weight

Priority queue: $\{T1, T2, T4, T5, T3, T7, T8, T6, T9\}$

Priority queue

- (1) Form a **ready queue** from the tasks in the priority queue which do not have any predecessors in the task graph still in the queue.
- (2) Assign tasks from the ready queue to processors in decreasing order of priorities.
- (3) When a task is executed remove the task from the list and update the ready queue.

Scheduling example

Ready queue	updated priority list	PE1	PE2	time
$\{T1\}$	$\{T2, T4, T5, T3, T7, T8, T6, T9\}$	T1	idle	0
$\{T2, T3\}$	$\{T2, T4, T5, T7, T8, T6, T9\}$	T2	T3	1
$\{T6\}$	$\{T2, T4, T5, T7, T8, T6, T9\}$	T2	T6	2
$\{T4, T5\}$	$\{T4, T5, T7, T8, T6, T9\}$	T4	T6	3
$\{T5\}$	$\{T4, T5, T7, T8, T9\}$	T4	T5	5
{}	$\{T5, T7, T8, T9\}$	idle	T5	7
$\{T7, T8\}$	$\{T7, T8, T9\}$	T7	T8	9
{}	$\{T7, T9\}$	T7	idle	13
$\{T9\}$	$\{T9\}$	T9	idle	16
{}	{}	idle	idle	17

Does the heuristic produce the optimal schedule?

PRAM - scheduling

The worst case performance of the heuristic for m processors is

$$\frac{t - t_{opt}}{t_{opt}} \le 1 - \frac{1}{P} .$$

The optimal schedule is at most twice as long as the derived one.

The lower bound on the perfomance is given by the critical path of T_0 .

Domain decomposition for matrix computations

Domain Decomposition:

- the data associated with the problem is decomposed, tasks work on portions of the data
- common for matrix like operations
 - assign rows, columns or submatrices of a matrix to different PEs

PRAM matrix-matrix multiply

$$C = A \cdot B \Rightarrow c(i,j) \leftarrow \sum_{k=1}^{n} a(i,k)b(k,j)$$

For a PRAM with "infinite" number of PEs:

• cost of a single "dot" product

For a PRAM with P PEs:

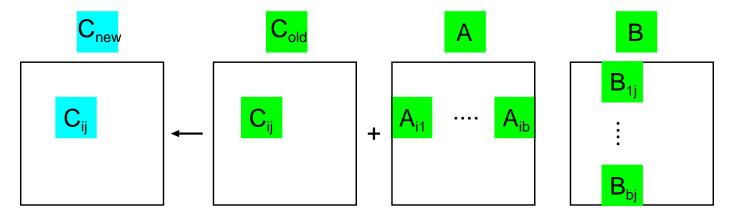
- assign $\frac{n}{P}$ elements c(i,j) of C to each PE
- compute dot products defining c(i,j)

Now consider a shared memory system composed of P CPUs, each with individual cache.

Block matrix-matrix multiply

For a single CPU we split A, B, C into blocks of size $b \times b$ (thus $n = b \cdot p$).

$$C(i,j) \leftarrow C(i,j) + \sum_{k=1}^{p} A(i,k)B(k,j)$$
 still holds.



Block matrix-matrix multiply

```
Sequential algorithm C(i,j) \leftarrow C(i,j) + \sum_{k=1}^{p} A(i,k)B(k,j)
for i = 1:p
for j = 1:p
load block C(i,j) into fast memory
for k = 1:p
load block A(i,k) into fast memory
load block B(k,j) into fast memory
C(i,j) \leftarrow C(i,j) + A(i,k)B(k,j)
store C(i,j) into slow memory
```

Parallel algorithm with P PEs:

• how do we distribute work over PEs?

Block matrix-matrix multiply

- Hopefully $P = p^2$
- Split C into P subblocks of size $\frac{n}{p} \times \frac{n}{P}$.
- Execute the sequential block matrix-matrix multiply on each CPU
- P CPUs want to load A(i,k) and B(k,j) simultaneously. Does this create congestion between shared memory and individual caches?
- Good final project.

 $G = (V, E), V = \{1, 2, ..., n\}$. Each edge $(i, j) \in E$ is assigned a non-negative distance (weight) w(i, j).

Find shortest paths joining any pair of nodes.

Define a matrix $W = \{w_{ij}\}$ as follows

$$w_{ij} = \begin{cases} 0 & i = j \\ w_{ij} & i \neq j, & (i,j) \in E \\ \infty & i \neq j, & (i,j) \notin E \end{cases}$$

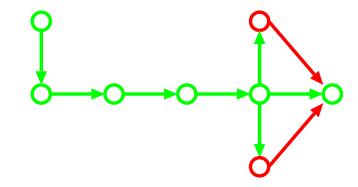
Also define another matrix $D^{(m)} = \{d_{ij}^{(m)}\}$ where

 $d_{ij}^{(m)}$ is a shortest path joining i and j containing at most m nodes

Assume $D^{(m)}$ is known. We want to compute $D^{(m+1)}$.

When m = n - 1 then $D^{(m+1)}$ gives us all node shortest path.

How can we get $D^{(m+1)}$ from $D^{(m)}$?



Consider a path from i to j through k where

- p(i,k) has at most m-1 edges
- p(k,j) has a single edge

We have

$$d_{ij}^{(m+1)} = \min_{1 \le k \le n} (d_{ik}^{(m)} + w_{kj})$$

Note, $d_{ik}^{(m)}$ can be ∞ .

Notice the correspondence

$$matrix multiply \Leftrightarrow minimum sum$$

L:
$$c_{ij} = \sum_{k=1}^{n} a_{ik} b_{kj} \Leftrightarrow \text{R:} \quad d_{ij}^{(m+1)} = \min_{1 \le k \le n} (d_{ik}^{(m)} + w_{kj})$$

"·" on the left corersponds to "+" on the right

"+" on the left corresponds to "min" on the right

Computation of $D^{(m+1)}$ can be viewed as multiplication of $D^{(m+1)}$ with W with appropriate interpretation of elementary operations involved.

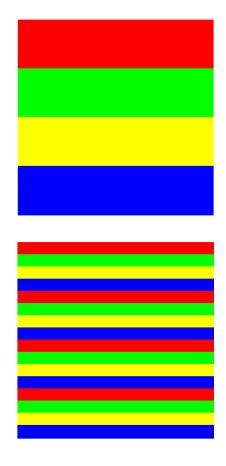
Cost?

Note that

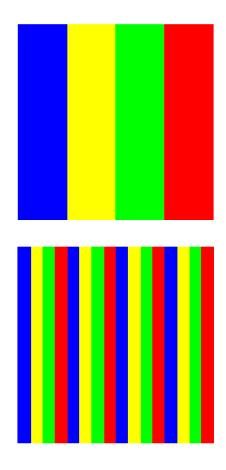
$$D^{(2)} = ?, D^{(m)} = ?$$

Good matrix-matrix multiplication algorithm needed.

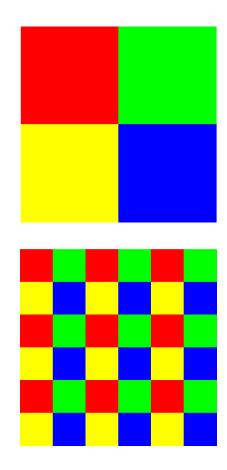
Matrix distributions



Matrix distributions



Matrix distributions



Triangular matrix multiply

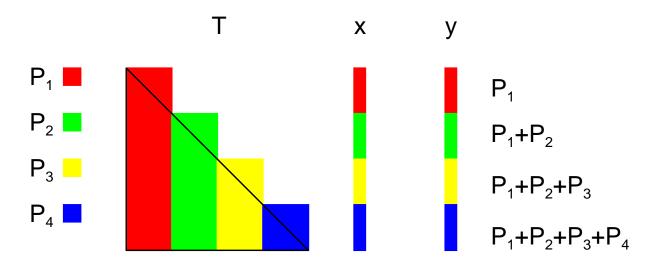
Matrices that are not "uniform".

$$y = \begin{pmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} t_{11} \\ t_{21} & t_{22} \\ t_{31} & t_{32} & t_{33} \\ \vdots \\ t_{n1} & t_{n2} & \cdots & t_{nn} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{pmatrix} = Tx$$

How do we distribut work among PEs?

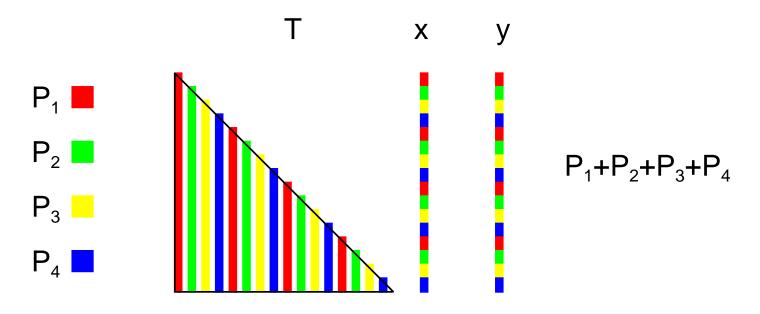
Triangular matrix multiply

1D block-column distribution:



- Do we need to synchronize work?
- Load balance?
- Idle PEs?
- Time on P CPUs?

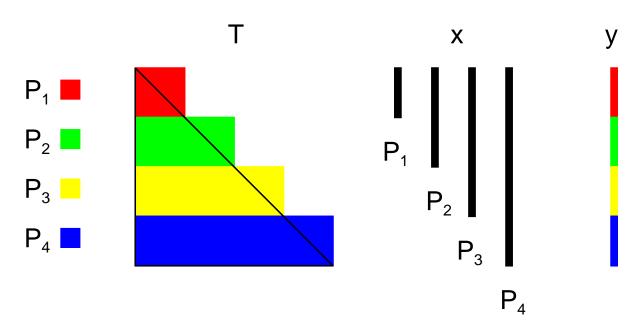
1D cyclic distribution:



- Do we need to synchronize work?
- Load balance?
- Idle PEs?
- Time on P CPUs?

Triangular matrix multiply

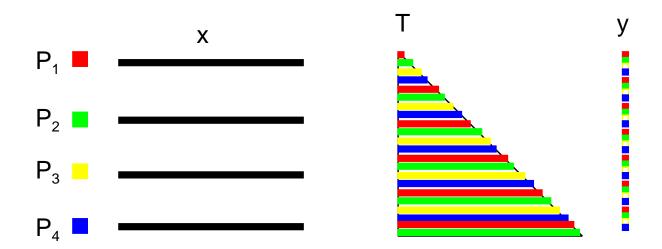
1D block-row distribution:



- Do we need to synchronize work?
- Load balance?
- Idle PEs?
- Time on P CPUs?

Triangular matrix multiply

1D cyclic distribution:



- Do we need to synchronize work?
- Load balance?
- Idle PEs?
- Time on P CPUs?

$$T^{(0)}x = \begin{pmatrix} t_{11} & & & & \\ t_{21} & t_{22} & & & \\ t_{31} & t_{32} & t_{33} & & \\ \vdots & & \ddots & \\ t_{n1} & t_{n2} & t_{n3} & \cdots & t_{nn} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} b_1 \\ b_2 \\ b_3 \\ \vdots \\ b_n \end{pmatrix} = b^{(0)}$$

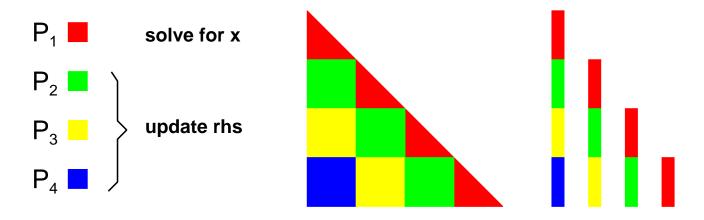
- sequential algorithm?
- parallel algorithm?

$$x_{1} = \frac{b_{1}}{a_{11}}, \ b^{(1)} = b^{(0)} - t_{:,1} \cdot x_{1}, \left(\begin{array}{ccc} t_{22} & & \\ t_{32} & t_{33} & \\ \vdots & & \ddots & \\ t_{n2} & t_{n3} & \cdots & t_{nn} \end{array}\right) \left(\begin{array}{c} x_{2} \\ x_{3} \\ \vdots \\ x_{n} \end{array}\right) = b_{2:n}^{(1)}$$

$$x_{2} = \frac{b_{2}^{(1)}}{a_{22}}, \ b^{(2)} = b^{(1)} - t_{:,2} \cdot x_{1}, \left(\begin{array}{ccc} t_{33} & & \\ t_{43} & t_{44} & \\ \vdots & & \ddots & \\ t_{n3} & t_{n4} & \cdots & t_{nn} \end{array}\right) \left(\begin{array}{c} x_{3} \\ x_{4} \\ \vdots \\ x_{n} \end{array}\right) = b_{3:n}^{(2)}$$

How do we distribute work among PEs?

Difficulty - dependencies between tasks.



- Do we need to synchronize work?
- Load balance?
- Idle PEs?
- Time on P CPUs?

What if the matrix is upper triangular?

$$T^{(0)}x = \begin{pmatrix} t_{11} & t_{12} & t_{13} & \cdots & t_{1n} \\ & t_{22} & t_{23} & \cdots & t_{2n} \\ & & t_{33} & \cdots & t_{3n} \\ & & & \ddots & \vdots \\ & & & t_{nn} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} b_1 \\ b_2 \\ b_3 \\ \vdots \\ b_n \end{pmatrix} = b^{(0)}$$

$Linear\ systems$ - $Guassian\ elimination$

- Model problem: Gaussian elimination
- Introduction to Pthreads