Principles of Parallel Algorithm Design

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Parallel Programming Models

Parallel program: one or more threads of control operating on data; model defines naming, operations, ordering

- Data parallel HPF, Fortran-D, Power C/Fortran
- Shared memory pthreads
- Message passing MPI, PVM
- Global address space

Why is Parallel Computing Hard?

- Amdahl's law insufficient available parallelism
 - $Speedup = 1/(fraction_enhanced/speedup_enhanced + (1-fraction_enhanced))$
- Overhead of communication and coordination
- Portability knowledge of underlying architecture often required

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• Task: arbitrarily defined piece of work done by the program

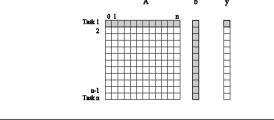
- Process (or thread): abstract entity that performs tasks
- Processor: phyical resource on which processes execute



Granularity of Task Decompositions

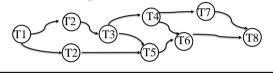
Task size (granularity) versus number of tasks

Example: Dense matrix-vector multiply
Fine grain: each task computes an individual element in y, large number of tasks
Coarse grain: each task computes multiple elements in y, small number of tasks
A b y



Decomposition into Tasks

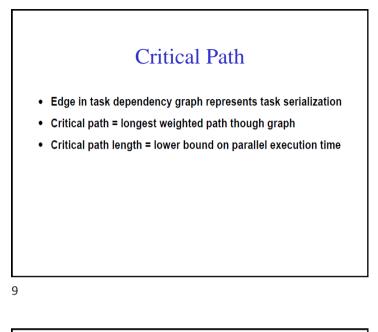
- Many different decompositions possible
 - Tasks may be independent or have dependencies requiring ordering
 - Tasks may execute identical or different code
 - Tasks may take the same or different amounts of time
- Tasks and dependencies may be abstracted into a task dependency DAG with nodes as tasks, edges as control dependence

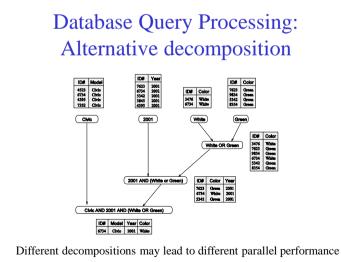


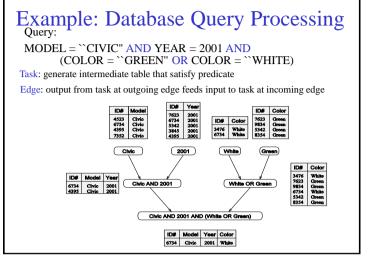
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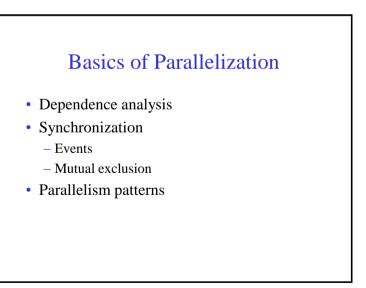
Degree of Concurrency

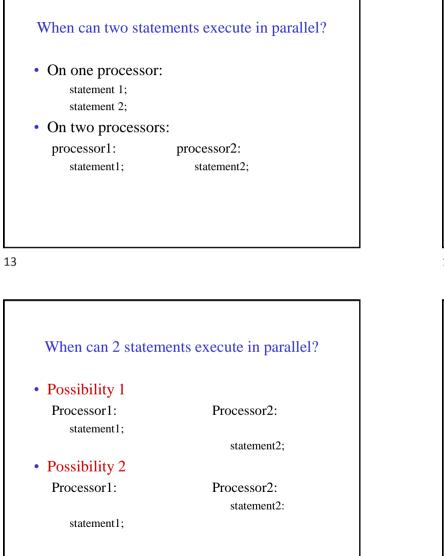
- *Degree of concurrency* of a decomposition: number of tasks that can execute in parallel – Increases with finer task granularity
 - increases with finer task granularity
- May change over program execution
- *Maximum degree of concurrency:* the largest at any point during execution
- Average degree of concurrency: average over the execution of the program











Fundamental Assumption

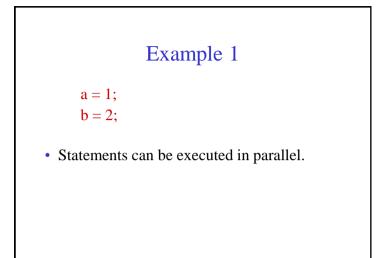
• Processors execute independently: no control over order of execution between processors

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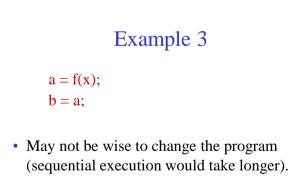
When can 2 statements execute in parallel?

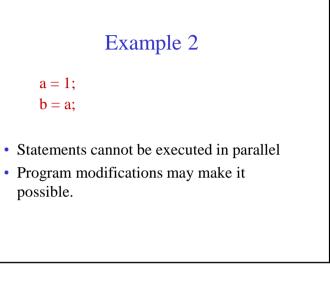
- Their order of execution must not matter!
- In other words, statement1; statement2; must be equivalent to

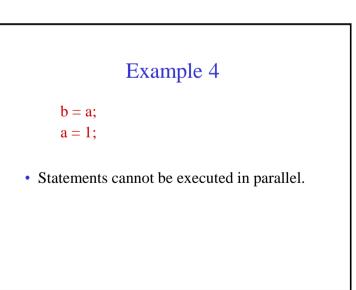
statement2; statement1;

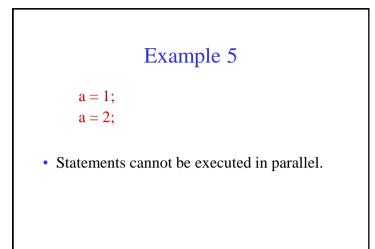












Anti-dependence

Statements S1, S2.

S2 has an anti-dependence on S1 iff

S2 writes a value read by S1.

True dependence

Statements S1, S2

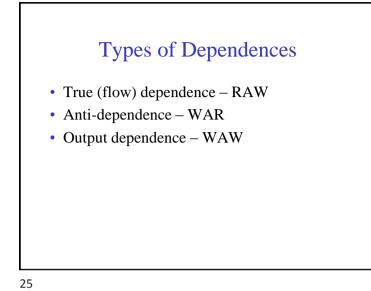
S2 has a true dependence on S1 iff S2 reads a value written by S1

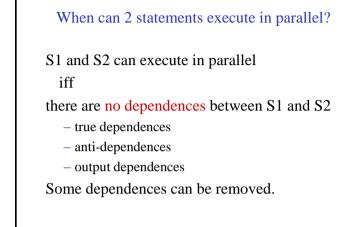
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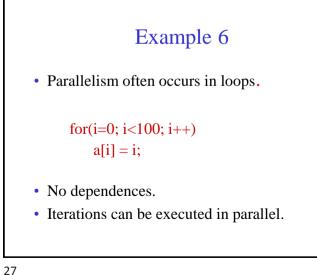
Output Dependence

Statements S1, S2.

S2 has an output dependence on S1 iff S2 writes a variable written by S1.







Example 7 for(i=0; i<100; i++) { a[i] = i; b[i] = 2*i; } Iterations and statements can be executed in parallel.

Example 8

for(i=0;i<100;i++) a[i] = i;for(i=0;i<100;i++) b[i] = 2*i;

Iterations and loops can be executed in parallel.

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Example 10

for(i=0; i<100; i++) a[i] = f(a[i-1]);

- Dependence between a[i] and a[i-1].
- Loop iterations are not parallelizable.

Example 9 for(i=0; i<100; i++)

a[i] = a[i] + 100;

- There is a dependence ... on itself!
- Loop is still parallelizable.

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Loop-Carried Dependence

- A loop-carried dependence is a dependence that is present only if the statements occur in two different instances of a loop
- Otherwise, we call it a loop-independent dependence
- Loop-carried dependences limit loop iteration parallelization

Example 11

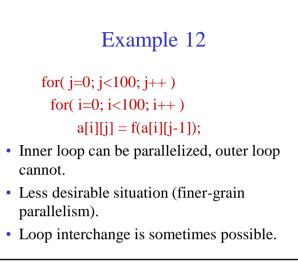
$$\begin{split} & \text{for}(i{=}0;\,i{<}100;\,i{+}{+}\;) \\ & \text{for}(j{=}0;\,j{<}100;\,j{+}{+}\;) \\ & a[i][j] = f(a[i][j{-}1]); \end{split}$$

- Loop-independent dependence on i.
- Loop-carried dependence on j.
- Outer loop can be parallelized, inner loop cannot.

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Level of loop-carried dependence

- Is the nesting depth of the loop that carries the dependence.
- Indicates which loops can be parallelized.



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Be careful ... Example 13

printf("a"); printf("b");

Statements have a hidden output dependence due to the output stream.

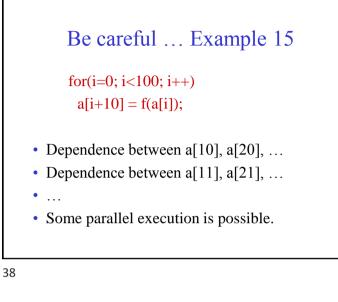
Be careful ... Example 14

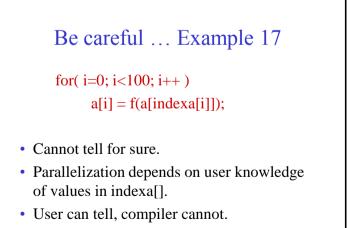
a = f(x);b = g(x);

Statements could have a hidden dependence if f and g update the same variable.

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Be careful ... Example 16
for(i=1; i<100;i++) {</p>
a[i] = ...;
... = a[i-1];
• Dependence between a[i] and a[i-1]
• Complete parallel execution impossible
• Pipelined parallel execution possible





An aside

- Parallelizing compilers analyze program dependences to decide parallelization.
- In parallelization by hand, user does the same analysis.
- Compiler more convenient and more correct
- User more powerful, can use knowledge of data values

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Synchronization

- Used to enforce dependences
- Control the ordering of events on different processors
 - Events signal(x) and wait(x)
 - Fork-Join or barrier synchronization (global)
 - Mutual exclusion/critical sections

To remember

- Statement order must not matter.
- Statements must not have dependences.
- Some dependences can be removed.
- Some dependences may not be obvious.

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Example 1: Creating Parallelism by Enforcing Dependences for(i=1; i<100; i++) { a[i] = ...;;

... = a[i-1];

- }
- Loop-carried dependence, not parallelizable



- Suppose we had a set of primitives, signal(x) and wait(x).
- wait(x) blocks unless a signal(x) has occurred.
- signal(x) does not block, but causes a wait(x) to unblock, or causes a future wait(x) not to block.

Example 1 (continued)

- Note that here it matters which iterations are assigned to which processor.
- It does not matter for correctness, but it matters for performance.
- Cyclic assignment is probably best.

Example 1: Enforcing Dependencies (continued) for(i=...; i<...; i++) { a[i] = ...; signal(e_a[i]); ...; wait(e_a[i-1]); ... = a[i-1]; }

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Example 2: Enforcing Dependences

for(i=0; i<100; i++) a[i] = f(i);x = g(a); for(i=0; i<100; i++) b[i] = x + h(a[i]);

- First loop can be run in parallel.
- Middle statement is sequential.
- Second loop can be run in parallel.

Example 2 (continued)

- We will need to make parallel execution stop after first loop and resume at the beginning of the second loop.
- Two (standard) ways of doing that:
 - fork() join()
 - barrier synchronization

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Example 2 (continued)

fork();

for(i=...; i<...; i++) a[i] = f(i); join(); x = g(a); fork(); for(i=...; i<...; i++) b[i] = x + h(a[i]); join();

Fork-Join Synchronization

- fork() causes a number of processes to be created and to be run in parallel.
- join() causes all these processes to wait until all of them have executed a join().

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Eliminating Dependences

- Privatization or scalar expansion
- Reduction (common pattern)

Example: Scalar Expansion or Privatization

for (I = 0; I < 100; I++) T = A[I]; A[I] = B[I]; B[I] = T;

Loop-carried anti-dependence on T Eliminate by converting T into an array or by making T private to each loop iteration

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Removing Dependences: Reduction

sum = 0.0; for(i=0; i<100; i++) sum += a[i];

- Loop-carried dependence on sum.
- Cannot be parallelized, but ...

Example: Scalar Expansion

for (I = 0; I < 100; I++)T [I]= A[I];A[I] = B[I];B[I] = T[I];

Loop-carried anti-dependence eliminated

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Reduction (continued)

```
for( i=0; i<...; i++ ) sum[i] = 0.0;
fork();
for( j=...; j<...; j++ ) sum[i] += a[j];
join();
sum = 0.0;
for( i=0; i<...; i++ ) sum += sum[i];</pre>
```

Common pattern often with explicit support e.g., sum = reduce (+, a, 0, 100) CAVEAT: Operator must be commutative and associative

Acknowledgements

Slides reflect content from Willy Zwaenepoel and from Grama/Gupta/Karypis/Kumar that accompany their corresponding course/textbooks and have been adapted to suit the content of this course