Sources of Parallelism

- Statements
  - called "control parallel"
  - can perform a series of steps in parallel
  - basis of dataflow computers
- Loops
  - called "data parallel"
  - most common source of parallelism
  - each processor gets one (or more) iterations to perform

Applications

- Easy (embarrassingly parallel)
  - multiple independent jobs (i.e..., different simulations)
- Scientific
  - linear algebra
  - particle simulations
- Databases
  - biggest success of parallel computing
  - exploits semantics of relational calculus
- AI
  - search problems
  - pattern recognition and image processing (main SIMD use)

Issues in Application Performance

- Speedup
  - ratio of time on n nodes to time on a single node
  - hold problem size fixed
  - should really compare to best serial time
  - goal is linear speedup
  - super-linear speedup is possible due to:
    - adding more memory
    - search problems
- Iso-Speedup
  - scale data size up with number of nodes
  - goal is a flat horizontal curve
- Amdahl's Law
  - max speedup is 1/(serial fraction of time)
- Computation to Communication Ratio
  - goal is to maximize this ratio

How to Write Parallel Programs

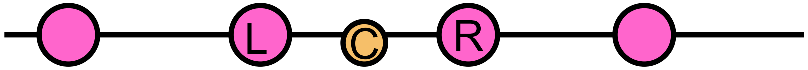
- Use old serial code
  - compiler converts it to parallel
  - called the dusty deck problem
- Serial Language plus Communication Library
  - no compiler changes required!
  - PVM and MPI use this approach
- New language for parallel computing
  - requires all code to be re-written
  - hard to create a language that provides performance on different platforms
- Hybrid Approach
  - HPF - add data distribution commands to code
  - add parallel loops and synchronization operations

Application Example - Weather

- Typical of many scientific codes
  - computes results for three dimensional space
  - compute results at multiple time steps
  - uses equations to describe physics/chemistry of the problem
  - grids are used to discretize continuous space
    - granularity of grids is important to speed/accuracy
- Simplifications (for example, not in real code)
  - earth is flat (no mountains)
  - earth is round (poles are really flat, earth buldges at equator)
  - second order properties

Grid Points

- Divide Continuous space into discrete parts
  - for this code, grid size is fixed and uniform
    - possible to change grid size or use multiple grids
  - use three grids
    - two for latitude and longitude
    - one for elevation
    - Total of M * N * L points
- Design Choice: where is the grid point?
  - left, right, or center of the grid



  - in multiple dimensions this multiples:
    - for 3 dimensions have 27 possible points

Variables

- One dimensional
  - m - geo-potential (gravitational effects)
- Two dimensional
  - pi - “shifted” surface pressure
  - sigmadot - vertical component of the wind velocity
- Three dimensional (primary variables)
  - <u,v> - wind velocity/direction vector
  - T - temperature
  - q - specific humidity
  - p - pressure
- Not included
  - clouds
  - precipitation
  - can be derived from others

Serial Computation

- Convert equations to discrete form
- Update from time t to t + delta t

```
foreach longitude, latitude, altitude
        ustar[i,j,k] = n * pi[i,j] * u[i,j,k]
        vstar[i,j,k] = m[j] * pi[i,j] * v[i,j,k]
        sdot[i,j,k] = pi[i,j] * sigmadot[i,j]
end
foreach longitude, latitude, altitude
        D = 4 * ((ustar[i,j,k] + ustar[i-1,j,k]) * (q[i,j,k] + q[i-1,j,k]) +
                        terms in {i,j,k}{+,-}{1,2}
        piq[i,j,k] = piq[i,j,k] + D * delat
        similar terms for piu, piv, piT, and pi
end
foreach longitude, latitude, altitude
        q[i,j,k] = piq[i,j,k]/pi[i,j,k]
        u[i,j,k] = piu[i,j,k]/pi[i,j,k]
        v[i,j,k] = piv[i,j,k]/pi[i,j,k]
        T[i,j,k] = piT[i,j,k]/pi[i,j,k]
end
```

Shared Memory Version

- in each loop nest, iterations are independent
- use a parallel for-loop for each loop nest
- synchronize (barrier) after each loop nest
  - this is overly conservative, but works
  - could use a single sync variabe per item, but would incurr excessive overhead
- potential parallelism is M * N * L
- private variables: D, i, j, k
- Advantages of shared memory
  - easier to get something working (ignoring performance)
- Hard to debug
  - other processors can modify shared data

Distributed Memory Weather

- decompose data to specific processors
  - assign a cube to each processor
    - maximize volume to surface ratio
    - minimizes communication/computation ratio
  - called a <block,block,block> distribution
- need to communicate {i,j,k}{+,-}{1,2} terms at boundaries
  - use send/receive to move the data
  - no need for barriers, send/receive operations provide sync
    - sends earier in computation too hide comm time
- Advantages
  - easier to debug
  - consider data locality explicity with data decomposition
- Problems
  - harder to get the code running

Seismic Code

- Given echo data, compute under sea map
- Computation model
  - designed for a collection of workstations
  - uses variation of RPC model
  - workers are given an independent trace to compute
    - requires little communication
    - supports load balancing (1,000 traces is typical)
- Performance
  - max mfops = $O((F * nz * B^*)^{1/2})$
  - F - single processor MFLOPS
  - nz - linear dimension of input array
  - B^* - effective communication bandwidth
    - $B^* = B/(1 + BL/w) \approx B/7$ for Ethernet (10msec lat., w=1400)
  - real limit to performance was latency **not** bandwidth

Database Applications

- Too much data to fit in memory (or sometimes disk)
  - data mining applications (K-Mart has a 4-5TB database)
  - imaging applications (NASA has a site with 0.25 petabytes)
    - use a fork lift to load tapes by the pallet
- Sources of parallelism
  - within a large transaction
  - among multiple transactions
- Join operation
  - form a single table from two tables based on a common field
  - try to split join attribute in disjoint buckets
    - if know data distribution is uniform its easy
    - if not, try hashing

Speedup in Join parallelism

- Books claims a speed up of$1/p^2$ is possible
  - split each relation into p buckets
    - each bucket is a disjoint subset of the joint attribute
  - each processor only has to consider N/p tuples per relation
    - join is $O(n^2)$ so each processor does $O((N/p)^2)$ work
    - so spedup is $O(N^2/p^2)/O(N^2) = O(1/p^2)$
- **this is a lie!**
    - could split into 1/p buckets on one processor
    - time would then be $O(p * (N/p)^2) = O(N^2/p)$
    - so speedup is $O(N^2/p^2)/O(N^2/p) = O(1/p)$
      - Amdahls law is not violated

Parallel Search (TSP)

- may appear to be faster than 1/n
  - but this is not really the case either
- Algorithm
  - compute a path on a processor
    - if our path is shorter than the shortest one, send it to the others.
    - stop searching a path when it is longer than the shortest.
  - before computing next path, check for word of a new min path
  - stop when all paths have been explored.
- Why it appears to be faster than 1/n speedup
  - we found the a path that was shorter sooner
  - however, the reason for this is a different search order!

Ensuring a fair speedup

- T_{serial} = faster of
  - best known serial algorithm
  - simulation of parallel computation
    - use parallel algorithm
    - run all processes on one processor
  - parallel algorithm run on one processor
- If it appears to be super-linear
  - check for memory hierarchy
    - increased cache or real memory may be reason
  - verify order operations is the same in parallel and serial cases

Quantitative Speedup

- Consider master-worker
  - one master and n worker processes
  - communication time increases as a linear function of n

  $T_p = TCOMP_p + TCOMM_p$

  $TCOMP_p = T_s/P$

  $1/S_p = T_p/T_s = 1/P + TCOMM_p/T_s$

  $TCOMM_p$ is $P * TCOMM_1$

  $1/S_p = 1/p + p * TCOMM_1/T_s = 1/P + P/r_1$

  where $r_1 = T_s/TCOMM_1$

  $d(1/S_p)/dP = 0 \dashrightarrow P_{opt} = r_1^{1/2}$ and $S_{opt} = 0.5\ r_1^{1/2}$
- For hierarchy of masters
  - $TCOMM_p = (1+\log P)TCOMM_1$
  - $P_{opt} = r_1$ and $S_{opt} = r_1/(1 + \log r_1)$