Limitations to ideal parallelization

- Communication
- Load imbalance
- Serial portions of code
- Extra computations not in sequential code
- Memory bandwidth limitations
- OpenMP thread creation/scheduling
- Conflicts in shared caches

Execution Time

- $t = t_{comp} + t_{comm}$ (non-overlapped)
- Plot against p
- Execution rate (flop rate)
  - What is reasonable? How does it compare to peak flop rate? How does it compare to peak memory rate for DRAM or cache?
- Be aware of timer skew and granularity
- Can also measure time breakdown (t_{comp} and t_{comm} and components of them)
- Other measurements
  - Hardware performance counters (PAPI)
  - MPI performance measurement and visualization (VAMPIR)

Speedup

- $S = t_1 / t_p$
- Plot against p
- t_1 is time for “best” sequential solution
  - What is good speedup depends on what the code is doing (i.e., the problem being solved); an embarrassingly parallel code should have perfect speedup
  - Beware of speedup reported using bad sequential codes
- Relative speedup, e.g. $S = t_4 / t_p$
- Superlinear speedup is possible
  - Due to caches (smaller local problem sizes)
  - Due to parallel problem having less work than sequential problem


Savage Chickens
by Doug Savage
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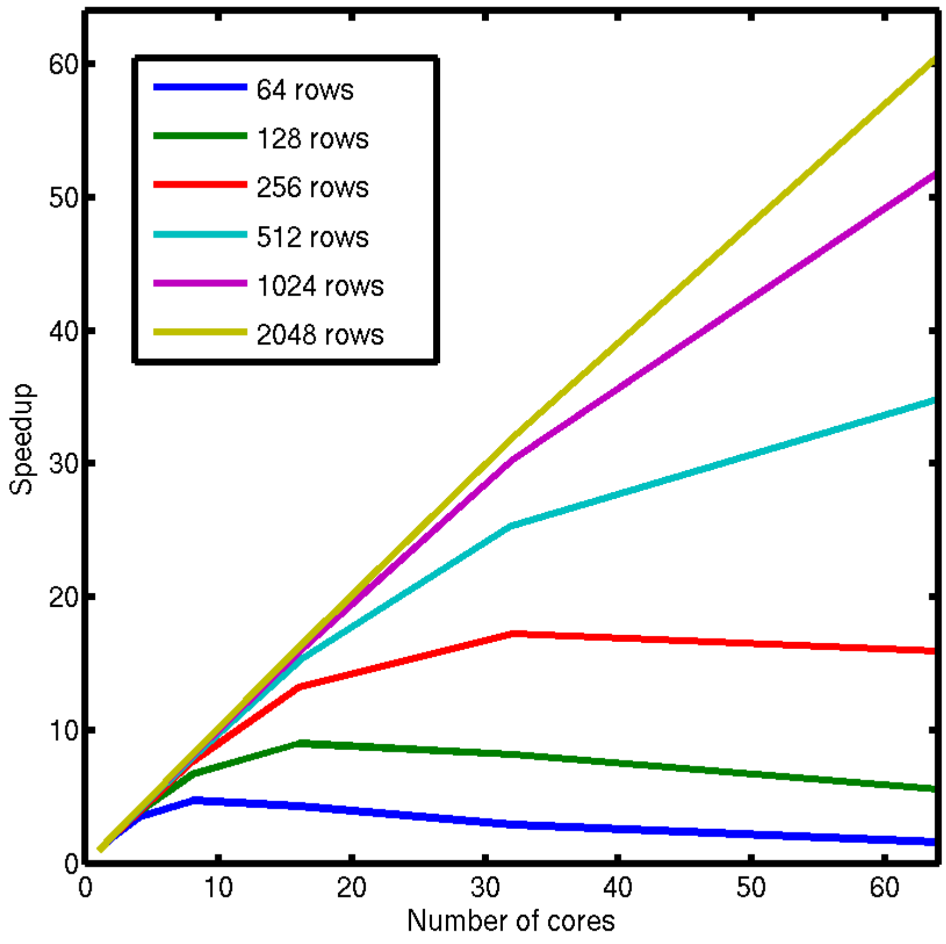
Speedup often depends on problem size



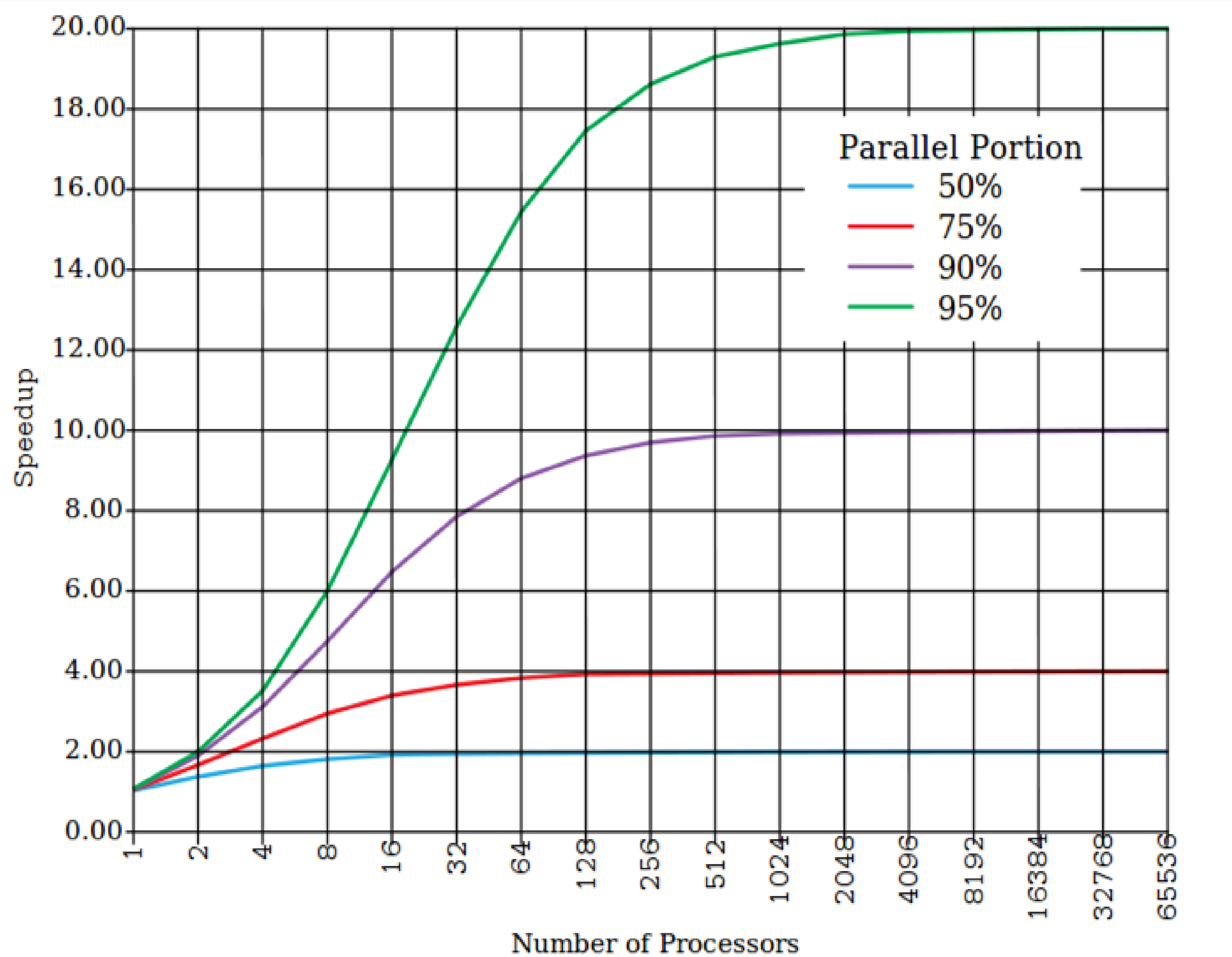
Efficiency

- $E = [\, t_1 / p \,] / t_p = S_p / p$
- Plot against p; efficiency generally decreases as p increases
- Can also define relative efficiency
- How do you maximize throughput?
  - Consider how to minimize the time to run n parallel jobs
  - Maximizing throughput is at odds with minimizing runtime of a particular job

Load Balance

- b = perfectly balanced time / actual time
- b = average t_i / max t_i
- b is an upper bound on the efficiency

Amdahl's Law (1967)



Amdahl's Law

- f = sequential fraction of sequential program
- Speedup is bounded by 1/f

$$t_1 = f + g = 1$$
$$t_p = f + g/p$$

$$S = \frac{t_1}{t_p} = \frac{1}{f + \frac{1-f}{p}}$$

Scaled Speedup

- Speedup when the problem size is increased proportionally with the number of processors
  - for p processors, the problem size is proportional to p (amount of work is proportional to p)
- Plot against p
- Also called *weak speedup* (regular scalability is called *strong speedup*)
- We can also define *scaled efficiency*

Gustafson's Law

- Analogue of Amdahl's Law for scaled problem sizes
- F = sequential fraction of parallel program
- What is the speedup as a function of p ?

$$t_1 = F + (1 - F)p$$
$$t_p = F + (1 - F)p/p$$

$$S = \frac{t_1}{t_p} = \frac{F+(1-F)p}{F+(1-F)} = F + (1 - F)p$$

Scalability

- Scalability is the ability of a program to continue speeding up when p is increased (defined for strong scalability and weak scalability)
  - e.g., a program has strong scalability up to 64 processors
- Scalability also applies to algorithms
  - Scalable algorithm = amount of work increases proportionally with problem size (or almost proportionally)

log-log plots

- $t = 2n^3$
  Take log of both slides:
  $\log t = 3 \log n + \log 2$
  which has the form $y = mx + b$ which is a straight line with slope m and intercept b

- $t = 2n^2$
  $\log t = 2 \log n + \log 2$

log plots

- How would you plot $t = 2^n$?
- What does it look like on a log-log plot?
- On what kind of plot is this function a straight line?

- Log and log-log plots can be useful when plotting functions that change rapidly or functions over a very large domain
- Log and log-log plots can be used to estimate function parameters (when the functional form is known)