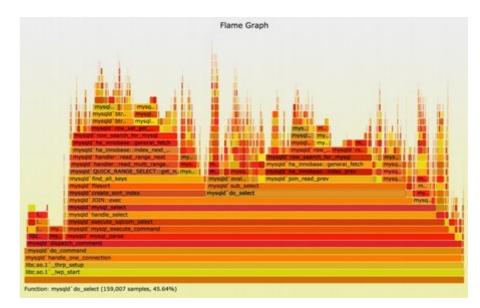
CS 470 Spring 2019

Mike Lam, Professor



Flame graph from brendangregg.com

Performance Analysis

Performance analysis

- Why do we parallelize our programs?
 - So that they run faster!

Performance analysis

- How do we evaluate whether we've done a good job in parallelizing a program?
 - Asymptotic analysis (e.g., for distributed sum)
 - Empirical analysis

Empirical analysis issues

- How do you measure time-to-solution accurately?
 - CPU cycles, OS clock "ticks", wall time, etc.
- How do you compare across systems?
 - Differing CPUs, memories, OSes, etc.
- How do you compare against the original?
 - 1-core parallel version will likely be slower
- How do you assess scalability?
 - Does performance improve as you add cores?
 - How do you quantify the improvement?
 - Is there a limit to how far we can improve performance?

Best practices

- Measure wall time for specific code regions of interest
 - Ignore startup and I/O time if not relevant
 - Make sure you have a high-resolution timer!
 - /usr/bin/time -v for whole programs
 - gettimeofday() from sys/time.h for Pthreads
 - omp_get_wtime() for OpenMP
 - MPI_Wtime() for MPI
 - Use barriers if necessary to make sure all threads/processes have finished before you stop a timer

Best practices

- Control for variance
 - Do all experiments on the same machine or cluster
 - Maximum of one thread per core and one job per node
 - Our cluster can support 8 threads per node (or 16 if hyperthreading, but this is not always recommended)
 - Run multiple trials and use minimum time
 - Avoids OS interference or noise
 - Use /shared/bin/hyperfine on cluster
 - Track variance across trials to measure system noise
 - If your variance is high or if your slowest and fastest time are relatively far apart, it's probably noise!

Empirical analysis

$$T_s$$
 = serial time $S = speedup = \frac{T_S}{T_P}$ should
increase
as p grows T_p = parallel time $p = \#$ of processes $E = efficiency = \frac{S}{p} = \frac{T_S}{pT_P}$ usually
decreases
as p grows

r =serial % of original program

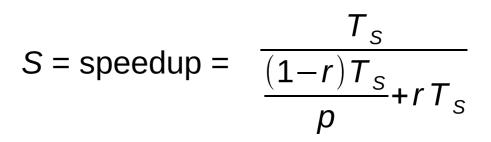
$$T_{p} = \frac{(1-r)T_{s}}{p} + rT_{s} \qquad S = \text{speedup} = \frac{T_{s}}{\frac{(1-r)T_{s}}{p} + rT_{s}}$$

$$\text{Amdahl's Law: } S \leq \frac{1}{r} \text{ as } p \text{ increases}$$

Amdahl's Law

p = # of processors

r = serial % of program

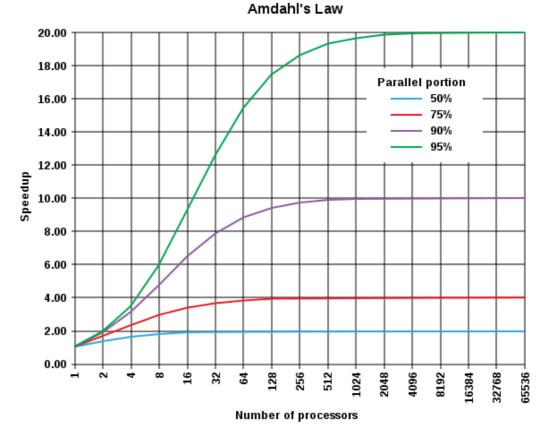


Amdahl's Law:

$$S \leq \frac{1}{r}$$
 as *p* increases

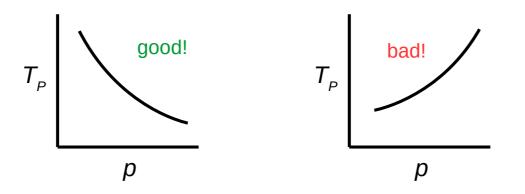
 $r = 50\% \rightarrow$ speedup limited to 2x $r = 25\% \rightarrow$ speedup limited to 4x $r = 10\% \rightarrow$ speedup limited to 10x $r = 5\% \rightarrow$ speedup limited to 20x

Speedup limited inversely proportionally by serial %



Scaling

- Generally, we don't care about any particular T_P
 - Or with how it compares to T_s (except as a sanity check)
- More important: how T_P , S, and E change as p increases
 - And/or as the problem size increases
 - Similar to asymptotic analysis in CS 240
 - In general, a program is scalable if E remains fixed as p and the problem size increase at fixed rates
 - Most common: graph T_P on y-axis vs. p on logarithmic x-axis



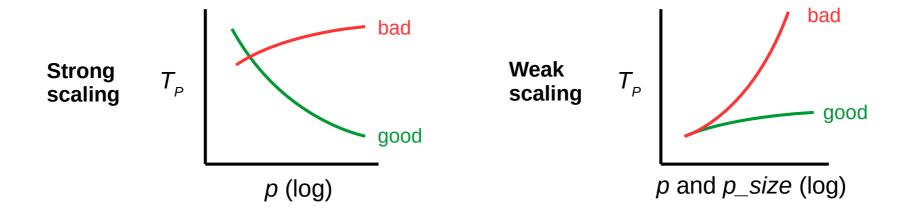
Scaling

- Strong scaling means we can keep the efficiency fixed without increasing the problem size
- Weak scaling means we can keep the efficiency fixed by increasing the problem size at the same rate as the process/thread count
 - Rate of work (e.g., Mop/s) per core remains roughly fixed

$$E = \text{efficiency} = \frac{S}{p} = \frac{T_S}{pT_P} \quad \substack{\text{usually} \\ \text{decreases} \\ \text{as } p \text{ grows}}$$

Scaling

- Strong scaling: as p increases, T_P decreases
 - Linear speedup: same rate of change (2x procs \rightarrow half time)
 - Sublinear (most common) / superlinear (exceedingly rare) speedup
 - Be careful to interpret linear vs. logarithmic axes correctly
- Weak scaling: as p increases AND the problem size increases proportionally, T_P stays roughly the same



Cluster access

- Detailed instructions online: w3.cs.jmu.edu/lam2mo/cs470/cluster.html
- Connect to login node via SSH
 - Hostname: login.cluster.cs.jmu.edu
 - User/password: (your e-ID and password)
- Recommended conveniences
 - Set up public/private key access from stu
 - Set up .ssh/config entries
 - Install Spack for access to more software

Cluster access

- Things to play with:
 - "squeue" or "watch squeue" to see jobs
 - "srun <command>" to run an interactive job
 - Use "-n " to launch *p* processes
 - Use "-N <n>" to request n nodes (defaults to p/8)
 - The given "<command>" will run in every process
 - "salloc <command>" to run an interactive MPI job
 - Must run "module load mpi" first
 - Use "-n " to launch *p* MPI processes

```
srun hostname
srun -n 4 hostname
srun -n 16 hostname
srun -N 4 hostname
srun sleep 5
srun -N 2 sleep 5
module load mpi
salloc -n 1 mpirun /shared/mpi-pi/mpipi
salloc -n 2 mpirun /shared/mpi-pi/mpipi
salloc -n 8 mpirun /shared/mpi-pi/mpipi
salloc -n 16 mpirun /shared/mpi-pi/mpipi
(etc.)
What's the max n?
```

Job management

- SLURM (Simple Linux Utility for Resource Management) is a piece of system software outside the OS (a.k.a. middleware) that handles job submission and scheduling on our cluster
- An interactive job takes control of your terminal
 - Run with srun or salloc
 - You may interact with it (provide standard input, etc.)
 - You also have to wait for it to finish
 - Similar to a foreground shell job
- A batch job runs in the background without interaction
 - Create a shell script and run it with sbatch
 - Sends output to a file (named "slurm-JOBID.out" by default)
 - Use squeue to check to see if it has finished

Batch jobs

- To run a batch job on the cluster, create a shell script and run it with sbatch
- Bash example:

```
#!/bin/bash
#
#SBATCH --job-name=hostname
#SBATCH --nodes=1
#SBATCH --ntasks=1
```

<your commands go here>

Running experiments

• Common experimentation patterns in Bash:

```
# run common thread counts
for t in 1 2 4 8 16; do
        OMP_NUM_THREADS=$t <cmd>
        done
```