Concurrent Programming I

HPPS

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Based on slides by:
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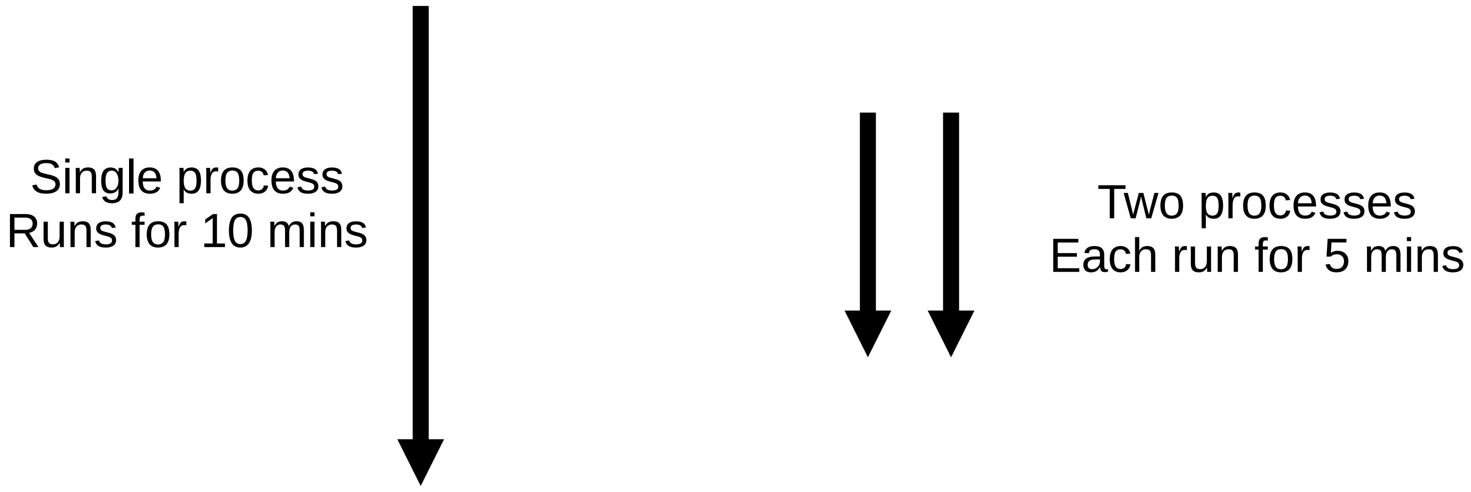
Concurrent Programming

- So far we've talked about threads and processes each running a complete programme
- Each programme has been sequential in nature
- We can spread processing over several threads or processes, each part of the same programme
- Twice the resources means twice the speed! (Nope)

The Basic Idea

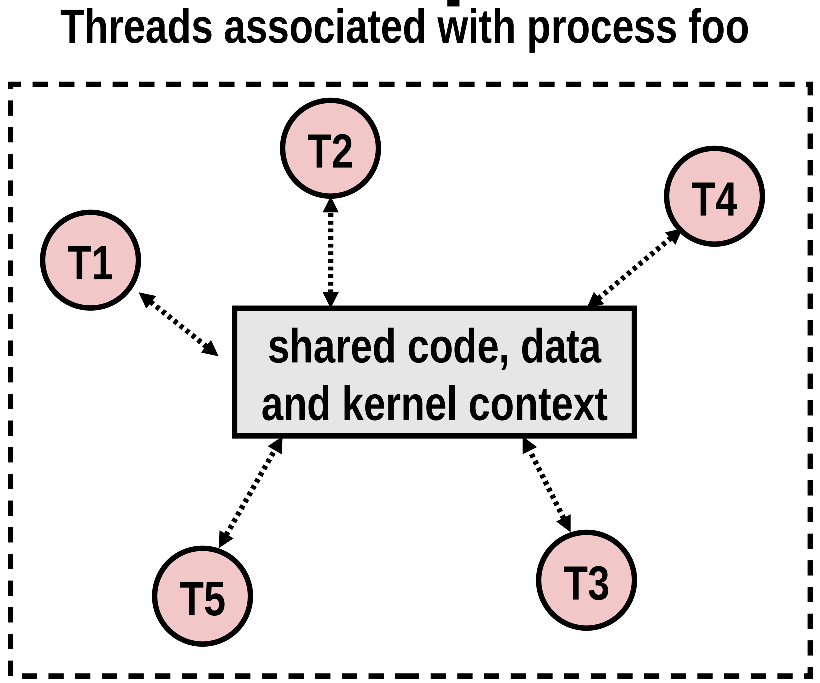
- We can break our processing over several workers

- Many hands make light work



Logical View of Threads

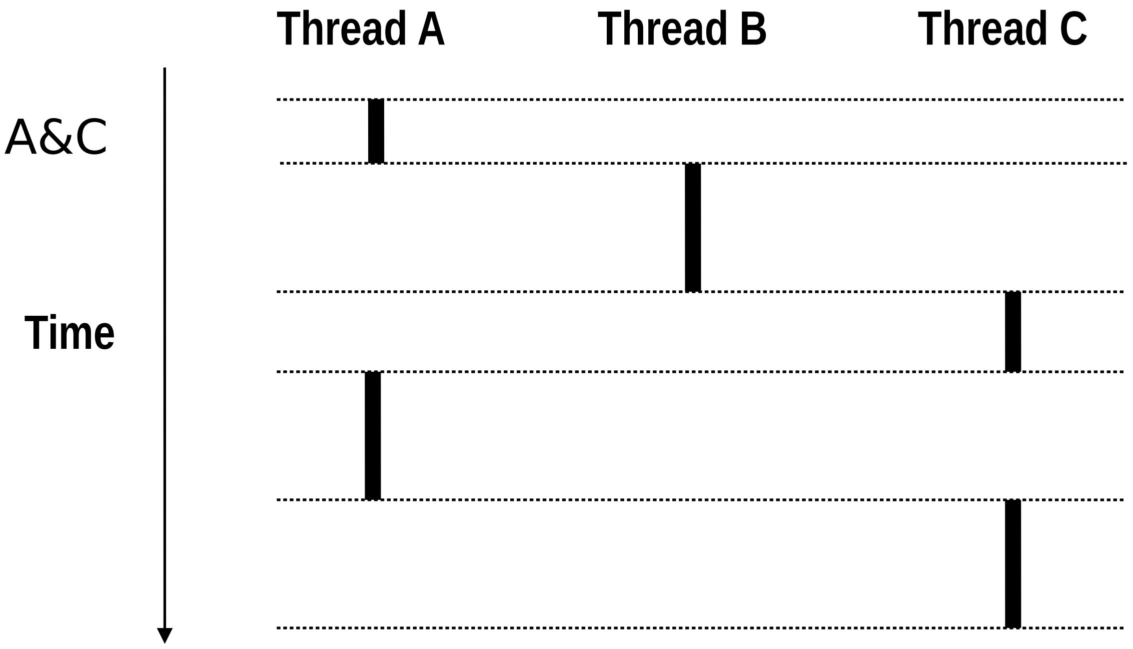
- Threads associated with process form a pool of peers
- Each thread can be processed in parallel


Threads associated with process foo
T1
T2
T4
shared code, data and kernel context
T5
T3

Concurrent Threads

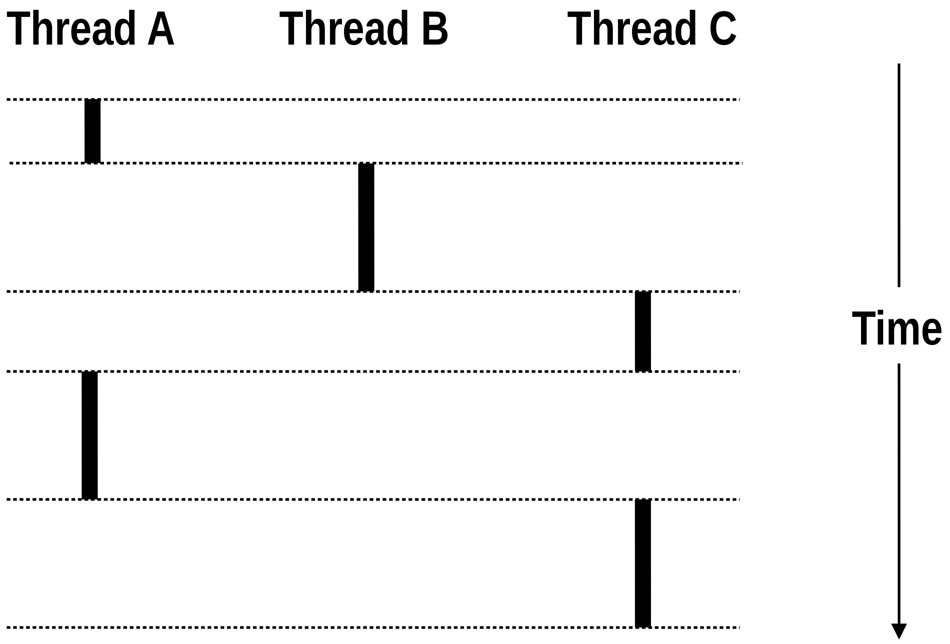
- **Two threads are *concurrent* if their flows overlap in time**
- **Otherwise, they are sequential**

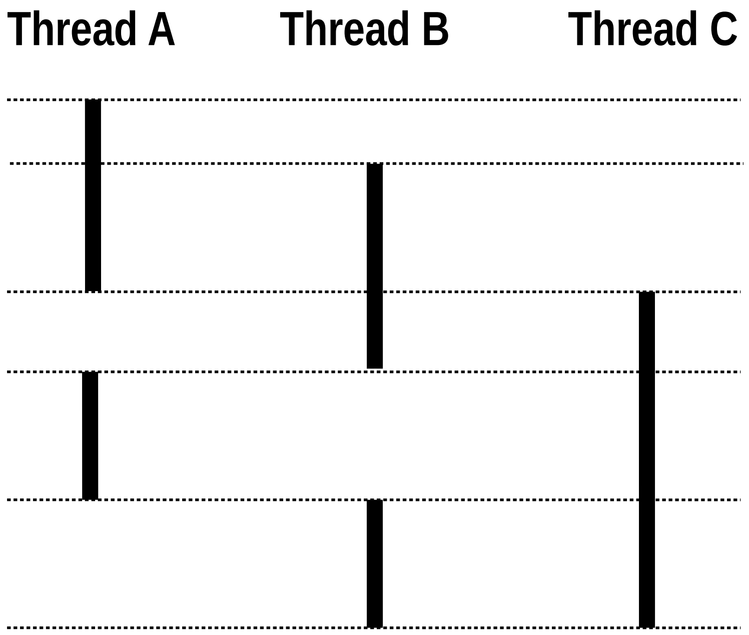
- **Examples:**
  - Concurrent: A & B, A&C
  - Sequential: B & C



Concurrent and Parallel Threads

- **Single Core Processor**
  - Simulate parallelism by time slicing
- **Multi-Core Processor**
  - Can have true parallelism





Run 3 threads on 2 cores

Parallel Systems are the default

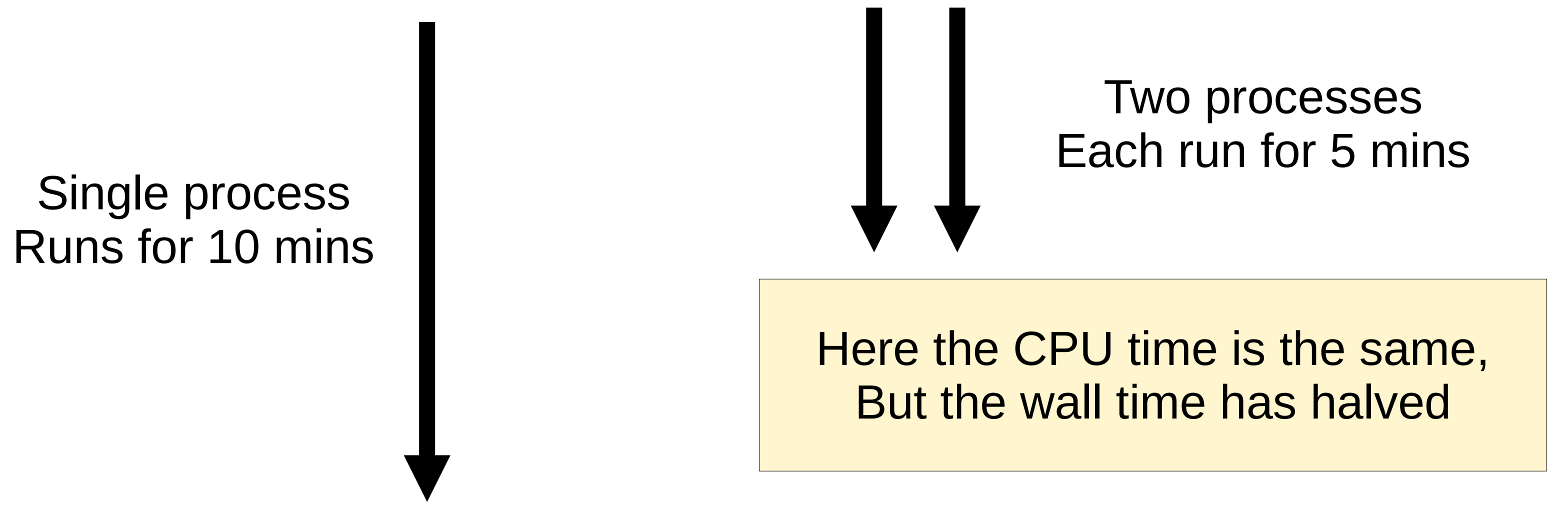
- **For many years now mulit-core systems have been standard**
- **If we paid for 8 cores, we want to use them!**
- **...and not just on running background processes with slightly fewer context switches, we want a single programme to use the all of the hardware**

Parallelism is about speed.

- How do we quantify whether parallelisation made a program faster, and by how much?
- How can we estimate the potential benefit of parallelising a program?
- Are there limits to the potential gains of parallelism?So far we've talked about threads and processes each running a complete programme

Latency

- **Often called runtime**
- **How long it takes for a program to run on some workload.**
- **Both difficult and easy to measure**
- ***Wall time* is the time it takes in the real world.**
- ***CPU time* is the total amount of time spent executing code counting all processors.**



Here the CPU time is the same,
But the wall time has halved

Latency

- Suppose we have two programmes, P_1 and P_2 that each perform the same task, and take T_1 and T_2 respectively:

$$\boxed{\text{Latency} = \frac{T_1}{T_2}}$$

- Speedup greater than one means P_2 is faster than P_1 , else it is slower.
- P_1 and P_2 must solve the same problem for their latencies to be comparable.
- HINT: This is a good metric to include in any reportorting on your own programmes

Throughput

- Sometimes latency is inappropriate—what is the running time of a potentially-infinite web server?
- Can measure latency for individual requests, but is that really useful?

$$\boxed{\text{Throughput} = \frac{\text{Workload}}{\text{Time}}}$$

- E.g. web requests served per second, or number of bytes processed per clock cycle.
- Using throughput we can compare programs that have different workloads.

Speedup in Throughput

- Suppose we have two programmes, P_1 and P_2 that each perform the same task, and have a throughput of Q_1 and Q_2 respectively:

$$\boxed{\text{Throughput Speedup} = \frac{Q_1}{Q_2}}$$

- Speedup greater than one means P_2 is faster than P_1 , else it is slower.
- P_1 and P_2 must solve the same problem for their throughputs to be comparable.
- HINT: This is another good metric to include in any reportorting on your own programmes

Scalability

- **Basically how well our system improves (or not) as we make it bigger**

How the system improves in its capacity (runtime or throughput) as we add more resources, such as more processors

How the system throughput changes as we add more workload

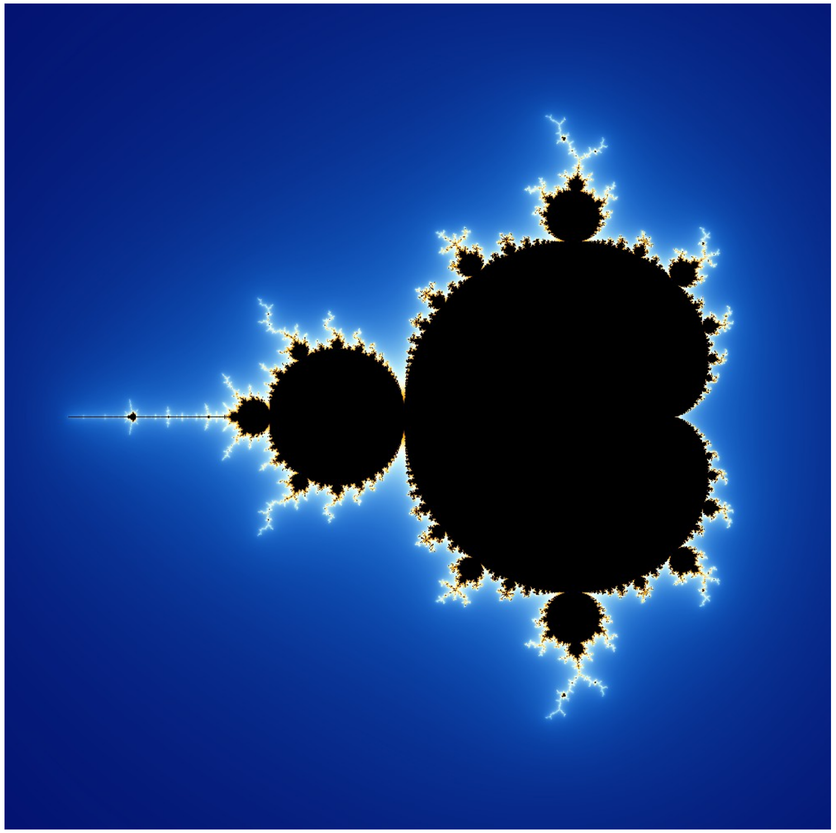
- **Both are similar, but we are altering different parameters in our system**

Scalability Example

- Rendering Mandelbrot fractals
- Each pixel can be computed independently
- The image size corresponds to the workload
- Regarding parallelism, there are

  two sorts of scalability that we are

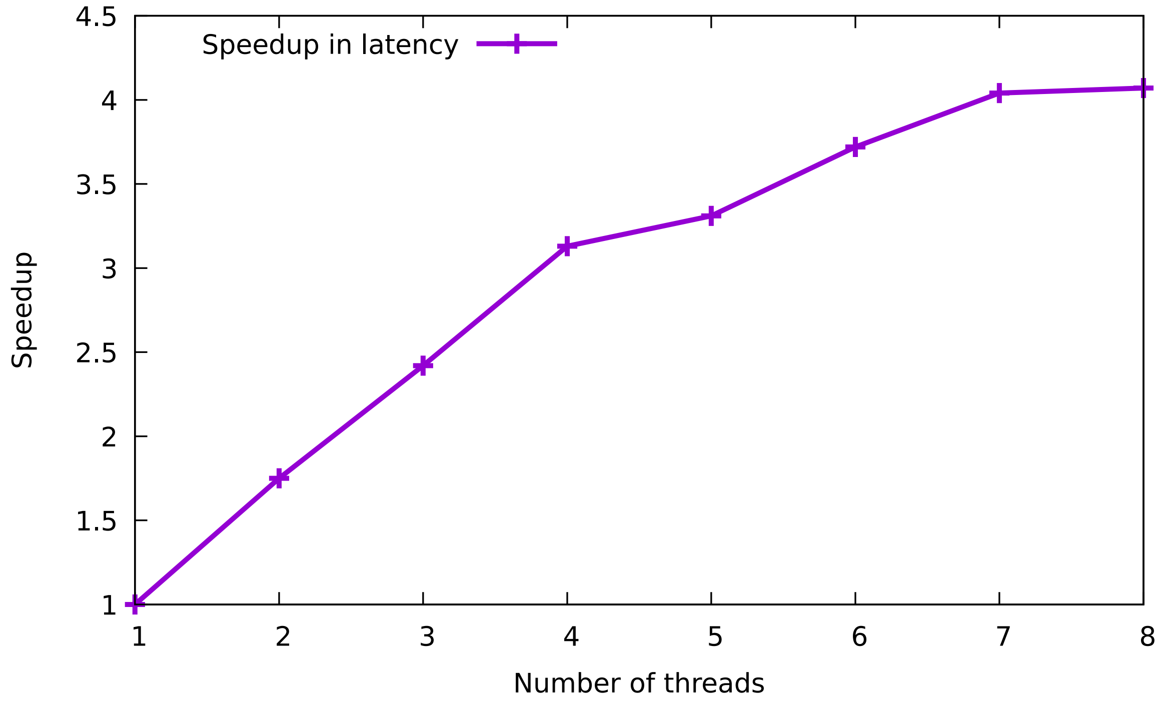
  interested in.



Strong Scaling

- **How the runtime varies with the number of processors for a fixed problem size.**

Speedup graph for rendering a 10^4 pixel Mandelbrot fractal as we use more threads:

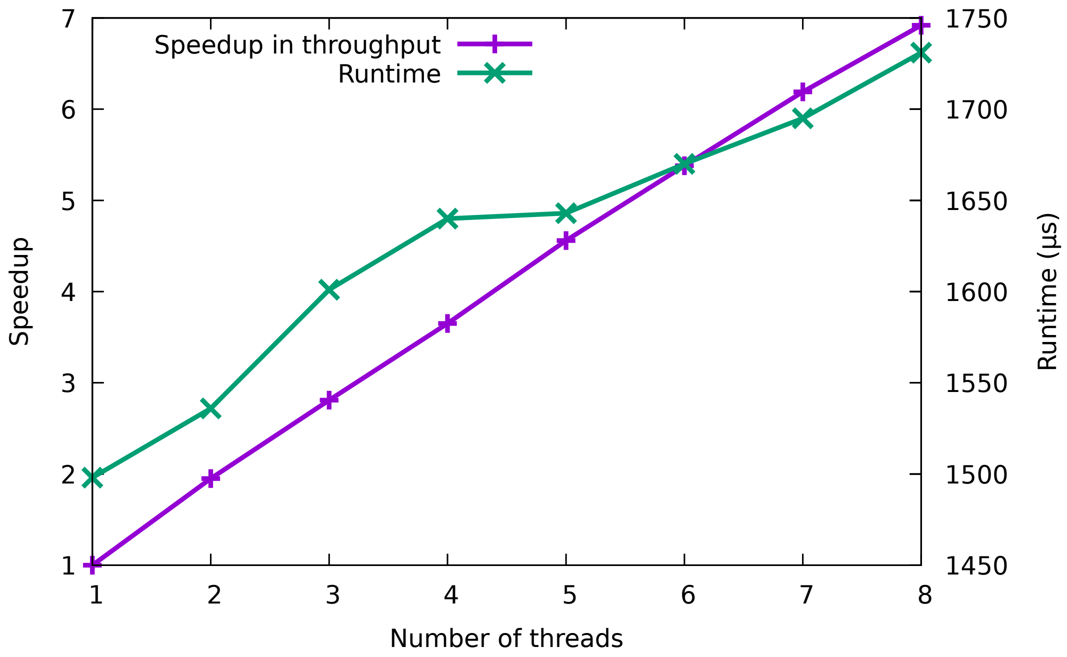


- **This shows sub-linear strong scalability—8 threads barely gets us 4 × speedup**

Weak Scaling

- **How the runtime varies with the number of processors for a fixed problem size relative to the number of processors.**

Speedup graph for rendering a Mandelbrot fractal with 10^4 *pixels per thread*:



- **Pretty decent weak scalability! By far more common than strong scalability.**

How do we estimate the potential benefits of parallelising a program, without just implementing it and measuring how well it goes?

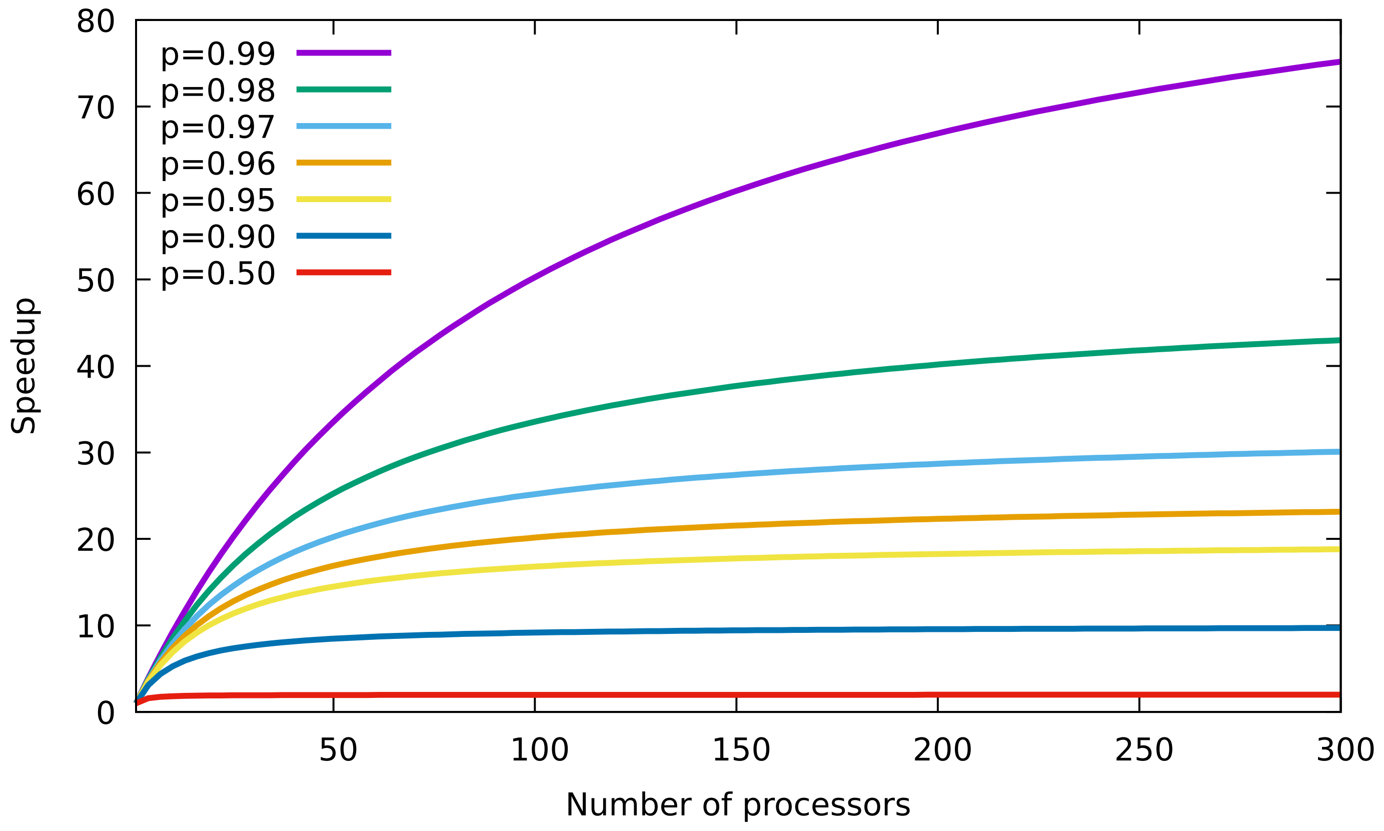
Amdahl's Law

- If *p* is the proportion of execution time that benefits from parallelisation, then S(N) is maximum theoretical speedup achievable by execution on N processors, and is given by:

$$\boxed{S(N) = \frac{1}{(1-p) + \frac{p}{N}}}$$

- Why can *p* not equal 1?
- Reading, writing and other fundamentally sequential parts mean *p* will never be 1 in practice

Amdahl’s Law


80
70
60
50
40
30
20
10
0
50
100
150
200
250
300
Speedup
Number of processors
p=0.99
p=0.98
p=0.97
p=0.96
p=0.95
p=0.90
p=0.50

Amdahl’s Law

- **Amdahl’s Law predicts strong scalability.**
- **For a fixed problem size, there will always come a point of diminishing returns.**
- **Makes parallelisation seem pointless…**

But…

- **You have a simulation that runs in 1 hour.**
- **Then you get a computer that is ten times faster.**
- **Usually you don’t decide to run the simulation in six minutes, instead you make a simulation that is ten times as precise and still runs in 1 hour.**
- **Consider weather forecasting...**
- **Bigger machines let us solve bigger problems in the same time!**

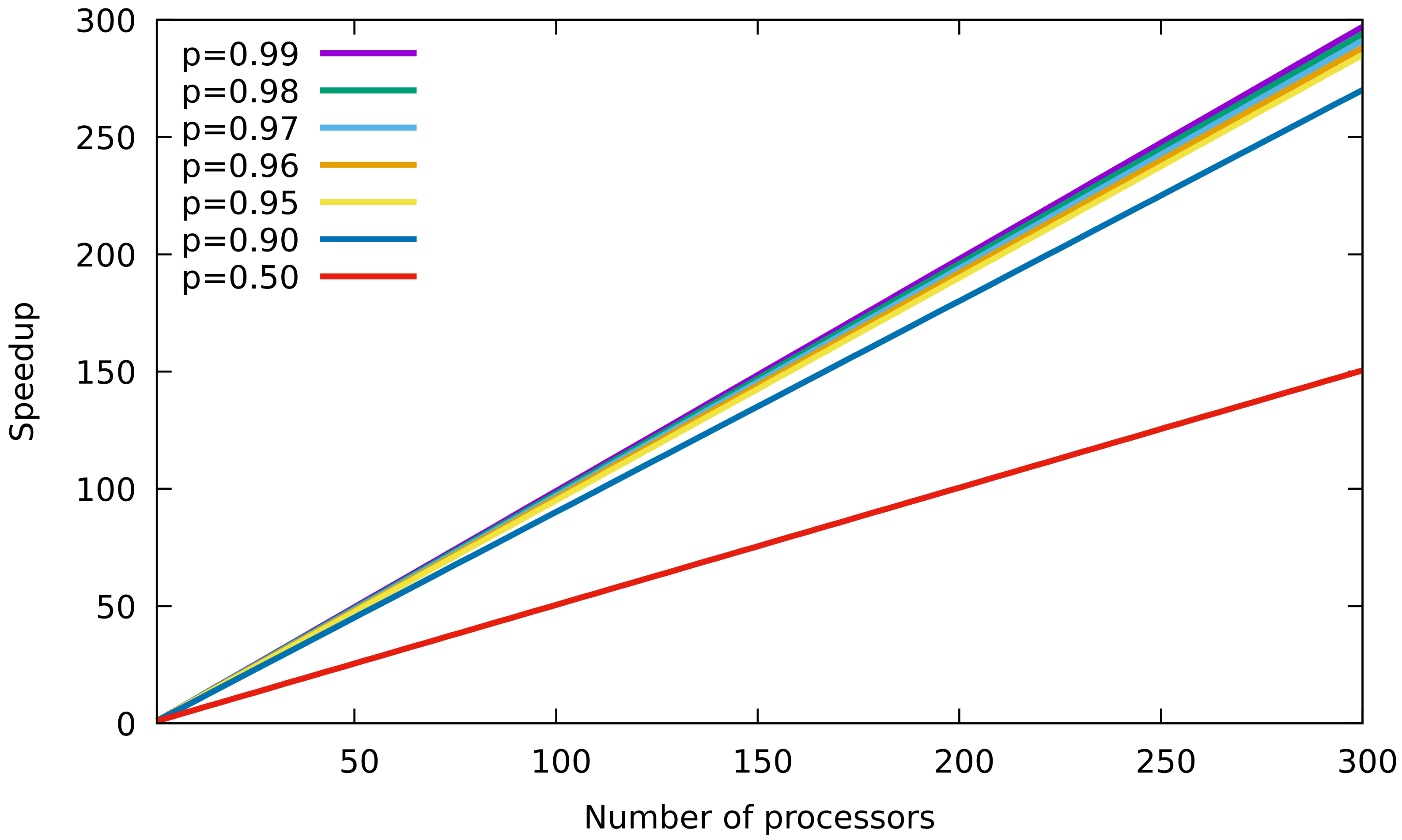
Gustafson’s Law

- If *s* is the proportion of execution time that must be sequential, then S(N) is maximum theoretical speedup achievable by execution on N processors, and is given by:

$$\boxed{S(N) = N + (1-N) \times s}$$

- Assumes that parallel workload increases just as fast as number of processors.
- Predicts weak scalability.
- In practice often more relevant than Amdahl’s Law.

Gustafson’s Law



The Fine Print

- Both Amdahl’s and Gustafson’s Laws are idealised abstractions and ignore important real-world concerns:
  - Locality.
  - Communication.
  - Synchronisation.
- But they are still a good theoretical framework for estimating the value of parallelising some program.
- Neither should be used to calculate timings or parallelisation in an implemented system.

How do we start throwing threads at our problems?

Parallel Loops

- For scientific computing, we are mostly concerned with parallelising straightforward loops such as this matrix multiplcation code

```
void matmul(int n , const double *x ,
                  const double *y , double *out ) {
     for ( int i = 0 ; i < n ; i++) {
          for ( int j = 0 ; j < n ; j++) {
               out [ i *n+j ] = 0 ;
               for ( int l = 0 ; l < n ; l++) {
                    out [ i *n+j ] += x [ i *n+j ] * y [ i *n+j ] ;
               }
          }
     }
}
```

- Iterations of the outer two loops are independent.
- Can be computed by different threads.

Simplest OpenMP Example

```
#pragma omp parallel for
for (int i = 0 ; i < n ; i++) {
      A[i] = A[i] * 2;
}
```

- *Directives* used to indicate how run C program in parallel.
- *Clauses* (covered later) can be used to customise the behaviour.
- Semantics are the *sequential elision*—how the program would behave if we ignored the directives.
- We are only scratching the surface of OpenMP in this course!

Simplest OpenMP Example

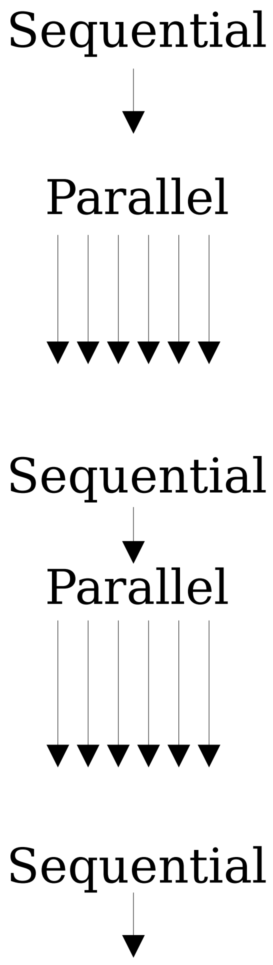
```
print ("Program Starts\n");
n = 1000;

#pragma omp parallel for
for (int i=0; i<n; i++) {
      A[i] = B[i] + C[i];
}

m = 500;

#pragma omp parallel for
for (int j=0; j<m; j++) {
      p[j] = q[j] - r[j];
}

print ("Program Ends\n");
exit(0),
```



- **Program starts sequential.**
- **Parallel regions split across multiple threads.**
- **Parallel region ends when all threads done.**
- **Worker threads kept running in background.**

Compilation

```
#include <stdio.h>
#include <stdlib.h>

int main (void) {
      int n = 100000000;
      int *arr = malloc (n*sizeof(int)) ;

      #pragma omp parallel for
      for (int i=0; i<n; i++) {
            arr[ i ] = i ;
      }

      free(arr);
}
```

```
$ gcc -o openmp-example openmp-example.c -fopenmp
```

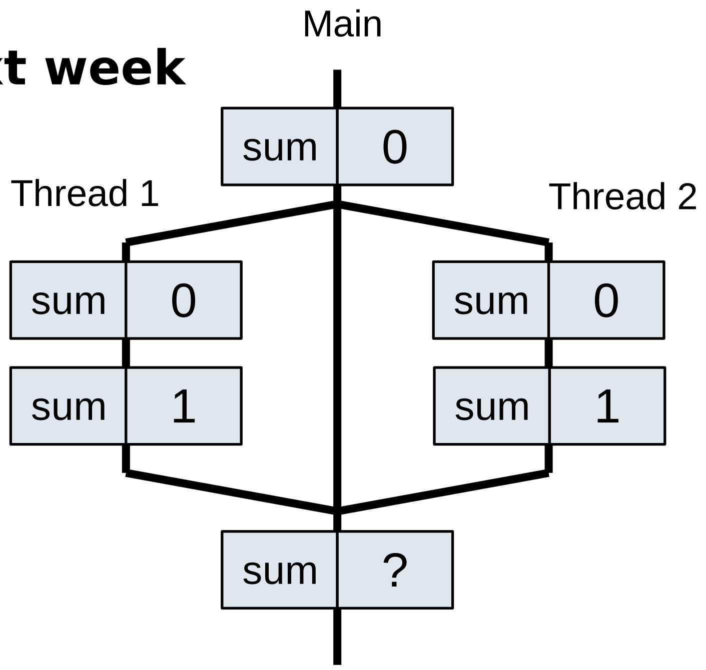
Controlling the number of threads

```
$ time OMP_NUM_THREADS=1 ./openmp-example
real    0m0.124s    Wall time
user    0m0.034s    CPU time (user)
sys     0m0.090s    CPU time (system)
$ time OMP_NUM_THREADS=2 ./openmp-example
real    0m0.076s    Wall time
user    0m0.033s    CPU time (user)
sys     0m0.104s    CPU time (system)
$ time OMP_NUM_THREADS=3 ./openmp-example
real    0m0.054s    Wall time
user    0m0.039s    CPU time (user)
sys     0m0.133s    CPU time (system)
$ time OMP_NUM_THREADS=4 ./openmp-example
real    0m0.046s    Wall time
user    0m0.054s    CPU time (user)
sys     0m0.184s    CPU time (system)
```

Memory model

- **Variables declared inside a loop iteration are private.**
- **Variables declared outside are shared.**
- **Be extremely careful when modifying shared variables—OpenMP will not protect you!**
- **This is known as a race condition, multiple threads are reading and writing to the same location. Who gets there first? We don't know!**
- **We will cover this in more depth next week**

```
Double sum=0;
#pragma omp parallel for
for (int i = 0 ; i < n ; i++) {
      sum += A[i];
}
```



Reductions

- Instead of doing a summation sequentially

$$(((((((x_0 + x_1) + x_2) + x_3) + x_4) + x_5) + x_6) + x_7)$$

- we can do it like:

$$(x_0 + x_1 + x_2 + x_3) + (x_4 + x_5 + x_6 + x_7)$$

- and have one compute the left part, and a second one compute the right, combining their results at the end.

Is this valid?

Reductions

- Instead of doing a summation sequentially

$$(((((((x_0 \oplus x_1) \oplus x_2) \oplus x_3) \oplus x_4) \oplus x_5) \oplus x_6) \oplus x_7)$$

- we can do it like:

$$(x_0 \oplus x_1 \oplus x_2 \oplus x_3) \oplus (x_4 \oplus x_5 \oplus x_6 \oplus x_7)$$

- and have one compute the left part, and a second one compute the right, combining their results at the end.

What about now?

Reductions

- A binary operator $\oplus : \alpha \to \alpha \to \alpha$ is said to be *commutative* if

$$x \oplus y = y \oplus x$$

- It is associative if

$$x \oplus (y \oplus z) = (x \oplus y) \oplus z$$

- We can do a parallel “sum” with any associative operator, called a reduction.
- For convenience, we also tend to require a neutral element $0_\oplus$:

$$x \oplus 0_\oplus = 0_\oplus \oplus x = x$$

Reduction example

```
double dotprod (int n, double *x, double *y) {
    double sum = 0 ;
    #pragma omp parallel for reduction (+: sum)
    for (int i=0; i<n; i++) {
        sum += x[i] * y[i] ;
    }
    return sum ;
}
```

- **Must initialise accumulator variable to neutral element.**
- **Must explicitly tell OpenMP the combining operator (+, ∗, −, &&, || , &, |, ^, max, or min).**

Parallelising Matrix Multiplication

```
void matmul_seq(int n , const double *x ,
                        const double *y, double *out) {
     for (int i=0; i<n; i++) {
          for (int j=0; j<n; j++) {
               double acc = 0;
               for (int l=0; l<n; l++) {
                    acc += x[i*n+l] * y[j*n+l] ;
               }
               out[i*n+j] = acc;
          }
     }
}
```

- **Runtime for n=1000: 2.69s.**
- **Three nested loops.**
- **Which do we parallelise, and how?**

Parallelising Matrix Multiplication

```
void matmul_seq(int n , const double *x ,
                            const double *y, double *out) {
      #pragma omp parallel for
      for (int i=0; i<n; i++) {
            for (int j=0; j<n; j++) {
                  double acc = 0;
                  for (int l=0; l<n; l++) {
                        acc += x[i*n+l] * y[j*n+l] ;
                  }
                  out[i*n+j] = acc;
            }
      }
}
```

- **Runtime: 0.80s (was. 2.69s seq) — pretty good for adding one line of code!**
- **But this only parallelises across the rows of the result matrix.**

Parallelising Matrix Multiplication

```
void matmul_seq(int n , const double ∗x ,
                               const double ∗y, double ∗out) {
       #pragma omp parallel for collapse(2)
       for (int i=0; i<n; i++) {
              for (int j=0; j<n; j++) {
                     double acc = 0;
                     for (int l=0; l<n; l++) {
                            acc += x[i∗n+l] ∗ y[j∗n+l] ;
                     }
                     out[i∗n+j] = acc;
              }
       }
}
```

- **collapse(2) clause combines loops to one parallel n*n iteration loop,**
- **Runtime: 0.93s (was 0.80s without collapse) — not much impact here.**
- **Would matter more if we had fewer iterations in outer loop.**

Parallelising Matrix Multiplication

```
void matmul_seq(int n , const double *x ,
                             const double *y, double *out) {
      for (int i=0; i<n; i++) {
            for (int j=0; j<n; j++) {
                  double acc = 0;
                  #pragma omp parallel for reduction(+:acc)
                  for (int l=0; l<n; l++) {
                        acc += x[i*n+l] * y[j*n+l] ;
                  }
                  out[i*n+j] = acc;
            }
      }
}
```

- **Runtime: 2.48s (vs. 2.69s sequential)—this sucks.**
- **Almost always better to parallelise outermost loops.**

Parallelising Matrix Multiplication

```
void matmul_seq(int n , const double *x ,
                            const double *y, double *out) {
      #pragma omp parallel for
      for (int j=0; j<n; j++) {
            for (int i=0; i<n; i++) {
                  double acc = 0;
                  for (int l=0; l<n; l++) {
                        acc += x[i*n+l] * y[j*n+l] ;
                  }
                  out[i*n+j] = acc;
            }
      }
}
```

- **Runtime: 0.80s (was. 0.80 first ordering)**
- **No real effect here as both loop are the same, but can exploit locality for some small but easy speedup**

Scheduling Clauses

- **By default, OpenMP splits the iterations of a parallel loop evenly among the threads (static scheduling). This is not always optimal.**

```
int fib (int n) {
      if (n <= 1) {
            return 1;
      } else {
            return fib(n−1) + fib(n−2);
      }
}
```

- **Consider a loop that computes fib(i) for each i<n.**
- **Since time to compute fib(i) is over twice that of fib(i-1), the threads with the early iterations finish much faster than the threads with the later iterations.**

```
#pragma omp parallel for schedule(static)
for (int i=0; i<n; i++) {
      fibs[i] = fib(i);
}
```

Dynamic Scheduling

- **Dynamic scheduling assigns each thread an iteration, and is given more iterations when it finishes.**
- **No idle threads (as long as there are unclaimed iterations to run).**

```
#pragma omp parallel for schedule(dynamic)
for (int i=0; i<n; i++) {
      fibs[i] = fib(i);
}
```

- **On my machine static ran in 5.2s, where dynamic ran in 2.27s—much better!**
- **By default, assigns single iterations at a time, which is slow for very large loops with quick iterations.**
- **Use schedule(dynamic,K) to schedule K iterations at a time to threads.**

Summary

- Parallelism is about speedup.
- Describe performance differences with speedup.
  - Latency for programs that compute the same thing.
  - Throughput if not.
- Strong scaling is solving the same problem faster.
- Weak scaling is solving a bigger problem in the same time.
- OpenMP is a simple language extension for parallelising loops in C programs.
- Use #pragma omp parallel for to parallelise a for-loop.
- Generally parallelising the outer most loop works best