

# Parallel Programming Patterns

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Overview and Concepts



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# Outline

- Why parallel programming?
- Decomposition
  - Geometric decomposition
  - Task farm
  - Pipeline
  - Loop parallelism
- Performance metrics and scaling
  - Amdahl's law
  - Gustafson's law

# Why use parallel programming?

It is harder than serial so why bother?

# Why?

- Parallel programming is more difficult than its sequential counterpart
- However we are reaching limitations in uniprocessor design
  - Physical limitations to size and speed of a single chip
  - Developing new processor technology is very expensive
  - Some fundamental limits such as speed of light and size of atoms
- Parallelism is not a silver bullet
  - There are many additional considerations
  - Careful thought is required to take advantage of parallel machines

# Performance

- A key aim is to solve problems faster
  - To improve the time to solution
  - Enable new scientific problems to be solved
- To exploit parallel computers, we need to split the program up between different processors
- Ideally, would like program to run  $P$  times faster on  $P$  processors
  - Not all parts of program can be successfully split up
  - Splitting the program up may introduce additional overheads such as communication

# Parallel tasks

- How we split a problem up in parallel is critical
  1. Limit communication (especially the number of messages)
  2. Balance the load so all processors are equally busy
- Tightly coupled problems require lots of interaction between their parallel tasks
- Embarrassingly parallel problems require very little (or no) interaction between their parallel tasks
  - E.g. the image sharpening exercise
- In reality most problems sit somewhere between two extremes

# Decomposition

How do we split problems up to solve efficiently in parallel?

# Decomposition

- One of the most challenging, but also most important, decisions is how to split the problem up
- How you do this depends upon a number of factors
  - The nature of the problem
  - The amount of communication required
  - Support from implementation technologies
- We are going to look at some frequently used decompositions
  - will be illustrated by later Fractal and CFD practical examples

# Geometric decomposition

- Take advantage of the geometric properties of a problem

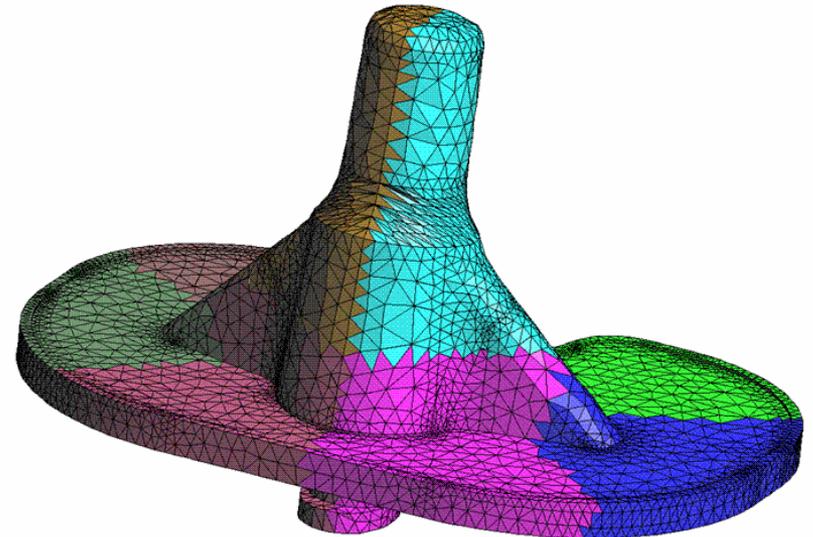
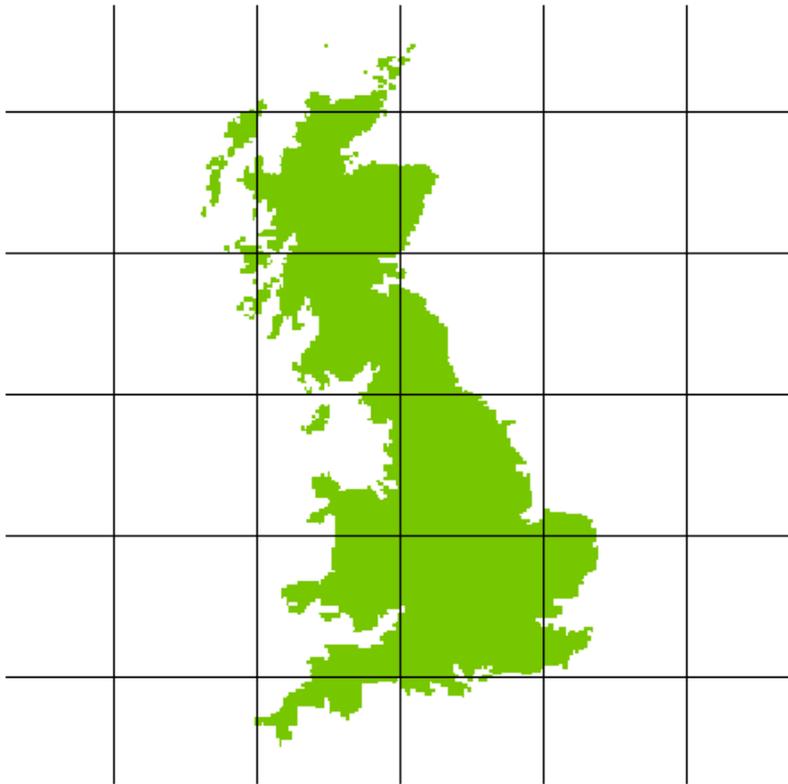
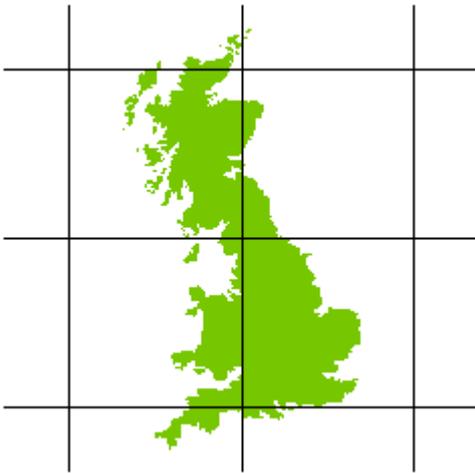


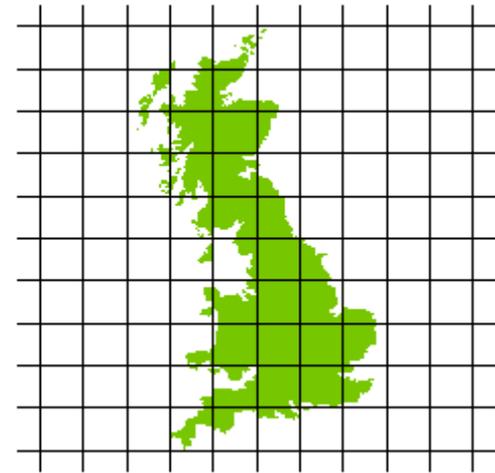
Image from ITWM: <http://www.itwm.fraunhofer.de/en/departments/flow-and-material-simulation/mechanics-of-materials/domain-decomposition-and-parallel-mesh-generation.html>

# Geometric decomposition

- Splitting the problem up does have an associated cost
  - Namely communication between processors
  - Need to carefully consider granularity
  - Aim to minimise communication and maximise computation



- Granularity
  - size of chunks of work



- Chunks too large
  - too little parallelism

- Chunks too small
  - communications rule

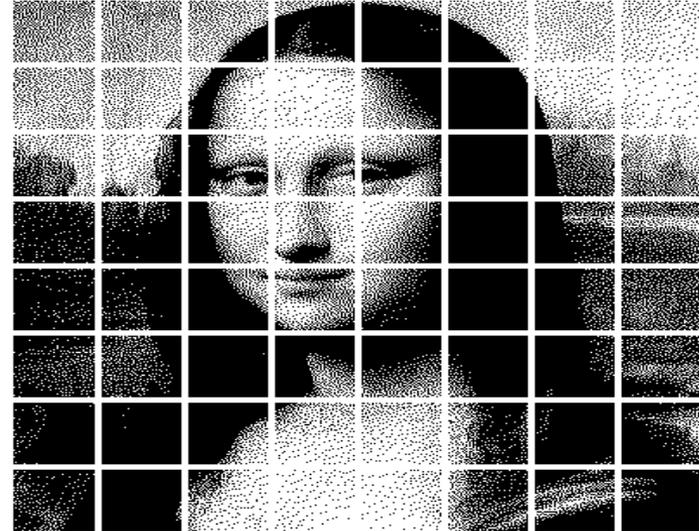
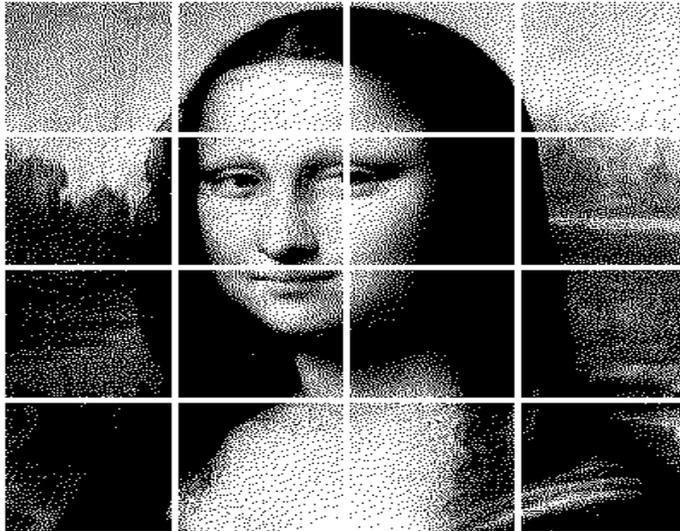
# Halo swapping

- Swap data in bulk at pre-defined intervals
- Often only need information on the boundaries
- Many small messages result in far greater overhead



# Load imbalance

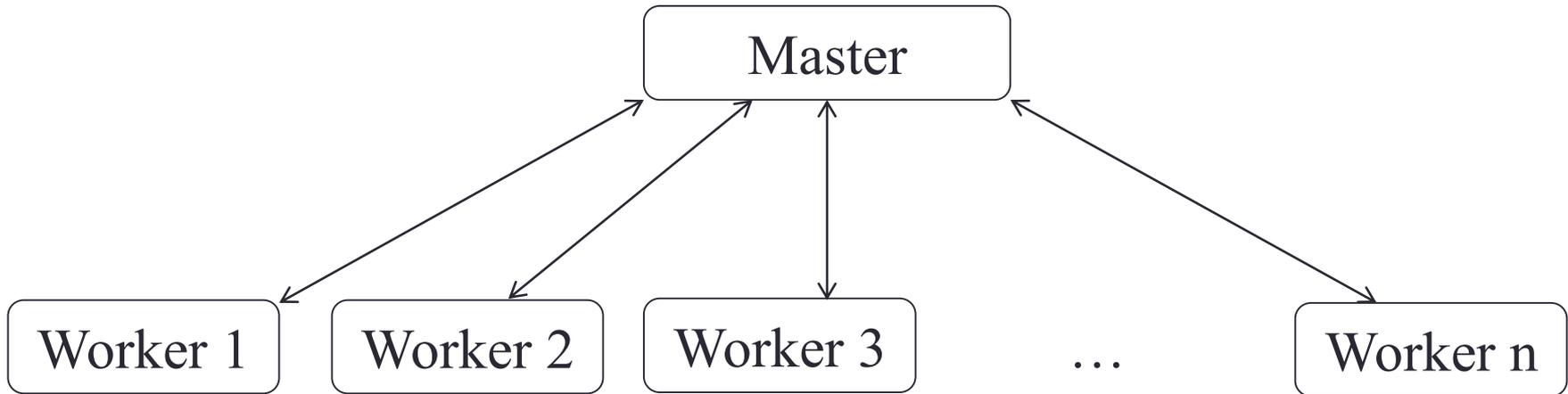
- Execution time determined by slowest processor
  - each processor should have (roughly) the same amount of work, i.e. they should be load balanced



- Assign multiple partitions per processor
  - see Fractal example
  - Additional techniques such as work stealing available

# Task farm (master worker)

- Split the problem up into distinct, independent, tasks



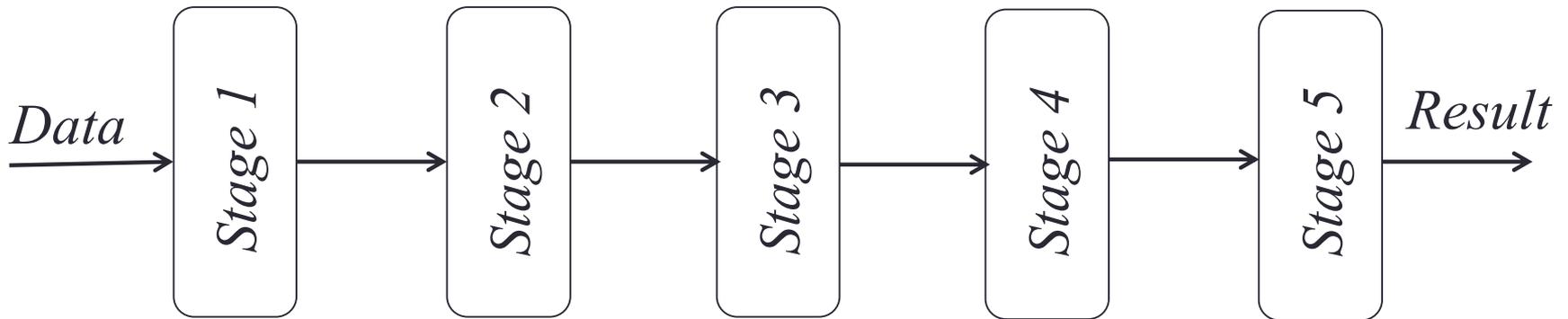
- Master process sends task to a worker
- Worker process sends results back to the master
- The number of tasks is often much greater than the number of workers and tasks get allocated to idle workers

# Task farm considerations

- Communication is between the master and the workers
  - Communication between the workers can complicate things
- The master process can become a bottleneck
  - Workers are idle waiting for the master to send them a task or acknowledge receipt of results
  - Potential solution: implement work stealing
- Resilience – what happens if a worker stops responding?
  - Master could maintain a list of tasks and redistribute that work's work

# Pipelines

- A problem involves operating on many pieces of data in turn. The overall calculation can be viewed as data flowing through a sequence of stages and being operated on at each stage.



- Each stage runs on a processor, each processor communicates with the processor holding the next stage
- One way flow of data

# Example: pipeline with 4 processors



- Each processor (one per colour) is responsible for a different task or stage of the pipeline
- Each processor acts on data (numbered) as they move through the pipeline

# Examples of pipelines

- CPU architectures
  - Fetch, decode, execute, write back
  - Intel Pentium 4 had a 20 stage pipeline
- Unix shell
  - i.e. `cat datafile | grep "energy" | awk '{print $2, $3}'`
- Graphics/GPU pipeline
- *A generalisation of pipeline (a workflow, or dataflow) is becoming more and more relevant to large, distributed scientific workflows*
- *Can combine the pipeline with other decompositions*

# Loop parallelism

- Serial programs can often be dominated by computationally intensive loops.
- Can be applied incrementally, in small steps based upon a working code
  - This makes the decomposition very useful
  - Often large restructuring of the code is not required
  - e.g. compare different parallelisations for later CFD exercise
- Tends to work best with small scale parallelism
  - Not suited to all architectures
  - Not suited to all loops
- If the runtime is not dominated by loops, or some loops can not be parallelised then these factors can dominate (Amdahl's law.)

# Example of loop parallelism:

```
int main(int argc, char *argv[])
{
    const int N = 100000;
    int i, a[N];

    #pragma omp parallel for
    for (i=0; i < N; i++)
        a[i] = 2 * a[i];

    return 0;
}
```

- If we ignore all parallelisation directives then should just run in serial
- Technologies have lots of additional support for tuning this

# Performance metrics and scaling

How is my parallel code performing and scaling?

# Performance metrics

- Measure the execution time  $T$ 
  - how do we quantify performance improvements?

- Speed up
    - typically  $S(N,P) < P$
- $$S(N,P) = \frac{T(N,1)}{T(N,P)}$$

- Parallel efficiency
    - typically  $E(N,P) < 1$
- $$E(N,P) = \frac{S(N,P)}{P} = \frac{T(N,1)}{P T(N,P)}$$

- Serial efficiency
    - typically  $E(N) \leq 1$
- $$E(N) = \frac{T_{best}(N)}{T(N,1)}$$

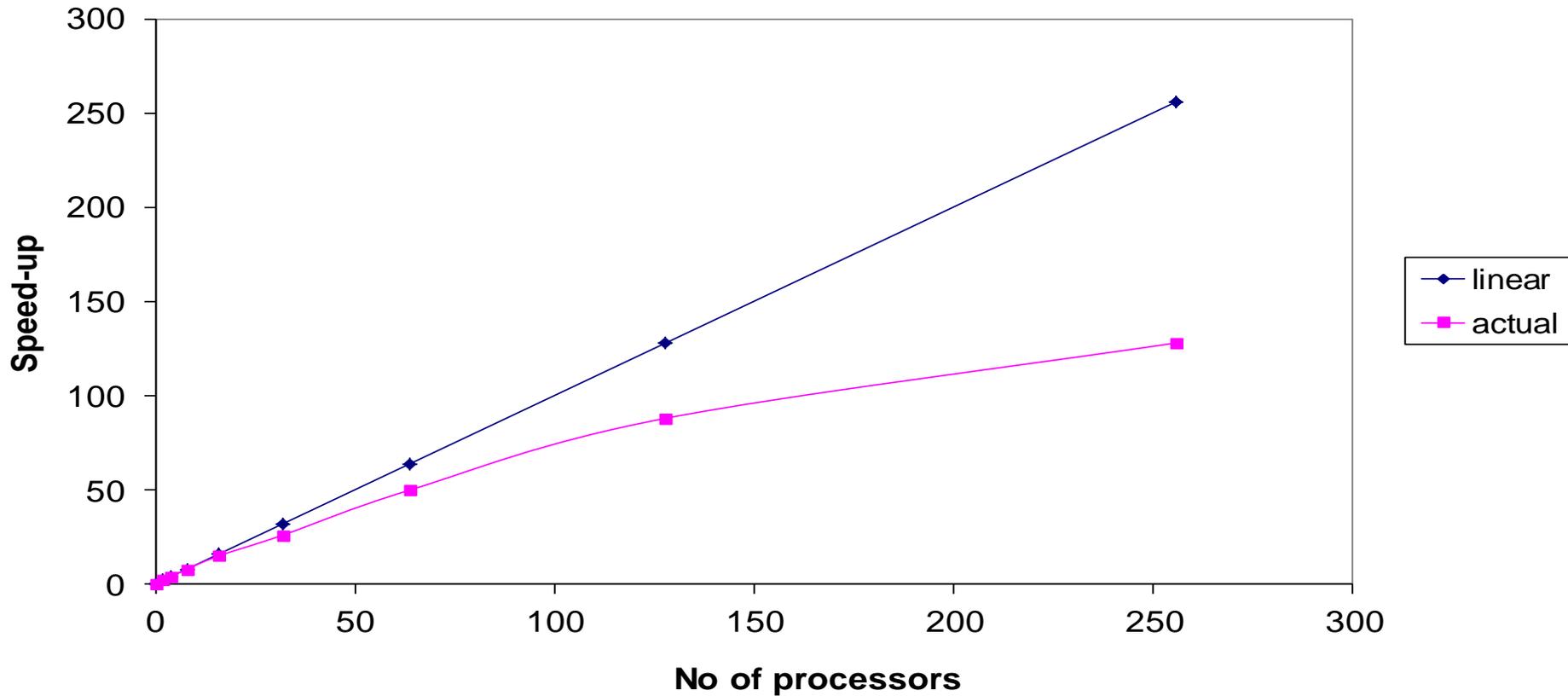
*Where  $N$  is the size of the problem and  $P$  the number of processors*

# Scaling

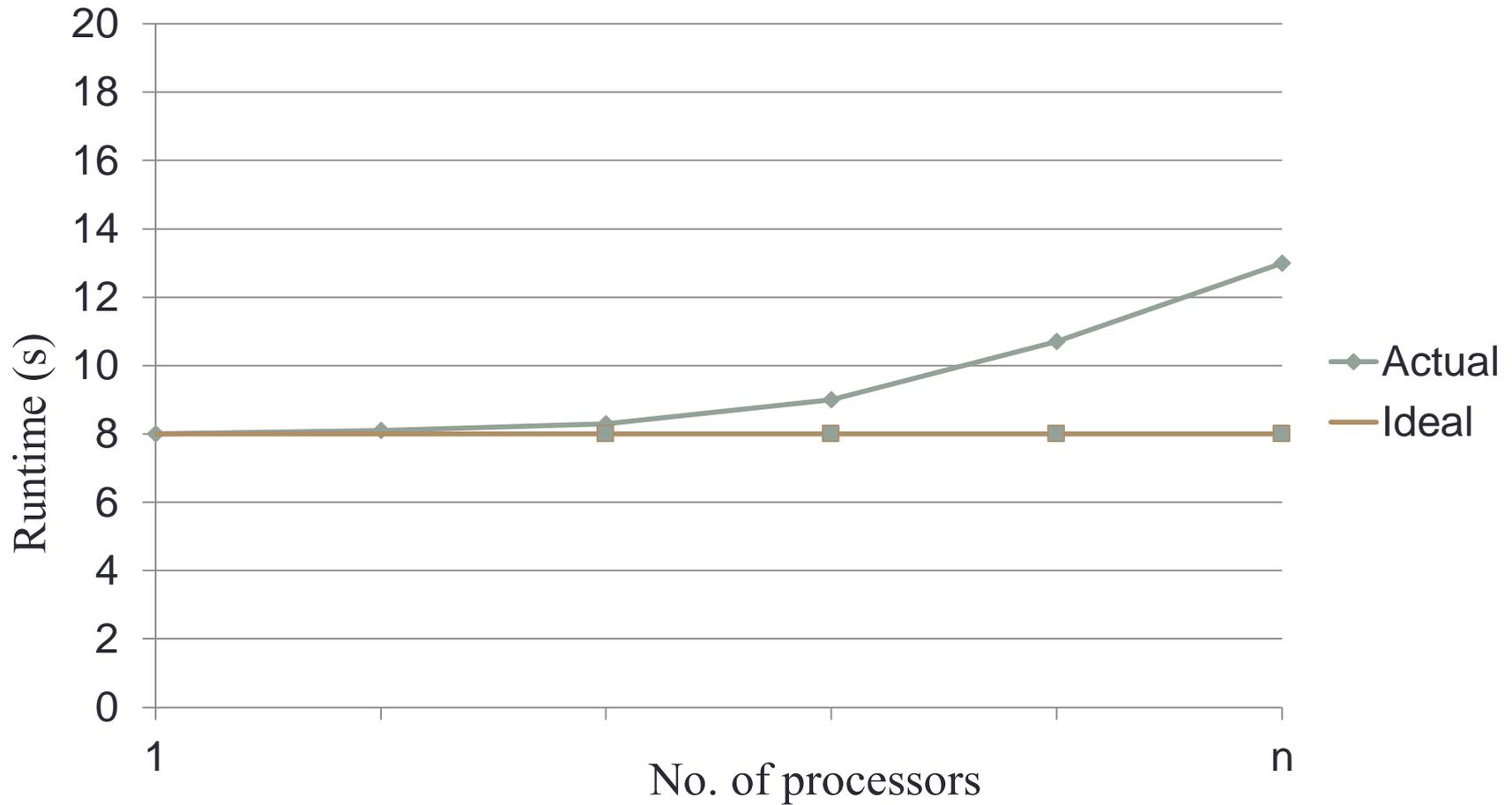
- *Scaling* is how the performance of a parallel application changes as the number of processors is increased
- There are two different types of scaling:
  - *Strong Scaling* – total problem size stays the same as the number of processors increases
  - *Weak Scaling* – the problem size increases at the same rate as the number of processors, keeping the amount of work per processor the same
- Strong scaling is generally more useful and more difficult to achieve than weak scaling

# Strong scaling

Speed-up vs No of processors



# Weak scaling



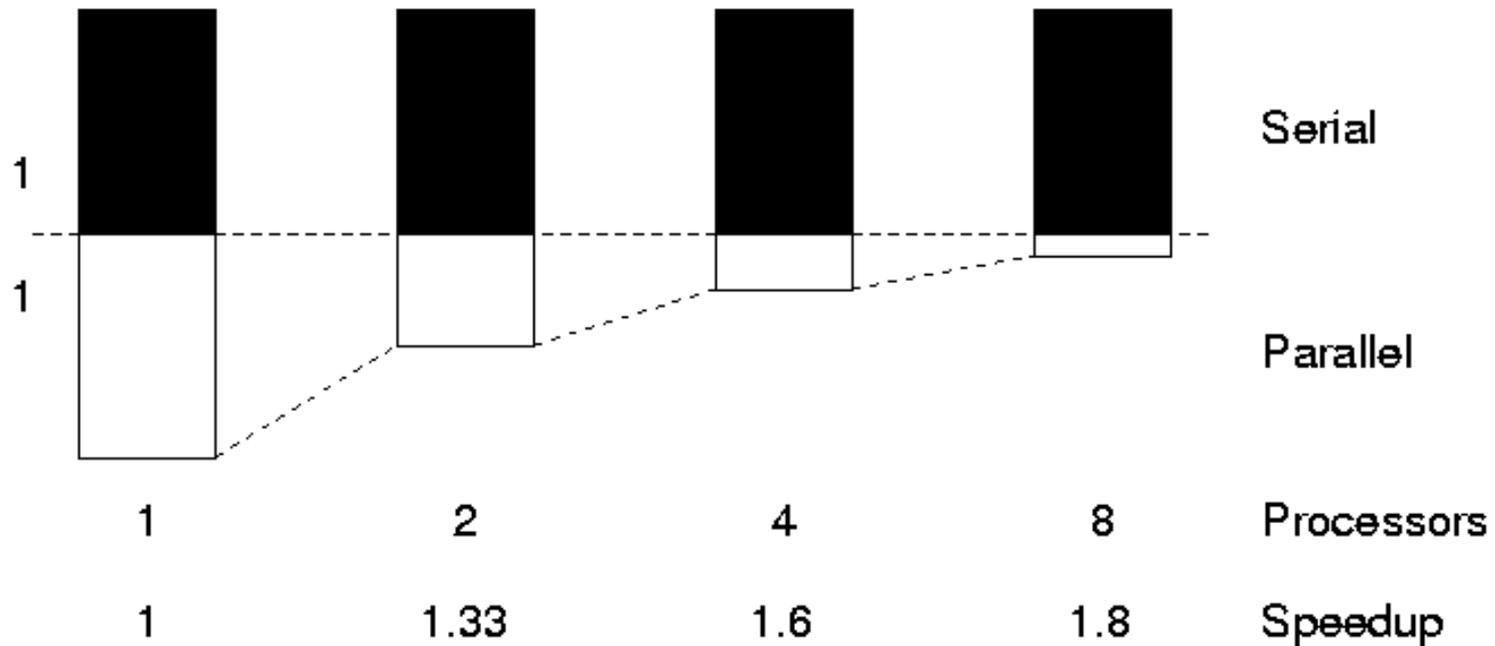
# The serial fraction

An inherent limit to speed up when we parallelise problems

# The serial section of code

*“The performance improvement to be gained by parallelisation is limited by the proportion of the code which is serial”*

*Gene Amdahl, 1967*



# Amdahl's law

- A typical program has two categories of components
  - Inherently sequential sections: can't be run in parallel
  - Potentially parallel sections
- Assume fraction  $\alpha$  is serial and parallel part is 100% efficient:

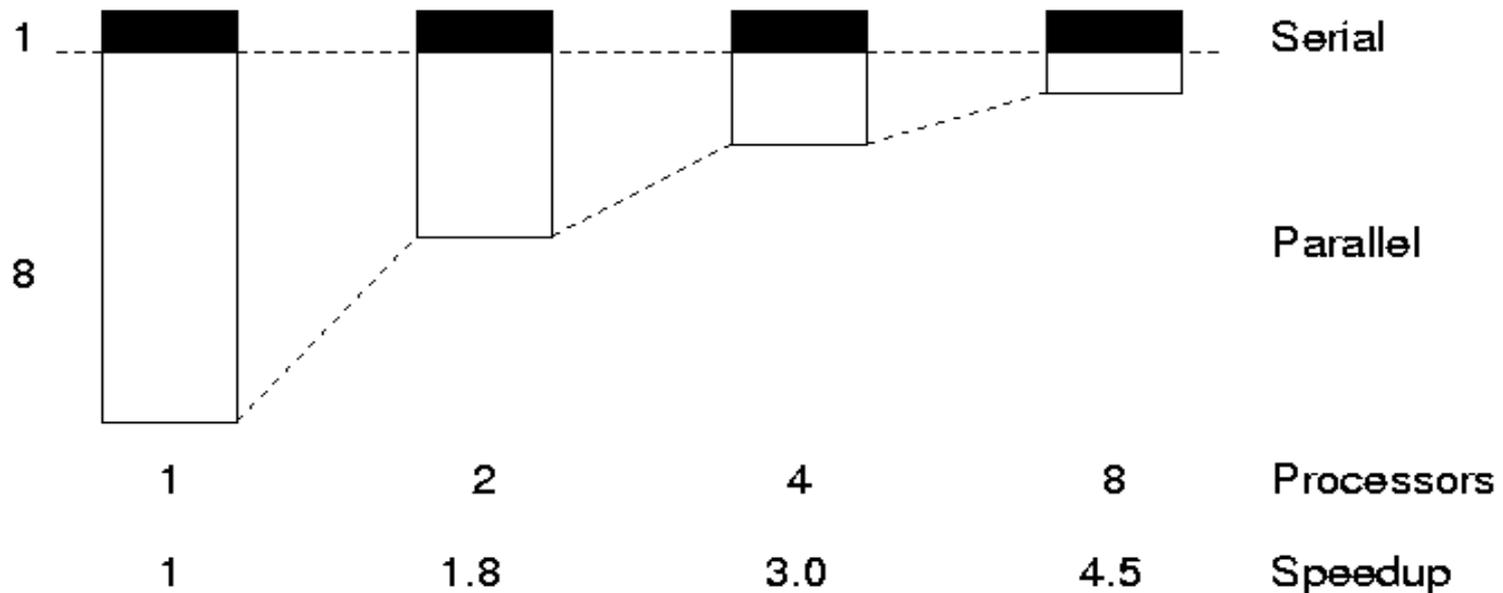
- Parallel runtime 
$$T(N, P) = \alpha T(N, 1) + \frac{(1 - \alpha)T(N, 1)}{P}$$

- Parallel speedup 
$$S(N, P) = \frac{T(N, 1)}{T(N, P)} = \frac{P}{\alpha P + (1 - \alpha)}$$

- We are fundamentally limited by the serial fraction
  - For  $\alpha = 0$ ,  $S = P$  as expected (i.e. *efficiency* = 100%)
  - Otherwise, speedup limited by  $1/\alpha$  for any  $P$ 
    - For  $\alpha = 0.1$ ;  $1/0.1 = 10$  therefore 10 times maximum speed up
    - For  $\alpha = 0.1$ ;  $S(N, 16) = 6.4$ ,  $S(N, 1024) = 9.9$

# Gustafson's Law

- We need larger problems for larger numbers of CPUs



- Whilst we are still limited by the serial fraction, it becomes less important

# Utilising Large Parallel Machines

- Assume parallel part is proportional to  $N$

- and that serial fraction  $\alpha$  is independent of  $N$

- time 
$$T(N, P) = T_{serial}(N, P) + T_{parallel}(N, P)$$
$$= \alpha T(1, 1) + \frac{(1 - \alpha)NT(1, 1)}{P}$$

- speedup 
$$S(N, P) = \frac{T(N, 1)}{T(N, P)} = \frac{\alpha + (1 - \alpha)N}{\alpha + (1 - \alpha)\frac{N}{P}}$$

- Scale problem size with CPUs, i.e. set  $N = P$  (weak scaling)

- speedup 
$$S(P, P) = \alpha + (1 - \alpha)P$$

- efficiency 
$$E(P, P) = \alpha/P + (1 - \alpha)$$

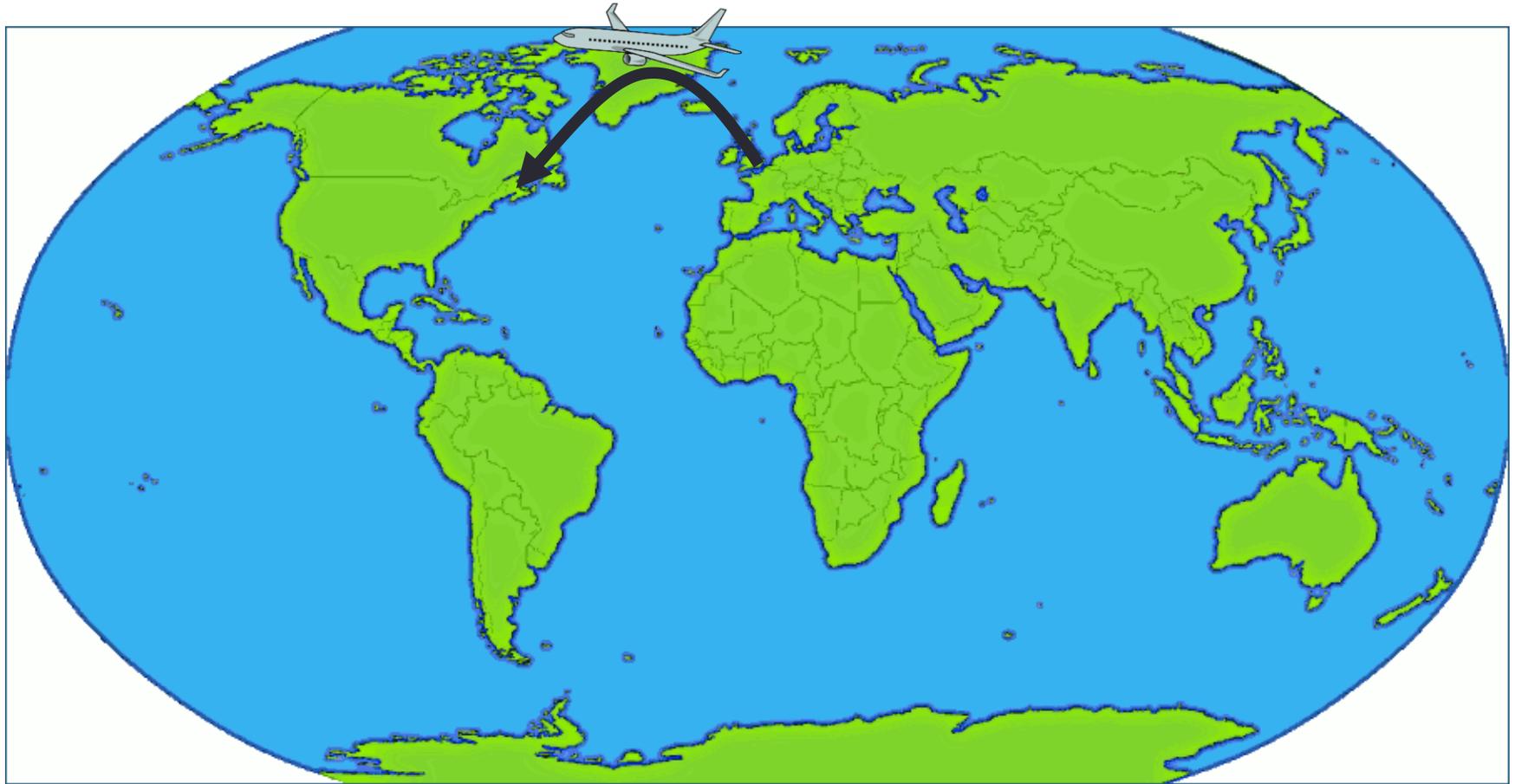
# Gustafson's Law

- If you increase the amount of work done by each parallel task then the serial component will not dominate
  - Increase the problem size to maintain scaling
  - Can do this by adding extra complexity or increasing the overall problem size
- Assume 10% serial fraction for initial problem size:

Number of processors	Strong scaling (Amdahl's law)	Weak scaling (Gustafson's law)
16	6.4	14.5
1024	9.9	922

Due to the scaling of  $N$ , the serial fraction effectively becomes  $\alpha/P$

# Analogy: Flying London to New York



# Buckingham Palace to Empire State

- By airplane
  - Distance: 5600 km; speed: 600 mph
    - Flight time: 8 hours
- But.....
  - 2 hours to check in at the airport in London
  - 2 hours to get through immigration & collect bag in NY
  - Fixed overhead of 4 hours; total journey time: 4 + 8 = 12 hours
- Triple the flight speed with Concorde to 1800 mph
  - Flight time: 2 hours 40 mins
    - But still need to spend 4 hours in airports
  - Total journey time = 2hrs 40 mins + 4 hours = 6 hrs 40 mins
    - Speedup of 1.8 not 3.0
- Amdahl's law!  $\alpha = 4/12 = 0.33$ ; max speedup = 3 (i.e. 4 hours)

# Flying London to Sydney



# Buckingham Palace to Sydney Opera

- By airplane
  - Distance: 14400 miles; speed: 600 mph; flight time; 24 hours
  - Serial overhead **stays the same**
    - total time:  $4 + 24 = 28$  hours
- Triple the flight speed
  - Total time = 4 hours + 8 hours = 12 hours
  - Speedup = 2.3 (as opposed to 1.8 for New York)
- Gustafson's law!
  - Bigger problems scale better
  - Increase **both** distance (i.e.  $N$ ) **and** max speed (i.e.  $P$ ) by three
  - Maintain same balance: 4 “serial” + 8 “parallel”

# Load imbalance

Keeping processors equally busy

# Load Imbalance

- These laws all assumed all processors are equally busy
  - But what happens if some run out of work?
- Specific case
  - Four people pack boxes with cans of soup: 1 minute per box

Person	Anna	Paul	David	Helen	Total
# boxes	6	1	3	2	12

- Takes 6 minutes as everyone is waiting for Anna to finish!
  - If we gave everyone same number of boxes, would take 3 minutes
- Scalability isn't everything
  - Make the best use of the processors at hand before increasing the number of processors

# Quantifying Load Imbalance

- Define Load Imbalance Factor

$$LIF = \text{maximum load} / \text{average load}$$

- For perfectly balanced problems  $LIF = 1.0$ , as expected
    - In general,  $LIF > 1.0$
  - $LIF$  tells you how much faster your calculation could be with balanced load
- 
- Box packing
    - $LIF = 6/3 = 2$
    - Initial time = 6 minutes
    - Best time = 6 minutes / 2 = 3 minutes

# Summary

# Summary

- There are many considerations when parallelising code
- A variety of patterns exist that can provide well known approaches to parallelising a serial problem
  - You will see examples of some of these during the practical sessions
- Scaling is important, as the more a code scales the larger a machine it can take advantage of
  - can consider weak and strong scaling
  - in practice, overheads limit the scalability of real parallel programs
  - Amdahl's law models these in terms of serial and parallel fractions
  - larger problems generally scale better: Gustafson's law
- Load balance is also a crucial factor
- Metrics exist to give you an indication of how well your code performs and scales