

Parallel design patterns

ARCHER course

Comparing parallel algorithms



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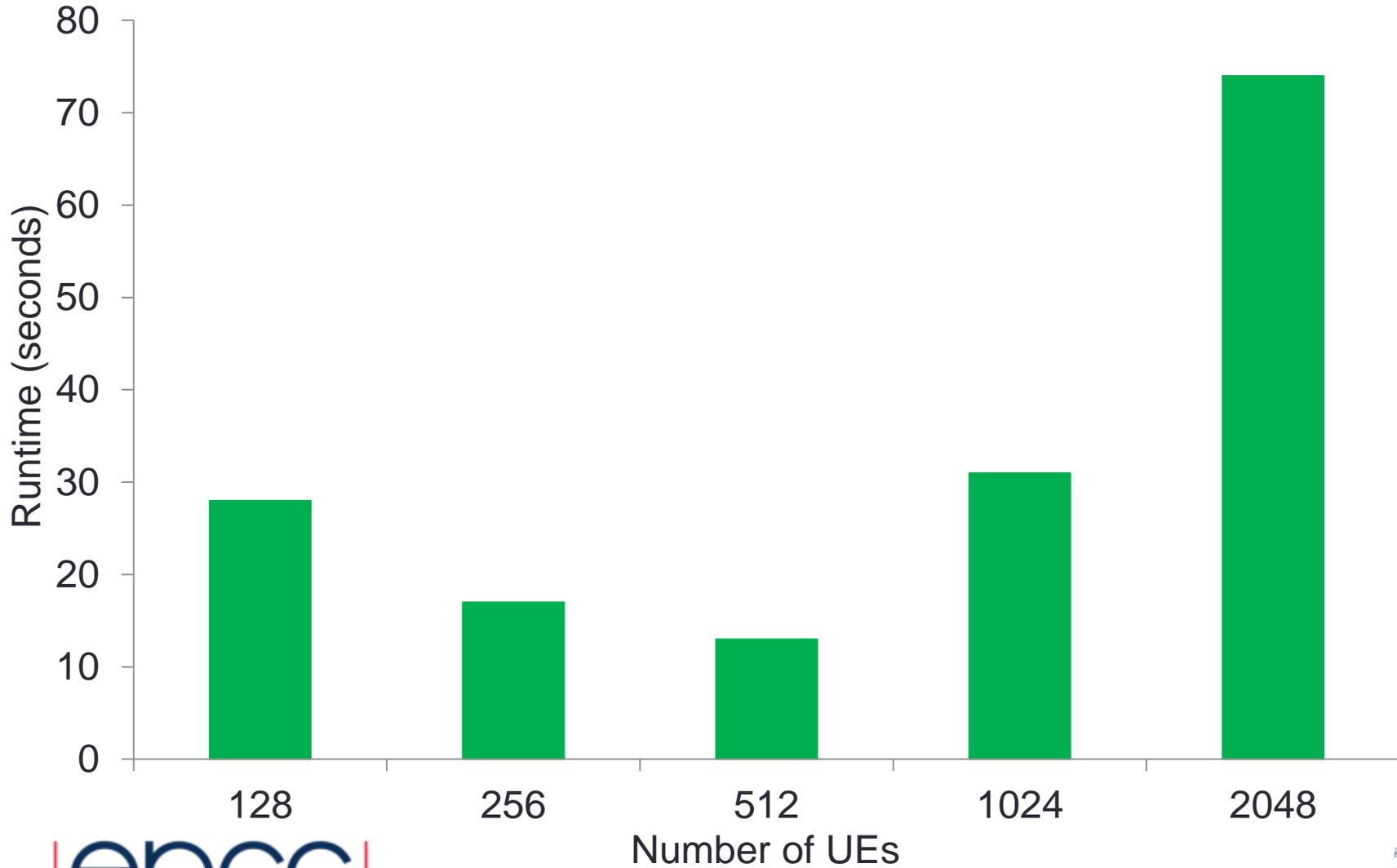
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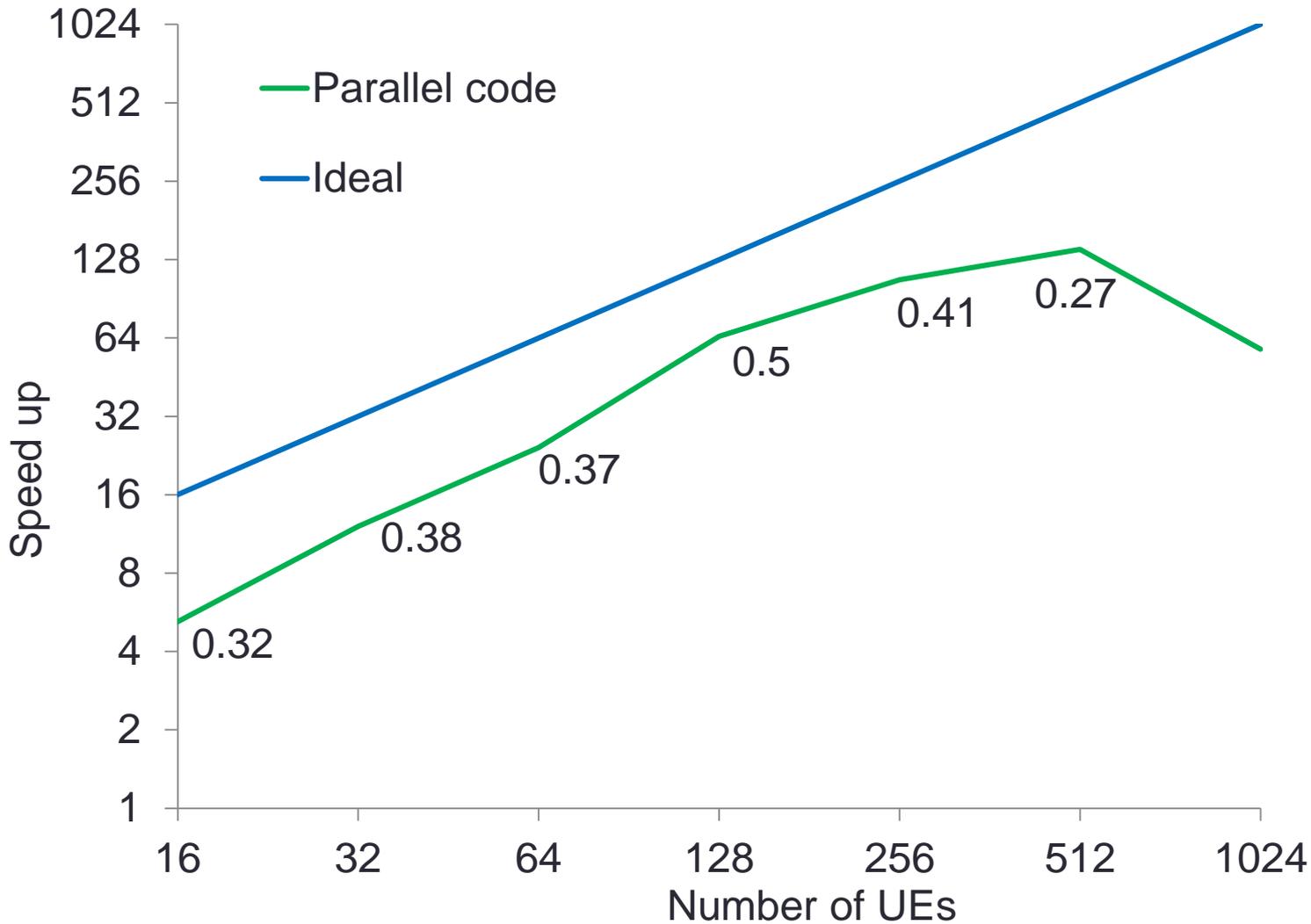
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What's the problem?



Speed up and parallel efficiency



$$S(n) = \frac{T_1}{T_n}$$

$$E(n) = \frac{S(n)}{P}$$

So what's the issue?

- Empirical studies are fine, but it requires an existing parallel code to benchmark and study
- Be careful what you claim, how many data points is enough to make certain claims?
- How can we predict performance and scalability at higher core counts or with certain modifications made to the algorithm?
- How much insight can we really get (i.e. where is my bottleneck?)

So how can we talk sensibly about parallel algorithms (i.e. compare them) without explicit measurement?

Amdahl's law

- A fraction, α , is completely serial

- Parallel runtime $T(N, P) = \alpha T(N, 1) + \frac{(1-\alpha)T(N, 1)}{P}$
 - Assuming parallel part is 100% efficient

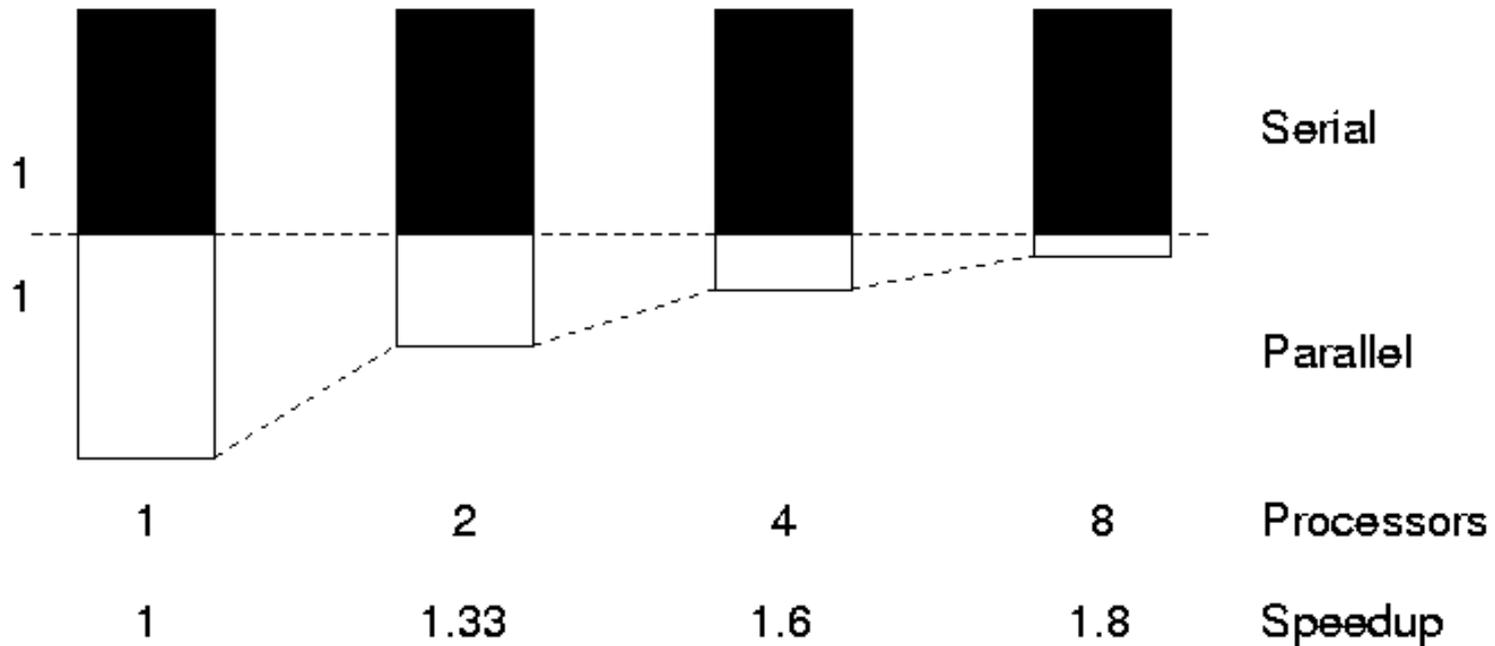
- Parallel speedup $S(N, P) = \frac{T(N, 1)}{T(N, P)} = \frac{P}{\alpha P + (1 - \alpha)}$

- 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 $\alpha = 0.1$; $S(N, 16) = 6.4$, $S(N, 1024) = 9.9$

The serial section of code

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

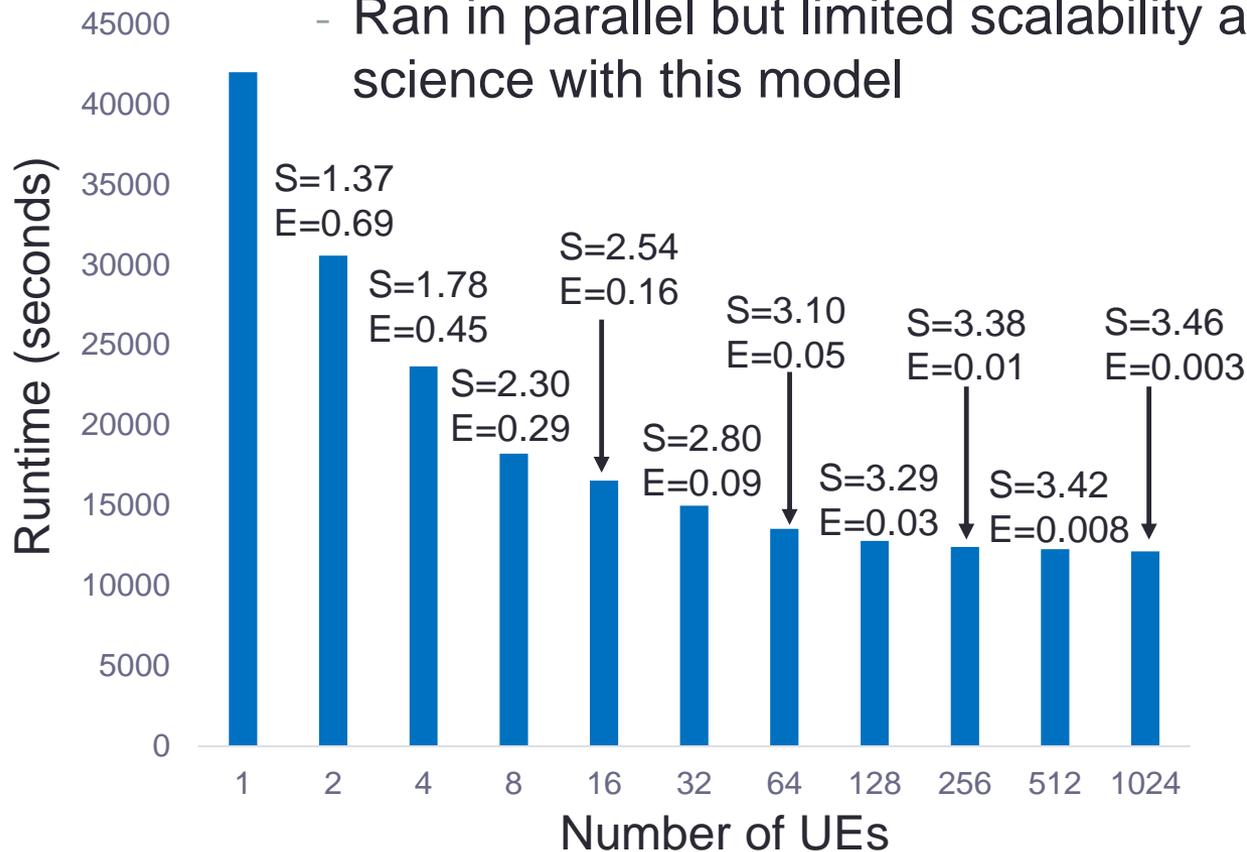
Gene Amdahl, 1967



eCSE project on BGS spline model

- Model for predicting the geomagnetic field lines of the earth

- Ran in parallel but limited scalability and wanted to do more science with this model



Algorithm time complexity examples

```
for (i=0;i<50;i++) {  
    result=result+a[0]  
}
```

$50 * (2 + 3 + 1) = O(1)$

```
for (i=0;i<n;i++) {  
    result=result+a[i]  
}
```

$n * (2 + 3 + 1) = O(n)$

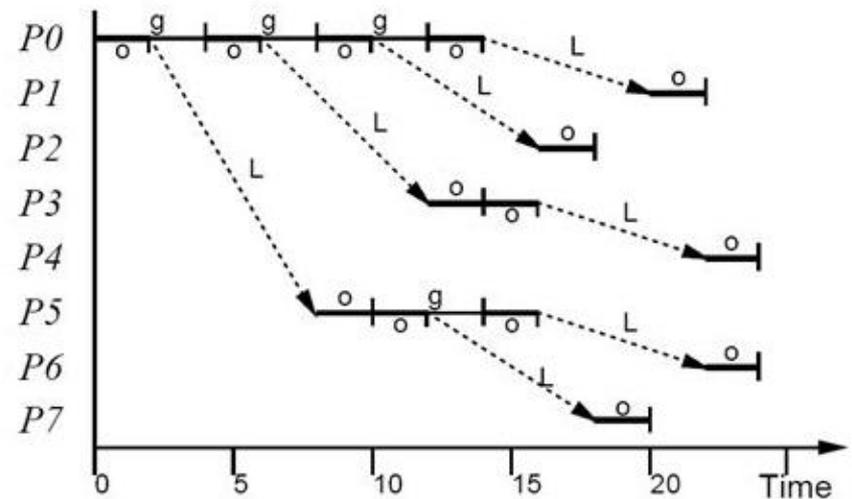
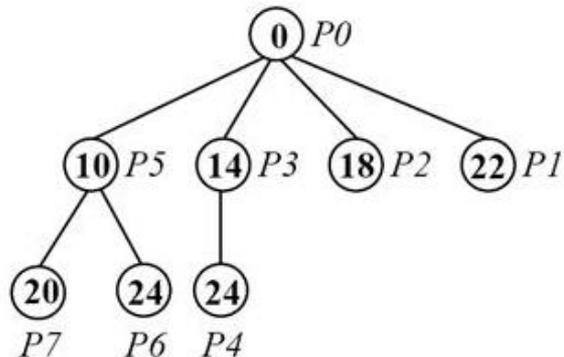
```
for (i=0;i<n;i++) {  
    for (j=0;j<n;j++) {  
        result=result+a[i]  
    }  
}
```

$n * (2 + n * (2 + 3 + 1)) = O(n*n) = O(n^2)$

- *Concerned with how the runtime grows as a function of the input size (n)*

But much more complex in the parallel world!

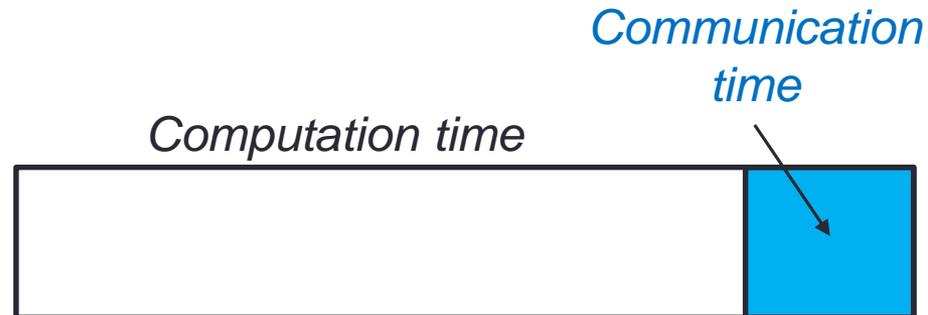
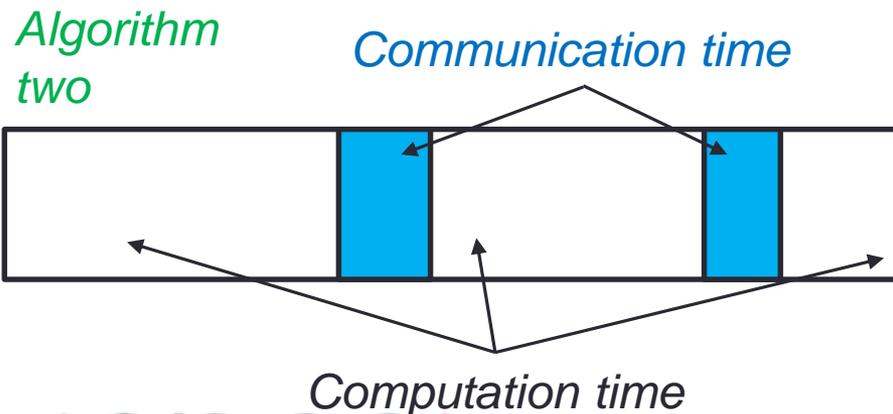
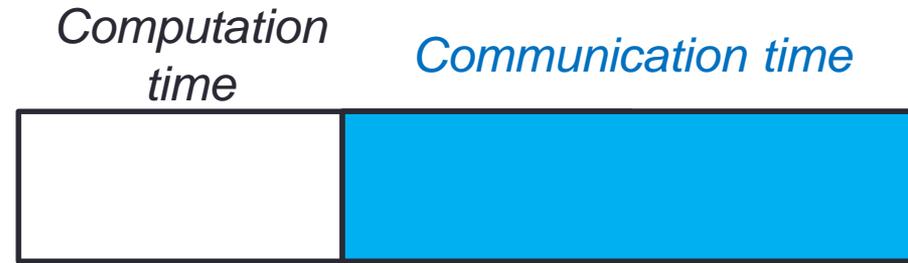
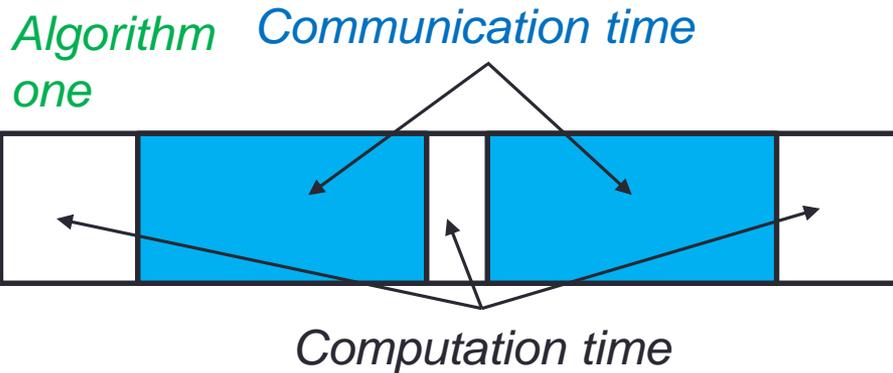
- A number of different ways of modelling this
- Log P is one common approach in the literature
 - L is the latency of the communication medium (cycles)
 - o is the overhead of sending and receiving messages (cycles)
 - g is the gap required between messages due to bandwidth limitations (cycles)
 - P is the number of UEs



Example taken from <http://slideplayer.com/slide/8123828/> where $P=8$, $L=6$, $g=4$, $o=2$

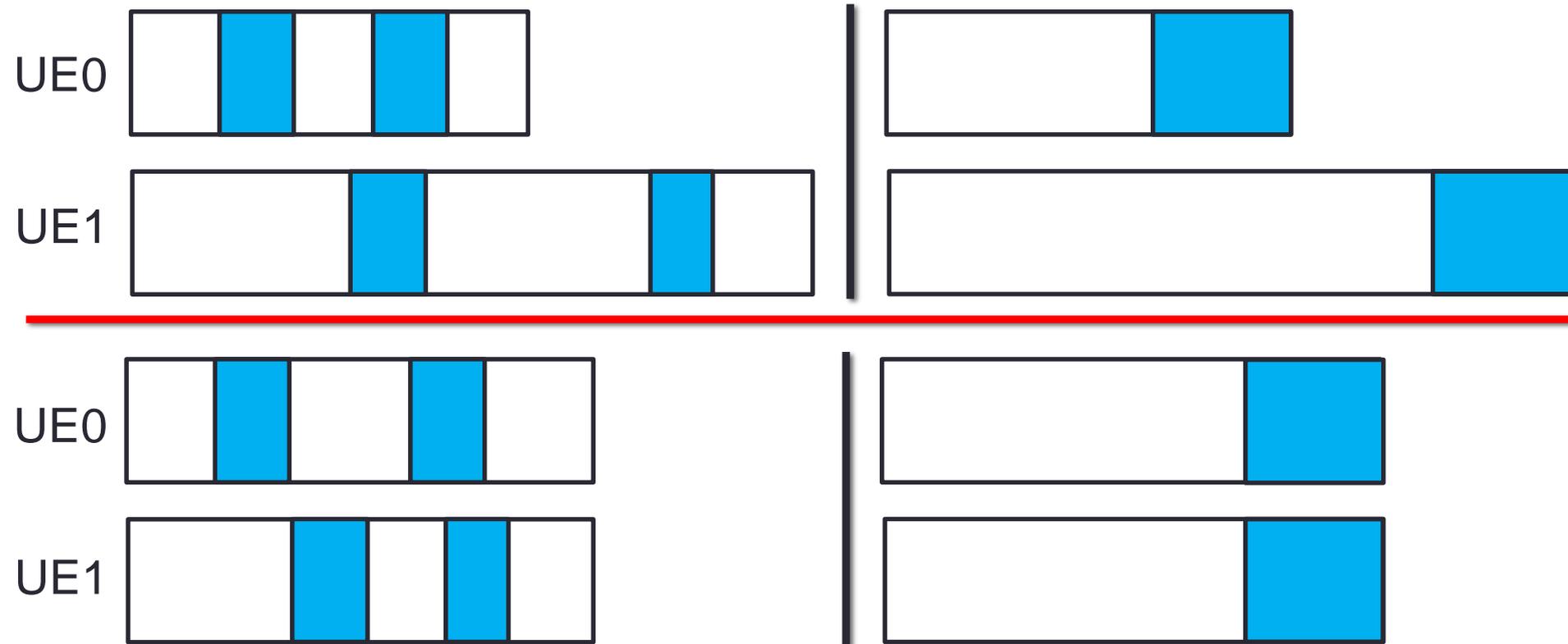
What are we looking to optimise

1. Communication to computation ratio



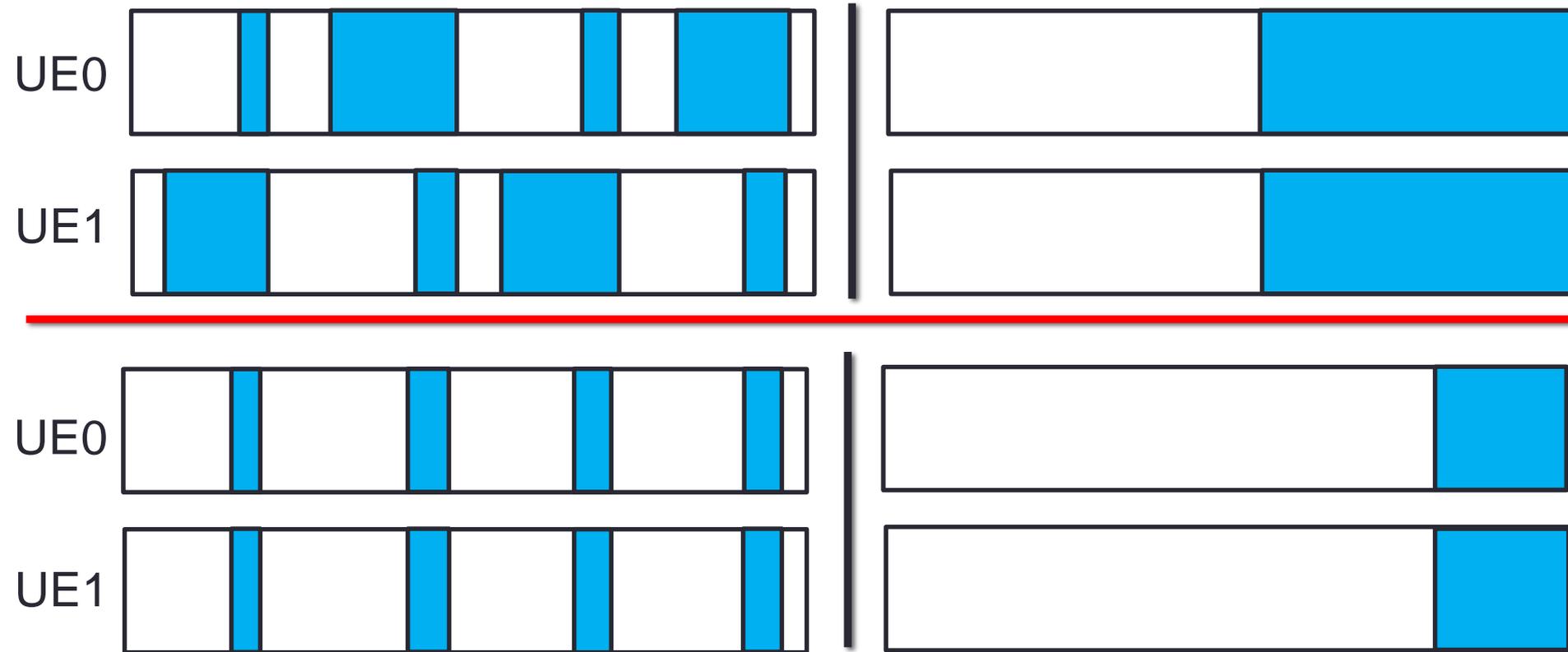
What are we looking to optimise

2. Load balance between processes

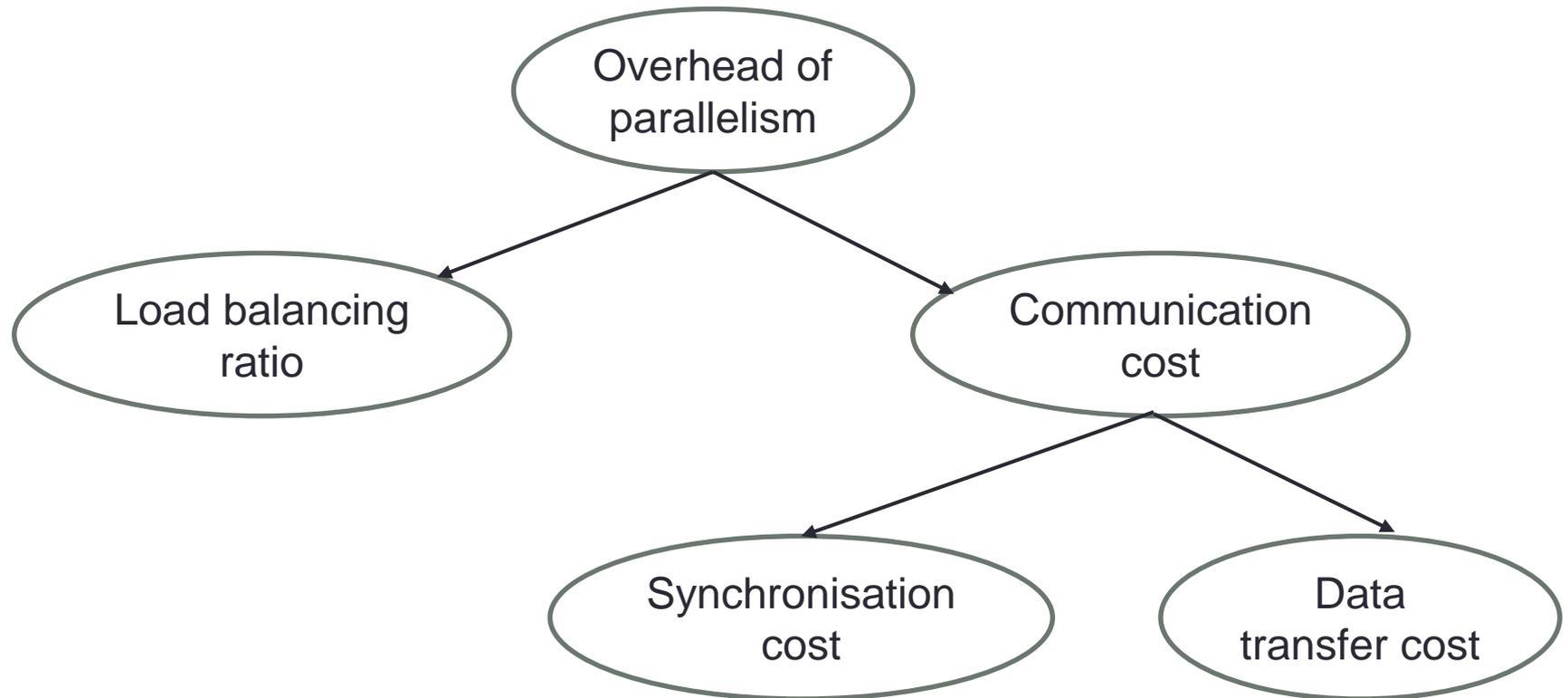


What are we looking to optimise

3. Synchronisation costs



Parallelism overhead



- Needs to be balanced against the computational complexity
- Need to consider code maintainability

Can be obvious from code

```
if (rank == 0) {  
    for (i=0;i<1000;i++) {  
        a[i]=.....  
    }  
    send a to rank 1  
    b=recv from rank 1  
}
```

```
if (rank == 1) {  
    b=recv from rank 0  
    for (i=0;i<100;i++) {  
        a[i]=.....  
    }  
    send a to rank 0  
}
```



A slight improvement....

```
if (rank == 0) {  
    for (i=0;i<1000;i++) {  
        a[i]=.....  
    }  
    send a to rank 1  
    b=recv from rank 1  
}
```

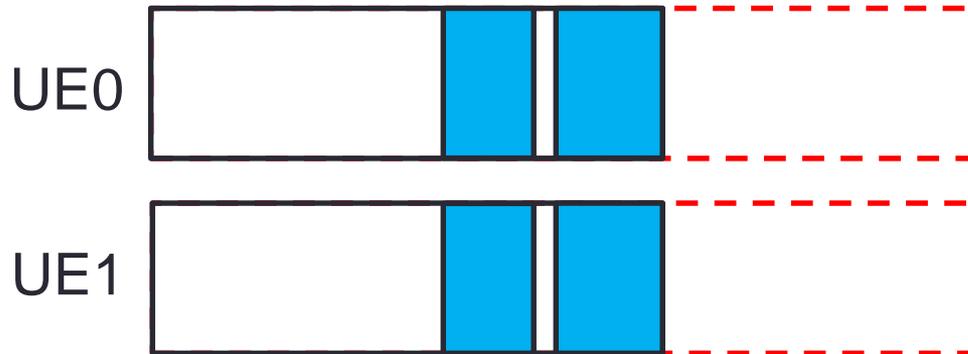
```
if (rank == 1) {  
    for (i=0;i<100;i++) {  
        a[i]=.....  
    }  
    b=recv from rank 0  
    send a to rank 0  
}
```



More of an improvement....

```
if (rank == 0) {  
    for (i=0;i<550;i++) {  
        a[i]=.....  
    }  
    send a to rank 1  
    b=recv from rank 1  
}
```

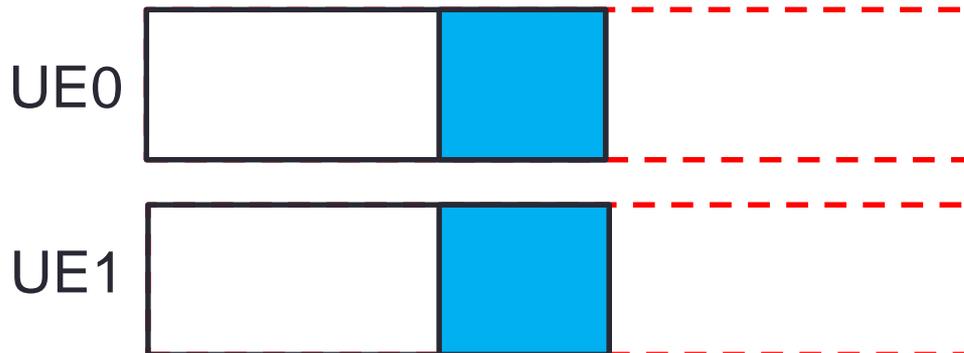
```
if (rank == 1) {  
    for (i=0;i<550;i++) {  
        a[i]=.....  
    }  
    b=recv from rank 0  
    send a to rank 0  
}
```



Potentially even better

```
if (rank == 0) {  
    b=nonblocking recv from rank 1  
    for (i=0;i<550;i++) {  
        a[i]=.....  
    }  
    nonblocking send a to rank 1  
    wait on all comms  
}
```

```
if (rank == 1) {  
    b=nonblocking recv from rank 0  
    for (i=0;i<550;i++) {  
        a[i]=.....  
    }  
    nonblocking send a to rank 0  
    wait on all comms  
}
```

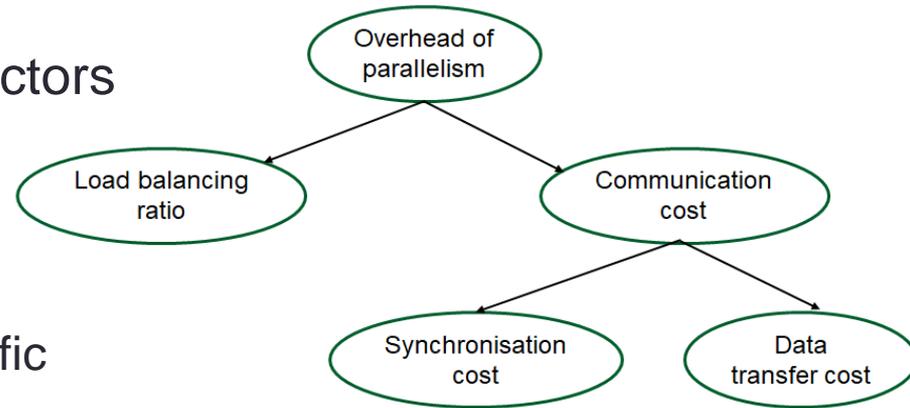


Still requires expertise.....

- Algorithm analysis is not simple and requires programmer insight & reasoning

- There are very many contributing factors

- Machine specific factors
- Compiler optimisations
- Underlying libraries and runtime
- Interconnect and current network traffic
- The time of day and year



- Theoretical ways can be unwieldy in practice, so often intuition is needed

- Consider what the overhead of parallelism is and how to reduce it

But we don't get this for free!

- Efficiency
 - Speed, memory, storage
- Scalability
 - Large machines, large problems
- Simplicity of the code
 - Development, debugging, verification, modification, maintenance
- Portability
 - Software nearly always outlives its original target platform
- There is rarely *one right answer* and a good design often boils down to a number of *tradeoffs*
- Parallel optimisations can increase sequential time complexity