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Speedup: Amdahl's Law

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Amdahl's Law reveals a natural upper bound on the speedup that is theoretically possible even before we add in implementation overheads

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We still have the 10% sequential part

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Speedup: Amdahl's Law

So the speedup is

$$S_\infty = \frac{\text{time on a sequential processor}}{\text{time on parallel processors}} = \frac{100}{10} = 10$$

A speedup of 10 even on an infinite number of processors

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A speedup of 10 even on an infinite number of processors

It doesn't even matter what the problem is, or what hardware we have

This is Amdahl's Law:

> *Every program has a natural limit on the maximum speedup it can attain, regardless of the number of processors used*

Analysis

Speedup: Amdahl's Law

We can quantify Amdahl's Law:

Let $T = T_{\text{seq}} + T_{\text{par}}$ be the time spent in the sequential and parallel parts of our problem on a sequential processor

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Let $T = T_{\text{seq}} + T_{\text{par}}$ be the time spent in the sequential and parallel parts of our problem on a sequential processor

Then the *maximum* speedup S_p using p processors on the parallel part is

$$S_p \leq \frac{T_{\text{seq}} + T_{\text{par}}}{T_{\text{seq}} + T_{\text{par}}/p}$$

where we have perfectly parallelised the parallel part

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This limit is determined by the time taken in the sequential part of the computation

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Speedup: Amdahl's Law

To see this consider the fraction $x = T_{\text{seq}}/(T_{\text{seq}} + T_{\text{par}})$ which is the proportion of the sequential part within the whole

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And so

$$S_\infty \leq \frac{1}{x}$$

is bounded

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All Amdahl says is that an upper limit exists

Your program may not get anywhere close to that limit and often in real programs, does not

Analysis

Speedup: Amdahl's Law

In real programs, there are many other factors that affect speedup, so that the speedup may well vary all over the place as p increases

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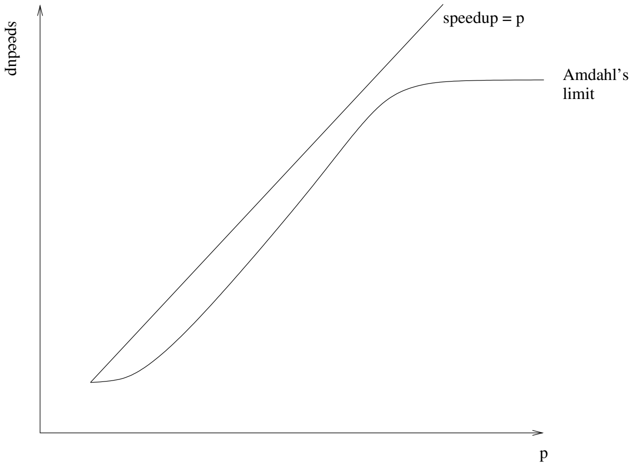
In real programs, there are many other factors that affect speedup, so that the speedup may well vary all over the place as p increases

It can even decrease as p gets larger

Analysis

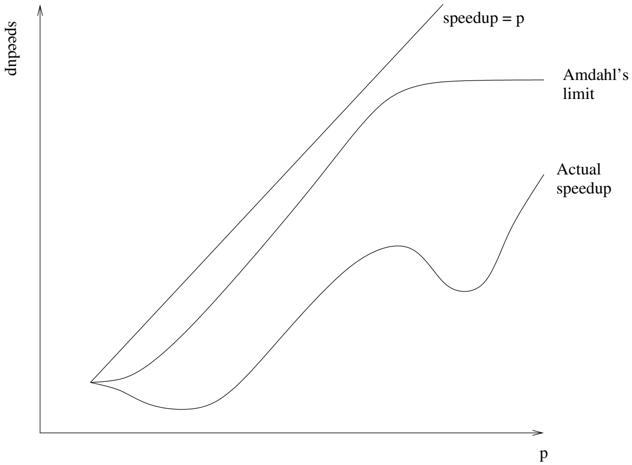
Speedup: Amdahl's Law



Speedup in theory

Analysis

Speedup: Amdahl's Law



Speedup in practice

Analysis

Speedup: Amdahl's Law

To emphasize: all we know is that actual speedup is below Amdahl's limit

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Exercise Show that if $0 \leq x \leq 1$, then

$$\frac{1}{x + (1 - x)/p} \leq p$$

Exercise What is the maximum speedup of a program that is 100% sequential?

Analysis

Speedup: Gustafson's Law

Amdahl's law is real: there is a natural limit on speedup *for a given problem*

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Gustafson's Law (occasionally called *Gustafson-Barsis's Law*) gives us another limit

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Speedup: Gustafson's Law

Suppose we have a problem of size n

$$S_p(n) \leq \frac{1}{x_n + (1 - x_n)/p}$$

where $S_p(n)$ is the speedup on p processors for a problem of size n; x_n is the fraction of the computation spent sequentially

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So

$$S_p(\infty) \leq p$$

i.e., we now get a speedup limit that is the "perfect" speedup p — on an infinitely sized problem

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Speedup: Amdahl's Law, Gustafson' Law

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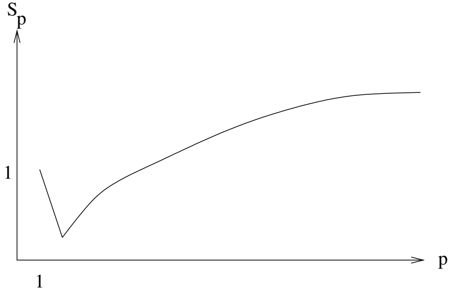
This should convince you that even a simple measure like speedup can be problematic!

But it does re-emphasise the fact that parallelism is not about making things faster, but about making things larger

Analysis

Speedup

Speedup is a simple measure, often proving that your parallel program is slower than it ought to be



Typical speedup curve

Sometimes it takes p to be surprisingly large before you even catch up with the uniprocessor time with $S_p = 1$ (sometimes never!)

Analysis

Speedup

Very common is the low start, a modest increase, then a tailing off

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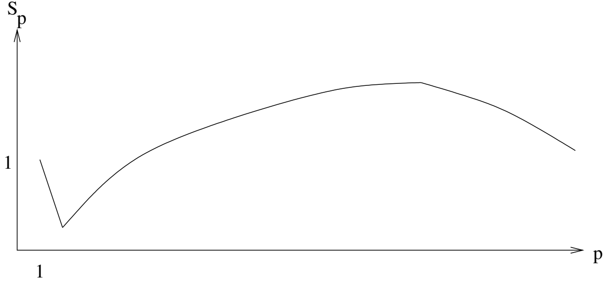
But taking it further



Adding more processors

We might eventually find adding processors makes it slower!

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Speedup

This is usually due to increased communications between the processors adding more overhead but not more speedup, perhaps due to Amdahl

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Of course, these are only typical behaviours: a given program may behave quite differently from all of this

Exercise Consider what might be the difference between a sequential implementation of something and a parallel implementation running on one processor

Analysis

Superlinear Speedup

You will get used to seeing $S_p < p$

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This can happen for a variety of reasons, some technological, and some more philosophical

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Superlinear Speedup

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Of course, this takes a certain kind of low-communication, easily dividable problem to work; and the right hardware

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(This helps with cache coherence!)

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Here is an example to illustrate the issue

We have bubblesort running on a uniprocessor: we wish to make it run on a parallel machine

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Superlinear Speedup

One way of doing this is:

- split the data into equal halves
- bubblesort each half in parallel
- merge the two sorted lists together

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Depending on the number of processors we have, we can keep recursively dividing

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So bubblesorting the two halves (in parallel) takes time

$$(n/2)^2/2 + O(n/2) = n^2/8 + O(n)$$

Analysis

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Merging n values takes $O(n)$, giving a total of

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What is happening?

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Time to bubblesort halves: $2 \times (n^2/8 + O(n)) = n^2/4 + O(n)$; time to merge $O(n)$; total $n^2/4 + O(n)$

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So we win even on a uniprocessor

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Merge sort has complexity $O(n \log n)$

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It may not always be possible to have a suitable parallel version of an algorithm: in such a case “speedup” is not meaningful

In most real cases we don’t get this effect, but it’s worth being aware that it can happen

Analysis

Speedup

Some people go further and define speedup as

$$S_p = \frac{\text{time of the best possible sequential algorithm}}{\text{time on } p \text{ parallel processors}}$$

but this has its own problems, not least that we might not know the best possible sequential way of doing things

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And we now might be comparing two completely unrelated algorithms

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So, again, we are not really comparing like with like

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You would need to ensure each run had the same randomness to be properly comparable; or run many times and take an average time

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Other problems fare less well — in terms of speed — from parallelisation!