Advanced R Programming - Lecture 6

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Today

Questions since last time?

Writing fast code

Speed is important!

Writing fast code

Speed is important!

Time to write code

Writing fast code

Speed is important!

Time to write code
Time to maintain (understand) code

Writing fast code

Speed is important!

Time to write code
Time to maintain (understand) code
Time to execute code

Old Adage About Software

"You can have it Good, Fast, Cheap. Pick any two."

Performance

1. Performance
2. Complexity

Complexity affects performance...

Performance

1. Performance
2. Complexity

Complexity affects performance...

...but performance does'nt affect complexity

Computational complexity

Theoretical worst case

Big-Oh notation

Basic operations

Relationship: operations to problem size

Big Oh

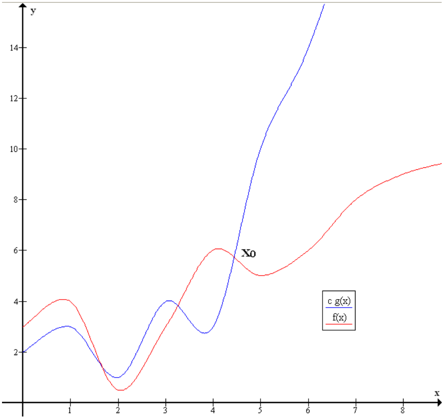
"How fast does a function grow?"

$$f(n) = O(g(n))$$

$$|f(n)| \leq C * |g(n)| \forall n > X_0$$

n number of operations

Big Oh



Big Oh

Example

$$f(n) = n^2 + 100n + 100$$

Big Oh

Example

$$f(n) = n^2 + 100n + 100$$

$$f(n) = O(n^2)$$

Complexities

Big Oh	Name	Example
$O(1)$	constant	assignments
$O(log(N))$	logarithmic	binary search (of sorted input)
$O(N)$	linear	max
$O(N^2)$	quadratic	naive vector-matrix mult.
$O(N^c)$	polynomial	naive matrix-matrix mult.
$O(c^n)$	exponential	brute force cracking of password

Determine complexity

```
statement 1
statement 2
...
statement c
```

$O(1)$

Determine complexity

```
if(a)
  statement a
else
  statement b
```

max(O(a),O(b))

Determine complexity

```
for(i in 1:N)
  statement i
```

O(n)

Determine complexity

```
for(i in 1:N)
  for (j in 1:M)
    statement i,j
```

O(M * N)

Determine complexity

```
for(i in 1:N)
  g(i)
```

$$g(n) = O(n^2)$$

$$O(n^3)$$

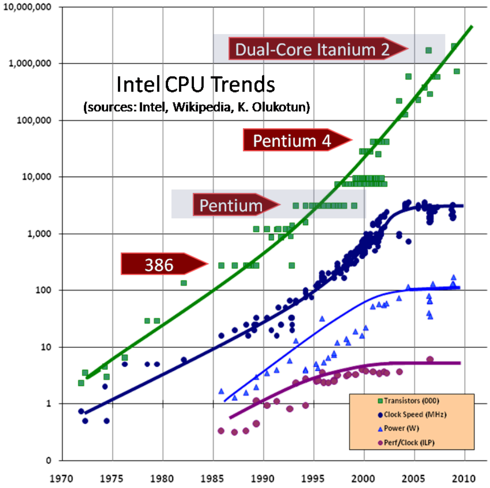
What is parallelism?

Multiple cores

Each core work with its own part

Cores can exchange information

Why parallelism?



Why parallelism?

Single core limits

Handling larger data

Solving problems faster

More and more important

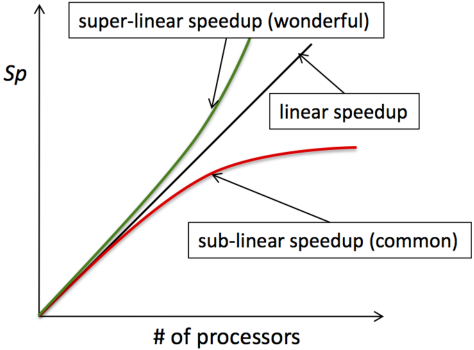
Types of parallelism

Multicore systems

Distributed systems

Graphical processing units (GPU)

Speedup



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Theoretical limits

Strong scaling: Amdahl's law

Weak scaling: Gustafsons law

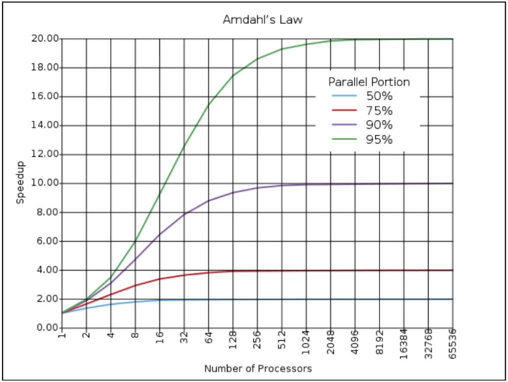
Amdahl's law

$$S_p = \frac{1}{f_s + \frac{f_p}{P}}$$

Where:

$$f_s = \text{serial fraction of code}$$
$$f_p = \text{serial fraction of code}$$
$$P = \text{number of cores}$$

Amdahl's law



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Gustafsons law

$$S_p = P - \alpha * (P - 1)$$

Where:

$\alpha =$ the largest non-parallelizable fraction of any parallel process
$P =$ number of cores

Practical problems

Costs of parallelism

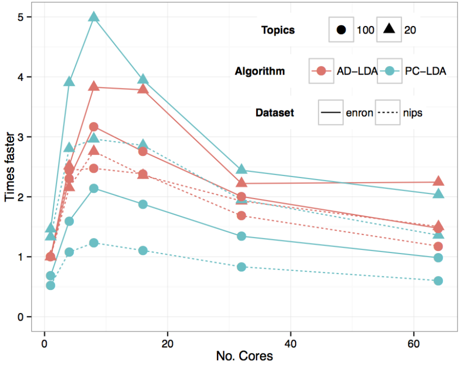
communication

load balancing

scheduling

fine-grained vs embarrassingly parallel

Practical problems



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Donald E. Knuth on Optimization

Programmers waste enormous amounts of time thinking about, or worrying about, the speed of noncritical parts of their programs, and these attempts at efficiency actually have a strong negative impact when debugging and maintenance are considered.
- Donald E. Knuth

Performance

Depends on many things

1. Code
2. Complexity
3. Compiler
4. Hardware
5. Language

If you don't measure, you don't optimize!

How to optimize

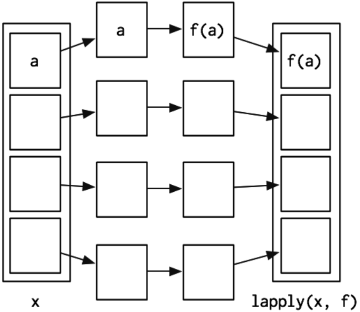
1. Write code that works with accompanying test suite
2. Profile your code for bottlenecks
3. Try to eliminate the bottle necks
4. Redo 2-3 until fast enough

Improvements

1. Look for existing solutions.
2. Do less work.
3. Vectorise.
4. Parallelize.
5. Avoid copies.

Parallelism in R

Based on lapply()



parallel package

Two approaches:

1. mclapply()
2. parLapply()

mclapply()

Pros

Simple to use

Low overhead (startup)

Cons

Do not work with windows

Only multicore

parLapply(type="psock")

Pros

Works everywhere

Good for testing/developing

Cons

Slow on multiple nodes

parLapply(type="mpi")

Pros

Good for multiple computers Good for production

Cons

Can be used interactively Needs Rmpi package

Example

example

Rcpp

Using C++ code in R

Need C++ compiler (look here)

Often called interfacing

Similar can be done with Java and Fortran

Extremely fast!

But just handle bottlenecks!

Fibonacci

$$f(n) = \begin{cases} n, & \text{if } n < 2 \\ F(n-1) + F(n-2), & \text{otherwise} \end{cases}$$

Fibonacci R

```
fr <- function(n) {
        if (n < 2) return(n)
        f(n-1) + f(n-2)
}
```

```
system.time(fr(30))
user   system elapsed
2.246   0.171   2.451
```

Fibonacci C++

```
library(Rcpp)

cppFunction(code = '
  int fcpp(int n) {
    if (n < 2) return(n);
    return(fcpp(n-1) + fcpp(n-2));
  }
')

system.time(fcpp(30))
user        system      elapsed
0.007000000 0.000000000 0.006999999
```

Memoization

A simple optimization technique

Store results of function calls

If called again, returns old value

Depend on functional programming

Memoise in R

```
> library(memoise)
> a <- function(x) runif(1)
> replicate(3, a())
[1] 0.6709919 0.3490709 0.4772027
> b <- memoise(a)
> replicate(3, b())
[1] 0.1867441 0.1867441 0.1867441
```

Memoise in R

```
> c <- memoise(function(x) {Sys.sleep(1); runif(1)})
> system.time(print(c()))
[1] 0.7816399
user  system elapsed
0.003   0.004   1.001
> system.time(print(c()))
[1] 0.7816399
user  system elapsed
0.001   0.000   0.000
> forget(c)
[1] TRUE
> system.time(print(c()))
[1] 0.9234995
user  system elapsed
0.003   0.004   1.001
```

The End... for today.

Questions?

See you next time!