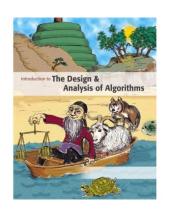




Introduction to

Algorithm Design and Analysis

[2] Asymptotics



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In the Last Class...

- Algorithm the spirit of computing
 - Model of computation
- Algorithm design and analysis
 - o Design
 - Correctness proof by induction
 - o Analysis
 - Worst-case / average-case complexity



Asymptotic Behavior

- Asymptotic growth rate of functions
 - o Basic idea
- Key notations
 - \circ O, Ω, Θ
 - \circ 0, ω
- Brute force enumeration
 - o By iteration
 - o By recursion

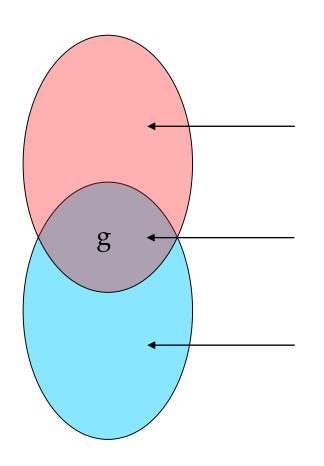


How to Compare Two Algorithms

- Algorithm analysis, with simplifications
 - Measuring the cost by the number of critical operations
 - o Large input size only
 - Only the leading term in f(n) is considered
 - Constant coefficients are ignored
- Capturing the essential part in the cost in a mathematical way
 - o Asymptotic growth rate of f(n)



Relative Growth Rate



 Ω (g):functions that grow at least as fast as g

 Θ (g):functions that grow at the same rate as g

O(g):functions that grow no faster as g



"Big Oh"

- Basic idea $f(n) \in O(g(n))$
 - For sufficiently large input size, g(n) is an upper bound for f(n)
- Definition " εN "
 - o Giving g: N→R⁺, then O(g) is the set of f:N→R⁺, such that for some c∈R⁺ and some n_0 ∈N, f(n)≤cg(n) for all n≥ n_0
- Definition " $lim_{n\to\infty}$ "

o
$$f \in O(g)$$
 if $\lim_{n \to \infty} \frac{f(n)}{g(n)} = c < \infty$



Example

• Let f(n)=n², g(n)=nlogn, then: L'Hospital's rule



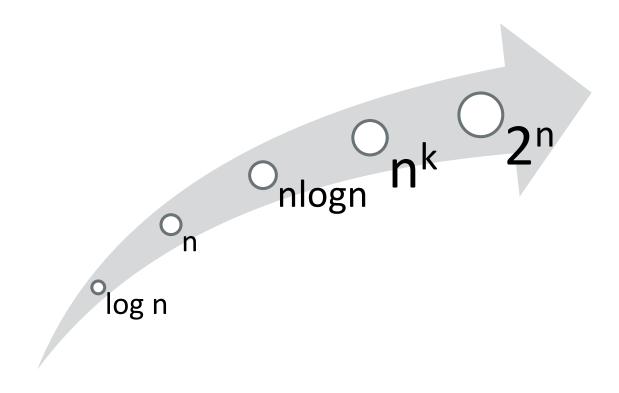
o f∉O(g), since

$$\lim_{n \to \infty} \frac{n^2}{n \log n} = \lim_{n \to \infty} \frac{n}{\log n} = \lim_{n \to \infty} \frac{1}{\frac{1}{n \ln 2}} = +\infty$$

o g∈O(f), since

$$\lim_{n \to \infty} \frac{n \log n}{n^2} = \lim_{n \to \infty} \frac{\log n}{n} = \lim_{n \to \infty} \frac{1}{n \ln 2} = 0$$

Asymptotic Growth Rate





Asymptotic Order

- Logarithm log n $log n \in O(n^{\alpha})$ for any $\alpha > 0$
- Power n^k

$$n^k \in O(c^n)$$
 for any $c>1$

• Factorial *n!*

$$n! \approx \sqrt{2\pi n} \left(\frac{n}{e}\right)^n$$
 (Stirling's formula)

"Big Ω "

- Basic idea of $f(n) \in \Omega(g(n))$
 - o Dual of "O"
- Definition " εN "
 - o Giving g: N→R⁺, then $\Omega(g)$ is the set of f:N→R⁺, such that for some $c \in R^+$ and some $n_0 \in N$, $f(n) \ge cg(n)$ for all $n \ge n_0$
- Definition " $lim_{n\to\infty}$ "
 - o $f \in \Omega(g)$ if $\lim_{n \to \infty} \frac{f(n)}{g(n)} = c > 0$ (the limit may be ∞)



- Basic idea of $f(n) \in \Theta(g(n))$
 - o Roughly the same

$$\circ \Theta(g) = O(g) \cap \Omega(g)$$

- Definition " εN "
 - o Giving $g: N \to R^+$, then $\Theta(g)$ is the set of $f: N \to R^+$, such that for some $c_1, c_2 \in R^+$ and some $n_0 \in N$,

$$0 \le c_1 g(n) \le f(n) \le c_2 g(n)$$
, for all $n \ge n_0$

• Definition – " $lim_{n\to\infty}$ "

o
$$f \in \Theta(g)$$
 if $\lim_{n \to \infty} \frac{f(n)}{g(n)} = c \ (0 < c < \infty)$



Some Empirical Data

algorithm		1	2	3	4
Run time in <i>ns</i>		1.3 <i>n</i> ³	10 <i>n</i> ²	47 <i>n</i> log <i>n</i>	48 <i>n</i>
time for size	10 ³ 10 ⁴ 10 ⁵ 10 ⁶ 10 ⁷	1.3s 22m 15d 41yrs 41mill	10ms 1s 1.7m 2.8hrs 1.7wks	0.4ms 6ms 78ms 0.94s 11s	0.05 <i>ms</i> 0.5 <i>ms</i> 5 <i>ms</i> 48m <i>s</i> 0.48 <i>s</i>
max Size in time	sec min hr day	920 3,600 14,000 41,000	10,000 77,000 6.0×10 ⁵ 2.9×10 ⁶	1.0×10 ⁶ 4.9×10 ⁷ 2.4×10 ⁹ 5.0×10 ¹⁰	2.1×10 ⁷ 1.3×10 ⁹ 7.6×10 ¹⁰ 1.8×10 ¹²
time for 10 times size		×1000	×100	×10+	×10

on 400Mhz Pentium II, in C

from: Jon Bentley: *Programming Pearls*



Properties of O, Ω and Θ

- Transitive property:
 - o If f∈O(g) and g∈O(h), then f∈O(h)
- Symmetric properties
 - o $f \in O(g)$ if and only if $g \in \Omega(f)$
 - $\circ f \in \Theta(g)$ if and only if $g \in \Theta(f)$
- Order of sum function
 - $\circ O(f+g)=O(\max(f,g))$

"Little Oh"

- Basic idea of $f(n) \in o(g(n))$
 - o Non-ignorable gap between f and its upper bound g
- Definition –" εN "
 - o Giving $g:N \to R^+$, then o(g) is the set of $f:N \to R^+$, such that for any c∈ R^+ , there exists some $n_0 \in N$,

$$0 \le f(n) < cg(n)$$
, for all $n \ge n_0$

• Definition – " $lim_{n\to\infty}$ "

$$\circ f \in o(g) \text{ if } \lim_{n \to \infty} \frac{f(n)}{g(n)} = 0$$

"Little ω"

- Basic idea of $f(n) \in \omega(g(n))$
 - o Dual of "o"
- Definition " εN "
 - o Giving $g:N \to R^+$, then $\omega(g)$ is the set of $f:N \to R^+$, such that for any c∈ R^+ , there exists some $n_0 \in N$,

$$0 \le cg(n) < f(n)$$
, for all $n \ge n_0$

• Definition – " $lim_{n\to\infty}$ "

o
$$f \in \omega(g)$$
 if $\lim_{n \to \infty} \frac{f(n)}{g(n)} = \infty$

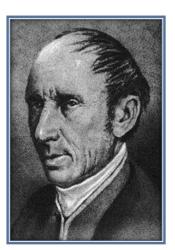
Do you know Infinity

Mathematical analysis

(Differentiation / integration)

- o Early years
- Firm foundationof mathematical analysis





- How to talk about infinity?
 - o (εN) -definition
 - $\circ (\varepsilon \delta)$ -definition

Weierstrass





Brute Force Enumeration by Iteration

- Swapping array elements
 - o <time, space>
 - From $<O(n^2)$, O(1)>
 - To <O(n), O(n)>
 - To <O(n), O(1)>
- Maximum subsequence sum
 - o Time
 - From O(n³)
 - To $O(n^2)$
 - To O(n log n)
 - To O(n)



Swapping Array Elements

- E.g., $1,2,3,4 \mid 5,6,7 \Rightarrow 5,6,7,1,2,3,4$
- Brute force

Space sensitive

	Time	Space
BF1	O(n²)	O(1)
BF2	O(n)	O(n)
Your Task	O(n)	O(1)

Your task

Time sensitive

o Both time and space efficient



Max-sum Subsequence

• The problem: Given a sequence *S* of integer, find the largest sum of a consecutive subsequence of *S*. (0, if all negative items)

```
o An example: -2, 11, -4, 13, -5, -2; the result 20: (11, -4, 13)
A brute-force algorithm:
                                                                    the sequence
MaxSum = 0;
 for (i = 0; i < N; i++)
  for (j = i; j < N; j++)
                                   i=0
   ThisSum = 0;
                                        i=1
   for (k = i; k \le j; k++)
   ThisSum += A[k];
                                            i=2
   if (ThisSum > MaxSum)
    MaxSum = ThisSum;
                                 in O(n^3)
 return MaxSum;
                                                                      i=n-1
```



More Precise Complexity

The total cost is:
$$\sum_{i=0}^{n-1} \sum_{j=i}^{n-1} \sum_{k=i}^{j} 1$$

$$\sum_{i=1}^{j} 1 = j - i + 1$$

$$\sum_{j=i}^{n-1} (j-i+1) = 1+2+\ldots+(n-i) = \frac{(n-i+1)(n-i)}{2}$$

$$\sum_{i=0}^{n-1} \frac{(n-i+1)(n-i)}{2} = \sum_{i=1}^{n} \frac{(n-i+2)(n-i+1)}{2}$$

$$= \frac{1}{2} \sum_{i=1}^{n} i^{2} - (n + \frac{3}{2}) \sum_{i=1}^{n} i + \frac{1}{2} (n^{2} + 3n + 2) \sum_{i=1}^{n} 1$$

$$=\frac{n^3+3n^2+2n}{6}$$

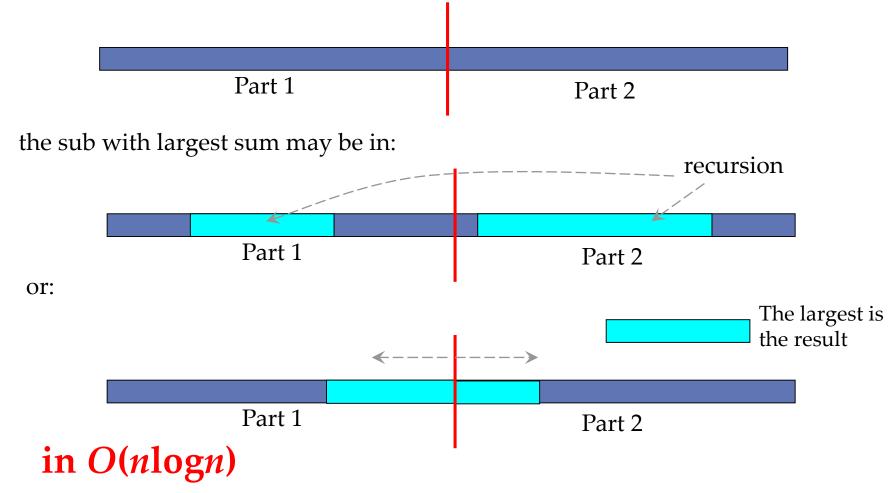


Decreasing the number of loops

```
An improved algorithm
MaxSum = 0;
 for (i = 0; i < N; i++)
                                                             the sequence
  ThisSum = 0;
                              i=0
  for (j = i; j < N; j++)
                                   i=1
                                        i=2
   ThisSum += A[j];
   if (ThisSum > MaxSum)
    MaxSum = ThisSum;
                             in O(n^2)
                                                                    i=n-1
 return MaxSum;
```



Power of Divide and Conquer





Power of Divide and Conquer

```
Center = (Left + Right) / 2;
MaxLeftSum = MaxSubSum(A, Left, Center); MaxRightSum = MaxSubSum(A, Center + 1,
Right);
 MaxLeftBorderSum = 0; LeftBorderSum = 0;
for (i = Center; i >= Left; i--)
 LeftBorderSum += A[i];
 if (LeftBorderSum > MaxLeftBorderSum) MaxLeftBorderSum = LeftBorderSum;
                                                     Note: this is the core part of
 MaxRightBorderSum = 0; RightBorderSum = 0;
                                                     the procedure, with base case
for (i = Center + 1; i <= Right; i++)
                                                     and wrap omitted.
  RightBorderSum += A[i];
 if (RightBorderSum > MaxRightBorderSum) MaxRightBorderSum = RightBorderSum;
return Max3(MaxLeftSum, MaxRightSum,
     MaxLeftBorderSum + MaxRightBorderSum);
```

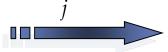


A Linear Algorithm

First scan the array to eliminate the case of "all negative integers"

```
ThisSum = MaxSum = 0;
for (j = 0; j < N; j++)
{
  ThisSum += A[j];
  if (ThisSum > MaxSum)
    MaxSum = ThisSum;
  else if (ThisSum < 0)
    ThisSum = 0;
}
return MaxSum;
```

the sequence



This is an example of "online algorithm"

in O(n)

Negative item or subsequence cannot be a prefix of the subsequence we want.



Brute Force Enumeration by Recursion

Job scheduling

- o Problem definition
- o Brute force recursion
- o Further improvements

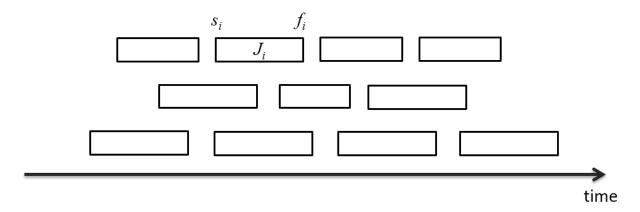
• Matrix chain multiplication

- o Problem definition
- Brute force recursion(s)
- o Further improvements



Job Scheduling

- Jobs: $J_i = [s_i, j_i]$
- Max number of compatible jobs
- Further improvements
 - o Dynamic programming (L16)
 - o Greedy algorithms (L14)



Matrix Chain Multiplication

• The task:

Find the product: $A_1 \times A_2 \times ... \times A_{n-1} \times A_n$ A_i is 2-dimentional array of different legal size

The Challenge:

- o Matrix multiplication is associative
- Different computing order results in great difference in the number of operations

The problem:

Which is the best computing order



Cost of Matrix Multiplication

$$C_{i,j} = \sum_{k=1}^{q} a_{ik} b_{kj} \begin{subarray}{ll} An example: $A_1 \times A_2 \times A_3 \times A_4$ \\ 30 \times 1 & 1 \times 40 & 40 \times 10 & 10 \times 25 \\ ((A_1 \times A_2) \times A_3) \times A_4 : & 20700 \text{ multiplications} \\ A_1 \times (A_2 \times (A_3 \times A_4)) : & 11750 \\ (A_1 \times A_2) \times (A_3 \times A_4) : & 41200 \\ A_1 \times ((A_2 \times A_3) \times A_4) : & 1400 \\ \hline \end{subarray}$$

C has $p \times r$ elements as $c_{i,j}$

So, pqr multiplications altogether



Solutions

- Brute force recursion (L16)
 - o BF1
 - o BF2

- Dynamic programming (L16)
 - o Based on brute force recursion 2



Thank you!

Q & A

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