Introduction to

Algorithm Design and Analysis

[02] Asymptotics

Jingwei Xu
http://cs.nju.edu.cn/ics/people/jingweixu/
index.html
Institute of Computer Software
Nanjing University

In the Last Class...

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

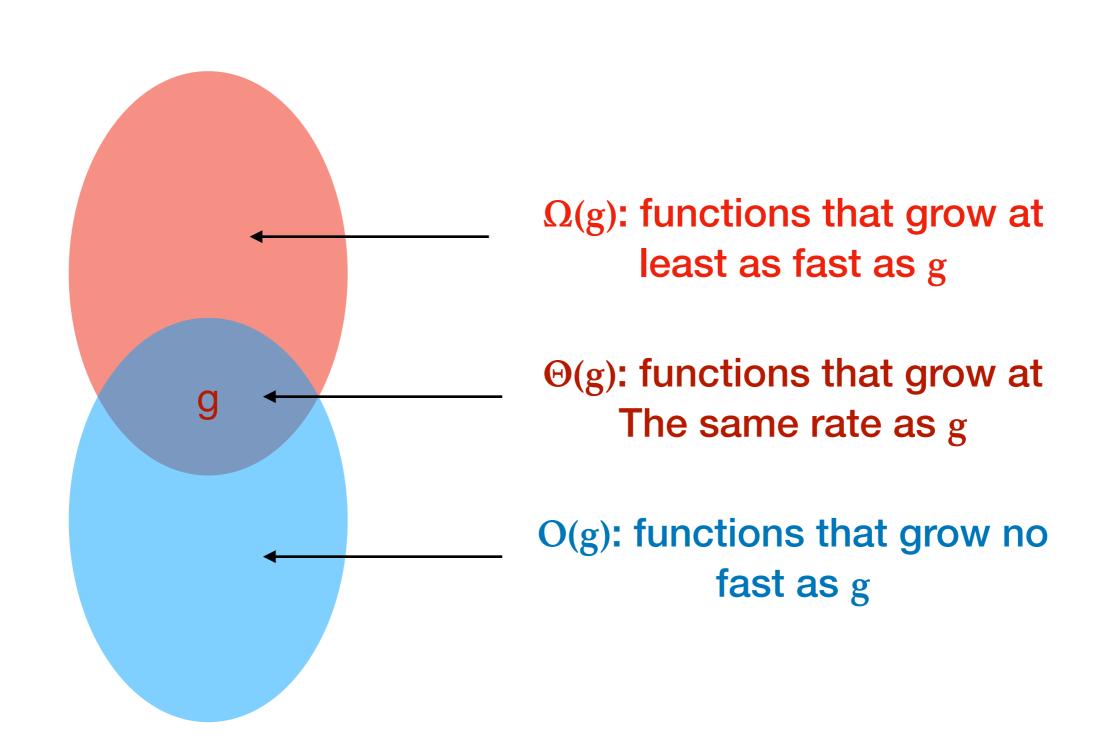
Asymptotic Behavior

- Asymptotic growth rate of functions
 - Basic idea
- Key notations
 - Ο, Ω, Θ
 - ο, ω
- Brute force enumeration
 - By iteration
 - By recursion

How to Compare Two Algorithms

- Algorithm analysis, with simplifications
 - Measuring the cost by the number of critical operations
 - 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
 - Asymptotic growth rate of f(n)

Relative Growth Rate



"Big Oh"

- Basic idea f(n)∈O(g(n))
 - For sufficiently large input size, g(n) is an upper bound for f(n)
- Definition "ε-N"
 - Giving g: $N \rightarrow R^+$, then O(g) is the set of f: $N \rightarrow R^+$, such that for some $c \in R^+$ and some $n_0 \in N$, $f(n) \le cg(n)$ for all $n \ge n_0$
- Definition "lim_{n→∞}"

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

The limit may not exist, though it usually does.

Example

• Let f(n)=n², g(n)=nlogn, then:

L'Hospital's rule

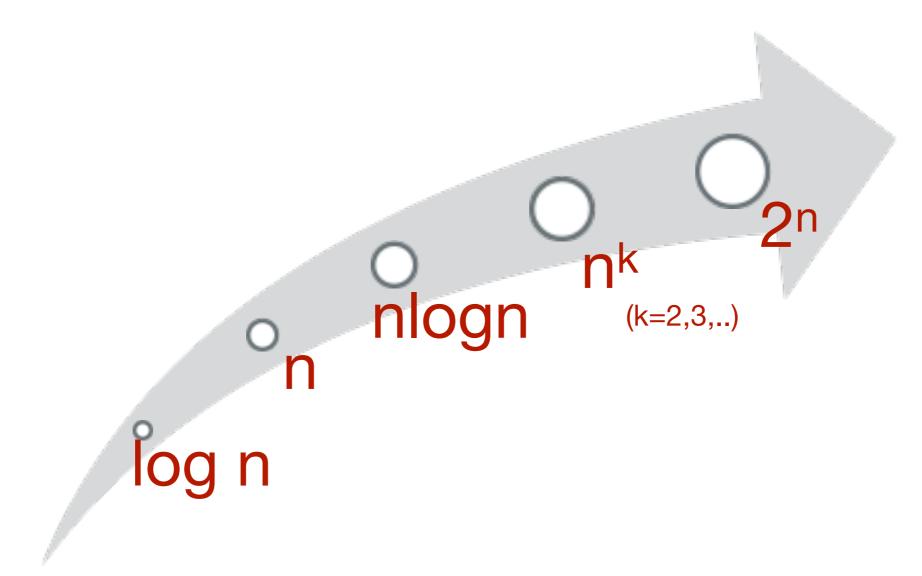
f∉O(g), since

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

• 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 logn

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

Power n^k

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

Factorial n!

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

"Big Ω "

- Basic idea f(n)∈Ω(g(n))
 - Dual of "O"
- Definition "ε-N"
 - Giving g: $N \rightarrow R^+$, then $\Omega(g)$ is the set of f: $N \rightarrow R^+$, 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→∞}"
 - $\displaystyle f \in \Omega(g)$ if $\displaystyle \lim_{n \to \infty} \frac{f(n)}{g(n)} = c > 0$ the limit may be ∞

The Set O

- Basic idea f(n)∈Θ(g(n))
 - Roughly the same
 - $\Theta(g) = O(g) \cap \Omega(g)$
- Definition "ε-N"
 - Giving g: N→R+, then Θ(g) is the set of f: N→R+, such that
 for some c₁,c₂∈R+ and some n₀∈N, 0≤c₁g(n)≤f(n)≤c₂g(n),
 for all n≥n₀
- Definition "lim_{n→∞}"

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

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	47nlogn	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
 - if $f \in O(g)$ and $g \in O(h)$, then $f \in O(h)$
- Symmetric properties
 - $f \in O(g)$ if and only if $g \in \Omega(f)$
 - $f \in \Theta(g)$ if and only if $g \in \Theta(f)$
- Order of sum function
 - O(f+g)=O(max(f,g))

"Little Oh"

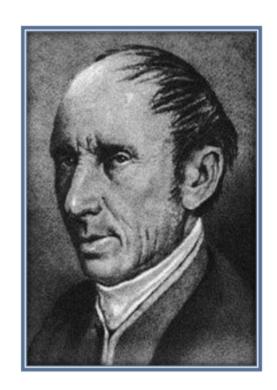
- Basic idea f(n)∈o(g(n))
 - Non-ignorable gap between f and its upper bound g
- Definition "ε-N"
 - Giving g: N→R+, then o(g) is the set of f: N→R+, such that for any c∈R+, there exists some n₀∈N,
 0<f(n)<cg(n), for all n≥n₀
- Definition "lim_{n→∞}"
 - feo(g) if $\lim_{n \to \infty} \frac{f(n)}{g(n)} = 0$

"Little ω"

- Basic idea f(n)∈ω(g(n))
 - Dual of "o"
- Definition "ε-N"
 - Giving g: N→R+, then ω(g) is the set of f: N→R+, such that for any c∈R+, there exists some n₀∈N,
 0≤cg(n)<f(n), for all n≥n₀
- Definition "lim_{n→∞}"
 - feo(g) if $\lim_{n \to \infty} \frac{f(n)}{g(n)} = \infty$

Do You Know Infinity

- Mathematical analysis
 - Firm foundation



Cauchy

- How to talk about infinity?
 - (ε-N)-definition
 - $(\epsilon \delta)$ -definition



Weierstrass

Brute Force Enumeration by Iteration

- Swapping array elements
 - <time, space>
 - From $<O(n^2)$, O(1)>
 - To <O(n), O(n)>
 - To <O(n), O(1)>
- Maximum subsequence sum
 - Time
 - From O(n³)
 - To O(n²)
 - To O(nlogn)
 - To O(n)

Swapping Array Elements

• E.g., 1,2,3,4 | 5,6,7 => 5,6,7,1,2,3,4

Brute force

Space sensitive

	Time	Space	
BF1	$O(n^2)$	O(1)	
BF2	O(n)	O(n)	
Your Task	O(n)	O(1)	
ır task	Tir	Time sensitive	

Your task

Both time and space efficient

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

```
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for(i = 0; i < N; i++)
 for(i = i; i < N; i++){
   ThisSum = 0;
   for(k = i; k \le j; k++)
                                    i=1
      ThisSum += A[k];
   if(ThisSum > MaxSum)
      MaxSum = ThisSum;
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                                    i=1
      ThisSum += A[k];
                                         i=2
    if(ThisSum > MaxSum)
      MaxSum = ThisSum;
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                                    i=1
      ThisSum += A[k];
                                         i=2
    if(ThisSum > MaxSum)
      MaxSum = ThisSum;
return MaxSum;
                                                          i=n-1
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   for(k = i; k \le j; k++)
                                     i=1
      ThisSum += A[k];
                                          i=2
    if(ThisSum > MaxSum)
      MaxSum = ThisSum;
                                   in O(n<sup>3</sup>)
return MaxSum;
                                                            i=n-1
```

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

n-1 n-1 j

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$$\sum_{i=0}^{j} \sum_{j=i}^{j} \sum_{k=i}^{1} 1$$

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

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

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

n-1 n-1 j

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

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

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

$$\sum_{i=0}^{n-1} \frac{(n-i+1)(n-i)}{2} = \sum_{i=1}^{n} \frac{(n-i+2)(n-i+1)}{2}$$
$$= \frac{1}{2} \sum_{i=1}^{n} i^2 - (n+\frac{3}{2}) \sum_{i=1}^{n} i + \frac{1}{2} (n^2 + 3n + 2) \sum_{i=1}^{n} 1$$

n-1 n-1 j

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

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

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

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

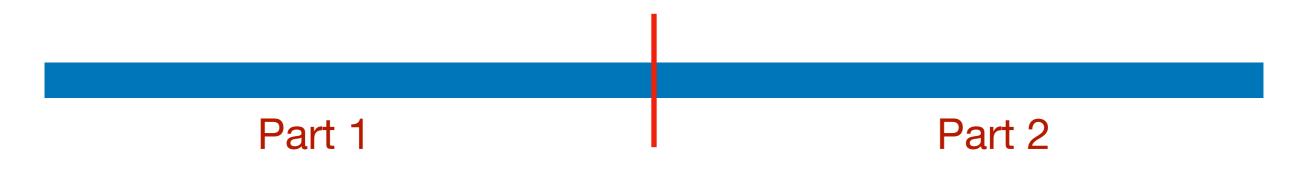
$$= \frac{1}{2} \sum_{i=1}^{n} i^2 - (n+\frac{3}{2}) \sum_{i=1}^{n} i + \frac{1}{2} (n^2 + 3n + 2) \sum_{i=1}^{n} 1$$

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

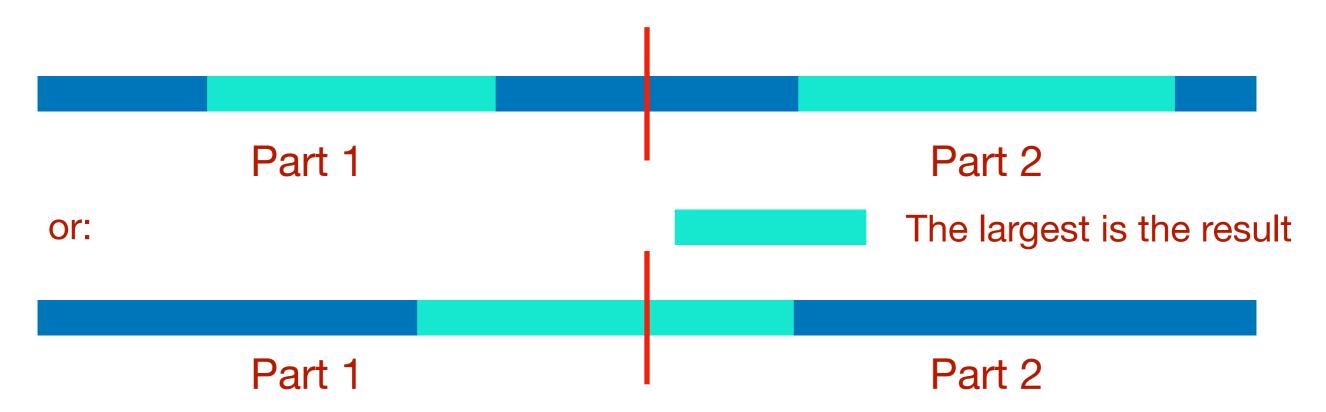
Decreasing the Number of Loops

```
The sequence
A improved algorithm:
MaxSum = 0;
                               i=0
                                    i=1
for(i = 0; i < N; i++){
 ThisSum = 0;
 for(j = i; j < N; j++){
     ThisSum += A[i];
     if(ThisSum > MaxSum)
        MaxSum = ThisSum;
                              in O(n<sup>2</sup>)
return MaxSum;
```

Power of Divide and Conquer



The sub with largest sum may be in:



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;
MaxRightBorderSum = 0; RightBorderSum = 0;
for (i = Center + 1; i \le Right; i++)
 RightBorderSum += A[i];
 if (RightBorderSum > MaxRightBorderSum) MaxRightBorderSum = RightBorderSum;
return Max3(MaxLeftSum, MaxRightSum, MaxLeftBorderSum + MaxRightBorderSum);
                            Note: this is the core part of
```

the procedure, with base

case and wrap omitted.

in O(nlogn)

A Linear Algorithm

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

The sequence



This is an example of "online algorithm"

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

Brute Force Enumeration By Recursion

Job scheduling

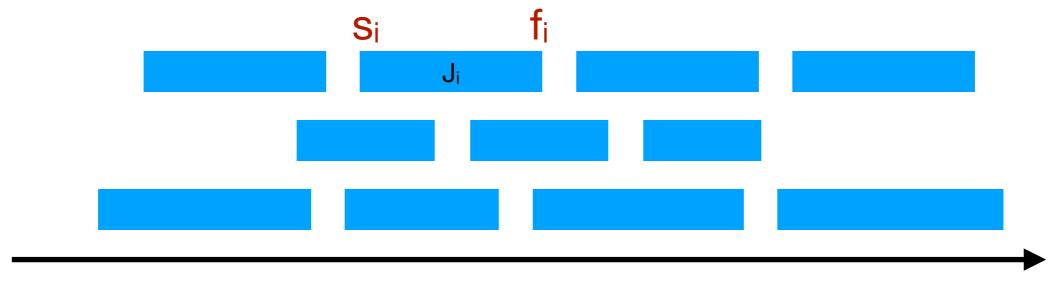
- Problem definition
- Brute force recursion
- Further improvements

Matrix chain multiplication

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

Job Scheduling

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



Matrix Chain Multiplication

• The task:

- Find the product: A₁ x A₂ x ... x A_{n-1} x A_n
- A_i is 2-dimentional array of different legal size

• The Challenge:

- 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

An example: $A_1 \times A_2 \times A_3 \times A_4$

30x1 1x40 40x10 10x25

 $((A_1 \times A_2) \times A_3) \times A_4$: 20700 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

Solutions

- Brute force recursion (L16)
 - BF1
 - BF2
- Dynamic programming (L16)
 - Based on brute force recursion 2

Thank you! Q & A