Algorithm Design and Analysis

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Abstract

The lecture note of 2025 Fall Algorithm Design and Analysis by professor 呂學一. 希望我可以活著度過這學期∼∼∼∼

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Chapter 0

Introduction

Lecture 1

0.1 Design and Analysis

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0.1.1 Design

Remark. Find the point to cut into the problem.

Question (Coffee and Milk). 把 500 毫升的咖啡倒入 10 毫升，再從 510 毫升牛奶咖啡取 10 毫升倒入 490 毫升牛奶中，試問兩邊比例？

Answer. 兩邊都固定 500 毫升，一邊少的必定出現在另一邊，**切入點對了根本不用計算** ⊛

0.1.2 Analysis

Question (Card). 把牌洗亂（平均）需要幾次？

Note. **定義何為亂？**
排列出現機率皆為

$$\frac{1}{52!}$$

七次是充分必要條件（嚴謹分析 on paper） n card should shuffle $\frac{3}{2}\log_2 n + \theta$ times. ⊛

Definition 0.1.1 (亂). With n-cards, we have to let the probbability of every combination become

$$\frac{1}{n!}$$

Question (Top-in shuffle). Consider Top-in shuffle with the cards. How to get it "randomly" ?

Answer. Define the k-th section to be 初始底牌從底下數上來是 k-th card.

1. bottom $k-1$ cards must be 亂
2. 每次都可以用 n/k 次將他洗亂，因為出現機率皆為 k/n

We can shuffle $n \cdot H_n$ times. ⊛

Theorem 0.1.1. 底下 $k-1$ 張卡片永遠是亂的

Proof. 考慮 top-in shuffle，利用數學歸納法

- 第一輪要插入底牌下方，只有 1 個空隙，因此必須插入，因此插入的機率是
$$\frac{1}{1!}$$
- 底下如果有 k 張牌，假設下面 k 張是亂的，表示他的排列 $k!$ 種，每種順序機率都是
$$\frac{1}{k!}$$
- 再插入一張，共有 $k+1$ 個空隙，排起來每種順序出現的機率為
$$\frac{1}{(k+1)} \cdot \frac{1}{k!} = \frac{1}{(k+1)!}$$
符合亂的定義

■

第 k 階段插入到下面都是從 n 個空隙裡面找到 k 個空隙插入，因此出現機率必定為 $\frac{k}{n}$，因此需要 shuffle 次數為
$$\frac{n}{k}$$
接著考慮第 n 階段，底牌不是亂的，因此要再洗一次，因此最終的和為
$$\sum_{i=1}^{n} \frac{n}{i} = n \cdot \sum_{i=1}^{n} \frac{1}{i} = n \cdot H_n$$

Note. choose another card to be "bottom", 可以減少第一次的 $1/n$ 就可以少 $n/1$ 次 shuffle. 因此可以把次數減少為：
$$n \cdot H_n - n$$

Remark. **簡單的分析點交換就可以造成巨大的影響**

0.2 Jargons

Definition 0.2.1 (Problems). 「問題」(Problem) 是一個對應關係，就是一個函數

- 演算法核心是在探討問題的解決難易度
- 有些問題確定很難，就不用妄想想出簡單演算法

Definition 0.2.2 (Instance). 「個例」(instance)，也就是問題的合法輸入

Definition 0.2.3 (Computation Model). 「計算模型」(Computation Model)，也就是遊戲規則，同個問題在不同的規則下可能難易度不同

- Comparision base & Computation base

Definition 0.2.4 (Algorithm). 「演算法」Algorithm is a detail step-by-step instruction

- 符合規則
- 詳細步驟

Definition 0.2.5 (Hardness). 「難度」(Hardness)，想知道一個「**問題**」有多難解，用最厲害的一個「**解法**」，對於每個「**個例**」，都至少要用多少「**工夫**」才能解完

- 魔方問題：對於所有解法，存在至少一個初始 instance 讓解法需要 20 次才能轉完，切入點是找到一個固定的初始狀態，這是一個已經最佳化的問題

Theorem 0.2.1 (Confirm Hardness). 用 **upper bound** 和 **lower bound** 去夾起來決定難度

- 當 **upper bound** = **lower bound** 的時候，我們才知道問題的確切難度
- 有些情況，就算夾起來也不一定可以確定難度

Proof.

$$\begin{array}{c} \boxed{\text{upper bound}} \\ \Downarrow \\ \\ \\ \\ \Uparrow \\ \boxed{\text{lower bound}} \end{array} \quad \Rightarrow \quad \begin{array}{c} \boxed{\text{upper bound}} \\ \Downarrow \\ \Uparrow \\ \boxed{\text{lower bound}} \end{array}$$

■

Note. 我們在這門課都討論 worst case

Chapter 1

Complexity for a Problem

Lecture 2

1.1 函數成長率 (Rate of Growth)

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Question (棋癡國王與文武大臣). 國王愛下棋，文武大臣要獎賞

- 武大臣每下一個棋子，獎賞多一袋米，起始為一袋米
- 文大臣每下一個棋子，獎賞雙倍，起始為一粒米

Answer. 棋盤 64 格

- 武大臣：n 袋米
- 文大臣：2^n 粒米

2^n 的成長率遠遠高於 n，單位的影響不及成長率 ⊛

1.2 成長率的比較

Note. 雖然 200 年前就有 Asymptotic Notation 的概念，但直到 1970 年代才被演算法分析之父 Donald Ervin Knuth 正式定義到 CS 領域內。

Question (Why Asymptotic Notation). 為什麼要用 Asymptotic Notation？

Answer. 問題難度通常單位不一致

- $n = 3$ 魔方問題要 20 轉
- n 個信封的老大問題要 $n - 1$ 次比較

兩者難度無法比較 ⊛

Definition 1.2.1 (Rate of Growth). 沒有人有明確定義，但是成長率很好比較，有很多東西也是無法定義但可以比較，e.g. 無限集合可以比大小。

1.3 Big Oh Notation

Definition 1.3.1 (Big Oh Notation). For functions $f, g : \mathbb{N} \to \mathbb{R}$, we write

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

to satisfy the extistence of positive constants c and n_0 such that the inequality

$$0 \leq f(n) \leq c \cdot g(n)$$

holds for all integer $n \geq n_0$.

Note. $f(n), g(n)$ should be non-negative for sufficiently large n.

The definition of

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

says that there exist a positive constant c such that the value of $f(n)$ is upper-bounded by $c \cdot g(n)$ for all sufficiently large positive n.

Remark. 因此 $O(g(n))$ 可以理解成一個成長率不高過 g 的函數所成的集合

1.3.1 等號左邊也有 Big-Oh

Definition 1.3.2. The equality $O(g(n)) = O(h(n))$ signifies that

$$f(n) = O(h(n))$$

holds for all functions $f(n)$ with

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

i.e. $O(g(n)) = O(h(n))$ signifies that $f(n) = O(g(n))$ implies $f(n) = O(h(n))$.

The equality $=$ in $O(g(n)) = O(h(n))$ is more like $\subseteq$, i.e., $O(g(n)) \subseteq O(h(n))$.

Theorem 1.3.1. $O(g(n)) = O(h(n))$ if and only if $g(n) = O(h(n))$.

Proof. Consider the two directions separately.

- For the $(\Rightarrow)$ case: We can easily proof that

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

  then we can deduce that

  $$g(n) = O(g(n)) = O(h(n))$$

- For the $(\Leftarrow)$ case:

> As previously seen (Definition 1.3.1).
>
> $$g(n) = O(h(n)) \quad \Rightarrow \quad \exists\, c_1, n_1 > 0,\ \forall n \geq n_1,\ 0 \leq g(n) \leq c_1 \cdot h(n)$$

Let f be the function such that $f(n) = O(g(n))$. Then, by definition, we can deduce that

$$\exists\, c_2, n_2 > 0,\ \forall n \geq n_2,\ 0 \leq f(n) \leq c_2 \cdot g(n).$$

Assume $n \geq \max\{n_1, n_2\}$. Then, we have

$$0 \leq f(n) \leq c_2 \cdot g(n) \leq c_2 \cdot (c_1 \cdot h(n)) = (c_1 c_2) \cdot h(n).$$

Thus, we can conclude that

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

Hence,

$$O(g(n)) = O(h(n)) \Leftrightarrow g(n) = O(h(n)).$$

■

1.4 Big-Oh 的運算

Question. 所以，Big-Oh 相加的意思是什麼？

Definition 1.4.1 (Big-Oh Addition)**.** The equality

$$O(g_1(n)) + O(g_2(n)) = O(h(n))$$

signifies that the equality

$$f_1(n) + f_2(n) = O(h(n))$$

holds for any functions $f_1(n)$ and $f_1(n)$ with

$$f_1(n) = O(g_1(n))$$

$$f_2(n) = O(g_2(n)).$$

That is, $f_1(n) = O(g_1(n))$ and $f_2(n) = O(g_2(n))$ together imply $f_1(n) + f_2(n) = O(h(n))$.

Remark. 雖然 $O(g_1(n)) + O(g_2(n))$ 看起來像是兩個集合的聯集，但相同集合想法**無法帶到減乘除**。

Definition 1.4.2 (Big-Oh $\circ$)**.** The equality

$$O(g_1(n)) \circ O(g_2(n)) = O(h(n))$$

$$g_1(n) \circ O(g_2(n)) = O(h(n))$$

集合的復合操作

Notation.

$$\{f_1(n) \circ f_2(n) \mid f_1(n) \in S_1 \text{ and } f_2(n) \in S_2\}$$

可以被理解成

- 把 $=$ 解成 $\subseteq$
- 把 $g_1(n)$ 理解成 $\{g_1\}$
- $O(g1(n))$ 解為成長率不超過 g_1 的成長率的所有函數所組成的集合

Remark. 減乘除應被理解成與剛剛加法類似的模式，而無法被理解為集合的運算

Definition 1.4.3 (Big-Oh $-$, $\cdot$, $/$). (Take $-$ as the example) The equality

$$O(g_1(n)) - O(g_2(n)) = O(h(n))$$

signifies the equality

$$f_1(n) - f_2(n) = O(h(n))$$

holds for any functions $f_1(n)$ and $f_2(n)$ with

$$f_1(n) = O(g_1(n))$$

$$f_2(n) = O(g_2(n))$$

Question. Proof or disproof:

$$O(n)^{O(\log_2 n)} = O(2^n)$$

Answer. First, we take log on both sides:

$$\text{LHS} = O(\log n) \cdot O(\log n) = (O(\log n))^2$$

$$\text{RHS} = O(n)$$

LHS grows slower than RHS, therefore the original statement is true. ⊛

Remark. log 的底數不影響成長率，因此可忽略。

Definition 1.4.4 (Big-Oh 套 Big-Oh). The equality

$$O(O(g(n))) = O(h(n))$$

signifies that the equality

$$O(f(n)) = O(h(n))$$

holds for any function f with

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

i.e. $f(n) = O(g(n))$ implies $O(f(n)) = O(h(n))$.

Theorem 1.4.1. $g(n) = O(h(n))$ if and only if $O(O(g(n))) = O(h(n))$

Proof. Consider the two directions separately.

- For the $(\Rightarrow)$ case:

  > **As previously seen** (Definition 1.3.1).
  >
  > $$g(n) = O(h(n)) \implies \exists\, c_0, n_0 > 0,\ \forall n \geq n_0,\ 0 \leq g(n) \leq c_0 \cdot h(n)$$

  $f(n) = O(O(g(n)))$ signifies that for $c_1, c_2, n_1, n_2 > 0$

  $$\forall n \geq n_1,\ 0 \leq f(n) \leq c_2 \cdot u(n); \quad \forall n \geq n_2,\ 0 \leq u(n) \leq c_1 \cdot g(n)$$

  Get all together, we have

  $$0 \leq f(n) \leq c_2 \cdot (c_1 \cdot g(n)) \leq c_2 c_1 c_0 \cdot h(n) \quad \implies \quad f(n) = O(h(n))$$

  Thus, we can conclude that

  $$O(O(g(n))) = O(h(n))$$

- We can easily proof that

  $$g(n) \subseteq O(g(n)) \subseteq O(O(g(n)))$$

  Then we can get

  $$g(n) = O(O(g(n))) = O(h(n))$$

Hence, $g(n) = O(h(n)) \Leftrightarrow O(O(g(n))) = O(h(n))$ ■

Theorem 1.4.2 (Rules of Computation in Big-Oh)**.** The following statements hold for functions $f, g : \mathbb{N} \to \mathbb{R}$ such that there is a constant n_0 such that $f(n)$ and $g(n)$ for any integer $n \geq n_0$:

- **Rule 1**: $f(n) = O(f(n))$.
- **Rule 2**: If c is a positive constant, then $c \cdot f(n) = O(f(n))$.
- **Rule 3**: $f(n) = O(g(n))$ if and only if $O(f(n)) = O(g(n))$.
- **Rule 4**: $O(f(n)) \cdot O(g(n)) = O(f(n) \cdot g(n))$.
- **Rule 5**: $O(f(n) \cdot g(n)) = f(n) \cdot O(g(n))$

Proof. For **Rule 5**: By the Definition 1.3.1, $u(n) = O(f(n) \cdot g(n))$ signifies that there exist positive constants c_1 and n_1 such that the inequality

$$\exists\, c_0, n_0 > 0,\ \forall n \geq n_0,\ 0 \leq u(n) \leq c_0 \cdot f(n) \cdot g(n)$$

the definition of $u(n) = f(n) \cdot O(g(n))$ is

$$\exists\, c_1, n_1 > 0,\ \forall n \geq n_1,\ 0 \leq u(n) \leq f(n) \cdot c_1 \cdot g(n)$$

which are equivilence to each other. ■

1.5 More Asymptotic Notation

Definition 1.5.1 (Little-oh). For any function $f, g : \mathbb{N} \to \mathbb{R}$, we write

$$f(n) = o(g(n))$$

to signify that for any constant $c > 0$, there is a positive constant $n_0(c)$ such that

$$0 \leq f(n) < c \cdot g(n)$$

holds for each integer $n \geq n_0(c)$

> **Note.** $n_0(c)$ is a function of c. When we $n_0(c)$ is a constant, we means that it does not depend on n.

白話來說 $f(n) = o(g(n))$ 的定義是說，不管是多小的常數 c，要 n 夠大（i.e., $n \geq n_0(c)$），

$$0 \leq f(n) < c \cdot g(n)$$

都還是成立。

Example.

$$n = o(n^2)$$

Observe that for any positive constant c, as long as $n > \frac{1}{c}$, we have

$$0 \leq n < c \cdot n^2$$

Therefore, we may let $n_0(c) = \frac{1}{c} + 1$ and have $n = o(n^2)$ proved.

Definition 1.5.2 (Other notation). The other notation can be defined via O and o notation:

- We write $f(n) = \Omega(g(n))$ if
$$g(n) = O(f(n)).$$
- We write $f(n) = \Theta(g(n))$ if
$$f(n) = O(g(n)) \text{ and } f(n) = \Omega(g(n))$$
- We write $f(n) = \omega(g(n))$ if
$$g(n) = o(n)$$

Limit notation 可以幫我們判斷各種 Asymptotic Notation:

- If
$$\lim_{n\to\infty} \frac{f(n)}{g(n)} = 0$$
, the we can guess $f(n) = o(g(n))$.
- If
$$\lim_{n\to\infty} \frac{f(n)}{g(n)} = c$$
, the we can guess $f(n) = \Theta(g(n))$.

- If
$$\lim_{n\to\infty} \frac{f(n)}{g(n)} = \infty$$
, the we can guess $f(n) = \omega(g(n))$.

然而，極限不一定應可以推至 Asymptotic Notation:

- Let $f(n) = g(n) = (-1)^n$. We have
$$\lim_{n\to\infty} \frac{f(n)}{g(n)} = 1,$$
but $f(n) \neq O(g(n))$, $f(n) \neq \Omega(g(n))$, and $f(n) \neq \Theta(g(n))$.
- Let $f(n) = (-1)^n$ and $g(n) = n \cdot (-1)^n$. We have
$$\lim_{n\to\infty} \frac{f(n)}{g(n)} = 0,$$
but $f(n) \neq o(g(n))$.
- Let $f(n) = 2 + (-1)^n$ and $g(n) = 2 - (-1)^n$. We have
$$f(n) = \Theta(g(n)),$$
but $\lim_{n\to\infty} \frac{f(n)}{g(n)}$ does not exist.

Question. Can we just use $\leq$ instead of $<$ in the definition of o ?

Answer. In most part of it will be right. However there will be a special situation:
$$o(0) = 0$$
which is definetly wrong. ⊛

Question. 為何不都用 $\exists\, c_0, n_0$ 或都用 $\forall c, n_0(c)$?

Answer. 如果都用 $\exists\, c_0, n_0$，那 o 就會退化，變成 O 而已，並且 $<, \leq$ 是沒有太大差別的

> **Proof.** Suppose that $\hat{n}_0(c)$ is the constant ensured by the $\leq$-version. We simply let
> $$n_0(c) = \max(m_0, \hat{n}_0(c/2)).$$
> As a result, for any positive constant c, if $n \geq n_0(c)$, we have $g(n) > 0$ and thus
> $$\begin{aligned} 0 < f(n) &\leq \frac{c}{2} \cdot g(n) \\ &< c \cdot g(n). \end{aligned}$$
> ■

證畢，由此可知符號並無太大影響，不可讓 o 退化 ⊛

Lecture 3

1.6 問題的難度

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如果，

- P 不比 Q 難且
- Q 不比 P 簡單

那兩個問題的難度相同（兩者等價）

Definition 1.6.1. We say that the (worst-case) time complexity of Problem P is $\Theta(f(n))$ if

- the time complexity of Problem P is $O(f(n))$, i.e.

  there exists an $O(f(n))$-time algorithm that solves Problem P

- the time complexity of Problem P is $\Omega(f(n))$, i.e.

  any algorithm that solves Problem P requires $\Omega(f(n))$ time (in the worst case).

  對於任何演算法，只要存在一組 instance 可以達成，一組 $\Omega(f(n))$ 即可推出

Note. 若沒有特別說，n 代表的是 input(instance) size，儲存資料所需的容量

Note. 「正確的演算法」就是對於所有合法輸入都可以對應出正確的輸出，的解決問題方法

1.7 演算法複雜度比較

$$f(n) = O(g(n)) : \begin{cases} O(f(n)) = O(g(n)) \\ o(f(n)) = O(g(n)) \\ \Theta(f(n)) = O(g(n)) \end{cases}$$

$$f(n) = \Omega(g(n)) : \begin{cases} \Omega(f(n)) = \Omega(g(n)) \\ \omega(f(n)) = \Omega(g(n)) \\ \Theta(f(n)) = \Omega(g(n)) \end{cases}$$

$$f(n) = \Theta(g(n)) : \begin{cases} \Theta(f(n)) = \Theta(g(n)) \end{cases}$$

$$f(n) = o(g(n)) : \begin{cases} O(f(n)) = o(g(n)) \\ o(f(n)) = o(g(n)) \\ \Theta(f(n)) = o(g(n)) \end{cases}$$

$$f(n) = \omega(g(n)) : \begin{cases} \Omega(f(n)) = \omega(g(n)) \\ \omega(f(n)) = \omega(g(n)) \\ \Theta(f(n)) = \omega(g(n)) \end{cases}$$

Comparing Algorithm A and B, We say that Algorithm A is no worse than Algorithm B in terms of worst-case time complexity if there exists a function $f : \mathbb{N} \to \mathbb{R}$ such that

- Algorithm A runs in time $O(f(n))$
- Algorithm B runs in time $\Omega(f(n))$ (in the worst case)

> **Remark.** 第一句 Big-Oh 並沒有出現「in the worst case」是因為我們在此處分析的是「**worst case complexity**」，所以其實在 lower bound 分析的時和通常也不說。

Comparing Algorithm A and B, We say that Algorithm A is strictly better than Algorithm B in terms of worst-case time complexity if there exists a function $f : \mathbb{N} \to \mathbb{R}$ such that

- Algorithm A runs in time $O(f(n))$
- Algorithm B runs in time $\omega(f(n))$ (in the worst case)

or

- Algorithm A runs in time $o(f(n))$
- Algorithm B runs in time $\Omega(f(n))$ (in the worst case)

1.8 分析演算法複雜度下界

儘管有些 case 可以，但 Big-Omega 不可以跟 Big-Oh 一樣分析（多增加）

> **Remark.** **Ω-time 必須要一組一組 instance 分析**

1.9 問題上下界 vs 演算法上下界

- 一個問題 P 的任何正確演算法 A 的複雜度上界都是問題 $O(f(n))$ 都是問題 P 的複雜度上界
- 一個問題 P 的複雜度下界 $\Omega(f(n))$ 都是 P 的任何正確演算法 A 的複雜度下界

Chapter 2

演算法的設計與分析

2.1 Half Sorted

Definition 2.1.1 (Half Sorting Problem). An n-element array A is half-sorted if

$$A[i] \leq A\left[\left\lfloor \frac{i}{2} \right\rfloor\right]$$

holds for each index i with $2 \leq i \leq n$.

Half-sorting Problem:

- Input:

  An array A of n distinct numbers.

- Output:

  A half-sorted array that is reordered from A.

Note. 正確的輸出未必唯一，因此輸入輸出就不是一個函數，而是一個「relation」

2.1.1 排序法 Sorting method

Theorem 2.1.1. 歸約 Reduction（問題重整），把問題的難度如果問題 P 可以「多項式時間歸約」成問題 Q，就寫作

$$P \leq_p Q$$

意思是：只要能解決問題 Q，就能透過快速轉換來解決問題 P，所以：

- 如果 Q 是容易的（有快速演算法），那麼 P 也會是容易的。
- 如果 P 已知很難，那麼 Q 至少也不會比較容易。

Note. 把問題的性質變強，便可以順便證明性質較弱的問題

因此，我們知道用排序法一定可以解決半排法，我們可以把半排問題「歸約」到「排序」問題，因此我們首先分析一下快速排序法：

Listing 2.1: Quicksort in Python

```python
def qsort(A, l, r):
    if l >= r:
        return
    (i, j, k) = (l, r, A[l])

    while i != j:
        while A[j] > k and i < j:
            j -= 1
        while A[i] <= k and i < j:
            i += 1
        if i < j:
            (A[i], A[j]) = (A[j], A[i])

    (A[l], A[i]) = (A[i], k)

    qsort(A, l, i-1)
    qsort(A, i+1, r)
```

我們必須分析他的正確性及複雜度

Theorem 2.1.2. The function `qsort()` is correct.

Proof. First, we know that every round of `qsort()` will let the array become:

$$A[l\ ..\ p-1] < A[p] < A[p+1\ ..\ r] \quad A[p] = \text{pivot}$$

(How to proof)

Let m be the number of elements in the array. By the induction, we can start with

- Case $m = 1$: The array is well sorted.
- Case $\forall t \leq m \to (m+1)$: Every round of iteration we can get a p such that

  $$\forall x \in A[l\ ..\ p-1],\ x \leq A[p], \quad \forall y \in A[p+1\ ..\ r],\ y \geq A[p]$$

  We assume that array with length equal to t, $\forall t \leq m$, has been sorted. Then we can know that that `qsort(A, l, p-1)`, `qsort(A, p+1, r)` is well sorted. Thus, we can combined $A[l\ ..\ p-1]$, $A[p]$, $A[p+1\ ..\ r]$ to get a well-sorted array $A[l\ ..\ r]$ with length m.

Hence, by induction, `qsort()` is correct. ■

Then, we can stat to analyze the time complexity (worst case):

2.1.2 順調法

Definition 2.1.2 (順調法).

為了方便觀察我們可以將這個陣列化成樹的形式（不是真的改變資料結構）

- Each $A[i]$-to-root path is increasing

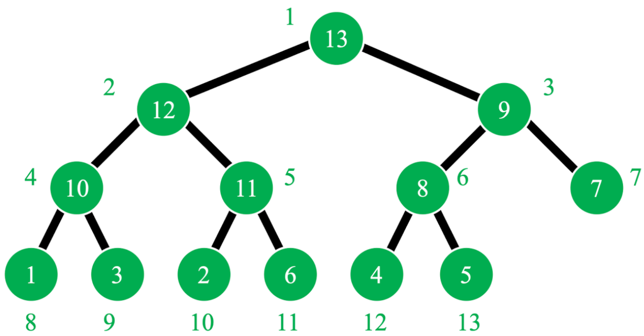

Figure 2.1: Display with Tree structure

2.1.3 逆調法

算上面算比較少，樹的上下是不對稱的

Lecture 4

2.2 Sorting Problem

25 Sep. 14:20

> **Note.** quick sort

> **Note.** half sort sort

2.2.1 排序問題下界

解決了排序問題的下界就可以一次解決

- The (worst-case) time complexity of the comparison-based sorting problem is $\Omega(n \log n)$.
- The $O(n \log n)$-time analysis for the Half-Sort-Sort algorithm is tight.
- Learning Reduction

Definition 2.2.1 (Permutation Problem). For the instance

- Input: An array A of n distinct integers.
- Output: Reorder the n-index array $B = [1, 2, \cdots, n]$ such that

$$A[B[1]] < A[B[2]] < \cdots < A[B[n]].$$

排列難度 $\leq$ 排序難度。If the comparison-based sorting problem can be solved in $O(f(n))$ time, then so can the comparison-based permutation problem.

2.3 Amortized Analysis

Lecture 5

9 Oct. 14:20

Question. Let $T : \mathbb{N} \to \mathbb{R}^+$ satisfy

$$T(2n) - 2T(n) = O(n)$$

for all n which are powers of 2. Prove that $T(n) = O(n \log n)$ for all n that are powers of two.

Chapter 3

Advanced Analysis Techniques

3.1 Greedy Algorithm

Question. Task selection problem:

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3.2 Devide and Conquer

3.3 Dynamic Programming