COMP 3711 Course Notes

Design and Analysis of Algorithms

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ALGORITHMS

COMP 3711 Design and Analysis of Algorithms

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Contents

1 Asymptotic Notation

Upper Bounds $T(n) = O(f(n))$
if exist constants $c > 0$ and $n_0 \geq 0$ such that for all $n \geq n_0$, $T(n) \leq c \cdot f(n)$.
Lower Bounds $T(n) = \Omega(f(n))$
if exist constants $c > 0$ and $n_0 \geq 0$ such that for all $n \geq n_0$, $T(n) \geq c \cdot f(n)$.
Tight Bounds $T(n) = \Theta(f(n))$
if $T(n) = O(f(n))$ and $T(n) = \Omega(f(n))$.
Note: Here ”=” means ”is”, not equal.

2 Introduction - The Sorting Problem

2.1 Selection Sort

Algorithm 1: Selection Sort

```
Input: An array A[1...n] of elements
Output: Array A[1...n] of elements in sorted order (asending)
for i ← 1 to n − 1 do
    for j ← i + 1 to n do
        if A[i] > A[j] then
            swap A[i] and A[j]
        end
    end
end
```

Running Time: $\frac{n(n-1)}{2}$
Best-Case = Worst-Case: $T(n) = \Theta(\frac{n(n-1)}{2}) = \Theta(n^2)$

2.2 Insertion Sort

Algorithm 2: Insertion Sort

```
Input: An array A[1...n] of elements
Output: Array A[1...n] of elements in sorted order (asending)
for i ← 2 to n do
    j ← i − 1 while j ≥ 1 and A[j] > A[j + 1] do
        swap A[j] and A[j + 1]
    end
    j ← j − 1
end
```

Running Time: Depends on the input array, ranges between $(n-1)$ and $\frac{n(n-1)}{2}$
Best-Case: $T(n) = n - 1 = \Theta(n)$ (Useless)
Worst-Case: $T(n) = \Theta(\frac{n(n-1)}{2}) = \Theta(n^2)$ (Commonly-Used)
Average-Case: $T(n) = \Theta(\sum_{i=2}^{n} \frac{i-1}{2}) = \Theta(\frac{n(n-1)}{4}) = \Theta(n^2)$ (Sometimes Used)

2.3 Wild-Guess Sort

Running Time: Depends on the random generation, could be faster than the insertion sort.

2.4 Worst-Case Analysis

The algorithm’s worst case running time is $O(f(n)) \implies$ On all inputs of (large) size n, the running time of the algorithm is $\leq c \cdot f(n)$.

Algorithm 3: Wild-Guess Sort

Input: An array $A[1...n]$ of elements
Output: Array $A[1...n]$ of elements in sorted order (asending)
$\pi \leftarrow [4, 7, 1, 3, 8, 11, 5, ...]$ Create random permutation Check if $A[\pi[i]] \leq A[\pi[i+1]]$ for all $i = 1, 2, ..., n-1$ If yes, output A according to π and terminate else $Insertion - Sort(A)$

The algorithm's worst case running time is $\Omega(f(n)) \implies$ There exists at least one input of (large) size n for which the running time of the algorithm is $\geq c \cdot f(n)$.

Thus, Insertion sort runs in $\Theta(n^2)$ time.

Notice

Selection sort, insertion sort, and wild-guess sort all have worst-case running time $\Theta(n^2)$. How to distinguish between them?

- Closer examination of hidden constants
- Careful analysis of typical expected inputs
- Other factors such as cache efficiency, parallelization are important
- Empirical comparison

Stirling's Formula

Prove that $\log(n!) = \Theta(n \log n)$

First $\log(n!) = O(n \log n)$ since:

$$\log(n!) = \sum_{i=1}^{n} \log i \leq n \times \log n = O(n \log n)$$

Second $\log(n!) = \Omega(n \log n)$ since:

$$\log(n!) = \sum_{i=1}^{n} \log i \geq \sum_{i=n/2}^{n} \log i \geq n/2 \times \log n/2 = n/2(\log n - \log 2) = \Omega(n \log n)$$

Thus, $\log(n!) = \Theta(n \log n)$

3 Divide & Conquer

Main idea of D & C: Solve a problem of size n by breaking it into one or more smaller problems of size less than n. Solve the smaller problems recursively and combine their solutions, to solve the large problem.

3.1 Binary Search

Example: Binary Search

Input: A sorted array $A[1,...,n]$, and an element x

Output: Return the position of x, if it is in A; otherwise output nil

Idea of the binary search: Set $q \leftarrow$ middle of the array. If $x = A[q]$, return q. If $x < A[q]$, search $A[1,...,q-1]$, else search $A[q+1,...,n]$.

Algorithm 4: Binary Search

Input: Array $A[1...n]$ of elements in sorted order
`BinarySearch(`$A[], p, r, x$`)`$(p, r$ being the left & right iteration, x being the element being searched)
if $p > r$ **then**
  return *nil*
end
$q \leftarrow [(p+r)/2]$
if $x = A[q]$ **then**
  return q
end
if $x < A[q]$ **then**
  `BinarySearch(`$A[], p, q-1, x$`)`
end
else
  `BinarySearch(`$A[], q+1, r, x$`)`
end

Recurrence of the algorithm, supposing $T(n)$ being the number of the comparisons needed for n elements: $T(n) = T(\frac{n}{2}) + 2$ if $n > 1$, with $T(1) = 2$.

$\implies T(n) = 2\log_2 n + 2 \implies O(\log n)$ algorithm

Example: Binary Search in Rotated Array

Suppose you are given a sorted array A of n distinct numbers that has been rotated k steps, for some unknown integer k between 1 and $n-1$. That is, $A[1...k]$ is sorted in increasing order, and $A[k+1...n]$ is also sorted in increasing order, and $A[n] < A[1]$.

Design an $O(\log n)$-time algorithm that for any given x, finds x in the rotated sorted array, or reports that it does not exist.

Algorithm:

First conduct a $O(\log n)$ algorithm to find the value of k, then search for the target value in either the first part or the second part.

$Find - x(A, x)$
$k \leftarrow Find - k(A, 1, n)$ (First find k)
$if\ x \geq A[1]\ then\ return\ BinarySearch(A, 1, k, x)$
$Else\ return\ BinarySearch(A, k+1, n, x)$

Example: Finding the last 0

You are given an array $A[1...n]$ that contains a sequence of 0 followed by a sequence of 1 (e.g., 0001111111). A contains k 0(s) ($k > 0$ and $k << n$) and at least one 1.

Design an $O(\log k)$-time algorithm that finds the position k of the last 0.

Algorithm:

$i \leftarrow 1$
$while\ A[i] = 0$
    $i \leftarrow 2i$
$find - k(A[i/2...i])$

3.2 Merge Sort

Principle of the Merge Sort:

- Divide array into two halves.
- Recursively sort each half.
- Merge two halves to make sorted whole.

Algorithm 5: Merge Sort

```
MergeSort(A, p, r) (p, r being the left & right side of the array to be sorted)
if p = r then
  | return
end
q ← [(p + r)/2]
MergeSort(A, p, q)
MergeSort(A, q + 1, r)
Merge(A, p, q, r)
First Call: MergeSort(A, 1, n)
```

Algorithm 6: Merge

```
Input: Two Arrays L ← A[p...q] and R ← A[q + 1...r] of elements in sorted order
Merge(A, p, q, r)
Append ∞ at the end of L and R
i ← 1, j ← 1
for k ← p to r do
  if L[i] ≤ R[j] then
    A[k] ← L[i]
    i ← i + 1
  end
  else
    A[k] ← R[j]
    j ← j + 1
  end
end
```

Let $T(n)$ be the running time of the algorithm on an array of size n.

Merge Sort Recurrence:

$$T(n) \leq T(\lfloor n/2 \rfloor) + T(\lceil n/2 \rceil) + O(n), \quad n > 1, \quad T(1) = O(1)$$

Simplification:

$$\implies T(n) = 2T(n/2) + n, \quad n > 1, \quad T(1) = 1$$

Result:

$$T(n) = n \log_2 n + n = O(n \log n)$$

3.3 Inversion Counting

Definition of the Inversion Numbers: Given array $A[1...n]$, two elements $A[i]$ and $A[j]$ are inverted if $i < j$ but $A[i] > A[j]$. The inversion number of A is the number of inverted pairs.

Theorem:
The number of swaps used by Insertion Sort = Inversion Number (Proved by induction on the size of the array)
Algorithm to Compute Inversion Number:
Algorithm 1: Check all $\Theta(n^2)$ pairs.
Algorithm 2: Run Insertion Sort and count the number of swaps -Also $\Theta(n^2)$ time.
Algorithm 3: Divide and Conquer

3.3.1 Counting Inversions: Divide-and-Conquer

Principle of the Algorithm:
- Divide: divide array into two halves
- Conquer: recursively count inversions in each half
- Conbine: count inversions where a_i and a_j are in different halves, and return sum of three quantities

Inversion counting during the combine step is very similar to the Merge Algorithm (Algorithm 6), by counting the sum of each inversion number of the right array (indicated by $I[j]$) comparing to the left array.

Algorithm 7: Inversion Count during Combination

Input: Two Arrays $L \leftarrow A[p...q]$ and $R \leftarrow A[q+1...r]$ of elements in sorted order
`Count`(A, p, q, r)
$i \leftarrow 1,\ j \leftarrow 1,\ c \leftarrow 0$
while $(i \leq q - p + 1) \&\& (j \leq r - q)$ **do**
  if $L[i] \leq R[j]$ **then**
    $i \leftarrow i + 1$
  end
  else
    $I[j] = q - p - i + 2$
    $c \leftarrow c + I[j]$
    $j \leftarrow j + 1$
  end
end

The time-complexity of the algorithm is $\Theta(n \log n)$, same as the Merge Sort.

3.3.2 Implementation of the Algorithm

Algorithm 8: Main Algorithm

`Sort-and-Count`(A, p, r)
if $p = r$ **then**
  return *0*
end
$q \leftarrow \lfloor (p + r)/2 \rfloor$
$c_1 \leftarrow$ `Sort-and-Count`(A, p, q)
$c_2 \leftarrow$ `Sort-and-Count`$(A, q + 1, r)$
$c_3 \leftarrow$ `Merge-and-Count`(A, p, q, r)
return $c_1 + c_2 + c_3$
First Call: `Sort-and-Count`$(A, 1, n)$

Algorithm 9: Merge-and-Count

```
Input: Two Arrays L ← A[p...q] and R ← A[q+1...r] of elements in sorted order
Merge-and-Count(A, p, q, r)
Append ∞ at the end of L and R
i ← 1, j ← 1, c ← 0
for k ← p to r do
    if L[i] ≤ R[j] then
        A[k] ← L[i]
        i ← i + 1
    end
    else
        A[k] ← R[j]
        j ← j + 1
        c ← c + q − p − i + 2
    end
end
return c
```

3.4 Basic Summary of D&C: Problem Size & Number of Problems

Observations of D&C in Logarithmic Patterns:

- Break up problem of size n into p parts of size n/q.
- Solve parts recursively and combine solutions into overall solution.
- At level i, we break i times and we have p^i problems of size n/q^i.
- When we cannot break up any more, usually when the problem size becomes 1. Usually $i \approx \log_q n$.

The number of problems at (bottom) level $\log_q n$ is $p^i = p^{\log_q n} = n^{\log_q p}$.

Observations of D&C in Non-Logarithmic Patterns:

- Break up problem of size n into $p(\leq 2)$ parts of size $n-q$. (e.g. $q = 1$ for Hanoi Problem)
- Assume that $q = 1$
- At level i, we break i times and we have p^i problems of size $n-i$.
- If we stop when the problem size becomes 1, then $n - i = 1 \implies i = n - 1$.

The number of problems at (bottom) level $n-1$ is: $p^i = p^{n-1}$.

3.5 Maximum Contiguous Subarray

Example: The Maximum Subarray Problem

Input: An array of numbers $A[1, ..., n]$, both positive and negative

Output: Find the maximum $V(i,j)$, where $V(i,j) = \sum_{k=i}^{j} A[k]$

Brute-Force Algorithm

Idea: Calculate the value of $V(i,j)$ for each pair $i \leq j$ and return the maximum value.
Requires three nested for-loop, time complexity: $\Theta(n^3)$.

A Data-Reuse Algorithm

Idea: $V(i,j) = V(i,j-1) + A[j]$
Requires two nested for-loop, time complexity: $\Theta(n^2)$.

3.5.1 A D&C Algorithm

Idea: Cut the array into two halves, all subarrays can be classified into three cases: entirely in the first/second half, or crosses the cut.

Compare with the merge sort: Whole algorithm will run in $\Theta(n \log n)$ time if the cross-cut can be solved in $O(n)$ time.

Algorithm 10: Maximum Subarray

```
MaxSubArray(A, p, r)
if p = r then
  | return A[p]
end
q ← ⌊(p + r)/2⌋
M_1 ← MaxSubArray(A, p, q)
M_2 ← MaxSubArray(A, q + 1, r)
L_m, R_m ← −∞
V ← 0
for i ← q to p do
  | V ← V + A[i]
  | if V > L_m then
  |   | L_m ← V
  | end
end
V ← 0
for i ← q + 1 to r do
  | V ← V + A[i]
  | if V > R_m then
  |   | R_m ← V
  | end
end
return max(M_1, M_2, L_m + R_m)
First Call: MaxSubArray(A, 1, n)
```

Recurrence: $T(n) = 2T(n/2) + n \implies T(n) = \Theta(n \log n)$

3.5.2 Kadane's Algorithm

Idea: Based on the principles of **Dynamic Programming**. Let $V[i]$ be the (local) maximum sub-array that ends at $A[i]$, then we let:

- $V[1] = A[1]$
- $V[i] = \max(A[i], A[i] + V[i-1])$

The maximum of $V[i]$, namely V_{max} is the maximum continuous subarray found so far.

Algorithm 11: Kadane's Algorithm

```
V_max ← −∞; V ← 0; start ← 1; end ← 1; temp ← 1 (Note: start & end specify the maximum sub-array)
for i ← 1 to n do
  | V ← V + A[i]
  | if V < A[i] then // Implies V[i − 1] is negative, restart from the current position
  |   | V ← A[i]; temp ← i
  | end
  | if V > V + max then // Found a max sum, update start and end
  |   | V_max ← V; start ← temp; end ← i
  | end
end
```

Time Complexity: $\Theta(n)$

Example: Maximizing Stock Profits

You are presented with an array $p[1 \ldots n]$ where $p[i]$ is the price of the stock on day i.

Design an divide-and-conquer algorithm that finds a strategy to make as much money as possible, i.e., it finds a pair i, j with $1 \leq i \leq j \leq n$ such that $p[j] - p[i]$ is maximized over all possible such pairs. Note that you are only allowed to buy the stock once and then sell it later.

Idea 1: Divide and Conquer

- Cut the array into two halves.
- All i, j solutions can be classified into three cases: both i, j are entirely in the first(second) half, or i is in the left half while j is in the right half.
- Maximizing a Case 3 result $p[j] - p[i]$ means finding the smallest value in the first half and the largest in the second half.

Time Complexity: $T(n) = 2T(n/2) + n \implies T(n) = \Theta(n \log n)$

Idea 2: Kadane's Algorithm

- Create a **Profit** array with $Profit[i] = Price[i+1] - Price[i]$.
- Perform the Kadane's Algorithm.

Time Complexity: $O(n)$

3.6 Integer Multiplication

3.6.1 A Simple D&C Algorithm for Integer Multiplication

Goal: Given two n-bit binary integers a and b, compute: $a \cdot b$.
Idea: Multiplication by 2^k can be done in one time unit by a left shift of k bits.

- Rewrite the two numbers as $a = 2^{n/2}a_1 + a_0$, $b = 2^{n/2}b_1 + b_0$.
- The product becomes: $a \cdot b = (2^{n/2}a_1 + a_0)(2^{n/2}b_1 + b_0) = 2^n a_1 b_1 + 2^{n/2}(a_1 b_0 + a_0 b_1) + a_0 b_0$
- The new computation requires 4 products of integers, each with $n/2$ bits.
- Apply D&C by splitting a problem of size n, to 4 problems of size $n/2$.

Algorithm 12: Binary Multiplication

```
Multiply(A, B)
n ← size of A
if n = 1 then
  | return A[1] · B[1]
end
mid ← ⌊n/2⌋
U ← Multiply (A[mid + 1..n], B[mid + 1..n]) // a1b1
V ← Multiply (A[mid + 1..n], B[1..mid]) // a1b0
W ← Multiply (A[1..mid], B[mid + 1..n]) // a0b1
Z ← Multiply (A[1..mid], B[1..mid]) // a0b0
M[1..2n] ← 0
M[1..n] ← Z // a0b0
M[mid + 1..] ← M[mid + 1..] ⊕ V ⊕ W // +[(a1b0 + a0b1) ≪ (left shift) n/2]
M[2mid + 1..] ← M[2mid + 1..] ⊕ U // +[a1b1 ≪ n]
return M
```

Time Complexity: $T(n) = 4T(n/2) + n \implies T(n) = \Theta(n^2)$

3.6.2 Karatsuba Multiplication

Goal: Given two n-bit binary integers a and b, compute: $a \cdot b$.
Idea:
- We've seen that $ab = a_1b_12^n + (a_1b_0 + a_0b_1)2^{n/2} + a_0b_0$, so we only need the result of $a_1b_0 + a_0b_1$.
- Note that $a_1b_0 + a_0b_1 = (a_1 + a_0)(b_1 + b_0) - a_1b_1 - a_0b_0$, thus only requires performing 3 multiplications of size $n/2$.

Algorithm 13: Binary Multiplication (Karatsuba's Multiplication Algorithm)

```
Multiply(A, B)
n ← size of A
if n = 1 then
 | return A[1] · B[1]
end
mid ← ⌊n/2⌋
U ← Multiply (A[mid + 1..n], B[mid + 1..n]) // a_1 b_1
Z ← Multiply (A[1..mid], B[1..mid]) // a_0 b_0
A' ← A[mid + 1..n] ⊕ A[1..mid] // a_1 + a_0
B' ← B[mid + 1..n] ⊕ B[1..mid] // b_1 + b_0
Y ← Multiply (A', B') // (a_1 + a_0)(b_! + b_0)
M[1..2n] ← 0
M[1..n] ← Z // a_0 b_0
M[mid + 1..] ← M[mid + 1..] ⊕ Y ⊖ U ⊖ Z // +[(a_1 b_0 + a_0 b_1) ≪ (left shift) n/2]
M[2mid + 1..] ← M[2mid + 1..] ⊕ U // +[a_1 b_1 ≪ n]
return M
```

Time Complexity: $T(n) = 3T(n/2) + n \implies T(n) = \Theta(n^{\log_2 3}) = \Theta(n^{1.585\cdots})$
For recent research, see: Integer Multiplication in $O(n \log n)$ Time (David Harvey & Joris van der Hoeven, 2021)

3.7 Matrix Multiplication

$$\begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & c_{22} & \cdots & c_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ c_{n1} & c_{n2} & \cdots & c_{nn} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1n} \\ b_{21} & b_{22} & \cdots & b_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ b_{n1} & b_{n2} & \cdots & b_{nn} \end{bmatrix} \qquad c_{ij} = \sum_{k=1}^{n} a_{ik}b_{kj}$$

Brute Force Method: $\Theta(n^3)$ time.

3.7.1 A D&C Solution to Matrix Multiplication

$$\begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix} = \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \qquad \begin{cases} C_{11} = (A_{11} \times B_{11}) + (A_{12} \times B_{21}) \\ C_{12} = (A_{11} \times B_{12}) + (A_{12} \times B_{22}) \\ C_{21} = (A_{21} \times B_{11}) + (A_{22} \times B_{21}) \\ C_{22} = (A_{21} \times B_{12}) + (A_{22} \times B_{22}) \end{cases}$$

Recursion: $T(n) = 8T(n/2) + O(n^2) \implies T(n) = O(n^3)$

3.7.2 Strassen's Matrix Multiplication Algorithm

Idea: Muliply 2-by-2 block matrices with only 7 multiplications

$$\begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix} = \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}$$

$$\begin{cases} P_1 = A_{11} \times (B_{12} - B_{22}) \\ P_2 = (A_{11} + A_{12}) \times B_{22} \\ P_3 = (A_{21} + A_{22}) \times B_{11} \\ P_4 = A_{22} \times (B_{21} - B_{11}) \\ P_5 = (A_{11} + A_{12}) \times (B_{11} + B_{22}) \\ P_6 = (A_{12} - A_{22}) \times (B_{21} + B_{22}) \\ P_7 = (A_{11} - A_{21}) \times (B_{11} + B_{12}) \end{cases} \qquad \begin{cases} C_{11} = P_5 + P_4 - P_2 + P_6 \\ C_{12} = P_1 + P_2 \\ C_{21} = P_3 + P_4 \\ C_{22} = P_5 + P_1 - P_3 - P_7 \end{cases}$$

Recursion: $T(n) = 7T(n/2) + n^2 \implies T(n) = \Theta(n^{\log_2 7}) = \Theta(n^{2.807\cdots})$
For recent research, see: Powers of Tensors and Fast Matrix Multiplication (Le Gall, 2014)
Conjecture: Close to $\Theta(n^2)$

3.8 Master Theorem

For recurrences of form

$$T(n) = aT(n/b) + f(n) \text{ or } T(n) \leq aT(n/b) + f(n), \text{ Let } c \equiv \log_b a$$

where
- $a \geq 1$ and $b > 1$ both being constants
- $f(n)$ is a (asymptotically) positive polynomial function
- n/b could be either $\lfloor n/b \rfloor$ or $\lceil n/b \rceil$

3.8.1 Master Theorem for Equalities

(1) Work Increases: $f(n) = O(n^{c-\epsilon})$ for some $\epsilon \implies T(n) = \Theta(n^c)$

(2) Work Remains: $f(n) = \Theta(n^c \log^k n)$ for $k > -1 \implies T(n) = \Theta(n^c \log^{k+1} n)$
Note: For the case $k = -1$, $T(n) = \Theta(n^c \log \log n)$; For the case $k < -1$, $T(n) = \Theta(n^c)$

(3) Work Decreases: $f(n) = \Omega(n^{c+\epsilon})$ for some $\epsilon \implies T(n) = \Theta(f(n))$
Note: Rigorously, the third case requires $af(n/b) \leq kf(n)$ for some $k < 1$ and sufficiently large n

(4) For a special case $T(n) = \sum_i T(\alpha_i n) + n$ where $\alpha_i > 0$ with $\sum_i \alpha_i < 1$, we have $T(n) = \Theta(n)$

3.8.2 Master Theorem for Inequalities

(1) Work Increases: $f(n) = O(n^{c-\epsilon})$ for some $\epsilon \implies T(n) = O(n^c)$

(2) Work Remains: $f(n) = O(n^c) \implies T(n) = O(n^c \log n)$

(3) Work Decreases: $f(n) = \Omega(n^{c+\epsilon})$ for some $\epsilon \implies T(n) = O(f(n))$

4 Advanced Sorting Algorithms

4.1 Probability & Statistics, Random Permutation

$$E[X] = \sum i \cdot Pr[X = i]$$

$$E[X + Y] = E[X] + E[Y]$$

For independent random variables X & Y,

$$E[XY] = E[X] \cdot E[Y]$$

Algorithm 14: Random Permutation

```
RandomPermute(A)
n ← A.length
for i ← 1 to n do
|  swap A[i] with A[Random(1, i)]
end
```

4.2 Randomized Algorithm - Quicksort

Idea: Quicksort chooses item as pivot. It partitions array so that all items less than or equal to pivot are on the left and all items greater than pivot on the right. It then recursively Quicksorts left and right sides.

Algorithm 15: Quicksort

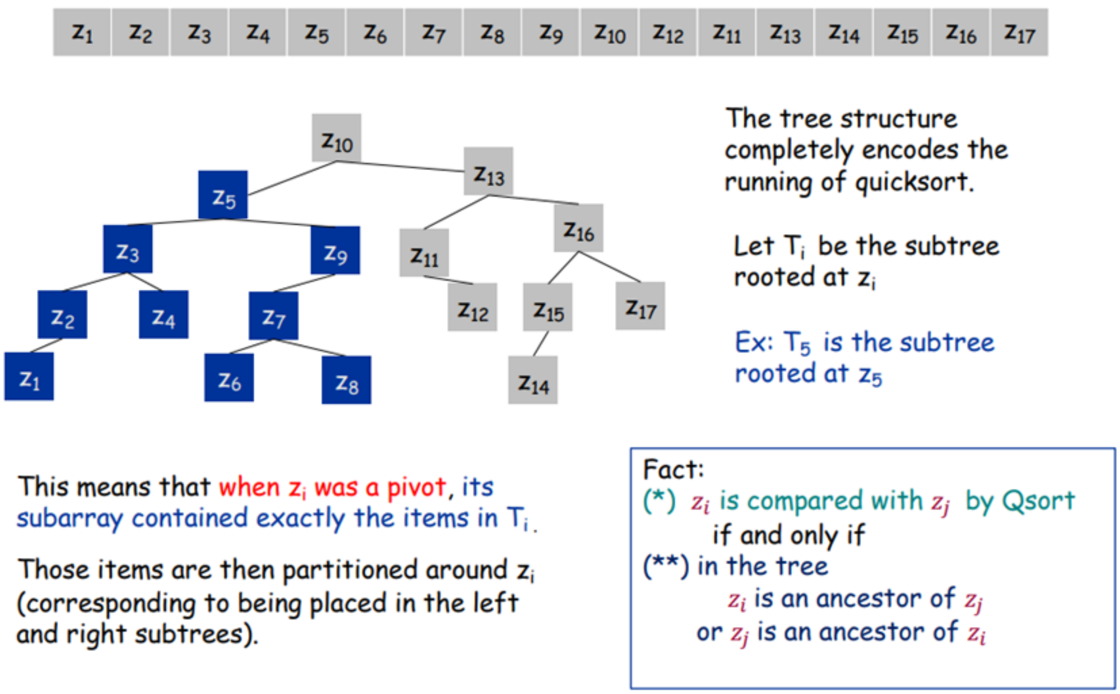
```
Quicksort(A, p, r) // Array from A[p] to A[r]
if p ≥ r then
|  return
end
q =Partition (A, p, r) // Set a new pivot position
Quicksort (A, p, q − 1)
Quicksort (A, q + 1, r)
First Call: MaxSubArray(A, 1, n)

Partition(A, p, r)
x ← A[r] // Set the last item as pivot, or randomly swap away the last item before choosing the pivot
i ← p − 1
for j ← p to r − 1 do
|  if A[j] ≤ x then
|  |  i ← i + 1
|  |  swap A[i] and A[j] // Put all items ≤ A[r] on the left
|  end
end
swap A[i + 1] and A[r]
return i + 1
```

4.2.1 Running Time

Best Case: Always select the median element as the pivot - $\Theta(n \log n)$ time.
Worst Case: Always select the smallest (or the largest) element - $\Theta(n^2)$ time.

To make running time independent of input, we can randomly choose an element as the pivot by swapping it with last item in array before running the partition.

4.2.2 Binary Tree Representation



4.2.3 Expected Running Time for Random-Based Quicksort

- Two elements z_i and z_j are compared at most once, iff z_i or z_j is the first to be chosen among $z_i, \cdots, z_j$
- The probability above (any indicated two elements z_i and z_j are compared) is $\frac{2}{j-1+1}$

$$\implies E_{\text{Num of comparisons made}} = \sum_{i<j} \frac{2}{j-1+1} = O(n \log n)$$

4.2.4 Find the i-th Smallest Element Using Quicksort

Example: Find the i-th Smallest Element

Given an unsorted array $A[1 \dots n]$ and an integer i, return the i-th smallest element of $A[1 \dots n]$.

Idea:
1. Choose a Pivot x from $A[p \dots r]$
2. Partition A around x. (linear time)
3. After partitioning, pivot x will be at known location q

If $i = q - p + 1$, then x is the actual solution

If $i < q - p + 1$, then the i-th element of $A[p \dots r]$ is the i-th element of $A[p \dots q-1]$, solve recursively

If $i > q - p + 1$, then the i-th element of $A[p \dots r]$ is the $j = (i - q + p - 1)$-th element of $A[q+1 \dots r]$, solve recursively

Algorithm 16: i-th Smallest Element

```
Select(A, p, r, i)
if p = r then
  | return A[p]
end
Randomly choose an element in A[p ... r] as the pivot and swap it with A[r]
q ←Partition(A, p, r)
k ←q − p + 1
if i = k then
  | return A[q]
end
else if i < k then
  | return Select(A, p, q − 1, i)
end
else
  | return Select(A, q + 1, r, i − k)
end
First Call: Select(A, 1, n, i)
```

4.2.5 Expected Running Time for Finding the i-th Smallest Element

• A pivot is "good" if it's between the 25%- and 75%-percentile of sorted A, eliminating at least $1/4$ of the array. The probability for such "good" pivot is $1/2$.

• Let i-th stage be the time between the i-th good pivot (not including) and the $(i+1)$-st good pivot (including), $i = 0, 1, 2, \cdots$, then the expected pivots selected within a stage is 2.

• Let Y_i = the running time of i-th stage, X_i = the num. of pivots (recursive calls) in i-th stage. Then $Y_i \leq X_i(3/4)^i n$.

$$\implies E[Y_i] \leq E[X_i(3/4)^i n] = 2(3/4)^i n \implies \text{Expected Total Running Time} \leq E[\sum_i Y_i] \leq \sum_i 2(3/4)^i n = O(n)$$

Example: i-th Smallest Element in Two Sorted Arrays

Given two sorted arrays $A1$ and $A2$ of sizes m and n. Design an algorithm to find the k-th smallest element in the union of the elements in $A1$ and $A2$ ($k \leq m + n$).

Algorithm 17: i-th Smallest Element in Two Sorted Arrays

```
Search(array A1, array A2, start1 1, end1 k, start2 1, end2 k, Order k)
Main Idea: Compare elements A1[k/2] and A2[k/2]
if A1[k/2] < A2[k/2] then
  | Eliminate first half of A1
  | return Search(A1, A2, k/2 + 1, end1, start2, end2, k/2)
end
else
  | Eliminate first half of A2
  | return Search(A1, A2, start1, end1, k/2 + 1, end2, k/2)
end
```

Time Complexity: $\Theta(\log k)$

4.3 Heapsort

4.3.1 Priority Queues

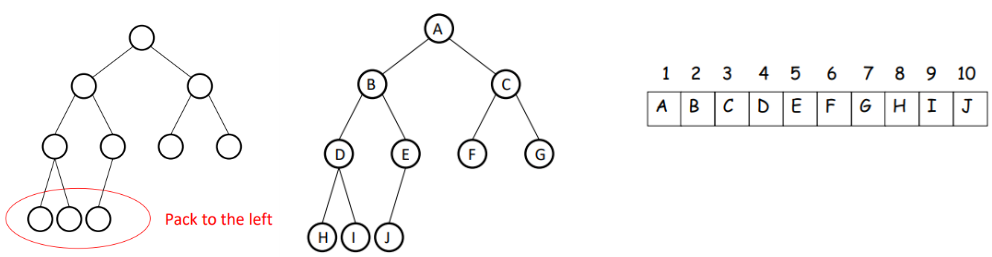
Main Idea: Processing the shortest job first - Extracting the smallest element from the queue.
A Priority Queue is an abstract data structure that supports two operations: Insert & Extract-Min.
Implementations:
1. Unsorted list + a pointer to the smallest element: $O(1)$ Insert & $O(n)$ Extract-Min
2. Sorted doubly linked list + a pointer to first element: $O(n)$ Insert & $O(1)$ Extract-Min

4.3.2 Binary Heap Implementation

- All levels are full except possibly the lowest level
- If the lowest level is not full, then nodes must be packed to the left
- The value of a node is at least the value of its parent —Min-heap
- Both Insert & Extract-Min can be done in $O(\log n)$ time

> **Notice**
> The binary tree here is DIFFERENT from the Binary Search Tree, which requires ALL left nodes $<$ parent, while ALL right nodes $>$ parent.

Array Implementation of Heap
- The root is in array position 1
- For any element in array position i, the left child is in position $2i$, the right child is in position $2i + 1$, the parent is in position $\lfloor i/2 \rfloor$



4.3.3 Heapsort

Insert
- Add the new element to the next available position at the lowest level.
- Restore the min-heap property if violated.

Algorithm 18: Add item x to heap $A[1 \ldots i-1]$

`Insert`(x, i)
$A[i] \leftarrow x$
$j = i$
while $j > 1$ *and* $A[j] < A[\lfloor j/2 \rfloor]$ **do** // $A[j]$ is less than its parent
| Swap $A[j]$ and $A[\lfloor j/2 \rfloor]$
end
$j = \lfloor j/2 \rfloor$

Time Complexity: $O(\log n)$

Extract-Min: Should preserve both min-heap property & completeness

• Copy the last element to the root (overwrite).

• Restore the min-heap property by percolating (or bubbling down): if the element is larger than either of its children, then interchange it with the smaller of its children.

Algorithm 19: Remove the smallest item $A[1]$ in the heap $A[1 \dots i]$

`Extract-Min`(i)
Output($A[1]$)
Swap $A[1]$ and $A[i]$
$A[i] = \infty$, $j = 1$, $l = A[2j]$, $r = A[2j+1]$ // Left & Right Children
while $A[j] > \min(l, r)$ **do** // if $A[j]$ is larger than a child, swap with the smaller child
  if $l < r$ **then**
    Swap $A[j]$ with $A[2j]$, $j = 2j$
  end
  else
    Swap $A[j]$ with $A[2j+1]$, $j = 2j+1$
  end
  $l = A[2j], r = A[2j+1]$
end

Time Complexity: $O(\log n)$
Total Time Complexity: Build a binary heap of n elements & Perform n Extract-Min operations: $O(n \log n)$

Example: Merging k Sorted Arrays

Suppose that you have k sorted arrays, each with n elements, and you want to combine them into a single sorted array of kn elements.

Solution 1: Merge the first two arrays, then merge it with the third, and so on. Time Complexity $= \sum_{i=2}^{k} in = O(k^2 n)$

Solution 2: Divide recursively k sorted arrays into two parts, conduct the merging for the subproblems. $T(k) = 2T(k/2) + kn \implies$ Time Complexity $= T(k) = O(kn \log k)$

Solution 3 (Heapsort): Insert the first element of each array into an empty min-heap. Extract-min every time and insert the next item of in the same array as the one being extracted. Time Complexity $= O(kn \log k)$

[**Operation Implementation**]

Decrease-Key: Decreases the value of one specified element (Used in Dijkstra's Algorithm)

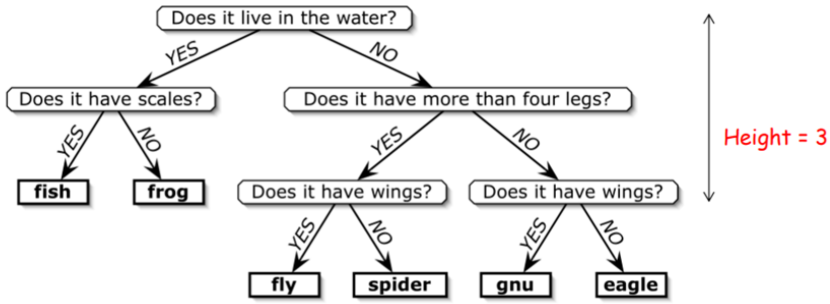
Modification of the heaps to support it in $O(\log n)$ time: Change the heap tree to a binary search tree.

For more information, see: Binary Heap (Wikipedia)
Some websites markdown: Zhihu Web 1 Web 2

4.4 Linear-Time Sorting

4.4.1 Decision Trees and Lower Bounds

Decision Tree Model



A decision tree to choose one of six animals.

Fact: A binary tree with n leaves must have height $\Omega(\log n)$.

Theorem: Any algorithm for finding location of given element in a sorted array of size n must have running time $\Omega(\log n)$ in the decision-tree model.

> **Theorem:** Any **comparison-based sorting algorithm** (only by using comparisons without using thetr accurate values) requires $\Omega(n \log n)$ time.
>
> Given n numbers, there are $n!$ possible permutations, resulting in the tree height being $\Omega(\log(n!))$. Thus, the time complexity is bounded as $\Omega(\log(n!)) = \Omega(n \log n)$.

4.4.2 Linear-time Sorting

Counting-Sort

- Assumes that the elements are integers from 1 to k

Algorithm 20: Counting-Sort Algorithm

Input: $A[1 \cdots n]$ where $A[j] \in 1, 2, \cdots, k$
Output: $B[1 \cdots n]$, sorted

```
Counting-Sort(A, B, k)
Let C[1 ··· k] be a new array
for i ← 1 to k do  // Initialize Counters
|  C[i] ← 0
end
for j ← 1 to n do  // Count the number of each element
|  C[A[j]] ← C[A[j]] + 1
end
for i ← 2 to k do  // Count the accumulative number of elements
|  C[i] ← C[i] + C[i − 1]
end
for j ← n to 1 do  // Move the items into proper location
|  B[C[A[j]]] ← A[j]
|  C[A[j]] ← C[A[j]] − 1
end
```

Time Complexity: $\Theta(n + k)$
Space Complexity: $\Theta(n + k)$

Radix-Sort

Algorithm 21: Radix-Sort Algorithm

Input: An array of n numbers, each has at most d digits
Output: A sorted array
`Radix-Sort`(A, d)
for $i \leftarrow 1$ *to* d **do**
| Use Counting-Sort to sort array A on digit i
end

Time Complexity: $\Theta(d(n+k))$

4.5 Sorting Reprise & Comparison

	Insertion Sort	Merge Sort	Quick Sort	Heap Sort	Radix Sort
Running Time	$\Theta(n^2)$	$\Theta(n \log n)$	$\Theta(n \log n)$	$\Theta(n \log n)$	$\Theta(d(n+k))$
Randomized	No	No	Yes	No	No
Working Space	$\Theta(1)$	$\Theta(n)$	$\Theta(\log n)$	$\Theta(1)$	$\Theta(n+k)$
Comparison-Based	Yes	Yes	Yes	Yes	No
Stable	Yes	Yes	No	No	Yes
Cache Performance	Good	Good	Good	Bad	Bad
Parallelization	No	Excellent	Good	No	No