

COMP3506 NOTES

Week 1

ADT – abstract data type

- Specifies type of data stored
- Specifies supported operations
- Specifies types of parameters for operations
- What it does, not how it does it
- Java Interfaces
- CDT – concrete data type
- Implementation of an ADT

Arrays

- Data structure consisting of a group of elements having a single name that are accessed by indexing
- Occupies a contiguous area of storage – Provides constant-time access to an indexed memory location
- Each element has the same data type

Week 1 & 2 – analysis

Data structure – systematic way of organizing and accessing data Algorithm – procedure for performing a task

Complexity

Experimental analysis

- Need to implement algorithm – may be difficult
- Comparing requires same hardware and software environment
- Not indicative of run times of other inputs

Theoretical Analysis

- Use high level description of algorithm
- Function of input size n
- Takes into account all possible inputs (including bad ones)
- Independent of software and hardware

How to analyse

- Express algorithm as pseudo-code
- Count primitive operations
- Describe algorithm as $f(n)$
- Perform asymptotic analysis describing limiting behaviour

Big-O notation describes an upper bound on a function $f(n)$ is $O(g(n))$ if $f(n)$ is asymptotically greater than or equal to $g(n)$

Given functions $f(n)$ and $g(n)$, we say that

$f(n) \in O(g(n))$

If there are positive constants c and n_0 such that

$f(n) \leq c \cdot g(n) \text{ for } n \geq n_0$

Big-Omega Notation describes a lower bound on a function

$f(n) \in \Omega(g(n))$ if $f(n) \in O(g(n))$ and there exist positive constants c and n_0 such that

$c \cdot g(n) \leq f(n) \leq g(n) \text{ for all } n \geq n_0$

Big-Theta notation describes a tight bound on a function

(If one exists) if $f(n)$ is asymptotically equal to $g(n)$

Important, as practical experimental runtime can differ depending on hardware used! Thus, best to use a theoretical approach to compare algorithms.

Pseudo-Code Details

- Control flow
 - if ... then ... [else ...]
 - while ... do ...
 - repeat ... until ...
 - for ... do ...
 - Indentation replaces braces
- Method declaration
 - **Algorithm** *method (arg₁, arg₂)*
 - Input ...
 - Output ...
- Method call
 - **method (arg₁, arg₂)**
 - Return value
 - **return expression**
 - Mathematical formatting
 - $= n^2$
 - \leftarrow (Assignment)
 - \sim Like " $=$ " in Java
 - \equiv (Equality testing)
 - Expressions

Week 2: Recursion

Express the following recurrence in big-O notation

$T(n) = O(1)$ if $n = 1$; $T(n) + T(n/3)$ otherwise

$T(n) = O(1) + T(n/3) = O(1) + O(1) + T(n/9) = O(1) + O(1) + T(n/27)$ in $\log_3 n$ base: 3

Recursion: when a method calls itself

- Test for base cases
- Begin by testing for a set of base cases
 - there should be at least one
- Every possible chain of recursive calls must eventually reach a base case
- Handle of each base case should not use recursion

Linear Recursion

- Perform a single recursive call
- Define each possible recursive call so that it makes progress towards a base case
- Easily converted into iterative forms

Tail Recursion

- Tail recursion occurs when a linearly recursive method makes its recursive call as its last step
- Easily converted into iterative forms

Binary Recursion

- Binary recursion occurs whenever there are two calls for each non-base case

Multiple Recursion

- It makes potentially many recursive calls not just one or two
- Multiple recursion is a way of enumerating all possible combinations of a set of elements

Divide and Conquer

Binary search uses the Divide and Conquer paradigm

- Divide - Break the problem into smaller subproblems of the same type
- Recur - Recursively solve these subproblems
- Conquer - Combine the solutions for the subproblems into a solution for the problem itself

Recursion Activity

- Use recursion to design an algorithm that sorts an array of integers
- We will call this Selection Sort

Running time of *selectionSort*: Analysis of Binary Search

$T(n) = O(n) + T(n-1)$
 $= O(n) + O(n-1) + T(n-2)$
 $= O(n) + O(n-1) + O(n-2) + T(n-3)$

... decreases by one each call, so there will be n recursive calls in total

$T(n) = 1 + 2 + 3 + \dots + n - 1 + n$

$T(n) = n + 1/2 n(n-1)$

Algorithm *printIntegers(n)*

Input: an integer n , n representing the number of integers to print

Output: printed integers from 0 to $n-1$ (no return value)

So it is clear that the loop in *printIntegers* will iterate n times

We cannot make the assumption that printing has $O(1)$ time complexity, as printing an integer takes time proportional to the number of digits in a single number, k , as $k = \text{floor}(\log_{10}(n) + 1)$.

Since k is clearly $O(n)$, the overall running time of *printIntegers* is $O(n \log n)$.

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Multi-way tree

- each node stores d-1 key-element items (d children, d > 2)
- leaves store nothing, serve as placeholders
- children ordered between keys in parent
- in-order traversal can be extended to multi-way trees
- multi-way searching similar to binary searching – reaching leaf terminates search unsuccessfully

(2,4) tree

- multi-way tree, each node has 2-4 children
- Node-Size Property: internal node has at most four children
- Depth Property: all external nodes have same depth
- insert at parent of leaf reached by searching for k – may overflow. insert takes $O(\log n)$ time

Height of a (2,4) Tree

- Since there are at least 2^i items at depth i and no items at depth h, we have $n = 1 + 2 + 4 + \dots + 2^{h-1} = 2^h - 1$
- Thus $h \leq \log(n+1)$
- Searching takes $O(\log n)$ time

Overflow and Split

- Handle an overflow at a 5-node v with a split operation
 - let $v_1 \dots v_5$ be the children of v and $k_1 \dots k_5$ be the keys of v
 - node v is replaced nodes v' and v''
 - + v' is a 3-node with keys k_1, k_2 , and children v_1, v_2, v_3
 - + v'' is a 2-node with keys k_3, k_4, k_5
 - k_i is inserted into the parent u of v (a new root may be created)
- Overflow may propagate to the parent node u

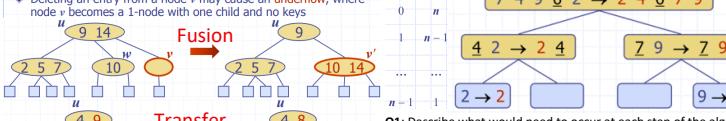
- if root overflows, add new root above existing one
- delete – if leaf, just remove. otherwise, replace by in-order successor. $O(\log n)$

Analysis of Deletion

- Let T be a (2,4) tree with n items
 - $O(\log n)$ height
- In a deletion operation
 - visit $O(\log n)$ nodes to locate the node from which to delete the entry
 - handle an underflow with a series of $O(\log n)$ fusions, followed by at most one transfer
 - each fusion and transfer takes $O(1)$ time
- Thus, deleting an item from a (2,4) tree takes $O(\log n)$ time

Underflow and Fusion

- Deleting an entry from a node v may cause an underflow, where node v becomes a 1-node with one child and no keys



Comparison of Map Implementations

	Search	Insert	Delete	Notes
Hash Table	1 expected	1 expected	1 expected	o no ordered map methods o simple to implement
Skip List	$\log n$ high prob.	$\log n$ high prob.	$\log n$ high prob.	o randomised insertion o simple to implement
AVL and (2,4) Tree	$\log n$ worst-case	$\log n$ worst-case	$\log n$ worst-case	o complex to implement

B-trees - Version of the (a,b) tree data structure, best-known method for maintaining a map in external memory

- B-tree of order d is (a,b,c) tree with a = d-2 and b = d - external memory split into disk blocks.

- want to minimize disk transfer – $/O$ complexity
- (a,b,c) tree has between a and b children for each node where $2 \leq a \leq b+1$ and All external nodes have the same depth

- if parameters set appropriately, can get good disk performance operations similar to (2,4) tree

- each operation only requires one disk access at each level of tree

Height of an (a,b,c) tree storing n entries

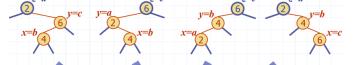
- $O(\log n + \log b)$, which is $O(\log(bn))$
- $O(\log n + \log a)$, which is $O(\log n)$

Red-black trees

- representation of (2,4) tree by binary search tree where each node is red or black
- Root property: root is black
- external property: every leaf is black
- internal property: children of a red node are black
- depth property: all leaves have the same black depth
- $O(\log(n))$ height as at most twice height of (2,4)

Remediying Double Red

Case 1: s is black



Case 2: s is red



Case 3: y is red



- Deletion in a red-black tree takes $O(\log n)$ time

Insertion

- remedy double red
 - Red-black tree action (2,4) tree action
 - result
 - restructuring
 - rebalancing
 - split

Deletion

- remedy double block
 - Red-black tree action (2,4) tree action
 - result
 - restructuring
 - rebalancing
 - fusion
 - restructuring
 - rebalancing
 - adjustment

Week 2 & 3 & 10 – Sorting and selection

E.g. Give a list of 4 numbers that exhibits the best-case runtime when sorted using insertion sort - Sol: 1,2,3,4

Inserting sort process

- Select the first unsorted element
- Swap other elements to the right to create the connect position and shift the unsorted element
- Advance the marker to the right one element
- Worst-case (array is in descending order): $O(n^2)$
- Best-case (array is already sorted): $O(n)$

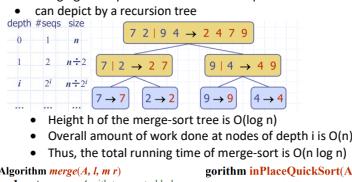
Selection Sort Process

- Scan each element of the array – find the largest (emax)
- Swap emax with the last element of the array
- Repeat this process on the first $n-1$ elements

Merge sort

- Guaranteed $O(n \log n)$ running time
- accesses data in sequential manner – good for sorting on disk
- Divide – split sequence S in half
- Recur – recursively sort S₁ and S₂
- Conquer – merge S₁ and S₂
- merging – compare first elements of sequences

can depict by a recursion tree



• Height h of the merge-sort tree is $O(\log n)$

• Overall amount of work done at nodes of depth i is $O(n)$

• Thus, the total running time of merge-sort is $O(n \log n)$

Algorithm $merge(A, l, r, m)$

```
Input an array A with two sorted halves
Output sorted union of A[l..m] and A[m..r]
```

$n_j \leftarrow m + 1$ // size of first half of A

$n_r \leftarrow r - m$ // size of second half of A

$L \leftarrow$ copy of $A[l..m]$, $R \leftarrow$ copy of $A[m..r]$

$i \leftarrow 0$, $j \leftarrow 0$, $k \leftarrow l$

while $i < n_l$ and $j < n_r$ do // merge into A

 if $L[i] < R[j]$ then

 A[k++ = L[i++]]

 white $i < n_l$ do // copy rest of L into A

 A[k++ = L[i++]]

 white $j < n_r$ do // copy rest of R into A

 A[k++ = R[j++]]

Quick sort

• $O(n \log(n))$ expected, worst case $O(n^2)$

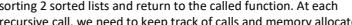
• divide – pick random pivot element x, partition S into:

- o L: elements less than x
- o E: elements equal to x
- o G: elements greater than x

• recur: sort L and G

• conquer: rejoin L, E, G

depth time



• Worst case: pivot is unique min or max element

• Good call: $|L|, |G| < 0.75 \cdot n$ - happens 50% of time

• so, expect to need $2 \log_2 n$ steps

Algorithm $inPlaceQuickSort(A, l, r)$

Input array A, indices l and r

Output array A with elements of index between l and r rearranged in increasing order

if $l \geq r$ then

 return

 i ← random integer between l and r

 x ← A[i]

 (h, k) ← inPlacePartition(A, x)

 inPlaceQuickSort(A, l, h - 1)

 inPlaceQuickSort(A, k + 1, r)

 inPlace quick sort: reorder sequence where it currently is

Algorithm $inPlaceQuickSort(A, l, r, m)$

Input array A, indices l and r

Output sorted union of A[l..m] and A[m..r]

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while $i < n_l$ and $j < n_r$ do // merge into A

 if $L[i] < R[j]$ then

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 white $i < n_l$ do // copy rest of L into A

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 A[k++ = L[i++]]

 white $i < n_l$ do // copy rest of L into A

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Algorithm $inPlaceQuickSort(A, l, r, m)$

Input array A, indices l and r

Output sorted union of A[l..m] and A[m..r]

$n_j \leftarrow m + 1$ // size of first half of A

$n_r \leftarrow r - m$ // size of second half of A

$L \leftarrow$ copy of $A[l..m]$, $R \leftarrow$ copy of $A[m..r]$

$i \leftarrow 0$, $j \leftarrow 0$, $k \leftarrow l$

while $i < n_l$ and $j < n_r$ do // merge into A