

Binary (max) Heap Quick Review

Representation change example

An almost-complete Binary Tree does min heaps)

See also Weiss, **Chapter 21 (Weiss**

- All levels, except possibly the last, are full
- On the last level all nodes are as far left as possible
- No parent is smaller than either of its children
- A great way to represent a **Priority Queue**
- Representing a binary heap as an array:

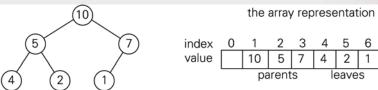


FIGURE 6.10 Heap and its array representation

Insertion and RemoveMax

- Insert an item:
 - Insert at the next position (end of the array) to maintain an almost-complete tree, then "percolate up" within the tree to restore heap property.
- RemoveMax:
 - Move last element of the heap to replace the root, then "percolate down" to restore heap property.
- Both operations are Θ(log n).
- Many more details (done for min-heaps):
 - http://www.rose hulman.edu/class/csse/csse230/201230/Slides/18 Heaps.pdf

Heap utilitiy functions

```
def percolateDown(a,i, n):
      "Within the n elements of A to be "re-heapified", the two subtrees of A[i]
       are already maxheaps. Repeatedly exchange the element currently in A[i] with
       the largest of its children until the tree whose root is a[i] is a max heap. """
   current = i # root position for subtree we are heapifying lastNodeWithChild = n//2 # if a node number is higher than this, it is a leaf.
   while current <= lastNodeWithChild:
        max = current
        if a[max] < a[2*current]: # if it is larger than its left child.
    max = 2*current</pre>
        if 2*current < n and a[max] < a[2*current+1]: # But if there is a right child,
            max = 2*current + 1
                                                    # right child may be larger than either
        if max == current:
            break # larger than its children, so we are done.
        swap(a, current, max) # otherwise, exchange, move down tree, and check again.
def percolateUp(a,n):
    Assume that elements 1 through n-1 are a heap; add element n and "re-heapify"!
    # compare to parent and swap until not larger than parent.
   current = n
   while current > 1: # or until this value is in the root.
   if a[current//2] >= a[current]:
        swap(a, current, current//2)
current //= 2
```

Code is on-line, linked from the schedule page



HeapSort

- Arrange array into a heap. (details next slide)
- for i = n downto 2:
 a[1]↔a[i], then "reheapify" a[1]..a[i-1]



HeapSort Code

```
# The next two functions tdo the same thing; take an unordered
# array and turn it into a max-heap. In HW 10, you will show
# that the secondis much more efficient than the first.
# So this first one is not actually called in this code.
def heapifyByInsert(a, n):
    """ Repeatedly insert elements into the heap.
        Worst case number of element exchanges:
           sum of depths of nodes."""
    for i in range(2, n+1):
        percolateUp(a, i)
def buildHeap(a, n):
    """ Each time through the loop, each of node i's two
        subtreees is already a heap.
        Find the correct position to move the root down to
        in order to "reheapify."
       Worst case number of element exchanges:
           sum of heights of nodes."""
    for i in range (n//2, 0, -1):
       percolateDown(a, i, n)
def heapSort(a, n):
   buildHeap(a, n)
    for i in range(n, 1, -1):
        swap(a, 1, i)
        percolateDown(a, 1, i-1)
```

HeapSort: Build Initial Heap

- Two approaches:
 - for i = 2 to n
 percolateUp(i)
 - for j = n/2 downto 1
 percolateDown(j)
- Which is faster, and why?
- What does this say about overall big-theta running time for HeapSort?



Polynomial Evaluation Problem Reductiion

TRANSFORM AND CONQUER



Horner's Rule

- It involves a representation change.
- Instead of $a_n x^n + a_{n-1} x^{n-1} + \dots + a_1 x + a_0$, which requires a lot of multiplications, we write
- $(... (a_n x + a_{n-1})x + ... + a_1)x + a_0$
- code on next slide



Horner's Rule Code

• This is clearly $\Theta(n)$.

```
def polyEvalHorner(p, x):
    """ p is a list representing the coefficients.
        p[i] is the coefficient of x^i.
        x is where we are to evaluate p. """
    sum = 0
    for i in range(len(p)-1, -1, -1):
        sum = sum * x + p[i]
    return sum

# evaluate 4x^3 + 3x^2 + 2x + 1 at x=2
print polyEvalHorner([1, 2, 3, 4], 2)
```

Problem Reduction

- Express an instance of a problem in terms of an instance of another problem that we already know how to solve.
- There needs to be a one-to-one mapping between problems in the original domain and problems in the new domain.
- **Example:** In quickhull, we reduced the problem of determining whether a point is to the left of a line to the problem of computing a simple 3x3 determinant.
- Example: Moldy chocolate problem in HW 9.
 The big question: What problem to reduce it to? (You'll answer that one in the homework)

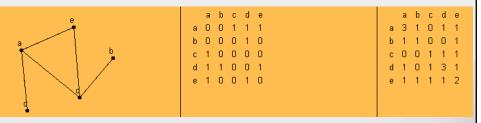
Least Common Multiple

- Let m and n be integers. Find their LCM.
- Factoring is hard.
- But we can reduce the LCM problem to the GCD problem, and then use Euclid's algorithm.
- Note that lcm(m,n)·gcd(m,n) = m·n
- This makes it easy to find lcm(m,n)



Paths and Adjacency Matrices

 We can count paths from A to B in a graph by looking at powers of the graph's adjacency matrix.



For this example, I used the applet from http://oneweb.utc.edu/~Christopher-Mawata/petersen2/lesson7.htm, which is no longer accessible

Linear programming

- We want to maximize/minimize a linear function $\sum_{i=1}^{n} c_i x_i$, subject to **constraints**, which are linear equations or inequalities involving the n variables $x_1,...,x_n$.
- The constraints define a region, so we seek to maximize the function within that region.
- If the function has a maximum or minimum in the region it happens at one of the vertices of the convex hull of the region.
- The simplex method is a well-known algorithm for solving linear programming problems. We will not deal with it in this course.
- The Operations Research courses cover linear programming in some detail.

Integer Programming

- A linear programming problem is called an integer programming problem if the values of the variables must all be integers.
- The knapsack problem can be reduced to an integer programming problem:
- maximize $\sum_{i=1}^{n} x_i v_i$ subject to the constraints $\sum_{i=1}^{n} x_i w_i < W$ and $\mathbf{x}_i \in \{0, 1\}$ for i=1, ..., n



Sometimes using a little more space saves a lot of time

SPACE-TIME TRADEOFFS



Space vs time tradeoffs

- Often we can find a faster algorithm if we are willing to use additional space.
- Examples:



Space vs time tradeoffs

- Often we can find a faster algorithm if we are willing to use additional space.
- Give some examples (quiz question)
- Examples:
 - Binary heap vs simple sorted array. Uses one extra array position
 - Merge sort
 - Radix sort and Bucket Sort
 - Anagram finder
 - Binary Search Tree (extra space for the pointers)
 - AVL Tree (extra space for the balance code)



Hashing Highlights

- We cover this pretty thoroughly in CSSE 230, and Levitin does a good job of reviewing it concisely, so I'll have you read it on your own (section 7.3).
- On the next slides you'll find a list of things you should know (some of them expressed here as questions)
- Details in Levitin section 7.3 and Weiss chapter 20.
- Outline of what you need to know is on the next slides.
- Will not cover them in great detail in class, since they are typically covered well in 230.
- **Today:** talk with students near you and answer the last two questions on today's handout.



Hashing – You should know, part 1

- Hash table logically contains key-value pairs.
- Represented as an array of size m. H[0..m-1] Typically m is larger than the number of pairs currently in the table.
- Hash function h(K) takes key K to a number in range 0..m
- Hash function goals:
 - Distribute keys as evenly as possible in the table.
 - Easy to compute.
 - Does not require m to be a lot larger than the number of keys in the table.

Hashing – You should know, part 2

- Load factor: ratio of used table slots to total table slots.
 - Smaller → better time efficiency (fewer collisions)
 - Larger → better space efficiency
- Two main approaches to collision resolution
 - Open addressing
 - Se
- Open addressing basic idea
 - When there is a collision during insertion, systematically check later slots (with wraparound) until we find an empty spot.
 - When searching, we systematically move through the array in the same way we did upon insertion until we find the key we are looking for or an empty slot.

Hashing – You should know, part 3

- Open addressing linear probing
 - When there is a collision, check the next cell, then the next one,..., (with wraparound)
 - Let α be the load factor, and let S and U be the expected number of probes for successful and unsuccessful searches. Expected values for S and

U are

α	$\tfrac{1}{2}(1+\tfrac{1}{1-\alpha})$	$\frac{1}{2}(1+\frac{1}{(1-\alpha)^2})$
50%	1.5	2.5
75%	2.5	8.5
90%	5.5	50.5



Hashing – You should know, part 4

- Open addressing double hashing
 - When there is a collision, use another hash function s(K) to decide how much to increment by when searching for an empty location in the table
 - So we look in H(k), H(k) + s(k), H(k) + 2s(k), ..., with everything being done mod m.
 - If we we want to utilize all possible array positions, gcd(m, s(k)) must be 1. If m is prime, this will happen.



Hashing – You should know, part 5

- Separate chaining
 - Each of the m positions in the array contains a link ot a structure (perhaps a linked list) that can hold multiple values.
 - Does not have the clustering problem that can come from open addressing.

$$S \approx 1 + \frac{\alpha}{2}$$
 and $U = \alpha$,

For more details, including quadratic probing, see
 Weiss Chapter 20 or my CSSE 230 slides (linked from the schedule page)