Heaps

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Define the height of a node in a tree as the number of edges on the longest path from that node down to a leaf.

The height of the tree, $H$, is the height of its root.
The *level* of the root is 0, the children of the root are at level 1. In general, the children of a node of level $k$ are at level $k + 1$. 

![Heap Diagram]

- Node 0
- Node 1 (level 1)
  - Node 1 (level 2)
    - Node 2 (level 3)
      - Node 3
      - Node 4
    - Node 2
  - Node 1 (level 2)
    - Node 2
    - Node 2

- Node 3
- Node 3
- Node 3
- Node 4
Heaps and Pre-Heaps

- In a binary tree, there are at most $2^k$ nodes at level $k$.
- If the highest level is completely filled in, that level contains $2^H$ nodes, and the tree contains $1 + 2 + 4 + \cdots + 2^H = 2^{H+1} - 1$ nodes.
- A *heap* is a special kind of a binary tree (do not confuse with the CS term related to memory allocation!).
- Let us define a *pre-heap* as follows:
  - All leaves are on at most two adjacent levels.
  - Except maybe the lowest level, all the levels are completely filled. The leaves on the lowest level are filled in, without gaps, from the left.
Notice that it can be represented as a simple array.

The nodes are tagged by their height.

All the levels less than 3 are completely filled in, and there are a total of $2^3 - 1$ nodes at those levels.
If we have a pre-heap with \( n \) nodes, denote its height by \( H \).
As seen above, we must have \( 2^H \leq n \leq 2^{H+1} - 1 < 2^{H+1} \).
Equivalently, \( H = \lfloor \log_2 n \rfloor \)

**Lemma**

*In a pre-heap with \( n \) elements, there are \( \lceil \frac{n}{2} \rceil \) leaves.*

**Proof.**

- Some leaves are at level \( H \), and some are at level \( H - 1 \).
- Since the number of nodes at level \( H - 1 \) or less is \( 2^H - 1 \), the number of leaves at level \( H \) is \( n - (2^H - 1) \).
- The parent of node \( n \) is node \( \lfloor \frac{n}{2} \rfloor \), and that node is the last node of height 1.
Pre-Heap Properties

Proof (Cont.)

- So all the rest of the nodes at level \( H - 1 \) are of height 0, i.e., are leaf nodes.
- Therefore the number of leaves at level \( H - 1 \) is \((2^H - 1) - \left\lfloor \frac{n}{2} \right\rfloor\).
- Hence the total number of leaves is

\[
n - (2^H - 1) + (2^H - 1) - \left\lfloor \frac{n}{2} \right\rfloor = n - \left\lfloor \frac{n}{2} \right\rfloor = \left\lceil \frac{n}{2} \right\rceil
\]
Pre-Heap Properties

Level 0
Level 1
Level 2
Level 3
Level H-1
Level H

node $2^{H-1}$

node $2^H$ 

node $n$

Level H-1

Level H
Corollary

*In a pre-heap with height $H$, there are at most $2^H$ leaves.*

Proof.

If $n$ is the number of elements in the pre-heap, we know that $2^H \leq n \leq 2^{H+1} - 1 < 2^{H+1}$. Then by the Lemma, the number of leaves is

$$\left\lfloor \frac{n}{2} \right\rfloor \leq \frac{2^{H+1}}{2} = 2^H$$
Pre-Heap Properties

**Theorem**

In a pre-heap with \( n \) elements, there are at most \( \frac{n}{2^h} \) nodes at height \( h \).

**Proof.**

- We have just seen that there are at most \( 2^H \) leaves in such a tree, and the leaves are just the nodes at height 0.
- If we take away the leaves, we have a smaller pre-heap with at most \( 2^{H-1} \) leaves, and these leaves are exactly the nodes at height 1 in the original tree.
- Continuing, we see that there are at most \( 2^{H-h} \) nodes at height \( h \) in the original tree, therefore \( 2^{H-h} = \frac{2^H}{2^h} \leq \frac{n}{2^h} \).
Definition

- A *heap* is a binary tree with a key in each node.
- The keys must be comparable.
- Additionally, the heap must have the following properties:
  - All leaves are on at most two adjacent levels.
  - With the possible exception of the lowest level, all the levels are completely filled. The leaves on the lowest level are filled in, without gaps, from the left.
  - The key at each node is greater than or equal to the key in any descendant of that node.
Note that another way of phrasing the third condition would be:
- The key in the root is greater than or equal to that of its children, and its left and right subtrees are again heaps.

Thus every heap is a pre-heap.

Even though the shape of a heap containing \( n \) elements is uniquely determined (since it is a pre-heap), the arrangement of those \( n \) elements is not.
Example – Two Heaps With the Same Set of Keys
The Heapify Procedure

- The fundamental procedure to build a heap.
- We have a binary tree in the shape of a heap (but perhaps not actually a heap).
- We represent the tree as an array $A[1..n]$, where $n$ is the size of the heap.
- We look at node $i$ (holding the value $A[i]$). We assume that:
  - The tree rooted at $l = \text{Left}(i)$ is a heap.
  - The tree rooted at $r = \text{Right}(i)$ is a heap.
- However, we do not assume that the tree rooted at $i$ is a heap.
- Heapify works by letting the value $A[i]$ “float down” to its proper position in the heap.
Algorithm 1 Heapify(A, i)

1: \( l \leftarrow \text{Left}(i) \)
2: \( r \leftarrow \text{Right}(i) \)
3: \( \text{if } l \leq \text{Heapsize}[A] \text{ and } A[l] > A[i] \text{ then} \)
4: \( \text{largest} \leftarrow l \)
5: \( \text{else} \)
6: \( \text{largest} \leftarrow i \)
7: \( \text{end if} \)
8: \( \text{if } r \leq \text{heapsize}[A] \text{ and } A[r] > A[\text{largest}] \text{ then} \)
9: \( \text{largest} \leftarrow r \)
10: \( \text{end if} \)
11: \( \text{if } \text{largest} \neq i \text{ then} \)
12: \( \text{exchange} A[i] \leftrightarrow A[\text{largest}] \)
13: \( \text{Heapify}(A, \text{largest}) \)
14: \( \text{end if} \)
The time needed to run Heapify on a subtree of size \( n \) rooted at a given node \( i \) is

- time \( \Theta(1) \) to fix up the relationships among the elements \( A[i] \), \( A[\text{Left}(i)] \), and \( A[\text{Right}(i)] \)
- time to run Heapify on a subtree rooted at one of the children of node \( i \).

That subtree has size at most \( 2n/3 \) – the worst case occurs when the last row of the tree is exactly half full.

So the running time \( T(n) \) can be characterized by the recurrence

\[
T(n) \leq T(2n/3) + \Theta(1)
\]

This falls into case 2 of the “master theorem”, and so we must have \( T(n) = O(\log n) \)
Building a Heap

The heap is built from the bottom up, starting at the first non-leaf node.

Algorithm 2 BuildHeap(A)

1: heapsize[A] ← length[A]
2: for i ← ⌊length[A]/2⌋ to 1 do
3:   Heapify(A, i)
4: end for

To prove that this is correct We use the following loop invariant:

Lemma

At the start of each iteration of the for loop, each node i + 1, i + 2, ..., n is the root of a heap.
Proof of Correctness

Proof.

- On the first iteration of the loop, $i = \lfloor n/2 \rfloor$. Each node $\lfloor n/2 \rfloor + 1, \lfloor n/2 \rfloor + 2, \ldots, n$ is a leaf and is thus the root of a trivial heap.

- Inductive step – going from $i + 1$ to $i$, we assume that each element $i + 1, i + 2, \ldots, n$ is the root of a heap.

- Therefore each of the two children of node $i$ (i.e., nodes $2i$ and $2i + 1$) is the root of a heap.

- Therefore the call to $Heapify(A, i)$ makes $i$ the root of a heap.

- Further, all nodes which are not descendants of $i$ are untouched by the call to $Heapify(A, i)$, (Do you see why?) and so we can conclude that each node $i, i + 1, \ldots, n$ is now the root of a heap.
The number of elements of the heap at height $h$ is $\leq \frac{n}{2^h}$, and the cost of running Heapify on a node of height $h$ is $O(h)$.

The root of a heap of $n$ elements has height $\lfloor \log_2 n \rfloor$.

Therefore the worst-case cost of running BuildHeap on a heap of $n$ elements is bounded by

$$\sum_{h=0}^{\lfloor \log_2 n \rfloor} \frac{n}{2^h} O(h) = O\left(n \sum_{h=0}^{\lfloor \log_2 n \rfloor} \frac{h}{2^h}\right) = O(n)$$

since the sum converges, so we don’t care what the upper bound of the summation is.
Heap Properties

- Heaps give us partial information about the order of elements in a set.
- We can tell immediately what the largest element is.
- They are really cheap to build and can be stored in a simple array.
- This makes them very useful for various applications.
Algorithm 3 Heapsort(A)

1: `BuildHeap(A)`
2: for $i \leftarrow \text{length}[A]$ to 2 do
4: $\text{heapsize}[A] \leftarrow \text{heapsize}[A] - 1$
5: `Heapify(A, 1)`
6: end for

The call to `BuildHeap` takes time $O(n)$. Each of the $n - 1$ calls to `Heapify` takes time $O(\log n)$. Hence the total running time is (in the worst case) $O(n \log n)$. 
Definition

A priority queue is a data structure that maintains a set $S$ of elements, each with an associated value called a key. (As usual, the keys must be comparable.) The priority queue supports the following operations:

- $\text{Insert}(S, x)$ inserts the element $x$ into the set $S$.
- $\text{Maximum}(S)$ returns the element of $S$ with the largest key.
- $\text{ExtractMax}(S)$ removes and returns the element of $S$ with the largest key.
- $\text{IncreaseKey}(S, x, k)$ increases the value of element $x$’s key to the new value $k$, which is assumed to be at least as large as $x$’s current key value.

A priority queue can be implemented using a heap.
Algorithm 4 HeapMaximum(A)
1: return A[1]

Obviously, the run time is $O(1)$.

Algorithm 5 HeapExtractMax(A)
1: if heapsize[A] < 1 then
2: ERROR – heap underflow
3: end if
4: maxx ← A[1]
6: heapsize[A] ← heapsize[A] − 1
7: Heapify(A, 1)
8: return maxx

Here the running time is dominated by the call to Heapify, so it is $O(\log n)$. 
Algorithm 6 HeapIncreaseKey(A, i, key)

1: if $key < A[i]$ then
2:   ERROR – new key is smaller than current key
3: end if
4: $A[i] \leftarrow key$
5: while $i > 1$ and $A[\text{Parent}(i)] < A[i]$ do
6:   exchange $A[i] \leftrightarrow A[\text{Parent}(i)]$
7:   $i \leftarrow \text{Parent}(i)$
8: end while

We just increase the key of $A[i]$, and then let that node “float up” to its proper position.
HeapIncreaseKey – Example

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Algorithm 7 HeapInsert(A, key)

1: heapsize[A] ← heapsize[A] + 1
2: A[heapsize[A]] ← −∞
3: HeapIncreaseKey(A, heapsize[A], key)

The running time here is again $O(\log_2 n)$. Thus, a heap supports any priority queue operation on a set of size $n$ in $O(\log n)$ time.