

COL 702 Lecture 6

Potential function of a ^{state} (data structure)

$$\phi : S \rightarrow \mathbb{R}$$

Initial state is S_0

$$\phi(S_0) : \phi_0$$

$$S_0 \rightarrow S_1 \rightarrow S_2 \dots$$

$$\phi_0 \quad \phi_1 \quad \phi_2 \quad \dots$$

let the work done be denoted by w_i when we move from S_i to S_{i+1} which is the actual work done

$$\text{Amortized work} : A_i = w_i + \underbrace{\phi(S_{i+1}) - \phi(S_i)}_{\text{change in potential}}$$

Total work done over a sequence of n updates

$$W = \sum_{i=0}^{n-1} w_i$$

$$\begin{aligned} \text{Total Amortized work} &= \sum_i (w_i + \phi_{i+1} - \phi_i) \\ &= W + [\cancel{\phi_1 - \phi_0} + \cancel{\phi_2 - \phi_1} \dots \phi_n - \phi_0] \end{aligned}$$

$$\text{Total amortized work} = \text{Actual work} + \phi_f - \phi_i$$

ϕ_f : final ϕ_i : initial

$$\text{If } \phi_f - \phi_i \geq 0 \Rightarrow \text{Total work} \leq \text{Amortized work}$$

$$\left(\text{In general Total work} = \text{Amortized work} + \phi_i - \phi_f \right)$$

Example : Stack operations push, pop, Empty stack

$\phi(\text{Stack})$: # of elements in stack

$$\phi_i(\text{Empty stack}) = 0 \quad \phi_f \geq \phi_i$$

Push : Actual work : 1 Amortized work : 1 + 1 (change in potential) = 2

Scaling by factor c
change the constant.

Pop : Actual work : 1 Amortized work : 1 - 1 = 0

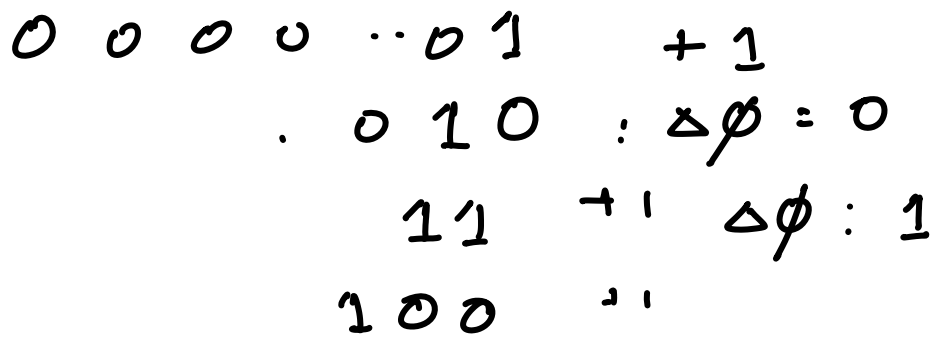
Empty stack : Actual work #elements
Amortized work : #elements - #elements = 0

$$\text{Cost of } m \text{ stack operations} \leq \text{amortized cost of } m \text{ ops} \leq 2 \cdot m$$

Example 2: Counter Problem

Potential function : # bits equal to 1

Amortized cost of increment :
 (worst case) # bits that flip to 1 -
 # bits that flip to 0



Amortized cost ≤ 1

$$\begin{array}{r}
 011111 \\
 1\underline{00000}
 \end{array}$$

Application to Binomial Heaps :

Suppose we keep inserting elements to a Binomial Heap : $O(1)$ from analogy with the counter

Semi dynamic dictionary problem

Supports insertions and search

(Not \downarrow deletion)

We will prefer using arrays



Goal : Support search and insertion in $O(\log n)$ time $\begin{cases} O(\log^2 n) \\ O(\log^3 n) \end{cases}$

Idea : Suppose we store the elements in multiple sorted arrays

Cost of search : $\sum_i \log(n_i)$

n_i is the size of array i

For example with $\log n$ arrays, we can bound by $O(\log n \times \log n) = O(\log^2 n)$

Insertion : If an existing array has extra space, insert it in the array or else create a new array "of twice the size"

Consider arrays of size 2^i $i \geq 0$

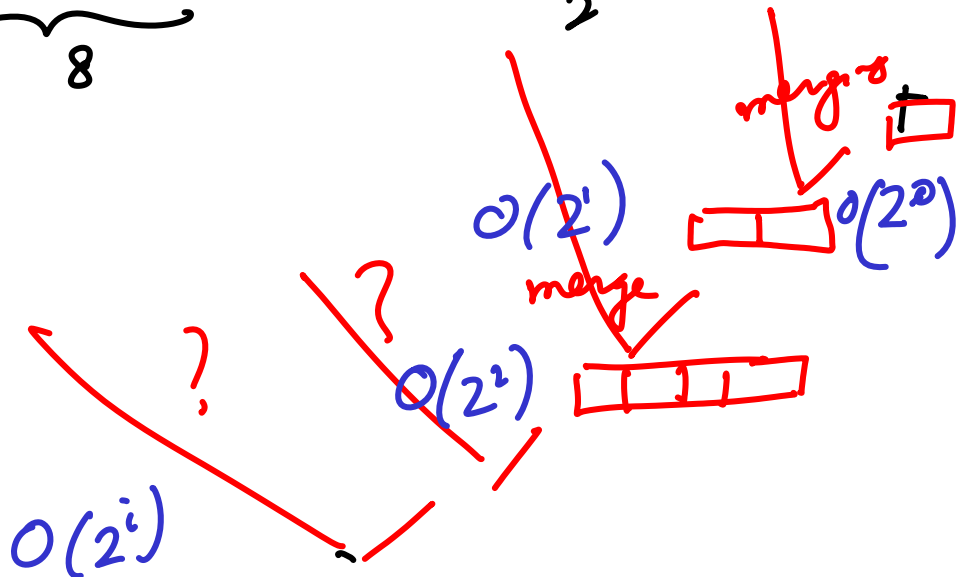
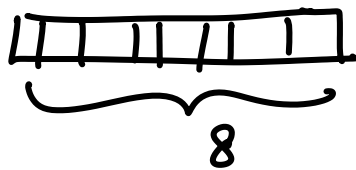
Like in Binomial heaps, we can repr any number n using at most $\log n$ such arrays \Rightarrow Search-time $O(\log^2 n)$

(At most one array of size 2^i) ($\log n$ binary search)

Insertion: Create an array of size 1 and "merge" with the existing arrays

Until there are no array of size 2^i starting with $i=0$
we merge two arrays of sizes 2^i

11 elements



Worst case cost :

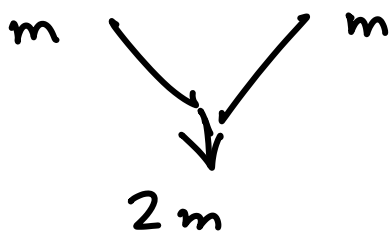
$$\sum_{1 \leq j \leq k} O(2^j)$$

$$\leq O(2^{k+1}) \sim O(2^k)$$

Amortized cost?

Guess $O(\log n)$
amortized cost

When we merge two arrays of size m



Cost is $O(2m)$

$O(\# \text{ elements involved})$

Let us pretend that we have
a counter with each element that
stores the cost of merging



$$\sum c_i = \text{cost of operations} = \text{running time}$$

Define amortized cost on the charges
and analyse the algorithm

Define potential function for each element