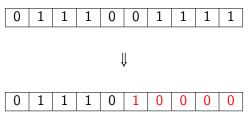
## Amortization

Tufts University

# Warm-up Question

How much time does it take to Increment() a bit counter?



# Cheat of the day

$$\sum_{i=0}^{\infty} \frac{1}{2^i} = 1 + \frac{1}{2} + \frac{1}{4} + \dots = 2$$

# Introducing amortized analysis

Formal version of average runtime Used when we repeatedly call same operations Some operations will be expensive others will be cheap How to combine average with big O and  $\Omega$ ?

#### Back to bit counter

```
Say counter has \log_2 n bits

Start at 0. Call Increment() n times

Runtime is \Theta(c_i) where c_i is number of changed bits

Worst-case runtime of one Increment()?

c_i = \# \text{bits} (from 011...1 to 10...0)
```

#### Lemma

The total time used in n executions of INCREMENT() is  $\Theta(n)$ 

## Brute force math

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0	1	1
0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	1	0	1
0	0	0	0	0	0	0	1	1	0
1	1	1	1	1	1	1	1	1	1

How many changes in the lowest order digit? n changes What about second lowest order digit? n/2 changes And highest order digit? one change Total number of changes =  $\sum_{i=0}^{\log n} \frac{n}{2^i} = n \sum_{i=0}^{\log n} \frac{1}{2^i} < 2n$   $\Rightarrow$  Runtime needed by the n operations is O(n)

### Amortized runtime

#### Lemma

The total time used in n executions of INCREMENT() is  $\Theta(n)$ 

A single operation could take  $\Theta(\#bits)$ , but most need  $\Theta(1)$ 

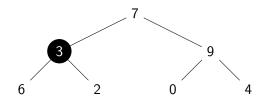
On "average" each execution needs O(1)On "average" each execution needs O(1)

**Amortized** cost of INCREMENT() over n operations is O(1)

 $\Leftrightarrow$  The n executions will need  $n \cdot O(1)$  time in the worst case

For short, we say INCREMENT has O(1) amortized cost

## Remember bottom up heap construction?



Insert all numbers at once. Fix from leaves upwards At each node we have to  $\operatorname{sink}$  root  $\Rightarrow \Theta(\log n_i)$   $n_i$  = number of elements in the sub-heap Sometimes  $n_i$  is big but often  $n_i$  is small n sink operations need  $\Theta(n)$  time in total  $\Rightarrow \Theta(1)$  amortized runtime

#### Potential method

#### General technique for computing amortized runtime

- ▶ Main idea: set a goal g runtime per operation
- ▶ Let *c<sub>i</sub>* cost of *i*-th operation
- ► Compare  $c_i$  against our goal If  $c_i < g$  we gain potential If  $c_i > g$  we lose potential
- Goal: always maintain positive potential
  - $\Rightarrow$  Average runtime is gn remaining potential

### **Definitions**

**Key point**: define a potential function  $\Phi$  to the DS In the bit vector: Potential  $\Phi(\text{bit vector}) = \#$  of 1s in vector  $c_i$  cost of i-th operation (in bit vector,  $c_i = \#$  of bits changed)  $\phi_i = \text{potential after } i$ -th operation  $\hat{c}_i = c_i + \phi_i - \phi_{i-1}$ 

Counter	Ci	Ф	ĉį
00000			
00001			
00010			
00011			
	:		

## Lemma

If 
$$\phi_0 = 0$$
 and  $\Phi \ge 0$ , then  $\sum_i \hat{c}_i \ge \sum_i c_i$ 

#### Proof.

$$\sum_{i} \hat{c}_{i} = \sum_{i} (c_{i} + \phi_{i} - \phi_{i-1}) = \sum_{i} (c_{i}) + \phi_{n} - \phi_{0} \ge \sum_{i} c_{i}$$

## Potential method

We know 
$$\sum_i \hat{c}_i \ge \sum_i c_i$$
  
**Goal**: show  $\hat{c}_i = O(1)$   
 $\Rightarrow \sum_i c_i \le \sum_i \hat{c}_i \le n \cdot O(1) = O(n)$ 

#### Lemma

In the bit vector problem, it holds that  $\hat{c}_i = 2$  for any  $i \ge 0$ 

Proof.

Counter 
$$X = \begin{bmatrix} \text{Rest of vector} & 0 & 1 & 1 & 1 \end{bmatrix}$$

sequence of 1s

$$X + 1 =$$
 Rest of vector  $\begin{vmatrix} 1 & 0 & 0 \end{vmatrix}$ 

## Summary

- 1. Defined a potential function  $\Phi$ , representing cost of structure
- 2. Defined amortized cost  $\hat{c}_i$  (real cost + change in potential) Real cost varies wildly but amortized remains consistent
- 3. Show that runtime=  $\sum_i c_i \le \sum_i \hat{c}_i$
- 4. Give an upper bound on  $\hat{c}_i$
- 5. Combine above steps to obtain amortized bound

#### In order to use the potential you should

- ▶ Define a potential function  $\Phi$  $\Phi(\text{start}) = 0, \ \Phi \ge 0$
- Give an upper bound on  $\hat{c}_i$

### Accountant method

Alternative version for bounding amortized runtime:

- Use a virtual currency:
  - User **deposits** coins when invoking an operation To compute we must **withdraw** coins
- ▶ Each coin can be used to do O(1) computations
- Golden rule: never run out of coins

# Example 3: Dynamic Array

Simple data structure

Data pointer + 2 counters (current size/max capacity)

Insertion is often fast (first empty slot)  $\Rightarrow \Theta(1)$ 

If full, we double size of array. Copy everything and insert

 $\Rightarrow \Theta(n)$  runtime if this happens

Let's prove that amortized insertion time is O(1)

### **Accountant approach**

Two operations involved in n insertions

Insert Insertion when array has space. User deposits 3 coins in each invocation

Resize Grow array when full. Implicitly invoked. 0 coins deposited

# Checking balance

#### Let's look at INSERTION

3 coins are deposited

Insertion needs O(1) number of operations

Check if space, insert, increase counter

O(1) operations  $\Rightarrow 1$  coin withdrawn

Net gain: 2 coins. We associate them to the inserted element

#### What about EXPAND?

0 coins are deposited. Must withdraw coins to pay for runtime **Key property**: only when array full.

Items in second half have 2 coins saved each.

⇒ one coin per element in array!

Withdraw 1 coin for element we copy onto bigger array

⇒ Use all coins but never go negative

After expansion half of the array is full

# Big picture

#### **Theorem**

n insertions in a dynamic array will need  $\Theta(n)$  time in total. (or insertion in a dynamic array uses  $\Theta(1)$  amortized time).

User deposits 3 coins per INSERT (0 on EXPAND) n operations invoked  $\Rightarrow 3n$  coins deposited Coins withdrawn each time computer spends time Never go negative balance  $\Rightarrow$  at most 3n coins withdrawn Each coin is O(1) operations  $\Rightarrow$  at most  $3n \cdot O(1)$  time spent

## Food for thought

Showed that insertion on DA needs  $\Theta(1)$  amortized What did we change? Nothing! Amortized analysis just changes... analysis Same algorithm, just better bounds Brute force counting Just count. Needs critical idea

Potential Associate a Potential to data structure

Change in potential flattens amortized runtime

Accounting Associate runtime to coins

Keep track of deposit/withdrawals

Never run out of coins