

**ISSUE**

- We can compute upper-bounds on the costs of a specific algorithmic solution to a problem.
- To design better algorithms, it is also important to compute lower-bounds on the cost of solving a problem algorithmically, i.e. the minimum cost of any algorithmic solution to a particular problem.
- In other words, in addition to computing the **O()** cost of an algorithm, it is useful to be able to calculate the  **$\Omega()$  cost of a problem**
- If a problem is known to have a  $\Omega(f)$  lower bound cost and it has a known algorithmic solution which is  $O(f)$ , then the bound  $f$  is said to be **tight**.

Problem	Lower bound	Tightness
Sorting an array of $n$ elements	$\Omega(n \log n)$	Yes
Sorting an array of $n$ elements	$\Omega(n)$	
Searching in a sorted array of $n$ elements	$\Omega(\log n)$	
Element uniqueness of $n$ elements	$\Omega(n \log n)$	
$n$ -digit integer multiplication	$\Omega(n)$	
Addition of two $n \times n$ matrices	$\Omega(n^2)$	
Multiplication of two $n \times n$ matrices	$\Omega(n^2)$	

**TRIVIAL LOWER BOUNDS**Approach

- For any problem which must calculate  $m$  outputs out of  $n$  inputs, any algorithmic solution will at least "read" the  $n$  inputs and "write" the  $m$  outputs.
- The minimum cost of an algorithmic solution to a problem with  $n$  inputs and  $m$  outputs is  $\max(n,m)$ .
- Be careful in deciding how many elements must be processed – e.g. searching for an element in a sorted array

Examples

- Finding maximum of  $n$  elements:  $n$  inputs, 1 output
- Sorting an array of  $n$  elements:  $n$  inputs,  $n$  outputs
- Evaluating the polynomial  $a_n x^n + a_{n-1} x^{n-1} + \dots + a_2 x^2 + a_1 x^1 + a_0 x^0$
- Any problem that generates an  $n \times m$  matrix
- Generating all the permutations of  $n$  elements
- Generating all the subsets of a set of  $n$  elements

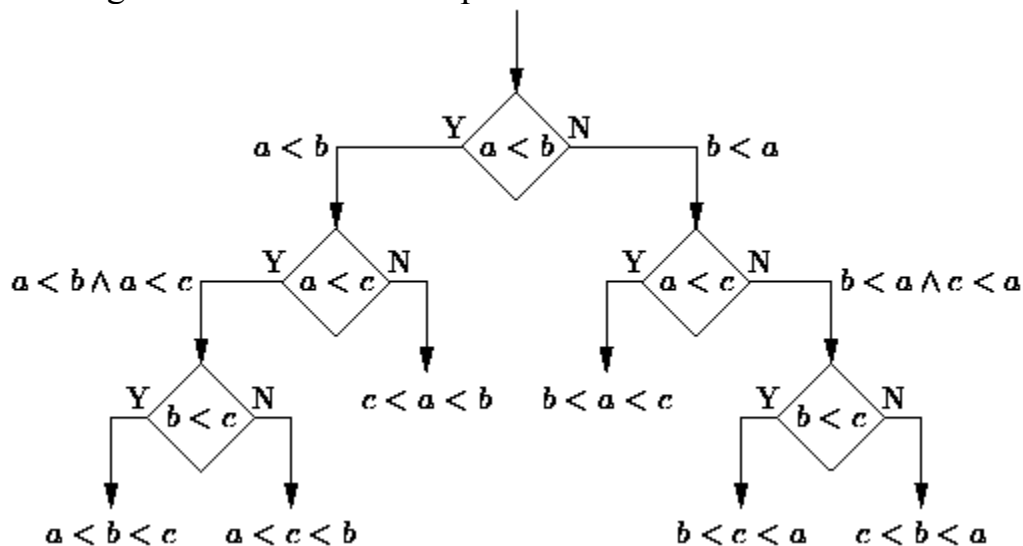
## DECISION TREES

### Approach

- Some algorithms compare the inputs against each other
- Build a **decision tree**: tree which shows all the possible comparisons and their outcomes.
  - Internal nodes represent comparisons.
  - Leaves represent outcomes.
- Number of comparisons in worst case = depth of tree = longest length between root and any of its leaves.

### Example - Sorting

- Sorting: decision tree for comparison based sort of 3 distinct elements



- Any comparison-based sorting algorithm can be represented by a decision tree
- Number of leaves (possible outcomes)  $\geq n!$  (# of permutations)
- Height of binary tree with  $n!$  leaves  $\geq \lceil \log_2 n! \rceil$
- Minimum number of comparisons in the worst case  $\geq \lceil \log_2 n! \rceil$  for any comparison-based sorting algorithm
- $\lceil \log_2 n! \rceil \approx n \log_2 n$
- This lower bound is tight (merge sort)

## ADVERSARY ARGUMENTS

### Definition

**Adversary argument:** a method of proving a lower bound by playing role of adversary that makes algorithm work the hardest by adjusting input

### Approach

- Algorithm A is a correct algorithm to solve a problem. It has an adversary D
- A asks D a set of questions, and D is allowed to answer in such a way to make A ask as many questions as possible.
- The number of questions represents the worst case performance of the algorithm

### Example - Finding number in a set

- Problem: “Guess ” a number between 1 and n with yes/no comparison questions
- Adversary D: Puts the number in a larger of the two subsets generated by last question
- D can force A to ask  $\lceil \log_2 n \rceil$  questions  
→ Searching through a sorted list costs  $\Omega(\log_2 n)$

### Example - Merging two sorted lists of size n

- Problem: Merging two sorted lists of size n  
 $a_1 < a_2 < \dots < a_n$  and  $b_1 < b_2 < \dots < b_n$
- Adversary:  $a_i < b_j$  iff  $i < j$
- Output  $b_1 < a_1 < b_2 < a_2 < \dots < b_n < a_n$   
requires  $2n-1$  comparisons of adjacent elements

## PROBLEM REDUCTION

### Approach

- Need a lower bound for problem P
- You know that problem P is at least as hard as problem Q (i.e. P might be harder/more expensive than Q)
- You know that problem Q has a lower bound  $\Omega(f)$  (i.e. Q is at least as expensive as  $C \cdot f$  for some constant C)
- You can conclude that  $\Omega(f)$  is also a lower bound for P

### Example - Euclidian Minimum Spanning Tree

- Problem P: Find Minimum Spanning Tree for n points in Cartesian plane.  
Note that this is not the same problem as finding the MST of a graph.  
We need a lower bound for this problem.
- Problem Q:
  - Element uniqueness problem: are there duplicates in a set of n values?
  - It is known that  $\text{cost}(Q) \in \Omega(n \log n)$
- Want to show that P is at least as hard as Q, i.e.  $\text{Cost}(P) \geq \text{Cost}(Q)$   
to conclude that  $\text{cost}(P) \in \Omega(n \log n)$
- **Reduce** Q to P, i.e. Solve Q with P
  - Transform each element x of Q into a point (x,0)       $\text{Cost}_1 \in \theta(n)$
  - Find MST for these points       $\text{Cost}_2 = \text{Cost}(P)$
  - Traverse MST to look for a zero-length edge       $\text{Cost}_3 \in \theta(n)$   
because MST has n-1 edges
- Reasoning by contradiction:
  - If  $\text{Cost}(P)$  can be asymptotically lower than  $\Omega(n \log n)$   
i.e.  $\text{Cost}(P) \in o(n \log n)$
  - Then Q can be solved at that lower cost +  $\theta(n)$
  - But any cost which is  $\theta(n)$  is also  $o(n \log n)$
  - i.e. Q can be solved using two components which are both  $o(n \log n)$   
i.e.  $Q \in o(n \log n)$   
this contradicts the fact that  $\text{cost}(Q) \in \Omega(n \log n)$