<u>*Lower bound*</u>: an estimate on a minimum amount of work needed to solve a given problem

#### **Examples:**

- **Q** number of comparisons needed to find the largest element in a set of *n* numbers
- **Q** number of comparisons needed to sort an array of size *n*
- **Q** number of comparisons necessary for searching in a sorted array
- **Q** number of multiplications needed to multiply two *n*-by-*n* matrices

## Lower Bounds (cont.)

#### **Q** Lower bound can be

• an exact count

• an efficiency class (Ω)

**Q** <u>*Tight*</u> lower bound: there exists an algorithm with the same efficiency as the lower bound

Problem	Lower bound	Tightness
sorting	$\Omega(n\log n)$	yes
searching in a sorted array	$\Omega(\log n)$	yes
element uniqueness	$\Omega(n \log n)$	yes
<i>n</i> -digit integer multiplication	$\Omega(n)$	unknown
multiplication of <i>n</i> -by- <i>n</i> matrices	$\Omega(n^2)$	unknown

# Methods for Establishing Lower Bounds

- **&** trivial lower bounds
- **@** information-theoretic arguments (decision trees)
- **adversary arguments**
- **&** problem reduction

## **Trivial Lower Bounds**

<u>*Trivial lower bounds*</u>: based on counting the number of items that must be processed in input and generated as output

Examples

- **Q** finding max element
- **&** polynomial evaluation
- & sorting
- **&** element uniqueness
- **&** Hamiltonian circuit existence

Conclusions

**a** may and may not be useful

**be careful in deciding how many elements <u>must</u> be processed** A. Levitin "Introduction to the Design & Analysis of Algorithms," 3rd ed., Ch. 11 ©2012 Pearson Education, Inc. Upper Saddle River, NJ. All Rights Reserved.

### **Decision Trees**

<u>Decision tree</u> — a convenient model of algorithms involving comparisons in which:

- **Q** internal nodes represent comparisons
- *Q* leaves represent outcomes

#### **Decision tree for 3-element insertion sort**



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## **Decision Trees and Sorting Algorithms**

- Any comparison-based sorting algorithm can be represented by a decision tree
- **Q** Number of leaves (outcomes)  $\geq n!$
- **A** Height of binary tree with *n*! leaves  $\geq \lceil \log_2 n! \rceil$
- **A** Minimum number of comparisons in the worst case  $\geq \lceil \log_2 n! \rceil$  for any comparison-based sorting algorithm
- $\mathcal{Q} \left\lceil \log_2 n! \right\rceil \approx n \log_2 n$
- **Q** This lower bound is tight (mergesort)

### **Adversary Arguments**

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

Example 1: "Guessing" a number between 1 and *n* with yes/no questionsAdversary: Puts the number in a larger of the two subsets generated by last question

Example 2: Merging two sorted lists of size n  $a_1 < a_2 < ... < a_n$  and  $b_1 < b_2 < ... < b_n$ Adversary:  $a_i < b_j$  iff i < jOutput  $b_1 < a_1 < b_2 < a_2 < ... < b_n < a_n$  requires 2*n*-1 comparisons of adjacent "Introduction to the Design & Analysis of Algorithms," 3rd ed., Ch. 11 ©2012 Pearson Education, Inc. Upper Saddle River, NJ. All Rights Reserved.

#### **Lower Bounds by Problem Reduction**

Idea: If problem P is at least as hard as problem Q, then a lower bound for Q is also a lower bound for P.
Hence, find problem Q with a known lower bound that can be reduced to problem P in question.

Example: *P* is finding MST for *n* points in Cartesian plane Q is element uniqueness problem (known to be in  $\Omega(n \log n)$ )

## **Classifying Problem Complexity**

Is the problem <u>tractable</u>, i.e., is there a polynomial-time (O(p(n))) algorithm that solves it?

**Possible answers:** 

**&** yes (give examples)

#### **S** 10

- because it's been proved that no algorithm exists at all (e.g., Turing's <u>halting problem</u>)
- because it's been be proved that any algorithm takes exponential time

## **Problem Types: Optimization and Decision**

- **Q** <u>Optimization problem</u>: find a solution that maximizes or minimizes some objective function
- **§** <u>Decision problem</u>: answer yes/no to a question
- Many problems have decision and optimization versions.

**E.g.:** traveling salesman problem *Q* optimization: find Hamiltonian cycle of minimum length *Q* decision: find Hamiltonian cycle of length  $\leq m$ 

## Decision problems are more convenient for formal investigation of their complexity.



<u>*P*</u>: the class of decision problems that are solvable in O(p(n)) time, where p(n) is a polynomial of problem's input size n

Examples: **Q** searching

- **&** element uniqueness
- **&** graph connectivity
- **&** graph acyclicity

**Q** primality testing (finally proved in 2002)

#### Class NP

<u>NP</u> (*nondeterministic polynomial*): class of decision problems whose proposed solutions can be verified in polynomial time = solvable by a *nondeterministic polynomial algorithm* 

A *nondeterministic polynomial algorithm* is an abstract two-stage procedure that:

*Q* generates a random string purported to solve the problem *Q* checks whether this solution is correct in polynomial time
By definition, it solves the problem if it's capable of generating and verifying a solution on one of its tries

#### Why this definition?

**a** led to development of the rich theory called "computational complexity"
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## **Example: CNF satisfiability**

**Problem:** Is a boolean expression in its conjunctive normal form (CNF) satisfiable, i.e., are there values of its variables that makes it true?

This problem is in NP. Nondeterministic algorithm:

- **Q** Guess truth assignment
- Substitute the values into the CNF formula to see if it evaluates to true

Example:  $(A | \neg B | \neg C) \& (A | B) \& (\neg B | \neg D | E) \& (\neg D | \neg E)$ Truth assignments: A B C D E 0 0 0 0 0 ...1 1 1 1 1

#### Checking phase: O(*n*)

## What problems are in NP?

- **&** Hamiltonian circuit existence
- **Q** Partition problem: Is it possible to partition a set of *n* integers into two disjoint subsets with the same sum?
- Decision versions of TSP, knapsack problem, graph coloring, and many other combinatorial optimization problems. (Few exceptions include: MST, shortest paths)
- All the problems in *P* can also be solved in this manner (no guessing is necessary), so we have:
   P ⊂ NP

#### **& Big question:** P = NP?

## **NP-Complete Problems**

A decision problem *D* is <u>*NP*-complete</u> if it's as hard as any problem in *NP*, i.e.,

- $\partial D$  is in NP
- **Q** every problem in *NP* is polynomial-time reducible to **D**



#### Cook's theorem (1971): CNF-sat is NP-complete A. Levitin "Introduction to the Design & Analysis of Algorithms," 3rd ed., Ch. 1T ©2012 Pearson

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## **NP-Complete Problems (cont.)**

Other *NP*-complete problems obtained through polynomialtime reductions from a known *NP*-complete problem



#### Examples: TSP, knapsack, partition, graph-coloring and hundreds of other problems of combinatorial nature

#### **P** = N**P** ? Dilemma Revisited

- **a** P = NP would imply that every problem in *NP*, including all *NP*-complete problems, could be solved in polynomial time
- **Q** If a polynomial-time algorithm for just one *NP*-complete problem is discovered, then every problem in *NP* can be solved in polynomial time, i.e., P = NP



## **Q** Most but not all researchers believe that $P \neq NP$ , i.e. *P* is a proper subset of *NP*