# Computational Complexity

#### **Decision Problem**

Running a decision problem on a TM.

- Once encoded, the encoded instance is provided as input to a TM.
- The TM must then
  - Determine if the input is a valid encoding
  - Run and halt:
    - In accept state if the answer for the input is yes
    - In reject state if the answer for the input is no
- If such a TM exists for a given decision problem, the problem is <u>decidable</u> or <u>solvable</u>. Otherwise the problem is called <u>undecidable</u> or <u>unsolvable</u>.

# What Makes a Good Algorithm?

- Suppose we know that a decision problem is decidable. How do we know that there is a good algorithm that solves the problem?
  - Consider the complexity of a TM that can solve the problem.

# Complexity

- Complexity refers to the rate at which the storage or time required to solve the problem grows as a function of the length of the input to the algorithm
  - T(n) = time complexity (amount of time an algorithm will take based on input)
  - S(n) = space complexity (amount of space an algorithm will take based on input)
- We'll focus on time complexity

# Complexity

#### Definition 7.1

- Let M be a deterministic TM that halts on all inputs. The time complexity of M is the function T:  $N \rightarrow N$ where T(n) is the maximum number of steps that M uses on any input of length n.
- n is used to represent the length (encoding) of the input string
- T(n) can be thought of as the number of TM "moves" needed to accept or reject

#### Asymptotic Analysis

- Based on the idea that as the input to an algorithm gets large:
  - The complexity will become proportional to a known function.
  - Only worry about the highest order term
  - Notation:
    - O (Big–O) upper bound on the complexity
    - $\Theta$  (Big-Theta) tight bounds on the complexity

#### Asymptotic Analysis

#### Big-O (order of)

- $T(n) \in O(f(n))$  if and only if there are constants:
  - c > 0 and  $n_0 \ge 0$  such that
  - $T(n) \le cf(n)$  for all  $n \ge n_0$
- What this means
  - The algorithm may have some lower order "start-up" costs
  - Eventually, when the size of the input gets large enough ( $n \ge n_0$ ), the runtime will be bounded above by a scaled (c > 0) function f(n).
    - Using c allows us to ignore constant factors when discussing asymptotic complexity

#### **Algorithm Efficiencies**

Axes are log scale, so all polynomial terms look linear here



### What Complexity is Acceptable?

- So what should be the cutoff between a "good" algorithm and a "bad" algorithm?
  - In the 1960s, it was proposed:
    - A "good" algorithm is one whose running time is a polynomial function of the size of the input
    - Other algorithms are "bad"
  - This definition was adopted:
    - A problem is called <u>tractable</u> if there exists a "good" (polynomial time) algorithm that solves it.
    - A problem is called <u>intractable</u> otherwise.

#### Is this a Valid Cutoff?

Assuming 1 million computations per second

|                                |        |         | Size n  | ze n      |                   |                      |
|--------------------------------|--------|---------|---------|-----------|-------------------|----------------------|
| Time<br>complexity<br>function | 10     | 20      | 30      | 40        | 50                | 60                   |
| n                              | .00001 | .00002  | .00003  | .00004    | .00005            | .00006               |
|                                | second | second  | second  | second    | second            | second               |
| n <sup>2</sup>                 | .0001  | .0004   | .0009   | .0016     | .0025             | .0036                |
|                                | second | second  | second  | second    | second            | second               |
| n <sup>3</sup>                 | .001   | .008    | .027    | .064      | .125              | .216                 |
|                                | second | second  | second  | second    | second            | second               |
| n <sup>5</sup>                 | .1     | 3.2     | 24.3    | 1.7       | 5.2               | 13.0                 |
|                                | second | seconds | seconds | minutes   | minutes           | minutes              |
| 2 <i><sup>n</sup></i>          | .001   | 1.0     | 17.9    | 12.7      | 35.7              | 366                  |
|                                | second | second  | minutes | days      | years             | centuries            |
| 3 <sup>n</sup>                 | .059   | 58      | 6.5     | 3855      | 2×10 <sup>8</sup> | 1.3×10 <sup>13</sup> |
|                                | second | minutes | years   | centuries | centuries         | centuries            |

- The class P contains all decision problems that are decidable by an algorithm that runs in polynomial time in the size of the input.
  - Does this define a class of languages?
  - Yes:
    - Each language is a specific decision problem whose encodings of "yes instances" (the language) is decided by a deterministic TM, M, where M decides that particular language in polynomial time.
  - <u>Recall: These languages are decidable</u>

The class P is robust

- It is the same class for all reasonable deterministic computational models
  - All reasonable deterministic computational models are polynomially equivalent
  - So if an algorithm runs in polynomial time using one given reasonable deterministic computational model, it also runs in polynomial time using other reasonable computational models
  - This means we don't have to worry about the specific computational model in use when showing that a language is contained in P

- To show that a decision problem is in P, we have to consider two aspects:
  - The algorithm runs in polynomial time in the size of the input string
  - A "reasonable encoding" is used to convert objects into strings
    - Polynomial-time (with respect to the size of the original input) to convert to a string

- Thus to show that a problem is in P, it suffices to analyze a high-level description
  - Describe a TM algorithm
    - Describe/assume a reasonable encoding that takes polynomial time
    - Show that the number of stages is polynomial in the size of the input
    - Show that the cost of running each stage is polynomial in the size of the input
- In doing so, we are discarding polynomial differences in algorithms.
  - Not that these are unimportant!

#### CFLs in P

- > Sipser, pg. 290-291
  - Every context-free language is a member of P
  - Proof uses dynamic programming technique (covered in Analysis of Algorithms class)

# **Polynomially Verifiable**

- A verifier for a language A is an algorithm V, where A = { w | V accepts <w,c> for some string c}.
- A polynomial time verifier runs in polynomial time in the length of w.
- The string c is called the certificate, or proof, that w is in A.

NP is the class of languages that have polynomial-time verifiers

- So, it may be that the algorithm can't run in polynomial time, but at least a specific certificate (or proof) that shows that the string is in the language can be checked in polynomial time
  - (that's all polynomial verifiability means given a certificate, you can use that to confirm in polynomial time that the string should be accepted)

### Another View of the Class NP

#### Theorem 7.20:

 A language is in NP if and only if it is decided by some non-deterministic polynomial time Turing Machine

> Remember that P requires the language to be decidable in polynomial time by a deterministic TM. So NP allows extra flexibility. There may be an exponential number of paths, but as long as they all compute in polynomial time, it's in NP.

# Clearly P is a subset of NP Does P=NP?

(a deterministic TM is just a special case of a NDTM that only has one branch of computation, so anything in P is in NP)

