# CSCI203

Week 2 – Lecture B

#### More on Complexity

- Last week we looked at the idea of Complexity Classes.
- ► These included:
  - Constant: the difficulty of the problem is independent of its size;
  - ► Logarithmic: the difficulty of the problems grows slowly as the problem size increases;
  - Linear: the difficulty increases at the same rate as the problem size grows;
  - Linearithmic: grows as n log n;
  - ► Quadratic: grows as n²;
  - Exponential: Grows as 2n;
  - Factorial: grows as n!

#### Order of Complexity

- ► A very useful way to talk about complexity is to use the concept of "order of".
- ► This idea allows us to directly compare complexity as well as allowing us to simplify the way in which we represent complexity.
- ► There are three standard order of complexity measures in common use:
  - ▶ Big Oh;
  - ➤ Omega;
  - ▶ Theta.

### Big Oh notation

- Consider the following function:
  - $t(n) = 12n^2 + 17/3 n + 7/5$
- For  $n \ge 1$ ,  $t(n) \le 12n^2 + 17/3 n^2 + 7/5 n^2 = 286/15n^2$ 
  - ▶ This is a constant (286/15) times a simple function  $n^2$
- ▶ We say that t(n) is in the order of  $n^2$ .
- ▶ We can write  $t(n) \in O(n^2)$ ; t(n) is in "big Oh" of  $n^2$
- ► More formally, O(f(n)) is the set of all functions t such that  $t(n) \le cf(n)$ , for some positive real constant c for all  $n \ge n_0$

# O(f(n))

- Note that O(f(n)) is the set of all functions that behave in the same general way:
  - They all grow at a rate that is no faster than f(n).
- We say that O(f(n)) is the set of all functions bounded above by f(n).

#### Asymptotic Notation

- It is legitimate to talk about the order of f(n) even if f(n) is badly behaved below  $n_0$
- Some texts use the notation t(n) = O(f(n)) which, given that O(f(n)) is a set, is strictly incorrect
- The maximum rule:  $O(f(n)+g(n)) = O(\max(f(n),g(n)))$ 
  - ► E.g.  $O(n^3 + n^2 + n \log n) = O(\max(n^3, n^2, n \log n)) = O(n^3)$

#### Comparing functions

- ▶ We can use the following results to determine the relationship between two functions, f(n) and g(n).
  - If  $\lim_{n\to\infty} \frac{f(n)}{g(n)} \in R^+$  then  $f(n) \in O(g(n))$  and  $g(n) \in O(f(n))$
  - If  $\lim_{n\to\infty} \frac{f(n)}{g(n)} = 0$  then  $f(n) \in O(g(n))$  but  $g(n) \notin O(f(n))$
  - If  $\lim_{n\to\infty} \frac{f(n)}{g(n)} = +\infty$  then  $f(n) \notin O(g(n))$  but  $g(n) \in O(f(n))$

#### Other Asymptotic Notation: Omega

- ightharpoonup O(f(n)) is the set of all functions that are *less than* the limiting function.
- ▶ This is not always a very useful measure.
- ► An alternative is Omega notation.
- ▶ A function t(n) is in Omega of f(n) if, for sufficiently large values of n, t(n) is less than some constant times f(n).
- We say that  $\Omega(f(n))$  is the set of all functions bounded below by f(n).

#### Relating O and $\Omega$

- ▶ If we have two functions f(n) and g(n), the following is true:
  - $ightharpoonup f(n) \in \Omega(g(n)) \text{ iff } g(n) \in O(f(n))$
- That is to say that f(n) is bounded below by g(n) if and only if g(n) is bounded above by f(n).
- ▶ Both of O and  $\Omega$  are *loose* bounds. A function can be in one of these and yet grow much more slowly (or quickly) than the bounding function.
  - ► E.g.  $n^2 \in O(n!)$  and  $n! \in \Omega$   $n^2$ .
- ► A third notation allows us to create a tighter bound for some functions.

## Theta, a tighter bound.

- $\triangleright$  Sometimes, we can find a function f(n) so that:
  - $\blacktriangleright t(n) \in O(f(n))$
  - $\blacktriangleright t(n) \in \Omega(f(n))$
- ► That is, the same function is both an upper bound and a lower bound.
- ▶ In this case we say that  $t(n) \in \Theta(f(n))$

#### Bounds and Algorithms

- We can make use of all three of these bounds in analyzing algorithms, as follows:
  - $\triangleright$  O(f(n)), the upper bound, is related to the worst-case behavior of the algorithm.
  - $\triangleright \Omega(f(n))$ , the lower bound, is related to the best-case behavior.
  - $\triangleright \Theta(f(n))$  is related to the average or typical-case behavior.
- In this subject, we will usually be interested in the typicalcase behavior of an algorithm although we will sometimes examine best- (and worst-) case behaviors.