ECE358: Foundations of Computing

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### Contents

	0.1	Introduction and Course Information	1	
1	Ma	th Review	<b>2</b>	
	1.1	Logarithms	2	
	1.2	Sequences and Series		
	1.3	Combinatorics		
2	Asy	emptotics	4	
3	Graphs			
	3.1	Definitions	6	
4	Tre	es	8	
	4.1	Definitions	8	
5	$\operatorname{Pro}$	of Methods 1	0	
	5.1	Induction	0	
	5.2	Contradiction	0	
	5.3	Master Theorem	1	
	5.4	Substitution	1	

### 0.1 Introduction and Course Information

This document offers an overview of the ECE358 course. They comprise my condensed course notes for the course. No promises are made relating to the correctness or completeness of the course notes. These notes are meant to highlight difficult concepts and explain them simply, not to comprehensively review the entire course.

#### **Course Information**

• Professors: Prof. Andreas Veneris and Prof. Zissis Poulos

 $\bullet$  Course: Engineering Science, Machine Intelligence Option

• Term: 2020 Fall

### Math Review

### 1.1 Logarithms

#### Logarithm Rules:

- **Definition:**  $a = b^c$  iff  $log_b a = c$ .
- $a = b^{\log_b a}$ .
- $\log_c(ab) = \log_c a + \log_c b$ .
- $\log_c(a^n) = n \log_c(a)$ .
- $\log_b(a) = \log_a(b)$ .
- $\log(1/a) = -\log a$ .
- $\log(a/c) = \log a \log c$ .
- $\bullet \ a^{\log n} = n^{\log a}.$

#### Variations on Logarithm

$$\log^{(i)} n = \begin{cases} n & \text{iff } i = 0\\ \log(\log^{(i)} n) & \text{otherwise} \end{cases}$$
 (1.1)

$$\log^* n = \begin{cases} 0 & \text{if } n \le 1\\ 1 + \log^*(\log n) & \text{otherwise} \end{cases}$$
 (1.2)

### 1.2 Sequences and Series

Theorem 1 Fibonnaci Definition

$$F_i = F_{i-1} + F_{i-2} \tag{1.3}$$

Where  $F_0 = 0$ ,  $F_1 = 1$ .

$$F_i = \frac{\phi^i - \hat{\phi}^i}{\sqrt{5}} \tag{1.4}$$

Where  $\phi = \frac{1+\sqrt{5}}{2}$ ,  $\hat{\phi} = \frac{1-\sqrt{5}}{2}$ 

Theorem 2 Arithmetic Series

$$\sum_{i=1}^{n} = \frac{n(n+1)}{2} = \Theta(n^2) \tag{1.5}$$

Theorem 3 Geometric Series

$$\sum_{k=0}^{n} x^k = \frac{x^{n+1} - 1}{x - 1} \tag{1.6}$$

Theorem 4 Infinite Series

$$\sum_{k=0}^{\infty} x^k = \frac{1}{1-x} \text{ iff } |x| < 1$$
 (1.7)

**Theorem 5** Telescoping Series

$$\sum_{i=1}^{n} a_i - a_{i-1} = a_n - a_0 \sum_{i=1}^{n} a_i - a_{i+1} = a_0 - a_n$$
 (1.8)

### 1.3 Combinatorics

Theorem 6 Binomial Coefficient

$$(x+y)^{r} = \sum_{i=0}^{r} {r \choose i} x^{i} y^{r-i}$$
 (1.9)

Where  $\binom{r}{i}$  is the binomial coefficient which equals

$$\frac{r!}{i!(r-i)!}$$

## Asymptotics

What are Asymptotics? Analysis method for performance and complexity of an algorithm (space/memory, time/clock cycle complexity).

- Tight Bound:  $\Theta()$ .
- Worst Case: O().
- Best Case:  $\Omega()$
- Average & Expected Case: Randomized + probabilistic analysis. Not a focus for the course.
- Amortized Case: Discused later on. "Average worst case".

#### **Useful Facts**

- $\bullet$   $\Theta$  bound is not always possible to find.
- Transitivity: if  $f(n) = \Theta(g(n))$  and  $g(n) = \Theta(h(n))$ , then  $f(n) = \Theta(h(n))$ .
- Symmetry:  $f(n) = \Theta(g(n))$  if and only if  $g(n) = \Theta(f(n))$ .
- Transpose: f(n) = O(g(n)) if and only if  $g(n)\Omega(f(n))$ .
- $n^a \in O(n^b)$  iff a < b.
- $\log_a(n) \in O(\log_b(n)) \, \forall a, b.$
- $c^n \in O(d^n)$  iff  $c \le d$ .

• If  $f(n) \in O(f'(n))$  and  $g(n) \in O(g'(n))$  then

$$f(n) \cdot g(n) \in O(f'(n) \cdot g'(n))$$

$$f(n) + g(n) \in O(\max(f'(n), g'(n)))$$

**Theorem 7** Big O Definition f(n) = O(g(n)) if and only if: There exists c > 0 and  $n_0 > 0$  such that

$$0 \le f(n) \le cg(n) \,\forall n \ge n_0 \tag{2.1}$$

**Theorem 8** Big  $\Omega$  Definition

"Lower Bound" Big  $\Omega$  Definition:  $f(n) = \Omega(h(n))$  if and only if: There exists  $c_1, n_1 > 0$  such that

$$0 \le c_1 h(n) \le f(n) \,\forall n \ge n_1 \tag{2.2}$$

**Theorem 9**  $Big \Theta Definition$ 

"Tight Bound" Big  $\Theta$  Definition:  $f(n) = \Theta(g(n))$  if and only if: There exists  $c_1, c_2, n_0 > 0$  such that

$$0 \le c_1 g(n) \le f(n) \le c_2 g(n) \,\forall n > n_0 \tag{2.3}$$

# Graphs

### 3.1 Definitions

**Theorem 10** Graph Definition A **graph** is a collection of **vertices** and **edges** represented by

$$G = (V, E) \tag{3.1}$$

Graphs can be:

- Directed or Undirected.
- Weighted or Unweighted.

Path: A sequence of edges between adjacent vertices.

- Simple Path: No vertex is repeated in the path.
- Cycle: A path that starts and ends with the same vertex.
- A **connected** graph has a path between any two vertices (else it is **disconnected**)

**Bipartite Graphs:** A graph is **bipartite** if and only if vertices V can be divided into  $V_1, V_2$  such that:

- 1.  $V_1 \cap V_2 = \emptyset$ .
- 2.  $V_1 \cup V_2 = V$ .
- 3. Adjacencies exist only between elements and  $V_1$  and  $V_2$  (i.e., vertices within each set are disconnected from each other, but are connected to elements from the other set).

Vertex Degree is the number of edges adjacent to a vertex (includes incoming and outgoing edges).

- In-degree is the number of incoming edges.
- Out-degree is the number of outgoing edges.

Clique: For all  $v_1, v_2 \in V$ , there exists an edge connecting them (i.e. a fully-connected set of vertices).

Representations for Graphs: We either use an adjacency matrix or an adjacency matrix.

- Adjacency List: Each element in the list represents a vertex and "has" a collection of **pointers** connecting them to other elements of the list.
  - **Time Complexity:** O(n) Determining if  $E_{v_1,v_2}$  exists would, at worst, require you to check n pointers arising from vertex  $v_1$  and/or  $v_2$ .
  - Space Complexity: O(|E|) with worst case that  $|E| = n^2$  for clique.
- Adjacency Matrix: Matrix contains weights connecting  $v_i$  to  $v_j$  at index  $M_{i,j}$ .
  - Time Complexity: O(1) Just check address  $M_{i,j}$  and  $M_{j,i}$ .
  - Space Complexity:  $O(n^2 \text{ every time.})$

### **Trees**

#### 4.1 Definitions

**Theorem 11** Tree Definition A tree is a connected, acyclic, undirected graph.

- Root node is usually defined.
- Parent node is the 'next node up' going toward the root.
- Child node is one of the 'next node(s) down' going away from the root.
- Binary tree:  $\leq 2$  children per node.
- **Depth of node:** Length of path from  $root \rightarrow node$ .
- Height of node: Number of edges on the longest path from the  $node \rightarrow leaf$ .
- Complete k-ary tree: Every internal node has k children and all leaves are at the same depth.

Theorem 12 One-for-all Tree Theorem If one of these is true, they all are:

- G is a tree.
- Every pair of vertices  $v_1, v_2 \in G$  is connected by a **unique**, **simple** path.
- G is disconnected, but becomes disconnected when one edge is removed.

- G is connected with |E| = |V| 1.
- G is acyclic.
- If an edge is added G becomes cyclic.

### **Proof Methods**

#### 5.1 Induction

**Basic Idea:** To prove by induction, we show that the statement holds for some base case n = 1, then show that the statement holding for aritrary n implies that the statement holds for n + 1. That concludes the proof.

**Basis:** We prove that the statement holds for some set values of n (usually n = 1 or n = 0, 1, ..., 4).

**Hypothesis:** We hypothesize that the thing we are trying to prove is true.

**Inductive Step:** We "plug in" the n+1 case to the hypothesis and show that it boils down to the n case and some algebraic equivalence. Then you can make the claim that it holds for all n.

#### 5.2 Contradiction

**Basic Idea:** Given a true or false proposition P, we assume that  $\neg P$  ("not P") holds. After some clever algebra and symbol-shunting, we get a contradiction. This implies that P must hold instead.

**Illustrative Example:** P: If  $x^2 - 5x + 4 < 0$ , then x > 0.

• To prove P, we assume towards a contradiction (ATaC) that  $\neg P$  holds. That is, we assume that if  $x^2 - 5x + 4 < 0$  then  $x \le 0$ .

• But then:

$$x^2 < 5x - 4 x^2 < 0 (5.1)$$

Results in a contradiction! Therefore P must hold.

#### 5.3 Master Theorem

This provides a "hammer" to prove the time complexity of recurrent functions.

**Theorem 13** The Master Theorem Let  $a \ge 1$  and  $b \ge 1$  and f(n) be some function.

$$T(n) = aT(\frac{n}{b}) + f(n) \tag{5.2}$$

Case 1:  $f(n) = O(n^{\log_b a - \epsilon})$  for some  $\epsilon > 0$ . Then

$$T(n) = \Theta(n^{\log_b a})$$

Case 2:  $f(n) = \Theta(n^{\log_b a})$ . Then

$$T(n) = \Theta(n^{\log_b a} \log n)$$

Case 3:  $f(n) = \Omega(n^{\log_b a + \epsilon})$  for some  $\epsilon > 0$  **AND**  $af(n/b) \le cf(n)$  for 0 < c < 1. Then

$$T(n) = \Theta(f(n))$$

.

### 5.4 Substitution

Substitution is a method for determining the closed from runtime of an algorithm via induction.

**Example – Mergesort:** The runtime for mergesort is recursively defined as  $T(n) = 2T(\lceil n/2 \rceil) + n$ .

1. We start by **guessing**  $T(n) = O(n \log n)$ .

2. We **hypothesize** that  $T(n) = O(n \log n)$  for all cases  $\leq n$ , meaning that

$$T(n/2) \le c \lfloor n/2 \rfloor \log \lfloor n/2 \rfloor$$

3. **Inductive step:** We prove that

$$T(n) \le cn \log n$$

Which is pretty obvious from there.