

ASSIGNMENT - 1.

CENG01: ANALYSIS & DESIGN OF ALGORITHMS

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Q1 (i) Big Oh (O -Notation)

→ Binds a function from Above - Asymptotic upper bound

$$O(g(n)) = \{f(n) : \exists c, n_0 > 0 \text{ s.t. } 0 \leq f(n) \leq cg(n) \forall n \geq n_0\}$$

→ Since O Notn describes the upper bound, its used to bound the worst case running time of an algorithm.

(ii) Ω Notation

→ Binds a function from below - Asymptotic lower bound.

$$\Omega(g(n)) = \{f(n) : \exists c, n_0 > 0 \text{ s.t. } 0 \leq cg(n) \leq f(n) \forall n \geq n_0\}$$

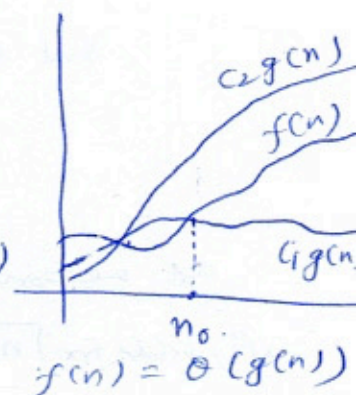
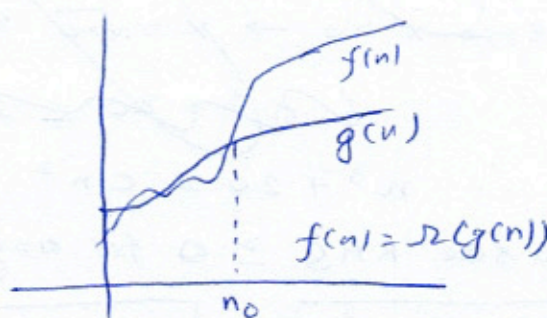
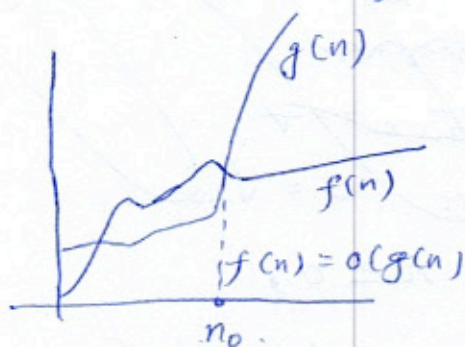
→ Its used to bind the best case running time of an algorithm.

(iii) Θ Notation

→ Asymptotically binds a function from above & below \therefore sandwiching.

$$\Theta(g(n)) = \{f(n) : \exists c_1, c_2, n_0 > 0 \text{ s.t. } c_1g(n) \leq f(n) \leq c_2g(n) \forall n \geq n_0\}$$

→ Its used to bind the average case running time of an algorithm.



(i) To prove $T(n) = n^3 + 20n + 1$ is $O(n^3)$

Acc. to definition of $O(g(n))$, $T(n) \leq cg(n)$ for all $n \geq n_0$, $c, n_0 > 0$.

$$n^3 + 20n + 1 \leq cn^3 \quad \text{--- (1)}$$

$$\frac{n^3}{n^3} + \frac{20n}{n^3} + \frac{1}{n^3} \leq c.$$

$$1 + \frac{20}{n} + \frac{1}{n^3} \leq c.$$

for $n \geq n_0 = 1$, $f(n) = 1 + \frac{20}{1} + \frac{1}{1} = 22$.

$$f(n) = 1 + \frac{20}{n} + \frac{1}{n^3} \Rightarrow f'(n) = -\frac{20}{n^2} + \frac{3}{n^4}$$

$$f'(n) = 0 \Rightarrow -\frac{20}{n^2} + \frac{3}{n^4} = 0 \quad \text{No global Minus.}$$

\Rightarrow (1) holds for $n \geq n_0 = 1$, $f(n) = 1 + \frac{20}{1} + \frac{1}{1} = 22$

$$c \geq 22$$

\Rightarrow hence proved.

(ii) To prove $T(n) = n^3 + 20n$ is $\Omega(n^2)$

Acc. to definition of $\Theta(g(n))$, $T(n) = \Omega(g(n))$ if $T(n) \geq cg(n)$ for all $n \geq n_0$, $c, n_0 > 0$.

$$n^3 + 20n \geq cn^2 \quad \text{--- (1)}$$

$$\frac{n^3}{n^2} + \frac{20n}{n^2} \geq c.$$

$$n + \frac{20}{n} \geq c.$$

$$f(x) = x + \frac{20}{x} \Rightarrow f'(x) = 1 - \frac{20}{x^2}$$

$$f'(x) = 0 \text{ for local extrema} \Rightarrow 1 - \frac{20}{x^2} = 0 \Rightarrow x^2 = 20$$

$$\text{but since } x > 0 \Rightarrow x = \sqrt{20}.$$

$$\therefore n^3 + 20n \geq 2\sqrt{20}n^2$$

$$\therefore n^3 + 20n \geq cn^2 \text{ for } c = \sqrt{20}$$

as we can see $RHS \geq 0$ for any $n \geq 0$,

\Rightarrow (1) holds for $n \geq n_0 = 1 \Rightarrow c = 21 \Rightarrow$ hence proved.

Q2 (i) Recurrence Equation for running time $T(n)$ of Strassen's algorithm for matrix multiplication.

$$T(n) = \begin{cases} \Theta(1) & \text{if } n = 1. \\ 7T(n/2) + \Theta(n^2) & \text{if } n > 1. \end{cases}$$

using Master's theorem,

$$T(n) = aT(n/b) + f(n) \rightarrow a = 7, b = 2, f(n) = n^2$$

$$n^2 = n^{10/2} \rightarrow \epsilon > 0$$

$$\text{Case I: } T(n) = \Theta(n^{\log_b a}) = \Theta(n^{\log_2 7}) \approx \Theta(n^{2.81})$$

(ii) Strassen's Algorithm for matrix multiplication.

MatMul - Strassen (A, B)

1. $n = A$ rows.
2. Let C be a $n \times n$ matrix.
3. if $n = 1$.
4. $C(n, n) = A(n, n) \cdot B(n, n)$.
5. else
6. $S_1 = B(1..n/2, n/2+1..n) - B(n/2+1..n, n/2+1..n)$
7. $S_2 = A(1..n/2, 1..n/2) + A(1..n/2, n/2+1..n)$
8. $S_3 = A(n/2+1..n, 1..n/2) + A(n/2+1..n, n/2+1..n)$
9. $S_4 = B(n/2+1..n, 1..n/2) - B(1..n/2, 1..n/2)$
10. $S_5 = A(1..n/2, 1..n/2) + A(n/2+1..n, n/2+1..n)$
11. $S_6 = B(1..n/2, 1..n/2) + B(n/2+1..n, n/2+1..n)$
12. $S_7 = A(1..n/2, n/2+1..n) - A(n/2+1..n, n/2+1..n)$
13. $S_8 = B(n/2+1..n, 1..n/2) + B(n/2+1..n, n/2+1..n)$
14. $S_9 = A(1..n/2, 1..n/2) - A(n/2+1..n, 1..n/2)$
15. $S_{10} = B(1..n/2, n/2+1..n) + B(1..n/2, 1..n/2)$
16. $P_1 = \text{MatMul-Strassen}(A(1..n/2, 1..n/2), S_1)$
17. $P_2 = \text{MatMul-Strassen}(S_2, B(n/2+1..n, n/2+1..n))$
18. $P_3 = \text{MatMul-Strassen}(S_3, B(1..n/2, 1..n/2))$
19. $P_4 = \text{MatMul-Strassen}(A(n/2+1..n, n/2+1..n), S_4)$
20. $P_5 = \text{MatMul-Strassen}(S_5, S_6)$
21. $P_6 = \text{MatMul-Strassen}(S_7, S_8)$
22. $P_7 = \text{MatMul-Strassen}(S_9, S_{10})$
23. $C(1..n/2, 1..n/2) = P_5 + P_4 - P_2 + P_6$
24. $C(1..n/2, n/2+1..n) = P_1 + P_2$
25. $C(n/2+1..n, 1..n/2) = P_3 + P_4$
26. $C(n/2+1..n, n/2+1..n) = P_5 + P_1 - P_3 - P_7$
27. return C

$$A = \begin{bmatrix} 3 & 4 \\ 5 & 6 \end{bmatrix} \quad B = \begin{bmatrix} 7 & 8 \\ 8 & 9 \end{bmatrix}$$

$$A_{11} = 3$$

$$B_{11} = 7$$

$$A_{12} = 4$$

$$B_{12} = 8$$

$$A_{21} = 5$$

$$B_{21} = 8$$

$$A_{22} = 6$$

$$B_{22} = 9$$

$$S_1 = B_{12} - B_{22} = 8 - 9 = -1$$

$$S_2 = A_{11} + A_{12} = 3 + 4 = 7$$

$$S_3 = A_{21} + A_{22} = 5 + 6 = 11$$

$$S_4 = B_{21} - B_{11} = 8 - 7 = 1$$

$$S_5 = A_{11} + A_{22} = 3 + 6 = 9$$

$$S_6 = B_{11} + B_{22} = 7 + 9 = 16$$

$$S_7 = A_{12} - A_{22} = 4 - 6 = -2$$

$$S_8 = B_{21} + B_{22} = 8 + 9 = 17$$

$$S_9 = A_{11} - A_{21} = 3 - 5 = -2$$

$$S_{10} = B_{11} + B_{12} = 7 + 8 = 15$$

$$P_1 = A_{11} \times S_1 = \cancel{A_{11} \times B_{12}} \rightarrow \cancel{A_{11} \times B_{22}} = 3 \times (-1) = -3$$

$$P_2 = S_2 \times B_{22} = 7 \times 9 = 63$$

$$P_3 = S_3 \times B_{11} = 11 \times 7 = 77$$

$$P_4 = A_{22} \times S_4 = 6 \times 1 = 6$$

$$P_5 = S_5 \times S_6 = 9 \times 16 = 144$$

$$P_6 = S_7 \times S_8 = -2 \times 17 = -34$$

$$P_7 = S_9 \times S_{10} = -2 \times 15 = -30$$

$$C_{11} = P_5 + P_4 - P_2 + P_6 = 144 + 6 - 63 - 34 = 53$$

$$C_{12} = P_1 + P_2 = -3 + 63 = 60$$

$$C_{21} = P_3 + P_4 = 77 + 6 = 83$$

$$C_{22} = P_5 + P_1 - P_3 - P_7 = 144 - 3 - 77 + 30 = 94$$

$$\therefore \begin{bmatrix} 3 & 4 \\ 5 & 6 \end{bmatrix} \times \begin{bmatrix} 7 & 8 \\ 8 & 9 \end{bmatrix} = \begin{bmatrix} 53 & 60 \\ 83 & 94 \end{bmatrix}$$

Q 3. Optimal Substructure of Fractional Knapsack Problem

Assume that X is the optimal solution with value V to problem S with knapsack capacity W .

To prove: $X' = X - x_j$ is an optimal solution to subproblem $S' = S - \{j\}$ and the knapsack capacity $W' = W - w_j$.

Proof (by contradiction).

Assume X' is not optimal to S' and we've another solution X'' to S' that has higher total value $V'' > V$, then $X'' \cup \{x_j\}$ is a solⁿ with value $V'' + v_j > V' + v_j = V$. This is a contradiction because V is assumed to be optimal in the beginning.

Greedy choice property of fractional knapsack problem.

Greedy choice prop: Let j be the item with maximum v_i/w_i , then \exists an optimal solⁿ in which you take as much frac^t of item j as possible.

Proof (by contradiction)

- Suppose there exists an optimal solution in which we didn't take as much of item j as possible.
- If the knapsack is not full, add some more ~~item~~ of item j , and we've a higher value solⁿ.

(Contradiction)

- we thus assume knapsack is full.

- there must exist some item $k \neq j$ with $\frac{v_k}{w_k} < \frac{v_j}{w_j}$ that's in the knapsack.

- we also must have that not all of j is in knapsack.

- we can therefore take a piece of k , with wt. ϵ out of knapsack k & put a piece of j with ϵ weight in knapsack.

- This increases knapsack value by

$$\epsilon \times \frac{v_j}{w_j} - \epsilon \frac{v_k}{w_k} > 0.$$

which is a contradiction to original solⁿ being optimal.

\therefore we can use greedy strategy to design an algorithm for fractional knapsack.

Greedy Fractional Knapsack (V, W, capacity)

1. wt taken = 0
2. profit = 0
3. sort items I in decreasing order of v/w $O(n \log n)$
4. for each item i in sorted list. $O(n)$
5. if (wt-taken + $w_i \leq$ capacity) $O(1)$
6. wt-taken += w_i .
7. profit += v_i .
8. else. $O(1)$
9. remaining = capacity - wt-taken
10. profit += remaining * (v_i/w_i).
11. break
12. return profit

$O(1)$

$T = O(n \log n)$

I :	1	2	3	4	5	6	7
W :	2	3	5	7	1	4	1
V :	10	5	15	7	6	18	3
V/W :	5	1.67	3	1	6	4.5	3

sorted by v/w

V/W :	6	5	4.5	3	3	1.67	1
I :	5	1	6	3	7	2	4
W :	1	2	4	5	1	3	7
V :	6	10	18	15	3	5	7

			1+2	3+4	7+5	12+1
wt taken	0	1	3	7	12	13
profit	0	6	16	34	49	52
items taken	{}	{I5}	{I5, I1}	{I5, I1, I6}	{I5, I1, I6, I3}	{I5, I1, I6, I3, I7}

$13 + 3 = 16 > \text{capacity} = 15$

$52 + (15 - 13) \left(\frac{5}{3} \right) = 55.33$

{ I5, I1, I6, I3, I7, $\frac{5}{3} \times I2$ }

$13 + 3 = 16 > \text{capacity} = 15$

$13 + 2 = 15$

$52 + (15 - 13) \left(\frac{5}{3} \right) = 55.33$

{ I5, I1, I6, I3, I7, $\frac{5}{3} \times I2$ }

Maximum profit = 55.33 with items I5, I1, I6, I3, I7, $\frac{5}{3} I2$ in knapsack.

Q4.

Definitions

Subsequence: Given a sequence $X = \langle x_1, x_2, \dots, x_m \rangle$, another sequence $Z = \langle z_1, z_2, \dots, z_k \rangle$ is a subsequence of X if there exists a strictly increasing sequence $\langle i_1, i_2, \dots, i_k \rangle$ of indices in X s.t. for all $j = 1, 2, \dots, k$ we have $x_{i_j} = z_j$.

eg. $Z = \langle B, C, D, B \rangle$ is a subsequence of $X = \langle A, B, C, B, D, A, B \rangle$ with index seq $\langle 2, 3, 5, 7 \rangle$

Common subsequence: A sequence Z is a common subseq. of X & Y if Z is a subsequence of both X & Y .

eg. $X = \langle A, B, C, B, D, A, B \rangle$
 $Y = \langle B, D, C, A, B, A \rangle$
 $Z = \langle B, C, A \rangle$ is a subseq of X & Y .

Problem statement

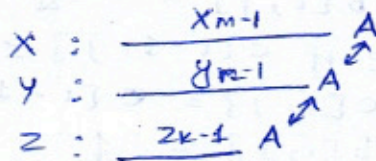
LCS problem: Given two sequences $X = \langle x_1, x_2, \dots, x_m \rangle$ and $Y = \langle y_1, y_2, \dots, y_n \rangle$, find the maximum length subsequence of X & Y .

Problem characterization

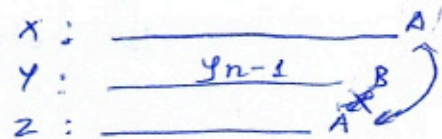
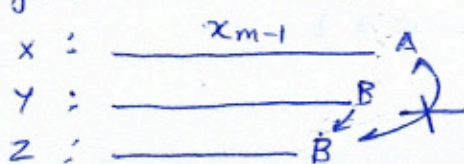
① LCS has optimal substructure property.

Let $X = \langle x_1, x_2, \dots, x_m \rangle$ &
 $Y = \langle y_1, y_2, \dots, y_n \rangle$ be sequences
 & $Z = \langle z_1, z_2, \dots, z_k \rangle$ be LCS of X & Y .

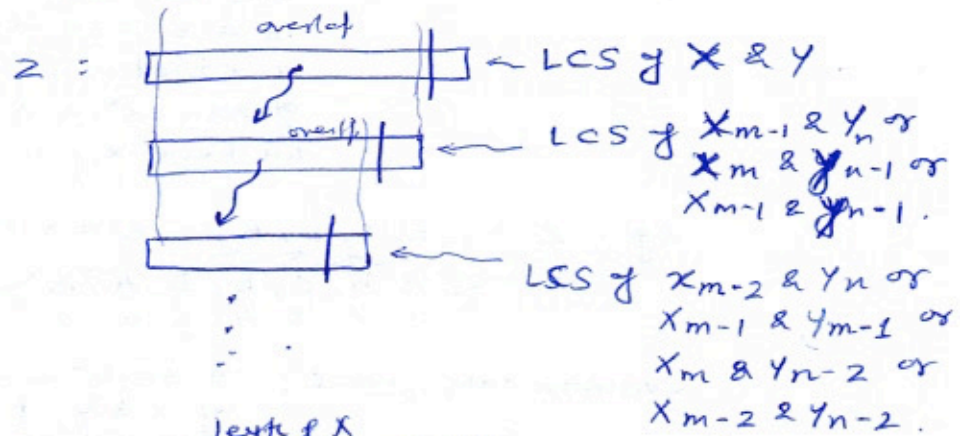
1. if $x_m = y_n$ then $z_k = x_m = y_n$ & z_{k-1} is LCS of x_{m-1} & y_{n-1} .



2. if $x_m \neq y_n$, then $z_k \neq x_m \Rightarrow Z$ is LCS of x_{m-1} & Y
 3. if $x_m \neq y_n$, then $z_k \neq y_n \Rightarrow Z$ is LCS of X & y_{n-1}



- (2) LCS has overlapping subproblems property.
 LCS of two sequences contains within it the
 LCS of prefixes of the two sequences.



∴ LCS has only $\Theta(mn)$ distinct subproblems.
 Here we can apply 2 dimensional bottom up DP to
 solve the problem efficiently

Dynamic Programming Algo for LCS

- LCS - Length (X, Y)
1. $m = X.length$
 2. $n = Y.length$
 3. let $b[1..m, 1..n] \in c[0..m, 0..n]$ be new table
 4. for $i = 1$ to m
 5. $c[i, 0] = 0$
 6. for $j = 0$ to n
 7. $c[0, j] = 0$
 8. for $i = 1$ to m
 9. for $j = 1$ to n
 10. if $x_i == y_j$
 11. $c[i, j] = c[i-1, j-1] + 1$
 12. $b[i, j] = "\swarrow"$
 13. else if $c[i-1, j] \geq c[i, j-1]$
 14. $c[i, j] = c[i-1, j]$
 15. $b[i, j] = "\downarrow"$
 16. else $c[i, j] = c[i, j-1]$
 17. $b[i, j] = "\rightarrow"$
 18. return c & b .

PRINT-LCS (b, X, i, j).

1. if $i=0$ or $j=0$.

2. return

3. if $b[i, j] = "\searrow"$

4. PRINT-LCS (b, X, $i-1, j-1$).

5. print x_i

6. else if $b[i, j] = "\downarrow"$

7. PRINT-LCS (b, X, $i-1, j$).

8. else PRINT-LCS (b, X, $i, j-1$)

Switch call is
PRINT-LCS (b, X, x.left, y.left)

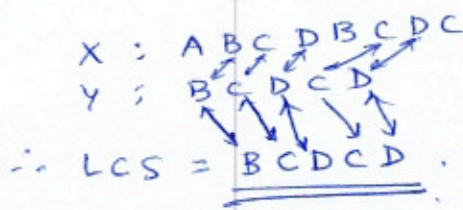
(i)

X = ABCDBCDC

Y = BCDCD

		j	0	1	2	3	4	5
				B	C	D	C	D
i	x_i		0	0	0	0	0	0
0				A≠B	A≠C	A≠D	A≠C	A≠D
1	A		0	0	0	0	0	0
2	B		0	B=B	B≠C	B≠D	B≠C	B≠D
3	C		0	C≠B	C=C	C≠D	C=C	C≠D
4	D		0	D≠B	D≠C	D=D	D≠C	D=D
5	B		0	B=B	B≠C	B≠D	B≠C	B≠D
6	C		0	C≠B	C=C	C≠D	C=C	C≠D
7	D		0	D≠B	D≠C	D=D	D≠C	D=D
8	C		0	C≠B	C=C	C≠D	C=C	C≠D

			1	2	3	4	5
			B	C	D	C	D
1	A		↘	↓	↓	↓	↓
2	B		↘	→	→	→	→
3	C		↓	↘	→	→	→
4	D		↓	↓	↘	→	↘
5	B		↘	↓	↘	↓	↓
6	C		↓	↘	↓	↘	→
7	D		↓	↓	↘	↓	↘
8	C		↓	↘	↓	↘	↘



PL(b, X, 8, 5)
 ↓
 PL(b, X, 7, 5)
 ↓
 PL(b, X, 6, 4) → $x_5 = 'D'$
 ↓
 PL(b, X, 5, 3) → $x_4 = 'C'$
 ↓
 PL(b, X, 4, 3)
 ↓
 PL(b, X, 3, 2) → $x_3 = 'D'$
 ↓
 PL(b, X, 2, 1) → $x_2 = 'C'$
 ↓
 PL(b, X, 1, 0) → $x_1 = 'B'$
 ↪ return

X = " POLYNOMIAL "

Y = " EXPONENTIAL "

J: 0 1 2 3 4 5 6 7 8 9 10 11

i: 0 1 2 3 4 5 6 7 8 9 10

X_i	0	0	0	0	0	0	0	0	0	0	0	0
P	0	0	0	1	1	1	1	1	1	1	1	1
O	0	0	0	1	2	2	2	2	2	2	2	2
L	0	0	0	1	2	2	2	2	2	2	2	3
Y	0	0	0	1	2	2	2	2	2	2	2	3
N	0	0	0	1	2	3	3	3	3	3	3	3
O	0	0	0	1	2	3	3	3	3	3	3	3
M	0	0	0	1	2	3	3	3	3	3	3	3
I	0	0	0	1	2	3	3	3	3	4	4	4
A	0	0	0	1	2	3	3	3	3	4	5	5
L	0	0	0	1	2	3	3	3	3	4	5	6

EXPONENTIAL

P	↓	↓	↘	→	→	→	→	→	→	→	→	→
O	↓	↓	↓	↘	↘	↘	→	→	→	→	→	→
L	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↘
Y	↓	↓	↓	↓	↓	↓	↓	↘	↓	↓	↓	↓
N	↓	↓	↓	↓	↓	↓	↓	↘	→	→	→	→
O	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓
M	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓
I	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↘	→
A	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↘	→
L	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↘

X: POLYNOMIAL
 Y: EXPONENTIAL
 LCS: PONIAL

Q 5.

NP-class

Set of all decision problems solved by a non deterministic machine in polynomial time
or.

It is a complexity class that represents set of all decision problems where the answer is 'yes' have proofs that can be verified in polynomial time.

This means, if someone gives us an instance of the problem and a certificate (sometimes called witness) to the answer being yes, we can check that it is correct in polynomial time.

eg. INTEGER FACTORIZATION.

pbm: given integers n & m , is there an integer f with $1 < f < m$ such that f divides n ?

This is a decision pbm because answers are yes or no. If someone hands us an instance of the pbm (ie n & m) and an integer f s.t. $1 < f < m$, and claim that f is a factor of n (the certificate), we can check the answer in polynomial time by performing the division n/f .

NP-complete

NPC is a complexity class which represents the set of all problems X in NP for which it is possible to reduce any other NP pbm Y to X in polynomial time.

This means that we can solve Y quickly if we know how to solve X quickly. Y is reducible to X , if there is a polynomial time algorithm f to transform instances y of Y to instances $x = f(y)$ of X in polynomial time, with the property that the answer to y is yes, iff the answer to $f(y)$ is yes.

eg. 3SAT (a Boolean satisfiability problem)

problem: given a conjunction (ANDs) of 3-clause disjunctions (ORs), i.e. stmt. of form

$$\begin{aligned} & (v_{11} \text{ OR } \bar{v}_{21} \text{ OR } v_{31}) \text{ AND} \\ & (v_{12} \text{ OR } v_{22} \text{ OR } v_{32}) \text{ AND} \\ & \dots \text{ AND} \\ & (v_{1n} \text{ OR } v_{2n} \text{ OR } v_{3n}) \end{aligned}$$

where v_{ij} is a boolean variable or negation of a variable from a finite predefined list (x_1, x_2, \dots, x_n)

It can be shown that every NP problem can be reduced to 3SAT: Cook's theorem.

NP problems are important because if a deterministic polynomial time algorithm is found to solve any one of them, then every NP problem is solvable in polynomial time.

NP-Hard

These are the problems which are at least as hard as the NP-complete problems. All NP-H problems do not have to be NP, and they do not have to be decision problems.

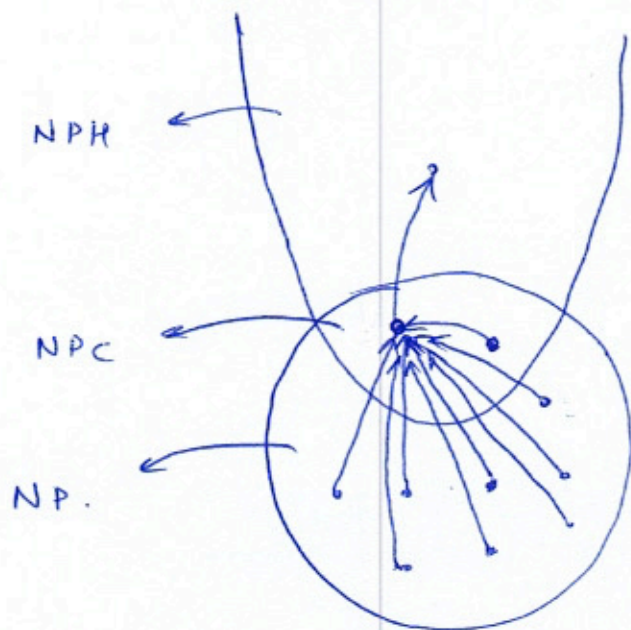
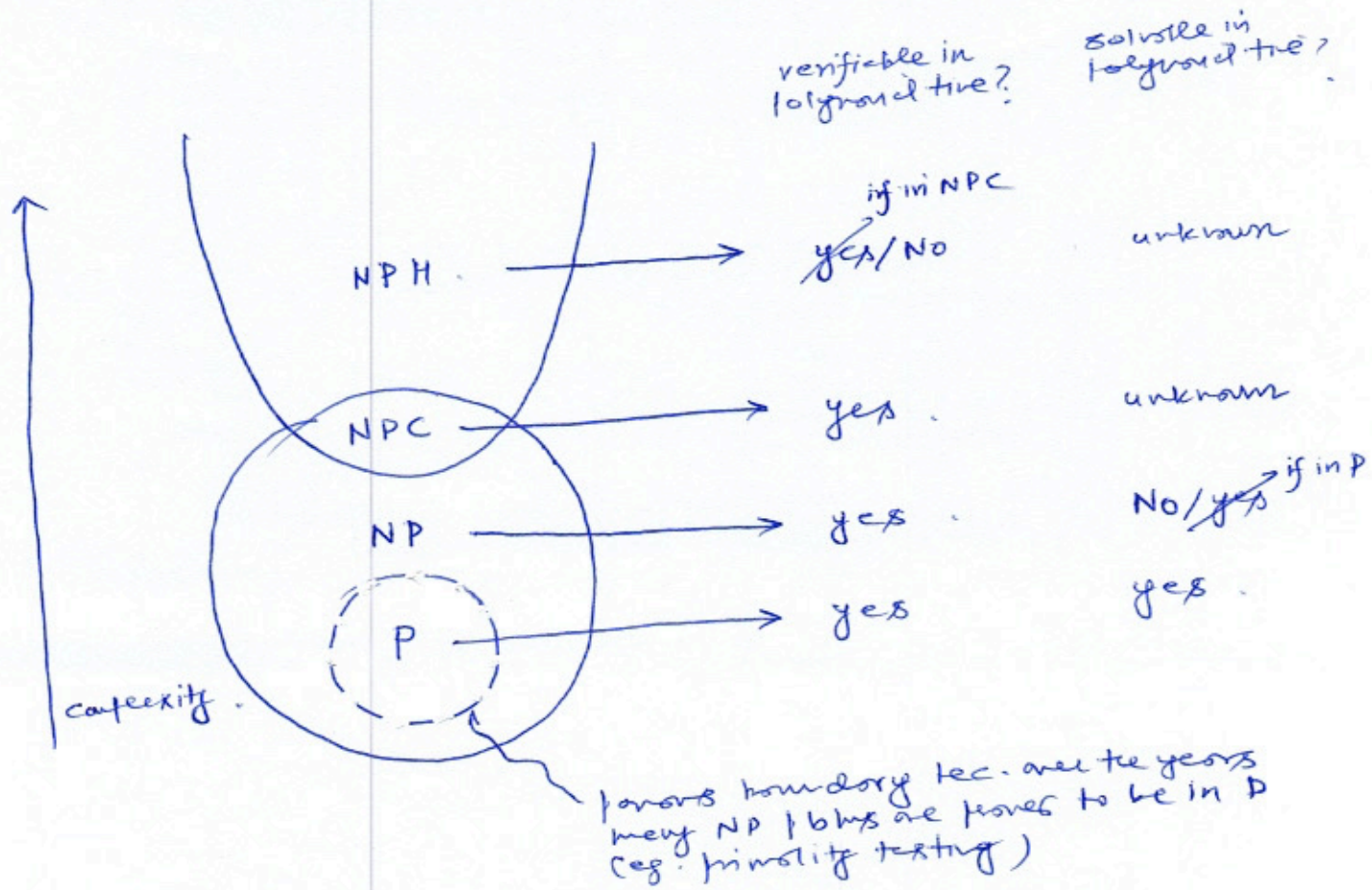
~~The precise definition is a problem is~~

A problem X is NP-hard, if there is an NP-complete problem Y , such that Y is reducible to X in polynomial time.

But since any NP-complete problem can be reduced to any other NP-complete problem in polynomial time, all NP-complete problems can be reduced to any NP-hard problem in polynomial time. Then, if there is a solution to one NP-hard problem in polynomial time, there is a solution to all NP problems in polynomial time.

eg. HALTING PROBLEM

problem: given a program P and input I , will it halt?



$i \rightarrow j$ indicates i is reducible to j in polynomial time.