

~~NP HARD & NP COMPLETE PROBLEM:~~

Polynomial Time:

- Linear Search : n
- Binary Search : $\log n$
- Insertion Sort : n^2
- Merge Sort : $n \log n$
- Matrix Multiplication : n^3

Exponential Time:

- 0/1 Knapsack : 2^n
- TSP : 2^n
- Sum of subsets : 2^n
- Graph Colouring : 2^n
- Hamiltonian Cycle : 2^n

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UNIT-5

NP-Hard and NP Complete Problem:

Polynomial time (P)
(Deterministic)

- MST, Optimal Merge
- Searching patterns
- Sorting
- Matrix Chain Multiplication

→ Huffman Coding

→ Single source Shortest path.

* algorithm NSearch (A, n, key)

{ j = choice(); } → O(1)

if (key == A[j])

{ write(j); }

success(); } → O(1)

write(0);

failure(); } → O(1)

→ choice(); → returns a position

which will probably have a key element from the given array.

Non-Polynomial Time (NP)

→ 0/1 Knapsack

→ N-Queens

→ TSP

→ Hamiltonian Cycle

→ Graph Colouring

↓

complexity is in exponential form

O(1)

constant

time

algorithm

* choice()
success()
failure()

} Non-deterministic
functions.

→ NP Hard & NP complete provide a set of rules.

* In order to solve the exponential time algorithms in polynomial time complexity

→ Reducibility is a property which deals with if we are having one instance of one problem; if we can convert it to other problem and if we are having (a) solution; which satisfies all the problem.

→ Satisfiability Problem: (SAT)

Conjunctive Normal Form

$$(x_1 \wedge \bar{x}_2 \wedge x_3) \vee (\bar{x}_1 \wedge x_2 \wedge \bar{x}_3).$$

→ We need to check 2^3 combinations in order to tell for which formula it is true.

It can be defined as whenever conjunctive normal form of n boolean variables are given; find all possible combinations of x_1, x_2, \dots, x_n for which the formula is true.

* Algorithm $\text{Eval}(E, n)$

```
{ for i := 1 to n do
     $x_i = \text{choice}(T, F)$ 
    if ( $E(x_1, x_2, \dots, x_n)$ ) then
        success()
        else failure()
    }
}
```

→ algorithm NSort($A[n]$)

```
{ for i := 1 to n do  $B[i] := 0$ ;
    for i := 1 to n do
        { j = choice(1, n);
            if  $B[j] \neq 0$  then Failure();
                 $B[j] := A[i] >$ 
            for i := 1 to n-1 do
                if  $A[i] > A[i+1]$  then swap( $A[i], A[i+1]$ )
        }
}
```

if $B[i] > B[i+1]$

then Failure();

write ($B[1:n]$);

Success();

}

* Satisfiability: (a, b) are the

→ NP hard & NP complete are the frameworks designed to find the algorithms for exponential time complexity problems.

→ When we are unable to write deterministic (polynomial) type algorithms we write non-deterministic algorithms.

→ Deterministic algorithms:

↳ we know the significance of each and every step of the algorithm.

→ Non-Deterministic algorithms:

↳ we use non-deterministic functions such as choice(), success(), failure() whose

description we are not known presently.

~~P → set of deterministic~~

P → set of deterministic algorithms which take polynomial time.

NP → set of non-deterministic algorithms which take polynomial time.

$$P \subseteq NP$$



* We require a base problem which helps in solving the exponential time problems which is given Satisfiability Problem.

* Satisfiability Problem (CNF):

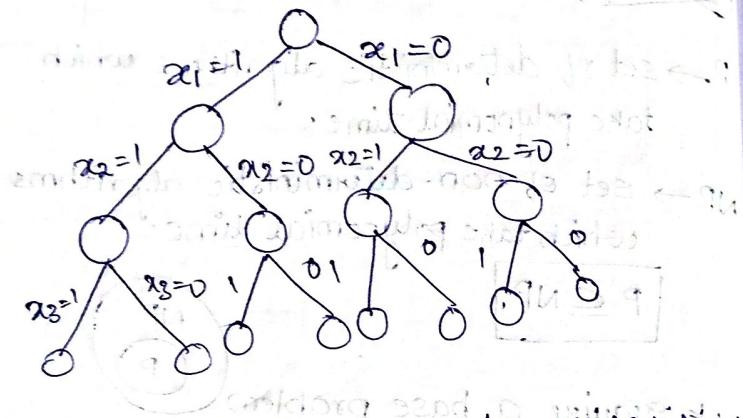
Propositional Calculus formula using Boolean variables (using $\wedge \vee \neg$).

$$x_i = \{x_1, x_2, x_3\}$$

$$CNF = (\underbrace{x_1 \vee \bar{x}_2 \vee x_3}_{\text{clause } C_1}) \wedge (\underbrace{\bar{x}_1 \vee x_2 \vee \bar{x}_3}_{\text{clause } C_2})$$

→ Satisfiability problem helps in finding out the values of x_i such that the CNF problem is satisfied.

if there n variables x_1, x_2, \dots, x_n
 $\Rightarrow 2^n$ combinations $\underline{\text{in } 2^n \text{ time}}$.



→ We have to show that if satisfiability problem is solved in polynomial time then all the exponential time problems can be solved ~~also~~ in polynomial time.

Satisfiability \rightarrow NP hard
 0/1 KS, TSP, SS, GC, HC \rightarrow Hard problem.

→ To show the relation b/w Hard problems & Satisfiability problem,

(*) we use the procedure of Reductions.

* Reduction:

→ We take an example of Satisfiability problem and convert it to 0/1 Knapsack or any of the Hard problem.

Lat $\propto L$ O/1 Knapsack
 I_1 I_2

If any algorithm satisfies 0/1 KS or Lat problem; it shall solve the other one too.

→ Conversion of the algorithm generated shall take polynomial time.

∴ Satisfiability is NP hard hence any problem that can be related also shall be known as NP hard.

→ Reduction property satisfies transitivity hence if:

$$\text{Sat} \propto L_1 \Leftrightarrow L_1 \propto L_2 \Rightarrow \text{Sat} \propto L_2$$

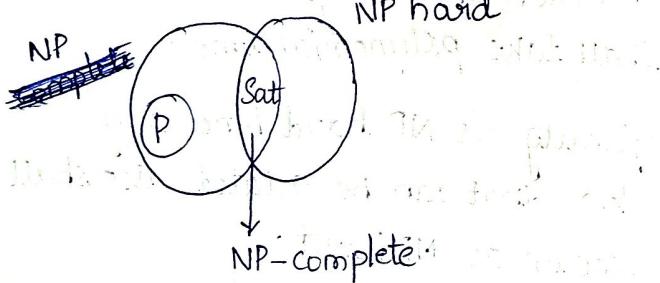
Then problems L_1 & L_2 become NP hard.

→ For the satisfiability ~~algorithm~~ problem we ~~are~~ having a non-deterministic algorithm.

→ If a problem has a non-deterministic algorithm; ~~we~~ it called NP hard & NP complete problem.

Sat problem: NP hard & NP complete

If a problem L is formed from sat problem then L is called NP hard and if we write a Non-deterministic algorithm then it is called NP complete.



$P=NP \Rightarrow$ It is existing but we don't know.

↓
COOK's Theorem: dat problem is in P iff P is ~~NP~~.

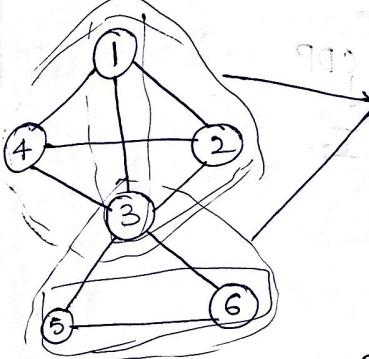
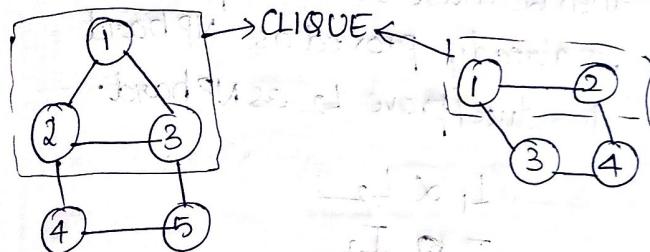
* Clique Decision Problem:

↳ NP hard graph problem:
Complete graph: for every vertex there is an edge connecting to other vertices

$$\rightarrow |V| = n \quad |E| = \frac{n(n-1)}{2}$$

* ~~Subgraph of a graph~~
which is
→ CLIQUE.

* Subgraph of any graph which is a complete graph is called clique.



Ex: find if a graph has
clique of size k .
Answer is Yes/No

→ Decision Problem: Whose answer is Yes/No
(GWA (SVD) (T/F))

→ Optimization Problem: Whose question

deals with max/min

deals with max/min.
Ex.: find the max clique size.

If a decision problem is NP hard
then optimization is called NP hard.
→ Procedure to prove CDP as NP hard.

If a problem given is denoted as L_2

then we must select a problem L_1 which is already proved as NP hard to reduce/prove L_2 as NP hard.

$$L_1 \propto L_2$$

$$I_1 \otimes I_2$$

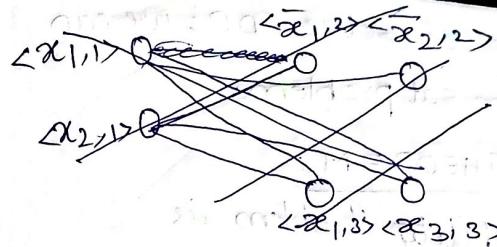
Satisfiability \propto CDP

we must take CNF formula to reduce to

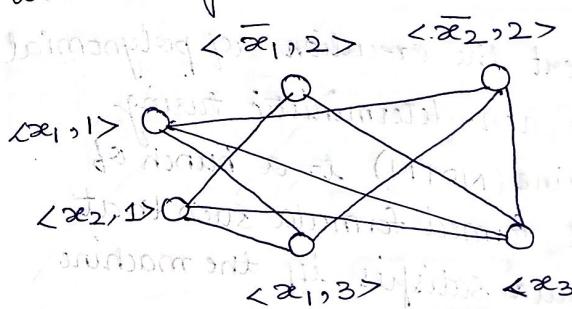
$$F = (x_1 \vee x_2) \wedge (\bar{x}_1 \vee \bar{x}_2) \wedge (x_1 \vee x_3)$$

$$F = \bigwedge_{i=1}^k C_i$$

$\therefore k=3$
we must have a clique of size 3



- $V = \{ \langle a, i \rangle \mid a \in c_i \}$
- $E = \{ \langle a, i \rangle \langle b, j \rangle \mid i \neq j \text{ and } b \neq \bar{a} \}$
- We must not connect the ~~clique edges~~ of similar clauses.
- We must not connect the vertex with its negation.



- clique of size of 3
- x_1, x_2, x_3
- 0 1

$$F = (0 \vee 1) \wedge (1 \vee 0) \wedge (0 \vee 1)$$

$$= 1 \wedge 1 \wedge 1 = 1$$

~~HARD~~ \Rightarrow If we can solve CDP; we can solve the sat problem.

* COOK'S THEOREM:

\rightarrow Satisfiability Problem is NP complete.

\downarrow
SAT is a propositional logic which gives TRUE as O/P for any assignment.

3CNF \rightarrow $\begin{cases} \rightarrow \text{Conjunctive Normal form} \\ \rightarrow \text{every clause has 3 literals.} \end{cases}$

① Convert the execution of polynomial time non-deterministic turing machine (NDTM) to a bunch of well formed formula such that formula satisfies iff the machine accepts input.

② Show the sum of the lengths of a formula is polynomial in the size of the problem.

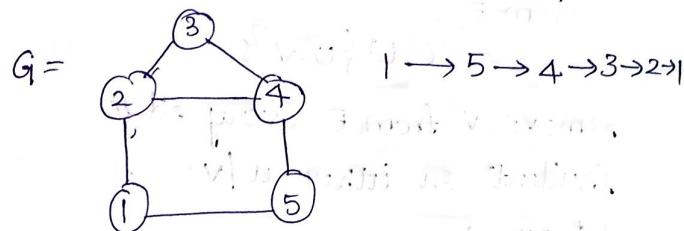
* TSP as NP-hard:

Corresponding decision problem to TSP is to determine whether the complete directed graph $G = (V, E)$ with an edge cost $c(u, v)$ has a tour cost almost M.

TSP decision problem:

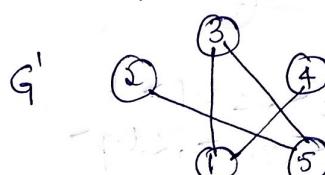
Hamiltonian \propto TSP.

① Consider a graph $G = (V, E)$ be a instance of the Hamiltonian cycle and we need to construct an instance of TSP.



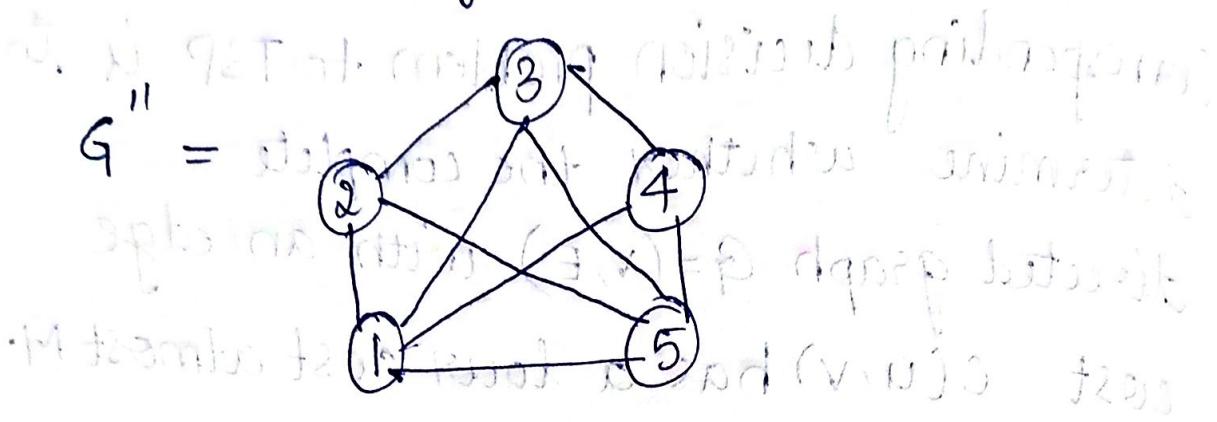
② To form a TSP construct a complete graph G' which is V, E'

$$\text{i.e. } G' = (V, E')$$



(Consider the edges which are not in G that gives G')

Now complete graph is $G + G$



Approx-Vertex-Cover(G)

$$C = \emptyset$$

while $E' = E$. (while $E \neq \emptyset$ or C is empty)

choose an edge $\{u, v\}$ from E' .

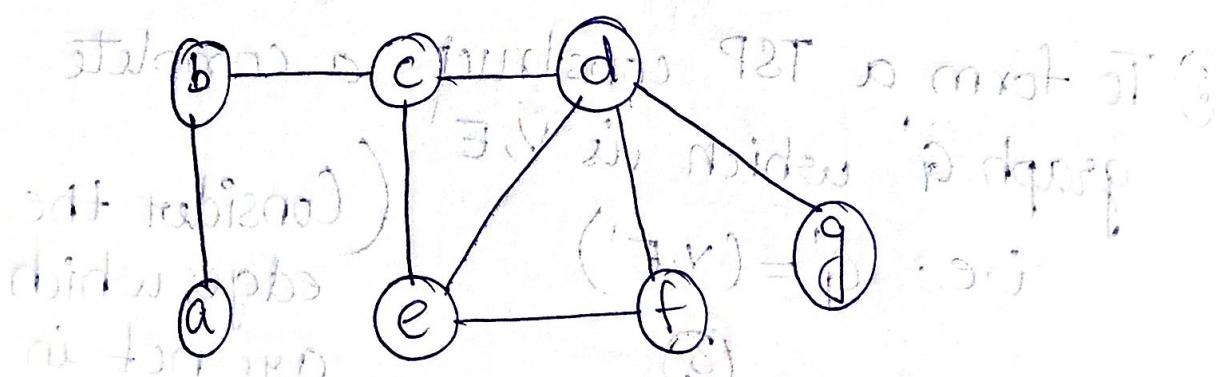
Let $\{u, v\}$ be an arbitrary edge
from E'

$$E' - \{u, v\} = C \cup \{u, v\}$$

remove v from E every edge

incident on either u / v :

return C



cover: $\{\langle b, c \rangle, \langle d, f \rangle\}$

cover: $\{\langle b, c \rangle, \langle e, f \rangle, \langle d, g \rangle\}$