

# Coping with NP-completeness: Special Cases

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The fact that a problem is **NP**-complete does not exclude an efficient algorithm for special cases of the problem.

# Outline

① 2-Satisfiability

② Independent Sets in Trees

## This part

- Striking connection between strongly connected components of a graph and formulas in 2-CNF
- A linear time algorithm for 2-SAT

## 2-Satisfiability (2-SAT)

**Input:** A set of clauses, each containing at most two literals (that is, a 2-CNF formula).

**Output:** Find a satisfying assignment (if exists).

## Example

- $(x \vee y)(\bar{z})(z \vee \bar{x})$  is satisfied by  
 $x = 0, y = 1, z = 0$

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- In other words, if  $\ell_1 = 0$ , then  $\ell_2 = 1$  and if  $\ell_2 = 0$ , then  $\ell_1 = 1$

## Definition

**Implication** is a binary logical operation denoted by  $\Rightarrow$  and defined by the following truth table:

$x$	$y$	$x \Rightarrow y$
0	0	1
0	1	1
1	0	0
1	1	1

## Definition

For a 2-CNF formula, its **implication graph** is constructed as follows:

- for each variable  $x$ , introduce two vertices labeled by  $x$  and  $\bar{x}$ ;
- for each 2-clause  $(\ell_1 \vee \ell_2)$ , introduce two directed edges  $\bar{\ell}_1 \rightarrow \ell_2$  and  $\bar{\ell}_2 \rightarrow \ell_1$
- for each 1-clause  $(\ell)$ , introduce an edge  $\bar{\ell} \rightarrow \ell$

## Definition

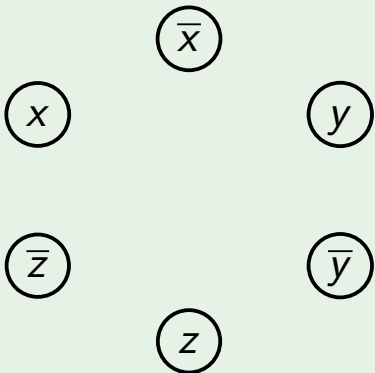
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Encodes all implications imposed by the formula.

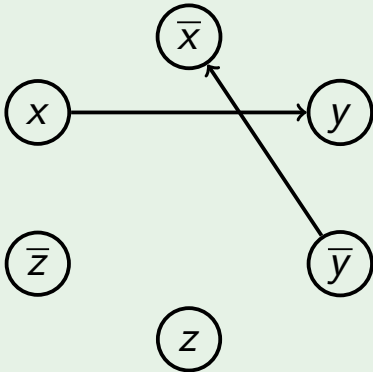
$$(\bar{x} \vee y)(\bar{y} \vee z)(x \vee \bar{z})(z \vee y)$$

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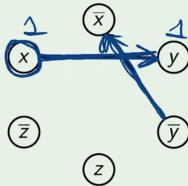


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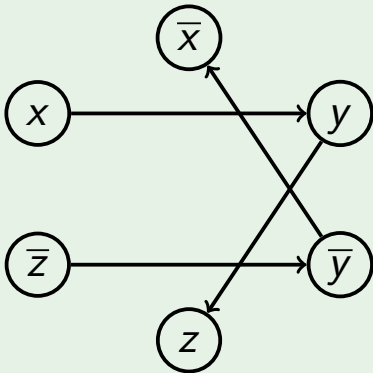


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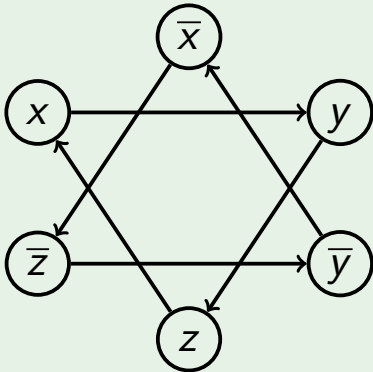
\* if  $\bar{x}=0$  ( $x=1$ ) then  
 $y=1$   
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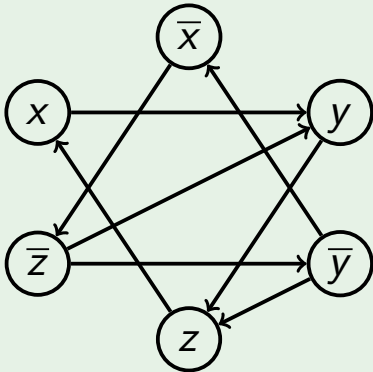
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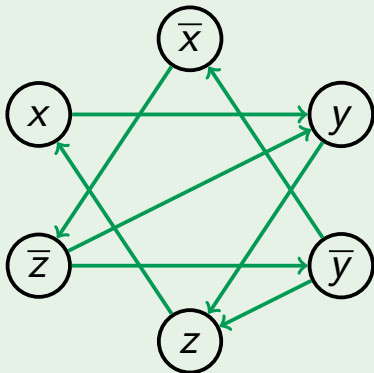
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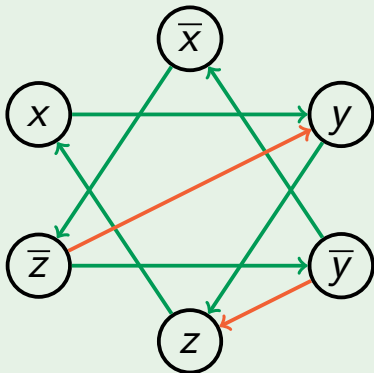


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$$x = 1, y = 1, z = 1$$

$$(\bar{x} \vee y)(\bar{y} \vee z)(x \vee \bar{z})(z \vee y)$$



Two edges over here are falsified meaning beginning of this edge is 1 while the end is 0

Meaning truth (1) does not imply false (0)

$$x = 0, y = 0, z = 0$$

Thus, our goal is to assign truth values to the variables so that each edge in the implication graph is “satisfied”, that is, there is no edge from 1 to 0.

# Skew-Symmetry

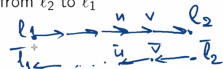
- The graph is skew-symmetric: if there is an edge  $\ell_1 \rightarrow \ell_2$ , then there is an edge  $\bar{\ell}_2 \rightarrow \bar{\ell}_1$



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# Transitivity

## Lemma

If all the edges are satisfied by an assignment and there is a path from  $\ell_1$  to  $\ell_2$ , then it cannot be the case that  $\ell_1 = 1$  and  $\ell_2 = 0$ .

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## Proof

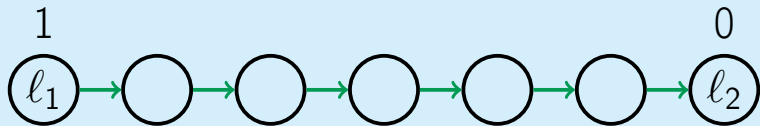


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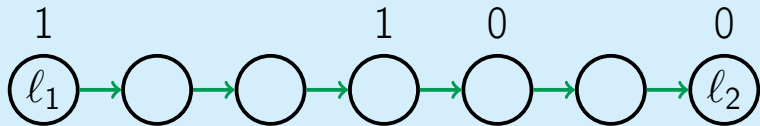


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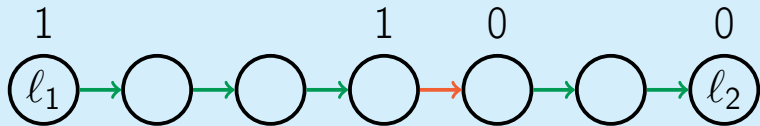


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- In particular, if a SCC contains a variable together with its negation, then the formula is unsatisfiable
- It turns out that otherwise the formula is satisfiable!

## 2SAT(2-CNF $F$ )

construct the implication graph  $G$

find SCC's of  $G$

for all variables  $x$ :

Note that every step of this Algo takes linear time hence this is a linear time algorithm

if  $x$  and  $\bar{x}$  lie in the same SCC of  $G$ :

return "unsatisfiable"

find a topological ordering of SCC's

for all SCC's  $C$  in reverse order:

if literals of  $C$  are not assigned yet:

set all of them to 1

set their negations to 0

return the satisfying assignment

CNF Formula is unsatisfiable if its implication graph contains a variable implied to its negation in strongly connected component.

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for all SCC's  $C$  in reverse order:
    if literals of  $C$  are not assigned yet:
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        set their negations to 0
return the satisfying assignment
```

Running time:  $O(|F|)$

## Lemma

The algorithm 2SAT is correct.

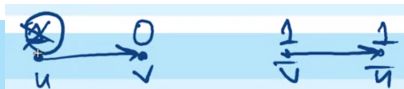
## Proof

- When a literal is set to 1, all the literals that are reachable from it have already been set to 1 (since we process SCC's in reverse topological order).

# Lemma

The algorithm 2SAT is correct.

## Proof



If  $\neg u$  and  $\neg v$  are assigned 1 then  $u$  and  $v$  has to be 0.  $u = 1$  (as shown) is a contradiction

- When a literal is set to 1, all the literals that are reachable from it have already been set to 1 (since we process SCC's in reverse topological order).  
As we are assigning values in reverse topological order we always guarantee that the assigned value is 1 on the right side of implication graph ( $v$  is always 1 in  $u \rightarrow v$ )
- When a literal is set to 0, all the literals it is reachable from have already been set to 0 (by skew-symmetry).  
Does this mean even the edge from 0 to 1 is not present ? ☐

# Outline

① 2-Satisfiability

② Independent Sets in Trees

# Planning a company party

You are organizing a company party. You would like to invite as many people as possible with a single constraint: no person should attend a party with his or her direct boss.

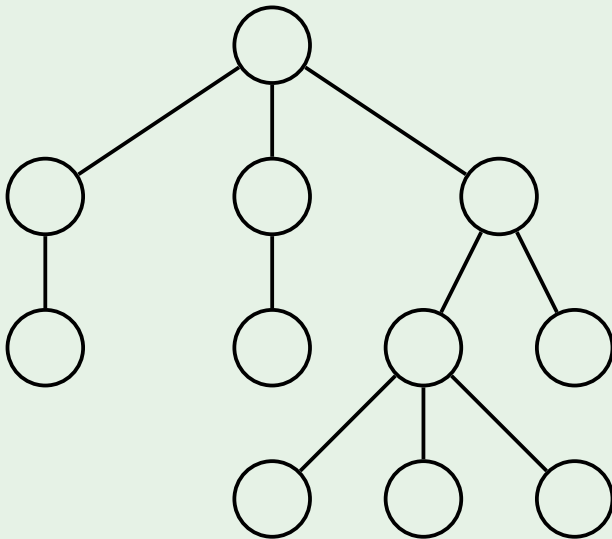
## Maximum independent set in a tree

**Input:** A tree.

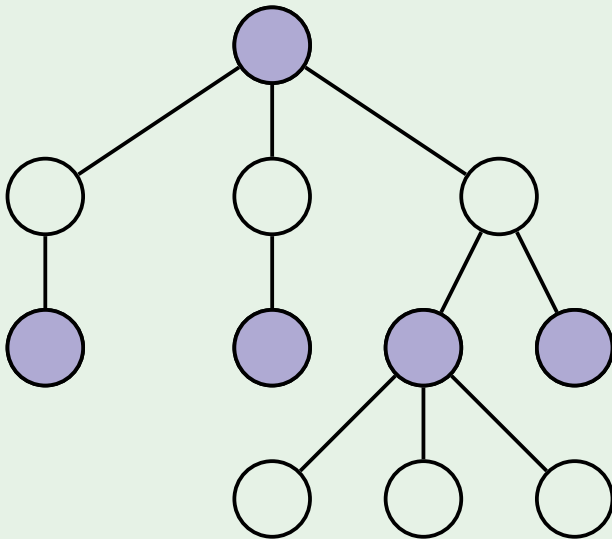
**Output:** An independent set (i.e., a subset of vertices no two of which are adjacent) of maximum size.



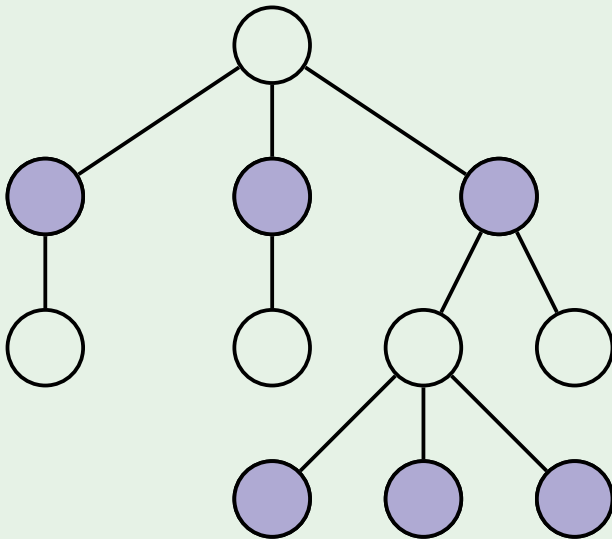
# Example



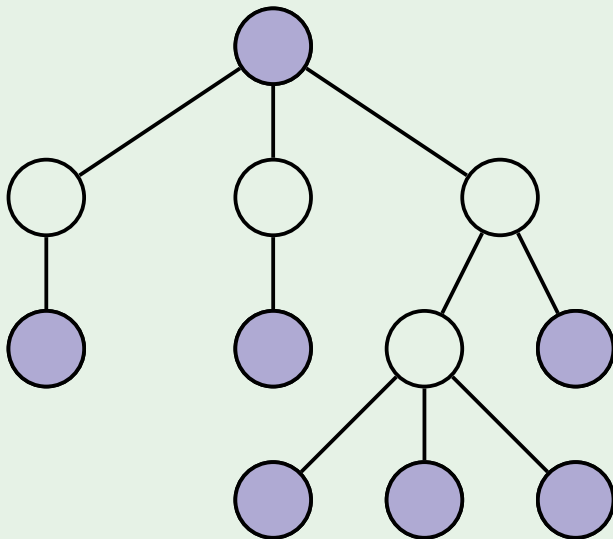
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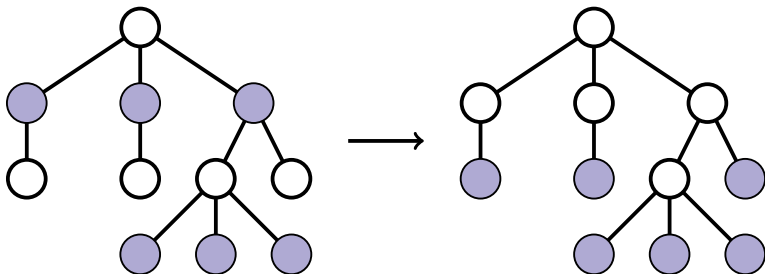


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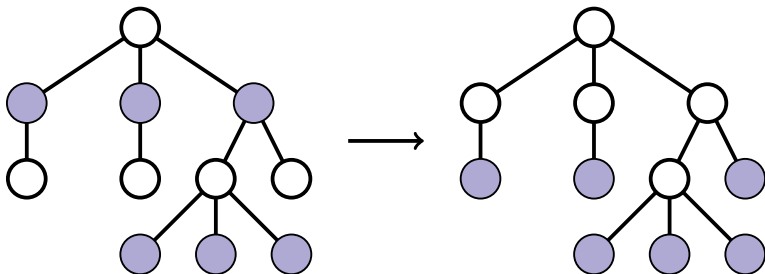
# Safe move

For any leaf, there exists an optimal solution including this leaf.



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It is safe to take all the leaves.

## PartyGreedy( $T$ )

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while  $T$  is not empty:  
    take all the leaves to the solution  
    remove them and their parents from  $T$   
return the constructed solution
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For each vertex you keep track of number of its children's. You actually do not remove any vertex from the tree itself but you keep the track of current number of children's for each vertex so when you remove a vertex you decrease by one the number of children of it's parent and you also maintain a queue that contains the vertices that does not have any children so at each iteration you know all the leaves of the current tree these are exactly the vertices with no childrens

Running time:  $O(|T|)$  (for each vertex, maintain the number of its children).



## Planning a company party

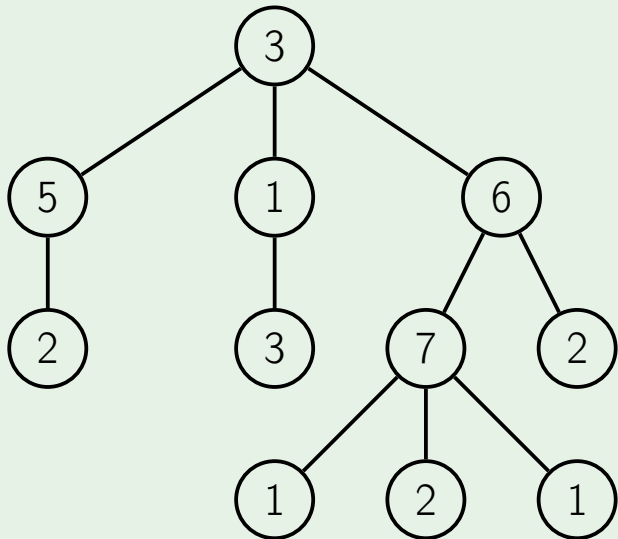
You are organizing a company party again. However this time, instead of maximizing the number of attendees, you would like to maximize the total fun factor.

## Maximum weighted independent set in trees

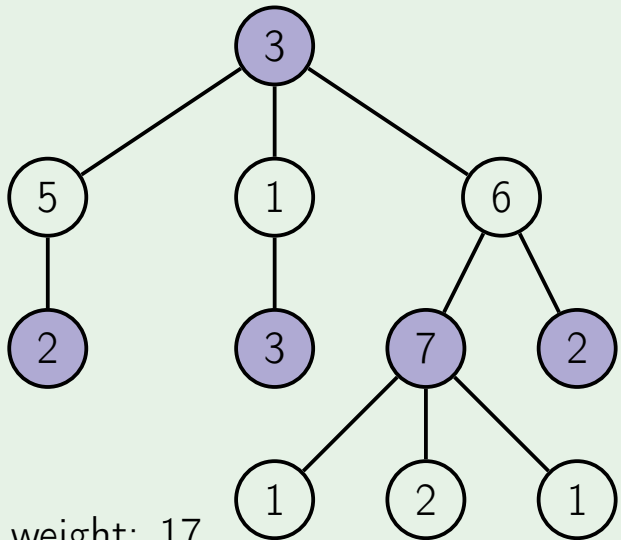
**Input:** A tree  $T$  with weights on vertices.

**Output:** An independent set (i.e., a subset of vertices no two of which are adjacent) of maximum total weight.

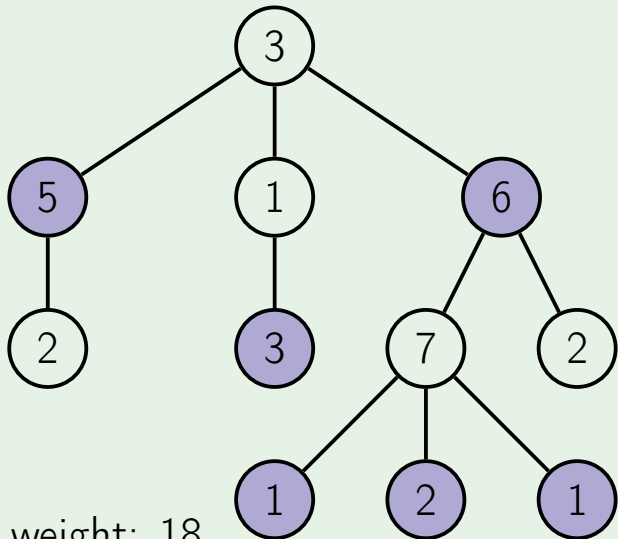
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# Example



total weight: 18

# Subproblems

- $D(v)$  is the maximum weight of an independent set in a subtree rooted at  $v$

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- $D(v)$  is the maximum weight of an independent set in a subtree rooted at  $v$
- Recurrence relation:  $D(v)$  is

$$\max \left\{ w(v) + \sum_{\substack{\text{grandchildren} \\ w \text{ of } v}} D(w), \sum_{\substack{\text{children} \\ w \text{ of } v}} D(w) \right\}$$

There are basically two cases either we include  $v$  into solution or we do not include it. If we include it then it contributes its weight to the total fun factor but we cannot take any of its children's in the solution as then it won't be an independent set. However, we can take anything from subtree's root at its grandchildren.

## Function FunParty( $v$ )

```
if  $D(v) = \infty$ :  
    if  $v$  has no children:  
         $D(v) \leftarrow w(v)$ 
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    else:  
         $m_1 \leftarrow w(v)$   
    for all children  $u$  of  $v$ :  
        for all children  $w$  of  $u$ :  
             $m_1 \leftarrow m_1 + \text{FunParty}(w)$ 
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    if  $v$  has no children:  
         $D(v) \leftarrow w(v)$  Running time  $O(|T|)$   
    else:  
         $m_1 \leftarrow w(v)$   
        for all children  $u$  of  $v$ :  
            for all children  $w$  of  $u$ :  
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        for all children  $u$  of  $v$ :  
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if  $D(v) = \infty$ :
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    else:
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        for all children  $u$  of  $v$ :
            for all children  $w$  of  $u$ :
                 $m_1 \leftarrow m_1 + \text{FunParty}(w)$ 
         $m_0 \leftarrow 0$ 
        for all children  $u$  of  $v$ :
             $m_0 \leftarrow m_0 + \text{FunParty}(u)$ 
         $D(v) \leftarrow \max(m_1, m_0)$ 
return  $D(v)$  Value returned here if already computed before
```

## Question

What does this function compute?

What does this function compute? It is a recursive algorithm for finding the maximum value of a function  $D(v)$  over all vertices  $v$  of a graph. The function  $D(v)$  is defined as the maximum value of  $w(v)$  plus the maximum value of  $D(u)$  for all children  $u$  of  $v$ . The function  $D(v)$  is computed for all vertices  $v$  of the graph. The function  $D(v)$  is computed for all vertices  $v$  of the graph. The function  $D(v)$  is computed for all vertices  $v$  of the graph.

A. The maximum value of  $w(v)$ .

B. The maximum value of  $D(u)$ .

C. The maximum value of  $D(v)$ .

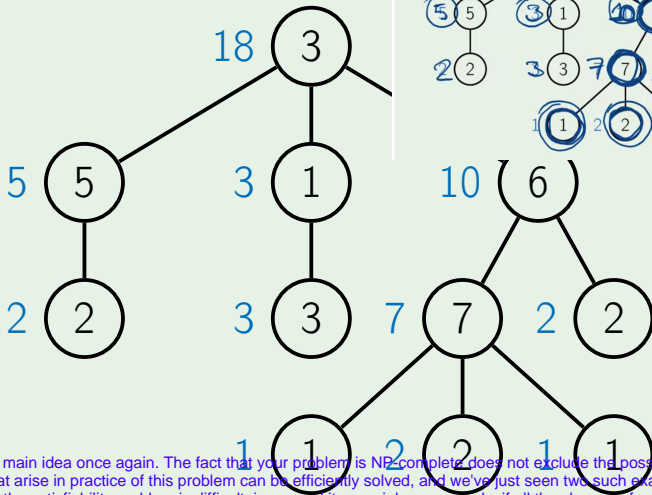
D. The maximum value of  $D(v)$ .

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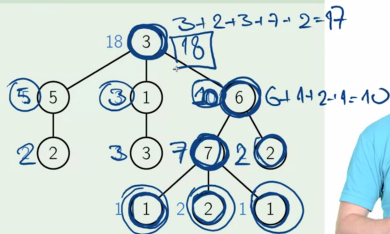
F. The maximum value of  $D(v)$ .

Running time is  $O(|T|)$  because for each vertex there is just one serious call to fun party. By serious I mean a call which actually is inside this IF loop which gives rise to some computation, because after the first time when we are inside this loop for the vertex  $v$ , we will store the value in  $D(v)$  and then for any further call for  $\text{FunParty}(v)$  we just return the value immediately.

# Example



## Example



Let me remind you the main idea once again. The fact that your problem is NP-complete does not exclude the possibilities that some special cases that arise in practice of this problem can be efficiently solved, and we've just seen two such examples. Despite of the fact that the satisfiability problem is difficult, in general its special case namely, if all the clauses of a formula contain at most two literals can be easily solved in minimal time. The second example was about independent set. This problem is hard in general, so given a graph, it is difficult to implement an algorithm which always finds an optimum size independent set of a graph. But, if you know that all of your graphs that are arrive in your application are trees, then it is easier to implement a linear time algorithm that will find an optimal answer quickly.