

## HARDNESS P, NP, NP-complete

P = problems that can be solved in  $\text{poly}(n)$  time (e.g. sorting, min-cut)

NP = problems that admit a  $\text{poly}(n)$ -time certificate (e.g. SAT)  
↳ non-deterministic

$\text{NP} \subseteq \text{P}$  ? BIG QUESTION

### NP-Complete (NPC)

$\pi \in \text{NP}$  s.t.  $\forall \pi' \in \text{NP}$  "polynomially reduces to"  $\pi$

(VC, SAT  
etc.)

Th Cook-Levin

SAT  $\in$  NPC

EXACT SOLUTIONS  $\rightarrow$  parameterized algorithm (FPT)

$\hookrightarrow$  fixed-parameter tractable

APPROXIMATED SOLUTIONS  $\rightarrow$  optimization problems

$\hookrightarrow$  min cost  
 $\hookrightarrow$  max benefit

We saw VC = vertex cover (minimize # nodes)

► r-approximation = algorithm which provides a solution  $\tilde{S}$  s.t.

$$\min : \frac{\text{cost}(\tilde{S})}{\text{OPT}} \leq r$$

$$\text{cost}(\tilde{S}) \leq 2 \cdot \text{OPT}$$

VC is a 2-approx

$$\max : \frac{\text{OPT}}{\text{cost}(\tilde{S})} \leq r$$

MAX-CUT (MC) is a 2-approx

$$\text{cost}(\tilde{S}) \geq \frac{1}{2} \cdot \text{OPT}$$

$$r > 1$$

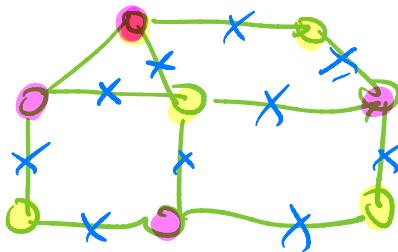
## MAX-CUT

We saw MIN-CUT

cut :  $V = V_1 \cup V_2$  (2-coloring)

$$V_1 \cap V_2 = \emptyset$$

cutset  $E(V_1, V_2) = \{uv \in E : u \in V_1 \text{ and } v \in V_2\}$



MIN-CUT

vs

MAX-CUT

$\min E(V_1, V_2)$

NPC

3 ways to get a 2-approx for MAX-CUT

$$\text{cost}(\tilde{S}) = |E(V, V)| \geq \frac{1}{2} \text{ OPT}$$

0.5 (the higher, the better)

the best know is 0.878

Goemans, Williamson

- ① local search  
 ② greedy  
 ③ randomization

# ① LOCAL SEARCH

$$S = V, \quad V_2 = V - S$$

$$S = \{\}$$

while  $\exists u \in V$  change its set ( $u \in S \Rightarrow u \in V - S$ )  
 $(u \in V - S \Rightarrow u \notin S)$ )

s.t.  $E(S, V - S)$  **STRICTLY increases**

do if  $u \in S$  then  $S \leftarrow S \setminus \{u\}$

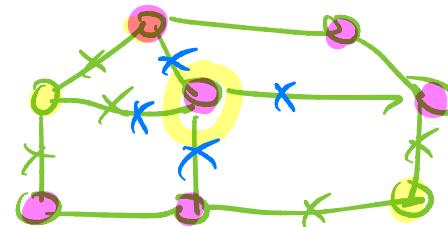
else  $S \leftarrow S \cup \{u\}$

return  $V_1 = S, V_2 = V - S$

a) the algorithm terminates as  $|E(S, V - S)|$  strictly increases

$$\text{and } |E(S, V - S)| \leq |E|$$

no more than  $|E|$  steps



b) It provides a 2-approximation

we do not know  $OPT \dots$  so we establish an upper bound  $UB \geq OPT$

**LOCAL MAXIMUM**

and prove that  $\text{cost}(S) \geq \frac{1}{2} UB$  (hence,  $\geq \frac{1}{2} OPT$ )

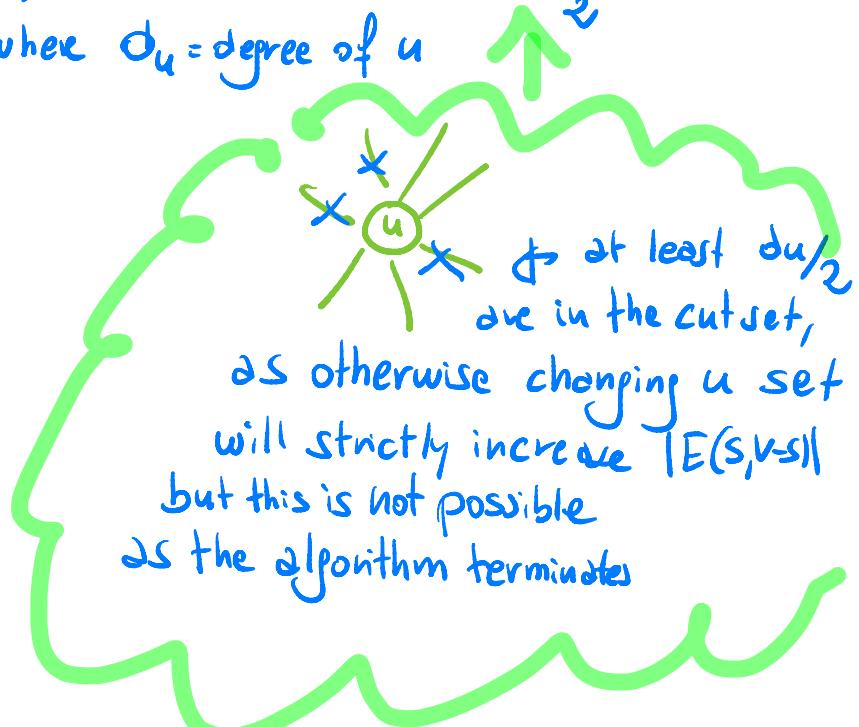
$$UB = |E|$$

To see this: after the algorithm ends, each node  $u$  has  $\geq \frac{d_u}{2}$  incident edges in  $E(S, V-S)$ , where  $d_u = \text{degree of } u$

We prove that

$$|E(S, V-S)| \geq \frac{1}{2} |E|$$

$$\begin{aligned} |E(S, V-S)| &= \frac{\sum_{u \in V} \text{#edges incident to } u \text{ in } E(S, V-S)}{2} \geq \\ &\geq \frac{\sum_{u \in V} d_u / 2}{2} \\ &= \frac{2|E|/2}{2} = \frac{|E|}{2} \end{aligned}$$



## ② Greedy

number the nodes from 1 to n (any order is fine)

$$S = \{ \}$$

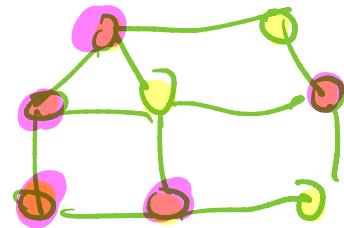
for  $u = 1, 2, \dots, n :$

$$\begin{array}{l} u \in S \rightarrow |E(S, V-S)| \\ u \in V-S \rightarrow |E(S, V-S)| \end{array} \} \text{ choose the largest}$$

return  $V_1 = S, V_2 = V - S$

a) it takes  $n = |V|$  steps

b)  $|E(S, V-S)| \geq \frac{|E|}{2}$



Let's consider edge  $i \xrightarrow{ } j$  and w.l.o.g.  $i < j$

The "fate" of edge  $ij$  is decided by the color of  $j$  rather than the color of  $i$

► node  $j$  is "responsible" for edge  $ij$  iff  $i < j$

$$r_u = |\{v \in V : uv \in E \text{ and } u > v\}|$$

Claim #edges for which  $u$  is responsible and belong to  $E(S, V-S)$  final

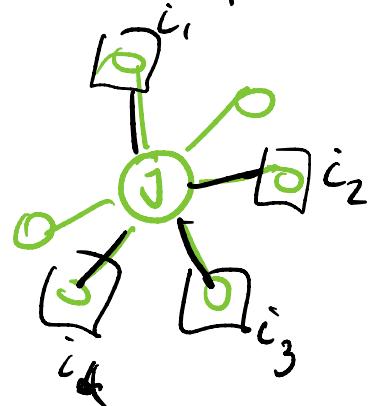
$$\geq \frac{r_u}{2}$$

$$|E(S, V-S)| = \sum_{u \in V} \# \text{edges for which } u \text{ is responsible and belong to the cutsize} \geq \sum_{u \in V} \frac{r_u}{2} = \frac{|E|}{2}$$

we do not divide by 2

as each edge has exactly one responsible node

$$\sum r_u = |E|$$



$$i_1, i_2, i_3, i_4 < j$$

$$r_j = 4$$

### ③ Randomization

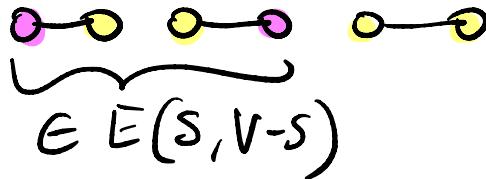
Assign a random color  $X: V \rightarrow \{0,1\}$  uniformly and independently

$uv \in E$  is in  $E(S, V-S)$  iff  $X(u) \neq X(v)$

$S = \{u \in V : X(u) = 0\}$ ,  $V_1 = S$ ,  $V_2 = V - S$



$$\Pr(\text{edge } uv \in E(S, V-S)) = \frac{1}{2}$$



Indicator Variable

$$X_{uv} = \begin{cases} 1 & \text{if } uv \in E(S, V-S) \\ 0 & \text{o.w.} \end{cases}$$

$$|E(S, V-S)| = \sum_{uv \in E} X_{uv} \Rightarrow E[|E(S, V-S)|] = \sum_{uv \in E} E[X_{uv}] = \sum_{uv \in E} \frac{1}{2} = \frac{|E|}{2}$$