

APPROXIMATION ALGORITHMS

- NPC decision problems often correspond to hard optimization problems of huge practical impact: we cannot give up on them!

Different approaches: sol. method

1. Non-polynomial algorithms:

sometimes suitable for "small" instances. Interesting sub-category:

Pseudopolynomial algorithms

complexity polynomial in the values (and NOT the size of their encoding)

EXAMPLE: Using dynamic programming we can obtain an algorithm for SS with running time $O(|S| \cdot t)$

(homework: |S| $\leq t$ - boolean table A:

$$A[i, j] = 1 \Leftrightarrow \exists S' \subseteq \{s_1, \dots, s_t\} : \sum_{s \in S'} s = j$$

$i \in |S|, 0 \leq j \leq t$. Solution in

in $A[|S|, t]$. Work out recurrence)

$|S| \cdot t$ is polynomial in the value t but NOT in the length of its encoding $O(\log t)$

2. Restriction of the instance set: solve the problem on a subset of instances for which there is a polynomial algorithm

EXAMPLE :

2-CNF-SAT $\in \text{P}$

TREE-VERTEX-COVER $\in \text{P}$

SMALL-TARGET SUBSET SUM $\in \text{P}$

($t \in O(\log^k(\sum_{\text{SES}}))$)

3. "intelligent" exhaustive search (O.R. approach) : e.g. branch-and-bound : try to get optimal solution while avoiding to examine all feasible solutions (pruning strategies). Heuristic methods : no upper bound on worst-case running time.

Other heuristics : local-search, tabu-search, simulated annealing : may return nonoptimal solution (local optimum) (\rightarrow see OR2)

4. APPROXIMATION ALGORITHMS: return
 a feasible solution whose cost is
 within a given error margin from
 the optimal solution in worst-case
polynomial time

EXAMPLE: Return, in linear time, a vertex cover of size at most twice the size of the minimum vertex cover

3 vs 4: We want hard guarantees on time and solution quality

(Sometimes a solution obtained through 4. is used as a starting solution for the heuristics of 3.)

Let Π be an optimization problem with positive integer cost function: problem di ott.
 $\Pi \subseteq \mathcal{S} \times \mathcal{I}$, $\forall i \in \mathcal{I}: I(i) = \{s \in \mathcal{S}: i \in \Pi \rightarrow \text{sol. accettabile}\}$

$C: \mathcal{S} \rightarrow \mathbb{N} - \{0\}$ and let

$s^*(i) = \arg \min_{\substack{\text{max} \\ \text{sol.}}} \{C(s): s \in I(i)\}$

funtione di costo

DEF: Let A_π be an algorithm such that $\forall i \in \mathcal{I} : A_\pi(i) \in \mathcal{D}(i)$. \Rightarrow job i is feasible

Say that A_π is a $\rho(u)$ -approximation algorithm for Π if $\forall i \in \mathcal{I}, l_{il} = u$:

$$\max \left\{ \frac{c(s^*(i))}{c(A_\pi(i))}, \frac{c(A_\pi(i))}{c(s^*(i))} \right\} \leq \rho(u)$$

approximation ratio

OBSERVATION 1: The above max is always ≥ 1 :
 $\Rightarrow \rho(u) \geq 1, \forall u$. Better approximation achieved for $\rho(u)$ closer to 1. ($\forall u : \rho(u) = 1$: EXACT ALGORITHM)

OBSERVATION 2: For maximization problems the above max is always the first term, and for minimization problems the second. Equivalently:

$$c(A_\pi(i)) \begin{cases} \geq \frac{c(s^*(i))}{\rho(u)} & \text{MAX. PROBLEMS} \\ & (\text{fraction } \rho(u)) \\ \leq c(s^*(i)) \cdot \rho(u) & \text{MIN. PROBLEMS} \\ & (\text{factor } \rho(u)) \end{cases}$$

An approximation algorithm finds feasible solutions of "controlled quality". Also, it provides bounds on the optimal solution

In particular:

$$c(S^*(i)) \leq c(A_{\pi}(i)) g(u) \text{ MAX.}$$

upper bound on $c(S^*(i))$

$$c(S^*(i)) \geq \frac{c(A_{\pi}(i))}{g(u)} \text{ MIN}$$

lower bound on $c(S^*(i))$

DEF We say that Π is $\rho(u)$ -approximable in polynomial time if there exists a $\rho(u)$ -approximation algorithm A_{Π} for Π running in polynomial time.

Hard optimization problems are not all equal w.r.t. approximation: some are $\rho = O(1)$ -approximable (in poly. time), some only feature $\rho(u)$ with $\lim_{u \rightarrow \infty} \rho(u) = \infty$ -

We can often prove that if $P \neq NP$ there cannot exist a poly-time $\rho(u)$ -approximation algorithm for some function $\rho(u)$. (INAPPROXIMABILITY RESULTS).

EXAMPLE : If $P \neq NP$ there cannot exist a $\tilde{g}(|V|) = \tilde{O}(|V|^{1-\epsilon})$ poly-time approximation algorithm for MAX-CLIQUE, for any fixed ϵ [Arora et al. 1990]

there are also "easier hard" problems which admit very "precise" approximation algorithms :

DEF : An approximation scheme for an optimization problem Π is a two-input algorithm

$$A_{\Pi}(i, \epsilon) : i \in J, \epsilon > 0$$

such that, for any fixed ϵ , $A_{\Pi}(i, \epsilon)$ is a $\tilde{g}(n) = (1+\epsilon)$ -approximation algorithm for Π .

DEF. An Approximation Scheme is Polynomial-Time (PTAS) if, for any fixed ϵ , $A_{\Pi}(i, \epsilon)$ runs in time polynomial in $n = |i|$

Observe that under the above definition, running times such as

$$O(n^{1/\epsilon})$$

are polynomial in n (for fixed ϵ)

This is not completely satisfactory: e.g., if I want to reduce the "error" ϵ by a factor k :

$$O(n^{1/\epsilon}) \rightsquigarrow O(n^{1/(\epsilon/k)}) = O((n^{1/\epsilon})^k).$$

Time exponential in the improvement

It would be desirable that a constant-factor improvement in quality yields a constant-factor increase in running time;

DEF An **Approximation Scheme** is

Fully-Polynomial Time (FPTAS) if the running time of $A_{\pi}(i, \epsilon)$ is polynomial both in n and $\frac{1}{\epsilon}$

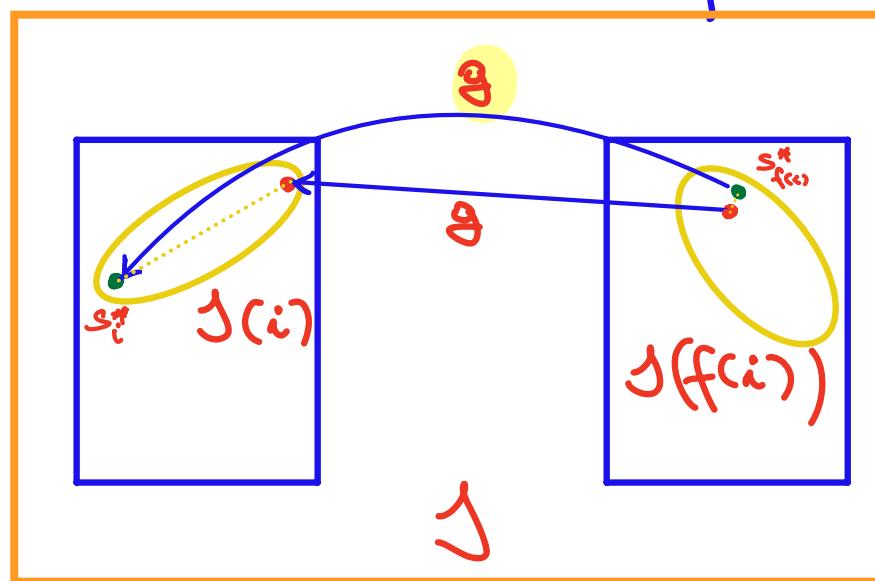
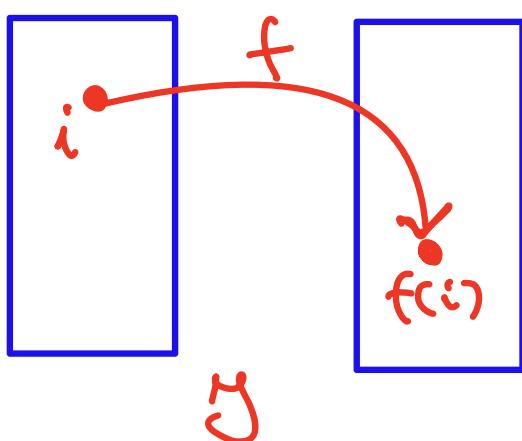
e.g. $T_{A_{\pi}}(n, \epsilon) = O\left(\frac{1}{\epsilon^2} n^3\right)$

More

While optimization problems associated to NPC problems are all equivalent w.r.t. exact solution, they behave differently w.r.t. approximation.

Intuition : The idea of reducibility can be extended to optimization problems using an extra function

g , mapping each element of $\mathcal{S}(i)$ into an element of $\mathcal{S}(f(i))$



Function g maps optimal solutions in $\mathcal{S}(f(i))$ into optimal solutions in $\mathcal{S}(i)$, however the mapping does not necessarily preserve the approximation quality!

A TWO-APPROXIMATION ALGORITHM FOR (MINIMUM) VERTEX COVER

Optimization version: given $G = (V, E)$, undirected, determine its vertex cover.
 $V^* \subseteq V$ ($\forall \{u, v\} \in E: (u \in V^*) \vee (v \in V^*)$) of minimum size.

Spesso, bastano alg. semplici con approccio greedy

We will prove that a simple greedy approach yields a good quality solution.

In analisi, collegiamo costo VC a costo di sol. al problema + semplice

IDEA : 1. GREEDY CHOICE: consider an arbitrary edge $\{u, v\}$ and ADD BOTH u and v to the vertex cover. (OBS: NOT INTUITIVE!)

2. CLEAN-UP: remove all covered edges from E: $E' = E - \{e \in E : \{u, v\} \cap e \neq \emptyset\}$

APPROX-VERTEX-COVER ($G = (V, E)$)

$V' \leftarrow \emptyset$

$E' \leftarrow E$

while ($E' \neq \emptyset$) do

* select $\{u, v\} \in E'$, arbitrary * GC

$V' \leftarrow V' \cup \{u\} \cup \{v\}$

$E' \leftarrow E' - \{e \in E' : \{u, v\} \cap e \neq \emptyset\}$ c.v.

return V'

The algorithm correctly returns a vertex cover (I eliminate an edge only when it is covered by some selected node)

Running time: $O(|V| + |E|) = O(|G|)$
 (every time I select edge $\{u, v\}$, I remove the two adjacency lists of u and v .)

TOUGH PART OF THE ANALYSIS: approximation ratio.

Let A be the set of edges selected by A-V-C(G) at each iteration of the while loop. \Downarrow accumulate truth later elaboration

PROPERTY: $\forall e_1 \neq e_2 \in A: e_1 \cap e_2 = \emptyset$

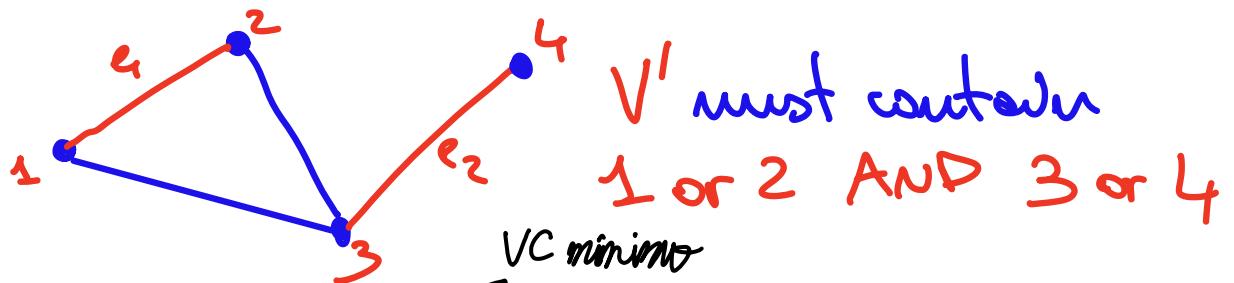
The edges in A do not share endpoints (since at each iteration all edges sharing one endpoint with the selected edge are removed)

A set of edges A not sharing endpoints is called a matching

locare da offrire in grafo

FACT: If a graph $G = (V, E)$ contains a matching $A \subseteq E$, then for any vertex-cover $V' \subseteq V$ we have $|V'| \geq |A|$

PROOF: There must be at least one endpoint of each edge e in A in V' , or otherwise e would not be covered.



COROLLARY: $|V^*| \geq |A|$

Algorithm A-V-C(G) returns a vertex cover V' , with $|V'| = 2|A|$

We have

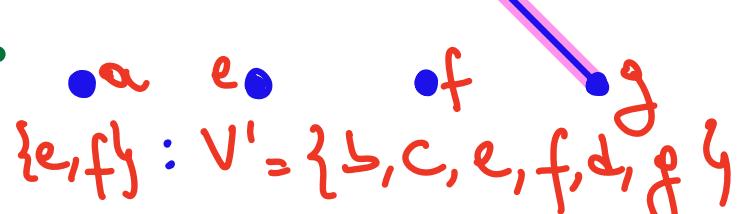
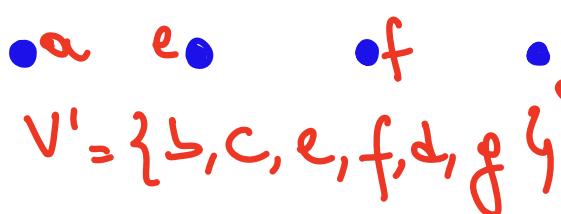
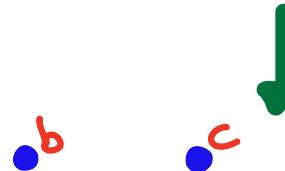
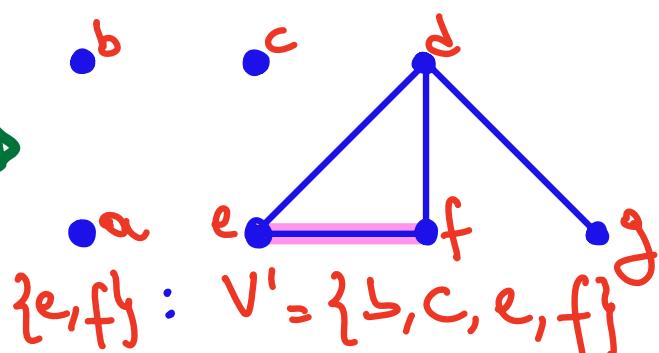
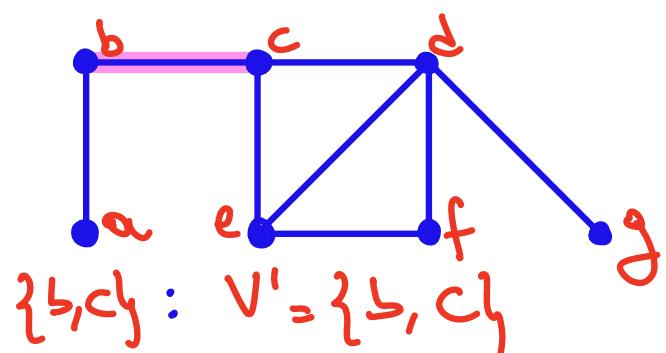
$$\rho = \frac{|V'|}{|V^*|} \leq \frac{2|A|}{|A|} = 2$$

IMPORTANT: To prove an upper bound to ρ , we always need:

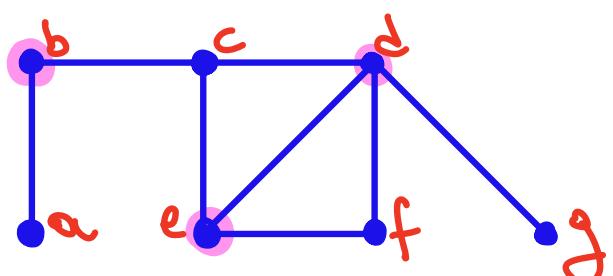
- a lower bound to $c(s^*)$ MINIMIZATION
- an upper bound to $c(s^*)$ MAXIMIZATION

We can show that the bound on
the approximation ratio is tight
by exhibiting an instance for
which

$$c(A_{\pi}(i)) = g \cdot c(S^*(i)) \text{ (MIN)}$$



$|V'| = 6$ but :



$$|V'| = 2|V^*|$$

$\Rightarrow |V'| = 2|V^*|$ (tight approximation!)

LESSONS LEARNED: To get a bound on the approximation we need to establish explicit bounds (lower or upper) on CCS^* .

For VC, we establish such a (lower) bound by relating $|V^*|$ (cannot be computed) to the size of an easily obtainable construct (\geq matching A of G).

We will see that this approach can be used for other problems.

OBSERVATION: The matching A constructs implicitly by $A = V - C(G)$ is maximal, in the sense that $\forall e \in E: A \cup \{e\}$ is not a matching - (PROVE IT!)

EXERCISE: Prove that the set of all nodes forming the edges of a maximal matching are a vertex cover