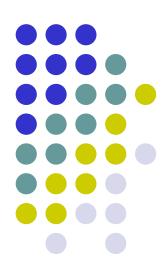
Web Algorithms

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Optimization problems



- Def: An optimization problem π is a quadruple $(I_{\pi}, S_{\pi}, m_{\pi}, goal_{\pi})$ with:
 - I_{π} set of input instances of π ;
 - $S_{\pi}(x)$ set of feasible solutions of instance $x \in I_{\pi}$
 - $m_{\pi}(x,y)$ (integral) measure of feasible solution $y \in S_{\pi}(x)$ for input $x \in I_{\pi}$
 - goal_π∈{min,max} specifies whether we have a minimization or maximization problem





- We assume that $m_{\pi}(x,y)$ is always an integer number
 - our computational models can only deal with rational approximation of reals
 - Scaling such reals we can get equivalent integer numbers
 - Integer values already reveal the intrinsic difficulties of the problems

- When clear from the context in the sequel
 - π will be omitted
 - m(x,y) will be denoted simply as m.

Example: definition of the Clique optimization problem



- I : graph *G*=(*V*,*E*)
- S: $\{U \subseteq V \mid \{u,v\} \in E \ \forall u,v \in U\}$
- m(G,U) = |U|
- goal = max

We can describe optimization problems in the following more informal and simpler form:

Max Clique

- INPUT: graph G=(V,E)
- SOLUTION: $U \subseteq V$ such that $\{u,v\} \in E \ \forall u,v \in U$
- MEASURE: |U|





Min Vertex Cover

- INPUT: graph G=(V,E)
- SOLUTION: $U \subseteq V$ such that $u \in U$ or $v \in U$ $\forall \{u,v\} \in E$
- MEASURE: |U|



Min TSP (Traveling Salesman Problem)

- INPUT: set of cities $C = \{c_1, c_2, \dots, c_n\}$ and distances $d(c_i, c_j) \in N$ for every pair of cities $c_i, c_j \in C$
- SOLUTION: A tour of all the cities, that is a permutation $< c_{p(1)}$, $c_{p(2)}$, ..., $c_{p(n)}$ > describing the order of visit of the cities
- MEASURE: tour length, that is

$$\left(\sum_{i=1}^{n-1} d(c_{p(i)}, c_{p(i+1)})\right) + d(c_{p(n)}, c_{p(1)})$$



Optimal solution

Def: Given an instance $x \in I$ of π , a solution $y^* \in S(x)$ is optimal for x if $m(x,y^*) = goal \{m(x,y)|y \in S(x)\}$.

The measure of an optimal solution (or analogously of all the optimal solutions) of x is denoted as $m^*(x)$ or simply m^* .



Underlying decision problem

Every optimization problem has an underlying decision problem that can be obtained by introducing an integer k to the input instance and asking whether there exists a feasible solution of measure $\leq k$ (for MIN) and $\geq k$ (for MAX).

- Optimization problem: given an input x, find $y \in S(x)$ such that m(x,y) is minimum or maximum (according to the goal)
- Underlying decision problem: given an input x and an integer $k \ge 0$, is there $y \in S(x)$ such that $m(x,y) \le k$ (MIN) or $m(x,y) \ge k$ (MAX)?

Example: underlying decision problem of Max Clique



Max Clique

- INPUT: G=(V,E)
- SOLUTION: $U \subseteq V$ such that $\{u,v\} \in E \ \forall u,v \in U$
- MEASURE: |U|

Underlying decision problem:

- INPUT: G=(V,E) and integer k>0
- QUESTION: is there a clique U in G such that |U|≥k?

Remarks

- If there exists a polynomial algorithm A for the optimization problem then there exists a polynomial algorithm also for the underlying decision problem that works as follows:
 - 1. Executes A for determining the optimum solution y^* for input x
 - 2. Answers 1 if $m(x,y^*) \le k$ (MIN) or $m(x,y^*) \ge k$ (MAX)



 The optimization problem is at least as difficult as the underlying decision problem.

Complexity classes of optimization problems: PO



- An optimization problem π belongs to class PO if:
 - for every input x, $x \in I$ can be checked in polynomial time,
 - there exists a polynomial p such that for every $x \in I$ and $y \in S(x)$ it is $|y| \le p(|x|)$,
 - for every $x \in I$ and $y \in S(x)$, m(x,y) can be computed in polynomial time (with respect to |x|),
 - for every x∈I, an optimal solution y^{*} can be computed in polynomial time.

Ex.: Shortest path between two nodes, minimum spanning tree, etc...

Complexity classes of optimization problems: NPO



- An optimization problem π belongs to class NPO if:
 - for every input x, $x \in I$ can be checked in polynomial time,
 - there exists a polynomial p such that for every x∈I and y∈S(x) it is |y|≤p(|x|),
 - for every x∈I and y∈S(x), m(x,y) can be computed in polynomial time (with respect to |x|),
 - for every x∈I, an optimal solution y^{*} can be computed in polynomial time.

Ex.: Max Clique, Min Vertex Cover, Min TSP, ecc...

In practice ...



- PO = class optimization problems whose underlying decision problem belongs to P
- NPO = class optimization problems whose underlying decision problem belongs to NP

Clearly PO⊆NPO

 Def. An optimization problem in NPO is NP-HARD if its underlying decision problem is NP-Complete



- Theorem: If P≠NP a NP-HARD optimization problem cannot be solved in polynomial time (since it is at least as difficult as the underlying decision problem)
- Theorem: If P=NP then PO=NPO

Almost all the problems we will see in the sequel are *NP-HARD*, that is not efficiently solvable.

We will design for such problems algorithms that return solutions "close" to optimal ones.