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Definition 2

An α -approximation for an optimization problem is a polynomial-time algorithm that for all instances of the problem produces a solution whose value is within a factor of α of the value of an optimal solution.

Minimization Problem:

Let \mathcal{I} denote the set of problem instances, and let for a given instance $I \in \mathcal{I}$, $\mathcal{F}(I)$ denote the set of feasible solutions. Further let $\text{cost}(F)$ denote the **cost** of a feasible solution $F \in \mathcal{F}$.

Let for an algorithm A and instance $I \in \mathcal{I}$, $A(I) \in \mathcal{F}(I)$ denote the feasible solution computed by A . Then A is an approximation algorithm with approximation guarantee $\alpha \geq 1$ if

$$\forall I \in \mathcal{I} : \text{cost}(A(I)) \leq \alpha \cdot \min_{F \in \mathcal{F}(I)} \{\text{cost}(F)\} = \alpha \cdot \text{OPT}(I)$$

Maximization Problem:

Let \mathcal{I} denote the set of problem instances, and let for a given instance $I \in \mathcal{I}$, $\mathcal{F}(I)$ denote the set of feasible solutions. Further let $\text{profit}(F)$ denote the **profit** of a feasible solution $F \in \mathcal{F}$.

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Why approximation algorithms?

- ▶ They provide algorithms for hard combinatorial problems.
- ▶ They give a rigorous mathematical base for studying complexity.
- ▶ They provide a means to compare the difficulty of various optimization problems.
- ▶ Proving theorems may give a deeper theoretical understanding which in turn leads to new algorithmic approaches.

Why not?

- ▶ Sometimes the results are very pessimistic due to the fact that an algorithm has to provide a close-to-optimum solution on every instance.

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What can we hope for?

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A polynomial-time approximation scheme (PTAS) is a family of algorithms $\{A_\epsilon\}$, such that A_ϵ is a $(1 + \epsilon)$ -approximation algorithm (for minimization problems) or a $(1 - \epsilon)$ -approximation algorithm (for maximization problems).

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There are difficult problems!

The class MAX SNP (which we do not define) contains optimization problems like maximum cut or MAX-3SAT.

Theorem 4

For any MAX SNP-hard problem, there does not exist a polynomial-time approximation scheme, unless $P = NP$.

MAXCUT. Given a graph $G = (V, E)$; partition V into two disjoint pieces A and B s. t. the number of edges between both pieces is maximized.

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For any constant $\epsilon > 0$ there does not exist an $\Omega(n^{\epsilon-1})$ -approximation algorithm for the maximum clique problem on a given graph G with n nodes unless $P = NP$.

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