

Approximation Algorithms

- Approximation Algorithms for Optimization Problems: Types
- Absolute Approximation Algorithms
- Inapproximability by Absolute Approximate Algorithms
- Relative Approximation Algorithm
- Inapproximability by Relative Approximate Algorithms
- Polynomial Time Approximation Schemes
- Fully Polynomial Time Approximation Schemes

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When you prove a problem X to be NP-HARD, then as per the almost consensus opinion of $P \neq NP$, it essentially means

- 1 There is no polynomial time
- 2 deterministic algorithm
- 3 to exactly/optimally solve the problem X
- 4 for all possible input instances

What are the options? Things to consider when your problem is NP-HARD

Coping with NP-HARDNESS

- Do I need to solve the problem for all valid input instances?
 - Sometimes just need to solve a restricted version of the problem -
 - ▷ (special cases) that include realistic instances
- Is exponential-time OK for my instances?
 - Exponential-time algorithms are “not slow” ▷ they don't scale well
 - If relevant instances are small, then they may be acceptable
 - Can bring exponent/base of runtime down ▷ $2^n \rightarrow 2^{\sqrt{n}}$ or $2^n \rightarrow 1.5^n$
- Is non-optimality OK?
 - What if our algorithm is better than others ▷ faster than bruteforce



Approaches to tackle hard problems

- 1 Special Cases:** Relevant structure on which the problem is easy
 - Exact results in poly-time only for special cases or a range of parameters
- 2 Intelligent Exhaustive Search:** Exponential time in worst case
 - The base and/or exponent are usually smaller
 - Could be efficient on typical more realistic instances
 - Backtracking, Branch-and-Bound
- 3 Nearly exact solutions:** Output is 'close' to exact (optimal) solution
 - **Approximation Algorithms:** Solutions of guaranteed quality in poly-time
 - **Heuristic:** Solutions hopefully good in poly-time
- 4 Randomized Algorithms:** Use coin flips for making decisions
 - Typically used for approximation, also used for problems in P

Coping with NP-HARDNESS

To cope with NP-HARDNESS, sacrifice one of these features

Poly-time	Deterministic	Exact/Opt Solution	All cases/ Parameters	Algorithmic Paradigm
✓	✓	✓	✗	Special Cases Algorithms Fixed Parameter Tractability
✓	✓	✗	✓	Approximation Algorithms Heuristic Algorithms
✗	✓	✓	✓	Intelligent Exhaustive Search
✓	✗	$\mathbb{E}(\checkmark)$	✓	Monte Carlo Randomized Algorithm
$\mathbb{E}(\checkmark)$	✗	✓	✓	Las Vegas Randomized Algorithm

- Special cases of input instances (based on structure of a range of parameter(s))
- Approximation algorithms guarantee a bound on suboptimality
- Heuristics algorithms do not have any guarantee
- Randomized algorithms are generally used for problems in class P

Optimization Problems

An optimization problem P is characterized by three things

- \mathcal{I} : set of (valid) input instances
- $S(I)$: solution space, set of feasible solutions for an instance $I \in \mathcal{I}$
- $f : S(I) \rightarrow \mathbb{R}$: function giving value to each feasible solution

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Optimization Problem can be

- A **maximization problem**: Given $I \in \mathcal{I}$, the objective is to find a solution $s^* \in S(I)$ such that $f(s^*)$ is maximum, i.e.

$$\forall s \in S(I), f(s^*) \geq f(s)$$

- A **minimization problem** is defined analogously

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Note that optimal solution (s^*) need not be unique

Approximation Algorithms

Relax the requirement that algorithm always outputs optimal solution

Instead look for a feasible solution s' , whose value $f(s')$ is **close** to the value of optimal solution s^*

An approximation algorithm A for an optimization problem P , is a **polynomial time** algorithm that on input instance $I \in \mathcal{I}$ outputs a solution $s \in \mathcal{S}(I)$ **such that $f(s)$ is close to $f(s^*)$**

- $A(I)$: the solution output by A
- $\text{OPT}(I)$: an optimal solution

We seek worst case closeness guarantees on values of outputs of A

i.e. we try to bound $\max_{I \in \mathcal{I}} |f(A(I)) - f(\text{OPT}(I))|$

Absolute Approximation Algorithms

Given an optimization problem P with value function f on solution space

An algorithm A is called **absolute approximation** algorithm if there is a constant k such that for any instance I

$$|f(A(I)) - f(\text{OPT}(I))| \leq k$$

- For a minimization problem this means $f(A(I)) \leq f(\text{OPT}(I)) + k$
- For a maximization problem this means $f(A(I)) \geq f(\text{OPT}(I)) - k$

Approximation Factor/Ratio

Given an optimization problem P with value function f on solution space

The **approximation ratio** or **approximation factor** of an algorithm A is defined as the ratio 'between' value of output of A and value of OPT

- For minimization problem it is $f(A(I))/f(\text{OPT}(I))$
- For maximization problem it is $f(\text{OPT}(I))/f(A(I))$

▷ **Note:** approximation factor is always bigger than 1

Generally, approximation factor is defined as $\max \left\{ \frac{f(A(I))}{f(\text{OPT}(I))}, \frac{f(\text{OPT}(I))}{f(A(I))} \right\}$

Relative Approximation Algorithm

Given an optimization problem P with value function f on solution space

An algorithm A is called a $\alpha(n)$ -**approximate** algorithm, if for any instance I of size n , A achieves an approximation ratio $\alpha(n)$

- For a minimization problem this means $f(A(I)) \leq \alpha(n) \cdot f(\text{OPT}(I))$
- For a maximization problem this means $f(A(I)) \geq 1/\alpha(n) \cdot f(\text{OPT}(I))$

Constant Factor (relative) Approximation Algorithm

Given an optimization problem P with value function f on solution space

An algorithm A is called an α -**approximate** algorithm, if for any instance I , A achieves an approximation ratio α

- For a minimization problem this means $f(A(I)) \leq \alpha \cdot f(\text{OPT}(I))$
- For a maximization problem this means $f(A(I)) \geq 1/\alpha \cdot f(\text{OPT}(I))$

Approximation Error

Given an optimization problem P with value function f on solution space

The **approximation error** of A is its **approximation factor minus 1**

- For a minimization problem it is

$$f(A(I))/f(\text{OPT}(I)) - 1 = f(A(I)) - f(\text{OPT}(I))/f(\text{OPT}(I))$$

- For a maximization problem it is

$$f(\text{OPT}(I))/f(A(I)) - 1 = f(\text{OPT}(I)) - f(A(I))/f(A(I))$$

▷ Useful when approximation ratio is close to 1

Also called relative approximation error

Polynomial Time Approximation Scheme (PTAS)

Given an optimization problem P with value function f on solution space

A family of algorithms $A(\epsilon)$ is called a **polynomial time approximation scheme** if for a given parameter ϵ , on any instance I , $A(\epsilon)$ achieves an approximation error ϵ and runtime of A is polynomial in $|I| = n$

- For a minimization problem this means $f(A(I)) \leq (1 + \epsilon) \cdot f(\text{OPT}(I))$
- For a maximization problem this means $f(A(I)) \geq (1 - \epsilon) \cdot f(\text{OPT}(I))$

Runtime of A could be exponential in $1/\epsilon$

▷ e.g. $O(n^{1/\epsilon})$

Fully Polynomial Time Approximation Scheme (FPTAS)

Given an optimization problem P with value function f on solution space

A family of algorithms $A(\epsilon)$ is called a **fully polynomial time approximation scheme** if for a given ϵ , on any instance I , $A(\epsilon)$ achieves an approximation error ϵ and runtime of A is polynomial in $|I| = n$ and $1/\epsilon$

- For a minimization problem this means $f(A(I)) \leq (1 + \epsilon) \cdot f(\text{OPT}(I))$
- For a maximization problem this means $f(A(I)) \geq (1 - \epsilon) \cdot f(\text{OPT}(I))$

Runtime of A cannot be exponential in $1/\epsilon$

▷ e.g. $O(1/\epsilon^2 n^3)$

Constant factor decrease in ϵ increases runtime by a constant factor

Quality of Approximation: Types

Some simple exercises to clarify the definitions

- What does an k -absolute approximate algorithm mean for $k = 0$?
- What does an α -approximate algorithm mean for $\alpha = 1$?
- What is the error of 2-approximate algorithm?
- What is the approx. factor of an algor with 1% approx. error?
- Is α -approximate algorithm the same $\alpha = (1 + \epsilon)$ -PTAS ?

- An absolute approximate algorithm is the most desirable, why?
- Absolute approximate algorithms are rare, FPTAS is the next desirable
 - ▷ Not known for many problem, but when available they are almost as good as an optimal algorithm