

PACT Example Lecture: Approximation Algorithms

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These are notes for a lecture of **Approximation Algorithms**, in particular **LP-Rounding**, given by **Prof. Sanjeev Khanna** at the **PACT Princeton summer program**. These notes are only to be used for academic purposes.

α -approximation algorithm: Given a maximization problem **P**, an α -approximation algorithm A , for **P** is a poly-time algorithm that on any input I , outputs a solution satisfying the following:

$$A[I] \geq \frac{OPT(I)}{\alpha}$$

where $A[I]$ is the value of the approximation and $OPT(I)$ is the optimal value

*for minimization, $A[I] \leq \frac{OPT(I)}{\alpha}$

See a problem with this?:

How can you guarantee this without knowing what the optimal value is?

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example: **Max SAT**

Input: m clauses $c_1, c_2, c_3, \dots, c_m$ with some number of boolean literals

Goal: assignment of literals to maximize the number satisfiable clauses

2-approximation algorithm:

- randomly assign each literal a value of True or False
- take the complement
- determine which of these two assignments maximizes the number of satisfiable clauses. By the pigeon-hole principle, this can guarantee that the winning assignment satisfies at least $\frac{m}{2}$ literals

As shown by the example above, the solution to this problem is to **upperbound the optimal solution** and take this as $OPT(I)$. In this case, we upperbounded $OPT(I)$ with m

Linear Programming

Input:

- n variables $x_1, x_2, x_3, \dots, x_n$
- expression of these variables
- m conditions

Goal: assignment of variables to maximize the expression

e.g: Maximize $3x_1 + 7x_2 - 2x_3$ given

$$\begin{aligned}x_1 + 8x_2 &\leq 100 \\ 2x_1 - x_2 + 7x_3 &\leq 200\end{aligned}$$

Linear Programming is poly-time solvable

However, **Integer Linear Programming** is *NP-hard*. This problem is the same as linear programming, but the variable assignment must be all integers

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Approximation procedure:

- formulate your NP-hard problem as an integer linear programming problem
- drop the integer constraint and solve the resulting linear program
- **LP-round:** correct the solution to integers that satisfy the constraint
- This conversion process shifts your solution by α

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example: Minimum Vertex Cover $\rightarrow ILP$

Minimum Vertex Cover: Input: graph $G = \{V, E\}$ with n vertices v_1, v_2, \dots, v_n

Goal: find minimum *vertex cover* C *Step 1:* Convert to ILP:

Input: Let each vertex v_i correspond to a variable x_i Let

$$x_i = 1 \mid v_i \in C$$

$$x_i = 0 \mid v_i \notin C$$

constraints:

$$\forall \{u, v\} \in E, x_u + x_v \geq 1$$

$$\forall x_i, x_i = 0 \vee x_i = 1$$

Goal: Minimize $\sum_i^n x_i$

Step 2: drop integer constraint $\rightarrow 0 \leq x_i \leq 1$

Step 3: LP-rounding $\forall i$ if $x_i > \frac{1}{2}$ then set $x_i = 1 \rightarrow$ else $x_i = 0$

(intuition: choose the higher x_i of $\{u, v\}$ and set it to 1, the other to 0)

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Integrality Gap: worst case ratio between OPT integral solution and OPT fractional solution for a certain linear program

prove that for our algorithm of Minimum Vertex Cover $\rightarrow ILP$, the integrality gap is 2:

Take a complete graph $G : \{V, E\}$

$$|V| = \frac{n(n-1)}{2}$$

By pigeonhole principle, $n-1$ is the cardinality of the OPT vertex cover

Worst case: let x_i be $\frac{1}{2} \forall i \rightarrow \sum_i^n x_i = \frac{n}{2}$

As $n \rightarrow \infty, n-1 = 2(\frac{n}{2})$

Thus our algorithm has an integrality gap of 2

example: Minimum Set cover $\rightarrow ILP$

Minimum Set Cover:

Input: collection of m sets s_1, s_2, \dots, s_m where each $s_i \subset 1, 2, \dots, n = \text{Universe } U$

Goal: find minimum subcollection = S of sets whose union is U

Step 1: Let each set s_i correspond to a variable x_i

constraints:

$$x_i = 1 \mid s_i \text{ exists in } S, 0 \text{ else}$$

$$\forall j \exists \{1, 2, \dots, m\} x_{i_1} + x_{i_2} \geq 1$$

where $x_{i_1} + x_{i_2}, \dots =$ variables of sets in which j appears

Step 2: drop integrality constraint $\rightarrow 0 \leq x_i \leq 1$

Step 3: LP Rounding

Let K be the max number of times that one element appears in S

Thus if:

$$x_i > \frac{1}{k} \rightarrow x_i = 1$$

$$x_i < \frac{1}{k} \rightarrow x_i = 0$$

This works, but the integrality gap will be k , following the same logic of the previous example. In the worse case, $k = m$. In that case, why not just output all sets?

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randomized LP-rounding:

Choose set s_i in your solution with probability x_i

Then set a new variable $z_i \forall i$:

$$z_i = 1 \mid s_i \text{ exists } S, 0 \text{ else}$$

$$E[\sum_i^n E_i] = \sum_i^n x_i = \text{LP OPT}$$

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Check:

$$\Pr[\text{element } j \text{ is covered}] = 1 - \Pr[\text{element } j \text{ is not in by any included set}] = 1 - \prod_{j=1}^k (1 - x_{ij})$$

By identity $1 + x \leq e^x$, so $1 - e^{-\sum x_{ij}} \leq 1 - \frac{1}{e}$

How can we make this probability exactly $1 - \frac{1}{e}$?

Instead of including s_i with probability x_i , take with probability $2x_i \ln(n)$

$$\Pr[\text{element } j \text{ is covered}] = 1 - e^{-2 \ln(n) \sum x_{ij}} = 1 - \frac{1}{n^2}$$

$$\Pr[\text{at least one element is not covered}] = \frac{1}{n^2} n = \frac{1}{n} \rightarrow 0 \text{ as } n \rightarrow \infty$$