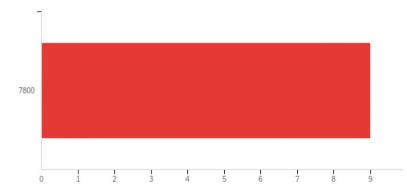
CS7800: Advanced Algorithms

Lecture 15: Approximation Algorithms II
* Covering Problems

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CourseNumber



#	Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
1	CourseNumber	7800.00	7800.00	7800.00	0.00	0.00	9

#	Answer	%	Count
1	7800	100.00%	9
	Total	100%	9

Maximum Coverage (variant of Set Cover) Inputs: Sets Sis---, Sm = & Is---, n3= U

A budget k Objective: Output sets $\{A_1, ..., A_k\} \subseteq \{S_1, ..., S_m\}$ maximizing $\{\bigcup_{i=1}^k A_i\}$

Recap: Problem is NP-hard to solve exactly

Greedy Maximum Coverage

For i=1,..., k:

| Pick the set A; E S,..., Sm3
| that cases the most new elements

Analyzing Greedy Set Cover

Fact #1: There exists a set that covers > Or elts

optimal set (k pieces) exists a set

Fact #2: At iteration i, exists a set that cover

that cover OPT-li-1 new elts

Iteration i of greedy li= #of elevers covered by greedy after interesons for the remaxing

k sets

OPT- 1:-1

elements, we can

cover opt-l:-1 u.th

Analyzing Greedy Contid

$$l_k = (l_k - l_{k-1}) + l_{k-1}$$

$$\frac{(1-\frac{1}{k})}{k} + \frac{(1-\frac{1}{k})}{k} + \frac{(1$$

$$= \frac{OPT}{k} \left(1 + \left(1 - \frac{1}{k} \right) + \left(1 - \frac{1}{k} \right)^{2} + \dots + \left(1 - \frac{1}{k} \right)^{k-1} \right)$$

$$= \frac{OPT}{k} \cdot \frac{1 - \left(1 - \frac{1}{k}\right)^k}{1 - \left(1 - \frac{1}{k}\right)^k} = OPT \cdot \left(1 - \left(1 - \frac{1}{k}\right)^k\right) \longrightarrow OPT \cdot \left(1 - \frac{1}{k}\right)$$

Vertex Cover (special case of Set Cover)

Inputs: An undirected graph G=(V,E)

Objective: Output nodes C=V such that for every

edge (u,v) & E either u & C or v & C (or both).

Recap: Problem is NP-hard to solve exactly

LP Relaxations and Rounding

IP for Vertex Cover

min Z Xu
Xu + Xv >, I for all (u,v) EE
Xu >, O
Xu integer

- · Exactly solves Veter Care
- · Optimal value is OPTIP

LP Relaxation

min Z Xu
Xu+xv>1 for (u,v) EE
Xu>, O
xu + IR

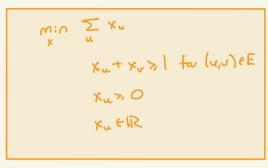
- · Optimal value OPTLP & OPTIP

LP Relaxations and Rounding

IP for Vertex Cover

min \(\times \times \)
\(\tim

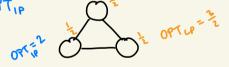
LP Relaxation



· Exactly solves Veter Caver

· Optimal value OPTLP & OPTIP

· Optimal value is OPTIP



A rounding algorithm takes a fractional solution xip and outputs an integer solution xip s.t. value (xip) < c · value(xip)

ROUNDLP & C- OPTLP & C- OPTZP

LP Relaxations and Kounding

IP for Vertex Cover

LP Relaxation

· Exactly solves Votes Cover

· Optimal value OPTLP & OPTIP

· Optimal value is OPTIP

Given xis for the Imear program, define $x_u^{IP} = \begin{cases} 1 & \text{if } x_u > \frac{1}{2} \\ 0 & \text{if } x_u < \frac{1}{2} \end{cases}$

at least one of
$$x_u=1$$
 and $x_v=1$ is true

Weighted Set Cover

Inputs: Sets Sis..., Sm = U (|U|=n)
Costs Cis..., Cm

Objective: Find a minimum cost collection of sets whose union is U

Recap: Problem is NP-hard to solve exactly

LP Relaxation for Set Cover

Primal min \(\sum_{i=1} \circ_i \circ_i \) s.t. \(\times \cong \cong \cong \); \(\times \cong \cong \) \(\times \cong \cong \) \(\times \cong \) \(X: >, 0

max = Pe

s.t. = Pe s c; for i=1...m

ees;

Pe > 0

Dual

For any feasible dual Epe3 Z

E Pe 3 OPTLP 3 OPTLP & GREEDY

Greedy Alg for Weighted Set Cover

Until all of U is covered choose S; minimizes to frew elts covered rateo · ge = ratio of the first set that cover e · Z qe = GREEDY

Fix some iteration. Suppose l elts of S_i are covered. Then the ratio of S_i is $\frac{c_i}{15il-l}$

Greedy Ally for Weighted Set Cover

Until all of U is covered

choose S; minimizes

tof new elts covered

ratio

· ge = ratio of the first set that cover e

Fix some iteration. Suppose I elts of Si are covered.

Then the ratio of S; 13 c: 15:1-e

Clm: For every S:, the jtb elt covered satisfies 9et 15:1-(j-1)

Greedy Alg for Weighted Set Cover

Je

Fix some iteration. Suppose I elts of Si are covered. Then the ratio of Si is $\frac{c_i}{15:1-1}$

Clm: For every S:, the jtb elt covered satisfies $qe^{\frac{c_i}{1}}$ $\frac{c_i}{1}$ $\frac{c_i}{1}$

$$\sum_{e \in S_{i}} q_{e} \leq \frac{c_{i}}{|S_{i}|} + \frac{c_{i}}{|S_{i}|-1} + \frac{c_{i}}{|S_{i}|-2} + \dots + \frac{c_{i}}{|S_{i}|}$$

$$= c_{i} \left(1 + \frac{1}{2} + \frac{1}{3} + \dots + \frac{1}{|S_{i}|}\right) \approx c_{i} \cdot |n|S_{i}| \leq c_{i} \cdot |n|(n)$$

 $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{i}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{i}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{i}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{i}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{i}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{i}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{i}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{i}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{i}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{i}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{i}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{i}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{i}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{i}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{i}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{i}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{i}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \overline{s} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right) = c_{\cdot}$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right) = c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right)$ $= c_{\cdot} \left(1 + \overline{c} + \dots + (s_{i}) \right$

LP Relaxation for Set Cover

Primal

Min
$$\sum_{i=1}^{m} c_i x_i$$

s.t. $\sum_{i:e \in S_i} x_i >_1$ for $e \in U(Pe)$
 $i:e \in S_i$

max = Pe

s.t. = Pe s c; for i=1...m

ees;

Pe > 0

2 pe & OPTLP & OPTIP & GREEDY

Dual

For any feasible dual spes
Pe =
$$\frac{g_e}{1000} = \frac{GREEDY}{10000}$$