

Strengthening Relaxations: P-D for Min-Knapsack

Important technique/idea: *strengthening* relaxations

Min-Knapsack:

Input: - Items $I = [n]$ - Demand $D \in \mathbb{R}_{\geq 0}$
- values $v: I \rightarrow \mathbb{R}_{\geq 0}$ - sizes $s: I \rightarrow \mathbb{R}_{\geq 0}$

Feasible solution: $X \subseteq I$ s.t. $\sum_{i \in X} v(i) \geq D$

Objective: $\min s(X) = \sum_{i \in X} s(i)$

Note: wLOG $v(i) \leq D \quad \forall i \in I$

Obvious LP relaxation:

$$\min \sum_{i \in I} s(i) x_i$$

$$\text{s.t.} \quad \sum_{i \in I} v(i) x_i \geq D$$

$$0 \leq x_i \leq 1 \quad \forall i \in I$$

Thm: $\exists$ LP an exact formulation

PF: Let x feasible integral solution to LP.

$$\Rightarrow \text{let } X = \{i \in I : x_i = 1\}$$

$$\Rightarrow \sum_{i \in X} v(i) = \sum_{i \in I} v(i) x_i \geq D, \text{ so } X \text{ feasible}$$

$$s(X) = \sum_{i \in I} s(i) x_i$$

Let X feasible solution to Min-knapsack.

$$\Rightarrow \text{let } x_i = \begin{cases} 1 & \text{if } i \in X \\ 0 & \text{otherwise} \end{cases}$$

$$\Rightarrow \sum_{i \in I} v(i) x_i = \sum_{i \in X} v(i) \geq 0 \quad (X \text{ feasible})$$

$$\sum_{i \in I} s(i) x_i = \sum_{i \in X} s(i)$$

So ILP exact. Is LP relaxation good?

Ex: $I = \{1, 2\}$

$$v(1) = 0-1 \quad s(1) = 0$$

$$v(2) = 0 \quad s(2) = 1$$

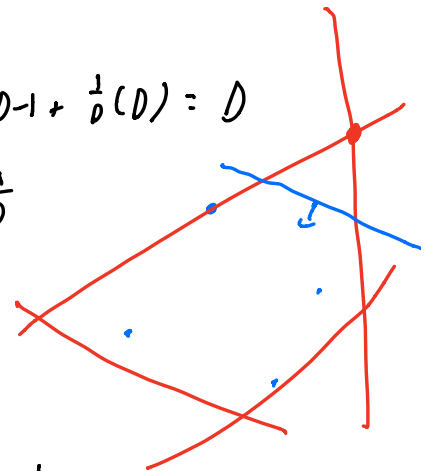
Only feasible solution: take item 2 $\Rightarrow \text{OPT} = 1$

LP solution:

$$x_1 = 1 \quad x_2 = \frac{1}{D} \quad \Rightarrow \quad \begin{aligned} \sum_{i=1}^2 v(i) x_i &= 0-1 + \frac{1}{D}(0) = 0 \\ \sum_{i=1}^2 s(i) x_i &= \frac{1}{D} \end{aligned}$$

$$\Rightarrow \text{integrality gap} = \frac{\text{OPT}}{\text{LP}} = \frac{1}{1/D} = D$$

(can be exponential in size of input!)



Can we add valid constraints (all integral solutions still feasible) to make LP better?

Different from Multicway Cut: adding extra constraints, not completely new LP

What went wrong in example?

- Bought "partial solution" of item 1

$\Rightarrow$ "remaining demand" = 1,

value of item 2 = $D > 1$

First WLOG was $v(i) \leq D \quad \forall i$

- After buying item 1, should "pretend" $v(2) = 1$, not $v(2) = D$

Generalize: suppose promise to buy $A \subseteq I$.

Constraint for "remaining" problem:

$$\sum_{i \in I} v(i) x_i \geq D$$

$$\sum_{i \in I \setminus A} \min(v(i), D - v(A)) x_i \geq D - v(A)$$

New LP: include **all** of these constraints!

$$\begin{aligned}
 \min \quad & \sum_{i \in I} s(i) x_i && = \sum_{i \in A} v(i) \\
 \text{s.t.} \quad & \sum_{i \in I \setminus A} \min(v(i), D - v(A)) x_i \geq D - v(A) && \forall A \subseteq I \\
 & x_i \geq 0 && \forall i \in I
 \end{aligned}$$

Note: when $A = \emptyset$ have original constraint

Knapsack Cover Inequalities: Carr, Fleischer, Lenz, Phillips '00

Why is this valid?

Lemma: Let X be feasible solution to Min-Knapsack.

Then $x_i = \begin{cases} 1 & \text{if } i \in X \\ 0 & \text{otherwise} \end{cases}$ is feasible LP solution

Pf: Consider some $A \subseteq I$.

$$X \text{ feasible} \Rightarrow \sum_{i \in X} v(i) \geq D$$

$$\Rightarrow \sum_{i \in X \setminus A} v(i) + \sum_{i \in X \cap A} v(i) \geq D$$

$$\begin{aligned}
 \Rightarrow \sum_{i \in X \setminus A} v(i) &\geq D - v(A \cap X) \\
 &\geq D - v(A)
 \end{aligned}$$

$$\Rightarrow \sum_{i \in X \setminus A} \min(v(i), D - v(A)) \geq D - v(A)$$

(if $\exists i$ s.t. $v(i) \geq D - v(A)$ satisfied, o/w also satisfied)

$$\Rightarrow \sum_{i \in X \setminus A} \min(v(i), D - v(A)) x_i \geq D - v(A) \quad (\text{def of } x_i)$$

$$\Rightarrow \sum_{i \in I \setminus A} \min(v(i), D - v(A)) x_i \geq D - v(A)$$

Sanity check: what does this do to our example?

$$\begin{aligned} v(1) &= D - 1 & s(1) &= 0 \\ v(2) &= 0 & s(2) &= 1 \end{aligned}$$

consider $A = \{1\}$

$$\Rightarrow \text{LP constraint for } A: \min(v(2), D - v(A)) x_2 \geq D - v(A)$$

$$\Rightarrow \min(D, 1) x_2 \geq 1$$

$$\Rightarrow x_2 \geq 1$$

Primal-Dual Algorithm:

Primal:

$$\min \sum_{i \in I} s(i) x_i$$

$$\text{s.t.} \quad \sum_{i \in I \setminus A} \min(v(i), D - v(A)) x_i \geq D - v(A) \quad \forall A \subseteq I$$

$$x_i \geq 0$$

$$\forall i \in I$$

Dual: variable $y_A \forall A \subseteq I$, constraint $\forall i \in I$

$$\max \sum_{A \subseteq I} (D - v(A)) y_A$$

$$\text{s.t.} \quad \sum_{A \subseteq I: i \notin A} \min(v(i), D - v(A)) y_A \leq r(i) \quad \forall i \in I$$

$$0 \leq y_A \quad \forall A \subseteq I$$

Alg:

- Init $y = \vec{0}$, $X = \emptyset$

- while $v(X) < D$ {

- increase y_x until some dual constraint becomes tight:

$$i \in I \setminus X \text{ s.t. } \sum_{A \subseteq I: i \notin A} \min(v(i), D - v(A)) y_A = r(i)$$

- $X = X \cup \{i\}$

}

- Return X

Lemma: $\vec{y}$ is feasible dual solution throughout algorithm

PF: True initially: $y = \vec{0}$

Consider some iteration, y feasible at beginning

$\Rightarrow X$ set at beginning of iteration.

If y_x increases, all i s.t. dual constraint tight
are in X

$\Rightarrow$ still feasible at end of iteration

Thm: 2-approximation

pf: X set returned by alg.

$$s(X) = \sum_{i \in X} s(i)$$

$$= \sum_{i \in X} \sum_{A \subseteq I: i \notin A} \min(u(i), D - u(A)) y_A \quad (\text{dot of alg})$$

$$= \sum_{A \subseteq I} \sum_{i \in X \setminus A} \min(u(i), D - u(A)) y_A \quad (\text{order of summation})$$

$$= \sum_{A \subseteq I} y_A \underbrace{\sum_{i \in X \setminus A} \min(u(i), D - u(A))}_{\text{want to bound for } A \text{ s.t. } y_A > 0}$$

Let A s.t. $y_A > 0$, $\Rightarrow A$ added by alg $\Rightarrow A \subseteq X$

Let l be last item added by alg, $\Rightarrow l \in X \setminus A$

Let $i \in X \setminus A$, $i \neq l$



$\Rightarrow v(A \cup \{i\}) < D$, since our alg would have finished before adding l

$$\Rightarrow v(A) + v(i) < D$$

$$\Rightarrow v(i) < D - v(A)$$

$$\Rightarrow \min(v(i), D - v(A)) = v(i)$$

$$\begin{aligned} &= \sum_{A \in \mathcal{I}} y_A (\min(v(l), D - v(A)) + \underbrace{\sum_{i \in X \setminus A: i \neq l} v(i)}_{v(X \setminus \{l\}) - v(A)}) \\ &= \sum_{A \in \mathcal{I}} y_A (\min(v(l), D - v(A)) + v(X \setminus \{l\}) - v(A)) \end{aligned}$$

$$< \sum_{A \in \mathcal{I}} y_A (D - v(A) + D - v(A))$$

$$= 2 \sum_{A \in \mathcal{I}} (D - v(A)) y_A$$

$$\leq 2 \cdot \text{OPT} \quad (\text{weak duality})$$