DM545/DM871 Linear and Integer Programming

Lecture 9 IP Modeling Formulations, Relaxations

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Outline

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Uncapacited Facility Location
Alternative Formulations

2. Relaxations

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Task: Which depots to open and which depots serve

Uncapacited Facility Location (UFL)

Given:

- depots $N = \{1, \ldots, n\}$
- clients $M = \{1, ..., m\}$
- fi fixed cost to use depot i
- transport cost for all orders cij

Variables: $y_j = \begin{cases} 1 & \text{if depot opened} \\ 0 & \text{otherwise} \end{cases}$

 x_{ii} fraction of demand of i satisfied by j

which client

Objective:

$$\min \sum_{i \in M} \sum_{j \in N} c_{ij} x_{ij} + \sum_{j \in N} f_j y_j$$

Constraints:

$$\sum_{j=1}^{n} x_{ij} = 1$$

$$\sum_{i=1}^{n} x_{ij} \le my_{i}$$

$$\forall i = 1, \ldots, m$$

$$\forall j \in N$$

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Good and Ideal Formulations

Definition (Formulation)

A polyhedron $P \subseteq \mathbb{R}^{n+p}$ is a formulation for a set $X \subseteq \mathbb{Z}^n \times \mathbb{R}^p$ if and only if $X = P \cap (\mathbb{Z}^n \times \mathbb{R}^p)$

That is, if it does not leave out any of the solutions of the feasible region X.

There are infinite formulations

Definition (Convex Hull)

Given a set $X \subseteq \mathbb{Z}^n$ the convex hull of X is defined as:

$$\operatorname{conv}(X) = \left\{ \mathbf{x} : \mathbf{x} = \sum_{i=1}^t \lambda_i \mathbf{x}^i, \qquad \sum_{i=1}^t \lambda_i = 1, \qquad \lambda_i \geq 0, \qquad \text{for } i = 1, \dots, t, \right.$$

$$\left. \text{for all finite subsets } \left\{ \mathbf{x}^1, \dots, \mathbf{x}^t \right\} \text{ of } X \right\}$$

Proposition

conv(X) is a polyhedron (ie, representable as $Ax \leq b$)

Proposition

Extreme points of conv(X) all lie in X

Hence:

$$\max\{c^Tx : x \in X\} \equiv \max\{c^Tx : x \in conv(X)\}\$$

However it might require exponential number of inequalities to describe conv(X) What makes a formulation better than another?

$$X \subseteq \text{conv}(X) \subseteq P_2 \subset P_1$$

 P_2 is better than P_1

Definition

Given a set $X \subseteq \mathbb{R}^n$ and two formulations P_1 and P_2 for X, P_2 is a better formulation than P_1 if $P_2 \subset P_1$

Example

$$P_1 = \text{UFL with } \sum_{i \in M} x_{ij} \le my_j \quad \forall j \in N$$

 $P_2 = \text{UFL with } x_{ij} \le y_i \quad \forall i \in M, j \in N$

$$P_2 \subset P_1$$

- $P_2 \subseteq P_1$ because summing $x_{ij} \le y_j$ over $i \in M$ we obtain $\sum_{i \in M} x_{ij} \le my_j$
- $P_2 \subset P_1$ because there exists a point in P_1 but not in P_2 : $m = 6 = 3 \cdot 2 = k \cdot n$

$$x_{10} = 1, x_{20} = 1, x_{30} = 1,$$

 $x_{41} = 1, x_{51} = 1, x_{61} = 1$

$$\sum_{i} x_{i0} \le 6y_0 \quad y_0 = 1/2$$
$$\sum_{i} x_{i1} \le 6y_1 \quad y_1 = 1/2$$

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Optimality and Relaxation

$$z = \max\{c(\mathbf{x}) : \mathbf{x} \in X \subseteq \mathbb{Z}^n\}$$
 How can we prove that \mathbf{x}^* is optimal? \overline{z} is UB \underline{z} is LB stop when $\overline{z} - z < \epsilon$

- Primal bounds (here lower bounds): every feasible solution gives a primal bound, it may be easy or hard to find, heuristics
- Dual bounds (here upper bounds): Relaxations

Optimality gap (SCIP):

- If primal and dual bound have opposite signs, the gap is "Infinity".
- If primal and dual bound have the same sign, the gap is

$$\frac{|pb - db|}{\min(|pb|, |db|)}$$

decreases monotonously during the solving process.

Proposition

Given: (IP)
$$z = \max\{c(x) : x \in X \subseteq \mathbb{R}^n\}$$
 a relaxation of it is: (RP) $z^R = \max\{f(x) : x \in T \subseteq \mathbb{R}^n\}$ if:

- (i) $X \subseteq T$ or
- (ii) $f(x) \ge c(x) \forall x \in X$

In other terms:

$$\max_{\mathsf{x}\in T} f(\mathsf{x}) \geq \left\{ \max_{\mathsf{x}\in T} c(\mathsf{x}) \atop \max_{\mathsf{x}\in X} f(\mathsf{x}) \right\} \geq \max_{\mathsf{x}\in X} c(\mathsf{x})$$

- T: candidate solutions;
- $X \subseteq T$ feasible solutions;
- $f(x) \ge c(x) \forall x \in X$

Relaxations

How to construct relaxations?

1. $IP : \max\{c^Tx : x \in P \cap \mathbb{Z}^n\}, \qquad P = \{x \in \mathbb{R}^n : Ax \le b\}$ $LP : \max\{c^Tx : x \in P\}$ Better formulations give better bounds $(P_1 \subseteq P_2)$

Proposition

- (i) If a relaxation LP is infeasible, the original problem IP is infeasible.
- (ii) Let x^* be optimal solution for LP. If $x^* \in X$ and $f(x^*) = c(x^*)$ then x^* is optimal for IP.
- 2. Combinatorial relaxations to easy problems that can be solved rapidly Eg: TSP to Assignment problem Eg: Symmetric TSP to 1-tree

3. Lagrangian relaxation

IP:
$$z = \max\{c^{T}x : Ax \le b, x \in X \subseteq \mathbb{Z}^{n}\}$$

$$LR: z(u) = \max\{c^{T}x + u(b - Ax) : x \in X\}$$

$$z(u) > z \qquad \forall u > 0$$

4. Duality:

Definition

Two problems:

$$z = \max\{c(x) : x \in X\}$$
 $w = \min\{w(u) : u \in U\}$

form a weak-dual pair if $c(x) \le w(u)$ for all $x \in X$ and all $u \in U$.

When z = w they form a strong-dual pair

Proposition

$$z = \max\{c^Tx : Ax \le b, x \in \mathbb{Z}_+^n\}$$
 and $w^{LP} = \min\{u^Tb : A^Tu \ge c, u \in \mathbb{R}_+^m\}$ (ie, dual of linear relaxation) form a weak-dual pair.

Proposition

Let IP and D be weak-dual pair:

- (i) If D is unbounded, then IP is infeasible
- (ii) If $x^* \in X$ and $u^* \in U$ satisfy $c(x^*) = w(u^*)$ then x^* is optimal for IP and u^* is optimal for D.

The advantage is that we do not need to solve an LP like in the LP relaxation to have a bound, any feasible dual solution gives a bound.

Examples

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Weak pairs:
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Matching: z = \max\{1^T x : Ax \le 1, x \in \mathbb{Z}_+^m\}
V. Covering: w = \min\{1^T y : A^T y \ge 1, y \in \mathbb{Z}_+^n\}
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Proof: consider LP relaxations, then $z \le z^{LP} = w^{LP} \le w$. (strong when graphs are bipartite)

Weak pairs:

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S. Packing: z = \max\{1^T x : Ax \le 1, x \in \mathbb{Z}_+^n\}
S. Covering: w = \min\{1^T y : A^T y \ge 1, y \in \mathbb{Z}_+^m\}
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