Linear Programming and Applications

- Diet problem
- History
- Network flow
- Branch and bound

Next up: LP geometry, solvers, duality

Linear programming

Given
$$A \in \mathbf{R}^{m \times n}$$
, $b \in \mathbf{R}^m$, $c \in \mathbf{R}^n$:
$$\min_x c^T x$$
 subject to
$$Ax = b$$

$$x \ge 0$$

- Other variations exist, but all equivalent after reformulations
- Historical importance
- Good solvers (simplex method, interior point methods)
- Generalized to "linear cone" solvers
 - $x \ge 0$ is replaced by x in second-order cone or semidefinite cone
 - Now we can solve lots of convex problems

Diet problem

minimize
$$c^T x$$

subject to $Ax = b, x \ge 0$

- minimum-cost diet
- x_i represents how many servings of food group i to eat
- c_i gives cost of 1 serving of food from group i
- $a_i^T x = b_i$ encodes nutritional recommendations
- $x \ge 0$ since you can't eat negative food

Important fields

- Operations research
 - Started with post-WWII military research
 - many applications in management science
 - often appears as relaxations of important combinatorial problems
 - e.g., assigning people to tasks, routing supplies, strategic planning,...
- Economics
 - 1939: Planning a country's economy (Kantorivich in USSR, Koopmans in US)
 - Planning in business (maximize utility subject to resource constraints)
- Combinatorial optimization
 - Linear relaxation gives lower bounds
 - Often used in branch-and-bound solvers

Assignment

Task: assign n people to n tasks

$$\begin{array}{ll} \underset{X \in \mathbf{R}^{n \times n}}{\text{maximize}} & \sum_{ij} X_{ij} \, W_{ij} \\ \text{subject to} & X^T e = e, \quad Xe = e \\ & X_{i,j} \in \{0,1\} \end{array}$$

- $X_{ij} = 1 \iff \text{person } i \text{ assigned to task } j$
- W_{ij} encodes preference of person i's assignment to task j
- linear equality constraint ensures only 1 assignment per person and per task
- combinatorial constraint $X_{i,j} \in \{0,1\}$ makes problem hard to solve
- relaxation: replace binary constraints with interval constraints:

$$X_{i,j} \in \{0,1\} \quad o \quad 0 \le X_{i,j} \le 1$$

Routing (aka, Traveling Salesman problem)

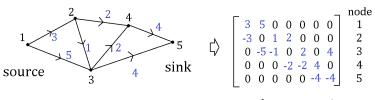
Task: assign a supply route for a truck, with n stops

$$\label{eq:minimize} \begin{aligned} & \underset{X \in \mathbf{R}^{n \times n}}{\text{minimize}} & & \sum_{ij} X_{ij} \, W_{ij} \\ & \text{subject to} & & X^T e = e, \quad Xe = e \\ & & \sum_{j} X_{1,j} = \sum_{i} X_{i,1} = 1 \\ & & \sum_{i \not \in S} \sum_{j \in S} X_{ij} \geq 1, \; \forall S \subseteq \{1,...,n\} \\ & & X_{i,j} \in \{0,1\} \end{aligned}$$

- $X_{ij} = 1$ if visit stop i right after stop j
- ullet second linear constraint: ensure truck leaves and returns at depo (i=1)
- third constraint: ensures route is connected
- relaxation: replace binary constraints with interval constraints:

$$X_{i,j} \in \{0,1\} \quad o \quad 0 \le X_{i,j} \le 1$$

Network flow



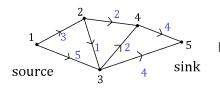
node-arc matrix

Appears in transportation, network routing, planning

- n nodes, m arcs (directed edges)
- $X \in \mathbf{R}^{n \times m}$ records flows from node i through arc j
- $C_L \le X \le C_U$ capacity constraints (eg, link capacities)
- if no edge between nodes i and j then $(C_L)_{ij} = (C_U)_{ij} = 0$
- flow conservation:

$$\sum_{j} X_{ij} = 0$$
 for all non-source non-sink nodes i

Network flow: Max-flow



	_						_	node
	3	5	0	0	0	0	0	1
	-3	0	1	2	0	0	0	2
>	0	-5	-1	0	2	0	4	3
	0	0	0	-2	-2	4	0	4
	0	0	0	0	0	-4	-4	5

node-arc matrix

$$\begin{array}{ll} \text{maximize} & \sum_{i=1}^n X_{1,i} & \text{Total flow} \\ \text{subject to} & C_L \leq X \leq C_U & \text{Capacity constraints} \\ & \sum_j X_{ij} = 0, \ \forall i \neq 1 & \text{Conservation of flow} \end{array}$$

Branch and bound

Mixed integer linear program

$$\label{eq:linear_model} \begin{aligned} & \underset{x \in \mathbf{R}^n}{\text{minimize}} & & c^{\mathsf{T}}x \\ & \text{subject to} & & \textit{Ax} = \textit{b}, \; \textit{Cx} \leq \textit{d} \\ & & \textit{x}_i \in \{0,1\}, \; i = 1, \dots, n \end{aligned}$$

- Generalizes assignment, routing, graph coloring, and more
- $x \in \mathbb{R}^n$ is **feasible** if

$$Ax = b, \quad Cx \le d, \quad x_i \in \{0, 1\}, \ i = 1, ..., n$$

Branch and bound

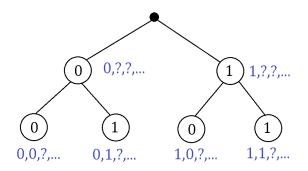
Mixed integer linear program

minimize
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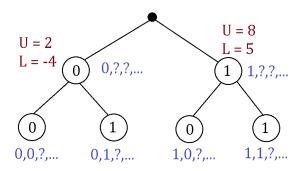
subject to $Ax = b, Cx \le d$
 $x_i \in \{0,1\}, i = 1,...,n$

- let $p(x) := c^T x$
- **Upper bound:** For any feasible x, $p(x) \ge p(x^*)$
- Lower bound: Consider \hat{x} the solution to relaxed problem

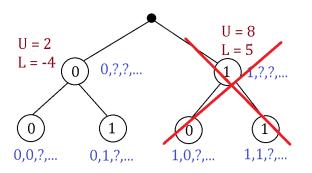
Then
$$p(\hat{x}) \leq p(x^*)$$



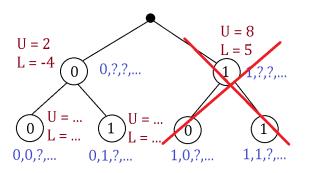
1. Binary tree traverses every possible value of x



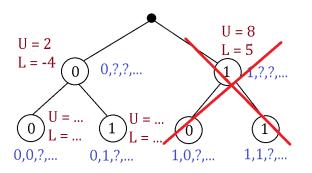
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- 5. B-B solvers require fast LP solvers, since they may be applied many times!