Linear Programming and Applications

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

Next up: LP geometry, solvers, duality

Linear programming

Given $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m$, $c \in \mathbb{R}^n$:

 $\begin{array}{ll} \underset{x}{\text{minimize}} & c^{T}x\\ \text{subject to} & Ax = b\\ & x \ge 0 \end{array}$

- 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

$$\begin{array}{ll} \underset{x}{\text{minimize}} & c^{T}x\\ \text{subject to} & Ax = b, \ x \geq 0 \end{array}$$

- 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

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

•
$$X_{ij} = 1 \iff$$
 person *i* 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:

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

Routing (aka, Traveling Salesman problem)

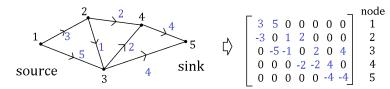
Task: assign a supply route for a truck, with n stops

$$\begin{array}{ll} \underset{X \in \mathbb{R}^{n \times n}}{\text{minimize}} & \sum_{ij} X_{ij} W_{ij} \\ \text{subject to} & X^T e = e, \quad Xe = e \\ & \sum_{j} X_{1,j} = \sum_{i} X_{i,1} = 1 \\ & \sum_{i \notin S} \sum_{j \in S} X_{ij} \geq 1, \; \forall S \subseteq \{1, ..., n\} \\ & X_{i,j} \in \{0, 1\} \end{array}$$

- $X_{ij} = 1$ if visit stop *i* right after stop *j*
- 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:

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

Network flow



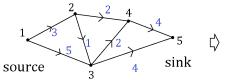
node-arc matrix

Appears in transportation, network routing, planning

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

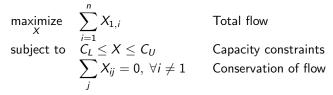
$$\sum_{j} X_{ij} = 0 \quad \text{for all non-source non-sink nodes } i$$

Network flow: Max-flow



$$\begin{bmatrix} 3 & 5 & 0 & 0 & 0 & 0 & 0 \\ -3 & 0 & 1 & 2 & 0 & 0 & 0 \\ 0 & -5 & -1 & 0 & 2 & 0 & 4 \\ 0 & 0 & 0 & -2 & -2 & 4 & 0 \\ 0 & 0 & 0 & 0 & 0 & -4 & -4 \end{bmatrix} \begin{bmatrix} node \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{bmatrix}$$

node-arc matrix



Branch and bound

Mixed integer linear program

$$\begin{array}{ll} \underset{x \in \mathbb{R}^{n}}{\text{minimize}} & c^{T}x\\ \text{subject to} & Ax = b, \ Cx \leq d\\ & x_{i} \in \{0,1\}, \ i = 1, \dots, n \end{array}$$

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

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

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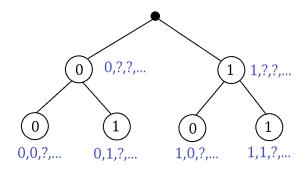
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• let $p(x) := c^T x$

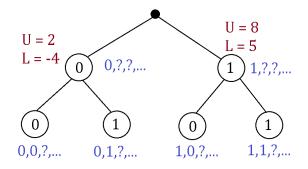
- **Upper bound:** For any feasible x, $p(x) \ge p(x^*)$
- Lower bound: Consider \hat{x} the solution to relaxed problem

$$\begin{array}{ll} \underset{x \in \mathbb{R}^{n}}{\text{minimize}} & c^{T}x\\ \text{subject to} & Ax = b, \ Cx \leq d\\ & 0 \leq x \leq e \end{array}$$

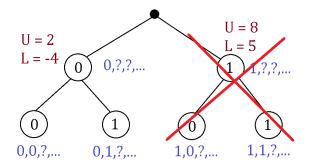
Then $p(\hat{x}) \leq p(x^*)$



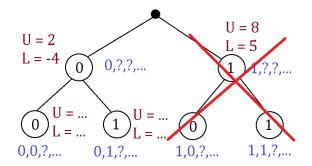
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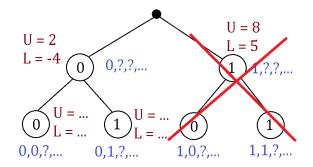
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- 5. B-B solvers require fast LP solvers, since they may be applied many times!