CS/ECE/ISYE524: Introduction to Optimization – Integer Optimization Models

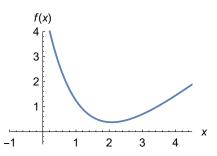
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April 1, 2024

Convex programs

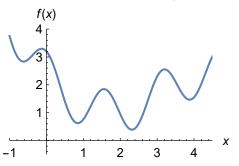
- In convex optimization, we have seen: LP, QP, QCQP, SOCP, SDP
- Can be efficiently solved
- Optimal cost can be bounded above and below
- Local optimum is global

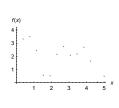


Nonconvex programs

- In general, cannot be efficiently solved
- Cost cannot be bounded easily
- Usually we can only guarantee local optimality
- Difficulty depends strongly on the instance

Continuous and Discrete problems:





Turn Focus To...

- Integer (linear) programs
 - A LP where some or all variables are discrete (boolean, integer, or general discrete-valued)
 - If all variables are integers, it's called IP or ILP
 - If variables are mixed, it's called MIP or MILP
- Nonconvex nonlinear programs
 - If continuous, it's called NLP
 - If discrete, it's called MINLP
- Approximation and relaxation
 - Can we solve solve a convex problem instead?
 - If not, can we approximate?

Discrete variables

Why are discrete variables sometimes necessary?

- 1. A decision variable is fundamentally discrete
 - ullet Whether a particular power plant is used or not $\{0,1\}$
 - Number of automobiles produced $\{0, 1, 2, ...\}$
 - Dollar bill amount {\$1,\$5,\$10,\$20,\$50,\$100}
 - But sometimes we can safely model a discrete variables as a continuous variable. Typically this is OK when the variable naturally has a large value and the quality of the solution would not suffer much from rounding down to the next integer.
 - Of the examples above, the "automobile" variable may be like this.

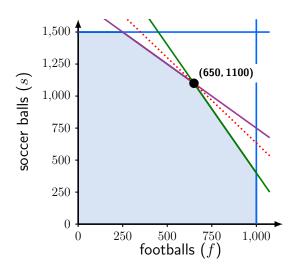
Discrete variables

Why are discrete variables sometimes necessary?

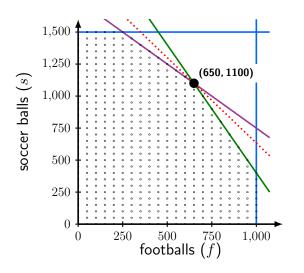
- 2. Used to represent a logic constraint algebraically.
 - "At most two of the three machines can run at once." $z_1 + z_2 + z_3 \le 2$ (z_i is 1 if machine i is running, 0 otherwise)
 - "If machine 1 is running, so is machine 2."

$$z_1 \leq z_2$$

- Goal: (logic constraint) ⇒ (LP with extra boolean variables)
- Boolean variables take the values 0 or 1. Also known as "binary variables" or "zero-one" variables.

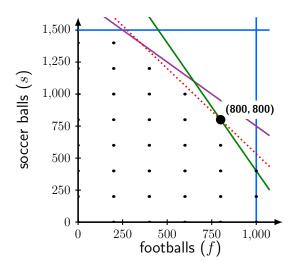


$$\begin{array}{ll} \max_{f,s} & 12f + 9s \\ \text{s.t.} & 4f + 2s \leq 4800 \\ & f + s \leq 1750 \\ & 0 \leq f \leq 1000 \\ & 0 < s < 1500 \end{array}$$



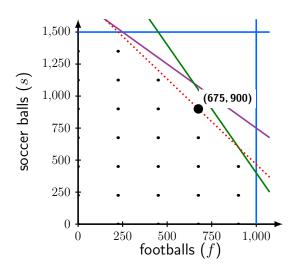
$$\max_{f,s} \quad 12f + 9s$$
 s.t. $4f + 2s \le 4800$ $f + s \le 1750$ $0 \le f \le 1000$ $0 \le s \le 1500$ f and s are multiples of 50

Same solution!



$$\begin{array}{ll} \max \limits_{f,s} & 12f + 9s \\ \text{s.t.} & 4f + 2s \leq 4800 \\ & f + s \leq 1750 \\ & 0 \leq f \leq 1000 \\ & 0 \leq s \leq 1500 \\ & f \text{ and } s \text{ are} \\ & \text{multiples of } 200 \end{array}$$

Boundary solution!



$$\max_{f,s} \quad \frac{12f + 9s}{s}$$
 s.t.
$$4f + 2s \le 4800$$

$$f + s \le 1750$$

$$0 \le f \le 1000$$

$$0 \le s \le 1500$$

$$f \text{ and } s \text{ are}$$

multiples of 225

Interior solution!

Mixed-Integer Linear Programs

maximize
$$c^{\mathsf{T}}x$$
subject to: $Ax \leq b$
 $x \geq 0$
 $x_i \in S_i$

where S_i can be:

- The real numbers, \mathbb{R}
- ullet The integers, $\mathbb Z$
- Boolean / Binary $\{0,1\}$
- A discrete set, $\{v_1, v_2, \ldots, v_k\}$

Mixed-integer programs

maximize
$$c^{\mathsf{T}}x$$
subject to: $Ax \leq b$
 $x \geq 0$
 $x_i \in S_i$

The solution can be

- Same as the LP version
- On a boundary
- In the interior

Rounding

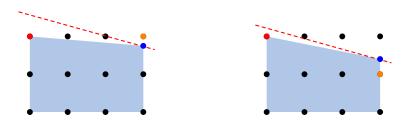
Back to the standard IP formulation:

Idea:

- Solve the problem for $x \in \mathbb{R}$ instead (a regular LP).
- Round each x_i in the solution to the nearest integer.
- This does not work in general! (But in some cases it does.)

Rounding

- If LP solution is already integral, then it is also the exact solution to the original IP. (e.g. min cost flow problems)
- Rounding can lead to an infeasible point
- Rounding can produce a point far from the optimal point



true optimum (•), relaxed optimum (•), rounded (•)

Convex relaxation

$$\underset{x \in S}{\text{minimize}} \quad f(x)$$

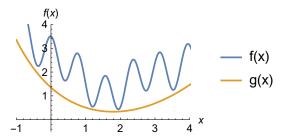
Two ideas we will discuss:

- Function relaxation: if f is troublesome, bound it with a function that is easier to work with, e.g. a convex function.
- **2** Constraint relaxation: If S is troublesome, find a bigger set that is easier to work with, e.g. a convex set.

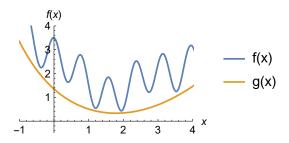
Function relaxation

$$f_{\mathsf{opt}} = \underset{x \in S}{\text{minimize}} \ f(x)$$

Suppose we can find g such that $g(x) \leq f(x)$ for all x. In other words g is a *lower bound* on f.



Function relaxation



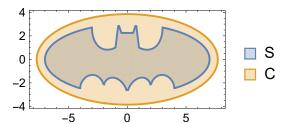
- Solve $g_{\text{opt}} = \min_{x \in S} g(x)$ and let \hat{x} be the corresponding x.
- We have the bounds: $g_{\text{opt}} = g(\hat{x}) \leq f_{\text{opt}} \leq f(\hat{x})$.
- If $f(\hat{x}) = g_{\text{opt}}$ then the bound is tight and $f_{\text{opt}} = f(\hat{x})$.

Pick a convex g so that g_{opt} and \hat{x} are easy to find!

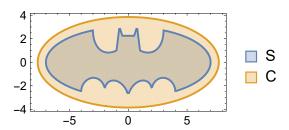
Constraint relaxation

$$f_{\mathsf{opt}} = \underset{x \in S}{\text{minimize}} \ f(x)$$

Suppose we can find some set C such that $S \subseteq C$. In other words, C is a *superset* of S.



Constraint relaxation



- Solve $h_{\text{opt}} = \min_{x \in C} f(x)$ and let \tilde{x} be the optimal x.
- We have the bound: $h_{\text{opt}} = f(\tilde{x}) \le f_{\text{opt}} \le f(x)$ for $x \in S$.
- If $\tilde{x} \in S$ then the bound is tight and $f_{\text{opt}} = f(\tilde{x})$.

Pick a convex C so that h_{opt} and \tilde{x} are easy to find!

Common relaxations

Boolean constraint:

$$x \in \{0,1\} \implies 0 \le x \le 1$$

If x_{opt} is 0 or 1, relaxation is exact.

Onvex equality:

$$f(x) = 0 \implies f(x) \le 0$$

If $f(x_{opt}) = 0$, relaxation is exact.

A constraint you don't like:

$$x \neq 3 \implies \text{ just remove the constraint!}$$

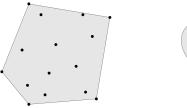
If $x_{opt} \neq 3$, relaxation is exact.

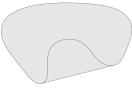
Convex hull

The **convex hull** of a set S, written conv(S) is the smallest convex set that contains S.

Equivalent definitions:

- ullet The set of all affine combinations of all points in S
- ullet The intersection of all convex sets containing S





Common examples

- Facility location
 - locating warehouses, services, etc.
- Scheduling/sequencing
 - scheduling airline crews. (Obviously can't have a crew assigned to two flights at the same time.)
- Multicommodity flows
 - transporting many different goods across a network
- Traveling salesman problems
 - routing deliveries

Knapsack problem

My knapsack holds at most 15 kg. I have the following items:

item number	1	2	3	4	5
weight	12 kg	2 kg	4 kg	1 kg	1 kg
value	\$4	\$2	\$10	\$2	\$1



How can I maximize the value of the items in my knapsack?

Let
$$z_i = \begin{cases} 1 & \text{knapsack contains item } i \\ 0 & \text{otherwise} \end{cases}$$

Knapsack problem

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How can I maximize the value of the items in my knapsack?

General (0,1) knapsack

- weights w_1, \ldots, w_n and limit W.
- values v_1, \ldots, v_n
- decision variables z_1, \ldots, z_n

$$\begin{array}{ll} \text{maximize} & \sum_{i=1}^n v_i z_i \\ \\ \text{subject to:} & \sum_{i=1}^n w_i z_i \leq W \\ \\ z_i \in \{0,1\} & \text{for } i=1,\dots,n \end{array}$$