

Optimization

min/max $f(x_1, x_2)$
subject to constraints

When can we solve efficiently?

Linear programming

$f(x_1, x_2)$ linear fn.
constraints linear

Example: Diet Problem

Athlete wants to max protein consumption
subject to ≤ 5 units of fat/day
 $\leq \$6$ /day

	protein/lb	fat/lb	\$/lb
steak	2	1	4
peanut butter (PB)	1	2	2

x_1 #lbs of steak/day
 x_2 #lbs of PB/day

$$\max 2x_1 + x_2$$
 ← objective fn
 subject to

$$\begin{cases} 4x_1 + x_2 \leq 6 \\ x_1 + 2x_2 \leq 5 \\ x_1, x_2 \geq 0 \end{cases}$$
 ← feasible set
 ← feasible region

feasible pt with max objective fn value is "optimal solution"

feasible set is "polyhedron": intersection of half spaces
if also bounded & nonempty \Rightarrow "polytope"

feasible set convex

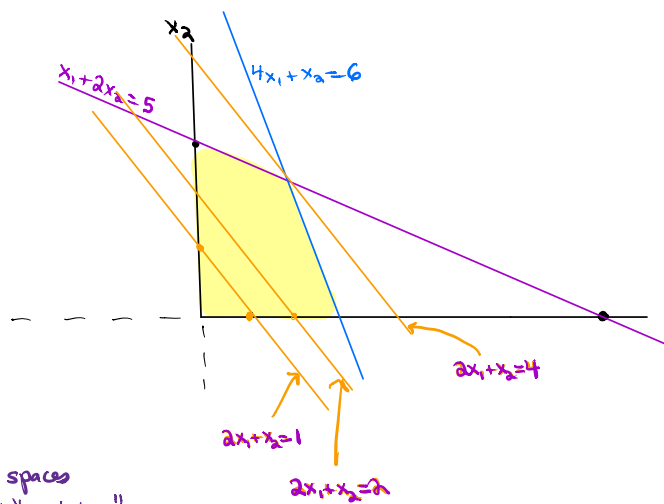
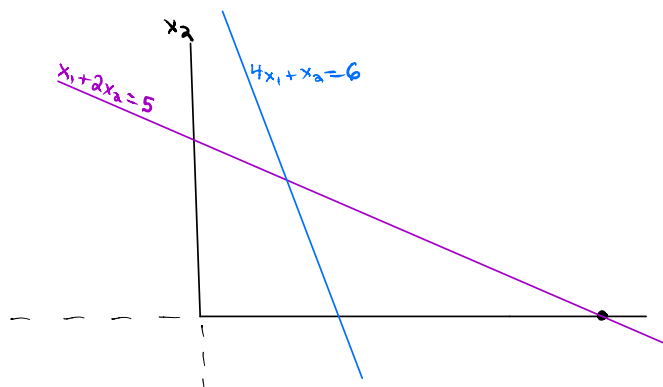
linear cost fns define family of parallel hyperplanes
optimal feasible pt must occur at corner, a.k.a. vertex
[can't be expressed as convex comb of feasible pts]

Unfortunately too many vertices to enumerate $\approx m^{\frac{n}{2}}$
 m constraints, n variables

Ex: $0 \leq x_i \leq 1$ is an n dimensional hypercube

Today

- randomized rounding of LPs
 - MAX 2SAT
 - congestion min
- project info tonight.



Input to LP problem

$$\begin{aligned} c &\in \mathbb{R}^n \\ A &\in \mathbb{R}^{m \times n} \\ b &\in \mathbb{R}^m \end{aligned}$$

find $x \in \mathbb{R}^n$ to
 $\max c \cdot x$
 subject to $Ax \leq b$
 $x_i \geq 0 \forall i$

$$\begin{aligned} \equiv \max & c_1x_1 + c_2x_2 + \dots + c_nx_n \\ \text{st.} & a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n \leq b_1 \\ & a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n \leq b_2 \\ & \vdots \\ & a_{m1}x_1 + a_{m2}x_2 + \dots + a_{mn}x_n \leq b_m \\ & x_1, x_2, \dots, x_n \geq 0 \end{aligned}$$

$$\begin{aligned} \max & 2x_1 + x_2 \\ \text{subject to} & 4x_1 + x_2 \leq 6 \\ & x_1 + 2x_2 \leq 5 \\ & x_1, x_2 \geq 0 \end{aligned}$$

$$\begin{aligned} c &= \begin{pmatrix} 2 \\ 1 \end{pmatrix} \\ A &= \begin{pmatrix} 4 & 1 \\ 1 & 2 \end{pmatrix} \\ b &= \begin{pmatrix} 6 \\ 5 \end{pmatrix} \end{aligned}$$

$$\begin{aligned} a \cdot x \geq b &\equiv -a \cdot x \leq -b \\ a \cdot x = b &\equiv \begin{aligned} a \cdot x &\geq b \\ a \cdot x &\leq b \end{aligned} \\ x \text{ unbounded} &\equiv \begin{aligned} x &= x^+ - x^- \\ x_i^+ x_i^- &\geq 0 \end{aligned} \end{aligned}$$

There are efficient algs for LP.

- simplex } exp worst case "smooth" polytime
- ellipsoid } polynomial time
- interior pt methods }

ellipsoid: sometimes even exponential-sized LPs can be solved in polytime

Bottom line: If you can formulate your problem as LP, it can be solved in time $\text{poly}(m, n, \log(\max\{a_{ij}, b_i, c_i\}))$

Using "linear-programming relaxations" to get approx algs for NP-hard problems & then apply randomized rounding

MAXSAT

Given a Boolean formula in CNF (and/or) n Boolean vars x_1, \dots, x_n m clauses C_1, \dots, C_m each clause is OR of some # of vars & negations

max-version even when all clauses have ≤ 2 literals

w_j weight of j^{th} clause

e.g. $x_3 \vee \bar{x}_5 \vee x_{11}$

MAXSAT: find assignment that maximized wt of satisfied clauses

MAX kSAT: all clauses have $\leq k$ literals
MAX EKSAT: all clauses have exactly k literals

Random assignment

<u>k</u>	<u>Pr(clause sat)</u>
1	
2	
3	
4	

We will consider MAX 2-SAT all clauses have 1 or 2 literals

Step 1: Formulate MAX-2SAT as integer linear program
where we require all vars to be $\in \{0,1\}$

Suppose input formula has n vars, m clauses

Define vars x_1, \dots, x_n \forall var in formula
 z_1, \dots, z_m \forall clause in formula

where $x_i = \begin{cases} 1 & \text{var } i \text{ T} \\ 0 & \text{o.w.} \end{cases}$ $z_j = \begin{cases} 1 & \text{if clause } j \text{ satisfied} \\ 0 & \text{o.w.} \end{cases}$

$$\begin{aligned} \text{Ex } C_j &= (x_1 \vee x_2) \\ (1-x_1) + x_2 &\geq z_j \\ C_j &= (x_5) \\ x_5 &\geq z_j \\ &\vdots \end{aligned}$$

integer linear programming is NP-hard though!

Step 2: Relax to a LP and solve $\Rightarrow z_1^*, \dots, z_m^*, x_1^*, \dots, x_n^*$ fractional
OPT_J(a)

$$\max \sum_{j=1}^m w_j z_j$$

$$\sum_{i \in C_j} y_{ij} \geq z_j \quad j=1, \dots, m$$

where $y_{ij} = \begin{cases} x_i & \text{if } i \text{ var is pos in } C_j \\ 1-x_i & \text{if } i \text{ var is neg in } C_j \end{cases}$

$$x_i \in \{0, 1\} \quad i=1, \dots, n$$
$$z_j \in \{0, 1\} \quad j=1, \dots, m$$

Key observation:

Step 3: Round the soln \Rightarrow integer soln

Corollary:

- Similar analysis shows randomized rounding gives $1 - \frac{1}{e}$ approx alg for MAXSAT

- Choosing better f - randomized rounding soln
- unbiased randomized alg
 $\Rightarrow \frac{3}{4}$ approx alg

- solving LP & then setting

$x_i \begin{cases} \rightarrow \text{True w.p. } f(x_i^*) \\ \rightarrow \text{False o.w.} \end{cases}$

where $f: [0,1] \rightarrow [0,1]$

$$1 - 4^{-x} \leq f(x) \leq 4^{x-1}$$

gives $\frac{3}{4}$ approx alg.

Best possible if we compare our solution against OPT_{LP}

$$\text{Ex: } (x_1, v_{x_2}) \wedge (x_1, \bar{v}_{x_2}) \wedge (\bar{x}_1, v_{x_2}) \wedge (\bar{x}_1, \bar{v}_{x_2})$$

Randomized rounding summary

important technique for obtaining approx algs for NP-hard problems

Recipe

1. Set problem up as integer linear program. vars $\in \{0,1\}$
2. Relax ILP \rightarrow LP vars $\in [0,1]$
3. Solve LP to optimality $\rightarrow x_i^* \in [0,1]$
4. Construct solution by randomly rounding vars $\rightarrow \{0,1\}$
treat x_i^* as probability
5. bound quality of soln by comparing to LP opt

Another example: Congestion minimization

Input: directed graph $G=(V,E)$
Set of pairs $(s_i, t_i) \quad i=1..k$
Output: path P_i from s_i to $t_i \quad \forall i=1..k$
s.t. Congestion is minimized
max # paths that intersect any edge

NP-hard

Approx alg via randomized rounding

- ① Set up ILP [multi commodity flow]
vars $f_i(e) \in \{0,1\}$ flow from s_i to t_i on edge e
 C congestion

min C
subject to

$$\sum_{\substack{e \text{ s.t.} \\ e=(u \rightarrow v) \\ \text{for some } u}} f_i(e) = \sum_{\substack{e \text{ s.t.} \\ e=(v \rightarrow u) \\ \text{for some } u}} f_i(e)$$

$$\forall v \neq s_i, t_i \\ \forall i$$

conservation of flow

$$\sum_{\substack{e \text{ s.t.} \\ e=(s_i \rightarrow u) \\ \text{for some } u}} f_i(e) = 1$$

$$\forall i$$

route 1 unit of flow from s_i to t_i

$$\sum_i f_i(e) \leq C$$

congestion bound

$$f_i(e) \in \{0,1\} \quad \forall i, e$$

② Relax to LP

③ Solve LP

④ Round soln

⑤ Bound result.

Theorem If $C^* \geq c \ln n$ for some const c , then whp the max congestion on any edge $\leq C^* + \sqrt{c C^* \ln n}$
 \Rightarrow approx ratio ≤ 2

Proof Fix $e = (u \rightarrow v)$
Let $X_i(e) = \begin{cases} 1 & \text{if } e \in P_i \\ 0 & \text{o.w.} \end{cases}$
 $E(X_i(e)) = \sum_{\substack{P_i \text{ s.t.} \\ e \in P_i}} f_P^i = f_i^*(e)$

If only know $C^* \geq 1$

Theorem $\Pr(\text{any edge has congestion} \geq \frac{6 \ln n}{\ln \ln n} C^*) \leq \frac{1}{n}$

gives approx ratio of α

Proof Fix $e = (u \rightarrow v)$
 Let $X_i(e) = \begin{cases} 1 & \text{if } p_i \in P \\ 0 & \text{otherwise} \end{cases}$
 $E(X_i(e)) = \sum_{p_i \in P} f_p^i = f_i^*(e)$

Let $X(e) = \sum_{i=1}^k X_i(e) \Rightarrow \forall e \quad E(X(e)) = \sum_{i=1}^k f_i^*(e) \leq C^*$

$\Pr(X(e) \geq \alpha C^*) \leq e^{-c^{*}[(1+\delta)\alpha C^* - C^*]} \quad [\text{Chernoff bound}]$

$$\Pr(X(e) \geq \alpha C^*) \leq e^{-c^{*}[\alpha \ln \alpha + 1 - \alpha]} \leq e^{-\alpha \ln \alpha + 1}$$

\uparrow
 $C^* \geq 1$

$$\leq e^{-3 \ln n} = \frac{1}{n^3}$$

$$\alpha \ln \alpha + 1 - \alpha$$

$$= \frac{6 \ln n}{\ln \ln n} \left[\ln \ln n + \ln 6 - \ln \ln n - 1 \right]$$

$$\geq 3 \ln n$$

$\Rightarrow \Pr(\text{any edge has congestion} \geq \alpha C^*) \leq \sum_e \Pr(X(e) \geq \alpha C^*)$
 $\leq n^2 \cdot \frac{1}{n^3} = \frac{1}{n}$

\uparrow
 union bound

Optimal!

\exists graphs with $\frac{\text{OPT}}{C^*} = \Omega\left(\frac{\ln n}{\ln \ln n}\right)$ integrality gap

so can't do better with such an approach

Hardness (directed graphs)

Every poly time alg has $\Omega\left(\frac{\ln n}{\log \log n}\right)$ approx ratio unless $\text{NP} \in \text{BPTIME}(n^{o(\log n)})$

MAXCUT

Recall assign each vertex at random to side

Input: $G=(V,E)$ $w_{ij} \quad \forall (i,j) \in E$

Goal: partition vertex set so as to max weight of edges crossing cut.

IP formulation of MAXCUT

$$x_i = \begin{cases} 0 & \text{on one side of partition} \\ 1 & \text{on other side} \end{cases}$$

$$z_{ij} = \begin{cases} 1 & \text{edge } (i,j) \text{ cut} \\ 0 & \text{o.w.} \end{cases}$$

$$\max \sum_{(i,j) \in E} w_{ij} z_{ij}$$

$$z_{ij} \leq x_i + x_j \quad \forall (i,j) \in E$$

$$z_{ij} \leq 2 - (x_i + x_j) \quad \forall (i,j) \in E$$

$$x_i \in \{0,1\} \quad i \in V$$

$$z_{ij} \in \{0,1\} \quad \forall (i,j) \in E$$

Another approach

First, rotation change

$$\forall i. \quad x_i \in \{-1, +1\}$$

$$\text{define } y_{ij} = x_i x_j \quad \forall i, j \in V$$

$$\begin{array}{l} \text{Want } \exists x_i \quad \forall i \in V \\ \text{s.t. } y_{ij} = x_i x_j \quad \forall (i, j) \end{array}$$

$$\begin{array}{l} \max \sum_{(i,j) \in E} w_{ij} \frac{1}{2} (1 - y_{ij}) \\ y_{ij} = y_{ji} \quad \forall i, j \in V \\ y_{ii} = 1 \quad \forall i \in V \end{array}$$

purple + brown is exact.

SDP rounding

Intro to semidefinite programming

linear programming where vars are entries in a PSD matrix

Defn

If A is a symmetric n by n matrix then A is a positive semidefinite (psd) matrix $\equiv A \succeq 0$ if any of the following equivalent conditions hold

- ① $\forall c \in \mathbb{R}^n, c^T A c \geq 0$
- ② A has nonnegative eigenvalues
- ③ $A = V^T V$ for some $m \times n$ matrix $V, m \geq n$
- ④ $A = \sum_{i=1}^m \lambda_i x_i x_i^T$ for some $\lambda_i \geq 0$ and orthonormal vectors $x_i \in \mathbb{R}^n$

Semidefinite program (SDP)

$$\begin{aligned} \max \text{ or min } & \sum_{i,j} c_{ij} x_{ij} \\ \text{subject to } & \sum_{i,j} a_{ijk} x_{ij} = b_k \\ & x_{ij} = x_{ji} \quad \forall i,j \\ & X = (x_{ij}) \succeq 0 \end{aligned}$$

\equiv Vector program

$$\begin{aligned} \max \text{ or min } & \sum_{i,j} c_{ij} (v_i \cdot v_j) \\ \text{subject to } & \sum_{i,j} a_{ijk} (v_i \cdot v_j) = b_k \\ & v_i \in \mathbb{R}^n \quad i=1, \dots, n \end{aligned}$$

given $X \Rightarrow X = V^T V;$
set v_i to be i^{th} col of V

Key fact:

SDPs can be solved to within additive error ϵ in time $\text{poly}(\text{size of input}, \log(\frac{1}{\epsilon}))$
in our discussions, we ignore additive error ϵ

