

Problems / Subproblems

- Linear Systems ($Ax = b$)
- Linear Programming
- Semidefinite Programming (and Cholesky Decomposition)
- Eigenvalue Computation.

Linear systems

- Gaussian Elimination can solve in time $O(n^3)$ ← row ops do not change the set of solutions.
and bit complexity remains poly-bounded.
- Cramer's rule says size of solutions is poly-bounded

LPs:

Write LP in equational form $\max(c^T x \mid Ax = b, x \geq 0)$ $K \subseteq \mathbb{R}^n$ $A \in \mathbb{Q}^{m \times n}$

Then: if K is non empty and the optimal value is ~~not~~ bounded, then

\exists a basic feasible solution that achieves the optimum x^*

i.e. \exists n tight LI constraints that define x^*

So sps $B \subseteq [m+n]$ st $\begin{bmatrix} A \\ I \end{bmatrix}_B x^* = \begin{bmatrix} b \\ 0 \end{bmatrix}_B$.
↑ basis
↑ submatrix of $[A]$ indexed by B
← subvectors of $\begin{bmatrix} b \\ 0 \end{bmatrix}$ indexed by B

Again, Cramer's rule says x^* has poly-bounded bit complexity,
being ratio of two determinants of the input.

Shows that
LP \in NP.

- ~~SDPs~~ Eigenvalues / vectors.

These may be irrational! $\begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}$ has eigenvalues $\pm\sqrt{2}$

So cannot write these down exactly!

- SDPs

Two kinds of problems.

- Captures eigenvalue problems — e.g. $\min t$
 $\text{st } tI - A \succeq 0$

computes the λ_{\max} . So solutions may be irrational.

- But even when solutions are integral, problems.

The bit-complexity of optimal solution may be exponential in inputs.

$$\min \left\{ x_n : \begin{pmatrix} 1 & 2 \\ 2 & x_1 \\ & 1 & x_1 \\ & x_1 & x_2 \\ & & 1 & x_2 \\ & & x_2 & x_3 \\ & & & \ddots \end{pmatrix} \succeq 0 \right\}$$

Then want $\begin{pmatrix} 1 & 2 \\ 2 & x_1 \end{pmatrix} \succeq 0$ $\begin{pmatrix} 1 & x_i \\ x_i & x_{i+1} \end{pmatrix} \succeq 0 \Rightarrow x_{i+1} \geq x_i^2. \quad x_1 \geq 4$
 $\Rightarrow x_t \geq 2^{2^t}. \quad \text{☹}$

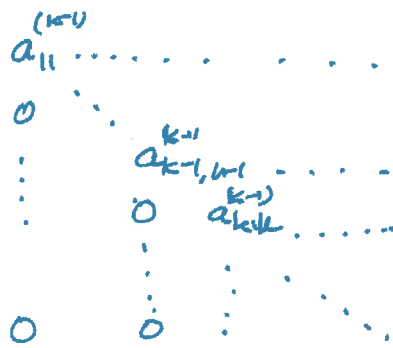
In general with SDPs, this is bad news, so
 must also agree that the solutions we ~~get~~ want have poly-bounded bit
 complexity

and that we can afford to work with approximations to them.

Bit Complexity of Gaussian Elimination

$A^{(0)} = K \times n$ matrix using G.E., $A^{(0)} = A$

$a_{ij}^{(k)}$ = ij th entry of $A^{(k)}$.



$$a_{ij}^{(k)} = a_{ij}^{(k-1)} - a_{kj}^{(k-1)} \cdot \frac{a_{ik}^{(k-1)}}{a_{kk}^{(k-1)}}$$

for $i \geq k+1, j \geq k$

(*)
$$a_{ij}^{(k)} = \frac{a_{ij}^{(k-1)} a_{kk}^{(k-1)} - a_{kj}^{(k-1)} a_{ik}^{(k-1)}}{a_{kk}^{(k-1)}} = \frac{\det \text{ of the } 2 \times 2 \text{ matrix } \begin{pmatrix} a_{kk}^{(k-1)} & a_{kj}^{(k-1)} \\ a_{ik}^{(k-1)} & a_{ij}^{(k-1)} \end{pmatrix}}{a_{kk}^{(k-1)}}$$

Claim: can be represented using few bits.

Thm 1: $a_{ij}^{(k)} = \frac{\det(B_{ij}^{(k)})}{\det(D^{(k)})}$ for $i, j \geq k+1$ (***)

where $D^{(k)} = A^{(k)} \begin{matrix} \{1 \dots k\} \times \{1 \dots k\} \\ \{1 \dots k, i\} \times \{1 \dots k, j\} \end{matrix}$
 $D_{ij}^{(k)} = A^{(k)} \begin{matrix} \{1 \dots k\} \times \{1 \dots k\} \\ \{1 \dots k, i\} \times \{1 \dots k, j\} \end{matrix}$

Fact 2: Both these matrices have small determinants.

⇒ Putting the two together, get that numbers blow up only to a limited extent (i.e. bit-complexity of numbers is bounded by $n \times$ orig. bit-complexity).

Pf of Thm 1: $D_{ij}^{(k)} = \begin{pmatrix} a_{11}^{(k)} & \dots & \dots \\ \vdots & \ddots & \vdots \\ 0 & \dots & a_{kk}^{(k)} & \dots \\ \vdots & \vdots & \vdots & \ddots \\ 0 & \dots & \dots & \dots & a_{ij}^{(k)} \end{pmatrix} \Rightarrow \det \text{ is product of diagonals}$

$D^{(k)} = \begin{pmatrix} a_{11}^{(k)} & \dots & \dots \\ \vdots & \ddots & \vdots \\ 0 & \dots & \dots & \dots & a_{kk}^{(k)} \end{pmatrix} \Rightarrow \text{ratio of det is exactly } a_{ij}^{(k)}$



Pf of Fact 2: $D_{ij}^{(k)}$ obtained from $D_{ij}^{(0)}$ by row operations

$$D_{(1..k)}^{(k)} \dots D_{(1..k)}^{(0)}$$

both submatrices of $A \Rightarrow$ have bounded determinants by the Hadamard bound, say

$$\text{that } \det(A) \leq \|a_1\| \cdot \|a_2\| \cdot \dots \cdot \|a_n\|.$$

↑ volume of parallelepiped ↑ product of sides.



Note: $\det(D^{(k)}) = \det(D_{kk}^{(k-1)})$

define $\Delta_{ij}^k = \det(D_{ij}^{(k)})$

so. can use (*) & (**) on previous page to get

$$\Delta_{ij}^{k+1} = \frac{\Delta_{ij}^k \Delta_{k+1, k+1}^k - \Delta_{i, k+1}^k \Delta_{k+1, j}^k}{\Delta_{kk}^{k-1}}$$

and this a determinant of some submatrix of A , so integer^(!) can

use this as recurrence to work completely within the set of integers.

finally use (*) to get back $a_{ij}^{(n)}$.



BTW: if $A = \begin{pmatrix} 1 & & & & \\ -1 & & & & \\ & \dots & & & \\ & & \dots & & \\ & & & \dots & \\ & & & & \dots \end{pmatrix}$ then get $\begin{pmatrix} 1 & & & & \\ & 1 & & & \\ & & 1 & & \\ & & & 1 & \\ 0 & & & & 16 \end{pmatrix}$. So

numbers do get large.

BTW 2: If not super comfortable with this, check out Trefethen & Bau for basics, the Lovasz-Grass notes for this Edmonds proof, etc.

Aside: Can also do modular arithmetic and Chinese Remaindering, which has its own issues.

Solving LPs:

Two polytime approaches

- Ellipsoid type algorithms
- Interior Point algorithms.

Basic Subroutine: Feasibility.

[Given convex compact set $K \subseteq \mathbb{R}^n$,
find a point $x \in K$ or show that $\text{vol}(K) \leq \epsilon$.

How is this set given?

Via a separation oracle:

Input: a point $c \in \mathbb{R}^n$

Output: YES if $c \in K$.

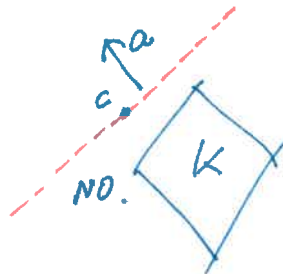
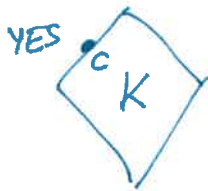
NO if $c \notin K$. In this case output a hyperplane separating c from K .

i.e. a vector a , ~~with~~ $a \neq 0$

$$\text{st. } K \subseteq \{z \in \mathbb{R}^n \mid a^T z < a^T c\}$$

"strong" separation oracle.

c for "check" or "center"



In general can handle even weak separations where tolerate errors of $\epsilon > 0$,

but let's not go there for now.

See [GLS80] for many details.

General Approach: "Binary Search"

Suppose know that

~~(1) $K \subseteq \text{Ball}(0, R)$ for some $R > 0$.~~

~~(2) \exists point x_0 , satisfying $\forall x \in K, a^T x > a_0^T x_0$.~~

At each time, maintain region $E^{(t)}$ s.t.

(a) $E^{(0)} \supseteq K$

(b) at each time test point $c^{(t)}$ "center" of $E^{(t)}$. by separation oracle.

if NO, find $E^{(t+1)}$

s.t. $E^{(t+1)}$ contains $E^{(t)} \cap \{x \mid a^{(t)T} x < a^{(t)T} c^{(t)}\}$

K lies here
by induction

K lies here
since in NO case

if YES,
done!!

$\Rightarrow K \subseteq E^{(t+1)}$

(c) Argue that $\text{vol}(E^{(t+1)}) \leq \text{vol}(E^{(t)}) \cdot (1-\delta)$.

~~(d) Show that $\text{vol}(K) \geq \text{some } \epsilon$.~~

So after T steps, $\text{vol}(E^{(T)}) \leq \text{vol}(E^{(0)}) \cdot e^{-\delta T}$

and hence setting $T = \frac{1}{\delta} \cdot \ln\left(\frac{\text{vol}(E^{(0)})}{\epsilon}\right)$, gives that $\text{vol}(E^{(T)}) \leq \epsilon$.

$\Rightarrow \text{vol}(K) \leq \epsilon$

since $K \subseteq E^{(T)}$

This solves feasibility problem in T steps/oracle calls. ☺

In case all calls were NO,
if some call gave YES,
already done!

Things to do:

Aside

(1) Show that can choose $\epsilon^{(0)}$ st. $\text{vol}(\epsilon^{(0)}) \leq 2^{\text{poly}(\text{bit complexity}, n)}$ ^L none for LPs.

(2) Ensure that $\delta = 1/\text{poly}(L, n)$

for whatever choice of shape ϵ and notion of center c being chosen.

(3) For feasibility problem to be useful, need to show that small volume means something useful.

Looking ahead to LPs.

- suppose K is non empty and full dimensional, $\Rightarrow \text{vol}(K) > 0$

can show that $\text{vol}(K) \geq 2^{-\text{poly}(n, L)}$

So if set $\epsilon = 2^{-\text{poly}(n, L)}$ then will get contradiction, and hence one call to oracle must return YES.

Aside

— X —

Right now: focus on getting solution for Feasibility problem, with "good" δ .

• Ax. Levin / Newman (60s) define

$$\epsilon^{(t)} = \epsilon^{(t-1)} \cap \text{feasible region}, \epsilon^{(0)} = \text{some ball containing } K.$$

$$c^{(t)} = \text{centroid of } \epsilon^{(t)}.$$

get $\delta = \Theta(1)$ but difficult to compute centroids.

• Khachiyan '79 used idea of Nachum Shor '70.

$$\epsilon^{(t)} = \text{ellipsoid that contains } \epsilon^{(t-1)} \cap \text{feasible region}$$

$$c^{(t)} = \text{center of ellipsoid}$$

1st poly time algo. for LPs.

get $\delta \approx \frac{\epsilon^{(0)}}{n}$. Needs to control the bit precision of numbers involved, since perform square roots, etc.

Today: use "simplices" idea of B. Yamnitski & Leonid Levin '82

- $\mathcal{E}^{(t)}$: simplex that contains $\mathcal{E}^{(t-1)} \cap \text{feasible}$, $\mathcal{E}^{(0)}$: simplex also.

- but $\delta = \Theta\left(\frac{1}{n^2}\right)$.

Now no longer need sq. roots, but naively the bit precision may also increase, so need to do "truncation" / "rounding". see [Bartels 2000]

— x —

The Simplicies Method

(as opposed to the Simplex Method of George Dantzig) 😊

- start with $S^0 = \text{conv}(v_0^0 \dots v_n^0)$. Set $c^{(t)} = \text{centroid of } S^{(t)}$.

- Each time that we get NO,

compute new simplex S^{t+1} by shifting some vertices of S^t .

s.t. $\text{vol}(S^{t+1}) \leq \text{vol}(S^t) (1 - \Theta\left(\frac{1}{n^2}\right))$

In more detail:

1) $S^t = \text{conv}(v_0^t \dots v_n^t)$.

2) $c^t = \frac{1}{n+1} \sum_{i=0}^n v_i^t$

3) if NO, get back $a \in \mathbb{R}^n$

s.t. $K \subseteq \{x \mid a^T x < a^T c^t\}$

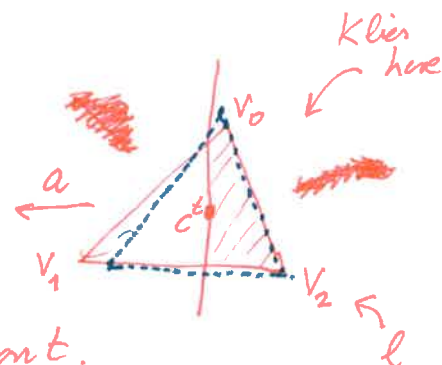
a) define $e(x) := \langle a, c^t - x \rangle$. So $K \subseteq \{x \mid e(x) > 0\}$

b) define $i = \arg \max_j e(v_j^t)$

← non zero value $e(v_i^t)$ if $K \neq \emptyset$, since all v_i^t cannot be on hyperplane.

c) $\forall i$, define $v_i^{t+1} := \left(1 - \frac{1}{d_i}\right) v_i^t + \frac{1}{d_i} v_i^t$

where $d_i = \left(1 - \frac{e(v_i^t)}{n^2 \cdot e(v_i^t)}\right)$



Observations:

- $d_i \geq 0 \forall i$

- Points on same side of hyperplane $\{e(x)=0\}$ as v_e

have $e(v_i) > 0 \Rightarrow d_i < 1 \Rightarrow \sqrt{d_i} > 1$

so these points move away from v_e

Points on the other side of hyperplane (the "infeasible" side) have $e(v_i) \leq 0$

so they move closer to v_e .

$$v_i' = v_e + \frac{v_i - v_e}{d_i}$$

Want to show:

Fact 1: for any point x in $S^t \cap \{x \mid e(x) > 0\} \Rightarrow x \in S^{t+1}$.

Hence $K \subseteq S^{t+1}$.

Fact 2: $\text{vol}(S^{t+1}) \leq \text{vol}(S^t) \cdot (1 - \delta(\frac{1}{n^2}))$.

\uparrow this is the δ parameter from earlier.

Proof of Fact 1: (use v_0, \dots, v_n for old points, v_0', \dots, v_n' for new ones)

Let $x = \sum \lambda_i v_i$, and $e(x) > 0$.

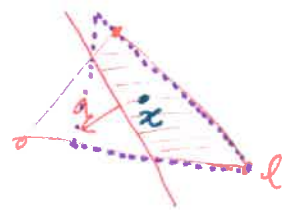
$\uparrow \lambda_i \geq 0, \sum \lambda_i = 1$.

define $\lambda_i' = \begin{cases} \lambda_i d_i & \forall i \neq l \\ d_l \lambda_l + \frac{e(x)}{n^2 e(v_e)} & \text{if } i=l. \end{cases}$

• $\lambda_i' \geq 0$ because all terms are positive.

$$\bullet \sum_i \lambda_i' = \sum_i \lambda_i d_i + \frac{e(x)}{n^2 e(v_e)}$$

$$= \sum_i \lambda_i d_i + \frac{e(x)}{n^2 e(v_e)} = \sum_i \lambda_i \left(1 - \frac{e(v_i)}{n^2 e(v_e)}\right) + \frac{e(x)}{n^2 e(v_e)}$$



$$= \sum \lambda_i - \left[\frac{\sum \lambda_i e(v_i) - e(x)}{n^2 e(v_0)} \right]$$

$$= 1.$$

but e is linear
 so $\sum \lambda_i e(v_i)$
 $= e(\sum \lambda_i v_i) = e(x)$

• Finally, claim that $x = \sum \lambda_i' v_i'$.

$$\sum \lambda_i' v_i' = \sum \lambda_i d_i \left(\frac{v_0 + v_i - v_0}{d_i} \right) + \frac{e(x)}{n^2 e(v_0)} v_0$$

$$= v_0 (\sum \lambda_i d_i) + \sum \lambda_i v_i - (\sum \lambda_i) v_0 + \frac{e(x)}{n^2 e(v_0)} v_0$$

$$\sum \lambda_i' v_i' = \sum_i \lambda_i d_i \left((1 - \frac{1}{d_i}) v_0 + \frac{v_i}{d_i} \right) + \frac{e(x)}{n^2 e(v_0)} v_0$$

$$v_0 \sum \lambda_i (d_i - 1) + \sum \lambda_i v_i + \frac{e(x)}{n^2 e(v_0)} v_0$$

$$- v_0 \cdot \frac{\sum \lambda_i e(v_i)}{n^2 e(v_0)}$$

negative of last term

$$= x.$$

End of Proof of Fact 1.

Fact 2: Volume of S^{th} smaller than S^k by factor $\frac{1}{n^2}$.

Pf: Volume of a simplex = $\frac{1}{n!} \det \begin{pmatrix} v_1 - v_0 \\ v_2 - v_0 \\ \vdots \\ v_n - v_0 \end{pmatrix}$.

conv(v_0, v_1, \dots, v_n)

For simplicity say that $v_1 = v_0$. ~~and say v_1 is the zero vector.~~

then recall $v_i' = v_0 + \frac{v_i - v_0}{d_i}$ $v_0' = v_0$.

$$\text{vol}(S) = \frac{1}{n!} \cdot \det \begin{pmatrix} v_1' - v_0' \\ \vdots \\ v_n' - v_0' \end{pmatrix} = \frac{1}{n!} \det \begin{pmatrix} \frac{v_1 - v_0}{d_1} \\ \vdots \\ \frac{v_n - v_0}{d_n} \end{pmatrix} = \frac{\text{vol}(S)}{\prod_{i \neq 0} d_i}$$

How small can $\prod_{i \neq 0} d_i$ be?

- By construction: $d_i = 1 - \frac{e(v_i)}{n^2 e(v_0)} \geq 1 - \frac{1}{n^2}$ since $e(v_0) \geq e(v_i)$

- Moreover $\sum_{i \neq 0} d_i = \sum_{i \neq 0} \left(1 - \frac{e(v_i)}{n^2 e(v_0)} \right)$

$$= n - \sum_{i=0}^n \frac{e(v_i)}{n^2 e(v_0)} + \frac{e(v_0)}{n^2 e(v_0)}$$

$$\begin{matrix} \downarrow & & \downarrow \frac{1}{n^2} \\ \frac{e(\text{centroid})}{n^2 e(v_0)} = 0 & & \text{by defn of } e(x) = \sigma^T(c-x). \end{matrix}$$

$$= n + \frac{1}{n^2}$$

So to minimize $\prod_{i \neq 0} d_i$ subject to $d_i \geq 1 - \frac{1}{n^2}$ and $\sum_{i \neq 0} d_i = n + \frac{1}{n^2}$

have all equal to $1 - \frac{1}{n^2}$ and last one be $1 + \frac{1}{n}$.

which gives $\geq \left(1 - \frac{1}{n^2}\right)^{n-1} \cdot \left(1 + \frac{1}{n}\right) = \frac{\left(1 - \frac{1}{n^2}\right)^n}{\left(1 - \frac{1}{n}\right)}$

Taylor series says this is $\approx \left(1 - \frac{1}{n^2}\right)^n \approx 1 - \frac{1}{n^2}$

+ $\frac{1}{2n^4}$

Taking logs, $\log\left(\frac{(1-\frac{1}{n})^n}{(1-\frac{1}{n})}\right) = -n \cdot \sum_{i=1}^{\infty} \frac{1}{i n^i} + \sum_{i=1}^{\infty} \frac{1}{i n^i}$

$$\approx \left(-\frac{n}{n^2} - \frac{n}{2n^3} - \frac{n}{3n^4} \dots\right) + \left(\frac{1}{n} + \frac{1}{2n^2} + \frac{1}{3n^3} \dots\right)$$

$$\geq \frac{1}{2n^2} - \frac{1}{6n^3}$$

$$\Rightarrow \prod d_i \geq e^{\frac{1}{2n^2} - \frac{1}{6n^3}}$$

$$\Rightarrow \text{reduction in volume} \leq e^{-\frac{1}{2n^2} + \frac{1}{6n^3}} \approx \left(1 - \Theta\left(\frac{1}{n^2}\right)\right) \text{ when } n \text{ large.}$$

Same kind of ideas hold for the Ellipsoid algo, but now deal with psd matrices defining these ellipsoids.

One concern, btw: the numbers in the description of V_i may blow up. So Sven Bortolotti gives a rounding technique to "blow up" the simplex a bit and get vertices defined using bounded precision. See paper for details.

Solves feasibility problem. To use to solve LP feasibility, use the fact that

① ~~original polytope can be~~

there is an optimal solution

↓ that has bounded bit precision (so putting a bounding box around it)

discuss soon...

↑ ~~equivalent~~ for full dimensional polytopes

of the form $|x_i| \leq 2^{\text{poly}(n)}$
is OK

Hence volume of $S^0 \leq 2^{\text{poly}(n)}$

② if $\text{vol}(K) > 0 \Rightarrow \text{vol}(K) > 2^{-\text{poly}(nL)} \Rightarrow$ setting ϵ to this value is OK

$\Rightarrow \text{runtime} = \frac{1}{\epsilon} \cdot \log\left(\frac{\text{vol}(S^0)}{\epsilon}\right) = n^2 \cdot \text{poly}(nL).$



Next: Separation oracles —