

Ellipsoid Algo

First known polynomial-time algo for solving LPs (complexity is not known to be polynomial-time)

Very import. in theoretical computer science, can solve LPs in time $\text{poly}(n)$, even if the # constraints is exponential in n

Practically, both simplex & interior-pt. algos perform much better.

Basic problem solved by ellipsoid algo is feasibility:

Given a bounded convex set $P \subseteq \mathbb{R}^n$, find $x \in P$, if it exists.

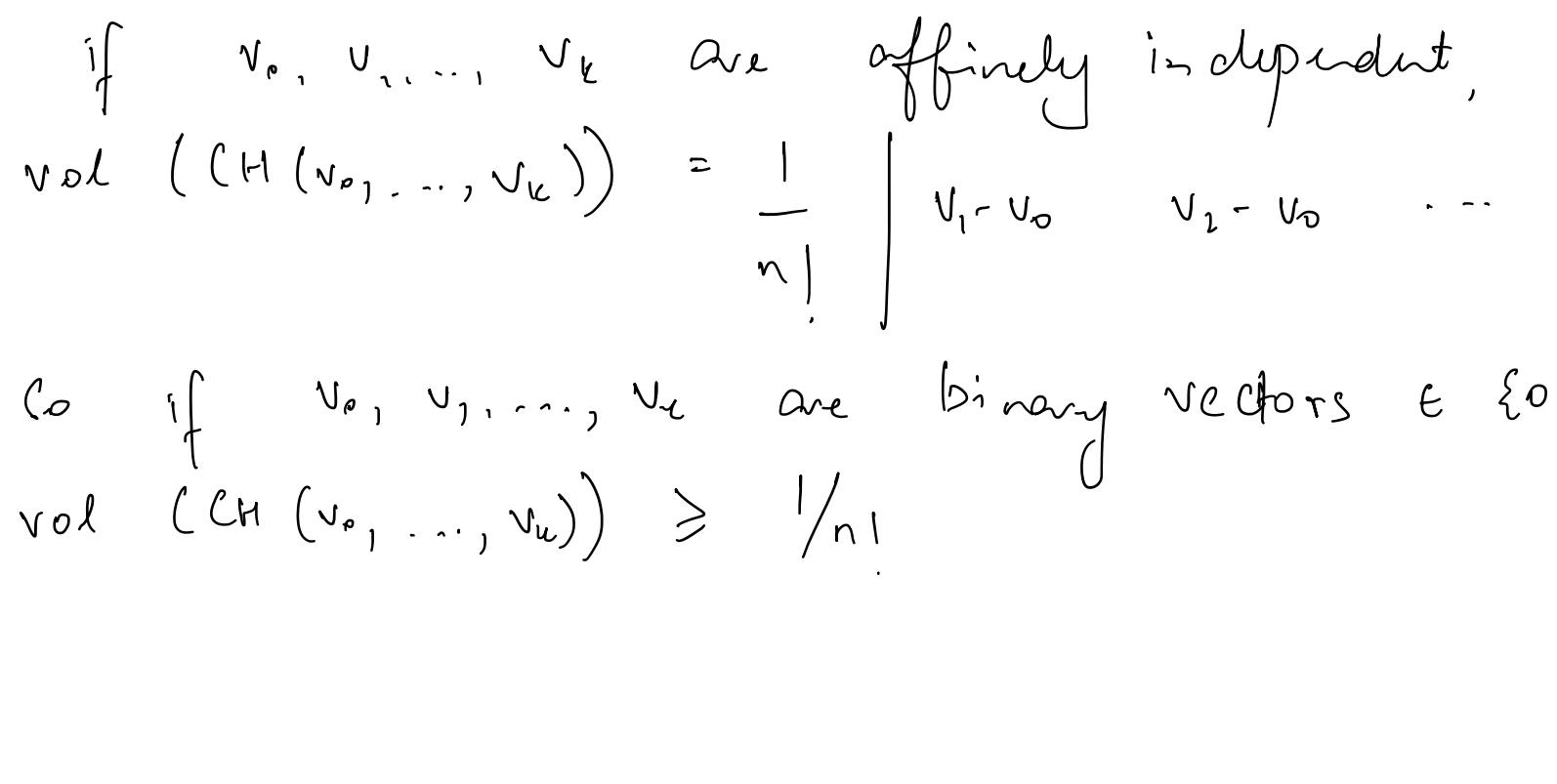
Will show later that we can reduce solving a linear program (i.e., optimization) to this feasibility problem.

So what is an ellipsoid?

An ellipsoid is an affine transformation of the unit ball.

i.e., $B_0 = \{x \in \mathbb{R}^n : \|x\| \leq 1\}$

Then $E = \{B^T x + c : x \in B_0\}$ where B is an invertible matrix



where the axes now correspond to the eigenvectors of B^T , and the lengths correspond to the eigenvalues.

Claim: the ellipsoid $E = \{B^T x + c : x \in B_0\}$ is equivalent to the set $\{x \in \mathbb{R}^n : (x - c)^T B^T B (x - c) \leq 1\}$ (example, check if B is a diagonal matrix)

Now any positive definite matrix B can be written as

$$B = B^T B \text{, where } B \text{ is also positive definite}$$

Then we write an ellipsoid as

$$E(c, A) = \{x \in \mathbb{R}^n : (x - c)^T A^{-1} (x - c) \leq 1\}$$

so that, if $A^{-1} = B^T B$,

$$E(c, A) = \{B^T x + c : x \in B_0\}$$

Volume of an ellipsoid:

$$\text{- volume of ball of radius } R = \frac{\pi^{n/2} R^n}{\Gamma(\frac{n}{2} + 1)}$$

↑ gamma fn. $\sim (\frac{n}{2})!$ if n is even

$$\text{- volume of ellipsoid } E(c, A) = \text{Vol}(B_0) \times \det(B),$$

where $A^{-1} = B^T B$

- what about polyhedra?

Defn: Vectors $v_0, v_1, \dots, v_k \in \mathbb{R}^n$ are affinely independent if the vectors $v_1 - v_0, v_2 - v_0, \dots, v_k - v_0$ are linearly independent.

The if v_0, v_1, \dots, v_k are affinely independent,

$$\text{vol}(\text{CH}(v_0, \dots, v_k)) = \frac{1}{n!} \begin{vmatrix} v_1 - v_0 & v_2 - v_0 & \dots & v_k - v_0 \end{vmatrix}$$

Co if v_0, v_1, \dots, v_k are binary vectors $\in \{0, 1\}^n$,

$$\text{vol}(\text{CH}(v_0, \dots, v_k)) \geq \frac{1}{n!}$$

Basic idea of ellipsoid.

Given a polytope of the form $P = \{x \in \mathbb{R}^n : Ax \leq b\}$, we maintain an ellipsoid that contains the feasible region, iteratively shrink this ellipsoid

- Let E_0 be an ellipsoid s.t. $P \subseteq E_0$

- for $k = 0, 1, \dots$

- if center c_k of $E_k = E(c_k, A_k)$ $\notin P$,

- find a "violated constraint" / "separating hyperplane"

$$Ax \leq b \text{ s.t. } a_k c_k > b$$

- find a smaller ellipsoid $E_{k+1}(c_{k+1}, A_{k+1})$ s.t.

$$E_k \cap \{x : Ax \leq b\} \subseteq E_{k+1}$$

- $k \leftarrow k+1$

$$\text{s.t. } P \subseteq E_k$$

Lemma: Given $E_k = E(c_k, A_k)$ and a violated constraint $ax \leq b$ (s.t. $a_k c_k > b$), we find an ellipsoid E_{k+1} s.t.

$$\text{(i)} \quad P \subseteq E_k \cap \{x : Ax \leq b\} \subseteq E_{k+1}$$

$$\text{(ii)} \quad \frac{\text{vol}(E_{k+1})}{\text{vol}(E_k)} < e^{-\frac{1}{2} \log(n)}$$

Then after k iterations, $\text{vol}(E_k) \leq e^{-\frac{k}{2} \log(n)}$

Thus to run ellipsoid, we need:

(1) An initial ellipsoid $E_0 \supseteq P$

(2) A lower bound ϵ on the volume of P , if non-empty

(note that P must be full-dimensional)

(3) A "separation mode": given $x^* \in \mathbb{R}^n$, either find $x \in P$ or return $x^* \notin P$.

$$x \in P \quad \text{if } x^* \in P$$

$$x^* \notin P \quad \text{if } x^* \notin P$$

Note that we don't need to know the entire P in advance, just need E_0 , ϵ , a separation mode.

Step 1: getting E_0 .

LP-specific e.g., if $P \subseteq \{0, 1\}^n$,

$$\text{then } E_0 = E(0, \frac{1}{\sqrt{n}})$$

Step 2: lower bound ϵ

for combinatorial optimization, $P \subseteq \{0, 1\}^n$

if P is full-dimensional (contains non-affinely independent binary vectors) then

$$\text{vol}(P) \geq \frac{1}{n!}$$

Step 3: Separating hyperplane: application specific.

This completes the description of ellipsoid for feasibility.

Q1: what about optimization?

Problem is: $\min \{c^T x : Ax \geq b\}$

Basic idea: find smallest λ s.t. $P_\lambda = \{x \in \mathbb{R}^n : Ax \leq b, c^T x \leq \lambda\}$ is feasible.

by binary search.

Q2: How many steps of binary search?

Q3: What about lower bound on size of P_λ ?

We know w that if P_λ is feasible, then an extreme pt. of P_λ is feasible.

Q4: Let $c_{\text{max}} = \|c\|_\infty$ (introduced assumption). Then the optimal soln. for $\min c^T x : Ax \leq b$ also has bit complexity $\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}})$.

thus can find opt. in $O(\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}}))$ iterations.

Q5: What about lower bound on size of P_λ ?

We know w that if P_λ is feasible, then an extreme pt. of P_λ is feasible.

Q6: Let $c_{\text{max}} = \|c\|_\infty$ (introduced assumption). Then the optimal soln. for $\min c^T x : Ax \leq b$ also has bit complexity $\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}})$.

thus can find opt. in $O(\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}}))$ iterations.

Q7: What about lower bound on size of P_λ ?

We know w that if P_λ is feasible, then an extreme pt. of P_λ is feasible.

Q8: Let $c_{\text{max}} = \|c\|_\infty$ (introduced assumption). Then the optimal soln. for $\min c^T x : Ax \leq b$ also has bit complexity $\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}})$.

thus can find opt. in $O(\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}}))$ iterations.

Q9: What about lower bound on size of P_λ ?

We know w that if P_λ is feasible, then an extreme pt. of P_λ is feasible.

Q10: Let $c_{\text{max}} = \|c\|_\infty$ (introduced assumption). Then the optimal soln. for $\min c^T x : Ax \leq b$ also has bit complexity $\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}})$.

thus can find opt. in $O(\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}}))$ iterations.

Q11: What about lower bound on size of P_λ ?

We know w that if P_λ is feasible, then an extreme pt. of P_λ is feasible.

Q12: Let $c_{\text{max}} = \|c\|_\infty$ (introduced assumption). Then the optimal soln. for $\min c^T x : Ax \leq b$ also has bit complexity $\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}})$.

thus can find opt. in $O(\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}}))$ iterations.

Q13: What about lower bound on size of P_λ ?

We know w that if P_λ is feasible, then an extreme pt. of P_λ is feasible.

Q14: Let $c_{\text{max}} = \|c\|_\infty$ (introduced assumption). Then the optimal soln. for $\min c^T x : Ax \leq b$ also has bit complexity $\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}})$.

thus can find opt. in $O(\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}}))$ iterations.

Q15: What about lower bound on size of P_λ ?

We know w that if P_λ is feasible, then an extreme pt. of P_λ is feasible.

Q16: Let $c_{\text{max}} = \|c\|_\infty$ (introduced assumption). Then the optimal soln. for $\min c^T x : Ax \leq b$ also has bit complexity $\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}})$.

thus can find opt. in $O(\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}}))$ iterations.

Q17: What about lower bound on size of P_λ ?

We know w that if P_λ is feasible, then an extreme pt. of P_λ is feasible.

Q18: Let $c_{\text{max}} = \|c\|_\infty$ (introduced assumption). Then the optimal soln. for $\min c^T x : Ax \leq b$ also has bit complexity $\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}})$.

thus can find opt. in $O(\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}}))$ iterations.

Q19: What about lower bound on size of P_λ ?

We know w that if P_λ is feasible, then an extreme pt. of P_λ is feasible.

Q20: Let $c_{\text{max}} = \|c\|_\infty$ (introduced assumption). Then the optimal soln. for $\min c^T x : Ax \leq b$ also has bit complexity $\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}})$.

thus can find opt. in $O(\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}}))$ iterations.

Q21: What about lower bound on size of P_λ ?

We know w that if P_λ is feasible, then an extreme pt. of P_λ is feasible.

Q22: Let $c_{\text{max}} = \|c\|_\infty$ (introduced assumption). Then the optimal soln. for $\min c^T x : Ax \leq b$ also has bit complexity $\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}})$.

thus can find opt. in $O(\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}}))$ iterations.

Q23: What about lower bound on size of P_λ ?

We know w that if P_λ is feasible, then an extreme pt. of P_λ is feasible.

Q24: Let $c_{\text{max}} = \|c\|_\infty$ (introduced assumption). Then the optimal soln. for $\min c^T x : Ax \leq b$ also has bit complexity $\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}})$.

thus can find opt. in $O(\log(\frac{1}{\epsilon} \cdot \frac{1}{c_{\text{max}}}))$ iterations.

Q25: What about lower bound on size of P_λ ?

We know w that if P_λ is feasible, then an extreme pt. of P_λ is feasible.

Q26: Let $c_{\text{max}} = \|c\|_\infty$ (introduced assumption). Then the optimal soln. for $\min c^T x : Ax \leq b$ also has bit complexity $\log(\frac{1}{\epsilon$