

## Lecture 19: Solving Linear Programs

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## 1 Recap

In Lecture 18, we have talked about **Linear Programming (LP)**. LP refers to the following problem. We are given an input of the following  $m$  constraints (inequalities):

$$K \subset \mathbb{R}^n = \begin{cases} a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n \leq b_1 \\ a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n \leq b_2 \\ \vdots \\ a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n \leq b_m \end{cases} \quad (1)$$

where  $a_{ij}, b_i \in \mathbb{Q}$ , for  $i \in [m], j \in [n]$ . Our goals are 1) to determine whether a solution exists, i.e.,  $K \neq \emptyset$  and 2) to maximize  $c^T x$  for some  $c \in \mathbb{Q}^n$  such that  $x \in K$ , if  $K \neq \emptyset$ . We will focus on goal 1). For goal 2), we can add one more constraint  $c^T x \geq \text{opt}$  to  $K$  and binary search for  $\text{opt}$ .

## 2 Solving Linear Programs

Actually, besides (1), LP also has other forms. Notice that for each  $x_i$ , we can rewrite it to  $x_i = x_i^+ - x_i^-$  where  $x_i^+, x_i^- \geq 0$ . Therefore, after doing this transformation, (1) will become the following **Standard Form**:

$$K = \begin{cases} Ax \leq b \\ x \geq 0. \end{cases} \quad (2)$$

Let  $A^{(i)}$  denote the  $i$ -th row of  $A$ . Then we can find that for each row  $A^{(i)}$ ,  $A^{(i)} \cdot x \leq b_i \Leftrightarrow A^{(i)} \cdot x + s_i = b_i, s_i \geq 0$ . After adding  $s_i$ 's, (2) will become the following **Equational Form**:

$$K = \begin{cases} A'(x, s)^T = b \\ x \geq 0, s \geq 0 \end{cases} \quad \text{i.e.} \quad K = \begin{cases} Ax = b \\ x \geq 0 \end{cases} \quad (3)$$

Therefore, it suffices to solve (3) in order to solve (1).

**Definition 1.** Suppose  $b = \frac{p}{q} \in \mathbb{Q}$  where  $p, q \in \mathbb{Z}$ . Define  $|b\rangle = |p\rangle + |q\rangle = \lceil \log_2 |p| \rceil + \lceil \log_2 |q| \rceil$ .

**Theorem 1.** Given  $K \subset \mathbb{R}^n = \left\{ \begin{array}{l} Ax = b \\ x \geq 0 \end{array} \right.$ , let  $L = |A\rangle + |b\rangle = \sum_{ij} |a_{ij}\rangle + \sum_i |b_i\rangle$  be the size of input. If  $K \neq \emptyset$ , there exists  $x \in K$  such that  $|x\rangle = \text{poly}(L)$ .

*Proof.* If we consider the geometric meanings of our constraints, then the set of solutions for  $Ax = b$  is an affine linear subspace in  $\mathbb{R}^n$ . Suppose its dimension is  $m$ . We will prove this theorem via mathematical induction on  $m$ .

If  $m = 0$ ,  $K$  is a single point and  $Ax = b$  gives a solution  $x$  in  $K$ , which can be found in polynomial time by Gaussian Elimination. And this proves that  $|x\rangle = \text{poly}(L)$ . If  $m = 1$ ,  $Ax = b$  defines a line. The line can't be parallel to all hyperplanes defined by  $x_i = 0$ . It means that there exists a  $i \in [n]$  such that  $\left\{ \begin{array}{l} Ax = b \\ x_i = 0 \end{array} \right.$  gives a solution  $x$  with  $|x\rangle = \text{poly}(L)$ . If  $m = 2$ ,  $Ax = b$  defines a 2-dimensional hyperplane. Therefore, there exists  $i \in [n]$  such that  $x_i = 0$  intersects with the plane. And  $\left\{ \begin{array}{l} Ax = b \\ x_i = 0 \end{array} \right.$  defines a line. And we can use former approach when  $m = 1$  to find a solution  $x$  with  $|x\rangle = \text{poly}(L)$ . Generally, for dimension  $m > 2$ , we can reduce it to the case when dimension is  $m - 1$ .  $\square$

**Corollary 2.** Let  $K \subset \mathbb{R}^n = \left\{ \begin{array}{l} Ax = b \\ x \geq 0 \end{array} \right.$ . If  $K \neq \emptyset$ , there exists a bounding box  $B = \{x : \forall i, 0 \leq x_i \leq B_i\}$  such that  $K \cap B \neq \emptyset$  with  $|B\rangle = \sum_i |B_i\rangle = \text{poly}(L)$ .

**Definition 2.**  $LP'$  is the problem that given  $K \subset \mathbb{R}^n = \left\{ \begin{array}{l} Ax \leq b \\ x_i \geq 0 \end{array} \right.$ , our goal changes to the following: if  $\text{vol}(K) \geq V$ , then output  $x \in K$  where  $V = 2^{-\text{poly}(L)}$  otherwise output nothing.

**Theorem 3.** If we can solve  $LP'$  in polynomial time, we can also solve  $LP$  in polynomial time.

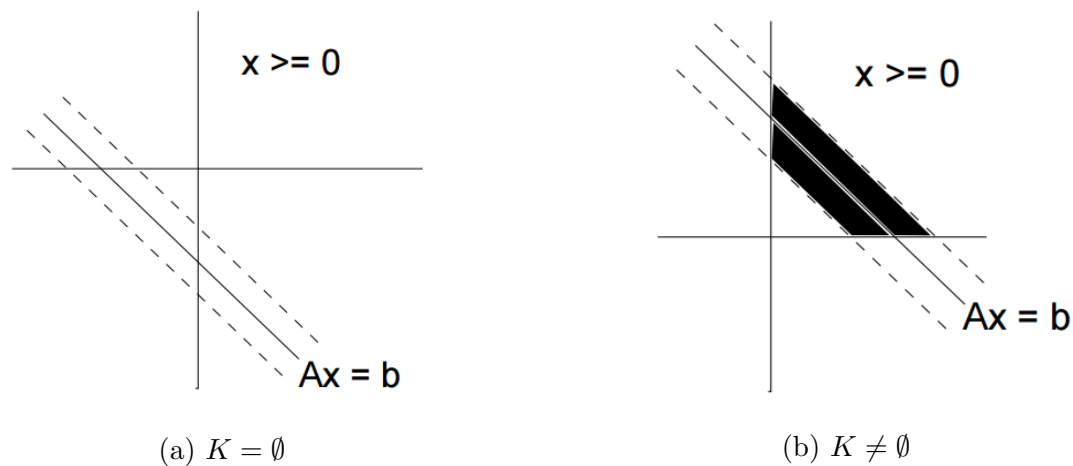
**Remark 3.1.**  $LP'$  is a more relaxed (easier) task than  $LP$ .

*Proof Sketch.* If  $K = \emptyset$ , let  $\gamma$  be the distance from  $\{x : Ax = b\}$  to  $\{x \geq 0\}$ . One can show that  $\gamma \geq 2^{-\text{poly}(L)} = \gamma_0$ . Let  $K' = \{x : -\gamma_0 \leq Ax - b \leq \gamma_0, x \geq 0\}$ . We will get  $K' \neq \emptyset$ .

If  $K \neq \emptyset$ ,  $K'$  has volume at least  $\left(\frac{\gamma_0}{2^{\text{poly}(L)}}\right)^n = 2^{-\text{poly}(L)}$ . Therefore, if  $LP'$  is solvable in polynomial time, we can relax  $K$  to  $K'$ . After that, we can trigger the  $LP'$  solver.

Here is a geometric view in  $\mathbb{R}^2$ .

$\square$

Figure 1: A geometric view in  $\mathbb{R}^2$ 

## 2.1 The Ellipsoid Method for LP

In this subsection, we will introduce a concrete method for solving LP. The high level idea is that we maintain an ellipsoid that contains  $K$ . We can assume  $\text{vol}(K) \geq 2^{-\text{poly}(L)} = V$  by Theorem 3. Here is the algorithm.

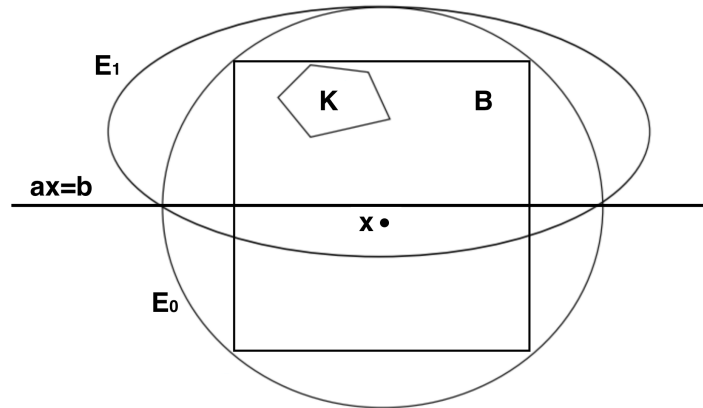
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### Algorithm 1 The Ellipsoid Algorithm

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- 1: **Input:**  $K \subset \mathbb{R}^n = \begin{cases} Ax \leq b \\ x \geq 0 \end{cases}$ .
  - 2: **Initialization:** Let  $E_0$  be the smallest ellipsoid containing the bounding box  $B$  defined in Corollary 2. Set  $i = 1$ .
  - 3: **while** TRUE **do**
  - 4:     Let  $x$  be the center of  $E_{i-1}$ .
  - 5:     **if**  $x \in K$  **then**
  - 6:         **Output:**  $x$ .
  - 7:     **else**
  - 8:         Find an arbitrary linear constrain that is violated namely  $a \cdot x \leq b$ . Let  $E_i$  be the smallest ellipsoid containing  $E_{i-1} \cap \{x : a \cdot x \leq b\}$ .
  - 9:     **if**  $\text{vol}(E_i) < V$  **then**
  - 10:         **Output:** NO SOLLUTION.
  - 11:      $i = i + 1$ .
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The following graph gives a geometric view of picking  $E_1$ .

Figure 2: A geometric view of picking  $E_1$ 

If a solution is returned, it must be a feasible solution of  $K$ . If NO SOLUTION returned,  $\text{vol}(K)$  must be  $< V = 2^{-\text{poly}(L)}$  since  $K \subset E_i$  for any  $i$ . Therefore, we only need to bound the number of iterations performed.

**Claim 4.** For every  $i = 1, 2, 3, \dots$ ,  $\frac{\text{vol}(E_i)}{\text{vol}(E_{i-1})} \leq 1 - \frac{1}{3n}$ .

*Proof.* Since every ellipsoid can be obtained via invertible linear transformations from a unit ball, and the volume is preserved upon a scaling factor (the determinant of the linear transformation matrix), we can assume w.l.o.g. that  $E_{i-1}$  is the unit ball.

Now the worst case for the separating hyperplane is to go through the origin. Assume w.l.o.g. that it is  $x_1 \geq 0$ .

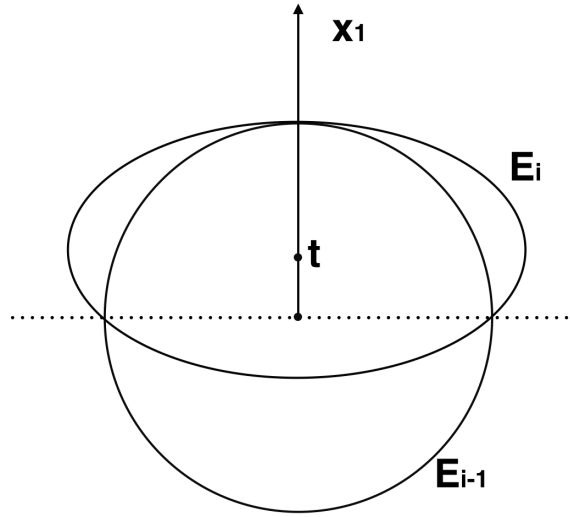
Let  $E_i$  be centered at  $(t, 0, \dots, 0)$  ( $t < 1/2$ ). Let the semi-axis along  $x_1$  be  $(1 - t)$  and semi-axis along other directions be  $s$ , i.e.  $E_i$  satisfies the following equation:

$$\frac{(x_1 - t)^2}{(1 - t)^2} + \frac{x_2^2}{s^2} + \dots + \frac{x_n^2}{s^2} \leq 1.$$

To contain the half ball  $E_{i-1} \cap \{x : x_1 \geq 0\}$  in  $E_i$ , we only need  $(0, 1, 0, \dots, 0) \in E_{i-1}$ , i.e.

$$\frac{t^2}{(1 - t)^2} + \frac{1}{s^2} \leq 1.$$

Here is the geometric view of above procedure.

Figure 3: A geometric view of computing  $E_i$ 

From this inequality, we can get  $s^2 \geq \frac{(1-t)^2}{1-2t}$ . Set  $s^2 = \frac{(1-t)^2}{1-2t}$  and  $t = \frac{1}{2n}$ . We have

$$\begin{aligned}
 \frac{\text{vol}(E_i)}{\text{vol}(E_{i-1})} &= (1-t) \cdot s^{n-1} \\
 &= \left( \frac{(1-t)^2}{1-2t} \right)^{(n-1)/2} (1-t) \\
 &= \left( \frac{1 - 1/n + 1/(4n^2)}{1 - 1/n} \right)^{(n-1)/2} \left( 1 - \frac{1}{2n} \right) \\
 &= \left( 1 + \frac{1}{4n(n-1)} \right)^{(n-1)/2} \left( 1 - \frac{1}{2n} \right) \\
 &\leq \left( e^{\frac{1}{4n(n-1)}} \right)^{(n-1)/2} e^{-\frac{1}{2n}} \\
 &= e^{-\frac{3}{8n}} \\
 &\leq 1 - \frac{1}{3n}.
 \end{aligned}$$

In general, if  $E_i$  is not the unit ball, let  $\sigma$  be the invertible linear transformation such that  $\sigma(\text{unit ball}) = E_i$ . Let  $\det(\sigma)$  be the determinant of the matrix associated with  $\sigma$ . Let  $a' \cdot x \leq b'$  be the half-space obtained by  $\sigma^{-1}(\{a \cdot x \leq b\})$ . Let  $E'_i$  be the smallest ellipsoid containing  $\text{unit ball} \cap \{a' \cdot x \leq b'\}$ . By previous discussion:

$$\frac{\text{vol}(E'_i)}{\text{vol}(\text{unit ball})} \leq 1 - \frac{1}{3n}.$$

Let  $E_i = \sigma(E'_i)$ . We know that  $E_i$  contains  $E_{i-1} \cap \{a \cdot x \leq b\}$  since  $\sigma$  is bijective. Finally, we will have

$$\frac{\text{vol}(E'_i)}{\text{vol}(\text{unit ball})} = \frac{\det(\sigma) \cdot \text{vol}(E'_i)}{\det(\sigma) \cdot \text{vol}(\text{unit ball})} \leq 1 - \frac{1}{3n}.$$

□

**Claim 5.** *The Ellipsoid Algorithm terminates within  $\text{poly}(L)$  iterations.*

*Proof.* Suppose the algorithm does not terminate after  $i$  iterations. Then we must have  $\text{vol}(E_i) \geq V = 2^{-\text{poly}(L)}$ . Also by selection of  $E_0$ , we have  $\text{vol}(E_0) \leq 2^{O(n)} \cdot \text{vol}(B) \leq 2^{\text{poly}(L)}$ . Further by claim 4,  $\frac{\text{vol}(E_i)}{\text{vol}(E_0)} \leq (1 - \frac{1}{3n})^i$ . Therefore,

$$\begin{aligned} i &\leq \frac{\log(\text{vol}(E_i)/\text{vol}(E_0))}{\log(1 - \frac{1}{3n})} \\ &\leq O(n) \cdot \log(2^{\text{poly}(L)}/2^{-\text{poly}(L)}) \\ &= O(n) \cdot \text{poly}(L) \\ &= \text{poly}(L). \end{aligned}$$

With above argument, we will get this algorithm terminates within  $\text{poly}(L)$  iterations. □

## Reference

- a) <http://www.cs.cmu.edu/~odonnell/toolkit13/lecture13.pdf>
- b) <https://www.cs.cmu.edu/afs/cs.cmu.edu/academic/class/15859-f11/www/notes/lecture08.pdf>