

Last time, we introduced the Method of Centers of Gravity (MCG) and the Ellipsoid Method of Yudin and Nemirovski (1976) and Shor (1977), which is a simple modification of MCG.

We represent an ellipsoid by

$$E(B, y) := \{x \in \mathbf{R}^n : (x - y)^\top B^{-1}(x - y) \leq 1\},$$

where  $y \in \mathbf{R}^n$ , and  $B = B^\top \in \mathbf{R}^{n \times n}$  is symmetric positive definite.

Observe that  $C = [-1, 1]^n \subseteq E(nI, 0) = \{x \in \mathbf{R}^n : x^\top \frac{1}{n}Ix \leq 1\} = \{x \in \mathbf{R}^n : \|x\|_2 \leq \sqrt{n}\}$  (Figure 1). Hence, if  $E_0 = E(nI, 0)$ , then  $(E_0, *)$  is a localizer and  $\text{vol}(E_0) \leq (2\sqrt{n})^n$ .

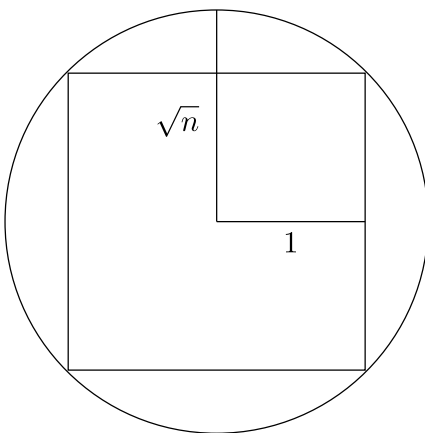


Figure 1:  $E(nI, 0) = \{x \in \mathbf{R}^n : x^\top \frac{1}{n}Ix \leq 1\} = \{x \in \mathbf{R}^n : \|x\|_2 \leq \sqrt{n}\}$ .

### The Ellipsoid Method Algorithm:

- Initialize with  $E_0 = E(nI, 0)$ ,  $z = *$ .
- At iteration  $k$ , we are given a localizer  $(E_k, z_k)$ , where  $E_k = E(B_k, x_k)$  and  $x_k$  is the center of gravity of  $E_k$ . Call the oracle at  $x_k$ .
- If  $x_k \notin G \cap \text{int}(C)$ , the oracle returns a separating hyperplane  $G \subseteq \{x : v_k^\top x \leq v_k^\top x_k\}$ . Set  $z_{k+1} := z_k$ ,  $a_k := v_k$ .
- If  $x_k \in G \cap \text{int}(C)$ , the oracle returns  $f(x_k)$ ,  $g(x_k) \in \partial f(x_k)$ . Set  $z_{k+1} := \text{argmin}\{f(x_k), f(z_k)\}$ , and  $a_k := g(x_k)$ .
- Set  $E_{k+1}$  to be the minimum volume ellipsoid containing  $E_k^{1/2} := \{x \in E_k : a_k^\top x \leq a_k^\top x_k\}$  (Figure 2).

- Stop if  $\text{vol}(E_{k+1}) < \delta^n$  and  $z_{k+1} = *$  (then  $G = \emptyset$ ) or if  $z_{k+1} \in G$  and  $\text{vol}(E_{k+1}) < (\varepsilon\delta)^n$  (then  $\epsilon(z_{k+1}, f, G) < \epsilon$ ).

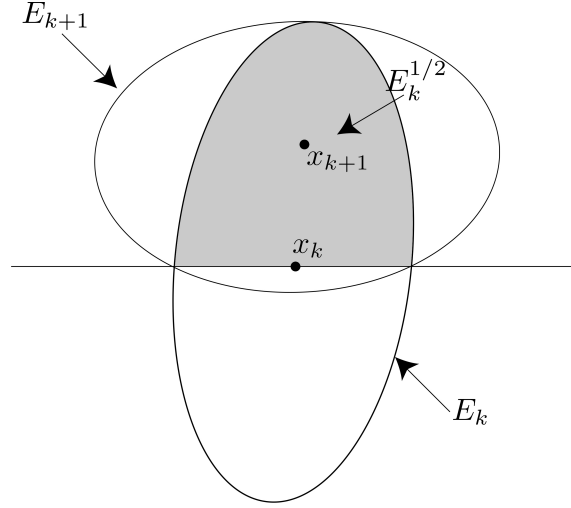


Figure 2: Ellipsoid Method

**Proposition 1.** For every  $k$ ,  $(E_k, z_k)$  is a localizer of  $(f, G)$ .

*Proof.* The proof is exactly analogous to the proof of the Method of Centers of Gravity from last lecture (i.e., Proposition 2).  $\square$

**Proposition 2.**  $E_{k+1} = E(B_{k+1}, x_{k+1})$ , where

$$x_{k+1} = x_k - \tau \frac{B_k a_k}{\sqrt{a_k^\top B_k a_k}}, \quad B_{k+1} = \delta \left( B_k - \sigma \frac{B_k a_k a_k^\top B_k}{a_k^\top B_k a_k} \right),$$

with  $\tau = \frac{1}{n+1}$ ,  $\delta = \frac{n^2}{n^2-1}$ , and  $\sigma = \frac{2}{n+1}$ .

Note that we are always assuming that  $n > 1$ . In fact, we will prove a stronger proposition for which Proposition 2 is a special case ( $\alpha = 0$ ).

**Proposition 3.** Let  $E = E(B, y)$  and  $-\frac{1}{n} \leq \alpha < 1$ . Then the minimum volume ellipsoid containing  $E_\alpha = \{x \in E : a^\top x \leq a^\top y - \alpha \sqrt{a^\top B a}\}$  is  $E_+ := E(B_+, y_+)$ , where

$$B_+ = \delta \left( B - \sigma \frac{B a a^\top B}{a^\top B a} \right) \quad \text{and} \quad y_+ = y - \tau \frac{B a}{\sqrt{a^\top B a}}.$$

Here,  $\tau = \frac{1+n\alpha}{n+1}$ ,  $\delta = \frac{(1-\alpha^2)n^2}{n^2-1}$ , and  $\sigma = \frac{2(1+n\alpha)}{(n+1)(1+\alpha)}$ . Moreover,

$$\frac{\text{vol}(E_+)}{\text{vol}(E)} = \frac{n}{n+1} \left( \frac{n^2}{n^2-1} \right)^{\frac{n-1}{2}} (1-\alpha)(1-\alpha^2)^{\frac{n-1}{2}}.$$

This is at most  $\exp\left(-\frac{1}{2(n+1)}\right)$  if  $\alpha \geq 0$ .

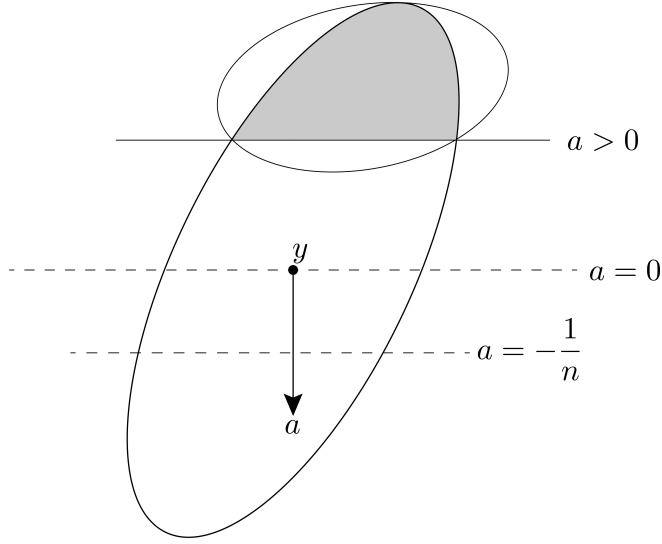


Figure 3: Minimum Volume Ellipsoid. If  $\alpha \leq -\frac{1}{n}$ ,  $E_+ = E$ .

We'll prove Proposition 3 next time using the following Lemmata.

**Lemma 1.** Let  $B = B^\top \in \mathbf{R}^{n \times n}$  be symmetric positive definite. Then:

- (a)  $B$  has a unique symmetric positive definite square root, denoted by  $B^{1/2}$ , satisfying  $B^{1/2}B^{1/2} = B$ .
- (b)  $E(B, y) = \{y + B^{1/2}w : \|w\|_2 \leq 1\}$ .
- (c)  $\text{vol}(E(B, y)) = \sqrt{\det(B)} \text{vol}(\text{unit ball})$ .
- (d) For any  $0 \neq a \in \mathbf{R}^n$ ,  $a^\top x$  is maximized/minimized over  $E(B, y)$  at  $y \pm \frac{Ba}{\sqrt{a^\top Ba}}$  with optimal values  $a^\top y \pm \sqrt{a^\top Ba}$ .

*Proof.*

- (a) Write  $B = QDQ^\top$ , with  $Q$  orthogonal (the columns of  $Q$  are the eigenvectors of  $B$ ) and  $D$  diagonal (the diagonal entries are the eigenvalues of  $B$ ). Then, set  $D^{1/2}$  to be the diagonal matrix containing the positive square roots of the eigenvalues and set  $B^{1/2} = QD^{1/2}Q^\top$ . Check that  $B = B^{1/2}B^{1/2}$ . We will not prove uniqueness here.
- (b) Write  $B^{-1/2} = (B^{1/2})^{-1} = (B^{-1})^{1/2}$ . If  $x = y + B^{1/2}w$ ,  $\|w\| \leq 1$ , then

$$(x - y)^\top B^{-1}(x - y) = w^\top B^{1/2}(B^{1/2}B^{1/2})^{-1}B^{1/2}w = w^\top w \leq 1.$$

Conversely, if  $(x - y)^\top B^{-1}(x - y) = (x - y)^\top B^{-1/2}B^{-1/2}(x - y) \leq 1$ . Define  $w := B^{-1/2}(x - y)$  and note that

$$\|w\| = \|B^{-1/2}(x - y)\| \leq 1.$$

(c)  $\text{vol}(E(B, y)) = \text{vol}(\{y + B^{1/2}w : \|w\| \leq 1\}) = \det B^{1/2} \text{vol}(\text{unit ball}) = \sqrt{\det(B)} \text{vol}(\text{unit ball})$ .

(d) Note that

$$\begin{aligned} \max\{a^\top x : x \in E(B, y)\} &= \max\{a^\top (y + B^{1/2}w) : \|w\| \leq 1\} \\ &= a^\top y + \max\{a^\top B^{1/2}w : \|w\| \leq 1\} \\ &\stackrel{(i)}{=} a^\top y + \|B^{1/2}a\|, \end{aligned}$$

where (i) follows by setting  $w = \frac{B^{1/2}a}{\|B^{1/2}a\|} = \frac{B^{1/2}a}{\sqrt{a^\top B a}}$ , whence the result for maximizing. Similarly for minimizing. This gives both the optimal value and the optimizing point.

□

**Lemma 2.** (Sherman - Morrison - Woodbury) Let  $A \in \mathbf{R}^{n \times n}$  be invertible and  $U, V \in \mathbf{R}^{n \times k}$ , where  $k < n$ . Then

(a)  $\det(A + UV^\top) = \det(A) \det(I_k + V^\top A^{-1}U)$ .

(b)  $A + UV^\top$  is invertible if and only if  $I_k + V^\top A^{-1}U$  is invertible.

(c) If this holds,

$$(A + UV^\top)^{-1} = A^{-1} + \underbrace{A^{-1}U(I_k + V^\top A^{-1}U)^{-1}V^\top A^{-1}}_{\text{rank} \leq k}.$$

*Proof.*

(a) Consider

$$\begin{aligned} \begin{bmatrix} A & U \\ -V^\top & I_k \end{bmatrix} &= \begin{bmatrix} A + UV^\top & U \\ 0 & I_k \end{bmatrix} \begin{bmatrix} I_n & 0 \\ -V^\top & I_k \end{bmatrix} \\ &= \begin{bmatrix} I_n & 0 \\ -V^\top A^{-1} & I_k \end{bmatrix} \begin{bmatrix} A & U \\ 0 & I_k + V^\top A^{-1}U \end{bmatrix}. \end{aligned}$$

By taking determinants of the two RHS, we conclude that  $\det(A + UV^\top) = \det(A) \det(I_k + V^\top A^{-1}U)$ .

(b) Follows trivially from (a).

(c) Define  $B := I_k + V^\top A^{-1}U$ . Then from the equations above,

$$\begin{bmatrix} A + UV^\top & U \\ 0 & I_k \end{bmatrix} = \begin{bmatrix} I_n & 0 \\ -V^\top A^{-1} & I_k \end{bmatrix} \begin{bmatrix} A & U \\ 0 & B \end{bmatrix} \begin{bmatrix} I_n & 0 \\ -V^\top & I_k \end{bmatrix}^{-1}.$$

By inverting both sides of the equation, we have,

$$\begin{bmatrix} (A + UV^\top)^{-1} & -(A + UV^\top)^{-1}U \\ 0 & I_k \end{bmatrix} = \begin{bmatrix} I_n & 0 \\ -V^\top & I_k \end{bmatrix} \begin{bmatrix} A^{-1} & -A^{-1}UB^{-1} \\ 0 & B^{-1} \end{bmatrix} \begin{bmatrix} I_n & 0 \\ V^\top A^{-1} & I_k \end{bmatrix}.$$

The top left hand block gives the desired result.

□

Next time, we will prove Proposition 3. We will first show that  $E_+$  contains  $E_\alpha$  and then sketch the proof of its minimality. Define  $\bar{a} := \frac{a}{\sqrt{a^\top B a}}$  and note that  $\bar{a}^\top B \bar{a} = 1$ . Therefore, by Lemma 1,  $-1 \leq \bar{a}^\top (x - y) \leq 1$ , for all  $x \in E$ . Then,

$$\begin{aligned} a^\top x \leq a^\top y - \alpha \sqrt{a^\top B a} & \text{ is equivalent to} \\ \bar{a}^\top x \leq \bar{a}^\top y - \alpha. \end{aligned}$$

Therefore,  $x \in E_\alpha$  if and only if  $(x - y)^\top B^{-1}(x - y) \leq 1$  and  $-1 \leq \bar{a}^\top (x - y) \leq -\alpha$  or equivalently,  $(\bar{a}^\top (x - y) + \alpha)(\bar{a}^\top (x - y) + 1) \leq 0$ . Thus we have two quadratics.

OR 631: Mathematical Programming II. Spring 2014.  
 Homework Set 3. Due: Tuesday April 15.

1. This question and the next are concerned with central cuts. Suppose we have an ellipsoid  $E := E(B, y)$ , and we add two cuts symmetrically placed with respect to the center  $y$ . Consider

$$\bar{E}_\alpha := \{x \in E : a^T y - \alpha \sqrt{a^T B a} \leq a^T x \leq a^T y + \alpha \sqrt{a^T B a}\}$$

for some nonzero  $a \in \mathbf{R}^n$  and some  $0 \leq \alpha \leq 1$ .

- a) Write the condition for  $x$  to lie in  $\bar{E}_\alpha$  as two quadratics.
- b) By combining these two quadratics suitably, find an ellipsoid  $E(B_+, y_+)$  that contains  $\bar{E}_\alpha$ , depending on a scalar parameter  $\sigma$ .
- c) Find the value of  $\sigma$  that minimizes the volume of the resulting ellipsoid as a function of  $\alpha$ . Show that for  $\alpha = n^{-1/2}$  this ellipsoid is just  $E$ , while for  $\alpha$  smaller than this it gives an ellipsoid of smaller volume than  $E$ . (In fact, this is the minimum-volume ellipsoid among all those containing  $\bar{E}_\alpha$ , not just those obtained this way.)

2. Consider a centrally symmetric polytope, a bounded polyhedron of the form  $P := \{x \in \mathbf{R}^n : -b \leq Ax \leq b\}$  for some  $A, b$ .

- a) Show that there is a minimum-volume ellipsoid  $E = E(B, y)$  containing  $P$ .
- b) Show that any such must have  $y = 0$ , i.e., it must be centrally symmetric also.
- c) Show that, if  $E(B, 0)$  is a (the) minimum-volume ellipsoid containing  $P$ , then  $\{n^{-1/2}x : x \in E(B, 0)\}$  is contained in  $P$ .

(Hence such polytopes can be rounded to a factor  $\sqrt{n}$ , not  $n$  as in the general case. In fact, this holds for any centrally symmetric convex body.)

3. Suppose that  $P := \{x \in \mathbf{R}^n : A^T x \leq e\}$  is bounded (where  $e$  is the vector of ones as usual). Assume that the function  $B \rightarrow -\ln \det B$  is convex as a function of the entries of the symmetric matrix  $B$ .

- a) Show how the problem of finding the maximum volume ellipsoid with center  $y$  contained in  $P$  can be written as an optimization problem with a finite number of constraints. (Argue that the positive semidefiniteness constraint can be eliminated.)
- b) Exhibit a feasible solution to this problem.
- c) Show that if the center  $y$  is restricted to be 0, your optimization problem can be converted to one with linear constraints on  $B$ .
- d) Now return to the general case, where  $y$  is a variable. Try to rewrite the optimization problem with convex constraints (you may want to consider the symmetric square root).