

Lower Bounds for Global Optimization

Problem

$$\min_{x \in B} f(x)$$

$$x \in B$$

$$\text{where } B = \{x \in \mathbb{R}^n \mid \|x\| \leq R\}$$

- $\|\cdot\|$ can be arbitrary
- $R > 0$

Assume that f is Lipschitz continuous:

$$|f(x) - f(y)| \leq L\|x - y\|, \quad \forall x, y \in B$$

- $L > 0$

Goal: Find $\bar{x} \in B$: $f(\bar{x}) - f^* \leq \underline{\epsilon}$

Zeroth-order algorithms: $O(x) = \{f(x)\}$

Question: What is a lower bound for complexity of zeroth-order methods?

Packing

B - a ball with radius $R > 0$

$x_1, \dots, x_K \in B$ and $0 < r < R$.

Denote "small balls":

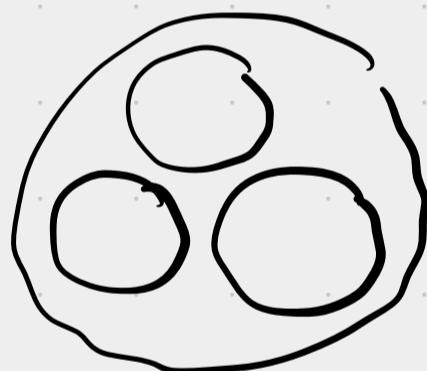
$$B_i = \{y \in \mathbb{R}^n \mid \|y - x_i\| \leq r\}$$

Def. We say $\{B_1, \dots, B_K\}$ is packing in B :

(1) Each $B_i \subset B$

(2) For any B_i, B_j : $\text{int } B_i \cap \text{int } B_j = \emptyset$.

Def. We say $\{B_1, \dots, B_K\}$ is a maximal packing in B if we cannot extend it.

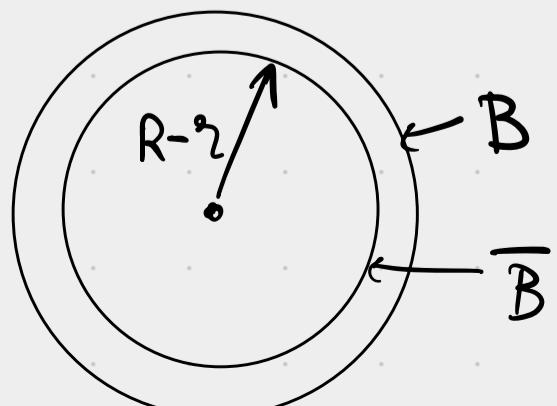


Theorem 1. Let $\{B_1, \dots, B_K\}$ - a maximal packing. Then

$$K \geq \left(\frac{R-r}{2r}\right)^n \approx \left(\frac{R}{r}\right)^n$$

Proof

① Consider shrunked ball $\bar{B} = \{y \in \mathbb{R}^n \mid \|y\| \leq R-r\}$



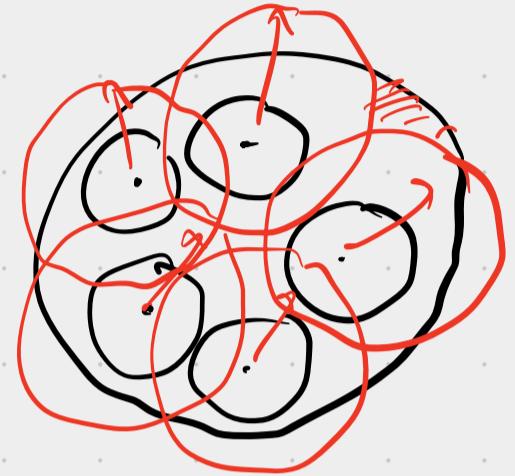
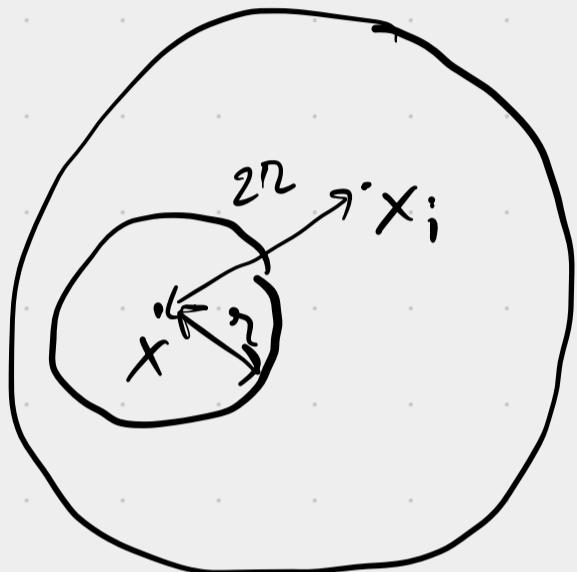
② For any $x \in \overline{B}$ $\exists x_i, 1 \leq i \leq K$ st.

$$\|x - x_i\| < 2r.$$

Otherwise, it means we can add to our packing

$$\{y \in \mathbb{R}^n \mid \|y - x\| \leq r\}$$

(?) the packing is maximal.



③ We got a covering

$$c_i = \{y \in \mathbb{R}^n : \|y - x_i\| \leq 2r\} \Rightarrow$$

$$\overline{B} \subset \bigcup_{i=1}^K c_i$$

④ Take the volume:

$$\begin{aligned} \text{Vol}(\overline{B}) &\leq \text{Vol}\left(\bigcup_{i=1}^K c_i\right) \leq \sum_{i=1}^K \text{Vol}(c_i) \\ &= K \cdot \text{Vol}(c_1) \end{aligned}$$

Denote $\alpha = \text{Vol}(\{y \in \mathbb{R}^n : \|y\| \leq 1\})$.

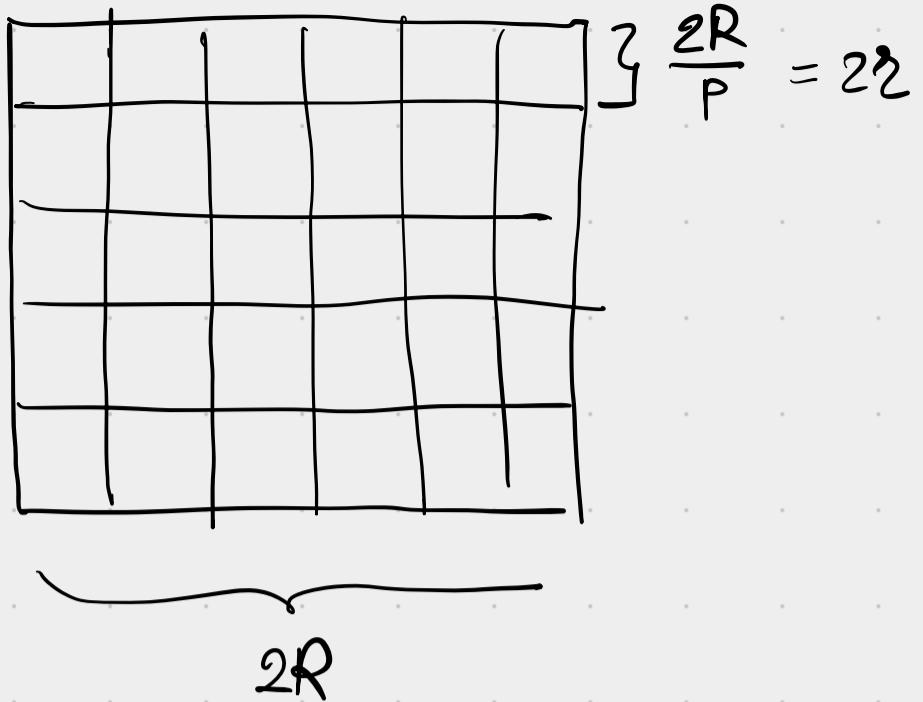
$$\text{Then: } \text{Vol}(c_1) = \alpha \cdot (2r)^n$$

$$\text{Vol}(\overline{B}) = \alpha \cdot (R-r)^n \Rightarrow K \geq \frac{(R-r)^n}{(2r)^n}. \quad \square$$

Remark. $\| \cdot \| = \| \cdot \|_\infty$

$$p \geq 1$$

$$K = p^n = \left(\frac{R}{r}\right)^n.$$



Resisting Oracle

An optimization algorithm:

$$x_{k+1} = A(O(x_0), \dots, O(x_k)).$$

Resisting oracle $O(\cdot)$

1. Should return information that is the worst for the algorithm.
2. In the end: \exists at least one funct. $f \in \mathcal{P}$ that is consistent with $O(x_0), \dots, O(x_k)$.

In our case:

$$O(x) = \{0\}.$$

The result x_k of an algorithm will be $f(x_k) = 0$.

Denote by $K(R, r, n)$ - a lower bound on size of a maximal packing of ball of radius $R > 0$ by small balls of radius $\geq r$ in \mathbb{R}^n .

By Th 1. $\Rightarrow K(R, \gamma, n) = \lceil \left(\frac{R-\gamma}{2\gamma} \right)^n \rceil$.

Theorem 2. let $0 < \gamma < R$. Consider any zeroth-order algorithm running for $k < K(R, \gamma, n) - 1$ iterations. Then,

\exists a Lipschitz function (with const. $L > 0$)

s.t. $f(x_k) - f^* = L\gamma$.

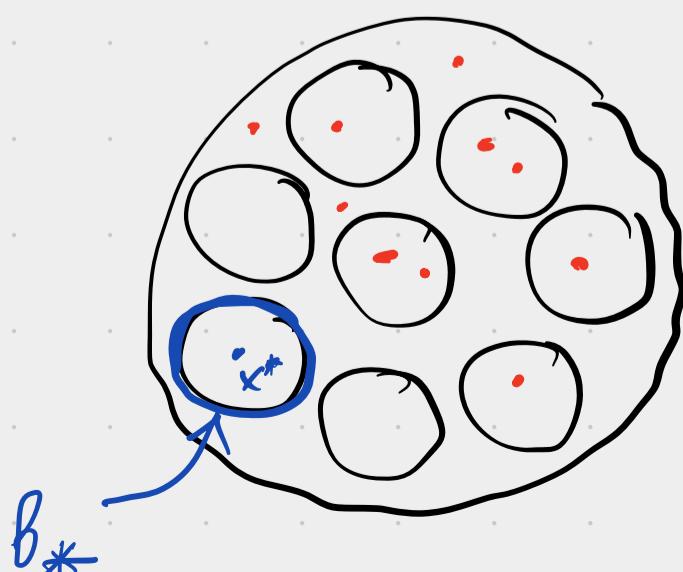
Proof let $\{x_0, \dots, x_n\} \in B$ be a sequence of points generated by the algorithm, when applied to the wisd. oracle. $\Rightarrow f(x_n) = 0$.

Now, consider any maximal packing of size $N \geq K(R, \gamma, n) \geq k+1$.

$\Rightarrow \exists$ a small ball B_* in our maximal packing s.t.

$$x_i \notin B_* \quad \forall 0 \leq i \leq k.$$

Denote by x^* the center of B_* .



Introduce: $f(x) = L \cdot \min \{0, \|x - x^*\| - r\}\right\}.$

(1) $f(x^*) = -rL$

(2) $f(x) = 0 \quad \forall x: \|x - x^*\| \geq r.$

(3) f is Lipschitz.

let $x, y \in B_r: \|x - x^*\| \leq r, \|y - x^*\| \leq r$. Then

$$\begin{aligned} f(x) - f(y) &= L \cdot \left(\|x - x^*\| - r - \|y - x^*\| + r \right) \\ &= L \left(\|x - x^*\| - \|y - x^*\| \right) \leq L \|x - y\|. \end{aligned}$$

let $x \notin B_r, y \in B_r$.

$$\begin{aligned} f(x) - f(y) &\leq L(\|x - x^*\| - r) - L(\|y - x^*\| - r) \\ &\leq L \|x - y\|. \end{aligned}$$

let $x \notin B_r, y \notin B_r$:

$$f(x) - f(y) = 0 \leq L \|x - y\|.$$

Therefore

$$f(x_n) - f^* = rL. \quad \square$$

Lower Bound

Theorem 3. let $L > 0$, $R > 0$, $\varepsilon > 0$. Assume: $\varepsilon < \frac{LR}{2}$.

Then, for any zeroth-order algorithm,
the complexity is bounded:

$$K \geq \lceil \left(\frac{LR}{4\varepsilon} - \frac{1}{2} \right)^n \rceil - 1.$$

Proof. $r = \frac{2\varepsilon}{L} < R$.

Notice,

$$\begin{aligned} K(R, r, n) &= \lceil \left(\frac{R-r}{2r} \right)^n \rceil = \lceil \left(\frac{R}{2r} - \frac{1}{2} \right)^n \rceil \\ &= \lceil \left(\frac{LR}{4\varepsilon} - \frac{1}{2} \right)^n \rceil. \end{aligned}$$

Th2: Assume $K < K(R, r, n) - 1$. Then,

$$f(x_k) - f^* = Lr = 2\varepsilon. \quad (?!)$$

\Rightarrow To solve the problem we need

$$K \geq K(R, r, n) - 1. \quad \square$$

$\|\cdot\| := \|\cdot\|_\infty \Rightarrow \underline{\text{Grid Search Algorithm}}$

has the complexity:

$$\mathcal{O}\left(\left[\frac{LR}{\epsilon}\right]^n\right)$$

- Grid Search is optimal for $\|\cdot\|_\infty$.
- Other norms — open question?