Optimization 1 - 098311 Winter 2021 - HW 8

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Problem 1:

Denote the following optimization problem P:

$$(P): \min \{f(x) : x \in Box[l, u]\}$$

where f is a continuously differentiable function over the box and $l \leq u \in \mathbb{R}^n$

We need to show that:

$$x^* \text{ is a stationary point of } P \iff \frac{\partial f}{\partial x_i}(x^*) \begin{cases} = 0 & l_i < x_i^* < u_i \\ \leq 0 & x_i^* = u_i \\ \geq 0 & x_i^* = l_i \end{cases}$$

proof of \Rightarrow

We know x^* is a stationary point.

Let's assume by contradiction that

$$\frac{\partial f}{\partial x_i}(x^*) \begin{cases} = 0 & l_i < x_i^* < u_i \\ \le 0 & x_i^* = u_i \\ \ge 0 & x_i^* = l_i \end{cases}$$

is not satisfied.

There are three cases which it happens:

case 1

$$\exists i : l_i < x_i^* < u_i$$

but:

$$\frac{\partial f}{\partial x_i}\left(x^*\right) \neq 0$$

if
$$\frac{\partial f}{\partial x_i}(x^*) > 0$$

lets choose $x \in \text{Box}[l, u]$ such that:

$$x_j = \begin{cases} x_j^* & j \neq i \\ l_i & j = i \end{cases}$$

$$\nabla f(x^*)^T (x - x^*) = \sum_{k=1}^n \nabla f(x^*)_k (x_k - x_k^*)$$
$$= \underbrace{\nabla f(x^*)_i}_{>0} \underbrace{(l_i - x_i^*)}_{<0} < 0$$

We got a contradiction to the stationarity of x^*

if
$$\frac{\partial f}{\partial x_i}(x^*) < 0$$

lets choose $x \in \text{Box}[l, u]$ such that:

$$x_{j} = \begin{cases} x_{j}^{*} & j \neq i \\ u_{i} & j = i \end{cases}$$

$$\nabla f (x^{*})^{T} (x - x^{*}) = \sum_{k=1}^{n} \nabla f (x^{*})_{k} (x_{k} - x_{k}^{*})$$

$$= \underbrace{\nabla f (x^{*})_{i}}_{<0} \underbrace{(u_{i} - x_{i}^{*})}_{>0} < 0$$

We got a contradiction to the stationarity of x^*

case 2

$$\exists i: x_i^* = u_i$$

but:

$$\frac{\partial f}{\partial x_i}\left(x^*\right) > 0$$

lets choose $x \in \text{Box}[l, u]$ such that:

$$x_{j} = \begin{cases} x_{j}^{*} & j \neq i \\ \frac{l_{j} + u_{j}}{2} & j = i \end{cases}$$

$$\nabla f \left(x^{*}\right)^{T} \left(x - x^{*}\right) = \sum_{k=1}^{n} \nabla f \left(x^{*}\right)_{k} \left(x_{k} - x_{k}^{*}\right)$$

$$= \nabla f \left(x^{*}\right)_{i} \left(\frac{l_{i} + u_{i}}{2} - u_{i}\right)$$

$$= \underbrace{\nabla f \left(x^{*}\right)_{i}}_{>0} \underbrace{\left(\frac{l_{i} - u_{i}}{2}\right)}_{<0} < 0$$

We got a contradiction to the stationarity of x^*

case 3

$$\exists i: x_i^* = l_i$$

but:

$$\frac{\partial f}{\partial x_i}\left(x^*\right) < 0$$

lets choose $x \in \text{Box}[l, u]$ such that:

$$x_j = \begin{cases} x_j^* & j \neq i \\ \frac{l_j + u_j}{2} & j = i \end{cases}$$

$$\nabla f(x^*)^T (x - x^*) = \sum_{k=1}^n \nabla f(x^*)_k (x_k - x_k^*)$$

$$= \nabla f(x^*)_i \left(\frac{l_i + u_i}{2} - l_i\right)$$

$$= \underbrace{\nabla f(x^*)_i}_{<0} \underbrace{\left(\frac{u_i - l_i}{2}\right)}_{>0} < 0$$

We got a contradiction to the stationarity of x^* each one of the possible cases led to a contradiction, thus:

$$x^*$$
 is a stationary point of $P \Rightarrow \frac{\partial f}{\partial x_i}(x^*)$
$$\begin{cases} = 0 & l_i < x_i^* < u_i \\ \leq 0 & x_i^* = u_i \\ \geq 0 & x_i^* = l_i \end{cases}$$

proof of \Leftarrow

we know that:

$$\frac{\partial f}{\partial x_i}(x^*) \begin{cases} = 0 & l_i < x_i^* < u_i \\ \le 0 & x_i^* = u_i \\ \ge 0 & x_i^* = l_i \end{cases}$$

We will show that x^* is a stationary point of P by definition:

let $x \in \text{Box}[l, u]$, meaning:

$$\forall i \in \{1, ..., n\} : l_i \le x_i \le u_i$$

$$\nabla f(x^*)^T (x - x^*) = \sum_{i=1}^n \nabla f(x^*)_i (x_i - x_i^*)$$

$$= \sum_{i=1}^n \nabla f(x^*)_i (x_i - x_i^*) \mathbb{I} \{l_i < x_i^* < u_i\} + \sum_{i=1}^n \nabla f(x^*)_i (x_i - x_i^*) \mathbb{I} \{x_i^* = l_i\} + \sum_{i=1}^n \nabla f(x^*)_i (x_i - u_i) \mathbb{I} \{x_i^* = u_i\} \ge 0$$

$$= 0 + \sum_{i=1}^n \underbrace{\nabla f(x^*)_i}_{>0} \underbrace{(x_i - l_i)}_{>0} \mathbb{I} \underbrace{\{x_i^* = l_i\}}_{>0} + \sum_{i=1}^n \underbrace{\nabla f(x^*)_i}_{<0} \underbrace{(x_i - u_i)}_{>0} \mathbb{I} \underbrace{\{x_i^* = u_i\}}_{>0} \ge 0$$

Thus, x^* is a stationary point, meaning:

$$x^*$$
 is a stationary point of $P \Leftarrow \frac{\partial f}{\partial x_i}(x^*)$
$$\begin{cases} = 0 & l_i < x_i^* < u_i \\ \leq 0 & x_i^* = u_i \\ \geq 0 & x_i^* = l_i \end{cases}$$

To conclude:

$$x^*$$
 is a stationary point of $P \iff \frac{\partial f}{\partial x_i}(x^*) \begin{cases} = 0 & l_i < x_i^* < u_i \\ \leq 0 & x_i^* = u_i \\ \geq 0 & x_i^* = l_i \end{cases}$

Problem 2:

Denote the following optimization problem P:

$$(P): \min \left\{ f\left(x\right) : x \in \Delta_n \right\}$$

where f is a continuously differentiable function over Δ_n .

$$x^*$$
 is a stationary point of $P \iff \exists \mu \in \mathbb{R} : \frac{\partial f}{\partial x_i}(x^*) \begin{cases} = \mu & x_i^* > 0 \\ \geq \mu & x_i^* = 0 \end{cases}$

proof of \Rightarrow

We know x^* is a stationary point.

Let's assume by contradiction that

$$\exists \mu \in \mathbb{R} : \frac{\partial f}{\partial x_i} (x^*) \begin{cases} = \mu & x_i^* > 0 \\ \ge \mu & x_i^* = 0 \end{cases}$$

is not satisfied.

meaning:

$$\forall \mu \in \mathbb{R}, \exists i : \frac{\partial f}{\partial x_i}(x^*) \neq \mu \cap x_i^* > 0 \text{ Or } \frac{\partial f}{\partial x_i}(x^*) < \mu \cap x_i^* = 0$$

especially for:

$$\mu = \min_{k \in \{i: x_i^* > 0\}} \nabla f(x^*)_k$$

The second condition will never hold since:

$$\mu = \min_{k \in \left\{i: x_i^* > 0\right\}} \nabla f\left(x^*\right)_k \leq \nabla f\left(x^*\right)_i < \mu \text{ (contradition)}$$

hence:

$$\exists i : \nabla f(x^*)_i \neq \mu \cap x_i^* > 0$$

since $\mu = \min_{k \in \{i: x_i^* > 0\}} \frac{\partial}{\partial x_k} f\left(x^*\right)$ we can conclude:

$$\exists i : \nabla f(x^*)_i > \mu$$

denote:

$$l = \arg\min_{k \in \{i: x_i > 0\}} \nabla f(x^*)_k$$

notice that:

since $\nabla f(x^*)_i > \mu$:

$$l \neq i$$

Lets choose $x = e_l \in \Delta_n$:

$$\nabla f(x^*)^T (x - x^*) = \sum_{k=1}^n \nabla f(x^*)_k (x_k - x_k^*)$$

$$= \sum_{k=1}^n \nabla f(x^*)_k x_k - \sum_{k=1}^n \nabla f(x^*)_k x_k^*$$

$$= \nabla f(x^*)_l - \sum_{k=1}^n \nabla f(x^*)_k x_k^*$$

$$= \nabla f(x^*)_l - \left(\underbrace{\nabla f(x^*)_i}_{>\mu} \underbrace{x_i^*}_{>0} + \sum_{k=1}^n \underbrace{\nabla f(x^*)_k}_{\geq\mu} \underbrace{x_k^*}_{\geq 0} \right)$$

$$< \nabla f(x^*)_l - \left(\mu x_i^* + \mu \sum_{k=1 \atop k \neq i}^n x_k^* \right)$$

$$= \mu - \mu \sum_{k=1}^n x_k^*$$

$$= \mu - \mu = 0$$

We got a contradiction to the stationarity of x^* , thus:

$$x^*$$
 is a stationary point of $P \Rightarrow \exists \mu \in \mathbb{R} : \frac{\partial f}{\partial x_i}(x^*) \begin{cases} = \mu & x_i^* > 0 \\ \geq \mu & x_i^* = 0 \end{cases}$

proof of \Leftarrow

we know that:

$$\exists \mu \in \mathbb{R} : \frac{\partial f}{\partial x_i} (x^*) \begin{cases} = \mu & x_i^* > 0 \\ \ge \mu & x_i^* = 0 \end{cases}$$

We will show that x^* is a stationary point of P by definition:

let $x \in \Delta_n$, meaning:

$$\sum_{i=1}^{n} x_i = 1, \ \forall i : x_i \ge 0$$

$$\nabla f(x^*)^T (x - x^*) = \sum_{i=1}^n \nabla f(x^*)_i (x_i - x_i^*)$$

$$= \sum_{i=1}^n \nabla f(x^*)_i (x_i - x_i^*) \mathbb{I} \{x_i^* > 0\} + \sum_{i=1}^n \nabla f(x^*)_i (x_i - x_i^*) \mathbb{I} \{x_i^* = 0\}$$

$$= \mu \sum_{i=1}^n (x_i - x_i^*) \mathbb{I} \{x_i^* > 0\} + \sum_{i=1}^n \underbrace{\nabla f(x^*)_i}_{\geq \mu} \underbrace{x_i \mathbb{I} \{x_i^* = 0\}}_{\geq 0}$$

$$\geq \mu \sum_{i=1}^n (x_i - x_i^*) \mathbb{I} \{x_i^* > 0\} + \mu \sum_{i=1}^n x_i \mathbb{I} \{x_i^* = 0\}$$

$$= \mu \left(\sum_{i=1}^n x_i \mathbb{I} \{x_i^* > 0\} - \sum_{i=1}^n x_i^* \mathbb{I} \{x_i^* > 0\} + \sum_{i=1}^n x_i \mathbb{I} \{x_i^* = 0\} \right)$$

$$= \mu \left(1 - \sum_{i=1}^n x_i^* \mathbb{I} \{x_i^* > 0\} \right)$$

$$= \mu \left(1 - \sum_{i=1}^n x_i^* \mathbb{I} \{x_i^* > 0\} \right)$$

$$= \mu \left(1 - 1 \right) = 0$$

(*) adding zeros to the summation

Thus, x^* is a stationary point, meaning:

$$x^*$$
 is a stationart point of $P \Leftarrow \exists \mu \in \mathbb{R} : \frac{\partial f}{\partial x_i}(x^*) \begin{cases} = \mu & x_i^* > 0 \\ \geq \mu & x_i^* = 0 \end{cases}$

To conclude:

$$x^*$$
 is a stationary point of $P \iff \exists \mu \in \mathbb{R} : \frac{\partial f}{\partial x_i}(x^*) \begin{cases} = \mu & x_i^* > 0 \\ \geq \mu & x_i^* = 0 \end{cases}$

Problem 3:

As was mentioned in class, stationarity in the unit ball is equivalence to the following condition:

$$\nabla f(x^*) = 0 \text{ OR } (||x^*|| = 1 \text{ AND } \exists \lambda \leq 0 : \nabla f(x^*) = \lambda x^*)$$

the first condition holds if and only if:

$$\nabla f\left(x^{*}\right) = 0$$

$$\iff 2Ax^{*} = 0$$

$$\iff Ax^{*} = 0$$

$$\iff \boxed{x^{*} = 0 \text{ OR } x^{*} \text{ is a singular eigen vector of } A}$$

the second condition holds if and only if

$$\exists \lambda \leq 0 : \nabla f(x^*) = \lambda x^*$$

$$\iff 2Ax^* = \lambda x^*$$

$$\iff Ax^* = \underbrace{\frac{\lambda}{2}}_{\leq 0} x^*$$

 $\iff x^* = 0 \text{ OR } x^* \text{ is a normalized eigen vector of } A \text{ with a non-positive eigen value}$

To conclude, the stationary points are:

$$x^* = 0$$

OR

 $x^* = \text{singular eigen vector of } A \text{ such that } ||x^*|| \leq 1$

OR

 x^* = normalized eigen vector of A with a negative eigen value

Problem 4:

 \mathbf{a}

Denote the following problems:

$$(ML) \min_{x \in \mathbb{R}^n} \sum_{i=1}^m (||x - a_i|| - d_i)^2$$

$$(ML2) \min_{\substack{x \in \mathbb{R}^n \\ u_i \in B[0,1]}} f(x, u_1, u_2, ..., u_m) = \sum_{i=1}^m (||x - a_i||^2 - 2d_i u_i^T (x - a_i) + d_i^2)$$

We need to show that x^* is an optimal solution of $(ML) \iff \exists u_1^*, ..., u_m^* \in B [0, 1]$ such that $x^*, u_1^*, ..., u_m^*$ are an optimal solution of (ML2).

 \Rightarrow

we know that:

$$x^* \in \arg\min_{x \in \mathbb{R}^n} \sum_{i=1}^m (||x - a_i|| - d_i)^2$$

notice that $\forall x \in \mathbb{R}^n, u_1, ..., u_m \in B [0, 1]$:

$$f(x, u_1, u_2, ..., u_m) = \sum_{i=1}^{m} (||x - a_i||^2 - 2d_i u_i^T (x - a_i) + d_i^2)$$

$$(C.S, d_i \ge 0) \ge \sum_{i=1}^{m} (||x - a_i||^2 - 2d_i ||u_i|| ||x - a_i|| + d_i^2)$$

$$(||u_i|| \le 1) \ge \sum_{i=1}^{m} (||x - a_i||^2 - 2d_i ||x - a_i|| + d_i^2)$$

$$= \sum_{i=1}^{m} (||x - a_i|| - d_i)^2$$

which means that the objective function of (ML) is an lower bound of the objective of (ML2).

Given x^* lets choose:

$$u_i^* = \begin{cases} \frac{x^* - a_i}{||x^* - a_i||} & x^* \neq a_i \\ e_1 & x^* = a_i \end{cases}$$

One can notice the $\forall i: u_i^* \in B[0,1]$.

 $\forall x \in \mathbb{R}^n, u_1, ..., u_m \in B [0, 1]:$

$$f(x^*, u_1^*, ..., u_m^*) = \sum_{i=1}^m \left(||x^* - a_i||^2 - 2d_i \left(u_i^* \right)^T (x^* - a_i) + d_i^2 \right)$$

$$= \sum_{i=1}^m \left(||x^* - a_i||^2 - 2d_i ||x^* - a_i|| + d_i^2 \right)$$

$$= \sum_{i=1}^m \left(||x^* - a_i|| - d_i \right)^2$$
(optimality of x^*) $\leq \sum_{i=1}^m \left(||x - a_i|| - d_i \right)^2$
(lower bound) $\leq f(x, u_1, u_2, ..., u_m)$

hence, we found $u_1^*,...,u_m^*\in B\left[0,1\right]$ such that $(x^*,u_1^*,...,u_m^*)$ are an optimal solution of (ML2).

 \Leftarrow

Let

$$(x^*, u_1^*, ..., u_m^*) \in \arg\min_{\substack{x \in \mathbb{R}^n \\ u_i \in B[0,1]}} f(x, u_1, u_2, ..., u_m)$$

we will show that:

$$f(x, u_1^*, ..., u_m^*) = \sum_{i=1}^m (||x - a_i|| - d_i)^2$$

we know from C.S that:

$$(u_i^*)^T (x^* - a_i) \le ||u_i^*|| ||x^* - a_i||$$

we will prove that the equality holds.

assuming by contradiction that:

$$(u_i^*)^T (x^* - a_i) < ||u_i^*|| ||x^* - a_i||$$

we get:

$$f(x^*, u_1^*, ..., u_m^*) = \sum_{i=1}^m \left(||x^* - a_i||^2 - 2d_i (u_i^*)^T (x^* - a_i) + d_i^2 \right)$$

$$(\text{assumption}) > \sum_{i=1}^m \left(||x^* - a_i||^2 - 2d_i ||u_i^*|| ||x^* - a_i|| + d_i^2 \right)$$

$$(||u_i|| \le 1) \ge \sum_{i=1}^m \left(||x^* - a_i||^2 - 2d_i ||x^* - a_i|| + d_i^2 \right)$$

$$= \sum_{i=1}^m \left(||x^* - a_i|| - d_i \right)^2$$

but if we choose $\hat{u_i}$ such that:

$$\hat{u}_i = \begin{cases} \frac{x^* - a_i}{||x^* - a_i||} & x^* \neq a_i \\ e_1 & x^* = a_i \end{cases}$$

we get:

$$f(x^*, u_1^*, ..., u_m^*) > \sum_{i=1}^m (||x - a_i|| - d_i)^2 = f(x^*, \hat{u_1}, ..., \hat{u_m})$$

The above equality comes from the first direction we have already proven.

and this is a contradiction to the optimality of $(x^*, u_1^*, ..., u_m^*)$

hence:

$$(u_i^*)^T (x^* - a_i) = ||u_i^*|| ||x^* - a_i||$$

Similarly, we will show in the same way that $\forall i$:

$$x^* \neq a_i \Rightarrow ||u_i^*|| = 1$$

Assuming by contradiction that $x^* \neq a_i$ but $||u_i^*|| < 1$.

by choosing the same \hat{u}_i as above we get:

$$f(x^*, u_1^*, ..., u_m^*) = \sum_{i=1}^m \left(||x^* - a_i||^2 - 2d_i (u_i^*)^T (x^* - a_i) + d_i^2 \right)$$

$$(\text{proven}) = \sum_{i=1}^m \left(||x^* - a_i||^2 - 2d_i ||u_i^*|| ||x^* - a_i|| + d_i^2 \right)$$

$$(||u_i|| < 1) > \sum_{i=1}^m \left(||x^* - a_i||^2 - 2d_i ||x^* - a_i|| + d_i^2 \right)$$

$$= \sum_{i=1}^m \left(||x^* - a_i|| - d_i \right)^2 = f(x^*, \hat{u_1}, ..., \hat{u_m})$$

and that is a contradiction to the optimality of $(x^*, u_1^*, ..., u_m^*)$. hence:

$$x^* \neq a_i \Rightarrow ||u_i^*|| = 1$$

by the two statement we have proven, we can conclude:

$$f(x^*, u_1^*, ..., u_m^*) = \sum_{i=1}^m (||x^* - a_i|| - d_i)^2$$

Finally, $\forall x \in \mathbb{R}^n$:

$$\sum_{i=1}^{m} (||x^* - a_i|| - d_i)^2 = f(x^*, u_1^*, ..., u_m^*)$$

(optimality of
$$x^*, u_i^*$$
) $\leq f(x, \hat{u_1}, ..., \hat{u_m})$
= $\sum_{i=1}^{m} (||x - a_i|| - d_i)^2$

meaning x^* is the optimal solution of (ML)

b)

$$f(x, u_1, u_2, ..., u_m) = \sum_{i=1}^{m} (||x - a_i||^2 - 2d_i u_i^T (x - a_i) + d_i^2)$$

let's find the gradiant of f:

$$\frac{\partial f(x, u_1, u_2, ..., u_m)}{\partial x} = \sum_{i=1}^m (2(x - a_i) - 2d_i u_i) = 2\sum_{i=1}^m (x - a_i - d_i u_i) =$$

$$= 2\left(mx - \sum_{i=1}^m (a_i + d_i u_i)\right)$$

$$\frac{\partial f(x, u_1, u_2, ..., u_m)}{\partial u_i} = -2d_i(x - a_i)$$

denote

$$z = \begin{pmatrix} x \\ u_1 \\ u_2 \\ \vdots \\ \vdots \\ u_m \end{pmatrix}, \tilde{z} = \begin{pmatrix} \tilde{x} \\ \tilde{u_1} \\ \tilde{u_2} \\ \vdots \\ \vdots \\ \tilde{u_m} \end{pmatrix}$$

$$\|\nabla f(z) - \nabla f(\tilde{z})\| =$$

$$\| \begin{pmatrix} mx - \sum_{i=1}^{m} a_i + d_i u_i \\ -d_1(x - a_1) \end{pmatrix} - \begin{pmatrix} m\tilde{x} - \sum_{i=1}^{m} a_i + d_i \tilde{u}_i \\ -d_1(\tilde{x} - a_1) \end{pmatrix} \| =$$

$$-d_m(x - a_m) \end{pmatrix} - 2 \begin{pmatrix} m\tilde{x} - \sum_{i=1}^{m} a_i + d_i \tilde{u}_i \\ -d_1(\tilde{x} - a_1) \end{pmatrix} \| =$$

$$-d_m(x - a_m) \end{pmatrix} - 2 \begin{pmatrix} m(x - \tilde{x}) - \sum_{i=1}^{m} d_i (u_i - \tilde{u}_i) \\ -d_1(x - \tilde{x}) \end{pmatrix} \| =$$

$$= 2 \begin{pmatrix} mI_n - d_1I_n - d_2I_n & \dots & d_mI_n \\ -d_1I_n & & & \\ & \ddots & & \\ & -d_mI_n \end{pmatrix} \begin{pmatrix} x - \tilde{x} \\ u_1 - \tilde{u}_1 \\ u_2 - \tilde{u}_2 \end{pmatrix} \| =$$

$$\leq 2 \|A\|_{2,2} \cdot \|z - \tilde{z}\|_{2}$$

where the last inequality comes from a lecture far away in the past.

Hence, a lipschitz constant of the gradient is given by:

$$L_{\nabla f} = 2 \left\| A \right\|_{2,2} = 2 \cdot \sqrt{\left| \lambda_{max} \left(A^T A \right) \right|}$$

Let's find the maximal eigenvalue of A^TA

denote:

$$A = \left(\begin{array}{cc} B & C \\ C^T & D \end{array}\right)$$

using the general property that (assuming D is invertible):

$$det \begin{pmatrix} A & B \\ C & D \end{pmatrix} = det (D) det (A - BD^{-1}C)$$

let's find the eigenvalues of A:

$$\lambda I_{(m+1)\cdot n} - A = \begin{pmatrix} \lambda I_n - B & -C \\ -C^T & \lambda I_{m\cdot n} - D \end{pmatrix} = \begin{pmatrix} \lambda I_n - mI_n & -C \\ -C^T & \lambda I_{m\cdot n} \end{pmatrix} = \begin{pmatrix} (\lambda - m) I_n & -C \\ -C^T & \lambda I_{m\cdot n} \end{pmatrix}$$

$$\det \left(\lambda I_{(m+1)\cdot n} - A\right) = \det \left(\lambda I_{m\cdot n}\right) \det \left(\left(\lambda - m\right) I_n - C\left(\lambda I_{m\cdot n}\right)^{-1} C^T\right) =$$

$$= \lambda^{m\cdot n} \det \left(\left(\lambda - m\right) I_n - \frac{1}{\lambda} CC^T\right) =$$

$$= \lambda^{m\cdot n} \det \left(\left(\lambda - m\right) I_n - \frac{\sum_{i=1}^m d_i^2}{\lambda} I_n\right) =$$

$$= \lambda^{m\cdot n} \det \left(\left(\lambda - m - \frac{\sum_{i=1}^m d_i^2}{\lambda}\right) I_n\right) =$$

$$= \lambda^{m\cdot n} \left(\lambda - m - \frac{\sum_{i=1}^m d_i^2}{\lambda}\right)^n$$

$$\lambda - m - \frac{\sum_{i=1}^{m} d_i^2}{\lambda} = 0$$

$$\lambda^2 - m\lambda - \sum_{i=1}^{m} d_i^2 = 0$$

$$\lambda_{1,2} = \frac{m \pm \sqrt{m^2 + 4\sum_{i=1}^{m} d_i^2}}{2}$$

hence:

 $\lambda = 0$ is an eigenvalue with $m \cdot n$ algebric multiplicity.

 $\lambda = \frac{m \pm \sqrt{m^2 + 4\sum_{i=1}^m d_i^2}}{2}$ are eigenvalues with n algebric multiplicity.

since A is symmetric then:

$$\sqrt{|\lambda_{max}(A^{T}A)|} = max |\lambda(A)| = \frac{m + \sqrt{m^2 + 4\sum_{i=1}^{m} d_i^2}}{2}$$

and the Lipshictz constant is:

$$L = 2 \cdot \left\| A \right\|_{2,2} = 2 \cdot \sqrt{\left| \lambda_{max} \left(A^T A \right) \right|} = m + \sqrt{m^2 + 4 \sum_{i=1}^m d_i^2}$$

c)

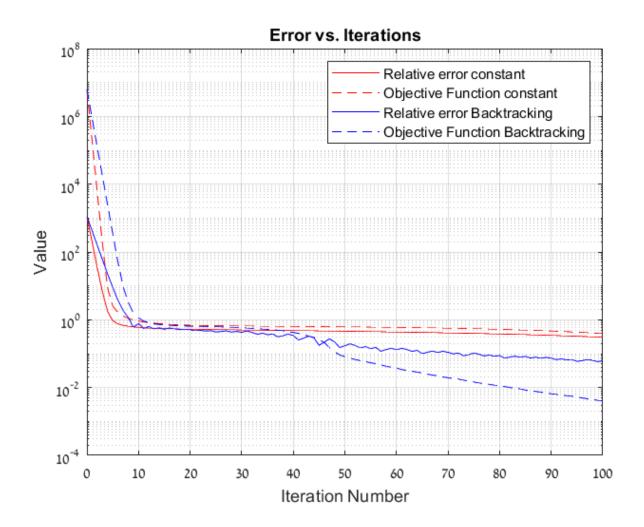


Figure 1: $L_{\nabla f} = 2 \cdot \sqrt{\lambda_{max} \left(A^T A\right)} = 12.117$

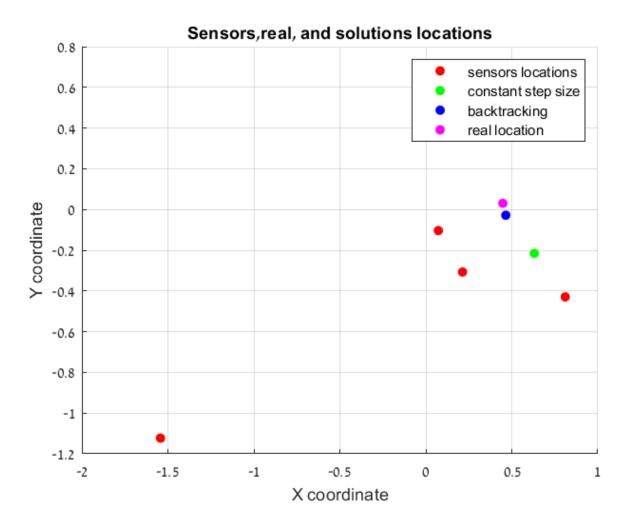


Figure 2: