

Math 650, Foundations of Optimization, Spring 2010

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Homework Assignment - 2

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Problem 1 Solution

$$f(x, y, z) = xyz.e^{-x-y-z}$$

By the first order necessary condition for critical points, we have

$$\nabla f(x, y, z) = 0 \Rightarrow$$

$$f_x(x, y, z) = \frac{\partial}{\partial x} f(x, y, z) = yz.(1-x).e^{-x-y-z} = 0 \Rightarrow y = 0 \vee z = 0 \vee x = 1$$

$$f_y(x, y, z) = \frac{\partial}{\partial y} f(x, y, z) = zx.(1-y).e^{-x-y-z} = 0 \Rightarrow z = 0 \vee x = 0 \vee y = 1$$

$$f_z(x, y, z) = \frac{\partial}{\partial z} f(x, y, z) = xy.(1-z).e^{-x-y-z} = 0 \Rightarrow x = 0 \vee y = 0 \vee z = 1$$

Hence, the set of all possible critical points:

$\{(0, 0, 0), (1, 0, 0), (0, 0, 1), (0, 1, 0), (1, 1, 1), (a, 0, 0), (0, a, 0), (0, 0, a)\}$, when $0 \neq a \in \mathbb{R}$, i.e., $\{(0, 0, 0), (1, 1, 1), (a, 0, 0), (0, a, 0), (0, 0, a)\}$, when $0 \neq a \in \mathbb{R}$

Now let's examine the second order sufficient conditions for finding the type of the critical point. For this we need to compute the Hessian matrix of $f(x, y, z)$

$$H(f(x, y, z)) = e^{-x-y-z} \begin{pmatrix} (2-x)yz & (1-x)(1-y)z & (1-z)(1-x)y \\ (1-x)(1-y)z & (2-y)zx & (1-y)(1-z)x \\ (1-z)(1-x)y & (1-y)(1-z)x & (2-z)xy \end{pmatrix}$$

Hence, we have,

$H(f(0,0,0)) = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$, not a strictly positive/negative definite matrix, or both a positive/negative semidefinite matrix.

$H(f(0,0,1)) = \begin{pmatrix} 0 & \frac{1}{e} & 0 \\ \frac{1}{e} & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$, $|H - \lambda I| = 0$ gives the characteristic polynomial $-\lambda^3 + \frac{\lambda}{e^2} = 0 \Rightarrow \lambda = 0, \pm(\frac{1}{e}) \Rightarrow$ the Hessian matrix has both positive and negative eigenvalues \Rightarrow an indefinite matrix $\Rightarrow (0,0,1)$ is a saddle point by the second order sufficient condition. (Also, by Sylvester's theorem we can see that $\det(H_1) = 0, \det(H_2) = -\frac{1}{e^2}$, hence not all leading principle diagonal matrices have strictly positive determinant).

Similarly, at points $(0,1,0)$ and $(1,0,0)$, the Hessian matrix has both $+ve$ and $-ve$ eigenvalues \Rightarrow the Hessian matrix is an indefinite matrix $\Rightarrow (0,1,0)$ and $(1,0,0)$ are saddle points.

Applying similar logic, we have all the critical points of the form $(0,0,a), (0,a,0), (a,0,0), a \neq 0$ as saddle points.

$H(f(1,1,1)) = \begin{pmatrix} e^3 & 0 & 0 \\ 0 & e^3 & 0 \\ 0 & 0 & e^3 \end{pmatrix}$, $|H - \lambda I| = 0$ gives the characteristic polynomial $(e^3 - \lambda)^3 = 0 \Rightarrow \lambda = e^3, e^3, e^3 \Rightarrow$ all the eigenvalues are strictly $+ve \Rightarrow H$ is a positive definite matrix $\Rightarrow (1,1,1)$ is a minimum point. (Also, by Sylvester's theorem we can see that $\det(H_i) = e^{3i} > 0, i = 1, 2, 3$, hence all leading principle diagonal matrices have strictly positive determinant).

$(1,1,1)$: local minimum (no other local minima \Rightarrow a global minimum too).
 $(0,0,a), (0,a,0), (a,0,0)$: saddle points when $a \neq 0$.
 $(0,0,0)$: can't say anything.

Problem 2 Solution

Given $f(x) = \frac{1}{2} \langle Ax, x \rangle + \langle c, x \rangle + a = \begin{pmatrix} x^T & 1 \end{pmatrix} \begin{pmatrix} A & c \\ c^T & a \end{pmatrix} \begin{pmatrix} x \\ 1 \end{pmatrix}$, with $A_{n \times n}$ symmetric $\Rightarrow \nabla f(x) = \frac{\partial f}{\partial x} = x^T A + c^T, H(f(x)) = \nabla^2 f(x) = A$.

Also, $f(x)$ is bounded from below $\Rightarrow \exists l_b \in \mathbb{R}^n \mid f(x) \geq l_b, \forall x \in \mathbb{R}^n$.
 $\Rightarrow f(0) = a \geq l_b \Rightarrow a - l_b \geq 0$.

Also, A is symmetric $\Rightarrow A$ is diagonalizable $\Rightarrow A = u\Lambda u^T$, with diagonal Λ and $u = [u_1 u_2 \dots u_n]$.

$$\begin{aligned} \Rightarrow f(x) &= \frac{1}{2} \langle u\Lambda u^T x, x \rangle + \langle c, x \rangle + a = \frac{1}{2} \langle \Lambda u^T x, u^T x \rangle + \langle c, x \rangle + a \\ &= \frac{1}{2} \langle \Lambda y, y \rangle + \langle c, x \rangle + a, \text{ where } y = u^T x, u^T : \mathbb{R}^n \rightarrow \mathbb{R}^n. \end{aligned}$$

$$\Rightarrow f(x) = \frac{1}{2} \sum_i \lambda_i y_i^2 + \sum_i c_i x_i + a \geq l_b, \forall x \in \mathbb{R}^n.$$

A is p.s.d.: Proof by contradiction

Let's assume to the contrary, i.e., A is not positive semidefinite $\Rightarrow \exists k \mid \lambda_k < 0$ and λ_k is an eigenvalue of A .

Now let's examine $f(x)$ at the point $x^* = (0, 0, \dots, z, \dots, 0, 0)$, where $(x_i = z, \text{ if } i = k)$ and $(x_i = 0, \forall i \neq k)$, where $z \in \mathbb{R}$.

$$\Rightarrow f(x^*) = \frac{1}{2} \lambda_k \sum_i u_{ik}^2 z^2 + c_k z + a. \text{ (since } x_k = z)$$

Let's denote $p = \sum_i u_{ik}^2 \geq 0$ and $q = c_k$, and consider the roots of the quadratic

$$f(x^*) - l_b = \frac{1}{2} p \lambda_k z^2 + qz + a - l_b = 0 \Rightarrow (z_1, z_2) = \frac{-q \pm \sqrt{q^2 - 2p\lambda_k(a-l_b)}}{p\lambda_k}.$$

We notice that $p, q^2, a - l_b \geq 0 \wedge \lambda_k < 0 \Rightarrow z_1, z_2 \in \mathbb{R}$ (discriminant ≥ 0).

If we choose z (we can always choose any $z \in \mathbb{R}$) s.t. $z \in (z_1, z_2)$, i.e., $\frac{-q - \sqrt{q^2 - 2p\lambda_k(a-l_b)}}{p\lambda_k} = z_1 < z < z_2 = \frac{-q + \sqrt{q^2 - 2p\lambda_k(a-l_b)}}{p\lambda_k}$

$$\Rightarrow f(x^*) - l_b = (z - z_1)(z - z_2) < 0 \Rightarrow f(x^*) < l_b, \text{ a contradiction.}$$

Hence, our initial assumption was wrong, i.e., the symmetric matrix A can not have any negative eigenvalue \Rightarrow all the eigenvalues of A must be non-negative real numbers $\Rightarrow A$ is positive semi-definite (Proved).

f has global minimum in \mathbb{R}^n

We consider the compact sublevel subset $\{f(x) \in \mathbb{R}^n : f(x) \leq l_b\}$ of \mathbb{R}^n and see that $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is a continuous (convex) function defined on the metric space \mathbb{R}^n . Hence, f achieves a global minimizer on \mathbb{R}^n .

Problem 3 Solution

Part (a)

Given $p(x) = \langle Bx, x \rangle + 2\langle b, x \rangle + c = (x^T \ 1) \begin{pmatrix} B & b \\ b^T & c \end{pmatrix} \begin{pmatrix} x \\ 1 \end{pmatrix}$, with $B_{n \times n}$ is positive definite.

By the first order necessary condition for the critical point at x^* , we have,
 $\nabla p(x^*) = \left[\frac{\partial p}{\partial x} \right]_{x^*} = 2(x^{*T} B + b^T) = 0 \Rightarrow x^{*T} B B^{-1} = -b^T B^{-1}$
 $\Rightarrow x^* = -B^{-1}b$
 $\Rightarrow p(x^*) = \langle b, B^{-1}b \rangle + 2\langle b, B^{-1}b \rangle + c = c - \langle B^{-1}b, b \rangle$,
 $(\exists B^{-1}$, since B is positive definite, i.e, all eigenvalues strictly positive, hence non-singular and invertible, also B is symmetric, $B^T = B$).

Also, $p(x)$ is strictly positive in $\mathbb{R}^n \Rightarrow p(x) > p(x^*) = c - \langle B^{-1}b, b \rangle > 0, \forall x \neq x^* \in \mathbb{R}^n$.

Now, the Hessian $H(p(x)) = \nabla^2 p(x) = 2B$ is positive definite, hence by second order sufficient condition, x^* is a local minimum.

As we can see from the first order necessary condition x^* is the only critical point for the function $p(x)$ and by the second order sufficient condition we see that it's the minimum point, hence the function is having the unique global minimum at x^* .

Part (b)

Choose $d = x^* = -B^{-1}b \in \mathbb{R}^n$.

$$\begin{aligned} & \begin{pmatrix} I_n & 0 \\ d^T & 1 \end{pmatrix} . A . \begin{pmatrix} I_n & d \\ 0 & 1 \end{pmatrix} = \begin{pmatrix} I_n & 0 \\ -b^T B^{-1} & 1 \end{pmatrix} \begin{pmatrix} B & b \\ b^T & c \end{pmatrix} \begin{pmatrix} I_n & -B^{-1}b \\ 0 & 1 \end{pmatrix} \\ &= \begin{pmatrix} B & b \\ 0 & -b^T B^{-1}b + c \end{pmatrix} \begin{pmatrix} I_n & -B^{-1}b \\ 0 & 1 \end{pmatrix} = \begin{pmatrix} B & 0 \\ 0 & -b^T B^{-1}b + c \end{pmatrix} \\ &\Rightarrow \det \left(\begin{pmatrix} I_n & 0 \\ d^T & 1 \end{pmatrix} . A . \begin{pmatrix} I_n & d \\ 0 & 1 \end{pmatrix} \right) = \det \begin{pmatrix} B & 0 \\ 0 & -b^T B^{-1}b + c \end{pmatrix} \\ &\Rightarrow \det \begin{pmatrix} I_n & 0 \\ d^T & 1 \end{pmatrix} . \det(A) . \det \begin{pmatrix} I_n & d \\ 0 & 1 \end{pmatrix} = \det \begin{pmatrix} B & 0 \\ 0 & -b^T B^{-1}b + c \end{pmatrix} \\ &\Rightarrow \det(A) = \det(B) . (c - b^T B^{-1}b) \text{ (Proved)} \end{aligned}$$

Part (c)

Proof (\Leftrightarrow) by induction on the dimension n of matrix $A_{n \times n}$

Base case: for $n = 1$ the proof is trivial (since A contains only one element).

Induction Hypothesis: Let's assume the result is true for n .

Induction Step: Let's prove the result for $n + 1$.

Let's consider the $(n + 1) \times (n + 1)$ symmetric matrices (A) of the form

$A = \begin{pmatrix} B & b \\ b^T & c \end{pmatrix}$, where B is a positive definite matrix as in part (b). We notice that all the positive $(n + 1) \times (n + 1)$ definite matrices will be of this form (hence will be a subset of this set) and they must be symmetric.

Now, consider the quadratic form $\langle Ay, y \rangle$ of the matrix A , where $y \in \mathbb{R}^{n+1}$. We notice that any such $y \in \mathbb{R}^{n+1}$ can be represented as $\begin{bmatrix} x \\ a \end{bmatrix}$, where $a \in \mathbb{R}$.

1. When $a = 0$, $\langle Ay, y \rangle = \langle Bx, x \rangle$ and B is positive definite $\Leftrightarrow A$ is positive definite (all leading principal minors are positive by induction hypothesis).

2. When $a \neq 0$, $\langle Ay, y \rangle = y^T A y = \begin{pmatrix} x^T & 1 \end{pmatrix} \begin{pmatrix} B & b \\ b^T & c \end{pmatrix} \begin{pmatrix} x \\ 1 \end{pmatrix} = p(x)$

From part (b), $\langle Ay, y \rangle = p(x) > 0 \Leftrightarrow c - \langle B^{-1}b, b \rangle > 0$.

Also, B is positive definite $\Rightarrow \det(B) > 0$ (by induction hypothesis)

$\Rightarrow \det A = \det B \cdot (c - \langle B^{-1}b, b \rangle) > 0$. Also, all leading principal minors of B are positive by induction hypothesis and $\det(A) > 0 \Leftrightarrow$ all leading principal minors of A are positive $\Leftrightarrow A$ is positive definite. (Proved)