

# MTH603/AM8211

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### Assignment Cover Page

Assignment Number: 3

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# Assignment 3

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## Question 1

[Question 1] Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  have continuous second partial derivatives. Consider  $x_0 \in \mathbb{R}^n$  for which  $\nabla f(x_0)$  is nonzero. Prove or disprove that for any  $d \in \mathbb{R}^n$  for which  $\nabla f(x_0) \cdot d < 0$ , we have that  $d$  is a descent direction starting from  $x_0$ .

## Solution

To prove this statement, we need to show that if  $\nabla f(x_0) \cdot d < 0$ , then  $d$  is a descent direction, meaning that the directional derivative of  $f$  in the direction of  $d$  is negative.

The directional derivative of  $f$  at a point  $x_0$  in the direction of a vector  $d$  is given by:

$$\nabla f(x_0) \cdot d$$

Given that  $\nabla f(x_0) \cdot d < 0$ , we have a negative directional derivative.

Now, we can use the properties of continuous second partial derivatives. Since  $f$  has continuous second partial derivatives, we can apply the Corollary for Taylor's Expansion:

We are given  $x_0, d \in \mathbb{R}^n$ . Take small enough  $\alpha$  approaching 0.

The Taylor expansion of  $f$  at a point  $x_0$  is given by:

$$f(x_0 + \alpha d) = f(x_0) + \alpha \nabla f(x_0) \cdot d + O(\alpha^2) < f(x_0)$$

Since  $\nabla f(x_0) \cdot d < 0$  and  $\alpha > 0$ , we can conclude that the second term  $\alpha \nabla f(x_0) \cdot d$  is negative. This means that arbitrarily defined  $d$  is indeed a descent direction starting from  $x_0$ .

Therefore, we have proven that for any  $d \in \mathbb{R}^n$  for which  $\nabla f(x_0) \cdot d < 0$ ,  $d$  is a descent direction starting from  $x_0$ .

## Question 2

[Question 2] Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  have continuous second partial derivatives, and assume that the Hessian of  $f$ ,  $H_f$ , is positive for all  $x \in \mathbb{R}^n$ . Prove that if  $\nabla f(x_0) = 0$ , then  $x_0$  is the unique global minimizer of  $f$ .

### Solution:

We want to show that if  $\nabla f(x_0) = 0$  and the Hessian of  $f$ ,  $\nabla^2 f(x)$ , is positive, then  $x_0$  is a global minimizer, and its uniqueness will follow from the positive definiteness of the Hessian. To prove that  $x_0$  is the unique global minimizer of  $f$ , we will use the fact that  $\nabla^2 f(x)$  is positive for all  $x$  in  $\mathbb{R}^n$ .

First, since  $f$  has continuous second partial derivatives, we can apply Taylor's Expansion of  $f$  around  $x_0$ :

$$f(x) = f(x_0) + \nabla f(x_0)^\top (x - x_0) + \frac{1}{2}(x - x_0)^\top H(x_0)(x - x_0) + \dots$$

Where  $H(x_0) = \nabla^2 f(x)$  is the Hessian matrix of  $f$  evaluated at  $x_0$ . Since  $\nabla f(x_0) = 0$ , the first-order term  $\nabla f(x_0)^\top (x - x_0)$  disappears, and we are left with:

$$f(x) = f(x_0) + 0 + \frac{1}{2}(x - x_0)^\top H(x_0)(x - x_0) + \dots$$

Now, because the Hessian matrix is positive definite, the quadratic form  $(x - x_0)^\top H(x_0)(x - x_0)$  is strictly positive for all  $x \neq x_0$ . This means that  $f(x) > f(x_0)$  for all  $x \neq x_0$ , which implies that  $x_0$  is a local minimum.

Since we have that  $x_0$  is a local minimum, and the Hessian is positive definite, this implies that  $f$  is convex function and  $x_0$  is therefore a global minimum. Furthermore, the uniqueness of the global minimum follows from the positive definiteness of the Hessian, as it guarantees that there are no other local minima near  $x_0$  that could compete with it.

Hence,  $x_0$  is the unique global minimizer of  $f$ .

### Question 3

[Question 3] Consider the non-linear function

$$f(x, y, z) = x^2y - xy + 3y^2 - y + 2z^2 + 372$$

- (a) Find the gradient and Hessian of  $f(x, y, z)$ .
- (b) Using the first order necessary optimality condition, find all candidate minimizers of  $f(x, y, z)$ .
- (c) Find the eigenvalues of the Hessian of  $f(x, y, z)$ .
- (d) Find all strict local minimizers of  $f(x, y, z)$ .

### Solution:

#### Solution to 3(a):

We have the following partial derivatives

$$\frac{\partial f}{\partial x} = 2xy - y$$

$$\frac{\partial f}{\partial y} = x^2 - x + 6y - 1$$

$$\frac{\partial f}{\partial z} = 4z$$

So, the gradient  $\nabla f(x, y, z)$  is a vector given by:

$$\nabla f(x, y, z) = \begin{bmatrix} 2xy - y \\ x^2 - x + 6y - 1 \\ 4z \end{bmatrix}$$

The second partial derivatives of  $f$  are as follows:

$$\frac{\partial^2 f}{\partial x^2} = 2y$$

$$\frac{\partial^2 f}{\partial y^2} = 6$$

$$\frac{\partial^2 f}{\partial z^2} = 4$$

$$\frac{\partial^2 f}{\partial x \partial y} = 2x - 1$$

$$\frac{\partial^2 f}{\partial x \partial z} = 0$$

$$\frac{\partial^2 f}{\partial y \partial z} = 0$$

So, the Hessian matrix  $\mathbf{H}$  is given by:

$$\mathbf{H} = \begin{bmatrix} 2y & 2x - 1 & 0 \\ 2x - 1 & 6 & 0 \\ 0 & 0 & 4 \end{bmatrix}$$

**Solution to 3(b):**

To find the candidate minimizers of  $f(x, y, z)$ , we need to use the first-order necessary optimality condition, which involves setting the gradient of  $f$  equal to the zero vector.

Recall that the gradient of  $f(x, y, z)$  is given by:

$$\nabla f(x, y, z) = \begin{bmatrix} 2xy - y \\ x^2 - x - 1 + 6y \\ 4z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

To find the candidate minimizers, we set  $\nabla f(x, y, z) = \mathbf{0}$ , where  $\mathbf{0}$  is the zero vector:

$$\begin{bmatrix} 2xy - y \\ x^2 - x - 1 + 6y \\ 4z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

Solving for  $x$ ,  $y$ , and  $z$ , we get the following system of equations:

$$\begin{aligned} 2xy - y &= 0 \\ x^2 - x - 1 + 6y &= 0 \\ 4z &= 0 \end{aligned}$$

The third equation  $4z = 0$  implies that  $z = 0$ .

The first two equations are as follows:

1. From the first equation  $2xy - y = 0$ , we can factor out  $2x$  to get:

$$y(2x - 1) = 0$$

This implies that either  $2x - 1 = 0$  or  $y = 0$ .

2. From the second equation  $x^2 - x - 1 + 6y = 0$ , we can isolate  $x^2 - x$  on one side:

$$x^2 - x = 1 - 6y$$

Now, let's consider the cases:

**Case 1:**  $y = 0$

If  $y = 0$ , then  $x^2 - x = 1 - 6(0) = 1$ . Substituting this into the second equation:

$$x^2 - x - 1 = 0$$

This gives  $x = \frac{1 \pm \sqrt{5}}{2}$  so  $(\frac{1+\sqrt{5}}{2}, 0, 0)$  and  $(\frac{1-\sqrt{5}}{2}, 0, 0)$  are candidates.

**Case 2:**  $2x - 1 = 0$

If  $x = \frac{1}{2}$ , then  $(\frac{1}{2})^2 - (\frac{1}{2}) = 1 - 6y = -\frac{1}{4}$ .

Solving for  $y$  gives:

$$y = \frac{1 + \frac{1}{4}}{6} = \frac{5}{24}$$

So, we have three candidates:

**Candidate 1:**  $\vec{x}_1 = (x, y, z) = (\frac{1}{2}, \frac{5}{24}, 0)$

**Candidate 2:**  $\vec{x}_2 = (x, y, z) = (\frac{1+\sqrt{5}}{2}, 0, 0)$

**Candidate 3:**  $\vec{x}_3 = (x, y, z) = (\frac{1-\sqrt{5}}{2}, 0, 0)$

It can be verified that  $\nabla f(x_i) = 0$  as required by the first order necessary optimality condition. Therefore, these are the candidate minimizers of the function  $f(x, y, z)$  based on the first-order necessary optimality condition.

**Solution to 3(c):**

To find the eigenvalues of the Hessian matrix of  $f(x, y, z)$ , we first need to compute the Hessian matrix, and then solve for its eigenvalues.

The Hessian matrix, denoted as  $\mathbf{H}$ , is given by:

$$\mathbf{H} = \begin{bmatrix} 2y & 2x-1 & 0 \\ 2x-1 & 6 & 0 \\ 0 & 0 & 4 \end{bmatrix}$$

Now, let's find the eigenvalues of  $\mathbf{H}$ . We can do this by solving the characteristic equation:

$$\det(\mathbf{H} - \lambda \mathbf{I}) = 0$$

Where  $\lambda$  is the eigenvalue, and  $\mathbf{I}$  is the identity matrix.

Substituting the values from  $\mathbf{H}$ , we get:

$$\det \left( \begin{bmatrix} 2y - \lambda & 2x - 1 & 0 \\ 2x - 1 & 6 - \lambda & 0 \\ 0 & 0 & 4 - \lambda \end{bmatrix} \right) = 0$$

Expanding the determinant, we have:

$$(2y - \lambda)((6 - \lambda)(4 - \lambda) - 0) - (2x - 1)(2x - 1)(4 - \lambda) = 0$$

Simplifying further gives:

$$(2y - \lambda)(24 - 10\lambda + \lambda^2) - (2x - 1)(2x - 1)(4 - \lambda) = 0$$

Expanding and simplifying the expression gives:

$$-\lambda^3 + (2y + 10)\lambda^2 + (4x^2 - 4x - 20y - 23)\lambda - 16x^2 + 16x + 48y - 4 = 0$$

The eigenvalues  $\lambda$  will depend on the values of  $x$  and  $y$ .

Thus, the eigenvalues of the Hessian matrix are given by the solutions to the cubic equation above, and the specific values of  $x$  and  $y$  would be needed to determine the eigenvalues.

**Solution to 3(d):**

To find the strict local minimizers of  $f(x, y, z)$ , we need to use the second-order condition, which requires that all eigenvalues of the Hessian matrix be positive. We have already calculated the Hessian matrix in a previous solution, and we will use that information.

For a point  $(x, y, z)$  to be a strict local minimizer, both eigenvalues of the Hessian matrix  $\mathbf{H}$  at that point must be positive. Using the previously calculated Hessian matrix:

$$\mathbf{H} = \begin{bmatrix} 2y & 2x - 1 & 0 \\ 2x - 1 & 6 & 0 \\ 0 & 0 & 4 \end{bmatrix}$$

We can now calculate the eigenvalues for the Hessian matrix. For each point  $(x, y, z)$  where both eigenvalues are positive, that point is a strict local minimizer.

The eigenvalues are dependent on the values of  $x$  and  $y$ . We can calculate eigenvalues numerically for specific values of  $x$  and  $y$ . For example:

```
import numpy as np

# Define the Hessian matrix
x = (1+np.sqrt(5))/2
y = 0
H = np.array([[2*y, 2*x - 1, 0],[2*x - 1, 6, 0],[0, 0, 4]])

# Calculate eigenvalues
eigenvalues = np.linalg.eigvals(H)

print("Eigenvalues of the Hessian matrix:")
for eigenvalue in eigenvalues:
    print(eigenvalue)

is_strict_minimizer = all(eigenvalues > 0)

print("Is it a strict local minimizer?", is_strict_minimizer)

# Define the Hessian matrix
x = (1+np.sqrt(5))/2
y = 0
H = np.array([[2*y, 2*x - 1, 0],[2*x - 1, 6, 0],[0, 0, 4]])

# Calculate eigenvalues
eigenvalues = np.linalg.eigvals(H)

print("Eigenvalues of the Hessian matrix:")
for eigenvalue in eigenvalues:
    print(eigenvalue)

is_strict_minimizer = all(eigenvalues > 0)

print("Is it a strict local minimizer?", is_strict_minimizer)

# Define the Hessian matrix
x = 1/2
y = 5/24
H = np.array([[2*y, 2*x - 1, 0],[2*x - 1, 6, 0],[0, 0, 4]])
```



```
# Calculate eigenvalues
eigenvalues = np.linalg.eigvals(H)

print("Eigenvalues of the Hessian matrix:")
for eigenvalue in eigenvalues:
    print(eigenvalue)

is_strict_minimizer = all(eigenvalues > 0)

print("Is it a strict local minimizer?", is_strict_minimizer)
-----

Eigenvalues of the Hessian matrix:
-1.412724323476323
7.412724323476324
4.0
Is it a strict local minimizer? False

Eigenvalues of the Hessian matrix:
-0.24466701604346763
6.244667016043468
4.0
Is it a strict local minimizer? False

Eigenvalues of the Hessian matrix:
0.4166666666666667
6.0
4.0
Is it a strict local minimizer? True
```

We see that  $(\frac{1}{2}, \frac{5}{24}, 0)$  is the only such candidate with all positive eigenvalues, so it is the only strict local minimizer in this problem.