

Multi-variable Unconstrained Optimization

Lecture Notes in Transportation Systems Engineering

@tvm@iitb

Prof. Tom V. Mathew

@tvm@iitb

Contents

1	Introduction	1
1.1	Notations	2
1.2	Algorithm	2
1.3	Numerical Illustration	3
	Exercises	3
	References	3
	Acknowledgments	4

1 Introduction

The problem is to maximize a function $f(\bar{x})$,

$$\text{Max } f(\bar{x}), \quad \bar{x} = (x_1, x_2, \dots, x_n) \quad (1)$$

The necessary condition for an optimal solution is:

$$\frac{\partial f(\bar{x})}{\partial x_j} \geq 0; \quad j = 1, 2, \dots, n. \quad (2)$$

The sufficient condition is $f(\bar{x})$ is concave.

If we cannot solve this analytically, then we go for numerical solution. In single variable case, we have only one direction of improvement, or one dimensional search. But innumerable directions are possible in the case multi-variable functions.

1.1 Notations

Define the gradient vector as:

$$\nabla f(\bar{x}) = \left(\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \dots, \frac{\partial f}{\partial x_n} \right) \quad (3)$$

The gradient at $\bar{x} = \bar{x}^k$ is the gradient vector evaluated at that point. The geometrical understanding of the gradient vector is the direction of the gradient vector ($\nabla f(\bar{x})$) from the origin to that point $\bar{x}^k$. The rate at which $f(\bar{x})$ increases is maximized if changes in $\bar{x}$ are in the direction of the gradient until it reaches $\bar{x}^*$ where $\nabla f(\bar{x}^*) = 0$; Ideally, $\bar{x}$ need to be incremented in the direction of the gradient until it reaches $\bar{x}^*$ where the $\nabla f(\bar{x}^*) = 0$. It may not be practically possible to move in the direction of $\nabla f(\bar{x})$. The better option is to keep moving in the fixed direction from the current trial solution until $f(\bar{x})$ stops improving. The stopping point will be the next trial solution and the gradient is calculated to determine the new direction. At each iteration:

$$\bar{x}^{k+1} = \bar{x}^k + t \times \nabla f(\bar{x}^k) \quad (4)$$

where t^* is the positive value of the t such that:

$$f(\bar{x} + t^* \nabla f(\bar{x})) = \max_{t \geq 0} [f(\bar{x}' + t \times \nabla f(\bar{x}'))]. \quad (5)$$

1.2 Algorithm

Step 0. Initialize: select the tolerance ϵ , set the iteration number $k = 0$, and select the starting point $\bar{x}^k$

Step 1. Direction: set $\bar{x}^{k+1} = \bar{x}^k + t^k \times \nabla f(\bar{x}^k)$ substitute $\bar{x}^{k+1}$ in $f(\bar{x})$ so that $g(t^k) = f(\bar{x}^k + t^k \times \nabla f(\bar{x}^k))$

Step 2. Optimum search: Use one dimensional search (numerical or analytical) to find t^{k*} that maximizes $g(t^k)$, i.e. $\max_{t^k \geq 0} [f(\bar{x}^k + t^k \times \nabla f(\bar{x}^k))]$.

Step 3. Update: reset $\bar{x}^{k+1} = \bar{x}^k + t^{k*} \times \nabla f(\bar{x}^k)$.

Step 4. Stopping rule: evaluate $\nabla f(\bar{x}^{k+1})$, check if $\left| \frac{\partial f}{\partial x_j} \right| \leq \epsilon, \quad \forall j = 1, 2, \dots, n$, and if so stop, otherwise set $k = k + 1$, and go to step 1.

1.3 Numerical Illustration

Max $f(\bar{x}) = 2x_1x_2 + 2x_2 - x_1^2 - 2x_2^2$. Assume the start point is origin.

Solution:

1. compute $\frac{\partial f}{\partial x_1} = -2x_1 + 2x_2$

@tvm@iitb

@tvm@iitb

2. compute $\frac{\partial f}{\partial x_2} = 2x_1 - 4x_2 + 2$

3. compute $\frac{\partial^2 f}{\partial x_1^2} = -2$

4. compute $\frac{\partial^2 f}{\partial x_2^2} = -4$

5. compute $\frac{\partial^2 f}{\partial x_1 \partial x_2} = 2$

@tvm@iitb

@tvm@iitb

6. Hessian is $\frac{\partial^2 f}{\partial x_1^2} \frac{\partial^2 f}{\partial x_2^2} - 2 \frac{\partial^2 f}{\partial x_1 \partial x_2} = 4$

7. the Hessian is positive definite and hence the function is strictly concave.

8. Step 0: Initial trial solution (given) $\bar{x} = (0, 0)$

@tvm@iitb

@tvm@iitb

9. hence, $\nabla f(\bar{x})|_{(0,0)} = (0, 2)$

10. Step 1: $x_1^1 = x_1^0 + t^0 \times 0 = 0$ and $x_2^1 = x_2^0 + t^0 \times 2 = 2t^0$

11. substitute in $f(\bar{x})$ i.e. $f(0, 2t^0)$ to get $4t^0 - 8t^{0^2}$

12. find t^{0*} by $\max_{t^0 \geq 0} (4t^0 - 8t^{0^2})$

@tvm@iitb

@tvm@iitb

13. i.e. $\frac{df}{dt^0} = 4 - 16t^0 = 0.25$. Hence, $t^{0*} = 0.25$.

14. Step 2: $\bar{x}^1 = (0, 0) + 0.25 \times ($

Exercises

1. Not Available

@tvm@iitb

@tvm@iitb

References

1. Frederick S Hillier and Gerald J Lieberman. *Introduction to Operations Research*. Tata McGraw-Hill Publishers, New Delhi, 2001.

Acknowledgments

I wish to thank several of my students and staff of NPTEL for their contribution in this lecture. I also appreciate your constructive feedback which may be sent to **tvm@civil.iitb.ac.in**

Prof. Tom V. Mathew
Department of Civil Engineering
Indian Institute of Technology Bombay, India

@tvm@iitb

@tvm@iitb

@tvm@iitb

@tvm@iitb

@tvm@iitb

@tvm@iitb

@tvm@iitb

@tvm@iitb

@tvm@iitb