

# Optimasi Tanpa Kendala: Multivariat

Pertemuan ke-5

STA1373- Optimisasi Statistika

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# METODE

**Table 6.1** Unconstrained Minimization Methods

| Direct search methods <sup>a</sup> | Descent methods <sup>b</sup>            |
|------------------------------------|---|
| Random search method               | Steepest descent (Cauchy) method        |
| Grid search method                 | Fletcher–Reeves method                  |
| Univariate method                  | Newton’s method                         |
| Pattern search methods             | Marquardt method                        |
| Powell’s method                    | Quasi-Newton methods                    |
|                                    | Davidon–Fletcher–Powell method          |
|                                    | Broyden–Fletcher–Goldfarb–Shanno method |
| Simplex method                     |   |

<sup>a</sup>Do not require the derivatives of the function.

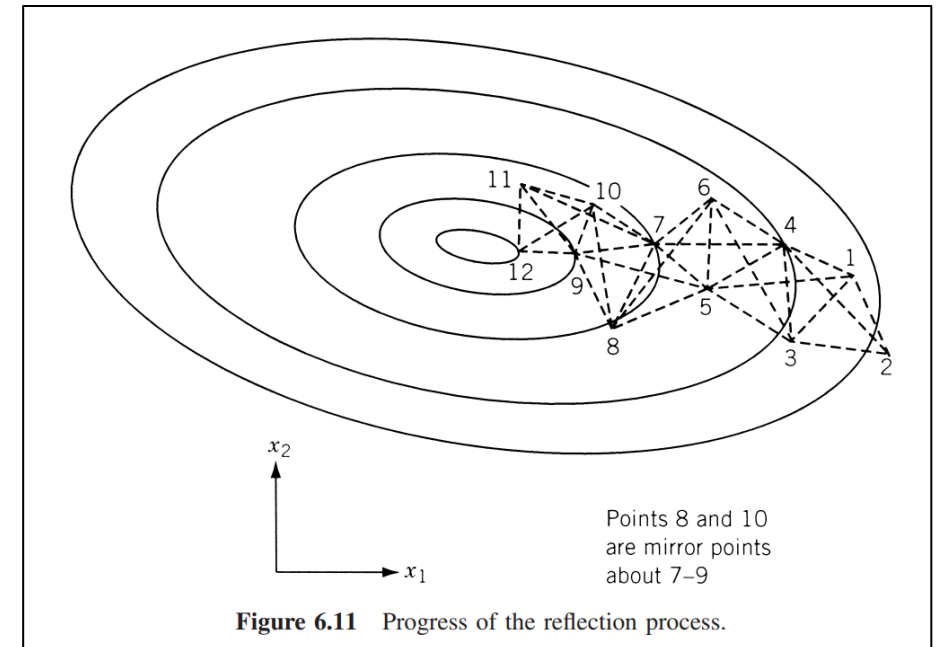
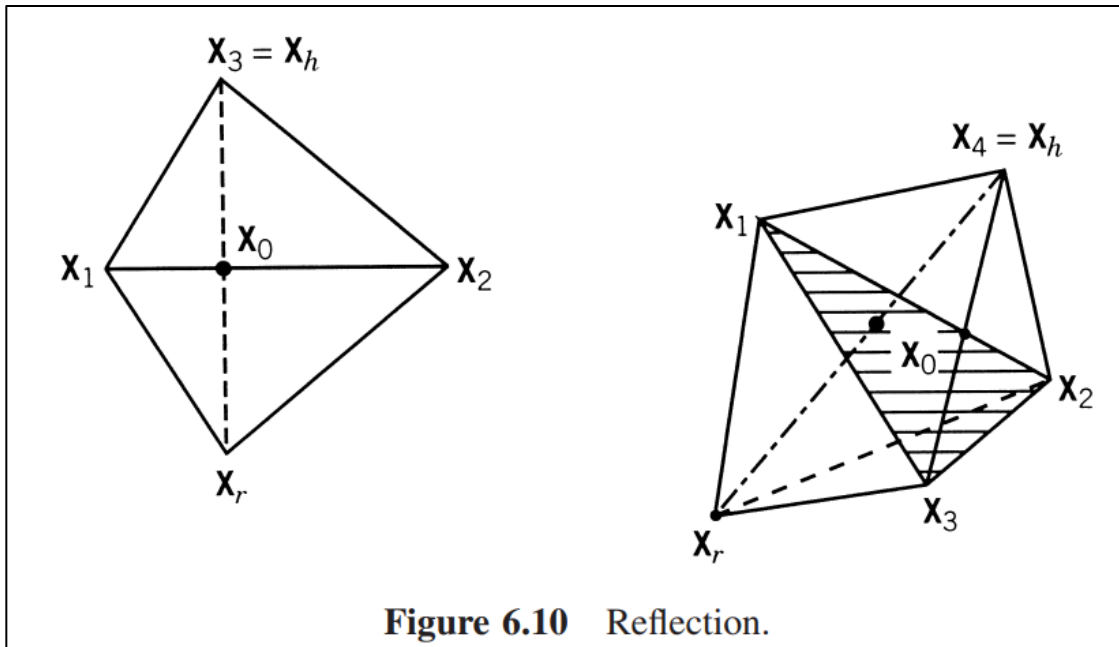
<sup>b</sup>Require the derivatives of the function.

# SIMPLEX METHOD

- This method was originally given by Spendley, Hext, and Himsworth; and was developed later by Nelder and Mead.
- **Definisi Simplex:** The geometric figure formed by a set of  $n + 1$  points in an  $n$ -dimensional space is called a simplex. When the points are equidistant, the simplex is said to be regular. Thus in two dimensions, the simplex is a triangle, and in three dimensions, it is a tetrahedron.
- **Basic idea simplex method:** compare the values of the objective function at the  $n + 1$  vertices of a general simplex and move the simplex gradually toward the optimum point during the iterative process.
- The movement of the simplex is achieved by using three operations, known as **reflection, contraction, and expansion**.

# REFLECTION

- If  $\mathbf{X}_h$  is the vertex corresponding to the highest value of the objective function among the vertices of a simplex, we can expect the point  $\mathbf{X}_r$  obtained by reflecting the point  $\mathbf{X}_h$  in the opposite face to have the smallest value. If this is the case, we can construct a new simplex by rejecting the point  $\mathbf{X}_h$  from the simplex and including the new point  $\mathbf{X}_r$ .



# REFLECTION

- Reflection point:  $\mathbf{X}_r = (1 + \alpha)\mathbf{X}_0 - \alpha\mathbf{X}_h$
- Vertex corresponding to the maximum function value ( $\mathbf{X}_h$ )

$$f(\mathbf{X}_h) = \max_{i=1 \text{ to } n+1} f(\mathbf{X}_i),$$

- Centroid of all the points  $\mathbf{X}_i$  except  $i = h$  ( $\mathbf{X}_0$ ):  $\mathbf{X}_0 = \frac{1}{n} \sum_{\substack{i=1 \\ i \neq h}}^{n+1} \mathbf{X}_i$
- Reflection coefficient ( $\alpha$ ):

$$\alpha = \frac{\text{distance between } \mathbf{X}_r \text{ and } \mathbf{X}_0}{\text{distance between } \mathbf{X}_h \text{ and } \mathbf{X}_0} ; \alpha > 0$$

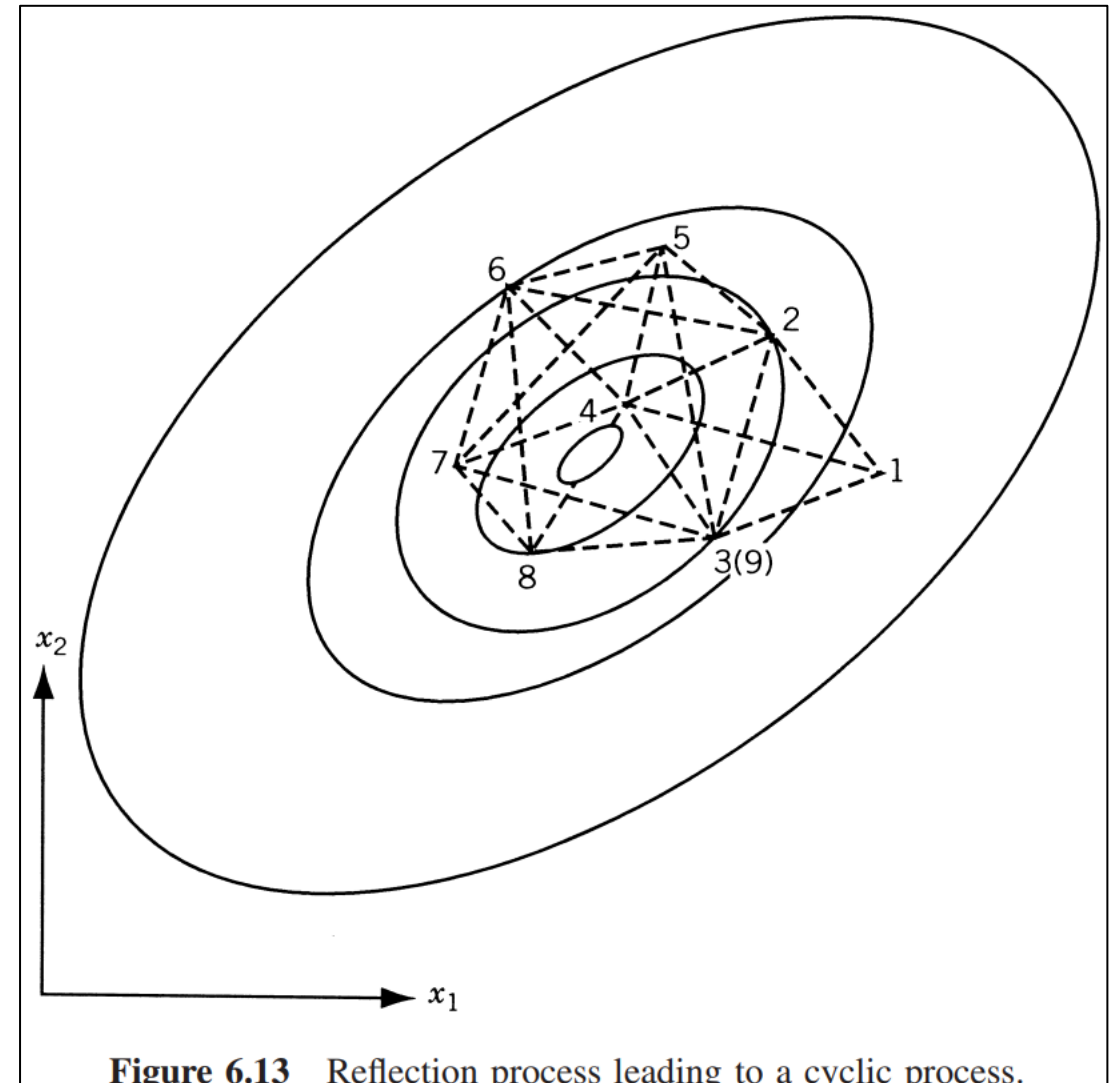
Thus  $\mathbf{X}_r$  will lie on the line joining  $\mathbf{X}_h$  and  $\mathbf{X}_0$ , on the far side of  $\mathbf{X}_0$  from  $\mathbf{X}_h$  with  $|\mathbf{X}_r - \mathbf{X}_0| = \alpha|\mathbf{X}_h - \mathbf{X}_0|$ . If  $f(\mathbf{X}_r)$  lies between  $f(\mathbf{X}_h)$  and  $f(\mathbf{X}_l)$ , where  $\mathbf{X}_l$  is the vertex corresponding to the minimum function value,

$$f(\mathbf{X}_l) = \min_{i=1 \text{ to } n+1} f(\mathbf{X}_i)$$

$\mathbf{X}_h$  is replaced by  $\mathbf{X}_r$  and a new simplex is started.

# REFLECTION

- Certain difficulties:  
if one of the simplexes (triangles in two dimensions) straddles a valley and if the reflected point  $X_r$  happens to have an objective function value equal to that of the point  $X_h$ , we will enter into a closed cycle of operations.



# EXPANSION

- If a reflection process gives a point  $\mathbf{X}_r$  for which  $f(\mathbf{X}_r) < f(\mathbf{X}_l)$ , (i.e., if the reflection produces a new minimum), one can generally expect to decrease the function value further by moving along the direction pointing from  $\mathbf{X}_0$  to  $\mathbf{X}_r$ . Hence we expand  $\mathbf{X}_r$  to  $\mathbf{X}_e$ .

$$\mathbf{X}_e = \gamma \mathbf{X}_r + (1 - \gamma) \mathbf{X}_0$$

- $\gamma$  is expansion coefficient:  $\gamma = \frac{\text{distance between } \mathbf{X}_e \text{ and } \mathbf{X}_0}{\text{distance between } \mathbf{X}_r \text{ and } \mathbf{X}_0} > 1$
- If  $f(\mathbf{X}_e) < f(\mathbf{X}_l)$ , we replace the point  $\mathbf{X}_h$  by  $\mathbf{X}_e$  and restart the process of reflection. On the other hand, if  $f(\mathbf{X}_e) > f(\mathbf{X}_l)$ , it means that the expansion process is not successful and hence we replace point  $\mathbf{X}_h$  by  $\mathbf{X}_r$  and start the reflection process again.

# CONTRACTION

- If the reflection process gives a point  $\mathbf{X}_r$  for which  $f(\mathbf{X}_r) > f(\mathbf{X}_i)$  for all  $i$  except  $i = h$ , and  $f(\mathbf{X}_r) < f(\mathbf{X}_h)$ , we replace point  $\mathbf{X}_h$  by  $\mathbf{X}_r$ . Thus the new  $\mathbf{X}_h$  will be  $\mathbf{X}_r$ . In this case we contract the simplex as follows:

$$\mathbf{X}_c = \beta \mathbf{X}_h + (1 - \beta) \mathbf{X}_0$$

where  $\beta$  is called the contraction coefficient ( $0 \leq \beta \leq 1$ ):

$$\beta = \frac{\text{distance between } \mathbf{X}_e \text{ and } \mathbf{X}_0}{\text{distance between } \mathbf{X}_h \text{ and } \mathbf{X}_0}$$

- If  $f(\mathbf{X}_r) > f(\mathbf{h})$ , we still use Eq. to find  $\mathbf{X}_c$  without changing the previous point  $\mathbf{X}_h$ . If the contraction process produces a point  $\mathbf{X}_c$  for which  $f(\mathbf{X}_c) < \min[f(\mathbf{X}_h), f(\mathbf{X}_r)]$ , we replace the point  $\mathbf{X}_h$  in  $\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_{n+1}$  by  $\mathbf{X}_c$  and proceed with the reflection process again. On the other hand, if  $f(\mathbf{X}_c) \geq \min[f(\mathbf{X}_h), f(\mathbf{X}_r)]$ , the contraction process will be a failure, and in this case we replace all  $\mathbf{X}_i$  by  $(\mathbf{X}_i + \mathbf{X}_l)/2$  and restart the reflection process.



# CONVERGENCY

- The method is assumed to have converged whenever the standard deviation of the function at the  $n + 1$  vertices of the current simplex is smaller than some prescribed small quantity  $\varepsilon$ .

$$Q = \left\{ \sum_{i=1}^{n+1} \frac{[f(\mathbf{X}_i) - f(\mathbf{X}_0)]^2}{n + 1} \right\}^{1/2} \leq \varepsilon$$

# Example

**Example 6.7** Minimize  $f(x_1, x_2) = x_1 - x_2 + 2x_1^2 + 2x_1x_2 + x_2^2$ . Take the points defining the initial simplex as

$$\mathbf{X}_1 = \begin{Bmatrix} 4.0 \\ 4.0 \end{Bmatrix}, \quad \mathbf{X}_2 = \begin{Bmatrix} 5.0 \\ 4.0 \end{Bmatrix}, \quad \text{and} \quad \mathbf{X}_3 = \begin{Bmatrix} 4.0 \\ 5.0 \end{Bmatrix}$$

and  $\alpha = 1.0$ ,  $\beta = 0.5$ , and  $\gamma = 2.0$ . For convergence, take the value of  $\varepsilon$  as 0.2.