

# Lagrange Multipliers

## Lagrange Multipliers

Equality Constraint

Inequality Constraint

Lagrange multipliers, a.k.a. undetermined multipliers, are used to find **the stationary points** of a function of several variables subject to one or more constraints.

## Equality Constraint

Sometime it may be difficult to find a analytic solution of the constraint between variables  $x_i$ . We can introduce a parameter  $\lambda$  called Lagrange multiplier. From a geometrical perspective, consider a  $D$ -dimensional variable  $\mathbf{x} = (x_1, \dots, x_D)^T$ . The constraint equation  $g(\mathbf{x}) = 0$  is a  $(D - 1)$ -dimensional surface in  $\mathbf{x}$ -space.

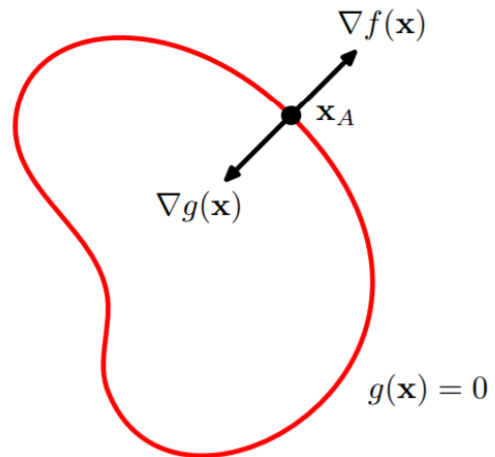
*Lemma-1.* At any point on the surface  $g(\mathbf{x}) = 0$  the gradient  $\nabla g$  will be orthogonal to the surface.

*Proof.* Consider a point  $\mathbf{x}$  on the surface, and consider a nearby point  $\mathbf{x} + \epsilon$  that also on the surface. If we make a Taylor expansion around this point, we have:

$$g(\mathbf{x} + \epsilon) \approx g(\mathbf{x}) + \epsilon^T \nabla g(\mathbf{x}) \quad (1)$$

because  $g(\mathbf{x} + \epsilon) = g(\mathbf{x})$ , we have  $\epsilon^T \nabla g(\mathbf{x}) \approx 0$ . And if  $\|\epsilon\| \rightarrow 0$ , we have  $\epsilon^T \nabla g(\mathbf{x}) = 0$ . And because at this time  $\epsilon$  is parallel to the surface  $g(\mathbf{x}) = 0$ , so  $\nabla g$  is normal to the surface.

A geometrical picture of the technique of Lagrange multipliers in which we seek to maximize a function  $f(\mathbf{x})$ , subject to the constraint  $g(\mathbf{x}) = 0$ . If  $\mathbf{x}$  is  $D$  dimensional, the constraint  $g(\mathbf{x}) = 0$  corresponds to a subspace of dimensionality  $D - 1$ , indicated by the red curve. The problem can be solved by optimizing the Lagrangian function  $L(\mathbf{x}, \lambda) = f(\mathbf{x}) + \lambda g(\mathbf{x})$ .



*Lemma-2.* If  $\mathbf{x}^*$  on  $g(\mathbf{x}) = 0$  and  $\forall \mathbf{x}$  on  $g(\mathbf{x}) = 0$ , we have  $f(\mathbf{x}^*) \geq f(\mathbf{x})$ , then  $\nabla f(\mathbf{x}^*)$  is orthogonal to the surface  $g(\mathbf{x}) = 0$ .

*Proof.* Otherwise we could increase the value of  $f(\mathbf{x})$  by moving a short distance along the surface.

From *Lemma-1* and *Lemma-2* we have:

$$\nabla f + \lambda \nabla g = 0 \quad (2)$$

where  $\lambda \neq 0$  is the Lagrange multiplier.

Then we can define the *Lagrangian* function

$$L(\mathbf{x}, \lambda) := f(\mathbf{x}) + \lambda g(\mathbf{x}) \quad (3)$$

And

$$\begin{aligned} \nabla_{\mathbf{x}} L &= 0 \Rightarrow \nabla f + \lambda \nabla g = 0 \\ \frac{\partial L}{\partial \lambda} &= 0 \Rightarrow g(\mathbf{x}) = 0 \end{aligned}$$

Thus to find the maximum of  $f$  s.t.  $g(\mathbf{x}) = 0$ , we solve the equation

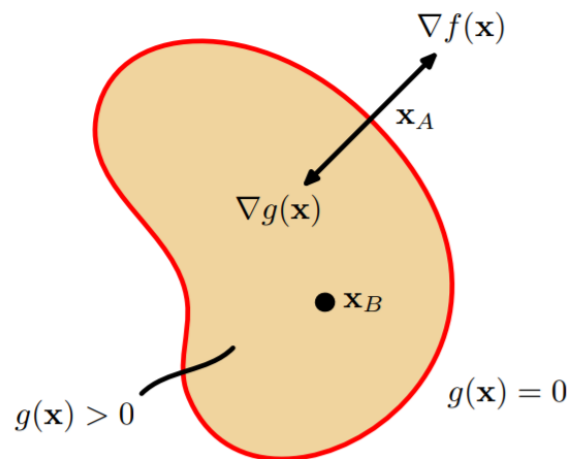
$$\begin{cases} \nabla_{\mathbf{x}} L = 0 & \Rightarrow \nabla f + \lambda \nabla g = 0 \\ \frac{\partial L}{\partial \lambda} = 0 & \Rightarrow g(\mathbf{x}) = 0 \end{cases} \quad (4)$$

and get a  $(D + 1)$ -dimension equations to get stationary points.

## Inequality Constraint

The problem of maximizing  $f$  with inequality constraint of the form  $g(\mathbf{x}) \geq 0$ .

Illustration of the problem of maximizing  $f(\mathbf{x})$  subject to the inequality constraint  $g(\mathbf{x}) \geq 0$ .




There are two kinds of solution possible.

- *inactive* constraint: The stationary point lies in the region  $g(\mathbf{x}) > 0$ . The function  $g(\mathbf{x})$  is useless,  $\lambda = 0$ .
- *active* constraint: The stationary point lies in the surface  $g(\mathbf{x}) = 0$ . This is analogous to the equality constraint case,  $\lambda \neq 0$ .

Note that now the sign of  $\lambda$  is crucial, because  $f$  only be at a maximum if its gradient is oriented away from the region  $g(\mathbf{x}) > 0$  (At this time, the stationary point lies in the surface  $g(\mathbf{x}) = 0$ . So the points in the region must has value less then the stationary point lies in the surface, which means the direction of gradient is oriented away from the region). Therefore  $\lambda > 0$  (if we want a minimum, we set  $\lambda < 0$ ).

For either cases, we have  $\lambda g(\mathbf{x}) = 0$ . Then we can define:

**KKT(Karush-Kuhn-Tucker) conditions**


$$g(\mathbf{x}) \geq 0$$

$$\lambda \geq 0$$

$$\lambda g(\mathbf{x}) = 0$$

And the solution is also straightforward.