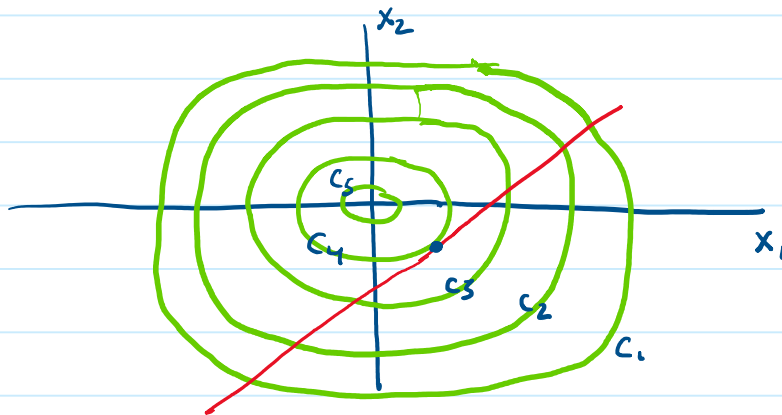


# Lagrange Multipliers

Monday, August 15, 2022 2:52 PM

Problem: we wish to optimize  $f(x)$  subject to the constraint that  $g(x) = 0$ .



— : contours of  $f(\vec{x})$

— :  $g(\vec{x}) = 0$

Note  $\nabla f(\vec{x}_0)$  is the direction of steepest ascent at  $\vec{x}_0$ . we can prove this as follows.

$$\nabla f(\vec{x}) = \begin{bmatrix} \frac{\partial f}{\partial x_1} & \frac{\partial f}{\partial x_2} & \dots & \frac{\partial f}{\partial x_n} \end{bmatrix}^T$$

The rate of change of  $f$  in the direction of  $\vec{v}$

$$\text{is } \begin{bmatrix} v_1 \frac{\partial f}{\partial x_1} & v_2 \frac{\partial f}{\partial x_2} & \dots & v_n \frac{\partial f}{\partial x_n} \end{bmatrix}^T = \nabla f \cdot \vec{v}.$$

$\nabla f \cdot \vec{v} = \|\nabla f\| \|\vec{v}\| \cos(\theta)$  where  $\theta$  is the angle between  $\nabla f$  and  $\vec{v}$ .  $\arg\max_{\theta} \cos \theta = 0$ ,

$$\text{So } \underset{\theta}{\text{argmax}} \nabla f \cdot \vec{v} = 0.$$

So the max rate of change of  $f$  is in the direction  $\nabla f$ .  
end note

We seek to minimize  $f(\vec{x})$  among the points where  $g(\vec{x}) = 0$ .  
 Note that when  $(\nabla f)(\vec{x}_0) \parallel (\nabla g)(\vec{x}_0)$ , moving along the constraint will not change  $f(\vec{x})$ , so we are at a local minimum or maximum. Lagrange multipliers allow us to find these points, which can be tested to determine the global maximum and minimum of  $f$  subject to constraint  $g(\vec{x}) = 0$ .

$(\nabla f)(\vec{x}_0) \parallel (\nabla g)(\vec{x}_0)$  means there is some  $\lambda$  such that  $(\nabla f)(\vec{x}_0) = -\lambda (\nabla g)(\vec{x}_0)$ .

Finding when

$$\nabla f + \lambda \nabla g = 0 \quad \text{for some } \lambda \text{ will yield potential maxima and minima we desire.}$$

The Lagrangian of a constrained optimization problem is defined as  $\mathcal{L}(\vec{x}, \lambda) = f(\vec{x}) + \lambda g(\vec{x})$ .

From above, we see we seek  $\vec{x}^*$  and  $\lambda^*$  such that  $\nabla \mathcal{L}(\vec{x}^*, \lambda^*) = 0$ .

$\lambda^*$  is found using the constraint(s).

Example:  $f(\vec{x}) = \vec{x}^T \vec{x}$   
 $g(\vec{x}) = \vec{x}^T \vec{a} - b = 0$

$$\mathcal{L}(\vec{x}, \lambda) = \vec{x}^T \vec{x} + \lambda (\vec{x}^T \vec{a} - b)$$

$$\nabla \mathcal{L}(\vec{x}, \lambda) = 2\vec{x}^* + \lambda \vec{a} = 0$$

$$\vec{x}^* = -\frac{\lambda \vec{a}}{2}$$

$$\vec{x}^{*T} \vec{a} - b = 0$$

$$-\frac{\lambda \vec{a}^T \vec{a}}{2} - b = 0$$

$$\lambda^* = -\frac{2b}{\vec{a}^T \vec{a}}$$

$$\vec{x}^* = -\frac{b}{\vec{a}^T \vec{a}} \vec{a}$$

$$f(\vec{x}^*) = \frac{b^2}{\vec{a}^T \vec{a}}$$