

Lagrange Multipliers

The method known as "Lagrange Multipliers" is an approach to the general problem of finding the maximum or minimum value of a function $g: \mathbb{R}^n \rightarrow \mathbb{R}$ when the variable is not allowed to range over all of \mathbb{R}^n but is constrained to lie in some subset. The method applies to subsets defined by the vanishing of a differentiable function $f: \mathbb{R}^n \rightarrow \mathbb{R}$. That is, the subset is of the form $\{\vec{x} \in \mathbb{R}^n : f(\vec{x}) = 0\}$.

The idea of the method is nicely illustrated by the case

that $f(x, y) = x^2 + y^2 - 1$, so the subset is the compact set

$\mathcal{C} = \{(x, y) : x^2 + y^2 = 1\}$, and the function g has the form $g(x, y) = Ax^2 + 2Bxy + Cy^2$. The function g of course attains its maximum and minimum

on the circle \mathcal{C} since \mathcal{C} is compact and g is continuous. To locate the

maximum and minimum points, we could note that \mathcal{C} can be traced out as

$$\gamma(t) = (\cos t, \sin t), \quad t \in [0, 2\pi].$$

Then $\frac{d}{dt} g(\gamma(t)) = \text{grad } g|_{(\cos t, \sin t)} \cdot \underbrace{(-\sin t, \cos t)}_{\gamma'(t)}$ by the Chain Rule. We

want this to be 0, since the derivative is 0 at maxima and minima.

Now $(-\sin t, \cos t)$ is perpendicular to $(\cos t, \sin t) = \frac{\mathbf{grad} f}{\|\mathbf{grad} f\|} \neq \vec{0}$. [This is

an aspect of the general idea that a "level curve" of a differentiable function $\mathbb{R}^2 \rightarrow \mathbb{R}$, is perpendicular to the gradient of the function.]

So $\mathbf{grad} g|_{\gamma(t)}$ being perpendicular to $(-\sin t, \cos t)$ is the same as $\mathbf{grad} g|_{\gamma(t)}$

being a multiple of $\mathbf{grad} f|_{\gamma(t)}$. Thus, we should look for (x, y) with

$x^2 + y^2 = 1$ and with $\lambda(x, y) = (2Ax + 2By, 2Bx + 2Cy)$ for some λ . This is

the same as saying that $\begin{pmatrix} A & B \\ B & C \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \frac{\lambda}{2} \begin{pmatrix} x \\ y \end{pmatrix}$

or (x, y) is an eigenvector of $\begin{pmatrix} A & B \\ B & C \end{pmatrix}$.

You can interpret this two ways: Since you know how to find eigenvectors for symmetric matrices, this shows how to solve the max/min problem--or at least to find candidates for the solutions. Looked at the other way around, the fact that g on $\{(x, y) : x^2 + y^2 = 1\}$ has a max and a min implies that eigenvectors exist! This example is very suggestive. The following theorem is what it suggests:

Theorem (Lagrange): If $f, g: U \subset \mathbb{R}^n \rightarrow \mathbb{R}$, where U is open, are continuously differentiable functions, if $f(p)=0$ but $\text{grad } f|_p \neq \vec{0}$, and if

$$g(p) = \sup \{ g(\vec{x}) : \vec{x} \in U \ \& \ f(\vec{x}) = 0 \} \text{ then } \exists \lambda \in \mathbb{R} \ \ni$$

$$\text{grad } g|_p = \lambda \cdot \text{grad } f|_p.$$

[The same holds if $g(p) = \inf \{ g(\vec{x}) : \vec{x} \in U \ \& \ f(\vec{x}) = 0 \}$ by applying the theorem to $-f$][NB: Continuity of $\text{grad } g$ is actually not needed!]

Proof: By translation and rotation of \mathbb{R}^n coordinates and by replacing f by

uf for a suitable $u \in \mathbb{R}, u \neq 0$, we can assume WOLOG that $\vec{p} = \vec{0}$ and

$\text{grad } f|_p = (0, \dots, 0, 1)$. By the Implicit Function Theorem, there is a

differentiable function $F: \mathbb{R}^{n-1} \rightarrow \mathbb{R}$ defined on a neighborhood of $(0, 0, \dots, 0)$

$\in \mathbb{R}^{n-1} \ni f(x_1, x_2, \dots, x_{n-1}, F(x_1, x_2, \dots, x_{n-1})) = 0$. Let

$\gamma_k(t) = (0, \dots, 0, t, 0, \dots, 0, F(0, \dots, 0, t, 0, \dots, 0))$, t in the k^{th} slots. Then

$\frac{d}{dt} f(\gamma_k(t))|_{t=0} = 0$ so $0 = \text{grad } f|_0 \cdot \gamma_k'(t)$. But $\text{grad } f|_0 \cdot \gamma_k'(t) =$ the n^{th}

component of $\gamma_k'(t) = \left(0, \dots, 1, 0, \dots, 0, \frac{\partial F}{\partial x_k} \Big|_{(0, \dots, 0)} \right)$.

Thus $\frac{\partial F}{\partial x_k} \Big|_{(0, \dots, 0)} = 0, \forall k=1, \dots, n-1$.

Next we compute $\left. \frac{d}{dt} g(\gamma_k(t)) \right|_{t=0}$, $k=1, \dots, n-1$. This must be 0 since $g(\vec{0})$

is a maximum for all points in $\{\vec{x} : \vec{x} \in U, f(\vec{x}) = 0\}$ and $f(\gamma_k(t)) = 0, \forall t$.

But $\left. \frac{d}{dt} g(\gamma_k(t)) \right|_{t=0} = \gamma_k'(0) \cdot \text{grad} g|_{\vec{0}}$ = the k^{th} component of $\text{grad} g|_{\vec{0}}$ by the

facts that $\left. \frac{\partial F}{\partial x_k} \right|_{(0, \dots, 0)} = 0$ and that

$\left. \gamma_k'(t) \right|_{t=0} = (0, \dots, 1, 0, \dots, \left. \frac{\partial F}{\partial x_k} \right|_{(0, \dots, 0)}) = (0, \dots, 1, 0, \dots, 0, 0)$. Thus only the n^{th}

component of $\text{grad} g|_{\vec{0}}$ can possibly be nonzero so that $\text{grad} g|_{\vec{0}}$ is a multiple

of $\text{grad} f|_{\vec{0}} = (0, \dots, 0, 1)$ as required. \square

This argument shows, as part of the proof, that the "level set"

$\{\vec{x} : f(\vec{x}) = 0\}$ is, in a neighborhood of $\vec{0}$, actually a "graph" over the

$(x_1, \dots, x_{n-1}, 0)$ coordinate hyperplane. In \mathbb{R}^3 , this would exhibit the level set

as locally a "smooth surface" in the intuitive (and precise, too) sense.

When $n > 3$, the level set is a "smooth hypersurface". This all depends on

$\text{grad} f|_p \neq \vec{0}$.

The intuition here is that if $\text{grad } g|_{\vec{0}}$ were not a multiple of $\text{grad } f|_{\vec{0}}$ then one could move in $\{\vec{x} : f(\vec{x}) = 0\}$ along the "projection" of $\text{grad } g|_{\vec{0}}$ on the (x_1, \dots, x_{n-1}) subspace and in that direction, g would have nonzero derivative, contradicting that g has a maximum on $\{\vec{x} : f(\vec{x}) = 0\}$ at $\vec{0}$. But the Implicit Function Theorem argument is crucial: otherwise one does not know that movement is possible in that direction while still remaining on the level "surface" $\{\vec{x} = (x_1, \dots, x_n) : f(\vec{x}) = 0\}$. If $n=2$ and $f(x, y) = x^2 + y^2$, for example, then $\{\vec{x} : f(\vec{x}) = 0\}$ contains only one point! No movement is possible.

Exercise: Given a symmetric matrix $A=(a_{ij})$ apply Lagrange multipliers to

$$f(\vec{x}) = \|\vec{x}\|^2 - 1 \text{ and } g(\vec{x}) = \sum a_{ij} x_i x_j = \sum_i a_{ii} x_i^2 + 2 \sum_{i < j} a_{ij} x_i x_j \text{ to prove the}$$

existence of an eigenvector of A (namely, $\vec{x} \ni f(\vec{x}) = 0$ and

$$g(\vec{x}_0) = \max \text{ of } g \text{ on } \{\vec{x} : f(\vec{x}) = 0\} \text{ is an eigenvector}).$$