

# 14 local extrema

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We're now going to switch over to <sup>the</sup> optimization half of the course, and get started with some basics.

## Switching to Vol 2 - Optimization

Def. 4.1 If  $J: E \rightarrow \mathbb{R}$  is a real-valued function defined on a normed vector space  $E$ , we say that  $J$  has a **local minimum** (or **relative min**) at the point  $u \in E$  if there is some open subset  $W \subseteq E$  containing  $u$  s.t.  $J(u) \leq J(w) \forall w \in W$ .

Similarly, a **local maximum** at  $u$  if  $J(u) \geq J(w) \forall w \in W$ .

**Local extremum** if either local minimum or maximum.

**Strict** if  $J(u) < J(w)$  for minimum or  $J(u) > J(w)$  for maximum.

Prop. 4.1 Let  $\Omega \subseteq E$  be an open subset. Let  $J: \Omega \rightarrow \mathbb{R}$  be a function. If  $J$  has a local extremum at  $u \in \Omega$ , and if  $J$  is differentiable at  $u$ , then  $dJ_u = J'(u) = 0$ .

$\xrightarrow{\text{notation for total derivative at } u}$

proof. Pick arbitrary  $v \in E$ . Since  $\Omega$  is open, for  $t$  small enough,  $u + tv \in \Omega$ , where  $t \in I \subseteq \mathbb{R}$  an open interval.

Let  $\varphi(t) = J(u + tv)$ , a well defined function  $\varphi: I \rightarrow \mathbb{R}$ .

Then  $\varphi'(0) = dJ_u(v)$  (derivative of  $J$  at  $u$  going in the  $v$  direction)

WLOG, assume  $u$  is a local minimum. Then

$$\varphi'(0) = \lim_{t \rightarrow 0^-} \frac{\varphi(t) - \varphi(0)}{t} \leq 0$$

$\xleftarrow{t \text{ approaching } 0 \text{ from the negative dir.}}$

$$\text{and } \varphi'(0) = \lim_{t \rightarrow 0^+} \frac{\varphi(t) - \varphi(0)}{t} \geq 0.$$

$\xrightarrow{t \text{ approaching } 0 \text{ from the positive direction}}$

$\Rightarrow \varphi'(0) = dJ_u(v) = 0$ . But  $v \in E$  is arbitrary, so  $dJ_u = 0$ . □

Def. 4.2 A pt  $u \in \Omega$  s.t.  $J'(u) = 0$  is called a **critical pt** of  $J$ .

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Aside: If  $E = \mathbb{R}^n$ ,  $dJ_u = 0$  is equivalent to

$$\begin{cases} \frac{\partial J}{\partial x_1}(u_1, \dots, u_n) = 0 \\ \vdots \\ \frac{\partial J}{\partial x_n}(u_1, \dots, u_n) = 0 \end{cases}$$

Def. 4.3 If  $J: \Omega \rightarrow \mathbb{R}$ , where  $\Omega$  is an open subset of a normed vector space  $E$ , and if  $U \subseteq \Omega$  is a subset, we say  $J$  has a **local minimum** (resp. **local maximum**) at the pt  $u \in U$  with respect to  $U$  if  $\exists$  an open subset  $W \subseteq \Omega$  containing  $u$  s.t.

$$\begin{aligned} & J(u) \leq J(w) \\ \text{resp. } & J(u) \geq J(w) \end{aligned} \quad \text{for all } w \in U \cap W.$$

Also called **local extremum** at  $u$  w.r.t.  $U$ .

These are known as **constrained local extrema**. The constraints defining  $U \subseteq \Omega$  are generally defined by a set of either equality or inequality constraints.

(1)  $U = \{x \in \Omega \mid \varphi_i(x) = 0, 1 \leq i \leq m\}$  where  $\varphi_i: \Omega \rightarrow \mathbb{R}$  are continuous (and usually differentiable) **equality constraints**

(2)  $U = \{x \in \Omega \mid \varphi_i(x) \leq 0, 1 \leq i \leq m\}$  where  $\varphi_i: \Omega \rightarrow \mathbb{R}$  are continuous (and usually differentiable) **inequality constraints**

Clearly, can write  $\varphi_i(x) = 0$  as combination of  $\varphi_i(x) \leq 0$ ,  $-\varphi_i(x) \leq 0$ , so the inequality constraints are more general. But they are harder to deal with, so we start our analysis with equality constraints.

Thm 4.1/4.3 (Necessary condition for constrained extremum in terms of Lagrange multipliers)

Let  $\Omega$  be an open subset of  $\mathbb{R}^n$ .

Consider  $m$   $C^1$ -functions  $\varphi_i: \Omega \rightarrow \mathbb{R}$

Let  $U = \{v \in \Omega \mid \varphi_i(v) = 0, 1 \leq i \leq m\}$ .

( $C^1$  means has continuous 1st derivative)

$\downarrow$  linear maps from  $\mathbb{R}^n \rightarrow \mathbb{R}$ .

Let  $u \in U$  be a pt s.t. the derivatives  $d\varphi_i(u) \in \mathcal{L}(\mathbb{R}^n; \mathbb{R})$  are linearly independent.

↳ Equivalently the  $m \times n$  matrix  $\left(\frac{\partial \varphi_i}{\partial x_j}\right)(u)$  has rank  $m$ .

If  $J: \mathcal{N} \rightarrow \mathbb{R}$  is a function which is differentiable at  $u \in U$  and if  $J$  has a local constrained extremum at  $u$ , then  $\exists m$  numbers  $\lambda_i(u) \in \mathbb{R}$ , uniquely defined, s.t.

$$dJ(u) + \lambda_1(u) d\varphi_1(u) + \dots + \lambda_m(u) d\varphi_m(u) = 0.$$

Equivalently

$$\nabla J(u) + \lambda_1(u) \nabla \varphi_1(u) + \dots + \lambda_m(u) \nabla \varphi_m(u) = 0.$$

↑ gradient

(Aside: gradient here is a vector, whereas the total differential is a map  $\mathbb{R}^n \rightarrow \mathbb{R}$ )

proof. Corollary of later theorem, so proof skipped for now.  
Later theorem not restricted to  $\mathbb{R}^n$ .

Def. 4.4 The numbers  $\lambda_i(u)$  are called the **Lagrange multipliers** associated with the constrained extremum  $u$ .

Def. 4.5 The **Lagrangian** associated with our constrained extremum problem is the function  $L: \mathcal{N} \times \mathbb{R}^m \rightarrow \mathbb{R}$  given by

$$L(v, \lambda) = J(v) + \lambda_1 \varphi_1(v) + \dots + \lambda_m \varphi_m(v),$$

with  $\lambda = (\lambda_1, \dots, \lambda_m)$ .

Prop 4.7 There exists some  $\mu = (\mu_1, \dots, \mu_m)$  and some  $u \in U$  s.t.

$$dJ(u) + \mu_1 d\varphi_1(u) + \dots + \mu_m d\varphi_m(u) = 0 \quad \text{iff}$$

$$dL(u, \mu) = 0, \quad (\text{or equivalently } \nabla L(u, \mu) = 0)$$

that is, iff  $(u, \mu)$  is a critical pt of the Lagrangian  $L$ .

proof.  $dL(u, \mu) = 0$   $\frac{\partial L}{\partial v}(u, \mu) = 0$

$\iff$   $\frac{\partial L}{\partial \lambda}(u, \mu) = 0$

prob.  $\mathcal{L}(u, \mu) = 0$

$$\Leftrightarrow \begin{aligned} \frac{\partial \mathcal{L}}{\partial \lambda_1}(u, \mu) &= 0 \\ &\vdots \\ \frac{\partial \mathcal{L}}{\partial \lambda_m}(u, \mu) &= 0 \end{aligned} \quad \text{by definition.}$$

So  $\frac{\partial \mathcal{L}}{\partial v}(u, \mu) = dJ(u) + \mu_1 d\varphi_1(u) + \dots + \mu_m d\varphi_m(u) = 0$

$$\frac{\partial \mathcal{L}}{\partial \lambda_i}(u, \mu) = \varphi_i(u) = 0 \quad \Leftrightarrow u \in U.$$

And of course the proof here goes both ways □

Notational aside:  $dJ(u) + \lambda_1 d\varphi_1(u) + \dots + \lambda_m d\varphi_m(u) = 0$

$\Downarrow$

$$\frac{\partial J}{\partial x_1}(u) + \lambda_1 \frac{\partial \varphi_1}{\partial x_1}(u) + \dots + \lambda_m \frac{\partial \varphi_m}{\partial x_1}(u) = 0$$

$\vdots$

$$\frac{\partial J}{\partial x_n}(u) + \lambda_1 \frac{\partial \varphi_1}{\partial x_n}(u) + \dots + \lambda_m \frac{\partial \varphi_m}{\partial x_n}(u) = 0$$

$\Downarrow$

$$\begin{bmatrix} \frac{\partial J}{\partial x_1}(u) \\ \vdots \\ \frac{\partial J}{\partial x_n}(u) \end{bmatrix} + \begin{bmatrix} \frac{\partial \varphi_1}{\partial x_1}(u) & \dots & \frac{\partial \varphi_m}{\partial x_1}(u) \\ \vdots & \ddots & \vdots \\ \frac{\partial \varphi_1}{\partial x_n}(u) & \dots & \frac{\partial \varphi_m}{\partial x_n}(u) \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \vdots \\ \lambda_m \end{bmatrix} = \vec{0}$$

$\Downarrow$

$$\underbrace{\nabla J(u)}_{\text{(grad)}} + \underbrace{(\text{Jac}(\varphi))^T}_{\text{(Jacobian)}} \vec{\lambda} = \vec{0}$$

Also,  $\mathcal{L}(u, \lambda) = J(u) + (\varphi_1(u), \dots, \varphi_m(u)) \vec{\lambda}$  in vector form.

Also,  $L(u, \lambda) = J(u) + (\varphi_1(u), \dots, \varphi_m(u)) \vec{\lambda}$  in vector form.

The Lagrangian encodes the constraints into the function, so an unconstrained critical pt of  $L$  is needed to have a constrained local extremum of  $J$ .

Note that this is not a sufficient condition.

Ex. 4.1 Let  $J: \mathbb{R}^3 \rightarrow \mathbb{R}$ ,  $J(x, y, z) = x + y + z^2$

and  $g: \mathbb{R}^3 \rightarrow \mathbb{R}$ ,  $g(x, y, z) = x^2 + y^2$ .

Let  $U = \{(x, y, z) \mid g(x, y, z) = 0\} = \{(0, 0, z) \mid z \in \mathbb{R}\}$ .

Clearly,  $J(0, 0, z) = z^2$ , so  $\min_{u \in U} J(u) = 0$ .  $u \in \mathbb{R}^3$

But suppose we use Lagrange multipliers "blindly" and assume an extremum at some  $u = \begin{pmatrix} 0 \\ 0 \\ z \end{pmatrix}$ .

$$dJ(u) + \lambda dg(u) = 0$$

$$\Rightarrow \frac{\partial J}{\partial x}(0, 0, z) = -\lambda \frac{\partial g}{\partial x}(0, 0, z) \quad \text{And} \quad \frac{\partial g}{\partial x}(x, y, z) = 2x$$

$$\frac{\partial J}{\partial y}(0, 0, z) = -\lambda \frac{\partial g}{\partial y}(0, 0, z) \quad \frac{\partial g}{\partial y}(x, y, z) = 2y$$

$$\frac{\partial J}{\partial z}(0, 0, z) = -\lambda \frac{\partial g}{\partial z}(0, 0, z) \quad \frac{\partial g}{\partial z}(x, y, z) = 0$$

$$\Rightarrow \frac{\partial J}{\partial x}(0, 0, z) = -\lambda \cdot 2x = 0 \quad \text{However} \quad \frac{\partial J}{\partial x}(x, y, z) = 1$$

$$\frac{\partial J}{\partial y}(0, 0, z) = -\lambda \cdot 2y = 0 \quad \frac{\partial J}{\partial y}(x, y, z) = 1$$

$$\frac{\partial J}{\partial z}(0, 0, z) = -\lambda \cdot 0 = 0. \quad \frac{\partial J}{\partial z}(x, y, z) = 2z \quad \text{by direct computation.}$$

Thus, we get a contradiction. What went wrong?

$$\text{Also} \quad \left[ \frac{\partial g}{\partial x}(0, 0, z) \quad \frac{\partial g}{\partial y}(0, 0, z) \quad \frac{\partial g}{\partial z}(0, 0, z) \right] = \left[ 0 \quad 0 \quad 0 \right]$$

Thus, we have

$$\text{Note } \left[ \frac{\partial g}{\partial x}(0,0,z) \quad \frac{\partial g}{\partial y}(0,0,z) \quad \frac{\partial g}{\partial z}(0,0,z) \right] = \begin{bmatrix} 0 & 0 & 0 \end{bmatrix}$$

Ex. 4.2 Let  $E_1 = \mathbb{R}$ ,  $E_2 = \mathbb{R}$ ,  $\Omega = \mathbb{R}^2$ , and

$$J(x_1, x_2) = -x_2$$

$$\varphi(x_1, x_2) = x_1^2 + x_2^2 - 1$$

Then  $U = \{(x_1, x_2) \in \mathbb{R}^2 \mid x_1^2 + x_2^2 = 1\}$  is the unit circle.

$$\nabla \varphi(x_1, x_2) = \begin{pmatrix} 2x_1 \\ 2x_2 \end{pmatrix}, \text{ so } \nabla \varphi(x_1, x_2) \neq 0 \quad \forall x_1^2 + x_2^2 = 1.$$

Then the Lagrangian  $L(x_1, x_2, \lambda) = -x_2 + \lambda(x_1^2 + x_2^2 - 1)$ .

If there exists a constrained local extremum, then

$$\nabla L(x_1, x_2, \lambda) = 0 \iff \frac{\partial L}{\partial x_1} = 2\lambda x_1 = 0$$

$$\frac{\partial L}{\partial x_2} = -1 + 2\lambda x_2 = 0$$

$$\frac{\partial L}{\partial \lambda} = x_1^2 + x_2^2 - 1 = 0$$

$$\Rightarrow \lambda \neq 0$$

$$\Rightarrow x_1 = 0$$

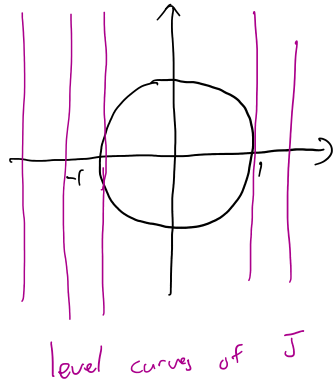
$$\Rightarrow x_2 = \pm 1$$

$$\Rightarrow \lambda = \frac{1}{2}, \quad (x_1, x_2) = (0, 1)$$

$$\text{or } \lambda = -\frac{1}{2}, \quad (x_1, x_2) = (0, -1)$$

Clearly,  $(0, 1)$  is a minimum and  $(0, -1)$  is a maximum for  $J(x_1, x_2) = -x_2$ .

Geometrically,



In order to be a constrained extrema, the constraint must be tangent to a level curve of  $J$ . If not, then we could move infinitesimally along the tangent, and change level curves, increasing or decreasing  $J$ . For this easier to think of the equivalent  $L = J - \lambda \varphi$   
 $\nabla L = 0 \Rightarrow \nabla J = \lambda \nabla \varphi$ .

Ex. 4.3

Let  $J$  be a quadratic function ↙ symmetric

$$J(v) = \frac{1}{2} v^T A v - v^T b, \quad A \in \mathbb{R}^{n \times n}, \quad b \in \mathbb{R}^n$$

with constraints  $Cv = d, \quad C \in \mathbb{R}^{m \times n}, \quad m < n, \quad d \in \mathbb{R}^m, \quad \text{rank}(C) = m.$

Then  $\varphi(v) = (Cv - d)^T$  (viewing  $\varphi(v)$  as a row vector  
 $v$  as a col vector)

$$\Rightarrow d\varphi(v)(w) = C^T w,$$

$$\text{rank}(J(\varphi|_u)) = m.$$

The Lagrangian  $L(v, \lambda) = \frac{1}{2} v^T A v - v^T b + (Cv - d)^T \lambda$   
 $= \frac{1}{2} v^T A v - v^T b + \lambda^T (Cv - d)$

Then the gradient

$$\nabla L(v, \lambda) = \begin{pmatrix} Av - b + C^T \lambda \\ Cv - d \end{pmatrix}$$

Thus, a necessary condition for a constrained local extremum is

$$Av + C^T \lambda = b$$

$$Cv = d$$

$$\Leftrightarrow \begin{pmatrix} A & C^T \\ \hline \end{pmatrix} \begin{pmatrix} v \\ \lambda \end{pmatrix} = \begin{pmatrix} b \\ d \end{pmatrix}$$

Recall  $\frac{\partial(x^T y)}{\partial x} = y$   
 $\frac{df(g, h)}{dx} = \frac{d(g^T)}{dx} \cdot \frac{\partial f(g, h)}{\partial g}$  Chain rule  
 $+ \frac{d(h^T)}{dx} \cdot \frac{\partial f(g, h)}{\partial h}$

$\frac{d(x^T A x)}{dx}$  let  $g(x) = x^T$   
 $h(x) = Ax$   
 $f(g, h) = gh.$   
 $= \frac{dx}{dx} \cdot h + \frac{d(x^T A^T)}{dx} \cdot g^T$   
 $= Ax + A^T x$   
 $= (A + A^T) x$

$$\Leftrightarrow \begin{pmatrix} A & C^T \\ C & 0 \end{pmatrix} \begin{pmatrix} v \\ \lambda \end{pmatrix} = \begin{pmatrix} b \\ d \end{pmatrix}$$

Note that this is a symmetric matrix. Later, we will show that  $J$  has a minimum iff  $A$  is pos. def. (not true for general symmetric  $A$ ).

Thm 4.2/4.2 (Necessary condition for a constrained extremum).

Let  $\Omega \subseteq E_1 \times E_2$  be an open subset of a product of normed vector spaces, with  $E_1$  a Banach space ( $E_1$  is complete), let  $\varphi: \Omega \rightarrow \mathbb{R}$  be a  $C^1$  function (so  $d\varphi(u)$  exists and is continuous for all  $u \in \Omega$ ), and let

$$U = \{(u_1, u_2) \in \Omega \mid \varphi(u_1, u_2) = 0\}.$$

Let  $u = (u_1, u_2) \in U$  be a point s.t.

$$\frac{\partial \varphi}{\partial x_2}(u_1, u_2) \in \mathcal{L}(E_2; \mathbb{R}) \quad \text{and} \quad \left( \frac{\partial \varphi}{\partial x_2}(u_1, u_2) \right)^{-1} \in \mathcal{L}(E_2; E_2),$$

and let  $J: \Omega \rightarrow \mathbb{R}$  be a function which is differentiable at  $u$ .

If  $J$  has a constrained local extremum at  $u$ , then there is a continuous linear form  $\Lambda(u) \in \mathcal{L}(E_2; \mathbb{R})$  s.t.

$$dJ(u) + \Lambda(u) \circ d\varphi(u) = 0.$$

Thm 3.3/3.14

proof. We will use the Implicit Function Thm, which shows that  $\exists$  open subsets  $U_1 \subseteq E_1$ ,  $U_2 \subseteq E_2$  and a continuous function

$g: U_1 \rightarrow U_2$  with  $(u_1, u_2) \in U_1 \times U_2 \subseteq U$  and such that

$$\varphi(v_1, g(v_1)) = 0. \quad \forall v_1 \in U_1.$$

Moreover,  $g$  is differentiable at  $u_1 \in U_1$ , and

$$dg(u_1) = - \left( \frac{\partial \varphi}{\partial x_2}(u) \right)^{-1} \circ \frac{\partial \varphi}{\partial x_1}(u)$$

Then the restriction of  $J$  to  $(U_1 \times U_2) \cap U$  yields a function  $G$



Then the restriction of  $J$  to  $(u_1 \times u_2) \cap U$  yields a function  $G$  of a single variable, with  $G(v_1) = J(u, g(v_1)) \quad \forall v_1 \in U_1$ .

$G$  is differentiable at  $u_1$  and has a local extremum at  $u_1$  on  $U_1$ , so  $dG(u_1) = 0$ .

By the chain rule,

$$\begin{aligned} dG(u_1) &= \frac{\partial J}{\partial x_1}(u) + \frac{\partial J}{\partial x_2}(u) \circ dg(u_1) \\ &= \frac{\partial J}{\partial x_1}(u) - \frac{\partial J}{\partial x_2}(u) \circ \left( \frac{\partial \varphi}{\partial x_2}(u) \right)^{-1} \circ \frac{\partial \varphi}{\partial x_1}(u) = 0 \end{aligned}$$

$$\Rightarrow \frac{\partial J}{\partial x_1}(u) = \frac{\partial J}{\partial x_2}(u) \circ \left( \frac{\partial \varphi}{\partial x_2}(u) \right)^{-1} \circ \frac{\partial \varphi}{\partial x_1}(u).$$

$$\text{Let } \Lambda(u) = - \frac{\partial J}{\partial x_2}(u) \circ \left( \frac{\partial \varphi}{\partial x_2}(u) \right)^{-1}.$$

$$\begin{aligned} \text{Then } dJ(u) &= \frac{\partial J}{\partial x_1}(u) + \frac{\partial J}{\partial x_2}(u) \\ &= \frac{\partial J}{\partial x_2}(u) \circ \left( \frac{\partial \varphi}{\partial x_2}(u) \right)^{-1} \circ \left( \frac{\partial \varphi}{\partial x_1}(u) + \frac{\partial \varphi}{\partial x_2}(u) \right) \\ &= -\Lambda(u) \circ d\varphi(u). \end{aligned}$$

$$\Rightarrow dJ(u) + \Lambda(u) \circ d\varphi(u) = 0.$$



Corollary: (proof of Thm 4.1/4.2)

Linear independence of  $m$  linear forms  $d\varphi_i(u)$

. . . ( . . . ) . . .

Linear independence of  $m$  linear forms  $d\varphi_i(u)$

$\Leftrightarrow$   $m \times n$  matrix  $A = \left( (\partial \varphi_i / \partial x_j)(u) \right)$  has rank  $m$ .

WLOG, can assume 1st  $m$  cols of  $A$  are lin. ind.

Let  $\varphi: \Omega \rightarrow \mathbb{R}^m$  be  $\varphi(v) = (\varphi_1(v) \dots \varphi_m(v))$ .

Then  $\frac{\partial \varphi}{\partial x_i}(u)$  is invertible and  $\frac{\partial \varphi}{\partial x_i}(u)$ ,  $\left(\frac{\partial \varphi}{\partial x_i}(u)\right)^{-1}$  are continuous,

so the last Thm applies

$\Rightarrow \exists$  continuous linear form  $\Lambda(u) \in \mathcal{L}(\mathbb{R}^m; \mathbb{R})$  s.t.

$$dJ(u) + \Lambda(u) \circ d\varphi(u) = 0$$

But  $\Lambda(u)$  is defined by a tuple  $(\lambda_1(u) \dots \lambda_m(u)) \in \mathbb{R}^m$ , so

$$\Rightarrow dJ(u) + \lambda_1(u) d\varphi_1(u) + \dots + \lambda_m(u) d\varphi_m(u) = 0$$

Uniqueness of  $\lambda_i(u)$ 's comes from linear ind. of  $d\varphi_i(u)$ 's. 

Next time we will see how to use second derivatives and convexity to find extrema.