

Proposition 3.1.1 (Lagrange Multiplier Theorem - Necessary Conditions) ^{NEP}

Let x^* be a local minimum of 'f' subject to $h(x)=0$, and assume that the constraint gradients $\nabla h_1(x^*), \dots, \nabla h_m(x^*)$ are linearly independent. Then there exists a unique vector $\lambda^* = (\lambda_1^*, \dots, \lambda_m^*)$ called **Lagrange multiplier vector**, such that

$$\nabla F(x^*) + \sum_{i=1}^m \lambda_i^* \nabla h_i(x^*) = 0$$

$$\begin{array}{l} \text{min } f(x) \\ \text{s.t. } h_1(x)=0 \\ \quad h_2(x)=0 \\ \quad \vdots \\ \quad h_m(x)=0 \end{array}$$

If in addition f and h are twice continuously

differentiable, we have

$$\mathcal{L}(x, \lambda) = F(x) + \lambda_1 h_1(x) + \lambda_2 h_2(x) + \dots + \lambda_m h_m(x)$$

$$y^T \left(\nabla^2 F(x^*) + \sum_{i=1}^m \lambda_i^* \nabla^2 h_i(x^*) \right) y \geq 0 \quad \forall y \in V(x^*)$$

where $V(x^*)$ is the subspace of the first order variations

$$V(x^*) = \{ y \mid \nabla h_i(x^*)^T y = 0, \quad i=1, \dots, m \}$$

$$\begin{array}{l} z^T \nabla^2 F(x^*) z \\ \text{is s.p.d. (semidefinite)} \\ A z = b \\ m \times n \end{array}$$

$$A = \begin{bmatrix} \nabla h_1(x^*)^T \\ \vdots \\ \nabla h_m(x^*)^T \end{bmatrix} \stackrel{z}{=} \begin{array}{l} a_1^T x = b_1 \\ a_2^T x = b_2 \\ \vdots \\ a_m^T x = b_m \end{array}$$

these are linearly independent
AT matrix has rank m .
 $n \times m$
all the columns of A^T are l.i.

$$\begin{array}{l} h_1(x) = a_1^T x - b_1 = 0 \\ h_2(x) = a_2^T x - b_2 = 0 \\ \vdots \\ h_m(x) = a_m^T x - b_m = 0 \end{array}$$

$$\left. \begin{array}{l} \nabla h_1(x) = a_1 \\ \nabla h_2(x) = a_2 \\ \vdots \\ \nabla h_m(x) = a_m \end{array} \right\}$$

regularity condition.

$$\begin{bmatrix} \nabla h_1(x), \nabla h_2(x), \dots, \nabla h_m(x) \end{bmatrix}_{n \times m}$$

rank of above matrix is not m , then:

Lagrange multiplier theorem is not applicable and we need to check optimality from a bottom up approach.

$$\begin{aligned} \min & f(x) \\ & h(x) = 0 \quad m\text{-eqns} \\ L(x, \lambda) = & f(x) + \sum_{i=1}^m \lambda_i h_i(x) \quad \text{is a function in } n+m \text{ variables} \end{aligned}$$

$$\left. \begin{aligned} \nabla_x L(x^*, \lambda^*) &= 0; \\ \nabla_\lambda L(x^*, \lambda^*) &= 0; \end{aligned} \right\} \text{optimal is the stationary point of the Lagrangian function.}$$

$$\frac{\partial L}{\partial x_1} = 0 \Rightarrow \frac{\partial f}{\partial x_1} \Big|_{x^*} + \sum_{i=1}^m \lambda_i^* \frac{\partial h_i}{\partial x_1} = 0$$

$$\vdots$$

$$\frac{\partial L}{\partial x_n} = 0 \Rightarrow \frac{\partial f}{\partial x_n} \Big|_{x^*} + \sum_{i=1}^m \lambda_i^* \frac{\partial h_i}{\partial x_n} = 0$$

$$\nabla f(x^*) + \sum_{i=1}^m \lambda_i^* \nabla h_i(x^*) = 0$$

$$\left. \begin{aligned} \frac{\partial L}{\partial x_1} = 0 &\Rightarrow h_1(x^*) = 0; \\ \frac{\partial L}{\partial x_2} = 0 &\Rightarrow h_2(x^*) = 0; \\ \vdots \\ \frac{\partial L}{\partial x_m} = 0 &\Rightarrow h_m(x^*) = 0 \end{aligned} \right\} x^* \text{ the optimal should be a feasible point.}$$

$$L(x, \lambda^*) = f(x) + \lambda_1^* h_1(x) + \lambda_2^* h_2(x) + \dots + \lambda_m^* h_m(x)$$

$$\frac{\partial^2 L}{\partial x_i \partial x_j} = \nabla^2 f(x) + \sum_{i=1}^m \lambda_i^* \nabla^2 h_i(x) \quad i, j = 1, \dots, m$$

$$\nabla^2 f(x) = \underbrace{\left[\frac{\partial^2 f}{\partial x_i \partial x_j} \right]}_{n \times n} \quad \nabla^2 h_i(x) = \underbrace{\left[\frac{\partial^2 h_i}{\partial x_i \partial x_j} \right]}_{n \times n}$$

curvature information.

$$\begin{aligned} \min \quad & x_1 + x_2 \\ \text{sub} \quad & x_1^2 + x_2^2 = 2 \end{aligned}$$

$$x_1 + x_2 = 0$$

$$x_1 = -x_2$$

$$x_1^2 + x_2^2 = 2$$

Circle $(0,0)$, and radius $\sqrt{2}$.

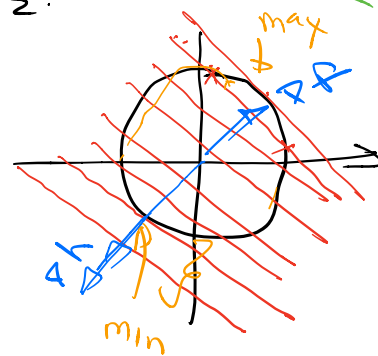
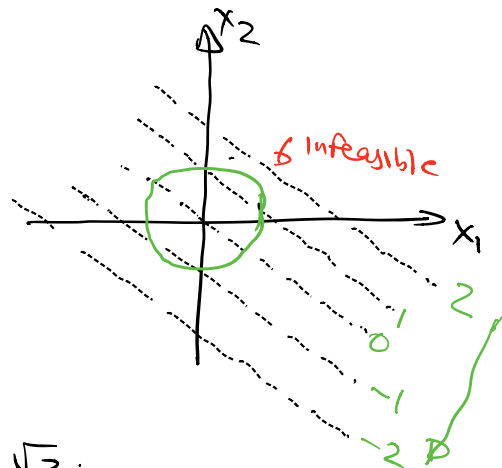
$$x^* = (-1, -1)$$

$$\nabla f(x^*) = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$\nabla h(x) = \begin{bmatrix} 2x_1 \\ 2x_2 \end{bmatrix}$$

$$\nabla h(x^*) = \begin{bmatrix} -2 \\ -2 \end{bmatrix}$$

$$\begin{bmatrix} 1 \\ 1 \end{bmatrix} + \frac{1}{2} \begin{bmatrix} -2 \\ -2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$



$$\nabla f(x^*) + \lambda \nabla h(x^*) = 0$$

$$\lambda = +\frac{1}{2}$$

Ex 3.1.1 [Bertsekas] [To illustrate, problem if regularity condition is not satisfied]

$$f(x) = x_1 + x_2$$

$$s.t. \quad h_1(x) = (x_1 - 1)^2 + x_2^2 - 1 = 0$$

$$h_2(x) = (x_1 - 2)^2 + x_2^2 - 4 = 0$$

$$(x_1 - 1)^2 + (x_2 - 0)^2 = 1^2$$

$$(x_1 - 2)^2 + (x_2 - 0)^2 = 2^2$$

Q) Does this problem have a optimal?

$$x^* = (0, 0)$$

There is only feasible point $(0, 0)$

$$\nabla h_1(x^*) = 2 \begin{bmatrix} x_1^* - 1 \\ x_2^* \end{bmatrix} = 2 \begin{bmatrix} -1 \\ 0 \end{bmatrix}$$

$$\nabla h_2(x^*) = 2 \begin{bmatrix} x_1^* - 2 \\ x_2^* \end{bmatrix} = 4 \begin{bmatrix} -1 \\ 0 \end{bmatrix}$$

Q) $\nabla h_1(x^*)$ and $\nabla h_2(x^*)$ are l.i.p

A) No!

$$2 \nabla h_1(x^*) - \nabla h_2(x^*) = 0;$$

