

Sufficiency theorem

Theorem

If:

- i) the feasible region S for (NLP) is compact
- ii) CQ holds throughout the feasible region
- iii) \bar{x} is the unique feasible solution to the KKT conditions

then

\bar{x} is the global minimum of f over S .

Proof

f over S is compact, so f achieves its bounds over S . (Weierstrass Thm)

Therefore, \exists global minimum \hat{x} of f over S .

CQ holds at \hat{x} .

\therefore the KKT conditions hold at \hat{x} .

$\therefore \hat{x} = \bar{x}$, i.e. \bar{x} is the global minimum of f over S //

Notes:

If \bar{x} strictly ~~feasible~~ ^{feasible}, and \bar{x} is a local minimum ~~and~~ and $C \in \mathbb{R}^n$ satisfied at \bar{x} then KKT conditions become $\nabla f(\bar{x}) = 0$

KKT condns for LP:

Consider

$$\begin{aligned} \max \quad & c^T x \\ \text{s.t.} \quad & Ax = b \\ & x \geq 0 \end{aligned}$$

Then $h_i(x) = b_i - \sum a_{ij} x_j$ $g_i(x) = -x_i$ $f(x) = c^T x$

So

$$\nabla f(x) = c$$

$$\nabla g_i(x) = -e_i \quad \text{the } i\text{th unit vector}$$

$$\nabla h_i(x) = -a_{ij} \quad \text{the } i\text{th row of } A$$

So KKT:

$\exists u, v$ st

$$c - \sum u_i e_i - \sum v_j a_{ij} = 0$$

$$\begin{aligned} u_i x_i &= 0 & \forall i \\ v_i &\geq 0 \end{aligned}$$

$c \exists u, v$ s.t.

$$c - u - A^T v = 0$$

$$\begin{aligned} x_i u_i &= 0 \\ u &\geq 0. \end{aligned}$$

ie $\exists u, v$ s.t.

$$A^T v \leq c$$

Dual feasibility

$$x^T (c - A^T v) = 0$$

Complementary slackness.

Notice that (CQ) :

feasible directions at \bar{x} are

$$\{d: Ad=0, d_i \geq 0 \text{ if } x_i=0\} = T.$$

Also,

$$\begin{aligned} H_0 \cap G' &= \{d: \nabla h_i(\bar{x})^T d = 0, \nabla g_i(\bar{x})^T d \leq 0 \text{ } i \in I\} \\ &= \{d: Ad=0, -d_i \leq 0 \text{ } i \in I\} \end{aligned}$$

So $T = H_0 \cap G'$.

conv if (NLP) is linearly constrained,
CQ holds throughout feasible region.

KKT Sufficient Conditions (Ineq constraints)

$$\begin{aligned} \text{min} & f(x) \\ \text{s.t.} & g_i(x) \leq 0 \quad i=1, \dots, m \end{aligned} \quad (\text{NLP})$$

Let f, g_i be convex. If \bar{x} is feasible and if $\exists \bar{u} \geq 0$ s.t.

$$\nabla f(\bar{x}) + \sum_{i=1}^m \bar{u}_i \nabla g_i(\bar{x}) = 0 \quad \text{and} \quad \bar{u}_i g_i(\bar{x}) = 0 \quad \forall i$$

then \bar{x} is a minimizing point.

Proof For any feasible x ,

$$\begin{aligned} f(x) - f(\bar{x}) &\geq \nabla f(\bar{x})^T (x - \bar{x}) && \text{Support inequality} \\ &= -\sum_{i=1}^m \bar{u}_i [\nabla g_i(\bar{x})^T (x - \bar{x})] \\ &\geq -\sum_{i=1}^m \bar{u}_i [g_i(x) - g_i(\bar{x})] \\ &= -\sum_{i=1}^m \bar{u}_i g_i(x) \\ &\geq 0 \quad \text{since } \bar{u}_i \geq 0, g_i(x) \leq 0. \end{aligned}$$



KKT Sufficient conditions (Eq constraints)

$$\min f(x)$$

$$\begin{aligned} g_i(x) &\leq 0 & i=1, \dots, m \\ h_j(x) &= 0 & j=1, \dots, p \end{aligned}$$

Let \bar{x} be feasible and assume $\exists \bar{u}, \bar{v}$ s.t.

$$\nabla f(\bar{x}) + \sum_{i=1}^m \bar{u}_i \nabla g_i(\bar{x}) + \sum_{j=1}^p \bar{v}_j \nabla h_j(\bar{x}) = 0$$

and $u_i g_i(\bar{x}) = 0, u_i \geq 0 \quad \forall i$

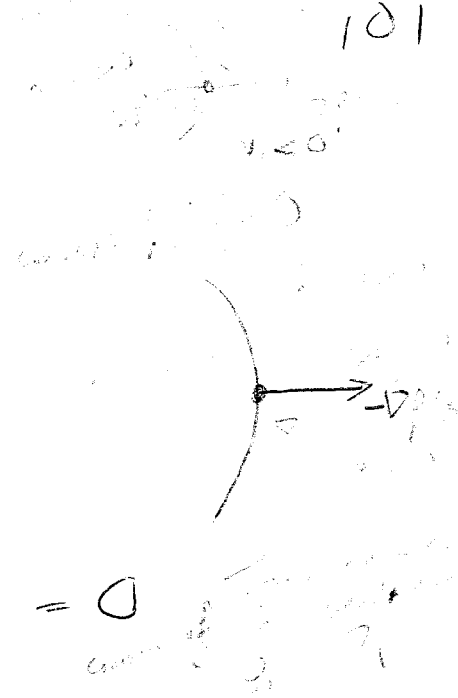
Further, assume: f, g_i are convex, $\bar{v}_j > 0 \Rightarrow h_j(\bar{x})$ convex (Let $J = \{j: \bar{v}_j > 0\}$)
 $\bar{v}_j < 0 \Rightarrow h_j(\bar{x})$ concave (Let $K = \{j: \bar{v}_j < 0\}$)

Then \bar{x} is a ~~local~~ minimizing point.

Proof ^{Let x be feasible} Then $f(x) - f(\bar{x}) \geq \nabla f(\bar{x})^T (x - \bar{x})$

$$\begin{aligned} &= - \left[\sum_{i=1}^m \bar{u}_i \nabla g_i(\bar{x})^T (x - \bar{x}) + \sum_{j \in J} \bar{v}_j \nabla h_j(\bar{x})^T (x - \bar{x}) \right] \\ &\geq - \left[\sum_{i=1}^m \bar{u}_i \{g_i(x) - g_i(\bar{x})\} + \sum_{j \in J} \bar{v}_j (h_j(x) - h_j(\bar{x})) \right. \\ &\quad \left. + \sum_{j \in K} \bar{v}_j (h_j(\bar{x}) - h_j(x)) \right] \\ &= - \sum_{i=1}^m \bar{u}_i g_i(x) \geq 0. \quad (h_j(x) - h_j(\bar{x}) = 0) \end{aligned}$$

NB: can relax to: level sets are convex/concave.

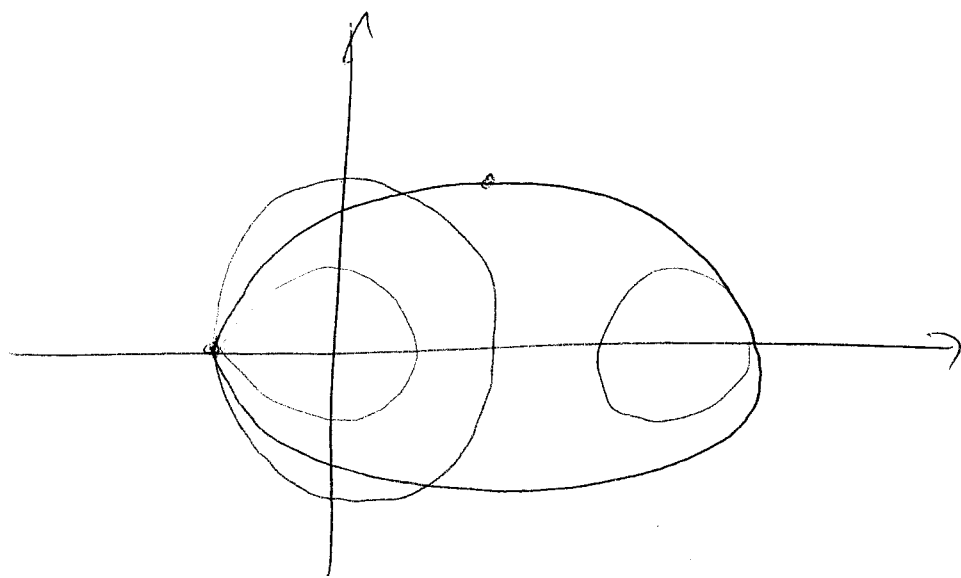


Necessity of condition on equality constraints:

$$\max x_1^2 + x_2^2$$

(0/a.

$$\text{s.t. } (x_1 - 1)^2 + 4x_2^2 = 4$$



$$\nabla h = \begin{bmatrix} 2(x_1 - 1) \\ 8x_2 \end{bmatrix} \quad \nabla f = \begin{bmatrix} 2x_1 \\ 2x_2 \end{bmatrix}$$

At $(-1, 0)$: multiplier is $-\frac{1}{2}$.

It is convex and I nearby better points.