

We have so far seen:

$$\left\{ \begin{array}{l} \text{minimize } f(x) \\ \text{s.t. } x \in \mathbb{R}^n \\ h_1(x) = 0 \\ \vdots \\ h_m(x) = 0 \end{array} \right.$$

Now we will consider inequality constraints:

$$\left\{ \begin{array}{l} \text{minimize } f(x) \\ \text{s.t. } g_1(x) \leq 0 \\ \vdots \\ g_m(x) \leq 0 \end{array} \right.$$

How do we solve this type of a problem?

K-K-T conditions. Karush - Kuhn - Tucker

Master's thesis 1939

Nonlinear programming

Proceedings of the 2nd Berkeley Symposium

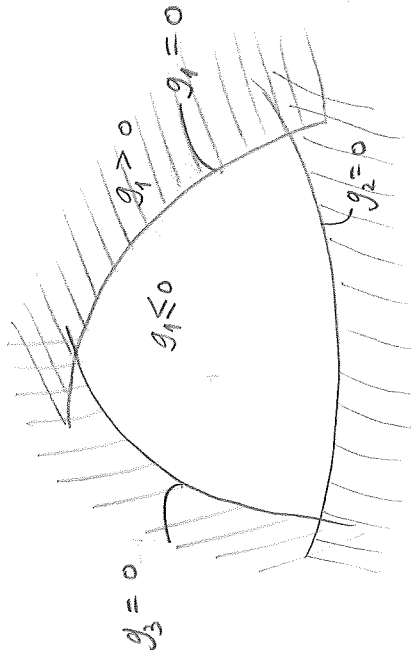
Minima of Functions of Several Variables with Inequalities as Side Constraints.

Univ. of Chicago

A mechanical analogue

Imagine a potential in \mathbb{R}^2 given by f .

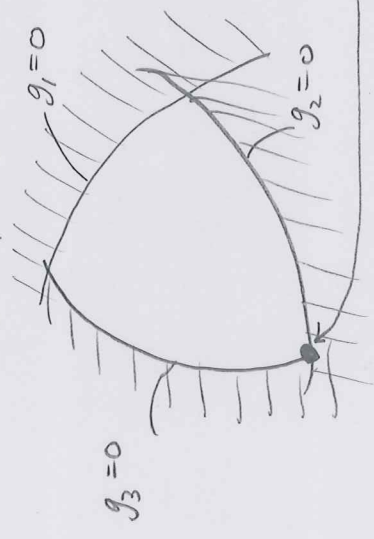
Suppose a particle is confined by walls described by $g_1(x) > 0$
 \vdots
 $g_m(x) > 0$.



Particle tries to minimize the potential energy.

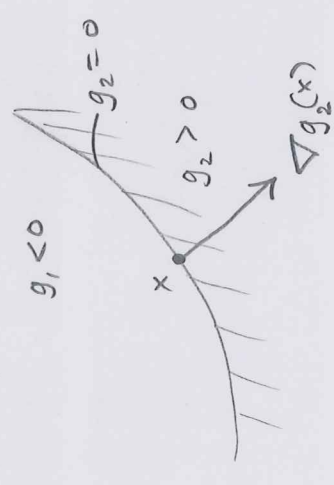
So the particle tries to solve

$$\left\{ \begin{array}{l} \text{minimize } f(x) \\ \text{s.t. } g_1(x) \leq 0 \\ \vdots \\ g_m(x) \leq 0 \end{array} \right.$$



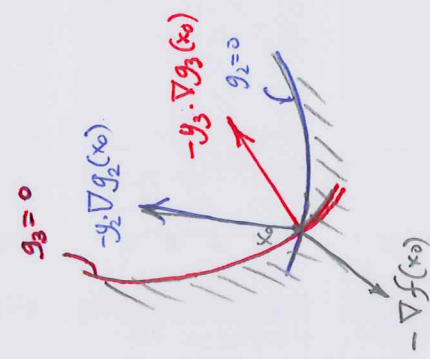
Suppose the particle comes to rest here.

The force on the particle is $-\nabla f(x_0)$ and this must be balanced by the normal forces from the walls.



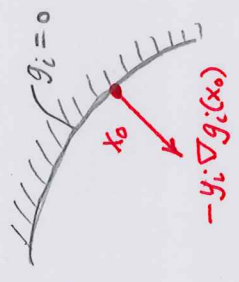
So normal force on the particle is $-y \cdot \nabla g_2(x)$ with $y > 0$.
 "Active" walls are wall 2 and wall 3, so we get

$$-\nabla f(x_0) - y_2 \nabla g_2(x_0) - y_3 \nabla g_3(x_0) = 0 \quad (\text{Balance of forces})$$



Two possible cases:

Particle is touching the i th wall



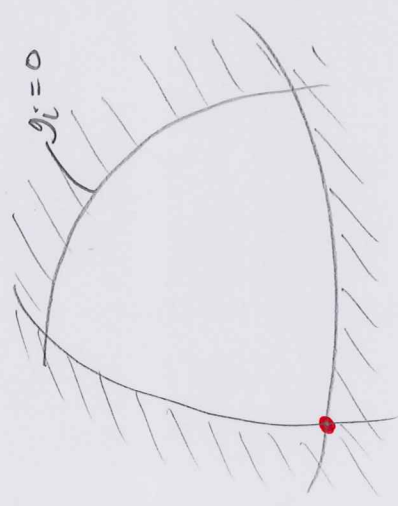
Normal force on particle from wall

$$y_i g_i(x_0)$$

$$\begin{aligned} & y_i \cdot \underbrace{g_i(x_0)}_{=0} \\ &= y_i \cdot 0 \\ &= 0 \end{aligned}$$

$$\begin{aligned} & -y_i \nabla g_i(x_0) \\ & \text{for some } y_i \geq 0 \end{aligned}$$

Particle is not touching the i th wall



$$\begin{aligned} 0 &= -y_i \nabla g_i(x_0) \\ & \text{with } y_i = 0 \end{aligned}$$

$$\begin{aligned} & \underbrace{y_i \cdot g_i(x_0)}_{=0} \\ &= 0 \cdot \boxed{*} \\ &= 0 \end{aligned}$$

So we arrive at the following KKT - conditions:

The optimal x_0 is s.t. $\exists y_1, \dots, y_m$ s.t.

$$(KKT-1) \quad \nabla f(x_0) + y_1 \nabla g_1(x_0) + \dots + y_m \nabla g_m(x_0) = 0 \quad (\text{Force balance.})$$

$$(KKT-2) \quad \left. \begin{array}{l} g_1(x_0) \leq 0 \\ \vdots \\ g_m(x_0) \leq 0 \end{array} \right\} \quad (\text{Particle is within the region enclosed by the walls.})$$

$$(KKT-3) \quad \left. \begin{array}{l} y_1 \geq 0 \\ \vdots \\ y_m \geq 0 \end{array} \right\} \quad (\text{The walls exert normal forces.})$$

$$(KKT-4) \quad \left. \begin{array}{l} y_1 g_1(x_0) = 0 \\ \vdots \\ y_m g_m(x_0) = 0 \end{array} \right\} \quad (\text{Only those walls which the particle touches can exert nontrivial normal forces.})$$

Theorem (Necessity of K-K-T conditions)

Consider the problem (P):
$$\begin{cases} \text{minimize} & f(x) \\ \text{s.t.} & g_1(x) \leq 0 \\ & \vdots \\ & g_m(x) \leq 0 \end{cases}$$

If x_0 is a local minimizer for (P) and x_0 is a "regular" point,

then $\exists y \in \mathbb{R}^m$ s.t.

(KKT-1) $\nabla f(x_0) + y_1 \nabla g_1(x_0) + \dots + y_m \nabla g_m(x_0) = 0$

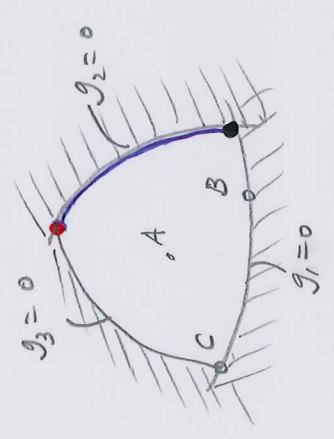
(KKT-2) $g_i(x_0) \leq 0, \quad i=1, \dots, m$

(KKT-3) $y_i \geq 0, \quad i=1, \dots, m$

(KKT-4) $y_i g_i(x_0) = 0, \quad i=1, \dots, m$

What does regular mean here?

"Active" index set of a feasible point: Given $x \in \mathcal{F}_a$, this is the set of i s.t. $g_i(x) = 0$.



Example:

For point A, $I_a(A) = \emptyset$

For point B, $I_a(B) = \{1\}$

For point C, $I_a(C) = \{1, 3\}$

This is useful to keep track of where the point is in the feasible set.

Example: If $I_a(x) = \{2, 3\}$, we know the point x is the red dot shown in the figure above.

If $I_a(x) = \{2\}$, we know the point x is on the blue wall

shown above, but is not the red dot or the black dot.

How to find out if a point $x_0 \in \mathcal{B}$ is regular?

Look at the vectors $\nabla g_i(x_0)$ for $i \in I_a(x_0)$.

There should be no linear combination of these vectors with non negative scalars giving 0 except for the trivial one (with all scalars zero).

Thus there do not exist scalars v_i ($i \in I_a(x_0)$), not all zeros,

$$\text{s.t. } \sum_{i \in I_a(x_0)} v_i \nabla g_i(x_0) = 0$$

$$\text{and } v_i \geq 0 \quad \forall i \in I_a(x_0).$$

Note that if $\nabla g_i(x_0)$ ($i \in I_a(x_0)$) are linearly independent, then

x_0 is regular.

Example

$$\left\{ \begin{array}{l} \text{minimize } x_1^2 + x_2^2 \\ \text{s.t. } x_1 + x_2 \geq 1 \\ x_2 \geq 0 \end{array} \right.$$

$$\left\{ \begin{array}{l} \text{minimize } f(x) \\ \text{s.t. } g_1(x) \leq 0 \\ g_2(x) \leq 0 \end{array} \right. \quad \text{where}$$

$$f(x) := x_1^2 + x_2^2$$

$$g_1(x) := 1 - x_1 - x_2$$

$$g_2(x) := -x_2$$

$$\nabla f(x) = [2x_1 \quad 2x_2]$$

$$\nabla g_1(x) = [-1 \quad -1]$$

$$\nabla g_2(x) = [0 \quad -1]$$

independent \Rightarrow every feasible point is regular.

$$\underline{\text{(KKT-1)}}$$

$$2x_1 - y_1 = 0$$

$$2x_2 - y_1 - y_2 = 0$$

$$\underline{\text{(KKT-2)}}$$

$$x_1 + x_2 \geq 1$$

$$x_2 \geq 0$$

$$\underline{\text{(KKT-3)}}$$

$$y_1 \geq 0$$

$$y_2 \geq 0$$

$$\underline{\text{(KKT-4)}}$$

$$y_1 \cdot (1 - x_1 - x_2) = 0$$

$$y_2 \cdot (-x_2) = 0$$

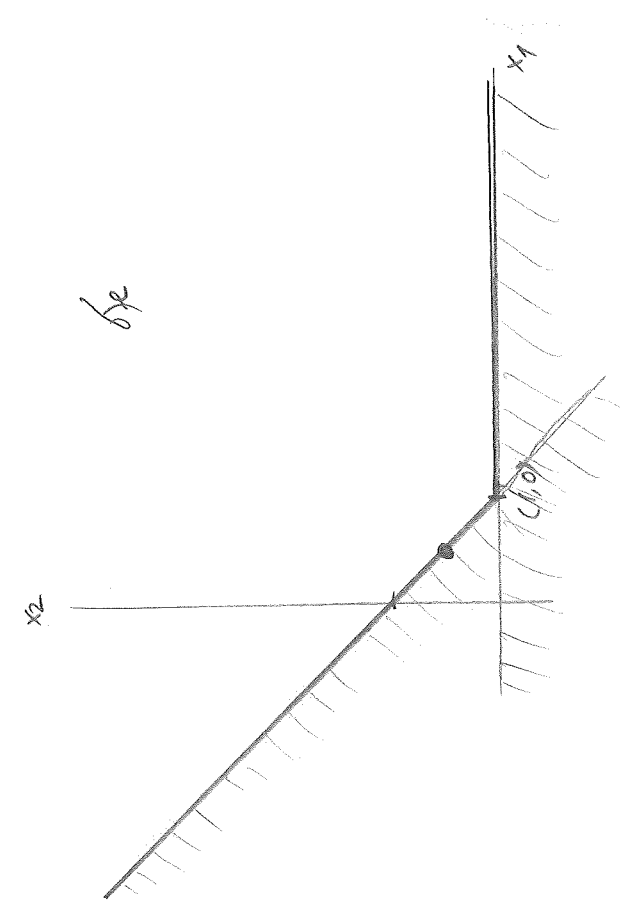
$$\begin{cases} y_1 > 0 \\ y_2 > 0 \end{cases}$$

KKT-4
 $x_1 + x_2 = 1 \Rightarrow x_1 = 1, x_2 = 0$
 $x_2 = 0$

KKT-1
 $y_1 = 2x_1 = 2 > 0$

$y_2 = 2x_2 - y_1 = 0 - 2 = -2 < 0$, violates KKT-3.

So no KKT points (x, y) in this case.



$$\begin{cases} y_1 > 0 \\ y_2 = 0 \end{cases}$$

KKT-4
 $x_1 + x_2 = 1$
KKT-1
 $2x_1 - y_1 = 0 \Rightarrow x_1 = x_2 = \frac{1}{2}$
 $2x_2 - y_1 = 0 \Rightarrow y_1 = 2x_1 = 1 > 0$

\exists a KKT point given by $x = (\frac{1}{2}, \frac{1}{2})$
 $y = (1, 0)$

$$\begin{cases} y_1 = 0 \\ y_2 > 0 \end{cases}$$

KKT-4
 $x_2 = 0 \Rightarrow x_1 = x_2 = 0$. But then $x_1 + x_2 = 0 \neq 1$, so KKT-2 is violated.
KKT-1
 $2x_1 = 0$
 $2x_2 - y_2 = 0$

So no KKT points in this case.

$$\begin{cases} y_1 = 0 \\ y_2 = 0 \end{cases}$$

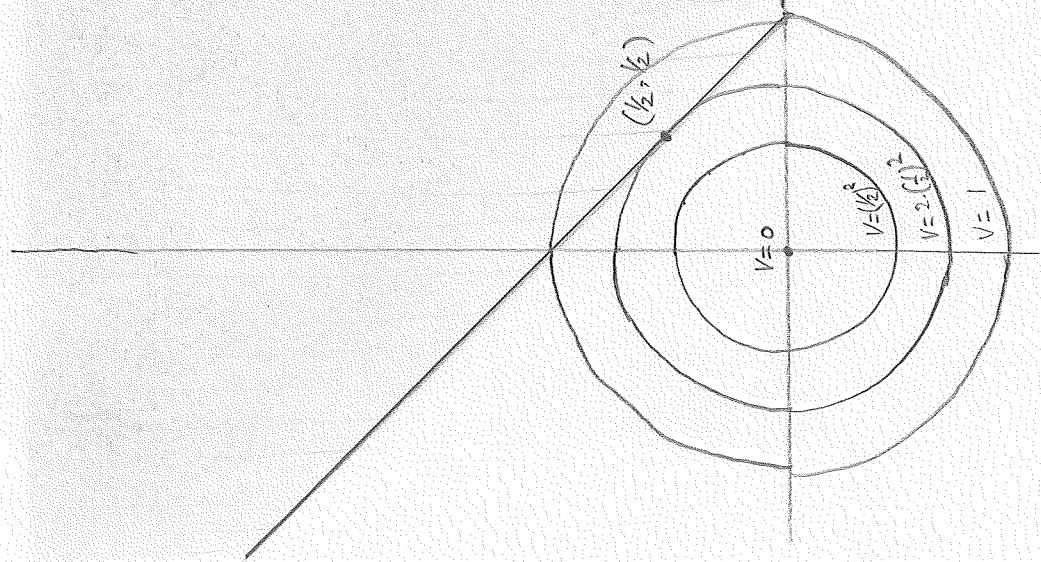
KKT-1
 $2x_1 = 0 \Rightarrow x_1 = x_2 = 0$. Again KKT-2 is violated.
 $2x_2 = 0$

So no KKT points in this case.

x_2

ρ_e

x_1



Example (Importance of the regularity condition)

Consider the problem

$$\begin{cases} \text{minimize } x_1 \\ \text{s.t. } x_2 \leq x_1^3 \\ x_2 \geq -x_1^3 \end{cases}$$

i.e.

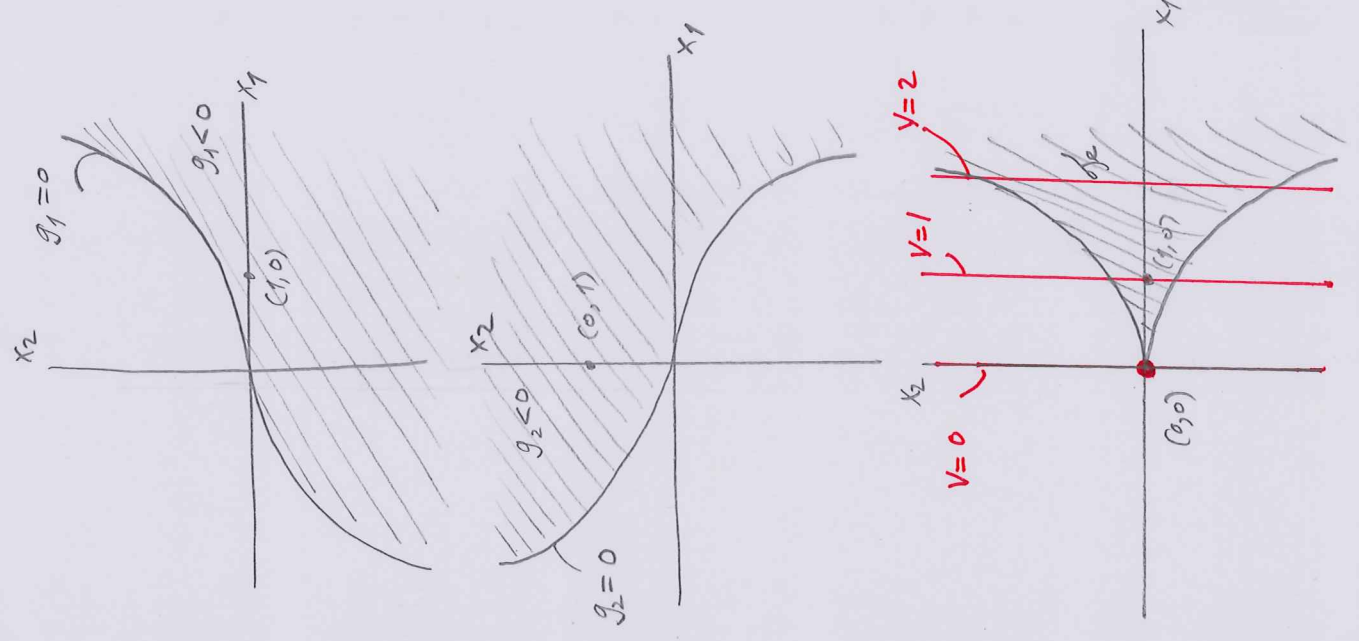
$$\begin{cases} \text{minimize } f(x) \\ \text{s.t. } g_1(x) \leq 0 \\ g_2(x) \leq 0 \end{cases}$$

where

$$\begin{aligned} f(x) &:= x_1 \\ g_1(x) &:= x_2 - x_1^3 \\ g_2(x) &:= -x_1^3 - x_2 \end{aligned}$$

Clearly $(0,0)$ is a global minimizer.

But the KKT - conditions are not satisfied!



$$\nabla f(x) = \begin{bmatrix} 1 & 0 \end{bmatrix}$$

$$\nabla g_1(x) = \begin{bmatrix} -3x_1^2 & 1 \end{bmatrix}$$

$$\nabla g_2(x) = \begin{bmatrix} -3x_1^2 & -1 \end{bmatrix}.$$

There is clearly no y_1, y_2 s.t.

$$\nabla f(x) + y_1 \nabla g_1(x) + y_2 \nabla g_2(x) = 0$$

(since $\begin{bmatrix} 1 & y_1 - y_2 \end{bmatrix} \neq \begin{bmatrix} 0 & 0 \end{bmatrix}$).

So KKT-1 can never be satisfied!

What went wrong? : The point $(0,0)$ is not regular.

Indeed, $1 \cdot \nabla g_1(0,0) + 1 \cdot \nabla g_2(0,0)$

$$= 1 \cdot \begin{bmatrix} 0 & 1 \end{bmatrix} + 1 \cdot \begin{bmatrix} 0 & -1 \end{bmatrix}$$

$$= \begin{bmatrix} 0 & 0 \end{bmatrix}$$

Sketch of the proof (of the theorem on necessity of the KKT-conditions).

Lemma. If x_0 is a local minimizer,

then there is no $d \in \mathbb{R}^n$ s.t.

$$\nabla f(x_0) \cdot d < 0 \text{ and}$$

$$\nabla g_i(x_0) \cdot d < 0 \quad \forall i \in I_a(x_0).$$

($\nabla g_i(x_0) \cdot d < 0 \quad \forall i \in I_a(x_0)$) means we can start from x_0 and go inside $\delta \epsilon$ in the direction of d .

$\nabla f(x_0) \cdot d < 0$ means we can also reduce the cost.

Clearly this is impossible since x_0 is a local minimizer.

Proof. Suppose $\exists d$ s.t.

$$\nabla g_i(x_0) \cdot d < 0 \quad \forall i \in I_a(x_0)$$

Consider $\psi(t) = g_i(x_0 + td)$, $t \in \mathbb{R}$

$$\psi'(t) = \nabla g_i(x_0 + td) \cdot d.$$

$$\psi'(0) = \nabla g_i(x_0) \cdot d < 0.$$

So $\psi'(t) < 0$ for small t 's.

We have

$$\psi(t) - \psi(0) = \int_0^t \underbrace{\psi'(x)}_{< 0} dx \quad \text{for } t > 0 \text{ small}$$

$$g_i(x_0 + td) - g(x_0) < 0 \quad \text{for small } t > 0$$

$$g_i(x_0 + td) < g(x_0) \leq 0 \quad \text{for small } t > 0$$

This is for i in $I_a(x_0)$

For other i , $g_i(x_0 + td) < 0$ for small $t > 0$ ($\because g_i(x_0) < 0$)

So for all i , $g_i(x_0 + td) < 0$ for small $t > 0$

We know that

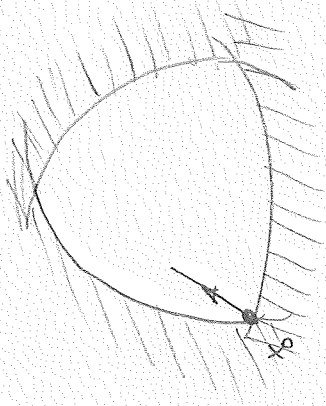
$$f(x) \geq f(x_0) \quad \text{for all } x \in J \text{ near } x_0$$

In particular for all small $t > 0$,

$$f(x_0 + td) \geq f(x_0)$$

$$\text{So } \frac{f(x_0 + td) - f(x_0)}{t} \geq 0 \quad \text{for all small } t > 0$$

$\nabla f(x_0) \cdot d \geq 0$. This completes the proof. \square



Farkas' lemma

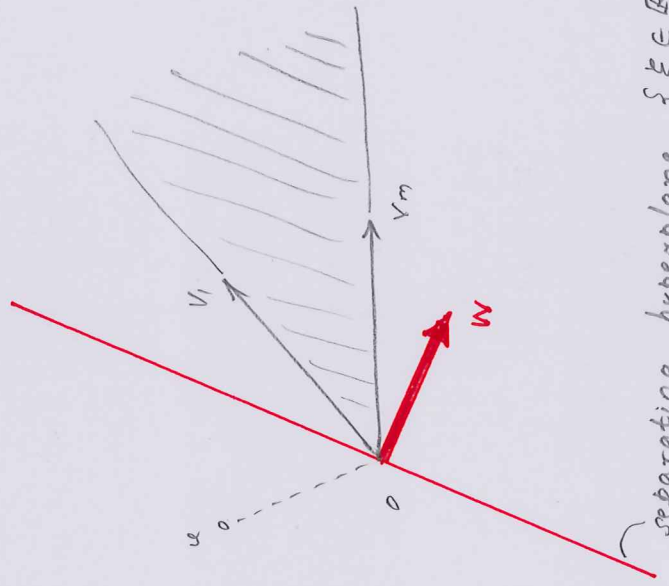
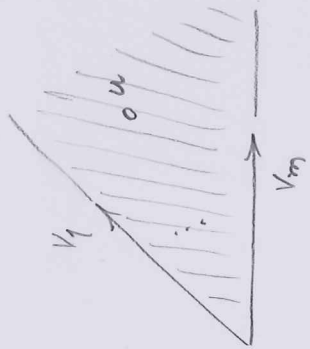
Let $v_1, \dots, v_m \in \mathbb{R}^n$,
 $u \in \mathbb{R}^n$.

Then one and only one of the following occurs:

(F1) $\exists w \in \mathbb{R}^n$ s.t. $w^T u < 0$ and $w^T v_1 \geq 0$
 \vdots
 $w^T v_m \geq 0$.

(F2) $\exists y_1 \geq 0$
 $y_m \geq 0$

s.t. $u = y_1 v_1 + \dots + y_m v_m$



separating hyperplane $\{x \in \mathbb{R}^n : w^T x = 0\}$

Lemma

+

Farkas' lemma

} gives the theorem on necessity of the KKT-conditions.

Use of KKT - necessary conditions:

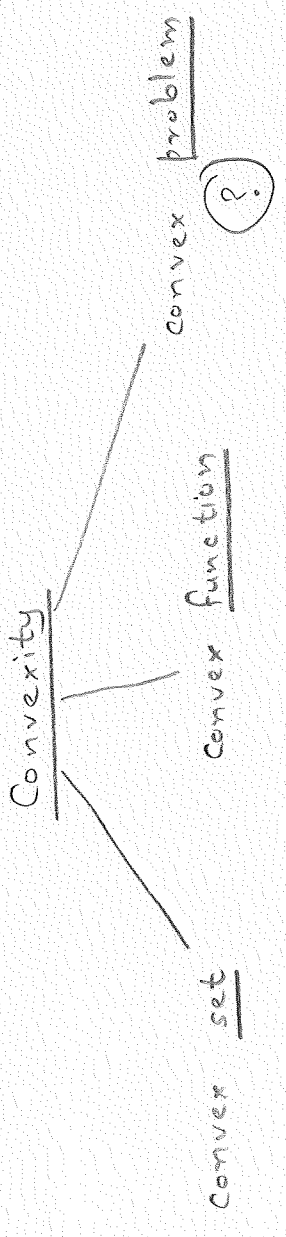
Narrows down the possibilities for a local minimizer.

If we know that the problem has a global minimizer

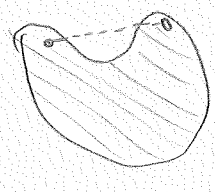
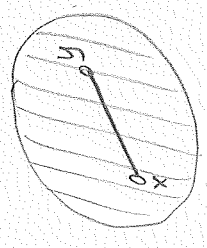
(for example using Weierstrass' theorem), then the

KKT - necessary conditions are very useful.

Useful for ruling out points that are not local minimizers.



Convex set: $C \subset \mathbb{R}^n$ is convex if $\forall x, y \in C \quad \forall t \in (0,1),$
 $(1-t)x + ty \in C.$



Convex function: $f: C \rightarrow \mathbb{R}$ is convex if $\forall x, y \in C \quad \forall t \in (0,1)$
 $f((1-t)x + ty) \leq (1-t)f(x) + tf(y).$

Theorem: If C has at least one interior point, then $f: C \rightarrow \mathbb{R}$ is convex $\Leftrightarrow \forall x \in C, F(x)$ is p.s.d.

What is a convex problem?

Consider (P): $\begin{cases} \text{minimize } f(x) \\ \text{s.t. } x \in \mathcal{C} \end{cases}$

The problem (P) is called a convex problem if

- (1) \mathcal{C} is a convex set and
- (2) $f: \mathcal{C} \rightarrow \mathbb{R}$ is a convex function.

Example

(F) (LP): $\begin{cases} \text{minimize } c^T x \\ \text{s.t. } Ax \leq b \end{cases}$ is a convex problem

Why? (1) $\mathcal{C} = \{ x \in \mathbb{R}^n : Ax \leq b \}$ is a convex set.

Let $x, y \in \mathcal{C}$. Then $\begin{matrix} Ax \leq b \\ Ay \leq b \end{matrix}$

Let $t \in (0, 1)$. Then $A((1-t)x + ty) = (1-t)Ax + tAy \leq (1-t)b + tb = b$.

So $(1-t)x + ty \in \mathcal{C}$. Hence \mathcal{C} is convex.

$$(2) \quad f(x) := c^T x$$

$f: \mathbb{R}^2 \rightarrow \mathbb{R}$ is a convex function. For $x, y \in \mathbb{R}^2$ and $t \in (0, 1)$ we have:

$$f((1-t)x + ty) = c^T ((1-t)x + ty) = (1-t)c^T x + t c^T y = (1-t)f(x) + t f(y) !$$

So all linear programming problems are convex

$$(II) \quad \begin{cases} \text{minimize} & x_1^2 + x_2^2 \\ \text{s.t} & x_1 + x_2 \geq 1 \\ & x_2 \geq 0 \end{cases} \quad \text{of the form } Ax \geq b$$

So f_e is convex.

Consider f given by $f(x) = x_1^2 + x_2^2$.

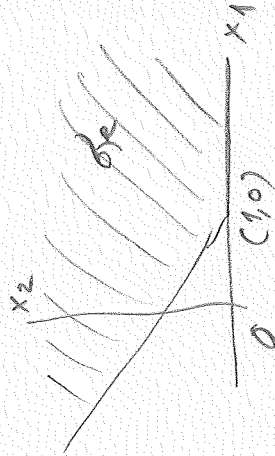
$$\nabla f(x) = [2x_1 \quad 2x_2]$$

is p.d. $\forall x \in \mathbb{R}^2$.

$$F(x) = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}$$

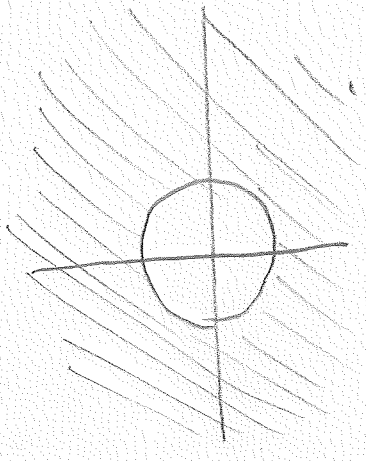
f_e has interior points.

So f is convex.



(III)
$$\begin{cases} \text{minimize} & x_1 + x_2 \\ \text{s.t.} & x_1^2 + x_2^2 \geq 1 \end{cases}$$

is not a convex problem, since the feasible set is not convex.



Take $x = (2, 0)$
 $y = (-2, 0)$
 $t = \frac{1}{2}$

$$(1-t)x + ty = \frac{1}{2}x + \frac{1}{2}y = \frac{1}{2}(0, 0) = (0, 0) \notin \text{fe}$$

(III)
$$\begin{cases} \text{minimize} & -x^2 \\ \text{s.t.} & x \in \mathbb{R} \end{cases}$$

is not a convex problem, since although \mathbb{R} is convex, the function $x \mapsto -x^2$ is not a convex function.

For example, take $x = -1, y = 1, t = \frac{1}{2}$.

Then $f((1-t)x + ty) = f\left(-\frac{1}{2} + \frac{1}{2}\right) = f(0) = 0$.

While $(1-t)f(x) + tf(y) = \frac{1}{2}(-1) + \frac{1}{2}(1) = -1$ and $0 \not\leq -1$.

