

## INTRODUCTION TO OPTIMIZATION THEORY

Recall the definition of an extremum:

DEF: Let  $f: \mathbb{R}^n \supseteq D \rightarrow \mathbb{R}$  and  $x^* \in D$   
s.t.  $\exists \varepsilon > 0 \forall |x - x^*| < \varepsilon$ : either

i)  $f(x) \geq f(x^*)$  (local min.)

ii)  $f(x) \leq f(x^*)$  (local max.)

then  $x^*$  is called an extremum.

### History

① 1628 Fermat's theorem

extremum  $f(x)$   
 $x \in D$

THM: Let  $f: \mathbb{R}^n \supseteq D \rightarrow \mathbb{R}$  diff. at  $x^* \in \mathbb{R}^n$ .  
 $x^*$  local extremum  $\Rightarrow \nabla f(x^*) = 0$ .

ALL: Discussion of boundary of  $D$ , non-diff. points of  $f$ , the stationary points, i.e.,  $f'(x^*) = 0$ . So one has to work backwards as  $\nabla f(x^*) = 0$  is only necessary but not suff.

② 1788 Lagrange's theorem

$$\min_{x \in D} f_0(x) \text{ subject to } \begin{cases} \forall i = 1, \dots, m: \\ f_i(x) = 0 \end{cases}$$

THM: Let  $f_i: \mathbb{R}^n \supseteq D \rightarrow \mathbb{R}$  be cont. diff. in neighborhood of local extremum  $x^* \in D \Rightarrow \exists \text{ } \neq z^* \in \mathbb{R}^{m+1}$  s.t.

$$L(x, z) := \sum_{i=0}^m z_i f_i(x)$$

fulfills for  $z = (z_0, \underline{z})$

$$\nabla_{(x, z)} L(x, z) |_{(x, z) = (x^*, z^*)} = 0.$$

$\nabla_x f_i(x^*)$   $i = 1, \dots, m$  are lin.-indep.  
 $z_0^* \neq 0$ .

ALL: Discussion of boundary of  $\{x \in D \mid f_i(x) = 0, i = 1, \dots, m\}$ , non-diff. points, and stationary points of Lagrangian, i.e., for  $z = (z_0, \underline{z})$

$$\nabla_{(x,z)} L(x,z) = 0 \quad (*)$$

$$\Leftrightarrow \begin{cases} \lambda x_i L(x,z) = 0 & i=1 \dots n \\ f_i(x) = 0 & i=1 \dots m \end{cases}$$

which are  $u+m+1$  unknowns for  $x \in \mathbb{R}^n$  and  $z \in \mathbb{R}^{m+1}$

Again one has to work backwards as (\*) is necessary but not sufficient.

But in case  $\nabla_x f_i(x^*)$   $i=1 \dots m$  are lin. indep. so can be done equal one which reduces the # of unknowns to  $u+m$ .

### ③ 1951 Karush-Kuhn-Tucker theorem

$$\min_{x \in \mathbb{R}^n} f_0(x) \text{ subject to } \begin{cases} \forall i=1 \dots m \\ f_i(x) \leq 0 \\ x \in C \text{ convex} \end{cases} \quad (P)$$

DEF: A subset of linear space is called convex if  $\forall x,y \in A$  also  $\{ \alpha x + (1-\alpha)y \mid \alpha \in [0,1] \} \subseteq A$ .

A function  $f$  is called convex if Jensen's inequality holds for any two points  $x,y$  in the domain &  $0 \leq \alpha \leq 1$

$$f(\alpha x + (1-\alpha)y) \leq \alpha f(x) + (1-\alpha)f(y)$$

Thm: Let  $f_i: \mathbb{R}^n \rightarrow \mathbb{R}$ ,  $i=0, \dots, m$  be convex.

• If  $x^*$  is a solution to (P), then:

$$\exists 0 \neq z^* \in \mathbb{R}^{m+1} \text{ s.t.}$$

$$(i) \min_{x \in C} L(x, z^*) = L(x^*, z^*)$$

$$(ii) z_i^* \geq 0 \text{ for } i=0 \dots m$$

$$(iii) z_i^* f_i(x^*) = 0 \text{ for } i=1 \dots m$$

• If  $\exists z^* \in \mathbb{R}^{m+1}$  with  $z_0^* \neq 0$ , then:

$$(i)-(iii) \Rightarrow x^* \text{ solves (P)}$$

• If  $\exists X \in C$  s.t.

$$\forall i=1 \dots m: f_i(X) < 0$$

$$\Rightarrow z_0^* \neq 0$$

} Slater cond.

• If Slater cond. holds

$$(i)-(iii) \Leftrightarrow \exists x^* \in C, z^* \in \mathbb{R}^{m+1}, z_0^* \neq 0$$

$$\text{s.t. } \forall x \in C, z \in \mathbb{R}^{m+1}, z_0 \neq 0$$

$$L(x, \frac{z}{z_0}) \geq L(x^*, \frac{z^*}{z_0^*}) \geq L(x^*, \frac{z}{z_0})$$

$$\text{and } \inf_{x \in C} L(x, \frac{z^*}{z_0^*}) = L(x^*, \frac{z^*}{z_0^*}) = \sup_{\substack{z \in \mathbb{R}^{m+1} \\ z_0 \neq 0}} L(x^*, \frac{z}{z_0})$$

The goal will be to understand and prove KKT based on some results of convex set theory.