

## Ch2 Optimality Condition

### ① Unconstrained Prob.

1. A direction  $d \rightarrow \nabla f(x)^T d < 0$

$\Downarrow$

$f(x+\lambda d) < f(x) \Rightarrow d$  下降方向

$\nabla f(x)^T d < 0$   
 $\Downarrow$

### 2. Optimality Condition for Un. Pb.

1) Sufficient

$\nabla f(\bar{x}) = 0$  &  $\nabla^2 f(\bar{x}) \succ 0$   $\Rightarrow$  strictly local minimum

2) Necessary

$\nabla f(\bar{x}) = 0$  &  $\nabla^2 f(\bar{x}) \succeq 0$

② Constrained Pb.

$\rightarrow$  suff.  $\Rightarrow$  Relatively Easy

$\rightarrow$  necc.  $\Rightarrow$  Need SOME GEOMETRIC LEMMA

Model:  $\min f(x)$

s.t.  $x \in S$

$\rightarrow$  Feasible Region

1.

Define  $F^<$   $F^<$   $F^{\leq}$   $F_0^{\leq}$

• easy to check

• essential DESCENT

$F_0^< \subseteq F^< \subseteq F^{\leq} \subseteq F_0^{\leq}$

improving direction

$d \in F^{\leq}$

$f(x+\lambda d) \leq f(x)$  for some  $\lambda$

$f(x+\lambda d) = f(x) + \lambda \nabla f(x)^T d + o(\lambda)$

important conclusion

$$\begin{cases} f \text{ convex} \Rightarrow \underline{F_0^{\leq}} = \underline{F^{\leq}} \\ f \text{ strictly convex} \Rightarrow \underline{F_0^{\leq}} = \underline{F^{\leq}} \end{cases}$$

## 2. Feasible direction D

$$d \in D \Leftrightarrow \bar{x} \in S, \bar{x} + \lambda d \in S \text{ for all } \lambda \in (0, \delta)$$

(3). General Optimality Condition about Constrained problem → Later will be applied to some certain case → Geometric

i) Necessary Part

$$\underline{F_0^{\leq}} \subseteq F^{\leq} \subseteq F^{\leq} \subseteq \underline{F_0^{\leq}} \quad \bar{x} \text{ local minimum}$$

$$\Rightarrow \underline{F^{\leq}} \cap D = \emptyset$$

$$(F_0^{\leq} \cap D = \emptyset)$$

$\Rightarrow$  easily



ii) Sufficient Part

Pf

$$f(x) < f(\bar{x})$$

$$\bar{x} - \bar{x} = d \in D$$

$$\hat{x} = \bar{x} + d$$

$$f(\bar{x} + d) < f(\bar{x})$$

$$d \in F^{\leq} = F_0^{\leq}$$

$$\Rightarrow d \in \underline{F_0^{\leq}} \cap D$$

$$\textcircled{1} \quad \underline{F_0^{\leq}} \cap D = \emptyset$$

$$\textcircled{2} \quad f \text{ convex at } \bar{x}$$

$$\textcircled{3} \quad S \text{ is locally convex}$$

$$\Rightarrow \bar{x} \text{ local minimum}$$

$$\bar{x} \rightarrow \underline{N_{\varepsilon}(\bar{x})}$$

$$\downarrow$$

$$x - \bar{x} \in D$$

## 3. Consider A subset Of Constrained Prob.

$$\begin{cases} \min f(x) \\ \text{s.t.} \quad \boxed{g_i(x) \leq 0} \quad i=1, \dots, m \\ \quad \quad \boxed{x \in X} \end{cases}$$

care about the  $\partial$  point

as for these points,

$$\underline{D = G^{\leq}}$$

Application of General Conclusion:

→ Optimality Condition



# 1) Necessary Part

$$\bar{x} \text{ local minimum} \Rightarrow \underbrace{F^* \cap G^*}_{\substack{\text{Smaller} \\ \text{algebraically}}} = \emptyset$$

$$\Rightarrow \underbrace{F_0^* \cap G_0^*}_{\substack{\text{Smaller} \\ \text{algebraically}}} = \emptyset$$

$$\underbrace{F_0^* \cap G_0^*}_{\substack{\text{Smaller} \\ \text{algebraically}}} = \emptyset$$

↓  
System no soln.

## ii) Sufficient Part

↓

Two version:

①

a)  $f$  is convex at  $\bar{x}$ .

$$\textcircled{2} \boxed{F_0^* \cap G_0^* = \emptyset} \text{ FJ}$$

③  $g_i$  strictly convex

$$\Rightarrow \begin{cases} \textcircled{1} S \text{ locally convex} \\ \textcircled{2} G_0^* = G^* \end{cases}$$

①

b)  $f$  convex

$$\textcircled{2} \boxed{F_0^* \cap G_0^* = \emptyset} \text{ KKT}$$

③  $g_i$  convex  $\Rightarrow S$  convex locally.

Only Trick is: use  $g_i$  convex  $\Rightarrow S$  locally convex at  $\bar{x}$

pf: we need to show:  $\exists N_\epsilon(\bar{x})$ .  $\forall x \in N_\epsilon(\bar{x})$ ,

$$\underbrace{\bar{x} - x \in d} \quad \underbrace{g_i(\bar{x}) = 0}_{g_i(x) \leq 0} \quad i \in I$$

$$\Rightarrow g_i(\bar{x} + \lambda d) = g_i(\dots) \leq g_i(\dots) + g_i(\dots) \leq 0$$

$$\Rightarrow \bar{x} + \lambda d \in S \Rightarrow \underline{d \in D = G^*}$$

Then FJ OPTIMALITY Condition

$$\nabla f(\bar{x})^T d < 0 \quad A = \begin{pmatrix} \nabla f(\bar{x})^T \\ \nabla g_i(\bar{x})^T \end{pmatrix}$$

$$\textcircled{1} \text{ Nec.} \Rightarrow \boxed{F_0^* \cap G_0^* = \emptyset} \Rightarrow \underline{A d < 0} \text{ 无解} \Leftrightarrow A^T p = 0 \quad p \geq 0 \quad p \neq 0 \text{ 有解}$$

② Sub

a) ① FJ

②  $g_i$  strictly convex

③  $f$  convex

$$A^T = (\nabla f(\bar{x}) \quad \nabla g_i(\bar{x}))$$

$$\Leftrightarrow \boxed{\mu_0 \nabla f(\bar{x}) + \sum_{i \in I} \mu_i \nabla g_i(\bar{x}) = 0}$$

$$\mu_0 \geq 0 \quad \mu_i \geq 0$$

[important]

$$\Leftrightarrow \begin{cases} \mu_0 \nabla f(\bar{x}) + \sum_{k=1}^m \mu_k \nabla g_k(\bar{x}) = 0 \\ \mu_i g_i(\bar{x}) = 0 \\ \mu \geq 0, \mu \neq 0 \end{cases}$$

KKT Optimality Condition.

- ① Necessary  $\Rightarrow$  Modification of FJ
- ② Sufficient

Actually Beyond:  $F^* \cap G^* = \emptyset$

$\Uparrow$   
need more requirement

$\{\nabla g_i(\bar{x}) : i \in I\}$  L.I.

Second-order Sufficient & Necessary Condition

$\downarrow$

① Lagrangian  $f^*$

$$\phi(x, u, v) = f(x) + \sum u_i g_i(x) + \sum v_i h_i(x)$$

$\downarrow$  for KKT point  $\bar{x}$ ,  $\exists \bar{u}, \bar{v}$ , s.t.  $\nabla \phi(\bar{x}, \bar{u}, \bar{v}) = 0$

$$\underline{L(x) = \phi(x, \bar{u}, \bar{v})}$$

② Sufficient Condition (second-order)  $\xrightarrow{\bar{x} \rightarrow \text{KKT Point}}$   
 $d^T \nabla^2 L(\bar{x}) d > 0$  for all  $d \in C \Rightarrow$  strict local optimum

$$C = \{d \neq 0 : \nabla g_i(\bar{x})^T d = 0, i \in I^+\}$$

$$\nabla g_i(\bar{x})^T d \leq 0, i \in I_0,$$

$$\nabla h_i(\bar{x})^T d = 0\}$$

③ Necessary Condition (Second-order)

$\bar{x}$  is local minimum & qualification constraint (LICQ)

$\Downarrow$



$$d^T \nabla^2 L(\bar{x}) d \geq 0 \quad \text{for all } d \in C$$