

① Convex

min<sub>x</sub> f(x)  
g(x) ≤ 0

f, g convex

h(x) = 0

→ conditions on L for convexity of optimization problem?



L(x) ≤ 0  
h(x) ≥ 0

→ h(x) ≤ 0  
→ -h(x) ≤ 0

L, -h convex  
↓  
h is affine. [∀x: g(x) ≤ 0]

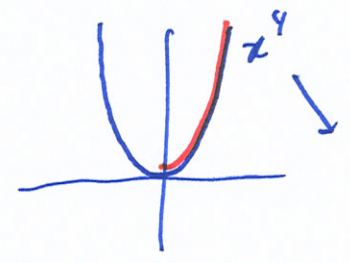
h(g(x))

g, h convex, h ↑ → h(g(·)) is convex

x<sup>4</sup>, 3|x|+5

→ (3|x|+5)<sup>4</sup> is convex. ✓

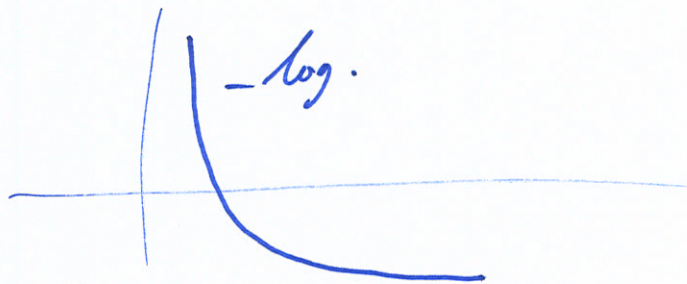
(3|x|-5)<sup>4</sup> is convex? not applicable



increasing for positive arguments

(2)

$-g, h$  convex,  $h \downarrow \rightarrow h(g(\cdot))$  is convex

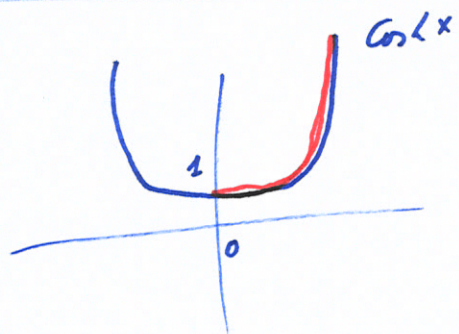


$$\underbrace{-\log}_{h} \left( \underbrace{4-x^2}_g \right) \rightarrow \text{convex} \quad x \in [-1, 1]$$

$\downarrow$   
 convex  
 $\downarrow$

$\downarrow$   
 $g$   
 $\hookrightarrow -g = -4 + x^2 \rightarrow \text{convex.}$

$$\cosh x = \frac{e^x + e^{-x}}{2}$$



$\rightarrow$  convex

$$\cosh(x^2 + y^2) \rightarrow \text{convex!}$$

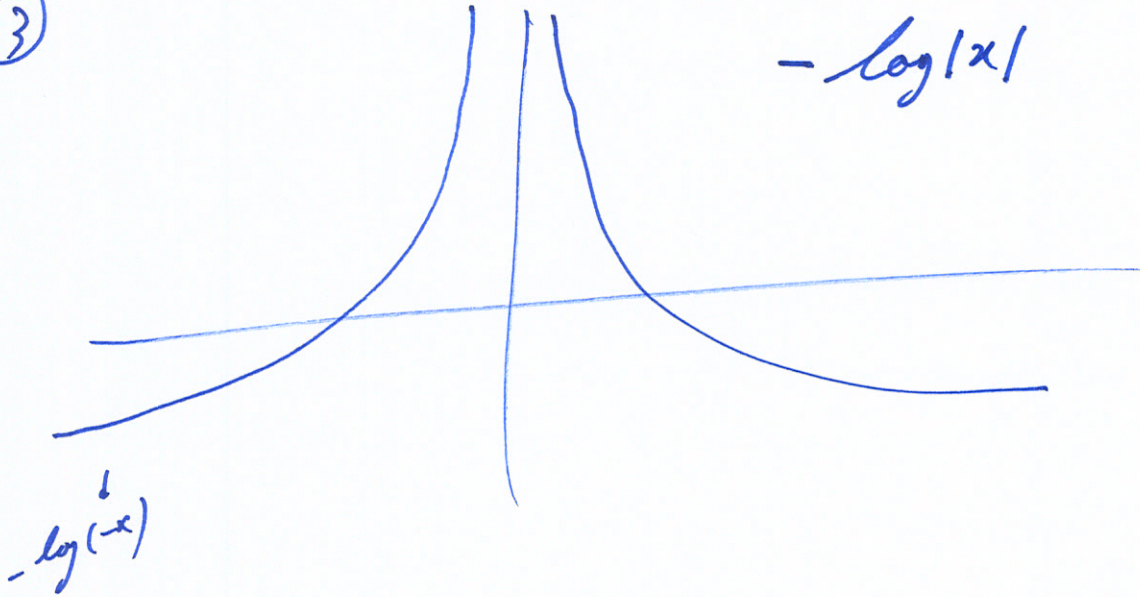
$\downarrow$        $\downarrow$   
 convex    convex  
 $\downarrow$        $\geq 0$

$\uparrow$  for pos. arguments

③

$-\log|x|$

domain:  $\mathbb{R} \setminus \{0\}$   
↓  
not convex



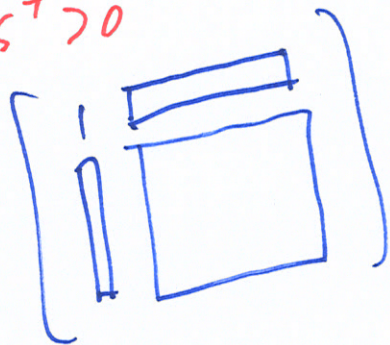
→ function is not convex

$\|x\| \leq r \rightarrow x^T x \leq r^2 \rightarrow x^T \frac{1}{r^2} x \leq 1$

$\rightarrow \begin{matrix} 1 & -x^T \frac{1}{r^2} x \\ \downarrow & \downarrow \\ Q & S \end{matrix} \geq 0$   
 $\downarrow$   
 $R^{-1}$   
 $\downarrow$   
 $R = r^2 I$

$\begin{bmatrix} Q & S \\ S^T & R \end{bmatrix} \succ 0$

$R \succ 0, Q - S R^{-1} S^T \succ 0$



$\rightarrow \begin{bmatrix} 1 & x^T \\ x & r^2 I \end{bmatrix} \geq 0$

linear matrix inequality in  $x$

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example

$$n=2 \quad \begin{bmatrix} 1 & x_1 & x_2 \\ x_1 & r_1 & 0 \\ x_2 & 0 & r_2 \end{bmatrix} \quad x^T$$

$$= F_0 + F_1 \lambda_1 + F_2 \lambda_2$$

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & r_1 & 0 \\ 0 & 0 & r_2 \end{bmatrix} \quad \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \\ \vdots & & \end{bmatrix}$$

"  $F_0^T$                       "  $F_1^T$                       "  $F_2^T$

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$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \quad p^T = P$$

$$= \lambda_1 \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + \lambda_2 \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + \lambda_3 \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$$

$\lambda_1$                        $E_{11}$                        $E_{12}$                        $E_{22}$   
 $\downarrow$                        $\downarrow$                        $\downarrow$                        $\downarrow$   
 $F_1$                        $F_2$                        $F_3$

(4)

$$F_0 + F_1 x_1 + F_2 x_2 + \dots + F_n x_n > 0$$

$$F_i = F_i^T$$

$$x \in \mathbb{R}^n$$

$$A^T P + P A < 0 \quad R > 0$$

$P \in \mathbb{R}^{n \times n}$ , symmetric

$$E_{ij} = \begin{bmatrix} 0 & 0 & 0 \\ \dots & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{matrix} i \\ j \end{matrix}$$

$$E_{ii} = \begin{bmatrix} 0 & 0 \\ \dots & 1 \\ 0 & 0 \end{bmatrix} i$$

$$P = \sum_{i \leq j} \mu_{ij} E_{ij} > 0$$

$F_i$  + symmetric  
 $B_{ij} = E_{ij}^T$

$$x = \begin{bmatrix} \mu_{11} \\ \mu_{12} \\ \vdots \\ \mu_{1n} \\ \mu_{22} \\ \mu_{21} \\ \vdots \\ \mu_{nn} \end{bmatrix}$$

$LMI$

$\mu_{11} \mu_{12} \dots \mu_{1n}$   
 $\mu_{21} \mu_{22} \dots \mu_{2n}$   
 $\vdots$   
 $\mu_{n1} \mu_{n2} \dots \mu_{nn}$

see (4) for a larger copy

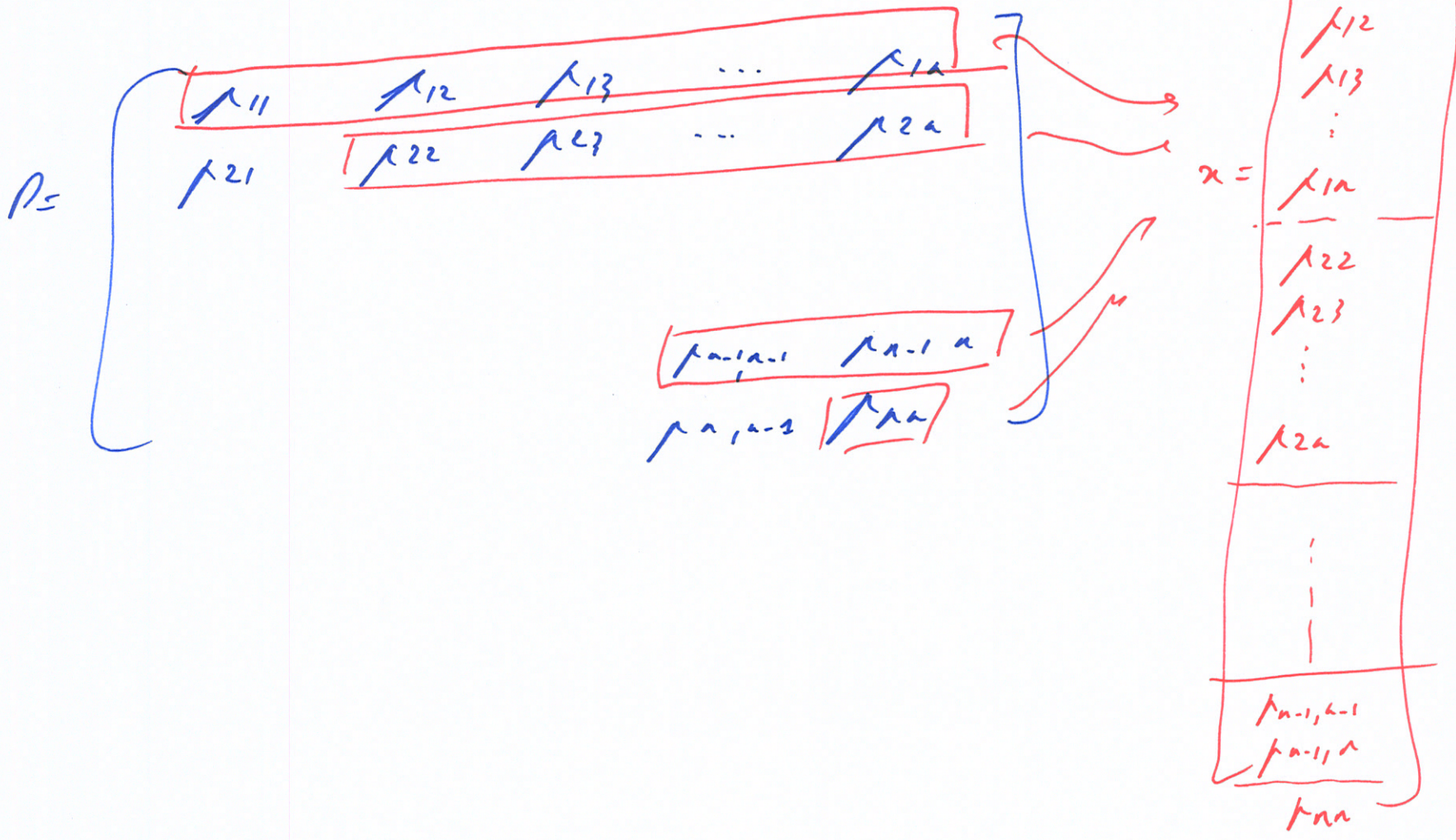
$$A^T \left( \sum \mu_{ij} E_{ij} \right) + \left( \sum \mu_{ij} E_{ij} \right) A =$$

$$\sum \mu_{ij} \underbrace{(A^T E_{ij} + E_{ij} A)}_{G_i = G_i^T} > 0$$

$$G_i^T = (A^T E_{ij} + E_{ij} A)^T = (A^T E_{ij})^T + (E_{ij} A)^T = E_{ij} A + A^T E_{ij} = G_i!$$

(4 km)

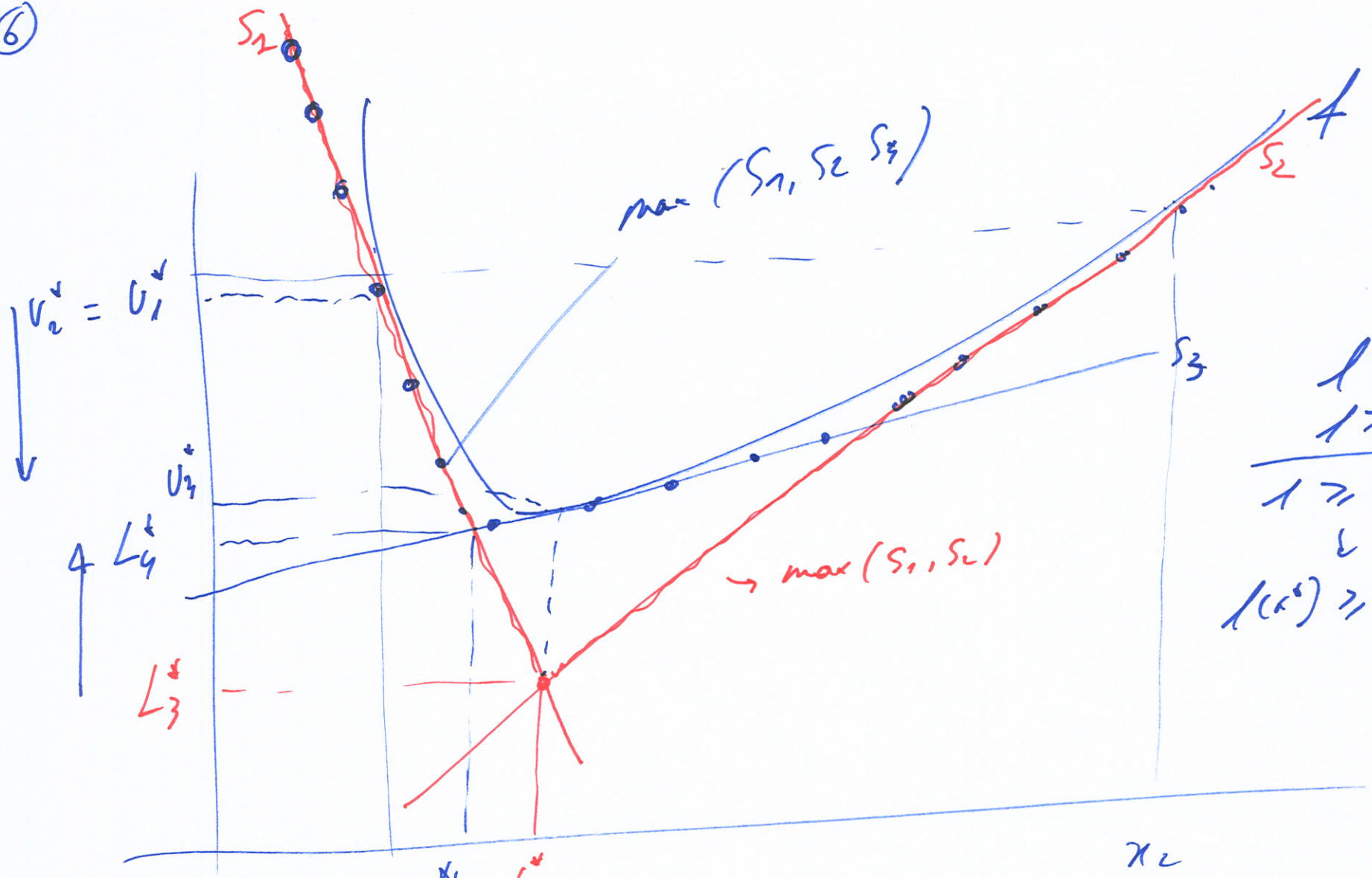
$\rho_{ij}$   
 $i \leq j$



⑤

$$\begin{array}{lcl} E_{11} & \rightarrow & F_1 \\ E_{12} & \rightarrow & F_2 \\ & & \vdots \\ E_{1n} & \rightarrow & F_n \\ E_{21} & \rightarrow & F_{n+1} \\ & & \vdots \\ E_{2n} & & \vdots \end{array}$$

⑥



$$\begin{array}{r}
 1 \geq S_1 \\
 1 \geq S_2 \\
 \hline
 1 \geq \max(S_1, S_2) \\
 \downarrow \\
 1(x^*) \geq \max(S_1(x^*), S_2(x^*))
 \end{array}$$

arg min  $\max(S_1, S_2)$   
 $\underbrace{\hspace{2cm}}_{V \text{ function.}}$



②

$$\min_x \max(S_1, S_2, \dots, S_k)$$

$S_i$  : affine

LP

$$\begin{array}{l} \min_{x, L_k} L_k \\ L_k \geq S_1 \\ L_k \geq S_2 \\ \vdots \\ L_k \geq S_k \end{array}$$

off/see in  $x$

$$L_k \geq \max(S_1, S_2, \dots, S_k)$$

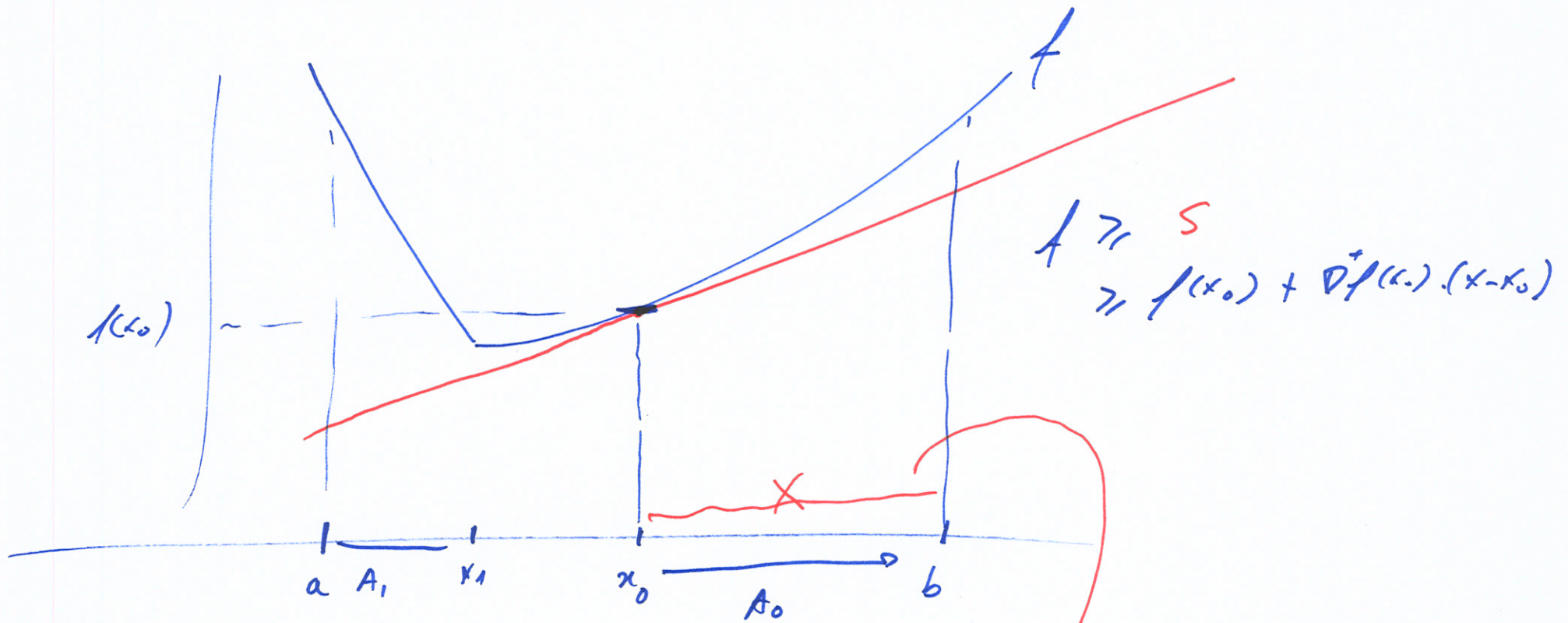
$$\min_x L_k$$

$\Downarrow$

$$L_k^* = \max(S_1^*, S_2^*, \dots, S_k^*)$$

$$\begin{array}{l} \max(4, 5) \\ \min L \\ L \geq 4 \\ L \geq 5 \end{array} \left. \vphantom{\begin{array}{l} \max(4, 5) \\ \min L \\ L \geq 4 \\ L \geq 5 \end{array}} \right\} C^* = 5$$

8



Here  $S \uparrow \rightarrow$  to right of  $x_0$  :  $S \geq f(x_0)$   
 $f(x) \geq f(x_0)$   
 $\rightarrow$  minimum will not be to right of  $x_0$

$$A_1 = \frac{A_0}{2} + \text{sgn}(Df(x_0))$$

$$x_1 = x_0 - A_1$$

⑨

$$\|x - x_0\| \leq r \quad \rightarrow \quad \| \quad \| \quad \swarrow \quad \| \leq r^2$$

$$(x - x_0)^T (x - x_0) \leq r^2$$

$$(x - x_0)^T \frac{1}{r^2} (x - x_0) \leq 1$$

$$\downarrow$$

$$\downarrow$$

$$A_0^{-1}$$

$\rightarrow$  Hyperball