



Necessity  
of  
 $\text{rel. int.}$

$$f^* = g^*$$

$$= \min_x f(x) + \sum u_i^* h_i(x) + \sum v_j^* l_j(x)$$

~~Because  $f(x) \leq f(x^*) + \sum u_i^* h_i(x) + \sum v_j^* l_j(x)$~~

$$\leq f(x^*) + \underbrace{\sum u_i^*}_{\geq 0} h_i(x^*) + \underbrace{\sum v_j^*}_{\leq 0} l_j(x^*)$$

$$= f(x^*)$$

Hence

actually an equality  $\Rightarrow$  stat. condition

$\Rightarrow$  actually an equality  $\Rightarrow$  comp. slackness

## Sufficiency of KKT

$$\begin{aligned} g^* &= g(u^*, v^*) = \min_x L(x, u^*, v^*) \\ &\stackrel{\text{stat. cond.}}{=} L(x^*, u^*, v^*) \\ &= f(x^*) + \underbrace{\sum_i u_i^* h_i(x^*)}_0 + \underbrace{\sum_j v_j^* l_j(x^*)}_0 \\ &\stackrel{\text{comp. slack}}{=} f(x^*) \end{aligned}$$

subg. of  $F$  at  $x$

$$0 \in \partial F(x)$$

$$\Leftrightarrow F(y) \geq F(x) + 0^T(y - x) \text{ all } y$$

$$\Leftrightarrow F(y) \geq F(x) \text{ all } y$$

$$\min_x f(x) + \mathbb{1}_{\{x \in C\}}$$

$$Ax = 0 \iff x \in N_y$$

rewrite problem in terms of  $y$

$$\min_y \frac{1}{2} y^T N^T Q N y + c^T N y$$

at sol.  $y^*$ , take  $x^* = Ny^*$

stat cond:  $\nabla_x \left( \frac{1}{2} x^T Q x + c^T x + u^T A x \right) = 0.$

QP  
with  
equality  
constraints

$$Qx + A^T u = -c$$

comp. slack:  $\rho$

prim feas:  $Ax = 0$

dual feas:  $\phi$

$$\begin{bmatrix} Q & A^T \\ A & 0 \end{bmatrix} \begin{bmatrix} x \\ u \end{bmatrix} = \begin{bmatrix} -c \\ 0 \end{bmatrix}$$

SV<sup>M</sup>

$$\nabla_{\beta} \left( \frac{1}{2} \|\beta\|_2^2 + \sum w_i (1 - \xi_i - y_i \beta^T x_i) \right) = 0$$

$$\beta - \sum w_i y_i x_i = 0$$

$$\boxed{\beta = \sum w_i y_i x_i}$$

stat.

$$\nabla_{\beta_0} \left( \sum w_i (1 - \xi_i - y_i \beta_0) \right) = 0$$

$$\boxed{\sum w_i y_i = 0}$$

$$\nabla_{\xi} \left( C \sum \xi_i - \sum v_i \xi_i + \sum w_i (1 - \xi_i - y_i (\beta^T x_i + \beta_0)) \right) = 0$$

$$\nabla_{y} \left( C \mathbf{1}^T y - \mathbf{v}^T y + w^T (1 - y) \right) = 0$$

$$C \mathbf{1} - \mathbf{v} - w = 0$$

$$\boxed{w = C \mathbf{1} - \mathbf{v}} \Rightarrow 0 \leq w \leq C$$

comp :  $\sum_i \xi_i = 0 \quad \text{all } i$

slack :  $w_i(1 - \xi_i - y_i(x_i^T \beta + \beta_0)) = 0 \quad \text{all } i$

primal fees : as in SVM

duel fees :  $v \geq 0, w \geq 0$

if  $1 - \xi_i > y_i(x_i^T \beta + \beta_0)$   
then  $w_i = 0$

Hessian

$$\tilde{X}^T \nabla^2 f(x\beta) X$$

$$X\gamma = 0 \quad , \quad \gamma \neq 0$$

Ex:  $f(u) = \|y - u\|_2^2$

loss is  $f(x\beta) = \|y - x\beta\|_2^2$

$$j \in S \Rightarrow x_j^T \nabla f(x\beta) \in (-\lambda, \lambda)$$

$$\Rightarrow \text{sign } s_j \in (-1, 1)$$

$$\Rightarrow \beta_j = 0$$

assume  $X_S$  is rank def.

$$-x_j^T \nabla f(x\beta) = \lambda s_j \quad j=1 \dots n$$

$s_i x_i$  is an affine combo of  $s_j x_j$

$$j \in S \setminus \{i\}$$

