

Example

min $f_0(x) = x^2$ subject to $f_1(x) = ax + b \leq 0$
 $x \in \mathbb{R}$

$$L(x, y) = f_0(x) + y_1 f_1(x) \quad \text{for } x \in \mathbb{R} \\ y \geq 0$$

$$\tilde{L}(y) = \min_{x \in \mathbb{R}} f_0(x) + y_1 f_1(x)$$

$$\frac{d}{dx} (f_0(x) + y_1 f_1(x)) = 0$$

$$2x + y_1 a = 0 \Leftrightarrow x = -y_1 \frac{a}{2}$$

$$(f_0(x) + y_1 f_1(x)) \Big|_{x = -y_1 \frac{a}{2}}$$

$$= y_1^2 \frac{a^2}{4} - y_1^2 \frac{a}{2} + y_1 b$$

$$= -y_1^2 \frac{a^2}{4} + y_1 b = \tilde{L}(y)$$

We do not need to check $x \rightarrow \pm\infty$

$$\sup_{y_1 \geq 0} \tilde{L}(y) = ?$$

$$\frac{d}{dy_1} \left(-y_1^2 \frac{a^2}{4} + y_1 b \right) = -y_1 \frac{a^2}{2} + b = 0$$

$$\Leftrightarrow y_1 = \frac{2b}{a^2}$$

$$\sup_{y \geq 0} \tilde{L}(y) = \begin{cases} \frac{2b}{a^2} \text{ for } b \geq 0 \Rightarrow x = -\frac{b}{a} \\ 0 \text{ for } b < 0 \Rightarrow x = 0 \end{cases}$$

PRIMAL & DUAL FORM OF SVM

I

Primal program

$$f_0(w, \xi) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^m \xi_i \longrightarrow \min$$

subject to constraints

$$f_i(w, \xi) = 1 - y^{(i)} w \cdot x^{(i)} - \xi_i \leq 0 \quad i=1 \dots m$$

$$g_j(w, \xi) = -\xi_j \leq 0 \quad j=1 \dots n$$

\Rightarrow Lagrange function

$$L(w, \xi, \alpha, \beta) = f_0(w, \xi) + \sum_{i=1}^m \alpha_i f_i(w, \xi) + \sum_{j=1}^n \beta_j g_j(w, \xi)$$

at optimum w, ξ, α, β we have KKT:

$$(I) \quad \left(\frac{\partial w}{\partial w}, \frac{\partial \xi}{\partial \xi} \right) \left[f_0(w, \xi) + \sum_{i=1}^m \alpha_i f_i(w, \xi) + \sum_{j=1}^n \beta_j g_j(w, \xi) \right] = 0$$

$$(II) \quad \alpha_i f_i(w, \xi) = 0, \quad \beta_j g_j(w, \xi) = 0, \quad \alpha_i \geq 0, \quad \beta_j \geq 0$$

for $i, j = 1 \dots m, n$

$$\frac{\partial w}{\partial w} f_0(w, \xi) = 0, \quad \frac{\partial w}{\partial w} f_0(w, \xi) = w, \quad \frac{\partial \xi}{\partial \xi} f_0(w, \xi) = C$$

$$\frac{\partial w}{\partial w} f_i(w, \xi) = -y^{(i)}, \quad \frac{\partial w}{\partial w} f_i(w, \xi) = -y^{(i)} x^{(i)}, \quad \frac{\partial \xi}{\partial \xi} f_i(w, \xi) = -\delta_{ik}$$

$$\frac{\partial w}{\partial w} g_j(w, \xi) = 0, \quad \frac{\partial w}{\partial w} g_j(w, \xi) = 0, \quad \frac{\partial \xi}{\partial \xi} g_j(w, \xi) = -\delta_{jk}$$

$$(I) \Leftrightarrow \sum_{i=1}^m \alpha_i y^{(i)} = 0$$

$$w = \sum_{i=1}^m \alpha_i y^{(i)} x^{(i)}$$

$$C = \alpha_i + \beta_i \quad i=1 \dots m$$

$$(II) \Leftrightarrow \alpha_i (1 - y^{(i)} w \cdot x^{(i)} - \xi_i) = 0 \quad \alpha_i \geq 0 \quad i=1 \dots m$$
$$\beta_j \xi_j = 0 \quad \beta_j \geq 0 \quad j=1 \dots n$$

We note again as in the lin. sep. case that due to (I)

$$w = \sum_{i=1}^m \alpha_i y^{(i)} x^{(i)}$$

where due to (II) only vectors fulfilling $\alpha_i \neq 0$, i.e.,

$$1 - y^{(i)} w \cdot x^{(i)} - \xi_i = 0$$

contribute \Rightarrow either support vectors with $\xi_i = 0$
or other vectors for $\xi_i \neq 0$. The latter however
must satisfy $\beta_i \xi_i = 0 \Rightarrow \beta_i = 0 \Rightarrow \alpha_i = C$.

Hence, vector contributing to w are either
support vectors or outliers with $\alpha_i = C$.

Note however that even though w is unique
as we have shown, the support vectors are not.

II

Dual program: Thanks to the KKT Theorem

III

We know that $\exists \bar{\alpha}, \bar{\beta}$ s.t.

$$\inf_{\omega, \xi} \{ f_0(\omega, \xi) \mid f_i(\omega, \xi) \leq 0, g_j(\omega, \xi) \leq 0 \\ i=1 \dots n, j=1 \dots m \}$$

$$= \inf_{\omega, \xi} L(\omega, \xi, \bar{\alpha}, \bar{\beta}) = \max_{\alpha, \beta \geq 0} \inf_{\omega, \xi} L(\omega, \xi, \alpha, \beta)$$

Furthermore, by KKT cond. we know how to express

$$\omega^* = \sum_{i=1}^n \alpha_i y^{(i)} x^{(i)}$$

$$\begin{aligned} \Rightarrow L(\omega^*, \xi, \alpha, \beta) &= \frac{1}{2} \left\| \sum_{i=1}^n \alpha_i y^{(i)} x^{(i)} \right\|^2 + C \sum_{i=1}^n \xi_i \\ &+ \sum_{i=1}^n \alpha_i (1 - y^{(i)}) \left[\omega_0 + \sum_{j=1}^n \alpha_j y^{(j)} x^{(j)} \right] - \xi_i \\ &+ \sum_{i=1}^n \beta_i (-\xi_i) \\ &= \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y^{(i)} y^{(j)} x^{(i)} \cdot x^{(j)} \\ &+ \sum_{i=1}^n [C - \alpha_i - \beta_i] \xi_i - \omega_0 \sum_{i=1}^n \alpha_i y^{(i)} \end{aligned}$$

Hence, we may formulate an equivalent problem

$$\begin{aligned} \tilde{f}_0(\alpha, \beta) &= \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i,j=1}^n \alpha_i \alpha_j y^{(i)} y^{(j)} x^{(i)} \cdot x^{(j)} \rightarrow \max \\ \text{subject to} & \alpha_i + \beta_i = C, \alpha_i, \beta_i \geq 0 \Leftrightarrow 0 \leq \alpha_i \leq C \\ \text{and} & \sum_{i=1}^n \alpha_i y^{(i)} = 0 \end{aligned}$$

NOTE: This program has several advantages:

IV

1) $\frac{d^2}{d\alpha} \tilde{f}_0(\alpha) = -y^{(i)} x^{(i)} \cdot y^{(j)} x^{(j)}$ which is negative semi-def.

$\Rightarrow \tilde{f}_0(\alpha)$ concave

2) Constraints are all affine

$\Rightarrow \exists!$ optimum and problem is always quadratic

We can furthermore express the activation output

$$h(x) = \omega x$$

by choosing our support vector $x^{(i)}$, i.e., $\omega x^{(i)} = y^{(i)}$

and computing

$$\begin{aligned} \omega_0 &= y^{(i)} - \omega \cdot x^{(i)} \\ &= y^{(i)} - \sum_{j=1}^n \alpha_j y^{(j)} x^{(j)} \cdot x^{(i)} \end{aligned}$$

\Rightarrow The activation does not depend on the particular values of $x^{(i)}$ but only on inner products.

• Activation function can be readily computed in dual form.