

# Formulating the optimization problem

## The optimization problem

**Problem:** Given two linearly separable sets of points  $A^\pm \subset \mathbb{R}^k$ :

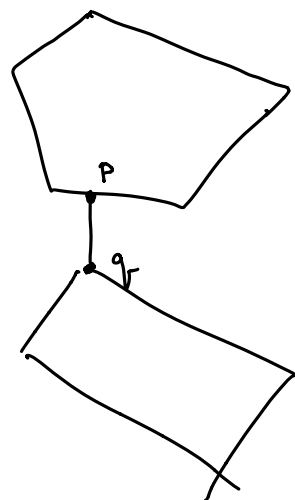
$$A^+ = \{x_1^+, \dots, x_{n_+}^+\} \quad \checkmark$$

and

$$A^- = \{x_1^-, \dots, x_{n_-}^-\} \quad \checkmark$$

Find points  $\underline{p} \in \underline{C(A^+)}$  and  $\underline{q} \in \underline{C(A^-)}$  so that

$$\|p - q\| = \min_{\substack{p' \in C(A^+) \\ q' \in C(A^-)}} \|p' - q'\|$$



## The optimization problem (continued)

As above, let our linearly separable sets be

$$A^+ = \{x_1^+, \dots, x_{n_+}^+\}$$

$$\begin{cases} \sum \lambda_i^+ x_i^+ \\ \lambda_i^+ \geq 0 \end{cases}$$

and

$$A^- = \{x_1^-, \dots, x_{n_-}^-\}$$

$$\begin{cases} \sum \lambda_i^- x_i^- \\ \lambda_i^- \geq 0 \end{cases}$$

**Problem 1:** Let  $\lambda^\pm = (\lambda_1^\pm, \dots, \lambda_{n_\pm}^\pm)$  be two vectors of real numbers of length  $n_\pm$  respectively. Define

$$w(\lambda^+, \lambda^-) = \sum_{i=1}^{n_+} \lambda_i^+ x_i^+ - \sum_{i=1}^{n_-} \lambda_i^- x_i^-.$$

Find  $\lambda^\pm$  such that  $\|w(\lambda^+, \lambda^-)\|^2$  is minimal subject to the conditions that all  $\lambda_i^\pm \geq 0$  and  $\sum_{i=1}^{n_\pm} \lambda_i^\pm = 1$ .

## The optimization problem (continued)

Notice that:

- $w(\lambda^+, \lambda^-)$  is a quadratic function in the  $\lambda$ 's with coefficients coming from the dot products of the  $x_i^\pm$ .

$$w(\lambda^+, \lambda^-) = \left( \sum \lambda_i^+ x_i^+ - \sum \lambda_i^- x_i^-, \sum \lambda_i^+ x_i^+ - \sum \lambda_i^- x_i^- \right)$$

$$= \text{many terms } \lambda_i^+ \lambda_j^+ (x_i^+, x_j^+)$$

- The constraints are *inequalities* rather than equalities, so a direct application of Lagrange multipliers as we learned in calculus won't work.

$$\lambda_i^+ \geq 0 \quad 1 = \sum \lambda_i^+ = \sum \lambda_i^-$$

$$\lambda_i^- \geq 0$$

- We will describe an iterative algorithm for solving this problem called Sequential Minimal Optimization, due to John Platt and introduced in 1998.

- First, though, we reformulate the problem slightly.

**Reformulating the constrained optimization problem.**

**Problem 2:** Let

$$Q(\lambda^+, \lambda^-) = \underbrace{\|w(\lambda^+, \lambda^-)\|^2}_{-\alpha} - \underbrace{\sum_{i=1}^{n_+} \lambda_i^+}_{-\alpha} - \underbrace{\sum_{i=1}^{n_-} \lambda_i^-}_{-\alpha}.$$

Let  $\lambda^\pm$  be values that minimize  $Q(\lambda^+, \lambda^-)$  where all  $\lambda_i^\pm \geq 0$  and

$$\alpha = \underbrace{\sum_{i=1}^{n_+} \lambda_i^+}_{-\alpha} = \underbrace{\sum_{i=1}^{n_-} \lambda_i^-}_{-\alpha}.$$

Then  $\alpha \neq 0$  at the  $(\lambda^+, \lambda^-)$  that yield the minimum and  $\tau^\pm = (1/\alpha)\lambda^\pm$  is a solution to optimization problem 1.

## Equivalence of the reformulated problem

**Proof:**

First let all  $\lambda_i^\pm = 0$  except  $\lambda = \lambda_1^\pm$ . Then  $w(\lambda^+, \lambda^-) = \lambda x_1^+ - \lambda x_1^-$

$$\underline{Q(\lambda^+, \lambda^-)} = \underset{\uparrow}{Q(\lambda)} = \underline{\lambda^2 \|x_1^+ - x_1^-\|^2 - 2\lambda}.$$

This takes its minimum value at  $\lambda = 1/\|x_1^+ - x_1^-\|^2$  and at that point

$$\underset{\downarrow}{Q(\lambda)} = -\frac{1}{\|x_1^+ - x_1^-\|^2} \leq 0.$$

Therefore the minimum value is negative. But if  $\alpha = 0$ , then all  $\lambda_i^\pm = 0$ , so  $Q = 0$  at such a point. Therefore  $\alpha \neq 0$  at the minimum value.

To show the equivalence, we have  $(\lambda^+, \lambda^-)$  solving problem 2 and  $(\sigma^+, \sigma^-)$  solving problem 1; and finally we have  $(\tau^+, \tau^-) = (1/\alpha)(\lambda^+, \lambda^-)$ .

1. Since  $(\tau^+, \tau^-)$  satisfy the constraints of problem 2, we have:

$$\underline{Q(\lambda^+, \lambda^-)} = \underbrace{\|w(\lambda^+, \lambda^-)\|^2}_{\uparrow \text{ minimum value}} - 2\alpha \leq \|w(\tau^+, \tau^-)\|^2 - 2 \quad \left( \tau^+, \tau^- = \left( \frac{1}{\alpha} \lambda^+, \frac{1}{\alpha} \lambda^- \right) \right)$$

2. Since  $(\tau^+, \tau^-)$  satisfy the constraints of problem 1, we have

$$\underbrace{\|w(\sigma^+, \sigma^-)\|^2}_{\uparrow \text{ minimum value}} \leq \|w(\tau^+, \tau^-)\|^2.$$

## Equivalence of optimization problems continued

3. From (2), we have

$$\begin{aligned} \underline{\|w(\alpha\sigma^+, \alpha\sigma^-)\|^2} &\leq \alpha^2 \|w(\tau^+, \tau^-)\|^2 = \|w(\lambda^+, \lambda^-)\|^2 \\ \therefore \underline{\|\sum \alpha \sigma_i^+ x_i^+ - \sum \alpha \sigma_i^- x_i^-\|^2} &= \alpha^2 \underline{\|w(\sigma^+, \sigma^-)\|^2} \\ &\leq \alpha^2 \|w(\tau^+, \tau^-)\|^2 \end{aligned}$$

4. Subtracting  $2\alpha$  from both sides of this inequality yields

$$\underline{\|w(\alpha\sigma^+, \alpha\sigma^-)\|^2 - 2\alpha} \leq \underline{Q(\lambda^+, \lambda^-)} = \underline{\|w(\lambda^+, \lambda^-)\|^2 - 2\alpha}$$

Since  $(\lambda^+, \lambda^-)$  minimize  $Q(\lambda^+, \lambda^-)$ , this inequality must be an equality. Therefore

$$\alpha^2 \underline{\|w(\sigma^+, \sigma^-)\|^2} = \alpha^2 \underline{\|w(\tau^+, \tau^-)\|^2}$$

so  $(\tau^+, \tau^-)$  also gives a minimal value for problem 1.