

# Line Assignment

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**Abstract**—This document contains a general solution to Question 16 of Exercise 2 in Chapter 11 of the class 12 NCERT textbook.

- 1) Find the shortest distance between the lines whose vector equations are

$$L_1 : \mathbf{x} = \mathbf{x}_1 + \lambda_1 \mathbf{m}_1 \quad (1)$$

$$L_2 : \mathbf{x} = \mathbf{x}_2 + \lambda_2 \mathbf{m}_2 \quad (2)$$

**Solution:** Let  $\mathbf{A}$  and  $\mathbf{B}$  be points on lines  $L_1$  and  $L_2$  respectively such that  $AB$  is normal to both lines. Define

$$\mathbf{M} \triangleq (\mathbf{m}_1 \quad \mathbf{m}_2) \quad (3)$$

$$\lambda \triangleq \begin{pmatrix} \lambda_1 \\ -\lambda_2 \end{pmatrix} \quad (4)$$

$$\mathbf{x} \triangleq \mathbf{x}_2 - \mathbf{x}_1 \quad (5)$$

Then, we have the following equations:

$$\mathbf{A} = \mathbf{x}_1 + \lambda_1 \mathbf{m}_1 \quad (6)$$

$$\mathbf{B} = \mathbf{x}_2 + \lambda_2 \mathbf{m}_2 \quad (7)$$

From (6) and (7), define the real-valued function  $f$  as

$$f(\lambda) \triangleq \|\mathbf{A} - \mathbf{B}\|^2 \quad (8)$$

$$= \|\mathbf{M}\lambda - \mathbf{x}\|^2 \quad (9)$$

$$= (\mathbf{M}\lambda - \mathbf{x})^\top (\mathbf{M}\lambda - \mathbf{x}) \quad (10)$$

$$= \lambda^\top (\mathbf{M}^\top \mathbf{M}) \lambda - 2\mathbf{x}^\top \mathbf{M}\lambda + \|\mathbf{x}\|^2 \quad (11)$$

From (11), we see that  $f$  is quadratic in  $\lambda$ . We now prove a useful lemma here.

**Lemma 1.** The quadratic form

$$q(\mathbf{x}) \triangleq \mathbf{x}^\top \mathbf{A} \mathbf{x} + \mathbf{b}^\top \mathbf{x} + c \quad (12)$$

is convex iff  $\mathbf{A}$  is positive semi-definite.

*Proof.* Consider two points  $\mathbf{x}_1$  and  $\mathbf{x}_2$ , and a

real constant  $0 \leq \mu \leq 1$ . Then,

$$\begin{aligned} & \mu f(\mathbf{x}_1) + (1 - \mu) f(\mathbf{x}_2) - f(\mu \mathbf{x}_1 + (1 - \mu) \mathbf{x}_2) \\ &= (\mu - \mu^2) \mathbf{x}_1^\top \mathbf{A} \mathbf{x}_1 + (1 - \mu - (1 - \mu)^2) \mathbf{x}_2^\top \mathbf{A} \mathbf{x}_2 \\ & \quad - 2\mu(1 - \mu) \mathbf{x}_1^\top \mathbf{A} \mathbf{x}_2 \end{aligned} \quad (13)$$

$$= \mu(1 - \mu) (\mathbf{x}_1^\top \mathbf{A} \mathbf{x}_1 - 2\mathbf{x}_1^\top \mathbf{A} \mathbf{x}_2 + \mathbf{x}_2^\top \mathbf{A} \mathbf{x}_2) \quad (14)$$

$$= \mu(1 - \mu) (\mathbf{x}_1 - \mathbf{x}_2)^\top \mathbf{A} (\mathbf{x}_1 - \mathbf{x}_2) \quad (15)$$

Since  $\mathbf{x}_1$  and  $\mathbf{x}_2$  are arbitrary, it follows from (15) that

$$\mu f(\mathbf{x}_1) + (1 - \mu) f(\mathbf{x}_2) \geq f(\mu \mathbf{x}_1 + (1 - \mu) \mathbf{x}_2) \quad (16)$$

iff  $\mathbf{A}$  is positive semi-definite, as required.  $\square$

Using the above lemma, we show that  $f$  is convex by showing that  $\mathbf{M}^\top \mathbf{M}$  is positive semi-definite. Indeed, for any  $\mathbf{p} \triangleq \begin{pmatrix} x \\ y \end{pmatrix}$ ,

$$\mathbf{p}^\top \mathbf{M}^\top \mathbf{M} \mathbf{p} = \|\mathbf{M} \mathbf{p}\|^2 \geq 0 \quad (17)$$

and thus,  $f$  is convex.

We need to minimize  $f$  as a function of  $\lambda$ . Thus, differentiating (11) using the chain rule,

$$\frac{df(\lambda)}{d\lambda} = \mathbf{M}^\top (\mathbf{M}\lambda - \mathbf{x}) + \mathbf{M} (\mathbf{M}\lambda - \mathbf{x})^\top \quad (18)$$

$$= 2\mathbf{M}^\top (\mathbf{M}\lambda - \mathbf{x}) \quad (19)$$

Setting (19) to zero gives

$$\mathbf{M}^\top \mathbf{M} \lambda = \mathbf{M}^\top \mathbf{x} \quad (20)$$

We have the following cases:

a) There exists a  $\lambda$  satisfying

$$\mathbf{M} \lambda = \mathbf{x} \quad (21)$$

$$\implies \lambda_1 \mathbf{m}_1 - \lambda_2 \mathbf{m}_2 = \mathbf{x}_2 - \mathbf{x}_1 \quad (22)$$

$$\implies \mathbf{x}_1 + \lambda_1 \mathbf{m}_1 = \mathbf{x}_2 + \lambda_2 \mathbf{m}_2 \quad (23)$$

Thus, both lines intersect at a point and the shortest distance between them is 0. To check for the existence of such a  $\lambda$ , we can bring the augmented matrix  $(\mathbf{M} \quad \mathbf{x})$

into row-reduced echelon form and check whether there is a pivot in the last column.

- b)  $\mathbf{M}^\top \mathbf{M}$  is singular. Since  $\mathbf{M}^\top \mathbf{M}$  is a square matrix of order 2, its rank must be 1. Further,

$$\det(\mathbf{M}^\top \mathbf{M}) = \begin{vmatrix} \mathbf{m}_1^\top \mathbf{m}_1 & \mathbf{m}_1^\top \mathbf{m}_2 \\ \mathbf{m}_1^\top \mathbf{m}_2 & \mathbf{m}_2^\top \mathbf{m}_2 \end{vmatrix} \quad (24)$$

$$= (\|\mathbf{m}_1\| \cdot \|\mathbf{m}_2\|)^2 - (\mathbf{m}_1^\top \mathbf{m}_2)^2 \quad (25)$$

Thus, equating the determinant to zero gives

$$\|\mathbf{m}_1\| \cdot \|\mathbf{m}_2\| = |\mathbf{m}_1^\top \mathbf{m}_2| \quad (26)$$

which implies that both lines are parallel to each other. Setting  $\mathbf{m}_2 = k\mathbf{m}_1, k \in \mathbb{R} \setminus \{0\}$ , we obtain one equation from (20).

$$\mathbf{m}_1^\top \mathbf{m}_1 (\lambda_1 - k\lambda_2) = \mathbf{m}_1^\top \mathbf{x} \quad (27)$$

$$\implies \lambda_1 - k\lambda_2 = \frac{\mathbf{m}_1^\top \mathbf{x}}{\|\mathbf{m}_1\|^2} \quad (28)$$

Therefore, the required shortest distance is

$$\|\mathbf{A} - \mathbf{B}\| = \left\| \frac{\mathbf{m}_1^\top \mathbf{x} \mathbf{m}_1}{\|\mathbf{m}_1\|^2} - \mathbf{x} \right\| \quad (29)$$

- c)  $\mathbf{M}^\top \mathbf{M}$  is nonsingular. This implies that the lines are skew. From (20),

$$\lambda = (\mathbf{M}^\top \mathbf{M})^{-1} \mathbf{M}^\top \mathbf{x} \quad (30)$$

and therefore, the shortest distance is

$$\|\mathbf{A} - \mathbf{B}\| = \left\| (\mathbf{M}(\mathbf{M}^\top \mathbf{M})^{-1} \mathbf{M}^\top - \mathbf{I}_n) \mathbf{x} \right\| \quad (31)$$

where  $\mathbf{I}_n$  is the identity matrix of order  $n$ .