

## Optimal Plane Fitting

Given a set of  $n$  points  $\mathbf{x}_i$ , for  $i = 1, \dots, n$ , consider a plane  $P$  that best fits to these data points:

$$P : \langle \mathbf{x} - \mathbf{c}, \mathbf{n} \rangle = 0,$$

where  $\mathbf{c}$  is a point on the plane and  $\mathbf{n}$  is a plane normal. We may assume

$$\langle \mathbf{n}, \mathbf{n} \rangle = 1. \tag{1}$$

An optimal plane that best fits to the given data points  $\mathbf{x}_i$  can be found as a solution to the following constrained optimization problem:

$$\begin{aligned} & \text{Minimize } \sum_{i=1}^n \langle \mathbf{x}_i - \mathbf{c}, \mathbf{n} \rangle^2, \\ & \text{subject to } \langle \mathbf{n}, \mathbf{n} \rangle = 1. \end{aligned}$$

Since there is no constraint on the point  $\mathbf{c}$ , an optimal solution satisfies

$$\sum_{i=1}^n -2 \langle \mathbf{x}_i - \mathbf{c}, \mathbf{n} \rangle \mathbf{n} = \mathbf{0}, \quad \text{or} \quad \left\langle n\mathbf{c} - \sum_{i=1}^n \mathbf{x}_i, \mathbf{n} \right\rangle \mathbf{n} = \mathbf{0},$$

The center of gravity of  $\mathbf{x}_i$ 's:

$$\mathbf{c} = \frac{1}{n} \sum_{i=1}^n \mathbf{x}_i$$

satisfies the above equation.

Now, let's consider an optimal solution for the unit normal vector  $\mathbf{n}$ . Using the Lagrange multiplier applied to the constraint  $\langle \mathbf{n}, \mathbf{n} \rangle = 1$ , we have the following relation:

$$\sum_{i=1}^n 2 \langle \mathbf{x}_i - \mathbf{c}, \mathbf{n} \rangle (\mathbf{x}_i - \mathbf{c}) - \lambda 2\mathbf{n} = \mathbf{0}.$$

Considering all vectors as column vectors, we have

$$\sum_{i=1}^n (\mathbf{x}_i - \mathbf{c})^T \mathbf{n} (\mathbf{x}_i - \mathbf{c}) = \lambda \mathbf{n},$$

and equivalently,

$$\sum_{i=1}^n (\mathbf{x}_i - \mathbf{c})(\mathbf{x}_i - \mathbf{c})^T \mathbf{n} = \lambda \mathbf{n}.$$

Now let a  $3 \times 3$  matrix  $A$  to be defined as

$$A = \sum_{i=1}^n (\mathbf{x}_i - \mathbf{c})(\mathbf{x}_i - \mathbf{c})^T,$$

then we have

$$A\mathbf{n} = \lambda \mathbf{n}.$$

Thus  $\mathbf{n}$  is an eigenvector of the matrix  $A$ . We select the eigenvector  $\mathbf{n}$  with the smallest eigenvalue.

## Optimal Line Fitting

Given a set of  $n$  points  $\mathbf{x}_i$ , for  $i = 1, \dots, n$ , consider two orthogonal planes  $P_1$  and  $P_2$ , the intersection line of which best fits to the data points:

$$P_1 : \langle \mathbf{x} - \mathbf{c}, \mathbf{n}_1 \rangle = 0,$$

$$P_2 : \langle \mathbf{x} - \mathbf{c}, \mathbf{n}_2 \rangle = 0,$$

where  $\mathbf{c}$  is a point on the intersection line, and  $\mathbf{n}_i$  is a plane normal to the plane  $P_i$ , ( $i = 1, 2$ ). We may assume that the plane normals  $\mathbf{n}_i$  satisfy

$$\langle \mathbf{n}_1, \mathbf{n}_1 \rangle = 1, \quad \langle \mathbf{n}_2, \mathbf{n}_2 \rangle = 1, \quad \langle \mathbf{n}_1, \mathbf{n}_2 \rangle = 0.$$

An optimal line that best fits to the given data points  $\mathbf{x}_i$  can be found as a solution to the following constrained optimization problem:

$$\text{Minimize } \sum_{i=1}^n \left( \langle \mathbf{x}_i - \mathbf{c}, \mathbf{n}_1 \rangle^2 + \langle \mathbf{x}_i - \mathbf{c}, \mathbf{n}_2 \rangle^2 \right)$$

$$\text{subject to } \langle \mathbf{n}_1, \mathbf{n}_1 \rangle = 1, \quad \langle \mathbf{n}_2, \mathbf{n}_2 \rangle = 1, \quad \langle \mathbf{n}_1, \mathbf{n}_2 \rangle = 0.$$

The optimal location of the point  $\mathbf{c}$  is similarly given as

$$\mathbf{c} = \frac{1}{n} \sum_{i=1}^n \mathbf{x}_i.$$

Using the Lagrange multipliers, we have

$$\sum_{i=1}^n (\mathbf{x}_i - \mathbf{c})(\mathbf{x}_i - \mathbf{c})^T \mathbf{n}_1 = A\mathbf{n}_1 = \lambda_1 \mathbf{n}_1 + \mu_1 \mathbf{n}_2,$$

$$\sum_{i=1}^n (\mathbf{x}_i - \mathbf{c})(\mathbf{x}_i - \mathbf{c})^T \mathbf{n}_2 = A\mathbf{n}_2 = \lambda_2 \mathbf{n}_2 + \mu_2 \mathbf{n}_1.$$

By setting  $\mu_1 = \mu_2 = 0$ , we have

$$A\mathbf{n}_1 = \lambda_1 \mathbf{n}_1, \quad A\mathbf{n}_2 = \lambda_2 \mathbf{n}_2.$$

Thus  $\mathbf{n}_1$  and  $\mathbf{n}_2$  are eigenvectors of the matrix  $A$ . We select the eigenvectors  $\mathbf{n}_i$  that correspond to the two smaller eigenvalues of  $A$ .