

Squared Euclidean Distance Matrix (SEDM)

$$(x_i, y_i, z_i)$$

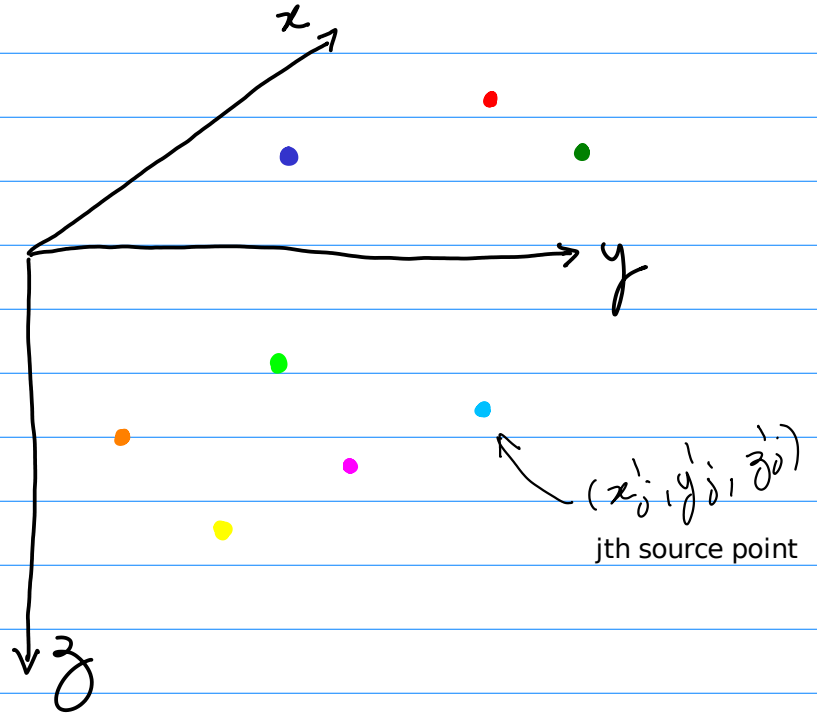
ith observation point

Observation points matrix

$$P = \begin{bmatrix} x_0 & x_1 & \dots & x_{N-1} \\ y_0 & y_1 & \dots & y_{N-1} \\ z_0 & z_1 & \dots & z_{N-1} \end{bmatrix}_{3 \times N}$$

Source points matrix

$$S = \begin{bmatrix} x'_0 & x'_1 & \dots & x'_{M-1} \\ y'_0 & y'_1 & \dots & y'_{M-1} \\ z'_0 & z'_1 & \dots & z'_{M-1} \end{bmatrix}_{3 \times M}$$



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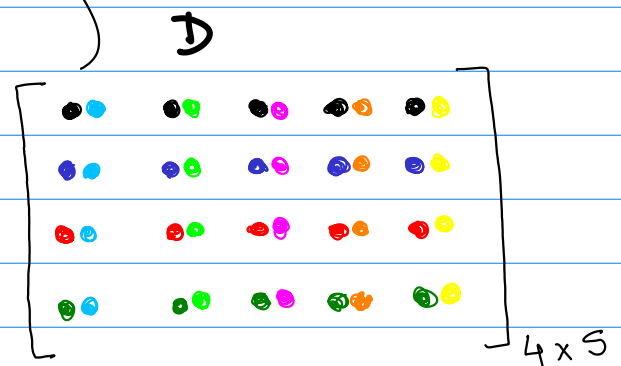
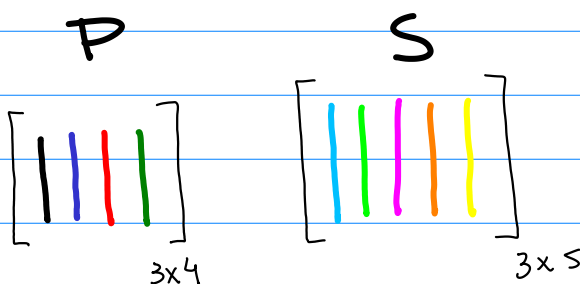
$$D = \begin{bmatrix} d_{00}^2 & \dots & d_{0M-1}^2 \\ \vdots & & \vdots \\ d_{N-10}^2 & \dots & d_{N-1M-1}^2 \end{bmatrix}_{N \times M}$$

Squared Euclidean distance

$$d_{ij}^2 = (x_i - x'_j)^2 + (y_i - y'_j)^2 + (z_i - z'_j)^2$$

$$i = 0, \dots, N-1 \quad j = 0, \dots, M-1$$

$$d_{ij}^2 = (x_i - x'_j)^2 + (y_i - y'_j)^2 + (z_i - z'_j)^2$$



$$\begin{aligned}
 d_{ij}^2 &= (\mathbf{p}_i - \mathbf{s}_j)^T (\mathbf{p}_i - \mathbf{s}_j) = \\
 &= (x_i - x_j')^2 + (y_i - y_j')^2 + (z_i - z_j')^2 \\
 &= (\underbrace{x_i^2}_{\text{blue}} - \overbrace{2x_i x_j'}^{\text{green}} + \underbrace{x_j'^2}_{\text{red}}) + (\underbrace{y_i^2}_{\text{blue}} - \overbrace{2y_i y_j'}^{\text{green}} + \underbrace{y_j'^2}_{\text{red}}) + (\underbrace{z_i^2}_{\text{blue}} - \overbrace{2z_i z_j'}^{\text{green}} + \underbrace{z_j'^2}_{\text{red}}) \\
 &= (\underbrace{x_i^2}_{\text{blue}} + \underbrace{y_i^2}_{\text{blue}} + \underbrace{z_i^2}_{\text{blue}}) + (\underbrace{x_j'^2}_{\text{red}} + \underbrace{y_j'^2}_{\text{red}} + \underbrace{z_j'^2}_{\text{red}}) - 2(\overbrace{x_i x_j'}^{\text{green}} + \overbrace{y_i y_j'}^{\text{green}} + \overbrace{z_i z_j'}^{\text{green}}) \\
 &= \mathbf{p}_i^T \mathbf{p}_i + \mathbf{s}_j^T \mathbf{s}_j - 2 \mathbf{p}_i^T \mathbf{s}_j
 \end{aligned}$$

$$\mathbf{p}_i = \begin{bmatrix} x_i \\ y_i \\ z_i \end{bmatrix}$$

ith row of matrix \mathbf{P}

$$\mathbf{s}_j = \begin{bmatrix} x_j' \\ y_j' \\ z_j' \end{bmatrix}$$

th row of matrix \mathbf{S}

constant values
along rows

$$\mathbf{D}_1 = \begin{bmatrix} \mathbf{p}_0^T \mathbf{p}_0 & \dots & \mathbf{p}_0^T \mathbf{p}_{N-1} \\ \vdots & & \vdots \\ \mathbf{p}_{N-1}^T \mathbf{p}_0 & \dots & \mathbf{p}_{N-1}^T \mathbf{p}_{N-1} \end{bmatrix}_{N \times M}$$

$$\mathbf{D}_2 = \begin{bmatrix} \mathbf{s}_0^T \mathbf{s}_0 & \dots & \mathbf{s}_{m-1}^T \mathbf{s}_{m-1} \\ \vdots & & \vdots \\ \mathbf{s}_0^T \mathbf{s}_0 & \dots & \mathbf{s}_{m-1}^T \mathbf{s}_{m-1} \end{bmatrix}_{N \times M}$$

constant values
along columns

$$\mathbf{D}_3 = 2 \begin{bmatrix} \mathbf{p}_0^T \mathbf{s}_0 & \mathbf{p}_0^T \mathbf{s}_{m-1} \\ \vdots & \vdots \\ \mathbf{p}_{N-1}^T \mathbf{s}_0 & \mathbf{p}_{N-1}^T \mathbf{s}_{m-1} \end{bmatrix}_{N \times M} = 2 \mathbf{P}^T \mathbf{S}$$

$$\mathbf{D} = \mathbf{D}_1 + \mathbf{D}_2 - \mathbf{D}_3$$

How to efficiently compute this with Numpy?

Matrix \mathbf{D}_1 can be rewritten as the outer product of an $N \times 1$ vector and a $1 \times M$ vector containing 1's.

Similarly, \mathbf{D}_2 can be rewritten as the outer product of an $N \times 1$ vector of 1's and a $1 \times M$ vector.

$$\mathbf{D}_1 = \begin{bmatrix} \mathbf{P}_0^T \mathbf{P}_0 \\ \vdots \\ \mathbf{P}_{N-1}^T \mathbf{P}_{N-1} \end{bmatrix}_{N \times 1} \cdot \begin{bmatrix} 1 & \dots & 1 \end{bmatrix}_{1 \times M}$$

$$\mathbf{D}_2 = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}_{N \times 1} \cdot \begin{bmatrix} \mathbf{s}_0^T \mathbf{s}_0 & \dots & \mathbf{s}_{m-1}^T \mathbf{s}_{m-1} \end{bmatrix}_{1 \times M}$$

So, matrix \mathbf{D} is given by:

$$\mathbf{D} = \overbrace{\begin{bmatrix} \mathbf{P}_0^T \mathbf{P}_0 \\ \vdots \\ \mathbf{P}_{N-1}^T \mathbf{P}_{N-1} \end{bmatrix}}^{\mathbf{D}_1} \cdot \begin{bmatrix} 1 & \dots & 1 \end{bmatrix} + \overbrace{\begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}}^{\mathbf{D}_2} \cdot \begin{bmatrix} \mathbf{s}_0^T \mathbf{s}_0 & \dots & \mathbf{s}_{m-1}^T \mathbf{s}_{m-1} \end{bmatrix} - 2 \mathbf{P}^T \mathbf{S}$$

However, we may use Numpy to compute this in a tricky way (See the function 'vectorized' in 'sedm.py'), according to the steps below:

① Hadamard product $\mathbf{P}_0 \mathbf{P} = \begin{bmatrix} x_0^2 & \dots & x_{N-1}^2 \\ y_0^2 & \dots & y_{N-1}^2 \\ z_0^2 & \dots & z_{N-1}^2 \end{bmatrix}_{3 \times N}$

② $\text{sum}(\mathbf{P}_0 \mathbf{P}, \text{axis}=0) = \begin{bmatrix} x_0^2 & \dots & x_{N-1}^2 \\ y_0^2 & \dots & y_{N-1}^2 \\ z_0^2 & \dots & z_{N-1}^2 \end{bmatrix}_{1 \times N}$ sum elements along the rows

$$= \begin{bmatrix} \mathbf{P}_0^T \mathbf{P}_0 & \dots & \mathbf{P}_{N-1}^T \mathbf{P}_{N-1} \end{bmatrix}_{1 \times N}$$

③ Hadamard product $\mathbf{S}_0 \mathbf{S} = \begin{bmatrix} x_0'^2 & \dots & x_{m-1}'^2 \\ y_0'^2 & \dots & y_{m-1}'^2 \\ z_0'^2 & \dots & z_{m-1}'^2 \end{bmatrix}_{3 \times m}$

④ $\text{sum}(\mathbf{S}_0 \mathbf{S}, \text{axis}=0) = \begin{bmatrix} x_0'^2 & \dots & x_{m-1}'^2 \\ y_0'^2 & \dots & y_{m-1}'^2 \\ z_0'^2 & \dots & z_{m-1}'^2 \end{bmatrix}_{1 \times m}$ sum elements along the rows

$$= \begin{bmatrix} \mathbf{s}_0^T \mathbf{s}_0 & \dots & \mathbf{s}_{m-1}^T \mathbf{s}_{m-1} \end{bmatrix}_{1 \times M}$$

$$\mathbf{D} = \begin{bmatrix} \mathbf{P}_0^T \mathbf{P}_0 & \dots & \mathbf{P}_{N-1}^T \mathbf{P}_{N-1} \end{bmatrix}_{1 \times N} \cdot \begin{bmatrix} 1 & \dots & 1 \end{bmatrix}_{1 \times M} + \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}_{N \times 1} \cdot \begin{bmatrix} \mathbf{s}_0^T \mathbf{s}_0 & \dots & \mathbf{s}_{m-1}^T \mathbf{s}_{m-1} \end{bmatrix}_{1 \times M} - 2 \mathbf{P}^T \mathbf{S}$$

NEW AXIS

Python uses Numpy broadcasting rules to compute matrix \mathbf{D} according to this equation. These rules, however, allow evaluating this equation without actually creating neither the vectors of 1's nor computing the outer products to form the full matrices \mathbf{D}_1 and \mathbf{D}_2 .