

# Euclidean Distance: Expectation, Variance, and Standard Deviation

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## 1 Euclidean Distance

$$D(\mathbf{X}, \mathbf{Y}) = \|\mathbf{X} - \mathbf{Y}\|_2 = \sqrt{\sum_{i=1}^n (x_i - y_i)^2}, \quad (1)$$

where,

- $\mathbf{X}, \mathbf{Y} \in \mathbb{R}^n$  are two vectors in range  $(a, b), a < b$ .
- $D \in \mathbb{R}$  is the Euclidean distance between  $\mathbf{X}$  and  $\mathbf{Y}$ .

## 2 Derivation of Expectation

To compute the expectation of the Euclidean distance  $D(\mathbf{X}, \mathbf{Y})$ , we first calculate the expected value of the square of the distance.

### 2.1 Expected Squared Difference for One Dimension

For each component  $x_i \in \mathbf{X}_{i=1, \dots, n}$  and  $y_i \in \mathbf{Y}_{i=1, \dots, n}$ , the expectation of the square of the difference uniformly distributed over  $(a, b)$  is:

$$\mathbb{E}[(x_i - y_i)^2] = \frac{(b - a)^2}{6} \in \mathbb{R} \quad (2)$$

### 2.2 Expected Squared Euclidean Distance

As the squared Euclidean distance is the sum of the squared differences over all  $n$  dimensions, its expectation is:

$$\mathbb{E}[D(\mathbf{X}, \mathbf{Y})^2] = n \cdot \frac{(b - a)^2}{6} \in \mathbb{R} \quad (3)$$

### 2.3 Expected Euclidean Distance

Taking the square root of the expected squared distance, the expectation of the Euclidean distance is as follows:

$$\mathbb{E}[D(\mathbf{X}, \mathbf{Y})] = \sqrt{\frac{n}{6}} \cdot (b - a) \in \mathbb{R} \quad (4)$$

### 3 Derivation of Variance

The variance of the Euclidean distance  $D(\mathbf{X}, \mathbf{Y})$  is obtained by first calculating the variance of the squared Euclidean distance.

#### 3.1 Variance of the Squared Difference

The variance of the squared difference  $(x_i - y_i)^2$  is given by:

$$\text{Var}[(x_i - y_i)^2] = \mathbb{E}[(x_i - y_i)^4] - (\mathbb{E}[(x_i - y_i)^2])^2 \quad (5)$$

For uniformly distributed  $x_i$  and  $y_i$  over  $(a, b)$ , we have:

$$\mathbb{E}[(x_i - y_i)^4] = \frac{(b - a)^4}{5} \in \mathbb{R} \quad (6)$$

Thus, the variance of  $(x_i - y_i)^2$  is:

$$\text{Var}[(x_i - y_i)^2] = (b - a)^4 \left( \frac{1}{5} - \frac{1}{36} \right) = (b - a)^4 \cdot \frac{31}{180} \in \mathbb{R} \quad (7)$$

#### 3.2 Variance of the Squared Euclidean Distance

The squared Euclidean distance is the sum of the squared differences across all  $n$  dimensions, so its variance is:

$$\text{Var}[D(\mathbf{X}, \mathbf{Y})^2] = n \cdot (b - a)^4 \cdot \frac{31}{180} \in \mathbb{R} \quad (8)$$

### 4 Derivation of Standard Deviation

Finally, the variance of the Euclidean distance  $D(\mathbf{x}, \mathbf{y})$  can be approximated using the delta method:

$$\text{Var}[D(\mathbf{X}, \mathbf{Y})] \approx \frac{1}{4} \cdot \frac{\text{Var}[D(\mathbf{X}, \mathbf{Y})^2]}{\mathbb{E}[D(\mathbf{X}, \mathbf{Y})^2]} \quad (9)$$

We know that:

$$\mathbb{E}[D(\mathbf{X}, \mathbf{Y})^2] = n \cdot \frac{(b - a)^2}{6} \in \mathbb{R} \quad (10)$$

Substituting, we get:

$$\text{Var}[D(\mathbf{X}, \mathbf{Y})] = \frac{31}{120} \cdot (b - a)^2 \in \mathbb{R} \quad (11)$$

Therefore, the standard deviation is:

$$\sigma(n) = \sqrt{\frac{31}{120}} \cdot (b - a) \approx 0.507 \cdot (b - a) \in \mathbb{R} \quad (12)$$