

Population $\mu \in \mathbb{R}^{p \times p}$

$$s_{ij} = \frac{1}{n} \sum_{p=1}^n (x_i - \bar{x}_i) (x_j - \bar{x}_j)^T$$

Sample $\bar{x} \in \mathbb{R}^{p \times p}$

$$s_{ij} = \frac{1}{n} \sum_{i=1}^n (x_{ii} - \bar{x}_i) (x_{ij} - \bar{x}_j)$$

$$\begin{aligned} \bar{x}_j &= \frac{x_{1j}}{n} \\ &= \frac{x_{2j}}{n} \\ &= \frac{x_{3j}}{n} \\ &\vdots \\ &= \frac{x_{nj}}{n} \end{aligned} \quad \bar{x} = \begin{pmatrix} \bar{x}_1 \\ \vdots \\ \bar{x}_p \end{pmatrix} \quad \bar{x}_j = \frac{\sum_{i=1}^n x_{ij}}{n}$$

unless sample data given the formulas are P.V.
practically they're deterministic.

Collect sample & sample data matrix.

$$\begin{bmatrix} \text{Sample} \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ \vdots \end{bmatrix}_{n \times p}$$

In \mathbb{R}^P , we have the sample points.

so in finite dims, all distances are equiv. (all norms are equiv. in F.dim).

2 sample pts x, y then
(euclidean distance) -

$$d(x, y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \dots + (x_p - y_p)^2}$$

$$\begin{bmatrix} x_1 & x_2 & x_3 \\ (\text{meters}) & (\text{hours}) & (\text{grams}) \end{bmatrix}$$

Flaw 1: diff. units of features; we need to make data collection unitless.

Suppose $p=3$.

x	1.9	4.8
y	6.0	5.1

$$d(x, y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + (x_3 - y_3)^2} = 48.17$$

Flaw 2: if feature very dominant; hide the properties of other features.

Flaw 3: doesn't capture the dependency of one feature on other.

Solved by providing weights to the components ($(x_i - y_i)^2$).

$$d(x, y) = \sqrt{\frac{x_1^2}{\sigma_{11}^2} + \frac{x_2^2}{\sigma_{22}^2} + \dots + \frac{x_p^2}{\sigma_{pp}^2}} \quad \left(\text{similar to } x \sim N(\mu, \Sigma) \right)$$

This makes the components unitless.

Now, each component of vector x, y is given a weight in distance calculation b/w x & y . & wt's \perp $1 \leq i \leq p$.

Dependency structure b/w feature in d -formula-

$$d(x, y) = \sqrt{\frac{x_1^2}{\sigma_{11}^2} + \frac{x_2^2}{\sigma_{22}^2} + \dots + \frac{x_p^2}{\sigma_{pp}^2}} = c \approx$$

$$x = \begin{pmatrix} x_1 \\ \vdots \\ x_p \end{pmatrix}$$

$$\frac{x_1^2}{c^2 \sigma_{11}^2} + \frac{x_2^2}{c^2 \sigma_{22}^2} + \dots + \frac{x_p^2}{c^2 \sigma_{pp}^2} = 1.$$

standard ellipse.

p -axis in ellipse (tilted ellipses)

semilength = $c \sqrt{\sigma_{ii}}$.

higher variance \Rightarrow elongated on that side.



Let $p=2$. (tilted ellipse bcz of dependency b/w two features).

$$x = (x_1, x_2)$$

rotation matrix:

$$\begin{pmatrix} x_1^* \\ x_2^* \end{pmatrix} = \begin{pmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} \cos \theta x_1 + \sin \theta x_2 \\ -\sin \theta x_1 + \cos \theta x_2 \end{pmatrix}$$

standard frame:

tilted frame:

orthonormal matrix:

$$P^T P = I$$

$$x_1^* - \bar{x}_1^* = \cos \theta (x_1 - \bar{x}_1) + \sin \theta (x_2 - \bar{x}_2)$$

$$x_2^* - \bar{x}_2^* = -\sin \theta (x_1 - \bar{x}_1) + \cos \theta (x_2 - \bar{x}_2)$$

shifting range to mean.

$$\text{Var}(x_1^*) = \cos^2 \theta \text{Var}(x_1) + \sin^2 \theta \text{Var}(x_2)$$

$$+ 2 \sin \theta \cdot \cos \theta \cdot \text{cov}(x_1, x_2)$$

$$\text{Var}(x_2^*) = \text{similarly}$$

$$d(\bar{x}, p) = \sqrt{\frac{(x_1^* - \bar{x}_1^*)^2}{\sigma_{11}^2} + \frac{(x_2^* - \bar{x}_2^*)^2}{\sigma_{22}^2}}$$

$$= \sqrt{a_{11}(x_1 - \bar{x}_1)^2 + 2a_{12}(x_1 - \bar{x}_1)(x_2 - \bar{x}_2) + a_{22}(x_2 - \bar{x}_2)^2}$$

$$\downarrow \text{constants in terms of } \sin \theta \text{ & } \cos \theta$$

$$(x - \bar{x})^T A (x - \bar{x}) \quad A = \begin{bmatrix} a_{11} & a_{12} \\ a_{12} & a_{22} \end{bmatrix}$$

$$= \langle x - \bar{x}, A(x - \bar{x}) \rangle$$

ratio.

we need the dist to be true, for which we need to have A as symmetric & semi definite, to define the inner product.

The role of A matrix is played by S^{-1} .

$\therefore S$ is symmetric \Rightarrow

S is always semi definite?

iff.

all minors ≥ 0 .

$$S_{11} \cdot S_{22} - S_{12} \cdot S_{21} \geq 0$$

$$S_{11} \cdot S_{22} - (S_{12})^2 \geq 0$$

$$\sqrt{S_{11} S_{22}} \geq S_{12}$$

$$\frac{S_{12}}{\sqrt{S_{11} S_{22}}} < 1$$

S positive semi def.

so one eigen val can be zero.

so inverse not possible

but for all practical purposes we take S to be positive definite.

$$d(x, p) = x^T S^{-1} x \rightarrow \text{Mahalanobis dist.}$$

$$S = \begin{bmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{bmatrix}$$

$$S_{11} > 0$$

$$S_{11} \cdot S_{22} - S_{12} \cdot S_{21} > 0$$

$$\sqrt{S_{11} S_{22}} > S_{12}$$

$$\frac{S_{12}}{\sqrt{S_{11} S_{22}}} < 1$$

S positive semi def.

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