



$\bar{x}_1, \bar{x}_2, \dots, \bar{x}_n$

Correlation. Binary Relation.

$\bar{x}, \bar{y}, \bar{y}, \bar{v} \in \mathbb{R}$

Distance (Metric), x, y const.

$|\bar{x} - \bar{y}|$ Euclid. Dist

$$|\bar{x} - \bar{y}| \rightarrow E|\bar{x} - \bar{y}| \rightarrow E|\bar{x} - \bar{y}|^2 \quad E|\bar{x} - \bar{y}|^2 = 0$$

$$\rightarrow (E|\bar{x} - \bar{y}|^2)^{\frac{1}{2}} = d(\bar{x}, \bar{y})$$

$$\bar{x} = \bar{y} \approx P(\bar{x} = \bar{y}) = 1$$

$$d(x, y) : L \times L \rightarrow \mathbb{R}_+$$

$$\textcircled{1} d(x, y) \geq 0. \quad d(x, y) = 0 \Leftrightarrow x = y.$$

$$\textcircled{2} d(x, y) = d(y, x).$$

$$\textcircled{3} d(x, y) + d(y, z) \geq d(x, z)$$

Mean Square Distance $(E|\bar{x} - \bar{y}|^2)^{\frac{1}{2}}$

$$E|\bar{x}|^2 + E|\bar{z}|^2$$

$$\geq E|\bar{x} - \bar{z}|^2$$

$$E|\bar{x}|^2 + E|\bar{z}|^2$$

$$- 2E(\bar{x}\bar{z})$$

$$(E|\bar{x}|^2)^{\frac{1}{2}} + (E|\bar{z}|^2)^{\frac{1}{2}}$$

$$\geq (E|\bar{x} - \bar{z}|^2)^{\frac{1}{2}}$$

$$(E|\bar{x}|^2 E|z|^2)^{\frac{1}{2}} \geq |E(\bar{x}z)| \quad \text{Cauchy-Schwarz}$$

$$x_1, \dots, x_n, y_1, \dots, y_n \in \mathbb{R}$$

$$\left(\sum_{k=1}^n |\bar{x}_k|^2 \sum_{k=1}^n |y_k|^2 \right)^{\frac{1}{2}} \geq \left| \sum_{k=1}^n x_k y_k \right|$$

$$f(x), g(x), \mathbb{R} \rightarrow \mathbb{R}$$

$$\left(\frac{x_1 + \dots + x_n}{n} \right)^2 \leq \frac{x_1^2 + \dots + x_n^2}{n}$$

Inner Product

$$x, y \in L, \langle x, y \rangle$$

$$\left(\int_{\mathbb{R}} f^2(x) dx \int_{\mathbb{R}} g^2(x) dx \right)^{\frac{1}{2}} \geq \left| \int_{\mathbb{R}} f(x) g(x) dx \right|$$

$$\textcircled{1} \langle x, x \rangle \geq 0 \quad \begin{matrix} \langle x, x \rangle = 0 \\ \Downarrow \\ x = 0 \end{matrix}$$

$$\textcircled{2} \text{ Bilinear: } \langle \alpha x + \beta y, z \rangle = \alpha \langle x, z \rangle + \beta \langle y, z \rangle$$

$$\langle x, \alpha y + \beta z \rangle = \alpha \langle x, y \rangle + \beta \langle x, z \rangle$$

$$\langle (x_1, \dots, x_n), (y_1, \dots, y_n) \rangle = \sum_{k=1}^n x_k y_k \quad \sum_{k=1}^n x_k^2 \geq 0$$

$$\langle f, g \rangle = \int_{\mathbb{R}} f(x) g(x) dx \quad \begin{matrix} \downarrow & \downarrow \\ (\alpha z_1 + \beta h)_f & \end{matrix}$$

$$\langle \bar{x}, y \rangle = E(\bar{x}y)$$

$$(E|X-Y|^2)^{\frac{1}{2}} = (E|X|^2 + E|Y|^2 - 2E(XY))^{\frac{1}{2}}. \quad E|X|^2 + E|Z|^2 \geq E|X-Z|^2$$

$E(XY)$. Correlation. Geometry

Angle. $\frac{\langle X, Y \rangle}{|X| |Y|} = \cos \angle(X, Y)$.

Hilbert Space

$$\frac{E(XY)}{|X|^{\frac{1}{2}} |Y|^{\frac{1}{2}}} = \cos \angle(X, Y)$$

$$\alpha = \frac{E(XY)}{E(X^2)}$$

$$\frac{2E(XZ)}{E|Z|^2} = \frac{2E(XZ)}{|Z|^2}$$

X, Y Orthogonal. $\angle(X, Y) = \frac{\pi}{2} \iff E(XY) = 0$.

Projection. $\text{Proj}_X Y = \frac{X}{\|X\|} \frac{E(XY)}{E(X^2)}$



$$C = \|Y\| \cos \angle(X, Y) = \frac{E(XY)}{|X|^{\frac{1}{2}} |Y|^{\frac{1}{2}}} |Y|^{\frac{1}{2}} = \frac{E(XY)}{(E|X|^2)^{\frac{1}{2}}}$$

$$\min_{\alpha} \|Y - \alpha X\| \rightarrow \min_{\alpha} \|Y - \alpha X\|^2 = \min_{\alpha} \alpha^2 \|X\|^2 - 2\alpha E(XY) + \|Y\|^2$$

$$R_X = E(X X^T) \quad R_X(i, j) = E(X_i X_j) \quad E(X_i X_j) = E(X_j X_i) \\ \frac{n(n+1)}{2}, \quad \frac{n(n-1)}{2} = \binom{n}{2} \quad \text{Correlation Matrix} \quad R_X \left(\begin{smallmatrix} 1 \\ \vdots \\ n \end{smallmatrix} \right) = R_X(j, i) = R_X(i, j) \\ \nabla_\alpha E(Y - \alpha^T X)^2 = -r_{XY} - r_{XY} + (R_X + R_X^T) \cdot \alpha \quad \downarrow \\ = 2R_X \cdot \alpha - 2r_{XY} = 0 \quad R_X = R_X^T \\ \Rightarrow R_X \cdot \alpha = r_{XY} \Rightarrow \alpha = R_X^{-1} \cdot r_{XY} \quad (\text{Yule-Walker})$$

$$Y \in \mathbb{R}, \quad X_1, \dots, X_n, \quad (X_1, \dots, X_n) \rightarrow Y, \quad \text{Linear Approximation} \\ X \in \mathbb{R}^n, \quad \alpha = (\alpha_1, \dots, \alpha_n)^T \quad \min_\alpha \|Y - \sum_{k=1}^n \alpha_k X_k\|^2 \quad X = (X_1, \dots, X_n)^T \\ \min_\alpha E(Y - \alpha^T X)^2 = \min_\alpha E(Y - \alpha^T X)(Y - \alpha^T X)^T \\ = \min_\alpha (E|Y|^2 - \alpha^T E(YX) - E(YX^T)\alpha + \alpha^T E(XX^T)\alpha) \\ = \min_\alpha (E|Y|^2 - \alpha^T r_{XY} - r_{XY}^T \alpha + \alpha^T R_X \alpha)$$

$$\int_{\Omega} x g(x) dx$$

$$1 = \int_{\Omega} g(x) dx.$$

mass density

\mathbb{R} . a determined constant.

$$\min_a E(\bar{X} - a)^2 \quad H(a) = E(\bar{X} - a)^2$$

$$\frac{d}{da} H(a) = -2 E(\bar{X} - a) = 0 \Rightarrow a = E(\bar{X})$$

$$E(\bar{X}_1 + \dots + \bar{X}_n) = E(\bar{X}_1) + \dots + E(\bar{X}_n)$$

Matching N persons, N hats.

$$I_k = \begin{cases} 0 & k \text{ person matched} \\ 1 & k \text{ person mismatch} \end{cases}$$

$$N = I_1 + \dots + I_n.$$

Sample Space. $\{A_1, A_2, \dots, A_n, \dots\} = \Omega$.

$$A_k \in \{H_1, \dots, H_n\}$$

$$\frac{(n-1)!}{n!} B_1 \subseteq \Omega, \text{ 1 person matched}$$

$$P(B_1 \cap B_2) B_2 \subseteq \Omega, \text{ 2 person matched}$$

$$= \frac{(n-2)!}{n!} B_n \subseteq \Omega, \text{ n person matched}$$

$$= \frac{1}{n(n-1)}$$

$$P(\bar{B}_1 \cap \bar{B}_2 \cap \dots \cap \bar{B}_n)$$

$$= P(\overline{B_1 \cup B_2 \cup \dots \cup B_n})$$

$$= 1 - P(B_1 \cup B_2 \cup \dots \cup B_n)$$

$$P(B_1 \cup B_2 \cup \dots \cup B_n) \quad (\text{Inclusion-Exclusion})$$

$$= \underline{P(B_1)} + \dots + P(B_n)$$

$$- \sum_{1 \leq i < j} P(B_i \cap B_j)$$

$$+ \sum_{1 \leq i < j < k} P(B_i \cap B_j \cap B_k) - \dots$$

$$= n \cdot \frac{1}{n} - \frac{n(n-1)}{2} \cdot \frac{1}{n(n-1)} + \frac{n(n-1)(n-2)}{3!} \cdot \frac{1}{n(n-1)(n-2)} + \dots$$

$$\exp(x)$$

$$= \sum_{k=0}^{\infty} \frac{(-1)^k x^k}{k!}$$

$$= 1 - \frac{1}{2!} + \frac{1}{3!}$$

$$- \frac{1}{4!} + \dots$$

$$P(\bar{B}_1 \cap \dots \cap \bar{B}_n)$$

$$= 1 - (1 - \frac{1}{2!} + \frac{1}{3!} - \frac{1}{4!} + \dots)$$

$$= \exp(-1)$$

$$E(N) = E(I_1 + \dots + I_n) = E(I_1) + \dots + E(I_n)$$

$$E(I_k) = 1 \cdot P(I_k=1) + 0 \cdot P(I_k=0)$$

$$= 1 \cdot \frac{1}{n} = \frac{1}{n}$$

$$E(N) = n \cdot \frac{1}{n} = 1$$

$\bar{x}(t) = \bar{x}(\omega, t)$. Sample Path.

$\bar{x}(t), \bar{x}(s)$. $E(\bar{x}(t)\bar{x}(s)) = R_{\bar{x}}(t, s)$. Binary Function.

(Auto)Correlation Function.

$$R_{\bar{x}}(t, t) \geq 0. \quad E|\bar{x}(t)|^2 \geq 0.$$

Cross-Correlation $E(\bar{x}(t)\bar{y}(s))$

$$R_{\bar{x}}(t, s) = R_{\bar{x}}(s, t)$$

$$|R_{\bar{x}}(t, s)| \leq (R_{\bar{x}}(t, t)R_{\bar{x}}(s, s))^{1/2}$$

Positive-Definite. $g(x, y)$ is Pd.

$$\Leftrightarrow \forall n \in \mathbb{N}^2 \quad \forall t_1, \dots, t_n \in \mathbb{R} \quad (g(t_i, t_j))_{i,j} = G. \quad G \text{ is Pd.}$$

$$G \in \mathbb{R}^{n \times n} \text{ is Pd} \Leftrightarrow \forall \alpha \in \mathbb{R}^n \quad \alpha^T G \alpha \geq 0.$$

$$R_X(t_i, t_j) = E(X(t_i) X(t_j)) \quad \text{Let } \underline{X} = (X(t_1), \dots, X(t_n))^T$$

$$G_X = E(\underline{X} \underline{X}^T) \quad \alpha^T G_X \alpha = \alpha^T E(\underline{X} \underline{X}^T) \alpha = E(\alpha^T \underline{X} \underline{X}^T \alpha) = E(\alpha^T \underline{X})^2 \geq 0$$

$$E(N) = E(I_1 + \dots + I_n) = E(I_1) + \dots + E(I_n).$$

$$E(I_k) = 1 \cdot P(I_k = 1) \quad \text{Characteristic Property}$$

$$\frac{1}{2}(A + A^T) = 1 \cdot \frac{1}{h} = \frac{1}{h} \quad \text{Correlation} \leftrightarrow \text{Positive Definite}$$

$$\alpha^T A \alpha = \alpha^T \left(\frac{1}{2}(A + A^T) \right) \alpha$$

$$R_X(t, t) \geq 0$$

$$\frac{1}{2}(R_X(t, s) + R_X(s, t))$$

$$\begin{pmatrix} R_X(t, t) & R_X(t, s) \\ R_X(s, t) & R_X(s, s) \end{pmatrix}$$