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Assignment 2

PROBLEM 1

(1)

$$\begin{aligned} P(X=1) &= P(X=1|Y=1) \cdot P(Y=1) + P(X=1|Y=0) \cdot P(Y=0) \\ &\quad \swarrow \quad \searrow \\ &= P(X=1|Y=1, Z=1) \cdot P(Y=1, Z=1) + P(X=1|Y=1, Z=0) \cdot P(Y=1, Z=0) \\ &= P(X=1|Y=1, Z=1) \cdot P(Y=1) \cdot P(Z=1) + P(X=1|Y=1, Z=0) \cdot P(Y=1) \cdot P(Z=0) \\ &= 0.6 \times 0.9 \times 0.8 + 0.1 \times 0.9 \times 0.2 = 0.45 \end{aligned}$$

$$P(X=1) = 0.45 + 0.02 = 0.47$$

(2) $E(Y) = 1 \times P(Y=1) + 0 \times P(Y=0)$

$$= 1 \times 0.9 + 0 \times 0.1$$

$$= 0.9$$

(3) $P(Y=115) = 0.9$

$$P(Y=20) = 1 - 0.9 = 0.1 \quad \rightarrow \quad E(Y) = 115 \times P(Y=115) + 20 \times P(Y=20)$$

$$= 115 \times 0.9 + 20 \times 0.1$$

$$= 105.5$$

PROBLEM 2

| | $P(X)$ | $P(\text{defect} X)$ |
|---|--------|------------------------|
| A | 0.2 | 0.02 |
| B | 0.3 | 0.01 |
| C | 0.5 | 0.0005 |

$X \in (A, B, C)$

total = 10,000

$$(1) P(\text{defective}) = 0.2 \times 0.02 + 0.3 \times 0.01 + 0.5 \times 0.0005 = 0.00725$$

$$(2) P(A | \text{defective}) = \frac{P(\text{defective} | A) \cdot P(A)}{P(\text{defective})} = \frac{0.02 \times 0.2}{0.00725} \approx 0.5517$$

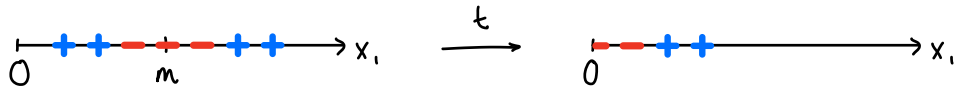
$$(3) P(B | \text{defective}) = \frac{P(\text{defective} | B) \cdot P(B)}{P(\text{defective})} = \frac{0.01 \times 0.3}{0.00725} \approx 0.41379$$

$$(4) P(C | \text{defective}) = \frac{P(\text{defective} | C) \cdot P(C)}{P(\text{defective})} = \frac{0.0005 \times 0.5}{0.00725} \approx 0.0207$$

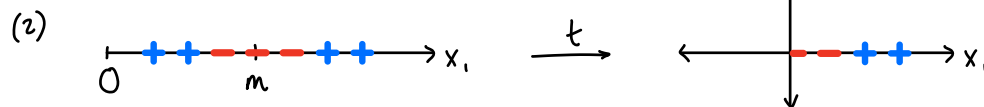
PROBLEM 3

Designing Transformations

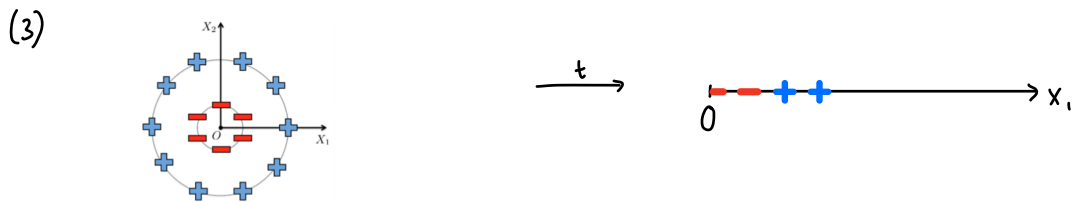
(1) $m = \text{median}$



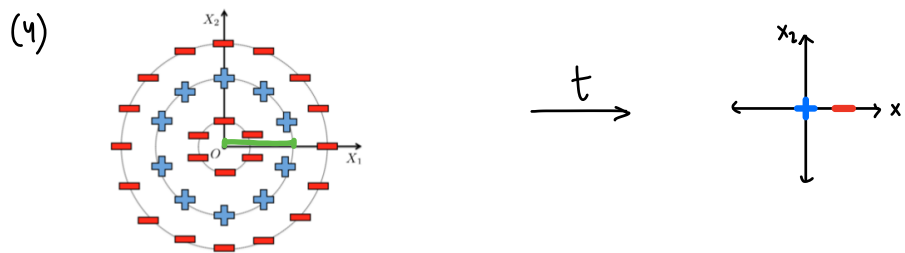
$$t(x) = |m - x|$$



$$t(x) = (|m - x|, 0)$$



$$t(x_1, x_2) = \sqrt{x_1^2 + x_2^2}$$



d = shortest distance from origin to second ring

$$t(x_1, x_2) = (|d - \sqrt{x_1^2 + x_2^2}|, 0)$$

Kernel or Not

(1) $k(x, z) = (xz + 1)^2 \rightarrow X = \begin{bmatrix} x_i \\ x_j \end{bmatrix} \quad z = \begin{bmatrix} z_i \\ z_j \end{bmatrix}$

$$(xz + 1)^2 = (xz)^2 + 2xz + 1$$

$$= x_i^2 z_i^2 + 2x_i z_i x_j z_j + x_i^2 z_j^2 + 2x_i z_i + 2x_j z_j + 1$$

$$xz = x_i z_i + x_j z_j$$

$$xz^2 = x_i^2 z_i^2 + 2x_i z_i x_j z_j + x_j^2 z_j^2$$

$$= \begin{bmatrix} x_i^2 \\ \sqrt{2} x_i x_j \\ x_i^2 \\ \sqrt{2} x_i \\ \sqrt{2} x_j \\ 1 \end{bmatrix} \cdot \begin{bmatrix} z_i^2 \\ \sqrt{2} z_i z_j \\ z_j^2 \\ \sqrt{2} z_i \\ \sqrt{2} z_j \\ 1 \end{bmatrix}$$

$$= \langle \phi(x), \phi(z) \rangle$$

✓ valid kernel

(2) $k(x, z) = (xz - 1)^3$

$$\begin{aligned} (a-1)^3 &= (a-1)^2(a-1) \\ &= (a^2 - 2a + 1)(a-1) \\ &= a^3 - 2a^2 + a - a^2 + 2a - 1 \\ &= a^3 - 3a^2 + 3a - 1 \end{aligned}$$

$$xz = x_i z_i + x_j z_j$$

$$xz^2 = x_i^2 z_i^2 + 2x_i z_i x_j z_j + x_j^2 z_j^2$$

$$xz^3 = x_i^3 z_i^3 + 2x_i^2 z_i^2 x_j z_j + x_i z_i \cdot x_j^2 z_j^2 + x_j z_j x_i^2 z_j^2 + 2x_i z_i x_j^2 z_j^2 + x_j^3 z_j^3$$

$$\begin{aligned} (xz - 1)^3 &= x_i^3 z_i^3 + 2x_i^2 z_i^2 x_j z_j + x_i z_i \cdot x_j^2 z_j^2 + x_j z_j x_i^2 z_j^2 + 2x_i z_i x_j^2 z_j^2 + x_j^3 z_j^3 \\ &\quad - 3x_i^2 z_i^2 - 6x_i z_i x_j z_j - 3x_j^2 z_j^2 \\ &\quad + x_i z_i + x_j z_j \\ &\quad - 1 \end{aligned}$$

↪ cannot express this in terms of $\langle \phi(x), \phi(z) \rangle$

↪ not a valid kernel

PROBLEM 4

(1) Exponential family distribution: $p(y; \eta) = b(y) \exp(\eta^T T(y) - a(\eta))$

$$\begin{aligned} p(y; \phi) &= (1-\phi)^{y-1} \phi \\ &= \exp[(y-1) \cdot \log(1-\phi) + \log(\phi)] \\ &= \exp[(y-1) \cdot \log(1-\phi) - \log(1 - \exp[\log(1-\phi)])] \quad \checkmark \end{aligned}$$

$$\begin{aligned} \eta &= \log(1-\phi) \\ a(\eta) &= -\log(1 - \exp(\eta)) \\ T(y) &= y-1 \\ b(y) &= 1 \end{aligned}$$

(2) From assumptions about GLMs:

$$\eta = w^T x$$

$$\begin{aligned} \log\text{-likelihood} &= \log \left[\exp[(y-1) \cdot \log(1-\phi) - \log(1 - \exp[\log(1-\phi)])] \right] \\ &= (y-1) \cdot \log(1-\phi) - \log(1 - \exp[\log(1-\phi)]) \\ &= \eta^T (y-1) - \log(1 - \exp(\eta)) \\ &= (w^T x)^T (y-1) - \log(1 - \exp(w^T x)) \\ &= (x^T w)(y-1) - \log(1 - \exp(w^T x)) \end{aligned}$$

$$\begin{aligned} \frac{\partial \log\text{-likelihood}}{\partial w} &= x^T (y-1) - (1 - \exp(w^T x))^{-1} \cdot \exp(w^T x) \cdot x \\ &= x^T (y-1) - \frac{\exp(w^T x) \cdot x}{1 - \exp(w^T x)} \end{aligned}$$

$$w \leftarrow w + \alpha \left(\frac{\partial \log\text{-likelihood}}{\partial w} \right)$$

$$w \leftarrow w + \alpha \left[x^T (y-1) - \frac{\exp(w^T x) \cdot x}{1 - \exp(w^T x)} \right]$$

PROBLEM 5 - attached (Python code)