





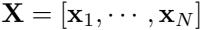
A pixelated, black and white representation of the text "Xavier's Law". The font is a stylized, blocky, and somewhat irregular typeface. The letters are composed of various shades of gray and black pixels, giving it a digital or retro aesthetic. The text is centered horizontally and occupies the middle portion of the image.

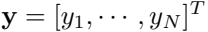












W E I S A I

A pixelated, black and white graphic of the word "EQUUS" in a stylized, blocky font. The letters are composed of various shades of gray and black pixels, giving it a digital or retro aesthetic. The 'E' is particularly prominent with its horizontal bars. The 'Q' has a distinct tail. The 'U' and 'S' are also clearly defined by the pixel pattern.

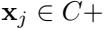






A pixelated, black and white representation of the text "Xmas is for the win". The characters are rendered in a blocky, digital font style, with each character composed of a grid of black and white pixels. The text is arranged in a single line, with spaces between the words. The overall aesthetic is reminiscent of early computer graphics or video game titles.











$\mathcal{P}_1(K)$

$\cdot \cdot \cdot$

$\mathcal{P}_2(K)$

QWERTYUIOPASDFGHJKLZXCVBNM

W

—
—

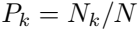
W

X

X
—
—

1

W











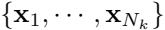
1999 2000



we are in the world

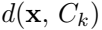






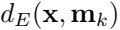


$$\mathbf{m}_k = \frac{1}{N_k} \sum_{n=1}^{N_k} \mathbf{x}_n, \quad \Sigma_k = \frac{1}{N_k} \sum_{n=1}^{N_k} (\mathbf{x}_n - \mathbf{m})^T (\mathbf{x}_n - \mathbf{m})$$



$$d(x, O) \leq \min(d(x, O_i) + 1, d(x, O_j) + 1, d(x, O_k) + 1)$$











Q1 ~ N(5, 1.2)
Q2 ~ N(5, 3)





১৯৭১ সালে বাংলাদেশের স্বাধীনতা লাভের পরে দেশের উন্নয়ন ও জনগণের কল্যাণের জন্য সরকার কর্তৃক প্রচেষ্টা চালানো হয়েছে।





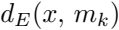














دعوتِ اسلامی کے لیے

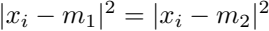
$$\begin{aligned}
 & \frac{d}{dt} \left(\frac{1}{2} m \dot{x}^2 \right) = \frac{d}{dt} \left(\frac{1}{2} m \dot{x}^2 \right) \\
 & \frac{d}{dt} \left(\frac{1}{2} m \dot{x}^2 \right) = \frac{d}{dt} \left(\frac{1}{2} m \dot{x}^2 \right)
 \end{aligned}$$





01 Nov 12, 02 Nov 12











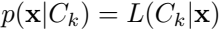
$$\begin{cases} d_M(x_1, C_1) = \frac{(x_1 - m_1)^2}{\sigma_1^2} = \frac{1}{1.2^2} = 0.69, & d_M(x_1, C_2) = \frac{(x_1 - m_1)^2}{\sigma_2^2} = \frac{1}{9} = 0.11 \\ d_M(x_2, C_1) = \frac{(x_1 - m_1)^2}{\sigma_1^2} = \frac{3}{1.2^2} = 6.25, & d_M(x_1, C_2) = \frac{(x_1 - m_1)^2}{\sigma_2^2} = \frac{3^2}{9} = 1 \end{cases}$$

$$P(C_k|x) = \frac{p(x, C_k)}{p(x)} = \frac{p(x|C_k)P(C_k)}{p(x)}$$

PERE



$$P_k = \frac{N_k}{N} = \frac{N_k}{\sum_{l=1}^K N_l}, \quad (k=1, \cdots, K)$$



$$p(\mathbf{x}|C_k) = N(\mathbf{x}, \mathbf{m}_k, \Sigma_k) = \frac{1}{(2\pi)^{d/2} |\Sigma_k|^{1/2}} \exp \left[-\frac{1}{2} (\mathbf{x} - \mathbf{m}_k)^T \Sigma_k^{-1} (\mathbf{x} - \mathbf{m}_k) \right]$$



$\frac{dx}{dt} = x(1-x)$





$$p(\mathbf{x}) = \sum_{k=1}^K p(\mathbf{x}, C_k) = \sum_{k=1}^K P_k p(\mathbf{x} | C_k) = \sum_{k=1}^K P_k \frac{1}{(2\pi)^{d/2} |\Sigma_k|^{1/2}} \exp \left[-\frac{1}{2} (\mathbf{x} - \mathbf{m}_k)^T \Sigma_k^{-1} (\mathbf{x} - \mathbf{m}_k) \right]$$



$$P(C_k|x) = \max_l \{P(C_l|x), (l=1, \cdots, K)\},$$





PLEASE JOIN ME





REPORT



ABXED + ABXED

PARADE PARADE PARADE

$$P_1 \int_{R_2} p(x/C_1) dx + P_2 \int_{R_1} p(x/C_2) dx$$

POSTER FOR POSTER





QUESTION: IS THERE A
RELATIONSHIP BETWEEN THE
NUMBER OF HOURS WORKED
AND THE NUMBER OF
MISTAKES MADE?

$$\mathbf{m}_k = \frac{1}{N_k} \sum_{i=1}^{N_k} \mathbf{x}_i, \quad \Sigma_k = \frac{1}{N_k} \sum_{i=1}^{N_k} (\mathbf{x}_i - \mathbf{m}_k)(\mathbf{x}_i - \mathbf{m}_k)^T, \quad (\mathbf{x}_i \in C_k)$$

100% 100% 100%

$$\log [p(x) / p_k] = \log p(x) - \log p_k$$

$$-\frac{1}{2}(\mathbf{x}-\mathbf{m}_k)^T\boldsymbol{\Sigma}_k^{-1}(\mathbf{x}-\mathbf{m}_k)-\frac{N}{2}\log(2\pi)-\frac{1}{2}\log|\boldsymbol{\Sigma}_k|+\log P_k-\log p(\mathbf{x})$$

100% 200%

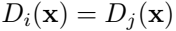
Wikipedia

$$D_k(x) = -\frac{1}{2}(x - \mathbf{m}_k)^T \Sigma_k^{-1}(x - \mathbf{m}_k) - \frac{1}{2} \log |\Sigma_k| + \log P_k$$

$$D(x) = \int_{-\infty}^x dx' D(x') = 1, \quad x \rightarrow \infty,$$

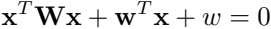


$$d_k(x) = (x - \mathbb{E}_k)^T \Sigma_k^{-1} (x - \mathbb{E}_k) + \log |\Sigma_k| - 2 \log P_k$$



$$-\frac{1}{2}(x-m_i)^T\Sigma_i^{-1}(x-m_i)-\frac{1}{2}\log|\Sigma_i|+\log P_i$$

$$-\frac{1}{2}(x-m_j)^T\Sigma_j^{-1}(x-m_j)-\frac{1}{2}\log|\Sigma_j|+\log P_j$$





$$\begin{aligned}
 &= \frac{1}{2} \left(\frac{1}{\Sigma} - \frac{1}{\Sigma} \right) \\
 &= \frac{1}{2} \left(\frac{1}{\Sigma} - \frac{1}{\Sigma} \right)
 \end{aligned}$$







$$-\frac{1}{2}(\mathbf{m}_i^T \Sigma_i^{-1} \mathbf{m}_i - \mathbf{m}_j^T \Sigma_j^{-1} \mathbf{m}_j) - \frac{1}{2} \log \frac{|\Sigma_i|}{|\Sigma_j|} + \log \frac{P_i}{P_j}$$

$$x^T w x + w^T x + w \begin{cases} > 0 \\ < 0 \end{cases} ,$$

$$x \in \left\{ \begin{array}{l} C_i \\ C_j \end{array} \right.$$

APRIL 1971



$$D_i(x) = -\frac{1}{2}(x - \mathbf{m}_i)^T \Sigma_i^{-1}(x - \mathbf{m}_i) - \frac{1}{2} \log |\Sigma_i|$$

$$d(x, z) = (x - \sqrt{x^2 - 1}) (x - 1) \log |z|$$

$$\begin{cases} d(x_1, C_1) = 0.69 + \log(1.2^2) = 1.06, & d_M(x_1, C_2) = 0.11 + \log(3^2) = 2.31 \\ d_M(x_2, C_1) = 6.25 + \log(1.2^2) = 6.61, & d_M(x_1, C_2) = 1 + \log(3^2) = 3.20 \end{cases}$$

100% 20

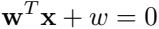


$$D_i(x) = -\frac{1}{2}(x - \mathbf{m}_i)^T \Sigma^{-1}(x - \mathbf{m}_i) + \log P_i$$



$$-\frac{1}{2}(x-\mathbf{m}_i)^T\Sigma^{-1}(x-\mathbf{m}_i)+\log P_i=-\frac{1}{2}(x-\mathbf{m}_j)^T\Sigma^{-1}(x-\mathbf{m}_j)+\log P_j$$



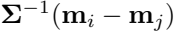


W = 1 - 10 - 10

$$v = -\frac{1}{2}(\mathbf{m}_i^T \Sigma^{-1} \mathbf{m}_i - \mathbf{m}_j^T \Sigma^{-1} \mathbf{m}_j) + \log \frac{P_i}{P_j}$$











3.21 = 3.21, 3.21



$$D_i(x) = -\frac{\|x - m_i\|^2}{2\sigma^2} + \log P_i$$

1009



31



$$\frac{\|x - m_i\|^2}{2\sigma^2} - \log p_i = \frac{\|x - m_j\|^2}{2\sigma^2} - \log p_j$$

$$\mathbf{w} = \mathbf{m}_i - \mathbf{m}_j, \quad u = -(\mathbf{m}_i^T \mathbf{m}_i - \mathbf{m}_j^T \mathbf{m}_j) + 2\sigma^2 \log \frac{P_i}{P_j}$$

$$D(x) = \sqrt{x} - \lfloor x \rfloor = |x| - \lfloor x \rfloor$$



Q200 = 450

$$\begin{bmatrix} 92 & 8 \\ 1 & 99 \end{bmatrix}$$

BE14050150200

175

25

36

164

1900-01-01

$$\begin{bmatrix} 196 & 3 & 1 \\ 0 & 191 & 9 \\ 3 & 33 & 164 \end{bmatrix}$$



$$\begin{bmatrix} 215 & 0 & 0 & 0 & 0 & 2 & 4 & 0 & 3 & 0 \\ 0 & 216 & 0 & 0 & 1 & 0 & 1 & 3 & 1 & 2 \\ 2 & 0 & 219 & 0 & 0 & 0 & 0 & 1 & 2 & 0 \\ 1 & 0 & 0 & 212 & 0 & 1 & 0 & 3 & 4 & 3 \\ 1 & 0 & 1 & 0 & 213 & 0 & 0 & 0 & 4 & 5 \\ 1 & 0 & 2 & 1 & 0 & 211 & 0 & 0 & 9 & 0 \\ 2 & 6 & 0 & 0 & 0 & 0 & 213 & 0 & 3 & 0 \\ 2 & 0 & 3 & 0 & 0 & 0 & 1 & 205 & 3 & 10 \\ 1 & 0 & 2 & 4 & 0 & 8 & 1 & 4 & 200 & 4 \\ 0 & 0 & 1 & 1 & 8 & 0 & 0 & 2 & 2 & 210 \end{bmatrix}$$

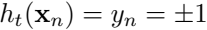
1992-1993

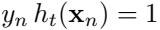


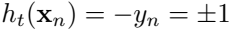
1991 + 1

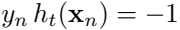
expanding the
range of
services
available to
the community
and
the
local
economy
and
the
local
economy

50%









$$\epsilon_t = \frac{\sum y_n h_t(x_n) - 1}{\sum_{n=1}^N w_t(n)}$$



$$1 - \epsilon_t = 1 - \frac{\sum y_n h_t(x_n) = -1}{\sum_{n=1}^N w_t(n)} = \frac{\sum y_n h_t(x_n) = 1}{\sum_{n=1}^N w_t(n)}$$



www.information.nl

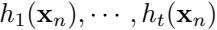
$$\epsilon_0 = \frac{1}{N} \sum_{y_n \neq h_0(x_n)} w_0(n) = \frac{\text{number of misclassified samples}}{\text{total number of samples}}$$

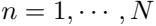














$$O_t h(x_n) + E_1(x_n) = O_t h(x_n) + E_1(x_n) + E_2(x_n)$$

$$\cdot \cdot \cdot = \sum_{i=1}^t a_i h_i(x_n)$$







$$H_t(x_n) = \text{sign}[F_t(x_n)] = \begin{cases} +1 & F_t(x_n) > 0 \\ -1 & F_t(x_n) < 0 \end{cases}$$





$$w_t(n) = e^{-y_n F_{t-1}(x_n)} \begin{cases} > 1 & \text{if } y_n F_{t-1}(x_n) < 0 \text{ (misclassification)} \\ < 1 & \text{if } y_n F_{t-1}(x_n) > 0 \text{ (correct classification)} \end{cases}$$





$$e^{-\sqrt{m}A} - 1(x) \leq e^{-\sqrt{m}B} - 1(x) + e^{-2(xm)} - 1(x)$$

$$e^{-\alpha_{t-1} y_n h_{t-1}(x_n)} e^{-y_n F_{t-2}(x_n)} = e^{-\alpha_{t-1} y_n h_{t-1}(x_n)} u_{t-1}(n)$$

$$v_1(x) = e^{-\alpha_0 x} \ln(x)$$

$$E_{t+1} = \sum_{n=1}^N w_{t+1}(n) = \sum_{n=1}^N e^{-y_n F_t(\mathbf{x}_n)} = \sum_{n=1}^N e^{-\alpha_t y_n h_t(\mathbf{x}_n)} w_t(n) \quad (t \geq 1)$$







$$E_{t+1} = \sum_{n=1}^N w_t(n) e^{-\alpha_t y_n h_t(\mathbf{x}_n)} = \sum_{y_n h_t(\mathbf{x}_n) = -1} w_t(n) e^{\alpha_t} + \sum_{y_n h_t(\mathbf{x}_n) = 1} w_t(n) e^{-\alpha_t}$$

$$\frac{dE_{t+1}}{d\alpha_t} = \sum_{y_n h_t(x_n)=-1} w_t(n) e^{\alpha_t} - \sum_{y_n h_t(x_n)=1} w_t(n) e^{-\alpha_t} = 0$$

$$\alpha_t = \frac{1}{2} \ln \left(\frac{\sum_{y_n h_t(x_n)=1} w_t(n)}{\sum_{y_n h_t(x_n)=-1} w_t(n)} \right) = \ln \sqrt{\frac{1 - \epsilon_t}{\epsilon_t}} > 0$$



$$e^{\alpha_t} = \sqrt{\frac{1 - \epsilon_t}{\epsilon_t}} > 1, \quad e^{-\alpha_t} = \sqrt{\frac{\epsilon_t}{1 - \epsilon_t}} < 1$$



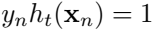




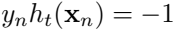


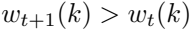


$$w_{t+1}(n) = w_t(n) e^{-\alpha_t y_n h_t(\mathbf{x}_n)} = \begin{cases} w_t(n) \sqrt{\frac{\frac{\epsilon_t}{1-\epsilon_t}}{1-\epsilon_t}} < w_t(n) & \text{if } y_n h_t(\mathbf{x}_n) = 1 \\ w_t(n) \sqrt{\frac{1-\epsilon_t}{\epsilon_t}} > w_t(n) & \text{if } y_n h_t(\mathbf{x}_n) = -1 \end{cases}$$



$\sin(x) + 1$







$$E_{t+1}$$



$$E_t$$

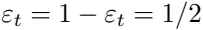
$$\frac{\sum_{n=1}^N w_{t+1}(n)}{\sum_{n=1}^N w_t(n)} = \frac{\sum_{n=1}^N w_t(n) e^{-\alpha_t y_n h_t(x_n)}}{\sum_{n=1}^N w_t(n)}$$

$$\frac{\sum y_n h_t(x_n) = -1 \quad w_t(n)}{\sum_{n=1}^N w_t(n)} e^{\alpha_t} + \frac{\sum y_n h_t(x_n) = 1 \quad w_t(n)}{\sum_{n=1}^N w_t(n)} e^{-\alpha_t}$$

$$\epsilon_t \sqrt{\frac{1 - \epsilon_t}{\epsilon_t}} + (1 - \epsilon_t) \sqrt{\frac{\epsilon_t}{1 - \epsilon_t}} = 2\sqrt{\epsilon_t(1 - \epsilon_t)} \leq 1$$

verbal





$$E = \int_V \left(\frac{1}{2} \epsilon_0 |\nabla \phi|^2 + \frac{1}{2} \mu_0 |\nabla \psi|^2 \right) dV$$



$$\lim_{t \rightarrow \infty} E_t \approx \lim_{t \rightarrow \infty} \left(2 \sqrt{e(1-e)} \right)^t E_0 = 0$$



$$x_n = P_{d_i}(x_n) = \frac{x_n^T d_i}{\|d_i\|}, \quad (n = 1, \cdots, N)$$



$$h(x_n) = \begin{cases} +1 & \text{if } x_n < T \\ -1 & \text{if } x_n \geq T \end{cases}$$

$$\epsilon_t = \sum_{n=1}^N w_t(n) \delta(h_t(x_n) - y_n) = \sum_{h_t(x_n) \neq y_n} w_t(n)$$

$$\mathbf{S}_b = \frac{1}{N} \left[N_- (\mathbf{m}_{-1} - \mathbf{m})(\mathbf{m}_{-1} - \mathbf{m})^T + N_+ (\mathbf{m}_{+1} - \mathbf{m})(\mathbf{m}_{+1} - \mathbf{m})^T \right]$$







$$\mathbf{m}_{\pm} = \frac{1}{N_{\pm}} \sum_{y_n = \pm 1} w(n) \mathbf{x}_n,$$

$$\mathbf{m} = \frac{1}{N} \sum_{n=1}^N w(n) \mathbf{x}_n$$



A pixelated, black and white image of the word "BRAIN" in a stylized, blocky font. The letters are composed of thick black strokes with some gray shading, giving it a digital or retro aesthetic. The word is centered horizontally.



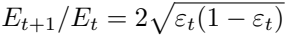
















1992-1993







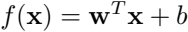
$$f(x) = w^T x + b = \sum_{i=1}^d x_i w_i + b = 0$$





$$f(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + b \quad \begin{cases} > 0 \\ = 0 \\ < 0 \end{cases} \quad ,$$

$$\left\{ \begin{array}{l} x \in C_+ \\ x \in H_0 \\ x \in C_- \end{array} \right.$$





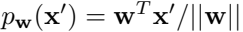
1997-1998

$$p_w(x) = \frac{w^T x}{\|w\|} = - \frac{b}{\|w\|}$$



$$d(H_0, 0) = |p_w(x)| = \frac{|b|}{|w|}$$







$$d(H_0, x') = \left| p_w(x') - p_w(x) \right| = \left| \frac{w^T x'}{\|w\|} - \frac{b}{\|w\|} \right| = \frac{|w^T x' + b|}{\|w\|} = \frac{|f(x')|}{\|w\|}$$



$$d(H_0, x_{sv} \in C_+) = d(H_0, x_{sv} \in C_-) = d(H_0, x_{sv}) = \frac{|f(x_{sv})|}{\|w\|}$$





$$\begin{cases} H_+ : f_+(x) = f(x) - c = w^T x + b - c = 0 \\ H_- : f_-(x) = f(x) + c = w^T x + b + c = 0 \end{cases}$$



$$d(H_{\pm}, 0) = \frac{|b \pm 1|}{|w|}$$

$$\left|d(H_{\pm},0)-d(H_0,0)\right|=\left|\frac{|b\pm 1|}{\|v\|}-\frac{|b|}{\|v\|}\right|=\frac{1}{\|v\|}$$



$\frac{1}{2} \ln \left(\frac{1 + \sqrt{1 - 4x}}{1 - \sqrt{1 - 4x}} \right)$

$$\begin{cases} f(x_n) - 1 = w^T x_n + b - 1 \geq 0 & \text{if } y_n = 1 \\ f(x_n) + 1 = w^T x_n + b + 1 \leq 0 & \text{if } y_n = -1 \end{cases}$$

$$\frac{1}{2} \frac{1}{w} = \frac{1}{2} w^2$$

$$v_n(x,w)+v_n(z,1)=v_n(1,0)$$

$$f(x) = w^T x + b = [w_1, w_2] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + b = [1, 2] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} - 1 = x_1 + 2x_2 - 1 = 0$$

$$d(H_0, 0) = \frac{|b|}{\|w\|} = \frac{1}{\sqrt{w_1^2 + w_2^2}} = \frac{1}{\sqrt{1^2 + 2^2}} = \frac{1}{\sqrt{5}} = 0.447$$

FORGET THE

$f(x) = 5 + 2x$
 $0.25 - 1 = 0$

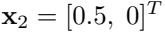


Q. E. D. = F. O. W. =

$10x1 = 142x025 = 142x025 = 0$



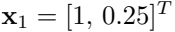
$$d(x_1, B) / w = 0.5 / \sqrt{5} = 0.2235$$



$2x^2 + 2x - 1 = 0$



$$d(x_2, I) = d(x_2) / |w| = 0.5 / \sqrt{5} = 0.2235$$



2020-2021

2021-1-10

$$\|f(x)\| = \|w^T x_1 + b\| = \|w^T x_2 + b\| = 0.5$$



$$\frac{d}{dx} \left(w x^2 + b x^2 + 1 \right) + \frac{d}{dx} \left(w x^2 + b x^2 + 1 \right)$$



2014-2015-2016



2014-2015

$$d(H_+, 0) = \frac{|-3|}{\|w\|} = 1.341, \quad d(H_-, 0) = \frac{|-1|}{\|w\|} = 0.447$$



$$d(H_-, H_+) = d(H_+, 0) - d(H_-, 0) = \frac{2}{\|w\|} = 0.894$$

Q&A: How to find a good job

$$L_p(w, b, a) = \frac{1}{2} w^T w + \sum_{n=1}^N a_n (1 - y_n (w^T x_n + b))$$







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1992

$$\frac{\partial}{\partial b} L_p(\mathbf{w}, b) = \frac{\partial}{\partial b} \left[\frac{1}{2} \mathbf{w}^T \mathbf{w} + \sum_{n=1}^N a_n (1 - y_n (\mathbf{w}^T \mathbf{x}_n + b)) \right] = \sum_{n=1}^N a_n y_n = 0$$

$$\frac{\partial}{\partial \mathbf{w}} L_p(\mathbf{w}, b) = \frac{\partial}{\partial \mathbf{w}} \left[\frac{1}{2} \mathbf{w}^T \mathbf{w} + \sum_{n=1}^N a_n (1 - y_n (\mathbf{w}^T \mathbf{x}_n + b)) \right] = \mathbf{w} - \sum_{n=1}^N a_n y_n \mathbf{x}_n = 0,$$

$$W = \sum_{n=1}^N a_n y_n x_n$$

World's Best

A pixelated, black and white graphic of the text "100% 100%". The characters are rendered in a bold, blocky font with a dithered or pixelated texture. The first "100%" is on the left, followed by a space, then another "100%". The overall style is reminiscent of early digital art or low-resolution computer graphics.

100%

$$\inf_{\mathbf{w}, b} L_p(\mathbf{w}, b, \alpha) = \inf_{\mathbf{w}, b} \left[\frac{1}{2} \mathbf{w}^T \mathbf{w} + \sum_{n=1}^N \alpha_n (1 - y_n (\mathbf{w}^T \mathbf{x}_n + b)) \right]$$

$$\inf_{w,b} \left[\frac{1}{2} w^T w + \sum_{n=1}^N a_n - w^T \sum_{n=1}^N a_n y_n x_n - b \sum_{n=1}^N a_n y_n \right]$$

$$\frac{1}{2} \left(\sum_{m=1}^N \alpha_m y_m x_m \right)^T \left(\sum_{n=1}^N \alpha_n y_n x_n \right) + \sum_{n=1}^N \alpha_n - \left(\sum_{m=1}^N \alpha_m y_m x_m \right)^T \left(\sum_{n=1}^N \alpha_n y_n x_n \right)$$

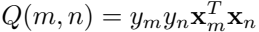
$$\sum_{n=1}^N a_n - \frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N a_n a_m y_n y_m (x_n^T x_m)$$

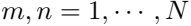
100%

$$L_d(\alpha) = \sum_{n=1}^N \alpha_n - \frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N \alpha_n \alpha_m y_n y_m (x_n^T x_m) = \mathbf{1}^T \alpha - \frac{1}{2} \alpha^T \mathbf{Q} \alpha$$

$$\sum_{n=1}^N a_n y_n = y^T a = 0, \quad a_n \geq 0 \quad (n = 1, \cdots, N)$$







$$w = \sum_{n=1}^N a_n y_n x_n = \sum_{n \in sv} a_n y_n x_n = \sum_{x_n \in C_+, n \in sv} a_n x_n - \sum_{x_n \in C_-, n \in sv} a_n x_n$$

$$u_n(x) = \frac{1}{n} \left(u_0(x) + \int_0^x u_0(t) dt \right)$$

$\frac{d}{dx} \left(x^2 + 1 \right) = 2x$



$$b = y_n - w^T x_n = y_n - \sum_{m \in sv} a_m y_m (x_m^T x_n), \quad (n \in sv)$$

$$f(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + b = \left(\sum_{n \in sv} a_n y_n \mathbf{x}_n \right)^T \mathbf{x} + b = \sum_{n \in sv} a_n y_n (\mathbf{x}_n^T \mathbf{x}) + b \quad \begin{cases} > 0 & \mathbf{x} \in C_+ \\ < 0 & \mathbf{x} \in C_- \end{cases}$$



$$\mathbf{W}^T \mathbf{W} = \left(\sum_{n \in sv} a_n y_n x_n^T \right) \left(\sum_{m \in sv} a_m y_m x_m \right) = \sum_{n \in sv} a_n y_n \sum_{m \in sv} a_m y_m (x_n^T x_m)$$

$$\sum_{n \in su} a_n y_n (y_n - b) = \sum_{n \in su} a_n (1 - y_n b) = \sum_{n \in su} a_n - b \sum_{n \in su} a_n y_n = \sum_{n \in su} a_n$$

$\nabla^2 \psi = 1$

$\psi = 0$

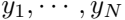
$\psi = 0$

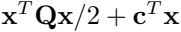
$$\frac{1}{\|w\|} = \left(\sum_{n \in su} a_n \right)^{-1/2}$$











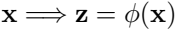


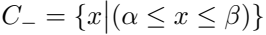


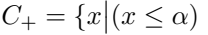
$$\mathbf{m}_- = \begin{bmatrix} 3.5 \\ 0 \end{bmatrix}, \quad \mathbf{S}_- = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}, \quad \mathbf{m}_+ = \begin{bmatrix} 0 \\ 3.5 \end{bmatrix}, \quad \mathbf{S}_+ = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

n	α_n	$\mathbf{x}_n = [x_1, x_2]$	y_n
40	0.52	$x = [4.43, 2.44]$	-1
52	3.11	$x = [1.17, 0.74]$	-1
103	3.64	$x = [1.30, 1.64]$	1

$$\mathbf{w} = \begin{bmatrix} -1.25 \\ 2.39 \end{bmatrix}, \quad b = -1.31$$









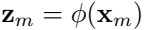
$$\mathbf{z} = \phi(x) = \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} x \\ (x - (a + \beta)/2)^2 \end{bmatrix}$$

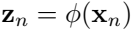
A series of 10 grayscale images showing the progression of a handwritten digit '4' from a noisy, pixelated state to a clean, sharp state. The images are arranged in a single row, separated by vertical white lines. The first image on the left is the most noisy and pixelated, while the last image on the right is the cleanest and most refined. The intermediate images show a gradual reduction in noise and an increase in the clarity of the digit's strokes.

$$\mathbf{z} = \phi(\mathbf{x}) = \begin{bmatrix} z_1 \\ z_2 \\ z_3 \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \\ x_1^2 + x_2^2 \end{bmatrix}$$

$$\mathbf{z} = \phi(\mathbf{x}) = \begin{bmatrix} z_1 \\ z_2 \\ z_3 \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \\ x_1 x_2 \end{bmatrix}$$





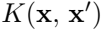


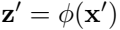
$$\begin{aligned}
 & \left(\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}x^2} dx \right)^2 = \frac{1}{2\pi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-\frac{1}{2}(x^2+y^2)} dx dy \\
 & = \frac{1}{2\pi} \int_0^{2\pi} \int_0^{\infty} e^{-\frac{1}{2}r^2} r dr d\theta = \frac{1}{2\pi} \int_0^{2\pi} d\theta \int_0^{\infty} e^{-\frac{1}{2}r^2} r dr \\
 & = \frac{1}{2\pi} \int_0^{2\pi} d\theta \left[-e^{-\frac{1}{2}r^2} \right]_0^{\infty} = \frac{1}{2\pi} \int_0^{2\pi} d\theta = 1
 \end{aligned}$$

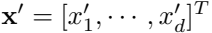












$$K(\mathbf{x}, \mathbf{x}') = \mathbf{x}^T \mathbf{x}' = \sum_{i=1}^d x_i x'_i$$

$$(x+y)^n = \sum_{k=0}^n \binom{n}{k} x^{n-k} y^k = \sum_{k=0}^n \frac{n!}{k!(n-k)!} x^{n-k} y^k$$

$$\binom{n}{k} = \frac{n!}{k!(n-k)!}$$



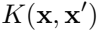


$$(x_1 + \dots + x_d)^n = \sum_{\sum_{i=1}^d k_i = n} \binom{n}{k_1, \dots, k_d} x_1^{k_1} \dots x_d^{k_d} = \sum_{\sum_{i=1}^d k_i = n} \frac{n!}{k_1! \dots k_d!} x_1^{k_1} \dots x_d^{k_d}$$

$$\binom{n}{k_1, \dots, k_d} = \frac{n!}{k_1! \cdot \dots \cdot k_d!}$$







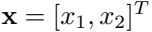
$$\frac{d}{dx} \left(x^2 \frac{dy}{dx} \right) = x^2 \frac{d^2 y}{dx^2} + 2x \frac{dy}{dx}$$

$$\sum_{\sum_{i=1}^d k_i = n} \frac{n!}{k_1! \cdots k_d!} (x_1 x_1')^{k_1} \cdots (x_d x_d')^{k_d} = \phi(\mathbf{x})^T \phi(\mathbf{x}') = \mathbf{z}^T \mathbf{z}'$$

$$\mathbf{z} = \phi(\mathbf{x}) = \left[\sqrt{\frac{n!}{k_1! \cdots k_d!}} \left(x_1^{k_1} \cdots x_d^{k_d} \right), \left(k_i \geq 0, \sum_{i=1}^d k_i = n \right) \right]^T$$

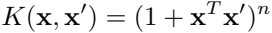






$$K(x, x) = (x^T x)^2 = (x_1^T x_1 + x_2^T x_2)^2 = (x_1^T x_1)^2 + 2x_1^T x_1 x_2^T x_2 + (x_2^T x_2)^2 = \phi(x)^T \phi(x) = z^T z$$

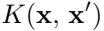




$$R(x, x) = e^{-\|x-x\|^2/2\sigma^2} = e^{-\gamma\|x-x\|^2/2}$$

1202

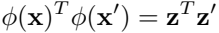




$$e^{-||x-x'||^2/2} = e^{-||x||^2/2} e^{-||x'||^2/2} e^{x^Tx'} = e^{-||x||^2/2} e^{-||x'||^2/2} \sum_{n=0}^{\infty} \frac{(x^Tx')^n}{n!}$$

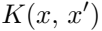
$$e^{-||\mathbf{x}||^2/2} \, e^{-||\mathbf{x}'||^2/2} \sum_{n=0}^{\infty} \left[\frac{1}{n!} \sum_{\sum_{i=1}^d k_i = n} \frac{n!}{k_1! \cdots k_d!} (x_1 x'_1)^{k_1} \cdots (x_d x'_d)^{k_d} \right]$$

$$\sum_{n=0}^{\infty} \sum_{\sum_{i=1}^d k_i = n} \left(e^{-||\mathbf{x}||^2/2} \frac{x_1^{k_1} \cdots x_d^{k_d}}{\sqrt{k_1! \cdots k_d!}} \right) \left(e^{-||\mathbf{x}'||^2/2} \frac{x_1'^{k_1} \cdots x_d'^{k_d}}{\sqrt{k_1! \cdots k_d!}} \right)$$



$$\mathbf{z} = \phi(\mathbf{x}) = \left[e^{-||\mathbf{x}||^2/2} \frac{x_1^{k_1} \cdots x_d^{k_d}}{\sqrt{k_1! \cdots k_d!}}, \left(n = 0, \cdots, \infty, \sum_{k=1}^n k_i = n \right) \right]^T$$



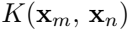


$$e^{-(x-x')^2/2} = e^{-x^2/2} e^{-x'^2/2} e^{xx'} = e^{-x^2/2} e^{-x'^2/2} \sum_{n=0}^{\infty} \frac{(xx')^n}{n!}$$

$$\sum_{n=0}^{\infty} \left(e^{-x^2/2} x^n / \sqrt{n!} \right) \left(e^{-x'^2/2} x'^n / \sqrt{n!} \right)$$

$$\mathbf{z} = \phi(x) = \left[e^{-x^2/2} x^n / \sqrt{n!}, (n = 0, \cdots, \infty) \right]^T$$





$$L_d(a) = \sum_{n=1}^N a_n - \frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N a_n a_m y_n y_m K(x_n, x_m)$$

$$b = y_n - \sum_{m \in sv} a_m y_m K(x_m, x_n), \quad (n \in sv)$$





$$f(\mathbf{z}) = \mathbf{w}^T \mathbf{z} + b = \sum_{n \in sv} a_n y_n (\mathbf{z}_n^T \mathbf{z}) + b = \sum_{n \in sv} a_n y_n K(\mathbf{x}_n, \mathbf{x}) + b \quad \begin{cases} > 0 & \mathbf{x} \in C_+ \\ < 0 & \mathbf{x} \in C_- \end{cases}$$



$\ln(x) = \ln\left(\frac{1}{x^{-1}}\right) = -\ln(x^{-1}) = -\ln\left(\frac{1}{x}\right) = -\ln(1 \cdot x^{-1}) = -\ln(1) - \ln(x^{-1}) = 0 - \ln(x^{-1}) = -\ln(x^{-1})$



$$W^TW + C \sum_{n=1}^N \xi_n$$

www.xp.w+0) + 0.1 = 0.

Enzo, John, and Mark



$$L_p(\mathbf{w}, b, \xi, \alpha, \mu) = \frac{1}{2} \mathbf{w}^T \mathbf{w} + C \sum_{n=1}^N \xi_n - \sum_{n=1}^N \alpha_n [y_n (\mathbf{w}^T \mathbf{x} + b) + \xi_n - 1] - \sum_{n=1}^N \mu_n \xi_n$$



$$\frac{\partial L_p}{\partial w} = w - \sum_{n=1}^N y_n a_n x_n = 0,$$

$$W = \sum_{n=1}^N y_n a_n x_n;$$

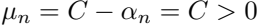
$$\frac{\partial L_p}{\partial b} = \sum_{n=1}^N y_n a_n = 0;$$

$$\frac{\partial L_p}{\partial \epsilon_n} = C - \alpha_n - \mu_n = 0;$$

www.xbox.com/en-us

$$\alpha_n [y_n(v^T x + b) + c_n - 1] = 0, \quad \forall n \in \mathcal{N} = 0,$$





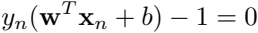


www.vivax.com





$$\sin \left(\frac{\pi}{2} \right) + \sin \left(\frac{\pi}{2} \right) = 1$$





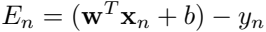




www.vivax.com

Wavelength λ is the distance between two consecutive crests or troughs of a wave. It is denoted by the Greek letter λ .

$$y_n(w^T x_n + b) - 1 = y_n(w^T x_n + b) - y_n^2 = y_n[w^T x_n + b - y_n] = y_n E_n$$



$$y_n E_n \begin{cases} \geq 0 & \text{if } a_n = 0 \\ = 0 & \text{if } 0 < a_n < C \\ \leq 0 & \text{if } a_n = C \end{cases}$$

$$L_d(a) = \sum_{n=1}^N a_n - \frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N a_n a_m y_n y_m x_m^T x_n + C \sum_{n=1}^N \xi_n - \sum_{n=1}^N a_n \xi_n - \sum_{n=1}^N \mu_n \xi_n$$

$$= \sum_{n=1}^N a_n - \frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N a_n a_m y_n y_m x_m^T x_n$$

$$0 \leq a_n \leq C,$$

$$\sum_{n=1}^N a_n y_n = 0$$





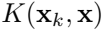




$$W = \sum_{n=1}^N y_n a_n x_n = \sum_{n \in sv} y_n a_n x_n$$

$$b = y_n - \sum_{i \in sv} y_i a_i x_i^T x_n = y_n - \sum_{i \in sv} y_i a_i K(x_i, x_n), \quad (n \in sv)$$





$$w^T x + b = \sum_{i \in sv} y_i a_i x_i^T x + b = \sum_{i \in sv} y_i a_i K(x_i, x) + b \begin{cases} > 0, & x \in C_+ \\ < 0, & x \in C_- \end{cases}$$

0123456789+123456789







$$L(a_i, a_j) = a_i + a_j - \frac{1}{2} (a_i^2 x_i^T x_i + a_j^2 x_j^T x_j + 2a_i a_j y_i y_j x_i^T x_j)$$

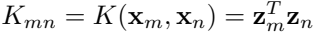
$$-\alpha_i y_i \left(\sum_{n \neq i} \alpha_n y_n x_n^T \right) x_i - \alpha_j y_j \left(\sum_{n \neq j} \alpha_n y_n x_n^T \right) x_j$$

$$a_i + a_j - \frac{1}{2}(a_1^2 K_{ii} + a_2^2 K_{jj} + 2a_i a_j y_i y_j K_{ij})$$

$$-a_i y_i \sum_{n \neq i} a_n y_n K_{ni} - a_j y_j \sum_{n \neq j} a_n y_n K_{nj}$$

$$0 \leq a_i, a_j \leq C,$$

$$\sum_{n=1}^N a_n y_n = 0$$



order = 1000000





$$a_i y_i + a_j y_j = - \sum_{n \neq i, j} a_n y_n$$



$$y_i^2 a_i + y_i y_j a_j = a_i + s a_j = \left(- \sum_{n \neq i, j} a_n y_n \right) y_i = \delta,$$





0 = 1/2 $\int_0^1 \frac{1}{x} dx$ over $0 < x < 1$

$$a_i^{\text{new}} + s_i^{\text{new}} = a_i^{\text{old}} + s_i^{\text{old}} = 0,$$

$$\Delta a_i = a_i^{\text{new}} - a_i^{\text{old}} = -s(a_i^{\text{new}} - a_i^{\text{old}}) = -s \Delta a_i$$

$$\sum_{n \neq i, j} a_n y_n x_n = W - a_i y_i x_i - a_j y_j x_j$$

we are 120



$$\sum_{n \neq i, j} a_n y_n K_{nk} = \sum_{n \neq i, j} a_n y_n K_{nk} - a_i y_i K_{ik} - a_j y_j K_{jk}$$

$$\left(\sum_{n \neq i,j} a_n y_n K_{nk} + b\right) - b - a_i y_i K_{ik} - a_j y_j K_{jk}$$

over the world

$$u_k = \sum_{n=1}^N a_n y_n K_{nk} + b$$



$$a_i + a_j - \frac{1}{2}(a_i^2 K_{ii} + a_j^2 K_{jj} + 2sa_i a_j K_{ij}) - a_i y_i v_i - a_j y_j v_j$$



1000

$$\delta + (1-s)\alpha_j - \frac{1}{2}(\delta - s\alpha_j)^2 K_{ii} - \frac{1}{2}\alpha_j^2 K_{jj}$$

Sd - Sd - Sd - Sd - Sd - Sd

$$\frac{1}{2}(2K_{ij}-K_{ii}-K_{jj})a_j^2 + [1-s+s\delta(K_{ii}-K_{ij})+y_j(v_i-v_j)]a_j + c$$



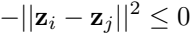


$$\frac{1}{2} (2K_{ij} - K_{ii} - K_{jj}) = \frac{1}{2} \eta$$





$$2K_{ij} - K_{ii} - K_{jj} = 2z_i^T z_j - z_i^T z_i - z_j^T z_j = -(z_i - z_j)^T (z_i - z_j)$$



$$1 - \sin(x) + \sin(x) = 1$$

1. $\frac{1}{2} \ln \left(\frac{1 + \sqrt{1 - 4x}}{1 - \sqrt{1 - 4x}} \right)$

$$+y_1[y_1 - b - ay_1K_1] - y_2[y_2 - b - ay_2K_2] - y_3[y_3 - b - ay_3K_3]$$

$$1 - s + s \operatorname{erf}(x) - \operatorname{erf}(x) + s \operatorname{erf}(x) - \operatorname{erf}(x)$$

$+y_2(v_2K_2 - v_3K_3 + v_4K_4 + v_5K_5)$

$\frac{d^2}{dt^2} \left(\frac{1}{2} m \dot{x}^2 \right) = \frac{d}{dt} \left(m \dot{x} \right) = m \ddot{x}$

$\psi(x) - \psi(y) + \psi(2x) - \psi(x) - \psi(x) - \psi(x)$

1994-1995

$$E_k = u_k - y_k = \sum_{n=1}^N a_n^{old} y_n K_{nk} + b - y_k \quad (k = 1, 2)$$



QED = 100%

$$L(a_j) = \frac{1}{2} \eta a_j^2 + [y_j(E_i - E_j) - a_j^{\text{old}} \eta] a_j$$

100%

$$\frac{d}{da_j} L(a_j)$$

मोक्ष + विज्ञान - विज्ञान - मोक्ष

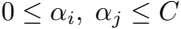
$$\frac{d^2}{da_j^2} L(a_j)$$





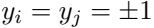
code

$$a_j^{new} = a_j^{old} + \frac{y_j(E_j - E_i)}{\eta} = a_j^{old} + \Delta a_j, \quad \Delta a_j = a_j^{new} - a_j^{old} = \frac{y_j(E_j - E_i)}{\eta},$$

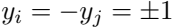












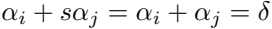








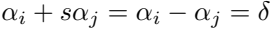




Wiederholungsfrage = *Wiederholung*

$\sin \theta = \cos \theta$

$$\begin{cases} L = \max(0, \delta - C) = \max(0, \alpha_i + \alpha_j - C) \\ H = \min(\delta, C) = \min(\alpha_i + \alpha_j, C) \end{cases}$$





$$\min_{\theta} \mathcal{L}(\theta) = \min_{\theta} \mathcal{L}(\theta)$$



$\ln(x) = \ln(x)$

$$\begin{cases} L = \max(0, -\delta) = \max(0, \alpha_j - \alpha_i) \\ H = \min(C - \delta, C) = \min(C + \alpha_j - \alpha_i, C) \end{cases}$$

$$\alpha_j^{new} \leftarrow \begin{cases} H & \text{if } \alpha_j^{new} \geq H \\ \alpha_j^{new} & \text{if } L < \alpha_j^{new} < H \\ L & \text{if } \alpha_j^{new} \leq L \end{cases}$$

$$a_i^{\text{new}} - a_i^{\text{old}} = s(a_i^{\text{old}} - a_i^{\text{new}})$$



$$\sum_{n \neq i, j} y_n \alpha_n^{\text{old}} x_n + y_i \alpha_i^{\text{new}} x_i + y_j \alpha_j^{\text{new}} x_j$$

$$w_{old} - y_i a_i x_i - y_j a_j x_j + y_i a_j x_i + y_j a_i x_j$$

$$w_0d + v_1\Delta v_1x_1 + v_2\Delta v_2x_2 = w_0d + \Delta v_1$$

$$\Delta W = W_{new} - W_{old} = y_1 \Delta v_1 x_1 + y_2 \Delta v_2 x_2$$



Review - Book = Review - Book

$$\sum_{n=1}^N a_n^{new} y_n K_{nk} + b^{new} - \sum_{n=1}^N a_n^{old} y_n K_{nk} - b^{old}$$

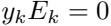
$$y_{\Delta} v_{ik} + y_{\Delta} v_{jk} + v_{new} - v_{old} \quad (k = 1, 2)$$

A pixelated, grayscale version of the letter 'O'. The letter is composed of a grid of squares in various shades of gray, ranging from light to dark, creating a textured, blocky appearance. The shape is roughly circular with a central void.

A pixelated, grayscale version of the Twitter bird logo. The bird is depicted in a circular, almost complete loop shape, with its head turned back towards its tail. The image is composed of various shades of gray and black pixels on a white background, giving it a retro, low-resolution appearance.









$$b_k^{new} = b_k^{old} + (E_k^{old} + \gamma_i \Delta a_i R_{ik} + \gamma_j \Delta a_j R_{jk}) \quad (k = 1$$











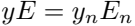






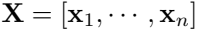
$$\ln \left(\frac{1}{1 + \frac{1}{2} \ln 2} \right)$$













Wavelength = 1500







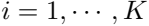
02 = 02 | 1 . 1 2 3



$$f_i(x) \begin{cases} > 0 \\ < 0 \end{cases},$$

$$\left\{ \begin{array}{l} x \in C_+ \\ x \in C_- \end{array} \right.$$

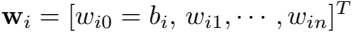


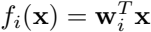


$$f(x) = \frac{1}{x} \cdot f(x) = 1 \cdot f(x)$$

A row of 10 grayscale images showing handwritten digits from 1 to 0. Each digit is rendered in a different style of pixelation or noise, ranging from clean to highly distorted. The digits are arranged horizontally, separated by spaces. The first digit is '1', followed by '2', '3', '4', '5', '6', '7', '8', '9', and finally '0'. The styles vary, with some showing significant pixelation and others appearing more like standard digital fonts.

2019.09.21





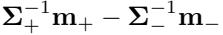


$f(x) = \ln(x)$. $f(x)$



$$f(x) = x^T W x + w^T x + v \begin{cases} \geq 0, & x \in C_+ \\ \leq 0, & x \in C_- \end{cases}$$

$$\begin{aligned}
 & - \frac{1}{2} \left(\Sigma + 1 - \Sigma - 1 \right) \\
 & + \left(\Sigma - 1 \right)
 \end{aligned}$$



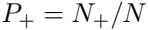
$$-\frac{1}{2}(\mathbf{m}_+^T \Sigma_+^{-1} \mathbf{m}_+ - \mathbf{m}_-^T \Sigma_-^{-1} \mathbf{m}_-) - \frac{1}{2} \log \frac{|\Sigma_+|}{|\Sigma_-|} + \log \frac{P(C_+)}{P(C_-)}$$

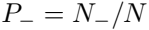




$$m_+ = \frac{1}{N_+} \sum_{x \in C_+} x,$$

$$m_- = \frac{1}{N_-} \sum_{x \in C_-} x$$









$$f(x) = W^T x + w = \left[\Sigma^{-1} (m_+ - m_-) \right]^T x + w = 0$$



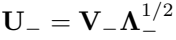




$$W=V\Lambda V^T=U U^T, \quad \Sigma^{-1}=V_{+}\Lambda_{+}V_{+}^T=U_{+}U_{+}^T, \quad \Sigma^{-1}=V_{-}\Lambda_{-}V_{-}^T=U_{-}U_{-}^T$$

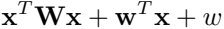
$$U = v a^{1/2},$$

$$U + v + a^{1/2}$$



$$\mathbf{w} = \Sigma_+^{-1} \mathbf{m}_+ - \Sigma_-^{-1} \mathbf{m}_- = \mathbf{U}_+ \mathbf{U}_+^T \frac{1}{N_+} \sum_{x_+ \in C_+} \mathbf{x}_+ - \mathbf{U}_- \mathbf{U}_-^T \frac{1}{N_-} \sum_{x_- \in C_-} \mathbf{x}_-$$





$$\mathbf{x}^T \mathbf{U} \mathbf{U}^T \mathbf{x} + \left(\frac{1}{N_+} \sum_{\mathbf{x}_+} \mathbf{x}_+^T \mathbf{U}_+ \mathbf{U}_+^T \right) \mathbf{x} - \left(\frac{1}{N_-} \sum_{\mathbf{x}_-} \mathbf{x}_-^T \mathbf{U}_- \mathbf{U}_-^T \right) \mathbf{x} + w$$

$$z^T z + \frac{1}{N_+} \Sigma (z_+^T z_+) - \frac{1}{N_-} \Sigma (z_-^T z_-) + v$$

$$\begin{cases} \mathbf{z}_{++} = \mathbf{U}_+^T \mathbf{x}_+ & (\mathbf{x}_+ \in C_+) \\ \mathbf{z}_{--} = \mathbf{U}_-^T \mathbf{x}_- & (\mathbf{x}_- \in C_-) \end{cases}, \quad \begin{cases} \mathbf{z} = \mathbf{U}^T \mathbf{x} \\ \mathbf{z}_+ = \mathbf{U}_+^T \mathbf{x} \\ \mathbf{z}_- = \mathbf{U}_-^T \mathbf{x} \end{cases}$$

$$f(\mathbf{x}) = K(\mathbf{z}, \mathbf{z}) + \frac{1}{N_+} \sum_{\mathbf{z}_{++}} K(\mathbf{z}_{++}, \mathbf{z}_{++}) - \frac{1}{N_-} \sum_{\mathbf{z}_{--}} K(\mathbf{z}_{--}, \mathbf{z}_{--}) + b = p(\mathbf{x}) + b$$



$x = \frac{1}{2} \ln \frac{1 + \sqrt{1 - 4x^2}}{1 - \sqrt{1 - 4x^2}}$





$$\left| \sum_{n=1}^k y_n \right| + \left| \sum_{n=k+1}^N y_n \right|, \quad (k=1, \cdots, N-1)$$

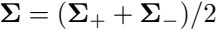






A pixelated, black and white representation of the mathematical expression "2 = 2x + 1". The characters are composed of a grid of black and gray pixels on a white background. The "2"s are stylized with a curved top. The "=" is a simple horizontal line. The "x" is formed by two intersecting diagonal lines. The "+" is a simple cross. The "1" is a single vertical line.

$$p(x) + b \begin{cases} \geq 0, & x \in C_+ \\ < 0, & x \in C_- \end{cases}$$

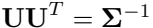


$$w^T x + v = \left[\Sigma^{-1} (m_+ - m_-) \right]^T x + v$$

$$\left[\mathbf{U} \mathbf{U}^T \left(\frac{1}{N_+} \sum_{\mathbf{x}_+} \mathbf{x}_+ - \frac{1}{N_-} \sum_{\mathbf{x}_-} \mathbf{x}_- \right) \right]^T \mathbf{x} + w$$

$$\frac{1}{N_+} \sum_{x_+} x_+^T U U^T x_+ - \frac{1}{N_-} \sum_{x_-} x_-^T U U^T x_- + w$$

$$\frac{1}{N_+} \sum_{z_+} z_+^T z - \frac{1}{N_-} \sum_{z_-} z_-^T z + w$$









$$f(x) = \frac{1}{N_+} \sum_{z_+} K(z_+, z) - \frac{1}{N_-} \sum_{z_-} K(z_-, z) + b$$

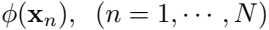


$$w^T x + v = (w^T + v^T) x + v$$

$$\frac{1}{N_+} \sum_{x_+} x_+^T x - \frac{1}{N_-} \sum_{x_-} x_-^T x + w$$

$$f(x) = \frac{1}{N_+} \sum_{x_+} K(x_+, x) - \frac{1}{N_-} \sum_{x_-} K(x_-, x) + b$$

1992年12月1日







$$\phi(\mathbf{m}_+ - \mathbf{m}_-) \neq \phi(\mathbf{m}_+) - \phi(\mathbf{m}_-), \quad \phi(\mathbf{m}_\pm) = \phi\left(\frac{1}{n_\pm} \sum_{\mathbf{x} \in C_\pm} \mathbf{x}\right) \neq \frac{1}{n_\pm} \sum_{\mathbf{x} \in C_\pm} \phi(\mathbf{x})$$

$$f(x) = \mathbf{z}^T \mathbf{z} + \frac{1}{N_+} \sum_{\mathbf{z}_{++}} K(\mathbf{z}_{++}, \mathbf{z}_{++}) - \frac{1}{N_-} \sum_{\mathbf{z}_{--}} K(\mathbf{z}_{--}, \mathbf{z}_{--}) + b$$



1992-1993



WISCONSIN-15-12-12



12









	<i>Kernel</i>	Matlab SVM	Kernel Bayes I	Kernel Bayes II	Kernel Bayes III
Test 1	linear	93.0%	88.0%	94.0%	94.0%
Test 2	linear	73.0%	80.0%	79.5%	96.5%
Test 3	RBF	98.5%	100%	100%	100%

$$\mathbf{m}_+ = \begin{bmatrix} -1 \\ 0 \end{bmatrix}, \quad \mathbf{m}_- = \begin{bmatrix} +1 \\ 0 \end{bmatrix}, \quad \Sigma_+ = \Sigma_- = 3 \times \begin{bmatrix} 1 & 0.5 \\ 0.5 & 0.5 \end{bmatrix}$$

Q400

Qeios

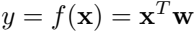
94.500

QOQ.500

Q9B.EOD

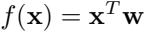


	<i>Kernel</i>	Matlab SVM	Kernel Bayes I	Kernel Bayes II	Kernel Bayes III
Test 1	Linear	58.75%	60.0%	60.25%	97.0%
Test 2	RBF	97.75%	98.50%	98.50%	99.50%
Test 3	RBF	98.0%	100%	100%	100%
Test 4	RBF	96.0%	98.5%	95.5%	97.0%



$\frac{d}{dx} \left(x^2 \right) = 2x$



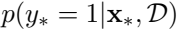


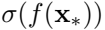






$\psi(\psi(x) = 1) \mid x \in D$

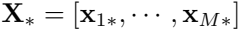




A pixelated, black and white graphic of the text "WORLD" in a stylized, blocky font. The letters are composed of various shades of gray and black pixels, giving it a retro, digital appearance. The "W" and "D" are particularly large and prominent.

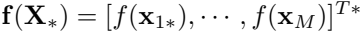
$$\int p(y_*) = 1 \mid x_*, f) p(f \mid x_*, \mathcal{D}) df$$

$$\int \sigma(f(x_*)) p(f|x_*, D) df = E_f[\sigma(f(x_*))] = \sigma(E_f f(x_*))$$



$$\int p(y_* = 1 | \mathbf{x}_*, f) p(f | \mathbf{x}_*, \mathcal{D}) df$$

$$\int \sigma(f(\mathbf{x}_*)) p(f|\mathbf{x}_*, \mathcal{D}) df = E_f[\sigma(f(\mathbf{x}_*))] = \sigma(E_f f(\mathbf{x}_*))$$







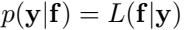






$$p(\mathbf{f}|D) = p(\mathbf{f}|\mathbf{X}, y) = \frac{p(y, \mathbf{f}|\mathbf{X})}{p(y|\mathbf{X})} = \frac{p(y|\mathbf{f}) p(\mathbf{f}|\mathbf{X})}{p(y|\mathbf{X})} \propto p(y|\mathbf{f}) p(\mathbf{f}|\mathbf{X})$$

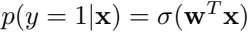
$$\frac{d}{dx} \left(x^2 \frac{dy}{dx} \right) = x^2 \frac{d^2 y}{dx^2} + 2x \frac{dy}{dx}$$



















A pixelated, black and white representation of the mathematical expression "2x=1|x=2". The characters are rendered in a blocky, digital font. The "2" is formed by a thick vertical line and a curved top. The "x" is formed by two intersecting diagonal lines. The "=" is represented by two parallel horizontal lines. The "|" is a single vertical line. The second "x" and "2" are also formed by thick lines and curves. The entire expression is centered on a white background.

A pixelated, black and white representation of the word "EUREKA" in a stylized, blocky font. The letters are composed of a grid of black and white pixels, giving it a retro, digital appearance. The word is centered horizontally and occupies most of the width of the image.

A pixelated, black and white representation of the mathematical expression $\exp(-1) \cdot \exp(x)$. The characters are rendered in a low-resolution, dithered style. The expression consists of the letter 'e' followed by an opening parenthesis '(', a minus sign '-', the number '1', a closing parenthesis ')', a multiplication sign 'x', and another 'e' followed by an opening parenthesis '(', the variable 'x', and a closing parenthesis ')'.

$$1 - p(v) = 1 - f(x) = 0 - f(x)$$



$\frac{d}{dx} \left(\frac{1}{x} \right) = -\frac{1}{x^2}$

$$p(y|\mathbf{f}) = \prod_{n=1}^N p(y_n|f_n) = \prod_{n=1}^N \sigma(y_n f_n)$$



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$$\text{cov}(f_m, f_n) = k(x_m, x_n) = \exp\left(-\frac{1}{a^2} ||x_m - x_n||^2\right), \quad (m, n = 1, \cdots, N)$$



















$$p(\mathbf{y}|\mathbf{f})p(\mathbf{f}|\mathbf{X})=p(\mathbf{y}|\mathbf{f})\mathcal{N}(\mathbf{0},\mathbf{K})=\prod_{n=1}^N\sigma(y_nf_n)\frac{1}{(2\pi)^{d/2}|\mathbf{K}|^{1/2}}\exp\left(-\frac{1}{2}\mathbf{f}^T\mathbf{K}^{-1}\mathbf{f}\right)$$

$$\prod_{n=1}^N \sigma(y_n f_n) \exp\left(-\frac{1}{2} \mathbf{f}^T \mathbf{K}^{-1} \mathbf{f}\right)$$



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$$\psi(\mathbf{f}) = \log p(\mathbf{f}|\mathcal{D}) = \sum_{n=1}^N \log \sigma(y_n f_n) - \frac{N}{2} \log(2\pi) - \frac{1}{2} \log |\mathbf{K}| - \frac{1}{2} \mathbf{f}^T \mathbf{K}^{-1} \mathbf{f}$$

100% 100% 100%

$$g_{\psi}(\mathbf{f}) = \frac{d}{d\mathbf{f}} \psi(\mathbf{f}) = \frac{d}{d\mathbf{f}} \log p(\mathbf{y}|\mathbf{f}) = \frac{d}{d\mathbf{f}} \left(\frac{1}{2} \mathbf{f}^T \mathbf{K}^{-1} \mathbf{f} \right) = \mathbf{w} - \mathbf{K}^{-1} \mathbf{f}$$

$$\mathbf{H}_\psi(\mathbf{f}) = \frac{d^2}{d\mathbf{f}^2} \psi(\mathbf{f}) = \frac{d}{d\mathbf{f}} \mathbf{g}_\psi(\mathbf{f}) = \frac{d}{d\mathbf{f}} (\mathbf{w} - \mathbf{K}^{-1} \mathbf{f}) = \mathbf{W} - \mathbf{K}^{-1}$$

$$w = \frac{d}{df} \log p(y|f), \quad W = \frac{d^2}{df^2} \log p(y|f) = \frac{dw}{df}$$

$$\frac{d}{df_n} \log p(y_n | f_n)$$

$$\frac{d}{df_n} \log(1 + \exp(-y_n f_n))^{-1} = \frac{y_n}{1 + \exp(y_n f_n)}$$

$$\frac{d^2}{df_n^2} \log p(y_n | f_n)$$

$$\frac{d}{df_n} \left[\frac{y_n}{1 + \exp(y_n f_n)} \right] = \frac{-\exp(-y_n f_n)}{(1 + \exp(-y_n f_n))^2}$$



$$\mathbf{w} = \frac{d}{d\mathbf{f}} \log p(\mathbf{y}|\mathbf{f}) = \begin{bmatrix} d/df_1 \\ \vdots \\ d/df_N \end{bmatrix} \sum_{n=1}^N \log p(y_n|f_n) = \begin{bmatrix} d \log p(y_1|f_1)/df_1 \\ \vdots \\ d \log p(y_N|f_N)/df_N \end{bmatrix} = \begin{bmatrix} \frac{y_1}{1+e^{y_1 f_1}} \\ \vdots \\ \frac{y_N}{1+e^{y_N f_N}} \end{bmatrix}$$

$$\frac{d^2}{d\mathbf{f}^2} \log p(\mathbf{y}|\mathbf{f}) = \begin{bmatrix} \frac{\partial^2}{\partial f_1 \partial f_1} & \cdots & \frac{\partial^2}{\partial f_1 \partial f_N} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2}{\partial f_N \partial f_1} & \cdots & \frac{\partial^2}{\partial f_N \partial f_N} \end{bmatrix} \sum_{n=1}^N \log p(y_n|f_n)$$

$$\text{diag} \left[\frac{d^2}{df_1^2} \log p(y_1|f_1), \dots, \frac{d^2}{df_N^2} \log p(y_N|f_N) \right] = \text{diag} \left[\frac{-e^{-y_1 f_1}}{(1 + e^{-y_1 f_1})^2}, \dots, \frac{-e^{-y_N f_N}}{(1 + e^{-y_N f_N})^2} \right]$$



[illegible]

Welding 101 for Dummies



$$\frac{d}{df} \psi(f) = -\Sigma^{-1} \psi(f - \mathbf{m} / D)$$

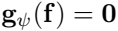
[illegible]

$$\frac{d^2}{dt^2}\psi(f) = -\frac{d}{dt}g_{\psi}(f) = -\Sigma^{-1}f/D$$

[illegible]

$H_v(f) = W - IK - 1 = Z + 1$

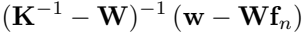
A pixelated, black and white graphic of the text "SPID = (K-1) - (W-1)". The characters are rendered in a blocky, digital font style. The equals sign is represented by two horizontal lines. The parentheses are simple curved lines. The minus signs are single horizontal strokes. The overall image has a low-resolution, 1-bit aesthetic.





$$f_n \mathbf{H}_v^{-1}(f_n) g_v(f_n) = f_n + (\mathbf{K}^{-1} \mathbf{V})^{-1} (\mathbf{V} - \mathbf{K}^{-1} f_n)$$

$$f_n + (I - V)^{-1} [(I - V)^{-1} f_n + w - Vf_n]$$





$$g_v(f) = \frac{d}{df} \psi(f) = w - K^{-1} f = 0,$$





2019年12月20日

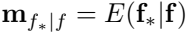


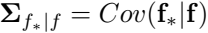
21st April 2020

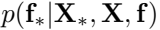




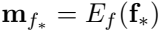


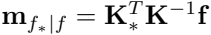






$$\begin{cases} \mathbb{M} f_* | f = \mathbb{K}_*^T \mathbb{K}^{-1} f \\ \Sigma f_* | f = \mathbb{K}_* - \mathbb{K}_*^T \mathbb{K}^{-1} \mathbb{K}_* \end{cases}$$

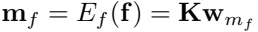


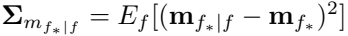


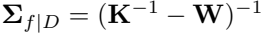




$$E(m, f) = E(K^T K^{-1} f) = K^T K^{-1} m, f$$







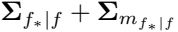




$$\Sigma \pi_{*|*} = K_*^T K_*^{-1} \Sigma / D K_*^{-1} K_* = K_*^T K_*^{-1} (K_*^{-1} W)^{-1} K_*^{-1} K_*$$







$$(IK_* \rightarrow IK^1 IK_*)(IK^1 IK_* \rightarrow IK^1 IK_*)$$

$$K \otimes K^{\vee} = K^{\vee} \otimes K$$

1A

+

B

1

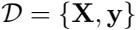
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21. 12. 2021

$$\int \sigma(f_*) p(f_* | \mathbf{x}_*, \mathcal{D}) df_*$$

$$E[f(X)] = E[f(X)]$$











A pixelated, black and white graphic of the word "GOD" in a stylized, blocky font. The letters are composed of various shades of gray and black pixels, giving it a digital or retro aesthetic. The "G" is large and prominent, followed by "O", "D", and "X". The entire image is set against a white background.





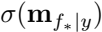




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WILLIAM

$$\mathbf{m}_0 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \quad \mathbf{m}_1 = \begin{bmatrix} -1 \\ 0 \end{bmatrix}, \quad \Sigma_0 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad \Sigma_1 = \begin{bmatrix} 1 & 0.9 \\ 0.9 & 1 \end{bmatrix}$$



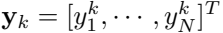








QWERTYUIOP



$$y_n^k = \begin{cases} 1 & \text{if } x_n \in C_k \\ 0 & \text{if } x_n \notin C_k \end{cases}$$

1992-1993



2021.09.21



$$\frac{d}{dx} \left(x^2 \frac{dy}{dx} \right) = 1 \quad \frac{d}{dx} \left(x^2 \frac{dy}{dx} \right) = 1$$

$$p_n^k = p(y_n^k = 1 | f_n^1, \dots, f_n^K) = \frac{\exp(f_n^k)}{\sum_{l=1}^K \exp(f_n^l)} = \begin{cases} 1 & \text{if } f_n^k = \infty \\ 0 & \text{if } f_n^k = -\infty \end{cases}$$



















$$\mathbf{y} = \begin{bmatrix} \mathbf{y}_1 \\ \vdots \\ \mathbf{y}_K \end{bmatrix} = \begin{bmatrix} y_1^1 \\ \vdots \\ y_N^1 \\ \vdots \\ y_1^K \\ \vdots \\ y_N^K \end{bmatrix}, \quad \mathbf{f} = \begin{bmatrix} \mathbf{f}_1 \\ \vdots \\ \mathbf{f}_K \end{bmatrix} = \begin{bmatrix} f_1^1 \\ \vdots \\ f_N^1 \\ \vdots \\ f_1^K \\ \vdots \\ f_N^K \end{bmatrix}, \quad \mathbf{p} = \begin{bmatrix} \mathbf{p}_1 \\ \vdots \\ \mathbf{p}_K \end{bmatrix} = \begin{bmatrix} p_1^1 \\ \vdots \\ p_N^1 \\ \vdots \\ p_1^K \\ \vdots \\ p_N^K \end{bmatrix}$$



$$p(\mathbf{y}|\mathbf{f}) = \prod_{n=1}^N \prod_{k=1}^K (p_n^k)^{y_n^k} = \prod_{n=1}^N \prod_{k=1}^K \left(\frac{\exp(f_n^k)}{\sum_{h=1}^K \exp(f_n^h)} \right)^{y_n^k}$$





$$\text{cov}(f_k(\mathbf{x}_m), f_k(\mathbf{x}_n)) = \text{cov}(f_m^k, f_n^k) = k(\mathbf{x}_m, \mathbf{x}_n) = \exp\left(-\frac{1}{a^2} ||\mathbf{x}_m - \mathbf{x}_n||^2\right), \quad (m, n = 1, \cdots, N)$$

What is wrong with this?





$$\mathbf{K} = \begin{bmatrix} \mathbf{K}_1 & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{K}_2 & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \cdots & \mathbf{0} & \mathbf{K}_K \end{bmatrix}$$

$$p(\mathbf{f}|\mathcal{D}) = p(\mathbf{f}|\mathbf{X}, y) \propto p(\mathbf{y}|\mathbf{f}) \, p(\mathbf{f}|\mathbf{X}) \propto \prod_{n=1}^N \prod_{k=1}^K \left(\frac{\exp(f_n^k)}{\sum_{h=1}^K \exp(f_n^h)} \right)^{y_n^k} \mathcal{N}(\mathbf{0}, \mathbf{K})$$

SEWED

2019-2020

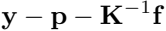


$$\log p(\mathbf{f}|\mathcal{D}) = \log p(\mathbf{y}|\mathbf{f}) + \log p(\mathbf{f}|\mathbf{X}) = \sum_{n=1}^N \sum_{k=1}^K y_n^k \left(f_n^k - \log \sum_{h=1}^K \exp(f_n^h) \right) + \log \mathcal{N}(\mathbf{0}, \mathbf{K})$$

$$y^T \mathbf{f} - \sum_{n=1}^N \sum_{k=1}^K \log \sum_{h=1}^K \exp(f_n^h) - \frac{N}{2} \log(2\pi) - \frac{1}{2} \log |\mathbf{K}| - \frac{1}{2} \mathbf{f}^T \mathbf{K}^{-1} \mathbf{f}$$



$$\frac{d}{d\mathbf{f}}\psi(\mathbf{f}) = \frac{d}{d\mathbf{f}}\left(y^T\mathbf{f} - \sum_{n=1}^N\sum_{k=1}^K\log\sum_{h=1}^K\exp(f_n^h) - \frac{N}{2}\log(2\pi) - \frac{1}{2}\log|\mathbf{K}| - \frac{1}{2}\mathbf{f}^T\mathbf{K}^{-1}\mathbf{f}\right)$$





$$\sum_{n=1}^N \sum_{k=1}^K \frac{d}{d\mathbf{f}} \log \sum_{h=1}^K \exp(f_n^h) = \sum_{n=1}^N \sum_{k=1}^K \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \frac{\exp(f_n^k)}{\sum_{h=1}^K \exp(f_n^h)} \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \sum_{n=1}^N \sum_{k=1}^K \begin{bmatrix} 0 \\ \vdots \\ 0 \\ p_n^k \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \mathbf{p}$$

১৫ই আগস্ট ১৯৪৭ খ্রিঃ

$$g_{\psi}(\mathbf{f}) \Big|_{\mathbf{f}=\mathbf{m}_f|D} = \mathbf{y} - \mathbf{P} - \mathbf{K}^{-1}\mathbf{f} \Big|_{\mathbf{f}=\mathbf{m}_f|D} = \mathbf{y} - \mathbf{P}_{m_f} - \mathbf{K}^{-1}\mathbf{m}_{f|D} = \mathbf{0},$$

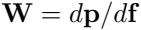
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$$\mathbf{H}_\psi(\mathbf{f}) = \frac{d^2}{d\mathbf{f}^2} \psi(\mathbf{f}) = \frac{d}{d\mathbf{f}} \mathbf{g}_\psi = \frac{d}{d\mathbf{f}} (\mathbf{y} - \mathbf{K}^{-1} \mathbf{f} - \mathbf{p}) = -\mathbf{K}^{-1} = -\mathbf{W} = -\Sigma_{f|D}^{-1}$$

$E_D = H_v(f) = H(w)$





$$\frac{\partial}{\partial f_j} p_i^k$$

$$\frac{\partial}{\partial f_j^l} \left[\frac{\exp(f_i^k)}{\sum_{h=1}^K \exp(f_i^h)} \right] = \frac{\exp(f_i^k) \left(\sum_{h=1}^K \exp(f_i^h) \right) \delta_{kl} - \exp(f_i^k) \exp(f_j^l)}{\left(\sum_{h=1}^K \exp(f_i^h) \right)^2} \delta_{ij}$$

$$\left[\frac{\exp(f_i^k)}{\sum_{h=1}^K \exp(f_i^h)} \delta_{kl} - \frac{\exp(f_i^k) \exp(f_j^l)}{\left(\sum_{h=1}^K \exp(f_i^h) \right)^2} \right] \delta_{ij} = (p_i^k \delta_{kl} - p_i^k p_j^l) \delta_{ij},$$

W. J. P. I.

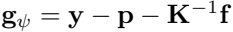




$$\mathbf{P} = \begin{bmatrix} \textit{diag}(\mathbf{p}_1) \\ \vdots \\ \textit{diag}(\mathbf{p}_K) \end{bmatrix}, \quad \textit{diag}(\mathbf{p}_k) = \begin{bmatrix} p_1^k & 0 & \cdots & 0 \\ 0 & p_2^k & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & p_N^k \end{bmatrix}, \quad (k = 1, \cdots, K)$$

$$\mathbf{P}\mathbf{P}^T = \begin{bmatrix} \text{diag}(\mathbf{p}_1) \\ \vdots \\ \text{diag}(\mathbf{p}_K) \end{bmatrix} [\text{diag}(\mathbf{p}_1), \cdots, \text{diag}(\mathbf{p}_K)] = \begin{bmatrix} \text{diag}(\mathbf{p}_1^2) & \cdots & \text{diag}(\mathbf{p}_1)\text{diag}(\mathbf{p}_K) \\ \vdots & \ddots & \vdots \\ \text{diag}(\mathbf{p}_K)\text{diag}(\mathbf{p}_1) & \cdots & \text{diag}(\mathbf{p}_K^2) \end{bmatrix}$$

$$diag(\mathbf{p}_k)diag(\mathbf{p}_l) = \begin{bmatrix} p_1^k p_1^l & 0 & \cdot \cdot \cdot & 0 \\ 0 & p_1^k p_1^l & \cdot \cdot \cdot & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \cdot \cdot \cdot & 0 & p_N^k p_N^l \end{bmatrix}$$



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$$f_n - H_{\nu}^1 f_n = f_n + (I - 1)(f_n - D)$$

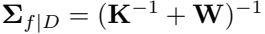
$$f_n + (I_n - 1)w) - 1 (I_n - 1)w f_n + w f_n + v - D)$$

$$E_1 + W_1 - W_2 + v - D$$

$$E(\mathbf{I}|\mathbf{I}^*) = E(\mathbf{I}|\mathbf{I}^* - \mathbf{1})$$

$$E^2 - 1 [E(v) - P_m] = E(v) - P_m$$

$$m_k = (E_k)^T (v_k - p_k), \quad (k = 1, \dots, N)$$



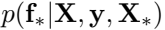
$$\Sigma \pi_{j*} = K_*^T K^{-1} \Sigma / D K_*^{-1} = K_*^T K^{-1} (K_*^{-1} + W)^{-1} K_*^{-1}$$

W. J. P. I.

2012-12-12

$$p_*^k = \frac{\exp(m_{f_*}^k)}{\sum_{l=1}^K \exp(m_{f_*}^l)}, \quad (k=1, \cdots, K)$$

Wormholes . . .



[illegible]

$$\begin{bmatrix} 197 & 3 & 0 \\ 0 & 195 & 5 \\ 1 & 21 & 178 \end{bmatrix}$$

13400 = 00225

193

7

6

194









$$d_B(C_i, C_j) = \frac{1}{4} (\mathbf{m}_i - \mathbf{m}_j)^T \left[\frac{\Sigma_i + \Sigma_j}{2} \right]^{-1} (\mathbf{m}_i - \mathbf{m}_j) + \log \left[\frac{\left| \frac{\Sigma_i + \Sigma_j}{2} \right|}{(|\Sigma_i| |\Sigma_j|)^{1/2}} \right]$$



WUOLAW

$$w_k = \frac{1}{n_i + n_j} [n_i w_i + n_j w_j]$$

$$\Sigma_k = \frac{1}{n_i + n_j} [n_i(\Sigma_i + (\mathbf{m}_i - \mathbf{m}_k)(\mathbf{m}_i - \mathbf{m}_k)^T) + n_j(\Sigma_j + (\mathbf{m}_j - \mathbf{m}_k)(\mathbf{m}_j - \mathbf{m}_k)^T)]$$











$\ln \left(\frac{v}{v_0} \right) = \ln \left(\frac{1}{1 + \frac{v_0}{v_0}} \right)$







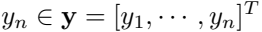




$$x \in \begin{cases} G_l & \text{if } D_l(x) > D_r(x) \\ G_r & \text{if } D_r(x) < D_l(x) \end{cases}$$



W E X P E R I M E N T A L





$$J = \sum_{n=1}^N \sum_{k=1}^K P_{nk} ||\mathbf{x}_n - \mathbf{m}_k||^2$$

$$p_{nk} = \begin{cases} 1 & \text{if } k = \arg \min_i \|x_n - m_i\| \\ 0 & \text{otherwise} \end{cases}$$



$$\frac{d}{d\mathbf{m}_k} J = 2 \sum_{n=1}^N P_{nk} ||\mathbf{x}_n - \mathbf{m}_k|| = 0$$

$$m_k = \frac{\sum_{n=1}^N P_{nk} x_n}{\sum_{n=1}^N P_{nk}} = \frac{1}{N_k} \sum_{n=1}^N P_{nk} x_n$$

Wx

=

Wx

=

1

Wx

A pixelated, black and white graphic of the text "100% 100% 100%". The text is rendered in a bold, blocky, and slightly irregular font, characteristic of early digital art or video game titles. The characters are composed of black and grey pixels, giving it a retro, digital appearance. The text is arranged in a single line, with the three "100%" units separated by spaces. The overall style is reminiscent of early computer graphics or video game titles.





$$\|x - \min_x\|_2 = \min_{1 \leq i \leq K} \|x - \min_i\|_2,$$

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1

1

$$\mathbf{m}_k^{(\ell+1)} = \frac{1}{N_k} \sum_{x \in C_k} \mathbf{x}, \quad (k = 1, \cdots, K)$$

$$\begin{aligned}
 \mathbb{I} \mathbb{I} \mathbb{I} x (v + 1) &= \mathbb{I} \mathbb{I} \mathbb{I} x (v) \\
 \mathbb{I} \mathbb{I} \mathbb{I} x &= 1, \cdot, \cdot, \cdot x (v)
 \end{aligned}$$



1500









	K=C-1=3			K=C=4				K=C+1=5				
Separability	1.76			2.56				2.58				
Intra-cluster distance	9.1	44.3	11.8	10.8	12.7	11.1	9.1	10.8	9.1	11.1	8.9	9.4

K=C-1=3		
	1	2
2	10.9	
3	21.9	184.7

K=C=4			
	1	2	3
2	4.0		
3	5.1	1.6	
4	2.4	2.3	4.4

K=C+1=5				
	1	2	3	4
2	4.0			
3	5.1	1.6		
4	7.0	4.3	0.3	
5	17.3	15.5	8.9	11.1









$$\begin{bmatrix} 1 & 27 & 3 & 166 & 0 & 0 & 3 & 24 & 0 & 0 \\ 0 & 1 & 13 & 0 & 210 & 0 & 0 & 0 & 0 & 0 \\ 0 & 3 & 16 & 0 & 3 & 180 & 9 & 8 & 5 & 0 \\ 1 & 0 & 88 & 1 & 0 & 0 & 5 & 1 & 128 & 0 \\ 4 & 1 & 52 & 0 & 26 & 0 & 0 & 6 & 0 & 135 \\ 1 & 1 & 10 & 0 & 0 & 0 & 0 & 167 & 43 & 2 \\ 0 & 161 & 5 & 14 & 13 & 2 & 0 & 29 & 0 & 0 \\ 4 & 0 & 70 & 0 & 5 & 4 & 137 & 3 & 1 & 0 \\ 4 & 1 & 69 & 2 & 1 & 3 & 2 & 31 & 110 & 1 \\ 92 & 0 & 101 & 1 & 1 & 1 & 5 & 0 & 2 & 21 \end{bmatrix}$$

$$p(\mathbf{x}) = \sum_{k=1}^K P_k \mathcal{N}(\mathbf{x}; \mathbf{m}_k, \Sigma_k) = \sum_{k=1}^K P_k \left[\frac{1}{(2\pi)^{d/2} |\Sigma_k|^{1/2}} \exp \left(-\frac{1}{2} (\mathbf{x} - \mathbf{m}_k)^T \Sigma_k^{-1} (\mathbf{x} - \mathbf{m}_k) \right) \right]$$

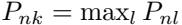
[illegible]

$$\int_{-\infty}^{\infty} p(\mathbf{x}) \, d\mathbf{x} = \sum_{k=1}^K P_k \int_{-\infty}^{\infty} \mathcal{N}(\mathbf{x}; \mathbf{m}_k, \Sigma_k) \, d\mathbf{x} = \sum_{k=1}^K P_k = 1$$

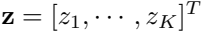
$\frac{1}{2} \ln \left(\frac{1 + \sqrt{1 - 4x}}{1 - \sqrt{1 - 4x}} \right)$

Q = P x W x L x R x I x S x T x U x V x W x X x Y x Z

Praxen
Praxen
Praxen



Wiederholung

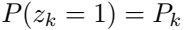


W E W O R D





QWERTYUIOPASDFGHJKLZXCVBNM



THE WORLD IS A VILLAGE

K Σ P_K $=$ 1 $K=1$

$$p(x, z_k = 1 | \theta) = p(x | z_k = 1, \theta) p(z_k = 1 | \theta)$$

$$p(\mathbf{x}|\theta) = \sum_{k=1}^K p(\mathbf{x}, z_k = 1|\theta) = \sum_{k=1}^K p(\mathbf{x}|z_k = 1, \theta) P(z_k = 1) = \sum_{k=1}^K P_k \mathcal{N}(\mathbf{x}; \mathbf{m}_k, \Sigma_k)$$

W E I D

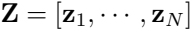
K \prod P_k^{2k} $k=1$

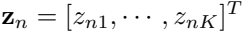


$$\prod_{k=1}^K \mathcal{N}(\mathbf{x}, \mathbf{\Pi}_k, \Sigma_k)^{z_k}$$

W E I D

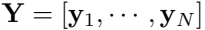
$$p(\mathbf{z}) \, p(\mathbf{x}|\mathbf{z}, \theta) = \prod_{k=1}^K \left(P_k \mathcal{N}(\mathbf{x}, \mathbf{m}_k, \Sigma_k) \right)^{z_k}$$















$$p(\mathbf{x}_n, \mathbf{z}_n | \theta) = \prod_{k=1}^K (P_k \mathcal{N}(\mathbf{x}_n, \mathbf{\Pi}_k, \Sigma_k))^{z_{nk}} \, , \qquad (n = 1, \cdots, N)$$



[illegible]

$$p(\mathbf{X}, \mathbf{Z} | \theta) = p([x_1, \cdots, x_N], [z_1, \cdots, z_N] | \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k, P_k(k = 1, \cdots, K))$$

$$\prod_{n=1}^N p(\mathbf{x}_n, \mathbf{z}_n | \theta) = \prod_{n=1}^N \prod_{k=1}^K (P_k \mathcal{N}(\mathbf{x}_n, \mathbf{m}_k, \Sigma_k))^{z_{nk}}$$

A pixelated, black and white graphic of the text "100% XP". The characters are rendered in a bold, blocky font with a dithered or pixelated texture. The "1" is a simple vertical bar. The "00" are circles with a thick border. The "%" is a standard percentage symbol. The "XP" is in a stylized, slightly irregular font. The entire graphic is set against a white background.

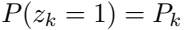
$$\log p(\mathbf{X}, \mathbf{Z}|\theta) = \log \left[\prod_{n=1}^N \prod_{k=1}^K (P_k \mathcal{N}(\mathbf{x}_n, \boldsymbol{\Pi}_k, \boldsymbol{\Sigma}_k))^{z_{nk}} \right]$$

$$\sum_{n=1}^N \sum_{k=1}^K z_{nk} [\log P_k + \log \mathcal{N}(\mathbf{x}_n, \mathbf{m}_k, \Sigma_k)]$$

1000

100% 100%

$$P_{nk} = P(z_{nk} = 1 | \mathbf{x}_n, \theta) = \frac{p(\mathbf{x}_n, z_{nk} = 1 | \theta)}{p(\mathbf{x}_n | \theta)} = \frac{P_k \mathcal{N}(\mathbf{x}_n; \mathbf{m}_k \Sigma_k)}{\sum_{l=1}^K P_l \mathcal{N}(\mathbf{x}_n; \mathbf{m}_l \Sigma_l)} \quad (n = 1, \dots, N; k = 1, \dots, K)$$



$$\sum_{k=1}^K P(z_k = 1) = \sum_{k=1}^K P_k = 1, \quad \sum_{k=1}^K P(z_{nk} = 1 | \mathbf{x}_n, \theta) = \sum_{k=1}^K P_{nk} = 1$$









100% 100%

$$E_Z \left[\sum_{n=1}^N \sum_{k=1}^K z_{nk} \left[\log P_k + \log \mathcal{N}(\mathbf{x}_n, \mathbf{m}_k, \Sigma_k) \right] \right]$$

$$\sum_{n=1}^N \sum_{k=1}^K E(z_{nk}) [\log P_k + \log \mathcal{N}(\mathbf{x}_n, \mathbf{m}_k, \Sigma_k)]$$

$$\sum_{n=1}^N \sum_{k=1}^K P_{nk} [\log P_k + \log \mathcal{N}(\mathbf{x}_n, \mathbf{m}_k, \Sigma_k)]$$

$$E(x_n) = 1 \quad P(x_n = 0) = 0 \quad P(x_n = 1) = 1$$

$$Q = P \cdot X = I \cdot X = 1 \cdot X$$

1234567890

1234567890

$$L(\theta, \lambda) = \sum_{n=1}^N \sum_{k=1}^K P_{nk} [\log P_k + \log \mathcal{N}(\mathbf{x}_n, \mathbf{m}_k, \Sigma_k)] + \lambda \left(\sum_{k=1}^K P_k - 1 \right)$$

$$\frac{\partial}{\partial P_k} \mathcal{L}(\theta, \lambda)$$

$$\frac{\partial}{\partial P_k} \left[\sum_{n=1}^N \sum_{k=1}^K P_{nk} [\log P_k + \log \mathcal{N}(\mathbf{x}_n, \mathbf{\Pi}_k, \Sigma_k)] + \lambda \left(\sum_{k=1}^K P_k - 1 \right) \right]$$

$$\sum_{n=1}^N P_{nk} \frac{1}{P_k} + \lambda = 0$$

$$\sum_{n=1}^N P_{nk} + P_k \lambda = N_k + P_k \lambda = 0$$

$$N_k = \sum_{n=1}^N P_{nk}$$

$$\sum_{k=1}^K N_k = \sum_{k=1}^K \left(\sum_{n=1}^N P_{nk} \right) = \sum_{n=1}^N \left(\sum_{k=1}^K P_{nk} \right) = \sum_{n=1}^N 1 = N$$

$$\sum_{k=1}^K (N_k + P_k \lambda) = \sum_{k=1}^K N_k + \lambda \left(\sum_{k=1}^K P_k \right) = N + \lambda = 0$$



$$p(z_k = 1) = P_k = \frac{N_k}{N} = \frac{1}{N} \sum_{n=1}^N P_{nk}$$

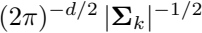
$$\frac{\partial}{\partial m_k} E_Z(\log L(\theta|\mathbf{X}, \mathbf{Z}))$$

$$\frac{\partial}{\partial \mathbf{m}_k} \left[\sum_{n=1}^N \sum_{k=1}^K P_{nk} [\log P_k + \log \mathcal{N}(\mathbf{x}_n, \mathbf{m}_k, \Sigma_k)] \right]$$

$$\sum_{n=1}^N P_{nk} \frac{\partial}{\partial \mathbf{m}_k} \log \mathcal{N}(\mathbf{x}_n, \mathbf{m}_k, \Sigma_k)$$

$$\sum_{n=1}^N P_{nk} \frac{\partial}{\partial \mathbf{m}_k} \left[-\frac{1}{2} (\mathbf{x}_n - \mathbf{m}_k)^T \boldsymbol{\Sigma}_k^{-1} (\mathbf{x}_n - \mathbf{m}_k) \right]$$

$$\frac{1}{2} \sum_{n=1}^N P_{nk} \Sigma_k^{-1} (\mathbf{x}_n - \mathbf{m}_k) = 0$$





$$\sum_{n=1}^N P_{nk}(x_n - \mathbf{m}_k) = \sum_{n=1}^N P_{nk}x_n - \sum_{n=1}^N P_{nk}\mathbf{m}_k = \sum_{n=1}^N P_{nk}x_n - N_k\mathbf{m}_k = \mathbf{0}$$

$$\mathbf{m}_k = \frac{1}{N_k} \sum_{n=1}^N P_{nk} \mathbf{x}_n$$

$$\frac{\partial}{\partial \Sigma_k} \left[\sum_{n=1}^N \sum_{k=1}^K P_{nk} [\log P_k + \log \mathcal{N}(\mathbf{x}_n, \mathbf{m}_k, \Sigma_k)] \right]$$

$$\sum_{n=1}^N P_{nk} \frac{\partial}{\partial \Sigma_k} \log \mathcal{N}(\mathbf{x}_n, \mathbf{\mu}_k, \Sigma_k)$$

$$-\frac{1}{2}\sum_{n=1}^N P_{nk}\left[\frac{\partial}{\partial \Sigma_k}\log|\Sigma_k|+\frac{\partial}{\partial \Sigma_k}(\mathbf{x}_n-\mathbf{m}_k)^T\Sigma_k^{-1}(\mathbf{x}_n-\mathbf{m}_k)\right]$$

$$-\frac{1}{2}\sum_{n=1}^N P_{nk}\left[\Sigma_k^{-1}-\Sigma_k^{-1}\left(x_n-\mathbf{m}_k\right)\left(x_n-\mathbf{m}_k\right)^T \Sigma_k^{-1}\right]=0$$

$$\frac{d}{dA} \log |A| = (A^{-1})^T, \quad \frac{d}{dA} (a^T A^{-1} b) = -(A^{-1})^T a b^T (A^{-1})^T$$

$$\sum_{n=1}^N P_{nk} \left(\Sigma_k - (x_n - \mathbf{m}_k)(x_n - \mathbf{m}_k)^T \right) = 0$$

$$\Sigma_k = \frac{1}{N_k} \sum_{n=1}^N P_{nk} (x_n - \mathbf{m}_k)(x_n - \mathbf{m}_k)^T$$

0 = PIR, ZK, EIR

$$P_{nk} = P(r_k = 1 | \mathbf{x}_n) = \frac{P_k \mathcal{N}(\mathbf{x}_n; \mathbf{m}_k, \Sigma_k)}{\sum_{l=1}^K P_l \mathcal{N}(\mathbf{x}_n; \mathbf{m}_l, \Sigma_l)}, \quad N_k = \sum_{n=1}^N P_{nk}$$







$$\frac{1}{N_k} \sum_{n=1}^N P_{nk} X_n$$



$$\frac{1}{N_k} \sum_{n=1}^N P_{nk} (\mathbf{x}_n - \mathbf{m}_k)(\mathbf{x}_n - \mathbf{m}_k)^T$$



Q. 1. Explain the following terms:





$$p(\mathbf{x}|z_k=1,\theta)=\mathcal{N}(\mathbf{x}|\mathbf{m}_k,\varepsilon\mathbf{I})=\frac{1}{(2\pi)^{d/2}\varepsilon^{1/2}}\exp\left(-\frac{1}{2\varepsilon}||\mathbf{x}-\mathbf{m}_k||^2\right)$$



$$P_{nk} = P(z_k = 1 | x_n, \theta) = \frac{P_k \mathcal{N}(x_n; \mathbf{m}_k, \Sigma_k)}{\sum_{l=1}^K P_l \mathcal{N}(x_n; \mathbf{m}_l, \Sigma_l)} = \frac{P_k \exp(-||x_n - \mathbf{m}_k||^2 / 2\epsilon)}{\sum_{l=1}^K P_l \exp(-||x_n - \mathbf{m}_l||^2 / 2\epsilon)}$$







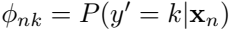
$$\lim_{\epsilon \rightarrow 0} P_{nk} = \lim_{\epsilon \rightarrow 0} \frac{P_k \exp(-||\mathbf{x}_n - \mathbf{m}_k||^2/2\epsilon)}{\sum_{l=1}^K P_l \exp(-||\mathbf{x}_n - \mathbf{m}_l||^2/2\epsilon)} = \begin{cases} 1 & \text{if } ||\mathbf{x}_n - \mathbf{m}_k|| = \min_l ||\mathbf{x}_n - \mathbf{m}_l|| \\ 0 & \text{otherwise} \end{cases}$$

For all





1992-1993



K-means

0	0	50
50	0	0
18	32	0

EM

0	0	50
45	5	0
0	50	0





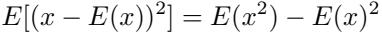


$$B(x|\mu) = \mu^x(1-\mu)^{1-x} = \begin{cases} \mu & \text{if } x = 1 \\ 1-\mu & \text{if } x = 0 \end{cases}$$

1993

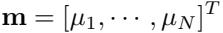
$$1P(x)=1+0P(x)=0=1x+0(1-x)=x$$

WORLD



$$1^2 P(x) = 1) + 0^2 P(x) = 0) - \mu^2 = \mu - \mu^2 = \mu(1 - \mu)$$





QWERTY

$$\Sigma = \text{diag}(\mu_i(1 - \mu_i)) = \begin{bmatrix} \mu_1(1 - \mu_1) & & & 0 \\ & \ddots & & \\ & & \ddots & \\ 0 & & & \mu_d(1 - \mu_d) \end{bmatrix}$$

1992-1993

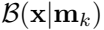
$$B(\mathbf{x}|\mathbf{m}) = \prod_{i=1}^d B(x_i|\mu_i) = \prod_{i=1}^d \mu_i^{x_i} (1-\mu_i)^{1-x_i}$$

$$\log \mathcal{B}(\mathbf{x}|\mathbf{m}) = \log \left(\prod_{i=1}^d \mathcal{B}(x_i|\mu_i) \right) = \sum_{i=1}^d [x_i \log \mu_i + (1 - x_i) \log(1 - \mu_i)]$$

$$p(\mathbf{x}|\mathbf{n}_k, P_k, (k = 1, \cdots, K)) = p(\mathbf{x}|\theta) = \sum_{k=1}^K P_k \mathcal{B}(\mathbf{x}, \mathbf{n}_k) = \sum_{k=1}^K P_k \prod_{i=1}^d \mu_{ki}^{x_i} (1 - \mu_{ki})^{1-x_i}$$

A pixelated, black and white graphic. On the left, the letters 'III' are rendered in a bold, blocky font. To the right of the letters is a stylized, pixelated figure of a person standing on a small platform. The figure is composed of several rectangular blocks, giving it a blocky appearance. The entire graphic is set against a white background.

Figure 1 consists of two horizontal bar charts. The top chart shows the distribution of the number of children per woman by country in 1990. The bottom chart shows the distribution in 2010. The x-axis represents the number of children per woman, ranging from 0 to 6. The y-axis lists the countries: India, China, USA, and Germany. The bars are color-coded: black for India, grey for China, white for USA, and dark grey for Germany. The 1990 chart shows a higher proportion of women with 4 or more children in India and China, while the 2010 chart shows a higher proportion of women with 2 or 3 children in India and China, and a higher proportion of women with 1 or 2 children in the USA and Germany.



$$\mathbf{m} = E(\mathbf{x}) = \sum_{k=1}^K P_k E_k(\mathbf{x}) = \sum_{k=1}^K P_k \mathbf{m}_k$$

20

5

10

11

K \prod $\mathcal{B}(\mathbf{x}, \mathbf{m}_k)^{z_k}$ $k=1$

$$p(\mathbf{z}|\theta) \, p(\mathbf{x}|\mathbf{z},\theta) = \prod_{k=1}^K \left(P_k \, \mathcal{B}(\mathbf{x}, \mathbf{m}_k) \right)^{z_k}$$

$$D([x_1, \dots, x_n], [z_1, \dots, z_n] | [x_n, P_n] = 1, \dots, [x_n])$$

$$\prod_{n=1}^N p(\mathbf{x}_n, \mathbf{z}_n | \theta) = \prod_{n=1}^N \prod_{k=1}^K (P_k \mathcal{B}(\mathbf{x}_n, \mathbf{m}_k))^{z_{nk}}$$

$$\log p(\mathbf{X}, \mathbf{Z}|\theta) = \log \prod_{n=1}^N \prod_{k=1}^K (P_k \mathcal{B}(\mathbf{x}_n, \mathbf{m}_k))^{z_{nk}}$$

$$\sum_{n=1}^N \sum_{k=1}^K z_{nk} [\log P_k + \log \mathcal{B}(\mathbf{x}_n, \mathbf{m}_k)]$$

$$P_{nk} = P(z_{nk} = 1 | \mathbf{x}_n, \theta) = \frac{p(\mathbf{x}_n, z_{nk} = 1 | \theta)}{p(\mathbf{x}_n) | \theta} = \frac{P_k \mathcal{B}(\mathbf{x}_n; \mathbf{m}_k)}{\sum_{l=1}^K P_l \mathcal{B}(\mathbf{x}_n; \mathbf{m}_l)} \quad (n = 1, \dots, N; \quad k = 1, \dots, K)$$



100% 100%

$$E_Z \sum_{n=1}^N \sum_{k=1}^K z_{nk} [\log P_k + \log \mathcal{B}(\mathbf{x}_n, \mathbf{m}_k)]$$

$$\sum_{n=1}^N \sum_{k=1}^K E(z_{nk}) \left[\log P_k + \log \prod_{i=1}^d \mu_{ki}^{x_{ni}} (1 - \mu_{ki})^{1-x_{ni}} \right]$$

$$\sum_{n=1}^N \sum_{k=1}^K P_{nk} \left[\log P_k + \sum_{i=1}^d \left[x_{ni} \log \mu_{ki} + (1 - x_{ni}) \log(1 - \mu_{ki}) \right] \right]$$

$$P_k = \frac{N_k}{N} = \frac{1}{N} \sum_{n=1}^N P_{nk}$$

$$\frac{\partial}{\partial m_k} E_Z(\log p(X, Z|\theta))$$

$$\frac{\partial}{\partial \mathbf{m}_k} \sum_{n=1}^N \sum_{k=1}^K P_{nk} \left[\log P_k + \sum_{i=1}^d [x_{ni} \log \mu_{ki} + (1 - x_{ni}) \log(1 - \mu_{ki})] \right]$$

$$\sum_{n=1}^N P_{nk} \frac{\partial}{\partial \mathbf{m}_k} \sum_{i=1}^d [x_{ni} \log \mu_{ki} + (1 - x_{ni}) \log(1 - \mu_{ki})] = \mathbf{0}$$

$$\sum_{n=1}^N P_{nk} \frac{d}{d\mu_{ki}} [x_{ni} \log \mu_{ki} + (1 - x_{ni}) \log(1 - \mu_{ki})]$$

$$\sum_{n=1}^N P_{nk} \left(\frac{x_{ni}}{\mu_{ki}} - \frac{1 - x_{ni}}{1 - \mu_{ki}} \right) = 0$$

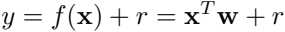
$$(1 - \mu_{ki}) \sum_{n=1}^N P_{nk} x_{ni} = \mu_{ki} \sum_{n=1}^N P_{nk} (1 - x_{ni}) = \mu_{ki} N_k - \mu_{ki} \sum_{n=1}^N P_{nk} x_{ni}$$



$$\mu_{ki} = \frac{1}{N_k} \sum_{n=1}^N P_{nk} \mathcal{L}_{ni} \quad (i = 1, \cdots, d)$$







0.01

$$f(x) = w^T x \begin{cases} < 0 \\ \geq 0 \end{cases},$$

$$x \in \begin{cases} C_0 \\ C_1 \end{cases}$$

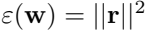
$D = \frac{1}{2} \left(\frac{1}{2} + \frac{1}{2} \right)$



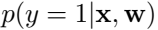




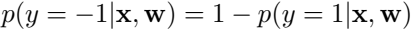




QX EOLW



POSTERIOR





$$\frac{1}{1 + e^{-z}} = \frac{e^z}{1 + e^z}$$

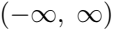


$$\int_{-\infty}^{\infty} \mathcal{N}(v|0,1) dv = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2}v^2\right) dv$$

$$\sigma(z) = \begin{cases} 0 & z = -\infty \\ 1 & z = \infty \end{cases}$$

A pixelated, black and white graphic of the word "EQUINOX" in a stylized, blocky font. The letters are composed of various shades of gray and black pixels, giving it a digital or retro aesthetic. The word is centered horizontally and occupies most of the width of the image.







0.1

QXWV=QW

A horizontal sequence of 12 grayscale images showing the progression of a handwritten digit '4' from left to right. The images are pixelated and show the stroke being drawn in black on a white background. The sequence starts with a vertical stroke on the left, followed by a horizontal stroke, then a diagonal stroke, and finally a vertical stroke on the right. The images are arranged in a row, with each image showing a different stage of the digit's formation.

$$1 - p(v) = 1 - x, w) = 1 - o(v) = 1 - j)$$

$$p(x|w) = p(x|w)$$

$\frac{d}{dt} \left(\frac{1}{2} m v^2 \right) = \frac{d}{dt} \left(\frac{1}{2} m \frac{dx}{dt} \frac{dx}{dt} \right)$





WOW! WE



$$\mathcal{L}(\mathbf{w}|\mathcal{D}) = p(\mathcal{D}|\mathbf{w}) = p(\mathbf{y}|\mathbf{X}, \mathbf{w}) = \prod_{n=1}^N p(y_n|\mathbf{x}_n, \mathbf{w}) = \prod_{n=1}^N \sigma(y_i f_i) = \prod_{n=1}^N \sigma(y_n \mathbf{x}_n^T \mathbf{w})$$



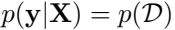






$$p(w|x, y) = \frac{p(y, w|x)}{p(y)} = \frac{p(y|x, w) p(w)}{p(y|x)} \propto p(y|x, w) p(w|x)$$

$$\prod_{n=1}^N p(y_n|x_n, \mathbf{w}) \mathcal{N}(\mathbf{0}, \Sigma_w) = \prod_{n=1}^N \sigma(y_n f_n) \frac{1}{(2\pi)^{d/2} |\Sigma_w|^{1/2}} \exp\left(-\frac{1}{2} \mathbf{w}^T \Sigma_w^{-1} \mathbf{w}\right)$$





$$\psi(\mathbf{w}) = \log p(\mathbf{w}|\mathcal{D}) = \sum_{n=1}^N \log \sigma(y_n f_n) - \frac{N}{2} \log(2\pi) - \frac{1}{2} \log |\Sigma_w| - \frac{1}{2} \mathbf{w}^T \Sigma_w^{-1} \mathbf{w}$$



QWERTY

$$\frac{d}{dw} \left(\sum_{n=1}^N \log \sigma(y_n f_n) \right) - \frac{d}{dw} \left(\frac{1}{2} w^T \Sigma_w^{-1} w \right)$$

$$\sum_{n=1}^N \frac{d}{dw} \left(\log \frac{1}{1 + e^{-y_n x_n^T w}} \right) - \Sigma^{-1} w$$

$$\sum_{n=1}^N \frac{y_n x_n}{1 + e^{y_n x_n^T w}} - \sum_w^{-1} w = 0$$



$$p(y_* = 1 | x_*, w) = \sigma(x_*^T w) = \sigma(f(x_*)) = \frac{1}{1 + \exp(x_*^T w)}$$

0123456789



0 1 2 3 4 5 6 7 8 9



— O'XV O'P=I, , X)

$$p(y \in C_i | x, W) = \frac{\exp(x^T w_i)}{\sum_{k=1}^K \exp(x^T w_k)} = \begin{cases} 0 & x^T w_i = -\infty \\ 1 & x^T w_i = \infty \end{cases}$$

