

11sec

$$f(v_1, \dots, v_n) = \sum_{i=1}^n \left[m_i \chi_{\{v_i < 0\}} + 1_{\{v_i \geq 0\}} \right]$$

प्रिंटर जैसे सिर्फ जैसी प्राप्ति करता है वह एक अचूक विकल्प है।

W.M. f. NL ~~1991~~ V.P.N. N.J. 1.70.1. wife IC f. p.viffe IC n.j.1

2) If $\mu \in \mathcal{M}_1(C, S(C))$ then $\mu^*(w) = (\mu_1(w_1), \dots, \mu_n(w_n))$

• C? jekk esp. i d, M/C

$$w_j \cdot x_i \geq w_{j,i} x_i \Rightarrow x_i(w_j - w_{j,i}) \geq 0 \Rightarrow x_i(w_j - w_{j,i}) + 1 > 0$$

• $\lim_{x \rightarrow a} f(x)$

... $\pi(M)$ $\times_{\mathbb{R}} \mathbb{R}^n$ \rightarrow (M, p) $\times_{\mathbb{R}}$ \mathbb{R}^n

$$y_i = w_j^T w_j x_i \Rightarrow y_i: w_j^T y_i \geq w_j^T x_i \Rightarrow x_i(w_j^T - w_j^T y_i) \leq 0$$

$$z_i = \min_{j \in \{1, 2\}} (w_{ij}^+ - w_{ij}^-) x_i \quad ; \quad \{1, 2\} \subseteq \{1, 2, 3\}$$

$$\bar{z} = \min_{i \in \Gamma_H} z_i$$

$$\forall i \in [n] \setminus \{j\} : (w_j - w_i)_i = \sum_{k=1}^{n-1} (w_j^k - w_i^k)_i = -\sum_{k=1}^{n-1} (w_j^k - w_i^k)_{ijk} \leq$$

$$\frac{y}{1} = \frac{-x}{2}$$

2. (2) $\lim_{x \rightarrow 0} \frac{\sin x}{x}$

For example, if $f(x) = x^2$, then $f'(x) = 2x$. This means that the slope of the tangent line at $x = 3$ is $2(3) = 6$.

Java -> If we use $f(x) = x^2$ then $f'(x) = 2x$

2 like

$$\max_{\beta = (\beta_1, \beta_2)} \sum_{i=1}^n \sum_{j=1}^L k_i k_j \beta_1 x_{ij} \beta_2 x_{2j} \text{ s.t. } \beta_1 \geq 0, \beta_2 \geq 0$$

$$(\beta_1, \beta_2) \in \{(m, m) \mid m \geq 0\}, \quad \beta_1 + \beta_2 = 0$$

$$\max_{\beta = (\beta_1, \beta_2)} \beta_1 + \beta_2 - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^L k_i k_j \beta_1 x_{ij} \beta_2 x_{2j}$$

$$\max_{\beta = (\beta_1, \beta_2)} \beta_1 + \beta_2 - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^L k_i k_j \beta_1 x_{ij} \beta_2 x_{2j} = 0 \quad \text{if } \beta_1, \beta_2 \geq 0$$

$$\max_{\beta_1} \beta_1 - \frac{1}{2} \left(\beta_1^2 (k_1^2 + k_2^2) \right) + \beta_1^2 (k_1 k_2) \quad \text{of interest}$$

$$2 - 2\beta_1 (k_1^2 + k_2^2) + 2\beta_1^2 (k_1 k_2) = 0$$

$$\beta_1^2 = \frac{2}{k_1^2 + k_2^2} \beta_1$$

$$\beta_1^2 = \frac{2}{(k_1 - k_2)^2} \beta_1$$

$$w = \sum_{i=1}^n \beta_1 x_{ij} y_i = \beta_1 (x_1 - x_2) = \beta_1 (k_1 - k_2)$$

$$w = \sum_{i=1}^n \beta_1 x_{ij} y_i = \beta_1 (x_1 - x_2) = \beta_1 (k_1 - k_2) = \frac{2(k_1 - k_2)}{(k_1 - k_2)^2}$$

$$\beta_1^2 (1 - \beta_1 (k_1 + k_2)) = 0 \quad \text{complementary slackness}$$

$$(k_1 + k_2) \leq 1 \quad \text{so } \beta_1 (k_1 + k_2) \leq 0 \quad \Rightarrow \quad \beta_1^2 = 0 \quad \Rightarrow \quad w = 0$$

$$1 - \beta_1 (k_1 + k_2) = 0$$

$$\beta_1 = \frac{2k_1 (k_1 + k_2)}{(k_1 + k_2)^2}$$

$$w = \beta_1 (k_1 + k_2)$$

3. Skew

Outflow \rightarrow flow into Δ is zero. \therefore $\int_{\partial\Delta} f(z) dz = 0$ \therefore $\int_{\partial\Delta} f(z) dz = 0$ Q.E.D.

Proof: Δ is a Jordan domain. Δ is closed and $\Delta \setminus \{z_0\}$ is connected.

Let $c \in \Delta \setminus \{z_0\}$. $\exists r > 0$ s.t. $B_r(c) \subset \Delta \setminus \{z_0\}$

$\therefore \int_{\partial B_r(c)} f(z) dz = 0$ $\therefore \int_{\partial B_r(c)} f(z) dz = 0$

$\int_{\partial\Delta} f(z) dz = \sum_{i=1}^n \int_{\partial D_i} f(z) dz + \int_{\partial B_r(c)} f(z) dz$

$f(z) \in \mathbb{C}[z]$: $\Rightarrow f(z) = \sum_{i=0}^n a_i z^i$ $\therefore \int_{\partial D_i} f(z) dz = a_i \int_{\partial D_i} z^i dz$

$\forall i \geq 1$ $\int_{\partial D_i} z^i dz = 0$ $\therefore \int_{\partial D_i} f(z) dz = a_i \int_{\partial D_i} z^i dz = 0$

$\therefore \int_{\partial\Delta} f(z) dz = a_0 \int_{\partial\Delta} dz = a_0 \cdot 2\pi i$

$a_0 = \lim_{r \rightarrow 0} f(z)$ $\therefore \int_{\partial\Delta} f(z) dz = \lim_{r \rightarrow 0} \int_{\partial B_r(c)} f(z) dz = \lim_{r \rightarrow 0} \int_{\partial B_r(c)} (w^*x_i + b_i) dz = b_i$

□

~~Definition~~
~~if~~

~~if~~

~~if~~ $f = (v_1, v_2, \dots, v_n)$ Q.E.D.

~~if~~ $y = (y_1, y_2, \dots, y_n)$

~~if~~ $f(w) = f(w_1, w_2, \dots, w_n) = f(w_1) + \sum_{i=1}^n (1 - \delta_i)(w_i x_i + b_i)$ \therefore ~~if~~

$$L(w, b, \xi, \lambda) = f(w_i, b) + \sum_{i=1}^n \lambda_i (1 - \xi_i - \xi_i(w^T x_i + b))$$

~~$$\frac{1}{2} \|w\|^2 - \lambda \Rightarrow \frac{1}{2} \|w\|^2 - \sum_{i=1}^n \lambda_i (1 - \xi_i - \xi_i(w^T x_i + b))$$~~

~~$$\nabla_w L = (x_i, \xi_i)$$~~

$$\nabla_w L = w - \sum_{i=1}^n \lambda_i \xi_i x_i = 0 \Rightarrow w = \sum_{i=1}^n \lambda_i \xi_i x_i$$

$$\nabla_b L = - \sum_{i=1}^n \lambda_i \xi_i = 0 \Rightarrow \sum_{i=1}^n \lambda_i \xi_i = 0 \Rightarrow \lambda \xi = 0$$

~~$$\nabla_{\xi_i} L = (\xi_i - \lambda_i) = 0 \Rightarrow \xi_i = \frac{\lambda_i}{c}$$~~

$$\xi_i = \frac{\lambda_i}{c} \quad \text{if } \lambda_i \neq 0 \quad \text{else } \xi_i = 0$$

$$\sum_{i=1}^n \lambda_i (1 - \xi_i - \xi_i(w^T x_i + b)) = \sum_{i=1}^n \lambda_i - \sum_{i=1}^n \lambda_i \xi_i - w^T \sum_{i=1}^n \lambda_i \xi_i x_i - b \sum_{i=1}^n \lambda_i \xi_i = 0$$

$$\sum_{i=1}^n \lambda_i \xi_i \|x_i\|^2 + \frac{\|w\|^2}{2c} - \frac{\|w\|^2}{2c} + \sum_{i=1}^n \lambda_i = \frac{\|w\|^2}{2c} - \frac{\|w\|^2}{2c} + \sum_{i=1}^n \lambda_i - \frac{1}{2} \sum_{i=1}^n \lambda_i \sum_{j=1}^n \lambda_j \|x_i\|^2$$

$$\star \quad \text{if } \lambda \neq 0 \quad \text{then } \lambda \in \{1, \dots, p\}$$

□

: (h) if $\lambda_i > 0$ then $\lambda_i \in (0, 1)$ $\Rightarrow \lambda_i \in (0, 1)$

$$\frac{1}{\lambda_i} \geq \frac{1}{2} \left(\sum_{j=1}^n \lambda_j x_j - \left(1 - \frac{1}{\lambda_i} \right) \right) = \sum_{j=1}^n \lambda_j x_j$$

$$\text{then } \sum_{i=1}^n \lambda_i x_i = 0 \quad : \text{p. 3 H. ch 1}$$

Now we can let $y = (1, \dots, 1)^T$ so $y^T w = \sum_{i=1}^n \lambda_i x_i = 0$

$$\frac{1}{2} \|w\|^2 + C \sum_{i=1}^n g_i \leq \frac{1}{2} \|w^*\|^2 + C - \sum_{i=1}^n g_i \leq \frac{1}{2} \|w^*\|^2 \quad : C \geq \|w^*\|^2$$

$\therefore \|w\| \leq \|w^*\| + \lambda \sum_{i=1}^n g_i \leq \|w^*\| + \sqrt{C} \sum_{i=1}^n g_i$

So w is SVA

$$\frac{1}{2} \|w\|^2 \leq \|w^*\|^2 \left(\frac{1}{2} - \sum_{i=1}^n g_i \right) \quad : \text{if } w \text{ is a V.S.V.}$$

Now $\|w\| \leq \|w^*\| + \lambda \sum_{i=1}^n g_i \leq \|w^*\| + \sqrt{C} \sum_{i=1}^n g_i$

$$\sum_{i=1}^n \lambda_i x_i \geq 1 \quad : \text{if } g_i \leq \frac{1}{\lambda_i} \text{ for all } i$$

□

5. Lineare

158-1

$$A \in \mathbb{R}^{n \times n}, \lambda \in \mathbb{R}, \phi = \begin{pmatrix} \psi(x_1) \\ \vdots \\ \psi(x_n) \end{pmatrix}$$

$$k_{ij} := \sum_{k=0}^n \binom{n}{k} (x_i x_j)^k = \sum_{k=0}^n \binom{n}{k} x_i^k \cdot \sqrt{\binom{n}{k}} \cdot x_j^k$$

$$\begin{pmatrix} 1 & x_1 & x_1^2 & \dots & x_1^n \\ 1 & x_2 & x_2^2 & \dots & x_2^n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_n & x_n^2 & \dots & x_n^n \end{pmatrix} \cdot \begin{pmatrix} \psi(x_1) \\ \vdots \\ \psi(x_n) \end{pmatrix} = \begin{pmatrix} k_{11} \\ \vdots \\ k_{nn} \end{pmatrix}$$

Wegen $\lambda \neq 0$ ist $\lambda I + A$ invertierbar

$$\sqrt{\begin{pmatrix} \psi(x_1) \\ \vdots \\ \psi(x_n) \end{pmatrix}} \cdot \begin{pmatrix} 1 & x_1 & x_1^2 & \dots & x_1^n \\ 1 & x_2 & x_2^2 & \dots & x_2^n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_n & x_n^2 & \dots & x_n^n \end{pmatrix}^{-1} \cdot \begin{pmatrix} \psi(x_1) \\ \vdots \\ \psi(x_n) \end{pmatrix} = \sqrt{\lambda} \cdot \begin{pmatrix} 1 & 1 & 1 & \dots & 1 \end{pmatrix}$$

$j \in \{1, \dots, n\}$

$$\sqrt{\binom{n}{j}} x_j = \sqrt{\lambda} \cdot 1$$

$\Rightarrow x_j = \sqrt{\frac{\lambda}{\binom{n}{j}}} = \sqrt{\frac{\lambda}{n!}} \cdot \sqrt{\binom{n}{j}}$

$$\begin{pmatrix} \sqrt{\binom{n}{0}} & \dots & \sqrt{\binom{n}{j}} & \dots & \sqrt{\binom{n}{n}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \sqrt{\binom{n}{0}} & \dots & \sqrt{\binom{n}{j}} & \dots & \sqrt{\binom{n}{n}} \end{pmatrix} \cdot \begin{pmatrix} x_0 \\ \vdots \\ x_j \\ \vdots \\ x_n \end{pmatrix} = \sqrt{\lambda} \cdot \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}$$

$$\begin{pmatrix} \sqrt{\binom{n}{0}} x_0 \\ \vdots \\ \sqrt{\binom{n}{j}} x_j \\ \vdots \\ \sqrt{\binom{n}{n}} x_n \end{pmatrix} = \sqrt{\lambda} \cdot \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}$$

$$\Rightarrow x_j = \sqrt{\frac{\lambda}{\binom{n}{j}}} = \sqrt{\frac{\lambda}{n!}} \cdot \sqrt{\binom{n}{j}}$$

$\Rightarrow x_i = \sqrt{\frac{\lambda}{\binom{n}{i}}} = \sqrt{\frac{\lambda}{n!}} \cdot \sqrt{\binom{n}{i}}$

$\therefore f(\lambda) \in \mathbb{R}$

□

(x)

(x)

2. f(x) = 1/(x^2 + 1) \rightarrow f'(x) = -2x/(x^2 + 1)^2 \rightarrow f''(x) = (2x^2 - 2)/(x^2 + 1)^3 \rightarrow f'''(x) = (6x^2 - 24x + 18)/(x^2 + 1)^4 \rightarrow f''''(x) = (12x^4 - 144x^3 + 540x^2 - 432x + 108)/(x^2 + 1)^5 \rightarrow ④

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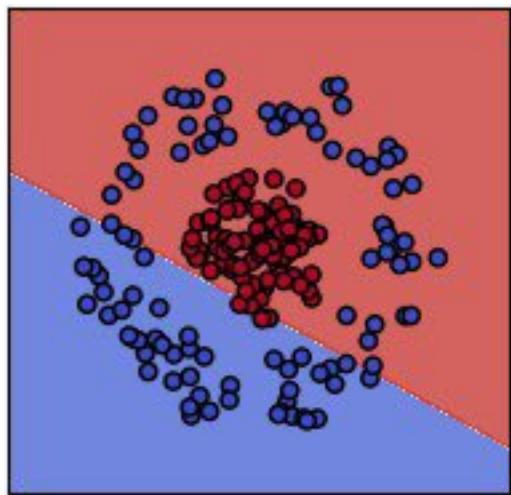
(x^2 + 1)^243

(x^2 + 1)^244

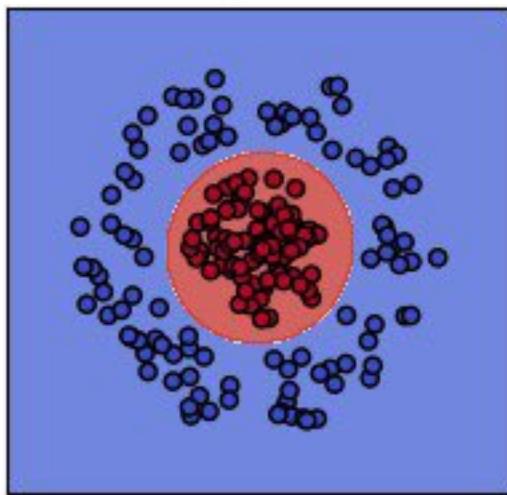
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pick this data -> we see that there is no linear relationship between the two variables. So we can't use RRF ->
we can't use RRF because it's overfitting the data. We can't use RRF because it's overfitting the data.
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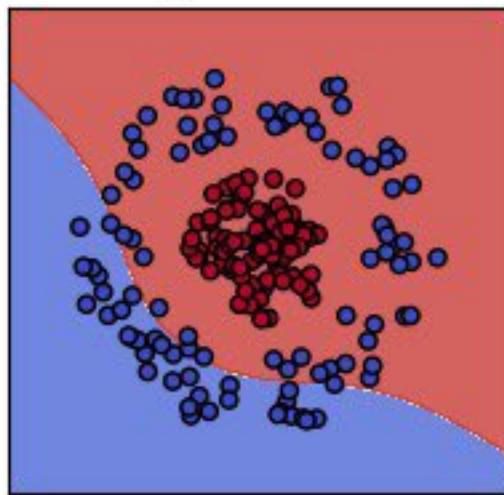
linear



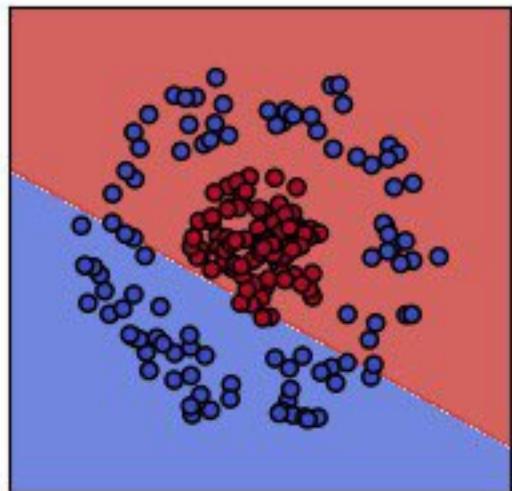
square



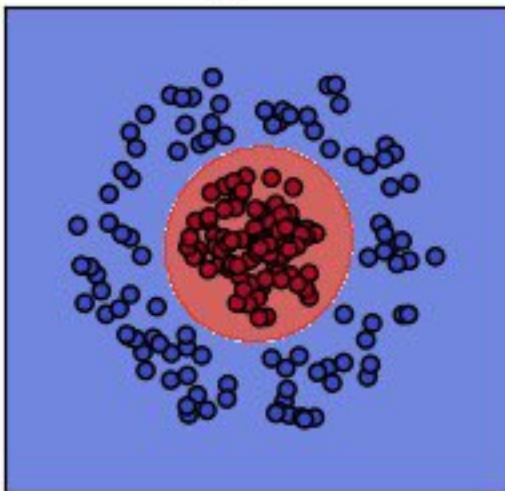
quadratic



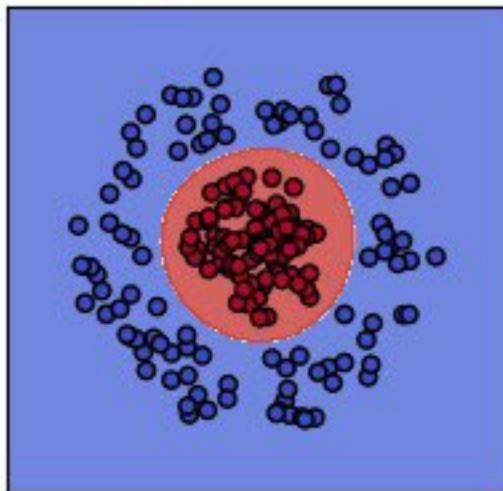
linear



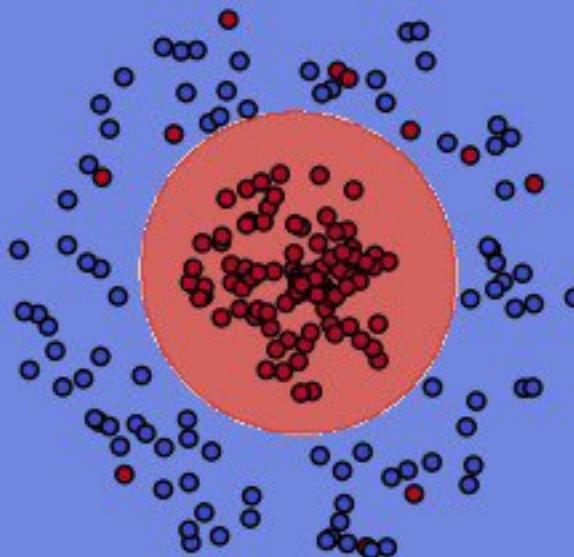
square



quadratic



square



RBF

