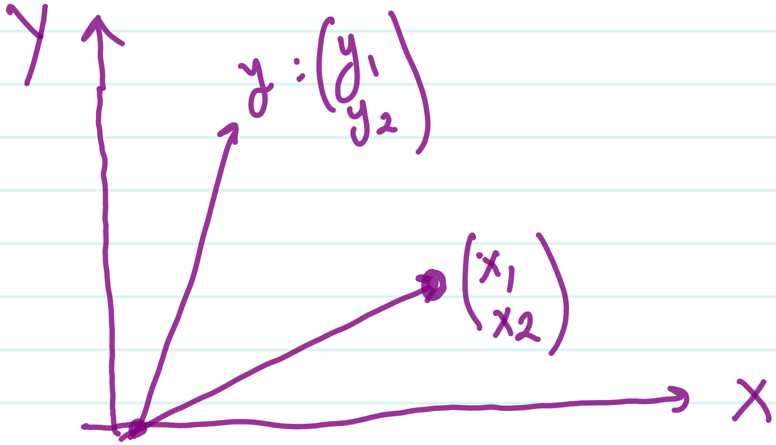


$$L_2 = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2}$$

$$L_2 = \sqrt{\sum_{i=1}^{d} (x_i - y_i)^2} \qquad \text{Euclid.} \qquad p = 2$$

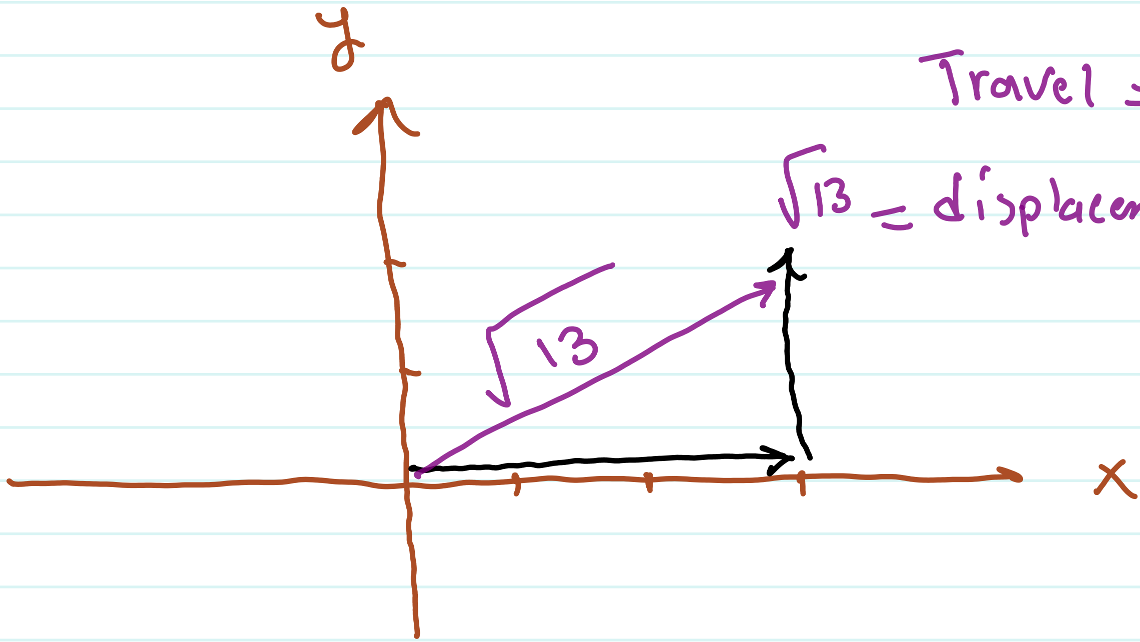
$$L_p = \sqrt[p]{\sum_{i=1}^{d} (x_i - y_i)^p} \qquad \text{Mink.}$$

$$p \in \mathbb{R}^+$$

$$0, \ \dots, \ \infty^+$$

$p=1$ $\quad L_1 = \sum_{i=1}^{d} |x_i - y_i|$ $\quad$ Manhatan $\quad p=1$

$p=\infty$ $\quad L_\infty \ \sup\left(|x_1 - y_1|, \ldots, |x_d - y_d|\right)$



Travel $= 5 \rightarrow L_1$

$\sqrt{13} =$ displacement $\rightarrow L_2$

$3 \quad L_\infty$

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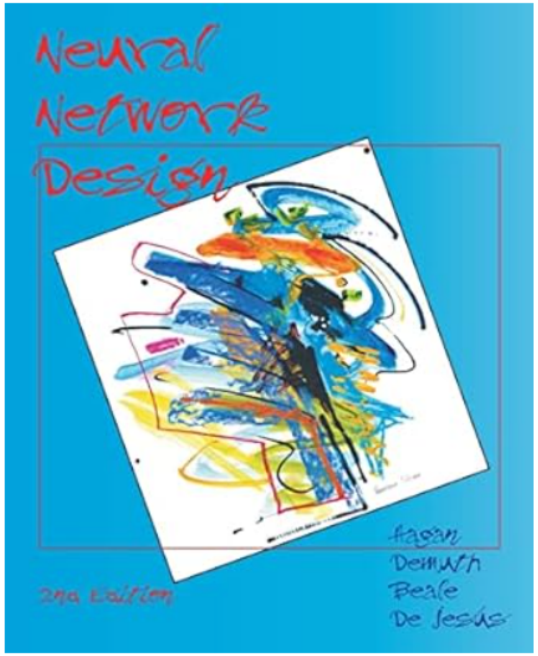

Neural Network Design (2nd Edition) 2nd ed. Edition

by Martin T Hagan (Author), Howard B Demuth (Author), Mark H Beale (Author), Orlando De Jesús (Author)

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This book, by the authors of the Neural Network Toolbox for MATLAB, provides a clear and detailed coverage of fundamental neural network architectures and learning rules. In it, the authors emphasize a coherent presentation of the principal neural networks, methods for training them and their applications to practical problems.FeaturesExtensive coverage of training methods for both feedforward networks (including multilayer and radial basis networks) and recurrent networks. In addition to conjugate gradient and Levenberg-Marquardt variations of the backpropagation algorithm, the text also covers Bayesian regularization and early stopping, which ensure the generalization ability of trained networks.Associative and competitive networks, including feature maps and learning vector quantization, are explained with simple building blocks.A chapter of practical training tips for function approximation, pattern recognition, clustering and prediction, along with five chapters presenting detailed real-world case studies.Detailed examples and numerous solved problems. Slides and comprehensive demonstration software can be downloaded from hagan.okstate.edu/nnd.html.

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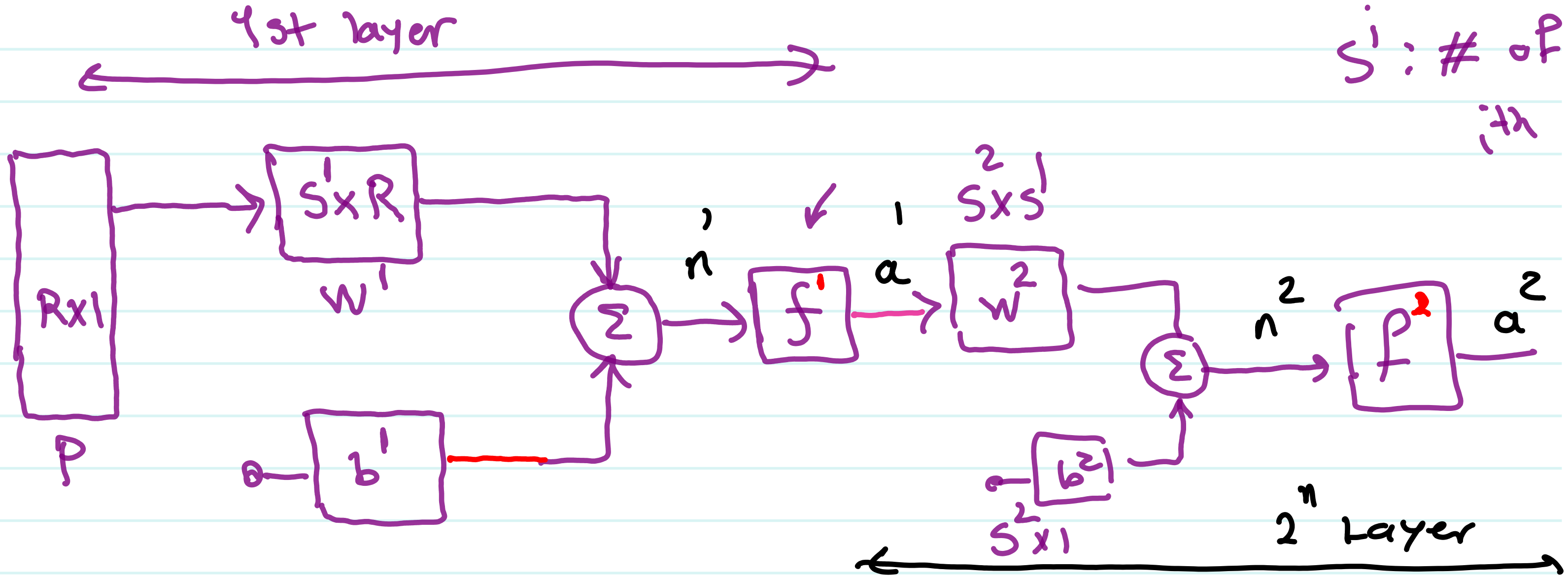
s^i : # of neurons in ith layer

S

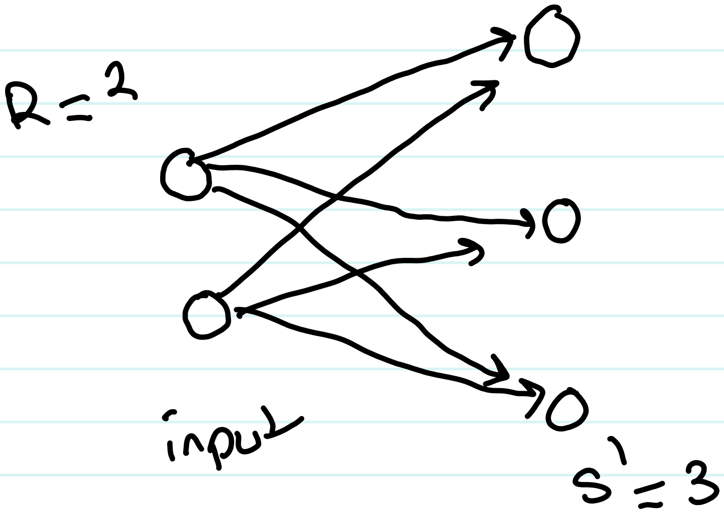


static NN Network

$$a^1 = f^1(W^1 p + b^1)$$

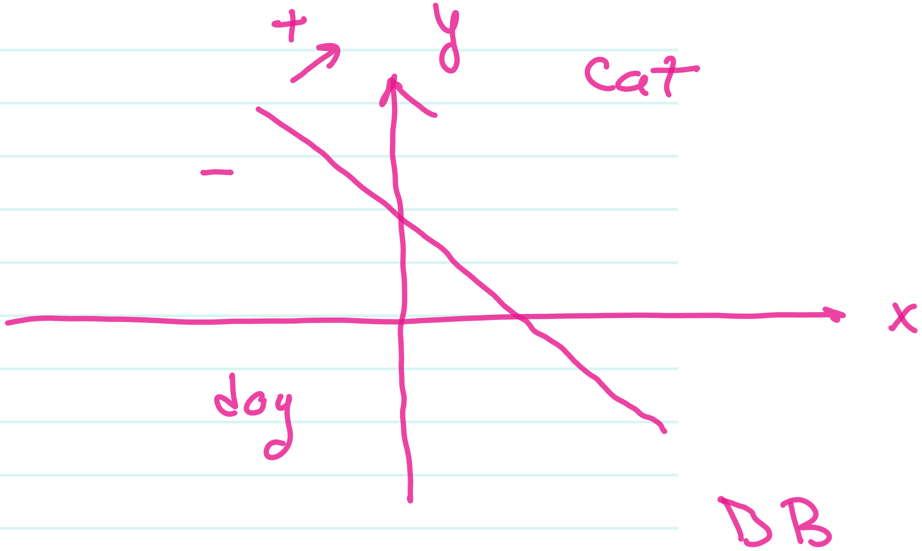
$$a^2 = f^2(W^2 a^1 + b^2)$$

$$W^1 = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1R} \\ w_{21} & & \ddots & \\ \vdots & & & \\ w_{S^1 1} & \cdots & & w_{S^1 R} \end{bmatrix}_{S^1 \times R}$$

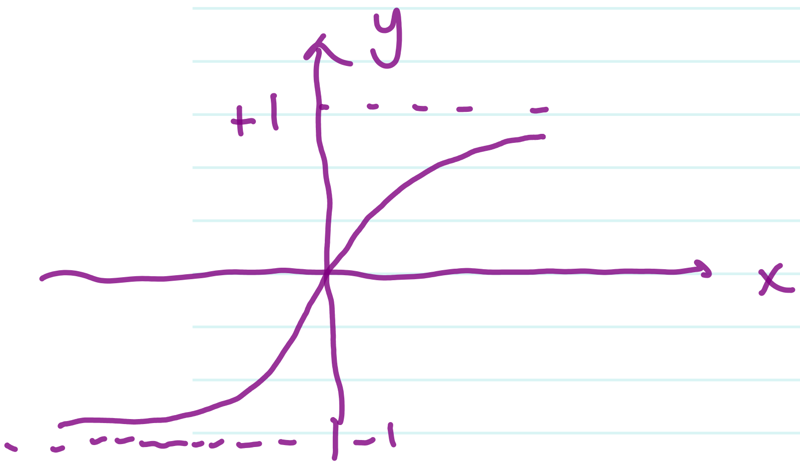


$$W^1 = \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \\ w_{31} & w_{32} \end{bmatrix}$$

$f(0) = \frac{1}{2}$



$f(x) = \tanh(x)$



$$\langle x, y \rangle = x^T \cdot y$$

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

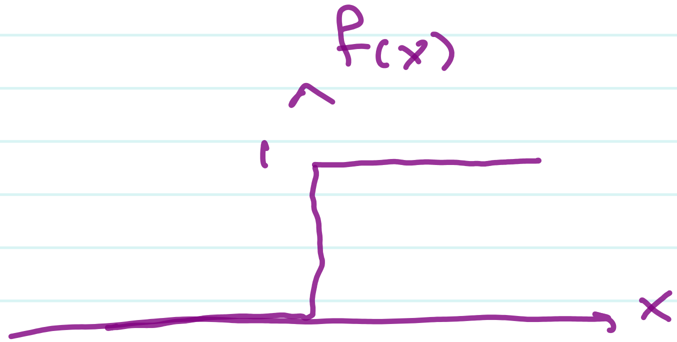
$$\langle x \cdot x \rangle = \sum x_i^2$$

$$SSE = \sum e_i^2 = e^T \cdot e$$

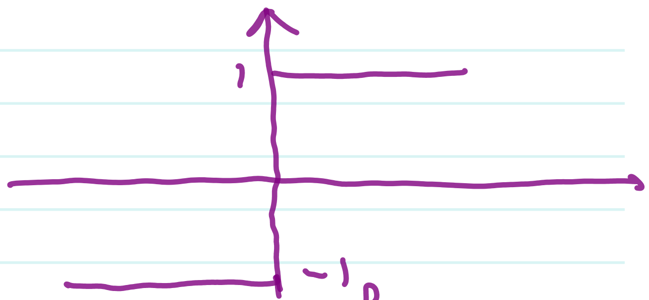
$$x^T \cdot x = \begin{bmatrix} x_1 & \dots & x_n \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = x_1^2 + \dots x_n^2$$

$S(x)$

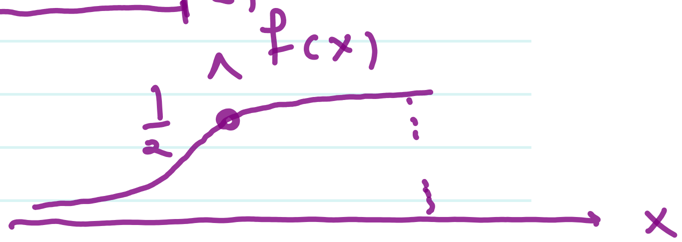
$$f(x) = \text{hardlim}(x) = \begin{cases} 1 & : x \geq 0 \\ 0 & : x < 0 \end{cases}$$



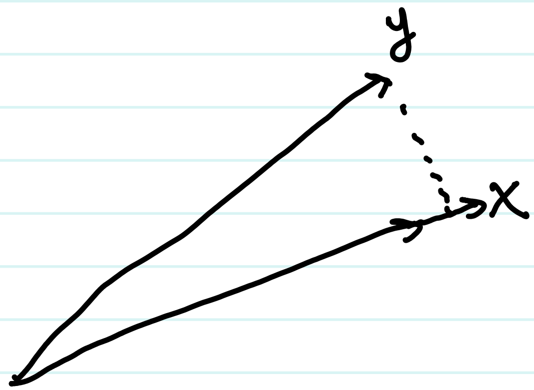
$$f(x) = \text{hardlims}(x) = \begin{cases} 1 & : x \geq 0 \\ -1 & : \text{Else} \end{cases}$$



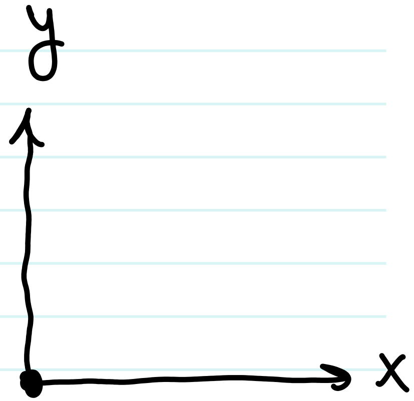
$$f(x) = \text{tansig}(x) = \frac{1}{1+e^{-x}}$$



$$\lim_{x \to -\infty} f(x) = 0 \qquad \lim_{x \to +\infty} f(x) = 1$$

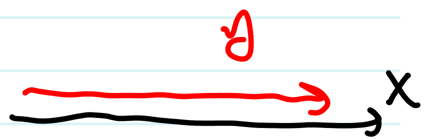


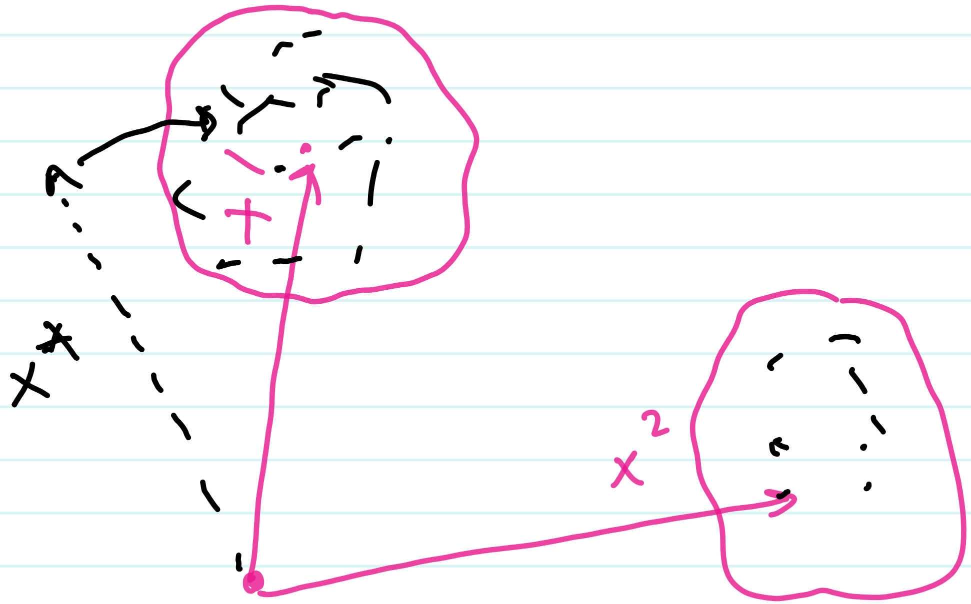
$x^T \cdot y =$



$x^T \cdot y = 0 \iff x \perp y$

$x^T \cdot y \to \max$ if $x = y$





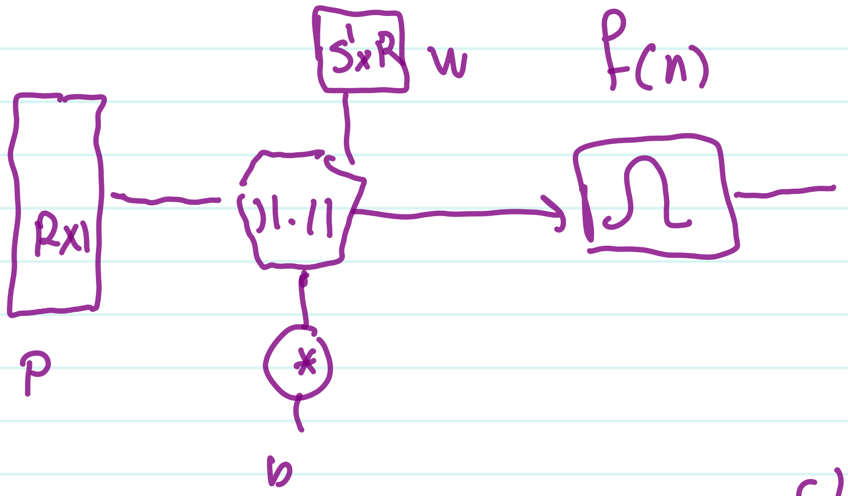
$$a^2 = f^2(w^2 a^1 + b^2)$$

$$a^2 = f^2[w^2 f^1(w^1 p + b^1) + b^2] = f^2 \circ f^1(\ )$$

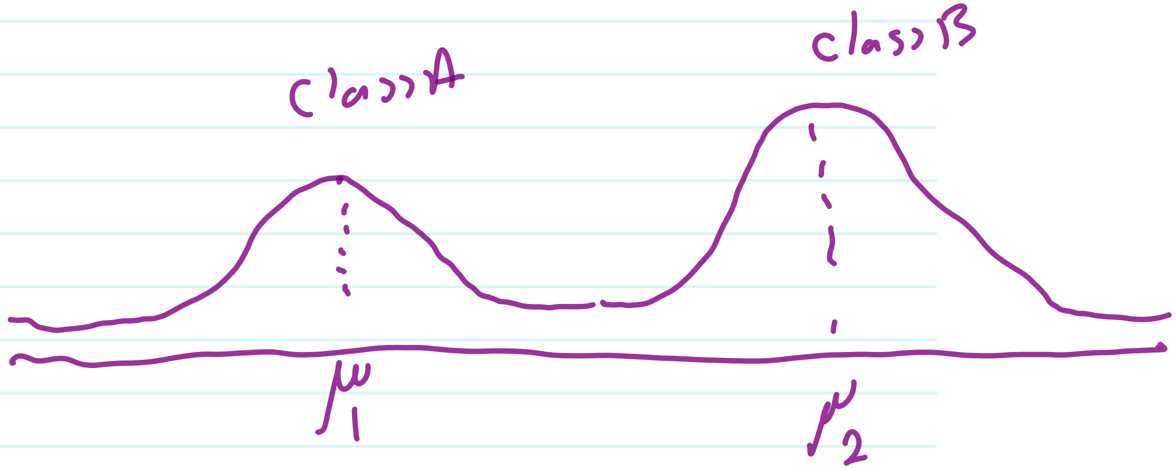
$$\vdots$$

$$a^K = f^K \circ f^{K-1} \circ \cdots \circ f^1(\ )$$

Radial Based Network (RBF)



$$f(n) = e^{-n}$$



- Let two vectors x & y to be defined as below.

point	x	y
p_1	0	2
p_2	2	0
p_3	3	1
p_4	5	1

L_1: p_1 _ p_2

$|0-2| + |0-2|$

L_2: $p_1 - p_2$

$\sqrt{(0-2)^2 + (0-2)^2} = \sqrt{8}$

L_∞: $\max(|x_1 - y_1|, \dots, |x_n - y_n|)$

$\max(|0-2|, |0-2|)$

$\max(|0-3|, |2-1|)$

- Calculate L_1, L_2 & L_∞ distances.

L_1	p_1	p_2	p_3	p_4
p_1	0	4	4	6
p_2	4	0	2	4
p_3	4	2	0	2
p_4	6	4	2	0

L_2	p_1	p_2	p_3	p_4
p_1	0	$\sqrt{8}$	$\sqrt{10}$	$\sqrt{26}$
p_2	$\sqrt{8}$	0	$\sqrt{2}$	$\sqrt{10}$
p_3	$\sqrt{10}$	$\sqrt{2}$	0	2
p_4	$\sqrt{26}$	$\sqrt{10}$	2	0

L_∞	p_1	p_2	p_3	p_4
p_1	0	2	3	5 ✓
p_2	2	0	1	3
p_3	3	1	0	2
p_4	5	3	2	0

$$Var(X) = E[(X - E[X])^2] = \int_{-\infty}^{\infty} (\lambda - \mu_x)^2 f_x(\lambda)\, d\lambda$$

$$\mu = E[X] = \int_{-\infty}^{\infty} \lambda f_x(\lambda)\, d\lambda$$

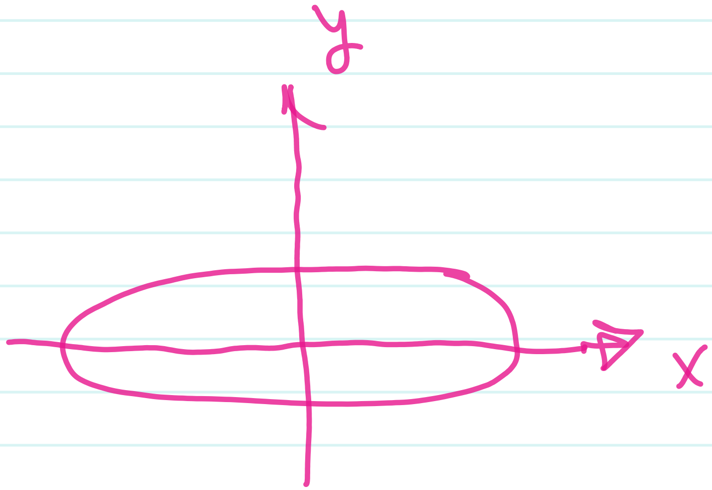
$$cov(x, y) = E[(x - \mu_x)(y - \mu_y)] =$$

$$= \iint_{-\infty}^{\infty} (\lambda_1 - \mu_x)(\lambda_2 - \mu_y) \underbrace{f_{xy}(\lambda_1, \lambda_2)}_{\text{Joint density function}} d\lambda_1\, d\lambda_2$$

$$C = \begin{bmatrix} a & -c \\ c & b \end{bmatrix}$$

$c \neq 0$

$C^T \neq C$



$$C = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$

$\boxed{\lambda_1 > \lambda_2}$

$\lambda_1 < \lambda_2$

$\lambda_1 = \lambda_2$

independency

$$f_{x,y}(\lambda_1, \lambda_2) \stackrel{?}{=} f_x(\lambda_1) \cdot f_y(\lambda_2)$$

$$f_{x|y}(\lambda_1|\lambda_2) = f_x(\lambda_1)$$