

In ICA problem is to obtain  $\underline{s}$ , Given  $\underline{x}$

$$\underline{s} = \tilde{A}^T \underline{x}$$

$$\text{let } \tilde{A}^T = w$$

- $\therefore \underline{s} = w \underline{x}$  itself is a linear combination of Given  $\underline{x}$ .

- \* How to get  $w$  (Background):  
- Consider a random variable  $s$  and obtain  $\underline{x} = a\underline{s}$ ,  $a$  is a constant, then

$$f_{\underline{x}}(\underline{x}) = f_s(s) \frac{f_s(s)}{|a|} = \frac{f_s\left(\frac{\underline{x}}{a}\right)}{|a|}$$



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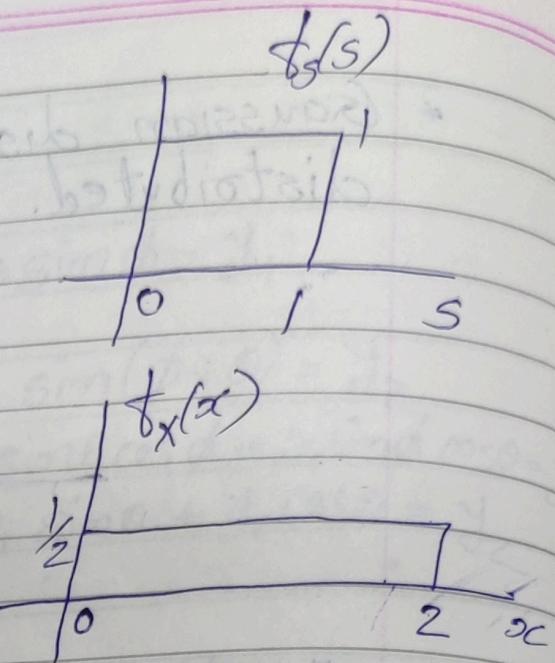
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e.g.  $x = 2s$ 

$$\rightarrow \text{then } f_x(x) = \frac{f_s(s)}{2} = \frac{f_s\left(\frac{x}{2}\right)}{2}$$

$$0 \leq s \leq 1$$

$$0 \leq x \leq 2$$



- If  $S_1, S_2$  are RVs. and  $x_1$  and  $x_2$  are linear transformation of  $S_1$  and  $S_2$  then

$$x_1 = a_{11}S_1 + a_{12}S_2$$

$$x_2 = a_{21}S_1 + a_{22}S_2$$

$$f_{x_1, x_2}(x_1, x_2) = \frac{f_{S_1, S_2}(S_1, S_2)}{|A|}$$

$\hookrightarrow$  Determinant of matrix and mod of that

- If RVs  $S_1, S_2, \dots, S_N$  are statistically independent then

$$f_{S_1, S_2, \dots, S_N}(S_1, S_2, \dots, S_N) = f_{S_1}(S_1) f_{S_2}(S_2) \dots f_{S_N}(S_N)$$

- Assume a density  $f$  for  $S_1, S_2, \dots, S_N$  vector RV with multivariate density function.

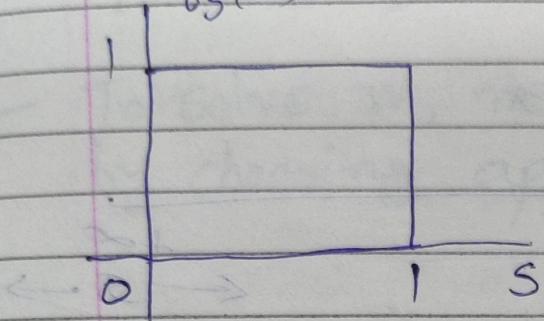


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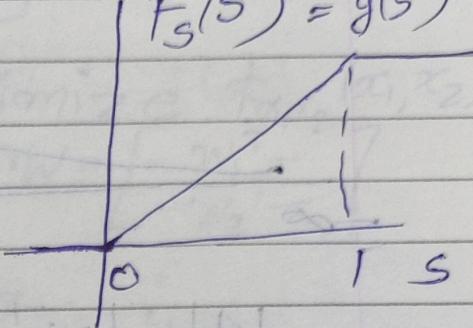
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\* Cumulative distribution ( $F_S(s)$ ):-

$$f_S(s)$$



$$F_S(s) = g(s)$$



$$\rightarrow f_S(s) = g'(s) = \frac{d(F_S(s))}{ds}$$

$$F_S(s_1) = P(S \leq s_1) \\ = \int_{-\infty}^{s_1} f_S(t) dt$$

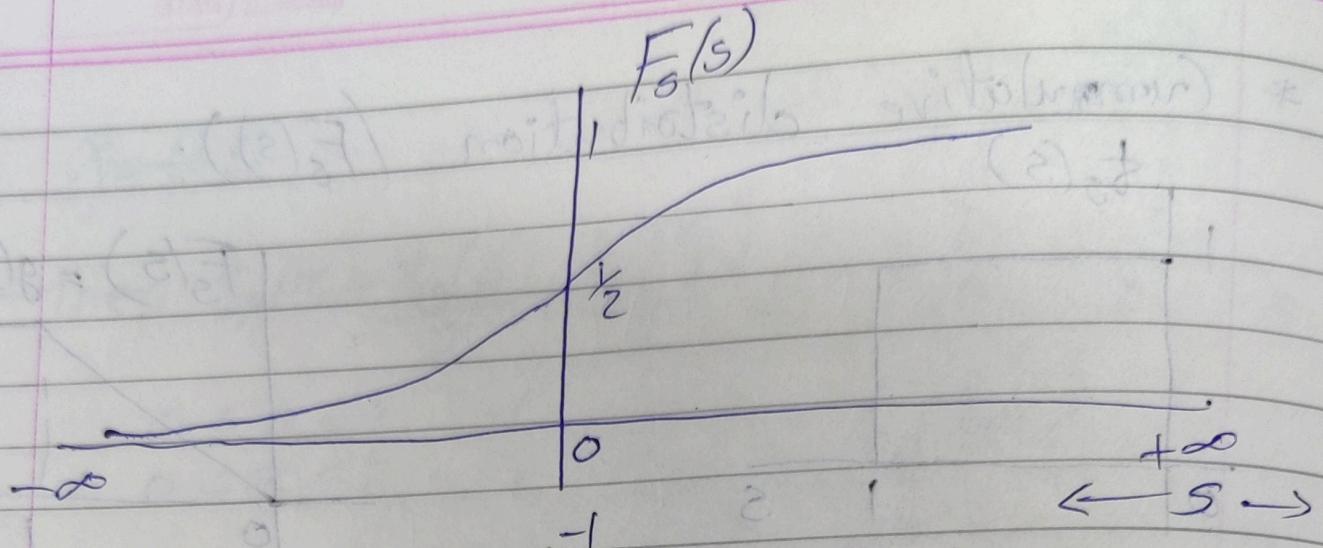
$\rightarrow$  We know that  $S = wX$  where  $w = A^{-1}$

- For  $N=2$

$$\begin{bmatrix} S_1 \\ S_2 \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \end{bmatrix} =$$

$$\begin{bmatrix} X_1 \\ X_2 \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} S_1 \\ S_2 \end{bmatrix}$$

- let us assume  $g(s) = F_S(s) = \frac{1}{1 + e^{-s}}$



$$|A| = |w^{-1}| = |w|$$

- From definition of pdf of multivariate density  $f^n$

$$f_{x_1, x_2, \dots, x_N}(x_1, x_2, \dots, x_N) = f_{s_1, s_2, \dots, s_N}(s_1, s_2, \dots, s_N) / |w|$$

- if  $N=2$

$$f_{x_1, x_2}(x_1, x_2) = f_{s_1, s_2}(s_1, s_2) / |w|$$

$$= f_{s_1}(s_1) f_{s_2}(s_2) / |w|$$

$$- w = \begin{bmatrix} -w_1^T \\ -w_2^T \\ -w_N^T \end{bmatrix}$$

$$w_i = \begin{bmatrix} w_{i1} \\ w_{i2} \end{bmatrix}$$

$$\therefore f_{x_1, x_2}(x_1, x_2) = f_{s_1}(w_1^T x) f_{s_2}(w_2^T x) / |w|$$

$$\rightarrow s_1 = w_{11} x_1 + w_{12} x_2$$

$$s_2 = w_{21} x_1 + w_{22} x_2$$

$$x_1 = x_1^{(1)} x_1^{(2)} \dots x_1^{(m)}$$

$$x_2 = x_2^{(1)} x_2^{(2)} \dots x_2^{(m)}$$



$$\begin{bmatrix} S_1^{(1)} \\ S_2^{(1)} \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{bmatrix} \begin{bmatrix} x_1^{(1)} \\ x_2^{(1)} \end{bmatrix}$$

- To solve  $w$ , we will maximize  $f_{x_1 x_2}(x_1, x_2)$  by choosing appropriate  $w = \begin{bmatrix} -w_1^T \\ -w_2^T \end{bmatrix}$

$$f_{x_1 x_2}(x_1, x_2) = f_{S_1}(w_1^T x) f_{S_2}(w_2^T x) |w|$$

$$f_{S_1}(w_1^T x) = g'(w_1^T x)$$



$$f_{S_2}(w_2^T x) = g'(w_2^T x)$$

~~→  $x_1$ ,  $x_2$  and~~

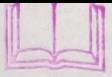
- We have to assume some density function of  $S_i$  and we can write the log likelihood  $\lambda(w)$  as

$$\max_w \lambda(w) = \sum_{i=1}^m \left[ \sum_{j=1}^N \log(g'(w_j^T x^{(i)})) + \log |w| \right]$$

→ We can maximize  $\lambda(w)$  or minimize  $-\lambda(w)$  by using stochastic gradient descent

→ For stochastic gradient descent

$$\lambda(w) = - \left[ \sum_{j=1}^N \log(g'(w_j^T x^{(i)})) + \log |w| \right]$$



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→ let us consider differentiation w.r.t.  
 $w_{11}, w_{12}, w_{21}, w_{22}$  where  $\square = 2$

$$\therefore l(w) = \sum_{j=1}^2 \log(g^1(w_j^T x^{(i)})) + \log|w|$$

$$\begin{aligned} &= \log(g^1(w_1^T x^{(i)})) + \log(g^1(w_2^T x^{(i)})) + \log|w| \\ &= \log(g^1(w_1^T x^{(i)})(1 - g^1(w_1^T x^{(i)}))) \\ &\quad + \log(g^1(w_2^T x^{(i)})(1 - g^1(w_2^T x^{(i)}))) + \log|w| \end{aligned}$$

$$\rightarrow \frac{\partial l(w)}{\partial w_{11}} = (1 - 2g^1(w_1^T x^{(i)})) \cdot x_1^{(i)}$$