Given the cumulative density from 
$$(cdf)$$
:-
$$g(s) = \frac{1}{1+e^{-\alpha s}}$$

$$g'(s) = \frac{\partial g}{\partial s} = \frac{\alpha e^{-\alpha s}}{(1+e^{-\alpha s})^2} = \alpha g(1-g)$$

For owr ICA problem, the log likelihood from was, m = no. of sources, n = no. of mic-recordings, t = no. of samples

W: (mxn) counising matrix. X:= (nxt) mixture

Now,

$$\frac{\partial g'(s)}{\partial \alpha} = g(1-g) + \alpha \frac{\partial g}{\partial \alpha} (1-g) + \alpha \frac{\partial g}{\partial \alpha} \times -\frac{\partial g}{\partial \alpha}$$

$$= g(1-g) + \alpha g(1-g)(1-g)s - \alpha g g(1-g)s$$

$$= g(1-g) + \alpha s g(1-g)(1-2g)$$

$$\frac{\partial g'(s)}{\partial \alpha} = g(1-g) + \alpha s g(1-g)(1-2g)$$

$$\frac{\partial g'}{\partial \alpha} = \frac{1}{\alpha} g' + g' \times s(1-2g) \Rightarrow \left(\frac{\partial g'}{\partial \alpha}\right) = \frac{1}{\alpha} + (1-2g)s \rightarrow 2$$

$$\frac{\partial}{\partial \alpha} = \frac{1}{\alpha} g' \times \frac{1}{\beta} \left(\frac{\partial}{\partial \alpha} \left(\frac{1}{2} W_{ix} X_{ij}\right)\right) + O$$

$$\frac{1}{\lambda} \frac{\partial}{\partial \alpha} = \frac{1}{\alpha} \frac{1}{\beta} \left(\frac{1}{\alpha} \left(\frac{1}{2} W_{ix} X_{ij}\right)\right) + O$$

$$\frac{1}{\lambda} \frac{\partial}{\partial \alpha} = \frac{1}{\alpha} \frac{1}{\beta} \left(\frac{1}{\alpha} \left(\frac{1}{\alpha} + \left(1-2g\left(\frac{1}{\alpha} W_{ix} X_{ij}\right)\right)\right) \left(\frac{1}{\alpha} W_{ix} X_{ij}\right)}{2} \left(\frac{1}{\alpha} \left(\frac{1}{\alpha} + \left(\frac{1}{\alpha} \frac{1}{\alpha} \frac{1}{$$

tr() -> trace.

Clearly g(WX) contains an'a' term, thus equating  $\frac{\partial \mathcal{L}}{\partial \alpha} = 0$  may not give a good expression to find  $\alpha'$ So we gradient descent algorithm to find the optimal  $\frac{\partial \mathcal{L}}{\partial \alpha} = \mathcal{L}\left(\frac{mt}{\alpha} + tr((1-2g(wx))(wx)^{T})\right), \quad \mathcal{L} = \prod_{i=1}^{m} \prod_{j=1}^{i} \frac{g'(wx)_{ij}}{j} |w|$ =)  $d_{k+1} = d_k + 1 \cdot d_x \left( \frac{mt}{a_k} + tr((1-2g(wx))(wx)^T) \right)$ ,  $d_x = d_x + 1 \cdot d_x \left( \frac{mt}{a_k} + tr((1-2g(wx))(wx)^T) \right)$ H x is a vector, i.e. each audio signal had it's own x value.  $d = \begin{cases} d_1 \\ d_2 \\ d_n \end{cases}, i.e_1, g(a_i, (WX)_{ij}) = \frac{1}{1 + e^{-\alpha_i(WX)_{ij}}}$ 

from previous eqs. (D), we can show that  $\frac{\partial g'(\alpha_{\mathbf{v}}(W^{\mathbf{v}})_{\mathbf{v}})}{\partial \alpha_{\mathbf{v}}} = \left(\frac{1}{\alpha_{\mathbf{v}}} + (1-2g(\alpha_{\mathbf{v}}(W^{\mathbf{v}})_{\mathbf{v}}))(W^{\mathbf{v}})_{\mathbf{v}}\right)g'(\alpha_{\mathbf{v}}(W^{\mathbf{v}})_{\mathbf{v}})$ 

$$\frac{1}{g(\alpha_{v},(wx)v_{j})} = \frac{1}{\alpha_{v}} + (1-2g(\alpha_{v},(wx)v_{j}))(wx)v_{j}}$$

$$\frac{1}{g(\alpha_{v},(wx)v_{j})}$$

$$\log(\mathcal{L}) = \sum_{i=1}^{m} \sum_{j=1}^{t} \log(g'(\alpha_i, (WX)_{ij})) + t\log|W| \longrightarrow \textcircled{\pm}$$

differentiating wet each component, or,

ifferentiating with each 
$$\frac{1}{2} \left( \frac{\partial g'(\alpha_{v_{1}}(Wx)_{v_{1}})}{\partial \alpha_{v_{1}}} \right) + 0$$

$$\frac{1}{2} \frac{\partial \mathcal{L}}{\partial \alpha_{v_{2}}} = \frac{1}{2} \left( \frac{\partial g'(\alpha_{v_{1}}(Wx)_{v_{1}})}{\partial \alpha_{v_{2}}} \right) + 0$$

$$\frac{1}{2} \frac{\partial \mathcal{L}}{\partial \alpha_{v_{2}}} = \frac{1}{2} \left( \frac{\partial g'(\alpha_{v_{1}}(Wx)_{v_{1}})}{\partial \alpha_{v_{2}}} \right) + 0$$

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$$\frac{1}{2} \frac{\partial \mathcal{L}}{\partial \alpha_{v}} = \underbrace{\frac{1}{2} \left( \frac{1}{\alpha_{v}} + \left( \frac{1 - 2g(\alpha_{v}, (Wx)_{vj})}{2} \right) (Wx)_{vj}}_{1} \right) - 3}_{2} \underbrace{5}_{j=1}$$

$$\frac{1}{2} \underbrace{\frac{\partial \mathcal{L}}{\partial \alpha_{v}}}_{1} = \underbrace{\frac{1}{2} \left( \frac{1}{\alpha_{v}} + \left( \frac{1 - 2g(\alpha_{v}, (Wx)_{vj})}{2} \right) (Wx)_{vj}}_{1} \right) - 3}_{2} \underbrace{5}_{j=1}$$

$$\frac{1}{2} \underbrace{\frac{\partial \mathcal{L}}{\partial \alpha_{v}}}_{1} = \underbrace{\frac{1}{2} \left( \frac{1}{\alpha_{v}} + \left( \frac{1 - 2g(\alpha_{v}, (Wx)_{vj})}{2} \right) (Wx)_{vj}}_{1} \right) - 3}_{2} \underbrace{5}_{j=1}$$

$$\frac{1}{2} \underbrace{\frac{\partial \mathcal{L}}{\partial \alpha_{v}}}_{1} = \underbrace{\frac{1}{2} \left( \frac{1}{\alpha_{v}} + \left( \frac{1 - 2g(\alpha_{v}, (Wx)_{vj})}{2} \right) (Wx)_{vj}}_{1} \right) - 3}_{2} \underbrace{5}_{j=1}$$

Now define  $G_1(s) = \frac{1}{1+e^{-s}}$ , Also define Diagonal matrix  $D_x$  as

$$D_{x} = \begin{cases} d_{1} & 0 & 0 & 0 \\ 0 & d_{2} & 0 & 0 \\ 0 & 0 & d_{3} & 0 \end{cases}$$

$$\frac{1}{2} \frac{\partial \mathcal{L}}{\partial \alpha_{i}} = \frac{t}{\alpha_{i}} + \frac{t}{j=1} \frac{(1-2G_{i}(D_{x}Wx)_{ij})(Wx)_{iv}}{(1-2G_{i}(D_{x}Wx))_{ij}(Wx)_{iv}}$$

$$= \frac{t}{\alpha_{v}} + \frac{t}{j=1} \frac{(1-2G_{i}(D_{x}Wx))_{vj}(Wx)_{iv}}{(Wx)_{iv}}$$

$$= \frac{t}{\alpha_{v}} + \frac{(1-2G_{i}(D_{x}Wx))(Wx)_{iv}}{(Wx)_{iv}}$$

$$\frac{1}{2} \frac{\partial d}{\partial x} = \frac{t}{x} + ((1-26i(D_xWx))(Wx))^{T}/v$$

$$\frac{\partial \mathcal{L}}{\partial \mathcal{L}} = \mathcal{L} \left[ t D_x^{-1} + (1 - 2G(D_x W x))(W x)^{T} \right]_{yy}$$

$$\frac{\partial \mathcal{L}}{\partial \mathcal{L}} = \mathcal{L} \left[ t D_x^{-1} + (1 - 2G(D_x W x))(W x)^{T} \right]_{yy}$$

Thus we can compute the diagonal elements of matrix H and we it for a gradient descent on the & vector

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