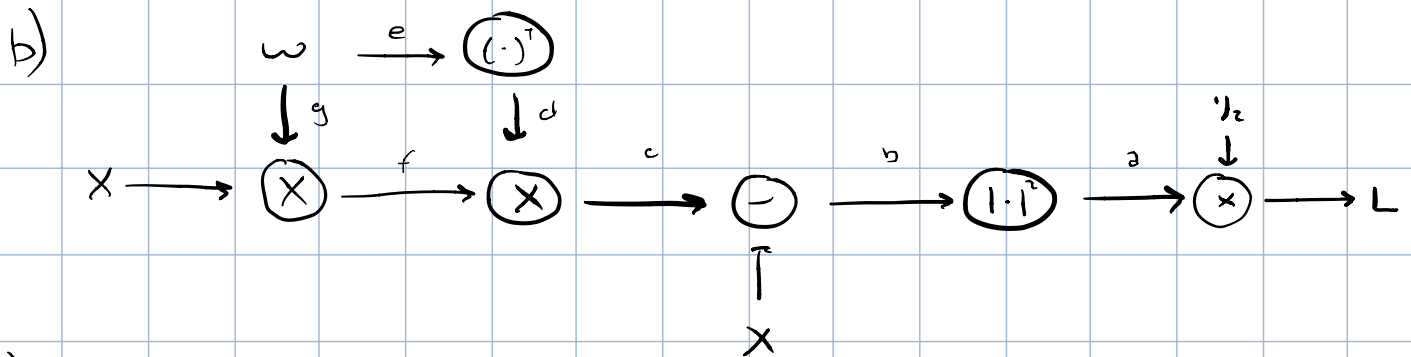


1) 2) This minimization finds a W that preserves info about x because it is equivalent to PCA where $h = f(x) = W^T x$, $g(h) = W h$. Also, we can view it in terms of SVD and the transpose - the rotations get reversed and only the scaling is left. Also $W^T W = I$ if W is orthogonal b/c W^T would be equal to W^{-1} .



c) Take the derivatives with respect to both paths and add them together. This is due to the total derivatives rule.

d) $L(a) = \frac{1}{2} a = \frac{1}{2} |W^T W x - x|^2$

$a(b) = |b|^2$

$b(c) = c - x$

$c(d, f) = d \cdot f$

$d(e) = e^T$

$f(g) = g \cdot x$

$$\frac{\partial L}{\partial W} = \frac{\partial a}{\partial e} \frac{\partial c}{\partial d} \frac{\partial b}{\partial c} \frac{\partial a}{\partial b} \frac{\partial L}{\partial a}$$

$$= \left(\left(1 - 2(W^T W x - x)^T \right) (W x)^T \right)^T$$

$$= (W^T W x - x) (W x)^T$$

$$= (W_X) (W^T W_X - X)^T$$

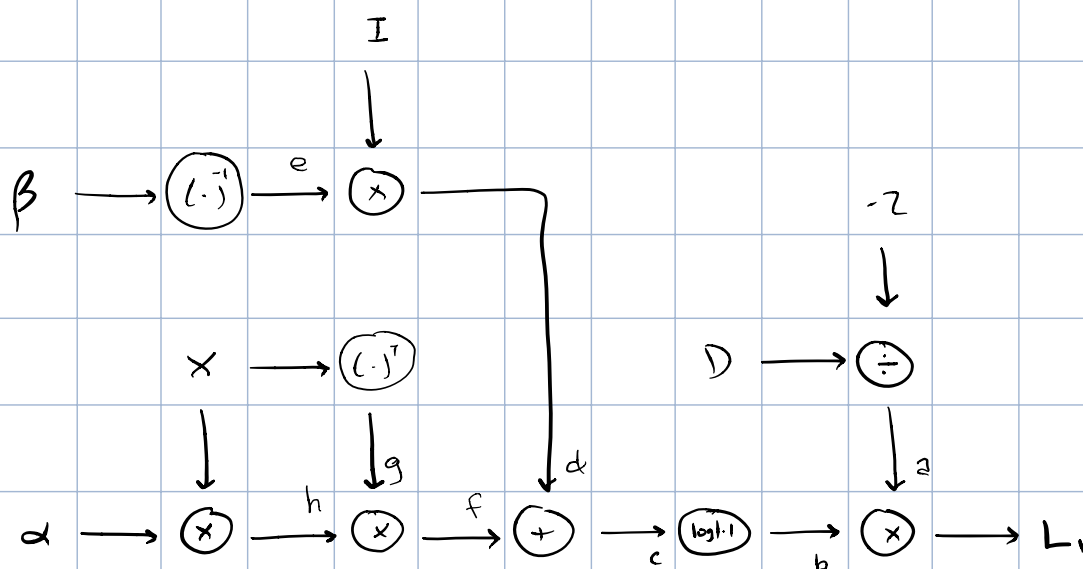
$$\frac{\partial L}{\partial W_2} = \frac{\partial f}{\partial g} \frac{\partial c}{\partial f} \frac{\partial b}{\partial c} \frac{\partial a}{\partial b} \frac{\partial L}{\partial a}$$

$$= W \left(\frac{1}{2} \right) \frac{2}{(W^T W_X - X)^T} \frac{1}{2} X^T$$

$$= W (W^T W_X - X) X^T$$

$$\nabla_W L = \nabla_{W_1} L + \nabla_{W_2} L = (W_X) (W^T W_X - X)^T + W (W^T W_X - X) X^T$$

$$2) a) L_1 = -\frac{D}{2} \log |\alpha X X^T + \beta^{-1} I|$$



$$b) L_1 = b a$$

$$b = \log |c|$$

$$c = f + d$$

$$f = h \cdot g$$

$$h = \alpha X$$

$$g = X^T$$

$$\frac{\partial L_1}{\partial X} = -\frac{D}{2} K^{-T} (\alpha X + d X) = -D K^{-T} \alpha X$$

$$\frac{\partial L_1}{\partial b} = a = -\frac{D}{2}$$

$$\frac{\partial b}{\partial c} = K^{-T}$$

$$\frac{\partial c}{\partial f} = 1$$

$$\frac{\partial f}{\partial g} = h = \alpha X$$

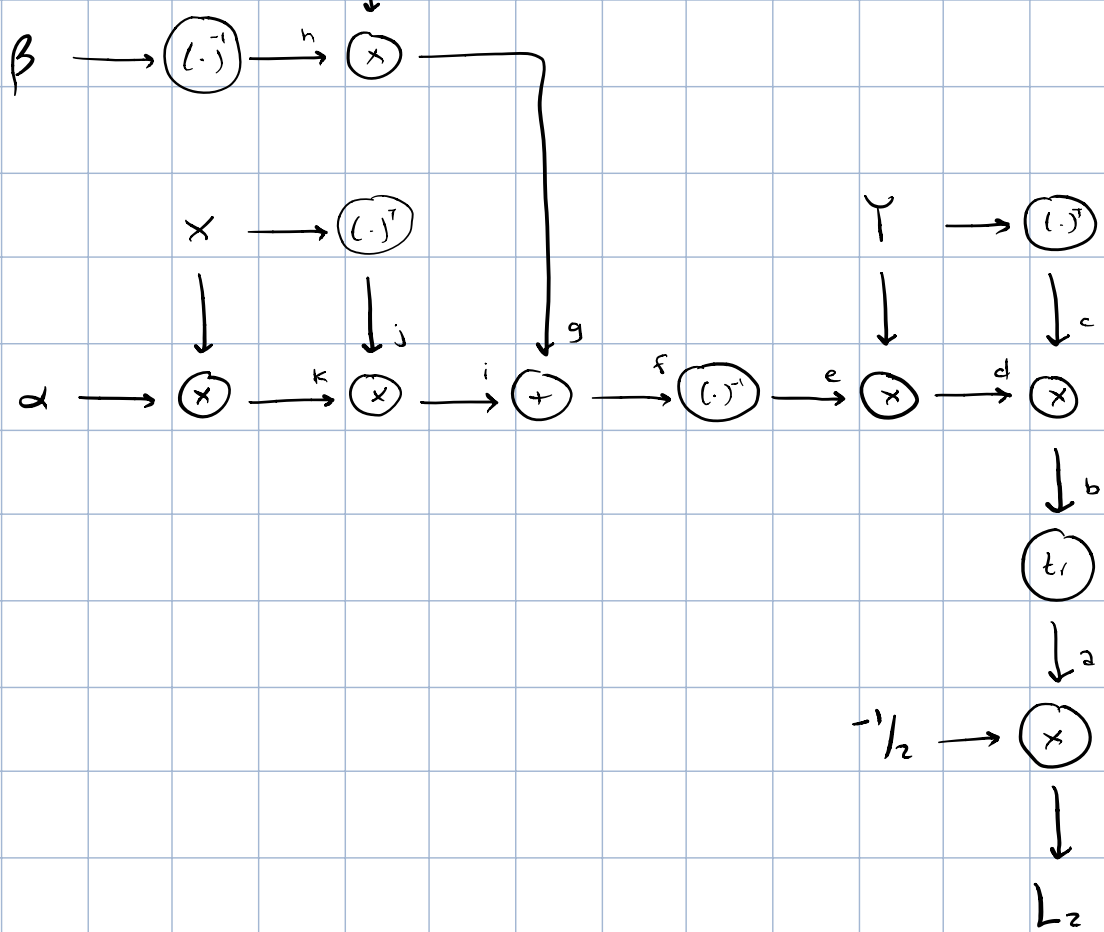
$$\frac{\partial g}{\partial X} = I$$

$$\frac{\partial f}{\partial h} = g^T = (X^T)^T$$

$$\frac{\partial h}{\partial X} = \alpha$$

$$c) L_2 = -\frac{1}{2} \text{tr} (\alpha X X^T + \beta^{-1} I)^{-1} Y Y^T$$

I



$$d) \frac{\partial L_2}{\partial x} = \frac{\partial L_2}{\partial x} \frac{\partial L_2}{\partial k} \quad \frac{\partial L_2}{\partial k} = -k^{-T} \frac{\partial L_2}{\partial k^{-1}} k^{-T}$$

$$\frac{\partial L_2}{\partial k^{-1}} = \frac{\partial}{\partial k^{-1}} \left(-\frac{1}{2} \text{tr}(k Y Y^T) \right)$$

$$= -\frac{1}{2} Y Y^T$$

$$\frac{\partial L_2}{\partial x} = \left(\frac{\partial L_2}{\partial x} + \frac{\partial L_2}{\partial x} \right) \leftarrow \text{from above}$$

$$\frac{\partial L_2}{\partial x} = \left(\frac{\partial L_2}{\partial x} \right) k^{-T} \left(\frac{1}{2} Y Y^T \right) k^{-T}$$

$$= \frac{\partial L_2}{\partial x} k^{-T} Y Y^T k^{-T}$$

$$e) \frac{\partial L}{\partial x} = \frac{\partial L_1}{\partial x} + \frac{\partial L_2}{\partial x}$$

$$= D k^{-T} \frac{\partial L_1}{\partial x} + \frac{\partial L_2}{\partial x} k^{-T} Y Y^T k^{-T}$$