

Show: 5g) 3b)

$$\cancel{A^T H A} \cdot \cancel{A^{-1}} = \cancel{A^{-1} H}$$

Show:

$$z^{i+1} = z^i + (A^T H(Az^i) A)^{-1} \cdot A^T \ell(Az^i)$$

Show:

$$z^{i+1} = A^{-1} x^{i+1} + (A^T H(x_i) A)^{-1} \cdot A^T \cdot \ell(x_i)$$

$$\text{Prove } \hat{=} A^{-1} (x^i + H(x_i)^{-1} \cdot \ell(x_i))$$

$$\Rightarrow \text{Show: } (A^T H(x_i) A)^{-1} \cdot A^T = A^{-1} \cdot H^{-1}$$

$$A^{-1} \cdot H(x)^{-1} \cdot (\cancel{A^T})^{-1} \cdot \cancel{A^T} = A^{-1} \cdot H^{-1}$$

$$\Rightarrow \boxed{A^{-1} H(x)^{-1} = A^{-1} \cdot H^{-1}}$$

59/2p.

$$\Rightarrow \nabla_{z_i z_j} g(z) = \sum_{k=1}^n A_{ki} \sum_{p=1}^n A_{pj} \cdot \left(\frac{d^2 f(Az)}{dx_k dx_p} \right) \text{ Hesse matrix}$$

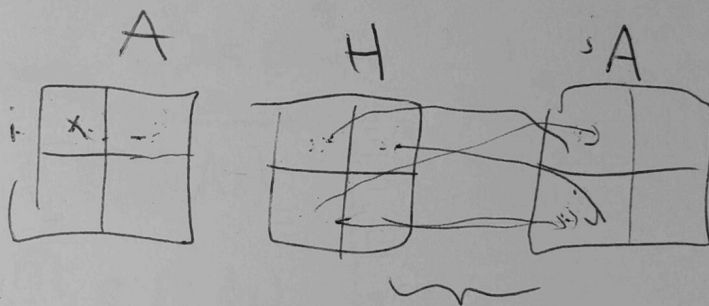
$$\Rightarrow \nabla_{z_i z_j} g(z) = \sum_{k=1}^n A_{ki} \cdot A_{kj} \cdot d^2 f(Az)$$

$$\Rightarrow z_i z_j g(z) = \sum_{k=1}^n A_{ki} \cdot \left(d_x^2 f(Az) \right)_k \cdot A_{kj}$$

$$= (A_{\cdot i})^T \Rightarrow z_i z_j g(z) = (A_{\cdot i})^T \cdot H(Az) \cdot A_{\cdot j}$$

$$\Rightarrow \nabla_{z^2} g(z) = A^T \nabla_x^2 f(Az) \cdot A$$

$$2 \times 2 \times 2 \times 2 =$$



$$g_{z^2}(z)_{ij} = \sum_{k=1}^n \sum_{p=1}^n A_{ki} \cdot A_{pj} \cdot H(Az)_{kp}$$

59) $g(z) = f(Az)$

$\Rightarrow \nabla_z g(z) =$

$$\frac{\nabla_z g(z)}{dz_i} = \sum_{k=1}^n \frac{df(Az)}{d(Az)_k} \cdot \frac{d(Az)_k}{dz_i}$$

$$= \sum_{k=1}^n \frac{df(Az)}{dx_k} \cdot A_{ki}$$

$$= A_{:,i}^T \cdot \nabla_x f(Az)$$

Transpose of i th column

$$\Rightarrow \nabla_z g(z) = A^T \nabla_x f(Az)$$

or $A^T \nabla_x f(Az)$

Now, $\nabla_x^2 g(z) =$

$$\nabla_x^2 g(z)_{ij} = \frac{d(A^T \nabla_x f(Az))_i}{dz_j} = \sum_{k=1}^n \frac{d(d_{xi} f(Az))}{dz_j}$$

$$= \sum_{k=1}^n \frac{d(\nabla_{x_i} f(Az))}{d(Az)_k} \cdot \frac{d(Az)_k}{dz_j}$$

59) 1)

Chain rule of $\frac{dg(z)}{dz}$ where $g(z) = f(Az)$

den and $\frac{df(x)}{dx}$ is known

5b)

$$\text{def } g(z) = f(Az)$$

$$\Rightarrow \nabla_z g(z) = \sum_{n=1}^n \frac{d(f(Az))}{dx_n} \cdot \frac{d(Az)}{dz_i}$$

$$= A^{\top} \nabla_{\theta} \ell(Az)$$

$$\Rightarrow z^{i+1} = z^i + A^{\top} \nabla_{\theta} \ell(Az^i)$$

$$x^{i+1} = x^i + \nabla_{\theta} \ell(x^i)$$

for 0 case:

$$x^1 = \nabla_{\theta} \ell(x^0)$$

$$x^{i+1} = x^i + \nabla_{\theta} \ell(x^i)$$

$$z^1 = A^{\top} \nabla_{\theta} \ell(0)$$

$$z^{i+1} = z^i + A^{\top} \nabla_{\theta} \ell(Az^i)$$

$$A^{-1}(A^{\top} \nabla_{\theta} \ell(0)) \text{ is not } \nabla_{\theta} \ell(x^0)$$

\hookrightarrow Now, with $z^i = A^{-1}x^i$:

$$A^{-1}(x^{i+1}) = A^{-1}x^i + A^{-1}\nabla_{\theta} \ell(x^i)$$

$$z^{i+1} = A^{-1}x^i + A^{\top} \nabla_{\theta} \ell(A \cdot A^{-1}x^i)$$

$$\text{but } z^{i+1} = A^{-1}x^i + A^{\top} \nabla_{\theta} \ell(x^i)$$

and A^{-1} not $A^{\top} \Rightarrow$ not linear invariant \emptyset

5b)

gradient descent:

$$\theta_j = \theta_j - \sum_{i=1}^m \nabla_{\theta} l(x^i)$$

$$\theta_j = \theta_j + \alpha (y^{(i)} - h_{\theta}(x^{(i)})) \cdot x_j^{(i)}$$

Lin reg:

$$\theta_j = \theta_j + \sum_{i=1}^m \alpha (y^{(i)} - \theta^T x^i) \cdot x_j^i$$

* For θ_j^0 : ~~$\sum_{i=1}^m$~~ $\alpha (y^{(i)} - \theta^T x^i) x_j^i$

One sample and one dim: ~~θ_j^0~~ $\alpha (y^{(i)} - 0) x_j$
 $\theta^i = \alpha \cdot y \cdot x_j$

2 dim: ~~θ_j^0~~

$$\theta_1' = \alpha (y - \theta) x_1 = \alpha (y) \cdot x_1$$

g(A