

$$\|Ax - b\|^2 = (Ax - b) \cdot (Ax - b)$$

$$Ax - b \rightarrow A_{ij} x_j - b_i \rightarrow \text{Einstein's notation}$$

$$(Ax - b) \cdot (Ax - b) = (A_{ij} x_j - b_i)(A_{ij} x_j - b_i)$$

$$e \cdot i \rightarrow a \cdot b = \sum_i a_i b_i = a_i b_i$$

$$\text{repeated} = \sum_i$$

$$\min_{\arg x} \|Ax - b\|^2 \rightarrow \nabla_x (\|Ax - b\|^2) = 0$$

$$\frac{\partial}{\partial x_k} [(A_{ij} x_j - b_i)(A_{ij} x_j - b_i)] = 0$$

$$2(A_{ij} x_j - b_i)(A_{ik}) = 0$$

$$2A_{ik}A_{ij}x_j - 2A_{ik}b_i = 0 \equiv 2 \sum_i \sum_j A_{ik}A_{ij}x_j - 2 \sum_i A_{ik}b_i = 0$$

$$F_k(x) = 0 \rightarrow \text{Eqn system in variables } x_j \rightarrow \text{Newton's Method}$$

$$J(F_k(x)) \Delta x = -F_k(x)$$

$$J(F_k(x)) = \frac{\partial F_k}{\partial x_l} \rightarrow J_{kl} = \frac{\partial F_k}{\partial x_l} = 2A_{ik}A_{il}$$

$$\text{Newton's} \rightarrow \frac{\partial F_k}{\partial x_l} \Delta x_l = -F_k(x)$$

$$2A_{ik}A_{il} \Delta x_l = -2A_{ik}A_{ij}x_j + 2A_{ik}b_i$$

$$A_{il} \Delta x_l = -A_{ij}x_j + b_i \equiv A_{ij} \Delta x_j = -A_{ij}x_j + b_i$$

$A_{ij}(x_j + \Delta x_j) = b_i \rightarrow$  original system

To minimize using Newton's method is the same as to solve the original system !!!

Therefore SDG is just capricious !!!

Now the Hessian  $\rightarrow H(f) = \frac{\partial^2 f}{\partial x_m \partial x_l} = H_{ml}$

$$f = \|Ax - b\|^2 = (A_{ij}x_j - b_i)(A_{ij}x_j - b_i)$$

$$\frac{\partial f}{\partial x_m} = 2 A_{im} (A_{ij}x_j - b_i) = 2 A_{im} A_{ij}x_j - 2 A_{im} b_i$$

$$\frac{\partial^2 f}{\partial x_m \partial x_l} = 2 A_{im} A_{il} \equiv H_{ml} = 2 A_{im} A_{il} \Rightarrow$$

$$H_{kl} = 2 A_{ik} A_{il}$$

$$H_{kl} = J_{kl}$$

conclusion: The hessian of the error is the same as the Jacobian of the minimization problem which was proved is the same as the original system solved by Newton's method

$$A^T A = A_{ik}^T A_{kj} = A_{ki} A_{kj}$$

$$\text{diag}(A^T A) = \sum_k A_{ki} A_{kj} = \sum_k A_{ki}^2$$

$$A_i^T A_i = \begin{bmatrix} A_{i1} \\ A_{i2} \\ \vdots \\ A_{in} \end{bmatrix} [A_{i1} \ A_{i2} \ \dots] = \begin{pmatrix} A_{i1}^2 & & \\ & A_{i2}^2 & \\ & & A_{in}^2 \end{pmatrix}$$

$$E = \frac{1}{2} \|Ax - b\|^2$$

$$E = \frac{1}{2} (A_{ij} x_j - b_i) (A_{ij} x_j - b_i)$$

$$\frac{\partial E}{\partial x_k} = \text{grad } E = \frac{1}{2} (A_{ij} x_j - b_i) A_{ik} + \frac{1}{2} A_{ik} (A_{ij} x_j - b_i)$$

$$= A_{ik} (A_{ij} x_j - b_i) = A_{ik} e_i$$

$$= A^T (Ax - b)$$

$$= \sum_j A_{ik} e_j = \frac{\partial E}{\partial x_k}$$

$$\begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} b_1 \\ b_2 \end{pmatrix} = \begin{pmatrix} a_{11}b_1 + a_{12}b_2 \\ a_{21}b_1 + a_{22}b_2 \end{pmatrix} = b_1 \begin{pmatrix} a_{11} \\ a_{21} \end{pmatrix} + b_2 \begin{pmatrix} a_{12} \\ a_{22} \end{pmatrix}$$

Gradient descent  $\rightarrow$

$$x^{k+1} = x^k - \lambda \nabla f(x^k)$$

Newton Direction  $\rightarrow$

$$x^{k+1} = x^k + \partial x^k$$

$$H(x^k) \partial x^k = -\nabla f(x^k)$$

$$x^{k+1} = x^k - H^{-1} \nabla f(x^k)$$

Also the local minimization model changes, thus

$$GD \rightarrow \text{model} \rightarrow f(x) \approx f(x^k) + \nabla f \cdot (x - x^k)$$

Newton model  $\rightarrow$

$$f(x) \approx f(x^k) + \nabla f(x^k)(x - x^k) + (x - x^k)^T H(x - x^k)$$

$$\frac{\partial}{\partial x_k} (A_{ij} x_j - b_i)^2 = 2 (A_{ij} x_j - b_i) A_{ik}$$

$$\frac{\partial^2}{\partial x_k \partial x_l} (A_{ij} x_j - b_i)^2 = 2 A_{ik} A_{il}$$

$$f = (a_1 x_1 + a_2 x_2 - b)^2$$

$$\frac{\partial f}{\partial x_1} = 2(a_1 x_1 + a_2 x_2 - b) a_1$$

$$\frac{\partial f}{\partial x_2} = 2(a_1 x_1 + a_2 x_2 - b) a_2$$

$$H = \begin{pmatrix} 2a_1^2 & 2a_1 a_2 \\ 2a_1 a_2 & 2a_2^2 \end{pmatrix}$$

$$\det H = 4a_1^2 a_2^2 - 4a_1^2 a_2^2 = 0??$$