

## Seminar 11

- 1. Find the second-order Taylor polynomial for the following functions at the given points:
- (a)  $f(x,y) = \sin(x+2y)$  at (0,0). (b)  $f(x,y) = e^{x+y}$  at (0,0) and (1,-1). (c)  $f(x,y) = \sin(x)\sin(y)$  at  $(\pi/2,\pi/2)$ . (d)  $f(x,y) = e^{-(x^2+y^2)}$  at (0,0).
- 2. Compute the Hessian matrix and its eigenvalues for the following:
  - (a)  $f(x,y) = (y-1)e^x + (x-1)e^y$  at (0,0). (b)  $f(x,y) = \sin(x)\cos(y)$  at  $(\pi/2,0)$ .
- 3. Find and classify the critical points for each of the following functions:
  - (x)  $f(x,y) = x^3 3x + y^2$ . (b)  $f(x,y) = x^3 + y^3 6xy$ .

- (c)  $f(x,y) = x^4 + y^4 4(x-y)^2$ . (d)  $f(x,y,z) = x^2 + y^2 + z^2 xy + x 2z$ .
- Let A be a symmetric  $n \times n$  matrix and the quadratic function  $f : \mathbb{R}^n \to R$ ,  $f(x) = \frac{1}{2}x^T Ax$ . Prove that  $\nabla f(x) = Ax$  and H(x) = A. Hint: use the Taylor expansion.
- 5. Let A be an  $m \times n$  matrix, b a vector in  $\mathbb{R}^m$  and the least squares minimization problem

$$\min_{x \in \mathbb{R}^n} ||Ax - b||^2.$$

Prove that the solution  $x^*$  of this problem satisfies (the so-called normal equations)

$$A^T A x^* = A^T b.$$

- 6.  $\bigstar$ [Python] Let A be a  $2 \times 2$  matrix and let the quadratic function  $f: \mathbb{R}^2 \to R$ ,  $f(x) = \frac{1}{2}x^T Ax$ .
  - (a) Give a matrix A such that f has a unique minimum.
  - (b) Give a matrix A such that f has a unique maximum.
  - (c) Give a matrix A such that f has a unique saddle point.

In each case plot the 3d surface, three contour lines and the gradient at three different points.

$$T_{x}(x,y) = \frac{1}{3}(x_{0},y_{0}) + \frac{1}{3}\frac{1}{3}(x_{0},y_{0}) \cdot (x_{0},y_{0}) + \frac{1}{2}(x_{0},y_{0}) + \frac{1}{2}$$

= 1+x+y+ (x+y)

$$T_{2}(1,1) = A + (A,1)(X_{1}, y_{1} - 1) + \frac{1}{2}(X_{1}, y_{2} - 1) \cdot \begin{pmatrix} A \\ A \end{pmatrix} \begin{pmatrix} X_{1} \\ Y_{1} \end{pmatrix} = \\ = 1 + X_{2} + Y_{2} + Y_{2} + \frac{1}{2}(X_{1}, y_{2} - 1) \cdot (X_{2} - X_{2} + Y_{2}) \cdot (Y_{1} - Y_{2}) = \\ = 1 + X_{2} + Y_{2} + \frac{1}{2} \cdot (X_{1} - Y_{2}) \cdot (X_{2} - Y_{2}) \cdot (X_{2$$

 $T_{2}(x,y) = \lambda + \frac{1}{4}(x,y) \begin{pmatrix} -2 & 0 \\ 0 & -2 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \lambda + \frac{1}{4}(x,y) \cdot (-2x,-2y) = \lambda + \frac{1}{4}(-2x^{2} - 2y^{2}) = \lambda - x^{2} - y^{2}$ 

2. Compute the Hessian matrix and its eigenvalues for the following:

(a) 
$$f(x,y) = (y-1)e^x + (x-1)e^y$$
 at  $(0,0)$ . (b)  $f(x,y) = \sin(x)\cos(y)$  at  $(\pi/2,0)$ .

(a) 
$$f(x,y) = (y-1)e^{x} + (x-1)e^{y}$$
 at  $(0,0)$ 

$$\frac{\partial f}{\partial x^{2}} = \frac{d}{dx} \left(\frac{\partial f}{\partial x}\right) = \frac{d}{dx} \left((y-1)e^{x} + e^{y}\right) = (y-1)e^{x}$$

$$\frac{\partial f}{\partial x^{2}} = (x-1)e^{y}$$

$$\frac{\partial f}{\partial x \partial y} = \frac{d}{dy} \left((y-1)e^{x} + e^{y}\right) = e^{x} + e^{y} = \frac{\partial^{2} f}{\partial y \partial x}$$

$$H(0,0) = \begin{bmatrix} -1 & 2 \\ 2 & -1 \end{bmatrix}$$

eigenvalus: 
$$A = \lambda \sigma$$
  
 $(A - \lambda I) \cdot \sigma = 0$ ,  $\nabla \neq 0$   
det  $(A - \lambda I) = 0$ 

(a) 
$$f(x,y) = x^3 - 3x + y^2$$
.  
 $\frac{\partial f}{\partial x} = 3x^2 - 3 = 0 \Rightarrow x = \pm 1$   
 $\frac{\partial f}{\partial y} = 2y = 0 \Rightarrow y = 0$   
 $\Rightarrow (1,0), (-1,0)$  orifical points

$$\frac{\partial^2 Q}{\partial x^2} = Qx$$

$$\frac{\partial^2 Q}{\partial x^2} = Q$$

$$\frac{\partial^2 Q}{\partial y^2} = Q$$

$$\begin{cases}
(x+h) = \int_{-1}^{1} x^{T}Ax & \forall \int_{-1}^{1} (x)h + \frac{1}{2}h^{T}H(x)h + \dots - \text{Taylor expansion} \\
4. \int_{-1}^{1} x^{T}Ax & \forall \int_{-1}^{1} (x)h + \frac{1}{2}h^{T}H(x)h + \dots - \text{Taylor expansion} \\
Method 1: \frac{\partial f}{\partial x_{1}} = ? \quad \text{a lot of work, don'} \qquad (a,b) = a \cdot b = a^{T}b \\
(AB)^{T} = B^{T}A^{T}$$

$$(AB)^{T} = B^{T}A^{T}$$

$$Method 2: \int_{-1}^{1} (x+h) - \frac{1}{2} (x+h)^{T}A(x+h) = \frac{1}{2}x^{T}Ax + \frac{1}{2}x^{T}Ah + \frac{1}{2}h^{T}Ax + \frac{1}{2}h^{T}Ah.$$

$$x^{T}Ah = \langle x, Ah \rangle - x \cdot \langle Ah \rangle = \langle Ah, x \rangle = \langle Ah \rangle^{T}x = h^{T}Ax = \langle Ah, Ax \rangle$$

$$\int_{-1}^{1} (x+h) = \int_{-1}^{1} (x) + \frac{1}{2}h^{T}Ah$$

$$\sqrt{f(x+h)} = \int_{-1}^{1} (x) + \frac{1}{2}h^{T}Ah$$

$$\sqrt{f(x)} = \int_{-1}^{1} (x) + \frac{1}{2}h^{T}Ah$$

5. Let A be an  $m \times n$  matrix, b a vector in  $R^m$  and the least squares minimization problem  $\min_{x \in \mathbb{R}^n} \|Ax - b\|^2.$ 

Prove that the solution  $x^*$  of this problem satisfies (the so-called normal equations)

$$A^T A x^* = A^T b.$$

$$\begin{cases} (x) = \|A_{X} - b\|^{2} = \langle A_{X} - b_{1} A_{X} - b^{2} \rangle \\ \{(x) \longrightarrow win = \} \quad \forall \{(x) = 0 \} \\ \{(x) = \langle A_{X}, A_{X} \rangle - 2\langle A_{X}, b^{2} - \langle b_{1} b_{2} \rangle \\ \langle A_{X}, A_{X} \rangle = (A_{X})^{T} A_{X} = x^{T} (A^{T} A_{1}) \times \\ \Rightarrow \{(x) = x^{T} (A^{T} A_{1}) \times - 2b^{T} A_{1} + \|b\|^{2} \\ \langle x, A^{T} b_{2} = x \cdot (A^{T} b_{1}) \\ \Rightarrow A^{T} A_{1} = A^{T} b \end{cases}$$