

Problem 1a) Theorem 2.3:

If  $x^*$  is a local minimizer of  $f$  and  $\nabla^2 f$  exists and is continuous in an open neighborhood of  $x^*$ , then  $\nabla f(x^*) = 0$  and  $\nabla^2 f(x^*)$  is positive semidefinite.

b) By showing that if  $\nabla^2 f < 0$ , i.e. not positive semidefinite, there exist a direction from  $x^*$  s.t. the value of  $f$  decreases,  $x^*$  is not a local minimizer and the theorem is proven by contradiction.

c) In theorem 2.4 it's required that  $\nabla^2 f$  is positive definite, i.e.,  $\nabla^2 f > 0$ . This is so  $\nabla^2 f = 0$  and we have multiple solution. If  $\nabla^2 f > 0 \forall x \in \mathcal{K}(x^*)$ , only  $x^*$  can be the local minimum.



## Problem 2

$$m_k(p) = f_k + p^T \nabla f_k + \frac{1}{2} p^T \nabla^2 f_k p \approx f(x_k + p)$$

a)  $\nabla_p m_k = \nabla f_k + \nabla^2 f_k p = 0$

$$\Rightarrow p_k^N = -(\nabla^2 f_k)^{-1} \nabla f_k \quad \square.$$

b) If  $\nabla^2 f_k = 0$ , the Newton direction is undefined.

If  $\nabla^2 f_k < 0$ , the Newton direction doesn't satisfy the descent property

$$\nabla f_k^T p_k^N = - \underbrace{\nabla f_k^T \nabla^2 f_k^{-1} \nabla f_k}_{< 0} < 0$$

and is therefore not suitable for a descent direction.

c)  $f(x) = \frac{1}{2} x^T G x + x^T c$

$$\nabla f_k = G x_k + c = 0 \Rightarrow x^* = -G^{-1} c$$

$$\nabla^2 f_k = G > 0 \quad \nabla^2 f^{-1} = G^{-1} > 0$$

$$p_k^N = -G^{-1}(G x_k + c) = -x_k - G^{-1} c$$

$$x_{k+1} = x_k + p_k^N = x_k - x_k - G^{-1} c = -G^{-1} c = x^*$$

Since  $\nabla^2 f_k = G > 0$ , the local minimizer is simply found by solving  $\nabla f(x^*) = 0 \Rightarrow x^* = -G^{-1} c$ .

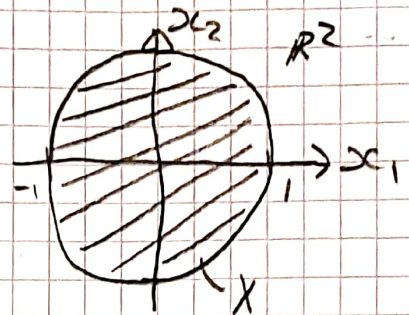
As shown, regardless of  $x_k$ , this value is obtained after a single iteration



using the Newton direction.

d)  $f(x) = \frac{1}{2}x^T G x + x^T c$        $x \in \{x \in \mathbb{R}^2 / x_1^2 + x_2^2 \leq 1\} = X$

$$G = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \quad c = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$



Definition of convexity

$$f(\alpha x + (1-\alpha)y) \leq \alpha f(x) + (1-\alpha)f(y) \quad \forall \alpha \in [0,1]$$

$$x, y \in X \rightarrow \alpha x + (1-\alpha)y \in X.$$

Convexity of domain X:

- let  $x, y \in X: x_1^2 + x_2^2 \leq 1, y_1^2 + y_2^2 \leq 1.$
- $\alpha(x_1^2 + x_2^2) + (1-\alpha)(y_1^2 + y_2^2)$   
 $= \underbrace{\alpha(x_1^2 + x_2^2)}_{\leq 1} - \underbrace{(y_1^2 + y_2^2)}_{\leq 1} + \underbrace{(y_1^2 + y_2^2)}_{\leq 1} \leq 1 \quad \forall \alpha \in [0,1].$   
 $\downarrow$   
at most = 1 ( $x=1, y=0$ )       $\alpha x + (1-\alpha)y \in X.$   
at least = -1 ( $x=0, y=1$ )

Convexity of f):

- let  $x, y \in X.$
- $G > 0$  because  $\begin{vmatrix} \lambda-2 & -1 \\ -1 & \lambda-2 \end{vmatrix} = (\lambda-2)^2 - 1 = 0$   
 $\lambda = 2 \pm 1 > 0.$

- $f(\alpha x + (1-\alpha)y) = (LHS)$   
 $= \alpha^2 \frac{1}{2} x^T G x + \alpha x^T c + (1-\alpha)^2 \frac{1}{2} y^T G y + (1-\alpha) y^T c$

- $\alpha f(x) + (1-\alpha)f(y) = (RHS)$   
 $= \alpha \frac{1}{2} x^T G x + \alpha x^T c + (1-\alpha) \frac{1}{2} y^T G y + (1-\alpha) y^T c$

→



Since  $\alpha \in [0, 1] \Rightarrow \alpha^2 < \alpha$ . Since the difference between (RHS) and (LHS) is  $\alpha^2$  and  $(1-\alpha)^2$  coefficients of the quadratic terms, and since  $G > 0 \Rightarrow (LHS) \leq (RHS)$ .  $\square$ .

It's shown that both the function and its domain is convex.

### Problem 3

$$f(x) = 100(x_2 - x_1^2)^2 + (1 - x_1)^2$$

$$\nabla f(x) = \begin{bmatrix} -400x_1(x_2 - x_1^2) - 2(1 - x_1) \\ 200(x_2 - x_1^2) \end{bmatrix}$$

$$\begin{aligned} \nabla^2 f(x) &= \begin{bmatrix} -400(x_2 - x_1^2) + 800x_1^2 + 2 & -400x_1 \\ -400x_1 & 200 \end{bmatrix} \\ &= \begin{bmatrix} 1200x_1^2 - 400x_2 + 2 & -400x_1 \\ -400x_1 & 200 \end{bmatrix} \end{aligned}$$

$$x^* = \begin{bmatrix} 1 & 1 \end{bmatrix}^T : \nabla f(x^*) = \begin{bmatrix} -400 \cdot 1(1 - 1^2) - 2(1 - 1) \\ 200(1 - 1^2) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \checkmark$$

$$\nabla^2 f(x^*) = \begin{bmatrix} 1200 \cdot 1^2 - 400 \cdot 1 + 2 & -400 \cdot 1 \\ -400 \cdot 1 & 200 \end{bmatrix} = \begin{bmatrix} 802 & -400 \\ -400 & 200 \end{bmatrix}$$

Both leading principal minors  $> 0 \Rightarrow \nabla^2 f(x^*) > 0 \checkmark$

Both first-order necessary condition and second order sufficient condition satisfied  $\Rightarrow \underline{\underline{x^*}}$  is local minimizer.