



### Problem 1 (25 %) Second-Order Necessary Conditions

- a Formulate Theorem 2.3 (page 15) as stated in the textbook.
- b Go through the proof so that you understand it. Briefly explain the proof.
- c Compare Theorem 2.3 and Theorem 2.4 (page 16). Why does Theorem 2.3 not give sufficient conditions for a strict local minimum?

### Problem 2 (40 %) The Newton Direction

Consider the model function  $m_k$  based on the second-order Taylor approximation (see equation (2.14) in the textbook):

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

- a Derive the Newton direction

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

using the model function  $m_k$ .

- b Assume that  $\nabla^2 f_k$  is not positive definite. In this case, is the Newton-direction  $p_k^N$  a descent direction? Is it even defined? Explain.
- c Given an unconstrained minimization problem with objective function

$$f(x) = \frac{1}{2} x^\top G x + x^\top c \quad (3)$$

with  $G = G^\top > 0$  and  $x \in \mathbb{R}^n$ . Show that an iteration algorithm based on the Newton direction (i.e.,  $x_{k+1} = x_k + p_k^N$ ) always converges to the optimum in *one step*.

- d Show that

$$f(x) = \frac{1}{2} x^\top G x + x^\top c, \quad x \in X, \quad X = \{x \in \mathbb{R}^2 \mid x_1^2 + x_2^2 \leq 1\} \quad (4)$$

where

$$G = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}, \quad c = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad (5)$$

is a convex function.

### Problem 3 (35 %) The Rosenbrock Function

Solve problem 2.1 in the textbook.