

**New Directions 2016: Mathematical Optimization**  
**August 2016**  
**Worksheet 1**

1. Compute the gradient and Hessian of the Rosenbrock function:

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

2. Prove that all isolated minimizers are strict. (One way to do this is to prove that “not isolated” implies “not strict”.)
3. (a) Give an example of a matrix that is *not* positive definite despite having all positive entries.  
(b) If  $A$  is a positive definite matrix, must its diagonal elements all be positive? Explain.
4. Suppose that  $f(x) = \frac{1}{2}x^T Ax$  where  $A$  is symmetric positive semidefinite. Show that  $f$  is convex, by proving that the following is true for all  $x, y \in \mathbb{R}^n$  and all  $\alpha \in [0, 1]$ :

$$f(x + \alpha(y - x)) \leq (1 - \alpha)f(x) + \alpha f(y).$$

5. Suppose that  $f(x) = x^T Ax$  where  $A$  is an  $n \times n$  matrix that is *not necessarily symmetric*. What is the Hessian  $\nabla^2 f(x)$ ?
6. Consider the sequence  $\{x_k\}$  defined by

$$x_k = \begin{cases} (1/4)^{2^k}, & \text{for } k \text{ even} \\ (x_{k-1}/k), & \text{for } k \text{ odd.} \end{cases}$$

Is this sequence  $Q$ -superlinearly convergent?  $Q$ -quadratically convergent?  $R$ -quadratically convergent?

7. Give an example of a sequence  $\{x_k\}$  of positive real numbers, that decreases to zero  $Q$ -superlinearly but not  $Q$ -quadratically.
8. Suppose that  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is a smooth convex function, and suppose that the set of minimizers  $S$  defined by  $S := \{x^* : f(x^*) \leq f(x) \text{ for all } x \in \mathbb{R}^n\}$  is nonempty. Show that  $S$  is a *closed* and *convex* set.

9. Show the interior and closure of a convex set are convex.
10. A point  $x \in \mathbb{R}^n$  is a *convex combination* of the points  $\{x^1, x^2, \dots, x^r\}$  in  $\mathbb{R}^n$  if for some real numbers  $\lambda_1, \lambda_2, \dots, \lambda_r$  that satisfy  $\sum \lambda_i = 1$  and  $\lambda_i \geq 0$ , we have  $x = \sum_{i=1}^r \lambda_i x^i$ . Show that a set  $S$  in  $\mathbb{R}^n$  is convex if and only if every convex combination of a finite number of points of  $S$  is in  $S$ .
11. A set  $C$  is a *cone* if for every  $\lambda > 0$  and every  $x \in C$ ,  $\lambda x \in C$ . Prove that a cone is convex if and only if it is closed under addition, that is,  $x, y \in C$  implies that  $x + y \in C$ .