

## Numerical Optimization - Sheet 1

If you are a student in mathematics please solve the exercises with no tag and the ones with the tag **Mathematics**. If you are a data science student please solve the problems with no tag and those with the tag **Data Science**. Submissions with tags other than your subject count as bonus points. The tag **Programming** marks programming exercises.

### Ex 1

(4 Points)

Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  be **convex**, that means

$$f((1-\lambda)x + \lambda y) \leq (1-\lambda) \cdot f(x) + \lambda \cdot f(y), \quad \forall x, y \in \mathbb{R}^n, \quad \forall \lambda \in [0, 1].$$

Show that any local minimum of  $f$  is already a global minimum.

Solution 1:

Let  $\hat{x}$  be a local minimum in an arbitrary, fixed (open) neighbourhood  $\hat{x} \in U \subset \mathbb{R}^n$ , i.e.

$$f(\hat{x}) \leq f(x)$$

for all  $x \in U$ . Let us assume there is a  $\hat{y} \in \mathbb{R}^n$  such that

$$f(\hat{y}) < f(\hat{x}).$$

We obtain, that for all  $\lambda \in (0, 1)$

$$f(\lambda \hat{x} + (1-\lambda)\hat{y}) \leq \lambda f(\hat{x}) + (1-\lambda)f(\hat{y}) < \lambda f(\hat{x}) + (1-\lambda)f(\hat{x}) = f(\hat{x}).$$

As  $U$  is open, there is a  $\hat{\lambda} \in (0, 1)$  such that  $\hat{\lambda}\hat{x} + (1-\hat{\lambda})\hat{y} \in U$  which yields a contradiction to the assumption of local optimality of  $\hat{x}$ .

### Ex 2

(4 Points)

Consider a linear mapping  $f : \mathbb{R}^n \rightarrow \mathbb{R}^m, x \mapsto Cx$ , defined by a matrix  $C \in \mathbb{R}^{m \times n}$  with  $m \leq n$ . Show that  $f$  being surjective is equivalent to the matrix  $C$  having full rank.

Solution 2:

**Definition rank** (see Elements of Mathematics)

Let  $A \in \mathbb{R}^{m \times n}$  be a real matrix with SVD  $A = U\Sigma V^\top$ . Then the rank of  $A$  is the number of positive singular values.

**Definition pseudoinverse of A** (see Elements of Mathematics)

Let  $A \in \mathbb{R}^{m \times n}$  be a real matrix with SVD  $A = U\Sigma V^\top$ . Then the pseudoinverse of  $A$  is defined by

$$A^+ := V\Sigma^+U^\top := V \left[ \begin{array}{ccc|ccc} \sigma_1^{-1} & & & & & \\ & \ddots & & & & \\ & & \sigma_k^{-1} & & & \\ \hline & & & & & \\ & & & & & \\ \dots & 0 & \dots & \dots & 0 & \dots \\ & & & & & \end{array} \right] U^\top.$$

**Definition surjective** (see Elements of Mathematics)

Let  $f : X \rightarrow Y$  be a function. Then  $f$  is called surjective if for any  $y \in Y$  there exists an  $x \in X$  such that  $f(x) = y$ .

**Proof:**

**Full Rank  $\Rightarrow$  Surjective**

Let  $y \in \mathbb{R}^m$  be arbitrary and set  $x := C^+y$ . Because  $C$  is of full rank we obtain

$$\Sigma\Sigma^+ = \text{id}_m.$$

Hence

$$Cx = CC^+y = U\Sigma VV^\top \Sigma^+ U^\top y = U\Sigma \text{id}_n \Sigma^+ U^\top y = U \text{id}_m U^\top y = \text{id}_m y = y.$$

**Surjective  $\Rightarrow$  Full Rank**

As  $f$  is surjective we know that for all  $k \in \{1, \dots, m\}$  there are  $x_k$  such that

$$u_k = Cx_k$$

for each column  $u_k$  of  $U \in \mathbb{R}^{m \times m}$ . The alternative representation

$$C = \sum_{i=1}^m \sigma_i u_i v_i^\top$$

yields

$$u_k = \sum_{i=1}^m \sigma_i u_i v_i^\top x_k = \sum_{i=1}^m \sigma_i u_i \alpha_i.$$

As the columns of  $U$  are linearly independent we obtain that  $\sigma_k \neq 0$  for all  $k \in \{1, \dots, m\}$ .

**Ex 3**

(4 Points)

Let  $f : \mathbb{R}^2 \rightarrow \mathbb{R}$  be defined as

$$f(x) = \frac{1}{2} [x_1^2 + 2x_1x_2 + 4x_2^2].$$

Find a scalar product such that  $\nabla f(x) = x \ \forall x \in \mathbb{R}^2$ .

Solution 3:

$$(x, y)_A := x^\top \begin{bmatrix} 1 & 1 \\ 1 & 4 \end{bmatrix} y$$

yields

$$\frac{\partial f}{\partial x} = (x_1 + x_2, 4x_2 + x_1).$$

The gradient is a vector  $g(x)$  such that

$$(g(x), v)_A = \frac{\partial f}{\partial x} v \quad \forall v \in \mathbb{R}^2.$$

We set  $g(x) := x$  and find

$$(x, e_1)_A = x_1 + x_2 = \frac{\partial f}{\partial x} e_1,$$

$$(x, e_2)_A = 4x_2 + x_1 = \frac{\partial f}{\partial x} e_2.$$

**Ex 4 Programming**

(3 Points)

Create a contour plot of the Rosenbrock function

$$f(x, y) = (a - x)^2 + b(y - x^2)^2,$$

for  $a = 1$  and  $b = 100$ . Try to approximately find the region of its global minimum in the plot.

**Hint:**

- You can obtain a logarithmic scaling of the contour lines in `plt.contour()` via the option `locator=ticker.LogLocator()`.
- Please submit the solution as iPython Notebook. Read the information page on Olat if you need information about Python 3 or iPython Notebooks.