

# Machine Learning Assignment # 2

## Universität Bern

Due date: 09/10/2019

**Late submissions will incur a penalty. Submit your answers in ILIAS (as a pdf or as a picture of your written notes if the handwriting is very clear). Submission instructions will be provided via email. You are not allowed to work with others.**

### Calculus review

[Total 100 points]

Recall that the Jacobian of a function  $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$  is an  $m \times n$  matrix of partial derivatives

$$Df(x) = \begin{bmatrix} \frac{\partial f_1(x)}{\partial x_1} & \frac{\partial f_1(x)}{\partial x_2} & \dots & \frac{\partial f_1(x)}{\partial x_n} \\ \frac{\partial f_2(x)}{\partial x_1} & \frac{\partial f_2(x)}{\partial x_2} & \dots & \frac{\partial f_2(x)}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_m(x)}{\partial x_1} & \frac{\partial f_m(x)}{\partial x_2} & \dots & \frac{\partial f_m(x)}{\partial x_n} \end{bmatrix}$$

where  $x = [x_1 \ x_2 \ \dots \ x_n]^\top$ ,  $f(x) = [f_1(x) \ f_2(x) \ \dots \ f_m(x)]^\top$  and  $\frac{\partial f_i(x)}{\partial x_j}$  is the partial derivative of the  $i$ -th output with respect to the  $j$ -th input. When  $f$  is a scalar-valued function (i.e., when  $f : \mathbb{R}^n \rightarrow \mathbb{R}$ ), the Jacobian  $Df(x)$  is a  $1 \times n$  matrix, i.e., it is a row vector. Its transpose is called the *gradient* of the function

$$\nabla f(x) = Df(x)^\top = \begin{bmatrix} \frac{\partial f(x)}{\partial x_1} \\ \frac{\partial f(x)}{\partial x_2} \\ \vdots \\ \frac{\partial f(x)}{\partial x_n} \end{bmatrix} \quad (1)$$

Also, recall that the **chain rule** is a tool to calculate gradients of function compositions. Suppose  $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$  is differentiable at  $x$  and  $g : \mathbb{R}^m \rightarrow \mathbb{R}^p$  is differentiable at  $f(x)$ . Define the composition  $h : \mathbb{R}^n \rightarrow \mathbb{R}^p$  by  $h(z) = g(f(z))$ . Then  $h$  is differentiable at  $x$ , with Jacobian

$$Dh(x) = Dg(z) \Big|_{z=f(x)} Df(x). \quad (2)$$

1. Consider the function  $g : \mathbb{R}^n \rightarrow \mathbb{R}$  with  $g(x) = x^\top x$ . We can readily calculate the gradient  $\nabla g(x) = 2x$  by noticing that

$$\forall j = 1, \dots, n \quad \frac{\partial x^\top x}{\partial x_j} = \frac{\partial x_j^2}{\partial x_j} = 2x_j \rightarrow \nabla g(x) = 2x. \quad (3)$$

Consider also the function  $a : \mathbb{R}^n \rightarrow \mathbb{R}^m$  with  $a(x) = Ax$ , and  $A \in \mathbb{R}^{m \times n}$ . The Jacobian of  $a(x)$  is  $Da(x) = A$ . Given this, answer the following questions by using the above definitions (show all the steps of your working)

- (a) Consider the function  $h : \mathbb{R}^n \rightarrow \mathbb{R}$  and  $h(x) = x^\top Qx$ , where  $Q \in \mathbb{R}^{n \times n}$  is a symmetric matrix. [15 points]  
Calculate  $\nabla h(x)$  by using the product rule, the gradient of  $g$  in eq. (3), and the Jacobian of the linear function  $a(x)$ .
- (b) Consider the function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$ , where  $f(x) = \|Ax - b\|^2$ ,  $A \in \mathbb{R}^{m \times n}$ , and  $b \in \mathbb{R}^m$ . [15 points]  
Calculate  $\nabla h(x)$  by using the chain rule in eq. (2), the gradient of  $g$  in eq. (3), and the Jacobian of the linear function  $a(x)$ .
- (c) Consider a function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$ . Suppose we have a matrix  $A \in \mathbb{R}^{n \times m}$  and a vector  $x \in \mathbb{R}^m$ . [10 points]  
Calculate  $\nabla_x f(Ax)$  as a function of  $\nabla_x f(x)$ .

(d) Show that

[10 points]

$$\frac{\partial}{\partial X} \sum_{i=1}^n \lambda_i = I$$

where  $X \in \mathbb{R}^{n \times n}$  and has eigenvalues  $\lambda_1 \dots \lambda_n$ .

(e) Show that

[10 points]

$$\frac{\partial}{\partial X} \prod_{i=1}^n \lambda_i = \det(X) X^{-T}$$

where  $X \in \mathbb{R}^{n \times n}$  and has eigenvalues  $\lambda_1 \dots \lambda_n$ .

2. Assume  $A \in \mathbb{R}^{m \times n}$ ,  $X \in \mathbb{R}^{m \times n}$ , and  $B \in \mathbb{R}^{m \times m}$ . Show that  $\nabla_X \text{tr}(AX^T B) = BA$ .

[10 points]

3. Solve the following equality constrained optimization problem:

[30 points]

$$\max_{x \in \mathbb{R}^n} x^\top A x \quad \text{subject to } b^\top x = 1$$

for a symmetric matrix  $A \in \mathbb{S}^n$ . Assume that  $A$  is invertible and  $b \neq 0$ .