

# Learning from Data 1, Tutorial Sheet 1 - Answers

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## 1. Vector Length - Norm (Euclidean)

$$\|\vec{v}\| = \sqrt{\vec{v} \cdot \vec{v}}$$

$$\text{Solution: } \|\vec{v}\| = \sqrt{6}$$

## 2. Angle between vectors

$$\cos(\theta) = \frac{\vec{x} \cdot \vec{y}}{\|\vec{x}\| \|\vec{y}\|}$$

$$\text{Solution: } \theta = 0.2502 \text{ [rad]}$$

## 3. MATLAB

Solution: see tutorial\_01.m file for commands.

## 4. Matrix operations, eigenvalues and eigenvectors

If  $A\vec{v} = \lambda\vec{v}$ , then  $\vec{v}$  is an *eigenvector* of  $A$  and  $\lambda$  is the associated *eigenvalue*

Solution:  $\vec{v}$  is an *eigenvector* of  $A$  with  $\lambda = -6$

## 5. Partial Derivatives

$$f(x, y, z) = (x + 2y)^2 \sin(xy)$$

Solution:

$$\frac{\partial f}{\partial x} = y(x + 2y)^2 \cos(xy) + 2(x + 2y) \sin(xy)$$

$$\frac{\partial f}{\partial y} = x(x + 2y)^2 \cos(xy) + 4(x + 2y) \sin(xy)$$

$$\frac{\partial f}{\partial z} = 0$$

## 6. Probability

Random variable  $X \equiv$  "number of requests satisfied"

Solution:

$$P(X = \text{"at least one"}) = P(X = 1) \cup P(X = 2) \cup P(X = 3) = 1 - P(X = 0)$$

$$P(X = 0) = \left(\frac{3}{4}\right)^3$$

$$P(X = \text{"at least one"}) = 0.5781$$

## 7. Distribution Functions

$$E[X] = \int_{-\infty}^{+\infty} x f(x) dx$$

$$VAR[X] = E[X^2] - E[X]^2$$

$$\text{Solution: } E[X] = \frac{1}{2} \text{ and } VAR[X] = \frac{1}{12}$$

## 8. Optimization

Notes:

If  $A$  is a positive definite symmetric matrix then the inverse matrix,  $A^{-1}$ , exists<sup>1</sup>.

$$(AB)^T = B^T A^T;$$

The gradient of a scalar function  $\phi$  (which is a vectorial quantity) is defined as:

$$\nabla\phi(x_1, \dots, x_n) \equiv \frac{\partial\phi}{\partial x_1}\vec{x}_1 + \dots + \frac{\partial\phi}{\partial x_n}\vec{x}_n$$

Solutions:

a) Unconstrained minimum of  $f(\vec{x})$ :

$$\nabla f(\vec{x}) = \vec{0}$$

$$\vec{x} = A^{-1}\vec{b}$$

b) Minimum of  $f(\vec{x})$  along  $\vec{x} = \vec{a} + t\vec{v}$ ,  $t \in \mathfrak{R}$

Substitute  $\vec{x}$  by  $\vec{a} + t\vec{v}$  and make  $\frac{df(\vec{x})}{dt} = 0$

$$t = \frac{\vec{b}^T \vec{v} - \vec{a}^T A \vec{v}}{\vec{v}^T A \vec{v}}$$

c) Unconstrained minimum for given  $A$  and  $\vec{b}$

$$\vec{x} = (7, -3)^T$$

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An  $n \times n$  Hermitian matrix  $A$  is called positive definite if  $x^T A x > 0$  for all nonzero  $x \in \mathfrak{R}^n$ ;

A real matrix is Hermitian *iff* (if and only if) it is symmetric ( $A^T = A$ );

The determinant of a positive definite matrix is positive;

A square matrix  $A$  has an inverse *iff* the determinant  $|A| \neq 0$ ;

Taking these into account, we can make the statement that if  $A$  is a positive definite symmetric matrix then the matrix inverse,  $A^{-1}$ , exists.