

Univ.-Prof. Dr. rer. nat. Rudolf Mathar

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Written Examination

Fundamentals of Big Data Analytics

Tuesday, March 21, 2017, 01:00 p.m.

Name: _____ Matr.-No.: _____

Field of study: _____

Please pay attention to the following:

- 1) The exam consists of **4 problems**. Please check the completeness of your copy. **Only** written solutions on these sheets will be considered. Removing the staples is **not** allowed.
- 2) The exam is passed with at least **50 points**.
- 3) You are free in choosing the order of working on the problems. Your solution shall clearly show the approach and intermediate arguments.
- 4) **Admitted materials:** The sheets handed out with the exam and a non-programmable calculator.
- 5) The results will be published on Friday evening, the 24.03.17, on the homepage of the institute.

The corrected exams can be inspected on Monday, 27.03.17, 14:00h. at the seminar room 333 of the Chair for Theoretical Information Technology, Kopernikusstr. 16.

Acknowledged: _____

(Signature)

Problem 1. (25 points)

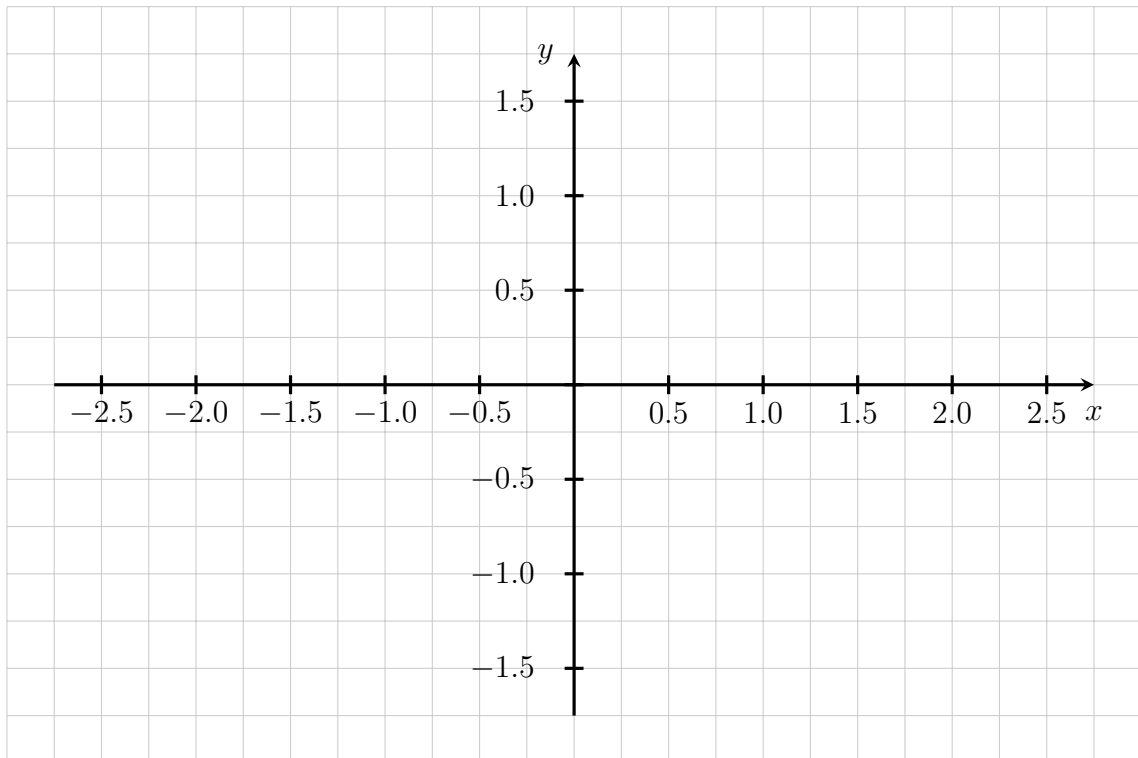
Analysis of Multivariate Densities and Maximum Likelihood Estimation:

Let $f_{\mathbf{Z}}(x, y)$ be the joint density of the random vector $\mathbf{Z} = (X, Y)^T$. It is given by

$$f_{\mathbf{Z}}(x, y) = \begin{cases} c, & 0 \leq y \leq a \quad \text{and} \quad y \leq x \leq y + a, \\ 0, & \text{otherwise} \end{cases}$$

for a proper number c with the parameter $a > 0$.

- a) Sketch the support (topview) of the density $f_{\mathbf{Z}}(x, y)$ for $a = 1$ and mark important points. (2P)



- b) What is the value of c as a function of a such that $f_{\mathbf{Z}}(x, y)$ is a proper density function. (2P)
- c) Calculate the missing value $\mu_X = E(X)$ of the mean vector

$$E(\mathbf{Z}) = \begin{pmatrix} \mu_X \\ \frac{1}{2} \end{pmatrix}$$

for $a = 1$. (3P)

- d) Compute the missing values of the covariance matrix

$$\Sigma_{\mathbf{Z}} = \begin{pmatrix} \frac{1}{6} & \sigma_{1,2} \\ \sigma_{2,1} & \sigma_{2,2} \end{pmatrix}$$

of the density $f_{\mathbf{Z}}$ for $a = 1$ by calculating the variance $\sigma_{2,2}$ of Y and the co-variances $\sigma_{1,2}$ and $\sigma_{2,1}$. (3+2+1P)

- e) Determine the marginal densities for X and Y for $a = 1$. (2+2P)

- f) Are X and Y independent random variables? Please justify the reason behind your answer. (1P)
- g) Calculate the mean vector $E(\mathbf{Z})$ and the covariance matrix $\text{Cov}(\mathbf{Z})$ for the general case $a > 0$. (1+1P)
- h) Assuming n IID random vectors $\mathbf{Z}_1, \mathbf{Z}_2, \dots, \mathbf{Z}_n$ with densities $f_{\mathbf{Z}_i}(x_i, y_i) = f_{\mathbf{Z}}(x_i, y_i)$, calculate the likelihood function $L(a, \mathbf{Z}_1, \mathbf{Z}_2, \dots, \mathbf{Z}_n)$. (1P)
- i) Show that the log-likelihood function $\ell(a, \mathbf{Z}_1, \mathbf{Z}_2, \dots, \mathbf{Z}_n) = \log(L(a, \mathbf{Z}_1, \mathbf{Z}_2, \dots, \mathbf{Z}_n))$ is strictly monotonic in a . (2P)
- j) Why is the quantity $\hat{a} = \max_{1 \leq i \leq n} \{y_i, x_i - y_i\}$ the maximum likelihood estimator for the parameter a ? (2P)

Problem 2. (25 points)

Principal Component Analysis:

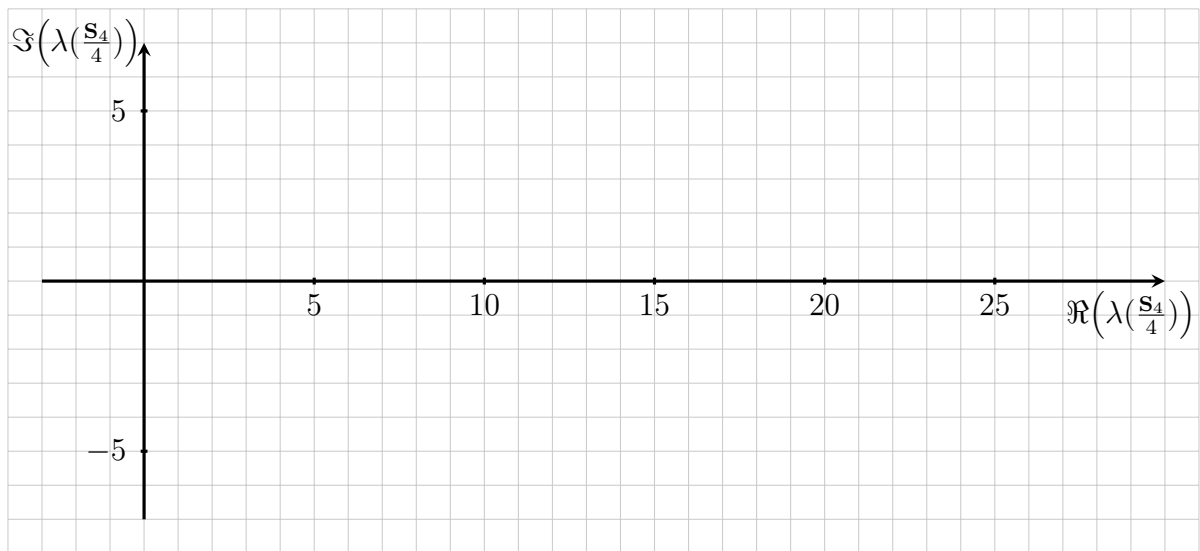
Part I

Assume four independent two-dimensional samples:

$$\mathbf{x}_1 = \sqrt{3} \begin{pmatrix} 4 \\ 4 \end{pmatrix}, \quad \mathbf{x}_2 = \sqrt{3} \begin{pmatrix} 4 \\ -4 \end{pmatrix}, \quad \mathbf{x}_3 = \sqrt{3} \begin{pmatrix} 0 \\ 8 \end{pmatrix}, \quad \mathbf{x}_4 = \sqrt{3} \begin{pmatrix} 0 \\ -4 \end{pmatrix}.$$

We suggest to keep the symbolic value $\sqrt{3}$ within your calculations without any conversion to a low-precision number!

- a) Calculate the sample mean $\bar{\mathbf{x}}_4$. (2P)
- b) Calculate the sample covariance matrix \mathbf{S}_4 . (4P)
- c) Determine the Gerschgorin's circles of the normalized matrix $\frac{1}{4}\mathbf{S}_4$ and sketch them on the complex domain. (4+2P)



- d) Is the matrix \mathbf{S}_4 positive definite, negative definite, or indefinite? Give a reason for your statement. (1P)

Part II

- e) Now we independently take n samples in total such that the corresponding sample covariance matrix \mathbf{S}_n is given by

$$\mathbf{S}_n = \begin{pmatrix} 14 & -14 \\ -14 & 110 \end{pmatrix}.$$

Calculate the spectral decomposition $\mathbf{V}\mathbf{\Lambda}\mathbf{V}^T$ of \mathbf{S}_n by determining the matrices \mathbf{V} and $\mathbf{\Lambda}$. (3+5P)

- f) Determine the best projection matrix \mathbf{Q} to transform the two-dimensional samples to a one-dimensional data and calculate the projection of \mathbf{x}_1 . (2+1P)
- g) Determine the residuum $\frac{1}{n-1} \max_{\mathbf{Q}} \sum_{i=1}^n \|\mathbf{Q}\mathbf{x}_i - \mathbf{Q}\bar{\mathbf{x}}_n\|^2$ for the above choice of \mathbf{Q} . (1P)

Problem 3. (25 points)**Discriminant Analysis:**

A training dataset consists of three-dimensional vectors belonging to three classes denoted by the labels $y_i \in \{1, 2, 3\}$. This dataset is given below.

Data	Label	Data	Label	Data	Label
$\mathbf{x}_1 = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$	$y_1 = 1$	$\mathbf{x}_4 = \begin{pmatrix} 1 \\ -1 \\ -1 \end{pmatrix}$	$y_4 = 2$	$\mathbf{x}_7 = \begin{pmatrix} -1 \\ 1 \\ 1 \end{pmatrix}$	$y_7 = 3$
$\mathbf{x}_2 = \begin{pmatrix} 1 \\ 2 \\ 0 \end{pmatrix}$	$y_2 = 1$	$\mathbf{x}_5 = \begin{pmatrix} 0 \\ -2 \\ -1 \end{pmatrix}$	$y_5 = 2$	$\mathbf{x}_8 = \begin{pmatrix} -1 \\ 0 \\ 2 \end{pmatrix}$	$y_8 = 3$
$\mathbf{x}_3 = \begin{pmatrix} 1 \\ 1 \\ -1 \end{pmatrix}$	$y_3 = 1$	$\mathbf{x}_6 = \begin{pmatrix} -1 \\ -1 \\ -1 \end{pmatrix}$	$y_6 = 2$	$\mathbf{x}_9 = \begin{pmatrix} -1 \\ -1 \\ 1 \end{pmatrix}$	$y_9 = 3$

Consider only those vectors \mathbf{x}_i in the dataset with labels $y_i = 1$ and $y_i = 2$.

- a) Find the matrix \mathbf{W} , that is the matrix corresponding to the sum of squares within groups. (5P)
- b) Find Fisher's linear discriminant rule for classification of vectors with labels $y_i = 1$ and $y_i = 2$. Explain each step. (3P)

Hint: For a matrix $\mathbf{A} = \begin{pmatrix} \alpha_1 \mathbf{x}^T \\ \alpha_2 \mathbf{x}^T \\ \alpha_3 \mathbf{x}^T \end{pmatrix} \in \mathbb{R}^{3 \times 3}$ and any $\mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \in \mathbb{R}^3$, the eigenvalues and its dominant eigenvector are given by $(0, 0, \text{tr}(\mathbf{A}))$ and $\begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{pmatrix}$, respectively.

Suppose that the vectors \mathbf{x}_i with label y_i are randomly drawn from a multivariate normal distribution with the covariance matrix Σ_i and the expected value $\boldsymbol{\mu}_i$ for $i = 1, 2, 3$.

- c) Find the maximum likelihood estimation of the expected values. (4P)
- d) If $\Sigma_1 = \Sigma_2 = \Sigma_3 = \Sigma$, find the maximum likelihood estimation of the covariance matrix $\hat{\Sigma}$ by using the whole dataset (5P).

Consider only those vectors \mathbf{x}_i in the dataset with labels $y_i = 2$ and $y_i = 3$.

- e) Find the maximum likelihood estimation of the covariance matrix, $\hat{\Sigma}$. (3P)
- f) Find the Gaussian maximum likelihood discriminant rule for classification of vectors with labels $y_i = 2$ and $y_i = 3$. Explain each step. (5P)

Problem 4. (25 points)

Support Vector Machines:

- a) Suppose that a training dataset is composed of vectors $\mathbf{x}_i \in \mathbb{R}^3$ belonging to two classes. The class membership is indicated by the labels $y_i \in \{-1, +1\}$. Suppose that the dataset is separable. A Support vector machine is used to find the maximum-margin hyperplane $\mathbf{a}^T \mathbf{x} + b = 0$. The primal optimization problem gives the optimal \mathbf{a}^* as $(1 \ 3 \ 0)^T$. Two support vectors with different labels are given as :

$$\mathbf{x}_1^T = (1 \ -1 \ 1), \quad \mathbf{x}_2^T = (-1 \ -1 \ -1)$$

Find the optimal value b^* . (3P)

Consider another training dataset that is non-separable. The following dual problem is solved for a support vector machine

$$\begin{aligned} \max_{\lambda} \quad & \sum_{i=1}^6 \lambda_i - \frac{1}{2} \sum_{i,j} y_i y_j \lambda_i \lambda_j \mathbf{x}_i^T \mathbf{x}_j \\ \text{s.t.} \quad & 0 \leq \lambda_i \leq 5 \quad \text{and} \quad \sum_{i=1}^6 \lambda_i y_i = 0. \end{aligned}$$

The dataset with the outputs of the optimization problem are given in the following table.

Data	Label	Solution	Data	Label	Solution
$\mathbf{x}_1 = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$	$y_1 = -1$	$\lambda_1^* = 0$	$\mathbf{x}_4 = \begin{pmatrix} 0.5 \\ -0.5 \end{pmatrix}$	$y_4 = 1$	$\lambda_4^* = 4.73$
$\mathbf{x}_2 = \begin{pmatrix} 2 \\ 0 \end{pmatrix}$	$y_2 = -1$	$\lambda_2^* = 0.67$	$\mathbf{x}_5 = \begin{pmatrix} -2 \\ 1 \end{pmatrix}$	$y_5 = 1$	$\lambda_5^* = 0.94$
$\mathbf{x}_3 = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$	$y_3 = -1$	$\lambda_3^* = 5$	$\mathbf{x}_6 = \begin{pmatrix} 0 \\ -1 \end{pmatrix}$	$y_6 = 1$	$\lambda_6^* = 0$

- b) Determine the support vectors. (4P)
- c) Find the maximum-margin hyperplane by finding \mathbf{a}^* and b^* . (6P)
- d) Suppose that a kernel is given by $K(\mathbf{x}, \mathbf{y}) = (2\mathbf{x}^T \mathbf{y} + 1)^2$ for $\mathbf{x}, \mathbf{y} \in \mathbb{R}^p$. Determine the feature mapping function $\phi(\mathbf{x})$, i.e., the function $\phi : \mathbb{R}^p \rightarrow \mathbb{R}^d$ where $K(\mathbf{x}, \mathbf{y}) = \phi(\mathbf{x})^T \phi(\mathbf{y})$. Determine the dimension of the feature space. (6P)

Consider a training dataset that is separable and consists of vectors $\mathbf{x}_i \in \mathbb{R}^p$ with labels $y_i \in \{-1, +1\}$.

- e) Write down the optimization problem for the kernel-based support vector machine using the kernel $K(\mathbf{x}, \mathbf{y}) = \exp(-\gamma \|\mathbf{x} - \mathbf{y}\|^2)$. (3P)
- f) Write down the kernel-based support vector machine classifier for this dataset. (3P)

Additional sheet

Problem:

Additional sheet

Problem:

Additional sheet

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Problem: