# MTSC 852 - Pattern Recognition Introduction to Pattern Recognition Project Assignments Due date: Sep. 10, 2015

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September 4, 2015

Problem 1 (20 points). Pattern Recognition System

- 1. Describe an application of pattern recognition related to your research. What are the features? What is the decision to be made? Speculate on how one can solve the problem. Limit your answer to one page.
- 2. Similarly to above item, describe an application of pattern recognition you would be interested in pursuing for fun in your life outside of work.

Problem 2 (30 points). Probability

Show that the normal distribution  $N(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$  satisfies  $E[x] = \int_{-\infty}^{\infty} N(x|\mu, \sigma^2) x dx = \mu.$ 

Next, by differentiating both sides of  $\int_{-\infty}^{\infty} N(x|\mu, \sigma^2) dx = 1$  with respect to  $\sigma^2$  show that the Gaussian satisfies  $E[x^2] = \int_{-\infty}^{\infty} N(x|\mu, \sigma^2) x^2 dx = \mu^2 + \sigma^2$ . Finally show that  $var[x] = E[x^2] - E[x]^2 = \sigma^2$  holds true.

#### Problem 3 (20 points). Diagnostic Test

After your yearly checkup, the doctor has bad news and good news. The bad news is that you tested position for a serious disease, and that the test is 99% accurate. This means that the probability of testing positive given that you have the disease is 0.99, as it is the probability of testing negative given that you do not have the disease. The good news is that this is a rare disease, striking only one in 10,000 people. Why is it good news that the disease is rare? What are the chances that you actually have the disease?

#### Programming Assignment 1 (30 points). Covariance Matrix

Let  $\Sigma_x = \begin{pmatrix} 64 & -25 \\ -25 & 64 \end{pmatrix}$ .

- 1. Verify that  $\Sigma_x$  is a valid covariance matrix.
- 2. Find the eigenvalues and eigenvectors of  $\Sigma_x$  by hand. Show all your work.
- 3. Write a program to find and verify the eigenvalues and eigenvectors of  $\Sigma_x$ .
- 4. We provide 200 data points sampled from distribution  $N(0, \Sigma_x)$ . Download the accompanying dataset (PR\_01\_Project.dat) from blackboard and plot the data points. Project the data on the covariance matrix eigenvectors and plot the transformed data. What is the difference between the two plots?

# MTSC 852 - Pattern Recognition Bayesian Decision Theory Project Assignments Due date: Sep. 22, 2015

Sokratis Makrogiannis, Ph.D.

September 16, 2015

**Problem 1** (20 points). Normal Distribution Calculate the entropy of a multidimensional Gaussian  $p(\mathbf{x}) = N(\mu, \Sigma)$ .

Problem 2 (20 points). Discriminant Functions for Normal Density

Suppose we have two normal distributions with the same covariances but different means:  $N(\mu_1, \Sigma)$ ,  $N(\mu_2, \Sigma)$ . In terms of their prior probabilities  $P(\omega_1)$  and  $P(\omega_2)$  state the condition that the Bayes decision boundary not pass between the two means (hint: show that  $\mathbf{w}^T(\mu_1 - \mathbf{x}_0)$  and  $\mathbf{w}^T(\mu_2 - \mathbf{x}_0)$ have the same sign).

**Programming Assignment 1** (30 points). Normal distribution and discriminant functions

- 1. Write a procedure to generate random samples according to a normal distribution  $N(\mu, \Sigma)$  in d dimensions.
- 2. Write a procedure to calculate the log discriminant function for a given multi-variate Gaussian distribution and prior probability.

- 3. Write a procedure to calculate the Euclidean distance between two arbitrary points.
- 4. Write a procedure to calculate the Mahalanobis distance between the mean  $\mu$  and an arbitrary point **x**, given the covariance matrix  $\Sigma$ .

Apply the above procedures to at least 3 datasets that you will generate in the first step.

Programming Assignment 2 (30 points). Central Limit Theorem

Illustrate the fact that the average of a large number of independent random variables will approximate a Gaussian by the following:

- 1. Write a program to generate n random integers from a uniform distribution  $U(x_l, x_u)$ .
- 2. Write a routine to choose  $x_l$  and  $x_u$  randomly, in the range  $-100 \le x_l < x_u \le 100$  and the number of samples n randomly in the range  $0 < n \le 1000$ .
- 3. Generate and plot a histogram of the accumulation of  $10^4$  points sampled as just described.
- 4. Calculate the mean and standard deviation of your histogram, and plot it.
- 5. Repeat the above for  $10^5$  and  $10^6$  points. Discuss your results.

# MTSC 852 - Pattern Recognition Parameter Estimation Techniques Project Assignments Due date: Oct. 20, 2015

Sokratis Makrogiannis, Ph.D.

October 13, 2015

**Problem 1** (20 points). Problems caused by dimensionality

Here we want to simplify a two-category classifier using shrinkage. Assume two distributions  $N(\mu_1, \Sigma_1), N(\mu_2, \Sigma_2)$ . Show that one must normalize the data to unit variance in order to be able to shrink an assumed common covariance matrix to identity matrix by applying  $\Sigma(\beta) = (1 - \beta)\Sigma + \beta \mathbf{I}$ , where  $0 < \beta < 1$ .

**Problem 2** (30 points). Fisher Linear Discriminant

Let  $p_{\boldsymbol{x}}(\boldsymbol{x}|\omega_i)$  be arbitrary densities with means  $\boldsymbol{\mu}_i$  and covariance matrices  $\Sigma_i$  -not necessarily normal- for i = 1, 2. Let  $\boldsymbol{y} = \boldsymbol{w}^T \boldsymbol{x}$  be a projection, and let the induced one-dimensional densities  $p(\boldsymbol{y}|\omega_i)$  have means  $\mu_i$  and covariances  $\sigma_i^2$ .

- 1. Show that the criterion function  $J_1(\boldsymbol{w}) = \frac{|\boldsymbol{\mu}_1 \boldsymbol{\mu}_2|^2}{\sigma_1^2 + \sigma_2^2}$  is maximized by  $\boldsymbol{w} = (\Sigma_1 + \Sigma_2)^{-1} (\boldsymbol{\mu}_1 \boldsymbol{\mu}_2).$
- 2. If  $P(\omega_i)$  is the prior probability for  $\omega_i$ , show that  $J_2(\boldsymbol{w}) = \frac{|\mu_1 \mu_2|^2}{P(\omega_1)\sigma_1^2 + P(\omega_2)\sigma_2^2}$ is maximized by  $\boldsymbol{w} = [P(\omega_1)\Sigma_1 + P(\omega_2)\Sigma_2]^{-1}(\boldsymbol{\mu_1} - \boldsymbol{\mu_2}).$

3. Which of these two functions is more closely related to the classic Fisher linear discriminant criterion function  $J(\boldsymbol{w}) = \frac{|m_{y1}-m_{y2}|^2}{s_{y1}^2+s_{y2}^2}$ ? Please explain.

**Programming Assignment 1** (50 points). Classification using shrinkage of covariance matrix

Consider the classification of Gaussian data using shrinkage of covariance matrices.

1. Generate 20 training points from each of three equally probable threedimensional Gaussian distributions  $N(\mu_i, Sigma_i)$  with the following parameters

$$\boldsymbol{\mu}_{1} = (0, 0, 0)^{T}, \quad \Sigma_{1} = diag [3, 5, 2]$$
$$\boldsymbol{\mu}_{2} = (1, 5, -3)^{T}, \quad \Sigma_{2} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 4 & 1 \\ 0 & 1 & 6 \end{pmatrix}$$
$$\boldsymbol{\mu}_{3} = (0, 0, 0)^{T}, \quad \Sigma_{3} = 10\mathbf{I}.$$

- 2. Write a program to estimate the means and covariances of the data.
- 3. Write a program that takes  $\alpha$  and shrinks these estimated covariance matrices according to  $\Sigma_i(\alpha) = \frac{(1-\alpha)n_i\Sigma_i + \alpha n\Sigma}{(1-\alpha)n_i + \alpha n}$ , where  $0 < \alpha < 1$  is the regularizing parameter,  $n_i$  is the number of samples for each class, n is the total number of samples, i = 1, ..., c and c is the number of classes.
- 4. Plot the training error as a function of  $\alpha$ , where  $0 < \alpha < 1$ .
- 5. Use your program from part 1 to generate 50 test points from each category. Plot the test error as a function of  $\alpha$ .

# MTSC 852 - Pattern Recognition Nonparametric Estimation Techniques Project Assignments Due date: November 12, 2015

Sokratis Makrogiannis, Ph.D.

November 5, 2015

#### **Problem 1** (30 points). Properties of Metrics

Prove that the Minkowski metric indeed possesses the four properties required of all metrics.

#### Programming Assignment 1 (35 points). Density estimation

Explore some of the properties of density estimation in the following way.

- 1. Write a program to generate points according to a uniform distribution in a unit cube,  $-1/2 \le x_i \le 1/2$  for i = 1, 2, 3. Generate 104 such points.
- 2. Write a program to estimate the density at the origin based on your 104 points as a function of the size of a cubical window function of size h. Plot your estimate as a function of h, for  $0 < h \le 1$ .
- 3. Evaluate the density at the origin using n of your points and the volume of a cube window which just encloses n points. Plot your estimate as a function of n = 1, ..., 104.
- 4. Write a program to generate 104 points from a spherical Gaussian density centered on the origin. Repeat (2) & (3) with your Gaussian data.

	ω1			$\omega_2$			$\omega_3$		
sample	$x_1$	$x_2$	$x_3$	$x_1$	$x_2$	$x_3$	$x_1$	$x_2$	$x_3$
1	0.28	1.31	-6.2	0.011	1.03	-0.21	1.36	2.17	0.14
2	0.07	0.58	-0.78	1.27	1.28	0.08	1.41	1.45	-0.38
3	1.54	2.01	-1.63	0.13	3.12	0.16	1.22	0.99	0.69
4	-0.44	1.18	-4.32	-0.21	1.23	-0.11	2.46	2.19	1.31
5	-0.81	0.21	5.73	-2.18	1.39	-0.19	0.68	0.79	0.87
6	1.52	3.16	2.77	0.34	1.96	-0.16	2.51	3.22	1.35
7	2.20	2.42	-0.19	-1.38	0.94	0.45	0.60	2.44	0.92
8	0.91	1.94	6.21	-0.12	0.82	0.17	0.64	0.13	0.97
9	0.65	1.93	4.38	-1.44	2.31	0.14	0.85	0.58	0.99
10	-0.26	0.82	-0.96	0.26	1.94	0.08	0.66	0.51	0.88

5. Discuss any qualitative differences between the functional dependencies of your estimation results for the uniform and Gaussian densities.

Table 1: Three-dimensional data sampled from three categories.

**Programming Assignment 2** (35 points). Consider k-nearest-neighbor density estimations in different numbers of dimensions

- 1. Write a program to find the k-nearest-neighbor density for n (unordered) points in one dimension. Use your program to plot such a density estimate for the  $x_1$  values in category  $\omega_3$  in the table above (and in file "ch4\_dhs\_samples.dat") for k = 1, 3 and 5.
- 2. Write a program to find the k-nearest-neighbor density estimate for n points in two dimensions. Use your program to plot such a density estimate for the  $(x_1, x_2)^T$  values in  $\omega_2$  for k = 1, 3 and 5.
- 3. Write a program to form a k-nearest-neighbor classifier for the threedimensional data from the three categories in the table above. Use your program with k = 1, 3, 5 to estimate the relative densities at the following points:  $(-0.41, 0.82, 0.88)^T$ ,  $(0.14, 0.72, 4.1)^T$  and  $(-0.81, 0.61, -0.38)^T$ .

# MTSC 852 - Pattern Recognition Linear Discriminant Functions Project Assignments Due date: November 30, 2015

Sokratis Makrogiannis, Ph.D.

November 23, 2015

**Problem 1** (30 points). Linear discriminant function properties

Consider a linear machine with discriminant functions  $g_i(\boldsymbol{x}) = \boldsymbol{w}^T \boldsymbol{x} + w_{i0}, 1, \ldots, c$ . Show that the decision regions are convex by showing that if  $\boldsymbol{x}_1 \in \mathcal{R}_i$  and  $\boldsymbol{x}_2 \in \mathcal{R}_i$ , then  $\lambda \boldsymbol{x}_1 + (1 - \lambda) \boldsymbol{x}_2 \in \mathcal{R}_i$  for  $0 \leq \lambda \leq 1$ .

Problem 2 (30 points). Gradient descent

Derive the equation  $n(k) = \frac{\|\nabla J\|}{\nabla J^T H \nabla J^T}$ , where J(.) depends on iteration step k for the gradient descent algorithm.

Programming Assignment 1 (40 points). Batch perceptron

Write a program to implement the batch Perceptron algorithm.

- 1. Starting with a = 0, apply your program to the training data from  $\omega_1$  and  $\omega_2$ . Note the number of iterations required for convergence.
- 2. Apply your program to  $\omega_3$  and  $\omega_2$ . Again note the number of iterations required for convergence.
- 3. Explain the difference between the iterations required in the two cases.

	$\omega_1$		$\omega_2$		$\omega_3$		$\omega_4$	
sample	$x_1$	$x_2$	$x_1$	$x_2$	$x_1$	$x_2$	$x_1$	$x_2$
1	0.1	1.1	7.1	4.2	-3.0	-2.9	-2.0	-8.4
2	6.8	7.1	-1.4	-4.3	0.5	8.7	-8.9	0.2
3	-3.5	-4.1	4.5	0.0	2.9	2.1	-4.2	-7.7
4	2.0	2.7	6.3	1.6	-0.1	5.2	-8.5	-3.2
5	4.1	2.8	4.2	1.9	-4.0	2.2	-6.7	-4.0
6	3.1	5.0	1.4	-3.2	-1.3	3.7	-0.5	-9.2
7	-0.8	-1.3	2.4	-4.0	-3.4	6.2	-5.3	-6.7
8	0.9	1.2	2.5	-6.1	-4.1	3.4	-8.7	-6.4
9	5.0	6.4	8.4	3.7	-5.1	1.6	-7.1	-9.7
10	3.9	4.0	4.1	-2.2	1.9	5.1	-8.0	-6.3

Table 1: Two-dimensional data sampled from three categories.