

Statistics 640
Spring, 2009

Data Mining and Statistical Learning

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Tu/Th 2:30-3:50 Keck Hall - 101
Office Hours: MW 1:30-2:30 or by appt.

First Assignment: Due in class January 13, 2009

Download the useful visualization software called *ggobi* from the web (find it) and install it on your PC or unix box. Also install the R language if you have not done so already. Grab the *zipcode data* from the course web site

www.stat.rice.edu/~scottdw/stat640/zip.code/

Each line of this file contains a single number between 0 and 9 followed by a vector of length 256 which contains a 16 by 16 grayscale image of a handwritten digit of that number. Choose any two digits, and extract all of the examples in the data file. Use the *ggobi* software to “visualize” these 256-dimensional vectors. In particular, try to determine if the data clouds for your 2 numbers “separate” in the high-dimensional space.

You may discuss your work (and collaborate) with others in the class, but turn in a short separate report of your findings. (Make sure you have a working version of *ggobi* of your own. There are interfaces between *ggobi* and R available as well.)

Multivariate Random Variable Background–For Class

1. vector random variable \mathbf{X} $p \times 1$

$$\mu = E \mathbf{X} = \begin{pmatrix} E X_1 \\ \vdots \\ E X_p \end{pmatrix}$$

$$\begin{aligned} \Sigma = \text{Cov}(\mathbf{X}) &= \begin{pmatrix} E[(X_i - \mu_i)(X_j - \mu_j)] \end{pmatrix} \\ &= E [(\mathbf{X} - \mu)(\mathbf{X} - \mu)^T] \quad (\text{outer product}) \end{aligned}$$

$$2. \mathbf{Y} = A\mathbf{X} + \mathbf{b} \quad q \times 1 \quad A \text{ is } q \times p$$

$$E\mathbf{Y} = A E\mathbf{X} + \mathbf{b} = A\mu_X + \mathbf{b}$$

$$\begin{aligned} \text{Cov}(\mathbf{Y}) &= E(\mathbf{Y} - \mu_Y)(\mathbf{Y} - \mu_Y)^T & \mathbf{Y} - \mu_Y &= A\mathbf{X} + \mathbf{b} - (A\mu_X + \mathbf{b}) \\ &= E[A(\mathbf{X} - \mu_X)(\mathbf{X} - \mu_X)^T A^T] \\ &= A\Sigma_X A^T & q \times q & \text{ by linearity} \end{aligned}$$

$$3. MN(\mu, \Sigma) \quad f(\mathbf{x}) = |2\pi\Sigma|^{-1/2} \exp\left(-\frac{1}{2}(\mathbf{x} - \mu)^T \Sigma^{-1}(\mathbf{x} - \mu)\right) \quad \text{or } (2\pi)^{-p/2} |\Sigma|^{-1/2}$$

$$4. \text{Spectral decomposition} \quad \Sigma \mathbf{e}_i = \lambda_i \mathbf{e}_i \quad \mathbf{e}_i \perp \mathbf{e}_j \iff \mathbf{e}_i^T \mathbf{e}_j = \delta_{ij}$$

$$\begin{aligned} \text{Note:} \quad \mathbf{a}^T \Sigma \mathbf{a} &= E[\mathbf{a}^T (\mathbf{X} - \mu)(\mathbf{X} - \mu)^T \mathbf{a}] = E[\mathbf{a}^T (\mathbf{X} - \mu)]^2 \geq 0 \\ \text{therefore } \mathbf{e}_i^T \Sigma \mathbf{e}_i &= \lambda_i \geq 0 \text{ and } \Sigma \text{ is p.s.d.} \quad (\text{pos def} \iff \lambda_i > 0) \end{aligned}$$

$$\text{Matrix form:} \quad \Sigma \mathbf{E} = \mathbf{E} \Lambda \quad \text{or} \quad \Sigma = \mathbf{E} \Lambda \mathbf{E}^T \quad \text{where } \mathbf{E} = [\mathbf{e}_1 \mathbf{e}_2 \dots \mathbf{e}_p]$$

$$5. \mathbf{X} \sim MN(\mu_X, \Sigma_X), \quad \mathbf{Y} = A\mathbf{X} + \mathbf{b} \sim MN(A\mu_X + \mathbf{b}, A\Sigma_X A^T)$$

$$6. \text{Assuming } \lambda_i > 0,$$

$$\begin{aligned} \Sigma &= \mathbf{E} \Lambda \mathbf{E}^t & \Sigma^{-1} &= \mathbf{E} \Lambda^{-1} \mathbf{E}^T \\ \Sigma^{1/2} &= \mathbf{E} \Lambda^{1/2} \mathbf{E}^t & \Sigma^{-1/2} &= \mathbf{E} \Lambda^{-1/2} \mathbf{E}^T \end{aligned}$$

$$7. \text{Sphering data}$$

$$\begin{aligned} Y = \Sigma_X^{-1/2} \mathbf{X} &\implies \Sigma_Y = \Sigma_X^{-1/2} \Sigma_X \Sigma_X^{-1/2} = I_p \\ \text{therefore } \mathbf{X} \sim MN(\mu_X, \Sigma_X) &\implies Y = \Sigma_X^{-1/2}(\mathbf{X} - \mu_X) \sim MN(\mathbf{0}, I_p) \end{aligned}$$

$$8. \text{Vector and matrix differentiation (for a symmetric matrix, } A)$$

$$\begin{aligned} g(\mathbf{x}) &= \mathbf{a}^T \mathbf{x} = \mathbf{x}^T \mathbf{a} & \nabla_x g(\mathbf{x}) &= \mathbf{a} \\ h(\mathbf{x}) &= \mathbf{x}^T A \mathbf{x} & \nabla_x h(\mathbf{x}) &= 2A\mathbf{x} \end{aligned}$$

Finally,

$$\nabla_x \nabla_x h(\mathbf{x}) = \nabla_x^2 h(\mathbf{x}) = 2A$$

which is sometimes written this way:

$$\nabla_x \nabla_x^T h(\mathbf{x}) = \nabla_x^2 h(\mathbf{x}) = 2A.$$

Reference: K.V. Mardia, J.T. Kent, and J.M. Bibby (1979). *Multivariate Analysis*, Academic Press, London.