Lecture 1

Introduction and Multivariate Data Exploration

Readings: Zelterman 2015 Chapter 1; Chapter 3

DSA 8070 Multivariate Analysis

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Agenda

- **1** Course Overview
- 2 Multivariate Data Exploration: Numerical Summary
- Multivariate Data Exploration: Graphical Summary



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Course Overview

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Introduction

 In many observational or experimental studies, measurements are collected simultaneously on more than one variable on each unit

 Multivariate analysis is the collection of statistical methods that can be used to (jointly) analyze these multiple measurements

⇒ some are extensions of familiar methods (t-test, ANOVA, Linear Regression, ...) while others are unique to multivariate analysis (PCA, CCA, Factor Analysis, ...)

To exploit potential "correlations" among the multiple measurements to improve inference



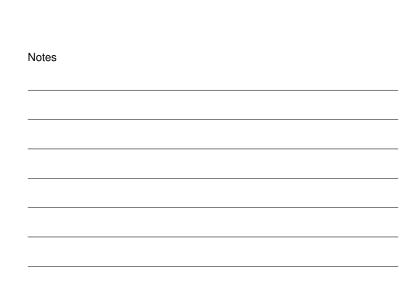
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Why Univariate Analysis Falls Short

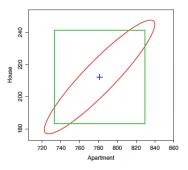
We've learned many tools for handling a single response variable (aka univariate analysis). Why bother with multivariate analysis?

- If variables are truly independent, analyzing each separately with histograms, box plots, or basic summary statistics is sufficient
- When variables influence each other, analyzing them in isolation misses important patterns and interactions
- Considering all variables together reveals connections that are invisible in separate analyses





Using Multivariate Methods Could Lead to Sharper Inference



Source: Fig. 1.1 of Zelterman 2015

Joint analysis captures relationships that improve accuracy!

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Dimensionality Reduction or Structural Simplification

 Goal: Reduce the "dimensionality" by representing many variables with a small number of (linear) combinations, without losing important information

• Example:

A single index of a patient's reaction to radiotherapy can be constructed from several related response measurements

This is dimensionality reduction because it replaces multiple variables with one composite measure, reducing the number of dimensions from many to one while still summarizing the essential information

Techniques:

- Principal Component Analysis (Week 8)
- Factor Analysis (Week 9)
- Multidimensional Scaling (Week 13)



Grouping or Classification

 Goal: Identify groups of "similar" units or classify units into previously defined groups.

Example:

Using the concentration of elements (copper, silver, tin, antimony) in bullet lead, the FBI can **identify** bullets from the same production batch

This is relevant because it groups items with similar characteristics from multiple measurements - the aim of grouping and classification

Techniques:

- Classification Analysis (Week 11)
- Cluster Analysis (Week 12)



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Dependence among Variables and Prediction

 Goal: Estimate relationships among variables and predict the value of some variables from others.

Example:

The association between test scores and several college performance variables can be used to predict a student's likelihood of success in college

This illustrates the goal because it models how variables are related and uses those relationships for prediction.

Techniques:

- Multivariate Regression (Weeks 5-6)
- Canonical Correlation Analysis (Week 10)

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Hypothesis Testing

 Goal: Test differences in mean vectors across groups and test hypotheses about covariance matrices.

• Examples:

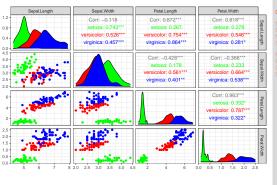
- Compare mean gasoline mileage, repair costs, and downtime for different truck models
- Check if the covariance structure of asset returns is the same before and after a market event

Techniques:

- \bullet Hotelling's T^2 and MANOVA (Week 4)
- Covariance Matrix Inference (Week 7)



Exploratory Data Analysis: A Powerful First Step in Multivariate Analysis [EDA, Tukey 1977]

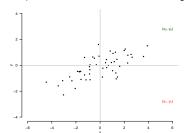


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Statistical Distance: A Core Concept in Multivariate Analysis

Multivariate methods rely on "distances" between data points: clustering (group units that are "close"); classification (allocate each unit to the "closest" group)



Question: which one $((x_0,y_0) \text{ or } (x_1,y_1))$ is closer the center of the observations? \Rightarrow We will learn **Mahalanobis distance** to formally answer this question

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Matrix Algebra (Week 2)

- Many operations performed on multivariate data are presented using vector/matrix notation, e.g., $X_{n \times p}$ (Data matrix); $\hat{\boldsymbol{\mu}}_{p\times 1}$ (estimated mean vector); $\hat{\boldsymbol{\Sigma}}_{p\times p}$ (estimated covaraince matrix)
- The computation of eigenvalues and eigenvectors (i.e., the spectral decomposition) plays an important role in multivariate analysis ⇒ reveals key directions and magnitudes of variation, forming the basis of many multivariate methods



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Multivariate Normal Distribution (Week 3)

• We will often assume that the joint distribution of $\boldsymbol{X} = (X_1, X_2, \dots, X_p)^{\mathrm{T}}$ follows a multivariate normal distribution with probability density function:

$$f(\boldsymbol{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{\frac{d}{2}} \det(\boldsymbol{\Sigma})^{\frac{1}{2}}} \exp\left[-\frac{1}{2}(\boldsymbol{x} - \boldsymbol{\mu})^{\mathrm{T}} \boldsymbol{\Sigma}^{-1} (\boldsymbol{x} - \boldsymbol{\mu})\right]$$

- The multivariate normal assumption is often useful:
 - Variables may be approximately multivariate normal, possibly after transformation.
 - By the Central Limit Theorem, many multivariate sample statistics have an approximately normal distribution, regardless of the population distribution.
 - We will also briefly cover copula models and nonparametric methods when the assumption is not appropriate.



Data Mining, Machine Learning, and Multivariate Analysis

- Data Mining is the process of extracting and discovering patterns (e.g., unexpected structures or relationships, trends, clusters, and outliers) in massive data sets
- Supervised learning and unsupervised learning are two most common problems in machine learning
- Data mining/machine learning applications usually involve many variables, often related in complex ways, hence techniques from multivariate analysis play an important role

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Multivariate Data Exploration: Numerical Summary



Organization of Data and Notation

- n: number of units; p: number of variables per unit \Rightarrow p=1 is univariate, p>1 is multivariate.
- x_{ik} : k-th measurement on unit i; unit i: $(x_{i1}, x_{i2}, \ldots, x_{ip})$. Measurements from n units can be arranged in matrix form:

$$X_{n \times p} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{bmatrix}$$

where rows correspond to units and columns to variables

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Descriptive Statistics: Sample Mean & Variance

 \bullet The sample mean of the k-th variable ($k=1,\cdots,p$) is computed as

$$\bar{x}_k = \frac{1}{n} \sum_{i=1}^n x_{ik}$$

• The sample variance of the *k*-th variable is usually computed as

$$s_k^2 = \frac{1}{n-1} \sum_{i=1}^n (x_{ik} - \bar{x}_k)^2$$

and the sample standard deviation is given by

$$s_k = \sqrt{s_k^2}$$

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Descriptive Statistics: Sample Covariance

ullet We often use s_{kk} to denote the sample variance for the k-th variable. Thus,

$$s_k^2 = \frac{1}{n-1} \sum_{i=1}^n (x_{ik} - \bar{x}_k)^2 = s_{kk}$$

ullet The sample covariance between variable k and variable j is computed as

$$s_{jk} = \frac{1}{n-1} \sum_{i=1}^{n} (x_{ij} - \bar{x}_j)(x_{ik} - \bar{x}_k)$$

ullet If variables k and j are independent, the population covariance is exactly zero, but the sample covariance will fluctuate around zero

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Descriptive Statistics: Sample Correlation

• The sample correlation between variables k and j is defined as

$$r_{jk} = \frac{s_{jk}}{\sqrt{s_{jj}}\sqrt{s_{kk}}}$$

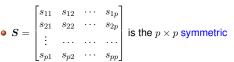
- ullet r_{jk} is symmetric $(r_{jk}=r_{kj})$ and lies between -1 and
- The sample correlation is equal to the sample covariance if measurements are standardized (i.e., $s_{kk} = s_{jj} = 1)$
- Covariance and correlation measure linear association. Other non-linear dependencies may exist among variables even if $r_{jk} = 0$
- ullet The sample correlation (r_{ij}) will vary about the value of the population correlation (ρ_{ij})



Matrix Representation of Sample Statistics

Sample statistics of a p-dimnesional multivariate data can be organized as vectors and matrices:

 $oldsymbol{ar{x}} = [ar{x}_1, ar{x}_2, \cdots, ar{x}_p]^{\mathrm{T}}$ is the p imes 1 vector of sample



matrix of variance (on the diagonal) and covariances (the off-diagonal elements)

$$\bullet \ \, \boldsymbol{R} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1p} \\ r_{21} & r_{22} & \cdots & r_{2p} \\ \vdots & \cdots & \cdots & \cdots \\ r_{p1} & r_{p2} & \cdots & r_{pp} \end{bmatrix} \text{ is the } p \times p \text{ symmetric}$$

matrix of sample correlations. Diagonal elements are all equal to 1

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Generalized Variance

- The generalized variance is a scalar value which generalizes variance for multivariate random variables
- \bullet The generalized variance is defined as the determinant of the (sample) covariance matrix $S, \det(S)$
- Example:

```
""{r}
data(mtcars)|
vars <- which(names(mtcars) %in% c("mpg", "disp", "hp", "drat", "wt"))
car <- mtcars[, vars]; S <- cov(car)
(genVar <- det(S))
""</pre>
[1] 3951786
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Multivariate Data Exploration: Graphical Summary



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Graphs and Visualization

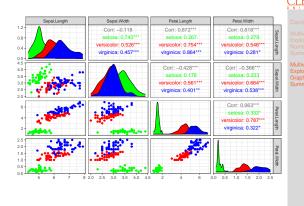
- Graphs reveal variable associations and unusual observations.
- $\begin{tabular}{ll} \bullet & \mbox{Visualizing multivariate data is challenging,} \\ \mbox{especially for } p>3. \end{tabular}$
- At minimum, use pairwise scatter plots.

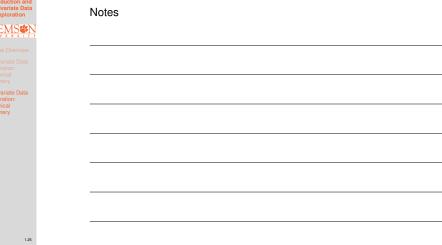
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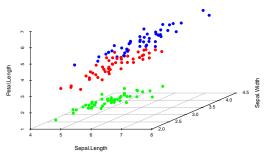
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Visualizing Data with *ggpairs*: Combining Scatterplots and Numerical Summaries





3D Scatter Plot

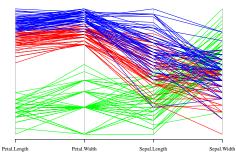




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Parallel Coordinate Plot

- Plots each observation across parallel axes (one per variable).
- Shows patterns, group differences, and outliers.
- Axis order and scaling affect interpretation.



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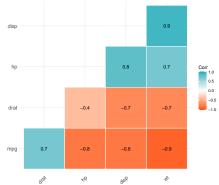
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> head(mtcars)

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Visualizing Summary Statistics



Visualize summary measures (e.g., correlation matrix) with color showing strength and direction of relationships

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Summary

In this lecture, we covered:

- A high-level overview of the course
- Summarizing multivariate data numerically
- Summarizing multivariate data graphically

In the next lecture, I will give a short review of Matrix Algebra

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