# STAT 8670 - Computational Methods in Statistics

Chi-Kuang Yeh

2025-07-06

# Table of contents

Pι	eface		4
	Desc	cription	4
		Prerequisites	4
		Instructor	4
	Offic	ce Hour	4
	Assi	gnment	4
	Mid	term	5
	Topi	ics and Corresponding Lectures	5
	Reco	ommended Textbooks	5
	Side	Readings	5
1	Dat	a Structure and R Programming	6
	1.1	Data type	6
		1.1.1 To change data type	7
	1.2	Operators	7
		1.2.1 Comparison Operator	7
		1.2.2 Logical Operator	8
	1.3	Indexing	8
	1.4	Naming	8
	1.5	Arrray and Matrix	8
	1.6	Key and Value Pair	8
	1.7	Data Frame	8
	1.8	Tidyverse	9
2	Opt	imization	10
	2.1		10
	2.2		11
	2.3		11
	2.4	<u> </u>	11
3	Res	ampling, Jackknife and Bootstrap	13
_	3.1	1 0	13
	3.1		13
	3.3		13
	$\frac{3.3}{3.4}$	Applications	13

References										
ı	Ар	pendix	15							
4	Appendix: Introduction to R?									
	4.1	$R \ldots \ldots \ldots \ldots \ldots \ldots \ldots$	16							
	4.2	IDE	16							
		4.2.1 Rstudio	16							
		4.2.2 Visual Studio Code (VS Code)	16							
		4.2.3 Positron	17							
	4.3	RStudio Layout	17							
	4.4	R Scripts	17							
	4.5	R Help	17							
	4.6	R Packages	17							
	4.7	R Markdown	18							
	4.8	Vectors	18							
	49	Data Sets	18							

**Preface** 

**Description** 

Topics included are optimization, numerical integration, bootstrapping, cross-validation and Jackknife, density estimation, smoothing, and use of the statistical computer package of S-

plus/R.

**Prerequisites** 

MATH 4752/6752 – Mathematical Statistics II, and the ability to program in a high-level

language.

Instructor

Chi-Kuang Yeh, I am a postdoctoral scholar at the Department of Statistics and Actuarial Science, McGill University.

• Office: 1216 Burnside Hall.

• Email: chi-kuang.yeh@mail.mcgill.ca.

Office Hour

[By appointment and a online link will be provided later]

**Assignment** 

 $\square$  Assignment 1: Date and topics TBA

4

# Midterm

 $\square$  Midterm 1: Date and topics TBA

# **Topics and Corresponding Lectures**

Those chapters are based on the lecture notes. This part will be updated frequently.

Topic	Lecture Covered
Optimization	TBA
Numerical integration	$\mathrm{TBA}$
Jackknife	$\mathrm{TBA}$
Bootstrap	$\mathrm{TBA}$
Cross-validation	$\mathrm{TBA}$
Smoothing	$\mathrm{TBA}$
Density estimation	TBA
Monte Carlo Methods	$\operatorname{TBA}$

# **Recommended Textbooks**

- Givens, G.H. and Hoeting, J.A. (2012). *Computational Statistics*. Wiley, New York.
- Rizzo, M.L. (2007) Statistical Computing with R. CRC Press, Roca Baton.
- Hothorn, T. and Everitt, B.S. (2006). A Handbook of Statistical Analyses Using R. CRC Press, Boca Raton.

# **Side Readings**

• Wickham, H., Çetinkaya-Rundel, M. and Grolemund, G. (2023). *R for Data Science*. O'Reilly.

# 1 Data Structure and R Programming

Data types, operators, variables

Two basic types of objects: (1) data & (2) functions

- Data: can be a number, a vector, a matrix, a dataframe, a list or other datatypes
- Function: a function is a set of instructions that takes input, processes it, and returns output. Functions can be built-in or user-defined.

# 1.1 Data type

- Boolean/Logical: Yes or No, Head or Tail, True or False
- Integers: Whole numbers  $\mathbb{Z}$ , e.g., 1, 2, 3, -1, -2, -3
- Characters: Text strings, e.g., "Hello", "World."
- Floats: Noninteger fractional numbers, e.g.,  $\pi$ , e.
- Missing data: NA in R, which stands for "Not Available." It is used to represent missing or undefined values in a dataset.

```
day <- c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday")
weather <- c("Raining", "Sunny", NA, "Windy", "Snowing")
data.frame(rbind(day, weather))</pre>
```

```
X1 X2 X3 X4 X5 day Monday Tuesday Wednesday Thursday Friday weather Raining Sunny <NA> Windy Snowing
```

• Other more complex types

# 1.1.1 To change data type

You may change the data type using the following functions, but the chance is that some of the information will be missing. Do this with caution!

```
x <- pi
print(x)</pre>
```

[1] 3.141593

```
x_int <- as.integer(x)
print(x_int)</pre>
```

[1] 3

Some of the conversion functions:

- as.integer(): Convert to integer.
- as.numeric(): Convert to numeric (float).
- as.character(): Convert to character.
- as.logical(): Convert to logical (boolean).
- as.Date(): Convert to date.
- as.factor(): Convert to factor (categorical variable).
- as.list(): Convert to list.
- as.matrix(): Convert to matrix.
- as.data.frame(): Convert to data frame.
- as.vector(): Convert to vector.
- as.complex(): Convert to complex number.

# 1.2 Operators

- Unary: With only **one** argument. E.g., -x (negation), !x (logical negation).
- Binary: With **two** arguments. E.g., x + y (addition), x y (subtraction), x \* y (multiplication), x / y (division).

### 1.2.1 Comparison Operator

Comparing two objects. E.g., x == y (equal), x != y (not equal), x < y (less than), x >= y (greater than), x <= y (less than or equal to), x >= y (greater than or equal to).

## 1.2.2 Logical Operator

Logical operators are used to combine or manipulate logical values (TRUE or FALSE). E.g., x & y (logical AND), x | y (logical OR), !x (logical NOT).

We shall note that the logical operators in R are vectorized,  $x \mid y$  and  $x \mid | y$  are different. The former is vectorized, while the latter is not.

```
x <- c(TRUE, FALSE, FALSE)
y <- c(TRUE, FALSE, FALSE)
x | y # [1] TRUE FALSE FALSE
x || y # This will return an error</pre>
```

# 1.3 Indexing

Indexing is a way to access or modify specific elements in a data structure. In  $\mathbf{R}$ , indexing can be done using square brackets [] for vectors and matrices, or the \$ operator for data frames. Note that the index starts from  $\mathbf{0}$  in  $\mathbf{R}$ , which is different from some other programming languages like Python.

# 1.4 Naming

# 1.5 Arrray and Matrix

# 1.6 Key and Value Pair

### 1.7 Data Frame

Dataframe is a two-dimensional, tabular data structure in R that can hold different types of variables (numeric, character, factor, etc.) in each column. It is similar to a spreadsheet or SQL table.

```
iris <- datasets::iris
head(iris)</pre>
```

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
1	5.1	3.5	1.4	0.2	setosa
2	4.9	3.0	1.4	0.2	setosa
3	4.7	3.2	1.3	0.2	setosa
4	4.6	3.1	1.5	0.2	setosa
5	5.0	3.6	1.4	0.2	setosa
6	5.4	3.9	1.7	0.4	setosa

# 1.8 Tidyverse

The tidyverse is a collection of open source packages for the R programming language introduced by Hadley Wickham and his team that "share an underlying design philosophy, grammar, and data structures" of tidy data. Characteristic features of tidyverse packages include extensive use of non-standard evaluation and encouraging piping.

```
## Load all tidyverse packages
library(tidyverse)

## Or load specific packages in the tidy family
library(dplyr) # Data manipulation
library(ggplot2) # Data visualization
library(readr) # Data import
library(tibble) # Tidy data frames
library(tidyr) # Data tidying
# ...
```

Some of the materials are adapted from CMU Stat36-350.

# 2 Optimization

The optimization plays an important role in statistical computing, especially in the context of maximum likelihood estimation (MLE) and other statistical inference methods. This chapter will cover various optimization techniques used in statistical computing.

For instance, for a linear regression

$$y = X\beta + \varepsilon$$
.

From regression class, we know that the (ordinary) least-squares estimation (OLE) for  $\beta$  is given by  $\hat{\beta} = (X^{\top}X)^{-1}X^{\top}y$ . It is convenient as the solution is in the **closed-form!** However, in the most case, the closed-form solutions will not be available.

For GLMs or non-linear regression, we need to do this **iterativelly**!

# 2.1 Speed comparison

```
set.seed(2017-07-13)
X <- matrix(rnorm(5000 * 100), 5000, 100)
y <- rnorm(5000)
library(microbenchmark)
microbenchmark(solve(t(X) %*% X) %*% t(X) %*% y)</pre>
```

Warning in microbenchmark(solve(t(X) %\*% X) %\*% t(X) %\*% y): less accurate nanosecond times to avoid potential integer overflows Unit: milliseconds

```
expr min lq mean median uq solve(t(X) %*% X) %*% t(X) %*% y 28.57097 29.23575 30.04752 29.87713 30.62448 max neval 32.21641 100
```

```
Unit: milliseconds

expr min lq mean median
solve(t(X) %*% X) %*% t(X) %*% y 28.39886 29.03231 29.73657 29.41512
solve(crossprod(X), crossprod(X, y)) 24.96937 25.01504 25.25663 25.05457

uq max neval
30.23379 32.94231 100
25.16457 28.50168 100
```

# 2.2 Type of Optimization Algorithms

There are in general two types of the optimization algorithms: (1). **deterministic** and (2). **metaheuristic**. Deterministic and metaheuristic algorithms represent two distinct paradigms in optimization. Deterministic methods, such as gradient descent, produce the same solution for a given input and follow a predictable path toward an optimum. In contrast, metaheuristic approaches—like genetic algorithms—incorporate randomness and do not guarantee the best possible solution. However, they are often more effective at avoiding local optima and exploring complex search spaces.

# 2.3 Heuristic Algorithms

Many of the heuristic algorithms are inspired by the nature, such as the genetic algorithm (GA) and particle swarm optimization (PSO). These algorithms are often used for complex optimization problems where traditional methods may struggle to find a solution. Some of the popular heuristic algorithms include:

- Genetic Algorithm (GA)
- Particle Swarm Optimization (PSO)
- Simulated Annealing (SA)
- Ant Colony Optimization (ACO)

# 2.4 Deterministic Algorithms

Numerical approximation, what you learned in the mathmeatical optimization course. Some of the algorithms include:

- Gradient Descent
- Newton's Method
- Conjugate Gradient Method
- Quasi-Newton Methods (e.g., BFGS)

• Interior Point Methods

They often reply on the KKT conditions.

Examples are borrowed from the following sources:

• Peng, R.D. Advanced Statistical Computing.

# 3 Resampling, Jackknife and Bootstrap

# 3.1 Introduction

This chapter covers resampling methods including the jackknife and bootstrap techniques.

# 3.2 Jackknife

The jackknife is a resampling technique used to estimate the bias and variance of a statistic.

# 3.3 Bootstrap

The bootstrap is a resampling method that allows estimation of the sampling distribution of almost any statistic using random sampling methods.

# 3.4 Applications

These methods are widely used in statistical inference and have applications in various fields.

# References

# Part I Appendix

# 4 Appendix: Introduction to R?

# 4.1 R

For conducting analyses with data sets of hundreds to thousands of observations, calculating by hand is not feasible and you will need a statistical software.  $\mathbf{R}$  is one of those.  $\mathbf{R}$  can also be thought of as a high-level programming language. In fact,  $\mathbf{R}$  is one of the top languages to be used by data analysts and data scientists. There are a lot of analysis packages in  $\mathbf{R}$  that are currently developed and maintained by researchers around the world to deal with different data problems. Most importantly,  $\mathbf{R}$  is free! In this section, we will learn how to use  $\mathbf{R}$  to conduct basic statistical analyses.

## **4.2 IDE**

### 4.2.1 Rstudio

RStudio is an integrated development environment (IDE) designed specifically for working with the **R** programming language. It provides a user-friendly interface that includes a source editor, console, environment pane, and tools for plotting, debugging, version control, and package management. RStudio supports both R and Python and is widely used for data analysis, statistical modeling, and reproducible research. It also integrates seamlessly with tools like R Markdown, Shiny, and Quarto, making it popular among data scientists, statisticians, and educators.

# 4.2.2 Visual Studio Code (VS Code)

VS Code is a versatile code editor that supports multiple programming languages, including R. With the R extension for VS Code, users can write and execute R code, access R's console, and utilize features like syntax highlighting, code completion, and debugging. While not as specialized as RStudio for R development, VS Code offers a lightweight alternative with extensive customization options and support for various programming tasks.

### 4.2.3 Positron

Positron IDE is the next-generation integrated development environment developed by Posit, the company behind RStudio. Designed to be a modern, extensible, and language-agnostic IDE, Positron builds on the strengths of RStudio while supporting a broader range of languages and workflows, including R, Python, and Quarto.

# 4.3 RStudio Layout

RStudio consists of several panes: - Source: Where you write scripts and markdown documents. - Console: Where you type and execute R commands. - Environment/History: Shows your variables and command history. - Files/Plots/Packages/Help/Viewer: For file management, viewing plots, managing packages, accessing help, and viewing web content.

# 4.4 R Scripts

R scripts are plain text files containing R code. You can create a new script in RStudio by clicking File > New File > R Script.

# 4.5 R Help

Use ?function\_name or help(function\_name) to access help for any R function. For example:

?mean
help(mean)

# 4.6 R Packages

Packages extend R's functionality. Install a package with:

install.packages("package\_name")

Load a package with:

```
library(package_name)
```

# 4.7 R Markdown

R Markdown allows you to combine text, code, and output in a single document. Create a new R Markdown file in RStudio via File > New File > R Markdown....

Recently, the posit team has developed a new version of the R Markdown called quarto document, with the file extension .qmd. It is still under rapid development.

# 4.8 Vectors

Vectors are the most basic data structure in R.

```
x <- c(1, 2, 3, 4, 5)
x
```

[1] 1 2 3 4 5

You can perform operations on vectors:

```
x * 2
```

[1] 2 4 6 8 10

### 4.9 Data Sets

Data frames are used for storing data tables. Create a data frame:

```
df <- data.frame(Name = c("Alice", "Bob"), Score = c(90, 85))
df</pre>
```

```
Name Score
1 Alice 90
2 Bob 85
```

You can import data from files using read.csv() or read.table().

This appendix is adapted from Why R?.